Data Science: Principles and Practice

Lecture 1: Introduction

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¹ Based on slides from Marek Rei

Data Science: Principles and Practice

- Introduction and motivation
- Practical basics
- Ourse logistics

What is Data Science?



Data Processing

crawling cleaning connecting



Statistics

measuring analyzing exploring



Machine Learning

modeling predicting simulating



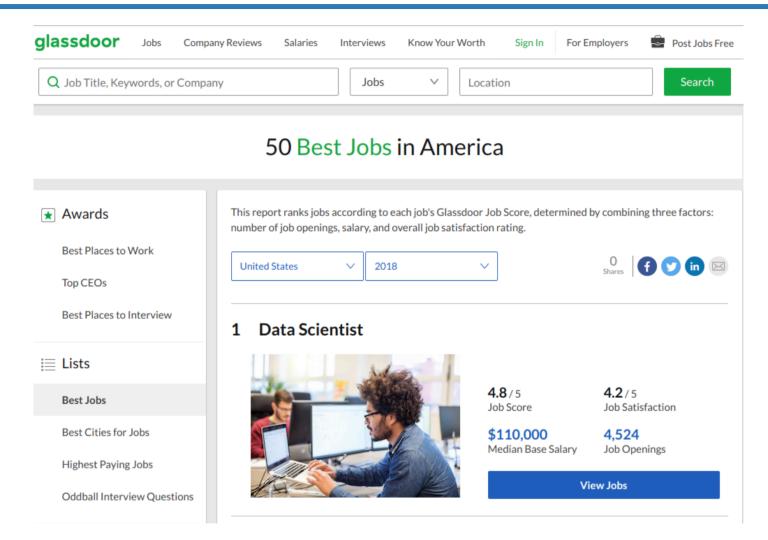
Visualization

investigating structuring presenting



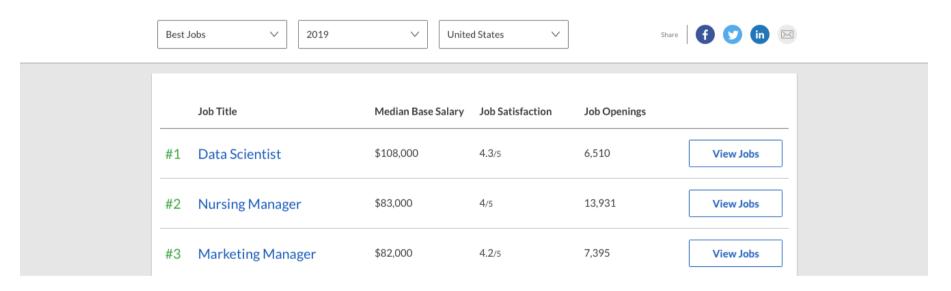
Big Data

processing parallelizing optimizing





50 Best Jobs in America for 2019





hen Jonathan Goldman arrived for work in June 2006 at LinkedIn, the business networking site, the place still felt like a start-up. The company had just under 8 million accounts, and the number was growing quickly as existing members invited their friends and colleagues to join. But users weren't seeking out connections with the people who were already on the site at the rate executives had expected. Something was apparently missing in the social experience. As one LinkedIn manager put it, "It was like arriving at a conference reception and realizing you don't know anyone. So you just stand in the corner signing your drink, and you probably leave early."

October 2012 Issue

Harvard
Business
Review

FROM THE OCTOBER 2012 ISSUE

Regulating the internet giants

The world's most valuable resource is no longer oil, but data

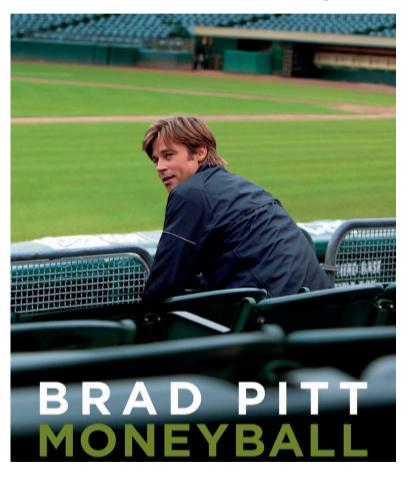
The data economy demands a new approach to antitrust rules



Case studies

- 01 Sports
- 02 Medicine
- 03 Politics

Data Science in Sports



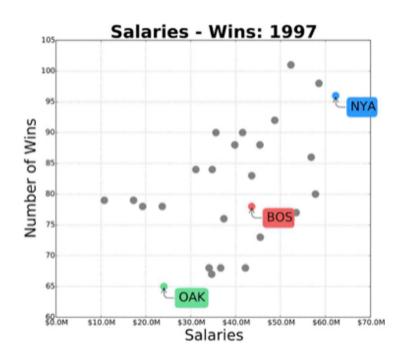
The market for baseball players was so inefficient... that superior management could run circles around taller piles of cash.

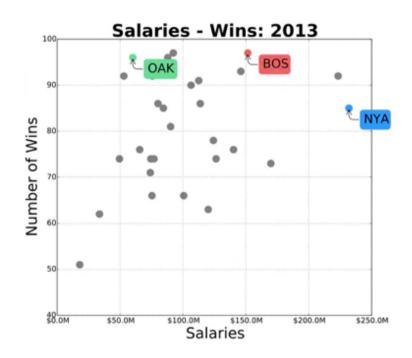
- Michael Lewis

Legendary 2002 season for Oakland Athletics.

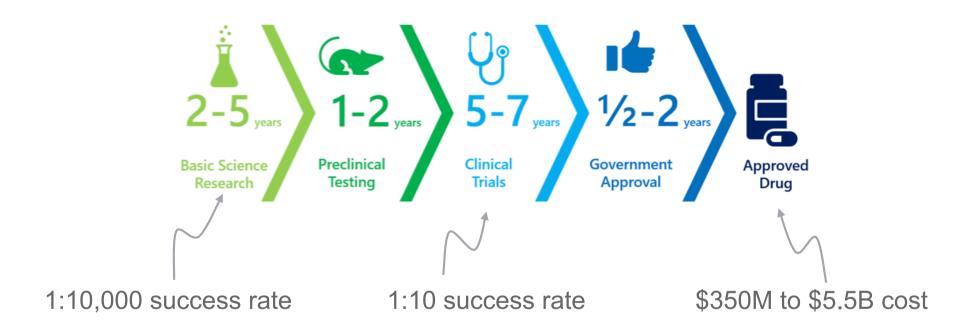
Manager Billy Beane put together an unexpected team using data science.

Data Science in Sports

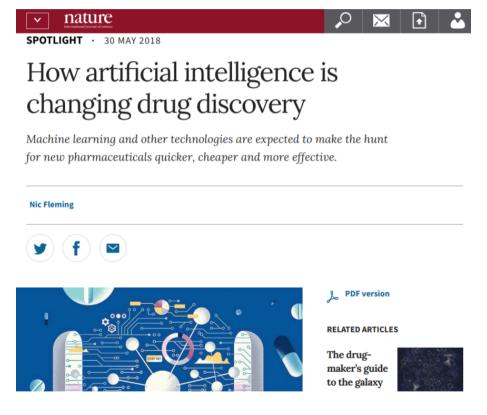


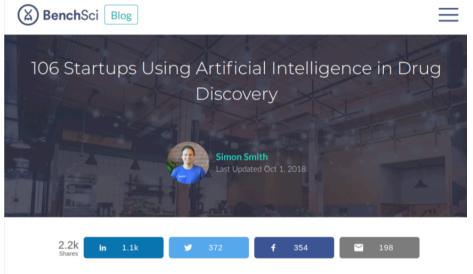


Data Science in Drug Discovery



Data Science in Drug Discovery





Some time ago, I wrote about how we're now in the long-tail of machine learning in drug discovery. I noted that we're moving past generalist applications of AI such as IBM Watson's to more specific, purpose-built tools. This got me thinking: What *are* all the startups applying artificial intelligence in drug discovery

FiveThirtyEight



Politics

Sports

Science & Health

Economics

Culture

NOV. 4. 2008. AT 6:16 PM

Today's Polls and Final Election Projection: Obama 349, McCain 189

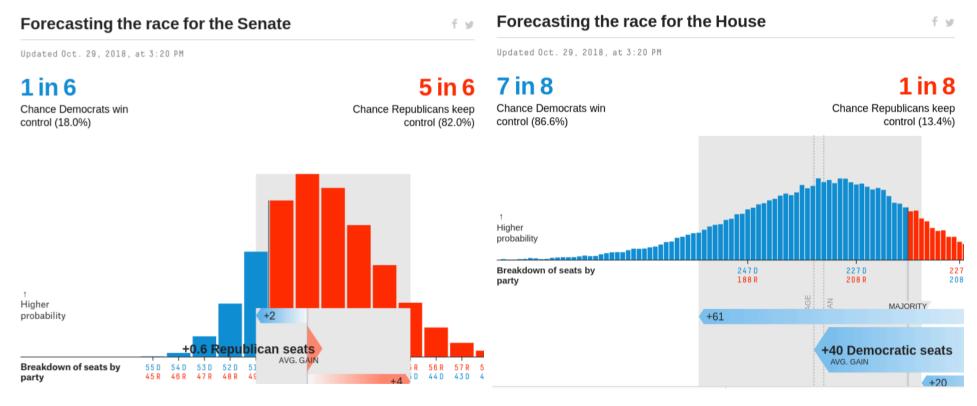
By Nate Silver



It's Tuesday, November 4th, 2008, Election Day in America. The last polls have straggled in, and show little sign of mercy for John McCain. Barack Obama appears poised for a decisive electoral victory.

Our model projects that Obama will win all states won by John Kerry in 2004, in addition to Iowa, New Mexico, Colorado, Ohio, Virginia, Nevada, Florida and North Carolina, while narrowly losing Missouri

Data Science in Politics



FiveThirtyEight



PA

We're forecasting the election with three models

O Polls-plus forecast What polls, the economy and historical data tell us about Nov. 8

O Polls-only forecast

What polls alone tell us about Nov. 8

O Now-cast

Who would win the election if it. were held today

National overview

Updates

National polls

States to watch

Colorado

Florida.

Georgia

lowa

Who will win the presidency?

SD

KS

CO



Chance of winning



OR

CA

NV

ΑZ







Arizona

https://projects.fivethirtyeight.com/2016-election-forecast/

Data Science in Commerce



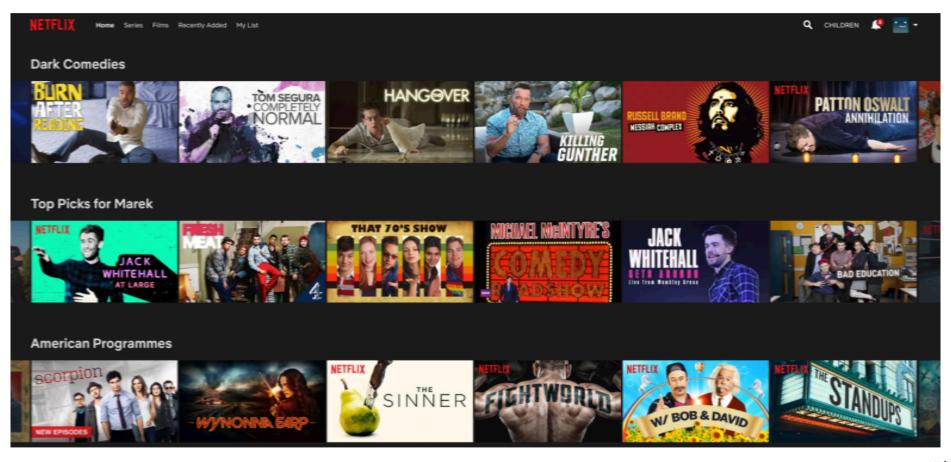


Pick of the day See all >





Data Science in Commerce



Netflix Challenge



In 2006, Netflix offered 1 million dollars for an improved movie recommendation algorithm.

Provided 100M movie ratings for training.

The goal: Improve over Netflix's own algorithm by 10% to get the prize.

Several teams joined up and claimed the prize on in 2009.

movie	user	date	score
1	56	2004-02-14	5
1	25363	2004-03-01	3
2	855321	2004-07-29	3
2	44562	2004-07-30	4
3	42357	2004-12-10	1
3	1345	2005-01-08	2

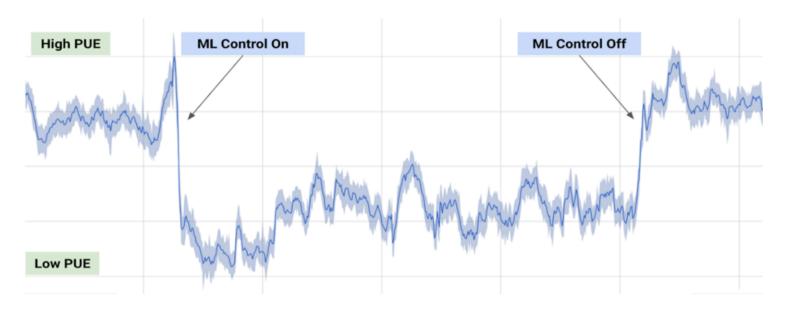
How Data Science can help solve Climate Change

Data-driven solutions will lead the Transition to Clean Energy

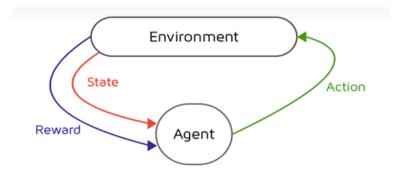




Photo by Bogdan Pasca on Unsplash

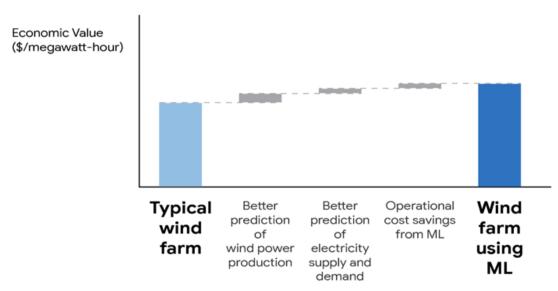


Our machine learning system was able to consistently achieve a 40 percent reduction in the amount of energy used for cooling, which equates to a 15 percent reduction in overall PUE overhead after accounting for electrical losses and other non-cooling inefficiencies. It also produced the lowest PUE the site had ever seen.



A number of **recent studies** propose Reinforcement Learning (RL, a branch of machine learning in which an **agent** interacts with an **environment**, becoming progressively better at a specified **goal** defined by a reward function) as the solution: applying this kind of algorithm to increase efficiency of different buildings shows incredible and **promising results**, with **up to 70%** (!!!) **reduction** in HVAC energy usage (source).

Machine learning can increase the value of wind energy



Illustrative results from 2018 Google/DeepMind field study

Getting Practical

Dataset: Country Statistics

World Bank data about 161 countries

- Country Name
- GDP per Capita (PPP USD)
- Population Density (persons per sq km)
- Population Growth Rate (%)
- Urban Population (%)
- Life Expectancy at Birth (avg years)
- Fertility Rate (births per woman)
- Infant Mortality (deaths per 1000 births)
- Enrolment Rate, Tertiary (%)
- Unemployment, Total (%)
- Estimated Control of Corruption (scale -2.5 to 2.5)
- Estimated Government Effectiveness (scale -2.5 to 2.5)
- Internet Users (%)

Dataset: Country Statistics

```
Country Name, GDP per Capita (PPP USD), Population Density (persons per sq km), Population Growth Rate (%), Urban
Population (%), Life Expectancy at Birth (avg years), Fertility Rate (births per woman), Infant Mortality (deaths
per 1000 births), "Enrolment Rate, Tertiary (%)", "Unemployment, Total (%)", Estimated Control of Corruption (scale
-2.5 to 2.5), Estimated Government Effectiveness (scale -2.5 to 2.5), Internet Users (%)
Afghanistan, 1560.67, 44.62, 2.44, 23.86, 60.07, 5.39, 71, 3.33, 8.5, -1.41, -1.4, 5.45
Albania, 9403.43, 115.11, 0.26, 54.45, 77.16, 1.75, 15, 54.85, 14.2, -0.72, -0.28, 54.66
Algeria.8515.35.15.86.1.89.73.71.70.75.2.83.25.6.31.46.10.-0.54.-0.55.15.23
Antiqua and Barbuda, 19640.35, 200.35, 1.03, 29.87, 75.5, 2.12, 9.2, 14.37, 8.4, 1.29, 0.48, 83.79
Argentina, 12016.2, 14.88, 0.88, 92.64, 75.84, 2.2, 12.7, 74.83, 7.2, -0.49, -0.25, 55.8
Armenia,8416.82,104.08,0.17,64.16,74.33,1.74,14.7,48.94,18.4,-0.62,-0.04,39.16
Australia,44597.83,2.91,1.6,89.34,81.85,1.87,4.1,83.24,5.2,2,1.61,82.35
Austria.43661.15.102.22.0.46.67.88.81.03.1.42.3.3.71.4.3.1.35.1.66.81
Azerbaijan, 10125.23, 110.98, 1.35, 53.89, 70.55, 1.92, 38.5, 19.65, 5.2, -1.13, -0.79, 54.2
Bahrain, 24590.49, 1701.01, 1.92, 88.76, 76.4, 2.12, 8.2, 33.46, 1.1, 0.39, 0.65, 88
Bangladesh, 1883.05, 1174.33, 1.19, 28.89, 69.89, 2.24, 33.1, 13.15, 5, -0.87, -0.83, 6.3
Barbados, 26487.77, 655.36, 0.5, 44.91, 74.97, 1.84, 16.9, 60.84, 11.6, 1.66, 1.45, 73.33
Belgium, 39751.48, 364.85, 0.85, 97.51, 80.49, 1.84, 3.4, 69.26, 7.5, 1.55.1.59.82
Belize,7936.84,13.87,2.43,44.59,73.49,2.74,15.7,21.37,8.2,0.01,-0.18,25
Benin, 1557.16, 86.73, 2.73, 45.56, 58.94, 5.21, 58.5, 12.37, 0.7, -0.92, -0.53, 3.8
Bhutan,6590.69,19,1.68,36.34,67.28,2.32,35.7,8.74,2.1,0.82,0.48,25.43
Bolivia,5195.58,9.53,1.65,67.22,66.63,3.31,39.3,37.69,3.4,-0.7,-0.37,34.19
Bosnia and Herzegovina, 9392.47, 75.28, -0.14, 48.81, 75.96, 1.25, 6.7, 37.74, 28.1, -0.3, -0.47.65.36
Brazil, 11715.7, 23.28, 0.87, 84.87, 73.35, 1.81, 12.9, 25.63, 6.7, -0.07, -0.12, 49.85
Brunei,52482.33,77.14,1.4,76.32,78.07,2.03,6.7,24.34,4.7,0.64,0.83,60.27
Bulgaria, 15932.63,67.69,-0.6,73.64,74.16,1.51,10.5,59.63,11.2,-0.24,0.14,55.15
Burkina Faso, 1512.97, 58.46, 2.86, 27.35, 55.44, 5.78, 65.8, 4.56, 3.3, -0.52, -0.63, 3.73
Burundi .551.27.371.51.3.19.11.21.53.14.6.21.66.9.3.17.0.5.-1.12.-1.33.1.22
Cambodia 2404 20 82 74 1 76 20 10 62 08 2 02 22 0 14 5 0 2 1 04 -0 82 4 04
```

Using Python. Why Python?



Fast to write and modify

Great for working with datasets

Portable

Most machine learning research happens in python

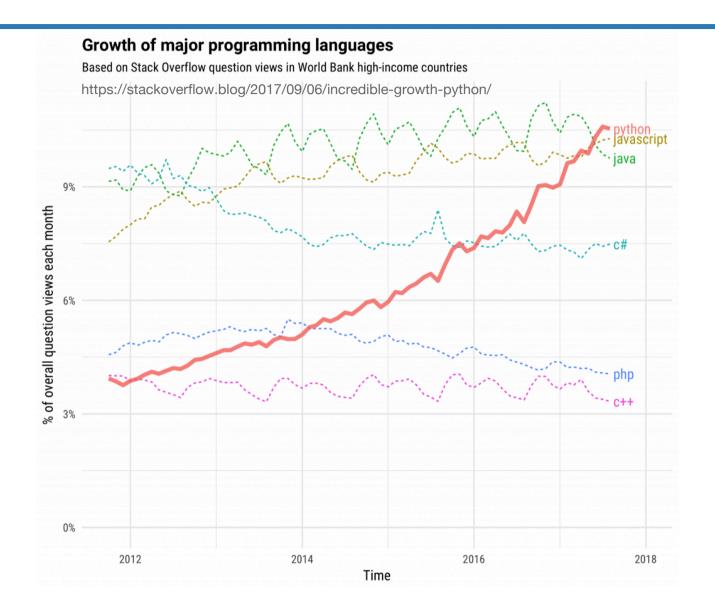
Actually useful for other things besides data science



Dynamically typed (can cause runtime errors)

Not as fast as lower-level languages (sometimes)

Not good for unusual platforms



Python Refresher

```
In [1]: import random

my_list = ["camel", "elephant", "crocodile"]
for word in my_list:
    print(word + " " +str(random.random()))
```

```
camel 0.5333896529549417
elephant 0.8289440919886492
crocodile 0.5635699354595317
```

Python tutorial: https://www.tutorialspoint.com/python/index.htm

Loading CSV files

```
In [2]: import pandas as pd

data = pd.read_csv('data/country-stats.csv')
    data.head()
```

Out[2]:

Country Name	GDP per Capita (PPP USD)	Population Density (persons per sq km)	Population Growth Rate (%)	Urban Population (%)	Life Expectancy at Birth (avg years)	Fertility Rate (births per woman)	Infant Mortality (deaths per 1000 births)
Afghanistan	1560.67	44.62	2.44	23.86	60.07	5.39	71.0
Albania	9403.43	115.11	0.26	54.45	77.16	1.75	15.0
Algeria	8515.35	15.86	1.89	73.71	70.75	2.83	25.6
Antigua and Barbuda	19640.35	200.35	1.03	29.87	75.50	2.12	9.2
Argentina	12016.20	14.88	0.88	92.64	75.84	2.20	12.7
	Afghanistan Albania Algeria Antigua and Barbuda	Country Name Capita (PPP USD) Afghanistan 1560.67 Albania 9403.43 Algeria 8515.35 Antigua and Barbuda 19640.35	Country Name Capita (PPP USD) Density (persons per sq km) Afghanistan 1560.67 44.62 Albania 9403.43 115.11 Algeria 8515.35 15.86 Antigua and 19640.35 200.35 Barbuda	Country Name Capita (PPP USD) Density (persons per sq km) Population Growth Rate (%) Afghanistan 1560.67 44.62 2.44 Albania 9403.43 115.11 0.26 Algeria 8515.35 15.86 1.89 Antigua and Barbuda 19640.35 200.35 1.03	Country Name Capita (PPP USD) Density (persons per sq km) Population Growth Rate (%) Population Population (%) Afghanistan 1560.67 44.62 2.44 23.86 Albania 9403.43 115.11 0.26 54.45 Algeria 8515.35 15.86 1.89 73.71 Antigua and Barbuda 19640.35 200.35 1.03 29.87	Country Name Capita (PPP USD) Density (persons per sq km) Population Growth Rate (%) Population Growth Rate (%) Expectancy at Birth (avg years) Afghanistan 1560.67 44.62 2.44 23.86 60.07 Albania 9403.43 115.11 0.26 54.45 77.16 Algeria 8515.35 15.86 1.89 73.71 70.75 Antigua and Barbuda 19640.35 200.35 1.03 29.87 75.50	Country Name Capita (PPP USD) Population Density (persons per sq km) Population Growth Rate (%) Urban Growth Rate (%) Expectancy at Birth (avg years) Rate (births per woman) Afghanistan 1560.67 44.62 2.44 23.86 60.07 5.39 Albania 9403.43 115.11 0.26 54.45 77.16 1.75 Algeria 8515.35 15.86 1.89 73.71 70.75 2.83 Antigua and Barbuda 19640.35 200.35 1.03 29.87 75.50 2.12

Common File Formats

CSV - comma-separated values

```
Bahrain, 24590.49, 1701.01, 1.92, 88.76, 76.4, 2.12, 8.2, 33.46, 1.1, 0.39, 0.65, 88
Bangladesh, 1883.05, 1174.33, 1.19, 28.89, 69.89, 2.24, 33.1, 13.15, 5, -0.87, -0.83, 6.3
Barbados, 26487.77, 655.36, 0.5, 44.91, 74.97, 1.84, 16.9, 60.84, 11.6, 1.66, 1.45, 73.33
Belgium, 39751.48, 364.85, 0.85, 97.51, 80.49, 1.84, 3.4, 69.26, 7.5, 1.55, 1.59, 82
```

TSV - tab-separated values

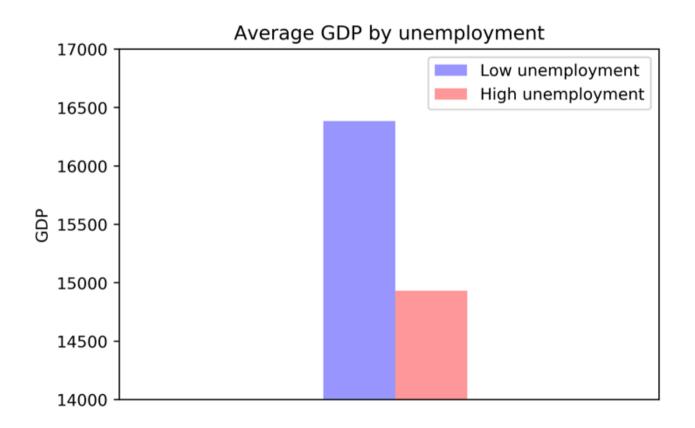
Bahrain	24590.49	1701.01	1.92	88.76	76.4	2.12	8.2	33.46
Bangladesh	1883.05	1174.33	1.19	28.89	69.89	2.24	33.	1 13.15
Barbados	26487.77	655.36	0.5	44.91	74.97	1.84	16.9	60.84
Belaium	39751.48	364.85	0.85	97.51	80.49	1.84	3.4	69.26

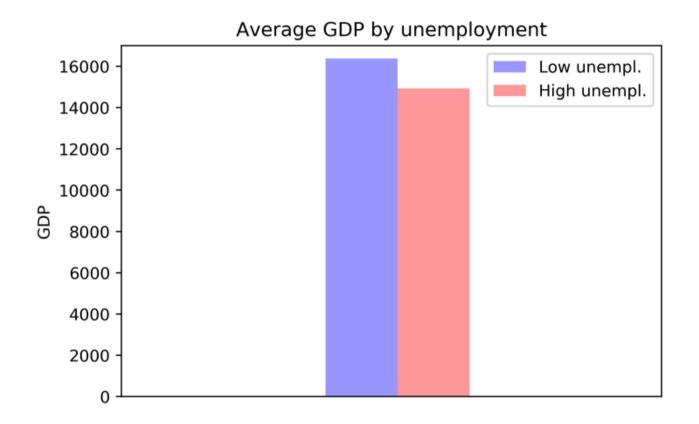
Common File Formats

JSON: JavaScript Object Notation

```
{
    "firstName": "John",
    "lastName": "Smith",
    "isAlive": true,
    "age": 27,
    "address": {
        "streetAddress": "21 2nd Street",
        "city": "New York",
        "state": "NY",
        "postalCode": "10021-3100"
    }
}
```

XML: Extensible Markup Language



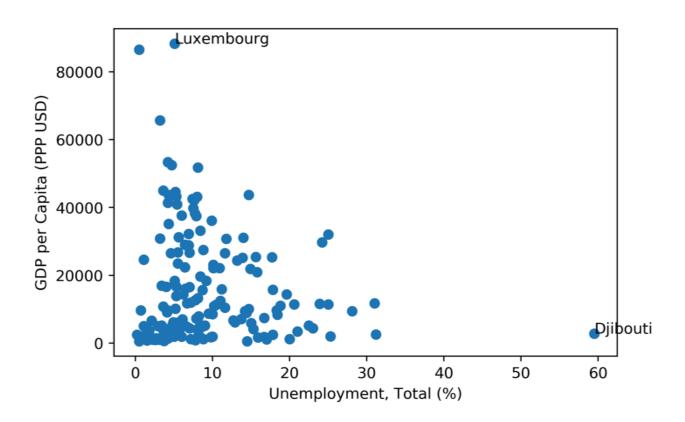


```
In [9]: low_unemployment_countries = data[data["Unemployment, Total (%)"] < 7]
    low_unemployment_countries["GDP per Capita (PPP USD)"].std()

Out[9]: 19752.912647780504

In [10]: high_unemployment_countries = data[data["Unemployment, Total (%)"] >= 7]
    high_unemployment_countries["GDP per Capita (PPP USD)"].std()

Out[10]: 12781.059320722152
```



Course Logistics

Course Objectives

Focusing on the practical aspects of data science

After this course you should be able to

- 1. Understand the principles of data science
- 2. Use the necessary software tools for data processing, statistics and machine learning
- 3. Visualize data, both for exploration and presentation
- 4. Rigorously analyze your data using a variety of approaches

Course Format

10 lectures

6 practicals

Assessment

- 20% from practicals (pass/fail)
- 80% from take-home assignment

Final assignment

- Practical exercise
- Given out after the lecture on 25 November
- Submit a report
- The report will be marked by two assessors

Course Syllabus

1. Introduction	Friday, 8 November
2. Linear Regression	Monday, 11 November
3. Practical1: Linear Regression	Tuesday, 12 November
4. Classification	Wednesday, 13 November
5. Practical2: Classification	Thursday, 14 November
6. Ensemble-based models	Monday, 18 November
7. Practical3: Ensemble models	Tuesday, 19 November
8. Visualization, part I	Wednesday, 20 November

Course Syllabus

9. Visualization, part II	Friday, 22 November		
10. Deep Learning basics	Monday, 25 November		
11. Practical4: Visualization	Tuesday, 26 November		
12. Deep Learning with TensorFlow	Wednesday, 27 November		
13. Practical5: Deep Learning I	Thursday, 28 November		
14. Deep Learning architectures	Friday, 29 November		
15. Challenges in Data Science	Monday, 2 December		
16. Practical6: Deep Learning II	Tuesday, 3 December		

Lecturers



Ekaterina Kochmar ek358



Guy Emerson gete2



Damon Wischik djw1005

Course Pages

Course homepage: https://www.cl.cam.ac.uk/teaching/1920/DataScill/

Azure Notebooks: https://notebooks.azure.com/ek358/projects/data-science-pnp-1920

Getting started with Azure Notebooks: https://notebooks.azure.com/ek358/projects/data-science-pnp-1920/getting-started.ipynb

Github: https://github.com/ekochmar/cl-datasci-pnp

