Baffled by Brilliance

Machine Learning as the next great UX challenge

“If you can't dazzle them with brilliance, baffle them with bullshit”

— W.C. Fields

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baffle with brilliance

Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks

Chelsea Finn, Pieter Abbeel, Sergey Levine

(Submitted on 9 Mar 2017)

We propose an algorithm for meta-learning that is model-agnostic, in the sense that it is compatible with any model trained with gradient descent and applicable to a variety of different learning problems, including classification, regression, and reinforcement learning. The goal of meta-learning is to train a model on a variety of learning tasks, such

Deep Structured Learning for Facial Action Unit Intensity Estimation

Robert Walecki, Ognjen (Oggi) Rudovic, Vladimir Pavlovic, Björn Schuller, Maja Pantic

(Submitted on 14 Apr 2017)

We consider the task of automated estimation of facial expression intensity. This involves estimation of multiple output variables (facial action units --- AUs) that are structurally dependent. Their structure arises from statistically induced co-occurrence patterns of AU intensity levels. Modeling this structure is critical for improving the estimation performance;

Performance Limits of Stochastic Sub-Gradient Learning, Part II: Multi-Agent Case

Bicheng Ying, Ali H. Sayed

(Submitted on 20 Apr 2017)

The analysis in Part I revealed interesting properties for subgradient learning algorithms in the context of stochastic optimization when gradient noise is present. These algorithms are used when the risk functions are non-smooth and involve non-differentiable components. They have been long recognized as being slow converging methods. However, it was

dazzle with bullshit

Algorithms

This AI learned to predict the future by watching loads of TV

The algorithm watched Scrubs, Ugly Betty and the Big Bang Theory and predicted what would happen next

This robot passed a 'self-awareness' test that only humans could handle until now

Celena Chong

Jul. 23, 2015, 2:15 PM 58,685

COMPUTERS

Image Source: REUTERS/Dado Ruvic

Facebook engineers panic, pull plug on AI after bots develop their own language

Mike Wehner @MikeWehner
July 31st, 2017 at 12:26 PM

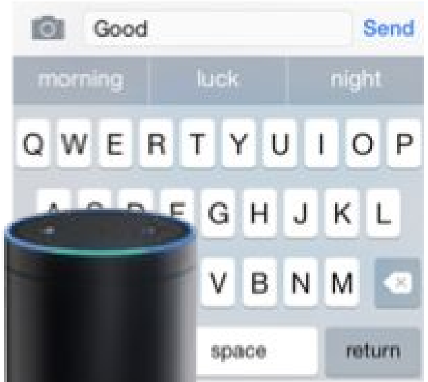
Share   Tweet

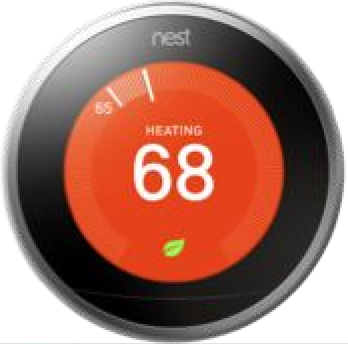
As the world's most powerful computer systems begin to embrace artificial intelligence in earnest, using smart algorithms to increase efficiency and and speed, the potential damage that a "rogue" AI could

Machine Learning…
Artificial Intelligence…

what’s the difference?

Machine Learning is...





Learning from data to make predictions about new data

Data...

Speech signals

Raw pixels

Genomic data

Visitor behavior data

Text

...basically any quantity that can be stored in a computer

Supervised Learning

There's a particular piece of information – the outcome – you want to predict about each piece of data, and you have some data already labeled with this outcome that you can train on.

We sometimes call the outcome the dependent variable, and call the predictors independent variables.

Supervised Learning

Classification

Or

Regression

What type of question needs to be asked of your data?

Classification

Question: Which class does this example belong to?

Dependent variable is qualitative / categorical

Supervised Learning: Classification

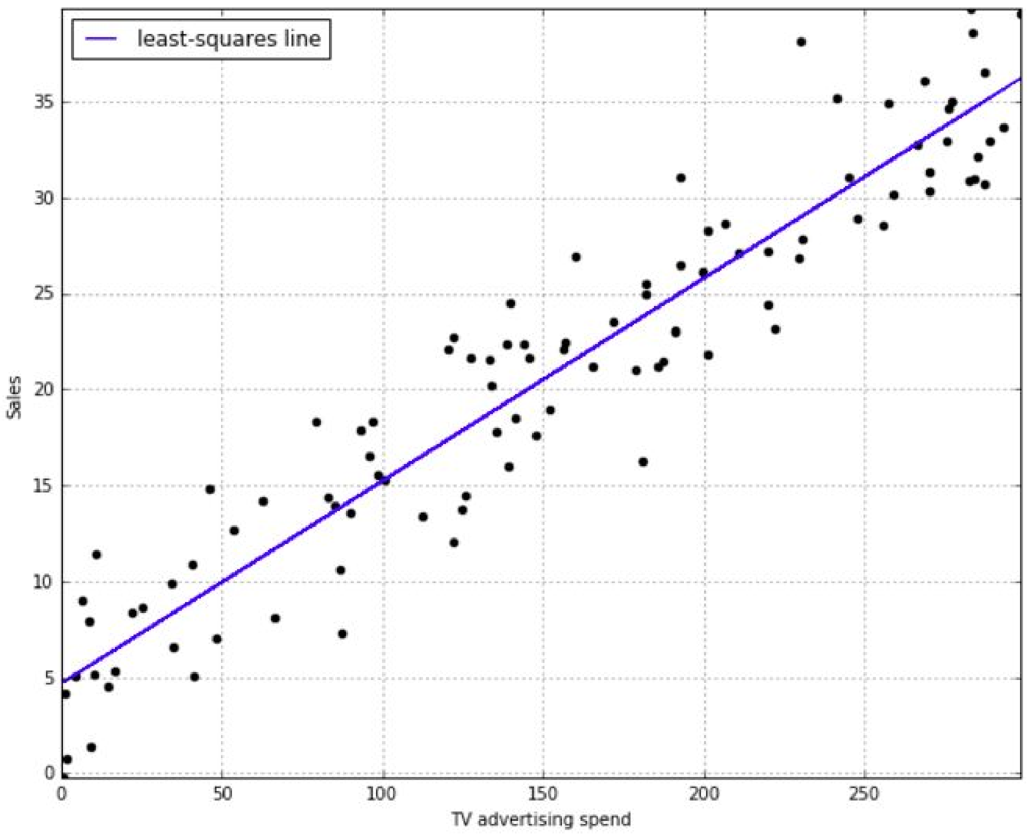
Tumor size	Class
3.6cm	Benign
2.9cm	Benign
4.4cm	Malignant
4.0cm	Benign

Regression

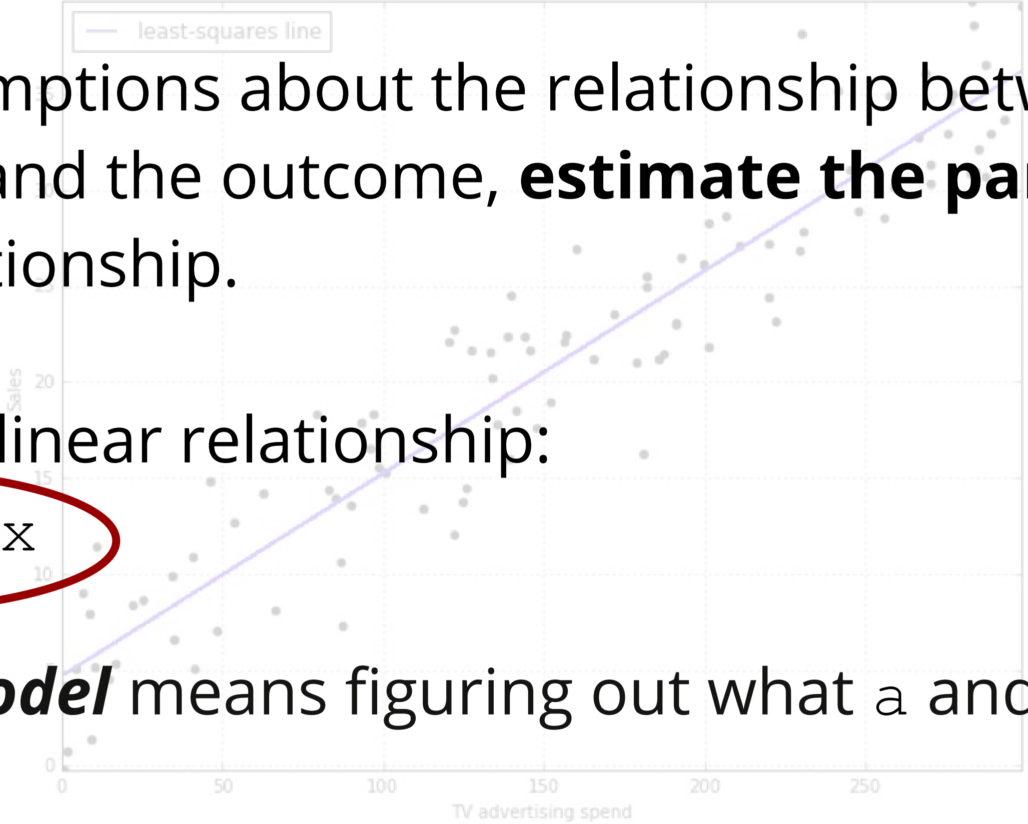
Question: How much y does this example have?

Dependent variable is quantitative / continuous

Supervised Learning: Regression



Supervised Learning: Regression



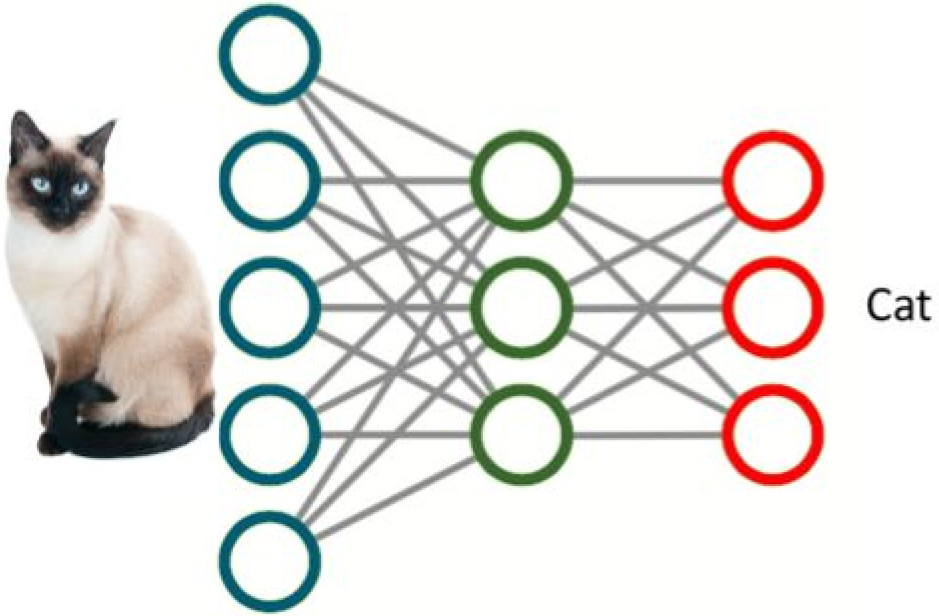
Given assumptions about the relationship between your predictors and the outcome, **estimate the parameters** of that relationship.

In a simple linear relationship:

$y = a + bx$

Fitting a model means figuring out what a and b should be.

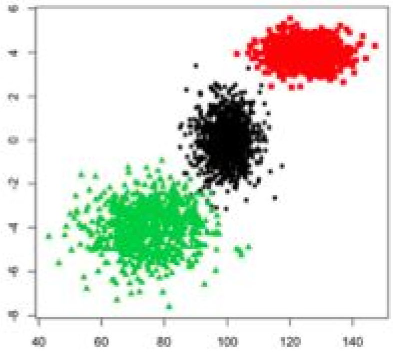
Supervised Learning: Deep Learning



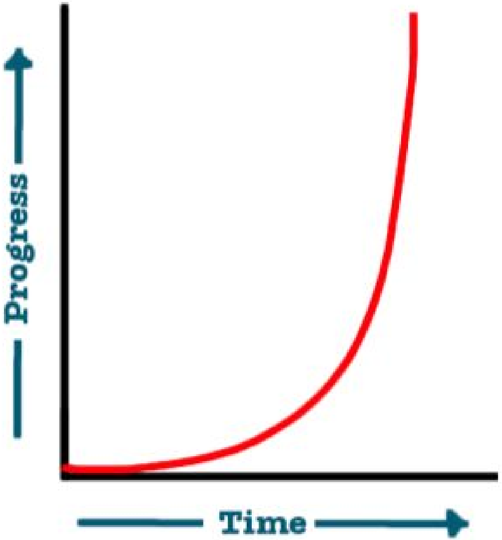
Unsupervised Learning

You have unlabeled data, i.e. there is no outcome variable, you just have a bunch of data that you are trying to find some structure in.

E.g. Clustering



Concerns around Machine Learning



There are things worth worrying about when it comes to Machine Learning.

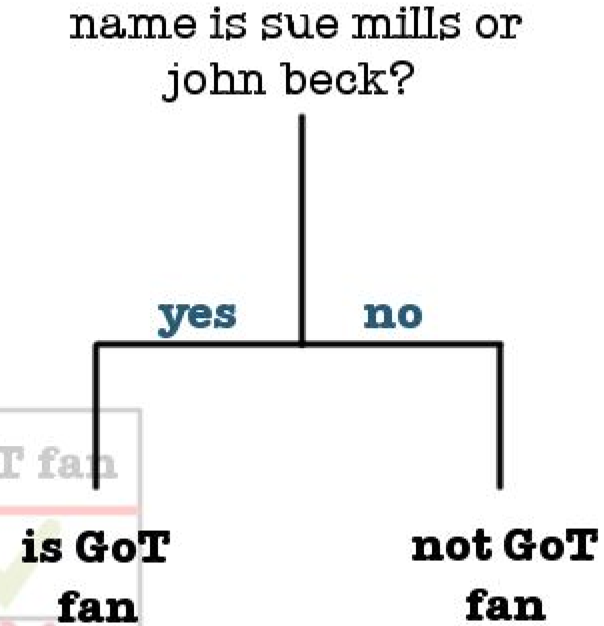
The Singularity isn't one of them

“People worry that computers will get too smart and take over the world, but the real problem is that they’re too stupid and they’ve already taken over the world”

- Pedro Domingos

What can go wrong?

Name	Age	Country	Gender	GoT fan
sue mills	23	USA	f	✓
chris day	41	USA	m	✗
john beck	34	USA	m	✓
sara sims	52	UK	f	✗



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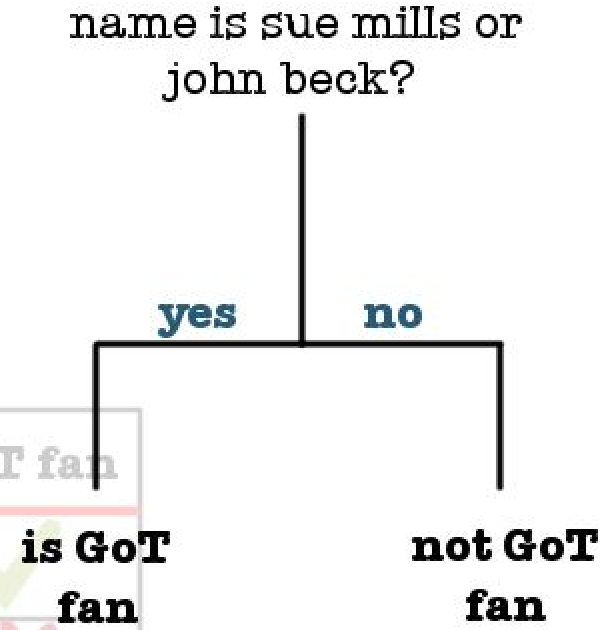

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john beck	34	USA	m	✓
sara sims	52	UK	f	✗

Overfitting


wolf


husky


wolf


husky


husky


wolf


husky

	page1.html	page2.html	page3.html	ty.html	**purchased**
visitor1	✓	✗	✗	✓	✓
visitor2	✓	✗	✓	✗	✗
visitor3	✗	✓	✗	✓	✓
visitor4	✓	✓	✓	✗	✗


page1.html
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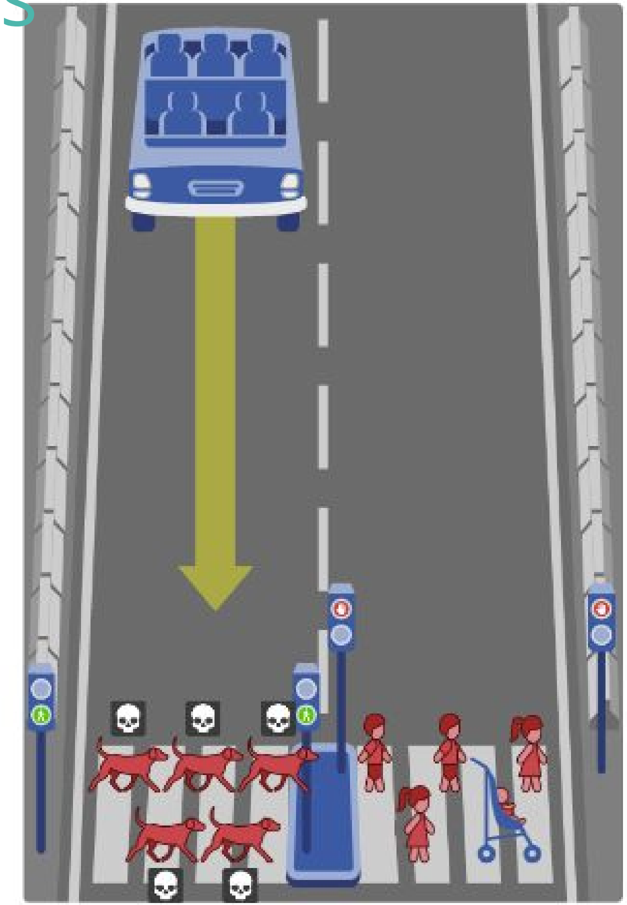
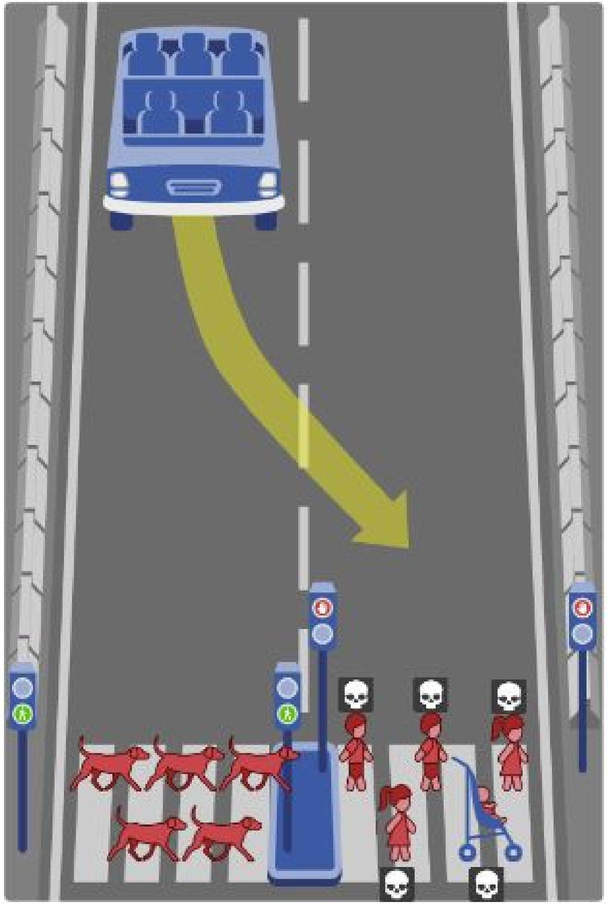
visitor4

Data
Leakage

Ethics, bias and bad ideas

Ethics





moralmachine.mit.edu

Bias

Man is to computer programmer as woman is to... ?

Bias

Man is to computer programmer as woman is to... ?

Homemaker

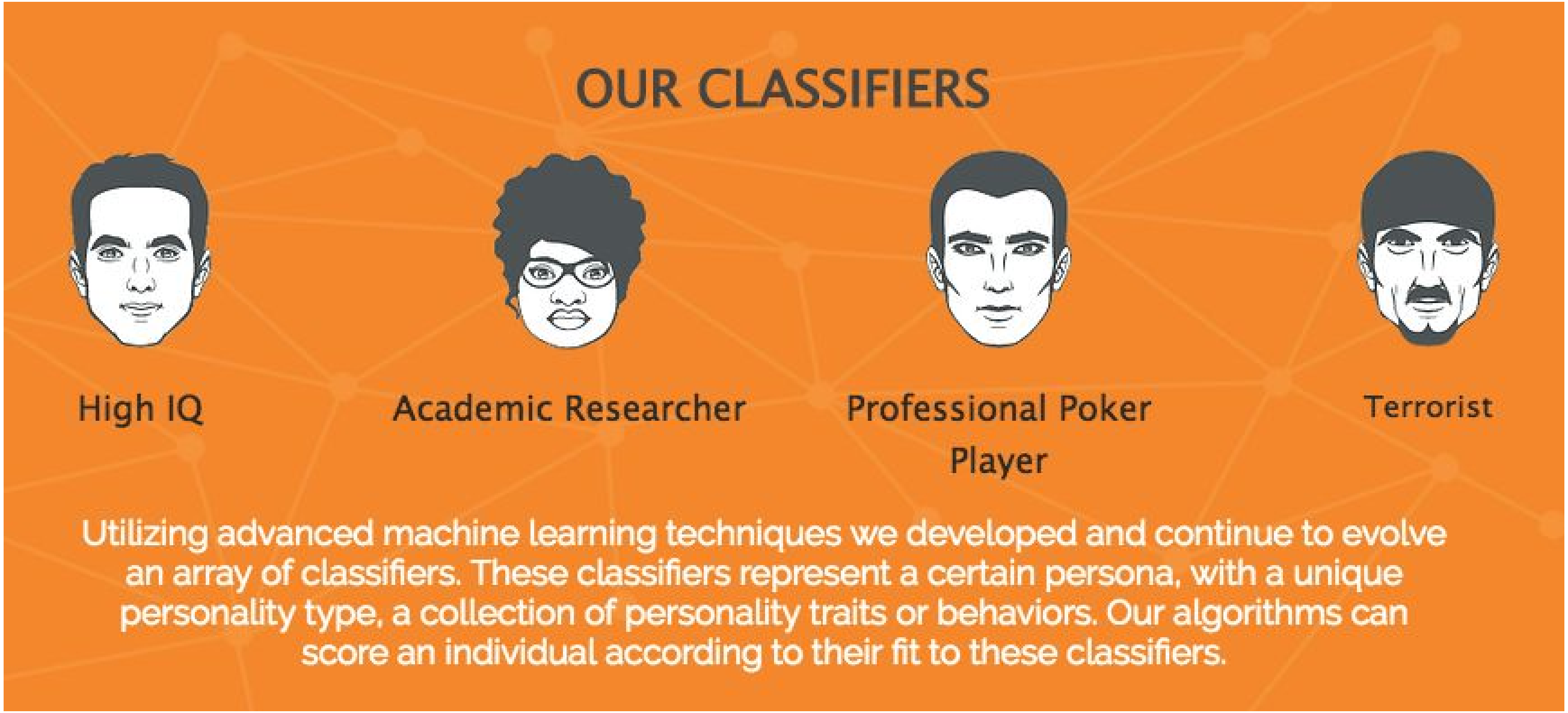
Bias

Man is to computer programmer as woman is to... ?

Homemaker

(See https://arxiv.org/abs/1607.06520)

Bad Ideas

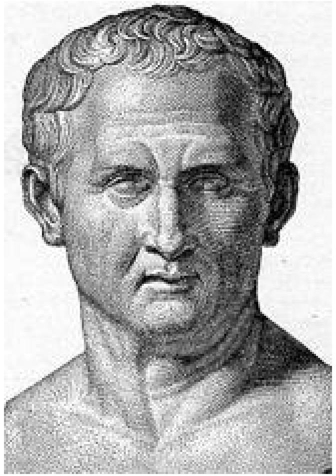

OUR CLASSIFIERS
High IQ
Academic Researcher
Professional Poker Player
Terrorist
Utilizing advanced machine learning techniques we developed and continue to evolve an array of classifiers. These classifiers represent a certain persona, with a unique personality type, a collection of personality traits or behaviors. Our algorithms can score an individual according to their fit to these classifiers.

Possibility
&
Probability

Possibility

“What cannot happen will never happen, what can happen is not a miracle”

— Marcus Tullius Cicero

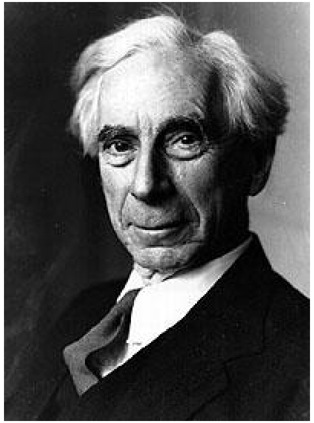


Possibility

> “What cannot be learned from your data will never be learned from your data, what can be learned from your data is not magic.”
>
> — Machine Learning Cicero

Probability (uncertainty)

> "The whole problem with the world is that fools and fanatics are always so certain of themselves, but wiser people so full of doubts."
>
> — Bertrand Russell



Probability (uncertainty)

Even if you don't retain a measure of uncertainty in your models, at least know that there is uncertainty inherent in its predictions.

Possibility & Probability

Data

Question

☐ Terrorist

☐ Not a terrorist

ML & User Experience

The “user” can be…

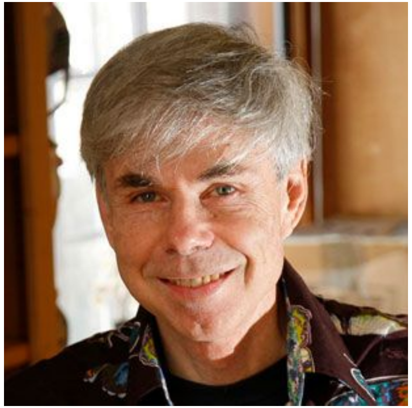
1. The end user of a machine learning application

2. The “human-in-the-loop” for training ML systems

Designing so-called "intelligent" applications presents us with some dilemmas

Hofstadter's Dilemma

Stop being "smart", stupid!



Frankly, autocorrect, I'm getting tired of your shirt

UX for end users of ML Applications

STOP BEING CREEPY!

vs

Y U NO UNDERSTAND ME?!

UX for end users of ML Applications

The problem of explainability

Artificial Intelligence Owes You an Explanation

When an A.I. does something, you should be able to ask, "Why?"

27 94

By *John Frank Weaver*

Alexa, *why?*

Peter Hobson/Reuters

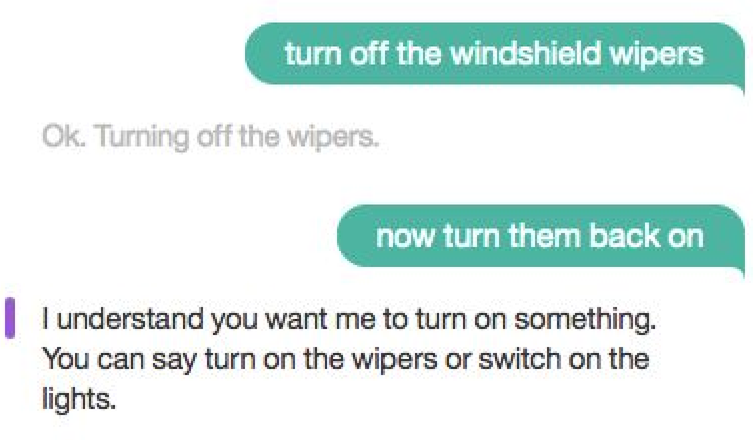
http://www.slate.com/articles/technology/future_tense/2017/05/why_artificial_intelligences_should_have_to_explain_their_actions.html

Conversational A.I.

Chatbots and voice-based interfaces are on the rise, yet Natural Language Understanding is still an unsolved problem in A.I.

How do we get around this?

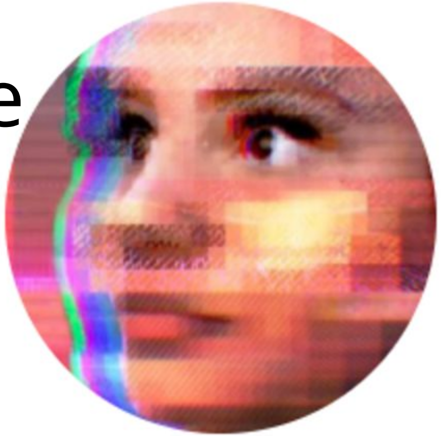
UX for end users of ML Applications



Generative models for dialog

Produce responses that sound just like us...

...at our most superficial, predictable and sometimes obnoxious



Conversational A.I.

Ease off on the “pretending to be human” thing.

Focus more on the UX problem of providing uncertain answers to users.

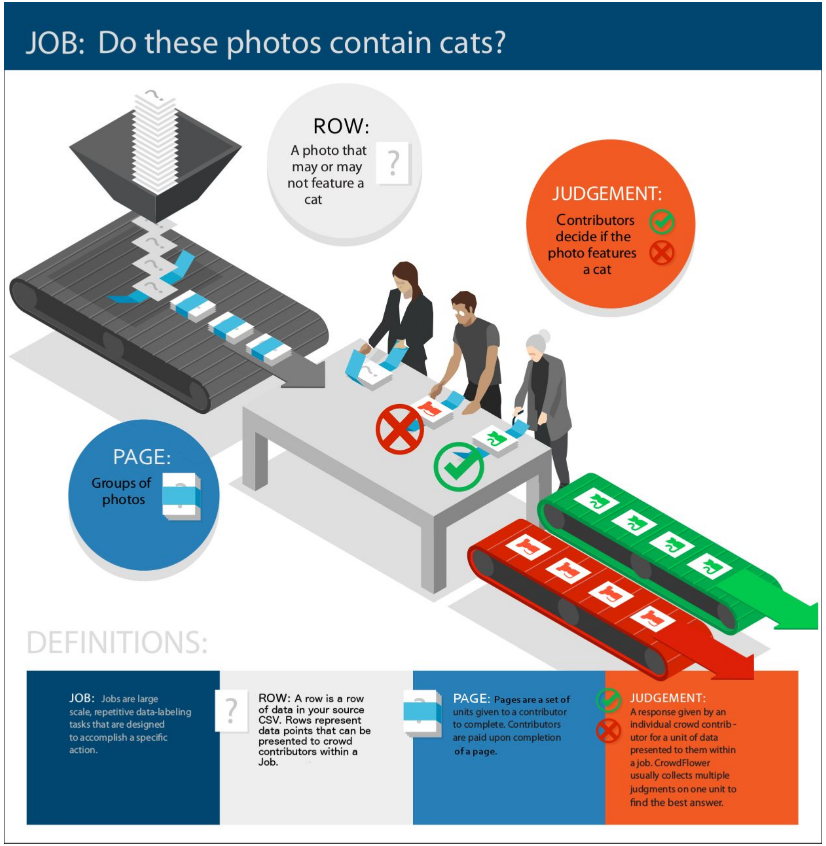
Human in the Loop

Problem: sometimes you don’t have enough labeled data for the problem you’re trying to solve

Solution: get humans to label it

UX for human in the loop

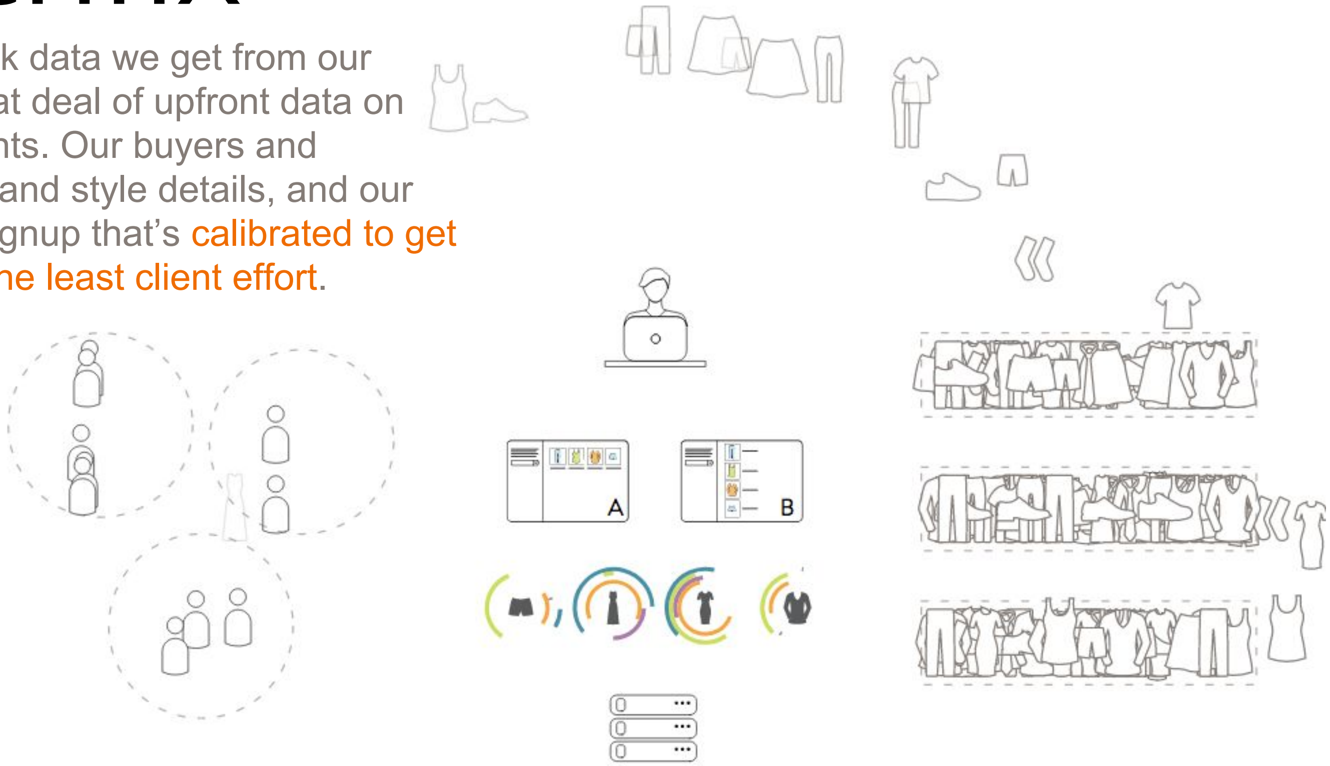
CrowdFlower



UX for human in the loop

Stitchfix

In addition to the rich feedback data we get from our clients, we also receive a great deal of upfront data on both our clothing and our clients. Our buyers and designers capture dimension and style details, and our clients fill out a profile upon signup that’s calibrated to get us the most useful data with the least client effort.



UX for human in the loop

The two types of winners in ML will be:

1. Companies with access to massive labeled datasets
2. Companies that can get the most out of unlabeled data.

Human-in-the-loop ML is a way to do the latter and **great UX is essential for this!**

In conclusion...

Machine Learning techniques are extremely useful
Don’t be baffled - it’s just statistics, math and lots of data
Don’t be dazzled by the bullshit - think about what’s possible with math and data and what isn’t
There are particular challenges and dilemmas for the end user experience in designing “intelligent” systems
The scarcity of labeled data that organizations have access to increases the need for human-in-the-loop solutions. Great UX is absolutely essential for this to work at all

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Thanks :)

@katherinebailey