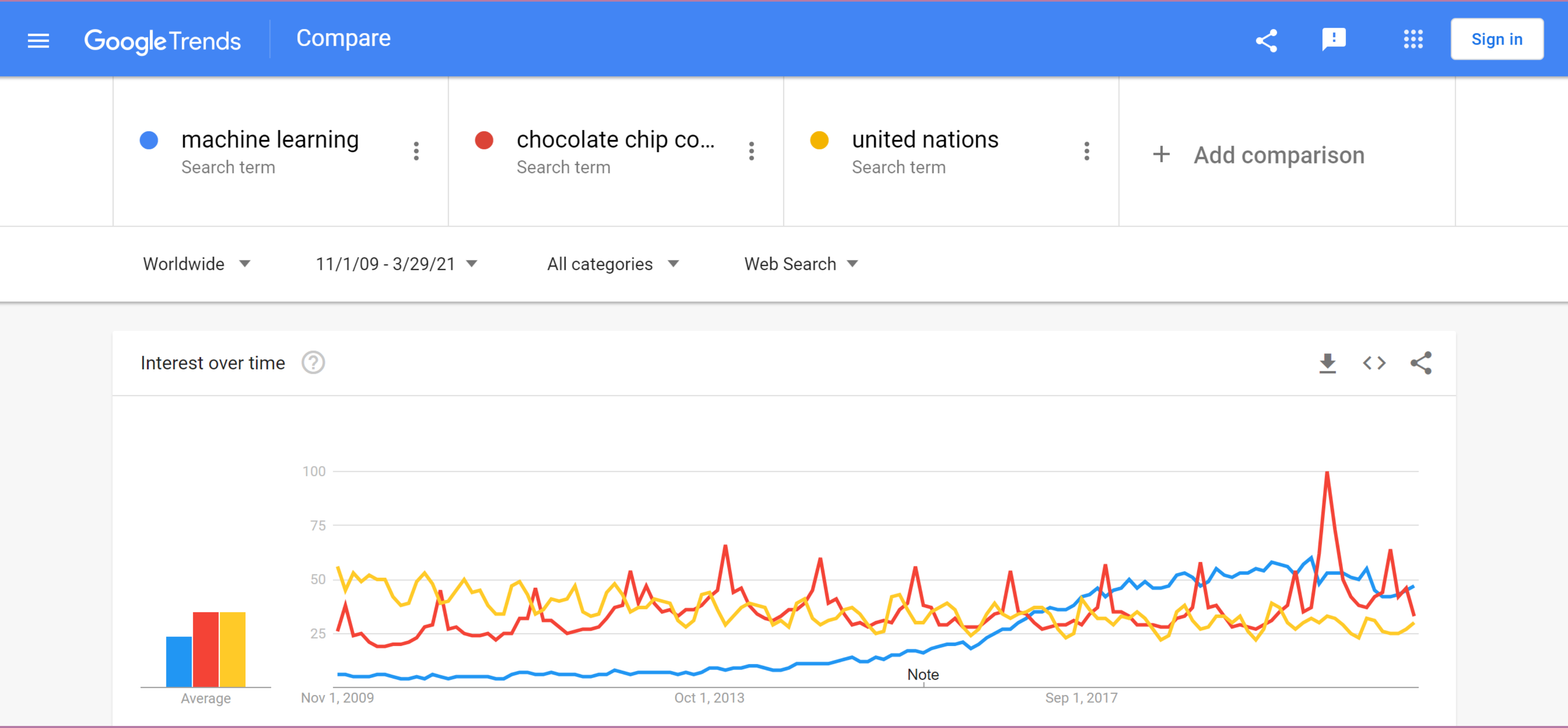
CSE/STAT 416

Introduction + Regression

Pemi Nguyen
University of Washington
March 28, 2022

Slides by Hunter Schafer

Machine Learning is changing the world.



Google Trends
Compare
Sign in
machine learning
Search term
chocolate chip co...
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+ Add comparison
Worldwide
11/1/09 - 3/29/21
All categories
Web Search
Interest over time
100
75
50
25
Note
Average
Nov 1, 2009
Oct 1, 2013
Sep 1, 2017

It's Everywhere!

Retail

PageRank
Search

Coupons

Movie
Distribution

Campaigning

Real Estate

Legal
Advice

Adsense
Advertising

Human
Resources

Dating

Networking

CRM

Music

Wearables

Disruptive companies
differentiated by
INTELLIGENT
APPLICATIONS
using
Machine Learning

It's Everywhere…

It’s Everywhere...

Eddy Dever
@EddyDever

Follow

It’s terrifying that both of these things are true at the same time in this world:

• computers drive cars around

• the state of the art test to check that you’re not a computer is whether you can successful identify stop signs in pictures

12:26 AM - 13 May 2018

5,644 Retweets **12,727** Likes

What is Machine Learning?

Generically (and vaguely)

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

Tom Mitchell (1998): a computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

Taxonomy of Machine Learning (Based on tasks)

SUPERVISED LEARNING

UNSUPERVISED LEARNING

REINFORCEMENT LEARNING

Taxonomy of Machine Learning (Based on tasks)

1. **Supervised Learning**
   - Training data is labeled, where inputs are paired with correct outputs
   - Infers a mapping function from the inputs to outputs
   - ***Examples:*** *image classification, stock price predictions*

2. **Unsupervised Learning**
   - Analyze and cluster unlabeled datasets
   - Discover patterns or data categorization without the need for human intervention
   - ***Examples:*** *DNA clustering, anomaly detection*

3. **Reinforcement Learning**
   - Not covered in this class (you can learn this in CSE 415 / 473 (Introduction to Artificial Intelligence)
   - Agents learn the optimal behaviors to obtain maximum reward through interactions with the environment and observations of how they responds.

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 / underfitting, model selection
- Decision boundaries

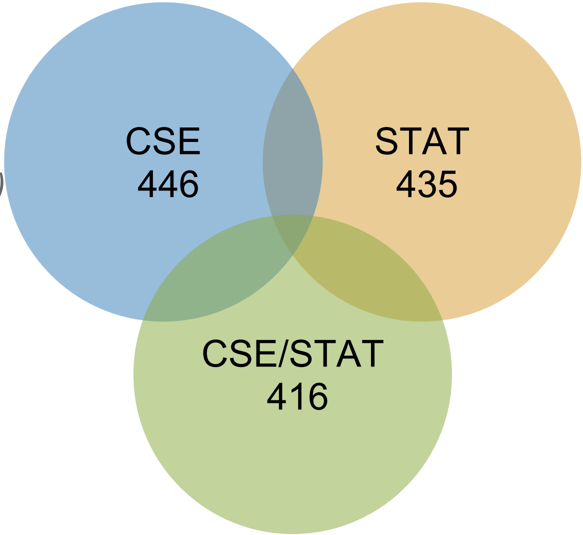
ML Course Landscape

CSE 446

CSE majors

Very technically demanding course

(which Pemi has taught as a TA for 4 quarters)



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
- Allow you to understand the ML concepts in an intuitive way.

Fun fact: ML is a very practical field, and intuitive thinking plays an important role for ML practitioners. There has not been a fully rigorous proof for the accuracy of neural networks, one of the main architecture of modern ML, but people still use intuitively understand how powerful they are.

- Focus on important ideas, avoid getting bogged down by math
- Exposed to Python, libraries and infrastructure to program ML problems
- 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?

Pemi Nguyen
Lecturer
he/him
peming@cs

Background

- UW CSE graduate
- Former Teaching Assistant and Content Development Contributor for CSE 311 (Discrete Math), CSE 312 (Probability & Stats for CS), CSE 446/546 (Machine Learning) for 7 quarters
- Former NLP Researcher at UWNLP
- Software Engineer at Facebook (starting June 2022)
- Disability & Accessibility Advocate

Contact

- Course Content + Logistics: [EdStem]
- Personal Matters: peming@cs.washington.edu

Pemi is not available for the first week. Hunter will take place as the substitute lecturer and Amal will help answer questions about logistics and stuff.

Who are the TAs?

Amal Nanavati
Head TA
he/they
amaln@cs

Sahil Verma
he/him
vsahil@cs

Wuwei Zhang
she/her
wz86@cs

Jack Zhou
he/him
zhoujack@uw

Rahul Biswas
he/him
rbiswas1@uw

Jerry Wei
he/him
zwei5@uw

Pranav Kamath
he/him
pranavpk@cs

Learning Reflections

Recap broader context of the past week.

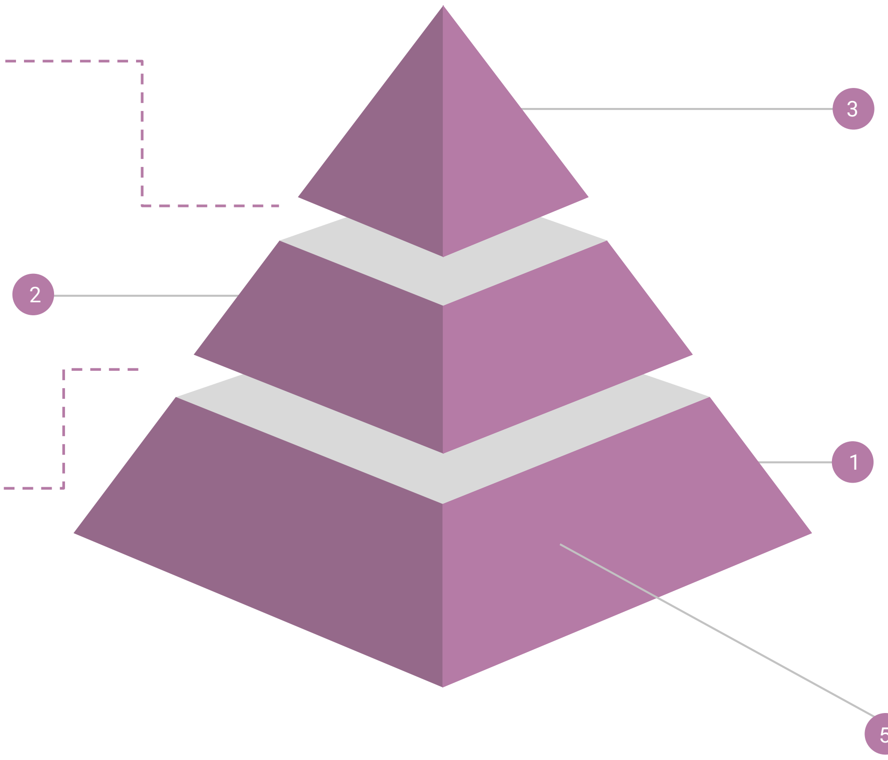
Sections

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

The emphasis is still on you **learning by doing.**

Checkpoints

Test your understanding of the last concept



Homeworks

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.**

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!

Extra credit opportunities

I believe that people deserve second chance if they don't perform well on some homeworks or exams. There are many opportunities for you to earn extra credit, which will be announced later in the quarter.

Mon	Tue	Wed	Thur	Fri
Lecture	Nothing	**Lecture**	**Section**	
Previous Checkpoint **Due 2pm PST (30 mins before lecture)**		Previous Checkpoint **Due 2PM PST (30 mins before lecture)**		Learning Refl. **Due** Previous HW **Due** Next HW **Released** **Due 11:59pm PST**

- **It's not required** to attend in lectures and section, but attending these sessions is **highly encouraged**
- Panopto for live lecture recordings and weekly section recordings by Rahul

Assessment

- **Weekly Homework Assignments (35%)**
  - **Number**: ~ 9 (drop 1)
  - You can submit in ***pairs*** (meaning, you can work individually or find a partner to work with)
  - Each Assignment has two parts that contribute to your grade
    - Programming (50%) – autograded, you receive scores right away
    - Conceptual (50%) – 1/2 autograded (won't receive scores until after deadlines) , 1/2 manually graded
- **Checkpoints (10%)**
  - Designed to be doable (30 mins) if you follow each previous lecture
  - **Number:** Approximately 20 (each lecture, drop 3)
- **Learning Reflections (10%)**
  - Full credit is expected (unless you don't show any effort)
  - You have to submit them ***individually***.
  - **Number:** Approximately 10 (each week, drop 1)
- **Midterm + Final Exams (45%)**
  - 15% for midterm and 20% for final
  - Open handwritten notes ***allowed***. No limit on length.
  - **Dates: TBD**

Extra credit opportunities

I don't believe in faulting people if they don't perform well in homeworks or exams occasionally. These are a number of ways to earn extra credit:

- Respond to other students' questions on EdStem as actively as possible. I won't give you a definite answer on how active you should be to be eligible. Just do your best and contribute to class discussions within your capacity.
- Write original, thoughtful analysis of interesting machine learning topics on EdStem, such as linking external sources and providing your opinions. I will endorse the well-written ones.
- Submit answers to extra credit problems from homeworks.
- Towards the end of the quarter, I will invite some researchers or ML practitioners to give talks on specific applications of ML. You can attend those and write a reflection on each event. More information on this later.

Homework Logistics

- **Late Days**
  - 6 Free Late Days for the whole quarter.
  - Can use up to 2 Late Days on homework assignments only
  - Each Late Day used after the 6 Free Late Days results in a -10% on that assignment
  - Learning reflections and checkpoints can be turned in up to a week later for 50% credit.
- **Collaboration**
  - You are encouraged to discuss assignments and concepts **at a high level** with anyone not in your group
    - If you are reading off parts of your solution, it's likely not high level
    - Discuss process, not answers!
  - All code and answers submitted must be yours or your homework partner's
- **Turn In**
  - Homework submissions (both coding + conceptual) and Learning reflections are turned in on **Gradescope**
  - Checkpoints are turned in on **EdStem**

Getting Help

The best place to get **asynchronous help** is EdStem. You can post questions (publicly or privately) to get help from peers or members of the course staff.

- You're encouraged to respond with your ideas to other posts!

The best place to get **synchronous help** is office hours or to form a study group.

- Office hours will be run on Zoom or on-campus (in CSE rooms). We will try to provide a balanced mix of virtual and in-person OHs to allow people to enjoy the benefits of both.

- We provide an unmoderated **Discord** channel for students in the class. Staff members won't monitor Discord, so please be civil and do not engage in any academic misconduct.

- We will try to help you meet peers this quarter to form study groups. More on this later!

Case Study 1

Regression:
Housing Prices

Poll Everywhere

Think

90 seconds

pollev.com/cs416

On your phone / laptop

What are the factors of determining the price of a house?

Fitting Data

Goal: Predict how much my house is worth

Have data from my neighborhood

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

Assumption:

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

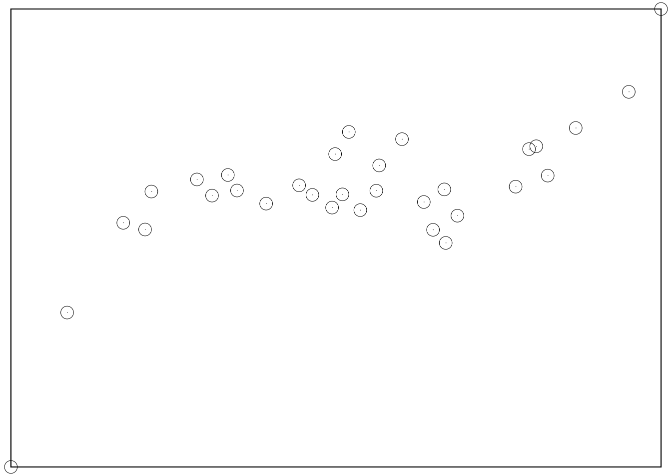
$$y \approx f(x)$$

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:

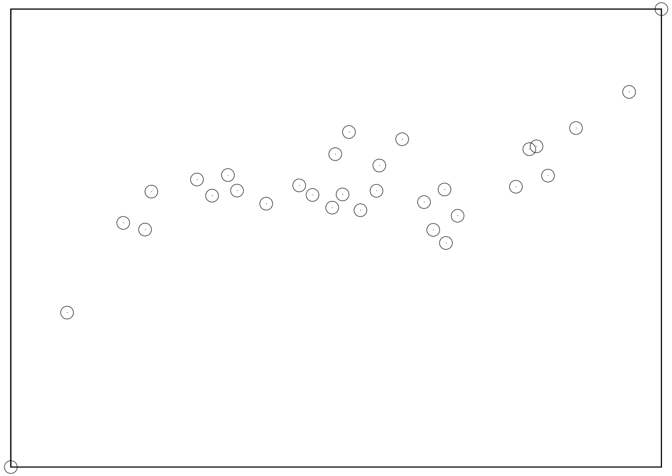
"Essentially, all models are wrong, but some are useful."
- George Box, 1987

Predictor

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

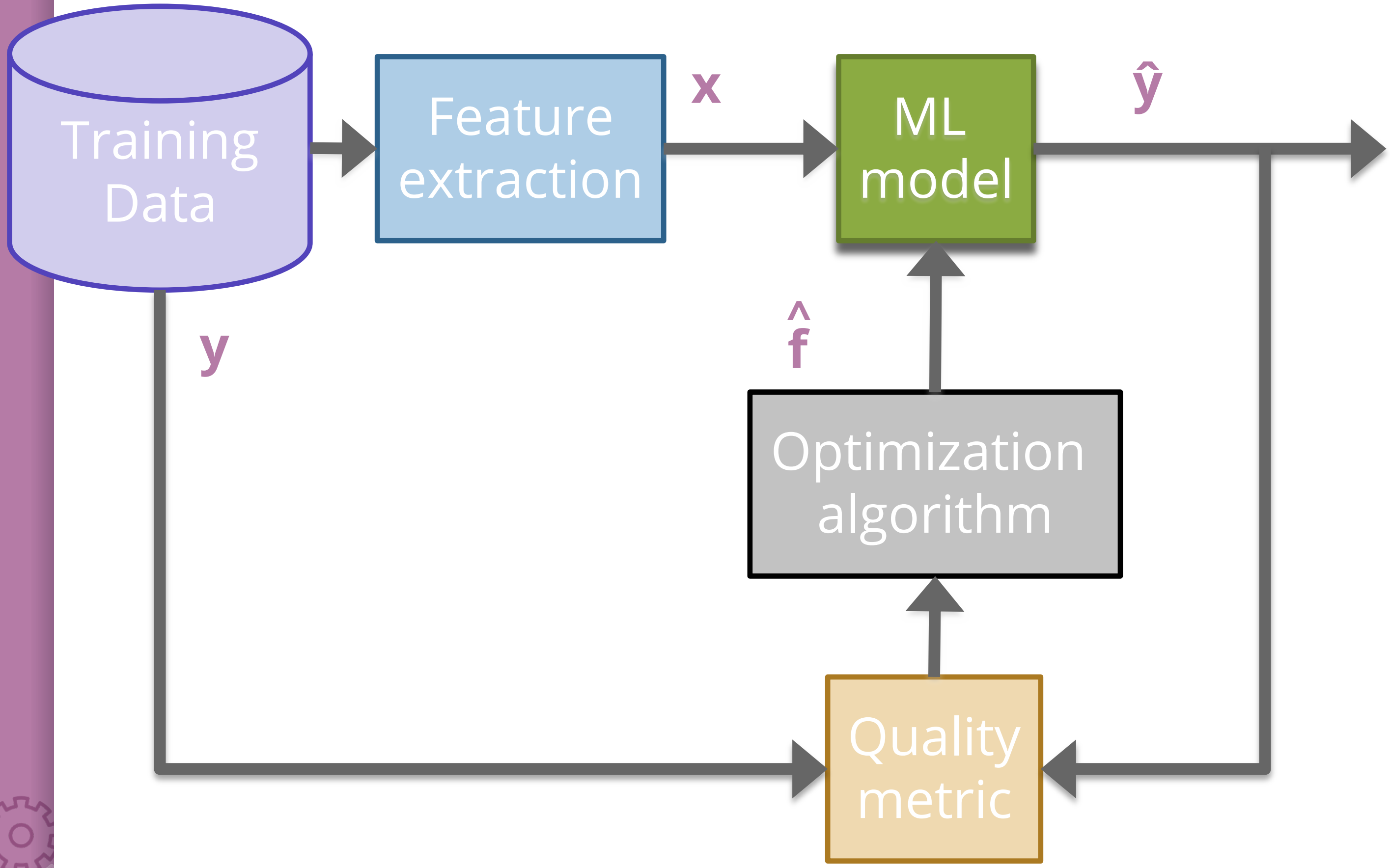
Use machine learning to learn a predictor $\hat{f}$ from the data

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



Small error on an example, means we had a good fit *for that point*

ML Pipeline


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

Regression

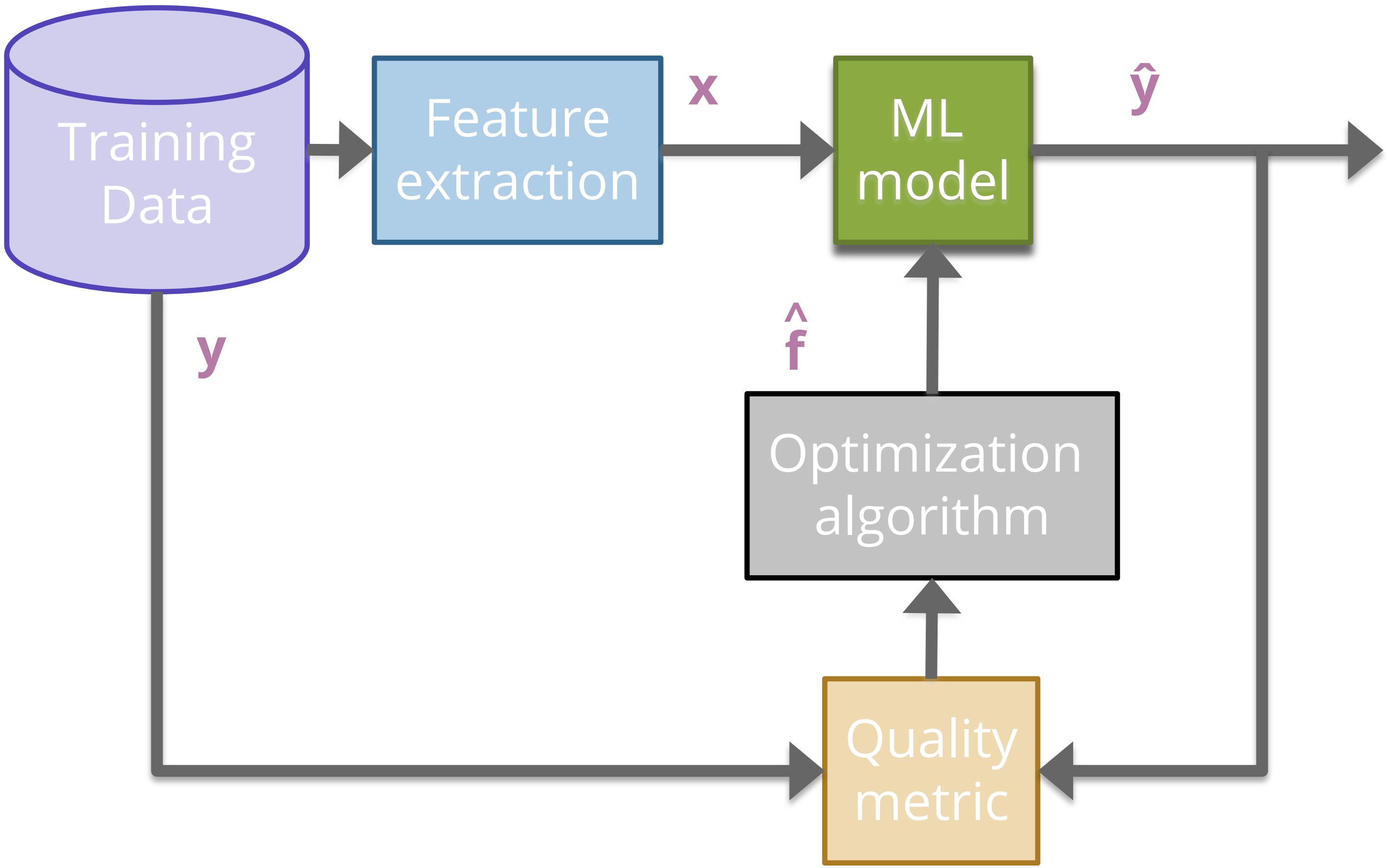
Is a supervised learning algorithm

Given a set of training data examples $X^{(1)}, X^{(2)}, \ldots, X^{(n)}$ associated to with set of continuous values $y^{(1)}, y^{(2)}, \ldots, y^{(n)}$ we want to build a predictor function that learns how to map $x^{(i)}$ to $y^{(i)}$.

Each example $x^{(i)}$ can have from 1 to many features $X_1^{(i)}, X_2^{(i)}, \ldots, X_d^{(i)}$. We want to establish the relationships between different features of our data in order to make a good prediction.

A typical regression problem is house price prediction.

Linear Regression



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Linear Regression Model

Assume we have a simple model with ***one feature***, where we establish a linear relationship between ***the area of a house*** i and ***its price***:

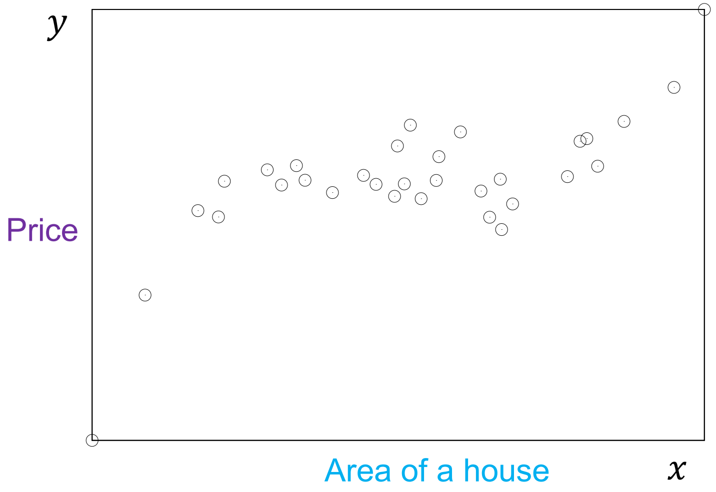
$$y^{(i)} = w_1 X^{(i)} + w_0$$

w, b are the **parameters** of our model that need to be learned

- w_0 is the intercept / **bias**, representing the starting price of a house
- w_1 is the slope / **weight** associated with **feature** ”area of a house”

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

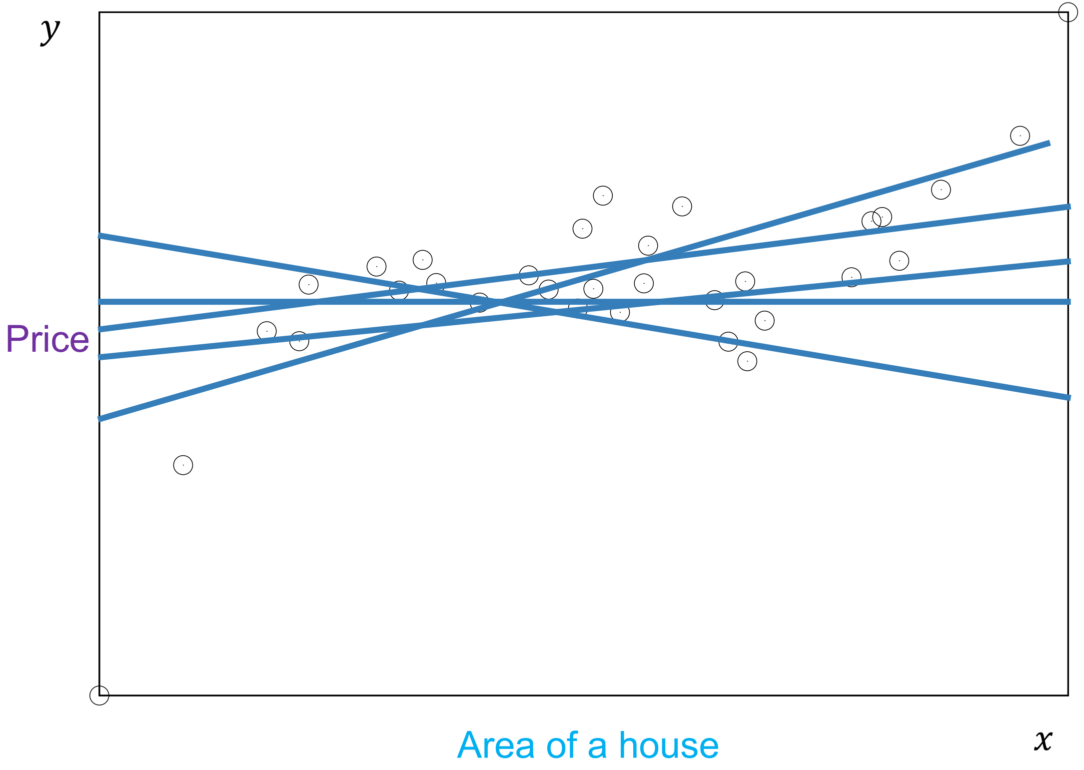
$$\hat{y} = \hat{w}_1 x + \hat{w}_0$$

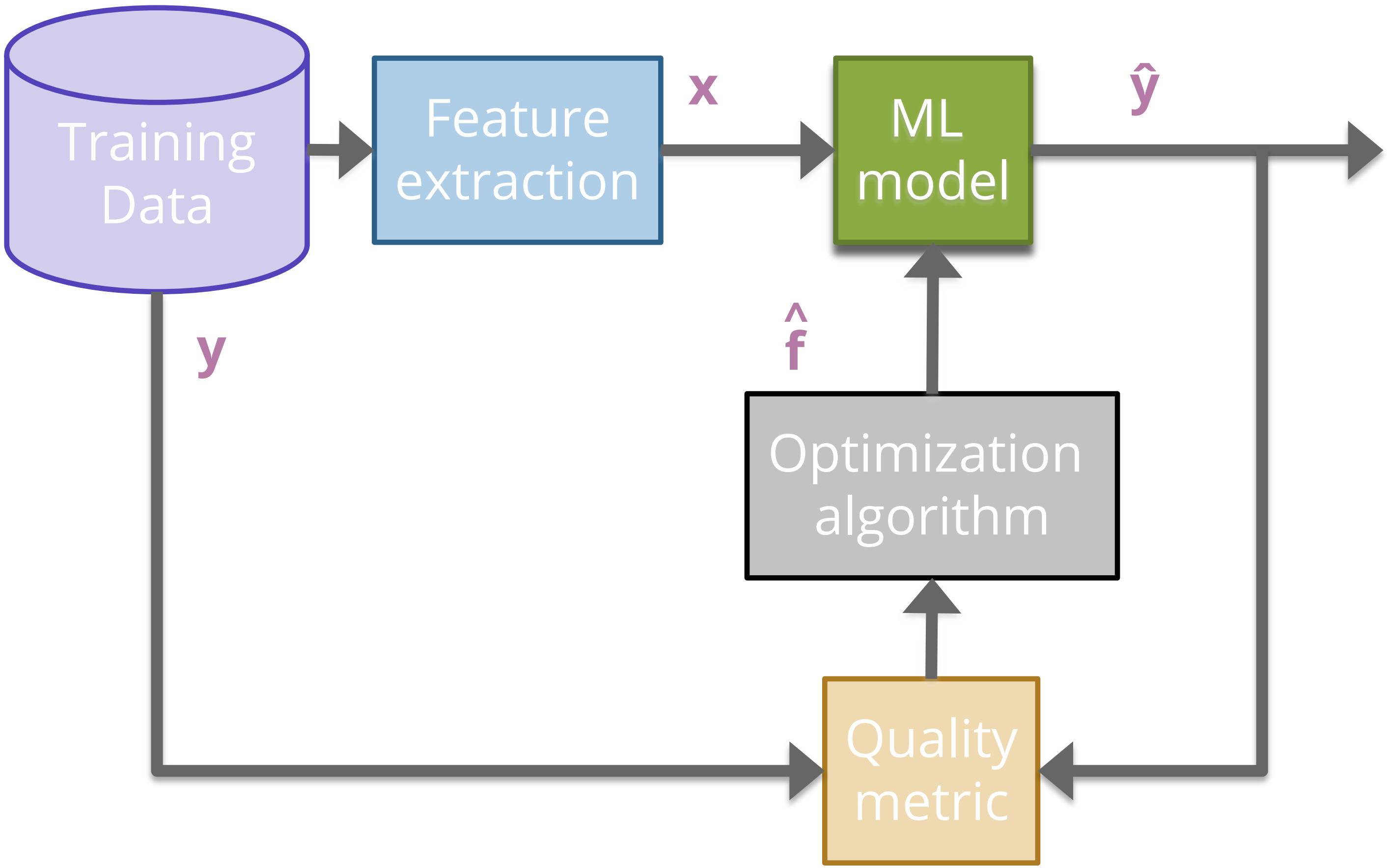


Basic Idea

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

What does best even mean here?





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Cost / Loss of predictor

Mean-Squared Error (MSE)

Define a cost / loss for a particular set of parameters

- Low cost / loss → Better fit
- Find settings that minimize the cost
- For regression, we will use MSE (mean-squared errors) as the default loss function.
  - Low error = Low loss = **Better predictor (hopefully)**

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

y: actual value

$\hat{y}$: predicted value

Note: There are a variety of loss functions in Machine Learning, such as Mean Absolute Error, Huber Loss for the regression task. However, **MSE** is usually the to-go loss function because of its easy implementation and has nicer mathematical properties (continuously differentiable, a statistic for Gaussian distribution ...)

Poll Everywhere

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Goal: Get you actively participating in your learning

Typical Activity

- Question is posted
- **Think** (1 min): Think about the question on your own
- **Pair** (2 min): Talk with your neighbor to discuss question
  - If you arrive at different conclusions, discuss your logic and figure out why you differ!
  - If you arrived at the same conclusion, discuss why the other answers might be wrong!
- **Share** (1 min): We discuss the conclusions as a class

During each of the **Think** and **Pair** stages, you will respond to the question via a Poll Everywhere poll

- Not worth any points, just here to help you learn!

Poll Everywhere

Think

1 min

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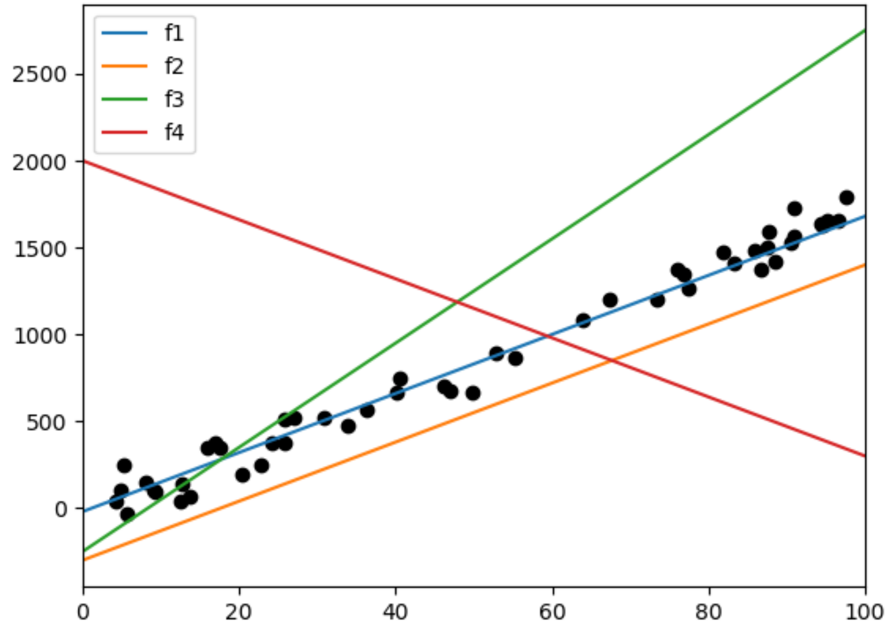
Sort the following lines by their MSE (mean-squared errors) on the data, from smallest to largest. (estimate, don't actually compute)



Poll Everywhere

Group

2 min

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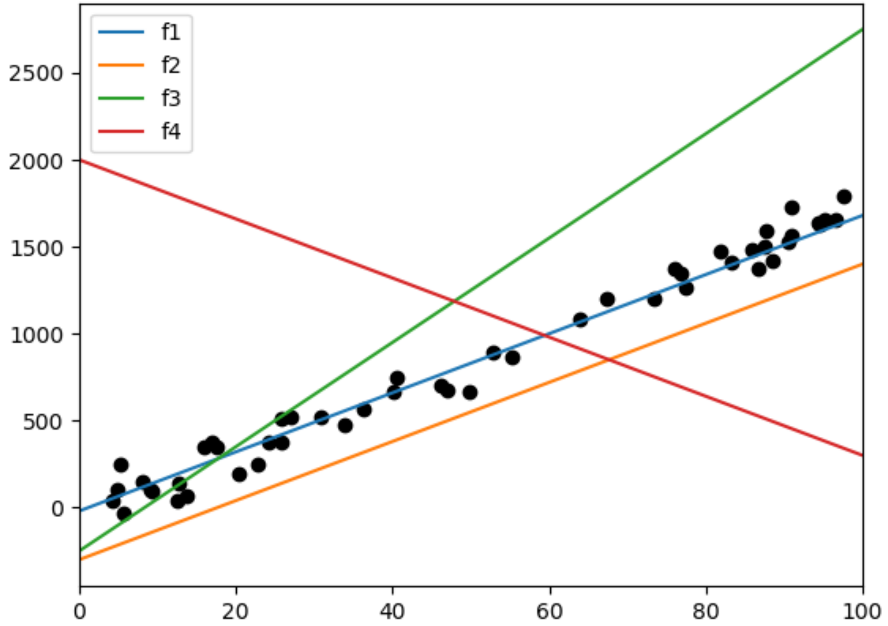
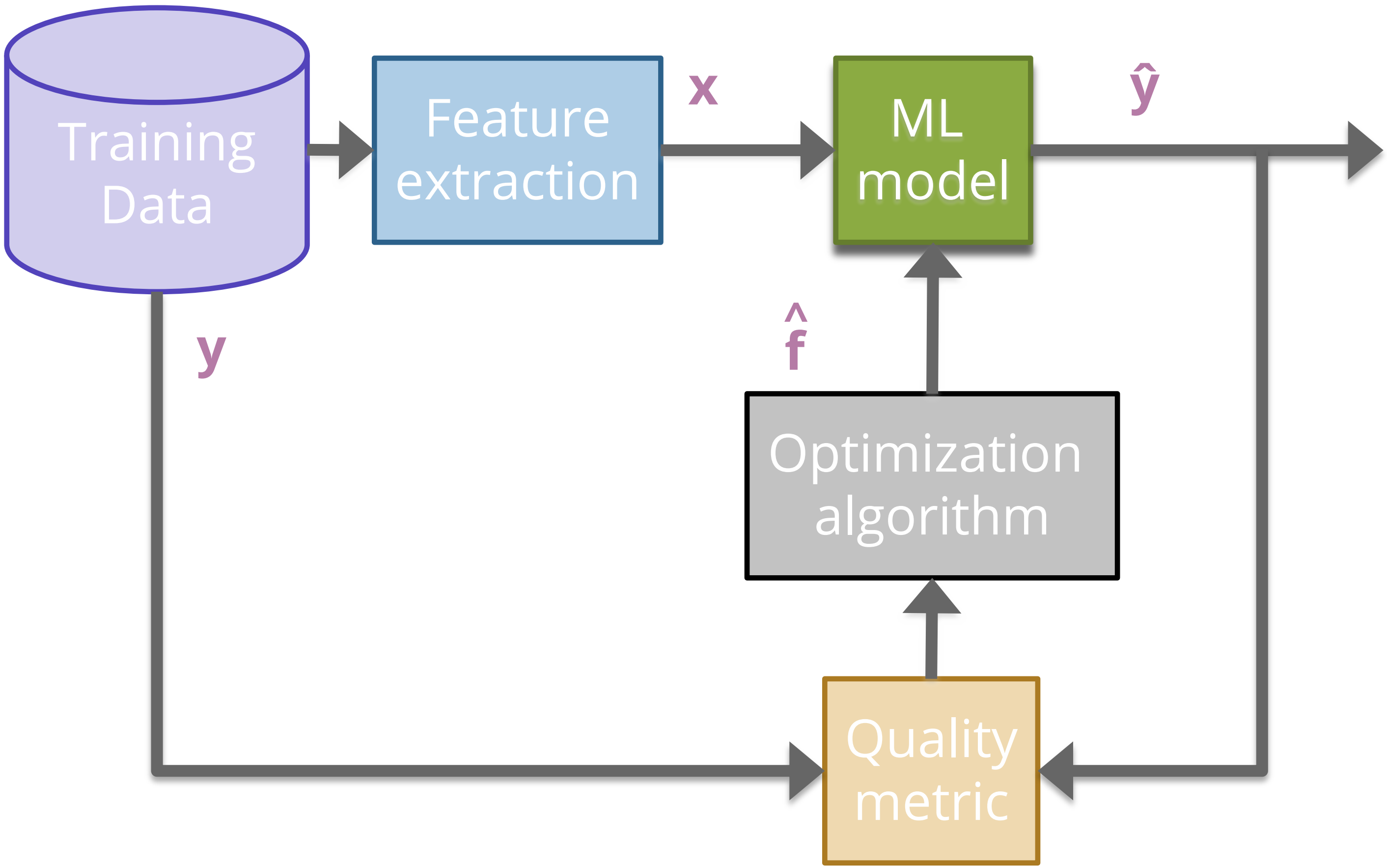
Sort the following lines by their MSE on the data, from smallest to largest. (estimate, don't actually compute)





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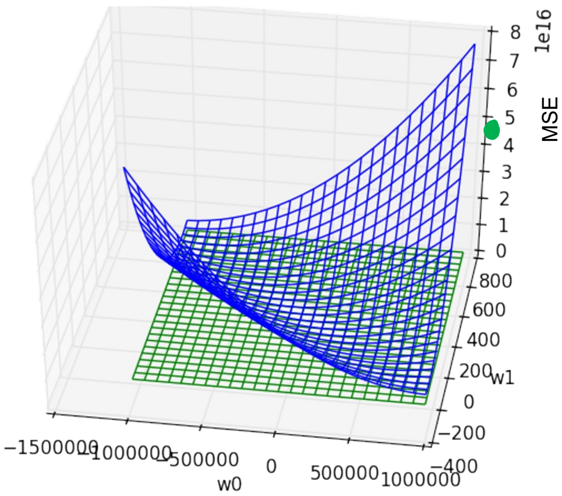
Minimizing Cost

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

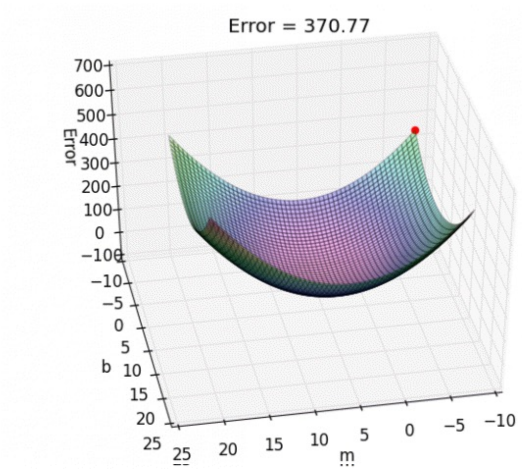


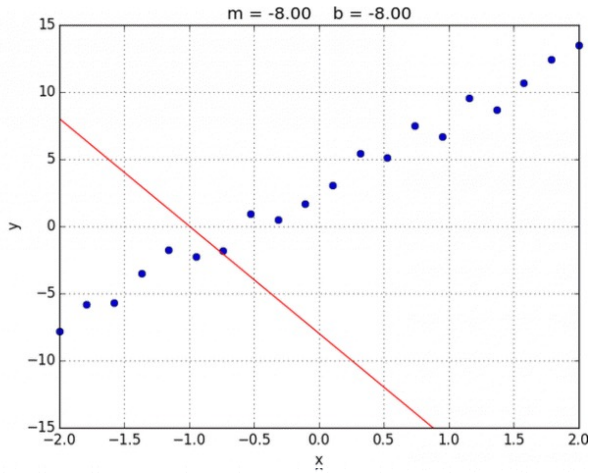
$$\hat{w}_0, \hat{w}_1 = \underset{w_0, w_1}{\operatorname{argmin}} MSE(w_0, w_1)$$

$$= \underset{w_0, w_1}{\operatorname{argmin}} \frac{1}{n} \sum_{i=1}^{n} \left(y_i - (w_0 + w_1 x_i)\right)^2$$

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

Gradient Descent





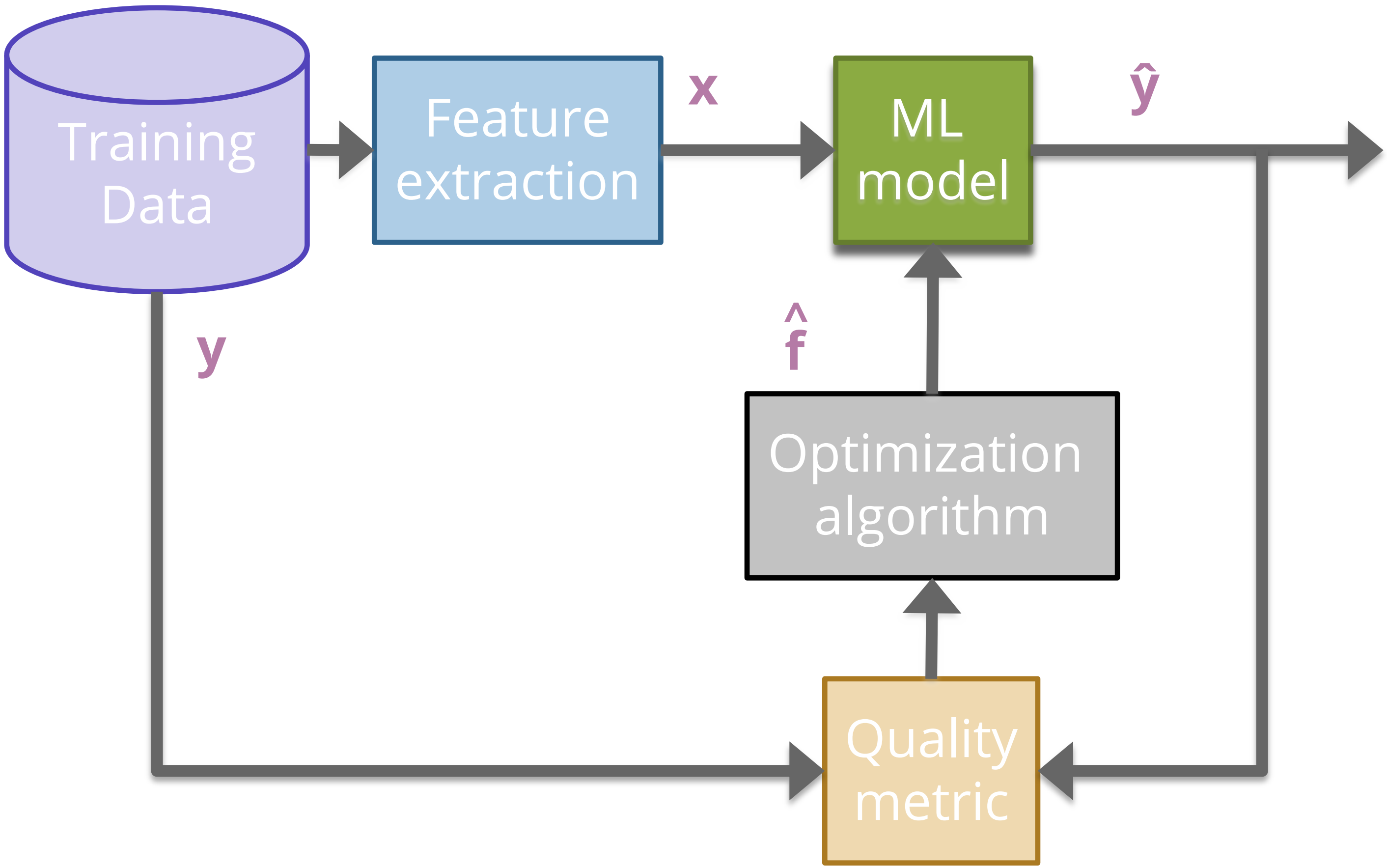
Instead of computing all possible points to find the minimum, just start at one point and "roll" down the hill.
Use the gradient (slope) to determine which direction is down.

Start at some (random) weights w
While we haven't converged:

$$w \ -= \alpha \nabla L(w)$$

- α: learning rate
- $\nabla L(w)$: the gradients of loss function L on a set of weights w

Brain Break



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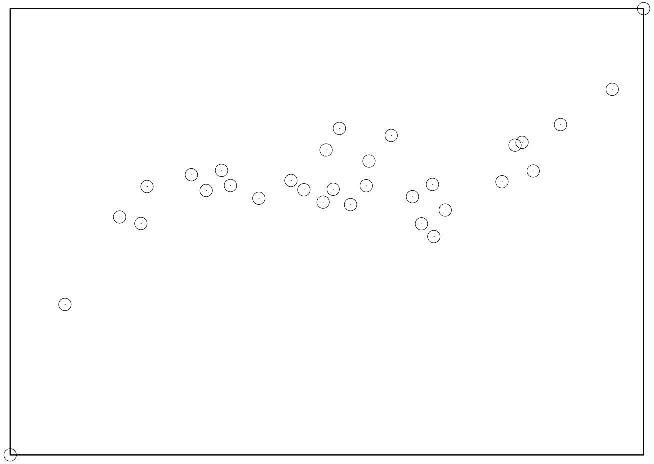
Higher Order Features

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!

$$y = w_0 + w_1 x + w_2 x^2 + w_3 x^3$$



Polynomial Regression

Model

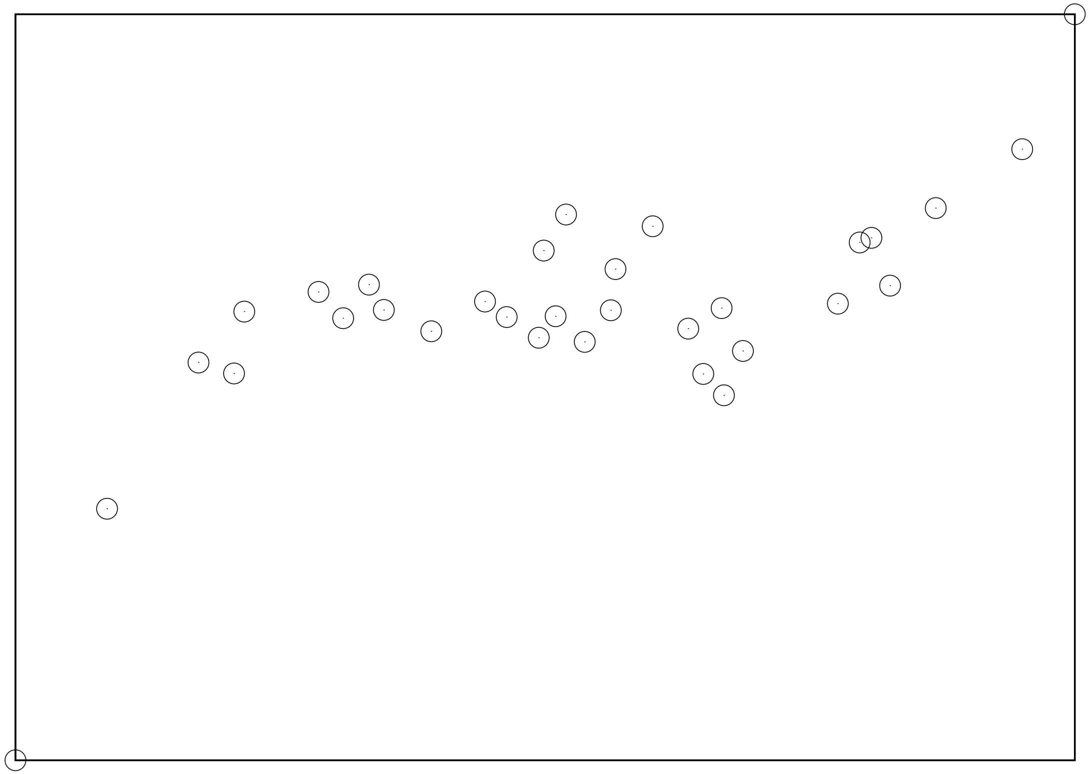
$$y = w_0 + w_1 x + w_2 x^2 + \dots + w_d x^d$$

To capture a non-linear relationship in the model, we can transform the original features into more features!

Feature	Value	Parameter
0	1 (constant)	w_0
1	x	w_1
2	x^2	w_2
...	$\dots$	$\dots$
p	x^d	w_d

How do you train it? Gradient descent (with more parameters)

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 reduce the number of features in a dataset by creating new features from the existing ones (and then discarding the original features).

Model

$$y = w_0 h_0(x) + w_1 h_1(x) + \ldots + w_D h_D(x)$$

$$= \sum_{j=0}^{D} w_j h_j(x)$$

Feature	Value	Parameter
0	$h_0(x)$ often 1 (constant)	w_0
1	$h_1(x)$	w_1
2	$h_2(x)$	w_2
…	…	…
d	$h_d(x)$	w_{d}

Adding Other Features

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

Each row is a data point.

Each column (except Value) represents a feature

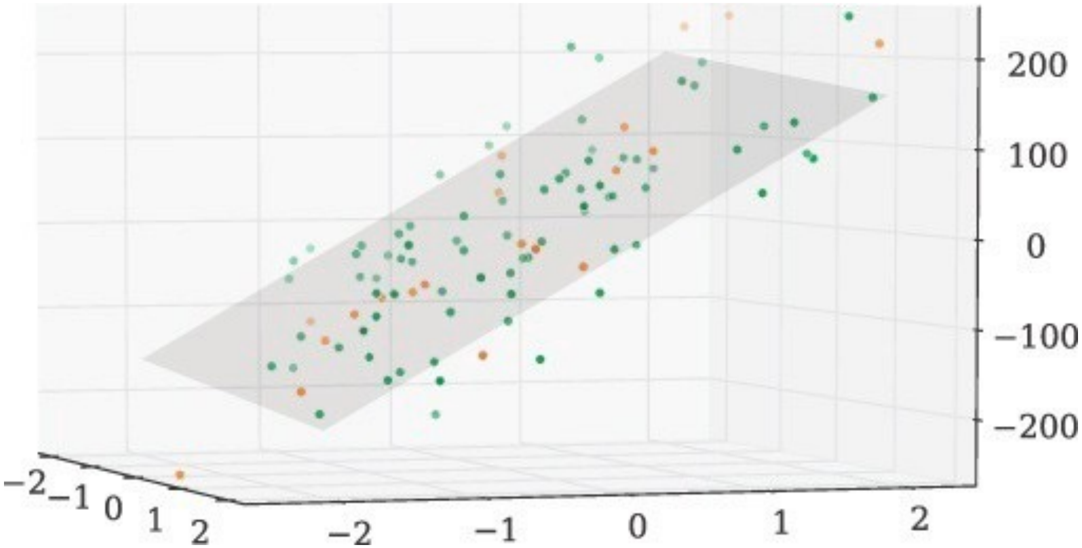
The last column (Price) contains the actual output values

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

More Inputs - Visually

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

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



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

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!

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	$h_D(x)$ … like $\log(x[7]) * x[2]$	w_D

Term recap

Supervised learning: The machine learning task of learning a function that maps an input to an output based on example input-output pairs.

Regression: A supervised learning task where the outputs are continuous values.

Feature:
- An attribute that we're selecting for our model
- Can come from the original dataset, or through some transformations (***feature extraction***)

Parameter: The weight or bias associated with a feature. The goal of machine learning is to adjust the weights to optimize the loss functions on training data.

Loss function: A function that computes the distance between the predicted output from a machine learning model and the actual output.

Machine learning model: An algorithm that combs through an amount of data to find patterns, make predictions, or generate insights

Optimization algorithm: An algorithm used to minimize the loss during training. The most common one is ***Gradient Descent***.

Linear Regression Recap

Dataset

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

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

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

Quality Metric / Loss function

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

Predictor

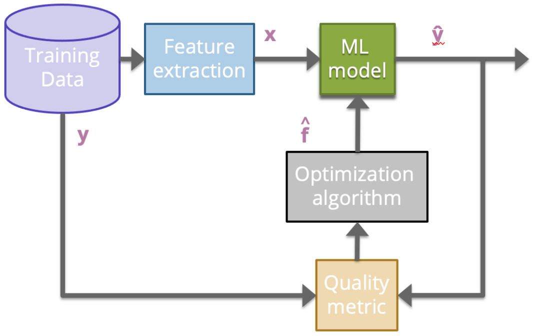
$$\hat{w} = \underset{w}{\operatorname{argmin}}\, MSE(w)$$

Optimization Algorithm

Optimized using Gradient Descent

Prediction

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



Deadlines & Other Logistics

Homework 0: (weight: near 0%)

- Aim to test your readiness for the course
- Coding portion on EdStem, at the Assessments tab (no submission required)
- Conceptual portion due on Gradescope **(due Friday 11:59 pm)**

Checkpoint 1: **Due Wednesday 2 pm**

Special quiz about Syllabus (on EdStem): **Due Friday 11:59 pm**

Reflection 1: **Due Friday 11:59 pm**

Homework 1 released on Friday

We will provide opportunities for you to find your homework partner later this week if you're interested.

Please check EdStem regularly for the latest updates on course logistics.