NLP for Fact-Checking and Claim Assessment

A Language Model based approach

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Overview

- Fake news & NLP
- Related work
- Proposed method
    - FEVER dataset
    - Language Models for classification
    - Learning & Validation
- Results & Discussion
- Conclusion & Perspective

Fake news & NLP

Fake news & NLP

SEARCH

NEW YORK POST

NEWS

Roger Stone: Bill Gates may have created coronavirus to microchip people

By Bob Fredericks

April 13, 2020 | 2:49pm | Updated

Fake news & NLP

Fake news

false, often sensational, information disseminated under the guise of news reporting.

Collins English Dictionary

Humans

have been proven irrational and vulnerable when differentiating between real and fake news. Typical accuracy ranges between 55% and 58%.

Xinyi Zhou, Reza Zafarani, Kai Shu, and Huan Liu. Fake news: Fundamental theories, detection strategies and challenges.

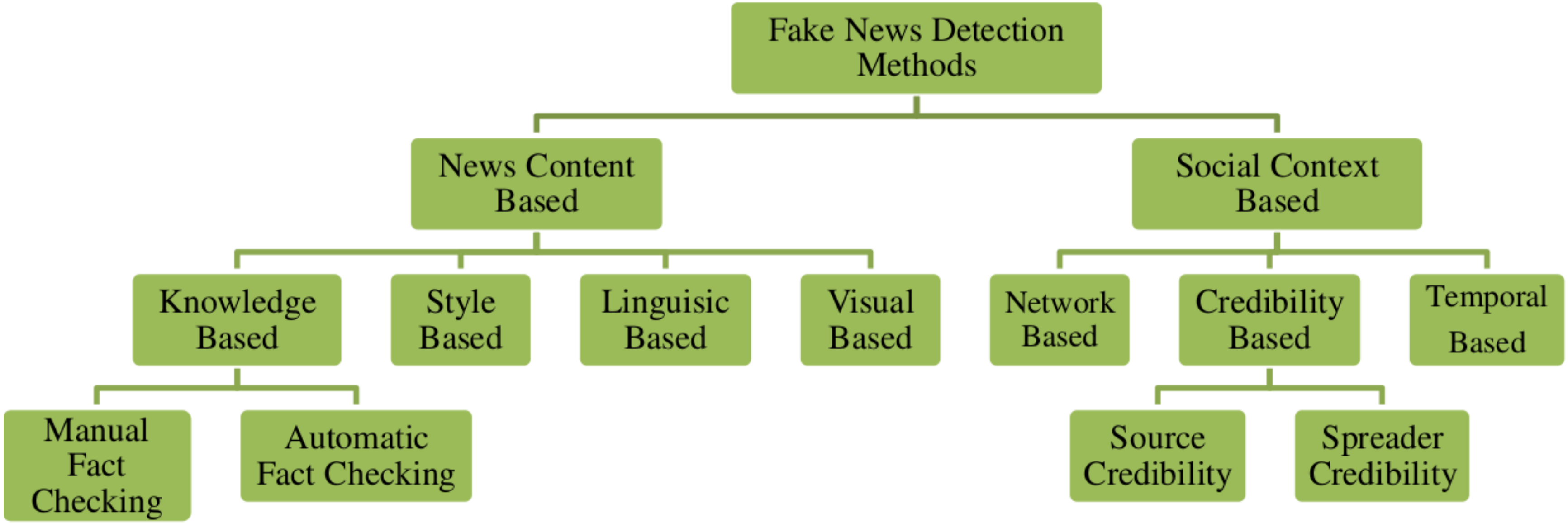
Fake news & NLP

<u>Automatic</u> fake news <u>detection</u> is a practical <u>NLP problem</u> useful to all online content providers.

- Reduce the human time and effort to detect fake news,
- Can sweep through huge data streams,
- Capable of ceasing the spreading much faster.

- How can we differentiate fake news from real news?
- At what level of confidence can we do so?
- What are the existing methods that solves this problem?

Related work



S Hangloo, B Arora. Fake News Detection Tools and Methods – A Review

Related work

Knowledge-based Fake News Detection

a method aims to assess news authenticity by comparing the knowledge extracted from to-be verified news content with known facts, also called fact-checking.

Anton Chernyavskiy, Dmitry Ilvovsky, and Preslav Nakov. Whatthewikifact: Fact-checking claims against wikipedia.

Style-based Fake News Detection

focuses on the style of writing, i.e. the form of a text rather than its meaning.

P. Przybyla. Capturing the style of fake news. In Proceedings of the AAAI Conference on Artificial Intelligence.

Related work

Propagation-based Fake News Detection

a principled way to characterize and understand hierarchical propagation network features. We perform a statistical comparative analysis over these features, including micro-level and macro-level, of fake news and real ones.

K. Shu, D. Mahudeswaran, S. Wang, and H. Liu. Hierarchical propagation networks for fake news detection: Investigation and exploitation.

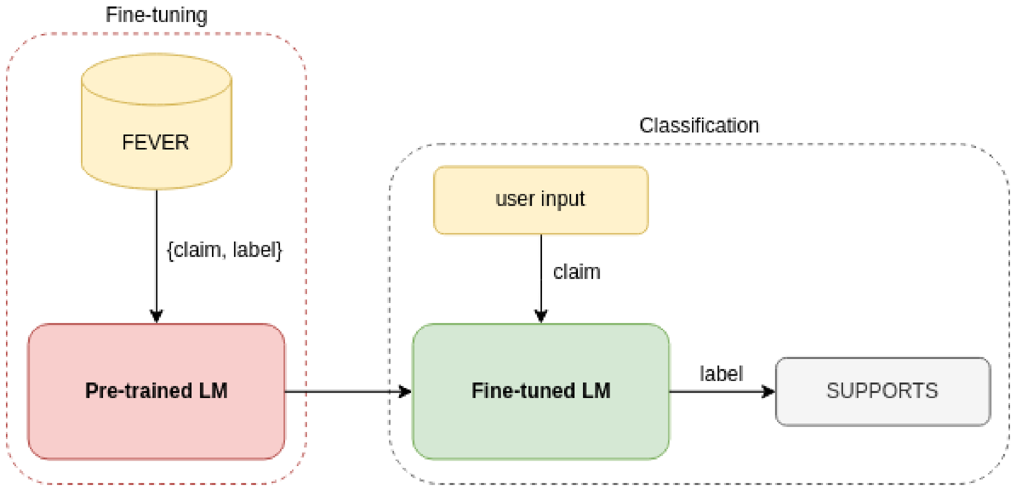
Language Model based Fact-Checking

a new approach that relies on fine-tuning state-of-art LMs like BERT that were pre-trained on Wikipedia’s articles in order to solve the claim classification problem.

Nayeon Lee, Belinda Z Li, Sinong Wang, Wen-tau Yih, Hao Ma, and Madian Khabsa. Language models as fact checkers?

Proposed Method

- We start by fine-tuning a set of LMs for the downstream task that is claim classification using the FEVER dataset,
- Then each model is employed to assess the validity of new input claims.



Proposed Method

FEVER dataset

FEVER (Fact Extraction and VERification)

consists of 185,445 claims generated by altering sentences extracted from Wikipedia. The claims are classified as Supported, Refuted or NotEnoughInfo.

James Thorne, Andreas Vlachos, Christos Christodoulopoulos, and Arpit Mittal. Fever: a large-scale dataset for fact extraction and verification.

Claim: The Rodney King riots took place in the most populous county in the USA.

`[wiki/Los_Angeles_Riots]`

The 1992 Los Angeles riots, also known as the Rodney King riots were a series of riots, lootings, arsons, and civil disturbances that occurred in Los Angeles County, California in April and May 1992.

`[wiki/Los_Angeles_County]`

Los Angeles County, officially the County of Los Angeles, is the most populous county in the USA.

Verdict: Supported

Proposed Method

FEVER dataset

ID	Claim	Label
79044	The Apple Store first opened in 2001.	1
117129	Adventure Time won an Oscar.	0
55061	Yamaha Corporation produces hardware.	2

EXAMPLES OF FEVER CLAIMS AND LABELS .

Split	SUPPORTS	REFUTES	NEI	Total
Train	80,035	29,775	35,639	145,449
Val	3,333	3,333	3,333	9,999
Test	3,333	3,333	3,333	9,999

DATASET SPLIT SIZES FOR SUPPORTS, REFUTES AND NOTENOUGHINFO (NEI) CLASSES .

Proposed Method

Language Models for classification

Comparison	BERT October 11, 2018	RoBERTa July 26, 2019	DistilBERT October 2, 2019	ALBERT September 26, 2019
Parameters	**Base:** 110M **Large:** 340M	**Base:** 125 **Large:** 355	**Base:** 66	**Base:** 12M **Large:** 18M
Layers / Hidden Dimensions / Self-Attention Heads	**Base:** 12 / 768 / 12 **Large:** 24 / 1024 / 16	**Base:** 12 / 768 / 12 **Large:** 24 / 1024 / 16	**Base:** 6 / 768 / 12	**Base:** 12 / 768 / 12 **Large:** 24 / 1024 / 16
Training Time	**Base:** 8 x V100 x 12d **Large:** 280 x V100 x 1d	1024 x V100 x 1 day (4-5x more than BERT)	**Base:** 8 x V100 x 3.5d (4 times less than BERT)	[not given] **Large:** 1.7x faster
Performance	Outperforming SOTA in Oct 2018	88.5 on GLUE	97% of BERT-base's performance on GLUE	89.4 on GLUE
Pre-Training Data	BooksCorpus + English Wikipedia = 16 GB	BERT + CCNews + OpenWebText + Stories = 160 GB	BooksCorpus + English Wikipedia = 16 GB	BooksCorpus + English Wikipedia = 16 GB
Method	Bidirectional Trans-former, MLM & NSP	BERT without NSP, Using Dynamic Masking	BERT Distillation	BERT with reduced para-meters & SOP (not NSP)

https://humboldt-wi.github.io/blog/research/information_systems_1920/uncertainty_identification_transformers/

Proposed Method

Language Models for classification

LMs used in this experiment:

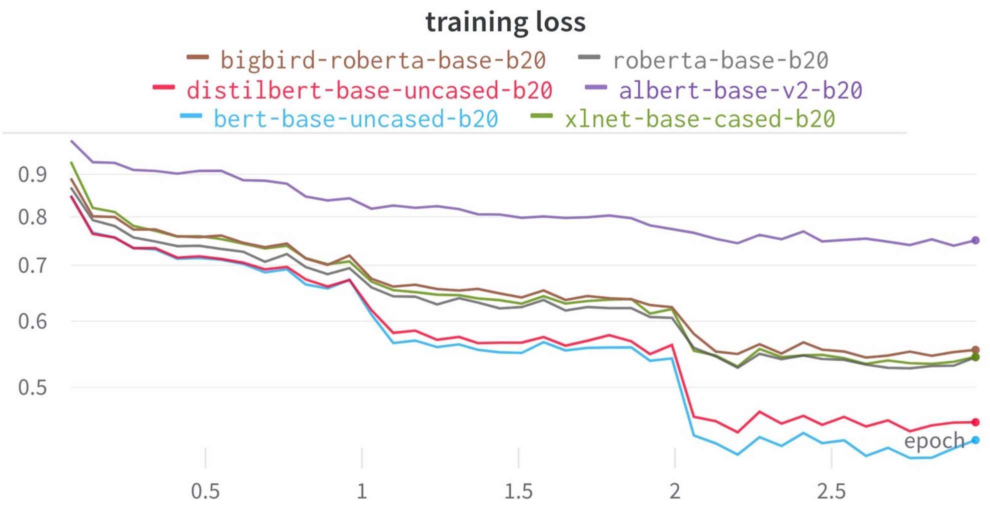
- BERT-base-uncased
- RoBERTa-base
- DistilBERT-base-uncased
- XLNET-base-cased
- ALBERT-base-v2
- BigBird-RoBERTa-base

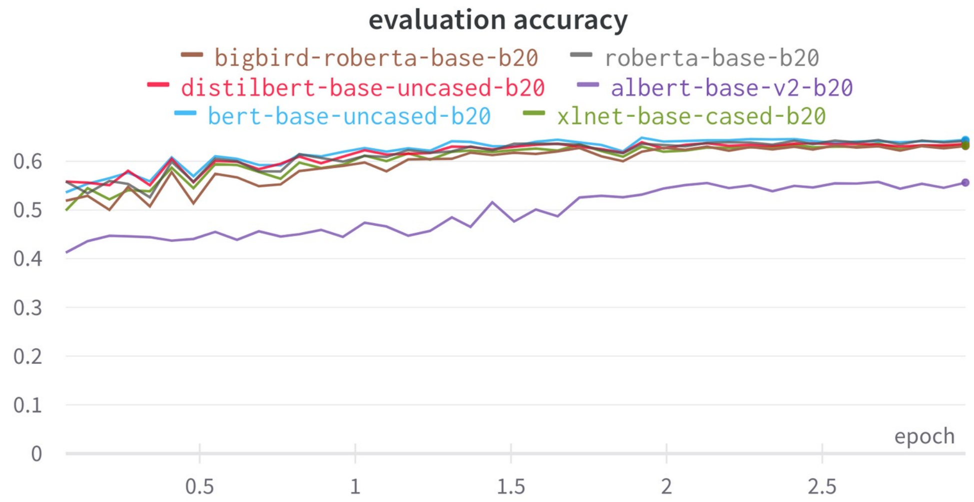
Hyperparameters:

- Tokenizer max sequence length: 128
- Output layer size: 3
- Activation function: GeLU
- Learning rate: 3e-5
- Optimization: Adam with linear decay
- Loss function: Cross-Entropy
- Epochs: 3
- Training batch size: 20
- Validation batch size: 20

Proposed Method

Learning & Validation





Results & Discussion

Fine-tuned model	Label	prec	recall	f1	accuracy	macro prec	macro recall	macro f1
BERT-base-uncased	SUPPORTS	0.55	0.78	0.64	**0.62**	0.63	**0.62**	**0.61**
	REFUTES	0.75	0.59	0.66				
	NEI	0.61	0.47	0.53				
ALBERT-base-v2	SUPPORTS	0.46	0.81	0.59	0.53	0.58	0.53	0.52
	REFUTES	0.77	0.46	0.58				
	NEI	0.50	0.33	0.40				
DistilBERT-base-uncased	SUPPORTS	0.54	0.78	0.64	0.61	0.63	0.61	**0.61**
	REFUTES	0.75	0.58	0.65				
	NEI	0.60	0.47	0.53				
RoBERTa-base	SUPPORTS	0.54	0.81	0.65	**0.62**	**0.64**	**0.62**	**0.61**
	REFUTES	0.75	0.59	0.66				
	NEI	0.63	0.45	0.53				
BigBird-RoBERTa-base	SUPPORTS	0.53	0.81	0.64	0.61	**0.64**	0.61	0.60
	REFUTES	0.75	0.58	0.66				
	NEI	0.63	0.44	0.52				
XLNET-base-cased	SUPPORTS	0.53	0.81	0.64	0.61	0.63	0.61	0.60
	REFUTES	0.74	0.59	0.65				
	NEI	0.63	0.43	0.51				
Related work	**Label**	**prec**	**recall**	**f1**	**accuracy**	**macro prec**	**macro recall**	**macro f1**
BERT-large [7]	SUPPORTS	0.54	0.67	0.59	0.57	0.57	0.57	0.57
	REFUTES	0.62	0.55	0.58				
	NEI	0.57	0.49	0.53				
FEVER Baseline [19]	-	-	-	-	0.49	-	-	-
Ohio State University [19]	-	-	-	-	0.50	-	-	-
Columbia NLP [19]	-	-	-	-	0.58	-	-	-
Papelo [19]	-	-	-	-	0.61	-	-	-
UNC-NLP [19]	-	-	-	-	0.68	-	-	-
DREAM [20]	-	-	-	-	**0.77**	-	-	-

Results & Discussion

- Pre-trained LMs can classify claims,
- Pre-trained LMs act as an independent source of knowledge,
- Our approach surpasses most of the existing fact-checking methods,

Conclusion & Perspective

Conclusion & Perspective