

SemEval-2019 Task 4: Hyperpartisan News Detection



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Task 4: Hyperpartisan News Detection Background

The left-right political spectrum is a system of classifying political positions, ideologies and parties. Left-wing politics and right-wing politics are often presented as opposed, although either may adopt stances from the other side. [\[Wikipedia\]](#)



A partisan is a politician who strongly supports their party's policies and is reluctant to compromise with political opponents.

The meaning of the term has changed dramatically: “partisan” now refers to an individual with a psychological identification with one of the major parties. [\[Wikipedia\]](#)

Task 4: Hyperpartisan News Detection Is it Fake News?

We see fake news as “disinformation displayed as news articles”

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FIRSTDRAFT

7 TYPES OF MIS- AND DISINFORMATION



SATIRE OR PARODY

No intention to cause harm but has potential to fool



MISLEADING CONTENT

Misleading use of information to frame an issue or individual



IMPOSTER CONTENT

When genuine sources are impersonated



FABRICATED CONTENT

New content is 100% false, designed to deceive and do harm



FALSE CONNECTION

When headlines, visuals or captions don't support the content



FALSE CONTEXT

When genuine content is shared with false contextual information



MANIPULATED CONTENT

When genuine information or imagery is manipulated to deceive

Image: Claire Wardle, First Draft

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Task 4: Hyperpartisan News Detection

Is it Fake News?

Motivations for mis- and disinformation:








FIRSTDRAFT		MISINFORMATION MATRIX					
	 SATIRE OR PARODY	 FALSE CONNECTION	 MISLEADING CONTENT	 FALSE CONTEXT	 IMPOSTER CONTENT	 MANIPULATED CONTENT	 FABRICATED CONTENT
POOR JOURNALISM		✓	✓	✓			
TO PARODY	✓				✓		✓
TO PROVOKE OR TO 'PUNK'					✓	✓	✓
PASSION				✓			
PARTISANSHIP			✓	✓			
PROFIT		✓			✓		✓
POLITICAL INFLUENCE			✓	✓		✓	✓
PROPAGANDA			✓	✓	✓	✓	✓

Image: Claire Wardle, First Draft

Task 4: Hyperpartisan News Detection Is it Fake News?

Motivations for mis- and disinformation: includes partisanship








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PASSION				✓			
PARTISANSHIP			✓	✓			
PROFIT		✓			✓		✓
POLITICAL INFLUENCE			✓	✓		✓	✓
PROPAGANDA			✓	✓	✓	✓	✓

Image: Claire Wardle, First Draft

Task 4: Hyperpartisan News Detection Is it Fake News?

Motivations for publishing hyperpartisan news are not just partisanship








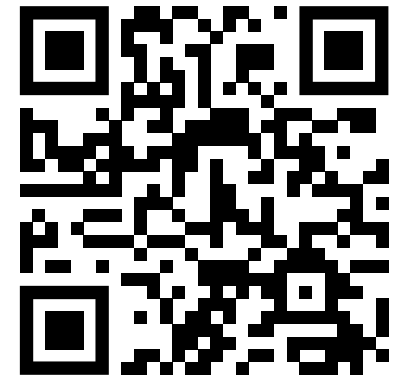
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	 SATIRE OR PARODY	 FALSE CONNECTION	 MISLEADING CONTENT	 FALSE CONTEXT	 IMPOSTER CONTENT	 MANIPULATED CONTENT	 FABRICATED CONTENT
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PASSION				✓			
PARTISANSHIP			✓	✓			
PROFIT		✓			✓		✓
POLITICAL INFLUENCE			✓	✓		✓	✓
PROPAGANDA			✓	✓	✓	✓	✓

Image: Claire Wardle, First Draft

Task 4: Hyperpartisan News Detection Data

Task: Given the text and markup of an online news article, decide whether the article is hyperpartisan or not.

- ❑ Dataset Annotated by Article: 1 273 articles.
- ❑ Manual annotation of each article by crowdworkers.
 - Articles from ~ 500 US news publishers
 - Crowdsworker reliability estimate by Beta reputation system (Ismail and Josang 2002)
 - Krippendorff's alpha of employed annotations (3 per article): 0.5
 - Public set: 645 articles; hidden test set: 628 articles, balanced
 - No publisher-overlap between sets



doi.org/10.5281/zenodo.1489920

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 - Krippendorff's alpha of employed annotations (3 per article): 0.5
 - Public set: 645 articles; hidden test set: 628 articles, balanced
 - No publisher-overlap between sets
- ❑ Dataset Annotated by Publisher: 754 000 articles.
- ❑ Manual annotation of each publisher by journalists.
 - Annotation of ~400 US news publishers by BuzzFeed and Media Bias Fact Check
 - Crawling of articles feeds
 - Content wrappers were implemented for each publisher
 - Filtering to political news, English, at least 40 words, correct encoding
 - Public set: 750 000 articles, balanced; hidden test set: 4 000 articles, balanced
 - No publisher-overlap between sets



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Task 4: Hyperpartisan News Detection Methods

Employed features

N-Grams character, word, part-of-speech

Embeddings BERT, Word2Vec, fastText, GloVe, ELMo, word clusters, sentences

Stylometry punctuation, structure, readability, lexicons, trigger words

Emotionality sentiment, emotion, subjectivity, polarity

Named entities nationalities, religious and political groups

Quotations count, discarded

Hyperlinks lists of hyperpartisan pages

Publication date year, month


Classifiers

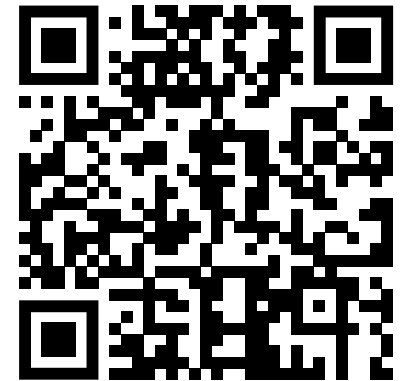
Convolutional neural networks, Long short term memory, Support vector machines, Random Forest, Linear model, Naive Bayes, XGBOOST, Maximum Entropy, Rule-based, ULMFit

Task 4: Hyperpartisan News Detection

Results on dataset annotated by article

Team	Authors	Acc.	Prec.	Rec.	F1.
Bertha von Suttner	Jiang et al.	0.822	0.871	0.755	0.809
Vernon Fenwick	Srivastava et al.	0.820	0.815	0.828	0.821
Sally Smedley	Hanawa et al.	0.809	0.823	0.787	0.805
Tom Jumbo Grumbo	Yeh et al.	0.806	0.858	0.732	0.790
Dick Preston	Isbister and Johansson	0.803	0.793	0.818	0.806
Borat Sagdiyev	Palić et al.	0.791	0.883	0.672	0.763
Morbo	Isbister and Johansson	0.790	0.772	0.822	0.796
Howard Beale	Mutlu et al	0.783	0.837	0.704	0.765
Ned Leeds	Stevanoski and Gievska	0.775	0.865	0.653	0.744
Clint Buchanan	Drissi et al.	0.771	0.832	0.678	0.747
+ 32 more					

- ❑ 322 registrations
- ❑ 184 virtual machines assigned
- ❑ 42 software submissions from as many teams
- ❑ Ongoing submissions in  TIRA



[pan.webis.de/semeval19/
semeval19-web/leaderboard.html](https://pan.webis.de/semeval19/semeval19-web/leaderboard.html)

Task 4: Hyperpartisan News Detection

Results on meta-learning dataset

Team	Authors	Acc.	Prec.	Rec.	F1.
Bertha von Suttner alone	Jiang et al.	0.851	0.901	0.788	0.841

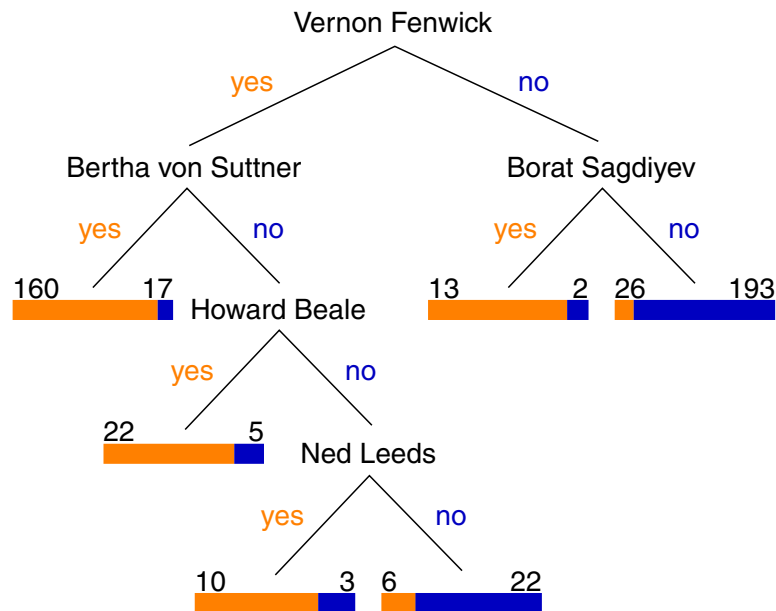
- ❑ Meta-learning dataset created from test dataset: 66% training, 33% test
- ❑ Accuracy higher (from 0.822)

Task 4: Hyperpartisan News Detection

Results on meta-learning dataset


Team	Authors	Acc.	Prec.	Rec.	F1.
Majority Vote	Kiesel et al.	0.885	0.892	0.875	0.883
J48-M10	Kiesel et al.	0.880	0.916	0.837	0.874
Bertha von Suttner alone	Jiang et al.	0.851	0.901	0.788	0.841

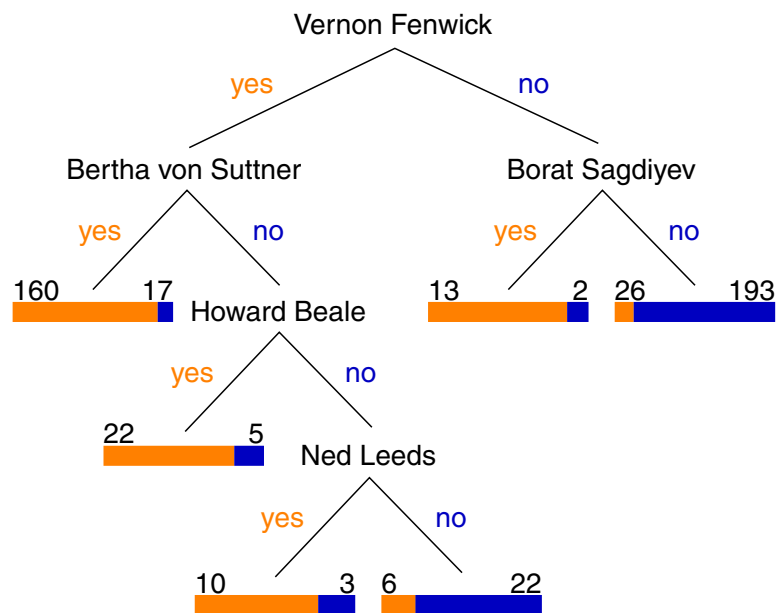
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- ❑ Baselines beat best single system



Task 4: Hyperpartisan News Detection Results on meta-learning dataset

Team	Authors	Acc.	Prec.	Rec.	F1.
Fernando Pessa	Cruz et al.	0.899	0.895	0.904	0.900
Spider Jerusalem	Alabdulkarim and Alhindi	0.899	0.903	0.894	0.899
Majority Vote	Kiesel et al.	0.885	0.892	0.875	0.883
J48-M10	Kiesel et al.	0.880	0.916	0.837	0.874
Bertha von Suttner alone	Jiang et al.	0.851	0.901	0.788	0.841


- ❑ Meta-learning dataset created from test dataset: 66% training, 33% test
- ❑ Accuracy higher (from 0.822)
- ❑ Baselines beat best single system
- ❑ Both participants beat the baselines
- ❑ They use a Random Forest and a weighted majority vote, respectively
- ❑ Ongoing submissions in  TIRA

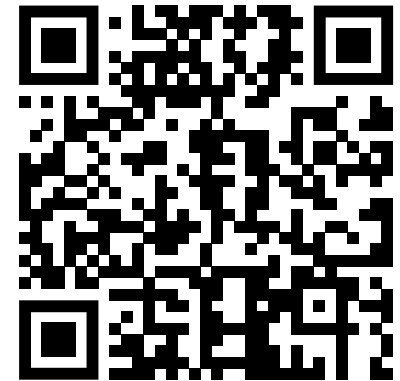


Task 4: Hyperpartisan News Detection

Results on dataset annotated by publisher

Team	Authors	Acc.	Prec.	Rec.	F1.
Tintin	Bestgen	0.706	0.742	0.632	0.683
Joseph Rouletabille	Moreno et al.	0.680	0.640	0.827	0.721
Brenda Starr	Papadopoulou et al.	0.664	0.627	0.807	0.706
Xenophilus Lovegood	Zehe et al.	0.663	0.632	0.781	0.699
Yeon Zi	Lee et al.	0.663	0.635	0.766	0.694
Miles Clarkson	Zhang et al.	0.652	0.612	0.832	0.705
Jack Ryder	Shaprin et al.	0.645	0.600	0.869	0.710
Bertha von Suttner	Jiang et al.	0.643	0.616	0.762	0.681
+ 16 more					
Robin Scherbatsky	Marx and Akut	0.524	0.822	0.062	0.116
+ 3 more					

- ❑ 28 teams (of 42)
- ❑ Accuracy lower (from 0.822)
- ❑ Most teams focused on the other dataset
- ❑ Ranking very different
- ❑ Ongoing submissions in  TIRA




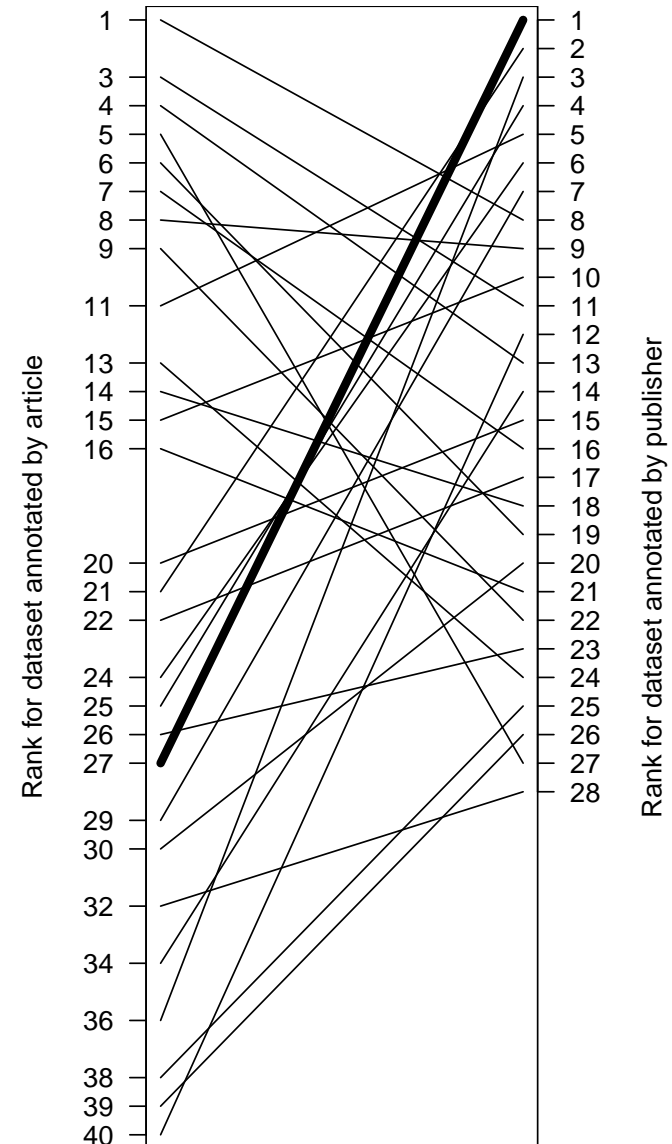
[pan.webis.de/semeval19/
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Task 4: Hyperpartisan News Detection

Comparison of dataset rankings

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Task 4: Hyperpartisan News Detection Conclusion

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- ❑ So far, 10 teams released their code open source

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Evaluations on *pan19-hyperpartisan-news-detection-by-article-test-dataset-2018-12-07*

User	Software	Run	Input run	accuracy
→ lorelai-rory-gilmore	software1	2019-06-03-04-13-49	2019-06-02-19-39-14	0.8248407643312102
bertha-von-suttner	software1	2019-01-22-22-37-04	2019-01-22-11-53-33	0.821656050955414
vernon-fenwick	software6	2019-01-28-11-03-17	2019-01-28-10-38-04	0.8200636942675159

...

→ betty-brant-leeds	software2	2019-06-02-14-59-59	2019-06-02-09-54-39	0.7898089171974523
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vernon-fenwick	software6	2019-01-28-11-03-17	2019-01-28-10-38-04	0.8200636942675159	
...					
➔ betty-brant-leeds	software2	2019-06-02-14-59-59	2019-06-02-09-54-39	0.7898089171974523	

- ❑ Challenge ahead: explainability