

CS 260: Foundations of Data Science

Prof. Sara Mathieson

Fall 2021



HVERFORD
COLLEGE

Welcome!

- If you are **enrolled or on the waitlist**, please sign in (sheet going around)
 - If not, you should not be here!
- Please fill out a **notecard**
- Let me know if you can't access **Piazza**

Outline for Aug 31

- Preliminaries
- Examples of Data Science and learning from data
- Syllabus highlights
- Python for this course
 - Numpy
 - Matplotlib

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Course Staff

- Instructor: Sara Mathieson (can call me Sara or Professor Mathieson)
- Teaching Assistants: Trang, Nasa, Yuxuan
- Class introductions: will do during class or lab on Thursday

Covid-related issues

- Mask should be worn at all times during class
 - Over both nose and mouth
- We will have a 5min water break each class
 - But of course feel free to leave the room whenever you need to
- If you feel ill at all, please stay home!
 - Email me for any absences
 - Slides/notes will be available

Note-taking

- I will post slides and board photos after every class
- In addition, we have about the right number of people for everyone to take notes once
- Required part of the course, counts toward participation
- Volunteer for today?

There will (hopefully!) be a baby

- I am due around Thanksgiving
- Few weeks before Thanksgiving may be over Zoom
- Prof. Farias will be taking over the course around Thanksgiving
- You can all vote on the name later on 😊

Discuss with a Partner

- Introduce yourselves
- Come up with your own definition of “Data Science”
- What are some examples of Data Science that you have encountered or would like to encounter?

* trends in data

* real-world applications

- climate change (Lab 2)

* prediction from data

- bionic ★

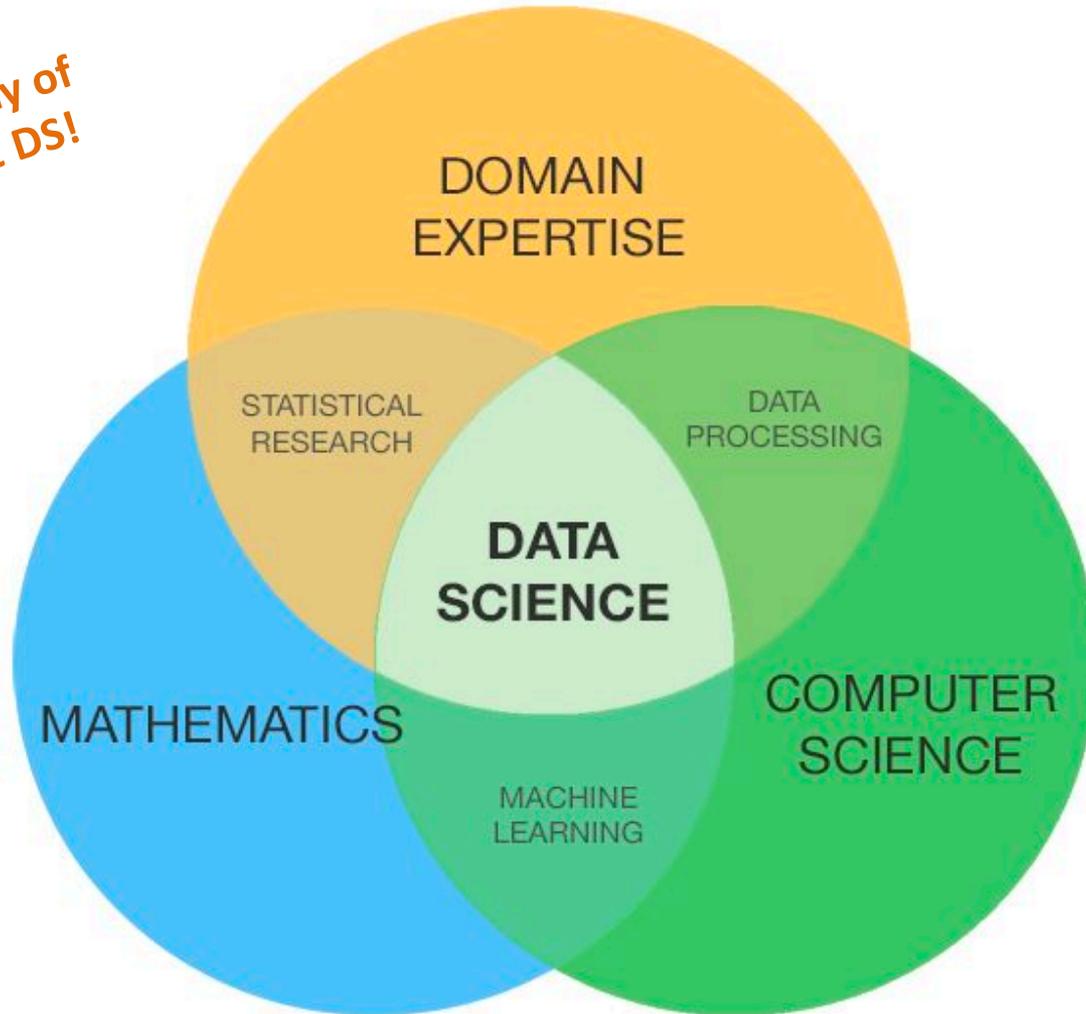
- social media

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Data Science Venn Diagrams

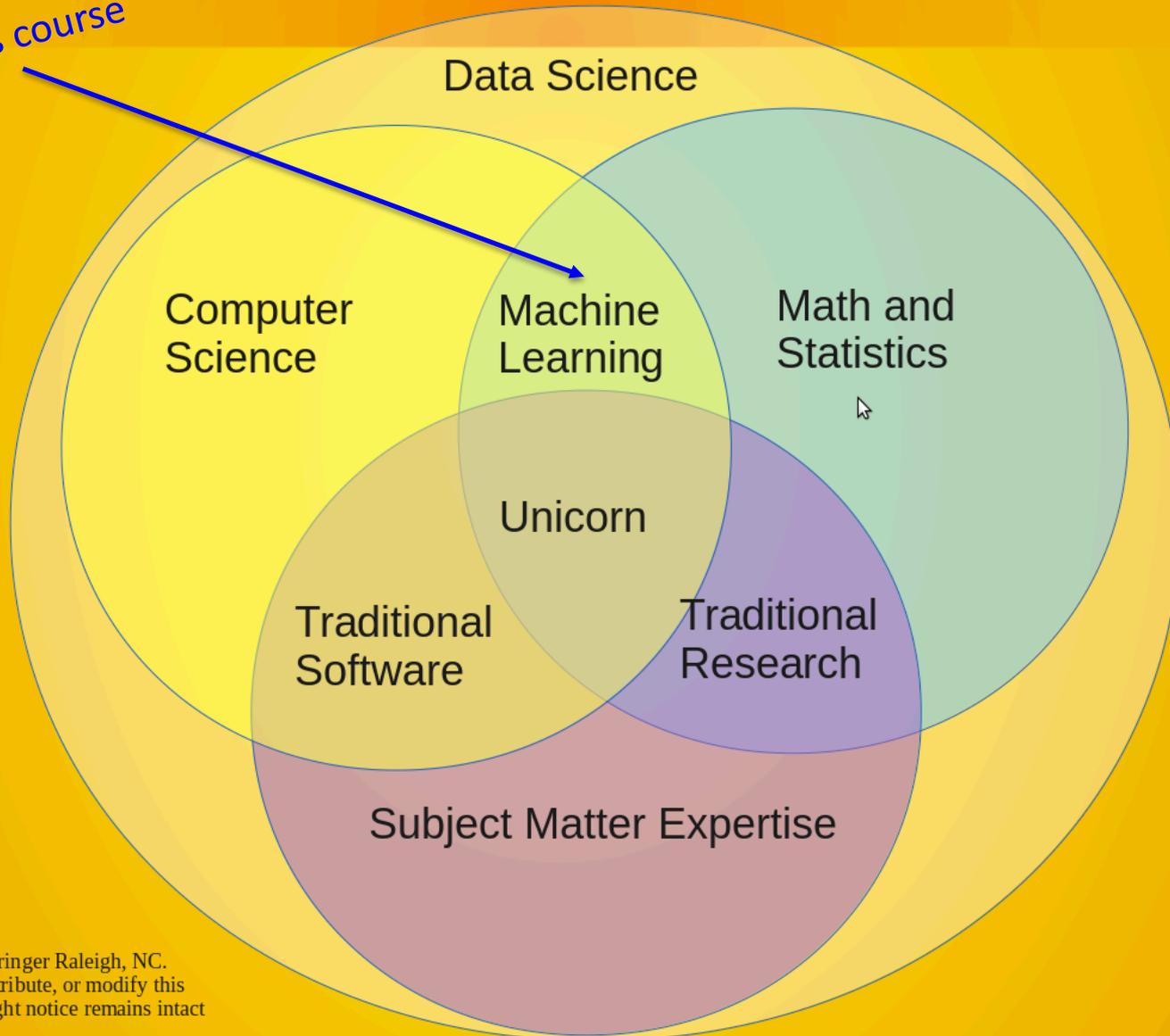
Not the only way of
thinking about DS!



Source: Palmer, Shelly. *Data Science for the C-Suite*.
New York: Digital Living Press, 2015. Print.

Data Science Venn Diagram v2.0

Focus for this course



KEY COMPETENCIES FOR AN UNDERGRADUATE DATA SCIENCE STUDENT

- Computational and statistical thinking
- Mathematical foundations
- Model building and assessment
- Algorithms and software foundation
- Data curation
- Knowledge transference—communication and responsibility

CS260 is not an entry level DS course

- “Math for Machine Learning”
- Meant to prepare students for 300-level data-oriented courses
 - Machine Learning (CS360)
 - Computational Linguistics (CS325)
 - Computer Vision
 - Computational Biology
- Most of these are in Python so we will also cover advanced Python topics and libraries

“Data Wrangling”



Featurization

Age	Category
54	
13	
27	
21	
72	
17	

Continuous

Discrete

Featurization

Age	Category
54	Adult
13	Minor
27	Adult
21	Adult
72	Senior
17	Minor

Continuous



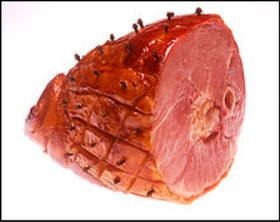
Discrete



Learning from data: classification

- Email filtering (spam vs. not-spam)

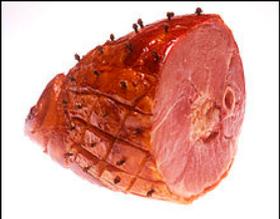


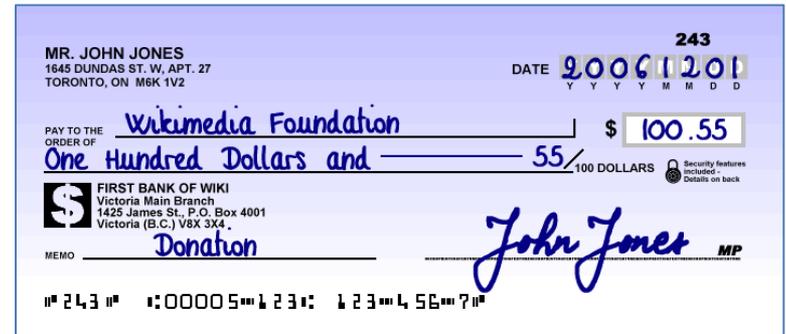
<p>From: cheapsales@buystufffromme.com To: ang@cs.stanford.edu Subject: Buy now!</p> <p>Deal of the week! Buy now! Rolex w4tchs - \$100 <u>Medicine</u> (any kind) - \$50 Also low cost M0rgages available.</p>	<p>From: Alfred Ng To: ang@cs.stanford.edu Subject: Christmas dates?</p> <p>Hey Andrew, Was talking to Mom about plans for Xmas. When do you get off work. Meet Dec 22? Alf</p>
	

Learning from data: classification

- Email filtering (spam vs. not-spam)

↓

<p>From: cheapsales@buystufffromme.com To: ang@cs.stanford.edu Subject: Buy now!</p> <p>Deal of the week! Buy now! Rolex w4tchs - \$100 Medicine (any kind) - \$50 Also low cost M0rgages available.</p> 	<p>From: Alfred Ng To: ang@cs.stanford.edu Subject: Christmas dates?</p> <p>Hey Andrew, Was talking to Mom about plans for Xmas. When do you get off work. Meet Dec 22? Alf</p> 
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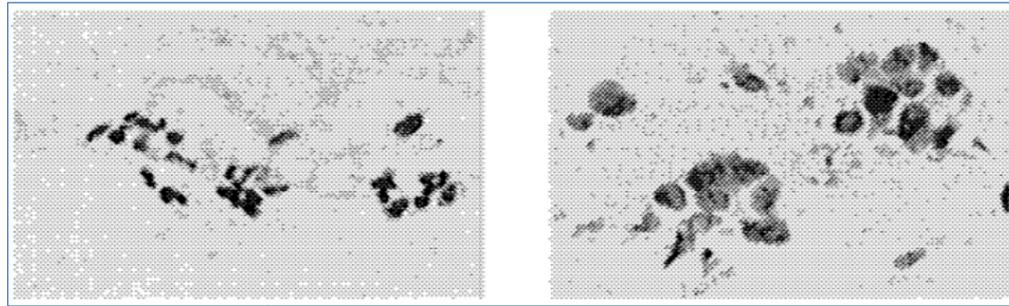
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⑈ 243 ⑈ ⑆ 00005 ⑆ 123 ⑆ 123 ⑆ 456 ⑆ 7 ⑈

- Handwriting recognition (digits in a check)

Learning from data: classification



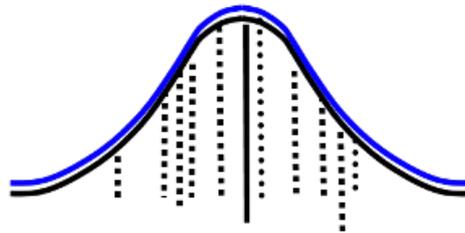
- Tumor detection (benign vs. malignant)

Statistical Tests

Do smokers weigh the same as non-smokers?

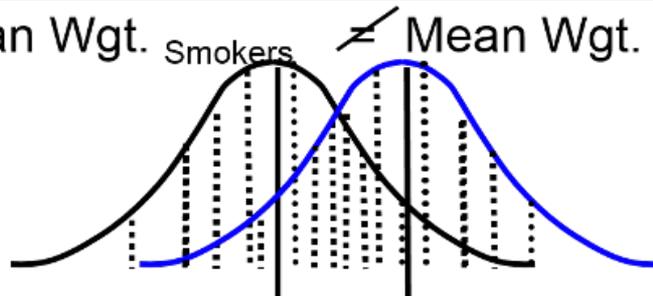
Null Hypothesis (H_0): the average weight does not differ

H_0 : Mean Wgt. smokers = Mean Wgt. Non-smokers

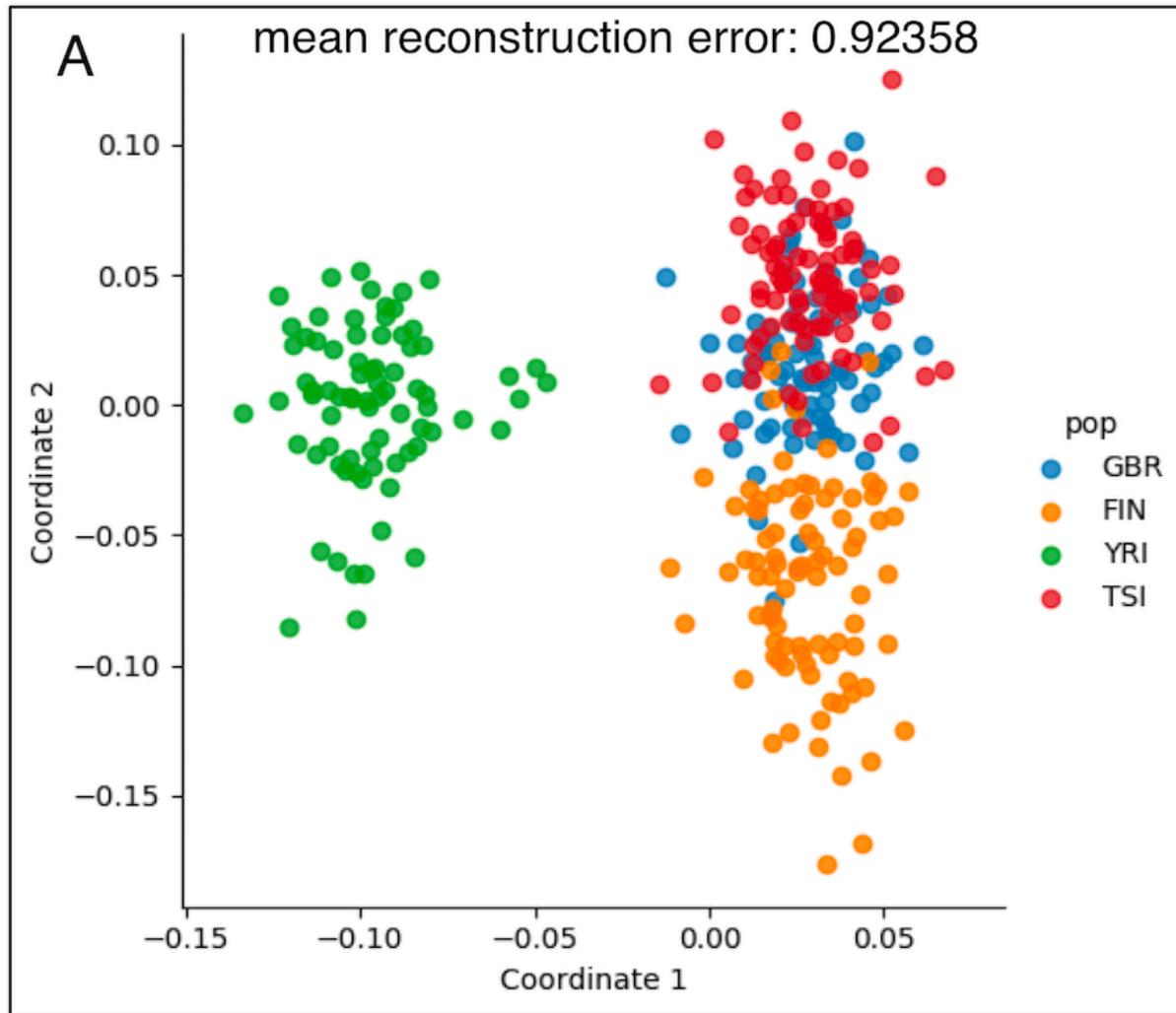


Alternative Hypothesis (H_A): the average weights differ

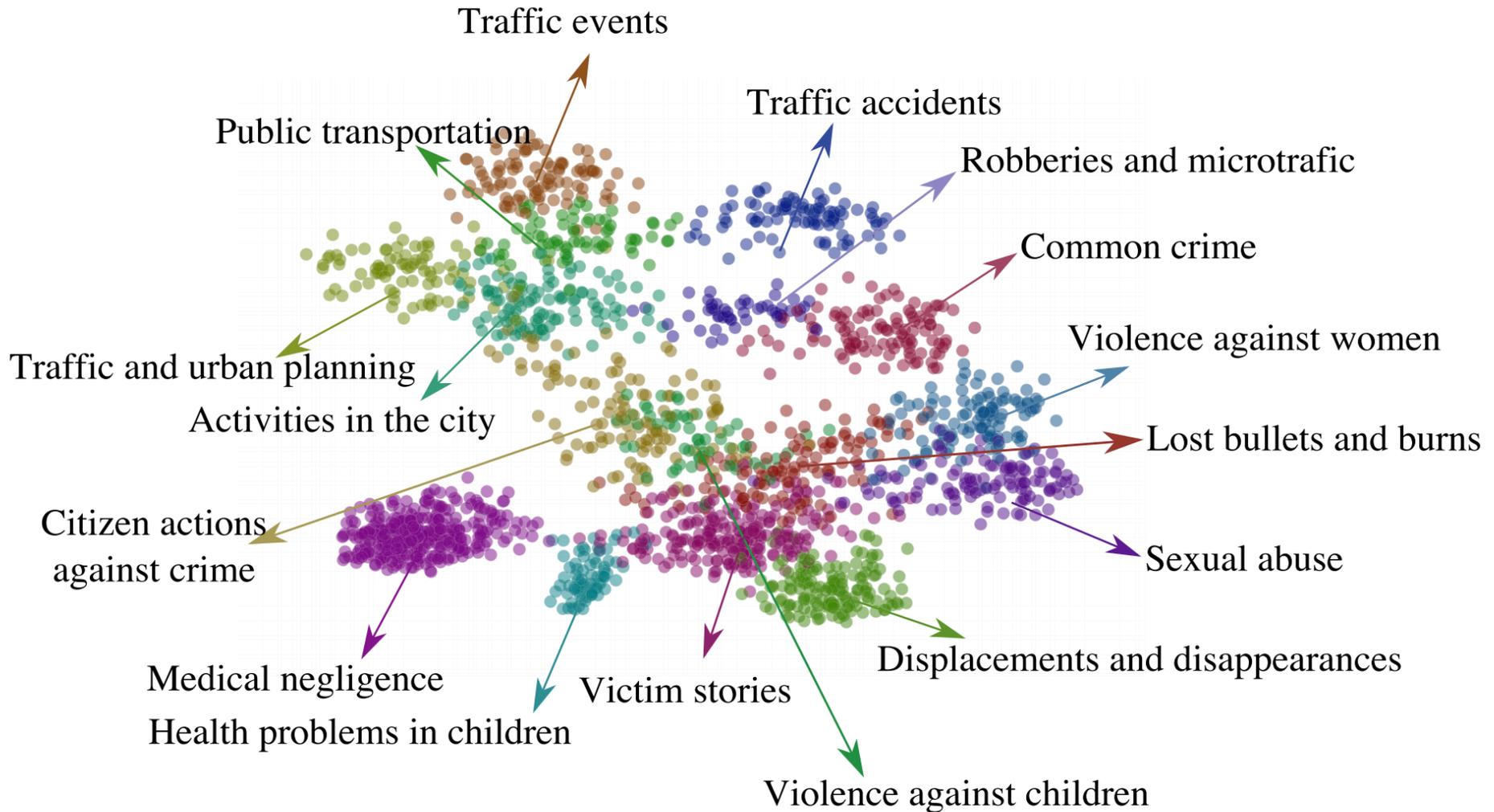
H_A : Mean Wgt. Smokers \neq Mean Wgt. Non-smokers



Data Visualization



Clustering Data

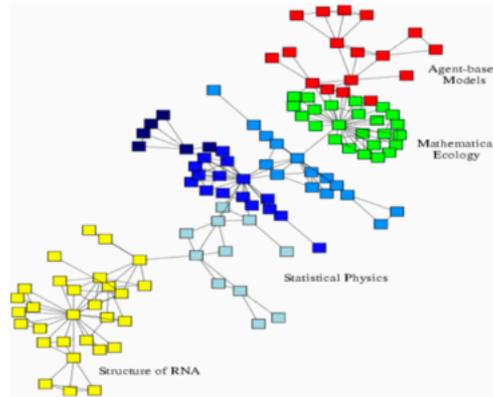


“Event detection in Colombian security Twitter news using fine-grained latent topic analysis”,
Vargas-Calderon *et al* (2019)

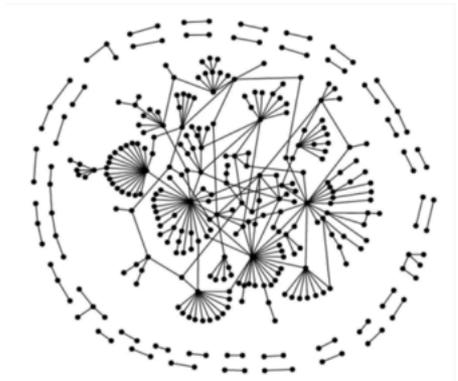
Learning from data: networks



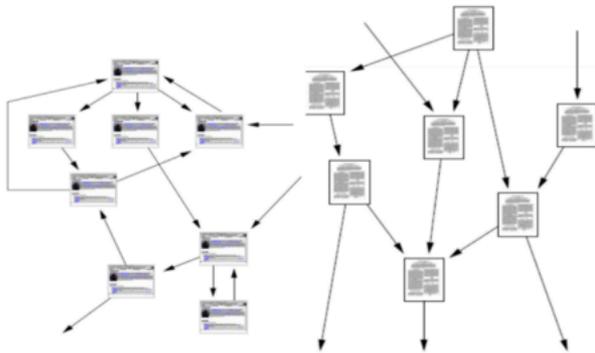
Social networks



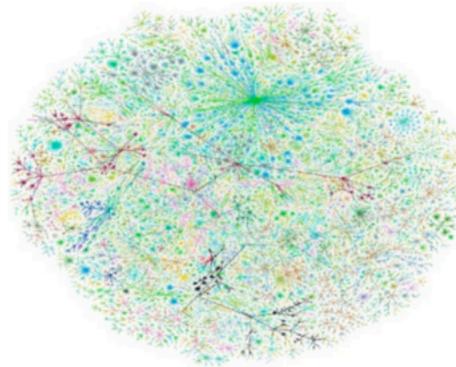
Economic networks



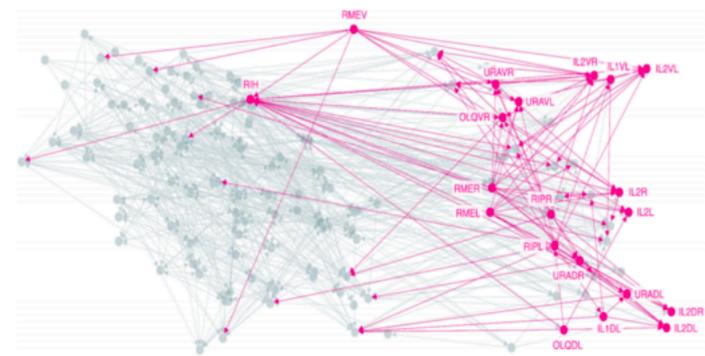
Biomedical networks



Information networks:
Web & citations



Internet



Networks of neurons

Natural Language Examples

- Text Classification
- Language Modeling
- Speech Recognition
- Caption Generation
- Machine Translation
- Document Summarization
- Question Answering

Machine reading comprehension

*Q: What was the theme?
A: "one world, one dream".*

*Q: What was the length of the race?
A: 137,000 km*

*Q: Was it larger than previous ones?
A: No*

*Q: Where did the race begin?
A: Olympia, Greece*

*Q: Is there anything notable about that place?
A: birthplace of Olympic Games*

*Q: Where did they go after?
A: Athens*

*Q: How many days was the race?
A: seven*

*Q: Did they visit any notable landmarks?
A: Panathinaiko Stadium*

*Q: And did they climb any mountains?
A:*

Target answers: *unknown or yes*

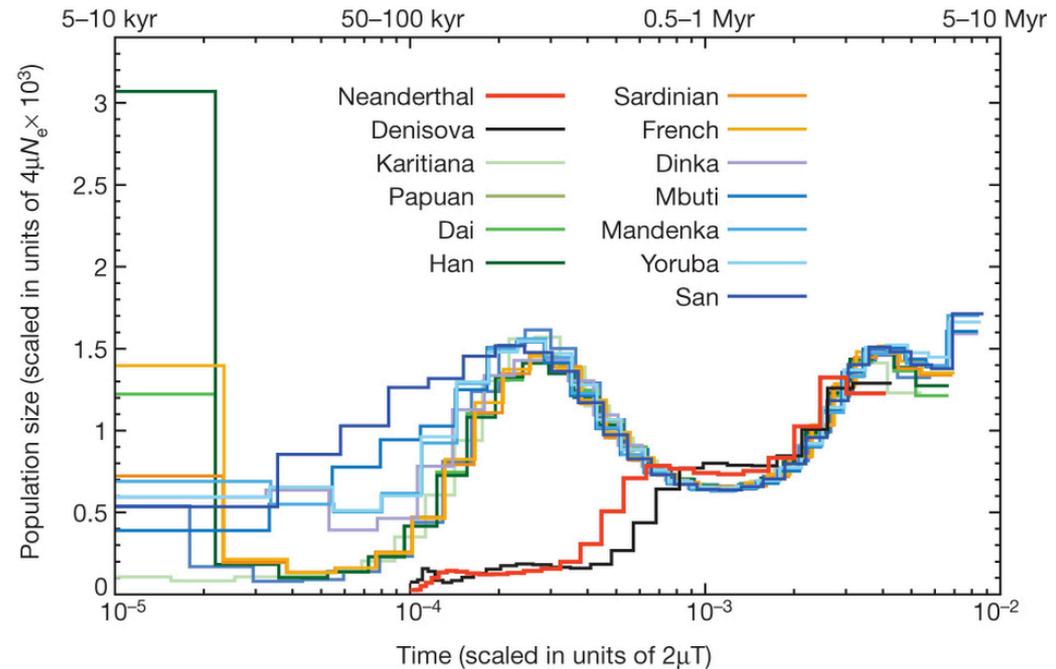
Model answer: Everest

<https://openai.com/blog/better-language-models/>

Biology examples

- Identify genes associated with disease
- Protein structure prediction
- Genes under natural selection
- Protein binding site prediction

- Population size changes

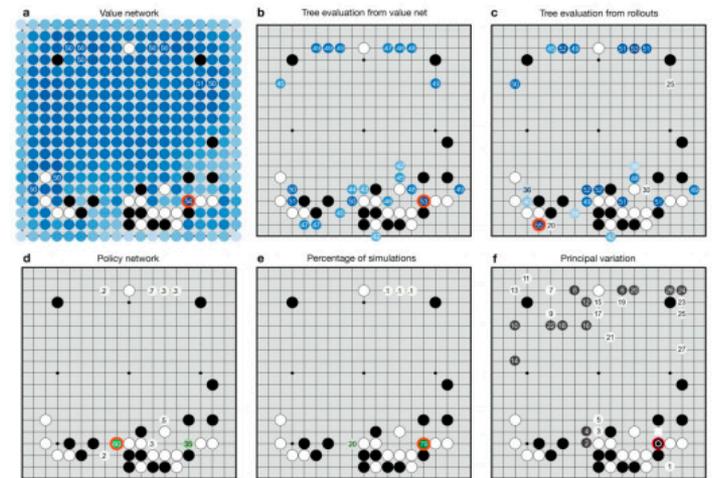


Modern Machine Learning examples



Self-driving cars are in our present and future

AlphaGo: moves humans never thought of



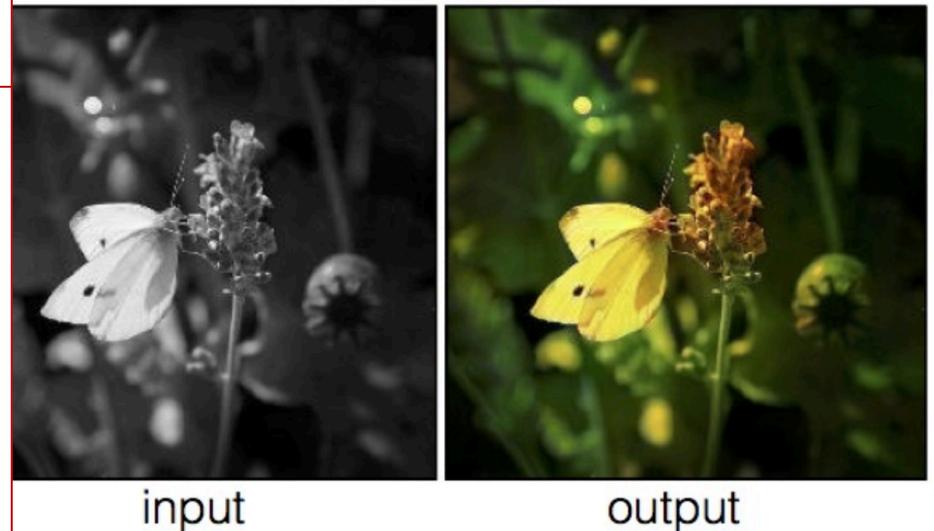
Modern Machine Learning examples

Edges to Photo



- Algorithms that learn how to create

BW to Color



[Image-to-Image Translation with Conditional Adversarial Nets \(Nov 2016\)](#)

Generative Models



Ian Goodfellow

@goodfellow_ian

Follow



4.5 years of GAN progress on face generation. arxiv.org/abs/1406.2661
arxiv.org/abs/1511.06434
arxiv.org/abs/1606.07536
arxiv.org/abs/1710.10196
arxiv.org/abs/1812.04948



4:40 PM - 14 Jan 2019

Generative models have also been used to create synthetic genomic data to maintain privacy

Ethics and Responsible use of Data

- Based on huge quantities of data, algorithms decide what you see online
 - Search results
 - Targeted ads
 - Newsfeed content
 - Removal of problematic content
- Even if data is “cleaned” to remove protected features (e.g. race, sex), these can be redundantly encoded

We must join the conversation

“When human beings acquired language, we learned not just how to listen but how to speak. When we gained literacy, we learned not just how to read but how to write. And as we move into an increasingly digital reality, we must learn not just how to use programs but how to make them.”

-Douglas Rushkoff

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Weekly schedule

	Week n	Week n+1	
	Sun	Sun	
Lab n posted	Mon	Mon	
	Tues	Tues	Lab n due Lab n+1 posted
Read and begin lab	Wed	Wed	
Ask questions in lab	Thurs	Thurs	
	Fri	Fri	
	Sat	Sat	

Class meetings (start at 10:05am, end at 11:25am)

Lab (Thursdays 12-1pm and 1-2pm)

- Lab attendance is required! Please email me if you will be missing lab
- Usually give a short introduction to everyone
- Occasionally pair-programming or warm-up exercises
- I will check in with everyone and answer questions individually or in groups

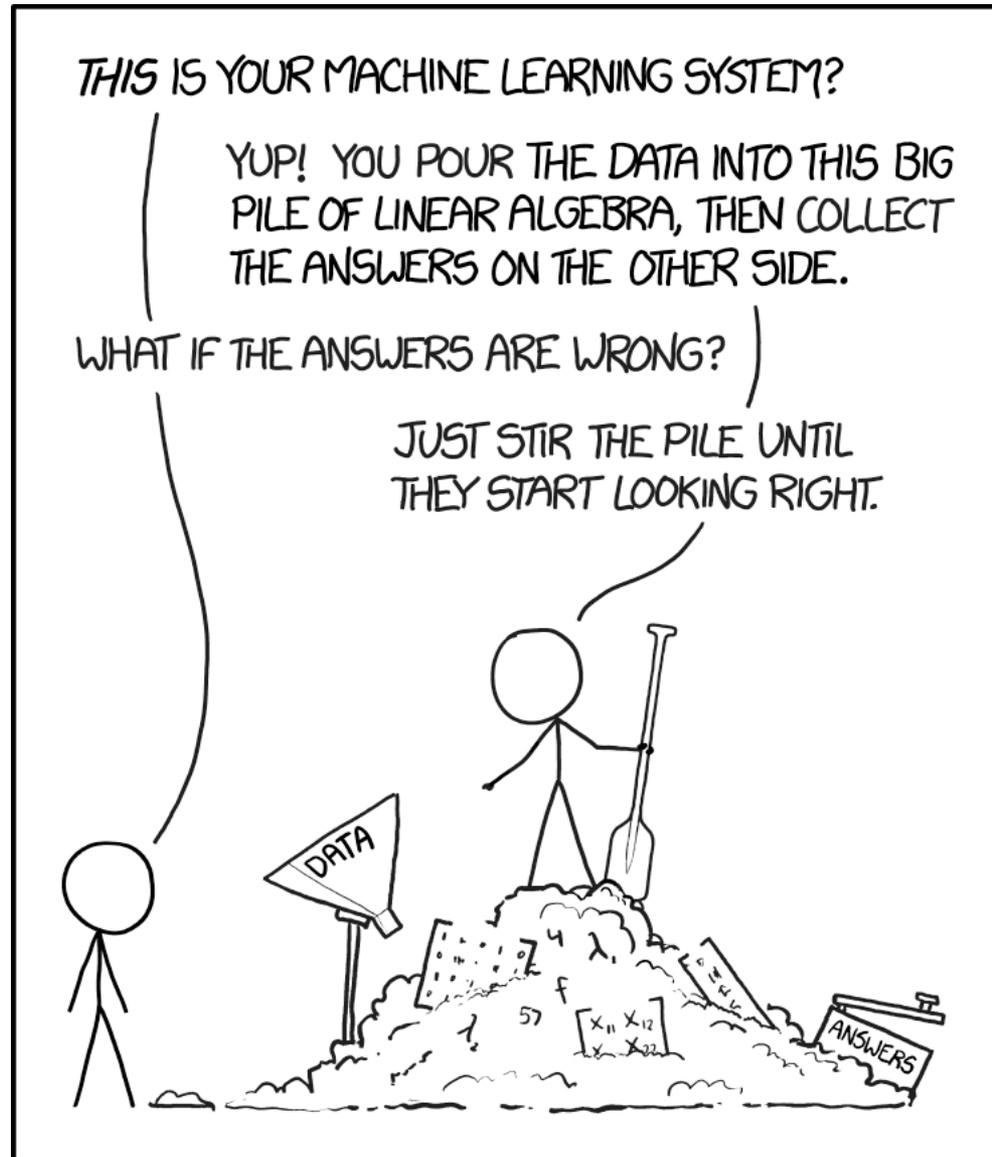
Learning Goals

- Understand how algorithms make **decisions based on data**
- Understand the **theoretical foundations of DS**
 - applied linear algebra, probability, statistics, modeling information theory, and optimization
- Be able to **implement** the theory and **apply** it to a variety of domains
- Analyze the **ethical use of data** and weigh tradeoffs in data collection and usage
- Understand and apply best practices in **data visualization**
- Throughout and during the **project**: hypothesis development, featurization, algorithm selection, interpretation of results, iteration, conclusions
- Comfort with using **advanced Python topics** such as libraries and object-oriented design

Topics (tentative)

- Representing data
- Common Python libraries
- Object-oriented Python
- Modeling
- Linear models
- Applied linear algebra
- Optimization
- Gradient descent
- Confusion matrices
- ROC curves
- Probabilistic modeling
- Naïve Bayes algorithm
- Ethics and protected features
- Information theory
- Data visualization
- Dimensionality reduction
- Clustering
- Introduction to statistics
- Hypothesis testing

There will be math!



Different Backgrounds

- Prerequisites: Data Structures, Discrete Math (co-req), Calculus I
- May or may not have statistics, probability, linear algebra, etc
- Class roster spans first-year through senior

Readings

- We will draw upon three online textbooks
- As well as supplemental online readings and research papers

Textbook:

You do not need to purchase a textbook for this course. We will draw from several online textbooks, as well as supplemental online readings and research papers.

- **Model-Based Machine Learning** by John Winn ("Winn" in schedule below)
 - **Mathematics for Machine Learning** by Deisenroth, Faisal, and Ong ("MML" in schedule below)
 - **A Course in Machine Learning** by Hal Duane III ("Duane" in schedule below)
 - (optional) **Visualization Analysis and Design** by Tamara Munzner
-

Course Components

- Labs (8 total): 35%
- Midterms: 40% (20% each)
- Final project: 15%
 - includes an oral presentation and “lab notebook”
- Participation: 10%
 - includes attendance, Piazza, note-taking, and general engagement with the course

My Expectations

- Come to class (Tu/Thurs) and lab (Th), **ON TIME**, and actively participate
 - Email me if you will be absent from class or lab
- Complete reading before lab on Thursday (some is technical, do your best)
- Come to office hours and TA hours. **My office hours: Tuesday 4-5:30pm in H204**
- Post questions on Piazza

WEEK	DAY	ANNOUNCEMENTS	TOPIC & READING	LABS
1	Aug 31		Introduction to Data Science and Python <ul style="list-style-type: none">• What can we learn from data?• Representing data• Crash course on Python• Numpy• Matplotlib (plotting in Python)• Classes and objects in Python• Dictionaries	Lab 1: Computing and plotting in Python
	Sep 02		Reading: <ul style="list-style-type: none">• MML Chap 1	

Syllabus Notes

(Note: you are responsible for reading the entire syllabus on the course webpage)

1. Notes and slides will be posted *after* class on the course webpage
2. Lab is **mandatory** (attendance will be taken)
3. Labs may have an optional **pair programming** component
4. You will get **4 late days** during the semester (up to 2 on any one assignment)
5. Extensions beyond these two days must be arranged with your **class dean**
6. **Email**: allow 24 hours for a response (more during weekends)
7. **Piazza**: should be used for all content/logistics questions

Participation

What counts as participation?

- Asking and answering questions in class (very important!)
 - Will call on groups, but only after giving you a few minutes to think/discuss
- Actively participating in in-class activities (group work, handouts, polls)
- Collaborating with your lab partner for any pair-programming exercises
- Note-taking on your assigned day
- Asking and answering questions on Piazza
 - Avoid long blocks of code and giving away answers
 - Only non-anonymous posts count toward participation grade
- Attending office hours and TA hours

Academic Integrity

Faculty statement on academic integrity

In a community that thrives on relationships between students and faculty that are based on trust and respect, it is crucial that students understand a professor's expectations and what it means to do academic work with integrity. Plagiarism and cheating, even if unintentional, undermine the values of the **Honor Code** and the ability of all students to benefit from the academic freedom and relationships of trust the Code facilitates. Plagiarism is using someone else's work or ideas and presenting them as your own without attribution. Plagiarism can also occur in more subtle forms, such as inadequate paraphrasing, failure to cite another person's idea even if not directly quoted, failure to attribute the synthesis of various sources in a review article to that author, or accidental incorporation of another's words into your own paper as a result of careless note-taking. Cheating is another form of academic dishonesty, and it includes not only copying, but also inappropriate collaboration, exceeding the time allowed, and discussion of the form, content, or degree of difficulty of an exam. Please be conscientious about your work, and check with me if anything is unclear.

Note for this course

+ No code from online!

Discussing ideas and approaches to problems with others on a general level is fine (in fact, we encourage you to discuss general strategies with each other), but you should **never read anyone else's code or let anyone else read your code.**

Academic Accommodations

Faculty statement on accommodations

Haverford College is committed to providing equal access to students with a disability. If you have (or think you have) a learning difference or disability – including mental health, medical, or physical impairment - please contact the Office of Access and Disability Services (ADS) at **hc-ads@haverford.edu**. The Coordinator will confidentially discuss the process to establish reasonable accommodations.

Students who have already been approved to receive academic accommodations and want to use their accommodations in this course should share their verification letter with me and also make arrangements to meet with me as soon as possible to discuss their specific accommodations. Please note that accommodations are **not retroactive** and require advance notice to implement.

It is a state law in Pennsylvania that individuals must be given advance notice if they are to be recorded. Therefore, any student who has a disability-related need to audio record this class must first be approved for this accommodation from the Coordinator of Access and Disability Services and then must speak with me. Other class members will need to be aware that this class may be recorded.

<https://www.haverford.edu/access-and-disability-services/accommodations/receiving-accommodations>

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Python style

- Decompose code into natural functions
- Avoid global variables (sometimes useful)
- Include a file header with purpose, author, and date
- Include headers for each function
- No lines over 80 chars
- Variable names implicitly show type
- Include line breaks and comments!

Python style

- “Snake-case” not “camel-case”
 - ~~linearSearch~~
 - linear_search
- Alphabetize imports and don't use “*”
 - ~~from numpy import *~~
 - import numpy as np

Python style examples

```
"""
Ask the user for their name and welcome them to CS21.
Author: Sara Mathieson
Date: 9/7/18
"""

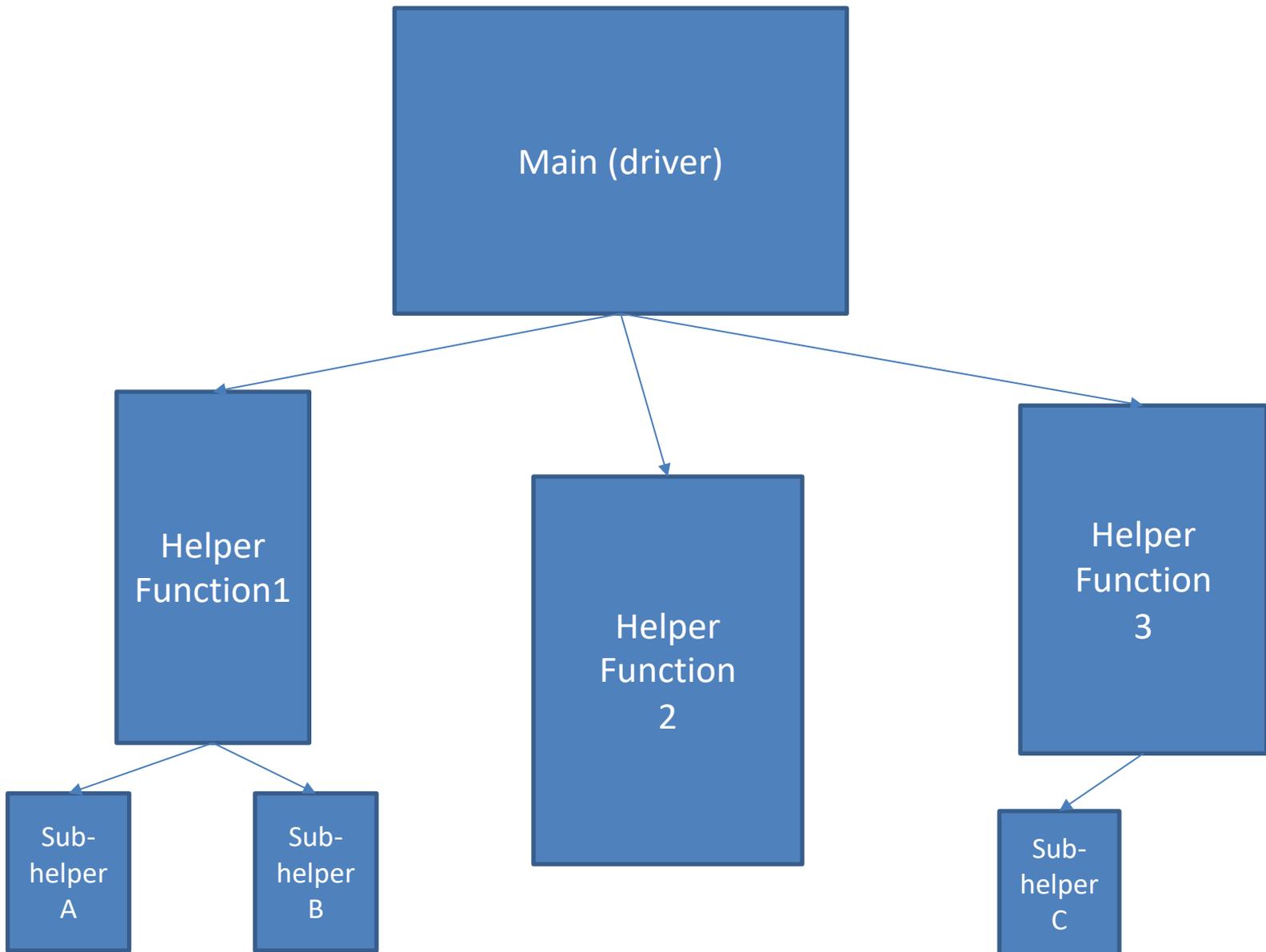
def main():

    # ask user for their name and print greeting
    name = input("Enter your name: ")
    print("Hello", name, "!")

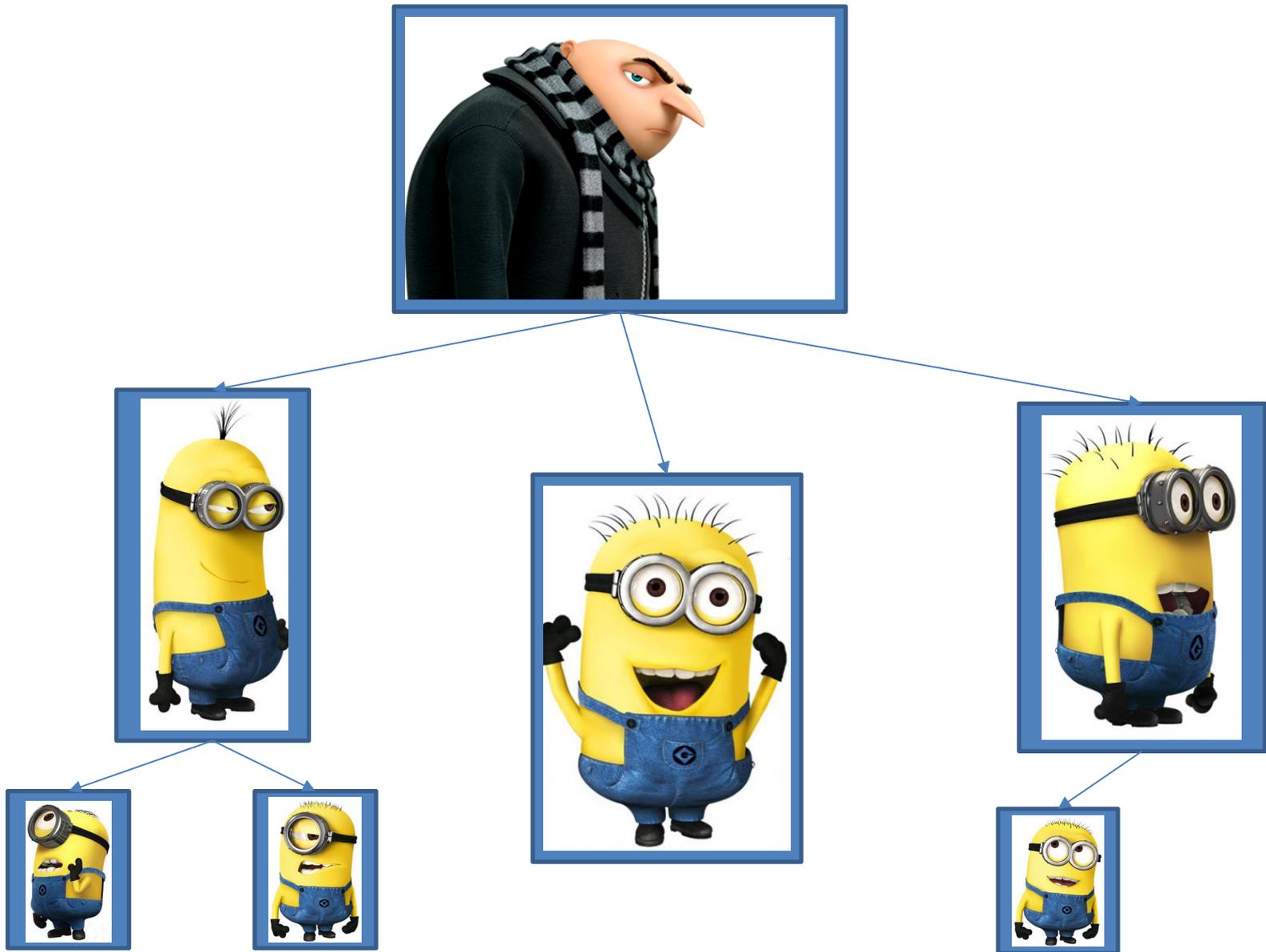
main()
```

```
def factorial(n):
    """
    Given a non-negative integer n, return n! = n*(n-1)*(n-2)...3*2*1.
    """
    fact = 1 # set up an accumulator variable
    for i in range(n):
        fact = fact * (i+1) # accumulator pattern
    return fact
```

Structure of main and “helper” functions



Structure of main and “helper” functions



Reminder: steps of top-down-design (TDD)

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- 1) Design a **high-level main function** that captures the basic idea of the program.

Reminder: steps of top-down-design (TDD)

- 1) Design a **high-level main function** that captures the basic idea of the program.
- 2) As you're writing/designing main, think about which details can be **abstracted into small tasks**. Make names for these functions and write their signatures below main.

Reminder: steps of top-down-design (TDD)

- 1) Design a **high-level main function** that captures the basic idea of the program.
- 2) As you're writing/designing main, think about which details can be **abstracted into small tasks**. Make names for these functions and write their signatures below main.
- 3) **“Stub” out the functions**. This means that they should work and return the correct type so that your code runs, but they don't do the correct task yet. For example, if a function should return a list, you can return []. Or if it returns a boolean, you can return False.

Reminder: steps of top-down-design (TDD)

- 1) Design a **high-level main function** that captures the basic idea of the program.
- 2) As you're writing/designing main, think about which details can be **abstracted into small tasks**. Make names for these functions and write their signatures below main.
- 3) **“Stub” out the functions**. This means that they should work and return the correct type so that your code runs, but they don't do the correct task yet. For example, if a function should return a list, you can return []. Or if it returns a boolean, you can return False.
- 4) Iterate on your design until you have a working main and stubbed out functions. Then start **implementing** the functions, starting from the “bottom up”.

Reasons to use TDD

- Creates code that is easier to implement, debug, modify, and extend
- Avoids going off in the wrong direction (i.e. implementing functions that are not useful or don't serve the program)
- Creates code that is easier for you or someone else to read and understand later on

DEMO + Handout 1

- Matplotlib
- Numpy

```
"""  
#header
```

```
"""
```

```
def main():
```

```
    phrase =
```

```
    letter =
```

```
    num_chars =
```

```
    count = 0
```

```
    for i in range(...
```

```
        if i == letter
```

```
            count += 1
```

```
    phrase[i]
```

Handout 1

```
    print("Number of %s : %i" %
```

```
main()
```

```
(letter, count))
```

```
"""
```

Given an input phrase and a letter, count how many times that letter appears in the phrase. For example:

```
phrase: creative code
```

```
letter: e
```

```
Number of e's: 3
```

```
Author: Jeff Knerr & Sara Mathieson
```

```
Date: 9/21/18
```

```
"""
```

Handout 1 (example solution)

```
def main():  
  
    # ask the user for a phrase and a letter  
    phrase = input("phrase: ")  
    letter = input("letter: ")  
    num_chars = len(phrase)  
  
    # set up accumulator variable count  
    count = 0  
    for i in range(num_chars):  
        # add on 1 each time we see the desired letter  
        if phrase[i] == letter:  
            count = count + 1  
  
    # example of string formatting (%s for str, %i for int)  
    print("Number of %s's: %i" % (letter, count))  
  
main()
```

TODO

- Read over **Lab 1**, accept assignment on github
- Come to office hours TODAY!
 - **4-5:30pm in this room**
- Reading: **MML Chap 1**