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| Data and text mining  Automatic Discovery of Adverse Drug Reactions through Chinese Social Media  Quanyang Liu1\*, Meizhuo Zhang2\*, Chen Ge1, Jiemin Wang2, Jia Wei2\*\*, Kenny Q. Zhu1\*\*  1Dept. CSE, Shanghai Jiao Tong University, 800 Dongchuan Road, Shanghai 200240, China  2R&D Information, AstraZeneca, 199 Liangjing Road, Pudong, Shanghai, 201203, China  \*The authors contributed equally to this work. \*\*Corresponding authors |

Abstract

**Motivation:** Despite tremendous efforts made before the release of every drug, some adverse drug reactions (ADRs) may go undetected and thus, cause harm to both the users and to the pharmaceutical companies. One plausible venue to collect evidence of such ADRs is from online social media, where patients and doctors discuss medical conditions and their treatments.

**Results:** We propose a semi-supervised learning framework that detects mentions of medications and colloquial ADR terms and extracts lexicon-syntactic features from natural language text to recognize positive associations between drug use and ADRs. The key contribution is an automatic label generation algorithm, which requires very little manual annotation. With this approach, we discovered a large number of side effects for a variety of popular medicines in real world scenarios.

**Availability:** A web demo is available at [http://adapt.seiee.sjtu.edu.cn/~qyliu/demo/](http://adapt.seiee.sjtu.edu.cn/~qyliu/demo-0917/) , which contains the ADRs mined for 46 popular medicines.

**Contact:** Jia Wei ([Jenny.Wei@astrazeneca.com](mailto:Jenny.Wei@astrazeneca.com)) and Kenny Q. Zhu ([kzhu@cs.sjtu.edu.cn](mailto:kzhu@cs.sjtu.edu.cn))

# Introduction

Determination of adverse drug reactions (ADR) is an important part of pharmaceutical research and drug development. Pre-marketing clinical trials are limited by the number of participants, the length of the study and the underlying economical burden for both the pharmaceutical companies and the patients. Some of the new adverse reactions to a drug are learned only when the drug is used in a wide spectrum of patients, with varied ethnicity, underlying diseases and a range of concomitant medication, in a post-launch setting. Furthermore, some reactions take a long time to develop- a process which goes well beyond the development cycles of the drugs. For example, Vioxx, an effective medicine for arthritis and acute pain, was approved by the FDA in 1999. Later in 2004, it was discovered to trigger heart disease and stroke, which were previously not considered seriously in clinical trials. Unknown ADRs partly led to more than 27,000 sudden deaths around the world[[1]](#footnote-1). Regulatory authorities and pharmaceutical companies make tremendous effort in avoiding such incidences by conducting post-launch Phase IV clinical trials. In the United States, drug companies spend up to $12,000 per patient in Phase IV clinical trials, with an average of $5,856[[2]](#footnote-2). Conducting such studies in an “*in silico*” fashion, i.e., collecting ADRs from pre-existing data sources, has become a valid complement, if not an attractive alternative, to costly Phase IV studies.

Recent years saw a growing research interest in mining adverse drug reactions from various data sources. Data sources can be divided into structured data and unstructured text data. and the approaches differ. Structured data primarily includes official adverse event reports collected by health authorities (Harpaz R et al., 2010; Harpaz R et al., 2012; Hahn U et al., 2012; Gurulingappa H et al., 2013). These reports are relatively easy to process due to their strict conformance to the adverse event reporting standards. However, the quantity of such reports is limited. Hence, they cannot catch many infrequent ADRs. Unstructured data so far includes biomedical literature, clinical notes or medical records, and online health discussions. These data sources pose more processing challenges because signals are embedded in natural language, which is inherently ambiguous and noisy. Biomedical literatures such as scientific papers are comparatively easier to mine (Wang et al., 2011; Yang et al., 2012) since the medication and adverse reaction are referred to by their formal names. However, the information therein is not up-to-date and is sometimes biased. Clinical resources were targeted using various methods, such as text mining for identifying ADRs from medicine uses (Warrer et al., 2012), rule-based methods to extract side effects from clinical narratives (Sohn et al., 2011) and retrospective medication orders along with inpatient laboratory results to identify ADRs (Liu et al., 2013). Privacy concerns and access restrictions are the biggest obstacles for its wide adoption. Compared to the above data sources, online social media, especially health discussion forums, provide the most comprehensive and timely information about medication use experiences. The large volume, colloquial use of natural language, spelling and grammatical errors are some of the major challenges in mining ADRs from such data sources.

Existing methods for social media text mining can be categorized into lexicon-based methods, statistical methods, rule-based method, advanced NLP and machine learning approaches (Sarker et al., 2015; Lardon et al., 2015). Most prior studies (Leaman et al. 2010; Yang et al. 2012; Benton et al. 2011; Wu et al. 2013; Ytes and Goharian, 2013; Liu et al., 2014; Jiang et al., 2013; Freifeld et al., 2014; Yeleswarapu et al., 2014) focused on expanding lexicons to find ADRs in text. In these lexicon-based methods, due to the novel adverse reaction phrases on websites, they could not recognize non-regular ADRs that are not contained in the lexicon. Besides, it suffers from poor approximate string matching caused by misspelled words. Some researchers instead utilized statistical (Li 2011; Wu et al 2012; Liu et al 2013), rule (pattern) based methods (Nikfarjam et al. 2011; Benton et al. 2011; Karimi et al. 2011; Yang et al. 2012); or NLP techniques (Sharif et al. 2014; Sarker and Gonzalez 2015). Moreover, a large number of studies have explored machine learning methods for the extraction of ADRs (see Lardon et al. (2015) and Sharker et al. (2015) for a more comprehensive review). These approaches utilize well-studied machine learning methods, and can offer reasonable accuracy. But they all require large volume of training data during the learning process, a tremendous amount of manual effort.

Although there is substantial previous research on ADRs extraction from English online forums, very limited research was done on Chinese data. To the best of our knowledge, this paper is the first attempt to mind ADRs from three popular social media sites, namely Xunyiwenyao[[3]](#footnote-4), Haodaifu[[4]](#footnote-5) and Sina Weibo[[5]](#footnote-6). Xunyiwenyao and Haodaifu are both online public forums for health related discussions. Each discussion thread is started with a patient’s question and followed by responses from multiple doctors or other patients (see Figure 1). Weibo is a Chinese microblogging website where a user can start a new conversation in which their friends may respond with comments or forward the discussion to other people. Weibo messages are terse and informal. The quality of such messages is lower than the first two data sources while the quantity is much larger.

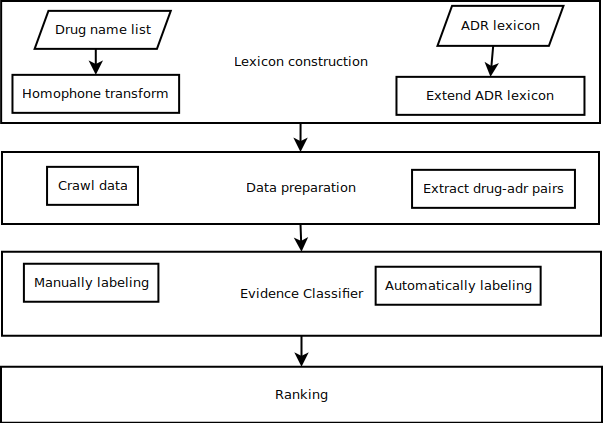
Figure 2 System framework



Figure 1 Question posted on Xunyiwenyao website

Herein, we propose a semi-supervised learning framework requiring very little manual annotations for mining ADRs from Chinese social media. As an alternative to the methods described above, we build a list of commonly misspelled drug names and extend the customized lexicon with colloquial words and adjective modifiers, in order to address the problem of irregular ADR terms and typos. We also focus on distinguishing between indications and ADRs by training a binary classifier, using SVM model. To train the classifier, we introduce an automatic labeling algorithm to generate large amount of training data.

# Materials and Methods

Our framework (depicted in Figure 2 is divided into four parts, namely constructing lexicons, extracting candidate ADRs, classifying evidences and finally ranking the ADRs.

1. Lexicon construction

We need two lexicons, one for the names of medications of interest; the other for ADRs to be recognized from text.

### Lexicon of medication

We start with a list that contains common names and registered trade names of known drugs. On social media, drug names may be spelled with variation, either by similar characters or homophones. For example, a drug called “耐信(Nexium)” may be misspelled as“奈信”, “耐心(patience)”, “乃信” and so on. Coverage is low if only the official drug names are used to search for relevant posts. To solve this problem, we expand each correct character in a drug name to several commonly misspelled characters in Chinese. For example, “耐” is extended to “奈” or “乃”, while “信” is extended to “心”, “新” and so on. However, if “耐信” is transformed to “耐心”, which is a commonly used Chinese word, many irrelevant posts containing “耐心” maybe returned. Thus common Chinese words which are clearly not drug names are filtered out.

### Basic ADR lexicon

The basic ADR lexicon comes from three sources: The NCI Common Terminology Criteria for Adverse Events (CTCAE) (Trotti et al. 2003), Sougou Pinyin ADRs lexicon[[6]](#footnote-7) and the ADR database[[7]](#footnote-8). CTCAE contains formal terms of the ADRs used for adverse event reporting to regulatory agencies. Sougou ADRs is utilized particularly for colloquial terms. Both CTCAE and Sougou ADRs are available in Chinese. The ADRs database coversmore than 6000 ADRs in English. It was translated into Chinese by Google Translate[[8]](#footnote-9). In addition, classification of these terms is very important. Because some words have the same or similar meaning, their result can be merged in the following analyzing steps. For example, “体重减少” (loss of weight) is the same as “体重下降” (drop in weight). If we classify both words in the same category, their result can be directly added and we get one total result for later discussion. Finally, based on MedDra’s category, we classify all the words into structured lexicon which has four levels. The lowest level contains ADR words from the three data sources. The three upper levels are custom categories in MedDra[[9]](#footnote-10). The first column in the left is the fourth level and the next three columns are the upper levels in MedDra.

### Extended ADR lexicon

To improve the ability to match colloquial terms in online discussion, we further expand our basic ADR lexicon by adding variations of the terms. For example, when a person has a headache, he or she may say “头痛(headache)” or “头有点痛(got a little headache)”, the latter of which is a slight variation with a degree modifier between an organ name and symptom word (such as “痛”), and is added to our extended lexicon.

There is a variety of such degree modifiers. We adopt a data-driven approach to mine such degree modifiers by pattern-matching an organ name, up to 5 characters and a symptom word, for example “头XXXXX 痛”, from online discussion corpus. The algorithm to extend ADR lexicon is presented briefly as follows.

Table 1 ADRs lexicon

|  |  |  |  |
| --- | --- | --- | --- |
| 5’-核苷酸酶下降  (5'-nucleotidase decline) | 各种肝功能分析  (Variety of liver function) | 肝胆系统检查  (Hepatobiliary system check) | 各类检查  (Various types of inspection) |
| 5’-核苷酸酶增加  (5'-nucleotidase increase) | 各种肝功能分析  (Variety of liver function) | 肝胆系统检查  (Hepatobiliary system check) | 各类检查  (Various types of inspection) |
| A型肝炎  (Hepatitis A) | 各种肝脏病毒感染  (Various liver virus infection) | 肝脏及肝胆类疾病  (Liver and hepatobiliary diseases) | 肝胆系统疾病  (Hepatobiliary system diseases) |
| BK病毒感染  (BK virus infection) | 多瘤病毒感染  (Polyomavirus infection) | 传染性病毒感染  (Contagious viral infection) | 感染及侵染类疾病  (Infection and infection diseases) |

**Algorithm: extend ADR lexicon**

// Construct regular expression patterns

for each term in basic ADRs do

if term contains organ then

construct a regular pattern

// Discover degree words

for each line in all data do

if line match a pattern then

count one for this word

// Extend lexicon

for each term in lexicon do

if term contains organ then

for each word in words list do

insert word into term to generate a new term

1. Data preparation

This section describes how we extract evidences of ADRs for drugs from the three Chinese social media. We discuss Weibo separately because the nature of posts on Weibo is substantially different from Xunyiwenyao and Haodaifu.

### Extraction of evidences

First, we preprocess all the user posts from three websites. If one post contains a drug name of interested, this post is considered as an “effective” target. All sentences in “effective” posts are segmented by ICTCLAS (Zhang et al., 2003), a Chinese word segmentation tool.

With the ADR lexicon, we can detect candidate ADR terms from the effective posts. However, when a drug name X is mentioned in a post, the user may not actually take that drug. Similarly, when an ADR term is mentioned, the user may not actually have the symptom, or the symptom may not be the result of taking X. So given a pair of a drug name and an ADR, we need to determine whether the ADR is truly the consequence of taking the drug, given context of the pair in the post. The context is defined as several consecutive sentences that contain a drug-ADR pair. The length of the context is a configurable parameter, and a larger one would discover more pairs but may decrease the accuracy. We set it to 55 segmented units to strike a balance. The following are two contexts showing a positive evidence and a negative evidence:

* 服用易瑞沙后头痛，眼睛复视，模糊 (After taking Iressa, got a headache, eye diplopia and blurred vision)
* 吃的是奥美拉唑，克拉霉素，阿莫西林，吗丁啉等药，咳嗽有所减少 (After taking Omeprazole, Clarithromycin, Amoxicillin, Domperidone and other drugs, cough lessened)

We will discuss how to classify evidences into positive and negative ones in the next section.

### Issues with Weibo posts

We have mentioned that the discussion volume of Weibo is higher than the other two, but the quality is poorer because:

* A doctor would post a message on Weibo after answering a question in Xunyiwenyao or Haodaifu, and which is already contained in the crawled data so it’s redundant;
* When users comment and forward a message, it rarely contains a complete sentence, which means it’s highly dependent on the original message and makes it harder to processing;
* Very few messages are really about ADRs. For example, there are 7734 messages about Betaloc that we crawled from Weibo, but only 1323 messages contain both Betaloc and a condition;
* There is lots of noise, such as advertisement from manufacturers, shown in Figure 3. In the previous example, out of 1323 messages containing both Betaloc and a condition, only 36% of the messages are really experience reports from the patients who have taken Betaloc.

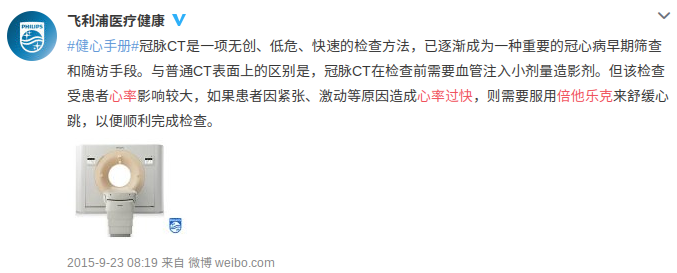


Figure 3 An advertisement on Weibo

1. Evidence Classifier

Given a drug name and a medical condition, identified by the extended lexicon, as well as their context in the original text, the problem of evidence classification is to determine whether the medical condition is actually an ADR resulting from the drug. Next we present a method to train such an evidence classifier. In particular, we show how to produce large amount of training data by automatic labeling.

### Building the training set

A supervised classifier requires labeled training data. However, manual labeling on user discussion posts can’t scale up because of the large amount of informal use of language and colloquial terms. Fortunately, information in the package insert of the drugs, e.g., the indications and the known side effects of the drug, can be used to automatically generate labeled data.

Our first and simple idea is to regard a pair of drug and medical condition as true if the medical condition is listed as a side effect in the package insert of the drug. Conversely, we regard the pair as false if the medical condition is listed as an indication of the drug. All other pairs are discarded from labeled data set. However, this approach is not perfect. For example, “头晕(dizzyness)” is a known ADR for Betaloc, but sometimes in the real discussion it serves as an indication:

* 突然感到头晕心慌,坐卧不安,去医院检查血压160.100心电图心动过速160次,开 了倍他乐克 (Suddenly I felt dizzy and flustered, restless, my blood pressure was at 160/100 andtachycardia electrocardiogram was at 160 times, and Iwas given Betaloc)

And “房颤(atrial fibrillation)” is an indication for Betaloc, but sometimes it is reported as if it’s a side effect:

* 后根据医嘱，可达龙减至1/4片每天，加服倍他乐克缓释片一片。一段时间后出现房颤 (According to the doctor’s advice, Cordarone was reduced to 1/4 tablets per day, plus one tablet of Betaloc (slow release). Atrial fibrillation occurred after a period of time)

Because the actual situation arising from patients experience may be more complicated than specified on the manual, we adopt a semi-supervised approach instead. We first manually label 400 sentences — 211 with positive labels and 211 with negative labels. We then train a simple SVM classifier using this small training set and use the classifier to predict all the sentences in the corpus. The features used are discussed at *Features extraction* section below. It’s the same as those for our final classifier, but with more training data we can cover more unseen token. If the classifier predicts a sentence to be positive, and the medical condition is a known ADR for the drug according to the manual, we mark this sentence as a positive training instance. If a sentence is predicted to be negative, and the condition in that sentence is a known indication of the drug, then we mark this sentence as a negative training instance.

With little manual effort, we have now obtained a much larger set of positive and negative training data --- 17,382 training instances in total. By manual validation, the accuracy of automatic labeling is 92%.

### Features extraction

Our main evidence classifier extracts the following features, after parsing the evidence sentences into dependency tree:

* Verbs before the drugs, e.g. “服用(take)” in “服用倍他乐克(take Betaloc)”;
* Verbs before the conditions, e.g. “感到(feel)” in “感到头晕(feel dizzy)”;
* Verbs after the conditions, e.g. “好转(improved)” in “头疼好转(headache improved)”;
* Preposition, conjunction and noun of locality, e.g. “因为(because of)” in “因为头疼(because of headaches)” and “后(after)” in “服用倍他乐克后(after taking Betaloc)”;
* Punctuation that surround drugs and conditions;
* The number of other drugs and other conditions between the drug and condition of interest;
* A Boolean value that indicates whether condition appears in front of the drug or not.

The verbs are hard to extract without parsing the sentences. They often occur along with modifiers in the Chinese language. For example, “头疼好转(headaches improved)” would often be expressed as “头疼稍微好转(headaches improved a little bit)”, and with the dependency tree we can extract “好转(improved)” from it easily.

### Training a classifier

We choose SVM as our primary classifier, because our feature vectors are high-dimensional (many different words). The overall training process is as follows:

1. Manually label some training data;
2. Train a classifier M’;
3. Use M’ and package inserts to generate more training data;
4. Train the final classifier M.

### Pattern based method

Beside the final semi-supervisor learning method, we have also tried a naïve pattern-based method to build a classifier. We extract preposition, conjunction and noun of locality from sentences as patterns from training data generated by package inserts, and each pattern has a weight which is its frequency of occurrence while a negative pattern will have a negative weight. For example, below are two patterns we extracted and their weight:

* drug ... 后 ... adr ... 4
* adr ... 后 ... drug ... -4

For a new sentence that can be matched to several patterns, the score is the sum of these patterns. Then a classifier is built based on the score: if the score is greater than 0, it’s positive; otherwise negative.

1. Ranking

For each drug, there are many candidate ADRs. We are interested in ADRs of high confidence. One way of ranking the ADRs of a drug is by the number of its appearances in positive evidence posts. This doesn’t work well because, most discussions about a drug involves the indications of the drug. For example, discussion about Betaloc would naturally include a lot of occurrences of the term “hypertension”. The absolute number of such mentions is very large, and consequently “hypertension” would be ranked highly as an ADR of Betaloc. To solve this problem, we rank the ADRs according to the frequency of the positive evidences minus that of the negative evidences. This approach effectively lowers the rankings of the indications of a drug, but promotes real ADRs.

# Results

We divide our evaluation into three parts. First we evaluate the accuracy of the classifier, by showing the accuracy of prediction of drug-ADR association. Then we run the automatically labeling algorithm iteratively and show the change of the F1-scores. Finally, we use MRRs (mean reciprocal rank) of ADRs and indications of package inserts to evaluate the end-to-end results. After evaluation of the platform, we show the top-ten discovered ADRs of several drugs, as verification and supplement for the package inserts.

## Data set

We have crawled user messages posted between January 2011 to April 2015 on Haodaifu and Xunyiwenyao containing 46 drugs, which treatment 12 broadly classified diseases. Table 2 summarizes the diseases and the number of corresponding drugs. The total number of crawled posts is 456,753. After preprocessing these posts, we obtain 170,196 drug-ADR pairs.

We manually labeled a number of randomly sampled pairs (along with their contexts), and from which we selected 211 positive pairs and 211 negative pairs as our initial training data.

Table 2 List of diseases and number of drugs studied

|  |  |  |  |
| --- | --- | --- | --- |
| **Diseases** | **Number of drugs** | **Diseases** | **Number of drugs** |
| Hypertension | 16 | Hyperacidity | 1 |
| Diabetes | 10 | Lung cancer | 1 |
| Asthma | 9 | Stomach disease | 1 |
| Statins | 3 | Rhinitis | 1 |
| Breast cancer | 1 | Schizophrenia | 1 |
| Anesthesia | 1 | Acute coronary syndrome | 1 |

## Drug-ADR association

For the test data set, we manually label 200 pairs of drug and ADR -- 100 positive pairs and 100 negative ones. Then we compare the classifier trained by three different labeling approaches: i) the 422 manually labeled pairs, ii) the labels generated directly from the package insert, and iii) semi-supervised labeling. In addition to the SVM classifier, we experimented with three other baseline approaches, namely an HMM (Hidden Markov model) based classifier (Sampathkumar et al., 2014), a CRFs (Conditional random fields) based classifier (Nikfarjam et al., 2015) and the pattern based classifier. The HMM and CRF classifiers were slightly modified to adapt to the Chinese input. For example we use ICTCLAS to segment and POS to tag the input sentences. The result is shown at Table 3.

Table 4 End-to-end rankings’ MRR

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | 易瑞沙(Iressa) | | 耐信(Nexium) | | 波依定(Plendil) | |
| ADRs | Indications | ADRs | Indications | ADRs | Indications |
| Manually label | 0.021 | 0.003 | 0.014 | **0.002** | 0.055 | **0.003** |
| Label only with package inserts | **0.035** | 0.003 | **0.022** | **0.002** | 0.046 | **0.003** |
| Semi-supervised labels | 0.027 | 0.003 | 0.015 | **0.002** | **0.072** | **0.003** |
| Patterns method | 0.024 | 0.003 | 0.009 | 0.003 | 0.025 | 0.004 |

Table 3 Accuracy of prediction of drug-condition associations

|  |  |  |  |
| --- | --- | --- | --- |
|  | Positive pairs | Negative pairs | F1 |
| Manual labels | 43/100 | 89/100 | 0.558 |
| Auto labels from inserts | 57/100 | 83/100 | 0.655 |
| Semi-supervised labels | **82/100** | **85/100** | **0.837** |
| HMM | 24/100 | 83/100 | 0.340 |
| CRFs | 37/100 | 90/100 | 0.503 |
| Pattern-based | 26/74 | 93/100 | 0.364 |

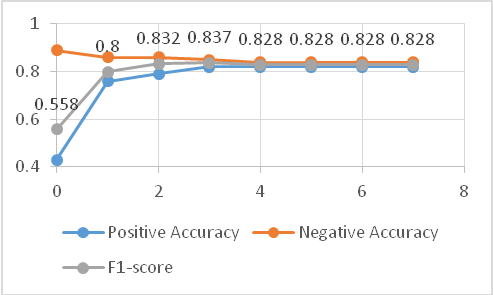


Figure 3 Accuracy at each iteration

## Bootstrapping of automatically labeling

Our semi-supervised automatic labeling algorithm uses the package inserts and classifier to generate more training data. One interesting thought is to use that newly obtained classifier to label even more training data, and thus build a newer classifier. This process can go on iteratively until no more new training data is obtained.

We select the 200 manually labeled sentences mentioned above as our test set, and the 422 sentences mentioned above as our initial training data. The algorithm is run multiple times until it converges. The result is shown in Figure 3.

## End-to-end ranking

Because our system returns a ranked list of possible ADRs given a drug, we evaluate the end-to-end performance of the system by the mean rank reciprocal (MRR)：

The reciprocal rank of a query response is the multiplicative inverse of the rank of the first correct answer. The mean reciprocal rank is the average of the reciprocal ranks of results for a sample of queries.[[10]](#footnote-11)

We expect the true ADR of a drug to rank high in the list while the true indication ranks lower in the list. The ground truth we use is the known ADRs and known indications of three well known drugs, namely, 易瑞沙(Iressa), 耐信(Nexium) and 波依定(Plendil). To do this evaluation, our classifier was trained using the data for all other drugs. Table 4 shows the results.

## Top-ten discovered ADRs

We show the most frequently reported ADRs (with percentages of their occurrences in the related posts in parenthesis) for 4 most discussed drugs for different indications in Table 5. ADRs that don’t have direct match in the package inserts are marked in red.

Table 5 Top 10 discovered ADRs for 4 common drugs

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **药物(Drugs)** | **耐信**  **(Nexium)** | **倍他乐克**  **(Betaloc)** | **易瑞沙**  **(Iressa)** | **思瑞康**  **(Seroquel)** |
| 副作用(ADRs) | 头晕(0.55%)  (Dizziness) | 恶心(0.65%)  (Nausea) | 皮疹(1.17%)  (Rash) | 嗜睡(1.78%)  (Drowsiness) |
| 抑郁(0.09%)  （Depression） | 耳鸣(0.25%)  (Tinnitus) | 腹泻(0.95%)  (Diarrhea) | 头晕(1.39%)  (Dizziness) |
| 失眠(0.27%)  (Insomnia) | 疲劳(0.33%)  （Fatigue） | 恶心(0.68%)  (Nausea) | 口干(0.48%)  (Dry mouth) |
| 口干(0.21%)  (Dry mouth) | 眩晕(0.22%)  (Dizziness) | 呕吐(0.93%)  (Vomit) | 恶心(0.51%)  (Nausea) |
| 皮肤过敏(0.05%)  (Skin allergies) | 腹痛(0.08%)  (Stomach ache) | 头晕(0.54%)  (Dizziness) | 便秘(0.76%)  (Constipation) |
| 眩晕(0.06%)  (Dizziness) | 嗜睡(0.11%)  (Drowsiness) | 瘙痒(0.40%)  (Itching) | 呕吐(0.37%)  (Vomit) |
| 药物过敏(0.06%)  (Drug allergy) | 视力模糊(0.05%)  (Blurred vision) | 乏力(0.48%)  (Weakness) | 疲倦(0.15%)  (Tired) |
| 咽喉痛(0.03%)  (Sore throat) | 瘙痒(0.08%)  (Itching) | 口腔溃疡(0.25%)  (Mouth ulcers) | 呼吸困难(0.12%)  (Difficulty breathing) |
| 全身乏力(0.05%)  (Malaise) | 便秘(0.09%)  (Constipation) | 头痛(0.46%)  (Headache) | 耳鸣(0.19%)  (Tinnitus) |
| 鼻塞(0.03%)  (Stuffy nose) | 黑便(0.03%)  (Melena) | 厌食(0.22%)  (Anoresia) | 贫血(0.08%)  (Anemia) |

# Discussion

As shown in Table 3, The semi-supervised labeling approach provides the best results with F1-score significantly higher than the other approaches. The HMM based method performs the worst, because it only utilizes the positive training data. As a result, the training data is only half of what’s used by the other methods. One interesting observation is that the positive accuracy is inversely correlated with the negative accuracy. This means a classifier is biased to produce either more positive labels or more negative labels. A good classifier, such as the one trained with the semi-supervised labels manages to strike a balance between the two biases and produce a better overall F1-score.

Figure 3 shows the result of the bootstrapping of our automatically labeling algorithm. We see that it quickly converges: there are no more labeled data generated after 7th iteration. There is a dramatic improvement in accuracy from the 0th iteration to the lst since more knowledge is acquired over time. The gain in accuracy saturates after a peak is reached at the 3rd iteration. We would then use the training data obtained at that time to train our final classifier.

In order to show the efficiency of end-to-end results of our approach, we calculate the MRRs for ADRs and indications, as shown in Table 4. We can see that our semi-supervised labeling method outperforms both the manually labeling method and the patterns method. However, sometimes it can be worse than labeling only with package inserts. The reason is that only using package inserts the trained classifier is overfitting to the package inserts and it may outperform our semi-supervised labeling method. But it underperforms when coming to drug-ADRs association’s accuracy.

In Table 5, we discovered many ADRs that are already included in the package inserts. Although these ADRs are known, the frequency statistics can be valuable for: i) verifying ADRs listed in the package inserts; ii) studying the relative frequency between the ADRs.

There are also a number of ADRs that without direct match in the manuals. These fall into several cases:

1. Synonyms of the known ADRs (eg. “视力模糊(Blurred vision)” is a synonym of “视力损害(Visual impairment)” for “倍他乐克(Betaloc)”)

While they are synonyms, the ADRs listed in package inserts are often some terminologies and the colloquial synonyms can help patients understand them easily.

1. Specialization of the known ADRs (eg. “失眠(Insomnia)” is a specialized case of “睡眠障碍(Sleep disorders)” for “耐信(Nexium)”)

Some ADRs from package inserts are very general terms. Our results give the insight of what specific disorders are actually encountered by the patients.

1. Newly discovered ADRs (eg. “头晕(Dizziness)” for “易瑞沙(Iressa)”)

This is the most valuable discovery for the drug maker in the analysis of the drug reactions in perhaps a small population previously not considered.

# Conclusion

We have proposed an effective framework for extracting and analyzing ADRs from Chinese online social media. It uses a lexicon-based method to extract ADRs from the data followed by a binary classifier to identify the positive evidences. In this framework, we introduce a data-driven algorithm to extend the ADRs lexicon. In order to build the evidence classifier, we propose an automatic labeling algorithm to produce large amount of labeled sentences. Completely relying on the information from the package inserts produces training data that is too noisy. Our tradeoff is a semi-supervised approach where we manually label a small set, then use these data and package inserts collectively to generate more training data. This algorithm is proven to be highly effective. It can be readily extended to other similar tasks.

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Appendix. A

Table 5 Drugs list

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Categories | Drugs name | Originators | Posts | Pairs |
| 高血压(Hypertension) | 缬沙坦(Valsartan) | Novartis | 4729 | 665 |
| 压宁定(Urapidil) | Takeda | 8403 | 19 |
| 特拉唑嗪(Terazosin) | Abbott | 6101 | 65 |
| 替米沙坦(Telmisartan) | Boehringer Ingelheim | 2190 | 61 |
| 瑞泰(Ramipril) | Sanofi | 1092 | 6 |
| 培哚普利(Perindopril) | Servier | 2470 | 68 |
| 氯沙坦钾(Losartan Potassium) | Bristol-Myers Squibb | 4001 | 187 |
| 氯沙坦钾-氢氯噻嗪(losartan/hydrochlorothiazide) | Bristol-Myers Squibb | 1803 | 12 |
| 赖诺普利(Lisinopril) | Merck & Co. | 1646 | 23 |
| 乐卡地平(Lercanidipine) | Recordati | 268 | 0 |
| 拉西地平(Lacidipine) | GlaxoSmithKline | 1539 | 24 |
| 伊索格拉啶(Irsogladine) | Nippon Shinyaku | 527 | 4 |
| 厄贝沙坦(Irbesartan) | Sanofi | 3511 | 127 |
| 吲达帕胺(Indapamide) | Servier | 3600 | 501 |
| 咪达普利(Imidapril) | Mitsubishi Tanabe Pharma | 1717 | 22 |
| 福辛普利(Fosinopril) | Bristol-Myers Squibb | 1876 | 0 |
| 多沙唑嗪(Doxazosin) | Pfizer | 1207 | 13 |
| 地尔硫卓(Diltiazem) | Ethypharm | 3160 | 41 |
| 地拉普利(Delapril) | Takeda | 95 | 0 |
| 卡维地洛(Carvedilol) | Roche | 724 | 42 |
| 坎地沙坦(Candesartan) | Takeda | 1639 | 0 |
| 布那唑嗪(Bunazosin) | Eisai | 2 | 0 |
| 富马酸比索洛尔(Bisoprolol fumarate) | Merck KGaA | 6887 | 95 |
| 贝尼地平盐酸盐(Benidipine hydrochloride) | Kyowa Hakko Kirin | 4277 | 77 |
| 阿替洛尔(Atenolol) | AstraZeneca | 5214 | 1555 |
| 尼群地平(Nitrendipine) | Bayer | 1329 | 11 |
| 阿罗洛尔(Arotinolol) | Sumitomo Dainippon Pharma | 2196 | 54 |
| 氨氯地平(Amlodipine) | Pfizer | 9674 | 385 |
| 阿利沙坦酯(Allisartan isoproxil) | Allist Pharmaceuticals | 3 | 0 |
| 阿利吉仑(Aliskiren) | Novartis | 130 | 0 |
| 倍他乐克(Betaloc) | AstraZeneca | 91477 | 14045 |
| 波依定(Plendil) | AstraZeneca | 23235 | 3340 |
| 糖尿病(Diabetes) | 倍欣(Voglibose) | Takeda | 1200 | 11 |
| 维格列汀(Vildagliptin) | Novartis | 212 | 0 |
| 捷诺维(Glactiv) | Merck & Co. | 362 | 60 |
| 安立泽(Onglyza) | AstraZeneca | 607 | 15 |
| 马来酸罗格列酮片(Rosiglitazone maleate) | GlaxoSmithKline | 1219 | 19 |
| 孚来迪片(Repaglinide) | Boehringer Ingelheim | 2054 | 23 |
| 盐酸匹格列酮(Pioglitazone hydrochloride) | Takeda | 2048 | 156 |
| 奥利司他(Orlistat) | Roche | 3508 | 69 |
| 那格列奈(Nateglinide) | Ajinomoto | 2268 | 27 |
| 米格列奈钙片(Mitiglinide) | Kissei | 32 | 0 |
| 瑞格列奈二甲双胍组合物(Metformin repaglinide) | Novo Nordisk | 3 | 0 |
| 诺和力(Liraglutide) | Novo Nordisk | 168 | 0 |
| 长秀霖(Basalin) | Gan & Lee | 983 | 40 |
| 甘精胰岛素(Insulin glargine) | Sanofi | 7670 | 73 |
| 门冬胰岛素注射液(Insulin Aspart) | Novo Nordisk | 1894 | 0 |
| 格列吡嗪控释片(Glipizide extended-release) | Pfizer | 525 | 1 |
| 万苏平(Glimepiride) | Sanofi | 1290 | 0 |
| 格列齐特(Gliclazide) | Servier | 2766 | 126 |
| 百泌达(Byetta) | AstraZeneca | 280 | 0 |
| 利拉利汀(Linagliptin) | Boehringer Ingelheim | 98 | 0 |
| 苯甲酸阿格列汀(Alogliptin benzoate) | Takeda | 28 | 0 |
| 阿卡波糖(Acarbose) | Bayer | 5287 | 265 |
| 哮喘(Asthma) | 扎鲁司特(Zafirlukast) | AstraZeneca | 135 | 0 |
| 茶碱(Theophylline) | 3M Pharmaceuticals | 10298 | 230 |
| 沙丁胺醇(Salbutamol) | GlaxoSmithKline | 4668 | 483 |
| 美喘清(Procaterol) | Otsuka | 8864 | 102 |
| 吡嘧司特钾(Pemirolast potassium) | Bristol-Myers Squibb | 2290 | 0 |
| 盐酸奥洛他定(Olopatadine hydrochloride) | Kyowa Hakko Kirin | 2268 | 0 |
| 孟鲁司特钠(Montelukast sodium) | Merck & Co. | 38857 | 1873 |
| 洛草氨酸氨丁三醇(Lodoxamide tromethamine) | Pfizer | 1856 | 0 |
| 福莫特罗(Formoterol) | AstraZeneca | 1613 | 33 |
| 丙酸氟替卡松(Fluticasone propionate) | GlaxoSmithKline | 5840 | 715 |
| 依匹斯汀(Epinastine) | Boehringer Ingelheim | 2163 | 0 |
| 阿米迪(Amiaid) | Nitto Denko | 2519 | 433 |
| 盐酸班布特罗(Bambuterol hydrochloride) | AstraZeneca | 952 | 16 |
| 普米克(Pulmicort) | AstraZeneca | 8905 | 3984 |
| 信必可(Symbicort) | AstraZeneca | 8458 | 3484 |
| 他汀类药物(Statins) | 阿伐他汀(Atorvastatin) | Pfizer | 2464 | 0 |
| 辛伐他汀(Simvastatin) | Merck & Co. | 7510 | 67 |
| 瑞舒伐他汀(Rosuvastain) | AstraZeneca | 5494 | 1202 |
| 普伐他汀(Pravastatin) | Sankyo Pharma Inc. | 2204 | 10 |
| 洛伐他汀(Lovastatin) | Merck & Co. | 3871 | 243 |
| 氟伐他汀(Fluvastatin) | Novartis | 2980 | 22 |
| 依折麦布辛伐他汀(Ezetimibe simvastatin) | Merck & Co. | 1557 | 0 |
| 匹伐他汀(Pitavastatin) | Nissan Chemical Industries | 105 | 0 |
| 西立伐他汀(Cerivastatin) | Pfizer | 43 | 0 |
| 美伐他汀(Mevastatin) | Daiichi-Sankyo | 29 | 0 |
| 氨氯地平阿托伐他汀(Atorvastatin amlodipine) | Pfizer | 209 | 0 |
| 烟酸辛伐他汀(Niacin simvastatin) | Abbott Laboratories | 1 | 0 |
| 烟酸洛伐他汀(Niacin lovastatin) | KOS Pharmaceuticals, Inc | 0 | 0 |
| 西格列汀辛伐他汀复合剂(Simvastatin sitagliptin) | Merck & Co. | 0 | 0 |
| 乳腺癌 | 阿那曲唑(Anastrozole) | AstraZeneca | 37463 | 1074 |
| 麻醉 | 得普利麻(Diprivan) | AstraZeneca | 1097 | 159 |
| 胃酸过多 | 洛赛克(Omeprazole) | AstraZeneca | 71525 | 1248 |
| 肺癌 | 易瑞沙(Iressa) | AstraZeneca | 14115 | 10028 |
| 胃病 | 耐信(Nexium) | AstraZeneca | 69491 | 29754 |
| 鼻炎 | 雷诺考特(Rhinocort) | AstraZeneca | 14852 | 1419 |
| 精神分裂 | 思瑞康(Seroquel) | AstraZeneca | 12310 | 4064 |
| 急性冠脉综合征 | 倍林达(Brilinta) | AstraZeneca | 430 | 67 |

1. https://en.wikipedia.org/wiki/Rofecoxib [↑](#footnote-ref-1)
2. https://www.cuttingedgeinfo.com/2011/us-phase-iv-budgets/ [↑](#footnote-ref-2)
3. http://club.xywy.com/ [↑](#footnote-ref-4)
4. http://www.haodf.com/ [↑](#footnote-ref-5)
5. http://weibo.com [↑](#footnote-ref-6)
6. Sogou Pinyin is a Chinese input method, and there are many lexicons available. And the interested one is the ADRs lexicon: <http://pinyin.sogou.com/dict/detail/index/644> . [↑](#footnote-ref-7)
7. A English database comes from Ye et al., 2014. [↑](#footnote-ref-8)
8. https://translate.google.com/ [↑](#footnote-ref-9)
9. http://www.meddra.org/ [↑](#footnote-ref-10)
10. https://en.wikipedia.org/wiki/Mean\_reciprocal\_rank [↑](#footnote-ref-11)