WHAT WE TALK ABOUT WHEN WE TALK ABOUT CORONAVIRUS

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0.1 Introduction

As the outbreak of the worldwide Cronovirus pandemic(COVID-19), there are more and more people getting involved into this battle with the virus. Many people, many medias are voicing their opinions over this pandemic. As the virus becomes under control in China(hopefully) from March 2020, China has gone through this outbreak cycle and there are loads of article talking about the virus in this period. Such articles are valuable for us to study the evolution of popular topics over the time. What's more, we can check that whether there is censorship on content on specific topics. As this pandemic still going on in the world, there are not so much text analysis about this online, and I hope that this work can shed a light on what the medias are talking about in China under the time of COVID-19.

The corpus contains 4209 articles published by 162 different medias. Some media are official accounts(e.g. CCTV News, 央视新闻) and some are personal blogs or wechat accounts(e.g. FangFang, 作家方方的博客). The raw data are collected from GitHub Project 'nCovMemory'(https://github.com/2019ncovmemory/nCovMemory, unavailable since April 25th. alternative GitHub repository https://github.com/invishantom/nCovMemory).

Two methods are implemented to analyse the textual data. The first one is Wordfish Model. I use this model to check the fixed effect of each media and see if this model can successfully classify different types of media. The main part is the Structural Topic Model(STM). STM enables us to investigate the interaction between topics and document-level variables, like date, deleted(whether the article is deleted after released), etc.

After implementing the models, we found that there're differences between non-fiction and narrative, deleted and not deleted articles. Also, we have found some topics that are more likely to be deleted in specific period as well as time-varying topic differences between narrative and non-fiction articles.

0.2 Motivation

I started to follow the news since the outbreak of COVID-19, when Wuhan Health Commission(武汉卫健委) reports 41 confirmed cases of unknown pneumonia on 3rn January. I became more and more nervous when COVID-19 seemed to lose control and much more people getting infected in China. At that time, the widespread of the virus, the lack of surgical masks caused much anxiety in the society. So many had changed in the past few month and it's hard for me to keep track of the happening things because the world is changing violently. Now as the virus becomes under control in China, I start to be able to look through the cycle of this outbreak and to analyse what is going on in this special period from a statistical perspective.

COVID-19 has drawn my main attention for months, for I'm really worried about my beloved ones getting infected. For months, I had read many news, many articles about the virus, but that's not enough for me to have an overview of the outbreak. I don't expect this project to have any contribution to scholarship, but I wish that I can help people better understand the recent times with the help of statistical methods. By now I haven't seen any works doing similar research over similar data like me and hopefully this work may be helpful in some sense.

0.3 Overview of the Data

0.3.1 From Raw Data to Segmented Words

The raw data comes from GitHub repo 'nCovMemory'(https://github.com/2019ncovmemory/nCovMemory). The data was downloaded on 24th March. The data contains 4233 online articles, published from 20th Dec, 2019 to 24th Mar, 2020. In the data, 21 articles are recorded for multiple times and we simply delete such misrecordings.

The raw data has the following variables: title, id, category, update date, media, is deleted, url and archive url. Since we don't have the content of the article in the data, we need to use methods like web scraping, OCR, ect to get the content. Web scraping are used for most of the articles. And thanks for the work of GitHub repo 'nCovMemory-Raw-Data'(https://github.com/Project-Gutenberg/nCovMemory-Raw-Data), I can easily get the content of some other articles which cannot be easily web scraped. However, there are still some neither appear in 'nCovMemory-Raw-Data', nor have available urls. For these articles, we use OCR(ABBYY Finereader 15, output available in https://github.com/wangmy22/ncov-text-analysis/tree/master/ocroutput) to detect the word content of their picture archive(available in other folder in 'nCovMemory') and then have a double check on these manually. For the rest of documents(some without available picture archive, some perform bad in OCR), we use the archive urls to get the textual data. Unfortunately, there are still 3 document fail by any ways above, we simply deleted them from the data.

The textual data are then segmented by 'JiebaR' package with specified user dictionary and stopword dictionary. The user dictionary and stopword dictionary are constructed by segmenting the data into 2 to 8 grams collocations. Then we calculate the Wald statistics and nested proportion for those allocations that appear more than 400 times. Collocations not fully nested and have a z value larger than 1.96 are kept. Next divide them manually into user dictionary and stopword dictionary(dictionaries available in https://github.com/wangmy22/ncov-text-analysis/tree/master/dict). The name of each media, as well as their abbreviations are also added into the stopword dictionary. All numbers(only in Arabic), english words and escape characters are also deleted from the content of articles.

As there are some article without any informative word content(only pictures or videos in the articles), we then discard those document with word count fewer than 200(most articles

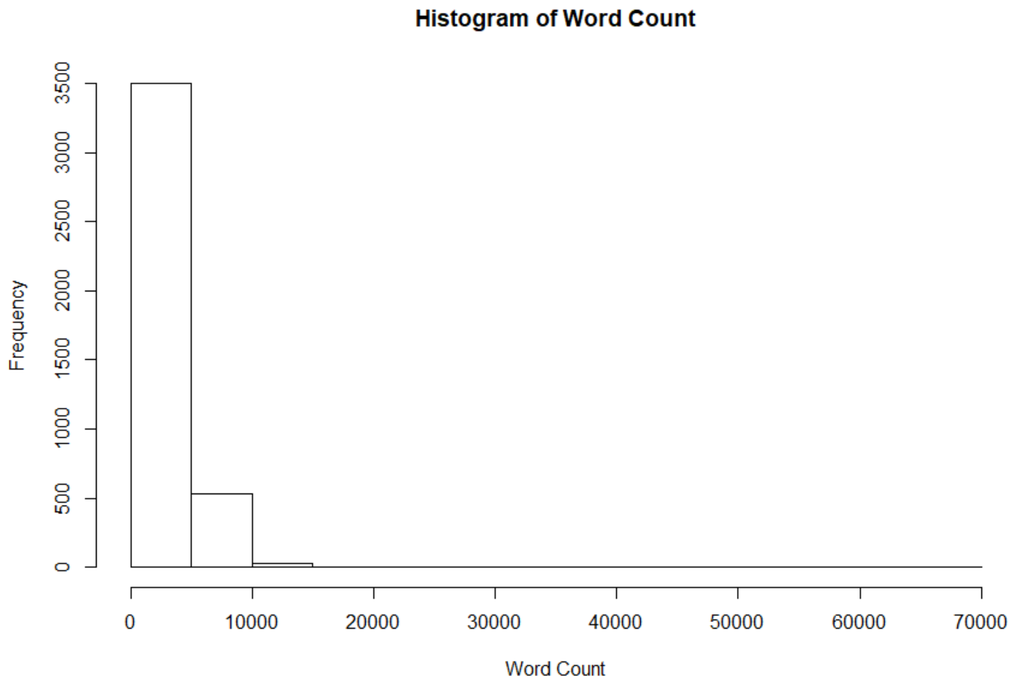

Figure 1: Histogram of Word Count

	Narrative	Non Fiction	Overall
Not Deleted	814	3164	3968
Deleted	27	64	91
Overall	841	3228	4069

Table 1: Basic Statistics of the Data

have some ads in the beginning and the end). The data ends up with 4069 articles, with 3551 from web scraping, 146 from 'nCovMemory-Raw-Data', 353 from OCR and 19 from archive website.

0.3.2 Basic Statistics of the Data

As we can see from the histogram of word count Fig.1, most documents have word count fewer than 10000, while the longest one has 67189 words(武汉新型冠状病毒肺炎大事记（2020 年 1 月 21 日—今）by 财新网).

Of the 4069 documents, 91 documents are deleted after being released and 841 are classified as 'narrative'. More details can be seen in Tab.1.

From Fig.2, we can see that the number of released article starts to increase after 20th Jan, the day when Nanshan Zhong(钟南山) confirmed that the virus can spread person-to-person and President Xi made instruction over for the epidemic. The daily release start to

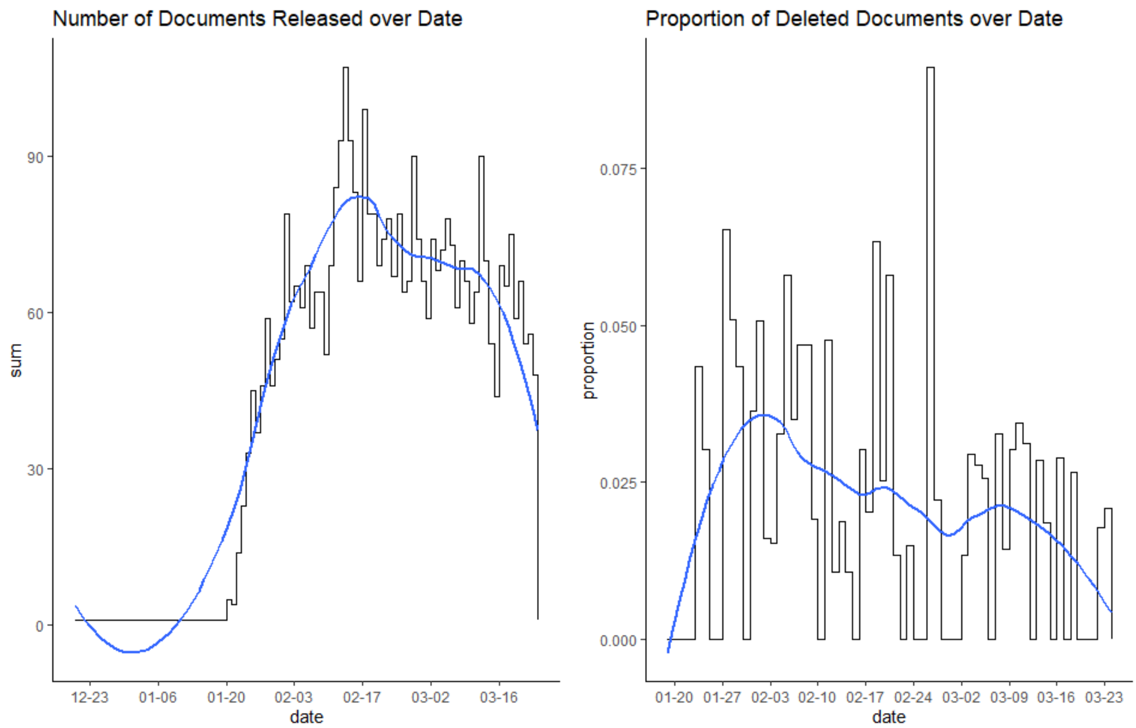

Figure 2: Releases over Date

decrease from mid Feb. The proportion of deleted documents shares similar trend like the number of documents.

0.4 Methods

Models used to analyse date in this project are Wordfish Model and Structural Topic Model. The reason I choose to use unsupervised learning is that I don't have much labeled data. All I have is the content, title, category, publish date and whether it's deleted. It would be difficult for me to implement sentiment analysis because I would spend much more time than I have in labeling the sentiment. Labeling myself may be too subjective also. What's more, as this is a large corpus(with more than 4000 documents and 20000 features after segmentation and removing stop words), if I use machine learning algorithm to predict what features account most for deleted or not, the results will be too messy. But still we can analyse the data by implementing unsupervised learning algorithm. And we do get some interesting and intuitive findings.

0.4.1 Wordfish Model to Extract Positions of Medias

Wordfish Model enables us to have a first impression of the data. There are 160 different medias overall and it's impossible for us to get to know each media well. Wordfish model can help us in estimating the position of different medias, thus we can get to know which two medias are similar and which two are different in the words they use, the topics they convey. All documents in our corpus are about the same topic, COVID-19, so it's reasonable to include all the documents as they are all relevant to the virus.

To construct the document-feature matrix used for Wordfish model, we need to transform the corpus into dfm and then group by the published medias. Then trim with minimum term frequency 10 on the dfm object.

As the Wordfish model need specification for direction, we set 'FangFang'(作家方方的博客) as the left opposite and 'Caixin News'(财新网) as the right opposite. 'Caixin News' is one of the most influential official medias in China. It has followed the pandemic from the outbreak and its content varies a lot, from virus to daily life. As the opposite, 'Fangfang' is a controversial person in China during this time of pandemic. Until recently she served as vice president of Hubei's Writer Association. Her series of article, 'Wuhan Diary', told people about the sufferings in Wuhan city. She was criticised about being too offensive on social medias.

0.4.2 Structural Topic Model

We use Stuctural Topic Model because it permits us to incorporate arbitrary metadata, defined as information about each document, into the topic model(Roberts, Stewart, Tingley, et al. 2014). Therefore, we are able to evaluate topic proportion under different value of covariates. Here in this project, we add three covariates into the model: publish date, is deleted and category as well as interaction term between date and is deleted, date and category. Then we can successfully control for publish date and see if the specific topic proportion vary with category and is deleted. What's more, we can have an overview of which topic is most likely to be deleted or to fall with certain category.

To construct the dfm matrix, we tranform coupus into raw dfm and then trim with minimum term frequency 20. Here we drops more words because the estimation of Structural Topic Model is really computational expensive. I also made some modification to the metadata. The publish date variable is transformed into the number of passed days from the first ducument because 'stm' function is not able to deal with date variable. The passed days variable is then passed to a 10-spline basis function to allow for non-linearity in the model.

To determine the number of topics, I first start running Structural Topic Model with spectral initialization and no prespecified number of topics. This process is repeated for 5 different seeds. Though this procedure have no statistical guarantees for 'true' numbers of topics(Roberts, Stewart, Tingley, et al. 2014), it can be a start point for us to begin estimation.

As the estimation of Structural Topic Model doesn't ensure the global minimum, we'd better to start from diffenrent seeds and choose the best one. We then start running 20 different models with 2 EM iterations, then choose the 4 with highest log-likelihood and run with at most 100 EM iterations. Then we can choose the best model based on their semantic coherence and exclusivity. This process is done with the help of 'selectModel' function in 'stm' packages.

If the metadata does have effect on topical preference, we would observe the topical preference varies across difference value of time.

As for censorship, a deleted article does not necessarily mean that it's censored. However, if the the decision of deletion is random, then we would observe similar topical preference between deleted and not deleted articles. If not so there may be some censorship.

0.5 Results

0.5.1 Wordfish Model

The interest of us is the position of each media. As we can see in Fig.3, most medias have theta lying in the middle of the plot. There's only one media have extremely small theta,' 邓安庆'(Denganqing). The media with the largest theta is 中国经济周刊 (China Economic Weekly).

If we classify medias which only publish narrative articles as 'narrative', and 'non-fiction' for those only publish non-fiction articles. The remaining medias have publish both narrative and non-fiction articles, they are classified as 'mixed'. If we plot the position by their types, we can see that 'narrative' media are more likely to have smaller theta than 'mixed' and 'non-fiction'.

More intuitively, we can see from the histogram and smoothed density in Fig.4 that 'non-fiction' medias have larger theta than the other two groups. 'Narrative' may have smaller theta than 'mixed' but this relationship is ambiguous in the density plot.

Similarly, we can classified those media with all articles not deleted as 'deleted'. If the media have one or more articles deleted, then it's classified as 'deleted'. This time we can see in Fig.5 that 'deleted' medias tend to have larger theta than 'not deleted' ones. But we are unable to make statistical inference here. I have try linear regression to check for such relationships, but it turns out the fitting is quite poor and not convincing. Simple regression may be problematic also.

The output from Wordfish Model shows that there are difference between different categories and whether the article is deleted. This result gives some intuitions in further incorporating such variables into the Structural Topic Model.

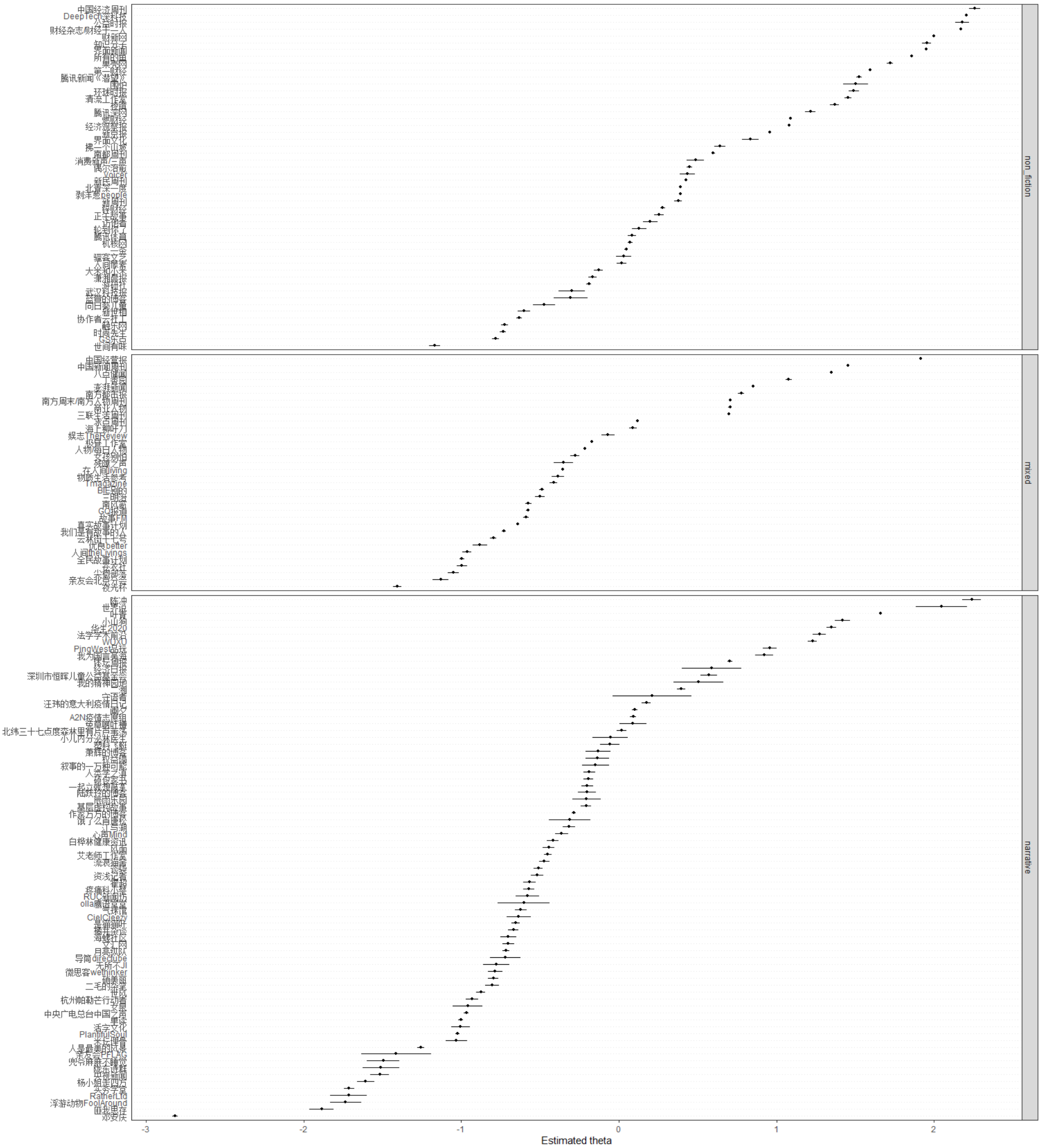

Figure 3: Position of medias by Category

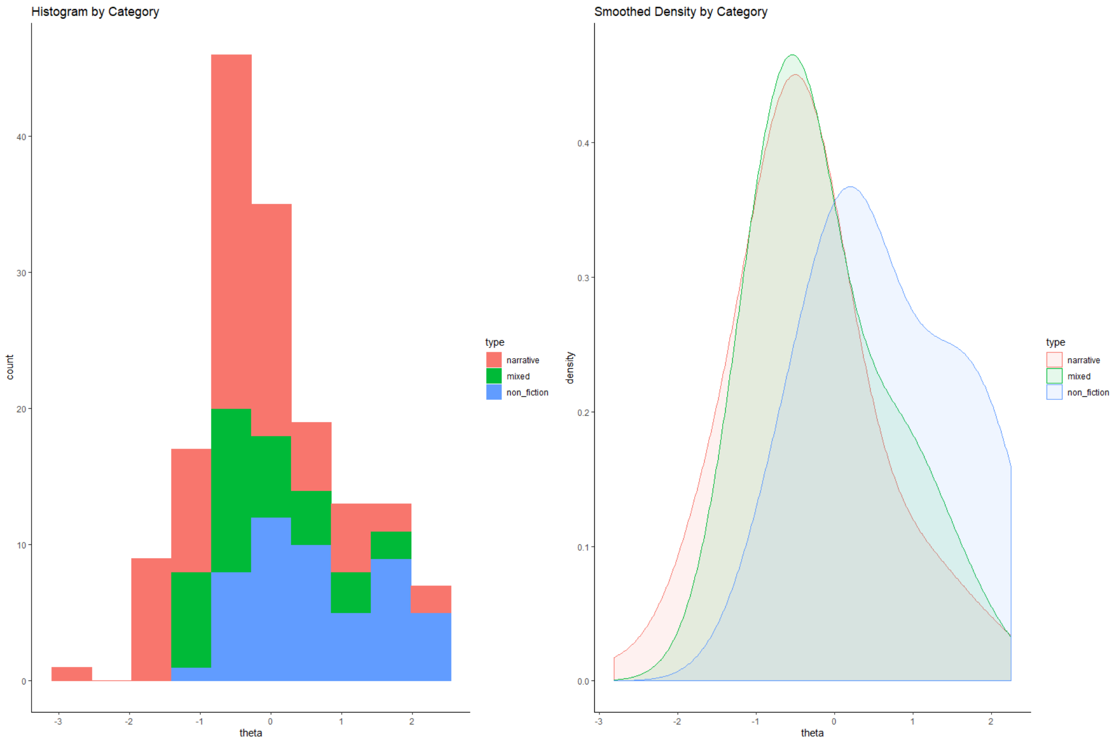

Figure 4: Histogram and Density by Category

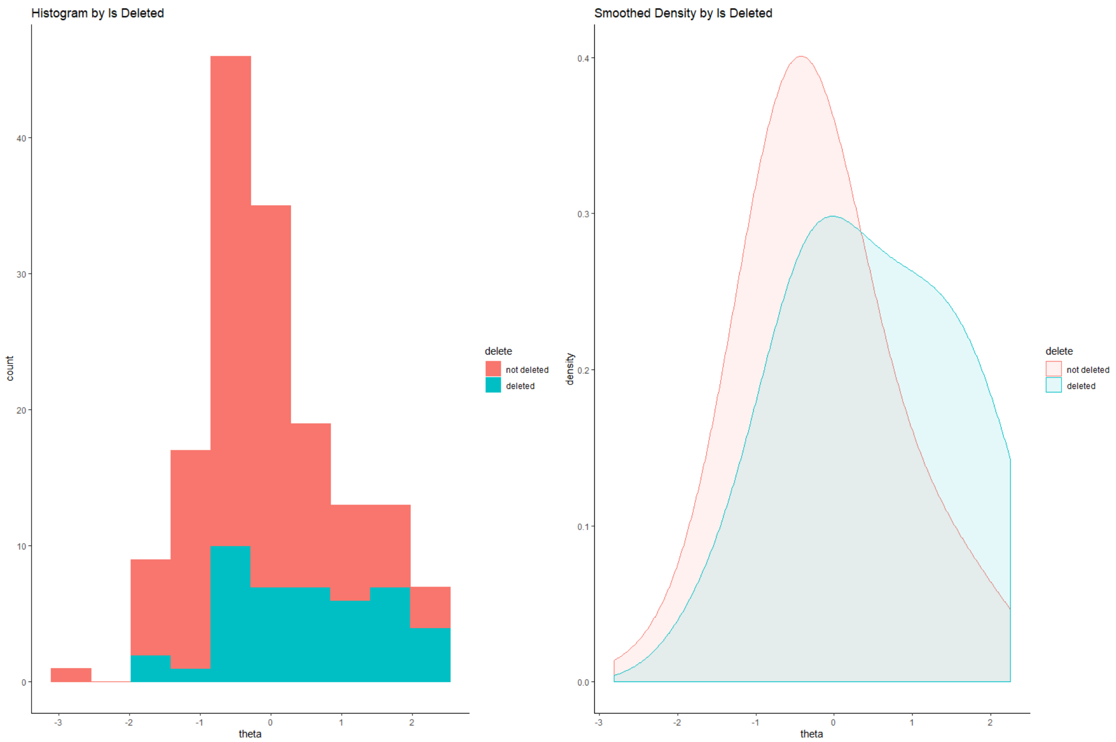

Figure 5: Histogram and Density by Deleted

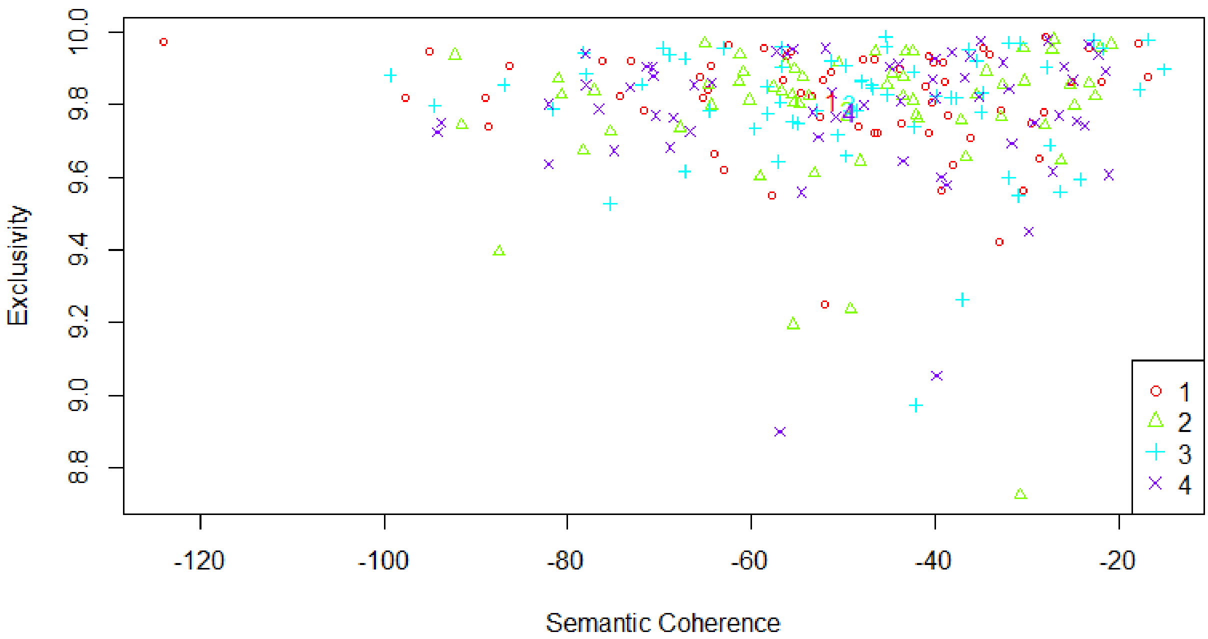

Figure 6: Exclusivity and Sementic Coherence of Models

0.5.2 Structural Topic Model

After running Structural Topic Model without specific number of topics, the number end up 67, 63, 52, 57, 64. Therefore, 60 is a reasonable number of topics for our data. Next the model is run for 20 times with different seed. As we can see in Fig.6, model 3 is nearest to the upper right corner, so we till use model 3 for further analysis. We can then calculate the most exclusive and frequent(FREX) words of each topics. Table 2 lists the top 8 words of each topics.

Here we can label some representative topics according to the most relevant words as well as the title of most relevant articles(most relevant article of each topic can be found in appendix). For example, topic 31 is about Doctor Wenliang Li. Topic 12(Shincheonji Church and South Korea), 26(Diamond Princess), 50(other countries), 53(Italy), 57(USA and Trump) are all about the pandemic in other countries. For most topics, the words in it do share similar semantic meanings.

The proportion of each topics does not vary too much. As we can see in Fig.7, Topic 25 has the highest frequency,with proportion about 0.04. Most topics account for around 2 percent each.

If the fitting of Structural Topic Model is poor, we would expect the topic proportion to be similar across different documents. In Fig.8 we can see that most topic proportion is close

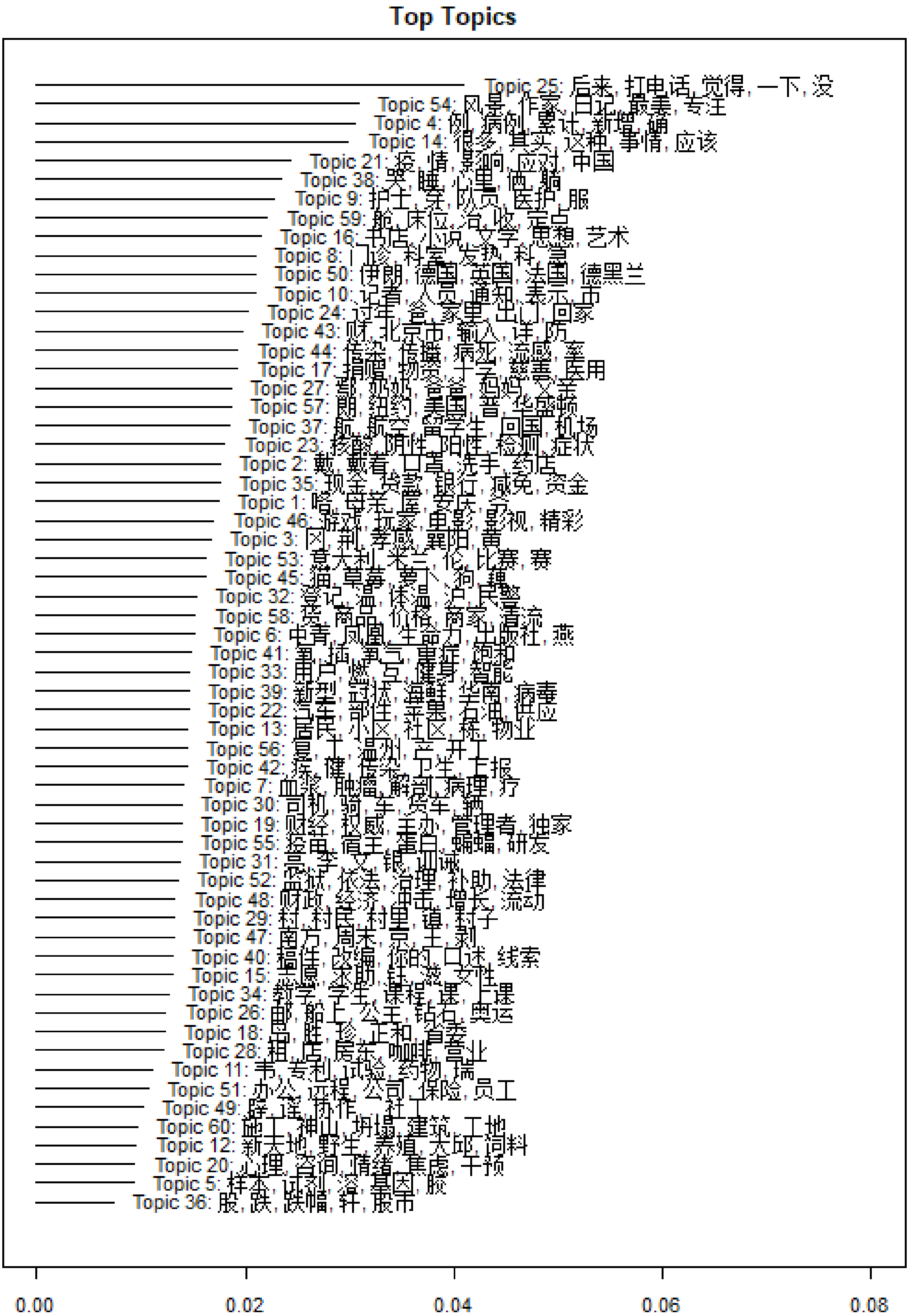

Figure 7: Expected Frequency of Topics

Figure 8: Histogram of Topic Proportion

to 0. For a specific topic, only few documents have large proportion to that topic, which means that each document only belongs to very few topics. The separation of topics can successfully classify our documents.

How does our metadata influence the proportion of topics? We can vary the value of category and is deleted and see how much the topic proportion has changed. If the covariate has no effect on our topics, we would expect the difference to be close to zero and insignificant statistically. In Fig.9 there is no topic with difference significantly differ from zero .As we only have 91 deleted articles, the confidence interval is large. We can only tell that maybe topic 30(Driving and Bees Feeding), topic 51(Recruit and Work) are more likely to be deleted(these are the only two significant topics if we set confidence interval to 0.8).

As for the effect of category on topics(Fig.10), topic 3(Cities in Hubei), 8(Medical Staff),

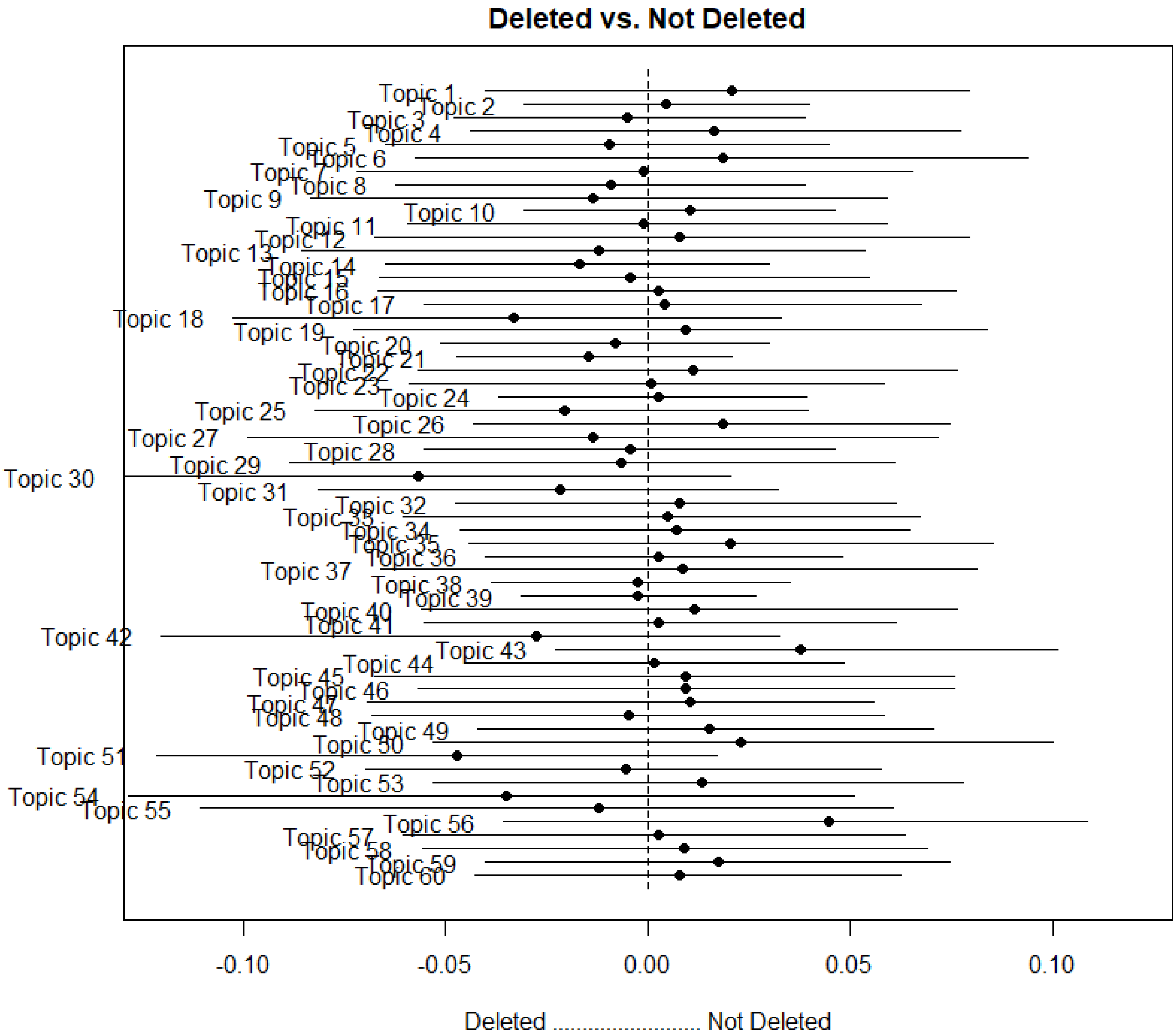

Figure 9: Topical Preference on Deleted

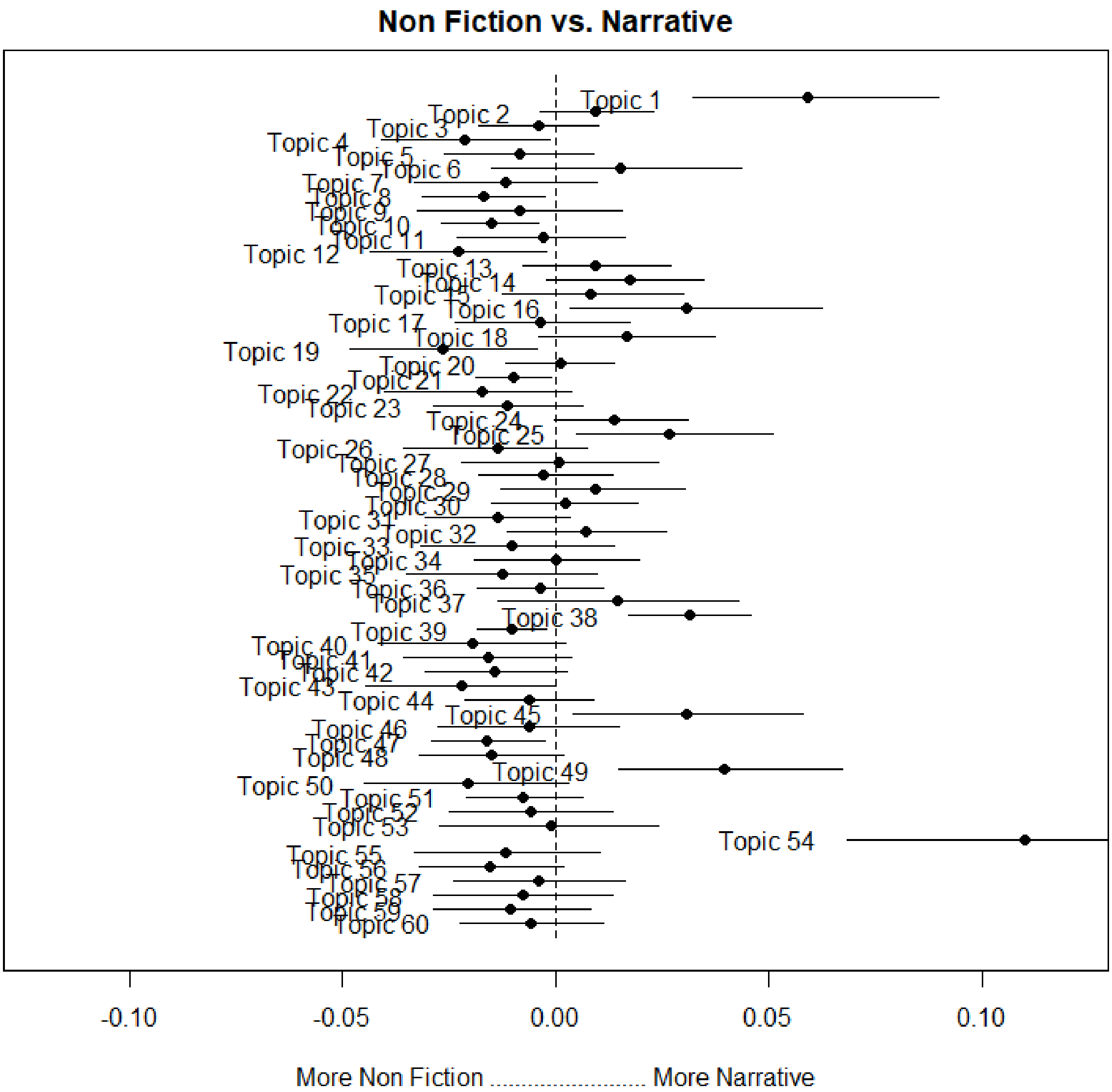

Figure 10: Topical Preference on Category

10(Pengpai News 澎湃新闻), 12(Shincheonji Church and South Korea), 19(Caijing Eleven 财经十一人), 21(Global Anti-epidemic), 39(Outbreak of COVID-19), 47(not clear) are significantly more likely to be a non fiction article. On the contrast, topic 1(Denganqing 邓安庆), 16(Lattitude 37 Degrees North 北纬三十七点度森林有片芦苇荡), 25(Voice of China 中央广电总台中国之声), 38(Parents and Grandparents), 45(Pets and Plants), 49(Social Worker 协作者云社工), 54(Landscape). Here I label some topics as the media name because the media take up more than 4 places in the 5 most relevant articles. It's clear that non-fiction topics are more likely to be reported by multiple medias, while narrative topics are probably classified by only one media. As the proportion of non-fiction and narrative is more balanced, the confidence interval is smaller.

We can also allow for variation of publish date. By applying 10-spline basis function to date variable, the effect of date shows non-linearity. Though there's no significant difference in Fig.9, we can see the difference is significant for some period of time after adding in publish date(See Fig.11).

For topic 5(Source and Transmission of Virus), the topical preference of deleted is higher at the beginning of outbreak. As the so-called source of virus(still unclear by now), Huanan Seafood Market, is the hot topic since the outbreak. And Fig.12 shows that this topic is more likely to be deleted on late January. Topic 8 and 9(Medical Staff,, Fig.13 and Fig.14) is more likely to be deleted on March. The same for topic 31(Doctor Wenliang Li, Fig.15), topic 37(International Student, Fig.16) on late March,topic 42(Health Commission, Fig.17) on mid March, topic 56(Resume Work, Fig.18) on late February and early March, topic 60(Collapse of Quarantine Hotel in Quanzhou, Fig.19) on mid March. This do correspond to the timeline, as doctor Wenliang Li died on 7th Feb, the outbreak in Europe and USA started on Mar, work resume started at around 10th Feb, hotel collapse happened on 7th Mar. We are observing patterns that such significant differences appear after the outbreak of events, thus we are confident that such statistically significant difference is true reflection of reality rather than by chance.

The time-varying topical preference on category is shown in Fig.20. For most topics, the proportion of narrative and non-fiction follow similar trend. However, for topic 2(Mask Wearing), 24(Lunar New Year), 29(Villages), 38(Parents and Granparents), they share a much higher proportion of narrative than non-fiction right after outbreak of virus. This means that these are some topics people care much about but not reported proportionally in the news.

0.6 Conclusions

This project use Wordfish Model and Structural Topic Model to analyse the 4069 articles about COVID-19 in China. There are difference of estimated media position between narrative and non-fiction, between deleted and not deleted. As this is media-level analysis, it's hard to derive useful conclusions from it, but it gives us some confidence in furthur topic-level analysis.

In Structural Topic Model, we found that topics, including doctor Wenliang Li, source and transmission of virus, medical staff, international student, health commission, resume work, collapse of quarantine hotel in Quanzhou, have higher probability to be deleted in specific period of time. This might be where censorship targeting at.

What's more, non-fiction articles, most of which are news, focus more on anti-epidemic itself and other countries, which personal articles, or narrative ones, pay more attention to mask wearing, lunar new year, village life and their beloved one.

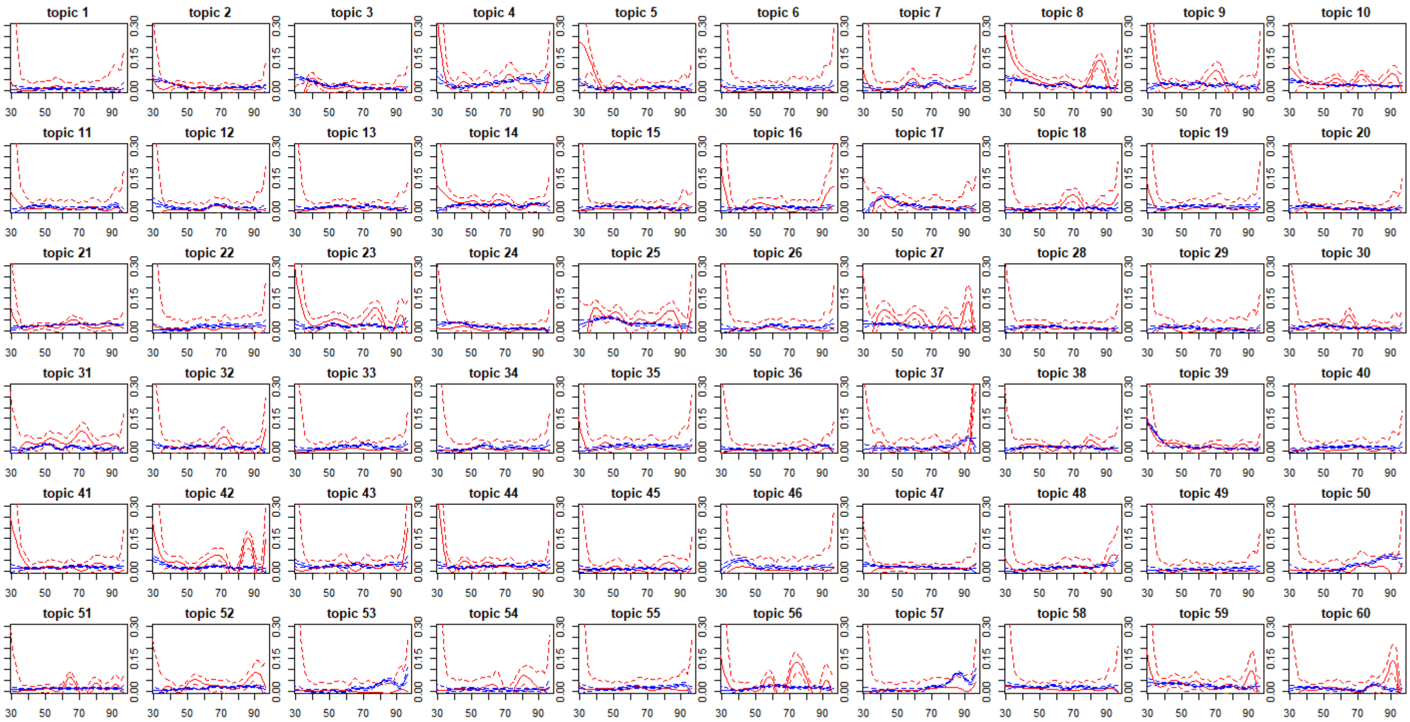

Figure 11: Topical Preference on Deleted and Date(Blue Not Deleted, Red Deleted)

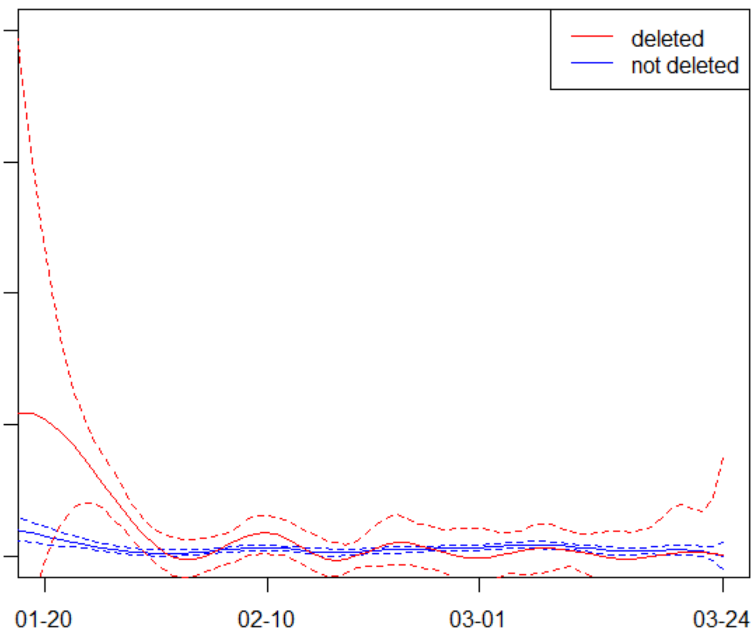

Figure 12: Topical Preference for Topic 5 on Deleted

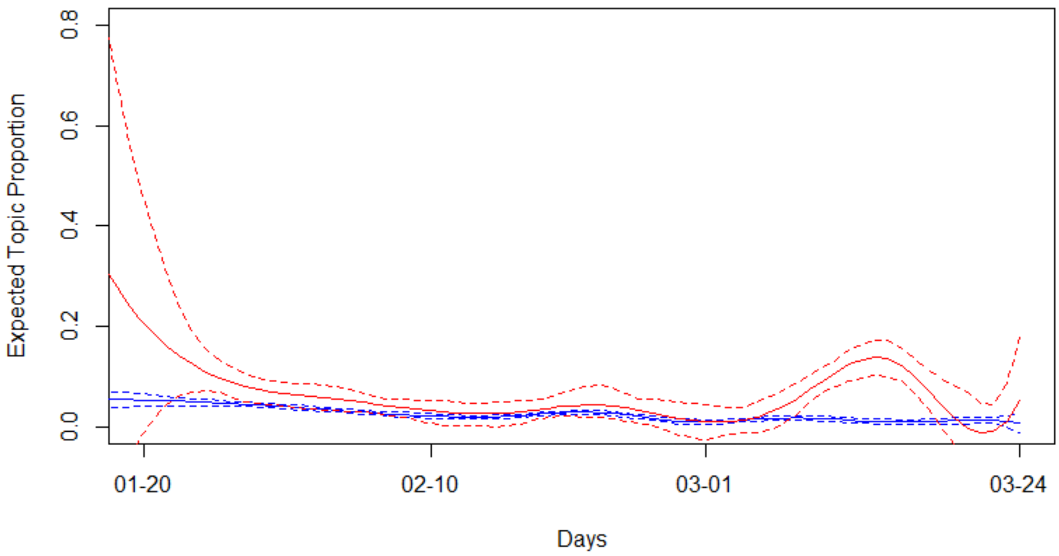

Figure 13: Topical Preference for Topic 8 on Deleted

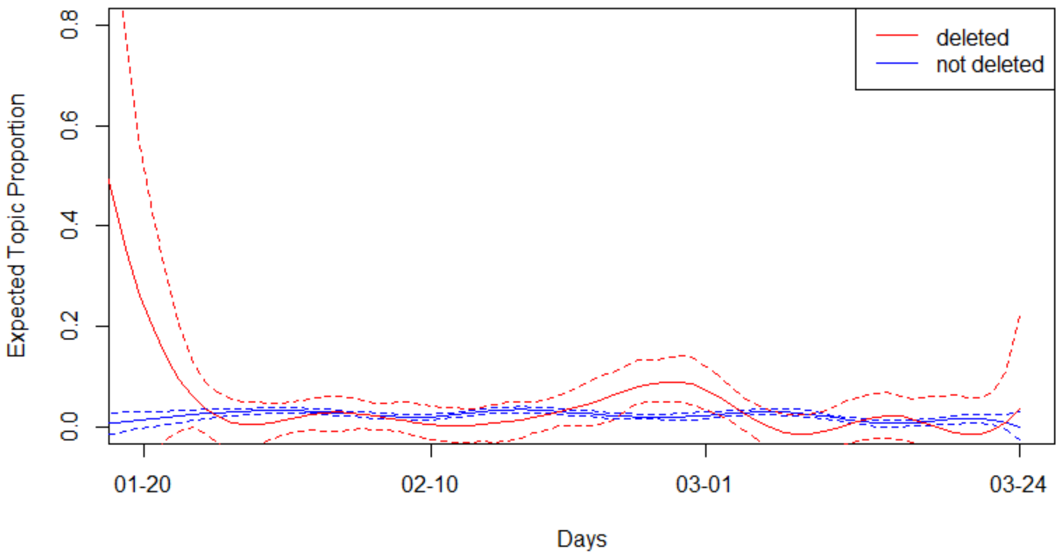

Figure 14: Topical Preference for Topic 9 on Deleted

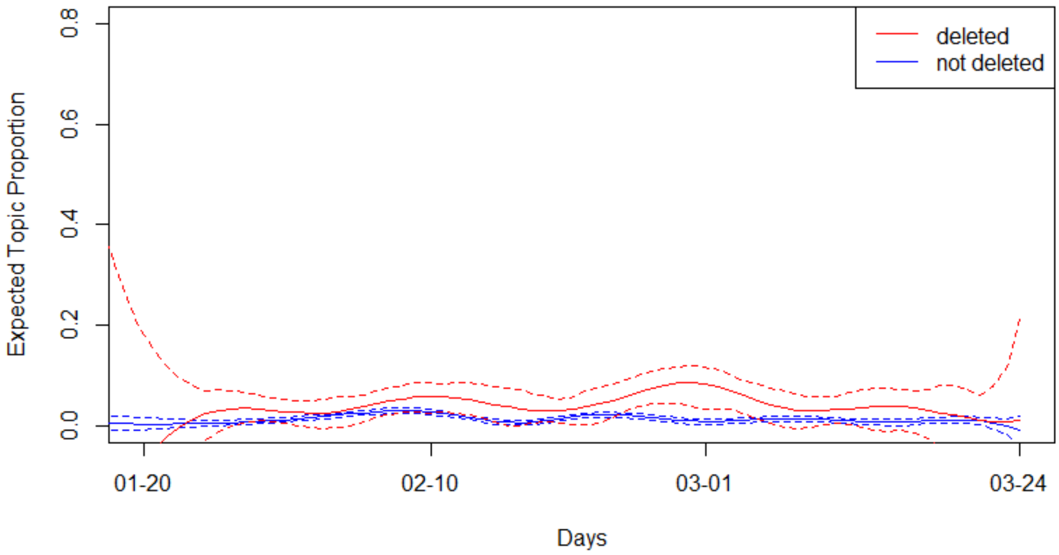

Figure 15: Topical Preference for Topic 31 on Deleted

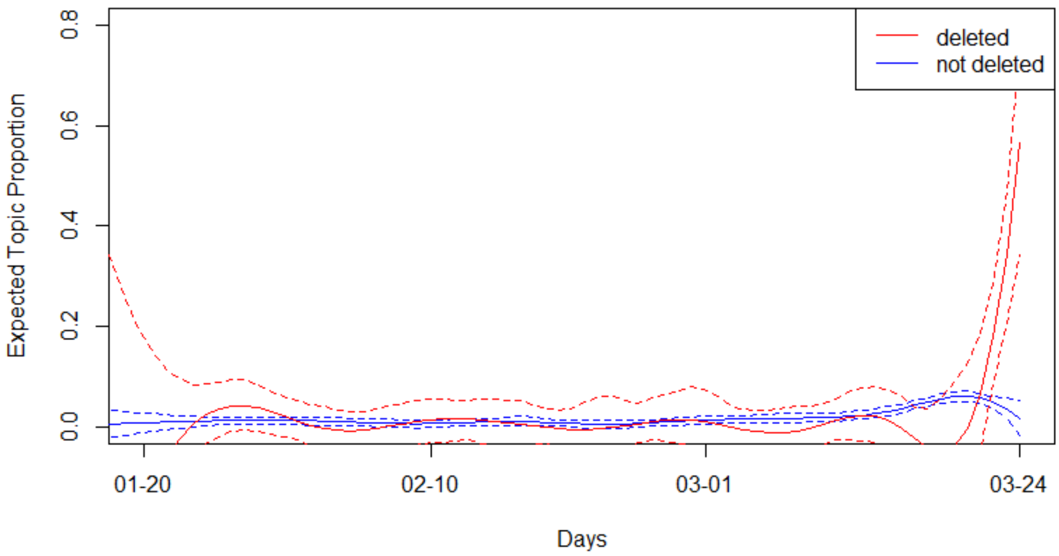

Figure 16: Topical Preference for Topic 37 on Deleted

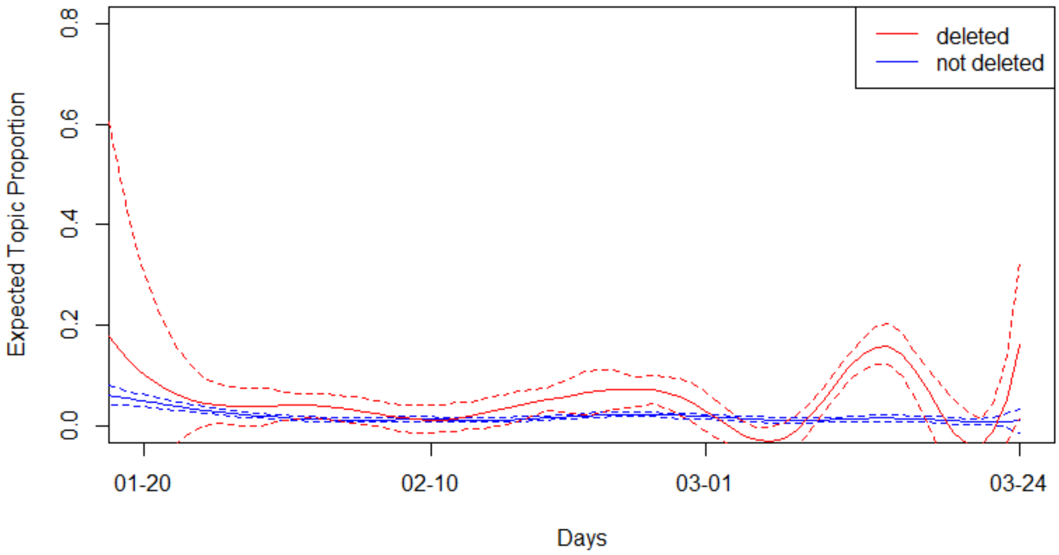

Figure 17: Topical Preference for Topic 42 on Deleted

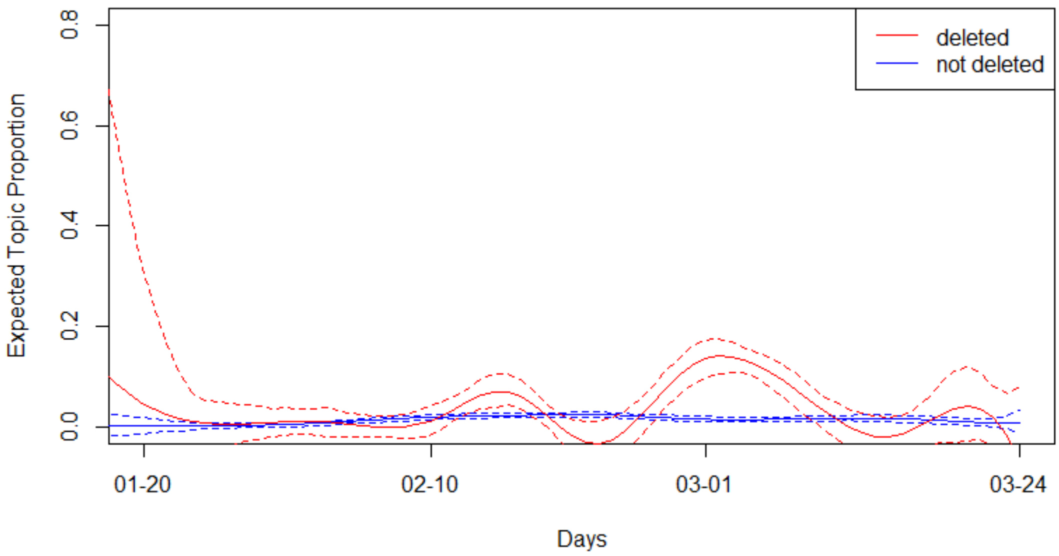

Figure 18: Topical Preference for Topic 56 on Deleted

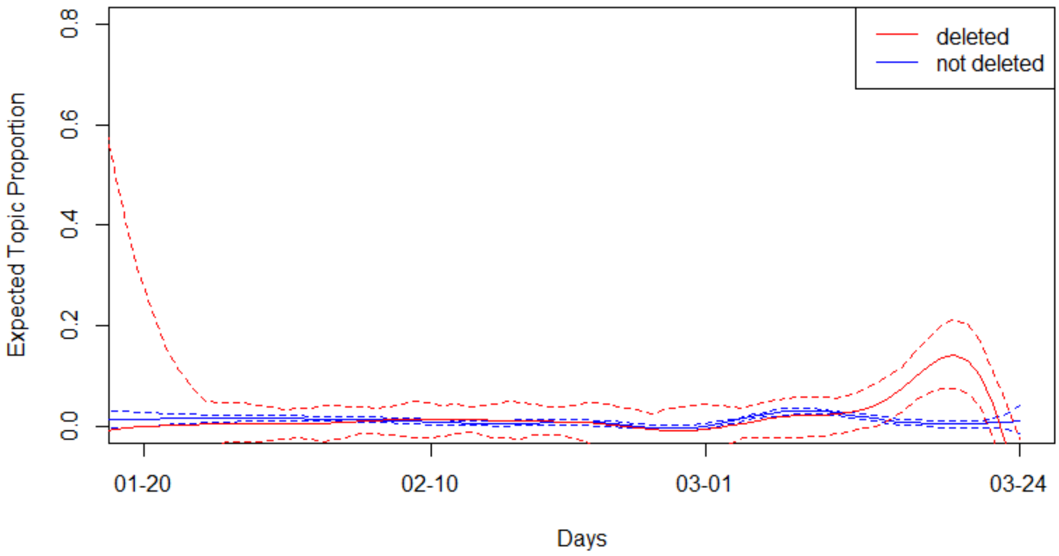

Figure 19: Topical Preference for Topic 60 on Deleted

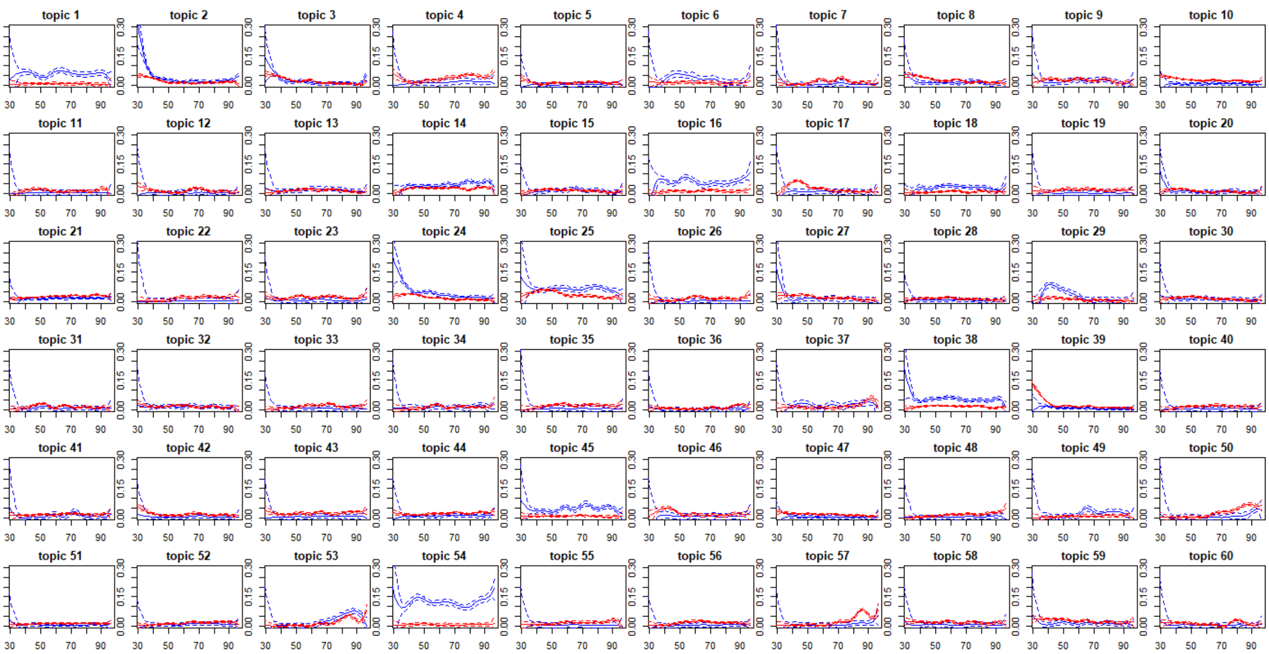

Figure 20: Topical Preference on Category and Date(Blue Narrative, Red Non-fiction)

	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8
Topic1	咯	母亲	屋	安庆	爷	娘	垸	摇
Topic2	戴	戴着	口罩	洗手	药店	佩	戴上	液
Topic3	冈	荆	孝感	襄阳	黄	鄂	州	天门
Topic4	例	病例	累计	新增	确	诊	死亡	报告
Topic5	样本	试剂	溶	基因	胶	实验	序	盒
Topic6	中青	凤凰	生命力	出版社	燕	琴	嫂	邱
Topic7	血浆	肿瘤	解剖	病理	疗	尸	移植	晖
Topic8	门诊	科室	发热	科	急	医生	医院	医务
Topic9	护士	穿	队员	医护	服	理发	队	下班
Topic10	记者	人员	通知	表示	市	指挥	工作	称
Topic11	韦	专利	试验	药物	瑞	匹	双黄	氯
Topic12	新天地	野生	养殖	大邱	饲料	教会	食用	动物
Topic13	居民	小区	社区	栋	物业	亭	百步	街道
Topic14	很多	其实	这种	事情	应该	非常	觉得	能够
Topic15	志愿	求助	钰	滋	女性	松鼠	救助	安心
Topic16	书店	小说	文学	思想	艺术	无话可说	瘟疫	音乐
Topic17	捐赠	物资	十字	慈善	医用	仓库	捐款	捐助
Topic18	岛	胜	珍	正和	省委	中央	援	书记
Topic19	财经	权威	主办	管理者	独家	学界	决策	刊物
Topic20	心理	咨询	情绪	焦虑	干预	热线	激	创伤
Topic21	疫	情	影响	应对	中国	时代	郑	迷
Topic22	汽车	部件	苹果	石油	供应	喷	熔	制造
Topic23	核酸	阴性	阳性	检测	症状	诊断	出院	咽
Topic24	过年	爸	家里	出门	回家	老家	年夜饭	妈
Topic25	后来	打电话	觉得	一下	没	晚上	不知道	那天
Topic26	邮	船上	公主	钻石	奥运	日本	东京	船员
Topic27	鄢	奶奶	爸爸	妈妈	父亲	婆婆	丈夫	发烧
Topic28	租	店	房东	咖啡	营业	公寓	自如	顾客
Topic29	村	村民	村里	镇	村子	县城	农村	镇上
Topic30	司机	骑	车	货车	辆	滴滴	高速	车队
Topic31	亮	李	文	银	训诫	眼科	去世	无效
Topic32	登记	温	体温	沪	民警	测	红外	测量
Topic33	用户	燃	互	健身	智能	线上	创业	模式
Topic34	教学	学生	课程	课	上课	课堂	教育	老师
Topic35	现金	贷款	银行	减免	资金	裁员	中小企业	蛋壳

Table 2 continued from previous page

	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8
Topic36	股	跌	跌幅	轩	股市	下跌	指数	储
Topic37	航	航空	留学生	回国	机场	机票	登机	飞机
Topic38	哭	睡	心里	俩	躺	聊天	一刻	爷爷
Topic39	新型	冠状	海鲜	华南	病毒	传	通报	卫
Topic40	稿件	改编	你的	口述	线索	添加	祺	注明
Topic41	氧	插	氧气	重症	饱和	金银	呼吸	危
Topic42	疾	健	传染	卫生	上报	卫	不明	预防
Topic43	财	北京市	输入	详	防	省份	境外	处分
Topic44	传染	传播	病死	流感	率	潜伏期	流行病	比例
Topic45	猫	草莓	萝卜	狗	藕	斤	冻	兔
Topic46	游戏	玩家	电影	影视	精彩	剧	影	粉丝
Topic47	南方	周末	京	王	剥	全文	伟	报
Topic48	财政	经济	冲击	增长	流动	速	改革	水平
Topic49	辟	谣	协作	.	社工	彤	科普	女工
Topic50	伊朗	德国	英国	法国	德黑兰	西班牙	瑞士	姆
Topic51	办公	远程	公司	保险	员工	费用	招聘	合同
Topic52	监狱	依法	治理	补助	法律	灾	罪	制度
Topic53	意大利	米兰	伦	比赛	赛	欧元	北部	罗马
Topic54	风景	作家	日记	最美	专注	今天	万物	尺度
Topic55	疫苗	宿主	蛋白	蝙蝠	研发	科学	序列	科研
Topic56	复	工	温州	产	开工	岗	企业	厂
Topic57	朗	纽约	美国	普	华盛顿	总统	加州	联邦
Topic58	货	商品	价格	商家	清流	代购	口罩	包装
Topic59	舱	床位	治	收	定点	医院	病床	透析
Topic60	施工	神山	坍塌	建筑	工地	消防	废	泉州市

Table 2: Relevant Words of Each Topics

Bibliography

Roberts, Margaret E, Brandon M Stewart, Dustin Tingley, et al. 2014. "stm: R package for structural topic models." Journal of Statistical Software 10 (2): 1–40.

.1 Appendix

Topic	Title	Deleted	Media
1	翻转的时光	FALSE	邓安庆
1	怎么写你都不够	FALSE	邓安庆
1	疑似武汉肺炎，居家隔离的第六天	FALSE	兜爷麻麻不睡觉
1	我们在一起做的事情	FALSE	邓安庆
1	一脚一个春天	FALSE	邓安庆
2	隔离前，她们去过 4 个城市，跟 80 多人吃过饭	FALSE	冰点周刊
2	记者手记 | 疫情笼罩纽约，哥伦比亚大学停课两天	FALSE	财新网
2	时疫琐记	FALSE	邓安庆
2	瑞士女议员因戴口罩被赶出议会大厅！如何理解“不戴口罩”的欧洲？	FALSE	中国经营报
2	德国疫情日记 ：德国人为什么不爱戴口罩？	FALSE	体坛周报
3	回武汉记（六）	FALSE	谈骁
3	回武汉记（五）	FALSE	谈骁
3	UP 主实拍：“空城”武汉的物价、交通、生活状态	FALSE	第一财经
3	封面报道之治理篇 | 襄阳：最后的出口	FALSE	财新网
3	襄阳：如何成为湖北唯一不“封城”的地级市	FALSE	南方周末/南方人物周刊
4	新增确诊 99 例，其中境外输入 24 例	FALSE	澎湃新闻
4	湖北以外新增 17 例，其中 16 例来自境外	FALSE	澎湃新闻
4	首次！全国新增治愈出院超过新增确诊	FALSE	澎湃新闻
4	肺炎日记 |2 月 27 日：国际疫情继续升级新增病例首超中国	FALSE	财新网
4	国内出现至少 5 例海外输入病例，世卫组织将疫情等级提至最高，以及其他 20 条疫情新闻	FALSE	所有的鱼
5	有研究探新冠病毒基因演化疑华南海鲜市场非原始来源	FALSE	财新网
5	华南海鲜市场不是病毒发源地，中科院团队基因追踪“零号病人”再进一步	FALSE	界面新闻
5	华南海鲜市场不是病毒发源地！中科院团队基因追踪“零号病人”再进一步	FALSE	DeepTech 深科技
5	气溶胶传播新冠病毒？医学专家提醒尚缺充分研究佐证	FALSE	财经杂志/财经十一人
5	科技部急征快速试剂盒，15 分钟检出新冠病毒可靠吗？	FALSE	中国新闻周刊
6	大年三十，父母送我们离开了湖北老家	FALSE	人间 theLivings
6	在疫情面前，小镇上的每个人都不一样	FALSE	人间 theLivings
6	老公进驻医院后，家门就是我们的鹊桥	FALSE	人间 theLivings
6	直到离开家时，我才真切感受到了恐惧	FALSE	人间 theLivings
6	武汉的餐饮人：在这个冬天等春天	FALSE	人间 theLivings
7	首例新冠危重症患者全肺活检病理报告：肺成了古铜色	FALSE	澎湃新闻
7	刘良团队首份新冠遗体解剖报告来了：和 SARS 有区别	FALSE	澎湃新闻
7	钟南山领衔最新新冠研究：这些病人风险最高	FALSE	澎湃新闻
7	新冠肺炎遗体解剖已完成 11 例，死者肺部有黏液性分泌物	FALSE	界面新闻
7	首例新冠遗体解剖结果将公布，手术前这个举动不一般	FALSE	澎湃新闻
8	亲历者讲述：武汉市中心医院医护人员被感染始末	FALSE	中国新闻周刊
8	武汉疫情调查追踪：医护感染应受关注	FALSE	财新网
8	一家“遍体鳞伤”的武汉三甲医院	FALSE	澎湃新闻
8	武汉同济医院一线医生口述：每天面对死亡，紧张但不恐惧——专访武汉同济医院心内科医生赵金召	FALSE	经济观察报
8	武汉市中心医院医护人员吐真情：疫情是面照妖镜	TRUE	环球时报
9	口述｜ ICU 男护士“Tony 蒋”，曾经也是手残党	FALSE	澎湃新闻
9	“我血管细，你们眼镜都糊了，是不好打针”	FALSE	澎湃新闻
9	抗疫、漫画、追星、拍 Vlog……这届 90 后护士另类又强大	FALSE	澎湃新闻
9	从崩溃到零感染，第一批援助医疗队在黄冈的 30 天	FALSE	一条
9	世界，我们需要帮助：中国医务人员柳叶刀发文，请求国际医疗支援	TRUE	丁香园
10	通知“严禁讨论疫情、擅自接受采访”，官方回应	FALSE	澎湃新闻
10	办理健康证还要缴费？官方回应：不违规	FALSE	澎湃新闻
10	云南彝良回应 150 名医务人员放弃抗疫补助	FALSE	界面新闻
10	一线医护补助最低 400 元，医院领导拿 8000 元，查！	FALSE	澎湃新闻
10	回武汉救命！在外停药的慢性疾病患者有希望了	FALSE	澎湃新闻
11	瑞德西韦与双黄连试验之比较，尚未起跑已分高下	FALSE	DeepTech 深科技
11	医学顶刊首发新冠临床试验结果：中国研究证实克力芝收效甚微，不能降低重症死亡率	FALSE	DeepTech 深科技
11	解药 | 无临床试验结果，院士李兰娟两款新冠荐药数据遭质疑	FALSE	财新网
11	瑞德西韦仿制药量产专利问题何解	FALSE	经济观察报
11	疫情当前何以回家：马尼拉中国旅客的漫漫回国路	FALSE	腾讯新闻《潜望》
12	深圳野生动物禁食条例征求意见这些动物被明确列入禁食黑名单……	FALSE	经济观察报
12	疫情过后还要养殖果子狸？江西省野保局：不属实，相关政策有待国家进一步明确	FALSE	界面新闻
12	全面禁止非法野生动物交易专家建议推出可食用动物白名单	FALSE	中国新闻周刊
12	封面调查 | 致命野味，非法盗猎和买卖为何屡禁不止？	FALSE	中国新闻周刊
12	全面禁食？2500 万网红竹鼠等待判决	FALSE	界面新闻
13	“万家宴”社区百步亭确诊多例新冠肺炎一小区 55 栋楼中 33 栋有发热病人	FALSE	经济观察报
13	上级压力大，居民不理解，基层干部难难难	FALSE	南风窗
13	武汉大爷：我只要草纸，就别捆绑卫生巾了吧	FALSE	南风窗
13	万家宴后的百步亭	FALSE	经济观察报
13	“武汉嫂子汉骂”火了后，成了社区志愿者	FALSE	澎湃新闻
14	团购群成了江湖，武汉人练就一身武功	FALSE	优良 better
14	他们开始为“新冠疫情”的医生制作游戏	FALSE	机核网
14	行思路｜ “我们爱我们的邻居”——口罩哨兵	FALSE	A2N 疫情志愿组
14	A2N 内部访谈 | 范老师：这也是我的事，我能做什么吗？	FALSE	A2N 疫情志愿组
14	A2N 内部访谈 | 陈知白，微光与炬火，怯懦与勇气	FALSE	A2N 疫情志愿组
15	我在湖北艾滋患者求助热线接电话	FALSE	极昼工作室

Table 3 continued from previous page

Topic	Title	Deleted	Media
15	疫情中的故事——困于大海，无药求生	FALSE	白桦林健康资讯
15	无声的战“疫”：武汉城内的聋哑人	FALSE	剥洋葱 people
15	一场为女性发起的「战疫」	FALSE	人物/每日人物
15	断药危机：封城封村之后的艾滋感染者	FALSE	人物/每日人物
16	北林散文诗集-预警全球灾疫处于爆发前夕	FALSE	北纬三十七点度森林里有片芦苇荡
16	志愿者｜我有点扛不住了	FALSE	北纬三十七点度森林里有片芦苇荡
16	【抗击新型肺炎自救】第二天	FALSE	北纬三十七点度森林里有片芦苇荡
16	【抗击新型肺炎自救】第一天	FALSE	北纬三十七点度森林里有片芦苇荡
16	【抗击新型肺炎自救】第三天	FALSE	北纬三十七点度森林里有片芦苇荡
17	捐赠物资“直达”武汉目标医院的另类样本：百万粉丝博主倒逼物流改变收件目的地	FALSE	经济观察报
17	校友会的战“疫”网：医疗物资补位者的进与退	FALSE	南方周末/南方人物周刊
17	意大利温州商人的捐赠神通：捐物资，也捐物流｜疫中人	FALSE	界面新闻
17	意大利温商的“闯关”之旅：海外个人捐赠为何如此难？	FALSE	界面新闻
17	武汉物资紧缺，民间力量把援助送进医院到底有多难？	FALSE	八点健闻
18	叶青：武汉出“硬招”了！	FALSE	叶青
18	中央指导组成员向疫情逝者默哀	FALSE	澎湃新闻
18	叶青：要跻身一流城市，武汉不能再有“瞎指挥”	FALSE	叶青
18	叶青：武汉 30 天，有件遗憾的事	FALSE	叶青
18	叶青：新冠肺炎与官僚主义一起反，才是正确选择	FALSE	叶青
19	新冠肺炎疫情大事记（上篇）	FALSE	财经杂志/财经十一人
19	新冠肺炎疫情大事记（中篇）	FALSE	财经杂志/财经十一人
19	数说疫情 0206：拐点渐近	FALSE	财经杂志/财经十一人
19	数说疫情 0215：非湖北地区新增病例 5 日后有望清零，湖北进入总攻阶段	FALSE	财经杂志/财经十一人
19	数说疫情 0209：洪峰通过，见“顶”可期	FALSE	财经杂志/财经十一人
20	压力太大，有援鄂医护整宿失眠	FALSE	澎湃新闻
20	疫情中的心理援助：寻找局部的安全	FALSE	GQ 报道
20	湖北一线心理咨询师：恐慌让他每半个小时测一次体温	FALSE	北青深一度
20	恐慌、焦虑、绝望……疫情之下，你还需要心理防护	FALSE	燃财经
20	“抗疫”的第二战线：有人整晚睡不着，有人远程提供紧急心理包扎	FALSE	人间像素
21	美国 CDC 前主任：一而再地，我们都在恐慌和忽视中循环	FALSE	中国新闻周刊
21	李铁：疫情较轻的城市应及时复工开业	FALSE	财经杂志/财经十一人
21	抗疫国际合作，习近平的“怎么做”和“为什么”	FALSE	中国新闻周刊
21	20 多国紧急状态，中国如何帮助抗疫？	FALSE	财经杂志/财经十一人
21	新冠疫情考验全球治理	FALSE	中国新闻周刊
22	疫情放大三星危机，越南基地缺人缺料缺协同	FALSE	财经杂志/财经十一人
22	疫情放大三星供应链危机，越南基地缺人缺料缺协同	FALSE	财经杂志/财经十一人
22	疫情严峻手机还得卖，3999 元的小米 10 能否突围？	FALSE	界面新闻
22	口罩“心脏”熔喷布这么缺，为什么厂商不借机上产线、扩产能？	FALSE	界面新闻
22	“我有口罩机却没有熔喷布”，口罩“心脏”价格从 2 万涨到 8 万	FALSE	界面新闻
23	武汉一方舱医院发布紧急通知：拟出院病友需加做病毒抗体检查	FALSE	澎湃新闻
23	44 名痊愈者 26 人复阳，专家建议出院标准要严，上海要查肛拭子	FALSE	中国新闻周刊
23	广东 14% 出院患者复检阳性，专家：可能仍具传染性	FALSE	中国新闻周刊
23	女子从武汉回来 21 天后无发热症状，第 4 次才确诊	FALSE	澎湃新闻
23	武汉政策加码：出院后还要集中隔离 2 周，新冠肺炎怎样才算治愈？	FALSE	八点健闻
24	封城十三天后：防疫时期的武汉玩家	FALSE	机核网
24	口述实录｜如果没有这场疫情，这一天是我穿上秀禾服结婚的日子	FALSE	世间有味
24	武汉的除夕夜，我一个人在家自行观察	FALSE	在人间 living
24	武汉的年夜饭：从来没有这么简单，从来没有这么重要	FALSE	新周刊
24	疫情风暴眼中的武汉居民生活	FALSE	南都周刊
25	口述实录：奶奶，是你在天上保佑我们吧｜武汉武汉	FALSE	中央广电总台中国之声
25	口述实录：大连小伙儿小强的武汉奇遇｜武汉武汉	FALSE	中央广电总台中国之声
25	口述实录：心怀恐惧，依然前行｜武汉武汉	FALSE	中央广电总台中国之声
25	这个春节，我在北京送外卖	FALSE	触乐网
25	口述实录：我记录的，是这个城市历史的一部分｜武汉武汉	FALSE	中央广电总台中国之声
26	奥运会可能变成冬奥会？日本奥运大臣：东京奥运会或推迟至年底举行	FALSE	中国经营报
26	追踪钻石公主号：邮轮上有两名内地乘客，一人已确诊	FALSE	财经杂志/财经十一人
26	又一邮轮被新冠肺炎疫情笼罩！乘客：像在“豪华监狱”	FALSE	中国经营报
26	挪威奥委会向国际奥委会建议推迟东京奥运会	FALSE	界面新闻
26	“钻石公主”号今日再下 600 人，各国接回后将继续隔离 14 天	FALSE	界面新闻
27	湖北 17 岁脑瘫儿死亡前一天，父亲多次拨打 120 和 110 求助无果	FALSE	大米和小米
27	家人疑似新冠肺炎被隔离，湖北 17 岁脑瘫儿独自在家 6 天后死亡	FALSE	大米和小米
27	黄冈死亡脑瘫儿父亲：隔离 7 天，收到孩子火化委托书	TRUE	真实故事计划
27	湖北脑瘫儿之死：多方曾介入救助父亲被隔离时想带其入院	FALSE	清流工作室
27	疫情中一夜长大的少年	FALSE	在人间 living
28	海底捞恢复营业的第一天，客人少得有点可怜	FALSE	界面新闻
28	广东餐饮业恢复堂食第一天：陶陶居被紧急叫停，极少数餐厅开放接待	FALSE	界面新闻
28	八合里海记牛肉火锅老板：月亏 6000 万，考虑卖房发工资	FALSE	界面新闻
28	香港四大核心商区空置商铺半年激增近一倍，尖沙咀最惨	FALSE	界面新闻
28	自如被指坐地起价，强制湖北籍租客隔离期间换房	FALSE	中国新闻周刊
29	谁也想不到，这个春节最该储备的年货是口罩	FALSE	三明治
29	封城第十五天，“今天也是，体温正常”｜三明治武汉每日书 12	FALSE	三明治
29	生活还要继续，但如果没有菜了……｜三明治武汉每日书 13	FALSE	三明治
29	武汉城内，我家报名了社区网格员志愿服务｜三明治武汉每日书 14	FALSE	三明治
29	预产期还有 6 天，我在武汉待产的医院被征用｜武汉日常每日书 05	FALSE	三明治

Table 3 continued from previous page

Topic	Title	Deleted	Media
30	鄂 M 卡车的归乡之路	FALSE	剥洋葱 people
30	死去的蜜蜂，未卜的追花路和无助的养蜂人	FALSE	界面新闻
30	养蜂人刘德成，无法再追花	FALSE	人物/每日人物
30	“千里逆行”送菜进鄂：执勤民警道谢不握手，司机称“这一趟跑得值!”	FALSE	北青深一度
30	疫区救援，我在武汉修汽车	FALSE	真实故事计划
31	李文亮医生的最后 40 天	FALSE	财经杂志/财经十一人
31	记者回忆与李文亮的对话：他自称是个小医生	FALSE	南方都市报
31	李文亮，没等到庆余年 2	FALSE	澎湃新闻
31	国家监委调查组发布李文亮有关情况调查通报	FALSE	财新网
31	李文亮有关情况调查结果公布	FALSE	中国新闻周刊
32	上海劝返无居住地入沪者，即使后备箱也严查	FALSE	界面新闻
32	藏在后备箱里进上海，居然成真了!	FALSE	澎湃新闻
32	复工第二周，记者走访上海地铁公交出租车，市内公共交通安全吗?	FALSE	新民周刊
32	一名外国人入境上海，需要过哪些关?	FALSE	澎湃新闻
32	疫情防控下，返岗北上广图景	FALSE	极昼工作室
33	中科创星米磊：疫情和新基建，正在推动自动驾驶爆发	FALSE	燃财经
33	新石器余恩源：送快递、送外卖，无人车正在加速替代人类	FALSE	燃财经
33	朱啸虎：创业企业不要倒在疫情结束后的“倒春寒”	FALSE	燃财经
33	后疫情时代，数字化能拯救企业吗	FALSE	财经杂志/财经十一人
33	快仓智能孙宇：疫情加速机器人应用，但无人车无人机送货还很远	FALSE	燃财经
34	艺术类校考延期，艺培机构在找出路	FALSE	界面新闻
34	当穷孩子也开始上网课	FALSE	真实故事计划
34	目前大规模线上教学效果如何？我们做了个调查	FALSE	澎湃新闻
34	“停课不停学”第一周，老师战网络，家长做噩梦	FALSE	南都周刊
34	“不想上网课，老师变主播”网课首日遭遇花式吐槽到底怎么了?	FALSE	经济观察报
35	贝壳：若无二手房交易，七成中介撑不过半年	FALSE	界面新闻
35	房企打响现金流“保卫战”	FALSE	中国经营报
35	售楼处关闭怎么办？房企这样“战疫”	FALSE	南都周刊
35	疫情之下，海天味业们高估值“神话”还能持续吗?	FALSE	界面新闻
35	全民宅家，疫情如何影响中国食品饮料消费市场?	FALSE	财经杂志/财经十一人
36	美联储的王炸加剧恐慌，只有疫苗才能拯救全球金融市场	FALSE	中国经营报
36	昨日 ICU，今日 KTV！暴跌暴涨后，全球金融市场何去何从?	FALSE	中国经营报
36	美股度过金融危机以来最黑暗一周，美联储表态	FALSE	澎湃新闻
36	美股又熔断！10 天 4 次，巴菲特：···	FALSE	中国经营报
36	华尔街陷疫：全球大萧条的第一声警报？|《财经》封面	FALSE	财经杂志/财经十一人
37	池莉：五十分之一，典型的一天	FALSE	夜光杯
37	胡展奋：中国最早口罩小考	FALSE	夜光杯
37	池莉：对不起，添麻烦了!	FALSE	夜光杯
37	龚静：宅相碎片	FALSE	夜光杯
37	孔明珠：我从沿街的窗户望出去	FALSE	夜光杯
38	爷爷，多希望你永远学不会用智能手机	FALSE	我们是有故事的人
38	在小区防疫的同性恋志愿者	FALSE	GS 乐点
38	一通武汉方舱来的电话：我要去火神山救我外婆	FALSE	故事 FM
38	疫情开始前，我想接父母来北京|北漂家政女工	FALSE	尖椒部落
38	我不是病毒，我在巴黎街头与 50 位陌生人拥抱	FALSE	在人间 living
39	不明原因肺炎忽现	FALSE	财新网
39	从“未见明显人传人”到“人传人”，复盘武汉疫情二十天	FALSE	第一财经
39	武汉新增病例 0 增长的 12 天，发生了什么?	FALSE	第一财经
39	武汉确认 27 例不明原因肺炎是病毒性肺炎，不确定是 SARS	FALSE	八点健闻
39	研究发现：华南海鲜市场并非新冠病毒发源地	FALSE	澎湃新闻
40	这个 6 岁上海小囡，用画笔成为战疫后方“小记者”!	FALSE	新民周刊
40	毕淑敏：生死之外，人生都是小事	FALSE	新民周刊
40	专访精神科专家谢斌教授，如何化解疫情带来的焦虑?	FALSE	新民周刊
40	独家|林青霞致前线抗疫英雄亲笔信背后的故事	FALSE	新民周刊
40	快递小哥汪勇感动了全国，却有人在利用他的事迹大肆敛财	FALSE	新民周刊
41	2596 名死者留下的遗憾，6 位一线医生讲述新冠重症治疗难题	FALSE	八点健闻
41	「我在和死神抢病人」|对话援鄂 ICU 医生李圣青	FALSE	人物/每日人物
41	双肺全白，通宵抢救！我的病人，生命现在以小时计	FALSE	海上柳叶刀
41	这是武汉“疫”线最真实的抢救实况|一只脚踏进鬼门关，被我们硬生生拽回来!	FALSE	海上柳叶刀
41	终极一战：与死神抢人	FALSE	南方周末/南方人物周刊
42	特别报道|疾控中心无辜吗?	FALSE	第一财经
42	武汉早期疫情上报为何一度中断	FALSE	冰点周刊
42	传染病网络直报系统投资了 7.3 亿，为何失灵了 28 天?	FALSE	财经杂志/财经十一人
42	名实不副地位太低——你可能不知道的中国疾控往事	FALSE	八点健闻
42	武汉疫情初期，网络直报系统为何失灵?	TRUE	剥洋葱 people
43	疫情总动员，各地怎么做|北京进一步严防，天津暂停清明祭扫	FALSE	财新网
43	疫情总动员，各地怎么做|保交通、重问责、迟开学	FALSE	财新网
43	“湖北疫情依旧严峻，坚决不能放松”	FALSE	澎湃新闻
43	疫情总动员，各地怎么做|多地严防境外输入湖北探索复产复工	FALSE	财新网
43	武汉监所一日新增 232 例累计确诊 806 例	FALSE	财新网
44	图说|和其他传染病相比，新冠病毒肺炎处于什么水平	FALSE	八点健闻
44	对话美国流行病学家：未发现的新冠感染者对我们意味着什么?	FALSE	人物/每日人物
44	十问杨功焕：新冠病毒很可能与人类长期共生	FALSE	财经杂志/财经十一人
44	隔离 14 天是多还是少？要用统计学来思考	FALSE	界面新闻

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Topic	Title	Deleted	Media
44	钟南山团队研究：若早 5 天干预，疫情减轻过半	FALSE	财新网
45	买菜群里的湖北人：半个土豆给猫半个土豆给自己	FALSE	人物/每日人物
45	DC 杂记 | 不完全疫时囤货指南	FALSE	RatherLtd
45	疫情日记 | 武汉封城的第三十四天	FALSE	PlantifulSoul
45	哀乐拼团	FALSE	艾老师工作室
45	疫情日记 | 武汉封城的第二十八天	FALSE	PlantifulSoul
46	“京郊草莓第一镇”自救记	FALSE	棱镜
46	把 5G 设备运进火神山！驰援武汉背后的物流链紧急重构	FALSE	棱镜
46	“每只利润四五厘”，中国口罩产业 17 年沉浮	FALSE	棱镜
46	为“火雷神山”工人发工资：开工第一天，5000 万工程款就下来了	FALSE	棱镜
46	轻症患者家属自述：冠状病毒肺炎很可恨，但没那么可怕	FALSE	棱镜
47	“平安归来，做我的最美新娘”	FALSE	澎湃新闻
47	北京隔离点入住者：除了不能出门，和住酒店没什么区别	FALSE	新京报
47	“爸爸妈妈是医生，现在他们在抗疫前线”	FALSE	南都周刊
47	我在武汉代喂宠物：它们死了，主人会伤心的	FALSE	澎湃新闻
47	留学韩国的中国学生：为什么我选择回国	FALSE	澎湃新闻
48	专访余永定：中国经济如何做好逆周期调控?	FALSE	财经杂志/财经十一人
48	疫情过后，该启动新一轮经济刺激计划吗?	FALSE	财经杂志/财经十一人
48	连平：中国经济或现小 V 型反弹，楼市政策应告别“一刀切”	FALSE	界面新闻
48	新冠疫情四重冲击，全球化要倒退?	FALSE	财经杂志/财经十一人
48	中国经济活动预计 4 月逐步恢复正常，疫情之后如何刺激各行业	FALSE	财经杂志/财经十一人
49	疫情下的深呼吸 | 我们也不知道该怎么办，只能等了	FALSE	协作者云社工
49	疫情下的深呼吸 | 希望他可以成为对社会有用的人	FALSE	协作者云社工
49	疫情下的深呼吸 | 希望能让孩子有个好一点的未来	FALSE	协作者云社工
49	疫情下的深呼吸 | 我还好，只要不生病就行	FALSE	协作者云社工
49	疫情下的深呼吸 | 我想把孩子带在身边	FALSE	协作者云社工
50	未来两周德黑兰会有 40% 居民感染？伊朗议员呼吁升级“封闭隔离”	FALSE	界面新闻
50	伊朗疫情排查 1400 万人，两处什叶派圣陵破天荒关闭	FALSE	界面新闻
50	伊朗新冠肺炎患者死亡人数达到 6 人，28 人被确诊	FALSE	界面新闻
50	伊朗副总统确诊感染新冠病毒	FALSE	界面新闻
50	确诊逼近 6000！伊朗拟“动武”管制交通，一名新晋女议员病逝	FALSE	界面新闻
51	直面史上最难春招：我的简历无处可去	FALSE	锌财经
51	史上最大规模在家办公开始：孩子是最大障碍频繁拉群是常态	FALSE	腾讯新闻《潜望》
51	超八成医务人员近期收入下降，8 大科室竞争激烈：疫情下的医疗春招	FALSE	丁香园
51	疫情之下，中国科技公司在线办公百态	FALSE	腾讯深网
51	深圳复工抢人大战：时薪加 5 块，速度要快	FALSE	界面新闻
52	疫情之下，巨灾风险治理如何进化?	FALSE	财经杂志/财经十一人
52	王振耀：疫情前所未见，需要跨部门协调响应，也要避免叠床架屋	FALSE	财经杂志/财经十一人
52	王宏伟：如何应对灾难复杂化新趋势?	FALSE	财经杂志/财经十一人
52	黄某英如何离汉进京的？官方公布调查结果	FALSE	中国新闻周刊
52	司法部牵头的联合调查组公布“女子离汉抵京事件”调查结果	FALSE	界面新闻
53	皇马全队开始隔离，西甲西乙联赛至少暂停两轮	FALSE	界面新闻
53	利用“封城”时间差，米兰人“大逃离”	FALSE	澎湃新闻
53	NBA 战疫进入生死时刻 8 小时紧急状态连升三级	FALSE	腾讯体育
53	NBA 想空场比赛，但需面对每场 2000 万门票损失和众球星反对	FALSE	界面新闻
53	米兰、威尼斯封城！意大利“战疫”升级军队待命	FALSE	界面新闻
54	不管你爱与不爱都是历史的尘埃	FALSE	人是最美的风景
54	抓一把阳光	FALSE	人是最美的风景
54	回武汉记（上）	FALSE	谈骁
54	生活的刺	FALSE	人是最美的风景
54	谈骁：回武汉记（中）	FALSE	谈骁
55	研究：酶切位点插入事件非独有新冠病毒源于自然重组	FALSE	财新网
55	疫苗设计新进展！新冠病毒 S 蛋白超清结构图绘制成功，但实用疫苗还需要更多时间	FALSE	DeepTech 深科技
55	新冠疫苗研发大赛正酣，不同技术路线究竟谁更有戏?	FALSE	中国新闻周刊
55	封面报道上篇 | 看清病毒的样子	FALSE	财新网
55	冷冻电镜下的新冠病毒“侦查战”，西湖大学团队重要病毒解析登 Science | 独家专访	FALSE	DeepTech 深科技
56	返岗复工农民工已达 7800 万，卫健委：未要求返岗前开具健康证明	FALSE	界面新闻
56	为达标复工率，浙江部分企业注水用电量	TRUE	财经杂志/财经十一人
56	包飞机发补贴！多地“抢人式”复工	FALSE	澎湃新闻
56	开灯开空调开机器“冲指标”全国复工数据有多少水分?	TRUE	财新网
56	困境与自救：疫情之下多地“包飞机、包高铁、包车”帮助企业复工	FALSE	新京报
57	特朗普不担心感染，“其实是装的”	FALSE	澎湃新闻
57	美国副总统、国务卿参加的会议，已有 2 人确诊	FALSE	澎湃新闻
57	特朗普就疫情发表讲话，宣布多项措施	FALSE	澎湃新闻
57	新冠疫情蔓延全美，特朗普连任增变数	FALSE	财经杂志/财经十一人
57	美国两名议员宣布自我隔离	FALSE	澎湃新闻
58	疯狂的假口罩：药店也售假募捐给武汉医院的物资现三无产品	FALSE	清流工作室
58	超 200 万只假飘安口罩流入市场，涉事“黑”作坊被查	FALSE	新京报
58	“被消失”的口罩：谁掀翻了边境线上的百万生意	FALSE	财经杂志/财经十一人
58	“被消失”的口罩：谁掀翻了边境线上的百万生意?	FALSE	财经杂志/财经十一人
58	一“枪”难求，买额温枪遭遇连环涨	FALSE	南都周刊
59	武汉最大的方舱医院，关门大吉!	FALSE	澎湃新闻
59	倒计时！武汉投用的方舱医院将全部休舱	FALSE	澎湃新闻
59	方舱医院里“跳舞姐”越来越多，但仍缺心理医生	FALSE	澎湃新闻

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Topic	Title	Deleted	Media
59	武汉可以从非典的经验中学到什么?	FALSE	第一财经
59	武汉 10 万床位待命：从居家隔离到集中隔离的艰难纠偏	FALSE	八点健闻
60	泉州楼祸	FALSE	中国经营报
60	她们在战疫：有人一月没见孩子，有人奔袭 500 公里回武汉	FALSE	三联生活周刊
60	泉州隔离酒店坍塌：被忽视的结构风险	FALSE	三联生活周刊
60	追问泉州坍塌酒店：装修改造是否违规？为何成为疫情隔离点?	FALSE	财经杂志/财经十一人
60	航拍泉州疫情隔离酒店坍塌现场：40 余人生还，知情人披露前情后果	FALSE	财经杂志/财经十一人