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Soft Metaphor Detection using Fuzzy c-means

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Abstract. Prior works in metaphor detection have largely focused on crisp binary classification of textual input into 'metaphorical' or 'literal' phrases. However, the journey of a metaphor from being *novel* when newly created to eventually being considered *dead* due to the acquired familiarity with the mapping over a time span, is a continuum. This observation guides us to the idea that a metaphorical text is indeed, partially literal and partially metaphorical. In this paper, we investigate the idea of soft metaphor detection by assigning membership values to fuzzy sets representing varying degrees of metaphoricity. We use a set of conceptual features and apply a simple unsupervised technique of Fuzzy c-means to illustrate fuzzy nature of metaphors. We report our experimental results on a dataset of nominal metaphors to illustrate the concept of soft metaphor detection and demonstrate their simultaneous membership in multiple classes by visualizing overlapping clusters, *metaphor* and *literal*.

1 Introduction

A metaphor is a cognitive phenomenon which maps an abstract concept in a target domain to a relatively concrete concept from a well-defined source domain to ease the understandability in communication [7]. The underlying idea is to discover patterns in the learned source domain which somehow helps in illustrating the abstract concept. The selected mapping *i.e.* metaphor also reflects the perception of a writer about the target concept. Let us consider a sentence:

An atom is a solar system. (a)

Here, the mapping is performed between the *solar system*(source domain) and *atom*(target domain). In this mapping, tiny particles such as *protons* revolving around the nucleus are analogous to *planets* and *nucleus* corresponds to *sun*. To comprehend the sentence (a), we import our existing knowledge about structure of the *solar system* such as *'planets revolve around the sun'*, *'a planet have an orbit'* to understand the model of an *atom*.

In the late 1980s, Nunberg categorized metaphors into two categories namely *dead metaphors* and *novel metaphors* [12]. As the terminology implies, dead metaphors are overly exploited mappings in daily parlance and thus adopt the metaphorical meaning as an extended literal interpretation. One such example is the usage of the word *gem* in the phrase 'My husband is a gem.' The word, *gem*[1] initially meant *'a crystalline rock that can be cut and polished for jewelry'* or *'a precious or semiprecious stone incorporated into a piece of jewelry'* but at present, its meaning extends to *'a person who is as brilliant and precious as a piece of jewelry'* which is a metaphorical interpretation. Dead metaphors are considered equivalent to literal text as one does not need to perform any mental mapping to interpret it. In contrast, novel metaphors are newly generated mappings and require common-sensical knowledge of concepts involved in the mapping to extract contextually coherent metaphorical interpretation.

Recent studies in metaphor detection have largely focused on crisp binary classification of textual input as metaphorical or literal [6,11,14,17]. However, a metaphor undergoes a process of gradual transition from being initially *novel* to eventually being considered *dead*. The transition begins from the state of highest metaphoricity when a metaphor is created and used for the first time and gradually declines to the lowest metaphoricity when it is considered to be a dead metaphor due to its frequent usage in common parlance. Thus, we argue that a hard classification of a given phrase exclusively to the classes *metaphor* or *literal* is not a pragmatic approach.

The extent of novelty or metaphoricity of a metaphor is determined by the uniqueness of the mapping between the source domain and the target domain concepts in a metaphorical expression. Working on the hypothesis that a novel metaphor is generated when an unseen or rare comparison is made between two unrelated concepts, we infer the extent of novelty of a metaphorical expression by examining the semantic relatedness between the mapped concepts. Semantic relatedness is a metric based on distributional hypothesis which states "words which are similar in meaning occur in similar contexts" [16]. A low co-occurrence frequency indicates a novel usage and thus, low relatedness between the mapped concepts. Other psychological features such as imageability [2,3], meaningfulness [14] and familiarity [18] indicate the propensity of a word being metaphorical.

In this paper, we investigate the concept of metaphoricity for a given textual phrase through the notion of degree of membership in fuzzy clusters [1]. We contend that a soft metaphor detection approach based on metaphoricity would lead to a more informative metaphor processing system. We perform unsupervised soft metaphor detection which classifies sampled data into three classes namely, *metaphor*, *literal* and *probably_metaphor*. The ternary classification creates a subset of doubtful cases which requires further processing thus improving

[1] WordNet search(*gem*): `https://goo.gl/ej2PUY`

the confidence of classified instances. We use the R package *e1071* [9] to implement FCM for our experiments and use a publicly available dataset of nominal metaphors provided in [13] to analyze the validity of the proposed soft metaphor detection approach.

The remainder of the paper is organized as follows. Section 2 provides a brief introduction to existing work in metaphor detection. In Sect. 3, we explain the application of FCM to determine metaphoricity for a textual input and report the results of a soft binary classification to identify metaphors in text. We conclude our work in Sect. 4.

2 Related Work

In this section, we discuss the prior studies on detection of nominal metaphors. Krishnakumaran et al. in [6] utilize WordNet [21] to verify the absence of hyponymy relations in the mapped subject and object to identify metaphorical usages. This establishes the variation in semantic categories and thus a non-literal mapping.

For example, consider the phrase 'My lawyer is a shark'. In this phrase, the lawyer with semantic category 'PERSON' is projected as a type of shark which is an 'ANIMAL'. Therefore, this phrase is marked as a metaphorical phrase.

However, the concept of hyponymy relation fails in case of polysemous words such as *chicken* which have multiple semantic categories *i.e.* 'ANIMAL' and 'FOOD'. In addition, a phrase with same semantic category for the subject and object is not necessarily a literal phrase [11]. One such example is 'My cat is a tiger.' In [11], Neuman *et al.* resolved this problem by incorporating a disambiguation step which uses co-occurrence frequency to identify most likely usage. Su et al. combines the hyponymy relation from WordNet with cosine distance between the source and target domains using *word2vec* embeddings [17].

The utility of conceptual metaphors revolves around understanding of the abstract concept that is conveyed in the target domain by relating it with a relatively concrete concept in the source domain [7]. Employing this hypothesis, Turney et al. in [20] and Klebanov et al. in [5] use the notion of relative abstractness between a word and its context to detect metaphors. Other psychological features (also known as conceptual features) such as imageability [2,14,19] and familiarity [18] have been also shown to be helpful in identifying metaphors. Rai et al. use fuzzy psychological features and *word2vec* embeddings to identify nominal metaphors [15]. They later approximate the crisp classes namely metaphorical and literal using a fuzzy rough set model to tackle imprecision and vagueness in psychological features [13].

The existing studies on metaphor detection emphasize on contrasting the source and target domain concepts, without taking into account the degree of novelty of the metaphorical expression. The existing work emphasizes on metaphor detection without analyzing the novelty of the metaphorical expression. To the best of our knowledge, there is no computational approach for any type of metaphors which explores the concept of fuzzy nature of a metaphor.

In this paper, we introduce the concept of *metaphoricity* to represent the continuous spectrum of possibilities between the extremes, *literal* and *metaphor*. The approach closest to our work is that proposed in [4]. However, they adopt a probabilistic approach, quantifying the likelihood of a phrase being metaphorical. On the other hand, our approach assigns membership values that quantify the degree to which a phrase may belong to different, yet overlapping classes of metaphoricity. The fuzzy approach has greater expressive power as it represents the realistic part-metaphorical, part-literal phases of a metaphorical expression in transition from its initial novel state to eventual dead state.

3 Soft Metaphor Detection using Fuzzy c-Means

In this section, we elaborate upon our proposed FCM driven approach to model the concept of metaphoricity and enable an unsupervised soft classification of a textual input into the fuzzy sets *metaphor*, *literal* and *probably_metaphor*.

3.1 Problem Representation

In this paper, we restrict the problem of soft metaphor detection to nominal metaphors. In nominal metaphorical expressions, an explicit mapping is performed between the subject in the target domain and an object in the source domain. We use a dependency parser to extract the subject and object for all input utterances. The extracted pairs of <subject,object> are used for feature extraction in the next phase.

3.2 Feature Extraction

We extract a set of conceptual features namely *concreteness, imageability, familiarity* and *meaningfulness* for the source and target domains using MRC Psycholinguistic Database [22]. These are augmented by a set of derived features comprising the relative difference between the psychological features of the subject and the object to capture the extent of variation in the selected phrase.

We compute the cosine similarity between pre-trained *word2vec* embeddings [10] of the source and target domains to quantify the semantic relatedness that conveys the novelty of a mapping. We use word embeddings since they effectively capture context and analogical relations between the concepts.

3.3 Fuzzy c-Means

Let $X = \{x_1, x_2, x_3, \ldots, x_N\}$ be a set of N sample points in an n-dimensional feature space $\mathbb{R}^n$. Let x_i^k represent the k^{th} feature of a sample point, x_i. Given a set of clusters $C = \{C_1, C_2, C_3, \ldots, C_c\}$, the fuzzy c-partitions of X are such that each sample, $x_i \in X$ has a membership value, μ_{ij} in cluster, $c_j \in C$ with conditions such that,

$\mu_{ij} \in \{0,1\},\ where\ 1 \leq i \leq N,\ 1 \leq j \leq c\ ;$
$\sum_{j=1}^{c} \mu_{ij} = 1,\ where\ 1 \leq i \leq N\ ;$
and $0 < \sum_{i=1}^{N} \mu_{ij} < N,\ where\ 1 \leq j \leq c\ .$

The inclusion of $x_i \in X$ in a fuzzy partition, C_j is determined by minimizing the objective function defined in (1).

$$J_m(C, v) = \sum_{i=1}^{N} \sum_{j=1}^{c} (\mu_{ij})^m |x_i - v_j|^2\ . \quad (1)$$

where $v = \{v_1, v_2, \ldots, v_c\}$ represents a vector for centre of clusters. m denotes weighting exponent to indicate the level of fuzziness, where $1 \leq m < \infty$. On the basis of number of clusters to be formed, the algorithm calculate the center, v_j of cluster, j, using (2).

$$v_j = \frac{\sum_{i=1}^{N} \mu_{ij}^m x_i}{\sum_{i=1}^{N} \mu_{ij}^m}\ . \quad (2)$$

Thereafter, randomly initialized membership, μ_{ij} of every sample point, $x_i \in X$ in every cluster $C_j \in C$ is updated using (3). The algorithm converges when the objective function, $J_m(C, v)$ ceases to improve by a fixed minimum threshold, $0 < \omega < 1$ or the specified number of iterations are over.

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{|x_i - v_j|}{|x_i - v_k|}\right)^{\frac{2}{m-1}}}\ . \quad (3)$$

In our case, there are two classes namely *metaphor* and *literal*, thus $c = 2$. The overlap between the clusters is considered to be *probably_metaphor* samples.

3.4 Experiments and Results

We used the R package *e1071* V1.6-8 [9] and *cluster* V2.0.6 [8] to implement FCM algorithm. We used a publicly available dataset of nominal metaphors provided in [13] for our experiments. In [13], the authors used the dataset to demonstrate a supervised metaphor detection model using fuzzy rough sets. Since, our approach is an unsupervised approach, we define a baseline to evaluate the effectiveness of our approach.

We show clusters formed using FCM clustering algorithm in Fig. 1. The cluster containing a majority of metaphorical samples is marked ‘1’ whereas the cluster containing mostly literal samples is marked ‘2’. For every sample in the dataset[2], we plotted their degree of membership in the created fuzzy clusters as shown in Fig. 2. The black line represents the membership value of instances for the cluster *literal* whereas the red line indicates the membership for the cluster *metaphor*.

For the baseline, we perform crisp classification using FCM. We mark a sample, i as *metaphor* if its membership values, μ_{M_i} in the cluster *metaphor* is higher

[2] Metaphoricity: `https://goo.gl/wmgjor`

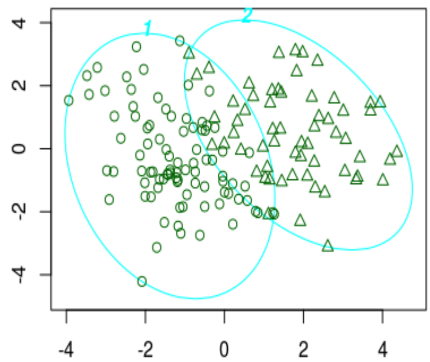

Fig. 1. Clustering using FCM (Clusters: '1'-Metaphor, '2'-Literal)

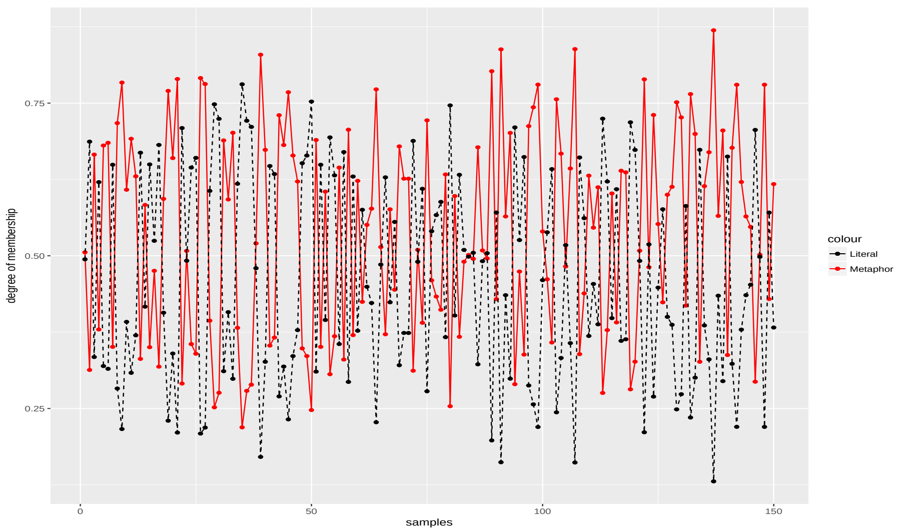

Fig. 2. Membership graph for metaphorical and literal samples. The x-axis represents the samples and y-axis indicates the degree of membership.

than its membership , μ_{L_i} in the cluster *literal*. The results for soft metaphor detection are summarized in Table 1. We formed three classes namely *metaphor*, *literal* and *probably_metaphor*. The class, *metaphor* consisted of samples having membership value, ≥ 0.52 in cluster, *metaphor* where as samples with membership value ≤ 0.48 were marked as literal samples. The class, *probably_metaphor* comprised of samples whose membership values lie in the range of (0.48, 0.52). The range is decided experimentally after examining the samples.

Table 1. Results

Approach	$A_{metaphor}$	$A_{literal}$	$A_{average}$	$\lvert probably\_metaphor \rvert$
Baseline(crisp classification)	62.67	81.34	72	NA
Soft Metaphor Detection	**71.6**	**82.14**	**75.91**	13

Legend: $A_{metaphor}$-Accuracy for class *metaphor*,
$A_{literal}$-Accuracy for class *literal*,
$A_{average}$- Average accuracy for *metaphor* and *literal* class,
$\lvert probably\_metaphor \rvert$-cardinality of set, *probably_metaphor*

In Table 1, the average accuracy for our proposed approach is 75.91% which is 3.91% more than the average accuracy of the baseline approach. We observe a significant improvement of 8.93% in the accuracy of class *metaphor* over the baseline. There is a minor increase of 0.8% in the accuracy of class *literal*.

On closer analysis, we observe that metaphorical samples such as 'The good news was an earthquake'(sample:48 in Fig. 2) and 'An atom is a solar system'(sample:50 in Fig. 2) were incorrectly classified as *literal*. The degree of membership for the sample '50' in cluster *literal* is 0.75 and thus 0.25 in *metaphor*. Despite the fact that it is a metaphorical sample, the frequent usage in daily parlance has nullified its novelty and thus its application as a metaphor. The sample '48' has membership value of 0.65 in the cluster 'literal'. This can be attributed to the high relatedness between the domains 'news' and 'earthquake'. Also for a human, it is difficult to unambiguously categorize the sample '48' as *metaphor* or *literal*.

Likewise, few literal samples such as 'Marriage is a legal contract.' are predicted as *metaphor*. Technically, marriage is a contract but it is seldom conveyed so. Low co-occurrence and thereby low relatedness between *marriage* and *contract* led to its false classification in the class *metaphor*.

From the results, we observe that soft metaphor detection do facilitate classification with higher accuracy and provides the scope for further analytical processing of doubtful cases.

The degree of membership in the fuzzy cluster '1'(metaphor) acts as the *metaphoricity* of a given metaphorical expression. In Table 2, we present the metaphoricity obtained for a subset of 6 samples from the dataset. The table includes two pairs of similar subject-object phrases, one embodying a much higher degree of metaphoricity than the other. These examples illustrate how an unfamiliarity in the mapping between source and target domain concepts bends a phrase towards metaphorical usage. The complete list is publicly available on the link[2].

Table 2. Metaphoricity (Membership in clusters-*metaphor*)

No. (Fig. 2)	Sample	Metaphoricity
9	New moon is a *banana.*	0.784
109	New moon is a curve.	0.438
31	His marriage was a short *leash.*	0.689
94	His marriage was controlling.	0.29
47	Control is *fertilizer.*	0.622
96	Control is encouraging.	0.338

In Table 3, we show the centroids of clusters in terms of the feature-values. The labels *conc*, *imag*, *mean* and *fam* denote the features *concreteness, imageability, meaningfulness and familiarity* respectively. The suffix *_o* indicates that the extracted feature is for target domain *i.e.* object in the case of nominal metaphors whereas the suffix *_d* indicates the difference between the values for the source and target domains.

Table 3. Feature-value for cluster-centroids in FCM

Feature	*conc_o*	*imag_o*	*mean_o*	*fam_o*	*conc_d*	*imag_d*	*relatedness*
Metaphor	0.772	0.698	0.502	0.656	0.633	0.498	0.177
Literal	0.538	0.447	0.277	0.604	0.498	0.371	0.183

Analysis Analyzing the clusters shown in Fig. 1, we observe that there is a significant overlap between the metaphor and literal clusters. The membership graph shown in Fig. 2 also strengthens the idea that a metaphorical text is indeed partially literal and a literal text is partially metaphorical. The highest membership degree in cluster 'metaphor' is 0.869 for *'Path through forest is a narrow lane.'* followed by *'The nearest star is a ball.'*. The lowest membership is 0.219 for *'Some tears are intriguing.'* followed by *'Atom is a solar system.'*. Few examples of *probably_metaphor* are given below.

My rat's fur is silk. (b)
Brain is a machine (c)

The sentences (b) and (c) are marked *metaphor* in the dataset. However, the membership degrees for these two phrases in the class, *metaphor* are 0.482 and 0.495 respectively. This supports our hypothesis that a metaphor gradually loses

[2] Metaphoricity: `https://goo.gl/wmgjor`

its novelty and thereby, its metaphoricity. The comparisons *atom-solar system*, *fur-silk* and *brain-machine* are quite common and so have low metaphoricity. On the other hand, we also observe that some literal samples such as *'My young cousin is thin.'*, *'My ex-husband is good.'* and *'Hostility is hidden.'* have higher membership in the metaphor class. This may be due to the assumption of rare co-occurrences as an indicator of novelty and thus a metaphorical text.

As shown in Table 3, the psychological features such as *concreteness, imageability, familiarity, meaningfulness* are relatively high for metaphorical class in concordance with the existing findings. The semantic relatedness for metaphorical samples is relatively lower than literal samples, as postulated by the theory of contextual incongruity. The relative difference between psychological features of source and target domains is also an important feature to determine metaphorical samples.

4 Conclusion

In this paper, we brought forth the idea that the journey of a metaphor from being novel to being considered dead is a continuum. We argued that soft metaphor classification, which entails assigning a degree of membership to various levels of metaphoricity is a more practical and informative approach towards metaphor processing than a crisp classification, due to the fuzzy nature of concepts in human language. Through an analysis of cluster formation, we verified the hypothesis that metaphors do involve an analogous comparison of concepts in a somewhat inscrutable domain with concepts in a relatively more concrete, imageable and meaningful domain. For our future work, we are focusing on treating the intermediate category of *probably_metaphor* to further analytical methods to predict their utility as metaphorical usage.

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