# Improving Star Rating as Trend-Aware Performance Metrics

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## 1 Research Context

Direct star rating prediction in the next time interval bin can be a bit tricky and unreliable. For instance, if we were to have a consistently increasing trend in stars for a particular business but then all of a sudden have a dip in performance, we want our streamlined rating prediction to be flexible enough so that we don't necessarily automatically fail in such scenarios. Taking the average of the n most recent reviews is hypothesized to not be the best metric to fine-tune in this way. The research is shifting gears a bit from the direct prediction of stars to validating whether or not the embedding by topics can preserve information about ratings. If you can predict the topic distribution of the future reviews, you can also predict the star rating of upcoming time windows. Star ratings are more volatile and less flexible metrics than topic distributions, since some topics are consistently high or low across all reviews.

## 2 Individual Work

**Kenta**

- Switched LDA embedding to the Gensim model.
- Investigated potential embedding;
  Using tf-idf for the time-intervals (promising)
  Tokenize by sentences before applying LDA (Increased the variance of sample distribution)
  Multiply the result of LDA by tf-idf of topics
- Studied Dynamic Topic Modeling. Able to implement with built-in gensim function
- Built a baseline classifier for LDA -> Star rating with fully connected neural net
- Test with 1,2,3 hidden layers
  Validation accuracy 70% for 3 classes (1, 5, else)
  Validation accuracy 40 - 50% for 5 classes (1,2,3,4,5)
- Generated embedding for the last hidden layer and applied t-SNE. Observed high dimensional clusters but not separated by ratings.

**Caroline**

- Constructed average predicted star offset vs baseline overall average star rating comparison for any given business
- Experimented with different parameter settings for SVM classifiers

## 3 Further Studies

**Kenta**

- Implement LSTM model, feed sequence of embeddings and predict the offset from the average star
- Run experiments with different parameters and different embeddings

- Write paper

**Caroline**

- Fine-tune SVM model to incorporate multiple different topics as features with different embedding techniques (genisim, etc.)
- Determine final comparisons between different embedding methods, corresponding impact as reflected in hyperparameters
- Finalizing plots for the final paper

# References


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