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FIP: Fake News Detection System Using Incompatibility Probability

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Abstract

We propose FIP, a new method for fake news detection. In this framework a topic is a statement about an event, such as a headline. News articles may refer to or elaborate on the supposed event. Our technique relies on calculating the incompatibility probability for news articles with respect to a topic based on their stances determined by a reviewer. In the relevant cases where a news article is related to a topic, the stances are ***agree***, ***disagree***, and ***discuss***, where the last option reflects uncertainty. As we show experimentally, the news articles with the highest incompatibility probability values are the best candidates for being fake news.

Keywords: fake news, incompatibility probability

1 Introduction

In recent years, the term "fake news" has been used extensively for disinformation, misinformation, hoaxes, propaganda, satire, rumors, click-bait, and junk news[1]. While some researchers do not believe that there is a precise definition of fake news [1], some other researchers define it as news articles that are intentionally made up to mislead or misinform readers and whose falsity is verifiable using other resources [2, 3]. A survey [4] summarized three major

identifying features of fake news: their form as a news article, their misleading intent that could be malicious or satirical, and their verifiable content as partially or completely false.

Fake news has a long history, going back at least to the famous Great Moon Hoax of April 1835, that the New York Sun newspaper published as a series of articles stating that a famous astronomer found life on the moon [5]. The study of fake news, especially rumors, can be traced back to the end of WWII [6, 7]. In recent decades, the amount of fake news has increased tremendously due to the development of the internet and social media.

While the original purpose of social media was not for spreading news but finding and maintaining relationships with friends, it became a breeding ground for real as well as fake news due to the following two factors. First, social media have a huge number of users who may spread news and information among themselves much faster than through any other media[1]. Research in [8] showed that social media have become an essential publishing tool for journalists [9, 10] as well as the primary way for readers to obtain the most up-to-date news [11]. Second, social media have very few (or no) limitations for posting information with little or no control and fact-checking. Therefore, the spread of news and information through them often leads to poor quality, unverified, and fake news[2, 12]. For example, 64% of users who use Twitter for news say that they have encountered some news later found to be fake, and 16% of Twitter news users mention that they retweeted or posted a tweet they later discovered to be false [13]. Furthermore, it was shown that lies spread six times faster than the truth on Twitter, and fake news is retweeted much more often than real news [14].

There may be different motivations for spreading fake news. For one thing, fake news articles may bring significant marketing and advertising profits for their providers [2]. Also, the providers of fake news may seek to influence public thoughts and opinions on certain subjects for political purposes [2]. In addition, the presence and increasing amount of deceptive agents, such as robots/bots, crawlers, and trolls, is considered another major source for spreading fake news and rumors [15, 16].

Unfortunately, fake news can have significant negative effect. by influencing public opinion and the understanding of certain events [8]. In the 2016 US presidential election, fake news concerning Hillary Clinton may have had a substantial impact on the final election result [1, 2]. Similarly, fake news also influenced the UK Brexit referendum [17] in 2016, and the French presidential election in 2017 [18]. In 2013 a fake tweet that President Obama had been injured in an explosion at the White House caused a drop in the stock market with the S&P 500 declining 0.9% — enough to wipe out $130 billion in stock value in a matter of seconds [19].

Because of the considerable recent increase of fake news, the interest of researchers about fake news, rumors, and the technology of their detection has grown substantially in the past few years. Figure 1 shows the number of

[1] https://socialnetworking.procon.org/

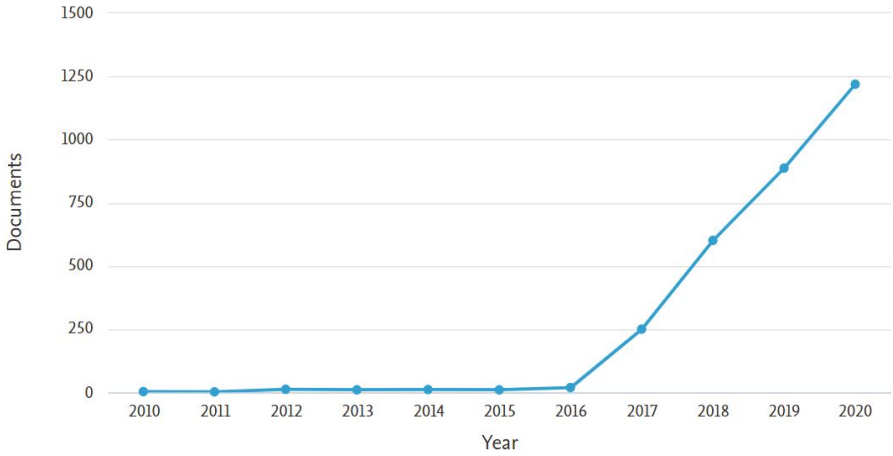

Fig. 1 The number of research documents related to fake news between 2010 and 2020 in the Scopus Database

research documents related to the key words "Fake News" published between 2010 and 2020, indexed through the Scopus Database [2]. Although only 3 related documents were found in 2010, fake news began to attract considerable attention right after 2016, probably because of its influence on the 2016 US presidential election. The number of related research documents reached 1219 in 2020.

In this paper we use an idea from our paper [20] and extend it to a novel framework, named FIP, to detect the fake news among a set of news articles using the incompatibility probability (IP) of the news articles. We introduce a systematic approach to define such probability based on properties of data and relationships among news articles. Using this incompatibility probability (IP), we can detect the news articles that are more incompatible with others. Those news articles are more likely fake or at least most worthy for further examination.

Our major contributions in this paper are as follows:

- We introduce a synergistic definition of news incompatibility based on properties of the data and relationships among the news articles.
- We develop the efficient FIP framework that systematically utilizes news incompatibility in order to evaluate the reliability of news articles. In particular, our framework allows us to detect fake news.
- We provide a comprehensive experimental study demonstrating the effectiveness of the proposed framework for fake news detection.

The plan of this paper is as follows. Section 2 describes related work. Our method of dealing with incompatibility is explained in Section 3. Section 4 provides the details of our experiments. The conclusion is given in Section 5.

[2] www.scopus.com

2 Related Work

2.1 Fake News Detection

Several recent survey papers summarize the broad range of research devoted to fake news including [16], [21], [22], [23], [4], [24], and [25]. The most important problem in this area is to identify fake news automatically or to detect the ones most worthy for further examination. As stated in the previous section, there are various types of fake news and there is a close connection with rumors. Therefore, fake news detection techniques have a considerable overlap with the recognition of rumors, fake opinion, fake accounts, hoaxes, and frauds. For that reason we comprise several algorithms from papers about those that can also be applied for fake news detection.

Fake news detection uses primarily three kinds of information:

- Some technologies utilize the content of news articles, including at the word, syntactic, and semantic levels. For example, the models in [26] and [27] effectively apply the word and syntactic level features of news articles. There are also models, such as the ones in [28],[29], [30], [31], [32], [33], [34], and [35], that apply neural networks to extract and apply semantic features in fake news detection, particularly due to the fast development of neural networks in natural language processing (NLP) in recent years.
- Some researchers focus on news profile features, such as the number of likes and propagation times, and user profile features, such as the number of posts, registration age, and the number of followers, while exploring information from social networks where the news is spread and to the people in the network. Researchers usually use these social network features with the content features together to identify fake news[36], [37], [38], [39], [40], [41], [42], and [43], as some studies concluded that systems cannot detect fake news accurately from only social network features. Numerous network structures can be acquired from this area, such as user-follow-user networks, news-agree/conflict-news networks, and user-spread-news networks [44], [45], [46], [47], [48], and [49].
- A smaller number of research projects target news fact checking, where the reference facts are in a preexisting knowledge base such as DBpedia [50], [51], and [52].

In our previous work, we introduced a framework, FaNDS[53], to detect fake news through a specific energy flow model applied to an inconsistency graph based on news stance conflicts. We also proposed a subjective opinions based model that can also handle the uncertain cases beside the obvious conflicts[54]. In this paper, we propose a new method, FIP, to evaluate the trustworthiness of news articles based on their incompatibility probability. This will be described in detail in Section 3, and tested in Section 4. Our new method has the following advantages:

- It provides a concise framework without a complex graph structure.

- It utilizes both conflicting and uncertainty relationship information.
- Labeled training data are not required.

3 The FIP Method for Fake News Detection

This section has three subsections. The first describes the setup for our work consisting of topics, news articles, and stances. The second gives the definition of pairwise incompatibility probability (IP). The third extends pairwise IP to other versions of IP that are used in the experiments to find fake news.

3.1 The Topic-News Article-Stance Framework

The problem we study in this paper is inspired by the Fake News Challenge (FNC-1) [3]. FNC-1 focuses on the stage named Stance Detection, which is the first stage of Fake News Detection to comprehend how different news articles report about a topic. Our new method takes a further step that focuses on the second stage of Fake News Detection, to discover which news articles are more likely to be fake news, based on the structure of the Topic-News Article-Stance data that we next explain.

We use three basic concepts for our reconstruction of the FNC-1 structure:

- Topic: a short sentence/statement expressing a main idea or point.
- News Article: a body of text with one or more paragraphs.
- Stance: a certain attitude or opinion of a news article to a topic. In FNC-1 an evaluator assigned one of four stances: *agree*, *discuss*, *disagree*, and *unrelated* to specific topic and news article pairs. We ignore *unrelated* because we deal only with the case where a news article is related to a topic. The meaning of *agree* and *disagree* are self-explanatory; *discuss* represents uncertainty. We will sometimes abbreviate *agree* to *a*, *discuss* to *di* and *disagree* to *da*.

Table 1 and Table 2 show examples of the Topic-News Article-Stance Structure. The first table gives an example of a topic and (portions of) 4 news articles that illustrate the different stances. For the second table we point out the following:

- There are 2 topics, T_a and T_b, and 7 news articles. T_a has 5 related news articles, 3 *agree*, 1 *disagree*, and 1 *discuss*. T_b has only 2 related news articles, 1 *agree*, and 1 *disagree*.
- For Topic T_a, News n_1, n_2, and n_3 have the same stance, *agree*; news n_4 has the opposite stance, *disagree*; and news n_5 has the uncertain stance, *discuss*. Thus n_1, n_2, and n_3 are compatible with each other. We consider each *agree* news to be more incompatible with the *disagree* news than with the *discuss* news.
- For Topic T_b, the 2 corresponding news, n_6 *agree* and n_7 *disagree*, are incompatible.

[3] http://www.fakenewschallenge.org/

Table 1 Example of the Topic-News Article-Stance Framework from FNC-1

Topic	Stance	News Article (Portion)
"Robert Plant Ripped up $800M Led Zeppelin Reunion Contract"	agree	"... Led Zeppelin's Robert Plant turned down £500 MILLION to reform supergroup. ..."
	disagree	"... No, Robert Plant did not rip up an $800 million deal to get Led Zeppelin back together. ..."
	discuss	"... Robert Plant reportedly tore up an $800 million Led Zeppelin reunion deal. ..."
	unrelated	"... Richard Branson's Virgin Galactic is set to launch SpaceShipTwo today. ..."

Table 2 Example of a Topic-News Article-Stance Structure Table

Topic ID	News ID	Stance
T_a	n_1	agree
T_a	n_2	agree
T_a	n_3	agree
T_a	n_4	disagree
T_a	n_5	discuss
T_b	n_6	agree
T_b	n_7	disagree

- Consider the incompatibility between n_1 and n_4 versus the incompatibility between n_6 and n_7. Intuitively, we consider the first incompatibility to be higher because the ratio of *agree* to *disagree* is higher, 3:1 versus 1:1.

3.2 Pairwise Incompatibility Probability (IP)

To quantitatively represent the incompatibility between two news articles related to the same topic, we apply and modify the concept of Incompatibility Probability (IP) from our previous work [20, 55] where it was defined in a different context. In this paper, we consider the incompatibility of a pair of news articles for a certain topic, such as (n_1, n_4) in T_a and (n_6, n_7) in T_b. Then we evaluate the IP of different pairs of news articles where a higher IP means more incompatible. For example, in Table 2, we assign $IP(n_1, n_4) > IP(n_1, n_5)$ because the incompatibility of *agree* and *disagree* is higher than the incompatibility of *agree* and *discuss*. We also assign $IP(n_1, n_4) > IP(n_6, n_7)$ as explained above, even though in both cases the stances are *agree* and *disagree*.

We start by assigning a numeric value v for each stance with the requirement that $v_{disagree} < v_{discuss} < v_{agree}$. This will give an *agree* and *disagree* pair a higher value than when one stance is *discuss*. We will later consider what happens if different values are assigned to the stances. We call the topic under consideration t. Let $N = \{n_1, \ldots, n_\ell\}$ be the set of news articles related to t. All of them have a stance for the topic. For example, if the stance of n_2 to t is *disagree* then $v_2 = v_{disagree}$.

As in our previous work, [20], our goal is to define a function $IP : N \times N \rightarrow [0, 1]$ such that $IP(n_i, n_i') < IP(n_j, n_j')$ means that the pair, n_i, n_i' is less incompatible than the pair n_j, n_j', with the following properties:

1. **Inconsistency:** $IP(n_i, n_j) = 1$ if and only if n_i and n_j are inconsistent.
2. **Complete compatibility:** $IP(n_i, n_j) = 0$ if and only if $v_{n_i} = v_{n_j}$.
3. **Symmetry:** $IP(n_i, n_j) = IP(n_j, n_i)$ for all $n_i, n_j \in N$.

As long as the number of fake news articles is small compared to the total number of news articles, the fake news will be more incompatible with other news than the ones that are real. We will use incompatibility probability (IP) this way to find the most likely fake news.

In the following, we assume that all the news articles are related to a single topic t.

As in our previous work [20], we start with the concept of *Basic Incompatibility Probability*, named BIP, to estimate the incompatibility probability of a pair based only on their stances. For this purpose we first define a value for each stance, and use the notation $[v_{disagree}, v_{discuss}, v_{agree}]$. Consider two news articles with ids n_i and n_j. We define

$$BIP(i, j) = \mid v_i - v_j \mid /(\mid v_{agree} \mid - \mid v_{disagree} \mid) \tag{1}$$

The range of $BIP_{i,j}$ is $[0, 1]$. It equals 0 when $v_i = v_j$ and 1 when one stance is *agree* and the other is *disagree*. Clearly, this definition satisfies the 3 desired properties for an incompatibility probability given above.

Next, we borrow the concept of *proximity ratio*, written as pr, from our previous work [20], which was applied to count the timing proximity of two medical reports along a time line. However, the Topic-News Article-Stance Structure has lower dimension without the time line, hence the proximity ratio takes a simpler form:

$$pr(i, j) = 1 - \mid v_i - v_j \mid /(\mid v_{agree} \mid - \mid v_{disagree} \mid) = 1 - BIP \tag{2}$$

Then, we borrow the concept of duration ratio, dr, to define a new term, also dr, but representing the distribution ratio, to consider the distribution ratio of the news articles with different stances. We use the notation

$$(num_{disagree},\ num_{discuss},\ num_{agree})$$

to represent the number of news articles with the corresponding stances. Therefore, the total number of news articles (related to t), is:

$$num_{total} = num_{disagree} + num_{discuss} + num_{agree}$$

Then we write num_i for the number of news articles whose stance is the same as that of n_i We finally get the definition of the *distribution ratio* (dr) as:

$$dr(i,j) = \begin{cases} 0, \ \ if \ \ i = j; \\ \dfrac{(\mid num_i - num_j \mid + a * (num_{total} - num_i - num_j))}{num_{total}}, \ \ if \ \ i \neq j; \end{cases} \tag{3}$$

where a is a parameter with range [0,1]. The parameter a is applied to take into consideration the number of news articles with the stance different from the stances of n_i and n_j. Essentially, the value of a represents the imprtance we attach to the articles with a different stance. In our experiments we use a = 0.5. The range of $dr_{i,j}$ is $[0, 1)$. It equals to 0 when $v_i = v_j$ and also when $num_i = num_j$ and $num_{total} = num_i + num_j$. It is close to 1 when $num_i >> num_j$ or vice versa. We will use dr, to lessen the incompatibility when two different opinions have a similar number of supporters.

Now we are ready to compute the incompatibility probability of a pair of news articles. We call this IP, the *pairwise IP*, since it is applied to compute pairwise incompatibility. Later, we will also introduce different but related incompatibility probabilities. The following formula gives a result that conforms well with our intuition:

$$\begin{aligned} IP(i,j) &= \sqrt{\frac{BIP(i,j) * dr(i,j) + BIP(i,j) * (1 - pr(i,j))}{2}} \\ &= \sqrt{\frac{BIP(i,j) * (1 + dr(i,j) - pr(i,j))}{2}} \\ &= \sqrt{\frac{BIP(i,j) * (BIP(i,j) + dr(i,j))}{2}} \end{aligned} \tag{4}$$

It can be seen that:

- A larger BIP results in a larger IP.
- A larger dr also results in a higher IP.
- The square root of the combination of BIP and dr is used to obtain a smoother change of IP as BIP and dr change.

Table 3 gives examples of four different distributions and the pair properties, including BIP, pr, dr, and IP, with the value set of $[1, 3, 5]$.

In discussing the pairwise IP values it suffices to indicate the two stances. For notation we place them in parentheses after IP such as IP($disagree$, $agree$). Table 3 shows some properties of the pairwise IP:

1. IP depends on three factors: type of pairs, the distribution of the news articles, and the values for $v_{disagree}$, $v_{discuss}$, and v_{agree}.

Table 3 Topic-News Article-Stance system with different distributions and the pairwise IP of the news article pairs

	distribution			pair properties					
id	$num_{disagree}$	$num_{discuss}$	num_{agree}	*i*	*j*	*BIP*	*pr*	*dr*	*IP*
1	1	0	1	disagree	agree	1.00	0.00	0.00	0.71
2	100	0	1	disagree	agree	1.00	0.00	0.98	0.99
3	0	1	1	discuss	agree	0.50	0.50	0.00	0.35
4	1	1	0	discuss	disagree	0.50	0.50	0.00	0.35

2. The *IP* in distributions 1 and 2 concern IP(*disagree*, *agree*). The *IP* in distributions 3 and 4 illustrate the case where one of the stances is *discuss*.
3. IP(*disagree*, *agree*) is larger than the IP of a pair where one stance is *discuss*.
4. IP(*disagree*, *agree*) is different for different distributions even when the *BIP* is the same, such as for distributions 1 and 2. IP is larger when the difference between the number of *agree* and *disagree* news articles is larger.

Table 4 Pairwise IP with different stance value sets

	distribution			IP with different value sets			
id	$num_{disagree}$	$num_{discuss}$	num_{agree}	[1,3,5]	[1,500,999]	[1,3,6]	[1,3,1000]
1	1	0	1	0.707	0.707	0.707	0.707
2	100	0	1	0.995	0.995	0.995	0.995
3	0	1	1	0.354	0.354	0.424	0.706
4	1	1	0	0.354	0.354	0.283	0.001

Table 4 shows how the IP value changes with different stance value sets. To explain the results in Table 4, we first define the *stance_ratio* as:

$$stance\_ratio = \frac{\mid v_{agree} - v_{discuss} \mid}{\mid v_{disagree} - v_{discuss} \mid} \tag{5}$$

The stance ratios are $\frac{5-3}{3-1} = 1$, $\frac{999-500}{500-1} = 1$, $\frac{-3}{3-1} = \frac{3}{2}$, and $\frac{1000-3}{3-1} = \frac{997}{2}$, respectively.

In Table 4:

- The distributions are the same as in Table 3.
- The IP values are the same for the stance value sets [1,3,5] and [1,500,999] because their stance_ratio is the same.
- IP(*disagree*, *agree*) is higher than IP(*agree*, *discuss*) and IP(*disagree*, *discuss*) for all cases.
- When $num_{agree} = num_{disagree}$, as for $id = 1$, BIP = 1 and dr = 0, so the value set does not affect IP(*disagree*,*agree*).

- For a specific distribution, IP(*disagree*,*discuss*) and IP(*agree*,*discuss*) may have different values for different stance value sets as shown for the cases where $id = 3, 4$.
- The stance_ratio controls the balance between IP(*disagree*,*discuss*) and IP(*agree*,*discuss*): $stance\_ratio > 1$ makes IP(*agree*,*discuss*) > IP(*disagree*,*discuss*), and vice versa.

We use $[1, 3, 5]$ with $stance\_ratio = 1$ as the default value set to treat *disagree* and *agree* equally with respect to *discuss*.

Overall, the value of IP of a pair of articles with different stances is determined by the following factors: the stance value set, the stance combination, the total number of related articles, and the distribution of the stances of the news articles.

3.3 Extensions of pairwise IP

In Section 3.2, we introduced pairwise IP to evaluate the incompatibility of a pair of news articles related to a topic. Actually, we are more interested in the incompatibility of each news article instead of a news pair, since our goal is to detect fake news or news worthy to check. To achieve this goal, we extend the definition of pairwise IP in two steps to *relative cumulative IP* which will be used to evaluate the incompatibility of news articles. In the following, we will introduce the terms "cumulative" and "relative", and we will just write "article" instead of "news article".

3.3.1 Cumulative IP

The only issue we consider about each article is its stance. It will be convenient to use the terminology *stance article* for an article with a specific stance for that topic. For example, we write *agree article* instead of 'article with stance *agree*'. Recall that we used a triple $(num_{disagree}, num_{discuss}, num_{agree})$ to indicate the numeric distribution of the article stances. Now we use the notation

$$\langle list\ of\ disagree\ articles\rangle\langle list\ of\ discuss\ articles\rangle\langle list\ of\ agree\ articles\rangle$$

For example, $\langle 1\rangle\langle 2, 3\rangle\langle 4, 5\rangle$ represent 5 articles, where article 1 is a *disagree* article, 2 and 3 are *discuss* articles, and 4 and 5 are *agree* articles. We define the cumulative IP for article i as:

$$IP_{cumulative}(i) = \sum_{j=1}^{\ell} IP(i, j) \tag{6}$$

where ℓ is the total number of articles. Table 5 shows all the pairwise IP values of this distribution followed by the cumulative IP for each article.

Table 5 Pairwise IP of distribution: $\langle 1\rangle\langle 2,3\rangle\langle 4,5\rangle$

	distribution			pair properties					
id	$num_{disagree}$	$num_{discuss}$	num_{agree}	*i*	*j*	*BIP*	*pr*	*dr*	*IP*
1	1	2	2	disagree	agree	1.00	0.00	0.40	0.84
				discuss	agree	0.50	0.50	0.10	0.39
				discuss	disagree	0.50	0.50	0.40	0.47

$$\begin{aligned} IP_{cumulative}(1) &= IP(1,1) + IP(1,2) + IP(1,3) + IP(1,4) + IP(1,5) \\ &= 0 + IP(disagree, discuss) + IP(disagree, discuss) \\ &+ IP(disagree, agree) + IP(disagree, agree) \\ &= 0 + 0.47 + 0.47 + 0.84 + 0.84 = 2.62 \end{aligned} \tag{7}$$

$$\begin{aligned} IP_{cumulative}(2) &= IP(2,1) + IP(2,2) + IP(2,3) + IP(2,4) + IP(2,5) \\ &= IP(discuss, disagree) + 0 + IP(discuss, discuss) \\ &+ IP(discuss, agree) + IP(discuss, agree) \\ &= 0.47 + 0 + 0 + 0.39 + 0.39 = 1.25 \end{aligned} \tag{8}$$

$$IP_{cumulative}(3) = IP_{cumulative}(2) = 1.25 \tag{9}$$

$$\begin{aligned} IP_{cumulative}(4) &= IP(4,1) + IP(4,2) + IP(4,3) + IP(4,4) + IP(4,5) \\ &= IP(agree, disagree) + IP(agree, discuss) \\ &+ IP(agree, discuss) + 0 + IP(agree, agree) \\ &= 0.84 + 0.39 + 0.39 + 0 + 0 = 1.62 \end{aligned} \tag{10}$$

$$IP_{cumulative}(5) = IP_{cumulative}(4) = 1.62 \tag{11}$$

Cumulative IP allows us to differentiate among individual articles. For example, in the distribution, $\langle 1\rangle\langle 2,3\rangle\langle 4,5\rangle$, as above, we obtain:

$$\begin{aligned} &IP_{cumulative}(1) > IP_{cumulative}(4) \\ &= IP_{cumulative}(5) > IP_{cumulative}(2) \\ &= IP_{cumulative}(3) \end{aligned} \tag{12}$$

For this example, there is:

$$IP_{cumulative}(disagree) > IP_{cumulative}(agree) > IP_{cumulative}(discuss)$$

based on the definitions of pairwise and cumulative IP, and the stance value set we used with stance_ratio equals to 1. This result is expected in this example for the following reasons:

- As the stance_ratio is 1 for the stance value set, a $disagree, discuss$ pair has the same BIP value as an $agree, discuss$ pair, as shown in Table 5.
- For the distribution $\langle 1\rangle\langle 2,3\rangle\langle 4,5\rangle$, *disagree* articles are in the minority, so they are considered less reliable. That is why the $disagree, discuss$ pair has a higher IP value, 0.47, than an $agree, discuss$ pair, 0.39, as shown in Table 5. Furthermore, the *disagree* article also has a higher *cumulative IP* based using the calculation in Equations 7 and 10.
- The number of *discuss* and *agree* articles is the same. However, *agree* has a stronger contrast than *discuss* to *disagree*, given that in the stance value set we defined, "discuss" is in the middle between *disagree* and *agree*. Thus, the pairwise IP of a $disagree, agree$ pair is higher than the one for $disagree, discuss$. Then the *cumulative IP* of an *agree* article is also higher than the one for a *discuss* article, as shown in Equations 12 and 10.

3.3.2 Relative Cumulative IP

Cumulative IP can be used to evaluate the incompatibility of individual articles. However, its value depends heavily on the value of N, the number of related articles. But N is an attribute of a topic not an article. For the purpose of comparing the IP values across topics in general we introduce the concept of *relative cumulative IP* whose range will be $[0, 1]$.

To obtain the relative cumulative IP, we first define the highest cumulative IP as IP_{hc} (for a topic with N related articles). This occurs in the distribution $(1, 0, N-1)$ or $(N-1, 0, 1)$. Then the highest cumulative IP is the cumulative IP of the only *disagree* article in $(1, 0, N-1)$ or the only *agree* article in $(N-1, 0, 1)$. Then, dealing with N articles, We calculate IP_{hc} as:

$$BIP(agree, disagree) = 1; \quad pr(agree, disagree) = 0;$$
$$dr(agree, disagree) = \frac{N-2}{N}$$

$$\begin{aligned} IP_(da, a, N) &= \sqrt{\frac{BIP(i,j) * (BIP(i,j) + dr(i,j))}{2}} \\ &= \sqrt{\frac{1 + \frac{N-2}{N}}{2}} = \sqrt{\frac{N-1}{N}} \end{aligned} \tag{13}$$

$$\begin{aligned} IP_{hc,N} &= IP(da, a) * number\_of\_pairs \\ &= \sqrt{(N-1)/N} * (N-1) \end{aligned} \tag{14}$$

Since $IP_{hc,N}$ is the highest cumulative IP for all distributions, any cumulative IP with the same N divided by it results in a new value in the range in $(0, 1]$. This is what we call the *relative cumulative IP*:

$$\begin{aligned} IP_{relative\ cumulative}(i) &= \frac{IP_{cumulative}(i)}{IP_{hc,N}} \\ &= \frac{\sum_{j=1}^{N} IP(i,j)}{\sqrt{(N-1)/N} * (N-1)} \end{aligned} \tag{15}$$

For the example mentioned in Section 3.3.1, $[n_1][n_2, n_3][n_4, n_5]$, the relative cumulative IP values are:

$$IP_{relative\ cumulative}(1) = \frac{2.62}{\sqrt{(5-1)/5} * (5-1)} = \frac{2.62}{3.58} = 0.73 \tag{16}$$

$$\begin{aligned} &IP_{relative\ cumulative}(2) = IP_{relative\ cumulative}(3) \\ &= \frac{1.25}{\sqrt{(5-1)/5} * (5-1)} = \frac{1.25}{3.58} = 0.35 \end{aligned} \tag{17}$$

$$\begin{aligned} &IP_{relative\ cumulative}(4) = IP_{relative\ cumulative}(5) \\ &= \frac{1.62}{\sqrt{(5-1)/5} * (5-1)} = \frac{1.62}{3.58} = 0.45 \end{aligned} \tag{18}$$

3.3.3 Cumulative for Topic IP

In the previous section, we extended pairwise IP to evaluate the relative cumulative IP for each article. In this section, we extend it to cumulative for topic IP to evaluate the incompatibility of a topic if we have multiple topics:

$$\begin{aligned} IP_{cumulative\ for\ topic} = &\sum_{i=1}^{I} IP_i(da, di) \\ &+ \sum_{j=1}^{J} IP_j(da, a) + \sum_{k=1}^{K} IP_k(a, di) \end{aligned} \tag{19}$$

where I, J, K are the number of article pairs, (da, di), (da, a), and (a, di), respectively.

4 Experimental Study

We start by giving the setup we used for the experiments. That is followed by various graphs showing the effectiveness of the proposed method. We first calculated the pairwise IP, then expanded it to $IP_{relative\ cumulative}$ for each article. $IP_{relative\ cumulative}$ is the most important variable in this paper as it can be applied to evaluate the articles' incompatibility and to detect the potential fake news. Articles with higher $IP_{relative\ cumulative}$ and certain stance, that is, *agree* or *disagree*, have more potential to be fake news. Articles with the uncertain stance *discuss* will not be considered to be fake news no matter the value of its $IP_{relative\ cumulative}$.

4.1 Experimental Setup

We conducted our experiments on a computer with a CPU of Intel Core i7-8750H, which has 6 cores with processor clocks at between 2.2 and 4.1 GHz. The RAM of the computer is 8GBx2(16Gb) DDR4-2666(1333Hz). We implemented our method and performed the experimental study using Python.

4.2 Study of distributions of article stance

4.2.1 Setup of 4 simulations with different distributions

In this section, we will study how the change of the distribution of the stances influences the values of pairwise IP, relative cumulative IP, and cumulative for topic IP.

First, we set up 4 simulations with different portions between disagree and agree articles, which increases from 0 to 1 :

- Simu1: There is no *disagree* stance and the portion of *disagree* to *agree* is 0.
- Simu2: The portion of *disagree* to *agree* is $\frac{1}{9}$.
- Simu3: The portion of *disagree* to *agree* is $\frac{1}{4}$.
- Simu4: There is an equal number of *disagree* and *agree* stances, so the portion of *disagree* to *agree* is 1.

Second, in each simulation, we set up 9 different distributions, with different portions of *discuss*, going down from 90% to 10%, with the total portion of *disagree* plus *agree* going up from 10% to 90%, respectively.

Finally, we assumed the existence of 100 articles for each simulation, with the value set of $[disagree, discuss, agree] = [1, 3, 5]$.

Overall, we were trying to mimic different kinds of situations in the real world, including but not limited to, *agree* dominating (*disagree* dominating has a mirrored trend since it has a same but opposite position), *discuss* dominating, and equally distributed. The details of the distributions are in Tables 6-9.

Table 6 The distribution of different stances in Simu1

Distribution Id	# of da	# of di	# of a
1	0	90	10
2	0	80	20
3	0	70	30
4	0	60	40
5	0	50	50
6	0	40	60
7	0	30	70
8	0	20	80
9	0	10	90

Table 7 The distribution of different stances in Simu2

Distribution Id	# of da	# of di	# of a
1	1	90	9
2	2	80	18
3	3	70	27
4	4	60	36
5	5	50	45
6	6	40	54
7	7	30	63
8	8	20	72
9	9	10	81

Table 8 The distribution of different stances in Simu3

Distribution Id	# of da	# of di	# of a
1	2	90	8
2	4	80	16
3	6	70	24
4	8	60	32
5	10	50	40
6	12	40	48
7	14	30	56
8	16	20	64
9	18	10	72

Table 9 The distribution of different stances in Simu4

Distribution Id	# of da	# of di	# of a
1	5	90	5
2	10	80	10
3	15	70	15
4	20	60	20
5	25	50	25
6	30	40	30
7	35	30	35
8	40	20	40
9	45	10	45

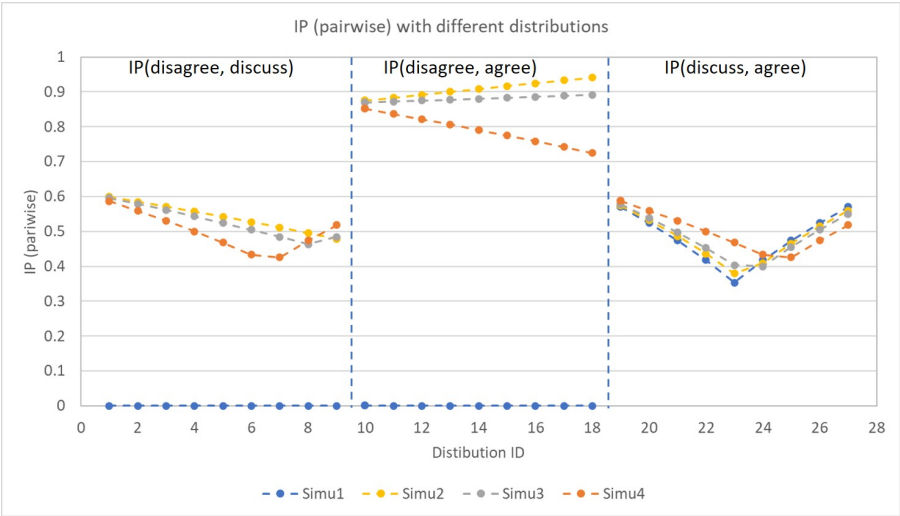

Fig. 2 pairwise IP with different distributions

4.2.2 Results for pairwise IP

Figure 2 shows the results for the pairwise IP of different distributions. We use the notation $IP(stance1, stance2)$ to indicate the pairwise IP of two articles with the two different stances.

- The four different colors represent the four simulations, as described in Section 4.2.1.
- The X-axis is the Distribution ID. The graph is divided vertically into 3 sections for the 3 different types of article pairs, $(disagree, discuss)$, $(disagree, agree)$, and $(discuss, agree)$. In each section, there are 9 points representing the 9 distributions described in Tables 6-9.

The following trends appear in Figure 2:

- Different distributions result in different pairwise IP values for different types of article pairs (different sections).
- The value of pairwise IP for Simu1 (blue color) in the first two sections is 0 because there is no *disagree* stance.
- The pairwise IP in the middle section are higher than the values in the left or right sections because the incompatibility between *disagree* and *agree* is defined to be larger than the other two cases.
- The overall pairwise IP of Simu2 and Simu3 in the left section (disagree) is a little bit higher than the one in the right section (agree). The reason is that there are always more agree articles than disagree in each distribution of Simu 2 and 3, which makes 'agree' more reliable.
- The trends of the change of pairwise IP in different sections are different due to the influence of the combination of different stance types and distributions as explained below.

– In the right section ($IP(agree, discuss)$), all four simulations have a "V" shape. The minimum point is more to the right as the portion of *disagree* to *agree* increases from 0 (Simu1), 1/9 (Simu2), 1/4 (Simu3), up to to 1/1 (Simu4).
– In the left section ($IP(disagree, discuss)$), two of the three non-zero simulations have a skewed "V" shape. However, the minimum point is more to the left as the portion of *disagree* and *agree* increases from 1/4 (Simu3), to 1/1 (Simu4).
– In the middle section ($IP(disagree, agree)$), the three non-zero simulations are all monotonic. The slope decreases from positive (1/9 (Simu2), and 1/4 (Simu3)), to negative (1/1 (Simu4)). The overall $IP(disagree, agree)$ also decreases when the portion of *disagree* and *agree* increase until 1, as the yellow line is above the grey line, and the grey line is above the orange line.

4.2.3 Results for relative cumulative IP

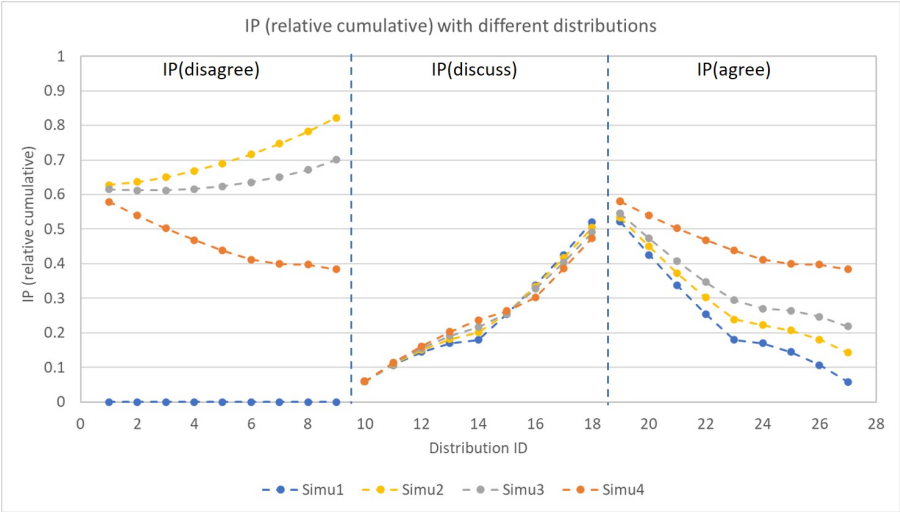

Fig. 3 relative cumulative IP with different distributions

Figure 3 shows the result of the relative cumulative IP values for different distributions. We write $IP(stance)$ for the relative cumulative IP of an article with that stance. The setup is the same as for Figure 2 except that the Y-axis now displays the relative cumulative IP as defined in Equation 15.

- The four different colors represent the four simulations, as described in Section 4.2.1.
- The X-axis is the Distribution ID. The graph is divided vertically into 3 sections for the 3 different types of articles, *disagree*, *discuss*, and *agree*,

Table 10 Comparison of relative cumulative IP for the *discuss* and *agree* stances

Simulation	IP(discuss)			IP(agree)		
	Ave	Min	Max	Ave	Min	Max
Simu1	0.24	0.06	0.52	0.24	0.06	0.52
Simu2	0.25	0.06	0.50	0.29	0.14	0.53
Simu3	0.28	0.06	0.49	0.34	0.22	0.54
Simu4	0.24	0.06	0.47	0.46	0.38	0.58

from left to right. In each section, there are 9 points representing the 9 distributions described in Tables 6-9.

The following trends appear in Figure 3:

- Different distributions result in different relative cumulative IP values for each of the 3 sections.
- The value of relative cumulative IP for Simu1 (blue color) in the left section is 0 because there is no *disagree* stance.
- The relative cumulative IP values in the left section (*disagree*) are relatively higher than the corresponding values in the right section (*agree*) in Simu3 and Simu4, since there are relatively fewer *disagree* articles than *agree* articles.
- The values for the average, min, and max of the corresponding distributions for $IP(discuss)$ in the middle section are lower than for $IP(agree)$ in the right section for each simulation in Table 10, except Simu1. This is a result due to two factors:
  - Generally, there are fewer *agree* articles than *discuss* articles making *discuss* more reliable resulting in smaller $IP_{relative\ cumulative}$ for *discuss*.
  - Furthermore, the incompatibility between *disagree* and *discuss* is smaller than the one between *disagree* and *agree*, making the sum of $IP(disagree, discuss)$ for $IP(discuss)$ smaller than the sum of $IP(disagree, agree)$ for $IP(agree)$ with the same number of pairs, as shown in Equations 17 and 18.
- The trends of the change of relative cumulative IP for different types (sections) in different simulations are different as explained below.
  - In the right section, $IP(agree)$, all four simulations decrease monotonically as the number of articles with the *agree* stance increases. The rate of decrease (the absolute value of the slope) decreases as the portion of *disagree* to *agree* stances increase from 0 (Simu1), 1/9 (Simu2), 1/4 (Simu3), up to 1/2 (Simu4).
  - In the middle section, $IP(discuss)$, all four simulations increase monotonically as the number of articles with the *discuss* stance decreases. However, the rates of decrease in the four simulations are relatively similar, compared to the right section.

– In the left section, IP(*disagree*), the minimum point of each simulation moves from left to the right as the portions of *disagree* articles to *agree* articles increase from 1/9 (Simu2), 1/4 (Simu3), to 1/1 (Simu4).

4.2.4 Results for cumulative for topic IP

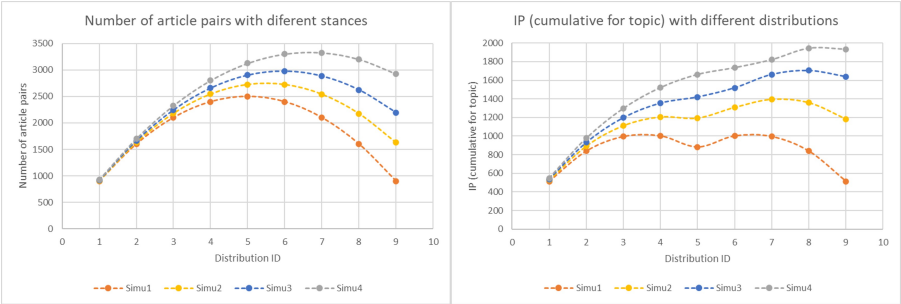

Fig. 4 Number of article pairs and cumulative for topic IP for different distributions

Figure 4 shows the results of cumulative for topic IP for different distributions. The following is the description of the Figure:

- The left graph shows the distribution of the number of article pairs with different stances in each simulation. The right graph shows the $IP_{cumulative\ for\ topic}$ of different distributions.
- The 4 different colors represent the 4 simulations described in Section 4.2.2.
- In each simulation (color), there are 9 different distributions (9 points), which are displayed on the X-axis as Distribution ID, the same as in Section 4.2.2.
- The Y-axis of the left graph represents the total number of article pairs, which is the sum of I, J, K in Equation 19. The Y-axis of the right graph displays the $IP_{cumulative\ for\ topic}$, given as Equation 19 in Section 3.3.3.

The following trends are shown in Figure 4:

- In the left graph, all four simulations have "rainbow" shapes. The ceiling (max value) of the rainbow moves to the right as the portion of *disagree* to *agree* articles increases from 0 (Simu1), 1/9 (Simu2), 1/4 (Simu3), to 1/1 (Simu4).
- In the right graph:
  - Different distributions result in different $IP_{cumulative\ for\ topic}$ values for all 36 different distributions: 4 simulations times 9 distributions in each simulation.
  - The average value of $IP_{cumulative\ for\ topic}$ increases when the portion of *disagree* articles to *agree* articles increases from 0 (Simu1), 1/9 (Simu2), 1/4 (Simu3), to 1/1 (Simu4). Simu1 ($portion_{disagree,agree} = 0$) stays the lowest while Simu4 ($portion_{disagree,agree} = 1/1$) stays the highest.

- The trend of the value of $IP_{cumulative\ for\ topic}$ in each simulation gradually changes from a "double-curve" shape (Simu1) to "single-curve" shape (Simu4) as the $portion_{disagree,agree}$ increases.
- Overall, the highest is 1945.5 with a distribution (40,20,40) as shown in Table 9. The lowest $IP_{cumulative\ for\ topic}$ is 513.1 with the highest discussion occupation, (0,90,10), as shown in Table 6.

4.3 Study of real cases from FNC-1

We extracted data from the Fake News Challenge (FNC-1) dataset [4]. FNC-1 focuses on the first stage of Fake News detection, called Stance Detection, to understand what other news organizations are saying about the topic. Our approach focuses on the second stage of Fake News Detection, to find which news is more likely to be fake news, based on the results of FNC-1. To illustrate the efficiency of our approach, we extracted 5 topics, with the original ids 1541, 92, 2542, 2122, and 1599, and 72 related news articles with the three stances *disagree*, *discuss*, and *agree*. Among the 72 news articles, there are 5 fake news, with ids 313, 736, 974, 1372, and 2125, one for each topic, which were detected by the FaNDs method and verified in our previous paper [**?**].

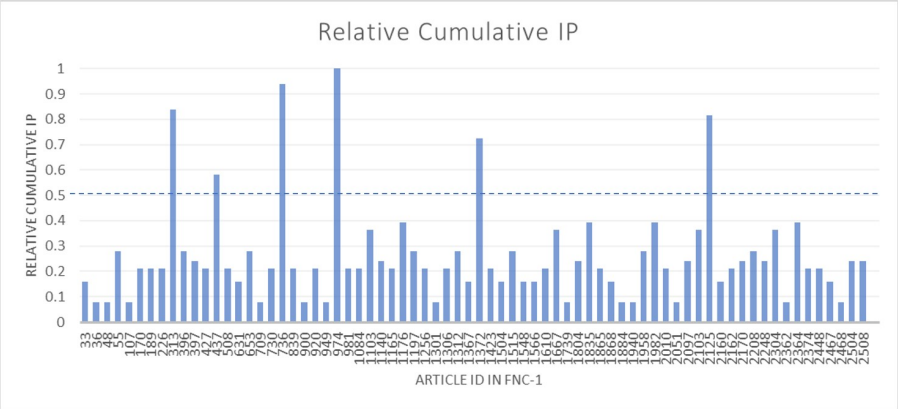

Fig. 5 Relative Cumulative IP of 72 News Articles from FNC-1 Dataset

Figure 5 shows the relative cumulative IP of the 72 news articles from the FNC-1 dataset. There are 6 articles, with ids 313, 437, 736, 974, 1372, and 2125, that have significantly higher relative cumulative IP than the others, applying 0.5 as a threshold. But as we don't consider *discuss* articles to be fake news, article 437 was deleted from this list leaving 5 articles that are indeed the only fake news in the list. This illustrates hoe our approach can effectively differentiate the fake news from the others, in a more efficient way than our previous FaNDS method, as it does not rely on a complex graph structure. In FaNDS we first generated a graph with articles as nodes, followed

[4] http://www.fakenewschallenge.org/

by mapping the pairwise relationships as edges. Then energy flowed between the nodes along the edges as pipes whose size was continuously changing, until convergence. Then, the final energy of the nodes was used to evaluate the reliability of the articles. The method presented in this paper is more concise and straightforward as we directly calculate the pairwise IP and the relative cumulative IP based on the defined formulas and then use them to evaluate the reliability of the articles. This efficiency advantage is expected to be more significant when the data set is much larger when solving real problems.

5 Conclusion and Future Work

We developed a new method, FIP, for detecting fake news, an increasingly significant issue. We first defined the concepts and formulas of pairwise IP, relative cumulative IP, and cumulative for topic IP, then explained how FIP works using those formulas to evaluate the reliability of the news and to detect fake news. We demonstrated our technique on both simulated data and the experimental data from the Fake News Challenge database, FNC-1. In the future, we plan to expand this method to study more complicated cases, such as the case where an article may be related to multiple topics.

6 Declarations

6.1 Ethical Approval and Consent to participate

Not applicable

6.2 Human and Animal Ethics

Not applicable

6.3 Consent for publication

Not applicable

6.4 Availability of supporting data

Not applicable

6.5 Competing interests

The authors have no conflicts of interest to declare that are relevant to the content of this article.

6.6 Funding

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6.7 Authors' contributions

Jiawei Xu, Vladimir Zadorozhny, and John Grant designed the framework.
Jiawei Xu completed the experiments.
Jiawei Xu wrote the main manuscript text.
Vladimir Zadorozhny and John Grant wrote the abstract and revised the manuscript.
All authors reviewed the manuscript.

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