

Project Instruction

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

Data Science CSE 40647/60647

Last updated: Sept. 28, 2017

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Project goal:

~~Individual project, NOT group project.~~

Team project (after voting in class, we some draw conclusions):

- A team will have at most 2 members (one or two).
- Students will give their partner's name (or N/A – if they do individual projects by their own) in HW3.
- Members in the same team will have the same score.

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.

Graders tend to grade individual projects/ undergraduates better than team projects/ graduates if they generate the same results.

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/o0f7qjb5mobmfvt/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 rd author)**

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

** The author information of a paper may not be complete. It may only have the 1st, 2nd, and 4th 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: Frequent pattern mining, measures (outlier-ness like Z-score), hand-crafted rule matching

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 *absolute support* of the pattern (i.e., count of the pattern in the text data) 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

Milestone 1: In HW3, we request students to report some numbers of their results on Task 1 and 2. (Oct. 3 due)

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.

Milestone 2: In HW4, we request students to report some numbers of their results on Task 3, 4, and 5. (Nov. 9 due)

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.

Final due: Nov. 30. Volunteer to present!

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 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.

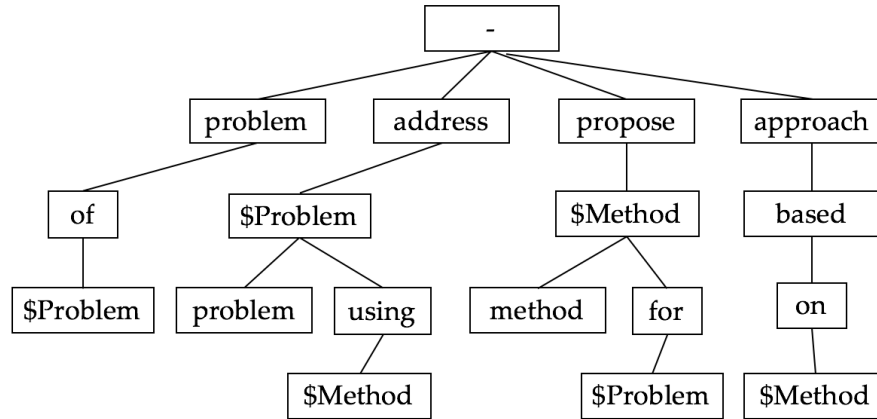
Techs: Constraint-based frequent pattern mining.

Hints:

1. An iterative process that first generate and evaluate the support of patterns such as “problem of \$Problem”, “address \$Problem problem”, “propose \$Method method”, “approach based on \$Method”, “propose \$Method for \$Problem”, “address \$Problem

using \$Method” and then recognize more entities and their types by matching the patterns in the text and repeat until convergence.

2. How to generate the patterns *efficiently*? How to match the text with patterns *efficiently*? The data structure of Trie Tree (<https://en.wikipedia.org/wiki/Trie>) is recommended. Suppose we have the above 6 patterns. We can construct a tree below. It is easier to search in the tree than to match string patterns.



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: Ensemble learning

Q12: Suppose we have multiple models/methods for a specific task (actually you do have if you’ve finished the required tasks). Can we use ensemble methods to further improve the performance?

Techs: Ensemble methods (bagging, Adaboost, etc.).

Task 13: Practice with advanced classification and clustering methods

Q13: Can you solve the above tasks with advanced classification models (e.g., SVMs, Neural Networks) and clustering methods (e.g., spectral clustering)?

Task 14: Other interesting tasks related to other data entries/attribute like “affiliation ranking on a specific method/problem”.

Task 15: 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.

dd15-p1006 the Social Sciences & University of Koblenz-Landau Martin Becker University of Würzburg wuerzburg.de Philipp Singer GESIS - Leibniz Institute for
dd15-p1015 the Social Sciences & University of Koblenz-Landau Denis Helic Graz University of Technology Andreas Hotho University of Würzburg and L3S
dd15-p1025 Hannover wuerzburg.de Markus Strohmaier GESIS - Leibniz Institute for the Social Sciences & University of Koblenz-Landau ABSTRACT We present
dd15-p1045 a new method for detecting interpretable subgroups with exceptional transition behavior in sequential data. Identifying such patterns has many potential
dd15-p1055 applications, e.g., for studying human mobility or analyzing the behavior of internet users. To tackle this task, we employ exceptional model mining,
dd15-p1075 which is a general approach for identifying interpretable data subsets that exhibit unusual interactions between a set of target attributes with respect to a
dd15-p1085 certain model class. Although exceptional model mining provides a well-suited framework for our problem, previously investigated model classes
dd15-p1095 cannot capture transition behavior. To that end, we introduce first-order Markov chains as a novel model class for exceptional model mining and present
dd15-p1105 a new transition measure that quantifies the exceptionality of transition subgroups. The measure compares the transition matrix of a subgroup and the
dd15-p1115 transition matrix of the entire data with the transition matrix of random dataset samples. In addition, our method can be
dd15-p1125 adapted to find subgroups that match or contradict given transition hypotheses. We demonstrate that our method is consistently able to recover
dd15-p1135 subgroups with exceptional transition models from synthetic data and illustrate its potential in two application examples. Our work is relevant for
dd15-p1175 researchers and practitioners interested in detecting exceptional transition behavior in sequential data. Keywords: Subgroup Discovery, Exceptional
dd15-p1185 Model Mining, Markov chains, Transitions, Sequential Data. 1. INTRODUCTION Exceptional Model Mining, a generalization of the classic subgroup
dd15-p1195 discovery task, is a framework that identifies patterns which contain unusual interactions between multiple target attributes. In order to obtain
dd15-p1205 operationalizable insights, it emphasizes the detection of easy-to-understand subgroups, i.e., it aims to find exceptional subgroups with descriptions
dd15-p1215 that are directly interpretable by domain experts. In general, exceptional model mining-Permission to make digital or hard copies of all or part of this work
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dd15-p1285 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
dd15-p1305 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
dd15-p1315 implicitly specified) candidate set, using only the instances covered by the respective subgroup. A subgroup is considered as exceptional or
dd15-p1325 interesting if its parameter values differ significantly from the ones of the overall dataset. While exceptional model mining has been implemented for a
dd15-p1335 variety of model classes including classification, regression, Bayesian network and rank models, it has not yet been applied using models
dd15-p1345 for sequential data. In this paper, we aim to apply exceptional model mining to discover interpretable subgroups with exceptional transition behavior.
dd15-p1375 This enables a new analysis method for a variety of applications. As one example, assume a human mobility dataset featuring user transitions between
dd15-p1385 locations. The overall transition model could for example show that people either move within their direct neighborhood or along main roads. Detecting
dd15-p1395 subgroups with exceptional transition behavior goes beyond this simple analysis: It allows to automatically identify subgroups of people (such as "male
dd15-p1405 tourists from France") or subsegments of time (such as "10 to 11 p.m.") that exhibit unusual movement characteristics, e.g., tourists moving
dd15-p1415 between points of interest or people walking along well-lit streets at night. Other application examples could include subgroups of web-users with
dd15-p1425 unusual transition behavior or subgroups of companies with unusual development over time. The main contribution of this paper is a new method
dd15-p1445 that enables mining subgroups with exceptional transition behavior by introducing first-order Markov chains as a novel model class for exceptional
dd15-p1455 model mining. Markov chains have been utilized for studying sequential data about, e.g., human behavior and mobility, recommendation, or
dd15-p1465 spamming. To apply exceptional model mining with this model, we derive an exceptional transition measure that quantifies the exceptionality of a subgroup's
dd15-p1475 transition model. It measures how much the transition matrix of a subgroup and the respective matrix of the entire data
dd15-p1485 deviates from the transition matrix of random dataset samples. This measure can be integrated into any known search algorithm. We also show how an
dd15-p1495 adaptation of our approach allows to find subgroups specifically matching (or contradicting) given hypotheses about transition behavior (cf.). This
dd15-p1505 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
dd15-p1515 the proposed approach with synthetic as well as real-world data. 965 The remainder of this work is organized as following: We summarize our
dd15-p1525 background in Section 2. Then, the main approach for mining subgroups with exceptional transition behavior is introduced in Section 3. Section 4
dd15-p1535 presents experiments and results. Finally, we discuss related work in Section 5, before we conclude in Section 6. 2. BACKGROUND Our solution
dd15-p1545 extends Exceptional Model Mining with first-order Markov Chain Models. In the following, we give a brief overview of both techniques. 2.1
dd15-p1555 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
dd15-p1565 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
dd15-p1575 cover c , i.e., the set of instances described by p , i.e., $c = \{I \mid p(I)\}$. In principle, our approach works with any pattern description language to describe

ignore

11 ca

12 kdd

13 acm

14 august

15 copyright

16 keywords

17 san francisco

18 introduction

19 isbn

20 experiments

Method

21 barabasi-albert

22 progressive sampling

23 heuristic

24 monte-carlo, montecarlo

25 non-linear optimization

26 map-reduce, mapreduce

27 poisson process

28 en algorithm

29 cmpp

30 random sampling

31 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

57

58 standard error

59 z-score

60 normality

61 p-value

62 critical value

63 total variation

64 statistical significance

65 quality measure

66 accuracy

67 euclidean norm, euclidean distance

68 infection rate

69

70 wikileaks

71 facebook

72 synthetic data

73 real-world

74 flickr

75 lastfm

76 bms-pos

77 fimi

78 sequential data

79 linkedin

80

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

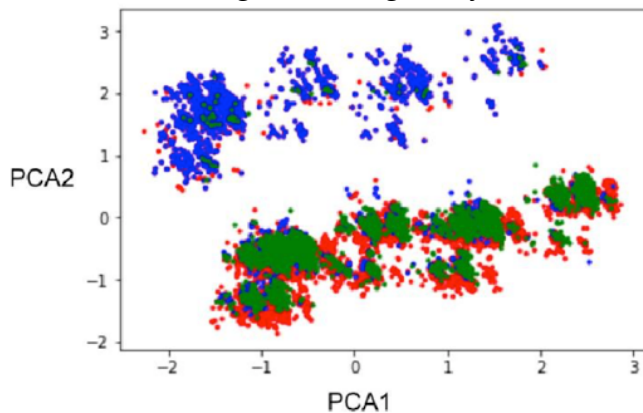


Fig.6 True label

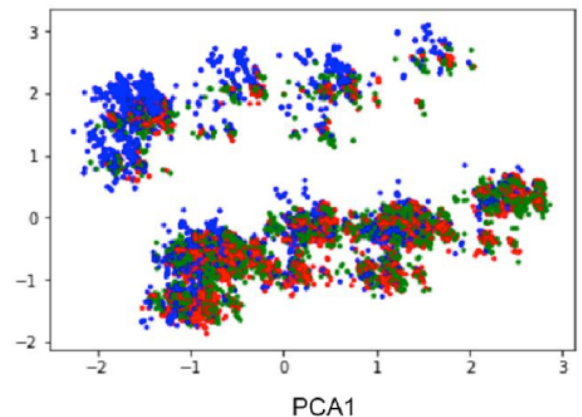
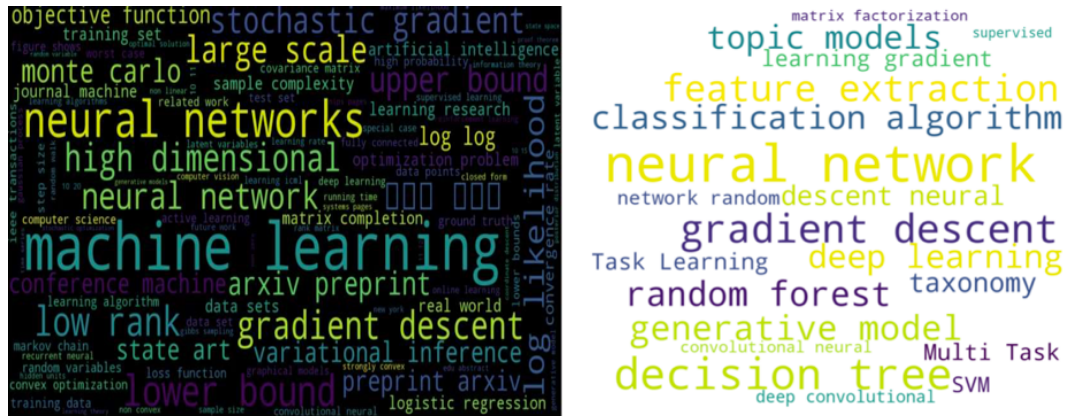


Fig.7 Clustering labels

(3) Word cloud of entity clusters



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

