FinRipple: Aligning Large Language Models with Financial Market for Event Ripple Effect Awareness

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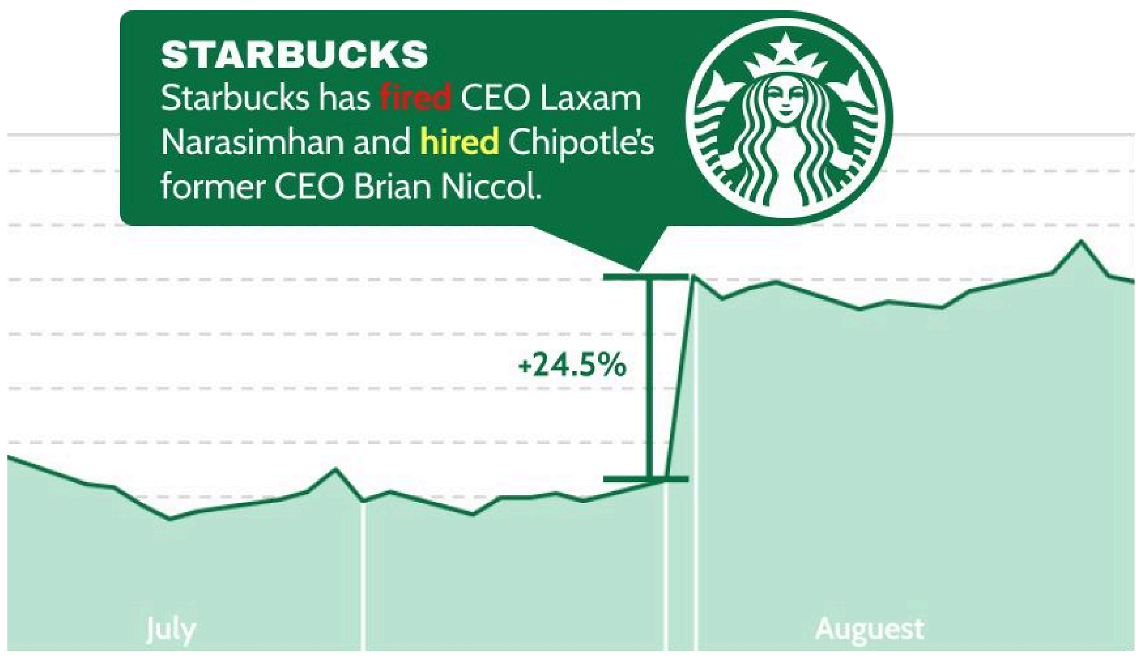
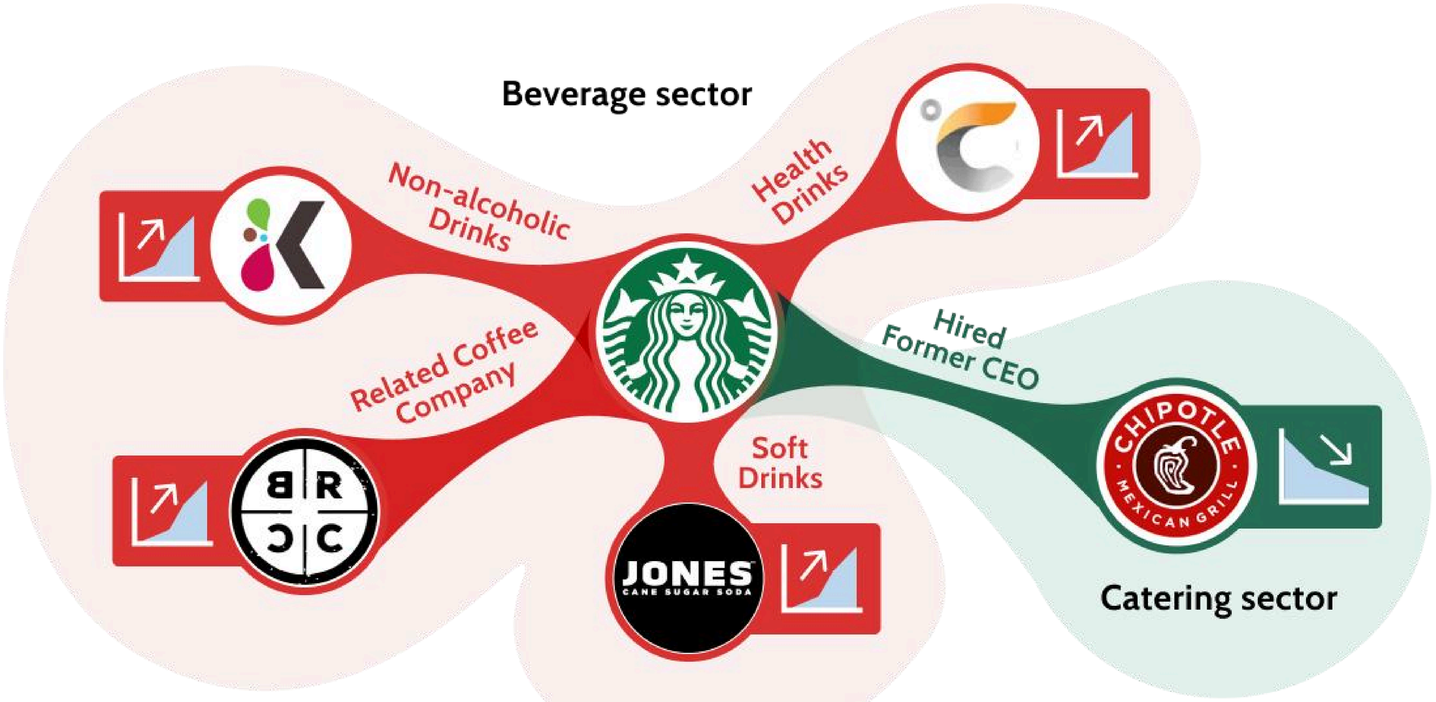
INTRODUCTION





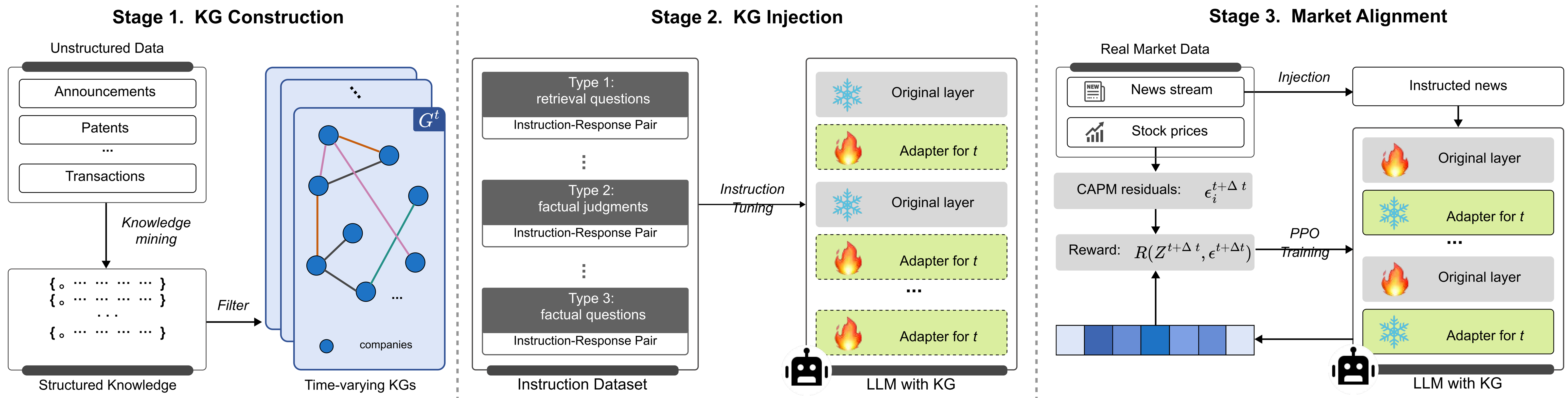
Background

- Traditional methods use static single-company analysis, **missing cross-entity ripple effects**.
- LLMs lack **market structure awareness** and cannot model **dynamic inter-company relationships** essential for ripple effect analysis.

Contributions

- FinRipple first formulates the "ripple effect prediction" task and provides an open-source benchmark with unified evaluation standards.
- The framework integrates classical asset pricing theory with LLMs, achieving strong performance in excess return prediction with high interpretability.
- Rigorous validation demonstrates real-world applicability in asset pricing and portfolio management, with transparent reasoning pathways for causal relationships.

FinRipple



The propagator $\Phi_{e_t,\theta}$ maps event-context pairs to forward shock distributions $\Phi_{e_t,\theta}: \underbrace{\mathcal{E}_t \times \mathcal{M}_t}_{\text{Event-Context}} \rightarrow \underbrace{\mathbb{R}^{\mathcal{C}_{t+\Delta t}}}_{\text{Shock Magnitudes}}$

Reward function: $$\mathcal{R}(Z,\epsilon) = \underbrace{\frac{Z\cdot\epsilon}{\|Z\|\|\epsilon\|}}_{\text{direction match}} + \lambda \underbrace{\frac{\sum_{j=1}^{|\mathcal{C}_{t+\Delta t}|}\min(|Z_j|,|\epsilon_j|)}{\|\epsilon\|_1}}_{\text{magnitude coverage}}$$

$\mathcal{C}_t$ captures the universe of public firms $\mathcal{E}_t$ captures the event space

ANALYSIS

Model	RAG			Zero-Shot			ICL			FinRipple/w-o alignment			FinRipple		
	Coef.	p-value	R^2	Coef.	p-value	R^2	Coef.	p-value	R^2	Coef.	p-value	R^2	Coef.	p-value	R^2
llama2-7b-chat	0.012	0.452	0.009	0.031	0.601	0.012	0.042	0.503	0.018	0.047	0.510	0.019	0.150*	0.030	0.083
llama2-13b-chat	0.103	0.305	0.054	0.079	0.349	0.039	0.098	0.281	0.061	0.102	0.287	0.058	0.242**	0.009	0.193
llama3-8b-instruct	0.091	0.318	0.047	0.072	0.402	0.037	0.107	0.254	0.058	0.110	0.249	0.060	0.278**	0.004	0.251
vicuna-7b-chat	0.118	0.247	0.063	0.102	0.298	0.052	0.129	0.198	0.081	0.125	0.205	0.074	0.330***	0.001	0.310
vicuna-13b-chat	0.248*	0.032	0.248	0.148	0.149	0.082	0.176	0.098	0.102	0.171*	0.040	0.108	0.395***	0.000	0.340
Phi-3.5-mini-instruct	0.082	0.395	0.032	0.065	0.498	0.019	0.094	0.347	0.052	0.096	0.340	0.045	0.245**	0.006	0.155
gemma-2-9b-it	0.097	0.298	0.048	0.083	0.354	0.038	0.112	0.245	0.063	0.109	0.252	0.061	0.290***	0.001	0.215
GPT 3.5	0.083	0.398	0.028	0.062	0.051	0.075	0.056**	0.004	0.112	/	/	/	/	/	/
GPT o1-preview	0.152	0.342	0.047	0.119	0.392	0.056	0.192	0.229	0.082	/	/	/	/	/	/
GPT 4o-mini	0.124	0.312	0.042	0.312*	0.013	0.035	0.104	0.879	0.103	/	/	/	/	/	/

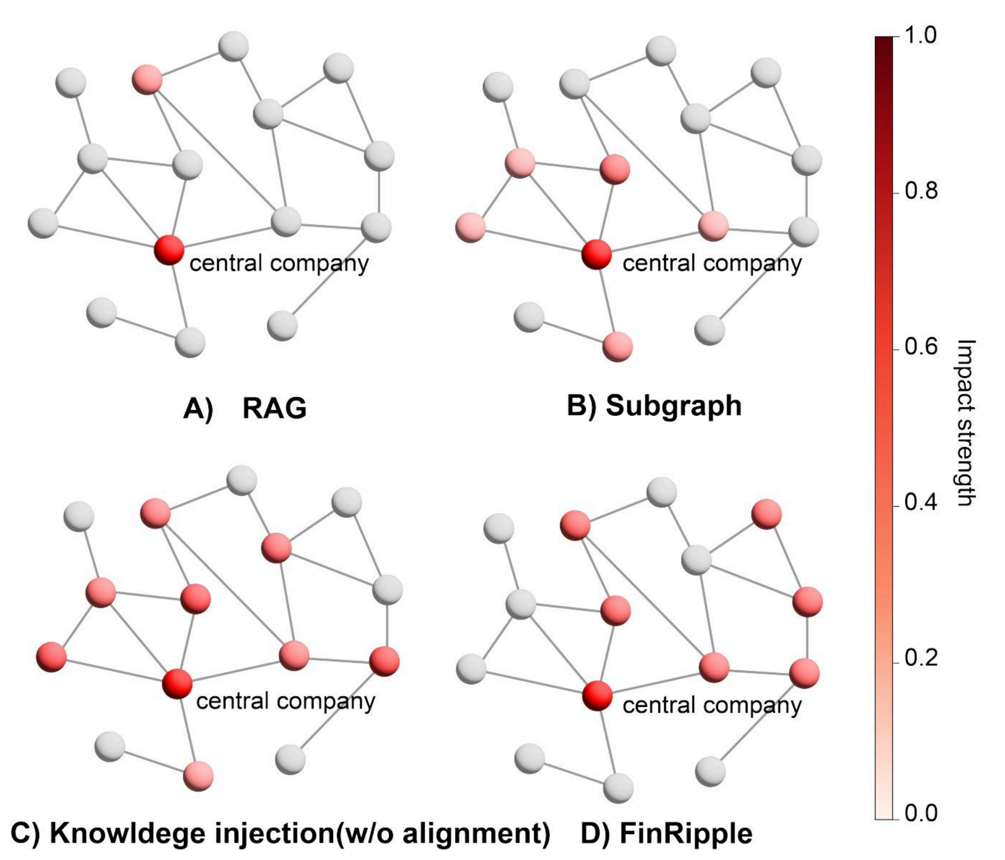
Financial Market Shocks

Portofolio Management

Knowledge Inject Analysis

Refusal-to-Answer Rate

Case Study



CONCLUSION

We present **FinRipple**, a novel training framework that empowers LLMs to analyze and predict the **ripple effects** of sudden events in financial markets. By constructing a **time-varying financial KG** and integrating it into the LLM using **adapters**, we align the model with the dynamic market structure **without retraining from scratch**. Our rigorous validation showcases FinRipple's strong potential in real-world applications like asset pricing and portfolio construction.