

A Multistage Pipeline for Discovering Rationales in Financial Reports

Anonymous ACL submission

Abstract

We address the task of discovering rationales between two narrative financial reports in consecutive years. This task requires modeling the complicated content of long financial documents, reasoning different relationships between the documents, and discovering relevant rationales for the relationships. Effective solutions improve the efficiency of financial practitioners in comprehending financial reports. In this paper, we leverage the intrinsic nature of the year-to-year structure of reports by defining a novel signal-highlighting task, for which we propose a multistage pipeline with domain-adaptive learning to discover relevant rationales regarding insightful signals in newly-published reports. We also build and publish a human-annotated dataset for our task. Experiments on our dataset validate the effectiveness of the proposed pipeline. Detailed analyses and ablation studies are also provided.

1 Introduction

With the rapid growth of information, many tasks involve streamlining information comprehension, especially in the field of natural language processing (NLP). Summarization, for example, selects a subset of sentences or generates new content that best represents the given document (Hermann et al., 2015; See et al., 2017; Cohan et al., 2018); reading comprehension answers questions about long documents or large document collections (Rajpurkar et al., 2016; Wang et al., 2019). These tasks all mine important signals and thus help humans save time and effort when comprehending the contents of textual resources.

In the context of finance, comprehending regulatory financial narrative reports is a classic example of efficiently mining important signals from a large amount of text. Financial reports contain rich information concerning specific financial entities; mining information from such reports provides insightful signals to users. For instance, Badertscher

et al. (2018); Ertugrul et al. (2017); You and Zhang (2009) indicate that textual features from financial reports contain valuable financial signals about future firm performance and market reactions. While these signals exist in newly-published reports, authorities such as the Securities and Exchange Commission (SEC) require that companies provide comprehensive and detailed information about their current status, such that these reports often contain much unimportant and already-known information. For example, for each company, annual 10-K reports between adjacent years often exhibit high token overlap ratios, say 0.826 on average (the *overlapping characteristic*),¹ making the acquisition of important signals in new reports a lengthy, tedious process.

Recent advances in NLP technology have included attempts to alleviate the problem caused by recurring information in finance documents. This problem can be addressed from a summarization perspective (e.g., Zmandar et al., 2021b; Orzhenovskii, 2021; Gokhan et al., 2021), but this type of approach requires high-quality human-labeled ground truth to ensure high-accuracy models. Other approaches leverage numerical information, such as stock return volatility and abnormal trading volumes—to locate important financial signals in financial reports (e.g., Kogan et al., 2009; Tsai and Wang, 2017; Rekabsaz et al., 2017; Agrawal et al., 2021; Lin et al., 2021). Nevertheless, signals discovered via such approaches depend greatly on the financial measures adopted as the ground truth, making it difficult to use them in more general scenarios.

Here, we approach financial report comprehension from a novel perspective. Inspired by the nature of the year-to-year overlap of financial reports, we propose a new signal-highlighting task together with a multistage pipeline. Specifically, for a cer-

¹Calculated from Item 7 of the reports of the 3,849 companies from 2011 to 2018 (see FINAL dataset in Section 4).

tain company, we treat the document published in the previous year as an information anchor (i.e., the reference) with which to construct a year-to-year structure to locate important financial signals in the report of the subsequent year (i.e., the target). First, we break down the document-to-document relationship into enumerated segment-to-segment relationships and filter out irrelevant or nearly identical segment pairs. We then leverage e-SNLI (Camburu et al., 2018), an external human-annotated dataset, for out-of-domain fine-tuning on BERT (Devlin et al., 2019); moreover, we propose a novel pseudo-labeling method together with a novel soft labeling loss for in-domain fine-tuning for the highlighting task. For experiments, we present a synthetic dataset consisting of 30,400 reference-to-target segment pairs for financial signal highlighting.² Experimental results validate the effectiveness of the proposed pipeline; detailed analyses and ablation studies are also provided.

2 Problem Definition

The year-to-year nature of financial reports enables us to leverage differences between company documents in consecutive years. As these differences sometimes reveal complex but insightful relationships within a pair of documents, we investigate such differences to further discover relationships through rationales, which are viewed as important signals in financial reports.

2.1 Reference-to-target Structure

Formally, for each company, \mathcal{D}_ℓ is a set containing all segments in its financial report at year ℓ , where each element $d \in \mathcal{D}_\ell$ refers to a single segment. While we regard a focal company’s financial report at year ℓ , \mathcal{D}_ℓ , as the *target* document, we view the same company’s report at year $\ell - 1$, $\mathcal{D}_{\ell-1}$, as the *reference* document. Given this annual nature (i.e., the reference-to-target structure) of financial reports, we further break down the document-to-document relationship between \mathcal{D}_ℓ and $\mathcal{D}_{\ell-1}$ into enumerated segment-to-segment relationships. We denote the set of enumerated segment pairs as $\bar{\mathcal{T}}$.³

However, as $\bar{\mathcal{T}}$ includes all pairs of segments enumerated from \mathcal{D}_ℓ , and $\mathcal{D}_{\ell-1}$ (i.e., $|\mathcal{D}_\ell||\mathcal{D}_{\ell-1}|$

²The dataset and codes are available at https://anonymous.4open.science/r/fin_signal_highlighting/.

³Note that each $(\mathcal{D}_\ell, \mathcal{D}_{\ell-1})$ pair corresponds to a set of segment pairs $\bar{\mathcal{T}}$; to simplify the notation, we do not use the subscript for $\bar{\mathcal{T}}$ to characterize the different sets.

(a) Segment pairs in \mathcal{T}^β	
2017 (ref.)	<i>Our most critical accounting policies relate to revenue recognition, inventory, pension and other post-retirement benefit costs, goodwill, ...</i>
2018 (target)	<i>Our most critical accounting policies relate to revenue recognition, inventory, pension and other post-retirement benefit costs, goodwill, ...</i>
(b) Segment pairs in \mathcal{T}^α	
2017 (ref.)	<i>Net sales in the Americas increased 5%, or \$201.8 million, to \$4,302.9 million.</i>
2018 (target)	<i>Net sales in the Americas decreased 1%, or \$58.5 million, to \$4,513.8 million.</i>

Table 1: Segment pair classification

pairs), intuitively, most segment pairs in $\bar{\mathcal{T}}$ have no interesting relationship. Hence, we reduce the set $\bar{\mathcal{T}}$ to \mathcal{T} by removing irrelevant segment pairs based on their syntactical similarities. Specifically, for each target segment $t \in \mathcal{D}_\ell$, we calculate the ROUGE-2 (Lin, 2004) scores between the target segment t and all reference segments $r \in \mathcal{D}_{\ell-1}$ and sort the reference segments according to their scores in descending order as $\bar{S}(t) = (r_1, r_2, \dots, r_{|\mathcal{D}_{\ell-1}|})$,⁴ where r_k denotes the reference segment with the k -th highest ROUGE-2 score for the target segment t . With $\bar{S}(t)$, we then discard reference segments that fall behind the largest ROUGE-2 difference out of all possible ROUGE-2 differences, resulting in a truncated set $S(t)$.⁵ Note that the difference is calculated between the two ROUGE-2 scores from (r_k, r_{k-1}) . Finally, with $S(t)$, the reduced segment pair set is $\mathcal{T} = \{(r, t) | (r, t) \in \bar{\mathcal{T}} \wedge r \in S(t)\}$.

To locate meaningful financial signals revealed by segment pair differences, we further classify each pair $(r, t) \in \mathcal{T}$ into the following two sets:

1. \mathcal{T}^β contains reference-to-target segment pairs with largely similar meanings (see Table 1(a)). Generally, there is no additionally noteworthy content in target segment t compared to reference segment r .
2. $\mathcal{T}^\alpha = \mathcal{T} \setminus \mathcal{T}^\beta$ contains segment pairs with dissimilar meanings (see Table 1(b)). Pairs in \mathcal{T}^α are further classified into two types based on their syntactic and semantic similarity, as discussed in Section 3.2.

⁴The round parentheses represent the ordered set.

⁵Empirically, there are often one to five remaining reference segments in the truncated set for a target segment t .

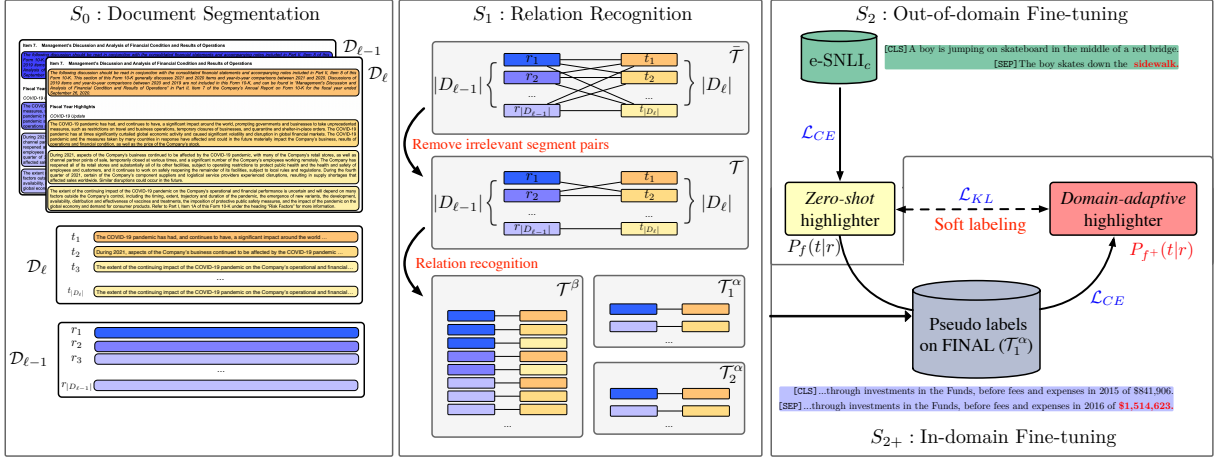


Figure 1: Proposed rationale discovery pipeline

2.2 Highlighting Task

We consider pairs in \mathcal{T}^α as the pairs of interest and provide rationales of underlying pairwise relationships by predicting the word importance for each segment pair $(r, t) \in \mathcal{T}^\alpha$ as

$$\mathbf{R} \triangleq P_f(t|r), \quad (1)$$

where \mathbf{R} indicates the word importance of a target segment t conditioned on reference segment r , and the highlighting model is denoted as f (detailed in Sections 3.3 and 3.4).

3 Proposed Pipeline

Here we describe the proposed multistage pipeline for discovering the rationale behind the reference-to-target structure in financial reports, as illustrated in Figure 1.

3.1 S_0 : Document Segmentation

Financial reports are multimodal, often covering multiple aspects and topics; each aspect or topic usually uses one to three consecutive sentences to convey its meaning. Therefore, instead of considering sentences as the basic unit of text, we here regard *uni-modal segments* as the smallest unit for financial documents. We first use spaCy API for sentence segmentation.⁶ Then, we utilize the fine-tuned cross-segment BERT (Lukasik et al., 2020) to obtain coherent uni-modal segments. Note that some studies show that breaking a document into uni-modal segments benefits downstream applications (Shtekh et al., 2018; Qiu et al., 2022; Chivers et al., 2022).

⁶<https://spacy.io/api/sentencizer>

3.2 S_1 : Relation Recognition

In this stage, a systematic procedure manages relation types \mathcal{T}^β and \mathcal{T}^α with semantic and syntactic similarity. Specifically, we use two functions, ROUGE-2 and Sentence-BERT (Reimers and Gurevych, 2019) cosine similarity,⁷ to assess the syntactic and semantic similarity between each reference-to-target pair $(r, t) \in \mathcal{T}$.⁸ The scores for the syntactic and semantic similarity are denoted as $\phi_{\text{syn}}(r, t)$ and $\phi_{\text{sem}}(r, t)$, respectively.⁹ We empirically design a rule-based procedure and classify each segment pair into three types.

1. *Insignificant* relations (\mathcal{T}^β) correspond to uninformative segment pairs with highly similar syntactic and semantic meanings between target and reference segment (i.e., $\phi_{\text{syn}} > \epsilon_{\text{syn}}$ and $\phi_{\text{sem}} > \epsilon_{\text{sem}}$).
2. *Revised* relations (\mathcal{T}_1^α) correspond to segment pairs that differ in some words only but disclose quite different meanings, resulting in a high $\phi_{\text{syn}}(r, t)$ but a relatively low $\phi_{\text{sem}}(r, t)$ (i.e., $\phi_{\text{syn}} > \epsilon_{\text{syn}}$ and $\phi_{\text{sem}} < \epsilon_{\text{sem}}$).
3. *Mismatched* relations (\mathcal{T}_2^α) correspond to segment pair meanings that are to some extent mutually exclusive, resulting in a low $\phi_{\text{syn}}(r, t)$ (i.e., $\phi_{\text{syn}} < \epsilon_{\text{syn}}$).

The procedure and the setting of the two thresholds (ϵ_{sem} and ϵ_{syn}) are also summarized in Figure 4 in Appendix C.

⁷We derive segment embeddings using average pooling.

⁸Note that before the following procedure, we first reduce the set $\tilde{\mathcal{T}}$ to \mathcal{T} by removing irrelevant segment pairs (see Section 2.1).

⁹Note that the scoring functions are not limited to these two but can be replaced with other suitable functions.

3.3 S_2 : Out-of-domain Fine-tuning

Here we pinpoint financial signals for segment pairs in $\mathcal{T}^\alpha = \mathcal{T}_1^\alpha \cup \mathcal{T}_2^\alpha$. Specifically, for each segment pair $(r, t) \in \mathcal{T}^\alpha$, we discover rationales as important words in target segment t , where the rationales are inferred conditioned on reference segment r (see Eq. (1)).

Binary token classification To accomplish this, we cast the word importance prediction as supervised binary token classification. First, we leverage the pre-trained BERT (Devlin et al., 2019) model to construct contextualized reference-to-target pair representations, where each pair of interest constitutes an input with special tokens as

$$\mathbf{h}_{(r,t)} = \text{BERT}([\text{CLS}]r[\text{SEP}]t),$$

where $\mathbf{h}_{(r,t)} \in \mathbb{R}^{n \times d}$ is the contextualized token representation of the pair, d is the dimension of each token representation, and n is the number of tokens in segment pair (r, t) . Second, on top of the token representation $\mathbf{h}_{(r,t)}$, we add a highlighting model $f(\cdot)$ (an MLP layer) with softmax activations. The resultant conditional word importance $P_f^j(t|r)$ for the j -th word in target segment t is

$$P_f^j(t|r) = \frac{\exp\left(\left(f\left(\mathbf{h}_{(r,t)}^j\right)[1]\right)/\tau\right)}{\sum_{i=1}^2 \exp\left(\left(f\left(\mathbf{h}_{(r,t)}^j\right)[i]\right)/\tau\right)}, \quad (2)$$

where $\mathbf{h}_{(r,t)}^j$ denotes the token representation of the j -th word in target segment t (i.e., the j -th row vector of $\mathbf{h}_{(r,t)}$), $f(\cdot) : \mathbb{R}^d \rightarrow \mathbb{R}^2$, and τ is a hyperparameter that controls the probability distribution.

Signal highlighting warm-up As we view signal highlighting as binary token classification, we first fine-tune the model $f(\cdot)$ on e-SNLI (Camburu et al., 2018), an external human-annotated dataset, to obtain a zero-shot model. Note that e-SNLI was compiled for explanation generation with human-annotated rationale words to distinguish relations of aligned sentence pairs (r', t') (i.e., premise and hypothesis) in natural language inference. We then treat the annotated words as the ground truth for the premise-to-hypothesis relation,¹⁰ which is similar to our reference-to-target structure. Formally, we adopt the binary cross-entropy objective for each

¹⁰Here, we specifically select *contradiction* pairs in e-SNLI as this relationship is closer to our goal than the other two.

token in hypothesis t' to fine-tune the BERT token representations and the highlighting model $f(\cdot)$ as

$$\mathcal{L}_{\text{CE}} = \sum_j - \left(Y_{t'}^j \log P_f^j(t'|r') + (1 - Y_{t'}^j) \log (1 - P_f^j(t'|r')) \right),$$

where $Y_{t'}$ is a vector in which each element $Y_{t'}^j$ indicates the binary label of word importance for the j -th word in hypothesis t' . We thus construct the out-of-domain zero-shot highlighting model by fine-tuning on e-SNLI, which is regarded as a baseline to proceed with the following financial domain adaptation (see Figure 1).

3.4 S_{2+} : In-domain Fine-tuning

Generally, for applications, particularly in niche domains like finance, models with a zero-shot setting may not be effective enough. Also, several studies show that language models exhibit poor performance under domain shift scenarios (Ben-David et al., 2006; Han and Eisenstein, 2019; Gururangan et al., 2020; Li et al., 2022). We account for this by equipping the proposed pipeline with an extra in-domain fine-tuning stage to enable our highlighting model to properly adapt to the financial domain. Specifically, we construct a domain-adaptive financial signal highlighting model $f_+(\cdot)$ with the following learning strategies: (1) pseudo-labeling with revised segment pairs in \mathcal{T}_1^α , and (2) further fine-tuning with soft labels.

Pseudo-labeling with revised segment pairs

We introduce a simple yet effective pseudo-labeling approach that uses revised segment pairs (i.e., \mathcal{T}_1^α) collected from stage S_1 (see Section 3.2). Recall that these segment pairs differ in some words only but have quite different meanings. Given such a property, we establish a heuristic labeling approach for pseudo-labels of financial signals. Intuitively, we treat all revised words in target segment t as important words and mark them as positive, and randomly sample other words as negative ones.¹¹

Further fine-tuning with soft labels

To compensate for deficiencies in such assertive binary pseudo-labels, we use soft labeling to make the token representations more generalized. Initially, as illustrated in Figure 1, we leverage the zero-shot highlighting model $f(\cdot)$ learned at stage S_2

¹¹We set the number of negative labels to three times that of the positive ones.

to calculate the approximate word importance of the revised segment pairs, the results of which are regarded as soft labels compared to the assertive pseudo-binary labels. We then construct the soft-labeling objective \mathcal{L}_{SL} as

$$\mathcal{L}_{\text{SL}} = \gamma \mathcal{L}_{\text{CE}} + (1 - \gamma) \mathcal{L}_{\text{KL}}, \quad (3)$$

where

$$\mathcal{L}_{\text{KL}} = \sum_j -\text{KL} \left(P_f^j(t|r) \parallel P_{f_+}^j(t|r) \right) \quad (4)$$

and γ is a hyperparameter that controls the impact of soft labeling. In Eqs. (3) and (4), $\text{KL}(\cdot)$ denotes Kullback–Leibler (KL) divergence, and $P_f(t|r)$ and $P_{f_+}(t|r)$ indicate the estimated probability distributions predicted by $f(\cdot)$ and $f_+(\cdot)$, respectively. Finally, we fine-tune the highlighting model $f_+(\cdot)$ with the pseudo-labels annotated on segments in \mathcal{T}_1^α by optimizing \mathcal{L}_{SL} in Eq. (3). Note that we not only utilize probabilities $P_f(t|r)$ as our training targets (i.e., soft labels) for \mathcal{L}_{KL} but we also adopt the warm-start token representations and highlighting layer $f(\cdot)$ as the initial checkpoint for fine-tuning $f_+(\cdot)$. In addition, we discover that hyperparameters τ and γ affect the performance significantly. We discuss the hyperparameter search in Appendix B.

4 The FINAL Dataset

We constructed FINAL (**FIN**ancial-**AL**pha), a financial signal highlighting dataset, consisting of 30,400 reference-to-target segment pairs in $\in \mathcal{T}^\alpha$.

4.1 Financial 10-K Corpus Preprocessing

We used Form 10-K filings collected from the Software Repository for Accounting and Finance,¹² where a Form 10-K is an annual report required by the U.S. SEC. Specifically, we used 10-K filings from 2011 to 2018, which comprise 63,336 filings from 12,960 public companies. To make the best use of the year-to-year information, we discarded companies for which the reports in some years were missing during the period; 3,849 companies ($3,849 \times 8 = 30,792$ reports total) remained after this filtering. We then randomly sampled 200 companies from the 3,849 companies with their annual reports to construct the dataset. In addition, while every 10-K annual report contains 15 schedules (e.g., Items 1, 1A, 1B, 2, 3, ..., 7, 7A, ...,

¹²<https://sraf.nd.edu/sec-edgar-data/>

(a) FINAL dataset

	Pairs	Avg. t	Avg. r	Avg. #w ₊	Avg. #w ₋
Train (\mathcal{T}_1^α)	30,000	31.3	33.2	3.7	60.8
Eval (\mathcal{T}_1^α)	200	33.2	31.3	5.5	25.9
Eval (\mathcal{T}_2^α)	200	29.6	29.0	11.0	18.0

(b) e-SNLI_c dataset

	Pairs	Avg. t	Avg. r	Avg. #w ₊	Avg. #w ₋
Train	183,160	8.2	14.1	2.0	6.2
Test	3237	8.1	15.3	2.1	6.0

Table 2: Dataset statistics

15),¹³ we extracted only Item 7 (Management’s Discussion and Analysis of Financial Conditions and Results of Operations (“MD&A”)) to form the FINAL dataset.¹⁴ Finally, we aligned each document \mathcal{D}_ℓ with its corresponding last-year document $\mathcal{D}_{\ell-1}$, resulting in 1,400 reference-to-target document pairs (i.e., 200 companies \times 7 year-to-year pairs).

4.2 Year-to-year Segment Pair Generation

After preprocessing, we followed the proposed multistage pipeline by first passing each document pair through stage S_0 to obtain an enumerated set of segment pairs $\bar{\mathcal{T}}$; we then reduced $\bar{\mathcal{T}}$ to \mathcal{T} by removing irrelevant segment pairs (see Section 2.1). Next, we followed the relation recognition stage S_1 in Section 3.2 to obtain the two groups of segment pairs: \mathcal{T}_1^α and \mathcal{T}_2^α . From each of these two groups, we randomly sampled 200 pairs for human annotation as our evaluation sets. Likewise, we randomly sampled 30,000 pairs from the rest of the revised segment pairs (i.e., \mathcal{T}_1^α) as the training set for the pseudo-labeling approach in Section 3.4.

4.3 Human Annotation

To evaluate the empirical effectiveness of the proposed pipeline, we manually annotated the sampled 400 segment pairs. For each segment pair (r, t) , we collected important words (i.e., financial signals) from three annotators. Specifically, the annotators were to distinguish which words in each target segment t to regard as important financial signals according to the context of the corresponding reference segment r . That is, the annotated words were to characterize the reference-to-target relationship or disclose extra information of interest,¹⁵ whereas

¹³https://en.wikipedia.org/wiki/Form_10-K

¹⁴This setting follows most of the literature regarding textual analysis of financial reports.

¹⁵The annotation guidelines are provided in Appendix D.

the rest of the words in t were labeled as negative. We further assessed the inter-rater reliability of the three annotations with Fleiss’ κ (Fleiss, 1971). For simplicity, we treated each word in the target segment as an independent classification task (containing roughly 12K words in the 400 evaluation pairs): for evaluation pairs from \mathcal{T}_1^α , $\kappa = 0.71$; for those from \mathcal{T}_2^α , $\kappa = 0.60$. The training and evaluation sets are described in Table 2(a), where Avg. $|t|$ and Avg. $|r|$ are the average lengths of target and reference segments, respectively, and Avg. $\#w_+$ and Avg. $\#w_-$ are the average numbers of words annotated as positive and negative, respectively.

5 Experiments

5.1 Evaluation Datasets

FINAL We evaluated the highlighting performance on the two evaluation sets with the human-annotated ground truth (see Table 2(a)).

e-SNLI_c We additionally evaluated the performance on e-SNLI. Particularly, in this paper, we used only the premise-to-hypothesis sentence pairs labeled as *contradiction* (denoted as e-SNLI_c) in the test set of the e-SNLI dataset for evaluation (see Table 2(b)).

5.2 Evaluation Metrics

Recall-sensitive metric In practice, financial practitioners are usually concerned more about the recall of the discovered signals than their precision due to the high cost of missing signals. Accordingly, we borrow the idea of R -precision (Buckley and Voorhees, 2000), a metric from the information retrieval field. In our case, R -precision (R -Prec) is the precision at R , where R is the number of annotated words in each target segment: if there are r annotated words among the top- R predicted words, then the R -precision is r/R .

Sequence agreement of word importance In addition, we measure the agreement between the predicted importance of words for each target segment (considered as a number sequence) and its corresponding ground-truth sequence. Specifically, we utilize the Pearson correlation coefficient (PCC) for evaluation.

Note that for R -Prec, we use majority voting to derive single ground-truth labels from the three annotators, whereas for PCC, we take the mean agreement of the three annotations as the ground

#	W.U.	Labeling		FINAL		e-SNLI _c	
		P	S	<i>R</i> -Prec	PCC	<i>R</i> -Prec	PCC
Zero-Shot							
1	✓	✗	✗	0.7469	0.6067	0.8565	0.7555
Pseudo few-shot							
2	✗	✓	✗	0.6968	0.6368	0.6302	0.5752
Domain-adaptive							
3	✓	✓	✗	0.7160	0.6555	0.8475	0.7305
4	✓	✓	✓	0.7865*	0.7290*	0.8605	0.7566

Table 3: Highlighting performance

truth. Note also that neither of the above two metrics requires a hard threshold to determine the important words for evaluation. Whereas R -Prec considers the words with the top- R highest predicted probabilities, PCC directly leverages the predicted probabilities of words as the importance of words for calculation.

5.3 Compared Methods

Zero-shot We fine-tuned the BERT-base model on the e-SNLI_c training set (see Table 2(b)) with the binary token classification cross-entropy objective (See Section 3.3 for details) and used this as a zero-shot approach for financial signal highlighting.

Pseudo few-shot Instead of using e-SNLI_c, we fine-tuned the BERT-base model on the 30,000 revised segment pairs in \mathcal{T}_1^α (see the “Train” data in Table 2(a)) with the pseudo-label tokens (see pseudo-labeling introduced in Section 3.4) and use this as a pseudo few-shot approach.

Domain-adaptive Using the zero-shot highlighting model as the initialization, we further performed in-domain fine-tuning (see stage S_2^+ in Section 3.4) for domain adaptation.

5.4 Empirical Results

5.4.1 Main Results for Signal Highlighting

Performance on FINAL Table 3 tabulates the highlighting performance under four conditions (i.e., #1–#4), where W.U. denotes that e-SNLI_c is used for warm-up fine-tuning (i.e., the zero-shot highlighting model), **P** and **S** denote pseudo and soft labeling, respectively, and ‘*’ denotes statistical significance with respect to the performance of zero-shot learning (#1) under a paired t -test with $p < 0.05$.

We first focus on the results of the main task on FINAL, where the listed results are those evaluated on the union of the two evaluation sets (including

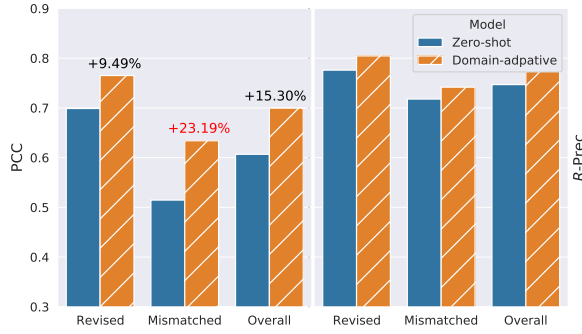


Figure 2: Highlighting effectiveness for different relations, including \mathcal{T}_1^α and \mathcal{T}_2^α with two evaluation metrics

400 segment pairs in total). As shown in the table, the proposed domain-adaptive approach using both pseudo and soft labeling techniques (i.e., condition #4) achieves the best R -Prec of 0.7865 and PCC of 0.7290. In addition, from the performance increase from condition #2 to #3, we observe that warm-up fine-tuning (W.U.) plays an essential role in financial signal highlighting. Similarly, soft labeling is also beneficial for our task, bringing a 10% performance improvement in both evaluation metrics (by comparing the results of conditions #3 and #4). However, from the results of conditions #1 and #3, we observe that adopting pseudo-labeling alone might not be helpful for this task, perhaps because the pseudo-labels constructed by the proposed heuristic approach (see Section 3.3) are too aggressive for unimportant tokens, resulting in a biased highlighting model. In sum, we offer two main observations from Table 3.

- The proposed domain-adaptive fine-tuning with pseudo and soft labeling is effective for signal highlighting in financial reports.
- Warm-up fine-tuning and soft labeling are two crucial components to constructing an effective domain-adaptive highlighting model.

Generalization ability between domains Table 3 also lists the results on the e-SNLI_c testing data: only the model with condition #4 performs on par with or even outperforms that with condition #1 (i.e., zero-shot), showing that the highlighting model fine-tuned by the proposed domain-adaptive approach exhibits good generalizability.

5.4.2 Analyses on Different Types of Target-reference Segment Pairs

To better understand the empirical advantages of the domain-adaptive approach, we further investigate the highlighting performance for different kinds of reference-to-target relations, \mathcal{T}_1^α (*revised*)

Reference settings		FINAL		e-SNLI _c	
		R -Prec	PCC	R -Prec	PCC
Empty	[PAD]	0.4834	0.4033	0.6553	0.5687
Same	t	0.5108	0.3850	0.5697	0.4994
Random	\tilde{r}	0.5345	0.4582	0.5658	0.4628
Original	r	0.7865	0.7290	0.8605	0.7566

Table 4: Impact of referenced knowledge sources

and \mathcal{T}_2^α (*mismatched*). Figure 2 compares the results of the zero-shot (#1) and domain-adaptive (#4) methods in terms of two metrics. We here focus on PCC, as R -precision considers only the set of important words (i.e., positive words) instead of all the words in each target segment. In the figure, we see that despite the significant PCC improvements on both *revised* and *mismatched* pairs, the benefit of domain adaptation on mismatched pairs is markedly greater than that on revised pairs, yielding a PCC improvement of approximately 23%. Perhaps the important words in the mismatched pairs are more uncertain, necessitating intensive domain adaptation more than the words in the revised pairs. Note that we fine-tuned the model on only 30,000 revised segment pairs in \mathcal{T}_1^α for domain adaptation; however, the highlighting results of mismatched pairs \mathcal{T}_2^α exhibit more significant improvement. This suggests that the proposed domain-adaptive approach addresses domain shift and yields a superior ability to infer word importance even for unfamiliar (unseen) relationships (See Appendix E also).

5.5 Ablation Studies

5.5.1 Impact of Referenced Sources

We first determined the impact of the reference segment, which is viewed as the context of a given target segment in terms of discovering the financial signals in the target segment. To this end, for each reference-to-target pair (r, t) , we substituted the original reference segment r (i.e., the most syntactically similar segment in the previous years' document $\mathcal{D}_{\ell-1}$) for other text and constructed a few variants of variant-to-target segment pairs for inference using the highlighting model. Specifically, we fixed the target segment but recast the BERT contextualized representation of variant pairs as

- **Empty**: A single [PAD] token is used as the reference segment (implying *none* in BERT);
- **Same**: The target segment is used as the reference segment;

Pseudo-labeling	FINAL		e-SNLI _c	
	<i>R</i> -Prec	PCC	<i>R</i> -Prec	PCC
Heuristic + Lexicon-based	0.6457	0.5774	0.6419	0.5847
+ Soft Label	0.6806	0.5932	0.8468	0.7261
Heuristic (#2)	0.6968	0.6368	0.6302	0.5752
+ Soft Label (#4)	0.7865	0.7290	0.8605	0.7566

Table 5: Different pseudo-labeling approaches

- **Random:** A randomly selected segment is used as the reference segment.

In Table 4, the original setup significantly outperforms the other three settings in both FINAL and e-SNLI_c. We conclude that the knowledge provided by the reference segments is critical for capturing important financial signals in the corresponding target segment.

5.5.2 Effect of Lexicon-based labeling

Recall that in Section 3.4, we introduced a heuristic pseudo-labeling approach that views all revised words in target segment t as important words and marks them as positive while we randomly sample other words as negative words. We here test the effect of additionally incorporating an external financial lexicon for pseudo-labeling. Specifically, we adopt the most representative financial sentiment lexicon—the *Loughran–McDonald Master Dictionary* (Loughran and McDonald, 2011)—and assume that in addition to the revised words in the heuristic approach, the 3,872 sentiment words in the dictionary also reveal important financial signals (i.e., are labeled as positive). Additionally, we treat the 20K most frequently-occurring words as well as the standard stopwords as negative words.

As shown in Table 5, surprisingly, adding the lexicon for pseudo-labeling does not improve performance but instead worsens the highlighting results. Although these financial sentiment words convey important financial signals, they are globally important among all financial reports. However, this characteristic precludes the use of the lexicon for company-specific reference-to-target highlighting, which is focused more on local relationships between a pair of segments.

6 Related Work

There are two main approaches for fast comprehension in the context of financial applications. The first approach proceeds from the perspective of summarization, a conventional NLP task. Zmandar et al. (2021a) proposed the Financial Narrative

Summarization shared task (FNS 2020) for summarizing annual UK reports. FNS collected annual reports from the London Stock Exchange and asked authors to choose sections in the report that could be considered a summary of the whole document as the ground truth. Although some methods for this task (Zmandar et al., 2021b; Orzhenovskii, 2021; Gokhan et al., 2021) yield efficient pipelines with strong ROUGE performance, these are not comprehensive enough to identify all signals under a recall-sensitive scenario. Specifically, users may miss important signals when leveraging model outputs under a ROUGE-guided policy; for example, identical sentences that differ only in one term (e.g., different sales numbers or antonyms) can convey huge dissimilarities in terms of meaning. Moreover, for such approaches, high-quality human-labeled ground truth information is necessary to ensure accurate models.

For most scenarios, however, such manual ground truth labels are unavailable. Therefore, many attempts have been made to discover rationales sensitive to particular numerical information, such as stock return volatility and excess returns. For instance, Kogan et al. (2009); Lin et al. (2021); Tsai and Wang (2017) leverage machine learning models to discover signals through the correlation of tokens and quantitative indicators from the financial market, Huang and Li (2011); Lin et al. (2011) adapt clustering methods to distill information from financial reports and automatically classify risk factors or stock price movements, and Agrawal et al. (2021) leverage attention scores learned from a hierarchical model to identify representative sentences in financial reports. Nevertheless, signals discovered via such approaches depend heavily on ground-truth financial measures, making it difficult to apply them in general scenarios.

7 Conclusion

This paper addresses the task of discovering insightful financial signals between two narrative financial reports in consecutive years. Using the reference-to-target textual structure of financial reports, we develop a multistage pipeline consisting mainly of relation recognition and signal highlighting stages. In particular, we propose learning strategies for domain-adaptive signal highlighting, including out-of-domain warm-up and in-domain fine-tuning. Empirical results confirm the effectiveness of the proposed domain-adaptation ap-

proaches. We also present the newly constructed FINAL dataset for further research.

Future work includes topics regarding 1) higher efficiency: integrating dense retrieval methods into our pipeline; 2) better effectiveness: developing multitask learning on large financial corpora as financial pre-trained representations; 3) cross-company relationship analysis: further company analysis beyond year-to-year relationships.

8 Limitations

We identify crucial financial signals in reports which can help financial practitioners to efficiently digest long financial documents. However, factors such as macroeconomics, stock prices, and public policies may affect how a financial practitioner views financial reports in practice. Confidential intelligence or social media may greatly affect the analysis results. Therefore, we limit our task to the scenario in which the content in the reports is the sole information available to users. Accordingly, to prevent bias in the annotation process, we acquire annotations from annotators under similar scenarios (graduate students majoring in accounting or other related fields) rather than from financial professionals.

References

Yash Agrawal, Vivek Anand, S Arunachalam, and Vasudeva Varma. 2021. [Hierarchical model for goal guided summarization of annual financial reports](#). In *Proc. of WWW*, pages 247–254.

Brad A Badertscher, Jeffrey J Burks, and Peter D Easton. 2018. [The market reaction to bank regulatory reports](#). *Rev. Account. Stud.*, 23(2):686–731.

Shai Ben-David, John Blitzer, Koby Crammer, and Fernando Pereira. 2006. [Analysis of representations for domain adaptation](#). In *Proc. of NIPS*, pages 137–144.

Chris Buckley and Ellen M. Voorhees. 2000. [Evaluating evaluation measure stability](#). In *Proc. of SIGIR*, page 33–40.

Oana-Maria Camburu, Tim Rocktäschel, Thomas Lukasiewicz, and Phil Blunsom. 2018. [e-SNLI: Natural language inference with natural language explanations](#). In *Proc. of NIPS*, pages 9539–9549.

Brian Chivers, Mason P. Jiang, Wonhee Lee, Amy Ng, I. Rapstine, and Natalya Alex Storer. 2022. [ANTS: A framework for retrieval of text segments in unstructured documents](#). In *Proc. of NAACL DeepLo Workshop*, pages 38–47.

Arman Cohan, Franck Dernoncourt, Doo Soon Kim, Trung Bui, Seokhwan Kim, Walter Chang, and Nazli Goharian. 2018. [A discourse-aware attention model for abstractive summarization of long documents](#). In *Proc. of NAACL*, pages 615–621.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. [BERT: Pre-training of deep bidirectional transformers for language understanding](#). In *Proc. of NAACL*, pages 4171–4186.

Mine Ertugrul, Jin Lei, Jiaping Qiu, and Chi Wan. 2017. [Annual report readability, tone ambiguity, and the cost of borrowing](#). *J. Financ. Quant. Anal.*, 52(2):811–836.

Joseph L. Fleiss. 1971. [Measuring nominal scale agreement among many raters](#). *Psychol. Bull.*, 76(5):378.

Tuba Gokhan, Phillip Smith, and Mark Lee. 2021. [Extractive financial narrative summarisation using sentencebert based clustering](#). In *Proc. of the FNP Workshop*, pages 94–98.

Suchin Gururangan, Ana Marasović, Swabha Swayamdipta, Kyle Lo, Iz Beltagy, Doug Downey, and Noah A. Smith. 2020. [Don’t stop pretraining: Adapt language models to domains and tasks](#). In *Proc. of ACL*, pages 8342–8360.

Xiaochuang Han and Jacob Eisenstein. 2019. [Unsupervised domain adaptation of contextualized embeddings for sequence labeling](#). In *Proc. of EMNLP-IJCNLP*, pages 4238–4248.

Karl Moritz Hermann, Tomáš Kočiský, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. [Teaching machines to read and comprehend](#). In *Proc. of NIPS*, page 1693–1701.

Ke-Wei Huang and Zhuolun Li. 2011. [A multilabel text classification algorithm for labeling risk factors in SEC form 10-K](#). *ACM Trans. Manag. Inf. Syst.*, 2(3):1–19.

Shimon Kogan, Dmitry Levin, Bryan R Routledge, Jacob S Sagi, and Noah A Smith. 2009. [Predicting risk from financial reports with regression](#). In *Proc. of NAACL HLT*, pages 272–280.

Tian Li, Xiang Chen, Zhen Dong, Kurt Keutzer, and Shanghang Zhang. 2022. [Domain-adaptive text classification with structured knowledge from unlabeled data](#). In *Proc. of IJCAI*, pages 4216–4222.

Chin-Yew Lin. 2004. [ROUGE: A package for automatic evaluation of summaries](#). In *Proc. of ACL*, pages 74–81.

Ming-Chih Lin, Anthony JT Lee, Rung-Tai Kao, and Kuo-Tay Chen. 2011. [Stock price movement prediction using representative prototypes of financial reports](#). *ACM Trans. Manag. Inf. Syst.*, 2(3):1–18.

- Ting-Wei Lin, Ruei-Yao Sun, Hsuan-Ling Chang, Chuan-Ju Wang, and Ming-Feng Tsai. 2021. [XRR: Explainable risk ranking for financial reports](#). In *Proc. of ECML-PKDD*, pages 253–268.
- Tim Loughran and Bill McDonald. 2011. [When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks](#). *J. Finance*, 66(1):35–65.
- Michał Łukasik, Boris Dadachev, Kishore Papineni, and Gonçalo Simões. 2020. [Text segmentation by cross segment attention](#). In *Proc. of EMNLP*, pages 4707–4716.
- Mikhail Orzhenskii. 2021. [T5-LONG-EXTRACT at FNS-2021 shared task](#). In *Proc. of FNP Workshop*, pages 67–69.
- Jielin Qiu, Jiacheng Zhu, Mengdi Xu, Franck Dernoncourt, Trung Bui, Zhaowen Wang, Bo Li, Ding Zhao, and Hailin Jin. 2022. [Semantics-consistent cross-domain summarization via optimal transport alignment](#). *arXiv:2210.04722*.
- Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. 2016. [SQuAD: 100,000+ questions for machine comprehension of text](#). In *Proc. of EMNLP*, pages 2383–2392.
- Nils Reimers and Iryna Gurevych. 2019. [Sentence-BERT: Sentence embeddings using Siamese BERT-networks](#). In *Proc. of EMNLP-IJCNLP*, pages 3982–3992.
- Navid Rekasas, Mihai Lupu, Artem Baklanov, Alexander Dür, Linda Andersson, and Allan Hanbury. 2017. [Volatility prediction using financial disclosures sentiments with word embedding-based IR models](#). In *Proc. of ACL*, pages 1712–1721.
- Abigail See, Peter J. Liu, and Christopher D. Manning. 2017. [Get to the point: Summarization with pointer-generator networks](#). In *Proc. of ACL*, pages 1073–1083.
- Gennady Shtekh, Polina Kazakova, Nikita Nikitinsky, and Nikolay Skachkov. 2018. [Applying topic segmentation to document-level information retrieval](#). In *Proc. of CEE-SECR*. Article no. 6.
- Ming-Feng Tsai and Chuan-Ju Wang. 2017. [On the risk prediction and analysis of soft information in finance reports](#). *Eur. J. Oper. Res.*, 257(1):243–250.
- Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2019. [SuperGLUE: A stickier benchmark for general-purpose language understanding systems](#). In *Proc. of NeurIPS*, page 3261–3275.
- Haifeng You and Xiao-jun Zhang. 2009. [Financial reporting complexity and investor underreaction to 10-K information](#). *Rev. Account. Stud.*, 14(4):559–586.
- Nadhem Zmandar, Mahmoud El-Haj, Paul Rayson, Marina Litvak, Gero George Giannakopoulos, Nikiforos Pittaras, et al. 2021a. [The financial narrative summarization shared task FNS 2021](#). In *Proc. of FNP Workshop*, pages 120–125.
- Nadhem Zmandar, Abhishek Singh, Mahmoud El-Haj, and Paul Rayson. 2021b. [Joint abstractive and extractive method for long financial document summarization](#). In *Proc. of FNP Workshop*, pages 99–105.

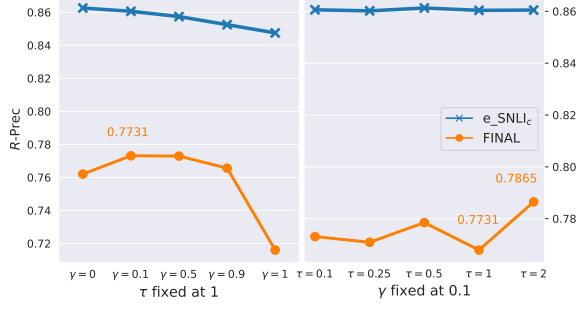


Figure 3: Domain-adaptive labeling

A Training Detail

All our model fine-tuning and inference (in Section 5 and Section 5.5) were done on an NVIDIA Tesla V100 32GB GPU. Each model fine-tuning can be done within three hours. We also ran all of the models with shared training settings, including the number of training steps, optimizers, and token batch sizes; we set other related training parameters as the default values.

B Hyperparameter Search

Recall that while the hyperparameter τ in Eq. (2) controls the probability distribution of the word importance, γ in Eq. (3) controls the impact of soft labeling. Figure 3 shows the performance in terms of R -Prec with different hyperparameter settings, where the left panel shows the results of τ fixed at 1 with γ ranging from 0 to 1, and the right panel shows that of γ fixed at 0.1 with τ ranging from 0.1 to 2. In the left panel of the figure, on FINAL, we see that solely adopting cross-entropy loss \mathcal{L}_{CE} ($\gamma = 1$) is not effective for fine-tuning the signal highlighting model, nor is adopting KL loss \mathcal{L}_{KL} ($\gamma = 0$) (see Eq. (3)); $\gamma = 0.1$ achieves the best R -Prec. These empirical results again validate the effectiveness of the proposed soft labeling for our highlighting task. In addition, we froze γ at 0.1 and experimented with different settings for the temperature parameter τ , the results of which are shown in the right panel of Figure 3, showing that $\tau = 2$ is the most effective setting. We thus set our final hyperparameters to $\tau = 2$ and $\gamma = 0.1$ to yield the best performance.

C Empirical Thresholds

For the relation recognition procedure in S_1 (see Section 3.2 and Figure 4), we empirically set the thresholds $\epsilon_{syn} = 0.6296$ and $\epsilon_{sem} = 0.9011$. Both numbers are the 50 percentiles of the cor-

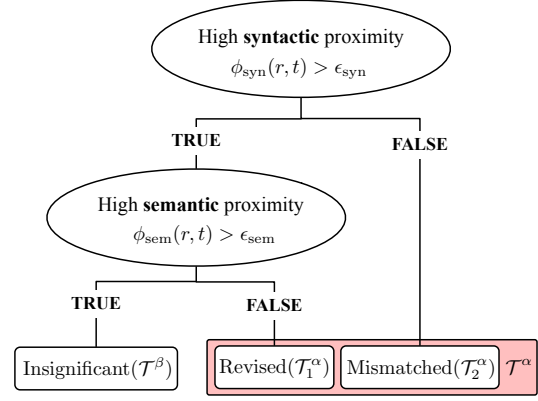


Figure 4: Relation recognition

responding similarity scores calculated from the reduced segment pair set (\mathcal{T}). Note that, in this work, we adopt a heuristic rule-based method for recognizing relations using similarity functions with hard thresholds. We leave the exploration of other similarity functions, thresholds, and approaches to future work.

D Annotation Guidelines

For each segment pair, the annotators were to focus on the semantic difference regarding the reference-to-target relationship and annotate words in the target segment as positive when the words were considered to be important financial signals. The following guidelines were given for the annotators' reference.

- **Changes:** Changing numbers or objects are important signals in financial reports (e.g., sales, cost, partnership, products, etc.).
- **Opposition:** Descriptive phrases that indicate distant semantic meanings (e.g., increased/decreased, effective/ineffective, etc.).
- **Precise:** Labeling words with high confidence as positive only (i.e., leaving ambiguous words as negative).
- **Extra information:** Identifying new information according to the context, for which the annotators were to consider the reference segment as the context (e.g., new policy, canceled deals, newly published products, etc.).

E Empirical Cases

In Table 6, we take two revised segment pairs (\mathcal{T}_1^α) and two mismatched segment pairs (\mathcal{T}_2^α) as examples. The underlined words are with the top- k highest importance predicted by the proposed multistage pipeline.

(a) Empirical examples of the revised segment pair (\mathcal{T}_1^α) [$k = 5$]

Reference segment Gross margin from manufacturing operations as a percentage of manufacturing revenues increased to 27% for the year ended December 31, 2014 from 23% for the comparable prior year period.

Target segment Gross margin from manufacturing operations as a percentage of manufacturing revenues decreased to 15% for the year ended December 31, 2016 from 23% for the comparable prior year period.

Reference segment We believe the increased sales achieved by our stores are the result of store growth and the high levels of customer service provided by our well-trained and technically proficient Team Members, superior inventory availability, including same day and over-night access to inventory in our regional distribution centers, enhanced services and programs offered in our stores, a broader selection of product offerings in most stores with a dynamic catalog system to identify and source parts, a targeted promotional and advertising effort through a variety of media and localized promotional events, continued improvement in the merchandising and store layouts of our stores, compensation programs for all store Team Members that provide incentives for performance and our continued focus on serving both DIY and professional service provider customers.

Target segment We believe the increased sales achieved by our stores were the result of store growth, sales from one additional day due to Leap Day for the year ended December 31, 2016, sales from the acquired 48 Bond stores, the high levels of customer service provided by our well-trained and technically proficient Team Members, superior inventory availability, including same day and over-night access to inventory in our regional distribution centers, enhanced services and programs offered in our stores, a broader selection of product offerings in most stores with a dynamic catalog system to identify and source parts, a targeted promotional and advertising effort through a variety of media and localized promotional events, continued improvement in the merchandising and store layouts of our stores, compensation programs for all store Team Members that provide incentives for performance and our continued focus on serving both DIY and professional service provider customers.

(b) Empirical examples of the mismatched segment pair (\mathcal{T}_2^α) [$k = 10$]

Reference segment This increase of 1.0%, as a percentage of revenues, was primarily attributable to higher compensation costs of 0.4% primarily related to higher wage rates, higher facility-related costs of 0.2% principally from the expansion of U.S. facilities and lease termination costs in connection with the Fourth Quarter 2011 Exit Plan, higher software maintenance of 0.2%, higher legal and professional fees of 0.1%, higher taxes of 0.1% and higher other costs of 0.3%, partially offset by lower equipment and maintenance costs of 0.3%.

Target segment The decrease in Americas general and administrative expenses, as a percentage of revenues, was primarily attributable to lower compensation costs of 0.6%, lower facility-related costs of 0.4% due to rationalization of facilities, lower equipment and maintenance costs of 0.2% and lower other costs of 0.1%.

Reference segment The remaining capacity is expected to be placed into service in line with the expected in-service date of the Sandpiper Project.

Target segment Three external parties filed motions requesting that the scoping process be re-opened or that a comment period be established because of the issuance of the Consent Decree settling the Line 6B pipeline crude oil release in Marshall, Michigan and the withdrawal of regulatory applications pending with the MNPUC with respect to the Sandpiper Project discussed above.

Table 6: Empirical cases in the FINAL evaluation set