Report: Q2 - Part 1

Muxi Chen

Abstract
Financial forecasting is a critical task in understanding and predicting a company's financial health and informing strategic decision-making. In this study, I explore several distinct approaches for forecasting key balance sheet components, including total assets, total liabilities, and shareholder equity.

Firstly, inspired by Velez-Pareja, I develop a rule-based average method that utilizes historical averages to predict future values, providing a simple yet interpretable baseline. Secondly, I implement a machine learning method, employing linear regression to directly forecast key balance sheet items without decomposition. Lastly, I explore a deep learning approach, incorporating a sequence-to-sequence neural network for time-series predictions.

These methods are evaluated on real-world quarterly balance sheet data, comparing their prediction accuracy, adherence to the accounting equation, and computational efficiency. My findings provide a comprehensive assessment of the performance of different approaches in financial forecasting, highlighting the limitations of each method and offering insights into building more accurate and reliable predictive models.

1 Definition of the Problem

Forecasting a company's financial statements, particularly the balance sheet, is a critical task for assessing its financial health and guiding strategic decision-making. The balance sheet consists of three primary components: assets, liabilities, and shareholder equity, which are governed by the fundamental accounting equation.

$$\text{Assets} = \text{Liabilities} + \text{Equity} \tag{1}$$

However, developing an accurate and transparent forecasting model poses significant challenges due to the following issues:

1. **Interdependency of Variables:** The components of the balance sheet are not independent. Changes in one field (e.g., liabilities) directly affect others (e.g., shareholder equity). A robust model must ensure consistency across these interdependent variables and uphold accounting identities.
2. **Avoidance of Plug Variables:** Traditional financial forecasting models often introduce "plug" variables (e.g., adjustments to cash, debt, or equity) to enforce the balance sheet equality. This approach conceals errors and undermines the model's reliability and interpretability.
3. **Circular Dependencies:** Many models suffer from circular dependencies, such as net income depending on interest expenses, which in turn depend on liabilities. These loops complicate calculations and can lead to instability in the model.

4. **Data Limitations:** Financial datasets often contain a limited number of historical records, requiring models to generalize effectively while maintaining accuracy. This is particularly challenging when using data-driven methods.

In this study, I aim to explore potential forecasting methods, addressing the mentioned limitations.

2 Potential Methods

The task of balance sheet forecasting has been approached using a variety of methodologies, ranging from traditional rule-based methods to modern machine learning and deep learning techniques. Each method has distinct advantages and limitations, which we analyze below.

2.1 Rule-Based Financial Models

Traditional rule-based methods rely on financial logic and accounting identities to predict balance sheet components. These models use predefined formulas to calculate variables such as total assets, liabilities, and equity based on historical trends and financial ratios. The methods proposed by Velez-Pareja[3;2] is one of such.

Advantages

- **Transparency:** Rule-based models explicitly define the relationships between variables, ensuring interpretability and consistency with accounting principles.
- **Simplicity:** These models are straightforward to implement and do not require extensive computational resources or large datasets.
- **Guaranteed Consistency:** By adhering strictly to accounting identities, these models avoid the need for plug variables and prevent circular dependencies.

Disadvantages

- **Limited Flexibility:** These models often fail to capture complex, non-linear relationships between financial variables.
- **Dependence on Assumptions:** Accuracy heavily relies on the validity of assumptions such as constant growth rates or stable financial ratios.
- **Poor Generalization:** Rule-based models may struggle to adapt to unexpected changes in a company's financial structure or external economic conditions.

2.2 Machine Learning Models

Machine learning (ML) models, such as linear regression, decision trees, and ensemble methods (e.g., random forests and gradient boosting), have gained popularity in financial forecasting due to their ability to capture complex relationships between variables.

Advantages

- **Data-Driven Insights:** ML models can learn patterns and relationships directly from data, reducing the need for predefined assumptions.
- **Flexibility:** These models can handle both linear and non-linear dependencies among variables, making them more adaptable than rule-based methods.
- **Scalability:** ML models can be applied to large datasets and used to forecast multiple financial components simultaneously.

Disadvantages

- **Data Requirements:** Even simple models like linear regression require some high-quality historical data to perform well, which is sometimes unavailable for financial forecasting.
- **Interpretability:** Many ML models lack transparency, making it difficult to explain predictions or ensure consistency with accounting identities.
- **Risk of Overfitting:** When trained on small datasets, these models may capture noise rather than meaningful patterns, leading to poor generalization.

2.3 Deep Learning Models

Deep learning (DL) models[5;6;4], such as recurrent neural networks (RNNs), long-short-term memory networks (LSTMs), and transformer-based models, have demonstrated remarkable success in time series forecasting tasks, including financial prediction.

Advantages

- **Capturing Complex Patterns:** DL models excel at identifying intricate non-linear relationships and temporal dependencies in data.
- **End-to-End Learning:** These models can process raw data and generate predictions without requiring manual feature engineering.
- **Versatility:** DL methods can integrate various types of financial data (e.g., balance sheets, income statements, macroeconomic indicators) into a unified framework.

Disadvantages

- **High Data Requirements:** DL models require extensive historical data to achieve reliable performance, which is impractical for balance sheet forecasting tasks in most cases.
- **Interpretability:** The interpretability of DL models are even worse than ML methods. It is often a black box.

3 Rule-based Method

In this study, I develop a rule-based method inspired by the work of Velez-Pareja. This approach forecasts key components of the balance sheet by decomposing them into subcomponents and predicting each using historical averages. The method adheres to fundamental accounting principles while providing a simple and interpretable framework for financial forecasting.

3.1 Predicting Assets

The total assets (totalAssets) are derived as the sum of current assets (totalCurrentAssets) and non-current assets (totalNonCurrentAssets), as shown in the following equation:

$$\text{totalAssets} = \text{totalCurrentAssets} + \text{totalNonCurrentAssets}$$

To forecast total assets, each subcomponent of current and non-current assets is predicted using historical averages.

Current Assets

Current assets (totalCurrentAssets) are directly predicted using historical averaging of past values. Although subcomponents such as cash, receivables, and inventory are available in the balance sheet, predicting the total value provides a more straightforward solution for this study.

Non-Current Assets

Non-current assets are decomposed into:

$$\begin{aligned}\text{totalNonCurrentAssets} = {} & \text{propertyPlantEquipment} + \text{intangibleAssets} \\ & + \text{longTermInvestments} + \text{otherNonCurrentAssets}\end{aligned}$$

Property, Plant, and Equipment (PP&E) are forecasted using:

$$\text{PP\&E}_{t+1} = \text{PP\&E}_t + \text{CapEx}_t - \text{Depreciation}_t$$

Where:

- Depreciation_t: Calculated as the average change in accumulated depreciation over historical periods.
- CapEx_t: Estimated using the historical average of capital expenditures.

Intangible Assets, **Long-Term Investments** and **Other Non-Current Assets** are all forecasted using historical averages, leveraging their stability in the historical data.

Summing Total Assets

Once all components are predicted, the total assets are computed as:

$$\text{totalAssets}_{t+1} = \text{totalCurrentAssets}_{t+1} + \text{totalNonCurrentAssets}_{t+1}$$

3.2 Predicting Liabilities and Shareholder Equity

Total Liabilities

Total liabilities are decomposed into current and non-current liabilities, each predicted using historical averages. This ensures that the predicted values align with observed historical patterns and maintain consistency with the accounting equation.

$$\text{totalLiabilities}_{t+1} = \text{totalCurrentLiabilities}_{t+1} + \text{totalNonCurrentLiabilities}_{t+1}$$

Shareholder Equity

Shareholder equity ($\text{totalShareholderEquity}_{t+1}$) is forecasted using:

$$\text{totalShareholderEquity}_{t+1} = \text{Retained Earnings}_{t+1} + \text{Common Stock}_{t+1}$$

Where:

- $\text{Retained Earnings}_{t+1}$: Predicted using historical averages, reflecting past trends in retained earnings.
- $\text{Common Stock}_{t+1}$: Assumed constant unless significant variability is observed in the historical data.

4 ML and DL Methods

In addition to the rule-based approach, I applied machine learning (ML) and deep learning (DL) methods to directly predict the key balance sheet components: total assets, total liabilities, and shareholder equity.

4.1 Machine Learning Method

The machine learning method employs linear regression to forecast each variable independently. Linear regression was chosen due to its simplicity, efficiency, and interpretability. By fitting a linear model to historical data, this approach captures the underlying trends and provides a robust baseline for forecasting balance sheet components. The model predicts each variable based on the temporal sequence of historical values, ensuring data-driven accuracy while remaining computationally lightweight.

4.2 Deep Learning Method

For the deep learning approach, I implemented the NLinear model. This method is specifically designed for time-series forecasting and incorporates a simple yet effective normalization process. The model works as follows:

- First, the input sequence is normalized by subtracting its last value.
- The normalized sequence is passed through a fully connected linear layer to predict future values.

- Finally, the subtracted value is added back to the prediction, ensuring the forecast remains consistent with the original scale of the input.

NLinear is a popular method in the field of time-series forecasting. It is light weight, so that it can be applied to balance sheet forecasting. It's design leverages the normalization step to stabilize input dynamics, making it particularly well-suited for financial time-series data where trends and scales can vary significantly.

4.3 Adjusting to Match Accounting Equation

While the ML and DL methods provide direct predictions for the three key variables, they do not inherently ensure the accounting equation is satisfied. To address this, I applied an adjustment process post-prediction:

$$\text{Assets}_{t+1} = \text{Liabilities}_{t+1} + \text{Equity}_{t+1}$$

The adjustment works as follows:

1. Compute the predicted sum of liabilities and equity.
2. Calculate the discrepancy between the predicted total assets and the sum of liabilities and equity.
3. Distribute the discrepancy proportionally across the three components—total assets, total liabilities, and shareholder equity—based on their relative magnitudes.

This adjustment ensures that the final predictions are consistent with the fundamental accounting principles while preserving the relative proportions of the original forecasts. It bridges the gap between data-driven predictions and the rigid constraints of financial accounting.

5 Experiments

In this section, we conduct experiments on several datasets with our method and several baseline methods.

5.1 Set up

I choose four companies to conduct experiments: Amazon, Apple and Google. Data are collected from alpha vantage[1], which provides a long historical balance sheet for a wide range of companies. For each dataset, I split first 80% as train set, and the last 20% as test set. All experiments are conducted with my MacBook(M1). Before experiments, I also check the effectiveness of data:

I verified that the accounting equation holds for each record in the dataset:

$$\text{Assets} = \text{Liabilities} + \text{Equity}$$

Any imbalances exceeding a small threshold (e.g., 1×10^{-5}) were flagged for further inspection. This step ensures the integrity of the dataset and highlights potential anomalies.

Company	**Shareholder Equity**	**Assets**	**Liabilities**	**Equation Error**
Google	2.16×10^{10}	6.40×10^{10}	1.26×10^{10}	3.10×10^{10}
Amazon	1.11×10^{11}	1.18×10^{11}	6.89×10^{10}	6.16×10^{10}
Apple	6.46×10^{9}	1.23×10^{10}	1.45×10^{10}	1.20×10^{7}

Table 1: Rule-based approach. Prediction Errors and Accounting Equation Consistency.

Company	**Shareholder Equity**	**Assets**	**Liabilities**	**Equation Error**
Google	6.82×10^{9}	1.27×10^{10}	1.02×10^{10}	0.0000
Amazon	9.32×10^{10}	1.95×10^{11}	1.02×10^{11}	0.0001
Apple	5.81×10^{10}	1.14×10^{11}	5.58×10^{10}	0.0001

Table 2: Machine learning approach. Prediction Errors and Accounting Equation Consistency.

Company	**Shareholder Equity**	**Assets**	**Liabilities**	**Equation Error**
Google	4.92×10^{9}	8.53×10^{9}	4.92×10^{9}	1.31×10^{4}
Amazon	1.25×10^{11}	1.28×10^{11}	6.00×10^{10}	1.82×10^{4}
Apple	1.04×10^{10}	1.67×10^{10}	1.78×10^{10}	1.04×10^{4}

Table 3: Deep learning approach. Prediction Errors and Accounting Equation Consistency.

5.2 Comparison of methods

I summarized the results in table 1, table 2 and table 3.

5.3 Discussion

We can observe that deep learning method significantly outperform baselines. Also, because of our adjusting mechanism, the prediction results of ML and DL methods match the accounting equation. However, in my perspective, there are still a large room for improvements.

Limitation of forecasting. I think the corner stone of further improvement of predictions is the data. The components in the balance sheet are often incorrect. This significantly affect the decomposition of components. For example, while liabilities is the summation of current liabilities and non-current liabilities in most cases. However, it only happens in 70% of the cases. This affects the learning of machine learning model and the establish of rules. I found the situation get worse when I try to decompose the components into finer grain.

Method design. For rule-based methods or machine learning methods, they are too sensitive to the incorrect data in the sheet. The recent predictions are far from perfects. Although we can detect or refine the values in the sheet, I do not think it is a good idea. In my experience, deep learning model can better handle such situation. However, it is obvious that large model cannot be directly applied to balance sheet, which is super small in data size. I had experiments about large models on small dataset in my paper[5]. In that case, large models are prone to overfit, making the prediction even worse than linear models.

However, this does not mean that financial forecasting cannot get any benefits from the recent progress in deep learning. There are some foundation deep learning models[4] in the field of time-series forecasting, which can be applied to this problem. These models can perform zero-shot predictions, utilizing the knowledge learned from a large-scale of training data. I will try and explore these methods in the next part of project.

References

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