ECE 20875
Python for Data Science
David Inouye and Qiang Qiu

(Adapted from material developed by Profs. Milind Kulkarni, Stanley Chan, Chris Brinton, David Inouye)

Section I: EE 129 + Zoom (Inouye)
Section II: ME 1061 + Zoom (Qiu)
Online Section: Zoom (Inouye)
what is data?
lots of different definitions
humans have used data forever

• Ever since Thag Simmons first thought, “Last time, we only sent two people to hunt the smilodon. Maybe this time we should send three?”
why do we use data?

• Analyzing data helps us make decisions and take actions
what has changed?

• There’s a lot more data
• Machines can also collect (and in turn use) it
• And we’re trying to do more with it
Prof. Milind Kulkarni (ECE) builds systems to make data analyses run faster

Prof. Bryan Pijanowski (Forestry) collects sound recordings from forests to study ecological change

Prof. Seungyoon Lee (Comm) analyzes social media behavior to understand how social networks help people process information

Prof. Jennifer Neville (CS) builds new machine learning tools to study graphs and networks

Prof. Chris Brinton (ECE) develops algorithms for modeling and optimizing social and communication networks from data

Are they doing data science?
what is data science?

• Collecting data from a wide variety of sources and putting them into a consistent format?
• Making observations about patterns in data?
• Visualizing trends in data?
• Identifying similarities between data points?
• Making predictions about what will happen in the future?
• Prescribing courses of action to take based on forecasts?
• Developing new machine learning and data mining algorithms?
• Accelerating analysis algorithms?
data science is a lot of things

- making predictions from data
- visualizing data
- collecting/organizing data
- building systems for data analysis
- interpreting data
- ethics
- identifying patterns in data
- dealing with privacy concerns
- analyzing data
- writing data analyses
data science is a lot of things

- making predictions from data
- visualizing data
- collecting/organizing data
- ethics
- identifying patterns in data
- building systems for data analysis
- interpreting data
- analyzing data
- dealing with privacy concerns
- writing data analyses
- making predictions from data
what industries has it impacted?

• Hard to think of one that is not being impacted by data science!

• **Medicine**: Analytics from wearable trackers, studying disease patterns, …

• **Retail**: Analyzing consumer behavior, predicting customer satisfaction, …

• **Transportation**: Assisted/autonomous navigation, predicting equipment failures, …

• **Education**: Tracking student engagement, personalizing learning content, …
what about python?

- General purpose programming language, first appeared in the 90s
- Easily recognized by use of whitespace indentation rather than {} brackets to enhance readability
- Becoming the industry standard for data science (competing with R)
- Many useful, open-source libraries: numpy, pandas, matplotlib, pytorch
- And standard control functions (e.g., loops) from lower-level languages to help structure programs
This is an introductory programming course that emphasizes data science problems with some math.

Other data science courses in ECE:

- ECE 30010 - Introduction to Machine Learning and Pattern Recognition
- ECE 47300 - Introduction to Artificial Intelligence
- ECE 57000 - Artificial Intelligence
- ECE 59500 - Machine Learning I

But data science is a Purdue-wide initiative!
syllabus break!
some data analysis examples
data analysis in “practice”

• Lets say we have a data set of applicants to Purdue

<table>
<thead>
<tr>
<th>Name</th>
<th>High school GPA</th>
<th>SAT Math</th>
<th>SAT R/W</th>
<th>Residence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jane Doe</td>
<td>4.7</td>
<td>760</td>
<td>700</td>
<td>Indiana</td>
</tr>
<tr>
<td>Purdue Pete</td>
<td>3.5</td>
<td>680</td>
<td>620</td>
<td>Indiana</td>
</tr>
<tr>
<td>B. O. Iler</td>
<td>3.0</td>
<td>800</td>
<td>650</td>
<td>Michigan</td>
</tr>
<tr>
<td>Engy Neer</td>
<td>4.2</td>
<td>750</td>
<td>590</td>
<td>North Carolina</td>
</tr>
<tr>
<td>Mark Faller</td>
<td>3.8</td>
<td>780</td>
<td>550</td>
<td>New Jersey</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

• What might we want to learn about them?
descriptive statistics

- Which students come from which states?
- What is the distribution of GPAs? SAT scores?
  - GPAs may need to be normalized to a consistent range across all schools
- Can build histograms, e.g., for the GPAs
  - But how do we know how big to make the buckets?
reasoning about data

• How do Purdue applicants compare to the national average?
  • \textit{Mean} GPA of applicants: 3.6
• Is this high or low?
  • Can \textit{sample} GPA of all high school students
• Suppose we collect 1000 GPAs and find a mean of 3.4
  • Does this mean Purdue students have a higher GPA on average?
• Need more information! In particular …
  • Was the sampling method we used \textit{unbiased}?
  • What is the \textit{variance} of the sample collected (i.e., the spread of GPAs)?
  • What \textit{confidence interval} can be built for the population mean (i.e., what is the likely range of the true mean GPA)?
making predictions

• Can we predict how successful a particular applicant might be at Purdue?
  • How do we define success? GPA?
  • Idea: Look at the application statistics of the current seniors and see if there is a relationship between these statistics and their current GPA
  • One way to find a relationship is using **linear regression**
  • Might tell you something like: “a Purdue student’s GPA can be predicted mostly by their high school GPA, with their SAT score having a lighter influence”
  • Many other prediction algorithms exist too
classification

• Can we make admissions decisions quicker through automation?

• Idea: Compare each applicant’s statistics to past applicants that were admitted, and to those that were rejected

• Train a classifier to analyze these past applicants and maximize the ability to predict whether a student would be accepted or not

  • For example, a *k*-nearest neighbor classifier would assess whether a given applicant is more similar to the pool of admitted applicants or to the rejected applicants

• Why might we run into trouble here?
What if we want to identify groups of students beyond “admitted” vs. “rejected”?

Idea: See if students cluster together according to some measure of distance

Some students look more like “nearby” students than students that are “far away”

Important question: What features of students should be considered for the clustering?

E.g., maybe don’t consider something like hair color!

With k-means clustering, k groups of students would be extracted based on “closeness”