Polarity and Factuality Classification using Artificial Intelligence

Mohammad Amin Samadi

Dr.Mohammad Hossein Manshaei and Dr.Zeinab Maleki

Department of Electrical and Computer Engineering, Isfahan University of Technology

1. Introduction

People's opinions are one of the most important sources of information. Information gathered from others experiences and knowledge, can broaden vision and therefore you can decide better. Medical issues are not an exception since throughout history people have been facing various problems regarding to it and have struggled to overcome them easily. Although information obtained through people specially in the medical field are not always precise and accurate, it can help people a lot in order to get a better sense of the condition they are in.

In this project, our goal was to classify replies posted on medical forums to certain qustions in two aspects of polarity and factuality using machine learning and deep learning algorithms. Polarity constited of three class: "positive", "negative", and "neutral" and factuality was also divided into three classes: "opinion", "experience", and "fact".

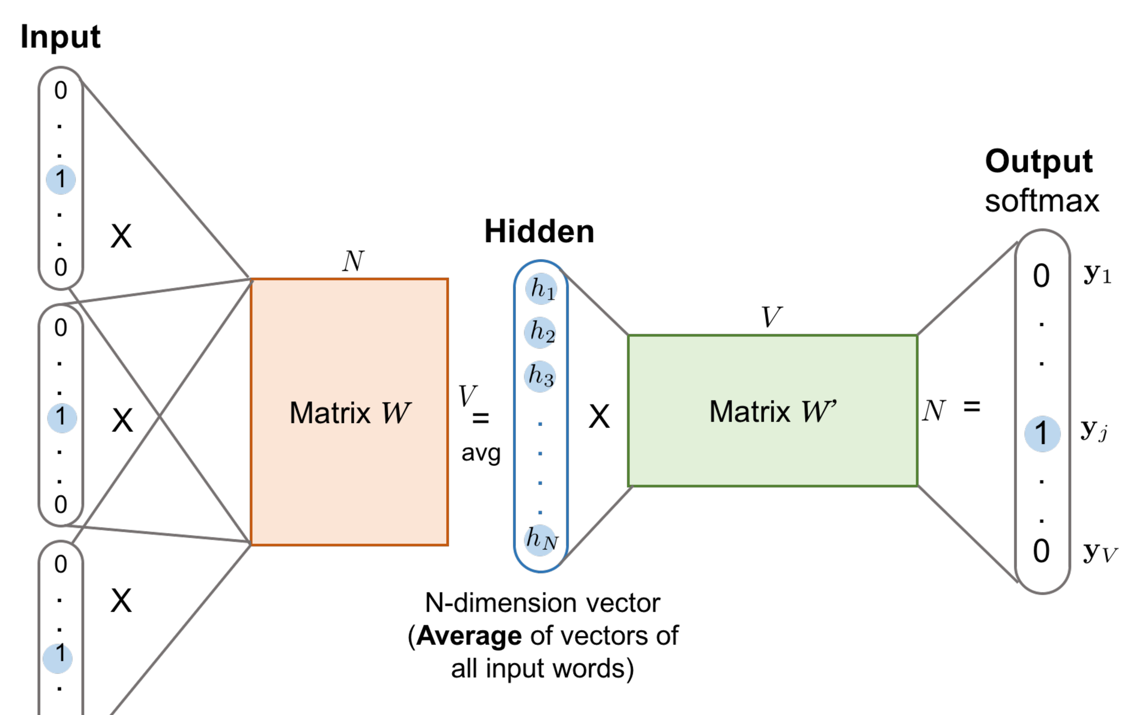
2. Dataset

Dataset[1] consists of roughly 3600 sentences in public medical forums which are labeled according to their polarity and factuality.

text	polarity	factuality
I have been a coffee drinker on and off since ...	NEUTRAL	EXPERIENCE
I notice now that I am older, and perhaps I ha...	NEGATIVE	OPINION
When I drink it, if I drink about 2 cups a day...	NEGATIVE	EXPERIENCE
I always kind of said oh it's just allergies f...	NEGATIVE	OPINION
but in fact when I do not consume coffee, I am...	POSITIVE	EXPERIENCE

3. Word Embedding

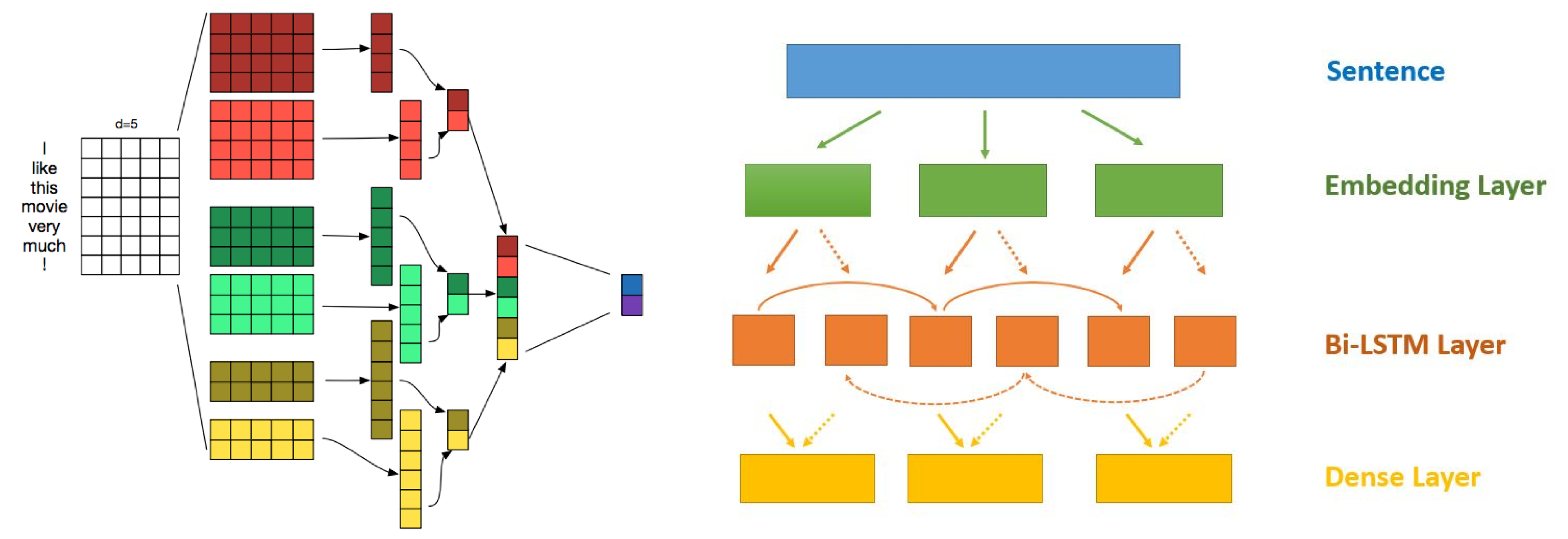
Word embedding algorithms[2] are used to represesnt words in a vector space with specific dimensions in an attempt to not only use memory more effeciently but also exhibit word's semantic and synthetic relationships. Main idea in word2vec algorithms is to represent words in a way that words co-occuring more frequently are represented with vectors more similar campared to those which do not co-occure.



4. Classification

Classifiers used in this project can be devided mainly into two categories:

- Classical machine learning using tf-idf algorithm
  - Gaussian Naive Bayes
  - Random Forest
  - Passive Aggressive Classifier
- Deep learning models using word embedding
  - 1D Convolutional Neural Network
  - Bidirectional LSTM
  - 1D CNN + bidirectional LSTM



5. Results

In this section, our goals were to evaluate proposed models and also to examine the influence of tf-idf parameters on machine learning algorithms performance. Results of polarity classification are on the left column and results of factuality is on the right. Passive aggressive and bidirectional LSTM had the best performance among classifiers.

		Gaussian NB			Passive Aggressive			Random Forest		
n-gram	features	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
1	5000	0.57	0.57	0.53	0.64	0.64	64	62	61	60
2		0.61	0.59	0.60	0.65	0.65	0.65	0.62	0.61	0.60
2	1000	0.52	0.44	0.44	0.61	0.60	0.59	0.58	0.58	0.58
	10000	0.61	0.59	0.59	0.66	0.66	0.66	0.63	0.63	0.62
	unlimited	0.61	0.59	0.60	0.67	0.65	0.63	0.60	0.59	0.58

Model	Precision	Recall	F1-Score
Bidirectional LSTM	0.73	0.72	0.71
One Dimensional CNN + Bi-LSTM	0.72	0.72	0.72
One Dimensional CNN	0.66	0.66	0.66

		Gaussian NB			Passive Aggressive			Random Forest		
n-gram	features	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
1	5000	0.61	0.59	0.59	0.65	0.65	0.64	0.61	0.62	0.61
2		0.64	0.63	0.63	0.64	0.65	0.64	0.60	0.61	0.60
2	1000	0.57	0.49	0.50	0.61	0.61	0.58	0.62	0.61	0.61
	10000	0.64	0.63	0.63	0.67	0.66	0.66	0.60	0.60	0.59
	unlimited	0.63	0.62	0.63	0.67	0.67	0.65	0.59	0.60	0.59

Model	Precision	Recall	F1-Score
Bidirectional LSTM	0.76	0.76	0.76
One Dimensional CNN + Bi-LSTM	0.74	0.75	0.74
One Dimensional CNN	0.74	0.75	0.74

6. Conclusion

1. Increasing parameters in machine learning algorithms can contribute to better performance but there must be an optimal value for that.
2. Deep learning algorithms and mainly LSTM models perfom better than machine learning algorithms and word embeddings also improve our classification significantly.

7. References

[1] Jorge Carrillo-de Albornoz, Javier Rodríguez-Vidal, and Laura Plaza. ediseases dataset, November 2018.

[2] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*, 2013.

[3] Yoon Kim. Convolutional neural networks for sentence classification. *arXiv preprint arXiv:1408.5882*, 2014.