JCBI
Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 05 Issue 02
2023

Research Article
https://doi.org/10.56979/502/2023

A Temporal Scope Prediction for Storyline Generation Using Events' Knowledge Graphs

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Received: April 03, 2023 **Accepted:** August 21, 2023 **Published:** September 17, 2023.

Abstract: Knowledge graphs (KGs) have become powerful tools for organizing and making sense of complex datasets, especially when time information is included. However, ensuring the accuracy of events in temporal knowledge graphs remains a challenge. To address this issue, researchers proposed a new approach that uses event storyline generation and visualization to analyze trends and situations. The proposed approach involves conducting experiments using traditional embedding techniques and a transformer-based BERT base model to generate temporal graph embeddings. These embeddings result in lower-dimensional representations that are easier to process and input into factorization machines, leading to improved event classification accuracy. The approach was tested using event-based datasets such as ICEWS and Wikidata12k, achieving an accuracy of 80% when compared to the baseline model. This approach shows promise for analyzing trends and situations, with potential applications in industries that require planning, such as disaster planning and cyber-physical systems. By using event storyline generation and visualization, the proposed approach can facilitate downstream applications, such as trend and situation analysis, and improve the accuracy of events in temporal knowledge graphs. This research highlights the significance of knowledge graphs in managing and analyzing vast amounts of data and emphasizes the importance of developing accurate and efficient strategies for decision-making.

Keywords: Knowledge graphs; Temporal Data; Event Storyline; Visualization; Embedding Techniques; BERT; Factorization Machines; Trend Analysis.

1. Introduction

In 2012, Google introduced the term Knowledge Graph (KG) to describe their use of graphs to enhance web search. By enabling users to browse objects, people, or locations instead of just matching keywords, KG revolutionized the search experience [1].

Following Google's lead, other companies like Amazon and Walmart have also incorporated KGs into their operations. KGs have numerous applications such as question answering, semantic search, recommendations, language understanding, and advanced analytics [2–8], Knowledge graphs consist of real-world entities and their relationships depicted in graphs. These graphs provide an extensive collection of entities, semantic attributes, and relationships within a specific domain or dataset, covering all semantic concepts. A Knowledge Graph (KG) is a collection of semantic relationships that establish connections between concepts and entities. These connections can represent real-world objects, events, situations, or abstract ideas [9,10]. KGs have been used to unify data from multiple sources and link various elements within each subject area, such as people, places, or objects, to provide a clearer understanding of the data and eliminate semantic ambiguities [11–13]. A number of methods and applications are being developed in these and related areas by the integration of large data [14,18], KG has several advantages over them. The primary purpose of a KG is to compile and communicate knowledge of the natural world in a specific knowledge expression format for use by applications [19,20]. The most common format for representing information in KGs is "SPO" triples, which consist of a subject (referred to as the head entity), a predicate (capturing a relationship), and an object (referred to as the tail entity) [21,22].

Traditionally, Knowledge Graphs (KGs) have been used to provide a static overview of multi-relational data. However, because they are often incomplete, it is necessary to infer additional information that is not present in the current knowledge. As a result, new facts are continuously added to the KG until it is complete. Despite the assumption that facts do not change over time, these static KGs are valid for the information they contain [23]. However, in real-world scenarios, this assumption is not always accurate. To address this issue, researchers have developed Temporal KGs, which annotate each fact or event with the time of its origin [24-27]. These facts are represented in temporal Knowledge Bases (KBs) using (s; r; o; T) tuples, where T represents the duration of the event. Additionally, recent research [28] has included time intervals in the edges of temporal KGs to depict the relationship between entities over time.This research aims to develop a methodology for classifying the temporal scope of events in knowledge graphs. At present, there is no framework that can generate and visualize storylines with temporally scoped predictions of Knowledge Graphs and automate future planning tasks for specific situations. The research will make the following contributions in this work are summaries as follows:

The pretrained RotatE model is utilized to refine the temporal graph embeddings. By doing so, the embeddings can better capture the changing patterns over time within the graph.

Utilizing the fine-tuned embeddings for downstream tasks such as classification.

This research generates and visualizes storylines to show the changes in the graph's structure over time. By utilizing temporal graph embeddings, it provides a comprehensive view of the graph's dynamics and enables identification of patterns and trends that are not apparent in raw data. The generated storylines offer a useful summary of the graph's temporal evolution, making it easier to interpret and communicate findings to stakeholders.

The study evaluates the effectiveness of the suggested solution by comparing its efficiency with that of existing framework approaches.

The paper is divided into several sections. The first section provides an introduction. In the second section, the literature related to the temporal scope of knowledge graphs is explored in terms of time points, time intervals, and both. The third section outlines the methodology used in the study. Finally, the fourth section presents the results of the experiment.

2. Materials and Methods

Various modern technologies are being developed and utilized with the help of knowledge graphs in numerous fields (e.g. [12,16,25-27,29]). Researchers have developed various techniques to use existing knowledge for development of applications using modern technology in numerous areas of literature (e.g. The researchers introduced a new deep evolutionary knowledge network that can capture the non-linearity of evolutionary entities over time and understand the behavior of entities and their contribution to the formation of facts. They presented a unified framework for knowledge evolution that includes a mathematical tool for temporal point processes (to model the occurrences of facts), a bilinear relationship score (to measure relation interaction), and a deep recurrent network to learn non-linearity [23,30,31].A novel approach for assessing link and time prediction was introduced. The researchers presented TIMEPLEX, a unique TKBC model that can forecast missing entities and missing intervals on benchmark datasets. TIMEPLEX uses tensor factorization of TKBC with complex-valued embeddings for relations, entities, and time. It can handle moderate temporal consistency constraints and takes advantage of the repetitive nature of certain facts/events and the temporal overlap between pairs of occurrences [24]. An extension of relational embeddings, including Naïve trans, Vector-based trans, Coefficient transE, and TRESCAL, was proposed for predicting temporal validity. However, relational embedding faces scalability and performance issues. On the other hand, the factorization machine addresses these concerns while also handling side information, making it well-suited for time-scope prediction tasks [28].

Generic statements can be used to infer missing statements using temporal knowledge base completion (TKBC). The researchers developed Time2Box, a new knowledge base embedding framework that can handle both atemporal and temporal assertions for different types of data. It can deal with scenarios where time is represented as an instant, left/right open interval, closed interval, or none, with a granularity of one year during the time interval I. The TKBC model was evaluated using two tasks: link prediction and time prediction, and it outperformed state-of-the-art result [25,26,32]. A system for determining the temporal scope of relational facts using distant supervision on Wikipedia data was also presented. Distant supervision is a two-stage model. In the first stage, a language model containing patterns of entity type is trained to extract the maximum k sentences that support the association. In the second stage, the timestamps of "start," "end," and "in" are classified. The temporal classification is based on a gradient-boosted decision tree and performed well on 6 out of 7 relationship types on a benchmark text analysis conference [33]. Another proposed model [34] covers different time validity and granularity. This system projects entities and relationships into timestamped layers and jointly learns entity and relation semantic information with time layers based on Gregorian division.

TRHyTE is research that provides a novel method for embedding temporal knowledge graphs. It uses hyperplane clustering to project knowledge graph items onto temporal-relational hyperplanes. To capture connections, its objective function maximizes both structural and material information. TRHyTE surpassed leading approaches in a triple temporal classification and temporal link prediction test, as well as in real-world applications. TRHyTE offers various applications in finance, healthcare, and social media. Study provides a streamlined method for discovering semantic linkages that use graph traversal and pattern-matching techniques. It delivers great accuracy and efficiency compared to previous approaches, making it scalable for huge knowledge networks. The contributions of this study include simplicity and a robust method for extracting semantic links from knowledge graphs, which has implications for various applications, including information retrieval, recommendation systems, and natural language processing.

The researchers performed cross-document co-reference (CDCR) across multiple domains. Unlike previous work that assumed all documents were different, this study referenced entities and concepts in both scientific work and newspapers. They developed an open-source annotation tool to examine the lexical representation of texts and compared their findings with baseline models, outperforming state-of-the-art results [35]. The current long-range transformer was improved by using dynamic global attention to access the entire input [36]. A unique pretraining strategy was developed to pretrain a collection of multi-related documents to understand cross-document connections. The multi-news dataset was used, and the model's perplexity was tested on the benchmark ECB+ Corpus, outperforming state-of-the-art results. A novel method for NLP with PDDL was demonstrated through intelligent planning-based story building. Semantic information from news was collected to create a domain knowledge model, which was then used to design the event storyline. The model generates not only past event information but also action sequence measurements. Actions (predicate, object, subject) are extracted using a dependency parsing tool and a domain model to obtain the initial and goal states from information. The GLAIVE planner is then used to plan the government's actions [37]. Researchers have employed various learning models for classification and prediction tasks [13,31,38-54]. Factorization Machines (FM) are supervised learning models that can transform any real-valued data into a low-dimensional latent factor space. They can be easily applied to a wide range of prediction tasks such as regression, classification, and ranking [55-58].

Table 1 presents a critical analysis that was conducted during the literature review process. Through this analysis, we discovered that existing work focuses on temporal scope prediction using various time granularities. However, none of these studies address storyline generation and its visualization simultaneously. Therefore, we sought to bridge this gap in existing research: we developed a novel approach to the temporal scope prediction using the ROTATE model, while also generating storylines and visualizations. Our proposed research demonstrates that the ROTATE model is highly effective in making accurate temporal predictions. Moreover, we showcase the effectiveness of our storyline generation and visualization techniques, which enable users to better understand complex temporal relationships.

Table 1. Critical Analysis

Article	Temporal Scope	Storyline Generation & Visualization
[1]	Yes, One-year granularity, Discrete data timestamped	No
[2]	Yes, One-year granularity for interval dataset, One-day granularity for ICEWS dataset	No

[3]	No	Yes, but not generate visualization
[4]	Yes, One-year granularity , Discrete data timestamped	No
[5]	Yes, Multiple granularity	No
[6]	Yes, Temporal granularity of 15 mints for global dataset, Temporal granularity of 24 hrs. for Integrated crisis	No

Author describe a large and sophisticated framework designed to reliably forecast the temporal span of occurrences. To ensure the experiment's success, various and highly authoritative datasets such as ICEWS14, ICEWS22, and Wikidata12k were carefully chosen for proposed work. The model's effectiveness was increased by combining the most sophisticated models available on the market - Transformer BERT (Base) and Pretrained ROTATE. Sensationalizing the model's performance and accuracy, subject, predict, and object (SPO) were hand-picked as essential parameters from these datasets. By constructing strong embeddings, the system grew skilled at capturing the subtleties and nuances that characterize the ever-changing graphs, giving insights beyond expectations. For the classification step, efficient and effective factorization machines were used. These devices were crucial in identifying and evaluating event facts and their correctness and validity. The entire design of the framework, as shown in Figure 1 , marks a watershed moment in the approach to interpreting and analyzing temporal data. With the ability to offer precise and dependable findings, this framework remains a strong and promising alternative to conventional methodologies.

2.1. Data Description

Three distinct datasets, namely ICEWS22, ICEWS14, and Wikidata12k, were selected as the temporal scope for analysis. In ICEWS14 and ICEWS22, there are 7,128 and 7,026 entities and 230 and 210 relations, respectively. In Wikidata12k are a total of 12,000 statements in Wikidata, which include time points and time intervals and 24 relations and events were extracted. Even though the work in [28] used wikidata180k, which included facts with a temporal. Annotation, the study in [59] extracted the temporally rich subgraph from wikidata180k while making sure the subgraph has start and endpoints. And ensure that no objects are joined by a single edge directly. For that, wikidata12k provides 40k triples with 12.5k entities and comprises. The most common rich relation/connection. This is the reason used wikidata12k to verify proposed results. The data statistics of the datasets used and their splits, which include train, validation, and test sets, are provided in Table 2.

Table 2. Dataset Statistics

	ICEWS14	ICEWS22	Wikidata
#Entities	7128	7026	12554
#Relations	230	210	24
#Time	[Date]	[Date]	[Year]
Train	63510	32552	28434
Valid	13610	6979	6094
Test	13610	6979	6093

2.2. Data Preprocessing:

The datasets were preprocessed using a specific methodology that involved the selection of facts based on the time of interest. The selected facts were assigned unique IDs to facilitate ease of analysis and tracking. The resulting preprocessed dataset was compiled, ensuring that the data was of high quality and free from any inconsistencies or errors. This allowed for a robust and reliable dataset to be used in subsequent phases of the project.

2.3. Embedding Generation:

The generation of embeddings was divided into two parts. In the first part, the facts were embedded using the BERT base model. BERT is a language model that combines textual information with metadata to enrich knowledge graph embeddings. A previous study utilized a pre-trained model to embed both temporal and atemporal entities into a low-dimensional vector space for use in a question-answer model

[60]. To achieve an accurate and complete analysis, this research treated facts differently than in previous studies. The research preprocessed the material facts into strings and the time aspect using one-hot encoding. This strategic strategy yielded complete vectors as inputs to the BERT base model. Cosine similarity was used to find similarities and differences between the various facts in the dataset to assess the efficiency of these embeddings. This rigorous method underlines the study's imaginative and adaptable character, paving the path for more precise and dependable results.

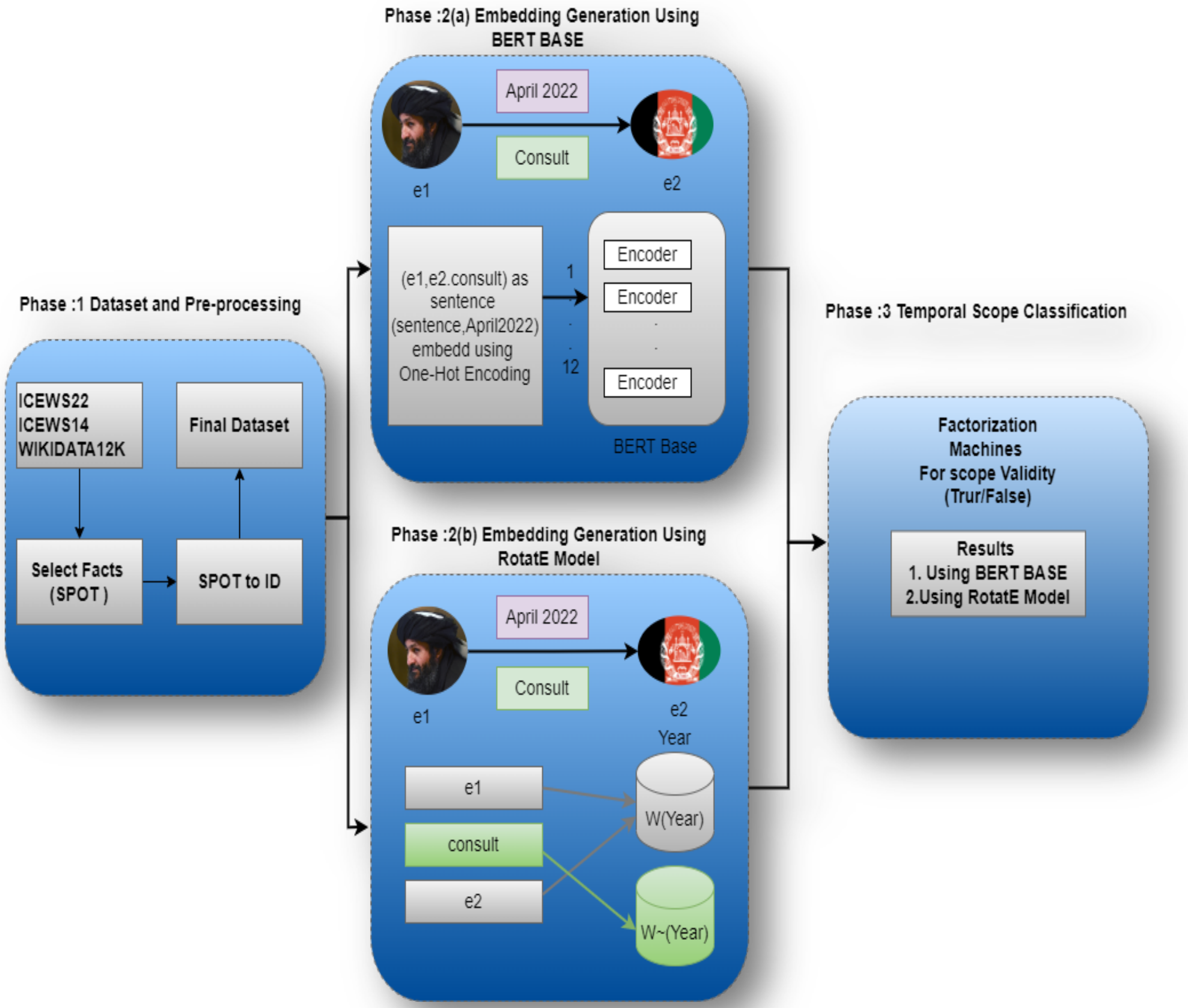

Figure 1. Proposed Methodology

The study's second method was to create embeddings using a pre-trained RotatE model, which gave fresh insights into dealing with connections and temporal aspects in datasets. To do this, time was considered a real Gregorian division, and each relation was specified as a rotation in the complex vector space from the source object to the destination item. Negative sampling methods improved efficiency and offered unparalleled granularity in capturing interactions between the dataset's many elements. Because the emphasis of this investigation was on temporal elements, a uniquely designed technique was used. The dimensions of the resultant embeddings were defined by the size of ∣Ti∣ x H2, with T indicating the time level (C, D, Y, M, D) and H representing the hidden dimension of the SPO triplets. The time level used was determined by the scope of the investigation and was specified as [(min, max), T]. This rigorous method allowed for more extensive knowledge of the dataset's temporal linkages, allowing for the discovery of subtle patterns and trends throughout time and leading to a more accurate data analysis. As a result, the experiment yielded unique insights into the interconnections of relationships and temporal dynamics in datasets, highlighting the study's boldness and inventive spirit.

2.4. Factorization Machines:

Factorization Machines were used in this experiment to capture the interaction between features when dealing with sparse and high-dimensional datasets. Factorization Machines are a generalized technique that allows feature engineering to replicate most factorization models. They were utilized in this experiment as a supervised learning algorithm for classification and regression tasks. Factorization Machines provide flexibility in feature extraction and high prediction accuracy. The major goal of this research was to establish the temporal span of knowledge graphs using events from temporal datasets. The first experiment used Bert-based embeddings with time handled as a string, whereas the second experiment used pre-trained Rotate embeddings with time regarded as a real Gregorian division. In all trials, Factorization Machines were utilized as the learning method for temporal scope categorization. This method combined stochastic gradient descent with adaptive learning, simplifying and improving the learning process and yielding more exact and dependable results. Overall, this cutting-edge experiment gives essential insights into the potential of Factorization Machines in managing temporal dynamics and effectively identifying knowledge graph temporal scopes in high-dimensional datasets.

3. Results

The proposed experiment performance was measured using standard measures such as accuracy, precision, recall, and F1-score. This experiment provided valuable insights into the use of Factorization Machines and how they can be utilized to handle complex data sets such as temporal knowledge graphs in a supervised learning environment.

3.1. Experimental Settings

To carry out the research experiment, we employed specific technologies and tools. Python version 3.9 was chosen as the programming language because of its wide array of libraries and tools for tasks such as data processing, analysis, and visualization. We employed the Google Colab Notebook development framework for the experiment, utilizing Python 3.9 as the selected language. Windows was selected as the operating system due to its dependable and efficient performance when running Python applications. The experiment was executed on a robust laptop with a Hair 11y c processor and ample memory. Additionally, we integrated an Nvidia 1060 graphics processing unit (GPU) into the experimental setup, which facilitated swift and efficient parallel processing, thereby speeding up the training and evaluation of deep learning models. Table 3 provides a summary of the various tools and technologies employed in the experimental setup, aiding in a better understanding of the setup and the resources utilized in the deep learning experiment.

Table 3. Experimental Parameters

Parameters	Values
Framework	Google Colab
Operating System	Windows
Hardware Platforms	Dell Spectre
GPU	Nvidia 1060
Programming Language	Python 3.9

3.2. Evaluation Matrix

In the current study, a range of evaluation metrics is employed to thoroughly evaluate the model's performance. These metrics include accuracy, precision, recall, sensitivity, specificity, F1-score, and the confusion matrix, aiming to attain exceptionally high levels of analytical precision and accuracy. Accuracy, which is the most easily understood metric, measures the percentage of correctly classified instances out of the total number of instances. This fundamental metric can be computed using the following equation:

$$\text{Accuracy}=(TP+TN)/(2TP+FP+FN+TN) \quad (1)$$

As a performance measurement, precision indicates the proportion of true positive predictions among all positive predictions, offering insights into the model's capacity to minimize false positives. This essential metric can be calculated using the provided equation:

$$\text{Precision}=TP/(TP+FP) \quad (2)$$

Recall, often referred to as sensitivity, is a crucial performance metric that evaluates the model's capacity to identify all true positive instances within the dataset. This invaluable metric can be calculated using the provided equation:

Recall=TP/(TP+FN) (3)

Specificity is a critical performance metric that assesses the model's capability to identify all negative instances within the dataset. It quantifies the proportion of true negative predictions among all negative instances in the dataset and can be computed using the equation provided:

Specificity=TN/(TN+FP) (4)

The F1-score, as a measure of excellence, combines the previously mentioned precision and recall metrics to create a unified and informative assessment of the overall model performance. This crucial metric is essential for evaluating the system's effectiveness and can be calculated using the provided equation:

F1 Score=(2*precession*Recall)/(Precession + Recall) (5)

3.3. Hyperparameters Setup

The proposed model is implemented using PyTorch library in python. The pretrained RotatE embedding produced using code in [36].Table 4 displays the experiments conducted on three different datasets, namely RotatE, BERT, and Factorization machines. It includes information about hyperparameters such as epochs, batch size, learning rate, and negative sampling. The hyper-parameters for both experiments for embeddings and factorization machines are shown in Table 4.

Table 4. Hyperparameters

Experiment	ICEWS14	ICEWS22	Wikidata
RotatE Model	Negative sample =0 Batch_size=1024 Learning rate=0.001	Negative sample =0 Batch_size=1024 Learning rate=0.001	Negative sample =128 Batch_size=1024 Learning rate=0.001
BERT Base		Num_fac=5 Epochs=5 Learning rate=0.001	
Factorization Machines	Num_fac=5 Epochs=50 Learning rate=0.001	Num_fac=5 Epochs=50 Learning rate=0.001	Num_fac=5 Epochs=50 Learning rate=0.001

3.4. Factorizations Machines

The factorization machines result on ICEWS22 using BERT BASE are shown in Table 5.

Table 5. Factorization Machines Results on ICEWS22 using BERT Base

Evaluation Matrix	Test
Accuracy	0.7595
Recall	0.8849
Precision	0.7948
F1-Score	0.8374

The results of factorization machines on ICEWS14 utilizing the Rotate model are presented in Table 6.

Table 6. Factorization Machines Results on ICEWS14 using RotatE

Evaluation Matrix	Train	Valid	Test
Accuracy	0.8245	0.8235	0.8262
Recall	0.9044	0.9051	0.9027
Precision	0.9009	0.8994	0.9005
F1-Score	0.9027	0.9023	0.9038

The results of factorization machines on ICEWS22 utilizing the Rotate model are available in Table 7.

Table 7. Factorization Machines Results on ICEWS22 using RotatE

Evaluation Matrix	Train	Valid	Test

Accuracy	0.7974	0.7963	0.7990
Recall	0.8724	0.8715	0.8729
Precision	0.8995	0.8991	0.9007
F1-Score	0.8857	0.8851	0.8866

Finally, the outcomes of factorization machines on Wikidata12k using the Rotate model can be found in Table 8.

Table 8. Factorization Machines Results on Wikidata12k

Evaluation Matrix	Test
Accuracy	0.8000
Recall	0.8700
Precision	0.9000
F1-Score	0.8900

In our experimentation with factorization machines, we evaluated their performance on three different datasets: ICEWS14, ICEWS22, and Wikidata12k. Our analysis revealed that compared to the baseline model, the use of factorization machines resulted in significant improvements across all three datasets. Furthermore, we found that our approach achieved even better results. Our results on Wikidata12k surpassed those of the reference model, making it the highest-performing model in our analysis.

Table 9 shows the Factorization machines results on ICEWS14, ICEWS22 and Wikidata12k with baseline model in [28] on Wikidata12k.

Table 9. Factorization Machines Results with Baseline Model

Models	Accuracy	Recall	Precision
ICEWS14	82.62	90.27	90.05
ICEWS22	79.90	87.29	90.07
Wikidata12K	80.00	87.00	90.00
Baseline [4]	60.23	71.27	58.44

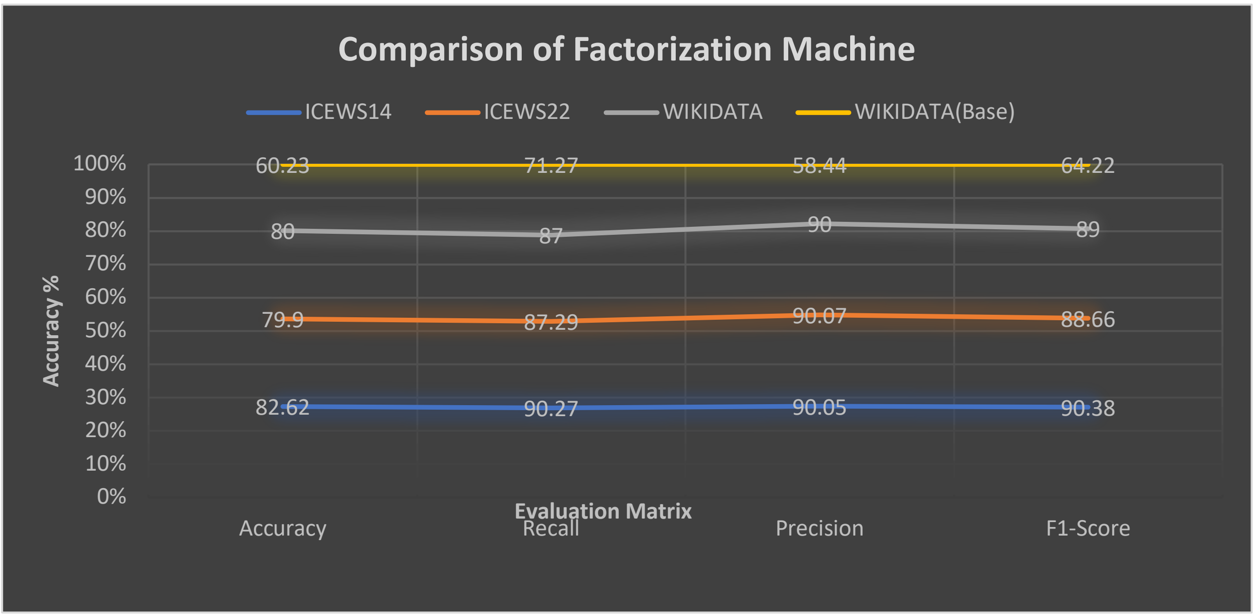

Figure 2. Graphical representation of the Factorization Machine with Baseline model

3.5. Storyline Visualization of ICEWS22 Dataset

ICEWS22 is a massive dataset that contains information about various events happening globally. Understanding the dynamics of this dataset is crucial in predicting future events and drawing insights into relationships between entities. To achieve this, it is essential to visualize the storyline of the dataset and track the evolution of entities and related changes over time. The storyline visualization shows the relationship changes between subject, predicate, and object entities with respect to time. Subject entities may include individuals, cities, countries, or groups. Predicate entities can include actions such as "consult," while object entities may be individuals, cities, countries, or groups. The visualization allows for an analysis of the relationship changes between entities over years, quarters, months, and dates. Moreover, if target entities have a relationship with the respective source entities at least five times, it indicates that they will likely have a relationship in the future as well.

By tracking these relationships, we can better understand how the world's entities interact with each other and how these interactions evolve over time. Visualization can provide valuable insights into geopolitical trends, trade relationships, and individual behavior.

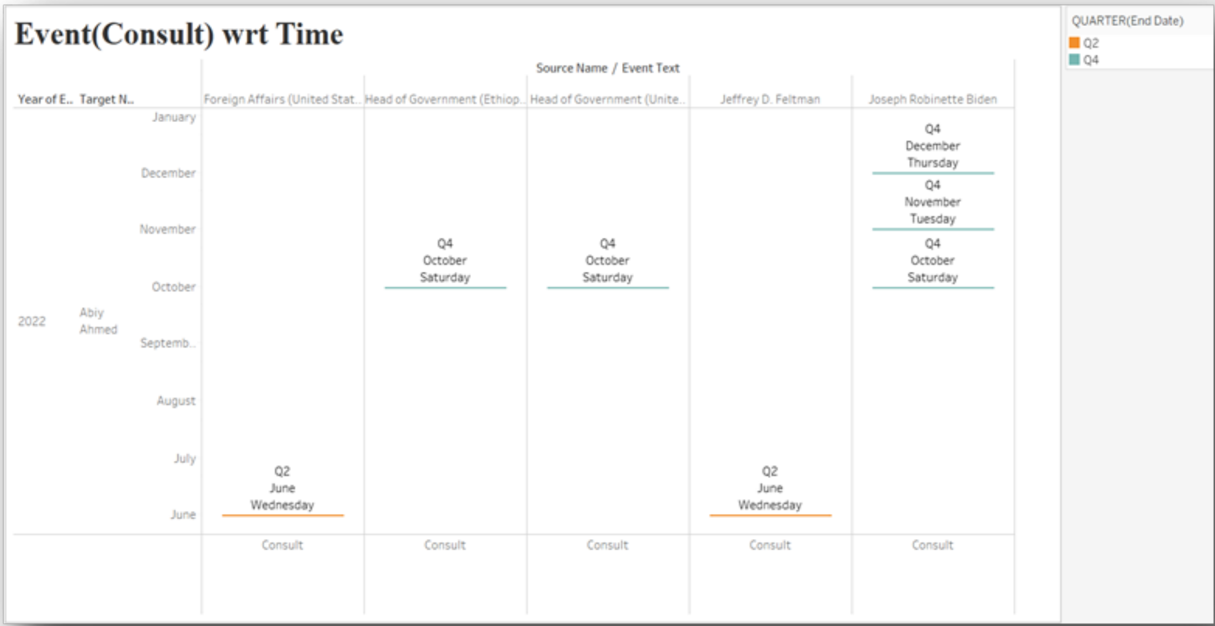

Figure 3a. Event (Consult) wrt Time

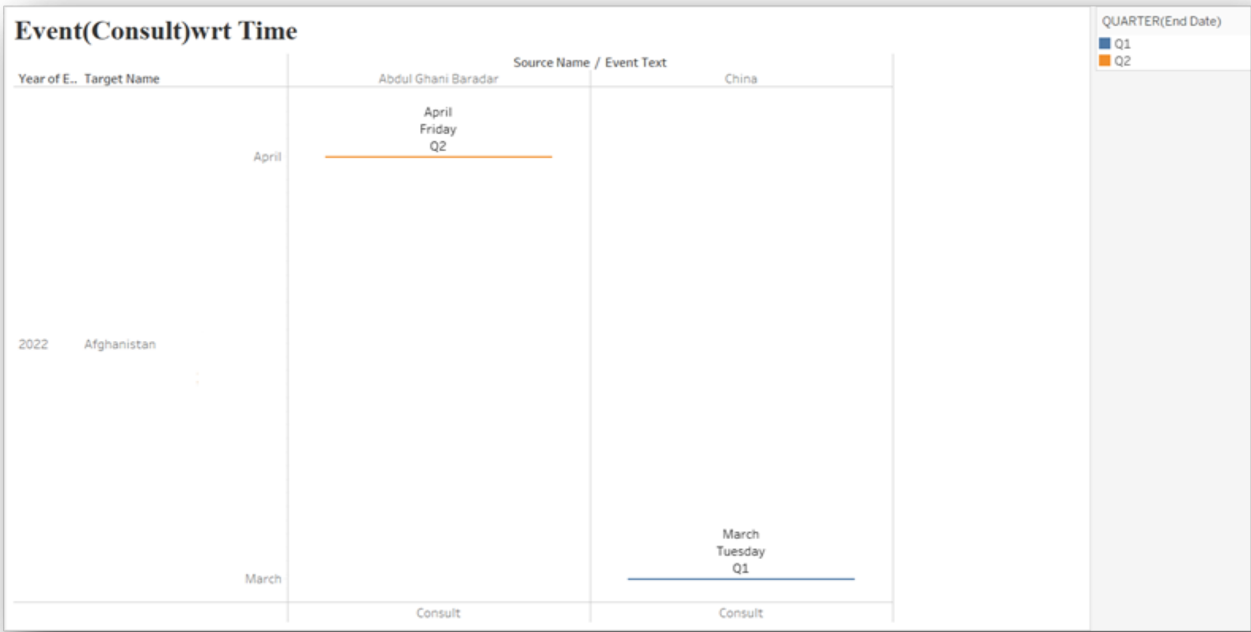

Figure 3b. Event (Consult) wrt Time

Figure 3c. Event (Consult) wrt Time

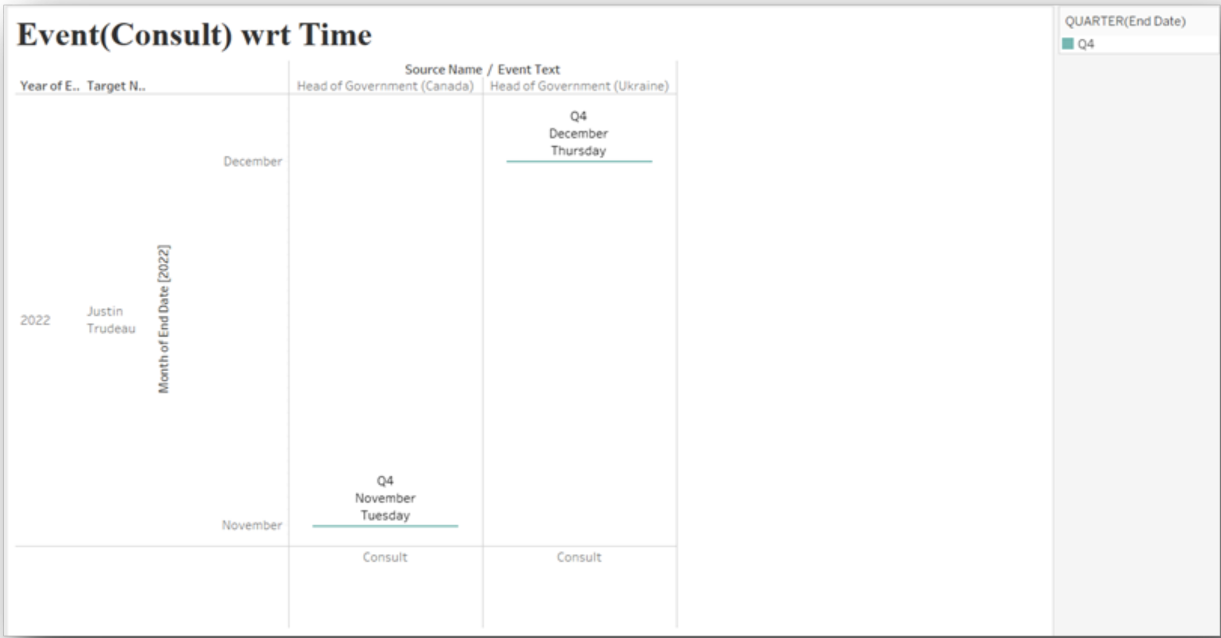

Figure 3d. Event (Consult) wrt Time

4. Discussion

The study addressed challenges related to temporal knowledge graphs and their metadata handling. Two experiments were conducted using different datasets to generate embeddings for entities and relationships over time. These embeddings were then used in a machine learning algorithm for classification. The study outperformed existing techniques, especially on the Wikidata12k dataset. The research introduced two frameworks for generating embeddings, which could enhance metadata handling in temporal knowledge graphs. The ultimate goal is to standardize information sharing, making real-world applications more automated and applicable to various domains. This development has the potential to revolutionize industries like machine learning, artificial intelligence, and medicine, promising enhanced productivity, and possibilities in different fields.

5. Conclusion

Temporal knowledge graphs pose challenges in handling metadata with entities and relationships, and existing techniques have scalability and reliability issues. This study conducts two experiments using the ICEWS14, ICEWS22 and Wikidaat12k datasets to generate embeddings for entities and relationships over time and input them to a machine learning algorithm for scope classification of temporal knowledge graphs. Experiment one uses the BERT model, while experiment two uses the pretrained RotatE embeddings for better contextual handling of entities and relationships over time. The generated embeddings undergo dimensionality reduction before inputting them into factorization machines for classification. The proposed study outperforms well when comparing the performance of factorization machines, specifically on the Wikidata12k dataset with the model described in.Our study proposed two frameworks for generating embeddings, which are utilized as input for the machine learning algorithm. These frameworks are expected to aid in efficiently handling the metadata with entities and relationships in temporal knowledge graphs. Going forward, our research aims to develop a standardized format for sharing all relevant information, thereby making real-world applications more automated. This standardization can be applicable across various domains, including but not limited to supply chain management and cyber-physical systems. With this development, stakeholders will have access to a more streamlined and efficient process for utilizing temporal knowledge graphs in their applications. This groundbreaking development not only heralds a new era of innovation but also paves the way for widespread adoption across an array of industries, including the realms of machine learning, artificial intelligence, natural language processing, medicine, and biology. Such a momentous stride forward undoubtedly promises a future teeming with myriad use cases, fostering enhanced productivity and unbounded possibilities in a multitude of fields.

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