Sina Weibo as a Corpus for Studying Public Opinions

Christine Kuang, Siqi Wu, and Angie Zhu

Department of Statistics, UC Berkeley

May 3, 2012

Outline

Introduction

- Opinions on microblogging and social networking websites

Introduction

- Opinions on microblogging and social networking websites
- Sina Weibo 新浪微博 is the largest microblogging website:
  accounted for 65% of China's microblog market as of December 2011

Introduction

- Opinions on microblogging and social networking websites
- Sina Weibo 新浪微博 is the largest microblogging website:
  accounted for 65% of China's microblog market as of December 2011
- Study public opinions using Sina Weibo as a corpus for a given topic

Topic

- Internet censorship in China

Topic

- Internet censorship in China
- Time sensitive

Topic

- Internet censorship in China
- Time sensitive
- Processing is topic-dependent

Topic

- Internet censorship in China
- Time sensitive
- Processing is topic-dependent
- Hot topic is preferred

Topic

- Internet censorship in China
- Time sensitive
- Processing is topic-dependent
- Hot topic is preferred
- Chosen topic: Han Han 韩寒

Background

- HAN Han 韩寒 (born 23 September 1982) is a Chinese best-selling author, professional rally driver, and wildly popular blogger

Photograph by Tony Law / Redux. Source: http://www.time.com/time/magazine/article/0,9171,1931619,00.html

Background

- HAN Han 韩寒 (born 23 September 1982) is a Chinese best-selling author, professional rally driver, and wildly popular blogger
- Published his first novel *Triple Gate* 三重门 at age of 17

Photograph by Tony Law / Redux. Source: http://www.time.com/time/magazine/article/0,9171,1931619,00.html

Background

- HAN Han 韩寒 (born 23 September 1982) is a Chinese best-selling author, professional rally driver, and wildly popular blogger
- Published his first novel *Triple Gate* 三重门 at age of 17
- High school dropout

Photograph by Tony Law / Redux. Source: http://www.time.com/time/magazine/article/0,9171,1931619,00.html

Background (Cont'd)

- Ghostwriting allegation against Han from January 2012

Background (Cont'd)

- Ghostwriting allegation against Han from January 2012
- FANG Zhouzi 方舟子, a scientific author and anti-fraud crusader, created widespread debate on the Internet

Background (Cont'd)

- Ghostwriting allegation against Han from January 2012
- FANG Zhouzi 方舟子, a scientific author and anti-fraud crusader, created widespread debate on the Internet
- *Light and Upright 光明与磊落*: photocopied manuscripts set, including his first novel *Triple Gate 三重门*

Background (Cont'd)

- Ghostwriting allegation against Han from January 2012
- FANG Zhouzi 方舟子, a scientific author and anti-fraud crusader, created widespread debate on the Internet
- *Light and Upright 光明与磊落*: photocopied manuscripts set, including his first novel *Triple Gate 三重门*
- Han received a death threat on April 15, 2012

Data Collection

- Topic searching via API:

Data Collection

- Topic searching via API:
  - Only the latest results are returned

Data Collection

- Topic searching via API:
    - Only the latest results are returned
    - Up to 30 each time

Data Collection

- Topic searching via API:
  - Only the latest results are returned
  - Up to 30 each time
- 22,398 posts collected on April 16 and 17, 2012

Data Collection

- Topic searching via API:
  - Only the latest results are returned
  - Up to 30 each time
- 22,398 posts collected on April 16 and 17, 2012
- UTF-8 encoding

Characteristics of Chinese Language

- No explicit delimiter

Characteristics of Chinese Language

- No explicit delimiter
- Ambiguities in phrases

Characteristics of Chinese Language

- No explicit delimiter
- Ambiguities in phrases
  - Context ambiguition: e.g., 他好吃

Characteristics of Chinese Language

- No explicit delimiter
- Ambiguities in phrases
  - Context ambiguition: e.g., 他好吃
  - Word definition ambiguition: e.g., 打

Characteristics of Chinese Language

- No explicit delimiter
- Ambiguities in phrases
  - Context ambiguition: e.g., 他好吃
  - Word definition ambiguition: e.g., 打
- Out-of-vocabulary words

Characteristics of Chinese Language

- No explicit delimiter
- Ambiguities in phrases
  - Context ambiguition: e.g., 他好吃
  - Word definition ambiguition: e.g., 打
- Out-of-vocabulary words
- No 1-to-1 correspondence between traditional and simplified Chinese

Characteristics of Sina Weibo Posts

1714080953 2012-04-16 10:01:59 //@ 風笑巨石: 那尊神容不得别人质疑? //@ 伯林 2011: 质疑派人士遭到人肉，人身攻击，甚至死亡威胁的时候，从来没有污名化整个挺韩派，也没有引起什么媒体关注，相比之下，韩寒如此炒作，太无良了，挺韩和批韩的双方本不至于如此撕裂

- Multiple forms

Characteristics of Sina Weibo Posts

1714080953 2012-04-16 10:01:59 //@ 風笑巨石: 那尊神容不得别人质疑? //@ 伯林 2011: 质疑派人士遭到人肉，人身攻击，甚至死亡威胁的时候，从来没有污名化整个挺韩派，也没有引起什么媒体关注，相比之下，韩寒如此炒作，太无良了，挺韩和批韩的双方本不至于如此撕裂

- Multiple forms
- Informal and short

Characteristics of Sina Weibo Posts

1714080953 2012-04-16 10:01:59 //@ 風笑巨石: 那尊神容不得别人质疑? //@ 伯林 2011: 质疑派人士遭到人肉，人身攻击，甚至死亡威胁的时候，从来没有污名化整个挺韩派，也没有引起什么媒体关注，相比之下，韩寒如此炒作，太无良了，挺韩和批韩的双方本不至于如此撕裂

- Multiple forms
- Informal and short
- Reposting: “//@”

Characteristics of Sina Weibo Posts

1714080953 2012-04-16 10:01:59 //@ 風笑巨石: 那尊神容不得别人质疑? //@ 伯林 2011: 质疑派人士遭到人肉，人身攻击，甚至死亡威胁的时候，从来没有污名化整个挺韩派，也没有引起什么媒体关注，相比之下，韩寒如此炒作，太无良了，挺韩和批韩的双方本不至于如此撕裂

- Multiple forms
- Informal and short
- Reposting: “//@”
- Spams

Characteristics of Sina Weibo Posts

1714080953 2012-04-16 10:01:59 //@ 風笑巨石: 那尊神容不得别人质疑? //@ 伯林 2011: 质疑派人士遭到人肉，人身攻击，甚至死亡威胁的时候，从来没有污名化整个挺韩派，也没有引起什么媒体关注，相比之下，韩寒如此炒作，太无良了，挺韩和批韩的双方本不至于如此撕裂

- Multiple forms
- Informal and short
- Reposting: “//@”
- Spams
- Emotion symbols

Characteristics of Sina Weibo Posts

1714080953 2012-04-16 10:01:59 //@ 風笑巨石: 那尊神容不得别人质疑? //@ 伯林 2011: 质疑派人士遭到人肉，人身攻击，甚至死亡威胁的时候，从来没有污名化整个挺韩派，也没有引起什么媒体关注，相比之下，韩寒如此炒作，太无良了，挺韩和批韩的双方本不至于如此撕裂

- Multiple forms
- Informal and short
- Reposting: “//@”
- Spams
- Emotion symbols
- Internet slangs

Characteristics of Sina Weibo Posts

1714080953 2012-04-16 10:01:59 //@ 風笑巨石: 那尊神容不得别人质疑? //@ 伯林 2011: 质疑派人士遭到人肉，人身攻击，甚至死亡威胁的时候，从来没有污名化整个挺韩派，也没有引起什么媒体关注，相比之下，韩寒如此炒作，太无良了，挺韩和批韩的双方本不至于如此撕裂

- Multiple forms
- Informal and short
- Reposting: “//@”
- Spams
- Emotion symbols
- Internet slangs
- Topic: “# 话题 #”

Pre-Tagging Processing

1165303315 2012-04-16 09:55:40 《韩寒收到网友死亡威胁》(来自 @ 新浪娱乐) http://t.cn/zOprKap 1165303315 2012-04-16 09:55:40 《Han Han received death threat online》(from @ 新浪娱乐) http://t.cn/zOprKap

- Remove user identification number and time stamp

Pre-Tagging Processing

1165303315 2012-04-16 09:55:40 《韩寒收到网友死亡威胁》(来自 @ 新浪娱乐) http://t.cn/zOprKap 1165303315 2012-04-16 09:55:40 《Han Han received death threat online》(from @ 新浪娱乐) http://t.cn/zOprKap

- Remove user identification number and time stamp
- Only the reposting user's comment is kept:
  If the resulting string is empty, it will be eliminated as well

Pre-Tagging Processing

1165303315 2012-04-16 09:55:40 《韩寒收到网友死亡威胁》 (来自 @ 新浪娱乐) http://t.cn/zOprKap 1165303315 2012-04-16 09:55:40 《Han Han received death threat online》 (from @ 新浪娱乐) http://t.cn/zOprKap

- Remove user identification number and time stamp
- Only the reposting user's comment is kept:
  If the resulting string is empty, it will be eliminated as well
- Remove URLs

Pre-Tagging Processing

1165303315 2012-04-16 09:55:40 《韩寒收到网友死亡威胁》(来自 @ 新浪娱乐) http://t.cn/zOprKap 1165303315 2012-04-16 09:55:40 《Han Han received death threat online》(from @ 新浪娱乐) http://t.cn/zOprKap

- Remove user identification number and time stamp
- Only the reposting user's comment is kept:
  If the resulting string is empty, it will be eliminated as well
- Remove URLs
- Remove duplicates

Pre-Tagging Processing

1165303315 2012-04-16 09:55:40 《韩寒收到网友死亡威胁》(来自 @ 新浪娱乐) http://t.cn/zOprKap 1165303315 2012-04-16 09:55:40 《Han Han received death threat online》(from @ 新浪娱乐) http://t.cn/zOprKap

- Remove user identification number and time stamp
- Only the reposting user's comment is kept:
  If the resulting string is empty, it will be eliminated as well
- Remove URLs
- Remove duplicates
- 13,070 posts left

Tagging

- Process: tagged 3000 total posts with four categories

Tagging

- Process: tagged 3000 total posts with four categories
- Examples:

Tagging

- Process: tagged 3000 total posts with four categories
- Examples:

  Positive 支持韩寒！ Support Han Han!

Tagging

- Process: tagged 3000 total posts with four categories
- Examples:

Positive 支持韩寒！ Support Han Han!

Negative 看到韩寒就恶心。Feel nauseous when I see Han Han.

Tagging

- Process: tagged 3000 total posts with four categories
- Examples:

Positive	支持韩寒！ Support Han Han!
Negative	看到韩寒就恶心。Feel nauseous when I see Han Han.

- Limitations:

Tagging

- Process: tagged 3000 total posts with four categories
- Examples:

  Positive 支持韩寒！ Support Han Han!

  Negative 看到韩寒就恶心。Feel nauseous when I see Han Han.

- Limitations:
  - Subjective responses:

    e.g., “that wasn’t too bad”

Tagging

- Process: tagged 3000 total posts with four categories
- Examples:

  Positive 支持韩寒！ Support Han Han!

  Negative 看到韩寒就恶心。Feel nauseous when I see Han Han.
- Limitations:
  - Subjective responses:
    e.g., “that wasn’t too bad”
  - Uncertain tags

Tagging

- Process: tagged 3000 total posts with four categories
- Examples:

  Positive 支持韩寒！ Support Han Han!

  Negative 看到韩寒就恶心。Feel nauseous when I see Han Han.
- Limitations:
  - Subjective responses:
    e.g., "that wasn't too bad"
  - Uncertain tags
    - Quotes

Tagging

- Process: tagged 3000 total posts with four categories
- Examples:

  Positive 支持韩寒！ Support Han Han!

  Negative 看到韩寒就恶心。Feel nauseous when I see Han Han.
- Limitations:
  - Subjective responses:
    e.g., "that wasn't too bad"
  - Uncertain tags
    - Quotes
    - Posts without subjects

Tagging

- Process: tagged 3000 total posts with four categories
- Examples:

  Positive 支持韩寒！ Support Han Han!

  Negative 看到韩寒就恶心。Feel nauseous when I see Han Han.

- Limitations:
  - Subjective responses:
    e.g., “that wasn’t too bad”
  - Uncertain tags
    - Quotes
    - Posts without subjects
    - Posts that just mention opposing author

Pre-Segmentation Processing

- Word segmentation is crucial for our word-based analysis

Pre-Segmentation Processing

- Word segmentation is crucial for our word-based analysis
- Substitute mentioning of topic-related usernames by the corresponding proper nouns

Pre-Segmentation Processing

- Word segmentation is crucial for our word-based analysis
- Substitute mentioning of topic-related usernames by the corresponding proper nouns
- Remove other mentioned usernames

Pre-Segmentation Processing

- Word segmentation is crucial for our word-based analysis
- Substitute mentioning of topic-related usernames by the corresponding proper nouns
- Remove other mentioned usernames
- Substitute emotional symbols and Internet slangs by the corresponding word surrounded by square brackets

Segmentation

- 汉语词法分析系统 ICTCLAS (Institute of Computing Technology, Chinese Lexical Analysis System) is a well known Chinese word segmentation system

Segmentation

- 汉语词法分析系统 ICTCLAS (Institute of Computing Technology, Chinese Lexical Analysis System) is a well known Chinese word segmentation system
- Chinese word segmentation, lexical tagging, named entity recognition, unknown words detection, and the user-defined dictionary

Segmentation

- 汉语词法分析系统 ICTCLAS (Institute of Computing Technology, Chinese Lexical Analysis System) is a well known Chinese word segmentation system
- Chinese word segmentation, lexical tagging, named entity recognition, unknown words detection, and the user-defined dictionary
- Examples from the user-defined dictionary:

Segmentation

- 汉语词法分析系统 ICTCLAS (Institute of Computing Technology, Chinese Lexical Analysis System) is a well known Chinese word segmentation system
- Chinese word segmentation, lexical tagging, named entity recognition, unknown words detection, and the user-defined dictionary
- Examples from the user-defined dictionary:

  围脖 (wei2 bo2, means "scarf") refers to 微博 (Weibo, wei1 bo2)

Segmentation

- 汉语词法分析系统 ICTCLAS (Institute of Computing Technology, Chinese Lexical Analysis System) is a well known Chinese word segmentation system
- Chinese word segmentation, lexical tagging, named entity recognition, unknown words detection, and the user-defined dictionary
- Examples from the user-defined dictionary:
  - **围脖** (wei2 bo2, means "scarf") refers to 微博 (Weibo, wei1 bo2)
  - **韩少** (韩: Han Han's surname, 少: abbreviation of 少爷, which means "young master of the house") refers to Han Han

Conjunction Rules

[Lee and Renganathan, 2011] suggested that special consideration should be given to

1. Although (part A), (part B).
2. (Part A), but (part B).
3. Although (part A), but (part B).

For each case, only part B will be kept.

Stop Words and Punctuation Elimination

- Remove prepositions, punctuation marks, English character strings, interjections, modal particles, onomatopoeia, and auxiliary words

Stop Words and Punctuation Elimination

- Remove prepositions, punctuation marks, English character strings, interjections, modal particles, onomatopoeia, and auxiliary words
- Remove pre-defined stop words and number strings

Word Frequency

- Extract the word frequency vector x_i from the i-th post

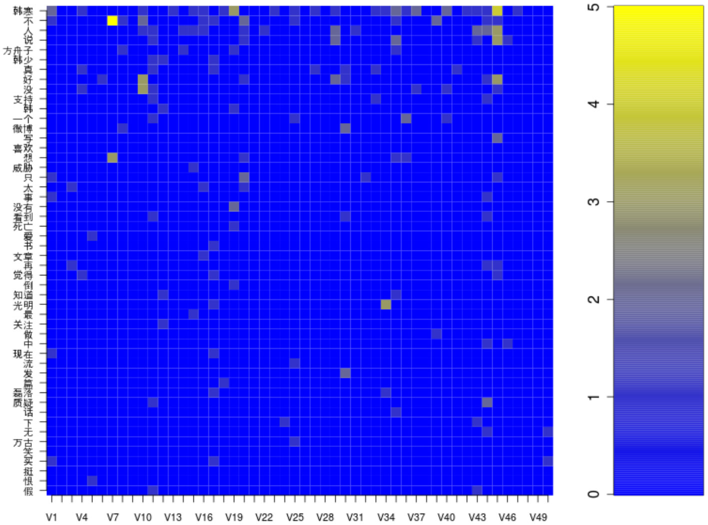
Word Frequency

- Extract the word frequency vector x_i from the i-th post
- Focus on words with overall frequency ≥ 10

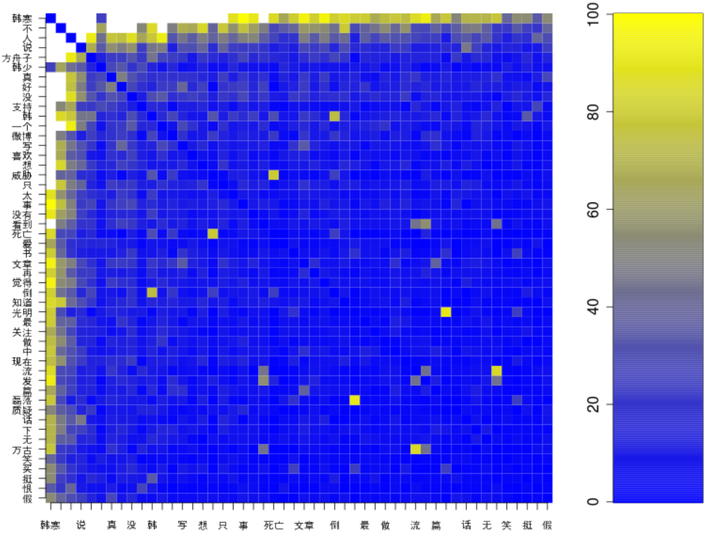
Word Frequency

- Extract the word frequency vector x_i from the i-th post
- Focus on words with overall frequency ≥ 10
- Construct the word frequency matrix $X = (x_1, \ldots, x_n)^T$. This will be our design matrix.

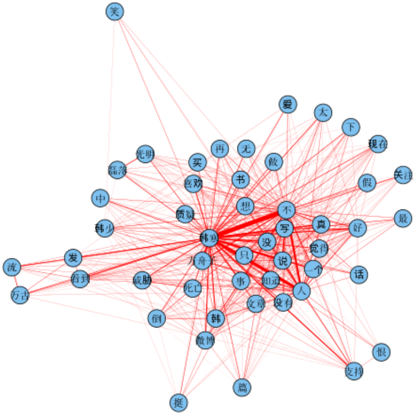
Word Frequency Visualization: Matrix Plot



Co-Occurrance



Co-Occurrance



Sparse Graphical Models

- Fact: if $x \in R^p$ follows $N(\mu, \Sigma)$, then for $i \neq j$

$$(x_i \perp\!\!\!\perp x_j) \mid \{x_{\text{all but } (i,j)}\} \textbf{ iff } (\Sigma^{-1})_{ij} = 0$$

Sparse Graphical Models

- Fact: if $x \in R^p$ follows $N(\mu, \Sigma)$, then for $i \neq j$

$$(x_i \perp\!\!\!\perp x_j) \mid \{x_{\text{all but }(i,j)}\} \textbf{ iff } (\Sigma^{-1})_{ij} = 0$$

- This motivates us to estimate Σ^{-1}.

Sparse Graphical Models

- Fact: if $x \in R^p$ follows $N(\mu, \Sigma)$, then for $i \neq j$

$$(x_i \perp\!\!\!\perp x_j) \mid \{x_{\text{all but } (i,j)}\} \textbf{ iff } (\Sigma^{-1})_{ij} = 0$$

- This motivates us to estimate Σ^{-1}.
- Let $x_1, x_2, ...x_n$ be IID $N(\nu, \Sigma)$ data. The joint likelihood of the data is

$$\begin{aligned} & f(x_1, \ldots, x_n | \mu, \Sigma) \\ &= \frac{1}{(2\pi \det(\Sigma))^{n/2}} \exp\left\{ -\frac{1}{2} \sum_{i=1}^{n} (x_i - \mu)^T \Sigma^{-1} (x_i - \mu) \right\}. \end{aligned}$$

Sparse Graphical Models (Cont'd)

- Log-likelihood:

$$l(\mu, \Sigma^{-1}) = -\frac{n}{2} \log \det (\Sigma) - \frac{1}{2} \sum_{i=1}^{n} (x_i - \mu)^T \Sigma^{-1} (x_i - \mu)$$

Sparse Graphical Models (Cont'd)

- Log-likelihood:

$$l(\mu, \Sigma^{-1}) = -\frac{n}{2} \log\det(\Sigma) - \frac{1}{2}\sum_{i=1}^{n}(x_i - \mu)^T\Sigma^{-1}(x_i - \mu)$$

- Do a maximum likelihood estimation (optimize over μ and $S = \Sigma^{-1}$; easy to see that the MLE for μ is $\bar{x}$):

$$\max_S \left\{ \frac{n}{2} \log\det(S) - \frac{1}{2}\sum_{i=1}^{n}(x_i - \bar{x})^T S(x_i - \bar{x}) \right\}$$

Sparse Graphical Models (Cont'd)

- Here comes the trace trick $\sum_{i=1}^{n}(x_i-\mu)^TS(x_i-\mu) = \mathbf{Tr}(\sum_{i=1}^{n}(x_i-\mu)(x_i-\mu)^TS) = n\mathbf{Tr}(\hat{\Sigma}S)$. We end up with the optimization problem for fitting a Gaussian graphical model:

$$\max_S \left\{ \log\det(S) - \mathbf{Tr}\left[\hat{\Sigma}S\right[\right\}$$

Sparse Graphical Models (Cont'd)

- Here comes the trace trick $\sum_{i=1}^{n}(x_i - \mu)^T S(x_i - \mu) = \mathbf{Tr}(\sum_{i=1}^{n}(x_i - \mu)(x_i - \mu)^T S) = n\mathbf{Tr}(\hat{\Sigma}S)$. We end up with the optimization problem for fitting a Gaussian graphical model:

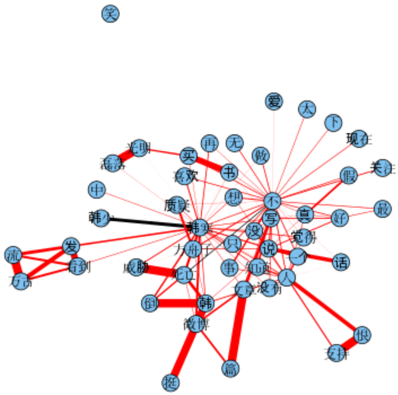
$$\max_{S}\left\{\log\det\left(S\right) - \mathbf{Tr}\left[\hat{\Sigma}S\right[\right\}$$

- Fitting a sparse Gaussian graphical model:

$$\max_{S}\left\{\log\det S - \mathbf{Tr}\left[\hat{\Sigma}S\right[- \lambda||S||_1\right\}$$

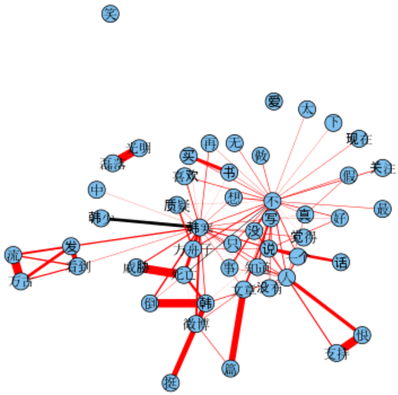
where $||S||_1 = \sum_{i,j}|s_{ij}|$. See, e.g. Banerjee et al. (2007) and Friedman et al. (2007).

Sparse Graphical Models: Results



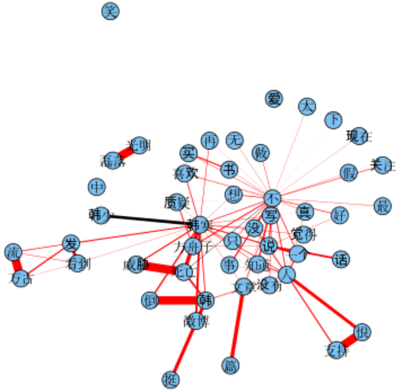
lambda = 0.01

Sparse Graphical Models: Results



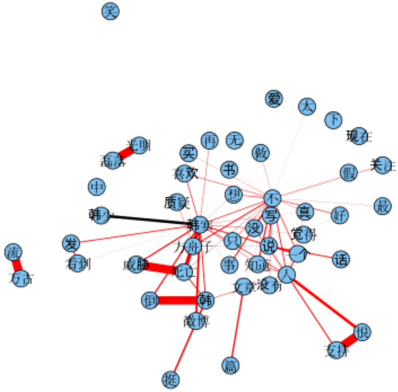
lambda = 0.01222

Sparse Graphical Models: Results



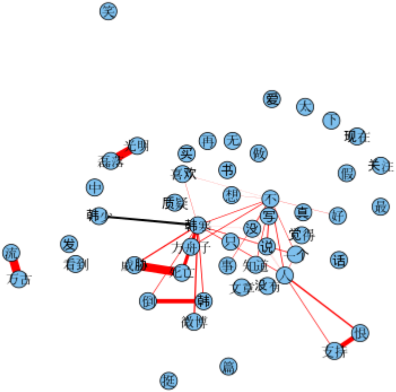
lambda = 0.01444

Sparse Graphical Models: Results



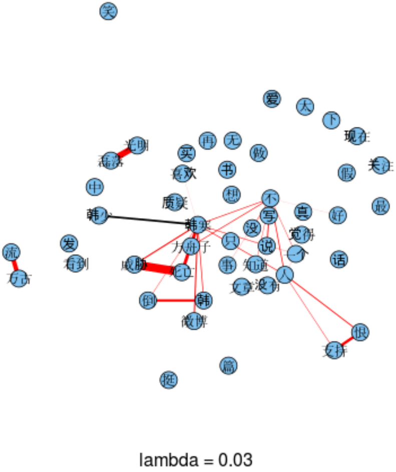
lambda = 0.01667

Sparse Graphical Models: Results



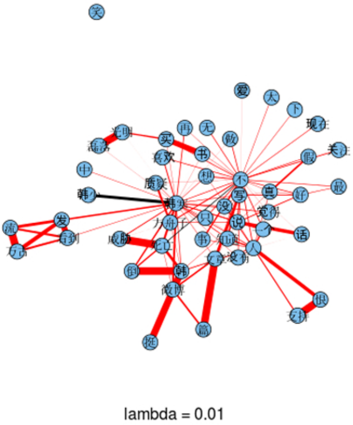
lambda = 0.02556

Sparse Graphical Models: Results

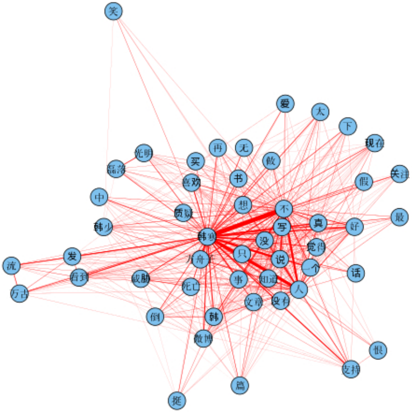


Sparse Graphical Models v.s. Co-Occurence

Sparse Graphical Models



Co-occurence



Classification

- $x_i \in R^p$ be the i-th row of $X \in R^{3000 \times 795}$

Classification

- $x_i \in R^p$ be the i-th row of $X \in R^{3000\times 795}$
- y_i the corresponding category. Assume $y_i \in \{-1, +1\}$, where the $+1$ can have the following meanings:

Classification

- $x_i \in R^p$ be the i-th row of $X \in R^{3000 \times 795}$
- y_i the corresponding category. Assume $y_i \in \{-1, +1\}$, where the $+1$ can have the following meanings:
  - positive opinion towards Han Han

Classification

- $x_i \in R^p$ be the i-th row of $X \in R^{3000\times 795}$
- y_i the corresponding category. Assume $y_i \in \{-1, +1\}$, where the $+1$ can have the following meanings:
  - positive opinion towards Han Han
  - negative opinion towards Han Han

Classification

- $x_i \in R^p$ be the i-th row of $X \in R^{3000\times795}$
- y_i the corresponding category. Assume $y_i \in \{-1, +1\}$, where the $+1$ can have the following meanings:
  - positive opinion towards Han Han
  - negative opinion towards Han Han
  - netural or unidentifiable opinion

Classification

- $x_i \in R^p$ be the i-th row of $X \in R^{3000\times 795}$
- y_i the corresponding category. Assume $y_i \in \{-1, +1\}$, where the $+1$ can have the following meanings:
  - positive opinion towards Han Han
  - negative opinion towards Han Han
  - netural or unidentifiable opinion
  - spam

Classification

- $x_i \in R^p$ be the i-th row of $X \in R^{3000 \times 795}$
- y_i the corresponding category. Assume $y_i \in \{-1, +1\}$, where the $+1$ can have the following meanings:
  - positive opinion towards Han Han
  - negative opinion towards Han Han
  - netural or unidentifiable opinion
  - spam
- Two classification methods: LASSO and l_1-norm SVM.

LASSO

- The Lasso approach (Tibshirani, (1996)):

$$\hat{\beta}(\lambda) = \arg\min_{\beta} \frac{1}{2}||y - (\beta_0 + X\beta)||_2^2 + \lambda||\beta||_1$$

LASSO

- The Lasso approach (Tibshirani, (1996)):

$$\hat{\beta}(\lambda) = \arg\min_{\beta} \frac{1}{2}||y - (\beta_0 + X\beta)||_2^2 + \lambda||\beta||_1$$

- The classifier:

$$\text{class}(x) = \textbf{sign}(\beta_0 + x^T\beta) \in \{-1, +1\}$$

LASSO

- The Lasso approach (Tibshirani, (1996)):

$$\hat{\beta}(\lambda) = \arg\min_{\beta} \frac{1}{2}||y - (\beta_0 + X\beta)||_2^2 + \lambda||\beta||_1$$

- The classifier:

$$\text{class}(x) = \textbf{sign}(\beta_0 + x^T\beta) \in \{-1, +1\}$$

- Four models for each category for classification

LASSO

- The Lasso approach (Tibshirani, (1996)):

$$\hat{\beta}(\lambda) = \arg\min_{\beta} \frac{1}{2}||y - (\beta_0 + X\beta)||_2^2 + \lambda||\beta||_1$$

- The classifier:

$$\text{class}(x) = \textbf{sign}(\beta_0 + x^T\beta) \in \{-1, +1\}$$

- Four models for each category for classification
- General overview of method

LASSO

- The Lasso approach (Tibshirani, (1996)):

$$\hat{\beta}(\lambda) = \arg\min_{\beta} \frac{1}{2}||y - (\beta_0 + X\beta)||_2^2 + \lambda||\beta||_1$$

- The classifier:

$$\text{class}(x) = \textbf{sign}(\beta_0 + x^T\beta) \in \{-1, +1\}$$

- Four models for each category for classification
- General overview of method
- General overview of application to data

LASSO

- The Lasso approach (Tibshirani, (1996)):

$$\hat{\beta}(\lambda) = \arg\min_{\beta} \frac{1}{2}||y - (\beta_0 + X\beta)||_2^2 + \lambda||\beta||_1$$

- The classifier:

$$\text{class}(x) = \textbf{sign}(\beta_0 + x^T\beta) \in \{-1, +1\}$$

- Four models for each category for classification
- General overview of method
- General overview of application to data
  - for 4 categories

LASSO

- The Lasso approach (Tibshirani, (1996)):

$$\hat{\beta}(\lambda) = \arg\min_{\beta} \frac{1}{2}||y - (\beta_0 + X\beta)||_2^2 + \lambda||\beta||_1$$

- The classifier:

$$\text{class}(x) = \textbf{sign}(\beta_0 + x^T\beta) \in \{-1, +1\}$$

- Four models for each category for classification
- General overview of method
- General overview of application to data
  - for 4 categories
  - 10 fold CV

LASSO

- The Lasso approach (Tibshirani, (1996)):

$$\hat{\beta}(\lambda) = \arg\min_{\beta} \frac{1}{2}||y - (\beta_0 + X\beta)||_2^2 + \lambda||\beta||_1$$

- The classifier:

$$\text{class}(x) = \textbf{sign}(\beta_0 + x^T\beta) \in \{-1, +1\}$$

- Four models for each category for classification
- General overview of method
- General overview of application to data
  - for 4 categories
  - 10 fold CV
  - Frequency matrix is 3000×795

LASSO

- The Lasso approach (Tibshirani, (1996)):

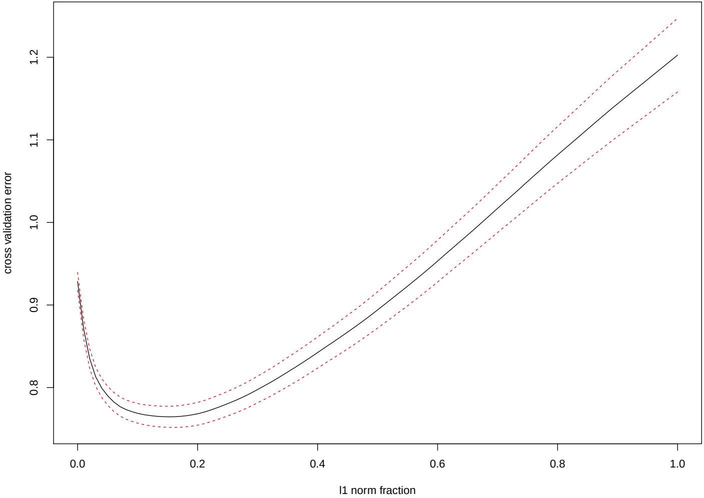
$$\hat{\beta}(\lambda) = \arg\min_{\beta} \frac{1}{2} ||y - (\beta_0 + X\beta)||_2^2 + \lambda ||\beta||_1$$

- The classifier:

$$\text{class}(x) = \textbf{sign}(\beta_0 + x^T \beta) \in \{-1, +1\}$$

- Four models for each category for classification
- General overview of method
- General overview of application to data
  - for 4 categories
  - 10 fold CV
  - Frequency matrix is 3000×795
  - classification error

Choosing λ: Cross-Validation



LASSO Results

- Three different ways to look at coefficients

LASSO Results

- Three different ways to look at coefficients
- Why: can look at the classifier:

$$\text{class}(x) = \mathbf{sign}(\beta_0 + x^T\beta) \in \{-1, +1\}$$

LASSO Results

- Three different ways to look at coefficients
- Why: can look at the classifier:

$$\text{class}(x) = \textbf{sign}(\beta_0 + x^T\beta) \in \{-1, +1\}$$

  - Absolute value: most relevant/predictive words

LASSO Results

- Three different ways to look at coefficients
- Why: can look at the classifier:

$$\text{class}(x) = \textbf{sign}(\beta_0 + x^T\beta) \in \{-1, +1\}$$

  - Absolute value: most relevant/predictive words
  - Positive: more likely to classify the post in $+1$ category (all other covariates being fixed)

LASSO Results

- Three different ways to look at coefficients
- Why: can look at the classifier:

$$\text{class}(x) = \textbf{sign}(\beta_0 + x^T\beta) \in \{-1, +1\}$$

  - Absolute value: most relevant/predictive words
  - Positive: more likely to classify the post in $+1$ category (all other covariates being fixed)
  - Negative: less likely to be in -1 category

Positive v.s. Nonpositive Classification Result

- $+1$: positive opinion;

Word	Absolute Coef.	Word	Positive Coef.	Word	Negative Coef.
加油 (keep going)	0.820	加油 (keep going)	0.820	样子 (manner)	-0.396
韩少 (Master Han)	0.644	韩少 (Master Han)	0.644	恋 (love)	-0.344
成熟 (mature)	0.546	成熟 (mature)	0.546	发表 (announce)	-0.336
顶 (support)	0.533	顶 (support)	0.533	道理 (rational)	-0.336
宽容 (tolerant)	0.518	宽容 (tolerant)	0.518	利益 (benefit)	-0.335

LASSO word images for the positive v.s. nonpositive classification.

Positive v.s. Nonpositive Classification Result

- +1: positive opinion;
- -1: non-positive opinion, including negative, neutral and spam.

Word	Absolute Coef.	Word	Positive Coef.	Word	Negative Coef.
加油 (keep going)	0.820	加油 (keep going)	0.820	样子 (manner)	-0.396
韩少 (Master Han)	0.644	韩少 (Master Han)	0.644	恋 (love)	-0.344
成熟 (mature)	0.546	成熟 (mature)	0.546	发表 (announce)	-0.336
顶 (support)	0.533	顶 (support)	0.533	道理 (rational)	-0.336
宽容 (tolerant)	0.518	宽容 (tolerant)	0.518	利益 (benefit)	-0.335

LASSO word images for the positive v.s. nonpositive classification.

Negative v.s. Nonnegative Classification Result

- +1: negative opinion;

Word	Absolute Coef.	Word	Positive Coef.	Word	Negative Coef.
讨厌 (hate)	0.481	讨厌 (hate)	0.481	支持 (support)	-0.008
无耻 (shameless)	0.412	无耻 (shameless)	0.412	不 (no)	0.000
恶心 (disgusting)	0.395	恶心 (disgusting)	0.395	人 (people/person)	0.000
骗子 (liar)	0.380	骗子 (liar)	0.380	说 (say)	0.000
扁 (beat up)	0.353	扁 (beat up)	0.353	方舟子 (FangZhouZi)	0.000

LASSO word images for the negative v.s. nonnegative classification.

Negative v.s. Nonnegative Classification Result

- +1: negative opinion;
- -1: non-negative opinion, including positive, neutral and spam.

Word	Absolute Coef.	Word	Positive Coef.	Word	Negative Coef.
讨厌 (hate)	0.481	讨厌 (hate)	0.481	支持 (support)	-0.008
无耻 (shameless)	0.412	无耻 (shameless)	0.412	不 (no)	0.000
恶心 (disgusting)	0.395	恶心 (disgusting)	0.395	人 (people/person)	0.000
骗子 (liar)	0.380	骗子 (liar)	0.380	说 (say)	0.000
扁 (beat up)	0.353	扁 (beat up)	0.353	方舟子 (FangZhouZi)	0.000

LASSO word images for the negative v.s. nonnegative classification.

Standard Support Vector Machine

- Again, linear decision function $f(x) = \beta_0 + \beta x$;

Standard Support Vector Machine

- Again, linear decision function $f(x) = \beta_0 + \beta x$;
- The classifier $Class(x) = \mathbf{sign}(f(x))$.

Standard Support Vector Machine

- Again, linear decision function $f(x) = \beta_0 + \beta x$;
- The classifier $Class(x) = \textbf{sign}(f(x))$.
- The support vector machine (SVM) (see, e.g. Hastie et al 2001):

$$\min_{\beta_0,\beta} \sum_{i=1}^{n} (1 - y_i f(x_i))_+ + \frac{\lambda}{2} ||\beta||_2,$$

where $z_+ = \max(0, z)$.

l_1-Norm Support Vector Machine

- Replacing the l_2-norm by l_1-norm yields the sparse SVM (Zhu et al 2003):

$$\min_{\beta_0,\beta}\left\{\sum_{i=1}^{n}(1-y_i(\beta_0+\beta^T x_i))_+ + \lambda||\beta||_1\right\}.$$

Positive v.s. Nonpositive Classification Result

- $+1$: positive opinion;

Word	Absolute Coef.	Word	Positive Coef.	Word	Negative Coef.
加油 (keep going)	2.340	加油 (keep going)	2.340	铁证 (clear evidence)	2.305
铁证 (clear evidence)	2.305	家人 (family)	2.269	接受 (accept)	2.061
家人 (family)	2.269	韩少 (Master Han)	1.969	媒体 (media)	1.907
接受 (accept)	2.061	成熟 (mature)	1.806	默默 (quietly)	1.883
韩少 (Master Han)	1.969	顶 (support)	1.803	四娘 (GUO Jingming)	1.762

Positive v.s. Nonpositive Classification Result

- +1: positive opinion;
- -1: non-positive opinion, including negative, neutral and spam.

Word	Absolute Coef.	Word	Positive Coef.	Word	Negative Coef.
加油 (keep going)	2.340	加油 (keep going)	2.340	铁证 (clear evidence)	2.305
铁证 (clear evidence)	2.305	家人 (family)	2.269	接受 (accept)	2.061
家人 (family)	2.269	韩少 (Master Han)	1.969	媒体 (media)	1.907
接受 (accept)	2.061	成熟 (mature)	1.806	默默 (quietly)	1.883
韩少 (Master Han)	1.969	顶 (support)	1.803	四娘 (GUO Jingming)	1.762

Positive v.s. Nonpositive Classification Result

- $+1$: positive opinion;
- -1: non-positive opinion, including negative, neutral and spam.
- Cross validation result:

Word	Absolute Coef.	Word	Positive Coef.	Word	Negative Coef.
加油 (keep going)	2.340	加油 (keep going)	2.340	铁证 (clear evidence)	2.305
铁证 (clear evidence)	2.305	家人 (family)	2.269	接受 (accept)	2.061
家人 (family)	2.269	韩少 (Master Han)	1.969	媒体 (media)	1.907
接受 (accept)	2.061	成熟 (mature)	1.806	默默 (quietly)	1.883
韩少 (Master Han)	1.969	顶 (support)	1.803	四娘 (GUO Jingming)	1.762

Positive v.s. Nonpositive Classification Result

- +1: positive opinion;
- -1: non-positive opinion, including negative, neutral and spam.
- Cross validation result:
  - training sample misclassification rate: 16.9%

Word	Absolute Coef.	Word	Positive Coef.	Word	Negative Coef.
加油 (keep going)	2.340	加油 (keep going)	2.340	铁证 (clear evidence)	2.305
铁证 (clear evidence)	2.305	家人 (family)	2.269	接受 (accept)	2.061
家人 (family)	2.269	韩少 (Master Han)	1.969	媒体 (media)	1.907
接受 (accept)	2.061	成熟 (mature)	1.806	默默 (quietly)	1.883
韩少 (Master Han)	1.969	顶 (support)	1.803	四娘 (GUO Jingming)	1.762

Positive v.s. Nonpositive Classification Result

- $+1$: positive opinion;
- -1: non-positive opinion, including negative, neutral and spam.
- Cross validation result:
  - training sample misclassification rate: 16.9%
  - testing sample misclassification rate: 28.2%

Word	Absolute Coef.	Word	Positive Coef.	Word	Negative Coef.
加油 (keep going)	2.340	加油 (keep going)	2.340	铁证 (clear evidence)	2.305
铁证 (clear evidence)	2.305	家人 (family)	2.269	接受 (accept)	2.061
家人 (family)	2.269	韩少 (Master Han)	1.969	媒体 (media)	1.907
接受 (accept)	2.061	成熟 (mature)	1.806	默默 (quietly)	1.883
韩少 (Master Han)	1.969	顶 (support)	1.803	四娘 (GUO Jingming)	1.762

Negative v.s. Nonnegative Classification Result

- $+1$: negative opinion;

Word	Absolute Coef.	Word	Positive Coef.	Word	Negative Coef.
扁 (beat up)	1.777	扁 (beat up)	1.777	脑子 (mind)	1.447
苦肉计 (the ruse of self-injury to win somebody's confidence)	1.708	苦肉计 (the ruse of self-injury to win somebody's confidence)	1.708	彻底 (completely)	1.290
恶心 (disgusting)	1.527	恶心 (disgusting)	1.527	送给 (give)	1.221
脑子 (asdf)	1.447	骗子 (liar)	1.301	感觉 (feel)	1.109
骗子 (liar)	1.301	公开 (open)	1.220	热点 (hot interest)	1.101

Negative v.s. Nonnegative Classification Result

- +1: negative opinion;
- -1: non-negative opinion, including positive, neutral and spam.

Word	Absolute Coef.	Word	Positive Coef.	Word	Negative Coef.
扁 (beat up)	1.777	扁 (beat up)	1.777	脑子 (mind)	1.447
苦肉计 (the ruse of self-injury to win somebody's confidence)	1.708	苦肉计 (the ruse of self-injury to win somebody's confidence)	1.708	彻底 (completely)	1.290
恶心 (disgusting)	1.527	恶心 (disgusting)	1.527	送给 (give)	1.221
脑子 (asdf)	1.447	骗子 (liar)	1.301	感觉 (feel)	1.109
骗子 (liar)	1.301	公开 (open)	1.220	热点 (hot interest)	1.101

Negative v.s. Nonnegative Classification Result

- $+1$: negative opinion;
- -1: non-negative opinion, including positive, neutral and spam.
- Cross validation result:

Word	Absolute Coef.	Word	Positive Coef.	Word	Negative Coef.
扁 (beat up)	1.777	扁 (beat up)	1.777	脑子 (mind)	1.447
苦肉计 (the ruse of self-injury to win somebody's confidence)	1.708	苦肉计 (the ruse of self-injury to win somebody's confidence)	1.708	彻底 (completely)	1.290
恶心 (disgusting)	1.527	恶心 (disgusting)	1.527	送给 (give)	1.221
脑子 (asdf)	1.447	骗子 (liar)	1.301	感觉 (feel)	1.109
骗子 (liar)	1.301	公开 (open)	1.220	热点 (hot interest)	1.101

Negative v.s. Nonnegative Classification Result

- $+1$: negative opinion;
- -1: non-negative opinion, including positive, neutral and spam.
- Cross validation result:
  - training sample misclassification rate: 6.4%

Word	Absolute Coef.	Word	Positive Coef.	Word	Negative Coef.
扁 (beat up)	1.777	扁 (beat up)	1.777	脑子 (mind)	1.447
苦肉计 (the ruse of self-injury to win somebody's confidence)	1.708	苦肉计 (the ruse of self-injury to win somebody's confidence)	1.708	彻底 (completely)	1.290
恶心 (disgusting)	1.527	恶心 (disgusting)	1.527	送给 (give)	1.221
脑子 (asdf)	1.447	骗子 (liar)	1.301	感觉 (feel)	1.109
骗子 (liar)	1.301	公开 (open)	1.220	热点 (hot interest)	1.101

Negative v.s. Nonnegative Classification Result

- +1: negative opinion;
- -1: non-negative opinion, including positive, neutral and spam.
- Cross validation result:
  - training sample misclassification rate: 6.4%
  - testing sample misclassification rate: 11.5%

Word	Absolute Coef.	Word	Positive Coef.	Word	Negative Coef.
扁 (beat up)	1.777	扁 (beat up)	1.777	脑子 (mind)	1.447
苦肉计 (the ruse of self-injury to win somebody's confidence)	1.708	苦肉计 (the ruse of self-injury to win somebody's confidence)	1.708	彻底 (completely)	1.290
恶心 (disgusting)	1.527	恶心 (disgusting)	1.527	送给 (give)	1.221
脑子 (asdf)	1.447	骗子 (liar)	1.301	感觉 (feel)	1.109
骗子 (liar)	1.301	公开 (open)	1.220	热点 (hot interest)	1.101

l_1-Norm SVM v.s. LASSO

Positive v.s. Nonpositive Classification Results
Positive coefficients

l_1-Norm SVM		LASSO	
Word	Postive Coef.	Word	Positive Coef.
加油 (keep going)	2.340	加油 (keep going)	0.820
家人 (family)	2.269	韩少 (Master Han)	0.644
韩少 (Master Han)	1.969	成熟 (mature)	0.546
成熟 (mature)	1.806	顶 (support)	0.533
顶 (support)	1.803	宽容 (tolerant)	0.518

Further Work

- Comparison with maximum entropy approach

Further Work

- Comparison with maximum entropy approach
- Graphical model to track reposting

Further Work

- Comparison with maximum entropy approach
- Graphical model to track reposting
- Statistical models for identifying Internet slangs

Further Work

- Comparison with maximum entropy approach
- Graphical model to track reposting
- Statistical models for identifying Internet slangs
- Sampling from large graphs