Lecture 1: Medical Databases

CSCI6410/EPAH6410/CSCI4148

Finlay Maguire (finlay.maguire@dal.ca)

Learning Objectives

- Overview of the types of medical database
- Ways of maintaining data privacy with medical databases and some of their trade-offs
- How and why ontologies and survey weights are used in medical databases

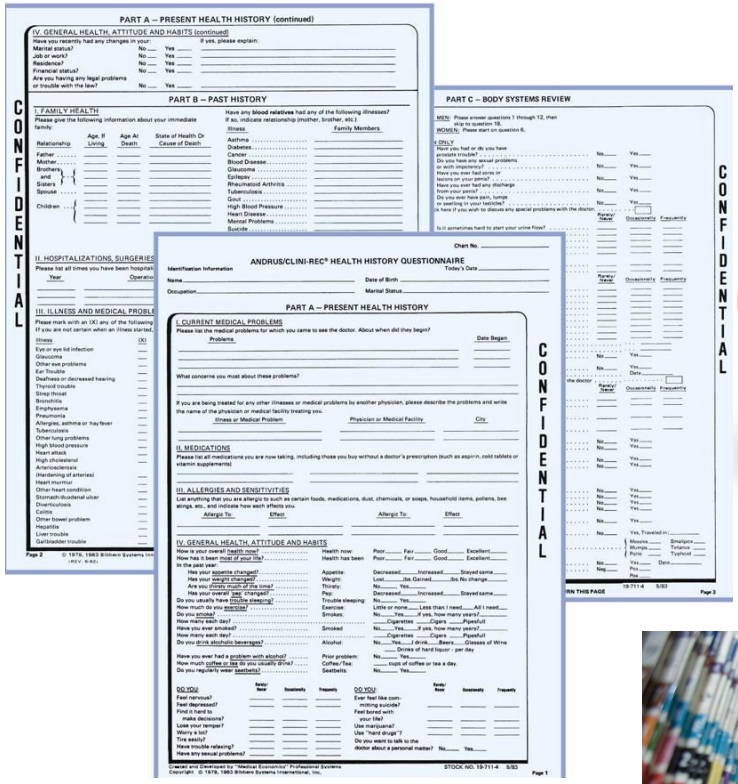
- Key strategies/approaches for exploratory data analysis
- Different types of dimensionality reduction
- Basics of supervised learning
- Accessing feature importances
- Aggregating simple/weak models to improve performance: boosting and bagging

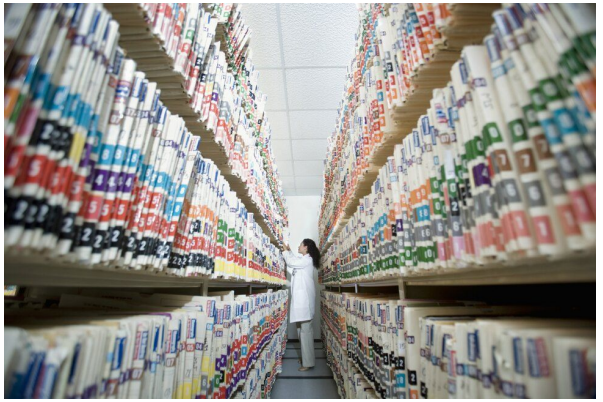
What is a database?

Databases (broadly) are ordered collections of data

Examples include:

- Medical Charts

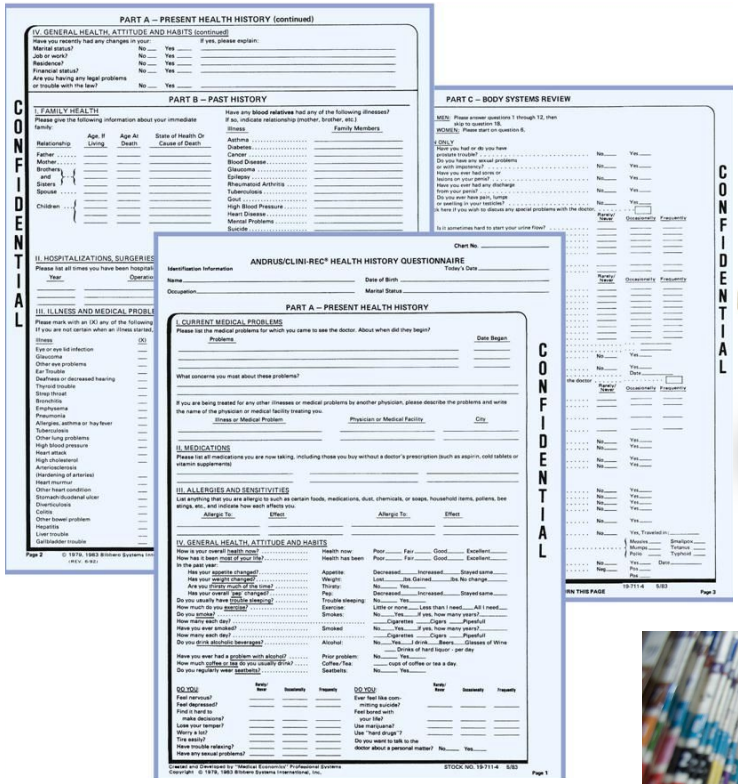


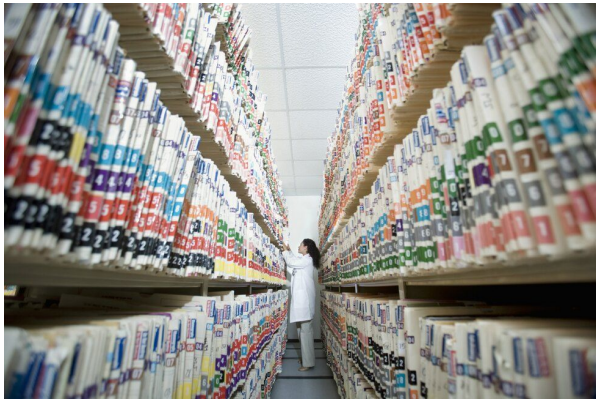


Databases (broadly) are ordered collections of data

Examples include:

- Medical Charts
- Phone Book
- Dictionaries
- Spreadsheet





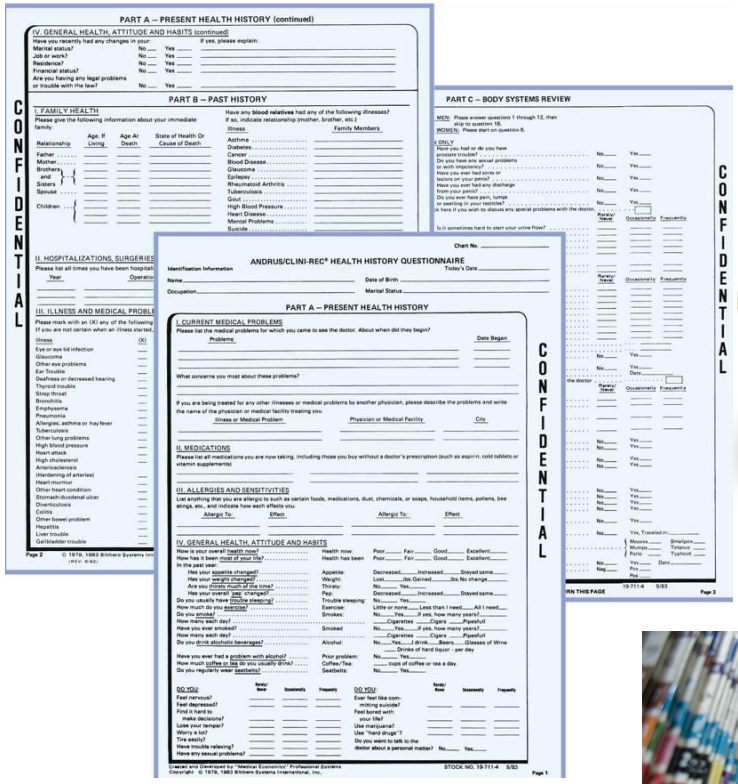
Databases (broadly) are ordered collections of data

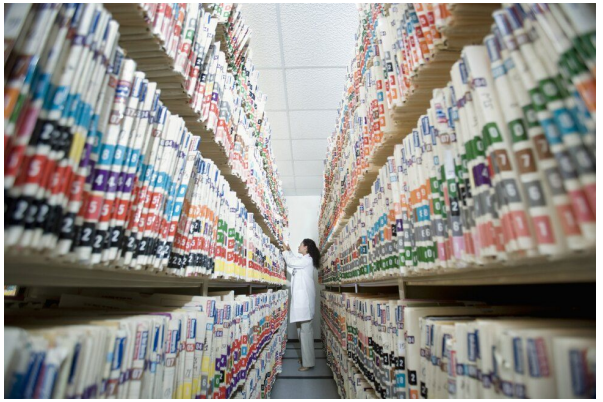
Examples include:

- Medical Charts
- Phone Book
- Dictionaries
- Spreadsheet

Ordering:

- Index
- Defined fields
- Standardisation

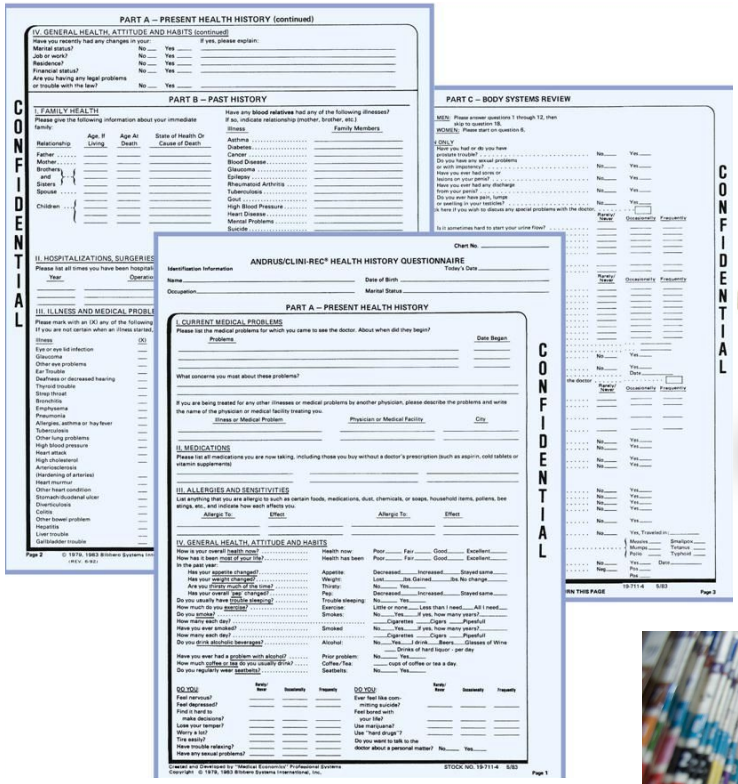




Databases (broadly) are ordered collections of data

Examples include:

- Medical Charts
- Phone Book
- Dictionaries
- Spreadsheet

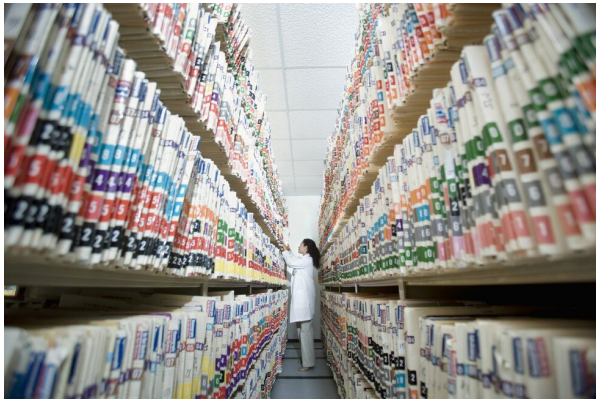


Ordering:

- Index
- Defined fields
- Standardisation

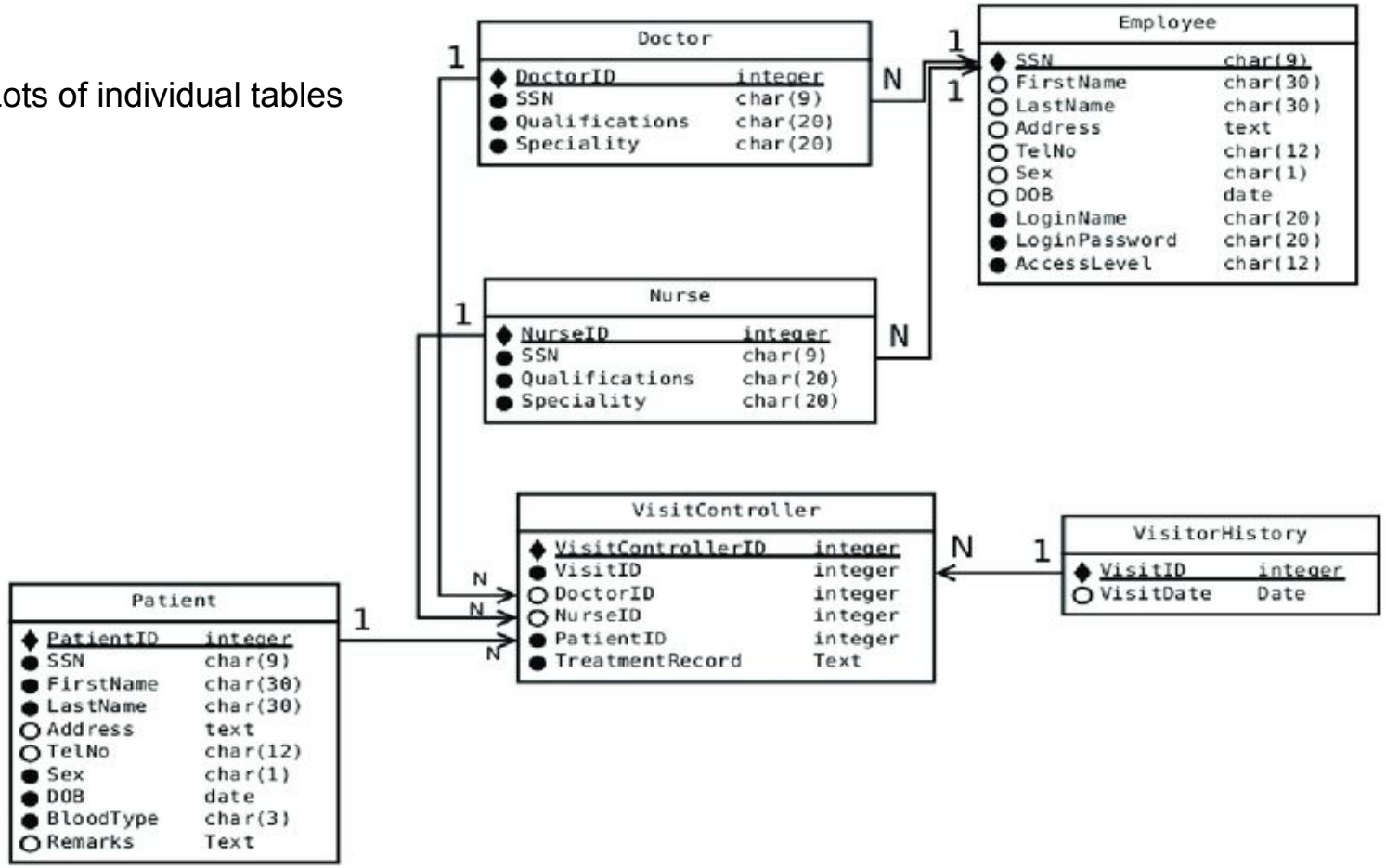
Organisation make some tasks easier/harder:

- Find all patients with the same condition
- Find the longest word in a dictionary
- Find an a number from an address in a phonebook



Most Common Type: Relational Databases

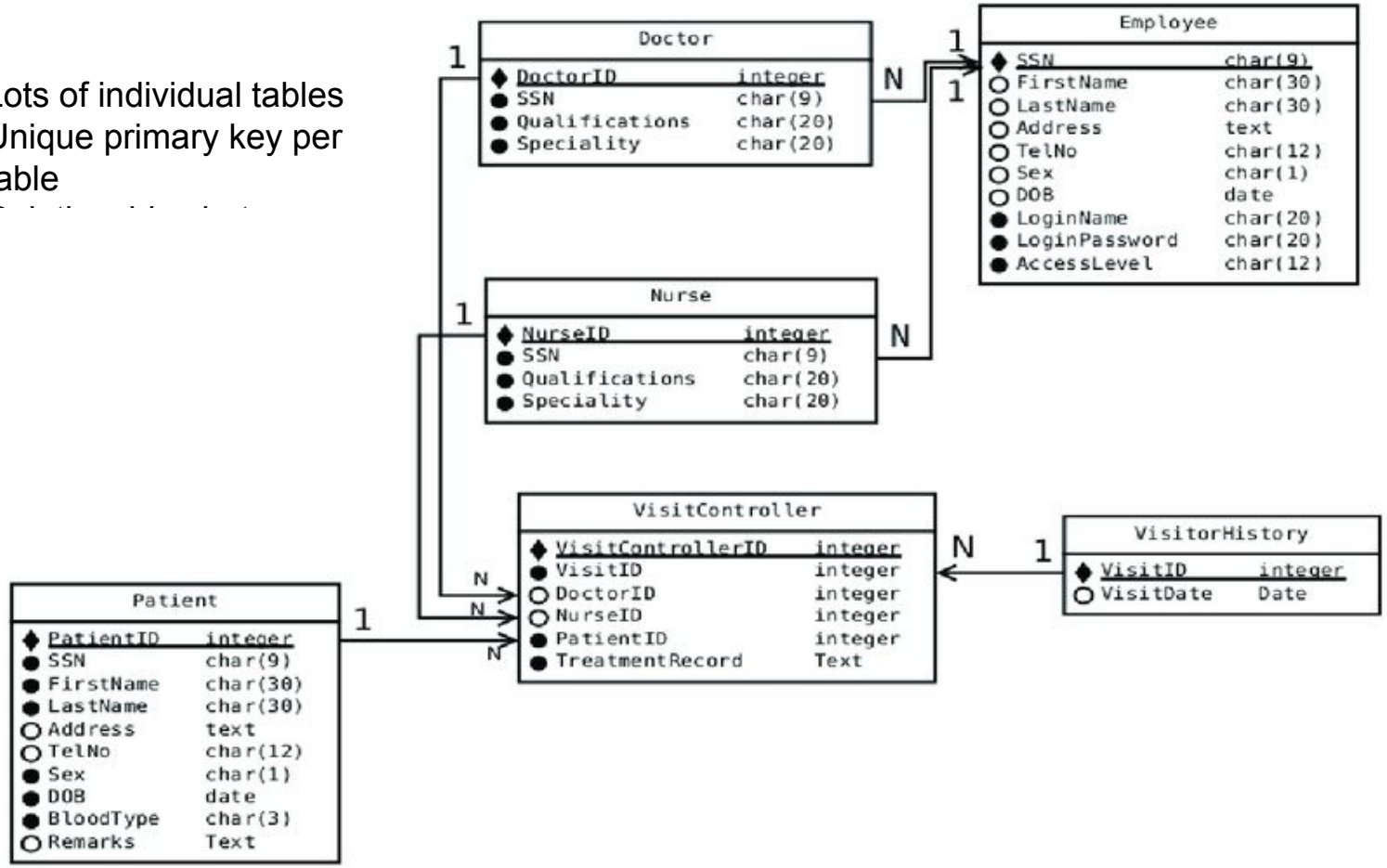
- Lots of individual tables



http://dx.doi.org/10.1016/j.procs.2015.08.441

Most Common Type: Relational Databases

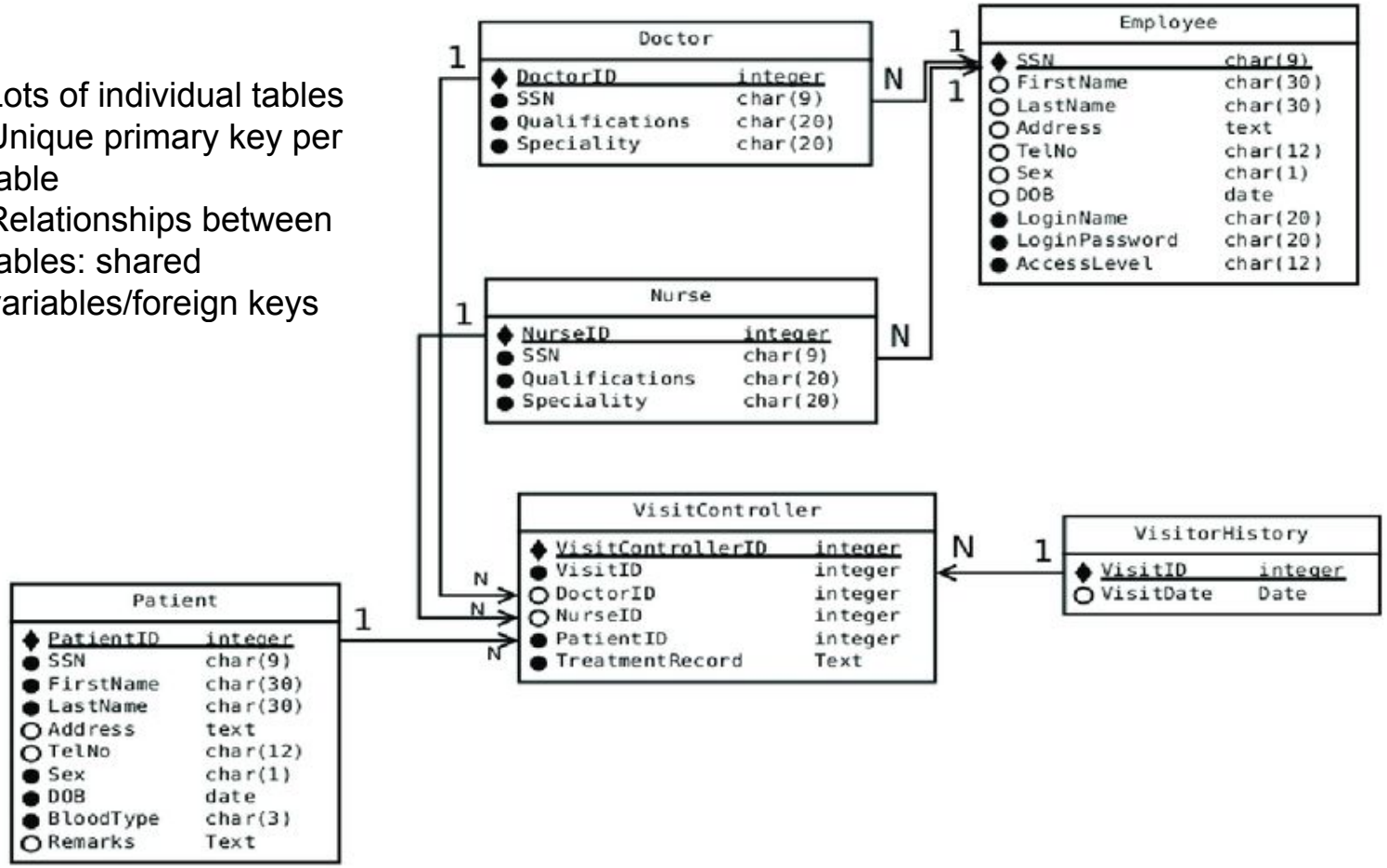
- Lots of individual tables
- Unique primary key per table



http://dx.doi.org/10.1016/j.procs.2015.08.441

Most Common Type: Relational Databases

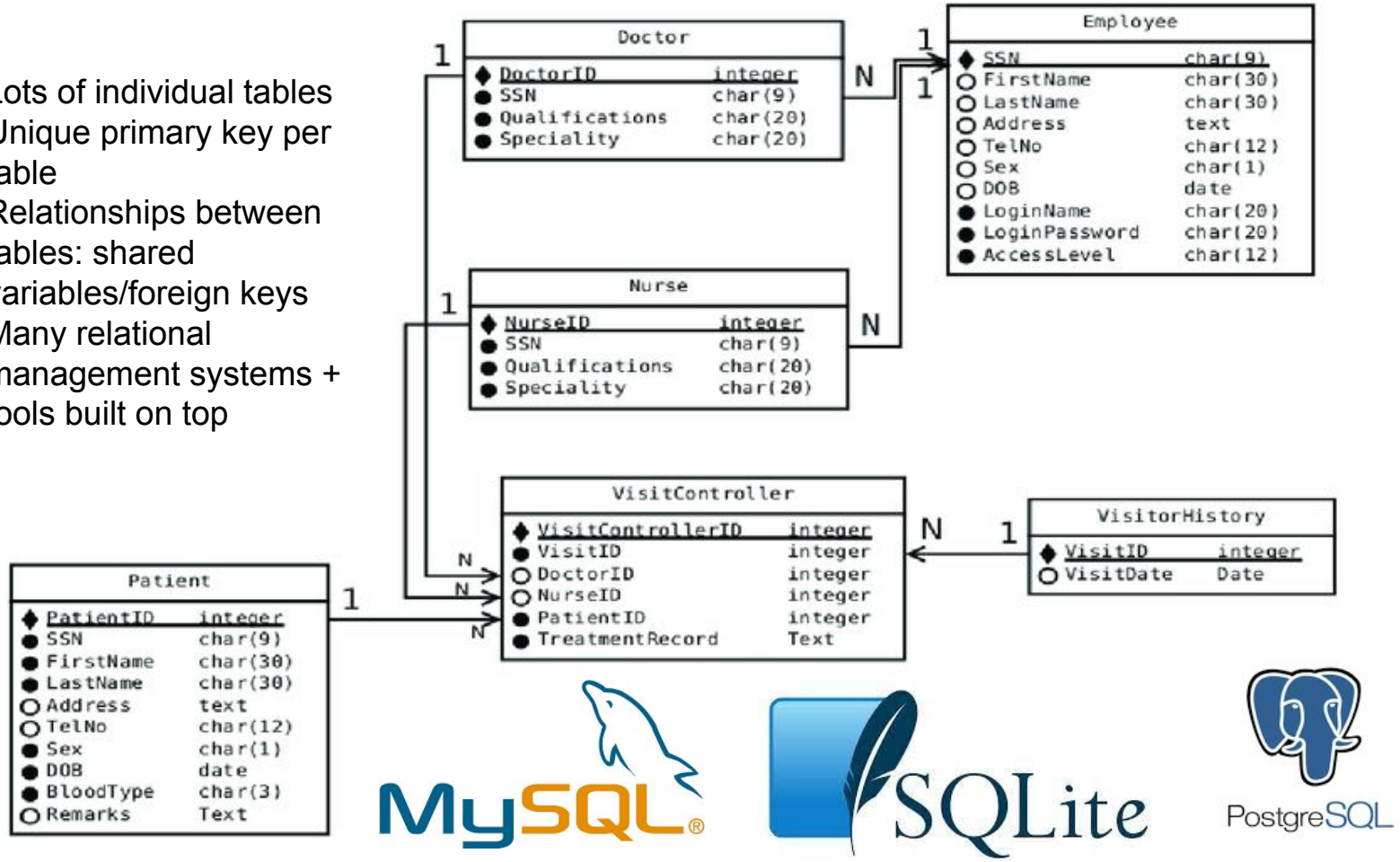
- Lots of individual tables
- Unique primary key per table
- Relationships between tables: shared variables/foreign keys



http://dx.doi.org/10.1016/j.procs.2015.08.441

Most Common Type: Relational Databases

- Lots of individual tables
- Unique primary key per table
- Relationships between tables: shared variables/foreign keys
- Many relational management systems + tools built on top



http://dx.doi.org/10.1016/j.procs.2015.08.441

REDCap
Research Electronic Data Capture

Queried using Structured Query Language (SQL)

- Non-procedural Language
- Standardised/powerful/flexible

https://dbplyr.tidyverse.org/articles/sql-translation.html

Queried using Structured Query Language (SQL)

- Non-procedural Language
- Standardised/powerful/flexible
- Basis of many data tools
- Well-supported by dbplyr

https://dbplyr.tidyverse.org/articles/sql-translation.html

Queried using Structured Query Language (SQL)

- Non-procedural Language
- Standardised/powerful/flexible
- Basis of many data tools
- Well-supported by dbplyr

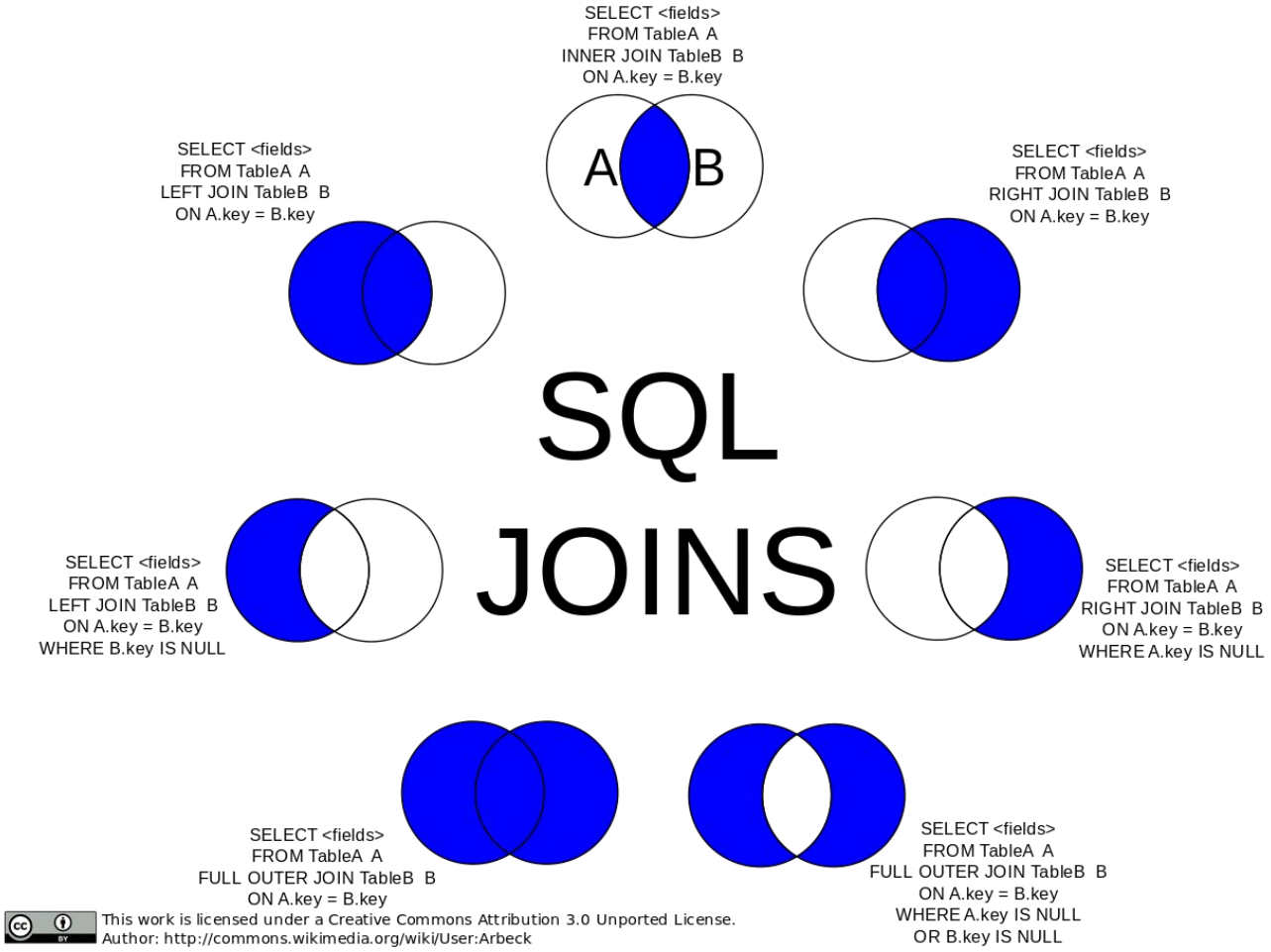
```
flights %>%
  select(contains("delay")) %>%
  show_query()
#> <SQL>
#> SELECT `dep_delay`, `arr_delay`
#> FROM `nycflights13::flights`
```

```
flights %>%
  group_by(month, day) %>%
  summarise(delay = mean(dep_delay)) %>%
  show_query()
#> Warning: Missing values are always removed in SQL.
#> Use `AVG(x, na.rm = TRUE)` to silence this warning
#> <SQL>
#> SELECT `month`, `day`, AVG(`dep_delay`) AS `delay`
#> FROM `nycflights13::flights`
#> GROUP BY `month`, `day`
```

```
flights %>%
  select(distance, air_time) %>%
  mutate(speed = distance / (air_time / 60)) %>%
  show_query()
#> <SQL>
#> SELECT `distance`, `air_time`, `distance` / (`air_time` / 60.0) AS `speed`
#> FROM (SELECT `distance`, `air_time`
#> FROM `nycflights13::flights`)
```

https://dbplyr.tidyverse.org/articles/sql-translation.html

SQL enables complex joins/queries

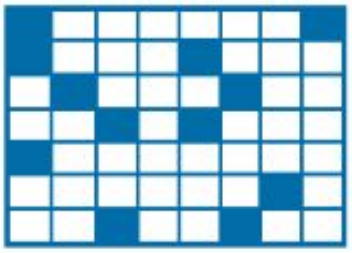


Are all databases relational?

Non-Relational Databases

- Less common than relational in medicine

https://phoenixnap.com/kb/database-types



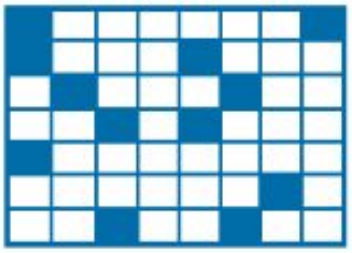
Column based

Google Big Query

Non-Relational Databases

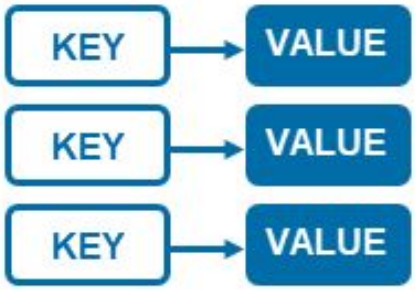
- Less common than relational in medicine

https://phoenixnap.com/kb/database-types



Column based

Google Big Query



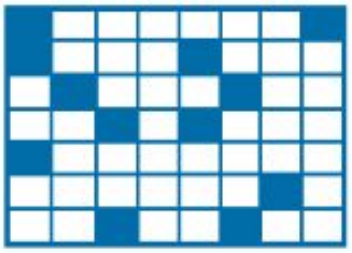
Key-value

redis

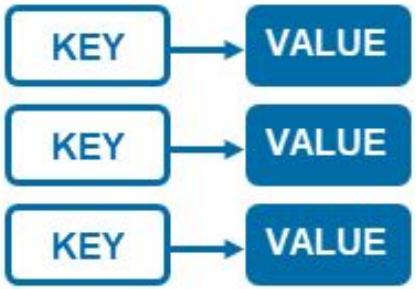
Non-Relational Databases

- Less common than relational in medicine

https://phoenixnap.com/kb/database-types



Column based



Key-value

Graph

Google Big Query

redis

neo4j

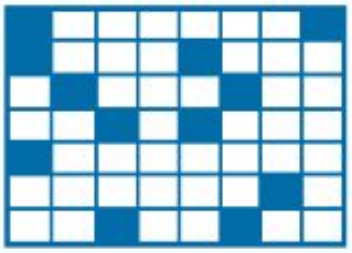
Non-Relational Databases

- Less common than relational in medicine
- Querying can be… very easy or very complicated

Find me the homepage of anyone known by Tim Berners-Lee.

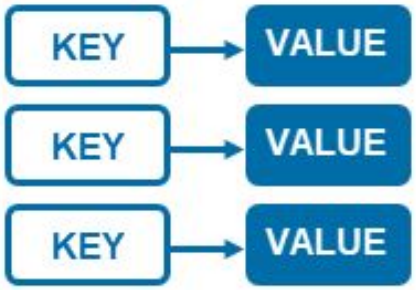
```
PREFIX foaf:  <http://xmlns.com/foaf/0.1/>
PREFIX card: <http://www.w3.org/People/Berners-Lee/card#>
SELECT ?homepage
FROM <http://www.w3.org/People/Berners-Lee/card>
WHERE {
    card:i foaf:knows ?known .
    ?known foaf:homepage ?homepage .
}
```

https://phoenixnap.com/kb/database-types



Column based

Google Big Query



Key-value

redis

Graph

neo4j

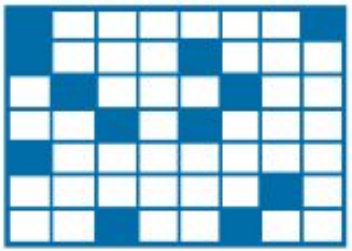
Non-Relational Databases

- Less common than relational in medicine
- Querying can be… very easy or very complicated

Find me the homepage of anyone known by Tim Berners-Lee.

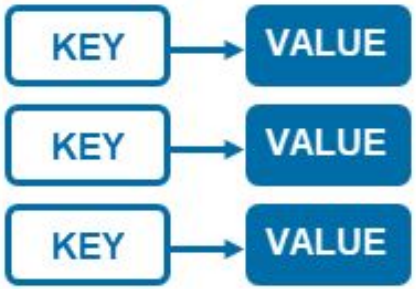
```
PREFIX foaf:  <http://xmlns.com/foaf/0.1/>
PREFIX card: <http://www.w3.org/People/Berners-Lee/card#>
SELECT ?homepage
FROM <http://www.w3.org/People/Berners-Lee/card>
WHERE {
    card:i foaf:knows ?known .
    ?known foaf:homepage ?homepage .
}
```

https://phoenixnap.com/kb/database-types



Column based

Google Big Query



Key-value

redis

Graph

neo4j

Document

mongoDB.

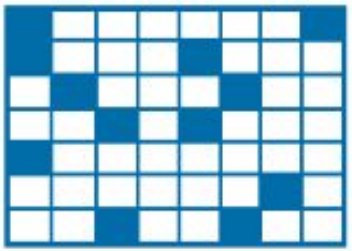
Non-Relational Databases

- Less common than relational in medicine
- Querying can be… very easy or very complicated
- Mostly for very large datasets:
  - User data / security audit data
  - Medical image data

Find me the homepage of anyone known by Tim Berners-Lee.

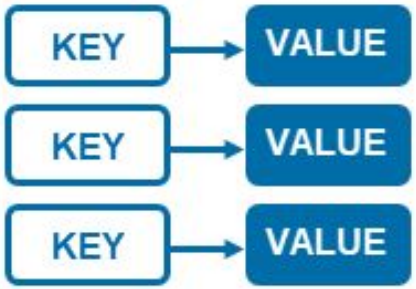
```
PREFIX foaf:  <http://xmlns.com/foaf/0.1/>
PREFIX card: <http://www.w3.org/People/Berners-Lee/card#>
SELECT ?homepage
FROM <http://www.w3.org/People/Berners-Lee/card>
WHERE {
    card:i foaf:knows ?known .
    ?known foaf:homepage ?homepage .
}
```

https://phoenixnap.com/kb/database-types



Column based

Google Big Query



Key-value

redis

Graph

neo4j

Document

mongoDB.

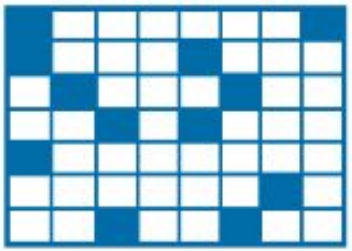
Non-Relational Databases

- Less common than relational in medicine
- Querying can be… very easy or very complicated
- Mostly for very large datasets:
  - User data / security audit data
  - Medical image data
- Or unusual data structures:
  - Contact tracing
  - Ontologies

Find me the homepage of anyone known by Tim Berners-Lee.

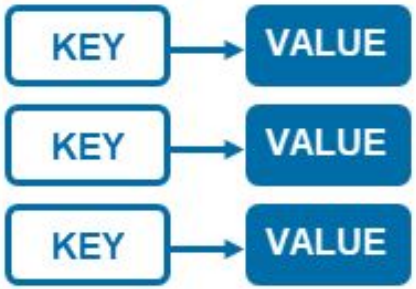
```
PREFIX foaf:  <http://xmlns.com/foaf/0.1/>
PREFIX card: <http://www.w3.org/People/Berners-Lee/card#>
SELECT ?homepage
FROM <http://www.w3.org/People/Berners-Lee/card>
WHERE {
    card:i foaf:knows ?known .
    ?known foaf:homepage ?homepage .
}
```

https://phoenixnap.com/kb/database-types



Column based

Google Big Query



Key-value

redis

Graph

neo4j

Document

mongoDB.

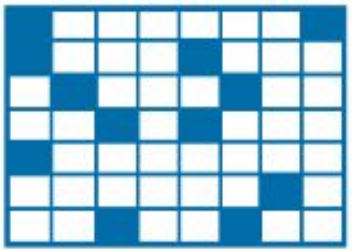
Non-Relational Databases

- Less common than relational in medicine
- Querying can be… very easy or very complicated
- Mostly for very large datasets:
  - User data / security audit data
  - Medical image data
- Or unusual data structures:
  - Contact tracing
  - Ontologies
- Or both:
  - Social media data

Find me the homepage of anyone known by Tim Berners-Lee.

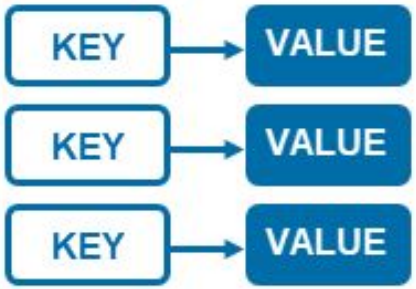
```
PREFIX foaf:  <http://xmlns.com/foaf/0.1/>
PREFIX card: <http://www.w3.org/People/Berners-Lee/card#>
SELECT ?homepage
FROM <http://www.w3.org/People/Berners-Lee/card>
WHERE {
    card:i foaf:knows ?known .
    ?known foaf:homepage ?homepage .
}
```

https://phoenixnap.com/kb/database-types



Column based

Google Big Query



Key-value

redis

Graph

neo4j

Document

mongoDB.

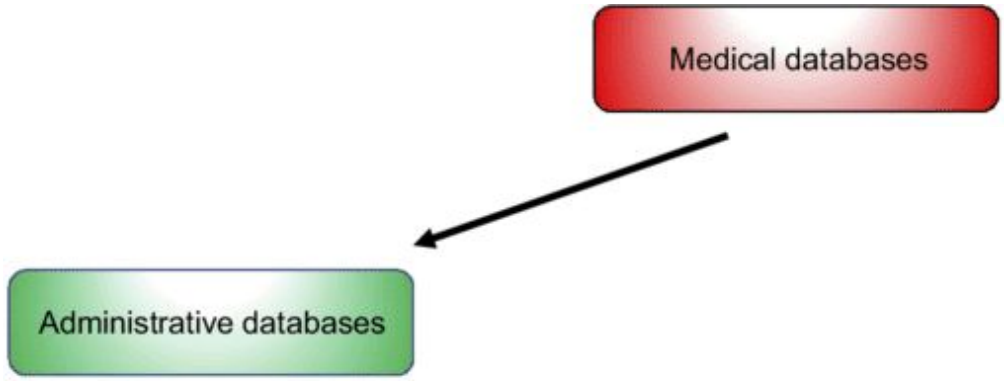
What are medical databases?

Many types of database

All types of registries and databases that contain health-related data

https://www.researchgate.net/figure/Classification-of-medical-databases_fig1_334421419

Many types of database

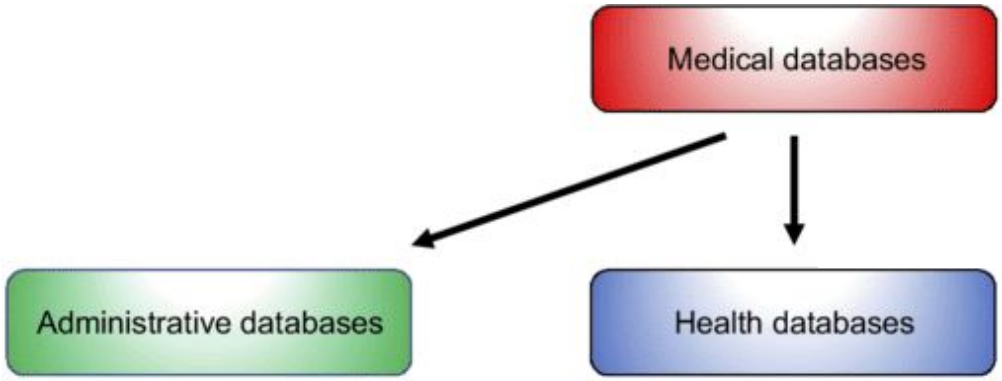


All types of registries and databases that contain health-related data

Register individuals according to geographic area, health insurance program, or attendance at a particular hospital or clinic

https://www.researchgate.net/figure/Classification-of-medical-databases_fig1_334421419

Many types of database



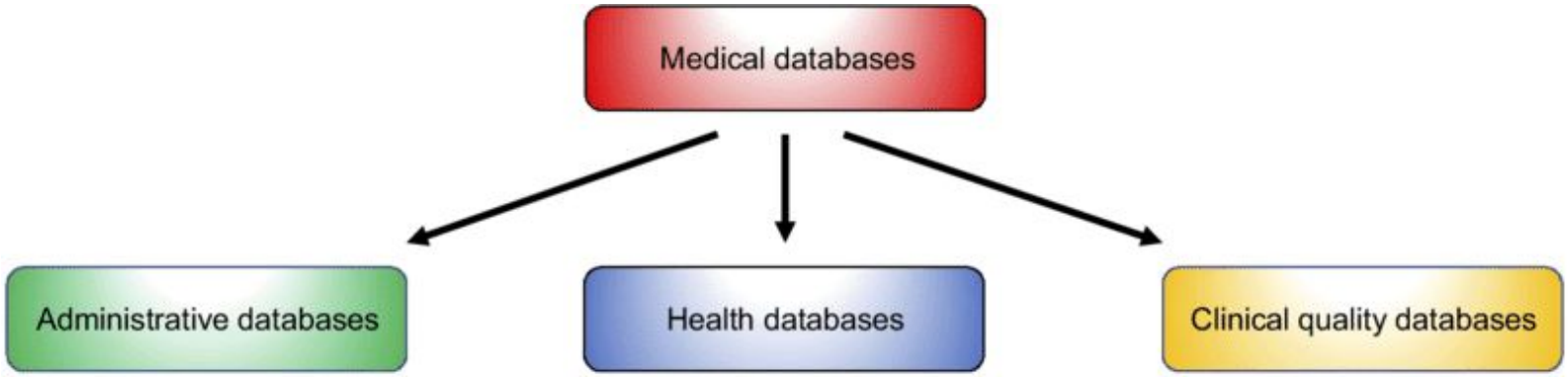
All types of registries and databases that contain health-related data

Register individuals according to geographic area, health insurance program, or attendance at a particular hospital or clinic

Register health data for the purpose of surveillance and research

https://www.researchgate.net/figure/Classification-of-medical-databases_fig1_334421419

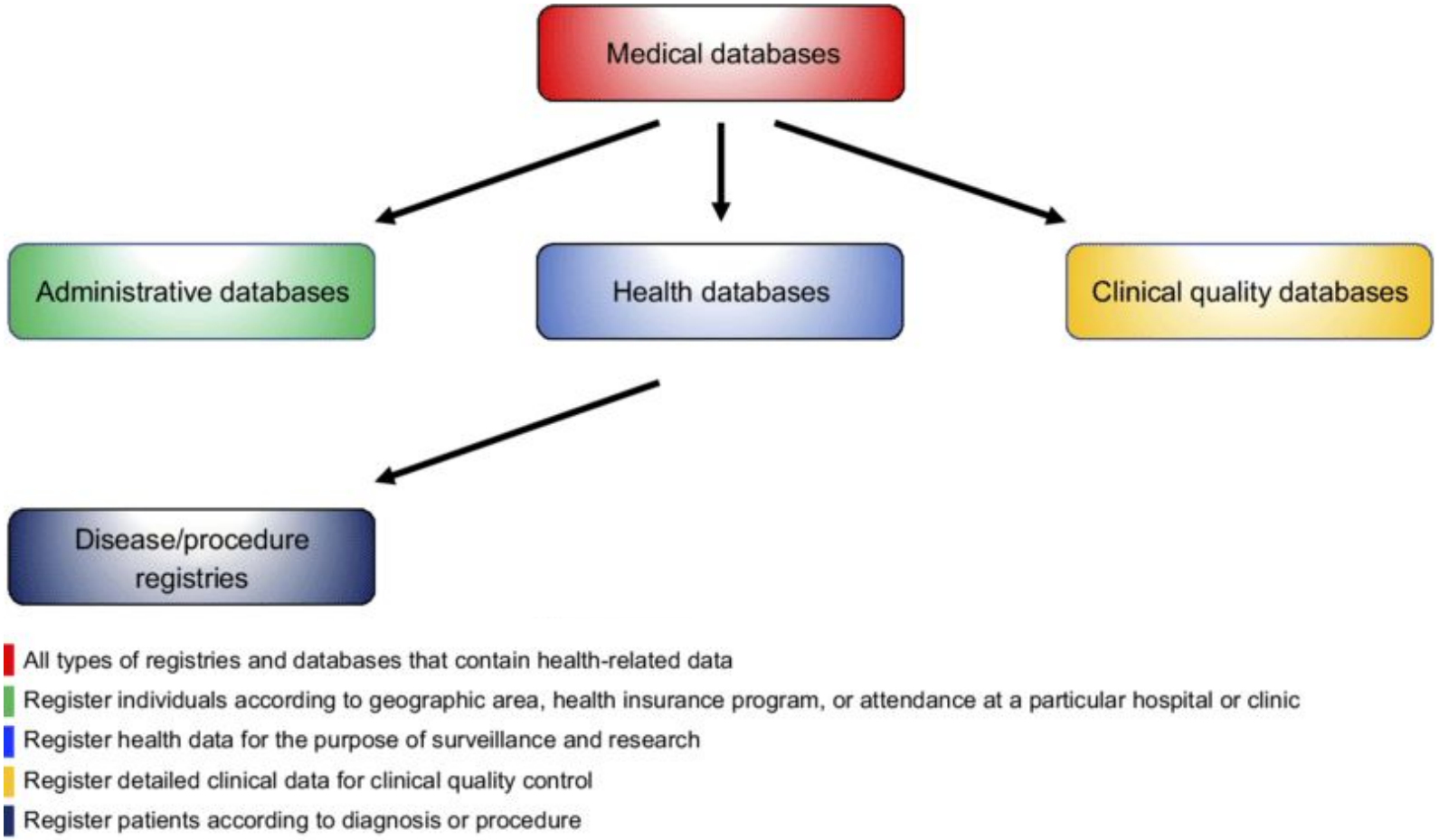
Many types of database



All types of registries and databases that contain health-related data
Register individuals according to geographic area, health insurance program, or attendance at a particular hospital or clinic
Register health data for the purpose of surveillance and research
Register detailed clinical data for clinical quality control

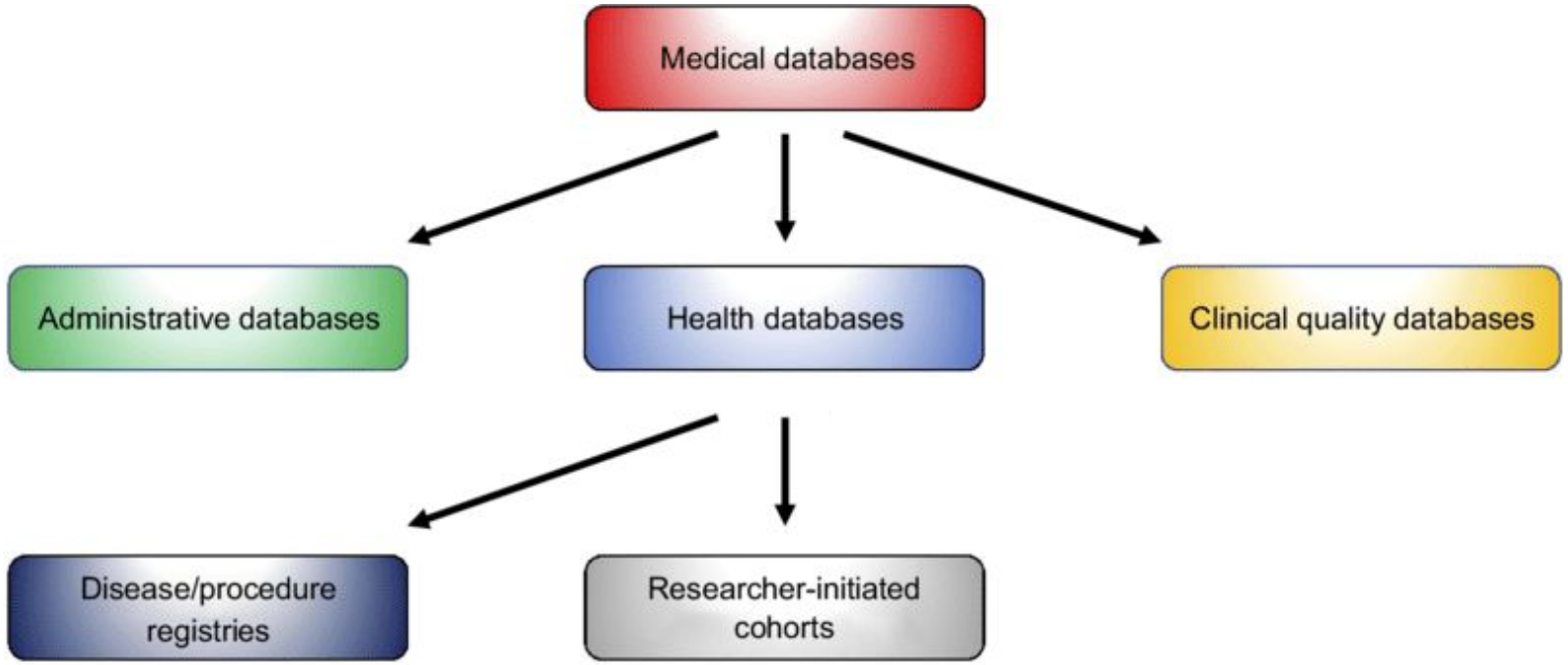
https://www.researchgate.net/figure/Classification-of-medical-databases_fig1_334421419

Many types of database



https://www.researchgate.net/figure/Classification-of-medical-databases_fig1_334421419

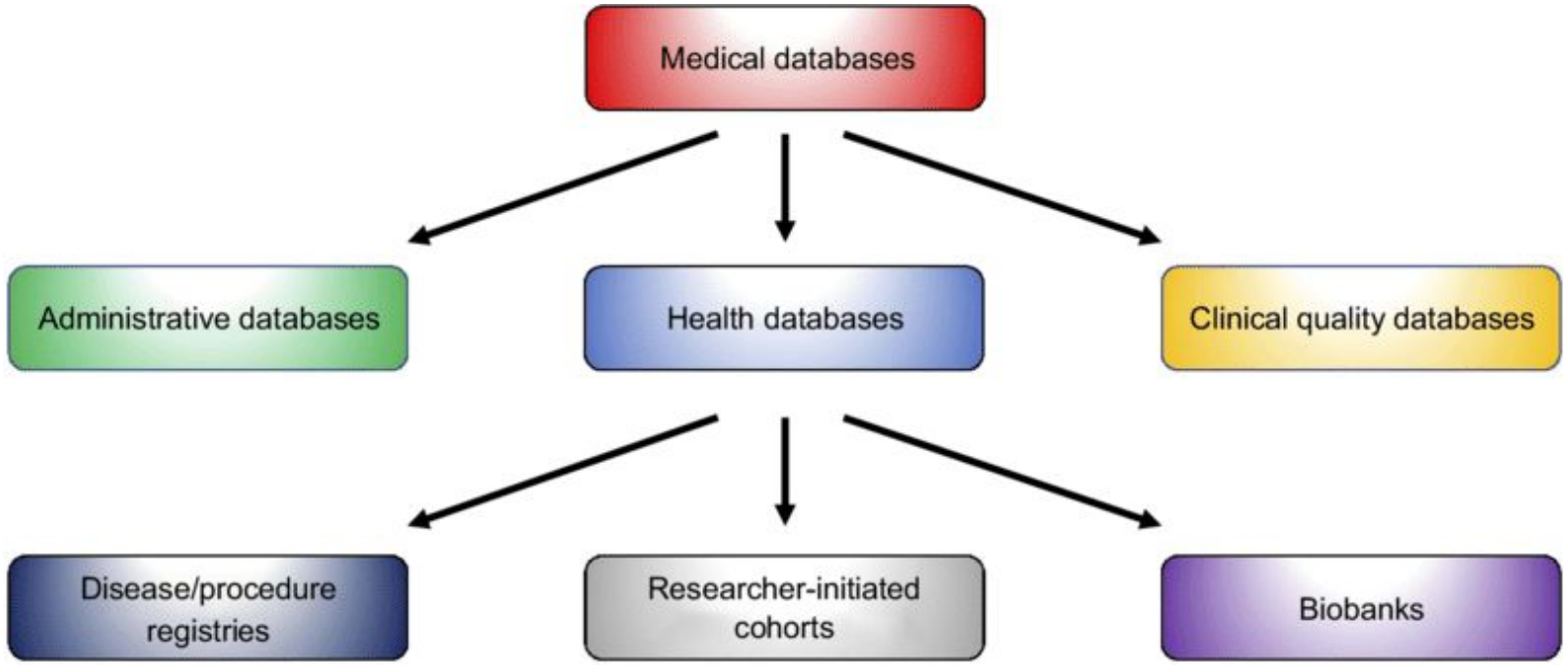
Many types of database



All types of registries and databases that contain health-related data
Register individuals according to geographic area, health insurance program, or attendance at a particular hospital or clinic
Register health data for the purpose of surveillance and research
Register detailed clinical data for clinical quality control
Register patients according to diagnosis or procedure
Register individuals according to prespecified criteria (eg, area of residency, age, sex, conscription, adoption, pregnancy, or survey participation)

https://www.researchgate.net/figure/Classification-of-medical-databases_fig1_334421419

Many types of database



All types of registries and databases that contain health-related data

Register individuals according to geographic area, health insurance program, or attendance at a particular hospital or clinic

Register health data for the purpose of surveillance and research

Register detailed clinical data for clinical quality control

Register patients according to diagnosis or procedure

Register individuals according to prespecified criteria (eg, area of residency, age, sex, conscription, adoption, pregnancy, or survey participation)

Store biological samples (eg, blood and tissue)

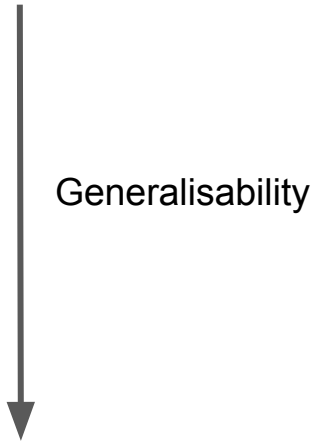
https://www.researchgate.net/figure/Classification-of-medical-databases_fig1_334421419

Consider primary record type

- Individual procedures e.g., arthroplasty
- Prescriptions e.g., colistin
- Disease/Illness e.g., ovarian cancer
- Hospital Admission/Discharge
- Individual health interactions
- Patient
- Person
- Population

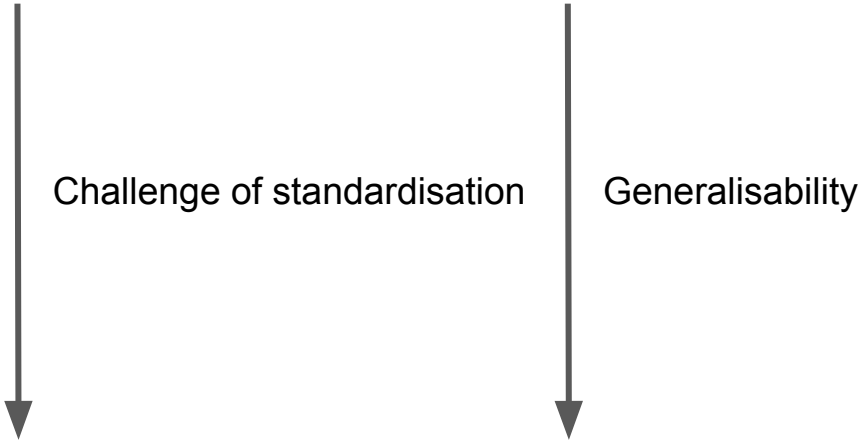
Sampling scope

- Single physician
- Group of physicians
- Hospital
- Health Authority
- Province
- National
- International



Sampling scope

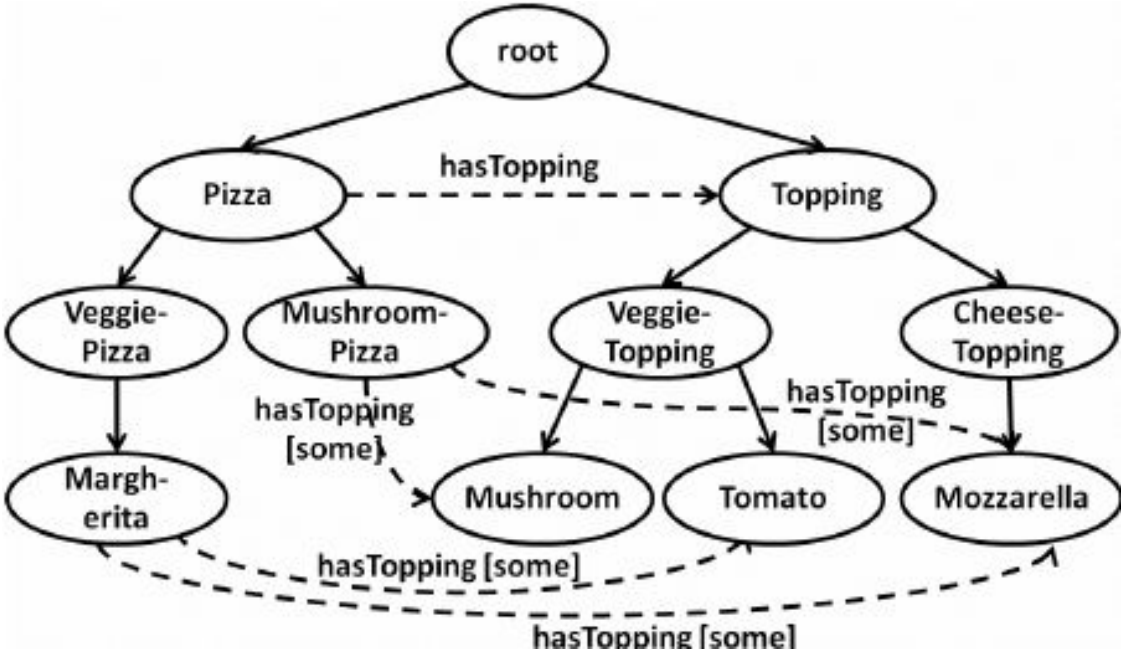
- Single physician
- Group of physicians
- Hospital
- Health Authority
- Province
- National
- International



How do medical databases try to handle standardisation?

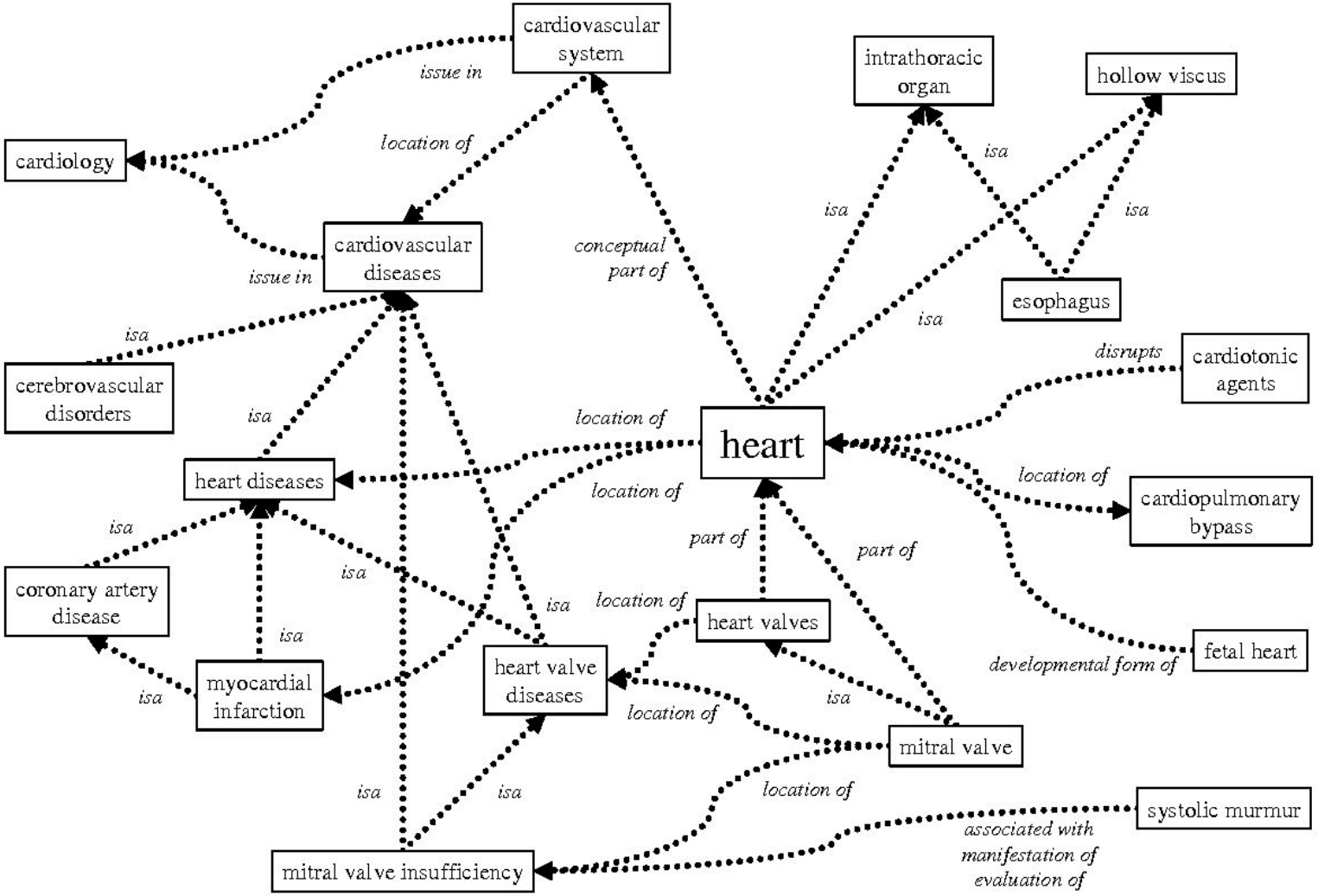
Ontologies for standardisation

- Standardised terms e.g., Pizza, Tomato, Mozzarella
- Standardised types of relationships between terms
- Acyclic links between terms
- Manual curation
- Automated curation



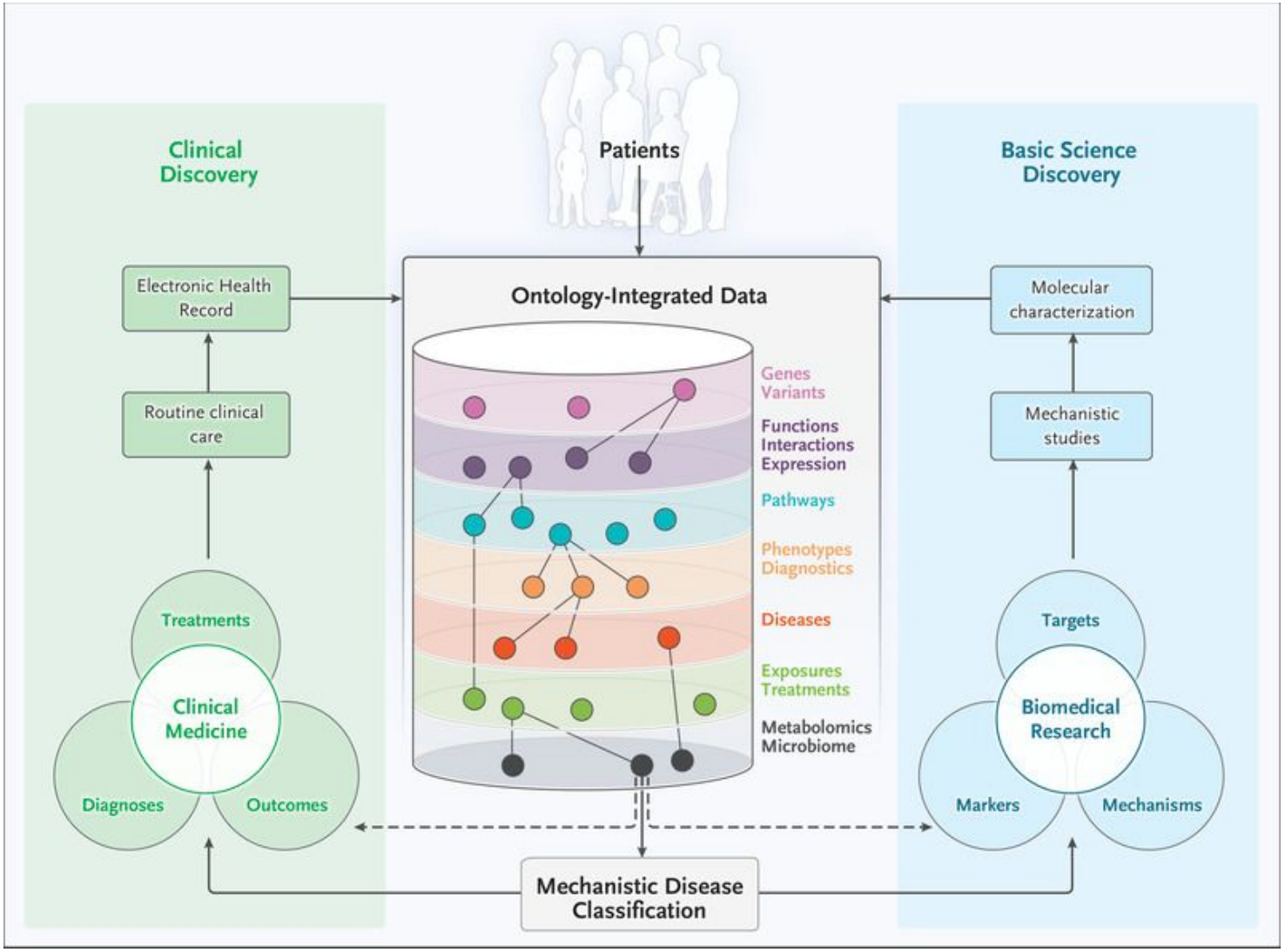
https://www.researchgate.net/figure/Example-pizza-ontology-represented-as-a-graph-G-a-and-a-changed-version-of-the-pizza_fig1_236842047

Medical Ontologies



https://www.semanticscholar.org/paper/Medical-Ontology-Research-Bodenreider/b27ef1466b5d0ca6b4b17d8d9e02406b996e0ba2

Ontologies for linking diverse types of data



https://www.nejm.org/doi/full/10.1056/NEJMra1615014

International Statistical Classification of Diseases and Related Health Problems (ICD-9, ICD-10)

- 2 ontologies
  - ICD-X-CM (medical diagnoses)
  - ICD-X-PCS (procedure coding)

International Statistical Classification of Diseases and Related Health Problems (ICD-9, ICD-10)

- 2 ontologies
  - ICD-X-CM (medical diagnoses)
  - ICD-X-PCS (procedure coding)
- ICD-9 -> ICD-10 (2015)

Differences Between ICD-9-CM and ICD-10 Code Sets		
	ICD-9-CM	**ICD-10 code sets**
Procedure	3,824 codes	71,924 codes
Diagnosis	14,025 codes	69, 823 codes

ICD-10 Code Structure Changes (selected details)		
	Old	**New**
Diagnosis Structure	ICD-9-CM • 3 -5 characters • First character is numeric or alpha • Characters 2-5 are numeric	ICD-10-CM • 3 -7 characters • Character 1 is alpha • Character 2 is numeric • Characters 3 – 7 can be alpha or numeric
Procedure Structure	ICD-9-CM • 3-4 characters • All characters are numeric • All codes have at least 3 characters	ICD-10-PCS • ICD-10-PCS has 7 characters • Each can be either alpha or numeric • Numbers 0-9; letters A-H, J-N, P-Z

https://www.cdc.gov/nchs/icd/icd10cm_pcs_background.htm

International Statistical Classification of Diseases and Related Health Problems (ICD-9, ICD-10)

- 2 ontologies
  - ICD-X-CM (medical diagnoses)
  - ICD-X-PCS (procedure coding)
- ICD-9 -> ICD-10 (2015)

- “V97.33XD: Sucked into jet engine, subsequent encounter.”
- “Y93.D: V91.07XD: Burn due to water-skis on fire, subsequent encounter.”
- “Z63.1: Problems in relationship with in-laws.”
- “W22.02XD: V95.43XS: Spacecraft collision injuring occupant, sequela.”

Differences Between ICD-9-CM and ICD-10 Code Sets		
	ICD-9-CM	ICD-10 code sets
Procedure	3,824 codes	71,924 codes
Diagnosis	14,025 codes	69, 823 codes

ICD-10 Code Structure Changes (selected details)		
	Old	New
Diagnosis Structure	ICD-9-CM • 3 -5 characters • First character is numeric or alpha • Characters 2-5 are numeric	ICD-10-CM • 3 -7 characters • Character 1 is alpha • Character 2 is numeric • Characters 3 – 7 can be alpha or numeric
Procedure Structure	ICD-9-CM • 3-4 characters • All characters are numeric • All codes have at least 3 characters	ICD-10-PCS • ICD-10-PCS has 7 characters • Each can be either alpha or numeric • Numbers 0-9; letters A-H, J-N, P-Z

https://www.cdc.gov/nchs/icd/icd10cm_pcs_background.htm

How do we sample for medical databases?

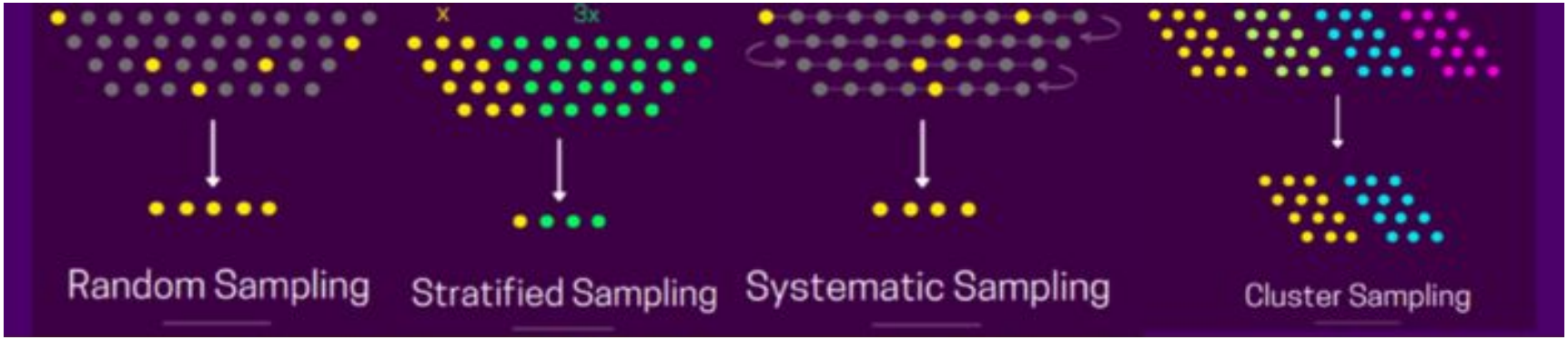
Sampling strategy

- Exhaustive isn’t always exhaustive
- Numerous and often quite complex!
- Major source of bias so always carefully explore

https://towardsdatascience.com/8-types-of-sampling-techniques-b21adcdd2124

Sampling strategy

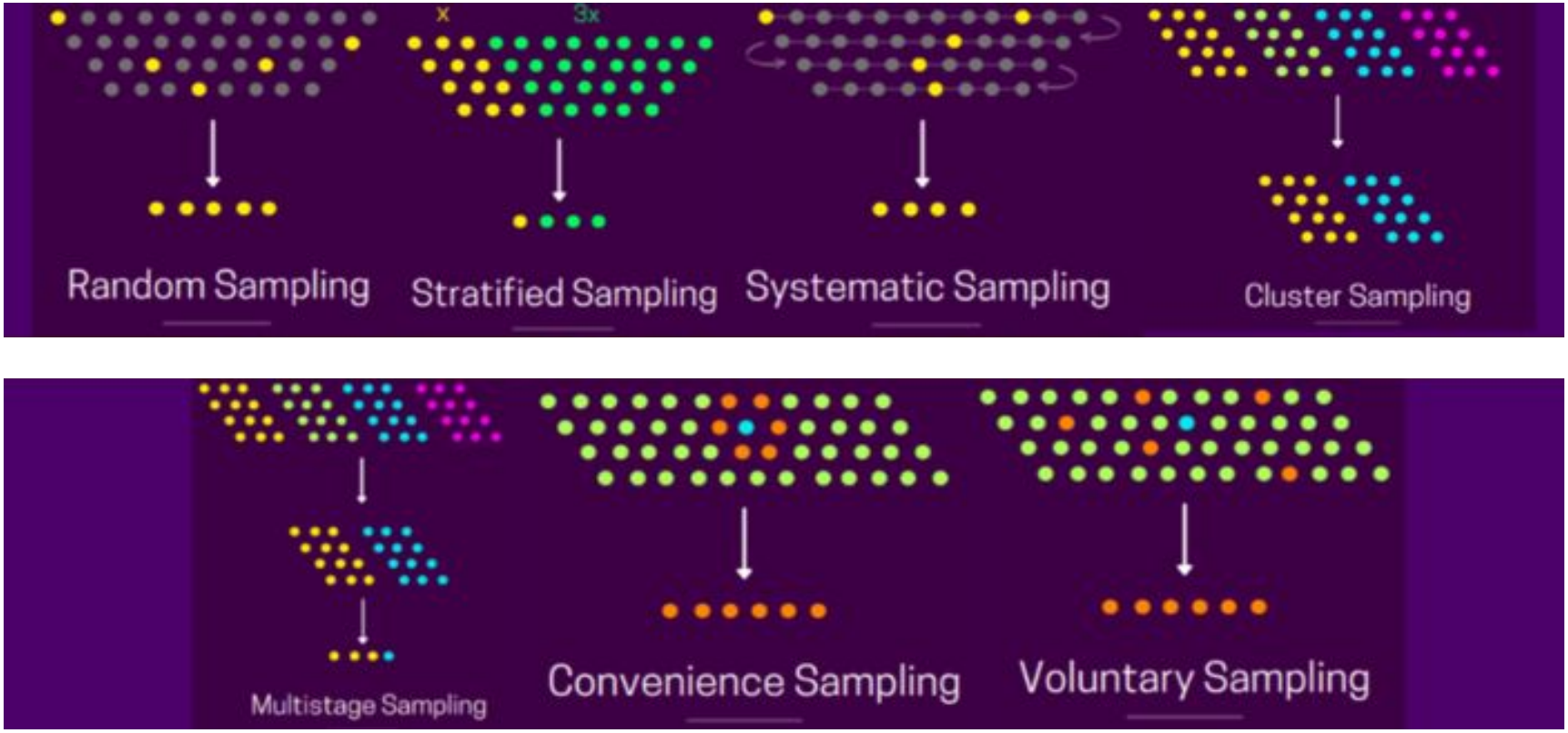
- Exhaustive isn’t always exhaustive
- Numerous and often quite complex!
- Major source of bias so always carefully explore



https://towardsdatascience.com/8-types-of-sampling-techniques-b21adcdd2124

Sampling strategy

- Exhaustive isn't always exhaustive
- Numerous and often quite complex!
- Major source of bias so always carefully explore



https://towardsdatascience.com/8-types-of-sampling-techniques-b21adcdd2124

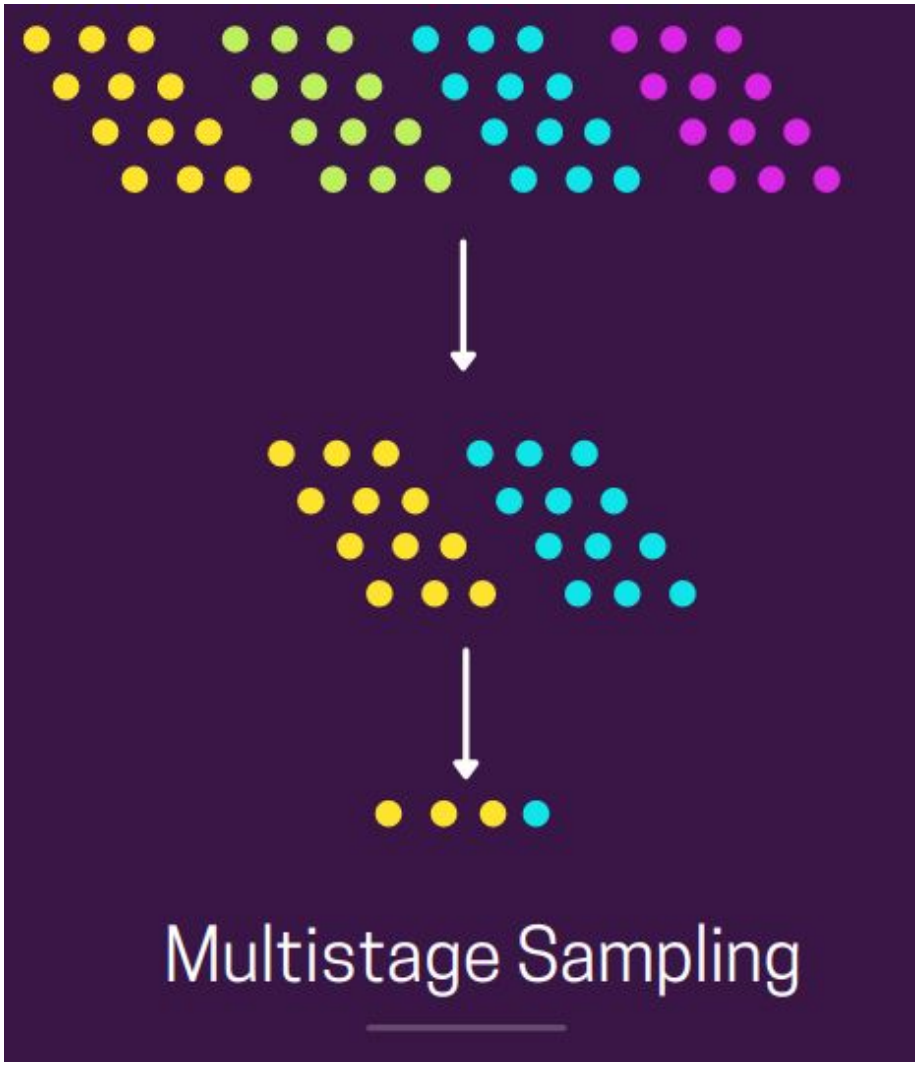
Survey weights

- Value/weight assigned to each record
- Make statistics calculated from database more representative of population
  - Weight=0.5 underweight this case
  - Weight=1
  - Weight=2 overweight the contribution of this case

Survey/Sample weights

- Value/weight assigned to each record
- Make statistics calculated from database more representative of population
  - Weight=0.5 underweight this case
  - Weight=1
  - Weight=2 overweight the contribution of this case

- Complex sampling strategies (e.g., deliberate oversampling of some populations, biasing recruitment) mean weights **MUST** be used.
- Often not directly supported by machine learning libraries (`sample_weights` implemented for some models)



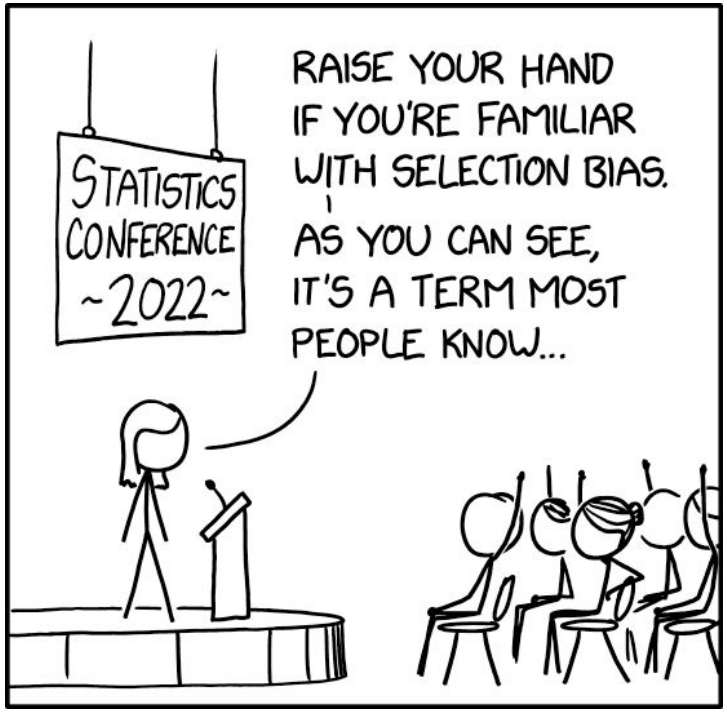
Types of weights

- Design Weights
  - Based on sampling strategy i.e., “design” of survey/database/data collection
  - Common to over-sample under-represented or rare groups
  - Need to correct for this or will overestimate statistics e.g., lower weight of over-sampled groups

Types of weights

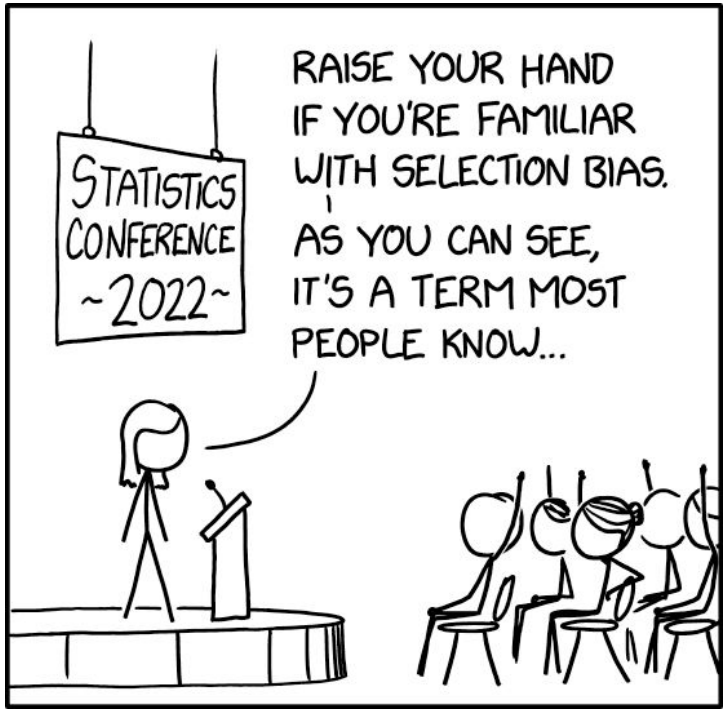
- Design Weights
  - Based on sampling strategy i.e., “design” of survey/database/data collection
  - Common to over-sample under-represented or rare groups
  - Need to correct for this or will overestimate statistics e.g., lower weight of over-sampled groups

- Post-stratification / Non-response weights
  - Based on collected data
  - Typically biases in whose data is collected
  - Over-represented groups need to be under-weighted



Types of weights

- Design Weights
  - Based on sampling strategy i.e., “design” of survey/database/data collection
  - Common to over-sample under-represented or rare groups
  - Need to correct for this or will overestimate statistics e.g., lower weight of over-sampled groups

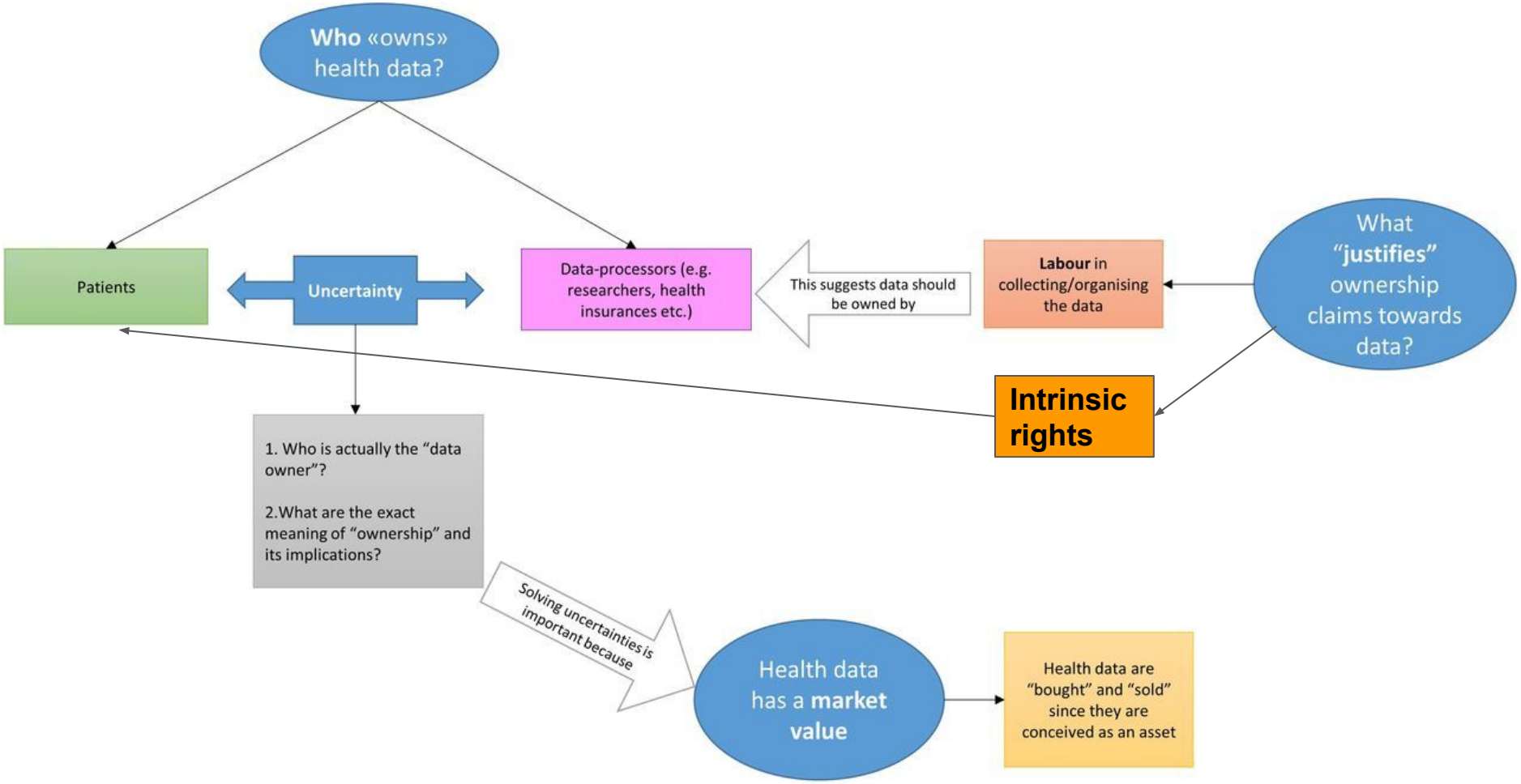


- Post-stratification / Non-response weights
  - Based on collected data
  - Typically biases in whose data is collected
  - Over-represented groups need to be under-weighted

- Often many different weights are combined:

Who actually owns this data?

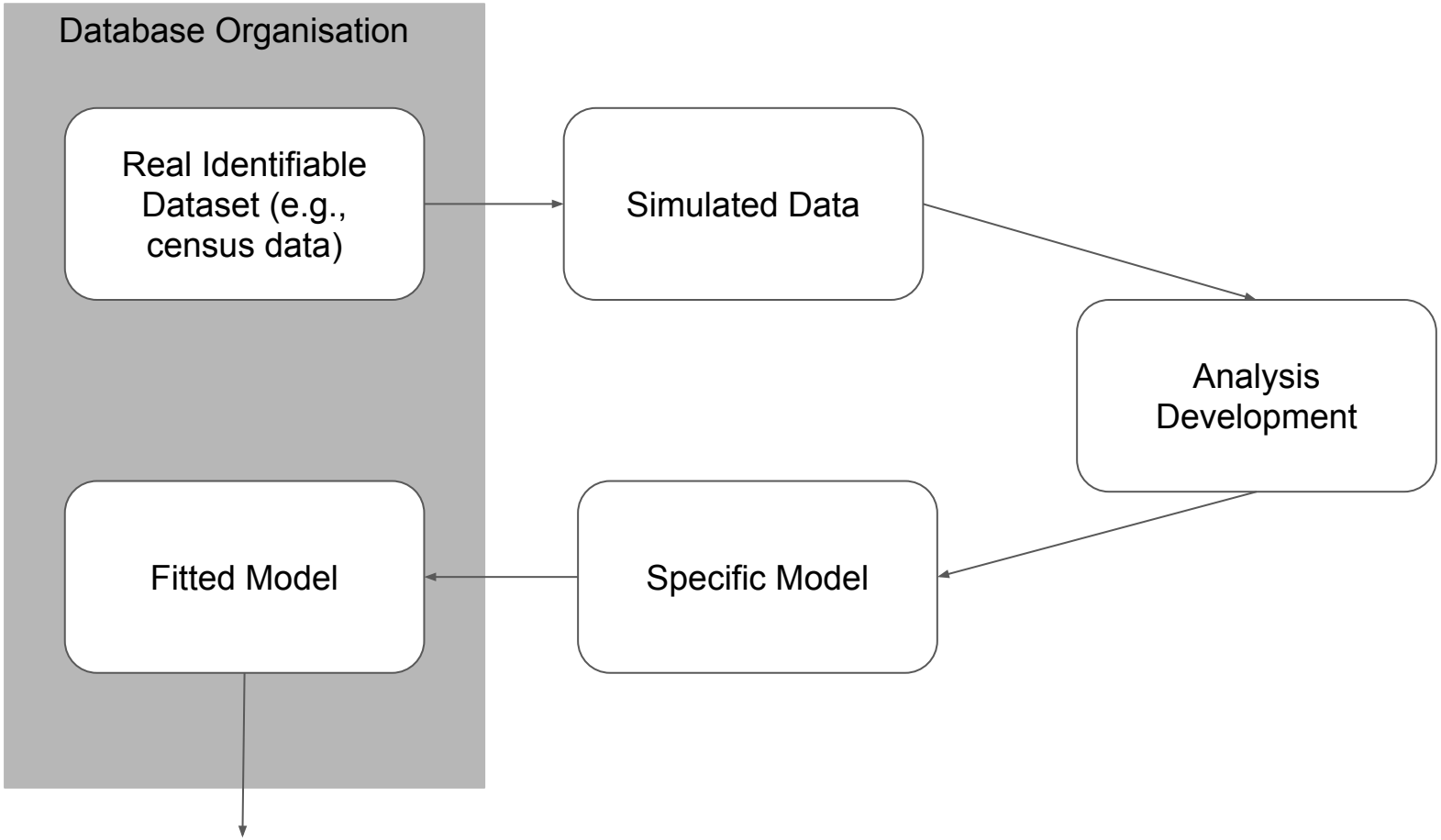
Data Ownership is Difficult



https://bmjopen.bmj.com/content/11/4/e045717

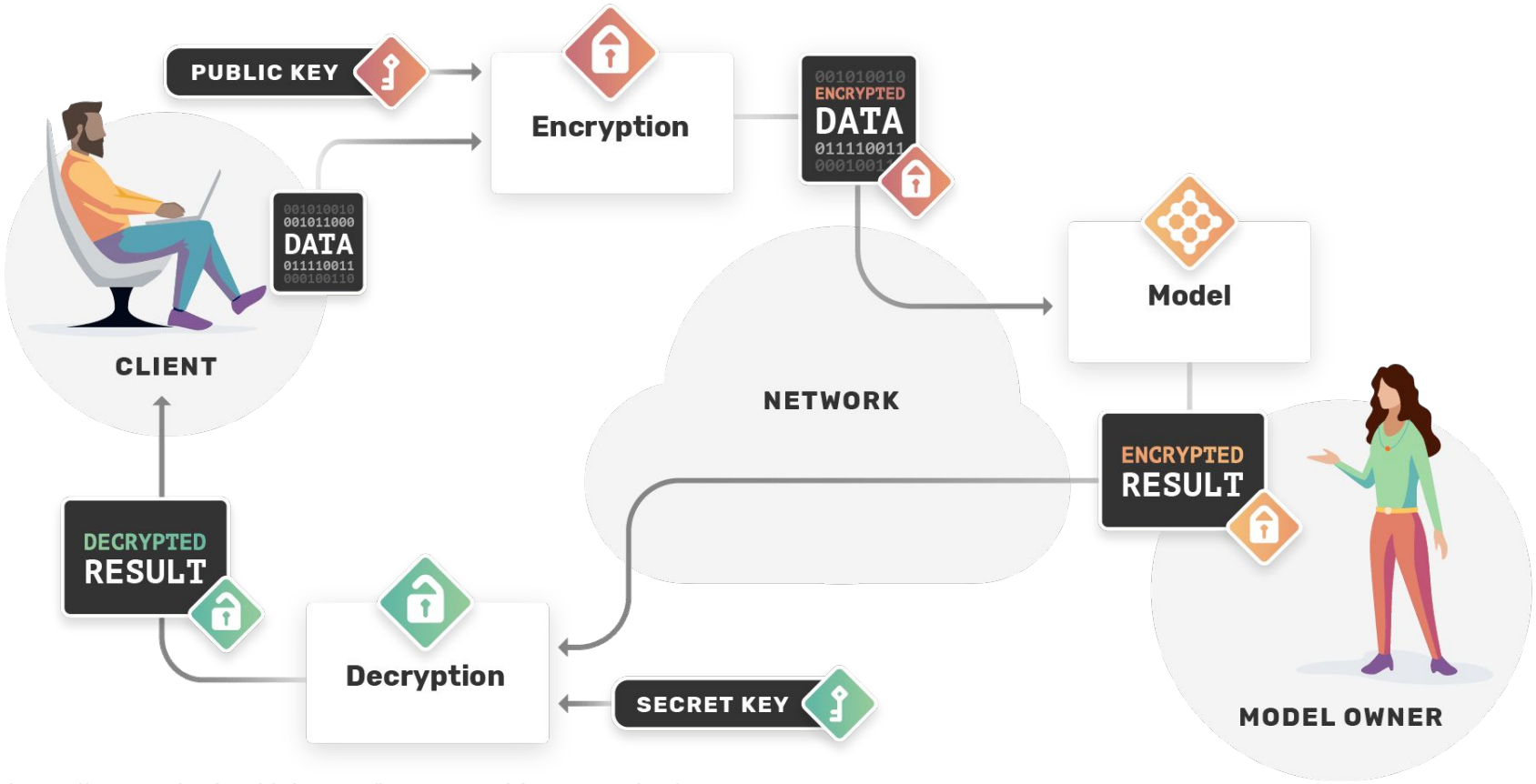
How do you protect privacy in these databases?

No direct data access



Shared data but encrypted: homomorphic encryption

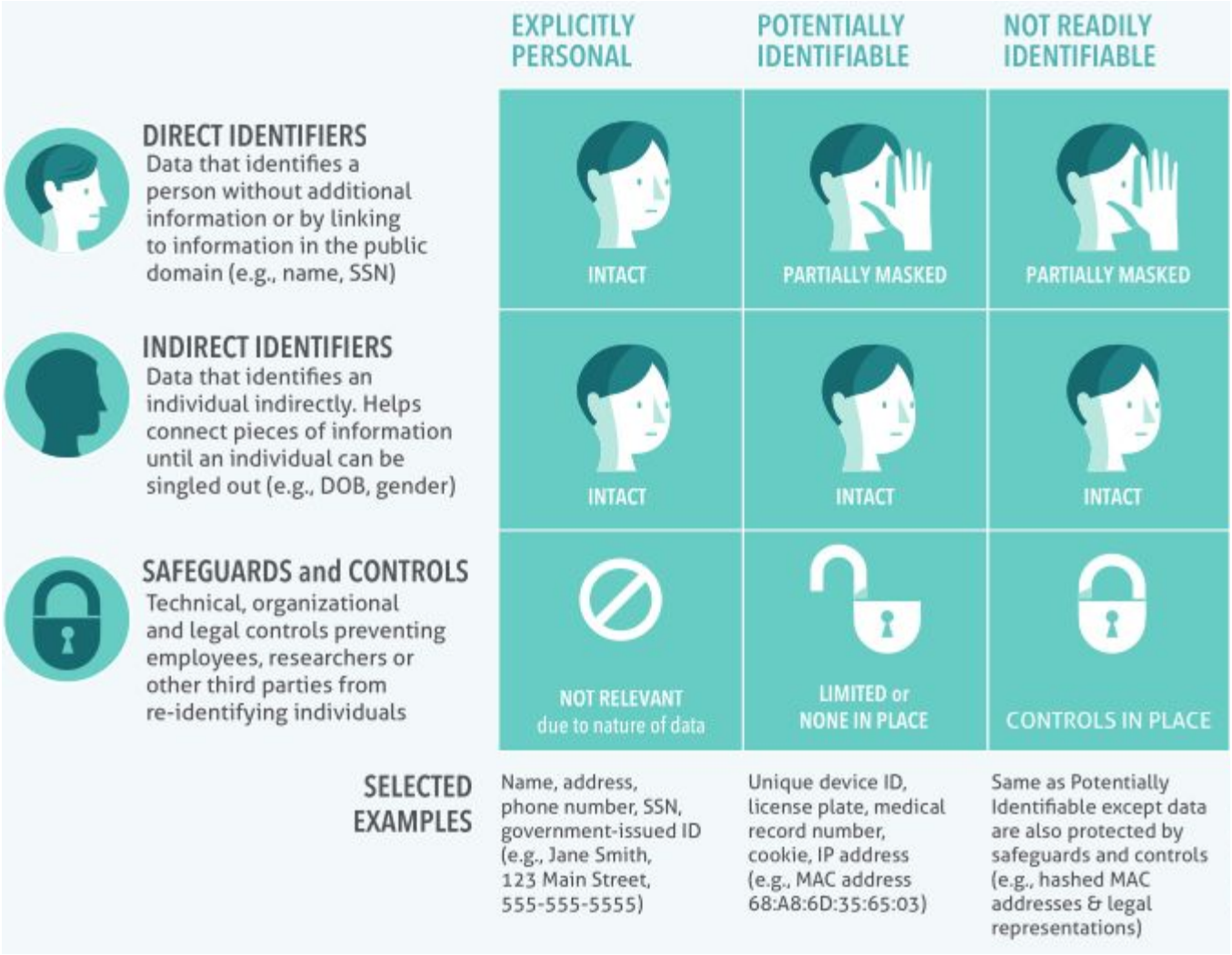
Partial to fully homomorphic encryption



https://research.aimultiple.com/homomorphic-encryption/

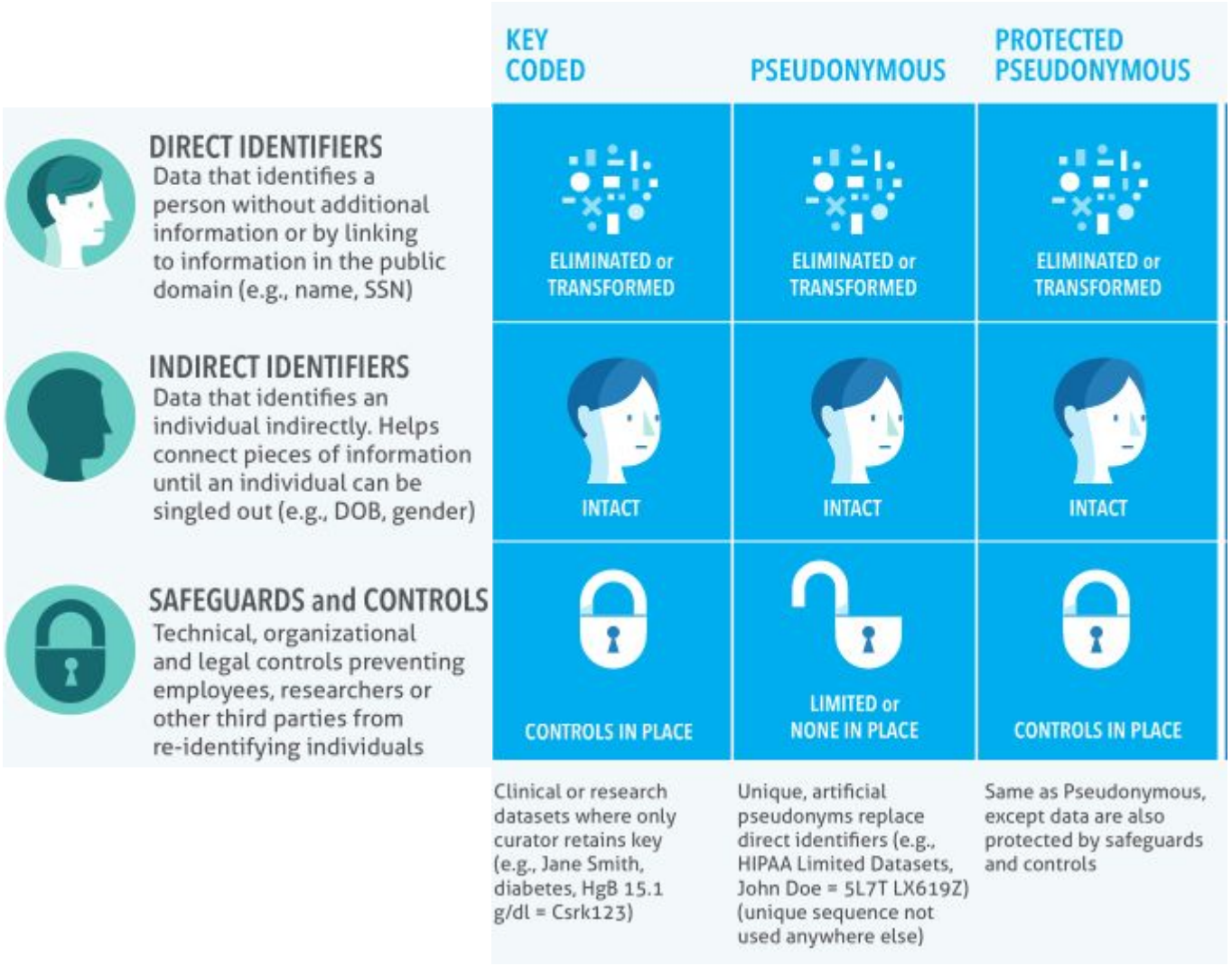
Both are difficult and limited… so how can we share data directly but safely?

Data privacy is a continuum



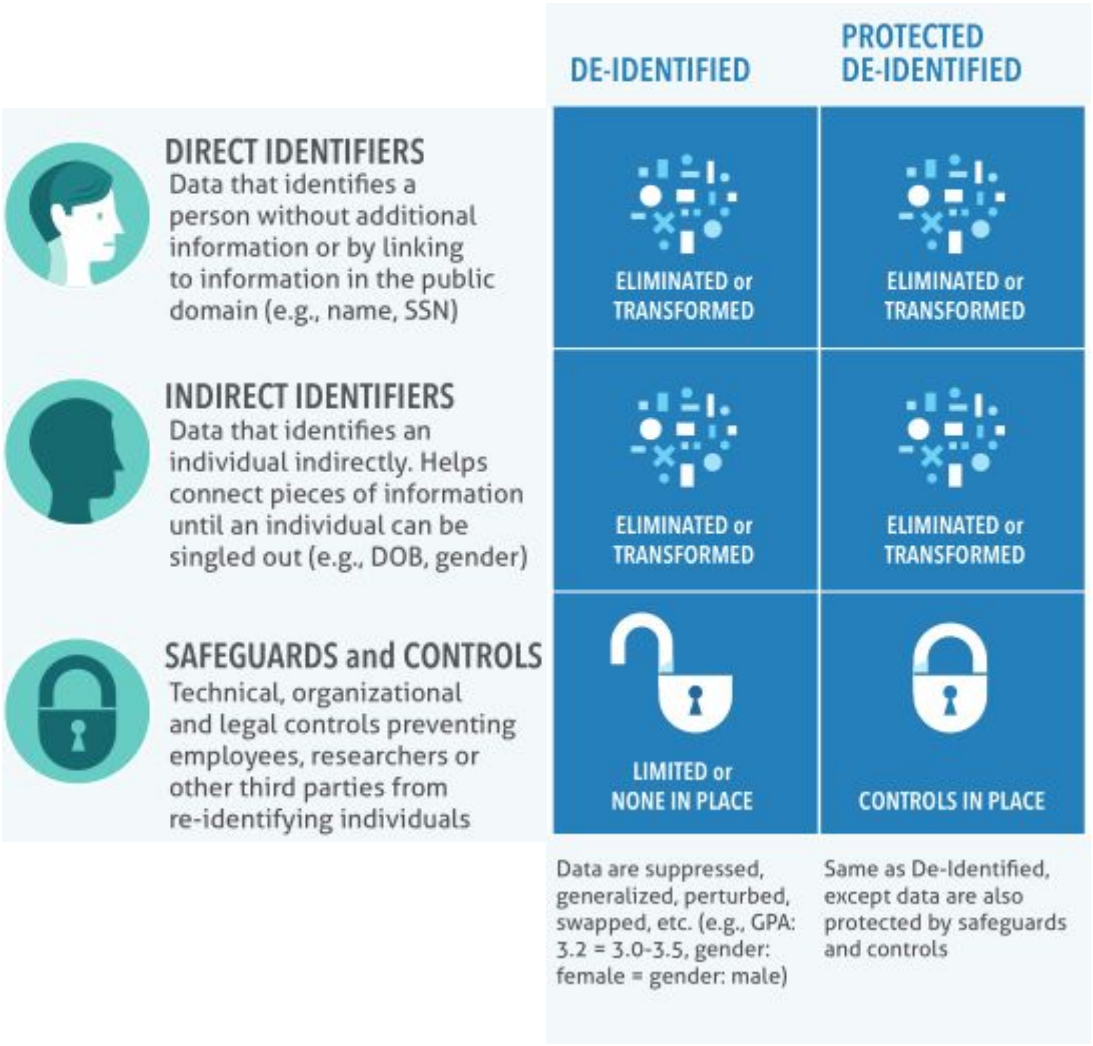
https://fpf.org/wp-content/uploads/2016/04/FPF_Visual-Guide-to-Practical-Data-DeID.pdf

Indirectly identifiable: Pseudonymous Data



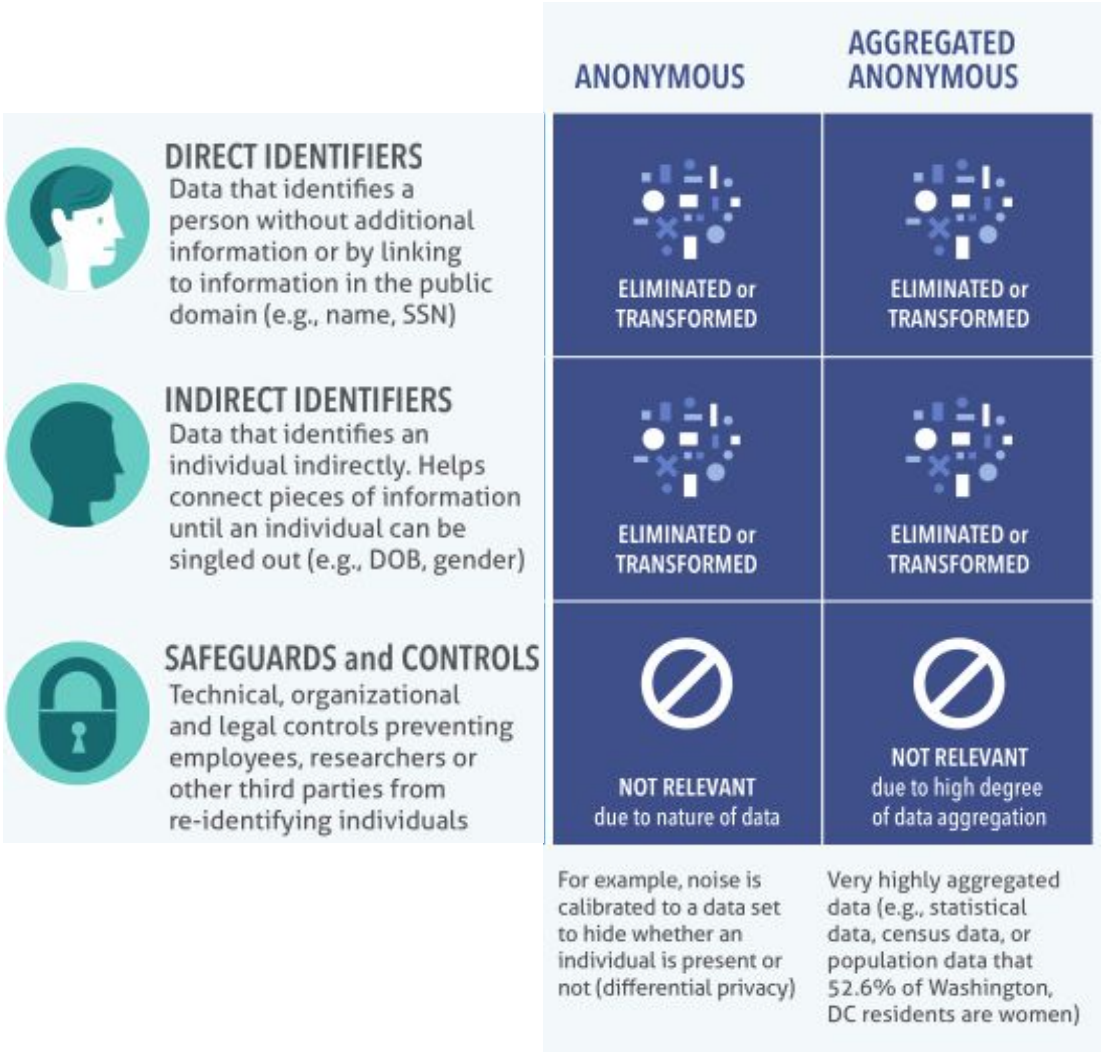
https://fpf.org/wp-content/uploads/2016/04/FPF_Visual-Guide-to-Practical-Data-DeID.pdf

Identifiers removed/broken: De-Identified Data



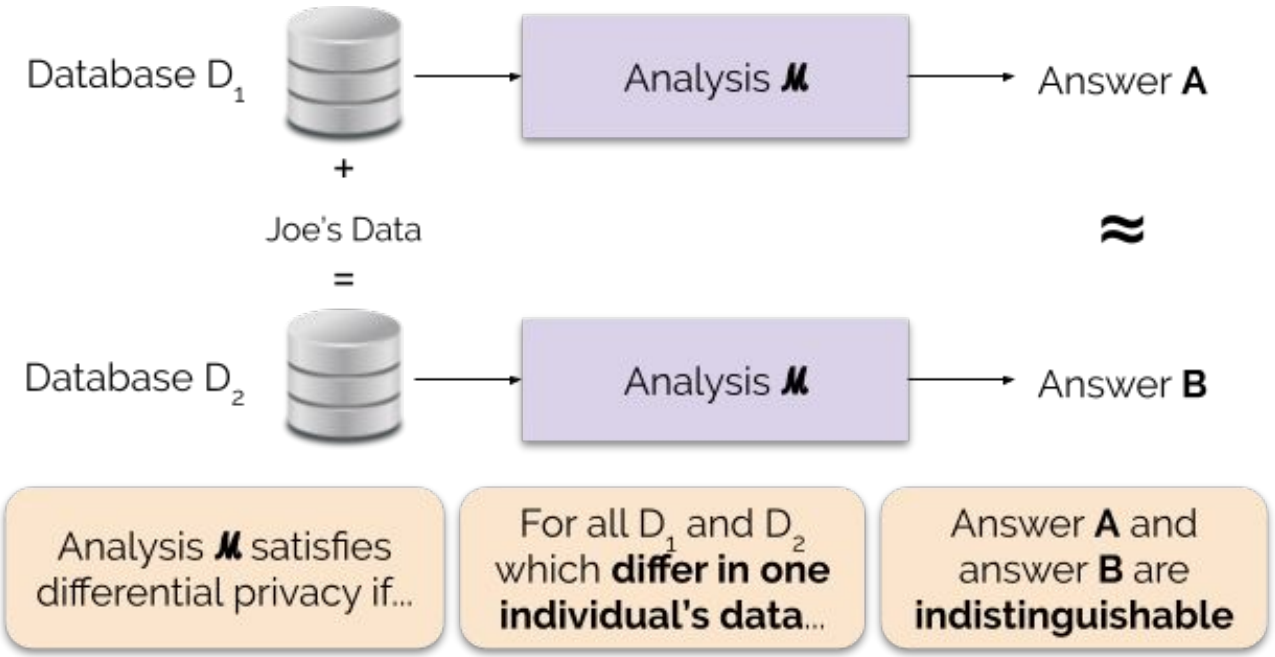
https://fpf.org/wp-content/uploads/2016/04/FPF_Visual-Guide-to-Practical-Data-DeID.pdf

Non-identifiability Guarantee: Anonymous Data



https://fpf.org/wp-content/uploads/2016/04/FPF_Visual-Guide-to-Practical-Data-DeID.pdf

Differential privacy: no singling out individuals



https://www.nist.gov/blogs/cybersecurity-insights/differential-privacy-privacy-preserving-data-analysis-introduction-our

Differential privacy: no singling out individuals

Analysis $\mathcal{M}$ satisfies differential privacy if...

For all D_1 and D_2 which **differ in one individual's data**...

Answer **A** and answer **B** are **indistinguishable**

Probability of seeing output O on input D_1

Probability of seeing output O on input D_2

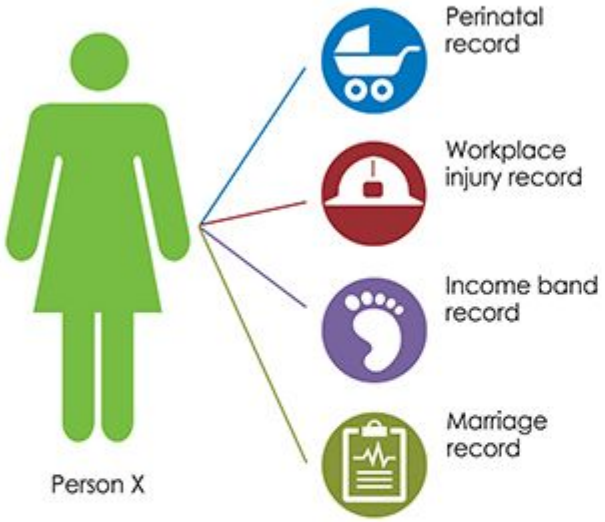
$$\frac{\Pr[\mathcal{M}(D_1) \in O]}{\Pr[\mathcal{M}(D_2) \in O]} \leq e^{\varepsilon}$$

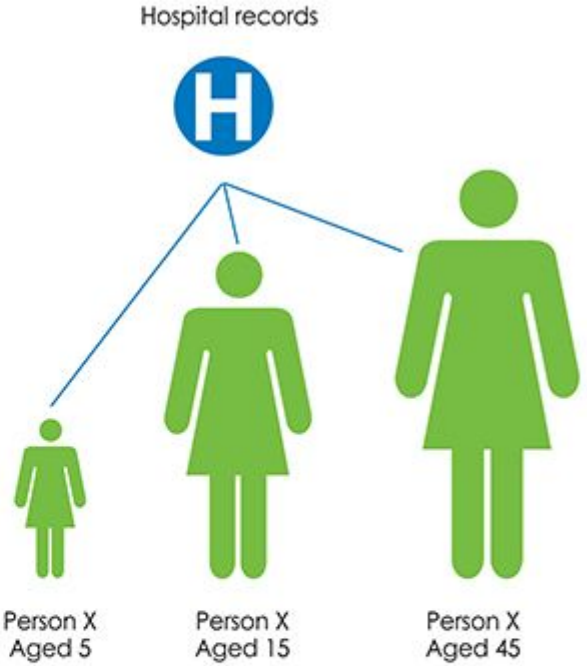
Indistinguishability: bounded ratio of probabilities

https://www.nist.gov/blogs/cybersecurity-insights/differential-privacy-privacy-preserving-data-analysis-introduction-our

Data linkage is powerful but dangerous

- Linking between databases and resources -> identifiability
- Can be done probabilistically
- Often needs additional ethics/applications
- Can break a lot of data privacy operations





Many different data access processes

- Buy access and get processed data
- Apply for individual fields and justify why
- Full pre-registration of analysis

Let’s take a short break!

So, you’ve got access to a database, what now?

Data Cleaning: even “simple” fields can be a nightmare

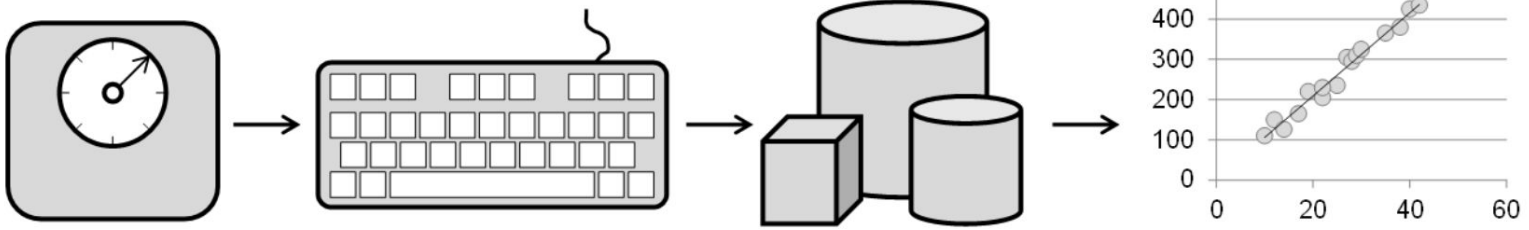
Data Quality

Actual value:
200.6 lbs.

Recorded value:
200 lbs.

Data warehouse value:
200 kg

Analytic value:
100 kg (mean 200 & 0)



Measured (same day)
• Validity challenge
198.9 | 198.9 | 198.9 lbs.
• Reliability challenge
200.6 | 198.9 | 202.2 lbs.

Measured (diff. days)

User Typed (one entry)
• Typos
200.6 lbs. → 20.06, 2006
• Mismatching units
200.6 lbs. → 200.6 kg
• Assumptions/truncations
200.6 lbs. → 200 lbs.
NULL → 0
• Free-text additions
200.6 lbs. → 200.6 pounds

DB Operations (one entry)
• Truncations/Rounding
200.6 → 200.0
• Error conversions
200.6 pounds → NULL
200.6 lbs. → 200.6 kg
• Cleaning
200+ lbs. → 200.0

Analytics (data points)
• Aggregation of data points
200 | 0 → mean of 100
• Selecting a representative
190 | 200 | 210 → 210 (first)
190 | 200 | 210 → 200 (mean)
190 | 200 | 210 → 210 (last)
• Removing outliers
200 | 200 | 350 → 200 | 200 | NULL

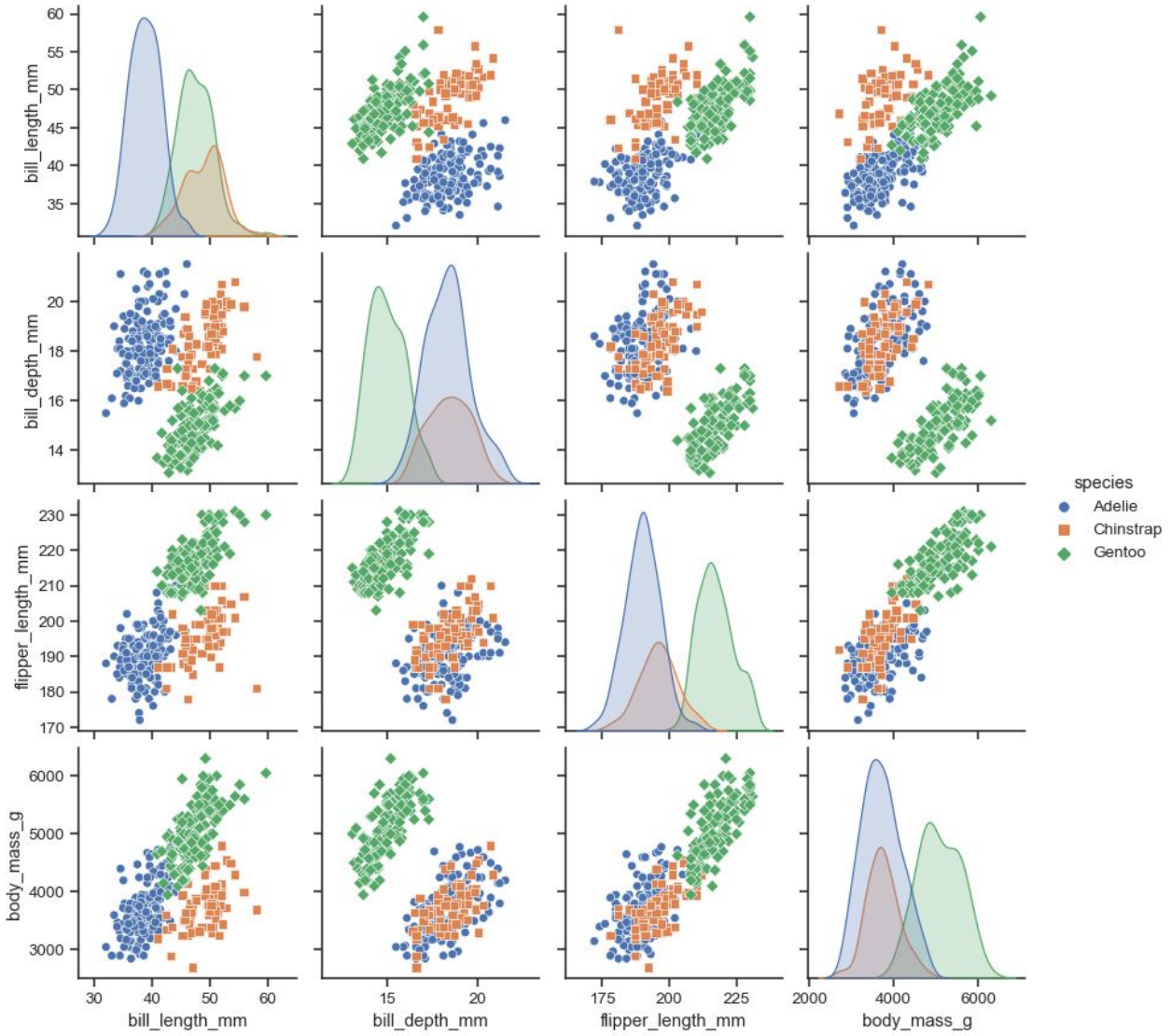
Under review

Slide from Dr. Hadi Kharrazi

9 months & >25 rules to clean weight

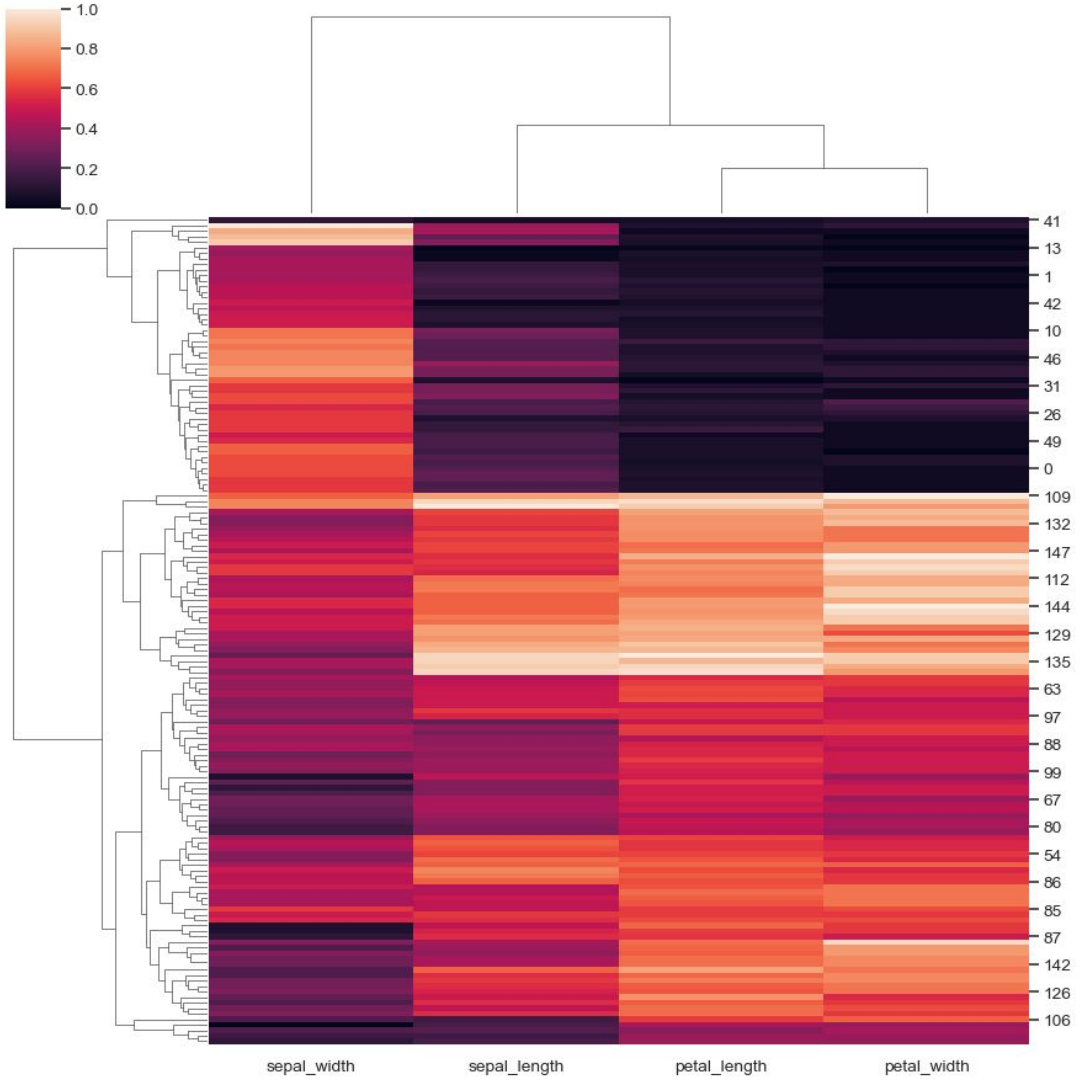
Exploratory Data Analysis

- Individual variable distributions
- Pairwise variable distributions
- Distributions relative to variable(s) of interest
- Point analysis of extreme values



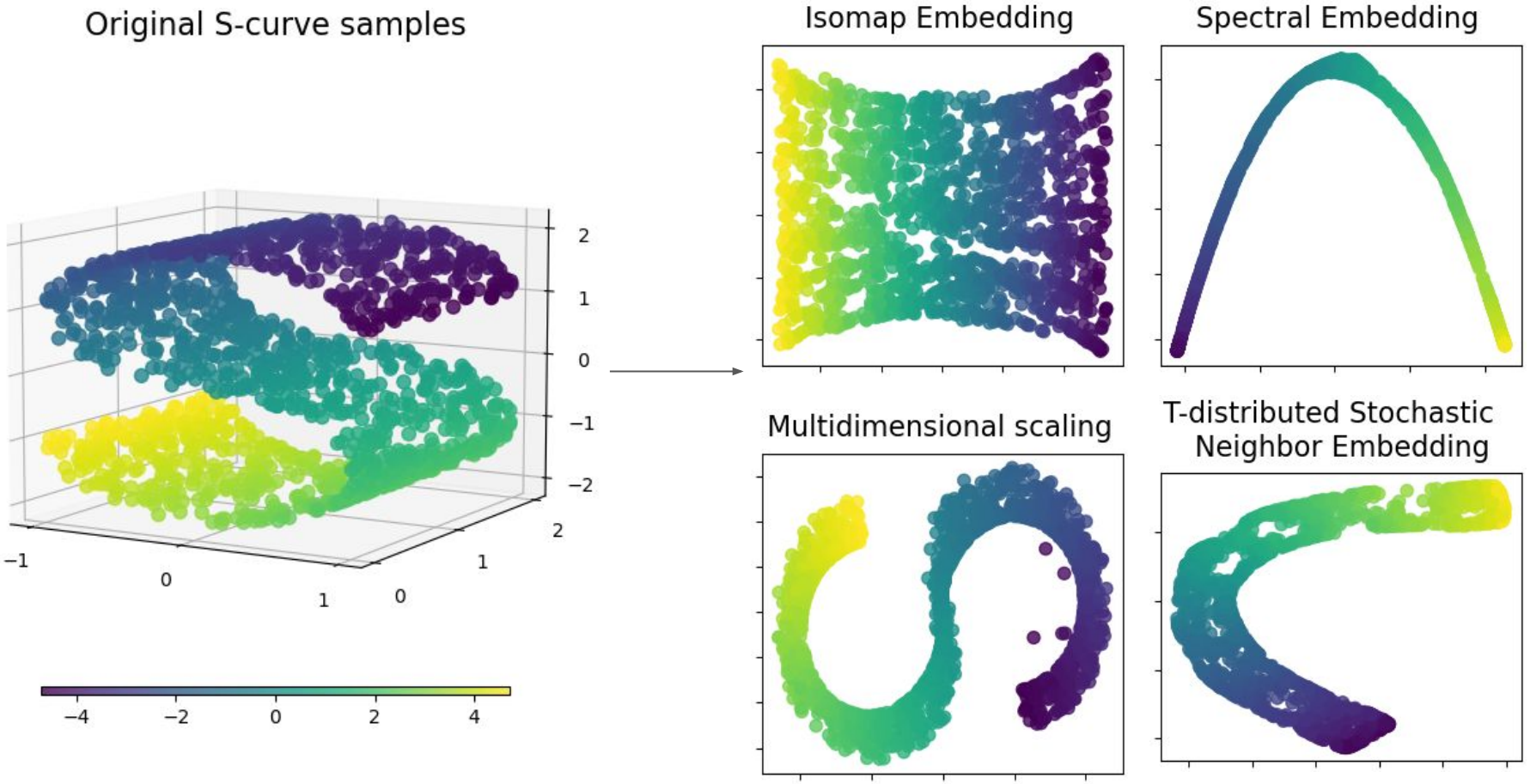
Exploratory Data Analysis

- Individual variable distributions
- Pairwise variable distributions
- Distributions relative to variable(s) of interest
- Hierarchical clustering of variables
- Point analysis of extreme values



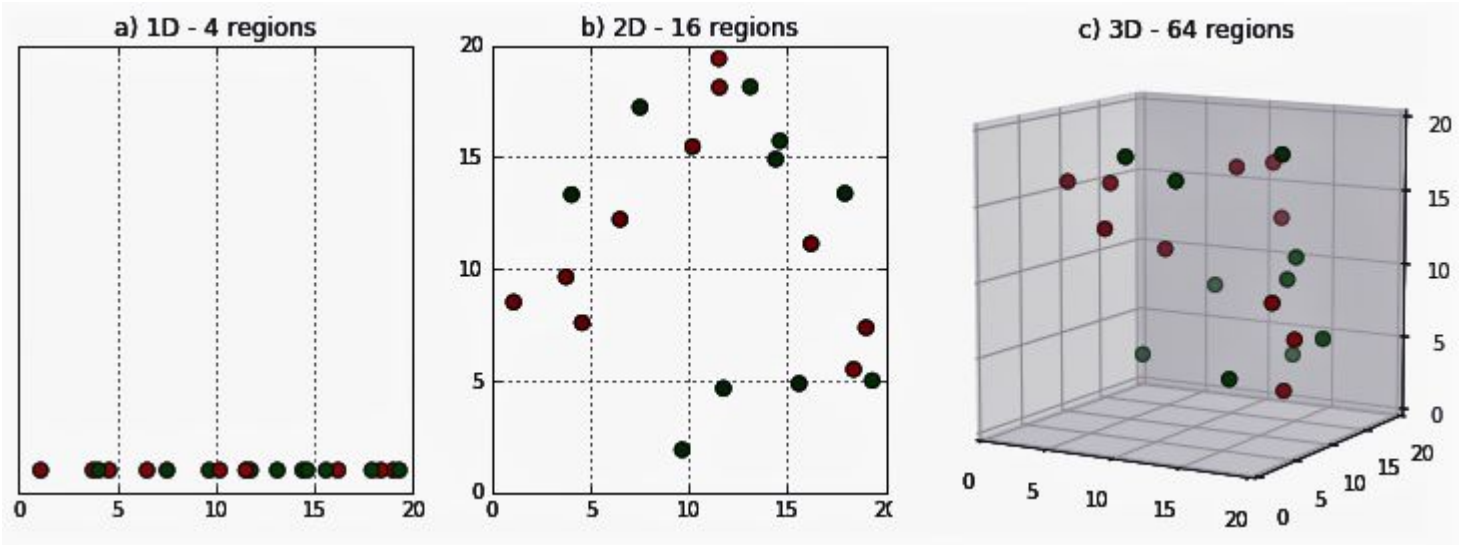
How do I look at all the data together?

Many dimensions to few: Manifold learning, Ordination, Decomposition, Dimensionality reduction



Why is this hard?

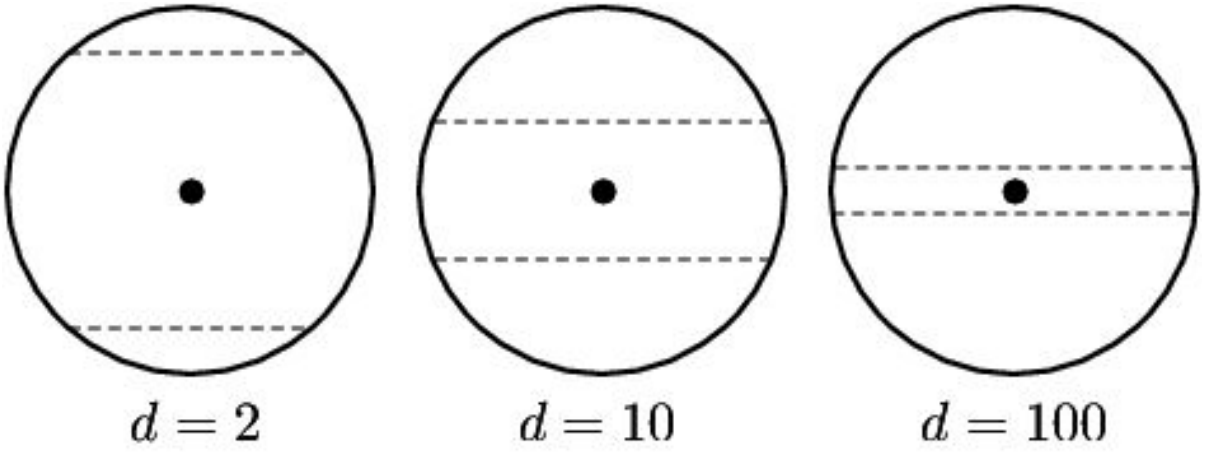
High dimensional data is sparse

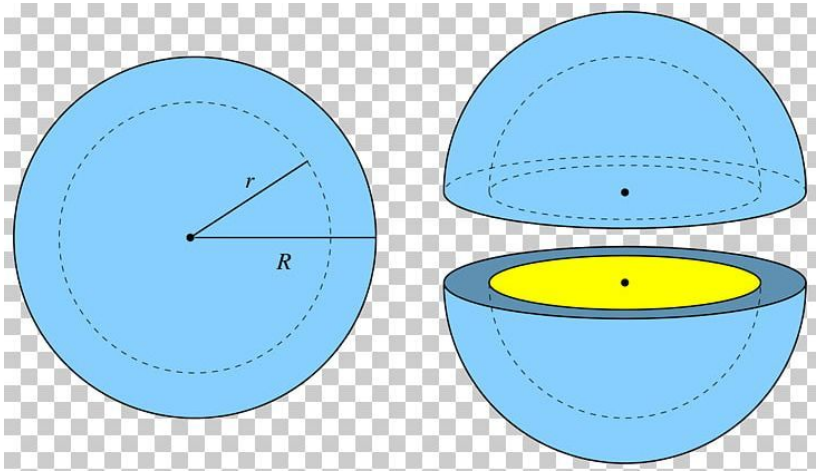


https://medium.com/analytics-vidhya/the-curse-of-dimensionality-and-its-cure-f9891ab72e5c

High dimensional space is counterintuitive

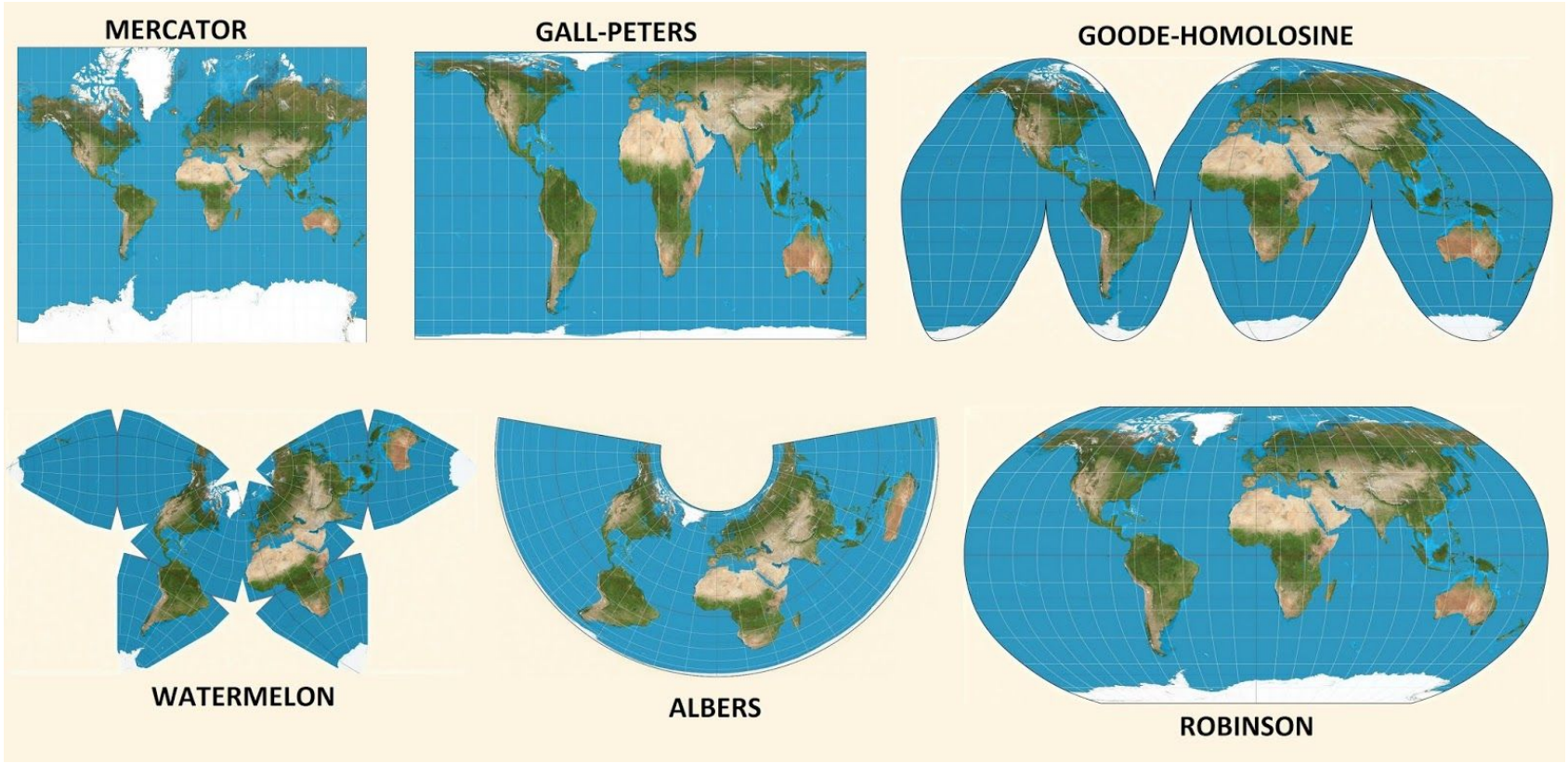
Orthogonality -> Band-size to capture 99% of the volume of a sphere:





Mass becomes increasingly “shell-like”

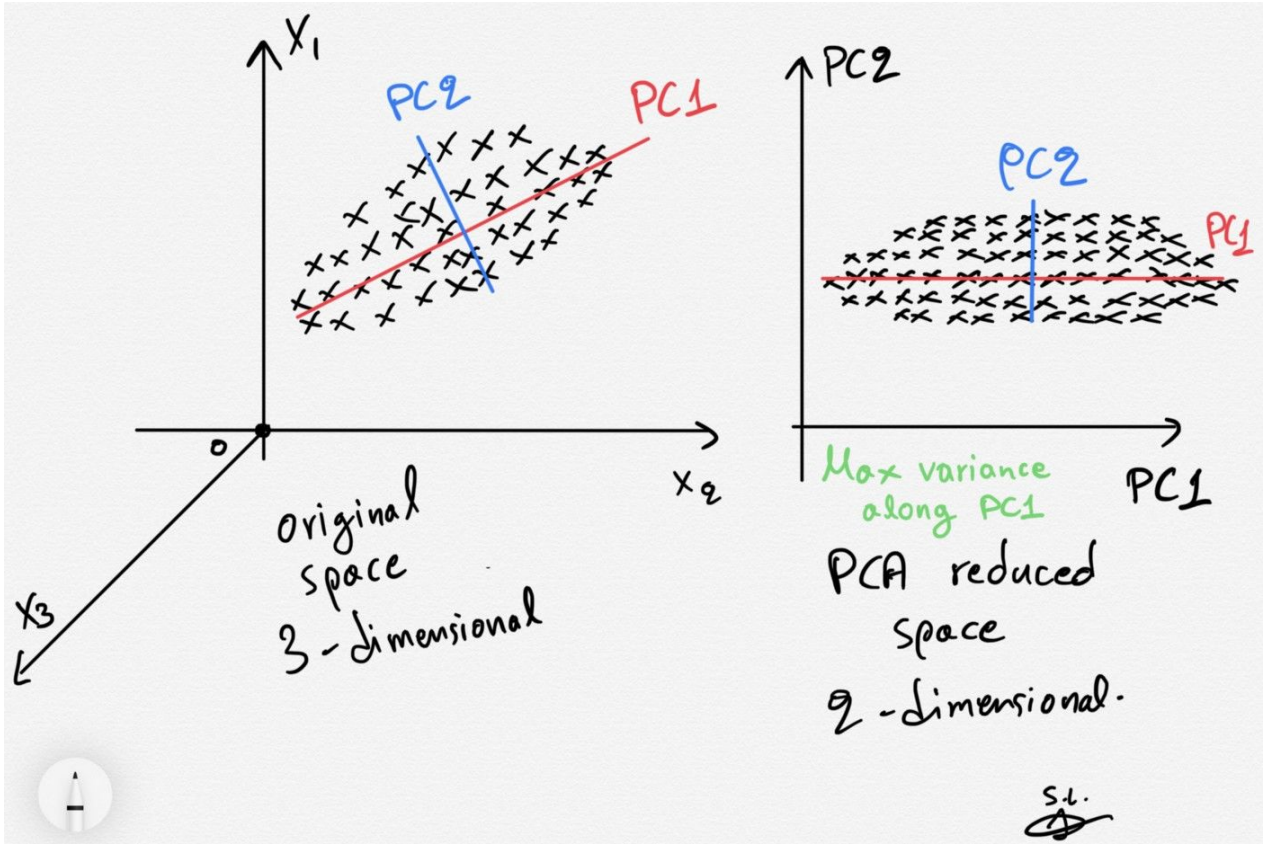
No representation is perfect



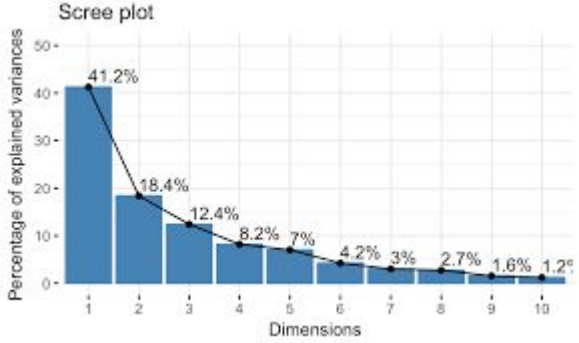
So, how can we do it?

Principal Component Analysis (PCA): Variance

Mean center data -> Generate Covariance Matrix ->
Eigendecomposition -> Sort Eigenvalues



- How many components? Scree/elbow plot



- What variables contribute most to PCs? BiPlot

https://towardsdatascience.com/pca-clearly-explained-how-when-why-to-use-it-and-feature-importance-a-guide-in-python-7c274582c37e

MultiDimensional Scaling (MDS): Distances

$$Stress_D(x_1, x_2, \ldots, x_N) = \sqrt{\sum_{i \neq j = 1,\ldots,N} (d_{ij} - ||x_i - x_j||)^2}$$

The goal of the algorithm is to minimize the value of stress.

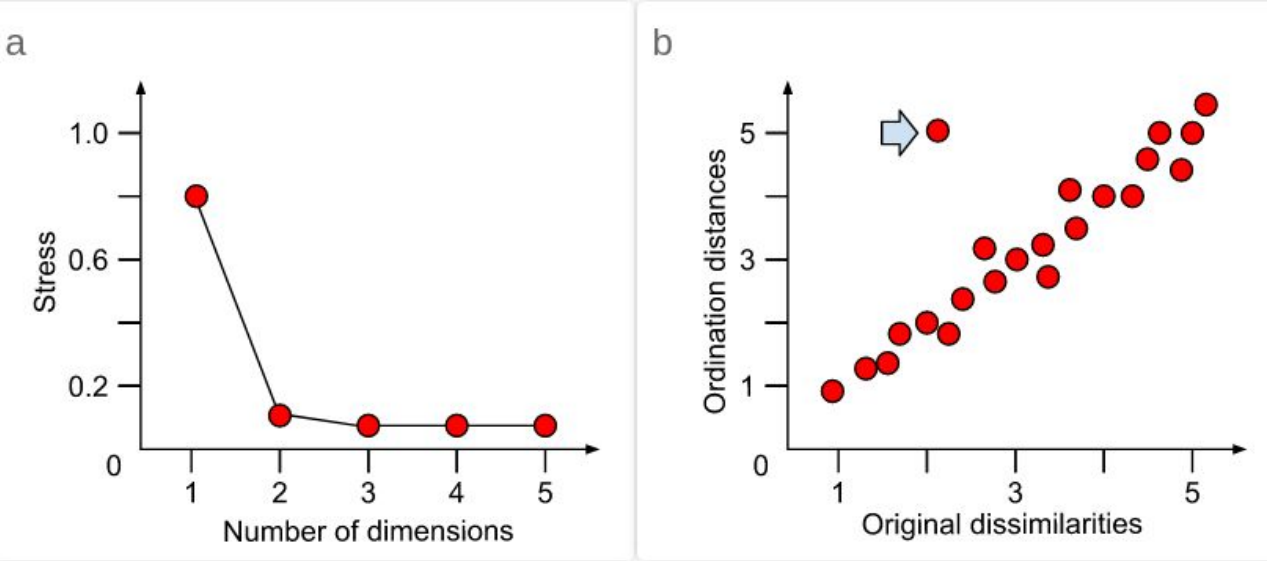
Where $x_1, \ldots, x_N$ are data points with their new set of coordinates in lower dimensional space.

d_{ij} is the actual distance we have calculated between the two corresponding data points in their original dimensional space.

$||x_i - x_j||$ is the distance between the two corresponding data points in their lower dimensional space.

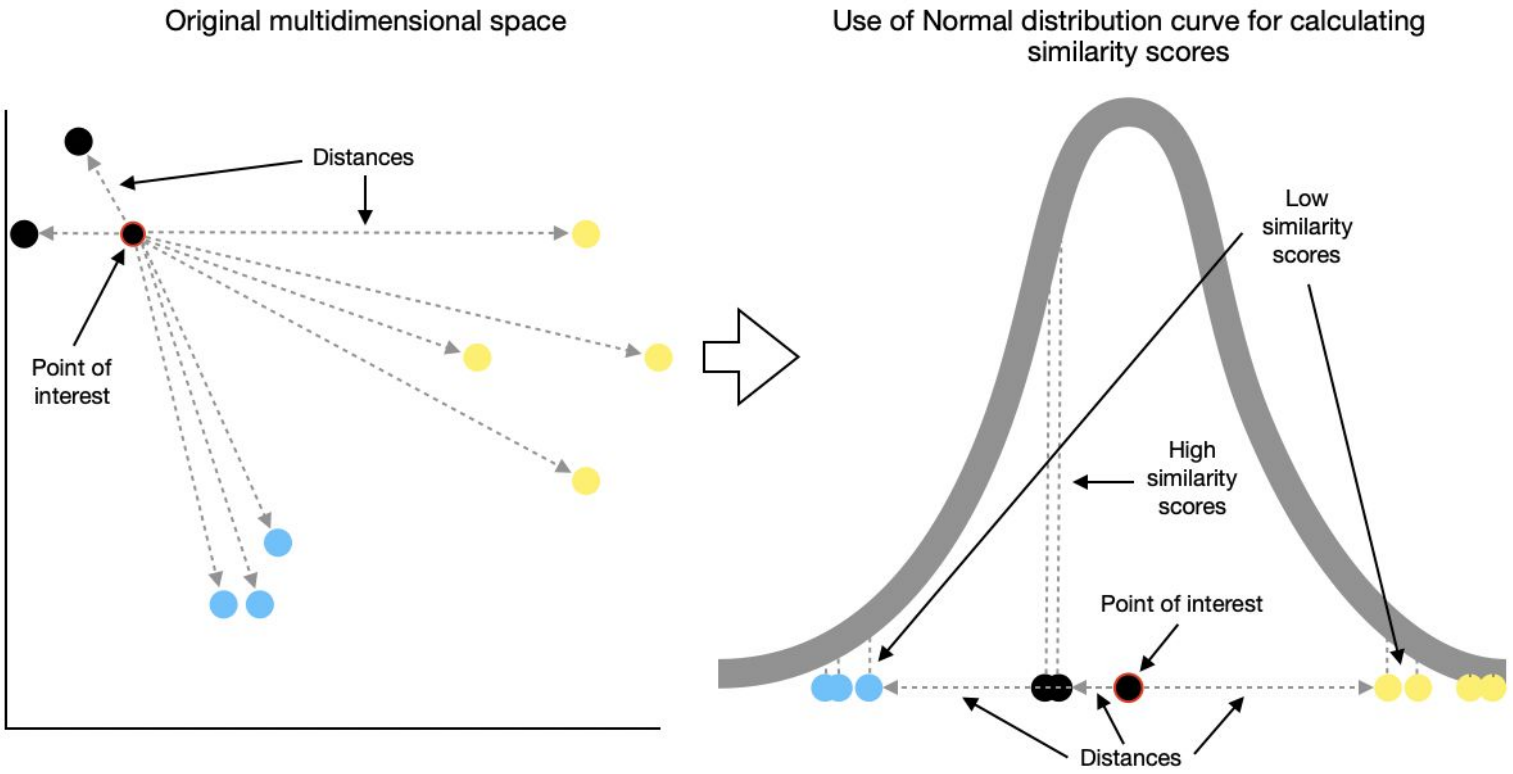
The closer the value of $||x_i - x_j||$ is to d_{ij} the

Non-Metric: Ranks

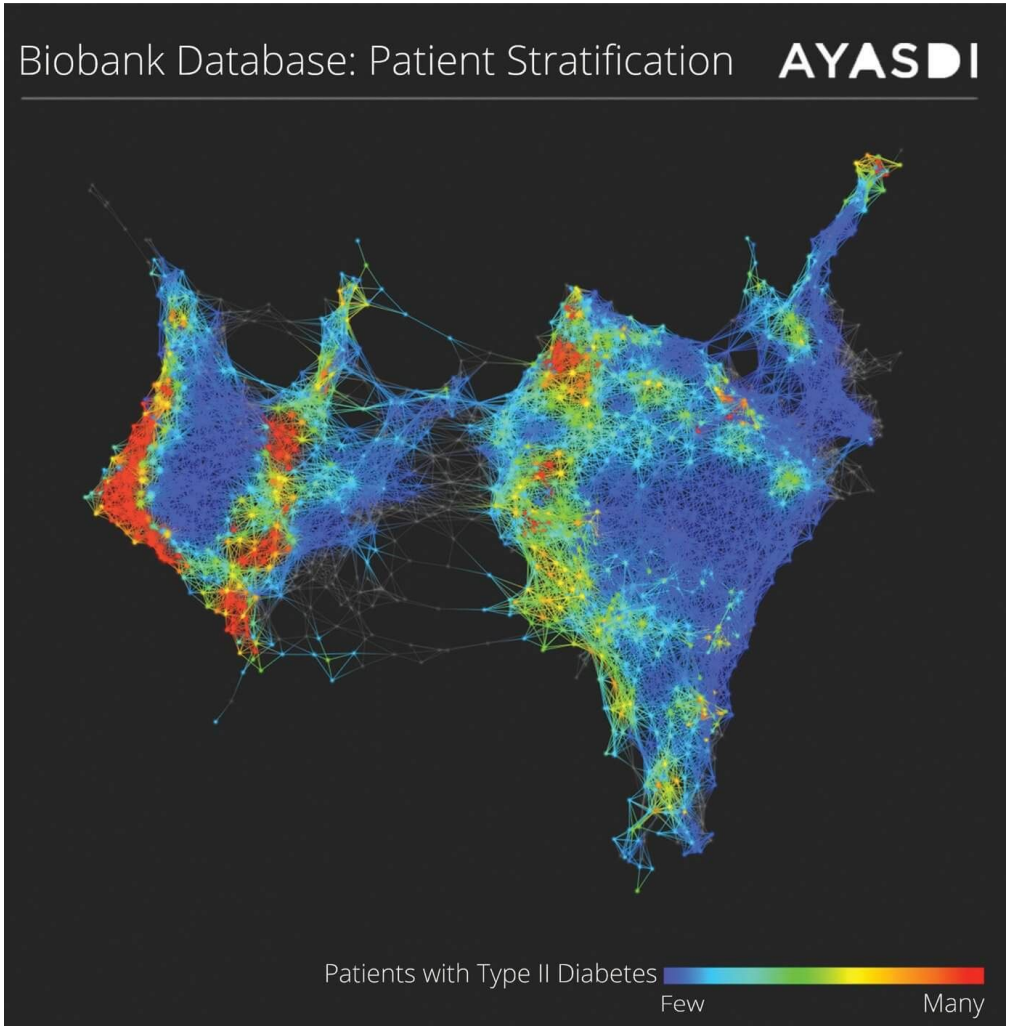


t-SNE/UMAP: Probabilities

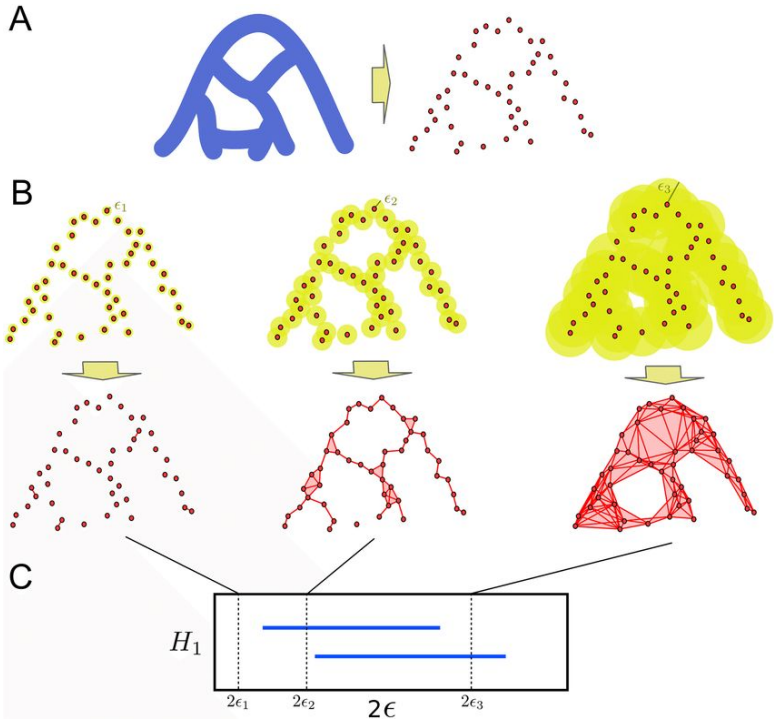
- Pairwise probability distribution in all dimensions
- Pairwise probability distribution in few dimensions
- Stochastic minimisation of KL divergence between distributions



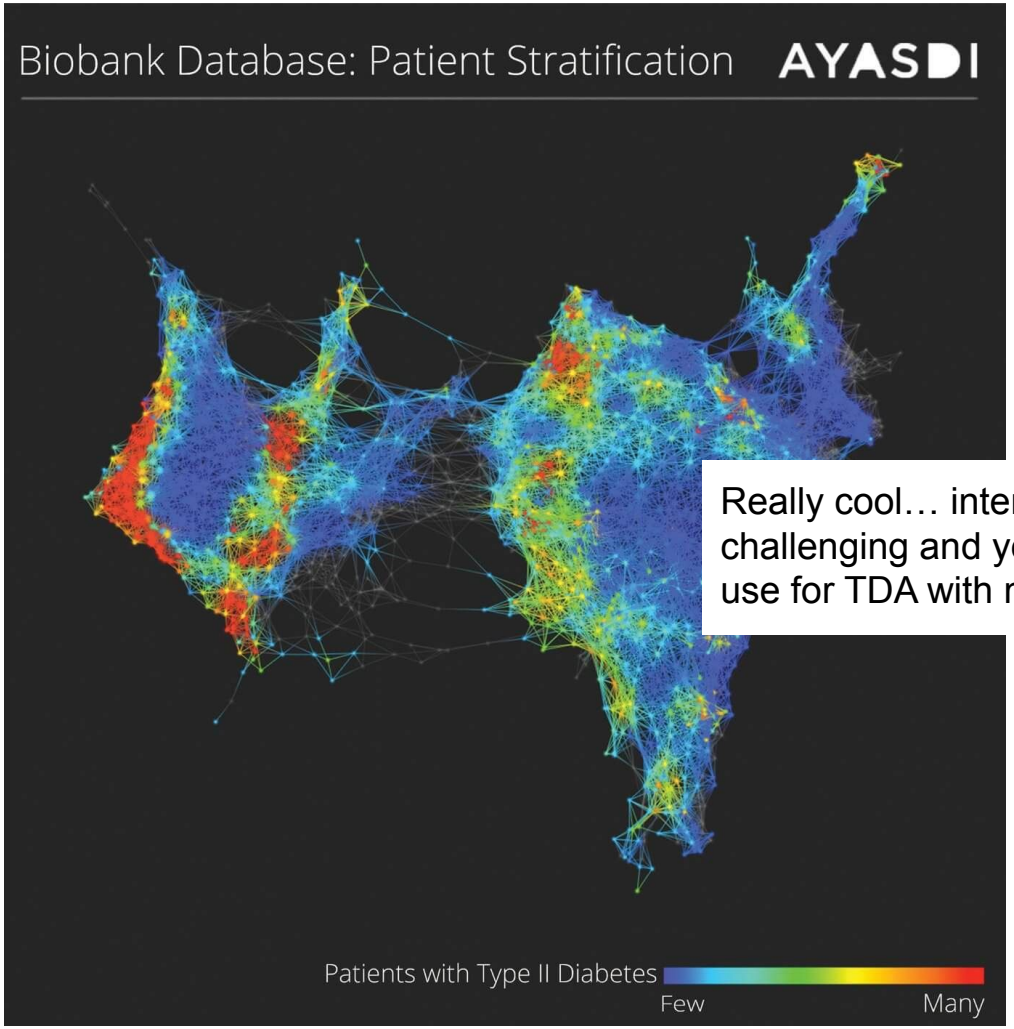
Topological Data Analysis



- Point clouds -> increase radius -> simplical complexes -> topological characteristics

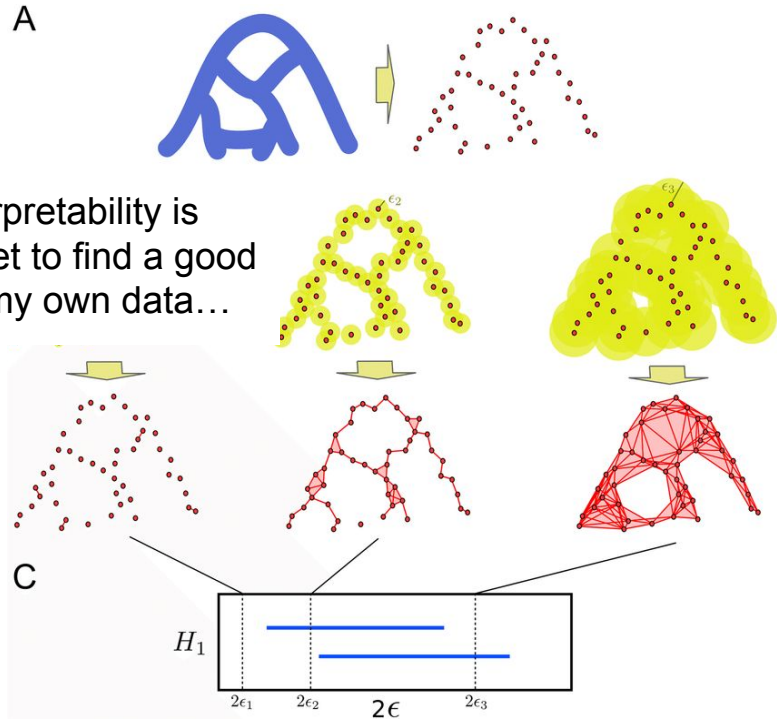


Topological Data Analysis



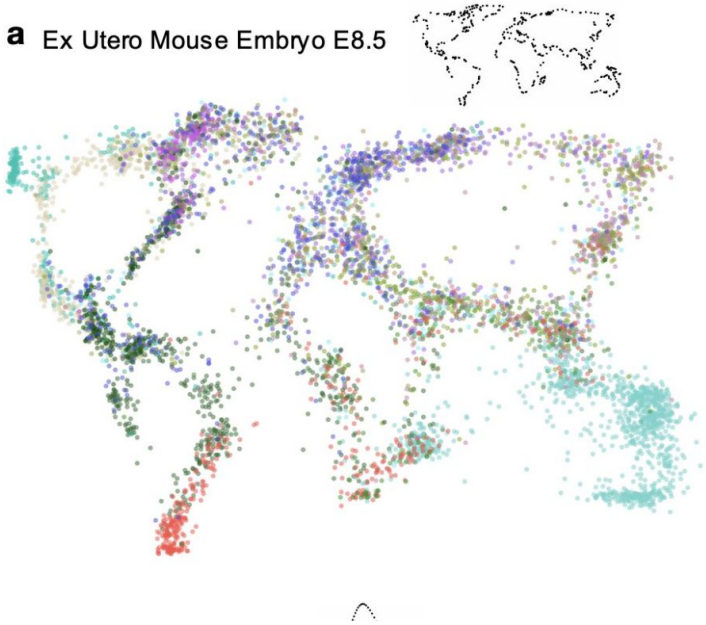
- Point clouds -> increase radius -> simplical complexes -> topological characteristics

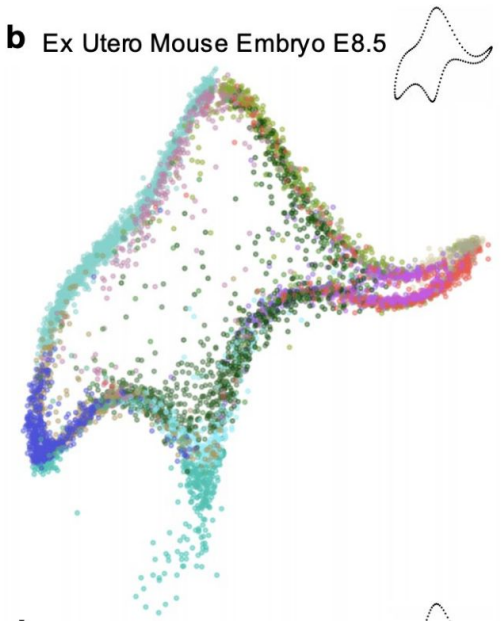
Really cool… interpretability is challenging and yet to find a good use for TDA with my own data…



Avoid over-interpreting single plots

- Sensitive to hyperparameters
- Beware analysing these non-linear projections
- Can contribute to confirmation bias

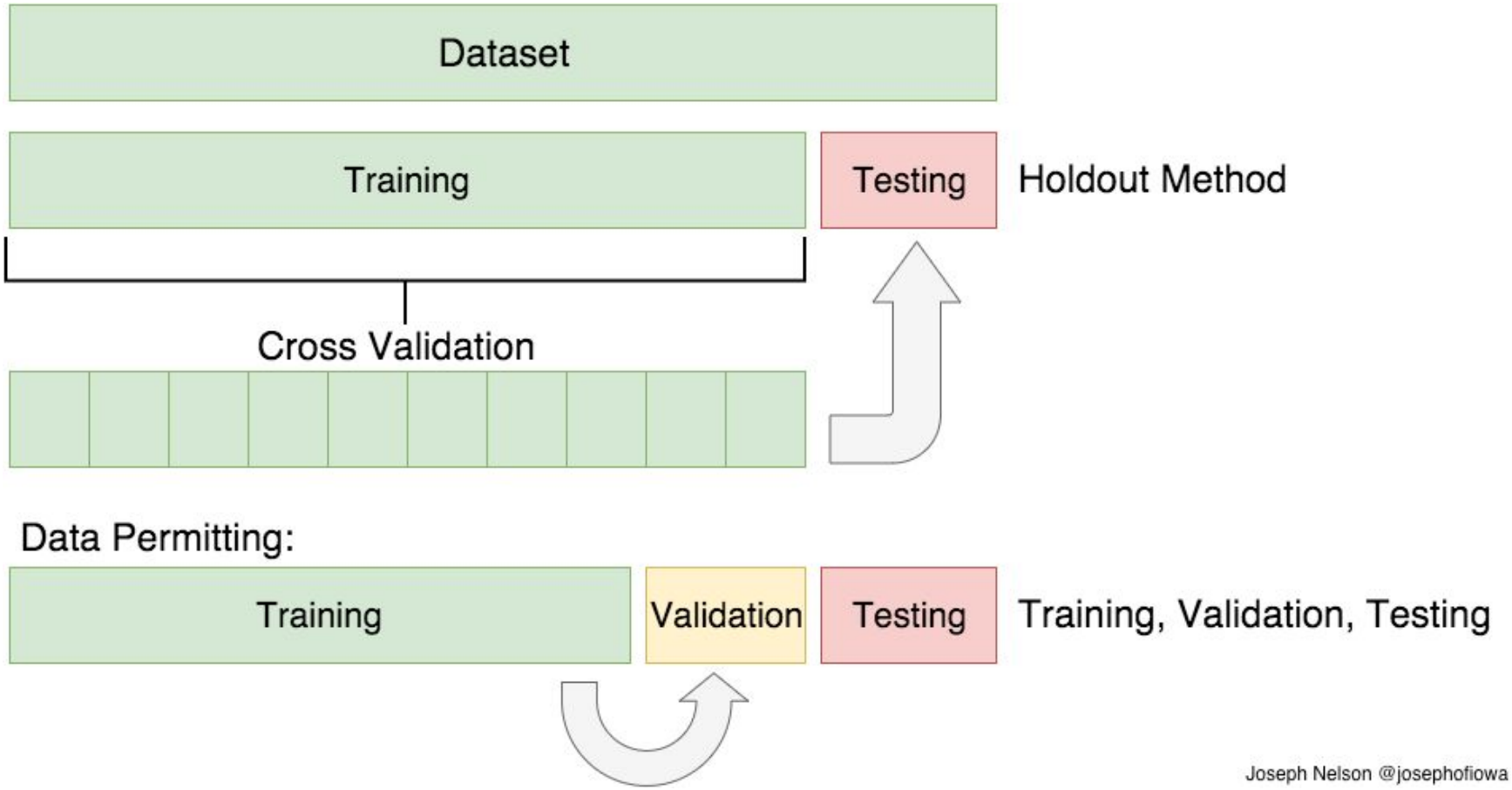




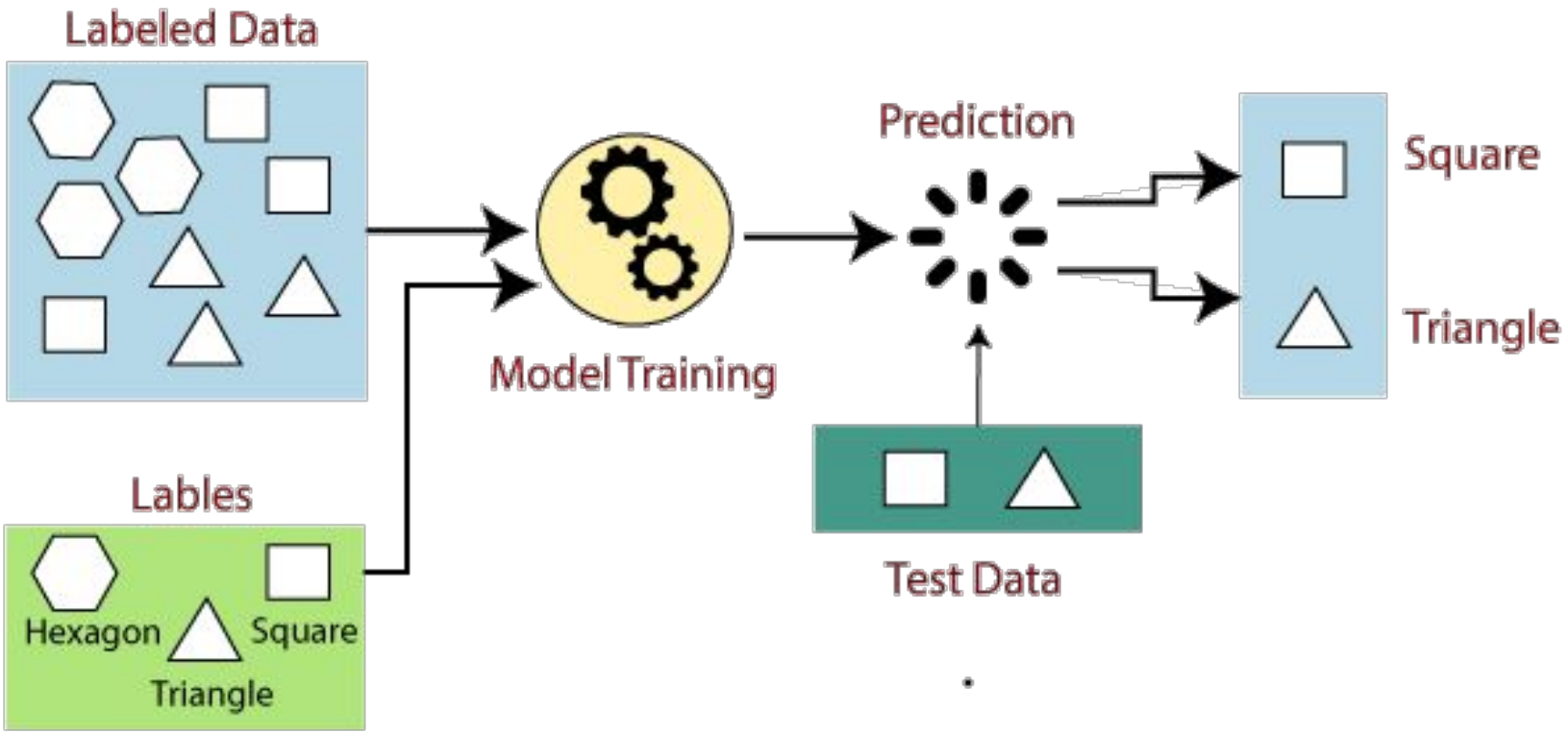
https://www.biorxiv.org/content/10.1101/2021.08.25.457696v3

Predicting using tabular data

Overfitting 101: Test-Train Split

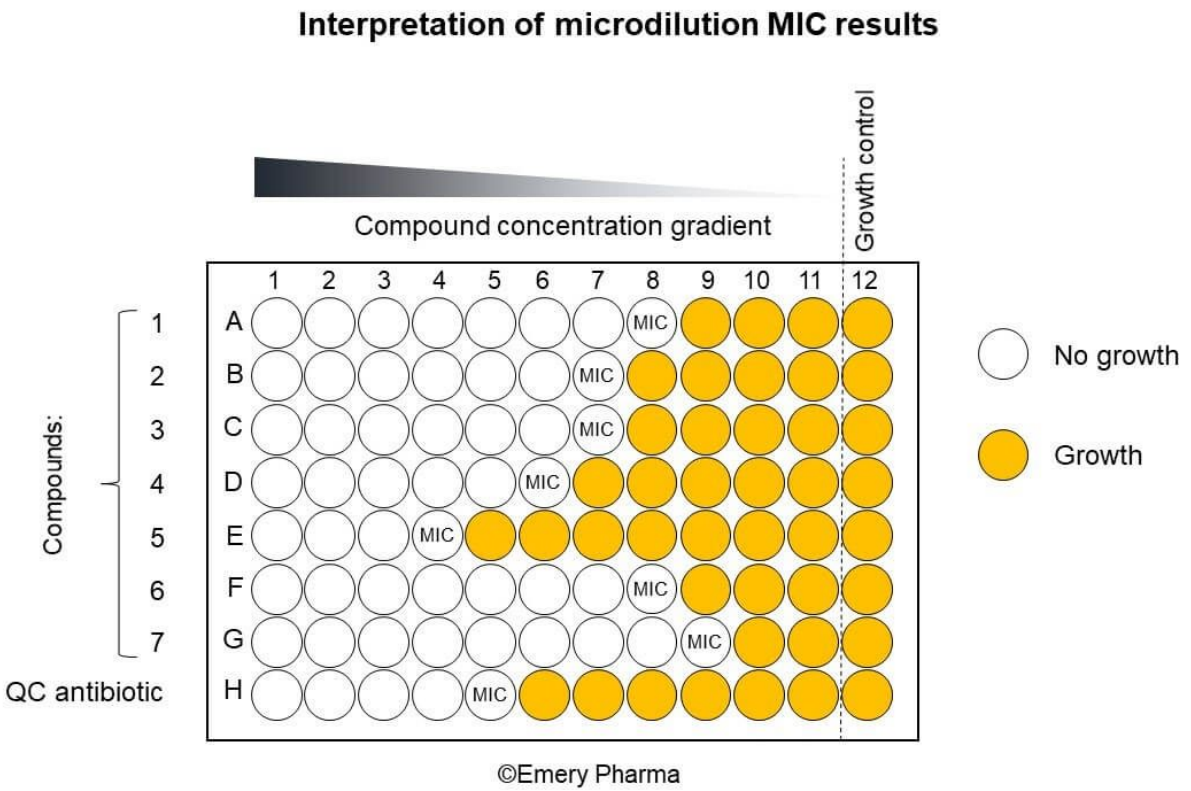


Predicting Labels or Values

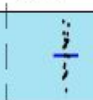
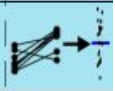
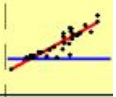
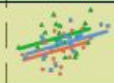


Values can be complex: interval prediction

- MIC > highest concentration = *right-censored*
- MIC < lowest concentration = *left-censored*
- Serial Dilutions: MIC of x actually [x/2, 2x] = *unequal error*

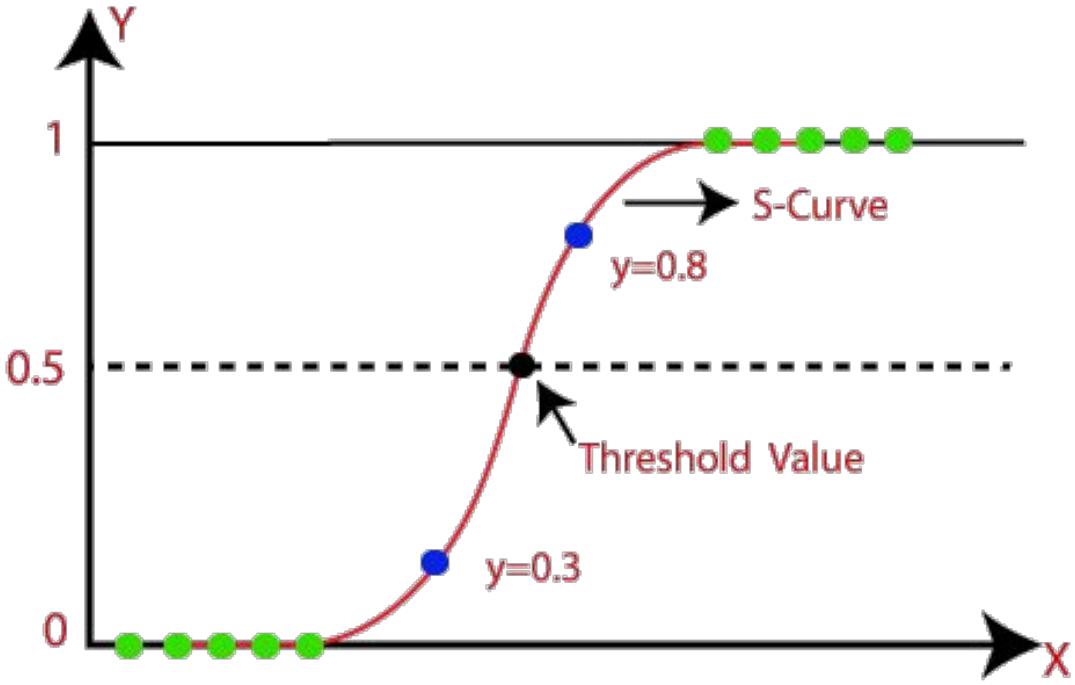


Start simple: linear regression

	Common name	Built-in function in R	Equivalent linear model in R	Exact?	The linear model in words	Icon
Simple regression: lm(y ~ 1 + x)	**y is independent of x** P: One-sample t-test N: Wilcoxon signed-rank	t.test(y) wilcox.test(y)	lm(y ~ 1) lm(signed_rank(y) ~ 1)	✓ for N >14	One number (intercept, i.e., the mean) predicts **y**. - (Same, but it predicts the *signed rank* of **y**.)	
	P: Paired-sample t-test N: Wilcoxon matched pairs	t.test(y_1, y_2, paired=TRUE) wilcox.test(y_1, y_2, paired=TRUE)	lm(y_2 - y_1 ~ 1) lm(signed_rank(y_2 - y_1) ~ 1)	✓ for N >14	One intercept predicts the pairwise $\mathbf{y_2}$-$\mathbf{y_1}$ differences. - (Same, but it predicts the *signed rank* of $\mathbf{y_2}$-$\mathbf{y_1}$.)	
	y ~ continuous x P: Pearson correlation N: Spearman correlation	cor.test(x, y, method='Pearson') cor.test(x, y, method='Spearman')	lm(y ~ 1 + x) lm(rank(y) ~ 1 + rank(x))	✓ for N >10	One intercept plus **x** multiplied by a number (slope) predicts **y**. - (Same, but with *ranked* **x** and **y**)	
	y ~ discrete x P: Two-sample t-test P: Welch's t-test N: Mann-Whitney U	t.test(y_1, y_2, var.equal=TRUE) t.test(y_1, y_2, var.equal=FALSE) wilcox.test(y_1, y_2)	lm(y ~ 1 + G_2)[A] gls(y ~ 1 + G_2, weights=…[B])[A] lm(signed_rank(y) ~ 1 + G_2)[A]	✓ ✓ for N >11	An intercept for **group 1** (plus a difference if **group 2**) predicts **y**. - (Same, but with one variance *per group* instead of one common.) - (Same, but it predicts the *signed rank* of **y**.)	
Multiple regression: lm(y ~ 1 + x_1 + x_2 +…)	P: One-way ANOVA N: Kruskal-Wallis	aov(y ~ group) kruskal.test(y ~ group)	lm(y ~ 1 + G_2 + G_3 +…+ G_N)[A] lm(rank(y) ~ 1 + G_2 + G_3 +…+ G_N)[A]	✓ for N >11	An intercept for **group 1** (plus a difference if group ≠ 1) predicts **y**. - (Same, but it predicts the *rank* of **y**.)	
	P: One-way ANCOVA	aov(y ~ group + x)	lm(y ~ 1 + G_2 + G_3 +…+ G_N + x)[A]	✓	- (Same, but plus a slope on **x**.) *Note: this is discrete AND continuous. ANCOVAs are ANOVAs with a continuous x.*	
	P: Two-way ANOVA	aov(y ~ group * sex)	lm(y ~ 1 + G_2 + G_3 +…+ G_N + S_2 + S_3 +…+ S_K + G_2*S_2 + G_3*S_3 + … + G_N*S_K)	✓	Interaction term: changing **sex** changes the **y ~ group** parameters. *Note: $\mathbf{G_{2\,to\,N}}$ is an indicator (0 or 1) for each non-intercept levels of the **group** variable. Similarly for $\mathbf{S_{2\,to\,K}}$ for sex. The first line (with G_i) is main effect of group, the second (with S_i) for sex and the third is the **group × sex** interaction. For two levels (e.g. male/female), line 2 would just be "S_2" and line 3 would be S_2 multiplied with each G_i.*	*[Coming]*
	Counts ~ discrete x N: Chi-square test	chisq.test(groupXsex_table)	**Equivalent log-linear model** glm(y ~ 1 + G_2 + G_3 + … + G_N + S_2 + S_3+ … + S_K + G_2*S_2 + G_3*S_3 +…+ G_N*S_K, family=…)[A]	✓	Interaction term: (Same as Two-way ANOVA.) *Note: Run glm using the following arguments: `glm(model, family=poisson())`* *As linear-model, the Chi-square test is $\log(y_i) = \log(N) + \log(\alpha_i) + \log(\beta_i) + \log(\alpha_i\beta_i)$ where α_i and β_i are proportions. See more info in the accompanying notebook.*	*Same as Two-way ANOVA*
	N: Goodness of fit	chisq.test(y)	glm(y ~ 1 + G_2 + G_3 +…+ G_N, family=…)[A]	✓	(Same as One-way ANOVA and see Chi-Square note.)	*1W-ANOVA*

https://lindeloev.github.io/tests-as-linear/

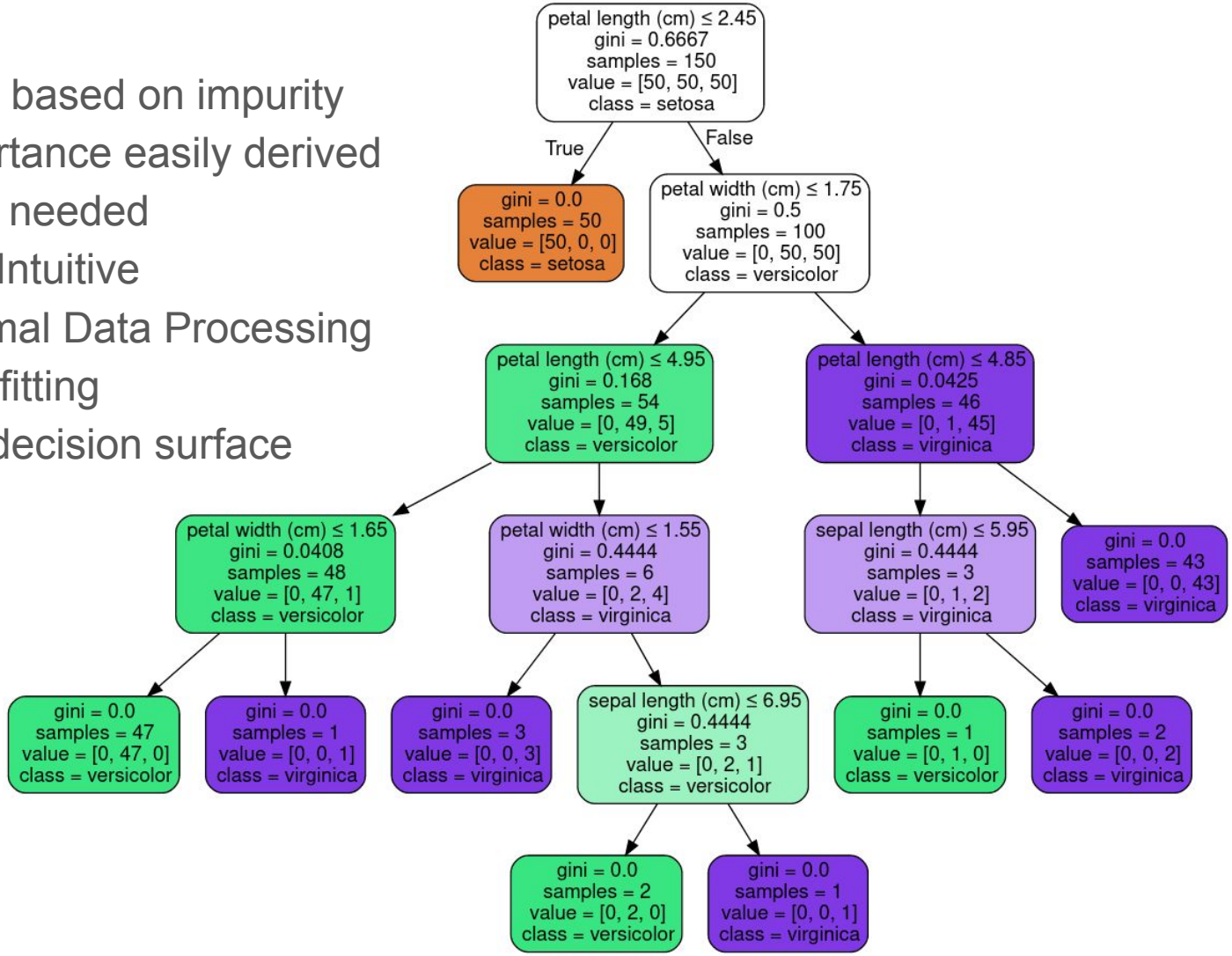
Add a sigmoid for classification



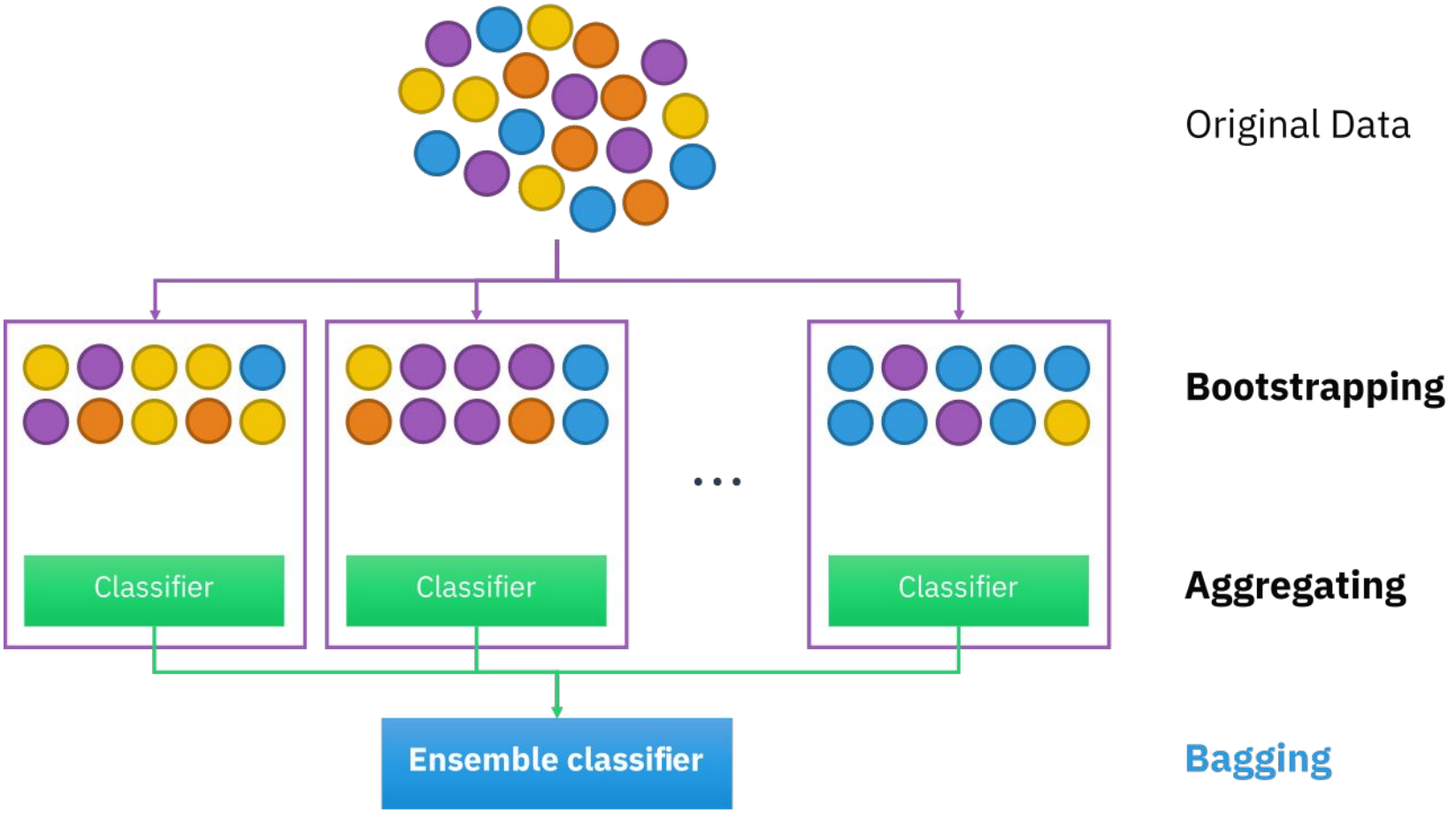
- Crude measure of feature importance (model coefficients)
- Specific feature selection can be a good idea
- Support for regularisation (Lasso/L1 -> sparsity vs Ridge/L2 -> minimal vs ElasticNet -> balance)
- Statistics has developed much better practices for treatment/interpretation of logistic regression

Decision Trees

- Dataset splits based on impurity
- Feature importance easily derived
- Pruning often needed
- Interpretable/Intuitive
- Require Minimal Data Processing
- Prone to overfitting
- Non-smooth decision surface

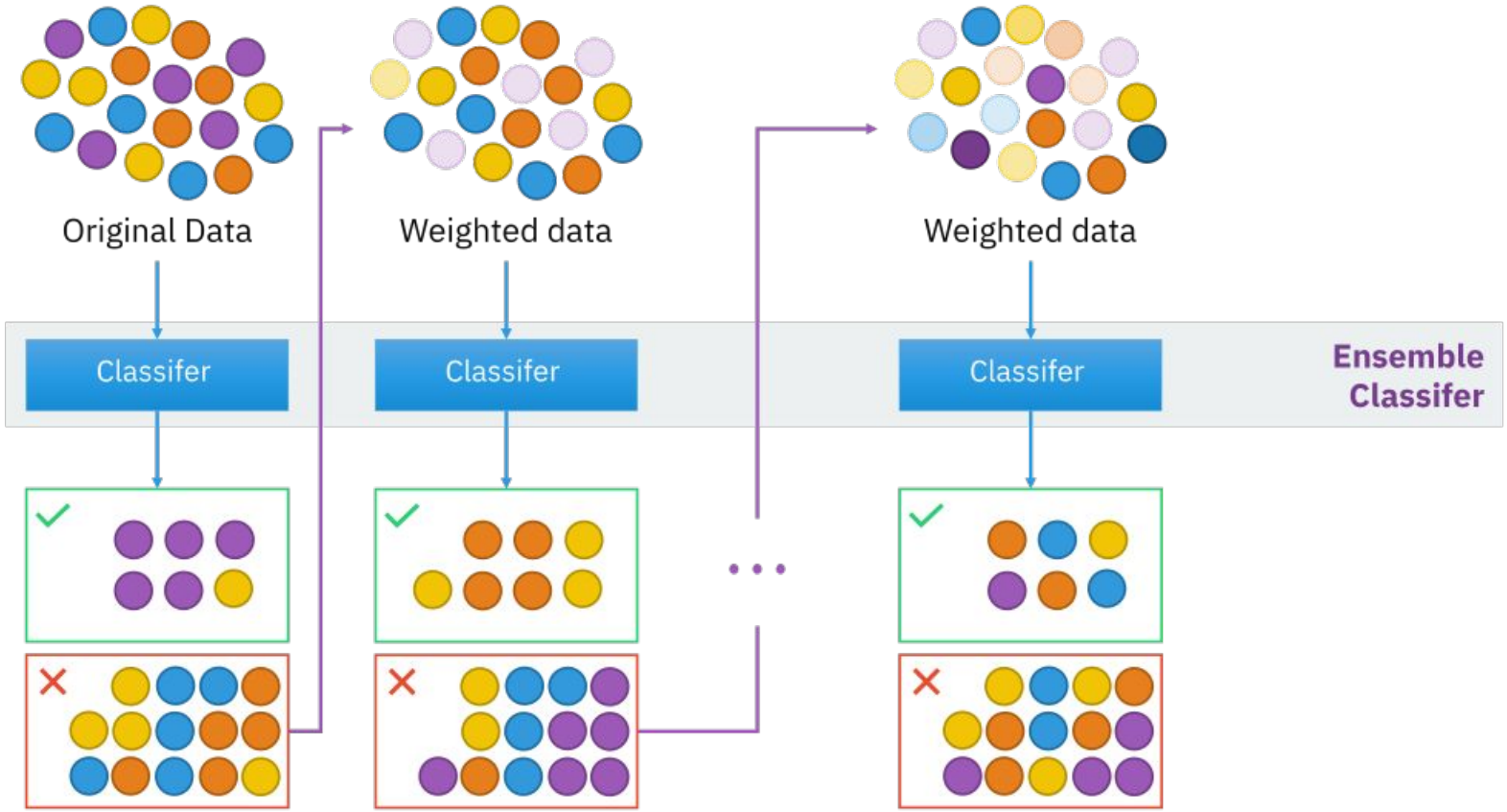


Many Decision Trees: Bagging



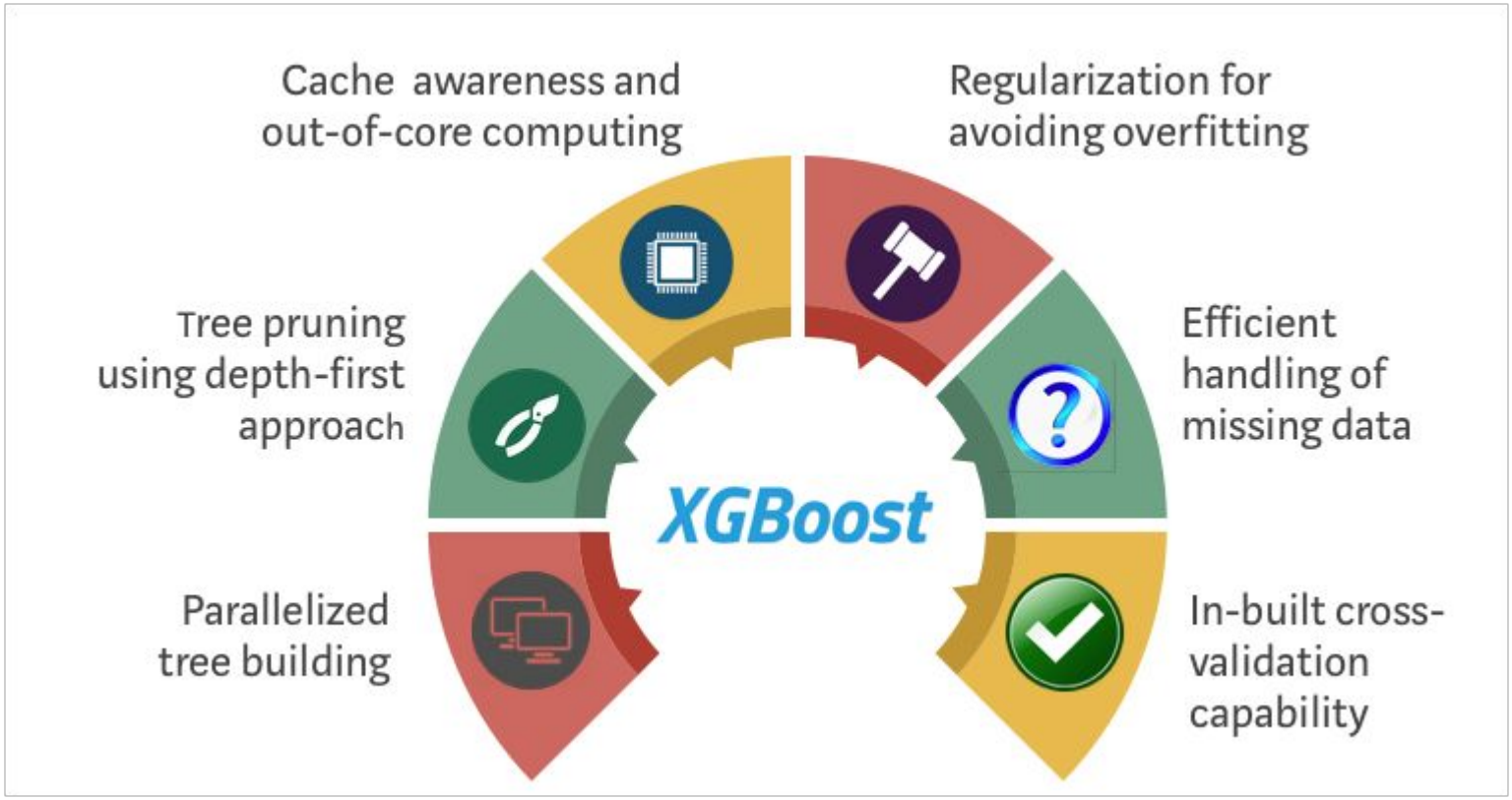
Random Forest: Bagging + Random Subset Per Split
Feature Importance: Average impurity decrease

Boosting: AdaBoost



Gradient Boosting: XGBoost

- Fix on pseudo-residuals instead of weights
- Use stochastic gradient descent



Overview

- Medical databases are usually relational and are defined by their origin, primary record type, scope, and sampling strategy
- Standardisation is important and ontologies support that in medical databases
- Survey weights are key to compensate for complex sampling
- There is a continuum of approaches to retain data privacy (and data ownership is a complex issue)
- Individual and joint distributions are key EDA tools
- Dimensionality reduction (PCA, MDS, t-SNE) is very useful but can be challenging/misleading
- Start with simple classifiers e.g., logistic regression/decision tree
- Combine weak classifiers via bagging (bootstrapping data: Random Forest special form) or boosting (sequential training model on errors: AdaBoost/XGBoost) to improve performance.
- XGBoost gold-standard but requires more tuning than AdaBoost