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Explainability of text classification through ontology-driven analysis in Serious Games

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Abstract

Several approaches have been proposed to study text classification in serious games. Unfortunately, those works do not investigate the impact of reasoning on text-based classification. This paper proposes a novel approach to give ontology-driven reasoning on predicted results by machine learning. Thus, we construct text embedding on the serious game data. Next, we use machine learning for prediction and DBpedia ontology for reasoning to analyze the enhancement in prediction results. We conduct a set of benchmarks using several well-known machine learning algorithms, leading to an accuracy of 97%.

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1. Introduction

Enhancing learning and comprehension in various fields has become more accessible by introducing serious games into analytical and educational processes. serious games have shown great promise in helping language learners acquire new words and improve their vocabulary. This paper explores the interface between ontology-driven analysis, game-based learning, and text classification, emphasizing educational serious game use. Because of their well-known capacity to foster active learning and intense player engagement, these games offer an ideal environment for testing cutting-edge instructional technology approaches. In recent years serious games and their educational potential have been the object of various studies.

This work introduced a novel method that improves the text classification process of word-related serious games through data analysis using ontology-based explainability. Several works on word embedding models, semantic learning techniques, and board-based serious games were examined to provide a thorough context for this research. The present study aims to create and apply a methodology that blends ontology-based reasoning with machine learning.

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This method seeks to offer semantic explanations that raise the learning process's educational potential and improve text classification accuracy in the context of serious games. Ontology-driven analysis and word embedding techniques were used to advance understanding of language and semantic relationships by a comprehensive study of a local Taboo Serious Game dataset^{1 2}.

The results of this research bring new insights into the design and analysis of educational technologies and demonstrate the potential of combining ontology-based explainability with serious games. The proposed model offers a more comprehensive and understandable explanation for classifications by bridging the gap between statistical machine learning and semantic web technologies; it can predict and reason simultaneously.

The methodology, experiments, and findings described in this work will illuminate the ongoing discussion of improving educational outcomes through technology-driven innovations. In the experimental phase of the research, a series of tests on a dataset derived from a Taboo Serious Game were conducted. The primary aim was to evaluate the effectiveness of an ontology-driven approach in improving the explainability and educational value of text classification within serious games. Word embedding techniques for capturing and quantifying the semantic relationships between words were crucial in transforming the textual data into a suitable format for machine learning models [1]. A variety of feature extraction techniques, such as Count Vectorization (CountVec), Word2Vec, and Term Frequency-Inverse Document Frequency (TFIDF), are used in conjunction with Multilayer Perceptron (MLP) and Gaussian Naive Bayes (GaussianNB) classifiers during the experiments. An understanding of the efficacy of various combinations of classifiers and feature extraction techniques is obtained by evaluating each method's performance according to its accuracy.

This paper is committed to exploring the application of ontology-based reasoning and machine learning algorithms to refine the process of text classification and provide semantically rich explanations for predictions. Section 2 discusses text classification in serious games and ontology-driven methods based on the literature. Section 3 is dedicated to the data collection, the main methods used in this work, and SPARQL implementation. Experimental setup and results are provided in Section 4. A detailed analysis of conclusions and future works is given in section 5.

2. Literature review

Numerous scholarly investigations have examined the impact of serious games on players [2, 3, 4]. The findings indicate that learning gains greater significance when players fully immerse themselves in the game and perceive the relevance of concepts in tangible situations. Serious games are recognized for their usefulness and benefit in achieving learning outcomes. Many studies have examined serious board-based games such as Taboo. The dataset on taboo topics was used to introduce a variety of new methodologies. The work presented in [5] outlines the concept and educational value of serious games and focuses, in particular, on vocabulary games that are intended to support language learning. This work particularly examines games that support the acquisition of foreign language vocabulary. Accidental and intentional learning strategies are contrasted: accidental learning occurs through activities not primarily aimed at learning, while intentional learning involves direct learning and memorization. The paper highlights the development and impact of a particular game, Semantic Taboo, which promotes learning by associating words with semantically similar and strengthening connections within a user's vocabulary.

Another critical constraint on Taboo serious games exploring word formation and lexical choice compares two models, word2vec and fastText, on the Taboo paradigm [6]. Word2vec constructs meanings based on the distribution of whole word tokens and treats words like "human," "tax officer," and "man" as entirely different. In contrast, fastText accounts for orthographic elements using substring vectors and associates words with common n-grams (like "man" in the previous examples).

Several studies have investigated serious games using the Taboo paradigm. However, the literature has not previously investigated ontology-based explainability in the Taboo paradigm. Game designers employed different analytical techniques and noted that such techniques aid in scrutinizing particular data to determine whether it aligns with a particular definition of game balance and in considering the game's design [7, 8, 9, 10]. With these methods, game

¹ <https://play.google.com/store/apps/details?id=co.game.taboo>

² <https://apps.apple.com/us/app/yasag/id1535380939>

logs are analyzed using Word2Vec to offer recommendations for game enhancements. Research for analyzing robot soccer logs involved using Word2vec, where activities like hitting and passing the ball, working as a team, and other similar activities were part of the protocol [7]. Based on this information, similarity in playing styles is measured and analyzed.

The importance of playing data analysis using word embeddings was demonstrated as a common method for natural language processing [8]. Using the well-known Word2Vec algorithm and a comprehensive analysis of numerous chess games shows how the resulting vector representation can disclose common knowledge and intricate details about the game, such as relative piece values and the organic spatial flow of matches. These findings imply that word embeddings are an inexpensive and easy method that can give a broad picture of a game's dynamics, assisting critics and designers in formulating fresh theories regarding the flow, structure, and design of a single game.

There is extensive literature on word representations and their applications using machine learning. It has been experimentally demonstrated that negative sampling is the most efficient algorithm for Word2Vec in topic segmentation regardless of the language used [11]. However, the choice of learning models should be carefully considered, as CBOW is better with frequent words and Skip-Gram is better with infrequent words. Compared to LSA and GloVe, Word2Vec, and GloVe are more effective, especially in word vector representations in a small-dimensional semantic space. A thorough comparison indicates that Word2Vec and GloVe are more effective than LSA for topic segmentation. Furthermore, Word2Vec performs better than GloVe, especially in terms of the dimensionality of the semantic space.

Conceptually similar work has also been carried out by Atanasova et al., which discusses the lack of guidance in selecting machine learning explainability techniques for specific tasks and architectures. However, many such techniques have been developed to make model decisions transparent [12]. The authors created a comprehensive set of diagnostic properties to evaluate various explainability techniques. This framework has been applied to evaluate different methods for text classification tasks and neural network architectures and compare the techniques' saliency scores with human judgments of importance. Results found at the end of the work suggest that gradient-based explanations perform best across different tasks and architectures. However, exceptions in the Confidence Indication diagnosis have been noted, where ShapSampl and LIME outperform others, even though these methods are overall slower and less effective in other diagnostic areas. Research suggests that while gradient-based methods are superior in most aspects, there is a trade-off between computational efficiency and the quality of explanations provided by different techniques.

There have been several attempts to combine machine learning and ontology-based reasoning [13, 14, 15, 17]. This combination for producing semantic explanations combining interpretable models and ontology-based interactive machine learning (IML) is presented in [13]. Using a novel ontology-based sampling technique, two examples create an anchor learning algorithm to focus the search for more insightful semantic explanations and represent semantic relationships between terms or features. The paper also provides guidelines for connecting extracted data, anchor texts, and ontology-based tuples to create concise semantic explanations. This innovative approach integrates domain knowledge to improve interpretability for machine learning models and data, outperforming traditional methods. The work essentially marks a development in improving domain-specific understanding to make machine-learning insights more comprehensible and available.

Serious game published in [14] maximizes user attractiveness and encourages long-lasting, beneficial dietary changes through a theory-driven game design approach and an inventive conceptual framework incorporating a recipe ontology. The ontological modeling of recipes creates a realistic and varied simulation environment, allowing for customization of the gaming experience. Three game genres—puzzle, roguelike, and cooking—each employs modern game design techniques and a gripping story to keep players interested. Take user interaction and experience into consideration. The novel serious game "Express Cooking Train," presented in this paper, aims to improve the user's NL and FL skills. To formally present related concepts, features, and constraints, ontological modeling has been used. In the meantime, an extended model based on an existing ontology by BBC has been created to meet the requirements of the serious game [15]. The need for a formal presentation of GBLS gameplay to design meaningful and engaging GBLSs is emphasized in [14].

The main purpose of this paper is to introduce a model that highlights the importance of defining gameplay through a formal model to facilitate machine-interpretable definitions of basic gameplay concepts and corresponding relationships. It requires defining the scope of the ontology, its concepts, relationships, and constraints and describing a glossary for all concepts and attributes. It represents the knowledge modeling itself and clarifies in the form of questions

the ontology must answer, such as: What are the key gameplay components? Do rules define the pedagogical aspect? The paper concludes by emphasizing how important an organized framework is to creating game-based learning systems (GBLS).

Despite many of studies in this area, a great deal of work must be done to add new abilities to serious games, especially in NLP, where human bias in the interpretation step is inevitable. This work investigates the methodology for explanation techniques for text classification based on data collected from Taboo game players.

3. Methodology

The present investigation aims to make ontology-based reasoning to provide explanations for machine learning-produced predictions. Using an organized knowledge framework, ontology to deduce new information or explanations for facts is known as ontological reasoning. It can assist in giving a semantic basis for a specific prediction made by an algorithm in the context of machine learning predictions.

3.1. Dataset

The practical part of this research has been implemented using the dataset from a local “Taboo Serious Game,” which consists of different kinds of cards that contain one main word and five taboo words. This game is designed based on an explanation and comprehension mechanism, which helps players memorize words and find new ways to explain the main word. Words on each card should be nouns and related to each other. This study analyzes 1454 of these cards, using a small subset of the total number of cards in the game. The dataset is divided into various categories, such as animals, humans, and foods, with each card consisting of a noun and five taboo words. Food, human, and animal labels comprise the dataset’s three primary categories. There are 561 items in the “Food” category, the most, and 487 items in the “Human” category. Food has the fewest items with 406 cards. The first 5 words are shown in Fig. 1.

word_tabu	first_word	second_word	third_word	fourth_word	fifth_word	category	
0	BEAR	YELLOW	HONEY	FURRY	BEE	SLEEP	animal
1	GRADUATE	SCHOOL	STUDY	GRADE	DEGREE	UNIVERSITY	human
2	SNAKE	ANACONDA	WATER	FEAR	ANIMAL	POISON	animal
3	APPLE	FRUIT	GREEN	PUMP	SWEET	RED	food
4	SNAKE	BEST	REPTILE	SLYTHERIN	SKIN	LONG	animal

Fig. 1. Top 5 Main Words and Related Words Across Various Categories

Words on this dataset do not contain stopwords. However, to use vectorization functions, we should group them into a single column (Fig. 2).

word_tabu	category	combined	
0	BEAR	animal	BEAR YELLOW HONEY FURRY BEE SLEEP
1	GRADUATE	human	GRADUATE SCHOOL STUDY GRADE DEGREE UNIVERSITY
2	SNAKE	animal	SNAKE ANACONDA WATER FEAR ANIMAL POISON
3	APPLE	food	APPLE FRUIT GREEN PUMP SWEET RED
4	SNAKE	animal	SNAKE BEST REPTILE SLYTHERIN SKIN LONG

Fig. 2. First 5 main word (word_tabu), its category, and a combined list of related or taboo words

We must use embedding methods such as Word2vec, TF-IDF, and CountVectorizer to convert the preprocessed data to vector formation to enable the mathematical expression of semantic proximity between words. Before that, the ‘combined’ column was converted to a list of arrays, so word2vec processed it. For example: [['word1', 'word2'], ['word3', 'word4']]. Each sentence or card, in this case, is converted to arrays so word2vec can be used on it.

3.2. Machine Learning models

Preprocessing and analysis of textual data collected from the Taboo game have been implemented using particular machine learning models. Word embedding models were used to transform data into a suitable format, and the Naive-Bayes classifier and a multi-layer perceptron were used to categorize the training data. This section gives a brief description of these algorithms for processing textual data.

3.2.1. Word Embedding

Text embeddings are a sophisticated method used in natural language processing (NLP) to represent text in a form that computers can understand. Instead of working with text directly, which is variable in length and highly complex due to the nuances of language, text embeddings translate words, sentences, or entire documents into vectors of real numbers in a high-dimensional space. This process involves capturing the semantic meaning of the text, allowing similar words or phrases to have similar embeddings, which makes it easier for algorithms to process and analyze textual data. This section outlines the embedding methods used in this research, such as Word2Vec and TF-IDF. Word2vec is an additional commonly utilized word embedding method. Creating vectors involves scanning the entire corpus and identifying the words with which the target word appears most frequently [17]. This also reveals how closely related the words are semantically. To estimate the best choice of model architecture to achieve the best possible results quickly, we first evaluated models trained on subsets of the training data, with the vocabulary limited to 1454x6 words.

Unlike One Hot Encoding and TF-IDF methods, the Word2Vec approach uses an unsupervised learning technique. It uses artificial neural networks and unlabeled data to create the Word2Vec model, which generates word vectors. This method is unique because the vector dimensions do not have to be equal to the dataset's total number of unique words. Handling large datasets is made more accessible by modifying the vector size according to the project's requirements and the corpus size. For example, One Hot Encoding would produce a 300,000-dimensional vector with only one non-zero value for each word in a corpus of 300,000 unique words. On the other hand, using Word2Vec to select a vector size of 300 (which can be changed to suit personal preference) eliminates the need to manage vectors with needlessly large dimensions.

Word2vec has two architectural approaches: the Continuous Bag of Words (CBOW) Model and the Skip-Gram Model [18, 19, 20]. CBOW was used in our research because of our small dataset and approach. This architecture is called a bag-of-words model, as the order of words in the context is not essential. The target word is predicted by the CBOW model based on the context words that surround it. Put differently, it makes predictions about the middle word based on the words that surround it. This model predicts the target word by combining all context words into a single vector. For example, in the text "MUSTARD YELLOW COLOR FOOD HAMBURGER SPICY," if we use "MUSTARD" as our target word, the CBOW model will take "YELLOW", "COLOR", "FOOD", "HAMBURGER", "SPICY" as context. This model is beneficial when we have a small dataset and is faster than the Skip-Gram model [19].

3.2.2. Gaussian Naive Bayesian Classifier

Naive Bayes classifiers are straightforward and reliable probabilistic classifiers that excel in text classification. The algorithm assumes features are conditionally independent of a class, a reasonable simplification for many real-world scenarios. The task of supervised classification is to take an input x and a fixed set of output classes $Y = \{y_1, y_2, \dots, y_N\}$ and return a predicted class $y \in Y$. In the supervised situation, we have a training set of N cards, each manually labeled with a class: $(c_1, y_1), (c_2, y_2), \dots, (c_N, y_N)$. We aim to learn a classifier capable of assigning a new card c to its correct class $y \in Y$, where Y is a set of helpful card classes. A probabilistic classifier also provides information about the probability that the observation is included in the class. This complete distribution across classes can be beneficial information for downstream decisions; when combining systems, it can be helpful not to make discrete decisions early on. Many types of machine learning algorithms are used to create classifiers. This section discusses the Naive Bayes. Different from descriptive classifiers, generative classifiers like Naive Bayes develop a model of how a class might generate some input data. Given an observation, they return the class name most likely to generate it. Discriminative classifiers like logistic regression learn which features from the input are most helpful in distinguishing between the different possible classes. While discriminative systems are often more accurate and, therefore, more commonly used,

generative classifiers still have a role to play. Gaussian Naive-Bayes used in this work classify data using probability, calculated as the value of the Gauss function:

$$P(x_i|c) = \frac{1}{\sqrt{2\pi\sigma_c^2}} e^{-\frac{(x_i-\mu_c)^2}{2\sigma_c^2}} \quad (1)$$

where x_i is the i_{th} feature, c is the class. μ and σ are the mean and variance of the feature x_i for class c , respectively. To classify a new instance, GNB calculates the posterior probability for each class and selects the class with the highest probability. This involves plugging in the new instance's feature values into each class's Gaussian probability density function, considering their prior probabilities, and then choosing the class that yields the highest posterior probability.

3.2.3. Multilayer perceptron

Alternative classifiers are investigated to comprehend the advantages and disadvantages of every model. Because multilayer perceptrons (MLPs) can capture intricate patterns and dependencies, MLP is another option that can be compared with our existing GNB classifier. MLP is a type of neural network with multiple layers of nodes, including input, hidden, and output layers. These nodes process input data through weighted sums and activation functions, allowing the network to learn complex patterns. MLPs are trained using backpropagation, which optimizes the weights. Text classification performance can be enhanced by selecting the most suitable model based on data characteristics and comparing the accuracy results of MLP and GNB.

3.3. Ontology

In information science, an ontology is an official representation of concepts and their connections within a domain. It defines entities, relationships, properties, rules, and constraints, among other essential elements. The Semantic Web, data integration, artificial intelligence, and information retrieval all use ontologies. Two examples are the Friend of a Friend (FOAF) ontology and the Web Ontology Language (OWL).

3.3.1. Wikipedia

Wikipedia is an online encyclopedia maintained by volunteers. It is free and openly collaboratively produced and hosted by the Wikimedia Foundation. Available in various languages, Wikipedia is used widely by researchers, teachers, and students as a learning tool. Worldwide, users are encouraged to participate and collaborate, and the website provides information on nearly any topic as a starting point. Numerous initiatives use Wikipedia's rich, unstructured content to extract, organize, and make data available for various uses, including data integration, research, and the Semantic Web.

3.3.2. DBpedia

DBpedia is a large-scale, multilingual knowledge base extracted from Wikipedia [21]. It contains structured information from Wikipedia pages, making it accessible for querying and linking. Using DBpedia for reasoning involves extracting semantic relationships and hierarchies to enrich predictions with background knowledge. This work used a simple protocol and RDF Query Language (SPARQL) over DBpedia to extract concepts by analyzing three types of information: human, animal, and food-associated words. Each entity is described by a unique Uniform Resource Identifier (URI) in DBpedia, representing an equivalent entity concept in Wikipedia URL. The attributes collected regarding entities are categorized into required and complementary classes. As part of the underlying requisite research, the required class of data, which includes the name of an entity, type, and entity representing URI, is considered. The complementary class of attributes includes abstract entities. The concept collection is based on entities defined in the English language. The concept extraction is performed through the OpenLink Virtuoso SPARQL endpoint. For example, a sample SPARQL query for extracting the entity type is shown in Fig. 3.

```

query_template = """
PREFIX dbo: <http://dbpedia.org/ontology/>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>

SELECT DISTINCT ?entity ?type
WHERE {{
  ?entity rdfs:label "{val}"@en .
  ?entity rdf:type ?type
}}
"""

```

Fig. 3. Example initial SPARQL query for getting entity and its type for further process

This part helps us to do reasoning after obtaining predictions from the chosen classifier.

3.3.3. BabelNet

Utilizing lexicographic and encyclopedic knowledge from WordNet, Wikipedia, and other language resources, BabelNet is a multilingual, lexicalized semantic network and ontology. Applications involving natural language processing (NLP), machine translation, and multilingual information retrieval will find it especially helpful as it attempts to provide an extensive repository of lexical and semantic information across multiple languages. Rich semantic relationships and translations that facilitate cross-lingual comprehension and semantic search are provided by BabelNet, which connects words and concepts across languages. As an alternative, DBpedia concentrates on obtaining structured data from Wikipedia and displays it as a rich, extensive knowledge base that includes various factual information.

Semantic Web technologies and linked data applications benefit greatly from the structured, queryable data about real-world entities that DBpedia focuses on providing. A strong and commonly used query language for RDF data, SPARQL is used in this query. DBpedia better serves applications requiring large amounts of factual data and structured information about entities. In contrast, BabelNet is best suited for linguistic applications and multilingual tasks due to its multilingual lexical information and semantic relationships. Comprehensive, connected data query and analysis is made easier with DBpedia thanks to its integration with the Linked Open Data (LOD) cloud and emphasis on linking to other datasets. BabelNet integrates lexical and semantic knowledge across languages, which is the primary difference between these two approaches. The focus of DBpedia is factorized, organized data extraction from Wikipedia. While both offer a robust documentation system and community support, DBpedia is a better choice because our project requires structured data about entities from our dataset.

4. Experiments and Results

4.1. Experiments

Experiments were carried out on the Taboo Serious Game dataset. The dataset is relatively balanced, which is beneficial as it reduces the risk of model bias toward the more represented classes. As a machine learning part, firstly, we use the word2vec vectorization method to preserve semantic relations and find similarities between words. This representation helps machine learning to understand and make predictions based on this representation of words. The window for Word2Vec is 5, and the size is 300. Min count is chosen as 3, so it ignores that words appear fewer than three times across all documents.

The number of iterations over the corpus epochs=100 means the training algorithm will pass over the data 100 times, which can improve the embeddings' quality and increase the training time. Using Word2Vec with Naive Bayes is not as straightforward as using CountVectorizer because of a fundamental mismatch in expectations: Out of two options considered to use, MultinomialNB (Multinomial Naive Bayes) expects discrete feature counts (like those produced by CountVectorizer), Word2Vec generates continuous, dense feature vectors. Additionally, MultinomialNB expects non-negative features, but Word2Vec vectors can contain negative values. That is why Word2Vec vectors with Gaussian Naive Bayes classifiers were used to experiment in this research. (Fig. 4).

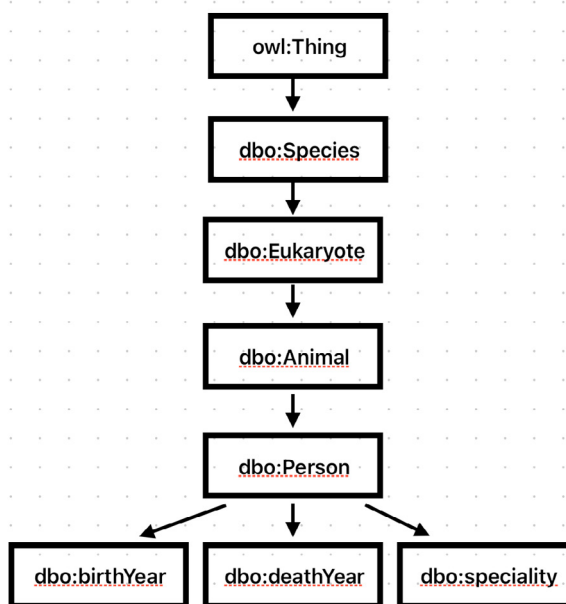


Fig. 4. DBpedia ontology-based structural tree for Person category

Using the Gaussian Naive Bayes (GaussianNB) model for prediction and then leveraging DBpedia for reasoning is an exciting approach that combines statistical machine learning with semantic web technologies for enriched analysis or explanation. This approach is particularly useful when you want the prediction and a deeper understanding or reasoning behind it. MLP was applied to the investigated dataset with different embeddings to compare the classification results. After the prediction system identifies an entity (e.g., an animal, food, or human), you can query DBpedia to retrieve its ontology. This ontology includes information about the entity's classification, properties, and relationship to other entities. By finding the root of an entity (such as determining that an entity is an animal, what type of animal it is, and its relation to other animals), you can provide a reasoned context or explanation for your prediction. Once the framework has a prediction result, DBpedia queries to retrieve its ontology with the predicted entity. SPARQL (SPARQL Protocol and RDF Query Language) is used to query DBpedia's RDF (Resource Description Framework) data.

4.2. Results

This section summarizes and discusses the main findings of the work. The accuracy outcomes of various classification strategies and feature extraction methodologies are displayed in Table 1. The highest accuracy for application of the MLP was found in conjunction with TFDIF; on the other hand, GaussianNB shows the best results together with Count Vectorizer. The outcomes demonstrate that, among the tested techniques, TFIDF is the most successful feature extraction method and that, overall, MLP outperforms GaussianNB. Notably, the accuracy of MLP using Count Vectorizer and MLP using TFIDF is not appreciably different, suggesting that Count Vectorizer is a powerful feature extraction technique.

In the context of reasoning, DBpedia Reasoning has a lower accuracy of 0.80. Classifiers can produce precise predictions based on related words, even in cases where the primary word is absent or erroneous. DBpedia Reasoning only considers the noun, ensures that it exists in the ontology, and finds its type by following it down to its root. We use ontology-based reasoners to address the noun's shortcomings in the expert review of the user-generated content. This raises the prospect of more work and advancement by incorporating enhanced word processing and reasoning abilities. The objective of solving these data set problems is to sharpen cognitive abilities.

During the evaluation, performance is assessed using various metrics. These metrics include accuracy, which measures the proportion of correct predictions; a confusion matrix that provides a breakdown of correct and incorrect

Table 1. Results of text classification using different ML methods together with feature extraction methods

N	ML and feature extraction methods	Testing accuracy (%)
1	Multilayer Perceptron + CountVec	0.97
2	Multilayer Perceptron + Word2Vec	0.95
3	Multilayer Perceptron + TFIDF	0.98
4	GaussianNB + CountVec	0.94
5	GaussianNB + Word2Vec	0.87
6	GaussianNB + TFIDF	0.93
7	DBpedia Reasoning	0.80

predictions by class; and recall, which measures the proportion of relevant instances successfully retrieved from the total set. The evaluation criteria were accuracy, precision, recall, F1 score, and support.

Results of the testing step show that 167 out of 168 in the animal category, 87 of 98 in the food category, and 98 out of 99 human category were found correctly. In the investigated dataset, many food words are human-related and, therefore, difficult to predict. This means that in the category “human,” there can be a noun related to the “food” category that our model cannot understand.

The ontology-based reasoning provided in Fig. 5 indicates a mismatch between the predicted and actual category of the main word. The text “BANANA YELLOW MONKEY FRUIT SWEET FOOD” led to a prediction of “human,” while the actual category is “food.” The main word is “Banana,” as indicated by the DBpedia URL provided, and the reasoning aligns correctly with the actual category by identifying it as “Food.” This suggests that while the model incorrectly predicted the category as “human,” the reasoning mechanism correctly associated the word “Banana” with food, demonstrating the ability of ontology-based reasoning to provide semantic context and correct categorical associations.

```
Words: BANANA YELLOW MONKEY FRUIT SWEET FOOD
prediction: human, real: food
Main Word: https://dbpedia.org/page/Banana
Reasoning: Food
```

Fig. 5. Reasoning result for “Banana”

Concrete main words on categories such as food, human, and animal mostly perform better accuracy than prediction. DBpedia ontology-driven information gives more accurate results; you can retrieve information about that reasoning if needed. In Fig. 6. The reasoning of the category ‘Bride’ aligns well with the prediction outcomes. In an abstract context, prediction can perform better than the driven approach, but in this work, reasoning is focused on concrete words.

```
Words: BRIDE WEDDING ENGAGEMENT RING GROOM MARRIAGE
prediction: human, real: human
Main Word: https://dbpedia.org/page/Bride
Reasoning: Human
```

Fig. 6. Reasoning result for “Bride”

5. Conclusion

This paper applied an ontology-based approach to classified text containing cards to incorporate reasoning. This approach was first built and validated on data taken from Taboo Serious Game. We then conducted several experiments utilizing our ontology-based method, word embeddings, such as word2vec, CountVec, and TFIDF with MLP

and GaussianNB for text classification. The research aims to display ontology-based reasoning to provide semantic explanations for classifications. The methodology analyzes a dataset from a "Taboo Serious Game" with cards containing main and taboo words to improve word memorization and comprehension through explanation mechanisms. The dataset comprises categories such as foods, humans, and animals.

Furthermore, we found that ontology-based reasoning is particularly effective in identifying false predictions of the classifiers. The argument is better in contexts where the text is concrete and can even provide short snippets of information about the words involved. Although predictions for abstract words are not the focus of our current work, it is noteworthy that DBpedia has revealed discrepancies in this area. This finding could be crucial for future research as it suggests that while our current models perform excellently in concrete contexts, there may be an opportunity to extend our methods to abstract scenarios and leverage the ontological framework to close the gap between concrete and abstract word classification.

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