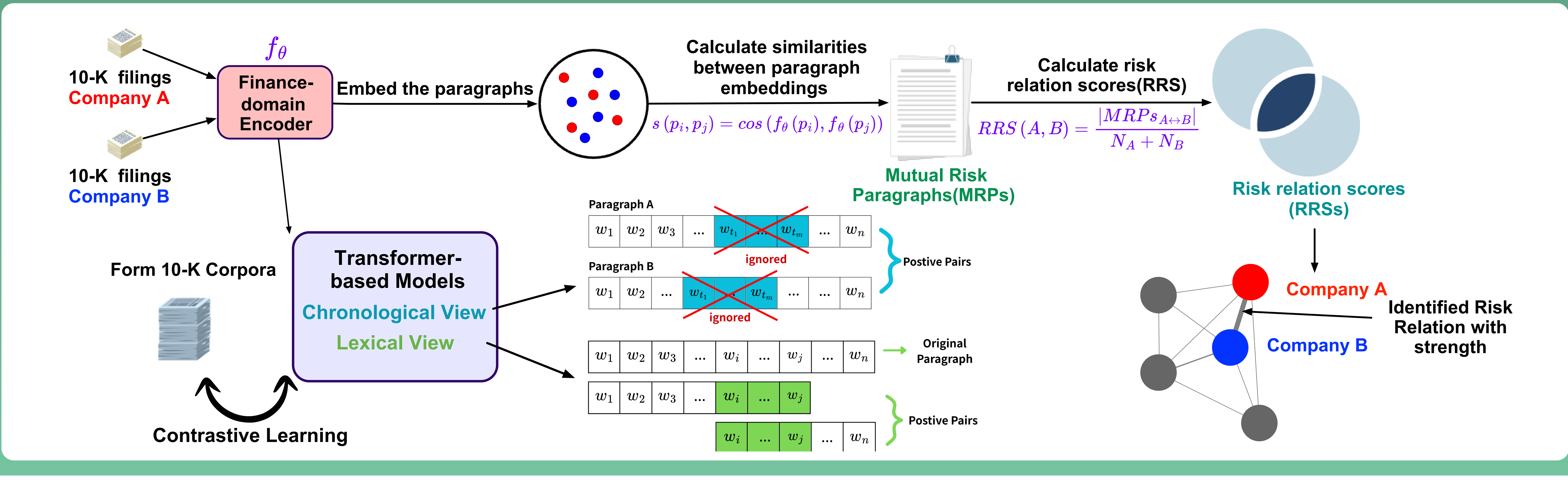
Financial Risk Relation Identification through Dual-view Adaptation

Wei-Ning Chiu*†, Yu-Hsiang Wang*, Andy Hsiao*, Yu-Shiang Huang*†, Chuan-Ju Wang*

†National Taiwan University, *Academia Sinica

Methodology Pipeline



Mutual Risk Paragraphs

Mutual Risk Paragraphs (MRPs) are pairs of risk disclosures from different firms' 10K that **describe similar exposures**—like supply chain or regulatory risks—using comparable language and timing. They reveal hidden inter-firm links and further provide **interpretability**. MRPs are defined by matching paragraphs from firm A (P_A) and firm B (P_B) with high similarity score $s(P_A, P_B)$. The formula is designed as follows:

$$\mathrm{MRPs}_A = \left\{ p_i \in \mathcal{P}_A \,\middle|\, \exists p_j \in \mathcal{P}_B : s(p_i, p_j) \geq \xi \right\},$$
$$\mathrm{MRPs}_B = \left\{ p_j \in \mathcal{P}_B \,\middle|\, \exists p_i \in \mathcal{P}_A : s(p_i, p_j) \geq \xi \right\},$$
$$\mathrm{MRPs}_{A\leftrightarrow B} = \mathrm{MRPs}_A \cup \mathrm{MRPs}_B,$$

Risk Relation Score

We define a Risk Relation Score (RRS) based on Mutual Risk Paragraphs (MRPs)—pairs of similar risk disclosures from two firms' 10-Ks. Using a fine-tuned encoder and cosine similarity (threshold ξ = 0.75), we compute RRS as the **ratio** of **MRPs** to the **sum of number of paragraphs from both firms**. RRS ranges from 0 to 1, offering a **transparent**, **symmetric**, and **interpretable** measure of shared risk strength. The formula is as follows (N_A/ N_B represent the number of paragraphs from firm A and B):

$$\mathrm{RRS}(A, B) = \frac{|\mathrm{MRPs}_{A\leftrightarrow B}|}{N_A + N_B}$$

Risk Relation Identification Evaluation

To validate the effectiveness of our **Risk Relation Scores** (RRS), we introduce ρ—a correlation metric between **RRS** and **the correlation of absolute daily stock returns (CAVDSR)** between firms. The key hypothesis is that firms exposed to similar risks tend to exhibit synchronized stock movements. A higher ρ indicates stronger alignment between textual risk signals and real-world market behavior. We also conduct an ablation study to assess the impact of the **lexical** and **chronological** views individually. Results show that both views contribute meaningfully, and our method consistently outperforms all baselines.

Methods	2020	2021	2022	2023	2024	Avg.
GICS Sector	0.1657	0.2881	0.2964	0.2971	0.2389	0.2572
GICS Industry	0.1806	0.3336	0.2961	0.3316	0.3115	0.2907
Bert-base-uncased	0.1199	0.3294	0.3484	0.2790	0.3214	0.2796
Contriever	0.2139	0.3972	0.3141	0.4119	0.4411	0.3556
DPR	0.2132	0.4000	0.3199	0.4150	0.4437	0.3584
FinBERT	0.1741	0.3469	0.3330	0.3213	0.3539	0.3058
SEC-BERT	0.2090	0.3982	0.3241	0.4123	0.4407	0.3569
Ours	**0.2161**	**0.4150**	**0.3421**	**0.4270**	**0.4553**	**0.3711**

	2020	2021	2022	2023	2024
Chronological	0.1659	0.3691	**0.3637**	0.3671	0.3908
Lexical	0.2137	0.4104	0.3336	0.4231	0.4510
Ours (both views)	**0.2161**	**0.4150**	0.3421	**0.4270**	**0.4553**

Downstream Application Example

In our second experiment, we integrate the extracted risk relations into a stock price movement prediction model. Specifically, we incorporate the Risk Relation Scores (RRS) as edge weights in the **Attribute-Driven Graph Attention Network (ADGAT)**, replacing predefined sector or competitor links. This allows the model to leverage nuanced, data-driven inter-firm risk connections. Results show that using our risk-based graph leads to a 2.3% improvement in AUC, demonstrating the practical value of our method in enhancing financial forecasting.

Method	Mean AUC ± Std
ADGAT (w/o our relation)	0.5807 ± 0.012
ADGAT (w/ our relation)	**0.5942 ± 0.006**
Improvement	2.32%

Retrieval Performance

We evaluate the retrieval capability of our fine-tuned financial encoder on the **MultiHiertt** benchmark—a challenging financial QA dataset requiring precise **paragraph retrieval**. We replace the retriever component in a two-stage retrieval pipeline with our encoder and compare it against several strong baselines. Our encoder achieves the highest performance across all retrieval metrics, confirming its effectiveness in capturing financial semantics and retrieving relevant content from regulatory filings.

Model	NDCG@1	NDCG@5	Precision@3	Precision@5	Recall@1	Recall@5
Bert-base-uncased	0.0343	0.0154	0.0160	0.0103	0.0049	0.0079
Contriever	0.1644	0.0951	0.0902	0.0610	0.0382	0.0715
DPR	0.1473	0.0803	0.0696	0.0480	0.0390	0.0581
FinBERT	0.0034	0.0026	0.0023	0.0021	0.0009	0.0019
SEC-BERT	0.0274	0.0143	0.0137	0.0089	0.0071	0.0097
Ours	**0.1952**	**0.1094**	**0.0993**	**0.0671**	**0.0508**	**0.0842**
Improvement	18.73%	15.03%	10.09%	10.00%	30.26%	17.76%