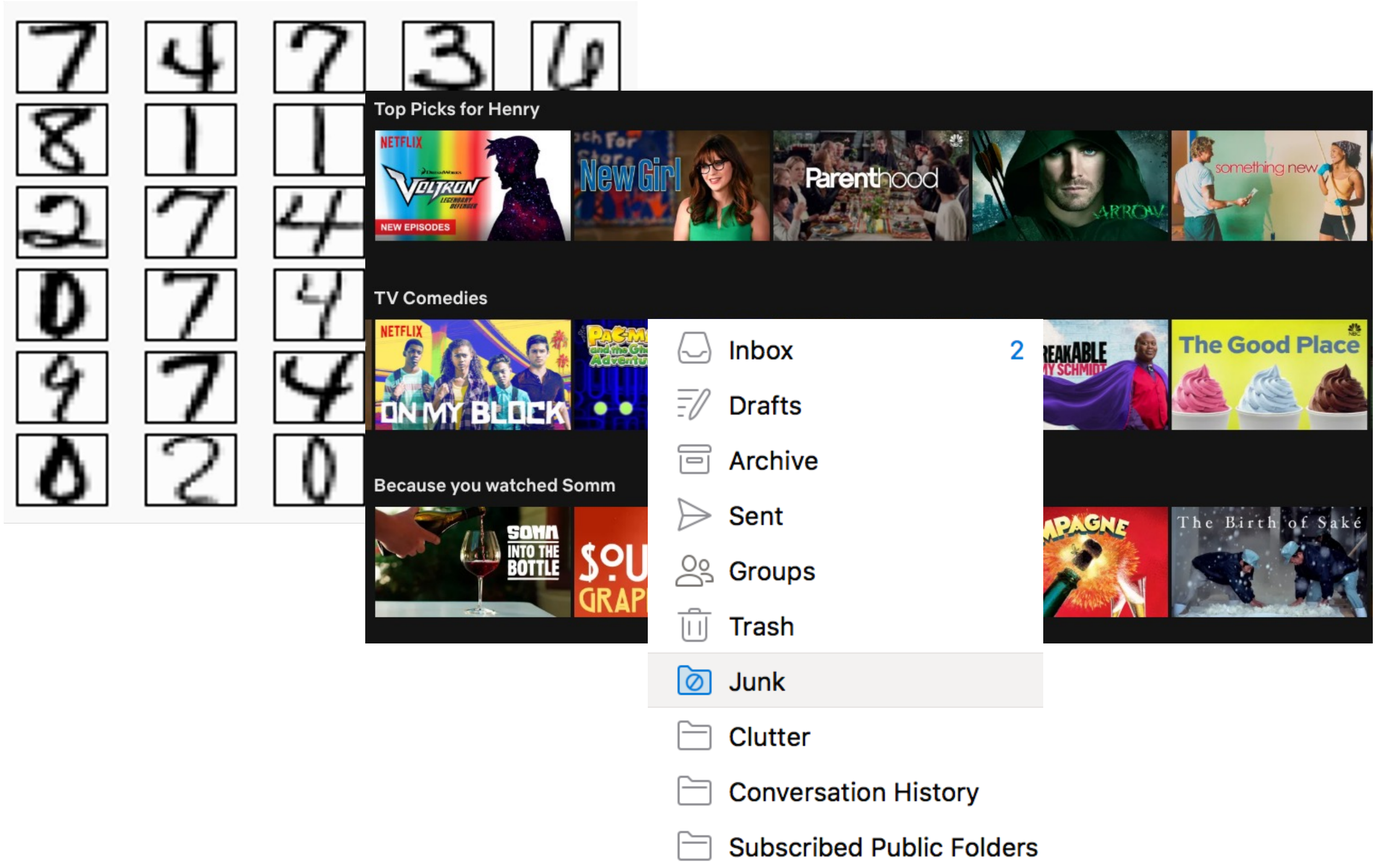
10-301/601: Introduction to Machine Learning Lecture 1 – Problem Formulation & Notation

Hoda Heidari, Henry Chai & Matt Gormley

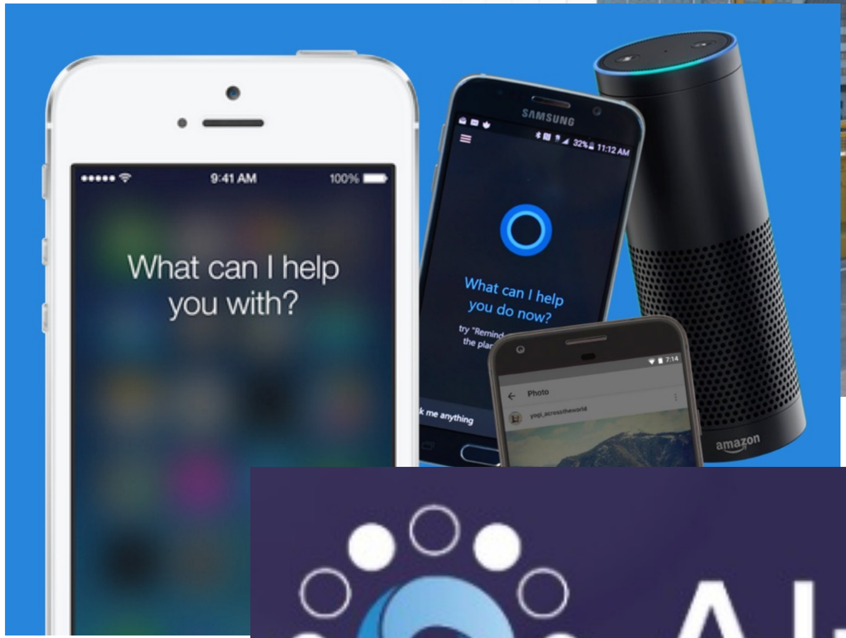
1/17/24

What is Machine Learning?

Machine Learning (A long long time ago…)



Machine Learning (A short time ago…)



AlphaGo

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
  - Performance metric, P
  - Experience, E

Defining a Machine Learning Task: Example

- Learning to approve loans/lines of credit

- Three components
  - Task, T
  - Performance metric, P
  - Experience, E

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)**

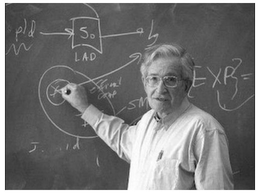
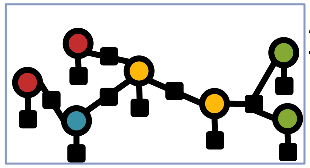
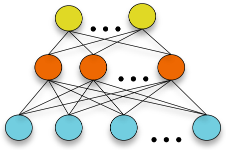
1. Task, *T*:

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

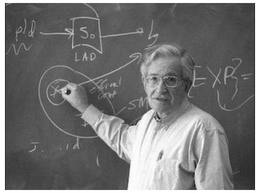
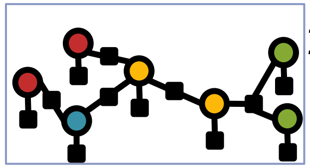
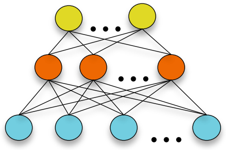
Solution #1: Expert Systems

- 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:~~ ~~type = MUSIC()~~ ~~elif "txt" in x:~~ ~~type = TXTMSG()~~ ~~elif "directions" in x:~~ ~~type = DIRECTIONS()~~

Capturing the Knowledge of Experts

1980  1990  2000  2010  2020

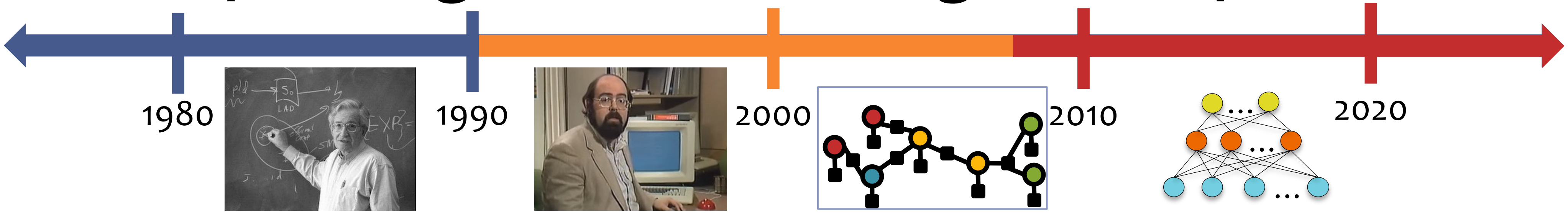
Solution #1: Expert Systems

- 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))

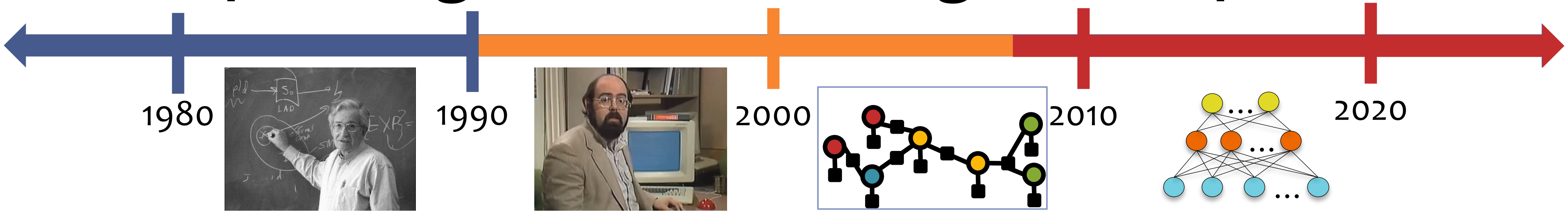
Capturing the Knowledge of Experts



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?`

$y^{(1)}$: `DIRECTIONS(here, nearest(Starbucks))`

$x^{(2)}$: `Show me the closest Starbucks`

$y^{(2)}$: `MAP(nearest(Starbucks))`

$x^{(3)}$: `Send a text to John that I'll be late`

$y^{(3)}$: `TXTNSG(John, I'll be late)`

$x^{(4)}$: `Set an alarm for seven in the morning`

$y^{(4)}$: `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

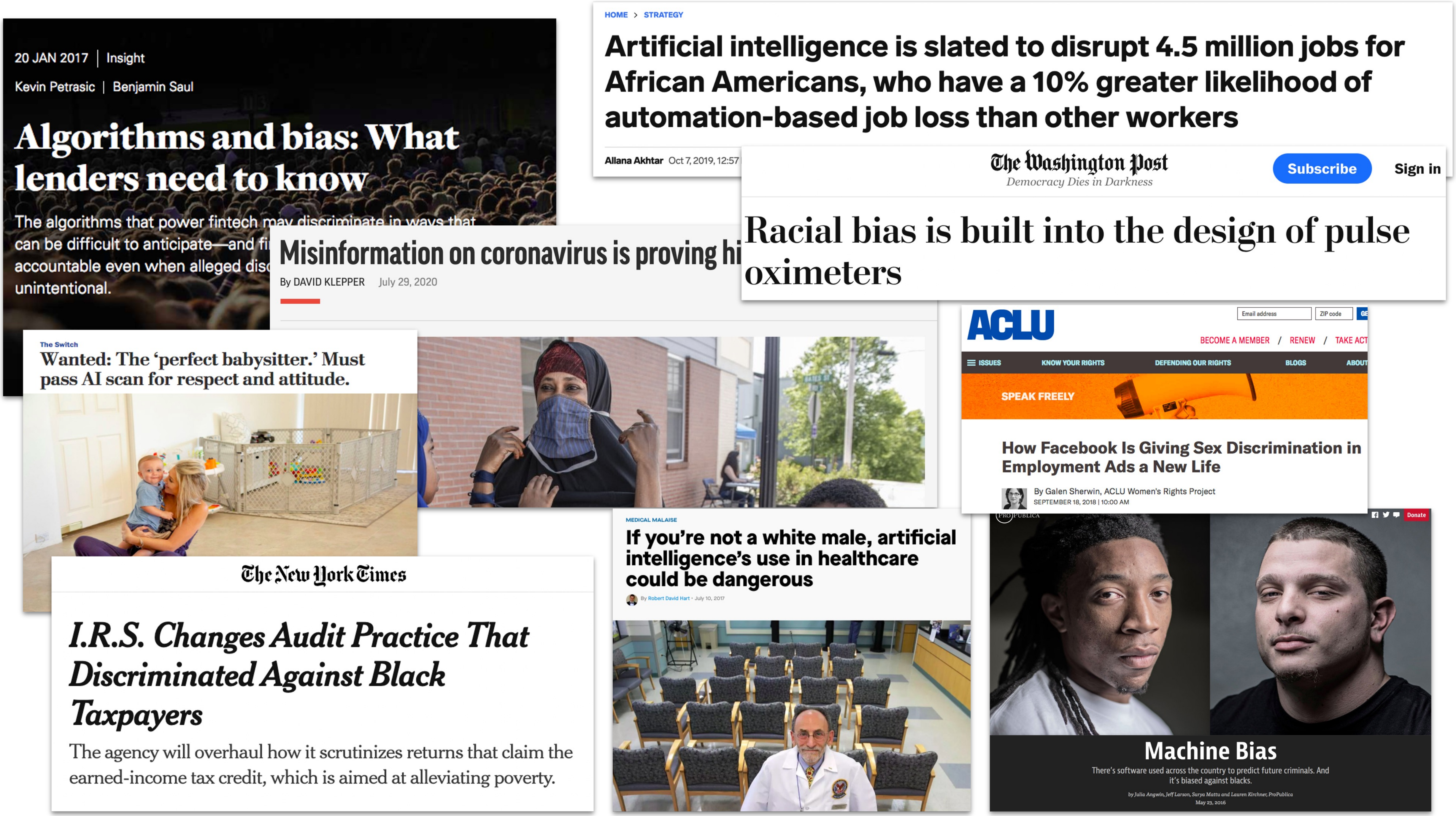
Well-posed Learning Problems

task, T	performance measure, P	experience, E

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

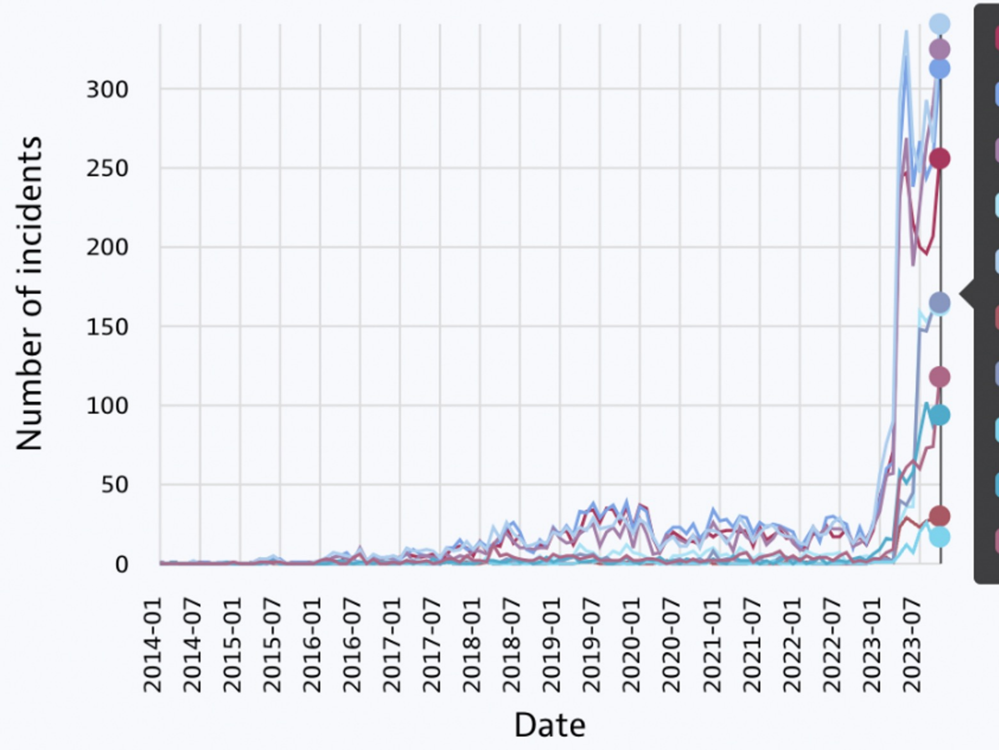
task, T	performance measure, P	experience, E


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
Allana 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
The Switch
Wanted: The 'perfect babysitter.' Must pass AI scan for respect and attitude.
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
SEPTEMBER 18, 2018 | 10:00 AM
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
By Robert David Hart · July 10, 2017
Donate
Machine Bias
There's software used across the country to predict future criminals. And it's biased against blacks.
by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica
May 23, 2016

AI Incidents on the Rise

Summary visualisations

Evolution of incidents by AI principle



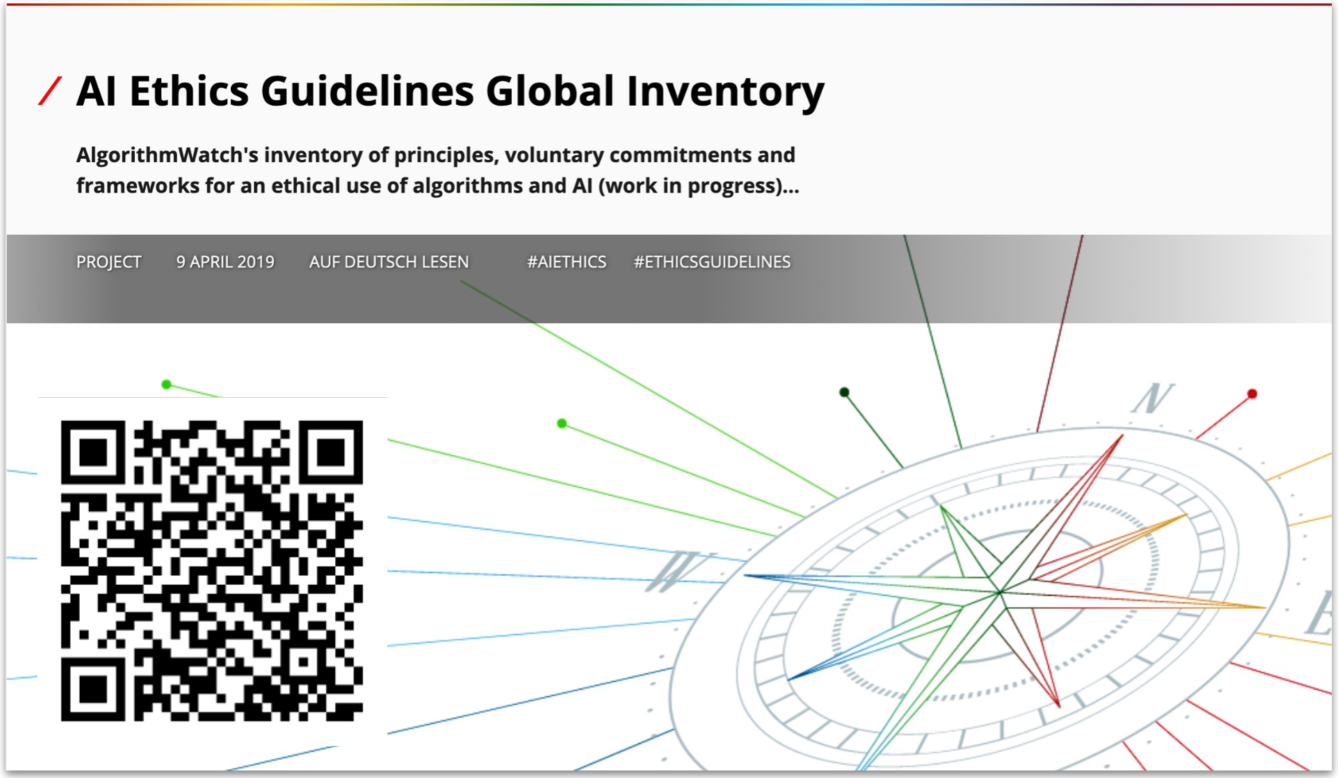
Summary statistics

	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
- …



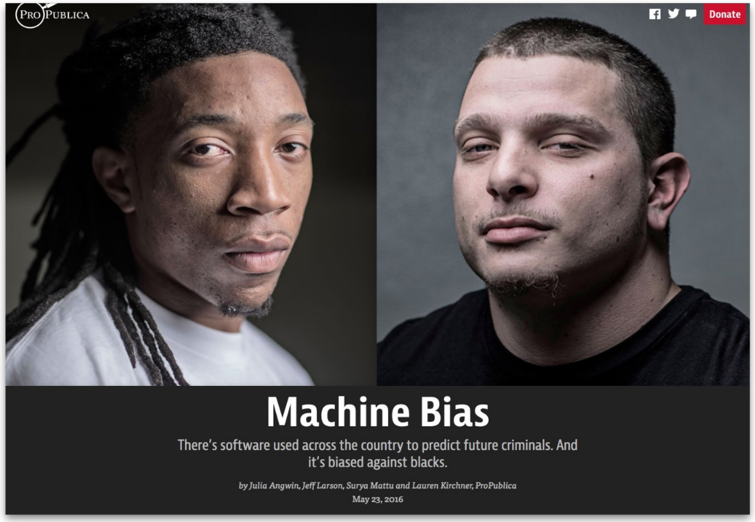
Presidential Executive Order 14110

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

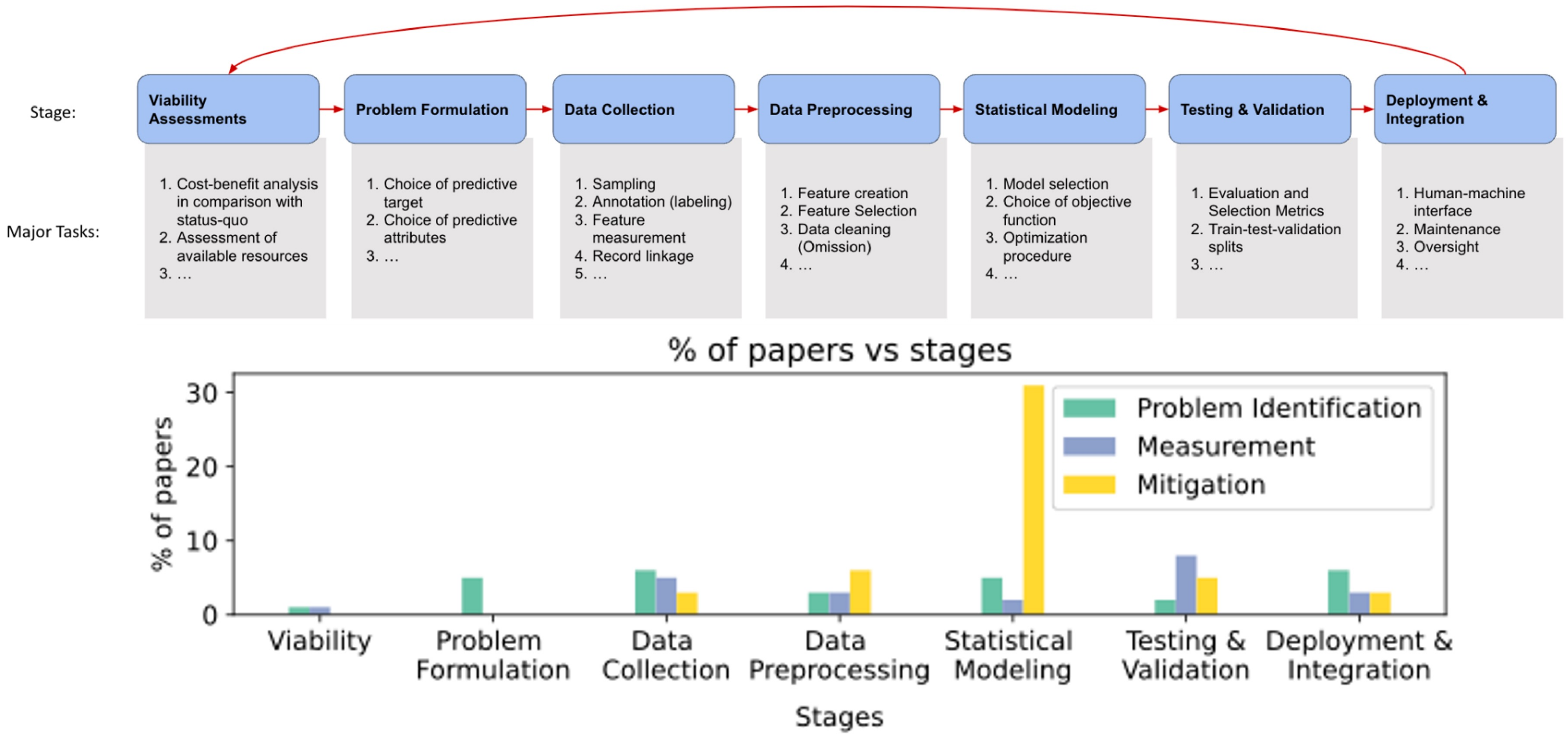
- **Group** notions

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 **(<u>supervised</u>) 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**

$$\overbrace{\text{features}}\qquad\overbrace{\text{labels}}$$

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

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

features

labels

data points

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!

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