Sentiment Analysis based Recommender System for Pet-Owner Compatibility

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***Abstract*— India has a significant demand for pet adoption – but the lack of resources and information make it a tiring process. Finding the compatible pet that fits your lifestyle and personality is extremely difficult and requires days of research at the very least. This creates the basis for a review-based analysis system that matches pets to the user's lifestyle. This paper proposes using sentiment analysis polarity classification to grade breeds according to four traits – Friendliness, Activeness, Destructivity and Maintenance. The proposed approach first builds domain-specific ontologies for reviews using ConceptNet. Subsequently, using a contextual emotion lexicon, semantic orientations of these expressions are determined relating to the entities retrieved in the first step. The generated report enables people to make more informed choices before adopting pets, thereby increasing pleasure and compatibility.**

Keywords— Pet Adoption, Pet Compatibility, Sentiment Analysis, Polarity Categorization, ConceptNet

I. Introduction

Pet ownership has an ancient legacy, dating as far back as the Egyptian Civilization, and has become increasingly popular since the 18th century. People tend to shower significant affection and money on their pets. It is a perplexing form of behaviour though, from a Darwinian standpoint because it involves providing for a member of another species without any obvious fitness benefits [1]. The intimate ties that people develop with their pets are delineated with pets functioning as both a source of security and an object of caregiving. Much like a parent-child relationship.

According to DeGroot [2], the emotional bond that many humans have with their pets equals and perhaps even surpasses the bond they develop with other humans. Numerous studies conducted over the years have revealed that "companionship" is the primary reason people retain pets, followed by "affection," "love," and "emotional attachment." [3,4,5]

The pet care industry in India is flourishing rapidly, with an average annual growth rate of 13.9%. This is illustrated in a study by Jeffery et al., which discovered that India ranks eighth globally for the fraction of web searches relating to pet adoption. In 2018, there were around 17 million and 1.5 million residences in India with pet dogs and cats, respectively. These figures are predicted to surge to more than 31 million by the end of 2023. This growth in pet-owning families has contributed to a significant boost in the value of pet food consumption, which topped 285 million US dollars in 2018, up from 139 million US dollars in 2014. [6]. According to another estimate, 600,000 pets are adopted in the country each year. [7]. And, with increasing awareness of low-cost pet-keeping possibilities and an increase in pet foster care facilities, these figures are likely to continue escalating.

Despite these large numbers, 85% of India's companion animals are homeless, equating to around 79.9 million dogs and cats. Only 8.8 million of these are in animal shelters, with the remainder being stray. [8].

Under pressure from citizens, and to enhance human-living conditions, stray animals, some of whom are hostile and disease vectors, are often picked up from the streets and relinquished. The municipality of Kerela (2007) ruthlessly seized thousands of dogs, put them in congested shelters or vehicles without adequate food or water, and then poisoned or electrocuted them [9]. Pets held in shelters for a prolonged period are also euthanized to limit the number of unwanted animal overpopulations. Although an exact number for the number of companion animals abandoned and euthanized in the country is difficult to obtain, the figure is undisputedly high. The problem, however, not only pertains to overpopulation but also mismanaged distribution.

Pet adoption can be a complex and tiring process, and often atypical of many other life decisions. We are largely oblivious of (and incapable to foresee) the life-alterations it carries brings along [10]. According to Frank and Carlisle [11], there is a substantial lot of uncertainty about the repercussions of pet parenting, and this uncertainty often leads the perceived costs to outweigh the perceived benefits. Many of these unpredicted costs, however, may be psychological.

But let's say a person decides to get a pet. In light of the data, they acquire from several, often contradictory sources, people have a wide range of preferences. Dog owners and prospective adopters seem to emphasize its behaviour and temperament, as well as its stature, breed, age, pelt, health, and whether or not the dog is purebred, neutered, or intact [12]. But even beyond adopting a pet, its compatibility with the owner remains under concern. Incompatible pets are often mistreated or left astray. Selecting a pet after evaluating its compatibility is the only solution to minimize this problem. However, doing so is extremely difficult and will need hours of reading online reviews (to start with). People are very likely to avoid doing so and will end up choosing pets that look aesthetically pleasing. However, like any relationship, the pet-owner relationship also needs compatibility for the sake of the satisfaction and health of both the pet and the owner. People often overlook this, increasing abandonment issues and intensifying the problems linked with it [3]. If people are assisted well before and during the adoption process and are provided with a means to choose, they are likely to be more satisfied in the long run. This creates the scope of a review-based analysis system that matches pets to the user's lifestyle.

Sentiment analysis of reviews provided by owners' experiences with their pets can automate the task of selecting compatible pets. Sentiment analysis examines the way people feel about particular things. The challenges outlined above can be addressed by providing people with a precise, analytical report on features that affect compatibility without them having to sift through tons of data themselves.

This paper proposes a system that utilizes sentiment analysis to evaluate pets under four categories – Friendliness, Activeness, Destructivity and Maintenance. The system consumes reviews from a variety of online sources and categorizes them using the sentiment analysis polarity categorization technique described in section 4 of this paper. The system works as a recommender system for the user. The outcome shows us how a certain breed fits into each of the four divisions, enabling users to decide on the pet that best fits their lifestyle.

II. Literature Review

Neidhart et. al. [12] found that adopters look for more information about the health and behaviors of prospective adoptees to make informed decisions. A streamlined process and help from authentic sources before, during and after the pet adoption process were found to be directly related to adopter satisfaction and pet retention. Along with this, directing potential owners to the ideal companion animals and giving them ready access to vaccination and veterinary sources were said to enhance satisfaction [12]. However, the number of animals and people in need is invariably larger than the number of volunteers and organizations willing to assist.

There exist websites globally that enable listing and adopting pets as well as provide resources to guide you through the process and lifespan of your pet. Petfinder.com is one such website operating in the US that hosts an extensive selection of animals – updated regularly. They also have multiple resources and blogs along with a vast database of shelters and rescue operators from every state. According to seranking.com, PetFinder sees monthly traffic of about 330k from India alone, even though it does not operate in the country. Another website adoptapet.com which also operates in the United States, and has Indian traffic of about 6.2k monthly. These results ranked highest for search keywords – 'adopt a pet', 'dog adoption near me' and 'dog breeds.' This clearly demonstrates that there is a scope for internet-based pet adoption in the country however, there is a vacuum in the said space. Therefore, introducing a system for facilitated adoption would be incredibly useful.

An individual's buying decisions are primarily influenced by four psychological factors - motivation, perception, learning, and attitude [13]. Buying or adopting a pet, if we review it as a life-altering purchase, isn't any different. All of these variables can be strongly impacted by increasing clarity and interactivity in the process. Interactivity, according to the Cambridge Dictionary, is the involvement of humans in the information exchange with computers. Sundar and Kim uncovered a "positive, linear effect of interactivity," in which more interactive stimuli were related to more positive views [14]. The influence of digital word-of-mouth on online purchase behavior has been empirically validated. Interactivity in virtual communities can have persuasive effects, which can promote pet adoption from internet sites [15, 16]. According to research done on e-commerce sites, features such as product reviews, user ratings, and currently popular selections can largely appeal to the online consumer [17].

Although reviews can impact acquisition, they do not affect satisfaction or compatibility. Opinions from those who have comparable expectations, on the other hand, will be a more accurate method. Therefore, conducting sentiment analysis on pet owner reviews can not only serve as a reference for other consumers but also help improve retention and contentment. Sentiment is an emotion-driven attitude, thought, or judgement. Sentiment analysis, also known as opinion mining, analyses people's feelings toward specific entities [18].

Based on the size of the text, sentiment polarity is classified at three levels: the document level, the phrase level, and the unit-facet level. The document level considers whether a document as a whole reflects a negative or positive sentiment, while the phrase level analyzes the sentiment categorization of each sentence. The unit-facet level eventually focuses at precisely what the reviewers like or hate. [18]

The three principal types of current sentiment analysis techniques are keyword recognition, lexical affinity, and statistical methods. The most basic of these is keyword detection, which is also arguably the most often used due to its accessibility and simplicity. At any of the aforementioned levels, the analytical procedure to categorize the polarity of the opinion combines the use of natural language processing (NLP), computational linguistics, and text analytics [19]. Polarity categorization tags reviews as positive, negative or neutral. An opinion lexicon is a library of opinion words with polarity values that reflect positive or negative attitudes, such as "pleasant," "great," "terrible," "dull," and so on [20]. This technique has two flaws: it fails to acknowledge impact when negation is implicated and overly relies on surface morphology [21].

For instance, this method can accurately categorize the phrase "this is good" as being positive, but it is likely to fall short when used to the phrase "this is not too bad." Moreover, the strategy depends on the utilization of subjective words that are just surface characteristics of the writing. In practice, many phrases express emotion through underlying content rather than affect adjectives. A statement like "The doctors said that I will never be able to walk again" for instance, which clearly provokes powerful emotions but contains no impact keywords, cannot be categorized using a keyword-spotting technique.

Lexical affinity is far more intricate than keyword spotting since it assigns words a probabilistic affinity for a certain emotion as opposed to only detecting words with observable emotion. For example, the term "accident" may hold a 75% chance of implying an unfavorable outcome, as in "traffic accident" or "he died in an accident."[21]. Typically, these probabilities are trained using linguistic datasets. While lexical affinity generally outperforms pure keyword detection, it may be misled by phrases like "I dodged an accident" (negation) or "I met my wife by accident". Additionally, according to the source of the linguistic datasets, lexical affinity probabilities are often skewed to a specific genre.

Statistical methods for text affect analysis operate by feeding a large training dataset of actively classified texts to a machine learning algorithm, such as Bayesian inference or support vector machine [22]. This system can learn not only the aversive value of impact keywords (as in keyword spotting), but also the polarity of other arbitrary words (as in lexical affinity) as well as word co-occurrence frequencies.
Fundamentally, Sentiment Analysis ranks among the most challenging tasks in Natural Language Processing. Opinion itself is a broad concept. Opinions and feelings differ dramatically from factual data since they are subjective. Opinions can be either regular or comparative, implicit or explicit. Another significant problem is separating direct and sarcastic statements [23]. However, the availability of large datasets over the internet and extensive research in this area continue to facilitate extraction and implementation.

III. Research Objective

The nature of the relationship between companion dogs and their owners can have a strong influence on the dog's quality of life, responsible ownership habits, and the likelihood that the dog will be relinquished. Correlations between dog satisfaction levels and dog-owner personality match, based on a survey, revealed four traits that were significantly associated with satisfaction: tendency to get along with others, likelihood of running outside, willingness to share possessions, and inclination to be destructive [24]. These findings imply that prospective pet owners would want to consider adopting dogs that are compatible with their personalities in terms of these traits. Along with this, another important aspect to take into account before adopting pets is the convenience of upkeep. The expenditures of pet ownership, including maintenance, regular vet visits, shedding, and grooming requirements, can swiftly exceed a budget if not carefully planned for [12]. Some owners prefer cats over dogs. Some people might like lap dogs while others favor guard dogs. Running enthusiasts might want to run with their pets, and so prefer active breeds. First-time owners and those who work long hours may prefer pets that don’t need much attention. while others may just want a cute and fluffy companion.
Therefore, based on research, factors that are ideal for pet compatibility can be classified into:

i. Friendliness – The breed’s relationship with other pets, family members, kids, and strangers.
ii. Activeness – Certain breeds need more room and exercise than others. Certain breeds are more prone to separation anxiety and need companions to go about. The lifestyle of the owner and living space plays a crucial role when selecting an active breed from a lazy one.
iii. Destructivity – Certain breeds (of dogs especially) love digging and dashing around. Such breeds will end up ripping apart and gnawing on household items if kept in small areas (like condos).
iv. Maintenance – Some pets need more frequent grooming than others (long-haired dogs and cats, for example). Some need frequent vet visits, special supplements, etc.

Evaluating a pet under these four headings can very well lead to more informed choices before adoption. Thus, it is ideal to use sentiment analysis to figure out people’s sentiment polarity for a breed under each of these characteristics. This approach bases the sentiments on reviews for specific pet breeds over the internet and behaves like a recommender system. The next section provides the approach suggested to accomplish this.

IV. Proposed System

A. *The SA Structure*

In the proposed methodology, we first build domain-specific ontologies for product reviews using ConceptNet. Further, we process the reviews and documents by POS tagging them. Using the ontology created in the first step, target words are identified, and the reviews are split up into four lists: friendliness, activeness, destructivity, and maintenance. Next, terms that express opinion or feelings are extracted, such as "very friendly," "excellent," "terrible," and so on. Further, using a contextual emotion lexicon, semantic orientations of these expressions are determined relating to the entities retrieved in the first step. The polarity values of the entities are then aggregated to produce the document's overall sentiment orientation. This is then used in to define the sentiment polarity for each subclass. The process flow for the described method is illustrated in Figure 1.

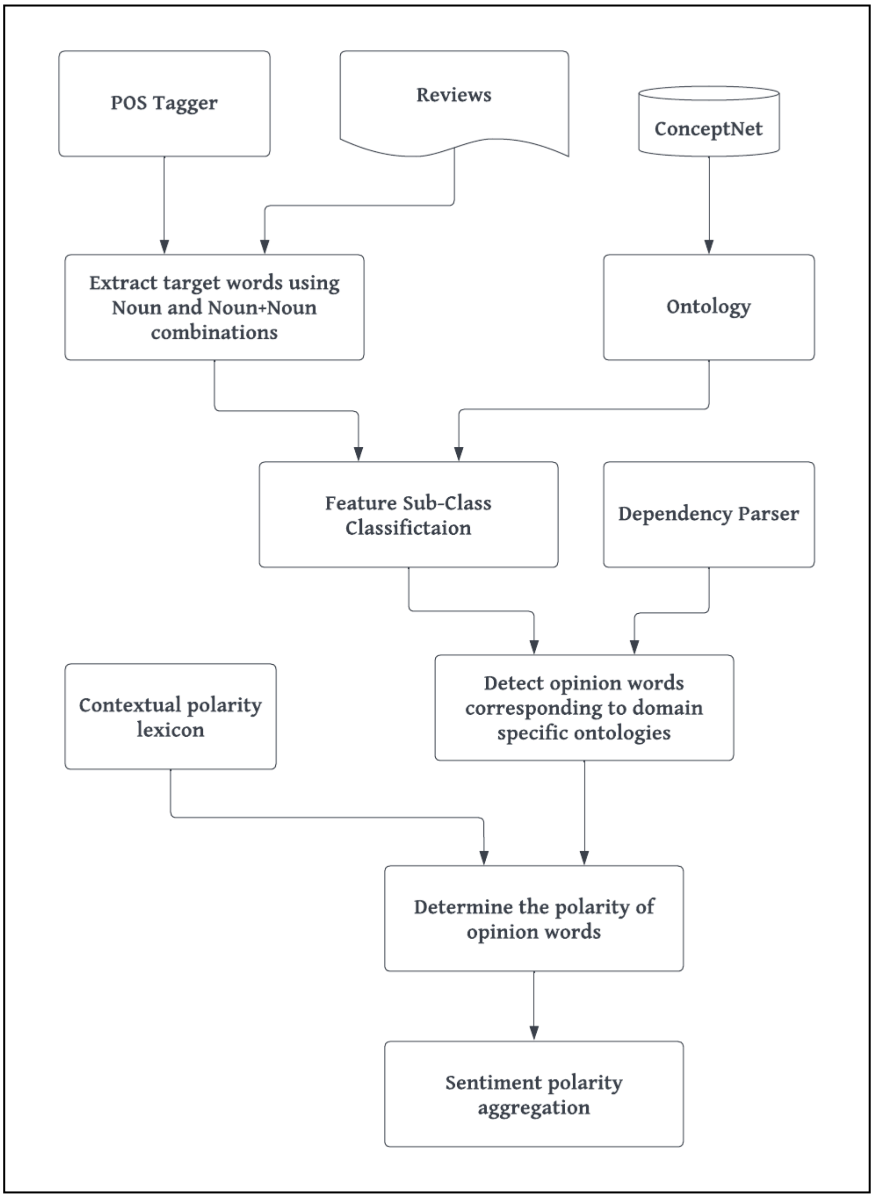

Fig. 1. Sentiment polarity aggregation process flow

B. SA Subtasks

a) **ConceptNet – Domain specific ontology:** Ontology is defined as the association of concepts with semantic relations. Inferring essential information from the text can improve from the use of semantic relations between concepts. ConceptNet is a vast semantic network comprised of a large number of common-sense concepts contributed by standard internet users [20]. An assertion in ConceptNet is characterized by five components: language, relation, concept 1, concept 2, and frequency. Concept 1 and Concept 2 are the two concepts that are related in an assertion. The Language attribute specifies the assertion's language (here English). The frequency attribute shows how frequently a certain relation is used with a particular concept. And relations show how the two ideas are related. For instance, in "Labrador IsA Dog" – Labrador and Dog are the two concepts linked by the relation IsA. This data is represented as a directed graph (Figure 2), where the nodes are concepts, and the labelled edges are the relationships connecting them. Figure 3 shows a knowledge graph of ConceptNet and Figure 4 gives a visual representation of ConceptNet graphs.

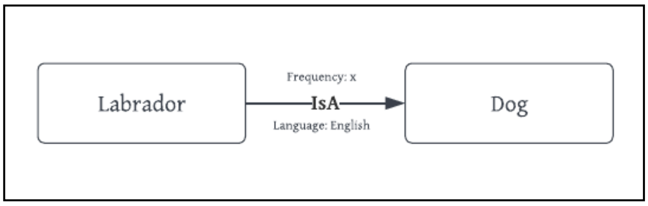

Fig. 2. ConceptNet Assertion

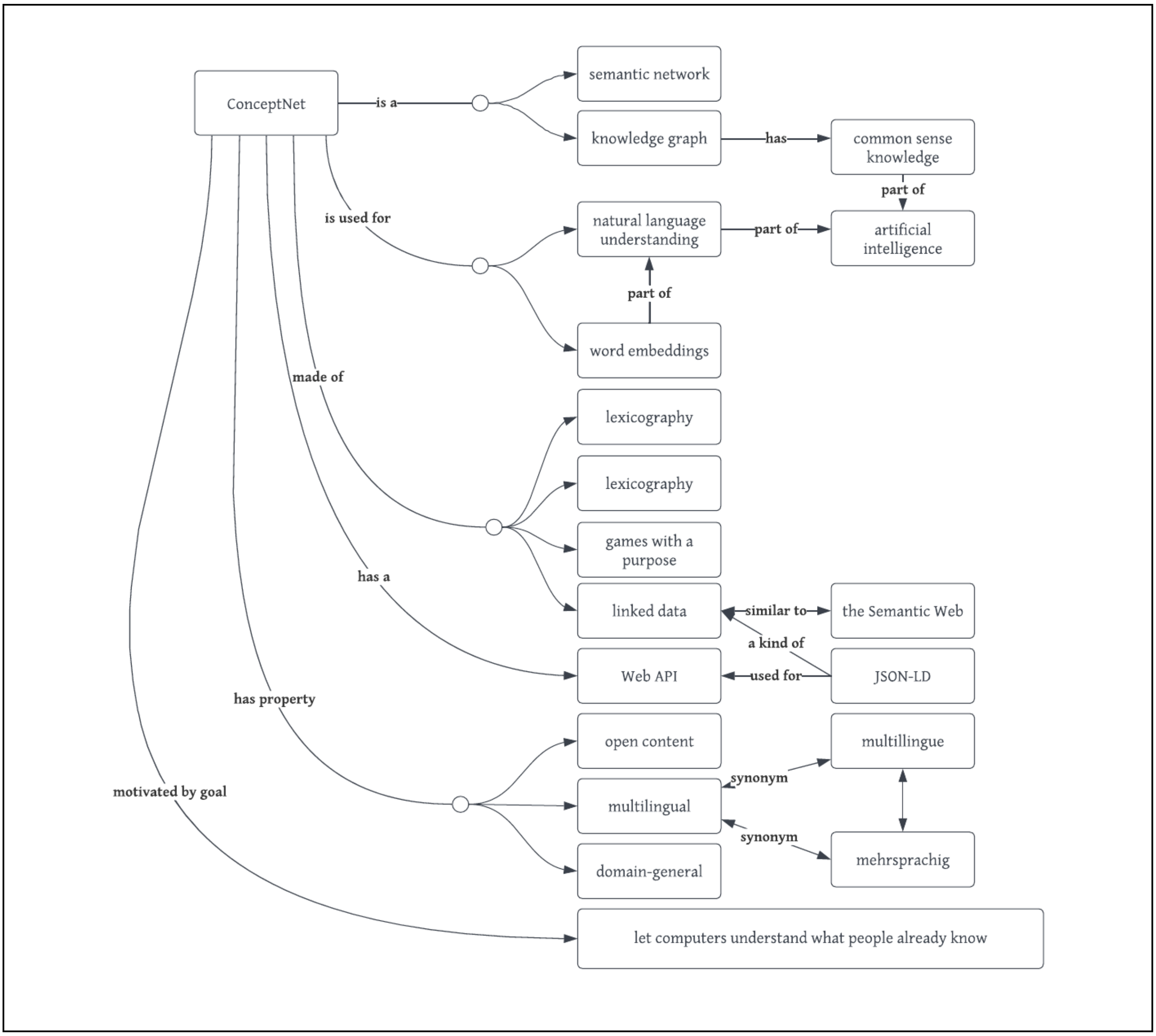

Fig. 3. ConceptNet knowledge graph [26]

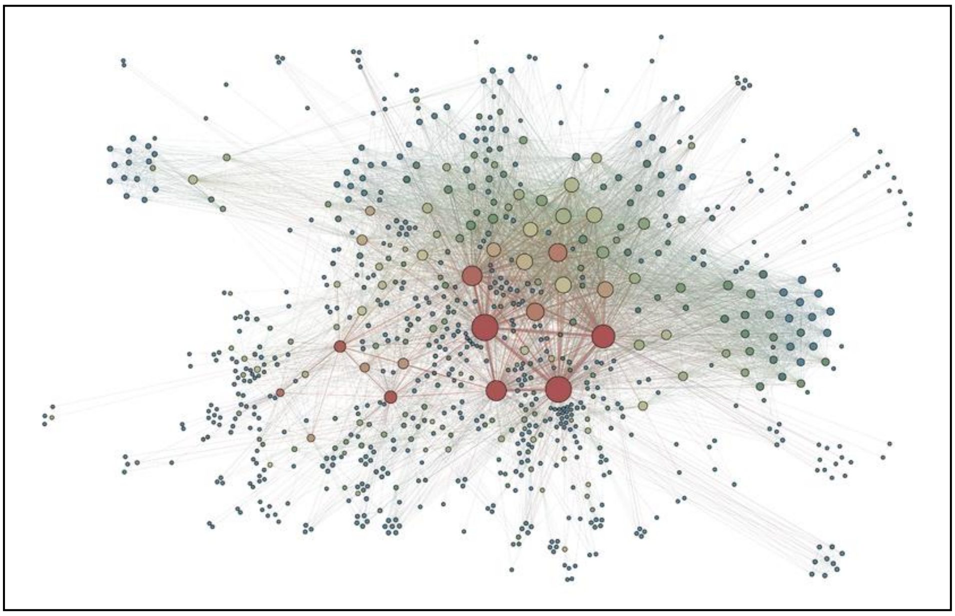
Fig. 4. ConceptNet visualization

In the proposed approach, we first build domain-specific ontologies for sentiment classification using ConceptNet (Algorithm 1). Friendly, active, destructive, and low-maintenance are used as starter words to build four primary ontologies. To meet our needs, and expand the ontologies, we integrate terms like:

i. Family and love under 'Friendly'
ii. Aggressive and Lap under 'Active'
iii. Bark, Bite and Calm under 'Destructive'
iv. Shedding, Health and Grooming under 'Low-Maintenance'

The ontologies for these words are combined with the primary ontologies to form four comprehensive ontologies. The constructed ontologies may well be viewed as a common-sense knowledge base composed of domain-specific ideas and the relationships that exist between them.

INPUT Raw Assertions related to domain extracted from ConceptNet.
OUTPUT Ontology with domain-concepts
Step 1. Every relation r in the ontology is constructed by connecting two concepts i.e., concept1 (c1) and concept2 (c2).
Step 2. Generate a graph structure using these relations. Root of this graph is the domain itself.
Step 3. We connect two vertices V1 (i.e. concept1) and V2 (i.e. concept2) with an edge E (i.e. relation r). Connect all the nodes extracted from ConceptNet to construct the ontology.
Step 4. First level nodes of this ontology are considered as new domain names and further synonyms are extracted for expansion of the ontology.
Step 5. Repeat Steps 1–3 to construct ontology for each synonym word of the main domain.
Step 6. Merge all the extracted ontology to generate a single domain specific ontology.

Algorithm 1. Building ontologies from common-sense knowledge base [20]

b) **Pre-processing:** The data fed into the feature extraction process must first go through a pre-processing phase. Initially, the input text is parsed into sentences, which are then evaluated using a Part-of-Speech (POS) Tagger. POS Taggers are an essential tool in Natural Language Processing that assist categorize words based on their parts of speech. Each word in a phrase has a linguistic identity that regulates how it is utilized. These linguistic identities are better known as the parts of speech. There are eight parts of speech in the English language - noun, pronoun, verb, adverb, adjective, conjunction, preposition, and interjection.

A POS tagger is valuable for two reasons: 1) Nouns and pronouns that are generally void of sentiment can be tagged and used to indicate the subject (target) of the sentence. 2) Words that can have more than one linguistic identity based on their usage in a sentence can be identified [18]. For example, as a verb, "enhanced" may convey a different degree of sentiment than as an adjective.
Stop words, white spaces, new line tags, html tags, emoticons, and special symbols are also removed during the pre-processing stage.

c) **Target identification:** The term "target" describes the subject on which the opinion is expressed. The objective of this stage is to define a review's targets. For instance, the phrase "Labradors get along well with kids" refers to the temperament of the dog breed "Labrador" with "kids." Both "Labrador" and "kids" are hence targets. This identification is done by extraction the noun and noun + noun terms are from the POS tagged reviews. Nouns that identify specific pet / breeds (such as "Labrador") are eliminated since they are solely utilized by crawlers for gathering data.

Post extraction, the remaining nouns are compared to the domain-specific ontologies built in step one. The four ontologies created in step 1 relate to feature-subclasses. The selected nouns are compiled into four lists – pertaining to each class – based on their target noun's ontology. These lists are used for further processing.

d) **Opinion identification:** The primary goal of a review is to express an opinion about a subject. Users often give their opinions on multiple features of a single subject. The following sentence, "Labradors get along well with kids, however they shed a lot," is an example of how a user may have a different opinion on each feature in the review document. The dog's temper with "kids" is graded "well" here, although the dog "sheds" "a lot." Identifying the correlation between the opinion target (feature) and the opinion words is essential for determining the sentiment behind each of these opinions. The opinion words that are relevant to the opinion targets are recognized using dependency parsing.

e) **Polarity categorization:** Polarity Categorization is a SA subtask that includes classifying the opinions as positive, negative, or neutral [25]. A polarity lexicon is a dictionary that contains words and phrases along with their polarity value. SentiWordNet is used to build the sentiment lexicon in our process.

SentiWordNet is a publicly accessible sentiment dictionary that has the sentiment score of POS tagged opinion words. SentiWordNet has around 2 million polarity-tagged adjectives, adverbs, verbs, and nouns. SentiWordNet is built on WordNet and a ternary classifier. The classifier is constructed on a "bag of synsets" model that makes use of a list of terms that have been manually disambiguated. The words in this lexicon are given three scores, each of which are between 0 and 1:

i. A Positive score
ii. A Negative score
iii. A Neutral score

The sum of all scores for a word is always 1. A positive score higher than the negative score indicates that the opinion word favors the target. A higher negative score implies that the opinion word is opposed to the target. A neutral score of 1 means that the word expresses no emotion.

After being detected in the previous step, opinion words are polarity categorized. The impact of the opinion word in calculating total polarity is calculated as - polarity * ontology height. Height of ontology determines the frequency and adequateness of the word in regard to the ontology starter term. In the end, the contribution of each opinion word is added together to calculate the review's overall polarity.

f) **Sentiment polarity aggregation:** The reviews and their polarity are therefore saved in the four lists generated during target identification. By summing the polarity of the reviews under each sub-class, the aggregate sentiment polarity of each sub-class is obtained. The aggregate sentiment is calculated as polarity * target word frequency in the subclass. The outcome is the breed's score (as positive or negative) for each sub-class, using which we can judge the breed's compatibility.

V. CONCLUSION

The market for pet adoption is unquestionably booming. People, however, continue to be misinformed, flummoxed, and confused. Adopting pets is a tough task, but selecting the ideal pet is even harder. There is very little help available in terms of choosing a compatible pet, and reading tons of reviews for doing so is extremely tiresome. The sentiment analysis polarity categorization process suggested in this paper will feed reviews from multiple web sources and generate a report on the polarity over four characteristics - Friendliness, Activeness, Destructivity and Maintenance. These traits have been found to have significant influence on pet compatibility, and the generated report is thus helpful for choosing pets that complement a person's lifestyle. Further improvements in this process are to include more categories for more accurate judgements and the ability to analyze comparative reviews.

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