Computational thinking
What have we been doing this semester?
use context essentials2021

"Hello, computer!"
"Hello, computer!"

'Hello, computer!'
We're not *especially* interested in Pyret or Python.

If you're programming 20 years from now, it will be in a different language, using different tools.
What have we been doing in these languages?
We’ve been practicing *computational thinking*.
“Modern computer science is the last 1 percent of the historical timeline of computational thinking. Computer scientists inherited and then perfected computational thinking from a long line of mathematicians, natural philosophers, scientists, and engineers all interested in performing large calculations and complex inferences without error.”

Peter J. Denning & Matti Tedre, *Computational Thinking*
Origins of computational thinking
Before the modern computer age, there was a profession of mathematically trained experts who performed complex calculations as teams.

They were called “computers”.
The first *electronic* computing machines were called “automatic computers” to distinguish them from the human variety.
Human computers and the leaders of human computing teams engaged in computational thinking long before the invention of electronic computers.
Early computational thinking can be seen going back to the records of the Babylonians, who wrote down general procedures for solving mathematical problems around starting around 1800 BCE.
Long before this class, you probably learned these kind of computational methods.
Euclid’s algorithm

One of the earliest methods, still taught to schoolchildren today, is from the Greek mathematician Euclid, around 300 BCE.

He gave a method to find the greatest common divisor (GCD) of two numbers, which is the largest integer that divides both numbers.
Euclid’s algorithm

Euclid noticed that the GCD of two numbers divides their difference.

So, he repeatedly replaced the larger number with their difference until both were the same.
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\[ \text{gcd}(48, 18) \]
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\[
gcd(48, 18) \\
\rightarrow gcd(30, 18)
\]
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\[ \text{gcd}(48, 18) \]
\[ \rightarrow \text{gcd}(30, 18) \]
\[ \rightarrow \text{gcd}(12, 18) \]
Euclid’s algorithm

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So, he repeatedly replaced the larger number with their difference until both were the same.

\[
gcd(48, 18) \\
\rightarrow gcd(30, 18) \\
\rightarrow gcd(12, 18) \\
\rightarrow gcd(12, 6)
\]
Euclid’s algorithm

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So, he repeatedly replaced the larger number with their difference until both were the same.

\[
\begin{align*}
gcd(48, 18) & \\
\rightarrow gcd(30, 18) & \\
\rightarrow gcd(12, 18) & \\
\rightarrow gcd(12, 6) & \\
\rightarrow gcd(6, 6) & \\
\end{align*}
\]
Euclid’s algorithm

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\[
\begin{align*}
gcd(48, 18) & \rightarrow gcd(30, 18) \\
& \rightarrow gcd(12, 18) \\
& \rightarrow gcd(12, 6) \\
& \rightarrow gcd(6, 6) \\
& \rightarrow 6
\end{align*}
\]
Sieve of Eratosthenes

This is another famous method dating back to the ancient Greeks, used to find all the prime numbers up to some limit.
Sieve of Eratosthenes

\[ 2 \ 3 \ 4 \ 5 \ 6 \ 7 \ 8 \ 9 \ 10 \ 11 \ 12 \ 13 \ 14 \ 15 \ 16 \ 17 \ 18 \]

We begin with a list of all the integers, from 2 to the limit.
Sieve of Eratosthenes

We cross out all the multiples of 2.
Sieve of Eratosthenes

Then all the multiples of 3.
Sieve of Eratosthenes

2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18

Then all the multiples of 5.
Sieve of Eratosthenes

2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18

And so on, leaving you with only the primes between 2 and the limit you chose.
Sieve of Eratosthenes

After each round of elimination, a new prime will be revealed, and the next round crosses out all its multiples.
These are computational procedures, carried out by hand!
Decomposing computing tasks
During the time leading up to World War II, the US Army developed ever more sophisticated artillery that could fire shells over several miles.

8-inch Mk. VI railway gun
Gunners needed to know how to aim their artillery given
the range,
the difference of elevation, and
the winds.
The Army commissioned teams of human computers to work out firing tables for these guns.

The gunners could then simply look up the proper angle and direction to aim their guns, given their measurement of range, elevation, and winds.
Around 1940, one of these teams comprised women working at Aberdeen Proving Ground in Maryland.
They organized into assembly lines, each doing a different stage of computation, until they compiled the firing tables.

Each assembly line was working on a different input, like running a function.

Each of the human computers in the assembly line was carrying out a part of the computation, like running a line of code.
The Army wanted to perform these computations at much larger scales and faster than humans could, which led to using the ENIAC electronic computer.
The method of decomposing the task into unambiguous steps that passed data between them moved from a *management principle* at Aberdeen to a *design principle* for automatic computers.
Programmable computers
No matter how simple and unambiguous the steps are made, human computers make mistakes – and lots of them!

So, inventors through the ages have sought to make computing machines to allow people to perform longer computations with fewer errors.
This was a slow process, taking us from…
The slide rule

c. 1620
Blaise Pascal’s mechanical calculator
1642
Precursors to the idea of a *programmable* computer originated well before the electronic computing age.

In the early 1700s, French textile weavers experimented with machines that could weave complex patterns using an automatic loom.
One of the more well known is the Jacquard loom, which was controlled by long chains of punched cards.
Plan 25 for Babbage’s Analytical Engine
1840
Babbage collaborated with a gifted mathematician, Ada Lovelace, who designed algorithms for the Analytical Engine, even though there was no machine to run them on.
Lovelace saw the Analytical Engine not as a mere calculator but as a processor of *any information that could be encoded in symbols*. This insight, that computing programs can calculate not only over numbers but over symbols that can stand for anything in the world, anticipated by a hundred years a key tenet of the modern computer age.

Lovelace saw the computer as an *information machine*. 
While Babbage’s designs for a programmable computer weren’t realized at the time, the age of electronics opened new possibilities.
Harvard Mark I
1944
ENIAC

C. 1945
Early computers were very difficult to program, working in languages that were closely tied to the hardware.
Grace Murray Hopper (Vassar ’28) popularized the idea of a compiler for machine-independent programming languages and defined FLOW-MATIC, the first English-like data processing language in the early 1950s.

Those ideas were later folded into the COBOL language (1959).
Since the 1950s, many programming languages have been defined, experienced popularity, and then been supplanted by new designs.
Today, Python is the most common programming language used for work in data science and artificial intelligence.
Programming no longer involves plugging in wires or punching cards, but it’s still hard!
In *The Mythical Man-Month* (1975), Turing Award recipient Fred Brooks writes:
“The programmer, like the poet, works only slightly removed from pure thought-stuff. He builds castles in the air, from air, creating by exertion of the imagination…”
“Few media of creation are so flexible, so easy to polish and rework, so readily capable of realizing grand conceptual structures. Yet the program construct, unlike the poet’s words, is real in the sense that it moves and works, producing visible outputs separate from the construct itself…”
“One types the correct incantation on a keyboard, and a display screen *comes to life*, showing things that never were nor could be... It prints results, draws pictures, produces sounds, moves arms. The magic of myth and legend has come true in our time...
“The computer resembles the magic of legend in this respect, too. If one character, one pause, of the incantation is not strictly in proper form, the magic doesn’t work. Human beings are not accustomed to being perfect, and few areas of human activity demand it. *Adjusting to the requirement for perfection is, I think, the most difficult part of learning to program.*”
Data science
What is data?
“Many people think of data as numbers alone, but data can also consist of words or stories, colors or sounds, or any type of information that is systematically collected, organized, and analyzed…”

D'Ignazio & Klein, “Introduction” in Data Feminism, 2020
On Exactitude in Science

...In that Empire, the Art of Cartography attained such Perfection that the map of a single Province occupied the entirety of a City, and the map of the Empire, the entirety of a Province. In time, those Unconscionable Maps no longer satisfied, and the Cartographers Guilds struck a Map of the Empire whose size was that of the Empire, and which coincided point for point with it. The following Generations, who were not so fond of the Study of Cartography as their Forebears had been, saw that that vast Map was Useless, and not without some Pitilessness was it, that they delivered it up to the Inclemencies of Sun and Winters. In the Deserts of the West, still today, there are Tattered Ruins of that Map, inhabited by Animals and Beggars; in all the Land there is no other Relic of the Disciplines of Geography.

—Suarez Miranda, *Viajes de varones prudentes*, Libro IV, Cap. XLV, Lerida, 1658
When we collect data, it’s like making a map:

We’re constructing a model, where we choose to represent only certain things.
Data is situated in the environment where it was gathered.

Consider Galton’s child-height data.

He gathered the data in England c. 1886.

What would happen if you tried to use it to predict heights in Poughkeepsie today? In Guatemala? In China?
Data gathering and privacy
Google's ad tracking is as creepy as Facebook's. Here's how to disable it

Google in June deleted a clause in its privacy settings that said it would not combine cookie information with personal information without consent.
The words and phrases we search for on Google, the times of day we are most active on Facebook, and the number of items we add to our Amazon carts are all tracked and stored as data – data that are then converted into corporate financial gain.

D'Ignazio & Klein, “Introduction” in Data Feminism, 2020
General Information

What is Sentiment140?
Sentiment140 allows you to discover the sentiment of a brand, product, or topic on Twitter.

How does this work?
You can read about our approach in our technical report: Twitter Sentiment Classification using Distant Supervision. There are also additional features that are not described in this paper.

How is this different?
Our approach is different from other sentiment analysis sites because:

- We use classifiers built from machine learning algorithms. Other products use a simpler keyword-based approach which may have higher precision but lower recall.
- We provide transparency for the classification results of individual tweets. Other sites only surface aggregated metrics, which makes it difficult to assess the accuracy of their classifiers.

Who created this?
Sentiment140 was created by Alec Go, Richa Bhavani, and lei Huo, who...

help.sentiment140.com
<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
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<td>122</td>
<td>itchy</td>
<td>robloposky</td>
<td>I'm itchy and miserable!</td>
<td></td>
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<tr>
<td>38</td>
<td>123</td>
<td>itchy</td>
<td>EdwinValencia</td>
<td>@seekerness no. I'm not itchy for now. Maybe later, lol.</td>
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<td>drewloewe</td>
<td>@spinuzzi: Has been a bit crazy, with steep learning curve, but LyX is really good for long docs. For anything shorter, it would be insane.</td>
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<td>Danny Gokey</td>
<td>VickyTigger</td>
<td>I'm listening to “FY.T” by Danny Gokey &lt;3 &lt;3 &lt;3 &lt;3 Aww, he's so amazing. I &lt;3 him so much :)</td>
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<td>babbllyabbbie</td>
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<td>133</td>
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<td>kisjaoquin</td>
<td>cant sleep... my tooth is aching.</td>
<td></td>
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<tr>
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<td>sleep</td>
<td>Whacktacular</td>
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<td>135</td>
<td>san francisco</td>
<td>Adrigonz</td>
<td>glad i didnt do Bay to Breakers today, it’s 1000 freaking degrees in San Francisco wtf</td>
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<td>san francisco</td>
<td>sulu34</td>
<td>is in San Francisco at Bay to Breakers.</td>
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<td>san francisco</td>
<td>schuylerr</td>
<td>just landed at San Francisco</td>
<td></td>
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<td>san francisco</td>
<td>MattBragoni</td>
<td>San Francisco today. Any suggestions?</td>
<td></td>
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<td>aig</td>
<td>KennyTRoland</td>
<td>?Obama Administration Must Stop Bonuses to AIG Ponzi Schemers ... <a href="http://bit.ly/2CUIg">http://bit.ly/2CUIg</a></td>
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<td>50</td>
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<td>aMild</td>
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<td>Trazor1</td>
<td>ShaunWoo hate’n on AIG</td>
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<td>star trek</td>
<td>mimknits</td>
<td>@YarnThing you will not regret going to see Star Trek. It was AWESOME!</td>
<td></td>
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<td>star trek</td>
<td>GeeRen</td>
<td>On my way to see Star Trek @ The Esquire.</td>
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<td>star trek</td>
<td>checkyesJess</td>
<td>Going to see star trek soon with my dad.</td>
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<td>Malcolm Gladwell</td>
<td>renano</td>
<td>annoying new trend on the internets: people picking apart michael lewis and malcolm gladwell.</td>
<td></td>
</tr>
</tbody>
</table>
Ethics of research using social media data is complex and rapidly evolving, with legitimate disagreements.
How Companies Learn Your Secrets

By Charles Duhigg
Feb. 16, 2012

Andrew Pole had just started working as a statistician for Target in 2002, when two colleagues from the marketing department
“As Pole’s computers crawled through the data, he was able to identify about 25 products that, when analyzed together, allowed him to assign each shopper a ‘pregnancy prediction’ score. More important, he could also estimate her due date to within a small window, so Target could send coupons timed to very specific stages of her pregnancy.

“One Target employee I spoke to provided a hypothetical example. Take a fictional Target shopper named Jenny Ward, who is 23, lives in Atlanta and in March bought cocoa-butter lotion, a purse large enough to double as a diaper bag, zinc and magnesium supplements and a bright blue rug. There’s, say, an 87 percent chance that she’s pregnant and that her delivery date is sometime in late August.”

Kashmir Hill, “How Target Figured Out a Teen Girl was Pregnant Before Her Father Did”, Forbes, 2012
Representing data
We see father and mother, giving the height of each in inches.

We can see this difference in these distributions by looking at a histogram of mother and father heights together:
We see father and mother, giving the height of each in inches.

We can see this difference in these distributions by looking at a histogram of mother and father heights together:

galton.hist(["mother", "father"], unit="inch")
About four-in-ten U.S. adults say forms should offer more than two gender options

By Nikki Graf

In 2019, at least seven states have started offering a third gender option on driver’s licenses for people who don’t identify as male or female, and at least four more plan to do so in 2020, according to Pew Research Center. States that offer a third gender option on driver’s licenses

- Available as of November 2019
- Available in 2020 or later

Related

- REPORT | SEP 5, 2019
  About one-in-five U.S. adults know someone who goes by a gender-neutral pronoun

- REPORT | JUL 27, 2021
  Rising shares of U.S. adults know someone who is transgender or goes by gender-neutral pronouns

- REPORT | DEC 18, 2017
  10 things we learned about gender issues in the U.S. in 2017

- REPORT | DEC 14, 2017
  Gender discrimination comes in
“...most of the data and data models we have inherited deal with structures of power, like gender and race, with a crudeness that would never pass muster in a peer-reviewed humanities publication.”

“I want us to be more ambitious, to hold ourselves to much higher standards when we are claiming to develop data-based work that depicts people’s lives.”

Data analysis and storytelling
Florence Nightingale created a visualization of mortality data from the Crimean War, which was published in *Notes on Matters Affecting the Health Efficiency, and Hospital Administration of the British Army* and was sent to Queen Victoria in 1858.
The Areas of the blue, red, & black wedges are each measured from the centre as the common vertex.

The blue wedges measured from the centre of the circle represent areas for area the deaths from Preventable or Mitigable Zymotic diseases: the red wedges measured from the centre the deaths from wounds: & the black wedges measured from the centre the deaths from all other causes.

The black line across the red triangle in Nov. 1854 marks the boundary of the deaths from all other causes during the month.

In October 1854, & April 1855, the black area coincides with the red; in January & February 1855, the blue coincides with the black.

The entire areas may be compared by following the blue, the red & the black lines enclosing them.
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Prediction and machine learning
Machine learning methods generally pick up on biases that are present in training data.

Some ML techniques will *amplify* biases in data.

Zhao et al. (2017) on image classifiers:

- In training data, women appear in cooking scenes 33% more often than men do.
- In the model's predictions for similar data, women are detected in cooking scenes 68% more often than men are.
Bias

“The program, Correctional Offender Management Profiling for Alternative Sanctions (Compas), was much more prone to mistakenly label black defendants as likely to reoffend – wrongly flagging them at almost twice the rate as white people (45% to 24%), according to the investigative organisation ProPublica.”

Bias

Police departments use a program called PredPol to predict hotspots where future crimes might occur.

Lum and a co-author gave PredPol historical drug-crime data from Oakland, CA.

PredPol showed a map of likely “crime hotspots” to deploy police to based on where they previously made arrests.

The program suggested majority Black neighborhoods about twice as often as white ones, although national statistics suggest drug use is much more evenly distributed.

Following the suggestions would produce a feedback loop of overpolicing.
“People expected AI to be unbiased; that’s just wrong. If the underlying data reflects stereotypes, or if you train AI from human culture, you will find these things.”

Joanna Bryson, University of Bath
“Instead of relying on algorithms, which we can be accused of manipulating for our benefit, we have turned to machine learning, an ingenious way of disclaiming responsibility for anything. *Machine learning is like money laundering for bias.* It’s a clean, mathematical apparatus that gives the status quo the aura of logical inevitability.”

Maciej Cegłowski, “The Moral Economy of Tech”
“…mechanical arts are of ambiguous use, serving as well for hurt as for remedy.”

Francis Bacon, *The Wisdom of the Ancients*, 1609
Computer Science I
—or, where do you go from here?
Congratulations on making it this far!
CS courses at Vassar
Major-required courses
- CMPU 101 - Computer Science I: Problem-Solving and Abstraction
- CMPU 102 - Computer Science II: Data Structures and Algorithms
- CMPU 145 - Foundations of Computer Science
- CMPU 203 - Computer Science III: Software Design and Implementation
- CMPU 224 - Computer Organization
- CMPU 240 - Theory of Computation
- CMPU 241 - Analysis of Algorithms
- CMPU 331 - Compilers
- CMPU 334 - Operating Systems

300-level electives (at least one for major)
- CMPU 324 - Computer Architecture
- CMPU 353 - Bioinformatics
- CMPU 365 - Artificial Intelligence
- CMPU 366 - Computational Linguistics
- CMPU 375 - Computer Networks
- CMPU 377 - Parallel Programming
- CMPU 378 - Graphics
- CMPU 379 - Computer Animation: Art, Science and Criticism
- CMPU 395 - Advanced Topics

Intensives (at least one for major)
- CMPU 310 - Topics in Virtualization
- CMPU 311 - Database Systems
- CMPU 312 - Applications of Artificial Intelligence
- CMPU 314 - Projects in Digital Media Production
- CMPU 315 - Computer Security

Correlate-required courses
- CMPU 101 - Computer Science I: Problem-Solving and Abstraction
- CMPU 102 - Computer Science II: Data Structures and Algorithms
- CMPU 145 - Foundations of Computer Science
- CMPU 240 or 241 - Theory of Computation or Analysis of Algorithms
- CMPU 2xx - Any other 200-level course
- CMPU 3xx - Any 300-level course

200-level electives (not required for major)
- CMPU 245 - Declarative Programming Models

Extra-departmental
- MATH 221 - Linear Algebra

*At least two CMPU-200 level courses required for every CMPU-300 level course.
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CMPU 102
Data Structures and Algorithms

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- CMPU 245 - Declarative Programming Models

Extra-departmental
- MATH 221 - Linear Algebra
**CMPU 145**

Foundations of Computer Science

Wait until Fall 2022! There will be an exciting new version of this course, designed to follow the new CMPU 101 you just took!
Try them out!

If you keep going with the CS major sequence, you work your way up to some really exciting courses, including…

- CMPU 365  Artificial Intelligence
- CMPU 366  Computational Linguistics

And, you know, probably some cool courses I don’t teach as well!
Further reading
"This is the best book on computers I have ever read."
—Peter Thomas, New Scientist

The Pattern on the Stone

The simple ideas that make computers work

W. Daniel Hillis
Artificial Intelligence

A Guide for Thinking Humans

Melanie Mitchell
That’s it!
Next time, we’ll review for the Exam 3 by working through practice problems and answering your questions.
go.vassar.edu/course/evals
Acknowledgments

This lecture incorporates material from:

Peter J. Denning & Matti Tedre, *Computational Thinking*

Miram Posner, UCLA

Edward Tufte, *Visual Explanations*