

## 1. Objective and Associated Decisions

### 1.1 Key Objective

The primary objective in this capstone case is to manage a portfolio of corporate and treasury bonds to generate profits by capitalizing on bond mispricing resulting from changes in zero-coupon rates and/or credit spreads. As fixed income traders, students will evaluate the impact of news items on the yield curve, credit ratings, and bond prices and exploit these changes.

### 1.2 Decision Steps

The decision process involves a few essential steps. Firstly, students should use zero-coupon rates to price treasury bonds and incorporate credit spreads to price corporate bonds. The Altman Z-score model is used to evaluate changes of the credit ratings for a company. Secondly, students should analyze news releases to assess their effects on the zero-coupon yield curve or corporate credit spreads. Students can then exploit mispriced bonds based on the expected movements of zero-coupon yield or credit ratings. Thirdly, participants should establish a trading strategy, deciding on long or short positions in treasury and corporate bonds while mitigating risks by employing hedging strategies, such as offsetting trades in treasury bonds to neutralize exposure to rate changes.

## 2. Strategies Description and derivation

### 2.1 Rates Trading

The strategy focuses exclusively on trading government bonds to avoid the hedging costs and spread volatility associated with corporate bonds, where P&L is influenced by macroeconomic news impacting the risk-free yield curve. The approach involves allocating all capital to government bonds following the release of relevant news, prioritizing those securities most sensitive to shifts in key economic indicators. Within this category, the strategy concentrates on 10-year Treasury bonds due to their higher duration and convexity, which amplify price fluctuations in response to changes in yields. Simulations conducted during the Capstone practice case reveal that longer-duration bonds like the 10-year tend to experience more significant repricing after broad macroeconomic events such as inflation or GDP announcements, as illustrated in figure 1. There are some situations where 2-year and 5-year bonds become the

focus. For example, changes in the overnight rate announced by central banks tend to have a more pronounced effect on 2-year bonds, reflecting expectations of near-term monetary policy shifts. Additionally, news related to the bid-cover ratio for 2-year or 5-year government bond auctions is more relevant for shorter maturities, as it directly reflects liquidity premiums and supply-demand dynamics, making shorter maturities more responsive.



*Figure 1: observed price movements of 2, 5, and 10-year government bonds respectively during a sample practice run, similar pattern with different price fluctuations are observed across*

## 2.2 Momentum Trading

In addition to the rates-based approach, an

## 2.3 News Trading

As established in the case parameters, news events serve as the sole external market driver, creating a strong correlation between news releases and security returns that presents significant profit opportunities. However, implementing a news-based trading strategy presents three primary challenges: distinguishing news-driven price change from random noise; attributing the prolonged, delayed and overlapping impact of news; and to rapidly process news that are unseen. To address these challenges, we developed a model with the following approach: First, we scraped and aggregated historical data to filter out random market noise. Second, we trained recurrent neural networks with GRU units [1] in PyTorch [2] to capture delayed and non-linear price effects following news releases. Third, we utilized pre-trained sentence embedder [3] and sentiment analysis [4] models to establish similarities between historical and unseen news events.

The resulting neural network architecture (see Appendix) processes both news content and historical price data. The model takes an input tensor comprising news and security prices from now to 8 tickers back, outputting price predictions for the next 9 tickers, which can be used in a

mean square error loss function for training. However, due to limited validation data, the model's accuracy plateaued at a validation loss of 0.45. To compensate for this limitation, we supplemented the model with a historical average price change lookup table.

Our trading strategy requires consensus among multiple predictive indicators before executing trades. Specifically, we require strong agreement ( $\geq 1\%$  predicted price change) from at least two of the following sources: neural network predictions, historical average returns, and fundamental interpretation. To illustrate this approach, consider our response to news of North Korean border tensions: the neural network predicted +2.127% for 5-year Gov bonds, historical average indicated +1.570% for 5-year Gov bonds, and fundamental analysis suggested increased short-to-medium term instability would drive up medium-term bond prices. With all three indicators aligned, we initiated a long position in 5-year Gov bonds. Notice that while our models and historical average indicated potentially larger gains in Crop Bond A, we prioritized the government bond due to its more transparent relationship with the news. Similarly, we can prioritize trading 10-year Gov bonds due to the same reasoning in section 2.1, despite not having the greatest predicted changes.

### 3. Outcome

#### 3.1 Rates Trading

The outcome is both profitable and consistent, with profits ranging between \$2 million and \$4 million per simulation, depending on the frequency and significance of rate-related news. These results are driven by a fast-reacting approach, ensuring that all available capital is promptly deployed upon the release of macroeconomic announcements. By focusing on government bonds, particularly 10-year Treasuries, the strategy exploits their higher duration and convexity, which amplifies price sensitivity to changes in interest rates. The P&L graph demonstrates that profits experience sharp increases following relevant announcements (see figure 2). These rate-related events cause shifts in the yield curve allowing the strategy to capture substantial returns. The effectiveness of the approach depends on identifying predictable price movements and entering positions before the market fully adjusts. The variation in profits across simulations highlights the dependence on the quantity and impact of rate-related announcements, underscoring the importance of macroeconomic factors in driving bond market volatility.

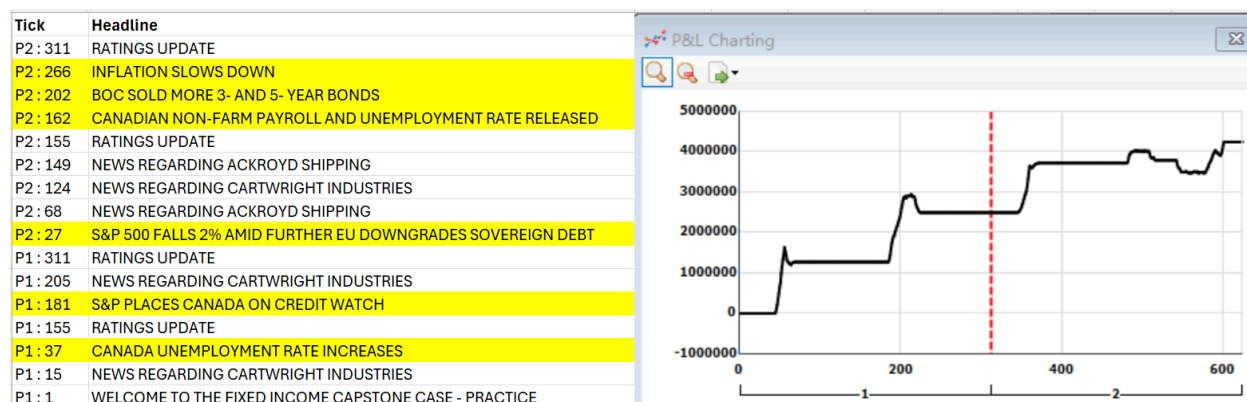


Figure 2: Rates relevant events highlighted in yellow cause sharp increase in P&L chart shown on the right

### 3.2 Momentum & News Trading

The implementation combines both momentum and news trading strategies in a complementary manner to maximize effectiveness. Our primary approach relies on the model's predictions for position pre-allocation to optimize potential profits. However, when the model generates unreliable predictions, we fall back on momentum-based trading to maintain profitability. This combined approach has demonstrated remarkable success, achieving second place in overall profits during the actual trading run with an average profit of \$3.6 million, while consistently exceeding \$4 million during practice sessions. To illustrate our methodology, consider a specific trading scenario: when presented with personal income news, we opted not to trade due to weak predictive signals and absence of clear momentum. In contrast, when analyzing the Canadian farm roll news, we identified a strong buying opportunity supported by both neural network predictions and historical average returns, further validated by the well-established relationship between employment data and medium to long-term government bond price movements. This example demonstrates how our strategy effectively integrates multiple signals to identify and execute high-confidence trades.

#### 4. Bibliography

- [1] K. Cho *et al.*, “Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation,” Sep. 03, 2014, *arXiv*: arXiv:1406.1078. doi: 10.48550/arXiv.1406.1078.
- [2] A. Paszke *et al.*, “PyTorch: An Imperative Style, High-Performance Deep Learning Library,” Dec. 03, 2019, *arXiv*: arXiv:1912.01703. doi: 10.48550/arXiv.1912.01703.
- [3] N. Reimers and I. Gurevych, “Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks,” Aug. 27, 2019, *arXiv*: arXiv:1908.10084. doi: 10.48550/arXiv.1908.10084.
- [4] D. Araci, “FinBERT: Financial Sentiment Analysis with Pre-trained Language Models,” Aug. 27, 2019, *arXiv*: arXiv:1908.10063. doi: 10.48550/arXiv.1908.10063

## 5. Appendix

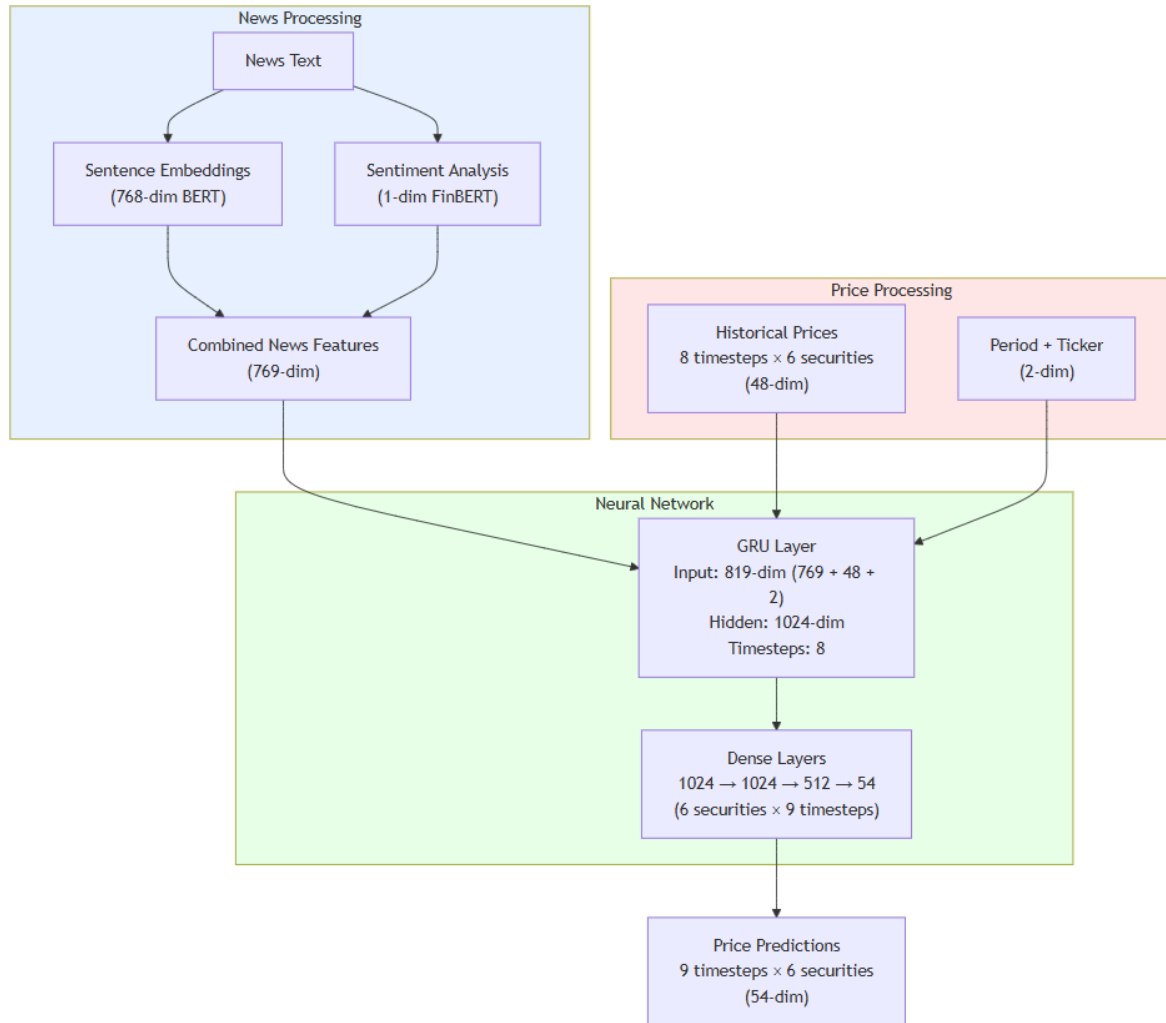


Figure 5: Mode architecture with dimensions on each layer

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price_predict.py > train_model
126 def train_model(model, train_loader, num_epochs, learning_rate):
149     # Zero gradients
150     optimizer.zero_grad()
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152     # Forward pass
153     outputs = model(inputs)
154     loss = criterion(outputs, labels)
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156     # Backward pass and optimize
157     loss.backward()
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efault value), which uses the default pickle module implicitly. It is possible to construct malicious pickle data which will execute arb  
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torch.serialization.add\_safe\_globals`. We recommend you start setting `weights\_only=True` for any use case where you don't have full con  
trol of the loaded file. Please open an issue on GitHub for any issues related to this experimental feature.  
model.load\_state\_dict(torch.load('price\_prediction\_model.pth'))  
PERSONAL INCOME FIGURES RELEASED - Statistics Canada released personal income figures yesterday, showing an increase of 0.5% in average  
weekly earnings. This is accompanied by a monthly increase in retail spending of 0.6%.  
Similar news found: PERSONAL INCOME FIGURES RELEASED - Statistics Canada released personal income figures yesterday, showing an increase  
of 0.5% in average weekly earnings. This is accompanied by a monthly increase in retail spending of 0.6%.  
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Similar news found: CANADIAN NON-FARM PAYROLL AND LABOR FORCE PARTICIPATION RATE - Canadian Non-farm payrolls rose by a consensus-toppin  
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Min column: CorpBondB, value: -0.0002743107941286

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Figure 4: News based price change predictions are made and shown in the interface.