Application of Tensor PLSA on Wiki-RfA Dataset

Jiali Lu

October 26, 2023

Overview

Wiki-RfA dataset[1] describes how one member in wikipedia community reacts to the request that another member becomes administrator. The dataset is composed of 189,004 votes among 11,381 members. Each vote has the following attributes:

- Source: the member who casts the vote, voter
- Target: the member who is subject to vote, votee
- Sentiment: the attitude of source towards target becoming administrator, could be support, neutral or oppose
- Comment: short text attached to the vote, usually explaining the reason to cast such a vote

And the task is to predict the sentiment attitude given source, target and comment.

Here I aim to showcase the interpretable modelling by Tensor Probabilistic Latent Semantic Analysis (tPLSA). It naturally combines the graph features (source/target) and text features (comment) to make accurate prediction, and the parameters have good interpretations.

Results

Model Specification

tPLSA assumes there is a latent variable called "class", and the attributes are independent given class. In other words, vote sentiment depends on source, target and comment only through class. This is shown in Figure 1. The "bag-of words" features are used for the comment attribute. Both the word features and the source and target are considered categorical. The parameters are thus the prior distribution of class and the conditional distribution of each feature given

[1] https://snap.stanford.edu/data/wiki-RfA.html

class. The hyperparameters include word count threshold, the minimal number of times a word appear in training set so that it is included as a feature; and the number of different classes.

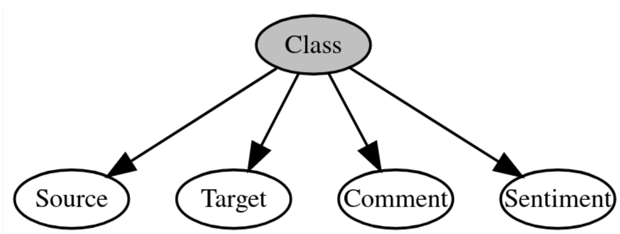

Figure 1: Modelling assumption: the attributes (source, target, comment and vote) are mutually independent given class. Class is a latent variable not observed and thus shown in grey.

Predictive Performance

The model achieves AUCROC of 0.905 on test set following standard training with early stopping, hyperparameter selection by hold-out validation and assessment of selected model on a separate test set. The word count threshold is chosen to be 20, and the number of different classes is set to be 16. Though AUCROC is not very sensitive to either.

Interpretation

For brievity, I will use a suboptimal model with 4 classes only. The 4 class model achieves AUCROC of 0.904, which is very close to our 16 class model anyway.

One can assign each source/voter i the class with highest probability, that is $c = \text{argmax}_x \Pr(class = x | source = i)$. tPLSA then group sources/voters together depending on their behavior. The voters in the 1st and 4th class tend to give support votes, while the 2nd class have more balanced votes and the 3rd class have many negative votes. Similarly the votee in the 1st and 4th class are highly regarded, while 2nd and 3rd class less so. This is illustrated in Figure 2. We can go further by studying the comments from typical members in each class and the comments towards them. This is omitted due to the limitation of space.

One can also find the typical words included in each class of comments, as shown in Table 1. Again the words in the 1st and 4th class tend to be more positive, while the others contain more negative words.

Figure 2: Average vote score between groups. The voters from 1st and 4th group tend to give more supportive vote and the votees are more highly regarded.

Class 1	Class 2	Class 3	Class 4
excellent	neutral	sorry	abuse
luck	leaning	poor	unlikely
nom (nominator)	attack	withdraw	sensible
background	ignore	unfortunately	competent
trustworthy	deletionist	recommend	intelligent

Table 1: typical words appearing in comments in each class of vote