

EMBEDDED VISION DESIGN 3

DATA

JEROEN VEEN



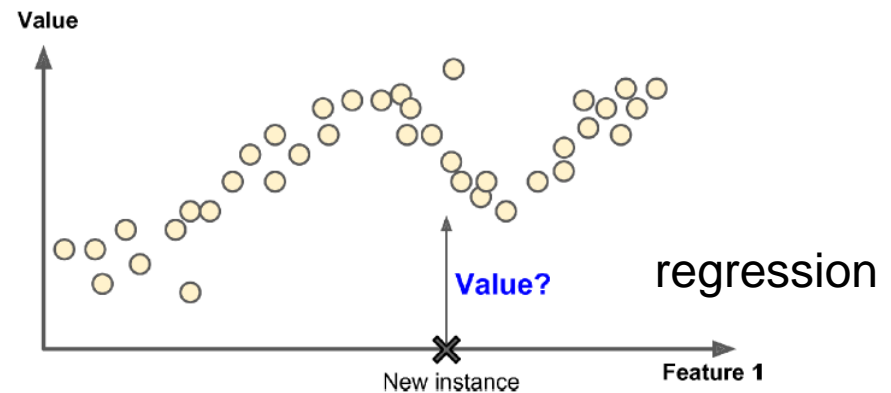
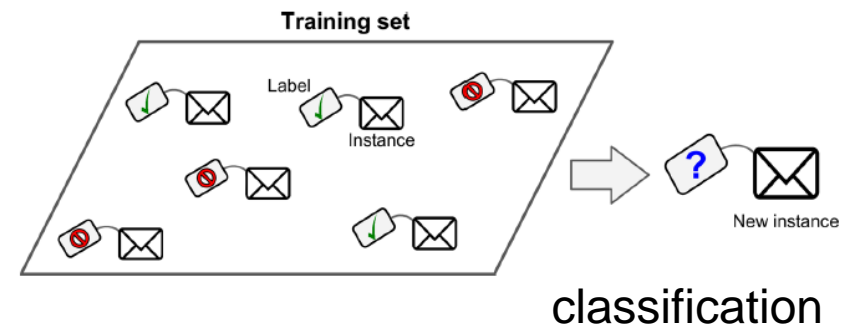
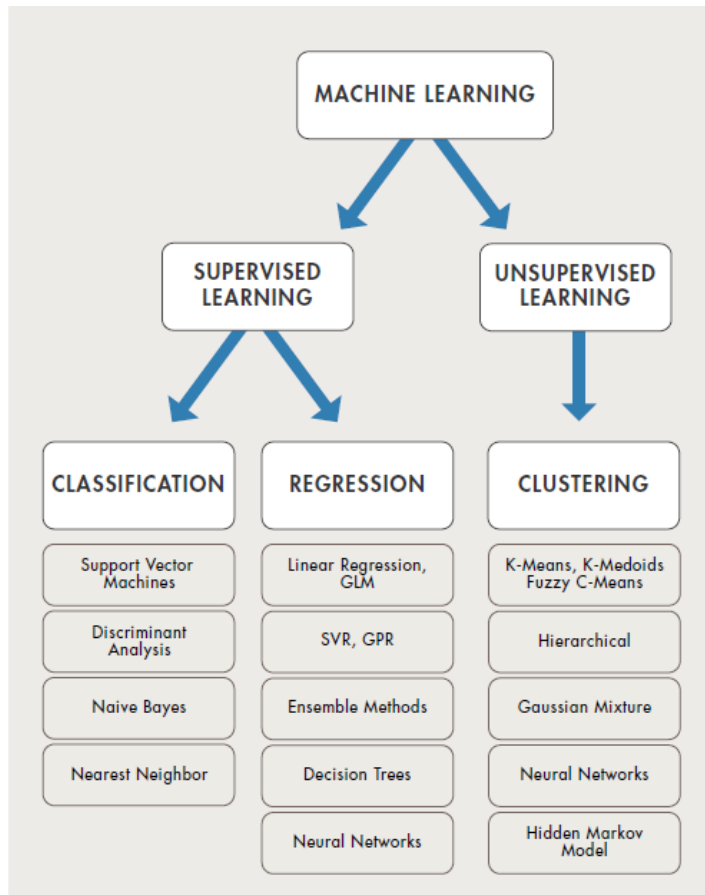
HAN_UNIVERSITY
OF APPLIED SCIENCES

CONTENTS

- Thinking about data
- Splitting your data
- Feature engineering
- Exploring your data
- Data preparation

“It is a capital mistake to theorize before one has data. Insensibly one begins to twist facts to suit theories, instead of theories to suit facts.” — Sir Arthur Conan Doyle, Sherlock Holmes

RECAP: MACHINE LEARNING APPROACHES

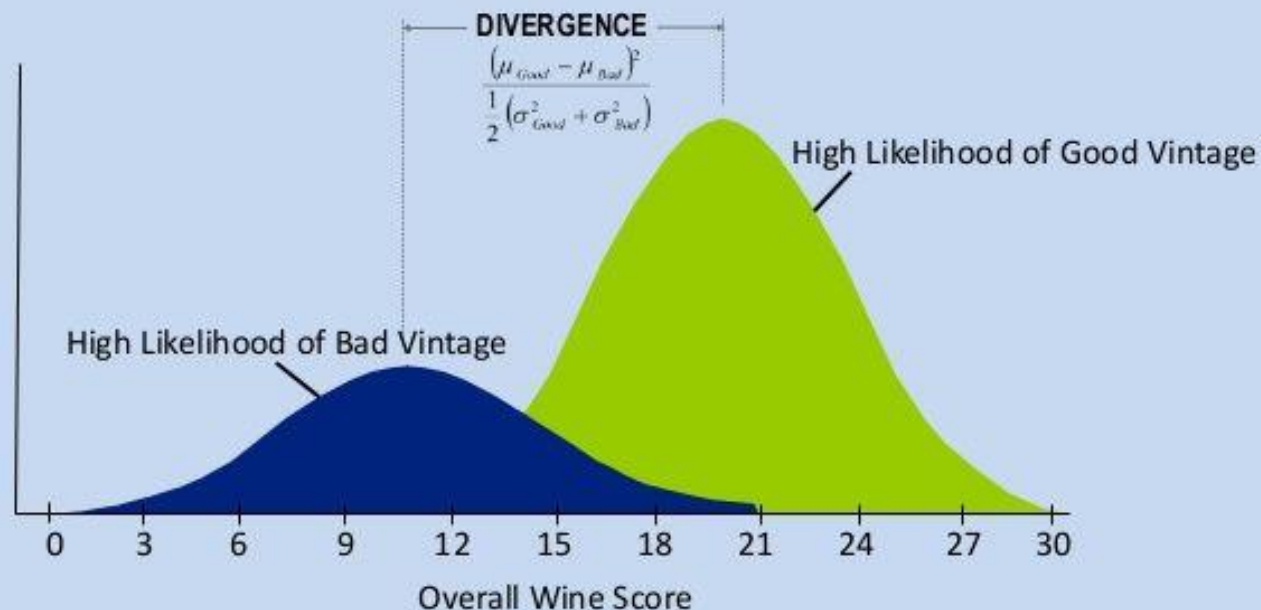


Source: Géron, ISBN: 9781492032632

REGRESSION EXAMPLE

Professor Ashenfelter's Predictive Model

4



Wine quality = 12.145 + 0.00117 winter rainfall
+ 0.0614 average growing season temperature
- 0.00386 harvest rainfall.

WORKING WITH REAL DATA

- Numerical information
- Values of quantitative variables
- Collected through measurement
- Usable for processing

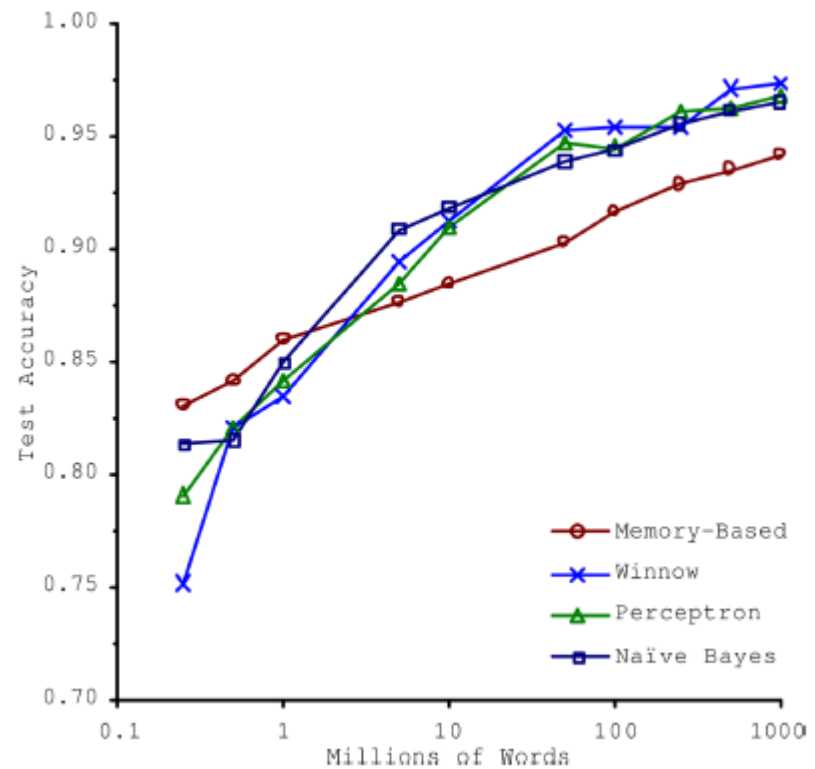


Source: https://en.wikipedia.org/wiki/Data#/media/File:Data_types_-_en.svg

Ultimate goal of data processing: Turn information into insight!

UNREASONABLE EFFECTIVENESS OF DATA

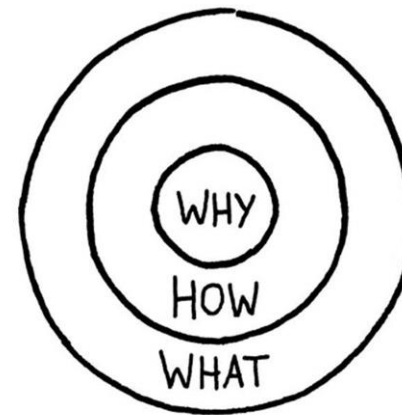
- Data matters more than algorithms!



Source: Peter Norvig et al 2009

DEFINE YOUR OBJECTIVE

- What do you want to achieve?
 - > Define a SMART objective
- What classes apply?
- What data is available?
- What attributes are present?
- What data should be collected?
- What features matter?



Source: Simon Sinek

Why = The Purpose

What is your cause? What do you believe?

Apple: We believe in challenging the status quo and doing this differently

How = The Process

Specific actions taken to realize the Why.

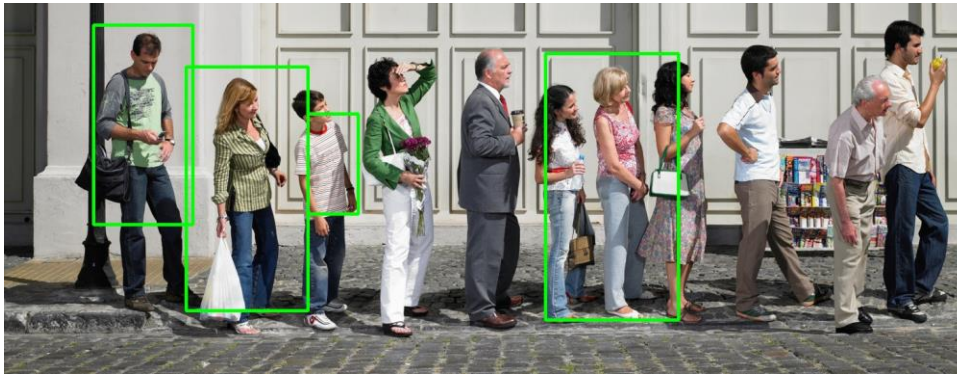
Apple: Our products are beautifully designed and easy to use

What = The Result

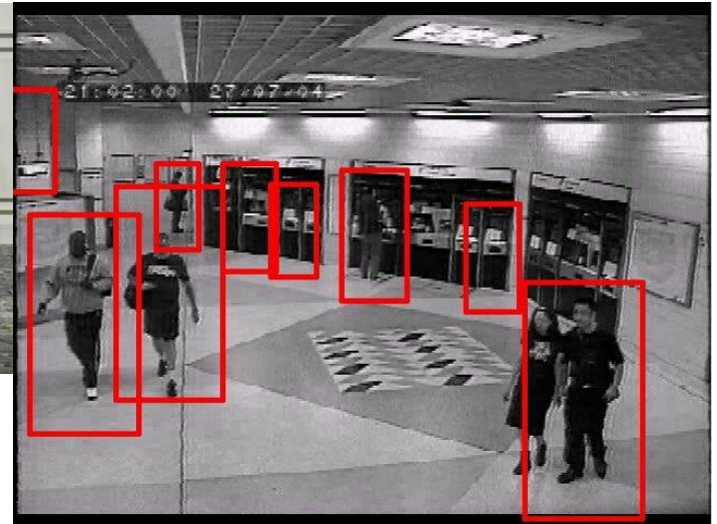
What do you do? The result of Why. Proof.

Apple: We make computers

EXAMPLE: PEOPLE DETECTION



Source: <https://thenextweb.com/wp-content/blogs.dir/1/files/2013/02/queue.jpg>

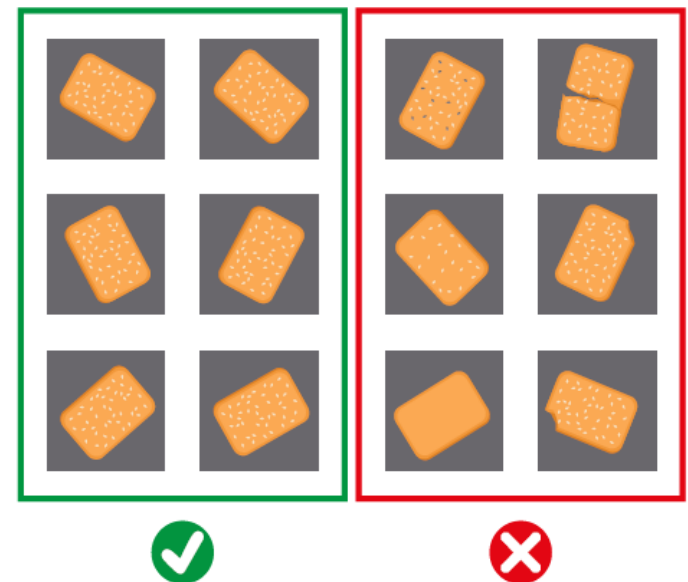


Source:
https://www.researchgate.net/profile/Hayley_Hung2/publication/24979



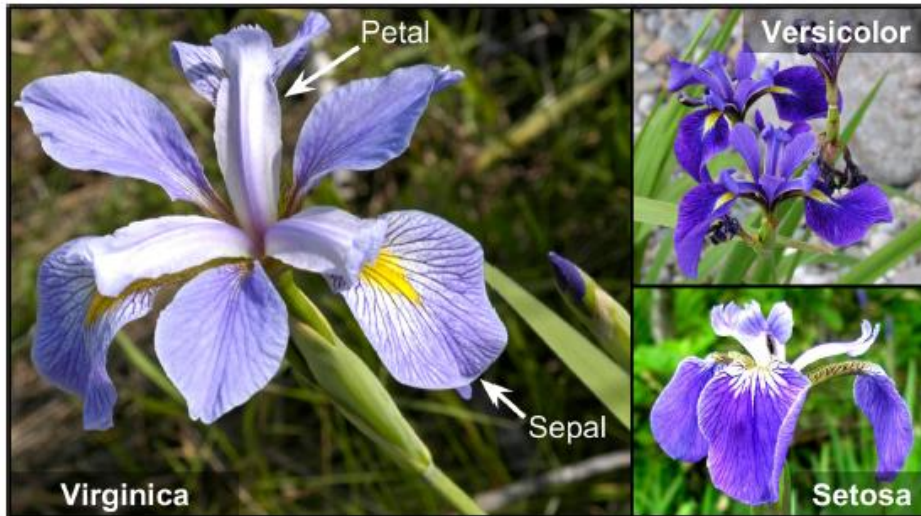
GETTING LABELED DATASETS

- Data acquisition
 - Field campaign
 - Controlled test set-ups
 - Scraping
- Data labelling
 - Domain experts
 - Hire data services
 - Control the experiments



Source: Basler, Artificial Intelligence in Image Processing

EXAMPLE: PUBLIC DATASETS



Source: Iris flower dataset

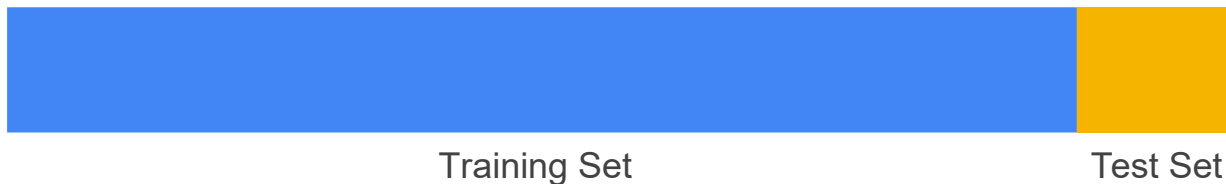


Source: MNIST database

See e.g. Scikit learn, Kaggle, Quandl, Google, Amazon

TRAINING AND TEST SETS: SPLITTING DATA

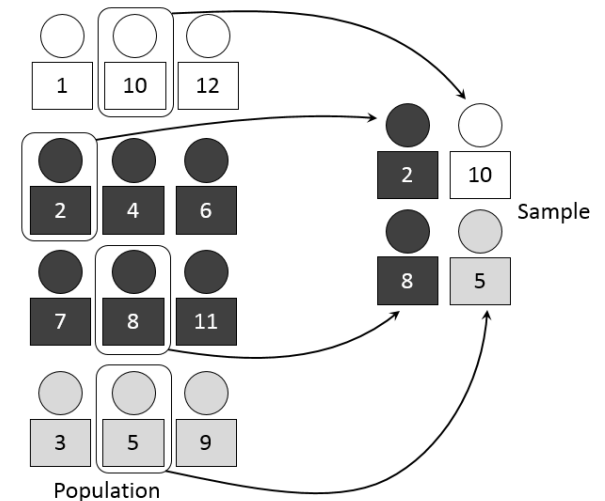
- **training set**—a subset to train a model.
- **test set**—a subset to test the trained model.
- You could imagine slicing the single data set as follows:



- Make sure that your test set meets the following two conditions:
 - Is large enough to yield statistically meaningful results.
 - Is representative of the data set as a whole. In other words, don't pick a test set with different characteristics than the training set.

STRATIFIED SAMPLING

- Make sure the test set properly reflects the population



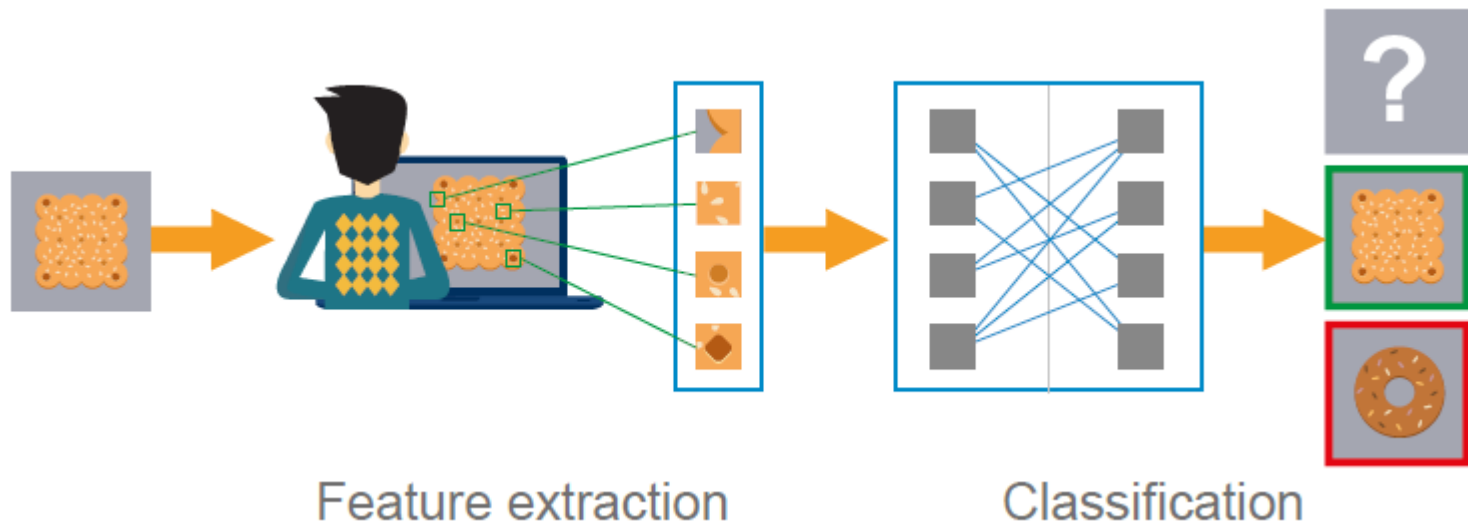
Never train on test data.

If you are seeing surprisingly good results on your evaluation metrics, it might be a sign that you are accidentally training on the test set. For example, high accuracy might indicate that test data has leaked into the training set.

Source: https://en.wikipedia.org/wiki/Stratified_sampling

FEATURE ENGINEERING

- Turn data into **feature vectors**
- Abstraction of an image



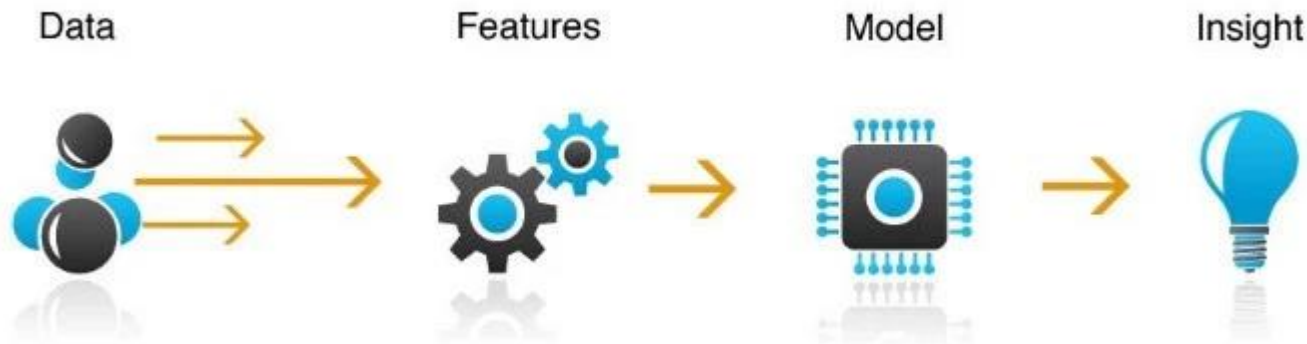
Source: Basler, Artificial Intelligence in Image Processing

WHAT MAKES A GOOD FEATURE?

<https://www.youtube.com/watch?v=N9fDIAfICMY&feature=youtu.be>

FEATURE ENGINEERING

- Select features
- Decompose features (e.g. area -> length, width)
- Extract features (e.g. aggregate, combinations)
- Creating new features by gathering new data
- Add promising transformations of features (e.g., $\log(x)$, \sqrt{x} , x^2 , etc.).



Source: VentureBeat

IMAGE FEATURE ENGINEERING

- Keypoints
- Extract descriptors
- Rotational and scaling invariance

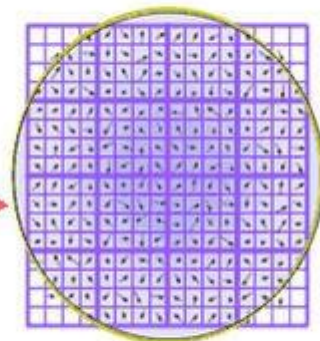
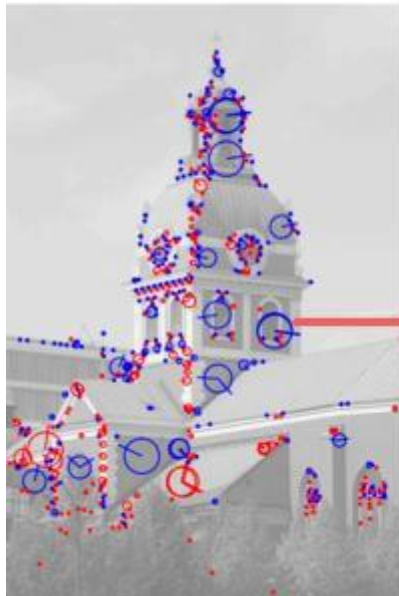
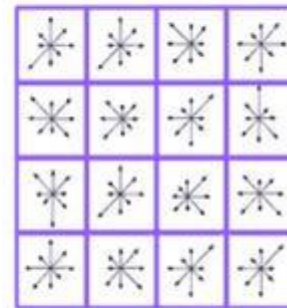
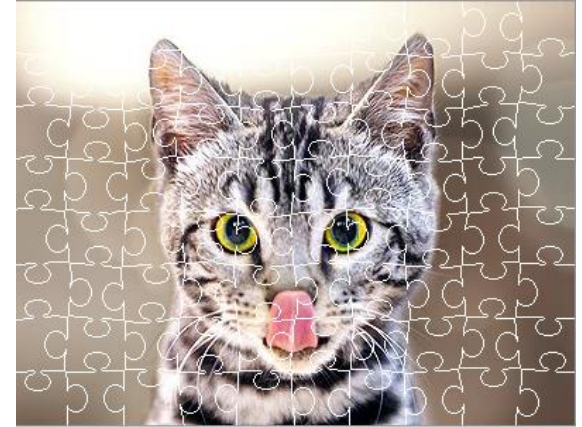


Image gradients



Keypoint descriptor



Source:
<https://whyevolutionistrue.files.wordpress.com/2013/01/screen-shot-2013-01-30-at-8-36-49-am.png>

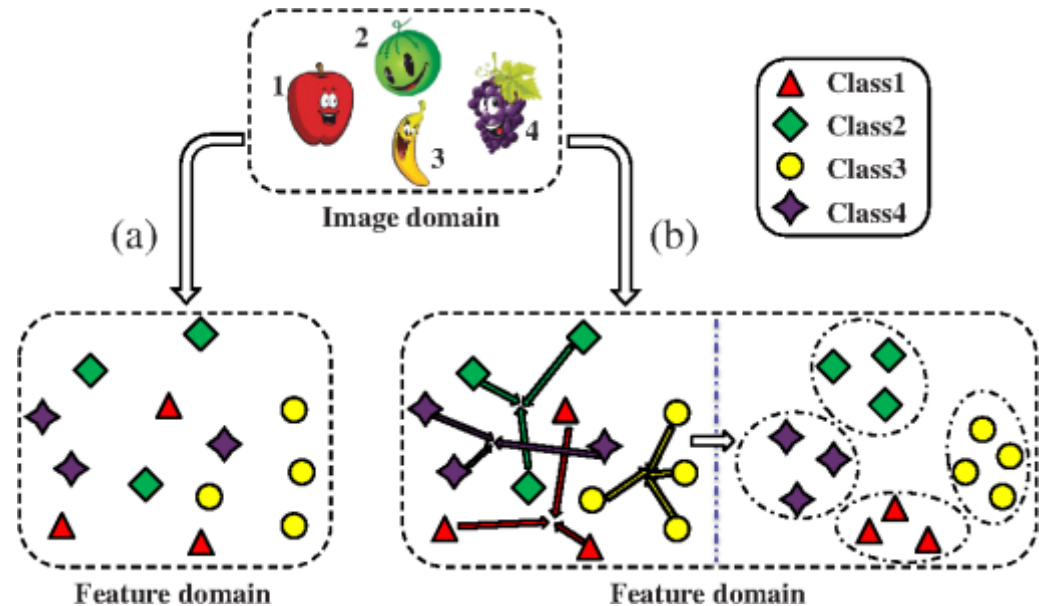
Source: https://miro.medium.com/max/1186/1*K68boX7fmtsYmyG2LlcmhQ.jpeg

KEYPOINT DETECTOR METHODS

- FAST: simple, and prone to error?
- SIFT: computationally expensive, but highly expressive.
- SURF: faster and more robust
- Star: optimized for measuring camera self-motion
- BRIEF: extracting feature descriptions
- BRISK
- ORB
- FREAK
-

QUALITIES OF GOOD FEATURES

- Informative
- Discriminating
- Independent
- Nearly unique

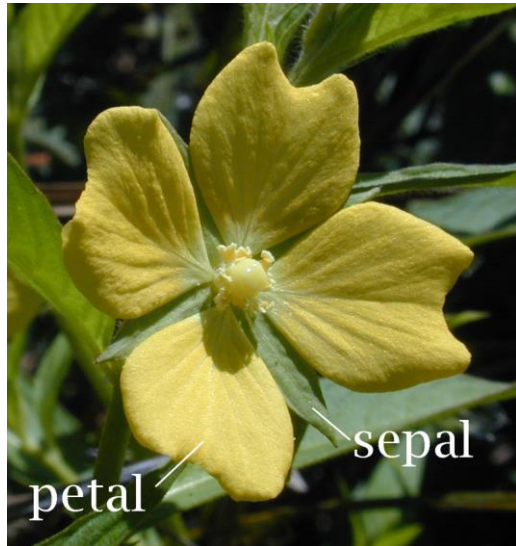


Source: <https://www.spiedigitallibrary.org/ContentImages/Journals/JEIME5/26/1/013023>

- NB later on feature scaling may be required

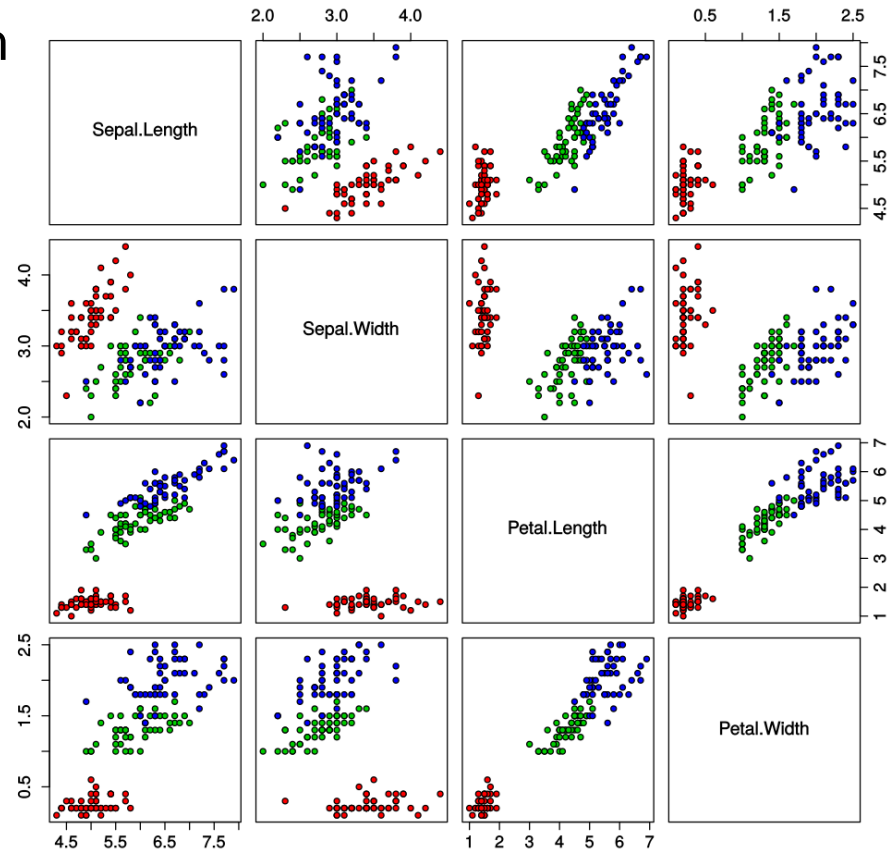
EXAMPLE: *IRIS* FLOWER DATA SET

- Sepal and petal width and length



Source: <https://en.wikipedia.org/wiki/Sepal>

Iris Data (red=setosa, green=versicolor, blue=virginica)

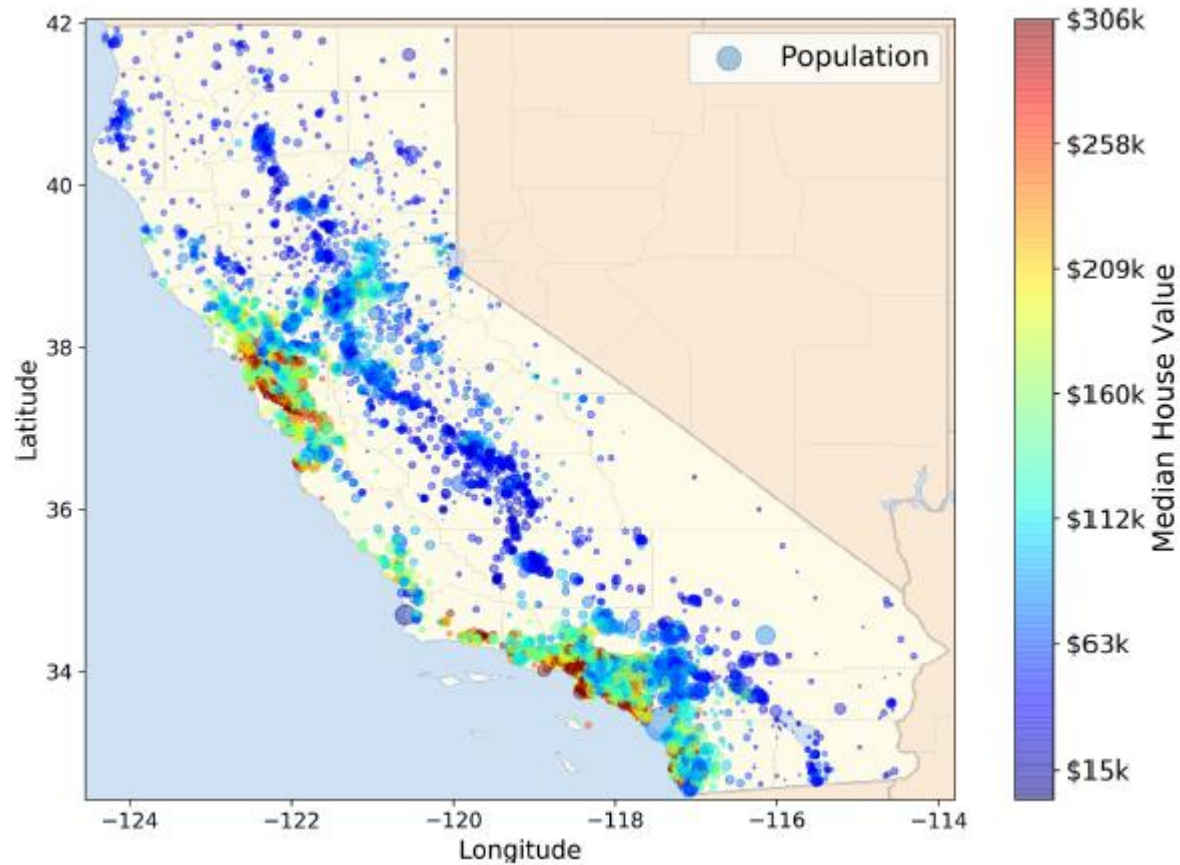


Source: https://en.wikipedia.org/wiki/Iris_flower_data_set

EXPLORE THE DATA

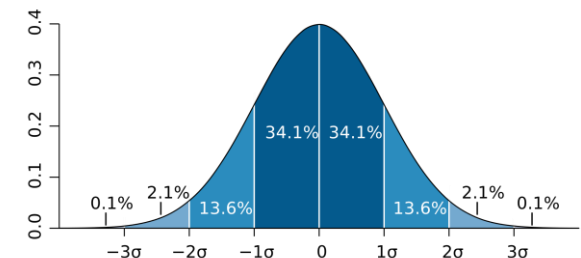
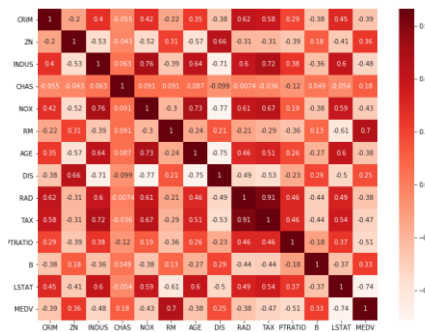
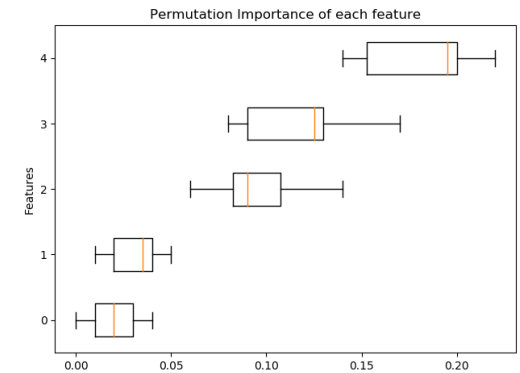
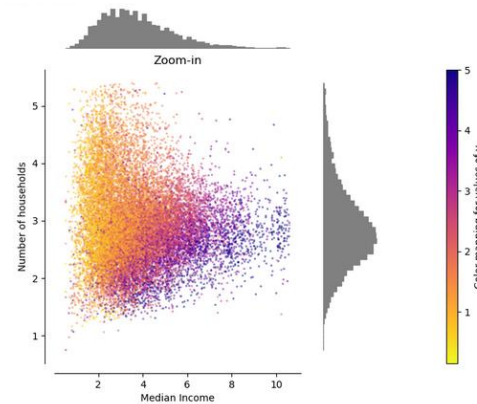
- Get insights from a domain expert
- Set aside a subset of the data for exploration
- Study each attribute and its characteristics
 - categorical, int/float, bounded/unbounded, text, structured,
 - Noisiness and type of noise (stochastic, outliers, rounding errors)
- Visualize the data
- Study the correlations between attributes
- Think about how you would solve the problem manually

EXAMPLE: CALIFORNIA HOUSING PRICES



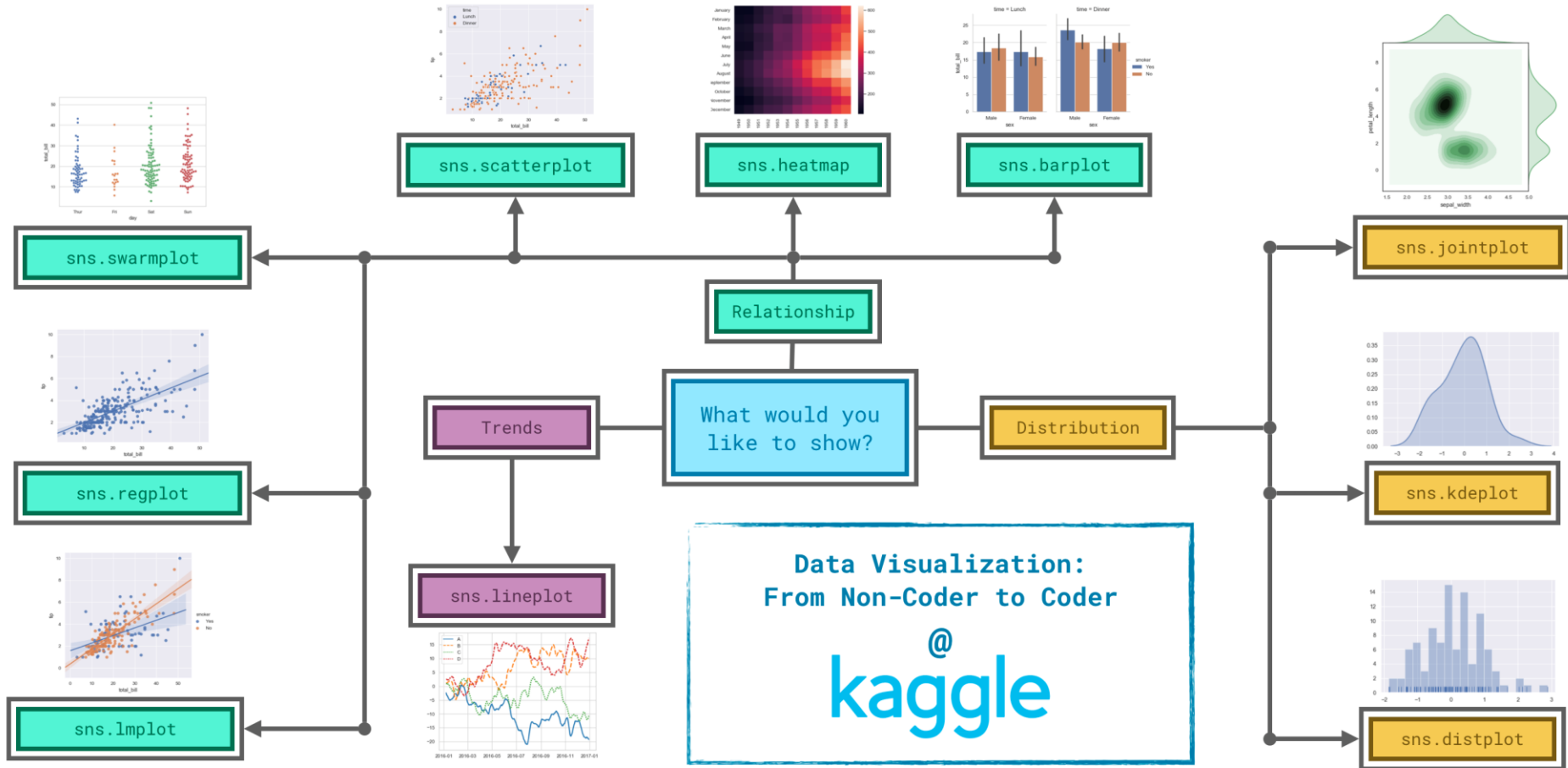
TOOLS FOR EXPLORATORY DATA ANALYSIS

- Univariate analysis
- Histogram
- Scatterplot
- Boxplot
- Correlation heatmap



Sources:

https://en.wikipedia.org/wiki/Exploratory_data_analysis
https://scikit-learn.org/stable/auto_examples/preprocessing/plot_all_scaling.html
https://en.wikipedia.org/wiki/Box_plot

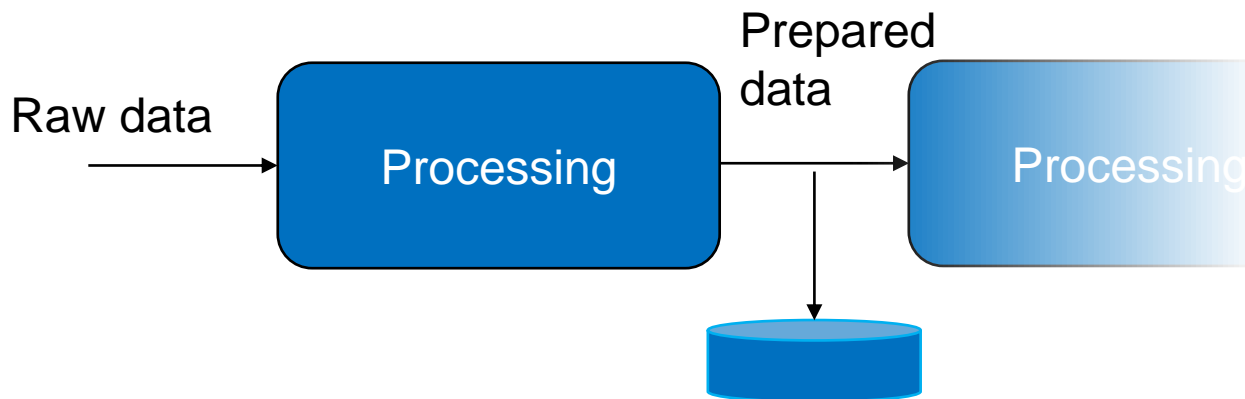


DATA QUALITY ISSUES

- Insufficient data. ML needs massive amounts of training data.
- Messy data. Data that contains a large amount of conflicting or misleading information.
- Dirty data. Data that contains missing values, categorical and character features with many levels, and inconsistent and erroneous values.
- Sparse data. Data that contains very few actual values and is instead composed of mostly zeros or missing values.
- Inadequate data. Data that is either unbalanced, incomplete or biased.

PIPELINES

- Sequence of data processing components
- First step is preparing the data

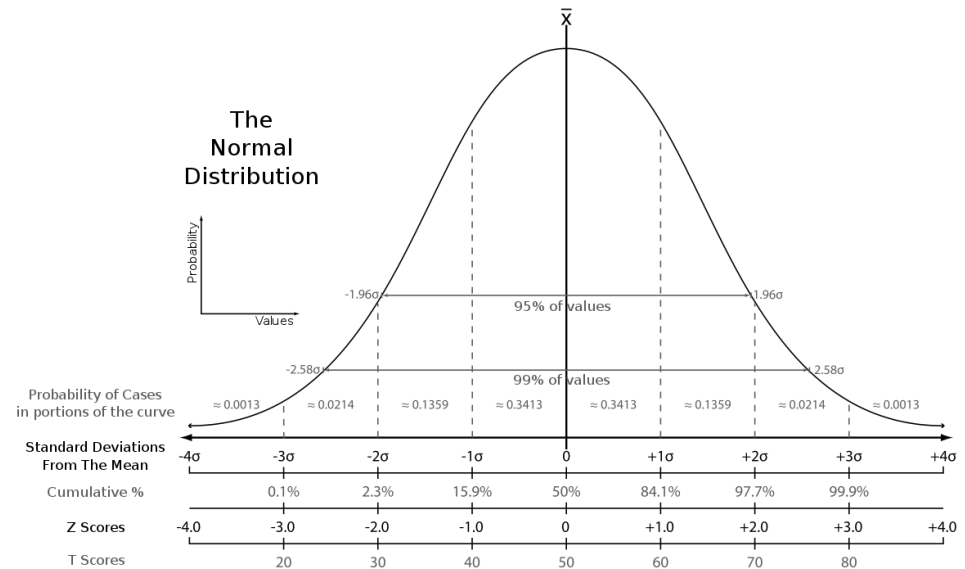


PREPARING DATA

- Data cleaning:
 - Fix or remove outliers (optional)
 - Fill in missing values (e.g., with zero, mean, median...) or drop their rows (or columns).
- Feature computation:
 - Selection
 - Transformation
- Feature scaling:
 - Standardize or normalize features.

EXAMPLE: OUTLIER DETECTION

- Assume feature values are normally distributed
- Compute Z-score of value
- Detect if z-score is above threshold
- Typically used in low dimensional feature space

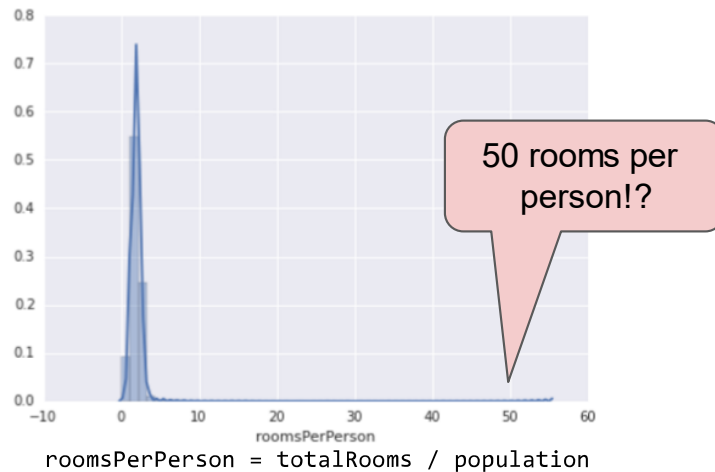


Source: https://en.wikipedia.org/wiki/Standard_score

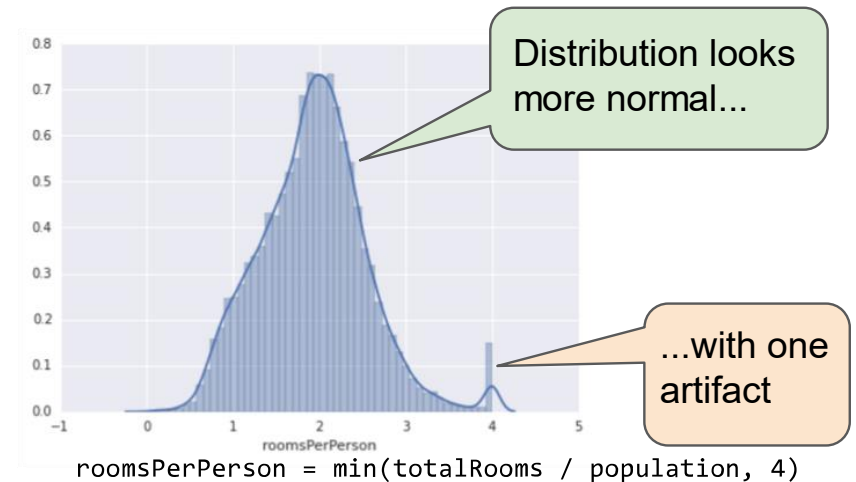
CLEANING DATA

- Scrubbing
 - Detect omitted values or duplicated examples and remove
 - Detecting bad feature values or labels can be far trickier
 - Outlier detection
 - Limited or sparse features / attributes
- Scaling
 - Avoid algorithm bias to features having a wider range
 - Help algorithms converge more quickly
 - Handling extreme outliers, e.g. log scaling, clipping

EXAMPLE: CLIPPING

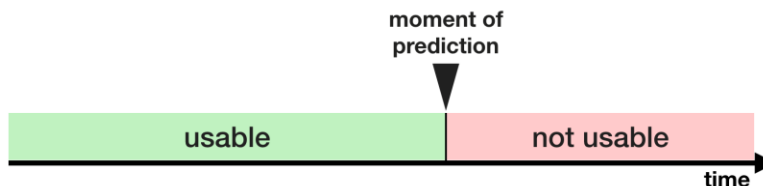


<https://developers.google.com/machine-learning/crash-course/representation/cleaning-data>



PITFALLS

- **Insufficient data**
- **Sampling bias:** your dataset is not representative of the cases you want to generalize to
- **Unbalanced data:** your dataset does not represent classes equally (skewed, nonresponse)
- **Non-stationary data:** distribution changes within the data set
- **Over/underfitting:** optimizing for the wrong thing by considering too many or too few features
- **Train-test contamination:** you fail to distinguish training data from validation data.
- **Target leakage:** your training data includes data that will not be available at the time you make predictions

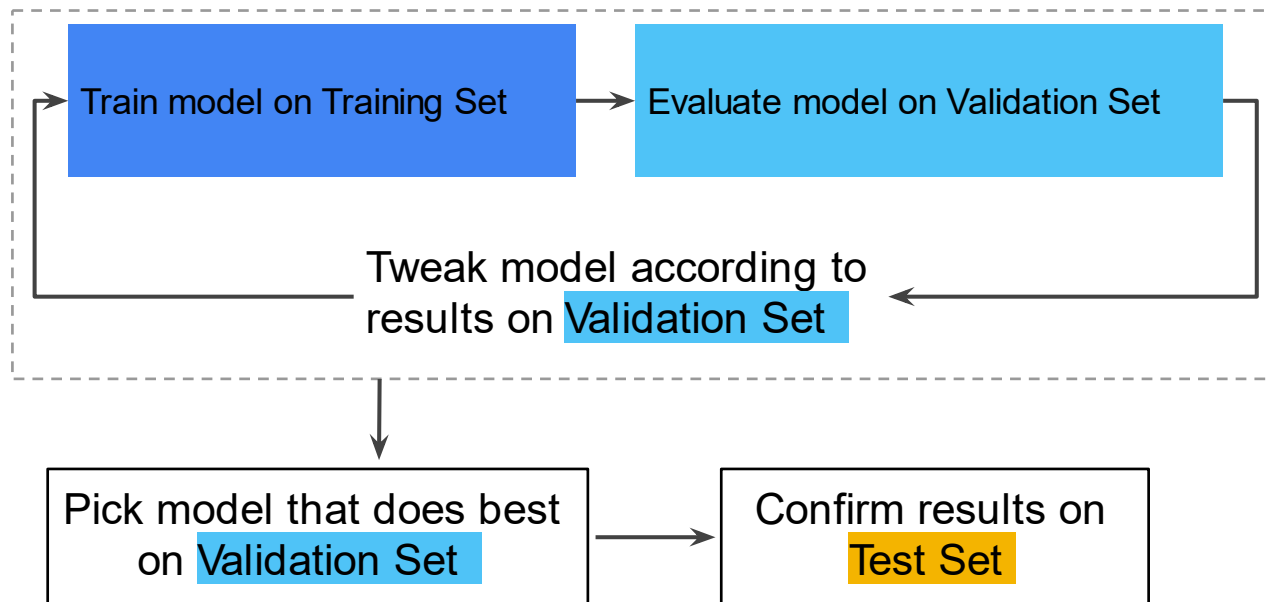


BIASES

- Selection bias: tendency to implicitly filter data based on some arbitrary criteria and then try to make sense out of it without realizing or acknowledging that we're working with incomplete data
- Availability bias: tendency to work with data that's easier to obtain rather than looking for data that is harder to gather but is more informative.
- False causality: tendency to assume that correlation implies causation
- Sunk cost fallacy: tendency to make decisions based on how much is already invested

INCLUDE VALIDATION

- Validation Set: Another Partition



NEXT WEEK

- Theory:
- Quiz
- Supervised machine learning: Support vector machines, Decision trees
- Hands-on:
- Exploratory data analysis
- -> to maximally benefit start collecting data