FinMath: Injecting a Tree-structured Solver for Question Answering over Financial Reports

Chenying Li†, Wenbo Ye‡, Yilun Zhao∗
†Northeastern University
‡Zhejiang University
∗Yale University
†li.chenyin@northeastern.edu
‡wenbo.17@intl.zju.edu.cn

Abstract

Answering questions over financial reports containing both tabular and textual data (hybrid data) is challenging as it requires models to select information from financial reports and perform complex quantitative analyses. Although current models have demonstrated a solid capability to solve simple questions, they struggle with complex questions that require a multiple-step numerical reasoning process. This paper proposes a new framework named FinMath, which improves the model’s numerical reasoning capacity by injecting a tree-structured neural model to perform multi-step numerical reasoning processes. Specifically, in the first phase, FinMath extracts supporting evidence from the financial reports given the question. And in the second phase, a tree-structured neural model is applied to generate a tree expression in a top-down recursive way. Experiments on the TAT-QA dataset show that FinMath improves the previous best result by 8.5% absolute for Exact Match (EM) score (50.1% to 58.6%) and 6.1% absolute for numeracy-focused F₁ score (58.0% to 64.1%).

Keywords: Financial NLP, Question Answering, Numerical Reasoning, Math Word Problems Solving

1. Introduction

The sheer volume of financial statements and tables makes it difficult and time-consuming for humans to access and analyze financial reports. Robust numerical reasoning over hybrid data combining both tabular and textual content faces unique challenges in this domain. TAT-QA dataset (Zhu et al., 2021) focuses on questions that require numerical reasoning over financial report pages containing both paragraphs and tables. As the example shown in Figure 1, the question “What was the percentage change in gaming between 2018 and 2019?” requires the QA system to analyze the given paragraphs and tables, locate relevant cells in the tabular content and then perform subtraction and division operations to get the final answer.

However, current best model over TAT-QA dataset, named TAGOP (Zhu et al., 2021), can only perform symbolic reasoning with a single type of pre-defined aggregation operators (e.g. change ratio, division), and might fail to answer complex questions requiring multi-step reasoning. To address these shortcomings, we present a new framework called FinMath, which can perform arbitrary steps of numerical reasoning given the arithmetic questions. Motivated by the recent works in the task of Math Word Problems (MWP) solving (Xie and Sun, 2019a; Li et al., 2020; Shen and Jin, 2020), a tree-structured neural model is applied in the FinMath framework. Specifically, for those arithmetic questions in TAT-QA, after extracting the supporting evidence, the tree-structured neural model uses top-down goal decomposition and bottom-up subtree embedding construction to directly predict the expression tree from questions and extracted evidence. Then the expression tree is executed to get the final answer.

The main contribution of this work can be summarized as follows:

- We propose a new framework named FinMath to answer financial questions in an expert-like way. Specifically, the model first understand the hybrid context of financial reports and extract supporting evidence given the questions. Then a tree-structured neural model is applied to perform multi-step numerical reasoning for those arithmetic questions in TAT-QA.

- The experimental results show FinMath significantly outperforms several state-of-the-art systems over TAT-QA dataset. Detailed ablation study shows that FinMath model improves the previous best result by 14.7% absolute for solving arithmetic questions, which illustrates the model’s capability of multi-step numerical reasoning.

2. Task Formulation.

Presented with a financial report consisting of textual contents $P$ and tabular contents $T$, given a question $Q$, the model first aims to classify whether the $Q$ is a spans selection question $Q_S$, or an arithmetic (numerical reasoning) question $Q_N$.

For $Q_S$ type questions, the task is to select all the predicted cells from $T$ and spans from $P$ as $X = \{x_0, x_1, \ldots, x_n\}$.

For $Q_N$ type question, the task is to:

1. Generate the numerical expression $E = \{w_0, w_1, \ldots, w_n\}$, where $w_i$ is constant quantity, mathematical operator, or numeric value from $X$.
Our commercial cloud revenue, which includes Office 365 Commercial, Azure, the commercial portion of LinkedIn, Dynamics 365, and other commercial cloud properties, was $38.1 billion, $26.6 billion and $16.2 billion in fiscal years 2019, 2018, and 2017, respectively. These amounts are primarily included in Office products and cloud services, Server products and cloud services, and LinkedIn in the table above.

### Arithmetic Question (44.3%):

What was the percentage change in gaming between 2018 and 2019?  
**Answer:** 9.98  
**Scale:** Percent  
**Derivation:** \((11,386 – 10,353) / 10,353\)

### Spans Selection Question (55.7%):  

How much revenue came from LinkedIn in 2017?  
**Answer:** 2,271  
**Scale:** million  
**Derivation:** -

Figure 1: Examples of TAT-QA dataset. The financial document contain both tabular and textual content. Given the question, the QA systems are required to locate the relevant spans in the document and perform numerical reasoning if necessary.

2. Execute the expression tree to get the answer A for the question:

\[
P(A|X, Q) = \sum P(E_i|X, Q) \tag{1}
\]

where \(\{E_i\}\) are all the correct numerical expressions to evaluate to get the answer.

For both type of questions, the model is also required to predict the scale of the answer, which might be \{None, Thousand, Million, Billion, Percent\}.

### 3. The FinMath Framework

To address the challenge of TAT-QA and improve the numerical reasoning capability of model, we propose a framework named FinMath. In the first phase, similar with TAGOP \cite{zhu2021tagop}, a sequence tagging module is applied to extract relevant cells from the table \(T\) and text spans from the paragraphs \(P\) as supporting evidence. And it also predicts the type of given question \(Q\) as spans selection question \(Q_S\) or numerical reasoning (arithmetic) question \(Q_N\). In the second phase, inspired by GTS \cite{xie2019towards} \cite{li2020neural} \cite{anonymous2022gts}, a tree-structured neural model is applied to perform numerical reasoning over arithmetic questions. Details of two modules are discussed below.

#### 3.1. Sequence Tagging

The given question, flattened table by row, and associated paragraphs are input sequentially to a RoBERTa \cite{liu2019roberta} encoder to obtain corresponding input representations. Then the model assigns each sub-token either \(I\) or \(O\) label. The cell in the table or word in the paragraph would be regarded as positive if any of its sub-tokens is tagged with \(I\). For spans selection questions \(Q_S\), the continuous words predicted as positive are combined as a span. And during the testing stage, all positive cells and spans are taken as the outputs. For arithmetic questions \(Q_N\), the tagged sequence \((x_1, x_2, \ldots, x_n)\) are used as input of tree-structured model in the second phase.

#### 3.2. Tree-structured Neural Model

An auto-regressive sequence-to-tree model similar to GTS \cite{xie2019towards} \cite{anonymous2022gts} is applied in FinMath to generate a numerical expression tree. The generation process can be summarized as following three steps:

**Encoding** Given all tokens \((q_1, q_2, \ldots, q_m)\) in questions \(Q_N\) and all tokens \((x_1, x_2, \ldots, x_n)\) in tagged sequence evidence \(X\), an embedding layer and a bidirectional GRU \cite{cho2014learning} are employed to encode all tokens as hidden states \((h_1, h_2, \ldots, h_{m+n})\), which are then concatenated as \(h^Q\) to represent problem \(Q_N\).

**Tree Initialization** The root node embedding \(q_0\) is initialized as \(h^Q\). The embedding of target vocabulary \(V_{tar}\) is initialized as:

\[
e(y|Q_N \cup X) = \begin{cases} 
E_o(y) & \text{if } y \in V_o \\
E_c(y) & \text{if } y \in V_c \\
h_{loc(y, Q_N \cup X)} & \text{if } y \in V_n 
\end{cases} \tag{2}
\]

where \(V_o, V_c, V_n\) denote the vocabulary set of operators, constant values, and numeric values appearing in \(Q_N \cup X\), respectively; \(E_o, E_c\) are two embedding matrices; \(loc(y, Q_N \cup X)\) is the position of \(y\) in \(Q_N \cup X\).

**Tree Decoding** The tree decoding process involves four modules:

1. **Context Module**: given the goal vector \(q\) and encoder outputs, it generates the context vector \(c\).
2. **Prediction Module**: given the goal vector \(q\) and context vector \(c\), it assigns the predicted token \(\hat{y}\) to token with highest decoding score \(s(\hat{y}|Q_N \cup X)\).
3. **Combination Module**: given the left sub-tree, a recursive neural network is applied to encode it as embedding \(t_l\).
Figure 2: Architecture of proposed FinMath framework.

4. **Left/Right Module**: given the goal vector \( q \) and predicted token \( \hat{y} \), if \( \hat{y} \) is an operator, left module is applied to generate the left sub-goal \( q_l \) as \( LM(q, e(\hat{y}|Q_N \cup X)) \). Otherwise, the right module is applied to generate the right sub-goal \( q_r \) as \( RM(q, t, e(\hat{y}|Q_N \cup X)) \). Here, the \( LM \) and \( RM \) are trainable networks, with implementation the same as GTS model.

The algorithm for tree decoding stage is described in Algorithm 1.

**Algorithm 1 Tree Decoding**

**Input:** \( q_0, (h_1, h_2, ..., h_{m+n}) \)

**Output:** expression tree

1: Generate context vectors \( c \)
2: Generate \( q_l, \hat{y} \)
3: while \( \hat{y} \in V_o \) do
4: \( \hat{y} = PredictionModule(q_l, c) \)
5: \( q_l = LM(q, e(\hat{y}|x)) \)
6: \( c = ContextModule(q, h_1, ..., h_{m+n}) \)
7: end while
8: Generate \( q_r, \hat{y}_r \)
9: Combine the embedding of subtree
10: if \( \hat{y}_r \in V_o \), then
11: Jump to line 2
12: else
13: Recursively find empty right node
14: if \( \hat{y}_r \in V_o \), then
15: Jump to line 2
16: else
17: return expression tree
18: end if
19: end if

4. **Experimental Settings**

4.1. **Baseline Systems**

**Textual QA Models** Two reading comprehension (RC) models over textual data are used as baselines: 1) BERT-RC (Devlin et al., 2019), which achieves promising performance on SQuAD (Rajpurkar et al., 2016; Rajpurkar et al., 2018), a machine reading comprehension dataset; and 2) NumNet+V2 (Ran et al., 2019), which achieves competent performance on DROP dataset (Dua et al., 2019) that requires the model to perform numerical reasoning over textual data.

**Tabular QA Model** TaPas (Herzig et al., 2020) for WikiTableQuestion dataset (Pasupat and Liang, 2015) is adopted for TAT-QA dataset.

**Hybrid QA Model** Two hybrid models over textual and tabular data are used as baselines: 1) HyBrider (Chen et al., 2020b), which is the baseline model for HybridQA (Chen et al., 2020b) and tackles hybrid data from Wikipedia; 2) TAGOP (Zhu et al., 2021), which is the state-of-the-art model of TAT-QA dataset. TAGOP first applies sequence tagging, which is also applied in FinMath, to extract relevant cells or text spans from the tables and paragraphs. Then it performs symbolic reasoning over the extracted evidence with a single type of pre-defined aggregation operators (e.g. change ratio, division). Compared with FinMath which can generate numerical expressions with arbitrary steps, TAGOP only supports a single type of aggregation operators, and might fail to answer complex questions requiring multi-step reasoning.

4.2. **Evaluation Metrics**

Following previous work, we use Exact Match (EM) and numeracy-focused F\(_1\) score as evaluation metrics.
Noted that the calculations of EM and F₁ score are the same for arithmetic question \( Q_N \).

### 4.3. Implementation Details

To ensure fairness, we use the same encoder (RoBERTa-large), batch size (32), and other training parameter settings (e.g., Adam optimizer, learning rate, etc.) as TAGOP to train FinMath. The training of FinMath model is conducted on two RTX 1080Ti within 12 hours. Since TAT-QA does not release the test set publicly, we use our own split of train, dev, and test set for evaluation (with proportion 8:1:1).

## 5. Results and Analysis

### 5.1. Overall Results

|   | Dev EM | Test EM | Dev F₁ | Test F₁ |
|---|--------|---------|--------|---------|
| HyBrider | 6.6    | 8.3     | 6.3    | 7.5     |
| BERT-RC  | 9.5    | 17.9    | 9.1    | 18.7    |
| TaPas for WTQ | 18.9  | 26.5    | 16.6   | 22.8    |
| NumNet+V2 | 38.1   | 48.3    | 37.0   | 46.9    |
| TAGOP     | 55.2   | 62.7    | 50.1   | 58.0    |
| FinMath   | 60.5   | 66.3    | 58.6   | 64.1    |

Table 1: Performance of FinMath compared with different baseline models on dev and test sets of TAT-QA dataset. The results of baseline models are copied from the original TAT-QA paper.

The evaluation results of baseline models and FinMath are summarized in Table 1. It is shown that our model performs better than any other baselines for both EM and F₁ metrics. Specifically, FinMath improves the previous best result (TAGOP) by 8.5% for EM score and 6.1% for F₁ score. The results demonstrate the effectiveness of FinMath in numerical reasoning over tabular and textual data.

### 5.2. Ablation Study

We also compare detailed performance of FinMath and TAGOP in different answer types of TAT-QA dataset, with the results shown in Table 2. It is shown that FinMath performs much better in arithmetic questions, reaching more than 20% improvement on both three kinds of answer sources. This is because the tree-structured numerical reasoning module in FinMath supports the model to perform a more complex reasoning process than TAGOP. Additionally, FinMath applies the same tagging sequence module as TAGOP, therefore, its performance on spans selection questions are similar with TAGOP.

## 6. Related Work

**Financial NLP** Financial NLP has attracted much attention recently. There have been some previous works in the financial domain like fraud detection (Han et al., 2018; Nourbakhsh and Bang, 2019; Wang et al., 2019), market prediction (Day and Lee, 2016; Akhtar et al., 2017) and financial opinion mining and question answering (Maia et al., 2018). More recently, pre-trained language models are presented for finance text mining. (Araci, 2019; Yang et al., 2020). And some recent works (Zhu et al., 2021; Chen et al., 2021; Zhao et al., 2022) focus on numerical reasoning over financial reports with tables.

**Numerical Reasoning** Numerical reasoning plays an important role in areas like question answering (Dua et al., 2019; Andor et al., 2019; Ran et al., 2019; Herzig et al., 2020; Chen et al., 2020a; Yin et al., 2020; Chen et al., 2021) and math word problems (MWP) solving (Xie and Sun, 2019b; Amini et al., 2019; Koncel-Kedziorski et al., 2016; Hendryckx et al., 2021; Hong et al., 2021). Current approaches usually regard solving MWP as a sequence to sequence task. And Seq2Seq model (Wang et al., 2017; Robaidek et al., 2018), with an encoder-decoder framework to generate the solution, has attracted much attention before 2018. Later some works (Xie and Sun, 2019a; Li et al., 2020) proposed tree-structured model to better fit the goal-driven mechanism in human problem solving.

## 7. Conclusion

In this paper, we have proposed FinMath, a novel framework that aims to conduct complex numerical reasoning on financial reports containing both tabular and textual data. We evaluate the effectiveness of FinMath on TAT-QA dataset. The results of comprehensive experiments showed that the proposed FinMath, with the tree-structured neural model to perform multi-step numerical reasoning, improves the previous best result by 8.5% absolute for Exact Match (EM) score and 6.1% absolute for numeracy-focused F₁ score.

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### Table 1: Performance of FinMath compared with different baseline models on dev and test sets of TAT-QA dataset. The results of baseline models are copied from the original TAT-QA paper.

| Answer Source | EM | F₁ | EM | F₁ |
|---------------|----|----|----|----|
| Table         | 59.5/63.6 | 60.7/64.4 | 41.6/41.6 | 59.6/59.6 |
| Text          | 43.4/69.8 | 42.2/68.9 | 27.3/27.3 | 43.4/43.4 |
| Text+Table    | 66.4/73.6 | 68.7/74.9 | 48.3/48.3 | 65.7/65.7 |
| Total         | 55.4/68.21 | 58.9/68.7 | 43.5/43.5 | 58.2/58.2 |

Table 2: Detailed experimental results of TAGOP and FinMath w.r.t. answer types and sources on test set of TAT-QA dataset.
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