Understanding Metaphors Using Emotions

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Understanding Metaphors using Emotions* ** ***

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Abstract Metaphors convey unspoken emotions and perceptions by creatively applying an evocative concept from the source domain to illustrate some latent idea in the target domain. Prior research on nominal metaphor interpretation focused on identifying those properties of the source domain which are highly related to the target domain concepts to discover the most likely sense of the metaphor's usage. In this paper, we bring forth a fresh perspective by observing that a metaphor is seldom without an emotion or sentiment; in fact, it is this very aspect which segregates it from its literal counterpart. We present an Emotion driven Metaphor Understanding system which assesses the affective dimensions of the source properties before assigning them as the most plausible sense in the context of the target domain.

In our approach, we use the web as a knowledge source to identify properties of the source domain. We resolve the bottleneck of non-availability of informative emotion-lexicons by using pre-trained *word2vec* embeddings to extract the latent emotions in the source domain properties. Adopting an unsupervised learning approach on a dataset of nominal metaphors, we demonstrate that

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in comparison with a single emotionless interpretation, a multi-sense interpretation of a metaphor using the gamut of emotions is more likely to provide a realistic presentation of its purport. We further demonstrate that an emotion driven interpretation is often preferred over an interpretation sans emotion. The results clearly indicate that it is beneficial to apply emotions for refining the process of metaphor understanding.

Keyword: Metaphor, World wide web, emotions, metaphor interpretation, nominal metaphor

1 Introduction

"Dwell on a metaphor long enough, even a relatively uninteresting one, and numerous and various interpretations come to mind.": Bergmann, 1982, pg. 231 [1]

A metaphor emerges when a correspondence is made between two dissimilar conceptual domains with the intent of expressing an idea which cannot be optimally expressed literally [2, 3]. The manifestations, that is metaphorical expressions, are drawn from a source domain to construe a target domain under certain set of features [4]. Once a metaphor is born, its novelty and expressiveness make it popular enough to get assimilated into linguistic usage. Over a period of time, a metaphor may become overused in common parlance, that is when it loses its *novelty* - the core reason for its existence. Consequently, it metamorphoses into a *dead metaphor*. Despite being ingrained in human language, the process of automated metaphor interpretation is a computationally hard problem due to complex influences in the evolution of human language. Nevertheless, its significance in achieving human computer interaction in the true sense is irrefutable.

Existing techniques for understanding nominal metaphors emphasize on identifying semantically related properties in the source and target domains, to establish the most likely sense of a metaphor [5, 6]. However, a metaphor encapsulates more than just its mapped properties. It embeds a subdued emotion and often evokes an affective reaction. Therefore, we contend that there is a need to adopt a more pragmatic approach which takes into account the affective reactions that a metaphor evokes.

In this paper, we bring forth a fresh perspective by analysing the problem of metaphor interpretation through different emotional filters. We develop an Emotion driven Metaphor Understanding(EMU) system which provides multiple senses for a metaphorical expression along different affective dimensions. This enables a more complete and affect inclusive interpretation of a metaphorical expression.

Our research establishes the following three points:

1. A metaphor can have multiple senses according to the perception of a reader towards the target domain T. In addition we state that the individual perception can be captured by treating the entire web as a reflection of human experiences which brings to fore different prevalent perceptions.
2. A metaphor is understood better when we perform an emotion infused interpretation which evokes one or more emotions, as compared with an interpretation that relies solely on identifying similarity between the mapped source-target concepts.
3. The pre-trained *word2vec* embeddings [7] are capable of capturing affective similarity between words and thus, can be used effectively to extract the intensity of inherent emotions in source domain properties.

To test our approach, we use a publicly available dataset of nominal metaphors provided in [8]. We evaluate the correctness of the predicted senses by inviting seven English speakers to rank their appropriateness on a Likert scale [9]. Further, we conduct a study to compare the suitability of emotional interpretations over a sense that does not take into account emotional content.

The rest of the paper is organized as follows. We explain the motivation behind this paper in section 2. In section 3, we provide a brief introduction to the existing work in metaphor interpretation. In section 4, we elaborate upon the proposed approach. This analyses the emotional aspect of a property while providing an interpretation of a metaphor. We present the experiments and analysis in section 5. We conclude in section 6.

2 Motivation

A nominal metaphor projects a target domain concept in the light of certain recognizable attributes of a source domain concept. The resulting construct highlights a specific facet of the target domain while simultaneously hiding other aspects which may not be of significance in the current context of discourse. The relatively well understood attributes or characteristics of the source domain are referred to as *properties* which help us in understanding the more abstract idea underlying the target domain [3].

Recently, few researchers have ventured to automate the process of metaphor understanding [5, 6]. The approaches identify related properties of the source and target domains to establish a possible meaning conveyed by the source domain. However, we believe that the true potential of a metaphor is in its open interpretation which evokes various affective senses based on the prior experiences of a reader [10]. This view is supported by Samur *et al.* who provide neural evidence to show the relationship between emotions and metaphorical language [11]. In [12], the authors observe that most people employ metaphorical expressions to describe emotional states. Consider the following example,

(a) Her eyes are *stars*.

Here, the author uses the word *star* metaphorically to convey his/her thoughts and emotions towards the subject's eyes. If we attempt to capture the author's notion for *star* literally, it would be difficult to retain all possible senses without being verbose. A literal yet compact substitute is 'Her eyes are big'. However, it is devoid of any emotion. It is unlikely that the author used the reference *star* just to highlight the size of her *eyes*. It is more plausible that the author meant *intense, luminous, dramatic, dreamy, forlorn* or *bright* eyes over the emotionless sense of *big* eyes. This example underscores the need to examine emotions while interpreting metaphors.

A deeper reflection helps us in comprehending the extensive effect of emotions in metaphor understanding. The emotional consideration towards any subject depends on one's own perceptions built from his/her prior experiences. Consequently, a metaphor may emit multiple senses according to the perception of the reader towards the mapped domain. Let us take a motivating example to illustrate this phenomenon.

(b) My lawyer is a *shark*.

Here, the author uses the metaphor *shark* to highlight certain characteristics of his/her *lawyer*. A reader who had a distressing experience with a *lawyer* may infer senses such as *aggressive, predatory* or *greedy* from the metaphor *shark*. On the contrary, someone with a positive perception towards *lawyer* may deduce *shark* to denote *strength* or *argumentative capabilities* of *lawyer*.

Note that there is a range of emotional overtures in both interpretations. The former interpretation not only expresses aggression or a greedy nature but also conveys a lack of trust with a hint towards the possible termination of contract with the lawyer. The latter interpretation conveys the subject's prowess as a lawyer, his/her significant stature supported by history of conclusive cases and the client's confidence in placing his/her faith in the lawyer. This clearly illustrates the wide variation in emotional senses that is conceivable while understanding a metaphor.

Taking cues from the above thread of discussion, we contend that the genesis, prevalence and understanding of metaphors is influenced by the congregation of individual perspectives, emotional experiences and cultural milieu of people who use them in their linguistic expression. This motivates us to adopt an emotion driven metaphor understanding system to identify a range of possible affective senses for a given metaphorical expression.

The web as a corpus: The main challenge in this process is to extract those properties of the source domain which hint towards possible affective reactions. To understand the emotions that a user may have developed towards the source domain, we require unfiltered outpourings of the user or the community of which s/he is a part of. Hand crafted knowledge resources such as WordNet [13] and Sardonicus[1] are structured sources of information. These sources though specialised do not encapsulate individual experiences, have limited coverage and usually ignore latent properties which do not seem obvious at first glance. On the other hand, the web is an open, autonomous and continuous receptacle of human experiences. Since it is an unstructured resource, it also captures the spontaneity and circumstances under which a concept evokes feelings or affective reactions of a user. This provides a faithful reproduction of human thoughts and conversational processes in the society. Therefore, we tap upon the web as a corpus for extracting emotion infused properties of a source domain.

The high coverage of the web as a knowledge source also helps in understanding uncanny comparisons which may not be conceivable in the first look and gradually comes to light. For example, consider the expression,

(c) My boyfriend is a *peach*.

The perceptual properties[2] listed in the Sardonicus for *peach* are *round, pleased, bald, pretty, succulent, ripe, rosy, delicious, juicy, cute, healthy, luscious, pleas-*

[1] `http://afflatus.ucd.ie/sardonicus/tree.jsp`

[2] `http://afflatus.ucd.ie/sardonicus/tree.jsp?noun=peach` accessed on Sept. 10, 2017

ant, innocent, sweet, downy, radiant, harmless, fresh, nourishing and *soft*. As we can notice, they all are directly related to the literal interpretation of *peach*. However, on using the web as corpus, we obtain senses such as *fuzzy, asian, artistic, sweet, shaved, undersized, adorable, weird, attractive, post-feminist etc.* These concepts are not all properties of *peach* but are culled from the various contexts in which the word *peach* is used in real conversations. The postings on the web provides a more realistic, context oriented meaning to the metaphorical expression.

3 Related Work

In this section, we provide a brief overview of the prior work on understanding nominal metaphors.

Kintsch models the interaction between the meanings of source and target domains [5]. He builds a LSA model to derive the semantic space for a word and thereafter, uses the metric of cosine distance to identify words which are mutually related to both of the domains. Martin develops a metaphor comprehension system, MIDAS which uses encoded interpretation of conventionalized metaphors to understand novel metaphors through the notion of concept distance between them [14]. In [15], Veale and Hao describe a 'fluid knowledge representation' model through conceptual 'talking points' extracted from WordNet and the web. They organize 'talking points' in *Slipnet* which facilitates operations such as insertion and deletion to discover a link between the target and source domains. One of the illustrations in [15] shows understanding the metaphorical expression, "*Make-up* is a *Western burqa*" as follows.

Make-up =>
$\equiv$ typically worn by women
$\sim$ expected to be worn by women
$\sim$ must be worn by women
$\sim$ must be worn by Muslim women
=> Burqa

Su *et al.* put forth the hypothesis that a property of the source domain is the interpretation of a metaphorical expression if the property has a latent similarity with one of the properties of the target domain. Two features A and B are said to have latent similarity if they are not synonym and there exists a word C such that it is a synonym of A and B. To populate the set of properties for the source and target domains, they use Sardonicus[1], a taxonomy for adjectives to extract perceptual properties of the source and target domains. To resolve the problem of data sparsity, they then expand the set of extracted properties using the synonymy relation in WordNet [16]. Xiao *et al.* propose *meta4meaning* model which extracts word associations from a corpus to extract source domain properties [17].

[1] `http://afflatus.ucd.ie/sardonicus/tree.jsp`

In [6], Su *et al.* propose an approach which does not require extraction of properties for the target domain. They extract properties of the source domain using Sardonicus and expand it using synonymy relation in WordNet. They then select the property of the source domain which has the maximum relatedness with the target domain. They compute relatedness using *word2vec* embeddings [7].

The above works emphasize on selecting the property of the source domain which is maximally related with the target domain. However, a metaphor often involves a subtle opinion or a subdued emotion towards the target domain based on one's perception. Furthermore, the issue of data sparsity and manual upgradation of hand crafted knowledge resources restrict the scope of possible senses for understanding metaphors. In this paper, we project the problem of metaphor interpretation from the angle of emotion and predict senses inspired from the affective reactions evoked by a metaphor. Our method does not require any hand crafted resources. It uses the web to capture context which may not even fall in the category of traditional properties of a source domain, but enable prediction of senses.

4 Understanding Metaphors using Emotions

Nominal metaphors entail an explicit comparison between the source and target domains through a copular verb such as *to be, was, is,* and *am.* Sentence (b) explicitly maps the target domain *lawyer* to the source domain *shark* using the copular verb *is.* Likewise, sentence (a) equate the target domain *eyes* to the source domain *stars* using the verb *are.* Nominal metaphors expressed in direct speech generally use the target concept as subject and the source concept as object. Hence, we use a simple dependency parser to identify the subject and the object in the input sentence. The final input to the EMU system is a tuple $< T, S >$ consisting of the target and source domain concepts respectively.

The block diagram of the proposed approach is shown in Fig. 1. The EMU system is divided in three phases namely, *Property Extraction*, *Emotion Extraction*, and *Property Transfer*. The first phase extracts the properties of the source domain from the web. The second phase generates emotion profile for the extracted properties. The final phase selects the set of properties to be transferred to the target domain. We explain the detailed working of these phases below.

4.1 Properties Extraction

The properties of the source domain concept S, are extracted by probing the web. This involves the following steps:

1. *Retrieve relevant documents*: We employ a search engine to retrieve text documents containing the term S from the web. This set of documents

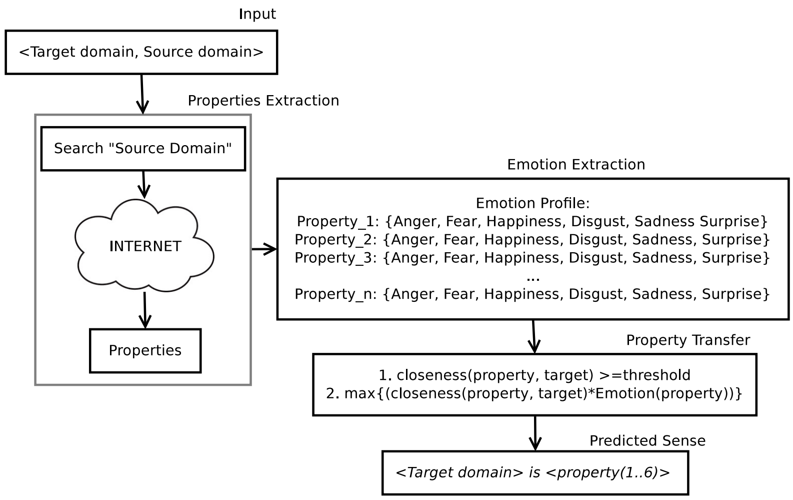


Fig. 1 Block Diagram for Emotion-driven Metaphor Understanding System

serve as a corpus C_{source} that contains all information which characterize the source domain.

2. *Extract the context*: These documents are pre-processed to capture the surrounding context of S. The inclusion of context helps in extracting latent concepts of the source domain along with the more obvious concepts that are usually included in a taxonomy or ontology for the source domain. We define context as the present sentence s_0 in which S is detected, its preceding sentence s_{-1} and its subsequent sentence s_{+1}.
3. *Extract properties*: The context is parsed with a Part of Speech (PoS) tagger to identify adjectives. Adjectives are descriptive terms that give personality to the identified source domain concept, thus serving as its distinctive properties.

Let us illustrate the above procedure with the help of sentence (b). Here, the domain of lawyer (the target domain) is transported to the domain of shark (the source domain). The above steps generate a profile for *shark*. One of the documents retrieved is as follows:

(d) *"If you think something is going to try to come and get me I need you guys to start screaming, 'Oh no, look out. Of course, Gaughan was never in any real danger and two assistants kept a watchful eye whenever the* ***sharks*** *came nearby. Still, he ducked several times to avoid contact with the sharks, the largest of which was more than 10 feet long, during the presentation.* [3]

The descriptive words *watchful*, *largest* and *long* are adjectives describing the phenomenon of domain *shark* within the given context of the text.

[3] `https://goo.gl/SXyoRd` accessed on Nov 10, 2017

4. *Filtering*: Of all adjectives identified, many may not be related to the source domain concept at all. To eliminate such noisy and unrelated terms in the context, this module verifies the semantic closeness of an extracted adjective p with the source concept S. We define *closeness*, $\alpha(p, S)$ as the cosine similarity between *word2vec* vector representations of the adjective p and the source domain S as given in eq. 1 below.

$$\alpha(p, S) = cos(p, S) = \frac{\mathbf{p}.\mathbf{S}}{|\mathbf{p}|.|\mathbf{S}|} \ . \tag{1}$$

where $\mathbf{p}$ and $\mathbf{S}$ are *word2vec* vector representations of the adjective p and the source domain S respectively. We apply the following two criteria for filtering:

(a) Some adjectives have very little connection with the source domain and may be eliminated. Only those adjectives whose *closeness* are above a predefined threshold $\gamma_L(source)$, are considered.

(b) On the other end of the spectrum, some adjectives are highly specific. It is worth noting that the source domain provides only a hint of what is being intended about the target domain. It is not an explicit translation but a metaphorical comparison. Thus, the highly specific adjectives of the the source domain are not applicable to the target domain and may be eliminated.
To clarify this point, let us consider a subset of extracted adjectives for *shark* in Table 1. The source domain *shark* comprises of attributes such as *mammal, aquarium, underwater, marine* and so on. Despite being very *close* to the source domain, it is obvious that these adjectives do not apply directly on the target domain *lawyer* - they are explicitly related to the domain of *shark*. In contrast, relatively abstract notions of *shark* such as *fierce, strong, aloof, impressive, victorious* and *dominant* do make sense even when applied in the context of a *lawyer*.
Therefore, we filter out highly specific terms whose *closeness* exceed a preset upper threshold $\gamma_U(source)$.

After combining both thresholds, if $\gamma_L(source) \leq \alpha(p, S) \leq \gamma_U(source)$ then the adjective p is retained as a property of S, else it is discarded. In Table 1, we provide a subset of adjectives for *shark* which illustrates the idea of thresholds. The only adjectives satisfying the criteria $0.072 \leq \alpha(p, shark) \leq 0.079$ are considered for later stages of EMU.
The thresholds $\gamma_L(source)$ and $\gamma_U(source)$ are experimentally tuned for a given dataset of nominal metaphors and the web corpus of their source domains.

4.2 Emotion Extraction from *word2vec*

Ekman and Dalgleish observed that humans share six basic emotions namely *anger*, *fear*, *happiness*, *disgust*, *sadness* and *surprise* across different cultures [18].

Table 1 Extracted Adjectives for *shark*

Adjective p	$\alpha(\mathbf{p}, shark)$
$\alpha(p, shark) > 0.079$	
mammal	0.537
aquarium	0.452
underwater	0.425
marine	0.381
$0.072 \leq \alpha(p, shark) \leq 0.079$	
fierce	0.03
strong	0.021
aloof	0.02
impressive	0.015
victorious	0.014
dominant	0.008
$\alpha(p, shark) < 0.072$	
disqualified	-0.042
crystal	-0.067
alphabetical	-0.0713
hazardous	-0.0719

Adopting this classification, we define the set of emotions as

$$\mathbf{E} = \{anger, fear, happiness, disgust, sadness.surprise\} \ .$$

Accordingly, the emotion profile **EP** of a property p is a vector in $\mathbb{R}^6$. It contains intensity $\forall e \in \mathbf{E}$ evoked by the property p. It is represented as:

$$\mathbf{EP} = \{\alpha(p, e_1), \alpha(p, e_2), \alpha(p, e_3), \alpha(p, e_4), \alpha(p, e_5), \alpha(p, e_6)\}$$

where $\alpha(p, e_i)$ represents the *closeness* of a property p with an emotion $e_i \in \mathbf{E}$. The subscript i denotes the index for elements in $\mathbf{E}$. By the term *closeness* of a property p with an emotion $e \in \mathbf{E}$, we here refer to affective affinity of the property to emote the emotion e.

One of the constraints that researchers face while extracting emotions is the lack of emotion-labelled resources. The existing manually compiled databases for emotions such as NRC Emotion Lexicon [19, 20] associate the various emotions in a given word using a binary scale. This does not provide information about their intensity. On the other hand, the lexicons such as WordNet-Affect [21] has limited coverage for synsets annotated for emotions.

Evidently, there is a need to develop an efficient method to determine the proclivity of a word towards various emotions. We employ *word2vec* embeddings prior trained on Google News corpus. Conceptually, the embeddings follow the notion of distributional hypothesis that is, "*a word is characterized by the company it keeps*" [22]. In other words, Pantel states "*words that occur in the same contexts tend to have similar meanings*" [23]. It is often used to understand the semantic orientation of a word by analysing co-occurring words in its vicinity. The trained embeddings are capable of capturing 'multiple degrees of similarity' between two words from different perspectives such as syntactic, inflectional and semantic [7]. Further, they have been used for applications such as sentiment analysis [24] and metaphor detection [8, 25]. In Section 5.3, we illustrate that the pre-trained *word2vec* embeddings can infer emotion intensities of affective words and are thus capable of segregating a set of affective words to their predominant emotion classes.

To elaborate, let us reconsider sentence (b) in which the word *shark* is used metaphorically. A comprehensive affective picture of *shark* is deducible by analysing the different contexts in which the word *shark* often occurs. One of the prevalent perceptions depicts the *shark* as a deadly and fearsome creature (as in sentence (d)). This predominantly evokes emotions namely *surprise* and *fear*. By observing the underlined descriptive word *watchful* in (d), we can partially derive the mentioned affective orientation.

The emotion profile **EP** for the property $watchful$ of the source domain *shark* is calculated as: $\{\alpha$('watchful', 'anger'), α('watchful', 'fear'), α('watchful', 'happiness'), α('watchful', 'disgust'), α('watchful', 'sadness'), α('watchful', 'surprise')$\}$ = $\{$0.1011,0.2548,-0.0144,0.0249,0.119,0.0531$\}$.

From the vector, we infer that the term *watchful* predominantly evokes the emotion *fear*. This is expected as the state of being *watchful* has a direct correlation with the *fear*. *Fear* is followed by the emotion *sadness*. The emotion *happiness* has a negative value, indicating its inverse relation with being watchful that is, a happy person is usually not watchful. It also evokes other emotions namely *anger, surprise*, *disgust* but with minor intensity. The vector so obtained faithfully sums up the inherent emotions in the word *watchful*.

4.3 Property Transfer

After generating the emotion profiles of source properties for a metaphor, we cull out a set of winning combinations of property-emotion that could represent its possible interpretations. This involves a two-step process:

1. *Choose properties related to target domain:* A property p is close to the target domain T if $\alpha(p,T) \geq \gamma_L(target)$ where $\gamma_L(target)$ is the minimum threshold value pre-set for *closeness* with the target domain. This step produces a set $\mathbf{P}$ of properties that are neither too close nor too far away from the source domain as in eq. 1 and are closely related with the target domain.
2. *Select the property to be transferred:* For every emotion $e \in \mathbf{E}$, we select that property $\hat{p}_e \in \mathbf{P}$ which most appropriately projects an intended meaning of the target domain. We formulate the criterion for choosing $\hat{p}_e$ in eq. 2.

$$\hat{p}_e = \underset{\forall p \in \mathbf{P}}{\arg\max} \left(\alpha(p,e) * \alpha(p,T) \right) . \tag{2}$$

This equation factors in both considerations that is, *closeness* of p with the target domain and emotion proclivity of p towards emotion e.

The above steps are repeated for each emotion $e \in \mathbf{E}$ to construct a corresponding interpretation: <Target domain, copular verb (is, was, am, can

be), $< e : \hat{p}_e >>$. There are six possible interpretations of a metaphor. Each of these interpretations can be viewed as a specific emotional sense.

For the emotion *fear*, the property $\hat{p}_{fear}$ that we experimentally deduced for the sentence (b) is *unscrupulous*. Then, with *fear* as the underlying emotion, the interpretation of the metaphor becomes 'My lawyer is <*fear*: unscrupulous>'. Similarly, for *happiness*, the selected property $\hat{p}_{happiness}$ is *stoic*. Therefore, the interpretation with respect to *happiness* is 'My lawyer is <*happiness*: stoic>'. Likewise, we obtain interpretations: 'My lawyer is <*anger/disgust*: uncaring>' for *anger* and *disgust*, 'My lawyer is <*sadness*: difficult>' for *sadness* and 'My lawyer is <*surprise*: ridiculous>' if we consider the aspect of *surprise*.

5 Experiments and Discussion

We implemented the proposed metaphor understanding system, EMU in Python V2.7. We used the Yandex[4] search engine to retrieve textual documents from the web. To parse the search results, we used the Stanford CoreNLP parser [26] in the NLTK package [27]. We utilised the package *Rtsne* [28] to plot word embeddings to illustrate the concept of affective similarity through *word2vec*.

The objective of our experiment is to test our following hypothesis:

$\mathcal{H}_1$: A metaphor can have multiple senses according to the perception of a reader towards the target domain T. In addition we state that the individual perception can be captured by treating the entire web as a reflection of human experiences which brings to fore different prevalent perceptions.

$\mathcal{H}_2$: As compared with an interpretation that is derived without considering emotions, a metaphor is better understood with an emotional interpretation, that is, with a sense that evokes a certain emotion or a set of emotions. By the term *better understood*, we mean a more precise and appropriate interpretation in accordance with the metaphorical usage.

5.1 Dataset

We used a publicly available dataset of nominal metaphors provided in [8]. Our assumption is that the metaphors to be interpreted are already detected, we thus use those instances in the dataset which are classified as *metaphor*, as input to our system. There are 75 metaphorical instances in the dataset. In this paper, we test our approach on lexical metaphors that is, single word or lexeme metaphors. We filtered out multi-word metaphorical expressions such as 'God-of-cricket' and 'breath-of-fresh-air' from the dataset.

5.2 Affective Affinity using *word2vec* embeddings

We first carried out an experiment to test whether *word2vec* embeddings are indeed effective in assessing the affective affinity of words. To verify, we

[4] `YandexSearchEngine:www.yandex.com`

Table 2 Distribution of Affective words in A

Class	**Emotion**	**#words**
1	Anger	210
2	Fear	125
3	Happiness/Joy	328
4	Disgust	44
5	Sadness	165
6	Surprise	62
	Total	934

hypothesise that the words of similar affective category have similar emotion profiles generated using *word2vec* embeddings. Moreover, the distance between emotion profiles for any two words indicate the intensity of their affective similarity. Lower the distance between two words, higher is the similarity between them.

We used a set A of affective words[5] from WordNet-Affect [21] to verify our hypothesis. There is a total of 934 words in A after removing duplicates. Each marked with a specific emotion $e \in \mathbf{E}$. The distribution of words for different emotional categories is shown in Table 2. For each word in A, we generated a six-dimensional emotion profile **EP** using eq. 1 as explained in Section 4.2. Thus, a word w in the set is represented as a tuple: $< w, \mathbf{EP}(w), Class >$. The $Class$ is a value $v \in \{1, 2, 3, \ldots, 6\}$ representing different emotional categories as given under the column 'Class' in Table 2.

Fig. 2 shows the t-sne plot [29] of words in A in the vector space of their emotion profiles. We clearly observe that words with similar affective categories are clustered together. For example, the word *jubilant* is closer to *gratifying* in the affective vector space in comparison with the word *miserably*. Therefore, the words *jubilant* and *gratifying* are more affectively similar to each other in comparison with the word *miserably*. This indicates that words which are close in the *word2vec* embedding space do belong to the same emotion category.

For clarity, we replotted the words in A using numeric classes as given under the column 'Class' in Table 2. in Fig. 5.2. We clearly notice the segregation among the sets of different classes. The plots illustrate the appropriateness of using emotion profiles from *word2vec* embeddings for identifying the emotions conveyed by any given word.

5.3 Comparison with Baseline

In order to compare our approach, we define a baseline approach B_T inspired from the approach proposed in [6]. The baseline, B_T chooses a set of six properties $p_{1,\ldots,6} \in P$ which are closest to the target domain T, as its applicable senses for metaphor interpretation. This approach considers the semantic

[5] Available under **Resources**: `http://web.eecs.umich.edu/~mihalcea/affectivetext/`

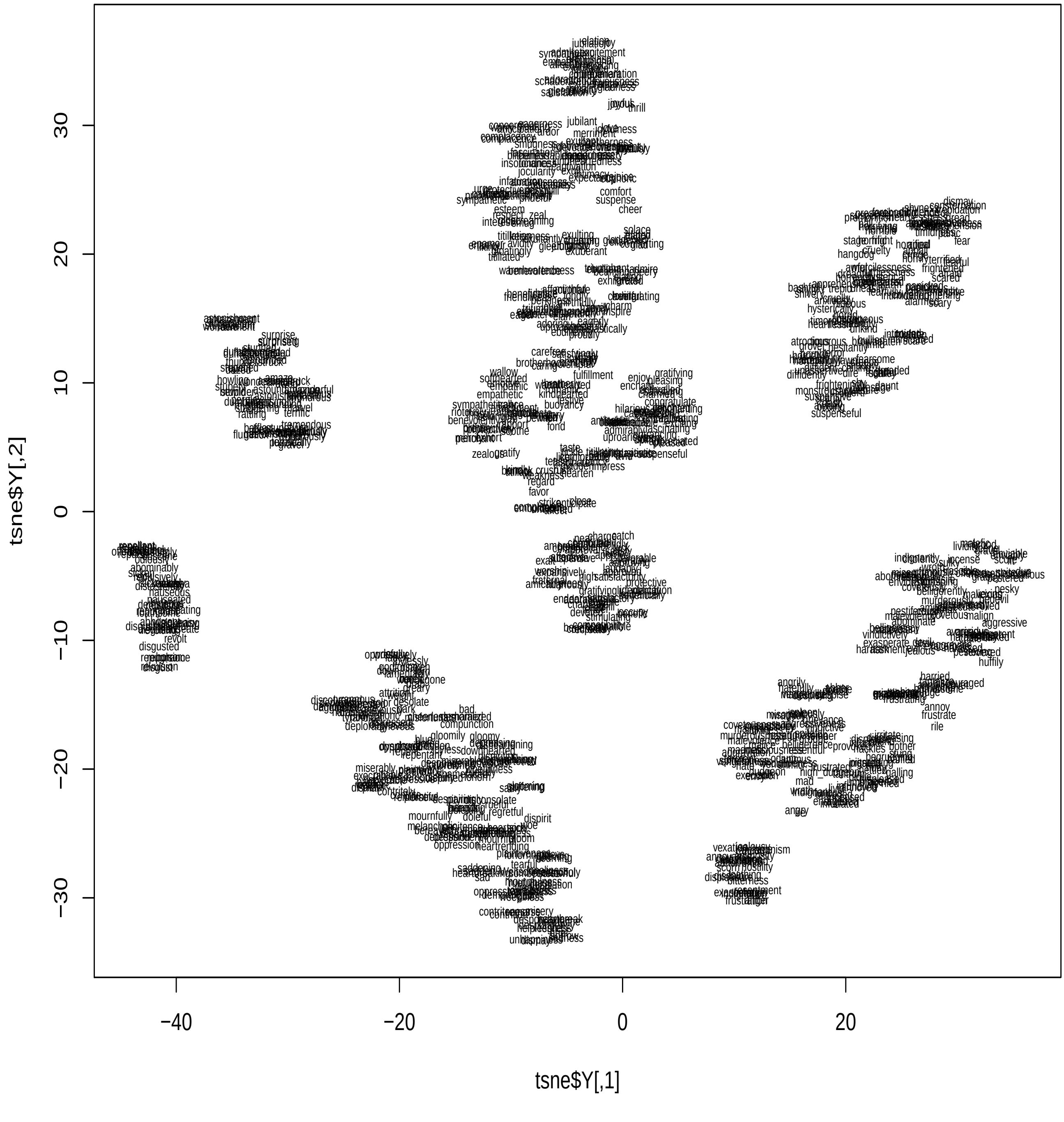
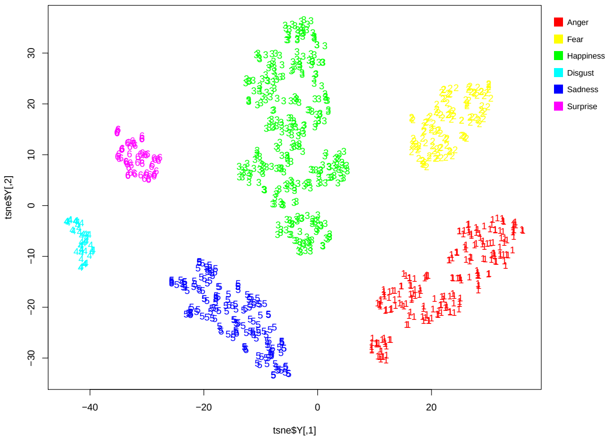


Fig. 2 Clusters of words in A with similar affective affinity



relatedness between the source properties and target, but does not factor in the emotional aspect.

5.3.1 Human Evaluators

The aim of evaluation is to identify agreement or disagreement with the emotional import of the projected meaning of a metaphor. Even though it is conveyed with English words in our work, we believe that the language of emotions is universal. Hence, there is an impetus for choosing people of different socio-cultural backgrounds, who are otherwise highly familiar with the English language. Also, there is enough discrimination between the six basic emotions for a non-native speaker to discern, when expressed in English.

Since metaphor understanding is a highly cognitive process, we invited seven non-native English speakers to evaluate the appropriateness of the predicted senses for a metaphorical expressions under the approaches, B_T and EMU. All of the evaluators were in the age group of 19-20 years. Three of them had Hindi as their mother tongue, two of them were native Bengali speakers and other two were native Marathi speakers. Three of them were female and the remaining of them were male. We ensured a level of proficiency in English of the evaluators at par with native speakers. Their medium of throughout school-level and college-level education is English. They had all scored more than hundred in the standard English proficiency test TOEFL[6].

All evaluators were asked to independently rate the appropriateness of each of the predicted senses on a Likert scale [9] of '1' to '5' where the denotation are:- '1': Highly inappropriate; '2': Somewhat inappropriate; '3': Average; '4': Somewhat appropriate and '5': Highly appropriate. If the average rating for a sense is below 3, then we mark it as an incorrect sense otherwise the sense is

[6] `https://www.ets.org/toefl`

considered as a correct interpretation. The same set of annotators were asked to rate the appropriateness for senses predicted by B_T and EMU. It may be noted that no author participated in this process of evaluation.

The collaborative evaluation process for B_T and EMU results in either 0, 1 or more than one appropriate interpretation of each metaphor. If none of the senses in the six dimensional set is marked as appropriate by any of the evaluators, then the set is considered incorrect else we take it as correct interpretation. If none of the evaluators agree upon any of the senses as the correct one, then we assume that there is no appropriate interpretation. If there is only one appropriate interpretation, then all the annotators converged to a single sense, implying that the proposed system was successful in understanding the given metaphorical expression. If there are more than one appropriate interpretations, then we consider all of them as correct senses.

5.3.2 Results

The multiple senses predicted by EMU for the instances in the dataset are given in Appendix A, Table A1. The incorrect senses are marked in italics.

Table 3 Performance Evaluation

Approach	**Accuracy** (in %)
B_T	83.82
EMU	**97.01**

The accuracy for B_T and EMU are given in Table 3. B_T approach provided an accuracy of 83.82% that is, it was able to suggest at least one appropriate sense for 83.82% of instances in the dataset. The EMU system performed the best with an accuracy of 97.01%. This demonstrates a major improvement of 13.19% more than B_T approach. The high accuracy validates that emotions provide an effective way of capturing the subjective interpretation of a metaphor. We also note that the instances which were wrongly interpreted through B_T can be understood correctly if different emotions are taken into account. Let us consider a metaphorical phrase to illustrate the impact of emotions on metaphor interpretation

(e) Music is *medicine.*

The set of senses obtained through B_T for the utterance in (e) is <*nourishing, creative, contemporary, latin, classical, folk*>. It may be noted that despite the six senses, all except one are quite related and talk about different types of music. In contrast, the EMU generated a set of dissimilar yet congruous senses as: {<*anger/disgust*: depressing>, <*fear*: knowledge>, <*happiness*: nourishing>, <*sadness/surprise*: soporific>} under different emotional parameters. This further strengthens our belief that a metaphor needs to be interpreted from different affective aspects to capture its most suitable subjective senses.

Nevertheless, we also found few cases where none of the evaluators agreed with any of the EMU generated senses. One such case is 'My team is a *jail*'. The senses generated by EMU under different emotions are {<*anger/fear/disgust/surprise*: fixed>, <*happiness/sadness*: safe>} as given in row:31 in Table A1. Another incomprehensible instance is 'An opponent is an *anchor*'. The senses generated by EMU in this case are {<*anger*: emotional>, <*fear/disgust/sadness*: terrible>, <*happiness/surprise*: interesting>}; all of them were marked as inappropriate in the evaluation process.

5.4 Testing hypothesis $\mathcal{H}_1$

To verify the first hypothesis $\mathcal{H}_1$ which states that a metaphor can have multiple senses, we invoke the EMU system to generate an interpretation of each metaphor in the corpus with respect to each of the six primary emotions: *i.e. anger*, *fear*, *happiness*, *disgust*, *sadness* and *surprise*.

Let us reconsider sentence (b) to illustrate the concept of multiple senses predicted by the proposed system. In sentence (b), a *lawyer* is compared with a *shark*. The senses generated through B_T approach are: <legal, guardian, innocent, federal, callous, angry>. From row:48 in Table A1, we observe that EMU generates the six emotional senses for the target *lawyer* as: {<*anger/disgust*: uncaring>, <*fear*: unscrupulous>, <*happiness*: stoic>, <*sadness*: difficult> and <*surprise*: ridiculous>}. If we replace any of the EMU senses with the word *shark* in the sentence (b), we find that none of them is incongruous or out of context description for *lawyer*. Moreover, it gives a complete idea of the different possible perspectives which can be imported from the source domain *shark* to the target domain *lawyer*. The other senses in **P** for the source-target pair, <lawyer, shark> are *predatory, weasel, malicious, sharp, famous, trustworthy, misleading, conclusive, intelligent, solitary* and *aggressive* which also serve as cogent interpretations for *lawyer*.

To further emphasize the concept of multiple senses, let us consider another sentence.

(f) Some teachers are *encyclopaedias*.

For sentence (f), the set of generated senses for the source concept *encyclopaedia* by B_T approach are <*academic, educational, catholic, religious, classical, scholarly*> whereas the EMU senses are: {<*anger/fear*:particularistic>, <*happiness*: knowledgeable>, <*disgust*: scientistic>, <*sadness*: educational> and <*surprise*: instructive>} as listed in row:15 of Table A1. It is interesting to note various senses which convey different perception towards *teacher* when compared with an *encyclopaedia*. These examples illustrate that emotion driven metaphor understanding bring forth multiple senses of a metaphor.

To validate $\mathcal{H}_1$, we analysed the dataset with respect to senses obtained from different emotional aspects. We computed the percentage of instances with different number of correct senses for B_T and EMU approaches. We illustrate

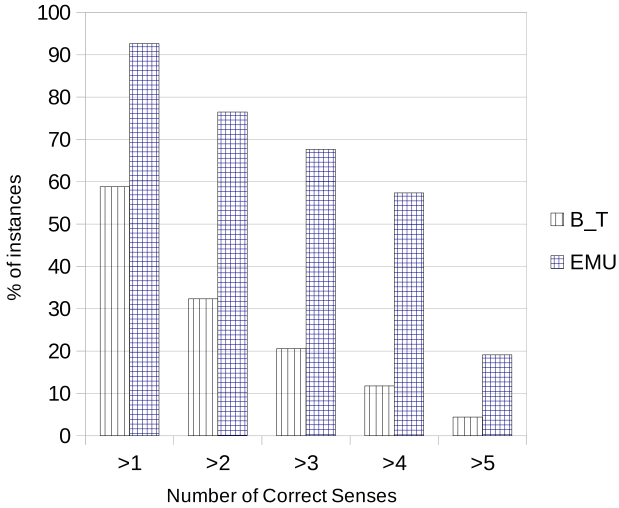


Fig. 3 Evaluating hypothesis $\mathcal{H}_1$ with regard to the number of possible correct sense

our observation in Fig. 3 where y-axis represent the percentage of instances in the dataset and x-axis lists the number of correct senses.

From the Fig. 3, we observe that 92.65% of instances in the dataset have more than one correct senses when generated through EMU. In contrast, B_T approach provides more than one correct sense only for 58.8% of instances. For EMU, 76.47% of the instances have more than two correct senses whereas it is 32.4% for B_T. The percentage decreased to 67.65% when the number of correct senses increased to more than three whereas for B_T, it reduced to 20.6%. Following the similar trend, the percentage of instances with more than four correct senses is 57.35% for EMU and 11.8% for B_T. Finally, the number of instances with more than five correct senses reduced to 19.12% for EMU whereas it is only 4.41% for B_T. These results clearly reveal that it is more likely to obtain appropriate metaphorical senses by bringing in different emotional parameters.

5.5 Testing hypothesis $\mathcal{H}_2$

In order to validate $\mathcal{H}_2$ which states that a metaphor is better understood with an emotional interpretation, we asked the evaluators whether they prefer any of the six interpretations generated by EMU over the set of emotion-less interpretations obtained through the baseline approach B_T. Since metaphor interpretation is a subjective task, it is not reasonable to undermine any of its usage contexts. Instead of assigning a specific sense, we provide all possible interpretations for B_T as well as EMU. To judge overall inclination of the evaluators, we assign the preferred sense as the one which received the highest average rating by seven annotators. If the highest rating is given to one of the senses suggested by EMU, then we consider the emotional sense as the preferred sense otherwise B_T sense is taken as the preferred sense. For example, let us consider a sentence.

(g) Control is *fertilizer*.

In sentence (g), the concept *fertilizer* is applied to illustrate the abstract concept *control*. The sense predicted by B_T is <*controlled, prevent, concentrated, improved, effective, biological*>. Its possible EMU senses are listed in row:16 of Table A1 as :{<*anger*: excessive>, <*fear*: susceptible>, <*happiness*: beneficial>, <*disgust/sadness*: unacceptable> and <*surprise*: problematic>}. As we can observe, the senses such as *unacceptable* or *beneficial* emote a subtle emotion as well as make sense in different context of usages. The different interpretations along different emotional aspects provide the flexibility of selecting a sense well aligned with a user's perceptions on *control* in his/her life. It also helps us in understanding latent meaning such as *problematic* or even *unacceptable* which we were not able to capture through B_T approach.

If we consider another instance given in row:2 of Table A1,

(h) My room is *Antarctica*.

In sentence (h), a *room* is compared with the continent *Antarctica*. The B_T approach suggests the senses <*subterranean, dark, tiny, hidden, small, daylight*> for the given utterance. The senses predicted by EMU are: {<*anger*: hidden>, <*fear/sadness*: dark>, <*happiness*: cool>, <*disgust*: lifeless>, <*surprise*: strange>}. It is interesting to observe different affective yet appropriate interpretations suggested by EMU.

From our experiments, we found that 47.06% of instances clearly had emotion based interpretations as their preferred sense. For 39.7% of instances, there was no clear preference that is, B_T and EMU senses had received the equal scores by evaluators. These observations lead credence to the idea of incorporating varying emotions while understanding a metaphor. Only for 13.24% instances, B_T senses were given the preference over the EMU senses. This may be attributed to the idea that when metaphors are just born, they are more likely to be interpreted variously. With time, one of the interpretations gain popularity and may become standard emotionless interpretation.

Let us consider a utterance, "Highways are *snakes*" to further clarify it. It is plausible to obtain somewhat emotional interpretations such as *slimy, slippery* or *dangerous* along with an emotionless sense *meandering* when it is recently discovered by a reader. It is therefore not unlikely to attach a subtle emotion while conveying it in a conversation. Over a period of time, the reader may predominantly begin to associate the concept of snakes in connection with Highways with the notion of *meandering*. More frequent usage will likely render it a dead metaphor.

6 Conclusion

In this paper, we introduced EMU, a metaphor understanding system that allows us to understand metaphors along multiple emotional perspectives. We harnessed the world wide web to extract properties of the source domain of a given metaphor in all possible contexts of its usage thus allowing us to explore various subjective connotations of the metaphor. Further, we used *word2vec* embeddings to generate the emotional profiles of source properties and identified a winning property for each emotion that suggests an appropriate emotional interpretation for the target concept.

Our experiments clearly demonstrate that EMU generates appropriate interpretations of metaphor along the six basic emotional senses. More significantly, we observed that an emotion oriented interpretation of a metaphor is deemed more appropriate than an interpretation sans emotion generated solely on the basis of *closeness* between source properties and the target domain. We thus conclude that instead of zeroing in on a single interpretation, it is more practical to offer a range of interpretations along various emotional senses. In future, we will adapt our approach to interpret metaphors other than nominal that occur in discourse.

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A Appendix

This section consists of tables obtained after conducting experiments.

Table A1: Multiple interpretations along emotional aspects

#	Sentence	Multi-sense generated w.r.t Emotion					
		anger	***fear***	***happiness***	***disgust***	***sadness***	***surprise***
1	An opponent is an **anchor**.	*emotional*	*terrible*	*interesting*	*terrible*	*terrible*	*interesting*
2	This room is **Antarctica**.	*hidden*	dark	cool	lifeless	dark	*strange*
3	The nearest star is **ball**.	big	*dangerous*	*awesome*	blue	*amazing*	big
4	New moon is a **banana**.	*volcanic*	dark	*beautiful*	yellowish	*beautiful*	*odd*
5	Some bladders are **barrels**.	ageing	hollow	hollow	hollow	hollow	hollow
6	Flood is **beast**.	storm	havoc	*hungry*	torrential	torrential	massive
7	The Great Plains are a **board**.	large	*wooden*	wide	wide	large	large
8	Alcohol is a **crutch**.	temporary	temporary	*enjoyable*	*typical*	*enjoyable*	*enjoyable*
9	A lie is a **dagger**.	antipathy	evil	hollow	antipathy	hollow	secret
10	Ideas can be **diamonds**.	perceived	imaginary	amazing	*shock*	amazing	amazing
11	Grandparents can be **donkeys**.	cranky	afraid	cranky	cranky	funny	funny
12	My professor is a **duck**.	stupid	careful	peculiar	stupid	stupid	peculiar
13	His bedroom is **dump**.	trash	slummy	cluttered	trash	cluttered	shabby
14	That news was an **earthquake**.	impending	impending	*anxious*	terrible	terrible	sudden
15	Some teachers are **encyclopaedias**.	particularistic	particularistic	knowledgeable	scientistic	educational	instructive
16	Control is **fertilizer**.	excessive	*susceptible*	beneficial	unacceptable	unacceptable	problematic
17	Jalapeno peppers are **fire**.	red	noxious	hot	red	bright	*fresh*
18	The senator is a **fossil**.	conservative	presumed	conservative	conservative	*petrified*	conservative
19	John is a **fox**.	traitorous	evil	*sweet*	traitorous	traitorous	hidden
20	Life is a **game**.	*violent*	real	learning	anarchy	funny	amazing
21	Her ex-husband is a **gem**.	*cursed*	*cursed*	pretty	*cursed*	*difficult*	pretty
22	Petroleum is **gold**.	*unrest*	*unrest*	sustainable	*unrest*	precious	monetary
23	A marriage is **hell**.	anguish	anguish	*loving*	anguish	*loving*	*blissful*
24	Marriage is an **institution**.	religious	societal	united	religious	*imperfect*	formal
25	My team is a **jail**.	*fixed*	*fixed*	*safe*	*fixed*	*safe*	*fixed*
26	My computer course is a **joke**.	stupid	terrible	terrible	terrible	terrible	*short*
27	Education is **lantern**.	willpower	willpower	*informed*	willpower	*informed*	informed
28	Her marriage is a short **leash**.	submissive	submissive	submissive	submissive	submissive	uncomfortable
29	Beaver is a **lumberjack**.	*stupid*	voracious	wild	peculiar	peculiar	peculiar
30	Brain is a **machine**.	rational	insidious	brilliant	insidious	insidious	subtle
31	Some tears are **magnets**.	intense	*uncomfortable*	*uncomfortable*	*uncomfortable*	*uncomfortable*	nervous
32	Music is **medicine**.	depressing	knowledge	nourishing	depressing	soporific	soporific
33	Time is **money**.	temporary	precious	precious	*uniform*	precious	significant
34	My kid is **monkey**.	maniac	maniac	fun	maniac	funny	*surprised*
35	A zoo is a **museum**.	public	public	fabulous	public	dilapidated	fabulous
36	A business is an **organism**.	selfish	unethical	stable	selfish	unethical	unethical
37	My boyfriend is **peach**.	*post-feminist*	*post-feminist*	adorable	strange	strange	strange
38	Dew on grass is **pearl**.	white	*dark*	cool	nacreous	beautiful	cool
39	Steven is a **pig**.	ignorant	ignorant	*willing*	ignorant	funny	*unusual*
40	That criminal's pathway is a **portrait**.	symbolic	permanent	*wonderful*	lifelong	*wonderful*	symbolic
41	Some dogs are **princesses**.	*resentful*	afraid	affectionate	affectionate	cute	unusual
42	That player is a **rail**.	*unbalanced*	dangerous	*keen*	straight	*unbalanced*	big
43	Insults are **razors**.	contentious	intimidating	serious	subjective	serious	*obvious*
44	The path through forest is a **ribbon**.	wide	*necessary*	*inspiring*	*wide*	*inspiring*	*inspiring*
45	My father is a **rock**.	rebellious	lonely	lonely	lonely	*limp*	big

Table A1: Multiple interpretations along emotional aspects

#	Sentence	Multi-sense generated w.r.t Emotion					
		anger	***fear***	***happiness***	***disgust***	***sadness***	***surprise***
46	My professor is a **savage**.	angriest	*stupid*	*stupid*	*stupid*	*stupid*	*strange*
47	Hope is **seed**.	bitter	bitter	*alive*	bitter	bitter	alive
48	My lawyer is a **shark**.	uncaring	unscrupulous	stoic	uncaring	difficult	*ridiculous*
49	Clouds are **ships** in a sea.	massive	distant	distant	*toxic*	distant	massive
50	My young cousin is a **shrimp**.	*drunken*	little	little	*drunken*	little	little
51	My rat's fur is **silk**.	coarse	artificial	comfortable	coarse	lustrous	warm
52	Some snores are **sirens**.	growl	growl	uncomfortable	growl	uncomfortable	growl
53	Her skin is **snow**.	deathlike	deathlike	cold	deathlike	beautiful	cold
54	A fisherman is a **spider**.	assassin	trap	*worried*	*tattered*	*strange*	*strange*
55	That student is a **spring**.	major	major	vibrant	*typical*	vibrant	special
56	Her eyes are **stars**.	intense	intense	blue	blue	bright	spectacular
57	My grandfather is **steel**.	tough	tough	tough	hard	tough	tough
58	Time is a **teacher**.	hard	motivating	supportive	*unappreciated*	helpful	*dramatic*
59	Time is **thief**.	cynical	careful	careful	cynical	cynical	serious
60	That basketball player was **thunder**.	loud	sincere	bright	loud	bright	sharp
61	Tree is an **umbrella**.	*ornamental*	*artificial*	shade	fancy	*rainy*	shade
62	Hostility is a **veil**.	distrust	distrust	shameful	distrust	shameful	distrust
63	Sadness is **volcano**.	unrest	deep	*quiet*	deep	*quiet*	*quiet*
64	Marriage is **war**.	bitter	unspoken	passionate	vindictive	terrible	inevitable
65	Intelligence is a **warehouse**.	*raw*	external	*physical*	raw	perishable	*assumed*
66	Trust is a **weapon**.	accountable	accountable	accountable	accountable	accountable	defensive
67	His class is a **zoo**.	*docile*	show	*healthy*	docile	popular	show

Legend: Bold text indicates source domain concept; Italicized senses denote interpretations marked as inappropriate by annotators