Linguistic Characteristics of Censorable Language on SinaWeibo

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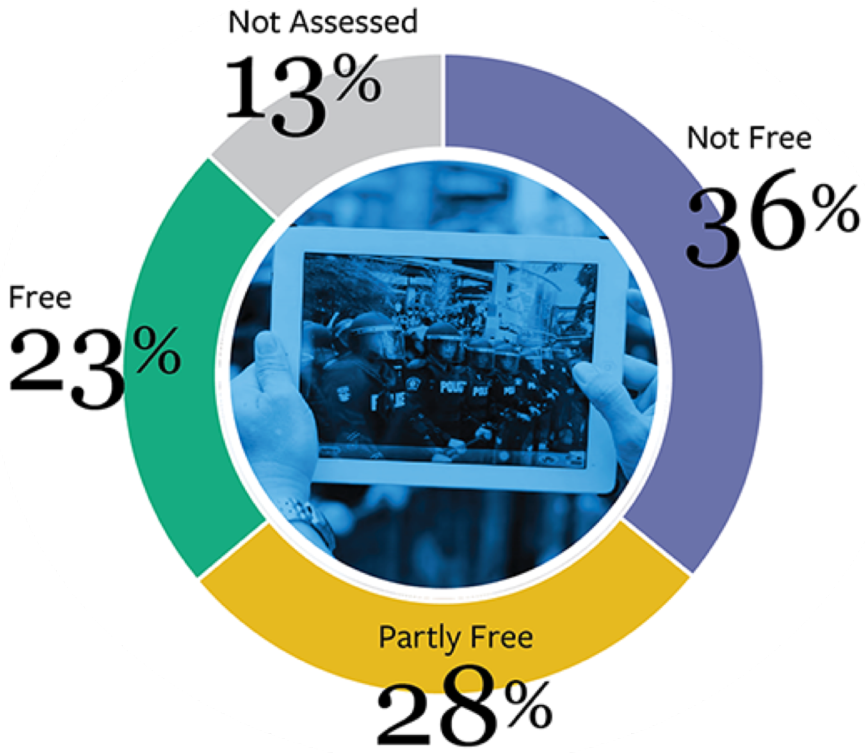
Problem



Souce: Freedom House (http://freedomonthenet.org)

As of 2017,

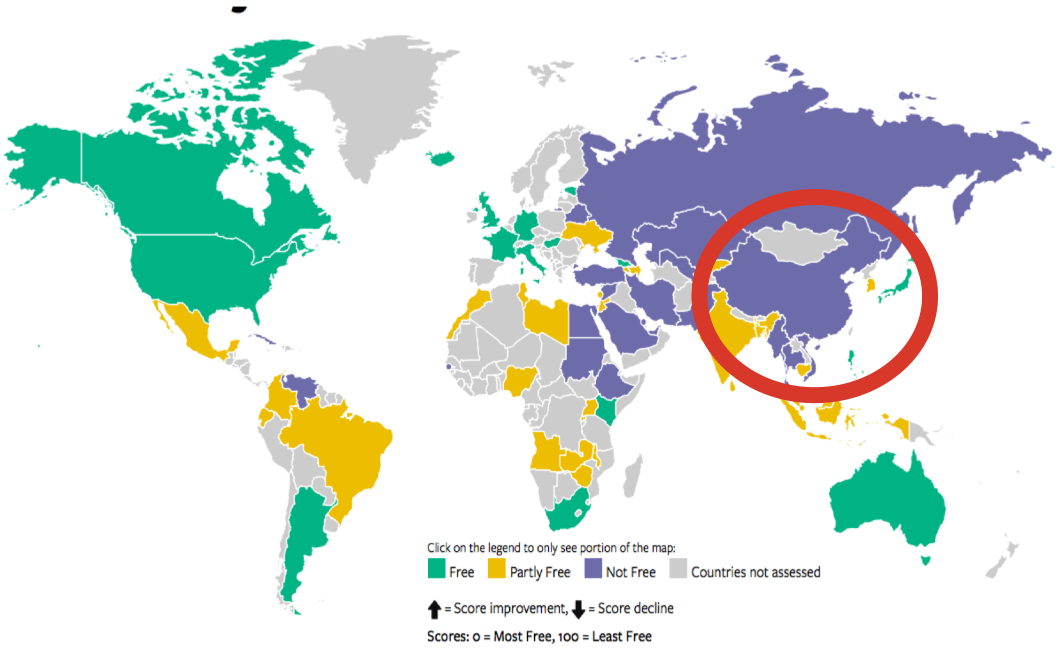
over 50% of the world's Internet users

have restricted access to

certain Social Media platforms

(e.g. Twitter, Facebook, Youtube)

Our Focus



Mainland China

One of the regions with the most serious censorship

Largest population in the world (~1.4 billion)

Weibo

Chinese equivalent of Twitter

> 300 million active monthly users

Censorship on Weibo

- Published content is subject to scrutiny ➜ would possibly be censored or deleted if it is considered to have violated Weibo's policies (e.g. not to publish content that hurts the country's or the government's reputation)

- Discussions on sensitive topics SOMETIMES get censored, but NOT ALWAYS (such tweets are accessible on the platform e.g scandals of Chinese officials and the Chinese government)

Related Work

Predicting censorship

- King et al. (2013) claim that negative comments about the state do not always lead to censorship. Rather, the presence of Collective Action Potential (the potential to cause collective action in real life) does.
- Bamman et al.(2012) find that the presence of a set of politically sensitive keywords in a Weibo blogpost contribute to higher chance of the post being censored.

Evading censorship

- Hiruncharoenvate et al. (2015) propose that use of homophones of sensitive keywords could help extend the time a post could remain available online.
- Lee (2016) claims that parodic satire could most likely survive censorship as it relies heavily on users' and censors' ability to detect sensitive topics based on context.

Our Work

- Collect a corpus of censored and uncensored blog posts on sensitive topics (but not necessarily on politics)
- Study the linguistic components of both the censored and uncensored posts on those topics (not just sensitive keywords)
- We build a classifier that predicts censorship decisions independent of discussion topics

Hypotheses

1. Censored and uncensored texts should have their own unique linguistic characteristics even on the same topic.
   a. Inspired by Sali et al. 2016 on frequency effect in information selection.
2. Uncensored content is easier for readers to process than censored content
   a. Lewandowsky et al.(2012): rejecting information requires cognitive effort whereas accepting information as truth is easier;
   b. Schwartz et al. (2008): people tend to make judgments based on their subjective feelings of how easy it is to recall or process information;

→ We see **censorship** as an agent that c**reates misinformed online experiences** by eliminating certain content and presenting events and opinions in a biased way

Data Sources

Uncensored
Sina Weibo

Censored
Freeweibo and WeiboScope

Topics Covered

Pollution and Food Safety
- The use of Gutter Oil as cooking oil in mainland China reported in 2010
- The Milk Scandal in 2008 when milk and infant formula made in China were found to be adulterated with melamine to make the products appeared to have high protein content.
- The ongoing severe Air Pollution problem in some cities in mainland China.

Internet Censorship and Propaganda
The ”fifty-cent party”(五毛党), a group of commentators that is believed to be hired by the Chinese authorities to manipulate public opinion in favor of the Communist Party.

Bo Xilai
A former Communist Party chief who was found guilty of corruption

Kindergarten Abuse
RYB(红黄蓝) Kindergarten Abuse in Beijing in 2017

Data Selection & Preprocessing

- Only blogposts that do not contain any images, hyperlinks or reblogged content are selected.

- Name of author, friend tags and hashtags are removed from all data.

- Since availability of censored data is generally lower, we first collect all available censored blogposts, and then based on the quantity of censored blogposts we collect corresponding number of uncensored blogposts that were published in the same date range as the censored counterpart.

- A word segmenter called Jieba has been used to segment all the data and the performance of Jeiba on our data has been manually checked.

The Corpus

Sub-corpus 1
Pollution &
Food Safety Issues

Sub-corpus 2
Internet Censorship &
Propaganda Issues

Sub-corpus 3
Bo Xilai Scandal

Sub-corpus 4
Kindergarten Abuse

Issue	Date	Search Term(s)	Censored Quantity	Uncensored Quantity
air pollution	3/2013 - 12/2017	smog (雾霾)	223	240
gutter oil	4/2012 - 9/2017	gutter oil (地沟油)	120	138
milk scandal	4/2012 - 7/2017	melamine (三聚氰胺) & toxic formula (毒奶粉)	49	85
Internet censorship	9/2013 - 11/2017	censor (屏蔽)	195	216
Internet propaganda	7/2014 - 12/2017	fifty-cent (五毛)	258	290
Bo Xilai	1/2015 - 11/2017	Bo Xilai (薄熙来)	125	75
kindergarten abuse	11/2017 - 12/2017	RYB (红黄蓝)	53	94
	TOTAL		1138	1023

Sample Data

Censored - Kindergarten Abuse

国外震怒，气炸了肺。 国内红黄蓝保留追究造谣者责任的权利。

(Overseas is furious. Here within the country RYB reserves the rights to hold people responsible for spreading rumors.)

Uncensored - Kindergarten Abuse

从携程亲子园到红黄蓝幼儿园，“虐童”案再次成为焦点，只希望类似的事件从此不会发 生，希望澄清的一切都是事实的真相，希望所有的小朋友都在阳光下健康成长。

(From Ctrip Day Care to RYB Kindergarten, ”child abuse” has once again become the news highlight. I just hope nothing similar will happen again, and all the clarifications are the truth. I hope all children can grow up healthily under the sun.)

Feature
Sensitive Keywords

Source 1
Wikipedia's
Chinese blacklisted keywords

Source 2
China Digital Times's
sensitive Sina Weibo search terms

- As accessibility of search results change from time to time, China Digital Times tests the "searchability" of each keyword and records the date of testing for reference.
- For each issue, we collect keywords that have been tested during the same time period as the published date of the blogposts
- We count the frequency of keywords in each blogpost and normalize it with length of blogpost

Feature
Sentiment

Sentiment analyzer of BaiduAI

- Designed to gauge sentiment of ”comment type” short texts.
- Outputs a set of sentiment scores for each blogpost - a positive sentiment percentage score and a negative sentiment percentage, which sum to 1.

Feature

LIWC (Linguistic Inquiry and Word Count)

- LIWC is a program that analyzes text on a word-by-word basis, calculating percentage of words that match each language dimension
  e.g. Pronouns, Function words, Social processes, Cognitive processes, Drives, Informal language etc.
  - It builds on previous research establishing strong links between linguistic patterns and personality/psychological state.

- We use the Chinese LIWC to extract the frequency of 95 word categories in each blogpost

Features
Character Frequency & Word Frequency

Character Frequency

Based on the character frequency list of modern Chinese compiled by Da (2004).

Word frequency

Based on Aihanyu's CNCorpus of modern Chinese which consists of about 9.5 million Chinese words.

- We calculate the average frequency of characters and words in each blogpost
- Character and Word frequency provides a picture of how often a certain character or word is used in modern Chinese texts. ➔ The lower the frequency, the less commonly used a character or word is.
- For words that appear very rarely (less than 50 times in the corpus), we count their frequency as 0.0001%.

Feature

Semantic Classes

The Chinese Thesaurus 同义词词林

Divides words into 12 semantic classes

(Human, Matter, Space and time, Abstract matter, Characteristics, Actions, Psychology, Human activities, States and phenomena, Relations, Auxiliary words, and Formulaic expressions).

A word might belong to more than one semantic class (more than one senses)

e.g. the word 上 belongs to 7 classes: Space and time, Actions, States and phenomena etc.

The more semantic classes a word belongs to, the more semantic variety it has.

We count the number of distinct semantic classes found in each post, normalize by dividing the number of words by the number of semantic classes

Feature
Readability I

- Inspired by Zheng (2005) and Sung et al. (2015), we take the mean of character frequency, word frequency and word count to semantic groups ratio as a score of text readability.

- For each individual component, a lower score means a lower readability (more difficult to read and understand). Therefore, the lower the mean of the 3 components, the lower readability a text has.

Features
Idioms & Readability II

- Idioms are annotated by Jieba's POS tagger.
- We normalize the raw count of idioms by the number of words in the blogpost.
- We find a negative correlation between the Readability I score and idioms ➜ suggests the higher the number of idioms in a text, the lower its readability.
- We incorporate the inverse of normalized idioms into Readability I to create a second version of the readability score (Readability II)

Feature

Word Embeddings & Eigenfeatures

- Train word vectors using the word2vec tool (Mikolov et al., 2013a; Mikolov et al., 2013b) on 300,000 Chinese articles provided by Wikipedia.

- Remove stop-words from each blogpost in our censorship corpus and compute a 200 dimensional vector for each blogpost.

- Compute the 200x200 covariance matrix for each document and determine the eigen decomposition of this matrix. The eigenvectors are the directions in which the data varies the most.

- The last 40 eigenvalues capture about 85% of total variance and are therefore used as features.

Automatic experiments

- 107 linguistic features (standardized as a z-score) and 40 eigenvalues for each blogpost.

- Standard feature selection (IG, 10-fold cross-validation) with respect to class for each sub-corpus.

- Experiment with Naive Bayes and SVM (with SMO) classifiers for each subcorpus:
    - **eigenvalues only**
    - **linguistic features only**
    - **combination of both**
    - **best features**

Classification Results

Bo Xilai subcorpus
Best performance: 72% accuracy

Features		Censored			Uncensored		
	Acc	Pre	Rec	F1	Pre	Rec	F1
NB all (147)	0.65	0.76	0.65	0.70	0.53	0.65	0.58
NB eigenvalues (40)	0.57	0.69	0.57	0.62	0.43	0.57	0.50
NB ling. features (107)	0.64	0.76	0.61	0.68	0.51	0.68	0.58
NB best features(17)	0.67	0.74	0.74	0.74	0.56	0.56	0.56
SMO all (147)	0.70	0.75	0.78	0.77	0.61	0.56	0.58
SMO eigenvalues (40)	0.62	0.63	0.92	0.75	0.44	0.11	0.17
SMO ling. features (107)	0.68	0.74	0.74	0.74	0.57	0.57	0.57
SMO best features (17)	0.72	0.71	0.91	0.80	0.73	0.39	0.50
majority class	0.63						

Kindergarten Abuse subcorpus
Best performance: 72% accuracy

Features		Censored			Uncensored		
	Acc	Pre	Rec	F1	Pre	Rec	F1
NB all (147)	0.63	0.49	0.64	0.55	0.75	0.62	0.68
NB eigenvalues (40)	0.58	0.45	0.72	0.55	0.76	0.50	0.60
NB ling. features (107)	0.64	0.50	0.59	0.54	0.74	0.67	0.70
NB best features (9)	0.72	0.64	0.53	0.58	0.76	0.83	0.72
SMO all (147)	0.63	0.47	0.34	0.40	0.68	0.79	0.73
SMO eigenvalues (40)	0.63	0.00	0.00	0.00	0.64	0.99	0.78
SMO ling. features (107)	0.65	0.53	0.36	0.43	0.69	0.82	0.75
SMO best features (9)	0.70	0.91	0.19	0.31	0.68	0.99	0.81
majority class	0.64						

Classification Results

Pollution & Food Safety subcorpus
Best performance: 72% accuracy

Features	Acc	Censored			Uncensored		
		Pre	Rec	F1	Pre	Rec	F1
NB all (147)	0.66	0.60	0.76	0.67	0.74	0.57	0.64
NB eigenvalues (40)	0.62	0.57	0.68	0.62	0.68	0.57	0.62
NB ling. features (107)	0.69	0.63	0.78	0.70	0.77	0.61	0.68
NB best features(69)	0.67	0.62	0.74	0.67	0.74	0.61	0.67
SMO all (147)	0.71	0.70	0.66	0.68	0.73	0.76	0.74
SMO eigenvalues (40)	0.60	0.56	0.63	0.59	0.65	0.58	0.61
SMO ling. features (107)	0.72	0.70	0.68	0.69	0.74	0.75	0.75
SMO best features (69)	0.71	0.69	0.68	0.68	0.73	0.74	0.73
majority class	0.54						

Internet Censorship & Propaganda subcorpus
Best performance: 67% accuracy

Features	Acc	Censored			Uncensored		
		Pre	Rec	F1	Pre	Rec	F1
NB all (147)	0.66	0.60	0.76	0.67	0.74	0.57	0.64
NB eigenvalues (40)	0.55	0.52	0.65	0.58	0.60	0.47	0.52
NB ling. features (107)	0.64	0.62	0.62	0.62	0.66	0.66	0.66
NB best features(33)	0.65	0.65	0.59	0.62	0.66	0.71	0.68
SMO all (147)	0.66	0.63	0.65	0.64	0.68	0.67	0.67
SMO eigenvalues (40)	0.56	0.55	0.40	0.46	0.57	0.70	0.63
SMO ling. features (107)	0.63	0.61	0.61	0.61	0.65	0.66	0.65
SMO best features (33)	0.67	0.64	0.66	0.65	0.67	0.67	0.67
majority class	0.53						

Human Baseline (Crowdsourcing)

- Crowdsourcing experiment on Amazon Mechanical Turk on the Bo Xilai data.
- Participants decide whether they think a post has been censored (Yes) or has not been censored (No) on Sina Weibo.
- Only responses that correctly answer all control questions are accepted and analyzed.
- Each blogpost has been judged by 4 to 8 different participants. The average accuracy of the human judges is 63.51%. (compared to 72% of SVM classifier)
- The inter-annotator agreement, however, is low (Cohen's kappa = 0.07), which suggests that the task of deciding what blogpost has been censored is extremely difficult.

Best Features

Across all topics:

- Readability
- WC
- WC/Semantic Classes
- Swear words (Informal Language)
- Anger (Affective Processes) (hate, kill, annoyed)
- Non-fluencies (Informal Language)
- Social processes (non-1st pers. pronouns; human interaction)
- Power (Drives) (superior, bully)
- Causation (Cognitive processes) (because, effect)

Best Features
Readability I

- Readability I (without idioms) and Word Count (WC) appear in all 4 sets of best features.
- The average readability score of all uncensored blogposts is higher (=easier) than that of censored.
- Readability I feature alone achieves comparable classification accuracies as using all features:

Bo Xilai subcorpus - 65%
Kindergarten Abuse subcorpus - 65%
Pollution & Food Safety subcorpus - 66%
Internet Censorship & Propaganda subcorpus - 54%

Readability and WC

- Suggests that censored content could be semantically less straightforward and/or use more uncommon words.

  → Possible explanation:
  uncensored content is easy to remember/easy to accept as truth/more influential?
  → Possible recommendation:
  To evade censorship simplify the language of your posts.

- Uncensored blogposts on average are longer.

  → Possible explanation: invites more attention?
  → Possible recommendation: Make posts longer.

- Each component of the readability metric did not perform as well as their combination.

Linguistic Characteristics of Censored vs Uncensored

For each subcorpus, we compare the average score of each feature between the 2 classes (by subtracting the censored average from the uncensored average). A +ve value indicates stronger association with the uncensored class; a -ve value with the censored class.

Features that are more associated with the **censored** class **across all 4 subcorpora**:

1. **third person plural pronoun** (‘they’) (*Social Processes)*
2. **swear** words (‘fuck’, ‘damn’, ‘shit’ etc.) (*Informal Language)*
3. words that express **anger** (‘hate’, ‘annoyed’, ‘kill’ etc.) (*Affective Processes: Negative Emotions)*
4. words that express **certainty** (‘always’, ‘never’ etc.) (*Cognitive Processes*)

Features that are more associated with the **uncensored** class **across all 4 subcorpora**:

1. **interrogatives** (‘how’, ‘when’, ‘what’ etc.) (*Other grammar)*
2. **Internet slang** (‘lol’, ‘plz’, ‘thx’ etc.) (*Informal Language)*
3. words that talk about **the present** (‘today’, ‘now’ etc.) (*Time Orientations)*
4. words that talk about **sadness** (‘crying’, ‘grief’ etc.) (*Affective Processes: Negative Emotions)*
5. words that talk about **vision** (‘view’, ‘see’ etc.) (*Perceptual Processes)*

Linguistic Characteristics of Censored vs Uncensored

Censored blogpost: furious, cursing manner and with certainty

Uncensored blogposts: more casual and appealing (the heavier use of the Internet slang), more focused on discussing or querying the current state of matter (interrogatives, present words, and vision words), or describe negative emotion in a less intimidating way

→ Hypothesis I: Censored and uncensored texts should have their own unique linguistic characteristics even on the same topic

Censored texts' characteristics and CAP (Collective Action Potential)

CAP - the potential to cause collective action in real life

Some of our findings show characteristics common with CAP – social engagement.

1. **third person plural pronoun** ('they')
2. **swear** words ('fuck', 'damn', 'shit' etc.)
3. words that express **anger** ('hate', 'annoyed', 'kill' etc.)
4. words that express **certainty** ('always', 'never' etc.)

Generally, the features typical of censored content convey social engagement, confidence and anger, and involve fewer words that refer to senses, but more words that describe cognitive processes.

Conclusion

- We built a corpus that consists of censored and uncensored Weibo blogposts covering various topics
- We have found linguistic features that characterize the two categories and built classifiers that achieve promising results.
- We deliberately did not use topics as classification features because some censorable topics vary throughout time and across countries, but linguistic fingerprints should not.

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Sample Data with Readability scores

Censored - Kindergarten Abuse

对于这样的无耻机构，口水是淹不死他们的，打官司也罚不了几毛钱 。 唯一的办法就是，所有中国人立即无条件抵制红黄蓝，让这家机构彻底破产倒闭。

(For such shameless institution, condemnation won't make them close down, and the lawsuit won't be able to fine them a lot. The only way is for all Chinese to immediately and unconditionally boycott RYB, and make the institution go bankrupt.)

Uncensored - Kindergarten Abuse

红黄蓝回应: 开除涉事教师刘某某, 立刻免去新天地幼儿园园长职务; 立刻组织优秀教育管理团队进驻新天地幼儿园, 确保幼儿园正常运营, 确保整个园所教师队伍的稳定.

(RYB responds: fire the involved teacher Liu and the headmaster of New World preschool; organizing an excellent education management team immediately for New World preschool to ensure smooth operation of the school and a stable team of teachers.)

	Censored (Standardized z-scores)	**Uncensored** (Standardized z-scores)
Readability	**-0.44**	**-0.40**
Character Frequency	-0.12	-0.19
Word Frequency	1.01	-0.73
Semantic class over WC	-0.44	-0.40

Sample Data with semantic class examples

Censored - Kindergarten Abuse

对于这样的无耻机构，口水是淹不死他们的，打官司也罚不了几毛钱 。 唯一的办法就是，所有中国人立即无条件抵制红黄蓝，让这家机构彻底破产倒闭。

(For such shameless institution, condemnation won't make them close down, and the lawsuit won't be able to fine them a lot. The only way is for all Chinese to immediately and unconditionally boycott RYB, and make the institution go bankrupt.)

对于 (Duìyú) 'for"
(Auxiliary Words) **1**
这样 (Zhèyàng) 'such'
(Auxiliary Words) **1**
的 (De) preposition/suffix/particle
(Matter, Characteristics, Auxiliary Words) **3**
无耻 (Wúchǐ) 'shameless'
(Characteristic) **1**
机构 (Jīgòu) 'organization/mechanism'
(Abstract Matter) **1**

Uncensored - Kindergarten Abuse

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(RYB responds: fire the involved teacher Liu and the headmaster of New World preschool; organizing an excellent education management team immediately for New World preschool to ensure smooth operation of the school and a stable team of teachers.)

组织 (Zǔzhī) 'organize/organization'
(Abstract Matter) **1**
优秀 (Yōuxiù) excellent'
(Characteristics) **1**
教育 (Jiàoyù) 'education'
(Abstract Matter, Human Activities) **2**
管理 (Guǎnlǐ) 'management'
(Human Activities) **1**
团队 (Tuánduì) team
(Abstract Matter) **1**