Mental Health Computing via Harvesting Social Media Data

Jia Jia
jjia@tsinghua.edu.cn
Tsinghua University
25/01/2018
Mental Health

- **Mental health** is a level of *psychological well-being*, or an absence of mental illness.

- The WHO states that the well-being of an individual is encompassed in the realization of their abilities, coping with normal *stresses* of life, productive work and contribution to their community.
What is Stress?

- Hans Selye in 1936: “Stress is the non-specific response of the body to any demand for change”
- **Stress**
  - can be caused by common life events like work, family, financial problems, etc

---

**Effects of great deal of stress in past month**

<table>
<thead>
<tr>
<th>Category</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Family life</td>
<td>75%</td>
</tr>
<tr>
<td>Health</td>
<td>74%</td>
</tr>
<tr>
<td>Work life (among employed)</td>
<td>70%</td>
</tr>
<tr>
<td>Social life with friends</td>
<td>68%</td>
</tr>
</tbody>
</table>

Source: NPR, Robert Wood Johnson Foundation, and Harvard School of Public Health
Is Stress clinical?

- **No! But**

- Chronic and excessive stress can cause
  - **Physical symptoms**: headache, insomnia, weight problems, heart diseases, etc
  - **Mental symptoms**: disorders, depression, anxiety, agitation, etc

- Excessive stress is also causing severe **social problems**
  - 41149 suicides in 2013 in America, 10th cause of death
  - Mental illness, contributes to 90% of completed suicides.
  - Cases:
    - Foxconn’s serial jumping suicides;
    - Karoshi 2011;

It is of significant importance for **social good** and **wellness** to **detect and relieve stress** before it leads to more severe problems!
How?

- Traditional stress detection methods
  - Face-to-Face Interview by professional psychologists
  - Self-report Questionnaires
    - Binary: stressed or non-stressed
    - Scale: a score indicating the psychological stress level
      - LEC, PSS, CPSS, The Holmes Rahe Life Stress inventory, etc
Can we make the mental health care from **reactive care** to **proactive care**?

*Social media* is changing the ways people do with their healthcare and wellness.
Social Media

The influence of Facebook, Twitter, YouTube and other social media giants has spread across modern society faster than the Black Death swept across 14th century Europe.

http://www.alliedhealthworld.com/visuals/tweet-day-keeps-doctors-away.html
CDW Healthcare saying that social media is changing the ways of healthcare, from health communication to patient care

http://www.cdwcommunity.com/resources/infographic/social-media/
Social Media

People are forming online support groups, becoming better educated on medical topics and diagnoses, and sharing reviews – wherever and whenever they want.

http://www.alliedhealthworld.com/visuals/tweet-day-keeps-doctors-away.html
• **Health 2.0.** The Economist (2007)
  • Researchers started to notice that the rise of “user-generated content”

• **Public Mental Health Care**
  • Using social media data for suicide monitoring in public

• **Individual Mental Health Care**
  • Using social media data for emotions, depression, or stress detection

• **Disease Detection & Tracking for Public Physical Health Care**
  • Using social media data to predict outbreaks of epidemics

• **Personalized Health Care via Multi-source, Multimedia data**
Milestone

- **Leveraging Social Media for Mental Health Care**
  - Hawton investigated the suicide factors in adolescents via keywords from several social media websites. (2012, Lancet)
  - Won built a model to predict the suicide numbers in America via social media data. (2012, PLOS ONE)
  - De Choudhury has tried to leverage Twitter data to predict depression. (2013, ICWSM)
  - Harman tried to leverage twitter data to quantify the mental health signals of users. (2014, ACL)
  - System: Moodscope (MSRA) and Suicide Intervention (Google, Facebook, Instagram)
Suicide Intervention

Need help? Singapore:

1800 221 4444
Samaritans of Singapore
Hours: 24 hours, 7 days a week
Languages: English
Website: www.samaritans.org.sg
The app would alert users that if everything’s fine and if he/she needs advisory or help. This is a great humanized progress!
Our Research Outline

- Stress Detection via Harvesting Social Media
  - **Binary Stress Detection** Based on Social Interactions (ACM Multimedia’14)
  - Beyond Binary Classification: **Stressor and Stress Level Detection** (IJCAI’16)
- From Stress Detection to Depression Detection
  - **Binary Depression Detection** : A Multimodal Dictionary Learning Solution (IJCAI’17)
  - **Depression Detection on More Platforms** : Cross-Domain Depression Detection (submitted)
Research 1: Stress Detection via Harvesting Social Media
Dataset & Labeling

- We establish a dataset including 400 million tweets from Sina Weibo, Tencent Weibo and Twitter
- 3 methods to label the dataset
  1. Sentence pattern
  2. Hashtags
  3. Professional stress scale
Labeling

- **Sentence pattern**
  - “We Feel ***” and Searching the Emotional Web (SD Kamvar, 2011)
  - “I feel stressed”, “I feel relaxed”
  - “最近压力好大”, “最近压力很大”

<table>
<thead>
<tr>
<th>Weibo-Stress dataset DB1</th>
<th>non-stressed</th>
<th>stressed</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>#tweets</td>
<td>253638</td>
<td>239038</td>
<td>492676</td>
</tr>
<tr>
<td>#users</td>
<td>12230</td>
<td>11074</td>
<td>23304</td>
</tr>
<tr>
<td>#weeks</td>
<td>17861</td>
<td>19136</td>
<td>36997</td>
</tr>
<tr>
<td>#tweets/week*</td>
<td>14.2</td>
<td>12.5</td>
<td>13.3</td>
</tr>
<tr>
<td>#weeks/user*</td>
<td>1.46</td>
<td>1.73</td>
<td>1.59</td>
</tr>
<tr>
<td>#interacted user/week*</td>
<td>5.79</td>
<td>6.99</td>
<td>6.35</td>
</tr>
</tbody>
</table>

* means average number

明明知道什么样
Labeling

- Hashtags
  - Using Hashtags as Labels for Supervised Learning of Emotions in Twitter Messages (M Hasan, 2014)

<table>
<thead>
<tr>
<th>Categories</th>
<th>Number of Tweets</th>
<th>Number of Images</th>
</tr>
</thead>
<tbody>
<tr>
<td>affection</td>
<td>3634</td>
<td>681</td>
</tr>
<tr>
<td>Work</td>
<td>3966</td>
<td>868</td>
</tr>
<tr>
<td>social</td>
<td>5747</td>
<td>1160</td>
</tr>
<tr>
<td>Physiological</td>
<td>13973</td>
<td>2017</td>
</tr>
<tr>
<td>others</td>
<td>14543</td>
<td>3186</td>
</tr>
<tr>
<td>None (not stressed)</td>
<td>14931</td>
<td>6014</td>
</tr>
<tr>
<td>Total</td>
<td>57785</td>
<td>13926</td>
</tr>
</tbody>
</table>
Labeling

- **Professional stress scale**
  - Some people would like to do professional stress scale tests and share the results to social media platforms, like PSTR

  我的心理压力测试结果是：【你的压力指数是 102】推荐你也来做一下：http://t.cn/zOhFbl2
  http://t.cn/zHIFcRH

<table>
<thead>
<tr>
<th>Platform</th>
<th>Stress label</th>
<th>Number of tweets</th>
<th>Number of users</th>
<th>Number of weeks</th>
<th>Tweets per week</th>
</tr>
</thead>
<tbody>
<tr>
<td>DB2:Sina Weibo</td>
<td>stressed</td>
<td>1459</td>
<td>98</td>
<td>98</td>
<td>14.9</td>
</tr>
<tr>
<td></td>
<td>non-stressed</td>
<td>1845</td>
<td>112</td>
<td>112</td>
<td>16.5</td>
</tr>
<tr>
<td></td>
<td>summation</td>
<td>3304</td>
<td>210</td>
<td>210</td>
<td>15.7</td>
</tr>
</tbody>
</table>
Data Observation on Self-Reported Stressed and non-stressed users

10k tweets which are labeled as stressed ones vs. randomly sampled tweets from twitter
### Data Observation (Image)

- Colors in images are related to emotions
  
  [S. R. Ireland etc., 1992], [Kobayashi, S. etc., 1991]

<table>
<thead>
<tr>
<th>Images &amp; Category</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>amusement</td>
<td>high brightness, middle saturation, warm color, circular shape (smooth and soft), very significant visual balance</td>
</tr>
<tr>
<td>anger</td>
<td>low brightness, curve shape (exaggerated)</td>
</tr>
<tr>
<td>awe</td>
<td>low saturation, high figure-ground color difference, trapezoid shape (regular), middle visual balance</td>
</tr>
<tr>
<td>contentment</td>
<td>middle brightness, low saturation contrast, middle visual balance</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Images &amp; Category</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>disgust</td>
<td>middle brightness, cool color, high texture complexity (make people feel uncomfortable)</td>
</tr>
<tr>
<td>excitement</td>
<td>high brightness, very high saturation, low saturation contrast</td>
</tr>
<tr>
<td>fear</td>
<td>low saturation, cool color, dull color, low color difference between figure and ground, cluttered composition</td>
</tr>
<tr>
<td>sad</td>
<td>middle brightness, low saturation, low saturation contrast, cool color, square shape (regular), line shape (regular), very high RT, symmetry</td>
</tr>
</tbody>
</table>
Data Observation (Social Structures and User Interactions)

- The social structure of stressed users’ friends tends to be less connected and less complicated, compared to non-stressed users.
Feasibility – Data Discrimination (Social Structures and User Interactions) (cont.)

- The chance that a none-stressed user becomes stressed increases to **three times** higher for a user with stressed neighbors than for one without stressed neighbors.

- The likelihood of a user being stressed increases with the number of stressed neighbors.
Interaction content of stressed users’ tweets contains much more words from categories like death, sadness, anxiety, anger, and negative emotions.
### Tweet-level Content Attributes

<table>
<thead>
<tr>
<th>Attributes</th>
<th>#</th>
<th>Introduction</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Text Attributes</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Emotion Words</td>
<td>2</td>
<td>Positive and Negative Emotion Words</td>
</tr>
<tr>
<td>Emoticons Numbers</td>
<td>2</td>
<td>Number of Positive and Negative Emoticons</td>
</tr>
<tr>
<td>Punctuation Marks</td>
<td>4</td>
<td>Punctuation Marks and Associated Emotion Words, like ………, !!!!, ?, 。 。 。</td>
</tr>
<tr>
<td>Degree Adverbs</td>
<td>2</td>
<td>Degree Adverbs and Associated Emotion Words, like “a bit”.</td>
</tr>
<tr>
<td><strong>Visual Attributes</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Five-color theme</td>
<td>15</td>
<td>A combination of five dominant in the HSV color space, representing the main color distribution of an image [Xiaohui Wang etc., 2013]</td>
</tr>
<tr>
<td>Saturation</td>
<td>2</td>
<td>The mean value of saturation and its contrast.</td>
</tr>
<tr>
<td>Brightness</td>
<td>2</td>
<td>The mean value of brightness and its contrast.</td>
</tr>
<tr>
<td>Warm or cool color</td>
<td>1</td>
<td>Ratio of cool colors with hue ([0-360]) in HSV space between 30 and 110.</td>
</tr>
<tr>
<td>Clear or dull color</td>
<td>1</td>
<td>Ratio of colors with brightness ([0-1]) and saturation less than 0.6.</td>
</tr>
<tr>
<td><strong>Social Attributes</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social Attention</td>
<td>6</td>
<td>Average and variance of number of Comments, retweeting and favorites.</td>
</tr>
</tbody>
</table>
# User-level Statistical Attributes

- Summarized from users’ tweets in a specific sampling period (one week in our work)

<table>
<thead>
<tr>
<th>Attributes</th>
<th>#</th>
<th>Introduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social Engagement</td>
<td>3</td>
<td>@-mentions, @-replies and the retweetings from a user’s friends.</td>
</tr>
<tr>
<td>Behavioral Attributes</td>
<td>29</td>
<td>Tweeting frequency; Tweeting time distribution – slot: 1 hour. Tweeting Type: image tweets, original tweets, information query, information sharing</td>
</tr>
<tr>
<td>Linguistic Style</td>
<td>10</td>
<td>10 categories from LIWC, from Social Interaction Content</td>
</tr>
</tbody>
</table>
## User-level Social Interaction Attributes

<table>
<thead>
<tr>
<th>Attributes</th>
<th>#</th>
<th>Introduction</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Social Interaction Content</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linguistic Style</td>
<td>1</td>
<td>10 categories from LIWC, from Social Interaction Content</td>
</tr>
<tr>
<td>Emoticons</td>
<td>2</td>
<td>Number of negative and positive Emoticons in Interaction Content</td>
</tr>
<tr>
<td><strong>Social Interaction Structure</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stressed neighbor count</td>
<td>1</td>
<td>the number of the user’s stressed neighbors.</td>
</tr>
<tr>
<td>Strong tie count</td>
<td>1</td>
<td>the number of stressed neighbors with strong tie</td>
</tr>
<tr>
<td>Weak tie count</td>
<td>1</td>
<td>the number of stressed neighbors with weak tie</td>
</tr>
<tr>
<td>Follower count</td>
<td>1</td>
<td>the number of the user’s fans.</td>
</tr>
<tr>
<td>Fans count</td>
<td>1</td>
<td>the number of the user’s fans.</td>
</tr>
<tr>
<td>Structural Distribution</td>
<td>8</td>
<td>the structure distribution of the user’s interacted friends</td>
</tr>
</tbody>
</table>
We propose a cross-media auto-encoder (CAE) to learn a joint representation from the cross-media social media data, which can solve the modality-missing problem.

ACM Multimedia 2014
We propose a CNN with CAE to learn the user-level stress from the cross-media time series data.
We propose a hybrid model combining Factor Graph model with CNN+CAE, to model the correlations of users’ social interactions and time-series tweet content.

Performance

- **Performance:**
  - 93.40% F1-Measure on Sina Weibo dataset D1
  - 87.85% F1-Measure on Sina Weibo with PSTR label dataset D2
  - 88.32% F1-Measure on Tencent Weibo dataset D3
  - 82.24% F1-Measure on Twitter dataset D4

Comparison of efficiency and effectiveness using different models (%).

<table>
<thead>
<tr>
<th>Method</th>
<th>Acc.</th>
<th>Rec.</th>
<th>Prec.</th>
<th>F1</th>
<th>CPU time</th>
</tr>
</thead>
<tbody>
<tr>
<td>LRC</td>
<td>76.18</td>
<td>87.94</td>
<td>78.58</td>
<td>83.00</td>
<td>39.43s</td>
</tr>
<tr>
<td>SVM</td>
<td>72.58</td>
<td>87.39</td>
<td>75.16</td>
<td>80.82</td>
<td>≈10min</td>
</tr>
<tr>
<td>RF</td>
<td>77.73</td>
<td>89.63</td>
<td>79.35</td>
<td>84.18</td>
<td>67.71s</td>
</tr>
<tr>
<td>GBDT</td>
<td>79.75</td>
<td>82.99</td>
<td>85.90</td>
<td>84.43</td>
<td>262.86s</td>
</tr>
<tr>
<td>FGM</td>
<td>91.55</td>
<td>96.56</td>
<td>90.44</td>
<td>93.40</td>
<td>≈20min</td>
</tr>
</tbody>
</table>

Research 2: Stressor and Stress Level Detection
Our work: stressor and stress level detection via social media

Motivation:
- Stress is composed of two key factors: stressor subject and stress level
- Different stressors incur different stress levels
- Stress is normal while over-whelming stress is terrible– for providing appropriate proactive care

Solutions:
- Extract a set of discriminant features
- Propose a hybrid model combining multi-task learning with CNN to identify the stressor subjects and stressor events of given social posts
- Lookup a standard psychological stress scale to measure the precise stressor and stress level (Social Readjustment Rating Scale)
Dataset

- **Collection Method**
  1. Manually define a set of keyword patterns collected from the LIWC dictionary for each stressor event category.
  2. Filter matched tweets from the aforementioned one billion Weibo dataset.
  3. Collect the top 12 stressor event categories and invited 30 volunteers to manually label the stressor events and stressor subjects of the tweets.

- **Dataset composition**
  - Nearly 2,000 stressed posts, each with a stressor event label and a stressor subject label.
  - Randomly selected 600 non-stressed posts as negative samples
  - Each sample is a single tweet
## Dataset

<table>
<thead>
<tr>
<th>Events</th>
<th>Labeled</th>
<th>Sampling words</th>
</tr>
</thead>
<tbody>
<tr>
<td>Marriage</td>
<td>227</td>
<td>marry wedding bride</td>
</tr>
<tr>
<td>Financial</td>
<td>114</td>
<td>income salary rent</td>
</tr>
<tr>
<td>Illness</td>
<td>424</td>
<td>hospital sick pain</td>
</tr>
<tr>
<td>School</td>
<td>171</td>
<td>school holiday finals</td>
</tr>
<tr>
<td>Birth</td>
<td>133</td>
<td>born life baby</td>
</tr>
<tr>
<td>Fired</td>
<td>102</td>
<td>fired job lose</td>
</tr>
<tr>
<td>Argue</td>
<td>107</td>
<td>cold war quarrel argue</td>
</tr>
<tr>
<td>Blamed</td>
<td>199</td>
<td>question blame afraid</td>
</tr>
<tr>
<td>Pregnancy</td>
<td>132</td>
<td>baby pregnant mother-to-be</td>
</tr>
<tr>
<td>Habits</td>
<td>102</td>
<td>revise habits smoke drink</td>
</tr>
<tr>
<td>Death</td>
<td>127</td>
<td>pass away R.I.P</td>
</tr>
<tr>
<td>Divorce</td>
<td>112</td>
<td>divorce ex-wife cry</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Category</th>
<th>Labeled</th>
<th>Sampling words</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>647</td>
<td>I my our we</td>
</tr>
<tr>
<td>family</td>
<td>277</td>
<td>mother daughter</td>
</tr>
<tr>
<td>friend</td>
<td>327</td>
<td>friend teammate</td>
</tr>
<tr>
<td>spouse</td>
<td>207</td>
<td>wife husband dear</td>
</tr>
<tr>
<td>boss</td>
<td>161</td>
<td>boss teacher tutor</td>
</tr>
<tr>
<td>relative</td>
<td>123</td>
<td>aunt uncle cousin</td>
</tr>
</tbody>
</table>

### Example Text Table

<table>
<thead>
<tr>
<th>Example Text</th>
<th>Subject</th>
<th>Events</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>My sister give birth to a child today.</td>
<td>Relative</td>
<td>Marriage</td>
<td>39</td>
</tr>
<tr>
<td>I am very angry about my boss!</td>
<td>I</td>
<td>Blamed</td>
<td>23</td>
</tr>
<tr>
<td>My wife passed away in accident recently.</td>
<td>Spouse</td>
<td>Death</td>
<td>100</td>
</tr>
<tr>
<td>My daughter caught flu this week.</td>
<td>Family</td>
<td>Illness</td>
<td>45</td>
</tr>
<tr>
<td>One of my roommate failed in the exam.</td>
<td>Friend</td>
<td>School</td>
<td>26</td>
</tr>
</tbody>
</table>
Hybrid model combining multi-task learning with CNN

1) Description component extracting features from input tweets;
2) Detection component integrating handcrafted and CNN features with Multi-Task Learning (MTL) where the CNN is fine-tuned by MTL to compose the hybrid model
3) Measurement component leveraging a psychological stress scale to estimate the stressor and the corresponding stress level
Performance

(a) Stressor Event Detection

(b) Stressor Subject Detection

(c) Stress Level Measurement

F1-Measure

- Stressor Event Detection: 90%
- Stressor Subject Detection: 81%
- Stress Level: 0-200
Research 3: Depression Detection via Harvesting Social Media
Motivation

• Depression is a leading cause of disability worldwide
  • 350 million people of all ages suffer from depression

• Clinical diagnosis is effective
  • Make face-to-face interviews referring to DSM criteria
  • Nine classes of depression symptoms are defined in the criteria, describing the distinguishing behaviors on daily lives

• But clinical diagnosis is not proactive
  • More than 70% of people in the early stages of depression would not consult the psychological doctors

▪ People are increasingly relying on social media platforms
  ▪ User generated contents (UGC) reflect daily lives and moods
  ▪ Online behaviors are not covered in previous depression criteria
A Multimodal Dictionary Learning Solution

- **Our work:** Binary depression detection via harvesting multimodal social media

- **Challenges:**
  - No public available large-scale benchmark datasets
  - Users’ behaviors on social media are multi-faceted
  - Few users’ behaviors are symptoms of depression

- **Solutions:**
  - Construct well-labeled datasets by rule-based heuristic methods
  - Extract six groups of depression-oriented features
  - Leverage multimodal dictionary learning method

Shen & Jia. Depression Detection via Harvesting Social Media: A Multimodal Dictionary Learning Solution (IJCAI 17’
Dataset

- **Dataset D1**
  - 1400 depressed samples selected by sentence pattern labeling (e.g. “I’m diagnosed depression”).
  - 1400 non-depressed samples that have never published tweets containing the key word “depress”.

- **Dataset D2**
  - 37000 depression-candidate samples, selected by just loosely contained the character string “depress”.

- **Each sample include:**
  - 4 weeks of tweets data + user profile

Shen & Jia. Depression Detection via Harvesting Social Media: A Multimodal Dictionary Learning Solution (IJCAI 17’)

Multimodal dictionary learning

Feature Extraction

Multimodal Depressive Dictionary Learning

Online Behavior

X¹
Social Network

D¹

X²
User Profile

D²

X³
Visual

D³

X⁴
Emotional

D⁴

X⁵
Topic-level

D⁵

X⁶
Domain-specific

D⁶

Joint Sparse Representation

Latent Features of Depression and Non-depression Dataset

Update \{D^s, w^s\} s \in \{1, ..., 6\}

Multimodal Classifier

Social Media
twitter

Multimodal Features

Detect depressed users

Posting Ratio at Late Night

Behaviors Analysis

Negative Words Count per Tweet

![Graph showing mean values and p-values for non-depressed and depressed users.

p-value = 7 \times 10^{-290}]

p-value = 5 \times 10^{-280}
Methods & Experiments

- **Method:** multimodal dictionary learning

- **General idea:**
  - Why dictionary learning
    - learning the latent and sparse representation
  - Why multimodal learning
    - jointly modeling the cross-modality relatedness to capture the common patterns and learn the joint sparse representations
  - Train a classifier to detect depressed users with the learned features specifically

- **Performance:** ~ 85% F1-Measure on D1 & D2

Shen&Jia. Depression Detection via Harvesting Social Media: A Multimodal Dictionary Learning Solution (IJCAI 17')
Depression Behaviors Discovery in Twitter

• **Posting time.** Depressed users post more tweets between 23:00 and 6:00, indicating that they are susceptible to insomnia.

• **Emotion catharsis.** All users say more about their bad moods, but depressed users express more emotions, especially negative emotions.

• **Self-awareness.** Depressed users use more first personal pronouns, which may reflect their suppressed monologues and strong senses of self-awareness.

• **Live sharing.** Depressed users post more antidepressant and depression symptom words, indicating that they are willing to share what they encountered in the real life.
Case Study: Depression Behaviors Discovery in Twitter

Proportion of Posting

Non-depressed
Depressed

T
Case Study: Depression Behaviors Discovery in Twitter

Depression-related words (10 tweets)

- First person count per tweet: $p-value=8\times10^{-109}$
- Negative words count per tweet: $p-value=7\times10^{-195}$
- Positive words count per tweet: $p-value=4\times10^{-79}$

Clear color ratio of avatar: $p-value=3\times10^{-14}$
Research 4 : Cross-domain Depression Detection
Cross-Domain depression detection

**Motivation:**

- We have self-reported data for training the depression detection model in **Twitter (Source Domain)**
- Probably insufficient labeled (self-reported depression) samples for model training in **other platforms (Target Domain, e.g. Weibo)**, due to cultural differences

**Match the pattern “I am diagnosed with depression” in 100 million randomly crawled tweets:**

- 481 users accessed in Twitter
- 142 users accessed in Weibo

- Utilizing the source domain dataset to improve depression detection performance for a target domain
Conclusion & Future Work
Conclusion

- **Current work:**
  - **Stage 1:** Online detection of mental health problems

- **Future work:**
  - **Stage 2:** Online-care of mental health problems
    - Find our applications by [http://hcsi.cs.tsinghua.edu.cn/](http://hcsi.cs.tsinghua.edu.cn/)
    - Demo: Anydraw, Senserun
  - **Stage 3:** Combination with offline researches
Thanks & Any question?