The Fake News Challenge as Natural Language Inference

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Abstract

The Fake News Challenge defines a task and dataset for stance detection where the goal is to determine the semantic relationship between an article's headline and body as either agrees with, disagrees with, discusses, or is unrelated to the headline. This task is very similar to the task of natural language inference where popular datasets are of the form given a premise and hypothesis sentence, the goal is to predict whether the premis entails, contradicts, or is neither (neutral) to the hypothesis sentence. Despite the similarities between these two tasks, the none top performing 3 systems from the Fake News Challenge utilize state of the art systems in natural language inference. In this work, we attempt to approach the Fake News Challenge as a natural language inference task, and try to understand if top performing natural language inference models perform similarly well (or even better) on this related task. We additionally use our results and ablations to try and understand what are the core similarities and differences between these two task.

1 Introduction

One commonality between the three top performing models on the Fake News Challenge is that they all utilize some deep neural model to get some representation of both the headline and the body, then use some multi-layer perceptron to combine the representations together to form a prediction. This heavily resembles the pattern seen in older works in natural language inference from around 2015-2016. This isn't surprising considering how related these two tasks seem to be, both requiring understanding and clasifying the semantic relationship between two bodies of text.

As some background, natural language inference is a widely researched task in natural language processing and is core to the overall goal of natural language understanding. Popular natural language inference datasets [][] formulate the task is given a pair a sentences (p, h) where p is the premise and h is the hypotheses, we must determine whether p semantically entails h, contradicts h or is neutral to h.

Models for natural language inference were previously also dominated by deep models (often times some deep convolutional or recurrent nerual network) that encode both the premise and hypothesis sentences into low dimensional latent representations which intend to capture the semantic content of the sentence. These models then combine two representations via some multi-layer perceptron or classification model. Since then models have been able to get performance gains by utilizing attention as a way to combine information across texts and force the model to produce representations of each text that are dependent on the content of their counterpart. We hypothesize that using similar techniques for the Fake News Challenge dataset will also yield similar gains as in the natural language inference setting.

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1.1 Hand Crafted Features

Another commonality between each of the top performing models on the Fake News Challenge is that they all use hand crafted features (such as TF-IDF, sentiment, etc) to supplement the deep model. Another goal we have is to understand the efficacy of these hand crafted features and how vital they are for the performance of the system. We plan to do this by incorperating them into our deep model and doing ablation testing.

1.2 Dataset Artifact Analysis

Something that was a recent finding in natrual language inference datsets is that there were annotation artifacts in the data that meant models could with considerably high accuracy predict the entail/contradict/neutral label by only observing the hypothesis sentence, completely ignoring the premise. Although the source of these annotation artifacts in other datasets seems to be a result of crowdsourcing data, which the Fake News Challenge does not do, it still would be useful to do the same type of testing that was used in Suchin et al. to understand the dataset further.

1.3 Contextual Embeddings

Another extension we plan on attempting (if time permits) is using contextual embeddings to replace the standard pretrained word vectors for out models. The current state of the art in natural language inference (as well as many other natural language processing tasks) is achieved through applying these contextual embedding systems, and we hope to see similar gains by adding these to our model.

2 Baseline Results

The text must be confined within a rectangle 5.5 inches (33 picas) wide and 9 inches (54 picas) long. The left margin is 1.5 inch (9 picas). Use 10 point type with a vertical spacing (leading) of 11 points. Times New Roman is the preferred typeface throughout, and will be selected for you by default. Paragraphs are separated by ½ line space (5.5 points), with no indentation.

The paper title should be 17 point, initial caps/lower case, bold, centered between two horizontal rules. The top rule should be 4 points thick and the bottom rule should be 1 point thick. Allow ¼ inch space above and below the title to rules. All pages should start at 1 inch (6 picas) from the top of the page.

For the final version, authors' names are set in boldface, and each name is centered above the corresponding address. The lead author's name is to be listed first (left-most), and the co-authors' names (if different address) are set to follow. If there is only one co-author, list both author and co-author side by side.

Please pay special attention to the instructions in Section 4 regarding figures, tables, acknowledgments, and references.

3 Headings: first level

All headings should be lower case (except for first word and proper nouns), flush left, and bold.

First-level headings should be in 12-point type.

3.1 Headings: second level

Second-level headings should be in 10-point type.

3.1.1 Headings: third level

Third-level headings should be in 10-point type.

Paragraphs There is also a `\paragraph` command available, which sets the heading in bold, flush left, and inline with the text, with the heading followed by 1 em of space.

4 Citations, figures, tables, references

These instructions apply to everyone.

4.1 Citations within the text

The `natbib` package will be loaded for you by default. Citations may be author/year or numeric, as long as you maintain internal consistency. As to the format of the references themselves, any style is acceptable as long as it is used consistently.

The documentation for `natbib` may be found at

`http://mirrors.ctan.org/macros/latex/contrib/natbib/natnotes.pdf`

Of note is the command `\citet`, which produces citations appropriate for use in inline text. For example,

```
\citet{hasselmo} investigated\dots
```

produces

> Hasselmo, et al. (1995) investigated...

If you wish to load the `natbib` package with options, you may add the following before loading the `nips_2018` package:

```
\PassOptionsToPackage{options}{natbib}
```

If `natbib` clashes with another package you load, you can add the optional argument `nonatbib` when loading the style file:

```
\usepackage[nonatbib]{nips_2018}
```

As submission is double blind, refer to your own published work in the third person. That is, use "In the previous work of Jones et al. [4]," not "In our previous work [4]." If you cite your other papers that are not widely available (e.g., a journal paper under review), use anonymous author names in the citation, e.g., an author of the form "A. Anonymous."

4.2 Footnotes

Footnotes should be used sparingly. If you do require a footnote, indicate footnotes with a number[1] in the text. Place the footnotes at the bottom of the page on which they appear. Precede the footnote with a horizontal rule of 2 inches (12 picas).

Note that footnotes are properly typeset *after* punctuation marks.[2]

4.3 Figures

All artwork must be neat, clean, and legible. Lines should be dark enough for purposes of reproduction. The figure number and caption always appear after the figure. Place one line space before the figure caption and one line space after the figure. The figure caption should be lower case (except for first word and proper nouns); figures are numbered consecutively.

You may use color figures. However, it is best for the figure captions and the paper body to be legible if the paper is printed in either black/white or in color.

4.4 Tables

All tables must be centered, neat, clean and legible. The table number and title always appear before the table. See Table 1.

[1] Sample of the first footnote.
[2] As in this example.

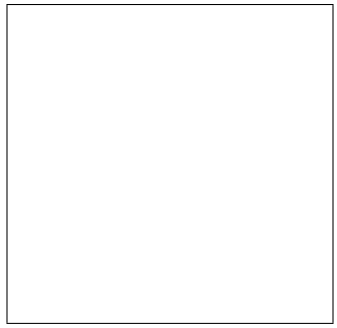

Figure 1: Sample figure caption.

Table 1: Sample table title

Part		
Name	Description	Size (μm)
Dendrite	Input terminal	$\sim$100
Axon	Output terminal	$\sim$10
Soma	Cell body	up to 10^6

Place one line space before the table title, one line space after the table title, and one line space after the table. The table title must be lower case (except for first word and proper nouns); tables are numbered consecutively.

Note that publication-quality tables *do not contain vertical rules.* We strongly suggest the use of the `booktabs` package, which allows for typesetting high-quality, professional tables:

`https://www.ctan.org/pkg/booktabs`

This package was used to typeset Table 1.

Acknowledgments

Use unnumbered third level headings for the acknowledgments. All acknowledgments go at the end of the paper. Do not include acknowledgments in the anonymized submission, only in the final paper.

References

[1] Alexander, J.A. & Mozer, M.C. (1995) Template-based algorithms for connectionist rule extraction. In G. Tesauro, D.S. Touretzky and T.K. Leen (eds.), *Advances in Neural Information Processing Systems 7*, pp. 609–616. Cambridge, MA: MIT Press.

[2] Bower, J.M. & Beeman, D. (1995) *The Book of GENESIS: Exploring Realistic Neural Models with the GEneral NEural SImulation System.* New York: TELOS/Springer–Verlag.

[3] Hasselmo, M.E., Schnell, E. & Barkai, E. (1995) Dynamics of learning and recall at excitatory recurrent synapses and cholinergic modulation in rat hippocampal region CA3. *Journal of Neuroscience* **15**(7):5249-5262.