Group 09

AIR-mazing Predictions:

Ranking of Retrieval Augmented Stock Market Prediction for Business Ideas

Kai Kainbacher: RAP-Model Training & Evaluation
Maximilian Legat: UI for Model Interaction & Model Pipeline
Jonathan Maier: RetrievalSystem & RAP-Model
Michael Sickl: Ranking-System Training & Evaluation

Repository: https://github.com/jonnyCap/AIR-Project

Repository

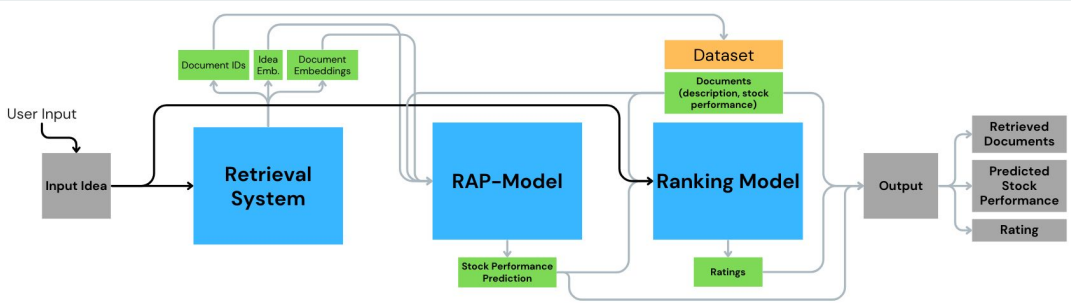
Motivation & Research Questions

- **Challenges in Traditional Stock Prediction -** Predicting stock performance for existing businesses is highly volatile and risky if used for investments.

- **Foundation for Strategic Planning:** Provides a solid starting point for assessing the feasibility and potential of new business ideas.

Can textual descriptions of a new business idea be used to predict its stock performance and rank it alongside existing market competitors?

Data & Methods



Dataset:

- Fetched different tickers from different locations
- Collected performance indicators, historical data and business description
- Used in Retrieval System & RAP-Model training (slight differences)
- Different Metrics for Ranked Model

Retrieval System:

- Encodes Idea with Bert
- Uses Cosine Similarity for finding most relevant documents
- Precomputed embeddings for retrieval dataset for better performance
- Optimized for batch processing

Retrieval Augmented Prediction Model:

- Makes predictions based on embedding of idea & similar companies
- Combine large Inputs through Fusion Layer
- Fusion Layers: Sequential Layers with normalization and activation functions
- Auxiliary inputs and autoregressive
- Final Prediction through LSTM and Output Layer
- Alternativ: Attention Optimized

Ranking Model:

- Predictions based on:
  - embedding of idea
  - normalized stock performance (12 months)
- Sequential Layers with normalization and activation functions
- Attention Layer

Results

Retrieval System:

- Calculated multiple metrics (k = 12)
- Precision@K, Recall@K, Mean Reciprocal Rank (MRR), Mean Average Precision (MAP), Normalized Discounted Cumulative Gain (nDCG)

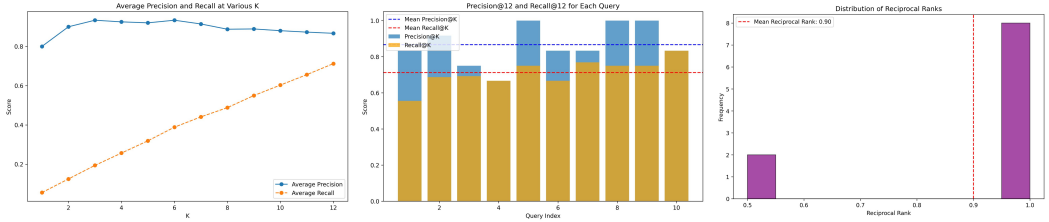
RAP-Model:

- Different trained models (w/o Auxiliary + Loss)
- Auxiliary + CustomLoss most potential
- Evaluation shows prediction range $20-$100
- Some promising results
- Inability to handle nonsensical input
- Autoregressive nature leads to “random” predictions

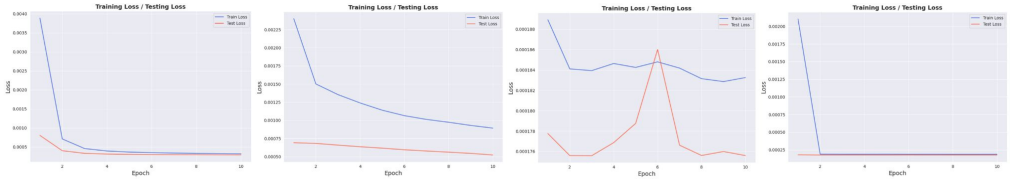
Ranking Model:

- Different trained models (score_2 & score_5)
- evaluation loss plateaued
- lack of correlation between business descriptions, stock performance and score
- Score_5 produced more transparent predictions
- Score_2 produced more accurate predictions

Retrieval System

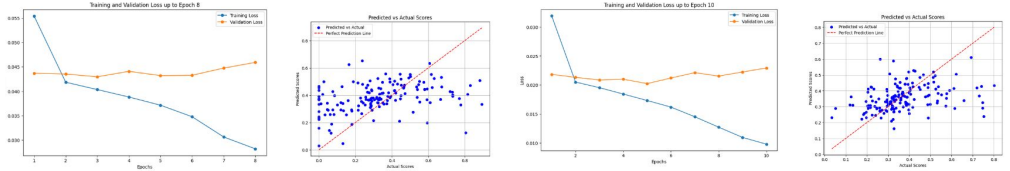


RAP-Model



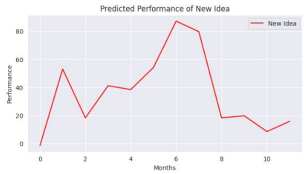
(a) No Auxiliary & Custom Loss (b) Auxiliary & Custom Loss (10 Epochs) (c) Auxiliary & Custom Loss (20 Epochs) (d) Auxiliary & SmoothL1Loss

Ranking Model

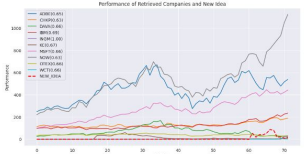


(a) Training & Validation Loss (Score 2) (b) Predicted vs. Actual Scores (Score 2) (c) Training & Validation Loss Score 5) (d) Predicted vs. Actual Scores (Score 5)

Conclusion



(a) No Auxiliary & SmoothL1Loss Prediction



(b) Stock Performances

Rank	Ticker	Ranking
6.	CHKP	0.4774
7.	NEW IDEA	0.4562
8.	ADBE	0.3890

Table: Model Ranking

A prediction based on a textual description of a business idea can indeed yield valuable insights into an ideas potential.

The retrieval of similar documents improves the value of these insights.

Challenges/Limitations/Future Work:

- Good for realistic data
- Very bad for unrealistic, odd ideas and nonsensical input (Missing Data)
- A little to optimistic (Mean stock performance is high, too few failed companies)
- Problems during Training (Retrieval Dataset is same as Training Dataset)
- Dataset will be very quickly outdated
- Similar pattern in all predictions due to recurring patterns in training data
- Predicts rather the performance for the past 12 months than for future 12 months