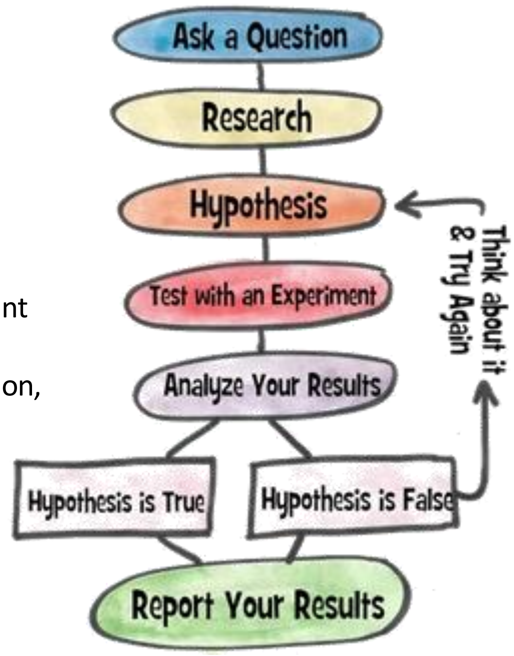
Material Summary: Introduction to Machine Learning

1. The Scientific Method



1.1 The Scientific Method Steps

- Ask a question
- Do a research
- Form a hypothesis
- Test the hypothesis with an experiment
  - Experiment works ⇒ Analyze the data
  - Experiment doesn't work ⇒ Fix experiment
- Results align with hypothesis ⇒ OK
- Results don't align with hypothesis ⇒ new question, new hypothesis
- Communicate the results

1.2 OSEMN Model

- Some guidelines on the process to extract meaningful information from data
  - Very similar to the scientific method
  - Can be viewed as a sequential process
    - Or just as some guidelines on how to do research
  - Read as "awesome"
    - Obtain data
    - Scrub data
    - Explore data
    - Model data
    - iNterpret the results

1.3 Applied Machine Learning Process

- This allows us to do our job faster and more reliably
  1. Problem definition
     - Make sure the problem is well-defined and that you're solving the right problem
  2. Data analysis
     - Get familiar with the available data
  3. Data preparation
     - Get the data ready for modelling
  4. Algorithm evaluation
     - Test and compare algorithms
  5. Result improvement
     - Use results to create better models (e.g. fine-tuning, ensembles)
  6. Result presentation
     - Describe the problem and solution to non-specialists

2. Machine Learning

2.1 Machine Learning

- We described a general process
  - We didn't explain ML in detail
- *"A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E."* – Tom Mitchell, Carnegie Mellon University
- More simply, making computers learn from data
  - And observing them getting better and better
  - Results: computers do things that they weren't explicitly told
- The field is vast (and expanding)
  - There are many sub-fields, variations and algorithms
  - … but the basis is still the same

2.2 Types of Machine Learning Algorithms

- Supervised learning
  - We train the program on previously known (labelled) data
  - After training, we expect it to make predictions on new data
  - Examples: regression, classification
- Unsupervised learning
  - We leave the program to find patterns in data
  - Examples: clustering analysis, dimensionality reduction
- Reinforcement learning
  - A form of unsupervised learning
  - The program learns continuously
  - Examples: learning to play a game by observing other players, learning to drive a car

2.3 Algorithms by Task

- **Statistical algorithms**
- **Regression** – predicting a continuous variable
- **Classification** – predicting class labels
- **Clustering** – finding compact groups of data points
- **Dimensionality reduction** – simplifying the input data
- **Recommendation** – suggest items for users
- **Optimization** – minimize / maximize a target function
- **Testing and improvement algorithms** – helper algorithms to select, fine-tune and optimize other ML algorithms
- … and more :)

3. Getting and Preparing Data

3.1 Common Libraries

- In Python, we use libraries to perform common operations
- **scikit-learn** – machine learning models
- **pandas** – working with data
  - Reading, tidying, cleaning, preparation

- **numpy** and **scipy** – numerical and scientific libraries
  - Contain a ton of useful functions for performing research
- **matplotlib** – plotting and data visualization
- There are many more we'd like to use but these are the most commonly used ones

3.2 Getting and Preparing Data

- *10 Minutes to pandas*
- *Pandas Cheat Sheet*
- *Full docs*
- Tidy up the data
- Preprocess the data w.r.t. the task at hand
- Explore the data
  - Exploratory data analysis
  - Don't forget to make graphs
- Create meaningful features
  - Feature {selection, extraction, engineering}
- Example: Titanic dataset

3.3 Example: Preparing Data for Modelling

- Most models require two additional steps
  - **Convert categorical variables** into **indicator variables**
  - **Normalize values** if needed (e.g., scale all variables from 0 to 1 using min-max scaling, or use Z-scores)
- Perform other model-specific transformations
  - E.g., your model may not work well with highly imbalanced data (when you look for anomalies)
- If possible, prepare several versions of the dataset
  - To see how a transformation affects model performance
- **Describe and document the entire process!**
  - Don't forget the rules for reproducible research