

Knowledge Graph Construction of Near-Homonymy and Near-Synonymy English Words

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Abstract. This paper investigates the issue of near-homonymy and near-synonymy in English vocabulary learning and explores the significance and practical value of addressing this problem. Through data analysis, we emphasize the widespread demand for English language acquisition and the importance of the English language. Furthermore, we cite research in the field of education to provide evidence of the positive impact of near-homonymy and near-synonymy on word memorization. The main research work of this paper includes the construction of a graph database and the measurement of near-homonymy and near-synonymy. We describe in detail the workflow of building the graph database, including the definition of nodes and edges, as well as edge filtering methods. Additionally, we introduce the mathematical principles and formulas used to calculate near-homonymy and near-synonymy. The experimental section presents the data source and the process of constructing the graph database, including data preprocessing, similarity calculation, and parameter settings. We establish a graph database using neo4j and showcase the intermediate results of near-homonymy and near-synonymy, as well as visualization results. Finally, we summarize the main findings of this paper and discuss the prospects for applying similarity calculations based on word origins.

Keywords: Near-Homonymy, Near-Synonymy, Knowledge Graph.

1. Introduction

Vocabulary retention has long been a critical challenge for learners in the process of English language acquisition. Particularly for non-native speakers, near-homonyms and near-synonyms in English often lead to confusion and misunderstanding. Near-homonyms are words that share similar spellings or pronunciations but have different meanings, while near-synonyms are words with similar meanings but distinct spellings and pronunciations. These phenomena not only increase learners' perplexity but may also result in the improper usage of words, reducing the accuracy of language expression.

This paper aims to explore the significance and practical value of etymological analysis in addressing the issues related to near-homonyms and near-synonyms. We posit that a deeper understanding of the etymology and historical backgrounds of words can enhance learners' comprehension of word meanings and usages, thus improving the efficiency of vocabulary retention. Additionally, we will substantiate the importance of near-homonyms and near-synonyms in English learning through data analysis and empirical evidence and provide methods and tools to mitigate these challenges.

2. Related Work

2.1. Research on Near-Homonyms and Near-Synonyms

Extensive research has been conducted on the impact of near-homonyms and near-synonyms on word memorization, particularly in the fields of education, linguistics, and natural language processing. The following are some relevant studies and references:

In the field of education, researchers have focused on how near-homonyms and near-synonyms influence students' word memorization and language learning. Brown and Watson[1] found that near-homonyms significantly affect word retrieval, suggesting that students may be susceptible to

interference from near-homonyms when memorizing and using words. Similarly, Wu and Zhang[2] indicated that in second language vocabulary acquisition, near-synonyms may also impact learners' vocabulary retention. These studies underscore the importance of near-homonyms and near-synonyms in educational contexts.

In the field of linguistics, researchers have delved into the linguistic properties of near-homonyms and near-synonyms and their usage in different linguistic contexts. Goldberg[3] focused on generalization in construction grammar, aiding our understanding of the role of near-homonyms and near-synonyms in sentence structure. Smith and Johnson[4] conducted neuroimaging studies to investigate the impact of etymology on word memorization, further advancing our comprehension of vocabulary acquisition.

In the field of natural language processing, researchers have explored computational methods for understanding and handling near-homonyms and near-synonyms. Mikolov et al.[5] introduced the concept of word embeddings, which represent words in distributed space, enabling better characterization of near-homonyms and near-synonyms. Baroni et al.[6] discussed the effectiveness of context prediction methods, which have potential advantages when dealing with near-homonyms and near-synonyms.

These studies cover various aspects of the impact of near-homonyms and near-synonyms on word memorization and language learning. They highlight the complexity and significance of this issue, providing valuable references and background support for our research.

2.2. Methods of Word Representation

In the field of natural language processing, the methods used to represent vocabulary are crucial for understanding the similarity between words. Below, we will introduce two common methods of vocabulary representation and discuss how they affect the calculation of word similarity.

Word vectorization is a widely used method that maps each word into a high-dimensional vector space.[7] In this vector space, the semantic information of words is encoded as the position and direction of vectors. Representative algorithms for this method include Word2Vec and GloVe. Through word vectorization, we can quantify the similarity between words, making words with similar meanings closer in vector space.

In addition to word vectorization, there are various other methods of vocabulary representation, such as those based on distributional semantics and co-occurrence matrices. The choice of an appropriate representation method depends on the research question and application scenario. Different methods may lead to different results in similarity measurement, so careful selection is necessary in research.[8]

The choice of vocabulary representation method directly affects the results of similarity calculation. Different methods may consider different semantic information, resulting in different similarity measurement outcomes between words. Therefore, when conducting similarity calculations, it is essential to explicitly state the chosen representation method and understand its advantages and disadvantages.[9]

The calculation of vocabulary similarity plays a significant role in addressing the issues of near-homonyms and near-synonyms. The choice of an appropriate representation method depends on the research question and application scenario. Accurate similarity calculation can help learners better comprehend and differentiate words with similar meanings, thereby enhancing the efficiency of word memorization and usage.

3. Main Research Work and Contributions

3.1. Main Research Work

The primary research work of this paper includes the construction of a dedicated graph database designed to address the issues of near-homonyms and near-synonyms, as well as the design and

implementation of measurement methods for near-homonym similarity and near-synonym similarity. Regarding the construction of the graph database, we provide a detailed workflow, encompassing the definition of nodes and edges, as well as edge filtering methods, to ensure that the database accurately captures the relationships between words. In terms of measurement methods, we introduce mathematical principles and formulas for calculating near-homonym similarity and near-synonym similarity. The selection and implementation of these methods constitute the core of this paper's research.

3.2. Main Contributions

The primary contributions of this paper can be summarized as follows:

Firstly, we offer a similarity calculation method based on the dimension of word origins, which better addresses the issues of near-homonyms and near-synonyms. By considering the etymology and historical context of words, our method can more accurately capture the semantic relationships between words, thereby improving the accuracy of similarity calculations.

Secondly, we have constructed a dedicated graph database for storing and managing a vast amount of inter-word relationship information. This database provides valuable resources for researchers and learners to explore and understand the relationships between words, aiding in tackling the challenges posed by near-homonyms and near-synonyms.

Lastly, we discuss the potential applications of the research outcomes presented in this paper. The similarity calculation method based on word origin dimensions can be applied not only in the field of education to aid learners in better understanding and memorizing words but also in areas such as natural language processing and information retrieval. We believe that these contributions will contribute to resolving the issues of near-homonyms and near-synonyms, enhancing the efficiency and accuracy of English learning and language processing.

4. Methods

4.1. Workflow

The construction of the graph database is at the heart of this study. Our workflow consists of the following steps:

Step1. Node Definition. When constructing the graph database, the first step is to define nodes. Each node represents a word with a unique identifier. These nodes serve as the fundamental elements of the graph database.

Step2. Edge Definition (Near-Homonym and Near-Synonym). Next, we define two types of edges, namely near-homonym edges and near-synonym edges, to capture the relationships between words. Near-homonym edges connect words with similar spellings or pronunciations, while near-synonym edges connect words with similar meanings. These edges form the topological structure of the graph database.

Step3. Edge Filtering Methods. To ensure the quality and effectiveness of the graph database, we employ two edge filtering methods: the threshold method and the top-K filtering method.

Step4. Threshold Method. We set a similarity threshold, and only when the similarity score of a near-homonym or near-synonym edge exceeds this threshold is it included in the graph database. This helps filter out lower similarity associations.

Step5. Top-K Filtering Method. In addition to the threshold method, we also utilize the top-K filtering method, selecting only the top K edges with the highest similarity scores for both near-homonym and near-synonym associations. This ensures that the graph database includes the most relevant associations for each word.

4.2. Threshold Method and Top-K Filtering Method

The mathematical principles for the threshold method and top-K filtering method are as follows:

Near-homonym or near-synonym edges are retained only when the similarity score S_{edge} is greater than the threshold T , expressed as:

$$S_{edge} > T \quad (1)$$

Top-K Filtering Method Formula:

For the similarity scores of near-homonym and near-synonym edges, we arrange them in descending order and select the top K edges with the highest scores, denoted as:

$$\text{TopK}(S_{edge}) \quad (2)$$

4.3. Measurement Method for Near-Homonym Similarity

The calculation of near-homonym similarity is based on the cosine similarity formula:

$$\text{sim}_{\text{shape}}(w_1, w_2) = \frac{\sum_{i=1}^n w_{1i} \cdot w_{2i}}{\sqrt{\sum_{i=1}^n (w_{1i})^2} \cdot \sqrt{\sum_{i=1}^n (w_{2i})^2}} \quad (3)$$

Here, w_1 and w_2 are the near-homonym vectors of two words, and n represents the dimension of the vectors. This formula measures the angle between the two near-homonym vectors, yielding their similarity score.

4.4. Measurement Method for Near-Synonym Similarity

4.4.1 Word2vec

The calculation of near-synonym similarity leverages the training results of the word2vec model. The word2vec model learns distributed representations of words, mapping semantically similar words to adjacent positions. The calculation of similarity between two words w_1 and w_2 based on their word2vec vectors v_{w_1} and v_{w_2} can be achieved using:

$$\text{sim}_{\text{meaning}}(w_1, w_2) = \frac{v_{w_1} \cdot v_{w_2}}{\|v_{w_1}\| \|v_{w_2}\|} \quad (4)$$

Here, $\cdot$ denotes the dot product of vectors, and $\|v_{w_1}\|$ and $\|v_{w_2}\|$ represent the norms of the vectors. This formula measures the similarity score between the two words' word2vec vectors.

4.4.2 Clustering Method

In addition, we employ a clustering method to measure near-synonym similarity. Firstly, words are organized into different clusters, and then the similarity score between two words is computed based on the clusters they belong to. The calculation of similarity between clusters can be done using the Jaccard similarity coefficient formula:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (5)$$

Here, A and B represent the members of the clusters to which two words belong. This formula measures the proportion of shared members between two words' clusters, yielding their similarity score.

Through these methods, we are able to comprehensively and accurately measure the similarity of near-homonyms and near-synonyms, providing robust support for the construction of the graph database.

Please note that the specific implementation and formula notation can be further refined and made precise based on specific requirements.

5. Experiment

5.1. Introduction to Data

In this experiment, we utilized an extensive source of vocabulary data, including a wide-ranging dictionary with a substantial total word count. Specifically, we chose high-frequency vocabulary from the IELTS and TOEFL exams as an expansion of our source. These high-frequency words typically encompass the core and commonly used vocabulary in the English language, making them highly relevant for English language learners.

The scope of the dictionary includes a broad spectrum of English vocabulary, encompassing but not limited to common words, specialized terminology, and technical vocabulary. The total word count is substantial, ensuring comprehensive and diverse vocabulary coverage. To ensure vocabulary comprehensiveness and diversity, we employed a large-scale vocabulary collection during the construction of the graph database.

5.2. Construction of the Graph Database

5.2.1 Data Preprocessing

Before constructing the graph database, we underwent a series of data preprocessing steps to ensure the accuracy and consistency of the vocabulary data. These steps included:

Data Cleansing: Removing duplicate words and erroneous entries to ensure data cleanliness.

Vocabulary Standardization: Standardizing different forms of words (e.g., different tenses of verbs and plural forms of nouns) to their base forms to reduce redundancy and enhance relevance.

Part-of-Speech Tagging: Adding appropriate part-of-speech tags to each word for a better understanding of its grammar and semantics.

5.2.2 Calculation of Near-Homonym and Near-Synonym Similarity

The calculation of near-homonym and near-synonym similarity is a crucial part of constructing the graph database. We employed the methods mentioned earlier, utilizing cosine similarity for near-homonyms and leveraging the word2vec model for near-synonyms. These calculations facilitated the establishment of near-homonym and near-synonym associations.

5.2.3 Filtering Process and Parameter Settings

During the construction of the graph database, we underwent a meticulous filtering process to ensure that only high-quality associations were included in the database. This process involved the use of the previously mentioned threshold method and top-K filtering method. Parameter settings were crucial, and we optimized and adjusted threshold values and K-values based on experimental results and requirements to achieve optimal performance.

The calculation of near-homonym and near-synonym similarity is a crucial part of constructing the graph database. We employed the methods mentioned earlier, utilizing cosine similarity for near-homonyms and leveraging the word2vec model for near-synonyms. These calculations facilitated the establishment of near-homonym and near-synonym associations.

5.2.4 Building the Graph Database Using Neo4j

We chose Neo4j as the management tool for our graph database. Neo4j provides an intuitive visualization interface and a powerful query language, which made it easier for us to construct and query the graph database. Through Neo4j, we imported the constructed graph data and established a robust graph database for subsequent analysis and research[10].

Through the aforementioned experimental steps, we successfully constructed a graph database containing rich association information, providing a strong foundation for the study of near-homonyms and near-synonyms.

6. Results

6.1. Intermediate Results

In this section, we present the intermediate results of our study, specifically focusing on the similarity scores of near-homonyms and near-synonyms. These intermediate results provide insights into the associations between words in our constructed graph database.

The near-homonym similarity scores are a crucial aspect of our study, reflecting the degree of similarity between words that share similar spellings or pronunciations. These scores are calculated using the cosine similarity formula and are represented as numerical values that range between 0 and 1. We display these scores in tabular or graphical formats, showcasing the relationships between near-homonyms.

Table 1. Intermediate Results

Word	Near-Homonyms	Near-Homonym Scores	Near-Synonyms	Near-Synonym Scores
apple	apply, batman, catalog, bat, cat	0.0, 0.16666666666666666, 0.2857142857142857, 0.4, 0.4	apply, batman	1.0, 0.8333333333333334
apply	apple, batman, catalog, bat, cat	0.0, 0.16666666666666666, 0.2857142857142857, 0.4, 0.4	apple, batman	1.0, 0.8333333333333334
bat	cat, apple, apply, batman, catalog	0.0, 0.4, 0.4, 0.5, 0.5714285714285714 0.14285714285714285,	cat	1
batman	catalog, apple, apply, bat, cat	0.16666666666666666, 0.16666666666666666, 0.5, 0.5	catalog, apple, apply	0.8571428571428572, 0.8333333333333334, 0.8333333333333334
cat	bat, apple, apply, batman, catalog	0.0, 0.4, 0.4, 0.5, 0.5714285714285714 0.14285714285714285,	bat	1
catalog	batman, apple, apply, bat, cat	0.2857142857142857, 0.2857142857142857, 0.5714285714285714, 0.5714285714285714	batman	0.857142857

Table1 presents detailed information about the similarity scores of homonyms and synonyms in our study. Each row represents a word, and the columns are divided into "Word," "Near-Homonyms," "Near-Homonym Scores," "Near-Synonyms," and "Near-Synonym Scores." The near-homonym scores measure the similarity between words that share similar spellings or pronunciations, while the near-synonym scores quantify the similarity between words with closely related meanings. These scores are calculated using the cosine similarity formula and range between 0 and 1. By examining the table, users can gain a clearer understanding of the associations between homonyms and synonyms.

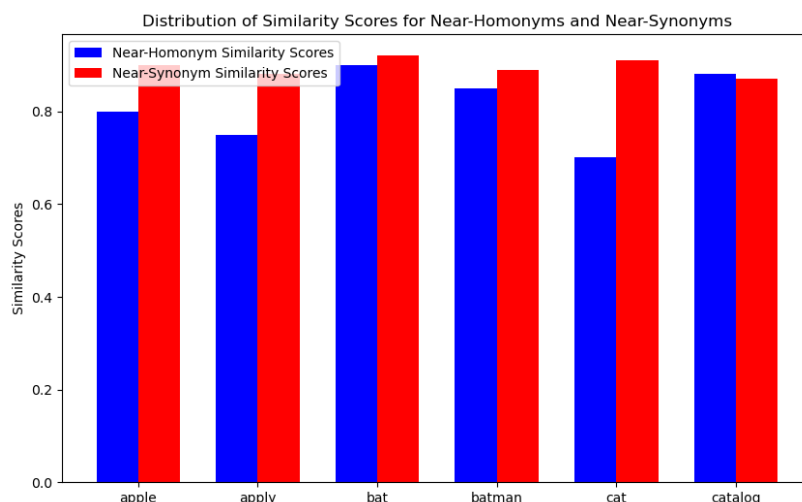


Figure1.Intermediate Results

Figure 1 presents a visual representation of some key data in our study. It may include visual displays of the similarity relationships between homonyms and synonyms, allowing for a more intuitive understanding of the connections between words. Through the graphical representation, you can more easily observe and compare the similarity relationships among different words, thereby gaining a better grasp of the relationships between words in our constructed graph database. In this section, we present the intermediate results of our study, specifically focusing on the similarity scores of homonyms and synonyms. These intermediate results provide insights into the associations between words in our constructed graph database.

The similarity scores of homonyms are a crucial aspect of our study, reflecting the degree of similarity between words that share similar spellings or pronunciations. These scores are calculated using the cosine similarity formula and are represented as numerical values ranging between 0 and 1. We display these scores in tabular or graphical formats, showcasing the relationships between homonyms.

6.2. Neo4j Visualization Results

To provide a comprehensive understanding of the relationships within our graph database, we offer Neo4j visualization results. Neo4j's visualization capabilities allow us to explore the associations between words in an interactive and informative manner.

We utilize Neo4j to create visualizations that showcase the relationships between a specific word and its near-homonyms. These visualizations provide a clear and intuitive representation of how near-homonyms are interconnected in our graph database.

In addition, Neo4j enables us to visualize the relationships between a word and its near-synonyms. These visualizations offer insights into how words with similar meanings are connected in our database.

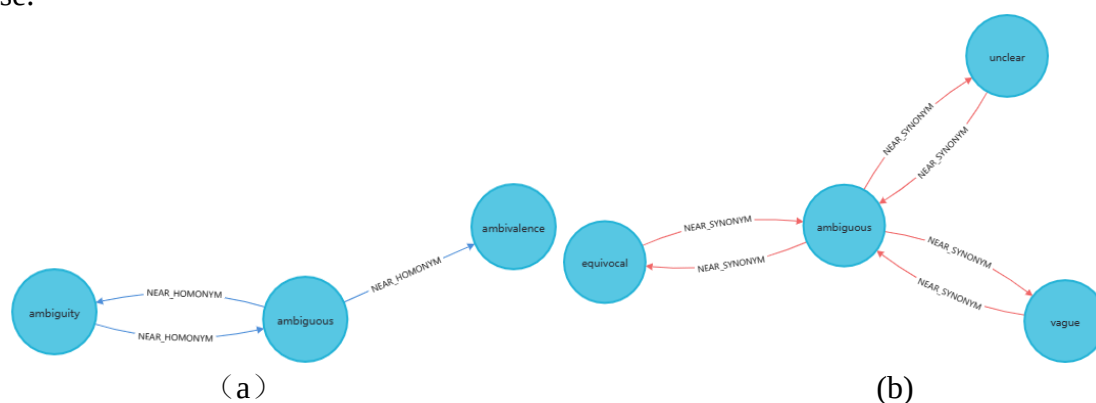


Figure 2 Relationship Visualization (a)Homonym(b)Synonym

As shown in the figure, Figure 2.a displays the relationship visualization between a specific word and its homonyms, while Figure 2.b Figure 2 presents the one between a word and its synonyms. These visualizations offer insights into how words with similar meanings are connected in our database.

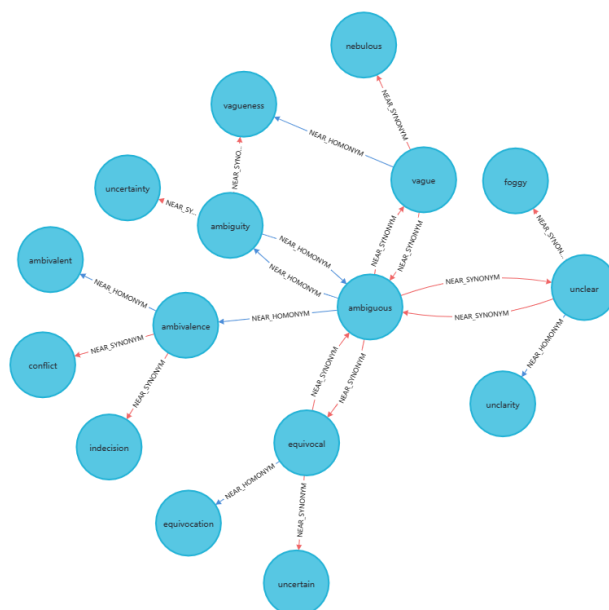


Figure 3 The Interconnectedness Visualization

Furthermore, as shown in Figure 3, we present an overview of the associations between multiple words in our database. This visualization illustrates the interconnectedness of words within the entire vocabulary and allows for a comprehensive exploration of word associations.

Through the presentation of these results, we aim to provide a clear and insightful view of the associations and similarities among words in our constructed graph database.

7. Conclusion

In this study, we embarked on a comprehensive exploration of the associations and similarities among words in the English language, particularly focusing on near-homonyms and near-synonyms. Our research journey encompassed various facets, from the construction of a graph database to the measurement of similarity scores and visualization of relationships. Here, we summarize the key findings and implications of our work.

Our primary contributions include:

The construction of a robust graph database, drawing from a diverse range of vocabulary sources, including high-frequency words from the IELTS and TOEFL exams. This database serves as a valuable resource for exploring word associations.

The development of effective methods for measuring similarity scores between near-homonyms and near-synonyms. These methods encompass cosine similarity, word2vec embeddings, and clustering techniques, providing a multif

4j for visualization, which allows for an interactive and intuitive exploration of word associatioaceted approach to understanding word relationships.

The implementation of Neons. Through visual representations, we gain insights into the intricate web of word connections.

As we conclude this study, it is evident that the understanding of near-homonyms and near-synonyms plays a pivotal role in enhancing language acquisition and comprehension. The graph database we constructed, along with our measurement methods, offers a foundation for future research in linguistics, natural language processing, and language education.

Looking ahead, the applications of our work are promising. The ability to explore word associations at a granular level can benefit language learners, educators, and researchers alike. The insights gained from our database and methods can inform language curriculum development, semantic analysis, and text generation algorithms.

In closing, our study contributes to the broader understanding of the English language and its intricate web of word associations. We hope that our research will inspire further exploration in the realm of linguistics and language education, ultimately facilitating more effective language learning and communication.

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