Analyzing Polticial Bias through A User-Friendly Interface

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- References

Problem

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- 2 Some hide facts to present a specific argument.
- 3 The average person lacks the time to see multi-faceted stories.

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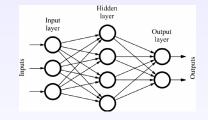
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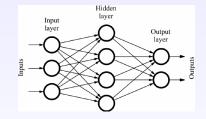
Related Work

- Iyyer et al. created political bias classifiers using Recursive Neural Network (RNN) models with Long Short Term Memory (LSTM) nodes with a high degree of accuracy.[1]
- Stanford researchers Arkajyoti Misra and Sanjib Basak showed that RNNs with LSTM nodes can also predict implicit political bias.[2]

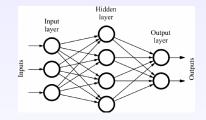
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- Organized into layers with interconnected nodes.
- Weighted edges connect nodes.
- Layers are successively computed based off computations from the lower layers.
- Nodes transform input using an activation function and then outputs result.



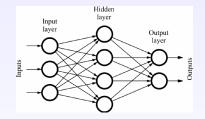
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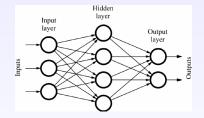
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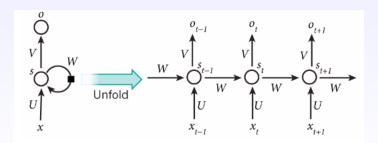
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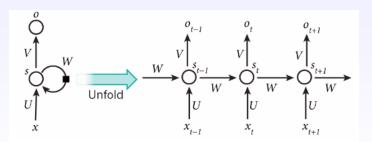


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- Perform same computations for every element in a sequence.
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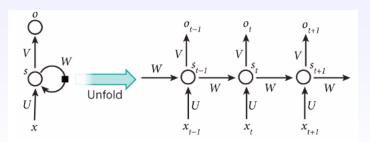


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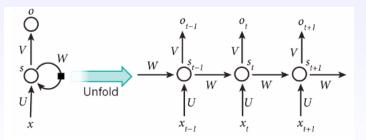




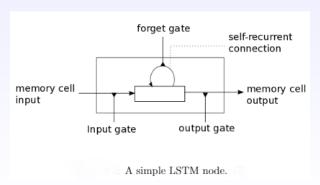
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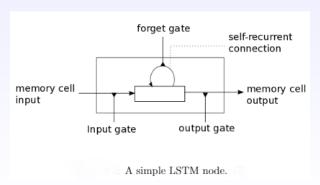
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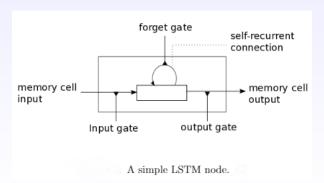
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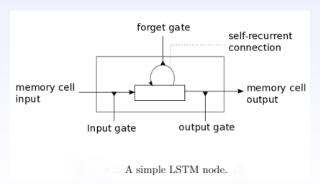
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F1 Score

Precision is measured as

$$\frac{true\ positives}{false\ positives + true\ positives},$$

while recall is measured as

$$\frac{\textit{true positives}}{\textit{false negatives} + \textit{true positives}}.$$

Measuring the amount of false positives and false negatives shows model's ability to not predict Type I and II errors.

The formula for calculating the F1 Score is:

F1 Score =
$$2 \times \frac{precision \times recall}{precision + recall}$$
.



• F1 Score: 0.90

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Possible Noise

Possible Noise:

- Various-sized datasets
- Complexity of language
- Small sentence sizes

Future Work

- Continue tuning RNN
- Collect larger datasets
- Scrape more news outlets
- Run against other algorithms
- Better user interface

Conclusion

Thank you professors Deverick and Lewis, as well as my friends and family for helping me complete this project! I was able to apply knowledge learned throughout my time here to create a useful and easy-to-use webpage that helps people understand the political atmosphere surrounding a news event.

References



Mohit lyyer, Peter Enns, Jordan Boyd-Graber, Philip Resnik. Political Ideology Detection Using Recursive Neural Networks http://www.aclweb.org/anthology/P/P14/P14-1105.pdf



Arkajyoti Misra and Sanjib Basak. *Political Bias Analysis* https://cs224d.stanford.edu/reports/MisraBasak.pdf