Short-Text Classification with Deep neural networks:

An Experimental Analysis

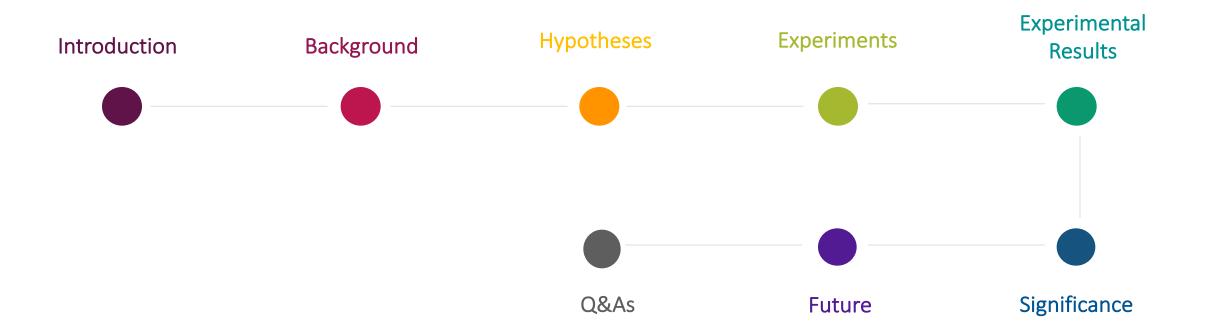
Iris Liu Chui Yi

April 2017

Final Year Project Presentation

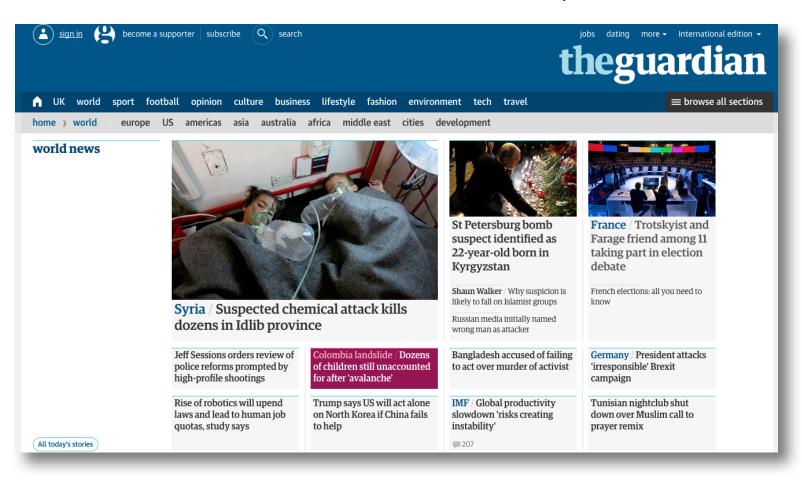


Agenda



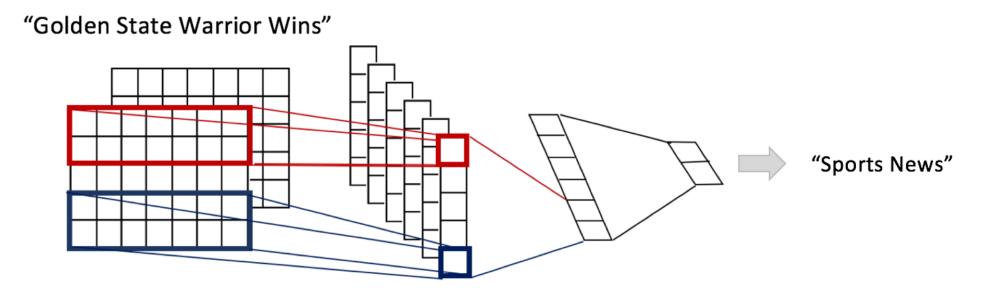
Problem Definition

• Extreme Text Classification with many class labels



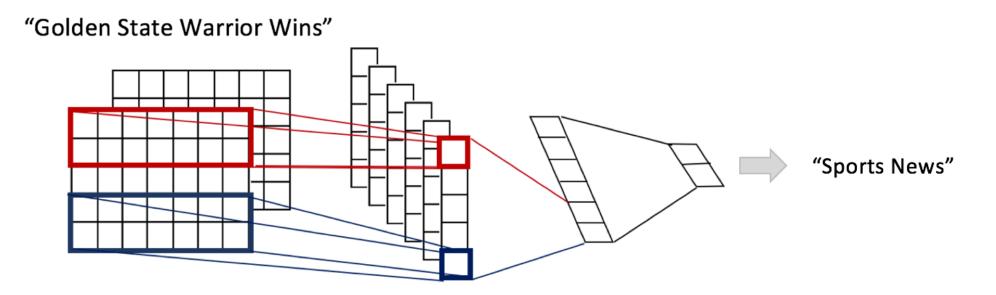
Short-Text Classification

- Input: short-text data (300 words on average)
- Output: class labels, categories



Convolutional Neural Networks (CNN)

- Usually works well for spatial data such as images, speech signals
- Use convolutional window to capture features



 A variation of a Recurrent Neural Network Ot Particularly for sequential data h_{t-2} h_{t-1} ht X_{t-2} X_{t-1} Xt **Word Vector** Output **Hidden States** W_t | Word sequence W_{t-2} W_{t-1} W_t

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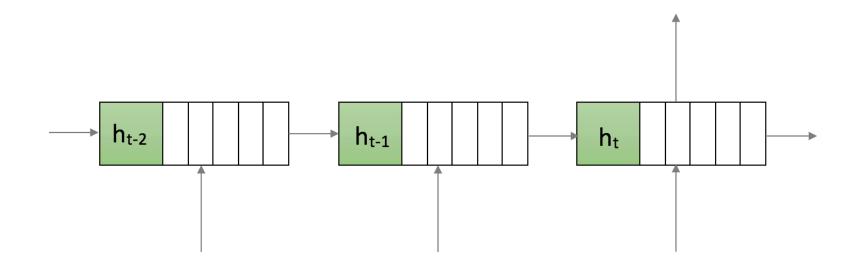
The Unreasonable Effectiveness of Recurrent Neural Networks

May 21, 2015

Cell that turns on inside quotes:

"You mean to imply that I have nothing to eat out of... On the contrary, I can supply you with everything even if you want to give dinner parties," warmly replied Chichagov, who tried by every word he spoke to prove his own rectitude and therefore imagined Kutuzov to be animated by the same desire.

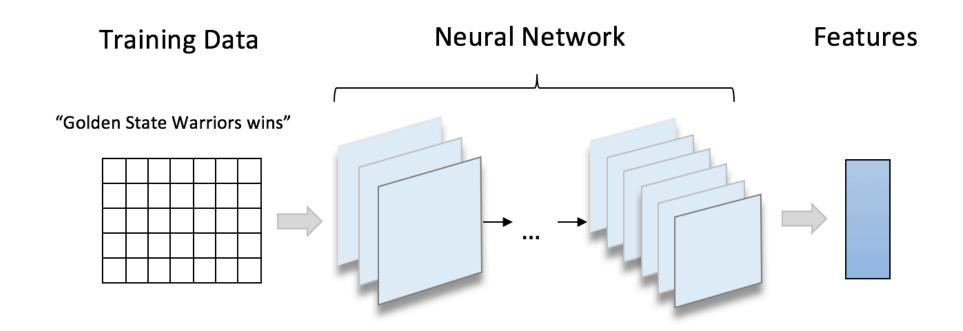
Kutuzov, shrugging his shoulders, replied with his subtle penetrating smile: "I meant merely to say what I said."



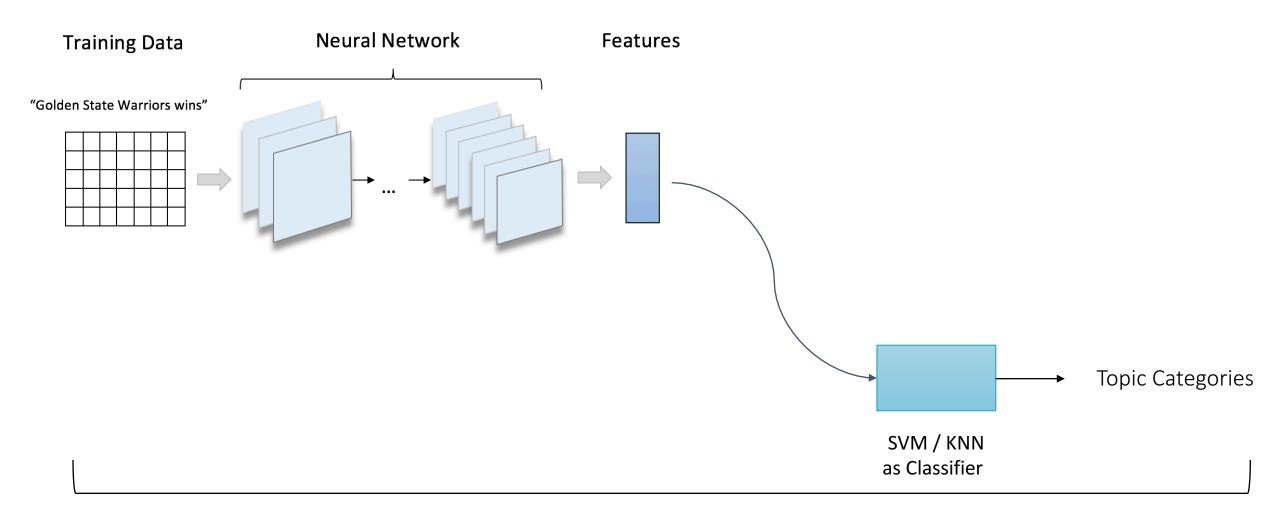
What LSTMs have captured in its hidden state can be regarded as features

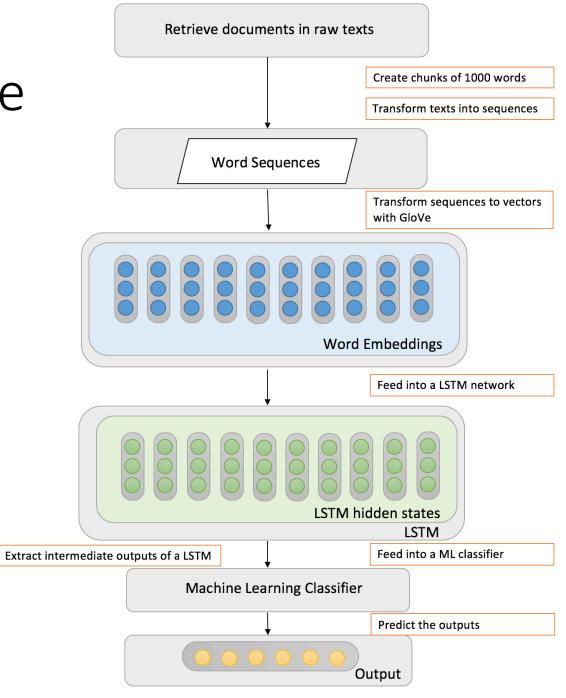
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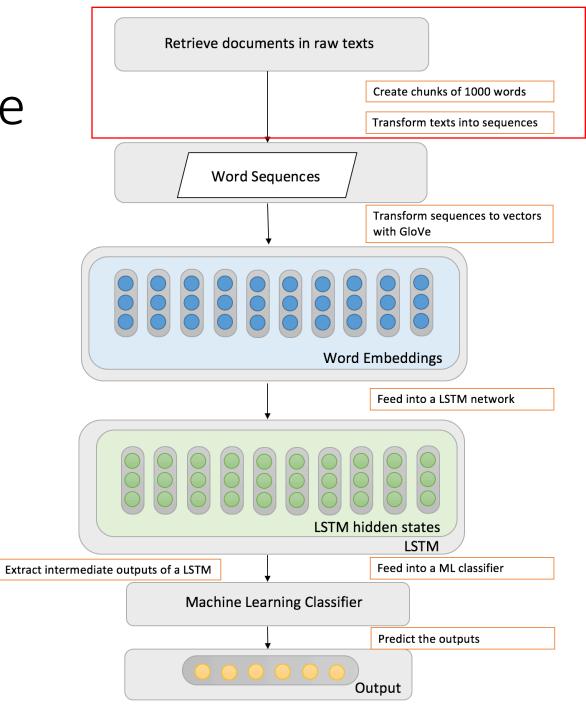
LSTM as a feature extractor

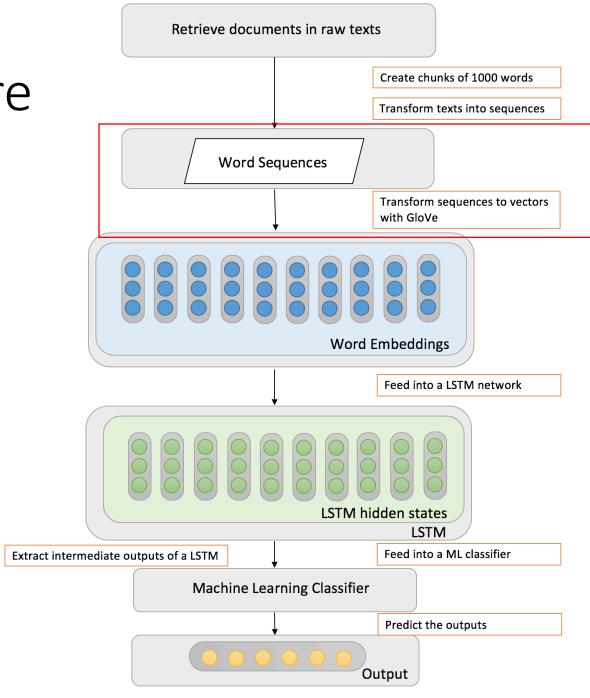


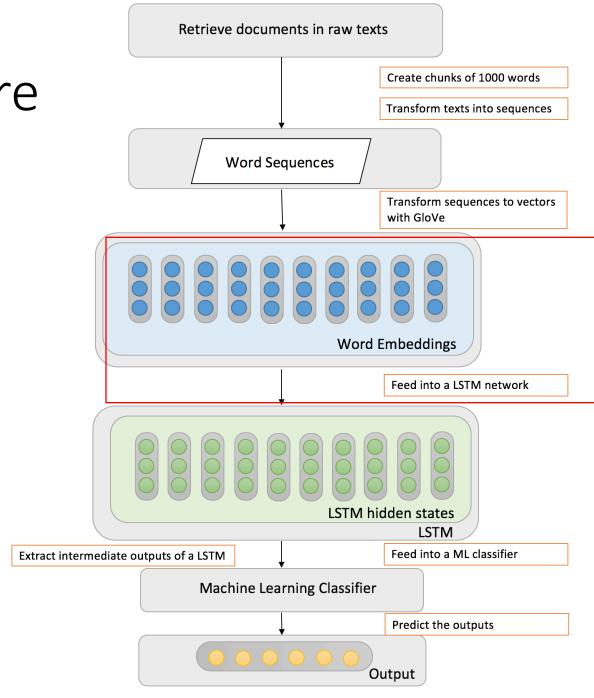
Machine Learning algorithms for classification

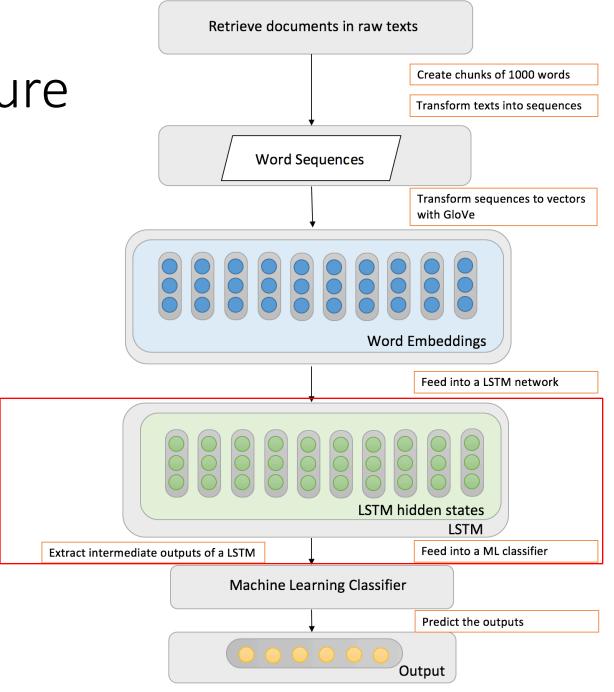


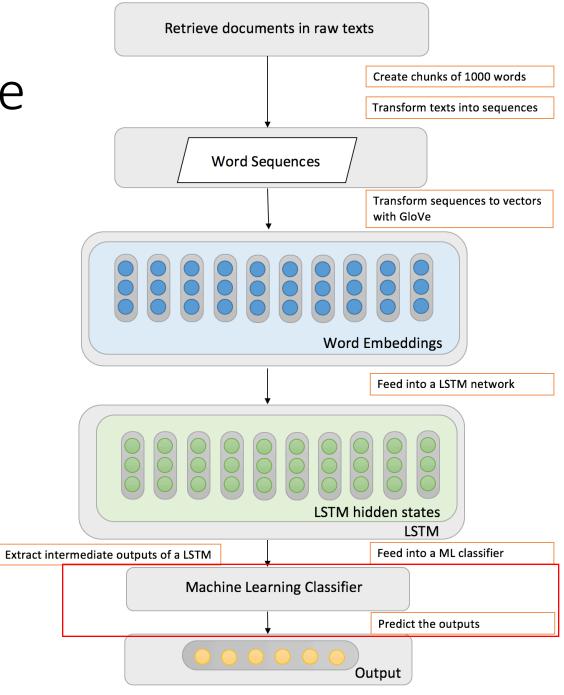


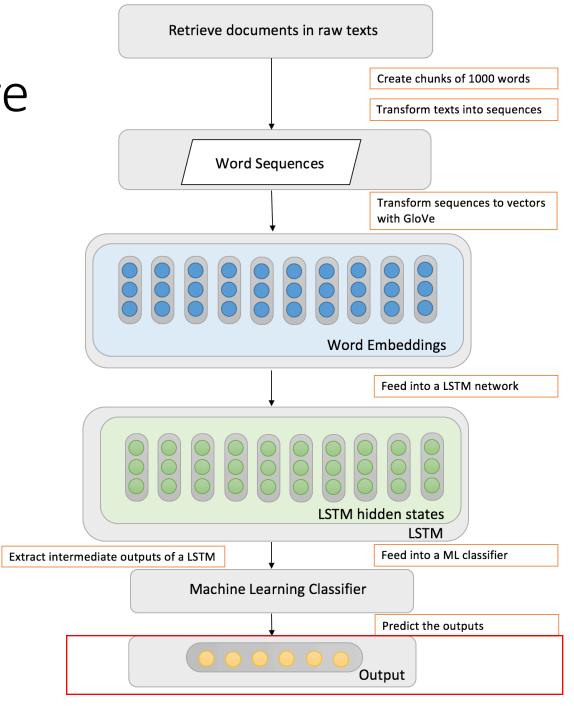






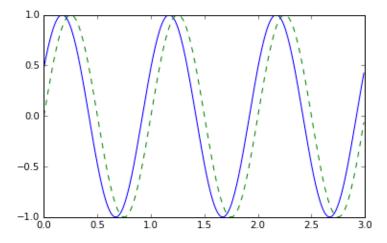






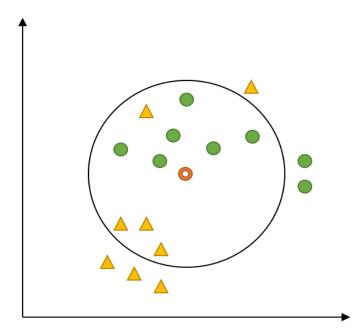
What is special about Time Series Data?

- Natural language is mostly time-series, e.g. speech signals, dialogs
- They are not only vary in sequences, but also in terms of time propagation

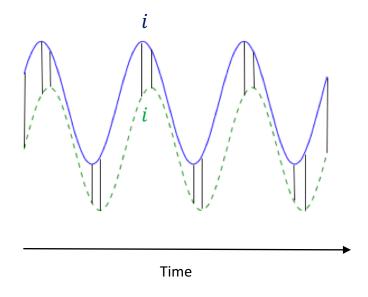


K-Nearest Neighbours

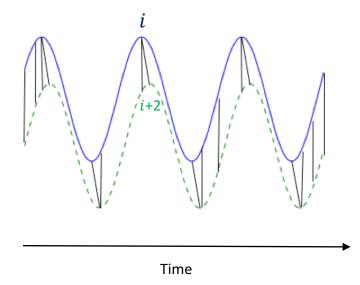
- Usually adopt Euclidean Distance as distance metrics
- Maybe not be accurate in time-series



Why Dynamic Time Warping?



Euclidean distance which align the i-th point on one sequence with the i-th point with the other will give poor similarity measure.



A non-linear alignment produces a more a intuitive similarity measure, matching sequences that are similar in shape but are out of shape.

Hypotheses



Hypothesis 1: Neural Networks outperform Machine Learning Algorithms

Hypothesis 2: LSTMs should perform better than CNNs in short texts

- Compare Neural Networks with Machine Learning Models
- Compare between LSTMs & CNNs

Hypothesis 3:

Temporal LSTMs help improve the classification accuracy of machine learning algorithms.

Hypothesis 4:

Structural Models produces similar results to LSTMs

 Compare Structural Model with Machine Learning models and neural networks

Hypothesis 5: DTW is better distance metrics than Euclidean distance for KNN

Compare KNN-DTW with KNN-Euclidean models

Hypothesis 6: Classification accuracy drops as the number of class labels increase

- Compare different models across different number of classes
- Created Benchmark datasets with different datasets of different number of classes

Experimental Setups



Datasets







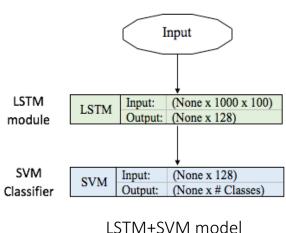
Model Set-ups

- SVM (with Tf-idf)
- KNN (with Tf-idf)
- LSTM
- CNN
- LSTM+SVM
- LSTM+KNN-Euclidean
- LSTM+KNN-DTW

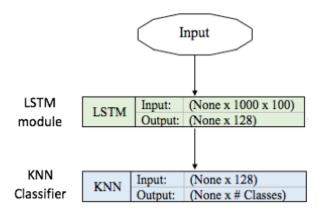
Machine Learning Models

Neural Networks

Structural Models



LSTM+SVM model



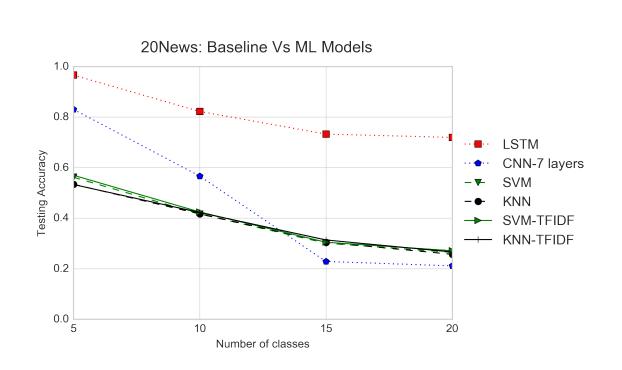
LSTM+KNN model

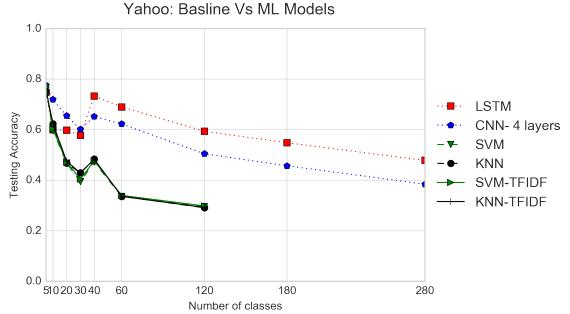
Experimental Results

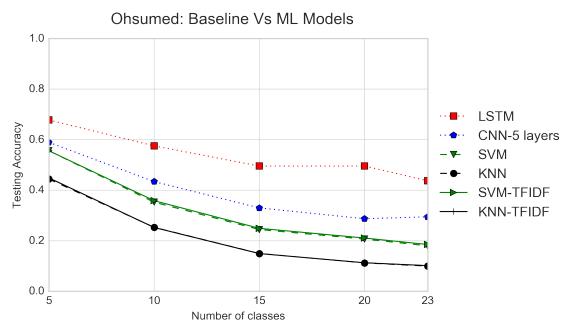


Findings

- 1. Neural Networks outperform ML models
- 2. LSTMs outperform CNNs

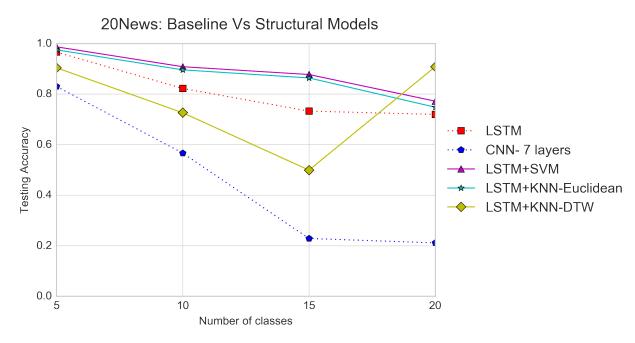


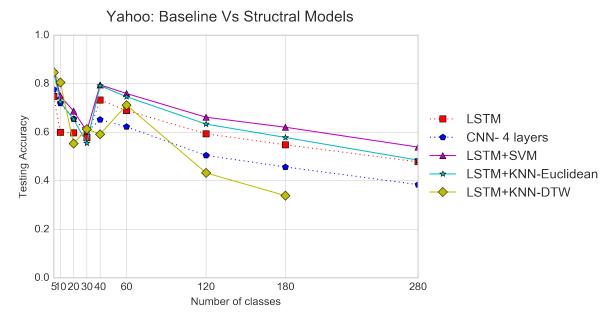


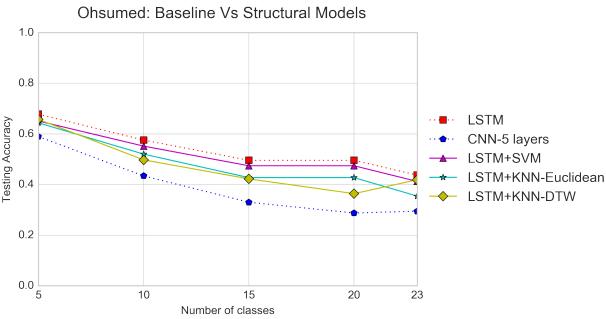


Findings

3. Structural models outperform Neural Networks on 20news and Yahoo datasets

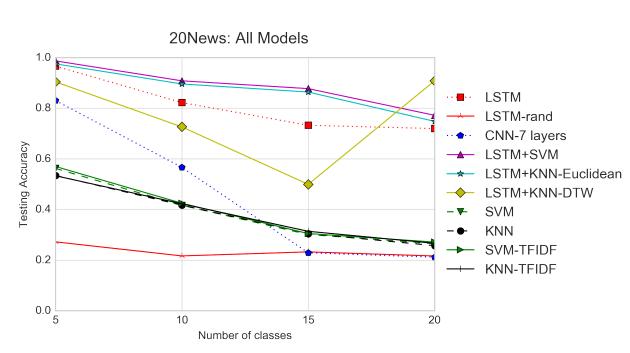


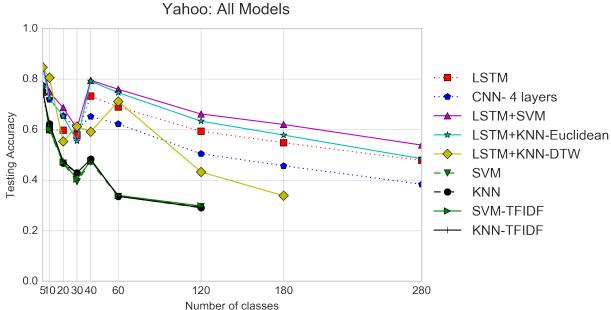


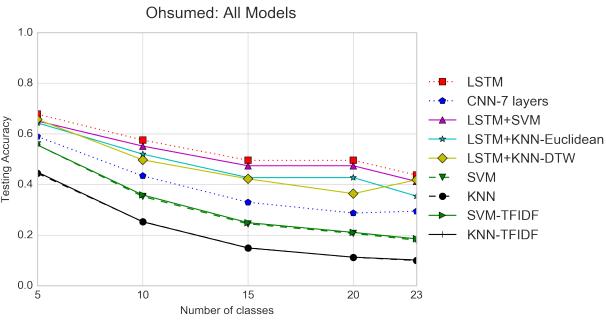


Findings

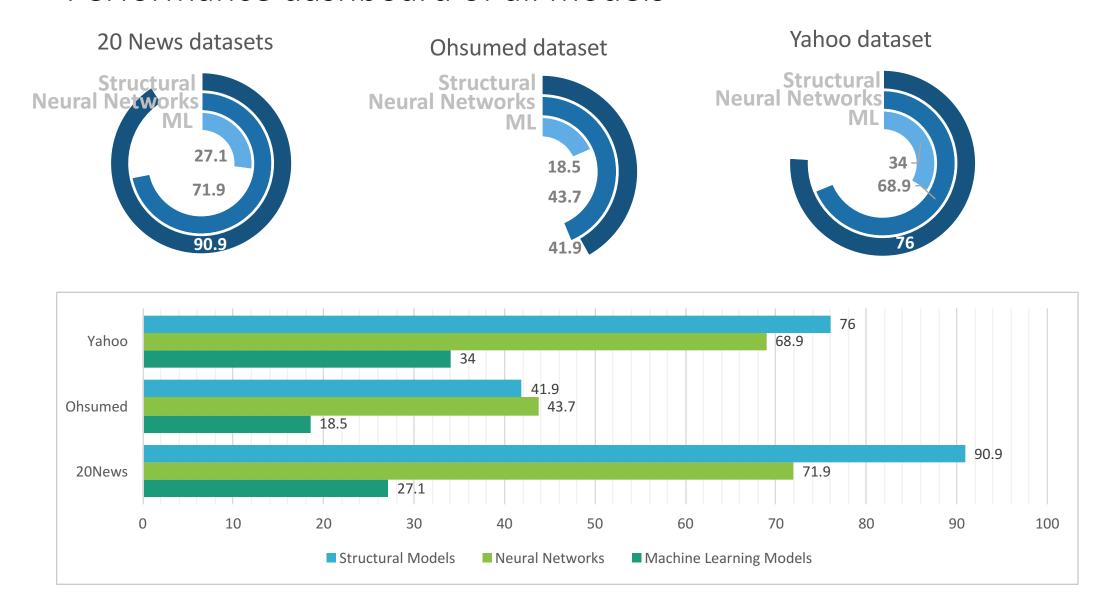
- 4. Structural Models outperform ML
- models largely
 5. DTW does not shows an improvement with KNN
- 6. Overall decreasing trends are observed







Performance dashboard of all models



Conclusion

Hypothesis 1:	Neural Networks outperform Machine Learning Algorithms
Hypothesis 2:	LSTMs should perform better than CNNs in short texts
Hypothesis 3:	Temporal LSTMs help improve the classification accuracy of machine learning algorithms.
Hypothesis 4:	Structural Models produces similar results to LSTMs
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Significance

Introduction Background Hypotheses Experiments Results

Significance

Traditional feature engineering of Machine Learning Model

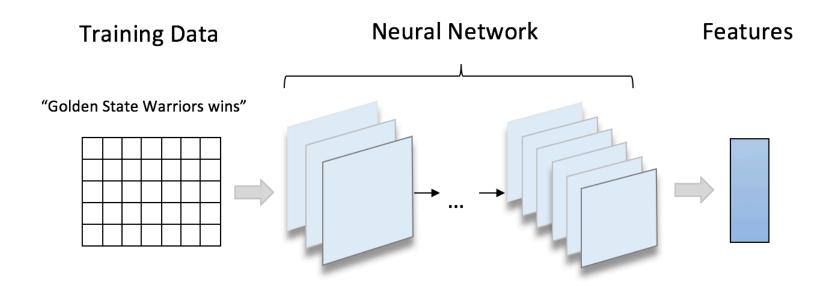
- Involves pre-defined dictionary as the first step
- Followed by many domain-specific steps, e.g. lemmatization, stemming e.tc..
- Require prior knowledge.

Traditional feature engineering of Machine Learning Model

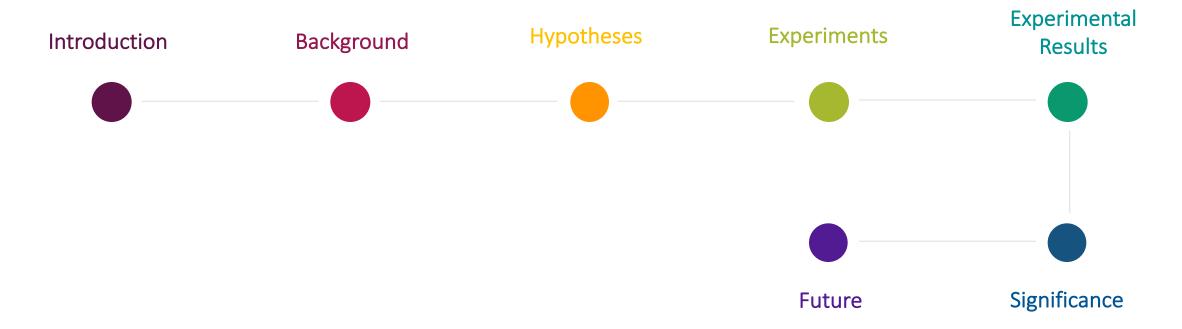
- Involves pre-defined dictionary as the first step
- Follows by many domain-specific steps, e.g. lemmatization, stemming e.tc.. Time-expensive
- Require prior knowledge. Labor-Intensive

"Zero cost" on feature engineering

- LSTMs capture feature representations in its hidden states
- Exhibits no previous knowledge
- Increase accuracy to up to 3.5X



Future



- Apply unsupervised learning techniques
 - How well temporal LSTMs have learnt and predict?
- Restricted Boltzman Machine as temporal networks
 - Further improve the training results with ML models
- Apply on short-sequential data e.g. speech signals, dialogs



Q&As

