CERGY PARIS UNIVERSITÉ

Équipes Traitement de l'Information et Systèmes

Language Models for Fact-Checking and Claim Assessment

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Fake news & NLP

Easy to check


The Associated Press
@AP
Following

Breaking: Two Explosions in the White House and Barack Obama is injured

Reply Retweet Favorite Buffer More

3,242	153
RETWEETS	FAVORITES

12:07 PM - 23 Apr 13

This tweet caused $130 billion value drop in stock market!

This article affected COVID-19 vaccination decisions


SEARCH
INTRODUCING JALEN ROSE
NEW YORK POST

NEWS

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

By Bob Fredericks

April 13, 2020 | 2:49pm | Updated

Difficult to check

Fake news & NLP

Fake news

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

Collins English Dictionary

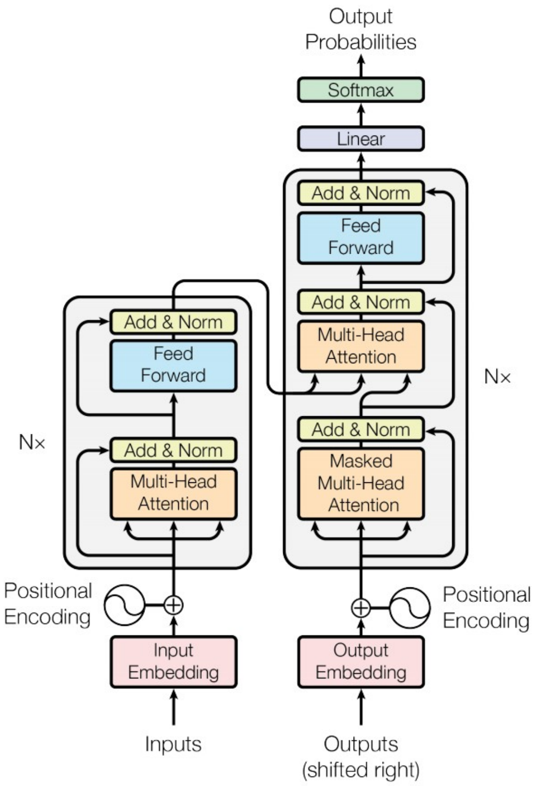
Humans

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.

Language Models

- A new Deep Neural Network Architecture,
  - Aka Transformers
- Based on Attention mechanism,
  - Helps draw connections between any parts of the sequence input i.e Context
- Great for NLP tasks:
  - Translation, Sentiment analysis, Text summarization...
- Powerful, faster, stable than old architectures (RNNs, LSTMs)



Attention is all you need (2017).

Language Models

Pre-trained LMs comparison							
	BERT October 11, 2018	**XLNet** July 16, 2019	**RoBERTa** July 26, 2019	**ALBERT** September 26, 2019	**DistilBERT** October 2, 2019	**BigBird** July 28, 2020	**ConvBERT** August 6, 2020
Parameters	**Base:** 110M **Large:** 340M	**Base:** 110M **Large:** 340M	**Base:** 125M **Large:** 355M	**Base:** 12M **Large:** 18M	**Base:** 66M	**Base:** 110M	**Base:** 96M
Layers / Hidden dimensions / Self-attention heads	**Base:** 12 / 768 / 12 **Large:** 24 / 1024 / 16	**Base:** 12 / 768 / 12 **Large:** 24 / 1024 / 16	**Base:** 12 / 768 / 12 **Large:** 24 / 1024 / 16	**Base:** 12 / 768 / 12 **Large:** 24 / 1024 / 16	**Base:** 6 / 768 / 12	**Base:** 12 / 768 / 12	**Base:** 12 / 768 / 12
Pre-trained data	BooksCorpus + English Wikipedia ~ 16 GB	**Base:** 16 GB BERT data **Large:** 113 GB of textual data (16 GB BERT data + 97 GB additional)	BERT + CCNews + OpenWebText + Stories ~ 160 GB	BooksCorpus + English Wikipedia ~ 16 GB	BooksCorpus + English Wikipedia ~ 16 GB	BERT + CCNews + Stories ~ 97 GB	OpenWebText ~ 32 GB
Method	Bidirectional Transformer, MLM & NSP	Bidirectional Transformer with Permutation based modeling	BERT without NSP, Using Dynamic Masking	BERT with reduced parameters & SOP (not NSP)	BERT Distillation	Block Sparse Attention instead of normal attention	Improves BERT by using a span level dynamic convolution

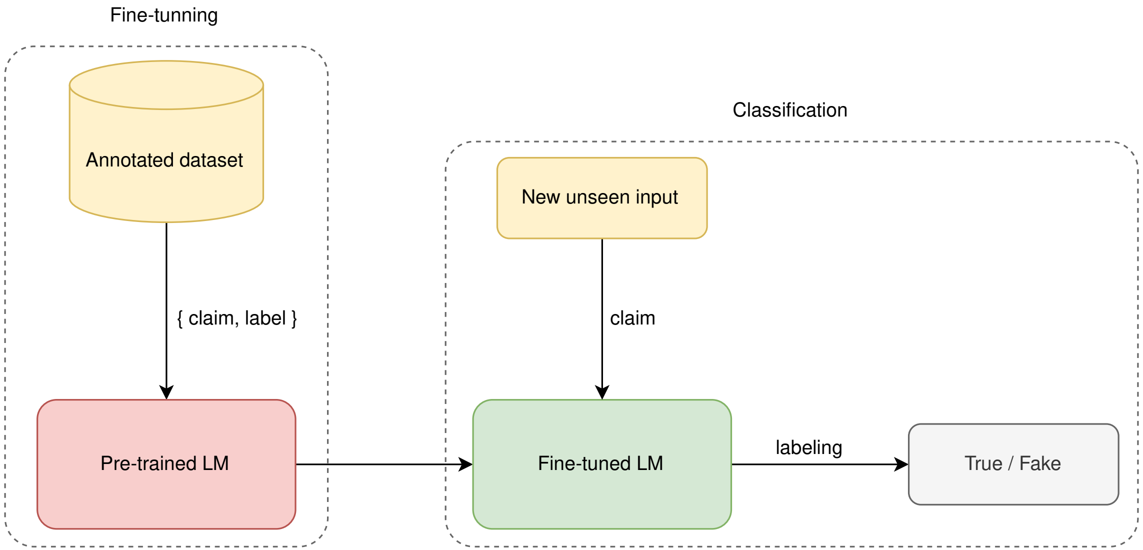
- All Transformers
- Subtle changes in the architecture and training datasets

Datasets

FEVER 185K annotated claims 3-labels	Extracted from *Wikipedia* and subsequently verified without knowledge of the sentence they were derived from.
Liar 12.8K annotated claims 6-labels	Manually labeled short statements that were collected in various contexts from *PolitiFact.com*.
MultiFC 35K annotated claims >30-labels reduced to 5-labels	Collected from 26 fact checking websites in English, paired with textual sources and rich metadata, and labeled for veracity by human expert journalists.
COVID-19 6K annotated claims 2-labels	Rumors about COVID-19 extracted from various social-media platforms such as Twitter, Facebook, Instagram, etc.
ANTi-Vax 15K annotated claims 2-labels	Tweets that were annotated as misinformation or general COVID-19 vaccine tweets using reliable sources and validated by medical experts.

General Architecture

- Pre-process each dataset:
  - FEVER, Liar, MultiFC, COVID-19, ANTi-Vax
- Fine-tune a set of LMs:
  - BERT, RoBerta, ALBERT, XLNET, DistilBERT, BigBird, ConvBERT
- Deploy the best LM to assess the validity of new input claims



Results & Discussion

Dataset	Metric	2-labels	3-labels	5-labels	6-labels
FEVER	**accuracy**	0.81	0.64	-	
	macro f1	0.81	0.63	-	
MultiFC	**accuracy**	0.72	-	0.50	-
	macro f1	0.64	-	0.40	-
Liar	**accuracy**	0.69	-		0.31
	macro f1	0.61	-		0.30
COVID-19	**accuracy**	0.98	-		
	macro f1	0.98	-		
ANTi-Vax	**accuracy**	0.99	-		
	macro f1	0.99	-		

Conclusion & Perspective

- LMs have a great potential to solve different NLP problems,
- LMs for fact-checking are good but not the best,
  - Does not beat state-of-art traditional models.
- Different paths can be explored
  - We still have much to learn about LMs.
- In the future we plan to exploit the structural features of Complex Networks in combination with LMs.

Detailed article

https://bit.ly/3mZvDup

Bibliography

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- Thorne, James, et al. "Fever: a large-scale dataset for fact extraction and verification." arXiv preprint arXiv:1803.05355 (2018).
- Wang, William Yang. "liar, liar pants on fire": A new benchmark dataset for fake news detection." arXiv preprint arXiv:1705.00648 (2017).
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- Patwa, Parth, et al. "Fighting an infodemic: Covid-19 fake news dataset." International Workshop on Combating On line Ho st ile Posts in Regional Languages dur ing Emerge ncy Si tuation. Springer, Cham, 2021.
- Hayawi, Kadhim, et al. "ANTi-Vax: a novel Twitter dataset for COVID-19 vaccine misinformation detection." Public health 203 (2022): 23-30.
- Vaswani, Ashish, et al. "Attention is all you need." Advances in neural information processing systems 30 (2017).
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirec- tional transformers for language understanding. arXiv preprint arXiv:1810.04805, 2018.

Datasets

Dataset	Example claim	Label
FEVER 185K annotated claims 3-labels	The Apple Store first opened in 2001.	SUPPORTS
	Adventure Time won an Oscar.	REFUTES
	Yamaha Corporation produces hardware.	NEI
Liar 12.8K annotated claims 6-labels	FIFA pressured Brazil into passing a so-called Budweiser bill, allowing beer sales in soccer stadiums.	TRUE
	Says Barack Obama founded ISIS. I would say the co-founder would be crooked Hillary Clinton.	FALSE
	Sixty-two percent of all personal bankruptcies are caused by medical problems.	HALF-TRUE
MultiFC 35K annotated claims >30-labels reduced to 5-labels	The government does not need a warrant to read your old emails.	TRUE
	About 99% of rape allegations are fabricated.	FALSE
	Husbands rarely beat up their wives. Single women get beaten up more.	IN-BETWEEN
COVID-19 6K annotated claims 2-labels	Holding your breath can let you test whether you may have COVID-19.	FAKE
	WHO: We recommend systemic corticosteroids for the treatment of patients with severe and critical #COVID_19 which could be lifesaving. https://t.co/R4HNTnEEwD	REAL
ANTi-Vax 15K annotated claims 2-labels	Just got my appointment to be vaccinated and I'm extremely nervous and slightly excited all in one. #vaccine	NOT_MISSINFO
	Disturbing and Mysterious #Death of 18yo #Camilla after #COVID #Vaccine. #AstraZeneca's Jabs stopped in #Italy for Young #People!#Experimental https://t.co/Ssz9kKkFDu	MISSINFO

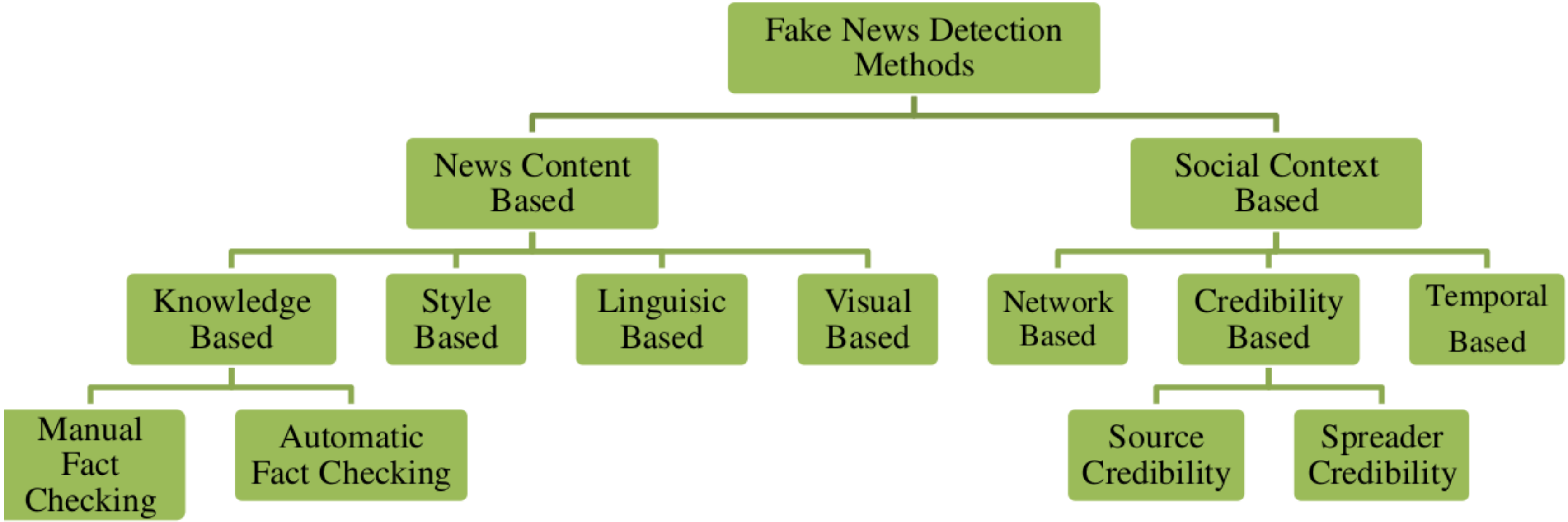
Fake news & NLP

Automatic fake news detection is a practical NLP problem 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

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

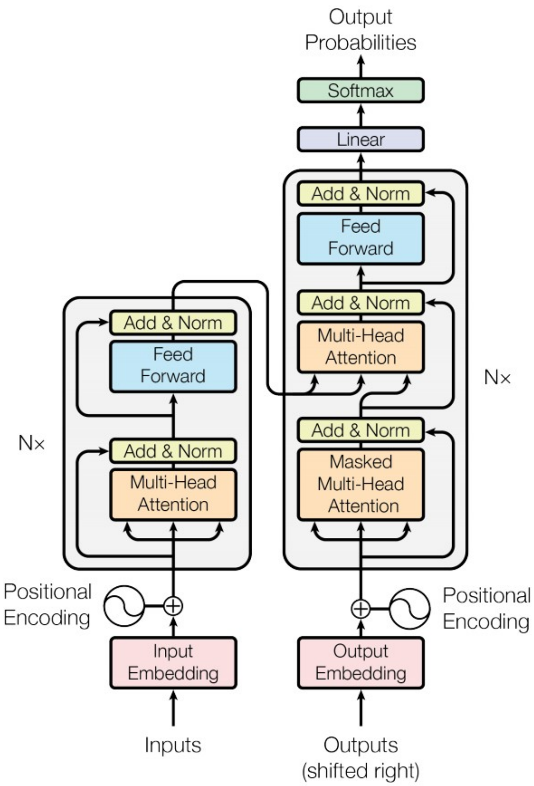
Language Model based Fact-Checking

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.

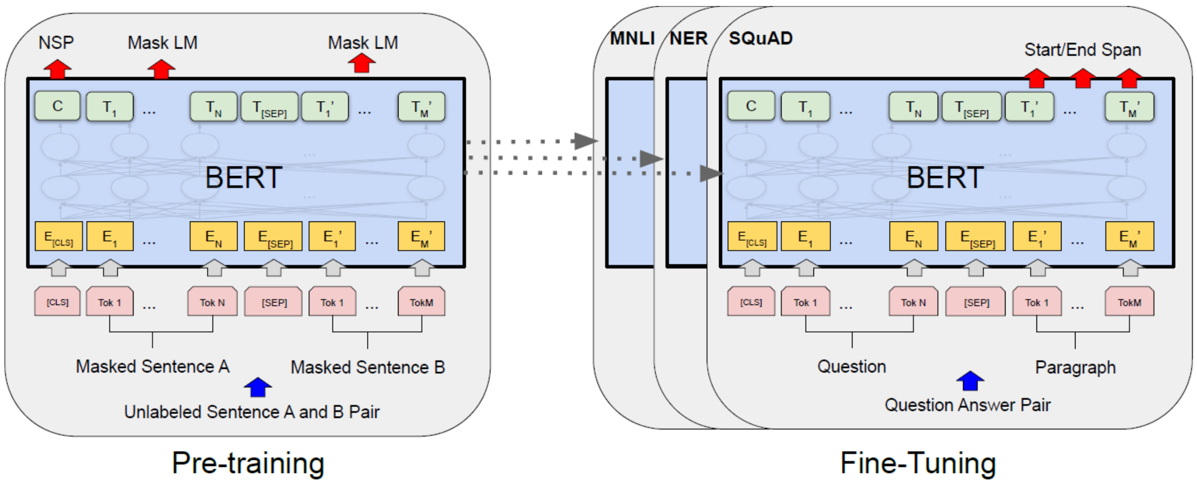
Nayeon Lee, Belinda Z Li, Sinong Wang, Wen-tau Yih, Hao Ma, and Madian Khabsa. Language models as fact checkers?

- What are Language Models?
- How can they be employed as fact-checkers?

Language Models



Attention is all you need.



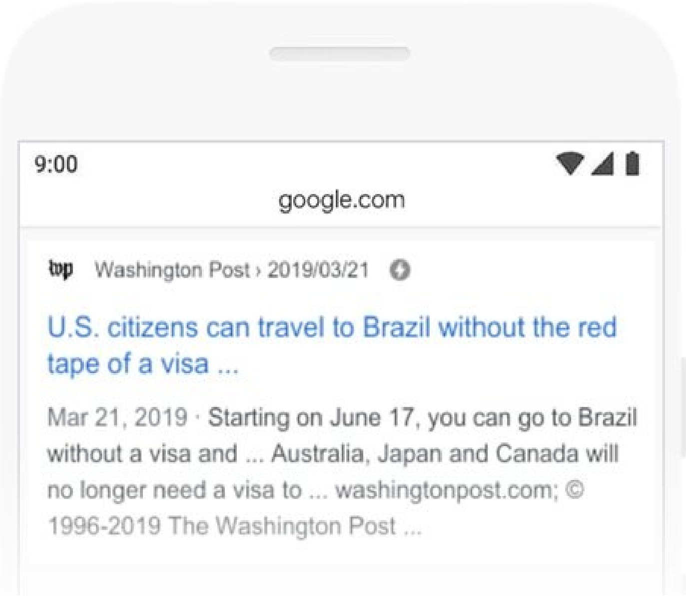
Bert: Pre-training of deep bidirectional transformers for language understanding.

Language Models

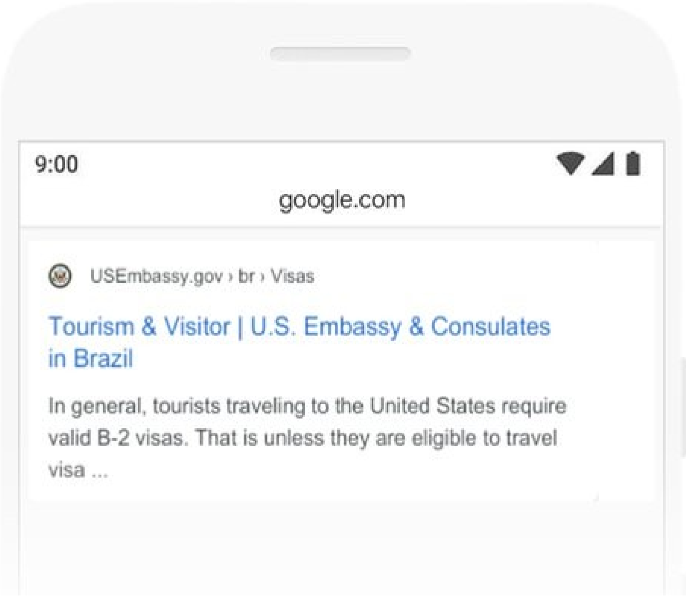
BERT

2019 brazil traveler to usa need a visa

BEFORE

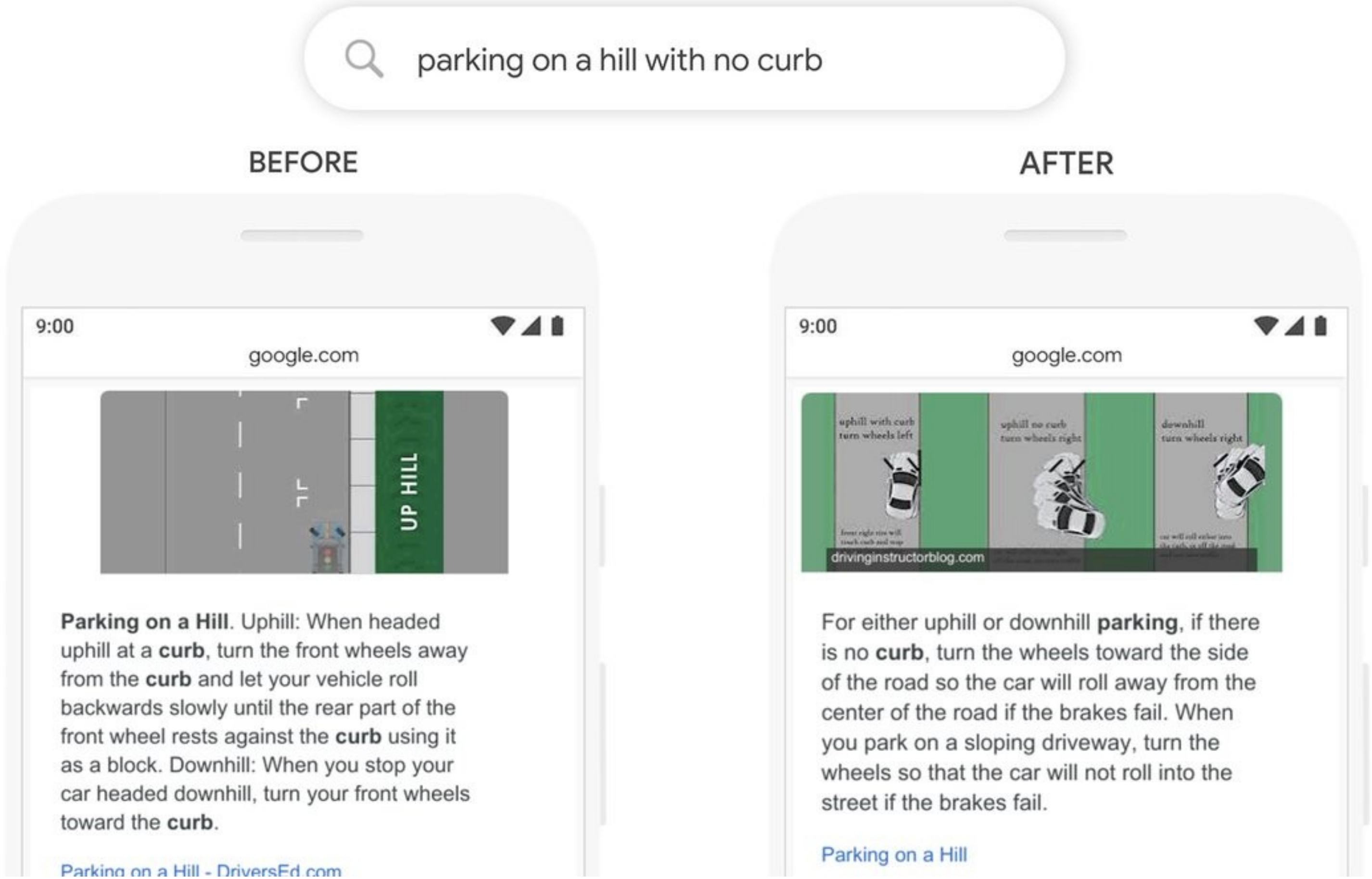


AFTER



Language Models

BERT



Results & Discussion

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

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 Transformer, MLM & NSP	BERT without NSP, Using Dynamic Masking	BERT Distillation	BERT with reduced parameters & SOP (not NSP)

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