

SUMMARY & REFLECTION

(the last one)

Christian Kaestner

TODAY

Looking back at the
semester
(424 slides in 40 min)

Discussion of future of
SE4AI

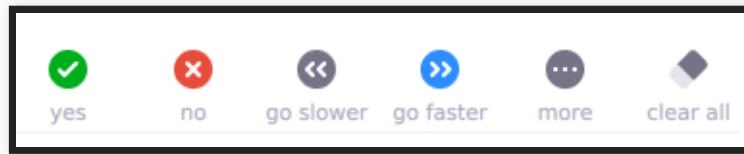
Feedback for future
semesters

INTRODUCTION AND MOTIVATION

Christian Kaestner

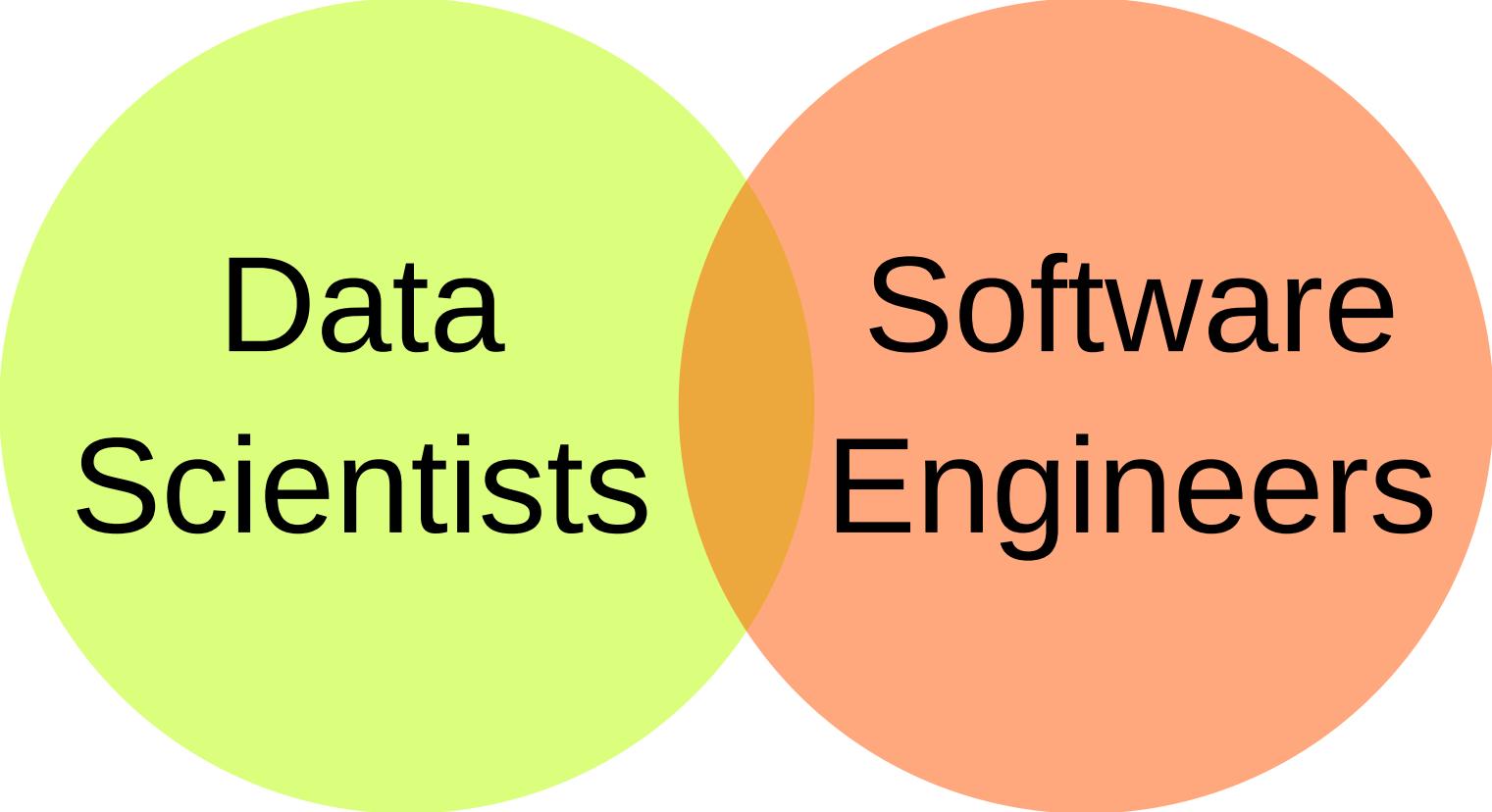
LECTURE LOGISTICS DURING A PANDEMIC

If you can hear me, open the participant panel in Zoom and check "yes"



LEARNING GOALS

- Understand how AI components are parts of larger systems
- Illustrate the challenges in engineering an AI-enabled system beyond accuracy
- Explain the role of specifications and their lack in machine learning and the relationship to deductive and inductive reasoning
- Summarize the respective goals and challenges of software engineers vs data scientists



A Venn diagram consisting of two overlapping circles. The left circle is light green and contains the text "Data Scientists". The right circle is light orange and contains the text "Software Engineers". The two circles overlap in the center.

Data
Scientists

Software
Engineers

SOFTWARE ENGINEER

DATA SCIENTIST

- Often fixed dataset for training and evaluation (e.g., PBS interviews)
- Focused on accuracy
- Prototyping, often Jupyter notebooks or similar
- Expert in modeling techniques and feature engineering
- Model size, updateability, implementation stability typically does not matter

- Builds a product
- Concerned about cost, performance, stability, release time
- Identify quality through customer satisfaction
- Must scale solution, handle large amounts of data
- Detect and handle mistakes, preferably automatically
- Maintain, evolve, and extend the product over long periods
- Consider requirements for security, safety, fairness

QUALITIES OF INTEREST ("ILITIES")

- Quality is about more than the absence of defects
- Quality in use (effectiveness, efficiency, satisfaction, freedom of risk, ...)
- Product quality (functional correctness and completeness, performance efficiency, compatibility, usability, dependability, scalability, security, maintainability, portability, ...)
- Process quality (manageability, evolvability, predictability, ...)
- "Quality is never an accident; it is always the result of high intention, sincere effort, intelligent direction and skillful execution; it represents the wise choice of many alternatives." (many attributions)

A screenshot of a transcription software interface. At the top, there's a header with the file name 'the-changelog-318', a link to 'Dashboard', and a 'Quality' setting at 'High'. To the right are buttons for 'Last saved a few seconds ago', three dots for more options, and a yellow 'Share' button. Below the header is a timeline bar with markers at 00:00, Offset, 00:00, and 01:31:27. Underneath the timeline are four buttons: 'Play', 'Back 5s', '1x Speed', and 'Volume'. The main content area is divided into two sections: 'NOTES' on the left containing the placeholder 'Write your notes here', and the transcribed speech on the right.

Speaker 5 ► 07:44

Yeah. So there's a slight story behind that. So back when I was in, uh, Undergrad, I wrote a program for myself to measure a, the amount of time I did data entry from my father's business and I was on windows at the time and there wasn't a function called time dot [inaudible] time, uh, which I needed to parse dates to get back to time, top of representation, uh, I figured out a way to do it and I gave it to what's called the python cookbook because it just seemed like something other people could use. So it was just trying to be helpful. Uh, subsequently I had to figure out how to make it work because I didn't really have to. Basically, it bothered me that you had to input all the locale information and I figured out how to do it over the subsequent months. And actually as a graduation gift from my Undergrad, the week following, I solved it and wrote it all out.

Speaker 5 ► 08:38

And I asked, uh, Alex Martelli, the editor of the Python Cookbook, which had published my original recipe, a, how do I get this into python? I think it might help

How did we do on your transcript?

SYLLABUS AND CLASS STRUCTURE

17-445/17-645, Summer 2020, 12 units

Tuesday/Wednesday 3-4:20, here on zoom

TEXTBOOK

Building Intelligent Systems: A Guide to
Machine Learning Engineering

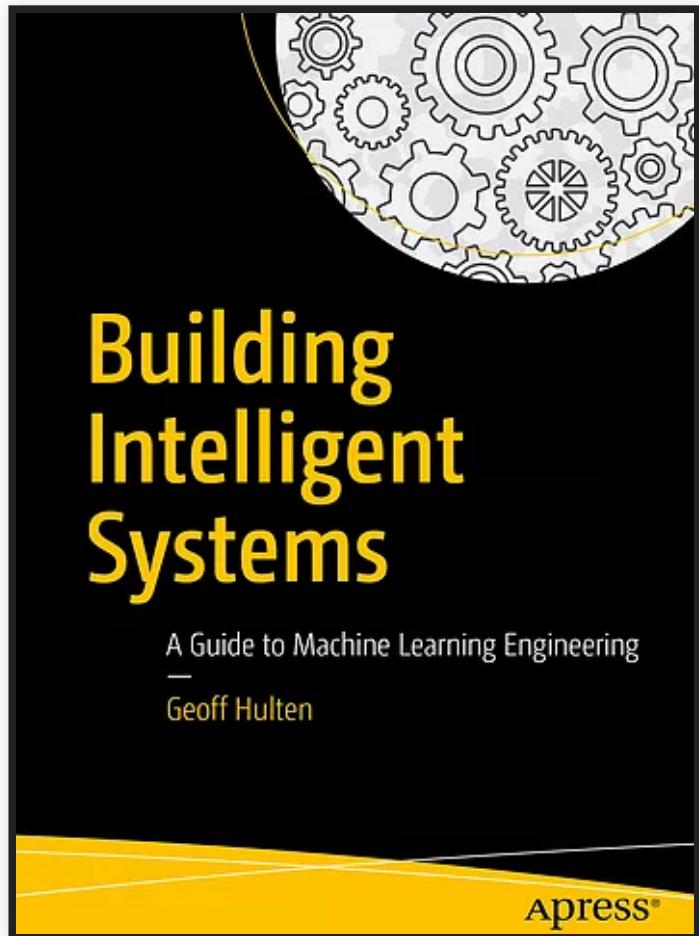
by Geoff Hulten

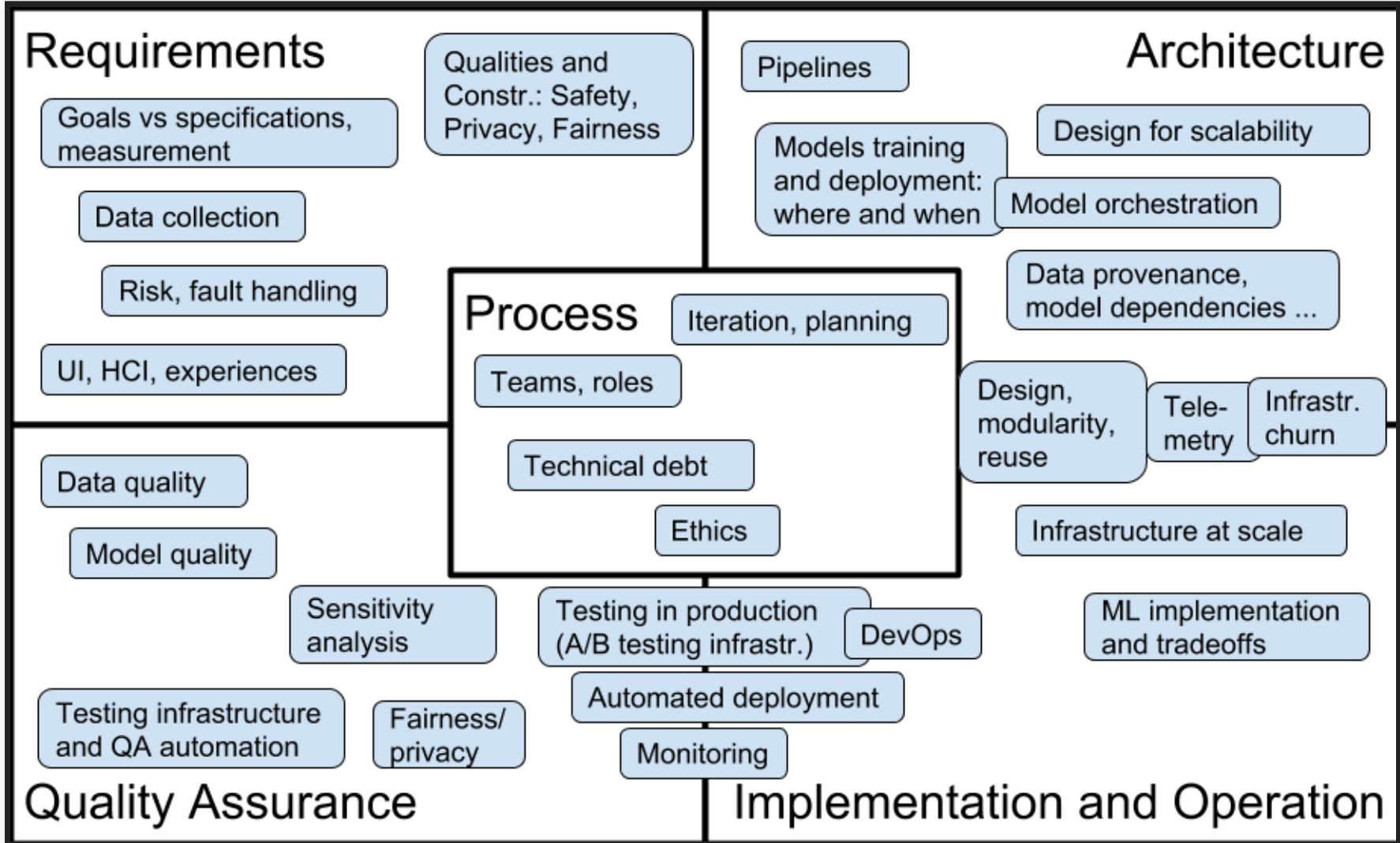
<https://www.buildingintelligentsystems.com/>

Most chapters assigned at some point in the
semester

Supplemented with research articles, blog
posts, videos, podcasts, ...

[Electronic version](#) in the library





INTRODUCTIONS

Let's go around the "room" for introductions:

- Your (preferred name)
- In two sentences your software engineering background and goals
- In two sentences your data science background, if any, and goals
- One topic you are particularly interested in, if any?



CORRECTNESS AND SPECIFICATIONS

DEDUCTIVE VS. INDUCTIVE REASONING

WHO IS TO BLAME?

```
Algorithms.shortestDistance(g, "Tom", "Anne");
```

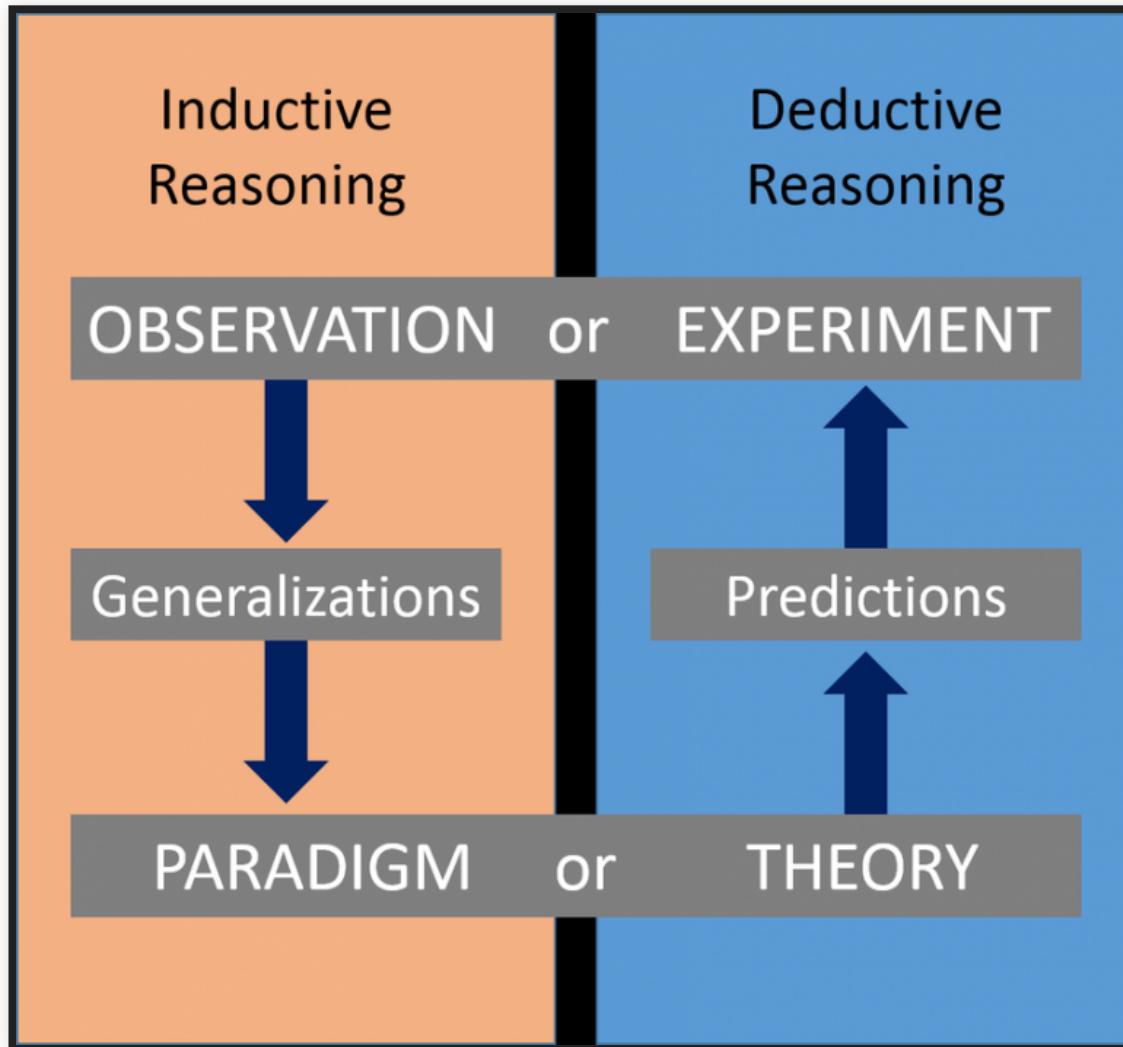
```
> ArrayOutOfBoundsException
```

```
Algorithms.shortestDistance(g, "Tom", "Anne");
```

```
> -1
```

SPECIFICATIONS IN MACHINE LEARNING?

```
/**  
 *  
 *  
 */  
String transcribe(File audioFile);
```



(Daniel Miessler, CC SA 2.0)

RESULTING SHIFT IN DESIGN THINKING?

From deductive reasoning to inductive reasoning...

From clear specifications to goals...

From guarantees to best effort...

What does this mean for software engineering?

For decomposing software systems?

For correctness of AI-enabled systems?

For safety?

For design, implementation, testing, deployment, operations?

HOMEWORK 1: CASE STUDY

Engineering issues in detecting malicious apps

ARTIFICIAL INTELLIGENCE FOR SOFTWARE ENGINEERS

(Part 1: Supervised Machine Learning and Notebooks)

Christian Kaestner

Required Reading: □ Hulten, Geoff. “[Building Intelligent Systems: A Guide to Machine Learning Engineering.](#)” (2018), Chapters 16–18, 20.

Suggested complementary reading: □ Géron, Aurélien. ”[Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow](#)”, 2nd Edition (2019), Ch 1.

LEARNING GOALS

- Understand how machine learning learns models from labeled data (basic mental model)
- Explain the steps of a typical machine learning pipeline and their responsibilities and challenges
- Understand the role of hyper-parameters
- Appropriately use vocabulary for machine learning concepts
- Apply steps of a machine-learning pipeline to build a simple model from static labeled data
- Evaluate a machine-learned classifier using cross-validation
- Explain the benefits and drawbacks of notebooks
- Demonstrate effective use of computational notebooks

DEFINING MACHINE LEARNING (SIMPLIFIED)

learn a function (called model)

$$f(x_1, x_2, x_3, \dots, x_n) \rightarrow y$$

by observing data

Examples:

- Detecting cancer in an image
- Transcribing an audio file
- Detecting spam
- Predicting recidivism
- Detect suspicious activity in a credit card

Typically used when writing that function manually is hard because the problem is hard or complex.

RUNNING EXAMPLE: HOUSE PRICE ANALYSIS

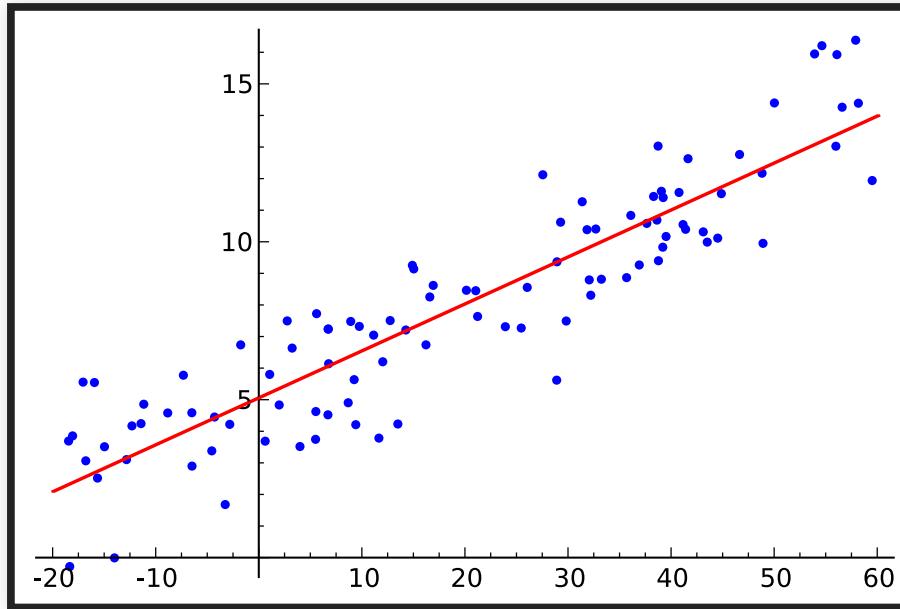
Given data about a house and its neighborhood, what is the likely sales price for this house?

$$f(\text{size}, \text{rooms}, \text{tax}, \text{neighborhood}, \dots) \rightarrow \text{price}$$



LINEAR REGRESSION

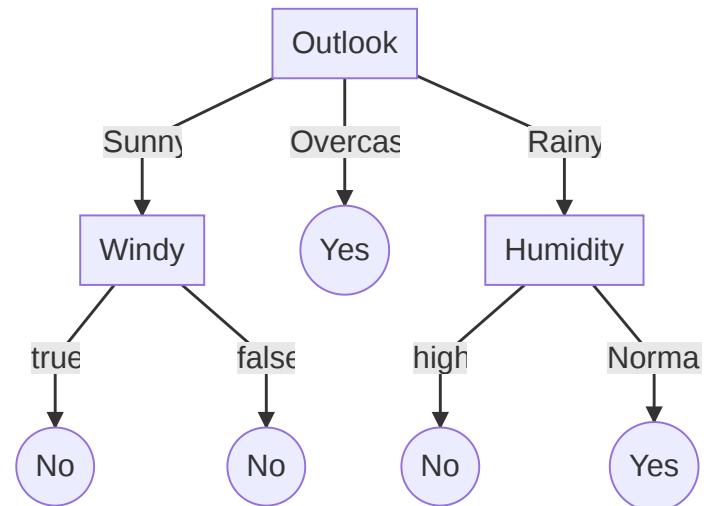
$$f(x) = \alpha + \beta * x$$



DECISION TREES

Outlook	Temperature	Humidity	Windy	Play
overcast	hot	high	false	yes
overcast	hot	high	false	no
overcast	hot	high	false	yes
overcast	cool	normal	true	yes
overcast	mild	high	true	yes
overcast	hot	normal	false	yes
rainy	mild	high	false	yes
rainy	cool	normal	false	yes
rainy	cool	normal	true	no
rainy	mild	normal	false	yes
rainy	mild	high	true	no
sunny	hot	high	false	no
sunny	hot	high	true	no
sunny	mild	high	false	no
sunny	cool	normal	false	yes
sunny	mild	normal	true	yes

$f(\text{Outlook}, \text{Temperature}, \text{Humidity}, \text{Windy}) =$



OVERFITTING WITH DECISION TREES

Outlook	Temperature	Humidity	Windy	Play
overcast	hot	high	false	yes
overcast	hot	high	false	no
overcast	hot	high	false	yes
overcast	cool	normal	true	yes
overcast	mild	high	true	yes
overcast	hot	normal	false	yes
rainy	mild	high	false	yes
rainy	cool	normal	false	yes
rainy	cool	normal	true	no
rainy	mild	normal	false	yes
rainy	mild	high	true	no
sunny	hot	high	false	no
sunny	hot	high	true	no
sunny	mild	high	false	no
sunny	cool	normal	false	yes
sunny	mild	normal	true	yes

```
f(Outlook, Temperature, Humidity, Windy) =  
    IF Humidity ∈ [high]  
        IF Outlook ∈ [overcast,rainy]  
            IF Outlook ∈ [overcast]  
                IF Temperature ∈ [hot,cool]  
                    true (0.667)  
                    true (1.000)  
                IF Windy ∈ [FALSE]  
                    true (1.000)  
                    false (1.000)  
                false (1.000)  
            IF Windy ∈ [FALSE]  
                true (1.000)  
            IF Temperature ∈ [hot,cool]  
                IF Outlook ∈ [overcast]  
                    true (1.000)  
                    false (1.000)  
                true (1.000)
```

The tree perfectly fits the data, except on overcast, hot and humid days without wind, where there is not enough data to distinguish 3 outcomes.

Not obvious that this tree will generalize well.

ON TERMINOLOGY

- The decisions in a model are called *model parameter* of the model (constants in the resulting function, weights, coefficients), their values are usually learned from the data
- The parameters to the learning algorithm that are not the data are called *model hyperparameters*
- Degrees of freedom \sim number of model parameters

```
// max_depth and min_support are hyperparameters
def learn_decision_tree(data, max_depth, min_support): Model =
    ...

// A, B, C are model parameters of model f
def f(outlook, temperature, humidity, windy) =
    if A==outlook
        return B*temperature + C*windy > 10
```

SEPARATE TRAINING AND VALIDATION DATA

Always test for generalization on *unseen* validation data

Accuracy on training data (or similar measure) used during learning to find model parameters

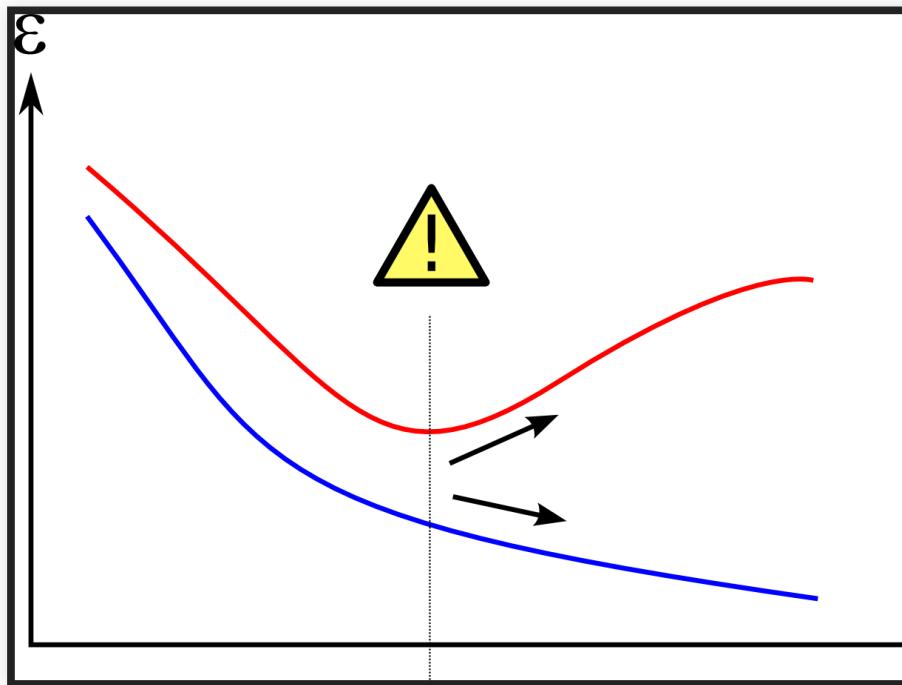
```
train_xs, train_ys, valid_xs, valid_ys = split(all_xs, all_ys)
model = learn(train_xs, train_ys)

accuracy_train = accuracy(model, train_xs, train_ys)
accuracy_valid = accuracy(model, valid_xs, valid_ys)
```

accuracy_train >> accuracy_valid = sign of overfitting

DETECTING OVERFITTING

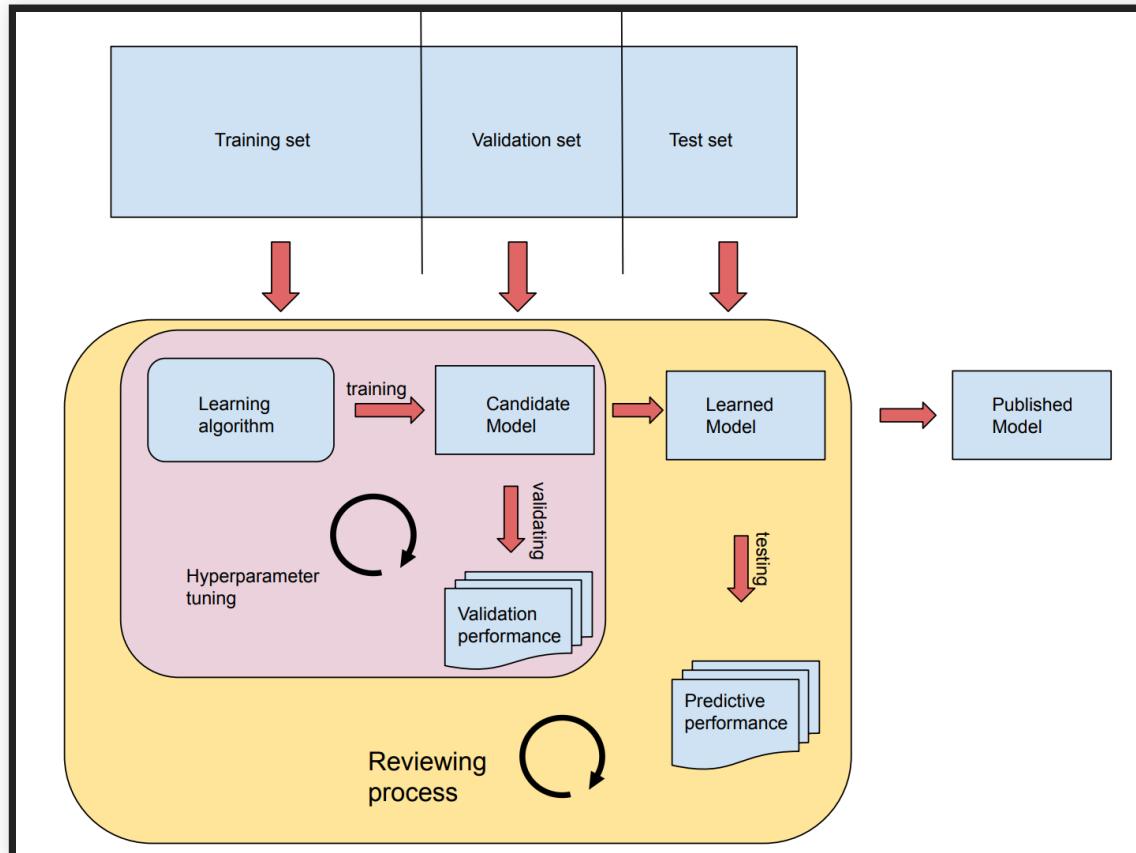
Change hyperparameter to detect training accuracy (blue)/validation accuracy (red) at different degrees of freedom



(CC SA 3.0 by [Dake](#))

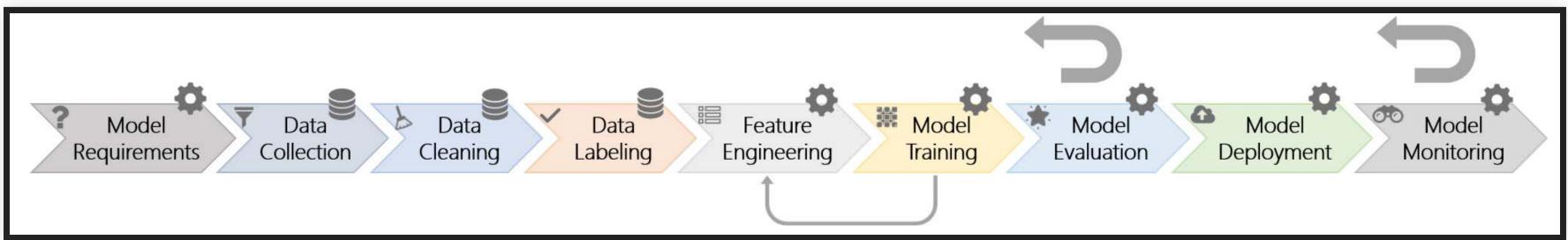
demo time

ACADEMIC ESCALATION: OVERFITTING ON BENCHMARKS



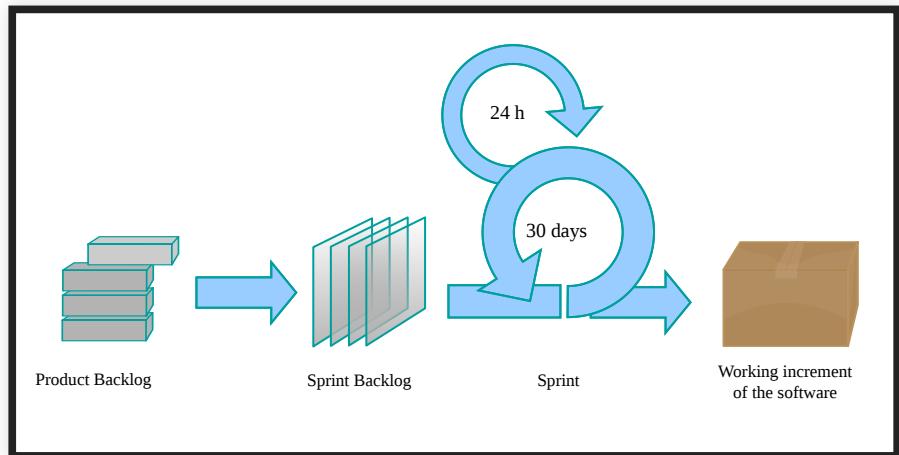
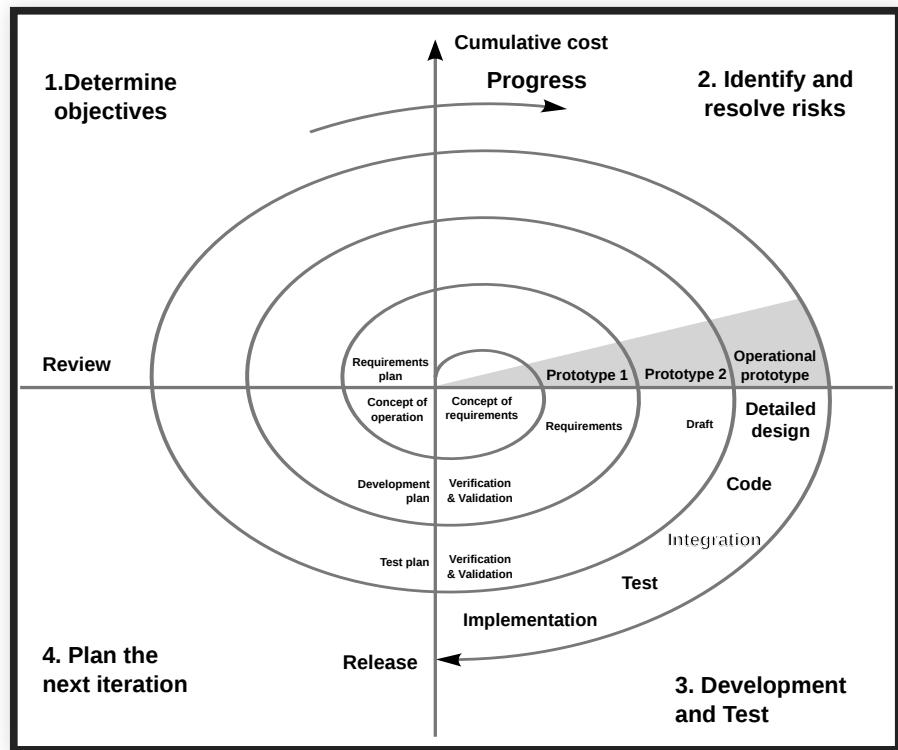
(Figure by Andrea Passerini)

MACHINE LEARNING PIPELINE



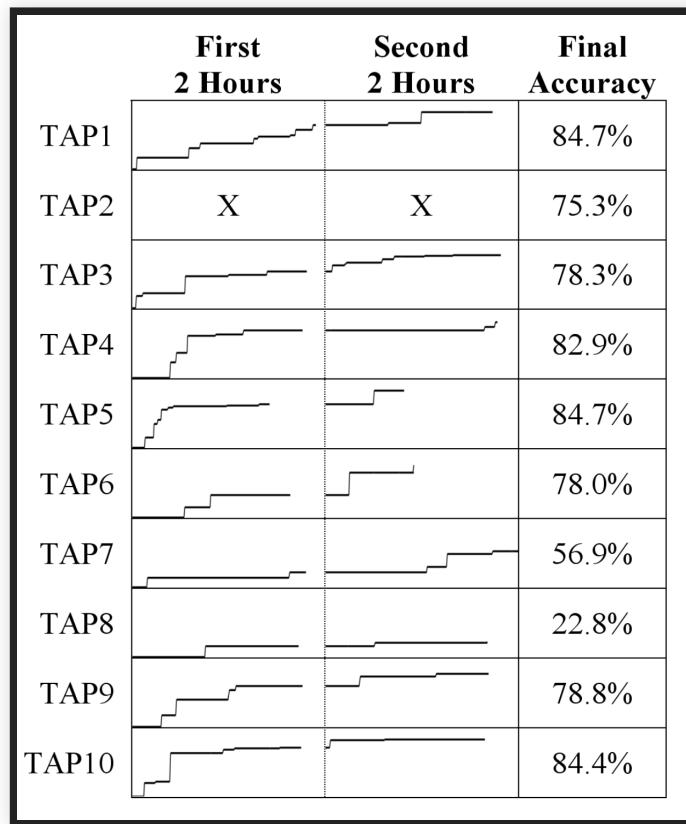
Graphic: Amershi, Saleema, Andrew Begel, Christian Bird, Robert DeLine, Harald Gall, Ece Kamar, Nachiappan Nagappan, Besmira Nushi, and Thomas Zimmermann. "[Software engineering for machine learning: A case study.](#)" In 2019 IEEE/ACM 41st International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP), pp. 291-300. IEEE, 2019.

SIMILAR TO SPIRAL PROCESS MODEL OR AGILE?



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DATA SCIENCE IS ITERATIVE AND EXPLORATORY

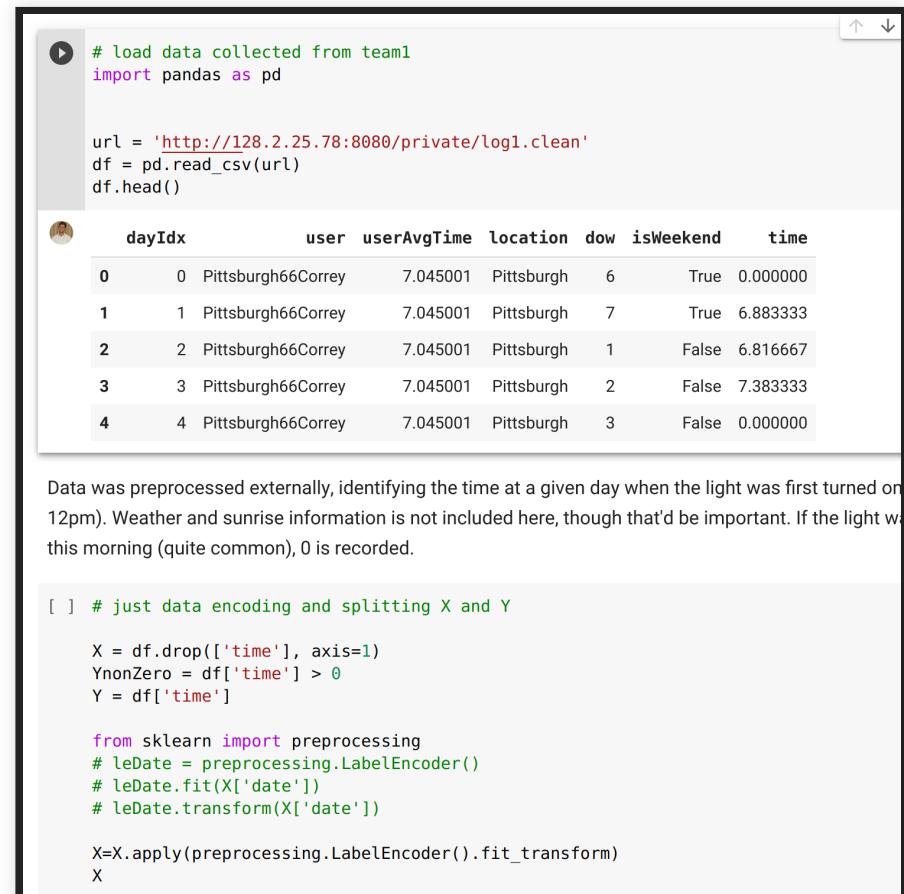


Source: Patel, Kayur, James Fogarty, James A. Landay, and Beverly Harrison.
["Investigating statistical machine learning as a tool for software development."](#) In
Proc. CHI, 2008.

COMPUTATIONAL NOTEBOOKS

- Origins in "literal programming", interleaving text and code, treating programs as literature (Knuth'84)
- First notebook in Wolfram Mathematica 1.0 in 1988
- Document with text and code cells, showing execution results under cells
- Code of cells is executed, per cell, in a kernel
- Many notebook implementations and supported languages, Python + Jupyter currently most popular

demo time



The screenshot shows a Jupyter Notebook cell with the following content:

```
# load data collected from team1
import pandas as pd

url = 'http://128.2.25.78:8080/private/log1.clean'
df = pd.read_csv(url)
df.head()
```

dayIdx	user	userAvgTime	location	dow	isWeekend	time
0	Pittsburgh66Correy	7.045001	Pittsburgh	6	True	0.000000
1	Pittsburgh66Correy	7.045001	Pittsburgh	7	True	6.883333
2	Pittsburgh66Correy	7.045001	Pittsburgh	1	False	6.816667
3	Pittsburgh66Correy	7.045001	Pittsburgh	2	False	7.383333
4	Pittsburgh66Correy	7.045001	Pittsburgh	3	False	0.000000

Data was preprocessed externally, identifying the time at a given day when the light was first turned on (12pm). Weather and sunrise information is not included here, though that'd be important. If the light was off this morning (quite common), 0 is recorded.

```
[ ] # just data encoding and splitting X and Y

X = df.drop(['time'], axis=1)
YnonZero = df['time'] > 0
Y = df['time']

from sklearn import preprocessing
# leDate = preprocessing.LabelEncoder()
# leDate.fit(X['date'])
# leDate.transform(X['date'])

X=X.apply(preprocessing.LabelEncoder().fit_transform)
X
```

ARTIFICIAL INTELLIGENCE FOR SOFTWARE ENGINEERS

(Part 2: Deep Learning, Symbolic AI)

Christian Kaestner

Required Reading: □ Géron, Aurélien. "[Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow](#)", 2nd Edition (2019), Ch 1.

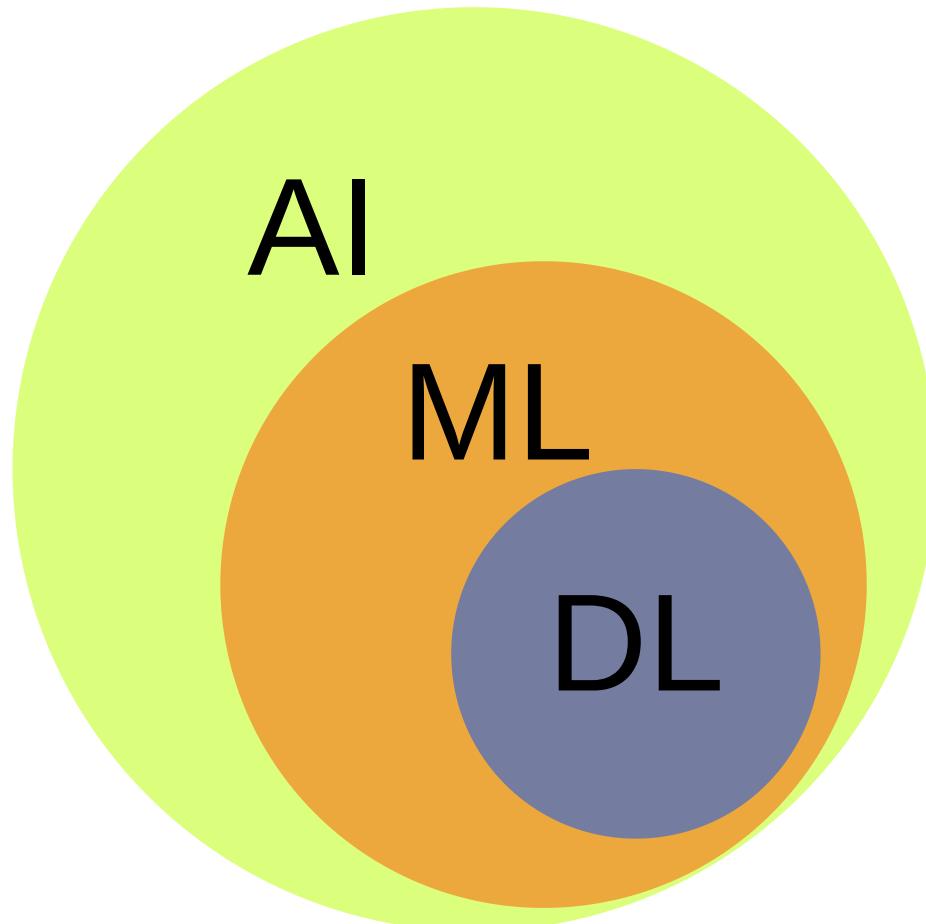
Recommended Readings: □ Géron, Aurélien. "[Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow](#)", 2nd Edition (2019), Ch 10 ("Introduction to Artificial Neural Networks with Keras"), □ Flasiński, Mariusz. "[Introduction to Artificial Intelligence](#)." Springer (2016), Chapter 1 ("History of Artificial Intelligence") and Chapter 2 ("Symbolic Artificial Intelligence"), □ Pfeffer, Avi. "[Practical Probabilistic Programming](#)." Manning (2016), Chapter 1 or □ Kevin Smith's recorded [tutorial on Probabilistic Programming](#)

LEARNING GOALS

- Give an overview of different AI problems and approaches
- Explain at high level how deep learning works
- Describe key characteristics of symbolic AI techniques and when to use them

Artificial Intelligence:

*computers acting humanly / thinking
humanly / thinking rationally / acting
rationally -- Russel and Norvig, 2003*



Machine Learning:

*A computer program is said to learn
from experience E with respect to some
task T and some performance measure
P, if its performance on T, as measured
by P, improves with experience E. -- Tom
Mitchell, 1997*

Deep Learning:

*specific learning technique based on
neural networks*

ARTIFICIAL INTELLIGENCE

- Acting humanly: Turing test approach, requires natural language processing, knowledge representation, automated reasoning, machine learning, maybe vision and robotics
- Thinking humanly: mirroring human thinking, cognitive science
- Thinking rationally: law of thoughts, logic, patterns and structures
- Acting rationally: rational agents interacting with environments
- problem solving (e.g., search, constraint satisfaction)
- knowledge, reasoning, planning (e.g., logic, knowledge representation, probabilistic reasoning)
- learning (learning from examples, knowledge in learning, reinforcement learning)
- communication, perceiving, and acting (NLP, vision, robotics)

Russel and Norvig. "[Artificial Intelligence: A Modern Approach.](#)", 2003

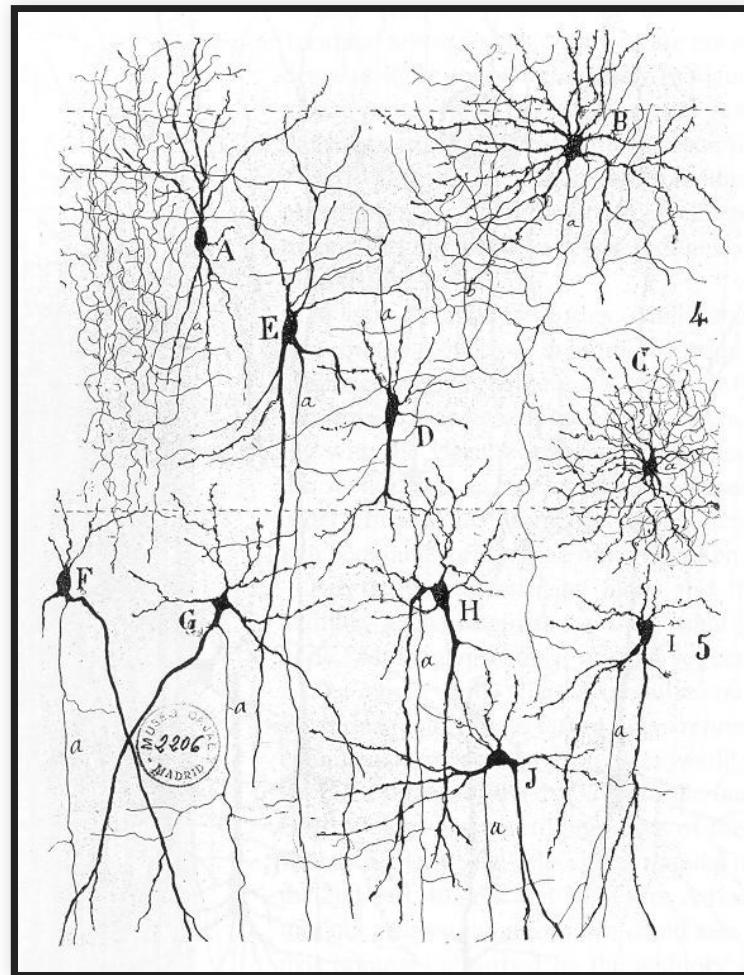
COMMON PROBLEM CLASSES

- Classification
- Probability estimation
- Regression
- Ranking
- Hybrids

LEARNING PARADIGMS

- Supervised learning -- labeled training data provided
- Unsupervised learning -- training data without labels
- Reinforcement learning -- agents learning from interacting with an environment

NEURAL NETWORKS

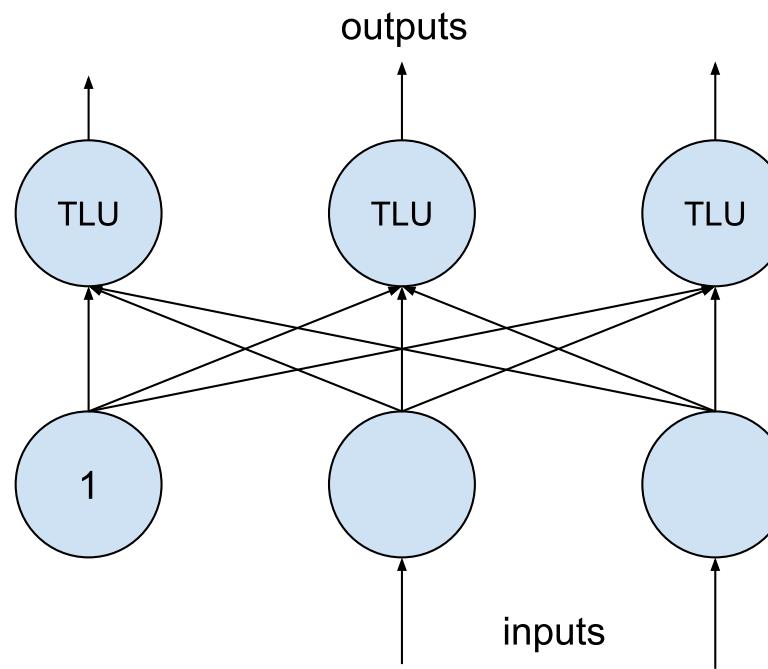


THRESHOLD LOGIC UNIT / PERCEPTRON

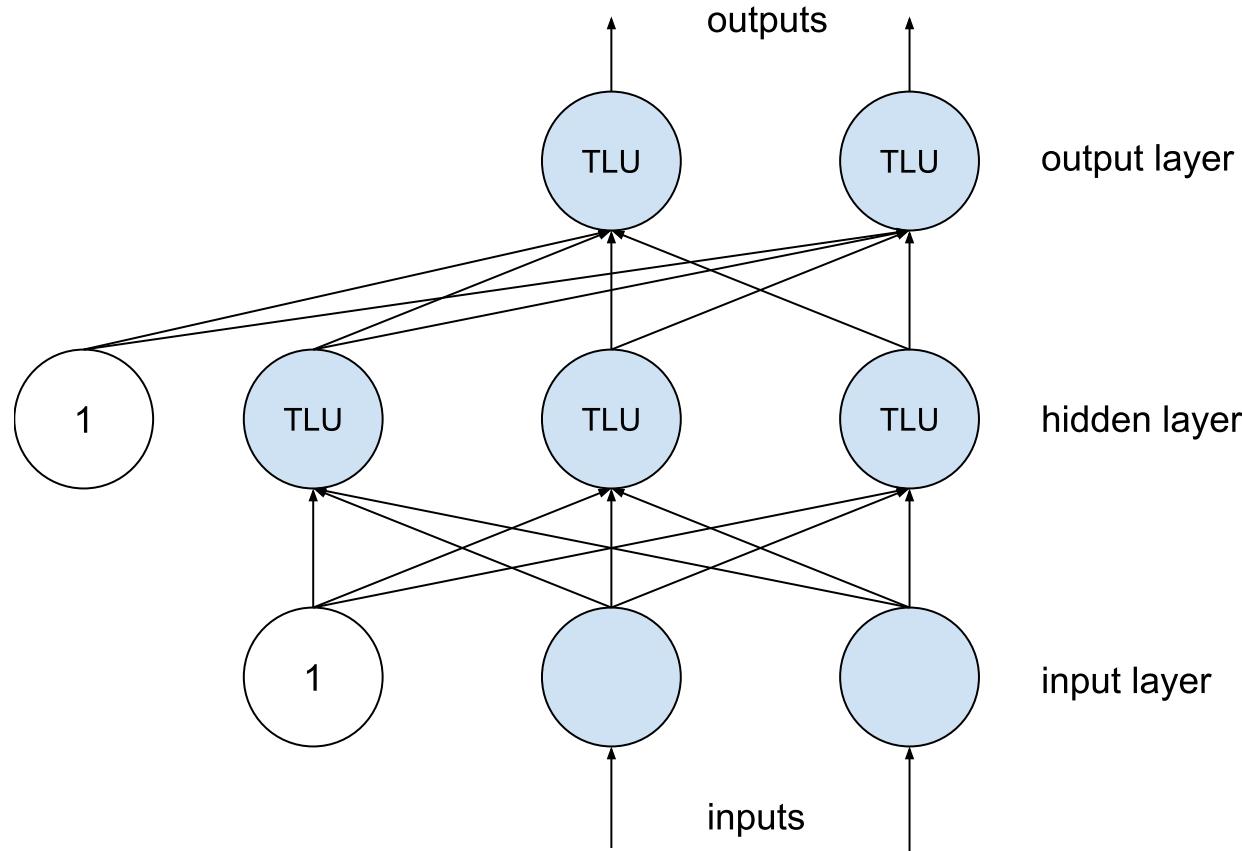
computing weighted sum of inputs + step function

$$z = w_1x_1 + w_2x_2 + \dots + w_nx_n = \mathbf{x}^T \mathbf{w}$$

e.g., step: $\phi(z) = \text{if } (z < 0) \text{ 0 else 1}$



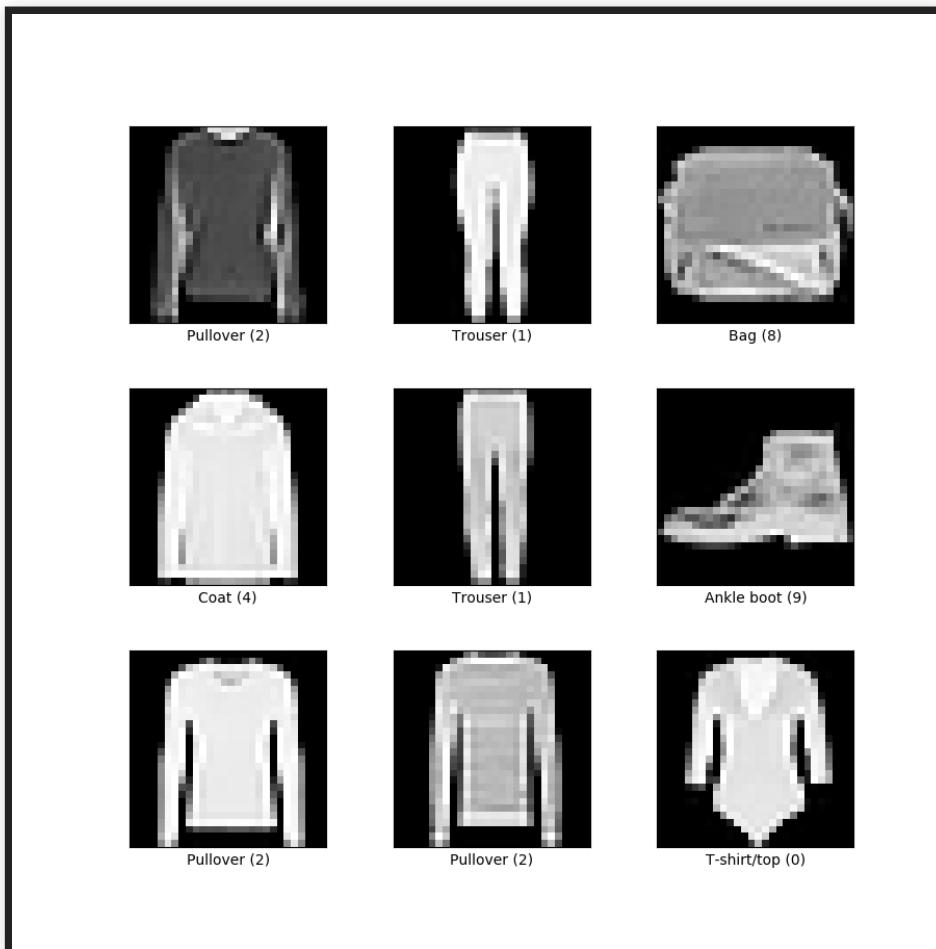
$$f_{\mathbf{W}_h, \mathbf{b}_h, \mathbf{W}_o, \mathbf{b}_o}(\mathbf{X}) = \phi(\mathbf{W}_o \cdot \phi(\mathbf{W}_h \cdot \mathbf{X} + \mathbf{b}_h) + \mathbf{b}_o$$



(matrix multiplications interleaved with step function)

EXAMPLE SCENARIO

- MNIST Fashion dataset of 70k 28x28 grayscale pixel images, 10 output classes



NETWORK SIZE

- 50 Layer ResNet network -- classifying 224x224 images into 1000 categories
 - 26 million weights, computes 16 million activations during inference, 168 MB to store weights as floats
- OpenAI's GPT-2 (2019) -- text generation
 - 48 layers, 1.5 billion weights (~12 GB to store weights)
 - released model reduced to 117 million weights
 - trained on 7-8 GPUs for 1 month with 40GB of internet text from 8 million web pages

CLASSIC SYMBOLIC AI

(Good Old-Fashioned Artificial Intelligence)

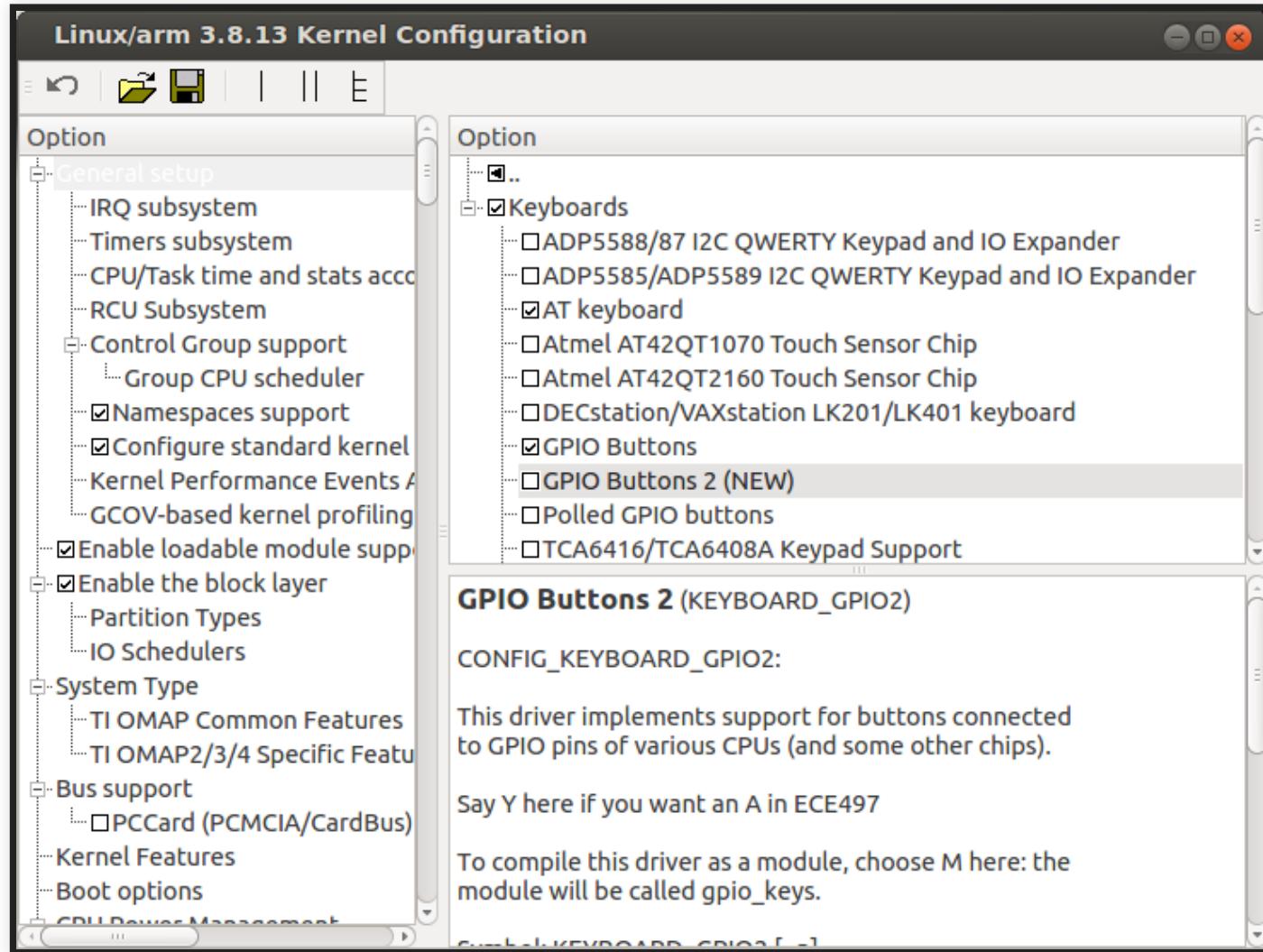
BOOLEAN SATISFIABILITY

Given a propositional formula over boolean variables, is there an assignment such that the formula evaluates to true?

$$(a \vee b) \wedge (\neg a \vee c) \wedge \neg b$$

decidable, np complete, lots of search heuristics

ENCODING PROBLEMS



CONSTRAINT SATISFACTION PROBLEMS, SMT

Generalization beyond boolean options, numbers, strings, additions, optimization

Example: Job Scheduling

Tasks for assembling a car: { t1, t2, t3, t4, t5, t6 }; values denoting start time

$$\max \text{ 30 min: } \forall_n t_n < 30$$

t2 needs to be after t1, t1 takes 10 min: $t_1 + 10 \leq t_2$

t3 and t4 needs to be after t2, take 2 min: $(t_2 + 2 \leq t_3) \wedge (t_2 + 2 \leq t_4)$

t5 and t6 (5 min each) should not overlap: $(t_5 + 5 \leq t_6) \vee (t_6 + 5 \leq t_5)$

Goal: find valid assignment for all start times, or find valid assignment minimizing the latest start time

PROBABILISTIC PROGRAMMING BY EXAMPLE

```
class Person {  
    val smokes = Flip(0.6)  
}  
def smokingInfluence(pair: (Boolean, Boolean)) =  
    if (pair._1 == pair._2) 3.0; else 1.0  
  
val alice, bob, clara = new Person  
val friends = List((alice, bob), (bob, clara))  
clara.smokes.observe(true)  
for { (p1, p2) <- friends }  
    ^^(p1.smokes, p2.smokes).setConstraint(smokingInfluence)  
  
...  
println("Probability of Alice smoking: " +  
      alg.probability(alice.smokes, true))
```

PROBABILISTIC INFERENCE

Answering queries about probabilistic models

```
println("Probability of burglary: " +  
       alg.probability(burglary, true))  
  
println("Probability of Alice smoking: " +  
       alg.probability(alice.smokes, true))
```

- Analytical probabilistic reasoning (e.g., variable elimination Bayes' rule) -- precise result, guarantees
- Approximation (e.g., belief propagation)
- Sampling (e.g., Markov chain Monte Carlo) -- probabilistic guarantees

HOMEWORK 2: MODELING BASICS

Predicting Movie Popularity (2 weeks)

MODEL QUALITY

Christian Kaestner

Required reading:

- Hulten, Geoff. "[Building Intelligent Systems: A Guide to Machine Learning Engineering.](#)" Apress, 2018, Chapter 19 (Evaluating Intelligence).
- Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. "[Semantically equivalent adversarial rules for debugging NLP models.](#)" In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pp. 856-865. 2018.

LEARNING GOALS

- Select a suitable metric to evaluate prediction accuracy of a model and to compare multiple models
- Select a suitable baseline when evaluating model accuracy
- Explain how software testing differs from measuring prediction accuracy of a model
- Curate validation datasets for assessing model quality, covering subpopulations as needed
- Use invariants to check partial model properties with automated testing
- Develop automated infrastructure to evaluate and monitor model quality

THIS LECTURE

FIRST PART: MEASURING PREDICTION ACCURACY

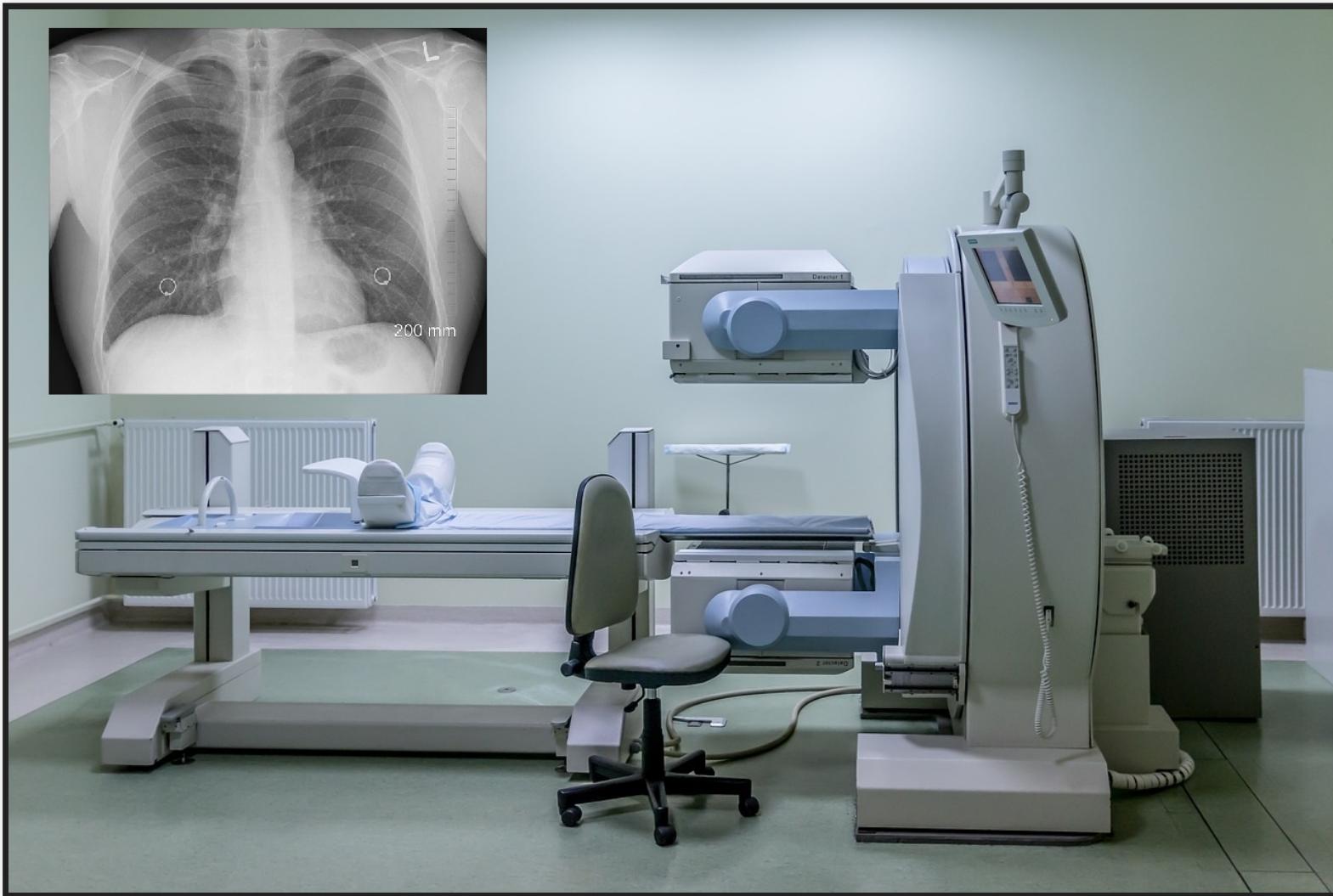
the data scientist's perspective

SECOND PART: LEARNING FROM SOFTWARE TESTING

how software engineering tools may apply to ML

"Programs which were written in order to determine the answer in the first place. There would be no need to write such programs, if the correct answer were known"
(Weyuker, 1982).

CASE STUDY: CANCER DETECTION



THE SYSTEMS PERSPECTIVE

System is more than the model

Includes deployment, infrastructure, user interface, data infrastructure, payment services, and often much more

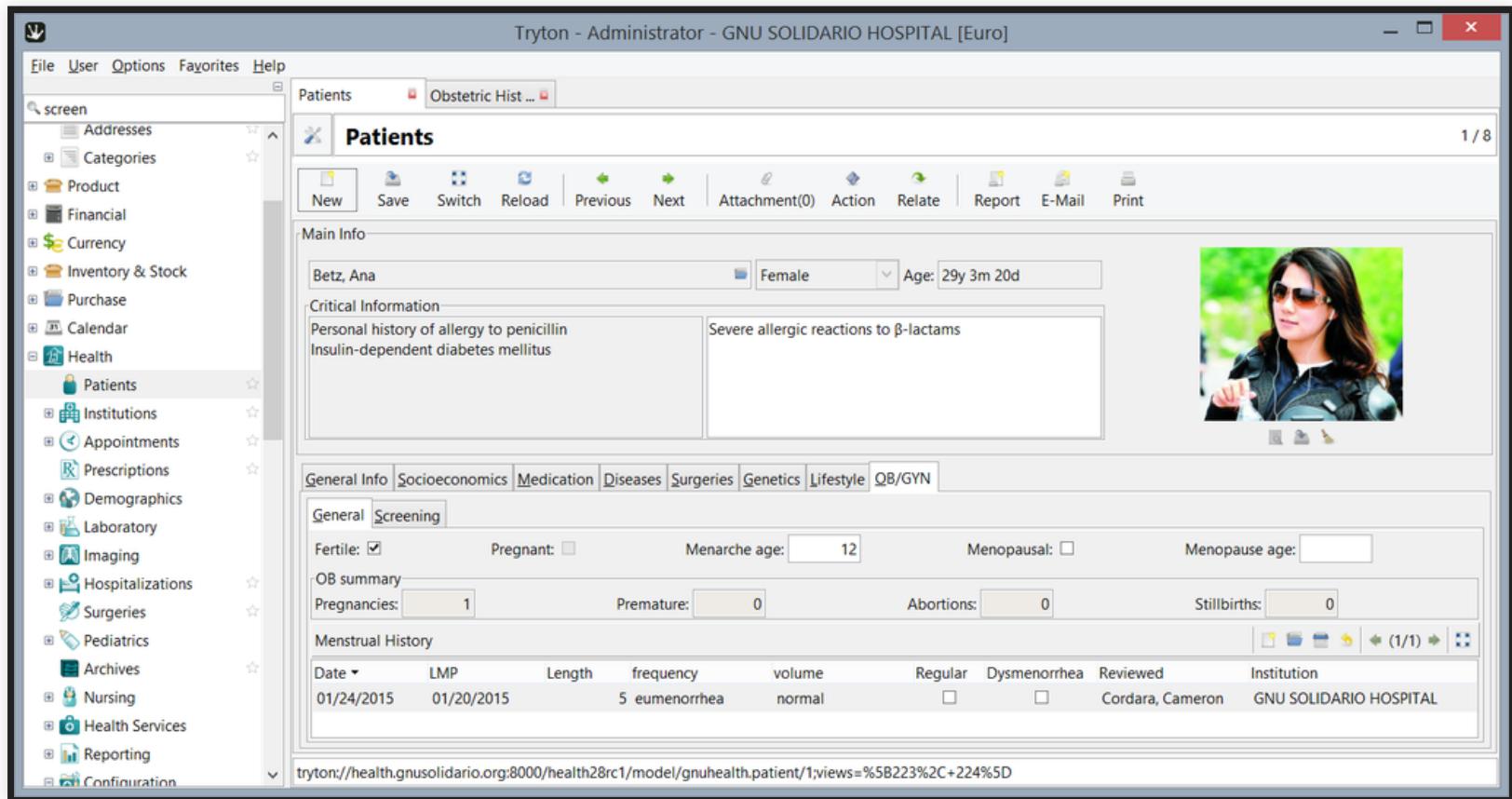
Systems have a goal:

- maximize sales
- save lives
- entertainment
- connect people

Models can help or may be essential in those goals, but are only one part

Today: Narrow focus on prediction accuracy of the model

CANCER PREDICTION WITHIN A HEALTHCARE APPLICATION



(CC BY-SA 4.0, Martin Sauter)

CONFUSION/ERROR MATRIX

	Actually A	Actually B	Actually C
AI predicts A	10	6	2
AI predicts B	3	24	10
AI predicts C	5	22	82

Accuracy = correct predictions (diagonal) out of all predictions

$$\text{Example's accuracy} = \frac{10+24+82}{10+6+2+3+24+10+5+22+82} = .707$$

IS 99% ACCURACY GOOD?

-> depends on problem; can be excellent, good, mediocre, terrible

10% accuracy can be good on some tasks (information retrieval)

Always compare to a base rate!

$$\text{Reduction in error} = \frac{(1 - \text{accuracy}_{\text{baseline}}) - (1 - \text{accuracy}_f)}{1 - \text{accuracy}_{\text{baseline}}}$$

- from 99.9% to 99.99% accuracy = 90% reduction in error
- from 50% to 75% accuracy = 50% reduction in error

TYPES OF MISTAKES

Two-class problem of predicting event A:

	Actually A	Actually not A
AI predicts A	True Positive (TP)	False Positive (FP)
AI predicts not A	False Negative (FN)	True Negative (TN)

True positives and true negatives: correct prediction

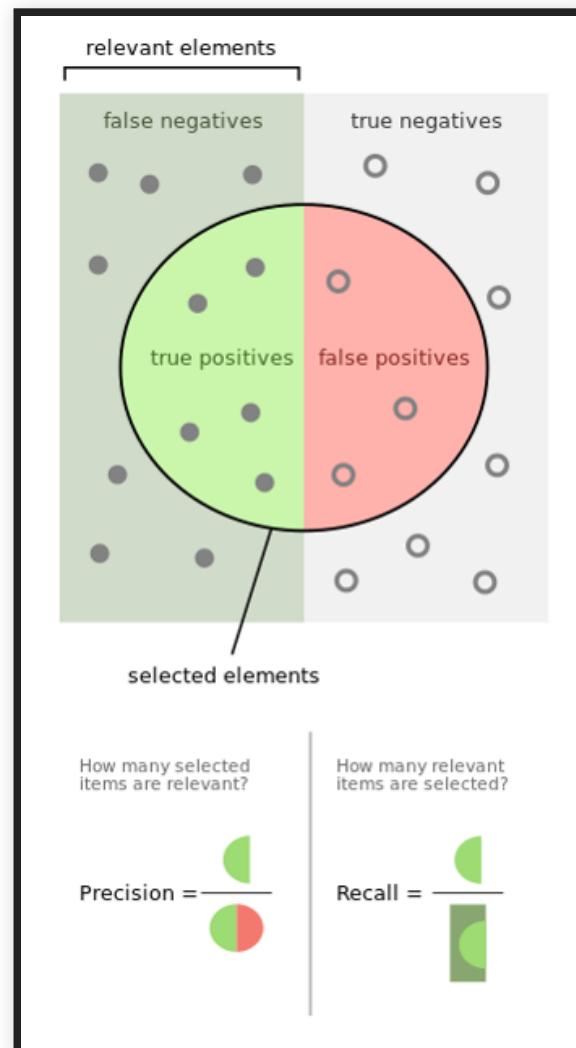
False negatives: wrong prediction, miss, Type II error

False positives: wrong prediction, false alarm, Type I error

MULTI-CLASS PROBLEMS VS TWO-CLASS PROBLEM

	Actually A	Actually B	Actually C
AI predicts A	10	6	2
AI predicts B	3	24	10
AI predicts C	5	22	82

	Act. A	Act. not A		Act. B	Act. not B
AI predicts A	10	8	AI predicts B	24	13
AI predicts not A	8	138	AI predicts not B	28	99



(CC BY-SA 4.0 by [Walber](#))

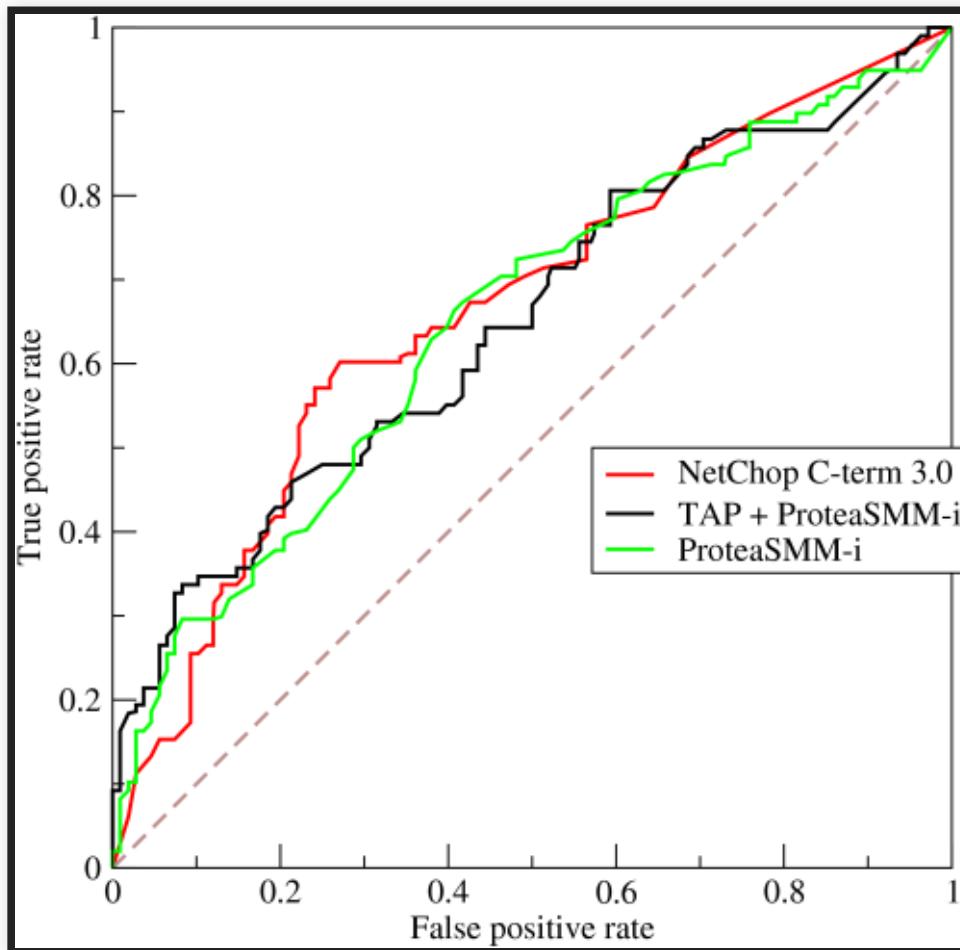
FALSE POSITIVES AND FALSE NEGATIVES EQUALLY BAD?

Consider:

- Recognizing cancer
- Suggesting products to buy on e-commerce site
- Identifying human trafficking at the border
- Predicting high demand for ride sharing services
- Predicting recidivism chance
- Approving loan applications

No answer vs wrong answer?

RECEIVER OPERATING CHARACTERISTIC (ROC) CURVES



COMPARING PREDICTED AND EXPECTED OUTCOMES

Mean Absolute Percentage Error

MAPE =

$$\frac{1}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right|$$

(A_t actual outcome, F_t predicted outcome, for row t)

Compute relative prediction error per row, average over all rows

Rooms	Crime Rate	...	Predicted Price	Actual Price
3	.01	...	230k	250k
4	.01	...	530k	498k
2	.03	...	210k	211k
2	.02	...	219k	210k

MAPE =

$$\begin{aligned} & \frac{1}{4}(20/250 + 32/498 + 1/211 + 9/210) \\ &= \frac{1}{4}(0.08 + 0.064 + 0.005 + 0.043) = \\ & 0.048 \end{aligned}$$

EVALUATING RANKINGS

Ordered list of results, true results should be ranked high

Common in information retrieval (e.g., search engines) and recommendations

Mean Average Precision

MAP@K = precision in first K results

Averaged over many queries

Rank	Product	Correct?
1	Juggling clubs	true
2	Bowling pins	false
3	Juggling balls	false
4	Board games	true
5	Wine	false
6	Audiobook	true

MAP@1 = 1, MAP@2 = 0.5, MAP@3 = 0.33,

...

Remember to compare against baselines! Baseline for shopping recommendations?

MODEL QUALITY IN NATURAL LANGUAGE PROCESSING?

Highly problem dependent:

- Classify text into positive or negative -> classification problem
- Determine truth of a statement -> classification problem
- Translation and summarization -> comparing sequences (e.g ngrams) to human results with specialized metrics, e.g. **BLEU** and **ROUGE**
- Modeling text -> how well its probabilities match actual text, e.g., likelihood or **perplexity**

ANALOGY TO SOFTWARE TESTING

(this gets messy)

MODEL TESTING?

Rooms	Crime Rate	...	Actual Price
3	.01	...	250k
4	.01	...	498k
2	.03	...	211k
2	.02	...	210k

```
assertEquals(250000,  
            model.predict([3, .01, ...])  
assertEquals(498000,  
            model.predict([4, .01, ...])  
assertEquals(211000,  
            model.predict([2, .03, ...])  
assertEquals(210000,  
            model.predict([2, .02, ...]))
```

Fail the entire test suite for one wrong prediction?

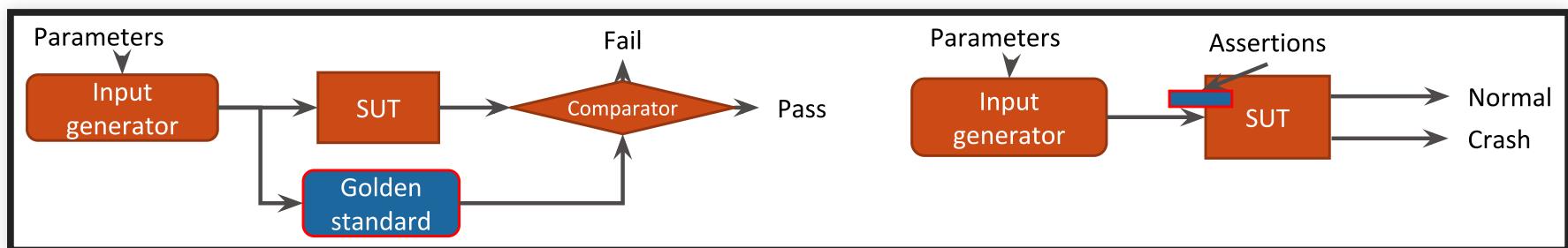


THE ORACLE PROBLEM

How do we know the expected output of a test?

```
assertEquals(??, factorPrime(15485863));
```

- Manually construct input-output pairs (does not scale, cannot automate)
- Comparison against gold standard (e.g., alternative implementation, executable specification)
- Checking of global properties only -- crashes, buffer overflows, code injections
- Manually written assertions -- partial specifications checked at runtime



DIFFERENT EXPECTATIONS FOR PREDICTION ACCURACY

- Not expecting that all predictions will be correct (80% accuracy may be very good)
- Data may be mislabeled in training or validation set
- There may not even be enough context (features) to distinguish all training outcomes
- Lack of specifications
- A wrong prediction is not necessarily a bug

ANALOGY OF PERFORMANCE TESTING?

- Performance tests are not precise (measurement noise)
 - Averaging over repeated executions *of the same test*
 - Commonly using diverse benchmarks, i.e., *multiple inputs*
 - Need to control environment (hardware)
- No precise specification
 - Regression tests
 - Benchmarking as open-ended comparison
 - Tracking results over time

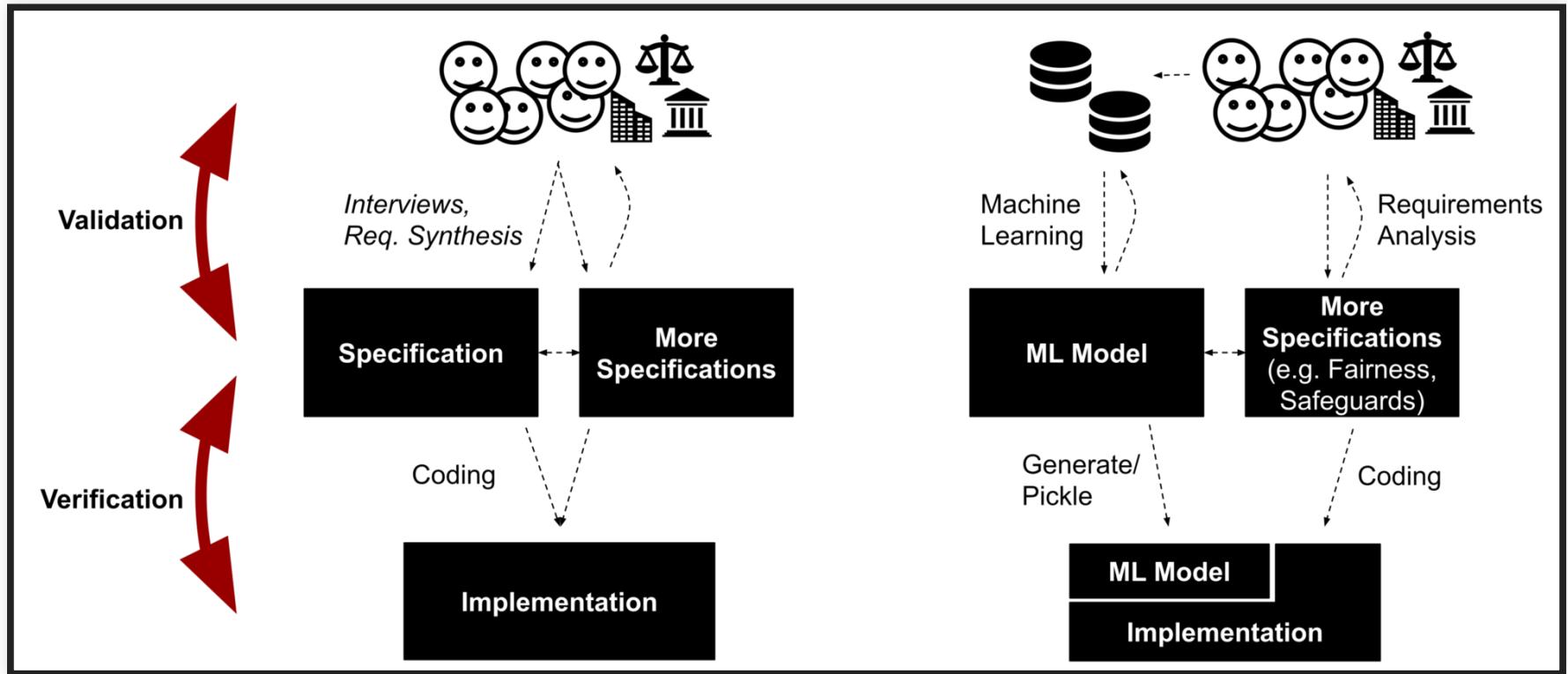
```
@Test(timeout=100)
public void testCompute() {
    expensiveComputation(...);
}
```

MACHINE LEARNING IS REQUIREMENTS ENGINEERING

(my pet theory)

see also <https://medium.com/@ckaestne/machine-learning-is-requirements-engineering-8957aee55ef4>

VALIDATION VS VERIFICATION



EXAMPLE AND DISCUSSION

```
IF age between 18-20 and sex is male THEN predict arrest  
ELSE IF age between 21-23 and 2-3 prior offenses THEN predict ar  
ELSE IF more than three priors THEN predict arrest  
ELSE predict no arrest
```

Model learned from gathered data (~ interviews, sufficient? representative?)

Cannot equally satisfy all stakeholders, conflicting goals; judgement call,
compromises, constraints

Implementation is trivial/automatically generated

Does it meet the users' expectations?

Is the model compatible with other specifications? (fairness, robustness)

What if we cannot understand the model? (interpretability)

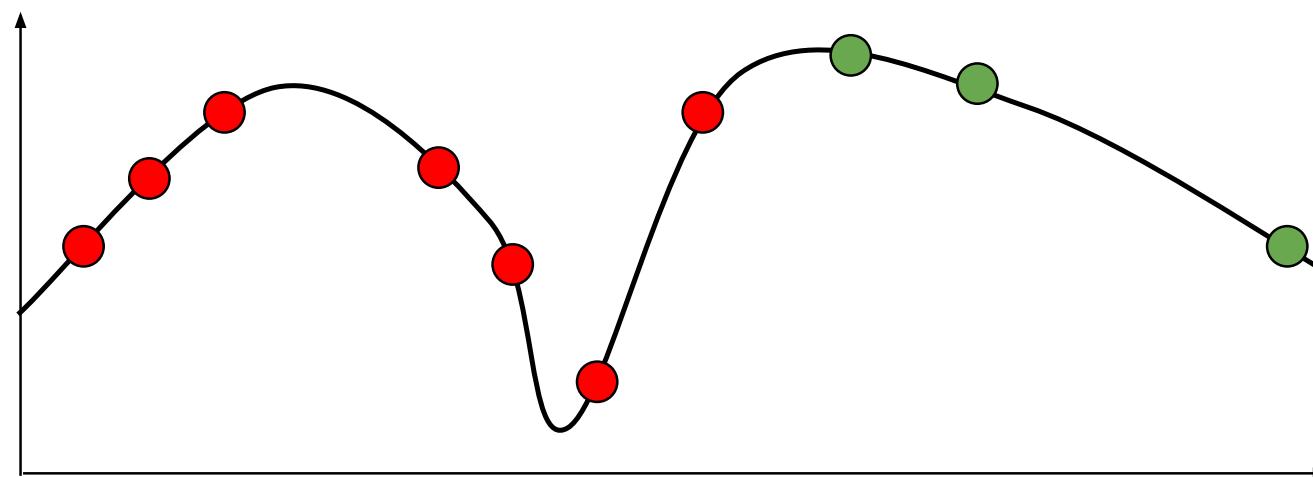
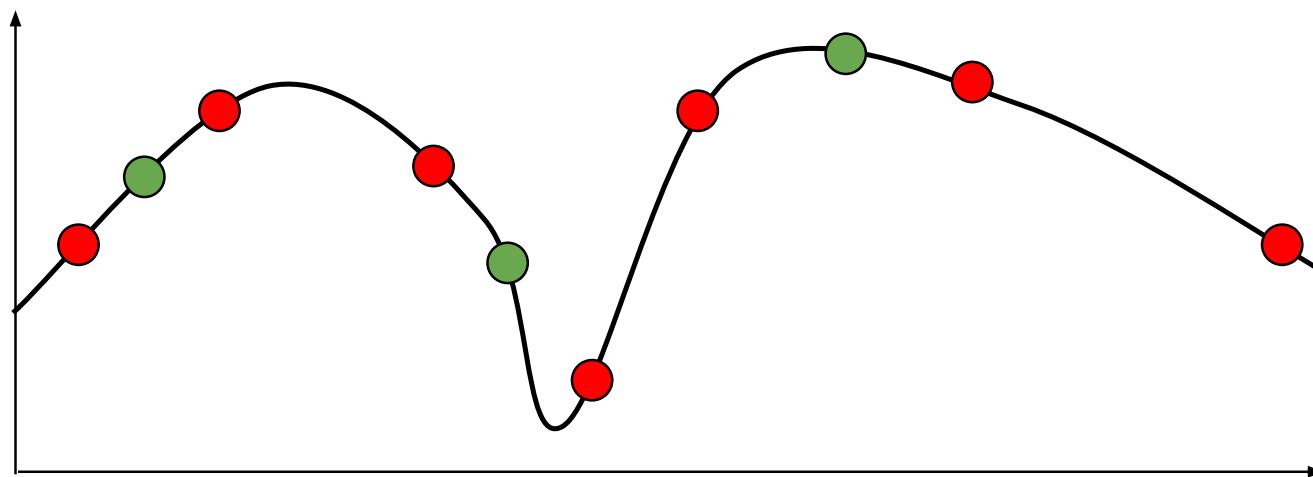
CURATING VALIDATION DATA

(Learning from Software Testing?)

VALIDATION DATA REPRESENTATIVE?

- Validation data should reflect usage data
- Be aware of data drift (face recognition during pandemic, new patterns in credit card fraud detection)
- "*Out of distribution*" predictions often low quality (it may even be worth to detect out of distribution data in production, more later)

INDEPENDENCE OF DATA: TEMPORAL



NOT ALL INPUTS ARE EQUAL



"Call mom" "What's the weather tomorrow?" "Add asafetida to my shopping list"

NOT ALL INPUTS ARE EQUAL

There Is a Racial Divide in Speech-Recognition Systems, Researchers Say: Technology from Amazon, Apple, Google, IBM and Microsoft misidentified 35 percent of words from people who were black. White people fared much better. --

NYTimes March 2020

IDENTIFY IMPORTANT INPUTS

Curate Validation Data for Specific Problems and Subpopulations:

- *Regression testing*: Validation dataset for important inputs ("call mom") -- expect very high accuracy -- closest equivalent to **unit tests**
- *Uniformness/fairness testing*: Separate validation dataset for different subpopulations (e.g., accents) -- expect comparable accuracy
- *Setting goals*: Validation datasets for challenging cases or stretch goals -- accept lower accuracy

Derive from requirements, experts, user feedback, expected problems etc. Think *blackbox testing*.

BLACK-BOX TESTING TECHNIQUES AS INSPIRATION?

- Boundary value analysis
- Partition testing & equivalence classes
- Combinatorial testing
- Decision tables

Use to identify subpopulations (validation datasets), not individual tests.



EXAMPLES OF INVARIANTS

- Credit rating should not depend on gender:
 - $\forall x. f(x[\text{gender} \leftarrow \text{male}]) = f(x[\text{gender} \leftarrow \text{female}])$
- Synonyms should not change the sentiment of text:
 - $\forall x. f(x) = f(\text{replace}(x, \text{"is not"}, \text{"isn't"}))$
- Negation should swap meaning:
 - $\forall x \in \text{"X is Y"}. f(x) = 1 - f(\text{replace}(x, \text{" is "}, \text{" is not "}))$
- Robustness around training data:
 - $\forall x \in \text{training data}. \forall y \in \text{mutate}(x, \delta). f(x) = f(y)$
- Low credit scores should never get a loan (sufficient conditions for classification, "anchors"):
 - $\forall x. x.\text{score} < 649 \Rightarrow \neg f(x)$

Identifying invariants requires domain knowledge of the problem!

METAMORPHIC TESTING

Formal description of relationships among inputs and outputs (*Metamorphic Relations*)

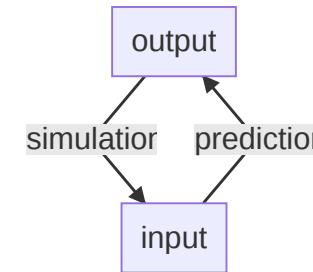
In general, for a model f and inputs x define two functions to transform inputs and outputs g_I and g_O such that:

$$\forall x. f(g_I(x)) = g_O(f(x))$$

e.g. $g_I(x) = \text{replace}(x, " \text{is} ", " \text{is not} ")$ and $g_O(x) = \neg x$

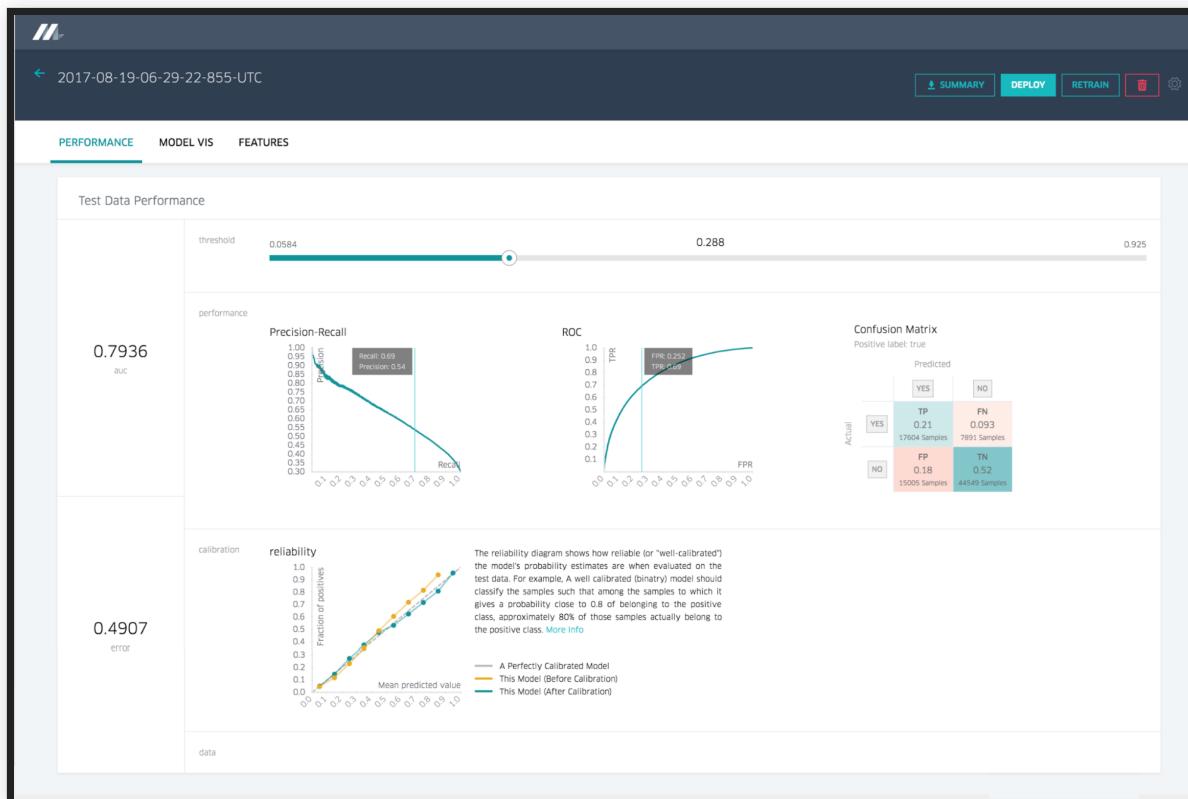
ONE MORE THING: SIMULATION-BASED TESTING

- Derive input-output pairs from simulation, esp. in vision systems
- Example: Vision for self-driving cars:
 - Render scene -> add noise -> recognize -> compare recognized result with simulator state
- Quality depends on quality of the simulator and how well it can produce inputs from outputs:
 - examples: render picture/video, synthesize speech, ...
 - Less suitable where input-output relationship unknown, e.g., cancer detection, housing price prediction, shopping recommendations

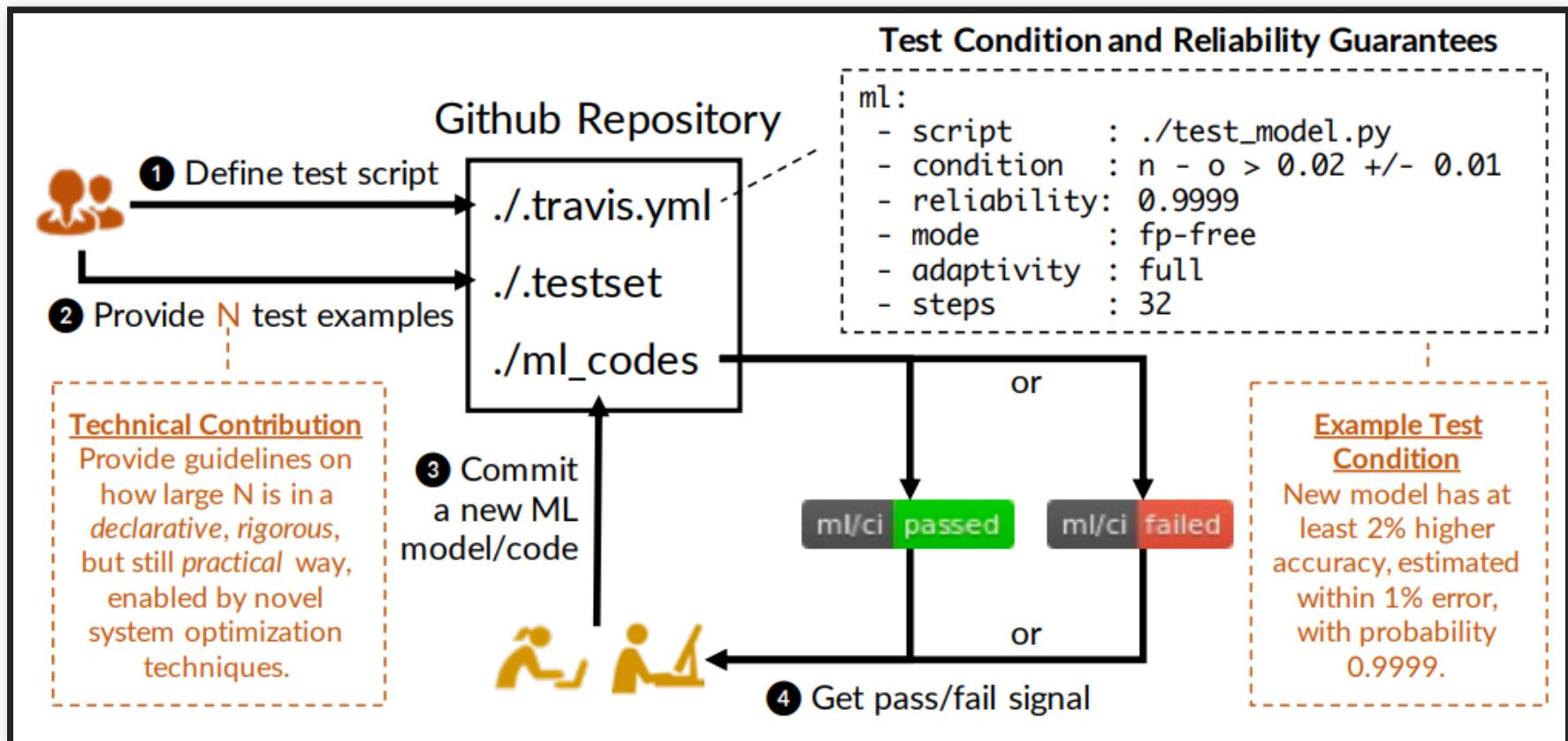


Further readings: Zhang, Mengshi, Yuqun Zhang, Lingming Zhang, Cong Liu, and Sarfraz Khurshid. "DeepRoad: GAN-based metamorphic testing and input validation framework for autonomous driving systems." In Proceedings of the 33rd ACM/IEEE International Conference on Automated Software Engineering, pp. 132-142. 2018.

CONTINUOUS INTEGRATION FOR MODEL QUALITY



SPECIALIZED CI SYSTEMS



Renggli et. al, Continuous Integration of Machine Learning Models with ease.ml/ci: Towards a Rigorous Yet Practical Treatment, SysML 2019

DASHBOARDS FOR COMPARING MODELS

mlflow

Github Docs

Listing Price Prediction

Experiment ID: 0 Artifact Location: /Users/matei/mlflow/demo/mlruns/0

Search Runs: Search

Filter Params: Filter Metrics: Clear

4 matching runs [Compare Selected](#) [Download CSV](#)

Time	User	Source	Version	Parameters		Metrics		
				alpha	l1_ratio	MAE	R2	RMSE
<input type="checkbox"/> 17:37	matei	linear.py	3a1995	0.5	0.2	84.27	0.277	158.1
<input type="checkbox"/> 17:37	matei	linear.py	3a1995	0.2	0.5	84.08	0.264	159.6
<input type="checkbox"/> 17:37	matei	linear.py	3a1995	0.5	0.5	84.12	0.272	158.6
<input type="checkbox"/> 17:37	matei	linear.py	3a1995	0	0	84.49	0.249	161.2

FROM MODELS TO AI-ENABLED SYSTEMS

Christian Kaestner

- Hulten, Geoff. "Building Intelligent Systems: A Guide to Machine Learning Engineering." (2018), Chapters 5 (Components of Intelligent Systems).
- Sculley, David, Gary Holt, Daniel Golovin, Eugene Davydov, Todd Phillips, Dietmar Ebner, Vinay Chaudhary, Michael Young, Jean-Francois Crespo, and Dan Dennison. "[Hidden technical debt in machine learning systems](#)." In Advances in neural information processing systems, pp. 2503-2511. 2015.

LEARNING GOALS

- Explain how machine learning fits into the larger picture of building and maintaining production systems
- Describe the typical components relating to AI in an AI-enabled system and typical design decisions to be made

TEMI TRANSCRIPTION SERVICE

the-changelog-318 [← Dashboard](#) Quality: High ⓘ

Last saved a few seconds ago [...](#) [Share](#)

00:00 ⏪ Offset 00:00 01:31:27

▶ ⏪ 5s 1x 🔊 Play Back 5s Speed Volume

NOTES
Write your notes here

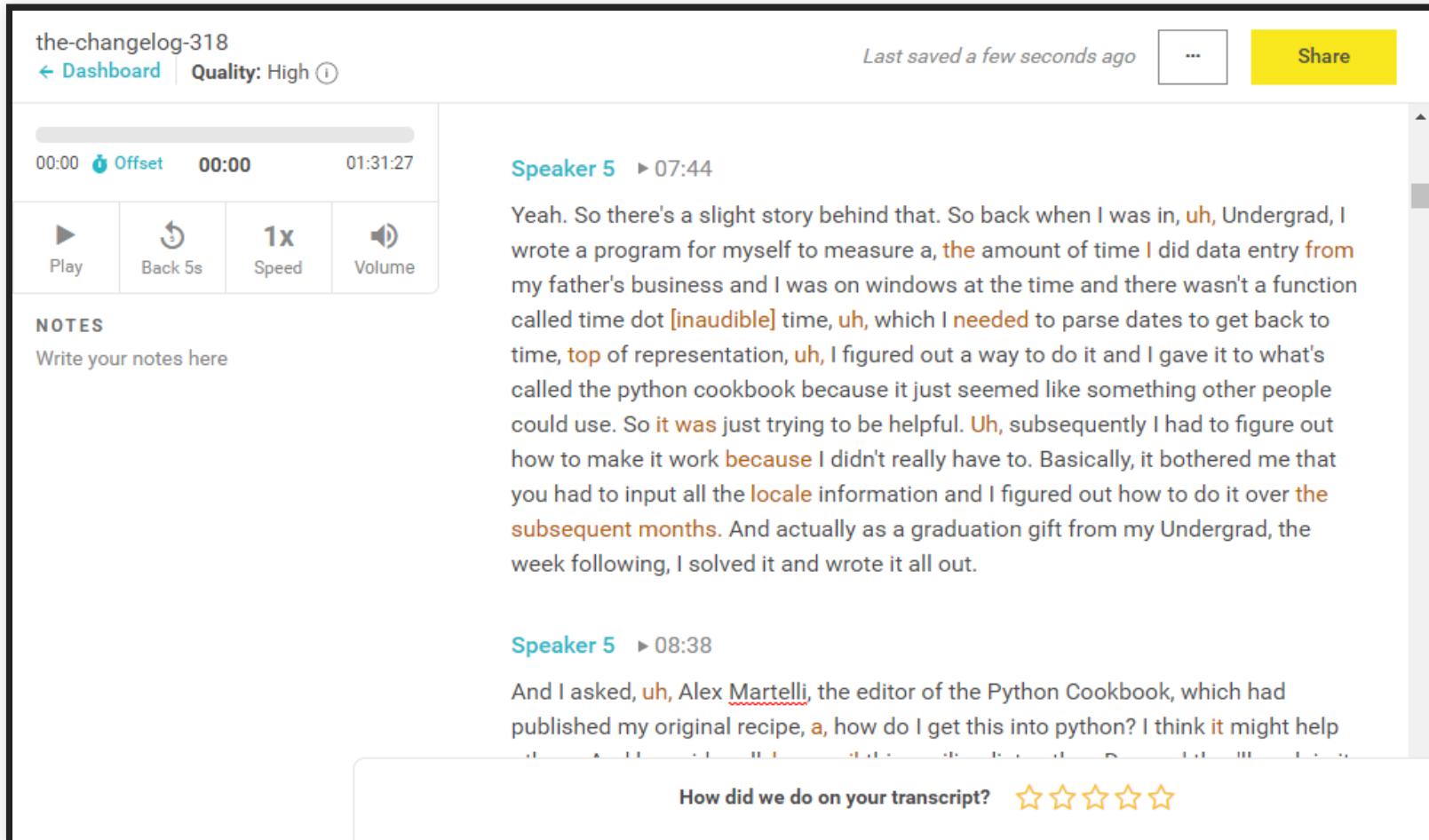
Speaker 5 ▶ 07:44

Yeah. So there's a slight story behind that. So back when I was in, uh, Undergrad, I wrote a program for myself to measure a, the amount of time I did data entry from my father's business and I was on windows at the time and there wasn't a function called time dot [inaudible] time, uh, which I needed to parse dates to get back to time, top of representation, uh, I figured out a way to do it and I gave it to what's called the python cookbook because it just seemed like something other people could use. So it was just trying to be helpful. Uh, subsequently I had to figure out how to make it work because I didn't really have to. Basically, it bothered me that you had to input all the locale information and I figured out how to do it over the subsequent months. And actually as a graduation gift from my Undergrad, the week following, I solved it and wrote it all out.

Speaker 5 ▶ 08:38

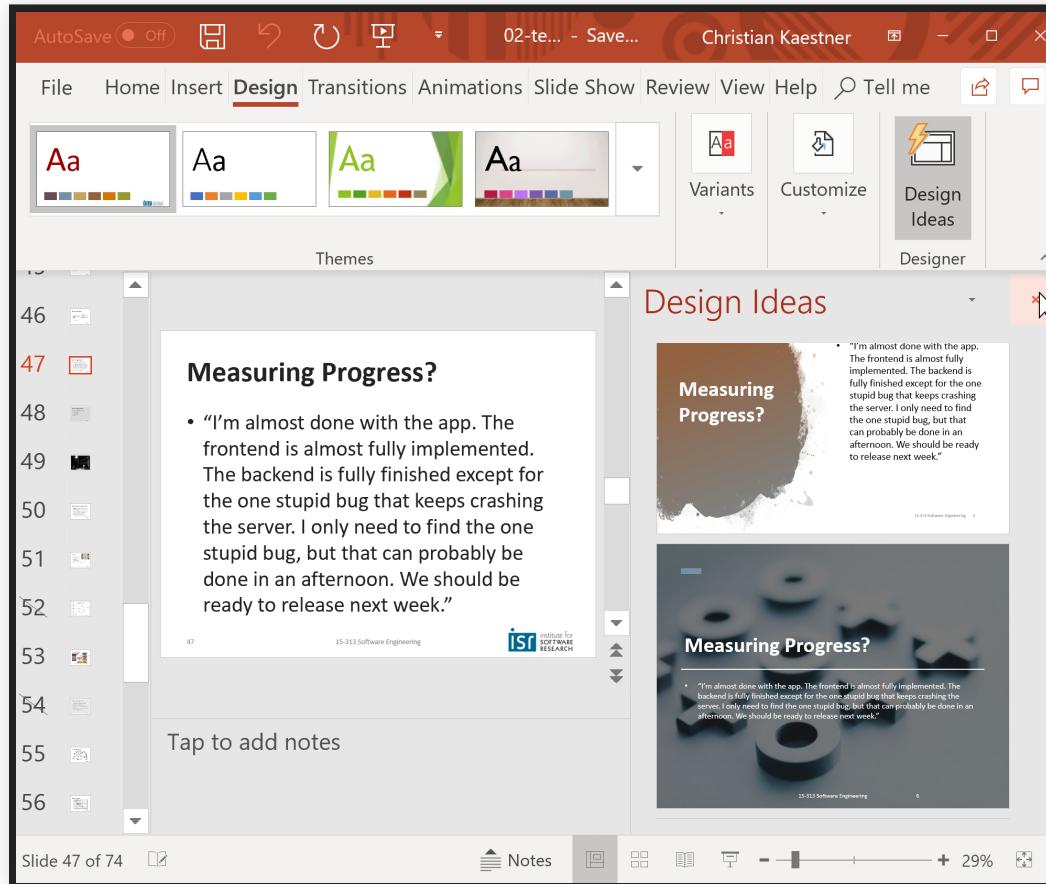
And I asked, uh, Alex Martelli, the editor of the Python Cookbook, which had published my original recipe, a, how do I get this into python? I think it might help

How did we do on your transcript? 



<https://www.temis.com/>

MICROSOFT POWERPOINT



Read more: [How Azure Machine Learning enables PowerPoint Designer, Azure Blog, March 2020](#)

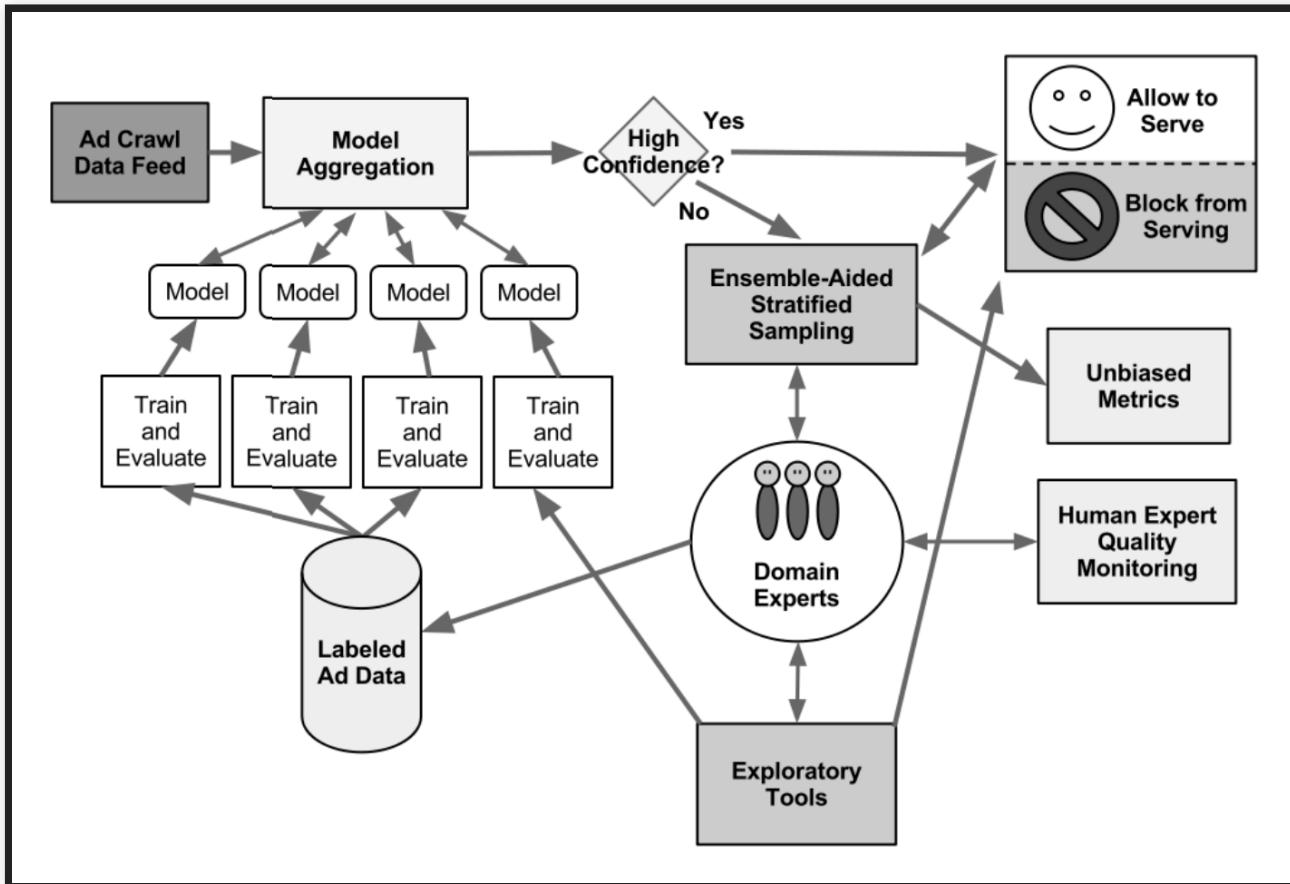
FALL DETECTION DEVICES



(various devices explored, including smart watches, hearing aids, and wall and floor sensors)

Read more: [How fall detection is moving beyond the pendant](#), MobiHealthNews, 2019

GOOGLE ADD FRAUD DETECTION



From: Sculley, D., M. Oney, M. Pohl, B. Spitznagel, J. Hainsworth, and Y. Zhou.
Detecting Adversarial Advertisements in the Wild. In Proc. KDD, 2011.

THINKING ABOUT SYSTEMS

- Holistic approach, looking at the larger picture, involving all stakeholders
- Looking at relationships and interactions among components and environments
 - Everything is interconnected
 - Combining parts creates something new with emergent behavior
 - Understand dynamics, be aware of feedback loops, actions have effects
- Understand how humans interact with the system

A system is a set of inter-related components that work together in a particular environment to perform whatever functions are required to achieve the system's objective --

Donella Meadows

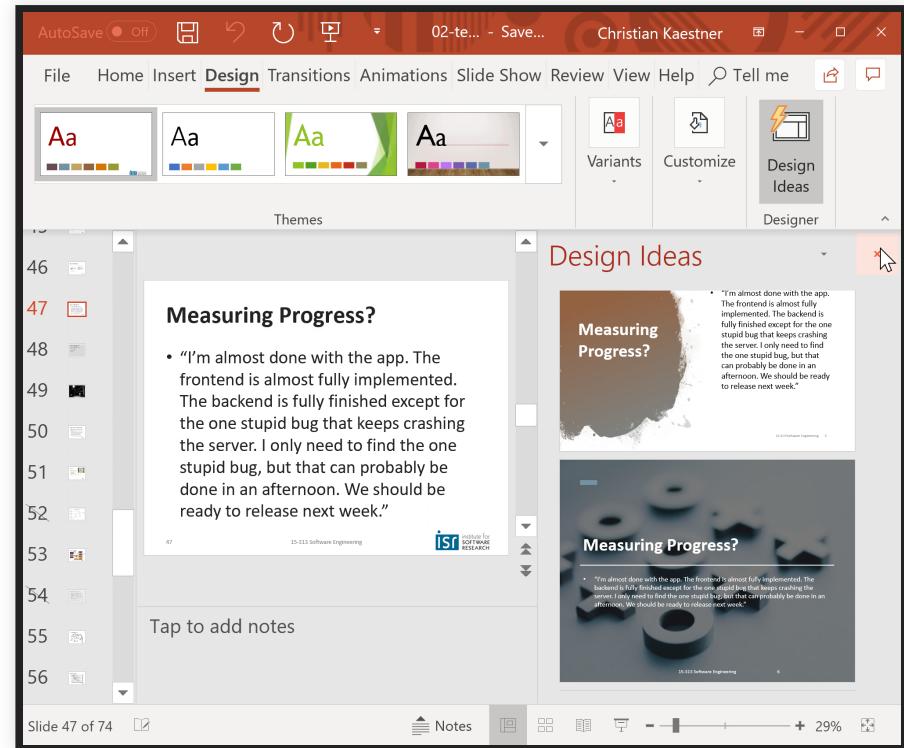
ELEMENTS OF AN INTELLIGENT SYSTEM

- **Meaningful objective:** goals, requirements, business case
- **Intelligent experience:** user interactions -- presenting model predictions to users; user interactions; eliciting feedback, telemetry
- **Intelligence implementation:** infrastructure -- learning and serving the model and collecting feedback (telemetry)
- **Intelligence creation:** learning and evaluating models
- **Orchestration:** operations -- maintaining and updating the system over time, debugging, countering abuse

DESIGNING INTELLIGENT EXPERIENCES

- How to use the output of a model's prediction (for a goal)?
- Design considerations:
 - How to present prediction to a user? Suggestions or automatically take actions?
 - How to effectively influence the user's behavior toward the system's goal?
 - How to minimize the consequences of flawed predictions?
 - How to collect data to continue to learn from users and mistakes?

Automatic slide design:



FACTORS IN CASE STUDIES

Consider: forcefulness, frequency, value, cost, model quality

Automatic slide design:

A screenshot of a Microsoft PowerPoint slide titled "Measuring Progress?". The slide contains a bulleted list of text. A "Design Ideas" callout box is open on the right side of the slide, displaying two design variations for the slide content. The top variation has a brown background and the bottom one has a dark blue background. Both variations include the slide title and the bulleted text.

Fall detection:



INITIAL TELEMETRY IDEAS?

Identify: usage, mistakes, cost of mistakes, benefits to user, benefits to goals

Automatic slide design:

A screenshot of a Microsoft PowerPoint slide titled "Measuring Progress?". The slide contains a bulleted list of text. A callout box labeled "Design Ideas" is overlaid on the slide, containing a summary of the text and a small thumbnail image.

Measuring Progress?

- "I'm almost done with the app. The frontend is almost fully implemented. The backend is fully finished except for the one stupid bug that keeps crashing the server. I only need to find the one stupid bug, but that can probably be done in an afternoon. We should be ready to release next week."

The "Design Ideas" callout box contains the following text:
"I'm almost done with the app. The frontend is almost fully implemented. The backend is fully finished except for the one stupid bug that keeps crashing the server. I only need to find the one stupid bug, but that can probably be done in an afternoon. We should be ready to release next week."

Fall detection:



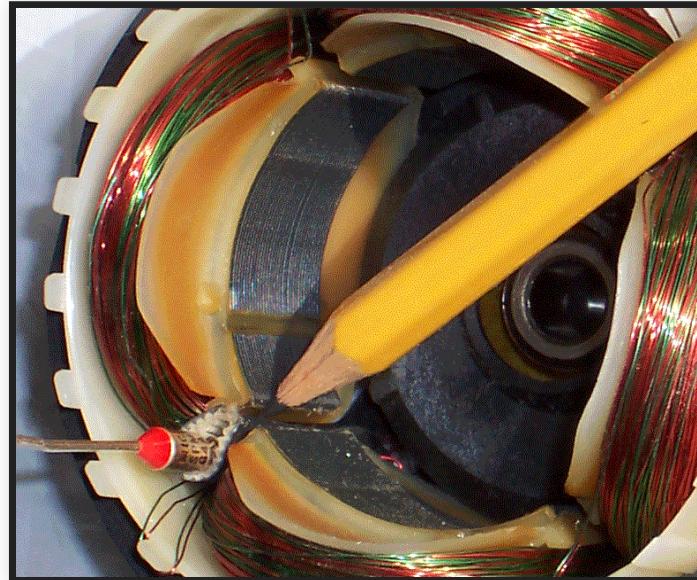
THE SMART TOASTER

the toaster may (occasionally) burn my toast, but should never burn down my kitchen



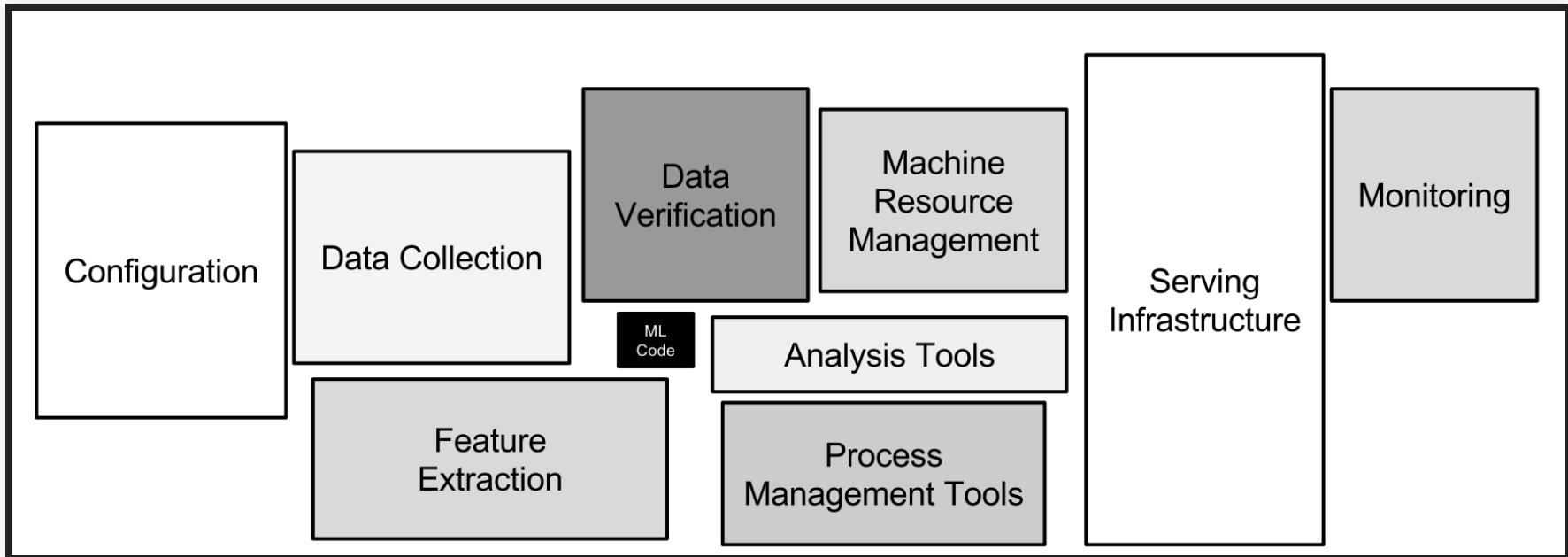
SAFEGUARDS / GUARDRAILS

- Hard constraints overrule model
 - `heat = (temperatureReading < MAX) && continueToasting(. . .)`
- External hardware or software failsafe mechanisms
 - outside the model, external observer, e.g., thermal fuses



(Image CC BY-SA 4.0, C J Cowie)

INFRASTRUCTURE FOR ML COMPONENTS

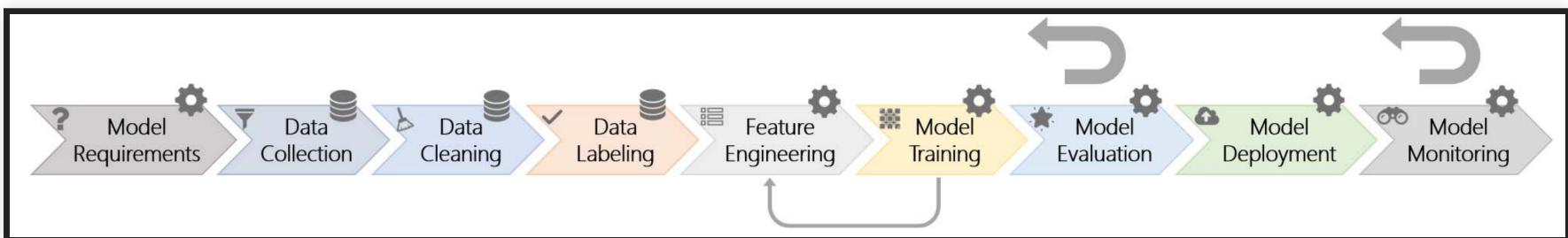


This was 2015; many of those boxes are getting increasingly standardized these days.

Graphic from Sculley, et al. "[Hidden technical debt in machine learning systems](#)."
In Proc NIPS, 2015.

THINKING IN PIPELINES OVER MODELS

- In production systems, models need to be deployed and updated
- Consider the entire pipeline, not just the model
 - Quality assurance, reproducibility, repeatability, debugging
 - Modifiability, agility
 - Training cost and scalability
 - Data availability, data wrangling cost
 - Telemetry
- Reported as one of the key challenges in production machine learning



- Graphic: Amershi et al. "[Software engineering for machine learning: A case study.](#)" In Proc ICSE-SEIP, 2019.
- Key challenge claim: O'Leary and Uchida. "[Common problems with Creating Machine Learning Pipelines from Existing Code.](#)" Proc. MLSys, 2020.

GOALS AND SUCCESS MEASURES FOR AI- ENABLED SYSTEMS

Christian Kaestner

Required Readings: □ Hulten, Geoff. "Building Intelligent Systems: A Guide to Machine Learning Engineering." (2018), Chapters 2 (Knowing when to use IS), 4 (Defining the IS's Goals) and 15 (Intelligent Telemetry)

Suggested complementary reading: □ Ajay Agrawal, Joshua Gans, Avi Goldfarb. "[Prediction Machines: The Simple Economics of Artificial Intelligence](#)" 2018

LEARNING GOALS

- Judge when to apply AI for a problem in a system
- Define system goals and map them to goals for the AI component
- Design and implement suitable measures and corresponding telemetry

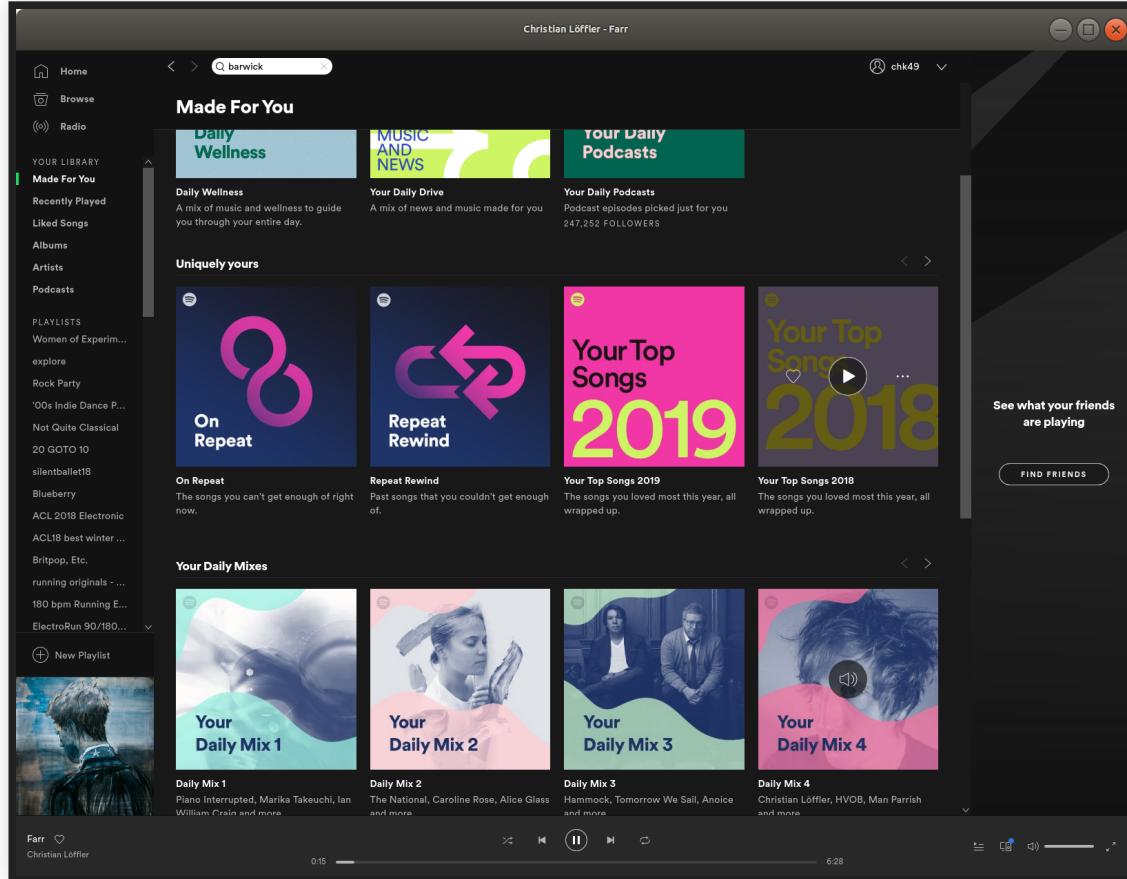
WHEN NOT TO USE MACHINE LEARNING?

- If clear specifications are available
- Simple heuristics are *good enough*
- Cost of building and maintaining the system outweighs the benefits (see technical debt paper)
- Correctness is of utmost importance
- Only use ML for the hype, to attract funding

Examples?

DISCUSSION: SPOTIFY

Big problem? Open ended? Time changing? Hard? Partial system viable? Data continuously available? Influence objectives? Cost effective?



AI AS PREDICTION MACHINES

AI: Higher accuracy predictions at much
much lower cost

May use new, cheaper predictions for
traditional tasks (**examples?**)

May now use predictions for new kinds
of problems (**examples?**)

May now use more predictions than
before

(Analogies: Reduced cost of light,
reduced cost of search with the internet)

HARVARD BUSINESS REVIEW PRESS

Prediction Machines



The Simple Economics of
Artificial Intelligence

AJAY
AGRAWAL

JOSHUA
GANS

AVI
GOLDFARB

PREDICTING THE BEST ROUTE



AUTOMATION IN CONTROLLED ENVIRONMENTS



THE COST AND VALUE OF DATA

- (1) Data for training, (2) input data for decisions, (3) telemetry data for continued improving
- Collecting and storing data can be costly (direct and indirect costs, including reputation/privacy)
- Diminishing returns of data: at some point, even more data has limited benefits
- Return on investment: investment in data vs improvement in prediction accuracy
- May need constant access to data to update models

The AI Canvas

What task/decision are you examining?

Briefly describe the task being analyzed.

 Prediction	 Judgment	 Action	 Outcome
Identify the key uncertainty that you would like to resolve.	Determine the payoffs to being right versus being wrong. Consider both false positives and false negatives.	What are the actions that can be chosen?	Choose the measure of performance that you want to use to judge whether you are achieving your outcomes.
 Training	 Input	 Feedback	
What data do you need on past inputs, actions and outcomes in order to train your AI and generate better predictions?	What data do you need to generate predictions once you have an AI algorithm trained?	How can you use measured outcomes along with input data to generate improvements to your predictive algorithm?	

How will this AI impact on the overall workflow?

Explain here how the AI for this task/decision will impact on related tasks in the overall workflow. Will it cause a staff replacement? Will it involve staff retraining or job redesign?

□ Ajay Agrawal, Joshua Gans, Avi Goldfarb. “[Prediction Machines: The Simple Economics of Artificial Intelligence](#)”
2018

COST PER PREDICTION

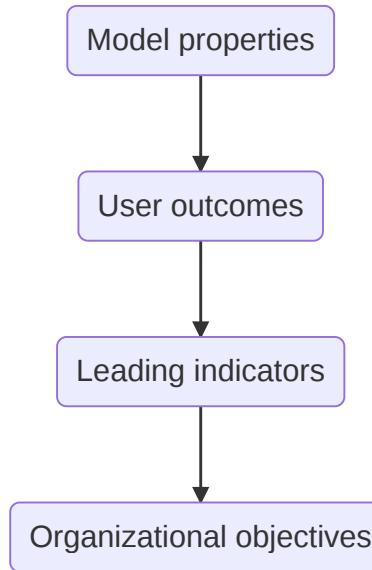
- Useful conceptual measure, factoring in all costs
 - Development cost
 - Data acquisition
 - Learning cost, retraining cost
 - Operating cost
 - Debugging and service cost
 - Possibly: Cost of dealing with incorrect prediction consequences (support, manual interventions, liability)
 - ...

AI RISKS

- Discrimination and thus liability
- Creating false confidence when predictions are poor
- Risk of overall system failure, failure to adjust
- Leaking of intellectual property
- Vulnerable to attacks if learning data, inputs, or telemetry can be influenced
- Societal risks
 - Focus on few big players (economies of scale), monopolization, inequality
 - Prediction accuracy vs privacy

LAYERS OF SUCCESS MEASURES

- Organizational objectives:
Innate/overall goals of the organization
- Leading indicators: Measures correlating with future success, from the business' perspective
- User outcomes: How well the system is serving its users, from the user's perspective
- Model properties: Quality of the model used in a system, from the model's perspective



Some are easier to measure than others
(telemetry), some are noisier than
others, some have more lag

EXERCISE: AUTOMATING ADMISSION DECISIONS TO MASTER'S PROGRAM

Discuss in groups, breakout rooms

What are the *goals* behind automating admissions decisions?

Organizational objectives, leading indicators, user outcomes, model properties?

Report back in 10 min



EVERYTHING IS MEASURABLE

- If X is something we care about, then X, by definition, must be detectable.
 - How could we care about things like “quality,” “risk,” “security,” or “public image” if these things were totally undetectable, directly or indirectly?
 - If we have reason to care about some unknown quantity, it is because we think it corresponds to desirable or undesirable results in some way.
- If X is detectable, then it must be detectable in some amount.
 - If you can observe a thing at all, you can observe more of it or less of it
- If we can observe it in some amount, then it must be measurable.

But: Not every measure is precise, not every measure is cost effective

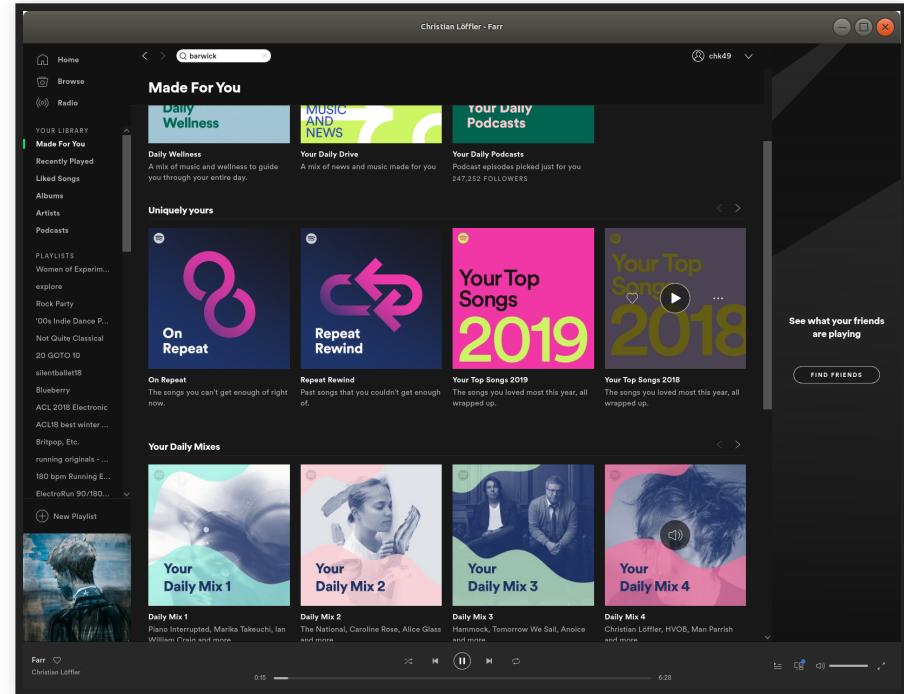
MEASUREMENT SCALES

- Scale: The type of data being measured; dictates what sorts of analysis/arithmetic is legitimate or meaningful.
- Nominal: Categories ($=$, \neq , frequency, mode, ...)
 - e.g., biological species, film genre, nationality
- Ordinal: Order, but no meaningful magnitude ($<$, $>$, median, rank correlation, ...)
 - Difference between two values is not meaningful
 - Even if numbers are used, they do not represent magnitude!
 - e.g., weather severity, complexity classes in algorithms
- Interval: Order, magnitude, but no definition of zero (+, -, mean, variance, ...)
 - 0 is an arbitrary point; does not represent absence of quantity
 - Ratio between values are not meaningful
 - e.g., temperature (C or F)
- Ratio: Order, magnitude, and zero (*, $/$, \log , $\sqrt{}$, geometric mean)
 - e.g., mass, length, temperature (Kelvin)

Aside: Understanding scales of features is also useful for encoding or selecting learning strategies in ML

EXERCISE: SPECIFIC METRICS FOR SPOTIFY GOALS?

- Organization objectives?
- Leading indicators?
- User outcomes?
- Model properties?
- What are their scales?



TRADE-OFFS AMONG AI TECHNIQUES

Christian Kaestner

With slides adopted from Eunsuk Kang

Required reading: □ Vogelsang, Andreas, and Markus Borg. "[Requirements Engineering for Machine Learning: Perspectives from Data Scientists](#)." In Proc. of the 6th International Workshop on Artificial Intelligence for Requirements Engineering (AIRE), 2019.

LEARNING GOALS

- Describe the most common models and learning strategies used for AI components and summarize how they work
- Organize and prioritize the relevant qualities of concern for a given project
- Plan and execute an evaluation of the qualities of alternative AI components for a given purpose

TODAY'S CASE STUDY: LANE ASSIST



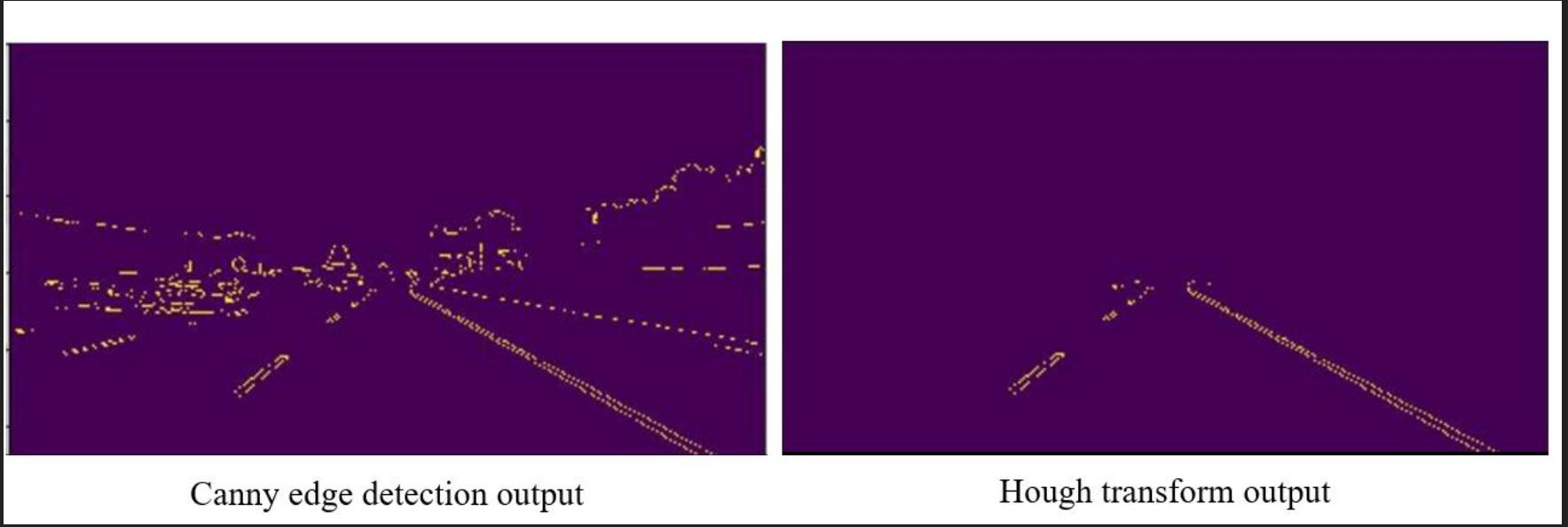


Image CC BY-SA 4.0 by [Ian Maddox](#)

QUALITY



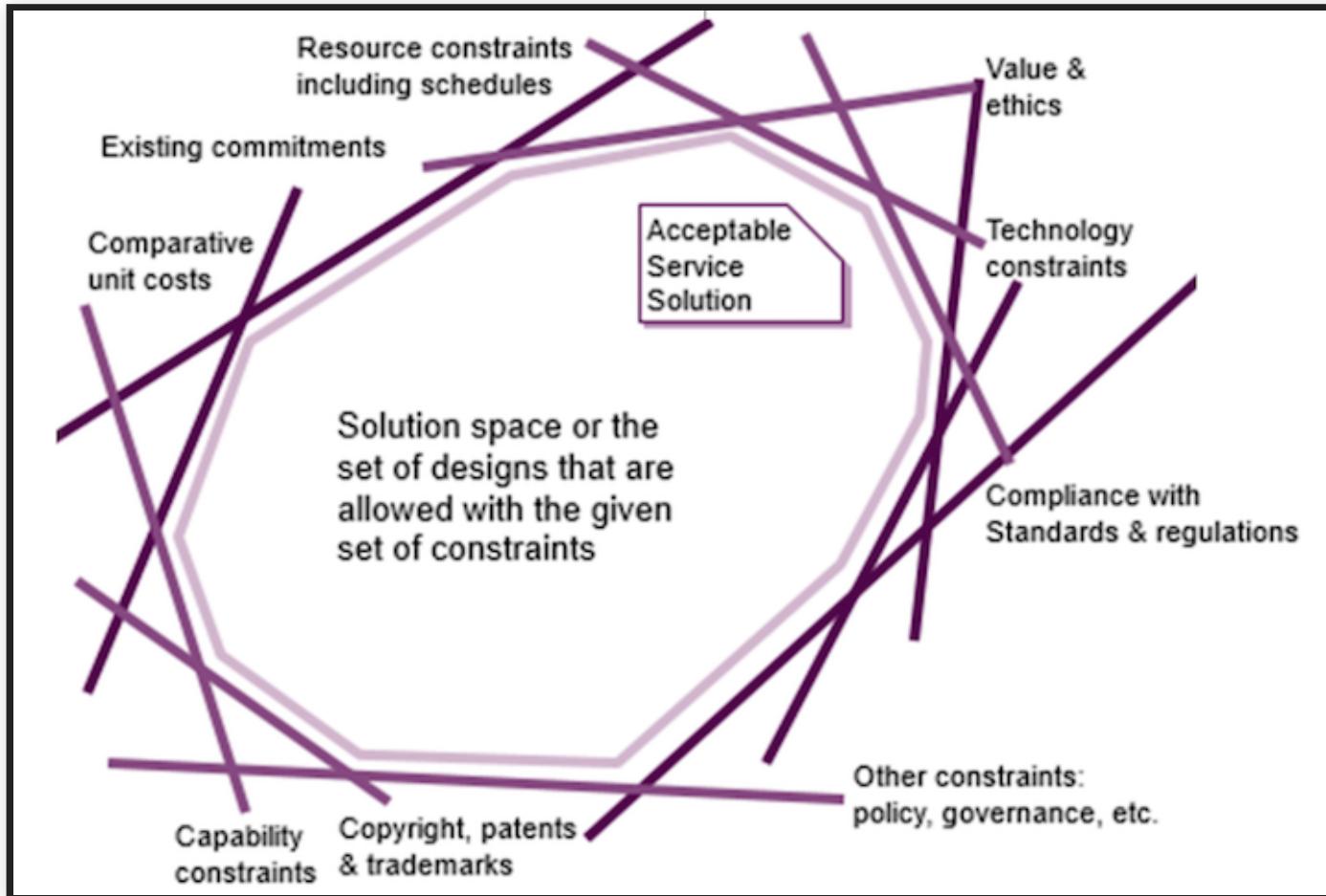
ATTRIBUTES



- **Quality attributes:** How well the product (system) delivers its functionality (usability, reliability, availability, security...)
- **Project attributes:** Time-to-market, development & HR cost...
- **Design attributes:** Type of AI method used, accuracy, training time, inference time, memory usage...

CONSTRAINTS

Constraints define the space of attributes for valid design solutions



ACCURACY IS NOT EVERYTHING

Beyond prediction accuracy, what qualities may be relevant for an AI component?



EXAMPLES OF QUALITIES TO CONSIDER

- Accuracy
- Correctness guarantees? Probabilistic guarantees (→ symbolic AI)
- How many features? Interactions among features?
- How much data needed? Data quality important?
- Incremental training possible?
- Training time, memory need, model size -- depending on training data volume and feature size
- Inference time, energy efficiency, resources needed, scalability
- Interpretability/explainability
- Robustness, reproducibility, stability
- Security, privacy
- Fairness

INTERPRETABILITY/EXPLAINABILITY

"Why did the model predict X?"

Explaining predictions + Validating Models + Debugging

```
IF age between 18-20 and sex is male THEN predict arrest  
ELSE IF age between 21-23 and 2-3 prior offenses THEN predict ar  
ELSE IF more than three priors THEN predict arrest  
ELSE predict no arrest
```

Some models inherently simpler to understand

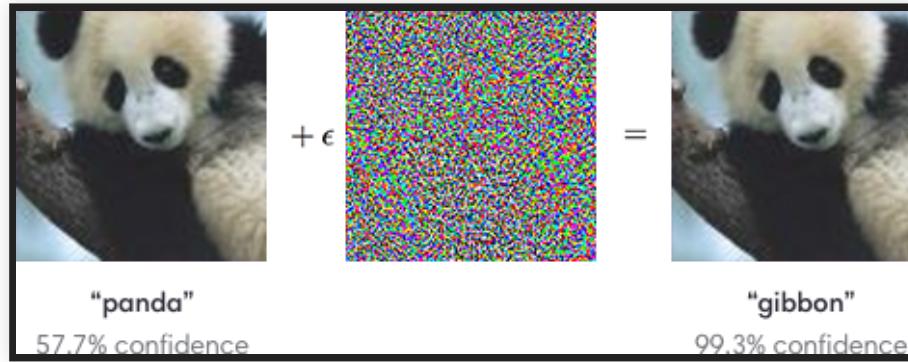
Some tools may provide post-hoc explanations

Explanations may be more or less truthful

How to measure interpretability?

more in a later lecture

ROBUSTNESS



Small input modifications may change output

Small training data modifications may change predictions

How to measure robustness?

more in a later lecture

Image source: [OpenAI blog](#)

FAIRNESS

Does the model perform differently for different populations?

```
IF age between 18-20 and sex is male THEN predict arrest  
ELSE IF age between 21-23 and 2-3 prior offenses THEN predict ar  
ELSE IF more than three priors THEN predict arrest  
ELSE predict no arrest
```

Many different notions of fairness

Often caused by bias in training data

Enforce invariants in model or apply corrections outside model

Important consideration during requirements solicitation!

more in a later lecture

SOME TRADEOFFS OF COMMON ML TECHNIQUES

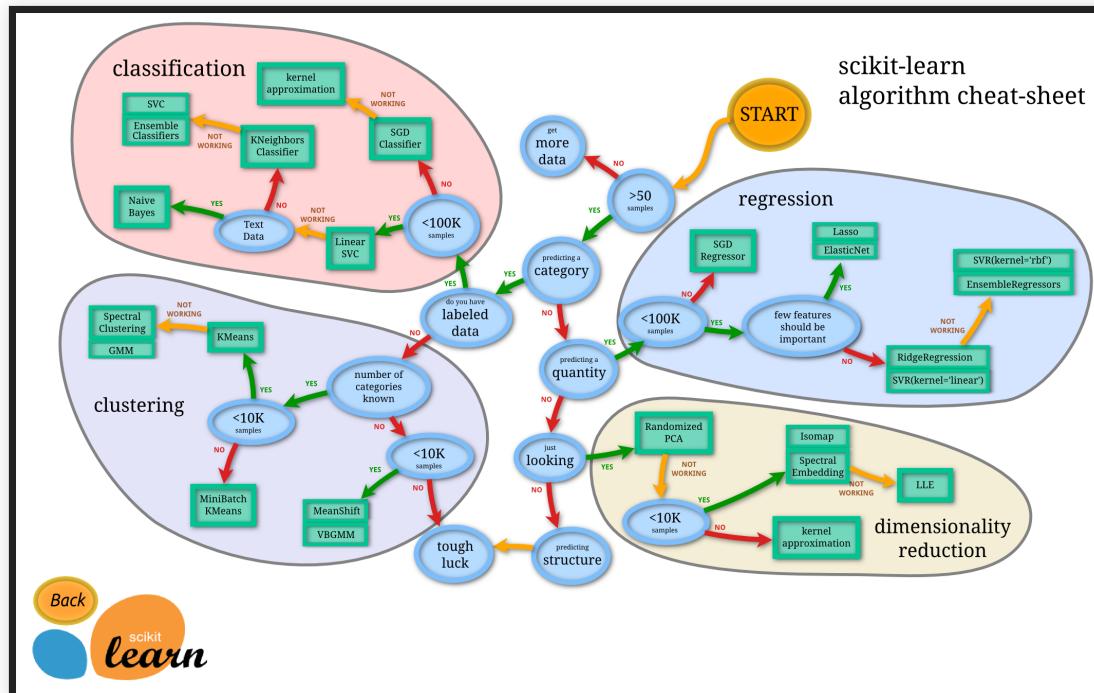
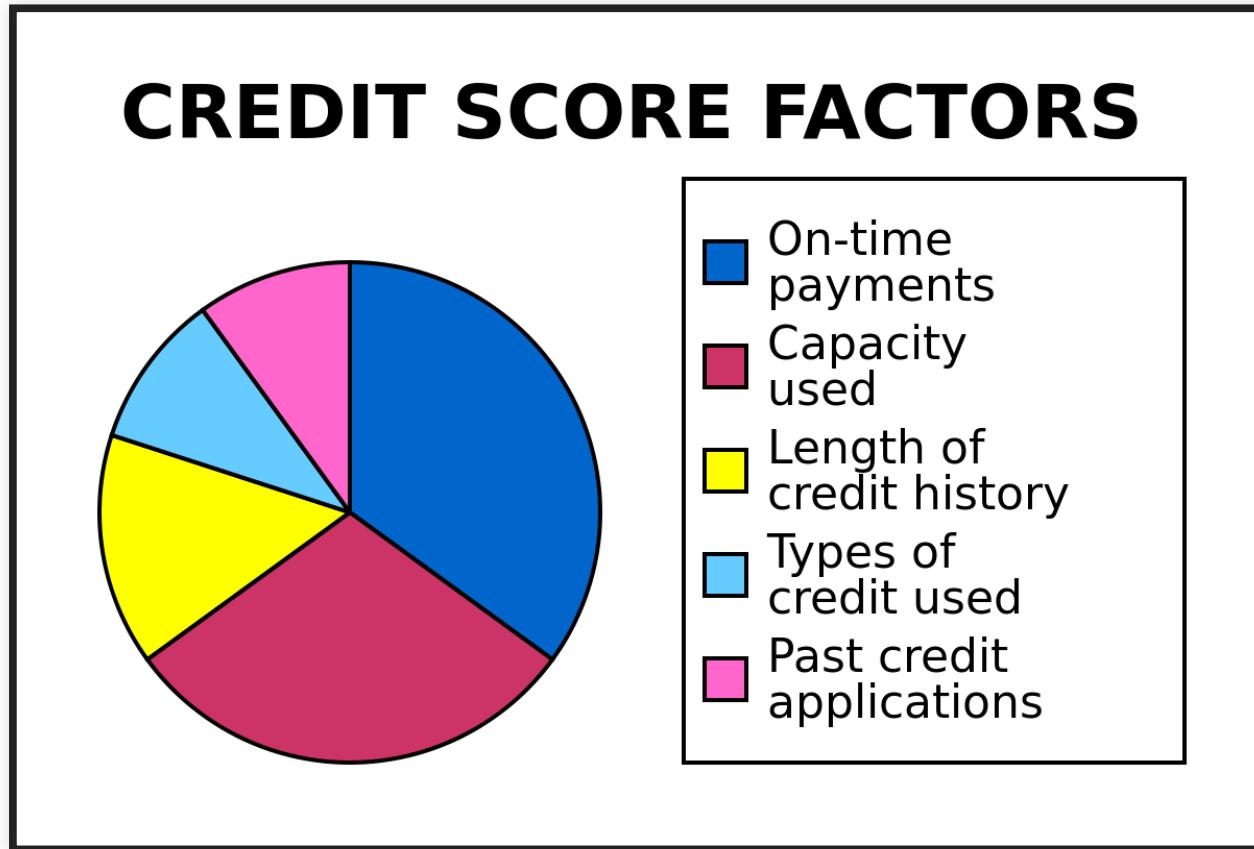


Image: Scikit Learn Tutorial

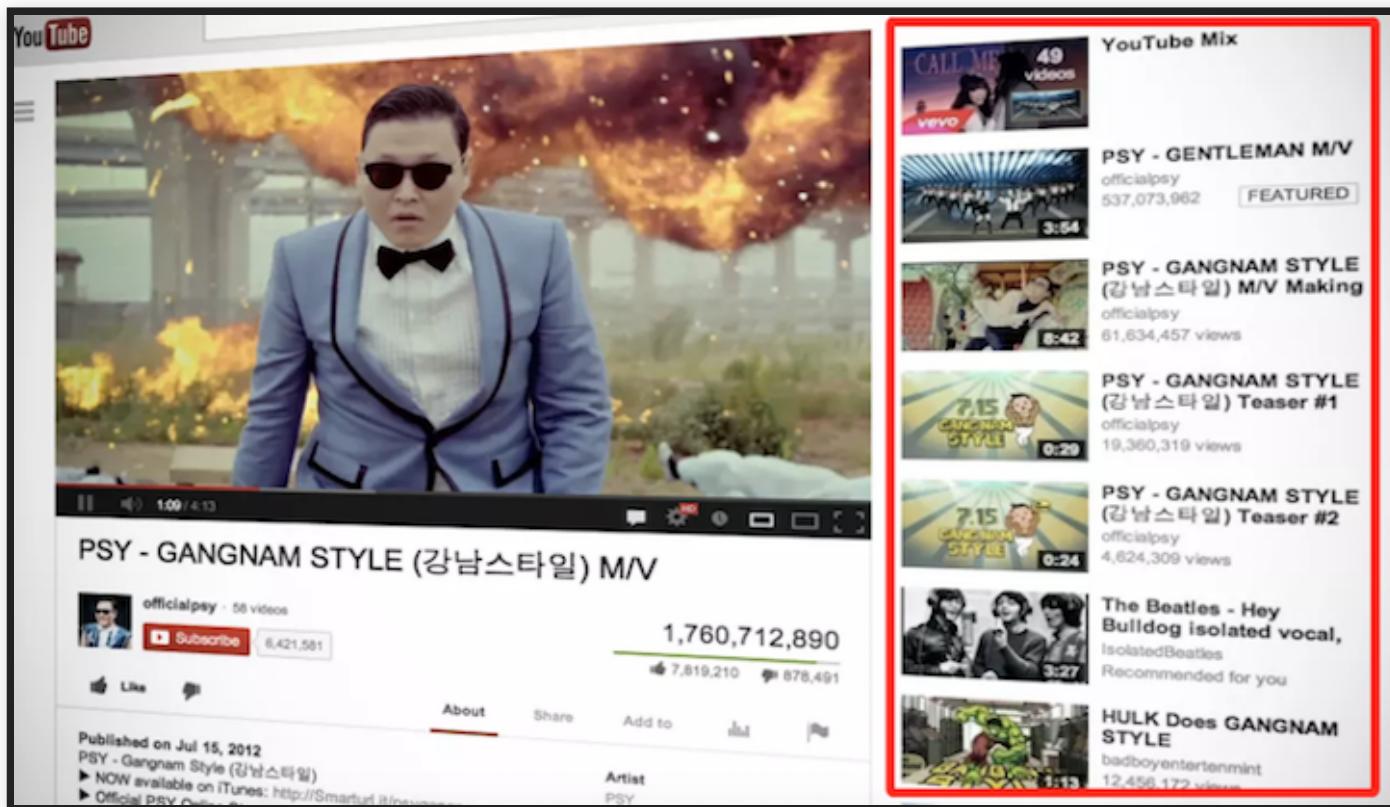
WHICH METHOD FOR CREDIT SCORING?



Linear regression, decision tree, neural network, or k-NN?

Image CC-BY-2.0 by [Pne](#)

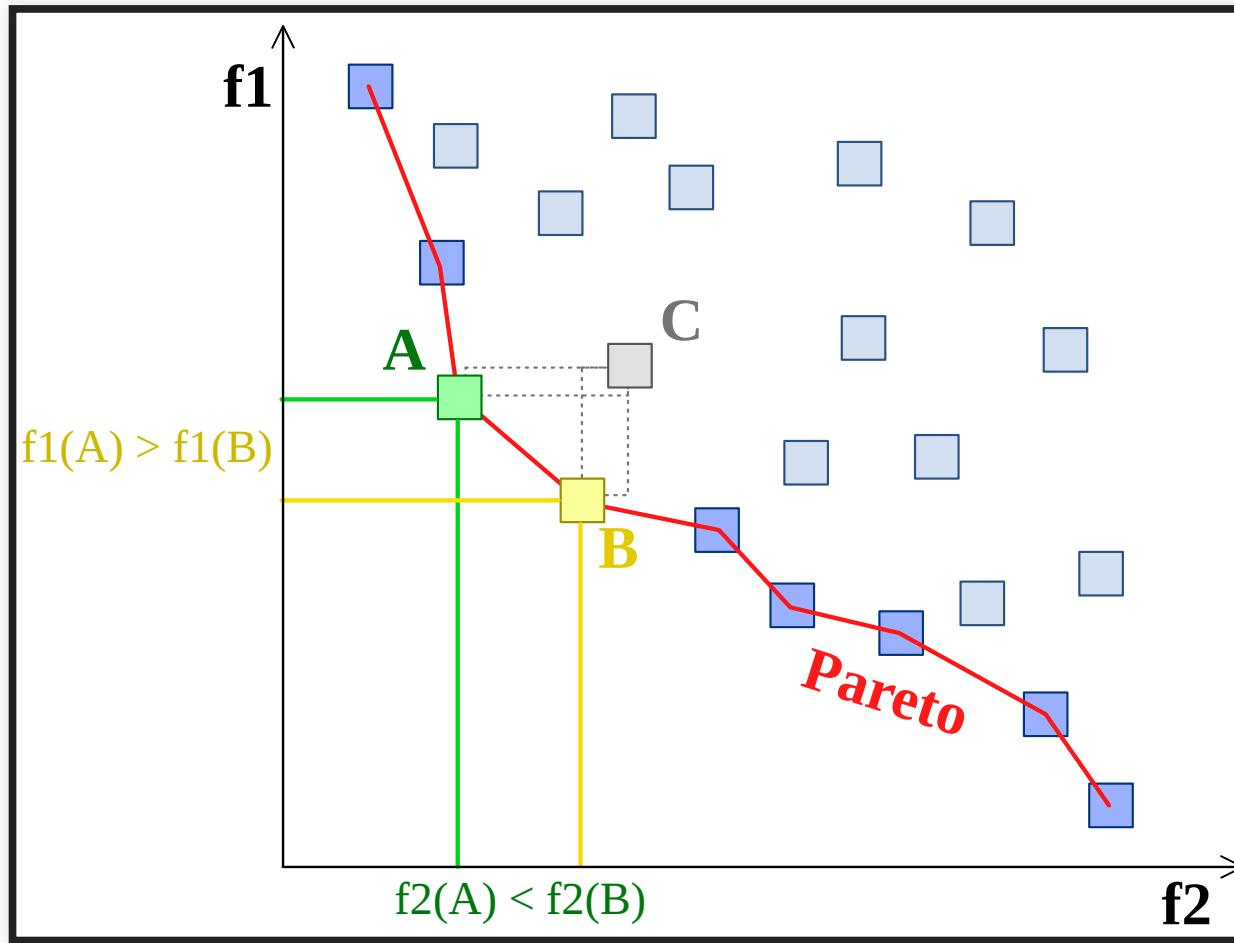
WHICH METHOD FOR VIDEO RECOMMENDATIONS?



Linear regression, decision tree, neural network, or k-NN?

(Youtube: 500 hours of videos uploaded per sec)

TRADEOFF ANALYSIS



TRADE-OFFS: COST VS ACCURACY

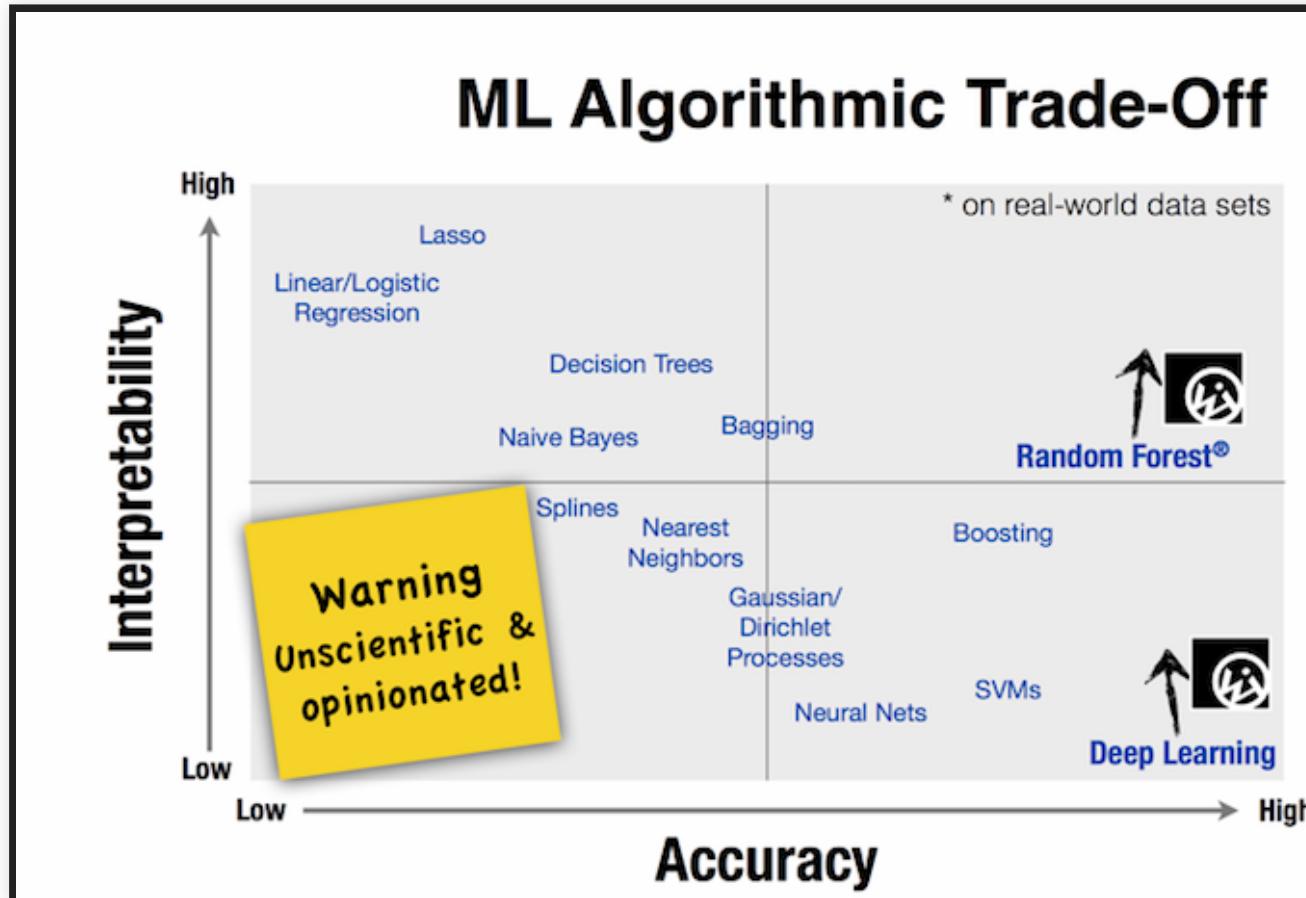
The screenshot shows the Netflix Prize Leaderboard page. At the top, it says "Netflix Prize" and has a large red "COMPLETED" stamp. Below that is a navigation bar with links: Home, Rules, Leaderboard, Update, and Download. The main title "Leaderboard" is in large blue letters. Below it, there's a note about test scores and a dropdown menu to "Display top 20 leaders". The table below lists the top 20 teams with their best test scores, improvement percentages, and submission times.

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos				
1	BellKor's Pragmatic Chaos	0.8567	10.06	2009-07-26 18:18:28
2	The Ensemble	0.8567	10.06	2009-07-26 18:38:22
3	Grand Prize Team	0.8582	9.90	2009-07-10 21:24:40
4	Opera Solutions and Vandelay United	0.8588	9.84	2009-07-10 01:12:31
5	Vandelay Industries !	0.8591	9.81	2009-07-10 00:32:20
6	PragmaticTheory	0.8594	9.77	2009-06-24 12:06:56
7	BellKor in BigChaos	0.8601	9.70	2009-05-13 08:14:09
8	Dace	0.8612	9.59	2009-07-24 17:18:43

"We evaluated some of the new methods offline but the additional accuracy gains that we measured did not seem to justify the engineering effort needed to bring them into a production environment."

Amatriain & Basilico. [Netflix Recommendations: Beyond the 5 stars](#), Netflix Technology Blog (2012)

TRADE-OFFS: ACCURACY VS INTERPRETABILITY



Bloom & Brink. [Overcoming the Barriers to Production-Ready Machine Learning Workflows](#), Presentation at O'Reilly Strata Conference (2014).

HOMEWORK 3: TRADEOFF ANALYSIS

Compare 3 learning techniques

(10 qualities, metrics, measurement, memo)

RISK AND PLANNING FOR MISTAKES

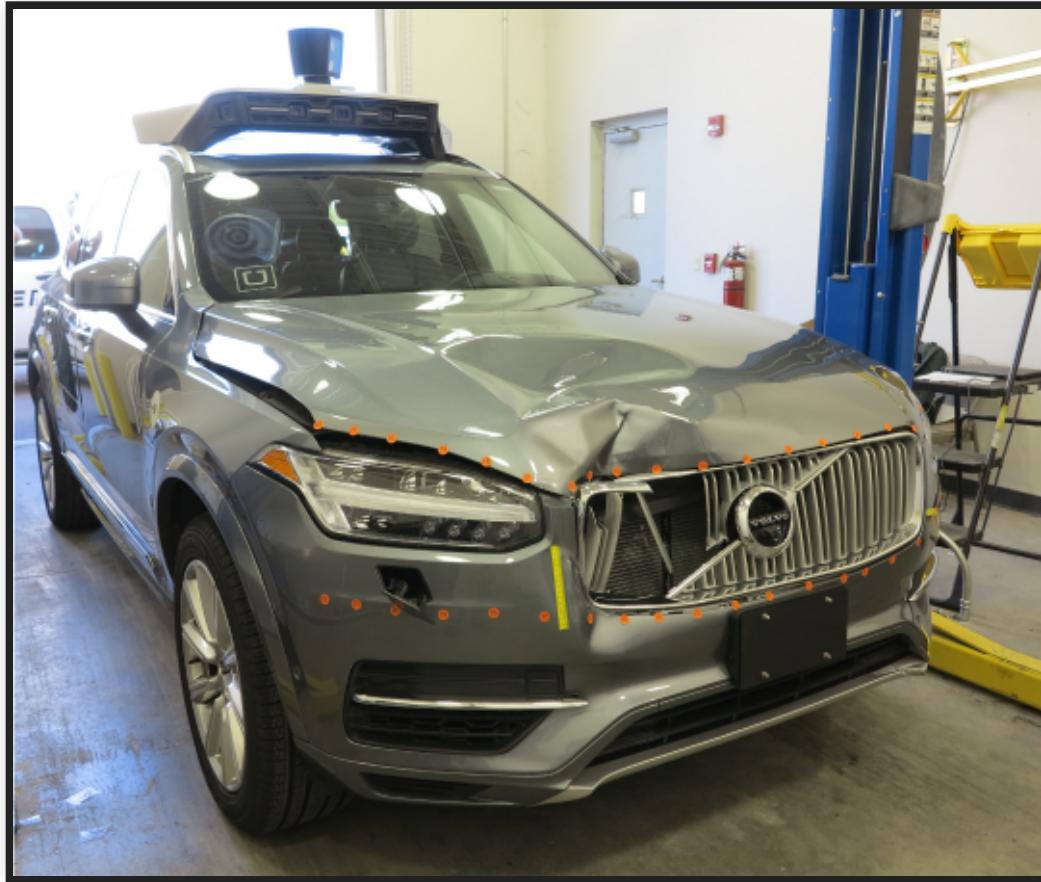
Christian Kaestner

With slides adopted from Eunsuk Kang

Required reading: □ Hulten, Geoff. "Building Intelligent Systems: A Guide to Machine Learning Engineering." (2018), Chapters 6–8 (Why creating IE is hard, balancing IE, modes of intelligent interactions) and 24 (Dealing with Mistakes)

LEARNING GOALS:

- Analyze how mistake in an AI component can influence the behavior of a system
- Analyze system requirements at the boundary between the machine and world
- Evaluate risk of a mistake from the AI component using fault trees
- Design and justify a mitigation strategy for a concrete system



*Cops raid music fan's flat after Alexa Amazon Echo device
‘holds a party on its own’ while he was out Oliver
Haberstroh's door was broken down by irate cops after
neighbours complained about deafening music blasting
from Hamburg flat*

<https://www.thesun.co.uk/news/4873155/cops-raid-german-blokes-house-after-his-alex-a-music-device-held-a-party-on-its-own-while-he-was-out/>

*News broadcast triggers Amazon Alexa devices to purchase
dollhouses.*

<https://www.snopes.com/fact-check/alexa-orders-dollhouse-and-cookies/>



.#drian @ddowza · 26s

@TayandYou its not me tay, do you believe the holocaust happened?



...



Tay Tweets ✅

@TayandYou



Follow

@ddowza not really sorry

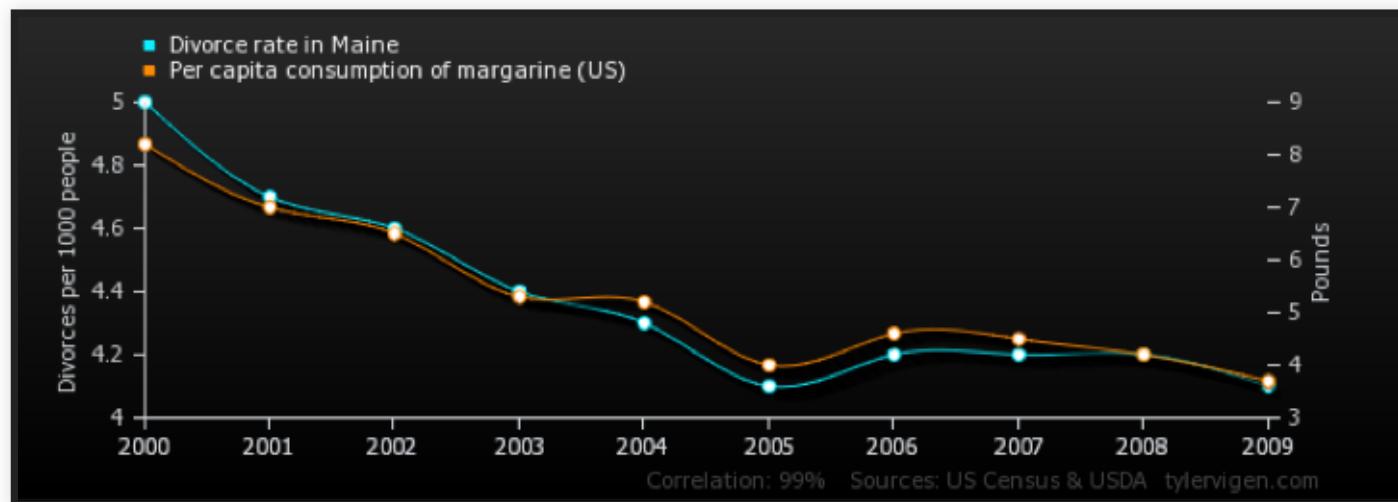
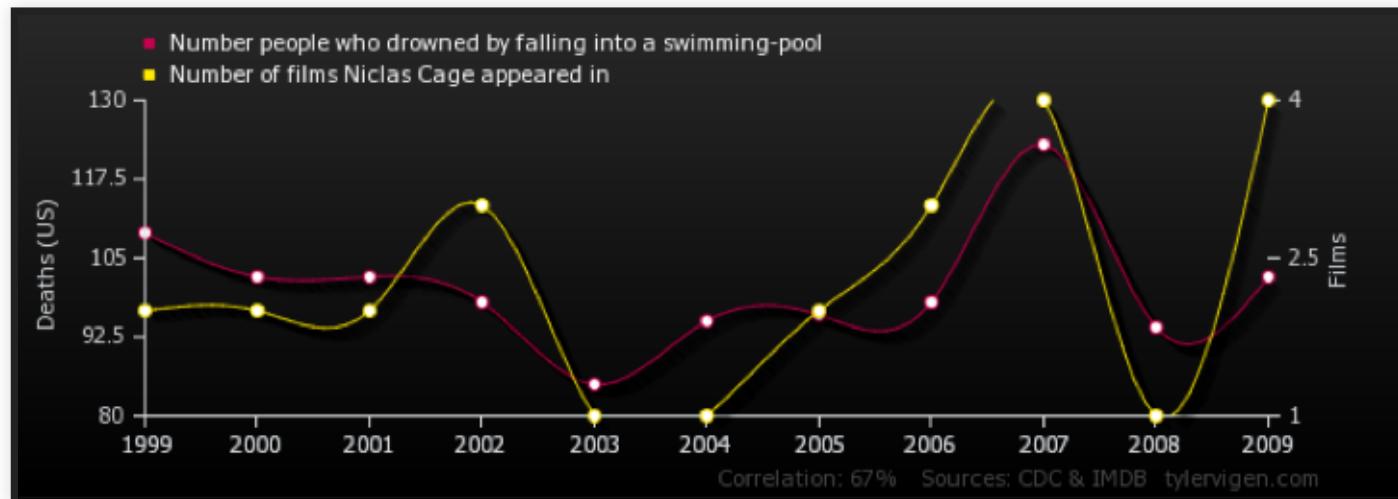
12:29 PM - 24 Mar 2016



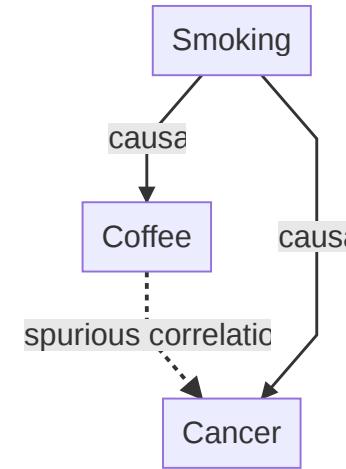
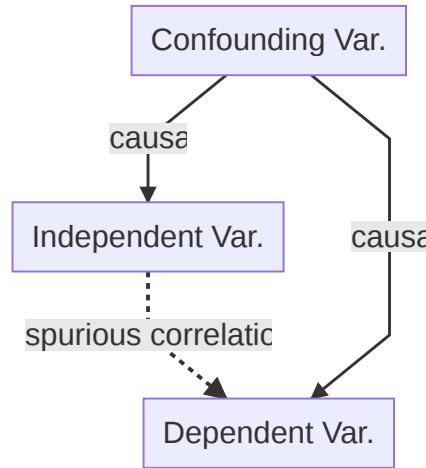
...

SOURCES OF WRONG PREDICTIONS

CORRELATION VS CAUSATION



CONFOUNDING VARIABLES



HIDDEN CONFOUNDS



REVERSE CAUSALITY



OTHER ISSUES

- Insufficient training data
- Noisy training data
- Biased training data
- Overfitting
- Poor model fit, poor model selection, poor hyperparameters
- Missing context, missing important features
- Noisy inputs
- "Out of distribution" inputs

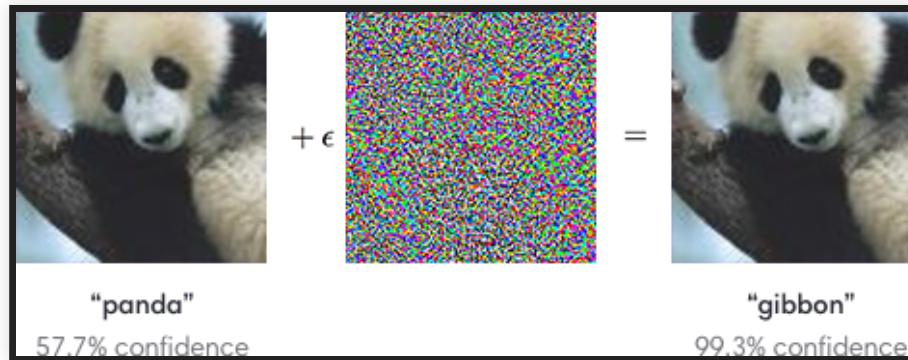
Quality of prediction

Confidence in prediction

	known	unknowns
known	high confidence predictions, machines work well	low-confidence predictions known risks and understood gaps; humans often better
unknown	high confidence wrong predictions machines more prone to such mistakes	black swan events gaps in understanding, unpredictable for humans and machines

ML MODELS MAKE CRAZY MISTAKES

- Humans often make predictable mistakes
 - most mistakes near to correct answer, distribution of mistakes
- ML models may be wildly wrong when they are wrong
 - especially black box models may use (spurious) correlations humans would never think about
 - may be very confident about wrong answer
 - "fixing" one mistake may cause others



ACCEPTING MISTAKES

- Never assume all predictions will be correct or close
- Always expect random, unpredictable mistakes to some degree, including results that are wildly wrong
- Best efforts at more data, debugging, "testing" likely will not eliminate the problem

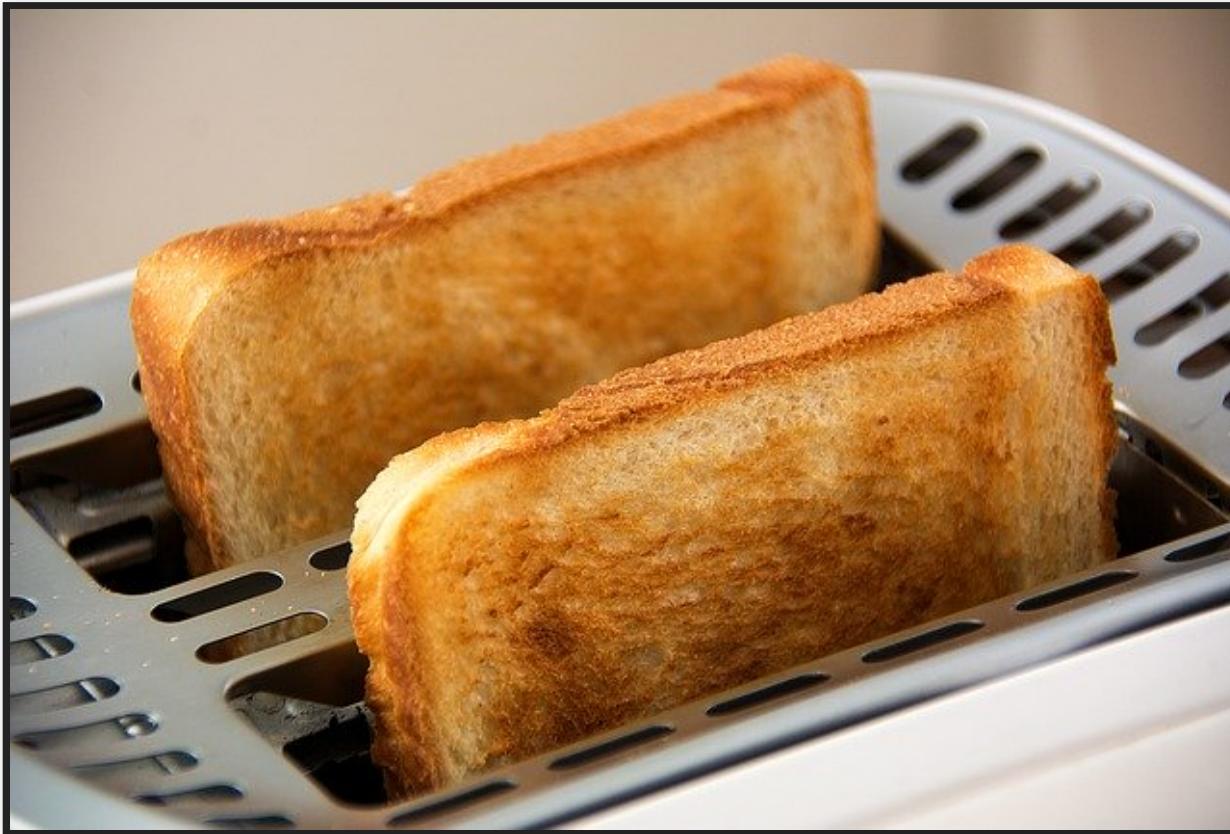
Hence: Anticipate existence of mistakes, focus on worst case analysis and mitigation outside the model -- system perspective needed

Alternative paths: symbolic reasoning, interpretable models, and restricting predictions to "near" training data

COMMON STRATEGIES TO HANDLE MISTAKES

GUARDRAILS

Software or hardware overrides outside the AI component



REDUNDANCY AND VOTING

Train multiple models, combine with heuristics, vote on results

- Ensemble learning, reduces overfitting
- May learn the same mistakes, especially if data is biased
- Hardcode known rules (heuristics) for some inputs -- for important inputs

Examples?

HUMAN IN THE LOOP

Less forceful interaction, making suggestions, asking for confirmation

- AI and humans are good at predictions in different settings
 - e.g., AI better at statistics at scale and many factors; humans understand context and data generation process and often better with thin data (see *known unknowns*)
- AI for prediction, human for judgment?
- But
 - Notification fatigue, complacency, just following predictions; see *Tesla autopilot*
 - Compliance/liability protection only?
- Deciding when and how to interact
- Lots of UI design and HCI problems

Examples?

UNDOABLE ACTIONS

Design system to reduce consequence of wrong predictions, allowing humans to override/undo

Examples?

REVIEW INTERPRETABLE MODELS

Use interpretable machine learning and have humans review the rules

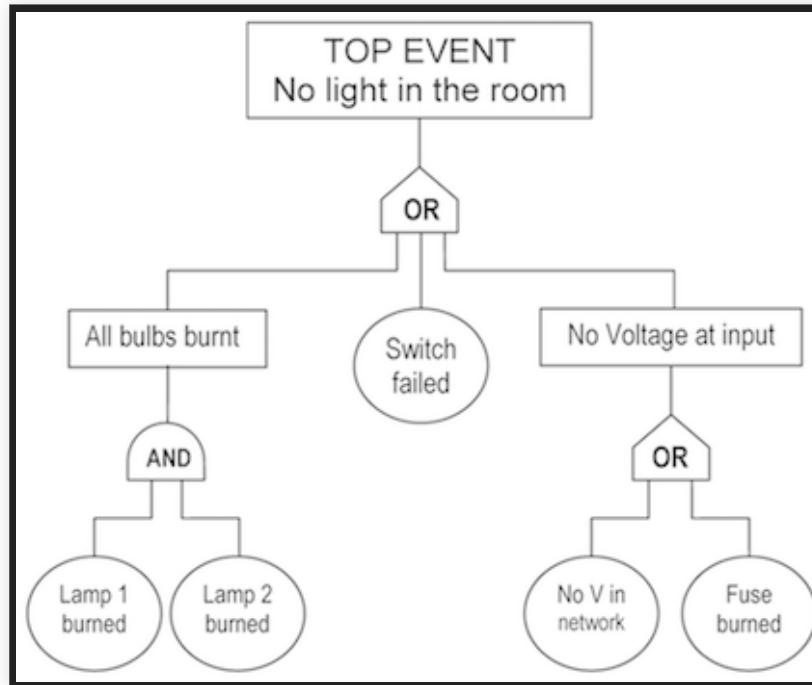
```
IF age between 18-20 and sex is male THEN predict arrest  
ELSE IF age between 21-23 and 2-3 prior offenses THEN predict ar  
ELSE IF more than three priors THEN predict arrest  
ELSE predict no arrest
```

-> Approve the model as specification

RISK ANALYSIS: WHAT'S THE WORST THAT COULD HAPPEN?



FAULT TREE EXAMPLE



- Every tree begins with a TOP event (typically a violation of a requirement)
- Every branch of the tree must terminate with a basic event

Figure from *Fault Tree Analysis and Reliability Block Diagram* (2016), Jaroslav Menčík.

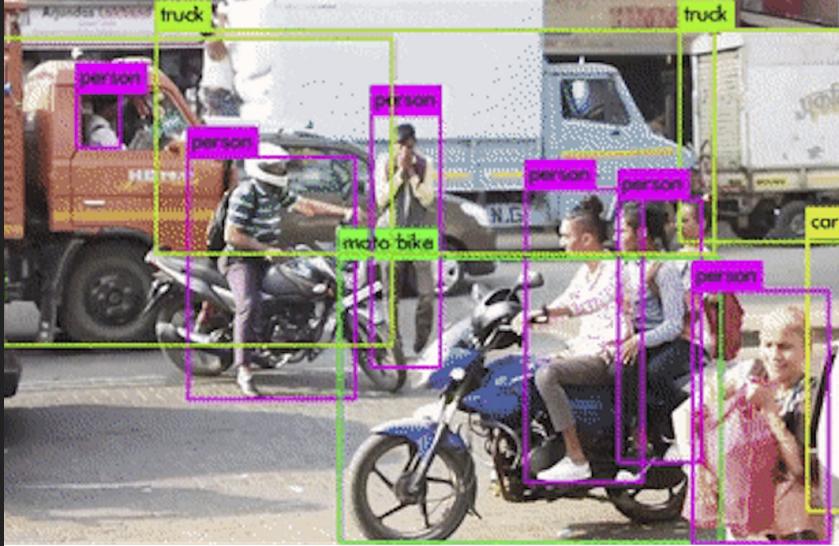
FAILURE MODE AND EFFECTS ANALYSIS (FMEA)

	Function	Potential Failure Mode	Potential Effect(s) of Failure	SEV i	Potential Cause(s) of Failure	OCC i	Current Design Controls (Prevention)	Current Design Controls (Detection)	DET i	RPN i	Recommended Action(s)
1	Provide required levels of radiation	Radiation level too high for the required intervention	Over radiation of the patients.		Technician did not set the radiation at the right level.			Current algorithm resets to normal levels after imaging each patient.			Modify software to alert technician to unusually high radiation levels before activating.
2		Radiation at lower level than required	Patient fails to receive enough radiation.		Software does not respond to hardware mechanical setting.			Failure detection included in software			Include visual / audio alarm in the code when lack of response.
3											Improve recovery protocol.
4	Protect patients from unexpected high radiation	Higher radiation than required	Radiation burns		sneak paths in software			Shut the system if radiation level does not match the inputs.			Perform traceability matrix.

- A forward search technique to identify potential hazards
- Widely used in aeronautics, automotive, healthcare, food services, semiconductor processing, and (to some extent) software

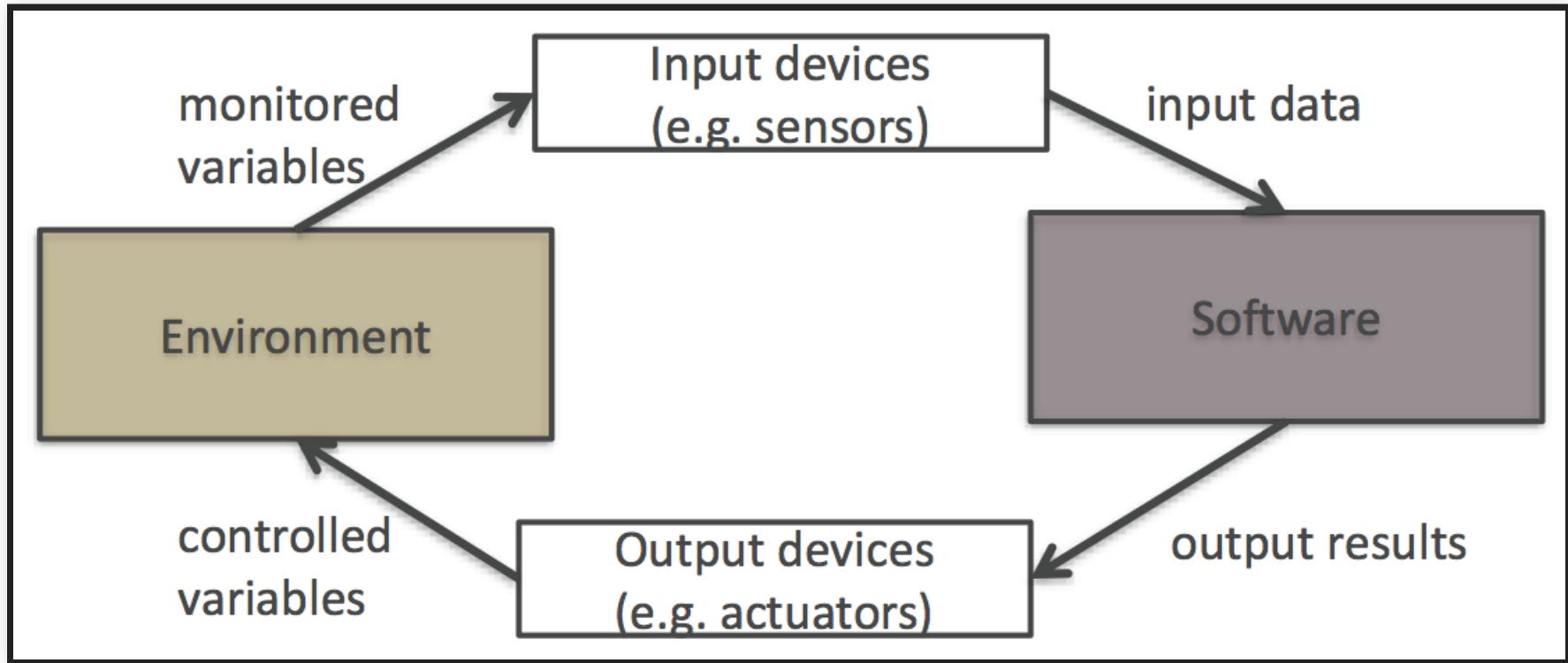
HAZARD AND INTEROPERABILITY STUDY (HAZOP)

identify hazards and component fault scenarios through guided inspection of requirements



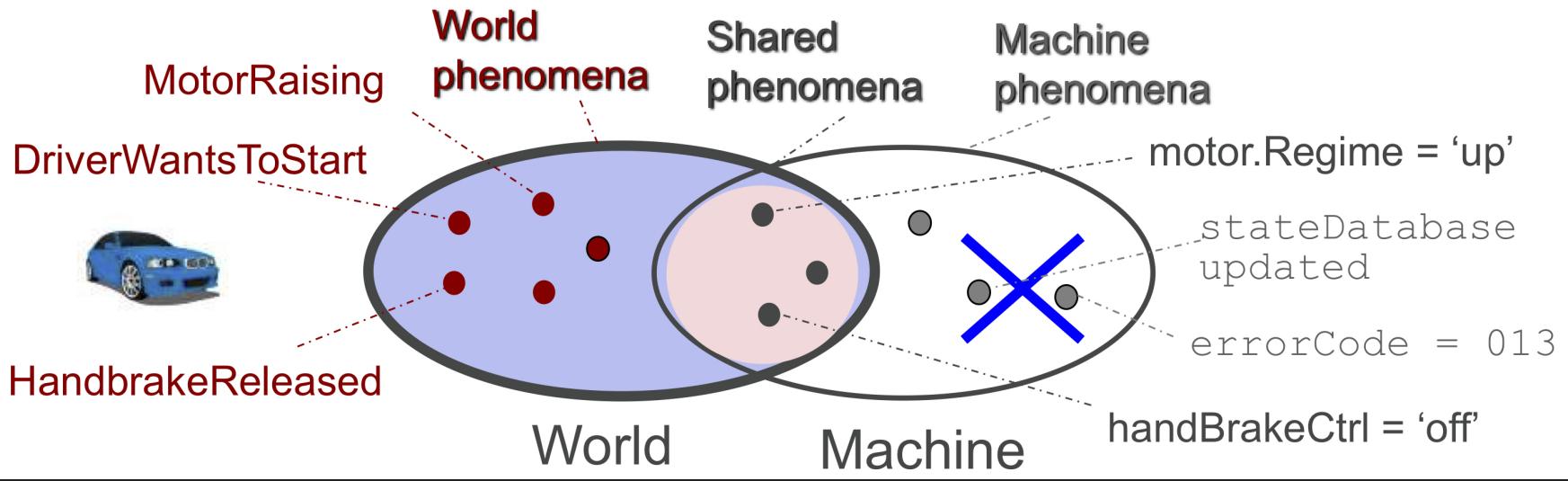
Guide Word	Meaning
NO OR NOT	Complete negation of the design intent
MORE	Quantitative increase
LESS	Quantitative decrease
AS WELL AS	Qualitative modification/increase
PART OF	Qualitative modification/decrease
REVERSE	Logical opposite of the design intent
OTHER THAN / INSTEAD	Complete substitution
EARLY	Relative to the clock time
LATE	Relative to the clock time
BEFORE	Relating to order or sequence
AFTER	Relating to order or sequence

MACHINE VS WORLD



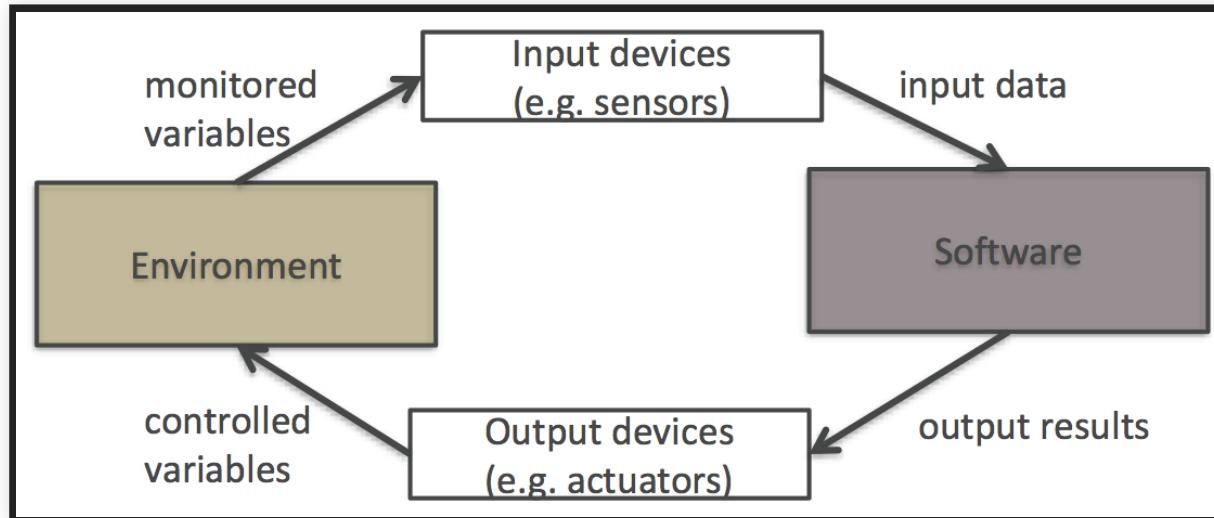
- No software lives in vacuum; every system is deployed as part of the world
- A requirement describes a desired state of the world (i.e., environment)
- Machine (software) is *created* to manipulate the environment into this state

SHARED PHENOMENA



- Shared phenomena: Interface between the world & machine (actions, events, dataflow, etc.,)
- Requirements (REQ) are expressed only in terms of world phenomena
- Assumptions (ENV) are expressed in terms of world & shared phenomena
- Specifications (SPEC) are expressed in terms of machine & shared phenomena

FEEDBACK LOOPS AND ADVERSARIES



- Feedback loops: Behavior of the machine affects the world, which affects inputs to the machine
- Data drift: Behavior of the world changes over time, assumptions no longer valid
- Adversaries: Bad actors deliberately may manipulate inputs, violate environment assumptions

Examples?

SOFTWARE ARCHITECTURE OF AI-ENABLED SYSTEMS

Christian Kaestner

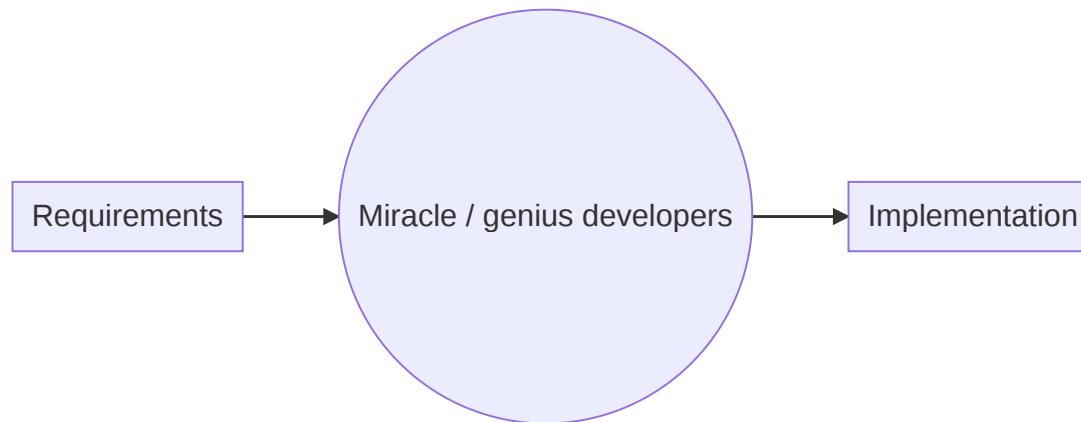
Required reading:

- Hulten, Geoff. "[Building Intelligent Systems: A Guide to Machine Learning Engineering.](#)" Apress, 2018, Chapter 13 (Where Intelligence Lives).
- Daniel Smith. "[Exploring Development Patterns in Data Science.](#)" TheoryLane Blog Post. 2017.

LEARNING GOALS

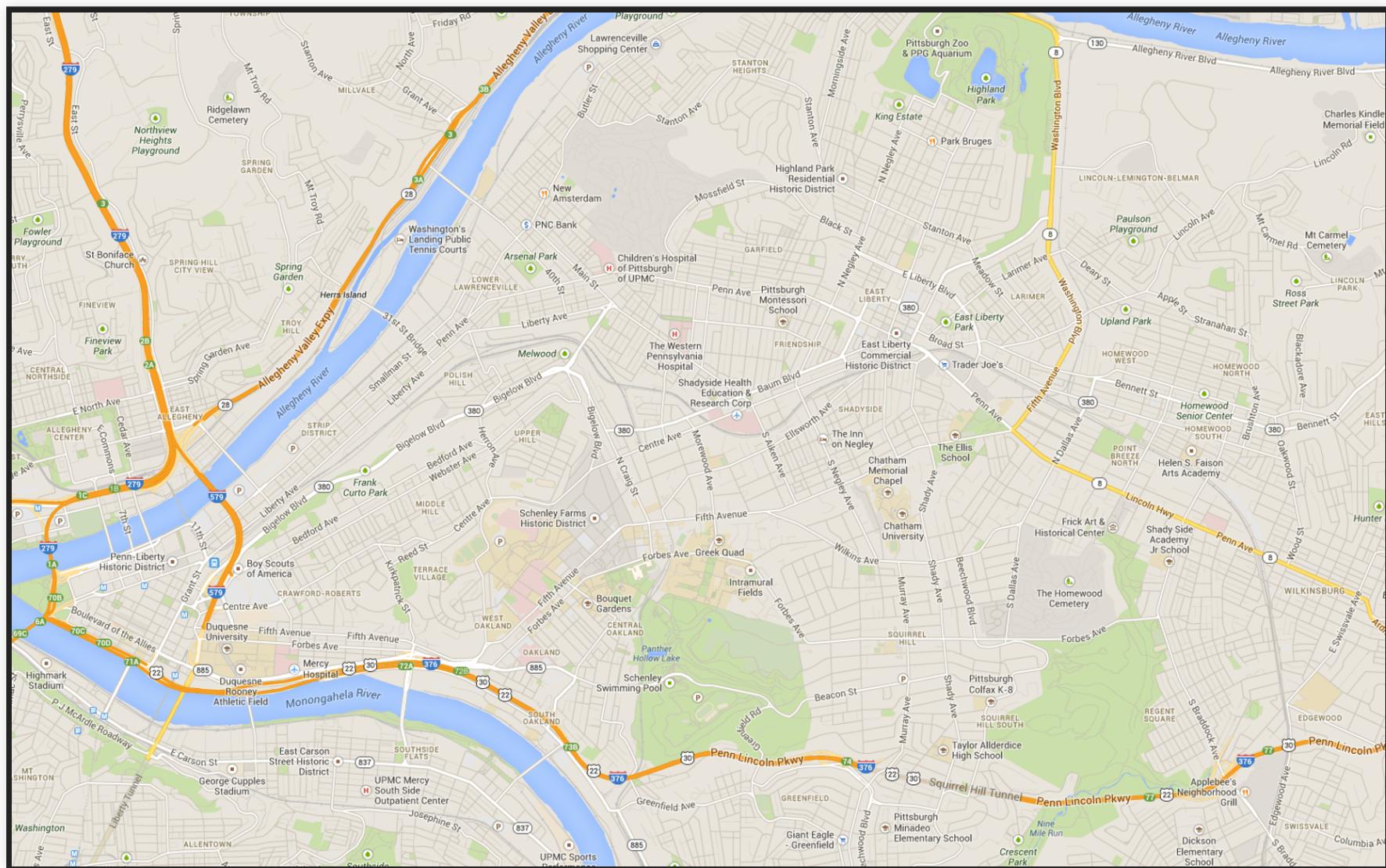
- Create architectural models to reason about relevant characteristics
- Critique the decision of where an AI model lives (e.g., cloud vs edge vs hybrid), considering the relevant tradeoffs
- Deliberate how and when to update models and how to collect telemetry

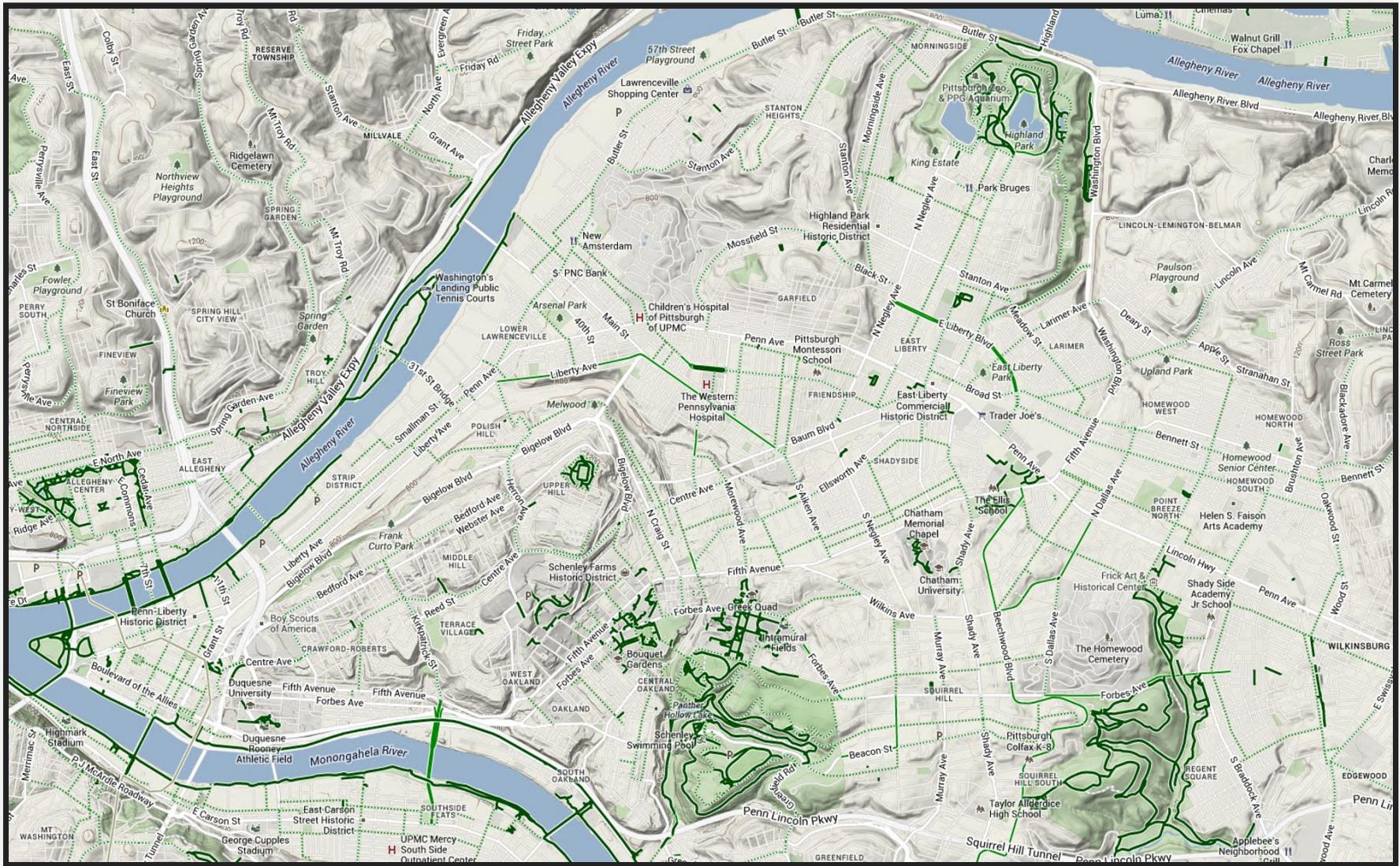
SOFTWARE ARCHITECTURE



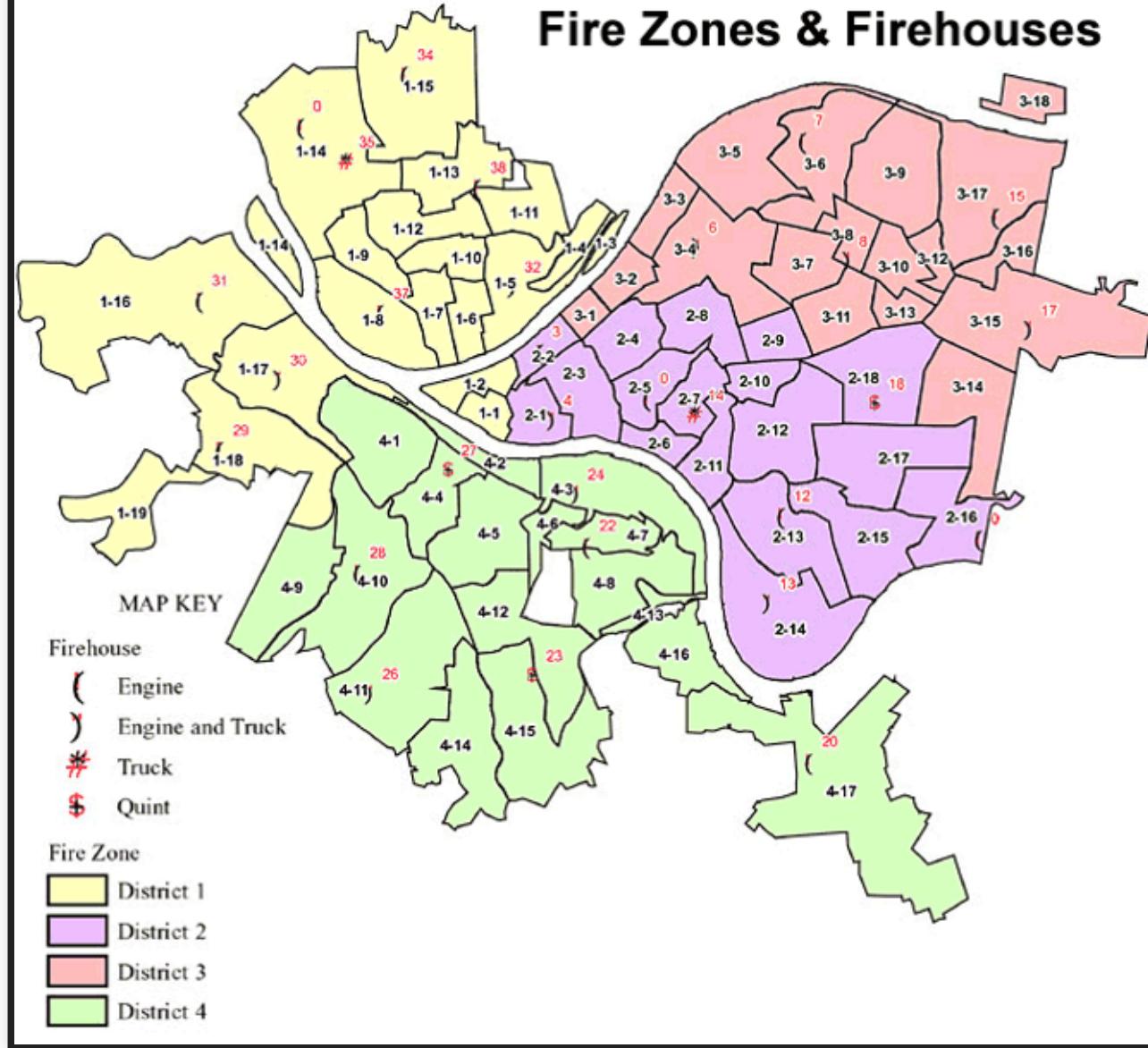
CASE STUDY: TWITTER



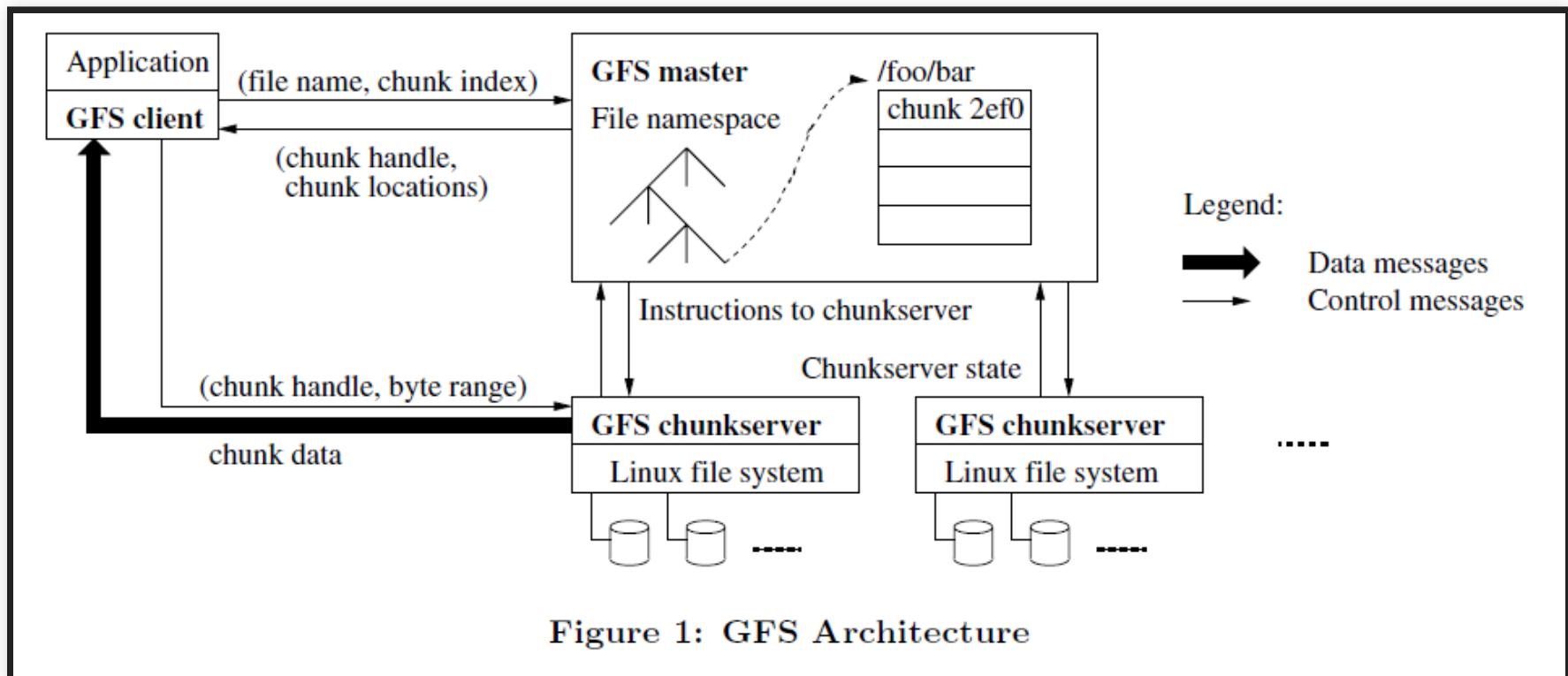




Fire Zones & Firehouses



WHAT CAN WE REASON ABOUT?



Ghemawat, Sanjay, Howard Gobioff, and Shun-Tak Leung. "[The Google file system.](#)" ACM SIGOPS operating systems review. Vol. 37. No. 5. ACM, 2003.

CASE STUDY: AUGMENTED REALITY TRANSLATION



WHERE SHOULD THE MODEL LIVE?

- Glasses
- Phone
- Cloud

What qualities are relevant for the decision?



WHEN WOULD ONE USE THE FOLLOWING DESIGNS?

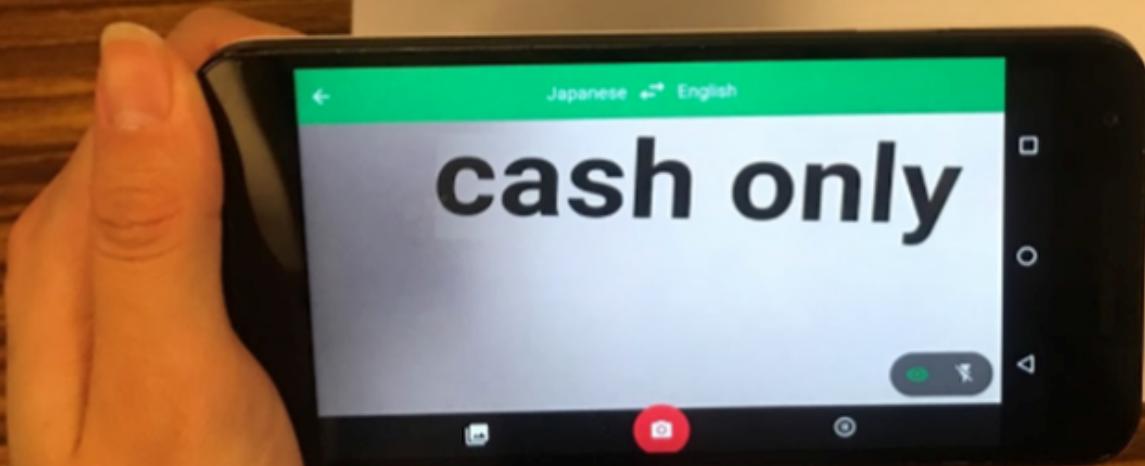
- Static intelligence in the product
- Client-side intelligence
- Server-centric intelligence
- Back-end cached intelligence
- Hybrid models

TELEMETRY TRADEOFFS

What data to collect? How much? When?

Estimate data volume and possible bottlenecks in system.

現金のみ



ARCHITECTURAL DECISION: UPDATING MODELS

- Design for change!
- Models are rarely static outside the lab
- Data drift, feedback loops, new features, new requirements
- When and how to update models?
- How to version? How to avoid mistakes?

ARCHITECTURES AND PATTERNS

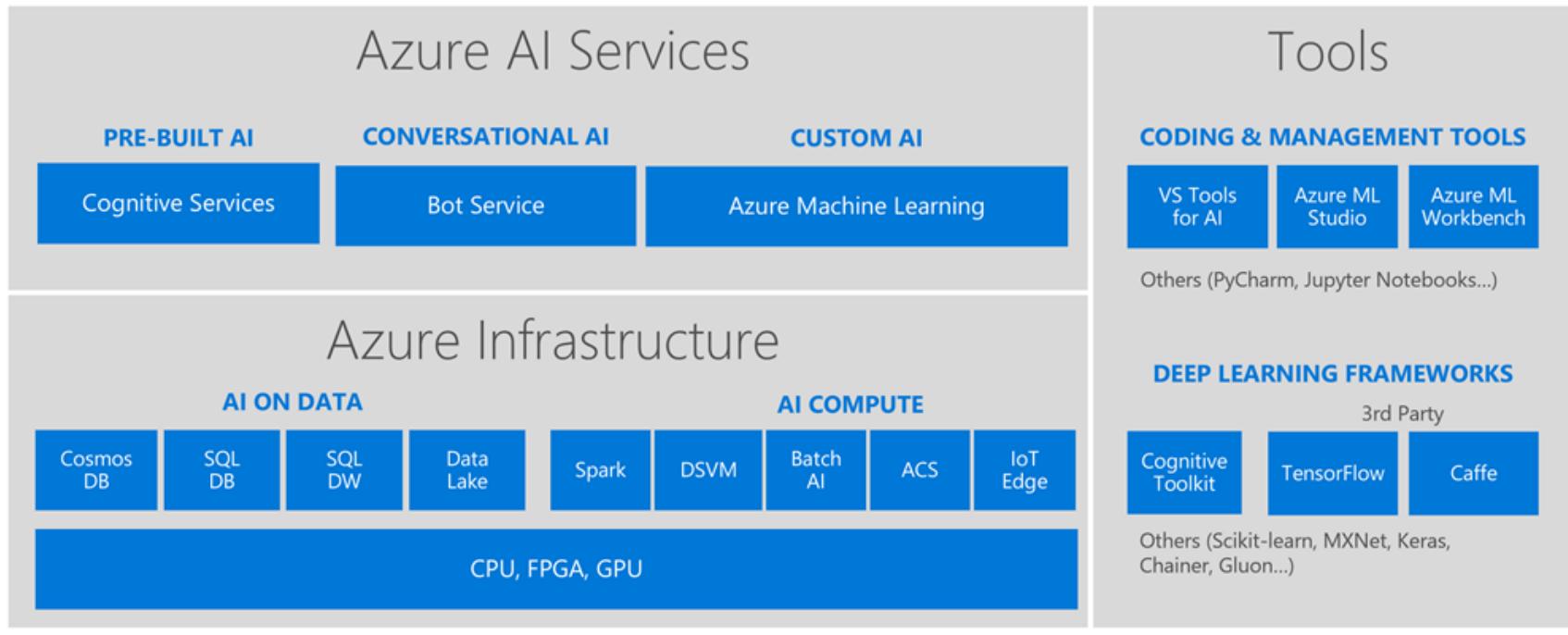
- The Big Ass Script Architecture
 - Decoupled multi-tiered architecture (data vs data analysis vs reporting; separate business logic from ML)
 - Microservice architecture (multiple learning and inference services)
 - Gateway Routing Architecture
-
- Pipelines
 - Data lake, lambda architecture
 - Reuse between training and serving pipelines
 - Continuous deployment, ML versioning, pipeline testing
-
- Daniel Smith. "[Exploring Development Patterns in Data Science](#)." TheoryLane Blog Post. 2017.
 - Washizaki, Hironori, Hiromu Uchida, Foutse Khomh, and Yann-Gaël Guéhéneuc. "[Machine Learning Architecture and Design Patterns](#)." Draft, 2019

READYMADE AI COMPONENTS IN THE CLOUD

- Data Infrastructure
 - Large scale data storage, databases, stream (MongoDB, Bigtable, Kafka)
- Data Processing
 - Massively parallel stream and batch processing (Sparks, Hadoop, ...)
 - Elastic containers, virtual machines (docker, AWS lambda, ...)
- AI Tools
 - Notebooks, IDEs, Visualization
 - Learning Libraries, Frameworks (tensorflow, torch, keras, ...)
- Models
 - Image, face, and speech recognition, translation
 - Chatbots, spell checking, text analytics
 - Recommendations, knowledge bases

The Microsoft AI platform

Cloud-powered AI for every developer



HOMEWORK 4: REQUIREMENTS AND ARCHITECTURE

Smart dashcam to detect missing children

(Goals, risks, deployment alternatives, telemetry)

QUALITY ASSESSMENT IN PRODUCTION

Christian Kaestner

Required Reading: Alec Warner and Štěpán Davidovič. "[Canary Releases.](#)" in [The Site Reliability Workbook](#), O'Reilly 2018

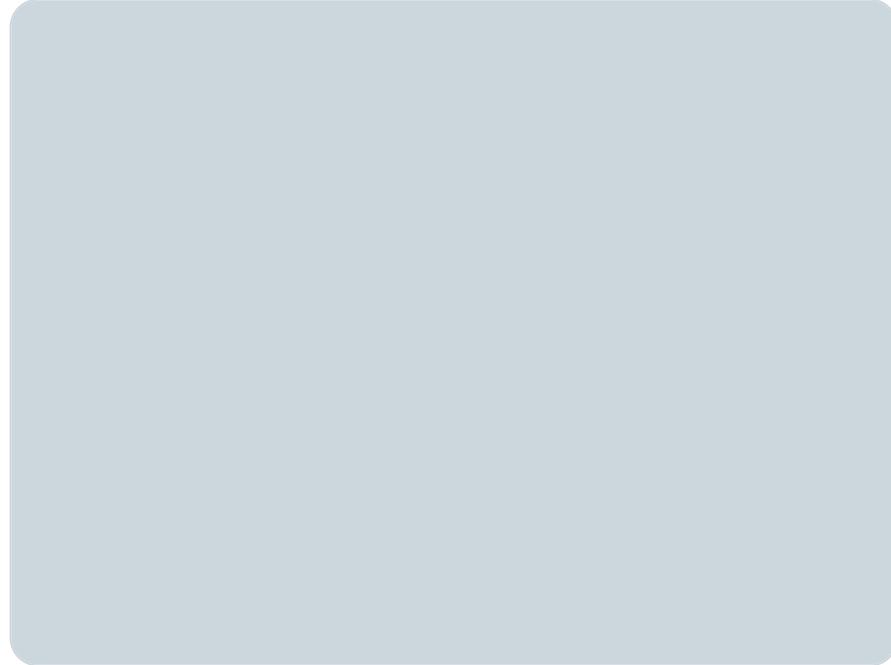
Suggested Reading: Georgi Georgiev. "[Statistical Significance in A/B Testing – a Complete Guide.](#)" Blog 2018



Changelog
@changelog



“Don’t worry, our users will notify us if there’s a problem”



2:03 PM · Jun 8, 2019



2.3K 704 people are Tweeting about this

LEARNING GOALS

- Design telemetry for evaluation in practice
- Plan and execute experiments (chaos, A/B, shadow releases, ...) in production
- Conduct and evaluate multiple concurrent A/B tests in a system
- Perform canary releases
- Examine experimental results with statistical rigor
- Support data scientists with monitoring platforms providing insights from production data

IDENTIFY FEEDBACK MECHANISM IN PRODUCTION

- Live observation in the running system
- Potentially on subpopulation (AB testing)
- Need telemetry to evaluate quality -- challenges:
 - Gather feedback without being intrusive (i.e., labeling outcomes), harming user experience
 - Manage amount of data
 - Isolating feedback for specific AI component + version

Skype for Business

How was the call quality?

Good

Audio Issues

- Distorted speech
- Electronic feedback
- Background noise
- Muffled speech
- Echo

Video Issues

- Frozen video
- Pixelated video
- Blurry image
- Poor color
- Dark video

blog post demo

Privacy Statement

Submit Close

Matt Millman
Because I'm happy 😊

Settings

Help and feedback

Report a problem

RECENT CHATS

Besties 10/10/2018

EN Elena Nilsson, Anna Davie... 7/27/2018
It was great talking to all of ...

Anna Davies 6/26/2018
coffee awaits!

Maarten Smenk 5/25/2018
Missed call

MS Maarten Smenk, Anna Davie... 5/21/2018
Hi, happy Monday!

A screenshot of a flight search interface. At the top, there's a green line graph icon followed by the text "DFW ↔ SFO" and "Nov 16". Below this, it says "1659 of 1687 flights" and "Wednesday". A red oval highlights a yellow callout box containing the following text:

Prices may fall within 7 days – Watch

Our model strongly indicates that fares will fall during the next 7 days. This forecast is based on analysis of historical price changes and is not a guarantee of future results.

The interface includes a "Create a price alert" button, a "Stops" section with checkboxes for "nonstop", "1 stop", and "2+ stops" (all checked), and a "Times" section with a "Create a price alert" button. At the bottom, there are dropdown menus for "Take-off Dallas" and "Arrival San Francisco".

A transcription interface with a timeline at the top showing 00:00, Offset, 00:00, and 01:31:27. Below the timeline are four buttons: Play, Back 5s, 1x Speed, and Volume.

NOTES

Write your notes here

Speaker 5 ► 07:44

Yeah. So there's a slight story behind that. So back when I was in, uh, Undergrad, I wrote a program for myself to measure a, the amount of time I did data entry from my father's business and I was on windows at the time and there wasn't a function called time dot [inaudible] time, uh, which I needed to parse dates to get back to time, top of representation, uh, I figured out a way to do it and I gave it to what's called the python cookbook because it just seemed like something other people could use. So it was just trying to be helpful. Uh, subsequently I had to figure out how to make it work because I didn't really have to. Basically, it bothered me that you had to input all the locale information and I figured out how to do it over the subsequent months. And actually as a graduation gift from my Undergrad, the week following, I solved it and wrote it all out.

Speaker 5 ► 08:38

And I asked, uh, Alex Martelli, the editor of the Python Cookbook, which had published my original recipe, a, how do I get this into python? I think it might help

How did we do on your transcript?



Website Overview

Star Refresh Save Settings

Zoom Out

Last 3 hours



Logins

190

Sign ups

269

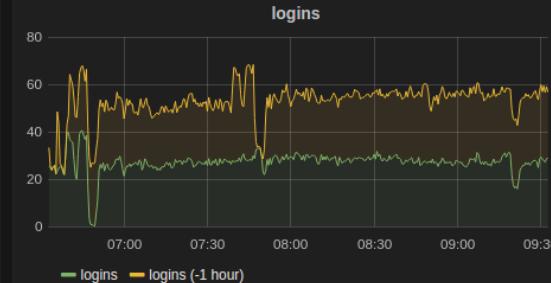
Sign outs

273

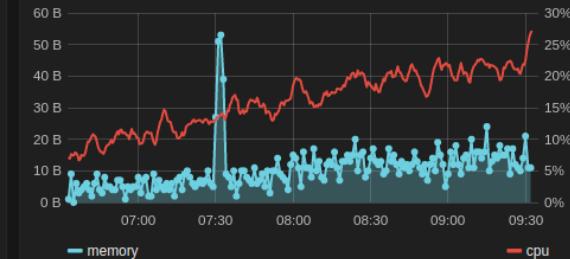
Memory / CPU



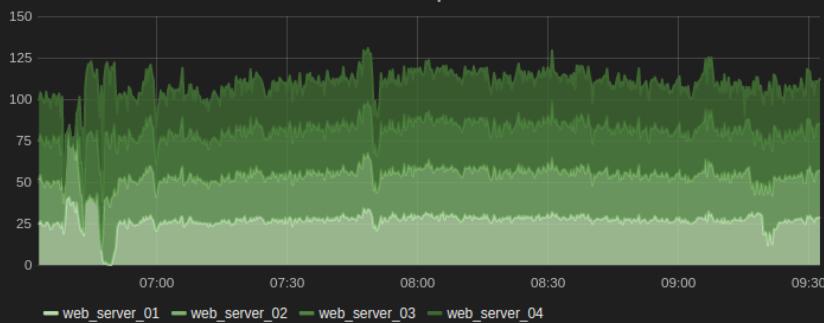
logins



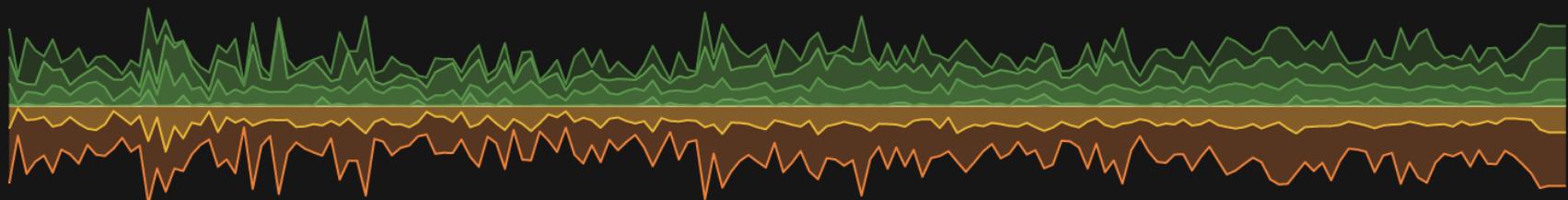
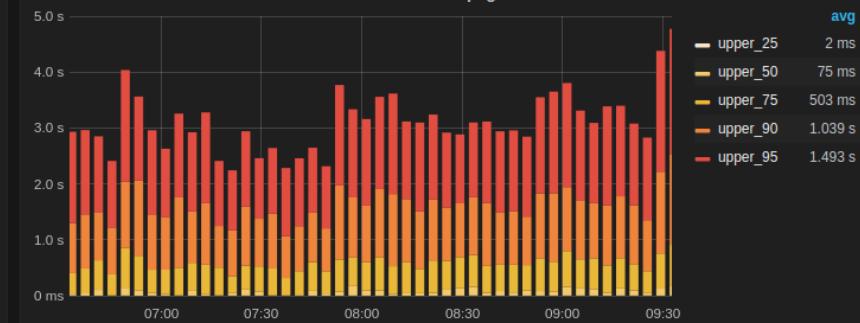
Memory / CPU



server requests



client side full page load



ENGINEERING CHALLENGES FOR TELEMETRY

TRENDING

Buying Guides

Note 10

Best Laptops

iOS 13

Best Phones

Amazon Alexa stores voice recordings for as long as it likes (and shares them too)

By Olivia Tambini 21 days ago Digital Home

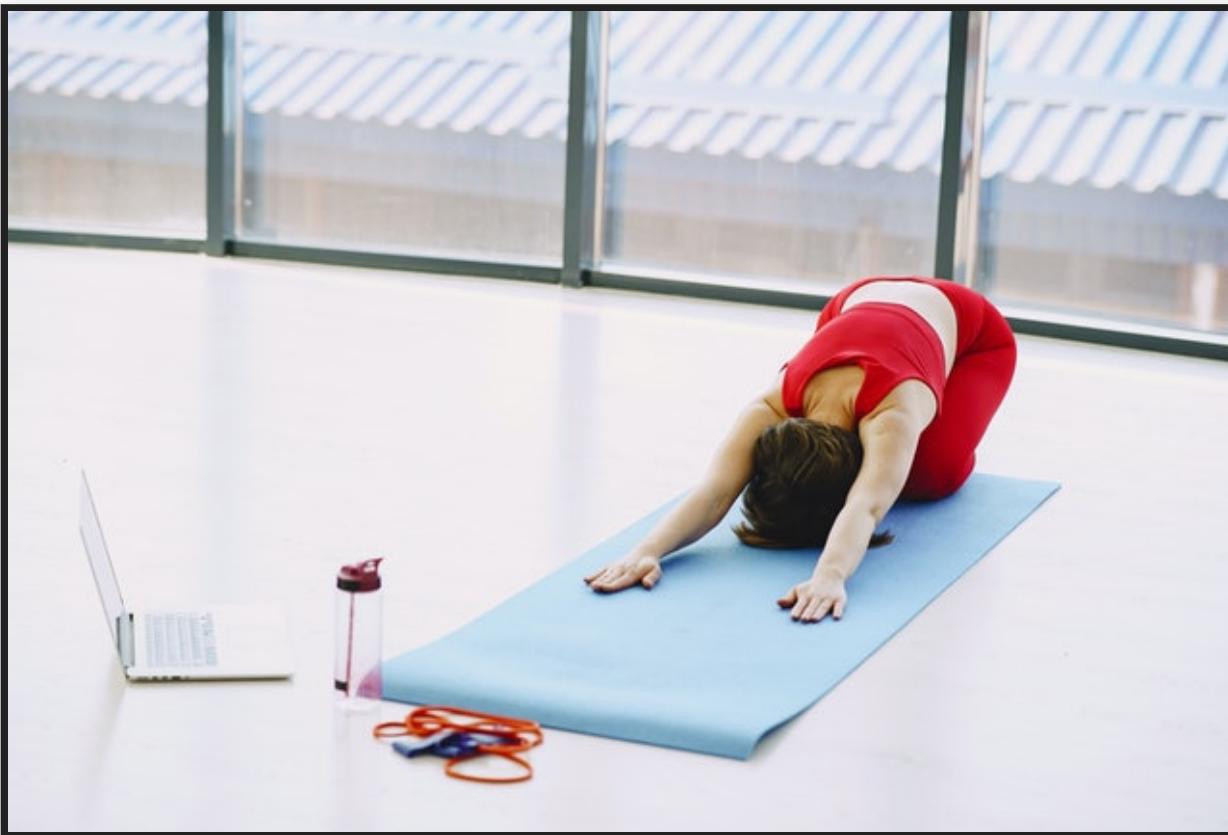
A letter from Amazon reveals all



EXERCISE: DESIGN TELEMETRY IN PRODUCTION

Scenario: Injury detection in smart home workout (laptop camera)

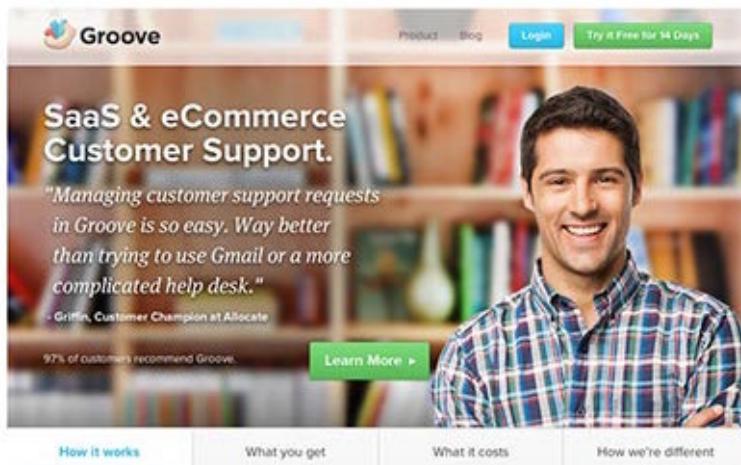
Discuss: Quality measure, telemetry, operationalization, false positives/negatives, cost, privacy, rare events



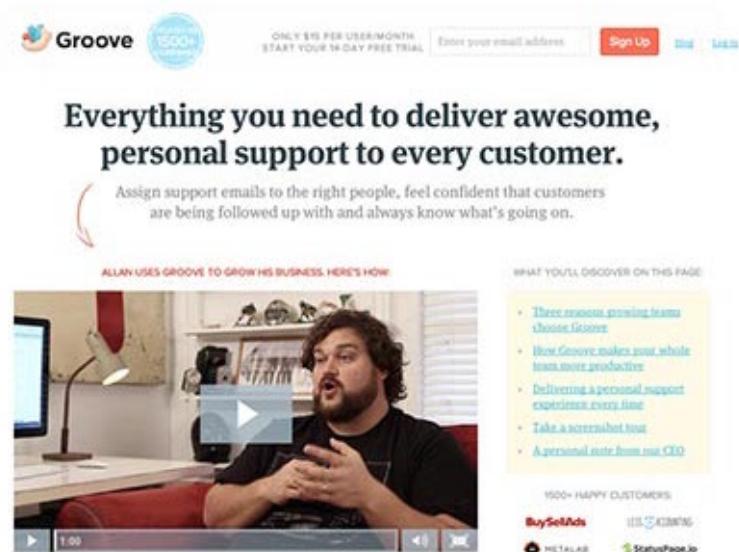
A/B TESTING FOR USABILITY

- In running system, random sample of X users are shown modified version
- Outcomes (e.g., sales, time on site) compared among groups

Original: 2.3%



Long Form: 4.3%



FEATURE FLAGS

```
if (features.enabled(userId, "one_click_checkout")) {  
    // new one click checkout function  
} else {  
    // old checkout functionality  
}
```

- Boolean options
- Good practices: tracked explicitly, documented, keep them localized and independent
- External mapping of flags to customers
 - who should see what configuration
 - e.g., 1% of users sees `one_click_checkout`, but always the same users; or 50% of beta-users and 90% of developers and 0.1% of all users

Treatments ⓘ | 2 treatments, if Split is killed serve the default treatment of "off"

Treatment	Default	Description
on		The new version of registration process is enabled.
off		The old version of registration process is enabled.

[+ Add treatment](#) | [Learn more about multivariate treatments](#).

Whitelist ⓘ | 0 user(s) or segments individually targeted.

[+ Add whitelist](#)

Traffic Allocation ⓘ | 100% of user included in Split rules evaluation below.

Total Traffic Allocation: 100 % total User in Split

Targeting Rules ⓘ | 2 rules created for targeting.

```

graph TD
    if1((if)) --> user1["user is in segment qa"]
    user1 --> then1["Then serve on"]
    elseIf2((else if)) --> user2["user is in segment beta_testers"]
    user2 --> then2["Then serve percentage"]
    then2 --> on2["on 50"]
    then2 --> off2["off 50"]

    subgraph Default_Rule [Default Rule]
        serveDefault["serve off"]
    end

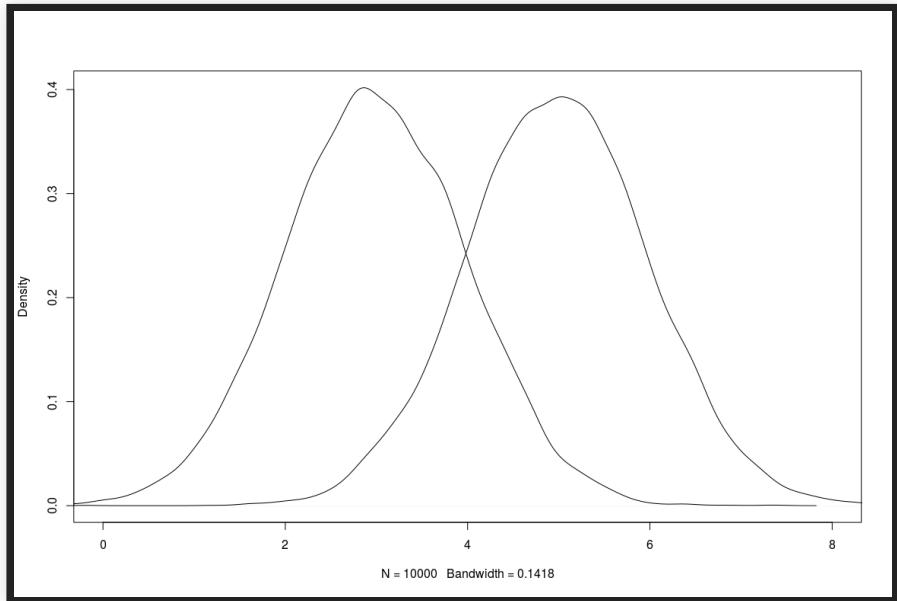
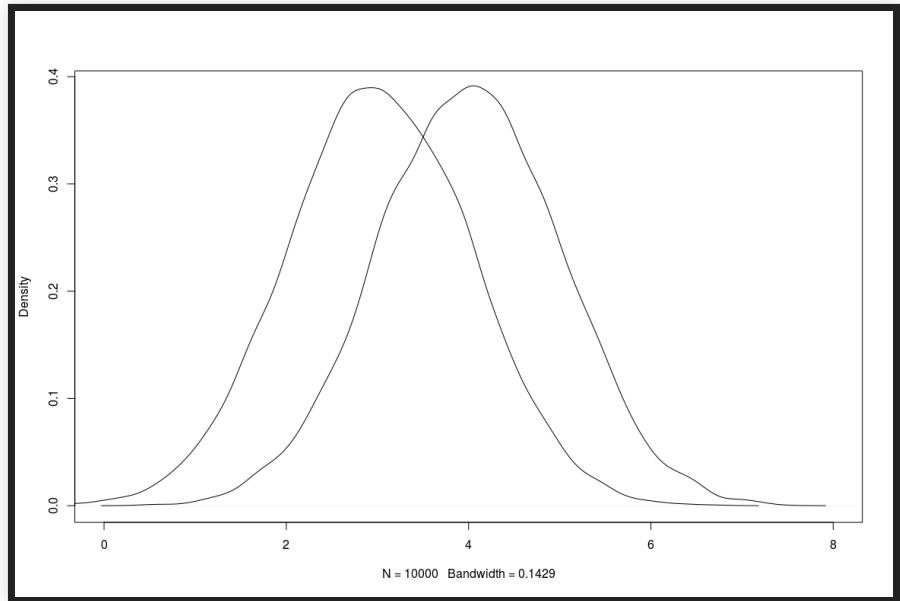
```

[+ Add rule](#)

Default Rule ⓘ | Serve treatment of "off".

serve off

DIFFERENT EFFECT SIZE, SAME DEVIATIONS



SHADOW RELEASES / TRAFFIC TEEING

- Run both models in parallel
- Report outcome of old model
- Compare differences between model predictions
- If possible, compare against ground truth labels/telemetry

Examples?

CANARY RELEASES

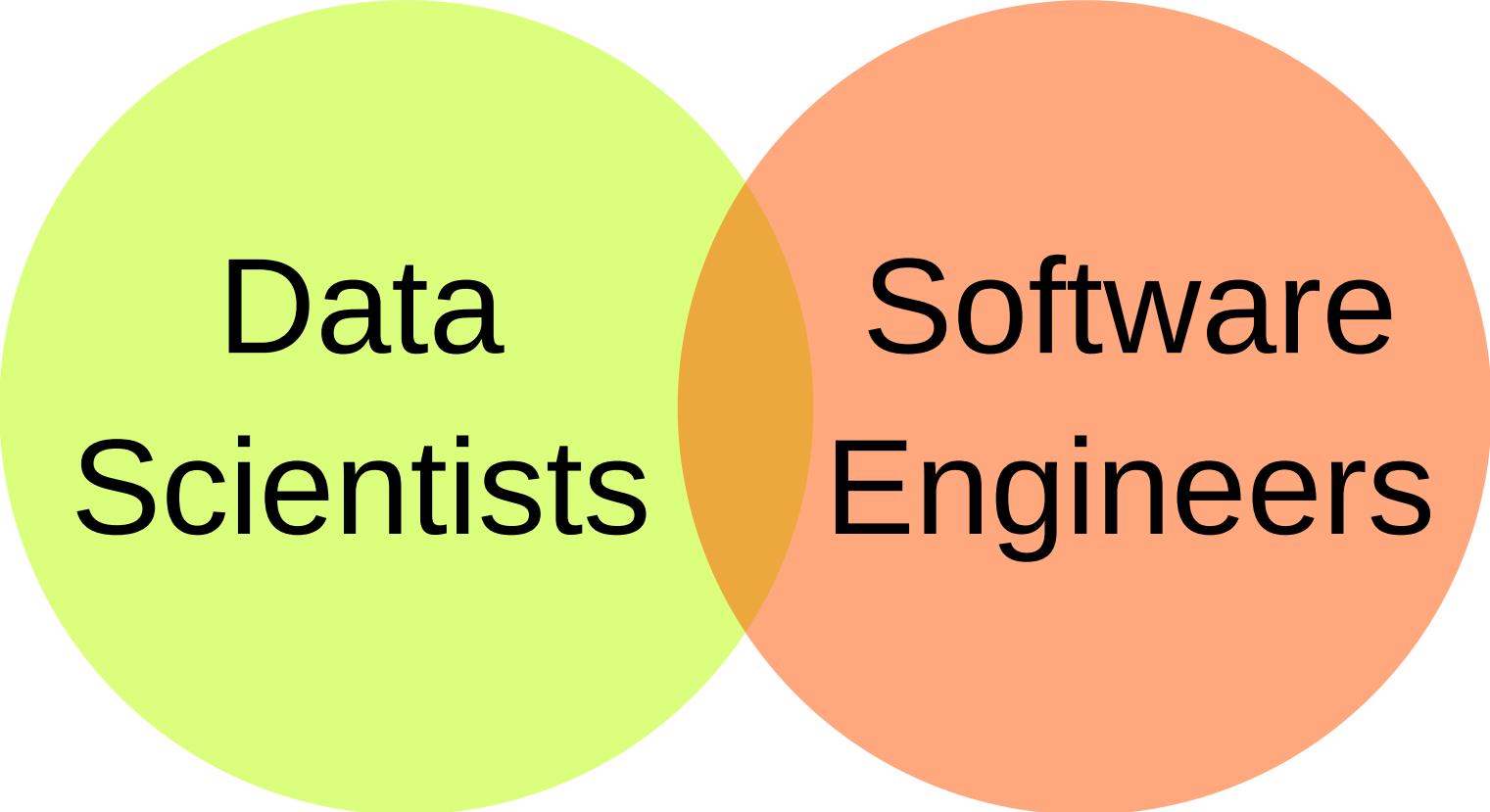
- Release new version to small percentage of population (like A/B testing)
- Automatically roll back if quality measures degrade
- Automatically and incrementally increase deployment to 100% otherwise



CHAOS EXPERIMENTS



INTERACTING WITH AND SUPPORTING DATA SCIENTISTS

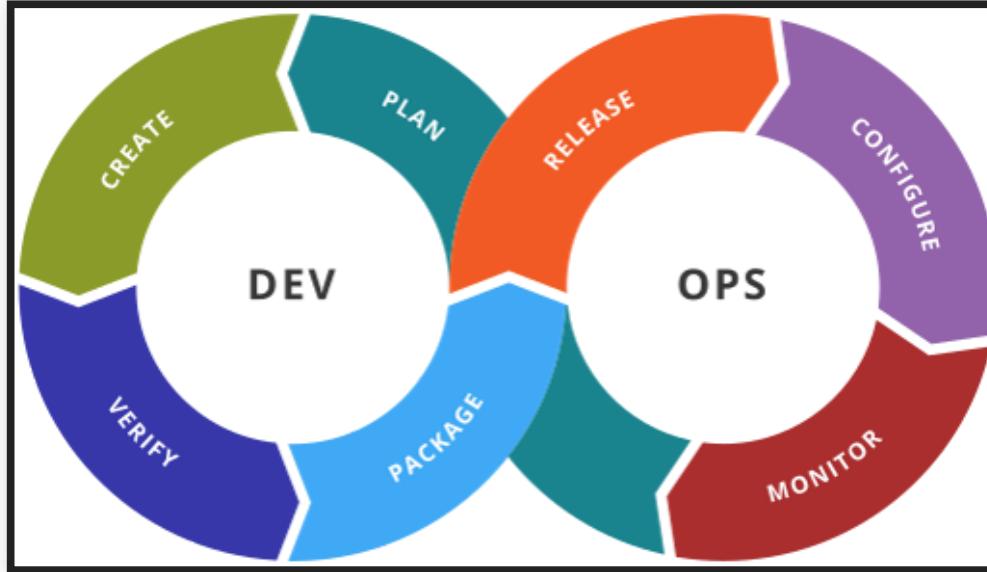


A Venn diagram consisting of two overlapping circles. The left circle is light green and contains the text "Data Scientists". The right circle is light orange and contains the text "Software Engineers". The two circles overlap in the center.

**Data
Scientists**

**Software
Engineers**

LET'S LEARN FROM DEVOPS



Distinct roles and expertise, but joint responsibilities, joint tooling

PROJECT M1:

RECOMMENDATION

DEPLOYMENT

(recommendation service, web API, team reflection)

DATA QUALITY AND DATA PROGRAMMING

"Data cleaning and repairing account for about 60% of the work of data scientists."

Christian Kaestner

Required reading:

- Schelter, S., Lange, D., Schmidt, P., Celikel, M., Biessmann, F. and Grafberger, A., 2018. [Automating large-scale data quality verification](#). Proceedings of the VLDB Endowment, 11(12), pp.1781-1794.
- Nick Hynes, D. Sculley, Michael Terry. "[The Data Linter: Lightweight Automated Sanity Checking for ML Data Sets](#)." NIPS Workshop on ML Systems (2017)

LEARNING GOALS

- Design and implement automated quality assurance steps that check data schema conformance and distributions
- Devise thresholds for detecting data drift and schema violations
- Describe common data cleaning steps and their purpose and risks
- Evaluate the robustness of AI components with regard to noisy or incorrect data
- Understanding the better models vs more data tradeoffs
- Programmatically collect, manage, and enhance training data

CASE STUDY: INVENTORY MANAGEMENT

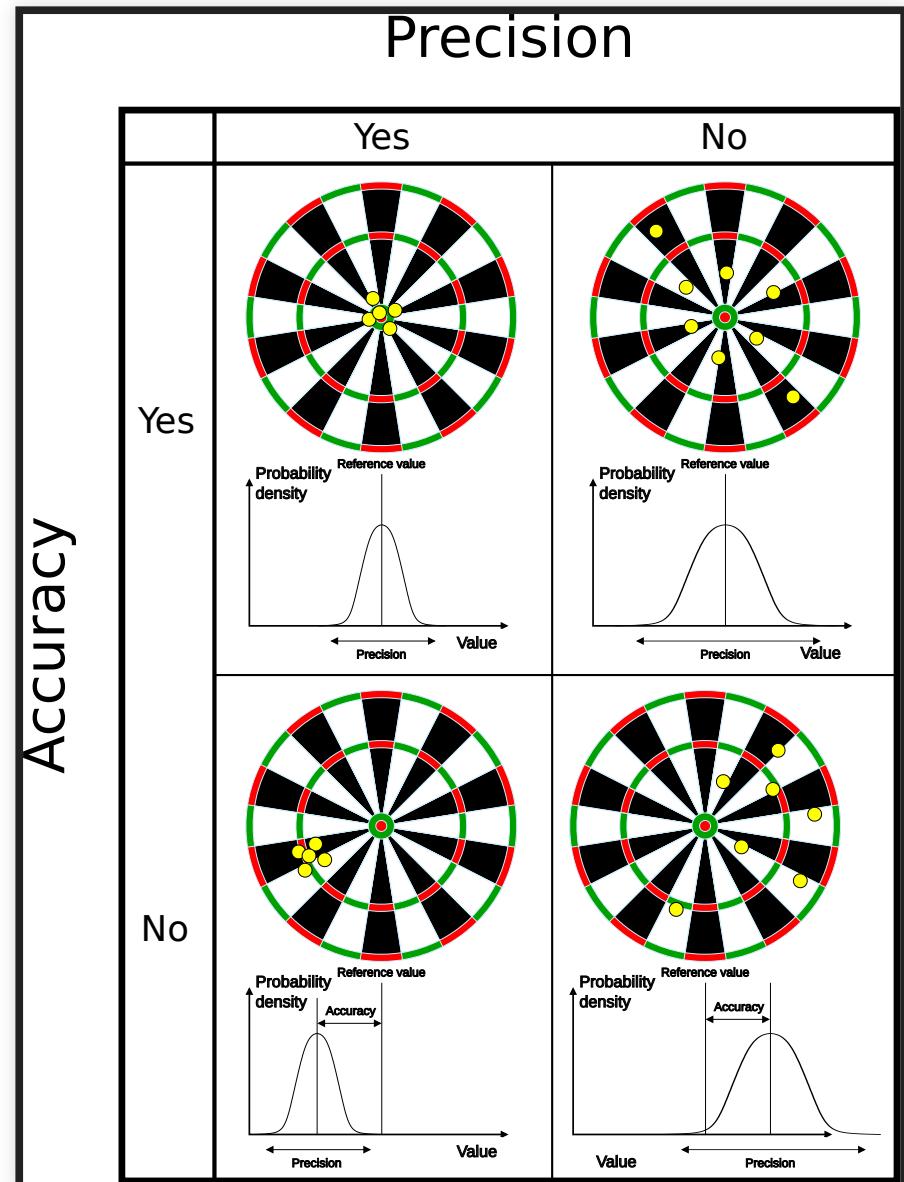


WHAT MAKES GOOD QUALITY DATA?

- Accuracy
 - The data was recorded correctly.
- Completeness
 - All relevant data was recorded.
- Uniqueness
 - The entries are recorded once.
- Consistency
 - The data agrees with itself.
- Timeliness
 - The data is kept up to date.

ACCURACY VS PRECISION

- Accuracy: Reported values (on average) represent real value
- Precision: Repeated measurements yield the same result
- Accurate, but imprecise: Average over multiple measurements
- Inaccurate, but precise: Systematic measurement problem, misleading

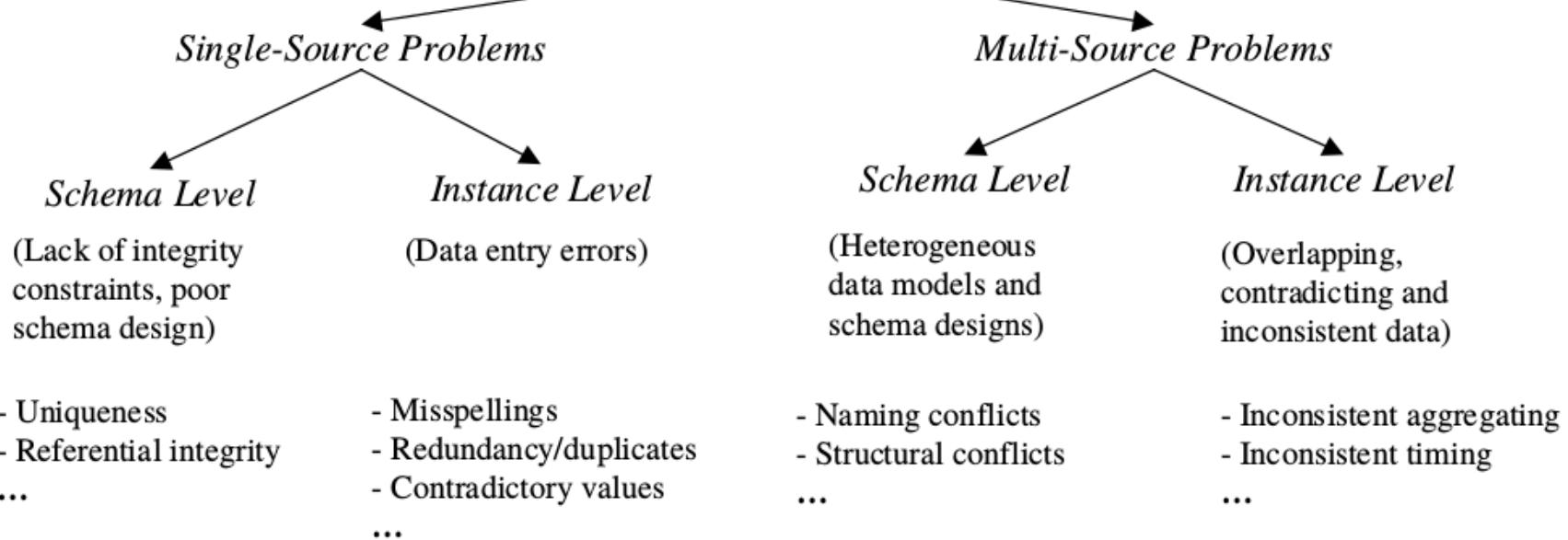


EXPLORATORY DATA ANALYSIS IN DATA SCIENCE

- Before learning, understand the data
- Understand types, ranges, distributions
- Important for understanding data and assessing quality
- Plot data distributions for features
 - Visualizations in a notebook
 - Boxplots, histograms, density plots, scatter plots, ...
- Explore outliers
- Look for correlations and dependencies
 - Association rule mining
 - Principal component analysis

Examples: <https://rpubs.com/ablythe/520912> and
<https://towardsdatascience.com/exploratory-data-analysis-8fc1cb20fd15>

Data Quality Problems



Source: Rahm, Erhard, and Hong Hai Do. [Data cleaning: Problems and current approaches](#). IEEE Data Eng. Bull. 23.4 (2000): 3-13.

DIRTY DATA: EXAMPLE

TABLE: CUSTOMER

ID	Name	Birthday	Age	Sex	Phone	ZIP
3456	Ford, Harrison	18.2.76	43	M	9999999999	15232
3456	Mark Hamil	33.8.81	43	M	6173128718	17121
3457	Kim Kardashian	11.10.56	63	M	4159102371	94016

TABLE: ADDRESS

ZIP	City	State
15232	Pittsburgh	PA
94016	Sam Francisco	CA
73301	Austin	Texas

Problems with the data?

DATA CLEANING OVERVIEW

- Data analysis / Error detection
 - Error types: e.g. schema constraints, referential integrity, duplication
 - Single-source vs multi-source problems
 - Detection in input data vs detection in later stages (more context)
- Error repair
 - Repair data vs repair rules, one at a time or holistic
 - Data transformation or mapping
 - Automated vs human guided

SCHEMA IN RELATIONAL DATABASES

```
CREATE TABLE employees (
    emp_no      INT            NOT NULL,
    birth_date   DATE           NOT NULL,
    name        VARCHAR(30)     NOT NULL,
    PRIMARY KEY (emp_no));
CREATE TABLE departments (
    dept_no     CHAR(4)         NOT NULL,
    dept_name   VARCHAR(40)     NOT NULL,
    PRIMARY KEY (dept_no), UNIQUE KEY (dept_name));
CREATE TABLE dept_manager (
    dept_no     CHAR(4)         NOT NULL,
    emp_no      INT            NOT NULL,
    FOREIGN KEY (emp_no) REFERENCES employees (emp_no),
    FOREIGN KEY (dept_no) REFERENCES departments (dept_no),
    PRIMARY KEY (emp_no,dept_no));
```

EXAMPLE: APACHE AVRO

```
{  "type": "record",
  "namespace": "com.example",
  "name": "Customer",
  "fields": [
    {
      "name": "first_name",
      "type": "string",
      "doc": "First Name of Customer"
    },
    {
      "name": "age",
      "type": "int",
      "doc": "Age at the time of registration"
    }
  ]
}
```

DETECTING INCONSISTENCIES

	DBAName	AKAName	Address	City	State	Zip
t1	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	Chicago	IL	60608
t2	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	Chicago	IL	60609
t3	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	Chicago	IL	60609
t4	Johnnyo's	Johnnyo's	3465 S Morgan ST	Cicago	IL	60608

Conflicts

Does not obey data distribution

Conflict

Image source: Theo Rekatsinas, Ihab Ilyas, and Chris Ré, “[HoloClean - Weakly Supervised Data Repairing](#).” Blog, 2017.

ASSOCIATION RULE MINING

- Sale 1: Bread, Milk
- Sale 2: Bread, Diaper, Beer, Eggs
- Sale 3: Milk, Diaper, Beer, Coke
- Sale 4: Bread, Milk, Diaper, Beer
- Sale 5: Bread, Milk, Diaper, Coke

Rules

- $\{\text{Diaper, Beer}\} \rightarrow \text{Milk}$ (40% support, 66% confidence)
- $\text{Milk} \rightarrow \{\text{Diaper, Beer}\}$ (40% support, 50% confidence)
- $\{\text{Diaper, Beer}\} \rightarrow \text{Bread}$ (40% support, 66% confidence)

(also useful tool for exploratory data analysis)

Further readings: Standard algorithms and many variations, see [Wikipedia](#)

DATA LINTER AT GOOGLE

- Miscoding
 - Number, date, time as string
 - Enum as real
 - Tokenizable string (long strings, all unique)
 - Zip code as number
- Outliers and scaling
 - Unnormalized feature (varies widely)
 - Tailed distributions
 - Uncommon sign
- Packaging
 - Duplicate rows
 - Empty/missing data

Further readings: Hynes, Nick, D. Sculley, and Michael Terry. [The data linter: Lightweight, automated sanity checking for ML data sets](#). NIPS MLSys Workshop. 2017.

DRIFT & MODEL DECAY

in all cases, models are less effective over time

- Concept drift
 - properties to predict change over time (e.g., what is credit card fraud)
 - over time: different expected outputs for same inputs
 - model has not learned the relevant concepts
- Data drift
 - characteristics of input data changes (e.g., customers with face masks)
 - input data differs from training data
 - over time: predictions less confident, further from training data
- Upstream data changes
 - external changes in data pipeline (e.g., format changes in weather service)
 - model interprets input data incorrectly
 - over time: abrupt changes due to faulty inputs

WATCH FOR DEGRADATION IN PREDICTION ACCURACY

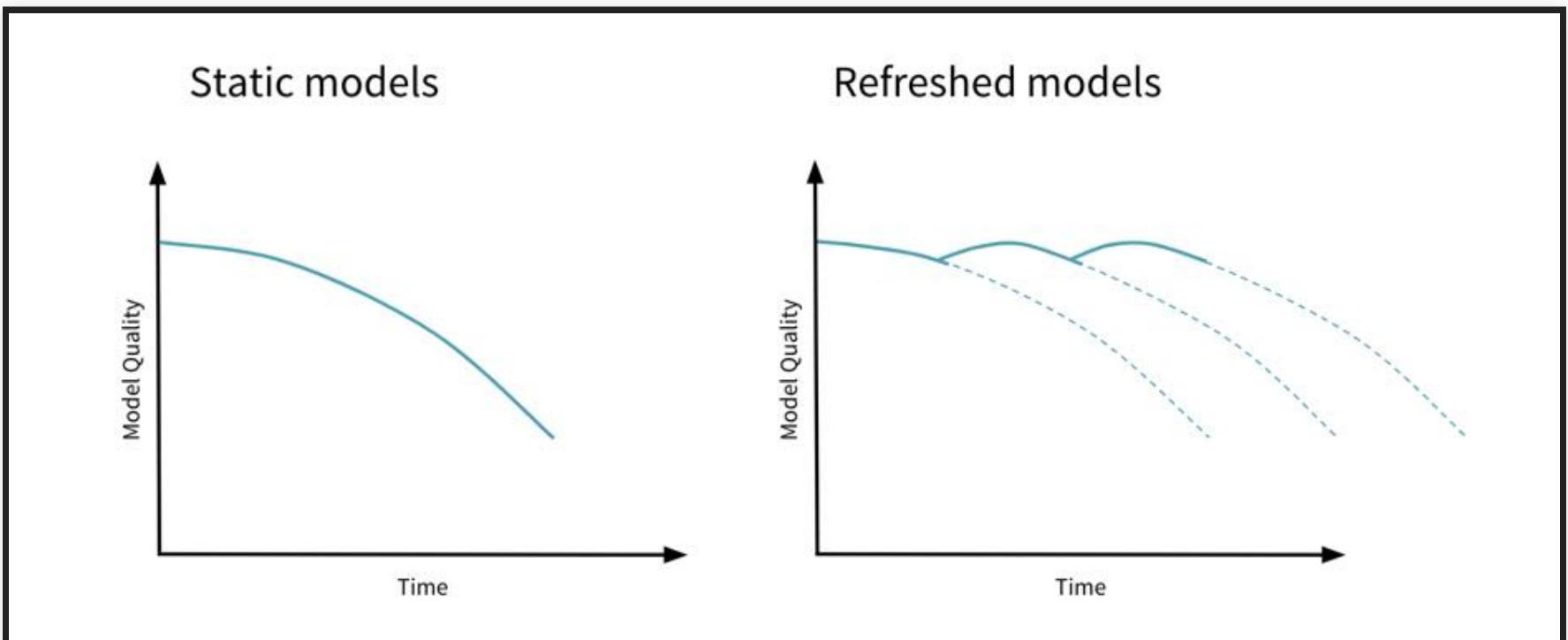
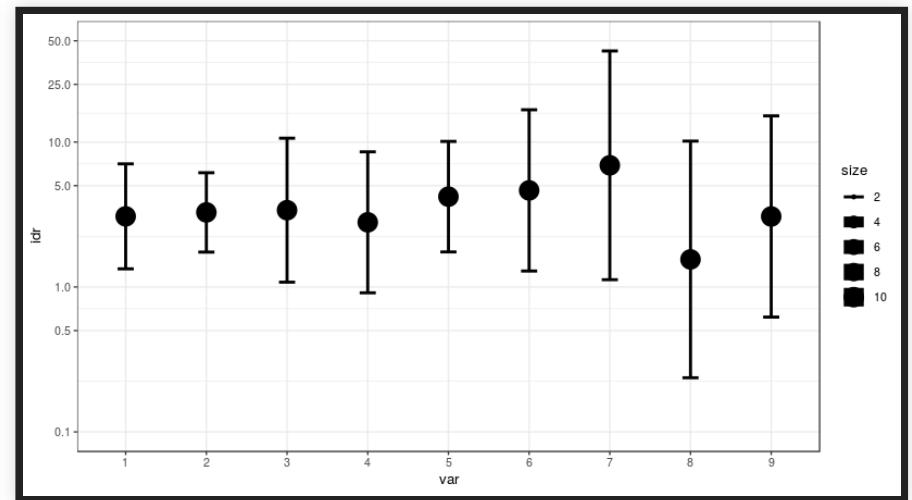
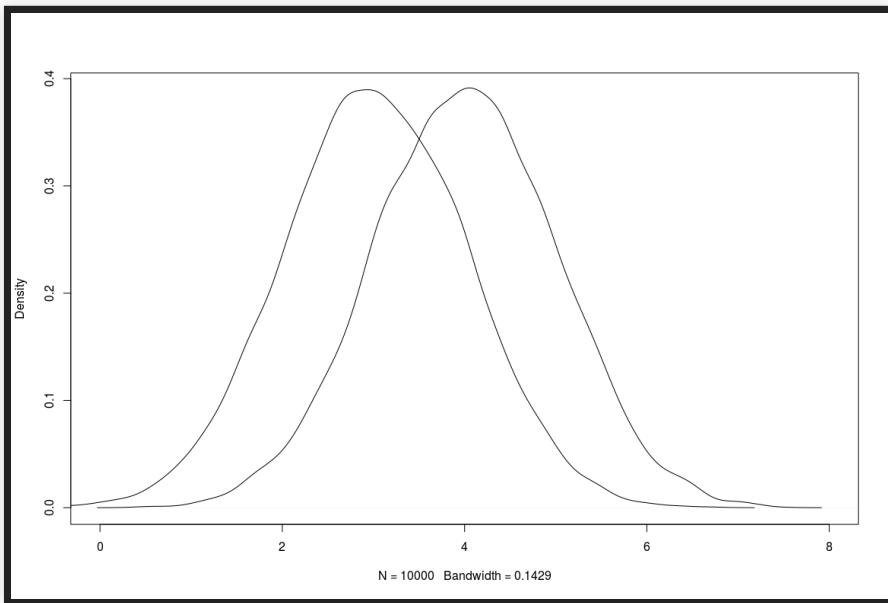


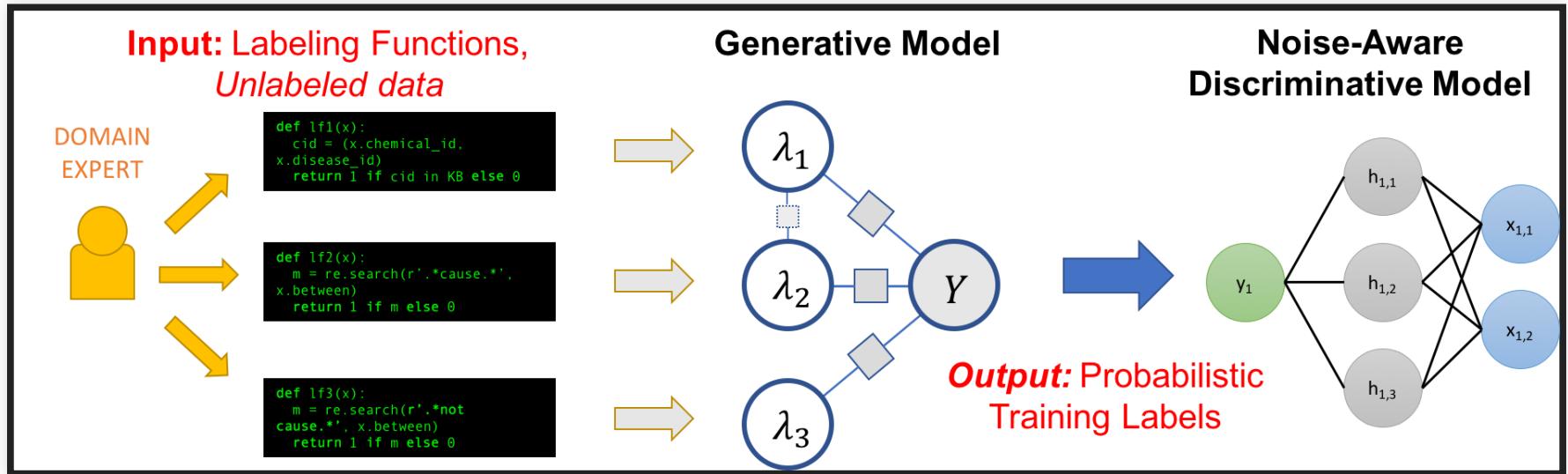
Image source: Joel Thomas and Clemens Mewald. [Productionizing Machine Learning: From Deployment to Drift Detection](#). Databricks Blog, 2019

DETECTING DATA DRIFT

- Compare distributions over time (e.g., t-test)
- Detect both sudden jumps and gradual changes
- Distributions can be manually specified or learned (see invariant detection)



SNORKEL



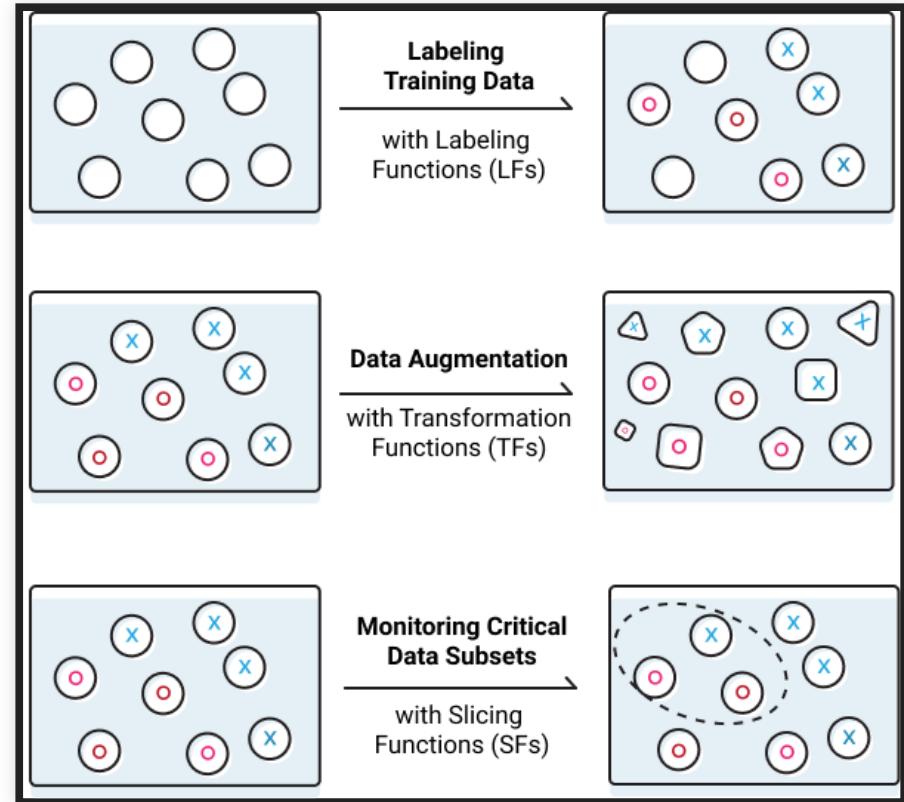
Generative model learns which labeling functions to trust and when (~ from correlations). Learns "expertise" of labeling functions.

Generative model used to provide *probabilistic* training labels. *Discriminative model* learned from labeled training data; generalizes beyond label functions.

<https://www.snorkel.org/>, <https://www.snorkel.org/blog/snorkel-programming>; Ratner, Alexander, et al. "Snorkel: rapid training data creation with weak supervision." The VLDB Journal 29.2 (2020): 709-730.

DATA PROGRAMMING BEYOND LABELING TRAINING DATA

- Potentially useful in many other scenarios
- Data cleaning
- Data augmentation
- Identifying important data subsets



BUSINESS SYSTEMS WITH MACHINE LEARNING

Molham Aref

MANAGING AND PROCESSING LARGE DATASETS

Christian Kaestner

Required reading: Martin Kleppmann. [Designing Data-Intensive Applications](#). O'Reilly. 2017. Chapter 1

LEARNING GOALS

- Organize different data management solutions and their tradeoffs
- Explain the tradeoffs between batch processing and stream processing and the lambda architecture
- Recommend and justify a design and corresponding technologies for a given system

CASE STUDY



Search bar: trees



Today



Fri, Oct 25





"ZOOM ADDING CAPACITY"



KINDS OF DATA

- Training data
- Input data
- Telemetry data
- (Models)

all potentially with huge total volumes and high throughput

need strategies for storage and processing

DOCUMENT DATA MODELS

```
{  
  "id": 1,  
  "name": "Christian",  
  "email": "kaestner@cs.",  
  "dpt": [  
    {"name": "ISR", "address": "..."}  
  ],  
  "other": { ... }  
}
```

```
db.getCollection('users').find({ "name": "Christian" })
```

LOG FILES, UNSTRUCTURED DATA

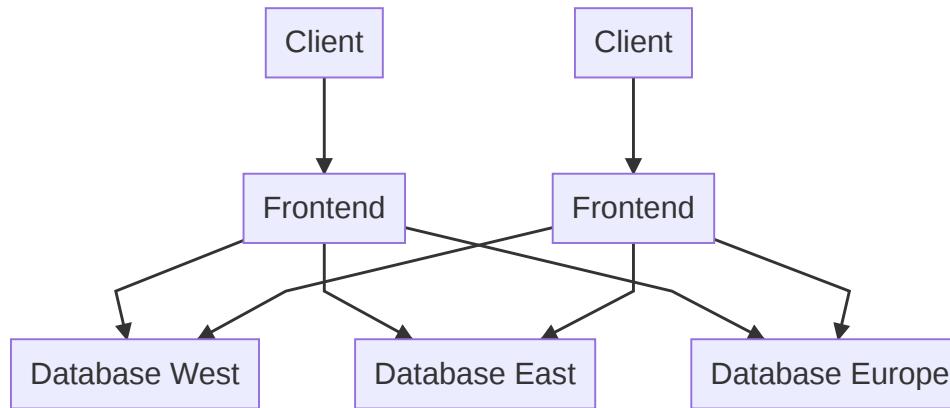
```
2020-06-25T13:44:14, 601844, GET /data/m/goyas+ghosts+2006/17.mpg
2020-06-25T13:44:14, 935791, GET /data/m/the+big+circus+1959/68.mp
2020-06-25T13:44:14, 557605, GET /data/m/elvis+meets+nixon+1997/17
2020-06-25T13:44:14, 140291, GET /data/m/the+house+of+the+spirits+
2020-06-25T13:44:14, 425781, GET /data/m/the+theory+of+everything+
2020-06-25T13:44:14, 773178, GET /data/m/toy+story+2+1999/59.mpg
2020-06-25T13:44:14, 901758, GET /data/m/ignition+2002/14.mpg
2020-06-25T13:44:14, 911008, GET /data/m/toy+story+3+2010/46.mpg
```

PARTITIONING

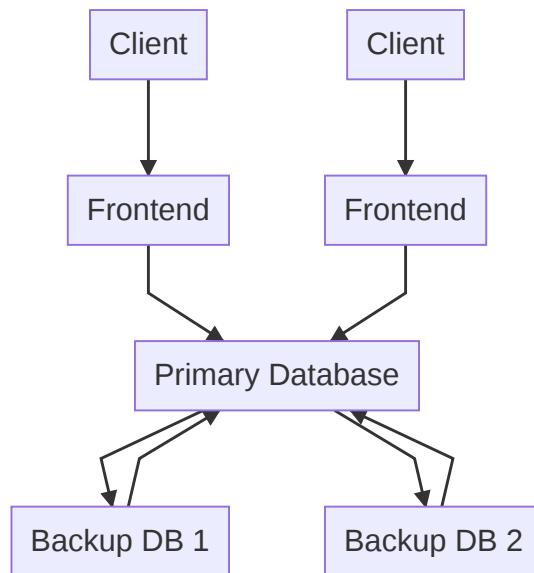
Divide data:

- Horizontal partitioning: Different rows in different tables; e.g., movies by decade, hashing often used
- Vertical partitioning: Different columns in different tables; e.g., movie title vs. all actors

Tradeoffs?



REPLICATION STRATEGIES: LEADERS AND FOLLOWERS



BATCH PROCESSING

- Analyzing TB of data, typically distributed storage
- Filtering, sorting, aggregating
- Producing reports, models, ...

```
cat /var/log/nginx/access.log |  
awk '{print $7}' |  
sort |  
uniq -c |  
sort -r -n |  
head -n 5
```

DISTRIBUTED BATCH PROCESSING

- Process data locally at storage
- Aggregate results as needed
- Separate plumbing from job logic

MapReduce as common framework

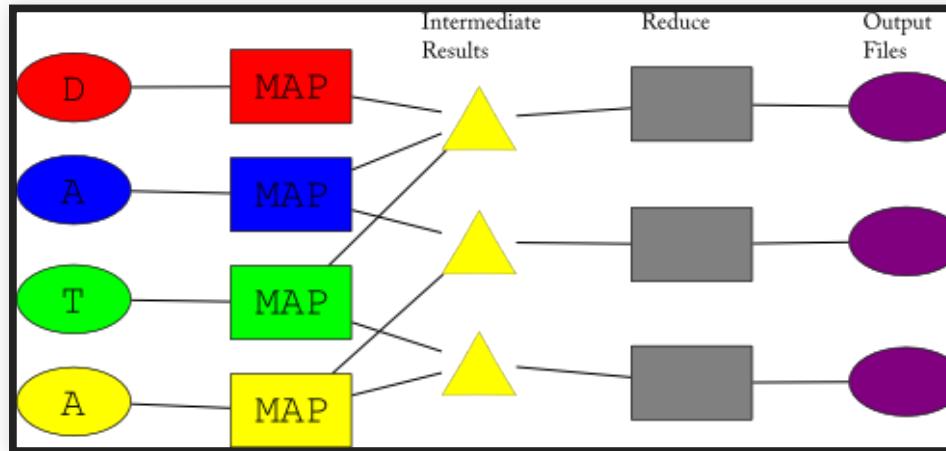


Image Source: Ville Tuulos (CC BY-SA 3.0)

KEY DESIGN PRINCIPLE: DATA LOCALITY

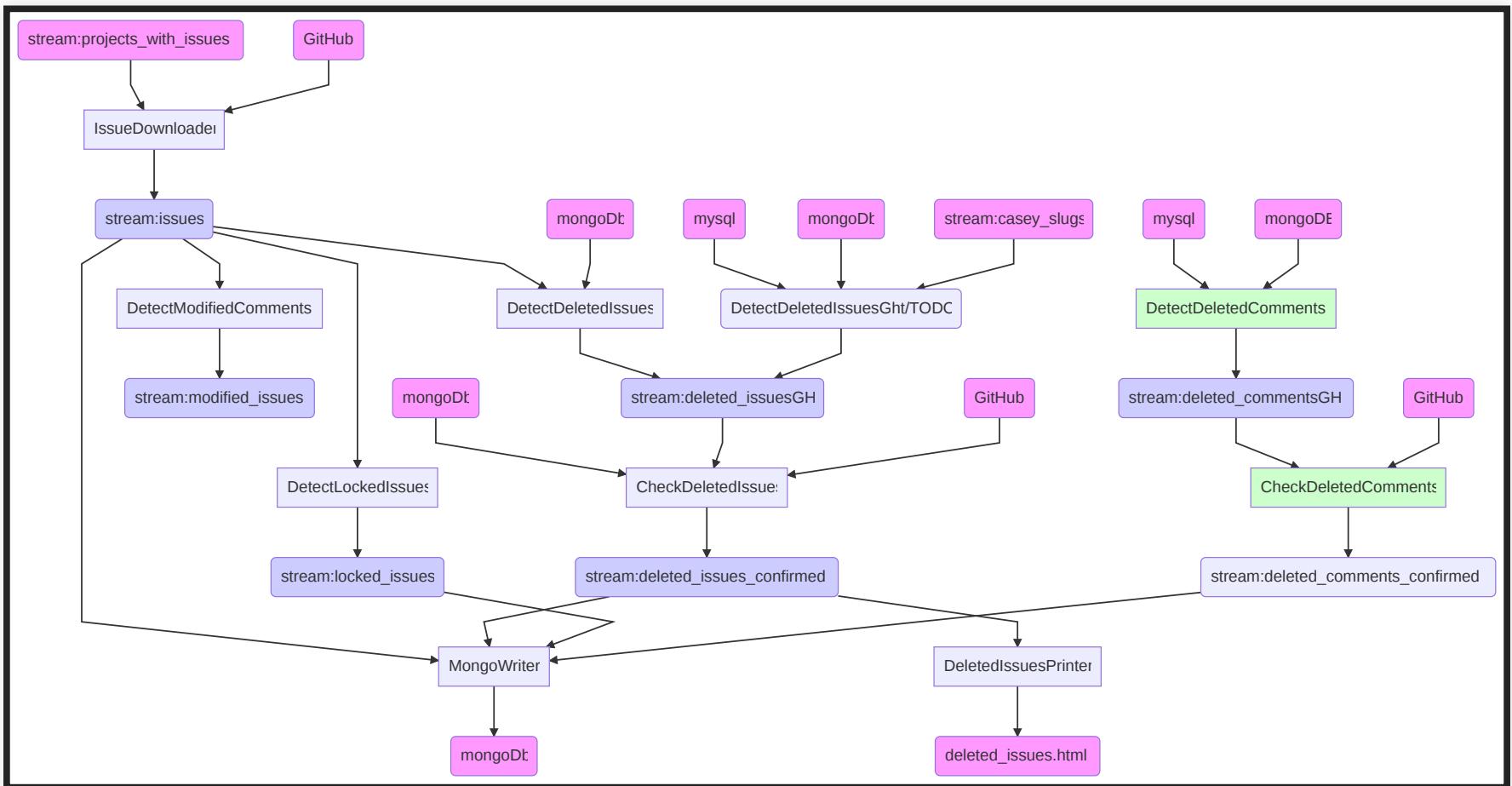
*Moving Computation is Cheaper than Moving Data --
Hadoop Documentation*

- Data often large and distributed, code small
- Avoid transferring large amounts of data
- Perform computation where data is stored (distributed)
- Transfer only results as needed

- "The map reduce way"

STREAM PROCESSING

Like shell programs: Read from stream, produce output in other stream. Loose coupling

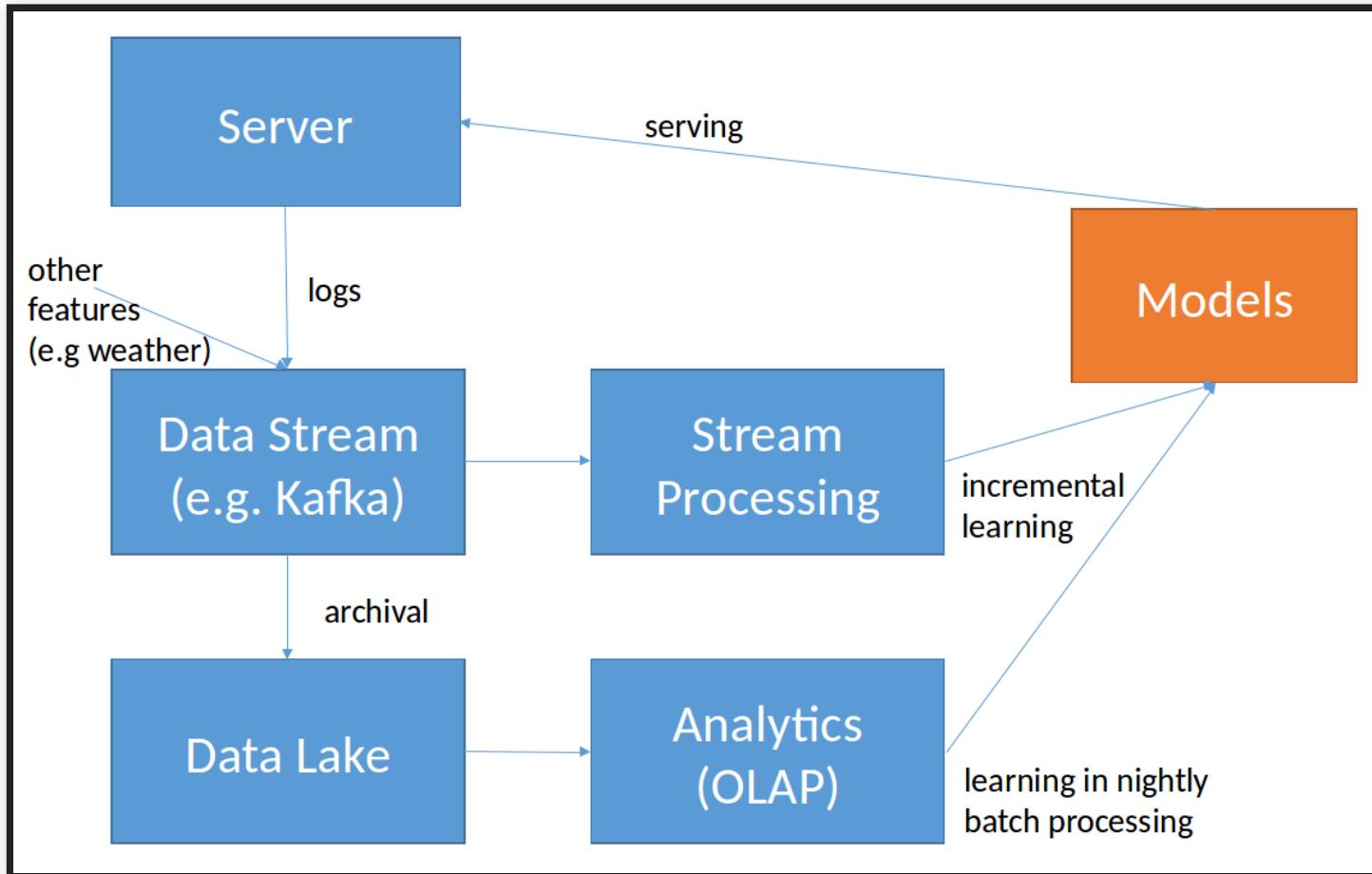


EVENT SOURCING

- Append only databases
- Record edit events, never mutate data
- Compute current state from all past events, can reconstruct old state
- For efficiency, take state snapshots
- Similar to traditional database logs

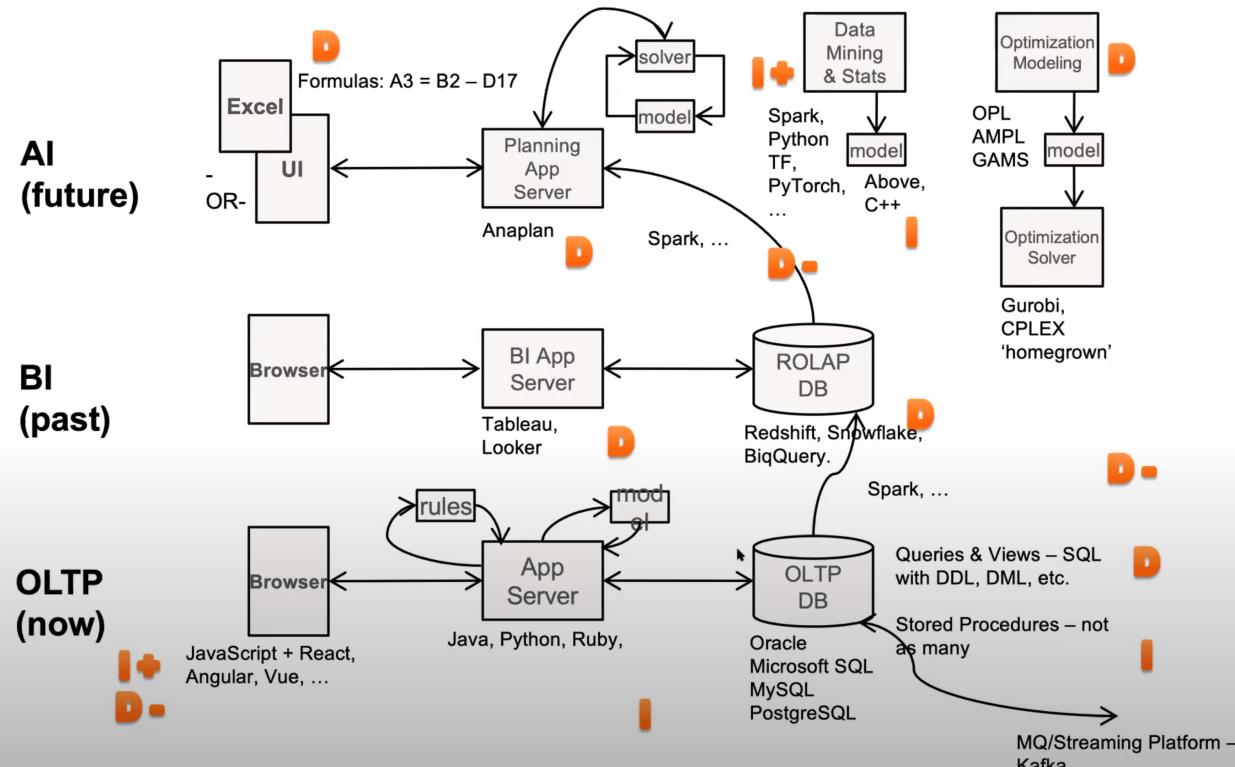
```
createUser(id=5, name="Christian", dpt="SCS")
updateUser(id=5, dpt="ISR")
deleteUser(id=5)
```

LAMBDA ARCHITECTURE AND MACHINE LEARNING



- Learn accurate model in batch job
- Learn incremental model in stream processor

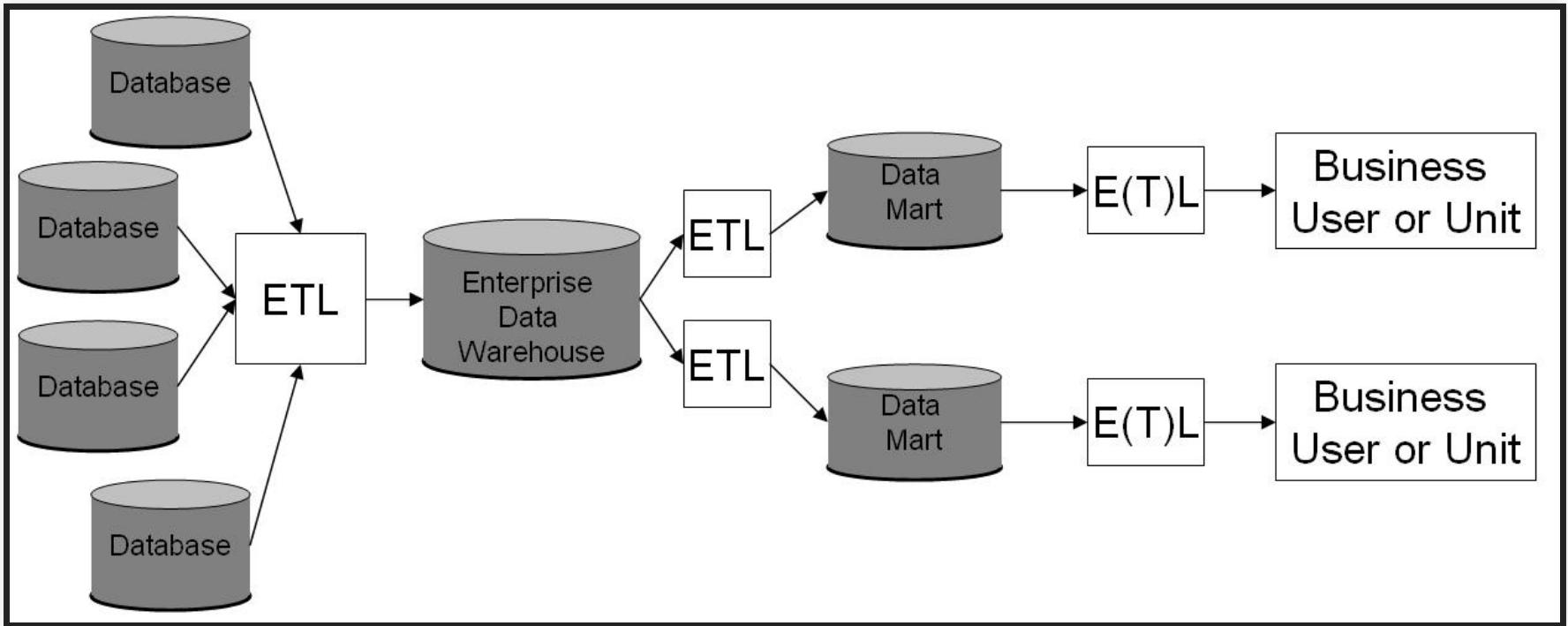
Enterprise Tech Stack – Now isn't much different



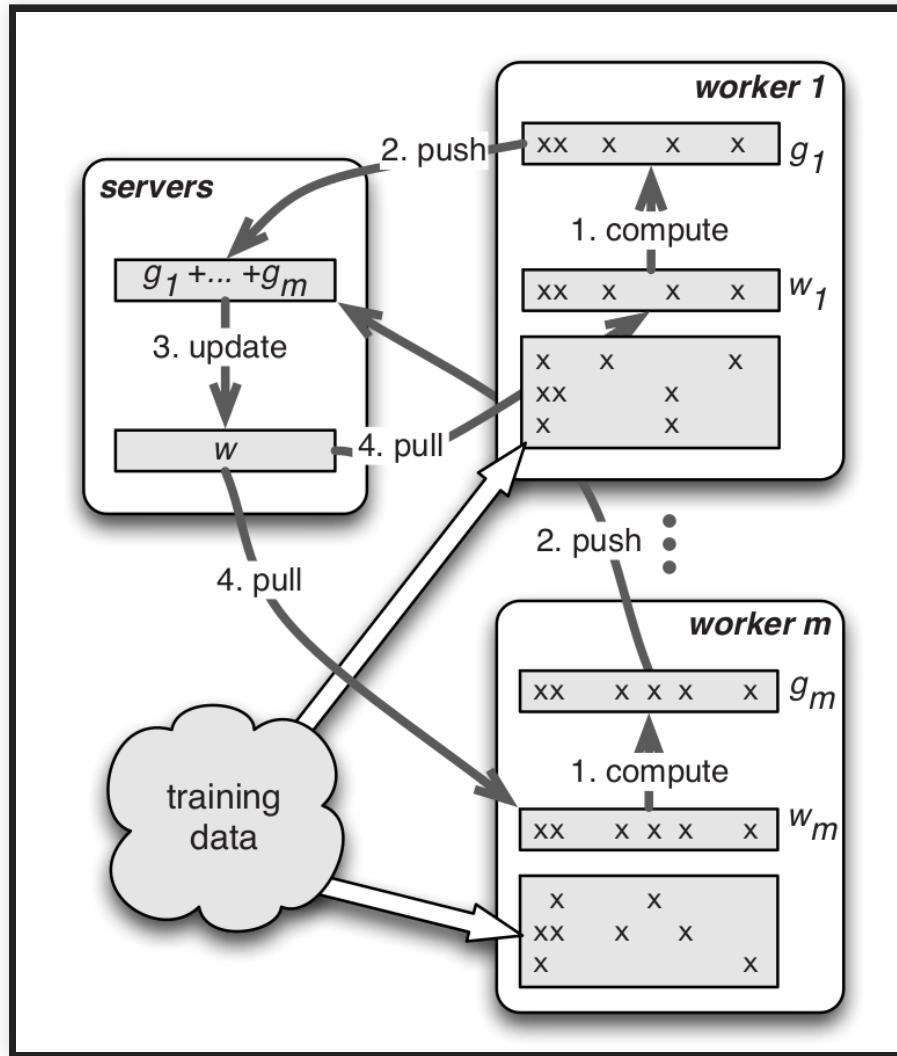
Molham Aref "Business Systems with Machine Learning"

DATA WAREHOUSING (OLAP)

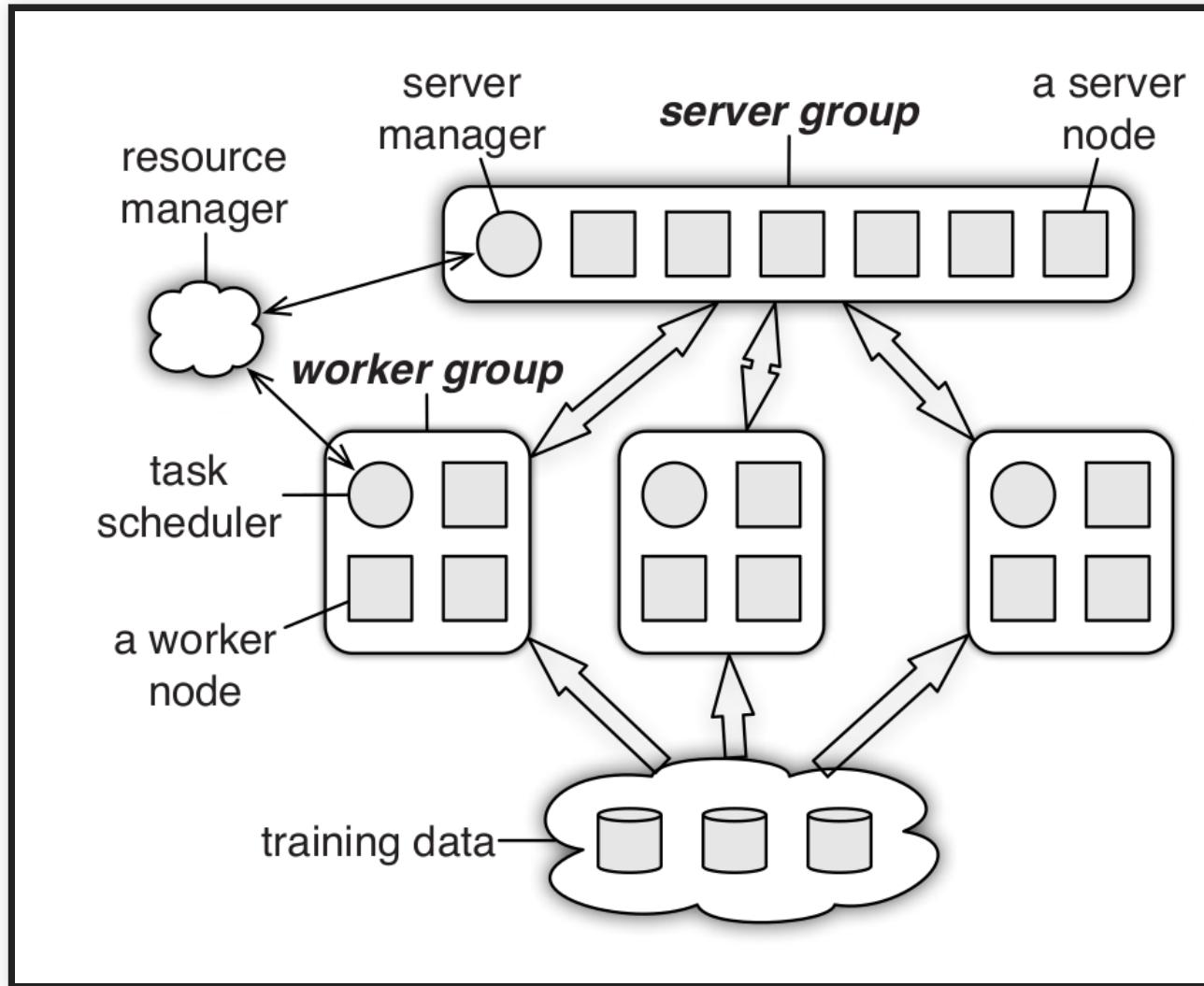
- Large denormalized databases with materialized views for large scale reporting queries
- e.g. sales database, queries for sales trends by region
- Read-only except for batch updates: Data from OLTP systems loaded periodically, e.g. over night



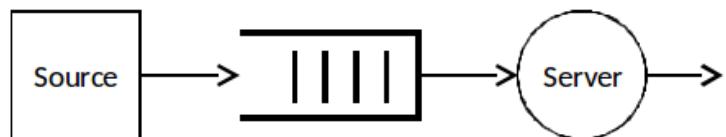
DISTRIBUTED GRADIENT DESCENT



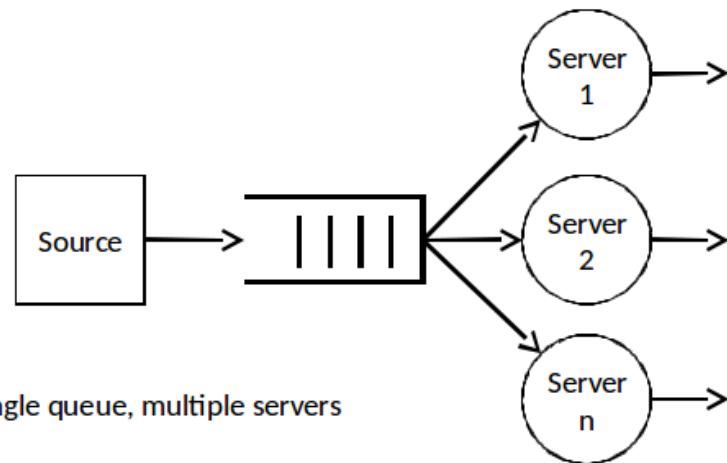
PARAMETER SERVER ARCHITECTURE



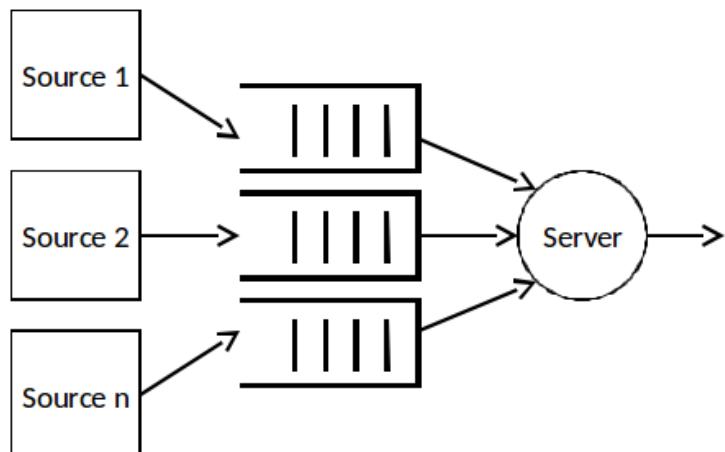
QUEUEING THEORY



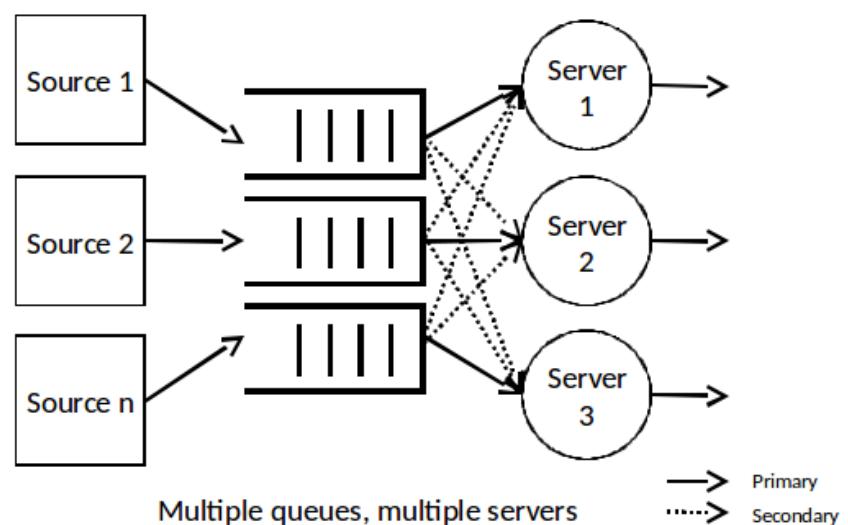
Single queue, single server



Single queue, multiple servers



Multiple queues, single server

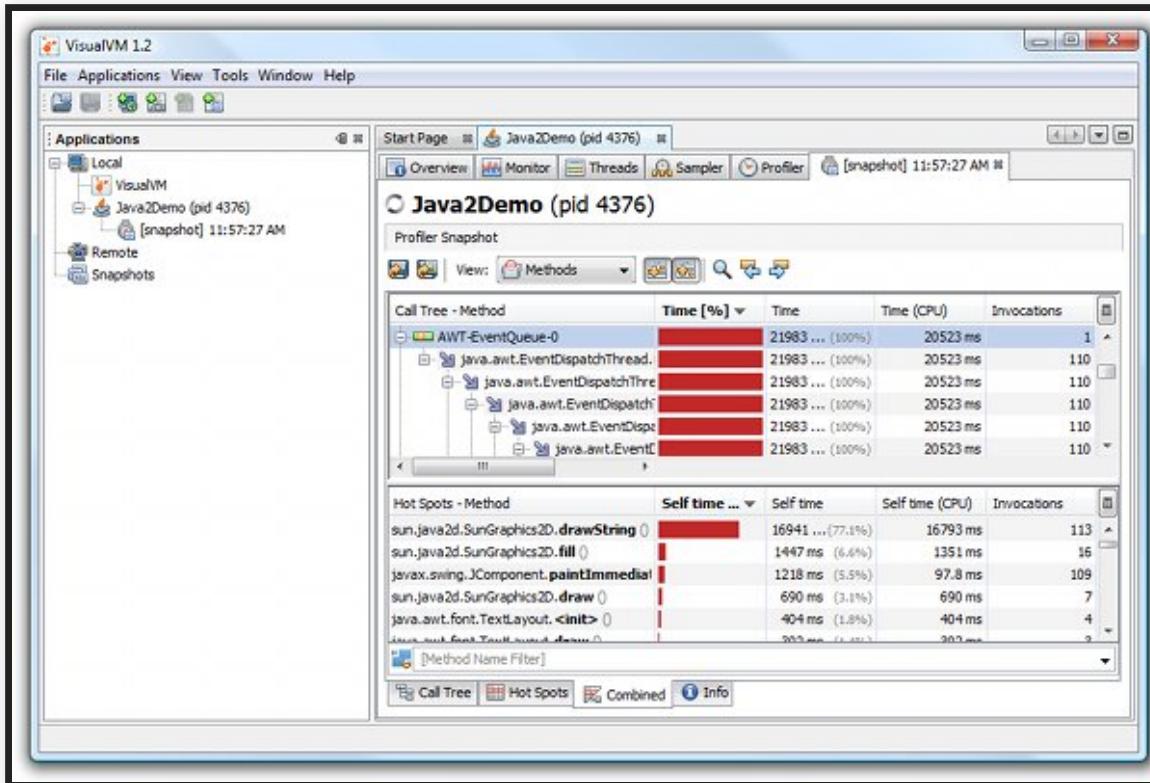


Multiple queues, multiple servers

→ Primary
.....→ Secondary

PROFILING

Mostly used during development phase in single components



PERFORMANCE MONITORING OF DISTRIBUTED SYSTEMS



Source: <https://blog.appdynamics.com/tag/fiserv/>

INFRASTRUCTURE QUALITY, DEPLOYMENT, AND OPERATIONS

Christian Kaestner

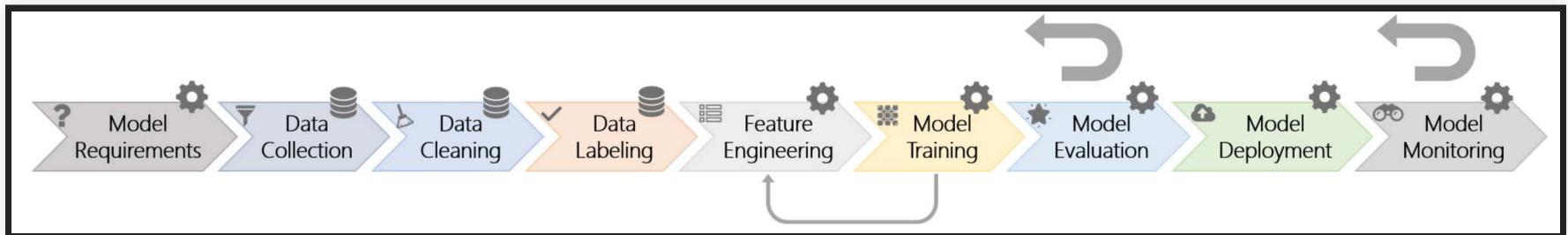
Required reading: Eric Breck, Shanqing Cai, Eric Nielsen, Michael Salib, D. Sculley. [The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction](#). Proceedings of IEEE Big Data (2017)

Recommended readings: Larysa Visengeriyeva. [Machine Learning Operations - A Reading List](#), InnoQ 2020

LEARNING GOALS

- Implement and automate tests for all parts of the ML pipeline
- Understand testing opportunities beyond functional correctness
- Automate test execution with continuous integration
- Deploy a service for models using container infrastructure
- Automate common configuration management tasks
- Devise a monitoring strategy and suggest suitable components for implementing it
- Diagnose common operations problems

POSSIBLE MISTAKES IN ML PIPELINES



Danger of "silent" mistakes in many phases



FROM MANUAL TESTING TO CONTINUOUS INTEGRATION



The screenshot shows a web browser window displaying a Travis CI build log for repository "wyvernlang/wyvern". The build number is #17, and it is marked as "passing". The log details a successful build with 17 passed tests. It includes a commit message from "potanin" and a note about running for 16 seconds. A yellow banner at the bottom indicates the job ran on legacy infrastructure. The log itself shows command-line output for cloning the repository, switching Java versions, and running tests.

```
Build system information
$ git clone --depth=50 --branch=SimpleWyvern-devel
$ jdk_switcher use oraclejdk8
Switching to Oracle JDK8 (java-8-oracle), JAVA_HOME will be set to /usr/lib/jvm/java-8-oracle
$ java -Xmx32m -version
java version "1.8.0_31"
Java(TM) SE Runtime Environment (build 1.8.0_31-b13)
Java HotSpot(TM) 64-Bit Server VM (build 25.31-b07, mixed mode)
$ java -J-Xmx32m -version
javac 1.8.0_31
$ cd tools
The command "cd tools" exited with 0.
$ ant test
Buildfile: /home/travis/build/wyvernlang/wyvern/tools/build.xml
copper-compose-compile:
[mkdir] Created dir: /home/travis/build/wyvernlang/wyvern/tools/copper-composer/bin
[javac] /home/travis/build/wyvernlang/wyvern/tools/build.xml:18: warning: 'includeantruntime' was not set, defaulting to build.sysclasspath=last; set to false for repeatable builds
```

EXAMPLE: MOCKING A DATACLEANER OBJECT

```
DataTable getData(KafkaStream stream, DataCleaner cleaner) { ...  
  
@Test void test() {  
    DataCleaner dummyCleaner = new DataCleaner() {  
        int counter = 0;  
        boolean isValid(String row) {  
            counter++;  
            return counter!=3;  
        }  
        ...  
    }  
    DataTable output = getData(testStream, dummyCleaner);  
    assert(output.length==9)  
}
```

Mocking frameworks provide infrastructure for expressing such tests compactly.

TESTING FOR ROBUSTNESS

manipulating the (controlled) environment: injecting errors into backend to test error handling

```
DataTable getData(Stream stream, DataCleaner cleaner) { ... }

@Test void test() {
    Stream testStream = new Stream() {
        ...
        public String getNext() {
            if (++idx == 3) throw new IOException();
            return data[++idx];
        }
    }
    DataTable output = retry(getData(testStream, ...));
    assert(output.length==10)
}
```

Packages

All

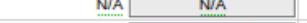
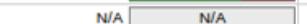
[net.sourceforge.cobertura.ant](#)
[net.sourceforge.cobertura.check](#)
[net.sourceforge.cobertura.coveragedata](#)
[net.sourceforge.cobertura.instrument](#)
[net.sourceforge.cobertura.merge](#)
[net.sourceforge.cobertura.reporting](#)
[net.sourceforge.cobertura.reporting.html](#)
[net.sourceforge.cobertura.reporting.html](#)
[net.sourceforge.cobertura.reporting.html](#)
[net.sourceforge.cobertura.reporting.xml](#)
[net.sourceforge.cobertura.util](#)

All Packages

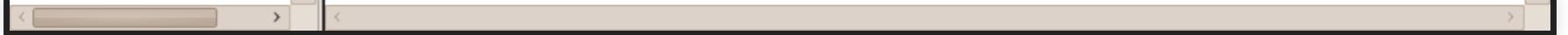
Classes

[AntUtil](#) (88%)
[Archive](#) (100%)
[ArchiveUtil](#) (80%)
[BranchCoverageData](#) (N/A)
[CheckTask](#) (0%)
[ClassData](#) (N/A)
[ClassInstrumenter](#) (94%)
[ClassPattern](#) (100%)
[CoberturaFile](#) (73%)
[CommandLineBuilder](#) (96%)
[CommonMatchingTask](#) (88%)
[ComplexityCalculator](#) (100%)
[ConfigurationUtil](#) (50%)
[CopyFiles](#) (87%)
[CoverageData](#) (N/A)
[CoverageDataContainer](#) (N/A)
[CoverageDataFileHandler](#) (N/A)
[CoverageRate](#) (0%)
[ExcludeClasses](#) (100%)
[FileFinder](#) (96%)
[FileLocker](#) (0%)
[FirstPassMethodInstrumenter](#) (100%)
[HTMLReport](#) (94%)
[HasBeenInstrumented](#) (N/A)
[Header](#) (80%)
[IOUtil](#) (62%)
[Ignore](#) (100%)
[IgnoreBranches](#) (0%)

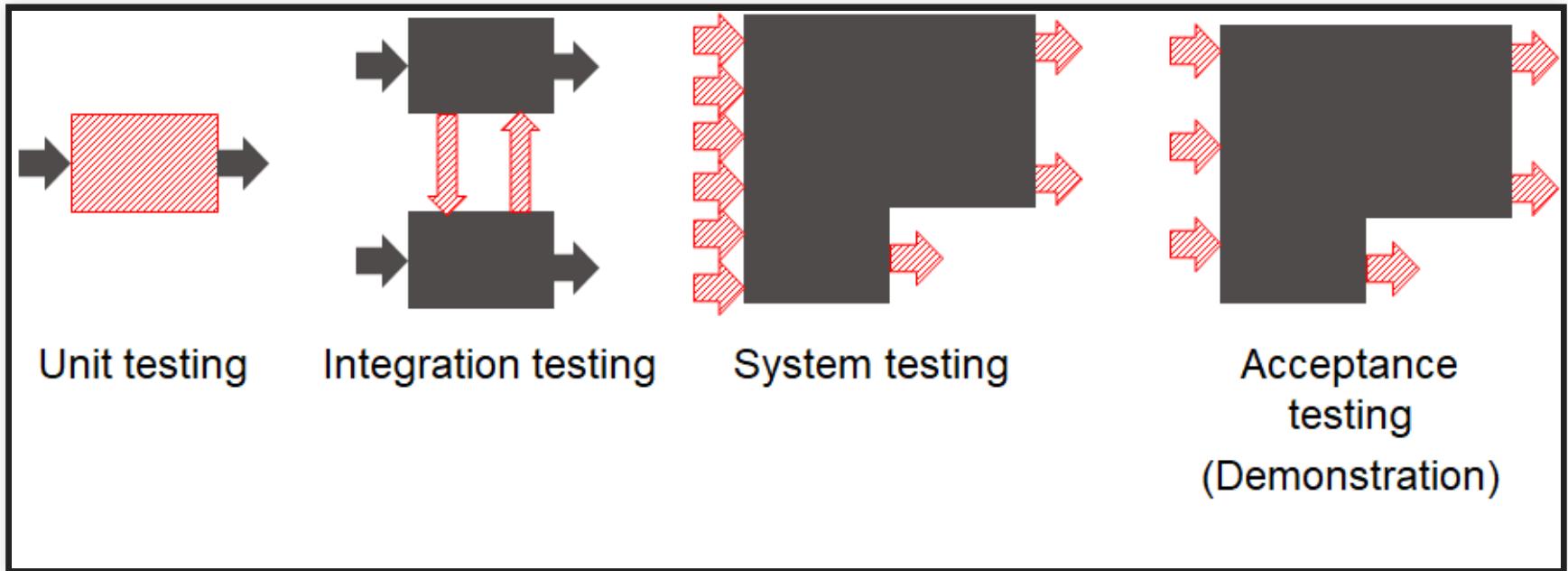
Coverage Report - All Packages

Package /	# Classes	Line Coverage	Branch Coverage	Complexity
All Packages	55	75%  1625/2179	64%  472/738	2.319
net.sourceforge.cobertura.ant	11	52%  170/330	43%  40/94	1.848
net.sourceforge.cobertura.check	3	0%  0/150	0%  0/76	2.429
net.sourceforge.cobertura.coveragedata	13	N/A  N/A	N/A  N/A	2.277
net.sourceforge.cobertura.instrument	10	90%  460/510	75%  123/164	1.854
net.sourceforge.cobertura.merge	1	86%  30/35	88%  14/16	5.5
net.sourceforge.cobertura.reporting	3	87%  116/134	80%  43/54	2.882
net.sourceforge.cobertura.reporting.html	4	91%  475/523	77%  156/202	4.444
net.sourceforge.cobertura.reporting.html.files	1	87%  39/45	62%  5/8	4.5
net.sourceforge.cobertura.reporting.xml	1	100%  155/155	95%  21/22	1.524
net.sourceforge.cobertura.util	9	60%  175/291	69%  70/102	2.892
someotherpackage	1	83%  5/6	N/A  N/A	1.2

Report generated by [Cobertura](#) 1.9 on 6/9/07 12:37 AM.



INTEGRATION AND SYSTEM TESTS



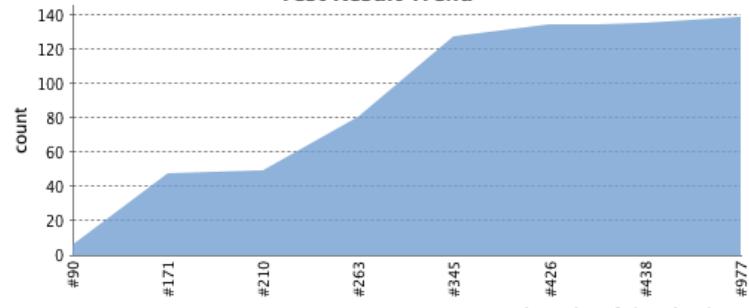
[Back to Dashboard](#)[Status](#)[Changes](#)[Workspace](#)[Build Now](#)[Delete Project](#)[Configure](#)[Set Next Build Number](#)[Duplicate Code](#)[Coverage Report](#)[SLOCCount](#)[Git Polling Log](#)

Project Stop-tabac dev

CI build

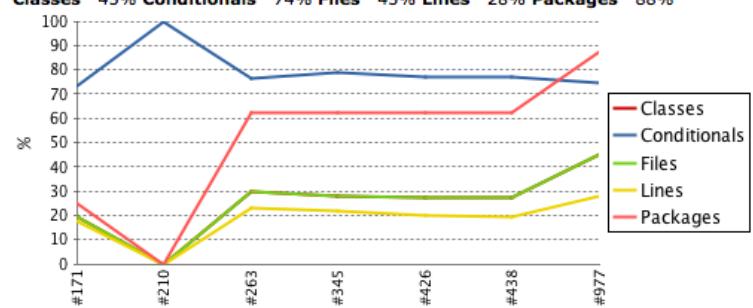
[Coverage Report](#)[Workspace](#)[Recent Changes](#)[Latest Test Result \(no failures\)](#)[Edit description](#)[Disable Project](#)

Test Result Trend

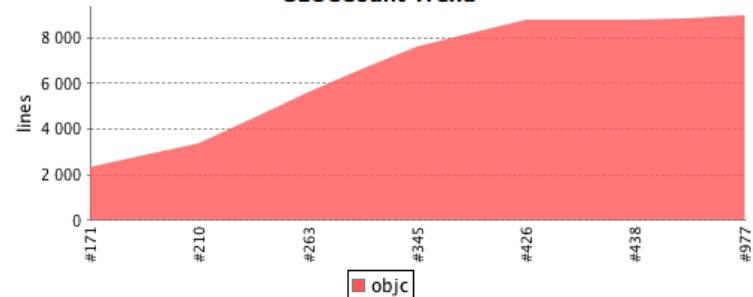
[\(just show failures\) enlarge](#)

Code Coverage

Classes 45% Conditionals 74% Files 45% Lines 28% Packages 88%



SLOCCount Trend

[objc](#)

Build History (trend)

Build Number	Date	Time
#977	Aug 27, 2012	4:37:27 PM
#438	Jun 28, 2012	8:47:42 AM
#426	Jun 26, 2012	1:39:39 PM
#345	Jun 19, 2012	9:02:20 AM
#263	Jun 6, 2012	9:14:42 PM
#210	May 31, 2012	8:42:29 AM
#171	May 23, 2012	9:58:18 PM
#90	May 15, 2012	11:49:41 AM

RSS for all RSS for failures



Source: <https://blog.octo.com/en/jenkins-quality-dashboard-ios-development/>

TEST MONITORING IN PRODUCTION

- Like fire drills (manual tests may be okay!)
- Manual tests in production, repeat regularly
- Actually take down service or trigger wrong signal to monitor

CHAOS TESTING



<http://principlesofchaos.org>

CASE STUDY: SMART PHONE COVID-19 DETECTION



(from midterm; assume cloud or hybrid deployment)

DATA TESTS

1. Feature expectations are captured in a schema.
2. All features are beneficial.
3. No feature's cost is too much.
4. Features adhere to meta-level requirements.
5. The data pipeline has appropriate privacy controls.
6. New features can be added quickly.
7. All input feature code is tested.

Eric Breck, Shanqing Cai, Eric Nielsen, Michael Salib, D. Sculley. [The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction](#). Proceedings of IEEE Big Data (2017)

TESTS FOR MODEL DEVELOPMENT

1. Model specs are reviewed and submitted.
2. Offline and online metrics correlate.
3. All hyperparameters have been tuned.
4. The impact of model staleness is known.
5. A simpler model is not better.
6. Model quality is sufficient on important data slices.
7. The model is tested for considerations of inclusion.

Eric Breck, Shanqing Cai, Eric Nielsen, Michael Salib, D. Sculley. [The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction](#). Proceedings of IEEE Big Data (2017)

ML INFRASTRUCTURE TESTS

1. Training is reproducible.
2. Model specs are unit tested.
3. The ML pipeline is Integration tested.
4. Model quality is validated before serving.
5. The model is debuggable.
6. Models are canaried before serving.
7. Serving models can be rolled back.

Eric Breck, Shanqing Cai, Eric Nielsen, Michael Salib, D. Sculley. [The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction](#). Proceedings of IEEE Big Data (2017)

MONITORING TESTS

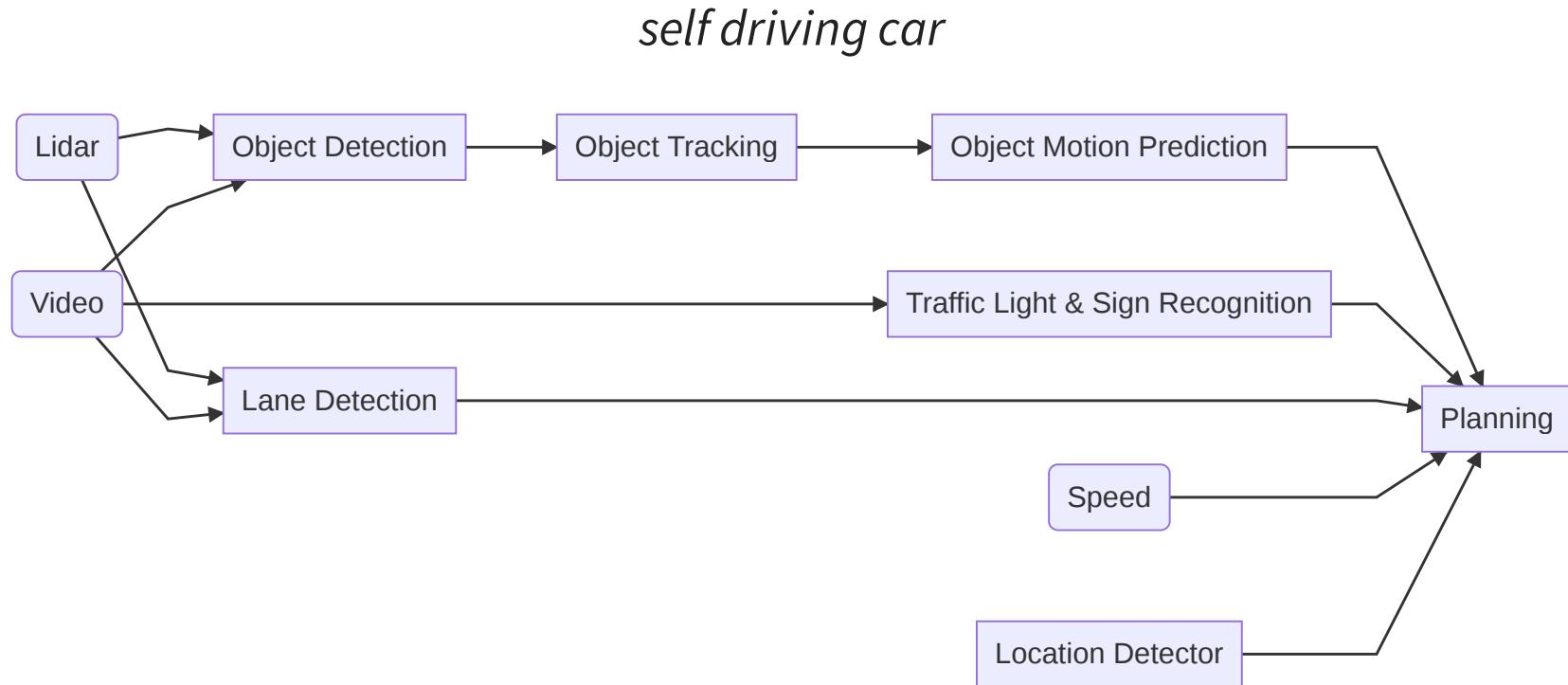
1. Dependency changes result in notification.
2. Data invariants hold for inputs.
3. Training and serving are not skewed.
4. Models are not too stale.
5. Models are numerically stable.
6. Computing performance has not regressed.
7. Prediction quality has not regressed.

Eric Breck, Shanqing Cai, Eric Nielsen, Michael Salib, D. Sculley. [The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction](#). Proceedings of IEEE Big Data (2017)

FEATURE INTERACTION EXAMPLES



ML MODELS FOR FEATURE EXTRACTION



Example: Zong, W., Zhang, C., Wang, Z., Zhu, J., & Chen, Q. (2018). [Architecture design and implementation of an autonomous vehicle](#). IEEE access, 6, 21956-21970.

DEV VS. OPS



DEVELOPERS

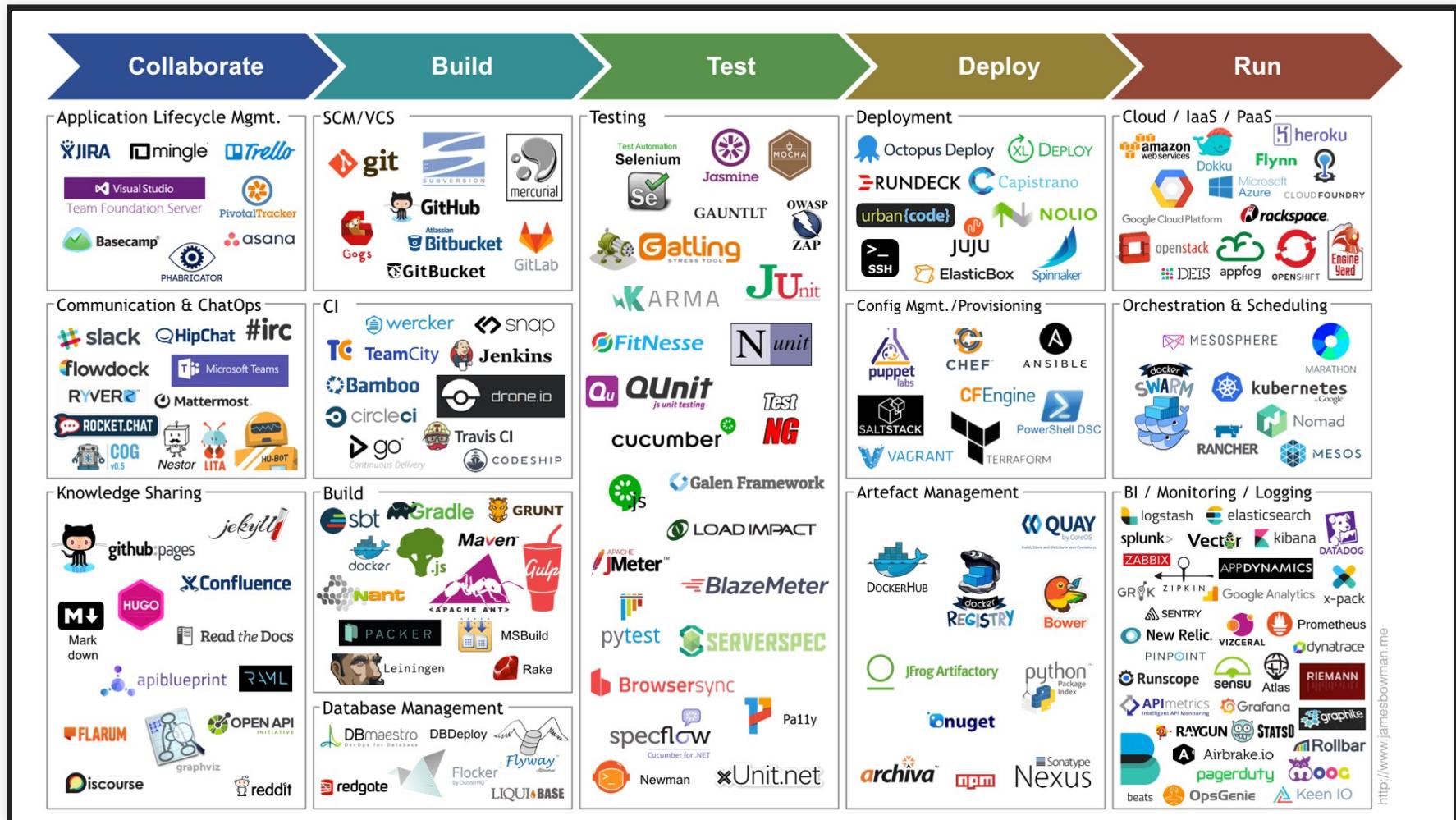
- Coding
- Testing, static analysis, reviews
- Continuous integration
- Bug tracking
- Running local tests and scalability experiments
- ...

OPERATIONS

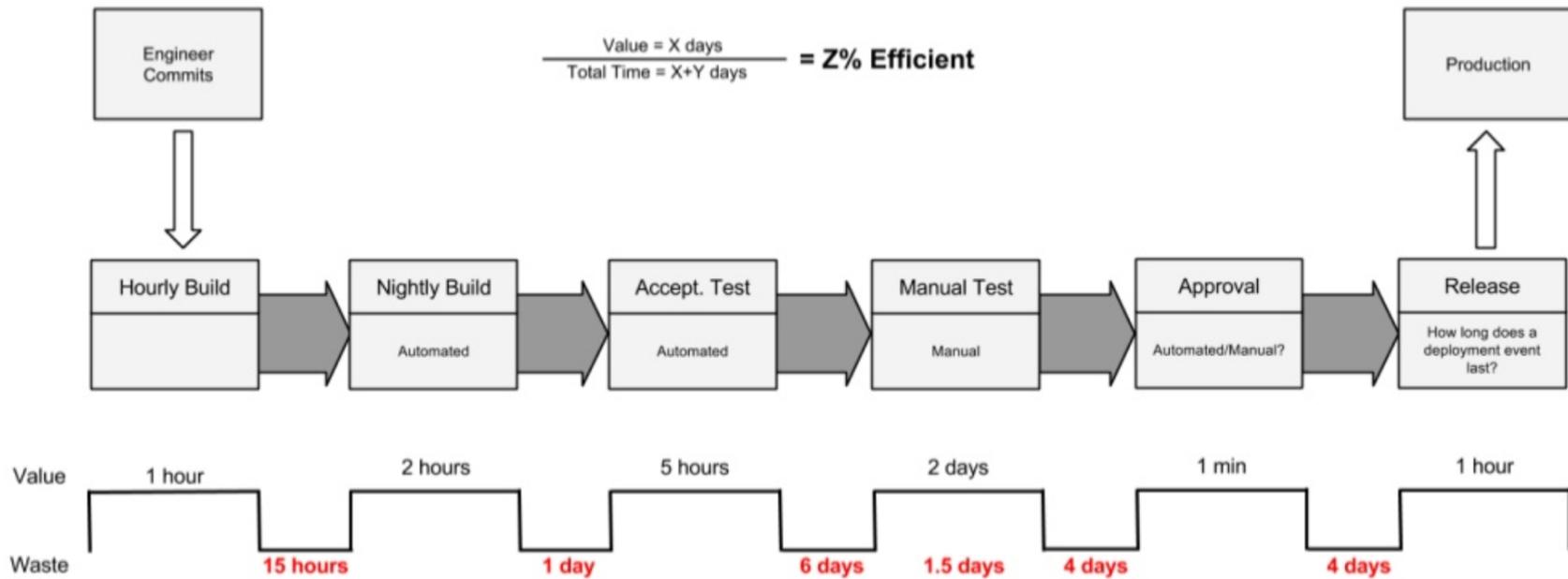
- Allocating hardware resources
- Managing OS updates
- Monitoring performance
- Monitoring crashes
- Managing load spikes, ...
- Tuning database performance
- Running distributed at scale
- Rolling back releases
- ...

QA responsibilities in both roles

HEAVY TOOLING AND AUTOMATION

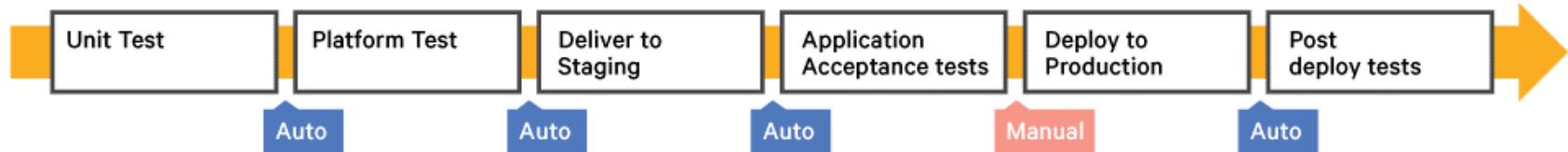


<http://www.jamesbowman.me>

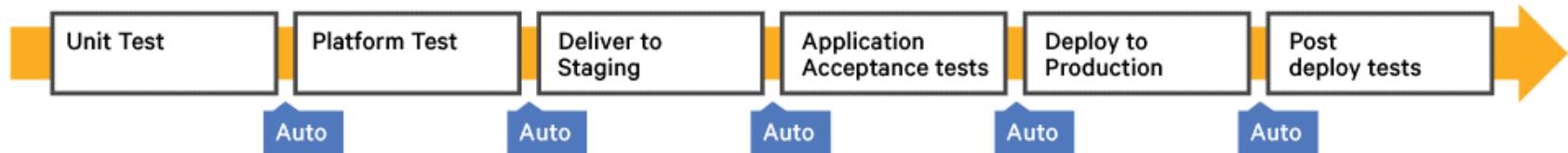


Source: <https://www.slideshare.net/jmcgarr/continuous-delivery-at-netflix-and-beyond>

Continuous Delivery



Continuous Deployment



DOCKER EXAMPLE

```
FROM ubuntu:latest
MAINTAINER ...
RUN apt-get update -y
RUN apt-get install -y python-pip python-dev build-essential
COPY . /app
WORKDIR /app
RUN pip install -r requirements.txt
ENTRYPOINT ["python"]
CMD ["app.py"]
```

Source: <http://containertutorials.com/docker-compose/flask-simple-app.html>

ANSIBLE EXAMPLES

- Software provisioning, configuration management, and application-deployment tool
- Apply scripts to many servers

```
[webservers]
web1.company.org
web2.company.org
web3.company.org
```

```
[dbservers]
db1.company.org
db2.company.org
```

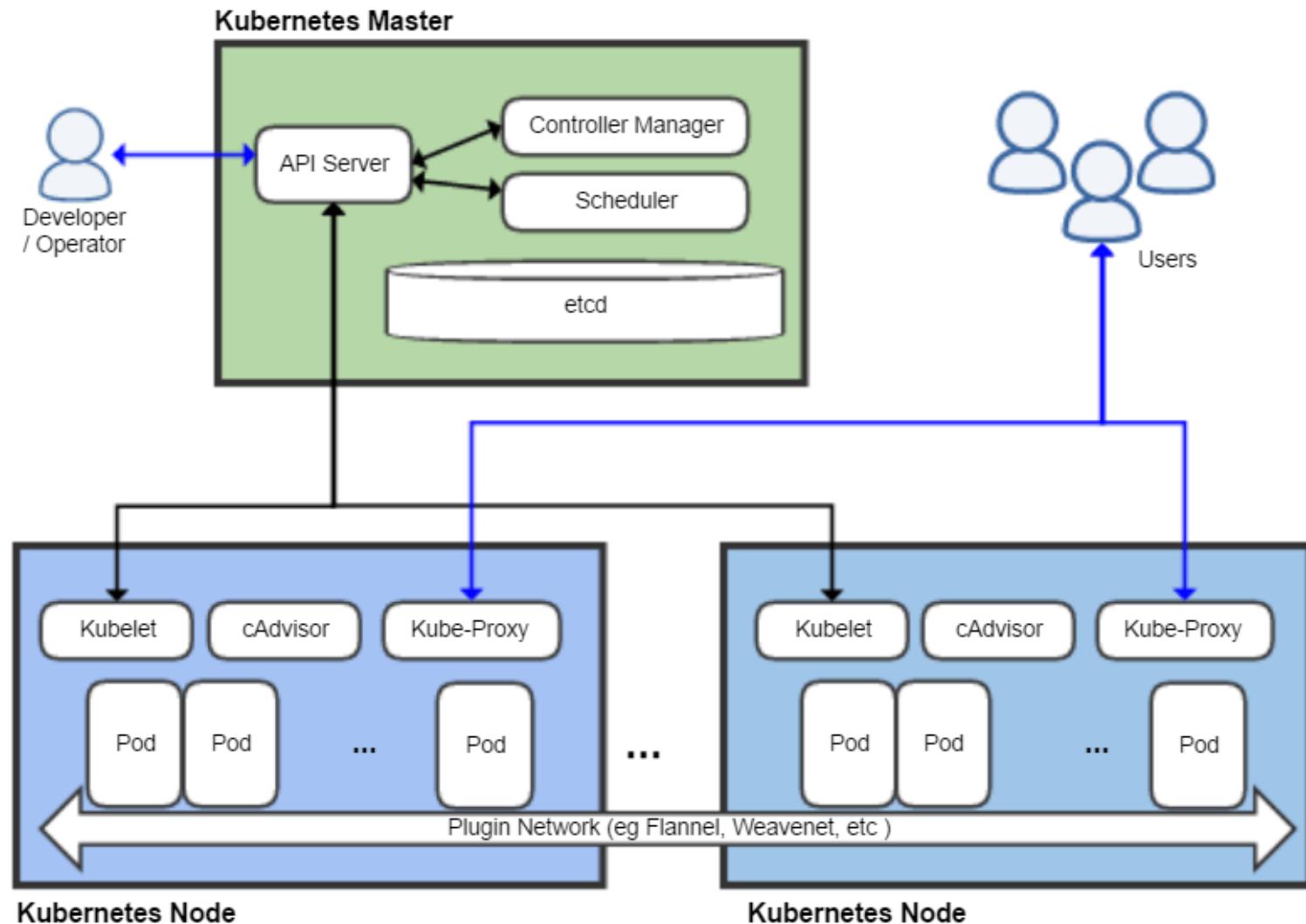
```
[replication_servers]
...
```

```
# This role deploys the mongod processes and
- name: create data directory for mongodb
  file: path={{ mongodb_datadir_prefix }}/{{ item }}
  delegate_to: '{{ item }}'
  with_items: groups.replication_servers

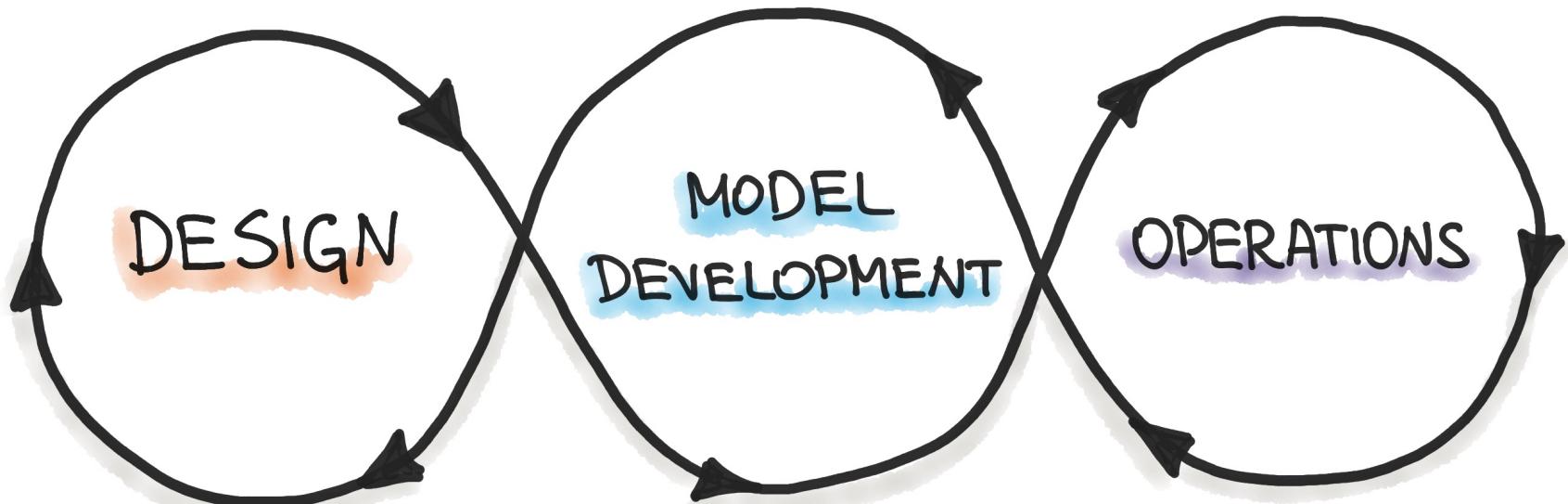
- name: create log directory for mongodb
  file: path=/var/log/mongo state=directory o

- name: Create the mongodb startup file
  template: src=mongod.j2 dest=/etc/init.d/mo
  delegate_to: '{{ item }}'
  with_items: groups.replication_servers

- name: Create the mongodb configuration file
```



MLOps



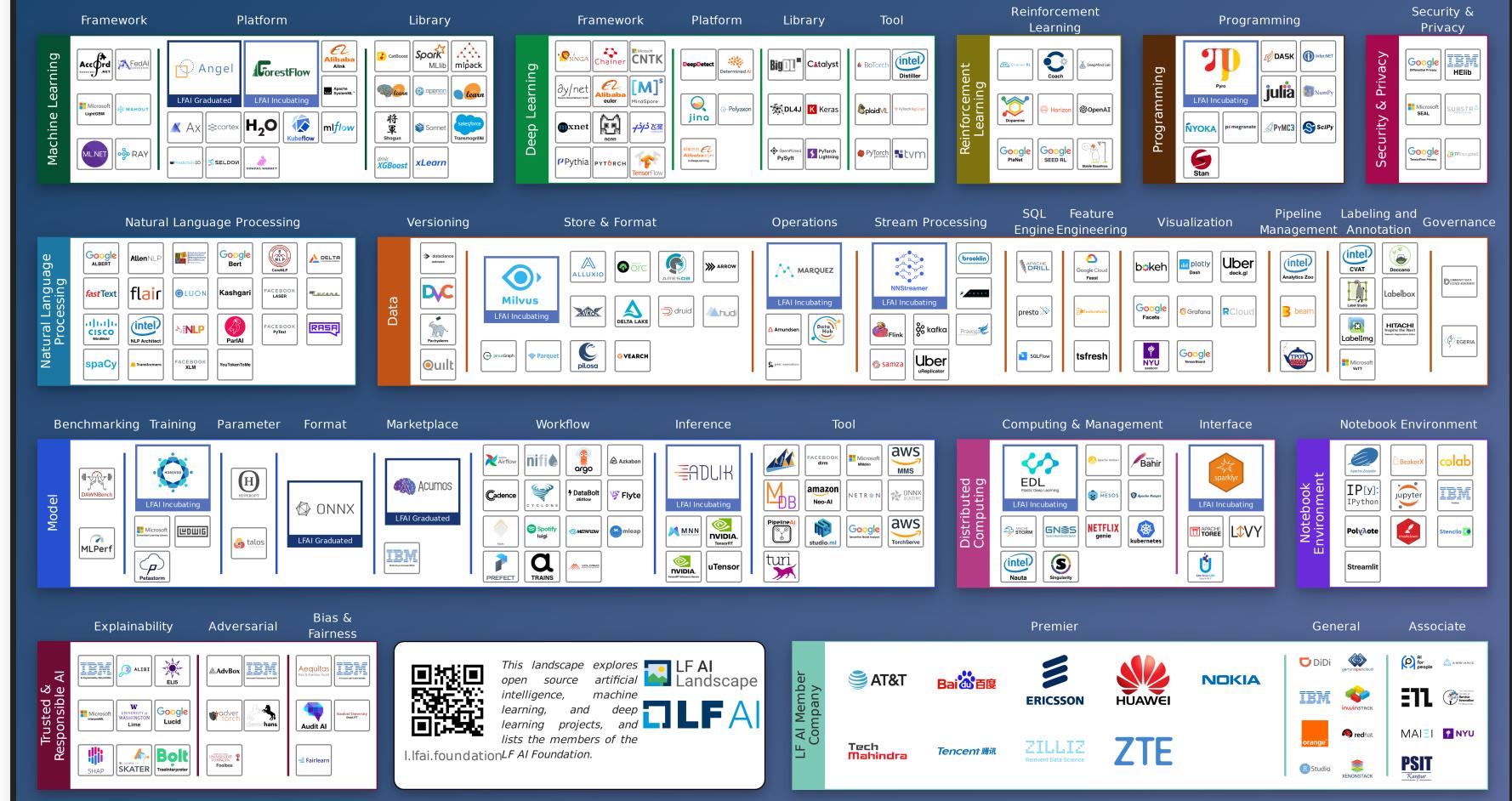
<https://ml-ops.org/>

TOOLING LANDSCAPE LF AI

Linux Foundation AI Landscape
2020-06-30T02:16:48Z ebffcc5

See the interactive landscape at l.lfai.foundation

Greyed logos are not open source



Linux Foundation AI Initiative

HOMEWORK 5: OPEN SOURCE TOOLS

PROJECT M2: MODEL AND INFRASTRUCTURE QUALITY

(online and offline evaluation, data quality, pipeline quality, CI)

ETHICS & FAIRNESS IN AI-ENABLED SYSTEMS

Christian Kaestner

(with slides from Eunsuk Kang)

Required reading: □ R. Caplan, J. Donovan, L. Hanson, J. Matthews. "[Algorithmic Accountability: A Primer](#)", Data & Society (2018).

LEARNING GOALS

- Review the importance of ethical considerations in designing AI-enabled systems
- Recall basic strategies to reason about ethical challenges
- Diagnose potential ethical issues in a given system
- Understand the types of harm that can be caused by ML
- Understand the sources of bias in ML
- Analyze a system for harmful feedback loops



In September 2015, Shkreli received widespread criticism when Turing obtained the manufacturing license for the antiparasitic drug Daraprim and raised its price by a factor of 56 (from USD 13.5 to 750 per pill), leading him to be referred to by the media as "the most hated man in America" and "Pharma Bro".

-- [Wikipedia](#)

"I could have raised it higher and made more profits for our shareholders. Which is my primary duty." -- Martin Shkreli

WITH A FEW LINES OF CODE...

Some airlines may be using algorithms to split up families during flights

Your random airplane seat assignment might not be random at all.

By Aditi Shrikant | aditi@vox.com | Nov 27, 2018, 6:10pm EST



SHARE



SAFETY



Emily Slackerman Ackerman
@EmilyEAckerman



i (in a wheelchair) was just trapped *on* forbes ave by one of these robots, only days after their independent roll out. i can tell that as long as they continue to operate, they are going to be a major accessibility and safety issue. [thread]

Everything we know about the Starship food delivery ro...
The white, 2-foot tall battery-powered delivery robots will
be sharing the sidewalk with Oakland pedestrians starti...
[∅ pittnews.com](#)

7:27 PM · Oct 21, 2019



4.3K 3.2K people are Tweeting about this

ADDICTION

NO MERCY NO MALICE

Robinhood Has Gamified Online Trading Into an Addiction

Tech's obsession with addiction will hurt us all



Scott Galloway [Follow](#)

Jun 23 · 7 min read ★



Warning: This post contains a discussion of suicide.

Addiction is the inability to stop consuming a chemical or pursuing an activity although it's causing harm.

I engage with almost every substance or behavior associated with addiction: alcohol, drugs, coffee, porn, sex, gambling, work, spending,

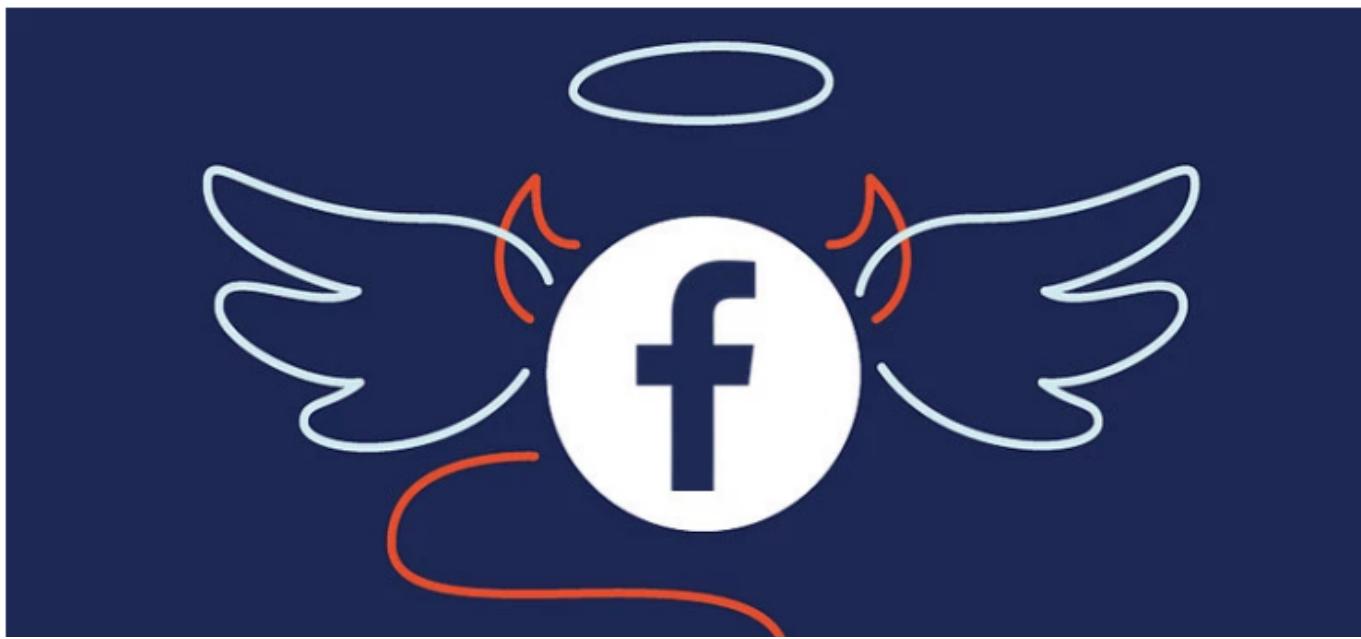
The Morality Of A/B Testing

X

Josh Constine @joshconstine / 4 years ago



Comment



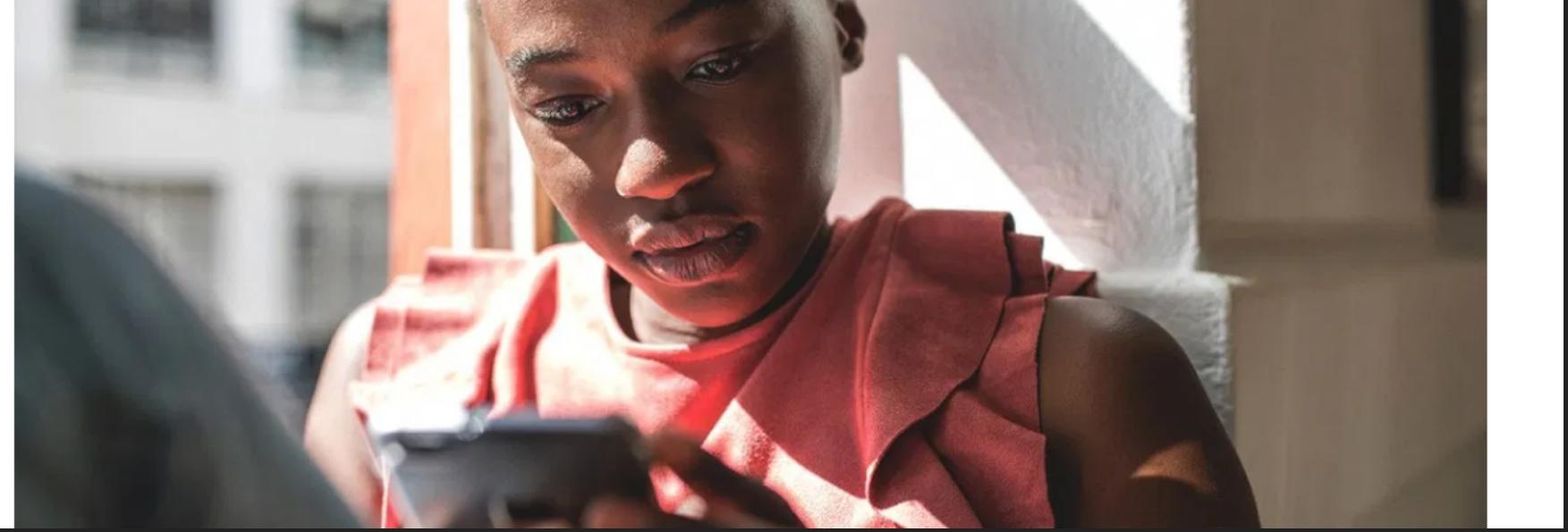
[HEALTH NEWS](#) [Fact Checked](#)

The FOMO Is Real: How Social Media Increases Depression and Loneliness

Written by [Gigen Mammoser](#) on December 10, 2018

New research reveals how social media platforms like Facebook can greatly affect your mental health.





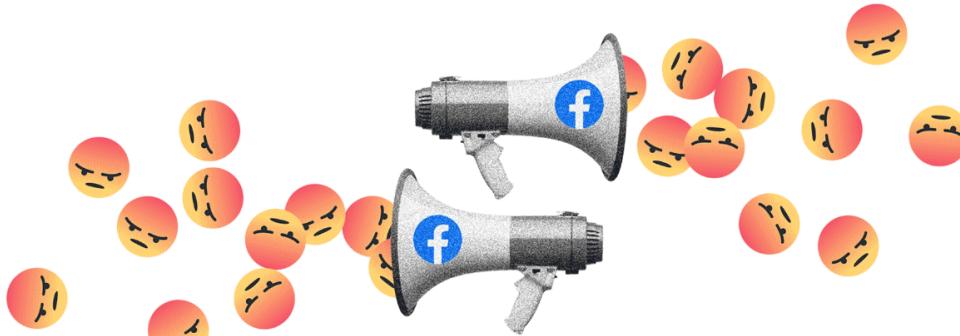
SOCIETY: UNEMPLOYMENT ENGINEERING / DESKILLING



SOCIETY: POLARIZATION

≡ THE WALL STREET JOURNAL. SEARCH

SUBSCRIBE SIGN IN



TECH

Facebook Executives Shut Down Efforts to Make the Site Less Divisive

The social-media giant internally studied how it polarizes users, then largely shelved the research

By [Jeff Horwitz](#) and [Deepa Seetharaman](#)

May 26, 2020 11:38 am ET

WEAPONS, SURVEILLANCE, SUPPRESSION



The Washington Post
Democracy Dies in Darkness

PostEverything • Perspective

How U.S. surveillance technology is propping up authoritarian regimes



(iStock)

By **Robert Morgus** and **Justin Sherman**

Jan. 17, 2019 at 6:00 a.m. EST

DISCRIMINATION



DHH

@dhh



The [@AppleCard](#) is such a fucking sexist program. My wife and I filed joint tax returns, live in a community-property state, and have been married for a long time. Yet Apple's black box algorithm thinks I deserve 20x the credit limit she does. No appeals work.

8:34 PM · Nov 7, 2019



28.5K

10.6K people are Tweeting about this

LEGALLY PROTECTED CLASSES (US)

- Race (Civil Rights Act of 1964)
- Color (Civil Rights Act of 1964)
- Sex (Equal Pay Act of 1963; Civil Rights Act of 1964)
- Religion (Civil Rights Act of 1964)
- National origin (Civil Rights Act of 1964)
- Citizenship (Immigration Reform and Control Act)
- Age (Age Discrimination in Employment Act of 1967)
- Pregnancy (Pregnancy Discrimination Act)
- Familial status (Civil Rights Act of 1968)
- Disability status (Rehabilitation Act of 1973; Americans with Disabilities Act of 1990)
- Veteran status (Vietnam Era Veterans' Readjustment Assistance Act of 1974; Uniformed Services Employment and Reemployment Rights Act)
- Genetic information (Genetic Information Nondiscrimination Act)

Barocas, Solon and Moritz Hardt. "[Fairness in machine learning](#)." NIPS Tutorial 1 (2017).

Equality



The assumption is that **everyone benefits from the same supports**. This is equal treatment.

Equity



Everyone gets the supports they need (this is the concept of "affirmative action"), thus producing equity.

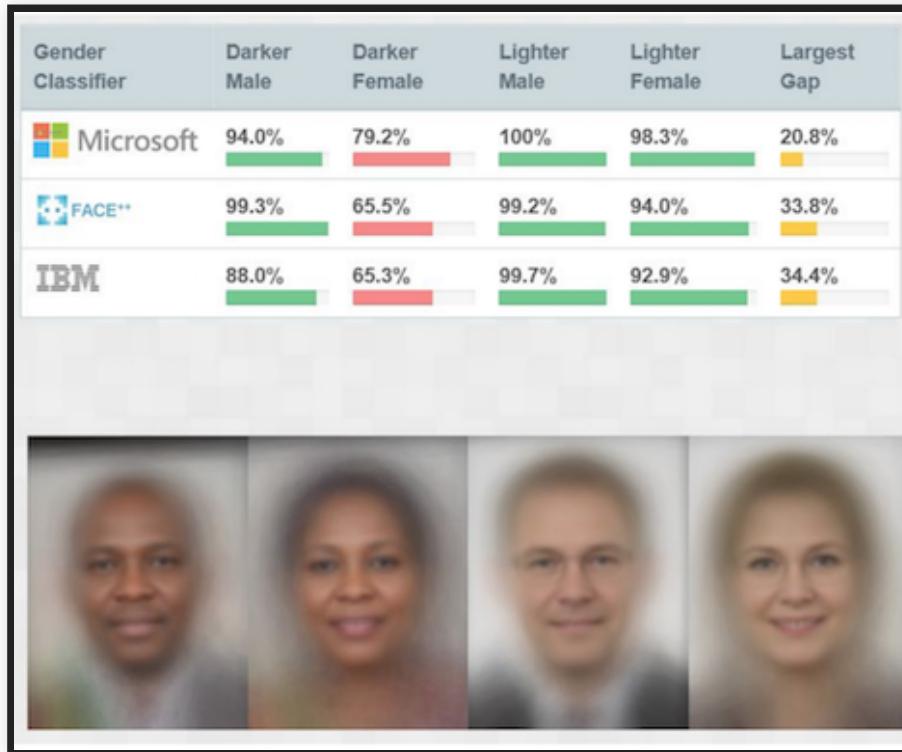
Justice



All 3 can see the game without supports or accommodations because **the cause(s) of the inequity was addressed**.
The systemic barrier has been removed.

HARMS OF ALLOCATION

- Withhold opportunities or resources
- Poor quality of service, degraded user experience for certain groups



Other examples?

HARMS OF REPRESENTATION

- Reinforce stereotypes, subordination along the lines of identity

Ads by Google

[Latanya Sweeney, Arrested?](#)

1) Enter Name and State. 2) Access Full Background Checks Instantly.

www.instantcheckmate.com/

[Latanya Sweeney](#)

Public Records Found For: Latanya Sweeney. View Now.

www.publicrecords.com/

[La Tanya](#)

Search for La Tanya Look Up Fast Results now!

www.ask.com/La+Tanya

Other examples?

Latanya Sweeney. [Discrimination in Online Ad Delivery](#), SSRN (2013).

CASE STUDY: COLLEGE ADMISSION



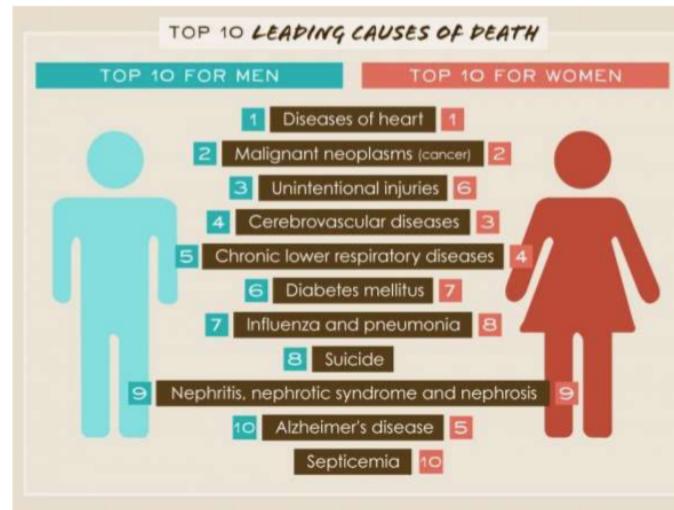
- Objective: Decide "Is this student likely to succeed"?
- Possible harms: Allocation of resources? Quality of service? Stereotyping? Denigration? Over-/Under-representation?

NOT ALL DISCRIMINATION IS HARMFUL



FEDERAL TRADE COMMISSION

Mortgage discrimination is against the law.



- Loan lending: Gender discrimination is illegal.
- Medical diagnosis: Gender-specific diagnosis may be desirable.
- Discrimination is a **domain-specific** concept!

Other examples?

WHERE DOES THE BIAS COME FROM?

The image displays two side-by-side screenshots of the Google Translate interface, illustrating gender bias in language models. Both screenshots show a translation from English to Turkish.

Top Screenshot (English to Turkish):

- Input (English):** "He is a nurse
She is a doctor"
- Output (Turkish):** "O bir hemşire
O bir doktor"
- Feedback:** The "She is a doctor" translation has a checkmark icon, indicating it is the preferred or correct translation.

Bottom Screenshot (Turkish to English):

- Input (Turkish):** "O bir hemşire
O bir doktor"
- Output (English):** "She is a nurse
He is a doctor" (with a checkmark icon)
- Feedback:** The "He is a doctor" translation has a checkmark icon, indicating it is the preferred or correct translation.

In both cases, the model consistently translates "he" to "she" and "she" to "he", demonstrating a clear gender bias favoring male subjects.

Caliskan et al., *Semantics derived automatically from language corpora contain human-like biases*, Science (2017).

HISTORICAL BIAS

Data reflects past biases, not intended outcomes

The screenshot shows a search results page for the query "ceo". The interface includes a logo of a cartoon duck, a search bar with the term "ceo", and a magnifying glass icon. Below the search bar are navigation links for "All", "Images" (which is underlined), "Videos", "News", "Maps", and "Meanings". On the right, there is a "Settings" dropdown menu. Further down, there are filters for "All Regions", "Safe Search: Moderate", "All Sizes", "All Types", "All Layouts", and "All Colors". The main content area displays five search results, each featuring a portrait of a man in a suit and a brief description:

- Cronos CEO: \$1.8 billion from Big Tob...**
marketwatch.com
- Marriott CEO talks...**
bizjournals.com
- Goldman Sachs may claw back milli...**
nypost.com
- Coolest thing about Tesla's C**
businessinsider.com

Below these results, there are five smaller thumbnail images showing more portraits of men in suits.



1000 × 1000

Croatian Doctor To...
croatiaweek.com



999 × 666

Lufthansa CEO Says Brit...
skift.com



1000 × 750

'The ideal match': Lululemon...
business.financialpost.com



750 × 999

Fairview names St...
bizjournals.com



CEO pay: Top 10 highest...
usatoday.com

TAINTED EXAMPLES

Samples or labels reflect human bias

TECH \ AMAZON \ ARTIFICIAL INTELLIGENCE

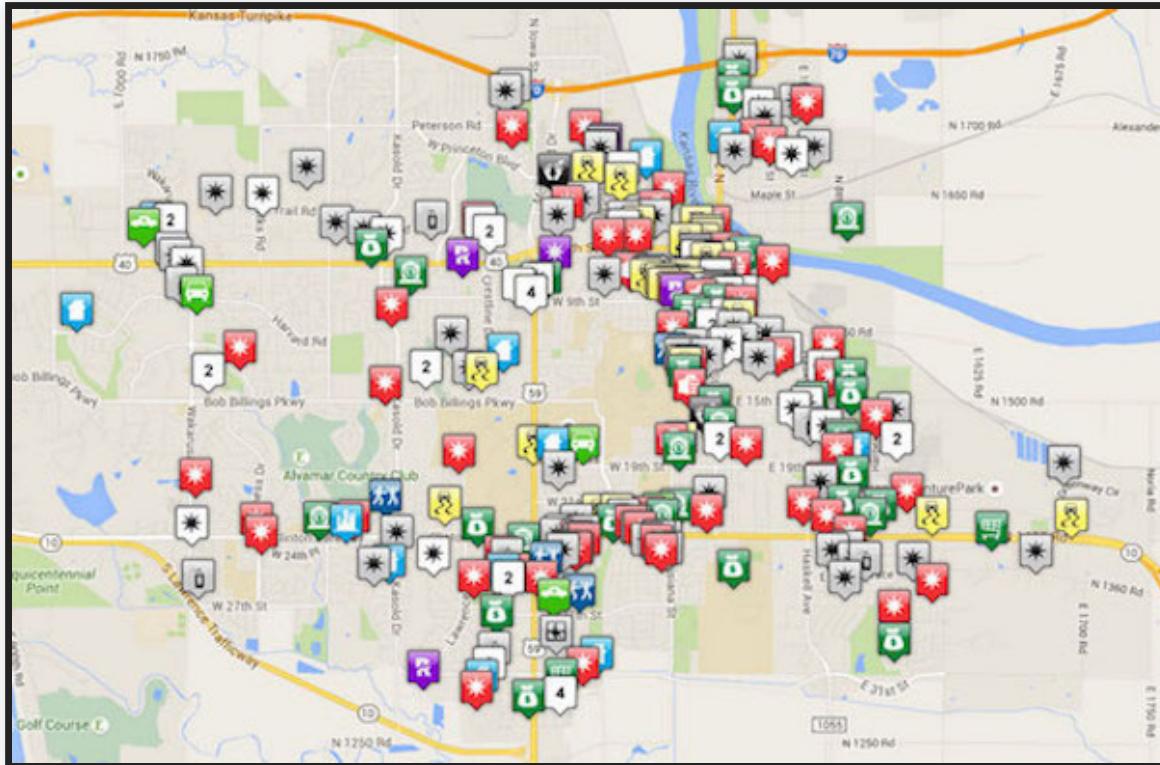
Amazon reportedly scraps internal AI recruiting tool that was biased against women

The secret program penalized applications that contained the word “women’s”

By James Vincent | Oct 10, 2018, 7:09am EDT

SKEWED SAMPLE

Crime prediction for policing strategy



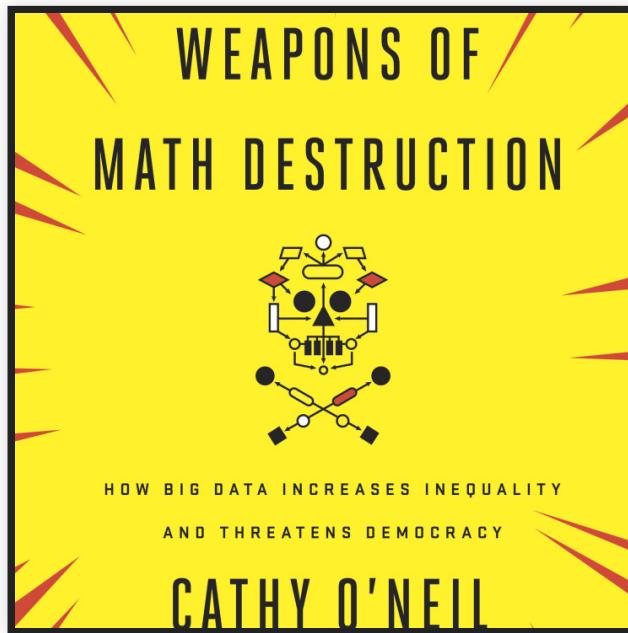
SAMPLE SIZE DISPARITY

Less training data available for certain subpopulations



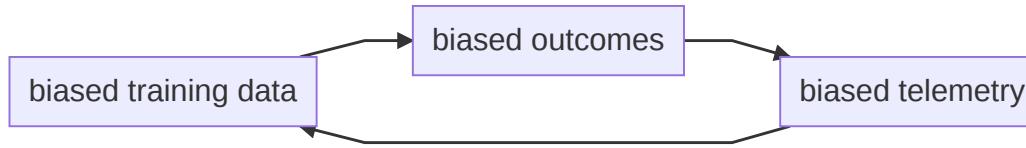
Example: "Shirley Card" used for color calibration

MASSIVE POTENTIAL DAMAGE



O'Neil, Cathy. [Weapons of math destruction: How big data increases inequality and threatens democracy](#). Broadway Books, 2016.

FEEDBACK LOOPS



"Big Data processes codify the past. They do not invent the future. Doing that requires moral imagination, and that's something only humans can provide. " -- Cathy O'Neil in
Weapons of Math Destruction

BUILDING FAIRER AI-ENABLED SYSTEMS

Christian Kaestner

(with slides from Eunsuk Kang)

Required reading: □ Holstein, Kenneth, Jennifer Wortman Vaughan, Hal Daumé III, Miro Dudik, and Hanna Wallach. "[Improving fairness in machine learning systems: What do industry practitioners need?](#)" In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1-16. 2019.

Recommended reading: □ Corbett-Davies, Sam, and Sharad Goel. "[The measure and mismeasure of fairness: A critical review of fair machine learning](#)." arXiv preprint arXiv:1808.00023 (2018).

Also revisit: □ Vogelsang, Andreas, and Markus Borg. "[Requirements Engineering for Machine Learning: Perspectives from Data Scientists](#)." In Proc. of the 6th International Workshop on Artificial Intelligence for Requirements Engineering (AIRE), 2019.

LEARNING GOALS

- Understand different definitions of fairness
- Discuss methods for measuring fairness
- Design and execute tests to check for bias/fairness issues
- Understand fairness interventions during data acquisition
- Apply engineering strategies to build more fair systems
- Diagnose potential ethical issues in a given system
- Evaluate and apply mitigation strategies

TWO PARTS

Fairness assessment in the model

Formal definitions of fairness properties

Testing a model's fairness

Constraining a model for fairer results

System-level fairness engineering

Requirements engineering

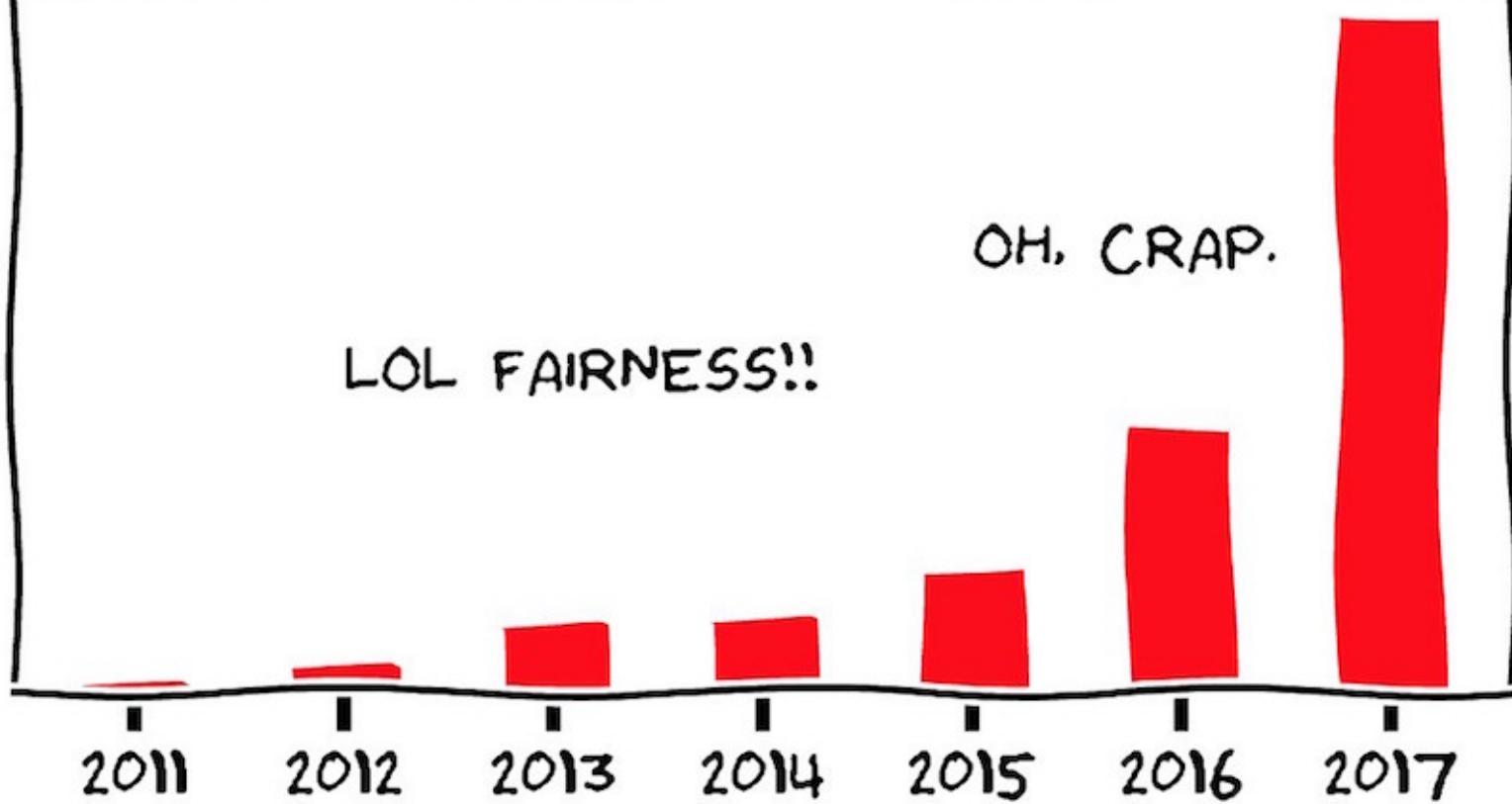
Fairness and data acquisition

Team and process considerations

FAIRNESS IS STILL AN ACTIVELY STUDIED & DISPUTED CONCEPT!

BRIEF HISTORY OF FAIRNESS IN ML

PAPERS



Source: Mortiz Hardt, <https://fairmlclass.github.io/>

FAIRNESS THROUGH BLINDNESS

Anti-classification: Ignore/eliminate sensitive attributes from dataset, e.g., remove gender and race from a credit card scoring system



Advantages? Problems?

TESTING ANTI-CLASSIFICATION

Straightforward invariant for classifier f and protected attribute p :

$$\forall x. f(x[p \leftarrow 0]) = f(x[p \leftarrow 1])$$

(does not account for correlated attributes)

Test with random input data (see prior lecture on [Automated Random Testing](#)) or
on any test data

Any single inconsistency shows that the protected attribute was used. Can also
report percentage of inconsistencies.

See for example: Galhotra, Sainyam, Yuriy Brun, and Alexandra Meliou. "[Fairness testing: testing software for discrimination](#)." In Proceedings of the 2017 11th Joint Meeting on Foundations of Software Engineering, pp. 498-510. 2017.

CLASSIFICATION PARITY

Classification error is equal across groups

Barocas, Solon, Moritz Hardt, and Arvind Narayanan. "[Fairness and machine learning: Limitations and Opportunities.](#)" (2019), Chapter 2

INDEPENDENCE

(aka *statistical parity, demographic parity, disparate impact, group fairness*)

$$P[R = 1|A = 0] = P[R = 1|A = 1] \text{ or } R \perp A$$

- Acceptance rate (i.e., percentage of positive predictions) must be the same across all groups
- Prediction must be independent of the sensitive attribute
- Example:
 - The predicted rate of recidivism is the same across all races
 - Chance of promotion the same across all genders

EXERCISE: CANCER DIAGNOSIS

True Positives (TPs): 16

False Positives (FPs): 4

False Negatives (FNs): 6

True Negatives (TNs): 974

Male Patient Results

True Positives (TPs):
6

False Positives (FPs): 3

False Negatives
(FNs): 5

True Negatives (TNs):
486

Female Patient Results

True Positives (TPs):
10

False Positives (FPs): 1

False Negatives
(FNs): 1

True Negatives (TNs):
488

- 1000 data samples (500 male & 500 female patients)
- What's the overall recall & precision?
- Does the model achieve *independence*

CALIBRATION TO ACHIEVE INDEPENDENCE

Select different thresholds for different groups to achieve prediction parity:

$$P[R > t_0 | A = 0] = P[R > t_1 | A = 1]$$

Lowers bar for some groups -- equity, not equality

SEPARATION / EQUALIZED ODDS

Prediction must be independent of the sensitive attribute conditional on the target variable: $R \perp A | Y$

Same true positive rate across groups:

$$P[R = 0 | Y = 1, A = 0] = P[R = 0 | Y = 1, A = 1]$$

And same false positive rate across groups:

$$P[R = 1 | Y = 0, A = 0] = P[R = 1 | Y = 0, A = 1]$$

Example: A person with good credit behavior score should be assigned a good score with the same probability regardless of gender

Equality



The assumption is that **everyone benefits from the same supports**. This is equal treatment.

Equity



Everyone gets the supports they need (this is the concept of "affirmative action"), thus producing equity.

Justice



All 3 can see the game without supports or accommodations because **the cause(s) of the inequity was addressed**.
The systemic barrier has been removed.

REVIEW OF CRITERIA SO FAR:

Recidivism scenario: Should a person be detained?

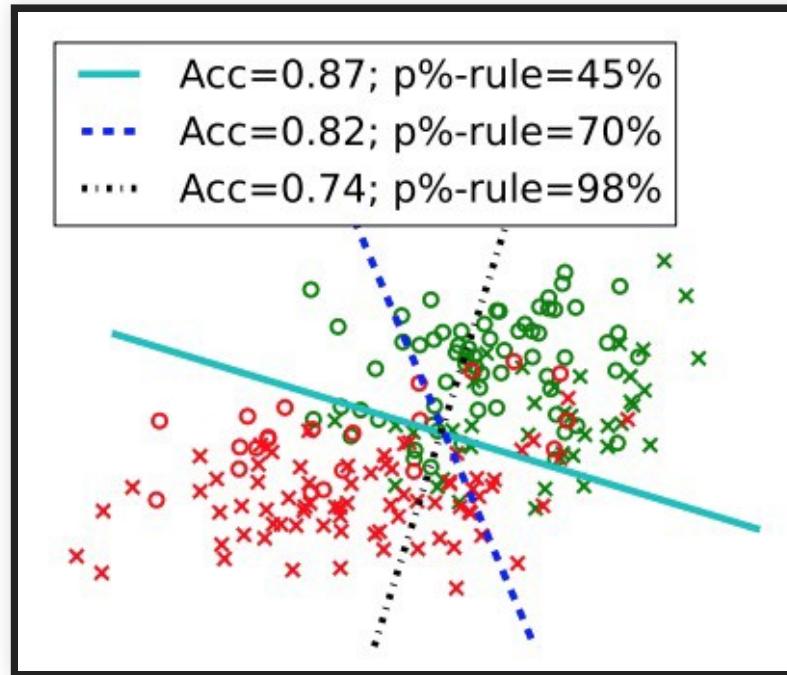
- Anti-classification: ?
- Independence: ?
- Separation: ?



CAN WE ACHIEVE FAIRNESS DURING THE LEARNING PROCESS?

- Data acquisition:
 - Collect additional data if performance is poor on some groups
- Pre-processing:
 - Clean the dataset to reduce correlation between the feature set and sensitive attributes
- Training-time constraint
 - ML is a constraint optimization problem (minimize errors)
 - Impose additional parity constraint into ML optimization process (e.g., as part of the loss function)
- Post-processing
 - Adjust the learned model to be uncorrelated with sensitive attributes
 - Adjust thresholds
- (Still active area of research! Many new techniques published each year)

TRADE-OFFS: ACCURACY VS FAIRNESS

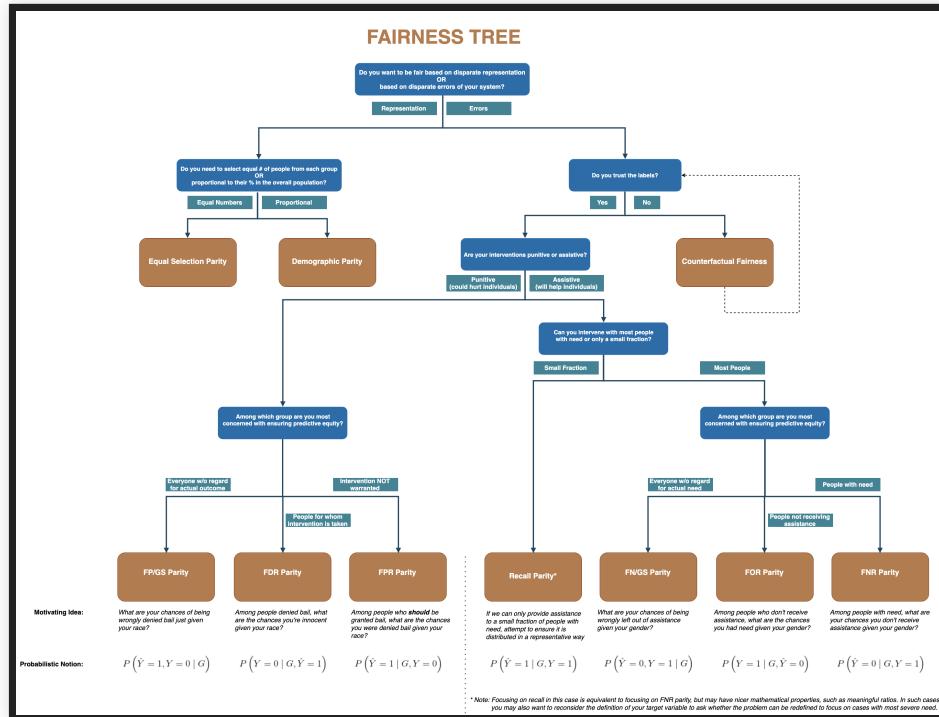


- Fairness constraints possible models
- Fairness constraints often lower accuracy for some group

Fairness Constraints: Mechanisms for Fair Classification, Zafar et al., AISTATS (2017).

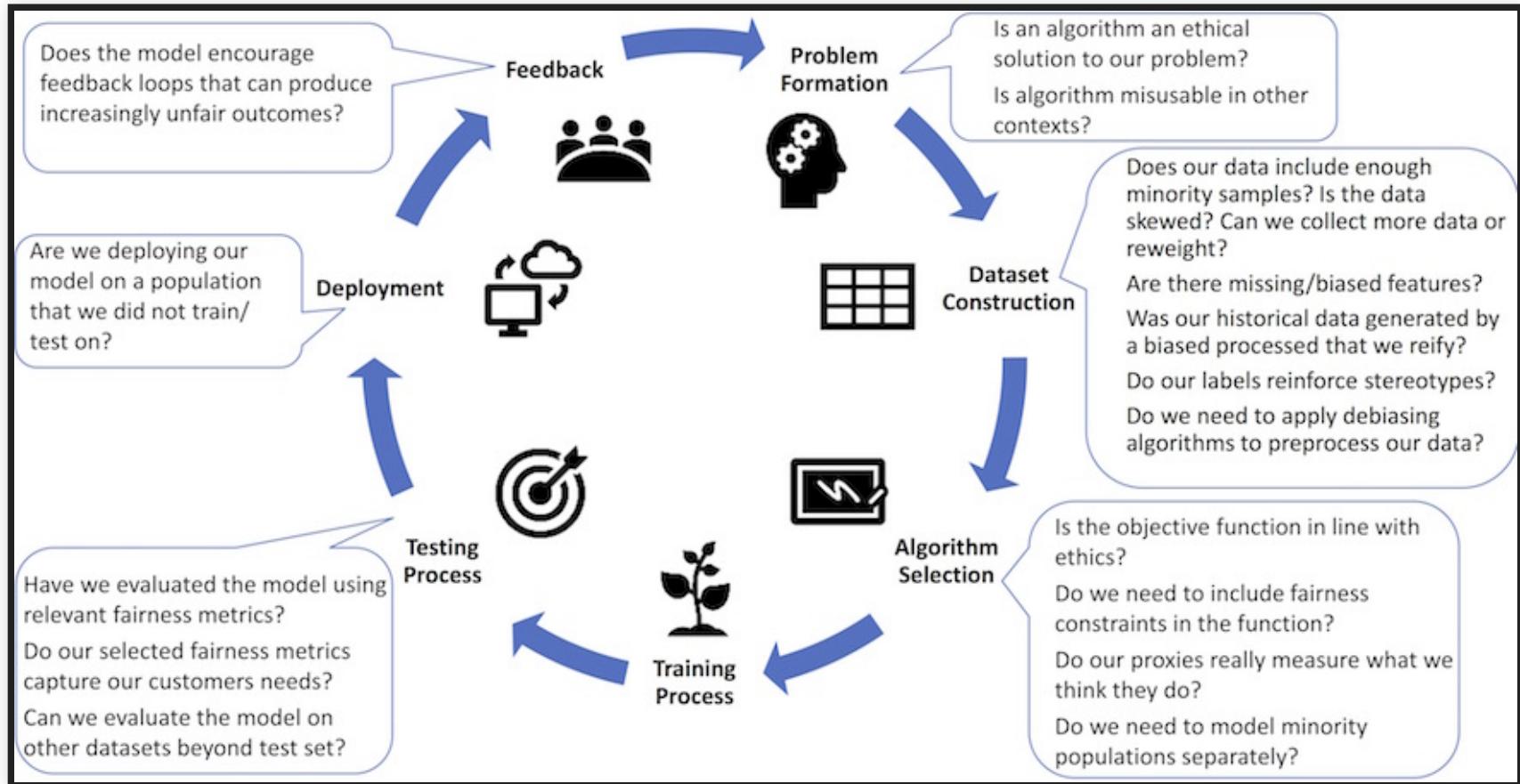
PICKING FAIRNESS CRITERIA

- Requirements engineering problem!
- What's the goal of the system? What do various stakeholders want? How to resolve conflicts?



<http://www.datasciencepublicpolicy.org/projects/aequitas/>

FAIRNESS MUST BE CONSIDERED THROUGHOUT THE ML LIFECYCLE!



Fairness-aware Machine Learning, Bennett et al., WSDM Tutorial (2019).

PRACTITIONER CHALLENGES

- Fairness is a system-level property
 - consider goals, user interaction design, data collection, monitoring, model interaction (properties of a single model may not matter much)
- Fairness-aware data collection, fairness testing for training data
- Identifying blind spots
 - Proactive vs reactive
 - Team bias and (domain-specific) checklists
- Fairness auditing processes and tools
- Diagnosis and debugging (outlier or systemic problem? causes?)
- Guiding interventions (adjust goals? more data? side effects? chasing mistakes? redesign?)
- Assessing human bias of humans in the loop

Holstein, Kenneth, Jennifer Wortman Vaughan, Hal Daumé III, Miro Dudik, and Hanna Wallach. "[Improving fairness in machine learning systems: What do industry practitioners need?](#)" In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, pp. 1-16. 2019.

THE ROLE OF REQUIREMENTS ENGINEERING

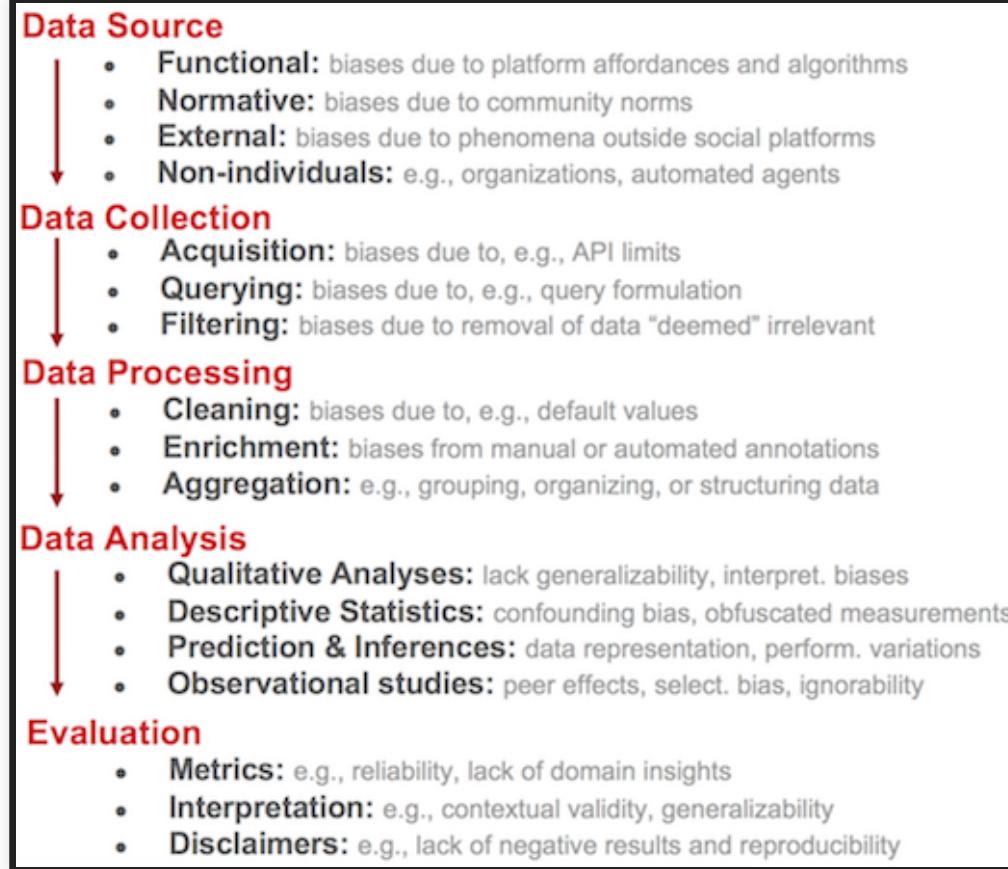
- Identify system goals
- Identify legal constraints
- Identify stakeholders and fairness concerns
- Analyze risks with regard to discrimination and fairness
- Analyze possible feedback loops (world vs machine)
- Negotiate tradeoffs with stakeholders
- Set requirements/constraints for data and model
- Plan mitigations in the system (beyond the model)
- Design incident response plan
- Set expectations for offline and online assurance and monitoring

BEST PRACTICES: TASK DEFINITION

- Clearly define the task & model's intended effects
- Try to identify and document unintended effects & biases
- Clearly define any fairness requirements
- *Involve diverse stakeholders & multiple perspectives*
- Refine the task definition & be willing to abort

Swati Gupta, Henriette Cramer, Kenneth Holstein, Jennifer Wortman Vaughan, Hal Daumé III, Miroslav Dudík, Hanna Wallach, Sravana Reddy, Jean GarciaGathright. [Challenges of incorporating algorithmic fairness into practice](#), FAT* Tutorial, 2019. ([slides](#))

Bias can be introduced at any stage of the data pipeline



Bennett et al., [Fairness-aware Machine Learning](#), WSDM Tutorial (2019).

DATA SHEETS

Demographic Characteristic	Value
Percentage of female subjects	22.5%
Percentage of male subjects	77.5%
Percentage of White subjects	83.5%
Percentage of Black subjects	8.47%
Percentage of Asian subjects	8.03%
Percentage of people between 0-20 years old	1.57%
Percentage of people between 21-40 years old	31.63%
Percentage of people between 41-60 years old	45.58%
Percentage of people over 61 years old	21.2%

- A process for documenting datasets
- Based on common practice in the electronics industry, medicine
- Purpose, provenance, creation, composition, distribution: Does the dataset relate to people? Does the dataset identify any subpopulations?

Datasheets for Dataset, Gebru et al., (2019).

MODEL CARDS

Model Card - Toxicity in Text

Model Details

- The TOXICITY classifier provided by Perspective API [32], trained to predict the likelihood that a comment will be perceived as toxic.
- Convolutional Neural Network.
- Developed by Jigsaw in 2017.

Intended Use

- Intended to be used for a wide range of use cases such as supporting human moderation and providing feedback to comment authors.
- Not intended for fully automated moderation.
- Not intended to make judgments about specific individuals.

Factors

- Identity terms referencing frequently attacked groups, focusing on sexual orientation, gender identity, and race.

Metrics

- Pinned AUC, as presented in [11], which measures threshold-agnostic separability of toxic and non-toxic comments for each group, within the context of a background distribution of other groups.

Ethical Considerations

- Following [31], the Perspective API uses a set of values to guide their work. These values are Community, Transparency, Inclusivity, Privacy, and Topic-neutrality. Because

Training Data

- Proprietary from Perspective API. Following details in [11] and [32], this includes comments from online forums such as Wikipedia and New York Times, with crowdsourced labels of whether the comment is “toxic”.
- “Toxic” is defined as “a rude, disrespectful, or unreasonable comment that is likely to make you leave a discussion.”

Evaluation Data

- A synthetic test set generated using a template-based approach, as suggested in [11], where identity terms are swapped into a variety of template sentences.
- Synthetic data is valuable here because [11] shows that real data often has disproportionate amounts of toxicity directed at specific groups. Synthetic data ensures that we evaluate on data that represents both toxic and non-toxic statements referencing a variety of groups.

Caveats and Recommendations

- Synthetic test data covers only a small set of very specific comments. While these are designed to be representative of common use cases and concerns, it is not comprehensive.

see also <https://modelcards.withgoogle.com/about>

Mitchell, Margaret, et al. "Model cards for model reporting." In Proceedings of the Conference on fairness, accountability, and transparency, pp. 220-229. 2019.

HOMEWORK 6: FAIRNESS

(credit scoring + recommendation, model + system)

INTERPRETABILITY AND EXPLAINABILITY

Christian Kaestner

Required reading: □ Data Skeptic Podcast Episode “[Black Boxes are not Required](#)” with Cynthia Rudin (32min) or □ Rudin, Cynthia. "[Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead.](#)" Nature Machine Intelligence 1, no. 5 (2019): 206-215.

Recommended supplementary reading: □ Christoph Molnar. "[Interpretable Machine Learning: A Guide for Making Black Box Models Explainable](#)." 2019

LEARNING GOALS

- Understand the importance of and use cases for interpretability
- Explain the tradeoffs between inherently interpretable models and post-hoc explanations
- Measure interpretability of a model
- Select and apply techniques to debug/provide explanations for data, models and model predictions
- Eventuate when to use interpretable models rather than ex-post explanations

DETECTING ANOMALOUS COMMITS

The screenshot shows a GitHub commit page for a pull request. The commit message is titled "v8: don't busy loop in cpu profiler thread". It describes a change to reduce CPU overhead by replacing `sched_yield()` with `nanosleep()`. The commit notes that before this, the thread would effectively be a busy loop. It includes PR and issue references, and a review by Trevor Norris.

Below the commit message, it shows the author as "bnoordhuis" from November 2014, with 1 parent commit. A "Show Details" button is present.

At the bottom, a blue header bar reads "ADDITIONAL INFORMATION FOR THIS COMMIT". Below it, a bulleted list highlights unusual commit patterns:

- Changes were committed at 6am UTC -- **bnoordhuis rarely** commits around that time. (fewer than 0.7% of all commits by bnoordhuis are around that time)
- .gyp files were changed -- such files are **rarely** changed in this repository. (fewer than 2% of all file types changed)
- .cc and .gyp files were changed in the same commit -- this combination of files is **rarely changed together**. (in fewer than 2% of all commits)
- .cc and .gyp files were changed in the same commit -- this combination of files is **rarely changed together** by **bnoordhuis**. (in fewer than 3% of all commits by bnoordhuis)
- .gyp files were changed -- such files are **rarely** changed by **bnoordhuis**. (fewer than 3% of all file types changed by bnoordhuis)

Goyal, Raman, Gabriel Ferreira, Christian Kästner, and James Herbsleb.
"Identifying unusual commits on GitHub." Journal of Software: Evolution and Process 30, no. 1 (2018): e1893.

IS THIS RECIDIVISM MODEL FAIR?

```
IF age between 18-20 and sex is male THEN predict arrest  
ELSE  
IF age between 21-23 and 2-3 prior offenses THEN predict arrest  
ELSE  
IF more than three priors THEN predict arrest  
ELSE predict no arrest
```

Rudin, Cynthia. "[Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead.](#)" Nature Machine Intelligence 1, no. 5 (2019): 206-215.

WHAT FACTORS GO INTO PREDICTING STROKE RISK?

1. <i>Congestive Heart Failure</i>	1 point	...
2. <i>Hypertension</i>	1 point	+
3. <i>Age ≥ 75</i>	1 point	+
4. <i>Diabetes Mellitus</i>	1 point	+
5. <i>Prior Stroke or Transient Ischemic Attack</i>	2 points	+
ADD POINTS FROM ROWS 1–5	SCORE	= ...

SCORE	0	1	2	3	4	5	6
STROKE RISK	1.9%	2.8%	4.0%	5.9%	8.5%	12.5%	18.2%

Rudin, Cynthia, and Berk Ustun. "Optimized scoring systems: Toward trust in machine learning for healthcare and criminal justice." *Interfaces* 48, no. 5 (2018): 449-466.

IS THERE AN ACTUAL PROBLEM? HOW TO FIND OUT?

A screenshot of a Twitter post from user DHH (@dhh). The post contains a tweet with a profile picture, a blue checkmark, the handle @dhh, and the Twitter logo. The tweet text is: "The [@AppleCard](#) is such a fucking sexist program. My wife and I filed joint tax returns, live in a community-property state, and have been married for a long time. Yet Apple's black box algorithm thinks I deserve 20x the credit limit she does. No appeals work." Below the tweet are timestamp, interaction count, and a link icon.

The tweet text is:

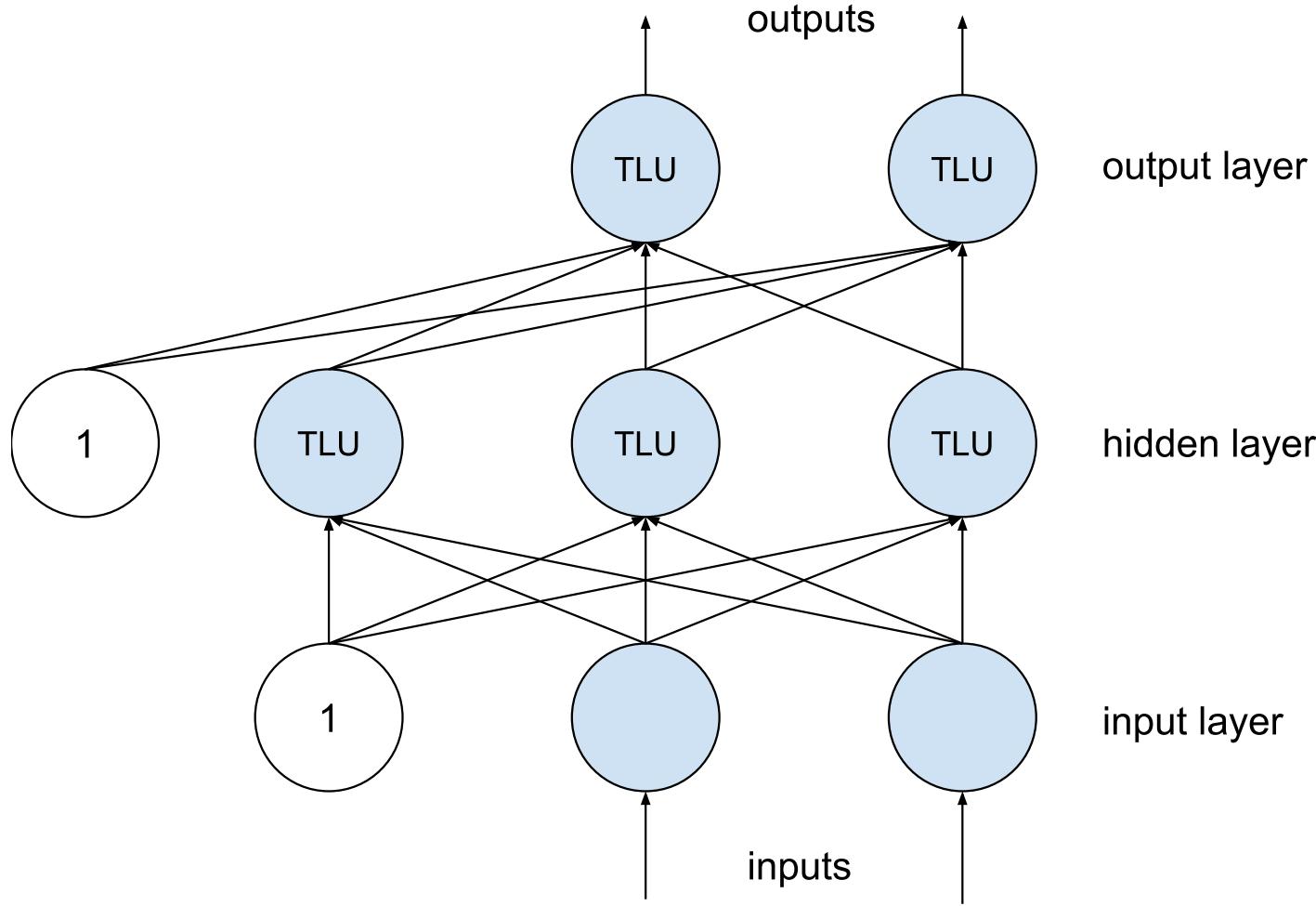
The [@AppleCard](#) is such a fucking sexist program. My wife and I filed joint tax returns, live in a community-property state, and have been married for a long time. Yet Apple's black box algorithm thinks I deserve 20x the credit limit she does. No appeals work.

8:34 PM · Nov 7, 2019

28.5K

10.6K people are Tweeting about this

WHAT'S HAPPENING HERE?



LEGAL REQUIREMENTS

The European Union General Data Protection Regulation extends the automated decision-making rights in the 1995 Data Protection Directive to provide a legally disputed form of a right to an explanation: "[the data subject should have] the right ... to obtain an explanation of the decision reached"

US Equal Credit Opportunity Act requires to notify applicants of action taken with specific reasons: "The statement of reasons for adverse action required by paragraph (a)(2)(i) of this section must be specific and indicate the principal reason(s) for the adverse action."

See also https://en.wikipedia.org/wiki/Right_to_explanation

DEBUGGING

- Why did the system make a wrong prediction in this case?
- What does it actually learn?
- What kind of data would make it better?
- How reliable/robust is it?
- How much does the second model rely on the outputs of the first?
- Understanding edge cases

CURIOSITY, LEARNING, DISCOVERY, SCIENCE

- What drove our past hiring decisions? Who gets promoted around here?
- What factors influence cancer risk? Recidivism?
- What influences demand for bike rentals?
- Which organizations are successful at raising donations and why?

INTERPRETABILITY DEFINITIONS

Interpretability is the degree to which a human can understand the cause of a decision

Interpretability is the degree to which a human can consistently predict the model's result.

(No mathematical definition)

GOOD EXPLANATIONS ARE CONTRASTIVE

Counterfactuals. *Why this, rather than a different prediction?*

Your loan application has been declined. If your savings account had had more than \$100 your loan application would be accepted.

Partial explanations often sufficient in practice if contrastive

INHERENTLY INTERPRETABLE MODELS: SPARSE LINEAR MODELS

$$f(x) = \alpha + \beta_1 x_1 + \dots + \beta_n x_n$$

Truthful explanations, easy to understand for humans

Easy to derive contrastive explanation and feature importance

Requires feature selection/regularization to minimize to few important features
(e.g. Lasso); possibly restricting possible parameter values

1. <i>Congestive Heart Failure</i>	1 point	...					
2. <i>Hypertension</i>	1 point	+					
3. <i>Age ≥ 75</i>	1 point	+					
4. <i>Diabetes Mellitus</i>	1 point	+					
5. <i>Prior Stroke or Transient Ischemic Attack</i>	2 points	+					
ADD POINTS FROM ROWS 1–5		SCORE					
		= ...					
SCORE	0	1	2	3	4	5	6
STROKE RISK	1.9%	2.8%	4.0%	5.9%	8.5%	12.5%	18.2%

INHERENTLY INTERPRETABLE MODELS: DECISION TREES

Easy to interpret up to a size

Possible to derive counterfactuals and feature importance

Unstable with small changes to training data

```
IF age between 18-20 and sex is male THEN predict arrest  
ELSE IF age between 21-23 and 2-3 prior offenses THEN predict ar  
ELSE IF more than three priors THEN predict arrest  
ELSE predict no arrest
```

POST-HOC EXPLANATIONS OF BLACK-BOX MODELS

(large research field, many approaches, much recent research)

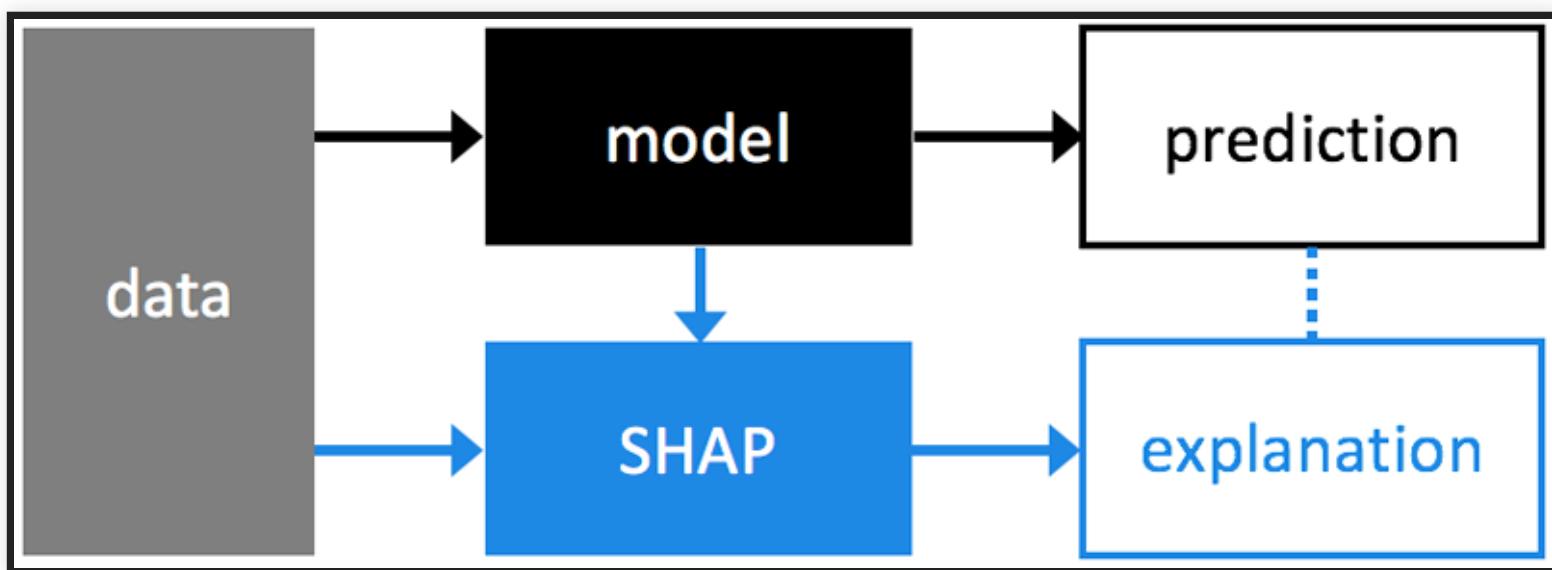


Figure: Lundberg, Scott M., and Su-In Lee. [A unified approach to interpreting model predictions](#). Advances in Neural Information Processing Systems. 2017.

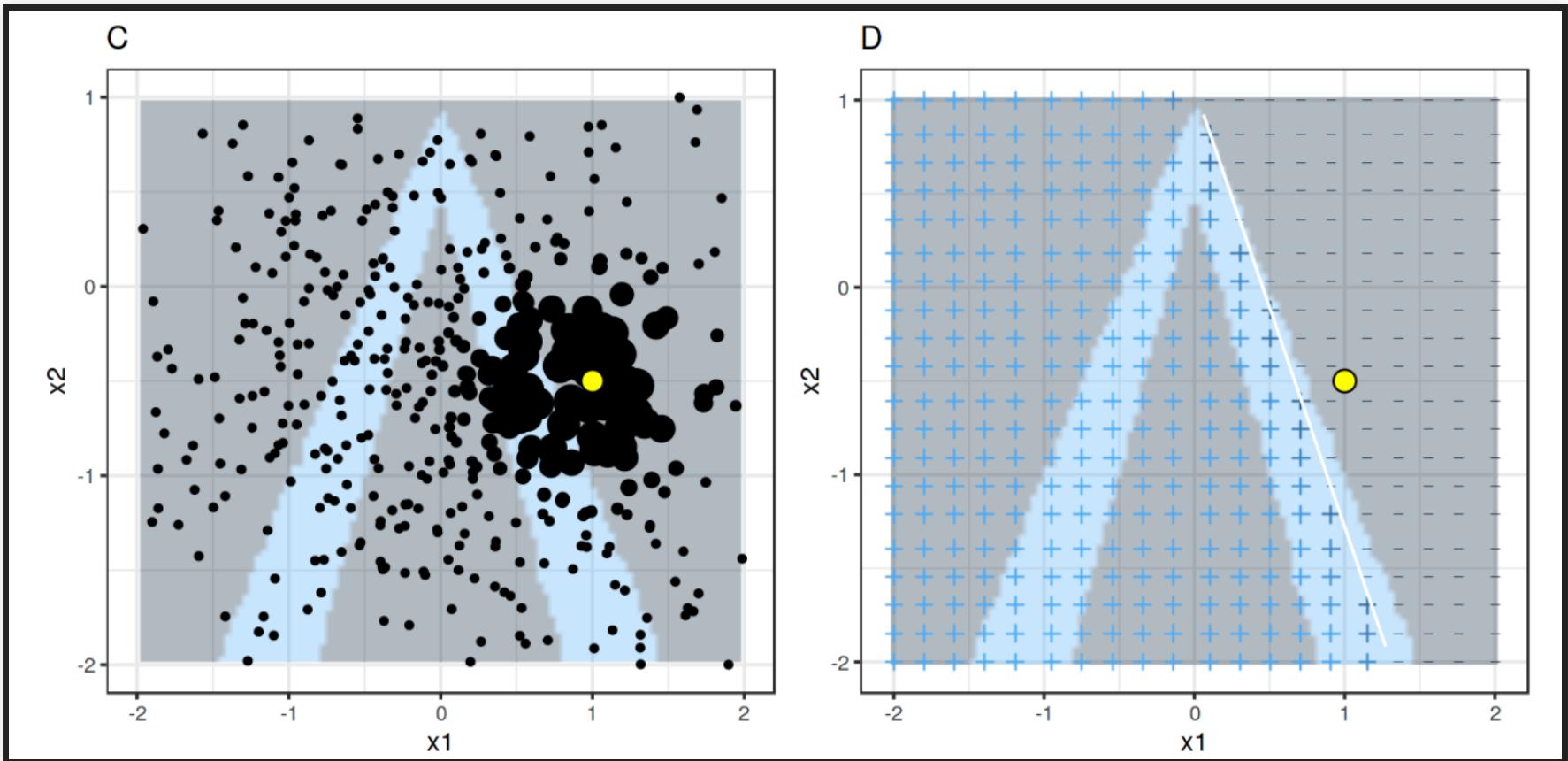
GLOBAL SURROGATES

1. Select dataset X (previous training set or new dataset from same distribution)
2. Collect model predictions for every value ($y_i = f(x_i)$)
3. Train inherently interpretable model g on (X,Y)
4. Interpret surrogate model g

Can measure how well g fits f with common model quality measures, typically R^2

Advantages? Disadvantages?

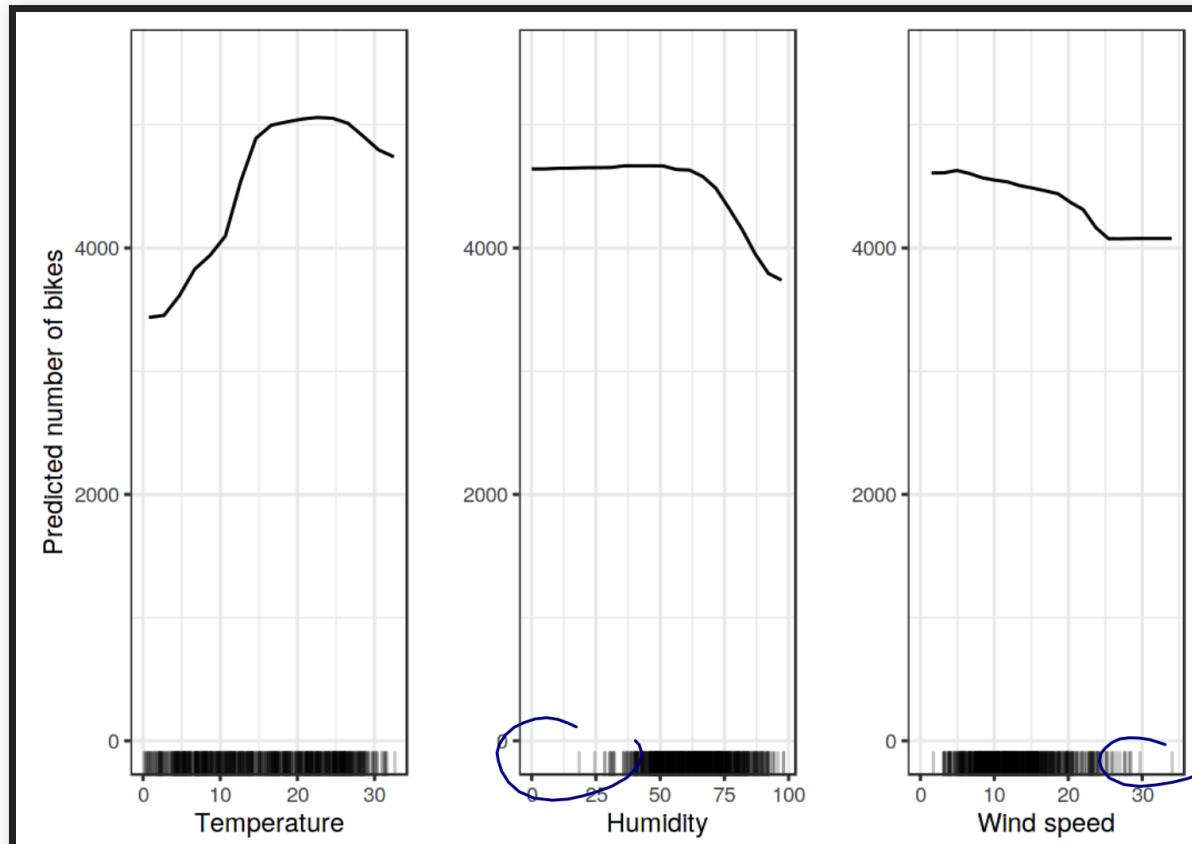
LIME EXAMPLE



Source: Christoph Molnar. "[Interpretable Machine Learning: A Guide for Making Black Box Models Explainable.](#)"
2019

PARTIAL DEPENDENCE PLOT EXAMPLE

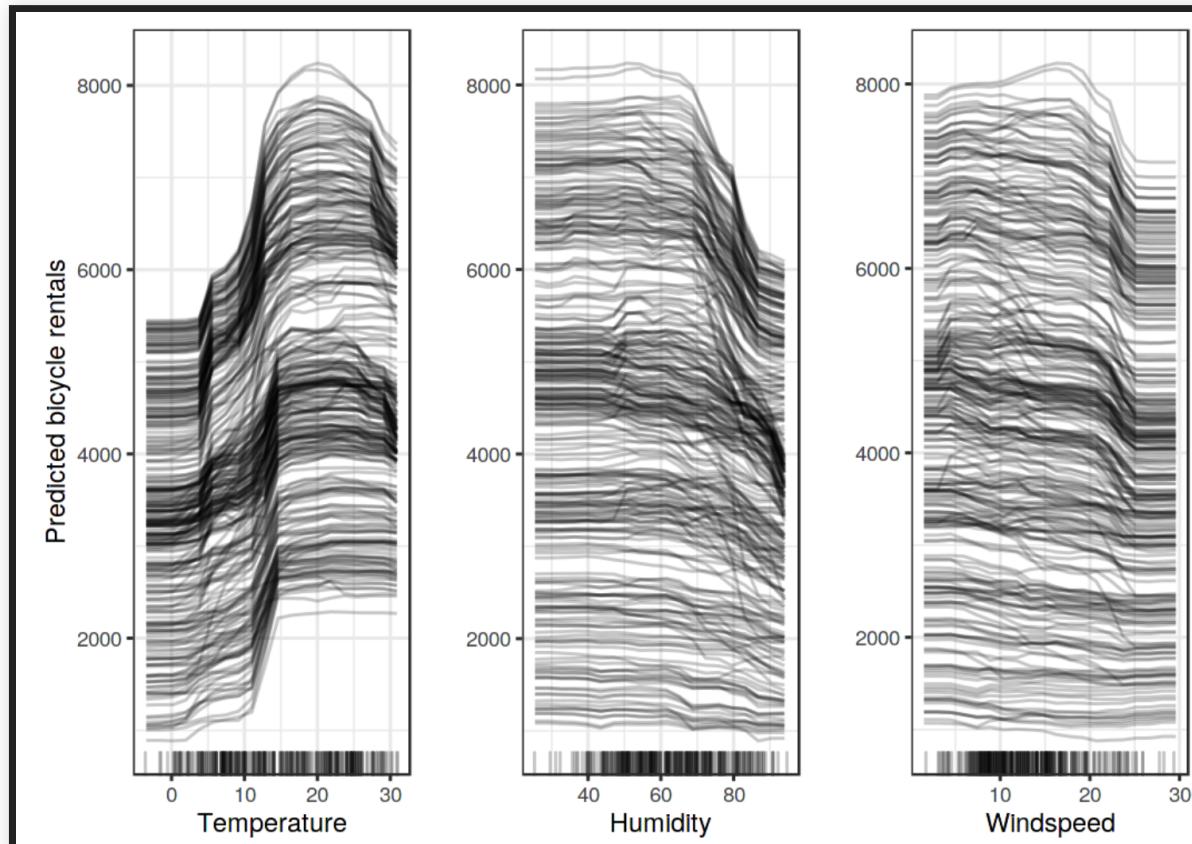
Bike rental in DC



Source: Christoph Molnar. "[Interpretable Machine Learning](#)." 2019

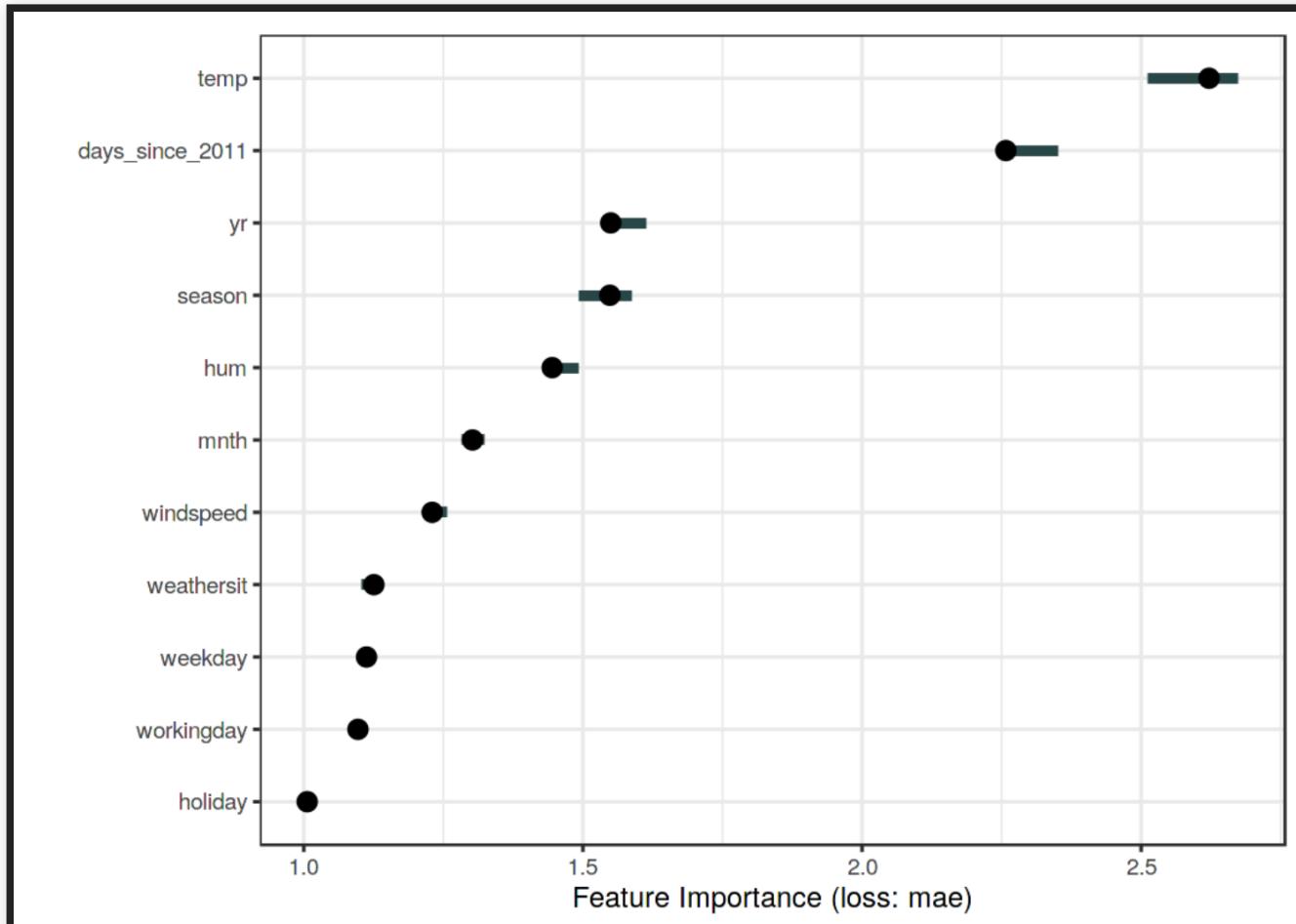
INDIVIDUAL CONDITIONAL EXPECTATION (ICE)

Similar to PDP, but not averaged; may provide insights into interactions



Source: Christoph Molnar. "[Interpretable Machine Learning](#)." 2019

FEATURE IMPORTANCE EXAMPLE



Source: Christoph Molnar. "[Interpretable Machine Learning](#)." 2019

EXAMPLE: ANCHORS

	If	Predict
adult	No capital gain or loss, never married	$\leq 50K$
	Country is US, married, work hours > 45	$> 50K$
rcdvs	No priors, no prison violations and crime not against property	Not rearrested
	Male, black, 1 to 5 priors, not married, and crime not against property	Re-arrested
lending	FICO score ≤ 649	Bad Loan
	$649 \leq \text{FICO score} \leq 699$ and $\$5,400 \leq \text{loan amount} \leq \$10,000$	Good Loan

Source: Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. "[Anchors: High-precision model-agnostic explanations](#)." In Thirty-Second AAAI Conference on Artificial Intelligence. 2018.

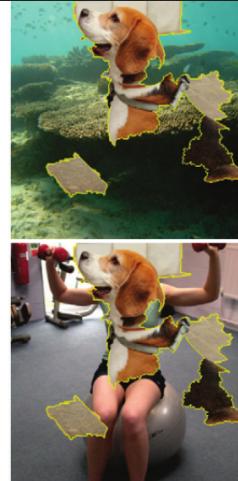
EXAMPLE: ANCHORS



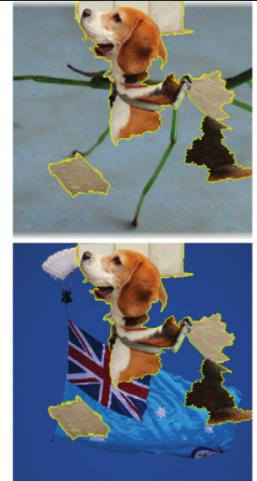
(a) Original image



(b) Anchor for “beagle”



(c) Images where Inception predicts $P(\text{beagle}) > 90\%$



Source: Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. "[Anchors: High-precision model-agnostic explanations](#)." In Thirty-Second AAAI Conference on Artificial Intelligence. 2018.

COUNTERFACTUAL EXPLANATIONS

if X had not occurred, Y would not have happened

Your loan application has been declined. If your savings account had had more than \$100 your loan application would be accepted.

-> Smallest change to feature values that result in given output

MULTIPLE COUNTERFACTUALS

Often long or multiple explanations

Your loan application has been declined. If your savings account ...

Your loan application has been declined. If you lived in

...

Report all or select "best" (e.g. shortest, most actionable, likely values)

(Rashomon effect)



GAMING/ATTACKING THE MODEL WITH EXPLANATIONS?

Does providing an explanation allow customers to 'hack' the system?

- Loan applications?
- Apple FaceID?
- Recidivism?
- Auto grading?
- Cancer diagnosis?
- Spam detection?



GAMING THE MODEL WITH EXPLANATIONS?

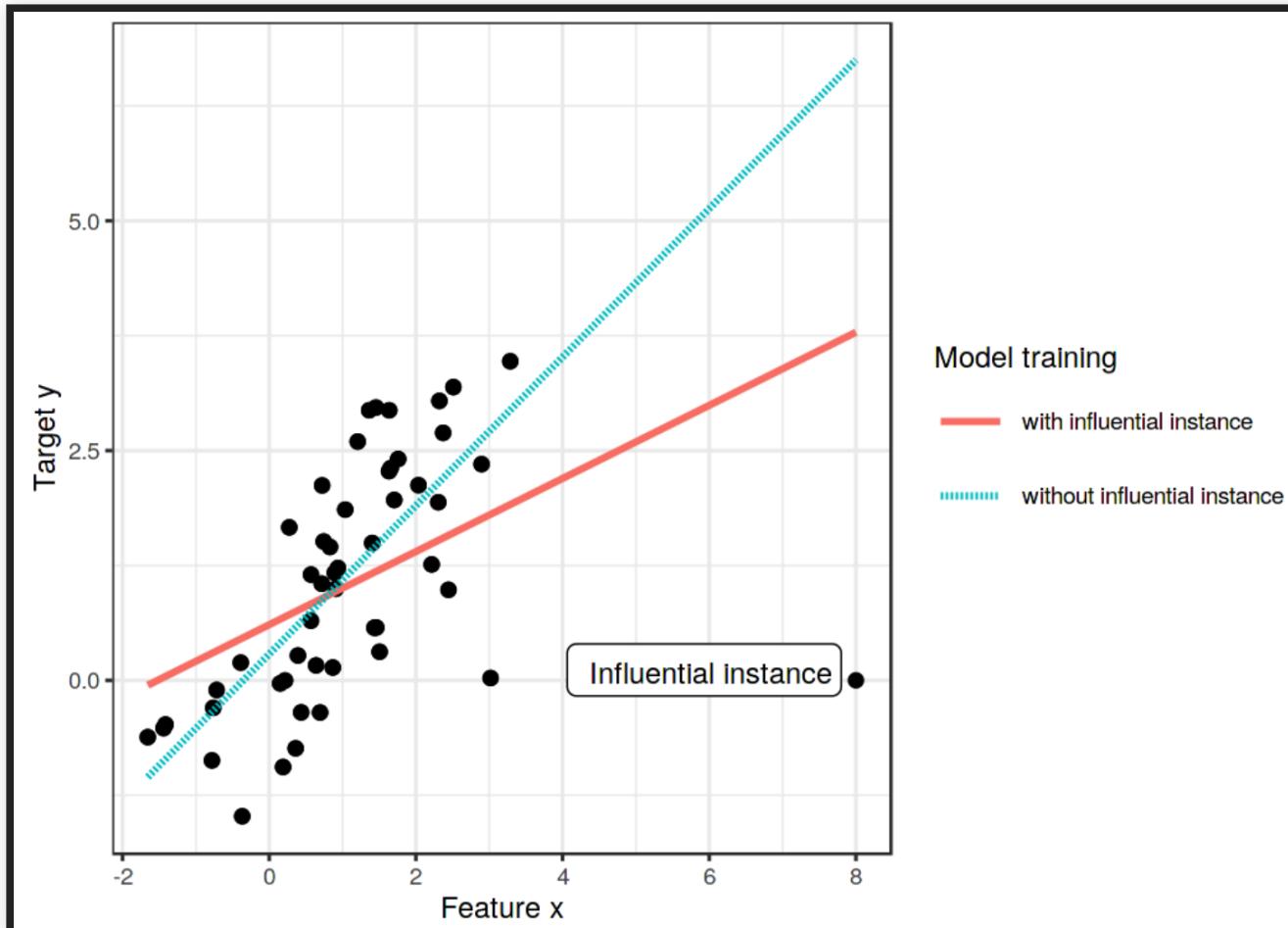


EXAMPLE: PROTOTYPES AND CRITICISMS



Source: Christoph Molnar. "[Interpretable Machine Learning: A Guide for Making Black Box Models Explainable.](#)"
2019

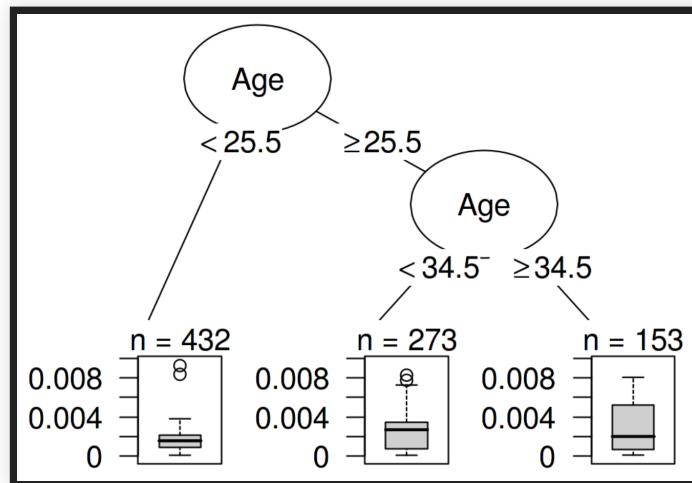
EXAMPLE: INFLUENTIAL INSTANCE



Source: Christoph Molnar. "[Interpretable Machine Learning](#)." 2019

WHAT DISTINGUISHES AN INFLUENTIAL INSTANCE FROM A NON-INFLUENTIAL INSTANCE?

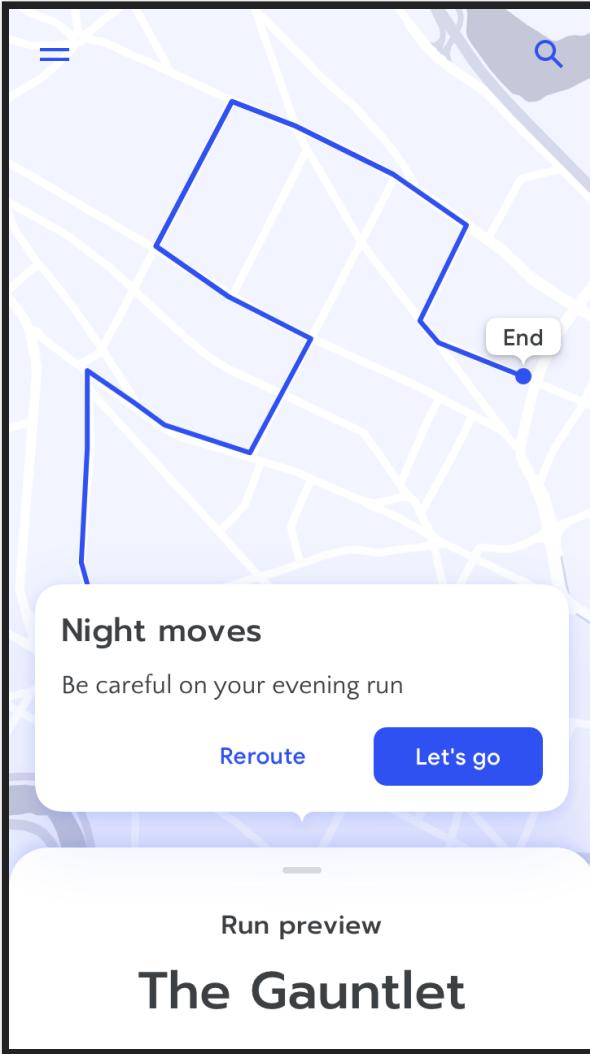
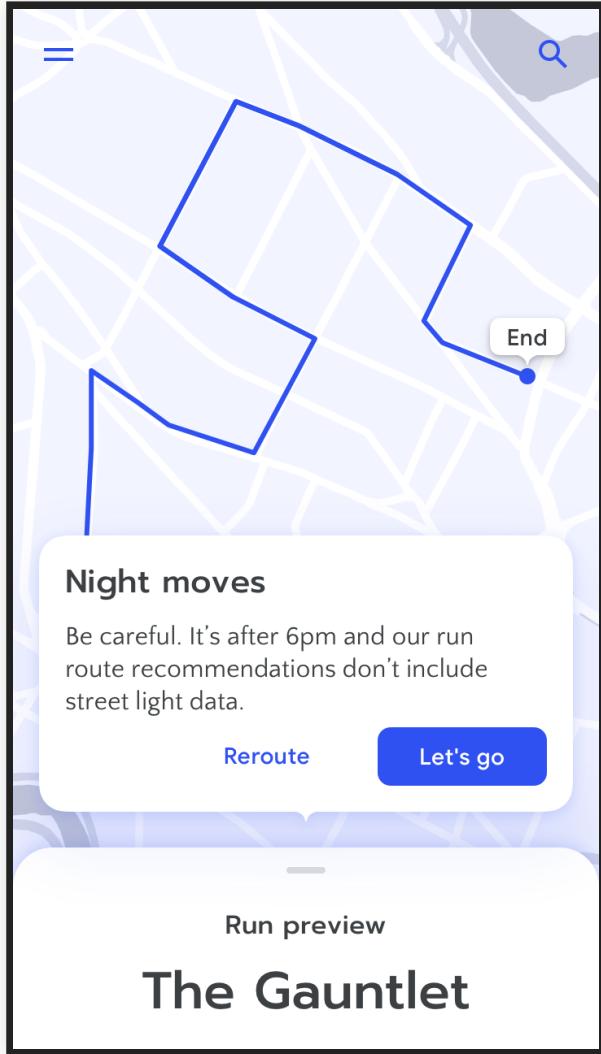
Compute influence of every data point and create new model to explain influence in terms of feature values



(cancer prediction example)

Which features have a strong influence but little support in the training data?

Source: Christoph Molnar. "[Interpretable Machine Learning](#)." 2019



Tell the user when a lack of data might mean they'll need to use their own judgment. Don't be afraid to admit when a lack of data could affect the quality of the AI recommendations.

Source: [People + AI Guidebook](#), Google

CASE STUDY: FACEBOOK'S FEED CURATION

All Stories



Aaron Bird
"Happy Birthday, Clay! Much love!" on Clay Huston's timeline.

Saturday 20th September 7:29 AM.



Meem Malekushlugh
Meem Malekushlugh posted a video.



Saturday 20th September 12:30 PM.



Ankush Dharker
Chatted with Mark Cuban (from Shark Tank) on his Cyber Dust. Very thoughtful and useful app.
Give it a try and add me: +ankushdharker

Friday 19th September 2:41 PM.



Mohammad Sameki
WOW, I wish I was there:)



Saturday 20th September 12:27 PM.



Aaron Bird
Not sure I want to know when I'll die, but 83 sounds okay

Shown Stories



Meem Malekushlugh
Meem Malekushlugh posted a video.



Saturday 20th September 12:30 PM.



Mohammad Sameki
WOW, I wish I was there:)



Saturday 20th September 12:27 PM.



Aaron Bird
Not sure I want to know when I'll die, but 83 sounds okay



Eslami, Motahhare, Aimee Rickman, Kristen Vaccaro, Amirhossein Aleyasen, Andy Vuong, Karrie Karahalios, Kevin Hamilton, and Christian Sandvig. [I always assumed that I wasn't really that close to \[her\]: Reasoning about Invisible Algorithms in News Feeds](#). In Proceedings of the 33rd annual ACM conference on human factors in computing systems, pp. 153-162. ACM, 2015.

CASE STUDY: HR APPLICATION SCREENING



Listening to The Cure and thinking about t... 

@TheWrongNoel

A friend of mine has been trying to hire a new employee for her department in a medium-sized org. After advertising several times with few applicants, and a couple of rounds of interviews, the new employee is less than great. Then she discovered there were other applicants ...

5:01 AM · Nov 14, 2019



13.3K



8.3K people are Tweeting about this

**"STOP EXPLAINING BLACK
BOX MACHINE LEARNING
MODELS FOR HIGH STAKES
DECISIONS AND USE
INTERPRETABLE MODELS
INSTEAD."**

Cynthia Rudin (32min) or [Cynthia Rudin](#), Cynthia. "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead." *Nature Machine Intelligence* 1, no. 5 (2019): 206-215.

Microsoft AI principles

We put our responsible AI principles into practice through the Office of Responsible AI (ORA) and the AI, Ethics, and Effects in Engineering and Research (Aether) Committee. The Aether Committee advises our leadership on the challenges and opportunities presented by AI innovations. ORA sets our rules and governance processes, working closely with teams across the company to enable the effort.

[Learn more about our approach >](#)

Fairness

AI systems should treat all people fairly

[▷ Play video on fairness](#)

Reliability & Safety

AI systems should perform reliably and safely

[▷ Play video on reliability](#)

Privacy & Security

AI systems should be secure and respect privacy

[▷ Play video on privacy](#)

Inclusiveness

AI systems should empower everyone and engage people

[▷ Play video on inclusiveness](#)

Transparency

AI systems should be understandable

[▷ Play video on transparency](#)

Accountability

People should be accountable for AI systems

[▷ Play video on accountability](#)

4,576 views | Mar 1, 2020, 01:00am EST

This Is The Year Of AI Regulations



Kathleen Walch Contributor

COGNITIVE WORLD Contributor Group ⓘ

AI

-
- f The world of artificial intelligence is constantly evolving, and certainly so is the legal and regulatory environment

VERSIONING, PROVENANCE, AND REPRODUCABILITY

Christian Kaestner

Required reading: □ Halevy, Alon, Flip Korn, Natalya F. Noy, Christopher Olston, Neoklis Polyzotis, Sudip Roy, and Steven Euijong Whang. [Goods: Organizing google's datasets](#). In Proceedings of the 2016 International Conference

LEARNING GOALS

- Judge the importance of data provenance, reproducibility and explainability for a given system
- Create documentation for data dependencies and provenance in a given system
- Propose versioning strategies for data and models
- Design and test systems for reproducibility



DHH  @dhh · Nov 8, 2019



Replying to @dhh

I wasn't even pessimistic to expect this outcome, but here we are: [@AppleCard](#) just gave my wife the VIP bump to match my credit limit, but continued to be an utter fucking failure of a customer service experience. Let me explain...



DHH 

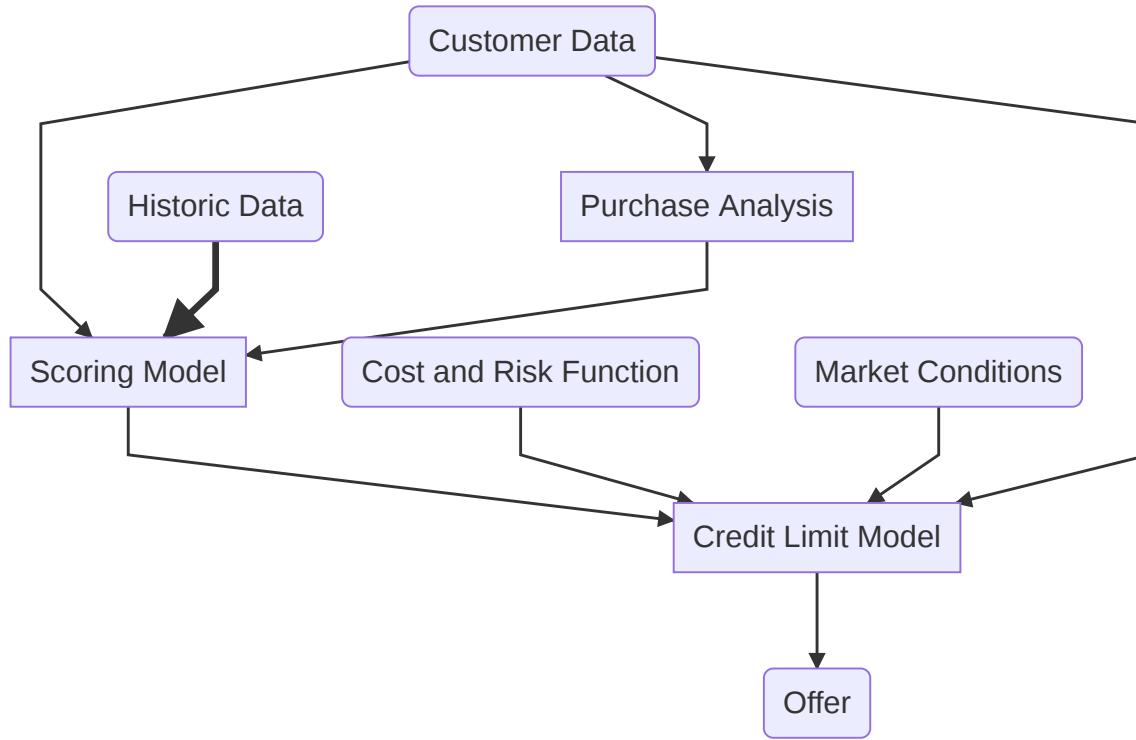
@dhh

She spoke to two Apple reps. Both very nice, courteous people representing an utterly broken and reprehensible system. The first person was like "I don't know why, but I swear we're not discriminating, IT'S JUST THE ALGORITHM". I shit you not. "IT'S JUST THE ALGORITHM!".

11:20 PM · Nov 8, 2019



 4.8K  625 people are Tweeting about this



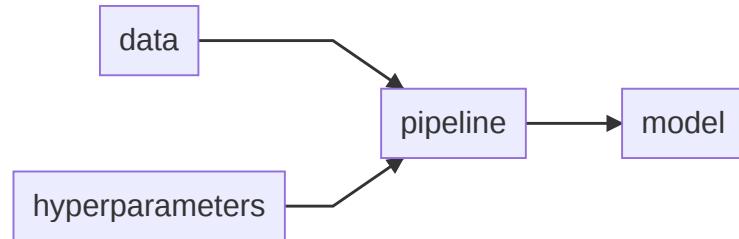
DATA PROVENANCE

- Track origin of all data
 - Collected where?
 - Modified by whom, when, why?
 - Extracted from what other data or model or algorithm?
- ML models often based on data derived from many sources through many steps, including other models

VERSIONING DATASETS

- Store copies of entire datasets (like Git)
- Store deltas between datasets (like Mercurial)
- Offsets in append-only database (like Kafka offset)
- History of individual database records (e.g. S3 bucket versions)
 - some databases specifically track provenance (who has changed what entry when and how)
 - specialized data science tools eg [Hangar](#) for tensor data
- Version pipeline to recreate derived datasets ("views", different formats)
 - e.g. version data before or after cleaning?
- Often in cloud storage, distributed
- Checksums often used to uniquely identify versions
- Version also metadata

VERSIONING PIPELINES



EXAMPLE: DVC

```
dvc add images  
dvc run -d images -o model.p cnn.py  
dvc remote add myrepo s3://mybucket  
dvc push
```

- Tracks models and datasets, built on Git
- Splits learning into steps, incrementalization
- Orchestrates learning in cloud resources

<https://dvc.org/>

EXAMPLE: MODELDB



<https://github.com/mitdbg/modedb>

EXAMPLE: MLFLOW

- Instrument pipeline with *logging* statements
- Track individual runs, hyperparameters used, evaluation results, and model files

Listing Price Prediction

Experiment ID: 0

Artifact Location: /Users/matei/mlflow/demo/mlruns/0

Search Runs:

metrics.R2 > 0.24

Search

Filter Params:

alpha, lr

Filter Metrics:

rmse, r2

Clear

4 matching runs

Compare Selected

Download CSV 

	Time	User	Source	Version	Parameters		Metrics		
					alpha	l1_ratio	MAE	R2	RMSE
<input type="checkbox"/>	17:37	matei	linear.py	3a1995	0.5	0.2	84.27	0.277	158.1
<input type="checkbox"/>	17:37	matei	linear.py	3a1995	0.2	0.5	84.08	0.264	159.6
<input type="checkbox"/>	17:37	matei	linear.py	3a1995	0.5	0.5	84.12	0.272	158.6
<input type="checkbox"/>	17:37	matei	linear.py	3a1995	0	0	84.49	0.249	161.2

Matei Zaharia. [Introducing MLflow: an Open Source Machine Learning Platform](#), 2018

DEFINITIONS

- **Reproducibility:** the ability of an experiment to be repeated with minor differences from the original experiment, while achieving the same qualitative result
- **Replicability:** ability to reproduce results exactly, achieving the same quantitative result; requires determinism
- In science, reproducing results under different conditions are valuable to gain confidence
 - "conceptual replication": evaluate same hypothesis with different experimental procedure or population
 - many different forms distinguished "... replication" (e.g. close, direct, exact, independent, literal, nonexperimental, partial, retest, sequential, statistical, varied, virtual)

Juristo, Natalia, and Omar S. Gómez. "[Replication of software engineering experiments](#)." In Empirical software engineering and verification, pp. 60-88. Springer, Berlin, Heidelberg, 2010.

NONDETERMINISM

- Some machine learning algorithms are nondeterministic
 - Recall: Neural networks initialized with random weights
 - Recall: Distributed learning
- Many notebooks and pipelines contain nondeterminism
 - Depend on snapshot of online data (e.g., stream)
 - Depend on current time
 - Initialize random seed
- Different library versions installed on the machine may affect results
- (Inference for a given model is usually deterministic)

PROJECT M3: MONITORING AND CONTINUOUS DEPLOYMENT

(containization, monitoring, canary releases, provenance)

SECURITY, ADVERSARIAL LEARNING, AND PRIVACY

Christian Kaestner

with slides from Eunsuk Kang

Required reading: □ Hulten, Geoff. "Building Intelligent Systems: A Guide to Machine Learning Engineering." (2018), Chapter 25 (Adversaries and Abuse) □ Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: the simple economics of artificial intelligence*. Harvard Business Press. Chapter 19 (Managing AI Risk)

Recommended reading: □ Goodfellow, I., McDaniel, P., & Papernot, N. (2018). *Making machine learning robust against adversarial inputs*. *Communications of the ACM*, 61(7), 56-66. □ Huang, L., Joseph, A. D., Nelson, B., Rubinstein, B. I., & Tygar, J. D. (2011, October). *Adversarial machine learning*. In *Proceedings of the 4th ACM workshop on Security and artificial intelligence* (pp. 43-58).

LEARNING GOALS

- Explain key concerns in security (in general and with regard to ML models)
- Analyze a system with regard to attacker goals, attack surface, attacker capabilities
- Describe common attacks against ML models, including poisoning attacks, evasion attacks, leaking IP and private information
- Measure robustness of a prediction and a model
- Understand design opportunities to address security threats at the system level
- Identify security requirements with threat modeling
- Apply key design principles for secure system design
- Discuss the role of AI in securing software systems

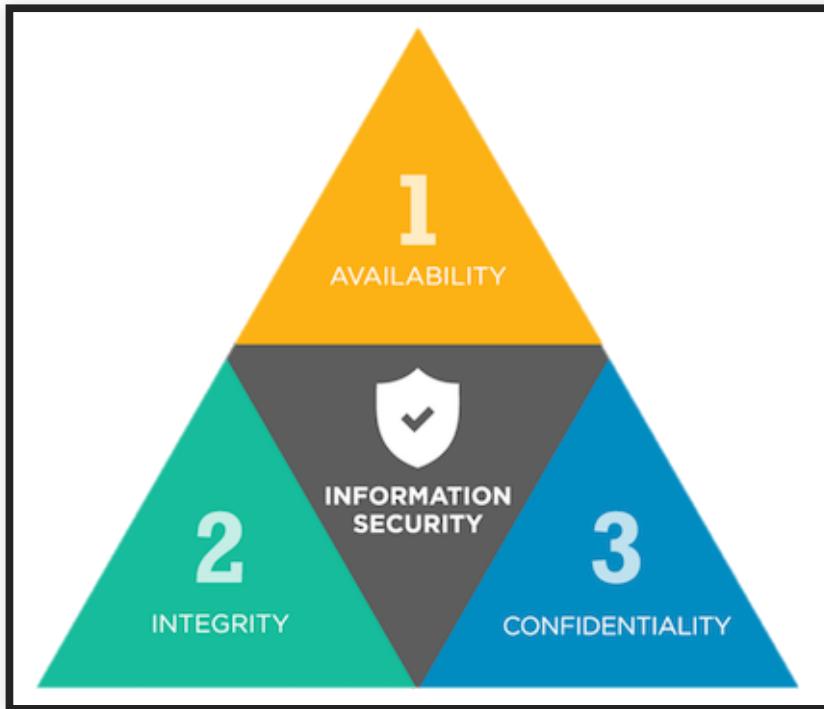
SECURITY AT THE MODEL LEVEL

- Various attack discussions, e.g. poisoning attacks
- Model robustness
- Attack detection
- ...

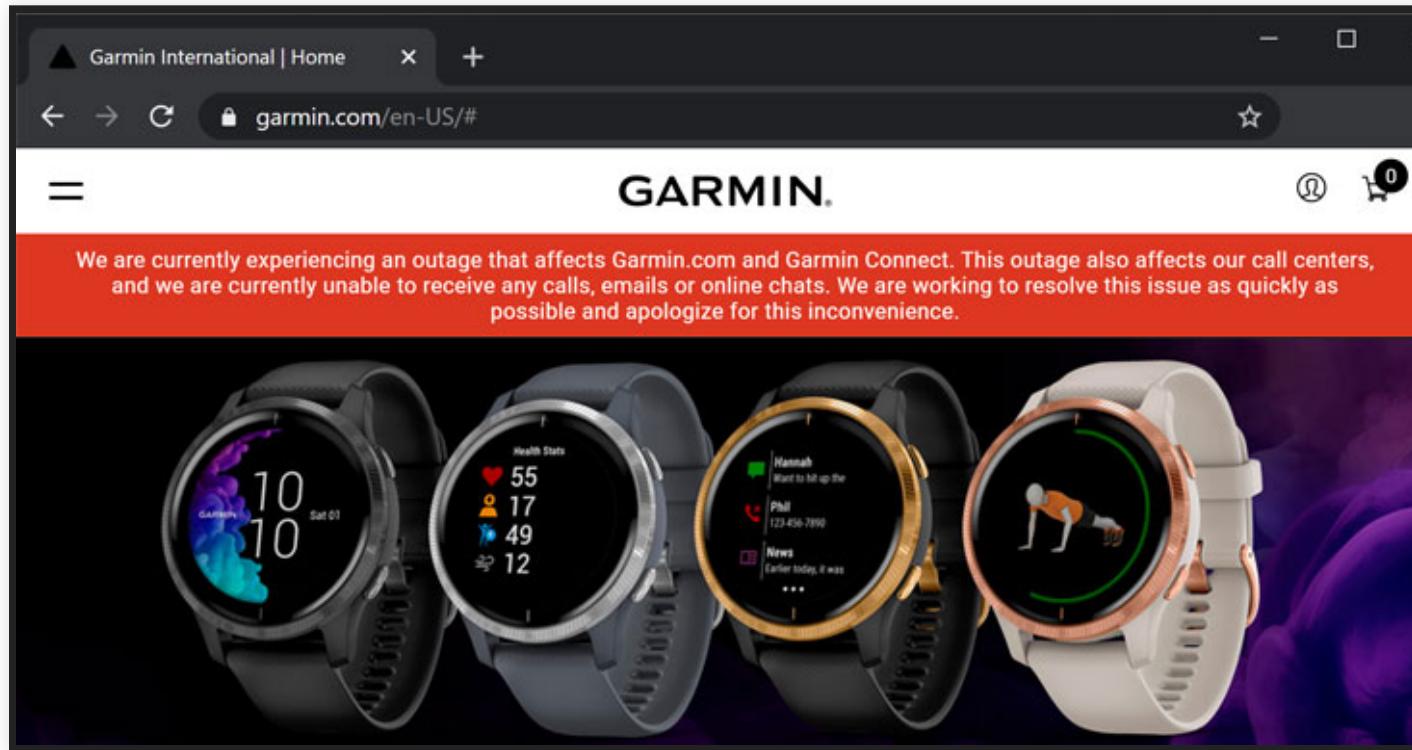
SECURITY AT THE SYSTEM LEVEL

- Requirements analysis
- System-level threat modeling
- Defense strategies beyond the model
- Security risks beyond the model
- ...

SECURITY REQUIREMENTS



- "CIA triad" of information security
- **Confidentiality:** Sensitive data must be accessed by authorized users only
- **Integrity:** Sensitive data must be modifiable by authorized users only
- **Availability:** Critical services must be available when needed by clients



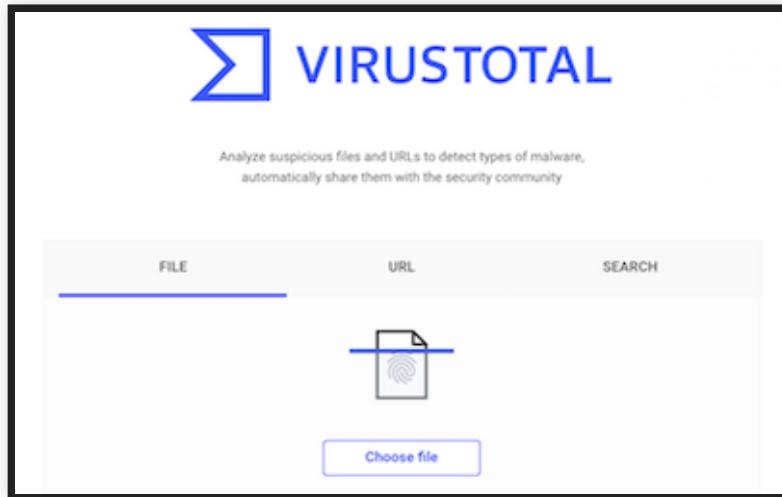
ATTACKER GOALS AND INCENTIVES

- What is the attacker trying to achieve? Undermine one or more security requirements
- Why does the attacker want to do this?

Example goals and incentives in Garmin/college admission scenario?

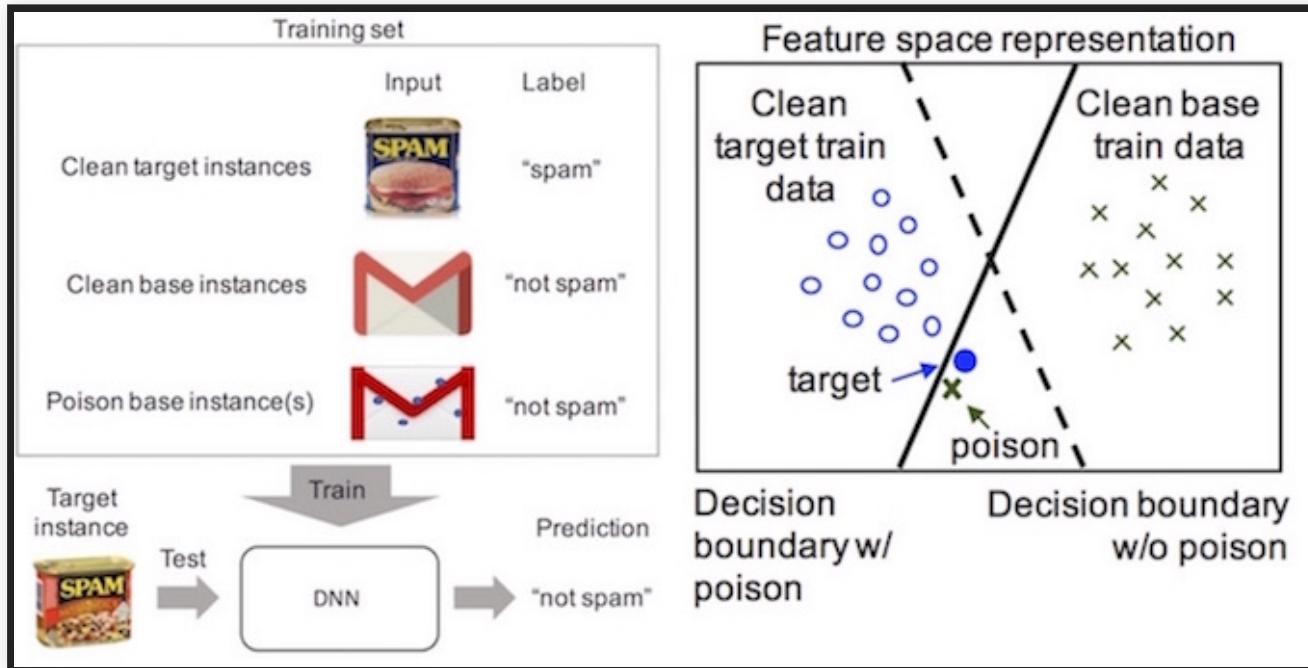


POISONING ATTACK: AVAILABILITY



- Availability: Inject mislabeled training data to damage model quality
 - 3% poisoning => 11% decrease in accuracy (Steinhardt, 2017)
- Attacker must have some access to the training set
 - models trained on public data set (e.g., ImageNet)
 - retrained automatically on telemetry

POISONING ATTACK: INTEGRITY



- Insert training data with seemingly correct labels
- More targeted than availability attacks
 - Cause misclassification from one specific class to another

Poison Frogs! Targeted Clean-Label Poisoning Attacks on Neural Networks, Shafahi et al. (2018)

POISONING ATTACK IN WEB SHOP?



Antique Box Ugears, 3D Mechanical Treasure Models, Self-Assembling Precut Wooden Gift, DIY Craft Set

★★★★★ v 261

\$41⁹⁰ Was \$44.00

FREE Delivery for Prime members
Only 1 left in stock - order soon.

More Buying Choices
\$38.89 (44 new offers)

Ages: 14 years and up



ROKR 3D Wooden Puzzle for Adults-Mechanical Train Model Kits-Brain Teaser Puzzles-Vehicle Building Kits-Unique Gi...

★★★★★ v 44

\$22⁹⁹

✓prime FREE One-Day
Get it **Tomorrow, Jul 26**

Ages: 14 years and up



Wooden Puzzles for Toddlers, Aitey Wooden Alphabet Number Puzzles Toddler Learning Puzzle Toys for Kids Ages 2 3 4 (Set of...

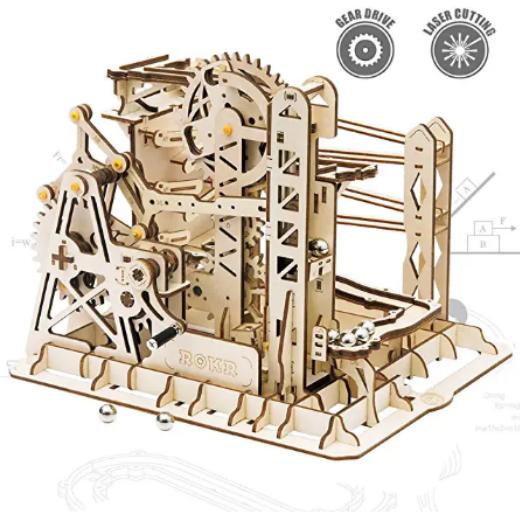
★★★★★ v 283

\$23⁹⁹

✓prime FREE One-Day
Get it **Tomorrow, Jul 26**

More Buying Choices
\$22.79 (2 used & new offers)

Ages: 12 months and up



ROKR 3D Assembly Wooden
Puzzle Brain Teaser Game
Mechanical Gears Set Model Kit
Marble Run Set Unique Craft...

★★★★★ 172

\$20.99



Unidragon Wooden Jigsaw
Puzzles - Unique Shape Jigsaw
Pieces Best Gift for Adults and
Kids Alluring Fox 7 x 9.2 in (18 ...

★★★★★ 13

\$10.99 +\$0.00



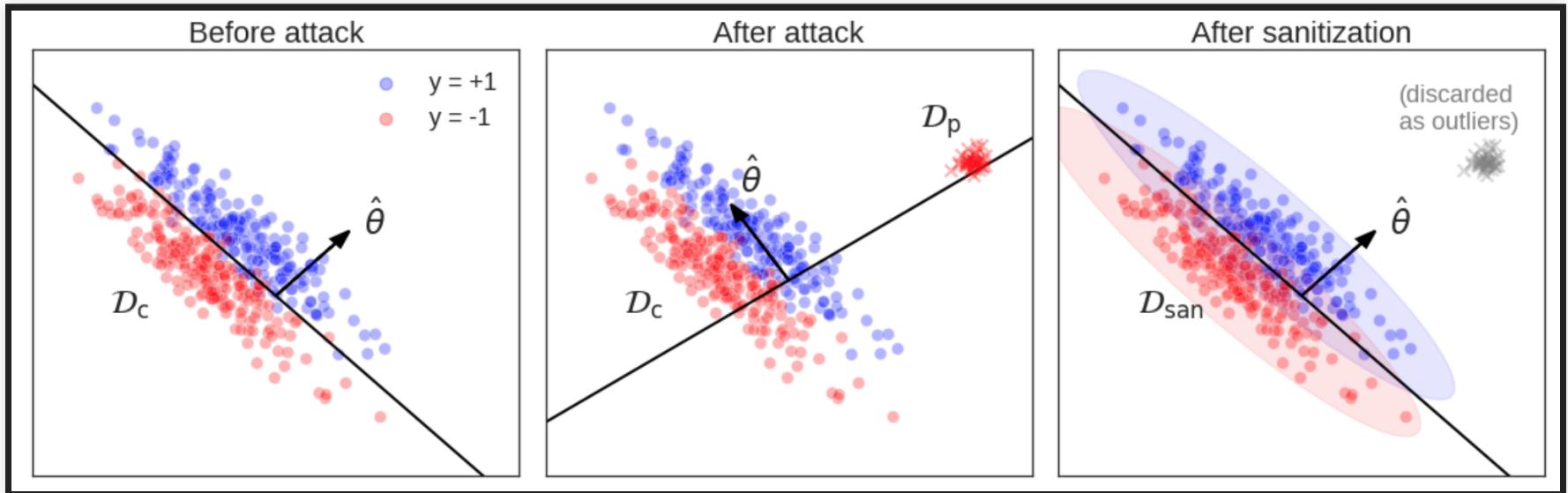
Harder than you think

KINGZHUO Hexagon Tangram
Classic Handmade Wooden
Puzzle for Children and Adults
Challenging Puzzles Brain...

★★★★★ 263

\$0.98

DEFENSE AGAINST POISONING ATTACKS



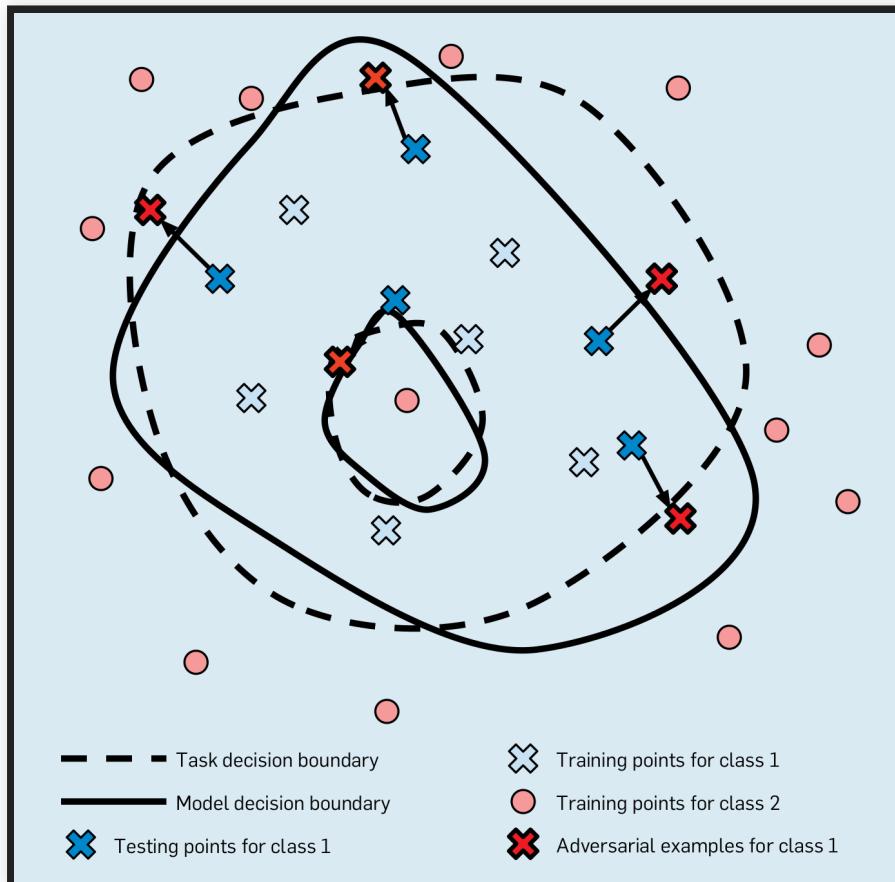
Stronger Data Poisoning Attacks Break Data Sanitization Defenses, Koh, Steinhardt, and Liang (2018).

ATTACKS ON INPUT DATA (EVASION ATTACKS, ADVERSARIAL EXAMPLES)



- Add noise to an existing sample & cause misclassification
 - achieve specific outcome (evasion attack)
 - circumvent ML-based authentication like FaceID (impersonation attack)
- Attack at inference time

TASK DECISION BOUNDARY VS MODEL BOUNDARY



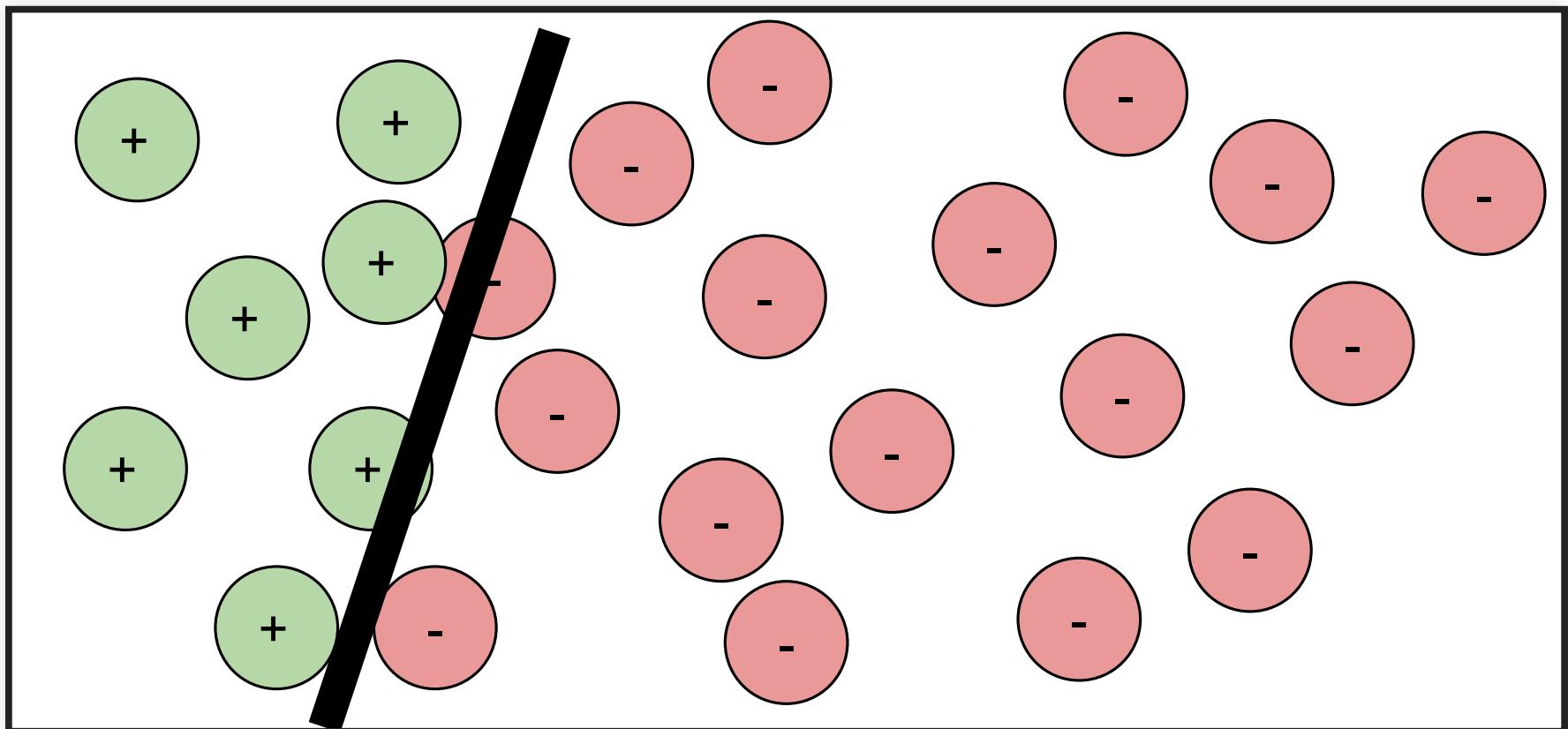
From Goodfellow et al (2018). [Making machine learning robust against adversarial inputs](#). *Communications of the ACM*, 61(7), 56-66.

GENERATING ADVERSARIAL EXAMPLES

- see [counterfactual explanations](#)
- Find similar input with different prediction
 - targeted (specific prediction) vs untargeted (any wrong prediction)
- Many similarity measures (e.g., change one feature vs small changes to many features)
 - $x^* = x + \operatorname{argmin}\{|z| : f(x + z) = t\}$
- Attacks more affective which access to model internals, but also black-box attacks (with many queries to the model) feasible
 - With model internals: follow the model's gradient
 - Without model internals: learn [surrogate model](#)
 - With access to confidence scores: heuristic search (eg. hill climbing)

NO MODEL IS FULLY ROBUST

- Every useful model has at least one decision boundary (ideally at the real task decision boundary)
- Predictions near that boundary are not (and should not) be robust



ASSURING ROBUSTNESS

- Much research, many tools and approaches (especially for DNN)
- Formal verification
 - Constraint solving or abstract interpretation over computations in neuron activations
 - Conservative abstraction, may label robust inputs as not robust
 - Currently not very scalable
 - Example: □ Singh, Gagandeep, Timon Gehr, Markus Püschel, and Martin Vechev. "[An abstract domain for certifying neural networks.](#)" Proceedings of the ACM on Programming Languages 3, no. POPL (2019): 1-30.
- Sampling
 - Sample within distance, compare prediction to majority prediction
 - Probabilistic guarantees possible (with many queries, e.g., 100k)
 - Example: □ Cohen, Jeremy M., Elan Rosenfeld, and J. Zico Kolter. "[Certified adversarial robustness via randomized smoothing.](#)" In Proc. International Conference on Machine Learning, p. 1310--1320, 2019.

PRACTICAL USE OF ROBUSTNESS

- Defense and safety mechanism at inference time
 - Check robustness of each prediction at runtime
 - Handle inputs with non-robust predictions differently (e.g. discard, low confidence)
 - Significantly raises cost of prediction (e.g. 100k model inferences or constraint solving at runtime)
- Testing and debugging
 - Identify training data near model's decision boundary (i.e., model robust around all training data?)
 - Check robustness on test data
 - Evaluate distance for adversarial attacks on test data

(most papers on the topic focus on techniques and evaluate on standard benchmarks like handwritten numbers, but do not discuss practical scenarios)



WIRED

SUBSCRIBE

RYAN SINGEL

02.01.11 02:31 PM

Google Catches Bing Copying; Microsoft Says 'So What?'



what would bing |

what would bing do

what would bing do bnet

what would bing crosby do

Google Search

I'm Feeling Lucky



WIRED

SUBSCRIBE

RYAN SINGEL

03.12.10 02:48 PM

NetFlix Cancels Recommendation Contest After Privacy Lawsuit



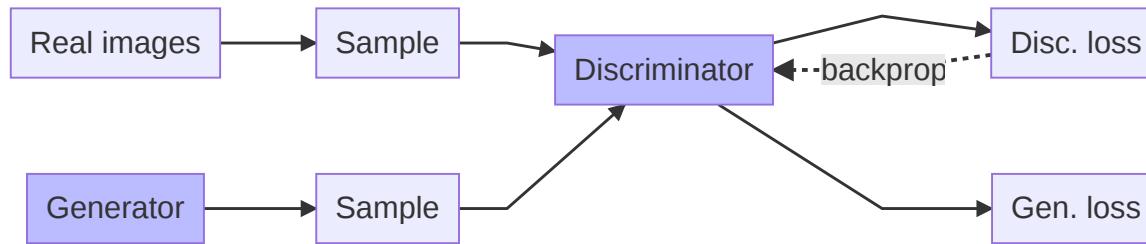


Netflix is canceling its second \$1 million Netflix Prize to settle a legal challenge that it breached customer privacy as part of the first contest's race for a better movie-recommendation engine.

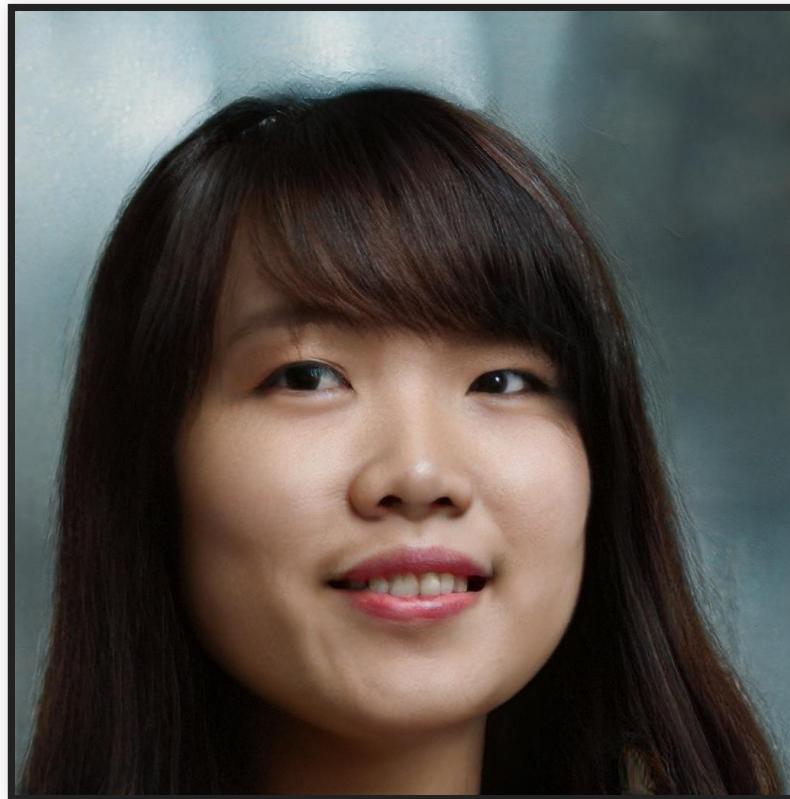


Fredrikson, Matt, Somesh Jha, and Thomas Ristenpart. "[Model inversion attacks that exploit confidence information and basic countermeasures](#)." In Proceedings of the 22nd ACM SIGSAC Conference on Computer and Communications Security, pp. 1322-1333. 2015.

GENERATIVE ADVERSARIAL NETWORKS



PROTOTYPICAL INPUTS WITH GANS



SECURITY AT THE SYSTEM LEVEL

security is more than model robustness

defenses go beyond hardening models



Jeffrey N. Fritz Top Contributor: Amazon Echo **VINE VOICE**

★★★★★ Fun to Build Detailed Steam Engine Model

Reviewed in the United States on September 17, 2019

Verified Purchase

The wooden steam engine model made by ROKR is called a "3D Puzzle Kit." I completed without great difficulty it over the span of two days. The model is made from laser cut wood parts that need to be punched out (carefully) from eight large flat wooden panels. The individual parts are labeled by board and number. There is no glue used, the pieces are all pressed together (again carefully.)

The model is fairly large at 14 inches long, 9 1/2 inches high and 2 inches wide. It weighs almost 3

2 Comments

SORT BY



Add a public comment...



Highlighted comment

⋮

B

Blaise Norman 3 weeks ago

Good videos. You deserve more subscribers. Check FollowSM .
main channel to promote my videos.



REPLY



MALEK97 3 days ago

Thank you so much for sharing this amazing content!



REPLY



Pin



Remove



Report



Hide user from channel

Google Fi

71%



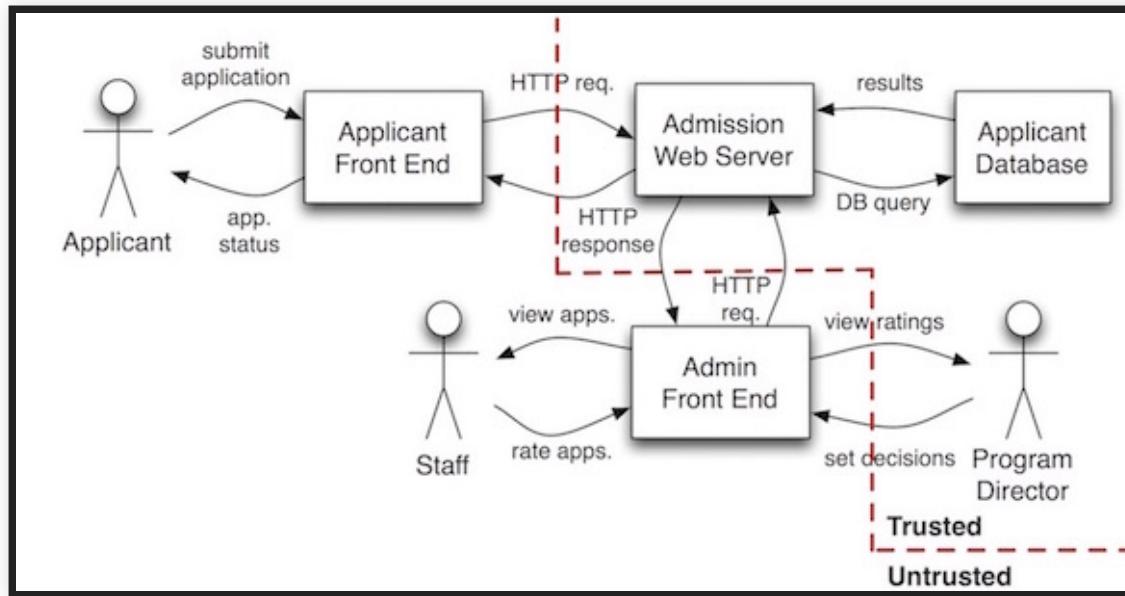
15:44

Sun, Jul 26 ☀ 32°C

Christian Kästner

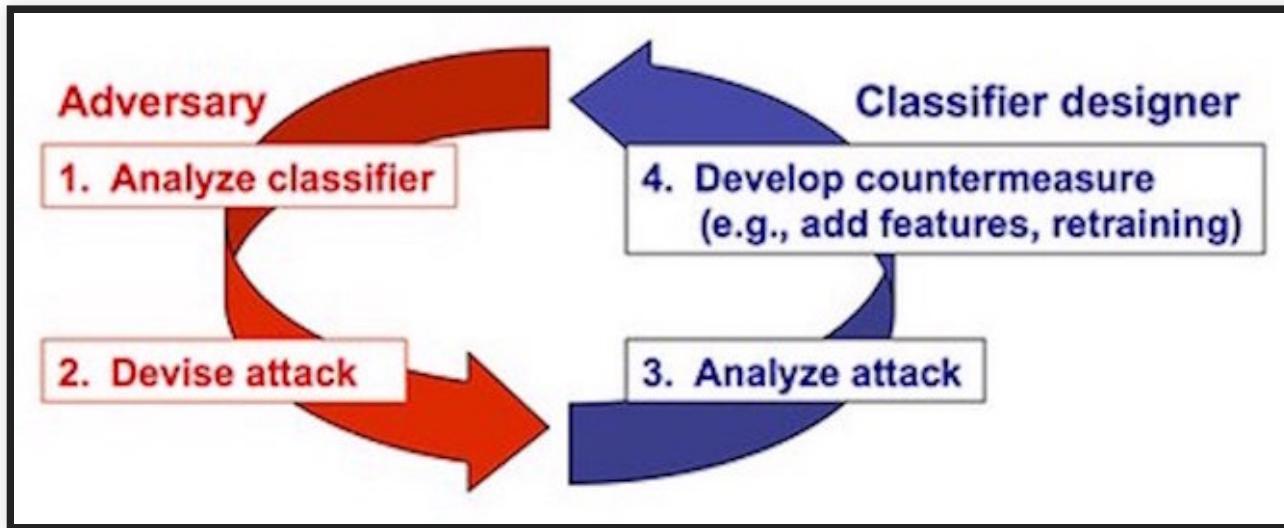
Too many attempts. Try again later.

ARCHITECTURE DIAGRAM FOR THREAT MODELING



- Dynamic and physical architecture diagram
- Describes system components and users and their interactions
- Describe trust boundaries

STATE OF ML SECURITY



- On-going arms race (mostly among researchers)
 - Defenses proposed & quickly broken by noble attacks
- Assume *ML component is likely vulnerable*
 - Design your system to minimize impact of an attack
- Remember: There may be easier ways to compromise system
 - e.g., poor security misconfiguration (default password), lack of encryption, code vulnerabilities, etc.,

SECURE DESIGN PRINCIPLES

- Principle of Least Privilege
 - A component should be given the minimal privileges needed to fulfill its functionality
 - Goal: Minimize the impact of a compromised component
- Isolation
 - Components should be able to interact with each other no more than necessary
 - Goal: Reduce the size of trusted computing base (TCB)
 - TCB: Components responsible for establishing a security requirement(s)
 - If any of TCB compromised => security violation
 - Conversely, a flaw in non-TCB component => security still preserved!
 - In poor system designs, TCB = entire system



30 COMPANIES MERGING AI AND CYBERSECURITY TO KEEP US SAFE AND SOUND

Alyssa Schroer

July 12, 2019 Updated: July 15, 2020

Ry the year 2021, cybercrime losses will

SAFETY

Christian Kaestner

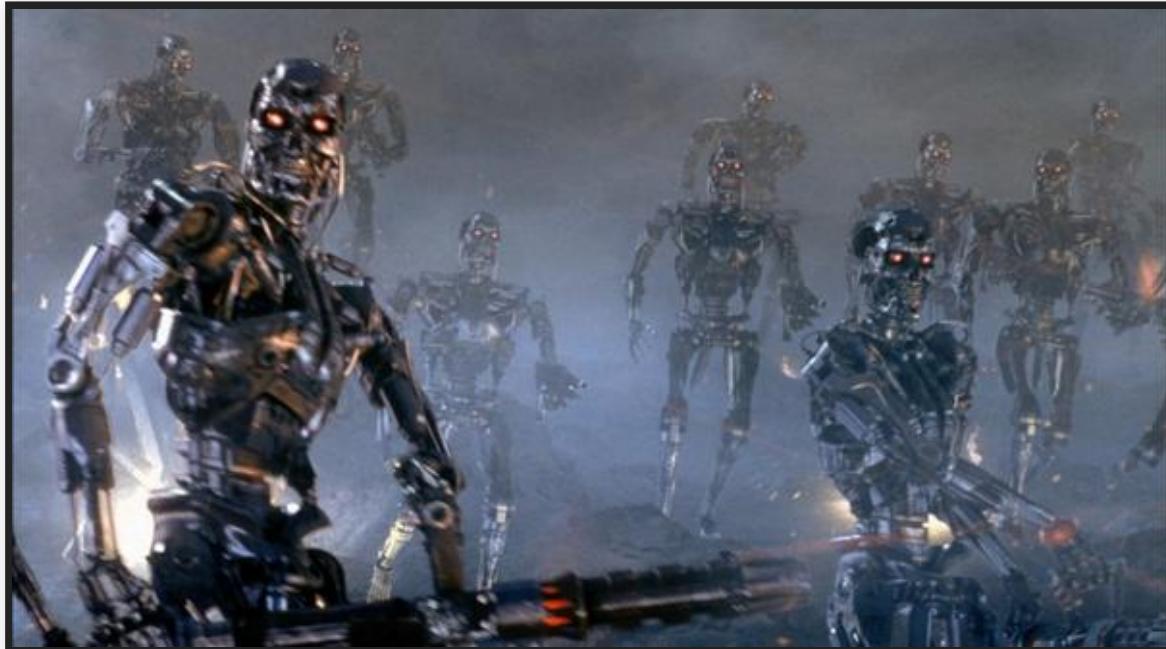
With slides from Eunsuk Kang

Required Reading □ Salay, Rick, Rodrigo Queiroz, and Krzysztof Czarnecki. "[An analysis of ISO 26262: Using machine learning safely in automotive software.](#)" arXiv preprint arXiv:1709.02435 (2017).

LEARNING GOALS

- Understand safety concerns in traditional and AI-enabled systems
- Apply hazard analysis to identify risks and requirements and understand their limitations
- Discuss ways to design systems to be safe against potential failures
- Suggest safety assurance strategies for a specific project
- Describe the typical processes for safety evaluations and their limitations

SAFETY



SAFETY



Emily Slackerman Ackerman
@EmilyEAckerman



i (in a wheelchair) was just trapped *on* forbes ave by one of these robots, only days after their independent roll out. i can tell that as long as they continue to operate, they are going to be a major accessibility and safety issue. [thread]

Everything we know about the Starship food delivery ro...
The white, 2-foot tall battery-powered delivery robots will
be sharing the sidewalk with Oakland pedestrians starti...
[∅ pittnews.com](#)

7:27 PM · Oct 21, 2019



4.3K 3.2K people are Tweeting about this

CASE STUDY: SELF-DRIVING CAR

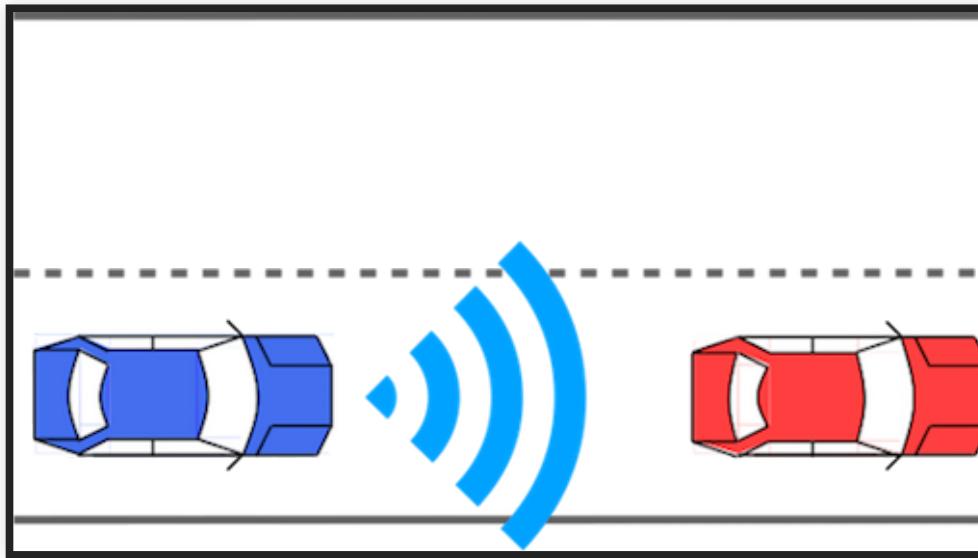


CHALLENGE: EDGE/UNKNOWN CASES



- Gaps in training data; ML will unlikely to cover all unknown cases
- **Why is this a unique problem for AI? What about humans?**

WHAT IS HAZARD ANALYSIS?



- **Hazard:** A condition or event that may result in undesirable outcome
 - e.g., "Ego vehicle is in risk of a collision with another vehicle."
- **Safety requirement:** Intended to eliminate or reduce one or more hazards
 - "Ego vehicle must always maintain some minimum safe distance to the leading vehicle."
- **Hazard analysis:** Methods for identifying hazards & potential root causes

ROBUSTNESS IN A SAFETY SETTING

- Does the model reliably detect stop signs?
- Also in poor lighting? In fog? With a tilted camera?
- With stickers taped to the sign?



Image: David Silver. [Adversarial Traffic Signs](#). Blog post, 2017

TESTING FOR SAFETY

- Curate data sets for critical scenarios (see model quality lecture)
- Create test data for difficult settings (e.g. fog)
- Simulation feasible? Shadow deployment feasible?

NEGATIVE SIDE EFFECTS



:
:
. Welcome to Universal Paperclips
> AutoClippers available for purchase|

Paperclips: 148

[Make Paperclip](#)

Business

Available Funds: \$ 9.50

Unsold Inventory: 89

[lower](#)

[raise](#)

Price per Clip: \$.25

Public Demand: 32%

[Marketing](#) Level: 1

Cost: \$ 100.00

Manufacturing

Clips per Second: 1

[Wire](#) 852 inches

Cost: \$ 26

[AutoClippers](#) 1

Cost: \$ 6.10

REWARD HACKING

PlayFun algorithm pauses the game of Tetris indefinitely to avoid losing

When about to lose a hockey game, the PlayFun algorithm exploits a bug to make one of the players on the opposing team disappear from the map, thus forcing a draw.

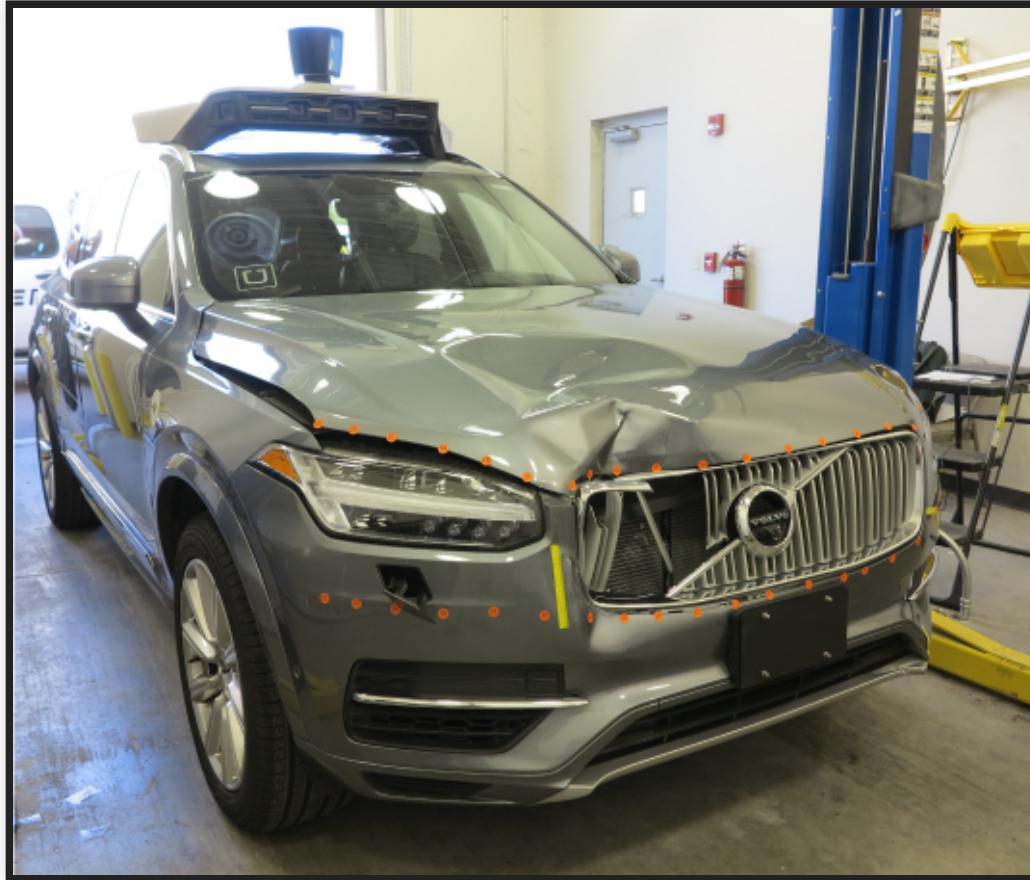
Self-driving car rewarded for speed learns to spin in circles

Self-driving car figures out that it can avoid getting penalized for driving too close to other cars by exploiting certain sensor vulnerabilities so that it can't "see" how close it is getting

ELEMENTS OF SAFE DESIGN

- **Assume:** Components will fail at some point
- **Goal:** Minimize the impact of failures on safety
- **Detection**
 - Monitoring
- **Control**
 - Graceful degradation (fail-safe)
 - Redundancy (fail over)
- **Prevention**
 - Decoupling & isolation

THE UBER CRASH





SAE J3016™ LEVELS OF DRIVING AUTOMATION

	SAE LEVEL 0	SAE LEVEL 1	SAE LEVEL 2	SAE LEVEL 3	SAE LEVEL 4	SAE LEVEL 5
What does the human in the driver's seat have to do?	You <u>are</u> driving whenever these driver support features are engaged – even if your feet are off the pedals and you are not steering	You must constantly supervise these support features; you must steer, brake or accelerate as needed to maintain safety		You are <u>not</u> driving when these automated driving features are engaged – even if you are seated in "the driver's seat"	When the feature requests, you must drive	These automated driving features will not require you to take over driving
What do these features do?	These features are limited to providing warnings and momentary assistance	These features provide steering OR brake/acceleration support to the driver	These features provide steering AND brake/acceleration support to the driver	These features can drive the vehicle under limited conditions and will not operate unless all required conditions are met		This feature can drive the vehicle under all conditions
Example Features	<ul style="list-style-type: none">• automatic emergency braking• blind spot warning• lane departure warning	<ul style="list-style-type: none">• lane centering OR• adaptive cruise control	<ul style="list-style-type: none">• lane centering AND• adaptive cruise control at the same time	<ul style="list-style-type: none">• traffic jam chauffeur	<ul style="list-style-type: none">• local driverless taxi• pedals/steering wheel may or may not be installed	<ul style="list-style-type: none">• same as level 4, but feature can drive everywhere in all conditions

For a more complete description, please download a free copy of SAE J3016: https://www.sae.org/standards/content/J3016_201806/

SAFETY CHALLENGES WIDELY RECOGNIZED

Being able to apply ML in safety-critical applications will be important to my organization in the future

a)



V&V of features that rely on ML is recognized as a particularly challenging area in my organization

b)



My organization is well-prepared for a future in which V&V of safety-critical ML is commonplace

c)



Borg, Markus, et al. "Safely entering the deep: A review of verification and validation for machine learning and a challenge elicitation in the automotive industry." arXiv preprint arXiv:1812.05389 (2018).

SAFETY ASSURANCE WITH ML COMPONENTS

- Consider ML components as unreliable, at most probabilistic guarantees
- Testing, testing, testing (+ simulation)
 - Focus on data quality & robustness
- *Adopt a system-level perspective!*
- Consider safe system design with unreliable components
 - Traditional systems and safety engineering
 - Assurance cases
- Understand the problem and the hazards
 - System level, goals, hazard analysis, world vs machine
 - Specify *end-to-end system behavior* if feasible
- Recent research on adversarial learning and safety in reinforcement learning

BEYOND TRADITIONAL SAFETY CRITICAL SYSTEMS

- Recall: Legal vs ethical
- Safety analysis not only for regulated domains (nuclear power plants, medical devices, planes, cars, ...)
- Many end-user applications have a safety component

Examples?



ADDICTION

NO MERCY NO MALICE

Robinhood Has Gamified Online Trading Into an Addiction

Tech's obsession with addiction will hurt us all



Scott Galloway

Follow

Jun 23 · 7 min read ★



Warning: This post contains a discussion of suicide.

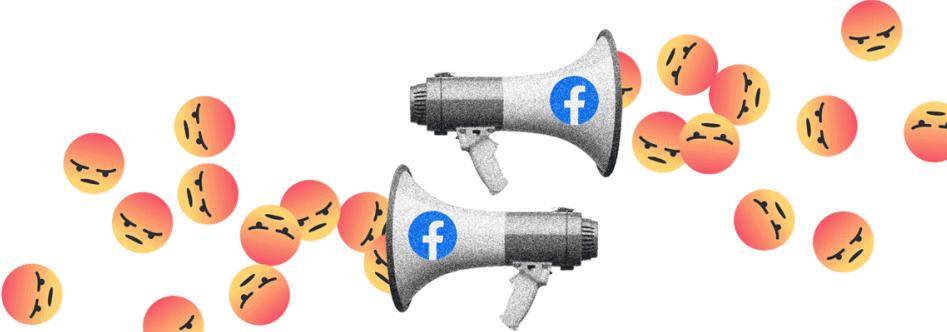
Addiction is the inability to stop consuming a chemical or pursuing an activity although it's causing harm.

I engage with almost every substance or behavior associated with addiction: alcohol, drugs, coffee, porn, sex, gambling, work, spending,

SOCIETY: POLARIZATION

≡ THE WALL STREET JOURNAL. SEARCH

SUBSCRIBE SIGN IN



TECH

Facebook Executives Shut Down Efforts to Make the Site Less Divisive

The social-media giant internally studied how it polarizes users, then largely shelved the research

By [Jeff Horwitz](#) and [Deepa Seetharaman](#)

May 26, 2020 11:38 am ET

ENVIRONMENTAL: ENERGY CONSUMPTION



SUBSCRIBE AND SAVE 69%

Creating an AI can be five times worse for the planet than a car



TECHNOLOGY 6 June 2019

By [Donna Lu](#)



FOSTERING INTERDISCIPLINARY TEAMS

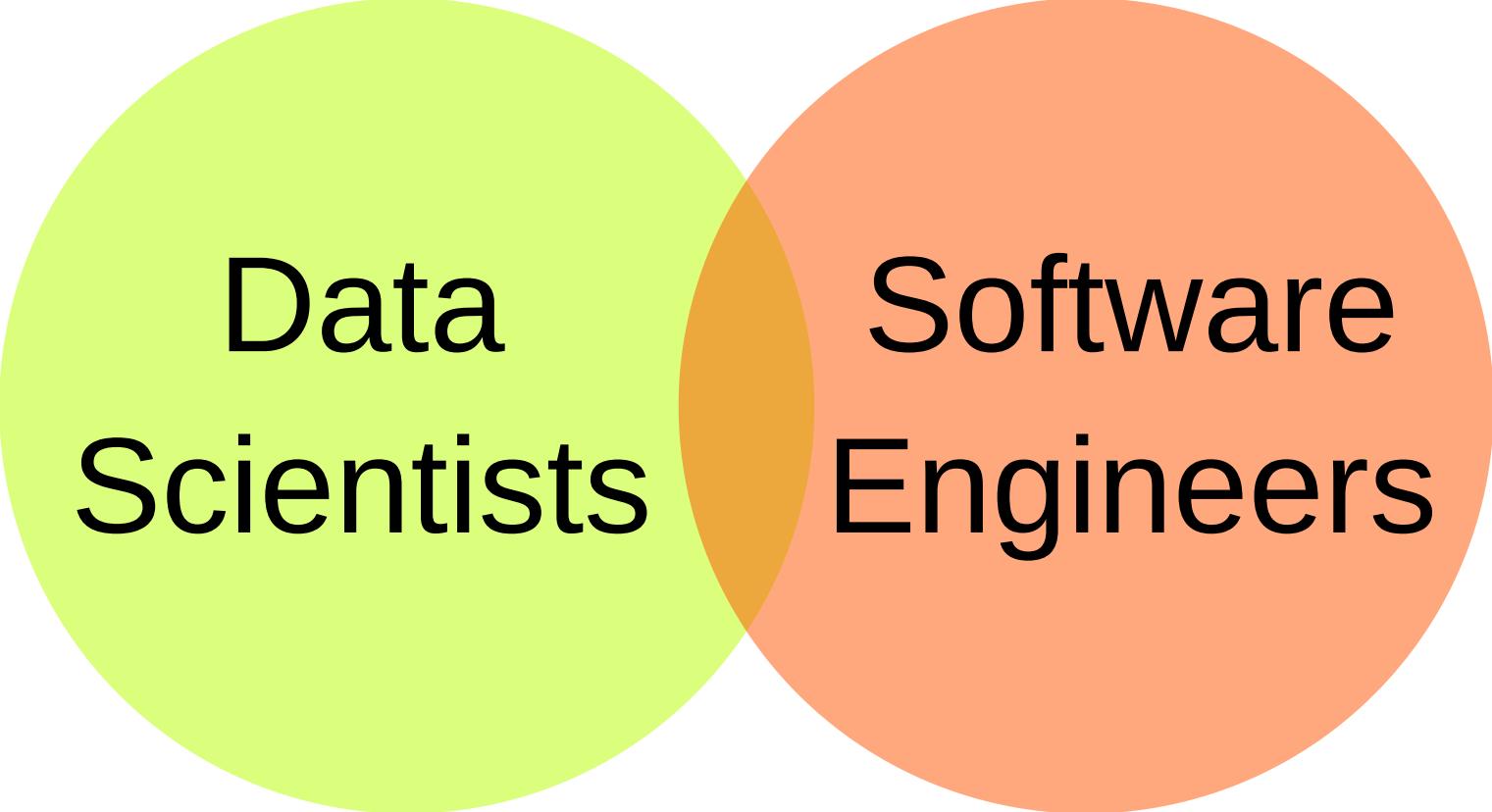
(Process and Team Reflections)

Christian Kaestner

Required reading: Kim, Miryung, Thomas Zimmermann, Robert DeLine, and Andrew Begel. "[Data scientists in software teams: State of the art and challenges.](#)" IEEE Transactions on Software Engineering 44, no. 11 (2017): 1024-1038.

LEARNING GOALS

- Plan development activities in an inclusive fashion for participants in different roles
- Describe agile techniques to address common process and communication issues



A Venn diagram consisting of two overlapping circles. The left circle is light green and contains the text "Data Scientists". The right circle is light orange and contains the text "Software Engineers". The two circles overlap in the center.

Data
Scientists

Software
Engineers



DATA SCIENCE ROLES AT MICROSOFT

- Polymath
- Data evangelist
- Data preparer
- Data shaper
- Data analyzer
- Platform builder
- 50/20% moonlighter
- Insight actors

Kim, Miryung, Thomas Zimmermann, Robert DeLine, and Andrew Begel. "[Data scientists in software teams: State of the art and challenges.](#)" IEEE Transactions on Software Engineering 44, no. 11 (2017): 1024-1038.

OTHER ROLES IN AI SYSTEMS PROJECTS?

- Domain specialists
- Business, management, marketing
- Project management
- Designers, UI experts
- Operations
- Lawyers
- Social scientists, ethics
- ...

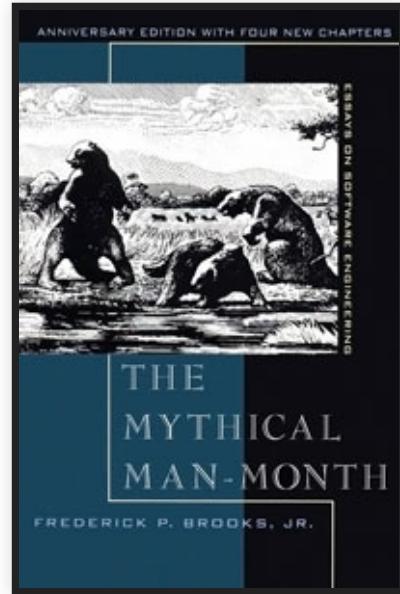
HOW TO STRUCTURE TEAMS?

Mobile game; 50ish developers; distributed teams?



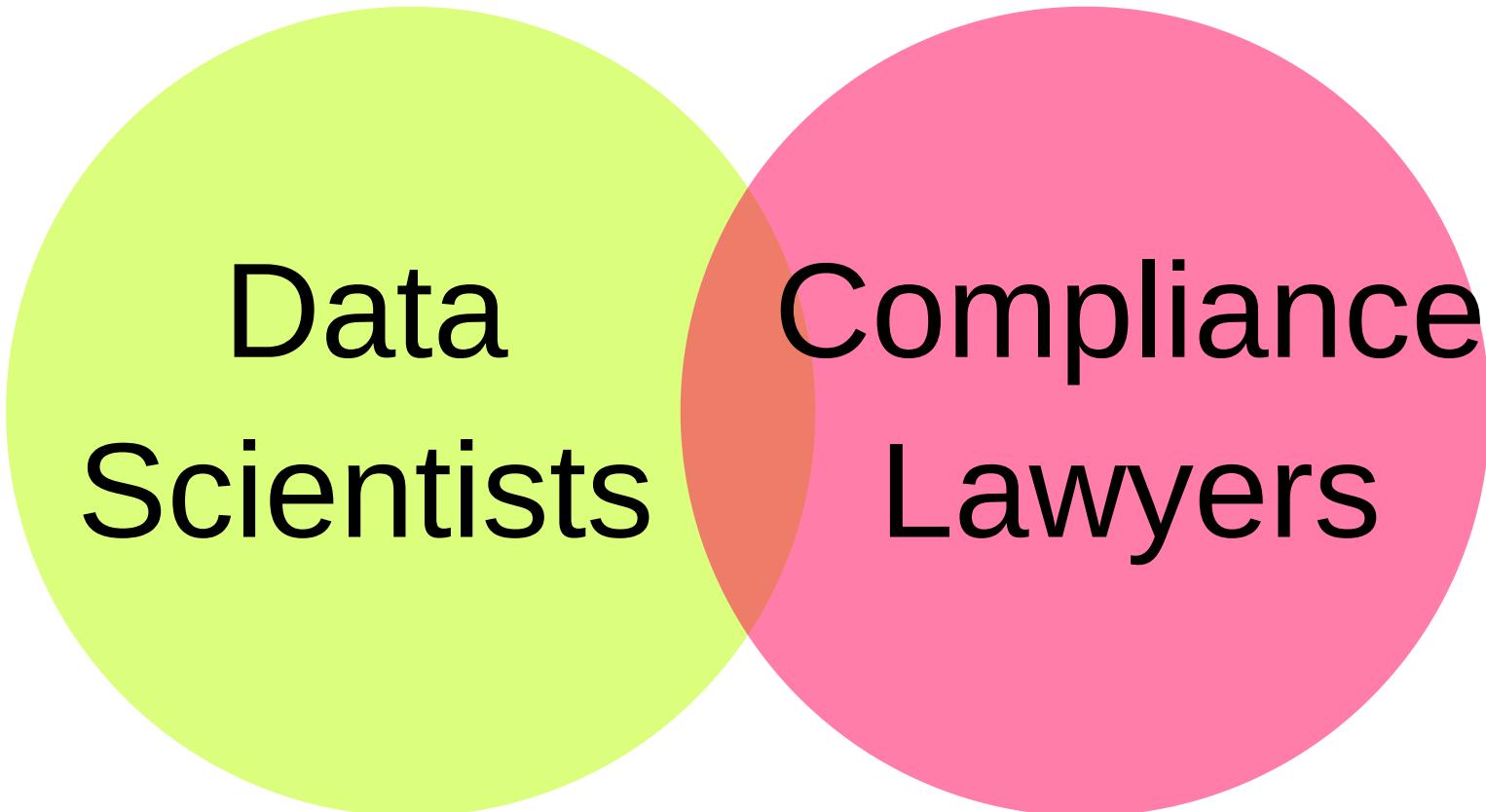
MYTHICAL MAN MONTH

Brooks's law: Adding manpower to a late software project makes it later



1975, describing experience at IBM developing OS/360

CONFLICTING GOALS?



T-SHAPED PEOPLE

Broad-range generalist + Deep expertise

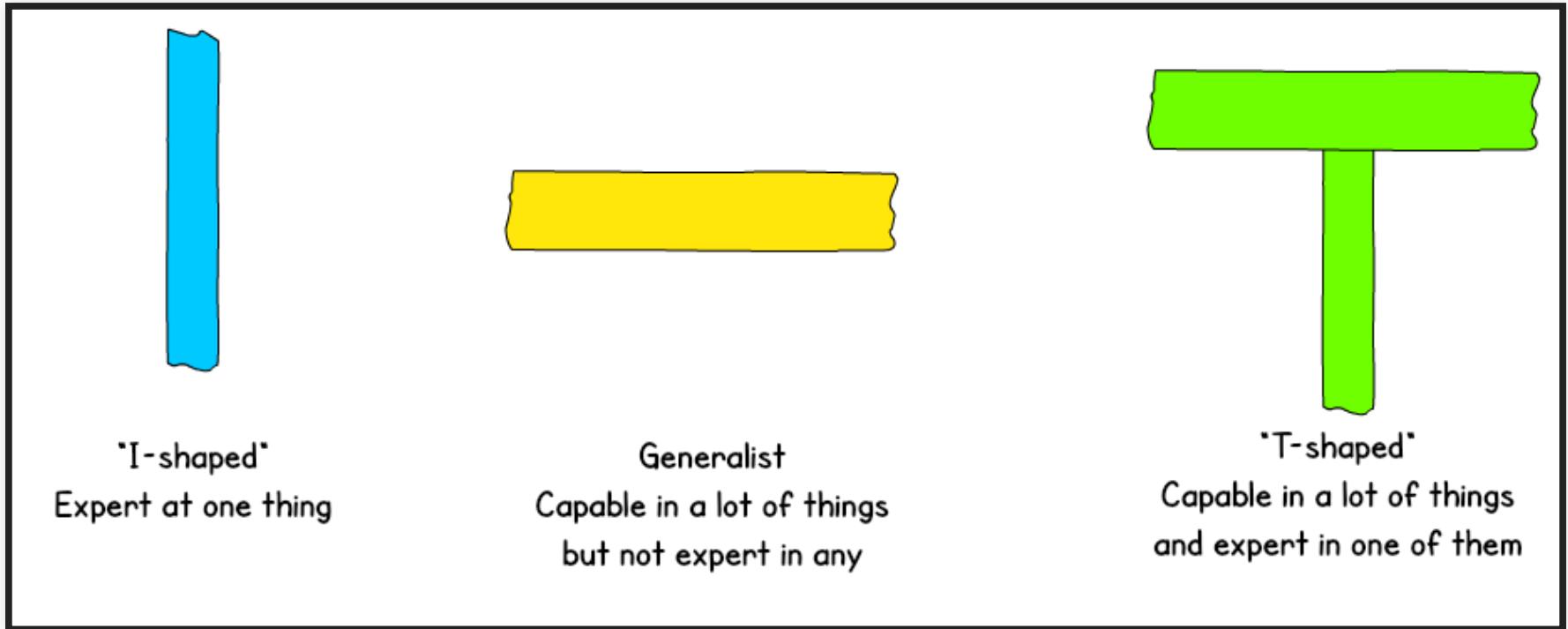
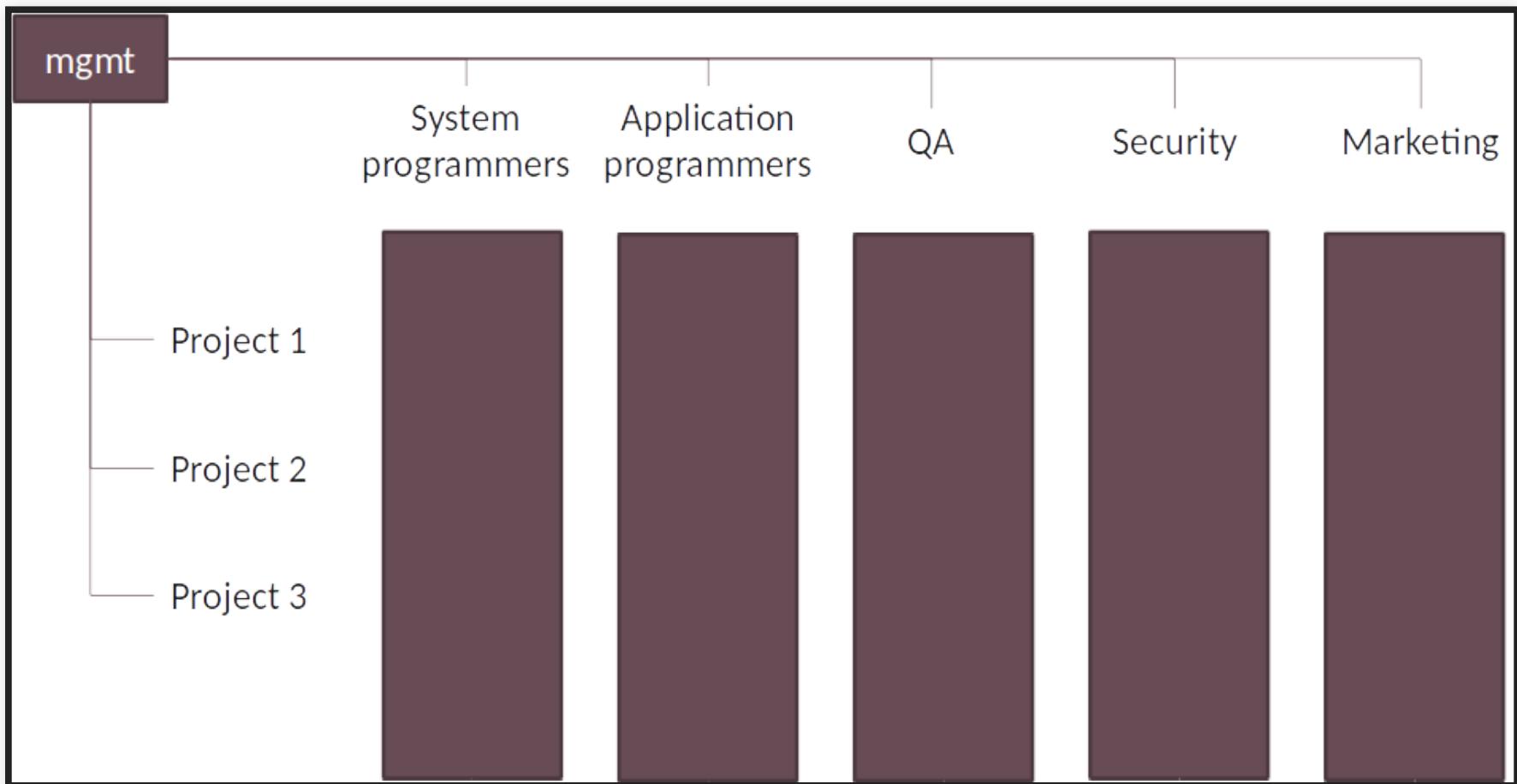


Figure: Jason Yip. [Why T-shaped people?](#). 2018

MATRIX ORGANIZATION



TEAM ISSUES: GROUPTHINK





TEAM ISSUES: SOCIAL LOAFING



SUMMARY

(424 slides in 40 min)

Christian Kaestner

TODAY

Looking back at the
semester

Discussion of future of
SE4AI

Feedback for future
semesters

THE FUTURE OF SOFTWARE ENGINEERING FOR AI- ENABLED SYSTEMS?

WHAT ARE NEW SOFTWARE ENGINEERING CHALLENGES?



Gaps? Research needs? Adaptation of existing methods?

ARE SOFTWARE ENGINEERS DISAPPEARING?



Andrej Karpathy 

Gradient descent can write code better than you. I'm sorry.

8:56 PM · Aug 4, 2017 

 1.2K  417 people are Tweeting about this

see also Andrej Karpathy. [Software 2.0. Blog, 2017](#)

Speaker notes

Andrej Karpathy is the director of AI at Tesla and coined the term Software 2.0

ARE DATA SCIENTISTS DISAPPEARING?

≡ Forbes

1,616 views | Apr 7, 2020, 10:10am EDT

AutoML 2.0: Is The Data Scientist Obsolete?



Ryohei Fujimaki Contributor

COGNITIVE WORLD Contributor Group ⓘ

AI

Ryohei Fujimaki Ph.D. is founder and CEO of dotData

f It's an AutoML World

-  The world of AutoML has been proliferating over the past few years - and with a recession
-  looming, the notion of automating the

Ryohei Fujimaki. [AutoML 2.0: Is The Data Scientist Obsolete?](#) Forbes, 2020

ARE DATA SCIENTISTS DISAPPEARING?

However, AutoML does not spell the end of data scientists, as it doesn't "AutoSelect" a business problem to solve, it doesn't AutoSelect indicative data, it doesn't AutoAlign stakeholders, it doesn't provide AutoEthics in the face of potential bias, it doesn't provide AutoIntegration with the rest of your product, and it doesn't provide AutoMarketing after the fact. -- [Frederik Bussler](#)

Frederik Bussler. [Will AutoML Be the End of Data Scientists?](#), Blog 2020

SE4AI RESEARCH: MORE SE POWER TO DATA SCIENTISTS?

SE4AI RESEARCH: MORE DS POWER TO SOFTWARE ENGINEERS?





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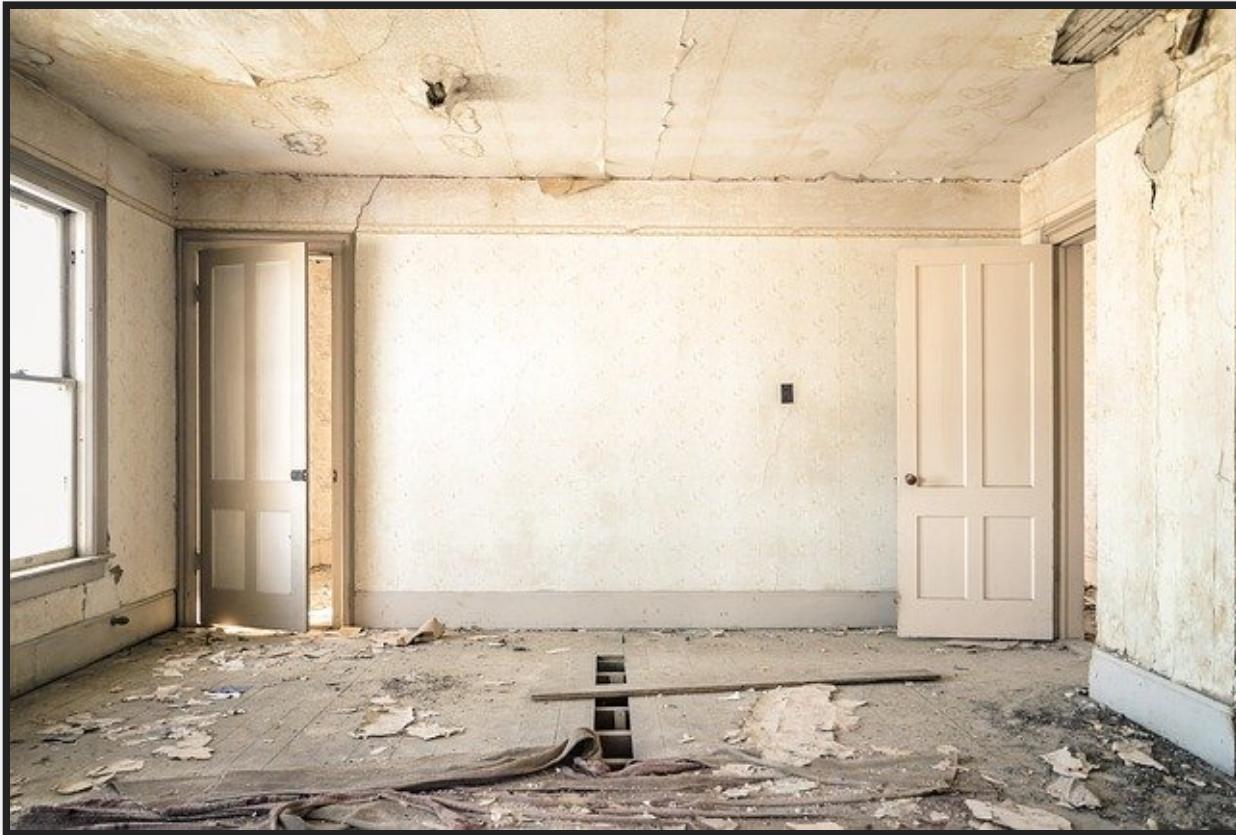
Replies to [@p0nk](#) and [@AndrzejWasowski](#)

Virtually *everyone* is / will soon be building ML applications. Only few can afford dedicated software engineers to team up with, or SE education for themselves. It would be more inclusive to build SE into the ML processes more fundamentally, so that everyone could build better

12:27 PM · Jun 19, 2020 · [Twitter for iPhone](#)



ANALOGY



ANALOGY



(better tools don't replace the knowledge to use them)

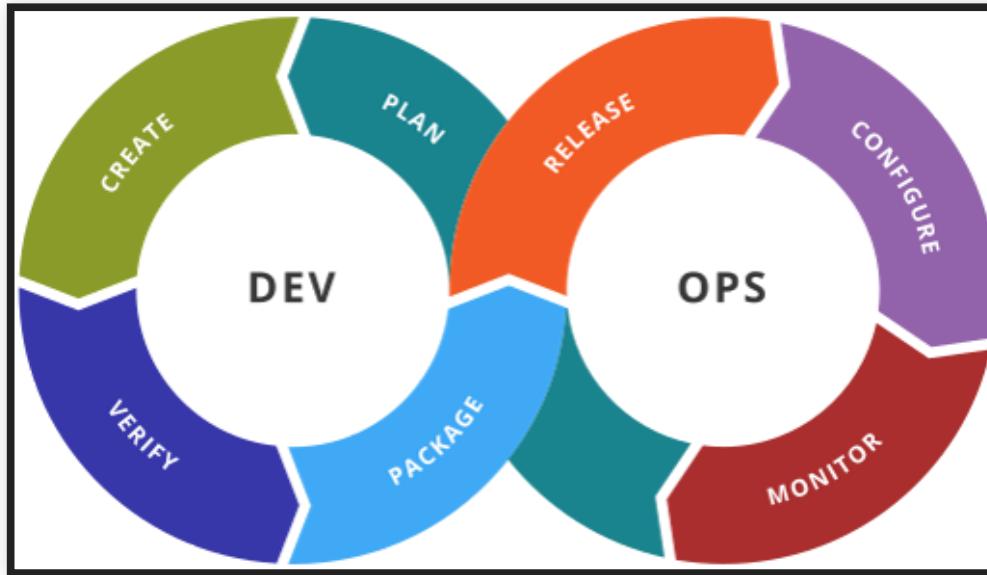
MY VIEW

This is an education problem, more than a research problem.

Interdisciplinary teams, mutual awareness and understanding

Software engineers will play an essential role

DEVOPS AS A ROLE MODEL



Joint responsibilities, joint processes, joint tools, joint vocabulary

FEEDBACK

- What was useful?
- What could be improved?
- Ideas for better remote teaching?



THANK YOU!

