Abstract

Automatic text summarization has experienced substantial progress in recent years. With this progress, the question has arisen whether the types of summaries that are typically generated by automatic summarization models align with users’ needs. ter Hoeve et al. (2020) answer this question negatively. Amongst others, they recommend focusing on generating summaries with more graphical elements. This is in line with what we know from the psycholinguistics literature about how humans process text. Motivated from these two angles, we propose a new task: summarization with graphical elements, and we verify that these summaries are helpful for a critical mass of people. We collect a high quality human labeled dataset to support research into the task. We present a number of baseline methods that show that the task is interesting and challenging. Hence, with this work we hope to inspire a new line of research within the automatic summarization community.

1 Introduction

Automatic text summarization has experienced substantial progress over the last couple of years, with the introduction of neural sequence to sequence models (e.g., Cheng and Lapata, 2016; See et al., 2017; Vaswani et al., 2017) and pretrained large language models (e.g., Devlin et al., 2019; Liu and Lapata, 2019; Lewis et al., 2020). There have been substantial improvements on automatic evaluation scores like ROUGE (Lin, 2004) and human evaluation metrics such as fluency. Nevertheless, recent work has questioned whether the field is progressing in the right direction.

Specifically, in line with Spärck Jones (1998), ter Hoeve et al. (2020) have argued that the users of automatically generated summaries are often ignored when designing automatic summarization methods. By means of a survey amongst heavy users of automatically generated summaries, they show that users’ needs do not fully align with current approaches to automatic text summarization. Amongst others, participants indicate being interested in summaries that contain more graphical elements, such as arrows and colored text. In this work we build upon the conclusions and recommendations of ter Hoeve et al. (2020) and introduce a new task: summarization with graphical elements.

In designing our task, we are also informed by the cognitive science and psycholinguistic literature on human text understanding. A popular model is the given-new strategy (Clark and Haviland, 1974; Haviland and Clark, 1974; Clark et al., 1977), which states that humans attach new information to already known, i.e., given, information in their memory, in order to build up a mental model of the information as a whole. Table 1 shows an example. In the first row one can read a short story. The second row depicts how new information is attached to given information as one continues to read the text. While building up this mental model, humans (unconsciously) select which information to keep, and which information can be forgotten (Kintsch and Van Dijk, 1978). That is, this process can be intuitively linked to summarization, as also noted by Cardenas et al. (2021).

We combine this psycholinguistic perspective
to a £1 million full-scale replica of Noah’s ark built by a carpenter who dreamt his country would flood. Tourists flock to what is now open to visitors and features two cinemas and a restaurant in Dordrecht.

**Johan Huyberts** spent three years building the gigantic wooden boat, which holds an array of life-size plastic animals. What happened is now open to visitors and features two cinemas and a restaurant in Dordrecht.

**Figure 1:** Example of a summary with graphical elements. In this example, nodes with outgoing edges are bold faced and underlined. The relations are marked with arrows, with the type of relation written on the arrow.

with the more HCI-centered perspective from ter Hoeve et al. (2020) to arrive at our task of **summarization with graphical elements**. The graphical elements that envisage are part of the output summaries. Figure 1 shows an example of such a summary. We detail the task description in Section 3. We collect a high quality human labeled dataset in order to be able to evaluate model performance on the task, which we detail in Section 4.3. We confirm that a critical number of people are interested in these types of summaries for a variety of different tasks (Section 6.1).

The main contributions made in this paper are:

**C1** We introduce a new task: **summarization with graphical elements**;

**C2** We collect a dataset, which we call **GRAPHEL-SUMS**, with high quality human labels to support research into the task; and

**C3** We present the first baseline results on the task, which show that the task is challenging and can inspire a lot of future work in this direction.

We make the code to run the experiments and to obtain the dataset freely available.¹

## 2 Related Work

We discuss related work on automatic text summarization and on information extraction.

### 2.1 Automatic text summarization

**Context factors.** Späck Jones (1998) formulates three context factors for automatic summarization: (i) **input**, (ii) **purpose**, and (iii) **output factors**. These factors describe (i) what the input to the summarization system looks like, (ii) what the goal of the summary is, and (iii) what the final summary looks like. A large part of the research on automatic summarization focuses on generating a condensed textual version (**output factors**) of a single or multiple document(s), often in the news or Wikipedia domain (**input factors**) (e.g., See et al., 2017; Koupaee and Wang, 2018; Liu and Lapata, 2019; Lewis et al., 2020). As noted by Späck Jones (1998), but also by Mani (2001) and by ter Hoeve et al. (2020), the **purpose factors** are often overlooked.

Recently, we have seen increased interest in different interpretations of the summary factors, especially in terms of the input factors. Examples include timeline summarization (e.g., Li et al., 2021; Yu et al., 2021), opinion summarization (e.g., Angelidis et al., 2021; Bražinskas et al., 2021) and dialogue summarization (e.g., Feigenblat et al., 2021; Liu et al., 2021). A smaller body of work focuses on different interpretations of the output factors. For example, faceted summarization (e.g., Meng et al., 2021) aims at constructing structured summaries. Other examples include building concept maps (Falke and Gurevych, 2017) and knowledge graphs (Wu et al., 2020). Our work also contributes a different interpretation of the output factors, as we construct summaries with graphical elements. An important distinguishing factor from the work on concept maps and knowledge graphs is that we build upon the recommendations of ter Hoeve et al. (2020) and take the purpose factors into account when designing our task. That is, we explicitly focus on the usefulness of our summaries for users. As a result, our output summaries contain longer textual phrases, placing our work in between the work on concept maps and knowledge graphs and more classic work on textual summarization.

**Abstractive and extracive summarization.** The field of automatic summarization can classically be divided into abstractive (e.g., Gehrmann...
We specifically use it for relation extraction. We make use of D, would be one of the triples for the summary in Figure 1. In Section 3 we give a detailed and formal description of our task. For our baselines we extract these summary triples from the summaries generated by BART and T5, linking our work to work on information extraction (IE). A number of neural approaches have been introduced for IE (e.g., Qian et al., 2018; Luan et al., 2019; Wadden et al., 2019). Summaries produced by recent approaches such as BART (Lewis et al., 2020) and T5 (Xue et al., 2021) are of very high quality in terms of fluency and grammaticality, yet they struggle with factual consistency (e.g., Cao et al., 2020; Maynez et al., 2020). Hence, there has been a surge in work that focuses on improving the factuality of generated summaries. These works focus either on the evaluation of summarization (e.g., Wang et al., 2020; Durmus et al., 2020), or on the modeling procedures themselves, for example by explicitly incorporating graph-based meaning representations in the modeling process (Ribeiro et al., 2022). In this work we use BART and T5 as the summarization backbone of our baselines, but we are excited to explore graph-based methods in future work.

2.2 Information extraction
The summaries in our task can be represented as relation triples. For example, (a £1 million full-scale replica of Noah’s ark, WHERE, in Dordrecht) would be one of the triples for the summary in Figure 1. In Section 3 we give a detailed and formal description of our task. For our baselines we extract these summary triples from the summaries generated by BART and T5, linking our work to work on information extraction (IE). A number of neural approaches have been introduced for IE (e.g., Qian et al., 2018; Luan et al., 2019; Wadden et al., 2019). We make use of DyGIE++ (Wadden et al., 2019), a BERT-based IE architecture for different IE tasks. We specifically use it for relation extraction.

3 Task description
In this section we describe the summarization with graphical elements task more formally. Given an input document $D = [x_0, \ldots, x_n]$ where $x_i$ refers to the $i^{th}$ token in document $D$, our task is to generate summarizing triples of the form $(y_{a_0} \ldots y_{a_k}, relation, y_{b_0} \ldots y_{b_k})$, where $y_{a_i}$ and $y_{b_i}$ are tokens, generated in an abstractive fashion. The triples can be thought of in a more graphical way as $(y_{a_0} \ldots y_{a_k})$ being a node with an outgoing edge and $(y_{b_0} \ldots y_{b_k})$ as a node with an incoming edge. The connecting edge is labeled with relation.

In order to improve the conciseness of the summary, our objective is to merge nodes with outgoing edges that refer to the same entity, making coreference resolution an important part of the task. This approach is in line with the given-new strategy. As an example, recall Table 1, where the phrases trained really hard and won a golden medal are linked to Laura, instead of making a new node for She, which is written in the original text.

The relations could be of any form, ranging from an open set to an empty set. In this work we choose to use a closed set of relations $L$. Explicitly labeling the relations, as opposed to leaving them empty, makes for a more interesting task. Given the nature of our data, in this work we define $L = \{\text{who, what, happens, what happened, what will happen, where, when, why}\}$. We discuss our dataset in more detail in the next section.

4 Dataset description
For our task we collect a human-labeled dataset, that we call GRAPHEL.SUMS, short for summaries with graphical elements. We seek to collect summary triples for each input document. Below, we explain our data selection and detail how we obtained the human labels. We end this section with a detailed description of the dataset’s statistics.

4.1 Requirements
In choosing the specifics of GRAPHEL.SUMS, we need to satisfy a number of requirements. First, the domain of the data needs to be fully understandable by human annotators in order to ensure high quality annotations. That is, we cannot choose a domain that can only be fully understood by domain experts, such as scientific documents. Moreover, annotators need to be able to fluently speak the language of the data. Secondly, the data naturally fits the task description, i.e., it is clear how summary triples can be constructed in a meaningful way. Finally, the data needs to be easily accessible for others to reproduce and build upon our work.

4.2 Decisions
Type of data. Keeping the requirements in mind, we opt to use the CNN/DM dataset (Hermann et al., 2015) as the basis of our data collection. The
dataset fits all listed requirements: (i) news documents do not require specific domain knowledge from annotators and our annotators are fluent in English, the language of the dataset; (ii) the story highlights from the CNN/DM dataset give us a way to construct abstractive summary triples and we can use the set of 5W’s — that are in the nature of news articles and have been used for automatic summarization before (Parton et al., 2009) — as our set of relations; and (iii) we are able to release the code to obtain a labeled version of the dataset, so that our work is reproducible. We acknowledge that the CNN/DM dataset and the (English) news domain in general have been studied extensively, yet a thorough exploration of alternatives convinced us that the CNN/DM dataset fits our requirements best to start with. We hope that more datasets will be collected for summarization with graphical elements in different domains and languages in the future.

As mentioned, we choose to use the 5W’s (who, what, where, when, why) as our relations and we choose to add three additional labels to be able to provide more temporal nuance and make the task more challenging: what happens, what happened and what will happen.

Including the title. In preparing our labeling task, we noticed that many of the story highlights are hard to understand without the title of the news article, as the highlights often refer back to information that was introduced in the title. Therefore, we add the titles to the summary abstracts. In our labeling procedure we confirm our intuition that the title is essential in 80% of the abstracts (Section 4.4).

Scale of human labeling. Given the intensity of the labeling procedure (see below), we opt to collect a human-labeled test set. Each document is labeled by three annotators. This allows us to account for the ambiguity in the summarization process during evaluation, i.e., there are multiple ways of correctly constructing a summary for a single document. We use this opportunity to shuffle the standard train, validation and test sets of the CNN/DM dataset. From the entire set, we select 500 documents for human labeling, which we publish with our code. The remaining documents can be used for a train and validation set.

4.3 Human labeling

In order to construct a high quality test set, we recruit three annotators with NLP expertise. The annotators need to construct summary triples, based on input abstracts from the CNN/DM dataset. Annotators are instructed via a detailed instruction manual, a video call in which the manual was discussed and there was room for communication via a chat channel. This allowed annotators to ask questions while doing the annotations, but also to report mistakes, which improved the quality control of the annotations (Section 4.3.1). Annotators were paid an hourly rate, removing the incentive to rush responses. Annotators were first asked to annotate a set of six articles, after which they received feedback on their annotations. During the remaining annotation task we checked the quality of the incoming annotations, by sampling annotations at random and inspecting them manually, to make sure annotators were still on the right track. All annotators annotated the same set of documents, resulting in three annotations per document (apart from a handful of documents where something went wrong with the annotations, see Section 4.3.1).

Each document is annotated in a Human Intelligence Task (HIT). Examples are given in Appendix A. Each HIT consists of the following:

(1) Introduction. Here we iterate the most important parts of the instruction manual.

(2) The actual task. Annotators are presented with an abstract taken from our test set, including the title. The abstract is explicitly divided into sentences. We automatically divide the abstract into constituents with the Berkely constituency parser (Kitaev and Klein, 2018), again per sentence. Annotators then need to select the relation triples per the guidance in the annotation manual. Annotators have the option to select that something was wrong with the presented abstract or the constituents. Annotators can also indicate if the first sentence of the abstract (i.e., the title of the article) was fully redundant. If they click that option, we ask them to not select any constituents from the first sentence. Lastly, annotators can check a box if they were particularly uncertain about their annotations.

4.3.1 Quality control

Within our budget we were able to obtain annotations for 295 documents. Annotators spent on average around 7 minutes on each HIT. In addition to the quality control we did during the annotation process, we also inspect annotators’ answers to the quality control questions: (i) whether something was wrong with the abstract or presented constituents, and (ii) whether they indicated to be
Table 2: Overlap statistics of annotators on human labeled test set. Const A refers to the first and Const B to the second constituent in a summary triple.

| Metric                      | Avg ± Std |
|-----------------------------|-----------|
| Hard F1                     | 0.21 ± 0.16 |
| Soft F1                     | 0.47 ± 0.18 |
| Jaccard w.r.t. Triple       | 0.13 ± 0.11 |
| Jaccard w.r.t. Const A      | 0.28 ± 0.16 |
| Jaccard w.r.t. Const B      | 0.32 ± 0.16 |
| Jaccard w.r.t. Relations    | 0.61 ± 0.17 |

Table 3: Dataset statistics of GRAPHELsums.

| Counts | % |
|--------|---|
| # Documents | 286 | 100 |
| # Three annotations per document | 268 | 93.7 |
| # Two annotations per document | 18 | 6.29 |
| # Triples | 5942 | – |
| Avg # triples per document | 7.07 ± 3.28 | – |

| # Who | 439 | 7.39 |
| # What | 1,407 | 23.7 |
| # What happens | 967 | 16.3 |
| # What happened | 2,075 | 34.9 |
| # What will happen | 149 | 2.51 |
| # Where | 339 | 5.71 |
| # When | 333 | 5.60 |
| # Why | 233 | 3.92 |

Issues with the presented abstract or constituents. Here we manually inspect the annotations of the HITs where a majority of the annotators indicated that there was something wrong, such as a mistake with the automatically generated constituents. This does not necessarily mean that the annotation is also wrong. We discard eight documents based on these answers. Moreover, we discard one more article because of preprocessing issues later in the pipeline.

Annotator uncertainty. We manually inspect all annotations where annotators indicated to be uncertain about a HIT and we discard twelve HITs.

Reported issues by annotators. Annotators had the option to report mistakes they made via chat. For example, sometimes annotators realised after submitting a HIT that they chose an incorrect label. Based on these reports we manually made changes to the annotations of six documents.

Overlap in annotations. For each HIT, we compute the pairwise macro $F_1$-scores for all annotator pairs. We compute both hard and soft scores. For the hard scores, we only count a selected triple if both annotators have exactly that triple in their annotations. However, this type of scoring is extremely conservative, especially given the nature and the ambiguity of the annotation task. Intuitively, we also want to assign points if the triple partially overlaps, but not entirely, for example because one annotator decided to include an article, whereas another annotator did not. Therefore, we also compute a soft score, where we greedily align the best matching triples and compute the lexical overlap between each of these and average them. We also compute the average Jaccard scores for annotators pairs. Specifically, we compute these scores for the entire triple, and for each individual component of the summary triple. These statistics are given in Table 2. From these scores, it becomes clear that the annotators are aligned in their annotations, yet it also shows that there are different ways to construct the summaries. This underlines our choice of collecting multiple annotations per data point. During evaluation of the task, the best matching annotation can be chosen as ground truth.

4.4 Dataset statistics

We present the statistics for the collected test set in Table 3. After quality control, our dataset consists of 286 documents, which is comparable to earlier work that constructed human annotated test sets for summarization (e.g., Wu et al., 2020). The vast majority of documents have three annotations. We also confirm our intuition about including the titles: in almost 80% of the cases the title was needed to understand the summary abstract. Lastly, we find that all relations are represented, with some very popular relations such as what happened and what.

5 Baselines

We provide a number of baselines for our task. All baselines consist of two steps: (i) a summarization step, and (ii) a relation extraction step. We leave entire end-to-end solutions as an inter-
esting and important direction for future work. For each of the steps, we choose well-performing and easily-accessible methods, that we adapt for our task where needed. We discuss each step below.

5.1 Step 1 – Summarization
For the summarization step, we finetune BART-large (Lewis et al., 2020) and T5 (Raffel et al., 2019). We train and validate the models on our train and validation splits for the CNN/DM dataset (Section 4). We report the inference scores on the abstracts in our test set. We use the Huggingface library\(^2\) (Wolf et al., 2020) and we finetune both models on 4 GPUs with 12GB of RAM each.

5.2 Step 2 – Relation extraction
We investigate two approaches for the relation extraction, which we discuss below.

5.2.1 Creating labels with Snorkel
We make use of Snorkel (Ratner et al., 2017) as a means to obtain summary triples. Snorkel is a well-documented method\(^3\) that generates (weak) labels for unlabeled data using on (noisy) labeling functions and trained generative models on top of these labeling functions. We use the obtained summary triples for two purposes: (i) to extract relations directly on the output of the summarization models, and (ii) to use as weak labels for training a relation extraction model. Our Snorkel pipeline consists of three stages: (i) candidate pairs selection, (ii) relation labeling, and (iii) final filtering. We discuss these stages in more detail below.

Candidate pairs selection. We use the Berkeley constituency parser (Kitaev and Klein, 2018) as a fast and high quality parser to obtain all constituents in a summary abstract. Next, we combine the constituents to make potential candidate pairs. Naively, one could simply combine all constituents that are found for an abstract. However, due to its quadratic complexity, this approach is very resource demanding. Instead, we make use of a few heuristics to make the candidate pairs. First, we discard all single token constituents that are of type IN, DT or CC, as these would not lead to valid candidate pairs. For the same reason, we also discard all constituents that only consist of a special token, such as a punctuation mark. Moreover, we make sure to not pair overlapping constituents. Finally, we set a threshold that constituents pairs can be at most two sentences apart. With this heuristic, we miss a small fraction of correct candidate pairs, yet it considerably speeds up the computation.

Relation labeling. In the second step, we construct labels for relations between the candidate pairs. For each possible relation, we construct Snorkel labeling functions. These functions are fuzzy heuristics, that together form a basis to train a model that gives a final weak label for a data point. In our work, we use these weak labels directly, and we also use them to train a relation extraction model (Section 5.2.2).

Final filtering. As a last step, we apply filtering to obtain the final set of weakly labeled data points. First, we determine the edge directions. Let us take constituents connected by the WHEN relation as an example. In these cases, the constituent that indicates the time should be the second constituent in the summary triple. Next, we filter out overlapping constituents. For example, imagine three possible triples: (event, WHEN, June 7), (event, WHEN, 2012), (event, WHEN, June 7, 2012). In this case, we make sure that only one of these potential data points is included in the weakly labeled training set. As a heuristic, we choose to include the data point with the longest string, arguing that this provides us with most information. Finally, we merge all coreferences and use the first occurrence of the referent in our summary triples, corresponding to the instructions for our human annotators. We use AllenNLP’s\(^4\) implementation of SpanBERT\(^5\) (Joshi et al., 2020) as a coreference parser, as we found that this parser gave us the most reliable results.

5.2.2 Trained relation extraction
We choose DyGIE++ (Wadden et al., 2019) as our trained relation extraction method. DyGIE++ has shown to be a well-performing method across several tasks and datasets, it is well documented and can be easily adapted to our task. We use the code as provided,\(^6\) but make a number of adaptations. First, the standard way of training DyGIE++ is to select relations on a per sentence basis, whereas our relations span multiple sentences. As men-

\(^{2}\)https://github.com/huggingface/transformers
\(^{3}\)https://www.snorkel.org/
\(^{4}\)https://allenai.org/allennlp
\(^{5}\)https://github.com/allenai/allennlp-models/blob/main/allennlp_models/modelcards/coref-spanbert.json
\(^{6}\)https://github.com/dwadden/dygiepp
tioned in the original work, DYGIE++ can also be used to select relations on the document level, i.e., cross-sentence. For our implementation, this means that we do not split the summaries in sentences, but treat the entire document as if it were a single sentence. We leave all punctuation marks in. We train DYGIE++ on 4 GPUs with 12GB RAM each. A cross-sentence approach is substantially more memory demanding than a within sentence approach. For this reason, we resort to training DYGIE++ on 10,000 summary abstracts from the training set, the maximum number of abstracts we could process with our machines. As a second adaptation to the original work, we evaluate the extracted relations on the same metrics that we evaluated the human annotations on.

6 Results

We evaluate our work from three angles, which we discuss in this section. The first question we ask is whether a critical mass of people is interested in our suggested summaries with graphical elements. We confirm that this is the case and present our setup for a human evaluation to test this in Section 6.1. Secondly, we evaluate our baseline models. We present an automatic evaluation in Section 6.2 and a human evaluation in Section 6.3. Thirdly, we perform a qualitative analysis of the performance of the baseline methods in Section 6.4.

6.1 Q1 – Human evaluation

First, we evaluate users’ preference for different types of summaries in different settings and scenarios. Specifically, we want to find out whether a critical mass of people is interested in the summaries with graphical elements. We stress that we do not necessarily aim for a majority of people wanting to use a summary with graphical elements. As noted in previous work (Spärck Jones, 1998; ter Hoeve et al., 2020), different people have different preferences in different contexts. For our evaluation we use the recommendations from ter Hoeve et al. (2020). That is, we make use of a simulated work task setting (Borlund, 2003) to evaluate three types of summaries in a pairwise manner on two purpose factors. Our scenario outline is the following: Imagine that you would like to quickly gather information about a certain news event. To help you quickly find your information, you have access to a summary that describes the news article.

The three summaries that we compare are:

1. A text only summary. For this we simply use the summary abstracts.
2. A summary with graphical elements. For this we use a human labeled ground truth summary. We manually convert the labeled triples to a graphical summary. We acknowledge that the precise lay-out may affect people’s judgements. The results of this human evaluation should therefore be taken as an indication of people’s preference and taking this work in production should include an additional design step.
3. Typeset control summary. To control for some of the bias discussed in the previous point, we add a summary that is pure text, yet contains text formatting: we bold face the first sentence and color all phrases that contain outgoing edges in the human labeled equivalent.

We evaluate the summaries on the purpose factors previewing and substituting as defined in Spärck Jones (1998) and used in ter Hoeve et al. (2020). That is, we ask the following two questions: Which summary is more useful to you to preview the full news article? and Which summary is more useful to you to substitute the full news article? We run this evaluation on Amazon Mechanical Turk. We compare summaries for two different news articles, to control for potential bias towards an article. We randomize the position of the articles on the page, to avoid position bias. We request 20 judgements per comparison per news article, i.e., 40 pairwise judgements in total. The crowd workers are U.S. based, have a HIT approval rate of at least 90% and at least 1000 accepted HITs.

For quality control, we add three questions at the start of each HIT. The first two questions are about the content of the summary and are different for each summary pair. We manually construct these questions based on the ground truth. We list the questions in Appendix B.3. In the third question, we ask which summary workers mainly used to answer the question. Significant failure to answer the first two questions results in a rejection of the HIT and we request new labels for the rejected HITs. In this manner we arrive at a total of 120 judgements. A full overview of the task is given in Figure 4 in Appendix B.

Findings. In the main body of the paper, we report the aggregated results on both news articles.

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7We also found that results did not substantially improve by adding more training data.

8http://www.requester.mturk.com/
Table 4: Results Human Evaluation Q1. Pairwise comparisons.

| Used   | Prefer A (%) | Prefer B (%) |
|--------|--------------|--------------|
| Graphical / Text | 35.0 | 65.0 |
| Graphical / Typeset | 50.0 | 50.0 |
| Typeset / Text | 72.5 | 27.5 |

| Prev   | Prefer A (%) | Prefer B (%) |
|--------|--------------|--------------|
| Graphical / Text | 35.0 | 65.0 |
| Graphical / Typeset | 47.5 | 52.5 |
| Typeset / Text | 75.0 | 25.0 |

| Sub    | Prefer A (%) | Prefer B (%) |
|--------|--------------|--------------|
| Graphical / Text | 30.0 | 70.0 |
| Graphical / Typeset | 32.5 | 67.5 |
| Typeset / Text | 65.0 | 35.0 |

In Table 4, as there are no substantial differences if we split the results per document. The results per document are given in Appendix B, in Table 9 and 10. From these results there are two main observations. First, a substantial fraction of crowd workers prefer a summary with graphical elements over the other two summaries for both purpose factors and a substantial fraction of the crowd workers used the graphical summary to find the answer to the questions about the content of the summary. It is not a majority, yet the group is clearly large enough to be convinced that summaries with graphical elements are an important focus point, which is in line with ter Hoeve et al. (2020). Second, the typeset summaries are very popular, much more so than the raw text summaries. This, again, points in the direction that adding graphical elements to summaries is an important research direction.

6.2 Q2 – Automatic evaluation

The second question that we evaluate is which baseline model performs best on our newly proposed task. First, we confirm that our summarization models score on par with the scores that are reported when evaluating on the entire test set from the CNN/DM dataset (Table 5).

Next, we evaluate the different relation extraction components. Apart from the summarization models with Snorkel and DyGIE++ labels, we also include the scores of applying Snorkel and DyGIE++ to the ground truth CNN/DM abstracts directly. We evaluate according to the same metrics as for the human labels and we use the best scoring ground truth to compute the final scores.

Table 5: Rouge scores summarization component.

| Model   | R1   | R2   | RL   | RLsum |
|---------|------|------|------|-------|
| BART-L  | 48.16| 22.81| 32.84| 44.49 |
| T5      | 46.63| 22.41| 32.97| 43.43 |

Findings. The results are given in Table 6. We also report additional metrics in Appendix D in Table 12. From the results a few things become clear. In general, we find that the scores are still far from the agreement scores of the human labeled annotations. This indicates that this is an interesting task with a lot of opportunity for future work. More specifically, we see that applying Snorkel labels directly gives us better results than training DyGIE++ on these labels. The additional summarization step also decreases the performance substantially, even though the produced summaries by both BART and T5 seem to be of high quality. We postulate that these summaries are still quite different from the human-written summaries, therefore decreasing the performance of the models that were trained on the human-written summaries.

We also compare the relations that are predicted in different setups. We find that the types of relations that are predicted are in line with the scores we find for the automatic metrics. Methods with lower recall scores predict fewer relations. In general, the distribution of relation counts are comparable amongst methods, but differ more for methods with lower scores. We share histograms in Appendix D, Figure 8 and 9.

6.3 Q2 – Human evaluation

We also evaluate the output of our baseline models with a human evaluation. Our setup is similar to the one in Section 6.1. Again, we compare summaries in a pairwise manner. This time, the summaries are produced by three different methods: (i) the human labeled ground truth, (ii) BART output followed by Snorkel labels, and (iii) BART output followed by DyGIE++ labels. We compare summaries for 15 different articles and we request 3 annotations per HIT to be able to compute the majority vote afterwards. We select our summaries randomly, but filter out summaries with potentially sensitive topics for crowd workers. We randomly select one of our human annotators per human-labeled summary.

As in Section 6.1, we manually create summaries based on the model output. Examples are given in Appendix C. We again ask questions about the content of the summary for quality control, that

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9Some documents could not be parsed in the Snorkel pipeline and we leave these out.
we construct based on the ground truth abstracts. Since not all generated summaries contain the answer to this question, we ask workers to answer ‘No Answer’ if the summary does not contain the answer to the question. This time, we ask which summary workers used after each open question, as sometimes one summary contains the answer to one question, while the other summary the answer to the other question. We also add an additional option where workers can indicate that none of the summaries contained the answer to the question. We publish a list of selected summaries and the corresponding questions together with our code.

In addition to the questions we asked in the first round of the human evaluation, we also ask which summaries workers find more informative and which ones they find more concise, in line with previous work (e.g., Paulus et al., 2017; Narayan et al., 2018a). We do not evaluate on fluency, as the nature of our summaries with graphical elements does not align with this metric. As an additional quality control question, we ask workers to indicate their favorite summary and to provide a short justification for their choice. As in Section 6.1, we obtain new annotations to replace rejected HITs and apply some filtering afterwards to ensure good quality annotations. This leaves us with a total of 134 annotations. An example of our task is given in Appendix C in Figure 5.

The results, based on majority votes, are given in Table 7 and Table 8. These results show that crowd workers prefer the human-annotated summaries on all metrics, followed by the version where we used BART and Snorkel. Summaries with graphical elements produced by BART and DyGIE++ are preferred least. Table 8 shows that these summaries often do not contain the answer to questions. These results are in line with the results on the automatic metrics.

6.4 Q3 – Qualitative observations

We manually inspect the outputs of the different methods that we compare in the human evaluation. First, we note that DyGIE++ still misses many relations. This is in line with the automatic scores for recall and the scores for the human evaluation. An example is given in Appendix C (Figure 6c). As a second observation, we note that many coref-
erences are missed, resulting in summaries that are less well-connected than their human-labeled counterparts. An example of this is given in Figure 7b in the appendix.

7 Discussion

In the previous section we showed that a substantial number of users is interested in summaries with graphical elements, in line with observations from ter Hoeve et al. (2020). We have also shown that current summarization and relation extraction methods still have difficulties with our task. For future work we plan to explore graph-based summarization methods to directly learn the summarization triples. Moreover, we see many opportunities to investigate model understanding with our task. As mentioned in Section 2.1, current automatic summarization models have difficulties with factual consistency and being able to generate correct summary triples, including correct relations, may require an additional level of factual consistency.

8 Conclusion

In this work we have proposed a new task: summarization with graphical elements. We have collected a high quality human-labeled dataset, GRAPHELSUMS, for the task and presented the results for a number of baselines. By means of automatic and human evaluations, we show that our task is a much wanted, and challenging, addition to the existing types of automatic summarization tasks. As such, our work can inspire a lot of follow up work in this direction. For future work we are interested in learning end-to-end methods for our task and using GRAPHELSUMS to explicitly work on factual consistency of automatic summarization models.

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Appendix

A Human labeling

Figure 2 and 3 show screen shots of the human labeling task.

B Q1 – Human evaluation

B.1 Examples of task setup

Figure 4 shows screen shots of the human evaluation task setup for question 1, where we investigate whether a critical mass of people is interested in summaries with graphical elements.
Label relations

Introduction

Thank you for helping out! Please refer to the annotation manual for precise details. If you have any questions or run into any issues, please ask them in our Slack channel. If you have any great insights that can help the other annotators, also please share them!

It may be useful to sketch the graphical summary on a piece of paper, so that you can quickly select the constituents afterwards. Because of the automatic nature of the constituent extraction, it can be that your ideal graphical summary is a little different from what you are able to make with the options below. In that case, select the constituents that are as close as possible to the ones you have in mind. You can tick a box in the first question, to indicate any issues.

Recall, this is the type of structure we are looking for:

![Diagram of a labeled event]

- **London bombing survivor**
  - What happened?
  - When? [2005]
  - Who?
  - Killed 55 people, including 4 suicide bombers.
  - Came one day after London was announced as the host for the 2012 Paralympics.

- **Martine Wright**
  - What happened? [Lost both legs and suffered severe arm injuries following blast on subway train]
  - When? [In 2012]

- Sets sights on Paralympics.

Annotating

Full text summary

ID: eb883c26be5a6b75d614738b221d6b1ee

0: Jesus Navas rues missed chances after Manchester City suffer defeat at Burnley .
1: Manchester City paid the price against Burnley , admits Jesus Navas .
3: George Boyd scored as City 's title chances suffered a serious blow .

1. Are there any problems with this summary or the constituents?

2. Select the first constituent

3. Select the relation

4. Select the second constituent

Selected constituents and relations:

- Add another relation
- Done

- Delete all selected

☐ I am particularly uncertain about my annotations for this HIT.

Figure 2: Overview of human labeling task. Figure consists of several screen shots of the task.
(a) Expansion of question 1.

(b) Partial expansion of selecting constituents.

(c) Expansion of selecting relations.

Figure 3: Human labeling task in more detail.
Choose the most useful summary

Introduction

Thank you for helping us out! Below we explain everything in full detail. Please make sure to read the instructions carefully. If you have any questions, please contact m.a.terhoeve@uva.nl before you start the task and we will clarify them for you.

Purpose: The aim of this survey is to find out which type of summary people find most useful.

Scenario outline: Imagine that you would like to quickly gather information about a certain news event. To help you quickly find your information, you have access to a summary that describes the news article.

Task: At each HIT, you will see two different summaries. The summaries describe the same news article, but have a different format. For example, one could be fully textual, whereas the other could include more graphical elements, such as arrows and colored text.

First, you will be asked two questions about the content of the summary. Please note that we will check the answers to these questions and significant failure to answer these questions correctly will result in the rejection of your HIT.

Second, you are asked to judge which of the two summaries is most useful to you in two hypothetical scenarios: (1) previewing the news article and (2) substituting the news article. Each of these scenarios is explained below:

1. Previewing the news article. You use the summary to quickly decide whether the news article contains the information you are looking for.
2. Substituting the news article. You use the summary to get all the information you need and never access the full news article.

Note that you can choose the same summary for both scenarios, but also a different one for each scenario. It really depends on your preference!

Questions

Part 1 - Please answer these questions about the content of the summary.

1. What is Ronaldo’s nationality?

2. What is Ronaldo expected to win?

Which summary did you mainly use to answer these two questions?

- Summary 1
- Summary 2

Part 2 - Judge the usefulness of the summaries in two scenarios: to preview the full news article and to substitute the full news article.

Recall that you can choose the same summary for both scenarios, or a different one for each scenario.

Which summary is more useful to you to preview the full news article?

- Summary 1
- Summary 2

Which summary is more useful to you to substitute the full news article?

- Summary 1
- Summary 2

Figure 4: Example of human evaluation task. These are three screen shots – Summary 1 and 2 have a larger font in the actual task interface so they are more easily readable for workers.
| Pair (A/B) | Prefer A (%) | Prefer B (%) |
|------------|--------------|--------------|
| Used       |              |              |
| Graphical / Text | 40.0         | 60.0         |
| Graphical / Typeset | 50.0         | 50.0         |
| Typeset / Text   | 85.0         | 15.0         |
| Prev         |              |              |
| Graphical / Text | 35.0         | 65.0         |
| Graphical / Typeset | 55.0         | 45.0         |
| Typeset / Text   | 90.0         | 10.0         |
| Sub          |              |              |
| Graphical / Text | 20.0         | 80.0         |
| Graphical / Typeset | 30.0         | 70.0         |
| Typeset / Text   | 75.0         | 25.0         |

Table 9: Results Human Evaluation. Pairwise comparisons. Results for Document 1.

| Pair (A/B) | Prefer A (%) | Prefer B (%) |
|------------|--------------|--------------|
| Used       |              |              |
| Graphical / Text | 30.0         | 70.0         |
| Graphical / Typeset | 50.0         | 50.0         |
| Typeset / Text   | 60.0         | 40.0         |
| Prev         |              |              |
| Graphical / Text | 35.0         | 65.0         |
| Graphical / Typeset | 40.0         | 60.0         |
| Typeset / Text   | 60.0         | 40.0         |
| Sub          |              |              |
| Graphical / Text | 40.0         | 60.0         |
| Graphical / Typeset | 35.0         | 65.0         |
| Typeset / Text   | 55.0         | 45.0         |

Table 10: Results Human Evaluation. Pairwise comparisons. Results for Document 2.

**B.2 Additional results human evaluation Q1**

In Table 9 and 10 we give the results of the human evaluation per document.
B.3 List of open questions

Document 1
1. How expensive was the replica of the ark?
2. What is the name of the carpenter?
3. Where is the replica of the ark?
4. How long did Johan Huyberts spend on building the ark?
5. What did the carpenter dream?
6. What can visitors do in the ark?

Document 2
1. What is Ronaldo’s nationality?
2. What is Ronaldo expected to win?
3. Where did Ronaldo open a museum?
4. How many goals has Ronaldo scored for Real Madrid this season?
5. What is the CR7 museum?
6. Who are on the short list together with Ronaldo?

C Q2 – Human evaluation

C.1 Examples of task setup
In Figure 5 we show screen shots of the task setup for the human evaluation where we compare the results of different methods on our task.
Introduction

Thanks for helping us out! Below we explain everything in full detail. Please make sure to read the instructions carefully. If you have any questions, please contact m.a.terhoeve@uva.nl before you start the task and we will clarify them for you.

Purpose: The aim of this survey is to evaluate different tools that can be used to generate summaries. These summaries all contain graphical elements, such as arrows and colored text. In short, we want to know which tool performs best!

Scenario outline: Imagine that you would like to quickly gather information about a certain news event. To help you quickly find your information, you have access to a summary that describes the news article.

Task: In every HIT you will see a news article and two different summaries of that news article. Some news articles are cut towards the end, so that they are not too long. This is indicated by ‘...’ The summaries are generated by two different systems.

First, you will be asked two questions about the content of the summary. Please note that we will check the answers to these questions and significant failure to answer these questions correctly will result in the rejection of your HIT. If none of the summaries contains the answer to the question, answer ‘no answer’ in the answer box and tick the box ‘None of the summaries contains the answer’ for the question that asks you which summary you used.

Second, keeping the scenario outline in mind, we ask you to judge the two systems on informativeness, conciseness and usefulness. We explain each of these metrics below and will give examples to make things more clear for you. Please make sure to carefully review these explanations and examples, until you are sure that you understand each of these metrics.

1. **Informativeness.** This means: By just looking at a summary, how well do you know what the document is about? If the summary tells you a lot, the summary is very informative. If the summary does not give you a lot of information, the summary is not informative.

   Below is an example of a very informative summary and an example of a very uninformative summary. The left summary is very informative, because it captures the key information from the article, namely that Ronaldo opened a museum dedicated to his football career and that he is on the shortlist to win the 2013 FIFA Ballon d’Or. The right summary does not contain any of this information, and even contains information that is incorrect according to the news article (namely that Ronaldo is Spanish).

### Summary 1

- Ronaldo opened a museum dedicated to his football career.
- He is on the shortlist to win the 2013 FIFA Ballon d’Or.

### Summary 2

- Ronaldo is on the shortlist to win the 2013 FIFA Ballon d’Or.
- He opened a museum dedicated to his football career.

2. **Conciseness.** This means: How short and clear are the summaries? If you think the summary contains too much information, or rather too little, then the conciseness is low. If the right amount of information is captured, the conciseness is high.

   Below is an example of a very concise summary and an example of a very inconcise summary. The left summary is very concise, because it only captures important information and none of the information is redundant. The right summary is very inconcise, because it shows the same information multiple times (for example that Ronaldo is Portuguese and that he scored many goals).

### Summary 1

- Ronaldo opened a museum dedicated to his football career.
- He is on the shortlist to win the 2013 FIFA Ballon d’Or.

### Summary 2

- Ronaldo opened a museum dedicated to his football career.
- He is on the shortlist to win the 2013 FIFA Ballon d’Or.
- Ronaldo is on the shortlist to win the 2013 FIFA Ballon d’Or.
- Ronaldo is a football player.

3. **Usefulness.** This means: How useful is a summary to you in two hypothetical scenarios: (1) previewing the news article and (2) substituting the news article. Each of these scenarios is explained below:
   - **Previewing** the news article. You use the summary to quickly decide whether the news article contains the information you are looking for.
   - **Substituting** the news article. You use the summary to get all the information you need and never access the full news article.

   Note that you can choose the same summary for both scenarios, but also a different one for each scenario. It really depends on your preference!

The last question is a general question. We would like to know which summary is your **favourite**. We also ask for a justification. Significant failure to answer this question will result in the rejection of your HIT.
Reference Article

(CNN) -- Romanian striker Adrian Mutu saw his late penalty saved by Gianluigi Buffon as world champions Italy scraped a 1-1 draw in Zurich to keep their Euro 2008 hopes hanging by a thread. Romanian players celebrate Adrian Mutu's opening goal in the thrilling 1-1 draw against Italy. Mutu had earlier given Romania the lead only for Christian Panucci to level a minute later. The result leaves Italy needing to beat France in their final match to qualify, while Romania also have a chance to progress if they defeat Netherlands in their final match. Italy coach Roberto Donadoni made five changes to his starting line-up, following the dismal opening 3-0 defeat by Netherlands, with World Cup winners Marco Materazzi and Gennaro Gattuso among those left out. Those changes looked to be working as the Azzurri started brightly, almost breaking the deadlock in the eighth minute when Alessandro Del Piero's close-range header from Simone Perrotta's cross went just wide of the near post. In the 15th minute, Romania should have gone in front but Mutu's left-footed strike from the edge of the area was parried away by Buffon. At the other end, Luci Toni latched onto Fabio Grosso's cross but his header went high over the bar. Buffon was then forced to fully stretch to clear Gabriel Tamas' free-kick towards the far post. Italy almost fell behind in the 19th minute when Cristian Chivu's free-kick rebounded off the far post after being deflected by Panucci, with Buffon already beaten. But the Italians were looking more dangerous. Both Del Piero and Toni headed wide from good positions, while Romania goalkeeper Bogdan Lobont made a fine one-handed save to deny Toni's header from Del Piero's corner having previously anticipated Giorgio Chiellini's cross into the box. Then, on the stroke of halftime, Toni appeared to have given Italy the lead with a header, but Norwegian referee Tom Henning ruled the effort out for offside. Disaster struck for Italy after the break when Gianluca Zambrotta's...
Part 2 - Now please answer the following questions about the two summaries that are shown above.

Which summary is more informative? ①
○ Summary 1
○ Summary 2

Which summary is more concise? ①
○ Summary 1
○ Summary 2

Which summary is more useful to you to preview the full news article? ①
○ Summary 1
○ Summary 2

Which summary is more useful to you to substitute the full news article? ①
○ Summary 1
○ Summary 2

Overall, which summary is your favourite? ①
○ Summary 1
○ Summary 2

Why is that summary your favourite?

Figure 5: Example of human evaluation task. These are screen shots – Summaries have a larger font in the actual task so they are more readable for workers.
C.2 Examples of generated summaries
Figure 6 and Figure 7 give examples of outputs of summaries with graphical elements, generated by different methods.
What happened recalls the day the Iron Curtain fell. CNN's Jonathan Mann
recalls the fall of the Cold War as a young traveling correspondent
and says he was amazed at how quickly it was toppled. CNN's John Deftarios
recalls seeing thousands of East Germans escape from the Soviet-dominated Eastern Europe.

Figure 6: Examples of summaries with graphical elements generated by different methods.
New astronomy software creates the first accurate visions of other worlds - including what Earth looked like 240 million years ago. What happens? The software 'renders' 3D worlds based on what we know, draws worlds based on their size, chemistry and distance from star, and can render our Earth from historical data.

(a) Human labeled summary.

(b) BART + Snorkel

(c) BART + DIEGIE++

Figure 7: Examples of summaries with graphical elements generated by different methods.
D Additional results automatic evaluation
|                      | Avg      | A        | B        | Rel       |
|----------------------|----------|----------|----------|-----------|
| GT Abstract + Snorkel| 0.065 ± 0.089 | 0.238 ± 0.175 | 0.19 ± 0.148 | 0.582 ± 0.256 |
| GT Abstract + DYGIE++ | 0.026 ± 0.057 | 0.161 ± 0.204 | 0.095 ± 0.103 | 0.409 ± 0.262 |
| BART + Snorkel       | 0.001 ± 0.009 | 0.086 ± 0.132 | 0.016 ± 0.041 | 0.535 ± 0.221 |
| T5 + Snorkel         | 0.003 ± 0.021 | 0.091 ± 0.134 | 0.017 ± 0.047 | 0.543 ± 0.224 |
| BART + DYGIE++       | 0.000 ± 0.005 | 0.056 ± 0.126 | 0.017 ± 0.047 | 0.352 ± 0.270 |
| T5 + DYGIE++         | 0.001 ± 0.008 | 0.065 ± 0.132 | 0.014 ± 0.045 | 0.345 ± 0.259 |

Table 11: Jaccard scores entire pipeline.

|                      |  |  |  |  |
| Soft Binary          | P | R | F1 |
|----------------------|--------|--------|--------|
| GT Abstract + Snorkel| 0.342 ± 0.241 | 0.262 ± 0.200 | 0.286 ± 0.202 |
| GT Abstract + DYGIE++| 0.237 ± 0.303 | 0.102 ± 0.139 | 0.132 ± 0.162 |
| BART + Snorkel       | 0.239 ± 0.219 | 0.173 ± 0.164 | 0.191 ± 0.170 |
| T5 + Snorkel         | 0.250 ± 0.247 | 0.179 ± 0.195 | 0.198 ± 0.194 |
| BART + DYGIE++       | 0.145 ± 0.268 | 0.056 ± 0.101 | 0.075 ± 0.129 |
| T5 + DYGIE++         | 0.137 ± 0.261 | 0.055 ± 0.102 | 0.072 ± 0.128 |

Table 12: We compute an additional soft matching score, where we count whether or not summary triples have overlap with the ground truth triples.
Figure 8: Histograms of relation counts for several baselines.

(a) Human labeled test set. Counts are averaged over the average number of annotations per document.

(b) GT Abstract + Snorkel

(c) GT Abstract + DyGIE++

(d) BART + Snorkel

(e) T5 + Snorkel

(f) BART + DyGIE++

(g) T5 + DyGIE++
Figure 9: Histograms of relation percentages for several baselines.