

Introduction to Machine Learning

From raw data to predictive models

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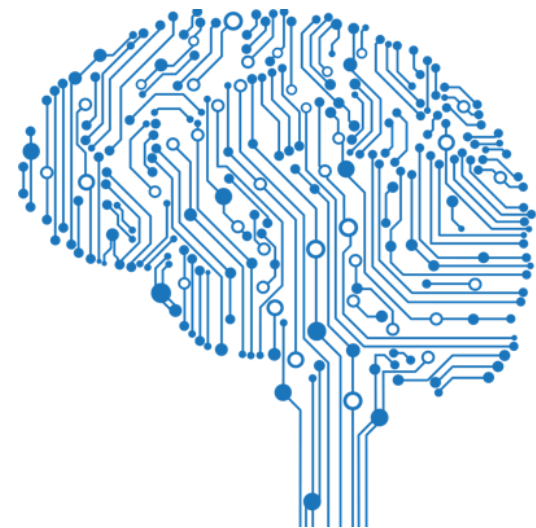


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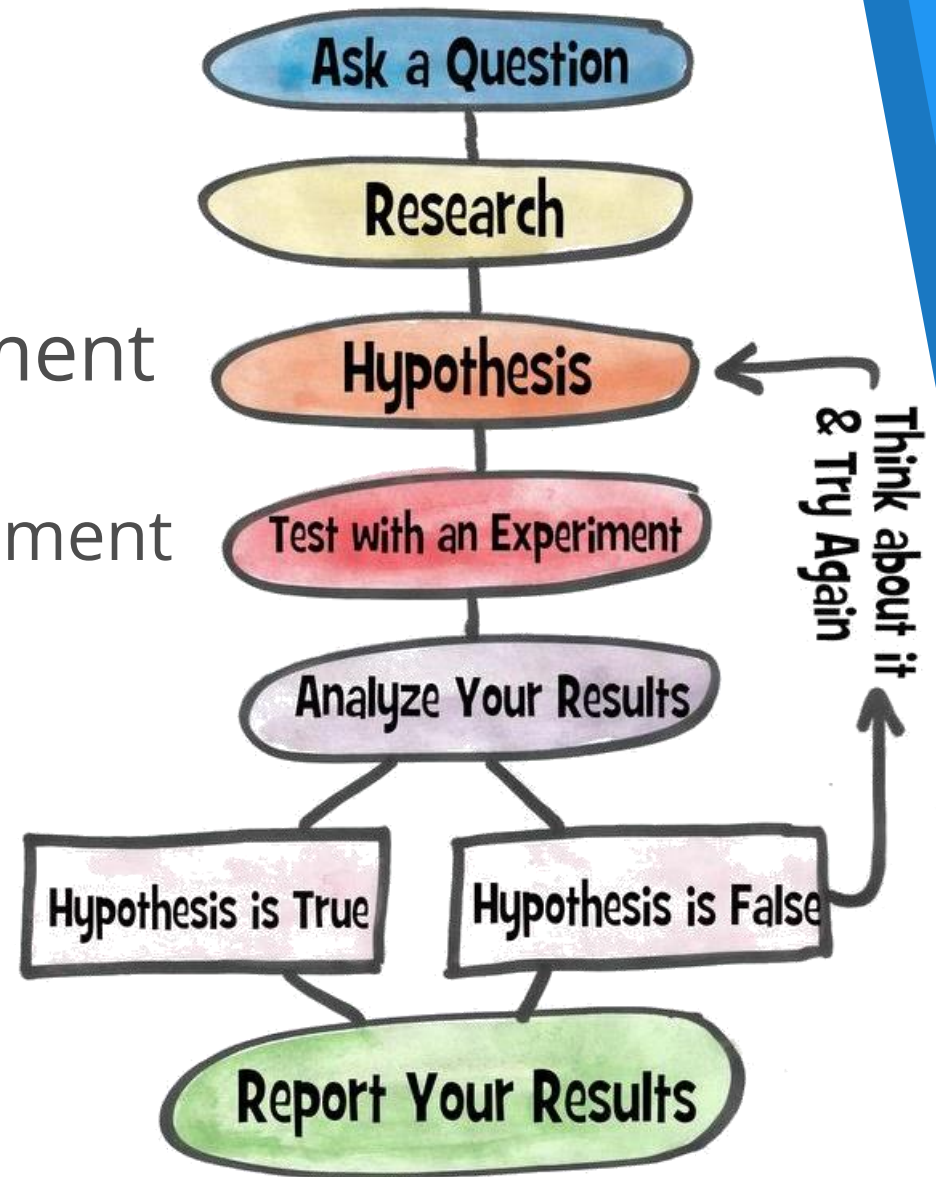
- sli.do: [#ml-intro](#)
- The scientific method – overview
 - Knowledge discovery from data
- Machine learning
 - Basic concepts
 - Algorithms (models) overview
- Setting up the work environment
- Getting, preparing and exploring data
 - Basic principles and guidelines

The Scientific Method

How to work with data...
the right way

The Scientific Method Steps

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



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"
1. **O**btain data
 2. **S**crub data
 3. **E**xplore data
 4. **M**odel data
 5. **iN**terpret the results

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





Machine Learning

Fundamental concepts

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

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

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 :)

Environment Setup

Download and install all tools

Anaconda

- You can install the Python interpreter and all libraries manually
 - Hard, boring and repetitive work
 - Error-prone
- Easy solution: platforms like **Anaconda**
 - Provide everything you need to get started with Python for science: interpreter, packages (720+), package manager, IDE
- Download from <https://www.continuum.io/downloads>
 - Current version (March 2018): Anaconda 5.1
 - Choose your platform (Windows, Linux, or MacOS)
 - Download the **Python 3.6** version
 - Follow the installer



Python Tools for Visual Studio (Optional)

- You can use the built-in IDE called **Spyder**
 - You can even use Notepad if that's your thing
- If you want to use another IDE, you have to configure it to work with Python
 - Syntax highlighting, autocomplete, etc.
- If you're using Visual Studio
 - Python Tools
 - <https://www.visualstudio.com/vs/python/>
- Visual Studio Code
 - If you prefer something lightweight, Visual Studio Code is a good alternative
 - <https://code.visualstudio.com/docs/languages/python>

Jupyter Notebook

- A very nice and clean way to document your research
- Included in Anaconda
- Can create documents that contain live code, equations, visualizations and explanatory text
 - HTML / CSS / JavaScript
 - Markdown
 - $\text{L}^{\text{A}}\text{T}_{\text{E}}\text{X}$
 - Python
- Start – use the Anaconda shortcut
 - ...or type into the Command Prompt

```
jupyter notebook
```

How to Use Jupyter

- Create a new notebook
 - New > Python 3
- Every piece of text or code is in a cell
 - Text cells just contain text or Markdown



- Code cells contain code (obviously)
 - Code can be executed
 - Jupyter "remembers" the code
- Execute cell: **Ctrl + Enter**
 - Or use the menus

The diagram shows a Jupyter code cell. The input part of the cell contains the text `In [2]: print("Hello world")`. The output of the cell is displayed below the input, showing the text `Hello world`.

Getting and Preparing Data

Preparing raw data for modelling

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

Getting Data

- Import pandas in your notebook or script
 - We usually give it an alias to make code shorter

```
import pandas as pd
```

- Read a dataset (table with data)

```
dataset = pd.read_table(...)
```

- The method contains a lot of options
- We can also read from other (non-local) sources
- Transform the data to make analysis easier
 - Tidy up the data
 - Attributes in columns
 - Observations in rows
 - Adding a new record = adding a single, complete row

country	year	cases	population
Afghanistan	1999	181	17071
Afghanistan	2000	2666	2095360
Brazil	1999	37737	17206362
Brazil	2000	80488	17404898
China	1999	212258	1270115272
China	2000	216716	1280426583

variables

country	year	cases	population
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values

Preparing Data

- Make other transformations as needed
 - Incorporate many datasets
 - Filter rows and columns
 - Group and aggregate values (e.g. sums by group)
 - Transform columns (e.g. apply a function to all values)
 - Change data types
 - Alter the distributions (e.g. log, minmax)
 - Calculate new columns (e.g. sum of two columns)
- All of these transformations are commonly used and have their own methods within pandas
 - [10 Minutes to pandas](#)
 - [Pandas Cheat Sheet](#)
 - [Full docs](#)

Exploring Data

- Running an ML model is a small part of the process
 - Before that, we have to get to know our data
- **Exploratory data analysis (EDA)**
 - "Playing around" with the data, looking for interesting features, distributions, correlations, causal relationships, etc. using "mind power"
- An important part of EDA is creating graphs
 - We use matplotlib for this
 - Histograms and boxplots – to represent distributions
 - Line and bar charts – to represent relationships and allow comparisons
 - Scatterplots – to represent correlation
 - ... and many others, depending on the case
 - We can even create our own charts if we need that



Example: Getting and Exploring Data

- Passengers on the Titanic
 - Dataset provided in the additional materials: `titanic.csv`
 - [Dataset info](#)
- Read the data (using pandas)
- Tidy up and clean the data
 - While also exploring the information
 - No "hard and fast" rules – you've got to use intuition
 - **Usual workflow:** start by inspecting variables and data types, move to single-variable distributions, then try to find relationships between two or more variables; transform the data if needed
 - Deal with missing values and outliers, normalize the data if needed

Example: Preparing Data for Modelling

- Most models require two additional steps
 - Convert categorical variables into indicator variables

```
dataset = pd.get_dummies(dataset)
```
 - Normalize values if needed (e.g. scale all variables from 0 to 1 using minmax 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 with different transformations to see whether a transformation affects model performance negatively
- **Describe and document the entire process!**

Example: AzureML

- In this course, we'll be using Python code to run and evaluate models
 - We'll create a nice, structured pipeline
 - But there are other solutions
- Microsoft AzureML Studio: <https://studio.azureml.net/>
 - Good for a demo if you're not experienced in coding
 - **Pros**
 - Free to try
 - Easy, visual representation of the workflow
 - Has many predefined modules; can also execute Python code
 - Runs on the cloud – no need to throttle your machine
 - **Cons**
 - Hides away or obscures some important implementation details
 - Running on the cloud is too expensive sometimes

Summary

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The image features a white background with two blue decorative bars. The top bar is a solid blue band at the very top. Below it is a thinner, darker blue band that curves slightly downwards from left to right. The bottom of the image is framed by a similar pattern of a thin dark blue band above a solid blue band, both curving upwards from left to right.

Questions?