北京邮電大學

本 科 毕 业 设 计（论文）

题目：社猜猜看这个毕设题目是什么

姓　　名　猜　猜

学　　院　信息与通信工程学院

专　　业　通信工程

班　　级　**2014211199**

学　　号　**2014210999**

班内序号　**99**

指导教师　猜　猜

2018 年 5 月

北 京 邮 电 大 学

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<tr><td>学生姓名</td><td>猜猜</td><td>学号</td><td>2014210999</td><td>班内序号</td><td>99</td></tr>
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<tr><td colspan="5">（英文）Just Guess What On Earth My Title is</td></tr>
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• Zubiaga A, Aker A, Bontcheva K, et al. Detection and Resolution of Rumours in Social Media: A Survey[J]. 2017.
• Jin Z, Cao J, Guo H, et al. Multimodal Fusion with Recurrent Neural Networks for Rumor Detection on Microblogs[C]// ACM, 2017:795-816.</td></tr>
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• 2018.1.1 ~ 2018.2.10 完成领域内容调研，模板对应部分撰写。
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• 2018.4.16~2018.4.30 进行模板设计评估和比较分析。
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<tr><td>调研论证</td><td colspan="2">能独立查阅文献和从事相关调研；能正确翻译外文资料；有收集、加工各种信息及获取新知识的能力和自学能力。</td><td>5</td><td>4</td><td>3.5</td><td>3</td><td>2</td><td></td><td></td></tr>
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<tr><td>能力水平</td><td colspan="2">能综合运用所学知识和技能去分析与解决毕业设计（论文）过程中遇到的实际问题；能正确处理实验数据；能对课题进行理论分析，得出有价值的结论。</td><td>5</td><td>4</td><td>3.5</td><td>3</td><td>2</td><td></td><td></td></tr>
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<tr><td>答辩准备</td><td>准备充分；有简洁、清晰、美观的演示文稿；准时到场。</td><td>5</td><td>4</td><td>3.5</td><td>3</td><td>2</td><td></td></tr>
<tr><td>内容陈述</td><td>语言表达简洁、流利、清楚、准确，思路清晰，重点突出，逻辑性强，概念清楚，论点正确；实验方法科学，分析归纳合理；结论严谨；表现出对毕业设计（论文）内容掌握透彻。</td><td>20</td><td>18</td><td>14</td><td>12</td><td>8</td><td></td></tr>
<tr><td>回答问题</td><td>回答问题准确、有深度、有理论根据、基本概念清晰。</td><td>10</td><td>8</td><td>7</td><td>6</td><td>4</td><td></td></tr>
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2． 此表原件一式三份，一份存入学生档案，一份装订到毕业论文中，一份交教务处存入档案馆。

北 京 邮 电 大 学

本科毕业设计（论文）诚信声明

本人声明所呈交的毕业设计（论文），题目《社交网络多媒体信息可信度评估》是本人在指导教师的指导下，独立进行研究工作所取得的成果。尽我所知，除了文中特别加以标注和致谢中所罗列的内容以外，论文中不包含其他人已经发表或撰写过的研究成果，也不包含为获得北京邮电大学或其他教育机构的学位或证书而使用过的材料。

申请学位论文与资料若有不实之处，本人承担一切相关责任。

本人签名：____________________　　日期：____________________

社猜猜看这个毕设题目是什么

摘　要

这是中文摘要的部分。
它可以拥有多段。

关键词　北京邮电大学　本科生　毕业设计　模板　示例

Have a try to guess what the title is

ABSTRACT

This is ABSTRACT.
You can write more than one paragraph here.

KEY WORDS BUPT undergraduate thesis template example

目　　录

第一章　绪论

说话人识别 (Speaker Verification, SV) 是指通过对说话人语音中的声学信息进行分析，自动识别说话人身份的一种技术。说话人识别在日常生活的各个领域都有着十分广泛的应用，有着至关重要的作用与广阔的市场。实现说话人识别系统，需要结合数字信号处理，模式识别等多学科的知识，是一个十分复杂的研究课题。截止目前，说话人识别相关技术的研究以及趋近成熟，在近些年也越来越多的投入商用。其中，GMM-UBM（Gaussian Mixture Model-Universal Background Model）系统[1] 和 i-Vector 系统[2] 表现最为出色，成为了说话人识别领域中最为常用的两个系统。但是，虽然说话人识别的相关研究已经取得了很好的效果，当把这些研究成果应用于实际环境的时候，仍然有很多需要解决的问题。比如经研究表明，在复杂的噪声环境下说话人识别系统的准确率会大大下降[3]。因此，如何提升说话人识别系统在噪声环境下的说话人识别准确率便成了十分重要的研究课题。

说话人识别系统的结构主要分为三部分，特征提取，模型运算，及匹配判决。在近几十年的说话人识别研究过程中，有很多研究者对不同的部分进行改进，并提升说话人识别系统在噪声环境下的说话人识别准确率。在判决和模型部分，将无噪声语音信息和有噪声语音信息结合的多环境条件训练模型，可以有效的提高说话人系统在复杂噪声环境下的说话人识别准确率[4]。在前端特征提取中，很多语音增强模型被利用在说话人识别系统的特征提取过程中，以最大限度的降低噪音对于原本说话人语音的影响[5]。

以此同时，近些年深度神经网络（Deep neural networks, DNN）的热潮席卷整个计算机领域，在计算机视觉，自然语言处理等方向上，深度神经网络有着极其出色的作用，大大的推动了相关技术的发展及其商用[6]。同时，在语音领域，深度神经网络也有着广泛的应用，应用深度神经网络的语音识别模型有着出色的效果[7]。随着深度神经网络及类型的方法在语音领域的成功，也有很多研究者尝试在说话人识别领域应用这项技术。2014 年首次有人提出了加入深度神经网络代替 GMM 的说话人识别模型[8]，以提升说话人识别准确率。同年，谷歌的研究人员也推出了完全使用深度学习的 d-vector 说话人识别模型[9]，并且在之后的几年中不断的更新着自己的模型，达到了不错的效果。但是截至目前，传统的 GMM-UBM 和 i-vector 模型仍然在说话人识别系统中占据主流地位，有着更好的效果。而且噪声等环境因素对于说话人模型的影响，要大于模型的选择，如何更好的提升噪声环境下的准确率才是当务之急。所以研究者们更多的着眼于用深度神经网络进行前端特征处理的工作，通过改进特征处理环节，尽可能减小噪声对于说话人识别模型的干扰[10][11]，而在后端模型的选择上，依然选择传统的隐变量模型。

随着深度学习的火热，更多衍生的深度神经网络模型被提出，其中，2014 年 Goodfellow 等人提出的生成对抗网络（Generative Adversarial Nets，GAN）受到了广泛的关注[12]，因为其对抗训练的效果极其出色，GAN 很快就被运用于图像生成处理等方向上。在语音处理领域，对抗网络也被用于搭建鲁棒语音识别模型[13] 和语音生成[14] 等研究中。

基于以上的背景，本课题的研究重点是神经网络特征在说话人认证系统中的鲁棒

性，研究如何借助深度神经网络的方法，提取说话人鲁棒语音特征，使通过这些特征训练的说话人识别系统，在噪声环境下的说话人识别准确率提升。本文的主要安排如下。第一章绪论主要介绍课题的背景与研究的意义；第二章主要介绍课题中使用的基于深度神经网络的模型结构及其原理；第三章主要介绍实验准备，实施的具体内容；第四章主要是对实验结果进行介绍并分析；第五章将得出本文的结论。

第二章　基于深度神经网络的鲁棒语音特征提取模型

说话人识别系统主要的结构主要分为三部分，特征提取，模型运算，及匹配判决。特征提取部分被认为是整个系统的前端（front-end），提取的特征需要能包含说话人语音的个性信息，梅尔倒谱系数（MFCCs）[15] 是目前最为常用的特征参数，这种倒谱参数在上世纪八十年代被提出并用于语音识别，具有较好的鲁棒性，虽然有很多新特征不断的被提出，但是 MFCCs 目前很难被取代，本文也将会使用从语音数据中提取的 MFCCs 特征参数。本文的研究也着重与前端部分，研究如何构造基于深度神经网络的鲁棒语音特征提取，并对他们的性能进行比较评价。

2.1　瓶颈鲁棒语音特征

MFCCs 作为最广泛应用的特征参数，应用于说话人识别系统中有两个缺点。第一个缺点是 MFCCs 是在很短的语音段内被提取出来的，而部分说话人特征只有对相对更长的语音进行分析才能得到，因此使用 MFCCs 可能不能很好的表征部分说话人特征。第二个缺点是，MFCCs 是为了语音识别而被设计出来的，虽然 MFCCs 也被证明可以用于说话人识别领域，但是它并不是最适合说话人识别系统的特征。因此，瓶颈特征被提了出来并应用于了说话人识别系统[16]。将从说话人语音中提取出来的 MFCCs 特征，放入神经网络模型中训练，并在特定的隐藏层提取出来，便得到了瓶颈语音特征。提取的瓶颈特征能够更有效的表征长时间段语音的特征，并且通过神经网络训练的特征还能更加适应说话人识别任务。因此瓶颈特征可以很好的弥补上述 MFCCs 的缺点，更加适用于说话人识别系统，并在相关的研究中已经得到了证明[17]。

2.2　深度神经网络鲁棒语音特征提取模型

2.3　对抗神经网络鲁棒语音特征提取模型

2.4　基准模型

2.4.1　STSA-MMSE

2.4.2　DNN based speech enhancement

2.4.3　SDN-BN

2.4.4　DAN-BN

第三章　实验

3.1　数据集

3.2　噪音

3.3　说话人识别系统

3.4　实验准备

第四章　结果与分析

损失函数变化曲线图特征图谱说话人识别等错率

表 4-1 EER (%) of the ASV system using different front-ends on different noise types and SNRs (dB)

noise	SNR	No Enh.	MMSE	DNN-SE	SD-BN	SAN-BN	DAN-BN	MAN-BN
White	00	45.90	30.95	40.14	27.89	27.02	27.55	**26.87**
	05	43.20	21.17	21.77	18.80	17.81	18.37	**17.69**
	10	34.61	13.95	**10.88**	11.26	11.35	12.61	11.39
	15	26.28	10.20	8.16	7.51	7.51	7.17	**6.83**
	20	16.91	8.50	6.80	5.68	5.29	5.44	**5.10**
	clean	6.99	5.80	5.67	4.08	3.41	3.66	**3.29**
	mean	28.98	15.10	15.57	12.54	12.07	12.47	**11.86**
Babble	00	19.05	29.04	16.67	**13.60**	17.87	15.99	15.65
	05	14.63	20.40	10.39	7.80	9.86	**8.16**	8.35
	10	11.69	12.59	7.50	5.10	5.44	4.76	**4.07**
	15	11.04	7.82	6.34	4.25	3.06	3.74	**2.94**
	20	9.18	6.29	5.78	3.74	3.40	3.61	**2.69**
	clean	6.99	5.80	5.67	4.08	3.41	3.66	**3.29**
	mean	12.10	13.66	8.73	6.43	7.17	6.65	**6.16**
Cantine	00	20.72	19.09	19.94	9.24	9.81	**9.18**	10.54
	05	19.20	12.37	9.18	6.00	5.86	**5.78**	5.81
	10	14.74	8.16	6.12	4.08	4.44	3.96	**3.74**
	15	11.81	6.80	5.78	3.86	3.06	3.40	**3.03**
	20	8.50	6.12	5.44	3.77	3.40	3.74	**3.06**
	clean	6.99	5.80	5.67	4.08	3.41	3.66	**3.29**
	mean	13.66	9.72	8.69	5.17	5.00	4.95	**4.91**
Market	00	29.40	25.51	21.77	**11.94**	14.43	13.50	13.52
	05	20.07	17.35	10.59	**6.46**	7.82	6.80	6.80
	10	15.00	11.90	7.48	**3.17**	4.42	4.78	3.75
	15	11.96	8.28	6.22	3.40	3.62	3.74	**3.06**
	20	8.93	7.35	5.76	3.74	3.40	3.40	**2.80**
	clean	6.99	5.80	5.67	4.08	3.41	3.66	**3.29**
	mean	15.39	12.70	9.58	**5.47**	6.18	5.73	5.53
Airplane	00	21.09	17.69	15.99	**7.14**	9.86	8.50	8.09
	05	15.99	12.58	8.99	4.81	6.46	**4.76**	**4.76**
	10	13.61	8.17	6.12	3.75	5.10	**3.32**	3.68
	15	11.66	6.53	6.12	3.67	4.08	3.40	**3.06**
	20	9.18	6.27	5.58	3.40	3.63	3.28	**3.02**
	clean	6.99	5.80	5.67	4.08	3.41	3.66	**3.29**
	mean	13.09	9.51	8.08	4.47	5.42	4.48	**4.31**

第五章　结论

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致　　谢

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附　　录

附录 1　缩略语表

英文缩写	英文名称	中文
AE	autoencoder	自编码器
CRF	conditional random field	条件随机场
LR	logistic regression	逻辑回归
LSTM	Long Short Term Memory	长短时记忆单元

附录 2　数学符号

数和数组

a	标量（整数或实数）
$\boldsymbol{a}$	向量
$dim()$	向量的维数
$\boldsymbol{A}$	矩阵
$\boldsymbol{A}^{\mathrm{T}}$	矩阵 $\mathbf{A}$ 的转置
$\boldsymbol{I}$	单位矩阵（维度依据上下文而定）
$diag(\boldsymbol{a})$	对角方阵，其中对角元素由向量 $\boldsymbol{a}$ 确定

外　文　译　文

真假新闻的在线传播

Soroush Vosoughi, Deb Roy, Sinan Aral
麻省理工学院

决策、合作、通信和市场领域的基础理论全都将对真实或准确度的概念化作为几乎一切人类努力的核心。然而，不论是真实信息还是虚假信息都会于在线媒体上迅速传播。定义什么是真、什么是假成了一种常见的政治策略，而不是基于一些各方同意的事实的争论。我们的经济也难免遭受虚假信息传播的影响。虚假流言会影响股价和大规模投资的动向，例如，在一条声称巴拉克·奥巴马在爆炸中受伤的推文发布后，股市市值蒸发了 1300 亿美元。的确，从自然灾害到恐怖袭击，我们对一切事情的反应都受到了扰乱。新的社交网络技术在使信息的传播速度变快和规模变大的同时，也便利了不实信息（即不准确或有误导性的信息）的传播。然而，尽管我们对信息和新闻的获取越来越多地收到这些新技术的引导，但我们仍然对他们在虚假信息传播上的作用知之甚少。尽管媒体对假新闻传播的轶事分析给予了相当多的关注，但仍然几乎没有针对不实信息扩散或其发布源头的大规模实证调查。目前，虚假信息传播的研究仅仅局限于小的、局部的样本的分析上，而这些分析忽略了两个最重要的科学问题：真实信息和虚假信息的传播有什么不同？哪些人类判断中的因素可以解释这些不同？

SOCIAL SCIENCE

The spread of true and false news online

Soroush Vosoughi,[1] Deb Roy,[1] Sinan Aral[2]*

We investigated the differential diffusion of all of the verified true and false news stories distributed on Twitter from 2006 to 2017. The data comprise ~126,000 stories tweeted by ~3 million people more than 4.5 million times. We classified news as true or false using information from six independent fact-checking organizations that exhibited 95 to 98% agreement on the classifications. Falsehood diffused significantly farther, faster, deeper, and more broadly than the truth in all categories of information, and the effects were more pronounced for false political news than for false news about terrorism, natural disasters, science, urban legends, or financial information. We found that false news was more novel than true news, which suggests that people were more likely to share novel information. Whereas false stories inspired fear, disgust, and surprise in replies, true stories inspired anticipation, sadness, joy, and trust. Contrary to conventional wisdom, robots accelerated the spread of true and false news at the same rate, implying that false news spreads more than the truth because humans, not robots, are more likely to spread it.

Foundational theories of decision-making (*1*–*3*), cooperation (*4*), communication (*5*), and markets (*6*) all view some conceptualization of truth or accuracy as central to the functioning of nearly every human endeavor. Yet, both true and false information spreads rapidly through online media. Defining what is true and false has become a common political strategy, replacing debates based on a mutually agreed on set of facts. Our economies are not immune to the spread of falsity either. False rumors have affected stock prices and the motivation for large-scale investments, for example, wiping out $130 billion in stock value after a false tweet claimed that Barack Obama was injured in an explosion (*7*). Indeed, our responses to everything from natural disasters (*8*, *9*) to terrorist attacks (*10*) have been disrupted by the spread of false news online.

New social technologies, which facilitate rapid information sharing and large-scale information cascades, can enable the spread of misinformation (i.e., information that is inaccurate or misleading). But although more and more of our access to information and news is guided by these new technologies (*11*), we know little about their contribution to the spread of falsity online. Though considerable attention has been paid to anecdotal analyses of the spread of false news by the media (*12*), there are few large-scale empirical investigations of the diffusion of misinformation or its social origins. Studies of the spread of misinformation are currently limited to analyses of small, ad hoc samples that ignore two of the most important scientific questions: How do truth and falsity diffuse differently, and what factors of human judgment explain these differences?

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Current work analyzes the spread of single rumors, like the discovery of the Higgs boson (*13*) or the Haitian earthquake of 2010 (*14*), and multiple rumors from a single disaster event, like the Boston Marathon bombing of 2013 (*10*), or it develops theoretical models of rumor diffusion (*15*), methods for rumor detection (*16*), credibility evaluation (*17*, *18*), or interventions to curtail the spread of rumors (*19*). But almost no studies comprehensively evaluate differences in the spread of truth and falsity across topics or examine why false news may spread differently than the truth. For example, although Del Vicario *et al.* (*20*) and Bessi *et al.* (*21*) studied the spread of scientific and conspiracy-theory stories, they did not evaluate their veracity. Scientific and conspiracy-theory stories can both be either true or false, and they differ on stylistic dimensions that are important to their spread but orthogonal to their veracity. To understand the spread of false news, it is necessary to examine diffusion after differentiating true and false scientific stories and true and false conspiracy-theory stories and controlling for the topical and stylistic differences between the categories themselves. The only study to date that segments rumors by veracity is that of Friggeri *et al.* (*19*), who analyzed ~4000 rumors spreading on Facebook and focused more on how fact checking affects rumor propagation than on how falsity diffuses differently than the truth (*22*).

In our current political climate and in the academic literature, a fluid terminology has arisen around "fake news," foreign interventions in U.S. politics through social media, and our understanding of what constitutes news, fake news, false news, rumors, rumor cascades, and other related terms. Although, at one time, it may have been appropriate to think of fake news as referring to the veracity of a news story, we now believe that this phrase has been irredeemably polarized in our current political and media climate. As politicians have implemented a political strategy of labeling news sources that do not support their positions as unreliable or fake news, whereas sources that support their positions are labeled reliable or not fake, the term has lost all connection to the actual veracity of the information presented, rendering it meaningless for use in academic classification. We have therefore explicitly avoided the term fake news throughout this paper and instead use the more objectively verifiable terms "true" or "false" news. Although the terms fake news and misinformation also imply a willful distortion of the truth, we do not make any claims about the intent of the purveyors of the information in our analyses. We instead focus our attention on veracity and stories that have been verified as true or false.

We also purposefully adopt a broad definition of the term news. Rather than defining what constitutes news on the basis of the institutional source of the assertions in a story, we refer to any asserted claim made on Twitter as news (we defend this decision in the supplementary materials section on "reliable sources," section S1.2). We define news as any story or claim with an assertion in it and a rumor as the social phenomena of a news story or claim spreading or diffusing through the Twitter network. That is, rumors are inherently social and involve the sharing of claims between people. News, on the other hand, is an assertion with claims, whether it is shared or not.

A rumor cascade begins on Twitter when a user makes an assertion about a topic in a tweet, which could include written text, photos, or links to articles online. Others then propagate the rumor by retweeting it. A rumor's diffusion process can be characterized as having one or more cascades, which we define as instances of a rumor-spreading pattern that exhibit an unbroken retweet chain with a common, singular origin. For example, an individual could start a rumor cascade by tweeting a story or claim with an assertion in it, and another individual could independently start a second cascade of the same rumor (pertaining to the same story or claim) that is completely independent of the first cascade, except that it pertains to the same story or claim. If they remain independent, they represent two cascades of the same rumor. Cascades can be as small as size one (meaning no one retweeted the original tweet). The number of cascades that make up a rumor is equal to the number of times the story or claim was independently tweeted by a user (not retweeted). So, if a rumor "A" is tweeted by 10 people separately, but not retweeted, it would have 10 cascades, each of size one. Conversely, if a second rumor "B" is independently tweeted by two people and each of those two tweets is retweeted 100 times, the rumor would consist of two cascades, each of size 100.

Here we investigate the differential diffusion of true, false, and mixed (partially true, partially false) news stories using a comprehensive data set of all of the fact-checked rumor cascades that spread on Twitter from its inception in 2006 to 2017. The data include ~126,000 rumor cascades spread by ~3 million people more than 4.5 million times. We sampled all rumor cascades investigated by six independent fact-checking organizations (snopes.com, politifact.com, factcheck.org, truthorfiction.com, hoax-slayer.com, and urbanlegends.about.com) by parsing the title, body, and verdict (true, false, or mixed) of each rumor investigation reported on their websites and automatically collecting the cascades corresponding to those rumors on Twitter. The result was a sample of rumor cascades whose veracity had been agreed on by these organizations between 95 and 98% of the time. We cataloged the diffusion of the rumor cascades by collecting all English-language replies to tweets that contained a link to any of the aforementioned websites from 2006 to 2017 and used optical character recognition to extract text from images where needed. For each reply tweet, we extracted the original tweet being replied to and all the retweets of the original tweet. Each retweet cascade represents a rumor propagating on Twitter that has been verified as true or false by the fact-checking organizations (see the supplementary materials for more details on cascade construction). We then quantified the cascades' depth (the number of retweet hops from the origin tweet over time, where a hop is a retweet by a new unique user), size (the number of users involved in the cascade over time), maximum breadth (the maximum number of users involved in the cascade at any depth), and structural virality (*23*) (a measure that interpolates between content spread through a single, large broadcast and that which spreads through multiple generations, with any one individual directly responsible for only a fraction of the total spread) (see the supplementary materials for more detail on the measurement of rumor diffusion).

As a rumor is retweeted, the depth, size, maximum breadth, and structural virality of the cascade increase (Fig. 1A). A greater fraction of false rumors experienced between 1 and 1000 cascades, whereas a greater fraction of true rumors experienced more than 1000 cascades (Fig. 1B); this was also true for rumors based on political news (Fig. 1D). The total number of false rumors peaked at the end of both 2013 and 2015 and again at the end of 2016, corresponding to the last U.S. presidential election (Fig. 1C). The data also show clear increases in the total number of false political rumors during the 2012 and 2016 U.S. presidential elections (Fig. 1E) and a spike in rumors that contained partially true and partially false information during the Russian annexation of Crimea in 2014 (Fig. 1E). Politics was the largest rumor category in our data, with ~45,000 cascades, followed by urban legends, business, terrorism, science, entertainment, and natural disasters (Fig. 1F).

When we analyzed the diffusion dynamics of true and false rumors, we found that falsehood diffused significantly farther, faster, deeper, and more broadly than the truth in all categories of information [Kolmogorov-Smirnov (K-S) tests are reported in tables S3 to S10]. A significantly greater fraction of false cascades than true cascades exceeded a depth of 10, and the top 0.01% of false cascades diffused eight hops deeper into the Twittersphere than the truth, diffusing to depths

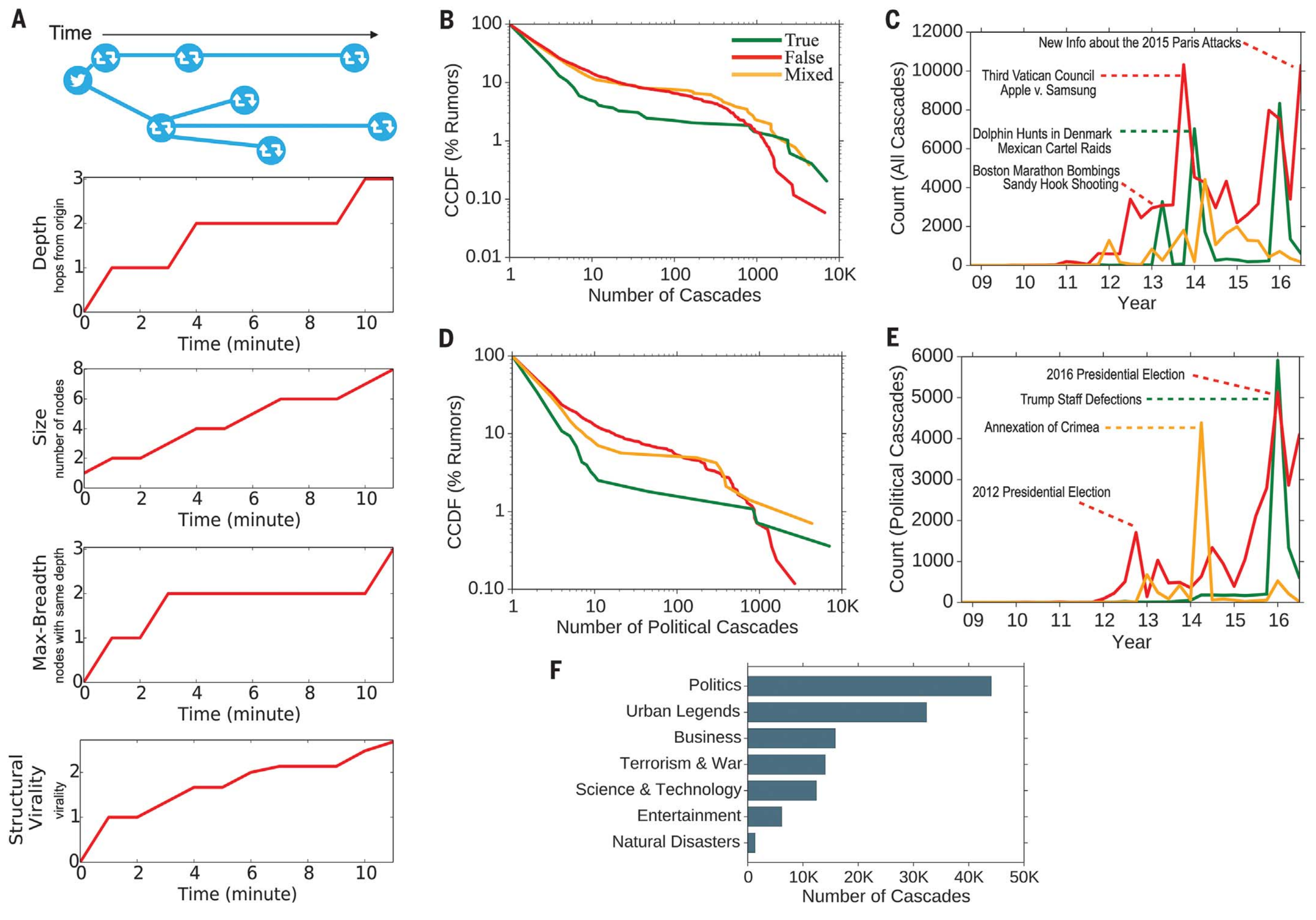


Fig. 1. Rumor cascades. (**A**) An example rumor cascade collected by our method as well as its depth, size, maximum breadth, and structural virality over time. "Nodes" are users. (**B**) The complementary cumulative distribution functions (CCDFs) of true, false, and mixed (partially true and partially false) cascades, measuring the fraction of rumors that exhibit a given number of cascades. (**C**) Quarterly counts of all true, false, and mixed rumor cascades that diffused on Twitter between 2006 and 2017, annotated with example rumors in each category. (**D**) The CCDFs of true, false, and mixed political cascades. (**E**) Quarterly counts of all true, false, and mixed political rumor cascades that diffused on Twitter between 2006 and 2017, annotated with example rumors in each category. (**F**) A histogram of the total number of rumor cascades in our data across the seven most frequent topical categories.

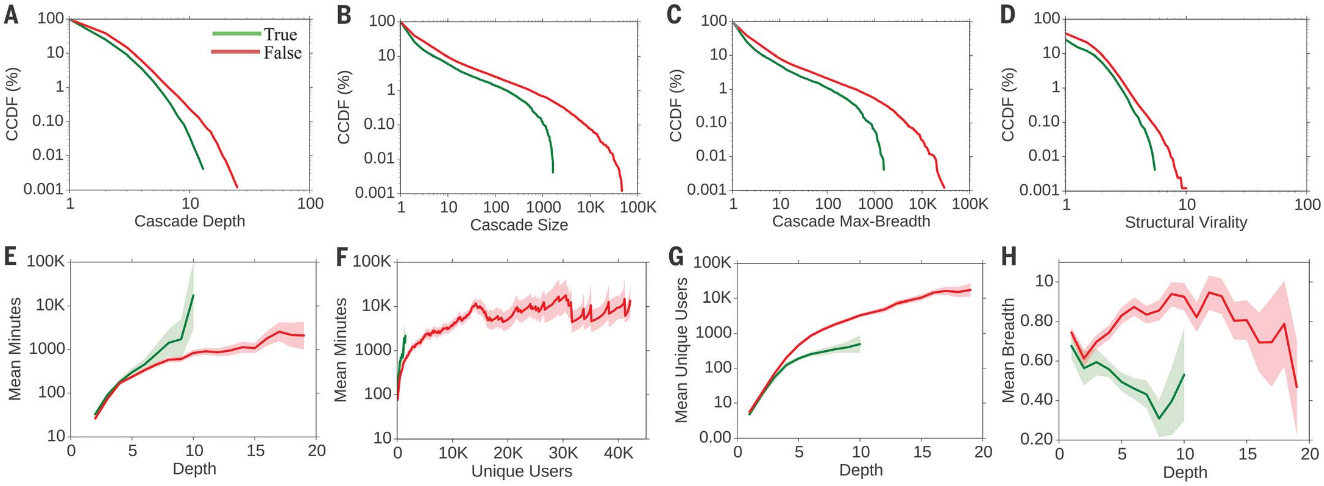


Fig. 2. Complementary cumulative distribution functions (CCDFs) of true and false rumor cascades. (**A**) Depth. (**B**) Size. (**C**) Maximum breadth. (**D**) Structural virality. (**E** and **F**) The number of minutes it takes for true and false rumor cascades to reach any (E) depth and (F) number of unique Twitter users. (**G**) The number of unique Twitter users reached at every depth and (**H**) the mean breadth of true and false rumor cascades at every depth. In (H), plot is lognormal. Standard errors were clustered at the rumor level (i.e., cascades belonging to the same rumor were clustered together; see supplementary materials for additional details).

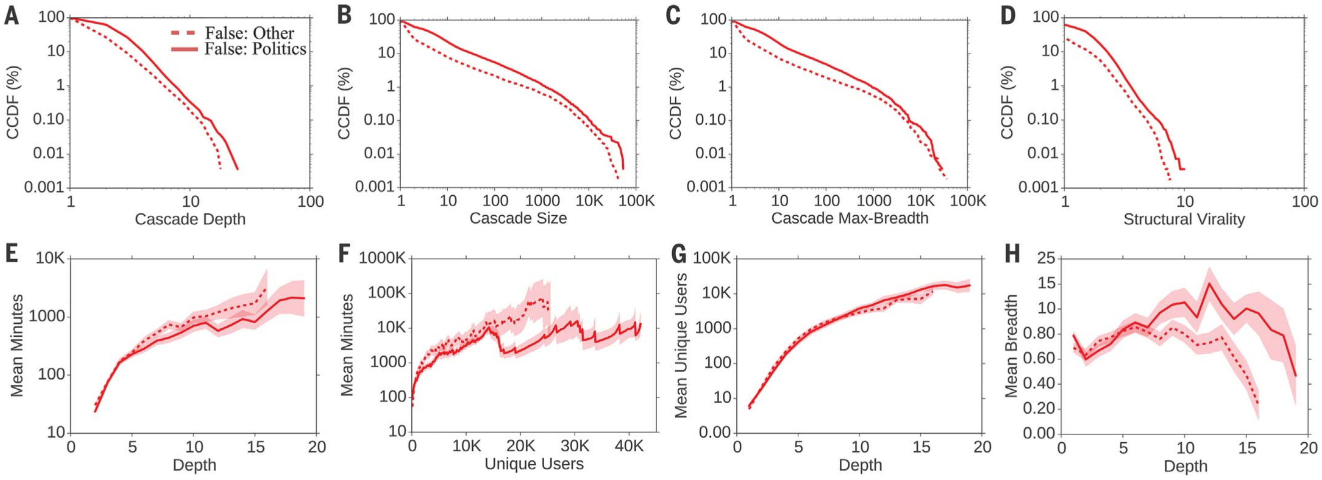


Fig. 3. Complementary cumulative distribution functions (CCDFs) of false political and other types of rumor cascades. (**A**) Depth. (**B**) Size. (**C**) Maximum breadth. (**D**) Structural virality. (**E** and **F**) The number of minutes it takes for false political and other false news cascades to reach any (E) depth and (F) number of unique Twitter users. (**G**) The number of unique Twitter users reached at every depth and (**H**) the mean breadth of these false rumor cascades at every depth. In (H), plot is lognormal. Standard errors were clustered at the rumor level.

greater than 19 hops from the origin tweet (Fig. 2A). Falsehood also reached far more people than the truth. Whereas the truth rarely diffused to more than 1000 people, the top 1% of false-news cascades routinely diffused to between 1000 and 100,000 people (Fig. 2B). Falsehood reached more people at every depth of a cascade than the truth, meaning that many more people retweeted falsehood than they did the truth (Fig. 2C). The spread of falsehood was aided by its virality, meaning that falsehood did not simply spread through broadcast dynamics but rather through peer-to-peer diffusion characterized by a viral branching process (Fig. 2D).

It took the truth about six times as long as falsehood to reach 1500 people (Fig. 2F) and 20 times as long as falsehood to reach a cascade depth of 10 (Fig. 2E). As the truth never diffused beyond a depth of 10, we saw that falsehood reached a depth of 19 nearly 10 times faster than the truth reached a depth of 10 (Fig. 2E). Falsehood also diffused significantly more broadly (Fig. 2H) and was retweeted by more unique users than the truth at every cascade depth (Fig. 2G).

False political news (Fig. 1D) traveled deeper (Fig. 3A) and more broadly (Fig. 3C), reached more people (Fig. 3B), and was more viral than any other category of false information (Fig. 3D). False political news also diffused deeper more quickly (Fig. 3E) and reached more than 20,000 people nearly three times faster than all other types of false news reached 10,000 people (Fig. 3F). Although the other categories of false news reached about the same number of unique users at depths between 1 and 10, false political news routinely reached the most unique users at depths greater than 10 (Fig. 3G). Although all other categories of false news traveled slightly more broadly at shallower depths, false political news traveled more broadly at greater depths, indicating that more-popular false political news items exhibited broader and more-accelerated diffusion dynamics

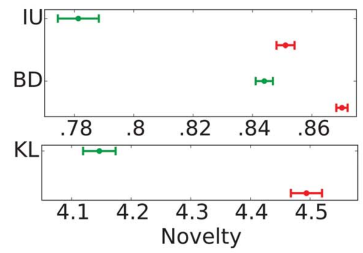
A

	median		mean		mean (log)		stdv (log)		ks-test
	false	true	false	true	false	true	false	true	
followers	410	466	2234	5240	2.62	2.68	0.69	0.88	D=0.104, p∼0.0
followees	383	509	1002	1707	2.59	2.72	0.85	0.96	D=0.136, p∼0.0
verified	0	0	0.002	0.006	nd	nd	nd	nd	D=0.005, p<0.001
engagement	9.52	9.54	19.70	24.65	0.91	0.90	0.65	0.76	D=0.054, p∼0.0
account age	982	1214	1072	1269	2.90	2.97	0.39	0.42	D=0.125, p∼0.0

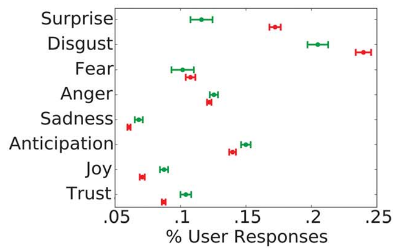
B

	coef	odds ratio	std err	z	P>|z|	[95.0% Conf. Int.]	
account age	0.0002	1.000160	2.07e-05	7.759	0.000	0.000	0.000
engagement	0.0066	1.006648	0.000	18.019	0.000	0.006	0.007
falsehood	0.5350	1.707489	0.084	6.366	0.000	0.370	0.700
followees	-1.639e-05	0.999984	8.73e-06	-1.877	0.060	-3.35e-05	7.22e-07
followers	5.192e-05	1.000052	7.77e-06	6.682	0.000	3.67e-05	6.72e-05
intercept	-2.3941	0.091257	0.072	-33.437	0.000	-2.534	-2.254
verified	1.4261	4.162467	0.090	15.915	0.000	1.250	1.602

C



D



E

	mean		variance		ks-test
	false	true	false	true	
IU	0.85	0.78	0.0052	0.0072	D=0.457, p∼0.0
KL	4.49	4.15	0.1618	0.0948	D=0.433, p∼0.0
BD	0.87	0.84	0.0008	0.0008	D=0.415, p∼0.0

F

	mean		variance		ks-test
	false	true	false	true	
surprise	0.172	0.116	0.0167	0.0072	D=0.205, p∼0.0
disgust	0.240	0.205	0.0260	0.0227	D=0.102, p∼0.0
fear	0.108	0.102	0.0120	0.0095	D=0.021, p∼0.164
anger	0.122	0.126	0.0074	0.0111	D=0.023, p∼0.078
sadness	0.061	0.068	0.0038	0.0065	D=0.037, p∼0.0
anticipation	0.140	0.150	0.0093	0.0154	D=0.038, p∼0.0
joy	0.071	0.087	0.0054	0.0104	D=0.061, p∼0.0
trust	0.087	0.104	0.0058	0.0119	D=0.060, p∼0.0

Fig. 4. Models estimating correlates of news diffusion, the novelty of true and false news, and the emotional content of replies to news. (**A**) Descriptive statistics on users who participated in true and false rumor cascades as well as K-S tests of the differences in the distributions of these measures across true and false rumor cascades. (**B**) Results of a logistic regression model estimating users' likelihood of retweeting a rumor as a function of variables shown at the left. coef, logit coefficient; *z*, *z* score. (**C**) Differences in the information uniqueness (IU), scaled Bhattacharyya distance (BD), and K-L divergence (KL) of true (green) and false (red) rumor tweets compared to the corpus of prior tweets the user was exposed to in the 60 days before retweeting the rumor tweet. (**D**) The emotional content of replies to true (green) and false (red) rumor tweets across seven dimensions categorized by the NRC. (**E**) Mean and variance of the IU, KL, and BD of true and false rumor tweets compared to the corpus of prior tweets the user has seen in the 60 days before seeing the rumor tweet as well as K-S tests of their differences across true and false rumors. (**F**) Mean and variance of the emotional content of replies to true and false rumor tweets across seven dimensions categorized by the NRC as well as K-S tests of their differences across true and false rumors. All standard errors are clustered at the rumor level, and all models are estimated with cluster-robust standard errors at the rumor level.

(Fig. 3H). Analysis of all news categories showed that news about politics, urban legends, and science spread to the most people, whereas news about politics and urban legends spread the fastest and were the most viral in terms of their structural virality (see fig. S11 for detailed comparisons across all topics).

One might suspect that structural elements of the network or individual characteristics of the users involved in the cascades explain why falsity travels with greater velocity than the truth. Perhaps those who spread falsity "followed" more people, had more followers, tweeted more often, were more often "verified" users, or had been on Twitter longer. But when we compared users involved in true and false rumor cascades, we found that the opposite was true in every case. Users who spread false news had significantly fewer followers (K-S test = 0.104, P ~ 0.0), followed significantly fewer people (K-S test = 0.136, P ~ 0.0), were significantly less active on Twitter (K-S test = 0.054, P ~ 0.0), were verified significantly less often (K-S test = 0.004, P < 0.001), and had been on Twitter for significantly less time (K-S test = 0.125, P ~ 0.0) (Fig. 4A). Falsehood diffused farther and faster than the truth despite these differences, not because of them.

When we estimated a model of the likelihood of retweeting, we found that falsehoods were 70% more likely to be retweeted than the truth (Wald chi-square test, P ~ 0.0), even when controlling for the account age, activity level, and number of followers and followees of the original tweeter, as well as whether the original tweeter was a verified user (Fig. 4B). Because user characteristics and network structure could not explain the differential diffusion of truth and falsity, we sought alternative explanations for the differences in their diffusion dynamics.

One alternative explanation emerges from information theory and Bayesian decision theory. Novelty attracts human attention (*24*), contributes to productive decision-making (*25*), and encourages information sharing (*26*) because novelty updates our understanding of the world. When information is novel, it is not only surprising, but also more valuable, both from an information theoretic perspective [in that it provides the greatest aid to decision-making (*25*)] and from a social perspective [in that it conveys social status on one that is "in the know" or has access to unique "inside" information (*26*)]. We therefore tested whether falsity was more novel than the truth and whether Twitter users were more likely to retweet information that was more novel.

To assess novelty, we randomly selected ~5000 users who propagated true and false rumors and extracted a random sample of ~25,000 tweets that they were exposed to in the 60 days prior to their decision to retweet a rumor. We then specified a latent Dirichlet Allocation Topic model (*27*), with 200 topics and trained on 10 million English-language tweets, to calculate the information distance between the rumor tweets and all the prior tweets that users were exposed to before retweeting the rumor tweets. This generated a probability distribution over the 200 topics for each tweet in our data set. We then measured how novel the information in the true and false rumors was by comparing the topic distributions of the rumor tweets with the topic distributions of the tweets to which users were exposed in the 60 days before their retweet. We found that false rumors were significantly more novel than the truth across all novelty metrics, displaying significantly higher information uniqueness (K-S test = 0.457, $P \sim 0.0$) (*28*), Kullback-Leibler (K-L) divergence (K-S test = 0.433, $P \sim 0.0$) (*29*), and Bhattacharyya distance (K-S test = 0.415, $P \sim 0.0$) (which is similar to the Hellinger distance) (*30*). The last two metrics measure differences between probability distributions representing the topical content of the incoming tweet and the corpus of previous tweets to which users were exposed.

Although false rumors were measurably more novel than true rumors, users may not have perceived them as such. We therefore assessed users' perceptions of the information contained in true and false rumors by comparing the emotional content of replies to true and false rumors. We categorized the emotion in the replies by using the leading lexicon curated by the National Research Council Canada (NRC), which provides a comprehensive list of ~140,000 English words and their associations with eight emotions based on Plutchik's (*31*) work on basic emotion—anger, fear, anticipation, trust, surprise, sadness, joy, and disgust (*32*)—and a list of ~32,000 Twitter hashtags and their weighted associations with the same emotions (*33*). We removed stop words and URLs from the reply tweets and calculated the fraction of words in the tweets that related to each of the eight emotions, creating a vector of emotion weights for each reply that summed to one across the emotions. We found that false rumors inspired replies expressing greater surprise (K-S test = 0.205, $P \sim 0.0$), corroborating the novelty hypothesis, and greater disgust (K-S test = 0.102, $P \sim 0.0$), whereas the truth inspired replies that expressed greater sadness (K-S test = 0.037, $P \sim 0.0$), anticipation (K-S test = 0.038, $P \sim 0.0$), joy (K-S test = 0.061, $P \sim 0.0$), and trust (K-S test = 0.060, $P \sim 0.0$) (Fig. 4, D and F). The emotions expressed in reply to falsehoods may illuminate additional factors, beyond novelty, that inspire people to share false news. Although we cannot claim that novelty causes retweets or that novelty is the only reason why false news is retweeted more often, we do find that false news is more novel and that novel information is more likely to be retweeted.

Numerous diagnostic statistics and manipulation checks validated our results and confirmed their robustness. First, as there were multiple cascades for every true and false rumor, the variance of and error terms associated with cascades corresponding to the same rumor will be correlated. We therefore specified cluster-robust standard errors and calculated all variance statistics clustered at the rumor level. We tested the robustness of our findings to this specification by comparing analyses with and without clustered errors and found that, although clustering reduced the precision of our estimates as expected, the directions, magnitudes, and significance of our results did not change, and chi-square ($P \sim 0.0$) and deviance (d) goodness-of-fit tests ($d = 3.4649 \times 10^{-6}$, $P \sim 1.0$) indicate that the models are well specified (see supplementary materials for more detail).

Second, a selection bias may arise from the restriction of our sample to tweets fact checked by the six organizations we relied on. Fact checking may select certain types of rumors or draw additional attention to them. To validate the robustness of our analysis to this selection and the generalizability of our results to all true and false rumor cascades, we independently verified a second sample of rumor cascades that were not verified by any fact-checking organization. These rumors were fact checked by three undergraduate students at Massachusetts Institute of Technology (MIT) and Wellesley College. We trained the students to detect and investigate rumors with our automated rumor-detection algorithm running on 3 million English-language tweets from 2016 (*34*). The undergraduate annotators investigated the veracity of the detected rumors using simple search queries on the web. We asked them to label the rumors as true, false, or mixed on the basis of their research and to discard all rumors previously investigated by one of the fact-checking organizations. The annotators, who worked independently and were not aware of one another, agreed on the veracity of 90% of the 13,240 rumor cascades that they investigated and achieved a Fleiss' kappa of 0.88. When we compared the diffusion dynamics of the true and false rumors that the annotators agreed on, we found results nearly identical to those estimated with our main data set (see fig. S17). False rumors in the robustness data set had greater depth (K-S test = 0.139, $P \sim 0.0$), size (K-S test = 0.131, $P \sim 0.0$), maximum breadth (K-S test = 0.139, $P \sim 0.0$), structural virality (K-S test = 0.066, $P \sim 0.0$), and speed (fig. S17) and a greater number of unique users at each depth (fig. S17). When we broadened the analysis to include majority-rule labeling, rather than unanimity, we again found the same results (see supplementary materials for results using majority-rule labeling).

Third, although the differential diffusion of truth and falsity is interesting with or without robot, or bot, activity, one may worry that our conclusions about human judgment may be biased by the presence of bots in our analysis. We therefore used a sophisticated bot-detection algorithm (*35*) to identify and remove all bots before running the analysis. When we added bot traffic back into the analysis, we found that none of our main conclusions changed—false news still spread farther, faster, deeper, and more broadly than the truth in all categories of information. The results remained the same when we removed all tweet cascades started by bots, including human retweets of original bot tweets (see supplementary materials, section S8.3) and when we used a second, independent bot-detection algorithm (see supplementary materials, section S8.3.5) and varied the algorithm's sensitivity threshold to verify the robustness of our analysis (see supplementary materials, section S8.3.4). Although the inclusion of bots, as measured by the two state-of-the-art bot-detection algorithms we used in our analysis, accelerated the spread of both true and false news, it affected their spread roughly equally. This suggests that false news spreads farther, faster, deeper, and more broadly than the truth because humans, not robots, are more likely to spread it.

Finally, more research on the behavioral explanations of differences in the diffusion of true and false news is clearly warranted. In particular, more robust identification of the factors of human judgment that drive the spread of true and false news online requires more direct interaction with users through interviews, surveys, lab experiments, and even neuroimaging. We encourage these and other approaches to the investigation of the factors of human judgment that drive the spread of true and false news in future work.

False news can drive the misallocation of resources during terror attacks and natural disasters, the misalignment of business investments, and misinformed elections. Unfortunately, although the amount of false news online is clearly increasing (Fig. 1, C and E), the scientific understanding of how and why false news spreads is currently based on ad hoc rather than large-scale systematic analyses. Our analysis of all the verified true and false rumors that spread on Twitter confirms that false news spreads more pervasively than the truth online. It also overturns conventional wisdom about how false news spreads. Though one might expect network structure and individual characteristics of spreaders to favor and promote false news, the opposite is true. The greater likelihood of people to retweet falsity more than the truth is what drives the spread of false news, despite network and individual factors that favor the truth. Furthermore, although recent testimony before congressional committees on misinformation in the United States has focused on the role of bots in spreading false news (*36*), we conclude that human behavior contributes more to the differential spread of falsity and truth than automated robots do. This implies that misinformation-containment policies should also emphasize behavioral interventions, like labeling and incentives to dissuade the spread of misinformation, rather than focusing exclusively on curtailing bots. Understanding how false news spreads is the first step toward containing it. We hope our work inspires more large-scale research into the causes and consequences of the spread of false news as well as its potential cures.

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ACKNOWLEDGMENTS

We are indebted to Twitter for providing funding and access to the data. We are also grateful to members of the MIT research community for invaluable discussions. The research was approved by the MIT institutional review board. The analysis code is freely available at https://goo.gl/forms/AKIlZujpexhN7fY33. The entire data set is also available, from the same link, upon signing an access agreement stating that (i) you shall only use the data set for the purpose of validating the results of the MIT study and for no other purpose; (ii) you shall not attempt to identify, reidentify, or otherwise deanonymize the data set; and (iii) you shall not further share, distribute, publish, or otherwise disseminate the data set. Those who wish to use the data for any other purposes can contact and make a separate agreement with Twitter.

SUPPLEMENTARY MATERIALS

www.sciencemag.org/content/359/6380/1146/suppl/DC1
Materials and Methods
Figs. S1 to S20
Tables S1 to S39
References (*37*–*75*)

14 September 2017; accepted 19 January 2018
10.1126/science.aap9559

北 京 邮 电 大 学

本科毕业设计（论文）开题报告

学院	信息与通信工程学院	专业	通信工程	班级	201421119
学生姓名	猜猜	学号	2014210999	班内序号	99
指导教师姓名	猜猜	所在单位	信息与通信工程学院	职称	教授
设计（论文）题目	（中文）猜猜看毕设题目是什么				
	（英文） Just Guess What On Earth My Title is				

一、 选题背景及意义

社交多媒体（social multimedia）是多媒体数据（multimedia）与社交媒体（social media）相结合的新型媒体形式。它是互联网技术发展过程中，人们对多样的媒体内容和新型的交互模式的需求中产生的。其中，多媒体数据极大地丰富了纯文本内容，而社会媒体网络提供了快速交流、传播多媒体内容的高效平台，两者相互转化。全世界内，最引人注目的社交媒体平台当属微博客（Microblog），其中以中文的新浪微博和英文的 Twitter 最为活跃， 各平台每时每刻产生并流动着种类繁多的大量信息。

微博客平台有着发布方便、传播迅速、受众广泛且总量大的特点。这种特点使得更多的官方媒体将其作为资讯发布的重要平台，同时更多的普通用户将其作为获取热点信息的重要来源。然而，在加速真实信息的有效传播的同时，微博客平台也成了虚假消息的温床，这一现象在社会和科学健康类话题中表现突出：在重大事件、突发事件和灾害事故消息等社会类话题中，虚假信息的传播严重扰乱了网络空间秩序，冲击着网民的认知，有的甚至导致了社会秩序的混乱（如日本福岛核电站泄露事件发生后我国的食用盐哄抢事件）和事件走向的转变（如 2016 年的美国总统选举）；在科学健康类话题中，耸人听闻的食品安全曝光（如“塑料紫菜”、“棉花肉松”）、不科学的食品安全警告（如“柿子和酸奶一起吃会中毒致死”）和错误的医疗手段（如“一滴血就能验癌”）极易对人们的认知造成误导，进一步带来不必要的麻烦和相应的经济冲击。

二、 研究的基本内容

对所提出算法进行性能的测试、比较和分析，针对结论面向未来发展方向进行探讨。

三、　研究方法及措施

从数据分布的角度上讲，检测谣言的这一类问题非常适合归入数据挖掘的经典问题——异常检测（anomaly detection）或离群点检测（outlier detection），一方面是因为谣言的种类繁多，若归入一大类，其与正常信息的边界可能会难以寻找；另一方面是即便虚假信息被认为泛滥成灾，但谣言在微博空间中仍是少数，可获取的谣言和非谣言比例失衡。

四、　研究工作的步骤与进度

2018.1.1 ~ 2018.2.10 完成领域内容调研，模板对应部分撰写。

2018.2.28~2018.4.15 完成相关模板研究，设计模板。

2018.4.16~2018.4.30 进行模板设计评估和比较分析。

2018.5.1~2018.5.15 模板整体撰写。

五、　主要参考文献

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指导教师签字		日期	年　月　日

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北 京 邮 电 大 学

本科毕业设计（论文）中期进展情况检查表

<table>
<tr><td>学院</td><td>信息与通信工程学院</td><td>专业</td><td>通信工程</td><td>班级</td><td>2014211199</td></tr>
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<tr><td>指导教师姓名</td><td></td><td>所在单位</td><td></td><td>职称</td><td></td></tr>
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实验结束后，对整体准确率（Accuracy）进行了统计，还得到了谣言和非谣言的精度（Precision）、召回率（Recall）和 F1 值（F1-Score）。</td></tr>
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• 完成外文文献的翻译。</td></tr>
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<tr><td>拟采取的办法</td><td colspan="4">拟补充部分实验和查阅领域经验进行讨论分析。</td></tr>
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