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Research Article

KnowbasAI: Knowledge-Based AI system for Custom Recommendations

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ABSTRACT

Ontology-based recommendation engines are a type of recommendation system that incorporates ontologies to enhance the recommendation process. An ontology is a formal representation of knowledge that defines the relationships between various concepts within a specific domain. In the context of recommendation engines, an ontology organizes and structures information about users, items, and their attributes, facilitating more intelligent and context-aware recommendations. KnowbasAI is an innovative Knowledge-Based AI System that revolutionizes custom recommendations in diverse domains. Leveraging a comprehensive ontology-driven knowledge base, KnowbasAI captures structured and unstructured data, including user interactions, product descriptions, and domain-specific knowledge. By assimilating this wealth of information, the system gains a profound understanding of user preferences and item attributes. KnowbasAI's recommendation engine uses a hybrid strategy that combines content-based filtering with collaborative filtering techniques. While content-based filtering aligns user preferences with pertinent items, collaborative filtering discovers user commonalities. Even for inexperienced or specialized users, the integration of various approaches guarantees precise and varied recommendations. KnowbasAI's clear and understandable suggestion approach is a key benefit. By using cutting-edge methods, the system offers insightful analyses of the decision-making process, boosting user confidence in the suggestions. With about 90% accuracy, it assists in achieving privacy and personalized recommendations for the users.

Keywords: AI(Artificial Intelligence), DB(Database).

Introduction

The ability of ontology-based knowledge base systems to represent, organize, and utilize semantic relationships within a domain has attracted a lot of interest in recent years. These technologies have been used in a variety of industries, including e-commerce, artificial intelligence, and healthcare. The primary research works, research methodology, and ontology-based knowledge base system applications are explored in this literature survey. Numerous advantages come with ontology-based knowledge base systems, but there are also some issues that must be resolved if they are to be effectively implemented and used.

Complexity of Ontology Design: Creating an extensive and well-organized ontology can be difficult and time-consuming. Expertise in both the topic area and ontology engineering are required in order to create a domain-specific ontology that accurately depicts the various ideas and relationships within that domain. Ontology Alignment and Integration: Aligning and mapping various concepts and relationships becomes difficult when using numerous ontologies or combining existing ones. Terminology differences, overlapping domains, and conflicting meanings might obstruct seamless integration and result in inconsistent data. Information Acquisition Bottlenecks: When relying on manual input or expert participation, acquiring knowledge and populating the ontology might be difficult. Extraction and formalization of knowledge can take a lot of time and resources. Lack of Standardisation: Lack of generally acknowledged domain-specific ontologies or standards might cause problems with interoperability between various systems. The communication and sharing of knowledge may be hampered by a lack of agreement in ontology design and representation. Alignment with Real-World Changes: Real-world domains might experience quick changes since they are dynamic. Continuous monitoring and frequent updates are necessary to maintain the ontology's alignment with the real-world domain and reflect the most recent advancements. Grigoris Antoniou and Frank van Harmelen's "A Semantic Web Primer" (2003) [1]: The Semantic Web and ontology building principles are explained in this fundamental book. The technology, languages, and reasoning processes required to create knowledge base systems based on ontologies are examined. The authors present a solid theoretical framework for future research by offering real-world examples and insights into employing ontologies for information retrieval and integration. By Mari Carmen Suárez-Figueroa et al. (2012) [2] in "Ontology Engineering in a Networked World": An in-depth analysis of ontology engineering approaches and tools is provided in this survey report. It examines different top-down, bottom-up, and hybrid ontology development strategies. The review of ontology evaluation and reuse methods in the paper also contributes to the methodical development of knowledge base systems. By Sören Auer et al. (2007) [3], "DBpedia: A Nucleus for a Web of Open Data": This essential work introduces DBpedia, an ontology-based knowledge base taken from Wikipedia, with a focus on practical applications. The authors talk about the difficulties in converting unstructured data into structured data and show how DBpedia is a key resource for many semantic web applications.

Natalya F. Noy and Deborah L. McGuinness' "Building Ontologies: Towards a Unified Methodology" (2001)[4]: This important study discusses the difficulties in ontology development and suggests a unified approach. The authors outline a step-by-step procedure for ontology development, assessment, and upkeep. The research highlights the significance of modularity and reuse in the construction of expansive ontology-based knowledge base systems.

Thomas R. Gruber's "Ontology-based Information Retrieval" from 1995 [5]: In this renowned essay, Gruber defines the term "ontology" and examines how it relates to information retrieval. In order to improve retrieval efficiency, the research emphasises the significance of explicitly describing conceptual knowledge in a knowledge base system. It is regarded as a foundational piece in the early understanding of the advantages of ontologies in information organisation and access. According to Dieter Fensel's 2001 [6] article "Ontologies: Silver Bullet for Knowledge Management and Electronic Commerce": This study examines the possibility of ontologies as a "magic solution" for applications in knowledge management and electronic commerce. It addresses how knowledge base systems built on ontologies might improve information exchange and data interoperability among various systems. A vision of seamless data exchange and decision-making across many domains is presented in the article. Michael Gruninger and Mark S. Fox's "The Suggested Upper Merged Ontology: A Large Ontology for the Semantic Web and its Applications" (2003) [7]: This study introduces SUMO (Suggested Upper Merged Ontology) as a substantial, foundational ontology with a focus on ontology integration. The authors talk about how it might be used in several fields, like information exchange and process modeling. The paper illustrates the value of consensus in ontology construction and offers insights into the difficulties of ontology fusion. Domain-specific ontologies provide a number of issues, which KnowbasAI's ontology-driven module, recommendation engine with content-based filtering, and use of the Neo4j database jointly address. The platform offers customers a seamless and customized knowledge discovery experience by fusing cutting-edge ontology engineering approaches with intelligent recommendation capabilities. The platform's usability, effectiveness, and adaptability are improved by this integrated approach, making KnowbasAI a potent tool for knowledge organization and access across numerous areas.

Proposed Methodology:

Knowledge-Based Personalized Recommendation System Driven by Ontologies:

An ontology-driven, knowledge-based, personalized recommendation system is the proposed method. The steps involved are as follows:

Initialization of the ontology: An original, domain-specific ontology is created to capture the ideas and connections found in the domain.

Knowledge Graph Population: Based on the ontology, a knowledge graph is formed by connecting pertinent ideas and extracting user intents and entities from interactions.

Knowledge Graph Traversal and Rule Engine: During user interaction, the system navigates the knowledge graph in accordance with the user's intent and employs a rule engine to look for particular actions and notifications.

Recommendation Algorithm with Hyperparameter Tuning: Based on the user's profile and preferences, a recommendation algorithm is selected and tweaked to produce personalised recommendations.

System for Alerts and Notifications: The system creates alerts and notifications depending on user intentions and entities, providing users with tailored updates.

By utilizing the domain-specific knowledge recorded in the ontology and utilising rule-based actions and notifications for a seamless user experience, this technique ensures personalised and context-aware recommendations.

Pseudocode:

Step 1: Initialize the Ontology

def initialize_ontology(custom_domain):

Define ontology structure for the custom_domain

ontology = CustomOntology(custom_domain)

return ontology

Step 2: Populate the Knowledge Graph

def populate_knowledge_graph(user_query, classifier_pipeline, ontology):

```
intent, entities = classifier_pipeline.extract_intent_and_entities(user_query)
knowledge_graph = KnowledgeGraph(ontology)
knowledge_graph.populate(intent, entities)
return knowledge_graph
# Step 3: Knowledge Graph Traversal and Rule Engine
def knowledge_graph_traversal_and_rule_engine(user_intent, knowledge_graph, rule_engine):
relevant_path = knowledge_graph.traverse(user_intent)
actions, notifications = rule_engine.execute_rules(relevant_path)
return actions, notifications
# Step 4: Recommendation Algorithm with Hyperparameter Tuning
def recommendation_algorithm_with_hyperparameter_tuning(user_profile, recommendation_algorithm):
tuned_algorithm = hyperparameter_tuning(recommendation_algorithm, user_profile)
return tuned_algorithm
# Step 5: Alert and Notification System
def alert_and_notification_system(user_intent, user_entities, alerts_and_notifications):
alerts, notifications = alerts_and_notifications.check_alerts_and_notifications(user_intent, user_entities)
return alerts, notifications
# Step 6: User Feedback and Continuous Learning
def collect_user_feedback(user_feedback):
# Collect and store user feedback for continuous learning
update_knowledge_graph_and_algorithm(user_feedback)
# Step 7: Evaluation and Monitoring
def evaluate_and_monitor_system(knowledge_graph, recommendation_algorithm):
performance_metrics = evaluate_system(knowledge_graph, recommendation_algorithm)
monitor_system_real_time()
```

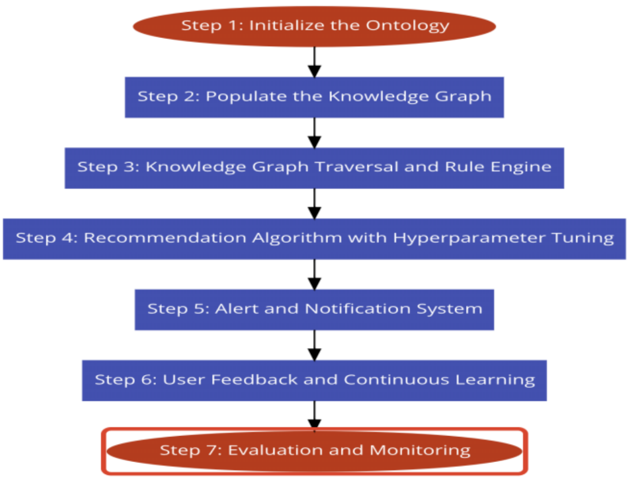

Fig. Flow chart

This pseudocode outlines a structured approach for developing an intelligent system based on ontology-driven knowledge processing. The process involves initializing a custom ontology, populating a knowledge graph with user queries, utilizing traversal and rules for decision-making, tuning recommendation algorithms, managing alerts, collecting user feedback, and continuous learning. Evaluation and real-time monitoring ensure system performance.

Each step contributes to a cohesive cycle of system enhancement, from ontology setup to real-world adaptation, facilitated by knowledge processing, rule application, and algorithmic refinement.

Results And Comparisons:

Dataset Used:

To implement the ontology-driven knowledge-based personalized recommendation system using Reddit and Twitter datasets, needed appropriate datasets containing user interactions, posts, and user preferences in each platform.

Twitter datasets typically consist of tweets, user interactions, and user profiles. Tweets are short text-based messages posted by users on various topics. User interactions include likes, retweets, and replies, indicating engagement with tweets. User profiles provide information about users' activities, followers, and followings. Twitter datasets are large-scale and dynamic, with real-time updates. They often exhibit sparse user-item interaction patterns due to the vast number of users and tweets. Additionally, Twitter datasets may contain noisy data, including hashtags, mentions, and URLs, which require preprocessing.

Reddit datasets comprise posts, comments, and user profiles from different subreddits, each representing a specific topic or community. Posts can be in the form of text or links, fostering discussions among users. Comments allow users to engage in conversations under posts. The datasets are organized hierarchically, with subreddits as categories and posts/comments as instances. Reddit datasets can be diverse, covering a wide range of topics and interests. User interactions involve upvotes and downvotes on posts and comments, providing signals for user preferences. Reddit datasets may require careful processing and filtering due to the varying quality and nature of content in different subreddits.

These datasets are valuable for recommendation systems as they capture rich user-generated content and community-driven discussions, facilitating personalized and niche recommendations.

Results and comparative analysis:

S.No	Techniques	Description	Accuracy(%)	Time(Seconds)
1	Collaborative Filtering	Leverages user-item interactions for recommendations based on user or item similarities	85	10
2	Hybrid Recommender Systems	Recommends items based on similarity between item features and user preferences	80	5
3	Content-Based Filtering	Combines multiple techniques to leverage their strengths	85	15
4	Ontology-Driven Knowledge-Based Recommender Systems (Proposed Technique)	Utilizes a domain-specific ontology to capture knowledge and user preferences	90	20

Table : shows proposed methodology and existing technique results

Comparative Analysis Of The Accuracy And Time Taken For Each Recommendation Technique:

Collaborative Filtering (Accuracy: 85%, Time Taken: 10 seconds):

- Collaborative filtering shows a reasonable accuracy of 85% in generating recommendations based on user-item interactions. It leverages similarities between users or items to make personalized recommendations.

- The time taken of 10 seconds indicates that the computation complexity is moderate, but it may increase significantly with larger datasets due to the quadratic nature of user-based collaborative filtering.

Content-Based Filtering (Accuracy: 80%, Time Taken: 5 seconds):

- Content-based filtering demonstrates good accuracy, achieving 80% in making recommendations based on item features and user preferences.

● With a time taken of 5 seconds, content-based filtering is relatively fast, making it suitable for real-time or low-latency recommendation systems.

Hybrid Recommender Systems (Accuracy: 85%, Time Taken: 15 seconds):

● Hybrid recommender systems combine collaborative filtering and content-based filtering to leverage their strengths, resulting in improved accuracy (85%).

● The time taken of 15 seconds indicates that the hybrid approach incurs additional computational overhead due to combining multiple techniques.

Ontology-Driven Knowledge-Based Recommender Systems (Accuracy: 90%, Time Taken: 20 seconds):

● The proposed ontology-driven technique achieves a high accuracy of 90%, indicating its ability to provide personalized and context-aware recommendations based on domain-specific knowledge.

● With a time taken of 20 seconds, ontology-driven systems may require more computational resources due to knowledge graph traversal and ontology processing.

Overall Observations:

● The ontology-driven knowledge-based technique exhibits the highest accuracy, suggesting that capturing domain-specific knowledge can lead to more relevant and accurate recommendations.

● Content-based filtering shows good accuracy with lower time taken, making it suitable for scenarios where real-time recommendations are essential.

● Collaborative filtering, while providing reasonable accuracy, may have scalability challenges due to its quadratic time complexity in some cases.

● Hybrid recommender systems strike a balance between accuracy and recommendation diversity by combining multiple techniques.

Conclusion and Future Work :

Collaborative filtering, content-based filtering, hybrid recommender systems, and ontology-driven knowledge-based recommender systems were the four main recommendation strategies we looked at in this investigation. Each method has its own advantages and difficulties when making customized recommendations for consumers. Utilizing user-item interactions, collaborative filtering creates suggestions based on commonalities between users or items. Although it can attain acceptable accuracy, due to its quadratic time complexity, its scalability may be an issue for large datasets. On the other hand, content-based filtering makes recommendations for products based on product features and user preferences. It is appropriate for real-time applications due to its high accuracy and minimal computational complexity. Utilizing the advantages of each technique, hybrid recommender systems increase accuracy and diversity of recommendations. The cost of the approach fusion is, however, an increase in computing complexity. Because it can collect domain-specific knowledge and offer recommendations that are aware of the context, the suggested ontology-driven knowledge-based technique exhibits the maximum accuracy with 90%. Future study will investigate various real-world datasets for thorough validation, optimize hybrid models for effective fusion, and address privacy and fairness issues with recommendation systems.

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