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

本科毕业设计（论文）任务书

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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 rowspan="2">设计(论文)题目</td><td colspan="5">（中文）猜猜看毕设题目是什么</td></tr>
<tr><td colspan="5">（英文）Just Guess What On Earth My Title is</td></tr>
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<tr><td colspan="5">科研项目负责人：</td></tr>
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主要任务及目标：

- 给出一个 LaTeX 模板。
- 减小大家花费在排版上的时间成本。
- 但是代价是需要有一点基础学习成本，但研究生时可能会用到。

主要内容：

同任务目标。

主要参考文献：

- Zubiaga A, Aker A, Bontcheva K, et al. Detection and Resolution of Rumours in Social Media: A Survey[J]. 2017.
- Yan Z, Chen W, Chai K Y, et al. Detecting rumors on Online Social Networks using multi-layer autoencoder[C]// IEEE Technology & Engineering Management Conference. IEEE, 2017:437-441.

进度安排：

- 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。

指导教师签字		日期	年　月　日

编号：________________

北京邮电大学本科生毕业设计（论文）成绩评定表

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师 单 位</td><td colspan="5"></td></tr>
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<tr><td>指 导 教 师</td><td>复 议</td></tr>
<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>
<tr><td>方案设计</td><td colspan="2">能独立提出符合选题的可行性研究方案、实验方案、设计方案，独立进行实验（如安装、调试、操作）和研究方案论证。</td><td>5</td><td>4</td><td>3.5</td><td>3</td><td>2</td><td></td><td></td></tr>
<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>
<tr><td>学习态度</td><td colspan="2">认真、勤奋、努力、诚实、严格遵守纪律，按期饱满完成规定的任务。</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>文本规范</td><td colspan="2">装订顺序正确，字体字号等与基本规范相符，符号统一，编号齐全，图表完备、整洁、正确。</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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评语：

指导教师签字：　　　　日期：　　年　　月　　日</td></tr>
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复议有权限修改指导教师评分，选择复议后指导教师评分将由复议评分替换</td></tr>
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答辩小组成绩评定	**评价内容**	**具体要求**	**分值**					**评分**
	选题	符合专业培养目标，符合社会实际、结合工程实际，难易适度，体现新颖性、综合性。	5	4	3.5	3	2	
	设计（论文）质量水平	全面完成任务书中规定的各项要求，文题相符，工作量饱满，写作规范，达到综合训练的要求，有理论成果和应用价值。	20	16	14	12	8	
	答辩准备	准备充分；有简洁、清晰、美观的演示文稿；准时到场。	5	4	3.5	3	2	
	内容陈述	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。	20	18	14	12	8	
	回答问题	回答问题准确、有深度、有理论根据、基本概念清晰。	10	8	7	6	4	
	答辩小组评分合计（满分 60 分）							
	意见： 答辩小组组长签字：____________ 年 月 日							
	答辩小组成员：							
学院意见	最终成绩：百分制__________； 五分制____________ 院长签章： 学院盖章： 年 月 日							
备注								

注：1. 毕业设计（论文）成绩由中期检查评分（满分 10 分）、指导教师评分/复议评分（满分 30 分）和答辩小组评分（满分 60 分）相加，得出百分制成绩，再按 100-90 分为“优”、89-80 分为“良”、79-70 分为“中”、69-60 分为“及格”、60 分以下为“不及格”的标准折合成五级分制成绩；

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《　　　　　　　　　　　　　　　　　　》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。

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本人签名：____________________　　　　日期：______________________

导师签名：____________________　　　　日期：______________________

基于 LLM 的交互式多模态图像编辑系统的设计与搭建

摘　要

这是中文摘要的部分。

它可以拥有多段。这是中文摘要的部分。

它可以拥有多段。

如果你写的太长，甚至可以到第二页。

关键词　北京邮电大学　本科生　毕业设计　模板　示例

Design and Construction of Interactive Multimodal Image Editing System Based on LLM

ABSTRACT

This is ABSTRACT.

You can write more than one paragraph here.

If your abstract is too long, it will take up more pages.

KEY WORDS BUPT undergraduate thesis template example

目　　录

第一章　绪论

1.1　项目背景

随着图像生成技术的不断发展，图像编辑作为其中的关键技术之一，应用广泛，涵盖了媒体娱乐、数字营销和智能医疗等多个领域。然而，传统的图像编辑模型存在着交互性差和生成图像质量受限的问题，迫使我们探索更先进的方法以提高图像生成的质量和用户交互性。通过深度学习和语言大模型的结合，我们有望构建一个创新的交互式图像编辑系统，为图像编辑领域带来新的可能性。

1.2　项目意义

通过结合深度学习和语言大模型，可以为图像编辑领域带来创新和进步。这样的研究对于推动图像处理领域的发展具有重要意义，可以应用于媒体娱乐、数字营销、智能医疗等多个领域，为用户提供更优质的图像编辑体验，促进相关产业的发展。

1.3　项目内容

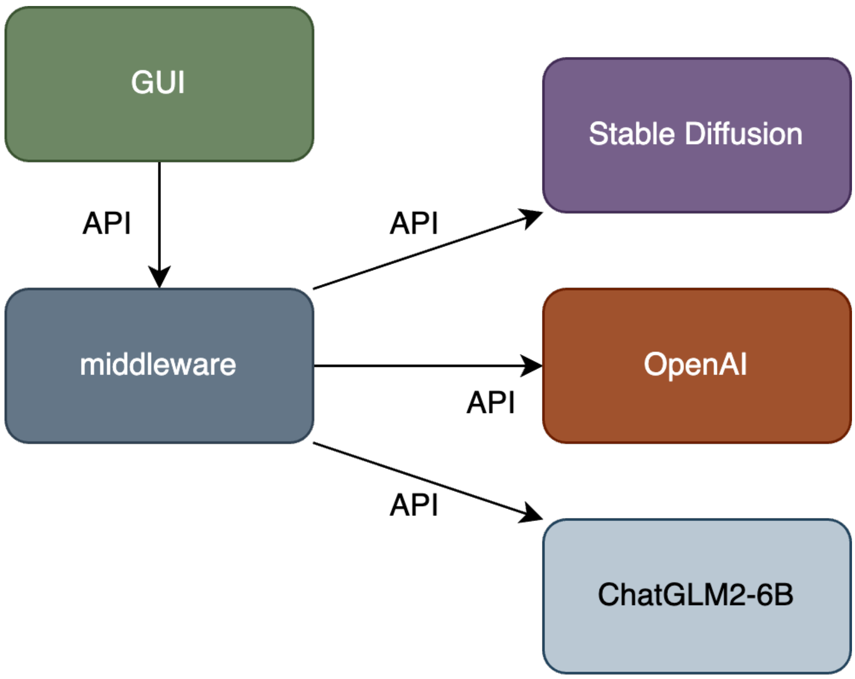

图 1-1

该项目主要实现了 GUI、middleware，并对 Stable Diffusion 和 ChatGLM2-6B 进行修改与适配。各个模块之间的关系如图 1-1 所示。

通过在基于 Stable Diffusion 的开源项目 stable-diffusion-webui 上进行扩展，本项目实现了通过 API 调用多种 Stable Diffusion 模型对图像进行修改的功能。

通过对 ChatGLM2-6B 进行微调，本项目实现了通过 API 调用针对本任务微调过的 ChatGLM2-6B 模型。

通过调用 OpenAI 的 API，本项目实现了多个功能：通过 GPT4V 生成图像修改的建议、通过 GPT3.5Turbo 辅助生成微调大语言模型的数据集和图像修改的指令、通过 DALL-E2 实现在 Stable Diffusion 不可用时作为替代模型对图像进行修改。

GUI 主要通过 python 语言实现，其构建了一个直观、易于使用的用户交互界面。在消耗大量计算资源的任务上，GUI 会通过 API 对 middleware 发出请求，减少了用户侧对计算资源的依赖，降低了用户的使用门槛。

middleware 使用 golang 语言搭建了一个后端服务，其接入了 Stable Diffusion、ChatGLM2-6B、OpenAI 的 API，并将这些 API 进行整合后向 GUI 提供 API。middleware 的建立实现了一对多服务的能力，提高了 GUI 调用多方 API 的便利性，同时通过统一配置提高了系统的可维护性。

第二章　总体方案设计

2.1　GUI

GUI 虽然承担计算任务较少，但却是承载本项目结构与逻辑的关键部分。通过使用符合规则的指令作为中枢，GUI 打通了大语言模型和图像生成模型之间的壁垒，使基于 LLM 的创新交互式图像编辑系统成为可能。GUI 的模块构成如表 2-1：

表 2-1　GUI 模块

模块	描述
BaseImage	接受上传的原始图片并预览
EditedImage	预览修改后的图片
Operation Board	执行指令
Settings	对系统进行设置
Chat	与大语言模型交互的聊天界面
Edit Image	对图像进行自定义遮罩和换脸等操作
Auto	执行自动化操作
Manual	系统使用说明

用户首先上传需要修改的图片，然后可在 Chat 模块中选择不同的大语言模型进行交互并得到相应的指令，最后在 Operation Board 模块中选择指令执行或一键全部执行。如果对自动生成的遮罩不满意，可在 Edit Image 中对遮罩进行修改。

在 Auto 模块中，用户可通过选择多张图片批量生成满足微调大语言模型微调所需的数据。其会循环地从给定的图片集中随机选择图片继续分割，将分割后的结果和特定的 prompt 通过 GPT3.5Turbo 生成对应的修改建议，再将分割的结果、生成的建议通过 GPT3.5Turbo 生成指令。

2.2　middleware

middleware 是项目的核心组件，通过整合多个平台的 API，为 GUI 提供统一的、简单易接入的 API 服务。其主要特点包括但不限于：1. API 整合：middleware 整合了多个平台的 API，包括图像生成模型、语言模型等，使得 GUI 可以通过统一的接口调用不同功能模块；2. 统一风格：middleware 设计了统一的 API 风格和路由规范，使得 GUI 可以轻松使用 API 服务，提高开发效率；3. 简单易接入：middleware 提供了简单易用的 API 服务，GUI 无需关注具体实现细节，只需按照简单的请求规范调用 API 即可；4. 稳定性和可靠性：middleware 基于 Golang 语言实现，具有高效的并发处理能力和稳定的运行性能，保证了 API 服务的稳定性和可靠性；5. 易于维护：middleware 采用了 Beego

框架，具有清晰的代码结构和模块化设计，易于维护和扩展，保证了项目的长期可持续发展。其向 GUI 提供的主要 API 如表 2-2 所示：

表 2-2 middleware 主要 API

API	路由	描述
PostSDTxt2Img	/v1/pics/txt2img	通过 Stable Diffusion 模型生成图片
PostSDImg2Img	/v1/pics/img2img	通过 Stable Diffusion 模型修改图片
PostDALLE2Edit	/v1/pics/openai/img2img	通过 DALL-E2 模型修改图片
GetLoras	/v1/pics/loras	获取可用的 LoRa 模型列表
PostHuggingFaceImgSegment	/v1/pics/huggingface/segment	获取图像分割结果
PostGPT3Dot5Turbo	/v1/chat/gpt3dot5turbo	调用 GPT3.5Turbo
PostGPT4	/v1/chat/gpt4	调用 GPT4
PostChatGLM2_6B	/v1/chat/glm2_6b	调用 ChatGLM2-6B
PostGPT4V	/v1/chat/gpt4v	调用 GPT4V

2.3 Stable Diffusion

由于本项目对于图像生成模型的要求较高且需求复杂，为了便于结合 Stable Diffusion 模型和其他前沿研究成果和开源社区项目，本项目在构建 Stable Diffusion 模块时以开源项目 stable-diffusion-webui[1]为基础，结合 Control Net[1] 和基于 DeepFake[2] 的开源项目 sd-webui-roop[2]，通过 API 为 middleware 提供服务。

2.4 OpenAI

本项目使用了 OpenAI[3]的 GPT3.5Turo、GPT4、GPT4V、DALL-E2 等模型，通过 API 调用 OpenAI 的模型。

2.5 ChatGLM2-6B

本项目使用开源的 ChatGLM2-6B 模型，使用开源项目 LLaMA-Factory[4]，利用本项目提供的数据自动生成功能所生成的数据集，使用 LoRa[3] 方法对模型进行微调以在本项目所需的任务中获得更佳的表现。微调后的模型通过 fastapi 提供 API 服务。

[1]https://github.com/AUTOMATIC1111/stable-diffusion-webui

[2]https://github.com/s0md3v/sd-webui-roop

[3]https://openai.com

[4]https://github.com/hiyouga/LLaMA-Factory

第三章　实现方法

3.1　图像处理有关的实现方法

3.1.1　图像自动遮罩

该项目提供了两种自动生成遮罩的方法：基于关键词对自动生成遮罩和基于已给出的点自动填充生成遮罩。两种方法都会首先使用图像分割模型对图像进行分割（如图3-1），然后生成原始的遮罩，最后会通过本项目设计的优化算法生成最终的遮罩。

(a)　(b)

图 3-1　图像分割结果：(a)原始图像，(b)分割结果

基于关键词自动生成遮罩的方法会根据关键词和图像分割结果生成自动原始的遮罩，该功能会遍历每个给出的关键词，若关键词与分割结果之一吻合，则会对相应的分割区域进行遮罩，生成原始的遮罩。

基于已给出的点自动填充生成遮罩的方法会根据在图片中标记的点和图像分割结果生成自动原始的遮罩，该功能会遍历每个给出的点，将该点所在的部分全部进行遮罩，最后生成原始的遮罩。

(a)　(b)

图 3-2　基于已给出的点自动填充生成遮罩：(a)标记后的图像，(b)生成的遮罩

第四章　基础模块示例

4.1　特殊文本类型

4.1.1　脚注

社交媒体是一种供用户创建在线社群来分享信息、观点、个人信息和其它内容（如视频）的电子化交流平台，社交网络服务（social network service, SNS）和微博客（microblogging）都属于社交媒体的范畴[4]，国外较为知名的有 Facebook[1]、Instagram[2]、Twitter[3]、LinkedIn[4]等，国内较为知名的有新浪微博[5]。

在社交媒体的强覆盖下，新闻信息的传播渠道也悄然了发生变化。[5]

4.1.2　定义、定理与引理等

定义 4.1 这是一条我也不知道在说什么的定义，反正我就是写在这里做个样子罢了，也没人会仔细读。*[6]*

定理 4.1 这是一条我也不知道在说什么的定理，反正我就是写在这里做个样子罢了，也没人会仔细读。

公理 4.1 这是一条我也不知道在说什么的公理，反正我就是写在这里做个样子罢了，也没人会仔细读。

引理 4.1 这是一条我也不知道在说什么的引理，反正我就是写在这里做个样子罢了，也没人会仔细读。

命题 4.1 这是一条我也不知道在说什么的命题，反正我就是写在这里做个样子罢了，也没人会仔细读。

推论 4.1 这是一条我也不知道在说什么的推论，反正我就是写在这里做个样子罢了，也没人会仔细读。

4.1.3　中英文文献、学位论文引用

根据美国皮尤研究中心的 2017 年 9 月发布的调查结果[7]，67% 的美国民众会从社交媒体上获取新闻信息，其中高使用频率用户占 20%。在国内，中国互联网信息中心

本项目来源于科研项目“基于 LaTeX 的本科毕业设计”，项目编号 1124

[1]http://www.facebook.com/

[2]https://www.instagram.com/

[3]http://www.twitter.com/

[4]http://www.linkedin.com/

[5]http://www.weibo.com/

《2016 年中国互联网新闻市场研究报告》[8] 也显示，社交媒体已逐渐成为新闻获取、评论、转发、跳转的重要渠道，在 2016 年下半年，曾经通过社交媒体获取过新闻资讯的用户比例高达 90.7%，在微信、微博等社交媒体参与新闻评论的比例分别为 62.8% 和 50.2%。社交媒体正在成为网络上热门事件生成并发酵的源头，在形成传播影响力后带动传统媒体跟进报道，最终形成更大规模的舆论浪潮。[9]

在国内，新浪微博由于其发布方便、传播迅速、受众广泛且总量大的特点，成为了虚假信息传播的重灾区：《中国新媒体发展报告（2013）》[?] 显示，2012 年的 100 件微博热点舆情案例中，有超过 1/3 出现谣言；《中国新媒体发展报告（2015）》[?] 对 2014 年传播较广、比较典型的 92 条假新闻进行了多维度分析，发现有 59% 的虚假新闻首发于新浪微博。

此等信息的传播严重损害了有关公众人物的名誉权，降低了社交媒体服务商的商业美誉度，扰乱了网络空间秩序，冲击着网民的认知，极易对民众造成误导，带来诸多麻烦和经济损失，甚至会导致社会秩序的混乱。针对社交媒体谣言采取行动成为了有关部门、服务提供商和广大民众的共同选择。[6]

4.2 图表及其引用

此处引用了简单的表 4-1 。

请注意，LaTeX 的图表排版规则决定了图表**不一定会乖乖呆在你插入的地方**，这是为了避免 Word 中由于图片尺寸不匹配在页面下部出现的的空白，所以请不要使用“下图”“下表”作为指向文字，应使用“图 1-1 所示”这样的表述。

表 4-1 基于浏览者行为的特征

特征	**描述**	**形式与理论范围**
点赞量	微博的点赞数量	数值，$\mathbb{N}$
评论量	微博的评论数量	数值，$\mathbb{N}$
转发量	微博的转发数量	数值，$\mathbb{N}$

此处引用了复杂的表 4-2 。

表 4-2 基于浏览者行为的复杂特征

类别	**特征**	**不知道叫什么的表头**	
		描述	**形式与理论范围**
正常互动	点赞量	微博的点赞数量	数值，$\mathbb{N}$
	评论量	微博的评论数量	数值，$\mathbb{N}$
	转发量	微博的转发数量	数值，$\mathbb{N}$
非正常互动	羡慕量	微博的羡慕数量	数值，$\mathbb{N}$

此处展示了更专业的表 4-3，一个好的表格没有竖线。

表 4-3 红警 2 名词解释

术语类别	缩略语	解释
	兵营	兵营（Barracks），《命令与征服 红色警戒 2：尤里的复仇》游戏中的一种生产建筑，用以生产步兵单位
	建造场	建造场（Construction Yard），《命令与征服 红色警戒 2：尤里的复仇》游戏中的一种基础建筑，用以支持其他建筑的建造
	矿厂	矿石精炼厂（Ore Refinery），《命令与征服 红色警戒 2：尤里的复仇》游戏中的一种资源建筑，用以将矿车采集的矿石转化为游戏资金
游戏	空指	空指部（Airforce Command Headquarters），《命令与征服 红色警戒 2：尤里的复仇》游戏中的一种资源建筑，用以提供雷达功能和 T2 科技及生产部分空军单位
	相机	游戏术语，特指游戏内的观察区域和视角
	重工	战车工厂（War Factory），《命令与征服 红色警戒 2：尤里的复仇》游戏中的一种生产建筑，用以生产载具单位
	战争迷雾	游戏术语，《命令与征服 红色警戒 2：尤里的复仇》中指黑色的未探索区域

此处引用了一张图。图 4-1 表示的是一个由含有 4 个神经元的输入层、含有 3 个神经元的隐藏层和含有 4 个神经元的输出层组成的自编码器，+1 代表偏置项。

4.3 公式与算法表示

4.3.1 例子：基于主成分分析

4.3.1.1 主成分分析算法

下面对主成分分析进行介绍。

主成分分析是一种简单的机器学习算法，其功能可以从两方面解释：一方面可以认为它提供了一种压缩数据的方式，另一方面也可以认为它是一种学习数据表示的无监督学习算法。[?] 通过 PCA，我们可以得到一个恰当的超平面及一个投影矩阵，通过投影矩阵，样本点将被投影在这一超平面上，且满足最大可分性（投影后样本点的方差最大化），直观上讲，也就是能尽可能分开。

对中心化后的样本点集 $\boldsymbol{X} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_i, ..., \boldsymbol{x}_m\}$（有 $\sum_{i=1}^{m} \boldsymbol{x}_i = 0$），考虑将其最大可分地投影到新坐标系 $\boldsymbol{W} = \{\boldsymbol{w}_1, \boldsymbol{w}_2, ..., \boldsymbol{w}_i, ..., \boldsymbol{w}_d\}$，其中 $\boldsymbol{w}_i$ 是标准正交基向量，满足 $\|\boldsymbol{w}_i\|_2 = 1$，$\boldsymbol{w}_i^T \boldsymbol{w}_j = 0$（$i \neq j$）。假设我们需要 d'（$d' < d$）个主成分，那么样

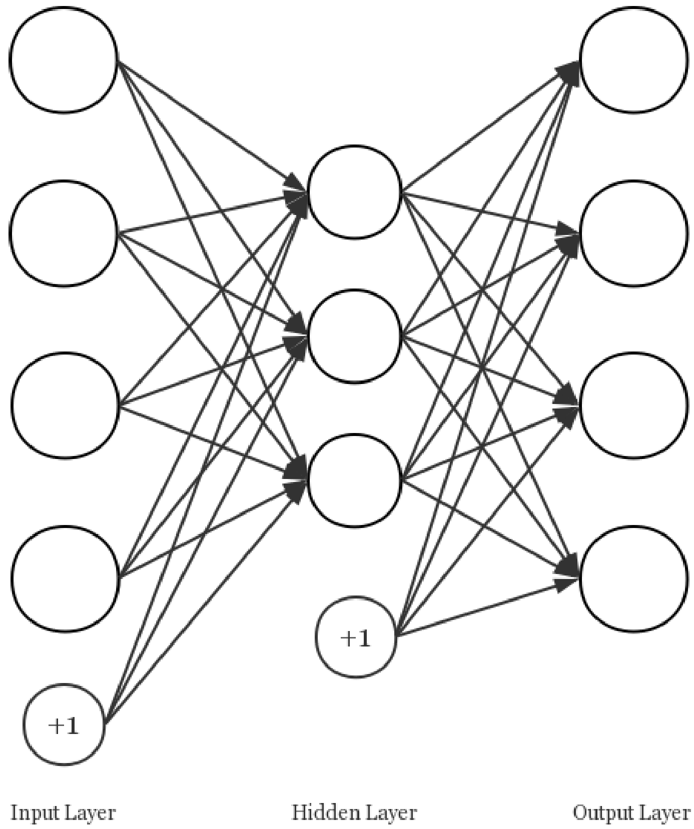

图 4-1 自编码器结构

(a) (b)

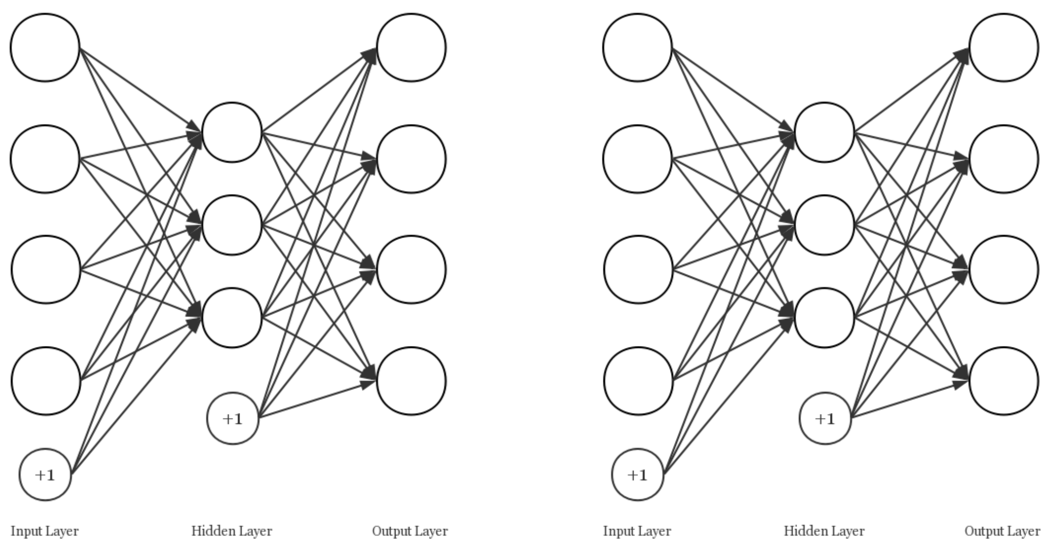

图 4-2 这是两个自编码器结构，我就是排一下子图的效果: (a)左边的自编码器，(b)右边的自编码器

本点 $\boldsymbol{x}_i$ 在低维坐标系中的投影是 $\boldsymbol{z}_i=(z_{i1};z_{i2};...;z_{id'})$，其中 $z_{ij}=\boldsymbol{w}_j^{\mathrm{T}}\boldsymbol{x}_i$，是 $\boldsymbol{x}_i$ 在低维坐标系下第 j 维的坐标。对整个样本集，投影后样本点的方差是

$$\begin{aligned}&\frac{1}{m}\sum_{i=1}^{m}\boldsymbol{z}_i^{\mathrm{T}}\boldsymbol{z}_i\\=&\frac{1}{m}\sum_{i=1}^{m}(\boldsymbol{x}_i^{\mathrm{T}}\boldsymbol{W})^{\mathrm{T}}(\boldsymbol{x}_i^{\mathrm{T}}\boldsymbol{W})\\=&\frac{1}{m}\sum_{i=1}^{m}\boldsymbol{W}^{\mathrm{T}}\boldsymbol{x}_i\boldsymbol{x}_i^{\mathrm{T}}\boldsymbol{W}\\=&\frac{1}{m}\boldsymbol{W}^{\mathrm{T}}\boldsymbol{X}\boldsymbol{X}^{\mathrm{T}}\boldsymbol{W}\end{aligned} \tag{式（4-1）}$$

由于我们知道新坐标系 $\boldsymbol{W}$ 的列向量是标准正交基向量，且样本点集 $\boldsymbol{X}$ 已经过中心化，则 PCA 的优化目标可以写为

$$\begin{aligned}\max_{\boldsymbol{W}}\quad & tr(\boldsymbol{W}^{\mathrm{T}}\boldsymbol{X}\boldsymbol{X}^{\mathrm{T}}\boldsymbol{W})\\ \text{s.t.}\quad & \boldsymbol{W}^{\mathrm{T}}\boldsymbol{W}=\boldsymbol{I}\end{aligned} \tag{式（4-2）}$$

由于 $\boldsymbol{X}\boldsymbol{X}^{\mathrm{T}}$ 是协方差矩阵，那么只需对它做特征值分解，即

$$\boldsymbol{X}^{\mathrm{T}}\boldsymbol{X}=\boldsymbol{W}\boldsymbol{\Lambda}\boldsymbol{W}^{\mathrm{T}} \tag{式（4-3）}$$

其中 $\boldsymbol{\Lambda}=diag(\boldsymbol{\lambda})$，$\boldsymbol{\lambda}=\{\lambda_1,\lambda_2,...,\lambda_m\}$。

具体地，考虑到它是半正定矩阵的二次型，存在最大值，可对式（4-2 ）使用拉格朗日乘数法

$$\boldsymbol{X}\boldsymbol{X}^{\mathrm{T}}\boldsymbol{w}_i=\lambda_i\boldsymbol{w}_i \tag{式（4-4）}$$

之后将求得的特征值降序排列，取前 d' 个特征值对应的特征向量组成所需的投影矩阵 $\boldsymbol{W}'=(\boldsymbol{w}_1,\boldsymbol{w}_2,...,\boldsymbol{w}_{d'})$，即可得到 PCA 的解。PCA 算法的描述如算法1所示。

算法 1 主成分分析（PCA）

输入： 样本集 $\boldsymbol{x}=\{\boldsymbol{x}_1,\boldsymbol{x}_2,...,\boldsymbol{x}_i,...,\boldsymbol{x}_m\}$，低维空间维数 d'

输出： 投影矩阵 $\boldsymbol{W}'=(\boldsymbol{w}_1,\boldsymbol{w}_2,...,\boldsymbol{w}_{d'})$

1: 对所有样本中心化 $\boldsymbol{x}_i\leftarrow\boldsymbol{x}_i-\frac{1}{m}\sum_{i=1}^{m}\boldsymbol{x}_i$

2: 计算样本的协方差 $\boldsymbol{X}\boldsymbol{X}^{\mathrm{T}}$

3: 对协方差矩阵 $\boldsymbol{X}\boldsymbol{X}^{\mathrm{T}}$ 做特征值分解

4: 取最大的 d' 个特征值所对应的特征向量 $\boldsymbol{w}_1,\boldsymbol{w}_2,...,\boldsymbol{w}_{d'}$

4.3.1.2 主成分分析可信度评估方法

记待判定微博 $\boldsymbol{w}_0$ 的经典特征向量为 $\boldsymbol{f}_0^c$，它的发布者在 $\boldsymbol{w_0}$ 前发布的 k 条微博为 $\boldsymbol{W} = \boldsymbol{w}_1, \boldsymbol{w}_2, \ldots, \boldsymbol{w}_k$，这 k 条微博对应的经典特征向量集为 $\boldsymbol{F}_W^c = \{\boldsymbol{f}_1^c, \boldsymbol{f}_2^c, \ldots, \boldsymbol{f}_k^c\}$。令 $label = 1$ 代表谣言，$label = 0$ 代表非谣言。算法的具体流程如算法2所示。

算法 2 基于 PCA 的信息可信度评估

输入： $\boldsymbol{f}_0^c$，$\boldsymbol{F}_W^c$，保留主成分数 n

输出： 标签 $label \in \{0, 1\}$

对所有特征向量应用 PCA，保留前 n 个主成分 $\boldsymbol{o}_i^c \leftarrow PCA(\boldsymbol{f}_i^c, n)$（$i = 0, 1, \ldots, k$）
计算 $\boldsymbol{F}_W^c$ 中各向量的平均距离 μ 和标准差 σ
计算阈值 $thr = \mu/\sigma$
if $\min_{1<j\leq k} \|\boldsymbol{o}_0^c - \boldsymbol{o}_j^c\|_2 > thr$ **then**
    $label \leftarrow 1$
else
    $label \leftarrow 0$
end if

4.4 代码表示

4.4.1 直接书写代码在.tex 中

下面的代码4-1是用 Python 编写的加法函数。

代码 4-1 加法

```python
def plusFunc(a, b):
  return a + b
```

4.4.2 引用代码文件

下面的代码4-2是用 Python 文件中引入的倒序打印 x 到 1 的函数，请查看 code 文件夹。

代码 4-2 倒序打印数字

```python
def numbers(x):
    if x > 0:
        print(x)
        numbers(x-1)
```

4.5 列表样式

4.5.1 使用圆点作为项目符号

- **第一章为基础模块示例**，是的，本章的名字就是基础模块示例，正如你看到这个样子。
- **第二章为不存在**，是的，其实它不存在。

4.5.2 使用数字作为项目符号

1. **第一章为基础模块示例**，是的，本章的名字就是基础模块示例，正如你看到这个样子。
2. **第二章为不存在**，是的，其实它不存在。

4.5.3 句中数字编号列表样式

1. **第一章为基础模块示例**，是的，本章的名字就是基础模块示例，正如你看到这个样子; 2. **第二章为不存在**，是的，其实它不存在。

第五章　为了目录撑到第二页

5.1　我不得不再添加一点内容

5.2　尽管这些章节一点正文都没有

5.3　是的

5.4　真的没有

5.5　我已经不知道说什么了

5.6　如果有，我们就祝愿一下学校教务处什么时候转变一下思维

5.7　把控制格式这种事情往前做

5.8　不要总是觉得折磨学生是合理的

5.9　你拿着教学管理岗位的工资

5.10　你需要折磨一下你自己才对

5.11　不要觉得我对别人要求太高，对自己太低

5.12　我对自己要求低的话也不至于想要修订这份模板

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致　　谢

此处请写致谢的内容。

它可以有多段。

附　　录

附录 1　缩略语表

表 附-1　基于浏览者行为的特征

特征	描述	形式与理论范围
点赞量	微博的点赞数量	数值，ℕ
评论量	微博的评论数量	数值，ℕ
转发量	微博的转发数量	数值，ℕ

表 附-2　基于浏览者行为的复杂特征

类别	特征	不知道叫什么的表头	
		描述	形式与理论范围
正常互动	点赞量	微博的点赞数量	数值，ℕ
	评论量	微博的评论数量	数值，ℕ
	转发量	微博的转发数量	数值，ℕ
非正常互动	羡慕量	微博的羡慕数量	数值，ℕ

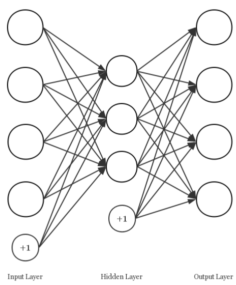

图 附-1　自编码器结构

代码 附-1　减法

```
def minusFunc(a, b):
  return a - b
```

$$\max_{\boldsymbol{W}} tr(\boldsymbol{W}^{\mathrm{T}}\boldsymbol{X}\boldsymbol{X}^{\mathrm{T}}\boldsymbol{W}) \qquad \text{式（附-1）}$$

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 资 料

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

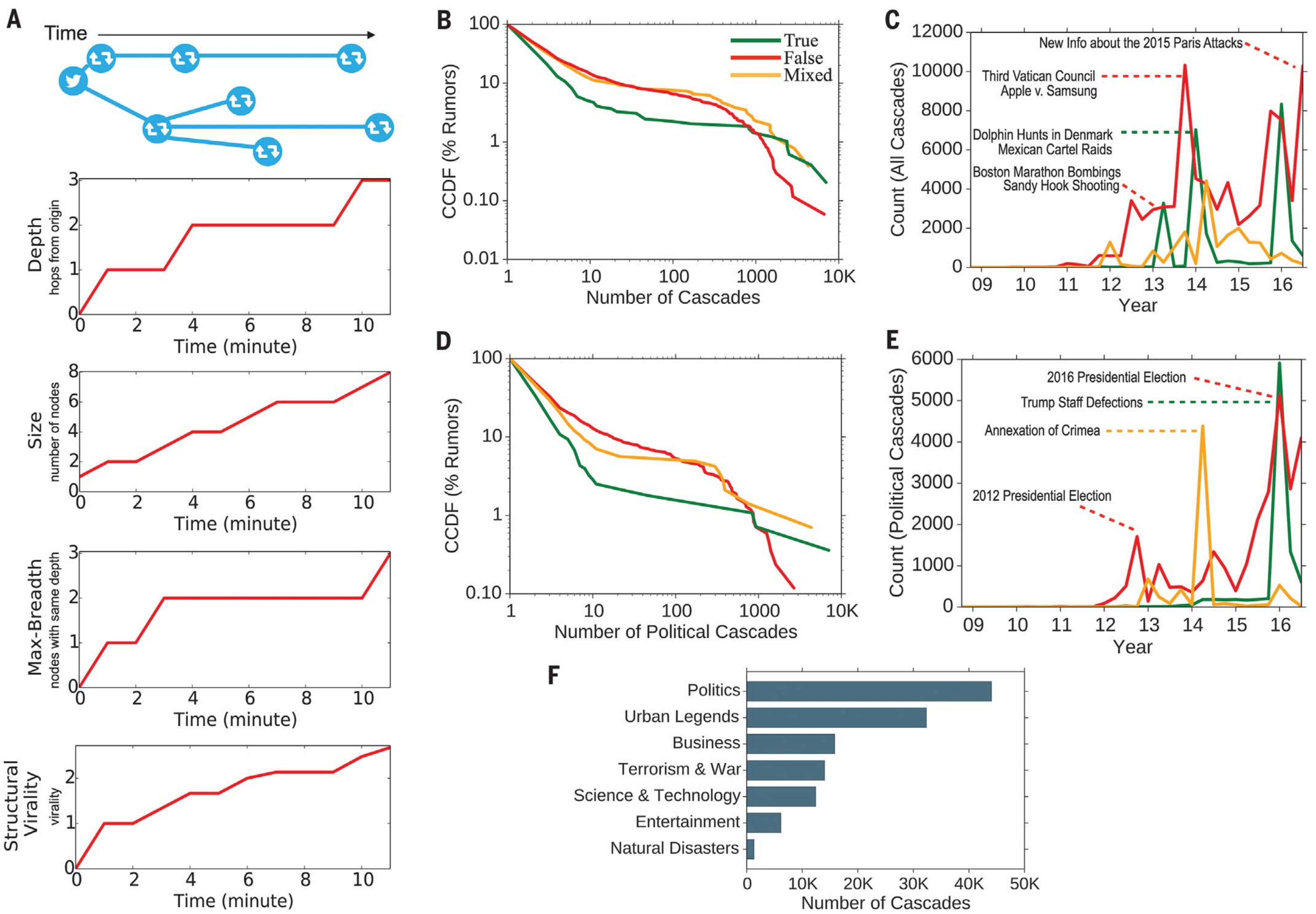


Fig. 1. Rumor cascades. (**A**) An example rumor cascade collected by our method as well as its depth, size, maximum breadth, and structural virality over time. "Nodes" are users. (**B**) The complementary cumulative distribution functions (CCDFs) of true, false, and mixed (partially true and partially 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.

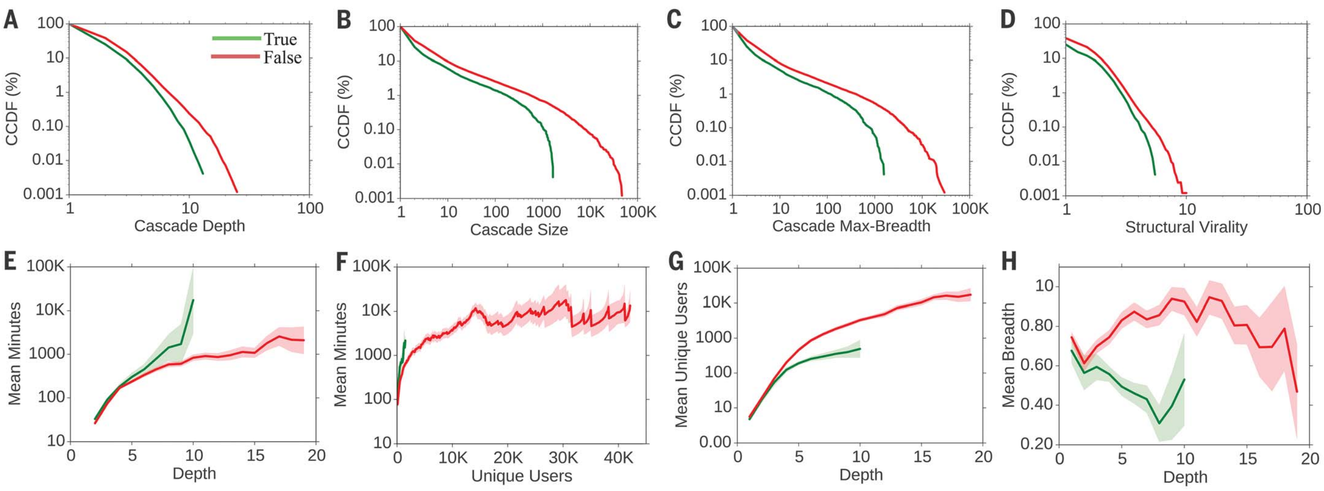


Fig. 2. Complementary cumulative distribution functions (CCDFs) of true and false rumor cascades. (**A**) Depth. (**B**) Size. (**C**) Maximum breadth. (**D**) Structural virality. (**E** and **F**) The number of minutes it takes for true and false rumor cascades to reach any (E) depth and (F) number 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).

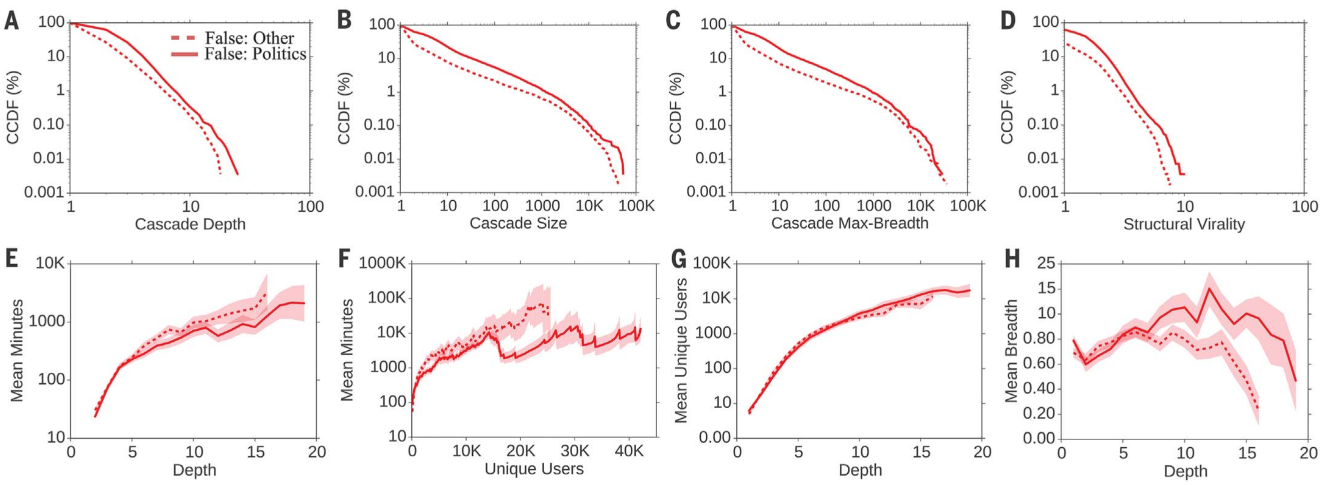


Fig. 3. Complementary cumulative distribution functions (CCDFs) of false political and other types of rumor cascades. (**A**) Depth. (**B**) Size. (**C**) Maximum breadth. (**D**) Structural virality. (**E** and **F**) The number of minutes it takes for false political and other false news cascades to 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

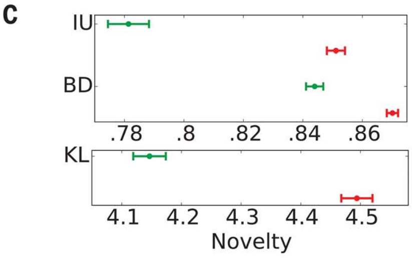
A

	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

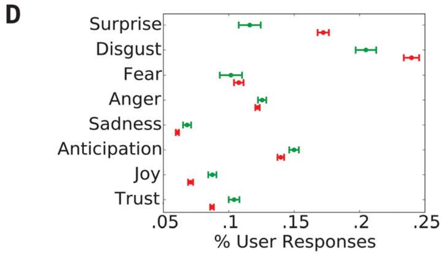
B

	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. coeff, 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

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

第一章　概述

1.1　概述

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?

$$\max_{\boldsymbol{W}} tr(\boldsymbol{W}^{\mathrm{T}}\boldsymbol{X}\boldsymbol{X}^{\mathrm{T}}\boldsymbol{W}) \qquad 式（外 1-1）$$

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第二章　我也不知道是什么

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？

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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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Savage D, Zhang X, Yu X, et al. Anomaly detection in online social networks[J]. Social Networks, 2014, 39(1):62-70.

Castillo C, Mendoza M, Poblete B. Information credibility on twitter[C]// International Conference on World Wide Web, WWW 2011, Hyderabad, India, March 28 - April. DBLP, 2011:675-684.

Jin Z, Cao J, Guo H, et al. Multimodal Fusion with Recurrent Neural Networks for Rumor Detection on Microblogs[C]//Proceedings of the 2017 ACM on Multimedia Conference. ACM, 2017: 795-816.

指导教师签字		日期	年 月 日

注：可根据开题报告的长度加页。

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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>
<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>
<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>
<tr><td rowspan="2">设计（论文）题目</td><td colspan="5">（中文）猜猜看毕设题目是什么</td></tr>
<tr><td colspan="5">（英文）Just Guess What On Earth My Title is</td></tr>
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完成有关实验。
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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<tr><td rowspan="2">尚需完成的任务</td><td colspan="5">• 完成整体架构和论文书写任务。
• 完成外文文献的翻译。</td></tr>
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<tr><td rowspan="2">存在问题和解决办法</td><td>存在问题</td><td colspan="4">模型中存在一些欠缺讨论分析的细节，如阈值选择等。</td></tr>
<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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检查小组意见	负责人签字：　　　　年　月　日

注：可根据长度加页。

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教师指导本科毕业设计（论文）记录表

<table>
<tr><td>学院</td><td></td><td>专业</td><td></td><td>班级</td><td></td></tr>
<tr><td>学生姓名</td><td></td><td>学号</td><td></td><td>班内序号</td><td></td></tr>
<tr><td>指导教师姓名</td><td></td><td>职称</td><td colspan="3"></td></tr>
<tr><td colspan="6">第 1－2 周记录：</td></tr>
<tr><td>指导教师签字</td><td></td><td>日期</td><td colspan="3">年　月　日</td></tr>
<tr><td colspan="6">第 3－4 周记录：</td></tr>
<tr><td>指导教师签字</td><td></td><td>日期</td><td colspan="3">年　月　日</td></tr>
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注：每 2 周指导内容记录在一个表格中，双面打印。