DATA MINING
LECTURE 2

Data Preprocessing

Exploratory Analysis

Post-processing

What is Data Mining?

- Data mining is the use of efficient techniques for the analysis of very large collections of data and the extraction of useful and possibly unexpected patterns in data.

- “Data mining is the analysis of (often large) observational data sets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data analyst” (Hand, Mannila, Smyth)

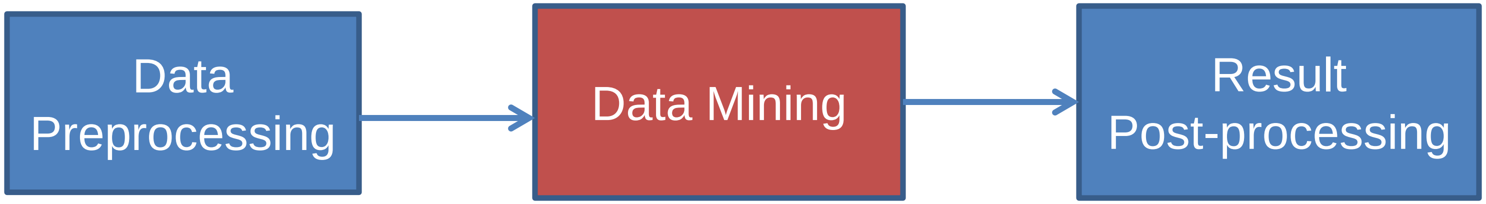
- “Data mining is the discovery of models for data” (Rajaraman, Ullman)
  - We can have the following types of models
    - Models that explain the data (e.g., a single function)
    - Models that predict the future data instances.
    - Models that summarize the data
    - Models the extract the most prominent features of the data.

Why do we need data mining?

- Really huge amounts of complex data generated from multiple sources and interconnected in different ways
  - Scientific data from different disciplines
    - Weather, astronomy, physics, biological microarrays, genomics
  - Huge text collections
    - The Web, scientific articles, news, tweets, facebook postings.
  - Transaction data
    - Retail store records, credit card records
  - Behavioral data
    - Mobile phone data, query logs, browsing behavior, ad clicks
  - Networked data
    - The Web, Social Networks, IM networks, email network, biological networks.
  - All these types of data can be combined in many ways
    - Facebook has a network, text, images, user behavior, ad transactions.
- We need to analyze this data to extract knowledge
  - Knowledge can be used for commercial or scientific purposes.
  - Our solutions should scale to the size of the data

The data analysis pipeline

- Mining is not the only step in the analysis process



- Preprocessing: real data is noisy, incomplete and inconsistent. Data cleaning is required to make sense of the data
  - Techniques: Sampling, Dimensionality Reduction, Feature selection.
  - A dirty work, but it is often the most important step for the analysis.
- Post-Processing: Make the data actionable and useful to the user
  - Statistical analysis of importance
  - Visualization.
- Pre- and Post-processing are often data mining tasks as well

Data Quality

- Examples of data quality problems:
  - Noise and outliers
  - Missing values
  - Duplicate data

Tid	Refund	Marital Status	Taxable Income	Cheat
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	10000K	Yes
6	No	NULL	60K	No
7	Yes	Divorced	220K	NULL
8	No	Single	85K	Yes
9	No	Married	90K	No
9	No	Single	90K	No

A mistake or a millionaire?

Missing values

Inconsistent duplicate entries

Sampling

- Sampling is the main technique employed for data selection.
  - It is often used for both the preliminary investigation of the data and the final data analysis.

- Statisticians sample because obtaining the entire set of data of interest is too expensive or time consuming.
  - Example: What is the average height of a person in Ioannina?
    - We cannot measure the height of everybody

- Sampling is used in data mining because processing the entire set of data of interest is too expensive or time consuming.
  - Example: We have 1M documents. What fraction has at least 100 words in common?
    - Computing number of common words for all pairs requires 10^{12} comparisons
  - Example: What fraction of tweets in a year contain the word “Greece”?
    - 300M tweets per day, if 100 characters on average, 86.5TB to store all tweets

Sampling …

- The key principle for effective sampling is the following:
  - using a sample will work almost as well as using the entire data sets, if the sample is representative
  - A sample is representative if it has approximately the same property (of interest) as the original set of data
  - Otherwise we say that the sample introduces some bias
  - What happens if we take a sample from the university campus to compute the average height of a person at Ioannina?

Types of Sampling

- Simple Random Sampling
  - There is an equal probability of selecting any particular item

- Sampling without replacement
  - As each item is selected, it is removed from the population

- Sampling with replacement
  - Objects are not removed from the population as they are selected for the sample.
    - In sampling with replacement, the same object can be picked up more than once. This makes analytical computation of probabilities easier
    - E.g., we have 100 people, 51 are women $P(W) = 0.51$, 49 men $P(M) = 0.49$. If I pick two persons what is the probability $P(W,W)$ that both are women?
      - Sampling with replacement: $P(W,W) = 0.51^2$
      - Sampling without replacement: $P(W,W) = 51/100 * 50/99$

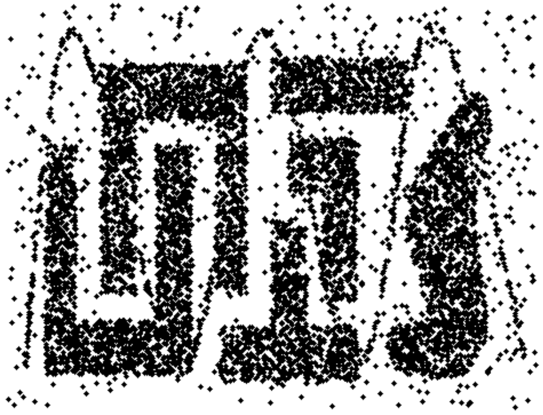
Types of Sampling

- Stratified sampling
  - Split the data into several groups; then draw random samples from each group.
    - Ensures that both groups are represented.
  - Example 1. I want to understand the differences between legitimate and fraudulent credit card transactions. 0.1% of transactions are fraudulent. What happens if I select 1000 transactions at random?
    - I get 1 fraudulent transaction (in expectation). Not enough to draw any conclusions. Solution: sample 1000 legitimate and 1000 fraudulent transactions

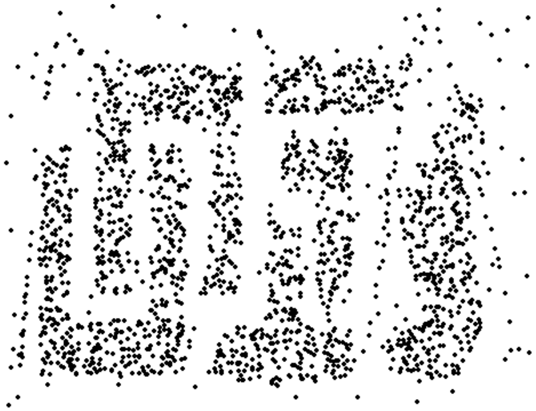
Probability Reminder: If an event has probability p of happening and I do N trials, the expected number of times the event occurs is pN

- Example 2. I want to answer the question: Do web pages that are linked have on average more words in common than those that are not? I have 1M pages, and 1M links, what happens if I select 10K pairs of pages at random?
  - Most likely I will not get any links. Solution: sample 10K random pairs, and 10K links

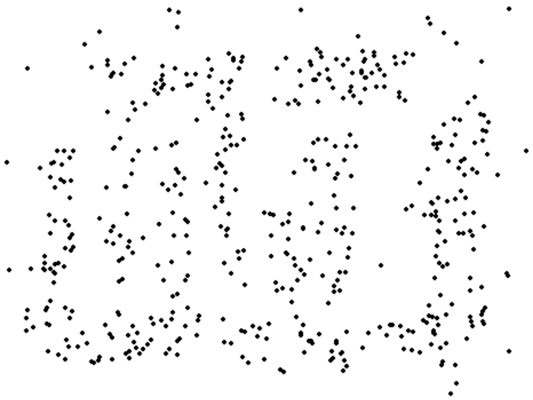
Sample Size



8000 points



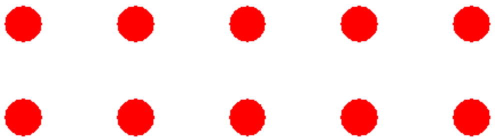
2000 Points

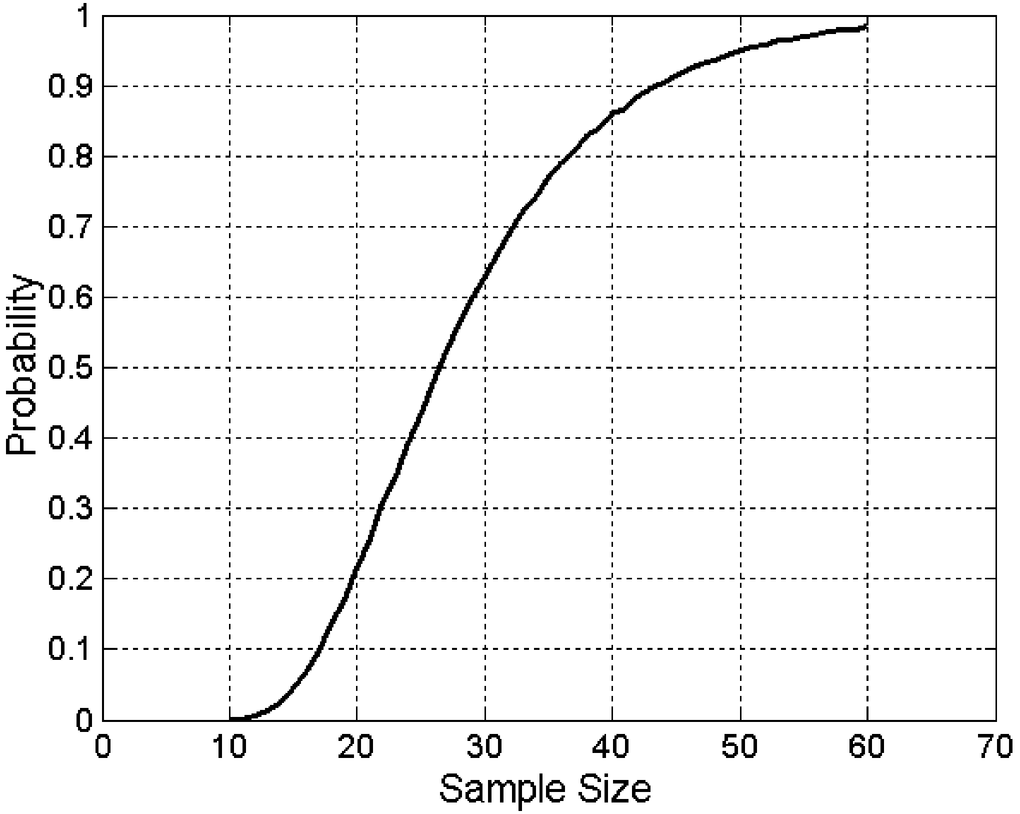


500 Points

Sample Size

- **What sample size is necessary to get at least one object from each of 10 groups.**





A data mining challenge

- You have N integers and you want to sample one integer uniformly at random. How do you do that?

- The integers are coming in a stream: you do not know the size of the stream in advance, and there is not enough memory to store the stream in memory. You can only keep a constant amount of integers in memory
- How do you sample?
  - Hint: if the stream ends after reading n integers the last integer in the stream should have probability 1/n to be selected.

- Reservoir Sampling:
  - Standard interview question for many companies

Reservoir sampling

- Algorithm: With probability 1/n select the n-th item of the stream and replace the previous choice.

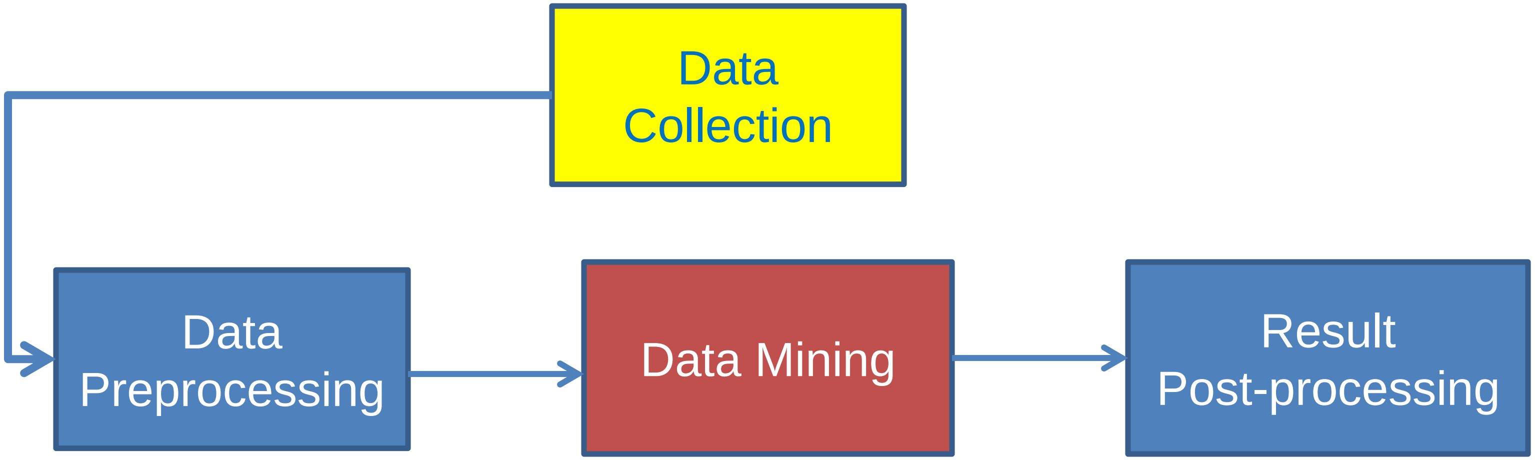
- Claim: Every item has probability 1/N to be selected after N items have been read.

- Proof
  - What is the probability of the n-the item to be selected?
    - $\frac{1}{n}$
  - What is the probability of the n-th items to survive for N-n rounds?
    - $\left(1-\frac{1}{n+1}\right)\left(1-\frac{1}{n+2}\right)\cdots\left(1-\frac{1}{N}\right)$

A (detailed) data preprocessing example

- Suppose we want to mine the comments/reviews of people on Yelp and Foursquare.

Data Collection



- Today there is an abundance of data online
  - Facebook, Twitter, Wikipedia, Web, etc…
- We can extract interesting information from this data, but first we need to collect it
  - Customized crawlers, use of public APIs
  - Additional cleaning/processing to parse out the useful parts
  - Respect of crawling etiquette

Mining Task

- Collect all reviews for the top-10 most reviewed restaurants in NY in Yelp
  - (thanks to Hady Law)

- Find few terms that best describe the restaurants.
- Algorithm?

Example data

- I heard so many good things about this place so I was pretty juiced to try it. I'm from Cali and I heard Shake Shack is comparable to IN-N-OUT and I gotta say, Shake Shake wins hands down. Surprisingly, the line was short and we waited about 10 MIN. to order. I ordered a regular cheeseburger, fries and a black/white shake. So yummerz. I love the location too! It's in the middle of the city and the view is breathtaking. Definitely one of my favorite places to eat in NYC.

- I'm from California and I must say, Shake Shack is better than IN-N-OUT, all day, err'day.

- Would I pay $15+ for a burger here? No. But for the price point they are asking for, this is a definite bang for your buck (though for some, the opportunity cost of waiting in line might outweigh the cost savings) Thankfully, I came in before the lunch swarm descended and I ordered a shake shack (the special burger with the patty + fried cheese &amp; portabella topping) and a coffee milk shake. The beef patty was very juicy and snugly packed within a soft potato roll. On the downside, I could do without the fried portabella-thingy, as the crispy taste conflicted with the juicy, tender burger. How does shake shack compare with in-and-out or 5-guys? I say a very close tie, and I think it comes down to personal affliations. On the shake side, true to its name, the shake was well churned and very thick and luscious. The coffee flavor added a tangy taste and complemented the vanilla shake well. Situated in an open space in NYC, the open air sitting allows you to munch on your burger while watching people zoom by around the city. It's an oddly calming experience, or perhaps it was the food coma I was slowly falling into. Great place with food at a great price.

First cut

- Do simple processing to “normalize” the data (remove punctuation, make into lower case, clear white spaces, other?)
- Break into words, keep the most popular words

the 27514	the 16710	the 16010	the 14241
and 14508	and 9139	and 9504	and 8237
i 13088	a 8583	i 7966	a 8182
a 12152	i 8415	to 6524	i 7001
to 10672	to 7003	a 6370	to 6727
of 8702	in 5363	it 5169	of 4874
ramen 8518	it 4606	of 5159	you 4515
was 8274	of 4365	is 4519	it 4308
is 6835	is 4340	sauce 4020	is 4016
it 6802	burger 432	in 3951	was 3791
in 6402	was 4070	this 3519	pastrami 3748
for 6145	for 3441	was 3453	in 3508
but 5254	but 3284	for 3327	for 3424
that 4540	shack 3278	you 3220	sandwich 2928
you 4366	shake 3172	that 2769	that 2728
with 4181	that 3005	but 2590	but 2715
pork 4115	you 2985	food 2497	on 2247
my 3841	my 2514	on 2350	this 2099
this 3487	line 2389	my 2311	my 2064
wait 3184	this 2242	cart 2236	with 2040
not 3016	fries 2240	chicken 2220	not 1655
we 2984	on 2204	with 2195	your 1622
at 2980	are 2142	rice 2049	so 1610
on 2922	with 2095	so 1825	have 1585

First cut

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the	27514
and	14508
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ramen	**8518**
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but	5254
that	4540
you	4366
with	4181
pork	**4115**
my	3841
this	3487
wait	3184
not	3016
we	2984
at	2980
on	2922

the	16710
and	9139
a	8583
i	8415
to	7003
in	5363
it	4606
of	4365
is	4340
burger	**432**
was	4070
for	3441
but	3284
shack	**3278**
shake	**3172**
that	3005
you	2985
my	2514
line	2389
this	2242
fries	**2240**
on	2204
are	2142
with	2095

the	16010
and	9504
i	7966
to	6524
a	6370
it	5169
of	5159
is	4519
sauce	**4020**
in	3951
this	3519
was	3453
for	3327
you	3220
that	2769
but	2590
food	2497
cart	**2236**
chicken	**2220**
with	2195
rice	2049
so	1825

the	14241
and	8237
a	8182
i	7001
to	6727
of	4874
you	4515
it	4308
is	4016
was	3791
pastrami	**3748**
in	3508
for	3424
sandwich	**2928**
that	2728
but	2715
on	2247
not	1655
your	1622
so	1610
have	1585

Most frequent words are stop words

Second cut

- Remove stop words
  - Stop-word lists can be found online.

```
a,about,above,after,again,against,all,am,an,and,any,are,aren't,as,at,be,be
cause,been,before,being,below,between,both,but,by,can't,cannot,could,could
n't,did,didn't,do,does,doesn't,doing,don't,down,during,each,few,for,from,f
urther,had,hadn't,has,hasn't,have,haven't,having,he,he'd,he'll,he's,her,he
re,here's,hers,herself,him,himself,his,how,how's,i,i'd,i'll,i'm,i've,if,in
,into,is,isn't,it,it's,its,itself,let's,me,more,most,mustn't,my,myself,no,
nor,not,of,off,on,once,only,or,other,ought,our,ours,ourselves,out,over,own
,same,shan't,she,she'd,she'll,she's,should,shouldn't,so,some,such,than,tha
t,that's,the,their,theirs,them,themselves,then,there,there's,these,they,th
ey'd,they'll,they're,they've,this,those,through,to,too,under,until,up,very
,was,wasn't,we,we'd,we'll,we're,we've,were,weren't,what,what's,when,when's
,where,where's,which,while,who,who's,whom,why,why's,with,won't,would,would
n't,you,you'd,you'll,you're,you've,your,yours,yourself,yourselves,
```

Second cut

- Remove stop words
  - Stop-word lists can be found online.

```
ramen 8572
pork 4152
wait 3195
good 2867
place 2361
noodles 2279
ippudo 2261
buns 2251
broth 2041
like 1902
just 1896
get 1641
time 1613
one 1460
really 1437
go 1366
food 1296
bowl 1272
can 1256
great 1172
best 1167
```

```
burger 4340
shack 3291
shake 3221
line 2397
fries 2260
good 1920
burgers 1643
wait 1508
just 1412
cheese 1307
like 1204
food 1175
get 1162
place 1159
one 1118
long 1013
go 995
time 951
park 887
can 860
best 849
```

```
sauce 4023
food 2507
cart 2239
chicken 2238
rice 2052
hot 1835
white 1782
line 1755
good 1629
lamb 1422
halal 1343
just 1338
get 1332
one 1222
like 1096
place 1052
go 965
can 878
night 832
time 794
long 792
people 790
```

```
pastrami 3782
sandwich 2934
place 1480
good 1341
get 1251
katz's 1223
just 1214
like 1207
meat 1168
one 1071
deli 984
best 965
go 961
ticket 955
food 896
sandwiches 813
can 812
beef 768
order 720
pickles 699
time 662
```

Second cut

- Remove stop words
  - Stop-word lists can be found online.

```
ramen 8572
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one 1071
deli 984
best 965
go 961
sandwiches 813
can 812
beef 768
order 720
pickles 699
time 662
```

Commonly used words in reviews, not so interesting

IDF

- Important words are the ones that are unique to the document (differentiating) compared to the rest of the collection
  - All reviews use the word “like”. This is not interesting
  - We want the words that characterize the specific restaurant

- Document Frequency $DF(w)$: fraction of documents that contain word w.

$$DF(w) = \frac{D(w)}{D}$$

$D(w)$: num of docs that contain word w
D: total number of documents

- Inverse Document Frequency $IDF(w)$:

$$IDF(w) = \log\left(\frac{1}{DF(w)}\right)$$

- Maximum when unique to one document : $IDF(w) = \log(D)$
- Minimum when the word is common to all documents: $IDF(w) = 0$

TF-IDF

- The words that are best for describing a document are the ones that are important for the document, but also unique to the document.

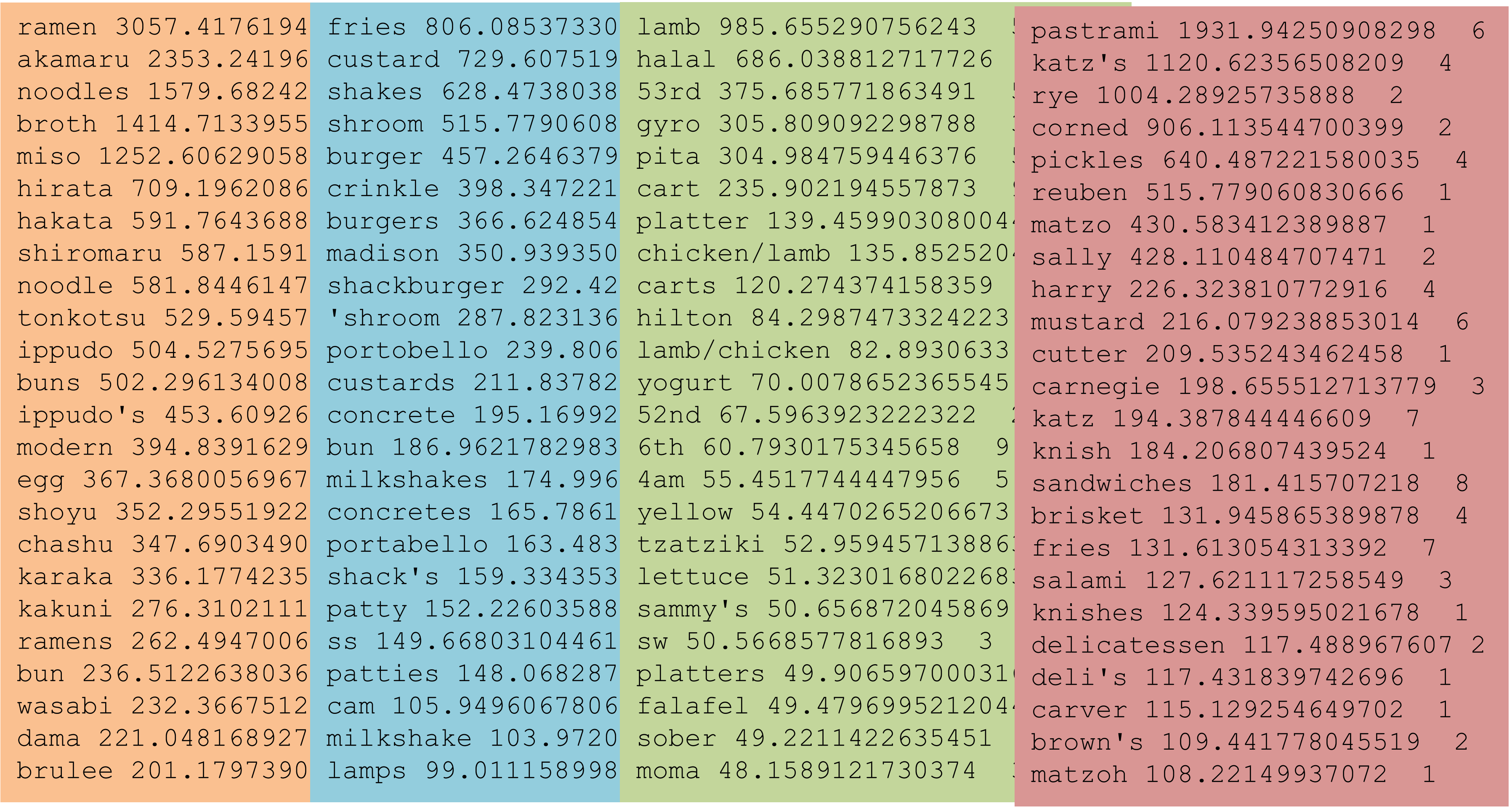
- TF(w,d): term frequency of word w in document d
  - Number of times that the word appears in the document
  - Natural measure of importance of the word for the document

- IDF(w): inverse document frequency
  - Natural measure of the uniqueness of the word w

- TF-IDF(w,d) = TF(w,d) × IDF(w)

Third cut

- Ordered by TF-IDF



```
ramen 3057.4176194
akamaru 2353.24196
noodles 1579.68242
broth 1414.7133955
miso 1252.60629058
hirata 709.1962086
hakata 591.7643688
shiromaru 587.1591
noodle 581.8446147
tonkotsu 529.59457
ippudo 504.5275695
buns 502.296134008
ippudo's 453.60926
modern 394.8391629
egg 367.3680056967
shoyu 352.29551922
chashu 347.6903490
karaka 336.1774235
kakuni 276.3102111
ramens 262.4947006
bun 236.5122638036
wasabi 232.3667512
dama 221.048168927
brulee 201.1797390
```

```
fries 806.08537330
custard 729.607519
shakes 628.4738038
shroom 515.7790608
burger 457.2646379
crinkle 398.347221
burgers 366.624854
madison 350.939350
shackburger 292.42
'shroom 287.823136
portobello 239.806
custards 211.83782
concrete 195.16992
bun 186.9621782983
milkshakes 174.996
concretes 165.7861
portabello 163.483
shack's 159.334353
patty 152.22603588
ss 149.66803104461
patties 148.068287
cam 105.9496067806
milkshake 103.9720
lamps 99.011158998
```

```
lamb 985.655290756243
halal 686.038812717726
53rd 375.685771863491
gyro 305.809092298788
pita 304.984759446376
cart 235.902194557873
platter 139.45990308004
chicken/lamb 135.852520
carts 120.274374158359
hilton 84.2987473324223
lamb/chicken 82.8930633
yogurt 70.0078652365545
52nd 67.5963923222322
6th 60.7930175345658  9
4am 55.4517744447956  5
yellow 54.4470265206673
tzatziki 52.95945713886
lettuce 51.32301680226
sammy's 50.656872045869
sw 50.5668577816893  3
platters 49.90659700031
falafel 49.47969952120
sober 49.2211422635451
moma 48.1589121730374
```

```
pastrami 1931.94250908298  6
katz's 1120.62356508209  4
rye 1004.28925735888  2
corned 906.113544700399  2
pickles 640.487221580035  4
reuben 515.779060830666  1
matzo 430.583412389887  1
sally 428.110484707471  2
harry 226.323810772916  4
mustard 216.079238853014  6
cutter 209.535243462458  1
carnegie 198.655512713779  3
katz 194.387844446609  7
knish 184.206807439524  1
sandwiches 181.415707218  8
brisket 131.945865389878  4
fries 131.613054313392  7
salami 127.621117258549  3
knishes 124.339595021678  1
delicatessen 117.488967607 2
deli's 117.431839742696  1
carver 115.129254649702  1
brown's 109.441778045519  2
matzoh 108.22149937072  1
```

Third cut

- TF-IDF takes care of stop words as well
- We do not need to remove the stopwords since they will get IDF(w) = 0

Decisions, decisions…

- When mining real data you often need to make some
  - What data should we collect? How much? For how long?
  - Should we throw out some data that does not seem to be useful?

An actual review

```
AAAAAAAAAAAAA
AAAAAAAAAAAAAAAAAAAAAAAAA AAAAAAAAAAAAAAAAAAAAAAAAA AAA
```

  - Too frequent data (stop words), too infrequent (errors?), erroneous data, missing data, outliers
  - How should we weight the different pieces of data?

- Most decisions are application dependent. Some information may be lost but we can usually live with it (most of the times)

- We should make our decisions clear since they affect our findings.

- Dealing with real data is hard…

Exploratory analysis of data

- Summary statistics: numbers that summarize properties of the data
  - Summarized properties include frequency, location and spread
    - Examples: location - mean
      spread - standard deviation
  - Most summary statistics can be calculated in a single pass through the data

Frequency and Mode

- The frequency of an attribute value is the percentage of time the value occurs in the data set
    - For example, given the attribute ‘gender’ and a representative population of people, the gender ‘female’ occurs about 50% of the time.
- The mode of a an attribute is the most frequent attribute value
- The notions of frequency and mode are typically used with categorical data

Percentiles

- For continuous data, the notion of a percentile is more useful.

Given an ordinal or continuous attribute *x* and a number *p* between 0 and 100, the *p*th percentile is a value x_p of x such that *p*% of the observed values of x are less than x_p.

- For instance, the 50th percentile is the value $x_{50\%}$ such that 50% of all values of x are less than $x_{50\%}$.

Measures of Location: Mean and Median

- The mean is the most common measure of the location of a set of points.
- However, the mean is very sensitive to outliers.
- Thus, the median or a trimmed mean is also commonly used.

$$\text{mean}(x) = \overline{x} = \frac{1}{m}\sum_{i=1}^{m} x_i$$

$$\text{median}(x) = \begin{cases} x_{(r+1)} & \text{if } m \text{ is odd, i.e., } m = 2r+1 \\ \frac{1}{2}(x_{(r)} + x_{(r+1)}) & \text{if } m \text{ is even, i.e., } m = 2r \end{cases}$$

Example

Tid	**Refund**	**Marital Status**	**Taxable Income**	**Cheat**
1	Yes	Single	125K	**No**
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9	No	Married	90K	**No**
10	No	Single	90K	**No**

Mean: 1090K

Trimmed mean (remove min, max): 105K

Median: (90+100)/2 = 95K

Measures of Spread: Range and Variance

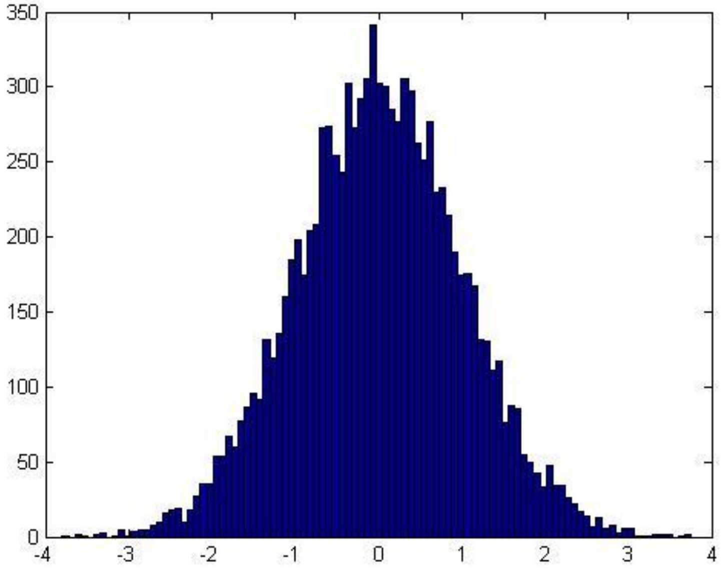
- Range is the difference between the max and min
- The variance or standard deviation is the most common measure of the spread of a set of points.

$$var(x) = \frac{1}{m}\sum_{i=1}^{m}(x - \bar{x})^2$$

$$\sigma(x) = \sqrt{var(x)}$$

Normal Distribution

- $\phi(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$

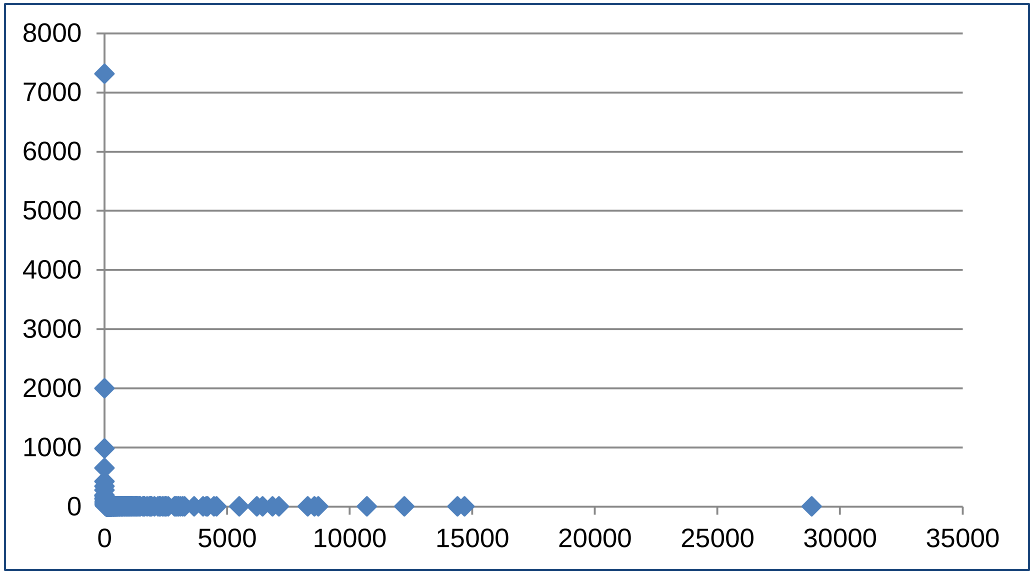


This is a value histogram

- An important distribution that characterizes many quantities and has a central role in probabilities and statistics.
  - Appears also in the central limit theorem
- Fully characterized by the mean μ and standard deviation σ

Not everything is normally distributed

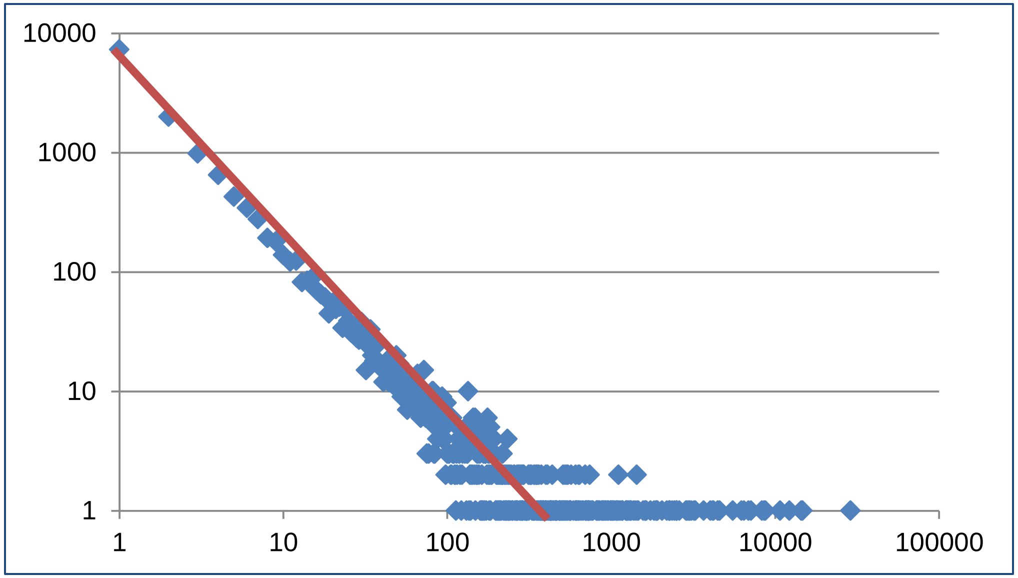
- Plot of number of words with x number of occurrences



- If this was a normal distribution we would not have a frequency as large as 28K

Power-law distribution

- We can understand the distribution of words if we take the log-log plot

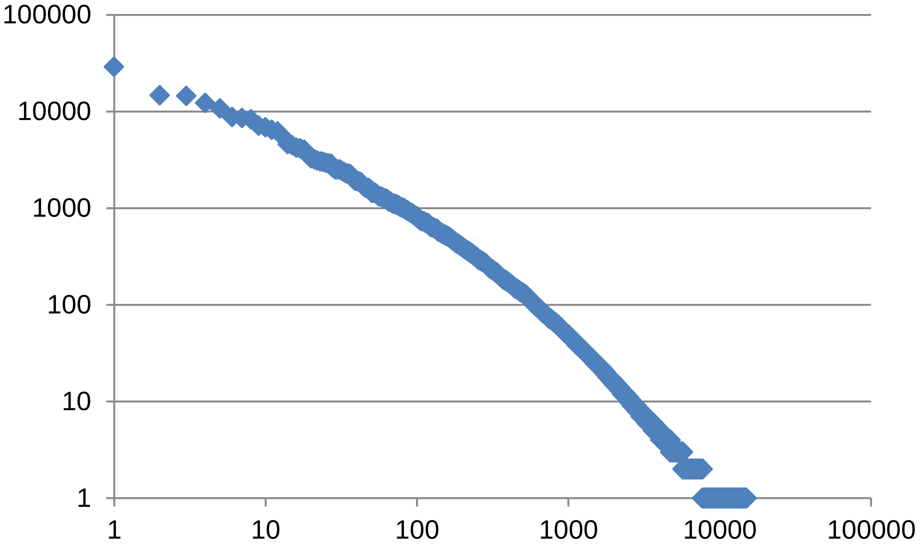


- Linear relationship in the log-log space

$$p(x = k) = k^{-a}$$

Zipf’s law

- Power laws can be detected by a linear relationship in the log-log space for the rank-frequency plot

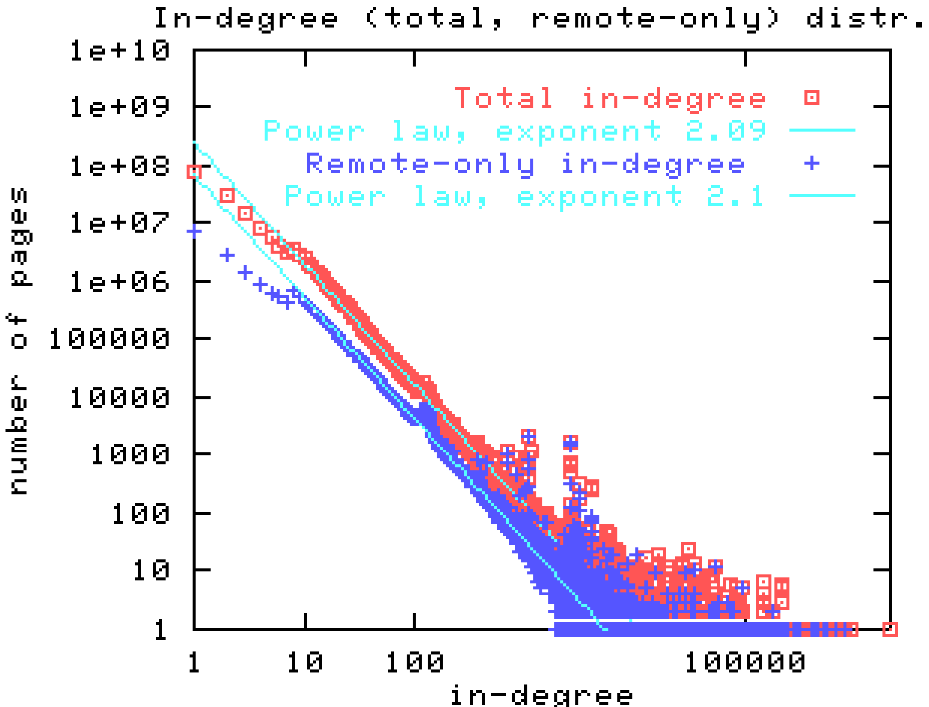


- $f(r)$: Frequency of the r-th most frequent word

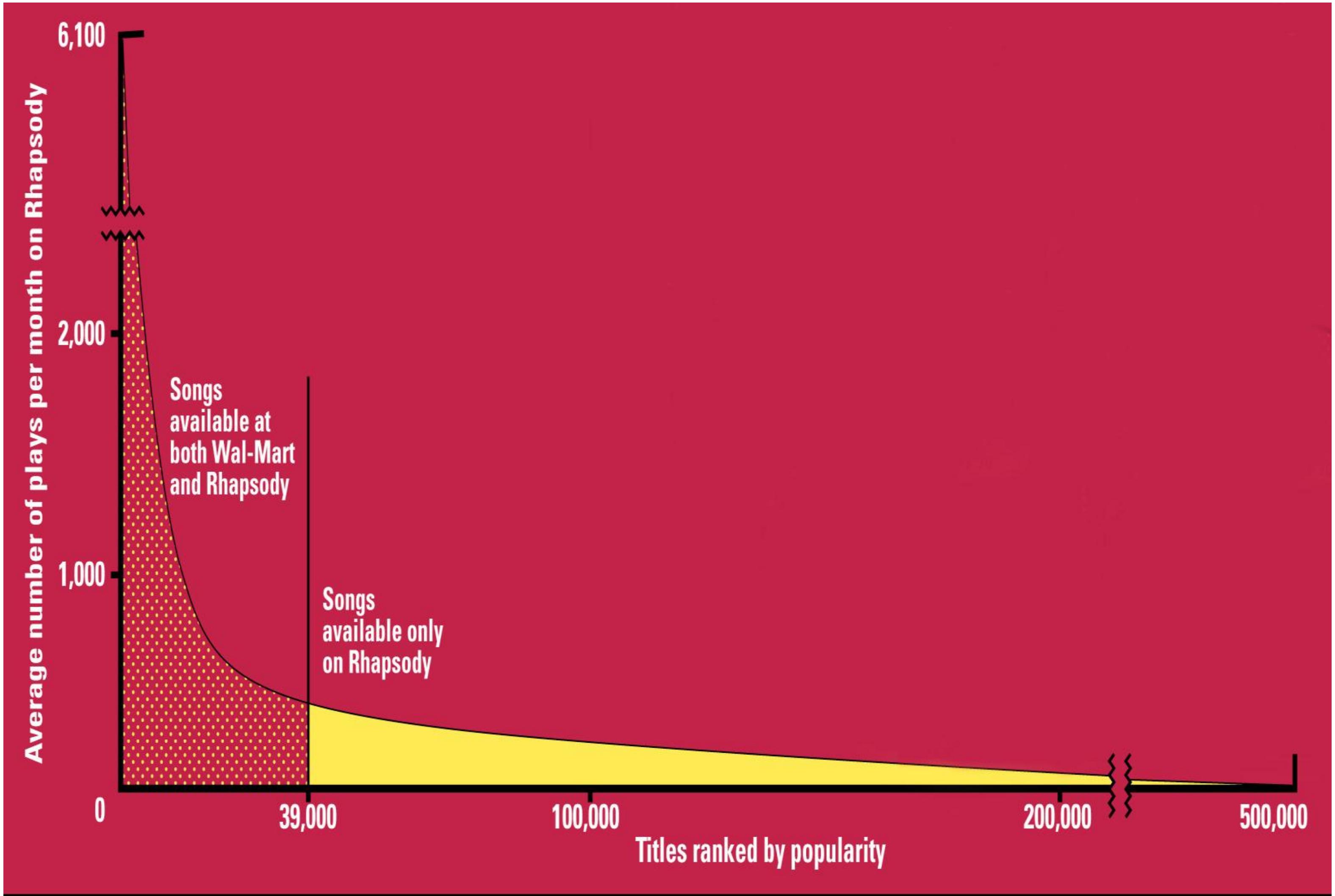
$$f(r) = r^{-\beta}$$

Power-laws are everywhere

- Incoming and outgoing links of web pages, number of friends in social networks, number of occurrences of words, file sizes, city sizes, income distribution, popularity of products and movies
  - Signature of human activity?
  - A mechanism that explains everything?
  - Rich get richer process



The Long Tail



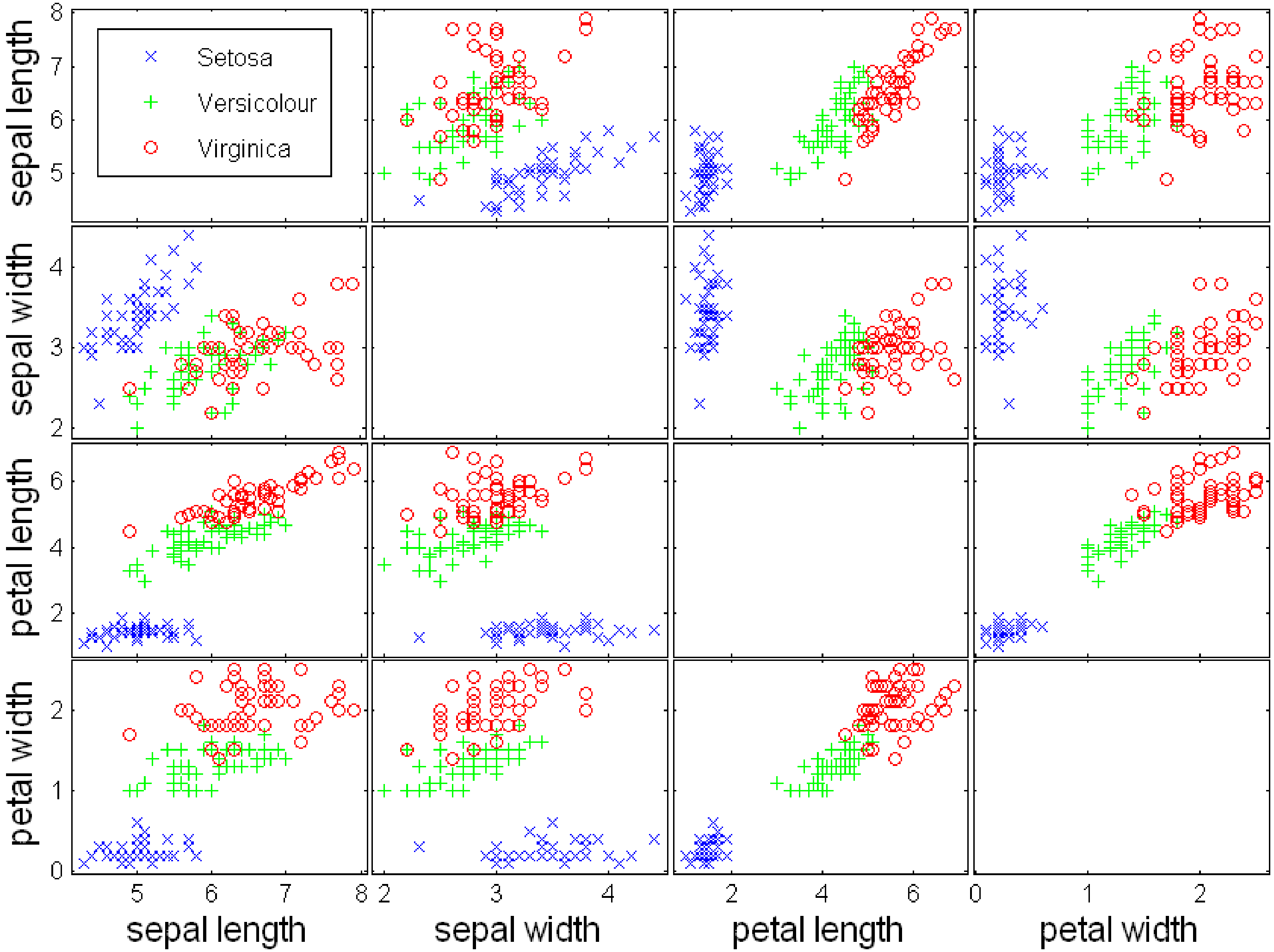
Source: Chris Anderson (2004)

Sources: Erik Brynjolfsson and Jeffrey Hu, MIT, and Michael Smith, Carnegie Mellon; Barnes & Noble; Netflix; RealNetworks

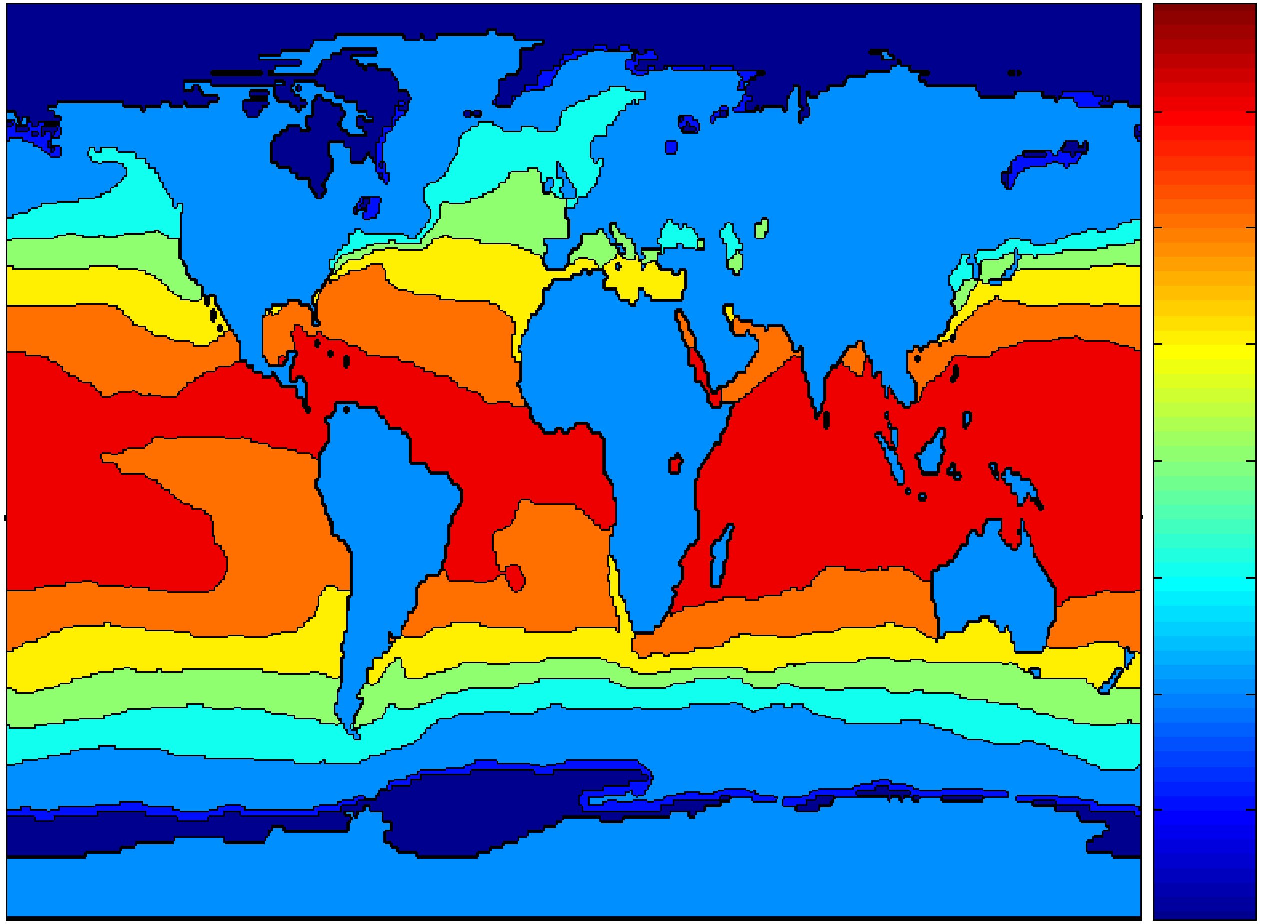
Post-processing

- Visualization
  - The human eye is a powerful analytical tool
  - If we visualize the data properly, we can discover patterns
  - Visualization is the way to present the data so that patterns can be seen
    - E.g., histograms and plots are a form of visualization
    - There are multiple techniques (a field on its own)

Scatter Plot Array of Iris Attributes



Contour Plot Example: SST Dec, 1998



Celsius

Meaningfulness of Answers

- A big data-mining risk is that you will “discover” patterns that are meaningless.
- Statisticians call it Bonferroni’s principle: (roughly) if you look in more places for interesting patterns than your amount of data will support, you are bound to find crap.
- The Rhine Paradox: a great example of how not to conduct scientific research.

Rhine Paradox – (1)

- Joseph Rhine was a parapsychologist in the 1950’s who hypothesized that some people had Extra-Sensory Perception.
- He devised (something like) an experiment where subjects were asked to guess 10 hidden cards – red or blue.
- He discovered that almost 1 in 1000 had ESP – they were able to get all 10 right!

Rhine Paradox – (2)

- He told these people they had ESP and called them in for another test of the same type.
- Alas, he discovered that almost all of them had lost their ESP.
- What did he conclude?
  - Answer on next slide.

Rhine Paradox – (3)

- He concluded that you shouldn’t tell people they have ESP; it causes them to lose it.