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Génération de résumés par abstraction

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Thèse acceptée le: . . . . . .

RÉSUMÉ

Cette thèse présente le résultat de plusieurs années de recherche dans le domaine de la génération automatique de résumés. Trois contributions majeures, présentées sous la forme d'articles publiés ou qui seront publiés prochainement, en forment le cœur. Elles retracent un cheminement qui part des méthodes par extraction en résumé jusqu'aux méthodes par abstraction.

L'expérience HexTac, sujet du premier article, a d'abord été menée pour évaluer le niveau de performance des êtres humains dans la rédaction de résumés par extraction de phrases. Les résultats montrent un écart important entre la performance humaine sous la contrainte d'extraire des phrases du texte source par rapport à la rédaction de résumés sans contrainte. Cette limite à la rédaction de résumés par extraction de phrases, observée empiriquement, démontre l'intérêt de développer d'autres approches automatiques pour le résumé.

Nous avons ensuite développé un premier système selon l'approche Fully Abstractive Summarization, qui se situe dans la catégorie des approches semi-extractives, comme la compression de phrases et la fusion de phrases. Le développement et l'évaluation du système, décrits dans le second article, ont permis de constater le grand défi de générer un résumé facile à lire sans faire de l'extraction de phrases. Dans cette approche, le niveau de compréhension du contenu du texte source demeure insuffisant pour guider le processus de sélection du contenu pour le résumé, comme dans les approches par extraction de phrases.

Enfin, l'approche par abstraction basée sur des connaissances nommée K-BABS est proposée dans un troisième article. Un repérage des éléments d'information pertinents est effectué, menant directement à la génération de phrases pour le résumé. Cette approche a été implémentée dans le système ABSUM, qui produit des résumés très courts mais riches en contenu. Ils ont été évalués selon les standards d'aujourd'hui et cette évaluation montre que des résumés hybrides formés à la fois de la sortie d'ABSUM et de phrases extraites ont un contenu informatif significativement plus élevé qu'un système provenant de l'état de l'art en extraction de phrases.

Mots clés : Résumés automatiques, Résumés par abstraction, Génération des langues naturelles, Traitement automatique des langues naturelles

ABSTRACT

This Ph.D. thesis is the result of several years of research on automatic text summarization. Three major contributions are presented in the form of published and yet to be published papers. They follow a path that moves away from extractive summarization and toward abstractive summarization.

The first article describes the HexTac experiment, which was conducted to evaluate the performance of humans summarizing text by extracting sentences. Results show a wide gap of performance between human summaries written by sentence extraction and those written without restriction. This empirical performance ceiling to sentence extraction demonstrates the need for new approaches to text summarization.

We then developed and implemented a system, which is the subject of the second article, using the Fully Abstractive Summarization approach. Though the name suggests otherwise, this approach is better categorized as semi-extractive, along with sentence compression and sentence fusion. Building and evaluating this system brought to light the great challenge associated with generating easily readable summaries without extracting sentences. In this approach, text understanding is not deep enough to provide help in the content selection process, as is the case in extractive summarization.

As the third contribution, a knowledge-based approach to abstractive summarization called K-BABS was proposed. Relevant content is identified by pattern matching on an analysis of the source text, and rules are applied to directly generate sentences for the summary. This approach is implemented in a system called ABSUM, which generates very short and content-rich summaries. An evaluation was performed according to today's standards. The evaluation shows that hybrid summaries generated by adding extracted sentences to ABSUM's output have significantly more content than a state-of-the-art extractive summarizer.

Mots clés Automatic Summarization, Abstractive Summarization, Natural Language Generation, Natural Language Processing

TABLE DES MATIÈRES

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CHAPITRE 1

INTRODUCTION

Dans notre monde surchargé en information, le grand besoin d'outils pour en faciliter l'accès n'est plus à démontrer. Un utilisateur désirant accéder à un certain contenu fait face à deux problèmes : la recherche de documents pertinents, et la recherche de l'information pertinente à l'intérieur des documents trouvés. De nombreux outils pour la recherche de documents sont maintenant disponibles ; la popularité des engins de recherche de documents sur Internet tel Google est d'ailleurs sans équivoque. Pour ce qui est de faciliter la recherche des informations pertinentes, peu d'outils sont disponibles et utilisés à grande échelle. La génération automatique de résumés est une solution envisageable pour améliorer l'efficacité de la consultation des documents.

Cette thèse présente le résultat de plusieurs années de recherche dans le domaine de la génération automatique de résumés. Trois contributions majeures, présentées sous la forme d'articles publiés ou qui le seront prochainement, en forment le cœur. Ce chapitre définit le problème et le contexte de recherche, tout en introduisant les articles qui seront reproduits.

1.1 Définition du problème

Nous voulons produire automatiquement un court résumé informatif à partir de plusieurs documents textuels portant sur un même sujet d'actualité.

Un résumé permet d'accéder rapidement aux éléments d'information importants dans des documents. Ce travail s'intéresse en particulier aux résumés de type informatif, c'est-à-dire ceux qui proposent une condensation du contenu d'un texte sans l'altérer et en ne gardant que l'essentiel. L'alternative serait de rédiger plutôt un résumé indicatif, qui propose de décrire les différentes sections du documents sans en donner les résultats.

Bien qu'il soit possible de produire des résumés pour des documents non-textuels ou multi-média, la tâche reste difficile, même en nous limitant à des documents textuels.

Le genre de texte à résumer joue également un grand rôle sur le type de résumé qui sera produit. Nous avons décidé de poursuivre dans la voie la plus fréquemment empruntée dans ces dernières années et nous nous sommes attardé aux résumés portant sur des textes de nouvelles provenant d'agences de presse, afin de pouvoir comparer notre approche à celles des autres chercheurs dans le domaine. Au cours de la dernière décennie, des campagnes d'évaluations annuelles de systèmes automatiques de génération de résumés ont eu lieu dans le cadre des conférences internationales Document Understanding Conference[1] (DUC), de 2001 à 2007, et Text Analysis Conference[2] (TAC), de 2008

[1] `http://duc.nist.gov/`

[2] `www.nist.gov/tac`

à 2011. Ces campagnes d'évaluation ont notamment rendu disponibles des corpus de nouvelles journalistiques et de résumés de celles-ci, sur lesquels il est possible de tester les systèmes et de les comparer.

Dans ce contexte, le résumé multi-documents est devenu la tâche la plus populaire, pour laquelle un résumé doit effectuer une condensation du contenu de plusieurs sources. Il s'agit d'agglomérer des informations et découvrir les éléments sur lesquels les sources sont en accord (les désaccords entre sources peuvent aussi être relevés dans le résumé).

Il est facile aujourd'hui d'obtenir en ligne un ensemble d'articles à propos d'un sujet d'actualité. Pour mieux répondre au besoin d'information du lecteur, il serait d'autant plus intéressant de lui proposer un résumé plus court que n'importe lequel de ces articles, et qui contiendrait l'essentiel des faits relatifs à l'événement d'intérêt. C'est justement le problème de recherche que nous traitons dans cette thèse.

1.2 Contexte de notre recherche

Les travaux de recherche présentés dans cette thèse sont le fruit d'une longue réflexion sur les méthodes de génération automatique de résumés. Cette réflexion a débuté dans le cadre de travaux de maîtrise [2], qui ont porté sur le problème des résumés multi-documents d'articles de journaux et mené au développement du News Symbolic Summarizer (NESS). Les résumés étaient générés à partir d'un groupe de 10 articles de journaux et d'une requête de l'utilisateur qui servait à orienter le résumé. Un deuxième résumé devait aussi être généré sur un deuxième groupe de 10 articles de journaux, en évitant de répéter toute information contenue dans le premier groupe de 10 articles.

L'approche utilisé dans NESS génère des résumés en extrayant des phrases provenant des articles à résumer. Elle se démarquait d'autres approches similaires par son côté symbolique, utilisant un parseur syntaxique et une base de donnée lexicale pour recueillir des connaissances linguistiques riches pour guider la sélection de phrases. Un score de pertinence pour chaque phrase de chacun des articles était calculé à partir de critères pondérés, certains critères étaient standards pour cette tâche, alors que d'autres étaient nouveaux. Les critères standards utilisés étaient la similarité entre les mots de la phrase et la requête, calculée à l'aide d'un poids TF$*$IDF, la position de la phrase dans le texte et le poids informationnel de la phrase, donné par la somme des poids IDF de tous les mots de la phrase. Les critères innovateurs étaient d'utiliser la profondeur d'arbre pour pondérer quels mots sont les plus représentatifs de la phrase et de faire appel à la base lexicale WordNet [13] pour inclure des synonymes dans le calcul de similarité.

NESS a été soumis à la campagne d'évaluation de résumés automatiques de TAC 2008. Deux versions du système ont été soumises pour la tâche de résumés orientés multi-documents, une avec tous les critères pondérés, l'autre sans les critères considérés nouveaux. Or, la version du système qui n'utilisait pas les outils linguistiques plus riches comme un parseur et WordNet a obtenu les meilleurs résultats. De fait, cette version du système a été meilleure non seulement que la version avec tous les critères, mais égale-

ment la meilleure soumission d'un système (autant au niveau de la qualité linguistique que du score global) de toute la campagne d'évaluation, qui comptait 57 soumissions. Cette soumission avait pourtant été considérée simplement comme une version de base (baseline) durant le développement de NESS.

1.2.1 Remise en question de l'approche par extraction de phrases

Les excellents résultats de la version dépouillée de NESS lors de TAC 2008 étaient surprenants. Il n'y avait à toute fin pratique aucune innovation dans cette version, si ce n'est l'effort considérable qui avait été consacré à pondérer les critères de sélection de phrases. Des approches déployant des modèles plus complexes ou utilisant des ressources nouvelles n'obtenaient pas de meilleurs résultats. Ceci était inquiétant pour l'avancement de la recherche en résumés automatiques. Jusqu'où pouvait-on aller avec des approches par extraction de phrases ?

C'est justement la question à laquelle a voulu répondre l'expérience Human Extraction for the Text Analysis Conference [10] (HexTac), sujet du chapitre 2 de la thèse. Lors des campagnes d'évaluation ouvertes à tous et dans la littérature en général, ce sont des résumés rédigés par des humains qui servent de base à la comparaison et aux évaluations automatiques. Ces modèles sont toujours composés sans contraintes et, bien qu'ils relèvent adéquatement l'écart qui existe entre les performances humaines et celles des machines, ils ne permettent pas de déterminer le degré de performance des systèmes sur la tâche spécifique d'extraction de phrases pour rédiger un résumé. HexTac proposait donc de comparer les systèmes automatiques avec des modèles de l'extraction de phrases écrits par des humains.

En collaboration avec les organisateurs de la compétition, mais à l'insu de la majorité des participants, un ensemble de résumés composés manuellement par extraction a été créé. HexTac a fait appel à cinq résumeurs pour rédiger les 88 résumés de la participation à la campagne d'évaluation de TAC 2009. Ces résumés d'une longueur de 100 mots ou moins ont été composés uniquement à partir de phrases contenues intégralement dans les documents à résumer et aucune modification des phrases n'a été faite.

Les résultats de cette expérience ont essentiellement mené à deux conclusions. Premièrement, l'écart de performance entre les résumés automatiques et les résumés produits manuellement par extraction est faible. Il reste donc peu de chemin à faire pour améliorer la performance des systèmes par extraction pure. Deuxièmement, l'écart de performance entre les résumés rédigés manuellement par extraction et ceux rédigés manuellement sans restrictions est très important. En d'autres mots, pour les résumés très courts, même si des être humains sélectionnent les phrases du résumé, les approches par extraction de phrases ne donnent pas des résultats satisfaisants. Pour se rapprocher des performances humaines, il faudra considérer d'autres catégories d'approches.

Nous profitons de cette section pour apporter quelques précisions sur l'article publié. À la section 3.3, la métrique d'évaluation ROUGE a été utilisée pour vérifier si HexTac pourrait adéquatement servir de modèles à la place des résumés de références rédigés

manuellement sans contrainte. ROUGE compare les n-grammes (ici des bigrammes ont été utilisés, puisqu'il s'agit du standard) des résumés générés automatiquement aux n-grammes de résumés modèles. La métrique proposée, HexTac-ROUGE, utilise comme modèles les résumés de HexTac plutôt que les résumés de référence. Les mêmes paramètres, i.e. ceux qui sont utilisés par les organisateurs de TAC 2009, ont été utilisés pour faire tourner ROUGE dans tous les cas. On note que HexTac-ROUGE est bien corrélé avec l'évaluation manuelle (les corrélations dans le tableau 4 sont des corrélations de Pearson), mais toutefois très nettement moins que le ROUGE standard, soit le ROUGE qui utilise les résumés de référence comme modèle.

Dans le but de continuer à participer annuellement à TAC, un nouveau système de rédaction de résumés par extraction nommé NESS2 [9] a également été produit pour TAC 2009. NESS2 se voulait relativement simple, étant donné que les resources linguistiques plus riches ne semblaient pas apporter une contribution positive aux résumés. Il cherchait à vérifier l'hypothèse selon laquelle un résumé par extraction gagnait à effectuer deux passes pour la sélection des phrases, l'une servant à donner un score de pertinence à chaque phrase, la seconde à sélectionner quel sous-ensemble de phrases ayant un score élevé formerait le meilleur résumé, avec le moins de redondance possible. Cette hypothèse fut vérifiée avec succès, et NESS2 a obtenu le 4^{e} meilleur score global et le 4^{e} meilleur score de qualité linguistique sur les 52 soumissions envoyées cette année-là. Encore une fois, un système par extraction relativement simple obtenait un score parmi les meilleurs. Ceci contribuait à confirmer les conclusions de HexTac : il y a sans doute peu à gagner à continuer d'optimiser les systèmes par extractions de phrases.

1.2.2 Résumer par division de phrases

On sépare habituellement les approches à la génération automatique de résumés de texte en deux classes : les résumés par extraction et les résumés par abstraction [12]. L'extraction consiste à former un résumé en retirant et réorganisant des groupes lexicaux (mots, propositions, phrases, paragraphes) de la source. À l'opposé, l'abstraction est une reformulation de la source qui peut inclure des entités textuelles n'apparaissant pas dans la source.

Bien que la plupart des systèmes automatiques produisent des résumés par extraction (de phrases), les conclusions de HexTac ne laissent pourtant pas de doute sur la voie à suivre pour progresser : il faudra se concentrer sur les approches par abstraction, ou à tout le moins sur les approches faisant nettement plus que simplement de l'extraction. Des approches qu'on pourrait considérer comme semi-extractives ont été proposées, comme la compression de phrases et la fusion de phrases.

Des travaux [5] effectués en 2010-2011 dans le cadre de cette thèse ont mené à une nouvelle approche semi-extractive pour la rédaction automatique de résumés, appelée Fully Abstractive Summarization, décrite au chapitre 3. L'élément central de celle-ci se trouve dans le concept de Information Item (InIt), qui est défini comme étant le plus petit élément d'information cohérent dans un texte ou dans une phrase. L'objectif est de

trouver ces InIts dans le texte source, de sélectionner ceux qui permettraient de répondre au besoin d'information de l'utilisateur, puis de générer un résumé contenant les InIts les plus pertinents.

Dans cette première tentative de générer des résumés par abstraction, un raccourci est utilisé pour simplifier la découverte et la manipulation des InIts. Les InIts sont représentés par des triplets sujet-verbe-complément d'objet direct. Une phrase courte au style télégraphique est générée pour chaque InIt avant que la sélection ne soit effectuée. Puis, le résumé est assemblé à partir de ces phrases générées en s'appuyant sur les méthodes habituellement employées dans l'extraction de phrases. Ceci s'apparente à d'autres méthodes comme la compression de phrases et la fusion de phrases, tout en offrant l'avantage d'avoir accès à des phrases très courtes lorsque vient le temps de les assembler pour le résumé.

Un système implémentant cette approche fut soumis aux campagnes d'évaluation de TAC 2010 [4] et TAC 2011 [6]. Les résultats montrent que l'approche n'est pas encore mature et qu'il reste beaucoup à faire au niveau de la génération de phrases syntaxiquement et sémantiquement correctes. Il était très probable, en effet, que ce système montre une faiblesse relative au niveau de la qualité linguistique par rapport aux autres approches automatiques, qui ont habituellement l'avantage d'extraire des phrases existantes telles quelles. Au niveau du contenu du résumé, le système ne performe pas mal, au point où le score global obtenu est particulièment élevé compte tenu de la faible qualité linguistique. Il n'en demeure pas moins que ce système n'est pas compétitif lorsque comparé aux meilleurs extracteurs de phrases.

En somme, cette initiative a permis d'observer à nouveau les failles inhérentes aux approches par abstraction qui n'effectuent que des manipulations syntaxiques. Ce système peut être décrit de façon plus directe comme effectuant de la division de phrases en plus courtes phrases ne contenant qu'une idée, ces phrases étant utilisées pour la rédaction du résumé, ce qui est similaire à réduire la taille de la phrase pour le résumé (compression de phrases).

Tout en réfléchissant aux façons qui pourraient être utilisées pour insérer de l'analyse sémantique ou de la compréhension du texte dans le système de résumé, un bref travail sur l'évaluation de résumés à l'aide de méthodes modernes d'apprentissage machine [3] a été effectué, menant à des résultats intéressants. La méthode standard pour l'évaluation automatique de résumés, ROUGE [11], obtient un très bon taux de corrélation avec les métriques manuelles, lorsque l'échantillon de résumés de chaque approche à comparer est élevé, mais un taux beaucoup plus faible lorsqu'on observe ses prédictions sur de petits échantillons. Le système d'évaluation automatique utilisant le Deep Learning a été développé et testé, ce qui a permis d'observer qu'il performe mieux que ROUGE sur les prédictions de performance de systèmes à comparer, lorsque de petits échantillons sont utilisés.

1.2.3 L'approche K-BABS et le système ABSUM

Les difficultés observées lors du développement de l'approche par division de phrases ont permis de constater que l'analyse syntaxique des phrases n'était pas suffisante pour obtenir le genre d'analyse en profondeur du contenu des documents à résumer nécessaire pour une approche réellement non-extractive. En tentant de produire à la main de bons résumés à partir des InIts trouvés dans l'approche par division des phrases, nous avons remarqué que quelques connaissances propres au domaine et à la tâche suffisaient pour guider adéquatement la découverte d'informations, sa sélection et la génération du résumé. Des travaux préliminaires [7] ont permis d'établir la faisabilité d'une approche où de telles connaissances sont mises à contribution.

Cette réflexion nous a permis de développer l'approche **K**nowledge**-B**ased **Ab**stractive **S**ummarization (K-BABS) [8] pour la génération automatique de résumés par abstraction, décrite au chapitre 4 qui inclut également une revue de littérature complète des approches par abstraction. L'architecture de K-BABS repose sur une analyse des documents sources et sur un plan, appelé Task Blueprint, qui décrit des transformations de la représentation du texte résultant de l'analyse vers du texte généré pour le résumé. Ces transformations encodent implicitement des connaissances à propos de la tâche à accomplir et du domaine ou du sujet des documents à résumer.

Le système **Ab**stractive **S**ummarizer of **U**niversité de **M**ontréal (ABSUM) a été réalisé pour la tâche de résumés guidés de TAC 2011, en suivant la théorie K-BABS. Deux task blueprints ont été contruits manuellement pour répondre à deux grandes catégories de sujets d'actualité. ABSUM génère de très courts résumés faciles à lire. Évalués sur le corpus de TAC 2011, les résumés générés par une combinaison de ABSUM et d'un système faisant partie de l'état de l'art en extraction de phrases contiennent plus d'informations pertinentes que tout autre système ayant participé à la campagne d'évaluation. Ces résumés sont significativement plus informatifs que si ABSUM n'était pas utilisé. De plus, les résumés produits par ABSUM ont une meilleure qualité linguistique et une densité de contenu presque deux fois supérieure aux autres systèmes automatiques.

En somme, l'utilisation d'ABSUM dans un contexte hybride représente l'état de l'art de la génération automatique de résumés textuels. L'approche K-BABS, qui sous-tend ABSUM, est d'ailleurs la contribution principale de cette thèse.

CHAPITRE 2

HEXTAC : GÉNÉRATION MANUELLE DE RÉSUMÉS PAR EXTRACTION

Pierre-Etienne Genest, Guy Lapalme et Mehdi Yousfi-Monod. HexTac : the Creation of a Manual Extractive Run. Dans *Proceedings of the Second Text Analysis Conference*, Gaithersburg, Maryland, USA, 2009. National Institute of Standards and Technology.

Cet article a été publié dans le cadre d'une participation spéciale à la conférence Text Analysis Conference 2009. Les résumés construits à l'aide de HexTac ont été utilisés comme nouvelle référence (baseline 3) par les organisateurs de la conférence, à l'insu des autres participants, pour évaluer la performance espérée des approches de génération de résumés par extraction de phrases.

HEXTAC: the Creation of a Manual Extractive Run

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Abstract

This article presents an attempt to establish an upper bound on purely extractive summarization techniques. Altogether, five human summarizers composed 88 standard and update summaries of the TAC 2009 competition. Only entire sentences of the source documents were selected by the human "extractors", without modification, to form 100-word summaries. These summaries obtained better scores than any automatic summarization system in both linguistic quality and overall responsiveness, while still doing worse than any human abstractive summarizer.

1 Introduction

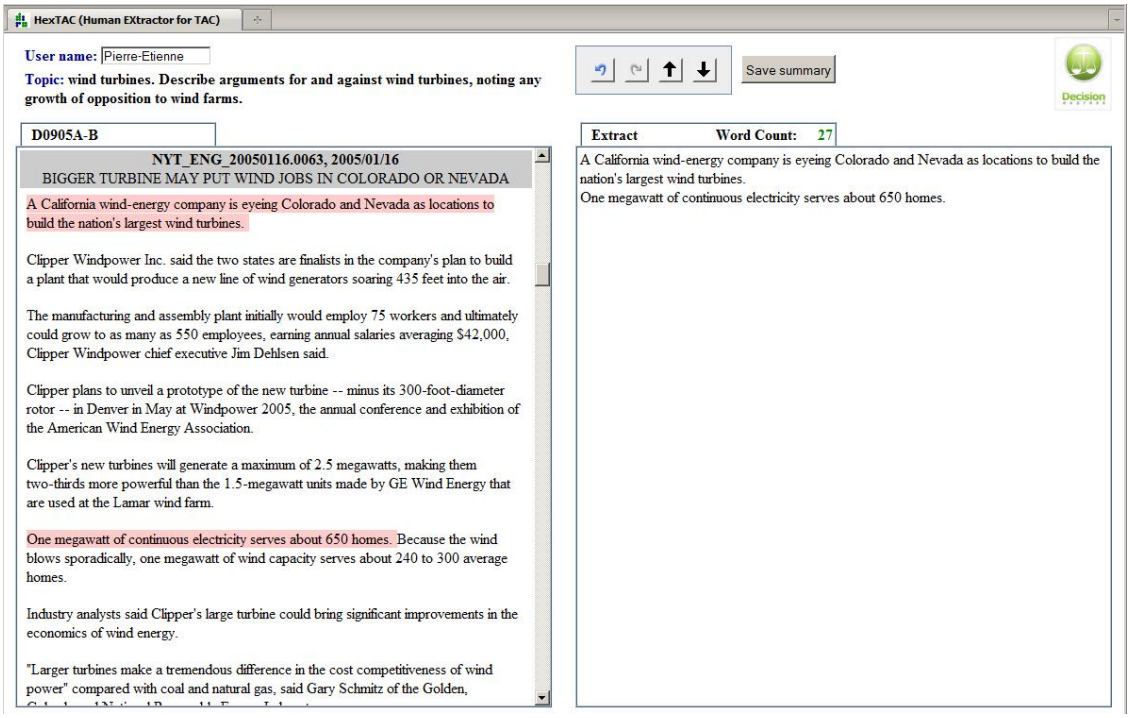
Year after year, notably at the Document Understanding Conference (DUC) and later the Text Analysis Conference (TAC), the best-performing summarization systems have been sentence extraction-based rather than abstractions of the source documents. However, in those conferences and in the literature, human-written model summaries are used for comparison and automatic evaluation. The model summaries are abstractive rather than extractive summaries. While these *gold standards* show how far computers are from achieving what humans can, it does not address the more restrictive – but probably no less interesting – question of how well one can solve the simpler problem of extracting sentences from documents for summarization. Some researchers in the summarization community even seem to consider this problem of extracting important sentences from groups of documents as *solved*!

We were also motivated in further studying extractive methods because in some areas, namely in the judicial domain, extraction is a method of choice because summary sentences can be safely used as jurisprudence without worrying that the original might have been *interpreted* by the human abstracter.

With the support of Hoa Trang Dang and members of the TAC steering committee, our team created an extractive manual run for this year's Update Summarization task, called *Human EXtraction for TAC* (HEXTAC), which appeared in the 2009 competition as baseline number 3.

This experiment was designed with the goal of quantifying how well humans could perform at extraction and comparing the results with automatic summarizers. HEXTAC is thus an attempt to establish an upper bound on purely extractive summarization techniques. Five human extractors composed the 88 standard and update summaries for the TAC 2009 competition. Only entire unedited sentences in the source documents were selected, to create summaries of 100 words or less. In practice, this meant selecting about three to five sentences out of the 232 (on average) in each cluster, a tedious and finally quite harder task that we had originally anticipated. We are glad that we have developed computer systems for that!

The methodology and context of the experimentation are described in section 2. Section 3 presents the results and discusses them. We conclude with lessons that we learned during this exercise.



1. Pick one of your assigned topic to work on. Always begin with part A, the standard summary.
2. Read the topic and all 10 of the articles in full (to know all of the information and to have read each sentence at least once). All of the information in part A must be well remembered to avoid any repetition of information in part B.
3. Extract sentences that answer the topic and best summarize the source documents. Select preferentially sentences that can be understood on their own (avoid problems of referential clarity).
4. Refine your sentence selection to bring the summary under the limit of 100 words, while maximizing the information content.
5. Re-order the sentences of the extract to improve readability and save your work.
6. Make sure to complete the update summary – part B – immediately after writing the standard summary. Follow the same steps as for part A, with the added criterion that extracted sentences must avoid repetition of information included in part A articles.

Figure 1: Screen shot of the HEXTAC interface for human extractors and the guidelines given to the human extractors. The left part of the screen contains the texts of all documents from a cluster from which only full sentences can be selected and dragged into the right part to build the summary. The total number of words is updated as each sentence is added to the summary. Sentences added to the summary can be removed and or reordered using drag and drop. Undo and redo of extraction operations are possible.

2 Methodology and Context

2.1 Interactive Human Extraction Interface

In order to simplify the handling and creation of extractive summaries, we developed a browser-based interface. It enables the users to build a summary step by step in a convenient environment. The summarizers can access the data, check which ones they should work on, save their summaries, and consult or modify them later. In the background, the system logs the access times and other peripheral data.

The extractive summaries are created on a single, user-friendly page, shown at the top of figure 1. From the top down and left to right, it contains a user name box, a topic description, the articles and their meta-data (ID, date of publication and title), the editing tools, the save button, and the extractive summary area.

All articles of a given cluster are shown one after the other. The text of the articles has been previously segmented into sentences although the original paragraph structure of the articles is kept. When the user hovers over a part of the text, the sentence covered by the mouse pointer is highlighted and its number of words is shown. The total number of words in the summary should this sentence be added is also temporarily updated. This sentence can then be double-clicked to be put into the summary area. The selected sentences are building blocks for the summary. They can be later removed or re-arranged in any order desired, but they can never be modified by the user in any way (the text areas of the browsers are *read-only*). No summary of more than 100 words can be accepted by the system as a valid submission, though they can still be saved temporarily. The whole system works equally well with drag-and-drop and with double-clicking and using buttons. Undo and redo buttons are also included for convenience.

This interface is an adaptation of a summary revision interface that we have developed in a project dealing with judgements in cooperation with NLP Technologies[1] (Farzindar and Lapalme, 2004) (Chieze et al., 2008).

[1] http://www.nlptechnologies.ca

2.2 Experimental Context

There were 44 topics to answer in the TAC 2009 competition, with a standard and an update part for each – 88 total summaries. The human extraction task was divided unevenly between five computer scientists, all specialized in NLP with experience in automatic summarization, including the three authors, who volunteered to do this manual work. They all used the interactive interface, while following the specific guidelines shown at the bottom of Figure 1. The summaries were all composed within about a week and submitted five days after the deadline for the automatic runs. As our laboratory was also submitting automatic runs (IDs 10 and 8) developed by the first author, he only started working on the manual process once our automatic runs had been submitted.

Table 1 shows how many summaries were written by each human extractor (HE) and the average time in minutes it took him to complete one summary (Part A or B). A total of 30 man-hour were required to complete the 88 summaries.

Summarizer ID	# summaries	Avg. time (min)
HE1	18	17
HE2	18	16
HE3	12	27
HE4	24	24
HE5	16	17
Average	18	20

Table 1: Number of summaries out of the 88 composed by each human extractor and the average time in minutes it took them.

2.3 Feedback from Participants

Following the experiment, we met with the human extractors who participated in the HEXTAC experiment to receive feedback on their experience.

The foremost opinion was that the interactive interface made everything a lot easier. According to the feedback, this tool saved a lot time and even helped in organizing thoughts. Using text editors and copy-paste would have made this task an even greater chore than it already was to some.

The extractors felt some frustration because of the inability to make even the smallest of textual modi-

fications to the sentences. Cutting down one or two words in one sentence would, in some cases, have permitted them to fit their preferred choice of sentences into the summary. Also, some sentences had great content but could not be included because of an unresolved personal pronoun anaphora or relative time reference, which would be easy for a human – and in some cases for a machine as well – to resolve.

The topic queries also caused some headaches, because they often times asked for a broad description or a list of several related events/opinions/etc., whereas the articles would only offer sentences with one piece of information at a time. Choosing which sentences to extract became a huge difficulty in those circumstances and, in general, subjective choices of what content to prioritize in the very limited space has been a big issue. At times, the tradeoff between quality of content and linguistic quality was also difficult to deal with.

Most extractors complained about the time commitment and the repetitiveness of the task. It was reported that doing several summaries in a row might decrease the level of attention to details of the extractors. On the other hand, many felt that the more extracts they completed, the easier the task became.

3 Results and Discussion

3.1 TAC 2009 Scores

HEXTAC is considered a baseline in TAC 2009, and it has run ID 3. Table 2 shows the scores of pyramid, linguistic quality and overall responsiveness for HEXTAC, the best score obtained by an automatic system, and the average of human abstractors.

Part A	Pyramid	Ling. Qual.	Ov. Resp.
Abstracts	0.683	8.915	8.830
HEXTAC	0.352	7.477	6.341
Best Auto	0.383	5.932	5.159
Part B			
Abstracts	0.606	8.807	8.506
HEXTAC	0.324	7.250	6.114
Best Auto	0.307	5.886	5.023

Table 2: Scores for HEXTAC when compared to the best automatic systems and the humans abstracts for parts A and B.

The overall responsiveness score is significantly higher for HEXTAC than for any automatic summarizer. This might come to a surprise to some, since we used pure extraction whereas the best systems often use sentence compression and/or reformulation. This superiority probably comes from the much higher linguistic quality of HEXTAC summaries, while the pyramid scores were on par with the best systems of the competition.

The human extracts still receive far lower scores than abstracts in all evaluation metrics, as expected. The difference in performance is easily understandable given the severe limitations that pure extraction puts on our summarizers. In particular, the amount of content that can be included in an extract is much less than in an abstract, as shown by the pyramid scores. The difference in linguistic quality probably arises because of some sentences with unresolved references that were still included by extractors, and mostly because pure extraction does not grant the flexibility required to create text that flows as nicely as abstracts can. We notice that the difference in linguistic quality between extracts and abstracts is much less noticeable than the difference in pyramid scores, thus hinting that good language quality can still be achieved without even any modification to the sentences.

We believe that these evaluation results can be interpreted as a soft upper-bound on what can theoretically be done by purely extractive methods. "Soft" because the extractors were not as competent as professional summarizers probably would have been and we have strong reasons to believe better extracts than those submitted exist. The known tradeoff between content and linguistic quality could play a role here, for example. The variations in the performance of the different extractors and the low inter-extractor agreement are other indicators that better extracts could likely be written. Nevertheless, the gap between the manual extracts and abstracts is so large that we can safely claim – now with numerical results to show for – that the performance of pure extraction summarization will never come close to what can be achieved by abstraction.

On the other hand, the results show that even using pure extracts, there is still significant improvements that can be made to improve the quality of the summaries we create automatically. It seems

that perhaps a lot of progress could still be made in aspects that increase linguistic quality like sentence ordering and avoiding redundancy, unresolved references, bad grammar in reformulated sentences, etc.

3.2 Inter-Extractor Agreement

We computed the inter-extractor agreement on a small sample of 16 summaries that have been written twice. On average, each extract has 0.58 sentence in common with one written by an other extractor, on an average of 3.88 sentences per summary. This gives roughly a 15% chance that a sentence selected by one extractor is also selected by another one working on the same topic. We consider this level of agreement to be very low, although it can be expected because of the redundancy in the source documents of a multi-document summarization corpus. Indeed, we have observed that some sentences were even repeated verbatim in more than one article of the same cluster, not to mention all the sentences which were nearly identical and had the same information content.

The scores obtained individually by each human extractor, on average, were very different for each one and in each metric, as can be seen in Table 3.

	Pyramid	Ling. Qual.	Overall Resp.
HE1	0.278	8.222	7.556
HE2	0.297	7.611	5.333
HE3	0.340	7.000	5.917
HE4	0.378	7.583	7.125
HE5	0.392	6.063	4.125

Table 3: Average scores for each human extractor.

The small sample size can partly explain the high variance of the scores between human extractors. Some summaries were harder to complete than others, because of the topic or the available sentences. Also, the extractors have had different types of experiences with summarization, they possessed different levels of knowledge on the topics given to them, and a different level of proficiency in English, which was not the native language of any of them.

3.3 HEXTAC as a ROUGE model

As part of our experiment, we ran the automatic summarization evaluation engine ROUGE on all the runs except for the baselines and human extracts, using HEXTAC as the model – we call this HEXTAC-ROUGE. We wanted to see how this evaluation would compare to the ROUGE evaluation based on 4 human abstraction models, with jack-knifing (the ROUGE metric used in TAC). The correlation coefficients between HEXTAC-ROUGE, ROUGE, and the overall responsiveness scores of all the participating systems (runs 4 through 55) are given in Table 4. All the ROUGE scores use ROUGE2.

	Part A	Part B
HEXTAC-ROUGE–ROUGE	0.80	0.85
HEXTAC-ROUGE–O. Resp.	0.78	0.91
ROUGE–O. Resp.	0.97	0.94

Table 4: Correlation coefficients between HEXTAC-ROUGE, ROUGE, and the overall responsiveness scores.

HEXTAC-ROUGE is fairly well correlated to both ROUGE and the overall responsiveness scores, with correlation coefficients between 78 and 91%. This shows that HEXTAC summaries are potential models for extractive systems to compare themselves with, obtaining better evaluation scores, as we have seen before. We believe that training a sentence selection engine on the manual extracts, using HEXTAC-ROUGE, is easier and more straightforward than training on ROUGE scores obtained from abstracts, because the model sentences can be found in the source documents.

4 Conclusion

The HEXTAC experiment presents a successful, reusable approach to human sentence extraction for summarization. We have developed a comprehensive methodology with detailed guidelines, and we now have a better idea of how much time is required to complete the summaries. We have observed that an interactive interface such as the one we used is an invaluable tool, in part because it reduced the amount of time spent on writing each extractive summary, thus keeping our extractors happier.

Viewed as an upper-bound on purely extractive summarization techniques, the competition results for HEXTAC lead to two main conclusions. First,

that significant improvements to current sentence selection engines and sentence ordering schemes can still be made since the current automatic summarizers do not achieve results comparable to those of human extracts yet. Second, that since there are large, now quantifiable gaps between the scores of human abstracts and extracts – mostly in the amount of content that can be included –, developing techniques to extract smaller segments than sentences or to compress or reformulate sentences is essential to make great improvements to the current techniques in the long-term.

We view the HEXTAC extracts as an interesting alternative to using the ROUGE scores based on abstracts for sentence selection engine training. The main attraction lies in the fact that the training is supervised through data that corresponds to the same challenge. Similarly, sentence ordering could perhaps be trained using HEXTAC summaries to supervise the learning.

More comprehensive information from humans, in the form of sentence evaluation, would lead to even much more valuable information for the purpose of supervised training. Humans could list all the sentences in the cluster that could potentially be of use in a summary, excluding anything with low content or bad linguistic form. They could then rate the sentences in that list and identify which ones are redundant and could not be included together. While this would be a monumentally larger amount of work, the gathered data would be more directly usable and the inter-annotator agreement would likely increased, improving the reliability of the data.

5 Acknowledgements

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CHAPITRE 3

GÉNÉRATION DE RÉSUMÉS PAR DIVISION DE PHRASES

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Framework for Abstractive Summarization using Text-to-Text Generation

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Abstract

We propose a new, ambitious framework for abstractive summarization, which aims at selecting the content of a summary not from sentences, but from an abstract representation of the source documents. This abstract representation relies on the concept of Information Items (INIT), which we define as the smallest element of coherent information in a text or a sentence. Our framework differs from previous abstractive summarization models in requiring a semantic analysis of the text. We present a first attempt made at developing a system from this framework, along with evaluation results for it from TAC 2010. We also present related work, both from within and outside of the automatic summarization domain.

1 Introduction

Summarization approaches can generally be categorized as extractive or abstractive (Mani, 2001). Most systems developped for the main international conference on text summarization, the Text Analysis Conference (TAC) (Owczarzak and Dang, 2010), predominantly use sentence extraction, including all the top-ranked systems, which make only minor post-editing of extracted sentences (Conroy et al., 2010) (Gillick et al., 2009) (Genest et al., 2008) (Chen et al., 2008).

Abstractive methods require a deeper analysis of the text and the ability to generate new sentences, which provide an obvious advantage in improving the focus of a summary, reducing its redundancy and keeping a good compression rate. According to a recent study (Genest et al., 2009b), there is an empirical limit intrinsic to pure extraction, as compared to abstraction. For these reasons, as well as for the technical and theoretical challenges involved, we were motivated to come up with an abstractive summarization model.

Recent abstractive approaches, such as sentence compression (Knight and Marcu, 2000) (Cohn and Lapata, 2009) and sentence fusion (Barzilay and McKeown, 2005) or revision (Tanaka et al., 2009) have focused on rewriting techniques, without consideration for a complete model which would include a transition to an abstract representation for content selection. We believe that a "fully abstractive" approach requires a separate process for the analysis of the text that serves as an intermediate step before the generation of sentences. This way, content selection can be applied to an abstract representation rather than to original sentences or generated sentences.

We propose the concept of *Information Items* (INIT) to help define the abstract representation. **An INIT is the smallest element of coherent information in a text or a sentence**. It can be something as simple as some entity's property or as complex as a whole description of an event or action. We believe that such a representation could eventually allow for directly answering queries or guided topic aspects, by generating sentences targeted to address specific information needs.

Figure 1 compares the workflow of our approach with other possibilities. Extractive summarization consists of selecting sentences directly from the

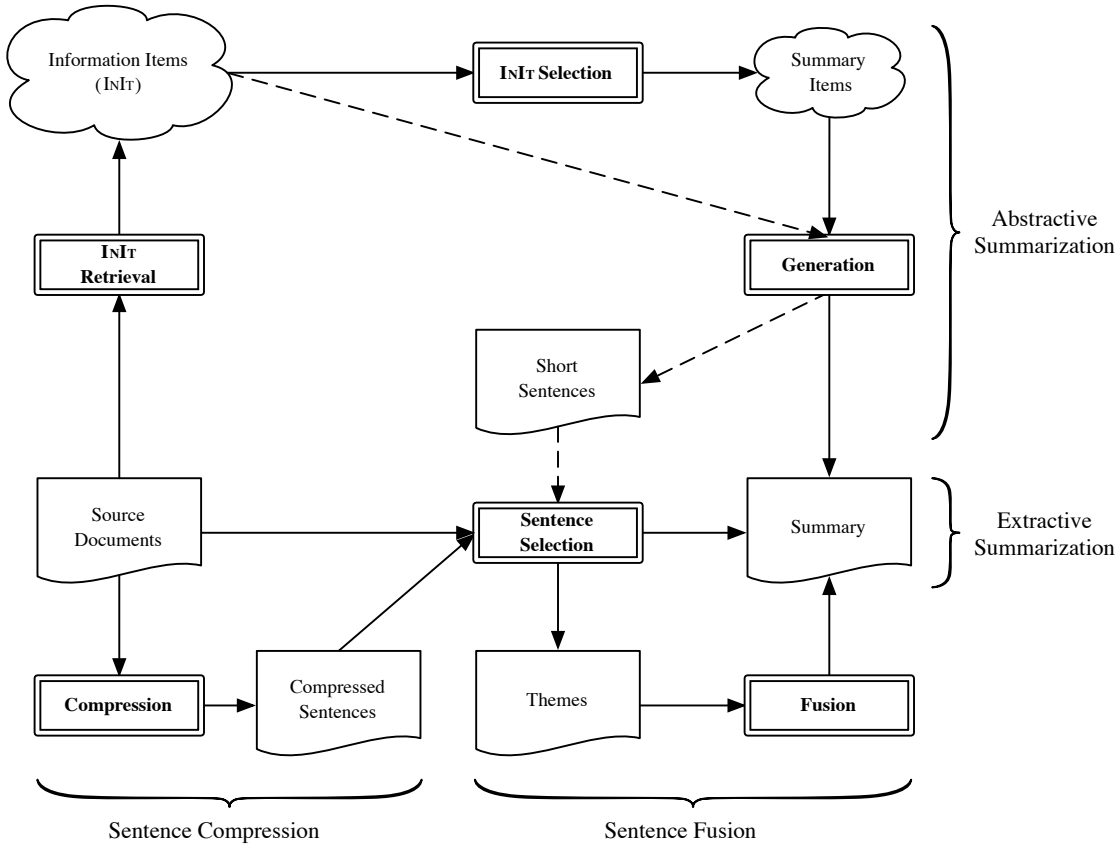

Figure 1: Workflow diagram of our suggested approach for abstractive summarization, compared to pure extractive summarization, sentence compression, and sentence fusion for summarization. The dashed line represents the simplified framework used in our first attempt at abstractive summarization (see section 2.4).

source documents and generating a summary from them. Sentence compression first compresses the sentences and chooses from those and the source documents' sentences to form a summary; it may also be completed in the reverse order, which is to select sentences from the source documents and then compress them for the summary. Sentence fusion first identifies themes (clusters of similar sentences) from the source documents and selects which themes are important for the summary (a process similar to the sentence selection of centroid-based extractive summarization methods (Radev et al., 2004)) and then generates a representative sentence for each theme by sentence fusion.

Our proposed abstractive summarization approach is fundamentally different because the selection of content is on Information Items rather than on sentences. The text-to-text generation aspect is also changed. Instead of purely going from whole sentences to generated sentences directly, there is now a text planning phase that occurs at the conceptual level, like in Natural Language Generation (NLG).

This approach has the advantage of generating typically short, information-focused sentences to produce a coherent, information rich, and less redundant summary. However, the difficulties are great: it is difficult for a machine to properly extract information from sentences at an abstract level, and text generated from noisy data will often be flawed. Generating sentences that do not all sound similar and generic is an additional challenge that we have for now circumvented by re-using the original sen-

tence structure to a large extent, which is a type of text-to-text generation. Even considering those difficulties, we believe that efforts in abstractive summarization constitute the future of summarization research, and thus that it is worthwhile to work towards that end.

In this paper, we present our new abstractive summarization framework in section 2. Section 3 describes and analyses our first attempt at using this framework, for the TAC 2010 multi-document news summarization task, followed by the competition's results in section 4. In this first attempt, we simplified the framework of section 2 to obtain early results which can help us as we move forward in this project. Related work is discussed in section 5, and we conclude in section 6.

2 Abstractive Summarization Framework

Our proposed framework for fully abstractive summarization is illustrated in figure 1. This section discusses how each step could be accomplished.

2.1 INIT Retrieval

An Information Item is the smallest element of coherent information in a text or a sentence. This intentionally vague definition leaves the implementation details to be decided based on resources available. The goal is to identify all entities in the text, their properties, predicates between them, and characteristics of the predicates. This seemingly unreachable goal, equivalent to machine reading, can be limited to the extent that we only need INITs to be precise and accurate enough to generate a summary from them.

The implementation of INITs is critical, as everything will depend on the abstract information available. Semantic Role Labeling (SRL) and predicate-logic analysis of text are two potential candidates for developing INIT Retrieval. Word-sense disambiguation, co-reference resolution and an analysis of word similarity seem important as well to complement the semantic analysis of the text.

2.2 INIT Selection

Given an analysis of the source documents that leads to a list of INITs, we may now proceed to select content for the summary. Frequency-based models, such as those used for extractive summarization, could be applied to INIT selection instead of sentence selection. This would result in favoring the most frequently occurring entities, predicates, and properties.

INIT selection could also easily be applied to tasks such as query-driven or guided summarization, in which the user information need is known and the summarization system attempts to address it. With smaller building blocks (INITs rather than sentences), it would be much easier to tailor summaries so that they include only relevant information.

2.3 Generation

Planning, summary planning in our case, provides the structure of the generated text. Most INITs do not lead to full sentences, and need to be combined into a sentence structure before being realized as text. Global decisions of the INIT selection step now lead to local decisions as to how to present the information to the reader, and in what order.

Text generation patterns can be used, based on some knowledge about the topic or the information needs of the user. One could use heuristic rules with different priority levels or pre-generated summary scenarios, to help decide how to structure sentences and order the summary. We believe that machine learning could be used to learn good summary structures as well.

Once the detailed planning is completed, the summary is realized with coherent syntax and punctuation. This phase may involve text-to-text generation, since the source documents' sentences provide a good starting point to generate sentences with varied and complex structures. The work of (Barzilay and McKeown, 2005) on sentence fusion shows an example of re-using the same syntactical structure of a source sentence to create a new one with a slightly different meaning.

2.4 First Attempt at Abstractive Summarization

The three-step plan that we laid down is very hard, and instead of tackling it head on, we decided to focus on certain aspects of it for now. We followed a simplified version of our framework, illustrated by the dashed line in Figure 1. It defers the content selection step to the selection of generated short sentences, rather than actually doing it abstractly as

Original Sentence The Cypriot airliner that crashed in Greece may have suffered a sudden loss of cabin pressure at high altitude, causing temperatures and oxygen levels to plummet and leaving everyone aboard suffocating and freezing to death, experts said Monday.

Information Items

1. airliner – crash – *null* (Greece, August 15, 2005)
2. airliner – suffer – loss (Greece, August 15, 2005)
3. loss – cause – *null* (Greece, August 15, 2005)
4. loss – leave – *null* (Greece, August 15, 2005)

Generated Sentences

1. A Cypriot airliner crashed.
2. A Cypriot airliner may have suffered a sudden loss of cabin pressure at high altitude.
3. A sudden loss of cabin pressure at high altitude caused temperatures and oxygen levels to plummet.
4. A sudden loss of cabin pressure at high altitude left everyone aboard suffocating and freezing to death.

Selected Generated Sentence as it appears in the summary

1. On August 15, 2005, a Cypriot airliner crashed in Greece.

Original Sentence At least 25 bears died in the greater Yellowstone area last year, including eight breeding-age females killed by people.

Information Items

1. bear – die – *null* (greater Yellowstone area, last year)
2. person – kill – female (greater Yellowstone area, last year)

Generated Sentences

1. 25 bears died.
2. Some people killed eight breeding-age females.

Selected Generated Sentence as it appears in the summary

1. Last year, 25 bears died in greater Yellowstone area.

Figure 2: Two example sentences and their processing by our 2010 system. In the summary, the date and location associated with an INIT are added to its generated sentence.

planned. The summary planning has to occur after generation and selection, in a *Summary Generation* step not shown explicitly on the workflow.

We have restricted our implementation of INITs to dated and located subject–verb–object(SVO) triples, thus relying purely on syntactical knowledge, rather than including the semantics required for our framework. Dates and locations receive a special treatment because we were interested in news summarization for this first attempt, and news articles are factual and give a lot of importance to date and location.

We did not try to combine more than one INIT in the same sentence, relying instead on short, to-the-

point sentences, with one INIT each. Figure 2 shows two examples of sentences that were generated from a source document sentence using the simplified abstractive summarization framework.

At first glance, the simplified version of our approach for generating sentences may seem similar to sentence compression. However, it differs in three important ways from the definition of the task of compression usually cited (Knight and Marcu, 2000):

- Our generated sentences intend to cover only one item of information and not all the important information of the original sentence.
- An input sentence may have several generated sentences associated to it, one for each of its INITs, where it normally has only one compressed sentence.
- Generated sentences sometimes include words that do not appear in the original sentence (like 'some' in the second example), whereas sentence compression is usually limited to word deletion.

3 Abstractive Summarization at TAC 2010

Our first attempt at full abstractive summarization took place in the context of the TAC 2010 multi-document news summarization task. This section describes briefly each module of our system, while (Genest and Lapalme, 2010) provides the implementation details.

3.1 INIT Retrieval

An INIT is defined as a dated and located subject–verb–object triple, relying mostly on syntactical analyses from the MINIPAR parser (Lin, 1998) and linguistic annotations from the GATE information extraction engine (Cunningham et al., 2002).

Every verb encountered forms the basis of a candidate INIT. The verb's subject and object are extracted, if they exist, from the parse tree. Each INIT is also tagged with a date and a location, if appropriate.

Many candidate INITs are rejected, for various reasons: the difficulty of generating a grammatical and meaningful sentence from them, the observed unreliability of parses that include them, or because it would lead to incorrect INITs most of the time. The rejection rules were created manually and cover a number of syntactical situations. Cases in which bad sentences can be generated remain, of course, even though about half the candidates are rejected. Examples of rejected Inits include those with verbs in infinitive form and those that are part of a conditional clause. Discarding a lot of available information is a significant limitation of this first attempt, which we will address as the first priority in the future.

3.2 Generation

From each INIT retrieved, we directly generate a new sentence, instead of first selecting INITs and planning the summary. This is accomplished using the original parse tree of the sentence from which the INIT is taken, and the NLG realizer SimpleNLG (Gatt and Reiter, 2009) to generate an actual sentence. Sample generated sentences are illustrated in Figure 2.

This process – a type of text-to-text generation – can be described as translating the parts that we want to keep from the dependency tree provided by the parser, into a format that the realizer understands. This way we keep track of what words play what role in the generated sentence and we select directly which parts of a sentence appear in a generated sentence for the summary. All of this is driven by the previous identification of INITs. We do not include any words identified as a date or a location in the sentence generation process, they will be generated if needed at the summary generation step, section 3.4.

Sentence generation follows the following steps:

- Generate a Noun Phrase (NP) to represent the subject if present
- Generate a NP to represent the object if present
- Generate a NP to represent the indirect object if present
- Generate a complement for the verb if one is present and only if there was no object
- Generate the Verb Phrase (VP) and link all the components together, ignoring anything else present in the original sentence

NP Generation

Noun phrase generation is based on the subtree of its head word in the dependency parse tree. The head

in the subtree becomes the head of the NP and children in its parse subtree are added based on manual rules that determine which children are realized and how.

Verb Complement Generation

When an INIT has no object, then we attempt to find another complement instead, in case the verb would have no interesting meaning without a complement. The first verb modifier that follows it in the sentence order is used, including for example prepositional phrases and infinitive clauses.

VP Generation

Finally, the verb phrases are generated from each verb and some of its children. The NPs generated for the subject, object and indirect object are added, as well as the verb complement if it was generated. If there is an object but no subject, the VP is set to passive, otherwise the active form is always used. The tense (past or present) of the VP is set to the tense of the verb in the original sentence, and most modifiers like auxiliaries and negation are conserved.

3.3 Sentence Selection

To determine which of the generated sentences should be used in the summary, we would have liked to choose from among the INITs directly. For example, selecting the most frequent INIT, or INITs containing the most frequent subject-verb pair seem reasonable at first. However, during development, no such naive implementation of selecting INITs provided satisfactory results, because of the low frequency of those constructs, and the difficulty to compare them semantically in our current level of abstraction. Thus this critical content selection step occurs after the sentence generation process. Only the generated sentences are considered for the sentence selection process; original sentences from the source documents are ignored.

We compute a score based on the frequencies of the terms in the sentences generated from the INITs and select sentences that way. Document frequency (DF) – the number of documents that include an entity in its original text – of the lemmas included in the generated sentence is the main scoring criterion. This criterion is commonly used for summaries of groups of similar documents. The generated sentences are ranked based on their average DF (the sum of the DF of all the unique lemmas in the sentence, divided by the total number of words in the sentence). Lemmas in a stop list and lemmas that are included in a sentence already selected in the summary have their DF reduced to 0, to avoid favoring frequent empty words, and to diminish redundancy in the summary.

3.4 Summary Generation

A final summary generation step is required in this first attempt, to account for the planning stage and to incorporate dates and locations for the generated sentences.

Sentence selection provides a ranking of the generated sentences and a number of sentences intentionally in excess of the size limit of the summary is first selected. Those sentences are ordered by the date of their INIT when it can be determined. Otherwise, the day before the date of publication of the article that included the INIT is used instead. All generated sentences with the same known date are grouped in a single coordinated sentence. The date is included directly as a pre-modifier "On *date*," at the beginning of the coordination.

Each INIT with a known location has its generated sentence appended with a post-modifier "in *location*", except if that location has already been mentioned in a previous INIT of the summary.

At the end of this process, the size of the summary is always above the size limit. We remove the least relevant generated sentence and restart the summary generation process. We keep taking away the least relevant generated sentence in a greedy way, until the length of the summary is under the size limit. This naive solution to never exceed the limit was chosen because we originally believed that our INITs always lead to short generated sentences. However, it turns out that some of the generated summaries are a bit too short because some sentences that were removed last were quite long.

4 Results and Discussion

Here, we present and discuss the results obtained by our system in the TAC 2010 summarization system evaluation. We only show results for the evaluation of standard multi-document summaries; there was

also an update task, but we did not develop a specific module for it. After ranking at or near the top with extractive approaches in past years (Genest et al., 2008) (Genest et al., 2009a), we expected a large drop in our evaluation results with our first attempt at abstractive summarization. In general, they are indeed on the low side, but mostly with regards to linguistic quality.

As shown in Table 1, the linguistic quality of our summaries was very low, in the bottom 5 of 43 participating automatic systems. This low linguistic score is understandable, because this was our first try at text generation and abstractive summarization, whereas the other systems that year used sentence extraction, with at most minor modifications made to the extracted sentences.

The cause of this low score is mostly our method for text generation, which still needs to be refined in several ways. The way we identify INITs, as we have already discussed, is not yet developped fully. Even in the context of the methodology outlined in section 3, and specifically 3.2, many improvements can still be made. Errors specific to the current state of our approach came from two major sources: incorrect parses, and insufficiently detailed and sometimes inappropriate rules for "translating" a part of a parse into generated text. A better parser would be helpful here and we will try other alternatives for dependency parsing in future work.

	Pyr.	Ling. Q.	Overall R.
AS	0.315	2.174	2.304
Avg	0.309	2.820	2.576
Best	0.425	3.457	3.174
Models	0.785	4.910	4.760
AS Rank	29	39	29

Table 1: Scores of pyramid, linguistic quality and overall responsiveness for our Abstractive Summarization (AS) system, the average of automatic systems (Avg), the best score of any automatic system (Best), and the average of the human-written models (Models). The rank is computed from amongst the 43 automatic summarization systems that participated in TAC 2010.

Although the linguistic quality was very low, our approach was given relatively good Pyramid (Nenkova et al., 2007) (a content metric) and overall responsiveness scores, near the average of automatic

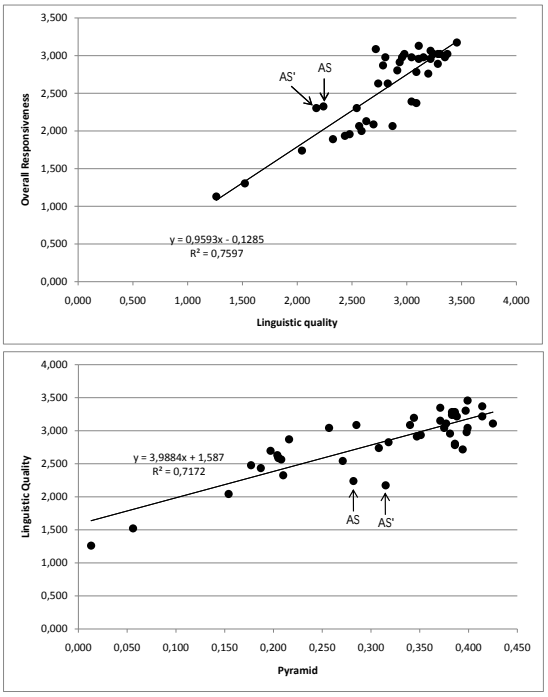

Figure 3: Scatter plots of overall responsiveness with respect to linguistic quality (top) and pyramid score with respect to linguistic quality (bottom), for all the systems competing in TAC 2010. The two runs identified with an arrow, AS and AS', were two similar versions of our abstractive summarization approach.

systems. This indicates that, even in a rough first try where content selection was not the main focus, our method is capable of producing summaries with reasonably good content and of reasonably good overall quality. There is a correlation between linguistic quality and the other two manual scores for most runs, but, as we can see in Figure 3, the two runs that we submitted stand out, even though linguistic quality plays a large role in establishing the overall responsiveness scores. We believe this to be representative of the great difference of our approach compared to extraction. By extension, following the trend, we hope that increasing the linguistic quality of our approach to the level of the top systems would yield content and overall scores above their current ones.

The type of summaries that our approach produces might also explain why it receives good content and overall scores, even with poor linguistic

quality. The generated sentences tend to be short, and although some few may have bad grammar or even little meaning, the fact that we can pack a lot of them shows that INITs give a lot more flexibility to the content selection module than whole sentences, that only few can fit in a small size limit such as 100 words. Large improvements are to be expected, since this system was developped over only a few months, and we haven't implemented the full scale of our framework described in section 2.

5 Related Work

We have already discussed alternative approaches to abstractive summarization in the introduction. This section focuses on other work dealing with the techniques we used.

Subject–Verb–Object (SVO) extraction is not new. Previous work by (Rusu et al., 2007) deals specifically with what the authors call triplet extraction, which is the same as SVO extraction. They have tried a variety of parsers, including MINIPAR, and they build parse trees to extract SVOs similarly to us. They applied this technique to extractive summarization in (Rusu et al., 2009) by building what the authors call semantic graphs, derived from triplets, and then using said graphs to identify the most interesting sentences for the summary. This purpose is not the same as ours, and triplet extraction was conducted quite superficially (and thus included a lot of noise), whereas we used several rules to clean up the SVOs that would serve as INITs.

Rewriting sentences one idea at a time, as we have done in this work, is also related to the field of text simplification. Text simplification has been associated with techniques that deal not only with helping readers with reading disabilities, but also to help NLP systems (Chandrasekar et al., 1996). The work of (Beigman Klebanov et al., 2004) simplifies sentences by using MINIPAR parses as a starting point, in a process similar to ours, for the purpose of helping information-seeking applications in their own task. (Vickrey and Koller, 2008) applies similar techniques, using a sequence of rule-based simplifications of sentences, to preprocess documents for Semantic Role Labeling. (Siddharthan et al., 2004) uses shallow techniques for syntactical simplification of text by removing relative clauses and appositives, before running a sentence clustering algorithm for multi-document summarization.

The kind of text-to-text generation involved in our work is related to approaches in paraphrasing (Androutsopoulos and Malakasiotis, 2010). Paraphrase generation produces sentences with similar meanings, but paraphrase extraction from texts requires a certain level of analysis. In our case, we are interested both in reformulating specific aspects of a sentence, but also in identifying parts of sentences (INITs) with similar meanings, for content selection. We believe that there will be more and more similarities between our work and the field of paraphrasing as we improve on our model and techniques.

6 Conclusion

We have proposed an ambitious new way of looking at abstractive summarization, with our proposed framework. We believe that this framework aims at the real goals of automatic summarization – controlling the content and structure of the summary. This requires both an ability to correctly analyze text, and an ability to generate text. We have described a first attempt at fully abstractive summarization that relies on text-to-text generation.

We find the early results of TAC 2010 quite satisfactory. Receiving a low linguistic quality score was expected, and we are satisfied with average performance in content and in overall responsiveness. It means that our text-to-text generation was good enough to produce understandable summaries.

Our next step will be to go deeper into the analysis of sentences. Generating sentences should rely less on the original sentence structure and more on the information meant to be transmitted. Thus, we want to move away from the current way we generate sentences, which is too similar to rule-based sentence compression. At the core of moving toward full abstraction, we need to redefine INITs so that they can be manipulated (compared, grouped, realized as sentences, etc.) more effectively. We intend to use tools and techniques that will enable us to find words and phrases of similar meanings, and to allow the generation of a sentence that is an aggregate of information found in several source sentences. In this way, we would be moving away from purely syntactical analysis and toward the use of semantics.

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CHAPITRE 4

GÉNÉRATION DE RÉSUMÉS PAR ABSTRACTION BASÉE SUR DES CONNAISSANCES

Pierre-Etienne Genest et Guy Lapalme. ABSUM : a Knowledge-Based Abstractive Summarizer. Soumis pour publication dans *Computational Linguistics*, 2013.

Cet article a été soumis au journal de l'ACL, Computational Linguistics, publié 4 fois par année aux éditions MIT Press Journals. Ce journal prestigieux est le plus ancien qui soit consacré exclusivement à l'analyse et au design de systèmes de traitement automatique des langues naturelles.

Un appendice situé à la fin de la thèse enrichit l'article avec des détails techniques et pratiques sur l'implantation du système.

ABSUM: a Knowledge-Based Abstractive Summarizer

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This paper introduces a flexible and scalable methodology for abstractive summarization called K-BABS. *Following the analysis of the source documents a knowledge base called a task blueprint is used to identify patterns in the representation of the source documents and generate summary text from them. This knowledge-based approach allows for implicit understanding and transformation of the source documents' content, given that the task blueprint is carefully crafted for the summarization task and domain of interest.* ABSUM *is a system that implements this methodology for the guided summarization task of the Text Analysis Conferences. Knowledge for two broad news categories has been manually encoded. Evaluation shows that the abstractive summaries of* ABSUM *have better linguistic quality and almost twice the content density of state-of-the-art extractive summaries. When used in combination with an extractive summarizer, evaluation shows that* ABSUM *improves the summarizer's coverage of the source documents by a statistically significant amount, and exceeds the content score of the state of the art in text summarization. A discussion of extensions to this work including ways to automate the knowledge acquisition procedure is included.*

1. Introduction

Abstractive summarization is one of the main goals of text summarization research, but also one of its greatest challenges. The authors of a recent literature review (Lloret and Palomar 2012) even conclude that "abstractive paradigms [...] will become one of the main challenges to solve" in text summarization. In building an abstractive summarization system, however, it is often hard to imagine where to begin and how to proceed in order to incorporate some kind of semantic understanding of the source documents to create a shorter text that contains only the relevant elements for the task at hand.

This paper introduces the **K**nowledge**-B**ased **Ab**stractive **S**ummarization (K-BABS) approach, to address various summarization tasks and domains in a flexible and scalable way. Its architecture relies on an analysis of the source documents and on a task blueprint. This resource describes how to transform the representation of the text into natural language for the summary. It implicitly encodes knowledge about the summarization task into rules applied by the summarization system. The task blueprint, which can be constructed automatically, semi-automatically, or manually, guides every step of the summarization process.

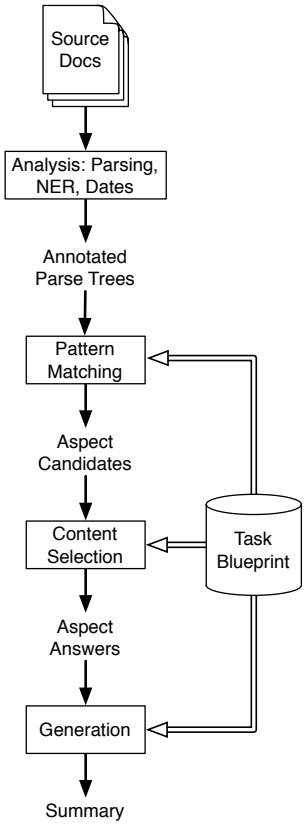

Figure 1
Workflow diagram for the architecture of ABSUM.

The **Ab**stractive **S**ummarizer of **U**niversité de **M**ontréal (ABSUM) is a system which implements K-BABS for the guided summarization task of the Text Analysis Conference[1] (TAC). Figure 1 shows the architecture of ABSUM. First, an analysis that includes the syntactical parsing and semantic tagging of the source documents is performed. Then, abstraction schemes defined in the (manually constructed) task blueprint are applied to the annotated parse trees to detect candidates for each aspect that needs to be covered in the summary. The answer for each aspect is selected by parameterizable heuristics in the content selection step, which takes into account that the analysis module is not error-free. Finally, the summary is generated based on a generation plan provided by the task blueprint, using templates to generate sentences for each aspect.

ABSUM shows excellent performance on a test set made up of two categories from TAC 2011's guided summarization track. The summaries generated are very short, content-rich, and

1 www.nist.gov/tac

of good linguistic quality. Their content density is almost two times superior to that of any other automatic summarizers, though they often lack coverage of the source documents. Thus, they gain to be complemented with sentences extracted automatically. When used in combination with a state of the art extractive summarizer, the evaluation shows that ABSUM increases the content of the summaries by a statistically significant amount, without negatively affecting linguistic quality.

This paper has the following organization. In order to put K-BABS in perspective, Section 2 discusses different approaches to summarization that have been proposed over time. Section 3 outlines the general approach K-BABS. Section 4 describes the abstractive summarizer ABSUM. The methodology and results of the evaluation performed are presented and analyzed in section 5. Section 6 is a discussion of K-BABS given the experimental results of ABSUM. Finally, Section 7 concludes.

2. Automatic Summarization Strategies

Summarization systems are usually considered to be either *extractive* (which typically refers to sentence extraction, with or without some post-processing edits allowed), or *abstractive* (which typically refers to everything else). (Spärck Jones 2007) suggests the term *non-extractive* instead of abstractive, to include strategies that do not produce abstracts, like synopses and reviews. This terminology is adopted in this paper, with the addition of the category *semi-extractive*, to refer to approaches that compress or merge sentences at a syntactical level, but do not produce new syntactical structures or lexical units.

2.1 The ITG Model

(Spärck Jones 1999) considers that the basic model of an automatic text summarizer has the following three stages, forming the acronym ITG:

1. *Interpretation* of the source text into a source text representation
2. *Transformation* of the source text representation into a summary representation
3. *Generation* of the summary text from the summary representation

Her model provides a "common means" for comparing systems based on "the real logic underlying [them]". The kind of transformation that is expected is a kind of compressive operation on the source text representation that can involve reasoning, inference, conceptualization, simplification, etc.

2.2 Extractive Summarization

In the last two decades, automatic text summarization has been dominated by extractive approaches that rely on shallow statistics. Graphs, centroids, latent semantics, machine learning, linear programming and other sophisticated statistics-based algorithms have become the state of the art. They tend to favor a bag-of-word or ngram representation of the text and make use of rudimentary knowledge resources, either general or domain-related, usually consisting of lists of words or cue phrases. Citing all relevant extractive approaches is outside the scope of this paper, and recent surveys (Nenkova and McKeown 2011) (Lloret and Palomar 2012) should be consulted for a more detailed discussion.

With regards to the ITG model, the interpretation of the source text in extractive summarization does not lead to a representation other than textual. The transformation step as defined above

is non-existent, while the generation step is reduced to selecting and ordering full sentences extracted from the source text. In this regard, the best-performing systems, which have been purely extractive prior to this work, have very limited text understanding capabilities.

It remains important to recognize the successes of extractive summarization. Though there is still a long way to go in text summarization, extractive systems already do a reasonable job at summarizing: in the latest evaluation campaign, TAC 2011, the average responsiveness of the top systems was considered "barely acceptable" by human assessment (Owczarzak and Dang 2011), which is nothing to scoff at. This level of performance is possible thanks to years of developing new extractive models and fine-tuning systems.

Nevertheless, there are good reasons to believe that extractive summarization is approaching a ceiling in performance. As has been stated by (Spärck Jones 2007), "the work on extractive summarizing has picked the low-hanging fruit, and the overall trend has been more technological than fundamental." Systems that claim to be different from one another have all become statistically indistinguishable in evaluation results (such as the top 10 submissions at the TAC 2011 evaluation campaign). The results of the HexTac (Genest et al. 2009) experiment, which evaluated the performance of humans doing pure sentence extraction, show that this ceiling in performance is rather unsatisfactory. Human sentence extraction turns out to perform poorly when compared to that of regular (abstractive) human summaries, and not that much better than the best automatic systems. Even though these results show that there is still some room to improve on the current extractive methods, there are good reasons to conclude that most of what can be done with extraction has been done and that little more significant improvement is to be expected, at least for the summarization of news articles; and a similar upper limit will likely be reached in time for other domains if they become the new focus of evaluation campaigns.

Overall, the best performance to be expected from approaches based only on sentence extraction is unsatisfactory.

2.3 Semi-Extractive Summarization

Semi-extractive summarization techniques are similar to extractive summarization in that they aim to construct the summary directly from extracted text, but do not limit the selection to whole sentences, and allow for word or phrase deletion, sentence compression and merging of phrases from different sentences.

The ADAM system by (Pollock and Zamora 1975) was perhaps the earliest work on semi-extractive summarization. ADAM edits the sentences after they have been extracted from the source text. This idea is used by many extractive systems today, mostly in the form of simple deletions, like removing unwanted words and phrases, and substitutions, such as resolving anaphoric pronouns by the referred entity. Approaches that incorporate sentence edition within a limited scope are typically considered to remain within the extractive summarization paradigm.

When more substantial sentence edition is performed, the term sentence compression is used instead. Sentence compression is a field that is studied in its own right, though summarization is usually considered among the NLP tasks for which it can be useful (Cohn and Lapata 2009). Sentence compression has also been studied specifically in the context of summarization (Knight and Marcu 2000) (Zajic et al. 2008). Sentence selection can be performed in the same way as in any of the extractive summarization systems, either before or after the compression. Sentence compression can also be considered as part of the summarization task itself, exploiting discourse information to drive the decisions of the compression process (Daumé and Marcu 2002). Sentence splitting (Genest and Lapalme 2011a) can be considered as a special kind of sentence compression in which each sentence is split into several very short sentences that each contain only one information item.

Sentence fusion is another category of semi-extractive summarization approaches that has been explored in recent years. In (Barzilay and McKeown 2005), themes (clusters of similar sentences) are first identified from the source documents and a selection is made of which themes are important for the summary. This process is similar to the sentence selection of centroid-based extractive summarization methods for multi-document summarization (Radev et al. 2004). A representative sentence for each theme is then generated by sentence fusion, using heuristics that add and remove parse tree fragments from a base sentence and then generating a sentence from the enhanced parse tree. (Krahmer et al. 2008) suggest that query-driven sentence fusion may be a more tractable task that improves readability, and also consider the union (without repetition) of sentences that are merged, rather than intersection. (Filippova and Strube 2008) introduce the use of semantic information to avoid incorrect fusions. (Tanaka et al. 2009) use a similar approach to address a very similar task called sentence revision, which considers always the lead sentence as the base sentence, and adds additional information from the rest of the document. Sentence fusion has also been accomplished by relying on tokenization and tagging rather than full parse trees by (Filippova 2010).

Semi-extractive summarization approaches rely on a syntactical manipulation of the source text to form new sentences. They typically manage to fit more salient information in the summary by removing extraneous details and joining similar information from different sources, thus also avoiding redundancies that are typical of extractive summarization. From the standpoint of the ITG model, the operations performed can hardly be considered a conceptual transformation from a source text representation to a summary representation, because they are conducted at a purely syntactical level. In this way, semi-extractive summarization remains similar to extractive summarization in terms of its capacity for text understanding.

Sentence compression and sentence fusion seem to lead to an improved performance in some cases, but it does not seem to have been tested on shared data sets from evaluation campaigns, and compared against state-of-the-art extractive systems. An exception to this statement is sentence splitting, but it performed rather poorly overall.

2.4 Non-Extractive Summarization

Contrary to the aforementioned strategies, non-extractive summarization typically relies on some form of text understanding in its process to generate a summary. The sentences that appear in non-extractive summaries usually cannot be generated by extraction and syntactical manipulations, often including new (unseen in the source text) sentence structures and new lexical units. Having access to some form of conceptual representation of the source text and/or the summary, it is often possible, in non-extractive summarization, to organize the structure of the summary in a meaningful way, as opposed to facing the problem of sentence ordering, typical of extractive and semi-extractive approaches.

A lot of work in artificial intelligence in the 1970s has been conducted on semantic analysis and has led to some applications to text summarization. This paper focuses instead on approaches that can be implemented in an unrestricted setting, as opposed to a controlled language setting or similar artificial scenarios where full semantic analysis may become feasible.

The FRUMP system (DeJong 1982) is a non-extractive summarization system that was applied to unrestricted text from a newswire agency, using an Information Extraction (IE) system. The text's topic is identified as one of the known topics, and the text is mapped to that topic's *sketchy script*. A sketchy script describes domain-specific world knowledge that the system uses to predict probable events in a chain of events as typically reported. Topics and sketchy scrips are manually written. They are used by the system to disambiguate word senses where necessary, infer some events (that were not reported but implied, or simply not recognized by the system's analysis) and drive the generation process. The output summary is typically an information-

rich generated sentence. DeJong reports on the difficulties of good coverage from the various resources (dictionary, analysis tools, topics, sketchy scripts), with over half of the missing or wrong stories associated to the lack of coverage of language and world knowledge resources.

This idea of using IE to accomplish non-extractive summarization has been used in other works as well. The SUMMONS system (Radev and McKeown 1998) produces summaries about multiple sources on terrorist activity using a pre-existing information extraction system to provide filled templates about each document. They report the source of each information item, reporting contradictions and changes over time. Discourse planning is used as part of the generation process. The RIPTIDES system (White et al. 2001) is another IE-based non-extractive summarizer using filled scenario templates as the source of information for the summary, and then generating a summary from these templates.

In all three IE-based systems presented here, the IE system used was designed for a purpose other than summarization. The summarization task was tackled from the angle of natural language generation from data, not really as a text-to-text task. This shows that these systems have a fully developed interpretation step within the ITG model. FRUMP reaches some minor transformation in which events can be inferred, and some selection and comparison of information is performed in SUMMONS and RIPTIDES to account for the multi-document task, but this accounts only for a fraction of the work; in all cases, the text and summary representations are the same. In other words, what *can* be extracted by IE is considered as being what *should* appear in the summary. The generation step is also much more in line with the ITG model than with extractive techniques. FRUMP and SUMMONS have not been formally evaluated against other automatic summarization systems. RIPTIDES showed an improvement over a simple extractive baseline.

A different approach, coined as knowledge-based text summarization, is the TOPIC summarization system (Hahn and Reimer 1999). The source text is parsed to map its content to a terminological knowledge representation based on manually crafted domain knowledge. Salience operators yield paragraph-level topic descriptions which can then be combined into a text graph of the whole document, which presents a hierarchy of its topics. A user may then select topics of interest by traversing this text graph, or a summary may be generated automatically with a degree of specificity that depends on how deeply the graph is explored. This work has a custom conceptual representation of the text in a form similar to templates, and also a different representation for the summary in the form of text graphs. The ITG model is thus fully deployed in TOPIC. This system is able to produce indicative summaries by exploring only the top levels of the text graph, and much more informative summaries as the text graph is explored. It does not appear that the system was completed and ready to be used widely with unrestricted text; no evaluation other than a qualitative assessment of selected outputs was provided.

Other abstractive summarization systems focus on adding indicative information about the source documents (Kan et al. 2001) (Saggion and Lapalme 2002). Indicative summaries provide information *about* the source text rather than only information found *within*. This cannot be done using only extraction or semi-extraction, given that it requires some understanding of the source text and of what kind of information should be reported to the user, usually including other sources of information than just the original text. A recent example comes from (Zhang et al. 2013), who propose to summarize Twitter discussions on a given topic by classifying related speech acts, and reporting separately the most salient statements, questions, suggestions and comments made by the tweet authors, in order to generate short summaries that are both informative and indicative.

3. K-BABS: A High-Level Approach for Abstractive Summarization

Intuitively, an ideal summarizer should be capable of reproducing or emulating all operations that humans perform when summarizing. According to observations by (Hasler 2007), the operations of deletion, insertion, replacement, reordering and merging, can allow humans to transform an extract into a good abstract. Many of these operations, while doable by a machine, are hard to apply at the right place in a predictable way, because they may be performed by humans for reasons that depend on a deep understanding of the text and world knowledge, and such understanding and knowledge are not typically available when machines perform operations such as reordering and merging. (Endres-Niggemeyer 1998) shows that all steps taken by human summarizers can be simulated by a computer program, but these steps go far beyond rewriting and are more about decision making, which is the real challenge, rather than the production itself. Using only rewriting rules without world knowledge, such as what is usually done in semi-extractive summarization, is probably insufficient if the aim is to reach a near human-level performance.

Thus, an ideal summarizer should have access to a way of understanding the source text based on world knowledge in order to generate a good summary. Given access to such resources, there is no reason to limit the summarizer only to rewriting rules, and abstractive (non-extractive) summarization is warranted. In other words, there is a need for intermediate representations of the text and the summary, as in the ITG model. A way to analyze the source text in a deep semantic way, to transform the resulting source text representation into a summary representation, and to generate natural language from that representation, is needed.

To make this ideal a reachable goal, and given the kind of tools available today for analysis of the source text, the transformation and generation steps of the ITG model may be conceptually wrapped up into a single operation, encoded in an *abstraction scheme*. The text is first analyzed into some intermediate representation, and then abstraction schemes are applied to transform this representation directly into summary text. This proposed approach is called **K**nowledge-**B**ased **Ab**stractive **S**ummarization (K-BABS).

3.1 Abstraction Schemes

Our implementation of abstraction schemes will be described in section 4.3, but they can be implemented in a variety of ways along the following principles:

1. Abstraction schemes *identify patterns in the source text representation*, which may include variables that need to be instantiated. For example, given a predicative intermediate representation, we could be interested in identifying this simple pattern, related to walking: WALKER(X), LOCATION(Y)), where X and Y are variables to be instantiated and the comma represents the “and” operator.
2. Abstraction schemes *provide a generation template*, which may include variables from the pattern. The template will generate textual output when the abstraction scheme’s pattern is identified in the source text representation. For example, the following is a simple generation template related to the previous pattern: X `walks` Y, which could be instantiated for example as John `walks` in the park.

Applying an abstraction scheme is thus equivalent to applying a transformation from source text representation directly to a textual output.

Relying on this kind of transformation has several advantages, which make K-BABS both flexible and scalable. The process of applying abstraction schemes by the summarization system

remains always the same, making this approach flexible from a programming standpoint, since new tasks only require a new set of abstraction schemes, obtained either manually or automatically. Increasing the coverage of the types of information to be described in the summary depends only on adding more abstraction schemes, in a relatively additive manner. The abstraction schemes can be simple and few in a first implementation, and become much more complex and numerous as new domains and new summarization scenarios are covered. Re-using abstraction schemes or modifying existing ones during this process make this approach very scalable.

The following toy example illustrates some possible uses of abstraction schemes in 3 different summarization scenarios:

> `John was very nervous as he walked into a student-packed classroom on the morning of the last day of high school. Copies were passed and three long hours later everyone was done. John was the first out, feeling confident that he would pass. Indeed, a month later he was proud to receive a diploma.`
>
> (1) Informative summary: `John walked into a classroom. Copies were passed. A month later, he received a diploma.`
>
> (2) Informative summary with reasoning: `John attended an examination taken on the last day of class. He obtained a passing grade. He was awarded his high school diploma.`
>
> (3) Indicative summary with reasoning: `This story is about John, an examination that he attended, a diploma that he received, and the emotions that he felt throughout.`

In order to write summaries such as (1), an information extraction system can fill slots about events related to going to class. Then, abstraction schemes are applied on this intermediate representation to transcribe IE template slot fillers into natural language for the summary. Assuming a simple IE template for the event of walking, our above abstraction scheme example can be reused, using the pattern: WALKER(X), LOCATION(Y); and the generation template: X `walked` Y; generating the summary phrase `John walked into a classroom`. The rest of the summary can be generated with similar abstraction schemes.

While summary (1) is not extractive, no new information is added either. Information that lies outside the scope of the event of interest is ignored and no reasoning is performed. Existing IE-based non-extractive summarization methods (Radev and McKeown 1998) (White et al. 2001) work in such a way, and in this sense they are directly compatible with the more general K-BABS approach.

Summary (2) makes use of abstraction schemes to perform a certain amount of reasoning. One way to go about it would be to detect a script that these events fit into, and then inspect the appropriate script, say, about events related to high school education. The source text representation becomes very high level, and an abstraction scheme pattern could be represented simply as this: SCRIPT_TRIGGERED(`Examination`), PROTAGONIST(X). The generation template would then be X `attended an examination`.

Reasoning is truly performed by a complex analysis tool that yields high-level information in the source text representation. In theory, abstraction schemes patterns can also be used to

accomplish the same kind of reasoning with access to the same kind of predicative intermediate representation as before. The pattern only needs to be more intricate and specific: LOCATED_INTO(X, `classroom`), PASS(_, `copy`) at time T1, BEING_DONE(X) at time T2, TEMPORALLY_BEFORE(T1, T2). The generation template would then be the same. Creating such an abstraction scheme requires some understanding, but applying the scheme is simple and straightforward.

Indicative summaries such as (3) may also be generated by applying abstraction schemes. In this case, the schemes would call for the recognition of entities and actions that involve them, assuming an interpretation step which provides some kind of semantic tagging and syntactical parsing. Again, the abstraction schemes perform transformation and generation in a single step. For example, a scheme could detect if there is an entity of type person, and it is observed as the subject of the verb `to feel` or the subject of the verb `to be` followed by a word that can be found in a list of emotions. If this occurs more then once in the source text, then the output should include a mention that the story is in part about emotions felt by that entity.

3.2 K-BABS Architecture

The basic premise of K-BABS is that well-defined abstraction schemes can be easy to read and execute by the machine, while implicitly performing transformations of arbitrary complexity on the source text representation, leading to natural language text that can be included in the summary. These abstraction schemes can be defined as transformations that match certain types of language manifestation patterns from an intermediate text representation and output generated natural language to satisfy a specific need that depends on the goals set for the summarizer. Because abstraction schemes encode not only world knowledge, but also knowledge about the task to perform, the knowledge base which contains all the schemes is called a *task blueprint*.

This implies a simple high-level architecture for K-BABS: first, analyze the source text into some intermediate representation; second, apply abstraction schemes from the task blueprint to generate the summary directly. Generally speaking, the task blueprint should not only provide abstraction schemes, but also a generation plan as well, to provide instructions for assembling the final summary while applying desired constraints on it, such as determine which abstraction schemes to favor in order to respect a size limit.

This approach thus depends on two key factors: the richness and accuracy of the intermediate representation provided in the analysis step, and the quality and coverage of the task blueprint. A set of analysis operations that should be sufficient in most cases includes: syntactical parsing, semantic tagging, word-sense disambiguation, and coreference resolution. The summary scenarios described in the toy example shown above can all be solved with abstraction schemes given access to such an analysis.

4. ABSUM: an Implementation of the K-BABS Approach

The **Ab**stractive **S**ummarizer of **U**niversité de **M**ontréal (ABSUM) has been implemented following the K-BABS approach, which has the advantage of providing a direct control over (and some understanding of) the content of the summary. It is designed to address the summarization task known as guided summarization and makes use of no pre-existing event extraction system.

ABSUM is split into three modules: analysis, which provides syntactical and semantic information about the source documents, task blueprint, which provides a full description (made up of hand-written abstraction schemes and a generation plan) of what the summarization system should do for each category, and the summarization system itself, which mostly runs the abstraction schemes from the task blueprint on the representation of the source documents given by the analysis. The summarization system itself is split into 3 steps, as illustrated in

Figure 1: pattern matching to identify aspect candidates, content selection to determine which candidates are aspect answers, and generation of summary in natural language. The remainder of this section describes the task of guided summarization, each of the three modules, and the process of generating hybrid summaries. These descriptions tend to remain rather factual and section 6 will provide a broader discussion.

4.1 Guided Summarization

The organizers of the evaluation campaigns Document Understanding Conference[2] (DUC), running from 2001 to 2007, and its successor the Text Analysis Conference (TAC), running a summarization task from 2008 to 2011, aimed to challenge system developers to move toward better text understanding, notably by suggesting new tasks like topic-oriented summarization, summarization at higher compression rates, multidocument summarization and update summarization. In hindsight, many observers are under the impression that it mostly had the effect of promoting a greater sophifistication of shallow statistics-based approaches, which is laudable, but probably not what was anticipated.

The latest summarization task starting at TAC in 2010, guided summarization, is probably the one best designed yet to motivate a move towards non-extractive approaches – it is also its stated goal. Guided summarization is an oriented multidocument task in which a category is attributed to each cluster of 10 source documents to summarize in 100 words or less. Five categories were selected: Accidents and Natural Disasters, Attacks, Health and Safety, Endangered Resources, and Investigations/Trials. For each category, a list of aspects to cover in the summary is given.

Figure 2 shows the aspects for the categories ATTACKS and ACCIDENTS AND NATURAL DISASTERS. These are the two categories currently supported in ABSUM. They were chosen because they have similar aspects, and because they include the aspects WHEN and WHERE, which seemed easier to address at first. The three other categories in TAC 2011 have fewer aspects and none about location and date; they are: HEALTH AND SAFETY, ENDANGERED RESOURCES, and INVESTIGATIONS AND TRIALS.

2.1	WHAT: what happened
2.2	WHEN: date, time, other temporal placement markers
2.3	WHERE: physical location
2.4	PERPETRATORS: individuals or groups responsible for the attack
2.5	WHY: reasons for the attack
2.6	WHO_AFFECTED: casualties (death, injury), or individuals otherwise negatively affected
2.7	DAMAGES: damages caused by the attack
2.8	COUNTERMEASURES: countermeasures, rescue efforts, prevention efforts, other reactions

Figure 2
Aspects for the ATTACKS category of TAC's guided summarization task. The category ACCIDENTS AND NATURAL DISASTERS has the same aspects, but excludes aspect 2.4.

4.2 Analysis

The goal of the analysis module is to provide an intermediate representation of the source documents that will then be used as input for applying the abstraction schemes. This includes

2 duc.nist.gov

dependency parsing of all the sentences in the source documents, morphological analysis to identify lemmas, recognizing named entities, and resolving dates. Because the task blueprint is only applicable if the syntactical and semantic information is relatively accurate, several strategies have been elaborated with the only purpose of increasing the accuracy of the parsing. These strategies are described here in great detail, in a desire to be thorough and transparent, and for this work to be reproducible.

4.2.1 Preprocessing. Preprocessing produces text files in one-sentence-per-line format from the SGML input files. Regular expression substitutions are used to clean up the text and make it uniform and as easy to parse as possible. Sentence segmentation is performed by a Java program which uses the class `java.text.BreakIterator` and a list of common abbreviations. Some sentences are filtered, such as those ending with an exclamation or interrogation mark.

4.2.2 Sentence Parsing and Morphological analysis. The freely available Stanford Parser is used to perform dependency parsing ("collapsed dependencies") on each sentence of each source document (de Marneffe et al. 2006). The also freely available GATE morphological analysis tool (Cunningham et al. 2002) is called to identify the lemma associated to each token, given the part-of-speech attributed to it by the Stanford Parser. Any improvements to the parsing might affect part-of-speech identification and in turn the accuracy of the morphological analysis.

4.2.3 Semantic Annotations and Additional Cleaning. An iterative process was designed to reduce parsing errors by using information from the semantic analysis to make the parsing task simpler at each step. In total, the Stanford Parser, as well as the morphological analyzer, are run three times, with two additional steps in between, called Preparation Steps 1 and 2.

Preparation Step 1. The cluster frequency and document frequency of all the lemmas are computed at this point, before any modification is made to the text. The cluster frequency is the frequency of a lemma in all the documents. The document frequency is the number of documents that contain at least one instance of a lemma. Lemmas are saved only as strings, not as a string and part-of-speech pair. These frequencies are used later during content selection.

To remove some badly parsed or content-poor sentences that the summarization system will have trouble dealing with, sentences containing less than 6 words, with no verb, are removed.

The named entity recognition system Stanford NER (Finkel et al. 2005) is run on all the source documents. The output provides tags on strings identified as either "person", "location", "organization" or "date" (other tags are ignored). In the case of an ambiguity, the most frequent tag for a string is selected. For each string tagged person, the given name, nobiliary particle, and surname are identified. The tag of a person's given name or surname will be changed to "person" if it was something else.

A new text document is generated for the purpose of the second parsing iteration, cleaned of named entities as follows. Person, location and organization strings are replaced by a new unique string. Given names and surnames that appear alone are also substituted by the full name's replacement string, in the unambiguous cases. The original strings are saved for use during the output stage of the summarization only. The motivation for these replacements is to simplify the work of the parser, where known noun phrases are replaced by a single entity that is unmistakeably identified as a noun by the parser.

Preparation Step 2. Some common sentence structures in the corpus put a date in a position which sometimes leads to parsing errors, e.g. `The government on Sunday sent a rescue team to [..]`, where `Sunday` will be incorrectly identified as a prepositional complement of `government`. Therefore, each date found in the text is removed, along with

accompanying words, in phrases such as `by last Tuesday` and `yesterday morning`. Regular expressions were built to identify a wide variety of such constructions. Each date is then resolved to a calendar date, month or year. The resolution of some relative dates requires the tense of the closest verb to be inspected. Dates that cannot be resolved are left untouched in the text. Parents of a removed date in the dependency tree will be identified as bearing that date. When a word could thus be attributed more than one date, neither will be kept.

After this final preparation step, the syntactical parser and morphological analyzer are run one last time, with observed improved accuracy. Figure 3 shows an example of the analysis provided by the Stanford Parser for a simple sentence. This is the kind of representation available to the abstraction schemes in the task blueprint, and on which the summarization system runs the pattern matching rules.

```
A second suicide bomber was reportedly killed by Israeli police
officers before he blew himself up in the mall.
```

DET(bomber, A)	AMOD(bomber, second)	NN(bomber, suicide)
NSUBJPASS(killed, bomber)	AUXPASS(killed, was)	ADVMOD(killed, reportedly)
ROOT(ROOT, killed)	AMOD(officers, Israeli)	NN(officers, police)
AGENT(killed, officers)	MARK(blew, before)	NSUBJ(blew, he)
ADVCL(killed, blew)	DOBJ(blew, himself)	PRT(blew, up)
DET(mall, the)	PREP_IN(blew, mall)	

Figure 3
A sentence from cluster 9 of the test set, with the topic "Dimona Attacks", and its representation by syntactical dependencies provided by the Stanford Parser in the analysis module.

4.3 The Task Blueprint

Scheme: killing

Pattern Matching	SUBJ_RELATIONS(*kill_verbs*, X)	→	WHO(X)
	OBJ_RELATIONS(*kill_verbs*, Y)	→	WHO_AFFECTED(Y)
	PREP_OF(murder_nouns, Y)	→	WHO_AFFECTED(Y)
	PREP_BY(murder_nouns, X)	→	WHO(X)
Generation Template	X *kill_verbs* Y		

Scheme: event

Pattern Matching	PREP_IN(*event_lemmas*, X), LOCATION(X)	→	WHERE(X)
	PREP_IN(*event_lemmas*, X), ORGANIZATION(X)	→	WHERE(X)
	PREP_AT(*event_lemmas*, X), LOCATION(X)	→	WHERE(X)
	PREP_AT(*event_lemmas*, X), ORGANIZATION(X)	→	WHERE(X)
	DEP(*event_lemmas*, Y), DATE(Y)	→	WHEN(Y)
	EVENT NOUN(Z)	→	WHAT(Z)
Generation Template	On Y, Z occur at/in X		

Figure 4
Abstraction schemes **killing** and **event**. The pattern matching rules define how to detect aspect candidates from the dependency parsing annotations and semantic information detected by the analysis module. The generation template defines how to realize a sentence for output. Notation: `word or lemma`, variable, *lemma group*, PREDICATE OR ASPECT. The special predicate DEP is the set of all the syntactical relations from the parser and the lemma group *event_lemmas* is a set of many verbs and nouns strongly related to the category.

The task blueprint contains instructions about how to find aspect candidates from documents, and how to generate sentences and a full summary from that information. It explicitly defines

abstraction schemes and provides a generation plan for generating abstractive summaries on a predefined domain (or category). The way in which the blueprint is interpreted and used by the system is described in section 4.4. The methodology that was used to construct the task blueprint is given in section 4.3.3.

4.3.1 Abstraction Schemes. An abstraction scheme defines pattern matching rules and a generation template, with the goal of finding a specific type of category-relevant information in the source documents, and generating a single sentence for output in the summary. Two example schemes of the task blueprint for the ATTACKS category are given in figure 4.

Pattern Matching Rules. These rules contain one or more predicates that must be unified with dependency parsing relations or semantic knowledge. Such predicates usually have three parts: a predicate type which is the equivalent to a type of syntactical relation, a head lemma, and a child lemma. Sets of relations and lemmas are used instead of a single instance, in practice. For example, a rule that intends to find some entity that is killed can be represented this way: OBJ_RELATIONS(*kill_verbs*, Y) → WHO_AFFECTED(Y), where *obj_relations* is a set of syntactical relations from the Stanford Parser like DOBJ and NSUBJPASS, and *kill_verbs* is a set of verb lemmas with related meaning and similar syntactical and semantic structures, such as `kill`, `murder`, `assassinate`, `shoot`, `stab`, `poison`, etc. Another type of predicate unifies a property to a variable, such as in the first rule of the scheme **Event**, where the predicate LOCATION(X) is found. Pattern matching rules determine strictly how candidates are found, be it candidates for the representative lemma of a lemma group or for category aspect candidates.

Generation Template. Each abstraction scheme must include one generation template, which describes how to generate a sentence containing the information found. It assumes that a selection within the candidates found by the unification of the pattern matching rules with the observed source documents is performed. Continuing with the example of the scheme **killing**, its generation template could simply be: X *kill_verbs* Y, which specifies that a verb from within the lemma group *kill_verbs* should have the subject X and the direct object Y. For each element of the generation template, a mention is made of whether or not that element is absolutely required to appear in the generated sentence. It is also mentioned whether or not the element can be several coordinated noun phrases or only one. In this example, the victim variable Y is required to be present and can contain several noun phrases, whereas it was decided that the perpetrator variable X may be omitted and that it must contain at most one noun phrase.

4.3.2 Generation Plan. The task blueprint must include a generation plan to describe how the summary will be constructed from the sentences generated by the abstraction schemes. The generation plan lists the schemes in the order in which their generated sentence will appear in the summary, and in this way provides the full structure of the summary. The processing of each abstraction scheme actually takes place sequentially in the summarization system, according to the order set out here in the generation plan. Figure 5 gives the generation plan for the ATTACKS category.

Being responsible for the structure of the summary, the generation plan may also provide indications to the abstraction schemes about what content to include or exclude from the summary. In the case of the ATTACKS category, for instance, the generation plan will prohibit the same entity to be declared as having been killed by someone, and also as having died, or as having been injured by that same person. Similarly, if the summary declares that some Mr. X has shot someone, the generation plan will prohibit the abstraction scheme **suspecting** from generating that Mr. X is suspected of conducting the attack. Without the generation plan, these kinds of redundancies would appear in the summaries by applying each abstraction scheme blindly.

Abstraction Scheme	Example structure of the generated sentence
event	On *a date*, *an attack/murder/shooting/etc.* occurred at/in *a location*.
beingHitGeneric	X was attacked/hit/struck.
killing	X killed/murdered/shot/etc. Y.
dying	X died.
injuring	X wounded/injured Y.
destroying	X was damaged/destroyed.
arresting	X was arrested.
suspecting	X was suspected of conducting the attack.
responsibilityClaim	X claimed responsibility for the attack.
helping	X sent/provided/offered support/aid/help.
beingRescued	X was rescued.
evacuating	X was evacuated.

Figure 5
An ordered list of abstraction schemes that serves as the generation plan for the category ATTACKS.

4.3.3 Methodology for Writing Task Blueprints. Two task blueprints were written for ABSUM, one on the ATTACKS category, and the other on the ACCIDENTS AND NATURAL DISASTERS category.

Several tools were used, starting with the development set made up of the TAC 2010 clusters, including example source documents, topics, and reference summaries for each category. An English thesaurus was consulted to help populate the various lists of the task blueprints, including some lists which are later described in the summarization system (section 4.4) like stoplists. This was also complemented by internet queries about English words and their usage. A list of the available syntactical dependencies of the Stanford Parser and an interface for running it on sentences are also necessary, for reference, but also for discovering typical sentence structures that may be analyzed in an incorrect or unexpected way by the parser.

The task blueprint writing process involved a lot of back and forth, between consulting the reference summaries to determine what should be said, observing the development set's documents and their language to determine what to look for and how it is analyzed by the parser, making modifications to the blueprint accordingly, and running the system on the development set to verify the effect of those modifications. Because the development set was so small (7 topics and a total of 70 documents per category), a lot of effort was spent trying to expand the rules and lists to as many unseen cases as could be foreseen.

4.4 Summarization System

The summarization system's input consists of the analysis of the source documents, and the task blueprint for its category, which provides the knowledge necessary to write an abstractive summary. The top-level algorithm for writing a summary is to read the generation plan and sequentially generate a sentence for each of the abstraction schemes, when possible. The generated sentences are concatenated together, separated by a space character.

The remainder of this section describes how to generate a sentence from a scheme description within the task blueprint, and an analyzed cluster of 10 NewsWire documents. This is accomplished in three steps: pattern matching, content selection, and sentence generation. The process will be illustrated by an example based on a document cluster with the topic "Dimona Attacks", taken from the test set, and the abstraction scheme **killing**, which appears in Figure 4. The story on the Dimona attacks is about two terrorists who attempted to blow themselves up with explosives in crowded areas; the first bomber was successful and the second was killed by

police. Figure 3 shows a sentence relevant to this example, and its representation after parsing by the analysis module.

4.4.1 Pattern Matching. An abstraction scheme's pattern matching rules contain one or more predicates, as discussed in section 4.3.1. Predicates may have one or two arguments, up to one of which may be a variable linked to an aspect of the category. Example rules and predicates are given in Figure 4.

Pattern matching begins by going through all the predicates and attempting to find matches for each one within the analyzed source documents. A rule is applied if all of its predicates have a match in the same sentence, given also that a variable or a lemma group that appears in more than one predicate of the same rule is matched to the same entity.

The application of a rule leads to the creation of a *candidate* for the generation process. This is the result of an instantiation of a variable or a choice within a lemma group, which provide a suggested lemma for the content of the generated sentence. Rules that contain a variable produce candidates for a specific aspect of the summary, and those candidates are called *aspect candidates*. Candidate identification is illustrated by the right-hand side of the rules in Figure 4.

On the example sentence from Figure 3, pattern matching attempts to apply the rules for the abstraction scheme **killing** (Figure 4). For example, the relation NSUBJPASS(`killed`, `bomber`) yields the aspect candidate WHO_AFFECTED(`bomber`), because each element of the syntactical relation matches the pattern: NSUBJPASS is a member of the syntactical relations group *obj_relations*, and `kill` is a member of the lemma group *kill_verbs*, so `bomber` instantiates X in the pattern matching rule. Similarly, the syntactical relation AGENT(`killed`, `officers`) yields the aspect candidate WHO(`officer`).

An aspect candidate is given a date if its source word bears a date or if one of his parents in the dependency tree does. Dates were attributed to words during Preparation Step 2 of the semantic annotation part of the analysis, described in section 4.2.3.

4.4.2 Content Selection. Content selection is the process of selecting the aspect candidate that will become the *aspect answer* for each aspect, and selecting its modifiers for generation, where appropriate. It also includes the selection of a lemma from each lemma group that must appear in the scheme's generated sentence, which is done in the same way as selecting aspect answers.

The content selection heuristics presented here were selected to maximize the accuracy of the information selected, and the readability of the sentences generated, because false and unreadable sentences often leave a bad impression to the reader who might dismiss the whole summary as useless. In other words, precision was somewhat favored over recall. This comes at the cost of preventing some valuable information from making it into the summary, because the number of abstraction schemes that lead to a sentence being generated in the summary is lower than could otherwise be possible.

Filtering Aspect Candidates. Before selecting aspect answers, the aspect candidates resulting from pattern matching are filtered according to several criteria. For instance, stoplists are used to avoid words that are undesired answers for a category aspect, such as `war`, which could be identified as the perpetrator of an attack, because it "caused deaths", or `other` because it refers to something else and that no coreference resolution is performed. Similarly, all words that can be considered a type of attack are not considered.

In the corpus used, some sentences can be repeated verbatim in more than one source document (often because they are two articles from the same press agency), leading to repeated aspect candidates. Repeated aspect candidates from identical sentences are filtered out.

The date is also a big factor in filtering out some candidates. In the categories covered, the date of the main event is considered to be the date identified in the special scheme called **Event**,

which is called first by each generation plan. In the other schemes, lemmas for which the most frequent date associated with its aspect candidates is not within a month of the main event's date are removed.

Aspect candidates for which the lemma has been selected in previous schemes for the same aspect are filtered if the current abstraction scheme disallows it.

Finally, all lemmas with a frequency of one within the remaining aspect candidates are removed, in case the information is not salient enough and to avoid relying too much on a single sentence parse, given that the parser makes mistakes. This is a heavy-handed choice which greatly emphasizes precision over recall, as per the intended design.

Selecting Aspect Answers. An aspect answer is a lemma selected to be the head of the noun phrase that will be generated to answer a category aspect. It is selected among the lemmas given by all the aspect candidates for that aspect (after filtering). If a coordinated noun phrase is allowed by the generation template, then all lemmas are used. Otherwise, the lemma that has the highest frequency among the remaining aspect candidates is selected. This choice of the lemma with the highest frequency as the noun phrase head may change later, if the resulting noun phrase with a different head would still contain that highest frequency lemma, though as a modifier.

To continue the Dimona attacks example, the application of pattern matching rules for the abstraction scheme **killing** on all the source documents yielded the following aspect candidates for the perpetrator (with frequencies in parentheses): `police`(4), `officer`(3), `blast`(1); and the following for the victims: `bomber`(4), `second`(2), `attacker`(1). Filtering removes `blast` and `attacker` because they have a frequency of 1. Thus, for now `police` and `bomber` are the selected aspect answers, with `officer` and `second` kept in reserve as alternative NP heads, and as favored modifiers. It is also needed to select a verb from within the *kill_verbs* group, and it is the lemma `kill` which was selected given the observed verbs: `kill`(17), and `shoot`(10).

Selecting Noun Modifiers for the Noun Phrase. Once a noun lemma has been selected as a candidate answer (or as one of several candidate answers in the case of a tie for highest frequency), its modifiers must be selected to form a noun phrase. Four types of modifiers are considered: noun-noun modifiers, numerical modifiers, adjectives, and "of" prepositional modifiers (a noun that modifies the head noun through the preposition `of`). These are directly observable in the dependency parse tree.

The combination of noun modifiers selected must be one that was observed at least once as part of a noun phrase that was an aspect candidate. To select which combination of modifiers is selected, a score for each combination is computed, based on all the occurrences of its modifiers as a modifier to the head noun in the source documents. The basic score is an average of the frequency of the modifiers of a combination. The frequency of each modifier is multiplied by 100 first, when the modifier is a noun-noun modifier whose lemma was another candidate for that aspect. A combination of modifiers which includes all the modifiers of another combination is given the score of the shorter one instead, if this improves the score – this favors a combination of more modifiers where available. In the end, the combination of modifiers with the highest score is selected.

Special care is given to numerical modifiers. If written in English, they are all translated into numerical strings (except for `one` which is only used to identify the singular number). This ensures that either spelling is equivalent and that numerical modifiers occupy less space in the summary.

When a prepositional modifier is selected, the whole process of selecting noun modifiers, capitalization, number and specifier must be recursively called on its lemma, to define this additional noun phrase, part of the larger one. This is not done on noun-noun modifiers, because

the Stanford Dependency Parser does not usually have a noun phrase as the noun-noun modifier of the head noun, resorting instead to a list of nouns each being a modifier to the head.

When it is possible to select another head lemma for the noun phrase while still keeping the aspect answer in the noun phrase (because that lemma appears as a modifier of the new head lemma), the whole process is restarted, this time with this new head, and requiring that the aspect answer appears as a modifier.

This occurs in the Dimona attacks example discussed previously, where the aspect answer `police` appears as a modifier of the other less frequent aspect candidate `officer`, thus this latter word is used and the modifiers selected are `Israeli` and `police`. The modifiers for the other aspect answers are `second` and `suicide` for `bomber`, and none for `second`.

Named Entities and Capitalization. Since lemmas in this system are always considered to be lowercase, it is needed to determine if the head noun of the noun phrase and any other nouns occurring as noun-noun modifiers require capitalization or not. If the lemma is one of the unique strings that were used as replacement for locations, organizations and persons in Preparation Step 1 (see section 4.2.3), then it will be reverted to its original realization, which is a capitalized string. Otherwise, a lemma which occurs more often capitalized than not within the source documents will be capitalized.

Selecting the Number and the Specifier. Noun phrases with a numerical modifier will be set to plural automatically. There is an exception for numbers that are incorrectly labeled as numerical modifiers, e.g. `a 7.0 magnitude earthquake`. When a singular head noun is observed in the source documents with a number greater than one as a numerical modifier, that modifier does not affect the number of the head noun for generation either. Noun phrases without a numerical modifier are set to singular or plural according to how frequently they were seen as one or the other in the source documents.

By default, singular noun phrases are attributed an indefinite article (`a` or `an`) as specifier and plural noun phrases are attributed no specifier. A noun phrase that contains a named entity is instead attributed the definite article (`the`) as specifier, except for locations that have not been observed with a definite specifier in the source document. Lemmas that have never been observed without a definite article in the source documents are attributed one for generation as well. Noun phrases that include a prepositional modifier always use the definite article. The lemma that is selected as the main event noun by the **Event** scheme will be attributed a definite article as specifier if it appears again in the summary. Finally, some lemmas always get a definite article, because of their special role in a category or for general reasons of readability, such as words with a meaning similar to `suspect` and `assailant`.

In the Dimona attacks example, all three noun phrases are singular and given the indefinite article `a` or `an`.

Removing Redundant Noun Phrases. Noun phrases generated to fill up a slot in the generation template of an abstraction scheme may be allowed to be coordinated or not, as mentioned before. In the case where a coordination is possible, redundancy between the coordinated noun phrases must be avoided.

When the head lemma of a noun phrase appears as a noun-noun modifier in another noun phrases, that noun phrase is removed. Similarly, a noun phrase that already appears as a prepositional modifier will not be included in the coordination either. This is to avoid cases such as “The hurricane hit the east coast of the United States and the United States”.

In the ongoing example, the noun phrase with `second` as its head is removed because this lemma appears as a modifier in the other noun phrase with which it would be coordinated. This avoids generating: `A second and a second suicide bomber were killed.`

Special Case: People. The lemma `person` often occurs as the head noun of noun phrases in the corpus used, for the categories of interest. Depending on the context, words with an implicitly similar meaning will be used in the source documents, such as `others`, `victims`, `casualties`, `people/persons`. They are all considered to be the same lemma by the system, which will always use the word `person` (and the plural form `people`) to represent them for generation.

Another option to detect this kind of information would have been to write pattern matching rules to deal specifically with finding the number of dead and injured. This may have worked equally well, but additional work would be needed in avoiding to mention the same information again in schemes that are more generic.

Because of the special role of counting people for news stories about attacks, accidents and natural disasters, the choice of a numerical modifier for the lemma `person` is critical. News stories will differ in terms of the number of deaths and so on, and favoring (quite gruesomely) the largest observed number among several options of numerical modifiers for a given aspect is the strategy that has been adopted. This tends to lead to a better summary also because of the nature of the source documents, which are often published on different dates and so the number of casualties is revised as more information becomes available. The alternative of selecting the most recent number has also been considered, but it has the downside of possibly choosing a number that was used in a context with a smaller scope; e.g. the latest article might report the number of casualties in one town, whereas the event of interest affected a large area.

A more involved approach would take into account the specificity and date of each number, and perhaps try to establish a confidence level for each one, but this was not implemented here.

Subject-Verb-Object Constraint. Selecting the candidate answers and the lemma from a lemma group that fill up the slots of an abstraction scheme's generation template is done independently. This may lead in some cases to falsehoods and nonsense. To avoid this problem, only subject-verb-objects triples that have been observed together at least once in the source documents are allowed.

The process of selecting subjects and objects is done greedily, starting with the subject. After a rejection, the process starts over iteratively at the level of selecting aspect answers. When no agreeing subjects and objects can be found, only one element is kept, whichever has been identified as required in the generation template, if any.

In the Dimona attacks example, some source document sentences (including the one shown at the beginning of this section) indeed contain a verb that is part of the *kill_verbs* group and that has `officer` as its subject, and `bomber` as its object. In some cases, such as this one, it may occur that the number of one of these lemmas is not the same as in the source sentence, because that decision was based on the frequency with which that lemma was used with either singular or plural.

4.4.3 Sentence Generation and Postprocessing. During Content Selection, all the elements of the abstraction scheme's generation template have been selected. This will include a verb and possibly noun phrases for either the role of subject or object. Cases in which no subject and no object are selected, or if a required element is missing, do not lead to a sentence being generated.

If more than one subject or more than one object has been selected, the noun phrases are coordinated and the resulting noun phrase is set to plural.

The verb is always set to the past tense because the summaries generated describe past events. If there is no subject, the verb is set to the passive voice.

The sentence is realized using the SimpleNLG (Gatt and Reiter 2009) library, which takes care of subject-verb agreement, verb tense and voice, noun phrase coordination, start-of-sentence

capitalization, and end-of-sentence punctuation. Some generation templates include a fixed end-of-sentence string to be appended, and SimpleNLG supports this possibility in a clean way.

After sentence generation, a tiny step of postprocessing reverts numbers back to the usual format that uses commas as thousand separators (the commas had been removed during preprocessing).

In the Dimona attacks example, the sentence generated for the **killing** abstraction scheme can be seen in Figure 6, where it appears as the second sentence of the summary generated by ABSUM. The other summaries generated on the test set can be found in Figure 10.

> On February 4, 2008, a suicide attack occurred in Dimona. An Israeli police officer killed a second suicide bomber. An Israeli woman and three Israelis died. The military wing of the Palestinian Fatah movement claimed responsibility for the attack.

Figure 6
Summary generated by ABSUM on cluster 9 of the test set, under the topic "Dimona Attacks".

4.5 Hybrid Summaries

ABSUM produces very short summaries, sometimes even less than 10 words long. This is the expected behavior of a system which greatly favors precision over recall in the content selection process. Thus, the summaries generated are always far shorter than 100 words long and lack coverage of the source document. For now, ABSUM does not have a size limit in the output, and, even then, it never comes close to outputting 100 words.

In order to give ABSUM a fair chance against 100-word long summaries during the evaluation process, a hybrid alternative that uses sentence extraction to lengthen the summary and reach the desired size is considered. This hybrid summarizer is forced to start the summary with the output of ABSUM, and then completes the summary using state-of-the-art extractive techniques.

This idea to have an abstractive/extractive summarization hybrid should probably be applied to any non-extractive system that is unable to cover all of the information desired, and it has been implemented before in the RIPTIDES summarizer (White et al. 2001). In the case of ABSUM, aspects such as "WHY" and "COUNTER-MEASURES" of the ATTACKS category will not be fully covered by the pattern matching rules, even in the best of cases, and in some cases, other aspects will not be covered correctly either. Bringing in some extracted sentences fills these gaps and provides a safeguard for when a topic is outside the range that is meant to be covered by ABSUM.

The automatic summarizer with the best overall responsiveness amongst all the participants of TAC 2011 was CLASSY (Conroy et al. 2011). Researchers John Conroy and Judith Schlesinger generously agreed to produce hybrid summaries that begin with the output of ABSUM and end with the output of their CLASSY 2011 extractive summarization system. They performed some slight modifications to their system in order to adjust to the additional abstractive input and to try to apply their redundancy avoidance to that content. The output of this extractive summarization system altered for the hybrid setting were provided to us and used during evaluation.

5. Evaluation

ABSUM has been evaluated according to the recent standards and methodology developed in the DUC and TAC evaluation campaigns. This includes the manual scoring of overall responsiveness, linguistic quality and content. Automatic scoring such as with ROUGE (Lin 2004) has not been performed because it is meant as an approximation of manual scoring, which is more reliable, and would therefore be meaningless in the face of manual scoring results.

The evaluation set contains 18 clusters of 10 NewsWire articles from TAC 2011's guided summarization track. The evaluation campaign provided 44 clusters, but only the ones with the categories ATTACKS and ACCIDENTS AND NATURAL DISASTERS were included, because other categories were not covered yet in ABSUM.

Five automatic summarizers were evaluated alongside with a human reference:

ABSUM as described in section 3.

CLASSY 2011 System with the best overall responsiveness in the standard guided summarization task of 2011. Output taken directly from TAC's official results.

ABSUM/CLASSY Hybrid Summaries that begin with ABSUM's output, and are completed by CLASSY 2011's system.

Extractive baseline This baseline extracts as many of the first sentences of the most recent document as possible without exceeding 100 words. Output taken directly from TAC's official results.

Abstractive baseline This is an abstractive approach that was submitted at TAC in 2011 (Genest and Lapalme 2011b). It splits sentences based on subject-verb-object triples in the analysis tree to produce short sentences, and selects the most salient one based on statistics-based heuristics.

Human-written models The human-written model was selected randomly for each cluster from the four available models, and used as a reference and upper limit for the evaluation.

The results of the manual evaluation are shown in Table 7, and each score is described below.

	Overall. R.	Ling. Qual.	Mod. Pyr.	Size	Content Density
ABSUM	2.07	3.67	0.277	22.6	0.0119
CLASSY 2011	3.20	3.39	0.520	98.0	0.0053
ABSUM/CLASSY Hybrid	3.31	3.28	0.600	97.6	0.0061
Extraction baseline	2.70	3.76	0.395	84.5	0.0046
Abstraction baseline	1.70	1.44	0.451	97.9	0.0046
Human-written models	4.54	4.69	-	96.6	-

Figure 7
Scores of overall responsiveness, linguistic quality, modified Pyramid, and content density, for ABSUM, the CLASSY 2011 summarizer, a hybrid of ABSUM and CLASSY 2011, an extractive summarizer baseline, an abstractive summarizer baseline, and human-written model summaries. The size is the average length of the summaries measured by their average number of words.

5.1 Linguistic Quality and Overall Responsiveness

Human assessors were asked to score the summaries according to the same guidelines as those used at TAC 2011 for overall responsiveness and linguistic quality. They can be found in Table 8. The assessors had access to the category aspect definitions, the cluster's topic name, the 10 articles, and the summaries themselves. They were not told which summaries came from what

source, and specifically asked to avoid any bias related to recognizing a summary as probably coming from the same source as another one from a different cluster.

Linguistic Quality	Assign an overall linguistic quality score based on consideration of the following factors: grammaticality, non-redundancy, referential clarity, focus, structure and coherence
Overall Responsiveness	Assign an overall responsiveness score based on both the linguistic quality of the summary and the amount of information in the summary that helps to satisfy the information need defined for the topic's category.

Figure 8
Manual evaluation guidelines given to the human assessors.

A total of 10 human assessors evaluated the summaries from the 18 clusters so that each summary was evaluated 3 times. Each assessor was thus given between 5 and 6 clusters to evaluate. The evaluation scores are whole integers between 1 and 5, with the following scale: very poor (1), poor, barely acceptable, good, very good (5).

ABSUM obtains a good linguistic quality score of 3.67 on average, which is much higher than the other automatic systems with the exception of the extractive baseline. This baseline usually gets good linguistic quality scores because the summary is composed of the leading sentences of an article written by a human. It is important to point out that because the size of the sample is so small, the difference of 0.28 point between the averages of ABSUM and CLASSY is not enough to conclude without a doubt that ABSUM has a better linguistic quality than CLASSY. As suggested in (Rankel et al. 2011), a Wilcoxon Signed Rank test, a paired statistical test for distributions that may not be normal, was performed, and a p-value of 0.12 was obtained, which allows for concluding that linguistic quality is probably improved in the short summaries over CLASSY, but that it is not certainly so from a statistical standpoint.

For both overall responsiveness and linguistic quality, CLASSY and the hybrid summaries are statistically indistinguishable, with the hybrid system having a slight edge in overall responsiveness, and CLASSY having a slight edge in linguistic quality. From talking with assessors, it appears that the non-redundancy criterion played the biggest role in lowering the linguistic quality scores for both of them. The hybrid also suffered from grammaticality problems sometimes caused by ABSUM, and CLASSY had a bit more problems with structure and coherence overall. Both systems greatly outperform the other automatic systems in overall responsiveness, including the baselines.

Unsurprisingly, the human-written summaries are far ahead in all respects.

To evaluate inter-annotator agreement, the number and degree of the differences in how each assessor ranks the six summaries on a given cluster was computed. For all pairs of summaries 1 and 2 and all pairs of assessors A and B, A and B are considered to agree if they both rank summaries 1 and 2 the same way (either 1 has a better score than 2, 2 has a better score than 1, or 1 has the same score as 2); A and B are considered to disagree if one of them gave the same score to 1 and 2 while the other gave different scores to one summary and the other; and A and B are considered to contradict each other otherwise, which is in cases where one assessor scores 1 better than 2 and the other scores 2 better than 1.

The result of this analysis is given in Figure 9. Overall, assessor agreement is satisfactory, with assessors agreeing in almost two thirds of cases. The number of contradictions is somewhat high at 10 percent, but it is to be expected in natural language processing evaluation tasks of this kind.

Overall Responsiveness		
Agreements	525	65%
Disagreements	210	26%
Contradictions	75	9%

Linguistic quality		
Agreements	511	63%
Disagreements	214	26%
Contradictions	85	10%

Figure 9
Agreements, disagreements and contradictions between assessor scores in the manual evaluation of overall responsiveness and linguistic quality.

5.2 Content: the modified Pyramid Score

As is usually done in the latest summarization evaluation campaigns, a Pyramid content score is also computed, according to the methodology outlined by (Nenkova et al. 2007). Because this evaluation is re-using the data set from the TAC 2011 evaluation campaign, the pyramids are readily available. Semantic Content Units (SCUs) were manually assigned to the ABSUM and hybrid summaries from those identified in the four human-written summaries from each cluster and normalized the scores according to the "modified Pyramid" methodology (without jackknifing). The resulting score can be interpreted as a percentage, where 0 means that the summary is information-less and 1 means that the summary contains the expected amount of information that would be found in a human-written summary. In Figure 7, human-written summaries have no pyramid score because they are themselves the reference.

The most striking result of the modified Pyramid evaluation is that the hybrid summaries have a much higher average than CLASSY's purely extractive ones. This difference is statistically significant according to a Wilcoxon Signed Rank test (p-value < 0.05). This means that **on average, ABSUM increases the amount of informative content of a state of the art system.** CLASSY was the chosen system to compare against, because it has the best overall responsiveness in the evaluation campaign, but it did not have the highest pyramid score at TAC 2011. The system (described in (Mason and Charniak 2011)) with the highest average Pyramid score on the 18 clusters of the test set had an average of 0.591, which is still inferior to the hybrid system's 0.600, though not significantly so.

5.3 Content Density

To account for variable summary lengths, the Pyramid metric was developed with the intent that the weight of the SCUs in a summary, which provides the Pyramid score, should be normalized by the total number of SCUs in the summary. This was very hard to implement in practice and this is why the modified Pyramid method is more widely used instead. It is only appropriate for summaries of roughly the same size, however, and so can be misleading in this case, where ABSUM outputs much shorter summaries than the other systems it is compared against.

To account for the varying summary sizes, content density is measured, where it is defined as the modified Pyramid of a summary divided by the number of words of the summary. The averages shown in Figure 7 represent an average of this content density score over 18 summaries.

The content density of ABSUM is higher than that of any other automatic system in the evaluation, by a factor of almost 2 to 1. This is also the case when compared to any other

Cluster Topic	Summary generated by ABSUM	C	L	O
1. Amish Shooting	On October 2, 2006, a shooting occurred in Lancaster County. Amish girls were assaulted. A suicidal gunman shot the classroom of girls and himself.	28	5.0	2.3
5. Plane Crash Indonesia	On January 1, 2007, a plane crash occurred in Indonesia. An Adam Air plane crashed. 90 people died.	27	4.0	2.0
8. Cyclone Sidr	On November 15, 2007, a cyclone occurred in Bangladesh. The cyclone caused a storm. The powerful cyclone hit the southwestern coast of Bangladesh. Hundreds died. Homes were destroyed. Thousands were evacuated.	43	3.7	2.7
9. Dimona Attack	On February 4, 2008, a suicide attack occurred in Dimona. An Israeli police officer killed a second suicide bomber. An Israeli woman and three Israelis died. The military wing of the Palestinian Fatah movement claimed responsibility for the attack.	34	4.0	2.3
10. Earthquake Sichuan	On May 12, 2008, an earthquake occurred in Sichuan. The powerful earthquake struck Sichuan province. 8,533 people died.	38	3.3	2.3
11. Finland Shooting	On November 7, 2007, a school shooting occurred in Finland. A teenaged gunman shot eight people and himself. Seven classmates, headmistresses, victims of a high school, five teenage boys, a wounded, 18-year-old pekka-eric Auvinen, two girls and three women died.	53	2.3	2.0
15. Oil Spill South Korea	On December 7, 2007, an accident occurred in South Korea.	6	3.7	1.0
16. VTech Shooting	On April 16, 2007, a campus shooting occurred at Virginia Tech. 32 people were killed.	24	5.0	2.0
22. Minnesota Bridge Collapse	On August 1, 2007, a ground collapse occurred in Minnesota. A bridge crashed. Seven people died. 79 people were injured.	26	3.0	1.7
23. USEmbassy Greece Attack	On January 12, 2007, a rocket attack occurred in Athens. The U.S. Embassy was struck. A third-floor bathroom was damaged. A domestic militant group was suspected of conducting the attack.	34	4.0	3.3
24. Indonesian Mud Volcano	In January 2007, an eruption occurred in East Java. 13 people died. The marine ecosystem was damaged.	15	4.3	2.0
26. Reporter Shoe Bush	In December 2008, a shoe attack occurred in Iraq.	7	3.0	1.0
30. Borneo Ferry Sinking	In January 2007, a ferry accident occurred. 13 survivors of the ferry disaster were rescued.	0	3.3	1.7
33. Glasgow Airport Attack	In June 2007, an airport attack occurred in Glasgow Airport. Two people were arrested. The airport was evacuated.	41	3.7	1.7
37. Crane Collapse	On March 15, 2008, a construction accident occurred. A towering crane crashed. Four people died. 24 people were injured. A five-story building and parts of five buildings were demolished. A building was evacuated.	65	3.3	2.7
39. Pirate Hijack Tanker	On November 15, 2008, Pirate attacks occurred in Bahrain. Merchant vessels, 92 ships and the large crude tanker Sirius Star were attacked.	5	2.7	1.7
40. Bangladesh Flood	On August 1, 2004, a monsoon flood occurred in Bangladesh. 126 people died. Standing crops and 250,000 houses were damaged.	29	3.3	1.7
42. Jaipur Bombs	On May 13, 2008, a terror attack occurred in India. A market was hit. 80 people were killed. Pakistan-based Islamic militants were suspected of conducting the attack.	26	4.3	3.3

Figure 10
The summaries generated by ABSUM on the test set, with their scores for **C**ontent (Modified Pyramid times 100), **L**inguistic quality, and **O**verall responsiveness. The latter two are an average of 3 assessments on a scale from 1 to 5. 18 of the 44 clusters from TAC 2011's official data set were used.

Cluster Topic	Summary generated by the ABSUM/CLASSY hybrid
8. Cyclone Sidr	*On November 15, 2007, a cyclone occurred in Bangladesh. The cyclone caused a storm. The powerful cyclone hit the southwestern coast of Bangladesh. Hundreds died. Homes were destroyed. Thousands were evacuated.* A fierce cyclone packing extreme winds and torrential rain smashed into Bangladesh's southwestern coast Thursday, wiping out homes and trees in what officials described as the worst storm in years. A powerful cyclone with strong winds started pounding on Bangladesh's south and southwestern coast from Thursday evening. The money will go to German relief organisations working in cooperation with local partners to alleviate suffering caused by Cyclone Sidr.
16. VTech Shooting	*On April 16, 2007, a campus shooting occurred at Virginia Tech. 32 people were killed.* Thirty-two people were killed and at least 15 injured in two shooting attacks at Virginia Tech on Monday during three hours of horror and chaos on this sprawling southwestern Virginia campus. U.S. President George W. Bush said at the memorial service held at Virginia Tech Tuesday that the shooting rampage marked "a day of sadness" for the entire nation. Virginia Tech President Charles Steger said Tuesday all classes for the rest of the week at the university have been canceled.
37. Crane Collapse	*On March 15, 2008, a construction accident occurred. A towering crane crashed. Four people died. 24 people were injured. A five-story building and parts of five buildings were demolished. A building was evacuated.* A piece of steel fell and sheared off one of the ties holding it to the building, causing the structure to detach and topple, said Stephen Kaplan, an owner of the Reliance Construction Group. Neighborhood residents said they had complained to the city several times about the construction at the site, saying crews worked illegal hours and the building was going up too fast.

Figure 11
Summaries generated by the ABSUM/CLASSY hybrid for 3 clusters of the test set. The first part of each summary, in *italics*, is the outputfrom ABSUM, while the rest is generated by sentence extraction with the CLASSY system.

automatic system in TAC 2011's evaluation campaign. Short summaries have an advantage when it comes to content density, because any system that shortens its output will typically improve its content density, by selecting sentences in which they have higher confidence. However, in ABSUM's case, not only the summaries are shorter, but the sentences are as well, and they tend to contain much less uninformative and useless bits of information than in extracted sentences. This also explains why adding ABSUM's sentences at the beginning of a state of the art system like CLASSY significantly improves its informative content.

5.4 Qualitative Observations

Figure 10 shows all the summaries that were automatically generated by ABSUM on the test set. This covers only the clusters with topics from within 2 of the categories, which explains why the topic numbers are not consecutive in the figure.

While the summaries are short, they are often very informative, such as in the case of the summary for "37. Crane Collapse". This 33 word long summary has a modified Pyramid score of 0.647 whereas CLASSY's 98 word long summary only has a score of 0.235. At the other end of the spectrum are the summaries for "26. Reporter shoe Bush" and "15. Korea Oil Spill" which provide very little relevant information. These cases highlight the typical problem of favoring precision over recall: spills and the kind of damage that they induce, as well as attacks such as a shoe attack which has no casualty or damage at all, were not observed in the development set nor foreseen, and so there were no rules to deal with them directly in the category's task blueprint.

The linguistic style of these summaries is by design telegraphic, generating intentionally short, to-the-point sentences to express content efficiently. However, even given that style, a few summaries remain awkward-sounding or even ungrammatical. The worst one in that regard is probably the summary for the topic "11. Finland Shooting", in which the third sentence includes false, confusing and redundant information, as well as a person's name which should be capitalized. Another interesting bad case is the summary for the topic "39. Pirate Hijack Tanker", which is informative but also awkward and misleading. The Sirius Star was attacked on the day mentioned, but the other ships were reportedly attacked earlier in the year and were not the focus of the source documents.

Generally speaking, there are however very few false facts in the summaries. Claiming false information as fact in abstractive summaries is a very serious problem that puts the credibility of the user in the system in jeopardy. This problem is much less present in extractive summaries, where the problem usually occurs only in cases where an anaphoric word gets resolved to the wrong antecedent. As mentioned before, ABSUM addresses this problem by being very strict in what will be allowed to be generated by the content selection process.

As can be seen in Figure 11, the hybrid summaries suffer a lot from redundancy issues, whether the abstractive part was short or long. This is especially apparent in the hybrid summary for the topic "8. Cyclone Sidr" where poor Bangladesh appears to be hit 3 to 4 times by the same cyclone, in a way that sounds extremely redundant.

The linguistic errors discussed for ABSUM apply to the hybrid as well, but not the problem of low coverage, since the extractive part fills in the information gaps, such as in the hybrid summary for the topic "16. VTech Shooting", where the extracted sentences add extra information, though the summary contains again an obvious repetition at the start of the third sentence.

The third hybrid summary is a good example of both parts doing their jobs well, where the abstractive content covers the most salient information in a very efficient way, and the extracted sentences add details and peripheral information.

6. Discussion

6.1 On the High Content Density of ABSUM

ABSUM's summaries have by far the highest content density during evaluation. They were also the shortest by far. Hybrids were built so that non-extractive summaries could be evaluated on the same task as the other systems, having a similar size.

On the other hand, it seems natural to also measure the content density of extractive summaries that have been restricted to be about as short as the non-extractive summaries, for comparison. Figure 12 presents a Pyramid evaluation of ABSUM and "CLASSY 1-sent", which

uses the same state-of-the-art extractive system as before, but forced to keep the summaries only one sentence long. That is, only the most salient extracted sentence from the CLASSY summaries are kept and evaluated for content and content density.

	Pyramid	Size	Content Density
ABSUM	0.277	22.6	0.0119
CLASSY 1-sent	0.270	27.0	0.0105

Figure 12
Pyramid (content) score, size and content density of ABSUM and a similarly-sized set of sentences comprised of only one extracted sentence.

The results show that ABSUM has a 13% higher content density over extractive summarization when they are restricted to a very short length. This result is similar to the previously observed 15% higher content density of the ABSUM/CLASSY hybrid over the extractive system CLASSY. In the case of this latest content evaluation on short summaries, however, the difference is not statistically significant, because of the higher variance of Pyramid results on short summaries.

Nevertheless, the hybrid summaries having significantly higher content than the extractive system can most likely be explained by a combination of two factors. Firstly, ABSUM appears to have higher content density then the first sentence of the extractive summary. Secondly, ABSUM sometimes manages to include content that does not even appear in the extractive system, therefore providing a clear advantage to the hybrid summary in those instances. Hybrid summarization makes use of two techniques that complement each other nicely: non-extractive summarization provides content about expected key points of a story with high precision and using few words, while extraction provides details of the particular story that are unexpected yet salient.

6.2 Going Back to K-BABS

K-BABS suggests that abstractive summarization can be conducted in two steps: analysis of the text into a source representation, and generation of the summary on the basis of abstraction schemes. In practice, applying this principle requires a methodology for content selection as well, and this is what ABSUM did. Ideally, this extra step should be more conceptual than it currently is, and many tricks and stratagems were required to ensure the quality of the final output. The abstraction schemes were written with no assumption of how to select content for generation, and in that sense they remain "pure", unconcerned with how to apply the knowledge it contains in a practical setting. Bringing together the information extracted from the pattern matching rules therefore required a lot of care in the content selection part of the summarization system.

The most limiting factor, however, does not lie in the way the abstraction schemes are written, but rather in the very first step: analysis. Tools for the analysis of text, and especially syntactical parsing, have become sufficiently accurate to make a system such as ABSUM possible, but other tools were not performing as well as would be necessary, especially noun phrase coreference resolution, for which no freely available system seemed to perform even remotely close to the level that would be required. Handling time better could go a long way, as well as dealing with documents or clusters that contain several events of the same type – this has led to several errors by ABSUM in the test set.

As the tools for analyzing syntax, more or less complex semantic information, text structure, coreferences, and so on, perform better, so will systems that implement the K-BABS approach. It will also have the effect of greatly simplifying the programming, since a lot of development

time was spent on preprocessing and the analysis module (aiming to reduce parsing errors) for ABSUM, and even much more on content selection heuristics that would balance its lack of noun phrase coreference resolution and the parsing inaccuracies that remained.

6.3 Differences between ABSUM and Other Non-Extractive Summarizers

K-BABS is conceptually a more general approach to non-extractive summarization than what has been previously proposed. There is no assumption made about the type of analysis that is performed. The abstraction schemes look for patterns in the source text representation that can be much richer than just taking the output of the analysis module as is. The transformations performed by the abstraction schemes are aimed directly at generating a summary, taking into account the specific summarization task at hand.

Previous systems, notably SUMMONS (Radev and McKeown 1998) and RIPTIDES (White et al. 2001), took the output of a pre-existing information extraction engine, which contained relevant information, and generated sentences to express that information in the form of a summary. Although on the surface, it may seem that the pattern matching rules and generation templates in ABSUM's abstraction schemes perform similarly, there are some important differences that are worth highlighting.

One of the key differences with previous work is that the slot fills in ABSUM are open-ended. Many aspect candidates are considered for inclusion as an aspect answer, allowing for the aggregation of information over varying sources, in combinations that appear in no unique document. This is made possible because no preexisting information extraction system is used, the task blueprints being written specifically for a pre-existing summarization task.

ABSUM makes direct use of redundancy and other criteria to exclude certain aspect candidates, thus partly solving the problem posed by bad parses and incorrect applications of pattern matching rules. In this regard, the heuristics used for the appropriate selection of content for the summary represent a departure from previous work on non-extractive summarization. In previous work such as SUMMONS (Radev and McKeown 1998) and RIPTIDES (White et al. 2001), there is a strong sense that information extraction slots are assumed to be filled correctly (and if they are not, that is not the summarization system's fault). SUMMONS even goes as far as to use generation operators to compare and contrast content from different documents, which necessarily assumes accurate template slot fills. Assuming relatively accurate slot fills is easier to do when the summarization task tackled is defined specifically around what is available in the output of an information extraction system, as was done for SUMMONS and RIPTIDES. ABSUM was designed to address a pre-defined summarization task, namely TAC 2011's Guided Summarization.

ABSUM's focus on precision over recall has lead to taking fewer risks overall, making for perhaps a less ambitious system, but we believe that this is why the performance of ABSUM turns out to be so good, even when compared with the state of the art in extractive summarization. No systematic evaluation of SUMMONS was conducted, and RIPTIDES was only compared against a very simple baseline. In both cases, only well-behaved examples were presented, whereas we have shown all of our results from the test set, including a lot of mistakes and an analysis of some of the errors produced by the system.

6.4 On the Automation of Abstraction Scheme Acquisition

An obvious development bottleneck in K-BABS has to do with building domain- and task-specific blueprints for the system. It requires considerable manual labor and will never fully cover everything that needs to be said about various aspects of a category or domain. This can be addressed by finding a way to acquire pattern matching rules (and perhaps generation templates

as well) automatically, and then possibly reviewing and correcting them manually, where needed. Here are some ways that have been used to extract similar kinds of patterns automatically and that might be adapted to the needs of ABSUM and other systems that might implement K-BABS.

Automatic schemata acquisition was first proposed by (Mooney and DeJong 1985), where consecutive actions performed by an entity are (to some extent) assumed to have a causal relationship or to lead to a common goal. When a set of actions lies outside the known schemata, a new one is created to account for this observation. Somewhat similarly, (Chambers and Jurafsky 2008) and (Chambers and Jurafsky 2009) perform the unsupervised learning of narrative schemas (also referred to as narrative event chains), and this has been applied to creating information extraction templates that extract the same kind of information found by ABSUM's pattern matching rules, in (Chambers and Jurafsky 2011). (Saggion 2013) also produces information extraction templates using unsupervised learning, but without using full parsing or semantic resources. The typical event participants and the event chains or narrative schemas are learned jointly, by relying on observed syntactical relations and coreference chains. This kind of knowledge can be used to generate pattern matching rules and generation templates to populate a task blueprint.

(Filatova et al. 2006) propose a methodology to automatically extract domain patterns from large corpora. In this work, a domain is a type of event, such as earthquakes and presidential elections. The most representative verbs of a domain are identified, and the most frequently observed syntactical patterns in which these verbs occur are considered as information extraction patterns. To apply such a technique in the case of guided summarization, for instance, would require a human to then manually select which template patterns fit with which aspect, and to add a generation template by hand. This would greatly speed up the task blueprint writing process. (Li et al. 2010) have a similar approach, but based on entities rather than verbs, in order to produce the kind of information extraction patterns that would, for example, fill slots for a Wikipedia infobox about a person or organization. This could also be relevant depending on the kind of summaries desired.

Overall automatically acquiring pattern matching rules for abstraction schemes such as the ones used in ABSUM appears feasible, but considerations of keeping a high precision would probably require human intervention as part of a semi-automatic strategy to fill in the task blueprint, and some amount of testing on a development set is required to prevent rules that tend to lead to false positives. There are plans to explore this in future work.

6.5 The Hybrid Summarization Setting and a New Task for Evaluation Campaigns

Another way to address the lack of coverage of manually (or automatically) constructed task blueprints is to develop summarization systems that are specifically designed for the purpose of generating the latter part of a hybrid summary, for which some aspects are known to be poorly covered.

An extractive summarization system designed for hybrid summarization will have to avoid redundancy with content over which it has no control. This is very different from the normal extractive summarization framework and has important consequences on system design. Some extractive summarizers attempt to select all the sentences at the same time, such as approaches that use linear programming (Gillick et al. 2009). In such a context, special constraints need to be added for avoiding redundancy with sentences that are outside the scope of the extractive summary. Also, many approaches use lists of words to favor sentences that answer specific aspects for guided summarization, such as (Conroy et al. 2011), and if one of those keywords is not in the summary but some sentence in the source text contains it, then that sentence is likely to be selected by the algorithm. This does not usually account for lexical variability and the abstract summary may choose one way to express the same thing that the extractive summary will absolutely want to include. To resolve this issue, it would be possible to have the abstract

summarizer communicate to the extractive one which aspects of the domain category it believes that it has answered, and which words and phrases are believed to answer those aspects.

The hybrid system could also be built from the combination of a non-extractive system and a semi-extractive system, the first implementing K-BABS such as ABSUM, followed by some kind of sentence compression-based approach. The compression could specifically be driven to remove phrases or words that are redundant with the fully abstractive part of the summary. This would be very useful in cases similar to the topic "VTech Shooting" in Figure 11, where removing the phrase `thirty-two people were killed` from the third sentence would greatly improve the hybrid summary, since that phrase is repeated verbatim. Obviously, the second sentence could be removed instead, which is something hybrid summaries with better interaction between the two systems should be able to accomplish.

Building extractive or semi-extractive summarization systems in the hybrid summarization setting requires its own experimentation, and while the type of abstractive summarizer and its quality will affect the task, the basic difficulties should remain the same. A new task for summarization evaluation campaigns could therefore be something along the lines of *summary completion*, in which the first half of the summary is provided, and the second half must be filled in to add more depth and details while avoiding repetitions. This is at the same time analogous to and different from update summarization, where an update summary should avoid repeating information assumed to be already known to the reader, from previously published documents. When elaborating the setting for evaluating summary completion systems, the summaries' first half could be written by humans, but the goal would be to apply the techniques developed in hybrid summarization.

Another challenge that the ABSUM/CLASSY hybrid does not address is whether using extracted information is always relevant or not. Assuming that the non-extractive summarizer is able to provide more generated sentences than it currently does, perhaps it still remains relevant to include some extracted sentences in the summary, in order to increase the coverage. After all, non-extractive summarizers – or at least those using IE or abstraction schemes – look for specific kinds of content in a top-down way, whereas extractive and semi-extractive summarizers perform a bottom-up discovery of relevant but sometimes unexpected material. To benefit from both requires a delicate balancing that calls for experimentation not yet performed in this work.

6.6 Adaptation of ABSUM to Other Tasks and Domains

Any language expert (used in a broad sense) should be able to write task blueprints for any new task or domain of interest, given enough time and the right tools. No programming proficiency is absolutely necessary, since the abstraction schemes are purely declarative (ABSUM's task blueprints are written in XML files). Elementary knowledge in syntactical analysis and world knowledge about the new task and domain (and some common sense!) should suffice. At the core of K-BABS is the abstraction scheme, and given the kinds of syntactical and semantic information that are made available by the analysis module, anyone can write abstraction scheme pattern matching rules and generation templates that will be used in a predictable manner by the summarization system. Writing a task blueprint for new categories is thus fairly straightforward, even though some care and a lot of trial and error are required for getting satisfactory results.

For ABSUM, a blueprint was written for one guided summarization category, alongside the development of the summarization system. The many design decisions for the summarization system, including the choice of several heuristics and parameters, are specific to the guided summarization task, the corpus, or more generally to the summarization of news, but not to a given topic category. Only when the system was completed did work begin on the second category. This provides insight into the amount of effort necessary to write a blueprint for a new

category, assuming that the context remains the same, namely the guided summarization of news articles.

The time spent to add an additional category can be considerable, and it was estimated to be around 100 man hours, purely for writing the task blueprint. Actually, a lot more time was spent to add functionalities to the summarization system in parallel to writing rules, because it did not support all the features necessary for tackling the new category. Some of those changes to the summarization system also affected processing of the first category as well. As more categories are added, the system will reasonably need fewer and fewer improvements and modifications, and only new task blueprints will need to be written, as is intended. The categories used by TAC are very broad (ATTACKS rather than school shootings, terrorist attacks, political assassinations, etc., and ACCIDENTS AND NATURAL DISASTERS rather than transportation accidents, earthquakes, tsunamis, etc.). The numerous kinds of events that must be covered in a single category consequently require numerous rules and more effort in constructing flexible word lists. More restricted categories would make task blueprint writing less time consuming and more intuitive.

For other types of input documents and other summarization tasks, some changes are likely necessary, especially with respect to the choices made regarding some of the content selection heuristics. As a simple example, the fact that aspect candidates that appear less than twice are filtered out was a design decision made to compensate for occasional bad parses, and because important information tends to be repeated in the context of multidocument news summarization with 10 source documents. The minimum frequency of 2 used here is a parameter (and there are a few more like it in the content selection module) that can be adjusted according to the needs of the task at hand. Most of the stoplists have to be revised depending on the tasks as well. More complex design decisions can be put into question depending on the needs of the task of interest, such as the choice of accepted noun modifiers, the constraint put on observed subject-verb-object triples, the special processing of words such as `people`, the constraint of giving at most two arguments (subject and object) to verbs during generation, etc.

Dealing with other tasks is already possible within the current implementation, because the generation template does not have to resemble the pattern matching rules, as is currently the case in ABSUM. Indicative summaries can be generated with only slight adjustments to the system. The kind of deep understanding of the documents enabled by the K-BABS approach also enables to compare and contrast different documents with very novel sentences generated for that purpose. This could prove very interesting in a variety of settings, such as multi-document summarization where inconsistencies between sources can be reported concisely, and update summarization where changes in some key elements can be reported explicitly. Multilingual summarization is another interesting angle that should be explored, since the generation templates of the abstraction schemes can be written in a different language, and only translating short phrases at a time would be necessary.

7. Conclusion

This work has demonstrated both the desirability and the feasibility of abstractive summarization. The K-BABS approach shows great promise, given the excellent evaluation results of ABSUM. Performance in the context of hybrid summarization is superior to the previous state of the art, in terms of the amount of content in the summary. It is also the first instance of an abstractive system performing better than state-of-the-art extractive systems on a shared task and according to a state of the art evaluation protocol.

This can probably be attributed to ABSUM's focus on achieving good precision, i.e. the attention that was given to avoid bad summaries arising from incorrect parses and bad applications of pattern matching rules. This empirical consideration which is a departure from previous

literature in abstractive summarization leads to very interesting theoretical questions given that it will always be the case that analysis tools will not be perfect, and so there will be a need to perform good abstractive summarization in spite of this challenge of dealing with noisy data. Is there a way to establish a confidence in certain aspect candidates? And what about their realization? What are other possible strategies to select a noun or verb phrase realization for an aspect answer, and which is best?

Even though ABSUM performed well during evaluation, it was not first developed with the goal of outperforming other approaches at all cost, but rather to test hypotheses about natural language understanding and processing, as exposed by the K-BABS approach, which also considers the flexibility and scalability of the approach as a necessary criterion. After all, the goal of summarization research should be, on one hand, to achieve good performance at the task of summarizing text today; and on the other hand, to develop and improve techniques and theories on language understanding and semantic analysis which will help address a variety of natural language processing tasks tomorrow. Whereas lately, it seems that researchers in text summarization have focused on the first goal at the detriment of the second, ABSUM reached the first goal by aiming at the second.

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CHAPITRE 5

CONCLUSION

Dans les mots de Kenneth Church [1], qui s'intéressait aux limites des approches empiristes en traitement automatique des langues : "We have a better chance of making progress on big open scientific questions if we address them head-on rather than finessing around them."

Ceci s'applique sans doute aussi dans le cas de la rédaction automatique de résumés, où faire de l'abstraction est une façon de s'attaquer au problème tête première, tandis que l'extraction contourne le problème pour le simplifier. Les conclusions de l'expérience HexTac, à savoir qu'il existe une limite empirique relativement basse pour les performances espérées en extraction de phrases, remettent justement en question l'intérêt de chercher à perfectionner les systèmes par extraction de phrases, alors qu'il était déjà évident que les approches par abstraction permettent de s'attaquer au problème directement, en reproduisant plus fidèlement la façon de faire des être humains.

L'approche semi-extractive par division de phrases s'inscrit parmi d'autres semblables comme la compression de phrases et la fusion de phrases, qui n'avaient cependant jamais été comparées à l'état de l'art auparavant. Malgré le potentiel beaucoup plus grand des approches semi-extractives par rapport aux approches par extraction de phrases, le niveau de performance de notre système montre que ces approches font face à un défi énorme au niveau du maintien d'une bonne qualité linguistique du résumé généré. De plus, elles ne semblent pas offrir, en pratique, d'avantages évidents en ce qui a trait à la sélection de contenu pour le résumé, ne profitant pas d'une meilleure compréhension du texte source.

L'approche par abstraction K-BABS, elle, effectue un repérage direct d'éléments de contenu ayant un sens connu, grâce à une base de connaissances adaptées à la tâche. Ceci mène à une compréhension du contenu et donc à une compréhension des phrases générées pour le résumé. Un plan de génération du résumé permet de produire un texte plus lisible et répondant plus directement au besoin d'information du lecteur. Seules les informations pertinentes apparaissent dans le résumé. Le système ABSUM possède toutes ces caractéristiques et ses performances démontrent à quel point cette catégorie d'approches améliore la densité de contenu du résumé. Son utilisation dans un contexte hybride avec un système état de l'art, permet d'améliorer significativement la quantité de contenu par rapport à une approche uniquement par extraction, établissant un nouvel état de l'art du résumé textuel.

Ces excellents résultats nous permettent de conclure à l'utilité des approches non-extractives pour la rédaction automatique de résumés. La faisabilité et la possibilité de mise à l'échelle sont également bien démontrées, puisqu'un système de résumé supportant un type donné d'"abstraction schemes" (AS) peut être ré-utilisé ensuite avec peu de changements, peu importe la tâche à accomplir. De plus, les AS existants peuvent

eux-mêmes être ré-utilisés dans un nouveau Task Blueprint, comme nous l'avons fait en passant du domaine des attaques à celui des accidents et des désastres naturels.

Nous avons également montré que le système ABSUM est bien différent des systèmes non-extractifs précédents, notamment par sa façon de gérer les erreurs d'analyse et de ne pas dépendre aveuglément d'un système d'extraction d'informations préexistant. Il utilise plutôt un parseur syntaxique pour l'analyse et nous croyons que la performance de systèmes semblables s'améliorera rapidement lorsque des outils d'analyse plus performants seront disponibles, notamment pour le repérage de groupes nominaux co-référents.

Nos travaux évoquent également une foule de questions non résolues ouvrant la porte à des travaux futures.

Tel que mentionné, le point névralgique de l'approche K-BABS se situe dans la création de la base de connaissances appelée Task Blueprint. Automatiser le processus de création de la base de connaissances, au moins en partie, permettrait de rendre K-BABS plus facilement et rapidement applicable à une variété de domaines et de tâches de résumé. Les méthodes non-supervisées pour le repérage de patrons d'événements sont sans doute le point de départ autour duquel développer l'acquisition automatique d'"abstraction schemes" (AS).

En y regardant de plus près, on se rend compte également que les AS peuvent être élaborés de plusieurs façons différentes et ceci mériterait d'être exploré davantage. Le type d'outil utilisé dans la phase d'analyse a un impact considérable sur la façon d'élaborer les AS. Selon que l'outil est peu élaboré (presqu'uniquement de la syntaxe), un peu plus avancé (extraction d'information) ou très élaboré (scripts, extraction d'événements), la représentation intermédiaire du texte source sera très différente. On peut supposer que plus l'outil est avancé, plus les patrons utilisés dans les AS pourront être simples, au risque de diminuer le contrôle sur le contenu disponible pour les résumés que l'on cherche à générer.

Également, il serait intéressant d'explorer les façons par lesquelles les AS peuvent interagir entre eux. Dans ABSUM, on évite de répéter de l'information déjà contenue dans un autre AS. Durant l'élaboration du système, des scénarios où la présence d'un AS dans le résumé interdisait la présence d'un autre ont aussi été testés. Mais il serait possible d'aller beaucoup plus loin dans cette direction. Du point de vue de la génération de texte, il serait intéressant de juxtaposer des propositions générées par plusieurs AS différents dans une même phrase générée, et de considérer des façons de faire la transition d'un à l'autre selon leur contenu.

Plus encore, du côté théorique, serait-il possible d'imaginer une structure hiérarchisée des AS, où un AS pourrait dépendre d'autres AS inférieurs pour générer des informations encore plus généralisées. Par exemple, étant donnés des AS où le même homme commet plusieurs meurtres différents, serait-il possible d'utiliser des patrons pour détecter des similitudes entre eux et générer une phrase qui identifierait cet homme comme un tueur en série ? Pour un long document source, il serait ainsi possible de contrôler le

niveau de détails du résumé selon les besoins du lecteur.

Un autre aspect très important de notre démarche a été de faire appel à un système de génération automatique de résumés par extraction pour complémenter la sortie du système par abstraction. Plusieurs questions restent non résolues à ce sujet. Par exemple, quels ajustements doivent être faits aux systèmes par extraction existants pour les spécialiser au contexte hybride ? Les phrases extraites doivent-elles nécessairement apparaître après les phrases générées par abstraction ? La proportion de mots provenant de l'abstraction et celle provenant de l'extraction peut être contrôlée, mais comment choisir la proportion menant au meilleur résumé dans un contexte précis ? On peut également se demander dans quelle mesure les informations supplémentaires que l'extraction permet d'aller chercher pourraient être insérées dans les phrases générées par abstraction, notamment en ajoutant des modifieurs aux groupes nominaux et verbaux.

En somme, il est clair que ce travail, montrant l'intérêt énorme que représente les approches de génération de résumés non-extractifs pour faciliter l'accès à l'information, se veut être un point de départ pour la recherche sur la génération de résumés par abstraction.

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Annexe I

Technical Appendix

This appendix provides extra technical details about preprocessing, the task blueprint and the summarization system, that were not included in “ABSUM : a Knowledge-Based Abstractive Summarizer”. The architecture of ABSUM is illustrated in Figure I.

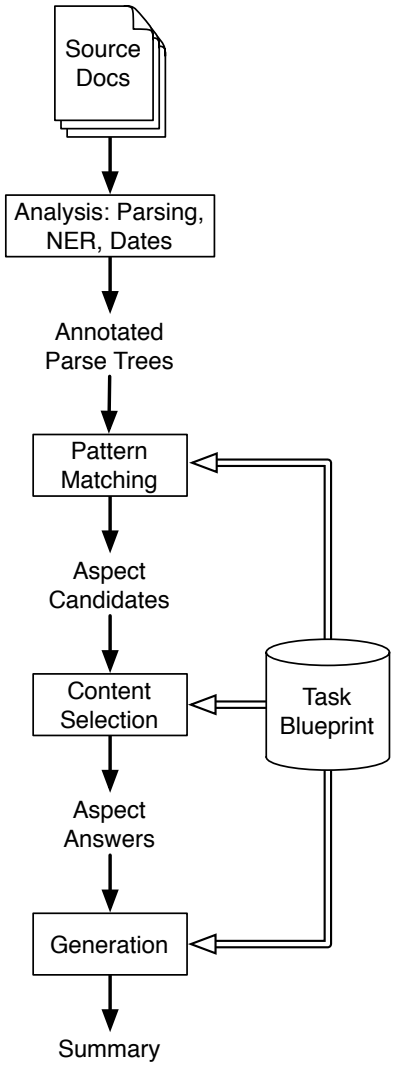

Figure I.1 – Workflow diagram for the architecture of ABSUM.

I.1 Preprocessing

Here is a more complete description of the steps taken to preprocess the documents. Preprocessing is considered as being part of the analysis module.

I.1.1 Input Format

The source documents of the test set that was used originate from the AQUAINT and AQUAINT-2 collections. Their format is a custom-made, well-formed SGML. We use a script to convert some characters into XML-compatible format, resulting in a well-formed XML document. From this, we extract the body (text) of the document and replace paragraph tags by line breaks, leaving only text.

I.1.2 Text Cleaning and Uniformization

Regular expression substitutions are used to clean up the text and make it uniform and as easy to parse as possible. Various types of quoting symbols are all substituted by a standard double-quote, and their position is adjusted (where needed) so that all quotes close before a punctuation mark, instead of after. Common English contractions are substituted by their longer form, such as `I am` instead of `I'm`. All parentheses are removed, along with their content, to simplify later processing. All SGML and HTML annotations are removed because they concern only text formatting. Several other unexpected occurrences are removed to avoid problems later in the analysis, such as repeated spaces, periods with spaces on each side, spaces before a punctuation mark, and the characters "*" and "+" which are usually of little interest in our corpus. For the purpose of uniformization, the character "%" is replaced by the word `percent` and the commas used as thousand separators are removed altogether. Finally, a Java program is used to remove all middle initials in the text, to avoid sentence segmentation errors and remove information that is often unimportant. Middle initials are identified by looking for a capital letter followed by a period, where the precedent token is a known capitalized first name, and the following token is also capitalized. The small loss of information that may occur because of this transformation is outweighed by the improvements that it provides to sentence segmentation and to processing named entities later on.

I.1.3 Sentence Segmentation

A Java program performs the sentence segmentation. It makes use of the Java class `java.text.BreakIterator` and a list of common abbreviations. The end result is a text document in one-sentence-per-line format.

I.1.4 Post-Segmentation Text Cleaning

A second text cleaning is performed on the segmented text, taking advantage of the sentence boundaries. Sentences that do not begin with a capital letter or do not end with a period are removed – some of these result from errors in segmentation, others by all kinds of artifacts in the corpus. Other removals are performed to avoid problems that occur because of certain corpus-specific behaviors, like meta-information included in the article's body by mistake. For the purpose of uniformity, several abbreviations are also replaced by their unabbreviated form, which can be done without error because sentence boundaries are known.

I.2 The Task Blueprint

The two task blueprints, which serve as knowledge bases, developped for the ATTACKS and ACCIDENTS AND NATURAL DISASTERS categories have been recorded in Extendable Markup Language (XML) files. These files have the following structure (enforced by an XML Schema found in Listing I.6).

First, lemma groups are declared. Listing I.1 shows four examples of lemma groups declared (as 'lemmaLists') in the XML file for the ATTACKS task blueprint. The boolean attribute 'eventList' identifies which words are part of the master list for generic event descriptors, currently used in the **event** abstraction scheme.

Similarly, groups of syntactical relations are declared before they are used, in the format shown in Listing I.2.

These lists are followed by the abstraction schemes, which provide pattern matching rules and a generation template, as shown in Figure I.2. Examples for the schemes **killing** and **helping** are provided respectively in Listings I.3 and I.4. Pattern matching rules are described in 'ieRules'. These rules contain a number of predicates that match with the parser's syntactical dependencies. The predicate patterns call predefined lists as needed and the special tag 'candidate' is used to match to any noun phrase that appears in that position. The aspect of an 'ieRule' identifies how to interpret the candidate found ; e.g. aspect 4 identifies the perpetrator of the attack. In the generation template, any lemma group called to be generated is resolved as one of its member lemmas. Selected candidates have an aspect number (same as the pattern matching rule used to find it), and the boolean attributes 'unique', for which true means that only one candidate should appear and false means that all candidates found should be generated, and 'required", for which true means that a sentence will only be generated if that candidate is found and false means that this candidate may be omitted. For now, the generation template only supports sentences in the form of subject-verb-object, with the option of inserting a fixed but arbitrary string at the end of the pattern.

Finally, the XML file for the task blueprint must include a generation plan (see Figure I.3), enumerating the schemes in the order they should appear in the summary. Listing I.5 shows how this appears in the task blueprint. The 'repeat' attribute determines whether

Listing I.1 – Some of the ATTACKS category's task blueprint lemma groups.

```
<lemmaList name="killVerbs" pos="verb" eventList="true">
    <lemma>kill</lemma>
    <lemma>murder</lemma>
    <lemma>assassinate</lemma>
    ...
</lemmaList>
<lemmaList name="killNouns" pos="noun" eventList="true">
    <lemma>killing</lemma>
    <lemma>murder</lemma>
    <lemma>homicide</lemma>
    ...
</lemmaList>
<lemmaList name="provideVerbs" pos="verb" eventList="false">
    <lemma>provide</lemma>
    <lemma>give</lemma>
    <lemma>bring</lemma>
    <lemma>deliver</lemma>
    <lemma>offer</lemma>
    <lemma>send</lemma>
</lemmaList>
<lemmaList name="helpNouns" pos="noun" eventList="false">
    <lemma>help</lemma>
    <lemma>support</lemma>
    <lemma>assistance</lemma>
    <lemma>relief</lemma>
    <lemma>aid</lemma>
</lemmaList>
```

Listing I.2 – Groups of syntactical relations declared in the task blueprint.

```
<syntacticalRelationList name="subjRelations">
    <syntacticalRelationListElement>
        nsubj
    </syntacticalRelationListElement>
    <syntacticalRelationListElement>
        agent
    </syntacticalRelationListElement>
</syntacticalRelationList>

<syntacticalRelationList name="objRelations">
    <syntacticalRelationListElement>
        dobj
    </syntacticalRelationListElement>
    <syntacticalRelationListElement>n
        subjpass
    </syntacticalRelationListElement>
</syntacticalRelationList>
```

Listing I.3 – Abstraction scheme **killing**.

```
<scheme name="killing">
    <!-- Killing verbs: X killed Y. -->
    <ieRule aspect="4">
        <predicate>
            <syntacticalRelation type="syntacticalRelationList">
                subjRelations</syntacticalRelation>
            <predicateElement type="lemmaList" pos="verb">
                killVerbs</predicateElement>
            <candidate/>
        </predicate>
    </ieRule>
    <ieRule aspect="6">
        <predicate>
            <syntacticalRelation type="syntacticalRelationList">
                objRelations</syntacticalRelation>
            <predicateElement type="lemmaList" pos="verb">
                killVerbs</predicateElement>
            <candidate/>
        </predicate>
    </ieRule>
    <!-- Killing nouns: The murder of Y by X. -->
    <ieRule aspect="4">
        <predicate>
            <syntacticalRelation type="syntacticalRelation">
                prep_by</syntacticalRelation>
            <predicateElement type="lemmaList" pos="noun">
                killNouns</predicateElement>
            <candidate/>
        </predicate>
    </ieRule>
    <ieRule aspect="6">
        <predicate>
            <syntacticalRelation type="syntacticalRelation">
                prep_of</syntacticalRelation>
            <predicateElement type="lemmaList" pos="noun">
                killNouns</predicateElement>
            <candidate/>
        </predicate>
    </ieRule>
    <!-- Generation Template -->
    <generationPattern>
        <subject>
            <selectedCandidate aspect="4"
                unique="true" required="false"/>
        </subject>
        <verb type="lemmaList">killVerbs</verb>
        <object>
            <selectedCandidate aspect="6"
                unique="false" required="true"/>
        </object>
    </generationPattern>
</scheme>
```

Listing I.4 – Abstraction scheme **helping**.

```
<scheme name="helping">
    <!-- X provided help -->
    <ieRule aspect="51">
        <predicate>
            <syntacticalRelation type="syntacticalRelationList">
                subjRelations</syntacticalRelation>
            <predicateElement type="lemmaList" pos="verb">
                provideVerbs</predicateElement>
            <candidate/>
        </predicate>
    </ieRule>
    <ieRule aspect="52">
        <predicate>
            <syntacticalRelation type="syntacticalRelationList">
                    objRelations</syntacticalRelation>
            <predicateElement type="lemmaList" pos="verb">
                provideVerbs</predicateElement>
            <predicateElement type="lemmaList" pos="noun">
                helpNouns</predicateElement>
        </predicate>
    </ieRule>
    <!-- Generation Template -->
    <generationPattern>
        <subject>
            <selectedCandidate aspect="51"
                unique="false" required="true"/>
        </subject>
        <verb type="lemmaList">provideVerbs</verb>
        <object>
            <selectedLemma type="lemmaList" required="true">
                    helpNouns</selectedLemma>
        </object>
    </generationPattern>
</scheme>
```

Scheme: killing

Pattern Matching	SUBJ_RELATIONS(*kill_verbs*, X)	→	WHO(X)
	OBJ_RELATIONS(*kill_verbs*, Y)	→	WHO_AFFECTED(Y)
	PREP_OF(`murder_nouns`, Y)	→	WHO_AFFECTED(Y)
	PREP_BY(`murder_nouns`, X)	→	WHO(X)
Generation Template	X *kill_verbs* Y		

Scheme: helping

Pattern Matching	SUBJ_RELATIONS(*provide_verbs*, X)	→	HELPER(X)
	OBJ_RELATIONS(*provide_verbs*, *help_nouns*)	→	-
Generation Template	X *provide_verbs help_nouns*		

Figure I.2 – The abstraction schemes for **killing** and **helping**. The pattern matching rules define how to detect aspect candidates from the dependency parsing annotations and semantic information detected by the analysis module. The generation template defines how to realize a sentence for output.

that scheme is allowed to repeat aspect answers for the same aspect. For example, the scheme **killing** may have found that `Jane` killed `John`, which are respectively answers for aspect numbers 4 and 6. When it is time to find an answer to aspect number 6 in the scheme **dying**, the aspect candidate `John` will likely be found again, but it will not be allowed to be selected as an aspect answer because the scheme has the 'repeat' attribute set to false. This prevents a summary from including the two redundant sentences `Jane murdered John` and John died. However, if `Jane` is an aspect candidate for aspect 6 in the scheme **arresting**, it will still be selected as an aspect answer because that scheme has the 'repeat' attribute set to true.

I.3 Summarization System

The summarization system is written in Java. It makes use of the libraries `javax.xml.parsers` and `org.w3c.dom` to read and navigate an XML formatted task blueprint.

The summarization system's average execution time is about 13 seconds on a desktop machine with two cores. The bottleneck for execution, however, lies in the execution of the analysis module and specifically with the execution of the parser. The analysis module's average execution time is about 100 seconds for a cluster of 10 documents (roughly 4000 words). The strategy used to improve parser accuracy in the analysis module involves executing the parser 3 times, and so with all preprocessing, analysis and summarization steps combined, the average total time to output a summary starting from the raw sgml input files is about five minutes and a half.

Abstraction Scheme	Example structure of the generated sentence
event	On *a date*, *an attack/murder/shooting/etc.* occurred at/in *a location*.
beingHitGeneric	X was attacked/hit/struck.
killing	X killed/murdered/shot/etc. Y.
dying	X died.
injuring	X wounded/injured Y.
destroying	X was damaged/destroyed.
arresting	X was arrested.
suspecting	X was suspected of conducting the attack.
responsibilityClaim	X claimed responsibility for the attack.
helping	X sent/provided/offered support/aid/help.
beingRescued	X was rescued.
evacuating	X was evacuated.

Figure I.3 – An ordered list of abstraction schemes that serves as the generation plan for the category ATTACKS.

Listing I.5 – Generation plan for the ATTACKS category.

```
<generationPlan>
    <generatedScheme schemeName="event" repeat="true"/>
    <generatedScheme schemeName="beingHit" repeat="true"/>
    <generatedScheme schemeName="killing" repeat="true"/>
    <generatedScheme schemeName="dying" repeat="false"/>
    <generatedScheme schemeName="injuring" repeat="false"/>
    <generatedScheme schemeName="destroying" repeat="false"/>
    <generatedScheme schemeName="arresting" repeat="true"/>
    <generatedScheme schemeName="suspecting" repeat="false"/>
    <generatedScheme schemeName="responsibilityClaim"
                     repeat="true"/>
    <generatedScheme schemeName="helping" repeat="true"/>
    <generatedScheme schemeName="beingRescued" repeat="true"/>
    <generatedScheme schemeName="evacuating" repeat="true"/>
</generationPlan>
```

Listing I.6 – The XML Schema (in Relax NG Compact format) used to validate the structure of the task blueprint XML files.

```
default namespace = "http://www-etud.iro.umontreal.ca/genestpe/"
datatypes xsd = "http://www.w3.org/2001/XMLSchema-datatypes"
start = taskBlueprint
taskBlueprint = element taskBlueprint {
        element guidedSummarizationCategory {xsd:nonNegativeInteger},
        lemmaList*,
        syntacticalRelationList*,
        scheme+,
        generationPlan }
lemmaList = element lemmaList {
        attribute name {text}, posAttribute,
        attribute eventList{xsd:boolean},
        element lemma{text}+ }
syntacticalRelationList = element syntacticalRelationList {
        attribute name {text},
        element syntacticalRelationListElement{text}+ }
scheme = element scheme {
        attribute name{text}, ieRule+, generationPattern }
generationPlan = element generationPlan {
        element generatedScheme{attribute schemeName{text},
        attribute repeat{xsd:boolean}}+ }
ieRule = element ieRule {
        attribute aspect{xsd:nonNegativeInteger}, predicate+ }
predicate = element predicate {
        syntacticalRelation, predElementHolder, predElementHolder }
syntacticalRelation = element anySyntacticalRelation {empty}
    | element syntacticalRelation {
        attribute type {"syntacticalRelation"|"syntacticalRelationList"},
        text }
predElementHolder = element candidate {empty}
    | element predicateElement {
        attribute type{"lemma"|"lemmaList"}, posAttribute?, text }
posAttribute = attribute pos{"verb"|"noun"|"adj"}
generationPattern = element generationPattern {
        element subject{generatedNP?},
        generationVerb,
        element object{generatedNP?},
        element endOfSentenceString{text}? }
generatedNP = element selectedCandidate {
        attribute aspect {xsd:nonNegativeInteger},
        attribute unique {xsd:boolean},
        attribute required {xsd:boolean} }
    | element selectedLemma {
        attribute type{"lemma"|"lemmaList"},
        attribute required{xsd:boolean},
        text }
generationVerb = element verb {
        attribute type{"lemma"|"lemmaList"}, text }
```

Annexe II

Evaluation Metrics

This appendix provides additional details about the evaluation metrics used and referenced in chapters 2 through 4.

II.1 Automatic Metrics and ROUGE

Automatic evaluation metrics all rely on reference summaries written by humans and compare system summaries against them. The most commonly used system is ROUGE, because it was found to correlate well with manual (human) assessments.

With ROUGE, reference summaries are called *models* and system summaries to be automatically evaluated are called *peers*. The idea is very simple, yet effective : a peer is evaluated with regards to the ngrams it has in common with the model, in terms of either precision, recall or F-measure. The most commonly used ROUGE metric for summaries of similar lengths is ROUGE-2 Recall, which measures the proportion of model bigrams that appear in the system summary that is evaluated.

II.2 Manual Metrics

Manual metrics require human assessment or annotation of a summary. Typical human assessments are linguistic quality and overall responsiveness. These represent respectively an assessment of a summary's readability, and a global assessment of the summary's performance on the summarization task, taking into account both readability and content. Even with strict guidelines, these assessments are subjective and lead to rather low inter-annotator agreement.

For content, the Pyramid method was developed to provide a less subjective quantitative figure for content evaluation. It involves the annotation of Summary Content Units (SCUs), first in the model summaries, and then in the system summaries. SCUs are text segments that express the same basic content. The final score of an evaluated summary represents a percentage of the expected number of (weighted) SCUs that should appear in a summary of that size. It is the most common way to evaluate the amount of content in a summary, and to compare summarization techniques based on the amount of content in the generated summaries.