Data Analysis, Statistics, Machine Learning

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Data

What is (are) data?

- A datum is a given (as in French donnée)
  - data is plural of datum
- Data may have many different forms
  - Set, Bag, List, Table, etc.
  - Many of these forms are amenable to data analysis
  - None of these forms is suitable for statistical analysis
- Statistics operate on variables, not data
  - A variable is a function mapping data objects to values
  - A random variable is a variable whose values are each associated with a probability p ($0 \leq p \leq 1$)
- Visualizations operate on data or variables

Data

Datasets

- A set cannot contain duplicate elements
- On IBM mainframes, datasets originally had a record structure
  - So each record is an element
  - But duplicate records can occur
  - So IBM mainframe datasets were really lists (ordered sets allowing duplicates)
- Nowadays, the term dataset is interpreted much more broadly
  - Flat files
  - Relational tables
  - Distributed databases
  - Graph databases
    - Object databases were a precursor
    - Objects can be images, emails, etc.
  - Streaming (real time) databases

Data

Flat files

- Flat file databases (e.g., FileMaker) store their data in tables
- Flat file tables have *n* rows and *p* columns
- The rows are independent of each other (no relations)
- The CSV file (Microsoft Excel export) is most popular text format
  - One row per record
  - Fields are separated by comma, blank, semicolon, vertical bar, etc.
  - There is no standard for CSV (like an IEEE standard), unfortunately
  - Thus, it's an art to import them
- Statistics packages (BMDP, SAS, SPSS) originally used this format
  - Each row corresponds to a **case** or **observation** or **sampling unit**
  - Each column (field) corresponds to a **variable**
  - Stat packages eventually moved to binary encoding of their files
  - But CSV text is often more compressed (especially for floats)
  - So stat package binaries are becoming less common

Data

Importing Text Files (including CSV)

Separators:

,	\t	Blank(s)	;	:	|

and a few other rare ones

Lines per record: one

Missing values:

,,	\t\t	;;	::	||	?	*	.	-	--	..	null	NaN

Header: optional (rows may contain fewer values than header)

Strings: strings may be surrounded by quotes

- They MUST be surrounded by quotes if they contain a separator or blanks
- Embedded quotes represented by “”

```
John,Doe,120 jefferson st.,Riverside, NJ, 08075
Jack,McGinnis,220 hobo Av.,Phila, PA,09119
"John ""Da Man""",Repici,120 Jefferson St.,Riverside, NJ,08075
Stephen,Tyler,"7452 Terrace ""At the Plaza"" road",SomeTown,SD, 91234
,Blankman,,SomeTown, SD, 00298
"Joan ""the bone"", Anne",Jet,"9th, at Terrace plc",Desert City,CO,00123
```

Data

Relational databases

- Edgar Codd invented the relational database
  - IBM refused to implement it until Codd shamed them
- According to Codd, a RDBMS cannot contain duplicate rows
  - But SQL allows it, much to Codd's annoyance
- The Codd model
  - A relation variable is a function relating values to objects
    - A relation variable has a domain
    - A domain is a set of scalar values of one type (integers, strings, etc.)
  - A "table" is a metaphor for a collection of relations
  - Each "row" of a table is a tuple
  - Each "column" is an attribute specifying a domain
  - Quotes are used here because tables are not relations
  - Tuples are unordered
  - Attributes are unordered

Data

- SQL (Sequential Query Language)
  - SQL was designed to manipulate tables
  - Tables are not relations
  - Some versions of SQL violate the relational model
  - SQL doesn't have a universally recognized specification
  - Tuples in the relational model are unordered sets of known values
  - But SQL doesn't talk tuples. It talks rows.
    - A row is an ordered set of known or unknown values with names
    - A row can have NULLs. A tuple cannot.
    - Duplicate rows are permitted. Duplicate tuples are not.
  - The consequence of all this is that SQL restricts us to a table model
  - And we have to customize our SQL to match a provider's standard

Data

- Analyses on Relational databases
  - We can do data analysis on tables
  - But there are problems doing statistics on tables
    - Many statistical methods presume a vector space
    - Each vector is an ordered tuple of real numbers
      - In the relational model, elements of a tuple are unordered
    - Time series methods assume rows are ordered (in time)
      - Not allowed in the relational model
    - A sample can contain duplicate rows (cases, observations)
      - Not allowed in the relational model
  - There are hacks to fix these problems
    - Add an index variable to allow duplicate rows
    - Impose an ordering on the columns of the table (using SQL)
    - Impose an ordering on the rows through an index or date variable

Data

Analyses on Relational databases

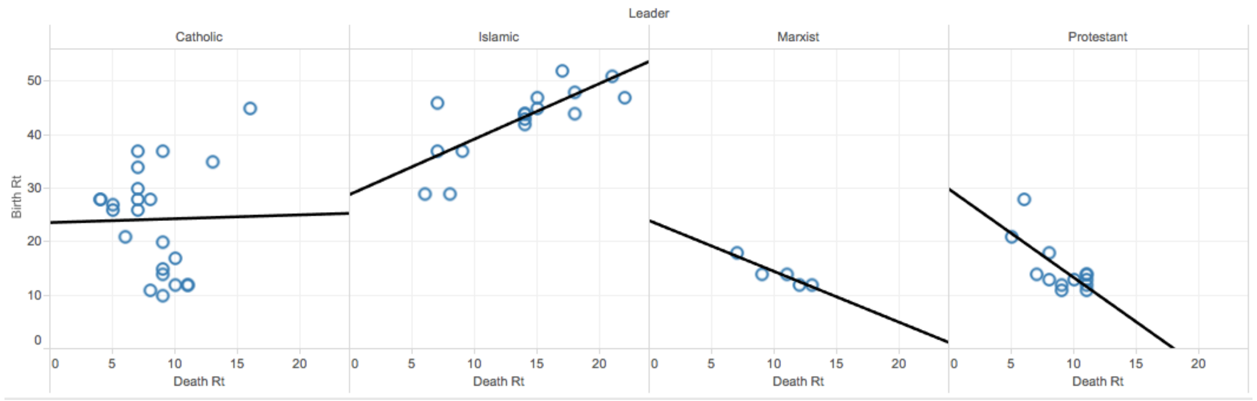
Aggregation

- Aggregate variables may not be independent across rows
- Aggregate variables are not necessarily normally distributed
  - Counts are not normally distributed
  - Sums and means of normal variables are normal
  - Sums and means of many other variables are normal if *n* is large
  - But variances and covariances of aggregates may pool heterogeneous sources
- **Ecological fallacy** can arise with inferences based on aggregation
  - Correlations at the group level can be much higher than those at the individual level
  - Aggregate behavior is not the same as individual behavior
  - There is no easy fix for this problem except to avoid aggregation in these cases
- Hierarchical models are designed to deal with this problem
  - But they are not practical in SQL
- **Simpson's paradox** can jeopardize inference based on aggregates
  - The story told by the aggregate is contradicted by the one told by the disaggregates

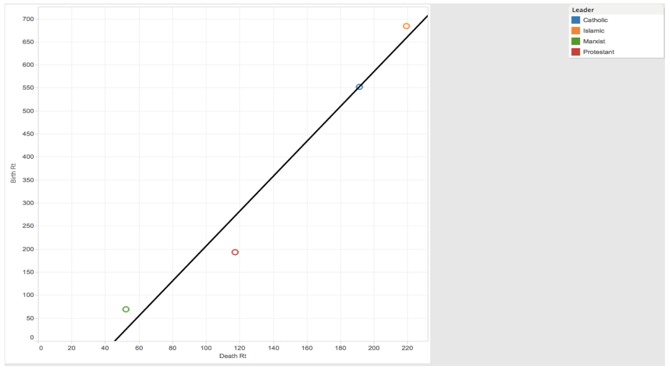
Data

Analyses on Relational databases

Simpson’s Paradox



Disaggregate



Aggregate

Data

Analyses on Relational databases

Database statistical analytics

- Some companies may not program statistics correctly
  - Database companies do not always have computational statisticians on staff
  - For example, numerous publications have revealed inaccuracies in Excel statistics
  - Accurate algorithms for even simple estimates (e.g., means) are not found in textbooks
  - Bottom line: trust entities whose business is statistics to get correct results
- Missing values often not handled correctly in database statistical algorithms
  - Databases represent missing values as NULL
  - NULL can mean “Does not apply” or “Don’t know” or “Refused to reply” etc.
  - Built-in algorithms may not process these appropriately (e.g., multiple imputation)
- One solution (used by SAS and R) is to embed appropriate calculations in database
  - Some databases accept C or Java embeddings under read/write restrictions
  - But database administrators HATE this

Data

Analyses on Relational databases

- Why can't we do inferential statistics on sums?
  - Sum depends on *n*
    - Sums of random variables do have a distribution
      - Which is normal-like if *n* is large
      - But they need to be identically distributed random variables
      - And we need to fix *n* to assume the distribution.
  - We need a variance estimate
    - We need to have a variance estimate, not a single sum, in order to assess risk
      - In certain circumstances (e.g., baseline variance for arcsine transform) we can do this, but not often
  - The entities on which the sums are based need to be comparable
    - These are not comparable
      - Total sales over superstores of different sizes and locations
      - Budgets of states of different populations
      - Total revenue of Microsoft, Facebook, Apple, Google, and Twitter
    - These are comparable
      - Sum of scores on individual items of a well-designed test
  - Inferences based on sums do not apply to their constituents
    - Inferences on classroom test scores cannot be applied to students

Data

Distributed File Systems

- The problem
  - In memory and classic databases cannot handle huge files
  - Distributed databases can but there are other problems involving complexity
  - Statistical calculations on single files do not scale well
- Map Reduce (Hadoop)
  - This Google invention distributes data over many cores
  - By slicing up data, many (but not all) statistical calculations can run in parallel
  - Hadoop is the open-source version of Map Reduce
- PSM (Pass Stream Merge)
  - Unlike Map Reduce, there is no central supervisor or hierarchy
  - Biological analogy
    - Lots of amoebas swimming around in cloud soup
  - Localizes three methods (Pass, Stream, Merge) in one class

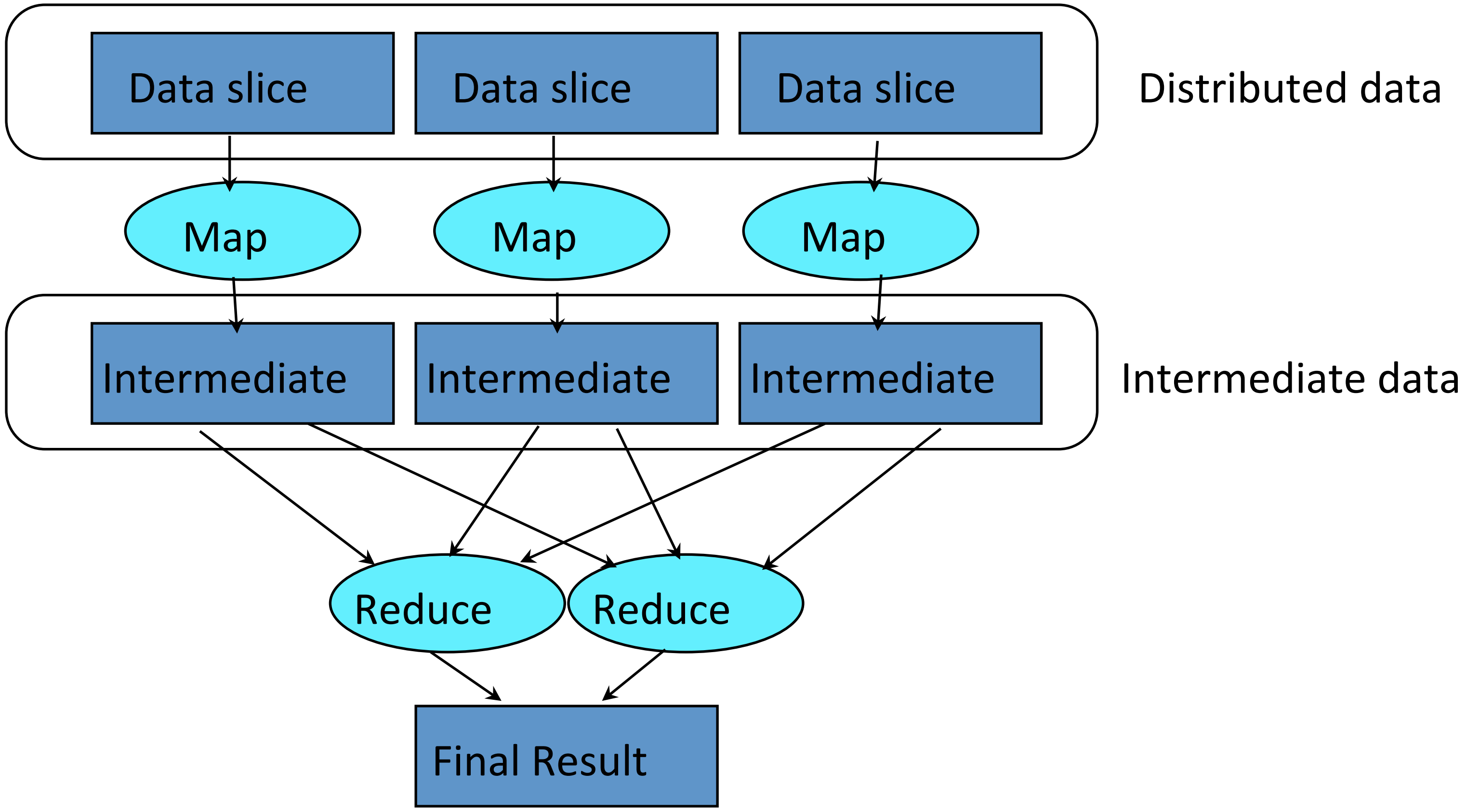
Data

Map Reduce (Hadoop)

- Fault tolerance
- I/O Scheduling
- Automatic parallelization and distribution
- Hadoop has hundreds of third-party vendors
- Works for many algorithms
- Slower than in-memory systems for some algorithms

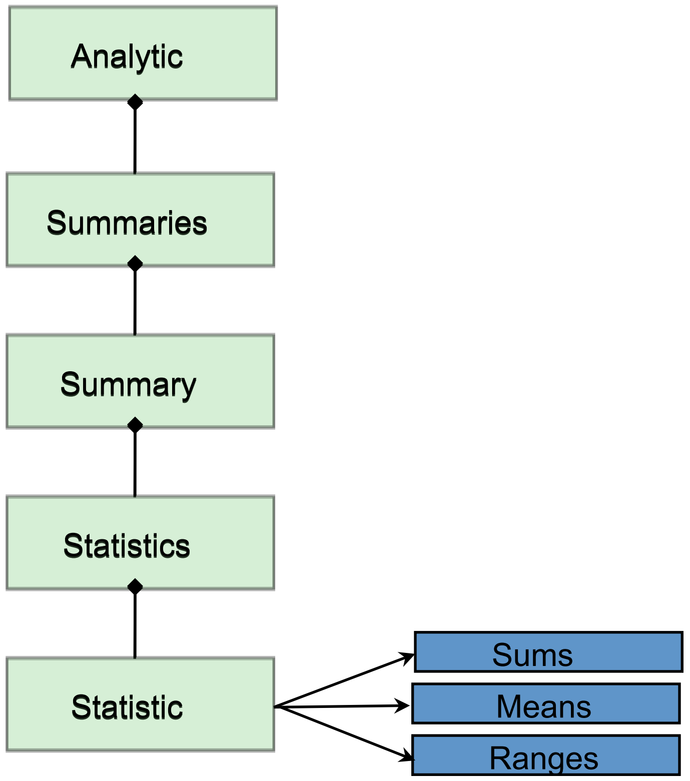
Data

Map Reduce (Hadoop)



Data

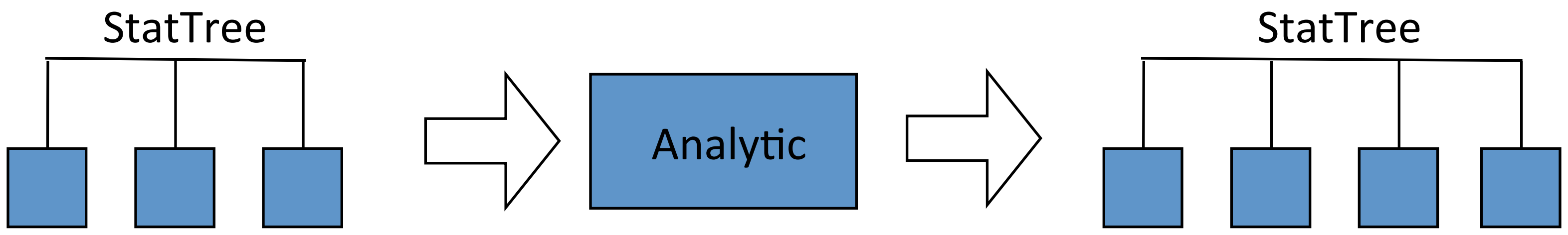
PSM (Pass Stream Merge)



Data

PSM (Pass Stream Merge)

A StatTree is a tree of Tables.
A Table is a table of data.
An input dataset is a Table.
An externalized Statistic is a Table.
Analytics input and output StatTrees.



Data

PSM (Pass Stream Merge)

PASS

```
Iterator iter = input.getIterator();
while (iter.hasNext()) {
    Row row = (Row) iter.next();
    double weight = row.getWeight();
    double[] data = row.getContinuousData();
    if (weight > 0) {
        for (int j = 0; j < data.length; j++) {
            double xd = weight * (data[j] – means[j]);
            double xj = data[j];
            counts[j]++;
            sums[j] += weight * xj;
            means[j] += xd / wcounts[j];
        }
    }
}
```

Data

PSM (Pass Stream Merge)

STREAM

```
Iterator iter = input.getIterator();
while (iter.hasNext()) {
    Row row = (Row) iter.next();
    double weight = row.getWeight();
    double[] data = row.getContinuousData();
    if (weight > 0) {
        for (int j = 0; j < data.length; j++) {
            double xd = weight * (data[j] – means[j]);
            double xj = data[j];
            if (add) {
                counts[j]++;
                sums[j] += weight * xj;
                means[j] += xd / wcounts[j];
            } else {
                counts[j]–;
                sums[j] -= weight * xj;
                means[j] -= xd / wcounts[j];
            }
        }
    }
}
```

Data

PSM (Pass Stream Merge)

MERGE

```
public void merge(Summary s1, Summary s2) {
    double[] means1 = Means.extractData(s1);
    double[] means2 = Means.extractData(s2);
    double[] wcounts1 = WeightedCounts.extractData(s1);
    double[] wcounts2 = WeightedCounts.extractData(s2);
    for (int i = 0; i < means1.length; i++) {
        means1[i] = (wcounts1[i] * means1[i] + wcounts2[i] * means2[i]) /
                (wcounts1[i] + wcounts2[i]);
    }
    Means.setData(s1, means1);
}
```

Data

Distributed File Systems

- What they are good for
  - Additive algorithms (ordinary regression, logistic regression, …)
- What they are bad for
  - Inefficient for nested iterative and interactive analytics
  - Nested iterative algorithms require multiple map/reduce steps
  - This propagates multiple files between MapReduce phases
  - And file processing is slow, even for in-memory files
  - Can be **slower** on some problems than single-thread table processing
  - The Hadoop hype conceals these problems
  - No OS can implement parallel processing for all algorithms automatically
  - For some algorithms, the only way is to customize parallelization

Data

- Graph databases
  - A graph $G = (V,E)$ is a pair of sets
    - V is a set of vertices (sometimes called nodes)
    - E is a set of edges (sometimes called arcs or links)
    - E induces a relation on V
  - The simplest file representation of a graph is a edge list text file
    - Each row is an edge
    - A program can parse this file to construct a list of nodes and a list of edges
  - Graph databases store nodes indexed by edges
    - Each node (an object) has a set of **properties**
    - Queries on graphs are especially efficient for traversal, etc.
    - Statistical analytics (degrees, centrality, diameter, etc.) are straightforward
    - Scalable (sparseness is built in to the schema)

Data

- Streaming (real time) databases
  - Data objects ordered in time
  - Data objects enter in real time
    - Stock market series
    - Instrumented data
    - Business metrics
  - Data objects retrievable with short delay
  - Statistical methods must be designed to handle streaming inputs
    - Running window (moving average, etc.)
    - Update/downdate methods
    - The PASS/STREAM/MERGE algorithm was designed to deal with these

Data

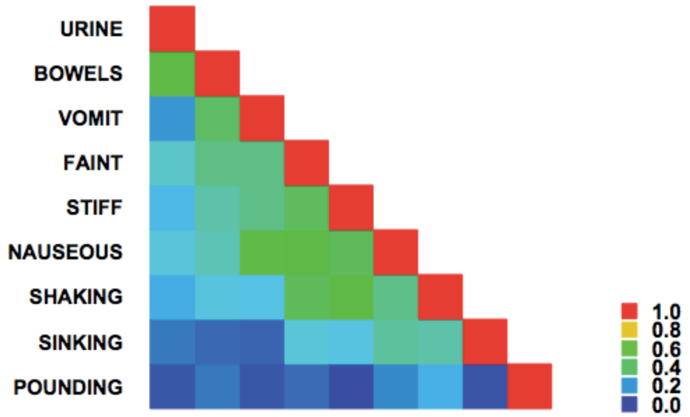
Symmetric matrices

- **S** is a symmetric matrix ($s_{ij} = s_{ji}$)
- Types of data that comprise symmetric matrices
  - Similarities
  - Dissimilarities
  - Distances
  - Correlations
  - Derived distances
- Analytic methods whose input is a symmetric matrix
  - Multidimensional Scaling (MDS)
  - Principal Components
  - Hierarchical Clustering

Data

Symmetric matrices

Start with a matrix **X** and transform elements into a single column



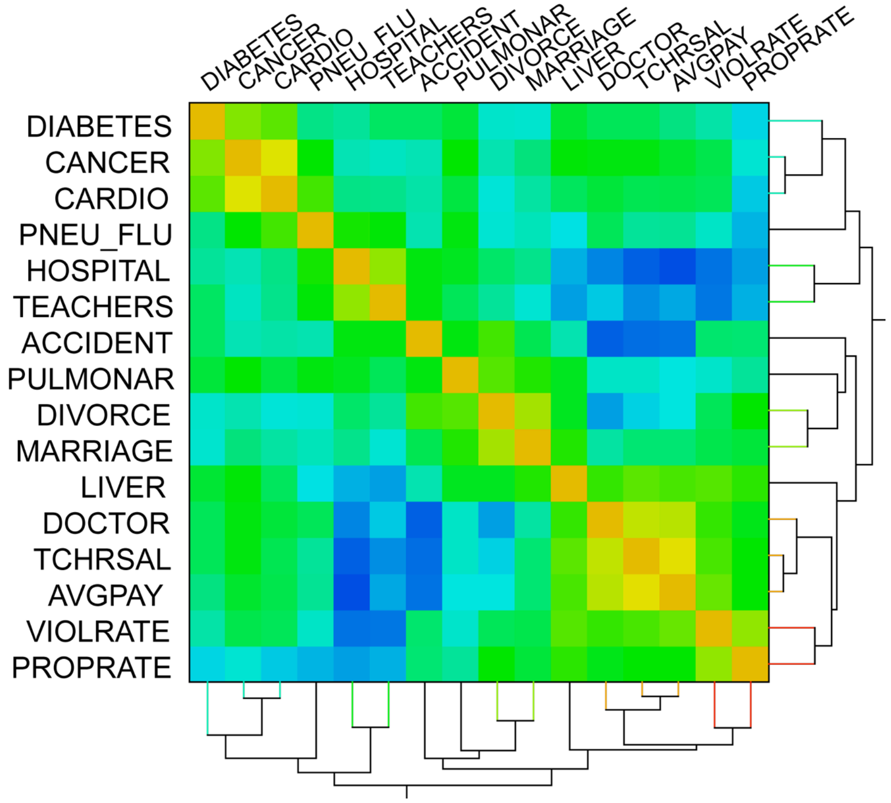
$$\begin{aligned}
&\mathit{reshape.rect}(): && k = n \cdot (i-1) + j \\
&\mathit{reshape.tri}(): && k = i \cdot (i-1)/2 + j : (i \geq j) \\
&\mathit{reshape.low}(): && k = (i-1) \cdot (i-2)/2 + j : (i > j) \\
&\mathit{reshape.diag}(): && k = i : (i = j)
\end{aligned}$$

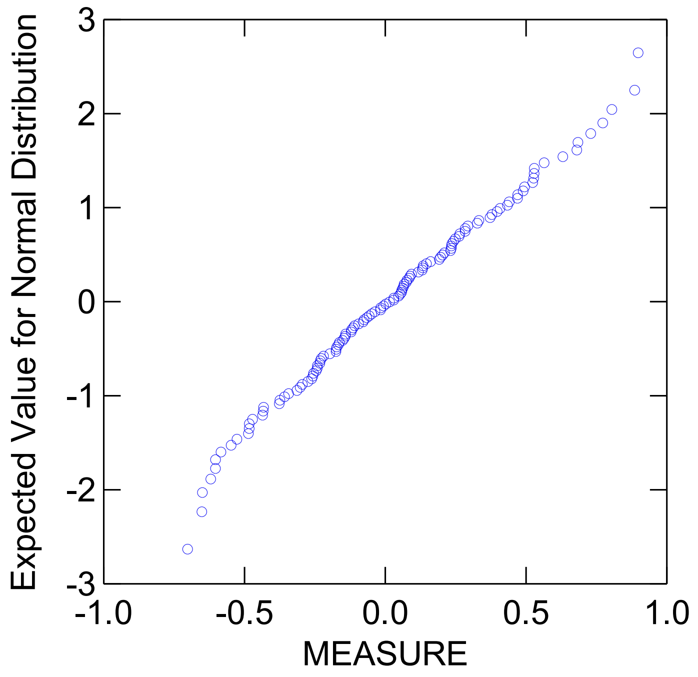
Sloane sequences database

Data

Symmetric matrices

Start with a matrix **X** and transform elements into a single column

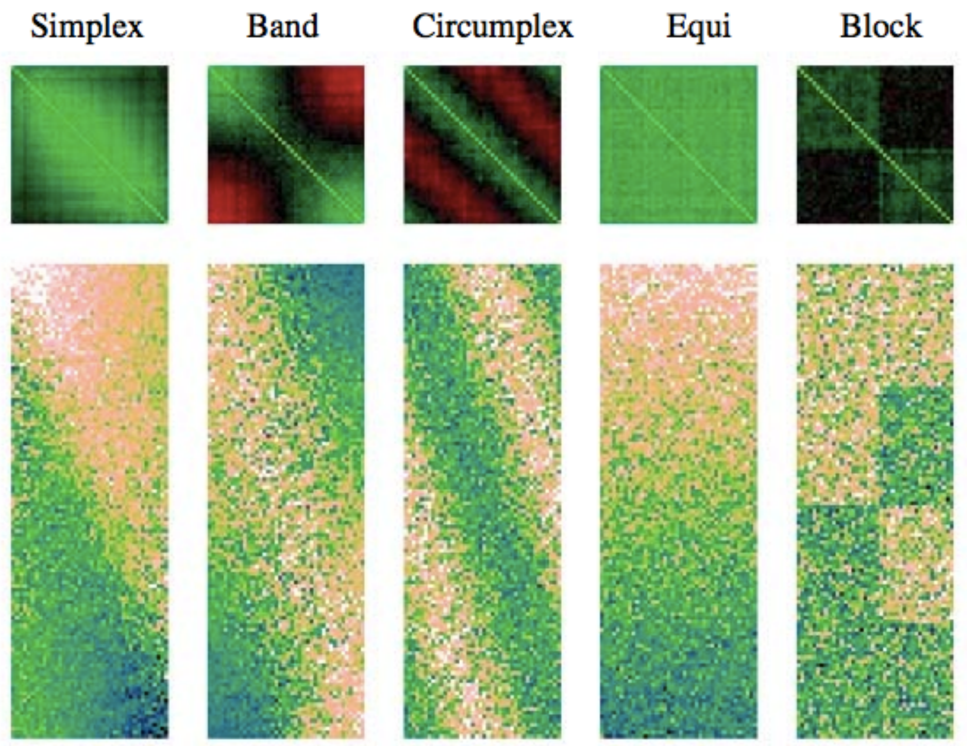




Data

Structured matrices

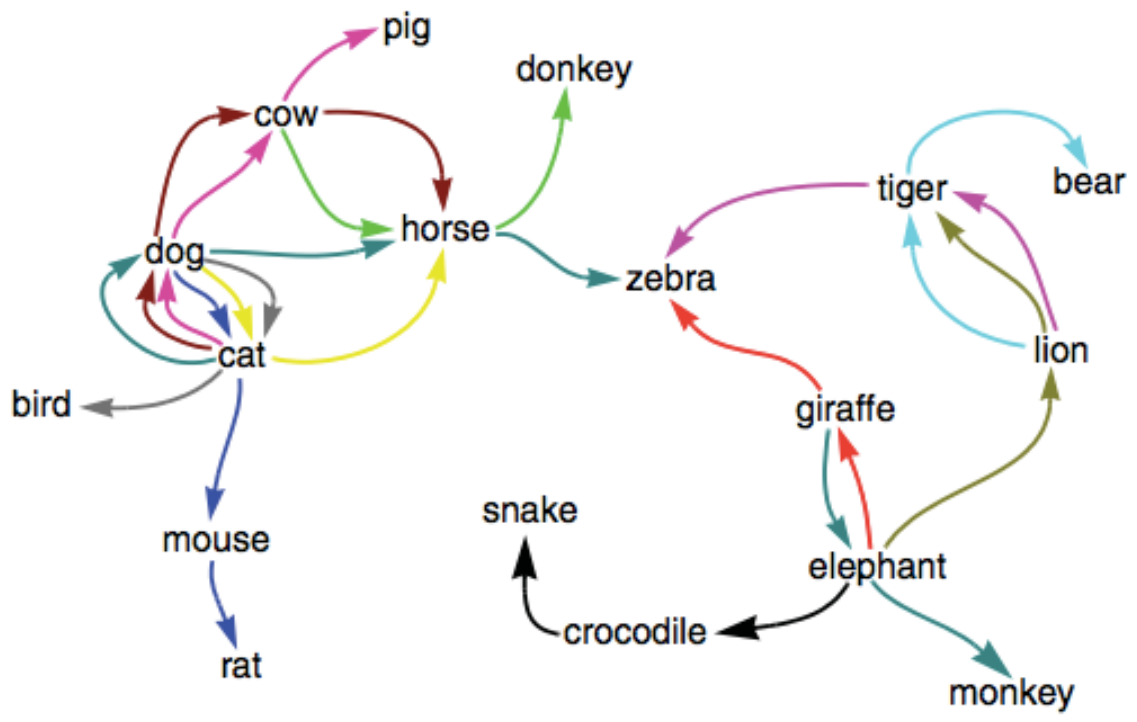
Sometimes data matrices are not i.i.d.



Data

Sequences

- A dataset may be an ordered list or a set of ordered lists
  - Sequence analysis


pig
donkey
cow
horse
tiger
bear
dog
zebra
cat
lion
bird
giraffe
snake
mouse
elephant
crocodile
rat
monkey