

# Project Instruction

## “Data Science Research Bot” (a.k.a. SciBot)

### Data Science CSE 40647/60647

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#### Project goal:

Individual project, NOT group project.

On a large real-world dataset, students should be able to:

- Process raw data: data cleaning, data integration, data reduction, dimension reduction
- Describe data warehouse, OLAP, data cube concepts and technology that work on multi-dimensional data
- Use Apriori and FP-Growth for frequent pattern mining
- Describe diverse patterns, sequential patterns, graph patterns
- Use Decision Tree, Naïve Bayes, Ensembles for classification
- Describe SVMs and Neural Networks for classification
- Use K-Partitioning Methods (K-Means, etc.) for clustering
- Describe Kernel-based Clustering and Density-based Clustering
- Use appropriate measures to evaluate results of different functionalities

Students are required to accomplish tasks that will be described as “required tasks” below. Students are encouraged to do more tasks as either the recommended ones or the ones they like to do. Basically, the ultimate goal is to enrich the functionalities of the “SciBot” using data science and technology.

One example of the functionalities could be:

>> *What problem do you want to find methods that are strongly associated with?*

>> *(by user) document classification*

>> *The methods that are associated with the problem “document classification” are:*

*support\_vector\_machines (relative support: 0.37, confidence: 0.25)*

*decision\_tree (relative support: 0.32, confidence: 0.21)*

...

Students are also required to write a project report/ paper to describe their achievement including the following points *for each task*: (1) Motivation and task definition, (2) Approach, (3) Results, and (4) Discussions.

**Grading policy: (25% of the final score)**

Students are required to submit their code package + “readme” (.ZIP) and project report/paper (.PDF). There is no paper template requirement.

Students will volunteer to present their SciBot (tech and results) in two lectures. Classmates and the instructor will grade them based on the presentation. For the students who do not present, the instructor will grade their projects after all the lectures end. Note that we will have comparative grading – finishing all the required tasks cannot make sure that you have all the points.

Students are encouraged to implement algorithms such as Apriori, FP-Growth, and K-Means Clustering by themselves instead of calling Python packages.

Students are also encouraged to use Python packages (e.g., numpy and scipy) when they use advanced techniques (e.g., SVMs, Neural Networks, word2vec) to address challenging tasks.

Students are encouraged to compare different methods on the same task and discuss their advantages and disadvantages. Reasoning is always welcome in the paper.

Students are encouraged to share any annotation data (e.g., labels, hand-crafted rules) but not any segment of codes.

Students are encouraged to make a GUI for the SciBot. They are also encouraged to give a better name to their bots than “SciBot”.

Graders should have higher expectations on graduates than undergraduates – not only on the project results (more tasks, better performances) but also on writing (a workshop-quality paper of strong reasoning). Undergraduates will be applied with a uniform grading policy no matter what majors they have.

The project due is Nov 30, 2017. There will be NO extension. Significant updates are welcome before the final exam – students can send the updates to the instructor after the due by e-mail but they have to submit one version before the due.

**Academic Dishonesty:**

- The CSE and du lac honor code will be strictly followed.
- All assignments are individual unless instructed. You can discuss the assignment at a high level, but you should independently and individually write down the answers and/or the program. The sharing and copying of homework solutions or programs or functions or exams will be considered cheating.
- All the references and sources should be carefully provided and cited.
- Entering Notre Dame you were required to study the on-line edition of the Academic Code of Honor, to pass a quiz on it, and to sign a pledge to abide by it. The full Code and a Student Guide to the Academic code of Honor are available at: <http://honorcode.nd.edu>.
- Perhaps the most fundamental sentence is the beginning of section IV-B: “The pledge to uphold the Academic Code of Honor includes an understanding that a

student's submitted work, graded or ungraded – examinations, draft copies, papers, homework assignments, extra credit work, etc. - must be his or her own."

### Dataset introduction:

The dataset has both structured and unstructured information of over five thousand data science research papers. It includes three zip files:

1. pdf.zip (4.7GB; unzip ~5.5 GB): raw unstructured data (actually you don't have to use this huge file)

<https://www.dropbox.com/s/460h772tpuceew5/pdf.zip?dl=0>

It has 64 folders/proceedings. Each folder is named as "[CONF][YEAR]":

- CONF: {icdm, kdd, wsdm, www}  
icdm: IEEE International Conference on Data Mining  
kdd: ACM SIGKDD Conference on Knowledge Discovery and Data Mining  
wsdm: ACM Conference on Web Search and Data Mining  
www: International Conference on World Wide Web
- YEAR: {94, 95, ..., 99, 00, 01, ..., 16}  
from 1994 to 2016

Each folder has an incomplete set of papers of the proceeding of CONF-YEAR. The papers are named as "[PDFID].pdf":

- PDFID: {icdm01-d0, ...}

2. text.zip (~95MB; unzip ~270MB): raw unstructured data

<https://www.dropbox.com/s/0ixj6dsvfjiigc3/text.zip?dl=0>

It has the same folder names and file names as pdf.zip. The only difference is the files' ext. name (".txt" here, ".pdf" in pdf.zip). A Python package was used to transfer \*.pdf into \*.txt, but the text looks incomplete and noisy.

- Practitioners are recommended to skip the REFERENCE section when they mine knowledge from the text data.

3. microsoft.zip (~24MB; unzip ~100MB): raw structured data

<https://www.dropbox.com/s/o9qzhbdd0pmk5wm/microsoft.zip?dl=0>

It has five files. All except "index.txt" were provided by Microsoft Academic Search (MAS) engine. "index.txt" was created by the instructor to bridge the structured and unstructured data with entry id (PDFID and PID).

(1) index.txt

Folder name in pdf.zip / txt.zip	PDFID (file name) in pdf.zip (*.pdf) / txt.zip (*.txt): (paper id in PDFs)	PID (paper id in MAS database)	TITLE (lower case)
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(2) Papers.txt

PID (paper id in MAS database)
TITLE_CASE (case sensitive)
TITLE (lower case)
YEAR (year of proceeding)
DATE_OF_PROCEEDING (not recommended to use)
DOI (not recommended to use)

CONF_FULL_NAME (not recommended to use)
CONF (abbreviation, lower case)*
N/A
CID (conference id; not proceeding id!)**
N/A

\* The dataset is noisy. NOT every entry can be correlated across the files, for example, CONF has conference names that are not included in {icdm, kdd, wsdm, www}.

\*\* One-to-one mapping between CONF and CID.

### (3) PaperKeywords.txt

PID (paper id in MAS database)
KEYWORD (keyword in lower case)*
KID (keyword id; not recommended to use)

*\* It has a very limited set of keywords. We will process the text data for more structured semantic information of the papers.*

### (4) PaperAuthorAffiliation.txt

PID (paper id in MAS database)
AID (author id in MAS database)
FID (affiliation id in MAS database)
AFF_ORG (original affiliation name, not recommended to use)
AFF (normalized affiliation name)*
SID (author sequence number: "1" = the first author, "3" = the 3 <sup>rd</sup> author)**

\* One-to-one mapping between AFF and FID.

\*\* The author information of a paper may not be complete. It may only have the 1<sup>st</sup>, 2<sup>nd</sup>, and 4<sup>th</sup> authors.

### (5) Authors.txt

AID (authored in MAS database)	AUT (author name in lower case)
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## Required tasks:

### Task 1: Data preprocessing

**Q1:** Given the above files from multiple sources, can we integrate the data, clean the data (work with incomplete/missing entries and redundancy/unnecessary entries), describe the data using statistics and visualization (distributions, etc.)? What are the data objects and what are the attributes?

**Techs:** Data cleaning, data integration, data description, statistical analysis, data visualization.

### Hints:

1. PDFID-PID mapping in index.txt can be used to integrate paper text (txt.zip), Papers.txt, PaperKeywords.txt and PaperAuthorAffiliation.txt.
2. AID can be used to integrate PaperAuthorAffiliation.txt and Authors.txt.

PDFID	(PID)	CONF	YEAR	LIST_AUTHOR	LIST_KEYWORD	...	TEXT	(PDF)

## Task 2: Entity mining: Candidate generation and quality assessment

**Q2:** Given the text data, can we mine entities, e.g., “text categorization”, “document classification”, “naïve bayes”, “decision tree”, “support vector machines”, “SVM”, “SVMs”? Can we propose at least one measure of entity quality and rank them by it?

**Techs:** Measures (outlier-ness like Z-score), hand-crafted rule matching, frequent pattern mining

### Hints:

1. Entity names are a subset of words or phrases. Relational phrases or stop phrases are not entity names, e.g., “turn\_out\_to\_be”, “in\_this\_paper”.
2. Use the given keyword list as entity / phrase candidates. Suppose a document has 1,000,000 words. It has 1,000 “decision” and 1,000 “tree”. Assuming an even distribution of the words, we may only have one “decision tree”. The observed number could be much bigger.
3. Rules of lexical features are useful for generating entity candidates. For example, we may often see “... Support Vector Machines ...”, “support vector machines (SVMs)”, “... non-negative matrix factorization (NMF) ...” Then we use outlier-ness to evaluate the quality of the candidates.
4. We may generate N-grams (N=2,3,4...) as phrase / entity candidates. However, the number could be huge. Can we use heuristics (like the rules above) to generate a proper-sized set of candidates?
5. If we consider phrase / entity candidates as patterns (word itemsets), another possible quality measure is the support of pattern if we consider each sentence / paragraph / paper as a transaction and words as items.
6. Label a set of quality entities. Evaluate the performance of different measures and different candidate sources / generation methods.

PDFID	LIST_ENTITY

## Task 3: Entity typing

**Q3:** Given quality entities and text data, can we assign types to the entities? Basically, we consider four major types: \$Problem, \$Method, \$Metric, \$Dataset.

\$Problem	text categorization, document classification, fraud detection ...
\$Method	naïve bayes, decision tree, support vector machines ...
\$Metric	accuracy, precision, recall, F1 score ...
\$Dataset	netflix, youtube, movielens, facebook, twitter, dblp ...

**Techs:** Measures (outlier-ness like Z-score), dimension reduction, classification

### Hints:

1. Take an entity as a data object. The attributes are contextual words around the entity in the text data. Suppose we have an N-size window and take each word in the window as an attribute. Then we can measure the probability of assigning a type to an entity. We assume that if the word “method”, “model” or “approach” has a high Z-score to appear in the context of an entity, the entity is likely to be typed as “\$Method”.
2. Here we carefully type entities. We want high accuracy but not good coverage. We use supervised methods (for classification – Naïve Bayes or decision tree or others) and feed with the set of contextual words (attributes) to type other

entities. If the number of attributes is too large, we can consider to use dimension reduction (like PCA or SVD).

PDFID	LIST_PROBLEM	LIST_METHOD	LIST_METRIC	LIST_DATASET

#### Task 4: Collaboration discovery

**Q4:** Given the paper-author data, find frequent author-sets (as patterns): which two/three/four authors often collaborate together?

**Techs:** Frequent pattern mining (Apriori, FP-Growth).

**Hints:**

1. Here each paper is considered as a transaction. Each author is an item.

#### Task 5: Problem-method association mining

**Q5:** Given the paper-problem-method data, find strong association rules, problem  $X \rightarrow$  method Y, or method  $X \rightarrow$  problem Y, of high support and confidence.

**Techs:** Association rule mining.

**Hints:**

1. Here each paper is considered as a transaction. Each problem/method is an item.

#### Task 6: Problem/method/author-to-conference classification

**Q6:** Given a problem/method/author, predict if a conference has papers of it.

**Techs:** Binary classification (Naïve Bayes, Decision Tree).

**Hints:**

1. What are the attributes (features) you want to use?
2. How to set up training and testing? Please evaluate the performance on different features, different models, and different setups.

#### Task 7: Paper clustering

**Q7:** Given a set of papers, cluster them into K groups.

**Techs:** K-partitioning clustering methods (K-Means).

**Hints:**

1. What are the attributes (features) you want to use?
2. Suppose  $K = 4$  and the ground-truth is the conference. Please evaluate the performance on different features and different methods.

### **Recommended tasks:**

#### Task 1+: Data preprocessing

**Q1+:** Study the data distributions: Do you find power-law, Poisson, or normal distributions between variables? Can you explain them?

**Techs:** Statistical analysis.

#### Task 2+: Entity mining: Candidate generation and quality assessment

**Q2+:** Can you use auxiliary sources (e.g., stop word list) or auxiliary criteria to further improve the quality of entity names you mined?

**Techs:** Classification (good entity name: "yes", "no").

#### Task 3+: Entity typing

**Q3+:** Can you use cluster analysis on the entities to type entities by clusters? Given what kind of features, the entities might be grouped together if they had the same type?

**Techs:** Clustering

Task 4+: Advisor-advisee discovery

**Q4+:** Can you find advisor-advisee relations from collaborations?

**Techs:** Measures (like Kulc).

Task 8: Manage the data with data cube

**Q8:** Given enriched structured data, can we construct a data cube and compute for iceberg cubes for query-based applications? E.g., expert recommendation: Given a problem, list authors, papers and other information that help related research.

**Techs:** Data cube, iceberg cube, closed cells, etc.

**Hints:**

1. Each paper is considered as a transaction. The cell maintains a set of papers. A paper may be in multiple cells. We count the size of paper set for the cube computation.
2. For a list of entities, the attribute types are dimensions (e.g., problem, method, dataset, author, conference); the attribute values are the dimension values (e.g., "naïve bayes", "decision tree").
3. More functionalities of the data cube, and efficiency analysis are welcome.

Task 9: Pattern-based entity recognition and typing

**Q9-1:** Given entity names, can we find frequent patterns around the entities? We replace concrete entity names as "\$Entity". You can find more entities via pattern matching.

**Q9-2:** Given seed typed entities (methods, problems, etc.), can we find concrete frequent patterns around the typed entities? We replace concrete method / problem entities as "\$Method" / "\$Problem". Those patterns indicate that you may be able to find more entities of the specific types.

**Techs:** Constraint-based frequent pattern mining.

**Hints:**

1. Evaluate the support of patterns such as "problem of \$Problem", "address the \$Problem problem", "method of \$Method", "approach based on the \$Method".
2. Recognizing more entities and their types by matching the patterns in the text.

PDFID	LIST_PROBLEM	LIST_METHOD	LIST_METRIC	LIST_DATASET

Task 10: Problem / method / author clustering

**Q10:** Given a set of problems / methods / authors, cluster them into K groups. Evaluate the clustering results in a proper way.

**Techs:** K-partitioning clustering methods (K-Means).

Task 11: Attribute discovery

**Q11:** Suppose we use rules to type digit number as \$Digit. Can we find the size of datasets used in the papers? Can we find the performance of methods?

**Techs:** Constraint-based frequent pattern mining.

Task 12: Practice with advanced classification and clustering methods



**Q12:** Can you solve the above tasks with advanced classification models (e.g., SVMs, Neural Networks) and clustering methods (e.g., spectral clustering)?

**Task 13:** Other interesting tasks related to other data entries/attribute like “affiliation ranking on a specific method/problem”.

**Task 14:** Data visualization is encouraged.

Examples: Project results from UIUC Summer 2017 Data mining course (10 weeks, 3 lectures per week, 5 written assignments).

(1) A Web UI to manually label “problems”, “methods”, “metrics”, etc.

0015-p1006  
0015-p1015  
0015-p1025  
0015-p1035  
0015-p1045  
0015-p1055  
0015-p1065  
0015-p1075  
0015-p1085  
0015-p109  
0015-p1095  
0015-p1105  
0015-p1115  
0015-p1125  
0015-p1135  
0015-p1145  
0015-p1155  
0015-p1165  
0015-p1175  
0015-p1185  
0015-p119  
0015-p1195  
0015-p1205  
0015-p1215  
0015-p1225  
0015-p1235  
0015-p1245  
0015-p1255  
0015-p1265  
0015-p1275  
0015-p1285  
0015-p129  
0015-p1295  
0015-p1305  
0015-p1315  
0015-p1325  
0015-p1335  
0015-p1345  
0015-p1355  
0015-p1365  
0015-p1375  
0015-p1385  
0015-p139  
0015-p1395  
0015-p1405  
0015-p1415  
0015-p1425  
0015-p1435  
0015-p1445  
0015-p1455  
0015-p1465  
0015-p1475  
0015-p1485  
0015-p149  
0015-p1495  
0015-p1503  
0015-p1523  
0015-p1533  
0015-p1543  
0015-p1553  
0015-p1563  
0015-p1573  
0015-p1583  
0015-p159  
0015-p1593  
0015-p1603  
0015-p1641  
0015-p1651  
0015-p1661  
0015-p1671

the Social Sciences & University of Koblenz-Landau Martin Becker University of Würzburg wuerzburg.de Philipp Singer GESIS - Leibniz Institute for the Social Sciences & University of Koblenz-Landau Denis Helic Graz University of Technology Andreas Hotho University of Würzburg and L3S Hannover wuerzburg.de Markus Strohmaier GESIS - Leibniz Institute for the Social Sciences & University of Koblenz-Landau ABSTRACT We present a new method for detecting **interpretable subgroups** with exceptional **transition behavior** in **sequential data**. Identifying such patterns has many potential applications, e.g., for studying human **mobility** or analyzing the behavior of internet users. To tackle this task, we employ **exceptional model mining**, which is a general approach for identifying **interpretable data subgroups** that exhibit unusual interactions between a set of target attributes with respect to a certain model class. Although **exceptional model mining** provides a well-suited framework for our problem, previously investigated model classes cannot capture **transition behavior**. To that end, we introduce first-order **Markov chains** as a novel model class for **exceptional model mining** and present a new **transition matrix** measure that quantifies the exceptionality of transition subgroups. The measure compares the **transition matrix** between the Markov transition matrix of a subgroup and the respective matrix of the entire data with the **transition matrix** of random dataset samples. In addition, our method can be adapted to find subgroups that match or contradict given transition hypotheses. We demonstrate that our method is consistently able to recover subgroups with **exceptional transition models** from **sequential data** and illustrate its potential in two application examples. Our work is relevant for researchers and practitioners interested in detecting **exceptional transition behavior** in **sequential data**. Keywords: **Subgroup Discovery**; **Exceptional Model Mining**; **Markov chains**; **Transitions**; **Sequential Data** 1. INTRODUCTION **Exceptional Model Mining**, a generalization of the classic **Subgroup Discovery** task, is a framework that identifies patterns which contain unusual interactions between multiple target attributes. In order to obtain operationalizable insights, it emphasizes the detection of easy-to-understand subgroups, i.e., it aims to find **exceptional subgroups** with descriptions that are directly interpretable by domain experts. In general, **exceptional model mining** is not made or distributed for profit or commercial advantage and that copies for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author must be honored. Abstracting with credit is permitted. To copy otherwise, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from: KDD'16, August 13 - 17, 2016, San Francisco, CA, USA 2016 Copyright held by the owner / author. Publication rights licensed to ACM. ISBN 978-1-4503-4232-2/16/08...\$15.00 DOI: ing operates as follows: A target model of a given model class is computed once over the entire dataset, resulting in a set of model parameters. The same parameters are also calculated for each subgroup in a large (often implicitly specified) candidate set, using only the instances covered by the respective subgroup. A subgroup is considered as exceptional or interesting if its parameter values differ significantly from the ones of the overall dataset. While **exceptional model mining** has been implemented for a variety of model classes including **classification**, **regression**, **Bayesian network** and **rank** **transition models**, it has not yet been applied using models for **sequential data**. In this paper, we aim to apply **exceptional model mining** to discover **interpretable subgroups** with exceptional **transition behavior**. This enables a new analysis method for a variety of applications. As one example, assume a human **mobility** dataset featuring user transitions between locations. The overall transition model could for example show that people either move within their direct neighborhood or along main roads. Detecting subgroups with exceptional **transition behavior** goes beyond this simple analysis: It allows to automatically identify subgroups of people (such as "male tourists from France") or subsegments of time (such as "10 to 11 p.m.") that exhibit unusual movement characteristics, e.g., tourists moving between points-of-interest or people walking along well-lit streets at night. Other application examples could include subgroups of web-users with unusual **navigation** behavior or subgroups of companies with unusual development over time, cf.. The main contribution of this paper is a new method that enables mining subgroups with exceptional **transition behavior** by introducing first-order **Markov chains** as a novel model class for **exceptional model mining**. **Markov chains** have been utilized for studying **sequential data** about, e.g., human **navigation** and **mobility**, **meteorology**, or **economics**. To apply **exceptional model mining** with this model, we derive an **exceptionality** measure that quantifies the exceptionality of a subgroup's transition model. It measures how much the **transition matrix** between the Markov transitions matrix of a subgroup and the respective matrix of the entire data deviates from the **transition matrix** of random dataset samples. This measure can be integrated into any known **search algorithm**. We also show how an adaptation of our approach allows to find subgroups specifically matching (or contradicting) given hypotheses about **transition behavior** (cf.). This enables the use of **exceptional model mining** for a new type of studies, i.e., the detailed analysis of such hypotheses. We demonstrate the potential of the proposed approach with synthetic as well as **real-world** data. 965 The remainder of this work is organized as following: We summarize our background in Section 2. Then, the main approach for mining subgroups with exceptional **transition behavior** is introduced in Section 3. Section 4 presents experiments and results. Finally, we discuss related work in Section 5, before we conclude in Section 6. 2. BACKGROUND Our solution extends **Exceptional Model Mining** with first-order **Markov Chain** Models. In the following, we give a brief overview of both techniques. 2.1 **Exceptional Model Mining** We formally define a dataset  $D$  as a multiset of data instances  $I$  described by a set of attributes  $A$  consisting of describing attributes  $AD$  and model attributes  $AM$ . A subgroup consists of a subgroup description  $p$ :  $D$  - that is given by a **Boolean function**, and a subgroup cover  $c$ , i.e., the set of instances described by  $p$ , i.e.,  $c = I$ . In principle, our approach works with any **pattern description language** to describe

Source:  
11 ca  
12 kdd  
13 acm  
14 august  
15 copyright  
16 keywords  
17 san francisco  
18 introduction  
19 isbn  
20 experiments

Method:  
20 barabasi-albert  
21 progressive sampling  
22 heuristic  
23 monte-carlo, montecarlo  
24 non-linear optimization  
25 map-reduce, mapreduce  
26 poisson process  
27 en algorithm  
28 cnmp  
29 random sampling  
30 linear system, linear model

Subgroup:  
47 large-scale network  
48 minimum-cut  
49 motif discovery  
50 rule discovery  
51 future event  
52 co-authorship network  
53 modularity  
54 paper recommendation  
55 eco-centric circle  
56 biological network

8 standard error  
9 z-score  
10 normality  
11 p-value  
12 critical value  
13 total variation  
14 statistical significance  
15 quality measure  
16 accuracy  
17 euclidean norm, euclidean distan

Data:  
1 wikileaks  
2 facebook  
3 synthetic data  
4 real-world  
5 flickr  
6 lastfm  
7 bms-pos  
8 fimi  
9 sequential data  
10 linkedin

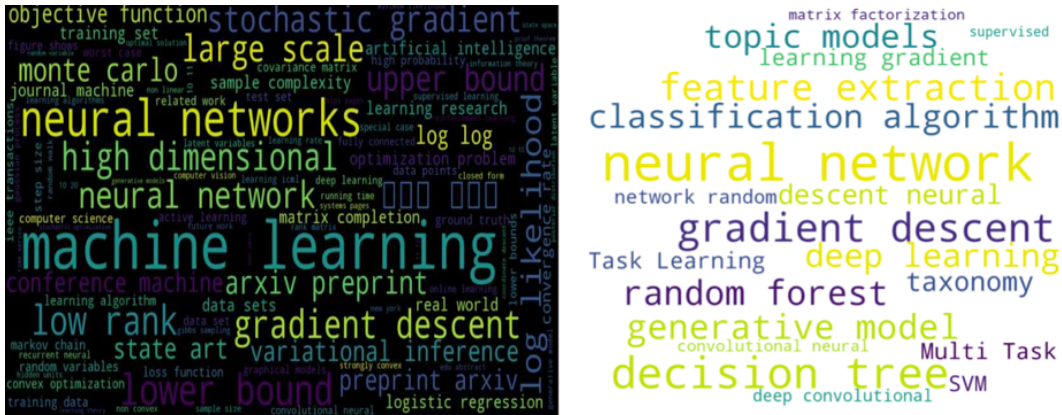
(2) Evaluating clustering analysis (K = 3) based on two PCA features.

Fig.6 True label

Fig.7 Clustering labels



### (3) Word cloud of entity clusters



(4) Classification performance (F1 score) vs training size (%) and #PCA features.

