Improving Human Needs Categorization of Events with Semantic Classification

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Abstract

Human Needs categories have been used to characterize the reason why an affective event is positive or negative. For example, “I got the flu” and “I got fired” are both negative (undesirable) events, but getting the flu is a Health problem while getting fired is a Financial problem. Previous work created learning models to assign events to Human Needs categories based on their words and contexts. In this paper, we introduce an intermediate step that assigns words to relevant semantic concepts. We create lightly supervised models that learn to label words with respect to 10 semantic concepts associated with Human Needs categories, and incorporate these labels as features for event categorization. Our results show that recognizing relevant semantic concepts improves both the recall and precision of Human Needs categorization for events.

1 Introduction

Affective events have a positive or negative impact on the people who experience the event. For example, being hired for a job is typically a beneficial (positive) event, but being fired is usually a detrimental (negative) event. Recognizing affective events is critical to understand people’s motivations, goals, desires, and empathy in narrative stories and conversations. Previous research has proposed several methods to recognize affective events and their polarity (e.g., (Deng et al., 2013; Vu et al., 2014; Reed et al., 2017; Ding and Riloff, 2016)). To achieve a deeper level of understanding, Ding and Riloff (2018a) further classified affective events into categories associated with theories of Human Needs (Maslow et al., 1970; Max-Neef et al., 1991) in psychology: Physiological, Health, Leisure, Social, Finance, and Cognition, to characterize the reason for the event’s affective polarity. For example, breaking your arm is a negative event because it violates a need to maintain one’s Health, but fighting with your spouse is negative because it violates a need for good Social relations with friends and family.

Human Needs categories naturally align with several broad conceptual classes, and we hypothesized that learning to recognize relevant semantic concepts would lead to more effective Human Needs categorization. For example, the Physiological need corresponds to basic functions such as breathing, sleeping, eating, and drinking. Learning to recognize FOOD/DRINK concepts should help identify events that belong to this category. Broadly, semantic concepts should help in two ways. First, semantic features are more general than words, which can suffer from sparsity. Second, given semantic features, a classifier can directly learn interactions between them, which should be more robust than interactions between individual words.

In this paper, we present lightly supervised classifiers that label words with respect to 10 semantic concepts associated with Human Needs categories: EMOTION, ENTERTAINMENT, EQUIPMENT, FOOD/DRINK, INTERPERSONAL, MEDICAL, MENTAL-PROCESS, MONEY/JOB, PEOPLE, and OTHER. Seed words for each semantic class are used as supervision, and pre-trained embedding vectors are used as word features. We explore three classification models: logistic regression, instance-based learning, and prototypical neural networks (Snell et al., 2017). Finally, the semantic class predictions are used as features for Human Needs event categorization, improving both recall and precision for this task.

2 Related Work

Previous work in NLP on affective events has primarily focused on identifying the affective polarity of events in narrative fables (Goyal et al,
Physiological human needs categories: further characterized affective events in terms of and Riloff, 2018b). Recently, Ding et al. (2018) (Ding and Riloff, 2016; Reed et al., 2017; Ding 2013; Deng and Wiebe, 2014), and personal blogs (Section 5) was generated from the ICWSM 2009 and 2011 blog corpora (Burton et al., 2009, 2011), so we selected seed words from these corpora as well. We used the following procedure to identify commonly used words for each category: we sorted all word lemmas by frequency and selected the k top-ranked words belonging to each semantic concept. We set k=10 for all classes, except we set k=20 for EMOTION and OTHER because they are extremely large categories. Table 1 shows the seeds selected for each semantic class.

### 3.2 Classification

We created three classification models: logistic regression, instance-based learning, and prototypical neural networks. For all three classifiers, we used the Word2Vec 300D pre-trained embeddings (Mikolov et al., 2013) as features. The seed words served as training examples, along with 500 randomly selected unlabeled words as additional seeds for the OTHER category, since it needs to represent a large and diverse “None-of-the-Above” class.

The first model is a one-vs.-rest logistic regression classifier, built using the sci-kit-learn toolkit (Pedregosa et al., 2011) with default parameters. The second model uses instance-based classification. This method first creates a prototype representation for each semantic class as the mean of the word embeddings of its seeds. Given a new words for each targeted semantic class. The affective events data set that we will use for our study

| SEMANTIC CONCEPTS | SEED WORDS |
|-------------------|------------|
| Health            | happy, sad, sick, hospital, doctor |
| Social            | family, friends, love, care |
| Emotional         | happy, sad, loves, hate |
| Financial         | money, budget, expenses, savings |
| Cognitive         | think, learn, study, remember |
| Physical          | health, fitness, exercise, rest |
| Occupational      | work, career, job, professional |
| Psychological     | anxiety, depression, stress |
| Aesthetic         | beautiful, artistic, creative |
| Hedonic           | enjoy, fun, entertainment |

Table 1: Semantic Concepts and Seed Words

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1 The k values were chosen arbitrarily without experimentation, so tuning these values could potentially further improve performance.

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word, a probability distribution is computed over the semantic classes as the softmax of the negative Euclidean distance to each class prototype. The class with the highest probability is chosen.

The third model uses prototypical neural networks (Snell et al., 2017), which have performed well on “few-shot” learning tasks with limited labeled training data, because of its simple inductive bias. We created a single layer feed-forward network with ReLU activations as the embedding function $f$. To learn parameters for $f$, we use the same training algorithm as Snell et al. (2017) except that we train on all semantic classes in each training episode, and both the support set and query set consist of 5 randomly selected examples per class. During training, we use the following parameters: the dimension of the embedding representation layer is 32, the learning rate is .01, and the weight decay is .0001. We train the model for 20 epochs with 100 episodes for each epoch.

To predict the class label for a new word, the process is the same as the instance-based model, except that the learned embedding is used. First, we create a prototype embedding $c_k$ for each semantic class $k$ using Equation 1, where $S_k$ contains all the labeled seed words for class $k$.

$$c_k = \frac{1}{|S_k|} \sum_{x_i \in S_k} f(x_i)$$  

Given a new word, a probability distribution over the classes is computed as the softmax of the negative Euclidean distance $d$ to each prototype, as shown in Equation 2.

$$p(y = k|x) = \frac{\exp(-d(f(x), c_k))}{\sum_{k'} \exp(-d(f(x), c_{k'}))}$$

4 Human Needs Categorization

Our goal is to explore whether semantic classification of terms can improve Human Needs categorization of affective events. Toward this end, we used the Human Needs categorization framework described in Ding and Riloff (2018a) which is a co-training model that iteratively trains two models with different views of the data: (1) an event expression classifier that uses the words in an event expression as input, and (2) an event context classifier that uses the sentence contexts that mention an event as input. An event expression is represented as a tuple consisting of 4 components: (Agent, Predicate, Theme, PP). The event expression classifier is a logistic regression model that takes the embedding of an event expression as input, which is computed as the average over the embeddings of its individual words. The architecture and models are the same, but in this paper we aim to improve the event expression classifier by incorporating semantic classification.

Given an event expression, we extract two types of semantic features from the head words of its 4 components. For each of the 4 head words, we create 10 real-valued features representing the confidence scores produced by the classifier for each of the 10 semantic classes. In addition, we create 10 binary features (one per semantic class) indicating whether any of the head words belongs to each class, based on the classifier’s predicted labels. Consequently, for each event expression the semantic classifier generates 50 semantic features.

5 Evaluation

We conducted two sets of experiments to evaluate the impact of our semantic classifiers. First, we show the results of adding semantic features to the event expression classifier for Human Needs categorization. Second, we evaluate the impact of the enhanced event expression classifier in the full co-training model. We used the evaluation data set created by Ding and Riloff (2018a), which contains 542 affective events with manually assigned Human Needs labels. To ensure a fair comparison, we used the same evaluation settings: we perform 3-fold cross-validation on the evaluation data and report the average Precision, Recall, and F1 scores over the folds.

5.1 Human Needs Categorization Results

Table 2 shows the results of experiments with the event expression classifier. The first row, Embed (D&R 2018a), shows the performance of Ding & Riloff’s original event expression classifier, which is a logistic regression model with event expression embeddings as features. The next three rows show the performance of a logistic regression model that uses our semantic features instead. We show results for semantic features produced by each of our three models: instance-based classification (Sem:InstBased), logistic regression (Sem:LR), and the prototypical neural network (Sem:ProtoNets). The LR and ProtoNets models
Table 2: Results for Human Needs Categorization with Event Expression Classifiers

Table 3: Results for Human Needs Categorization with Co-Training Models

5.2 Analysis of Semantic Classification

We also informally evaluated the quality of the semantic labels assigned by the semantic classifier, to better understand its strengths and weaknesses. One of the authors assigned each word in the evaluation data to one of the 10 semantic classes. Then we compared these human labels to the predicted labels from the semantic classifier.

Figure 1 shows the performance of the original co-training method D&R 2018a and our new method with semantic features learned by Embed+Sem:ProtoNets model after each iteration. This result shows that enhancing the event expression classifier with semantic features helps the co-training model improve more rapidly and achieve better performance than the original model for each iteration.

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Table 4 shows the performance for each semantic class. Overall, the classifier achieved a macro-averaged F1 score of 68.8%. Performance across the semantic classes varies, with several classes achieving high precision and high or moderate recall (OTHER, PEOPLE, ENTERTAINMENT, EMOTION, INTERPERSONAL, MENTAL-PROCESS), a few achieving high recall but low to moderate precision (FOOD/DRINK, MONEY/JOB), and a few with moderate recall and precision (EQUIPMENT, MEDICAL). Overall, these results demonstrate
that the semantic classifier produced fairly good predictions for most categories given only light supervision. One could almost certainly further improve these scores with more seed examples or by incorporating readily available external resources for categories such as EMOTION and MEDICAL, which would likely yield further gains for Human Needs categorization. More generally, our lightly supervised approach for training a semantic classifier demonstrates that one can rapidly create a classifier for a specific set of semantic concepts that are important for an application domain.

Table 4: Semantic Classification Results

| Semantic Classes       | Precision | Recall | F1  |
|------------------------|-----------|--------|-----|
| OTHER                  | 79.5      | 91.0   | 84.9|
| PEOPLE                 | 94.2      | 75.4   | 83.8|
| FOOD/DRINK             | 57.1      | 92.3   | 70.6|
| ENTERTAINMENT          | 89.1      | 54.7   | 67.8|
| EQUIPMENT              | 62.5      | 66.7   | 64.5|
| EMOTION                | 80.0      | 51.2   | 62.5|
| INTERPERSONAL          | 84.6      | 47.8   | 61.1|
| MENTAL-PROCESS         | 77.3      | 48.6   | 59.6|
| MEDICAL                | 64.5      | 51.3   | 57.1|
| MONEY/JOB              | 37.9      | 73.3   | 50.0|
| AVG                    | 72.7      | 65.2   | 68.8|

Table 5: Examples of Affective Events with Automatically Predicted Semantic Classes

Table 5 presents some examples of affective events and their semantic classes that are assigned by the Prototypical Networks Model. All the unlabeled words in the table were assigned to OTHER class5. Besides the words (e.g., “pleasureEMOTION”, “pizzaFOOD/DRINK”, “cooperateINTERPERSONAL”) that were classified correctly, some words in events also received incorrect semantic category labels. For example, the “work” in “house phone not work” and “epidural start to work” was incorrectly classified to MONEY/JOB, which suggests that it may be beneficial to further improve the performance of semantic categorization of words in events by considering the contextual meaning of polysemous words. In addition, our set of semantic classes was selected based on our intuition about what concepts are most relevant to the human needs categories, but it might be worthwhile for future work to more thoroughly explore a large set of semantic concepts.

6 Conclusions

We proposed to improve human needs categorization of affective events by adding semantic features that classify terms into related semantic concepts. We designed lightly supervised models that learn to classify words with respect to semantic concepts using only their pre-trained word embedding vectors and seed words as training data. We then showed that representing semantic concepts improves both the precision and recall for Human Needs categorization of events.

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