# Fake news detection in the era of social media

Mgr inż, Soveatin Kuntur

Supervisor: dr hab. Maria Ganzha, prof PW

Supporting Supervisor: dr inż. Anna Wróblewska

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# Timeline

- Motivation
- Example of fake news / Terminology
- Current state of the art
- Proposed approach
- Q&A

# Motivation

- https://www.menti.com/alah63tdbeub

# Terminology

| Terminology | Definition |
|---|---|
| False News | News articles that are potentially or intentionally misleading for the readers, as they are verifiable and deliberately false |
| Misinformation | Defined as information that is inaccurate or misleading. It could spread unintentionally due to honest reporting mistakes or incorrect interpretations. |
| Disinformation | In contrast from misinformation, disinformation is false information that is spread deliberately to deceive people or promote biased agenda. |
| Propaganda | Defined as information that tries to influence the emotions, the opinions and the actions of target audiences by means of deceptive, selectively omitted and one-sided messages. The purpose can be political, ideological or religious |

Source: Pierri, F., & Ceri, S. (2019). False news on social media: a data-driven survey. *ACM Sigmod Record*, *48*(2), 18-27.

Zhang, X., & Ghorbani, A. A. (2020). An overview of online fake news: Characterization, detection, and discussion. *Information Processing & Management*, *57*(2), 102025.

- Furthermore, a massive amount of incredible and misleading information is created and displayed through the Internet, which has arisen as a potential threat to online social communities, and had a deep negative impact on the Internet activities, such as online shopping, and social networking.



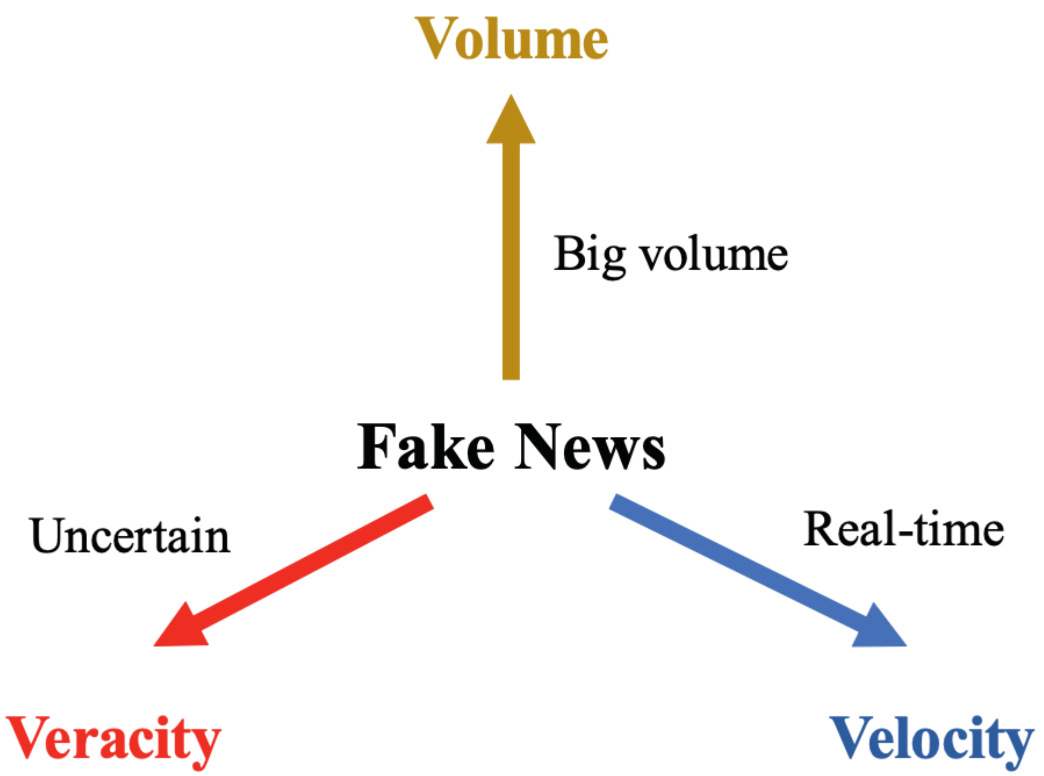



**Fig. 1.** The volume, velocity and veracity of fake news.

# Method

Traditional Approaches

Modern Approaches

# Method – Traditional Approaches

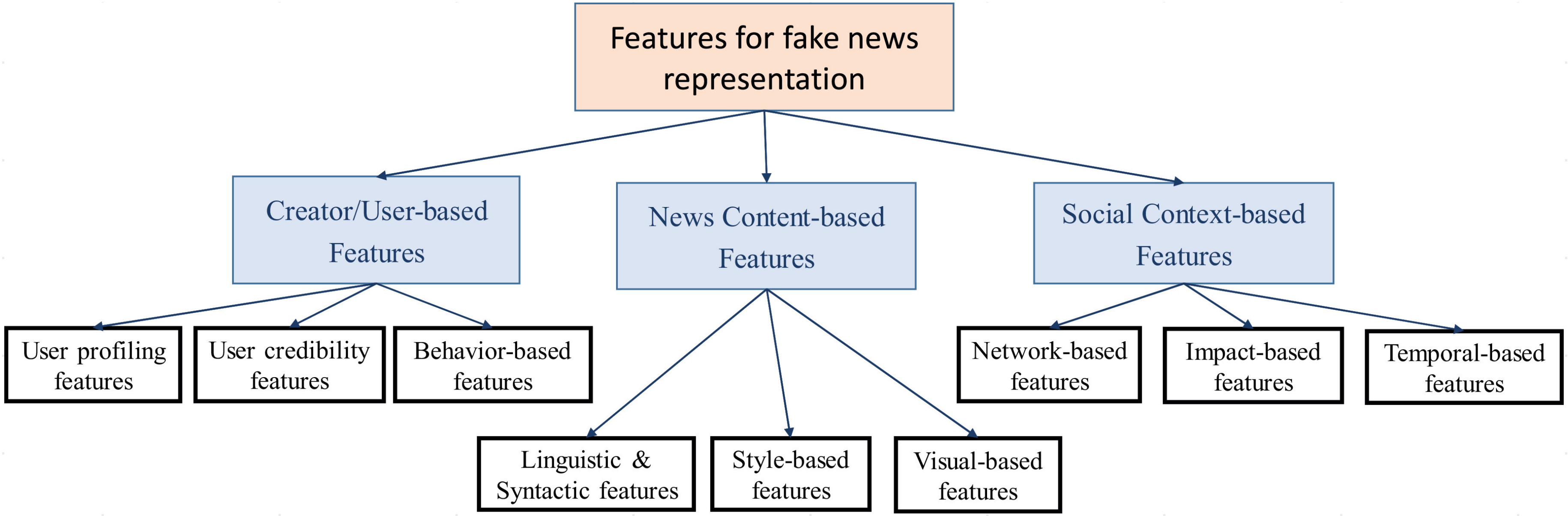
This segment is denoted as the traditional approach, as the detection of fake news is conducted manually on a per-news basis or not scaled to massive parallelism. Numerous websites offer verification services for fake news detection

# Method – Traditional Approaches

| Fast-checking website | Topics Covered | | | | | Source of the news | Rating levels |
|---|---|---|---|---|---|---|---|
| | Civic | Politics | Technology | Business | Other | | |
| Factcheck.org | yes | yes | yes | yes | yes | Claims or statements from political players | N/A |
| Politifact.com | yes | yes | yes | yes | yes | Claims or statements from political players | True, Mostly True, Half True, Mostly False, False, Pants on Fire |
| Factmata.com | no | yes | no | yes | no | N/A | N/A |

Source: Zhang, X., & Ghorbani, A. A. (2020). An overview of online fake news: Characterization, detection, and discussion. *Information Processing & Management*, *57*(2), 102025.

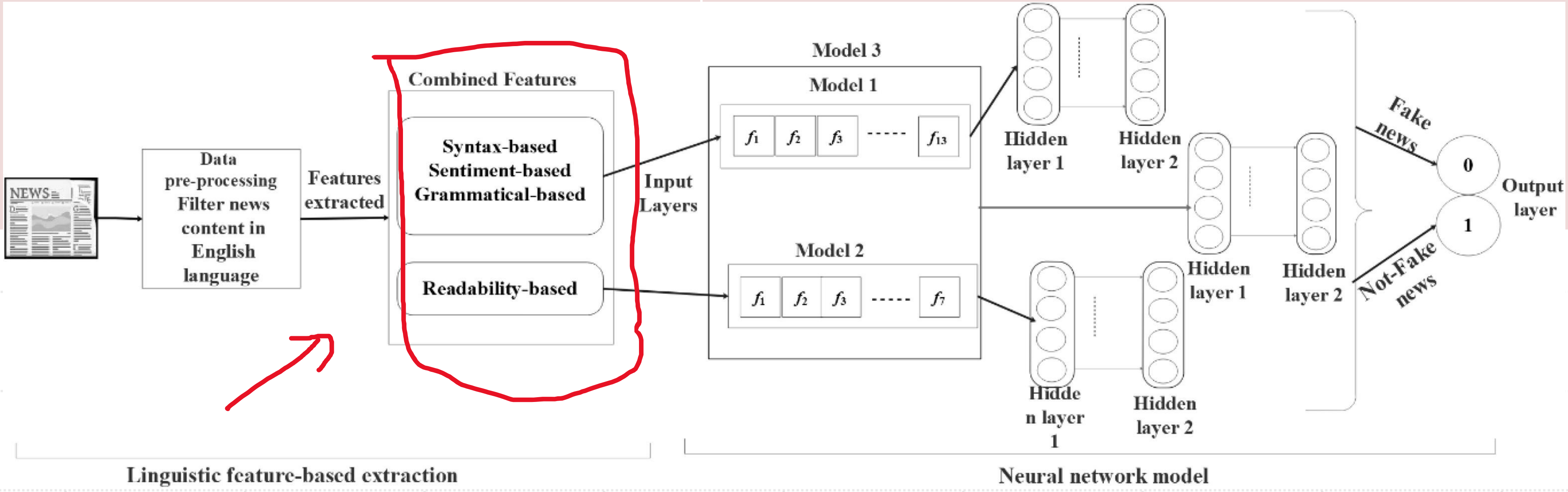
# Modern Approaches




Source: Zhang, X., & Ghorbani, A. A. (2020). An overview of online fake news: Characterization, detection, and discussion. *Information Processing & Management*, *57*(2), 102025.

# Modern Approaches – News content based feature

| Paper | Novelty |
|---|---|
| Anshika Choudhary and Anuja Arora. 2021. Linguistic feature based learning model for fake news detection and classification. Expert Systems with Applications 169 (2021), 114171 | |



# Modern Approaches – News content based feature Syntax based

Anshika Choudhary and Anuja Arora. 2021. Linguistic feature based learning model for fake news detection and classification. Expert Systems with Applications 169 (2021), 114171

Idea

Assume that fake news is produced by the same producer -> having the same writing style

Table 1. Syntax-based features.

| **Syntax-based features** | **Description** |
|---|---|
| Char count | Total no. of characters with and without spaces |
| Word count | Total no. of words in a given sentence |
| Title word count | Count the number of words in a given title |
| STOP word count | Count the total no. of stop words in a given sentence |
| Upper case word count | Count the number of uppercase words in a given sentence |
| Word density | Number of occurrences of the chosen keyword over the total no. of words in a given text. |

*Definitions 1*: Syntax-based evidences.

For a given news $A$,$X^{sy}$ consists of character count ($x_{cc}$), word count ($x_{wc}$), word density ($x_{wd}$), title word count ($x_{twc}$), and title uppercase ($x_{up}$), stop word count ($x_{stp}$).

$$X^{sy} = \{x_{cc}, x_{wc}, x_{wd}, x_{twc}, x_{up}, x_{stp}\}$$

# Modern Approaches – News content based feature

## Sentiment based

Table 2. Sentiment-based features.

| Sentiment-based features | Description |
|---|---|
| Polarity | It refers to positive and negative statements. It lies in the range of [−1,1] |
| Subjectivity | Expressing an opinion, views, or a person's feelings. It lies in the range of [0,1] |

*Definitions 2*: Sentiment-based evidences.

The following sentiment-based features of news *A*are - polarity ($x_{pol}$), and subjectivity ($x_{sub}$). $X^{sen}$={$x_{pol}$,$x_{sub}$}. Subjectivity is measures of sentiment being objective to subjective, Objective expressions are facts whereas subjective expressions are opinions, beliefs, or a person's feelings towards a specific topic. For example, of subjectivity and polarity for sentence, “Donald Trump is a great politician” is 0.9, 0.81 respectively.


- Anshika Choudhary and Anuja Arora. 2021. Linguistic feature based learning model for fake news detection and classification. Expert Systems with Applications 169 (2021), 114171

# Modern Approaches – News content based feature
# Grammatical evidences

Table 3. Grammatical features.

| Grammatical-based features | Example | Representation |
|---|---|---|
| Noun | Trump says nobody really knows if climate change is real. | Trump |
| Verb | | Is |
| Adjective | | Real |
| Pronoun | | If, nobody |
| Adverb | | Really |

*Definitions 3*: Grammatical evidences.

For a given news *A*, defining the grammatical features references as: noun count ($x_{nou}$), verb count ($x_{ver}$), adjective count ($x_{adj}$), adverb count ($x_{adv}$) and pronoun count ($x_{pro}$).

$$X^{gr} = \{x_{nou}, x_{ver}, x_{adj}, x_{adv}, x_{pro}\}$$

- Anshika Choudhary and Anuja Arora. 2021. Linguistic feature based learning model for fake news detection and classification. Expert Systems with Applications 169 (2021), 114171

# Modern Approaches – News content based feature Readability evidence

- Readability is a measure with which a reader can apprehend the written text. In simple language, the readability of a text relies on its content material i.e. the complexity of its vocabulary and syntax of its content

- Anshika Choudhary and Anuja Arora. 2021. Linguistic feature based learning model for fake news detection and classification. Expert Systems with Applications 169 (2021), 114171

Table 4. Readability features.

| Readability-based features | Description | Formulae |
|---|---|---|
| Flesch Reading Ease | Evaluate the difficulty pattern of the written text | $206.835-(1.015*ASL)-(84.6*ASW)$ |
| Automated Readability Index | Determined the level of understandability of English text | $4.71\left(\frac{x_{cc}}{x_{wc}}\right)+0.5\left(\frac{x_{wc}}{x_{st}}\right)$ |
| Gunning Fog index | Observing the writing problem | $0.4(ASL+PHW)$ |
| Coleman Liau | Focuses on characters in the text | $(0.0588*L)-(0.296*S)-15.8$ |
| Flesch-Kincaid score | Analyze the level of the written text | 3+*square root of Polysyllable Count* |
| The SMOG Index | Understand the formation of writing content | $(0.39*ASL)+(11.8*ASW)-15.59$ |
| Linsear write formula | Developed for the United States Air Force to calculate the readability of their technical manuals | $\frac{\left[\left(100-\frac{100*n_{wsy<3}}{n_w}\right)+\left(3*\frac{100*n_{wsy\leq 3}}{n_w}\right)\right]}{\left(100*\frac{n_{st}}{n_w}\right)}$ |

*Definitions 4*: Readability evidences.

Defining the Readability features: Flesch Reading Ease($x_{re}$), Automated Readability Index($x_{ari}$), Gunning Fog ($x_{gf}$), Coleman Liau ($x_{cl}$), Flesch-Kincaid Index ($x_{fki}$), The SMOG Index ($x_{smg}$), Linsear Write formula. ($x_{Lwf}$) in a news *A* shown in this table.

$$X^R = \{x_{re}, x_{ari}, x_{gf}, x_{cl}, x_{fki}, x_{smg}, x_{Lwf}\}$$

# Dataset used

This repository contains two popular and independent news

datasets, first one is Buzzfeed Political News Data was analysed for

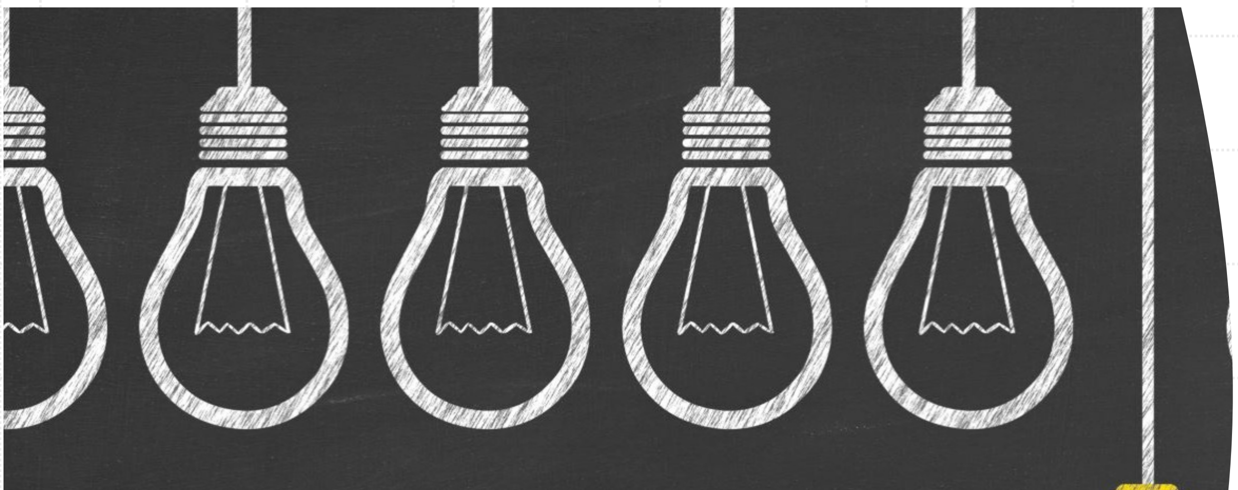
Buzzfeed News in articles and another one is Random Political News

Data

https://github.com/BenjaminDHorne/fakenewsdata1

**Table 5**
Descriptive details of dataset.

| Dataset name | News categories | News count | |
|---|---|---|---|
| | | Titles | Description |
| Buzzfeed political news | Fake news | 48 | 48 |
| | Real | 53 | 53 |
| Random political news | Fake | 75 | 75 |
| | Real | 75 | 75 |



| Model | Combination |
|---|---|
| Model 1 | syntax based features, sentiment based features, and grammatical features |
| Model 2 | readability feature |
| Model 3 | all the lingual features |

# Key idea from

- Anshika Choudhary and Anuja Arora. 2021. Linguistic feature based learning model for fake news detection and classification. Expert Systems with Applications 169 (2021), 114171

- Combining multiple feature extraction treat them as model

## Experiment Result

Anshika Choudhary and Anuja Arora. 2021. Linguistic feature based learning model for fake news detection and classification. Expert Systems with Applications 169 (2021), 114171

| Model | Experiment Setup | Result |
| --- | --- | --- |
| Model 1, Model 2, Model 3 | Epoch 100, batch size = 5 | Average accuracy 82%, 72%, 80% |
| Model 1, Model 2, Model 3 | Epoch 50, batch size = 10 | 84.12%, 77.67%, 84.52% |
| Model 1, Model 2, Model 3 | Epoch 500, batch size = 50 | Model 3 achieved average 86% |

# Experiment result cont

Key Point: Model 3 is effectively working than other 2 models because it has employed all feature together

# Modern Approaches – Creator/user content based feature

- Kai Shu, Suhang Wang, and Huan Liu. 2019. Beyond News Contents: The Role of Social Context for Fake News Detection. In Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining (WSDM '19). Association for Computing Machinery, New York, NY, USA, 312–320. https://doi.org/10.1145/3289600.3290994

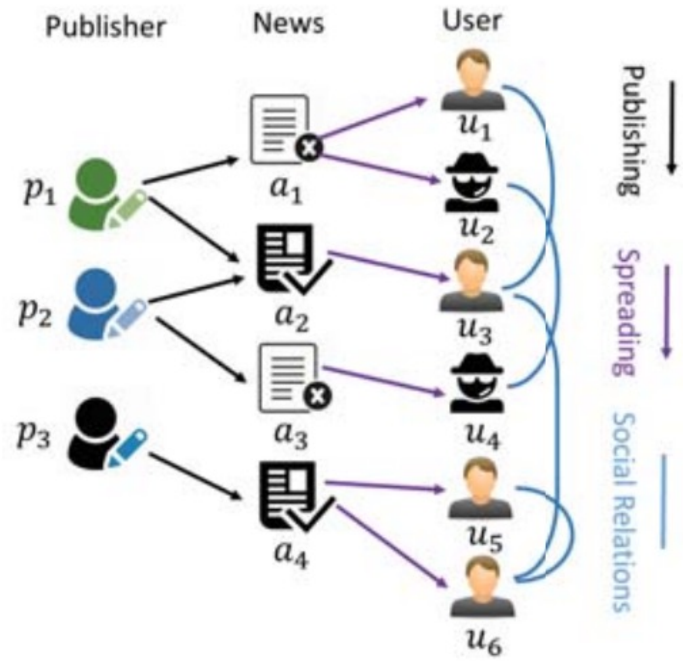



**Figure 1: An illustration of tri-relationship among publishers, news pieces, and users, during the news dissemination process. For example, an edge $(p \rightarrow a)$ demonstrates that publisher $p$ publishes news item $a$, an edge $(a \rightarrow u)$ represents news item $a$ is spread by user $u$, and an edge $(u_1 \leftrightarrow u_2)$ indicates the social relation between user $u_1$ and $u_2$.**

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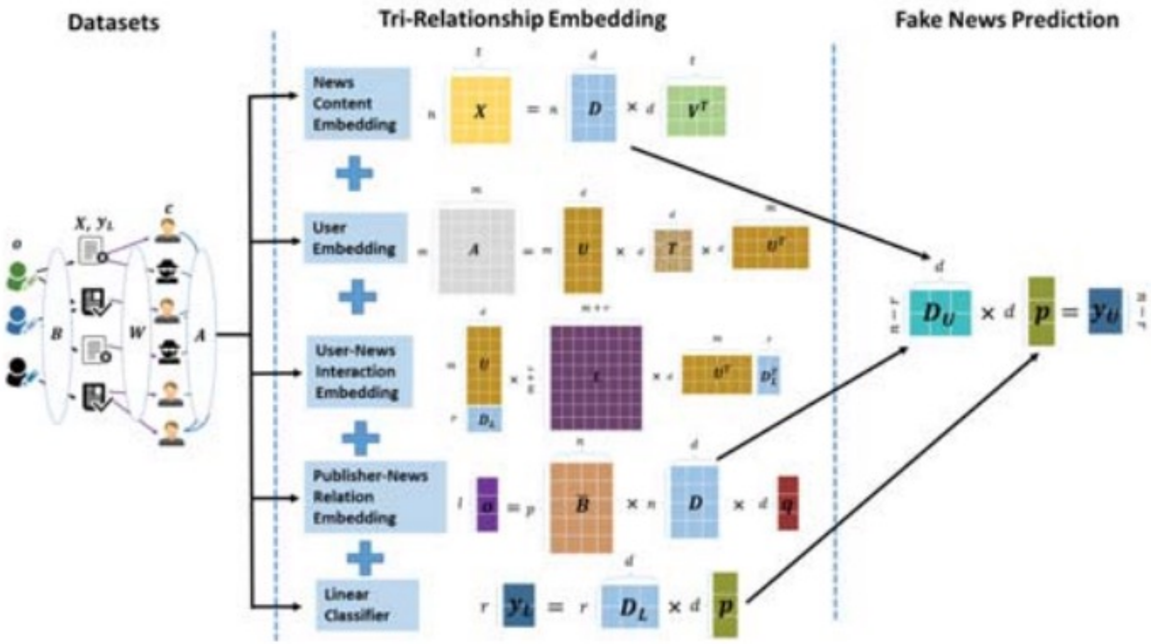



**Figure 2: The tri-relationship embedding framework, which consists of five components: news contents embedding, user embedding, user-news interaction embedding, publisher-news relation embedding, and news classification.**

# Modern Approaches – Creator/user content based feature Dataset

- By using benchmark dataset from fakenewsnet


- Kai Shu, Suhang Wang, and Huan Liu. 2019. Beyond News Contents: The Role of Social Context for Fake News Detection. In Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining (WSDM '19). Association for Computing Machinery, New York, NY, USA, 312–320. https://doi.org/10.1145/3289600.3290994


**Table 1: The statistics of FakeNewsNet dataset**

| Platform | BuzzFeed | PolitiFact |
|---|---|---|
| # Users | 15,257 | 23,865 |
| # Engagements | 25,240 | 37,259 |
| # Social Links | 634,750 | 574,744 |
| # Candidate news | 182 | 240 |
| # True news | 91 | 120 |
| # Fake news | 91 | 120 |
| # Publisher | 9 | 91 |

# Modern Approaches – Creator/user content based feature Experimental settings

- RTS stands for Rhetorical Structure Theory, which builds a tree structure to represent rhetorical relations among the words in the text. RST can extract style-based features of news by mapping the frequencies of rhetorical relations to a vector space
- Code: https://github.com/jiyfeng/DPLP
- Kai Shu, Suhang Wang, and Huan Liu. 2019. Beyond News Contents: The Role of Social Context for Fake News Detection. In Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining (WSDM '19). Association for Computing Machinery, New York, NY, USA, 312–320. https://doi.org/10.1145/3289600.3290994

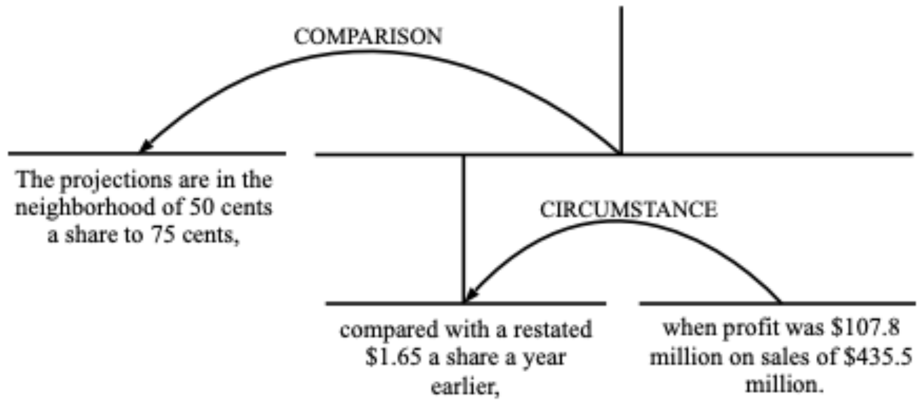



Figure 1: An example of RST discourse structure.

# Modern Approaches – Creator/user content based feature
# Experimental settings

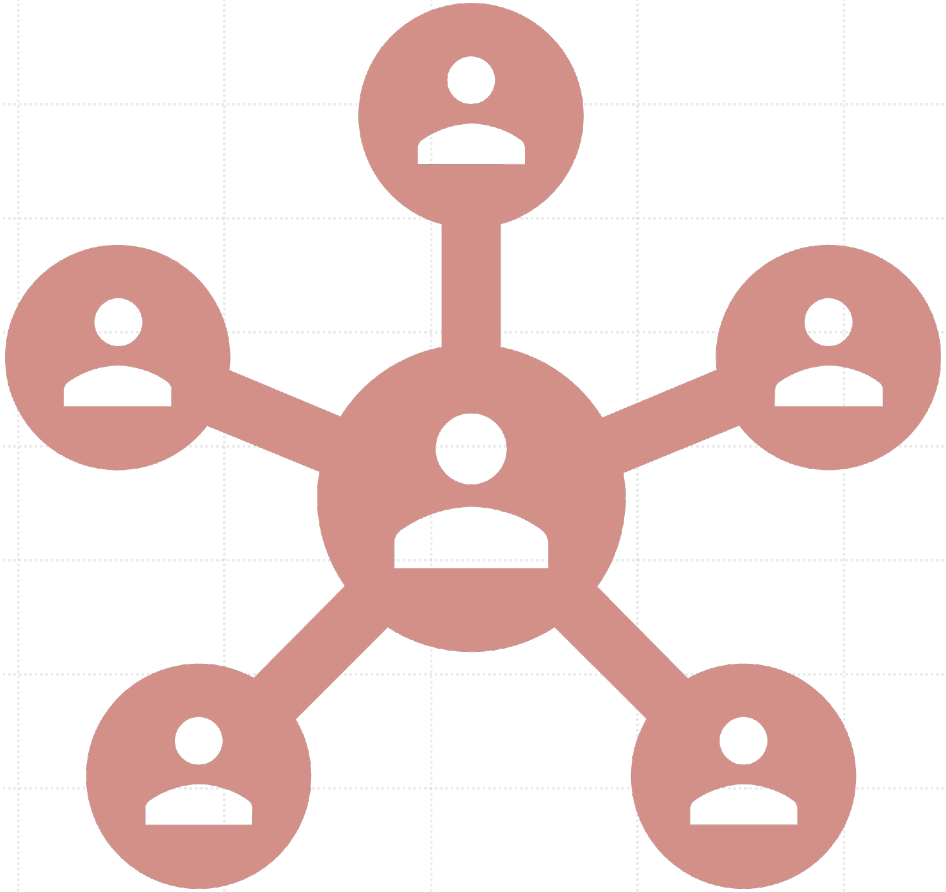
LIWC stands for Linguistic Inquiry and Word Count, which is widely used to extract the lexicons falling into psycholinguistic categories. It's based on a large sets of words that represent psycholinguistic processes, summary categories, and part-of-speech categories. It learns a feature vector from a psychology and deception perspective

Link: https://www.liwc.app/

# Modern Approaches – Creator/user content based feature Experimental settings

- Castillo extract various kinds of features from those users who have shared a news item on social media. The features are extracted from user profiles and friendship network. We also include the credibility score of users inferred

- Carlos Castillo, Marcelo Mendoza, and Barbara Poblete. 2011. Information credibility on twitter. In Proceedings of the 20th international conference on World wide web. ACM, 675–684



# Modern Approaches – Creator/user content based feature

## Experimental settings

- RST+Castillo, LIWC+Castillo


- James W Pennebaker, Ryan L Boyd, Kayla Jordan, and Kate Blackburn. 2015. The development and psychometric properties of LIWC2015. Technical Report
- Carlos Castillo, Marcelo Mendoza, and Barbara Poblete. 2011. Information credibility on twitter. In Proceedings of the 20th international conference on World wide web (WWW '11). Association for Computing Machinery, New York, NY, USA, 675–684. https://doi.org/10.1145/1963405.1963500
- Victoria L Rubin, N Conroy, and Yimin Chen. 2015. Towards news verification: Deception detection methods for news discourse. In Hawaii International Conference on System Sciences.

# Result

- Kai Shu, Suhang Wang, and Huan Liu. 2019. Beyond News Contents: The Role of Social Context for Fake News Detection. In Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining (WSDM '19). Association for Computing Machinery, New York, NY, USA, 312–320. https://doi.org/10.1145/3289600.3290994

**Table 2: Best performance comparison for fake news detection**

| Datasets | Metric | RST | LIWC | Castillo | RST+Castillo | LIWC+Castillo | TriFN |
|---|---|---|---|---|---|---|---|
| **BuzzFeed** | Accuracy | 0.600 ± 0.063 | 0.719 ± 0.074 | 0.800 ± 0.037 | 0.816 ± 0.052 | 0.825 ± 0.052 | **0.864 ± 0.026** |
| | Precision | 0.662 ± 0.109 | 0.722 ± 0.077 | 0.822 ± 0.077 | 0.879 ± 0.049 | 0.821 ± 0.061 | **0.849 ± 0.040** |
| | Recall | 0.615 ± 0.018 | 0.732 ± 0.171 | 0.776 ± 0.027 | 0.748 ± 0.098 | 0.829 ± 0.055 | **0.893 ± 0.013** |
| | F1 | 0.633 ± 0.056 | 0.709 ± 0.075 | 0.797 ± 0.044 | 0.805 ± 0.066 | 0.822 ± 0.035 | **0.870 ± 0.019** |
| **PolitiFact** | Accuracy | 0.604 ± 0.060 | 0.688 ± 0.063 | 0.796 ± 0.052 | 0.838 ± 0.036 | 0.829 ± 0.052 | **0.878 ± 0.017** |
| | Precision | 0.564 ± 0.064 | 0.725 ± 0.087 | 0.767 ± 0.056 | 0.851 ± 0.052 | 0.821 ± 0.116 | **0.867 ± 0.034** |
| | Recall | 0.705 ± 0.148 | 0.617 ± 0.100 | 0.889 ± 0.044 | 0.824 ± 0.063 | 0.879 ± 0.047 | **0.893 ± 0.023** |
| | F1 | 0.615 ± 0.074 | 0.666 ± 0.092 | 0.822 ± 0.037 | 0.835 ± 0.043 | 0.843 ± 0.054 | **0.880 ± 0.015** |

# Result

- Kai Shu, Suhang Wang, and Huan Liu. 2019. Beyond News Contents: The Role of Social Context for Fake News Detection. In Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining (WSDM '19). Association for Computing Machinery, New York, NY, USA, 312–320. https://doi.org/10.1145/3289600.3290994

**Table 3: Average F1 of baselines for different learning algorithms on BuzzFeed. Best scores are highlighted.**

| Method | RST | LIWC | Castillo | RST +Castillo | LIWC +Castillo |
|---|---|---|---|---|---|
| LogReg | 0.519 | 0.660 | 0.714 | 0.728 | 0.760 |
| NBayes | 0.511 | 0.370 | 0.600 | 0.716 | 0.680 |
| DTree | 0.566 | 0.581 | 0.736 | 0.681 | 0.772 |
| RForest | 0.538 | 0.709 | 0.767 | 0.805 | 0.733 |
| XGBoost | 0.480 | 0.672 | 0.797 | 0.795 | 0.782 |
| AdaBoost | 0.633 | 0.701 | 0.724 | 0.791 | 0.768 |
| GradBoost | 0.492 | 0.699 | 0.772 | 0.724 | 0.822 |

**Table 4: Average F1 of baselines for different learning algorithms on PolitiFact. Best scores are highlighted.**

| Method | RST | LIWC | Castillo | RST +Castillo | LIWC +Castillo |
|---|---|---|---|---|---|
| LogReg | 0.615 | 0.432 | 0.707 | 0.668 | 0.653 |
| NBayes | 0.537 | 0.486 | 0.442 | 0.746 | 0.687 |
| DTree | 0.514 | 0.661 | 0.771 | 0.792 | 0.772 |
| RForest | 0.463 | 0.586 | 0.767 | 0.835 | 0.836 |
| XGBoost | 0.552 | 0.648 | 0.822 | 0.783 | 0.823 |
| AdaBoost | 0.502 | 0.666 | 0.800 | 0.787 | 0.831 |
| GradBoost | 0.517 | 0.650 | 0.818 | 0.803 | 0.843 |

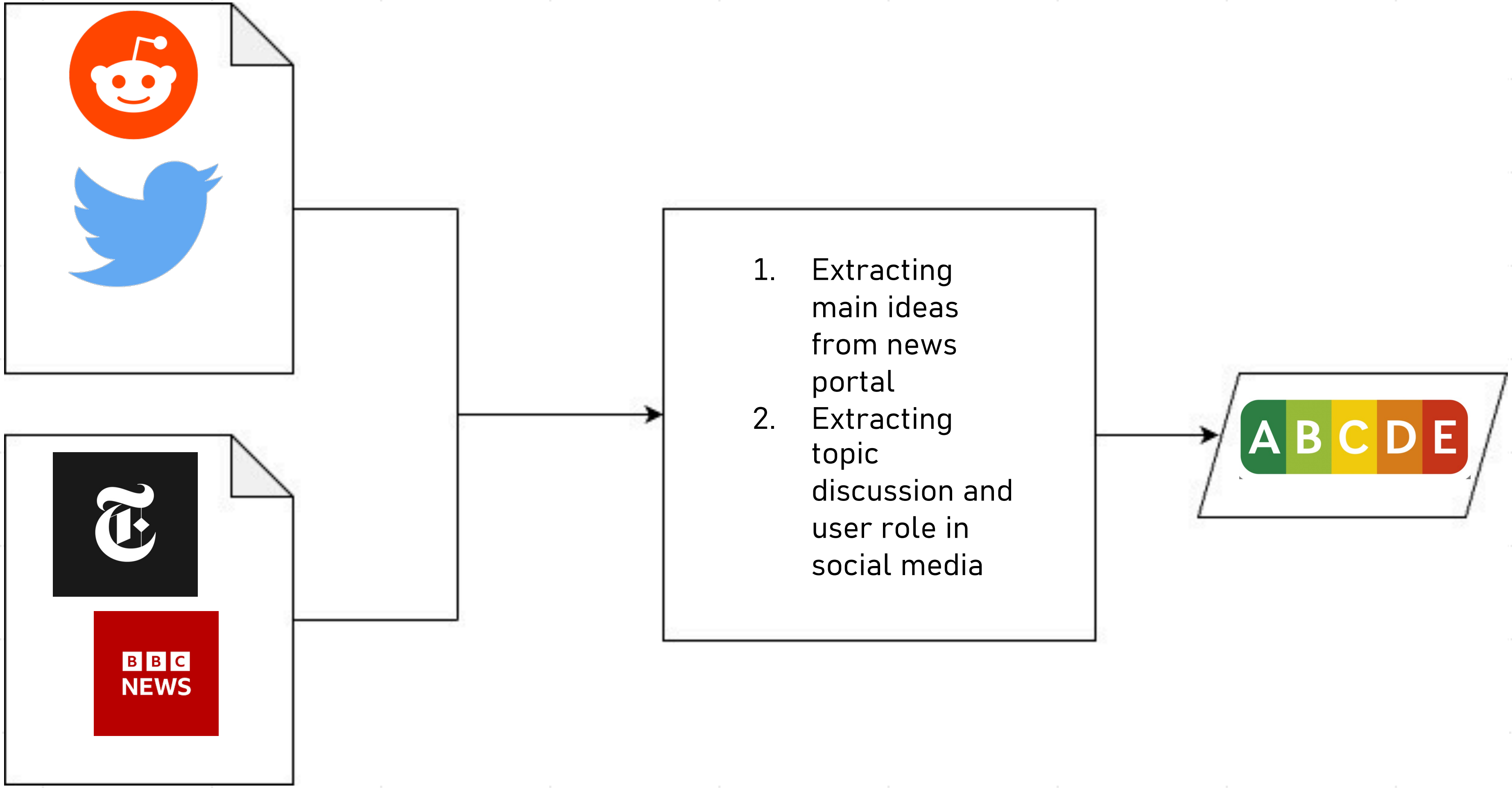
# Conclusion from both paper

- Feature extraction does play significant role
- Classification algorithm is already settled

# Proposed Approach for PhD Work

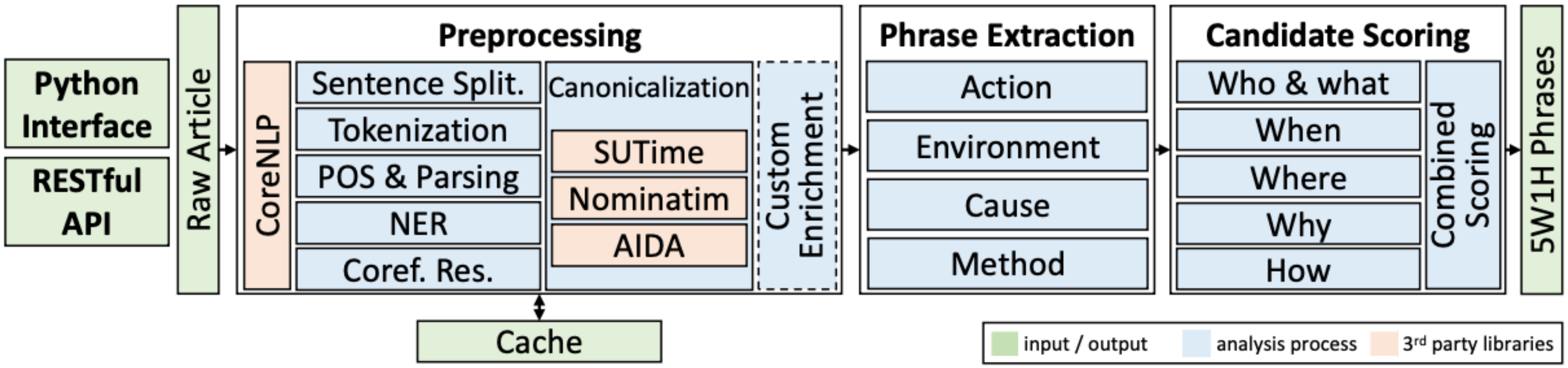
- Dataset limited to text form
- News content + Network content

# WORKFLOW


BBC NEWS
1. Extracting main ideas from news portal
2. Extracting topic discussion and user role in social media
A B C D E

# Treating dataset from news portal

- Hamborg, F., Breitinger, C., & Gipp, B. (2019). Giveme5w1h: A universal system for extracting main events from news articles. *arXiv preprint arXiv:1909.02766*.



# Challenge

- Time dimension (fake news this time/this hour, is it still fake news for the next couple of hours?)
- Data stream fake news detection
- Unbias dataset due to ethical AI

# Q&A

- Your valueable input is extremely needed! ;)