CSE 564
Visualization & Visual Analytics

Data Wrangling and Preparation

Klaus Mueller

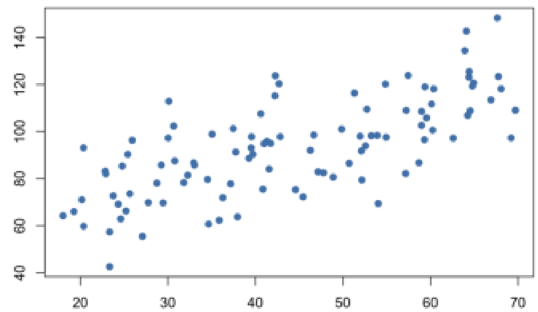
Computer Science Department
Stony Brook University

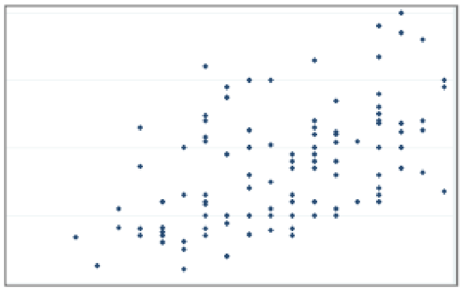
Lecture	Topic	Projects
1	Intro, schedule, and logistics	
2	Applications of visual analytics	
3	Basic tasks, data types	Project #1 out
4	Data assimilation and preparation	
5	Introduction to D3	
6	Bias in visualization	
7	Data reduction and dimension reduction	
8	Visual perception	Project #2(a) out
9	Visual cognition	
10	Visual design and aesthetics	
11	Cluster analysis: numerical data	
12	Cluster analysis: categorical data	Project #2(b) out
13	High-dimensional data visualization	
14	Dimensionality reduction and embedding methods	
15	Principles of interaction	
16	Midterm #1	
17	Visual analytics	Final project proposal call out
18	The visual sense making process	
19	Maps	
20	Visualization of hierarchies	Final project proposal due
21	Visualization of time-varying and time-series data	
22	Foundations of scientific and medical visualization	
23	Volume rendering	Project 3 out
24	Scientific and medical visualization	Final Project preliminary report due
25	Visual analytics system design and evaluation	
26	Memorable visualization and embellishments	
27	Infographics design	
28	Midterm #2	

Lab 1 Hint: Scatterplot

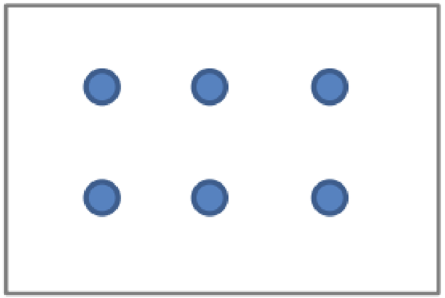
You can plot both numerical and categorical variables

- when one or both variables are numerical this is straightforward

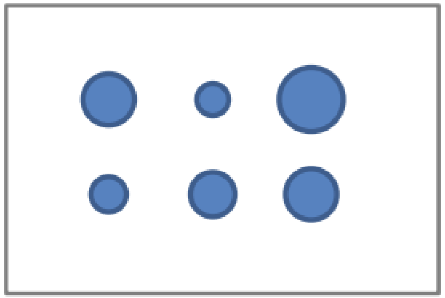




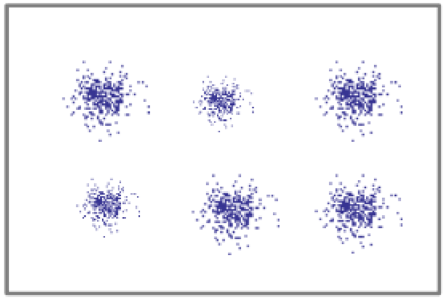
- when both variables are categorical you have three options



just overplot the points so they look like one point



scale disks in proportion to the number of points (more informative)

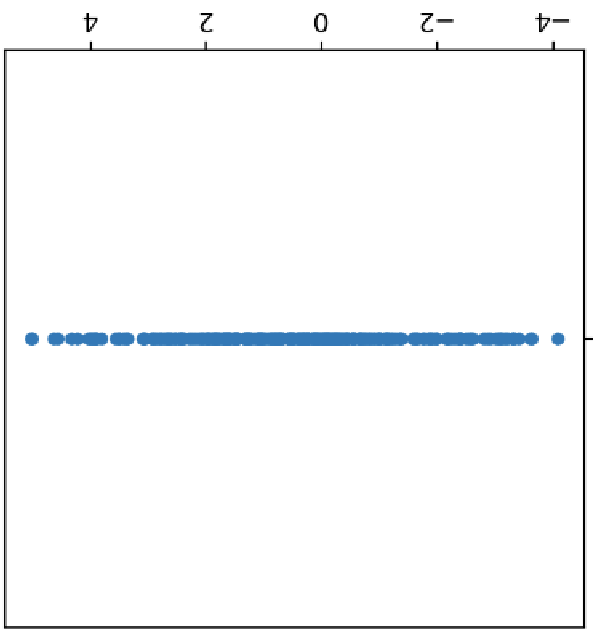


jitter each plotted point so a cluster with more points appears denser (more real)

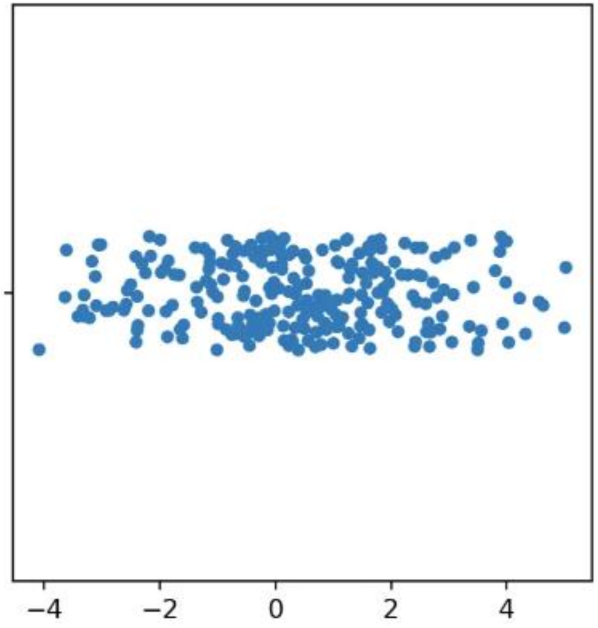
One more Scatterplot Hint

When you have one numerical and one categorical variable

- use strip plots



what you would get



with jittering in the categorical

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	B	C	D	E	F	G	H	I
1	**Name**	**Country**	**Miles Per Gallon**	**Accceleration**	**Horsepower**	**weight**	**cylinders**	**year**	**price**
2	Volkswagen Rabbit Dl	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	B	C	D	E	F	
1	**Name**	**Country**	**Miles Per Gallon**	**Accceleration**	**Horsepower**	**weight**	**cylir**
2	Volkswagen Rabbit Dl	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	

Project #1: Dataset Example

Multivariate - Quantitative data and Categorical data

Data Items

	A	B	C	D	E	F	G	H	I
1	Name	Country	Miles Per Gallon	Accceleration	Horsepower	weight	cylinders	year	price
2	Volkswagen Rabbit Dl	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
25	Toyota Corona	Japan	27,5	14,2	95	2560	4	78	2975

Categorical

Quantitative

Categorical (Ordinal)
Quantitative

Data types

Quantitative (Numerical)

Categorical (Ordinal)

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 Outwit Hub

If the data are spread across multiple webpages

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

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

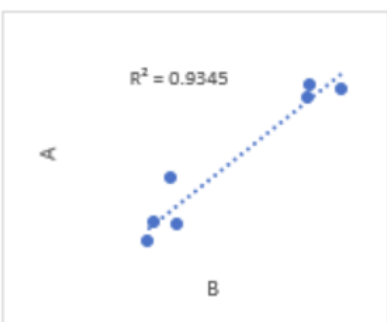
Age	Income	Team	Gender
23	24,200	Mets	M
39	50,245	Yankees	F
45	45,390	Yankees	F
22	32,300	Mets	M
52		Yankees	F
27	28,300	Mets	F
48	53,100	Yankees	M

- How would you estimate the missing value for income (imputation)?
  - ignore or put in a default value (will decimate the usable data)
  - manually fill in (can be tedious or infeasible for large data)
  - use the available value of the nearest neighbors
  - 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)
  - use a neural network trained on complete data

Multiple Imputation by Chained Equations (MICE)

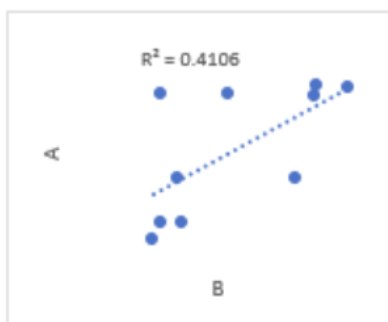
Missing data is in red. There is a strong correlation between A and B, so let's try to impute A using B and C.

A	B	C
0.93	1.40	1.53
0.24	0.46	0.76
	0.80	
0.95	1.24	1.46
0.23	0.57	
0.90		1.28
0.15	0.42	
0.47	0.54	0.63
	1.14	
0.89	1.23	1.45



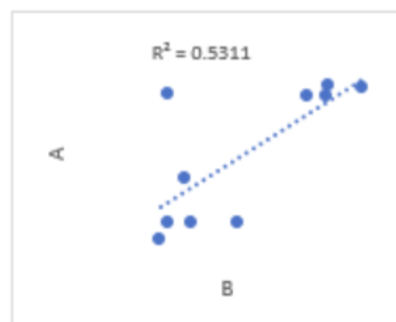
Missing data is filled in randomly. This dillutes the correlations, but allows us to impute using all available data.

A	B	C
0.93	1.40	1.53
0.24	0.46	0.76
0.90	0.80	1.53
0.95	1.24	1.46
0.23	0.57	1.28
0.90	0.46	1.28
0.15	0.42	1.53
0.47	0.54	0.63
0.47	1.14	1.28
0.89	1.23	1.45



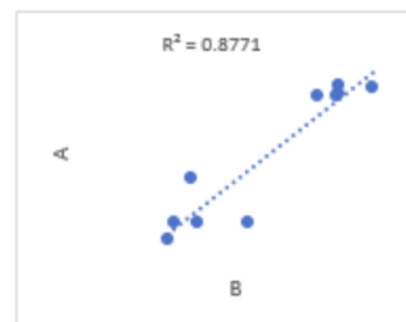
A random forest is used to predict A with B and C. Notice the correlation between A and B improved.

A	B	C
0.93	1.40	1.53
0.24	0.46	0.76
0.24	0.80	1.53
0.95	1.24	1.46
0.23	0.57	1.28
0.90	0.46	1.28
0.15	0.42	1.53
0.47	0.54	0.63
0.89	1.14	1.28
0.89	1.23	1.45



After Imputing B using A and C, we have achieved a correlation between A and B much closer to the original data.

A	B	C
0.93	1.40	1.53
0.24	0.46	0.76
0.24	0.80	1.53
0.95	1.24	1.46
0.23	0.57	1.28
0.90	1.24	1.28
0.15	0.42	1.53
0.47	0.54	0.63
0.89	1.14	1.28
0.89	1.23	1.45



continue till all specified variables have been imputed, may need to do more iterations (<5)

https://cran.r-project.org/web/packages/miceRanger/vignettes/miceAlgorithm.html

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

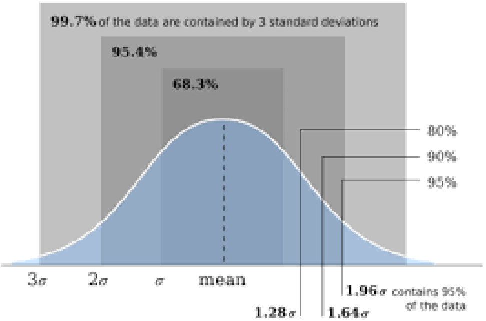
- min-max normalization

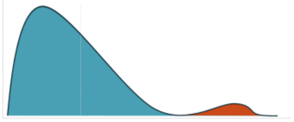
$$v' = \frac{v - min}{max - min}$$

- standardization / z-score normalization

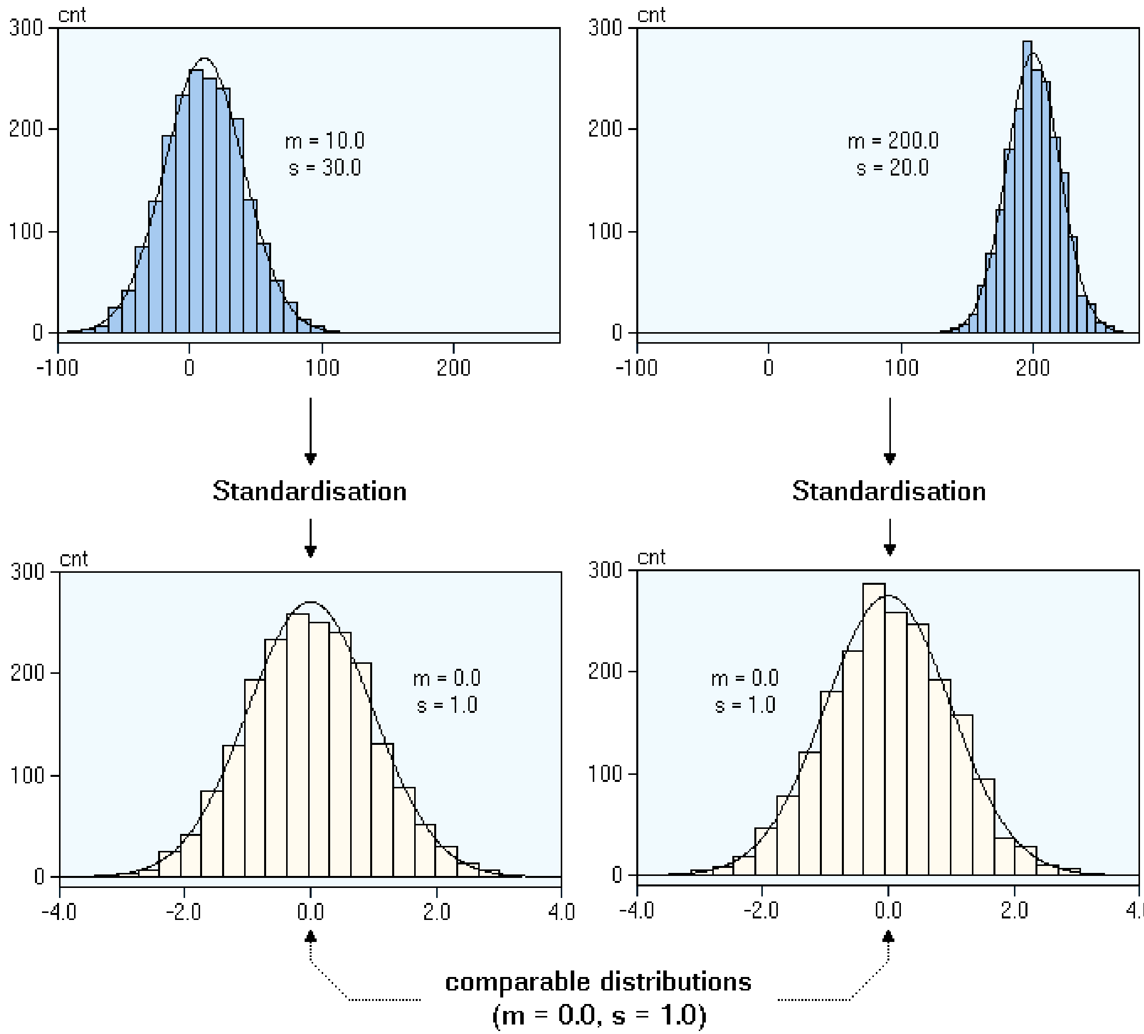
$$v' = \frac{v - \overline{v}}{\sigma_v}$$

- clipping tails and outliers
  - set all values beyond $\pm\, 3\sigma$ to value at 3σ
  - set values <5% (>95%) to value at 5% (95%)

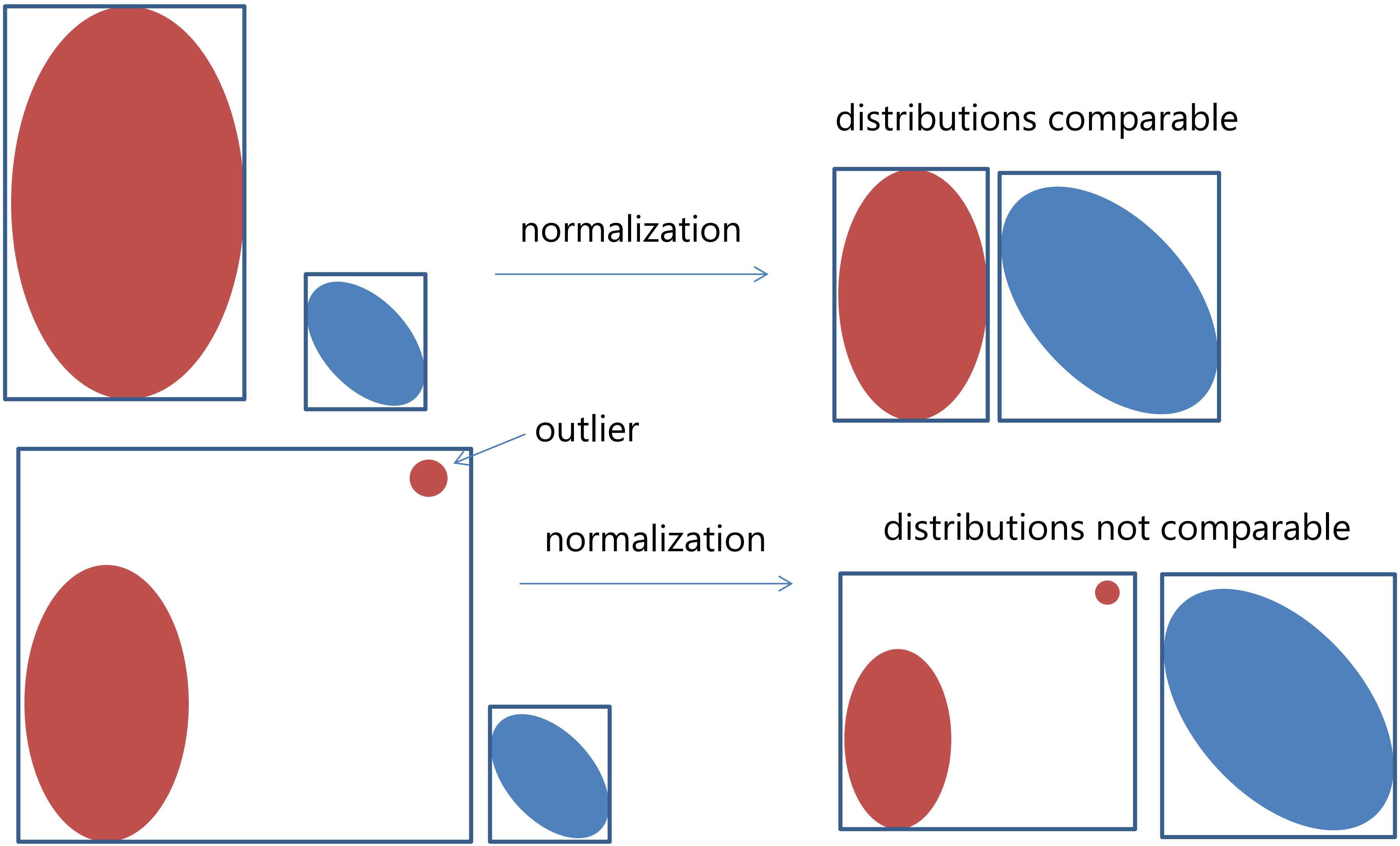




Standardization

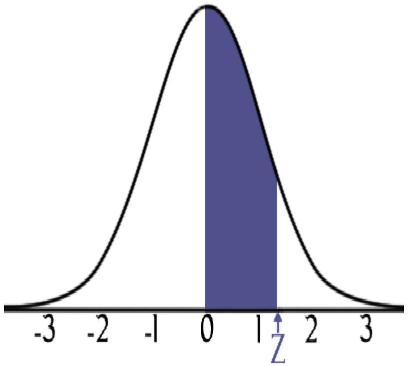


Normalization

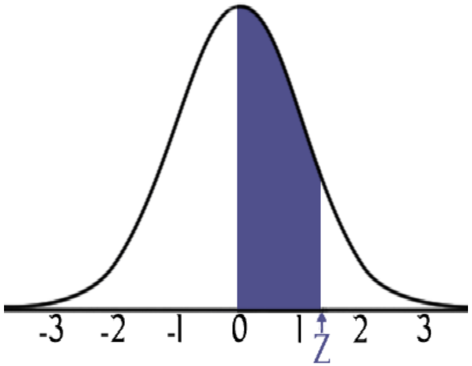


Standardization

Is standardization less or more sensitive to outliers?



without outlier

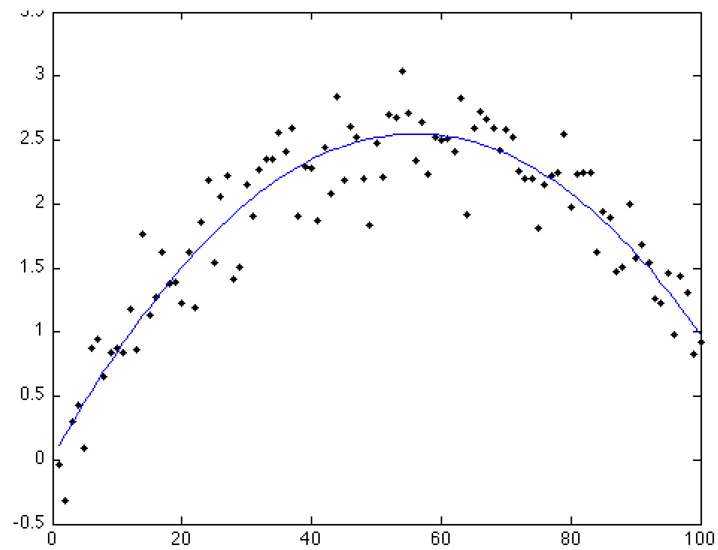


with outlier (just slightly extended)

But you need to set a reasonable cut-off point on each side

- normal distributions are infinite

Noisy Data



Noise = Random error in a measured variable

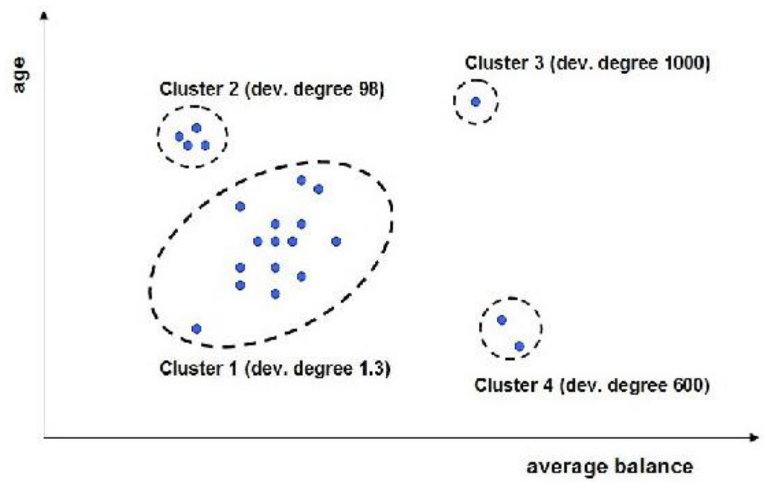
- faulty data collection instruments
- data entry problems
- data transmission problems
- technology limitation
- inconsistency in naming convention

Other data problems which require data cleaning

- duplicate records
- incomplete data
- inconsistent data

Noisy Data – What To Do

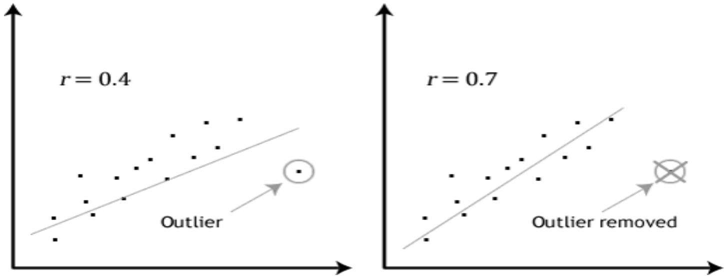
Binning method
- discussed last lecture



Clustering
- detect and remove outliers

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

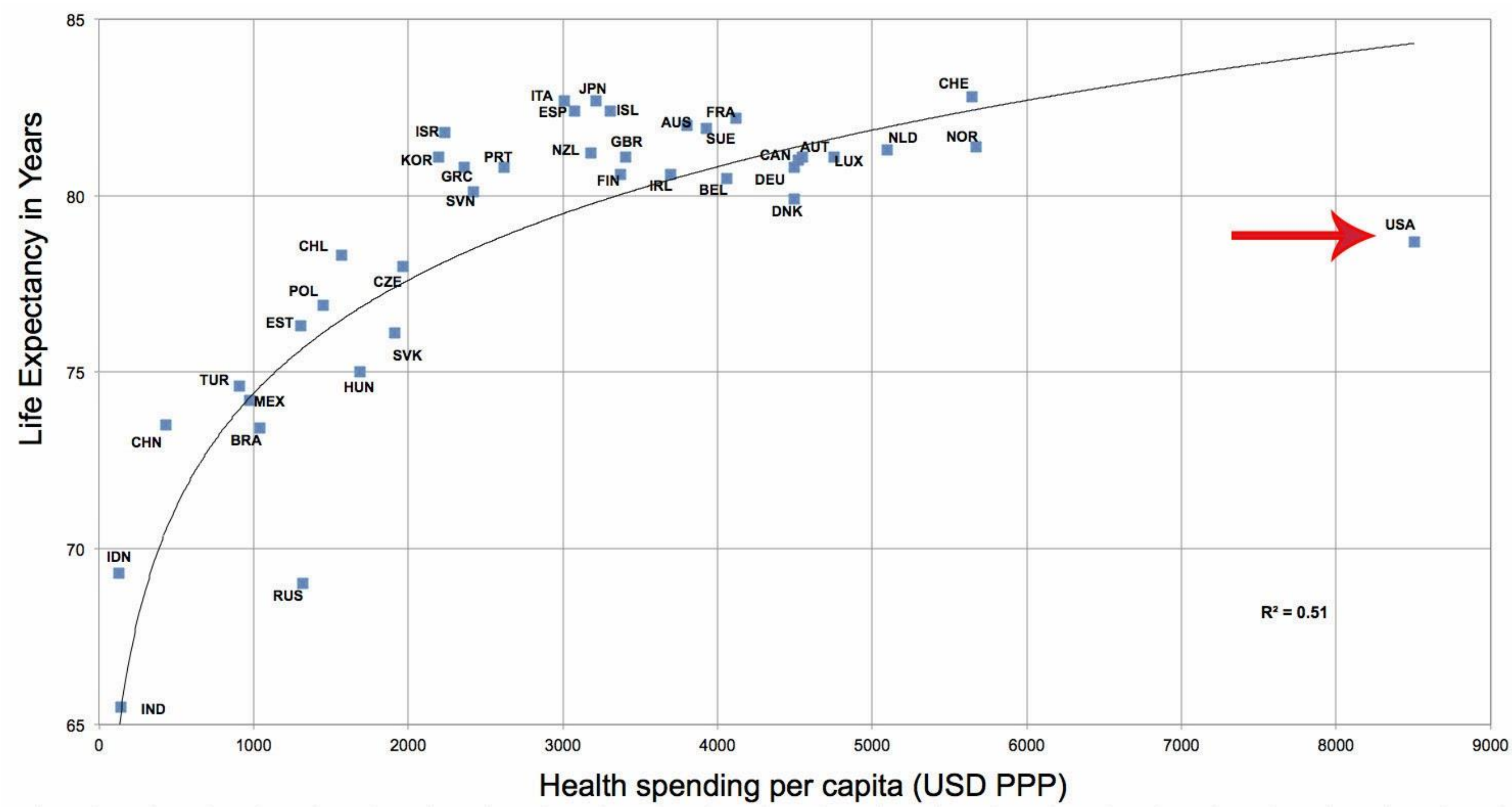
Regression
- smooth by fitting the data to a regression function



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

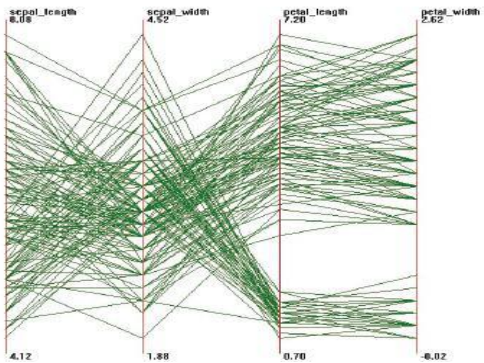
Inconsistencies in naming conventions or data codes

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

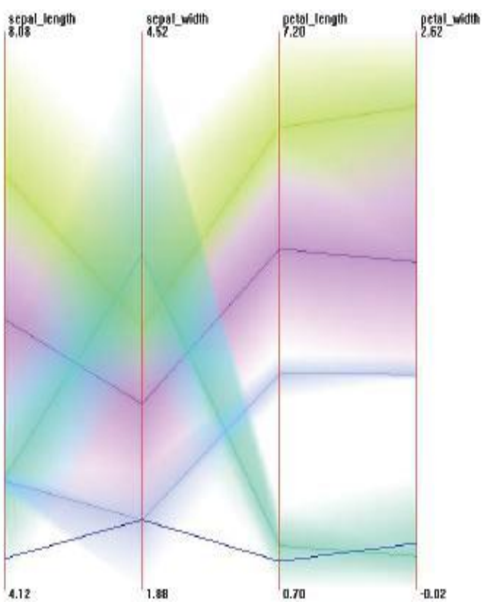
Redundant data

- duplicate tuples, which were received twice should be removed

Data Aggregation



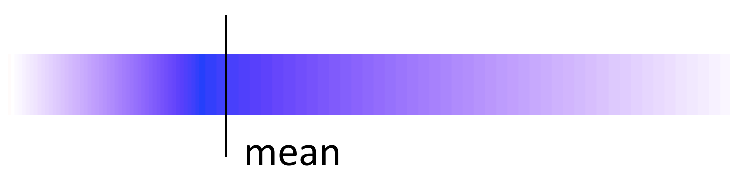
Raw parallel coordinate display



Aggregate parallel coordinate display

- 4 clusters shown in different colors
- means are visualized as opaque polylines
- cluster extents are mapped to semi-transparent shapes between each axis pair
- semi-transparencies determined by linear distance from cluster center to (clipped) extent

left cluster ext. for variable i



right cluster ext. for variable i

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

Data Fusion – How To (1)

Goal is to add new thematic aspects

- enable deeper and more far-fetching insights
- can open valuable opportunities for research and $$$

How to do it

- start off with a first dataset, such as a set of listings of houses
- ask, what would house buyers be interested in?
  - education for children (school quality, pre-K, …)
  - quality of life (entertainment, socializing, fitness, clean air, …)
  - infrastructure (shopping, airport, roads, …)
  - what else?
- make Google your best friend
  - determine a good attribute to link to other datasets (e.g. zip code)
  - then ask "primary education by zip code" or "livability by zip code"

Example: Fusing Different Thematic Datasets

House listing data

Address	Size	Bedrooms	Baths	Price	Zip Code
5 Nut Str.	2,345 sqft	3	1	$564k	11794

Education by zip code

Zip Code	School Name	Avg. SAT	Class Size	Cost
11794	Tree Top	1060	34	Public

Quality of life by zip code

Zip Code	Livability Score	Distance to Airport	Air Quality Score	Electricity Cost
11794	63	45 miles	89	$0.34/KW

Make sure that all data are from the same/similar year (when time matters)

Might need different keys for linking different thematic datasets

- for example zip code, state, county, and so on
- find associations for each in all tables and fuse
- duplicate information for coarse grained tables in finer-grained tables

But Data Integration Can Also Bring Ethical Problems

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

Name	Address	City	ZIP	DOB	Sex	Party	
Sue J. Carlson	900 Market St.	San Francisco	94142	9/15/61	female		

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

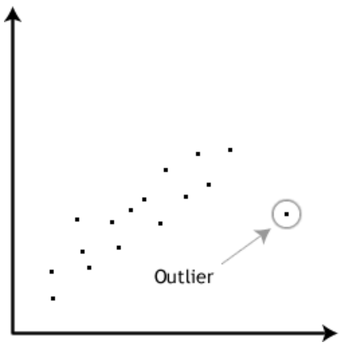
Data Fusion vs. Data Privacy

Data fusion can bring insight

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

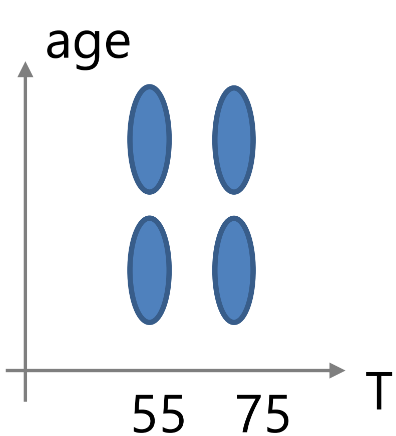
Visualization can bring insight

- 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?

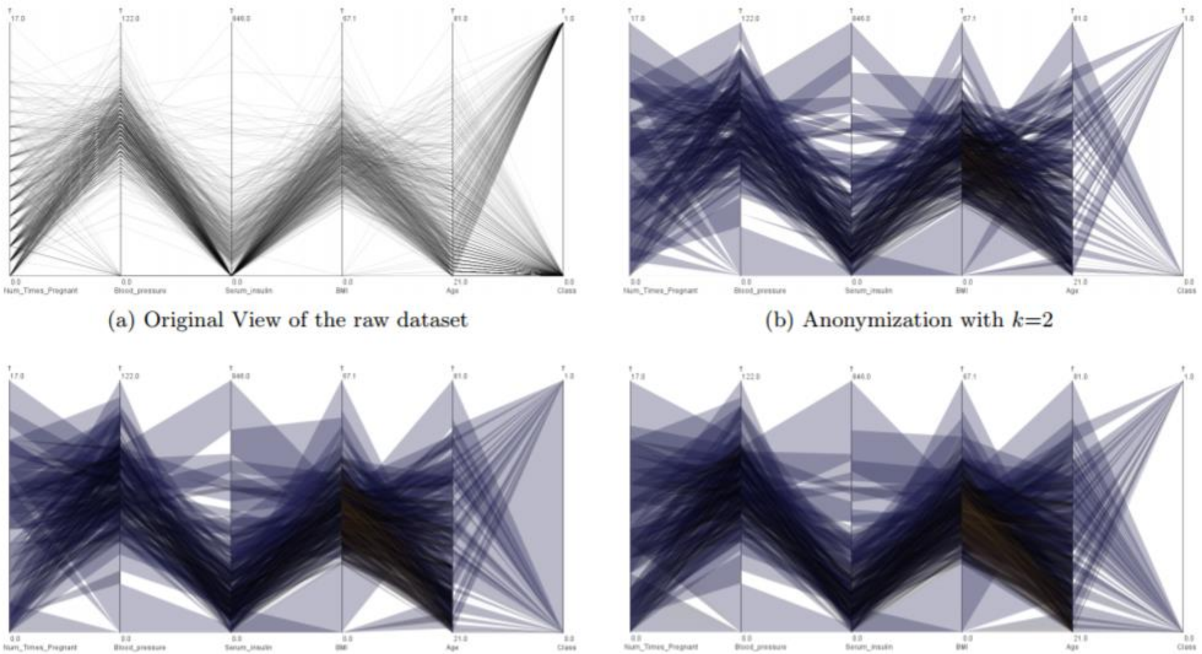
- k-anonymity (generalize)
- make data less specific → use binning
- age *groups*, zip code *groups*, etc...
- make blobs instead of points



Data Privacy With Parallel Coordinates Using k-Anonymity

Cluster records are aggregated into k-sized bins for each variable/dimension

- Dasgupta and Kosara show this for parallel coordinates [TVCG, 2011]
- see slides for data aggregation discussed before



(a) Original View of the raw dataset

(b) Anonymization with k=2

(c) Anonymization with k=3

(d) Anonymization with k=4

The Need for Data Reduction

Purpose

- reduce the data to a size that can be feasibly stored
- reduce the data so a mining algorithm can be feasibly run

Alternatives

- buy more storage
- buy more computers or faster ones
- develop more efficient algorithms (look beyond O-notation)

In practice, all of this is happening at the same time

- but the growth of data and complexities is faster
- and so data reduction is important

Data Reduction

Sampling

- random
- stratified

Data summarization

- binning (already discussed)
- clustering (see a future lecture)
- dimension reduction (see next lecture)

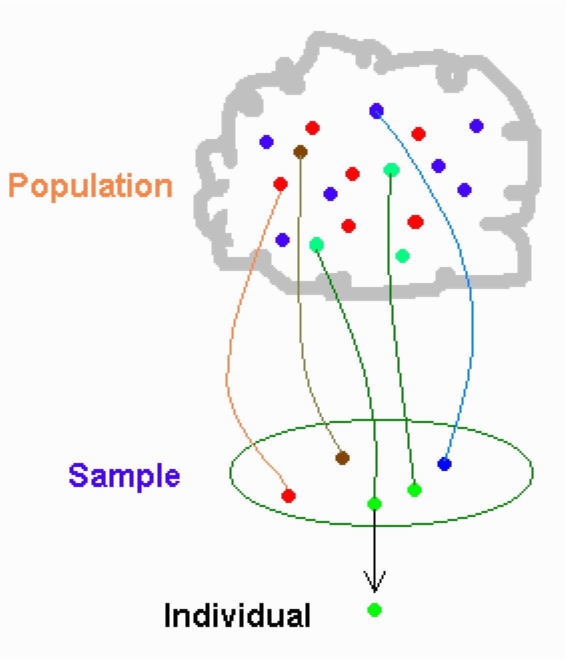
Sampling

The goal

- pick a representative subset of the data

Random sampling

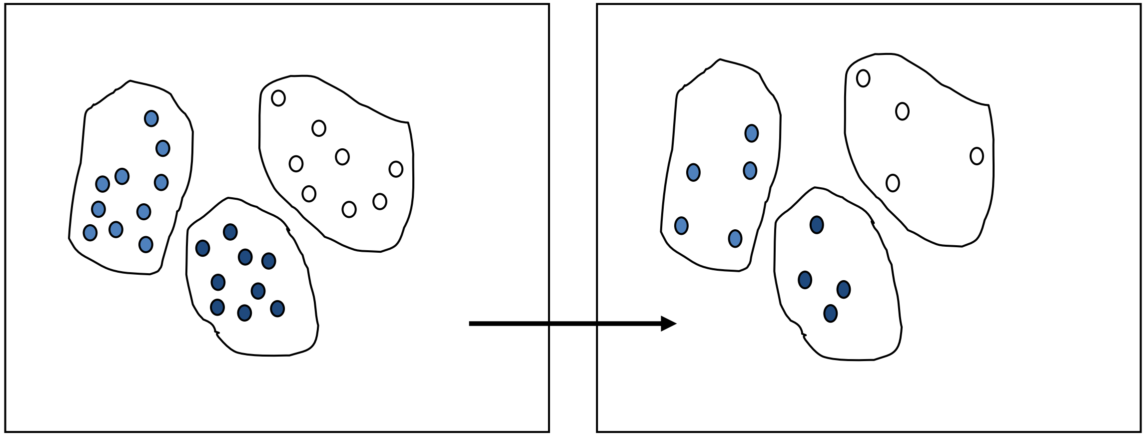
- pick sample points at random
- will work if the points are distributed uniformly
- this is usually not the case
- outliers will likely be missed
- so the sample will not be representative



Adaptive Sampling

Pick the samples according to some knowledge of the data distribution

- create a binning of some sort (outliers will form bins as well)
- also called *strata* (stratified sampling)
- the size of each bin represents its percentage in the population
- it guides the number of samples – bigger bins get more samples



sampling rate ~ cluster size

What's When Your data Is Too Small

Can you "hallucinate" or "invent" realistic data?

And if so, how would you go about this?

How to Hallucinate More data...

Data Augmentation

Strategy to artificially synthesize new data from existing data

- go from small data to big data

Data Augmentation in Machine learning

Important topic in deep learning

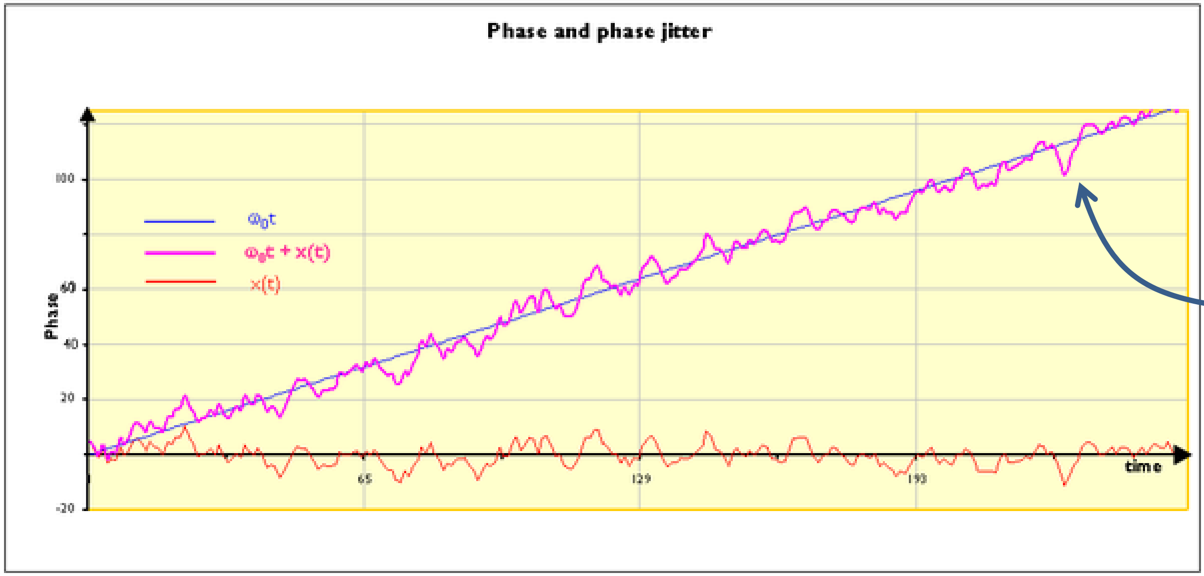
Common techniques are (for images)

- rotations
- translations
- zooms
- flips
- color perturbations
- crops
- add noise by *jittering*

What's Jittering?

Definition from dictionary

- act nervously
- "an anxious student who jittered at any provocation"



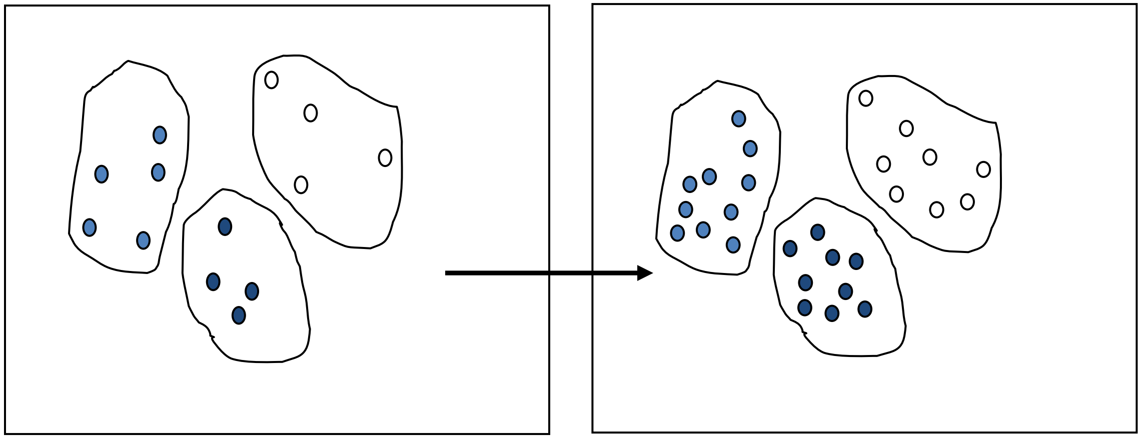
Jitter (noise)

- small random noise about a steady signal

Data Augmentation for Visualization & Visual Analytics

Generate new samples according to the data distributions

- cluster the data (outliers will form clusters as well)
- the size of each cluster represents its percentage in the population
- randomize new samples – bigger clusters get more samples
- add a small randomized value to either the mean or an existing sample
- do this for every dimension of the chosen mean or sample



augmentation rate ~ cluster size

Today's Take Aways

How to deal with

- missing data
- noisy data and outliers
- uneven and diverse data ranges

Various strategies for segmenting data to

- visualize overall trends and groups
- reduce data
- augment/enrich data
- enable techniques to ensure privacy

Enrich datasets by adding other thematic aspects

- obtained by additional attributes from other sources
- determine proper key attributes helpful for linking