



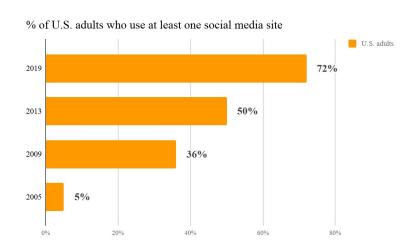


EMET: EMBEDDINGS FROM MULTILINGUAL-ENCODER TRANSFORMER FOR FAKE NEWS DETECTION

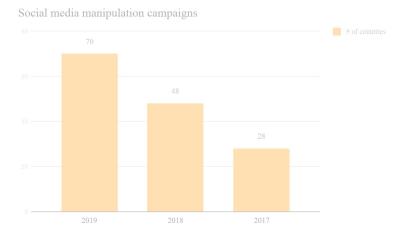
ICASSP May 04-08, 2020 Barcelona Stephane Schwarz, Antônio Theóphilo, and Anderson Rocha Institute of Computing, Unicamp, BR

Motivation





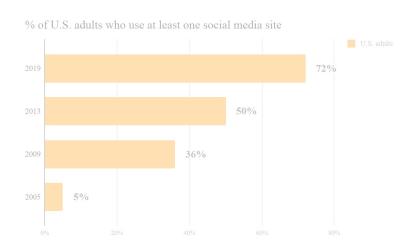
Pew Research Center [1]



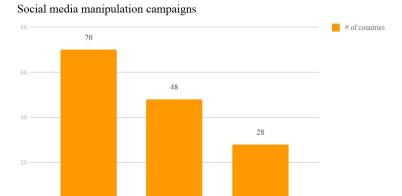
Oxford Internet Institute [2]

Motivation





Pew Research Center [1]



2017

2018

Oxford Internet Institute [2]

2019







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What is fake news?

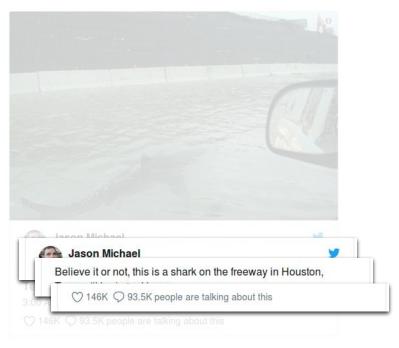




Prior Art: Heuristic-based



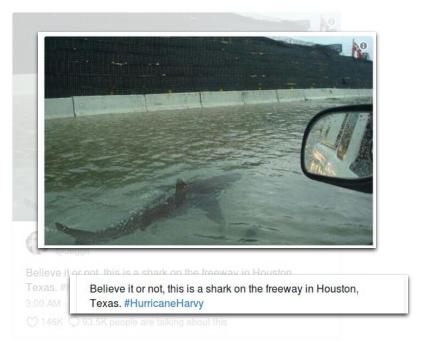
Caslillo et al. [3], Theóphilo et al.[5]



Prior Art: Multi-domain



Qi et al. [4]



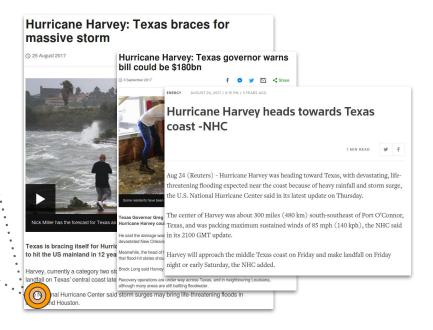
EMET: Our hypothesis



Jesus words: "Then you will know the truth, and the truth will set you free."

John 8: 32



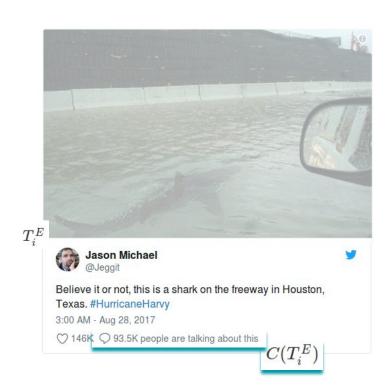






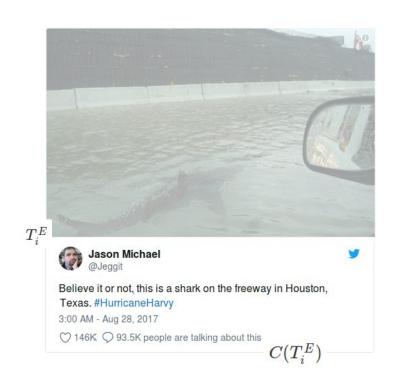
$$\mathcal{F}: (T_i^E \cdot C(T_i^E) \cdot N^E) \implies y$$

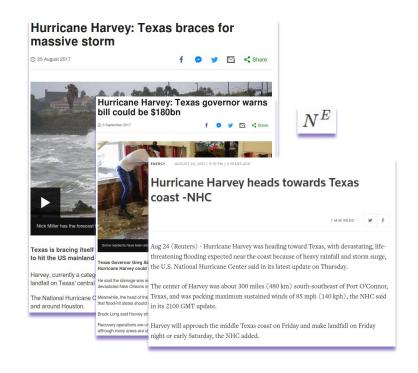




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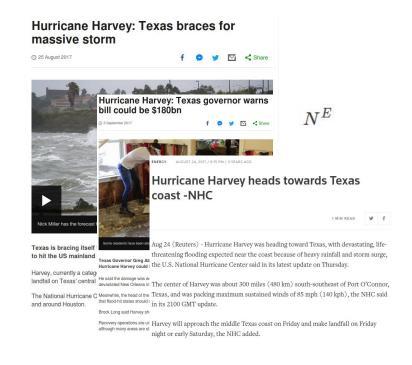




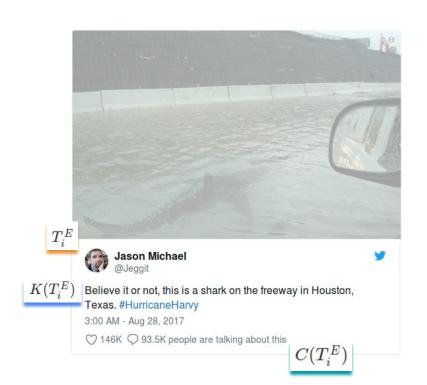


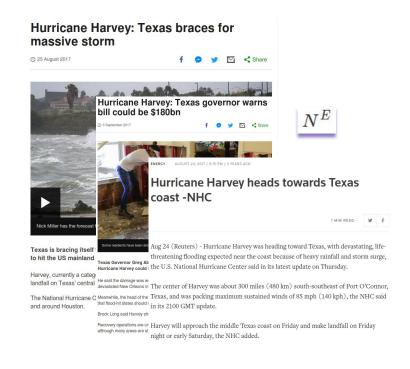






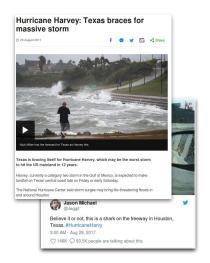


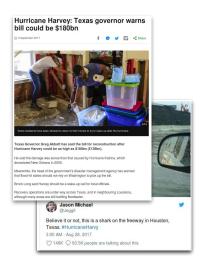


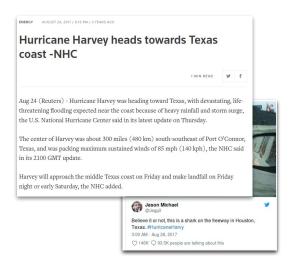


EMET: Dataset









Training News was obtained from BBC and for Test set from Reuters.

EMET: Dataset



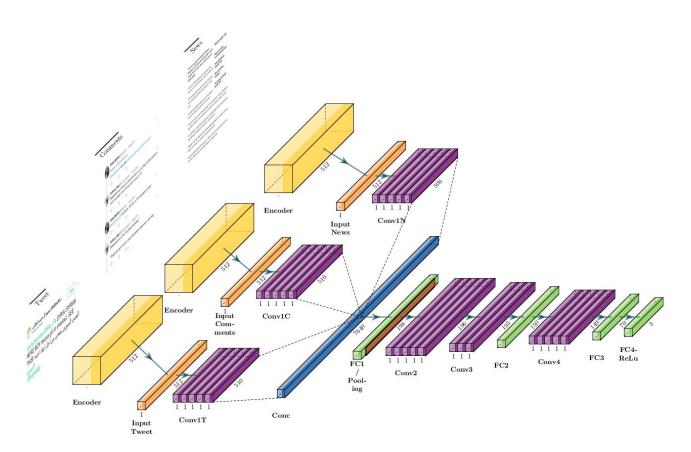
Class	Train	Test	Augmen. Train	Augmen. test
Real	4314	2200	9304	22000
Fake	6690	3732	23026	36262
Unknown	1416	600	2361	600

EMET: Dataset



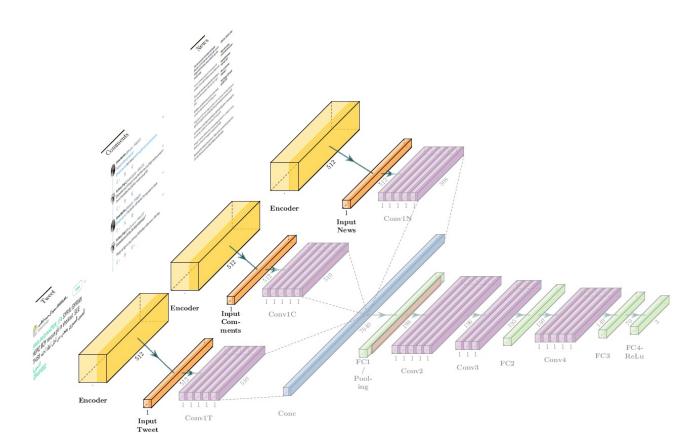
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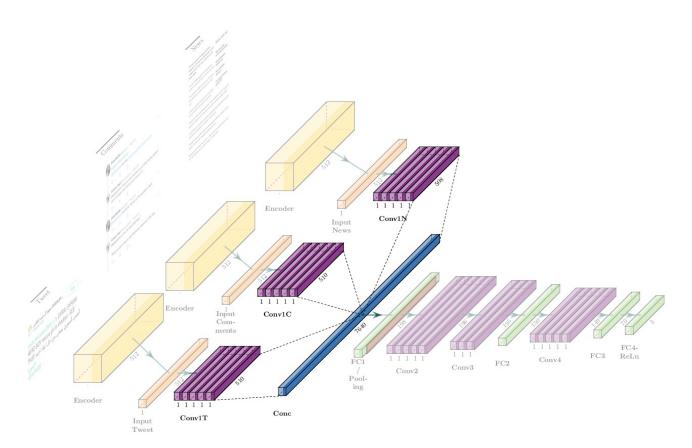
EMET: Input





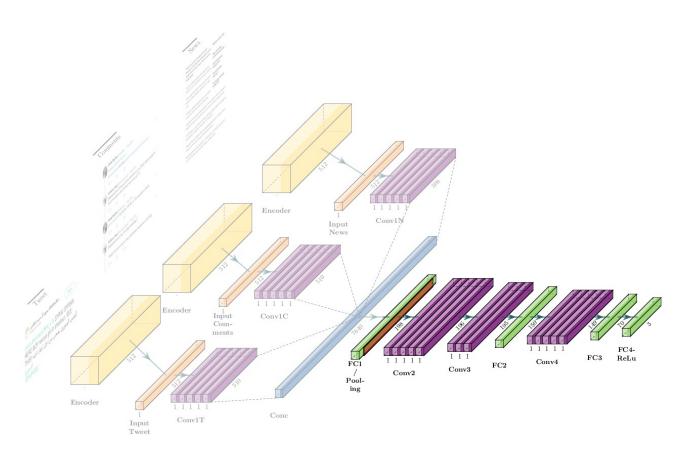
EMET: Convolution





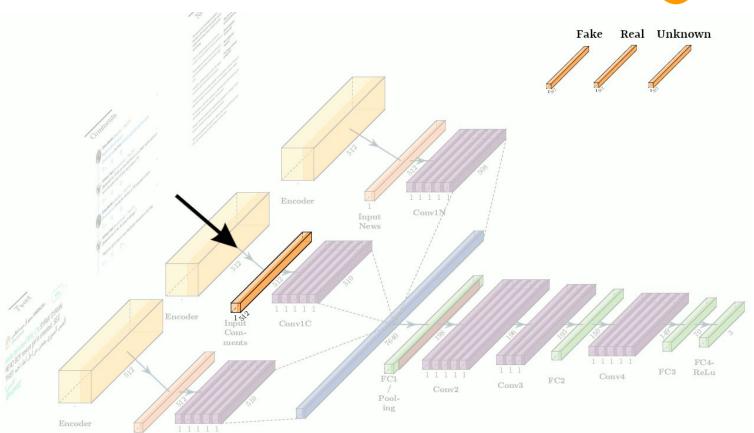
EMET: Fully-connected





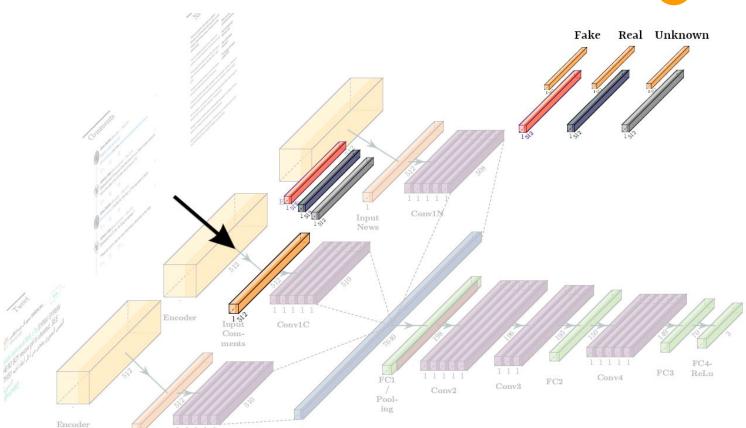
EMET: Classification Ensemble - Training





EMET: Classification Ensemble - Testing





Experimental Results: Questions



• How text embeddings from a multilingual encoder and the us-age of news pieces improve the identification of misleading content on social media?

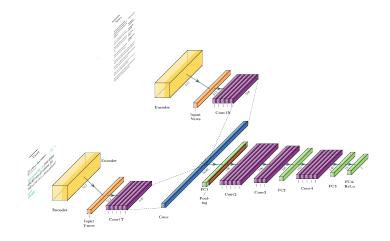
• How the comments contribute to improving classification performance?

• How the ensemble method capture general information to better model the test set?

Experimental Setup: Unchecked news (UNC)



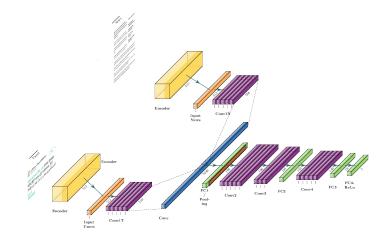
Method	Accuracy	Precision	Recall	F1
UCN	76.4	76.9	76.4	75.2
EANN-Text [6]	53.2	59.8	54.1	56.8
MVAE-Text [7]	52.6	52.7	53.9	53.2



Experimental Setup: Checked news (CN)



Method	Accuracy	Precision	Recall	F1
CN	92.92	92.99	92.92	92.94
EANN-Text	53.2	59.8	54.1	56.8
MVAE-Text	52.6	52.7	53.9	53.2



Experimental Results: Questions



• How text embeddings from a multilingual encoder and the us-age of news pieces improve the identification of misleading content on social media?

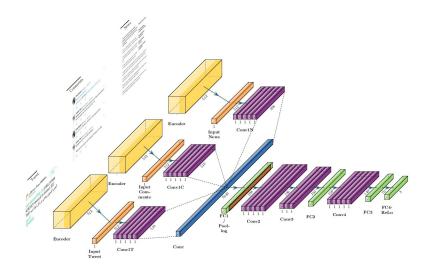
• How the comments contribute to improving classification performance?

• How the ensemble method capture general information to better model the test set?

Experimental Setup: CN and comments (CNC)



Method	Accuracy	Precision	Recall	F1
CN	92.92	92.99	92.92	92.94
CNC	93.47	93.91	93.47	93.61



Experimental Results: Questions



• How text embeddings from a multilingual encoder and the us-age of news pieces improve the identification of misleading content on social media?

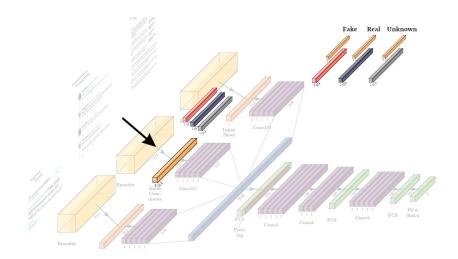
• How the comments contribute to improving classification performance?

• How the ensemble method capture general information to better model the test set?

Experimental Setup: CNC and ensemble (CNCE)



Method	Accuracy	Precision	Recall	F1
CNC	93.47	93.91	93.47	93.61
CNCE	94.08	91.31	91.21	91.26







EMET helps to address the problem of fake news detection on social media platforms in a multilingual scenario.

Future work



Explore Multi Domain data (Image + Text)

Acknowledgments













References



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[2] Samantha Bradshaw and Philip N. Howard. 2019 global inventory of organised social media manipulation.

https://comprop.oii.ox.ac.uk/wp-content/uploads/sites/93/2019/09/CyberTroop-Report19.pdf, 2019.[Online; accessed on October 10 th, 2019].

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[5] Antônio Theóphilo et al. A needle in a haystack? harnessing onomatopoeia and user-specific stylometrics for authorship attribution ICASSP IEEE micromessages. In 2019-2019 International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 2692–2696. IEEE, 2019.

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[8] Dhruv Khattar et al. Mvae: Multimodal variational autoencoder for fake news detection. In The World Wide Web Conference, pages 2915–2921. ACM, 2019.







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