MPST: A Corpus of Movie Plot Synopses with Tags

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Abstract

Social tagging of movies reveals a wide range of heterogeneous information about movies, like the genre, plot structure, soundtracks, metadata, visual and emotional experiences. Such information can be valuable in building automatic systems to create tags for movies. Automatic tagging systems can help recommendation engines to improve the retrieval of similar movies as well as help viewers to know what to expect from a movie in advance. In this paper, we set out to the task of collecting a corpus of movie plot synopses and tags. We describe a methodology that enabled us to build a fine-grained set of around 70 tags exposing heterogeneous characteristics of movie plots and the multi-label associations of these tags with some 14K movie plot synopses. We investigate how these tags correlate with movies and the flow of emotions throughout different types of movies. Finally, we use this corpus to explore the feasibility of inferring tags from plot synopses. We expect the corpus will be useful in other tasks where analysis of narratives is relevant.

Keywords: Tag generation for movies, Movie plot analysis, Multi-label dataset, Narrative texts

1. Introduction

Folksonomy (Vander Wal, 2005), also known as collaborative tagging or social tagging, is a popular way to gather community feedback about online items in the form of tags. User-generated tags in recommendation systems like IMDb and MovieLens provide different types of summarized attributes of movies. These tags are effective search keywords, are also useful for discovering social interests, and improving recommendation performance (Lambiotte and Ausloos, 2006; Szomszor et al., 2007; Li et al., 2008; Borne, 2013). In this regard, an interesting research question is: Can we learn to predict tags for a movie from its written plot synopsis? This question enables an enormous potential to understand the properties of plot synopses that correlate with the tags. For instance, a movie can be tagged with fantasy, murder and insanity, that represent different summarized attributes of the movie. The inference of multiple tags by analyzing the written plot synopsis of movies can benefit the recommendation engines. In addition, the consumers would have a useful set of tags representing the plot of a movie. Notwithstanding the usefulness of tags, its proper use in computational methods is challenging as the tag spaces are noisy and redundant (Katakis et al., 2008). Noise and redundancy issues arise because of differences in user perspectives and use of semantically similar tags. For example, the Movielens 20M dataset (Harper and Konstan, 2016), which provides tag assignments between ≈27K movies and ≈1,100 unique tags also suffers from these problems. Thus, a fine-grained tagset and their assignment to movie plots can help to overcome these obstacles.

In this work, (i) we present the MPST corpus that contains plot synopses of 14,828 movies and their associations with a set of 71 fine-grained tags; where each movie is tagged with one or more tags. (ii) We discuss the expected properties of this tagset and present the methodology we followed to create such tagset from multiple noisy tag spaces (Section 2.). We also present the process of mapping these tags to a set of movies and collecting the plot synopses for these movies. (iii) We analyze the correlations between the tags and track the flow of emotions throughout the plot synopses to investigate if the associations between tags and movies fit with what we expect in the real world (Section 3.). We also try to estimate the possible difficulty level of a multi-label classification approach to predict tags from the plot synopses. (iv) Finally, we create a benchmark system to predict tags using a set of traditional linguistic features extracted from plot synopses. To the best of our knowledge, this is the first corpus that provides multi-label associations between written plot synopses of movies and a fine-grained tagset. The corpus is freely available to download.

2. Creating the Movie Plot Synopses with Tags (MPST) Corpus

There are several datasets that provide plots or scripts of movies. Since their utilization in this work was difficult, we created a fine-grained tagset first and collected the synopses by ourselves. For example, MM-IMDb (Arevalo et al., 2017) provides plot summaries, posters, and metadata of ≈25K movies collected from IMDb. But these plot summaries are very short to capture different attributes of

| A Nightmare on Elm Street 3: Dream Warriors |
| Tags: fantasy, murder, cult, violence, horror, insanity |
| Tags (MPST) Corpus |
| 50 First Dates |
| Tags: comedy, prank, entertaining, romantic, flashback |

Table 1: Examples of tag assignments to movies from the corpus.
movies (average words per summary is 92.5 versus 986.47 in MPST). Another example is ScriptBase (Gorinski and Lapata, 2015), which provides scripts of 1,276 movies collected from IMSDb. But plot synopses are more readily available than the scripts and that helped us to create a bigger dataset. Finally, CMU Movie summary corpus (Bamman et al., 2013), contains ≈42K plot synopses of movies collected from Wikipedia. Due to the absence of IMDb id for these movies, we could not retrieve the tag association information for the movies in that corpus.

We created the corpus using MovieLens 20M dataset, Internet Movie Data Base (IMDb), and Wikipedia. To create a good corpus, we first defined some expected properties of the corpus (Section 2.1). Then we created a fine-grained set of tags that satisfies the expected properties (Section 2.2). We created mappings between the tags and a set of movies and collected the plot synopses for those movies. Figure 1 shows an overview of the data collection process that we will discuss in this section.

2.1. Corpus Requirements

We set the following expected properties for the corpus to make it ideal for future works:

- **Tags should express plot-related attributes that are easy to understand by people.**
  The goal is to predict tags from the written movie plots. Therefore relevant tags are those that capture properties of movie plots (e.g., structure of the plot, genre, emotional experience, storytelling style), and not attributes of the movie foreign to the plot, such as metadata.

- **The tagset should not be redundant.**
  Because we are interested in designing methods to automatically assign tags, having multiple tags that represent the same property is not desirable. For example, tags like cult, cult film, cult movie are closely related and should all be mapped to a single tag.

- **Tags should be well represented.**
  For each tag, there should be a sufficient number of plot synopses, so that the process of characterizing a tag does not become difficult for a machine learning system due to data sparseness.

- **Plot synopses should be free of noise and adequate in content.**
  Plot synopses should be free of noise like IMDb notifications and HTML tags. Each synopsis should have at least 10 sentences, as understanding stories from very short texts would be difficult for any learning system.

2.2. Towards a Fine-Grained Set of Tags

As shown in Figure 1, we collected a large number of tags from MovieLens 20M dataset and IMDb. To extract the tags commonly used by the users, we only kept the tags that were assigned to at least 100 movies. We manually examined these tags to shortlist the tags that could be relevant to movie plots. We discarded the tags that do not conform to our requirements. At the next step, we manually examined the tags in this shortlist to group semantically similar tags together. We got 71 clusters of tags by this process and set a generalized tag label to represent the tags of each cluster. For example, suspenseful, suspense, and tense were grouped into a cluster labeled suspenseful. Through this step, we overcame the redundancy issues in the tagset and created a more generalized version of the common tags related to the plot synopses. The tagset is shown as a word cloud in Figure 2.

We created the mapping between the movies and the 71 clusters using the tag assignment information we collected from MovieLens 20M dataset and IMDb. If a movie was tagged with one or more tags from any cluster, we assigned the respective cluster label to that movie. We used the IMDb IDs to crawl the plot synopses of the movies from IMDb. We collected synopses from Wikipedia for the movies without plot synopses in IMDb or if the synopses in Wikipedia were longer than the synopses in IMDb. These steps resulted in the MPST corpus that contains 14,828 movie plot synopses where each movie has one or more tags.

http://www.imsdb.com
Figure 3: Heatmap of Positive Pointwise Mutual Information (PPMI) between the tags. Dark blue squares represent high PPMI, and white squares represent low PPMI.

| Total plot synopses | 14,828 |
|---------------------|--------|
| Total tags          | 71     |
| Average tags per movie | 2.98  |
| Median value of tags per movie | 2     |
| STD of tags for a movie | 2.60  |
| Lowest number of tags for a movie | 1     |
| Highest number of tags for a movie | 25    |
| Average sentences per synopsis | 43.59 |
| Median value of sentences per synopsis | 32    |
| STD of sentences per synopsis | 47.5  |
| Highest number of sentences in a synopsis | 1,434 |
| Lowest number of sentences in a synopsis | 10    |
| Average words per synopsis | 986.47 |
| Median value of words per synopsis | 728   |
| STD of words per synopsis | 966.16 |
| Highest number of words in a synopsis | 13,576 |
| Lowest number of words in a synopsis | 72    |

Table 2: Brief statistics of the MPST corpus.

3. Data Statistics

Table 2 shows that the distribution of the number of tags assigned to movies, number of sentences, and number of words per movie are skewed. Most of the synopses are small in terms of the number of sentences, although the corpus contains some really large synopses with more than 1K sentences. Around half of the synopses have less than 33 sentences. A similar pattern is noticeable for the average number of tags assigned to the movies. Some movies have a large number of tags, but most of the movies are tagged with one or two tags only. Murder, violence, flashback, and romantic are the most frequent four tags in the corpus that are assigned to 5,732; 4,426; 2,937 and 2,906 movies respectively. Least frequent tags like non-fiction, christian film, autobiographical, and suicidal are assigned to less than 55 movies each.

3.1. Multi-label Statistics

Label cardinality (LC) and label density (LD) are two statistics that can influence the performance of multi-label learning methods (Tsoumakas and Katakis, 2006; Tsoumakas et al., 2010). Label cardinality is the average number of labels per example in the dataset as defined by Equation (1).

$$LC(D) = \frac{1}{|D|} \sum_{i=1}^{|D|} |Y_i|$$

Here, $|D|$ is the number of examples in dataset D and $Y_i$ is number of labels for the $i^{th}$ example. Label density is the average number of labels per example in the dataset divided by the total number of labels, as defined by Equation (2).

$$LD(D) = \frac{1}{|D|} \sum_{i=1}^{|D|} \frac{|Y_i|}{|L|}$$

Here, $|L|$ is the total number of labels in the dataset. Bernardini et al. (2014) analyzed the effects of cardinality and density on multiple datasets. They showed that, for two datasets with similar cardinalities, learning is harder for the one with lower density. And if the density is similar, learning is harder for the one with higher cardinality. For example, learning performance was better for the Genbase dataset (LC: 1.252, LD: 0.046) as compared to the Medical dataset (LC: 1.245, LD: 0.028), where they had similar cardinalities but the Medical dataset was less dense. On the other hand, performance was better for the Emotions dataset (LC: 1.869, LD: 0.311) as compared to the Yeast dataset (LC: 4.237, LD: 0.303), where they had similar density but cardinality of the Yeast dataset was higher. The label cardinality and label density of our dataset are 2.98 and 0.042, respectively. Based on the mentioned experiments, we suspect that a traditional multi-label classification approach for this dataset will be a challenge that opens the scope for exploring more scalable approaches.
3.2. Correlation between Tags

To find out significant correlations in the tagset, we compute the Positive Pointwise Mutual Information (PPMI) between the tags, which is a modification over the standard PMI (Church and Hanks, 1990; Dagan et al., 1993; Niwa and Nitta, 1994). PPMI between two tags \( t_1 \) and \( t_2 \) is computed by the following equation:

\[
PPMI(t_1; t_2) = \max (\log_2 \frac{P(t_1, t_2)}{P(t_1)P(t_2)}, 0) \quad (3)
\]

where, \( P(t_1, t_2) \) is the probability of tags \( t_1 \) and \( t_2 \) occurring together and \( P(t_1) \) and \( P(t_2) \) are the probabilities of tag \( t_1 \) and \( t_2 \), respectively. Figure 3 shows the heatmap correlation of PPMI values between a subset of tags. The figure shows interesting relations between the tags and supports our understanding of the real world scenario.

High PPMI scores show that cute, entertaining, dramatic, and sentimental movies can evoke feel-good mood, whereas lower PPMI scores between feel-good and sadist, cruelty, insanity, and violence suggest that these movies usually create a different type of impression on people. Also note that, these movies have stronger relations with horror, cruelty, and darkness which make them difficult to create the feel-good experience. It suggest that people tend to get inspiration from dramatic, thought-provoking, historical, and home movies. Christian films and science fiction are also good sources of inspiration. Grind-house, Christian, and non-fiction films do not usually have romantic elements. Romantic movies are usually cute and sentimental. Autobiographical movies usually have storytelling style and they are thought-provoking and philosophical. These relations, in fact, show that the movie tags within our corpus seem to portray a reasonable view of movie types based on our understanding of possible impressions from different types of movies.

3.3. Emotion Flow in the Synopses

NRC Emotion Lexicons (Mohammad and Turney, 2010) have been shown effective to capture the flow of emotions in narrative stories (Mohammad, 2011). It is a list of 14,182 words and their binary associations with eight types of elementary emotions from the Hourglass of Emotions model (Cambria et al., 2012) (anger, anticipation, joy, trust, disgust, sadness, surprise, and fear) with polarity.

In Figure 4, we try to inspect how the flows of emotions look like in different types of plots. The reason behind this investigation is to get a shallow idea about the potential feasibility of the collected plot synopses to predict tags. As general users have written the collected plot synopses and created the tags for movies on the web, there is always a possibility to have noise in the data. For example, in a real world scenario we will expect that horror movies will contain fear and sadness. On the other hand, comedy or funny movies will be filled with happiness.

In the figure we can observe that, emotions like joy and trust are dominant over disgust and anger in cute, feel-good, and romantic movie’s plots (a, b). We can observe sudden spikes in sadness in segment 4. The animated movie Bambi (1942) shows an interesting flow of different types of emotions. The dominance of joy and trust suddenly gets low at segment 14 and gets high again at segment 18, where fear, sadness, and anger get high at segment 14. It is quite self-explanatory that the plot are mixtures of positive and negative emotions where the lead characters go through difficult situations, fight enemies and face a happy ending (spike in joy and trust at the end) after climax scenes where enemies get defeated. The final segments of (b) indicate happy endings, but the rise of sadness and fear in (a) indicates that Stuck in Love (2012) does not have a happy ending.

We observe the opposite scenarios in cases of violent, dark, gothic, and suspenseful movies (c, d, e, and f) where

5 Version 0.92
fear, anger, and sadness dominate over joy and trust. The dominance of anger and fear is a good indicator of a movie having action, violence, and suspense. Female Prisoner Scorpion: Jailhouse 41 (1972) (e), has dominance of fear, sadness, and anger throughout the whole movie, and it is easy to guess that this movie has violence and cruelty portrayed through the lead characters. The flow of joy, trust, sadness, and fear alters at the middle of the movie Two Evil Eyes (1990) (f). Maybe it is the reason why people tagged it with plot twist. These observations give evidence of the connection between the flow of emotion in the plot synopses and the experience people can have from the movies, and they also match with what we expected.

4. A Machine Learning Approach for Predicting Tags using Plot Synopses

In this section, we will discuss about some preliminary experiments we conduct with the corpus for predicting tags for movies. We approach the task of predicting tags for movies as a multi-label classification problem and use various traditional linguistic features.

4.1. Hand-crafted Features

Lexical: We extract word n-grams (n=1,2,3), character n-grams (n=3,4) and two skip n-grams (n=2,3) from the plot synopses as they are strong lexical representations. We use term frequency-inverse document frequency (TF-IDF) as the weighting scheme.

Sentiments and Emotions: Sentiments are inherent part of stories and one of the key elements that determine the possible experiences found from a story. For example, depressive stories are expected to be full of sadness, anger, disgust and negativity, whereas a funny movie is possibly full of joy and surprise. In this work, we employ two approaches to capture sentiment related features.

- **Bag of Concepts**: As concept-level information have showed effectiveness in sentiment analysis (Cambria, 2013), we extract around 10K unique concepts from the plot synopses using the Sentic Concept parser. It breaks sentences into verb and noun clauses and extracts concepts from them using Parts of Speech (POS) based bigram rules (Rajagopal et al., 2013).

- **Affective Dimensions Scores**: The hourglass of emotions model (Cambria et al., 2012) categorized human emotions into four affective dimensions (attention, sensitivity, aptitude and pleasantness) starting from the study on human emotions by Plutchik (2001). Each of these affective dimensions is represented by six different activation levels called ‘sentic levels’. These make up to 24 distinct labels called ‘elementary emotions’ that represent the total emotional state of the human mind. SenticNet 4.0 (Cambria et al., 2016) knowledge base consists of 50,000 commonsense concepts with their semantics, polarity value and scores for the basic four affective dimensions. We used this knowledge base to compute average polarity, attention, sensitivity, aptitude, and pleasantness for the synopses.

We divide the plot synopses into three equal chunks based on words and extracted these two sentiment features for each chunk. We will discuss more about chunk-based sentiment representation later.

**Semantic Frames**: Semantic role labeling is a useful technique to assign abstract roles to the arguments of predicates or verbs of sentences. We use SEMAFORE frame-semantic parser to parse the frame-semantic structure using the FrameNet (Baker et al., 1998) frames. For each synopsis, we use the bag of frames representation weighted by normalized frequency as feature.

**Word Embeddings**: Word embeddings have been shown effectiveness in text classification problems by capturing semantic information. Hence, in order to capture the semantic representation of the plots, we average the word vectors of every word in the plot. We use the publicly available FastText pre-trained word embeddings.

**Agent Verbs and Patient Verbs**: Actions done and received by the characters can help to identify attributes of plots. For example, if the characters of a movie kill, take revenge, shoot, smuggle, chase; we can expect violence, murder, action from that story. We use the agent and patient verbs found in synopses to capture the actions. In this regard, we use Stanford CoreNLP library to parse the dependencies of the synopses. Then we extract the agent verbs (using nsubj or agent dependencies) and the patient verbs (using dobj, nsubjpass, iobj dependencies) as described in Bamman et al., (2013). We group these verbs into 500 clusters using the pre-trained word embeddings with the K-means clustering algorithm to reduce noise. We use the distribution of these clusters of the agent verbs and patient verbs over the synopses. We experimented with different values of K (K=100, 500, 1000, 1500), and 500 clusters helped to achieve better results.

4.2. Experimental Setup

Section 3. shows that the distribution of the number tags assigned to per movies is skewed. The average number of tags per movie is approximately three. We thus begin by experimenting with predicting a fixed number of three tags for each movie. Moreover, to get more detailed idea about movies, we create another set of five tags by predicting two additional tags.

We use random stratified split to divide the data into 80:20 train to test ratio. We use the One-versus-Rest approach to predict multiple tags for an instance. We experiment with logistic regression as the base classifier. We run five-fold cross-validation on the training data to evaluate different features and combinations. We tune the regularization parameter (C) using grid search technique over the best feature combination that includes all of the extracted features. We use the best parameter value (C=0.1) for training.

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[https://github.com/SenticNet/concept-parser](https://github.com/SenticNet/concept-parser)

[http://www.cs.cmu.edu/~ark/SEMAFOR](http://www.cs.cmu.edu/~ark/SEMAFOR)

[https://github.com/facebookresearch/fastText/blob/master/pretrained-vectors.md](https://github.com/facebookresearch/fastText/blob/master/pretrained-vectors.md)

*Train-test partition information is available with the dataset.
a model with all the training data and used that model for predicting tags for the test data.

**Majority and Random Baseline:** We define majority and random baselines to compare the performance of our proposed model in the task of predicting tags for movies. The majority baseline method assigns the most frequent three or five tags to all the movies. We chose three tags per movie as this is the average number of tags per movie in the dataset. Similarly, the random baseline assigns at random three or five tags to each movie.

**Evaluation Metrics:** Wu and Zhou (2016) illustrate the complications in evaluating multi-label classifiers by an example of determining the significance of mistakes for the following cases: one instance with three incorrect labels vs. three instances each with one incorrect label. It is complicated to tell which of these mistakes is more serious. Due to such complications, several evaluation methodologies have been proposed for this type of tasks (Tsoumakas and Katakis, 2006) [Wu and Zhou, 2016]. For example, hamming loss, average precision, ranking loss, one-error, coverage. [Schapire and Singer, 2000] [Fürnkranz et al., 2008], micro and macro averaged versions of F1 and AUC score [Tsoumakas et al., 2010] [Tsoumakas et al., 2011] [Lipton et al., 2015].

Another complication arises when the label distribution is sparse in a dataset. Less frequent tags could be underrepresented by models, but an ideal model should be able to discriminate among all the possible labels. Such an issue is very common in problems like image annotation, and existing works use mean per label recall and recall with recall>0 to measure the effectiveness of models in learning individual labels (Lavrenko et al., 2003) [Feng et al., 2004] [Carneiro et al., 2007] [Wang et al., 2009]. Here, we use two similar metrics: tag recall (TR) and tags learned (TL), along with traditional micro-F1 metric. Tag recall computes the average recall per tag and defined by the following equation.

$$TR = \frac{\sum_{i=1}^{T} |R_i|}{|T|} \tag{4}$$

Here, $|T|$ is the size of tagset in the corpus, and $R_i$ is recall of $i^{th}$ tag. Tags learned (TL) computes how many unique tags are being predicted by the system for the test data. These evaluation metrics will help us to investigate how well and how many distinct tags are being learned by the models. We evaluate the models using these three metrics in two settings. One is selecting the top three tags and another is selecting the top five tags.

### 4.3 Results and Analysis

Table 3 shows the performance of the hand-crafted features for predicting tags for movies. All the features beat the baselines in terms of micro-F1 and tag recall (TR). But another significant criterion to evaluate the performances is the number of unique tags predicted by the models, which is measured by the tags learned (TL) metric. We prefer such a model that is capable of creating diverse tagsets by capturing varieties of attributes of movies with reasonable accuracy. For instance, the random baseline used all of the tags in the dataset to assign to the movies but its accuracy is very poor. On the other hand, the majority baseline has better accuracy but it does not have diversity in the tagset. We can see that most of the individual features achieved almost similar micro-F1 scores, but they demonstrate difference in effectiveness to create diversity in predicted tags. Feature combinations seem to improve in TR and TL, but micro-F1 scores are almost similar to the individual features.

The lexical features show better performance compared to other features. Bag of concepts (BoC) shows similarity in performance. Combination of all lexical features demonstrates effectiveness in capturing a wide range of attributes of movies from the synopses, which is reflected by the better TR and TL scores. We present the results achieved on the test data in Table 4. Although the result is similar to the result we got with all features during cross-validation, number of predicted unique tags is higher in the test set. This result could be used as a baseline system to compare other methods developed in future as it uses several traditional linguistic features combination to predict tags.

**Chunk-based Sentiment Representation:** Narratives have patterns in ups and downs of sentiments [Vonnegut, 1981]. Reagan et al. (2016) showed that the pattern of changes in sentiments is significant for consumer experiences that results in success of stories. To capture such changes, we experiment with chunk-based sentiments.

| Top 3 | Top 5 |
|-------|-------|
| F1    | TR    | TL   | F1    | TR    | TL   |
|       |       |      |       |       |      |
| Baseline: Most Frequent | 29.7 | 4.225 | 3   | 31.5 | 7.042 | 5   |
| Baseline: Random | 4.20 | 4.328 | 71  | 5.40 | 7.281 | 71  |
| Unigram (U) | 37.6 | 7.883 | 22.6 | 37.1 | 11.945 | 27.4 |
| Bigram (B) | 36.5 | 7.216 | 19.6 | 36.1 | 10.808 | 24.8 |
| Trigram (T) | 31.3 | 5.204 | 15.4 | 32.4 | 8.461 | 21   |
| Char 3-gram (C3) | 37.0 | 7.419 | 22.2 | 36.6 | 11.264 | 27.4 |
| Char 4-gram (C4) | 37.7 | 7.799 | 22.6 | 37.0 | 11.582 | 27.2 |
| 2 skip-gram (2SG) | 34.2 | 6.289 | 19.4 | 34.5 | 9.875 | 25.2 |
| 2 skip 3 gram (2S3) | 30.8 | 4.951 | 12.8 | 32.1 | 8.109 | 18.2 |
| Bag of Concepts (BoC) | 35.7 | 7.984 | 29   | 35.9 | 12.473 | 34.8 |
| Concepts Scores (CS) | 31.1 | 4.662 | 7.8  | 32.4 | 7.512 | 8.2   |
| Word Embeddings | 36.8 | 6.744 | 13.2 | 36.1 | 10.074 | 17.8 |
| Semantic Frame | 33.4 | 5.551 | 13.4 | 33.9 | 8.394 | 15.2 |
| Agent Verbs | 32.9 | 5.050 | 7.2  | 33.2 | 7.714 | 8     |
| Patient Verbs | 33.1 | 5.134 | 7.4  | 33.5 | 7.843 | 8     |
| U+8+T | 37.2 | 8.732 | 30   | 36.8 | 13.576 | 36.8 |
| C3+C4 | 37.8 | 8.662 | 28.8 | 37.4 | 13.395 | 33.6 |
| U+8+T+C3+C4 | 37.1 | 9.991 | 36.8 | 36.8 | 15.871 | 45.8 |
| Al lexical | 36.7 | 10.046 | 37.6 | 36.5 | 15.838 | 46.4 |
| BoC + CS | 35.7 | 8.165 | 29.4 | 36.0 | 12.754 | 35.4 |
| All features | 36.9 | 10.364 | 39.6 | 36.8 | 16.271 | 47.8 |

Table 4: Results achieved on the test data using the best feature combination (all features) with tuned regularization parameter C.

| Top 3 | Top 5 |
|-------|-------|
| F1    | TR    | TL   | F1    | TR    | TL   |
|       |       |      |       |       |      |
| Baseline: Most Frequent | 29.7 | 4.233 | 3   | 28.4 | 14.082 | 5   |
| Baseline: Random | 4.20 | 4.211 | 71  | 6.36 | 15.044 | 71  |
| System | 37.3 | 10.522 | 47  | 37.3 | 16.772 | 52  |
and emotions representation. We divide the plot synopses into equally sized \( n \) chunks based on the word tokens and extract the sentiment and emotion features for each chunk. Then we run 5-fold cross validation on the training data to observe the effect of chunk-based sentiments and emotions representation. We report the results in Table 5. Results show that dividing synopses into multiple chunks and using sentiment and emotion features from each chunk improves the performance of tag prediction. Although we observe noticeable improvements up to three chunks, TL remains similar where micro-F1 scores start to drop when we use more than three chunks. We suspect that higher number of chunks create sparseness in the representation of sentiments and emotions that hurts the performance. So we use sentiments and emotions features using three chunks in further experiments. As the chunk-based representation shows improvement in results, we plan to work capturing the flow of sentiments throughout the plots more efficiently in future work.

Table 5: Experimental results obtained by 5-fold cross-validation using chunk-based sentiment representations. Chunk-based sentiment features were combined with the other features described in Section 4.1.

| Chunks | Top 3 | Top 5 |
|--------|-------|-------|
|        | FI    | TR    | TL    | FI    | TR    | TL    |
| 1      | 35.2  | 6.550 | 18.2  | 35.1  | 9.928 | 23.4  |
| 2      | 35.0  | 7.031 | 23.0  | 35.2  | 10.68 | 26.8  |
| 3      | 35.7  | 8.165 | 29.4  | 36.0  | 12.754| 35.4  |
| 4      | 35.1  | 8.153 | 30.6  | 35.4  | 12.723| 36.8  |
| 5      | 34.8  | 8.185 | 30.4  | 35.1  | 12.553| 36.8  |
| 6      | 34.3  | 7.976 | 31.2  | 34.9  | 12.725| 36.0  |

5. Conclusion

We have presented a new corpus of \( \approx 70 \) fine-grained tags and their associations with \( \approx 14K \) plot synopses of movies. In order to create the tagset, we tackled the challenge of extracting tags related to movie plots from noisy and redundant tag spaces created by user communities in MovieLens and IMDb. In this regard, we describe the methodology for creating the fine-grained tagset and mapping the tags to the plot synopses.

We present an analysis, where we try to find out the correlations between tags. These correlations seem to portray a reasonable set of movie types based on what we expect from certain types of movies in the real world. We also try to analyze the structure of some plots by tracking the flow of emotions throughout the synopses, where we observed that movies with similar tag groups seem to have similarities in the flow of emotions throughout the plots.

Finally, we create a benchmark system to predict tags from the synopses using a set of hand-crafted linguistic features. This dataset will be helpful to analyze and understand the linguistic characteristics of plot synopses of movies, which will in turn help to model certain types of abstractions as tags. For example, what type of events, word choices, character personas, relationships between characters, and plot structure make a movie mysterious or suspenseful or paranormal? Such investigations can help the research community to better exploit high-level information from narrative texts, and also help to build automatic systems to create tags for movies. The generation of tags from movie plots or narrative texts could also be a significant step towards solving the problem of automatic movie profile generation. Methodologies designed using the MPST corpus could also be used to analyze narrative texts from other domains, such as books and storyline of video games.

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