The Financial Narrative Summarisation Shared Task (FNS 2021)
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Abstract
This paper presents the results and findings of the Financial Narrative Summarisation Shared Task on summarising UK annual reports. The shared task was organised as part of the Financial Narrative Processing 2021 Workshop (FNP 2021 Workshop). The shared task included one main task which is the use of either abstractive or extractive automatic summarisers to summarise long documents in terms of UK financial annual reports. This shared task is the second to target financial documents. The data for the shared task was created and collected from publicly available UK annual reports published by firms listed on the London Stock Exchange. A total number of 10 systems from 5 different teams participated in the shared task. In addition, we had two baseline and two topline summarisers to help evaluate the results of the participating teams and compare them to the state-of-the-art systems.

1 What are financial narratives
Companies produce a variety of reports containing both narrative and numerical information at various times during their financial year, including annual financial reports. This creates vast amounts of financial information which can be impossible to navigate, handle and keep track of. This shows the vital need for automatic summarisation systems in order to reduce the time and effort of both the shareholders and investors.

2 Related Work
The increased availability of financial reports data has been met with research interest for applying automatic summarisation methods. The task of automatic text summarisation aims to produce a condensed, informative and non-redundant summaries from a single or multiple input texts (Nenkova and McKeown, 2011). This is achieved by either identifying and ranking subsets of the input text (i.e. extractive approaches ((Gupta and Lehali, 2010)), or by generating the summary from scratch (i.e. abstractive methods (Moratanch and Chitrakala, 2016)). Extractive methods have been a popular venue for summarising text due to their relative simplicity and the comparatively high requirements of abstractive methods for computational resources and available data.

Extractive summarisation utilises scoring approaches to identify and reorder parts of the input (e.g. sentences, phrases and/or passages), using a variety of feature extraction and evaluation methods (Luhn, 1958; Baxendale, 1958; Edmundson, 1959; Mori, 2002; McCargar, 2004; Giannakopoulos et al., 2008). Where adequate data is available, machine learning methods have been employed, such as Hidden Markov Models (Fung and Ngai, 2006), topic-based modelling (Aries et al., 2015), genetic algorithms (Litvak et al., 2010) and clustering methods (Radev et al., 2000; Liu and Lindroos, 2006; Kruengkrai and Jaruskulchai, 2003).

The employment of summarisation and natural language processing techniques in general has promising applications in the financial domain (El-Haj et al., 2019b). The SummariserPort system (de Oliveira et al., 2002) has been used to produce summaries for financial news, where it utilized lexical cohesion (Flowerdew and Mahlberg, 2009), using sentence linkage heuristics to generate the output summary. A summarisation system for financial news was proposed in (Filippova et al., 2009) generating query-based company-tailored summaries. This was done through using unsupervised sentence ranking with simple frequency-based features. Recently, statistical
features with heuristic approaches have been used to summarise financial textual disclosures (Cardinaels et al., 2019), generating summaries with reduced positive bias, leading to more conservative valuation judgements by investors that receive them. Further, the Financial Narrative Summarisation task (El-Haj, 2019) of the Multiling 2019 workshop (Giannakopoulos, 2019) involved the generation of structured summaries from financial narrative disclosures. Considering this body of work, the Financial Narrative Summarisation task (FNS 2020 (El-Haj et al., 2020a)) task resulted in the first large scale experimental results and state-of-the-art summarisation methods applied to financial data. The task focused on annual reports produced by UK firms listed on the London Stock Exchange (LSE). The shared task was held as part of the 1st Joint Workshop on Financial Narrative Processing and MultiLing Financial Summarisation (FNP-FNS 2020) (El-Haj et al., 2020b). The participating systems used a variety of techniques and methods ranging from rule based extraction methods (Litvak et al., 2020; Vhatkar et al., 2020; Arora and Radhakrishnan, 2020; Azzi and Kang, 2020) to traditional machine learning methods (Suarez et al., 2020; Vhatkar et al., 2020; Arora and Radhakrishnan, 2020) and high performing deep learning models (Agarwal et al., 2020; Singh, 2020; La Quatra and Cagliero, 2020; Vhatkar et al., 2020; Arora and Radhakrishnan, 2020; Azzi and Kang, 2020; Zheng et al., 2020).

One of the main challenges and limitations reported by the participants was the average length of annual reports (around 60,000 words), which made the training process difficult as it requires powerful resources (e.g. GPUs) to avoid long training time. In addition, participants argued that extracting both text and structure from PDF files with numerous tables, charts, and numerical data resulted in noisy data being extracted. Such feedback highlights interesting aspects and challenging components of Financial Narrative Summarisation, which presents a high difficulty task and an interesting research problem that is worth investigating. The 2021 Financial Narrative Summarization task (FNS 2021) promotes this effort by providing such a shared task in the FNP 2021 workshop.

3 Data Description

In the Financial Narrative Summarisation task we focus on annual reports produced by UK firms listed on The London Stock Exchange (LSE).

In the UK and elsewhere, annual report structure is much less rigid than those produced in the US. Companies produce glossy brochures with a much looser structure, which makes automatic summarisation of narratives in UK annual reports a challenging task.

For the FNS 2021 Shared task we use approximately 4,000 UK annual reports for firms listed on LSE, covering the period between 2002 and 2017 (El-Haj et al., 2014, 2019a).

We divided the full text within annual reports into training, testing and validation sets providing both the full text of each annual report along with gold-standard summaries.

In total there are 3,863 annual reports divided into training, testing and validation sets. Table 1 shows the dataset details.

| Data Type             | Train  | Validate | Test   |
|-----------------------|--------|----------|--------|
| Report full text      | 3,000  | 363      | 500    |
| Gold summaries        | 9,873  | 1,250    | 1,673  |

Table 1: FNS 2021 Shared Task Dataset

4 Data Availability

For the shared task we first provide the training and validation sets, which include the full text of each annual report along with the gold-standard summaries. On average, there are at least three gold-standard summaries for each annual report with some reports containing up to seven gold-standard summaries. The full test set is available only to organisers who evaluate the participating systems. The gold-standard summaries for the test set were not provided to participants in advance.

5 Eval-AI Platform

This year we introduced a new feature of the shared task which is hosting the task on Eval-AI open source AI challenge platform†.

Eval-AI (Yadav et al., 2019) is an open source platform for evaluating and comparing Machine Learning (ML) and Artificial Intelligence (AI)
algorithms. It is built to provide a scalable solution to the scientific research community and address the need to evaluate machine learning models by customisable metrics or through looping human evaluation. This will help researchers, students and data scientists to create, collaborate and participate in AI challenges organised around the world or by customising this platform and hosting it in a private cloud. This platform simplifies and standardises the process of benchmarking created models.

Using Eval-AI enabled us to automate the evaluation of the submissions and to use custom evaluation phases and protocols.

6 Task Description

For the purpose of this task each team was asked to produce one summary for each annual report. The summary length should not exceed 1000 words. We advised that the summary is generated/extracted based on the narrative sections.

Only one summary was allowed for each report, but participating teams were welcome to participate with more than one system. The participants were asked to follow a standard file naming process to aid the automatic evaluation process. Also, for standardisation and consistency all output summary files were required to be in UTF-8 file format.

Regarding generated outputs from a participant system, the following criteria were requested:

- Each team should produce a no more than 1000 words summary for each annual report in the testing set.
- One summary should be provided for each report.
- Each summary should be named following the pattern **ID**-**summary.txt**. Example: 25082-**summary.txt**.
- All outputs should be in UTF-8 file format.
- All output summaries should be compressed following the pattern <**TeamName**>_Summaries.tar.gz.

6.1 Evaluation

To evaluate the generated system summaries against the human gold-standard summaries we used the Java Rouge (JRouge) package for ROUGE, using multiple variants (i.e. ROUGE-1, ROUGE-2, ROUGE-L and ROUGE-SU4). (Ganesan, 2018)

7 Data Sample

Figure 1 shows the structure of the Financial Narrative Summarisation dataset. At the beginning of the shared task we provided the participants with two directories, corresponding to “training” and “validation” sets. Each contained the full text of the annual reports and the gold standard summaries.

The data was provided in plain text format in a directory structure as in Figure 1. Each annual report has a unique ID and it is used across in order to link the full text from an annual report to its gold-standard summaries.

For example, the gold standard summaries for the file called 19.txt in the training/annual_reports directory can be located in the training_gold_summaries as files with the same ID (19) as a prefix: 19_1.txt to 19_3.txt.

8 Baseline and Topline Summarisers

We compared the results of participating systems to four topline and baseline summarisers—MUSE (Litvak and Last, 2013), POLY (Litvak and Vanetik, 2013), TextRank (Mihalcea and Tarau, 2004), and LexRank (Erkan and Radev, 2004). See (El-Haj et al., 2020a) for more details on the topline and baseline summaries.

9 Participants and Systems

In total, 10 summarisation systems by five different teams have participated and submitted their system summaries to FNS 2021, which are presented in Table 2.
### 10 Results and Discussion

The participating systems used a variety of techniques and methods ranging from fine tuning pre-trained transformers to using high performing deep learning models and word embeddings. In addition, the participating teams used methods to investigate the hierarchy of the annual reports to try and detect structure and extract the narrative sections, in order to identify the parts in the report from which the gold summaries were extracted.

The majority of the applied techniques were extractive, since the dataset is highly structured with discrete sections. We report the use of T5 (Test-to-text transfer Transformer) (Raffel et al., 2019) and BERT-based (Devlin et al., 2018) extractive models. Some extractive summarisers used word embeddings such as word2vec (Mikolov et al., 2013). An end-to-end hybrid extractive-abstractive training method using pointer network generators have also been reported.

The results are reported in Table 3. Overall, the best model outperforms results compared to the baselines with ROUGE1 : 0.54, ROUGE-2 : 0.38, ROUGE-L : 0.52 and ROUGE-SU4 : 0.43. The results are sorted in descending order of Rouge-2 F1-score. The results show that all participating systems outperformed TextRank baseline and most systems (eight) systems performed better than the LexRank and POLY baselines. On the other hand, results from our topline MUSE system indicate that it is a challenging opponent, but we are happy to see that two participating systems have managed to outperform it. Such results will be used as a comparison line in the future, by incorporating them into a venue of results, techniques and approaches, which we hope will be useful to researchers working on Financial Text Summarisation.

| System/Metric | R-1 | R-2 | R-L | R-SU4 |
|---------------|-----|-----|-----|-------|
| orzhan        | 0.54| 0.38| 0.52| 0.43  |
| SRIB-lancs    | 0.52| 0.30| 0.46| 0.32  |
| MUSE          | 0.5 | 0.28| 0.45| 0.32  |
| SCE-1         | 0.5 | 0.27| 0.44| 0.30  |
| UoBNLP-2      | 0.48| 0.26| 0.4  | 0.29  |
| UoBNLP-3      | 0.47| 0.25| 0.4  | 0.29  |
| UoBNLP-1      | 0.47| 0.25| 0.4  | 0.29  |
| CILab_KIT     | 0.38| 0.17| 0.32| 0.21  |
| CILab_KIT-B   | 0.35| 0.16| 0.29| 0.20  |
| POLY          | 0.37| 0.12| 0.26| 0.18  |
| LEXRANK       | 0.26| 0.12| 0.22| 0.14  |
| SCE-3         | 0.33| 0.12| 0.27| 0.17  |
| SCE-2         | 0.35| 0.11| 0.26| 0.18  |
| TEXTRANK      | 0.17| 0.07| 0.21| 0.08  |

Table 3: ROUGE-1 and ROUGE-2 and ROUGE-L and ROUGE-SU4 F-measure scores.

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