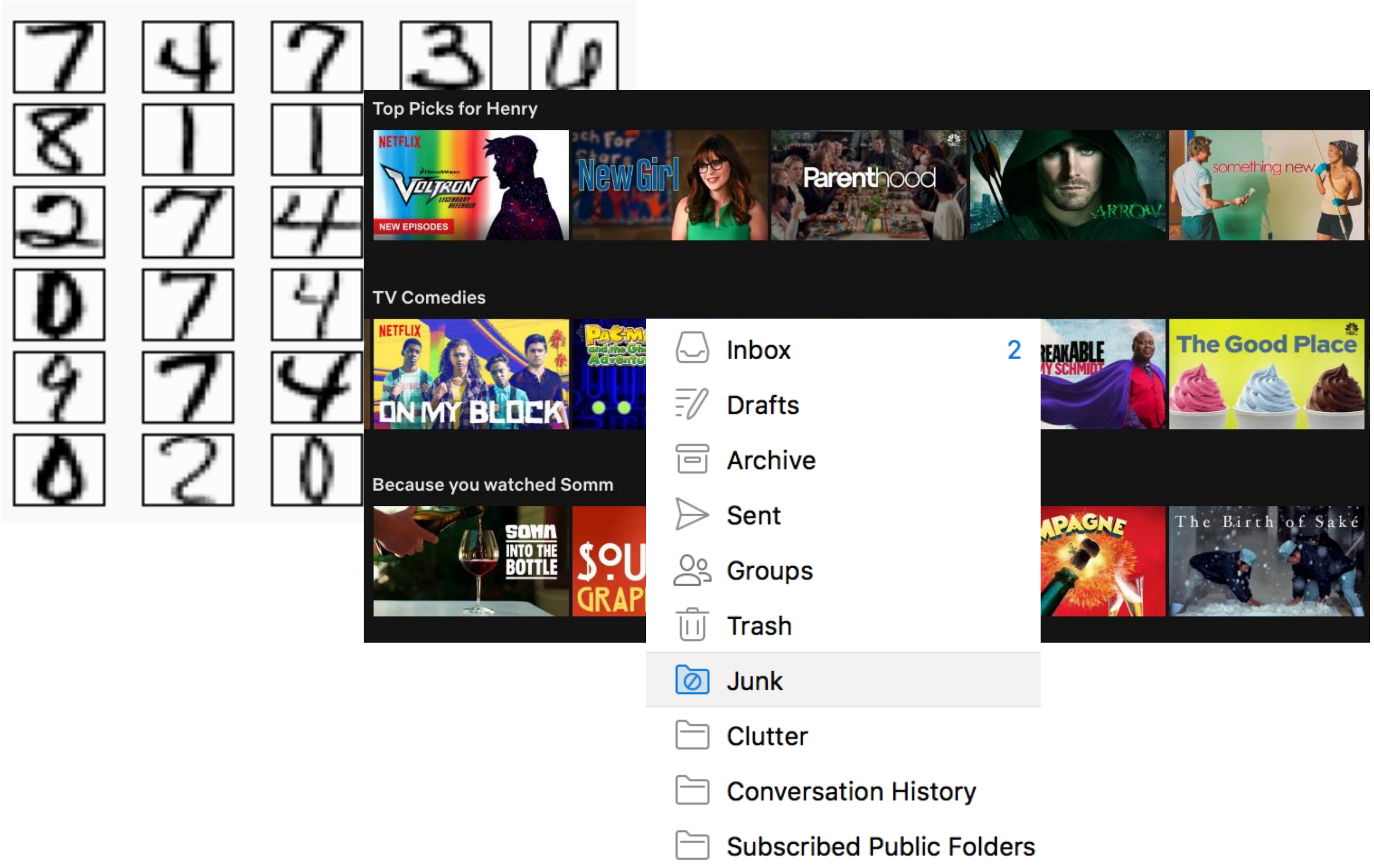
10-301/601: Introduction to Machine Learning Lecture 1 – Problem Formulation & Notation

Hoda Heidari, Henry Chai & Matt Gormley

1/17/24

What is Machine Learning?

Machine Learning (A long long time ago…)



Machine Learning (A short time ago...)

Machine Learning (Now)

Machine Learning (Now)

What is ~~Machine Learning~~ 10-301/601?

- Supervised Models
  - Decision Trees
  - KNN
  - Naïve Bayes
  - Perceptron
  - Logistic Regression
  - Linear Regression
  - Neural Networks
- Unsupervised Learning
- Ensemble Methods
- Deep Learning & Generative AI
- Learning Theory
- Reinforcement Learning
- Important Concepts
  - Feature Engineering
  - Regularization and Overfitting
  - Experimental Design
  - Societal Implications

What is Machine Learning?

Source: https://en.wikipedia.org/wiki/Panzanella

Defining a Machine Learning Task (Mitchell, 97)

- A computer program **learns** if its *performance*, *P*, at some *task*, *T*, improves with *experience*, *E*.
- Three components
  - Task, T
  - Performance metric, P
  - Experience, E

Defining a Machine Learning Task: Example

- Learning to approve loans/lines of credit
- Three components
  - Task, T
    decide whether or not to extend someone a loan
  - Performance metric, P
    minimizing the # of people who default
  - Experience, E
    interviews with loan officers

Defining a Machine Learning Task: Example

- Learning to approve loans/lines of credit

- Three components
  - Task, T
    predict the probability that someone defaults on a loan
  - Performance metric, P
    Amount of interest earned over ~10 years
  - Experience, E
    historical records of loan applications and defaults

Example Learning Problems

Learning to **respond to voice commands (Siri)**

1. Task, *T*:

2. Performance measure, *P*:

3. Experience, *E*:

Example Learning Problems

Learning to **respond to voice commands (Siri)**

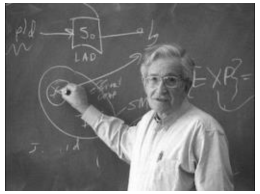
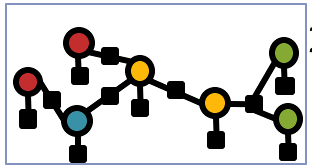
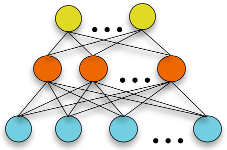
1. Task, *T*:

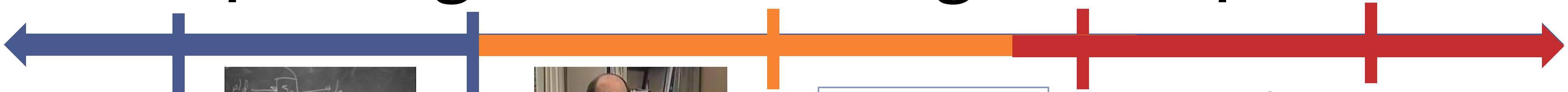
Given a transcribed sentence `x` predict the command `y`

Example:

```
x = "Give me directions to Starbucks"
y = DIRECTIONS(here, nearest(Starbucks))
```

Capturing the Knowledge of Experts

1980  1990  2000  2010  2020



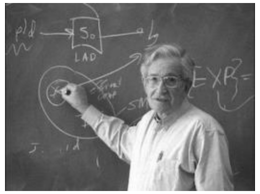
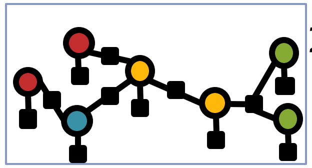
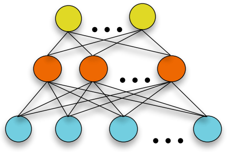
Solution #1: Expert Systems

- Over 20 years ago, we had rule-based systems:
  1. Put a bunch of linguists in a room
  2. Have them think about the structure of their native language and write down the rules they devise

Introspection…
x = "Give me directions to Starbucks"
x = "Send Jill a txt asking for directions"
x = "Play the song Chasing That Feeling by TXT"
x = "How do I get to Pitt's Department of Music"

Rules…
~~if "directions" in x:~~ ~~type = DIRECTIONS()~~
~~if "txt" in x:~~ ~~type = TXTMSG()~~ ~~elif "directions" in x:~~ ~~type = DIRECTIONS()~~
~~if "song" in x:~~ or "music" in x ~~type = MUSIC()~~ ~~elif "txt" in x:~~ ~~type = TXTMSG()~~ ~~elif "directions" in x:~~ ~~type = DIRECTIONS()~~

Capturing the Knowledge of Experts

1980  1990  2000  2010 

2020

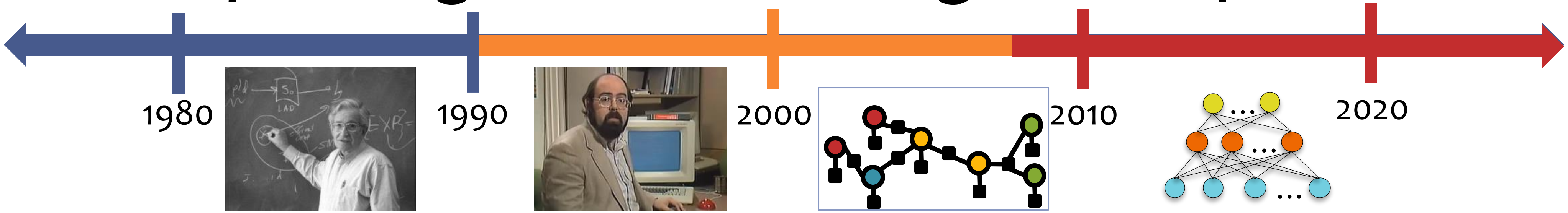
Solution #1: Expert Systems

- Over 20 years ago, we had rule-based systems:
  1. Put a bunch of linguists in a room
  2. Have them think about the structure of their native language and write down the rules they devise

Introspection…
x = "Give me directions to Starbucks"
x = "How do I get to Starbucks?"
x = "Where is the nearest Starbucks?"
x = "I need directions to Starbucks"
x = "Is there a Starbucks nearby?
x = "Starbucks now!"

Rules…
if x matches "give me directions to Z": cmd = DIRECTIONS(here, nearest(Z))
if x matches "how do i get to Z": cmd = DIRECTIONS(here, nearest(Z))
if x matches "where is the nearest Z": cmd = DIRECTIONS(here, nearest(Z))
if x matches "I need directions to Z": cmd = DIRECTIONS(here, nearest(Z))
if x matches "Is there a Z nearby": cmd = DIRECTIONS(here, nearest(Z))
if x matches "Z now!": cmd = DIRECTIONS(here, nearest(Z))

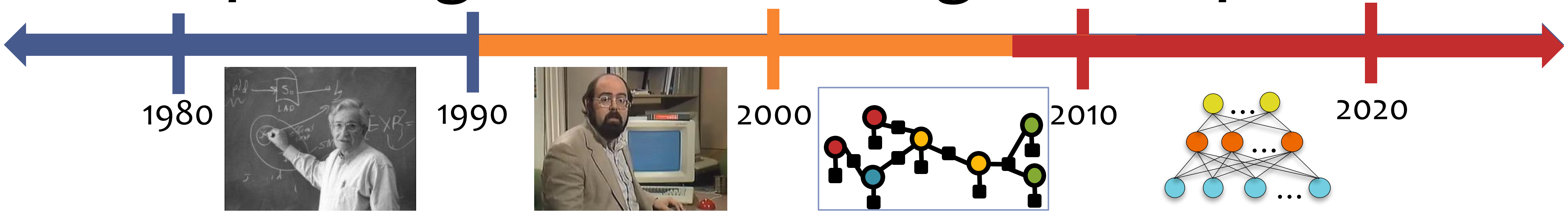
Capturing the Knowledge of Experts



Solution #2: Annotate Data and Learn

- Experts:
  - **Very good at** answering questions about specific cases
  - **Not very good at** telling **HOW** they do it
- 1990s: So why not just have them tell you what they do on **SPECIFIC CASES** and then let **MACHINE LEARNING** tell you how to come to the same decisions that they did

Capturing the Knowledge of Experts



Solution #2: Annotate Data and Learn

1. Collect raw sentences $\{x^{(1)}, \ldots, x^{(n)}\}$
2. Experts annotate their meaning $\{y^{(1)}, \ldots, y^{(n)}\}$

$x^{(1)}$: `How do I get to Starbucks?`	$x^{(3)}$: `Send a text to John that I'll be late`
$y^{(1)}$: `DIRECTIONS(here, nearest(Starbucks))`	$y^{(3)}$: `TXTNSG(John, I'll be late)`
$x^{(2)}$: `Show me the closest Starbucks`	$x^{(4)}$: `Set an alarm for seven in the morning`
$y^{(2)}$: `MAP(nearest(Starbucks))`	$y^{(4)}$: `SETALARM(7:00AM)`

Example Learning Problems

Learning to **respond to voice commands (Siri)**

1. Task, *T*:
   predicting action from speech
2. Performance measure, *P*:
   percent of correct actions taken in user pilot study
3. Experience, *E*:
   examples of (speech, action) pairs

Problem Formulation

Often, the same task can be formulated in more than one way.

Example: Loan applications

- creditworthiness/score (regression)
- probability of default (density estimation)
- loan decision (classification)

Problem Formulation:

What is the structure of our output prediction?

boolean	Binary Classification
categorical	Multiclass Classification
ordinal	Ordinal Classification
real	Regression
ordering	Ranking
multiple discrete	Structured Prediction
multiple continuous	(e.g. dynamical systems)
both discrete & cont.	(e.g. mixed graphical models)

Well-posed Learning Problems

In-Class Exercise

1. Select a **task**, T
2. Identify **performance measure**, P
3. Identify **experience**, E
4. Report ideas back to rest of class

Example Tasks

- Identify objects in an image
- Translate from one human language to another
- Recognize speech
- Assess risk (e.g. in loan application)
- Make decisions (e.g. in loan application)
- Assess potential (e.g. in admission decisions)
- Categorize a complex situation (e.g. medical diagnosis)
- Predict outcome (e.g. medical prognosis, stock prices, inflation, temperature)
- Predict events (default on loans, quitting school, war)
- Plan ahead under perfect knowledge (chess)
- Plan ahead under partial knowledge (poker, bridge)

Examples from Roni Rosenfeld

In-Class Exercise

1. Select a **task**, T
2. Identify **performance measure**, P
3. Identify **experience**, E
4. Report ideas back to rest of class

Well-posed Learning Problems

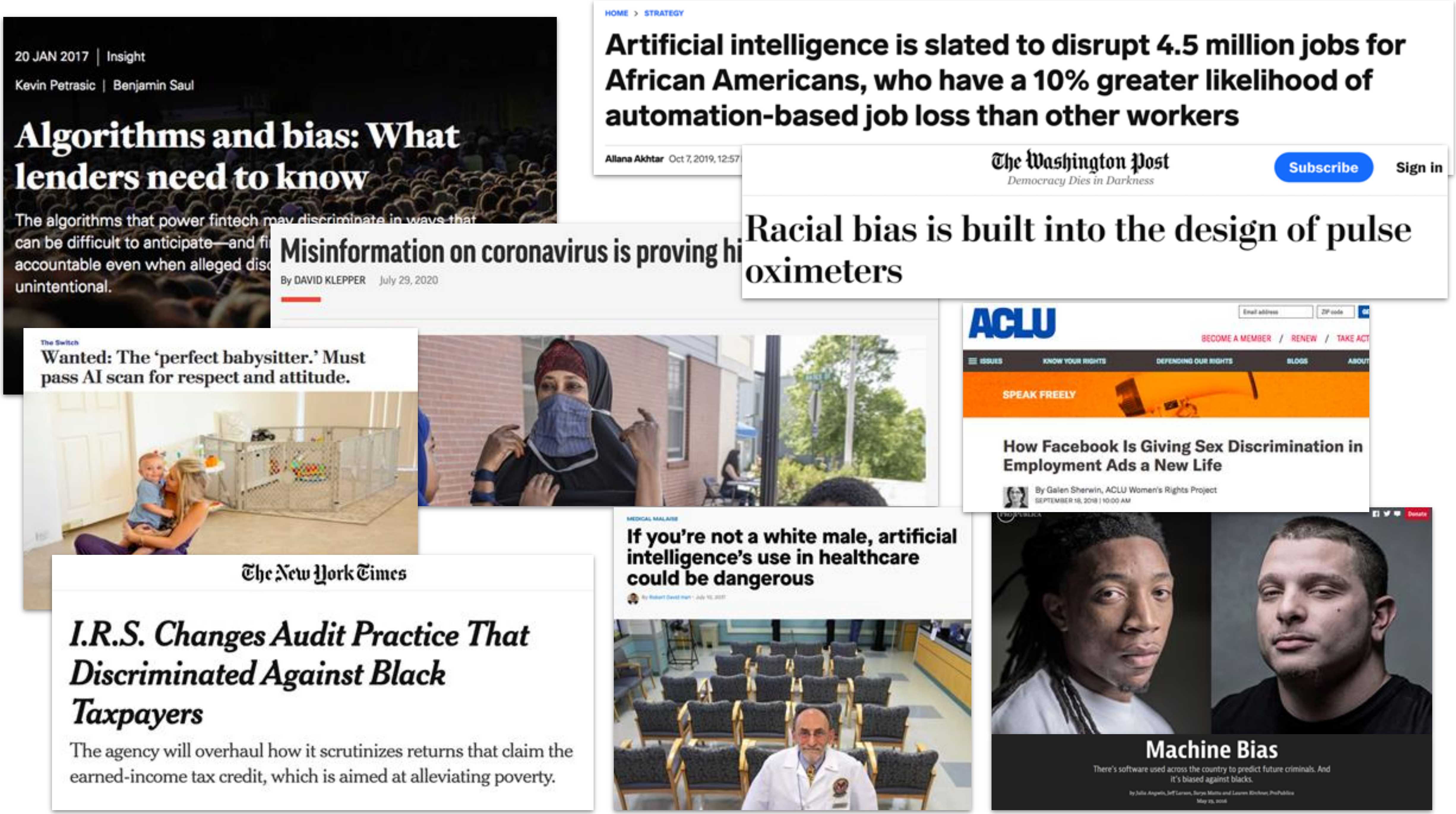
task, T	performance measure, P	experience, E
predicting the energy of an atomic system	difference between predicted energy and calculated energy	pairs of (atomic system, calc. energy)
deciding whether a musician played a note correctly	% of notes correctly labeled as "just right" vs. "not so good"	$\underbrace{\text{audio data}}_{\text{machine generated}}$, and $\underbrace{\text{note sheet}}_{\text{by human}}$ labels of ~~[illegible]~~ which notes were played poorly
medical prognosis: make the right diagnosis	compare prediction with 10 independent doctors' prognosis	data is ~~[illegible]~~ varied: verbal descriptions CT scans, MRI doctor's prognosis

In-Class Exercise

1. Select a **task**, T
2. Identify **performance measure**, P
3. Identify **experience**, E
4. Report ideas back to rest of class

Well-posed Learning Problems

task, T	performance measure, P	experience, E


20 JAN 2017 | Insight

Kevin Petrasic | Benjamin Saul

Algorithms and bias: What lenders need to know

The algorithms that power fintech may discriminate in ways that can be difficult to anticipate—and fi accountable even when alleged disc unintentional.

HOME > STRATEGY

Artificial intelligence is slated to disrupt 4.5 million jobs for African Americans, who have a 10% greater likelihood of automation-based job loss than other workers

Aliana Akhtar Oct 7, 2019, 12:57

The Washington Post

Democracy Dies in Darkness

Subscribe Sign in

Racial bias is built into the design of pulse oximeters

Misinformation on coronavirus is proving hi

By DAVID KLEPPER July 29, 2020

ACLU

BECOME A MEMBER / RENEW / TAKE ACT

ISSUES KNOW YOUR RIGHTS DEFENDING OUR RIGHTS BLOGS ABOUT

SPEAK FREELY

How Facebook Is Giving Sex Discrimination in Employment Ads a New Life

By Galen Sherwin, ACLU Women's Rights Project

The Switch

Wanted: The 'perfect babysitter.' Must pass AI scan for respect and attitude.

The New York Times

I.R.S. Changes Audit Practice That Discriminated Against Black Taxpayers

The agency will overhaul how it scrutinizes returns that claim the earned-income tax credit, which is aimed at alleviating poverty.

MEDICAL MALAISE

If you're not a white male, artificial intelligence's use in healthcare could be dangerous

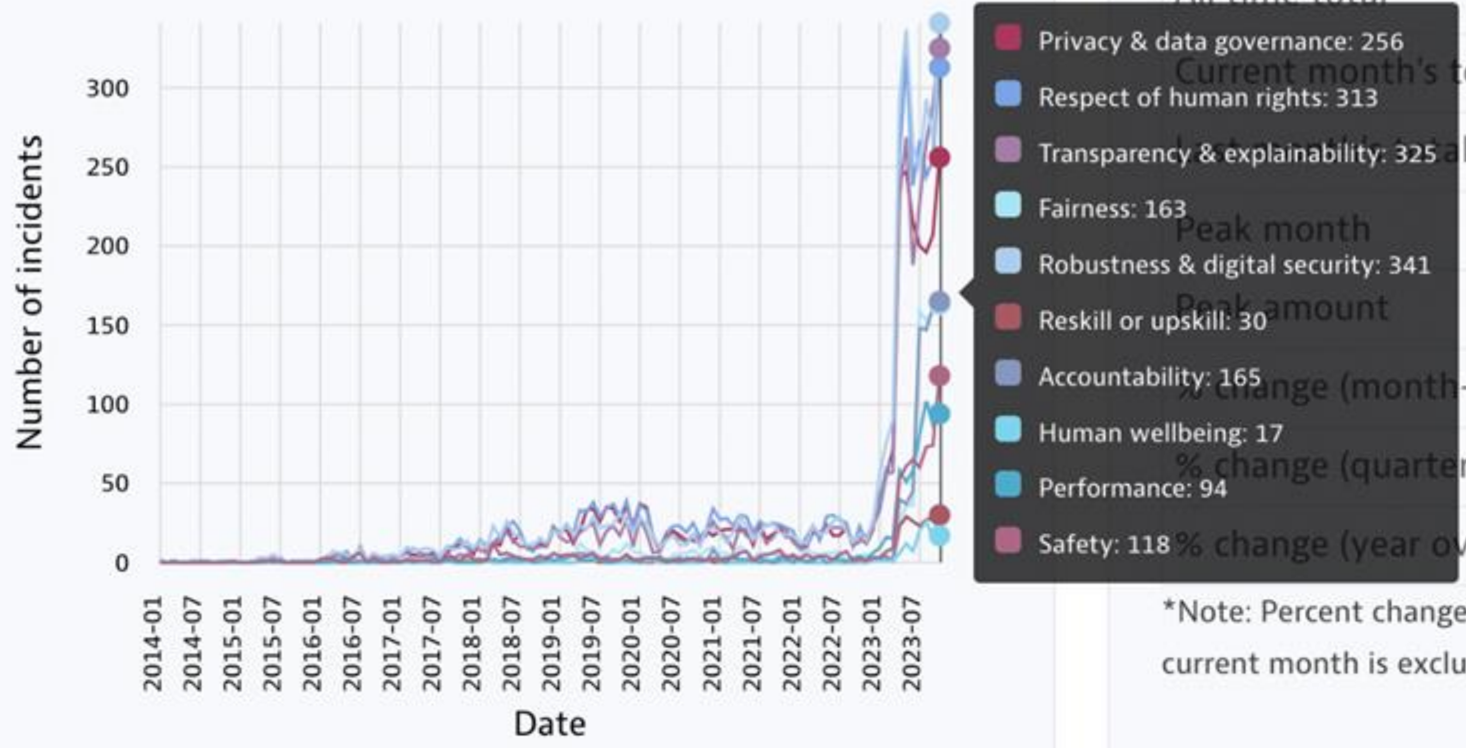
Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

AI Incidents on the Rise

Summary visualisations

Evolution of incidents by AI principle



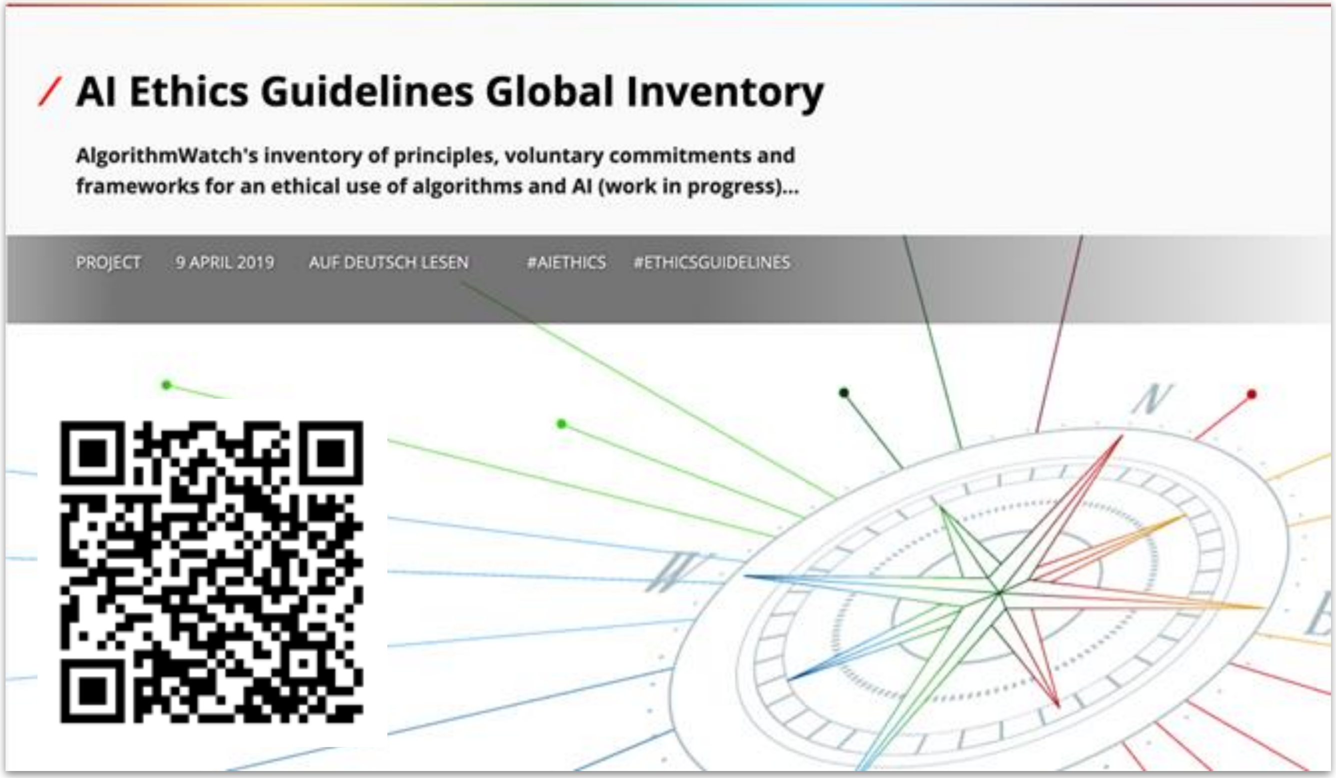
Summary statistics

	Incidents	Articles
All time total	6264	36345
Current month's total	317	1768
Last month's total	616	3227
Peak month	2023-10	2023-10
Peak amount	616	3227
% change (month-over-month)	23.2	51.22
% change (quarter-over-quarter)	13.01	13.87
% change (year over year)	961.58	690.9

*Note: Percent change is calculated based on preceding full months (i.e. the current month is excluded).

Principles

- Fairness
- Accountability
- Transparency
- Safety and reliability
- Security
- Privacy
- …



Presidential Executive Order 14110

1. Ensuring **safety and security** of AI
2. Responsible **innovation** and competition
3. Supporting **American workers**
4. Advancing **equity and civil rights**
5. **Protecting consumers**
6. Protecting **privacy and civil liberties**
7. Advancing **Federal use of AI**
8. Strengthening **American leadership** in AI

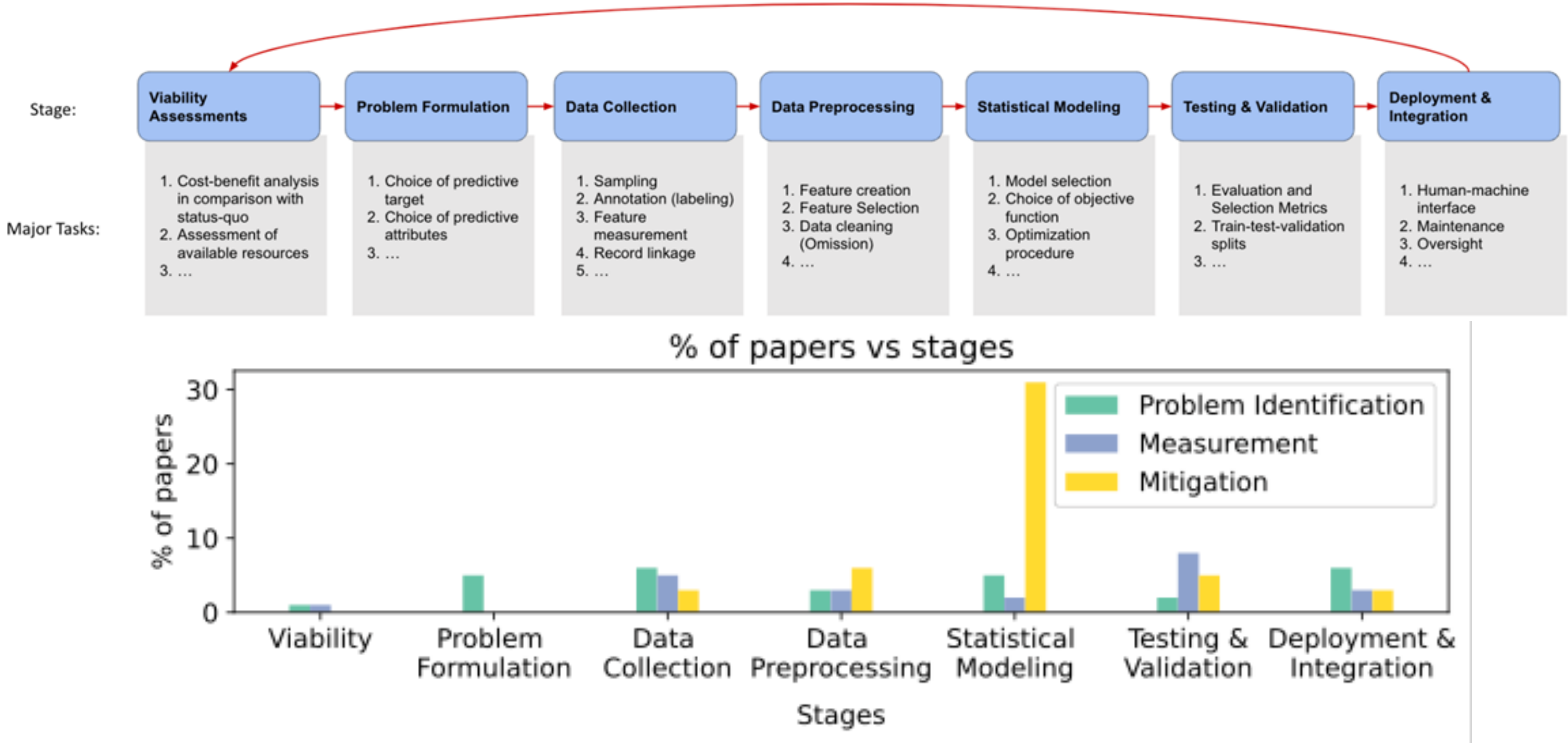
Mathematical Notions of Fairness

- **Group** notions

Notion of fairness	Equality of
Demographic Parity	$\mathbb{P}[\hat{Y} \mid S]$
Equality of Accuracy	$\mathbb{P}[(\hat{Y} - Y)^2 \mid S]$
Equality of FPR/FNR	$\mathbb{P}[\hat{Y} \mid Y, S]$
Equality of PPV/NPV	$\mathbb{P}[Y \mid \hat{Y}, S]$

- **Individual** notions
  - Treat similar individuals similarly.

Pipeline-aware Mitigation of Unfairness



Our first Machine Learning Task

- Learning to diagnose heart disease

  as a **(supervised) binary classification task**

features

labels

data points

Family History	Resting Blood Pressure	Cholesterol	Heart Disease?
Yes	Low	Normal	No
No	Medium	Normal	No
No	Low	Abnormal	Yes
Yes	Medium	Normal	Yes
Yes	High	Abnormal	Yes

Our first Machine Learning Task

- Learning to diagnose heart disease

  as a **(supervised) binary classification task**

features | labels

data points

Family History	Resting Blood Pressure	Cholesterol	Heart Disease?
Yes	Low	Normal	No
No	Medium	Normal	No
No	Low	Abnormal	Yes
Yes	Medium	Normal	Yes
Yes	High	Abnormal	Yes

Our first Machine Learning Task

- Learning to diagnose heart disease

  as a **(supervised)** <u>**binary classification**</u> **task**

features | labels

data points

Family History	Resting Blood Pressure	Cholesterol	Heart Disease?
Yes	Low	Normal	No
No	Medium	Normal	No
No	Low	Abnormal	Yes
Yes	Medium	Normal	Yes
Yes	High	Abnormal	Yes

Our first Machine Learning Task

- Learning to diagnose heart disease

  as a **(supervised)** **<u>classification</u> task**

features — labels

data points

Family History	Resting Blood Pressure	Cholesterol	Risk
Yes	Low	Normal	Low Risk
No	Medium	Normal	Low Risk
No	Low	Abnormal	Medium Risk
Yes	Medium	Normal	High Risk
Yes	High	Abnormal	High Risk

Our first Machine Learning Task

- Learning to diagnose heart disease

  as a **(supervised)** **<u>regression</u> task**

features   targets

data points

Family History	Resting Blood Pressure	Cholesterol	Medical Costs
Yes	Low	Normal	\$0
No	Medium	Normal	\$20
No	Low	Abnormal	\$30
Yes	Medium	Normal	\$100
Yes	High	Abnormal	\$5000

Our first Machine Learning Classifier

- A **classifier** is a function that takes feature values as input and outputs a label
- Majority vote classifier: always predict the most common label in the dataset

features | | | labels

Family History	Resting Blood Pressure	Cholesterol	Heart Disease?
Yes	Low	Normal	No
No	Medium	Normal	No
No	Low	Abnormal	Yes
Yes	Medium	Normal	Yes
Yes	High	Abnormal	Yes

data points

Is this a "good" Classifier?

- A **classifier** is a function that takes feature values as input and outputs a label
- Majority vote classifier: always predict the most common label in the dataset

features labels

data points

Family History	Resting Blood Pressure	Cholesterol	Heart Disease?
Yes	Low	Normal	No
No	Medium	Normal	No
No	Low	Abnormal	Yes
Yes	Medium	Normal	Yes
Yes	High	Abnormal	Yes

Training vs. Testing

- A **classifier** is a function that takes feature values as input and outputs a label
- Majority vote classifier: always predict the most common label in the **training** dataset (Yes)

training dataset

Family History	Resting Blood Pressure	Cholesterol	Heart Disease?
Yes	Low	Normal	No
No	Medium	Normal	No
No	Low	Abnormal	Yes
Yes	Medium	Normal	Yes
Yes	High	Abnormal	Yes

Training vs. Testing

- A **classifier** is a function that takes feature values as input and outputs a label
- Majority vote classifier: always predict the most common label in the **training** dataset (Yes)
- A **test** dataset is used to evaluate a classifier's **predictions**

test dataset

Family History	Resting Blood Pressure	Cholesterol	Heart Disease?	**Predictions**
No	Low	Normal	No	Yes
No	High	Abnormal	Yes	Yes
Yes	Medium	Abnormal	Yes	Yes

- The **error rate** is the proportion of data points where the prediction is wrong

Training vs. Testing

- A **classifier** is a function that takes feature values as input and outputs a label
- Majority vote classifier: always predict the most common label in the **training** dataset (Yes)
- A **test** dataset is used to evaluate a classifier's **predictions**

test dataset

Family History	Resting Blood Pressure	Cholesterol	Heart Disease?	**Predictions**
No	Low	Normal	No	Yes
No	High	Abnormal	Yes	Yes
Yes	Medium	Abnormal	Yes	Yes

- The **test error rate** is the proportion of data points in the test dataset where the prediction is wrong (1/3)

A Typical (Supervised) Machine Learning Routine

- Step 1 – training
  - Input: a labelled training dataset
  - Output: a classifier
- Step 2 – testing
  - Inputs: a classifier, a test dataset
  - Output: predictions for each test data point
- Step 3 – evaluation
  - Inputs: predictions from step 2, test dataset labels
  - Output: some measure of how good the predictions are; usually (but not always) error rate

Our first Machine Learning Classifier

- A **classifier** is a function that takes feature values as input and outputs a label
- Majority vote classifier: always predict the most common label in the training dataset

labels

data points

Heart Disease?
No
No
Yes
Yes
Yes

- This classifier completely ignores the features…

Our first Machine Learning Classifier

- A **classifier** is a function that takes feature values as input and outputs a label
- Majority vote classifier: always predict the most common label in the training dataset

labels

data points

Heart Disease?	Predictions
No	Yes
No	Yes
Yes	Yes
Yes	Yes
Yes	Yes

- The training error rate is $2/5$

Our second Machine Learning Classifier

- A **classifier** is a function that takes feature values as input and outputs a label
- Memorizer: if a set of features exists in the **training** dataset, predict its corresponding label; otherwise, predict the majority vote

Family History	Resting Blood Pressure	Cholesterol	Heart Disease?
Yes	Low	Normal	No
No	Medium	Normal	No
No	Low	Abnormal	Yes
Yes	Medium	Normal	Yes
Yes	High	Abnormal	Yes

Our second Machine Learning Classifier

- A **classifier** is a function that takes feature values as input and outputs a label
- Memorizer: if a set of features exists in the **training** dataset, predict its corresponding label; otherwise, predict the majority vote

Family History	Resting Blood Pressure	Cholesterol	Heart Disease?	Predictions
Yes	Low	Normal	No	No
No	Medium	Normal	No	No
No	Low	Abnormal	Yes	Yes
Yes	Medium	Normal	Yes	Yes
Yes	High	Abnormal	Yes	Yes

- The training error rate is 0!

Is the memorizer learning?

- A **classifier** is a function that takes feature values as input and outputs a label
- Memorizer: if a set of features exists in the **training** dataset, predict its corresponding label; otherwise, predict the majority vote

Family History	Resting Blood Pressure	Cholesterol	Heart Disease?	Predictions
Yes	Low	Normal	No	No
No	Medium	Normal	No	No
No	Low	Abnormal	Yes	Yes
Yes	Medium	Normal	Yes	Yes
Yes	High	Abnormal	Yes	Yes

- The training error rate is 0!

Our second Machine Learning Classifier

- A **classifier** is a function that takes feature values as input and outputs a label
- Memorizer: if a set of features exists in the **training** dataset, predict its corresponding label; otherwise, predict the majority vote
- The memorizer (typically) does not **generalize** well, i.e., it does not perform well on unseen data points
- In some sense, good generalization, i.e., the ability to make accurate predictions given a small training dataset, is the whole point of machine learning!

Learning Goals

- You should be able to

1. Formulate a well-posed learning problem for a real-world task by identifying the task, performance measure, and training experience
2. Describe common learning paradigms in terms of the type of data available, when it's available, the form of prediction, and the structure of the output prediction
3. Explain the difference between memorization and generalization [CIML]
4. Identify examples of the ethical responsibilities of an ML expert

Logistics: Course Website

http://www.cs.cmu.edu/~mgormley/courses/10601/

(or mlcourse.org)

Logistics: Course Syllabus

http://www.cs.cmu.edu/~mgormley/courses/10601/syllabus.html

- This whole section is **required** reading

Logistics: Grading

http://www.cs.cmu.edu/~mgormley/courses/10601/syllabus.html

- 50% homeworks
- 15% exam 1
- 15% exam 2
- 15% exam 3
- 5% participation

Logistics: Late Policy

http://www.cs.cmu.edu/~mgormley/courses/10601/syllabus.html

- You have 6 grace days for homework assignments
- Only 3 grace days may be used per homework
  - Only 2 grace days may be used on homeworks leading up to an exam (HW3, HW6, HW9)
- Late submissions w/o grace days will be penalized as:
  - 1 day late = 75% multiplicative penalty
  - 2 days late = 50% multiplicative penalty
  - 3 days late = 25% multiplicative penalty
- No submissions will be accepted more than 3 days late

Logistics: Collaboration Policy

http://www.cs.cmu.edu/~mgormley/courses/10601/syllabus.html

- Collaboration on homework assignments is encouraged but must be documented
- **You must always write your own code/answers**
  - You may not re-use code/previous versions of the homework, whether your own or otherwise
  - You may not use generative AI tools to complete any portion of the assignments
- Good approach to collaborating on programming assignments:
  1. Collectively sketch pseudocode on an impermanent surface, then
  2. Disperse, erase all notes and start from scratch

Logistics: Technologies

http://www.cs.cmu.edu/~mgormley/courses/10601/syllabus.html

- Piazza, for course discussion: https://piazza.com/class/lqzftil6bgtwd/
- Gradescope, for submitting homework assignments: https://www.gradescope.com/courses/693840
- Google Forms for in-class polls (more details next week)
- Panopto, for lecture recordings: https://scs.hosted.panopto.com/Panopto/Pages/Sessions/List.aspx?folderID=98a22931-8b47-4fa4-89c2-b0f1014438a0

Logistics: Lecture Schedule

http://www.cs.cmu.edu/~mgormley/courses/10601/schedule.html

Date	Lecture	Readings	Announcements
	Classification & Regression		
Wed, 17-Jan	Lecture 1 : Course Overview [slides]	• *Command Line and File I/O Tutorial*. 10601 Course Staff (2020). • *10601 Learning Objectives*. Matt Gormley (2023). • *Math Resources*. 10601 Course Staff (2023).	HW1 Out
Fri, 19-Jan	Recitation: HW1 [Handout] [Solutions]		
Mon, 22-Jan	Lecture 2 : Machine Learning as Function Approximation	• *10601 Notation Crib Sheet*. Matt Gormley (2023).	
Wed, 24-Jan	Lecture 3 : Decision Trees [Poll]	• *Visual Information Theory*. Christopher Olah (2015). blog. • *Decision Trees*. Hal Daumé III (2017). CIML, Chapter 1.	HW1 Due HW2 Out
Fri, 26-Jan	Recitation: HW2 [Handout] [Solutions]		
Mon, 29-Jan	Lecture 4 : k-Nearest Neighbors [Poll]	• *Geometry and Nearest Neighbors*. Hal Daumé III (2017). CIML, Chapter 3.	

Logistics: Lectures

- During lecture, you should ask lots of questions!
  - Interrupting (by raising a hand) to ask your question is strongly encouraged
  - Asking questions over Zoom or later via Piazza is also great
- When we ask you all a question, we really do want you to answer!
  - Even if you don’t answer, think it through as if we had called on you
- Interaction improves learning, in-class, at office hours and amongst yourselves (to a point of course)

Wait, was there something about a HW in that lecture schedule?

http://www.cs.cmu.edu/~mgormley/courses/10601/schedule.html

Date	Lecture	Readings	Announcements
	Classification & Regression		
Wed, 17-Jan	Lecture 1 : Course Overview	• *Command Line and File I/O Tutorial*. 10601 Course Staff (2020). • *10601 Learning Objectives*. Matt Gormley (2023). • *Math Resources*. 10601 Course Staff (2023).	HW1 Out
Fri, 19-Jan	Recitation: HW1 [Handout] [Solutions]		
Mon, 22-Jan	Lecture 2 : Machine Learning as Function Approximation	• *10601 Notation Crib Sheet*. Matt Gormley (2023).	
Wed, 24-Jan	Lecture 3 : Decision Trees [Poll]	• *Visual Information Theory*. Christopher Olah (2015). blog. • *Decision Trees*. Hal Daumé III (2017). CIML, Chapter 1.	HW1 Due HW2 Out
Fri, 26-Jan	Recitation: HW2 [Handout] [Solutions]		
Mon, 29-Jan	Lecture 4 : k-Nearest Neighbors [Poll]	• *Geometry and Nearest Neighbors*. Hal Daumé III (2017). CIML, Chapter 3.	

FAQ: Am I prepared to take this course?

- Answer: We don't know!
- But we have designed a way for you to assess your background knowledge for yourselves!
- HW1 released 1/17 (today!), due 1/24 at 11:59 PM
- Most HWs consist of two parts:
  - a written component
  - a programming component
- **Unique policies for HW1 only:**
  - Any written submission that receives a grade of 90% or higher will receive full credit
  - Any written submission that receives less than 90% can be resubmitted once for a (potentially) higher grade
  - You will have unlimited submissions to the autograder

Logistics: Exam Schedule

http://www.cs.cmu.edu/~mgormley/courses/10601/schedule.html

⋮

Mon, 19-Feb	Lecture 10 : Feature Engineering / Regularization [Poll]	• *Regularization for Deep Learning*. Ian Goodfellow, Yoshua Bengio, & Aaron Courville (2016). Deep Learning, Chapter 7.1 and 7.8.	
Mon, 19-Feb	Exam 1 (evening exam, details will be announced on Piazza)		HW4 Out

⋮

Wed, 27-Mar	Lecture 19 : Pre-training, Fine-tuning, In-context Learning [Poll]		
Thu, 28-Mar	Exam 2 (evening exam, details will be announced on Piazza)		HW7 Out

⋮

TBD, TBD	Exam 3 (during Final Exam Period -- exact time/date TBD by the registrar, details will be announced on Piazza)		

Logistics: Assignments

http://www.cs.cmu.edu/~mgormley/courses/10601/coursework.html

Assignments

There will be 9 homework assignments during the semester in addition to the exams. The assignments will consist of both theoretical and programming problems. Homework assignments will be released via a Piazza announcement explaining where to find the handout, starter code, LaTeX template, etc.

The links to the **Homework Handouts** and **Homework Exit Polls** will be provided below.

- Homework 1: Background Material (written / programming)
- Homework 2: Decision Trees (written / programming)
- Homework 3: KNN, Perceptron, and Linear Regression (written)
- Homework 4: Logistic Regression (written / programming)
- Homework 5: Neural Networks (written / programming)
- Homework 6: Generative Models (written)
- Homework 7: Transformers in PyTorch (written / programming)
- Homework 8: Reinforcement Learning (written / programming)
- Homework 9: Learning Paradigms (written)

Tentative release dates and due dates are listed on the Schedule page.

Exams

There will be three exams. The links to the **Practice Problems** and **Exam Exit Polls** will be provided below.

- Exam 1 (in-person): Lectures 1-7
- Exam 2 (in-person): Lectures 8-17
- Exam 3 (in-person): Lectures 18-27

Logistics: Office Hours

http://www.cs.cmu.edu/~mgormley/courses/10601/officehours.html