SuDocu: Summarizing Documents by Example

Anna Fariha  Matteo Brucato  Peter J. Haas  Alexandra Meliou
College of Information and Computer Sciences
University of Massachusetts, Amherst
{afariha, matteo, phaas, ameli}@cs.umass.edu

ABSTRACT

Text document summarization refers to the task of producing a brief representation of a document for easy human consumption. Existing text summarization techniques mostly focus on generic summarization, but users often require personalized summarization that targets their specific preferences and needs. However, precisely expressing preferences is challenging, and current methods are often ambiguous, outside the user’s control, or require costly training data. We propose a novel and effective way to express summarization intent (preferences) via examples: the user provides a few example summaries for a small number of documents in a collection, and the system summarizes the rest. We demonstrate SuDOCU, an example-based personalized Document Summarization system. Through a simple interface, SuDOCU allows the users to provide example summaries, learns the summarization intent from the examples, and produces summaries for new documents that reflect the user’s summarization intent. SuDOCU further explains the captured summarization intent in the form of a package query, an extension of a traditional SQL query that handles complex constraints and preferences over answer sets. SuDOCU combines topic modeling, semantic similarity discovery, and in-database optimization in a novel way to achieve example-driven document summarization. We demonstrate how SuDOCU can detect complex summarization intents from a few example summaries and produce accurate summaries for new documents effectively and efficiently.

1. INTRODUCTION

Document collections, such as Wikipedia, contain a wealth of information that can assist in many tasks. Yet, finding the right information quickly and easily is still a big challenge, despite all the advances in search engine technology, natural language processing, and machine learning. Consider the following scenario:

Example 1 (Trip planning). Alice wants to plan visits to interesting places around the USA. She wants to know interesting locations and typical weather conditions for each state, but finding this information on the Web is tedious and time-consuming. She knows that Wikipedia contains all the information she needs, but each page is large and full of facts that are not relevant to her interest (e.g., demographics, law, etc.). Alice can manually extract relevant summaries of at most 3 pages, by selecting a small set of sentences that correspond to her specific information needs (interesting places and weather). But to thoroughly research her options, she needs an automated way to do this for the remaining 47 states.

Surprisingly, today’s technology cannot help Alice! A search engine, like Google, is good at finding which web pages are likely to contain relevant information, but it would require many queries and Alice would need to be very thoughtful about search keywords in order to collect the relevant information for all 50 states. Alice tried to use Natural Language Processing (NLP) and Machine Learning (ML) techniques and found that text summarization tools may be helpful. However, most text summarization tools are “generic”: they produce summaries that are not tailored for her personal preferences and specific information needs. The summaries she obtained from these tools did not cover all important aspects of her task, but rather provided general information about the state’s politics, law, education, etc. Alice found that some summarization tools can be tailored with a user intent, and require a natural language question to express it. She picked a question answering system, like Alexa, and issued the following question: “What are some interesting places in Massachusetts and how extreme is the weather there?” Unfortunately, the system could not understand what Alice meant by “interesting places”—since interestingness is a very personal concept—and returned her sentences about places of general interest: MIT, Harvard Square, and Boston Public Library.

Alice is interested in natural sites: parks, lakes, mountains, seas, etc. While particular preferences may be hard to express precisely with a query, it is easy for Alice to identify relevant sentences within a document. For example, Alice selected the following sentences from Utah’s Wikipedia page as most relevant to her needs:

“...the state of Utah relies heavily on income from tourists and travelers visiting the state’s parks and ski resorts. Today, Utah State Parks manages 43 parks and several undeveloped areas totaling over 95,000 acres of land and more than 1,000,000 acres of water. With five national parks (Arches, Bryce Canyon, Canyonlands, Capitol Reef, and Zion), Utah has the third most national parks of any state after Alaska and California. Temperatures dropping below 0 °F should be expected on occasion in most areas of the state most years."

She would like to extract something similar to the summary of Example 1 for each of the 50 states. Luckily, she can now use SuDOCU, a personalized Document Summarization system, that enables users to specify their summarization intent by a few example summaries and produces personalized summaries for new documents. SuDOCU is an instance of a query-by-example system, tailored for text document summarization. The key motivation of SuDOCU is that asking a user to provide examples of their desired answers, rather than vague questions, is a more effective way to learn the true intent, especially for a complex summarization intent involving multiple topics, e.g., interesting places and weather.

We demonstrate SuDOCU, an end-to-end system that achieves example-driven personalized document summarization. The key idea (described in Section 3) is to view summarization as a combinatorial optimization problem where we want to extract a minimal set of sentences to form the summary, subject to constraints that require the overall topic coverage of the summary to be close to that.
of the examples. The document topics are modeled using a standard LDA approach, the constraints are created by adapting our prior algorithms for example-driven semantic similarity discovery [3], and the resulting integer linear program is solved in a scalable manner using our prior techniques for handling package queries [3].

In our first demonstration scenario, the attendees will impersonate Alice. They will observe first-hand how SuDocu detects their summarization intent from only a few example summaries of a few documents, and then efficiently produces summaries of new documents matching their intents. Participants will be free to specify their own intent by choosing different example summaries. We proceed to discuss how SuDocu’s personalized summarization differs from prior art (Section 2), provide a solution sketch (Section 3), and conclude with a detailed outline of our demonstration (Section 4).

2. CONTRAST WITH PRIOR ART

We focus on producing a personalized extractive summary of each document within a collection of documents. Such a summary directly selects sentences from the document to form the summary. In contrast, abstractive summarization, which synthesizes new sentences that embody a holistic understanding of the document, is a much harder task; even state-of-the-art deep learning methods struggle to produce human-readable summaries [9]. The key issues are: how to (1) express the user’s intent, and (2) select the set of sentences that, collectively, best satisfy the user’s intent.

In query-based summarization, users specify their intent in the form of an unstructured query—typically, a natural language question. For example, the question “What are some interesting places?” is very subjective, as different people consider different places as interesting. For a nature enthusiast, parks, lakes, oceans, and mountains are interesting; for an art enthusiast, museums, concerts, and plays are interesting. Some approaches use hints that represent user interest. Such hints take different forms, such as user-provided annotations [7], vision-based eye-tracking [10], user history and collaborative social influences [8], and so on. SuDocu allows the user to provide precise and concrete examples of the type of summaries they want, and does not require any training data. A possible way to adapt query-based summarization for example-driven summarization is to infer the underlying natural-language query from the example summaries, and then use an existing tool. However, computers understand structured queries with clear semantics—which can easily be constructed from examples—much better than natural language queries, so an example-based approach is both simpler and more accurate.

Early approaches to sentence selection would score each sentence based on some criteria and return the top-k sentences as a summary. This would often lead to the inclusion of redundant sentences. To tackle the issue of redundacy, later work [5] followed an ad hoc iterative greedy approach, leading to suboptimal summaries. Alternative approaches based on topic modeling identify a set of topics that the user cares about (perhaps extracted from examples) and then pick the best sentence per topic to construct the summary. However, such a summary can also be suboptimal, as sentences often cover multiple topics; a sentence that is not top-scoring in any single topic, but covers multiple topics well, might be excluded from the summary. While some approaches try to iteratively refine the summary quality [1], they are mostly based on heuristic approaches, e.g., A search that still do not guarantee optimality.

A shortcoming of the foregoing sentence-selection approaches is that they consider candidate sentences in isolation, rather than trying to select a set of sentences that collectively form a good summary. The problem of selecting the best set of sentences can be formulated as an integer program. Lin and Bilmes [6] provide an integer programming formulation with constraints and objectives involving general sentence score, diversity, and summary length, but with no connection to the user-provided examples. In contrast, our formulation can capture the summarization intent from the example summaries using constraints on how much each topic should be “covered” by the summary; roughly speaking, the coverage should resemble that of the user-provided examples. Also, because of the combinatorially large number of possible summaries, the formulation in [6] cannot generally scale to large dataset sizes. We use our previously-developed SketchRefine algorithm [3] to scale the resulting integer linear program to very large dataset sizes.

3. SOLUTION SKETCH

We now provide a solution sketch for SuDocu. Figure 1 depicts SuDocu’s end-to-end pipeline. SuDocu pre-processes a corpus of documents by extracting all the sentences, automatically identifying all the topics, and assigning topic scores to each sentence. After preprocessing, the user can interact with SuDocu’s interface and issue example summaries to specify their intent. We first describe how we model the user intent, and then discuss preprocessing, summarization intent discovery, and summary generation.

Modeling personalized extractive summaries. Following prior work on text summarization [6], we model the personalized summarization problem as an optimization problem. Given the example summaries, we define the optimal summary as the one with minimum length (in number of sentences) such that the topic-coverage of the summary is similar to that of the example summaries. In SuDocu, we construct a linear constraint over topic-coverage for each topic. Note that other formulations of the summarization intention are possible. For example, minimizing the distance between the summary and the set of example summaries, subject to a constraint on summary length. However, we use linear constraints and objective functions because they are easier to solve in a scalable way and work well in practice.

We express the optimization problem as a package query [3]. A package (summary) is a collection of tuples (sentences) from a relation (document) that (a) individually satisfy base predicates (traditional SQL selection predicates), and (b) collectively satisfy global predicates (package-specific predicates). A package query comprises base and global predicates that define the set of feasible packages and an objective function that defines a preference ranking among them. The Package Query Language (PaQL) is a simple extension to SQL that allows for the easy specification of global constraints and objectives.

Preprocessing. The first step of SuDocu involves extracting sentences from documents. In our implementation, we use Beautiful Soup, a library for extracting content from HTML pages. After sentence extraction, we identify all of their topics.
### Table: 50 US states learned from the Wikipedia pages of 50 US states.

<table>
<thead>
<tr>
<th>Topic</th>
<th>Related words (ordered by decreasing weight)</th>
</tr>
</thead>
<tbody>
<tr>
<td>topic_1 (politics)</td>
<td>(governor, 0.015), (election, 0.013), (elected, 0.013), (vote, 0.011), (democratic, 0.011), (majority, 0.009), (presidential, 0.008)</td>
</tr>
<tr>
<td>topic_2 (legislation)</td>
<td>(century, 0.012), (passed, 0.011), (legislation, 0.010), (constitution, 0.009), (created, 0.007), (law, 0.006), (political, 0.006)</td>
</tr>
<tr>
<td>topic_3 (urbanization)</td>
<td>(population, 0.077), (largest, 0.052), (city, 0.029), (percent, 0.019), (metropolitan, 0.012), (capital, 0.011), (people, 0.011)</td>
</tr>
<tr>
<td>topic_4 (economy)</td>
<td>(major, 0.023), (economy, 0.018), (largest, 0.013), (industry, 0.013), (home, 0.012), (billion, 0.011), (production, 0.011), (oil, 0.009)</td>
</tr>
<tr>
<td>topic_5 (demography)</td>
<td>(american, 0.029), (people, 0.021), (native, 0.018), (french, 0.015), (century, 0.015), (settlers, 0.012), (tribes, 0.010)</td>
</tr>
<tr>
<td>topic_6 (climate)</td>
<td>(climate, 0.071), (feet, 0.011), (temperature, 0.010), (rain, 0.010), (service, 0.010), (forests, 0.009), (summer, 0.009), (winter, 0.009)</td>
</tr>
<tr>
<td>topic_7 (location)</td>
<td>(northeast, 0.035), (west, 0.033), (south, 0.030), (east, 0.029), (southern, 0.022), (eastern, 0.020), (region, 0.020), (western, 0.019)</td>
</tr>
<tr>
<td>topic_8 (taxes)</td>
<td>(tax, 0.056), (income, 0.030), (rate, 0.029), (ranked, 0.021), (nation, 0.021), (sales, 0.017), (average, 0.015), (capita, 0.014)</td>
</tr>
<tr>
<td>topic_9 (education)</td>
<td>(government, 0.039), (school, 0.029), (county, 0.025), (public, 0.025), (federal, 0.025), (schools, 0.022), (law, 0.016)</td>
</tr>
<tr>
<td>topic_10 (general)</td>
<td>(national, 0.007), (major, 0.006), (popular, 0.005), (system, 0.004), (founded, 0.004), (home, 0.004), (construction, 0.004)</td>
</tr>
</tbody>
</table>

*Figure 2:* Topics of 50 US states, extracted automatically from Wikipedia using topic modeling, and few words with the highest weights for each topic.

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**Efficient summary generation.** Once the PaQL formulation of a package query is completed, the last step is to execute it. Package queries are combinatorial in nature, and solving package queries in general is NP-hard. If the problem is small enough, we can translate a package query directly into an equivalent integer linear program that can be solved with off-the-shelf software. For each tuple \( t_i \) in the input relation, the translation assigns a binary decision variable \( x_i \) corresponding to the inclusion/exclusion of \( t_i \) in the answer package. When there are so many candidate sentences that the solver either cannot load the problem in main memory or fails to find a solution, we apply the SKETCH\textsc{Refine} algorithm [3], a divide-and-conquer approach that returns a near-optimal solution having a provable approximation guarantee. Once the package query returns an optimal set of sentences for a document, \textsc{SudoCu} presents this summary to the user, along with the PaQL query that encapsulates the summarization intent.

### 4. DEMONSTRATION

We will demonstrate \textsc{SudoCu} on the Wikipedia pages of 50 US states—most participants will be familiar with this data domain. Our goal is to show that \textsc{SudoCu} can effectively detect the user’s summarization intent from only a few example summaries and produce personalized summaries effectively and efficiently. Figure [3] shows a screenshot of \textsc{SudoCu}’s graphical user interface. We will guide the participants through five steps, first impersonating Alice (a nature enthusiast) and then Bob (an economics student). We have annotated each step with a circle in Figure [3].

**Impersonating Alice.** In our first demonstration scenario, the user will impersonate Alice of Example [1].

**Step 1 (Document selection for manual summarization):** First, the user selects the state that she wishes to summarize manually. Selecting a state displays all of the sentences from its Wikipedia page in the UI. The user first selects Utah.

**Step 2 (Manual summarization):** The user goes over the sentence list and adds relevant sentences (by highlighting them) that she thinks should be in the summary, or removes previously selected sentences to refine the summary. Since Alice is a nature enthusiast, the user picks sentences that mostly talk about parks, ski resorts, plants, canyons, etc. Moreover, since Alice wants to know about the state’s climate, the user also selects a few sentences about temperature for each state. After summarizing Utah, the user repeats steps 1 and 2 for Arizona and Montana.

**Step 3 (Summary submission):** Once the user is done with manual summarization, she views her example summaries. If necessary, she can edit her summaries to fine tune them. The user is satisfied with her summaries at this point and requests \textsc{SudoCu} to discover her summarization intent. \textsc{SudoCu} processes the example summaries and generates a PaQL query that encodes the user’s summarization intent.
the work by himself, he decides to use S
of all 50 US states. Bob is lazy but smart. So, instead of doing all
gave him an assignment to write a report summarizing the economy
information technology . . . and a major tourist destination for out-
economy, with major sectors including transportation, education,
user specifies a new document to summarize and S
should be expected on occasion in
°C) should be expected on occasion in
Canada occasionally push into the state,
Temperatures varying greatly on cold nights.
which is in a landscape of
result than Alice, and how S
The state of Utah relies heavily on income
Utah was still able to figure out that oceans would be the most interesting
(based on topic similarity to canyons and parks) within Mas-
and the trails program.
the user views the example summaries, edits them if necessary, and submits them to request for summarization intent discovery, 4
the user selects a document for manual summarization, 2
the PaQL query in the explanation panel. The PaQL query is the
Canyons, Capitol Reef, and Zion.
Utah State Parks Museum in the Four Corners region and everywhere in between. Utah State Parks is also home to the state’s off highway vehicle office, state boating office and the trails program.[12,13]
step by step, the user is presented with the example summaries, edits them if necessary, and submits them to request for summarization intent discovery, 3
stated areas totaling over 39,000 acres of land and more than 1,000,000 acres of water. With five national parks (Arches, Bryce Canyon, Canyonlands, Capital Reef, and Zion), Utah has the third most national parks of any state after Alaska and California. Temperatures dropping below 0 °F (−18 °C) should be expected on occasion in most areas of the state most years.
The Rocky Mountain Front is a significant feature in the state’s north-central portion, and isolated island ranges that interrupt the parallel mountain ranges on both sides of the state. It contains the state’s highest peak, Grizzly Peak, at 12,799 feet high. Farther east, areas such as Naches State Park near Moutaineering and Medicine Rocks State Park near Elakala contain some of the most severe rockslides regions in the state. The coldest temperature on record for Montana is also the coldest temperature for the contiguous United States. On January 20, 1954, −65 °F (−54.4 °C) was recorded at a gold mining camp near Rogers Pass. Temperatures vary greatly on cold nights.

Step 4 (New document summarization): Once SuDocU fin-
ishes summarization intent discovery, it is now ready to sum-
rize new documents. In this step, the user has to specify a new
document for automatic summarization. Since Alice plans to visit
the East Coast, the user selects Massachusetts. SuDocU executes the PaQL query, while putting state = ‘Massachusetts’ in the WHERE clause, using SKETCHINDEX. The returned package con-
ists of a set of sentences and SuDocU shows them as the sum-
maries of Massachusetts. Massachusetts is by the Atlantic ocean,
there are no canyons or big mountains there. Although the user
never selected any sentence specifically about ocean, SuDocU was
still able to figure out that oceans would be the most interesting
place (based on topic similarity to canyons and parks) within Mas-
sachusetts to satisfy the user’s summarization intent. The summary
also contains a few lines about temperature, cold winter, and warm
summer, which is exactly what the user was looking for.

Step 5 (Summarization intent explanation): SuDocU shows
the PaQL query in the explanation panel. The PaQL query is the
underlying mechanism that SuDocU uses to produce personalized
summarization. A user can edit the PaQL query directly to further tune
her summarization intent. The query gives us the insight that the
user is mostly interested in topic_6 (climate) and topic_7 (loca-
tion). Since the topic name is not clear from the PaQL query, the
user hovers on topic_6, which displays the most related words for
the topic_6: climate, temperature, summer, winter, etc.

Impersonating Bob. Bob is an economics student and his teacher
gave him an assignment to write a report summarizing the economy
of all 50 US states. Bob is lazy but smart. So, instead of doing all
the work by himself, he decides to use SuDocU. In our second
demonstration scenario, the user will impersonate the user.
The steps are identical to the first demonstration scenario, but the
summarization intent is completely different. The user now se-
lects sentences that represent the state’s economy. For example, for
Utah, the user picks the sentence “The state has a highly diversified
economy, with major sectors including transportation, education,
information technology . . . and a major tourist destination for outdoor
recreation.” On completion of this demonstration, the partici-
pants will observe how Bob gets a completely different summariza-
tion result than Alice, and how SuDocU is able to match his
summarization intent based on the example summaries he provided.

Demonstration engagement. After our guided demonstration, im-
personating Alice and Bob, participants will be able to issue their
own summarization intent using different example summaries. Fur-
ther, they will also be able to plug their own datasets into SuDocU
and provide their own topic modeling. We will also make two ad-
tional datasets available for immediate use: Wikipedia pages of
100 US senators and 62 US national parks.

Through our demonstration, we will showcase how SuDocU can
effectively detect the user’s summarization intent from only a few
example summaries. The key takeaway our demonstration will
highlight is that summarization by example provides an easy way
to effectively communicate the summarization intent to achieve
personalized summarization.

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