

A Compare-and-contrast Multistage Pipeline for Uncovering Financial Signals in Financial Reports

Jia-Huei Ju¹, Yu-Shiang Huang^{1,3}, Cheng-Wei Lin¹, Che Lin^{2,3}, and Chuan-Ju Wang^{1,3}

¹Academia Sinica(AS), ²National Taiwan University(NTU), ³Graduate Program of Data Science, NTU & AS



Motivation

(*Form 10-K is an annual report and required by U.S. Securities and Exchange Commission.)

An empirical problem

- Analyzing financial reports (e.g., Form 10-K report*) requires lots of efforts.
- In fact, texts considered as signal is **extremely fewer** than those considered as unimportant.
- Reviewing financial reports requires **finance-specific** knowledge but also the **company-specific** understanding.

Thus, we propose

- A **compare-and-contrast pipeline** to tackle such empirical problems for financial applications.
- An evaluable **financial signal highlighting task** with datasets and evaluation measurements.

The Reference-to-target structure (of year-to-year financial reports)

- Consider the report of interest as the target, and its last year report as the reference.
- Break down the two reports into **multiple target-to-reference segment pairs**.
- The relationships of each pairs can be classified into:
 - Insignificant relation (T^β); Revised relations (T_1^α) and Mismatched relations (T_2^α)

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

Financial Signal Highlighting

Definition of highlighting tasks

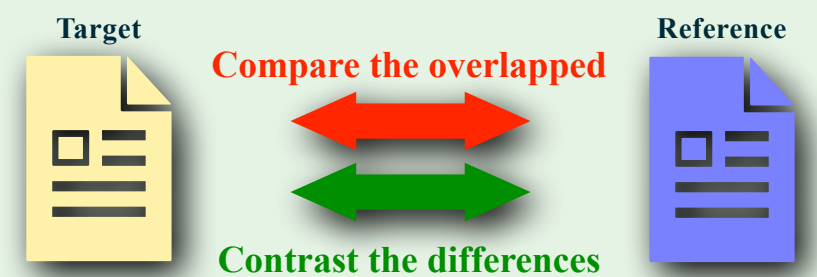
- Predict the **rationales** based on the reference-to-target pairs.
- Rationales indicate the predicted **word importance of a target segment t conditioned on reference segment r** as $\mathbf{R} \leftarrow P_f(t|r), (r,t) \in \{T_1^\alpha \cup T_2^\alpha\}$

Human annotations

- Hired annotators labeled the important words of 200 revised and 200 mismatched pairs.

Automatic evaluations

- R-Prec: measure the precision under the truncations; the truncation is the amount of annotated signals.
- PCC (Pearson's Correlation Coefficient): correlation between predicted word importance and annotations.



The Compare-and-contrast Multistage Pipeline

0. Document Segmentation

- Use cross-segment BERT to break documents into segments

1. Relation Recognition

- Calculate pairwise text similarity based on syntactic and semantics.
- Classify them into **revised and mismatched relations**

2. Signal Highlighting — Out-of-domain Fine-tuning

- Fine-tune on e-SNLI contradicted pairs as the **Zero-shot** highlighter f
- Recast the highlighting task into **binary token classification** task
- Contextualized representation of a reference-to-target pair:

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

2+. Signal Highlighting — In-domain Fine-tuning

- Fine-tune on the **hard and soft pseudo-labels** using
 - Hard labels: the **revised words** as labels (CrossEntropy)
 - Soft labels: the **probabilities** of Zero-shot model's prediction (KL Divergence)

$$L_{CE} = \sum_j - (Y_t^j \log P_f^j(t|r)) + (1 - Y_t^j) \log(1 - P_f^j(t|r))$$

$$L_{KL} = - \sum_j KL(P_f^j(t|r) || P_{f^+}^j(t|r))$$

- Fine-tune with the **warmed-up Zero-shot** highlighter for the final **domain-adaptive** highlighter f^+

Empirical Evaluation

Datasets

- 400 pairs of our released FINAL Eval set.
- 3,237 pairs of e-SNLI contradicted Test sets.

Results (of our domain-adaptive highlighter)

- Better performance on two types of pairs in FINAL
- Retrain generalization capability in e-SNLI
- Improve even more on unseen relation (the mismatched pairs)

#	W.U.	Labeling		FINAL		e-SNLI _c	
		P	S	R-Prec	PCC	R-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

