Data Analysis

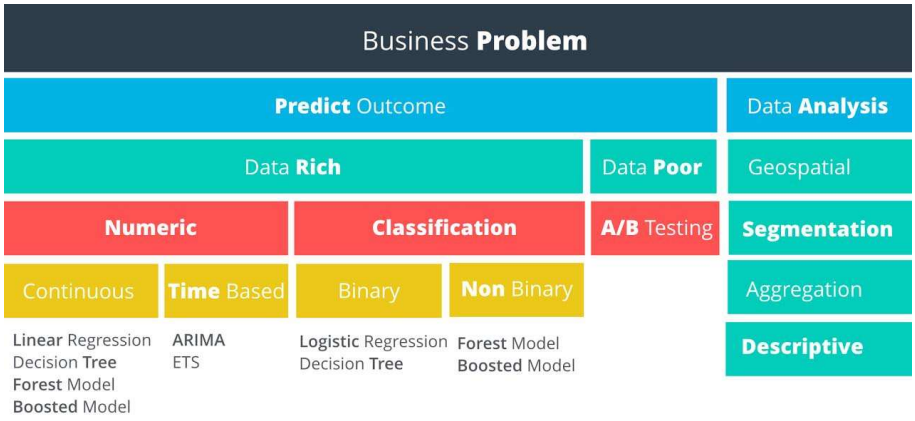
P1 – Statistics

Data Analysis Process Phases:

1. Question
2. Wrangling
    a. Data acquisition
    b. Data cleaning
3. Explore
    a. Build intuition
    b. Find patterns
4. Drawing conclusions or making predictions
    a. Usually requires statistics or
    b. Machine learning
5. Communication
    a. Blog post, paper, email, PowerPoint, conversation
    b. Data visualization is useful

CRISP Framework (**CR**oss **I**ndustry **S**tandard **P**rocess for **D**ata **M**ining)

1. Business Issue Understanding
2. Data Understanding
3. Data Preparation
4. Analysis / Modelling
5. Validation
6. Presentation / Visualization



Non-Predictive Analysis

- Geospatial (location based data e.g. geographic information)
- Segmentation (process of grouping data together e.g. demographic information)
- Aggregation (calculating a value across a group or dimension e.g. “slice and dice” information)
- Descriptive (simple summaries of a data sample e.g. mean, median, mode, standard deviation, interquartile range)

Predictive Analysis (predict a future outcome)

- **Data Poor**
  - If there is not sufficient usable data to solve the problem, then we need to set up an experiment to help us get the data we need, which is usually referred to as an **A/B Test**.
- **Data Rich**
  - Numeric Analysis
    - Regression Models
      - Continuous (Linear Regression, Decision Tree, Forest Model, Boosted Model)
      - Time-Based (Arima, ETS)
      - Count (not common in business)
  - Non-Numeric (Classification) Analysis
    - Classification Models
      - Binary (Logistic Regression, Decision Tree e.g. yes or no)
      - Non-Binary (Forest Model, Boosted Model e.g. small, medium, large)
- **Linear Regression**
  - $y = ax + b$
  - a → SLOPE(y, x)
  - b → INTERCEPT(y, x)
  - R → CORREL(y, x) → The closer r is to + or -1, the higher the correlation between x and y
  - R-squared → RSQ(y, x) → close to 1 would mean that nearly all variance in the target variable is explained by the model → > 0.7 strong model, > 0.5 pretty good, < 0.3 no useful.
- **Multiple Linear Regression**
  - $y = b0 + b1x1 + b2x2 + b3x3 + \ldots$
  - Analysis ToolPak Add-In Excel → Data Analysis → Regression
  - The adjusted R-squared value should be used
- **Linear Regression with Categorical Variables**
  - A much better way of using categorical variables in regression is to use “dummy variables”. A dummy variable can only take on two values, generally 0 or 1. You would add one dummy variable for one less than the number of unique values in the categorical variable. So, if the variable is binary, you'd add one dummy. If there are four categories, you'd add three dummy variables.
  - The **P value** is the probability that observed results occurred by chance, and that there is no actual relationship between the predictor and target variable. In other words, the p-value is the probability that the coefficient is zero. The lower the p-value the higher the probability that a relationship exists between the predictor and target variable. If the p-value is high, we should not rely on the coefficient estimate. When a predictor variable has a p-value below 0.05, the relationship between it and the target variable is considered statistically significant.

Valid research (survey)

- Good sample size
- Representative sample
- Sound methodology

Constructs – Operational Definition

- Population parameters (such as μ) are values that describe the entire population. Sample statistics (such as $\bar{x}$) are values that describe our sample; we use statistics to estimate the population parameters.
- Independent or predictor variable
- Dependent variable or outcome
- Extraneous factors or lurking variables
- Correlation does not imply causation!
- Double Blind experiment
- Show relationships → Observational studies or surveys
- Show causation → Controlled experiment

Visualizing Data

- Frequency f, Relative Frequency (0, 1) or Proportion p (0-100 %)
- Total Sum Σ
- Measures of centre
    - Mode: value where f is highest, most common value, occurs on the X-axis. Can describe any type of data (numerical or categorical). It isn't the same in different samples of the dataset.
        - no mode, uniform distributions
        - one mode distributions
        - multi modal mode distributions
    - Median (value in the middle) more robust than Mean when we have highly skewed distributions
    - Mean or Average take all values into account unlike the Mode
- Bin Size or Interval Size, Smaller bin size → less information, bigger bin size → larger frequency
    - Infinitely small bin size → the distribution shape is lost
        - We can model a distribution with a theoretical continuous distribution described by an equation. In normal theoretical distributions Mean = Median = Mode
- Histogram: x-axis is numerical/quantitative vs. Bar Graph: x-axis is categorical/qualitative
- n sample size vs. N population size
- Sometimes we cut off the upper and lower 25 %
    - Inter-Quartile Range = IQR = Q3-Q1
    - Outlier considered when it is < Q1-1.5(IQR) or > Q3+1.5(IQR)
- Visualize outliers, IQR, median, min and max with Match Boxplots
- Variability = average distance between each value and the mean (Mean of Deviation from Mean $x_i - \bar{x}$)
    - Because Average Deviation → 0, We consider Average Absolute Deviation or Squared Deviation
- Sum of Squares SS

- Variance = Average Squared Deviation (Sum of Squared Deviations divided by n)
- Standard Deviation σ = Square Root of Variance = most common measure of spread (Variability)
    - 68 % of data between 1σ and 95 % between 2σ
- In general, samples underestimate the amount of variability in a population, because samples tend to be values in the middle of the population
    - Bessel's Correction to correct this, dividing Variance with n-1 instead of n
    - Sample Standard Deviation s
- Standardizing the distribution → Find the z-score, the number of Standard Deviations each value x is from the Mean μ: $z = \frac{x-\mu}{\sigma}$
    - The new Mean of the standardizing distribution is 0 and the Standard Deviation σ is 1
- We can convert any normal distribution to standard normal distribution and then to a new normal distribution again with a new Mean and Standard Deviation.

Normal Distribution

- Probability Density Function (PDF) theoretically models the Normal Distribution curve.
- Absolute Frequency → Relative Frequency = Probability
- X-axis is horizontal asymptote
- Area = Probability of randomly selecting less than x = proportion in sample/population with scores less than x.
- z-table → gives probability p from z-scores for a standard normal distribution

Sampling Distributions

- Sampling Distribution = Distribution of Sample Means
- Mean of population = Mean of all possible sample means
- It is a Normal Distribution
- Ratio: σ of Population / SE of Sample Means = square root of our sample size → $\frac{\sigma}{SE} = \sqrt{n}$
- So, we can find the Standard Deviation of Sampling Distribution $SE = \frac{\sigma}{\sqrt{n}}$
- This is called Central Limit Theorem
    - From any population of any shape we can take samples – assuming their size is large enough – and plot the Sampling Distribution → we will get a Normal Distribution with a Standard Deviation equals to the Standard Deviation σ of the population divided by the square root of the Sample size n and this is called Standard Error SE.
- Larger Sample size → skinnier Distribution
    - As the Sample size n increases, the Standard Error decreases
    - Surer that the Mean of Sampling Distribution ≈ Mean of Population
    - Prove some kind of relationship
- The Mean of Sampling Distribution, M ≈ Mean of Population, μ

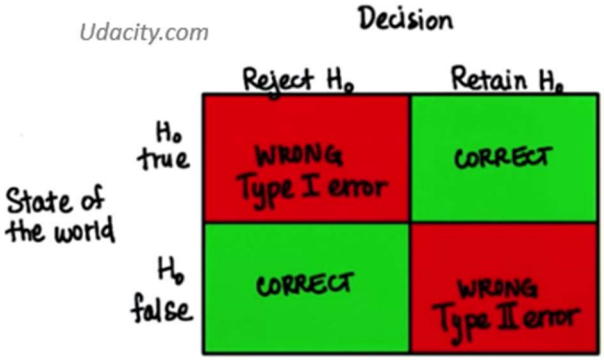
Estimation

- Point Estimate = Mean of Sample
- Margin of Error (half the width of CI), 2 $SE = \frac{2 \cdot \sigma}{\sqrt{n}}$
- 95% of Sample Means will be within 2 SE or exactly 1.96 SE (from z-table) in a Sampling Distribution
- Critical Values of z = ±1.96
- Confidence Intervals CI with 95%
    - Interval Estimate: $\bar{x} \pm (z - score) \cdot \left(\frac{\sigma}{\sqrt{n}}\right)$
    - Bigger Sample → Smaller CI (more precise estimates)
    - A "treatment effect" occurs when the intervention affects the population mean. When the sample mean is far on the tails of the sampling distribution, and therefore unlikely to have occurred by chance, there is evidence for a treatment effect.

Hypothesis Testing

Z-Test (know population parameters)

- Critical Region and z-critical value
- One-Tailed
    - α-Levels: 0.05 (5%), z* = 1.65 / 0.01 (1%), z* = 2.32 / 0.001 (0.1%), z* = 3.08
        - If the probability of getting a sample mean is less than α, it is “unlikely” to occur
        - If a sample mean has a z-score greater than z*, it is “unlikely” to occur
- Significance
    - $z = \frac{\bar{x} - \mu}{(\sigma/\sqrt{n})}$, if z > z* then $\bar{x}$ is significant at p < α (didn’t occur by chance, something is going on)
- Two-Tailed (more conservative → cannot miss the opposite direction if we choose one-tailed)
    - α-Levels: 0.05 (5%), z* = ±1.96 / 0.01 (1%), z* = ±2.57 / 0.001 (0.1%), z* = ±3.32
- Hypotheses
    - “I” is for Intervention
    - Null, H_o: $\mu = \mu_I$, we can only obtain evidence to reject the null hypothesis (states no change)
    - Alternative, H_A: $\mu < \mu_I$ or $\mu > \mu_I$ or $\mu \neq \mu_I$
- Decision Errors



T-Test (not know population parameters)

- T-distribution: more prone to error, more spread out and thicker in the tails
- Defined by their degrees of freedom: e.g. the last option is always forced
- Effective Sample Size, n-1 (independent pieces of information)
- As degrees of freedom increases, the t-distribution better approximates the normal distribution
- T-Table, t critical values, column headers are α levels
- The further the value of $\bar{x}$ from μ_o in either direction the stronger the evidence that $\mu \neq \mu_o$
- One Sample t-test
    - Standard Error of the mean: $SE = \frac{s}{\sqrt{n}}$
    - $t_{statistic} = \frac{\bar{x}-\mu_0}{(s/\sqrt{n})}$
    - H_o: $\mu = \mu_o$, reject null if t-statistic is inside critical region (p-value < α level)
    - H_A: $\mu < \mu_o$ or $\mu > \mu_o$ or $\mu \neq \mu_o$
- P-value: probability of getting t-value
- Cohen's d: $d = \frac{\bar{x}-\mu_0}{s}$
    - Standardized mean difference that measures the distance between means in standardized units
    - The larger d is, the further $\bar{x}$ is from μ_o
- Confidence Interval CI, e.g. 100% - 5% (from α level = 0.05) = 95% CI
    - Interval Estimate: $\bar{x} \pm (t_{critical}) \cdot \left(\frac{s}{\sqrt{n}}\right)$
- Unlike a z-critical value, a t-critical value will change when you increase the sample size.

Dependent sample's design, t-test for paired samples

- Within-subject designs
    - Two conditions
    - Pre-test, post-test
        - Same variable – same sample before and after treatment
        - H_o: $\mu_{pre} = \mu_{post}$
    - Growth over time (longitudinal study)
        - H_o: $\mu_{time1} = \mu_{time2}$
    - $D_i = x_i - y_i$, take the difference of the paired samples
    - $(D_i - \bar{D})^2 \quad \rightarrow \quad SS = \sum(D_i - \bar{D})^2 \quad \rightarrow \quad s_D = \sqrt{\frac{\sum(D_i-\bar{D})^2}{n-1}} \quad or \quad s_D = \sqrt{s_1^2 + s_2^2}$
    - $t_{statistic} = \frac{\bar{D}-0}{(s_D/\sqrt{n})} \qquad or \qquad t_{statistic} = \frac{\mu_1-\mu_2}{(s_D/\sqrt{n})}$
    - $CI = \bar{D} \pm t_{critical} \cdot \left(\frac{s_D}{\sqrt{n}}\right)$, t-critical is taken from the t-table for two-tailed test

Effect Size Measure Types

- Mean difference, $\bar{x} - \mu$
    - It is good for variables with easy to understand meanings
- Standardized difference
    - Cohen's d – SD units
- Correlation measures
    - Coefficient of Determination: r^2 – proportion (%) of variation in one variable that is related to ("explained by") another variable → not related at $0.00 < r^2 < 1.00$ perfectly related
        - $r^2 = \frac{t^2_{statistic}}{t^2_{statistic}+df}$

Statistical Significance

- Rejected the null
- Results are not likely due to chance (sampling error)

Meaningfulness of results

- What was measured?
    - Variables with practical, social, or theoretical importance
- Effect size
- Can we rule out random chance?
- Can we rule out alternative explanations (lurking variables)?

Results Sections

1. Descriptive Statistics (M, SD) in
    - Text – Graphs – Tables
2. Inferential Statistics
    - Hypothesis Test
        - kind of test, e.g. one-sample t-test
        - test statistic, e.g. value of t
        - df
        - p-value
        - direction of test, e.g. one or two tail test
        - α level
        - APA style → t(df) = x.xx, p = .xx, direction
    - Confidence Interval
        - Confidence level, e.g. 95%
        - Lower limit

- Upper limit
- CI on what?
- APA style → Confidence interval on the mean difference; 95% CI = (4, 6)

3. Effect size measures
    - Cohen's d
    - r^2
    - APA style → d = x.xx, r^2 = .xx (we never write the leading 0 for proportions < 1)

Example (one-sample t-test)

μ = \$ 151; dependent variable = \$ spent per week on food; treatment = cost-saving program; n = 25

null = the program did not change the cost of food; alternative = the program reduced the cost of food

this is a one-tailed test in negative direction

$$H_0: \mu_{program} \geq 151 \qquad H_A: \mu_{program} < 151 \qquad df = n - 1 = 24$$

$t_{critical} = -1.711 \; for \; a \; level = .05$

$$SE = \frac{s}{\sqrt{n}} = \frac{50}{\sqrt{25}} = 10.00$$

$Mean \; difference, \bar{x} - \mu = 126 - 151 = -25$

$$t_{statistic} = \frac{\bar{x} - \mu}{(s/\sqrt{n})} = \frac{-25}{10.00} = -2.50 \qquad \rightarrow \qquad t_{statistic} \; falls \; in \; the \; critical \; region \qquad \rightarrow \qquad p < .05$$

$So, we \; can \; reject \; the \; null \; hypothesis \; and \; say \; that \; these \; results \; are \; statistically \; significant.$

$Are \; the \; results \; meaningful?$

$It \; depends \; because \; saving \; \$25 \; per \; week \; depends \; on \; how \; much \; money \; the \; people \; of \; our \; study \; make.$

$$Cohen's \; d = \frac{\bar{x} - \mu}{s} = \frac{-25}{50} = -0.50 \qquad \rightarrow \qquad these \; two \; means \; are \; half \; a \; standard \; deviation \; apart$$

$$r^2 = \frac{t^2_{statistic}}{t^2_{statistic} + df} = \frac{(-2.50)^2}{(-2.50)^2 + 24} = .21$$

$21\% \; of \; the \; differences \; in \; food \; prices \; for \; the \; sample \; of \; 25 \; people \; are \; due \; to \; the \; cost \; saving \; program.$

$$Margin \; of \; Error = t_{critical} \cdot SE = 2.064 \cdot 10.00 = 20.64$$

$$CI = \bar{x} \pm t_{critical} \cdot \left(\frac{s}{\sqrt{n}}\right) = 126 \pm 20.64 \qquad \rightarrow \qquad 95\% CI = (105.36, 146.64)$$

$If \; we \; implemented \; this \; cost \; saving \; program \; for \; all \; members, they \; would \; likely \; spend \; on \; average \; per \; week$ $between \; \$105 \; and \; \$147.$

Independent samples

Dependent Samples	Independent Samples
Two conditions	Experimental
Longitudinal	Observational
Pre-test, post-test	-
Advantages	**Disadvantages**
Controls for individual differences	The opposite
Use fewer subjects	
Cost-effective	
Less time-consuming	
Less expensive	
Disadvantages	**Advantages**
Carry-over effects	The opposite
Order may influence results	

- $SD = \sqrt{S_1^2 + S_2^2}$
- $Standard\ Error: SE = \sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}},\ assumes\ samples\ are\ approximately\ the\ same\ size$
- $Pooled\ Variance: S_p^2 = \frac{SS_1 + SS_2}{df_1 + d_2} \quad \rightarrow \quad corrected\ SE = \sqrt{\frac{S_p^2}{n_1} + \frac{S_p^2}{n_2}}$
- $t_{statistic} = \frac{(\bar{X}_1 - \bar{X}_2) - (\mu_1 - \mu_2)}{SE}$
- $H_0: \mu_1 - \mu_2 = 0$
- $H_A: \mu_1 - \mu_2 \neq 0$
- $df = (n_1 - 1) + (n_2 - 1) = n_1 + n_2 - 2$
- $d = \frac{\bar{X}_1 - \bar{X}_2}{S_p^2}$
- $CI = (\bar{X}_1 - \bar{X}_2) \pm t_{critical} \cdot SE \quad or \quad CI = (\bar{X}_2 - \bar{X}_1) \pm t_{critical} \cdot SE$

Excel

- Get external data
- String Functions: FIND, LEFT, RIGHT, MID, etc.
- Hide, Unhide columns
- Conditional Functions: IF, SUMIF, COUNTIF, IFNA, etc.
- VLOOKUP Function
    - 4th Parameter => True (classifying items) or False
    - Cannot look up in both directions
    - Slow for large data sets
- INDEX-MATCH Function
    - Can look up in both directions
    - Faster for large data sets
- Time and Date Functions: TIME, DATE, MONTH, WEEKDAY, WEEKNUM etc.
- Pivot Tables
    - They are more suitable for data analysis than functions
    - They do only simple analysis
    - They don't support scenario analysis when we compare two different filters => Array formulas can do this
    - Insert -> Pivot Table
    - Check => Add this data to the data model (useful to combine multiple tables)
    - Distinct Count
    - Power Pivot
    - Power Map
- Comparisons => Inside quotes " " followed by an ampersand &
    - COUNTIF($A$1:$A$10,">="&B2)
- Named Ranges => Cell reference (Right click on a cell or Formulas => Define a name)
    - There is no need to worry about dollar signs
    - Formulas are much easier to understand
    - $A$1:$A$10 => MaxLevel => COUNTIF(MaxLevel,">="&B2)
- Name Manager
    - The problem with Named Ranges comes up, when adding data to them.
        - Expand the named range
        - Better strategy is to make your named range consist of an entire column. Downsides are
            - Accidentally input unwanted values into the named range
            - Cannot use the column for anything else besides values in the named range
- Most common value function: MODE
- Data Tables => alternative practice to address the two previous problems
    - You don't have to update the Named Range
    - Select the data in worksheet => Insert Table => Check My table has headers
    - Table Tools -> Design => Change the name of the Table

    - We can Insert Slicer => Like an interactive filter
- ISERROR Function
- Intersection
- Paste special => Transpose => Named Ranges do NOT change!
- CONCATENATE Function
- FORMULAS -> Evaluate Formula
- Array Formulas and Structure => Make room in a spreadsheet
    - We can do calculations between ranges too, not just numbers
    - Control + Shift + Enter => Curly braces => Array calculations => Result = List
    - HOME => Filter
        - On rows only
        - Column filter => TRANSPOSE function => Array => Control + Shift + Enter
            - Make room for the transposed result. Not just a cell!
            - The transposed array will be updated # Copy => Paste Special (Transposed)
            - The function only maps the input data to the transposed array, it will not change the data types.
        - Some formulas can behave like “array”
        - Some formulas are “array” (type need to be array!) like Transpose
    - Double minus sign => - - (TRUE) = 1 and - - (FALSE) = 0
- Keep spreadsheet safe - Stress-test our spreadsheet!
    - Sanity checks, e.g. what property should probably hold for a margin? - Margin >= 0
    - Boundaries checks, e.g. 0 <= Percentage <= 100
    - Totals checks, e.g. SUM(Percentages) = 100%
    - Cross check
    - Validating user input
    - Tests are documentation
    - How to test
        - Home -> Conditional formatting
        - Funnel-style structure using formulas to check for errors
        - Gather all the tests in the spreadsheets together and give a final test in one value in one worksheet.
- Import CSV files
    - Refresh!
        - Uncheck Prompt for file name on refresh
        - Check Refresh data when opening the file
    - Merge csv files in terminal => *cat *.csv >merged.csv*
        - Data tab -> Remove Duplicates
- Pivot Tables and Charts
    - Insert Slicers
    - We can add column and formulas through Power Pivot -> Manage

- RELATED Function
- Conditional Formatting
    - Colour Formatting
    - Spark Lines => Visualise the data
        - See the trend in a single data series
        - Graphs are much more useful to compare different categories/datasets
    - Win/Loss spark lines shows whether each value is positive or negative instead of how high or low the values are.
- Pivot Charts - Add Chart Element
    - Add Trend Line
        - Linear Forecast => Add prediction line - Right click for more, e.g. equation
- Data -> Text to Columns => split the text into two columns
- Pivot Tables
    - Right click on cell -> Group
        - Grouping feature only works if "Add this data to the data model" is unchecked
- What-If Analysis
    - Goal Seek - Find the right input for the value you want
        - Data -> What-If Analysis -> Goal Seek
    - Data Table - See the results of multiple inputs at the same time
        - Data -> What-If Analysis -> Data Table
- Solver - More powerful than What-If analysis
    - Tools -> Excel Add-ins -> Enable Solver Add-In
        - Data -> Solver
            - We can change multiple variable cells
            - We can add constraints
- SUMPRODUCT Function
- Tables & Graphs for effective communication of data
    - Define my goal
        - Tables used when
            - look up individual values
            - compare individual values
            - precise values are required
            - there is more than one unit measured
            - both summary and detail values are included
        - Graphs used when
            - you want to show a pattern/trend
            - you want to reveal relationships between sets of values
    - Table Effective Design
        - Unidirectional with 1 category, Unidirectional with 2 categories & Bidirectional
        - Derived values close to the related columns

        - Columns we want to compare should be located close
        - Make the grid less heavy or remove the grid
        - Keep only the important lines to separate for example the headers from the body
        - Use more white space and increase the row height but not very much
        - Use more white space in columns when we want column orientation => if I want my table to be read column by column
        - Fill the cell to show attention or light fill a row and a column to guide the eyes
        - Align text left and numbers right
        - Increase levels of precision if it is necessary
        - Include thousand separator
- Graph Effective Design
    - Maintain visual correspondence to quantity
    - Try to stay close to the truth
    - Do not try to manipulate your readers
    - Stay away from 3D!
    - Basic Graphs
        - Scatter plot to highlight a relation between two variables
        - Line chart to show a trend or a time series
        - Bar or Column chart to compare different categories with each other
            - Bar or Column depends on the labels fit
            - Time series are best represented with Column charts
    - Avoid Pie charts
        - It is difficult for humans to estimate an area
    - White space
    - Do not use patterns, at least use greyscale if you cannot use colours with good contrast
    - Put legend to the bottom, not the default right of excel
    - Use aspect ratio wisely => 1:1.5 is quite good
    - 5 variables are the max
        - For more variables create several smaller graphs oriented horizontally or vertically (depends on what I want to show). Separate the graphs based on what you want to focus.
- Dashboard Design
    - What is the goal
    - What is the message
    - The design depends on the kind of screen or paper
    - Create a grid
        - Dashboard Title
        - Area Title
        - Chart Title
        - Chart Footer, and so on…
- CHAR(13) to add a line break on the Mac
- Chart Design tab -> Switch Row/Column

- Thermometer custom chart types => Compare similar variables
- Copy - Paste as Linked Picture
    - with linked picture, you can change original data content and have live updates
- Pivot Table -> Filter -> Top 10 functionality
- Open VBA Editor => Fn + ⌥ + F11

P2 – Intro to Data Analysis

Lists, functions and methods

- sub setting a list with brackets []
- sub setting lists of lists with brackets [][]
- slicing a list with x[begin:end]
- change element of a list to another element, e.g. x[2] = 'c'
- add an element at the end of a list, e.g. x = x + ['c']
- remove an element from a list, e.g. del(x[2])
- If you want to prevent changes in a list copy to also take effect in initial list, you'll have to do a more explicit copy of the list. You can do this with list() or by using [:].
- pip is a very commonly used tool to install and maintain Python packages.
- If numpy is imported as np, you need e.g. np.array() => import numpy as np
- The from numpy import array version will make it less clear in the code that you are using Numpy's array() function.

Numpy arrays

- numpy.array()
- In Numpy, calculations are performed element-wise. The first element of x and the first element of y are added. Similar for the second and third element of x and y.
- Numpy arrays can only hold elements with the same basic type. The string is the most 'general' and free form to store data, so all other data types are converted to strings. This is called type coercion.
- To subset both regular Numpy arrays, you can use square brackets []. You can also use Boolean Numpy arrays, e.g. high = y > 5 ; y[high]
- Sub setting using the square bracket notation on lists or arrays works the same.
- 2D Numpy arrays also offer more advanced ways of sub setting compared to regular Python lists of lists. To select the second row, use the index 1 before the comma. To select the third column, use the index 2 after the comma.
- Regular list of lists
    - x = [["a", "b"], ["c", "d"]]
    - [x[0][0], x[1][0]]
    - 'a' 'c'
- numpy
    - import numpy as np
    - np_x = np.array(x)
    - np_x[:,0]
    - 'a' 'c'
- Numpy offers many functions to calculate basic statistics, such as np.mean(), np.median() and np.std(), np.corrcoef(), e.g. np.mean(x[:,1])

Matplotlib

- import matplotlib.pyplot as plt

```
a = [1, 2, 3, 4]
b = [3, 9, 2, 6]
plt.plot(a, b)
plt.scatter(a, b)
plt.show()
```

- plt.xscale("log"); plt.hist(); plt.clf(); plt.xlabel(); plt.ylabel(); plt.fill_between(); plt.title(); plt.xticks(); plt.xticks(); plt.grid(); plt.text()
- e.g. plt.scatter(x = gdp_cap, y = life_exp, s = np.array(pop) * 2, c = col, alpha = 0.8)

  where c = col is a dictionary { 'Asia':'red', 'Europe':'green', 'Africa':'blue', 'Americas':'yellow', 'Oceania':'black' }

Pandas DataFrame

- 2D Numpy arrays can only contain values of the same basic type, a downside compared to Pandas if you're working on typical Data Science problems.
- Rows correspond to observations; columns correspond to variables, or properties, of these observations.
- import pandas as pd ; pd.read_csv('example', index_col = 0)
- To select an entire row by its row label when accessing data in a Pandas DataFrame use loc. Square brackets are used to get specific columns from a Pandas DataFrame. iloc is used if you want to select a row based on its position in the DataFrame, and not based on its row label.
- The single bracket version gives a Pandas Series, the double bracket version gives a Pandas DataFrame.

Questions to answer usually in data analysis

- How something varies over time?
- What is the highest and lowest levels?
  - Which subject have them?
  - Where is the subject of interest on the spectrum?
- How the variables relate to each other?
- Are there any consistent trends across variables?

Investigate a Dataset

Anaconda

- Create a new environment, e.g. conda create –n new_project python=3
- Activate the new environment, e.g. source activate new_project
- Install packages in my new environment, e.g. conda install numpy pandas matplotlib jupyter notebook
- List my packages, i.e. conda list

Python

CSVs in Python

1. Each row is a list, e.g. csv = [['A1', 'A2', 'A3'],
   ['B2', 'B2', 'B3']]
2. Each row is a dictionary (works well if we have headers),
   e.g. csv = [{'name1' : 'A1', 'name2' : 'A2', 'name3' : 'A3'},
   {'name1' : 'B2', 'name2' : 'B2', 'name3' : 'B3'}]

Import csv in Python

```
def read_csv(filename):
  with open(filename, 'rb') as f:
    reader = unicodecsv.DictReader(f)
    return list(reader)
```

Fix data types

csv library does not try to detect what type of data each column has

Investigate the data for inconsistencies

e.g. with 'len()' function find the total number of rows in the csv or the number of unique students with 'set()'

Import csv with Pandas

Example:

```
import pandas as pd
daily_engagement = pd.read_csv('daily_engagement_full.csv')
len(daily_engagement['acct'].unique())
```

Table 1. NumPy Arrays and Python Lists

Similarities	Differences
Access elements by position	Each element should have same type
Access a range of elements	Convenient functions
Use loops	Can be multi-dimensional
-	Vector operations
-	NumPy index Arrays
-	NumPy modify Arrays Not copy
-	NumPy implemented in C (fast!)

Examples

```
# Looping
if True:
  for country in countries:
    print 'Examining country {}'.format(country)

  for i in range(len(countries)):
    country = countries[i]
    country_employment = employment[i]
    print 'Country {} has employment {}'.format(country,
        country_employment)
```

Table 2. Vector operations

Math	Logical	Comparison
Add: +	And: &	Greater: >
Subtract: -	Or: |	Greater or equal: >=
Multiply: *	Not: ~	Less: <
Divide: /		Less or equal: <=
Exponentiate: **		Equal: ==
		Not equal: !=

Standardizing data

How does one data point compare to the rest?

- Convert each data point to number of standard deviations away from the mean
    - (values - values.mean()) / values.std() → *we keep negative signs!*

In-Place vs. Not In-Place

+= operates in-place while + does not

Operations that are not in-place are much easier to think about!

Table 3. Comparison of NumPy and Pandas

Pandas	NumPy (Numerical Python)
Series (more advanced)	Array (simpler)
Accessing elements	Accessing elements
Looping	Looping
Conventional functions	Conventional functions
Vector operations	Vector operations
Implemented in C (fast!)	Implemented in C (fast!)
Series index	-
Adding by Index	Adding by position
In 2D, columns can be of different type	-
2D (DataFrames) have index	-
DataFrames functions to each column	Functions (axis = 0 or axis = 1)
Functions (axis = 0 or axis = 1) or (axis = 'index' or axis = 'columns')	-

Examples

```
if True:
   s = pd.Series([1, 2, 3, 4, 5])
   def add_one(x):
      return x + 1
   print s.apply(add_one)          ≠          instead of applymap() for dataframes
```

```
import pandas as pd
import seaborn as sns
# The following code reads all the Gapminder data into Pandas DataFrames.
path = '/datasets/ud170/gapminder/'
employment = pd.read_csv(path + 'employment_above_15.csv', index_col='Country')
# The following code creates a Pandas Series for each variable for the United States.
employment_us = employment.loc['United States']
# Uncomment the following line of code to see the available country names
print employment.index.values
# Use the Series defined above to create a plot of each variable over time for the country of your choice.
employment_us.plot()
```

Two-Dimensional Data

- Python: List of lists
- NymPy: 2D array
- Pandas: DataFrame
- 2D arrays, as opposed to array of arrays:
    - More memory efficient
    - Accessing elements is a bit different → a[1, 3] rather than a[1][3]
    - mean(), std(), etc. operate on entire array
- By default, numpy calculates a population standard deviation, with "ddof = 0". On the other hand, pandas calculate a sample standard deviation, with "ddof = 1".
- groupby()
- merge()

Correlation Pearson's r

1. Standardize each value
2. Multiply each pair of values
3. Take the average

$$r = average\ of\ (x\ in\ standard\ units)\ \times\ (y\ in\ standard\ units)$$

- It is important to take the uncorrected standard deviation: var.std(ddof=0)

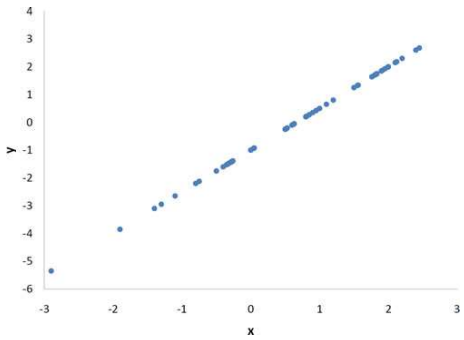


Figure 1. A perfect positive linear relationship, r = 1.

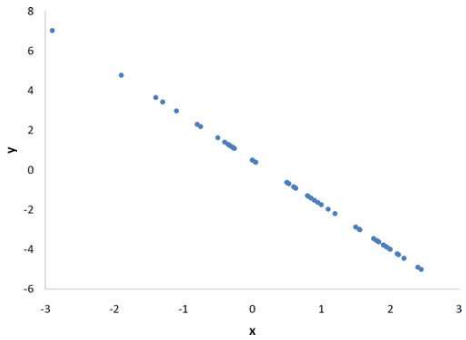


Figure 2. A perfect negative linear relationship, r = -1.

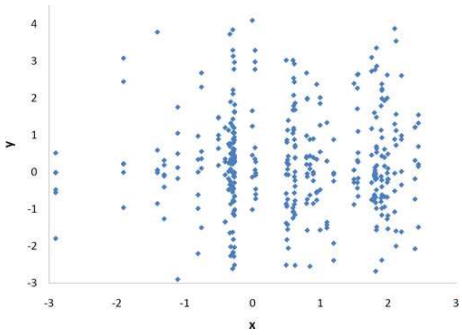
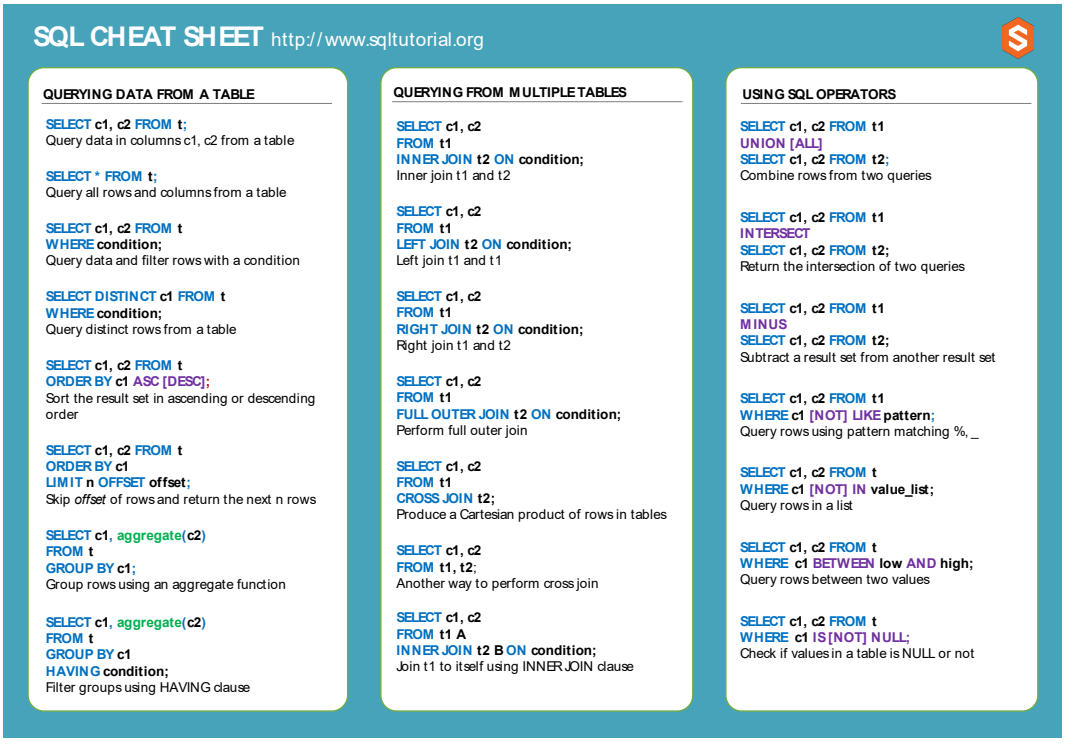
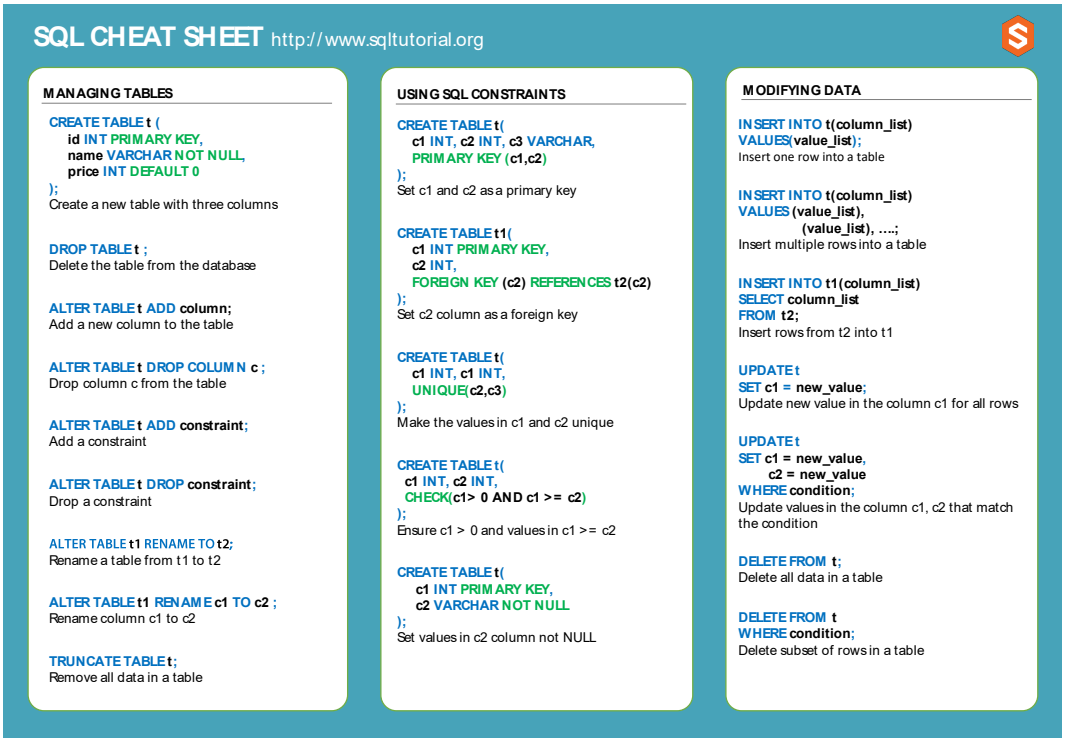


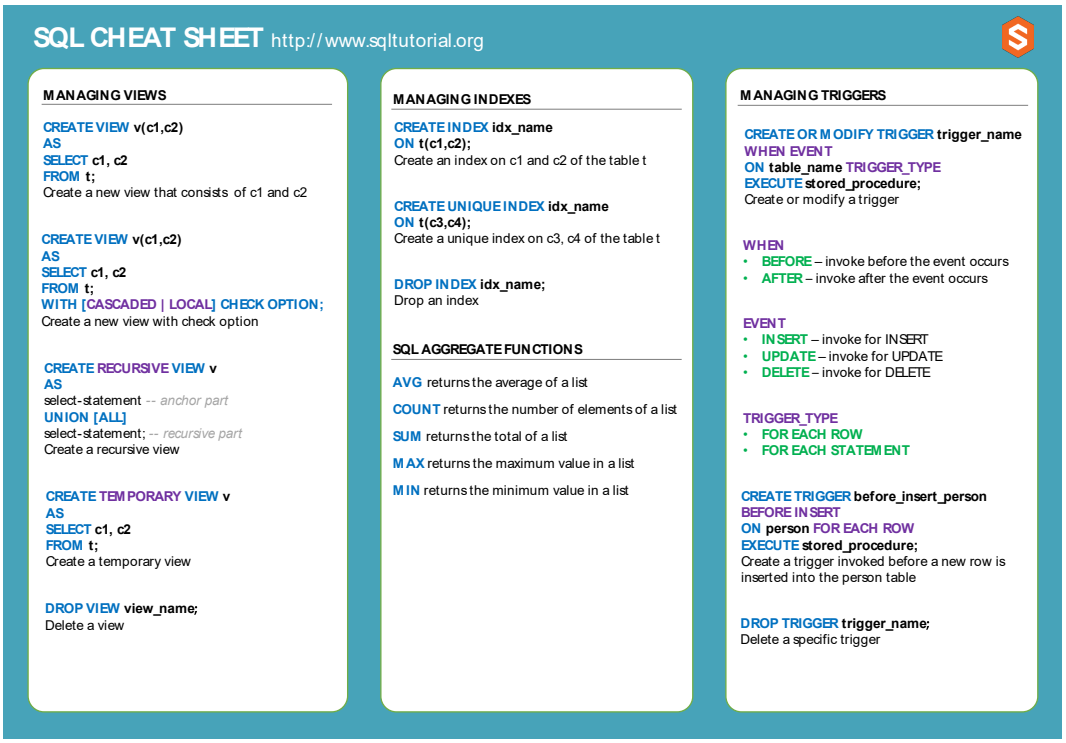
Figure 3. A scatter plot for which r = 0. Notice that there is no relationship between X and Y.

P3 – Data Wrangling

- **Gather Data**
  - Python string method strip() will come in handy to get rid of the extra whitespace (that includes newline character at the end of line).
  - Use csv module: import csv
  - Use xlrd module to work with excel files: import xlrd
  - Data Modelling in JSON
    - Items may have different fields
    - May have nested objects
    - May have nested arrays
- **Asses Data**
  - Test Assumptions about
    - Values
    - Data Types
    - Shape
  - Identify Errors or Outliers
- **Blueprint for Cleaning**
  - Audit your data, i.e. statistical analysis to check for outliers.
  - Create a data cleaning plan
    - Identify causes that dirty data appears
    - Define operations that will correct our data
    - Run a few tests to check the data cleaning plan
  - Execute the plan
  - Manually correct
- **SQL**







- Always put ‘single quotes’ around text strings and date/time values.
- **Text and string types**
  - **text** — a string of any length, like Python **str** or **unicode** types.
  - **char(n)** — a string of exactly *n* characters.
  - **varchar(n)** — a string of up to *n* characters.
- **Numeric types**
  - **integer** — an integer value, like Python **int**.
  - **real** — a floating-point value, like Python **float** (up to 6 decimal places).
  - **double precision** — a higher-precision floating-point value (up to 15 decimal places).

        - **decimal** — an exact decimal value.
    - **Date and time types**
        - **date** — a calendar date; including year, month, and day.
        - **time** — a time of day.
        - **timestamp** — a date and time together.

- **Examples**

```
SELECT Composer, Name FROM Track WHERE Composer='Van Halen';
SELECT Composer, SUM(Milliseconds) FROM Track WHERE Composer='Johann Sebastian Bach';
SELECT FirstName, LastName, Title, Birthdate FROM Employee;
INSERT INTO animals(name, birthdate, species) values('Alex', '2017-04-24', 'opossum');

SELECT BillingCountry, COUNT(*)
FROM Invoice
GROUP BY BillingCountry
ORDER BY COUNT(*)
DESC
LIMIT 3;

SELECT Email, FirstName, LastName, SUM(Total)
FROM Customer, Invoice
WHERE Customer.CustomerID = Invoice.CustomerID
GROUP BY Email
ORDER BY SUM(Total)
DESC
LIMIT 1;

SELECT Email, FirstName, LastName, Genre.Name
FROM Customer, Invoice, InvoiceLine, Track, Genre
WHERE Customer.CustomerId = Invoice.CustomerId
AND Invoice.InvoiceId = InvoiceLine.InvoiceId
AND InvoiceLine.TrackId = Track.TrackId
AND Track.GenreId = Genre.GenreId
AND Genre.Name = 'Rock'
GROUP BY Email
ORDER BY Email;

SELECT BillingCity, sum(Total)
FROM Invoice
GROUP BY BillingCity
ORDER BY sum(Total)
DESC
LIMIT 1;

SELECT BillingCity, COUNT(*), Genre.Name
FROM Invoice, InvoiceLine, Track, Genre
WHERE Invoice.InvoiceId = InvoiceLine.InvoiceId
AND InvoiceLine.TrackId = Track.TrackId
AND Track.GenreId = Genre.GenreId
AND BillingCity = 'Prague'
GROUP BY Genre.Name
ORDER BY COUNT(*)
DESC
LIMIT 3;

SELECT Artist.Name, COUNT(Genre.Name)
FROM Genre, Track, Album, Artist
WHERE Genre.GenreID = Track.GenreID
AND Track.AlbumID = Album.AlbumId
AND Album.ArtistId = Artist.ArtistId
AND Genre.Name ='Rock'
```

```
GROUP BY Artist.Name
ORDER BY COUNT(Genre.Name)
DESC
LIMIT 10;

SELECT BillingCity, COUNT(Track.TrackId) AS NumInvoices
FROM Invoice, InvoiceLine, Track, Genre
WHERE Invoice.InvoiceId = InvoiceLine.InvoiceId
AND InvoiceLine.TrackId = Track.TrackId
AND Track.GenreId = Genre.GenreId
GROUP BY BillingCity, Genre.Name
HAVING Invoice.BillingCountry='France' AND Genre.Name = 'Alternative & Punk'
ORDER BY NumInvoices
DESC
```

Normalised Design

In a normalised database, the relationships among the tables match the relationships that are really there among the data.

- Every row has the same number of columns.
- There is a unique key, and everything in a row says something about the key.
- Facts that don't relate to the key belong in different tables.
- Tables should not imply relationships that don't exist.

- **CREATE and DROP databases**

CREATE database name[options];

DROP database name[options];

DROP table name[options];

  - Primary key
  - Declaring Relationships: references

- **Self JOINs**

```
SELECT a.id, b.id, a.building, a.room
FROM residences as a, residences as b
WHERE a.building = b.building
AND a.room = b.room
AND a.id < b.id
ORDER BY a.building, a.room;

SELECT products.name, products.sku, count(sales.sku) AS num
FROM products LEFT join sales
ON products.sku = sales.sku
GROUP BY products.sku;
```

SQL supports a number of variations on the theme of joins. The kind of join that you have seen earlier in this course is called an *inner* join, and it is the most common kind of join — so common that SQL doesn't actually make us say "inner join" to do one.

But the second most common is the **left join**, and its mirror-image partner, the **right join**. The words "left" and "right" refer to the tables to the left and right of the join operator. (Above, the left table is **products** and the right table is **sales**.)

A regular (inner) join returns only those rows where the two tables have entries matching the join condition. A **left join** returns all those rows, plus the rows where the *left* table has an entry but the right table doesn't. And a **right join** does the same but for the *right* table.
(Just as "join" is short for "inner join", so too is "left join" actually short for "left outer join". But SQL lets us just say "left join", which is a lot less typing. So, we'll do that.)

SQL in Python

```
import sqlite3

# Fetch some student records from the database.
db = sqlite3.connect("students")
c = db.cursor()
query = "select name, id from students order by name;"
c.execute(query)
rows = c.fetchall()

# First, what data structure did we get?
print "Row data:"
print rows

# And let's loop over it too:
print
print "Student names:"
for row in rows:
  print "  ", row[0]

db.close()
```

```
import sqlite3

db = sqlite3.connect("testdb")
c = db.cursor()
c.execute("insert into balloons values ('blue', 'water')")
db.commit()
db.close()
```

- **Subqueries**

```
# Two Queries
def lightweights(cursor):
    """Returns a list of the players in the db whose weight is less than the average."""
    cursor.execute("select avg(weight) as av from players;")
    av = cursor.fetchall()[0][0]  # first column of first (and only) row
    cursor.execute("select name, weight from players where weight < " + str(av))
    return cursor.fetchall()

# Or One Query
def lightweights(cursor):
    """Returns a list of the players in the db whose weight is less than the average."""
    cursor.execute("select name, weight from players, (select avg(weight) as av from players) as subq where weight < av;")
    return cursor.fetchall()

# Or
def lightweights(cursor):
    """Returns a list of the players in the db whose weight is less than the average."""
    cursor.execute("select name, weight from players where weight < (select avg(weight) as av from players);")
    return cursor.fetchall()
```

```
SELECT sum(total)
FROM (SELECT count(*) AS total
        FROM Invoice
        GROUP BY BillingCountry
        ORDER BY total DESC
        LIMIT 5);

SELECT BillingCity, BillingState, BillingCountry, Total
FROM Invoice,
(SELECT avg(Total) as average FROM Invoice) as subquery
  WHERE Total > average;

SELECT FirstName, LastName, BillingCity, BillingCountry, Total
FROM Invoice JOIN Customer ON Invoice.CustomerId = Customer.Customer.Id JOIN
(SELECT avg(Total) As average
  FROM Invoice) AS subquery
WHERE Total > average;
```

- **VIEWS**

A VIEW is a SELECT query stored in the database in a way that lets you use it like a table.

```
CREATE VIEW course_size AS
SELECT course_id, count(*) AS num
FROM enrolment
GROUP BY course_id;
```

- **Example**

After all the success promoting your music tour last section, a new friend has asked to partner up and build your own music website! You'll need to rebuild your own database and import the data to your new system. Let's first take a closer look at how to build and populate your local database. The box below shows the Album table schema including Primary and Foreign Keys. Have a look at this table and the CREATE TABLE statement below to see how they relate.
First, disconnect from your Chinook database.

```
> .exit
```

Create a new database named whatever you'd like your store to be called.

```
$ sqlite3 UdaciousMusic.db
```

Now we can populate this database with our first table. Here's a graphic showing some information about the Album table. We can use this to build a table in our new database.

```
#####################################################################
#                  Table: Album                     #
#####################################################################
+-------------------+--------------+----------------+--------------+
|    Columns      |  Data Type  |   Primary Key  | Foreign Key |
+===================+==============+================+==============+
|    AlbumId        INTEGER         YES           NO      |
|    Title          TEXT            NO            NO      |
|    ArtistId       INTEGER         NO            YES     |
|    UnitPrice      REAL            NO            NO      |
|    Quantity       INTEGER         NO            NO      |
+===================+==============+================+==============+
```

We can use this information to decide how our schema should look. Do you see how the schema below reflects the table above?

```
CREATE TABLE Album
(
   AlbumId INTEGER PRIMARY KEY,
   Title TEXT,
   ArtistId INTEGER,
   FOREIGN KEY (ArtistId) REFERENCES Artist (ArtistId)
);
```

Try pasting the schema into your local database. Let's check to see if anything happened.

```
sqlite> .tables
```

Album <--- Do you see the Album table? I hope so!
Now, do we have any data in our new table?

```
sqlite> SELECT * FROM Album;
```

Do you see data? I hope not, we haven't added any yet!
Open the Album.sql tab. You can copy and paste these lines directly into your sqlite terminal. (Use Ctrl+A or Command+A to select all lines when the code editor is selected to select all the lines at once.)
Now try to run your query again. You've got data... NICE!

- **Export Data to CSV from Database**

```
sqlite > .mode csv
sqlite > .output newFile.csv
sqlite > SELECT * FROM myTable;
sqlite > .exit
```

- **Import CSV into a Table**

```
$ sqlite3 new.db   <--- If you'd like your csv's in a new database remember to make it first.
sqlite > CREATE TABLE myTable() <--- Build your schema!
sqlite > .mode csv
sqlite > .import newFile.csv myTable
```

- **Example**

Connect to the Chinook database.

```
import sqlite3

# Fetch records from chinook.db
db = sqlite3.connect("chinook.db")
c = db.cursor()
QUERY = "SELECT * FROM Invoice;"
c.execute(QUERY)
rows = c.fetchall()
# See query in Python
print "Row data:"
print rows

# See query by row
print "your output:"
for row in rows:
 print "  ", row[0:]

# See query as a pandas dataframe
import pandas as pd
```

```
df = pd.DataFrame(rows)
print df

db.close()
```

- **Example**

```
SELECT count(DISTINCT Customer.CustomerId)
FROM Customer JOIN Invoice JOIN InvoiceLine JOIN Track JOIN Genre
ON Customer.CustomerId = Invoice.CustomerId
AND Invoice.InvoiceId = InvoiceLine.InvoiceId
AND InvoiceLine.TrackID = Track.TrackId
AND Track.GenreId = Genre.GenreId
WHERE Genre.name = 'Jazz';
```

Intro to Machine Learning

Supervised Classification Algorithms

- Discrete: no order – no relationship
- **Naive Bayes (NB)**
  - Features (x) and Labels (y) → Scatter Plot
  - Classification by Eye
  - From Scatterplots to Predictions
  - From Scatterplots to Decision Surfaces
    - A Good Linear Decision Surface
  - Transition to Using Naive Bayes (NB)
    - NB Decision Boundary in Python
      - Getting Started With sklearn (Gaussian Naïve Bayes)

```
from sklearn.naive_bayes import GaussianNB
# create classifier
clf = GaussianNB()
# fit the classifier on the training features and labels
clf.fit(features_train, labels_train)
# make prediction
pred = clf.predict(features_test)
# calculate the accuracy on the test data
accuracy = clf.score(features_test, labels_test) # or
from sklearn.metrics import accuracy_score
accuracy = accuracy_score(pred, labels_test)
```

  - Bayes Rule (the holy grail of Probabilistic Inference)
    - Prior Probability x Test Evidence → Posterior Probability (Normalise)
    - Strength: good algorithm for working with text classification
    - Weakness: multiple words like Chicago Bulls
- **Support Vector Machines (SVM)**
  - Linear Hyperplane
    - Separating line that maximises distance to nearest point in either class (Margin)
    - Ignores outliers

```
from sklearn import svm
# create classifier
clf = svm.SVC()
# fit the classifier on the training features and labels
clf.fit(features_train, labels_train)
# make prediction
pred = clf.predict(features_test)
```

  - Non-Linear
    - Square X and Y and transform to a new coordinate system with Z
    - Absolute values of |X| or |Y|

        - Kernel Trick: linear, poly, rbf (default), sigmoid, precomputed or callable
        - SVM parameters: kernel, gamma, C → Stop Overfitting
- **Decision Trees (DT)**
    - Linear questions (Yes or No)

```
from sklearn import tree
# create classifier
clf = tree.DecisionTreeClassifier()
# fit the classifier on the training features and labels
clf.fit(features_train, labels_train)
# make prediction
pred = clf.predict(features_test)
```

    - DT parameters: criterion, splitter, max_depth, min_samples_split, etc. → Stop Overfitting
    - Entropy
        - Controls how a DT decides where to split the data
        - Definition: Measure of impurity in a bunch of examples → (0, 1)
        - $Entropy = \sum_i -(p_i) \log_2(p_i)$
        - Information Gain = Entropy (parent) – [Weighted average] Entropy (children)
            - DT maximise Information Gain
    - Bias-Variance Dilemma
- **k Nearest Neighbours (kNN)**
- **Random Forest**
- **Adaboost** (sometimes also called boosted decision tree)

Datasets & Questions (Enron example)

- **Person of Interest (POI)**
    1. Indicted
    2. Settled without admitting guilt
    3. Testified in exchange for immunity
- **Accuracy vs. Training Set Size**
    1. More data give a better result than a super fine-tuned algorithm
- **Types of Data**
    1. Numerical, e.g. salaries, no. of emails sent by a given person, etc.
    2. Categorical, e.g. female or male, job title, etc.
    3. Time Series, e.g. date or timestamps on emails
    4. Text, e.g. contents of emails, to/from fields of emails, etc.

Regression

- Continuous: order → Regression

```
from sklearn import linear_model
```

```
reg = linear_model.LinearRegression()
reg.fit(ages_train, net_worths_train)
```

- Evaluate Regression
    1. Linear Regression Error = Actual value – Predicted value
    2. Good Fit → Minimize
        - $\sum|error|$ or $\sum error^2$
        - Algorithms for Minimizing Squared Errors
            - Ordinary Least Squares (OLS)
            - Gradient Descent
        - There can be multiple lines that minimize $\sum|error|$, but only one line will minimize $\sum error^2$ (SSE)!
        - SSE isn't perfect → adding more data, SSE increases without necessarily a worse fitting.
        - R Squared Metric for Regression

Table 4. Comparing Classification & Regression

Property	Supervised Classification	Regression
Output Type	Discrete (class labels)	Continuous (number)
What are you trying to find?	Decision boundary	Best fit line
Evaluation	Accuracy	SSE

- Multivariate Regression

Outliers

- What causes outliers?
    1. Sensor malfunction (Ignore them)
    2. Data entry errors (Ignore them)
    3. Freak event (Pay attention)
- Outlier detection
    1. Train with all the data
    2. Remove outliers with the largest residual error
    3. Re-Train with the reduced data

Unsupervised Learning

Kind of things where you find structure in the data without labels (y).

- **Clustering**
    - **K-Means** algorithm

        - Assign
        - Optimise
        - sklearn.cluster.KMeans(n_clusters=8, max_iter=300, n_init=10)
        - Limitations
            - Bad local minimum
                - The more the cluster centres, the more the local minima
                - Run the algorithm multiple times to fix this

- **Feature Scaling**
    - Re-scale features usually between 0-1, so that be comparable
    - Formula: $x' = \frac{x - x_{min}}{x_{max} - x_{min}}$
    - Outliers can kind of mess up the rescaling
    - from sklearn.preprocessing import MinMaxScaler
    - Algorithms affected
        - SVM with RBF kernel
        - K-Means Clustering
    - Algorithms not affected
        - Decision Trees
        - Linear Regression

Learning from Text

- The length of each document is not standardised
- Bag of Words can analyse these approaches
    - Count the frequency of words
    - Word order does not matter
    - Long phrases give different input vectors
    - Cannot handle complex phrases
- from sklearn.feature_extraction.text import CountVectorizer
- Low-Information Words
    - Not all words are equal, e.g “the” and other stopwords which occurs frequently
    - At preprocessing stopwords must be removed
    - Getting stopwords from NLTK (Natural Language Tool Kit)

        import nltk
        nltk.download()
        from nltk.corpus import stopwords
        sw = stopwords.words(“english”)
- Stemming
    - Stemming to Consolidate Vocabulary
        - Not all unique words are different e.g. unresponsive, response, respond → respon
- Order of Operations in Text Processing
    1. Stemming

2. Bag of Words representation

- Weighting by Term Frequency
    - Rates the rare words higher
        - TF - Term Frequency
        - IDF - Inverse Document Frequency

Feature Selection

- Select best features (make everything as simple as possible)
- Add new features (find new patterns)
    1. Use my human intuition
    2. Code up the new feature
    3. Visualise
    4. Repeat
- Beware of bugs when making new features
- Why might you want to ignore a feature?
    - It is noisy
    - It causes over fitting
    - It is strongly related (highly correlated) with a feature that's already present
    - Additional features slow down training/testing process
- Features ≠ Information
    - Features attempt to access information
- Univariate Feature Selection
    - There are several go-to methods of automatically selecting your features in sklearn. Many of them fall under the umbrella of univariate feature selection, which treats each feature independently and asks how much power it gives you in classifying or regressing.
        - SelectPercentile
        - SelectKBest
- Few features used → high bias
- Balancing Error with Number of Features
    - Regularisation
        - Lasso Regression
            - Minimise SSE + $\lambda|\beta|$,
              where λ = parameter and
              β = coefficients of regression (related with no. of features)

Data Dimensionality

- Reducing the number of dimensions with Principal Component Analysis (PCA)
- Part of the beauty of PCA is that the data doesn't have to be perfectly 1D to find the principal axis!

- Compression While Preserving Information
    - Preserving information with SelectKBest (k = no. of features to keep)
- Composite features
    - Combining features into one feature using PCA
    - Variance - the willingness/flexibility of an algorithm to learn
    - Principal component of a dataset is the direction that has the maximum variance because retains the maximum amount of information in original data
- PCA for Feature Transformation - can automatically find patterns and reduce dimensionality
- At sklearn documentation for PCA, the max number of PCs is min(n_features, n_data_points)
- Review/Definition of PCA
    - Systematised way to transform input features into principal components, PCs
    - Use PCs as new features
    - PCs are directions in data that maximise variance (minimise information loss) when you project/compress down onto them
    - More variance of data along a PC, higher that PC is ranked
    - Most variance/most information → first PC, second-most variance (without overlapping with first PC) → second PC
    - Max no. of PCs = no. of input features
- When to use PCA
    - Latent features driving the patterns in data
    - Dimensionality reduction
        - Visualise high-dimensional data
        - Reduce noise
        - As a pre-processing method to make other algorithms (regression, classification) work better ← fewer inputs (e.g. eigenfaces - facial recognition)

Validation

- Benefits of Testing
    - Why use training and testing data?
        - Gives estimate of performance on an independent dataset
        - Serves as check on overfitting
- Train/Test Split in sklearn
    - Usually 10% or 20%
    - Cross-validation: evaluating estimator performance

      from sklearn.model_selection import train_test_split

      X_train, X_test, y_train, y_test = cross_validation.train_test_split(iris.data, iris.target, test_size=0.2, random_state=0)
- Where to use training vs. testing data
    - Train

1. pca.fit(training_features)
2. pca.transform(training_features)
3. svc.train(training_features)

- Test

  No pca.fit! We want to use same PCs and training data

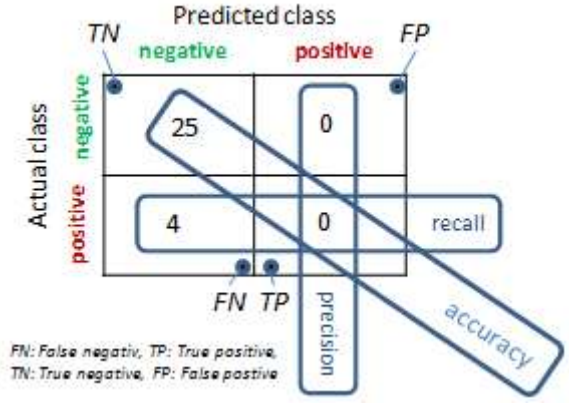
1. pca.transform(test_features)
2. svc.predict(test_features)

- K-Fold Cross Validation
  - In k-fold cross-validation, the original sample is randomly partitioned into k equal sized subsamples. Of the k subsamples, a single subsample is retained as the validation data for testing the model, and the remaining k-1 subsamples are used as training data. The cross-validation process is then repeated k times (the folds), with each of the k subsamples used exactly once as the validation data. The k results from the folds can then be averaged to produce a single estimation. The advantage of this method over repeated random sub-sampling (see below) is that all observations are used for both training and validation, and each observation is used for validation exactly once.
  - Maximise accuracy
  - If our original data comes in some sort of sorted fashion, then we will want to first shuffle the order of the data points before splitting them up into folds, or otherwise randomly assign data points to each fold. If we want to do this using KFold(), then we can add the "shuffle = True" parameter when setting up the cross-validation object.
  - If we have concerns about class imbalance, then we can use the StratifiedKFold() class instead. Where KFold() assigns points to folds without attention to output class, StratifiedKFold() assigns data points to folds so that each fold has approximately the same number of data points of each output class. This is most useful for when we have imbalanced numbers of data points in our outcome classes (e.g. one is rare compared to the others). For this class as well, we can use "shuffle = True" to shuffle the data points' order before splitting into folds.
- GridSearchCV is a way of systematically working through multiple combinations of parameter tunes, cross-validating as it goes to determine which tune gives the best performance. The beauty is that it can work through many combinations in only a couple extra lines of code.

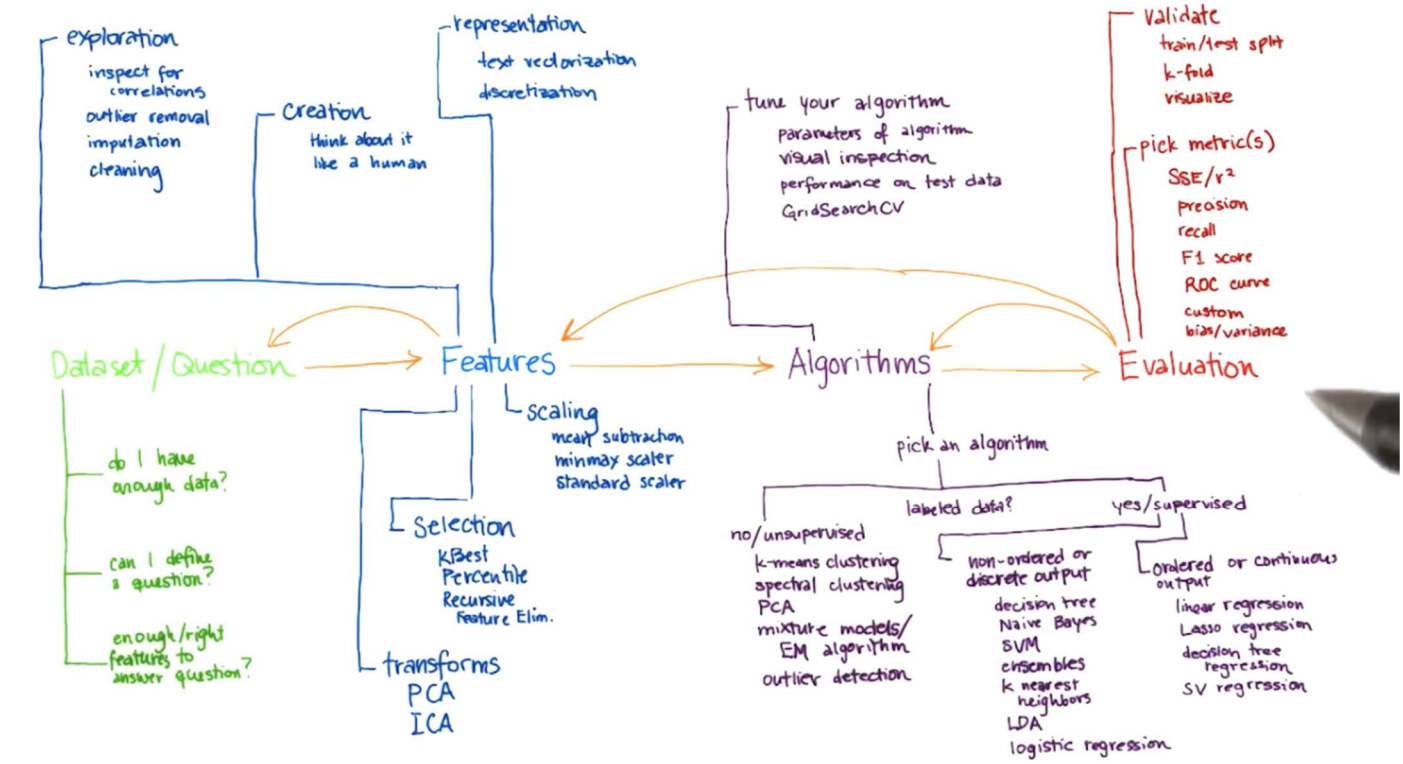
Evaluation Metrics

- Accuracy
  - No. of all data points labelled correctly divided by all data points
  - Shortcomings
    - Not ideal for skewed classes
- Confusion Matrices
- Precision and Recall

- Recall: True Positive / (True Positive + False Negative). Out of all the items that are truly positive, how many were correctly classified as positive. Or simply, how many positive items were 'recalled' from the dataset.
- Precision: True Positive / (True Positive + False Positive). Out of all the items labelled as positive, how many truly belong to the positive class.



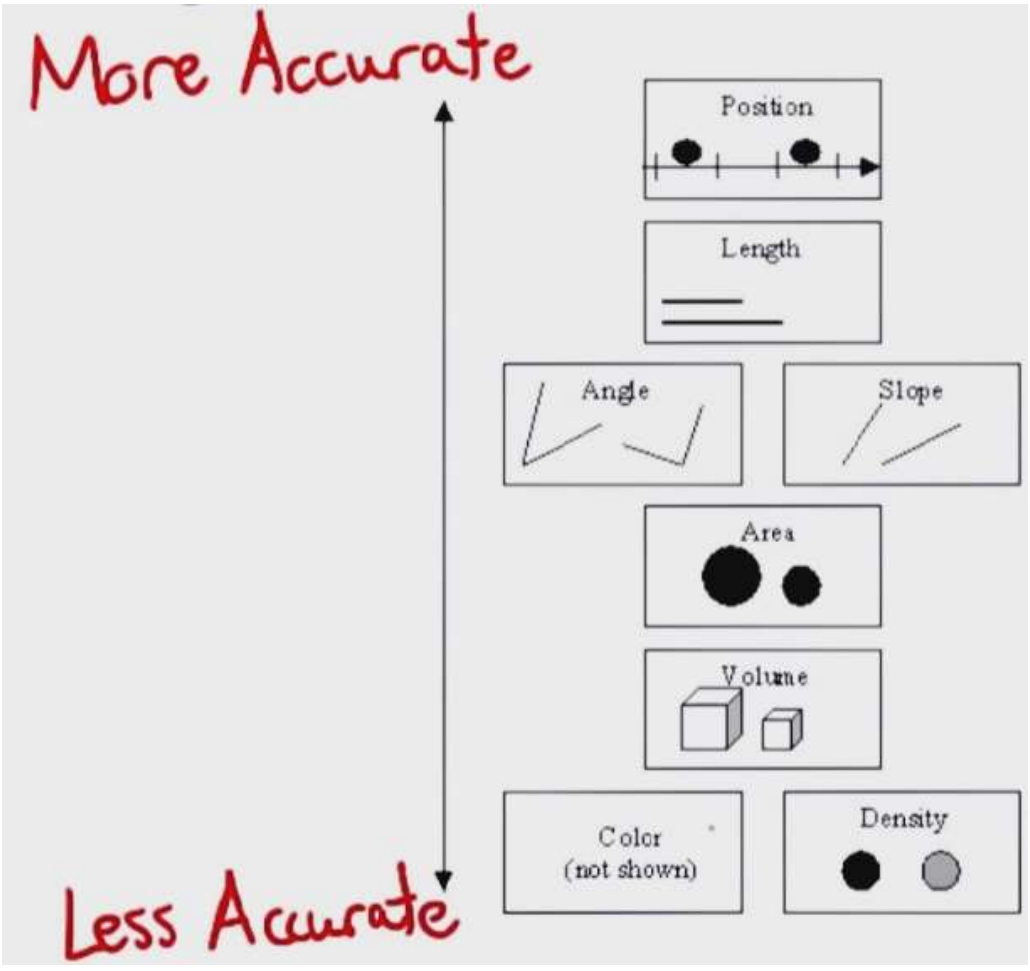
Summary



Data Visualization in Tableau

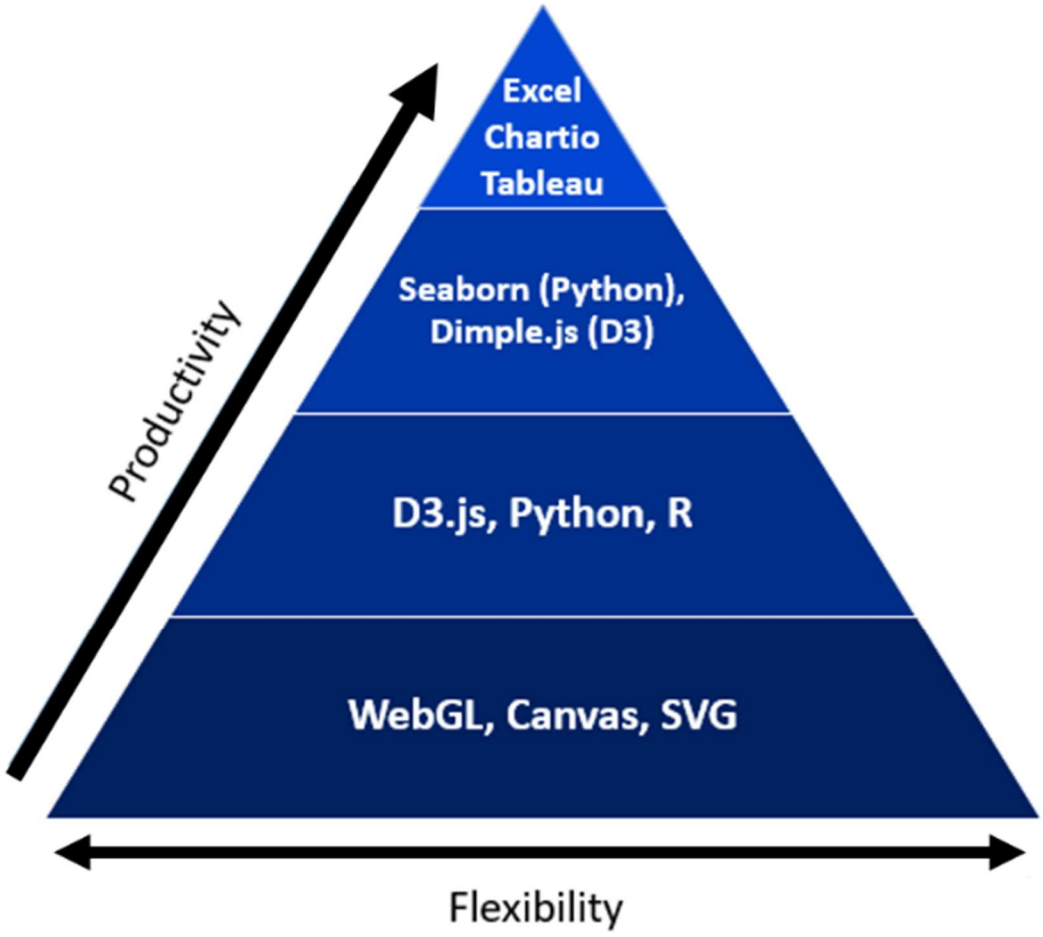
Data Visualization Fundamentals

- Data visualization helps our brains understand data
- Data Types
    - Quantitative
        - Continuous: time, height, weight, money, interest rates, temperature
        - Discrete: units sold, number of languages spoken, number of emails you received yesterday
    - Qualitative
        - Categorical: gender, hair color, country, industry, cat breed
        - Ordinal: Rankings, survey questions
- Rankings of Visual Encodings



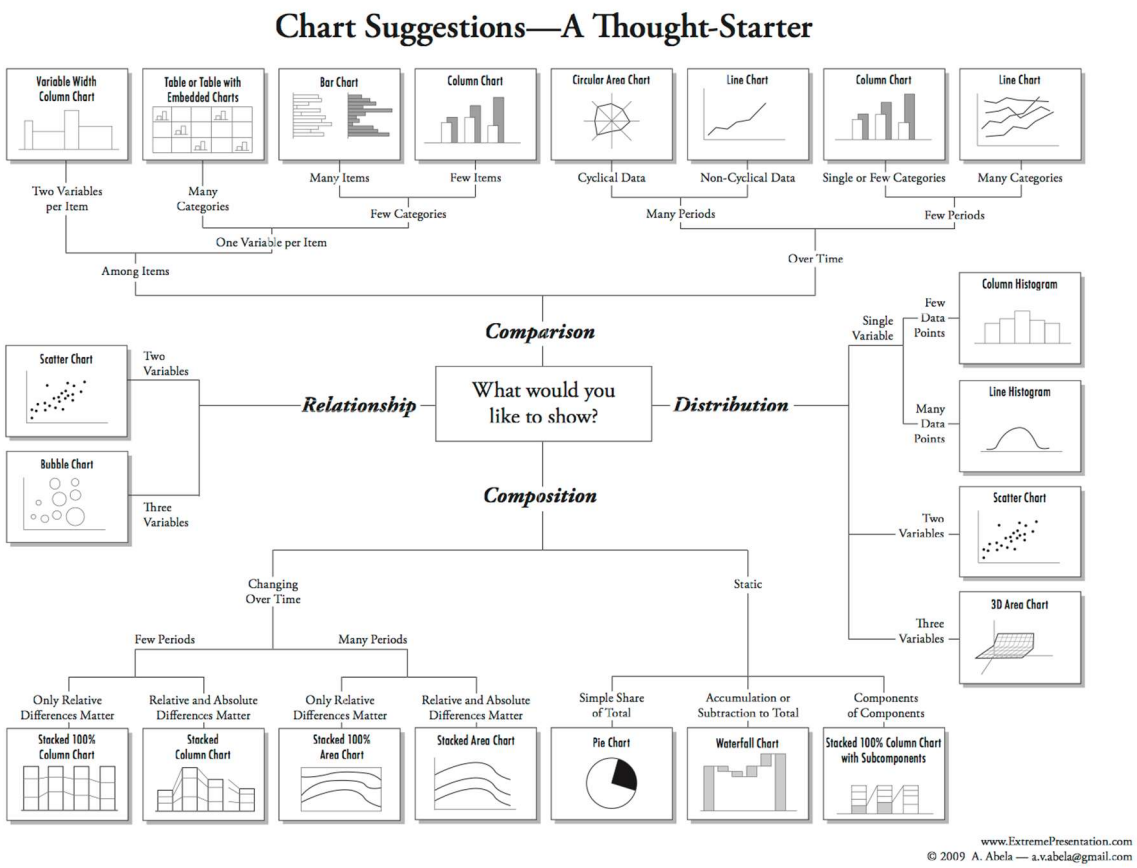
- The Data Analysis Process

- The Spectrum of Data Visualization



- Visual encodings are the mapping of data to display elements.
- Data visualizations that tell a story or convey information are considered to be explanatory
- Data Visualizations that let you discover trends or patterns in a data set are called exploratory data

Design Principles



Basic Graphs

- Bar chart - highlights individual values, supports comparisons, and can show rankings or deviations
- Boxplot - shows distributions and quantiles, especially useful when comparing distributions
- Pie chart - shows part-to-whole relationship and best suited for one category; poor for making comparisons
- Stacked bar chart - shows part-to-whole relationship and best suited for showing composition within categories and totals
- Bubble chart - shows how three or more sets of values vary; shows correlation
- Line chart - shows overall changes and patterns, usually over equally spaced intervals of time
- Map - values are encoded on physical locations and patterns may be drawn by comparing locations
- Scatterplot - shows how two pair sets of values (for example height and shoe size) vary; shows correlation

- **Practical Rules for Using Colour**

Rule #1 - If you want different objects of the same colour in a table or graph to look the same, make sure that the background—the colour that surrounds them—is consistent.

Rule #2 - If you want objects in a table or graph to be easily seen, use a background colour that contrasts sufficiently with the object.

Rule #3 - Use colour only when needed to serve a particular communication goal.

Rule #4 - Use different colours only when they correspond to differences of meaning in the data.

Rule #5 - Use soft, natural colours to display most information and bright and/or dark colours to highlight information that requires greater attention.

Rule #6 - When using colour to encode a sequential range of quantitative values, stick with a single hue (or a small set of closely related hues) and vary intensity from pale colours for low values to increasingly darker and brighter colours for high values.

Rule #7 - Non-data components of tables and graphs should be displayed just visibly enough to perform their role, but no more so, for excessive salience could cause them to distract attention from the data.

Rule #8 - To guarantee that most people who are colour-blind can distinguish groups of data that are colour coded, avoid using a combination of red and green in the same display.

Rule #9 - Avoid using visual effects in graphs.

- **Shape, size, and other tools**
    - Redundant encoding
- **Chart Junk**
- **Design integrity**

$$\text{Lie Factor} = \frac{\text{size of effect shown in graphic}}{\text{size of effect in data}}$$