# Forecasting Future Topic Trends in the Blockchain Domain: Using Graph Convolutional Network

Joint Workshop of the 4th Extraction and Evaluation of Knowledge Entities from Scientific Documents (EEKE2023) and the 3rd AI + Informetrics (AII2023)

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# Introduction

- In modern society, **keeping up with recent trends is crucial** for individuals and organizations to succeed, but it can be a difficult task.
- **Time series forecasting** has emerged as a promising approach, enabling the analysis of temporal data and the **discovery of patterns and trends**.
- Leveraging historical and current trends enables individuals and organizations to **gain a competitive advantage in the market**, particularly within the blockchain domain by making informed future predictions.

# Introduction

- Deep learning methods such as **LSTM and GCNs have shown promise for topic trend predictions** by capturing the temporal and structural dependencies between topics.

- However, **the integration of topic modeling into these models remains unexplored**, preventing a comprehensive grasp of the research field's main themes and sub-topics.

- We propose a new approach that **integrates topic modeling and GCNs to predict upcoming topic trends** within the **blockchain field**.

# Overall Workflow

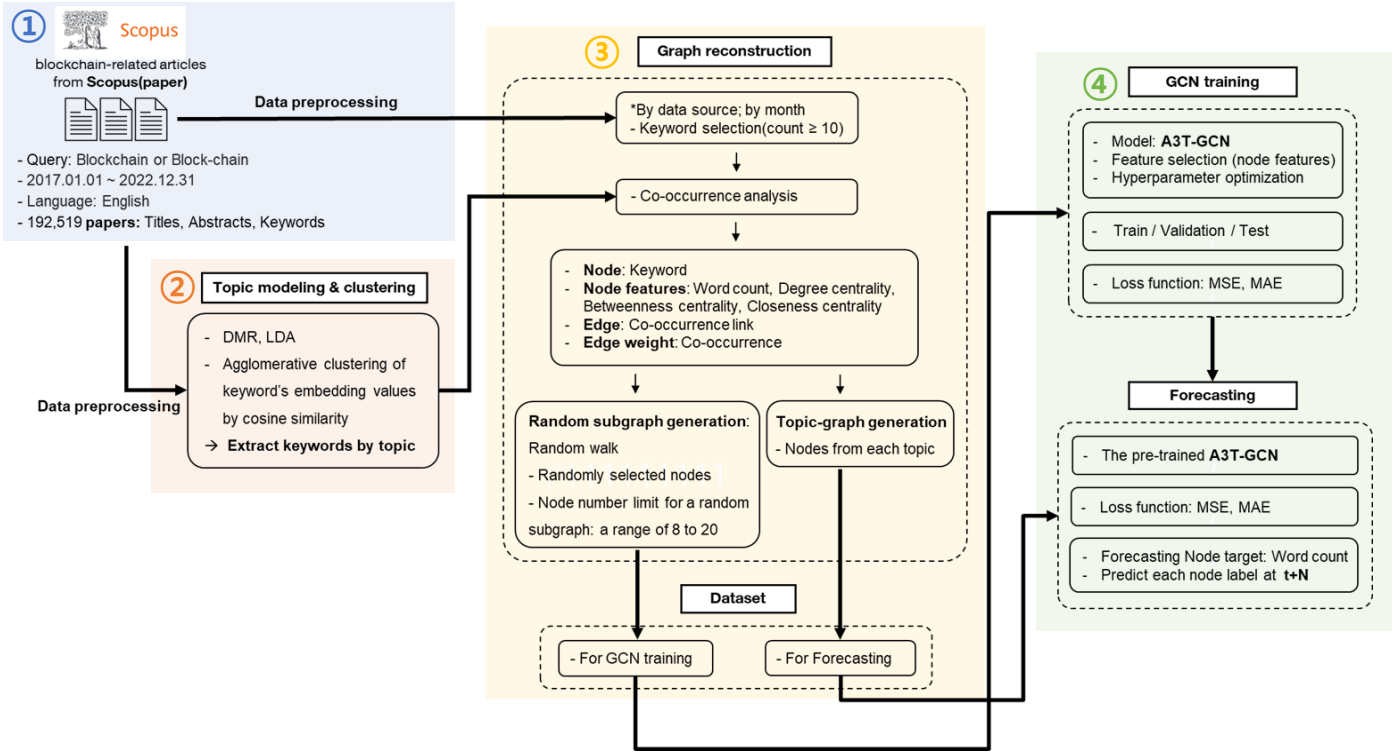



**Figure 1. The Overall Schematic Research Workflow**

# **Methodology:** ① Data Preparation

- Total of **192,519** papers were collected:
  - Target text: **Titles, Abstracts, Keywords** of research papers
  - Period: January 1st, 2017 ~ December 31st, 2022 (**72-month**)
  - Search query: **"Blockchain or Block-chain"** (in Scopus database)

- Based on this, we perform several preprocessing steps:

1) Convert all text to lowercase
2) Divide the text into sentence units using NLTK
3) Tokenize sentences into words
4) Employ NLTK for part-of-speech tagging
5) Retain words tagged as nouns(unigram)
6) Filter out stopwords (commonly used, meaningless, and major topic words)

→ **In this process, focus on relevant and meaningful terms.**

# **Methodology:** ② Topic Modeling and Clustering

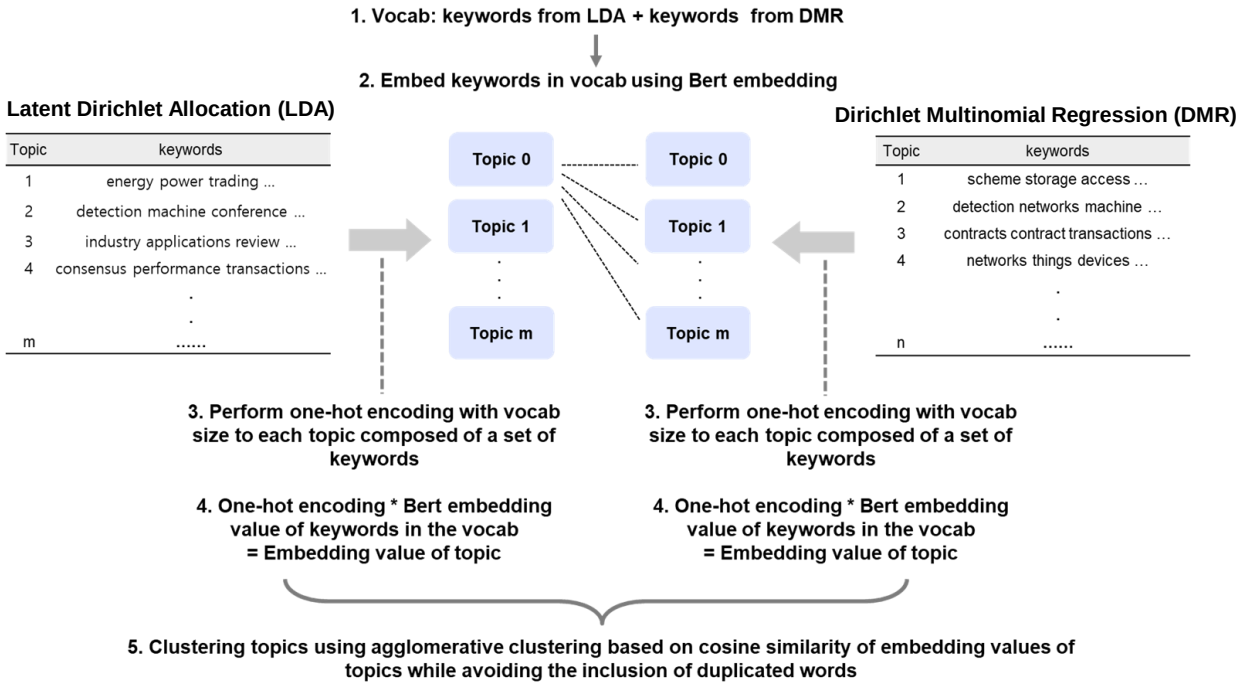



**Figure 2. Topic clustering using agglomerative clustering based on the cosine similarity of their embedding values.**

# Methodology: ③ Graph Reconstruction

## Time Serial Document Graph

- Every node and edge in the graph are annotated with their corresponding **monthly-based** features.
  **(72 time points → 72 time-specific graphs)**

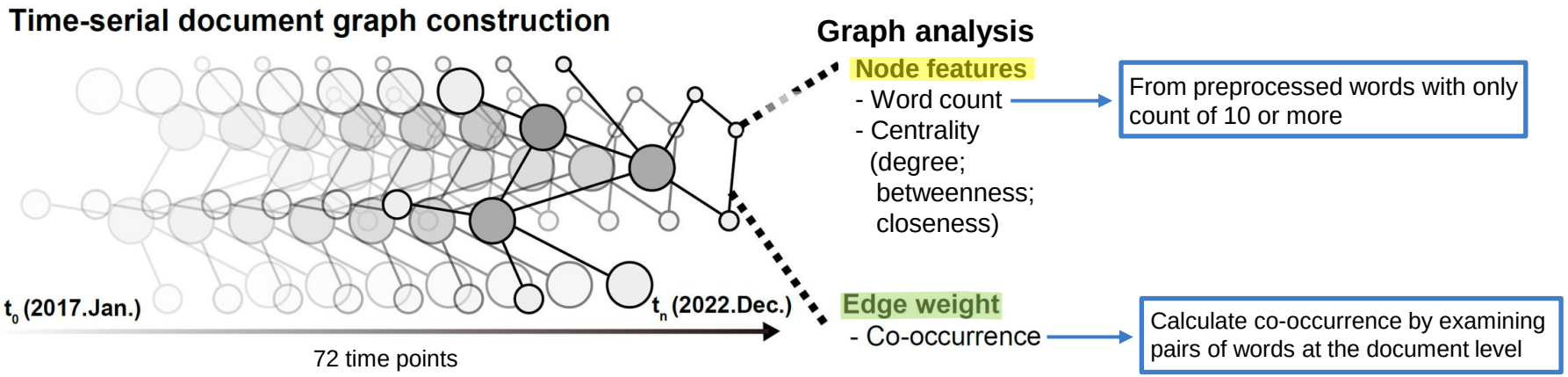



**Figure 3. (a) Document graph**

# Methodology: ③ Graph Reconstruction

- **Time Serial Random Subgraph**
  - Construct random subgraphs using the **random walk** method.
  - Employ random subgraphs for **training GCNs**.

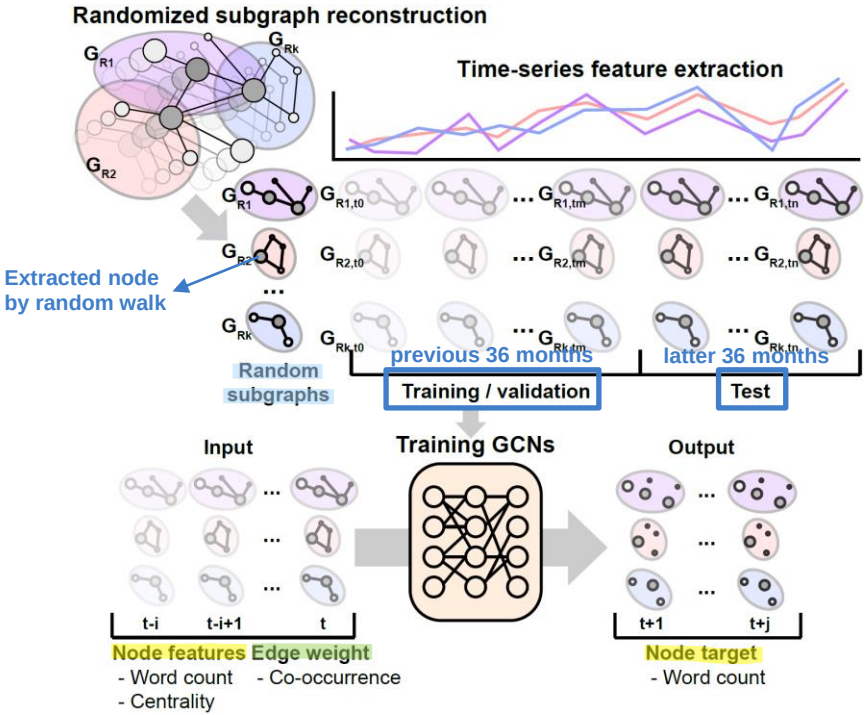



**Figure 3. (b) Random subgraphs**

# Methodology: ③ Graph Reconstruction

- **Time Serial Topic Subgraph**
  - Node: **topic keyword** (from LDA, DMR)
  - Employ topic subgraphs on a pre-trained GCN model for **forecasting.**

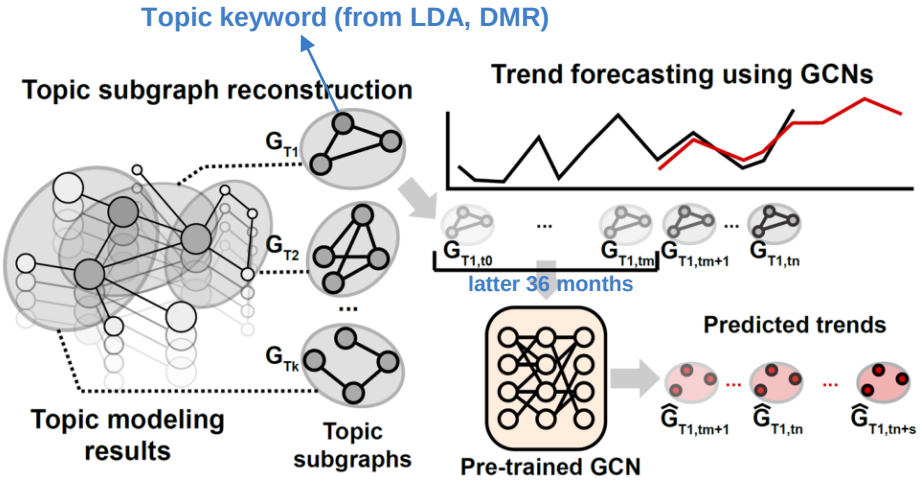



**Figure 3. (c) Topic subgraphs**

# **Methodology:** ④ Topic Trend Forecasting

## A3T-GCN Model

- **A3T-GCN** model effectively captures global variation trends by re-weighting historical information.
- To capture the changes in topic trends, we update the node features, and edge weight on a monthly basis when constructing the subgraphs.

  → Changes in the node's word count are assumed to indicate changes in topic trends.
- **Predict** changes in **word count(Node target)** using information such as centrality and co-occurrence.

# Methodology: ④ Topic Trend Forecasting

## Training A3T-GCN Model

- **Feature selection** on the node features and **hyperparameter optimization**.
- **Train** the **A3T-GCN model** using **random subgraphs** with a fixed lookback window of 12 months to predict **word count (Node target)** for future time periods (1, 3, 6, 9, or 12 months ahead).

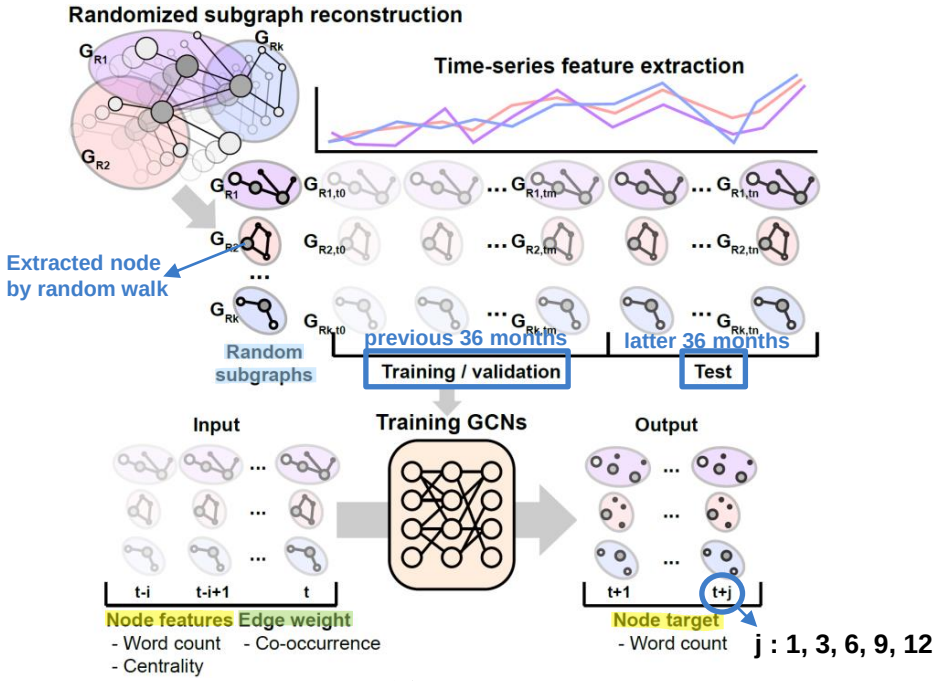



**Figure 3. (b) Random subgraphs**

# Methodology: ④ Topic Trend Forecasting

## Forecasting

- Employ **topic subgraphs** on a pre-trained A3T-GCN model for **forecasting** to predict **word count (Node target)** for future time periods (1, 3, 6, 9, or 12 months ahead).

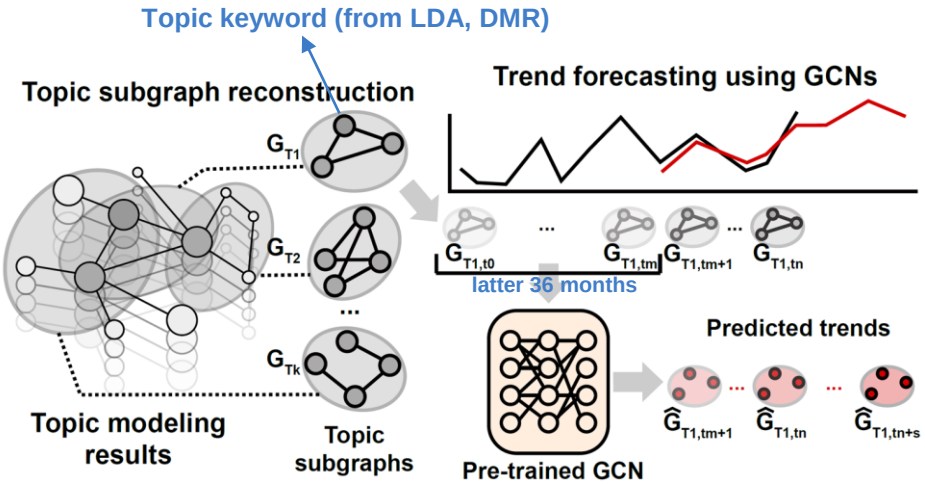



**Figure 3. (c) Topic subgraphs**

# **Results:** Topic Clustering

- This is the result of the clustering process for topic modeling.
- Evaluation Metric: Silhouette Score (Score was **0.8038** which represents good performance)

**Table 1. The results of topic clustering**

| Topic | Keywords |
|---|---|
| 1 | contracts; contract; ethereum; software; applications; voting; blockchains; smart; execution; framework; platform; service; architecture |
| 2 | scheme; privacy; access; authentication; encryption; control; storage; vehicles; secure; signature; storage; identity; protection |
| 3 | iot; internet; things; devices; networks; edge; communication; privacy; architecture; healthcare; health; applications |
| 4 | energy; power; trading; market; grid; electricity; transaction; consumption; demand; resources; resource |
| 5 | learning; detection; machine; networks; conference; algorithm; proceedings; topics; papers; prediction; image |
| 6 | health; healthcare; records; education; patients; patient; privacy; record; care; insurance |
| 7 | bitcoin; cryptocurrency; transactions; transaction; cryptocurrencies; payment; market; currency; money; price |
| 8 | supply; traceability; food; industry; logistics; chains; products; quality; manufacturing; production |
| 9 | consensus; nodes; block; protocol; algorithm; transaction; performance; transactions; mining; blockchains |
| 10 | service; trust; identity; platform; privacy; storage; services; solution; records; integrity |
| 11 | research; industry; review; applications; literature; adoption; application; economy; innovation; intelligence |

# **Results:** Time-series graphs and feature

- As the timeline of collected data has 72-time points, 72 time-specific subgraphs with word count, co-occurrence, and centralities have been extracted for each topic.

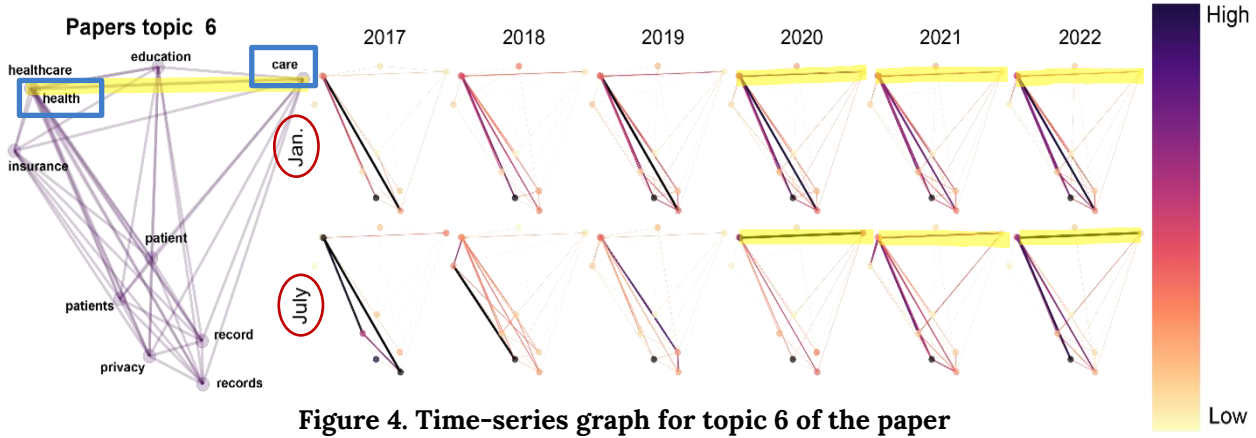



**Figure 4. Time-series graph for topic 6 of the paper**

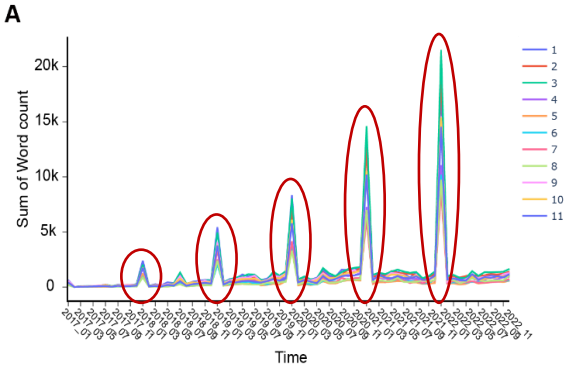
→ As a result, the structure of co-occurrence for topic subgraphs seems dynamic.

# **Results:** Time-series graphs and feature

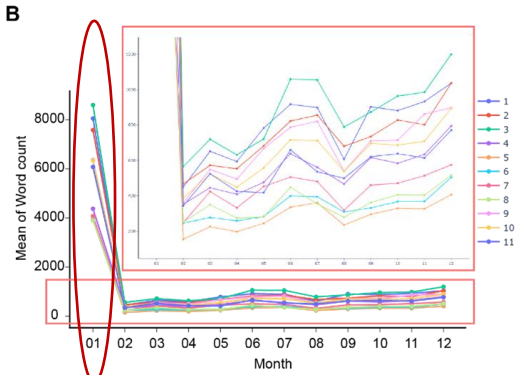
- Seasonality of paper documents, when analyzing word counts of topic keywords.

  → (a), (b) showed **month-specific trends.**

  → Word count in **January** was remarkably increased for all the topics every year.




(a) The whole timeline word count for each topic of papers




(b) The average word count by month for paper topics

**Figure 5. Seasonality of paper documents**

- Evaluation metrics: Mean Squared Error (MSE) and Mean Absolute Error (MAE).

The lowest MSE, MAE

# **Results:** Topic trend forecasting

**Feature selection**
(betweenness, closeness)

→

**Pre-train A3T-GCN**
(random subgraphs)

→

**Forecasting**
(topic subgraphs)

**Table 2. The results of the feature selection**

| Features | | | MSE | MAE |
|---|---|---|---|---|
| betweenness | closeness | degree | | |
| O | X | X | 0.01941 | 0.09639 |
| X | O | X | 0.02591 | 0.11322 |
| X | X | O | 0.02092 | 0.10229 |
| **O** | **O** | **X** | **0.01764** | **0.09616** |
| X | O | O | 0.01873 | 0.09704 |
| O | X | O | 0.02067 | 0.10174 |
| O | O | O | 0.01826 | 0.09719 |

**Table 3. Forecasting Results on Random Subgraphs(test dataset) with optimal A3T-GCN model**

| Random Subgraphs | | |
|---|---|---|
| Forecasting horizon | MSE | MAE |
| 1 | 0.02091 | 0.10093 |
| **3** | **0.01580** | **0.08669** |
| 6 | 0.02370 | 0,10147 |
| 9 | 0.03628 | 0.12595 |
| 12 | 0.04522 | 0.13420 |

**Table 4. Forecasting Results on topic graphs with pre-trained A3T-GCN model**

| Topic Graphs | | |
|---|---|---|
| Forecasting horizon | MSE | MAE |
| 1 | 0.01342 | 0.08850 |
| **3** | **0.00820** | **0.07501** |
| 6 | 0.01618 | 0.09025 |
| 9 | 0.02926 | 0.10925 |
| 12 | 0.03055 | 0.10695 |

# **Results:** Topic trend forecasting

- The **blue line** in the graph shows the **actual frequency** of keywords in the topic, while the **orange line** represents the **predicted word count**.
- The **predicted line** closely matches the **ground truth line**, indicating the effectiveness of the topic trend forecasting.

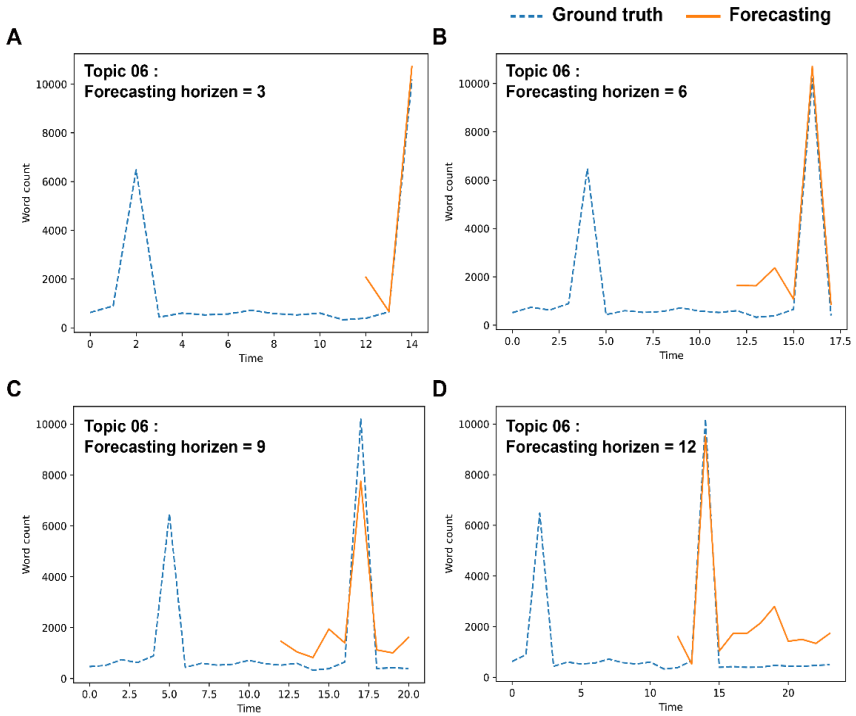



**Figure 6. The trend forecasting results for Topic 6.**

# **Results:** Topic trend forecasting

- The **predicted mean word count** exhibits **similar trends** and values to the **actual mean word count** across all forecasting horizons.

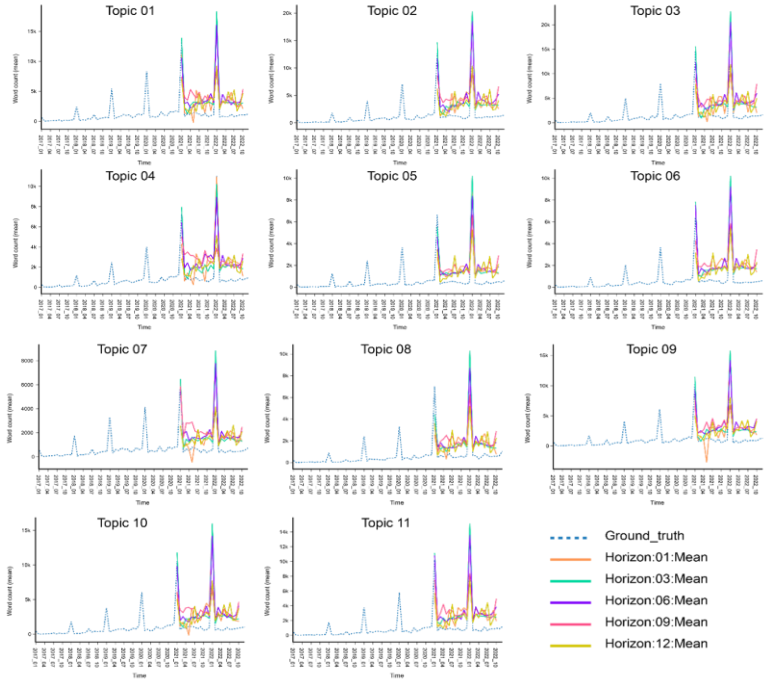



**Figure 7. Mean of word count for the topic trend forecasting models by forecasting horizon.**

# Conclusion

- We propose a novel approach for forecasting future topic trends in the blockchain domain **using a combination of topic modeling techniques and graph convolutional networks (GCNs).**

- GCN model shows **great performance in the prediction** of topic trends, even if it was trained using random subgraphs of the overall document.

- Our proposed approach has implications for **researchers, businesses, professionals, and policymakers**, as it can **provide valuable insights for making informed predictions about the future in the rapidly evolving blockchain field** by providing a powerful and reliable tool for trend forecasting and analysis.

# Conclusion

- Limitation and future work

1. Currently, our model is limited to the application of academic papers and cannot be extended to other data sources.
   → Our next step involves the design and training of GCN models tailored for forecasting topic trends in patent and news data.

2. Apart from A3T-GCN, we did not include experiments comparing our model with other models.
   → We plan to compare our proposed approach with other state-of-the-art time-series methodologies, including both deep-learning and traditional methods, to demonstrate its effectiveness and superiority in future research.

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# Thank You

# Q & A