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Detection of human relationships from their interactions on social media is a challenging problem with a wide range of applications in different areas like targeted marketing, cyber-crime, fraud, defense, planning, human resource, to name a few. All previous work in this area has only dealt with the most basic types of relationships. The proposed approach goes beyond the previous work to efficiently handle the hierarchy of social relationships. This paper introduces a novel technique named Quantifiable Social Relationship (QSR) analysis for quantifying social relationships to analyze relationships between agents from their textual conversations. QSR uses cross-disciplinary techniques from computational linguistics and cognitive psychology to identify relationships. QSR utilizes sentiment and behavioral styles displayed in the conversations for mapping them onto level II relationship categories. Then, for identifying the level III relationship categories, QSR uses level II relationships, sentiments, interactions, and word embeddings as key features. QSR employs natural language processing techniques for feature engineering and state-of-the-art embeddings generated by word2vec, global vectors (glove), and bidirectional encoder representations from transformers (bert). QSR combines the intrinsic conversational features with word embeddings for classifying relationships. QSR achieves an accuracy of up to 89% for classifying relationship subtypes. The evaluation shows that QSR can accurately identify the hierarchical relationships between agents by extracting intrinsic and extrinsic features from textual conversations between agents.

CCS Concepts: • **Computing methodologies → language resources**.

Additional Key Words and Phrases: Agents Interaction Model, social Relationship, Hierarchical Relationship Analysis, Quantifiable relationships, Behavioral Model, machine Learning

1 INTRODUCTION

People in the modern era communicate, interact, and socialize through social media platforms [1]. Intelligent agents are generally involved in different social networks with multiple roles. Even in a particular network, an

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agent may be assuming multiple roles depending upon her interaction with other agents [47]. As enterprises around the world seek an efficient way to monitor, listen, and analyze data gathered from social platforms, IoT provides them with a simple way to aggregate social data without using their time or energy. An SAE technique is used in privacy preservation, which transforms actual data into an encoded form to avoid inference attacks that can be derived through system-based ML techniques [40]. Despite that, privacy-preservation has been handled through ML techniques and efficient web APIs [17, 25, 26].

The underlying emotions influence human relationships in their interactions [34]. The interactions between agents evolve through time due to changes in the agent's actions and behaviors. While communicating in a social network, these interactions between agents are called relationships.

Humans spend approximately 32% to 75% of their time in social interactions [31]. Many internet users have faced cyber-crime in recent years. One successful approach for dealing with cyber-crime victimization is to analyze the social network communication and development of relationships on social platforms [15]. Relationship analysis is also beneficial for advertising agencies.Advertisements resonate better with the intended audience. It is also helpful to build better synergy [16]. Moreover, it is being used by trained Artificial Intelligence(AI)-based agents like helper robots and even chatbots for assisting with the troubleshooting process [23]. Such tools can also be useful for social network analysis, such as: finding a group of criminals in the social network.

In the last few years, the number of social network-based applications has increased [7]. They provide an up-to-date review of the state-of-the-art literature on social network analysis. This work proposes four different dimensions, i.e., (i) pattern discovery of knowledge, (ii) information fusion integration, (iii) scalability, and (iv) visualization techniques. Natural language processing (NLP) techniques automatically interpret and generate human language. Using NLP, we can automatically analyze how people communicate with each other using speech and text. We have numerous examples of NLP being used successfully, such as chatBot assistants, spam filters, sentiment analysis, emotion detection, information retrieval, NER, etc [48].

Social media's recent evolution has influenced every aspect of our lives, and its training popularity is increasing among young adults. Named-entity recognition (NER) is a subtask in information retrieval that tries to identify and classify named entities specified in the unstructured text and classify them into predefined types such as person names, organizations, locations, etc. For relation extraction, different machine learning techniques are used, i.e., hidden Markov models, conditional random fields, and support vector machines [50]. Stadtfeld et al. [41] states that important parts of human life are organized into social groups. Therefore, most research work focuses on social networks to analyze human actions. These actions can be of various kinds as they like or dislike each other, or they may be acquainted with their thoughts or similar beliefs [38]. The authors propose a general method for determining the boundary of social networks.

In this research work, we address the formulation and identification of relationships based on different levels of interactions. This research aims to identify the relationship between agents, so from this point onward, we refer to a person/human as an agent. We present a 3-tier hierarchical architecture for the classification of social relationships. Relationship classification is treated as an utterance classification problem. The proposed approach QSR utilizes Cornell Movie Dialogue Corpus [14] to validate our work. Using well-known libraries, i.e., NLTK, pandas, and sklearn for text analysis. We use the TextBlob library on the jupyter python framework for sentiment analysis of conversations.

This problem becomes more challenging when the system has to deal with more realistic agents. To the best of our knowledge, this is the first work that merges natural language processing and cognitive psychology for Text Analysis to extract social relationships among agents from their conversations.

This research provides the following contributions:

- Present a novel approach for identifying the relationship between agents by analyzing conversations between them.

- Annotation of a large corpus using the behavioral model of psychology, which utilizes sentiment types and behavior styles to classify level II relationships.
- Analyze the interactions among agents to explain how they play an important role in shaping social relationships.
- Generation of the model named QSR for the classification of level III relationship.
- Integrate the proposed features with state-of-the-art embeddings to identify the detailed analysis of the QSR approach.
- The evaluation shows that QSR can accurately identify the hierarchical relationships between agents by extracting intrinsic and extrinsic features from textual conversations between agents. QSR achieves an accuracy of up to 89% for relationship subtypes classification.

The rest of the article is structured as follows: Related literature and the necessary background are briefly discussed in Section 2. The proposed approach QSR, is explained in Section 3. We present the complete evaluation of data and network creation in Section 4. In Section 5, we present quantitative embedding results and use these embedding to make different comparisons as well. Then we discuss the findings in Section 6. Finally, Section 7 concludes the work.

2 RELATED WORK AND CORE NOTION OF BACKGROUND

This article reviews various text classification, sentiment analysis, and relationship identification approaches. Therefore, this section elucidates some of the research directions observed.

2.1 Agents communication in cognitive framework

Among different digital means of communication, the evolution of social media has been notable over the past decade. It has become one of the popular platforms to collect public opinions, sentiments, and emotions[21]. We can identify relationships between agents through them. P. B. Horton et al. [12] explains that according to social psychology, social relations between agents are divided into two main categories named primary and secondary.

In primary groups, we know other people personally as individual personalities. Usually, primary groups are small and interactive. The people in these groups are emotionally connected. However, secondary groups are often larger and impersonal. The relationship summarized in this type of group is personal, informal, traditional, sentimental, and general. To simulate human interactions, we need realistic behavior that holds all the properties of human society. These properties include the perception, relationships, emotions, and behavior of different humans with each other [6]. On the other hand, there are some secondary groups like Impersonal, Formal, Utilitarian, Realistic, and Specialized. They called them social agents and provided a model of social interaction and emotional cognition that researchers can apply to social agents to study their effects and observe agent actions.TransConv is another unique method that promotes the representation of both agents and their relationships through textual interactions [27]. For this purpose, several experiments were conducted on a real social network.

TransConv determines better agent and relationship embedding than other state-of-the-art knowledge graph embedding models. They used a BDI (Belief, Desire, Intention) model for the cognitive part of their architecture [20]. They also used the GAMA platform to build architecture. For example, they took bushfires in Australia to show the social links between agents; they considered two families to help each other survive. They worked on straightforward cases for finding relationships between different entities. This work can identify the group of different entities in societies. For both negative and positive emotions, emotion regulation abilities were found to be more significantly connected to substance use than emotion regulation techniques [45].

Kozlak et al. [35] discusses the importance of entities in a social network and also analyses the social relations between different entities. They used the social Network Analysis approach (SNA) to identify the importance of different entities and groups. They analyze the data on phone calls and internet blogs. This approach did not consider dependencies between entities. The cognitive framework of agents can be represented by the pyramid depicted in Figure 1.

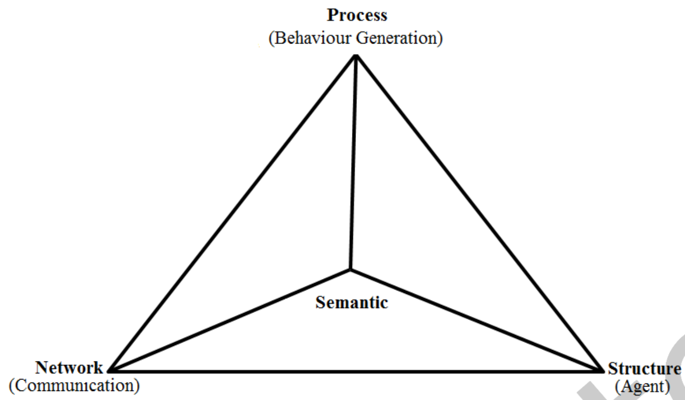


Fig. 1. cognitive Framework of Agents

2.2 Sentiment analysis and word polarity disambiguation

Researchers have tested various methods of automating the sentiment analysis process in natural language processing, data mining, and machine learning. Sentiment mining has become increasingly popular in recent years for analyzing social data on online forums, blogs, wikis, microblogging sites, and other interactive online media [9]. A novel approach for combining classical and deep learning models using MLP for economic sentiment analysis has been proposed by Akhtar et al. [2]. They develop different models based on CNN, GRU, and LSTM. The evaluation of the proposed technique is done on the dataset of SemEval-2017. The microblogs and news headlines datasets give the best results.

The concept of one-to-one mapping of sentiments has been taken from [12, 44]. Caragea et al. [11] worked on the sentiment scores to find the intensities and polarities of sentiments. They also determine the effects of evolving user sentiments over time. The sentiment features are typically obtained from tweet-specific sentiment lexicons. These lexicons are automatically extracted from tweets with sentiment-word hashtags and emotions [24]. In sentiment analysis, it is noted that semantic characteristics also play an important role when we measure the polarity of sentiment words. We use these characteristics to enhance the effectiveness of QSR in identifying relationships.

Saif et al. [37] also investigated semantic features in different Twitter datasets. The authors use different approaches to determining the polarity of sentiment for Twitter sentiment classification, i.e., substitution, augmentation, and interpolation. The polarity of sentiment analysis is determined at the phrase level, which helps in disambiguating the polarity of sentiment words with multiple connotations [32].

To resolve the polarity ambiguity, Singh et. al [39] propose a Bayesian Network-Based Contextual Polarity Disambiguation technique. The authors deal with sentiment polarity in a probabilistic manner, based on a word's local and global context. They compute the quantified amount of polarity of words in a given text. Others, such as H.S. Khawaja [22] attempted to create sentiment lexicons using semi-supervised learning to determine sentiment intensity. Moreover, various methods have been introduced to build ensemble learners. The techniques of ensemble learning are used to increase the learning accuracy [46] of the sentiment analysis task.

Akhtar et al. [3] introduced a multi-task ensemble framework for the prediction of intensity, emotion analysis, and sentiment mining. For this purpose, they combine three representations of deep learning with manual features. They evaluate their approach on four datasets associated with intensity, sentiment, and emotion. Affective computing and emotion analysis for other systems also have tremendous potential as sub-component technology. They will strengthen the skills of management of customer relationships and Recommendation Systems [8].

The wide areas of computational linguistic research are considerable for investigating emotion detection and emotion recognition [18]. They worked on a dataset of emotion dimensions to optimize affective computing systems and perform reviews analyses. Moreover, they perform mapping based on the polarity of the valence (V) and arousal (A) model for the sentiment classification of text. Multiple experiments on three standard datasets show that their approach outperforms state-of-the-art to find better contextual information in dialogues. Li et al. [28] presents the bidirectional emotional recurrent unit for conversational sentiment analysis as a fast, compact, and parameter-efficient party-ignorant framework.

2.3 Relationship Extraction

T. Wang et al. [43] proposed an SVM-based method for the extraction of hierarchical relations. Features derived through NLP tools and for experimentation, the ACE2004 corpus has been used. The features used in their research were Parts of speech tagging, entity class, entity subtype, and entity role. Moreover, semantic representation of the sentence and synonym set from wordnet is also used in [43]. This approach was very limited to extracting information from a large-scale-based ontology. D. Zelenko et al. [49] presented the method of extracting relations by measuring kernel functions between shallow parse trees. Moreover, G. Zhou et al. [50] proposed different lexical, semantic, and syntactic principles in feature-based relation extraction.

2.4 Hierarchy of relationships

Integrating research from sociology, cognitive psychology, and organizations, we explore some key aspects of the social hierarchy of relationships. We propose that hierarchy is an effective way of raising social relations. Furthermore, many psychologists identified the roles and behaviors of agents by analyzing their conversations [30].

There are two categories of relationships named close and distant in level I. In level II, close and distant relationships are categorized into four types: friend, family, pleasant, and unpleasant. Moreover, in level III, each category is divided into two subtypes.

Lin et al. [29] utilized a multi-agent system for analyzing the interactions between agents. They worked on close and distant relationships between agents and validated their friends and family dataset. In order to analyze level I relationships, i.e., close/distant, we followed the same approach as discussed in [29]. Figure 2 provides the complete 3-tier hierarchical architecture of social relationships. The Neighborhood Cumulative Reward Average Evaluation method has been proposed in this work. Summary along with the limitations of the research mentioned above works is presented in Table 1.

We determine the social relationships between multiple agents using the behavioral and psychological models of interactions. We followed all the basic definitions of social relationships as given by[5, 12]. Tables 2 and 3 describe level II and III relationships, respectively. We manually annotate the data using these descriptions.

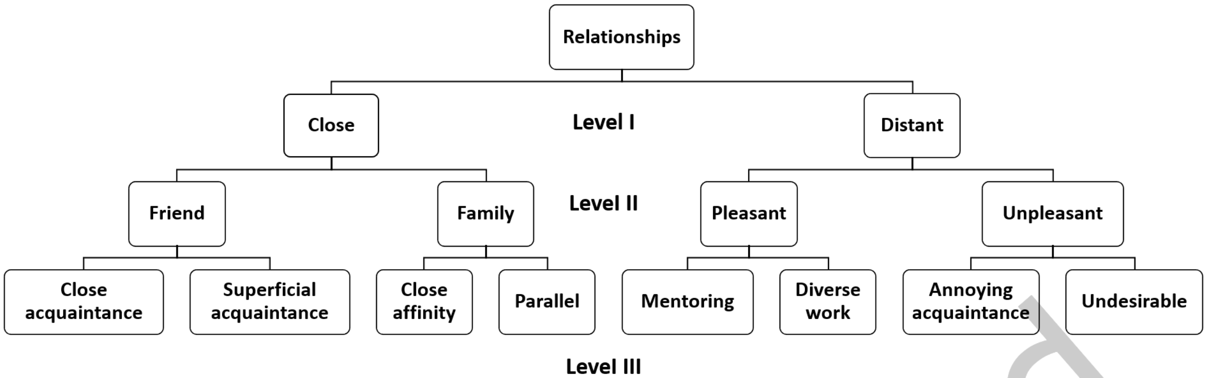


Fig. 2. 3-tier hierarchical architecture of social relationships adapted from [5, 12]

Table 1. Summary of relationship analysis studies

Paper	Methodology	Limitations	Relationship Type
Lin et al. [29]	Using Multi Agent Systems to model interactions	Inconsistency of interactions	Close/Distant
Zhou et al. [50]	Feature configuration based on n-gram analysis	Not a full person resolution method	Family
Yu et al. [47]	Taking spatial-temporal factors by analyzing cellphone data	Location only be recorded when cell phone in use	Family/Colleague
Kozlak et al. [35]	Group recognition through SNA	Does not consider dependencies between different groups	Social
Saira et al. [34]	Used an approach named RIEA	Work only on basic type of relationships	Family/friend/pleasant/unpleasant

Table 2. Basic description of (level II) relationships

Relationship Types	Description
Friend	The mutual relationship between two parties
Family	Defined roles tend to last longer
Pleasant	Close union of two dissimilar organisms
Unpleasant	Actions that furthers a person's interests

Table 3. Basic description of (level III) relationships

Relationship Types	Notation	Description
Close Acquaintance	q0	Make joint plans
Superficial Acquaintance	q1	Exchange greetings
Annoying Acquaintance	q2	Prefer to avoid interacting
Undesirable	q3	Have Fear to Contact
Diverse Work	q4	Understanding, Acceptance
Mentoring	q5	Mutually agreed upon goals
Consanguine	q6	Blood Relation
Conjugal	q7	Partner Relationship

3 QSR: AN APPROACH TOWARDS SOCIAL RELATIONSHIP ANALYSIS

The main goal of this research is to analyze the conversations among different agents to identify their relationships. Thus, the research questions that guided this work are:

RQ1: How can we use text-based conversations to predict agent-to-agent behavior?

RQ2: Does the different levels of interactions between agents shape social relationships?

This section describes the research approach we performed to answer our research questions.

3.1 Approach overview

QSR combines the concepts of cognitive psychology and NLP to extract different sentiments and map sentiments onto interactions to shape social relationships as shown in Fig.3. When we need to simulate social agents, we need

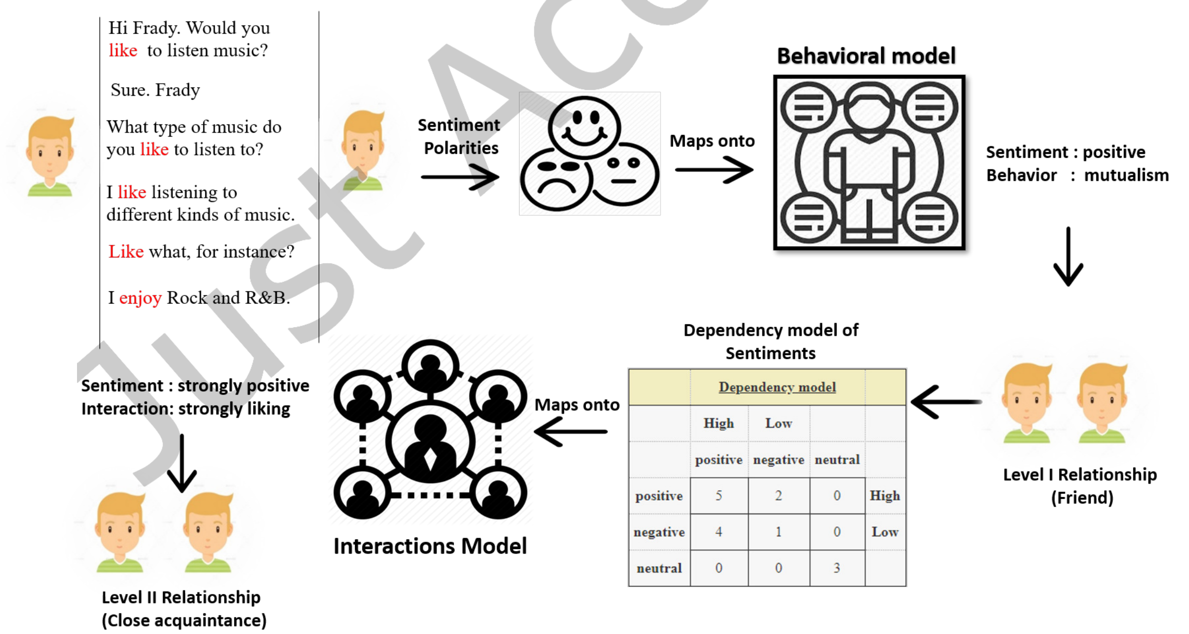


Fig. 3. Overview Research Approach

to analyze the relationships and connections. Many people interact with each other via social networks. If we want to analyze their behaviors, we need to integrate these relations and connections into agents [6]. Finding the agent's social interactions are a challenging job.

3.2 Work flow in detail

In this section, the proposed *QSR* technique is discussed in detail. The flow of *QSR* is shown in Figure 4. QSR consists of the following sequence of steps.

(1) Textual conversation is fed as input to QSR;
(2) In the pre-processing step, cleaning, steaming and contraction and unique characters are removed;
(3) The cleaned data is manually annotated with the behavior of the conversing agents towards each other; furthermore, the polarity and intensity of the sentiments between the agents are also calculated by using well known NLP technique;
(4) The behavior and sentiments (intensity + polarity) are deterministically mapped on to level II relationships stated in Table 2 using a predefined set of rules;
(5) Different word embeddings are used on the text for feature engineering. In this step, word embeddings are aggregated into sentence embeddings and then are used as features along with the interactions, sentiment, and level II relationship that are calculated in the previous step;
(6) Finally, various classifiers are used to map the input features onto level III relationships.

We represent the abstract level of the proposed approach in Algorithm 1 and graphically represented in Figure 4.

Algorithm 1 WORK-FLOW OF QSR

Initial parameters:

- i: a set of movies conversation dialogues
- j: a set of features {interactions, level II relationships, sentiments}
- k: a set of input embeddings {word2vec, glove, bert}
- l: a set of classifiers {KNN, DT, RF, NN}

Output: Conversations with associated relationship labels.

procedure IDENTIFYRELATIONS($conversingAgents$)
    for each $i \in conversations$ **do**
        $Preprocessing$ ←DIALOGUES[i]
RETURN $PreproccessedDailouges$
        FOR EACH $j \in features$ **DO**
            $FeatureExtracted$ ←FEATURES[i]
RETURN $FeatureExtracted$
            FOR EACH $k \in embeddings$ **DO**
                $sequence$ ←CONVERT[$dialogues$]
RETURN $sequences$
                FOR EACH $l \in classifiers$ **DO**
                    $relationshipLabels$ ←CLASSIFY[$dialogues$]
RETURN $relationshipLabels$

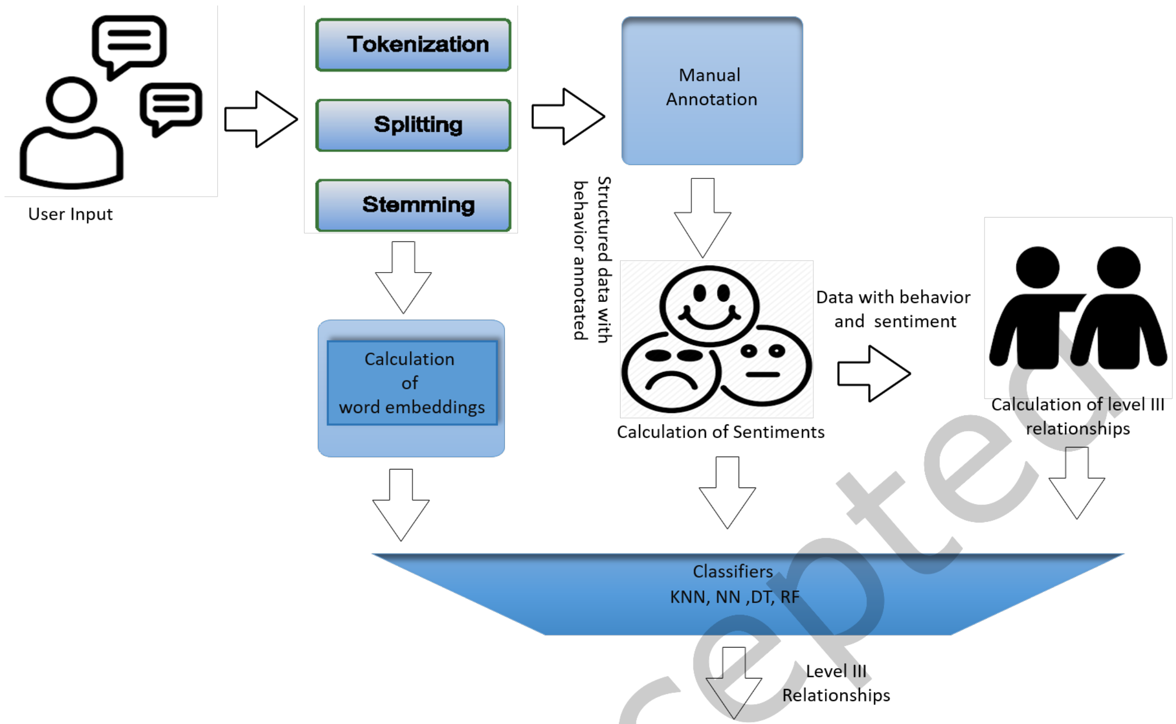


Fig. 4. The work-flow diagram of QSR

Now, these above steps are discussed in detail in the following sections.

3.3 Classifying conversations as level II relationships

RQ1 : How do we use text-based conversations to predict agent-to-agent behavior?

The goal of this question is to quantify the capacity of the tool to extract valuable knowledge from the data. To answer this question, we analyze the agent-to-agent conversations through the movie corpus. For analyzing behavior, we use the behavioral model of psychology which utilize sentiments of agents to analyze their behavior.

Table 4. Behavior types of agents w.r.t relationships adapted from [5]

Close relationships		Distant relationships	
friend	family	pleasant	unpleasant
Mutualism	Traditional	Cooperative	Opportunistic

In this phase, all the agent-to-agent conversations from the movie corpus are analyzed and behaviors of the participating agents towards each other are identified. The possible classes of behavior are mutualism, traditional, cooperative and opportunistic as shown in Table 4 .

We reckon that the sentiment of the conversation also plays an important role in calculating the accurate relationship between the agents. Therefore, sentiments involved in the conversations are calculated and used to input our classifier. Python-based TextBlob library is used for calculating the sentiments. Possible values of the

Algorithm 2 ALGORITHM FOR BASIC SENTIMENT ANALYSIS

```
procedure IdentifySentiments(dialogues)
    for each d ∈ dialogues do
        for each s ∈ sentiments do
            sentiments[s] ← extractSentiment(d)
            positive[s] ← extractpositive(intensity)
            negative[s] ←extractnegative(intensity)
            neutral[s] ← extractneutral(intensity)
            sentimentLabel[s] ← higherIntensitySentiment(dialouge)
RETURN sentimentLabel
```

sentiments are positive, negative, and neutral. The sentiment polarity score is a float within the range [-1,+1]. -1 is extremely negative, while +1 is extremely positive sentiment. The polarity score within [-1,0) is mapped to negative, within (0,1] to positive, and equals 0 to neutral. Figure 5 shows the distribution of the polarity for the conversations in the data set. The data set contains mostly neutral conversations with very few extreme values, as shown in Figure 5.

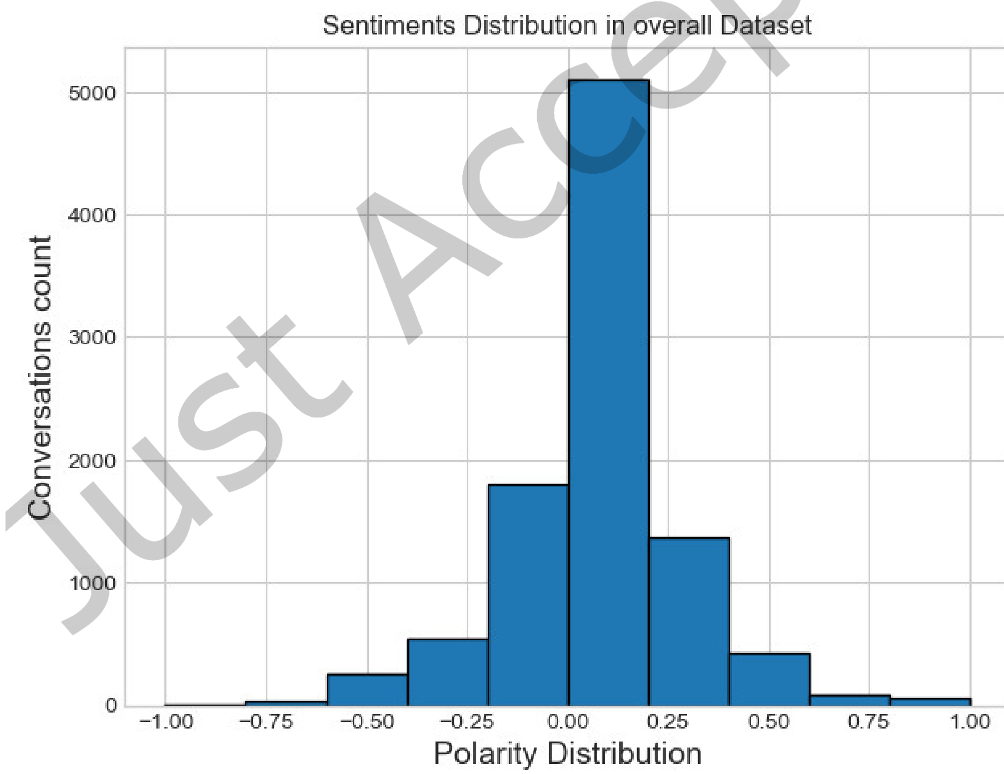


Fig. 5. Distribution of positive, negative, and neutral polarities in the data set.

We plot a 2D visualization to show the sentiment analysis given in Figure 5. Total conversations counts have been listed on the horizontal axis, and on the vertical axis, we show the sentiment polarity distribution. Here -1.00 means conversation is strongly negative, and 1.00 means strongly positive. We show the occurrence of particular sentiments within the overall conversations dataset. Each conversation set contains all sentiments but with different ratios. According to this distribution, we analyze that most conversations in our dataset are neutral (0.00).

The sentiment polarity of the complete conversation between the agents is used for this step. In the end, the behavior and sentiment values are mapped to level II relationships. Note that not all the sentiment and behavior values combinations make sense. These are shown by - in the Table 5.

Table 5. Mapping of behaviors and sentiments to level II relationships.

Sentiment / Behavior	Positive	Negative	Neutral
Mutualism	Friend	-	-
Traditional	Family	-	-
Cooperative	-	-	Pleasant
Opportunistic	-	Unpleasant	-

We describe complete network creation for the mapping of the behavior models onto different social relationships in Algorithm 3. We use two types of features, sentiment types, and behavior styles, to identify level II relationships.

Algorithm 3 ALGORITHM FOR (LEVEL II) RELATIONSHIP MAPPING

Initial parameters:

- R: a set of relationship types {friend, family, pleasant, unpleasant }
- B: a set of behavior styles {mutualism, traditional, cooperative, opportunistic }
- S: a set of sentiment types {positive, negative,neutral }

```
procedure CREATENETWORK(conversingAgents)
    for each ca ∈ conversations do
        for each sentiment ∈ S do
            for each behavior ∈ B do
                sentiment[S] ← EXTRACTSENTIMENTS(c)
                behavior[B] ← EXTRACTBEHAVIOR(c)
                conversingAgents[ca] ← BEHAVIORALMODEL(B, S)
RETURN conversingAgents
                relationship[R] ← EXTRACTRELATIONSHIPS(ca)
RETURN relationships
```

And the confusion matrix of best performing results are shown in Table 6.

3.4 Classifying conversations as level III relationships

The level II relationships assigned in the previous section are further specified into level III relationships. QSR goes beyond previous work in that our model uses the sentiments of both the agents and performs one-to-one mapping to low-level sentiments, as shown in Table 7.

In our model, for each dialogue of the conversation, the sentiments of the sender and receiver are calculated using the technique mentioned above. The dialogue is classified into one of the five possible categories based

Table 6. Confusion Matrix of the best performing results

Predicted \ Actual	friend	family	pleasant	unpleasant
friend	329	32	17	1
family	12	355	18	3
pleasant	8	24	328	1
unpleasant	2	9	7	378

on the sentiment values. The five sentiment classes are "strongly positive", "weakly positive", "neutral", "weakly negative", and "strongly negative". A dialogue is marked "strongly positive," "strongly negative," or "neutral" if both the conversing agents respond with positive, negative, or neutral comments, respectively. In the case of the opposite responses, the polarity of the greater magnitude comment is assigned to the dialogue.

Table 7. Mapping of sentiments for analyzing the agent-agent interaction

Agent1 \ Agent2	Positive	Negative	Neutral
Positive	Strongly Positive	Weakly $max(+,-)$	NA
Negative	Weakly $max(+,-)$	Strongly Negative	NA
Neutral	NA	NA	Neutral

RQ2: How do interactions play an important role in shaping the social relationships among different agents?

To answer this question, we analyze the agent-to-agent conversations in-depth, and the relationship analysis in level II w.r.t sentiments are mapped onto different interaction types. Each relationship has a distinct level of interaction. Possible values for interactions are "Close Affinity", "Mild Dislike", "Mild Liking", "Neutral", "Parallel", "Sociable", "Strongly Dislike," and "Strongly Liking." Like before, not all the level II relationship and sentiment map combinations are valid interaction types. For example, it is unlikely to have negative sentiments in a friendly relationship. Therefore, Friend + any negative sentiment is not a valid interaction. Valid combinations of the level II relationship and sentiment w.r.t interactions are shown in Table 8.

Table 8. Mapping of valid interactions set (QSR Features)

Relationship-Sentiment	Interaction
Family+Strongly Positive	Close Affinity
Unpleasant+Weakly Negative	Mild Dislike
Friend+Weakly Positive	Mild Liking
Pleasant+Neutral	Neutral
Family+Weakly Positive	Parallel
Pleasant+Weakly Positive	Sociable
Unpleasant+Strongly Negative	Strongly Dislike
Friend+Strongly Positive	Strongly Liking

In the final step, the level II relationship, sentiment, and interaction are fused with word embeddings and then mapped onto level III relationships using common classifiers.

Algorithm 4 RULES FOR MAPPING OF LEVEL III RELATIONSHIPS

Initial parameters:

- R: relationships {family, friend, pleasant, unpleasant}
- S: Sentiments {strongly positive, strongly negative, weakly positive, weakly negative, neutral}
- I: Interactions {strongly liking, mild liking, close affinity, parallel, neutral, sociable, strongly dislike, mild dislike}

procedure IDENTIFYINTERACTIONS(*conversingAgents*)
  Input: R_i, S_j, I_k ▷ where (i, j, k) represents each relationship, sentiment and interaction
  Output: *RelationshipLabel* (The notations q0, . . . , q7) ▷ as mentioned in Table 3
  for each $R_i \in relationships$ **do**
    for each $S_i \in Sentiments$ **do**
      for each $I_i \in Interactions$ **do**
        if R_i=*friend* && S_i=*stronglypositive* && I_i=*stronglyliking* **then**
          $q0 \leftarrow RelationshipLabel$
        else if R_i=*friend* && S_i=*weaklypositive* && I_i=*mildliking* **then**
          $q1 \leftarrow RelationshipLabel$
        else if R_i=*unpleasant* && S_i=*weaklynegative* && I_i=*milddislike* **then**
          $q2 \leftarrow RelationshipLabel$
        else if R_i=*unpleasant* && S_i=*stronglynegative* && I_i=*stronglydislike* **then**
          $q3 \leftarrow RelationshipLabel$
        else if R_i=*pleasant* && S_i=*neutral* && I_i=*neutral* **then**
          $q4 \leftarrow RelationshipLabel$
        else if R_i=*pleasant* && S_i=*weaklypositive* && I_i=*weaklypositive* **then**
          $q5 \leftarrow RelationshipLabel$
        else if R_i=*family* && S_i=*stronglypositive* && I_i=*closeaffinity* **then**
          $q6 \leftarrow RelationshipLabel$
        else if R_i=*family* && S_i=*weaklypositive* && I_i=*parallel* **then**
          $q7 \leftarrow RelationshipLabel$
        else *InvalidRelationshipLabel*
return $ConversingAgents \leftarrow RelationshipLabel$

QSR utilizes the rules mentioned above described in Table 8 for different mapping levels of interactions between multiple agents. Furthermore, these different interactions assist in classifying eight different relationships, referred to as level III relationships. We used sentiments, interactions, and level II relationships as a key feature for the identification of level III relationships as shown in Algorithm 4.

4 DATASET EVALUATION

This section describes the dataset and methodology for the experimentation and evaluation.

4.1 Data preparation

We use Cornell Movie Dialogue Corpus [14] to validate QSR. This data set includes various interacting agents in different plots from daily life. We believe that this data set can be a good alternative to the interactions available on social media. We select dialogues from 617 movies of different genres, i.e., Science Friction, Thriller, Romantic, Drama, and Fantasy. Table 9 shows a sample dialogue from a movie. This is to give readers some insight into the data set used.

Table 9. An instance of social dialogue.

Movie No	User Id	User Name	Dialogue
m54	u7739	David Lee	Hi Mrs. Boat Wright . . . I am sorry 'bout the way I acted the other day.
m54	u7747	Mrs. Boat Wright	Hello David
m54	u7739	David Lee	I'm used to it
m54	u7747	Mrs. Boat Wright	Don't pout now, David it's a long trip.
m54	u7739	David Lee	I'll walk.
m54	u7747	Mrs. Boat Wright	Come. I'll take you home. I don't know a damn thing, now stop bothering me about it.
m54	u7739	David Lee	But Miss Wright you . . .
m54	u7747	Mrs. Boat Wright	If I tell you I didn't . David that's what I mean
m54	u7739	David Lee	But I saw you . . . you looked in there, and you found out, Miss BoatWright.
m54	u7747	Mrs. Boat Wright	No, he was wrong, David I didn't find out.

In the preprocessing step, the data is processed using the built-in utilities of the natural language toolkit (NLTK) for data cleaning, stemming, contraction removal, stop words, and special character removal.

4.2 Network creation

After cleaning the data, a full network of interacting agents is created. Firstly, unique IDs are assigned to all the conversing pairs. The dialogues of all the conversing pairs are virtually grouped. Note that a character can have multiple interactions with different agents. This can be visualized as a node (character) with multiple edges to other nodes(representing the interacting agents) in the network. All the virtual groups with dialogues counting less than 15 are removed. The detailed statistic-measures related to the data set are given in Table 10.

4.3 Manual scheme of annotation

Numerous students with prior knowledge of general linguistics and psychology are employed as annotators. Three annotators label each conversation of the cleaned data. Eight relationship subcategories mentioned in Table 3 are used for labeling. The majority vote makes the final assignment. The same process is repeated in case of a conflict. The conversation is deleted if the conflict persists.

5 EXPERIMENTAL RESULTS AND FINDINGS

This section explains and discusses the experimental setup and the data set used in our experiments. Note that due to privacy reasons, there is no conversational data available publicly to test our proposed technique; therefore, we use the dataset from Cornell Movie Dialogue Corpus [14] to validate QSR as mentioned in Section 4.

We make an in-depth analysis of the interactions between conversing pairs and also analyze more types of relationships in hierarchical order as mentioned below in Section 5.3. The work done in [34] analyze four basic types of relationships by using two features attachment styles and association Class. They used three classifiers,

Table 10. Corpus Statistics

Whole Corpus Statistics	
Total Movies	617
Count of Sentences	3,04,712
Total number of tokens	3,176,701
Unique Word Count	81,357
Total number of Characters	10,292
Preprocessed Corpus Statistics	
Count of Sentences	3,04,495
Total number of tokens	3,159,844
Unique sentence count	2,50,607
Unique words count	81,073
Total number of Characters	9,035
Total Conversational Exchanges	2,20,579

KNN, DT, and NN, to test their approach. They achieve their best results by using NN with the accuracy of 85% [34]. The results by using the QSR method are better compared because we achieve an accuracy of 89% by using NN.

Feature engineering uses domain knowledge to extract features from raw data through data mining methods. These features are used to raise the performance of machine learning algorithms. We perform feature engineering for making different comparisons to prove our claim true. We use two approaches to evaluate features: the direct and QSR methods.

5.1 Parameter tuning for classification of relationship labels

A pre-trained model on 3-million words and phrases taken from the Google News data set comprises 100 billion words. We use word2vector with vector dimensions of 50, 100, 200, and 300 to test the accuracy. For bert, a vector of 768 dimensions is used. We evaluate QSR on the Cornell Movie Dialogue Corpus (look at Section 4 for details). This corpus consists of dialogues from 616 movies. There are 269633 sentences and 9703 conversations in total. The corpus is divided into training and test data with an 80:20 split.

State of the art classifiers for textual data, namely k-nearest neighbor (KNN), random forest (RF), decision tree (DT), and neural networks (NN), is used along with QSR. The experimental setup, other than the features set, is kept the same for both sets for a fair comparison. Standard measures, which are confusion matrix, accuracy, precision, recall, and F1-score, are reported for performance evaluation of QSR.

We use default parameters for KNN classifier tuning, i.e. neighbors = 5 and leaf-size = 30. For random forest (RF) classifier, sklearn. ensemble with parameters estimators=10, random-state=42 is used. For NN, the sklearn MLPClassifier library is used. During training, the number of iterations and hidden layers are optimized empirically. The best performance is observed using the adam classifier with 150 iterations and six hidden layers.

5.2 Direct method (Classification using word embedding)

Word embedding is useful for word representation and often results in several tasks. In the indirect method, we extract textual features using state-of-the-art word embedding. We choose different word embeddings for extracting features from text data. According to state-of-the-art, we use three types of word embeddings named word2vec, glove, and bert.

Glove embeddings: For getting vector representations of words, we use glove embeddings. The glove has vectors of 50d, 100d, 200d, and 300d. We evaluate the results on all dimensions, but at 300d, we find the best results through the MLP classifier. The main problem of the glove is to enrich information about the context of a word. In our task, we do not require capturing the deep context of the sentence. Because of this reason, this embedding does not give better results.

Word2vec embeddings: We also use a pre-trained word2vec model. It introduces word vectors for a 3-million-word vocabulary and phrases trained from a Google News dataset on around 100 billion words. We use the common python package called genism for this purpose.

The main difference between these two approaches is that in word2vec, skip-gram models attempt to capture one window at a time, and the glove tries to capture the total statistics counts. There are some problems in word2vec, as it will generate the same word embedding of the word "bank" for different context areas, while for each sentence, the word embedding for "bank" will be the same by using word2vec.

Bert embeddings: Bert is also a state-of-the-art tool for pre-training representations of languages. It can resolve the context issues generated by word2vec. Such models can extract high-quality contextual features from text data, and we can also fine-tune such models to a specific task. We evaluate results based on precision, recall F_1-score, and confusion matrix. By using bert, MLP gives the best score compared to all other classifiers and embeddings. We evaluate the results on bert using 768 dimensions. We represent all matrices' results to show variations between results. These results have been given by the Direct Method of feature engineering.

Two sets of experiments are conducted to test the effectiveness of QSR. In the first set, the three best word embeddings, glove, word2vec, and bert, are used to identify level III relationships. In the first set of experiments, textual features are extracted using word2vec, glove, and bert. The accuracy for each word embedding is shown in Table 11.

Table 11. Classification accuracy by using word embeddings

		NN	KNN	DT	RF
bert	Precision	0.77	0.57	0.50	0.83
	Recall	0.78	0.59	0.51	0.85
	Accuracy	0.78	0.59	0.52	0.85
	F1-Score	0.77	0.57	0.50	0.84
glove	Precision	0.78	0.50	0.55	0.74
	Recall	0.76	0.51	0.50	0.77
	Accuracy	0.76	0.52	0.48	0.77
	F1-Score	0.70	0.50	0.51	0.73
word2vec	Precision	0.79	0.64	0.57	0.82
	Recall	0.78	0.65	0.58	0.82
	Accuracy	0.79	0.63	0.58	0.82
	F1-Score	0.79	0.64	0.57	0.82

Bert and RF show the best score among all the setups. We believe it is due to the ability of bert to resolve better the context issues found in word2vec and glove. For word2vec, the best results are observed using the vector of size 300 with a Random Forest classifier.

5.3 QSR method (Classification using word embeddings + QSR features)

In the second set of experiments, we combine the features computed for our method called QSR with the features extracted from the word embeddings. The results of these experiments are shown in Table 12. There is an improvement in accuracy across the board. This shows the usefulness of the level II relationships, sentiments, and interaction as features for classification. The best results are reported by bert+QSR using NN.

In the second test, the embeddings mentioned in Section 5.2 are augmented with our method to check the improvement in the accuracy. Sentence embeddings are calculated from word embedding vectors by taking an average of the word vectors. Recall that the dimension of the word vector is predefined and fixed. The confusion matrix of the best setup is shown in Table 13.

Table 12. Classification accuracy by using word embeddings + QSR

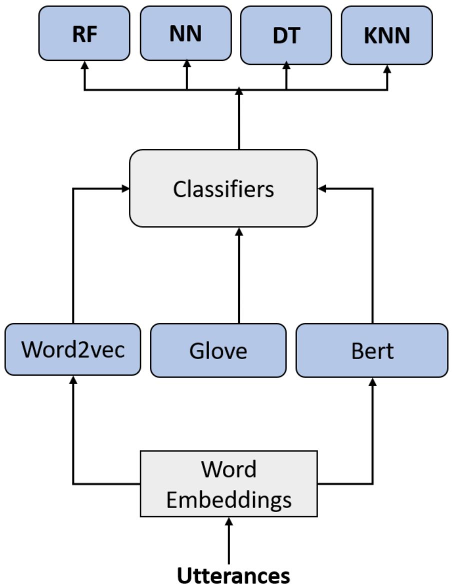
		NN	KNN	DT	RF
bert	Precision	0.91	0.80	0.68	0.86
	Recall	0.88	0.87	0.58	0.86
	Accuracy	0.88	0.87	0.71	0.88
	F1-Score	0.89	0.82	0.60	0.85
glove	Precision	0.80	0.70	0.66	0.84
	Recall	0.81	0.74	0.65	0.76
	Accuracy	0.85	0.66	0.66	0.85
	F1-Score	0.80	0.68	0.65	0.79
word2vec	Precision	0.83	0.78	0.64	0.81
	Recall	0.85	0.76	0.65	0.84
	Accuracy	0.81	0.76	0.65	0.84
	F1-Score	0.79	0.70	0.64	0.80

Table 13. Confusion Matrix of the best performing setup using QSR. The notations q0,. . . ,q7 are defined in Table 3.

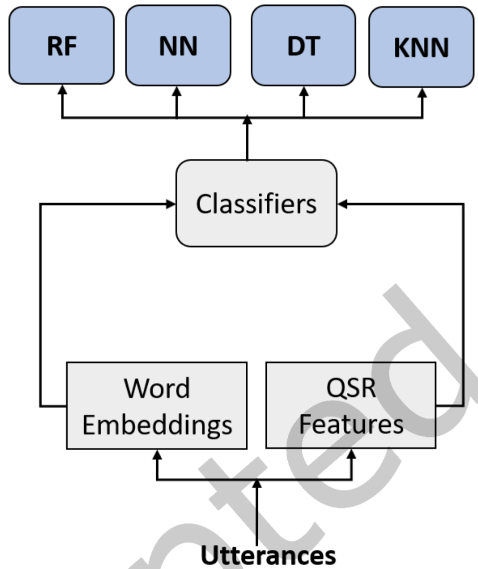
Actual / Predicted	q0	q1	q2	q3	q4	q5	q6	q7
q0	186	1	0	0	2	0	3	0
q1	0	154	0	0	3	1	9	0
q2	0	1	274	2	3	0	2	0
q3	0	3	0	158	4	0	1	0
q4	0	8	5	1	155	8	3	0
q5	0	0	0	0	8	243	0	0
q6	3	2	4	1	4	1	182	0
q7	0	1	0	1	1	0	0	123

The above mentioned results support our claim that the level of interactions and sentiments involved in the conversation is vital in identifying level III relationships between the agents.

For evaluating the performance of a classification model, we use a confusion matrix. Table 12 shows the confusion matrix generated by Neural Network(NN) by using our proposed method QSR. This shows that NN is performing better as it can analyze several relationship classes successfully. As seen in this table, there are fewer miss-classified examples. Figure 6 gives the overview of the architecture of the two setups, respectively.



(a) Direct method



(b) QSR Method

Fig. 6. Architecture of the two experimental setups

6 DISCUSSION

Much interest has developed in social sciences, especially in social relationships. Y. Cao *et al.* [10] described the importance of analyzing interpersonal relationships among agents who used social media applications like CSCW systems. Agents show their attitudes towards each other while interacting. These types of relationships determine the level of cooperativeness and mutualism between them. K. Nagao *et al.* [33] proposed an approach to identify social interactions between agents named multimodal conversation with social agents. Their work analyzed social interactions among agents through spoken conversation and facial expressions, etc. Despite the pervasive impact that social media has on how people in societies communicate with each other [13]. They described how multiple offline and online associates are connected. Facebook, Whatsapp, Instagram, and Twitter are typically used to get immediate communication and association between agents [19].

Interpersonal relationships and online social support positively correlated with Facebook [42]. Different agents connected each other through positive and negative interactions. Although, some personality traits, such as agreeableness, conscientiousness, and neuroticism, were negatively correlated with Facebook. We summarize that limited work has been done on social relationships using text-based conversations. Furthermore, there is no interaction-based mapping has done before. Despite these conceptual shortcomings, we followed the pragmatic approach of developing and validating quantifiable social relationships. The present research provides the following novel conclusions.

The first research step is we use a cross-disciplinary approach (level of certainty and level of dependency) for identifying relationships between multiple agents by using Cornell Movie Dialogue Corpus[36]. We use the behavioral factors described in [4]. The main factors of relationships are sentiments and behaviors among agents. Authors in [4] explained different relationships, such as interpersonal and business. The negative influence of opportunistic behavior caused an unpleasant relationship between colleagues. We generate the behavioral model for mapping friends, family, pleasant and unpleasant relationships. In this research, we called them primary (level II) relationships. We prove our first claim that we can predict primary or basic relationships using text-based conversations. Next, we classify primary relationships into eight subtypes: close acquaintance, superficial acquaintance, mentoring, diverse work, consanguine, conjugal, annoying acquaintance, and undesirable. We call them level III relationships. QSR presents the 3-tier hierarchical structure of relationships.

We prove our second claim true by looking at hierarchical relationship classification results. We show that level III relationships are dependent on both feature's level of interactions and sentiments w.r.t level II relationships. Moreover, we make eight different rules for identifying levels of interaction among agents according to their level II relationship type. As we try to classify the relationships using the direct and QSR method, results show that QSR is a better approach for relationship classification in which we combine our proposed features with state-of-the-art embeddings.

The real-time implementations of QSR are business intelligence, market analysis, and AI-based HR agents to make them realistic. It can also be used in cloud-based robotic systems. As far as complexity is concerned, adaptability could be challenging in the generic domain while using the proposed system. However, the proposed approach utilizes most generic relationship types in depth. Despite that, we could use intentional learning for adaptability concerns in the future. QSR can be implemented in both cloud-based and low-resource devices. The crucial part is a cognitive area in multi-agent systems. When we develop an intelligent autonomous system, we propose the reasoning mechanism according to the complexity of the domain.

7 CONCLUSION AND FUTURE WORK

This paper presented a novel approach for analyzing quantifiable relationships between multiple agents in this research work. QSR presented the 3-tier hierarchical structure of social relationships. We use a cross-disciplinary approach for identifying level II relationships between agents by using behavioral factors and sentiments. The results show that the level III relationships are better explained using interactions and sentiment features. Findings also show that QSR is a better approach for relationship classification when we combine our proposed features with state-of-the-art embeddings. The possible application of QSR in real-life is like business intelligence, market analysis, and AI-based HR agents. In future work, we will focus on the context of conversations to make accurate transformations in interactions. We plan to improve QSR by adding more NLP rules and experimenting with other combinations of NLP and cognitive psychology techniques. We also integrate this research into various customer service-based robots to make them more realistic and improve client responsiveness. This approach can be tested on different datasets with more interactions and relationship tags.

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