Sina Weibo as a Corpus for Studying Public Opinions

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Outline

Introduction

- Opinions on microblogging and social networking websites

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- Sina Weibo 新浪微博 is the largest microblogging website:
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- Study public opinions using Sina Weibo as a corpus for a given topic

Topic

- Internet censorship in China

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- Time sensitive

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- Hot topic is preferred
- Chosen topic: Han Han 韩寒

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- 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:

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- Substitute emotional symbols and Internet slangs by the corresponding word surrounded by square brackets

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  - **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.

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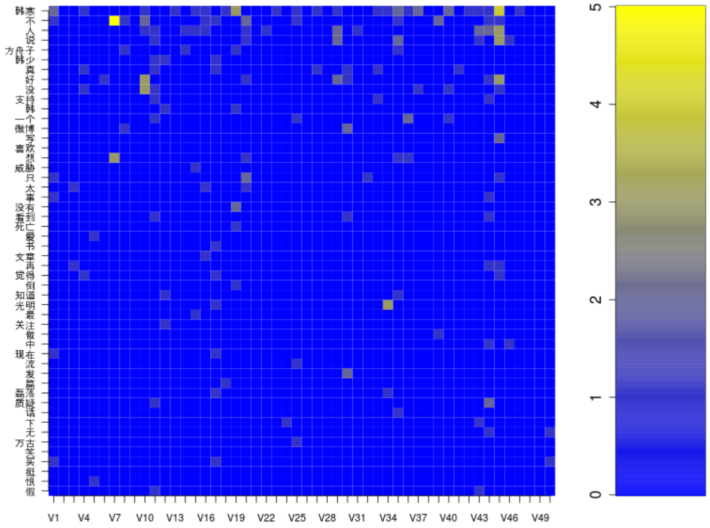
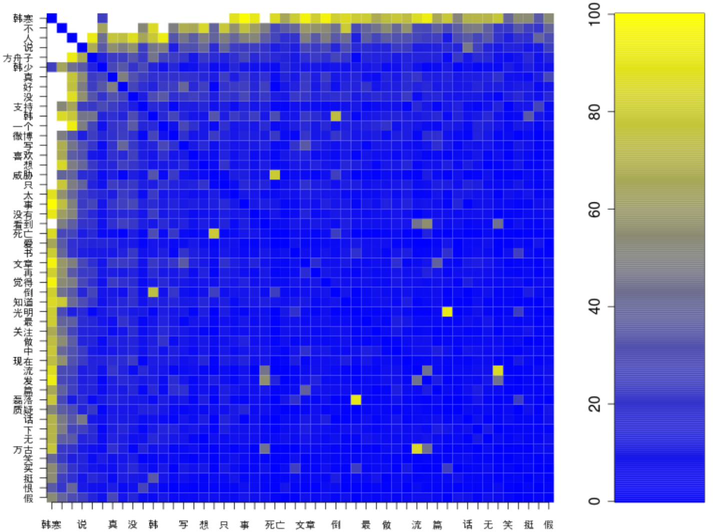
- Construct the word frequency matrix $X = (x_1, ..., x_n)^T$, where $n = 3000$. This will be our design matrix.

Word Frequency Visualization: Matrix Plot



Co-Occurrance



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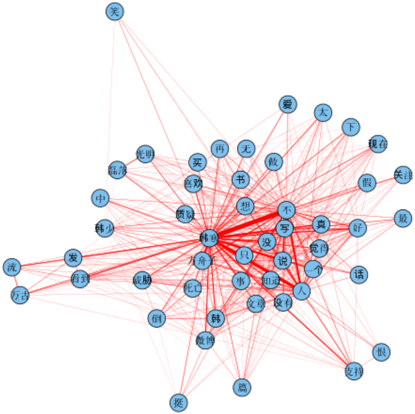

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- This motivates us to estimate Σ^{-1}.
- Let $x_1, x_2, ...x_n$ be IID $N(\mu, \Sigma)$ data. The joint likelihood of the data is

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

Sparse Graphical Models (Cont'd)

- Log-likelihood:

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

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

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

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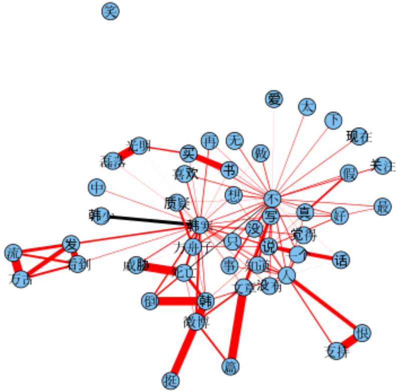
- Fitting a sparse Gaussian graphical model:

$$\max_S \left\{ \log\det S - \mathbf{Tr}(\hat{\Sigma}S) - \lambda \|S\|_1 \right\}$$

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

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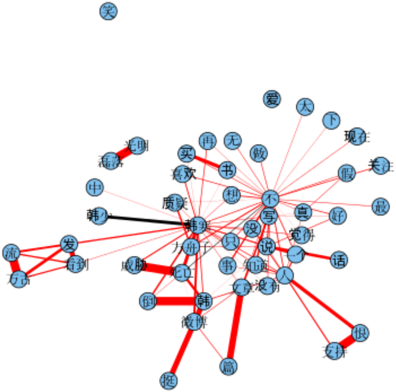

lambda = 0.01222

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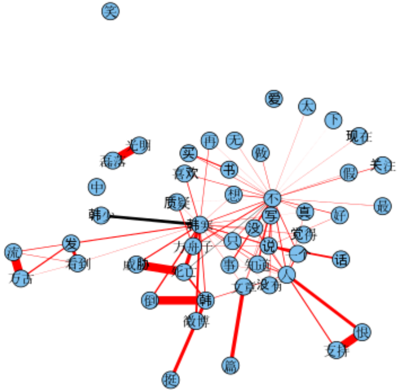

lambda = 0.01444

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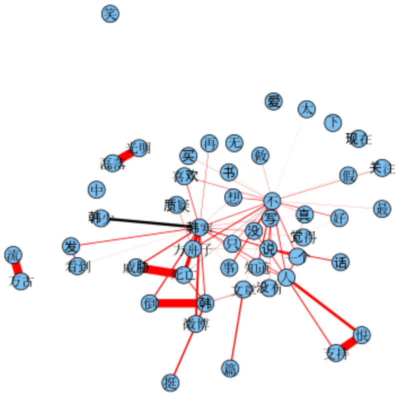

lambda = 0.01667

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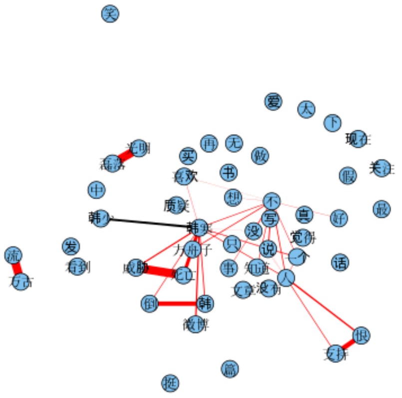

lambda = 0.02556

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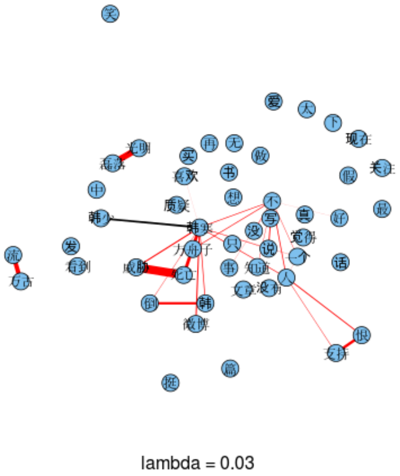
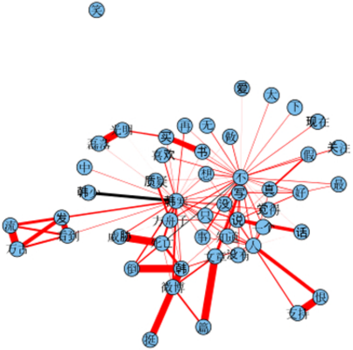


Sparse Graphical Models v.s. Co-Occurence

Sparse Graphical Models



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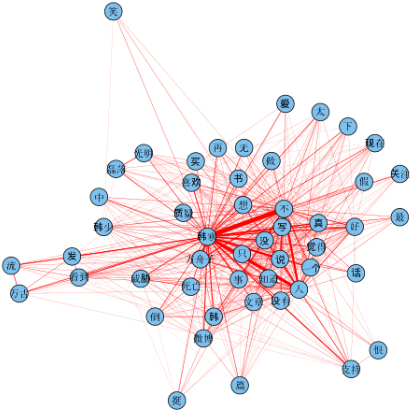

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  - netural or unidentifiable opinion

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- $x_i \in R^p$ be the i-th row of $X \in R^{n \times p}$, where $n = 3000$ and $p = 395$
- y_i: the corresponding category. Assume $y_i \in \{-1, +1\}$, where the $+1$ can have one (and only one) of the following meanings (at a time):
  - positive feeling about Han Han
  - negative feeling Han Han
  - netural or unidentifiable opinion
  - spam

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  - spam
- Two classification methods: LASSO and l_1-norm SVM.

LASSO

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

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

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

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- Four models for each category for classification
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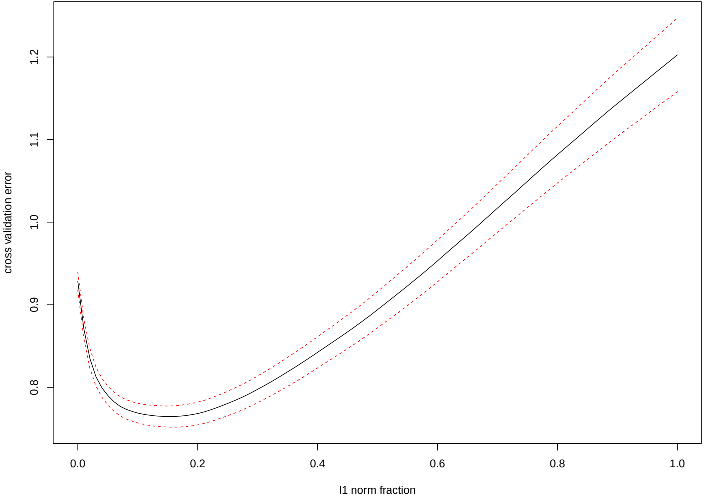
  - for 4 categories
  - 10 fold CV
  - classification error

Choosing λ: Cross-Validation



LASSO Coefficient interpretation

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

LASSO Coefficient interpretation

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- We can look at coefficients β
  - 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

- $y_i \in \{-1, +1\}$;

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

- $y_i \in \{-1, +1\}$;
- $+1$: positive opinion (about Han Han);

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

LASSO

Positive v.s. Nonpositive Classification Result

- $y_i \in \{-1, +1\}$;
- $+1$: positive opinion (about Han Han);
- -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
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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	-	-
恶心 (disgusting)	0.395	恶心 (disgusting)	0.395	-	-
骗子 (liar)	0.380	骗子 (liar)	0.380	-	-
扁 (beat up)	0.353	扁 (beat up)	0.353 -	- -	-

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	-	-
恶心 (disgusting)	0.395	恶心 (disgusting)	0.395	-	-
骗子 (liar)	0.380	骗子 (liar)	0.380	-	-
扁 (beat up)	0.353	扁 (beat up)	0.353 -	- -	-

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

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Standard Support Vector Machine

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

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

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):

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

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

- Computation: use the matlab **lpsvm** package by Fung and Mangasarian (2002)

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

l_1-SVM word images for the positive v.s. positive 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)	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
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韩少 (Master Han)	1.969	顶 (support)	1.803	四娘 (GUO Jingming)	1.762

l_1-SVM word images for the positive v.s. positive classification.

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
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l_1-SVM word images for the positive v.s. positive classification.

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
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l_1-SVM word images for the positive v.s. positive classification.

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
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韩少 (Master Han)	1.969	顶 (support)	1.803	四娘 (GUO Jingming)	1.762

l_1-SVM word images for the positive v.s. positive classification.

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

l_1-SVM 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.
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-SVM 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.
- 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
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骗子 (liar)	1.301	公开 (open)	1.220	热点 (hot interest)	1.101

l_1-SVM 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.
- 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
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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-SVM 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.
- 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
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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-SVM word images for the negative v.s. nonnegative classification

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

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- Graphical model to track reposting

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