

Statistics and Data Science 265

# **Introductory Machine Learning**

January 14

Yale

# Outline

- Administrative items
- Elements of Python
- Demos

# Office Hours

John Lafferty	Monday	10:30am
Jianliang He	Monday	2:30pm
William Huang	Monday	4:00pm
Ruiqi Li	Tuesday	6:00pm
Awni Altabaa	Wednesday	3:00pm
Yihan Bao	Wednesday	6:00pm
Dingyao Zhang	Thursday	8:00pm

# Recordings

- Lectures will be recorded
- Available on Canvas under “Media”
- Please attend class and only use recordings for review

# Upcoming

- Assignment 1 will be posted next week
- Topics: Classification and regression

**Bookmark this page!**

`https://ydata123.org/sp26/introml/calendar.html`

# Recap

- Last time: Course overview, logistics
- Any questions?

# Plan for Today

- Python elements
- Pandas and linear regression example
- Basics of classification, regression, overfitting



# Python primer: Concepts

- Python types: lists, tuples, strings, dictionaries
- Basics of iteration
- Comprehensions
- Arithmetic
- Printing
- NumPy and multi-dimensional arrays
- Array math
- DataFrames and pandas
- Matplotlib and basic plotting

# Python elements



+ Code + Text



- Python and Jupyter essentials for iML



This notebook was adapted from multiple resources including the Data8 curriculum, [Yale FENG201](#), and [Stanford CS231](#). It is intended to give you a quick “jumpstart” and introduction to the tools that we will use throughout the course, based on Python, Jupyter notebooks, and essential useful packages like `numpy` and `pandas`.

It's important to recognize that practice is crucial here—you need to write code and implement things, making mistakes along the way, to gain proficiency in this material.



Subtopics marked with the scream icon are a little more advanced, and can be skipped on a first reading.



- ▼ Get Started

## Different ways to run Python

1. Create a file using editor, then: `$ python myscript.py`
2. Run interpreter interactively `$ python`
3. Use a Python environment, e.g. Anaconda or Google Colab

We recommend Anaconda:

- easy to install
- easy to add additional packages
- allows creation of custom environments

But Google Colab is also a good option. We plan to create a video on how to use Google Colab.



# Resources

- Anaconda Python: <https://www.continuum.io>
- Jupyter notebooks: [jupyter-notebook.readthedocs.io](http://jupyter-notebook.readthedocs.io)
- PyCharm debugger: [www.jetbrains.com](http://www.jetbrains.com)
- *Introducing Python*, Bill Lubanovic, O'Reilly
- *Python in a Nutshell*, Alex Martelli et al., O'Reilly
- *Python Cookbook*, David Beazley, Brian K. Jones, O'Reilly
- Google's Python class:  
<https://www.youtube.com/watch?v=tKTZoB2Vjukxo>
- <https://docs.python.org/3.5/tutorial>
- *Lots* of other materials available on the web

# Pandas example

+ Code + Text

## ▼ The New York Times Covid-19 Database

The New York Times Covid-19 Database is a county-level database of confirmed cases and deaths, compiled from state and local governments and health departments across the United States. The initial release of the database was on Thursday, March 26, 2020, and it is updated daily.

These data have fueled many articles and graphics by The Times; these are updated regularly at <https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html>. The Times has created many visualizations that are effective communications of important information about the pandemic.

The data are publically available via GitHub: <https://github.com/nytimes/covid-19-data>. In this illustration we will only use the data aggregated at the state level.

```
[ ] import pandas as pd
import numpy as np

%matplotlib inline
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')

[ ] covid_table = pd.read_csv("https://raw.githubusercontent.com/nytimes/covid-19-data/master/us-states.csv")
covid_table = covid_table.drop('fips', axis=1)
covid_table.tail(20)
```

	date	state	cases	deaths
30464	2021-09-07	North Dakota	119995	1596
30465	2021-09-07	Northern Mariana Islands	248	2
30466	2021-09-07	Ohio	1262018	21020
30467	2021-09-07	Oklahoma	570923	8001
30468	2021-09-07	Oregon	888348	8885

# Some Terminology

- supervised vs. unsupervised
- classification vs. regression
- prediction vs. inference

# Supervised Learning vs. Unsupervised Learning

Supervised learning:

- Given a set of  $(x, y)$ , learn to predict  $y$  using  $x$ .
- e.g.
  - ▶ Predicting whether a loan will default based on customer characteristics

# Supervised Learning vs. Unsupervised Learning

## Supervised learning:

- Given a set of  $(x, y)$ , learn to predict  $y$  using  $x$ .
- e.g.
  - ▶ Predicting whether a loan will default based on customer characteristics

## Unsupervised learning:

- Given a set of  $x$ , learn underlying structure or relationships of  $x$ .
- e.g.
  - ▶ Identifying market segments with similar spending patterns.

# Classification vs. Regression

The `Income` dataset:

Education	Seniority	Income
21.58621	113.1034	99.91717
18.27586	119.3103	92.57913
12.06897	100.6897	34.67873
17.03448	187.5862	78.70281
19.93103	20.0000	68.00992
18.27586	26.2069	71.50449

Information for 30 *simulated*  
*individuals*.



# Classification vs. Regression

The `Income` dataset:

Education	Seniority	Income
21.58621	113.1034	99.91717
18.27586	119.3103	92.57913
12.06897	100.6897	34.67873
17.03448	187.5862	78.70281
19.93103	20.0000	68.00992
18.27586	26.2069	71.50449

Regression: Model `income` based on other characteristics.

Information for 30 *simulated individuals*.

# Classification vs. Regression

The Income dataset:

Education	Seniority	Income
21.58621	113.1034	99.91717
18.27586	119.3103	92.57913
12.06897	100.6897	34.67873
17.03448	187.5862	78.70281
19.93103	20.0000	68.00992
18.27586	26.2069	71.50449

Information for 30 *simulated*  
*individuals*.

Regression: Model **income**  
based on other  
characteristics.

Classification: Model **whether**  
**someone will earn above the**  
**median income** based on  
other characteristics.

# Inference vs. Prediction

The `Income` dataset:

Education	Seniority	Income
21.58621	113.1034	99.91717
18.27586	119.3103	92.57913
12.06897	100.6897	34.67873
17.03448	187.5862	78.70281
19.93103	20.0000	68.00992
18.27586	26.2069	71.50449

Prediction: accurately predict  $Y$  for new observations

Information for 30 *simulated* individuals.

# Inference vs. Prediction

The `Income` dataset:

Education	Seniority	Income
21.58621	113.1034	99.91717
18.27586	119.3103	92.57913
12.06897	100.6897	34.67873
17.03448	187.5862	78.70281
19.93103	20.0000	68.00992
18.27586	26.2069	71.50449

Prediction: accurately predict  $Y$  for new observations

Inference: explain the underlying relationship between  $Y$  and  $X$

Information for 30 *simulated* individuals.

# Example: Handwritten Digit Recognition

- Data: images of handwritten digits (grayscale pixel values)
- Classify images as digits 0 to 9.



# Example: Handwritten Digit Recognition

- Data: images of handwritten digits (grayscale pixel values)
- Classify images as digits 0 to 9.



80322-4129 80206

40004 14310

37879 05153

35502 75216

35460 44209

# Summary

- Two cultures: model based and prediction based
- Python, pandas, and linear regression example with Covid-19 data

Next week: Linear regression and classification

Class on Wed and Fri next week (MLK)