

# “You Should Probably Read This”: Hedge Detection in Text

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## Hedge Detection

### Problem:

Understanding the certainty level of a claim is crucial in areas such as medicine, finance, engineering, and many others where errors can lead to disastrous results.

### What if a doctor says:

“I think you need surgery  
immediately!”

*Hedges* are linguistic devices that are used to indicate uncertainty and mitigate orders.

### Hedge phrase identifiers:

- modal verbs (“could”, “might”, etc.)
- peacock expressions (“very likely”, “everyone”, “I think”, etc.)
- weasel words (“some believe”, “clearly”, etc.)

## Data and Contributions

### The CoNLL-2010 Wikipedia dataset

Wikipedia discussions pages are manually annotated as certain or uncertain.

### Corpus:

- 11110 - train sentences
- (10% is used as validation set)
- 9634 - test sentences
- F1-score

### Challenges:

- The dataset is very small and unbalanced
- The data has been around for over 10 years
- The results hasn't been improved for over 4 years.

## Related Work and Motivation

### Bag-of-Words



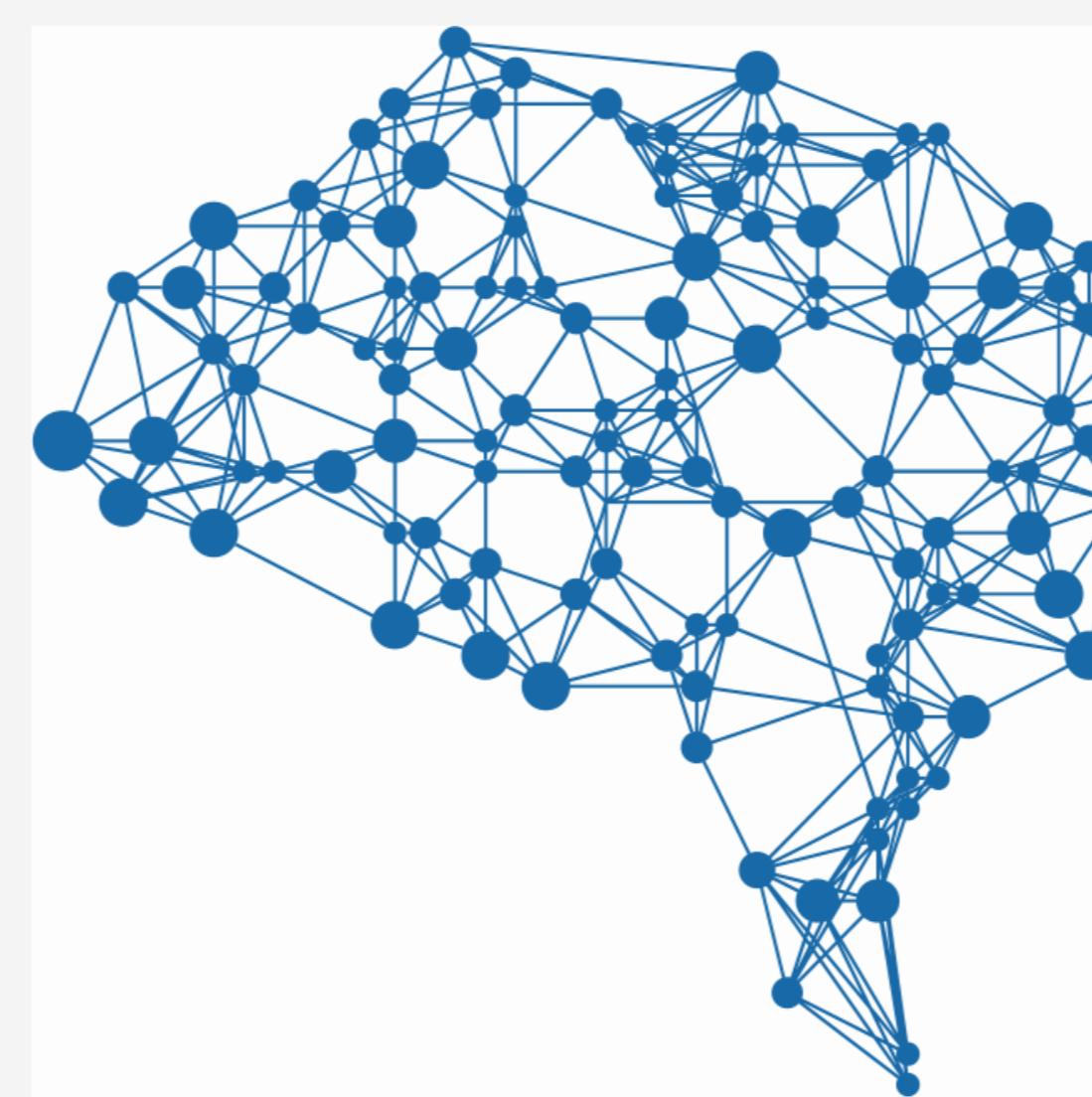
Result: F1 - 60.17

### Probabilistic



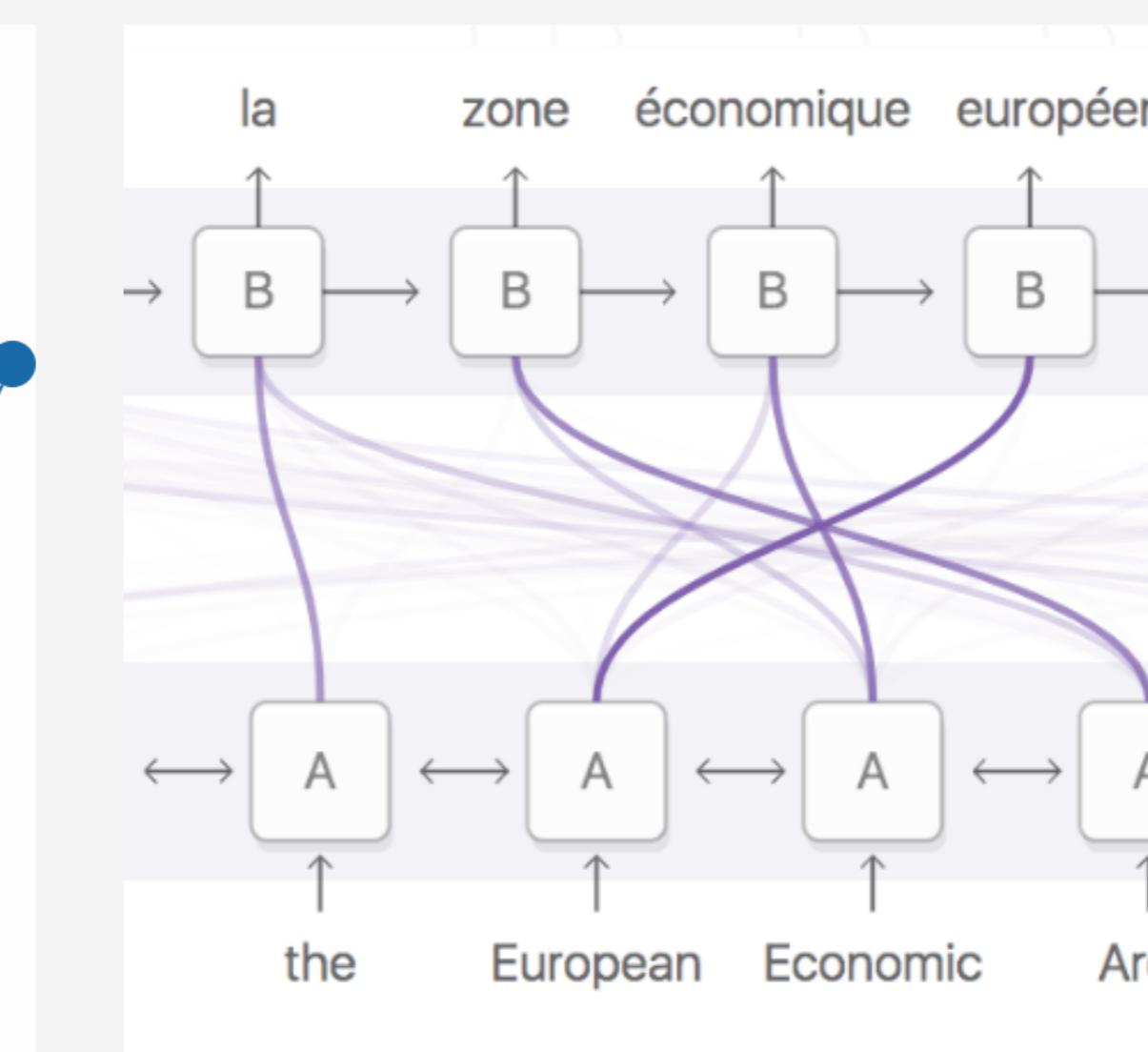
Result: F1 - 62.8

### Neural Networks



Result: F1 - 67.52

### Transformers



Result: None  
(BioScope: F1 - 85)

## Methods

### 1. Word Embeddings

Language Model	F1 Score
GoogleNews 300d	60.34
GloVe 100d	55.74
GloVe 300d 6B	<b>63.12</b>
GloVe 300d 840B	63.09
FastText 1M	62.08
FastText 2M	<b>63.57</b>
Custom Wiki 1Gb	61.99

### 2. NN Architectures

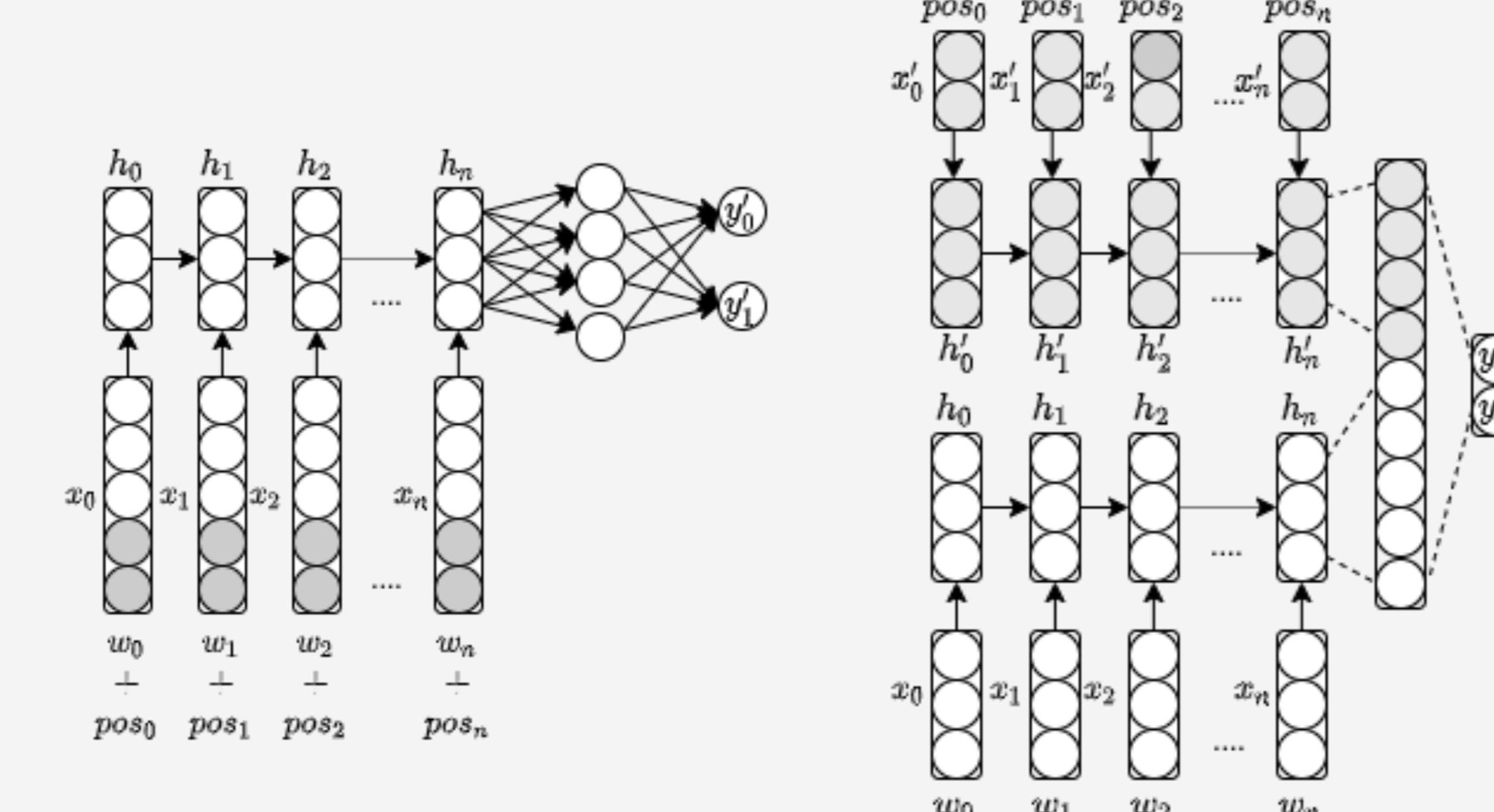
NN Model	Wiki 1G	GloVe	FastText	Mean	STD
CNN	57.38	58.34	59.36	58.36	0.99
GRU	62.07	64.23	65.04	<b>63.78</b>	1.54
LSTM	64.35	62.14	63.91	63.47	1.17
Transformer	57.18	57.91	54.74	56.61	1.66
CNN+At	56.86	58.22	62.79	59.29	3.11
GRU+At	62.13	63.33	65.40	63.62	1.65
LSTM+At	59.37	60.11	64.26	61.25	2.64
Mean	59.91	60.61	62.21		
STD	2.97	2.62	3.86		

### 3. POS Tags

NN Model	F1 score
GRU	47.54
LSTM	48.47
GRU+At	48.27
<b>LSTM+At</b>	<b>48.9</b>

### 4. POS and Word Joint Models

#### 4.1. Model Architectures



#### 4.2. Training Results

	Wiki 1G	FastText	Mean	STD
Joint Input				
GRU	65.81	66.08	<b>65.95</b>	0.19
LSTM	61.69	66.14	63.92	3.15
GRU+At	65.46	65.45	<b>65.46</b>	0.01
LSTM+At	66.57	64.26	65.42	1.63
Joint Model				
GRU+At	64.42	64.54	64.48	0.08
LSTM+At	64.22	62.47	63.35	1.24
<b>GRU&amp;LSTM+At</b>	<b>64.82</b>	<b>66.09</b>	<b>65.46</b>	0.90
Mean	64.71	65.00		
STD	1.56	1.36		

## Results

	Wiki 1G	FastText	Mean	STD
Joint Input				
GRU	68.25	67.69	67.97	0.40
GRU+At	68.97	66.32	67.65	1.87
Joint Model				
GRU&LSTM+At	<b>69.21</b>	<b>69.74</b>	<b>69.48</b>	<b>0.37</b>
Mean	68.81	67.92		
STD	0.50	1.72		

	Wiki 1G	GloVe	FastText	Mean	STD
CNN	60.00	62.92	64.28	62.40	2.19
GRU	<b>70.24</b>	67.54	68.97	<b>68.92</b>	1.35
LSTM	69.14	65.22	68.43	67.60	2.09
Transformer	63.27	65.22	68.43	65.64	2.61
CNN+At	58.44	65.77	66.83	63.68	4.57
GRU+At	68.22	66.81	67.11	67.38	0.74
LSTM+At	68.27	65.26	67.94	67.16	1.65
Joint Input					
GRU	68.25	66.74	67.69	67.56	0.76
LSTM	68.91	67.92	66.45	67.76	1.24
GRU+At	68.97	66.35	66.32	67.21	1.52
LSTM+At	69.00	64.54	64.15	65.90	2.69
Joint Model					
GRU+At	68.29	63.21	66.85	66.12	2.62
LSTM+At	68.27	62.31	65.74	65.44	2.99
<b>GRU&amp;LSTM+At</b>	<b>69.21</b>	<b>68.35</b>	<b>69.74</b>	<b>69.10</b>	<b>0.70</b>
Mean	67.03	65.58	67.07		
STD	3.68	1.87	1.63		

## Conclusion

- We find that joint GRU & LSTM attention model overall produces high scores across three language models.
- However, the top score of 70.24 is achieved with a domain specific language model with a GRU based neural network.

### The main contributions of this work are:

1. a comprehensive analysis of various neural network architectures and their performance on this task
2. a model formulation for including part-of-speech information in the input
3. a new top score on the CoNLL-2010 Wikipedia dataset