CSE 564 VISUALIZATION & VISUAL ANALYTICS

DATA PREPARATION & REPRESENTATION

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Lecture	Торіс	Projects				
1	Intro, schedule, and logistics					
2	Applications of visual analytics, basic tasks, data types					
3	Introduction to D3, basic vis techniques for non-spatial data	Project #1 out				
4	Data preparation and reduction					
5	Data types, notion of similarity and distance					
6	Visual perception and cognition					
7	Visual design and aesthetics	Project #1 due				
8	Statistics foundations	Project #2 out				
9	Data mining techniques: clusters, text, patterns, classifiers					
10	Data mining techniques: clusters, text, patterns, classifiers					
11	Computer graphics and volume rendering					
12	Techniques to visualize spatial (3D) data	Project #2 due				
13	Scientific and medical visualization	Project #3 out				
14	Scientific and medical visualization					
15	Midterm #1					
16	High-dimensional data, dimensionality reduction	Project #3 due				
17	Big data: data reduction, summarization					
18	Correlation and causal modeling					
19	Principles of interaction					
20	Visual analytics and the visual sense making process	Final project proposal due				
21	Evaluation and user studies					
22	Visualization of time-varying and time-series data					
23	Visualization of streaming data					
24	Visualization of graph data	Final Project preliminary report due				
25	Visualization of text data					
26	Midterm #2					
27	Data journalism					
	Final project presentations	Final Project slides and final report due				

RECTANGULAR DATASET

One data item

The variables

→ the attributes or properties we measured

The data items

→ the samples
(observations)
we obtained
from the
population of
all instances

	A	В	C	D	E	F	G	Н	1
1	Name	Country	Miles Per Gallon	Accceleration	Horsepower	weight	cylinders	year	price
2	Volkswagen Rabbit DI	Germany	43,1	21,5	48	1985	4	78	2400
3	Ford Fiesta	Germany	36,1	14,4	66	1800	4	78	1900
4	Mazda GLC Deluxe	Japan	32,8	19,4	52	1985	4	78	2200
5	Datsun B210 GX	Japan	39,4	18,6	70	2070	4	78	2725
6	Honda Civic CVCC	Japan	36,1	16,4	60	1800	4	78	2250
7	Oldsmobile Cutlass	USA	19,9	15,5	110	3365	8	78	3300
8	Dodge Diplomat	USA	19,4	13,2	140	3735	8	78	3125
9	Mercury Monarch	USA	20,2	12,8	139	3570	8	78	2850
10	Pontiac Phoenix	USA	19,2	19,2	105	3535	6	78	2800
11	Chevrolet Malibu	USA	20,5	18,2	95	3155	6	78	3275
12	Ford Fairmont A	USA	20,2	15,8	85	2965	6	78	2375
13	Ford Fairmont M	USA	25,1	15,4	88	2720	4	78	2275
14	Plymouth Volare	USA	20,5	17,2	100	3430	6	78	2700
15	AMC Concord	USA	19,4	17,2	90	3210	6	78	2300
16	Buick Century	USA	20,6	15,8	105	3380	6	78	3300
17	Mercury Zephyr	USA	20,8	16,7	85	3070	6	78	2425
18	Dodge Aspen	USA	18,6	18,7	110	3620	6	78	2700
19	AMC Concord D1	USA	18,1	15,1	120	3410	6	78	2425
20	Chevrolet MonteCarlo	USA	19,2	13,2	145	3425	8	78	3900
21	Buick RegalTurbo	USA	17,7	13,4	165	3445	6	78	4400
22	Ford Futura	Germany	18,1	11,2	139	3205	8	78	2525
23	Dodge Magnum XE	USA	17,5	13,7	140	4080	8	78	3000
24	Chevrolet Chevette	USA	30	16,5	68	2155	4	78	2100

RECTANGULAR DATASET

Also called the *Data Matrix*

Car performance metrics

or Survey question responses

or Patient characteristics

One data item

Car models

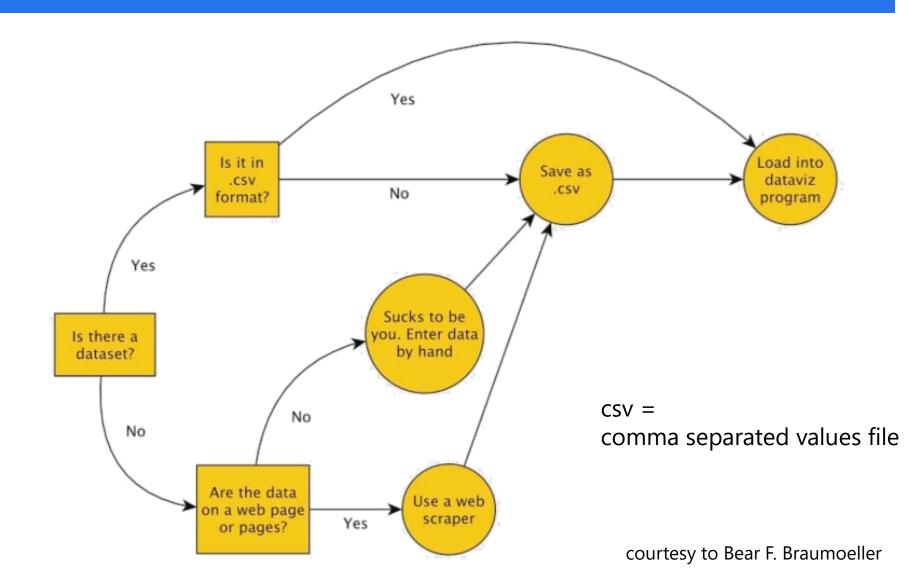
or Survey respondents

or Patients

• • • •

	A	В	С	D	E	F	
1	Name	Country	Miles Per Gallon	Accceleration	Horsepower	weight	cyli
2	Volkswagen Rabbit DI	Germany	43,1	21,5	48	1985	
3	Ford Fiesta	Germany	36,1	14,4	66	1800	
4	Mazda GLC Deluxe	Japan	32,8	19,4	52	1985	
5	Datsun B210 GX	Japan	39,4	18,6	70	2070	
6	Honda Civic CVCC	Japan	36,1	16,4	60	1800	
7	Oldsmobile Cutlass	USA	19,9	15,5	110	3365	
8	Dodge Diplomat	USA	19,4	13,2	140	3735	
9	Mercury Monarch	USA	20,2	12,8	139	3570	
10	Pontiac Phoenix	USA	19,2	19,2	105	3535	
11	Chevrolet Malibu	USA	20,5	18,2	95	3155	
12	Ford Fairmont A	USA	20,2	15,8	85	2965	
13	Ford Fairmont M	USA	25,1	15,4	88	2720	
14	Plymouth Volare	USA	20,5	17,2	100	3430	
15	AMC Concord	USA	19,4	17,2	90	3210	
16	Buick Century	USA	20.6	15.8	105	3380	

How To Import Data?



HOW TO GET DATA? (1)

Use Google

type the topic you like and perhaps 'data", ''database', csv', etc.

Other sources:

https://www.data.gov/

https://fedstats.sites.usa.gov/

http://data.worldbank.org/





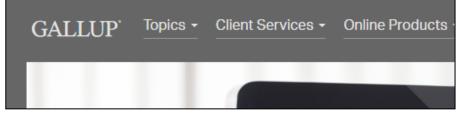


HOW TO GET DATA? (2)

Other sources:

http://www.gallup.com/products/184157/gallup-analytics-

<u>universities-colleges.aspx</u>



https://data.ny.gov/



https://www.kaggle.com/



DATASET EXAMPLE

Categorical

Multivariate - Quantitative data and Categorical data

Data Items

A	A	В	С	D	E	F	G	Н	1
1	Name	Country	Miles Per Gallon	Accceleration	Horsepower	weight	cylinders	year	price
2	Volkswagen Rabbit DI	Germany	43,1	21,5	48	1985	4	78	2400
3	Ford Fiesta	Germany	36,1	14,4	66	1800	4	78	1900
4	Mazda GLC Deluxe	Japan	32,8	19,4	52	1985	4	78	2200
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24	Chevrolet Chevette	USA	30	16,5	68	2155	4	78	2100
25	Toyota Corona	Japan	27,5	14,2	95	2560	4	78	2975
		1	٨	1	1	1	1		

Quantitative

Categorical (Ordinal)

Quantitative

Data types

Quantitative (Numerical) Categorical (Ordinal)

NOTES ON DATASET

Some advice

- avoid datasets where the majority of data is categorical (not overly exciting for binning, clustering, and so on)
- convert categories into numbers by assigning a numerical ID
- aim for datasets with more than 500 data points and 10 attributes
- if your dataset is larger, pick 500 sample points at random (for now)
- if you have too many attributes keep the ones of interest (prefer quantitative attributes)
- if the data set has text, images, video, logs, etc. convert them to numbers via appropriate mechanism as discussed in class
- produce a spreadsheet of rows (data items) and attributes (columns)

TABLES ON WEBPAGES

If the data are already in a rectangular table

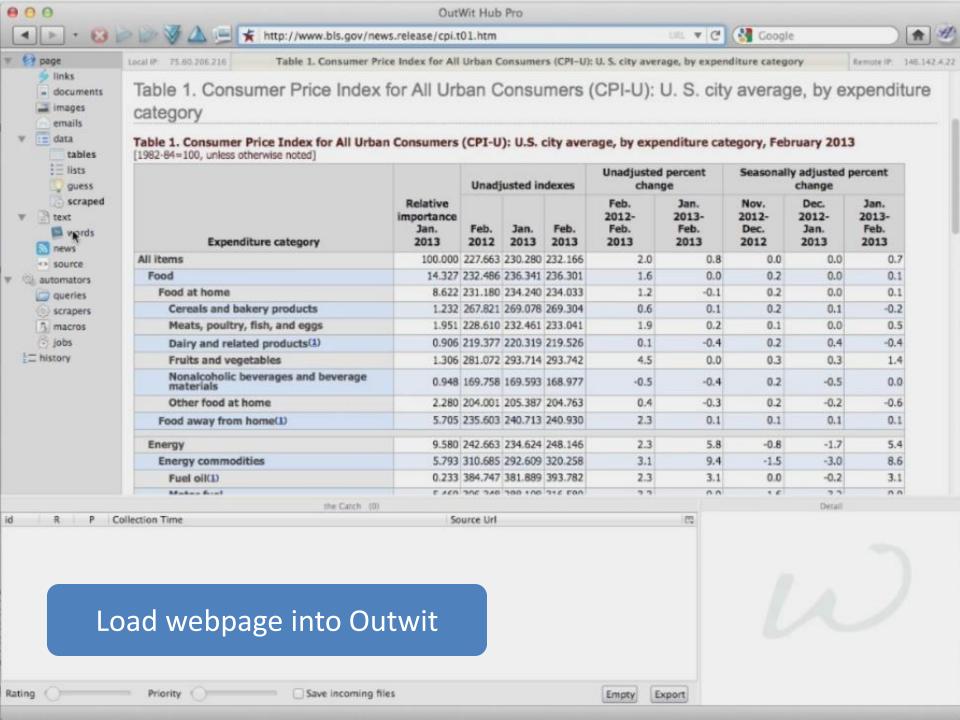
try cut and paste into Excel

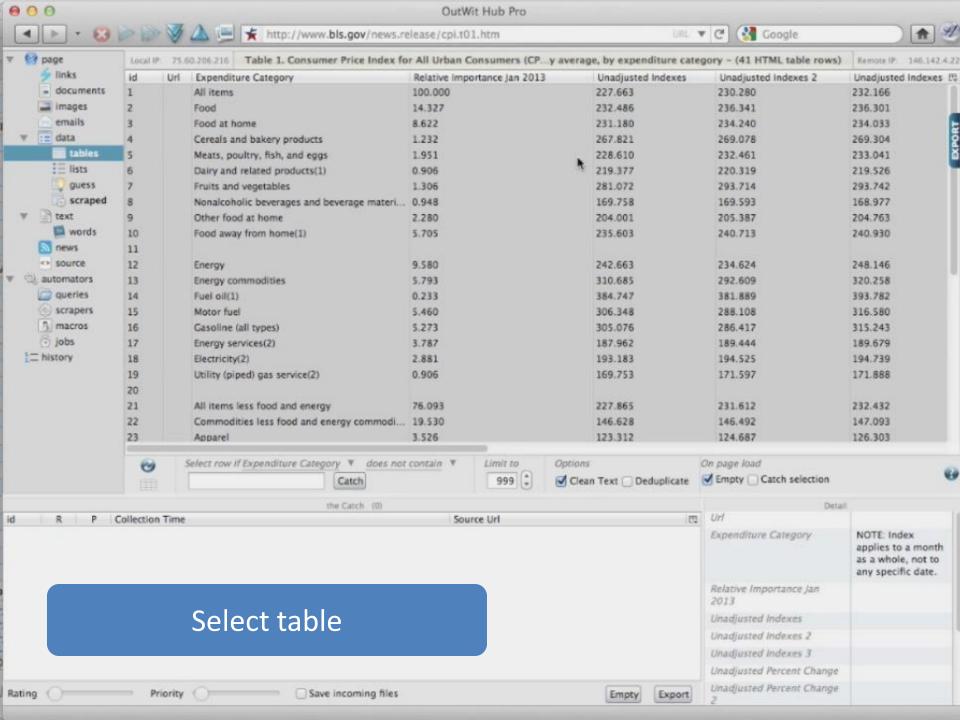
If the data are on one page but cut/paste is not working

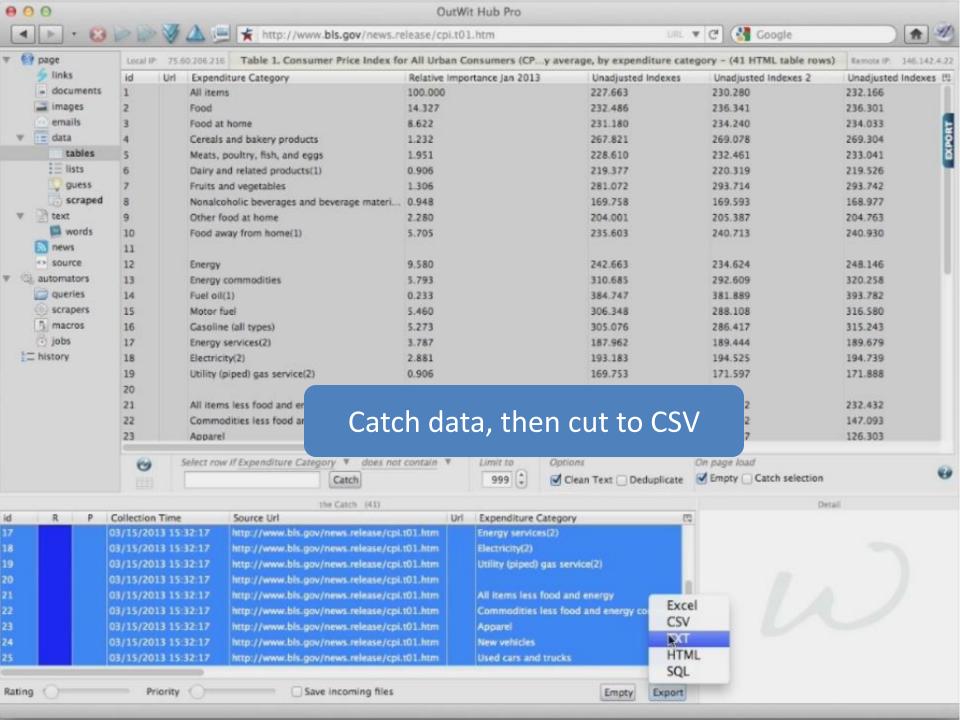
try a web scraper like <u>Outwit Hub</u>

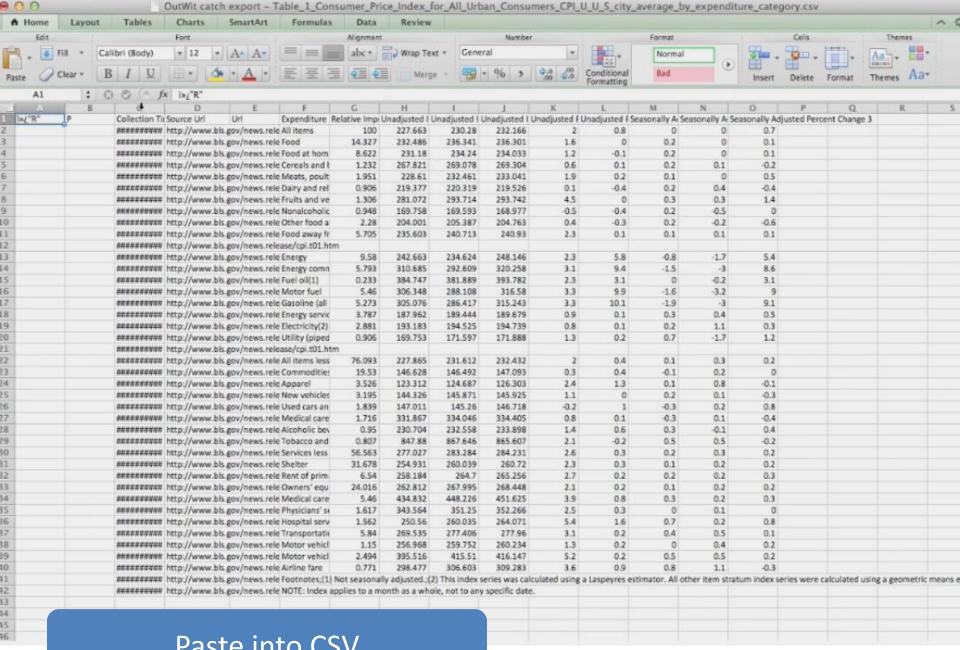
If the data are spread across multiple webpages

- try Outwit Hub's automators
- use python
- do it by hand (probably not)

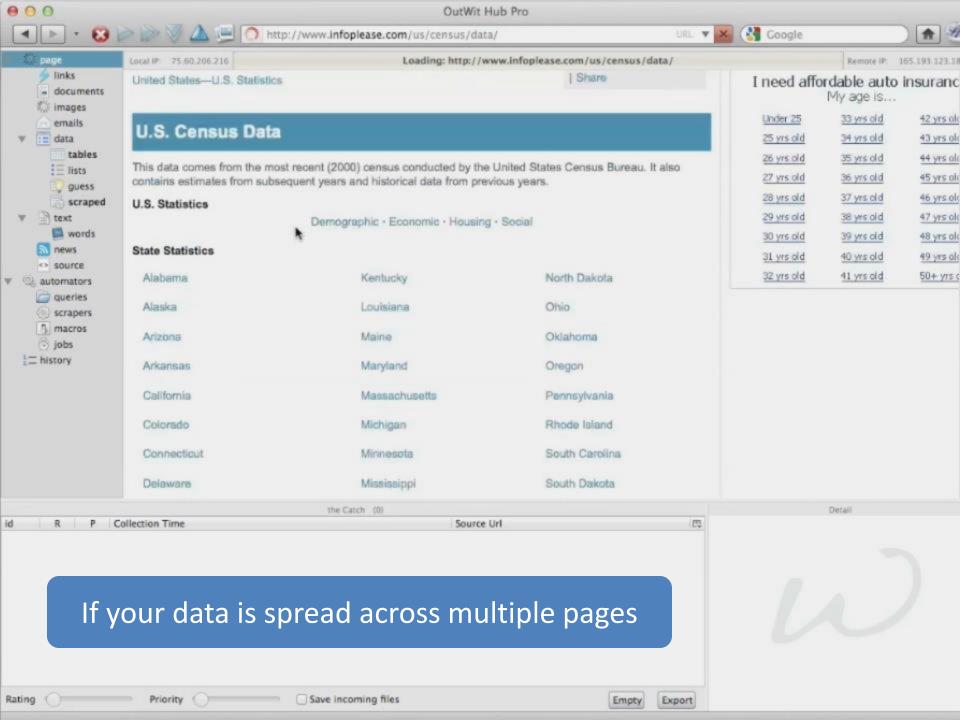


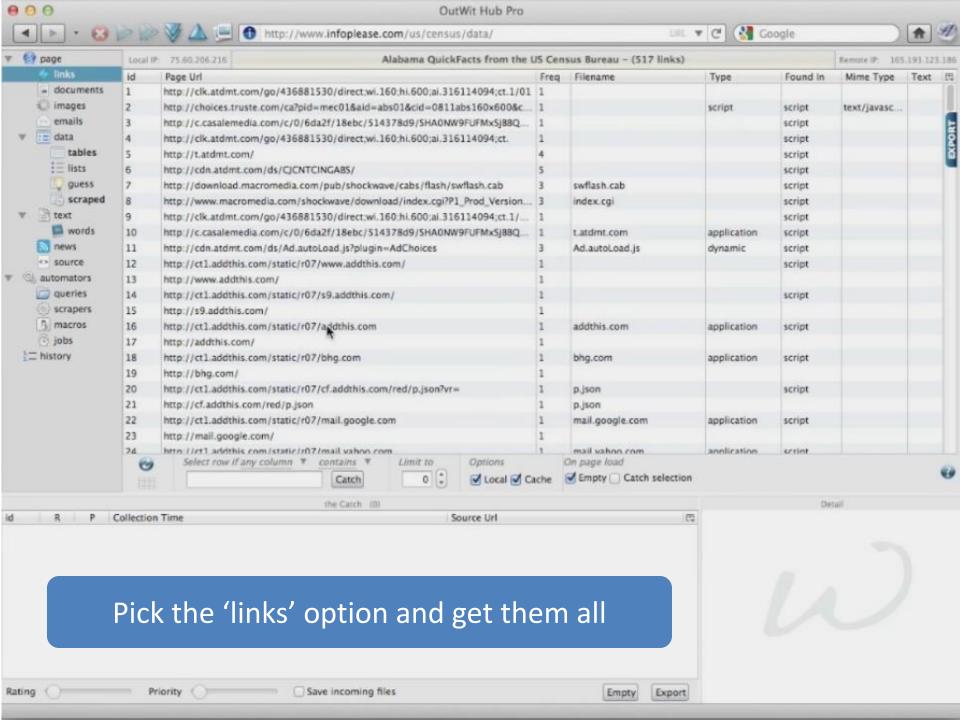


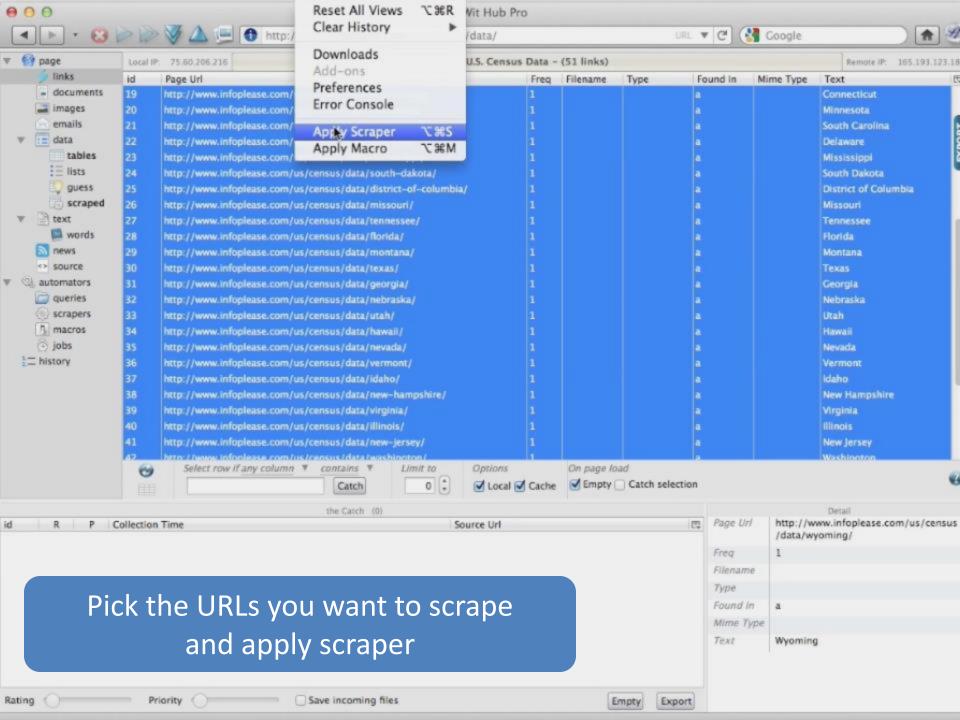


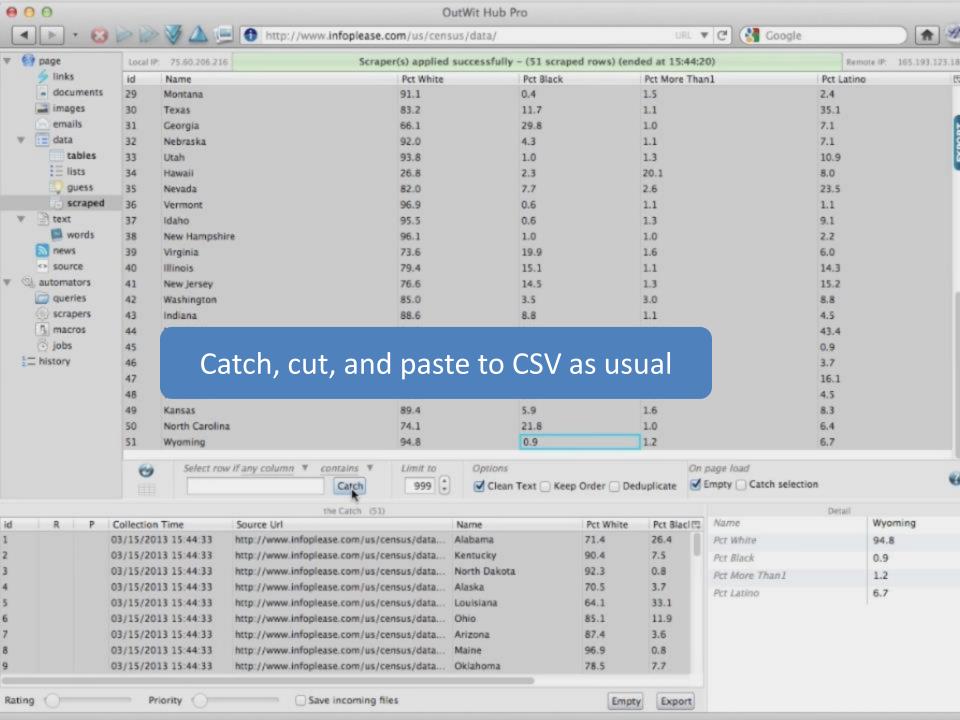


Paste into CSV









AFTER DOWNLOADING THE DATA ...

Do you think data are always clean and perfect?

Think again

Real world data are dirty

Data cleaning (wrangling)

- fill in missing values
- smooth noisy data
- identify or remove outliers
- resolve inconsistencies
- standardize/normalize data
- fuse/merge disjoint data



MISSING VALUES

Data is not always available

e. g, many tuples have no recorded value for several attributes,
 such as customer income in sales data

Missing data may be due to

- equipment malfunction
- inconsistent with other recorded data and thus deleted
- data not entered due to misunderstanding
- certain data may not be considered important at the time of entry
- many more reasons

MISSING DATA - EXAMPLE

Assume you get these baseball fan data

Age	Income	Team	Gender
23	24,200	Mets	M
39	50,245	Yankees	F
45	45,390	Yankees	F
22	32,300	Mets	M
52		Yankees	F
27	28,300	Mets	F
48	53,100	Yankees	M

- How would you estimate the missing value for income?
 - ignore or put in a default value (will decimate the usable data)
 - manually fill in (can be tedious or infeasible for large data)
 - average over all incomes
 - average over incomes of Yankee fans
 - average over incomes of female Yankees fans
 - use a probabilistic method (regression, Bayesian, decision tree)

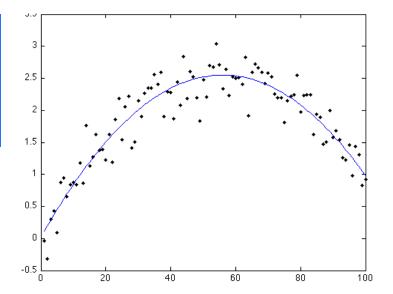
NOISY DATA

Noise = Random error in a measured variable

- faulty data collection instruments
- data entry problems
- data transmission problems
- technology limitation
- inconsistency in naming convention



- duplicate records
- incomplete data
- inconsistent data



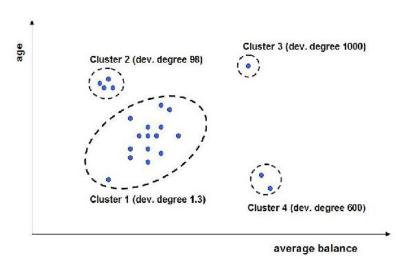
Noisy Data - What To Do

Binning method

discussed last lecture

Clustering

detect and remove outliers

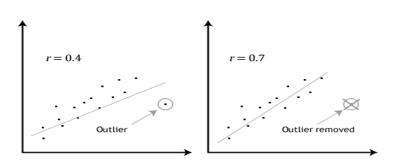


Semi-automated method

- combined computer and human inspection
- detect suspicious values and check manually (need visualization)

Regression

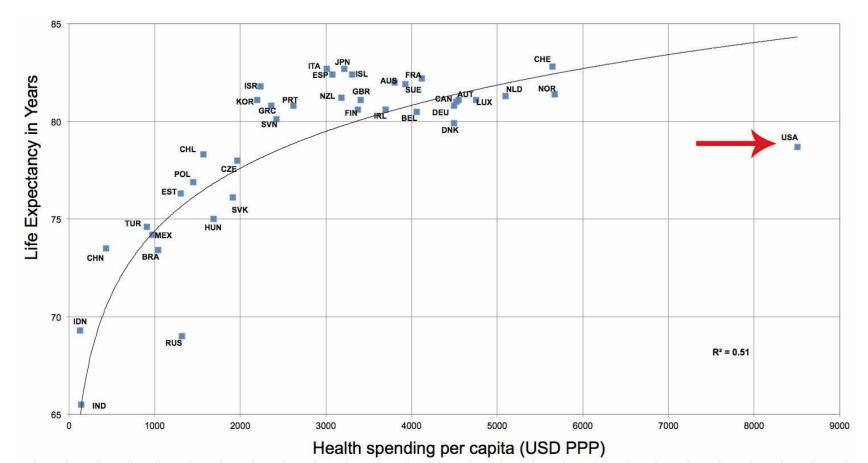
 smooth by fitting the data to a regression function



Noise Removal - A Word Of Caution

An outlier may not be noise

it may be an anomaly that is very valuable (e.g., the Higgs particle)



RESOLVE INCONSISTENCIES

Inconsistencies in naming conventions or data codes

e.g., 2/5/2002 could be 2 May 2002 or 5 Feb 2002

Redundant data

duplicate tuples, which were received twice should be removed

DATA TRANSFORMATION

Can help reduce influence of extreme values

See our discussion last lecture

DATA NORMALIZATION

Sometimes we like to have all variables on the same scale

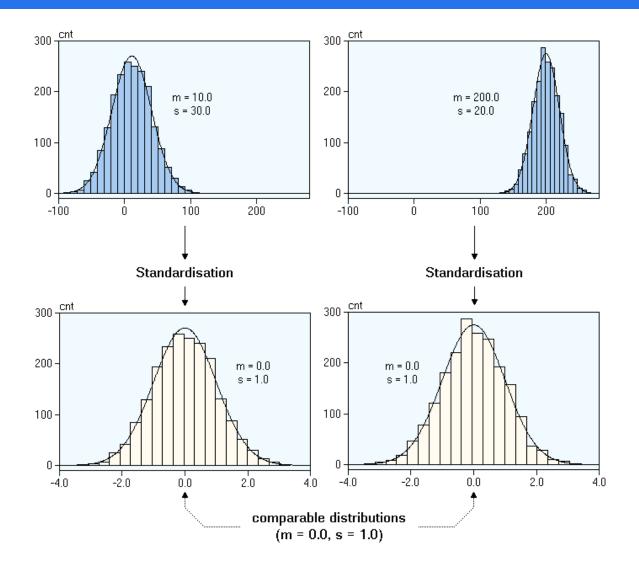
min-max normalization

$$v' = \frac{v - min}{max - min}$$

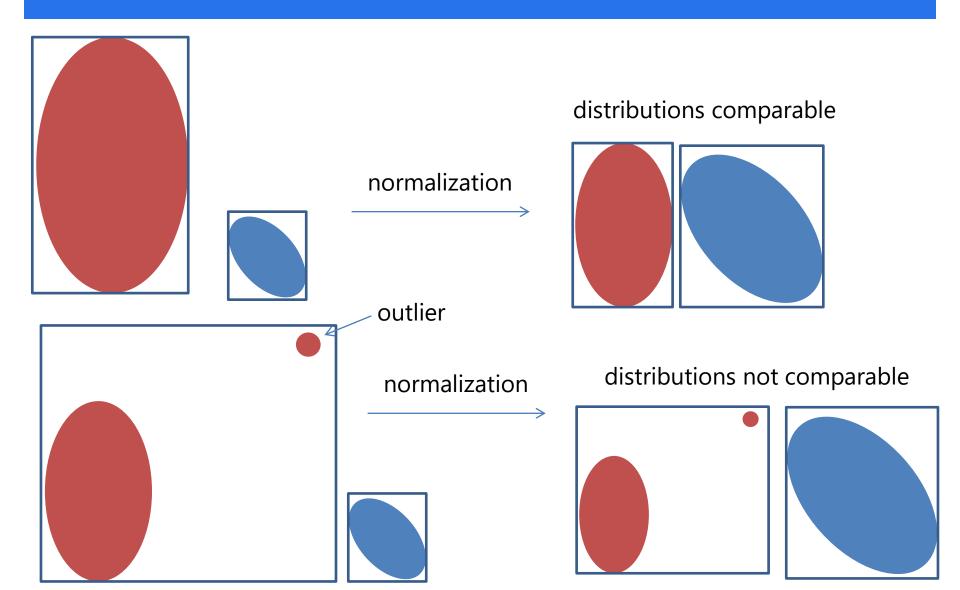
standardization / z-score normalization

$$v' = \frac{v - \overline{v}}{\sigma_v}$$

STANDARDIZATION

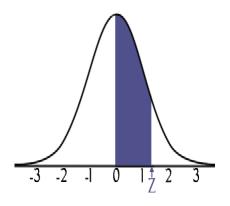


NORMALIZATION

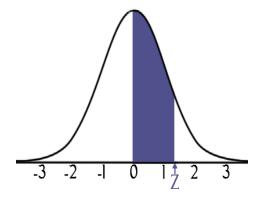


STANDARDIZATION

Is standardization less or more sensitive to outliers?



without outlier



with outlier (just slightly extended)

DATA INTEGRATION

Data integration/fusion

- multiple databases
- data cubes
- files
- notes

Produces new opportunities

- can gain more comprehensive insight (value > sum of parts)
- but watch out for synonymy and polysemy
- attributes with different labels may have the same meaning
 - "comical" and "hilarious"
- attributes with the same label may have different meaning
 - "jaguar" can be a cat or a car

But data integration can also bring ethical problems – see next

PRIVACY

Can you identify a person from these medical records?

SSN	Name	Race	Date Of Birth	Sex	ZIP	Marital Status	Health Problem
		asian	9/27/64	female	94139	divorced	hypertension
		asian	9/30/64	female	94139	divorced	obesity
		asian	4/18/64	male	94139	married	chest pain
		asian	4/15/64	male	94139	married	obesity
		black	3/13/63	male	94138	married	hypertension
		black	3/18/63	male	94138	married	shortness of breath
		black	9/13/64	female	94141	married	shortness of breath
		black	9/7/64	female	94141	married	obesity
		white	5/14/61	male	94138	single	chest pain
		white	05/08 61	male	94138	single	obesity
		white	9/15/61	female	94142	widow	shortness of breath

PRIVACY

What if you had a voter list

1	Name		Address	City	ZIP	DO	В	Sex	Party	
Sue .	Sue J. Carlson		000 Market St.	San Francisco	94142	9/15/61		female		
					7					
SSI	l Nam	e	Race	Date Of Birth	Sex	ZIP	Marital Status		Hea	lth Problem
			asian	9/27/64	female	94139	d	ivorced	hypertension	
			asian	9/30/64	female	94139	d	ivorced	obesity	
			asian	4/18/64	male	94139	r	married	chest pain	
			asian	4/15/64	male	94139	r	married	obesity	
			black	3/13/63	male	94138	r	married	hypertension	
			black	3/18/63	male	94138	r	married	shortr	ness of breath
			black	9/13/64	female	94141	r	narried	shortr	ness of breath
			black	9/7/64	female	94141	married			obesity
			white	5/14/61	male	94138		single	С	hest pain
			white	05/08 61	male	94138	single			obesity
			white	9/15/61	female	94142		widow	shortr	ness of breath

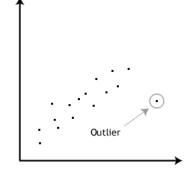
DATA FUSION VS. DATA PRIVACY

Data fusion can bring insight

- the purpose is not always good
- but often it is (criminal justice, market analysis,)

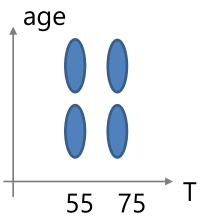
Visualization can bring insight

- the 94142 zip code would have been an outlier
- your visualization would have shown that nicely
- then you could have dug for complementary data



How to obfuscate for protection?

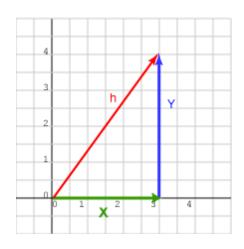
- k-anonymity (generalize)
- make data less specific → binning
- age groups, zip code groups, etc...
- make blobs instead of points

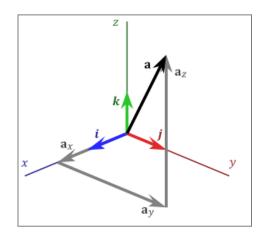


REPRESENTATION

Each data item is an N-dimensional vector (N variables)

recall 2D and 3D vectors in 2D and 3D space, respectively

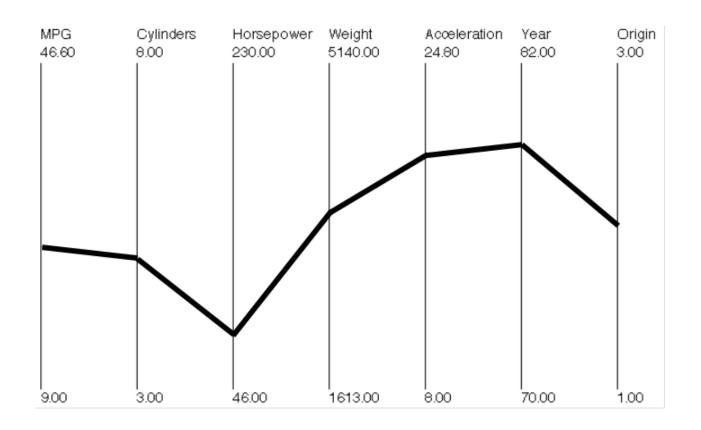




Now we have N-D attribute space

- the data axes extend into more than 3 orthogonal directions
- hard to imagine?
- that's why need good visualization methods

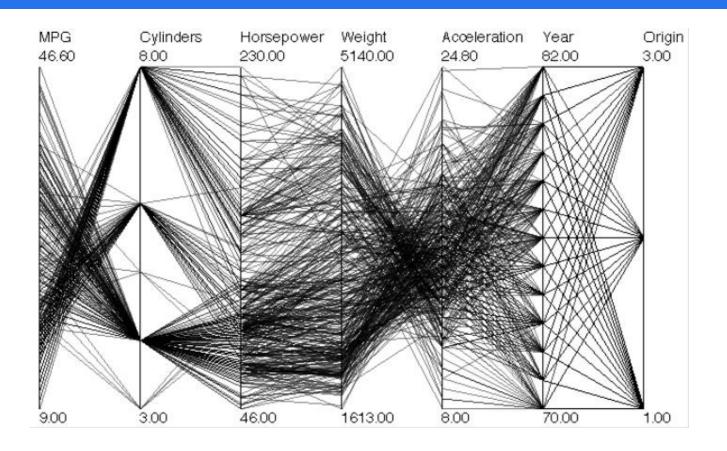
PARALLEL COORDINATES - 1 CAR



The N=7 data axes are arranged side by side

in parallel

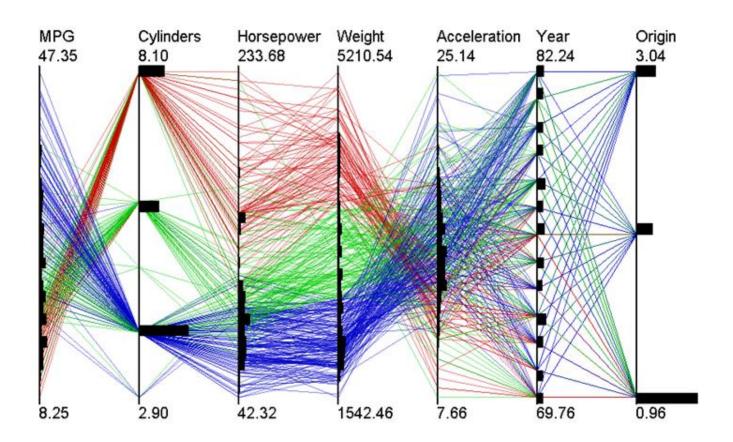
Parallel Coordinates – 100 Cars



Hard to see the individual cars?

what can we do?

Parallel Coordinates – 100 Cars



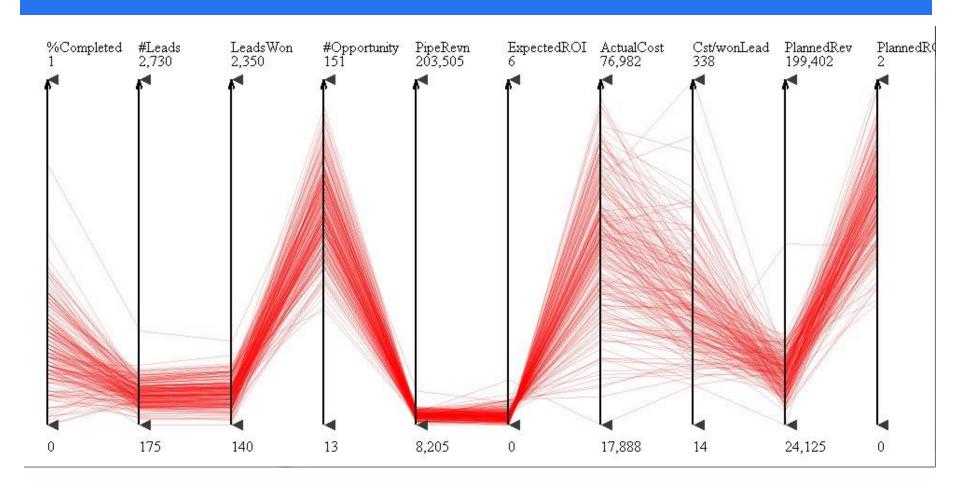
Grouping the cars into sub-populations

- this is called clustering
- can be automated or interactive (put the user in charge)

INTERACTIVE CLUSTERING WITH PARALLEL COORDINATES

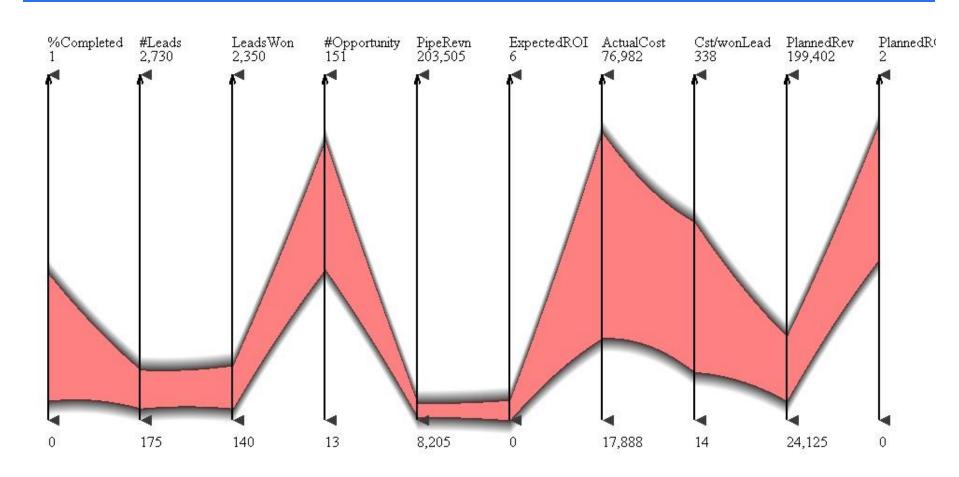
Interaction in Parallel Coordinate

ILLUSTRATIVE ABSTRACTION



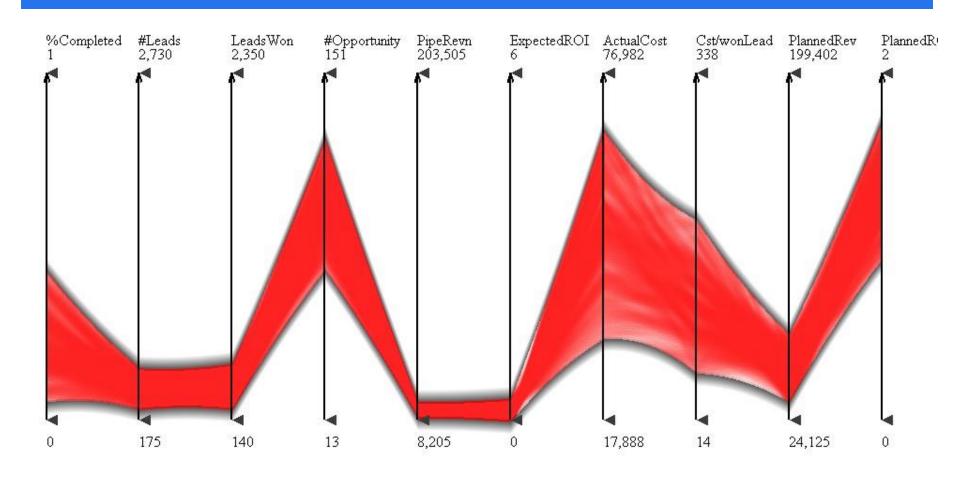
individual polylines

PC WITH ILLUSTRATIVE ABSTRACTION



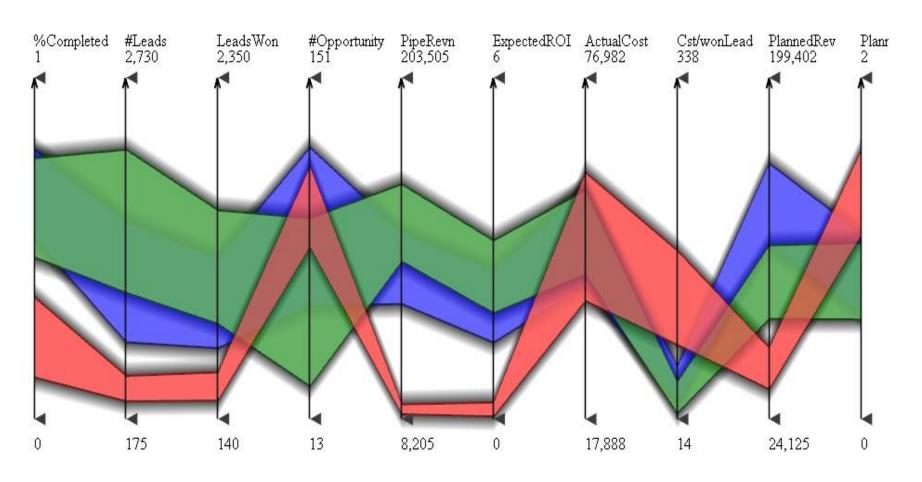
completely abstracted away

PC WITH ILLUSTRATIVE ABSTRACTION



blended partially

PC WITH ILLUSTRATIVE ABSTRACTION



all put together – three clusters

DATA PRIVACY WITH PARALLEL COORDINATES USING K-ANONYMITY

Cluster records intro k-sized bins for each variable/dimension

Dasgupta and Kosara show this for parallel coordinates [TVCG, 2011]

