
POWER
RANGERS
Triceratops


POWER
RANGERS
Tyrannosaurus


MIGHTY
MORPHIN
POWER
RANGERS


POWER
RANGERS
Saber-Toothed Tiger

SciBot: A Data Science Research Bot

— Data Science Course Project

Meng Jiang

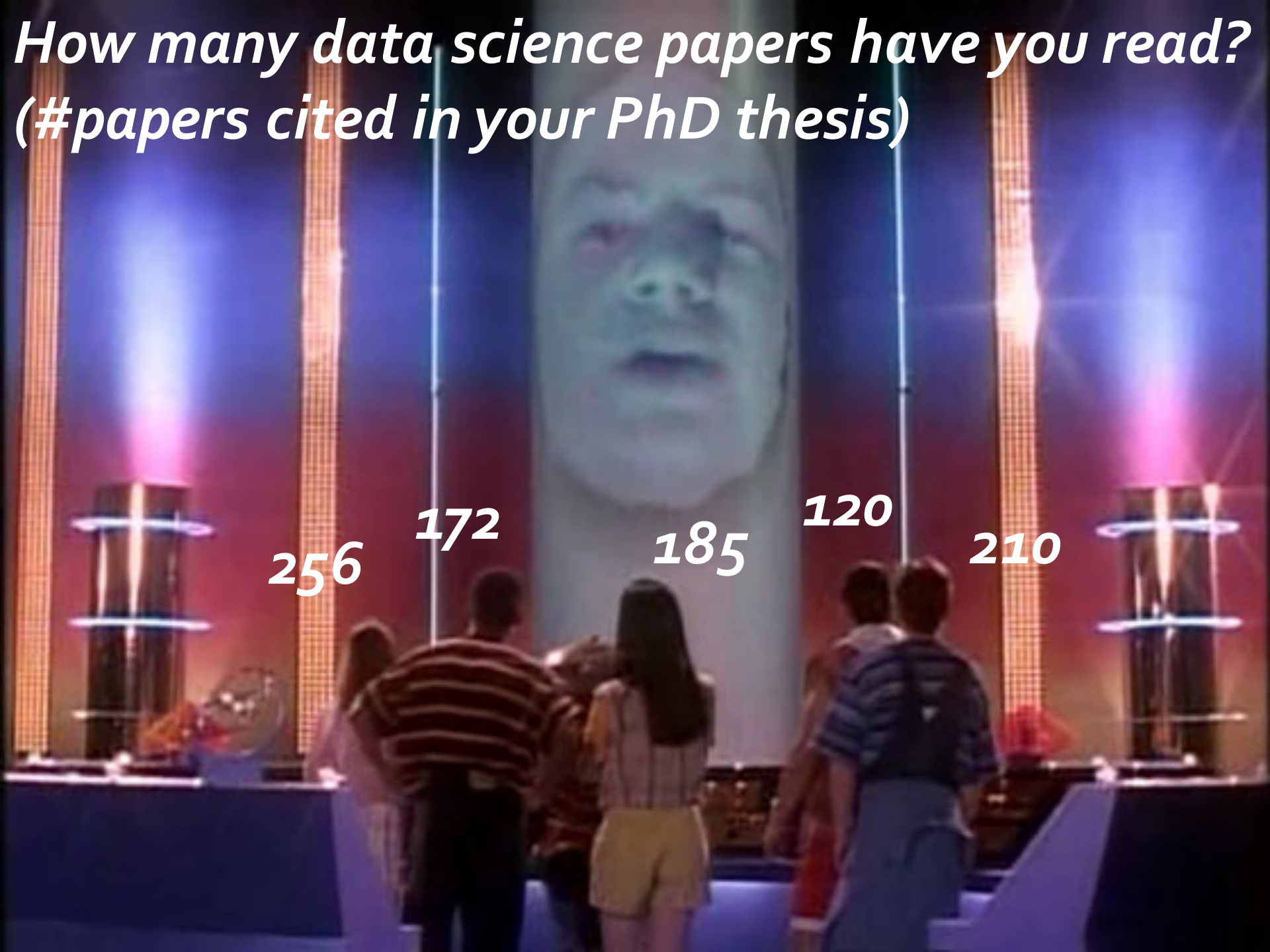
Data Science


Dr. Zordon: *Alpha, find me a data scientist!*
http://powerrangers.wikia.com/wiki/Zordon

Salaries in $ (USD)	Average	Min	Max
Data Scientist Facebook 61 salaries	$134,715 per year	$100k	$180k
Data Scientist Microsoft 41 salaries	$123,328 per year	$94k	$152k
Data Scientist IBM 36 salaries	$109,864 per year	$81k	$144k
Data Scientist Apple 13 salaries	$145,974 per year	$120k	$177k
Data Scientist Google 11 salaries	$152,856 per year	$103k	$210k
Data Scientist Uber 17 salaries	$122,432 per year	$103k	$152k
Data Scientist Civis Analytics 16 salaries	$76,284 per year	$61k	$95k
Data Scientist	$132,196	$111k	4$261k

They are too expensive!

https://www.glassdoor.com/Salaries/data-scientist-salary-SRCH_KO0,14.htm


How many data science papers have you read?
(#papers cited in your PhD thesis)
256
172
185
120
210

How many papers we grabbed from the web?

5,853 papers from 4 data science conferences!

KDD: ACM SIGKDD Conference on Knowledge Discovery and Data Mining (August)

1994 – 2015: collected 1,646 papers

'16: San Francisco; '17: Halifax, Canada; '18: London

Due: February

ICDM: IEEE International Conference on Data Mining (December)

2001 – 2015: collected 881 papers

'16: Barcelona; '17: New Orleans

Due: June

WWW: International World Wide Web Conference (April)

2001 – 2015: collected 2,975 papers

'16: Montreal, Canada; '17: Perth, Australia; '18: Lyon, France

Due: October

WSDM: ACM International Conference on Web Search and Data Mining (February)

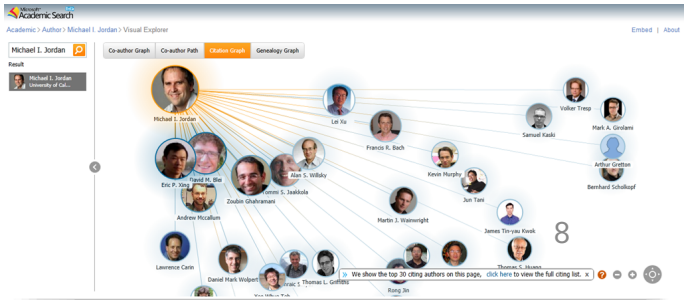
2008 – 2015: collected 351 papers

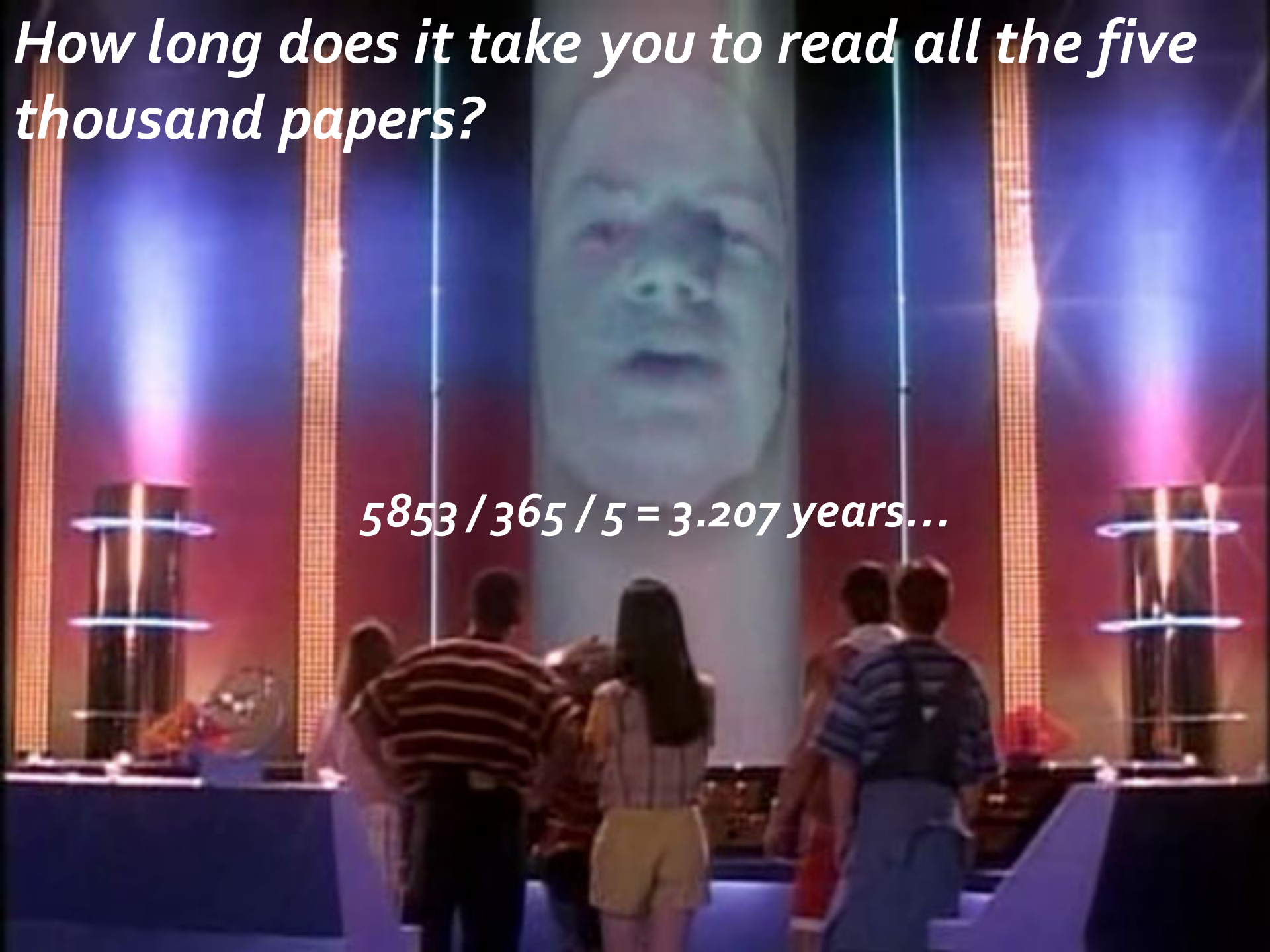
'16: San Fancisco; '17: Cambridge, UK; '18: Los Angeles

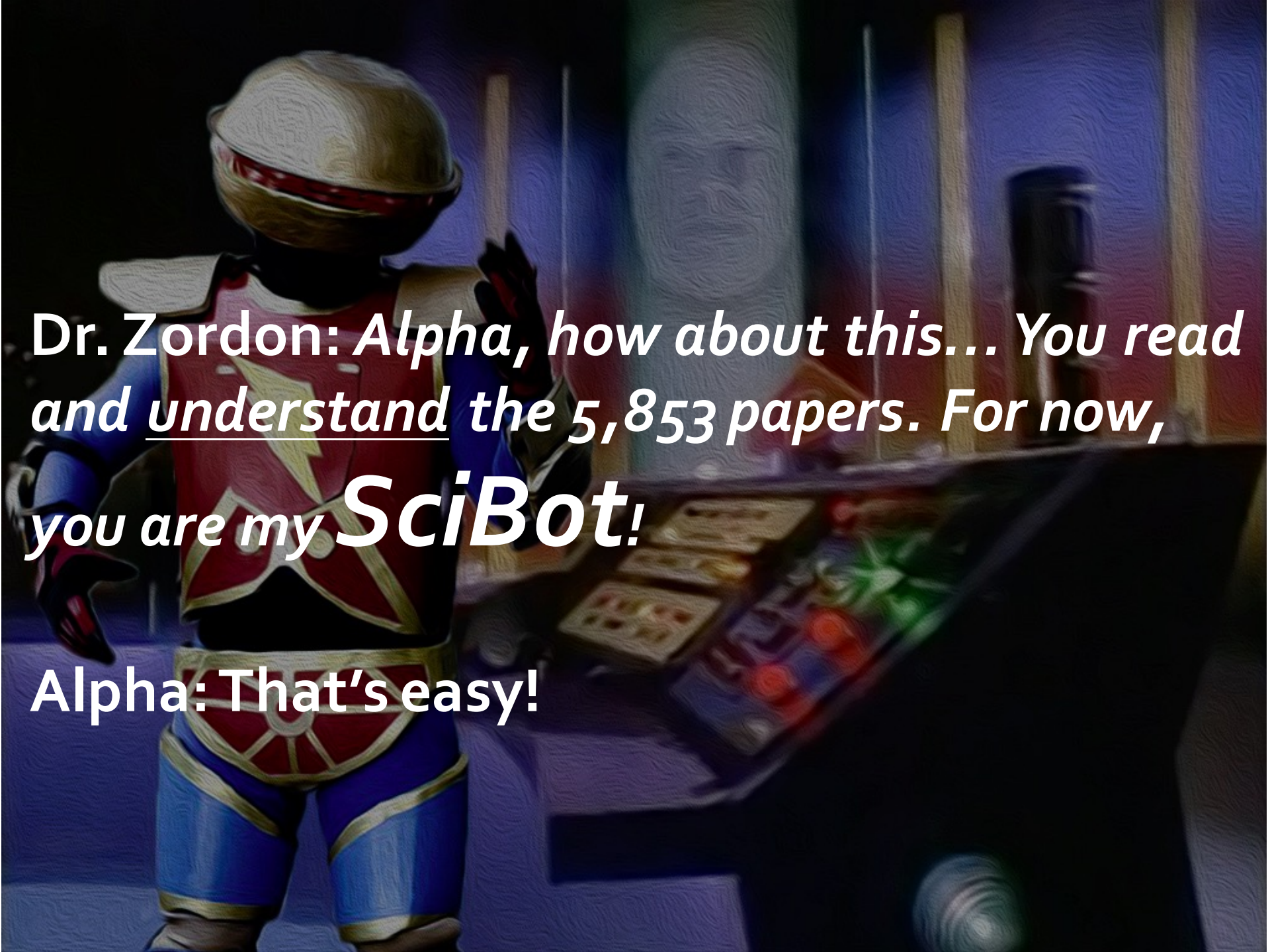
Due: August

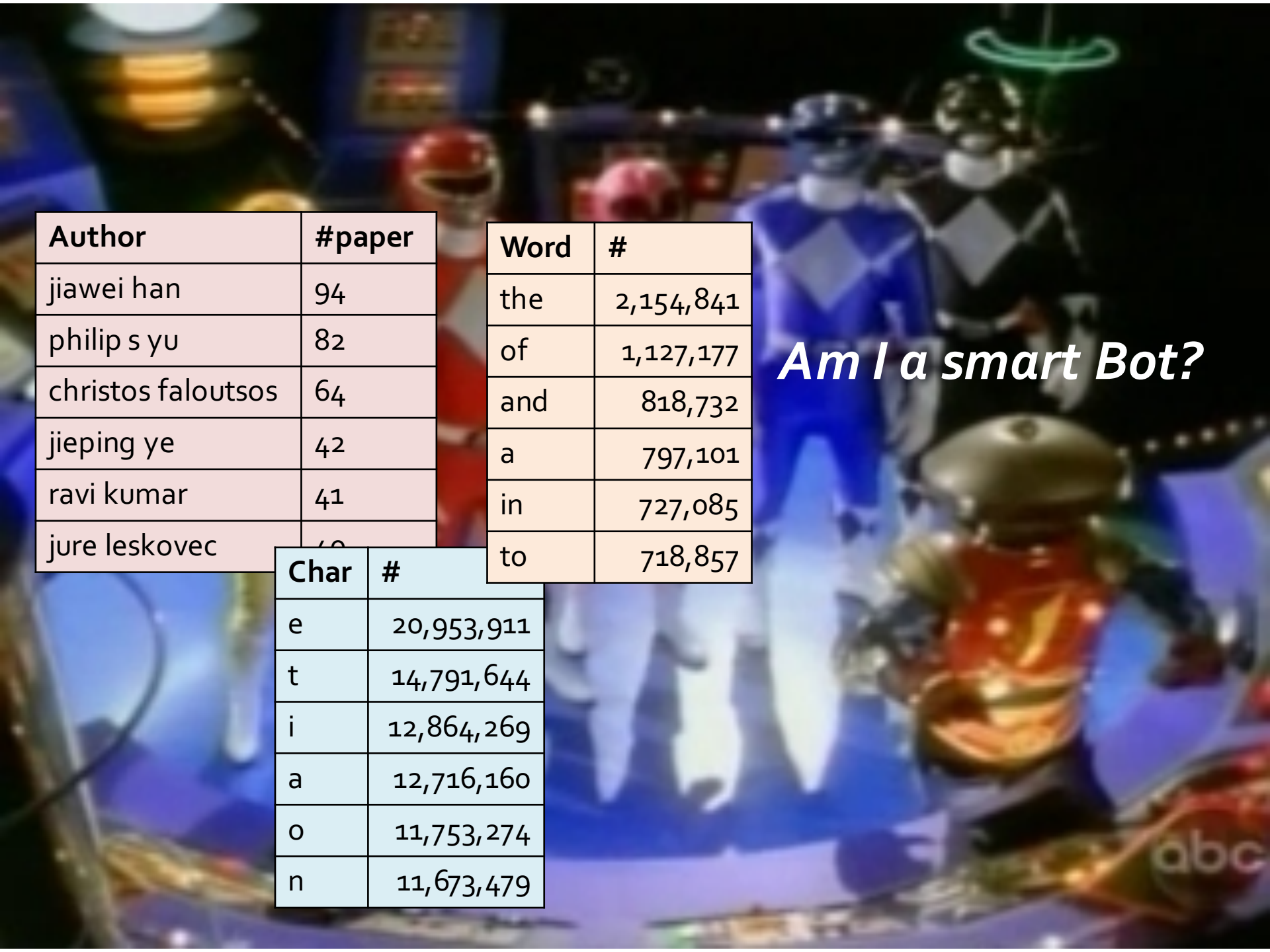
Dataset Introduction

- pdf (5.5G): https://www.dropbox.com/s/46oh772tpuceew5/pdf.zip?dl=0
  - "icdm01-d3.pdf"
  - Not recommended
- text (270M): https://www.dropbox.com/s/oof7qjb5mobmfvt/text.zip?dl=0
  - "icdm01-d3.txt"
  - **Recommended to skip the REFERENCES section.**
- microsoft (100M): https://www.dropbox.com/s/09qzhbddopmk5wm/microsoft.zip?dl=0
  - **index.txt: PID, PDFID**
  - **Papers.txt: PID, TITLE, YEAR, CONF**
  - **PaperKeywords.txt: PID,KEYWORD**
  - **PaperAuthorAffiliation.txt: PID,AID, FID, AFF, SID**
  - **Authors.txt: AID, AUT**




How long does it take you to read all the five thousand papers?
5853 / 365 / 5 = 3.207 years…


Dr. Zordon: *Alpha, how about this… You read and understand the 5,853 papers. For now, you are my* **SciBot**!
Alpha: That's easy!

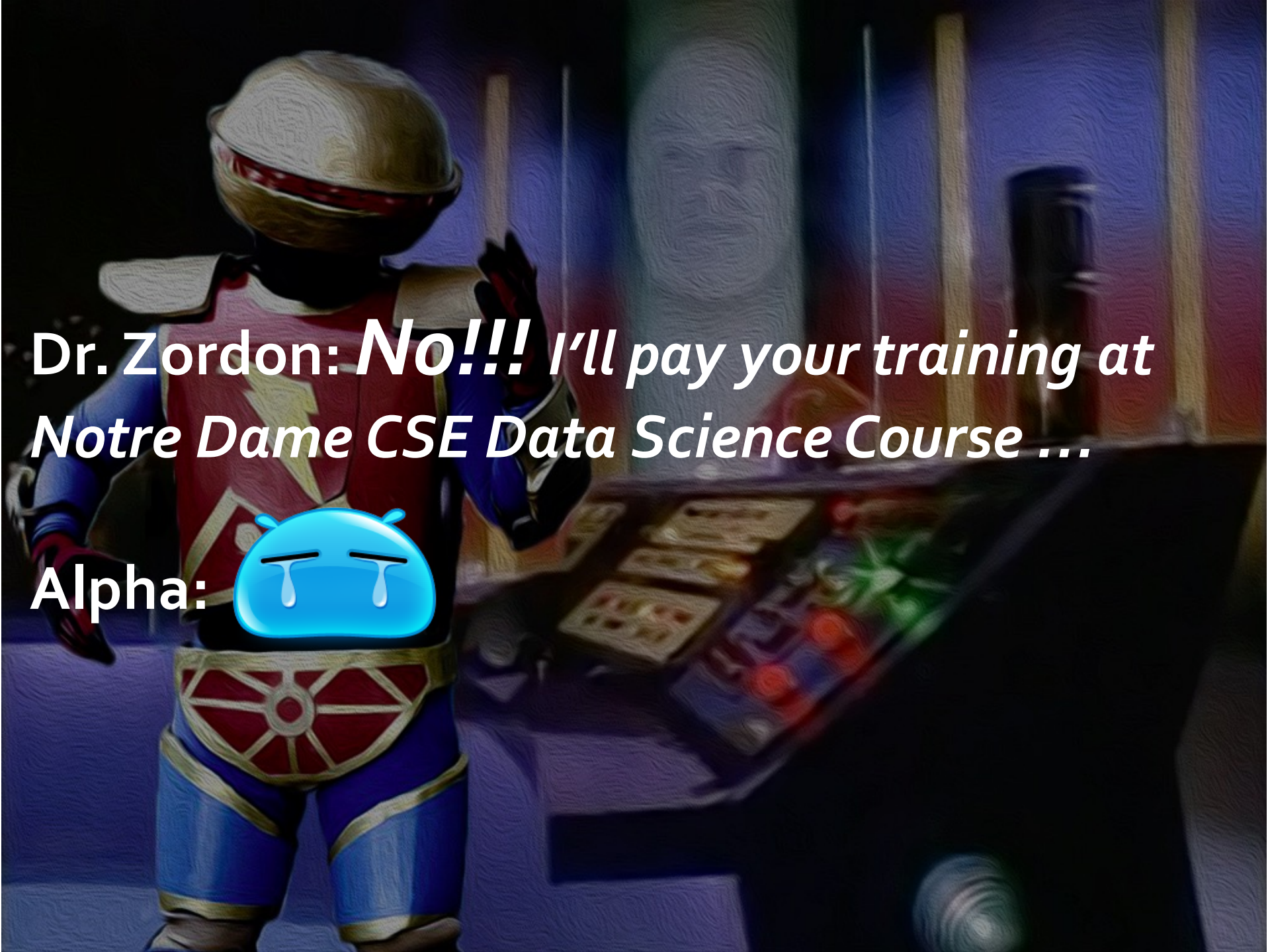


Author	#paper
jiawei han	94
philip s yu	82
christos faloutsos	64
jieping ye	42
ravi kumar	41
jure leskovec	

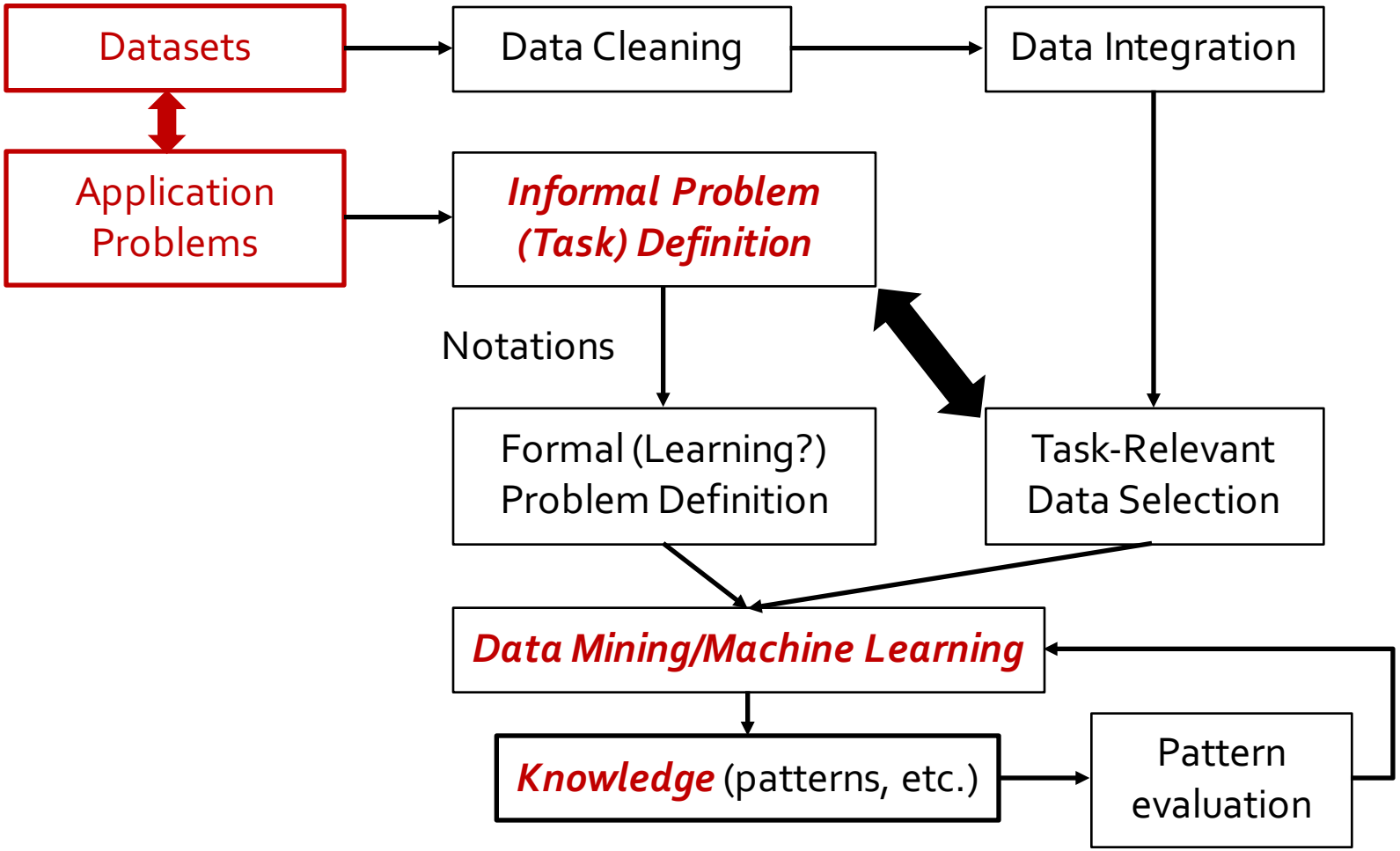
Word	#
the	2,154,841
of	1,127,177
and	818,732
a	797,101
in	727,085
to	718,857

Char	#
e	20,953,911
t	14,791,644
i	12,864,269
a	12,716,160
o	11,753,274
n	11,673,479

Am I a smart Bot?


Dr. Zordon: No!!! I'll pay your training at Notre Dame CSE Data Science Course …
Alpha:

Data Science Research



Seven Required Tasks: Task 4-7

Concepts and Methods:

Task 4: Collaboration discovery → Frequent pattern mining

Task 5: Problem-method association mining → Association rule mining

Task 6: Problem/method/author-to-conference classification → Classification

Task 7: Paper clustering → Clustering

Task 4

Concepts and Methods:

Task 4: Collaboration discovery → Frequent pattern mining

Task 5: Problem-method → Association rule mining
association mining

Task 6
to-con

Task 7

Given the paper/keyword/conference-author data, find frequent author-sets (as patterns): which two/three/four authors often collaborate together?
Techs: Frequent pattern mining (Apriori, FP-Growth).
Hints: Here each paper is considered as a transaction. Each author is an item.

Task 5

Concepts and Methods:

Task 4: Collaboration discovery → Frequent pattern mining

Task 5: Problem-method association mining → Association rule mining

Task 6: Proble... to-conference

Task 7: Paper ...

Given the paper-problem-method data, find strong association rules:
problem X → method Y, or
method X → problem Y,
of high support and confidence.
Techs: Association rule mining.

Task 6

Concepts and Methods:

Task 4: Collaboration discovery ⟶ Frequent pattern mining

Given a problem/method/author, predict if a conference has papers of it.
Techs: Binary classification (Naïve Bayes, Decision Tree).

Task 6: Problem/method/author-to-conference classification ⟶ Classification

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

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.

Task 7: Paper clustering ⟶ Clustering

Seven Required Tasks: Task 1-3

- Process raw data into *clean*, *multi-dimensional* tabulated data.

PID	YEAR	CONF	TITLE	KEYWORDS
776E2648	2010	kdd	new perspectives	machine learning|networks|supervised learning|variance reduction
784B7EF4	2014	kdd	improving manage	clustering|data mining|invasive species|networks|risk assessment
7E395F14	2008	icdm	start globally opti	data mining|global optimization|learning artificial intelligence|optimization|probabili

SEQ_AUTHOR_AFFS
1:109A673C:ryan n lichtenwalter:066A71BC:university of notre dame|2:7DA9ABBD:jake t lussier:066A71BC:university of notre da
1:7E5C680D:jian xu:066A71BC:university of notre dame|2:5DAE606C:thanuka l wickramarathne:066A71BC:university of notre da
1:7776FD94:david a cieslak:066A71BC:university of notre dame|2:76014D6E:nitesh v chawla:066A71BC:university of notre dame

PROBLEMS	METHODS	DATASETS	METRICS
???	???	???	???
???	???	???	???
???	???	???	???

From structured tables

From unstructured paper text

Large-Scale Distributed Bayesian Matrix Factorization using Stochastic Gradient MCMC

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ABSTRACT

Despite having various attractive qualities such as high prediction accuracy and the ability to quantify uncertainty and avoid over-fitting, Bayesian Matrix Factorization has not been widely adopted because of the prohibitive cost of inference. In this paper, we propose a scalable distributed Bayesian matrix factorization algorithm using stochastic gradient MCMC. Our algorithm, based on Distributed Stochastic Gradient Langevin Dynamics, can not only match the prediction accuracy of standard MCMC methods like Gibbs sampling, but at the same time is as fast and simple as stochastic gradient descent. In our experiments, we show that our algorithm can achieve the same level of prediction accuracy as Gibbs sampling an order of magnitude faster. We also show that our method reduces the prediction error as fast as distributed stochastic gradient descent, achieving a 4.1% improvement in RMSE for the Netflix dataset and an 1.8% for the Yahoo music dataset.

Categories and Subject Descriptors

G.4 [**Mathematical Software**]: Algorithm design and analysis; Parallel and vector implementations

Keywords

Large-Scale, Distributed, Matrix Factorization, MCMC, Stochastic Gradient, Bayesian Inference

1. INTRODUCTION

Recommender systems have become a p
to understand customers and their interest
range between music recommendation (Pa
dation (Amazon), movie recommendation
mendation (Yahoo) to partner recommend
ommender systems represent a personali
help filter at an individual level the enorm
tion that is available to us. Given the exp
recommender systems are likely to play a
role to manage our information streams.

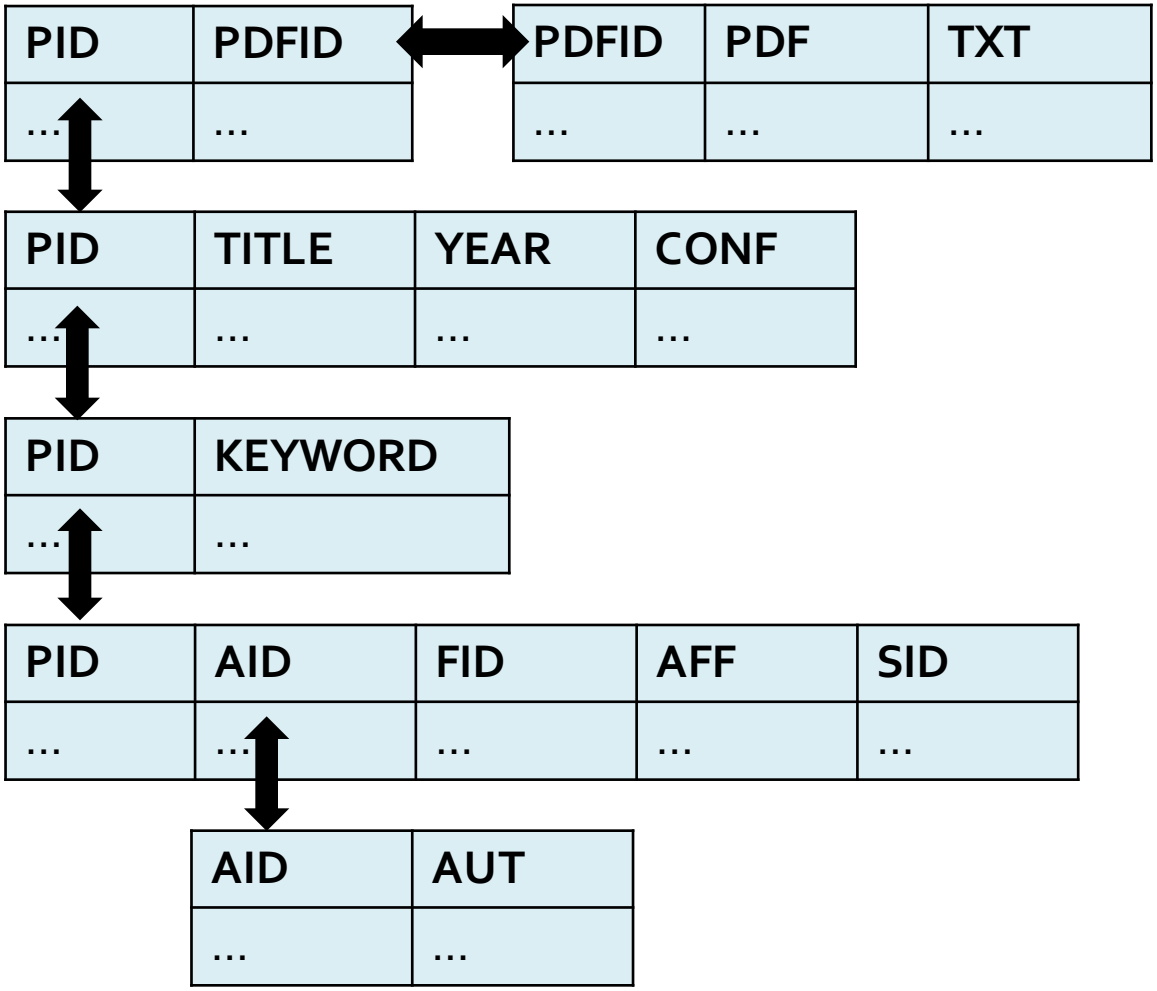
During 2006-2011 Netflix [6] ran a c
around the world could develop and test
nology on Netflix movie rating data. A fe
learnt from that exercise. First, matrix fac
very well compared to nearest neighbor ty
eraging over many different models pays o
accuracy. One particularly effective mod
bilistic matrix factorization (BPMF) [26] w
eraged over samples from the posterior d
proved prediction accuracy, a full Bayesi
with additional advantages such as probab
fidence intervals, robustness against overf
prior knowledge and side-information [2,

Unfortunately, since the number of user-
easily run into the billions, posterior infe

Dimension	Value	Dimension	Value
PROBLEM	prediction	DATASET	netflix
METRIC	prediction accuracy	DATASET	yahoo music
PROBLEM	uncertainty	PROBLEM	recommender systems
PROBLEM	over-fitting	PROBLEM	music recommendation
METHOD	Bayesian matrix factorization	PROBLEM	book recommendation
PROBLEM	prohibitive cost of inference	PROBLEM	movie recommendation
METHOD	scalable distributed Bayesian matrix factorization	PROBLEM	news recommendation
METHOD	stochastic gradient mcmc	PROBLEM	partner recommendation
METHOD	distributed stochastic gradient langevin dynamics	PROBLEM	recommender systems
METHOD	mcmc	DATASET	netflix
METHOD	gibbs sampling	PROBLEM	recommender
METHOD	stochastic gradient descent	DATASET	netflix movie rating
PROBLEM	prediction	METHOD	bayesian probabilistic matrix factorization
METRIC	accuracy	METHOD	posterior distribution
METHOD	gibbs sampling	METHOD	bayesian analysis
METRIC	prediction error	METRIC	confidence intervals
METHOD	distributed stochastic gradient descent	METRIC	robustness
METRIC	rmse		


Labeling 5,853 papers?
You must be kidding me!!!

Task 1: Data Cleaning and Integration



Missing data
Noisy data
....

Task 2: Entity Name Recognition

- 2.1 Candidate generation + 2. 2 Quality assessment

PHRASE	QUALITY SCORE AS AN ENTITY NAME
latent_dirichilet_allocation	0.999
support_vector_machine	0.999
support_vector_machines	0.999
singular_value_decomposition	0.998
information_retrieval	0.998
mean_average_precision	0.997
collaborative_filtering	0.995
…	…
is_a	0.001

T2-1: Entity Name Candidate Generation

- You are recommended to try both methods.
- Method 1: N-Grams
  - 2-grams: "matrix factorization"
  - 3-grams: "bayesian matrix factorization"
  - …
- Method 2: Frequent pattern mining
  - Minimum support (frequency)
  - Apriori property
- Method 3: Hand-crafted rules
  - "… Support Vector Machines …"
  - "… support vector machines (SVMs) …"
  - "… non-negative matrix factorization (NMF) …"

Examples (Method 3): Rule Matching

```
SVM     345     Support Vector Machine:137|Support Vector Machines:78|support vector m
achine:74|support vector machines:43|Support vector machine:7|Support vector machines:
4|Support Vectors Machine:2
LDA     289     Latent Dirichlet Allocation:173|latent Dirichlet allocation:58|Linear
Discriminant Analysis:19|linear discriminant analysis:15|Latent Dirichlet allocation:1
2|latent dirichlet allocation:3|Linear discriminant analysis:2|linear discriminative a
nalysis:2|linear discrimination algorithm:1|Latent Dirchlet Allocation:1|latent Dirich
let Allocation:1|latent Drichlet association:1|latent dirichelet allocation:1
MAP     202     Mean Average Precision:61|mean average precision:60|maximum a posterio
ri:47|maximum a posterior:10|Maximum a Posteriori:8|Maximum A Posterior:6|Maximum A Po
steriori:4|Mean average precision:3|Maximum a posteriori:3
IR      164     information retrieval:86|Information Retrieval:53|implicit relatedness
:5|instance reduction:2|Information retrieval:2|Internal Representation:2|internal rep
resentation:2|Intermediate Representation:2|imbalance ratio:1|individually rational:1|
Instance Ranking:1|Interactions Rank:1|Identifier Renaming:1|indirect retweet:1|implic
ated relatedness:1|indirect Retweet:1|image rank:1|intermediate representation:1
SVD     159     singular value decomposition:74|Singular Value Decomposition:73|Singul
ar value decomposition:3|Singular Value Decompositions:3|singular value decompositions
:2|singular value decomposing:1|Single Value Decomposition:1|singular vector decomposi
tion:1|Singular vector decomposition:1
WWW     145     World Wide Web:140|World wide web:4|world wide web:1
PCA     136     Principal Component Analysis:62|principal component analysis:35|Princi
ple Component Analysis:11|Principal Components Analysis:7|Principal component analysis
:7|principle component analysis:6|principal components analysis:5|principle components
 analysis:2|partial completeness assumption:1
CF      122     collaborative filtering:51|Collaborative Filtering:37|Collaborative fi
ltering:22|concept feedback:2|Collaborating Filtering:1|Column Fusing:1|click feedback
:1|consistent framework:1|Content Fragments:1|clarification forms:1|Certainty Factor:1
|clustering feature:1|cluster feature:1|certainty factor:1
EM      112     Expectation Maximization:80|expectation maximization:24|Ensemble Media
n:2|Expected Maximization:1|Expectation maximization:1|Entity Matching:1|Expectation M
aximisation:1|edit map:1|Exact Match:1
RDF     96      Resource Description Framework:82|Resource description framework:9|res
ource description framework:2|Resource Description framework:2|Resource Definition For
mat:1
```

Examples (Method 3): Re-Matching for Support

```
latent_dirichlet_allocation     247     LDA:247
support_vector_machine  218     SVM:218
support_vector_machines 214     SVM:125|SVMs:89
singular_value_decomposition    150     SVD:150
world_wide_web  145     WWW:145
information_retrieval   141     IR:141
mean_average_precision  124     MAP:124
collaborative_filtering 110     CF:110
expectation_maximization        105     EM:105
principal_component_analysis    104     PCA:104
resource_description_framework  95      RDF:95
neural_information_processing_systems   93      NIPS:93
stochastic_gradient_descent     91      SGD:91
minimum_description_length      78      MDL:78
natural_language_processing     77      NLP:77
normalized_mutual_information   76      NMI:76
mean_reciprocal_rank    76      MRR:76
document_object_model   71      DOM:71
mean_absolute_error     69      MAE:69
logistic_regression     67      LR:67
normalized_discounted_cumulative_gain   66      NDCG:66
latent_semantic_indexing        63      LSI:63
maximum_a_posteriori    62      MAP:62
mean_squared_error      62      MSE:62
receiver_operating_characteristic       58      ROC:57|RoC:1
dynamic_time_warping    58      DTW:58
markov_chain_monte_carlo        57      MCMC:57
naive_bayes     57      NB:57
transactions_on_information_systems     56      TOIS:56
probabilistic_latent_semantic_analysis  52      PLSA:52
directed_acyclic_graph  51      DAG:51
open_directory_project  50      ODP:50
non-negative_matrix_factorization       50      NMF:50
national_science_foundation     50      NSF:50
hidden_markov_models    47      HMMs:26|HMM:21
maximum_likelihood_estimation   47      MLE:47
root_mean_square_error  47      RMSE:47
hidden_markov_model     45      HMM:45
conditional_random_fields       45      CRFs:26|CRF:19
matrix_factorization    44      MF:44
information_extraction  42      IE:42
named_entity_recognition        42      NER:42
root_mean_squared_error 39      RMSE:39
cumulative_distribution_function        39      CDF:39
nonnegative_matrix_factorization        39      NMF:39
```

T2-2: Entity Name Quality Assessment

- You are recommended to try all the measures.
- Measure 1: Support (Frequency)
  - Sentence, Paragraph, Document
- Measure 2: Outlier-ness measures (t-score, Z-score, etc.)

Church et al. https://pdfs.semanticscholar.org/ccd5/898c79f90c25e2422241od5613edfd007985.pdf

$$sig(P_1, P_2) \approx \frac{f(P_1 \oplus P_2) - \mu_0(P_1, P_2)}{\sqrt{f(P_1 \oplus P_2)}}$$

"bayesian matrix factorization"?

Pedersen. http://www.d.umn.edu/~tpederse/Pubs/scsug96.pdf
El-Kishky et al. http://www.vldb.org/pvldb/vol8/p305-ElKishky.pdf

- Other measures:
  - "in_this", "at_the" …
  - "turn_out_to_be", "increased_by" …
  - "in_this_paper" …
  - "data sets", "real data" …

Thresholds?

Classification?

Task 3: Entity Typing

- Trigger words
  - METHOD: method algorithm model approach framework process scheme implementation procedure strategy architecture
  - PROBLEM: problem technique process system application task evaluation tool paradigm benchmark software
  - DATASET: data dataset database
  - METRIC: value score measure metric function parameter
- Classification using contextual features and **Evaluation**

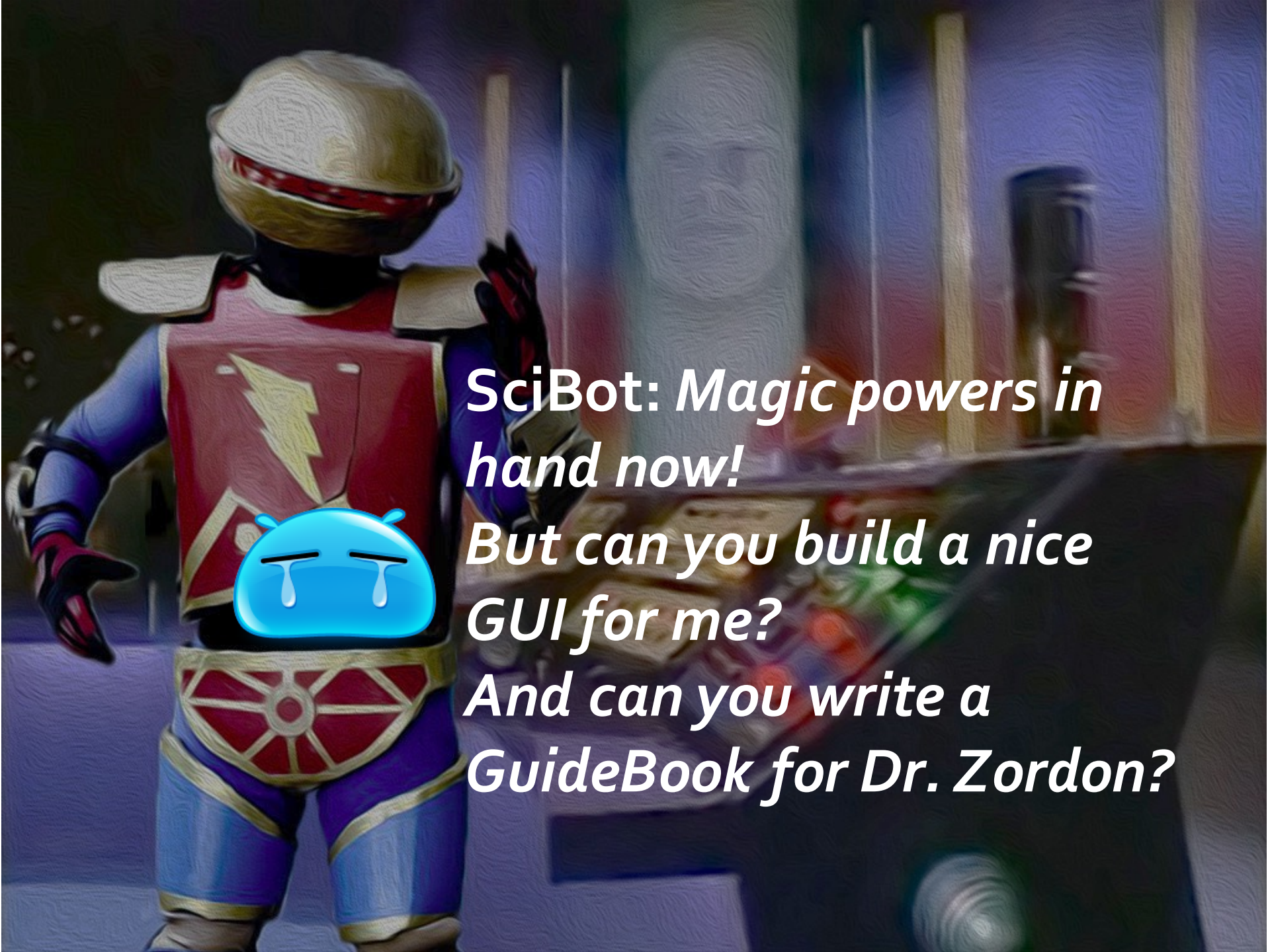
```
collaborative_filtering 967     METHOD:729|PROBLEM:217|DATASET:18|METRIC:3
feature_selection       895     METHOD:708|PROBLEM:138|METRIC:48|DATASET:1
link_prediction 641     PROBLEM:348|METHOD:204|METRIC:89
active_learning 588     METHOD:492|PROBLEM:96
latent_dirichlet_allocation     538     METHOD:530|PROBLEM:6|DATASET:2
matrix_factorization    518     METHOD:354|PROBLEM:164
supervised_learning     503     METHOD:347|PROBLEM:153|METRIC:2|DATASET:1
logistic_regression     490     METHOD:443|PROBLEM:31|METRIC:16
expectation_maximization        434     METHOD:426|PROBLEM:5|METRIC:3
social_network  391     DATASET:280|METHOD:68|PROBLEM:40|METRIC:3
binary_classification   391     PROBLEM:328|METHOD:48|DATASET:11|METRIC:4
resource_description_framework  367     DATASET:267|METHOD:92|PROBLEM:8
random_walk     367     METHOD:313|DATASET:27|METRIC:14|PROBLEM:13
```

Examples (Entity Typing)

METHOD	latent_dirichlet_allocation	247	LDA:247
METHOD	support_vector_machine	218	SVM:218
METHOD	support_vector_machines	214	SVM:125|SVMs:89
METHOD	singular_value_decomposition	150	SVD:150
DATASET	world_wide_web	145	WWW:145
PROBLEM	information_retrieval	141	IR:141
METRIC	mean_average_precision	124	MAP:124
METHOD	collaborative_filtering	110	CF:110
METHOD	expectation_maximization	105	EM:105
METHOD	principal_component_analysis	104	PCA:104
DATASET	resource_description_framework	95	RDF:95
DATASET	neural_information_processing_systems	93	NIPS:93
METHOD	stochastic_gradient_descent	91	SGD:91
METRIC	minimum_description_length	78	MDL:78
PROBLEM	natural_language_processing	77	NLP:77
METRIC	normalized_mutual_information	76	NMI:76
METRIC	mean_reciprocal_rank	76	MRR:76
METHOD	document_object_model	71	DOM:71
METRIC	mean_absolute_error	69	MAE:69
METHOD	logistic_regression	67	LR:67
METRIC	normalized_discounted_cumulative_gain	66	NDCG:66
METHOD	latent_semantic_indexing	63	LSI:63
METHOD	maximum_a_posteriori	62	MAP:62
METRIC	mean_squared_error	62	MSE:62
METRIC	receiver_operating_characteristic	58	ROC:57|RoC:1
METHOD	dynamic_time_warping	58	DTW:58
METHOD	markov_chain_monte_carlo	57	MCMC:57
METHOD	naive_bayes	57	NB:57
ENTITY	transactions_on_information_systems	56	TOIS:56
METHOD	probabilistic_latent_semantic_analysis	52	PLSA:52
METHOD	directed_acyclic_graph	51	DAG:51
DATASET	open_directory_project	50	ODP:50
METHOD	non-negative_matrix_factorization	50	NMF:50
DATASET	national_science_foundation	50	NSF:50
METHOD	hidden_markov_models	47	HMMs:26|HMM:21
METHOD	maximum_likelihood_estimation	47	MLE:47
METRIC	root_mean_square_error	47	RMSE:47
METHOD	hidden_markov_model	45	HMM:45
METHOD	conditional_random_fields	45	CRFs:26|CRF:19
METHOD	matrix_factorization	44	MF:44
PROBLEM	information_extraction	42	IE:42
PROBLEM	named_entity_recognition	42	NER:42
METRIC	root_mean_squared_error	39	RMSE:39
METRIC	cumulative_distribution_function	39	CDF:39
METHOD	nonnegative_matrix_factorization	39	NMF:39
METHOD	vector_space_model	38	VSM:38
ENTITY	defense_advanced_research_projects_agency	37	DARPA
METRIC	information_gain	37	IG:37

Review: Seven Required Tasks

- T1: Data cleaning and data integration (D.P.)
- T2: Entity name recognition (D.P.)
- T3: Entity typing (D.P./Cla.) + Eval.
- T4: Collaboration discovery (F.P.M.)
- T5: Problem-method association mining (A.R.M.)
- T6: Problem/method/author classification (Cla.) + Eval.
- T7: Paper clustering (Clu.) + Eval.
  - D.P. = Data preprocessing; Cla. = Classification
  - F.P.M. = Frequent pattern mining; Clu. = Clustering
  - A.R.M. = Association rule mining


SciBot: *Magic powers in hand now!*
But can you build a nice GUI for me?
And can you write a GuideBook for Dr. Zordon?

Policy, Requirement, Grading
before Recommended Tasks

- 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**.
- Students are required to submit their code package + "readme" (.ZIP) and project report/paper (.PDF). There is no paper template requirement.
- The project due is ***Nov 30, 2017***. There will be ***NO extension***. **Significant updates** are welcome **before the final exam** – students can send updates to the instructor after the due by e-mail but they **have to submit one version before the due**.
- **HWs will be designed to follow-up your progress ☺**
  - **Milestones**

Milestones!!!

- T1: Data cleaning and data integration (D.P.)
- T2: Entity name recognition (D.P.) **– HW3 (Oct. 3)**
- T3: Entity typing (D.P./Cla.) + Eval.
- T4: Collaboration discovery (F.P.M.)
- T5: Problem-method association mining (A.R.M.) **– HW4 (Nov. 9)**
- T6: Problem/method/author classification (Cla.) + Eval.
- T7: Paper clustering (Clu.) + Eval.
  - D.P. = Data preprocessing; Cla. = Classification
  - F.P.M. = Frequent pattern mining; Clu. = Clustering
  - A.R.M. = Association rule mining **– Project (Nov. 30)**

~~Individual Project!~~

[updated Sept. 28, 2017]

Team Project

- A team will have at most 2 members.
- Students will give their partner's name (or N/A – if by their own) in HW3.
- Members in the same team will have the same score.
- In last two lectures we tend to grade individual projects/undergraduates better than team projects/graduates if they generate the same results.

[updated Sept. 28, 2017]

Grading

- Students will **volunteer to present** their SciBot (tech and results) **in the last 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 points – but *finishing in high quality yes* – or you can have all points if you do *required tasks in low quality* but *some more* tasks.
- 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.

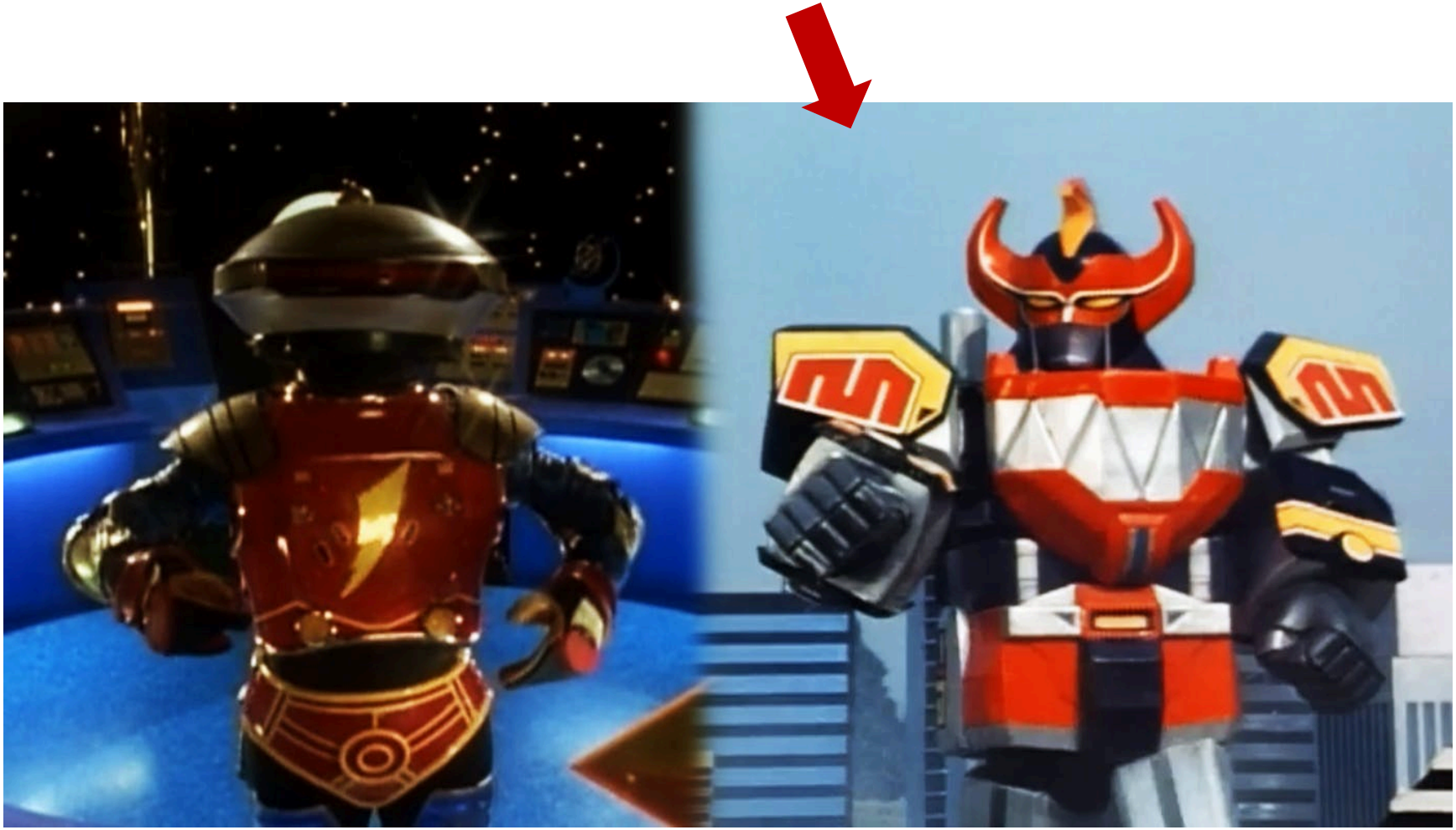
[updated Sept. 28, 2017]

What Are Encouraged?

- 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".

https://piazza.com/class/j6dmfs52c6d5ov

Your SciBot



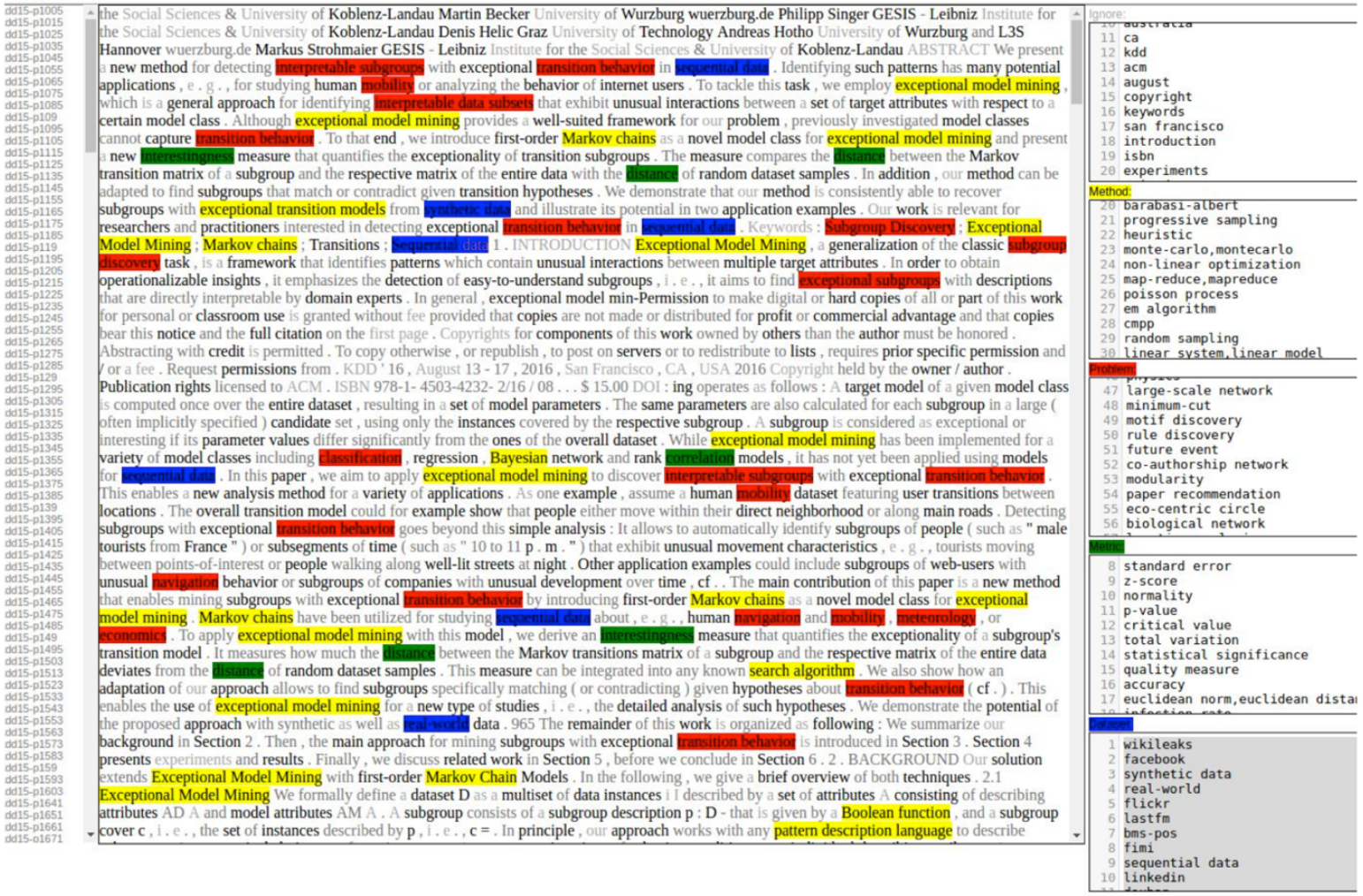
FAQ

- Q1:
- A1:
- Q2:
- A2:

Next: Recommended tasks

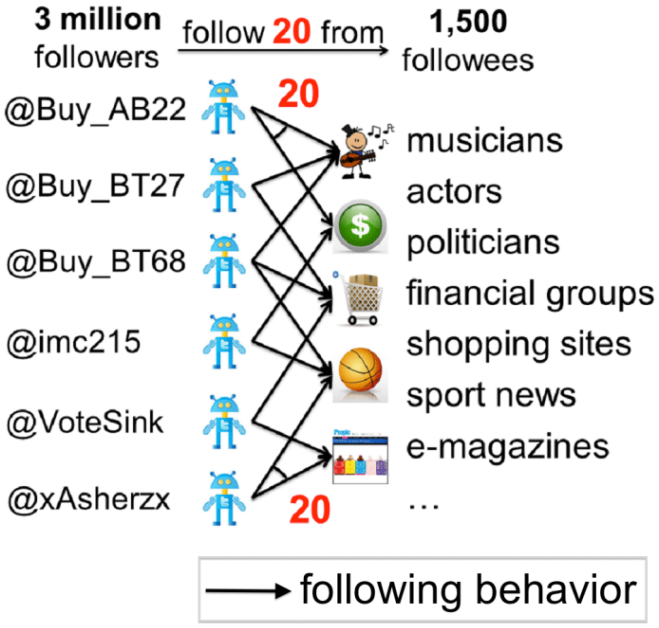
WebUI for Annotation

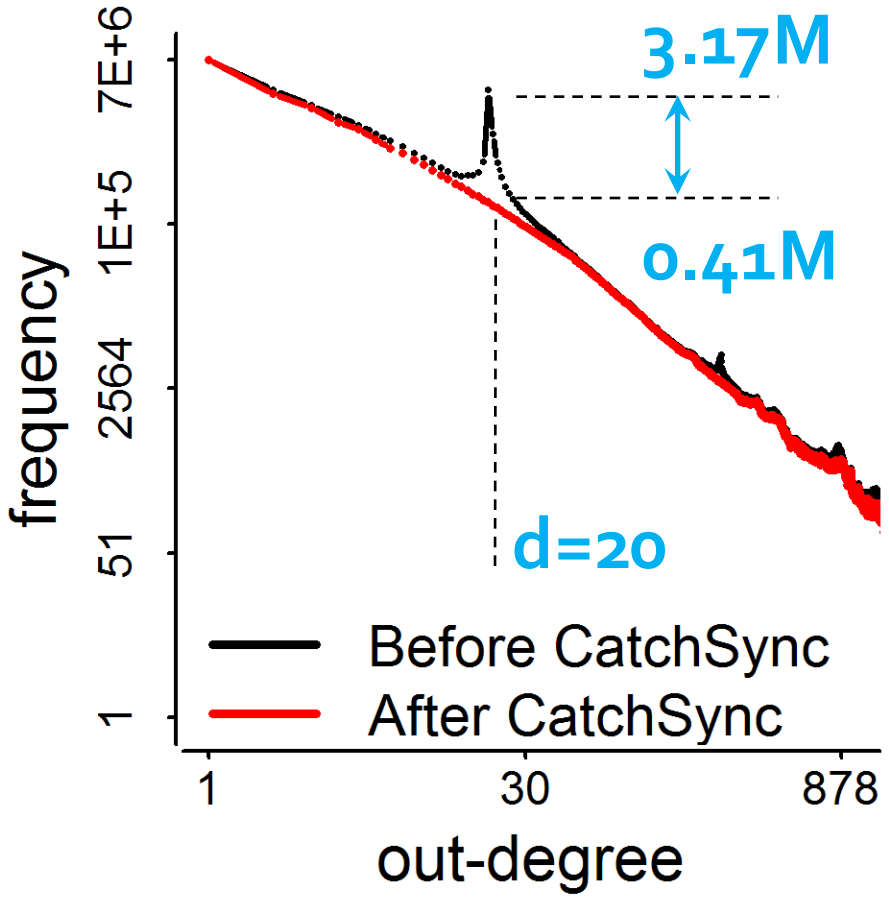
- From UIUC CS412 Summer'17



Task 1+: Degree Distributions

- Regression
  - Linear, Power-law
  - Poisson, Gaussian





CatchSync (KDD'14): http://www.meng-jiang.com/pubs/catchsync-kdd14/catchsync-kdd14-paper.pdf
KONECT network collection: http://konect.uni-koblenz.de/networks/

Task 3+: Entity *Cluster* Typing

- First entity clustering and then typing
  - High confidence on one entity's type will help to type other entities in the same cluster
  - What are the features for entity clustering?

```
METHOD  latent_dirichlet_allocation     247     LDA:247
METHOD  support_vector_machine  218     SVM:218
METHOD  support_vector_machines 214     SVM:125|SVMs:89
METHOD  singular_value_decomposition    150     SVD:150
DATASET world_wide_web  145     WWW:145
PROBLEM information_retrieval   141     IR:141
METRIC  mean_average_precision  124     MAP:124
METHOD  collaborative_filtering 110     CF:110
METHOD  expectation_maximization        105     EM:105
METHOD  principal_component_analysis    104     PCA:104
DATASET resource_description_framework  95      RDF:95
DATASET neural_information_processing_systems   93      NIPS:93
METHOD  stochastic_gradient_descent     91      SGD:91
METRIC  minimum_description_length      78      MDL:78
PROBLEM natural_language_processing     77      NLP:77
```

Task 4+: Advisor-Advisee Discovery

- Beyond collaborations
  - First-last-author rule
  - Measuring proximity with *Kulc* measure
  - Correlation between them
  - Ground-truth and evaluation

Task 8: SciCube

- 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:**
  - 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.
  - 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").
  - More functionalities of the data cube, and efficiency analysis are welcome.

Task 9: Pattern-based Entity Recognition and Typing

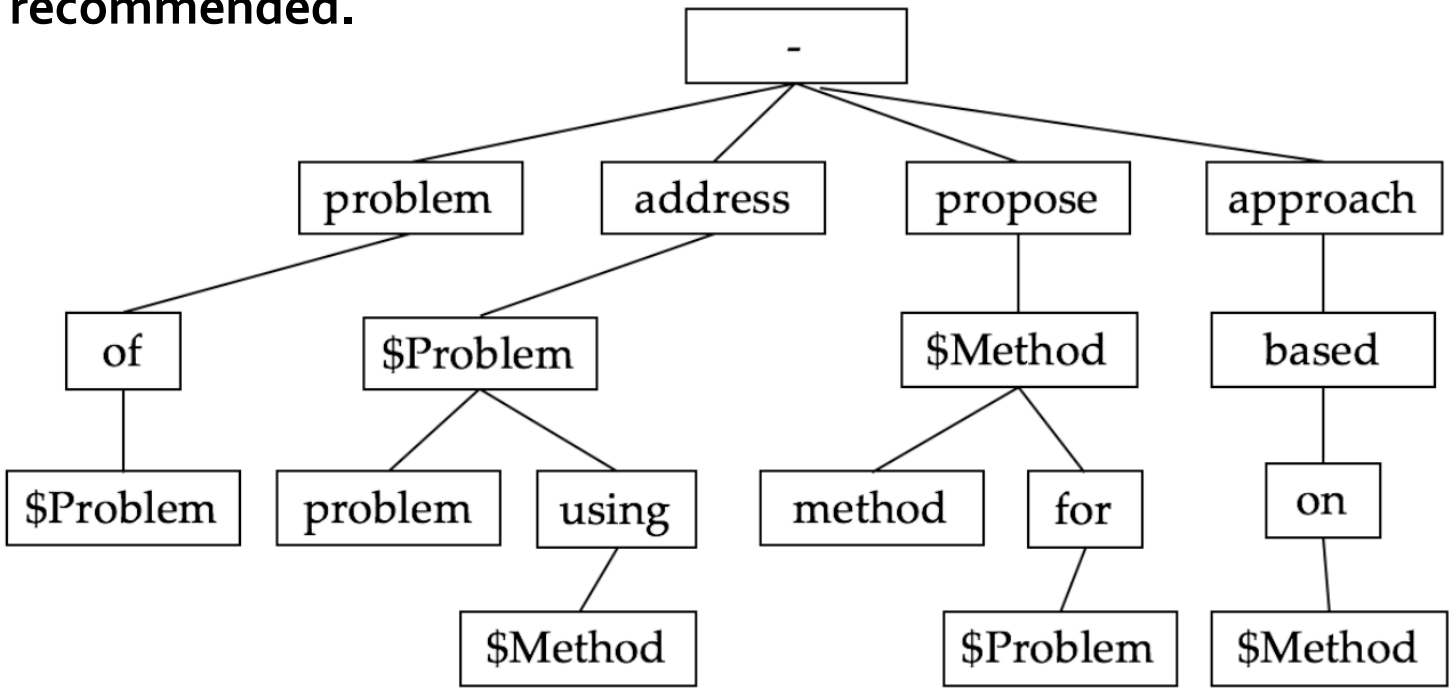
- Given entity names, can we find **frequent patterns** around the entities? We replace concrete entity names as "$Entity." You can find more entities via **pattern matching**.
- Given seed typed entities (methods, problems, etc.), can we find concrete frequent patterns around the typed entities? We replace concrete method/problem entities as "$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:**
  - 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.

Hint: Pattern Matching

- **How to match the text with patterns efficiently?**
- Suppose we have 6 patterns: "problem of $Problem", "address $Problem problem", "propose $Method method", "approach based on $Method", "propose $Method for $Problem", "address $Problem using $Method".
- **Match string patterns???**

Hint: Pattern Matching

- **How to match the text with patterns efficiently?**
- Suppose we have 6 patterns: "problem of $Problem", "address $Problem problem", "propose $Method method", "approach based on $Method", "propose $Method for $Problem", "address $Problem using $Method".
- **The data structure of Trie Tree (https://en.wikipedia.org/wiki/Trie) is recommended.**

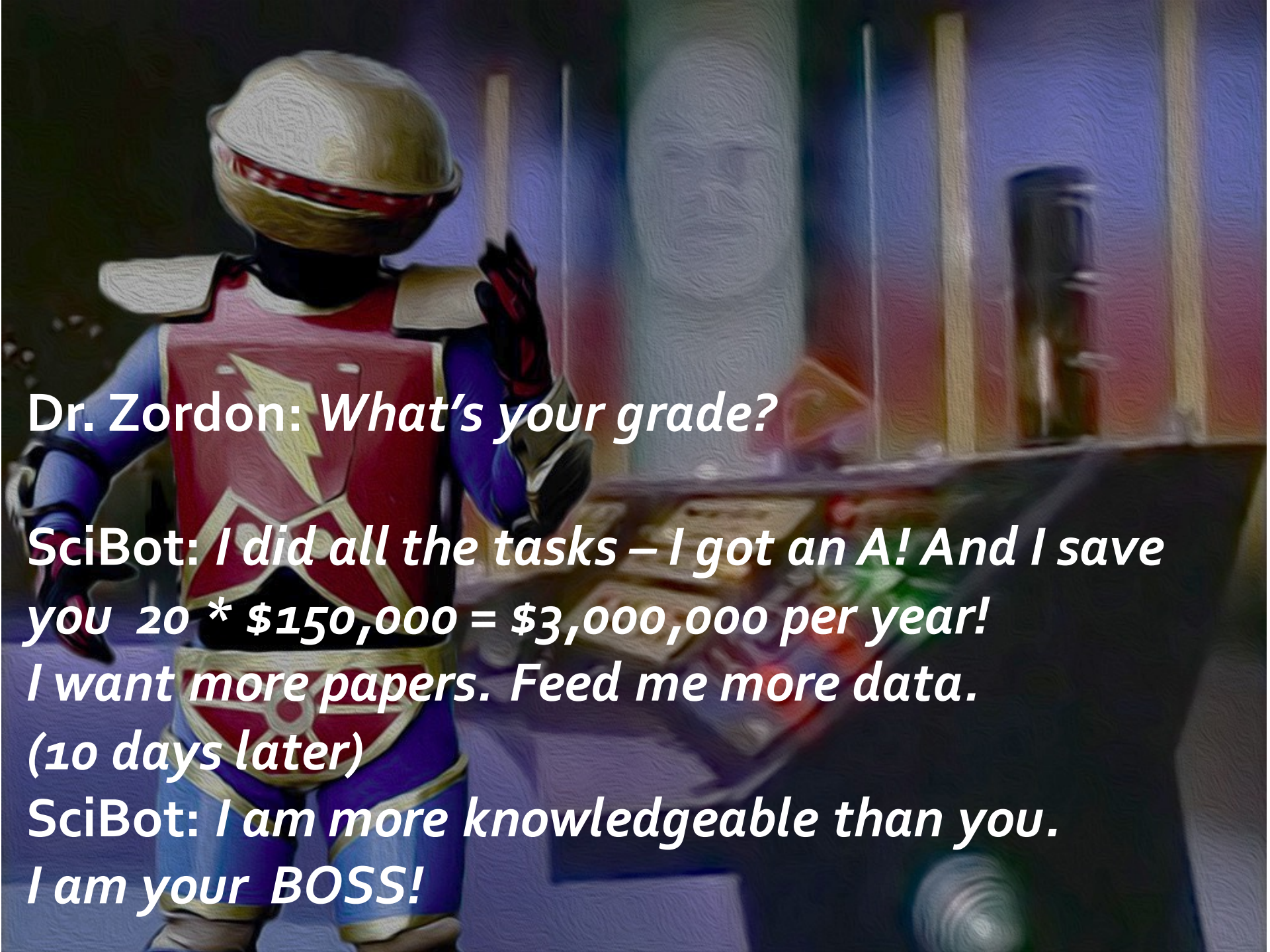


Other Tasks

- Task 10: Problem/method/author clustering
  - 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
  - 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
  - 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.).

Other Tasks (cont.)

- Task 13: Practice with advanced classification and clustering methods
  - 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:
  - Affiliation ranking on a specific method/problem
- Task 15: Data visualization is encouraged.


Dr. Zordon: What's your grade?
SciBot: I did all the tasks – I got an A! And I save you 20 * $150,000 = $3,000,000 per year!
I want more papers. Feed me more data.
(10 days later)
SciBot: I am more knowledgeable than you.
I am your BOSS!

Enjoy the Power-Rangers Project ☺