### Life as an ML Engineer

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Intro

# Things you already know

1. Interchangable Parts

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- 2. Testing

#### Things you already know

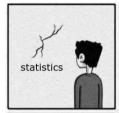
- 1. Interchangable Parts
- 2. Testing
- 3. Integration

1. Think about ML from an engineering perspective

#### **Objectives**

- 1. Think about ML from an engineering perspective
- 2. Learn some of the terminology used to help converse between Data Scientists and Engineers like:

#### ai vs statistics









you're going to need some data

### you need to know what you're trying to do

user stories

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- user stories
- business problem?

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- user stories
- business problem?
- black box function

look at your data

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- interpretability

### don't forget to look for prior art

- Look at UNet, YOLO, ResNet51, RetinaNet, and many other hyped algorithms.
- Tensorflow has many sets of "pre-trained" weights

### this was a whole section on data prep

new API

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new CSV from a customer

### things that matter for ML

normalizing or "whitening"

- normalizing or "whitening"
- binning

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- dimensionality reduction

### things that matter for ML

- normalizing or "whitening"
- binning
- missing values
- dimensionality reduction
- class imbalance

### algorithms

### pre-jargon

letters

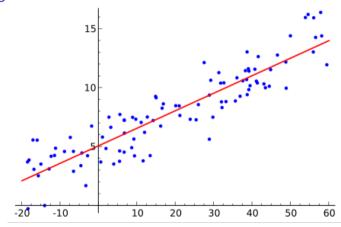
Life as an ML Engineer

- letters
- Y = mx + b

## pre-jargon (cont'd)

$$Y = Wx + b$$

### regression



#### what if there are multiple variables?

$$V = W_1x_1 + b$$

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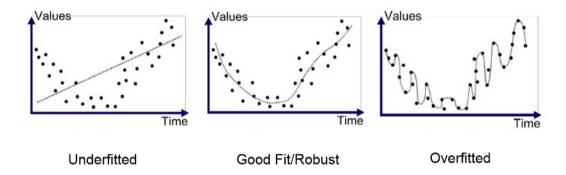
### what if there are multiple variables?

$$\triangleright y = W_1x_1 + b$$

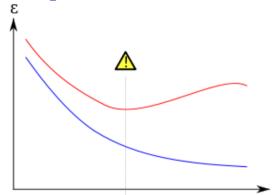
$$V = W_1x_1 + W_2x_2 + \ldots + b$$

$$\triangleright$$
  $y = Wx + b$ 

## overfitting







## data requirements

large data

Intro you're going to need some data oporithms gradient descent inference aka "pushing to production" tensors and flow graph questions? other resources occording to the production occording to the p

## data requirements

- ► large data
- data hacks

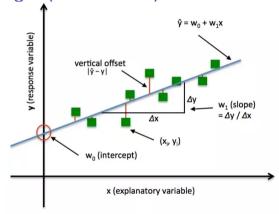
Intro you're going to need some data oponithms gradient descent inference aka "pushing to production" tensors and flow graph questions? other resources occording to the production occording to the p

### data requirements

- ► large data
- data hacks
  - data augmentation zoom, rotate, flip images

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gradient descent

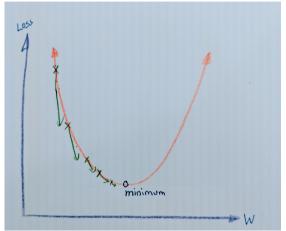


### little bit of math

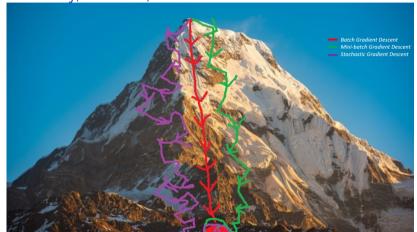
$$\sum_{x}(Wx+b-y_{x})^{2}$$

$$\underset{W,b}{\operatorname{arg\,min}} \sum_{x} (Wx + b - y_x)^2$$

## gradient descent



# stochasticity, batches, and mini-batches



what is truth?

- what is truth?
- testing?

- what is truth?
- testing?
- what can go wrong?

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- what is truth?
- testing?
- what can go wrong?
- "master" branch?

# scaling (performance, speed)

easy

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- well defined interfaces

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- shared nothing

# scaling (performance, speed)

- easy
- well defined interfaces.
- shared nothing
- load balancing

### model health

what if incoming data is different than training data?

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  - e.g., hot dog vs not hot dog, and someone gives it a brautwurst

#### model health

- what if incoming data is different than training data?
  - e.g., hot dog vs not hot dog, and someone gives it a brautwurst
  - or a real example, kangaroos on self driving cars

## **Operations**

get new data! prompt users for wrong responses

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- online learning: re-train nightly/hourly/steaming w/ new data

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- get new data! prompt users for wrong responses
- online learning: re-train nightly/hourly/steaming w/ new data
- active learning: figure out what labels you need to improve model performance

tensors and flow graph

#### tensors

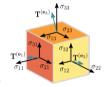
▶ linear relation between vectors, scalars, or other tensors

#### tensors

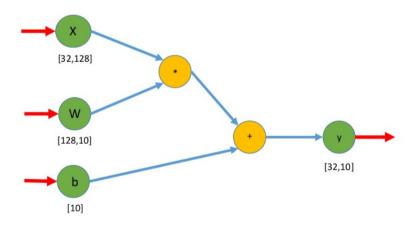
- linear relation between vectors, scalars, or other tensors
- practically: multi-dimensional array

#### tensors

- ▶ linear relation between vectors, scalars, or other tensors
- practically: multi-dimensional array



# computational flow graph (Directed-acyclic graph)



questions?

#### other resources

### other learning resources

- http://fast.ai
- https://hackernoon.com/choosing-the-right-machine-learning-algorithm-68126944ce1f
- http://ml-cheatsheet.readthedocs.io/en/latest/linear\_regression.html

Intro you're going to need some data algorithms gradient descent inference aka "pushing to production" tensors and flow graph questions? other resources

### image credits

- ai vs stats
- regression
- overfitting
- more overfitting
- loss functions
- gradient descent
- tensors
- tensorflow graph

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