EDSE: Entity Descriptive Search Engine On Eurpoean Football

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1 Abstract

Semantic search enhances search engine accuracy by understanding user intent and context, moving beyond traditional keyword searches. This interdisciplinary research utilizes various data types and techniques, including text, knowledge bases, and natural language queries. Despite advancements in modern search engines, they can still struggle with complex queries. For example, a search for "a song about being sad" will return a song with that exact title, and a query like "Which player has played for Inter Milan, AC Milan, Barcelona, and Real Madrid?" will also yield inaccurate results. Our research uses knowledge graphs and domain-specific templates to better handle such intricate questions in fields like football, demonstrating effective retrieval of complex information with targeted methods.

Through testing with complex queries about European football, we demonstrated that effective information retrieval can be achieved using simple methods with knowledge graphs. We also highlighted the potential of transformer models to enhance semantic search's sophistication for nuanced inquiries.

2 Introduction

The advent of big data and sophisticated natural language processing (NLP) technologies has transformed the landscape of information retrieval systems. Traditional search engines rely heavily on keyword matching (Rahman, 2013), often leading to results that may not fully capture the nuances and context of user queries. This limitation is particularly evident in specialized domains like sports, where the interplay of data and context significantly influences the accuracy and relevance of search results.

As mentioned earlier, traditional search engines can struggle with complex queries, which often result in inaccurate outcomes on major platforms like Google, Bing, and DuckDuckGo. This was our motivation to utilize knowledge graphs and domain-specific templates to enhance the accuracy of complex natural language queries in areas such as football.

3 Related Work

As far as we are aware, there are no similar systems that does the same task as our proposed system. However, there are works that are similar, or solve a sub-section of our related work.

Huang et al. (2022) proposed DEER, a descriptive knowledge graph which uses textual descriptions to model the relationship between entities. With this network, it is capable of answering the relationship between entities. However, this knowledge graph is designed to answer the relationship between 2 given entities, whereas we need to find the entities themselves for a given relationship.

There is also attempt at improving existing search engine, such as using Automatic Query Expansions (Kulkarni and Kale, 2021). However, existing search engines was not designed with semantic searching in mind, so their performance is fundamentally limited by its keyword based matching (Mala and Lobiyal, 2016). Our solution proposes a new architecture for solving this problem and does not confront to the same limitations.

Translating from Text to Cypher has also been previously attempted by Hains et al. (2019), but the paper still uses regular expression based matching and it is sparse on details. There are also other similar applications such as Text-to-SQL (Wong et al., 2023) and Text-to-SPARQL (Ochieng, 2020), but no Text-to-Cypher applications.

4 Methods

The method devised for addressing the task involves harnessing Knowledge Graphs (KG) as a solution. KGs serve as a structured format for organizing and representing knowledge. The overall goal is to respond to descriptive questions posed through natural language queries. The general workflow entails three main steps, 1) Constructing a Knowledge Graph; 2) Translating the natural language question into an executable query; and finally 3) Querying the graph to retrieve the desired result.

4.1 Constructing the Knowledge Graph

We have decided to choose Wikipedia as the primary data source due to its comprehensive coverage and the availability of tools that facilitate data extraction such as Wikiextractor (Attardi, 2015). The initial step involved downloading the full Wikidata dump and converting it to a manageable HTML format. Using Wikipedia's Categories and API, the team filtered and identified relevant Wikipedia IDs to isolate football-related content. This curated list of IDs enabled the fetching of detailed information from Wikipedia pages, primarily focusing on the relationships between players and clubs (captured through the Wikidata relationship ID *wdt:P54*). This process allowed for the effective mapping of all historical player-club associations within the top five European leagues, forming the basis for the Knowledge Graph's nodes.

While we could continue using GraphDB and SPARQL, we made the choice to discontinue their use for several reasons: Firstly, they are difficult to integrate with other languages. Secondly, its syntax proved to be excessively complex, posing significant obstacles. In light of these difficulties, we transitioned our approach to Neo4j. This shift was driven by the belief that the Cypher Query Language offered by Neo4j would be easier to work with. Additionally, we believe that Neo4j offers better flexibility and adaptability with other languages and technologies.

4.2 Natural Language to Query

Translating Natural Language to an executable query is a very challenging topic, and it is still an active area of research. For this project, we have tried 4 methods: **Regular Expression rules**, **Fine-tuned T5 Text to Query**, **Template rules**, and **ChatGPT Text to Query**. To limit the scope of this project, we also limited the categories of question we would be targeting. See Appendix B for the exact categories.

4.2.1 Regular Expression Rules

This is a straightforward approach to parse user input. It employs basic string matching techniques to investigate queries effectively through predefined categorized templates. This method is notably sensitive to both paraphrasing and typos.

4.2.2 Fine-tuned T5 Text to Query

We have opted for T5 (Raffel et al., 2020), an encoder-decoder model specifically designed for translation and summarization tasks. It has already been applied in a variety of natural language to code applications, such as Text-to-SQL (Li et al., 2023), Text-to-Code (Wang et al., 2021) and Text-to-SPARQL (Ochieng, 2020). Therefore, we are confident that it should be able to perform well for Text-to-Cypher task. Given our hardware constraints, particularly the limited VRAM of 12GB, we have selected T5-small as our model of choice. The training hardware will be done on a Nvidia Tesla P100 GPU.

In order to fine-tune T5, we need to have enough dataset to facilitate effective training. To our surprise, no suitable datasets were readily available. Although we stumbled upon a Text-to-CQL dataset (Guo et al., 2022), it was in Chinese, presenting a significant barrier. Additionally, while we discovered the CLEVR graph dataset (Mack and Jefferson, 2018), it was tailored specifically for trains, rendering it unsuitable for our purposes. This underscores the necessity for creating tailored datasets to meet the requirements of fine-tuning T5 effectively.

Therefore, in order to obtain enough dataset to fine-tune T5, we have decided to pursue two distinct methods to acquire datasets for fine-tuning T5: First, we translating the existing Text-to-CQL (Guo et al., 2022) dataset into English to make it suitable for our purposes. Second, we generating our dataset from scratch by employing pre-defined template sentences and incorporating football-related entities.

4.2.2.1 Translating Text-to-CQL Dataset

We've opted to host a translation engine directly on our server rather than relying on external APIs to prevent API rate limitations and costs. For our translation needs, we've employed the Facebook/NLLB-200-Distilled-1.3B engine (Team et al., 2022). This model is hosted on the same training server. The raw dataset contains around 7000 training data, 2000 test data and 1000 validation data. After translation and validating correctness, we are able to obtain 6562 training, 1878 test, and 936 validation data.

4.2.2.2 Generating Dataset

We crafted 12 sentence structures, each with about 10 paraphrases, ensuring broad coverage of question types and variations. These sentences are paired with actual entities from the database, forming sentence-query pairs. This dataset is then used to fine-tune T5, enhancing its ability to understand and generate responses for different query types and variations.

4.2.3 Template rules

The template method is inspired by Hains et al. (2019), who proposed a non-large language model approach to this problem. Based on its ways of dividing the problem into sub-tasks, we derived our own method and improvised. We are strongly motivated by this method because every query generated are explainable, making it easy to debug or tune. It also eliminates the possibility of syntax errors in the generated query, as the query produced are from templates, which we can ensure correctness.

4.2.3.1 Identify named entities

Identifying named entities is an existing problem in NLP, often called Named Entity Recognition (NER). Python frameworks like Spacy excel at this task. Leveraging the transformer model ‘en_core_web_trf‘, we employed Spacy to perform NER.

4.2.3.2 Fetching and substituting entities

We first query the list of players, list of clubs and leagues from our Knowledge Graph. We then used Gestalt Similarity Score (Black, 2021) to find the closest match of entities identified in step 4.2.3.1 from a list of entities queried from the Knowledge Graph. For instance, if the model identifies an entity as a PERSON, we search through the list of players. Similarly, if it identifies an entity as an ORG (Organization), we search through the list of clubs and leagues. The Gestalt Similarity Score is implemented by Python’s *difflib* standard library.

4.2.3.3 Finding the suitable Cypher Template

We are reusing the sentence templates that we used previously in 4.2.2.2, where we used it to generate our own dataset. We substituted each entity into each sentence template, and find the most semantically similar one to the original. This can be done by encoding both the original sentence and each substituted template into word embedding. Then, we compute the cosine similarity between the original sentence and each template sentence. This enables us to identify the most similar sentence template.

4.2.3.4 Query the Knowledge Graph

Since each template is associated with a pre-defined Cypher query, we can then substitute the entities into the corresponding Cypher template, and query the knowledge graph.

4.3 ChatGPT Text-to-Query

We utilized OpenAI’s API to generate Cypher queries by engineering prompts tailored to generate queries based on given questions. Additionally, we added regular expression rules to chatgpt in order to limit the query generated. These queries were then executed on our Neo4j database to retrieve the desired results. This streamlined approach facilitated efficient query generation and execution, enhancing the effectiveness of our database operations. Example of the prompt and the generated query will be in Appendix A.

5 Results

Due to the absence of comparable benchmarking systems, we recognized the inherent capability of our proposed knowledge graph to handle straightforward queries, such as identifying players affiliated with specific clubs or who participated in certain leagues. To evaluate our system comprehensively, we devised a set of 25 challenging questions inspired by "Sabaho Kora" (YouTube, 2023) an Egyptian show that features a challenge between two people on complex football-related questions. These questions were then verified using Wikipedia.

For instance, we analyzed the query equivalence between "who played for Real Madrid and Barcelona" and "who played for both El-Clasico teams." We designed the questions, constructed the correct query, and generated the query using our method. Subsequently, we compared the results. For more questions examples, see Tables 2, 3, 4 and 5 in Appendix A. This approach enabled us to assess our system’s performance against intricate queries without overstating its capabilities. Results are shown in table 1.

In our evaluation, key observations were made: Firstly, we found that correct query syntax is crucial as it guarantees accurate answers, highlighting the dependency on precise query formulation for reliable results. – Simply, if you input the correct query, you'll inevitably get the right answer – Secondly, the template-based method demonstrated notable rigidity in handling natural language, indicating a limitation in adapting to diverse linguistic expressions. Lastly, despite its simplicity, our solution exhibited strong performance in managing complex queries, suggesting that even straightforward systems can be highly effective in such tasks. However, we successfully answered the "Ronaldo R9" question correctly using all three methods.

Table 1: Evaluation

Method	Regex	Temp	GPT 3.5
Acc.	32%	72%	84%
Wrong	0	2 (Empty List)	0
Errors [1]	17	5	4

6 Discussion

It seems we have encounter the same major challenges as Text-to-SQL. These challenges primarily lie in accurately encoding the nuances of natural language utterances, generating the corresponding Cypher queries, and effectively translating the semantic nuances between these two very different forms of expression (Deng et al., 2022).

This observation highlights the limitations of smaller models like T5 Small in tasks that require deep semantic understanding. While such models are effective for text summarization and translation, they may struggle to fully grasp the complexities needed to translate accurately into database query languages. This limitation could partly be attributed to the smaller model size and potentially insufficient training data. However, our hypothesis, primarily informed by literature on SQL translation (Wong et al., 2023), suggests that the fundamental issue is the model's inherent inability to capture the complete semantic meaning required for such translations. That's why it basically just generated a "partially correct" query.

[1]Errors mean Cypher queries syntax errors.

6.1 Error analysis

As previously mentioned, the primary source of errors in generating Cypher queries relates to syntax; however, our evaluation reveals two additional shortcomings in our methods. Specifically, our Template Method failed to answer the following two questions, which ChatGPT managed to resolve accurately: "Who played for both teams in the North London Derby?" and "Who joined PSG after leaving Manchester United?" These failures are primarily due to the limitations in our named entity recognition (NER) system and overall semantic understanding. In the case of PSG, our method failed to recognize "PSG" as an abbreviation for Paris Saint-Germain. Similarly, for the North London Derby question, our system could not identify that the teams involved are Arsenal and Tottenham. This highlights the need for models with deep semantic understanding capabilities that can accurately interpret complex entity relationships and contextual nuances in natural language processing tasks.

7 Conclusion

In this project, we explored a variety of methods in generating Cypher queries. We also demonstrated how a relatively simple system could answer complex queries that even major search engines struggle with. We made good contributions by developing an expandable knowledge graph, creating an English Text to Cypher dataset, and designing a dataset generator. Our results successfully addressed the initial questions that motivated this project.

Additionally, we determined that for broader application, the optimal approach would involve adopting a mixture of experts model (Xue et al., 2022). This machine learning strategy utilizes a collection of specialized models, each expert tailored to different data subsets or problem aspects, coordinated by a gating model that directs inputs to the most appropriate expert.

Looking ahead, we aim to build a global football knowledge base that allows for open access. Furthermore, we will test our hypothesis using more capable hardware that can train a T5 large model, anticipating more robust results and insights into complex query handling.

Repository

https://github.com/flyrobot27/EDSE

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A Examples of Question and Query

Question 1: Who played for both teams in the North London derby?

Aspect	Details
Question	Who played for both teams in the North London derby?
Correct Query	MATCH (p:Player)-[:PLAYED_FOR]->(c1:Club), (p)-[:PLAYED_FOR]->(c2:Club) WHERE c1.name = '.Arsenal.' AND c2.name = '.Tottenham.' RETURN p.name
Template Method Query	MATCH (p:Player)-[:PLAYED_FOR]->(c:Club name: 'North London') RETURN p.name
ChatGPT Query	Same as Correct Query
Answer	Emmanuel Adebayor, and 14 others

Question 2: Who played for Ajax then transferred to Juventus before going to Inter Milan?

Aspect	Details
Question	Who played for Ajax then transferred to Juventus before going to Inter Milan?
Correct Query	MATCH (p:Player)-[:PLAYED_FOR]->(c1:Club), (p)-[:PLAYED_FOR]->(c2:Club), (p)-[:PLAYED_FOR]->(c3:Club) WHERE c1.name = '.*Ajax.*' AND c2.name = '.*Juventus.*' AND c3.name = '.*Inter Milan.*' RETURN p.name
Template Method Query	MATCH (p:Player)-[:PLAYED_FOR]->(c:Club) WHERE c.name IN ['A.C. Ajaccio', 'Juventus FC', 'Inter Milan'] RETURN p.name
ChatGPT Query	Same as Correct Query
Answer	Ibrahimovic

Question 3: A player who played for all top five European leagues?

Aspect	Details
Question	A player who played for all top five European leagues?
Correct Query	MATCH (p:Player)-[:PLAYED_FOR]->(c1:Club)-[:IS_IN]->(l1:League), (p)-[:PLAYED_FOR]->(c2:Club)-[:IS_IN]->(l2:League), (p)-[:PLAYED_FOR]->(c3:Club)-[:IS_IN]->(l3:League), (p)-[:PLAYED_FOR]->(c4:Club)-[:IS_IN]->(l4:League), (p)-[:PLAYED_FOR]->(c5:Club)-[:IS_IN]->(l5:League) WHERE l1.name = '.*Serie A.*' AND l2.name = '.*La Liga.*' AND l3.name = '.*Premier League.*' AND l4.name = '.*Bundesliga.*' AND l5.name = '.*Ligue 1.*' RETURN p.name
Template Method Query	Unable to parse
ChatGPT Query	Same as Correct Query
Answer	Ibrahimovic

Question 4: Who played for AC Milan, Real Madrid, Inter Milan and Barcelona?

Aspect	**Details**
Question	Who played for AC Milan, Real Madrid, Inter Milan and Barcelona?
Correct Query	MATCH (p:Player)-[:PLAYED_FOR]->(c1:Club), (p)-[:PLAYED_FOR]->(c2:Club), (p)-[:PLAYED_FOR]->(c3:Club), (p)-[:PLAYED_FOR]->(c4:Club) WHERE c1.name = '.*AC Milan.*' AND c2.name = '.*Real Madrid.*' AND c3.name = '.*Inter Milan.*' AND c4.name = '.*Barcelona.*' RETURN p.name
Template Method Query	Same as Correct Query
ChatGPT Query	Same as Correct Query
Answer	Ronaldo R9

B Question Categories and Template

Basic Queries about Player's Club History

- In which clubs has player X played during their career?
- Can you list the clubs associated with player X?
- What are the teams that player X has been part of?
- Name the clubs where player X has had a tenure.
- Which clubs have featured player X in their squad?
- Identify the clubs player X has been affiliated with.
- Enumerate the teams player X has played for.
- What clubs have been represented by player X?
- In which teams has player X made appearances?
- List the football clubs that have had player X as a member.

Queries about Club's Player Roster

- Who are the players that have played for club Y?
- Can you name the players who have been part of club Y's history?
- List the footballers associated with club Y.
- Identify the roster of players who have played in club Y.
- Who has been on the team roster for club Y?
- Enumerate the athletes who have represented club Y.
- What players have had stints at club Y?
- Provide the list of players who have worn club Y's jersey.
- Who are the past and present players of club Y?
- Which players have been officially listed for club Y?

Queries about Club's League Affiliation

- What league does club Z compete in?
- Can you name the league associated with club Z?
- In which league is club Z a participant?
- Identify the league where club Z plays.
- What is the competitive league for club Z?
- List the league affiliations of club Z.
- In which league has club Z been competing?
- Enumerate the leagues that include club Z.
- Which league features club Z as a competitor?
- Provide the name of the league where club Z is a team.

Queries about Players in a League

- Who are the players that have competed in league A?
- Can you list the players who have participated in league A?
- Name the players affiliated with league A.
- Identify all players who have played in league A.
- Which individuals have been part of league A's competitions?
- Enumerate the players who have had appearances in league A.
- What are the names of players who have been active in league A?
- Provide a list of athletes who have competed in league A.
- Who has been documented as playing in league A?
- List the footballers who have league A experience.

Comparative Queries about Players in Multiple Clubs

- Which players have been part of both club X and club Y?
- Can you identify players who played for both clubs X and Y?
- Name the athletes who have been in the squads of both X and Y.
- Who has worn the jerseys of both club X and club Y?
- List the players who have affiliations with both clubs X and Y.
- Enumerate players who have been on the rosters of both X and Y.
- What players have had tenures in both clubs X and Y?
- Identify the footballers who have served in both X and Y clubs.
- Who are the individuals that have been part of both club X and Y?
- Provide the names of players who have played for both X and Y clubs.

Queries about Players in Three Clubs

- Who are the players that have been in clubs X, Y, and Z?
- Can you list the players associated with clubs X, Y, and Z?
- Name the individuals who have played for X, Y, and Z.
- Identify the athletes who have been part of clubs X, Y, and Z.
- Enumerate the players who have affiliations with X, Y, and Z.
- What players have had tenures at clubs X, Y, and Z?
- Which footballers have been on the rosters of clubs X, Y, and Z?
- Who has worn the jerseys of clubs X, Y, and Z?
- List the individuals who have played in X, Y, and Z clubs.
- Provide the names of players affiliated with clubs X, Y, and Z.

Queries about Players with Most Clubs in a League

- Who has played for the most clubs within league A?
- Can you identify the player with the highest number of clubs in league A?
- Who holds the record for playing in the most clubs in league A?
- Name the player who has been part of the most clubs in league A.
- List the players ranked by the number of clubs they've played for in league A.
- Who has the broadest club history in league A?
- Enumerate players with the most club affiliations in league A.
- Which player has a diverse club portfolio in league A?
- Identify the top players by the number of clubs in league A.
- Provide the name of the player with the most club tenures in league A.

Teammate Queries

- Who were the teammates of player X while they were at club Y?
- Can you list all teammates of player X during their time in club Y?
- Name the players who shared the pitch with player X at club Y.
- Identify the squad members who played alongside player X in club Y.
- Which players were in club Y with player X?
- Enumerate the footballers who teamed up with player X at club Y.
- Who were the fellow players of player X in the roster of club Y?

- Provide the list of players who were in club Y at the same time as player X.
- Which athletes collaborated with player X in club Y's team?
- Who are the known teammates of player X in club Y's history?

Association Queries Across Clubs

- Who are the players that have played with player X in any club?
- Can you name the players who have been teammates with player X across different clubs?
- List the footballers who have shared the field with player X in their career.
- Identify the players who have been part of the same team as player X.
- Enumerate the athletes who have played alongside player X.
- What players have been in the same squad as player X in various clubs?
- Who has shared team membership with player X in professional football?
- Provide the names of players who have been teammates of player X.
- Which players have a history of playing with player X in any team?
- Who are the individuals that have been associated with player X in club football?

Career Path and Movement Between Clubs

- Which players have moved from club X to club Y?
- Can you list the players who transferred from club X to club Y?
- Name the footballers who have made the switch from club X to club Y.
- Identify the players who have had transfers between club X and club Y.
- Enumerate the athletes who transitioned from club X to club Y.
- What players have changed their club from X to Y during their career?
- Who has a transfer history from club X to club Y?
- Provide the names of players who moved from club X to club Y.
- Which players have a record of transferring from club X to club Y?
- Who are the footballers that went from playing in club X to playing in club Y?

Playing in Different Leagues

- Who has played in both League A and League B?
- Can you name the players who have appeared in both League A and League B?
- List the footballers who have competed in both League A and League B.
- Identify the athletes who have experience in both League A and League B.
- Enumerate the players who have had stints in both League A and League B.
- What players have the distinction of playing in both League A and League B?
- Who are the individuals with careers in both League A and League B?
- Provide the names of players who have participated in both League A and League B.
- Which players have a history in both League A and League B?
- Who are the footballers that have played in both League A and League B?