CSE/STAT 416

Introduction + Regression

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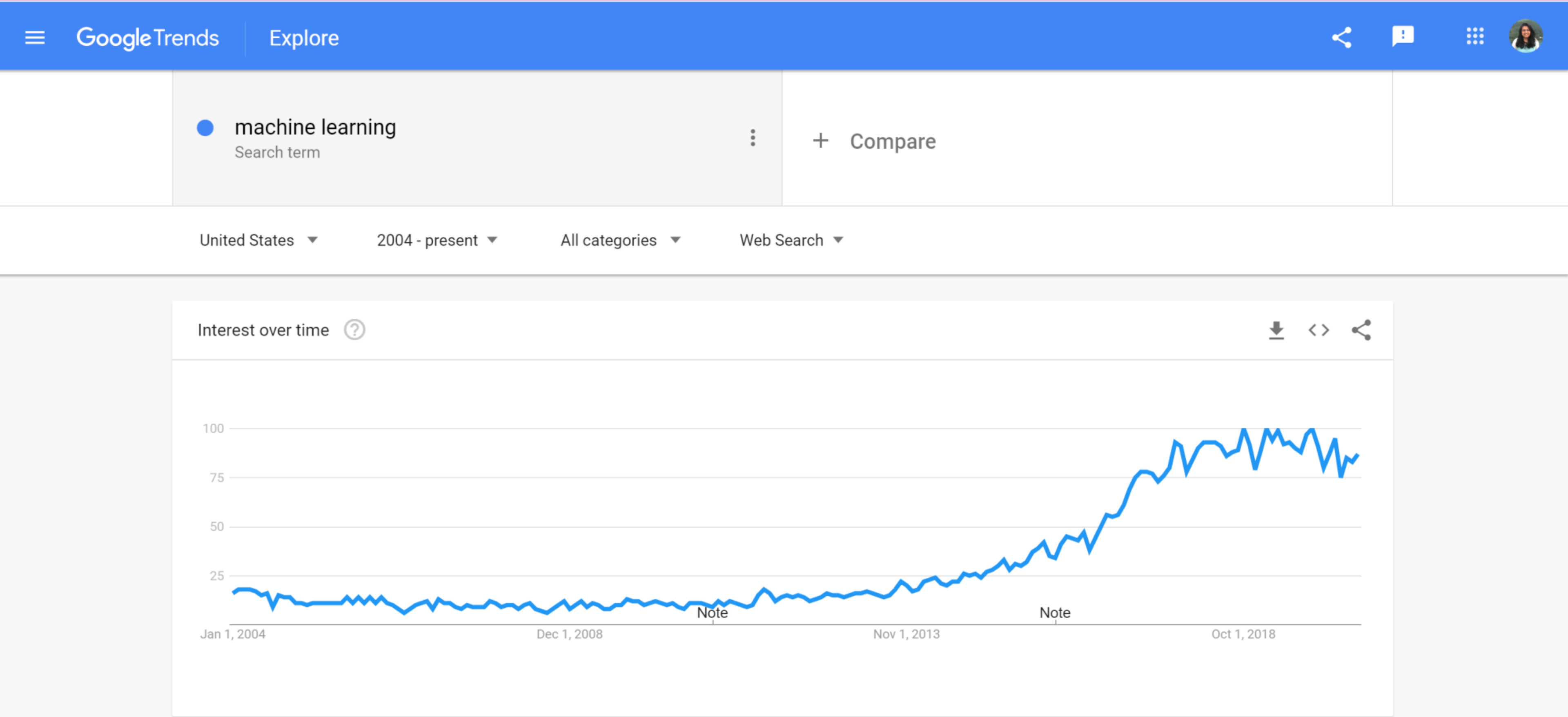
University of Washington
June 22, 2020

Slides and materials for this course courtesy of Hunter Schafer and Emily Fox.

Machine Learning is changing the world.



Google Trends
Explore
machine learning
Search term
+ Compare
United States
2004 - present
All categories
Web Search
Interest over time
100
75
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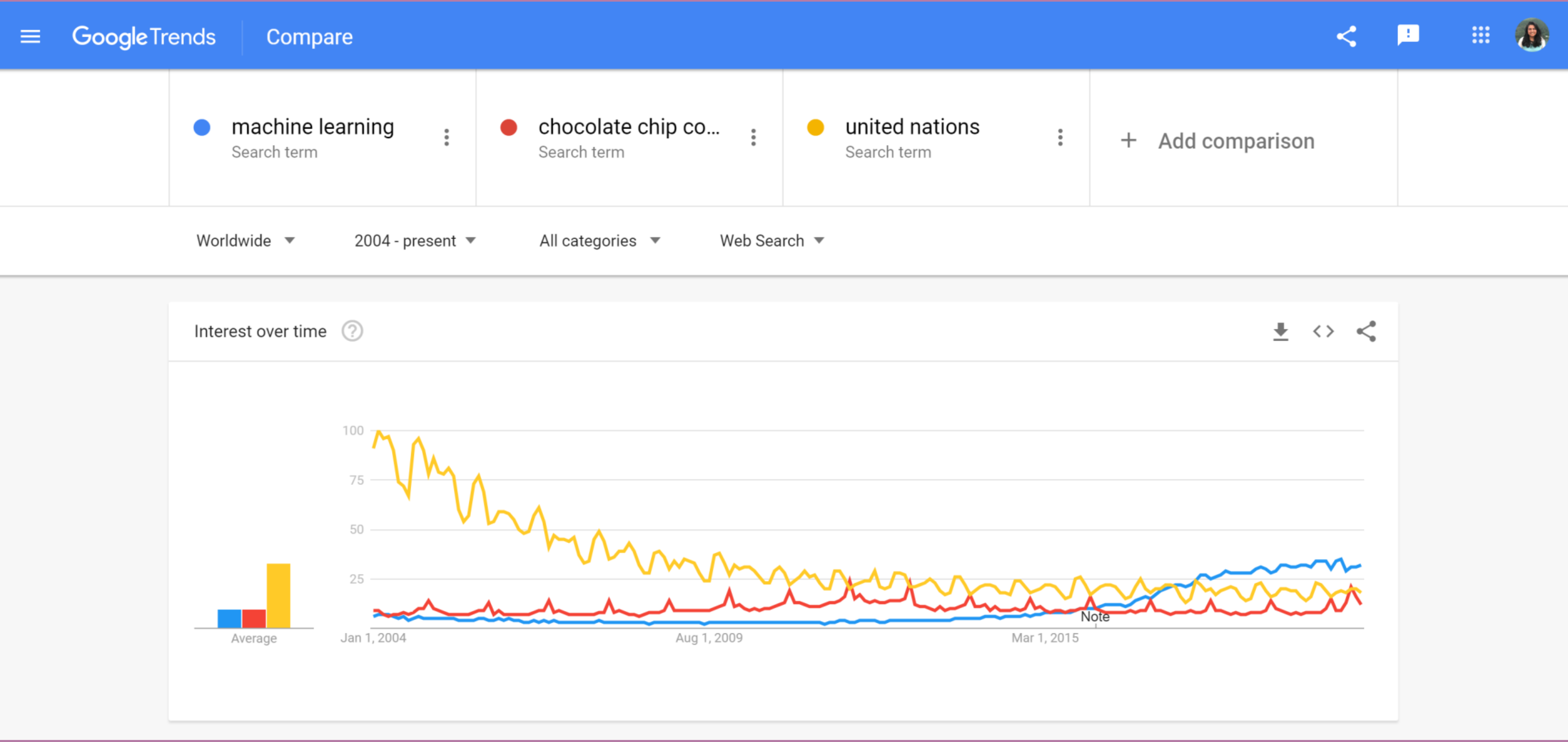
Note
Note
Jan 1, 2004
Dec 1, 2008
Nov 1, 2013
Oct 1, 2018


Google Trends
Compare
machine learning
Search term
chocolate chip co...
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Search term
+ Add comparison
Worldwide
2004 - present
All categories
Web Search
Interest over time
100
75
50
25
Average
Jan 1, 2004
Aug 1, 2009
Mar 1, 2015
Note

It's Everywhere!

amazon
Retail

Google PageRank
Search

Microsoft Office
Productivity Software

NETFLIX
Movie Distribution

Obama'08
Campaigning

Zillow
Real Estate

Avvo
Legal Advice

Google Adsense
Advertising

glassdoor
Human Resources

eHarmony
Dating

LinkedIn
Networking

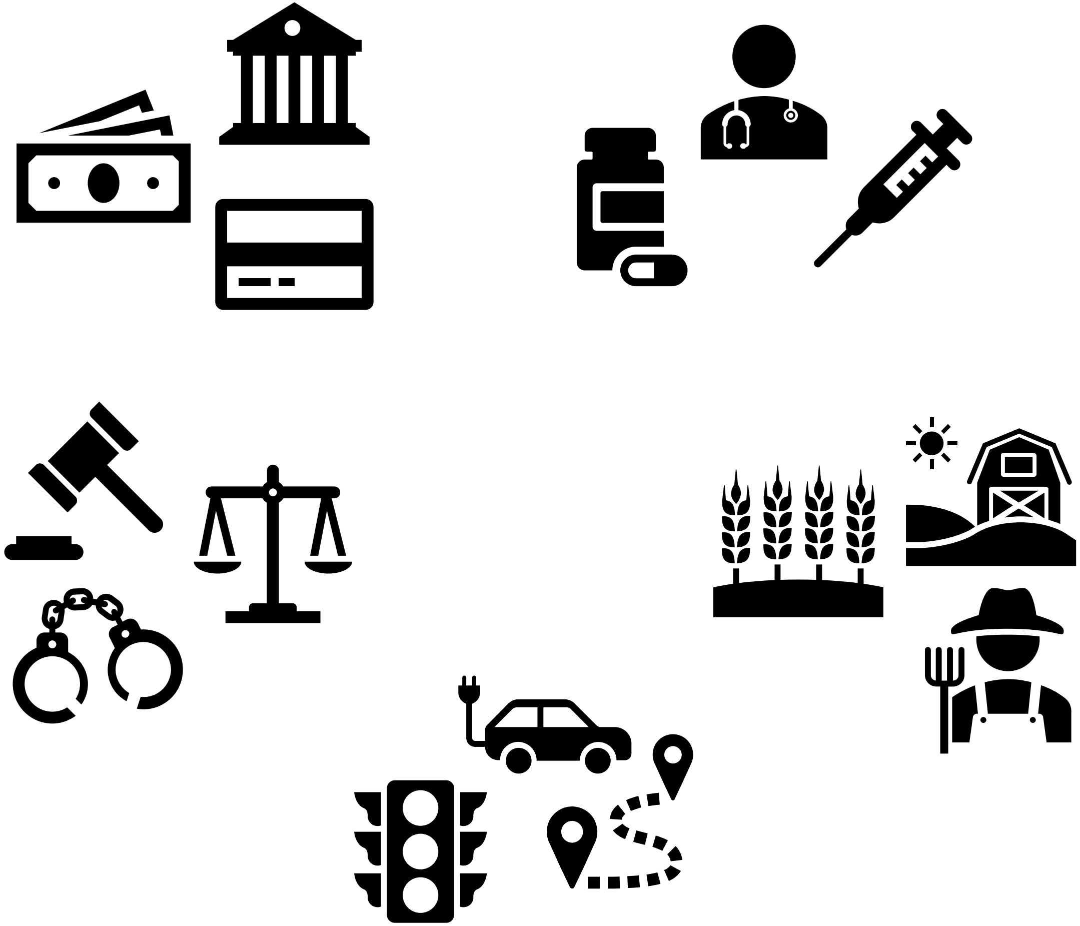
salesforce
CRM

PANDORA
Music

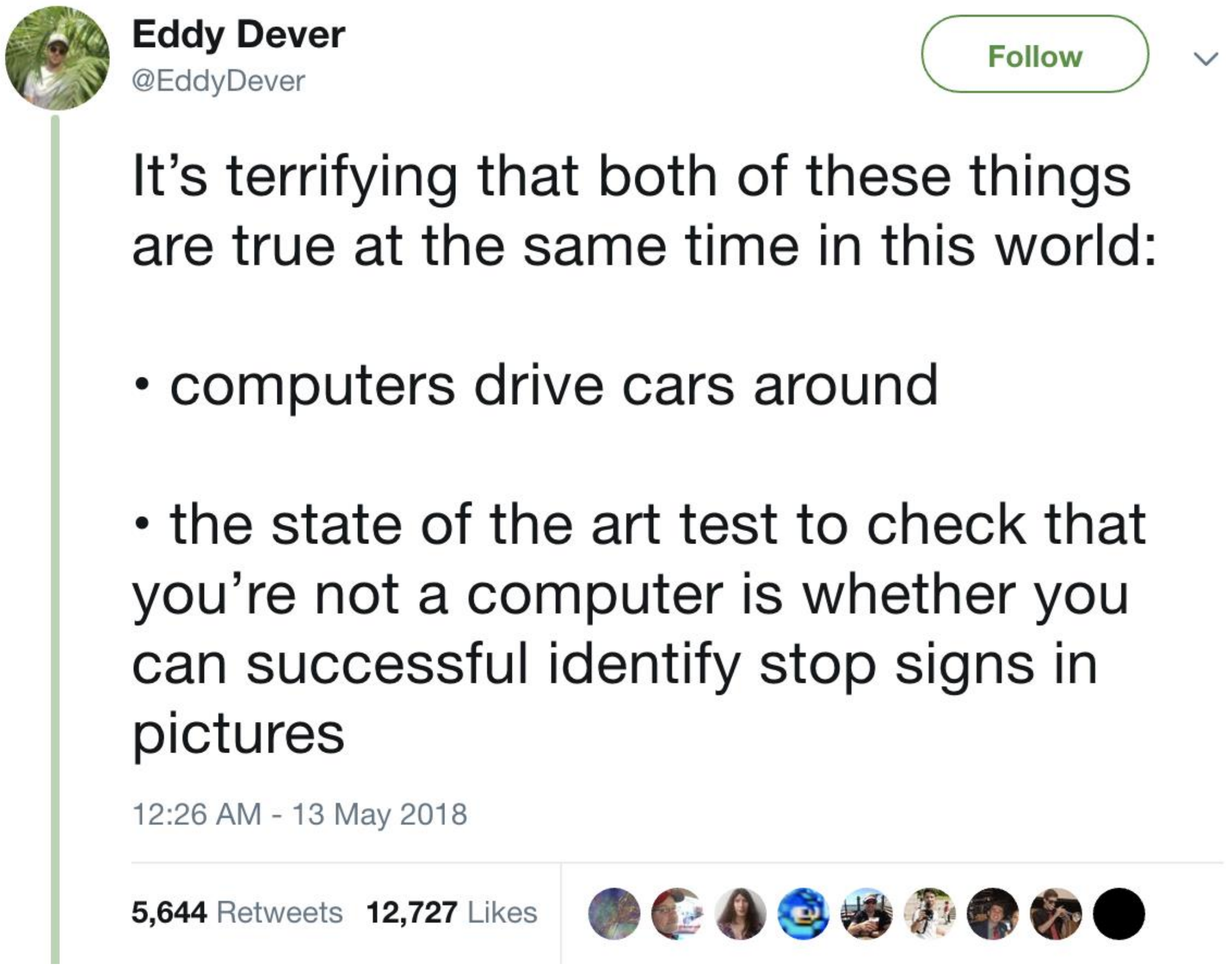
fitbit
Wearables

Disruptive companies differentiated by
INTELLIGENT APPLICATIONS
using
Machine Learning

It’s Everywhere...



It's Everywhere...



What is Machine Learning?

Generically (and vaguely)

Machine Learning is the study of algorithms that improve their **performance** at some **task** with **experience**

Course Overview

This course is broken up into 5 main case studies to explore ML in various contexts/applications.

1. Regression
   - Predicting housing prices
2. Classification
   - Positive/Negative reviews (Sentiment analysis)
3. Document Retrieval + Clustering
   - Find similar news articles
4. Recommender Systems
   - Given past purchases, what do we recommend to you?
5. Deep Learning
   - Recognizing objects in images

Course Topics

Models

- Linear regression, regularized approaches (ridge, LASSO)
- Linear classifiers: logistic regression
- Non-linear models: decision trees
- Nearest neighbors, clustering
- Recommender systems
- Deep learning

Algorithms

- *Gradient descent*
- Boosting
- K-means

Concepts

- Point estimation, MLE
- Loss functions, bias-variance tradeoff, cross-validation
- Sparsity, overfitting, model selection
- Decision boundaries

ML Course Landscape

CSE 446

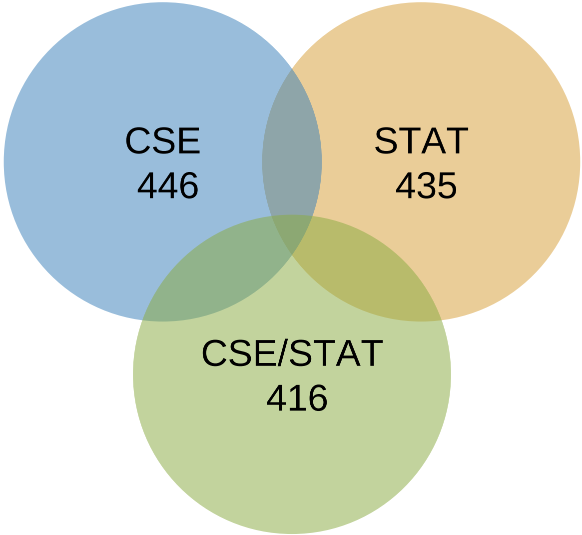
- CSE majors
- Very technical course

STAT 435

- STAT majors
- Very technical course

CSE/STAT 416

- Everyone else!
  - This is a super broad audience!
- Give everyone a strong foundational understanding of ML
  - More breadth than other courses, a little less depth



Level of Course

Our Motto

Everyone should be able to learn machine learning, so our job is to make tough concepts intuitive and applicable.

This means…

- Minimize pre-requisite knowledge
- Focus on important ideas, avoid getting bogged down by math
- Maximize ability to develop and deploy
- Use pre-written libraries to do many tasks
- Learn concepts in case studies

Does not mean course isn't fast paced! There are a lot of concepts to cover!

Course Logistics

Who am I?

- Vinitra Swamy
  - Lecturer, Paul G. Allen School for Computer Science & Engineering (CSE)
  - AI Software Engineer at Microsoft
    - AI Framework Interoperability
    - Open Neural Network eXchange (ONNX)
- Office Hours
  - Time: 4:00 pm - 5:00 pm, Fridays, or by appointment
  - Location: Zoom
- Contact
  - Personal Matters: vinitra@cs.washington.edu
  - Course Content + Logistics: Piazza

Who are the TAs?

AA (9:40)
AB (10:50)

Anne Wagner
amwag@uw

Jack Wu
hongjun@uw

AA (9:40)
AB (10:50)

AC (12:00)

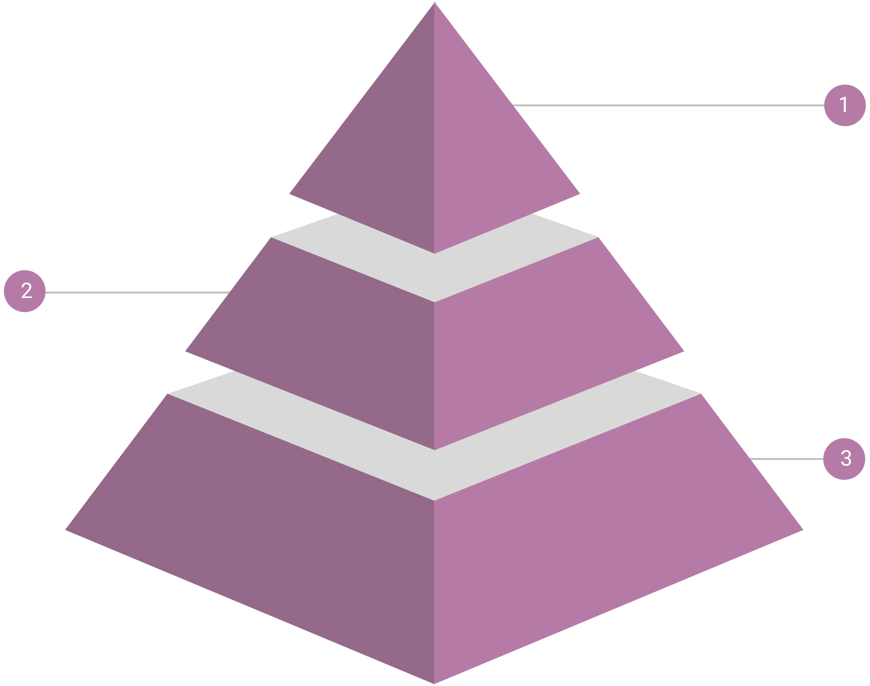
Ben Evans
bevans97@cs

Svetoslav Kolev
swetko@cs

AC (12:00)

Mon	Tue	Wed	Thur	Fri
Lecture	Nothing	**Lecture**	**Section**	Nothing
	Previous HW **Due**	Next HW **Released**		

- We happen to not record attendance in lectures and section, but attending these sessions is expected
- Participation component (5% of your grade)
- Zoom Recordings for Lecture (on Canvas)



Homework

With the scaffolding from **1 and 2**, you are probably now capable to tackle the homework. These will be complex and challenging, but you'll continue to **learn by doing.**

Sections

Practice material covered in **1** in a context where a TA can help you**.**

The emphasis is still on you l**earning by doing.**

Lectures

Introduced to material for the first time. Mixed with activities and demos to give you a chance to **learn by doing.**

No where near mastery yet!

Assessment

- Weekly Homework Assignments
  - **Weight**: 65%
  - **Number**: Approximately 8
  - Each Assignment has two parts that contribute to your grade separately:
    - Programming (50%)
    - Conceptual (15%)
- Participation
  - **Weight**: 5%
  - Answering PollEverywhere questions during lecture or up to 24 hours after (for students in different timezones)
- Final Exam
  - **Weight**: 30%
  - **Date:** Wednesday, August 19
  - **Location:** Online

Homework Logistics

- **Late Days**
  - 4 Free Late Days for the whole quarter.
  - Can use up to 2 Late Days on any assignment.
  - Each Late Day used after the 4 Free Late Days results in a -10% on that assignment

- **Collaboration**
  - You are encouraged to discuss assignments and concepts **at a high level**
    - If you have code in front of you in your discussion, probably **NOT** high level
    - Discuss process, not answers
  - All code and answers submitted must be your own

- **Turn In**
  - Everything completed and turned in on Gradescope
  - Multiple “assignments” on Gradescope per assignment

Case Study 1

Regression:
Housing Prices

Fitting Data

Goal: Predict how much my house is worth

Have data from my neighborhood

$$
n \text{ data points} \left\{
\begin{aligned}
(x_1, y_1) &= (\,2318\, sq.ft.\,,\ \$\,315k) \\
(x_2, y_2) &= (\,1985\, sq.ft.\,,\ \$\,295k) \\
(x_3, y_3) &= (\,2861\, sq.ft.\,,\ \$\,370k) \\
&\ \ \vdots \qquad\qquad \vdots \\
(x_n, y_n) &= (\,2055\, sq.ft.\,,\ \$\,320k)
\end{aligned}
\right.
$$

Assumption:

There is a relationship between $y \in \mathbb{R}$ and $x \in \mathbb{R}^d$

dimension $d = 1$

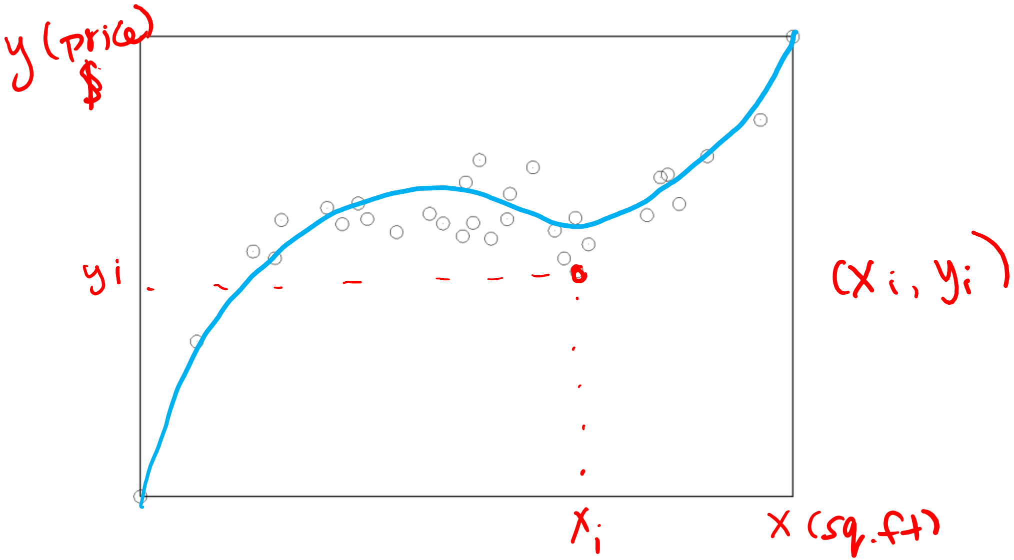
$$\boxed{y \approx f(x)}$$

x is the **input data.** Can potentially have many inputs

y is the **outcome/response/target/label/dependent variable**

Model

A **model** is how we *assume* the world works



Regression model:

$$y_i = f(x_i) + \varepsilon_i$$

$$E[\varepsilon_i] = 0$$

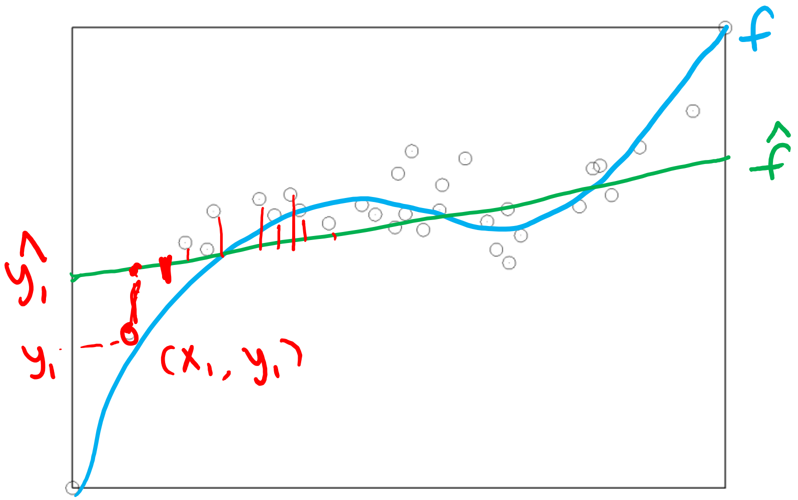
"Essentially, all models are wrong, but some are useful."
- George Box, 1987

Predictor

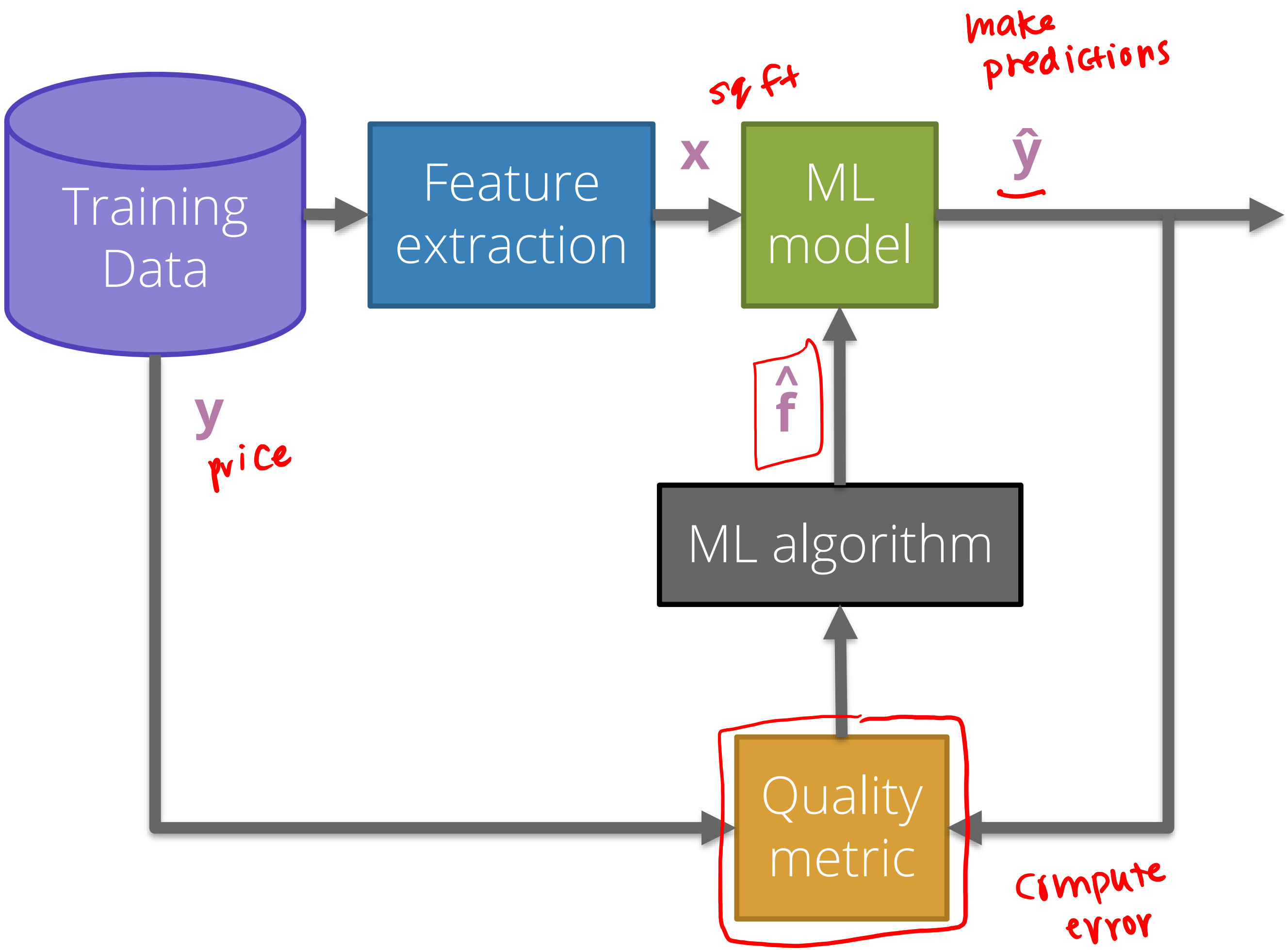
We don't know f! We need to learn it from the data!

Use machine learning to learn a predictor $\hat{f}$ from the data

For a given input x, predict: $\hat{y} = \hat{f}(x)$

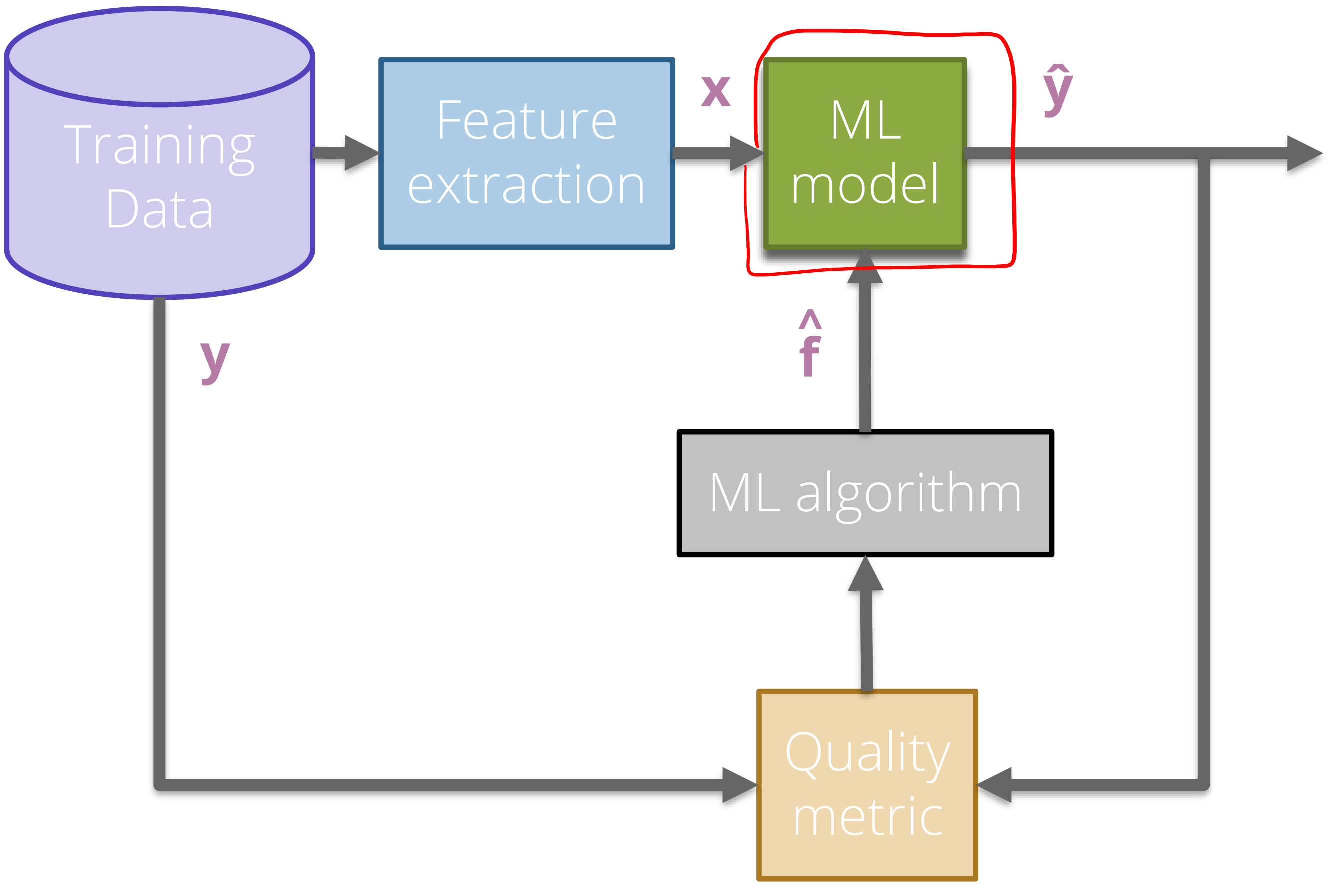


ML Pipeline



Training Data
Feature extraction
x
sq ft
ML model
make predictions
ŷ
y
price
f̂
ML algorithm
Quality metric
compute error

Linear Regression


Training Data
Feature extraction
x
ML model
ŷ
y
f̂
ML algorithm
Quality metric

Linear Regression Model

Assume the data is produced by a line.

$$y_i = \underbrace{w_0 + w_1 x_i}_{f(x_i)} + \epsilon_i$$

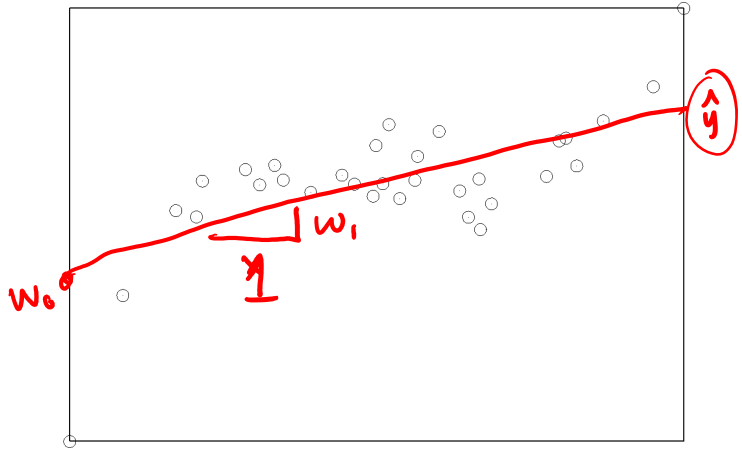
w_0, w_1 are the **parameters** of our model that need to be learned

- w_0 is the intercept ($ of the land with no house)
- w_1 is the slope ($ increase per increase in sq. ft)

40

Learn estimates of these parameters $\hat{w}_0, \hat{w}_1$ and use them to predict new value for any input x!

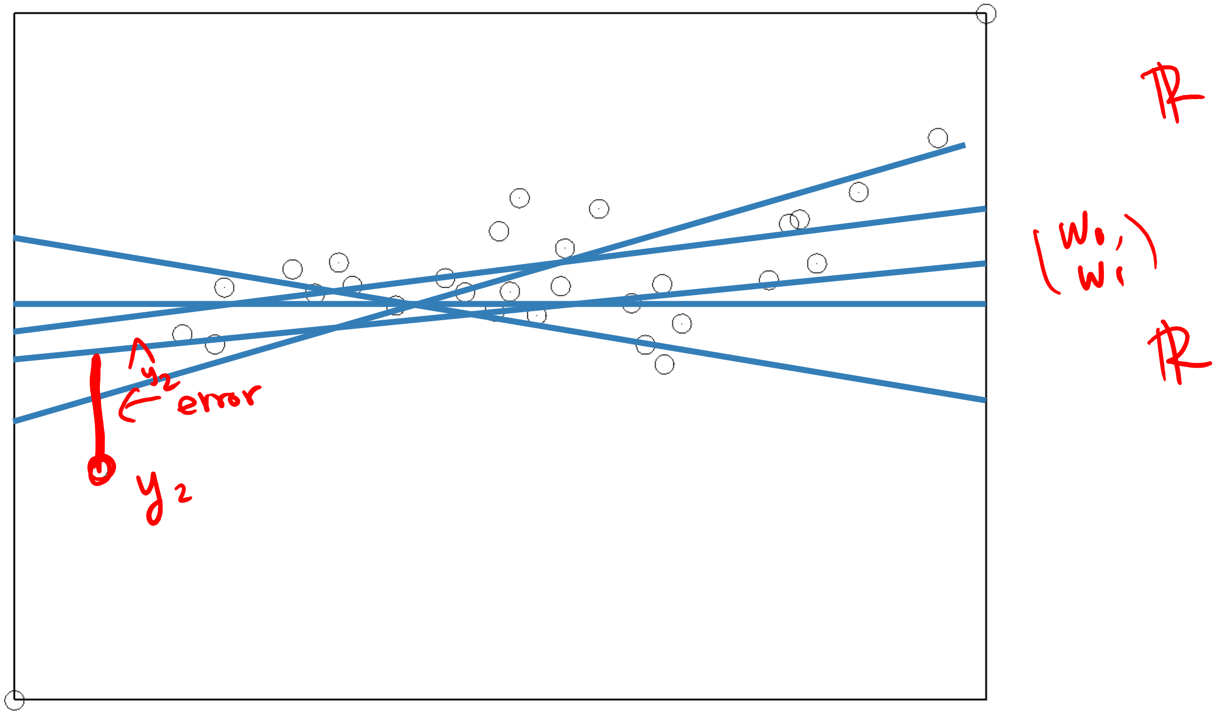
$$\hat{y} = \hat{w}_0 + \hat{w}_1 x$$

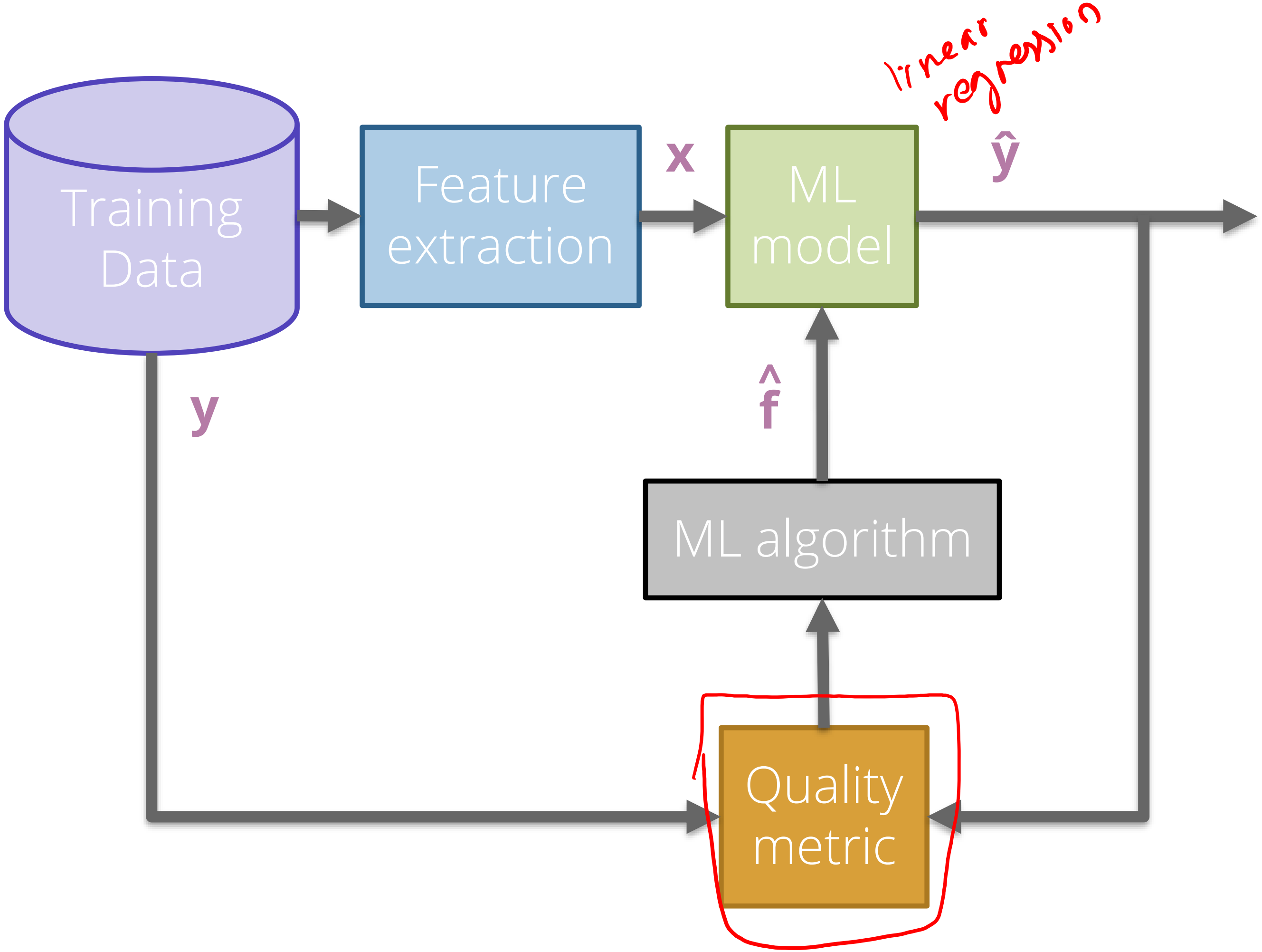


Basic Idea

Try a bunch of different lines and see which one is best!

What does best even mean here?





Training Data
Feature extraction
x
ML model
linear regression
ŷ
y
f̂
ML algorithm
Quality metric

“Cost” of predictor

Define a “cost” for a particular setting of parameters

- Low cost → Better fit
- Find settings that minimize the cost
- For regression, we will use the error as the cost.
  - Low error = Low cost = **Better predictor (hopefully)**

Note: There are other ways we can define cost which will result in different “best” predictors. We will see what these other costs are and how they affect the result.

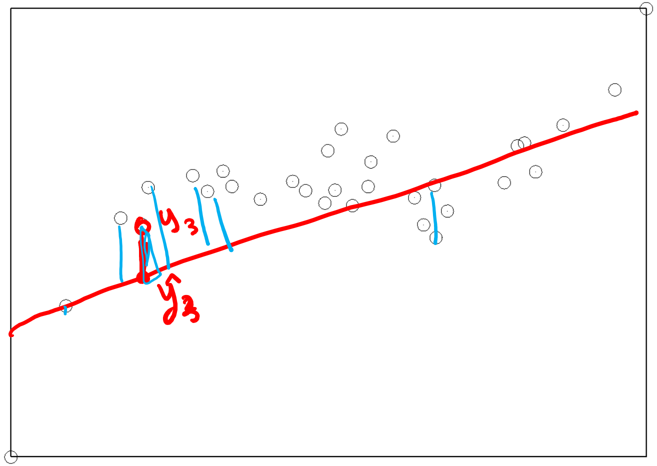
Residual Sum of Squares (RSS)

How to define error? **Residual sum of squares (RSS)**

$$RSS(w_0, w_1) = (y_1 - \hat{y}_1)^2 + (y_2 - \hat{y}_2)^2 + \ldots (y_n - \hat{y}_n)^2$$

$$= \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

$$= \sum_{i=1}^{n} (y_i - (w_0 + w_1 x_i))^2$$



$\hat{y}$

$$MSE_{(w_0,w_1)} = \frac{1}{n} RSS(w_0, w_1)$$

Poll Everywhere

pollev.com/cse416

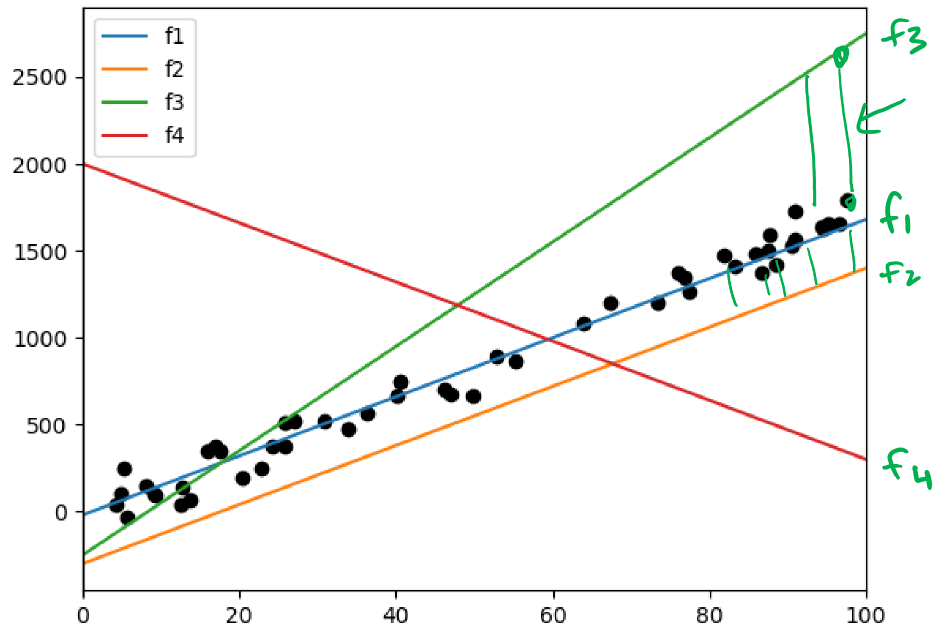
- **Goal**: Get you actively participating in your learning
  - **Think** (1 min): Think about the question on your own
    - Why is your answer choice correct?
    - Why are the other answer choices wrong?
  - **Answer** (1 min): Submit your answers on PollEverywhere
  - **Share** (1 min): We discuss the conclusions as a class
- During the **Answer** stage, you will respond to the question via a Poll Everywhere poll
  - Participation grade (5% of your grade)
    - Note: you're not penalized for answering incorrectly
    - After lecture, these will be open for 24 hours

Poll Everywhere

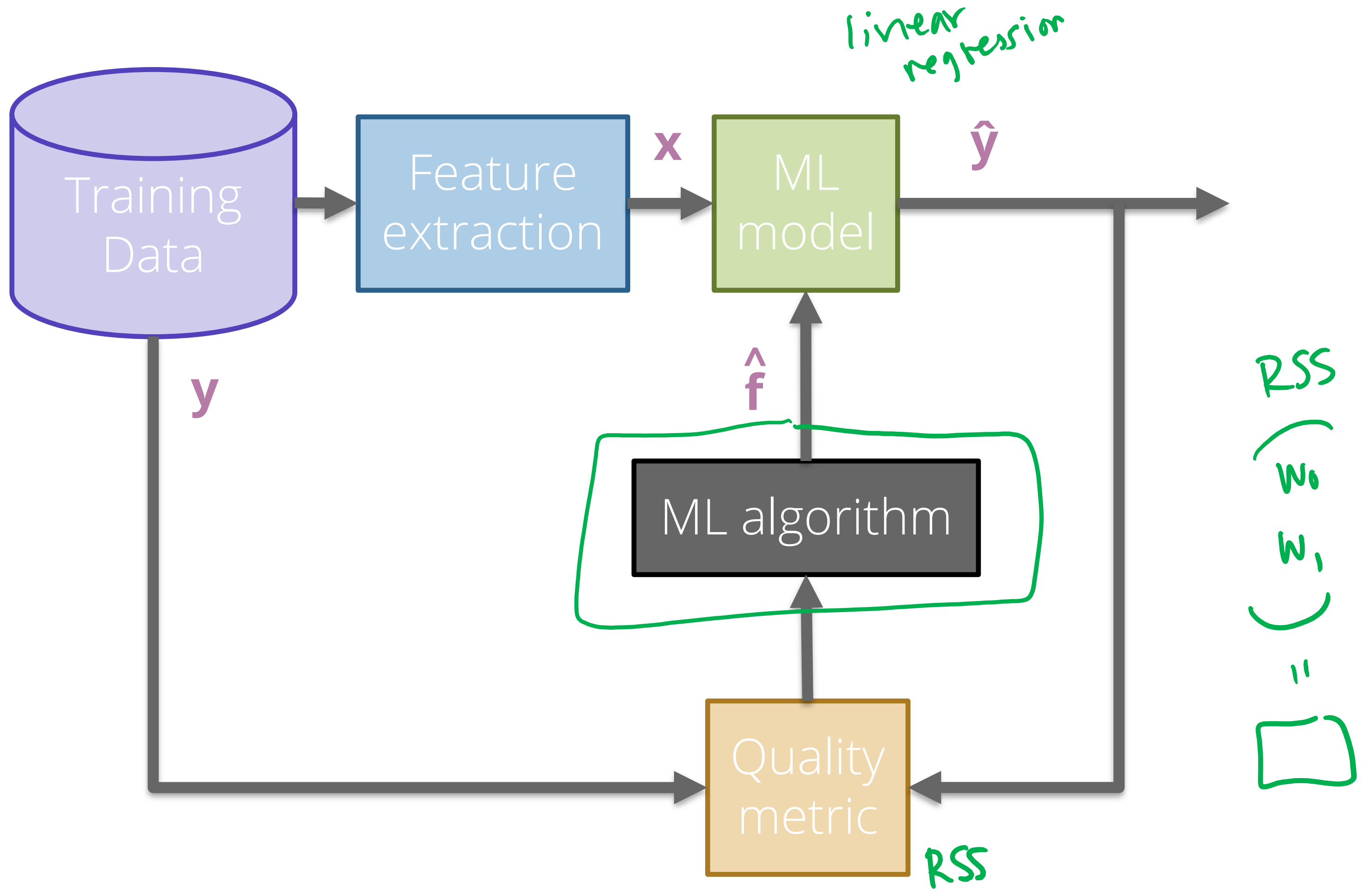
https://tinyurl.com/cse416-lec1

pollev.com/cse416

Sort the following lines by their RSS on the data, from smallest to largest. (estimate, don't actually compute)

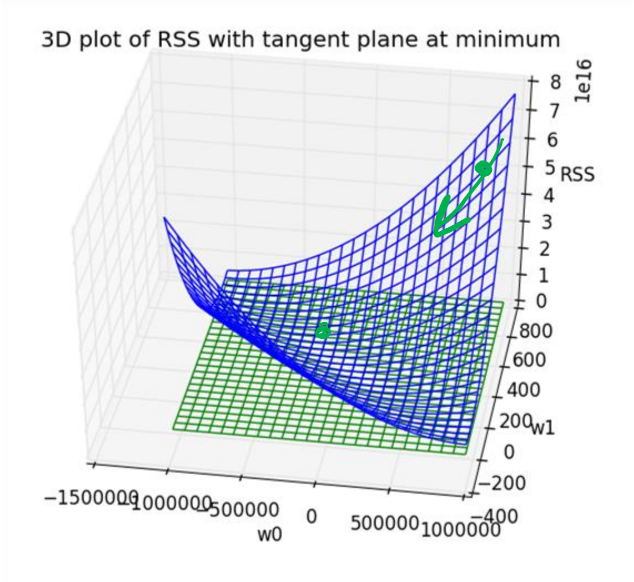


f1 < f2 < f3 < f4


linear regression
Training Data
Feature extraction
x
ML model
ŷ
y
f̂
ML algorithm
Quality metric
RSS
RSS
w0
w1
"

Minimizing Cost

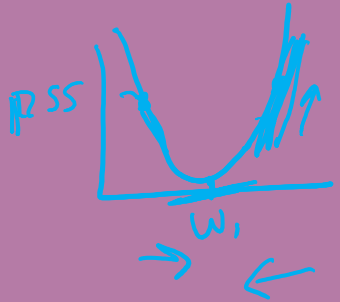
RSS is a function with inputs w_0, w_1, different settings have different RSS for a dataset

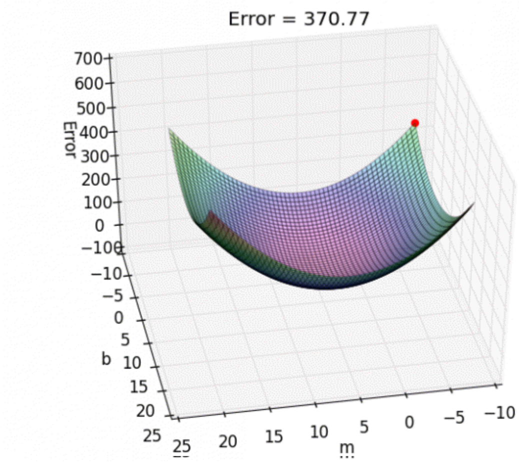


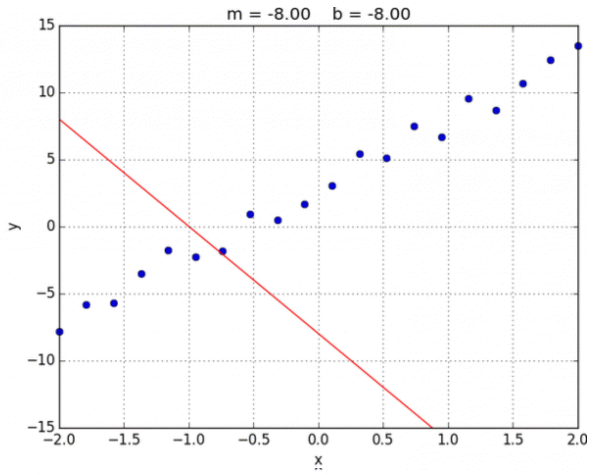
$$\hat{w}_0, \hat{w}_1 = \min_{w_0, w_1} RSS(w_0, w_1)$$
$$= \min_{w_0, w_1} \sum_{i=1}^{n} (y_i - (w_0 + w_1 x_i)^2)$$

Unfortunately, we can't try it out on all possible settings ☹

Gradient Descent







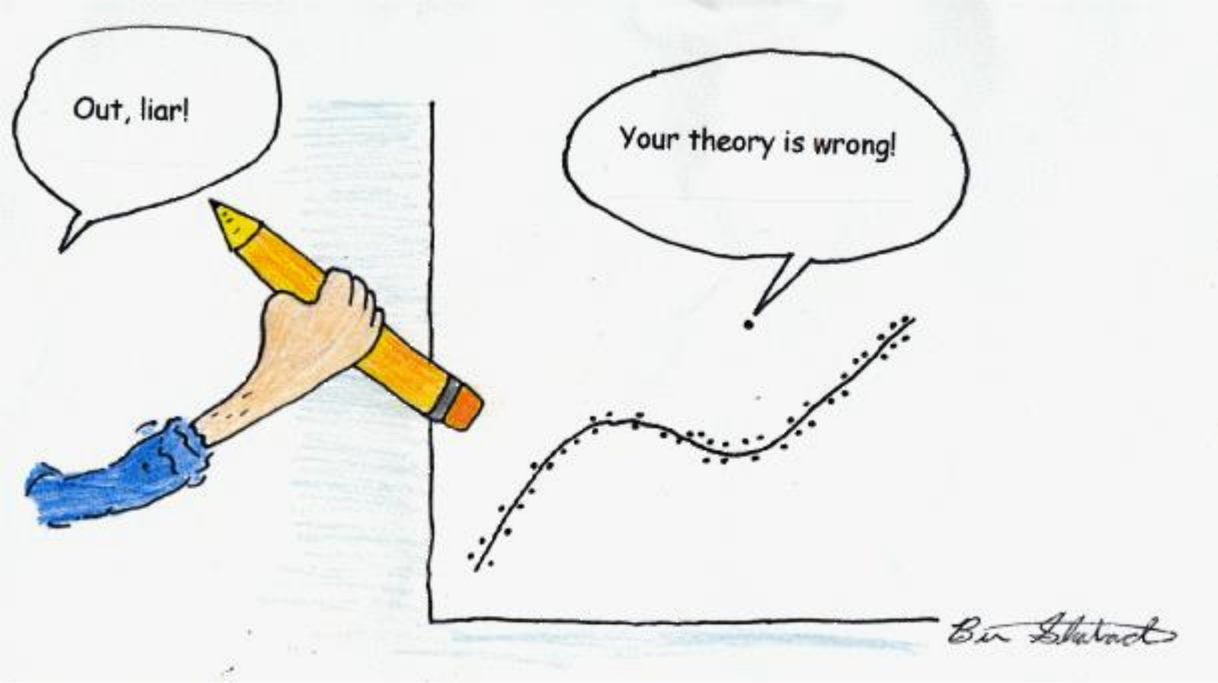
Instead of computing all possible points to find the minimum, just start at one point and “roll” down the hill.
Use the gradient (slope) to determine which direction is down.

start at some (random) point $w^{(0)}$ when $t = 0$

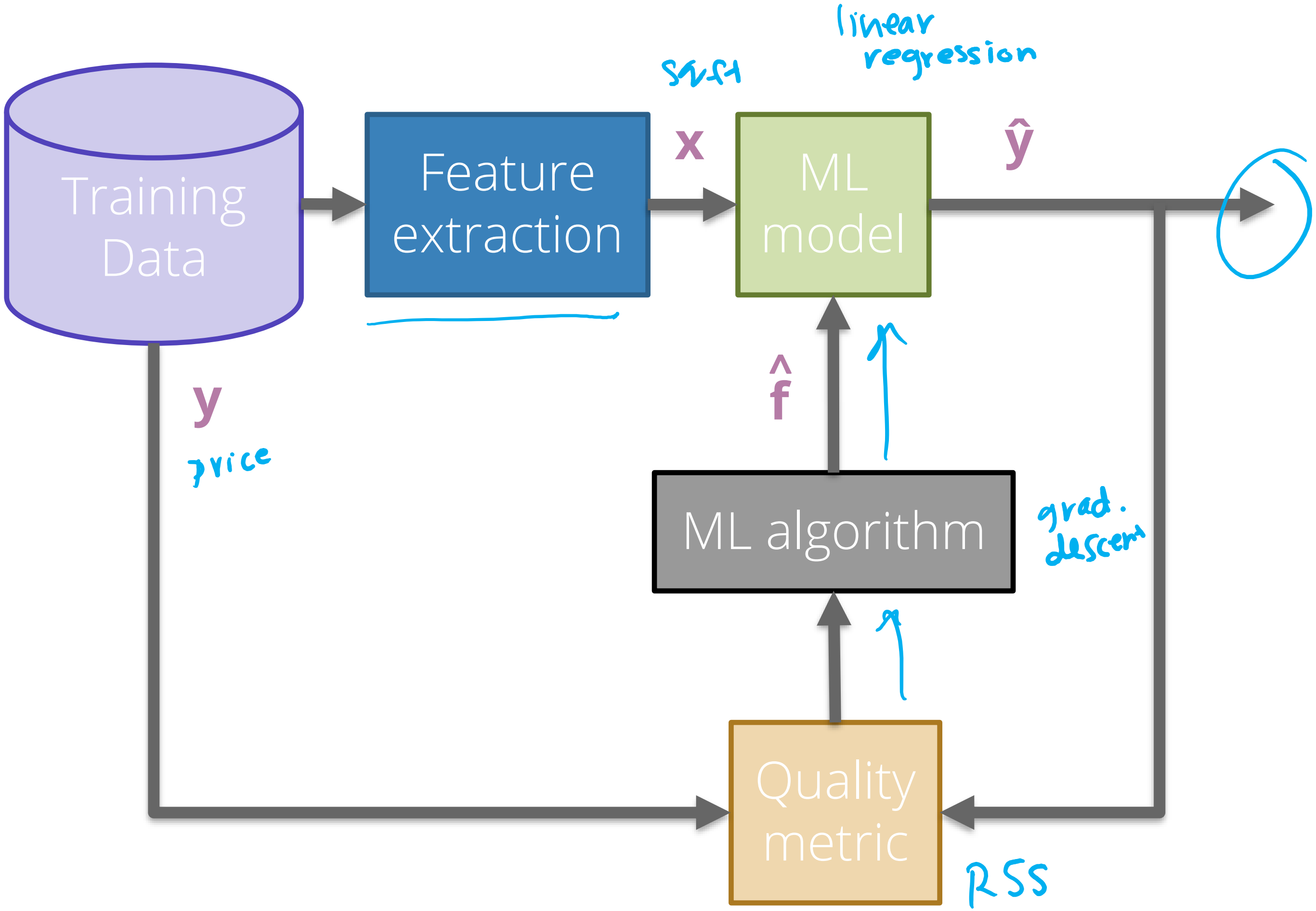
while we haven’t converged:

$$w^{(t+1)} = w^{(t)} - \eta \nabla RSS(w^{(t)})$$

Brain Break



Disclaimer: This is for your comedic entertainment. Please don't actually erase outliers ☺



Training Data
Feature extraction
ML model
ML algorithm
Quality metric
x
ŷ
y
f̂
linear regression
price
grad. descent
RSS

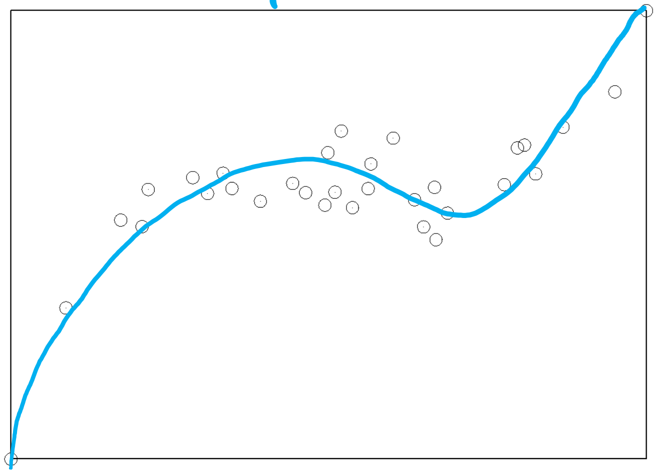
Higher Order Features

This data doesn't look exactly linear, why are we fitting a line instead of some higher-degree polynomial?

We can! We just have to use a slightly different model!

$$y_i = \underbrace{w_0 + w_1 x_i + w_2 x_i^2 + w_3 x_i^3}_{f(x_i)} + \epsilon_i$$

sq ft



Polynomial Regression

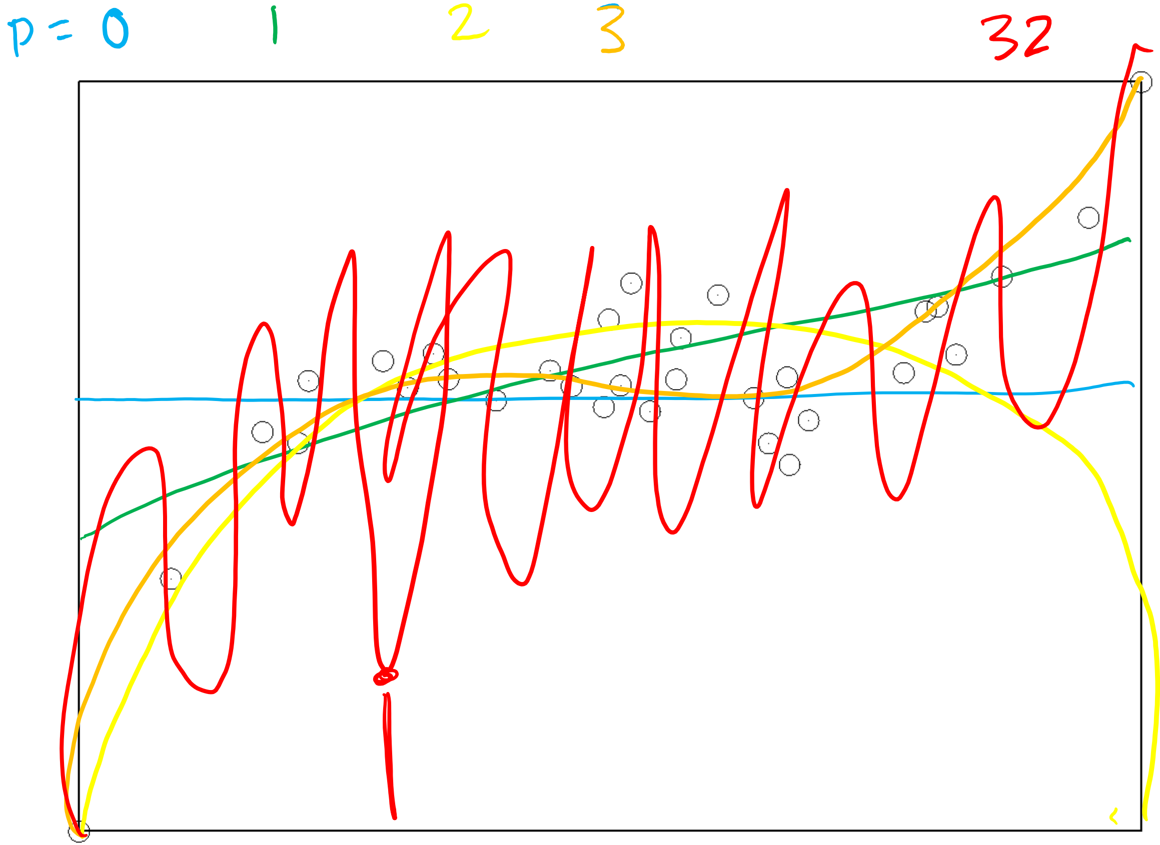
Model

$$y_i = w_0 + w_1 x_i + w_2 x_i + \dots + w_p x_i^p + \epsilon_i$$

Just like linear regression, but uses more features!

Feature	Value	Parameter
0	1 x^0	$\boxed{w_0}$
1	x	w_1
2	x^2	w_2
...	…	…
p	x^p	w_p

Polynomial Regression



How to decide what the right degree? Come back Wednesday!

Features

Features are the values we select or compute from the data inputs to put into our model. **Feature extraction** is the process of turning the data into features.

Model

1

$$y_i = w_0 h_0(x_i) + w_1 h_1(x_i) + \ldots + w_D h_D(x_i) + \epsilon_i$$

$$= \sum_{j=0}^{D} w_j h_j(x_i) + \epsilon_i$$

$d=1$
input dimension

Feature	Value	Parameter
0	$h_0(x)$ often 1 (constant)	w_0
1	$h_1(x)$ x^2+x	w_1
2	$h_2(x)$ e^x	w_2
…	…	…
D	$h_D(x)$ $\log(x)$	w_D

Adding Other Inputs

Generally we are given a data table of values we might look at that include more than one value per house.

- Each row is a single house.
- Each column (except Value) is a data input.

sq. ft.	# bathrooms	owner's age	…	value
1400	3	47	…	70,800
700	3	19	…	65,000
…	…	…	…	…
1250	2	36	…	100,000

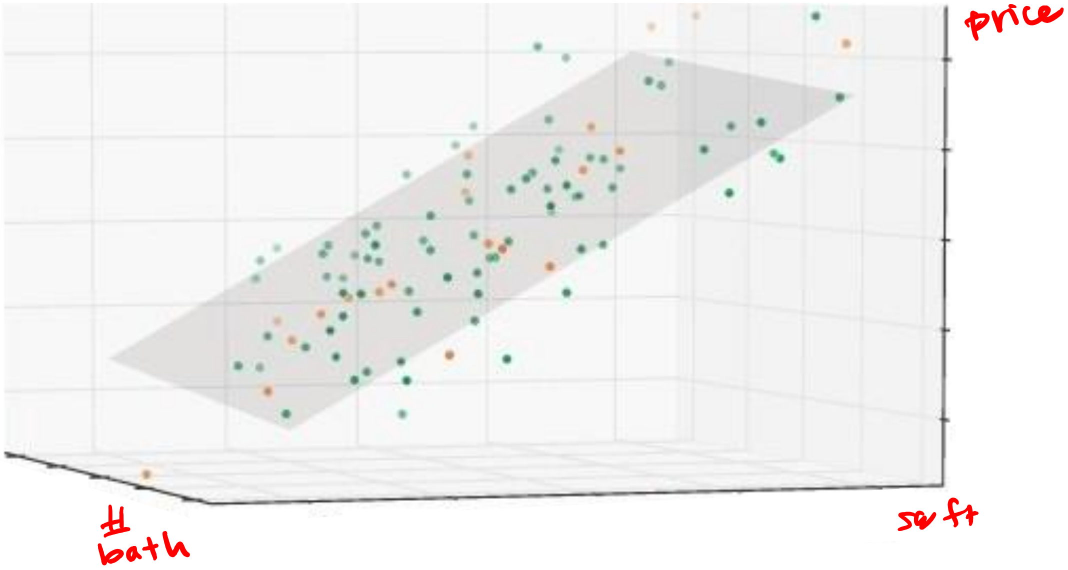
inputs

y

More Inputs - Visually

Adding more features to the model allows for more complex relationships to be learned

$$y_i = w_0 + w_1(sq.ft.) + w_2(\#\ bathrooms) + \epsilon_i$$



Coefficients tell us the rate of change if all other features are constant

Notation

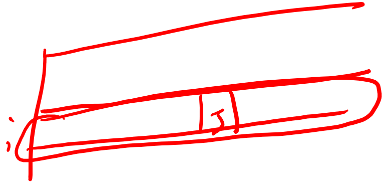
$$h(x) = \begin{bmatrix} h_0(x) \\ h_1(x) \\ \vdots \end{bmatrix}$$

Important: Distinction is the difference between a data *input* and a *feature*.

- Data inputs are columns of the raw data
- Features are the values (possibly transformed) for the model (done after our feature extraction $h(x)$)

Data Input: $x_i = (x_i[1], x_i[2], \dots, x_i[d])$

Output: y_i



- x_i is the i^{th} row
- $x_i[j]$ is the i^{th} row's j^{th} data input
- $h_j(x_i)$ is the j^{th} feature of the i^{th} row

$$\begin{matrix} 0 \\ \vdots \\ D \end{matrix}$$

Features

You can use anything you want as features and include as many of them as you want!

Generally, more features means a more complex model. This might not always be a good thing!

input = sq ft

Choosing good features is a bit of an art.

Feature	Value	Parameter
0	1 (constant)	w_0
1	$h_1(x)$ … x[1] = sq. ft.	w_1
2	$h_2(x)$ … x[2] = # bath	w_2
…	…	…
D	$h_D(x)$ … log(x[7]) * x[2]	w_D

sq. ft
$x[1]^2$

Linear Regression Recap

$w^T h(x)$

$w^T = [w_0 \ w_1 \ \dots \ w_D]$

$h(x) = \begin{bmatrix} h_0(x) \\ h_1(x) \\ \vdots \\ h_D(x) \end{bmatrix}$

Dataset

$\{(x_i, y_i)\}_{i=1}^n$ where $x \in \mathbb{R}^d$, $y \in \mathbb{R}$

Feature Extraction

$h(x)\colon \mathbb{R}^d \to \mathbb{R}^D$

$h(x) = (h_0(x), h_1(x), \dots, h_D(x))$

Regression Model

$$y = f(x) + \epsilon$$
$$= \boxed{\sum_{j=0}^{D} w_j h_j(x) + \epsilon}$$
$$= w^T h(x) + \epsilon$$

Quality Metric

$\hat{y}_i$

$$RSS(w) = \sum_{i=1}^{n} (y_i - w^T x_i)^2$$

Predictor

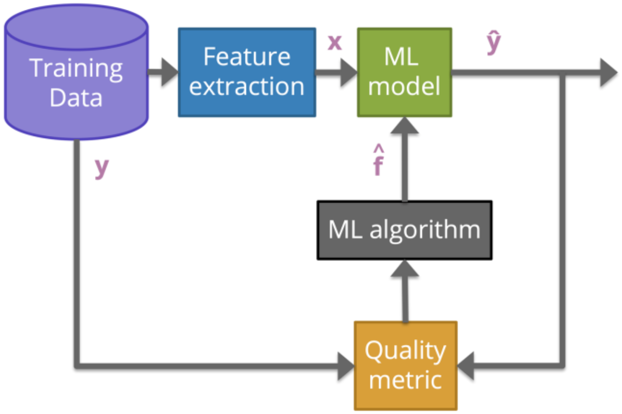
$$\hat{w} = \min_w RSS(w)$$

ML Algorithm

Optimized using Gradient Descent

Prediction

$$\hat{y} = \hat{w}^T h(x)$$



Notes