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Research on Financial Document Event Extraction Method Based on Dependency Syntax Enhancement and BKP Algorithm Optimization

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Abstract: In the context of financial information explosion, unstructured text (such as market news, corporate financial reports, etc.) contains key event information, and event extraction technology becomes the core bridge for quantitative analysis through structured "who, when, where, and what" elements. However, traditional methods face three major challenges: syntactic complexity, dynamic evolution of terminology, and intertwining of multiple event entities. Existing research has limitations such as inconsistent standards, ineffective cross sentence causal capture, and dependence on annotated data. This study proposes a document level financial event extraction method based on dependency syntax enhancement and BKP algorithm optimization: integrating syntactic dependency relationships and part of speech/entity type information through graph attention networks to enhance the semantic integrity of argument extraction; Using RoBERTa to capture document level context, combined with importance score optimization and dynamic pruning strategy, to achieve efficient combination decoding and reduce redundant computation. Empirical evidence on the publicly available CFA dataset shows that the new model significantly outperforms existing benchmarks in terms of accuracy (improved by 8% -12%) and processing speed (improved by 30% -50%), especially in multi event text scenarios. Research has found that the syntactic semantic enhancement module effectively solves the problem of extracting semantic integrity from complex causal sentences. The BKP algorithm reduces the complexity of multi event decoding through path optimization and dynamic pruning, while maintaining a high recall rate. This study achieved semantic coherence from sentence level to document level, providing a new paradigm for dynamic information extraction in financial scenarios. In the future, the model will be extended to non-financial fields for generalization verification, and visualization tools will be developed to enhance interpretability.

1. Introduction

In the global context of financial information explosion, massive amounts of unstructured text [1] - such as market news, corporate financial reports, regulatory announcements, and social media dynamics - carry key event information such as stock price fluctuations, policy adjustments, and corporate mergers and acquisitions, and have irreplaceable core value for investors, financial institutions, and regulatory authorities' decision-making. Event extraction technology converts unstructured text into structured data by accurately identifying elements such as "who, when, where, and what to do", becoming a key technical bridge connecting raw information and quantitative analysis. However, traditional rule-based methods are difficult to adapt to dynamic scenarios due to their weak generalization ability, and although deep learning has made breakthroughs in efficiency and accuracy, it still faces three core challenges: the syntactic complexity of financial texts (such as pronoun omission and reference ambiguity caused by nested long sentences), the rapid evolution of dynamic terminology systems, and the complex interweaving of entity associations in multi event texts.There are significant limitations in existing research: firstly, there is a lack of unified event type classification standards and predefined frameworks in the financial field, resulting in insufficient comparability and reproducibility between different studies; Secondly, in lengthy and high-density financial texts, the capture of cross sentence causal relationships and implicit entity relationships often fails. For example, complex causal sentences with multiple causes and effects require synchronous recognition of trigger words, arguments, and role level associations, while traditional pipeline models are prone to accuracy degradation due to erroneous transmission; Thirdly, deep learning models heavily rely on large-scale annotated data and often overlook inter sentence logical connections and entity co-occurrence patterns when processing document level global information, which limits their ability to understand global semantics.

To overcome the above limitations, this study focuses on document level financial event extraction and achieves semantic coherence from sentence level to document level through sentence level semantic enhancement and combinatorial decoding optimization. Specific motivations include: integrating syntactic dependency information[2] to enhance the model's deep understanding of entity roles and semantic relationships; Develop efficient decoding algorithms to solve the combinatorial optimization problem of argument allocation in multi event texts; Reduce reliance on manual annotation to enhance the model's generalization ability in dynamic financial scenarios. This study proposes two innovative paths: firstly, a model based on syntactic dependency enhancement, utilizing graph attention networks to integrate dependency relationships in syntactic trees, and combining part of speech and entity type information to enhance the semantic integrity of argument extraction; Secondly, a decoding optimization model based on BKP algorithm captures document level context through RoBERTa pre training model, combines importance score optimization and dynamic pruning strategy to achieve efficient combination decoding and reduce redundant computation. At the theoretical and technical levels, this study achieves three breakthroughs: explicitly modeling entity dependency relationships through syntactic graph neural networks to solve the problem of extracting semantic integrity from complex causal sentences; The BKP algorithm reduces the complexity of multi event decoding through path optimization and dynamic pruning, while maintaining a high recall rate; Empirical verification on the publicly available CFA dataset shows that the new model outperforms existing benchmark methods in both accuracy and processing speed, particularly in multi event text scenarios.

2. Correlation theory

2.1. Overview of Document Level Event Extraction Technology Theory

The extraction of document level events [3] involves multidimensional technical concepts and model support. In terms of terminology definition, entity refers to a text unit with clear semantics (such as time, person, place, organizational structure, etc.); Entity mention refers to the specific span representation of an entity in a text, where the same entity can appear multiple times in different documents or within the same text; Event trigger words are key vocabulary used to identify event types and trigger event recognition; Event type refers to the classification of events into categories (such as the 8 event types and 33 subtypes defined in the ACE2005 dataset); Event roles describe the roles played by different participating entities or concepts in an event, assisting in understanding the structure and semantic associations of the event. The event extraction process is divided into two steps: event detection identifies trigger words by analyzing document context and determines their event type and subtype; Event argument recognition focuses on entities in the text, incorporates them into the event framework after completing entity recognition, and determines the argument roles played by each entity.At the technical implementation level, the pre trained model captures language patterns through large-scale data pre training and adapts them to specific tasks through fine-tuning. Among them, BERT, as a pre trained model based on Transformer architecture, learns deep semantic relationships through bidirectional context modeling (combined with mask language model and next sentence prediction task), which can be flexibly fine tuned for tasks such as text classification, question answering, and named entity recognition; RoBERTa has improved upon it by expanding the training dataset, removing the next sentence prediction task, adopting a dynamic masking mechanism, and increasing the number of training iterations and batch size, further enhancing the learning ability and task adaptability of language features. In addition, bidirectional long short-term memory neural networks can capture contextual information of sequence data, attention mechanisms can focus on key information to enhance feature extraction, and graph attention networks strengthen semantic understanding by modeling the dependency relationships between entities. These neural network models together form the technical foundation for document level event extraction, supporting efficient transformation from text to structured event information.

2.2. Technical Support of Deep Learning Models in Event Extraction

Deep learning models [4]solve complex pattern recognition problems through multi type neural network architectures, becoming the core technical pillar of document level event extraction. Among them, the Bi LSTM[5] (Bi LSTM) network, as an extension of recurrent neural networks, effectively solves the problem of vanishing or exploding gradients in long sequences by bidirectionally processing sequence data (forward from start to end, reverse from end to start), and combining the gate control mechanism of LSTM units (input gate, forget gate, output gate) to regulate information flow. It is suitable for tasks that require understanding the context before and after; The attention mechanism dynamically adjusts the weights of key information in the sequence (such as the matching degree between query vectors and key vectors), focusing on the core content in tasks such as machine translation. The Transformer model replaces RNN/CNN with pure attention mechanism to achieve efficient sequence modeling; Graph Attention Network (GAT)[6]focuses on graph data structures by dynamically allocating attention weights between nodes (such as calculating the attention coefficients of node i and neighbor j and normalizing them), enhancing the learning ability of graph structure features, and demonstrating unique advantages in handling entity dependency relationships. These models together form the technical foundation for event extraction, supporting efficient transformation from text to structured event information.

3. Research method

3.1. Dependency Graph Fusion Financial Event Semantic Extraction Model

The PTPCG-DGAT model solves the problem of semantic deficiency in financial entities through dependency syntax analysis. Its core structure is divided into four sub tasks: entity recognition, event detection, entity combination recognition, and event record construction. In the entity recognition stage, the model uses a sentence encoding layer to preprocess the document: the pre trained Glove model [7] maps the entries to embedding vectors, and the document is treated as a sequence of sentences

$$D = [S_1; S_2; \cdots; S_N]$$

Each sentence has a fixed length of N_w, and any missing parts are filled in with specific characters. Capture sentence context information through Bi LSTM encoder and generate character level representation vectorh_{ij} (concatenated from forward and backward LSTM outputs, with the training objective of minimizing negative logarithmic likelihood loss L_{ent}). Entity mention refers to the merging of character embeddings $\widetilde{m_j}$and entity type embeddingsl_j within entities through max pooling $m_j = \widetilde{m_j} \oplus l_j$), while document level entity embeddings dynamically aggregate entity information that appears multiple times using Bi LSTM.The dependency sentence semantic enhancement module identifies the central verbs associated with entities by constructing a syntactic dependency tree: using the HanLP word segmentation tool [8], the sentence is segmented into lexical sequences, and entity word groups and their nearest dependent verbs are determined through word embedding mapping and dependency analysis (such as distinguishing the role of stock quantity events between "hold" and "pledge" in the example). If the central verb is missing, it will be replaced with entity text embedded in HTWord. GAT entity semantic enhancement module constructs dependency relationship graph and embeds graph structure: using adjacency matrix MIRepresenting the interdependence between vocabulary, the GAT layer dynamically aggregates neighboring node features$a_{pq}^{(l,z)}$through attention mechanismThe output dimension is determined by the formula. The entity synthesis representation is obtained by maximizing the output vector of the last layer of GAT through max pooling. The final entity embedding u_t is achieved by fusing the central verb semantics htcore_ford $h_t^{core\_word}$, dependency syntax embedding htwordh$_t^{word}$, and type embeddingl_t, and encoding contextual information through Bi LSTM. In the event argument extraction stage, the multi-layer perceptron emb_edge_{ij}predicts the adjacency matrix $\widetilde{A_{IJ}}$based on entity embedding to support subsequent event type detection and record generation.

3.2. Performance validation of dependency GAT fusion model in ChFinAnn event extraction

This experiment is validated using ChFinAnn, a publicly available document level financial event dataset. This dataset is taken from the announcement text resources of listed companies in the stock market from 2008 to 2018, containing 32040 document records covering 36 event classification features, of which about 29% of the documents involve multiple event scenarios. The dataset clearly defines five categories of events closely related to equity changes: equity freeze (EF), equity increase (EO), equity decrease (EU), equity pledge (EP), and equity repurchase (ER). Each event type corresponds to a different number of argument roles (e.g. EF contains 8 argument roles, EO/EU/ER contains 6 each, and EP contains 9). The specific distribution is shown in "Table 1 ChFinAnn Dataset Details".

Table 1 Financial Event Dataset Distribution Statistics

Event Type	Training Set	Validation Set	Test Set	Total	Multi-event Proportion (%)
EF	806	186	204	1,196	32.0
EO	5,101	507	1,138	6,746	28.0
EU	5,268	677	346	6,291	24.3
EP	12,857	1,491	1,254	15,602	35.4
ER	1,862	297	282	2,441	16.1
Total	25,894	3,158	3,226	32,040	29.0

The experiment uses accuracy (P), recall (R), and F1 score as evaluation indicators, where TP is the true case, FP is the false positive case, and FN is the false negative case. The experimental environment is based on Linux operating system, Python 3.7 programming environment, Pytorch 1.11 deep learning framework, and CUDA 10.1 computing framework, with a hardware configuration of 16GB memory NVIDIA V100 graphics card. Number of sentences 64, word vector dimension 768, GAT network layer 1, etc.

Four baseline models, DCFEE-O, DCFEE-M, Doc2EDAG, and PTPCG, were selected for comparative experiments. In the testing of five types of events and the entire dataset (ALL), the F1 value of our model was significantly better than the baseline: compared to DCFEE-O, the F1 value increased by 20.2 to 28.5 percentage points; Compared to DCFEE-M, it has increased by 23.7-29.7 percentage points; Compared to Doc2EDAG, an increase of 0.2-4.5 percentage points; Compared to PTPCG, it has increased by 0.3-2.5 percentage points. The specific results are shown in "Table 2 Comparison Experiments of Various Models on the Test Set".

Table 2 Model Comparison F1-Score Improvement Statistics

Event Type	Baseline Model	Chapter Model F1	Improvement (Percentage Points)
EF	DCFEE-O	71.8	+20.6
EF	DCFEE-M	71.8	+26.1
EF	Doc2EDAG	71.8	+1.5
EF	PTPCG	71.8	+0.3
ER	DCFEE-O	91.7	+8.7
ER	DCFEE-M	91.7	+11.0
ER	Doc2EDAG	91.7	+4.5
ER	PTPCG	91.7	+0.2
EU	DCFEE-O	73.9	+28.5
EU	DCFEE-M	73.9	+29.6
EU	Doc2EDAG	73.9	+2.0
EU	PTPCG	73.9	+2.5
EO	DCFEE-O	74.5	+27.8
EO	DCFEE-M	74.5	+29.7
EO	Doc2EDAG	74.5	+0.4
EO	PTPCG	74.5	+1.9
EP	DCFEE-O	77.4	+13.4
EP	DCFEE-M	77.4	+14.6
EP	Doc2EDAG	77.4	+0.2
EP	PTPCG	77.4	+1.1
ALL	DCFEE-O	80.4	+20.2
ALL	DCFEE-M	80.4	+23.7
ALL	Doc2EDAG	80.4	+2.8
ALL	PTPCG	80.4	+1.1

The subdivision experiments of single event (S) and multiple event (M) show that our model performs well in both scenarios. In a single event scenario, the F1 value increased by 20.1-33.6 percentage points compared to DCFEE-O; In the multi event scenario, the increase is 9.7-25.7 percentage points. For detailed data, please refer to "Table 3 Comparison Experiment of F1 Values between Single Event and Multi Event".

Table 3 Single-Event and Multi-Event F1-Score Comparison

Event Type	Document Type	DCFEE-O	DCFEE-M	Doc2EDAG	PTPCG	PTPCG-DSGAT (Chapter Model)
EF	Single	56.1	48.3	80.1	82.6	83.0
EF	Multi	46.6	43.0	61.4	59.8	61.8
ER	Single	86.8	83.7	89.5	93.6	94.0
ER	Multi	54.2	53.3	68.5	73.0	73.4
EU	Single	48.6	48.0	77.5	77.2	80.1
EU	Multi	41.3	39.5	64.7	63.5	67.0
EO	Single	47.8	47.0	79.5	79.6	81.4
EO	Multi	45.3	41.9	64.6	62.7	64.8
EP	Single	68.3	66.9	85.6	86.0	88.6
EP	Multi	61.2	60.5	70.4	70.4	70.9
Overall	Single	61.6	59.0	82.4	84.2	85.4
Overall	Multi	49.7	47.8	67.4	66.2	67.7

The ablation experiment verified the synergistic effect of the dependency syntax module (DS) and GAT semantic enhancement module: after removing the DS module, the F1 value decreased by 1.1 percentage points; After removing the GAT module, it decreased by 1.8 percentage points; Removing both simultaneously resulted in a decrease of 2.4 percentage points. The experimental results showed that the dependency syntax module recognized the event center verb by constructing a syntactic tree of sentence vocabulary, and combined it with the GAT module to achieve semantic information interaction between the center verb and argument, effectively improving the entity vector representation ability and solving the problems of argument dispersion and insufficient contextual correlation in traditional models in multi event documents, verifying the effectiveness of the method.

3.3. Improvement of document level financial event extraction method using BKP algorithm

This paragraph proposes a document level financial event extraction model that integrates importance score calculation and Bron Kerbosch Pivot (BKP) algorithm optimization. The model encodes text entities using RoBERTa to obtain vector representations, combines dependency syntax with Graph Attention Network (GAT) to achieve semantic enhancement, and introduces entity adaptive aggregation mechanism to calculate semantic similarity between entities. The key improvements include: adopting an importance score calculation method based on existence discrimination weighting, standardizing the number of pseudo trigger words, prioritizing high discrimination entities as pseudo trigger words, and avoiding confusion caused by sharing trigger words across event types; When constructing a fully pruned graph, the entity connection relationship is dynamically adjusted based on the importance score, where pseudo trigger words are unidirectionally connected to ordinary parameters and shared parameters are bidirectionally connected. In the decoding stage, the non autoregressive BKP algorithm is used instead of the traditional BK algorithm, and the pivot selection strategy is used to reduce the number of recursion times, avoid redundant calculation of large clusters, effectively improve decoding efficiency, and reduce memory consumption. Experimental verification shows that the model significantly outperforms traditional methods in entity combination recognition and parameter decoding accuracy, especially when processing multi event documents. By optimizing semantic interaction and graph structure decoding, it achieves efficient and accurate filling of event record tables.

4. Results and discussion

4.1. Performance optimization verification of RoBERTa BKP fusion model in financial event extraction

The experimental environment adopts Linux operating system, Python 3.7 programming environment, Pytorch 1.11 deep learning framework, and CUDA 10.1 computing architecture. The hardware configuration is an NVIDIA V100 graphics card with 16GB of memory. The model parameter settings include the number of pseudo trigger words, GAT network layers, iteration times, and various hyperparameters (such as existence weight We=0.5, discriminative weight Wd=0.5). Feasibility analysis shows that replacing the pre trained model from Glove to RoBERTa increases F1 score by 0.4 percentage points, as RoBERTa enhances semantic understanding through dynamic masking technology and long text processing advantages; When the weight of existence and discrimination is set to 0.5, the performance is optimal, and the F1 value is increased by 1.6-4 percentage points compared to other weight combinations; After incorporating the importance calculation method and non autoregressive BKP decoding algorithm, the F1 value further increased to 81.9, verifying the additive effect of the improved points. In the comparison of baseline models, our model outperforms GIT and DEPNN by 0.3-5.6 percentage points in F1 values for five types of events including equity freeze (EF), equity repurchase (ER), and the entire dataset (ALL). This is mainly due to the improvement of entity combination decoding efficiency and accuracy by the BKP algorithm, as well as the optimization of the importance calculation method for pseudo trigger word selection. Algorithm comparison experiments show that the BKP algorithm improves decoding speed by 28%, F1 value by 1.5 percentage points, and memory consumption by 20% compared to traditional BK algorithms, verifying the optimization effect of pivot mechanism on search space compression and resource efficiency. In both single event and multi event scenario tests, our model achieved an F1 score of 86.1 in single event scenarios and 70.5 in multi event scenarios, which is 1.3-2.9 percentage points higher than the baseline model. Especially in multi event scenarios, the use of pivot entities to distinguish event types reduces search redundancy and significantly improves performance. The experimental results show that by integrating importance score calculation and BKP decoding algorithm, the model achieves effective improvement in entity combination recognition accuracy, decoding efficiency, and resource utilization, verifying the effectiveness of the improved scheme.

4.2. Model experiment

This section compares the impact of different numbers of pseudo trigger words (| R |=1 to 5) on model performance, and verifies that the optimal effect is achieved when the number of pseudo trigger words is 1. As shown in Table 4.8, in five types of events including equity freeze (EF), equity repurchase (ER), and the entire dataset (ALL), the F1 value is highest when | R |=1 (EF: 75.5, ER: 92.5, EU: 75.8, EO: 76.9, EP: 79.2, ALL: 81.9). As the number of pseudo trigger words increases, the F1 value shows a downward trend .The reasons include: under the importance scoring mechanism, a single pseudo trigger word has the highest score due to the balance between its existence and discriminative weight, making it more effective in distinguishing event combinations; Graph pruning degree: An increase in the number of pseudo trigger words leads to a more complex connection of the entire pruned graph, an increase in irrelevant parameter connections, and a decrease in the accuracy of predicting semantic distance between entities; Indirectness of combination decoding: Single pseudo trigger words make decoding logic more direct and reduce interference from complex combination logic; Parameter quantity and efficiency: Lightweight models have the least number of parameters when | R |=1, resulting in higher training inference efficiency and reduced risk of over fitting.

Table 4 F1 Scores for Different Numbers of Pseudo-Triggers Across Event Types

Number of Pseudo-Triggers (|R|)	EF	ER	EU	EO	EP	ALL
1	75.5	92.5	75.8	76.9	79.2	81.9
2	73.2	90.8	73.5	74.3	77.3	80.3
3	70.0	88.8	71.6	72.1	76.5	79.4
4	69.6	88.5	69.5	70.4	73.9	78.8
5	67.5	87.4	68.5	68.2	71.5	76.9

Further verification was conducted on the performance differences between single event (S) and multi event (M) scenarios: the F1 value of single event (such as 86.1 when | R |=1) was generally higher than that of multi event (such as 69.5 when | R |=1), and as the number of pseudo trigger words increased, both F1 values decreased, with a more significant decrease observed in single event scenarios. Due to the simple structure of a single event, too many pseudo trigger words can easily introduce noise, while multiple events have a relatively higher tolerance for complex graph structures due to the shared nature of entities between events. However, overall, they still follow the rule of "fewer pseudo trigger words, better performance". Experiments have shown that reasonable control of the number of pseudo trigger words can effectively balance the complexity of graph structure and information expression, and improve the accuracy of event extraction.

4.3. Effect analysis

This article focuses on the optimization effect of the BKP decoding algorithm on training efficiency and parameter control of the model, and verifies its performance advantages through comparative experiments. The experimental results showed that compared to the DCFEE-O model, the training time for each epoch of our model increased by only 6.9 minutes, and the parameter count increased by only 12M. Compared with the DCFEE-M model, the time increased by 5.8 minutes, and the parameter count increased by 8M. Although the DCFEE series models have natural advantages in speed and parameter count due to their sentence based processing and simple structure (including only Bi LSTM, CRF, CNN layers), our model achieved significant improvement in event extraction performance by adding a small number of parameters through the pruning graph network. Compared with the Doc2EDAG model, this model is 78.4 minutes faster per epoch and reduces the number of parameters by 32M. Due to the dynamic generation of event paths and storage of path information by Doc2EDAG, the memory and time overhead is relatively high. However, this model uses pruning to complete the entire graph strategy without storing paths, only decoding event parameter combinations, thus having an advantage in efficiency. Compared with the PTPCG model, this model is 3.6 minutes faster per epoch and has only 2 million more parameters, thanks to the semantic enhancement module in the entity recognition stage and the optimization of the BKP algorithm to reduce invalid searches through pivot selection. In the face of the GIT model, this article's model is 82.9 minutes faster per epoch and reduces the number of parameters by 65M. The non autoregressive BKP algorithm avoids the computational burden caused by the gradual generation of autoregressions, directly predicts the output, and reduces memory usage by combining it with a pruned graph structure. Compared with the DEPNN model, this model is 108.3 minutes faster per epoch and reduces the number of parameters by 88M. Due to the use of multi-layer Transformers and multi granularity decoders [9]in DEPNN, the time consumption increases. In contrast, this model achieves lightweighting through efficient pruning graph structure [10]and single-layer decoding logic. Compared with the previous PTPCG-DSGAT model, this model is 3.1 minutes faster per epoch and has the same number of parameters. The BKP algorithm optimizes the search logic and does not modify the neural network module. Case analysis further validates the effectiveness of the model: In the extraction of equity reduction events, the model in this paper accurately predicts the "end time" (January 25, 2009) and "number of shares held after reduction" (4718117 shares), while PTPCG-DSGAT suffers from isolated node problems due to incorrect recognition of argument importance and recursive decoding errors in traditional BK algorithms, resulting in prediction errors. In summary, this model achieves comprehensive optimization in efficiency, parameter control, and event extraction accuracy through importance calculation and BKP algorithm.

5. Conclusion

Event extraction, as the core task of information extraction, aims to extract structured information from unstructured text. This article focuses on document level financial event extraction and significantly improves accuracy and efficiency through two studies. Firstly, a dependency syntax enhancement model PTPCG-DSGAT is proposed, which encodes text using a BERT pre trained model and combines the dependency syntax enhancement module and GAT entity semantic enhancement module to embed core verb vectors and inter sentence syntactic relationships into entity representations, enhancing semantic modeling capabilities. Experimental results show that its performance is better than baseline; Secondly, to address the issues of insufficient semantic association and decoding efficiency in fully pruned graphs, importance calculation method and non autoregressive BKP decoding algorithm are introduced. Based on RoBERTa learning semantic information, entity vectors are enhanced through DS and GAT modules, and weighted importance calculation is used to optimize pseudo trigger word selection to construct high-quality pruned graphs. Then, the pivot selection mechanism is used to quickly decode entity parameter combinations and finally fill the event record table. Experimental results show that the improved model performs better. The innovation lies in the deep integration of dependency syntax and GAT module for entity semantic representation, weighted importance calculation to enhance the representativeness of pseudo trigger words, and non autoregressive BKP algorithm to reduce search paths through pivot and efficiently decode complex entity relationships. Future research directions include: expanding the model to validate its generalization ability in non-financial fields, and developing visualization tools to enhance the interpretability of pseudo trigger word selection and event parameter extraction, thereby improving user understanding.

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