



CS 6375

Linear Regression

Rishabh Iyer
University of Texas at Dallas

Course Info.



- Instructor: Rishabh Iyer
 - Office: ECSS 3.405
 - Office hours:
- TA:TBD
 - Office hours and location: TBD
- Course website:
- Book: none required

Recap: Course Topics



- **Supervised Learning**
 - SVMs & kernel methods
 - Decision trees, Random Forests, Gradient Boosted Trees
 - Nearest Neighbor: KNN Classifiers
 - Logistic Regression
 - Neural networks
 - Probabilistic models: Bayesian networks, Naïve Bayes
- **Unsupervised Learning**
 - Clustering: k-means & spectral clustering
 - Dimensionality reduction
 - PCA
 - Matrix Factorizations
- **Parameter estimation**
 - Bayesian methods, MAP estimation, maximum likelihood estimation, expectation maximization, ...
- **Evaluation**
 - AOC, cross-validation, precision/recall
- **Statistical Methods**
 - Boosting, bagging, bootstrapping
 - Sampling
- **Reinforcement Learning, Semi-supervised Learning, Active Learning,**

Recap: Grading



- 4-5 problem sets (50%)
 - See collaboration policy on the web
 - Mix of theory and programming (in Python)
 - Available and turned in on eLearning
 - Approximately one assignment every 2-3 weeks
- Midterm Exam (20%)
- Final Exam (30%)

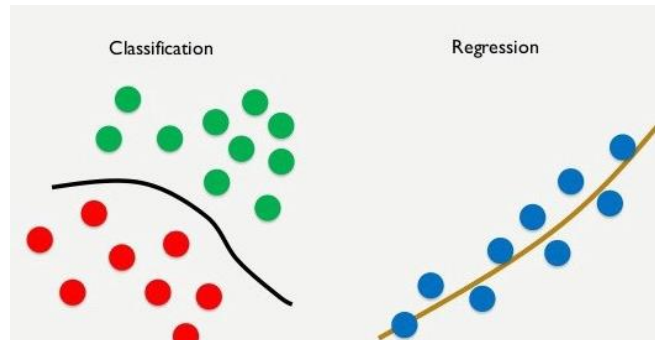
-subject to change-

Part I: Recap of Supervised Learning and Linear Regression Setup

Recap: Supervised Learning



- **Input:** $(x^{(1)}, y^{(1)}), \dots, (x^{(M)}, y^{(M)})$
 - $x^{(m)}$ is the m^{th} data item and $y^{(m)}$ is the m^{th} **label**
- **Goal:** find a function f such that $f(x^{(m)})$ is a “good approximation” to $y^{(m)}$
 - Can use it to predict y values for previously unseen x values

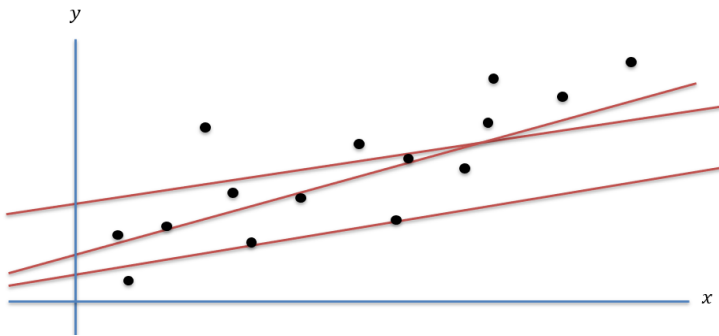


Recap: Classification vs Regression

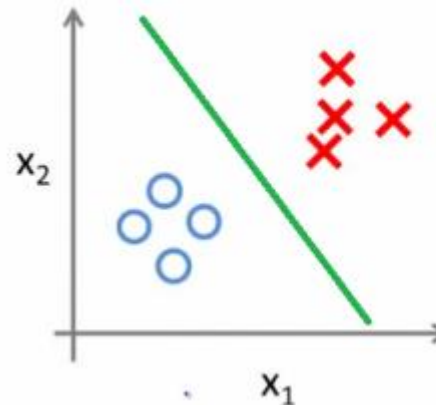


Classification vs Regression

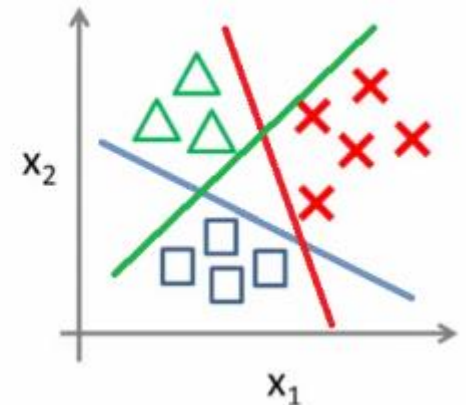
- Input: pairs of points $(x^{(1)}, y^{(1)}), \dots, (x^{(M)}, y^{(M)})$ with $x^{(m)} \in \mathbb{R}^n$
- Regression case: $y^{(m)} \in \mathbb{R}$
- Classification case: $y^{(m)} \in [0, k - 1]$ [k-class classification]
- If $k = 2$, we get Binary classification



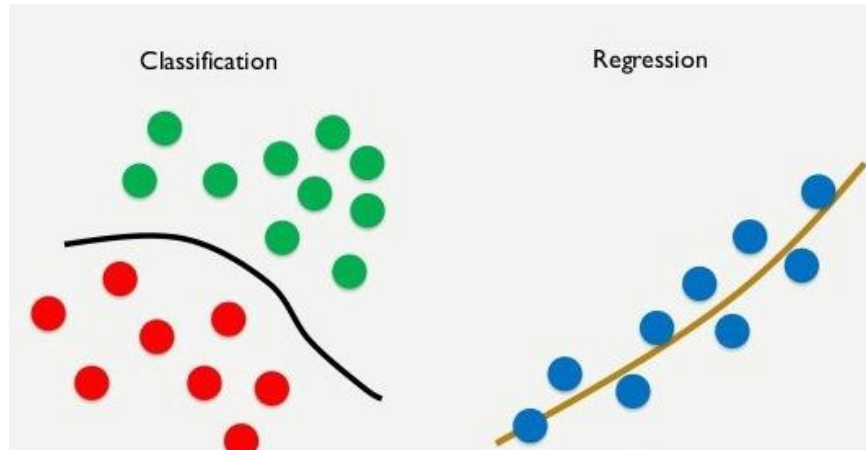
Binary classification:



Multi-class classification:



Recap: Examples of Supervised Learning



Classification

- Spam email detection
- Handwritten digit recognition
- Medical Diagnosis
- Fraud Detection
- Face Recognition

Regression

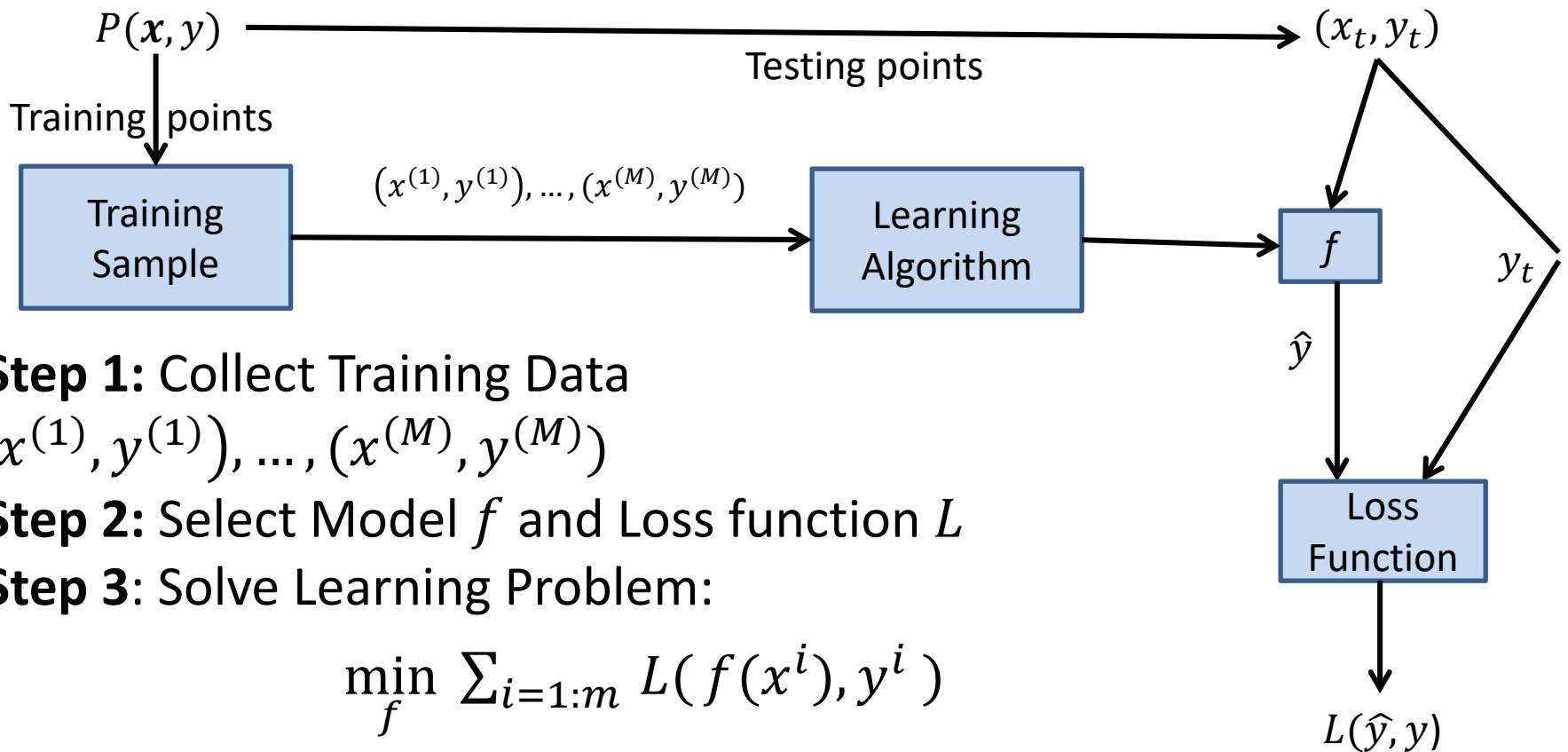
- Housing Price Prediction
- Stock Market Prediction
- Weather Prediction
- Market Analysis and Business Trends

Recap: Hypothesis Space



- **Hypothesis space (Aka Model):** set of allowable functions $f: X \rightarrow Y$
- Goal: find the “best” element of the hypothesis space
 - How do we measure the quality of f ?

Recap: Supervised Learning Workflow



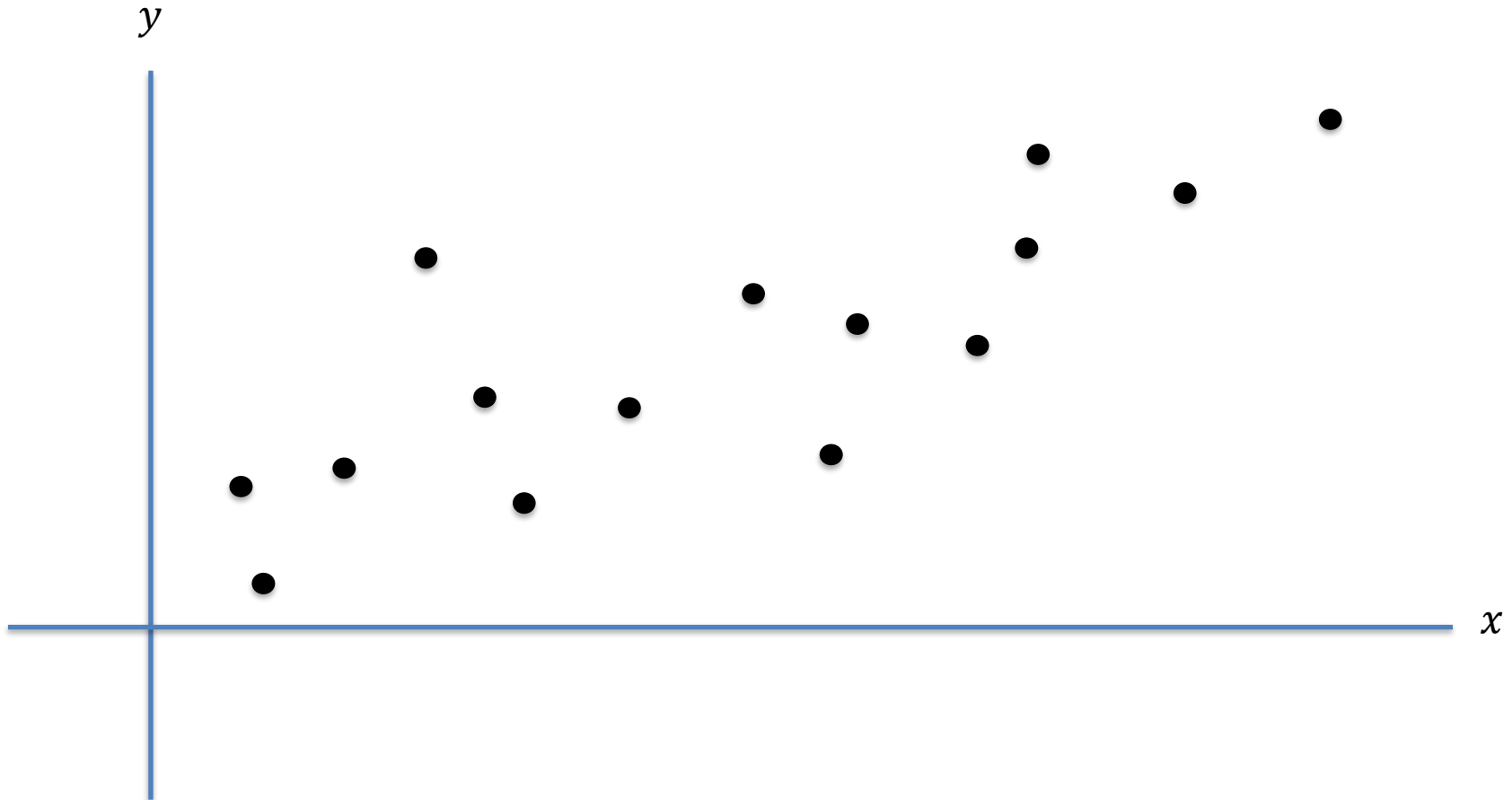
- **Step 1:** Collect Training Data $(x^{(1)}, y^{(1)}), \dots, (x^{(M)}, y^{(M)})$
- **Step 2:** Select Model f and Loss function L
- **Step 3:** Solve Learning Problem:

$$\min_f \sum_{i=1:m} L(f(x^i), y^i)$$

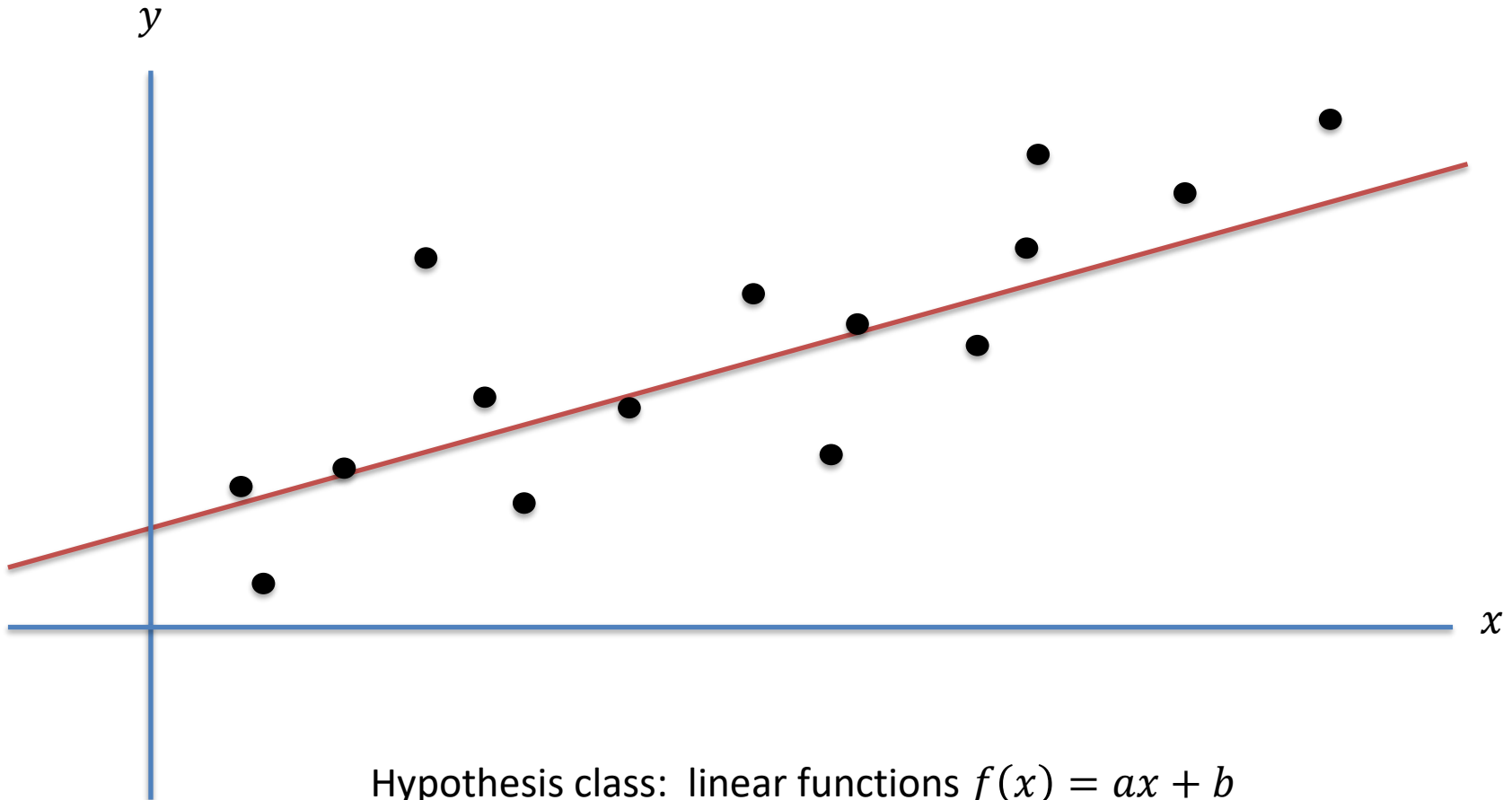
- **Step 4:** Obtain Predictions $\hat{y}_t = f(x_t)$ on all **Test Data**
- **Step 5:** Evaluation -- Measure the error $Err(\hat{y}_t, y_t)$

- Simple linear regression
 - Input: pairs of points $(x^{(1)}, y^{(1)}), \dots, (x^{(M)}, y^{(M)})$ with $x^{(m)} \in \mathbb{R}^d$ and $y^{(m)} \in \mathbb{R}$ (Regression)
 - Hypothesis space: set of linear functions $f(x) = a^T x + b$ with $a \in \mathbb{R}^n, b \in \mathbb{R}$
 - In one dimension, $a, b \in \mathbb{R}$ and $f(x) = ax + b$
 - Error metric and Loss Function: squared difference between the predicted value and the actual value

Regression



Regression



Hypothesis class: linear functions $f(x) = ax + b$

How do we compute the error of a specific hypothesis?

Linear Regression



- For any data point, x , the learning algorithm predicts $f(x)$
- In typical regression applications, measure the fit using a squared **loss function**

$$L(f) = \frac{1}{M} \sum_m (f(x^{(m)}) - y^{(m)})^2$$

- Want to minimize the average loss on the **training data**
- The optimal linear hypothesis is then given by

$$\min_{a,b} \frac{1}{M} \sum_m (ax^{(m)} + b - y^{(m)})^2$$

Linear Regression



$$\min_{a,b} \frac{1}{M} \sum_m (ax^{(m)} + b - y^{(m)})^2$$

- How do we find the optimal a and b ?

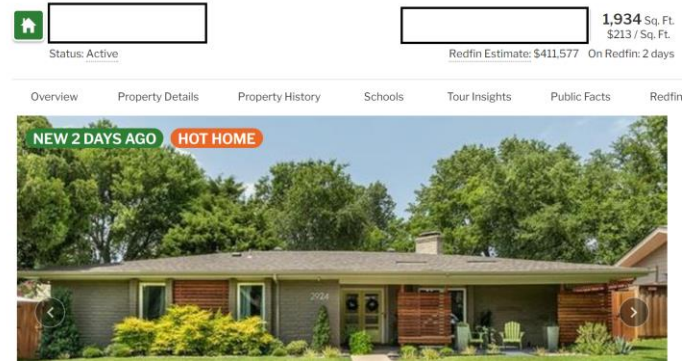
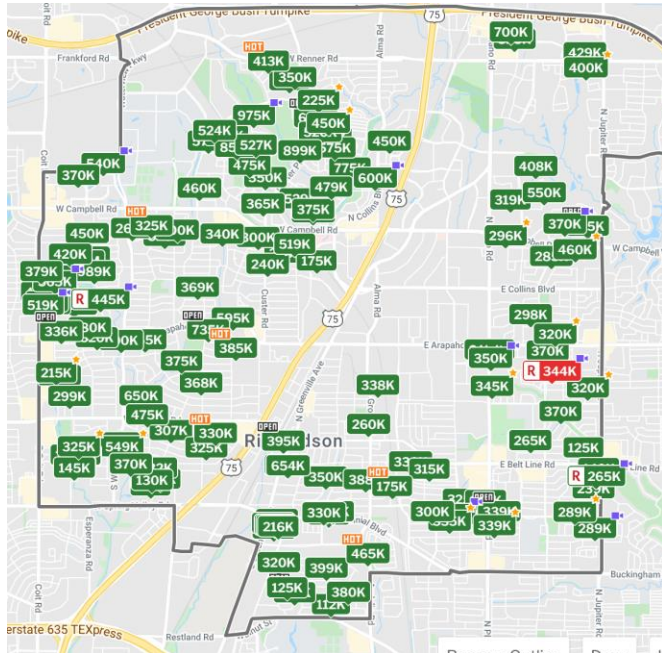
$$\min_{a,b} \frac{1}{M} \sum_m (ax^{(m)} + b - y^{(m)})^2$$

- How do we find the optimal a and b ?
 - Solution 1: take derivatives and solve
(there is a closed form solution!)
 - Solution 2: use gradient descent

$$\min_{a,b} \frac{1}{M} \sum_m (ax^{(m)} + b - y^{(m)})^2$$

- How do we find the optimal a and b ?
 - Solution 1: take derivatives and solve
(there is a closed form solution!)
 - Solution 2: use gradient descent
 - This approach is much more likely to be useful for general loss functions

Recap – Housing Price Prediction Application



Home Facts

Status	Active	Time on Redfin	2 days
Property Type	Residential, Single Family	HOA Dues	\$4/month
Year Built	1969	Style	Single Detached, Mid-Century Modern, Ranch, Traditional
Community	Canyon Creek Country Club 9	Lot Size	10,019 Sq. Ft.
MLS#	14375892		

Part II: Gradient Descent and Optimization

Iterative method to minimize a (convex) differentiable function f

A function $f: \mathbb{R}^n \rightarrow \mathbb{R}$ is convex if

$$\lambda f(x) + (1 - \lambda)f(y) \geq f(\lambda x + (1 - \lambda)y)$$

for all $\lambda \in [0,1]$ and all $x, y \in \mathbb{R}^n$

Iterative method to minimize a (convex) differentiable function f

- Pick an initial point x_0
- Iterate until convergence

$$x_{t+1} = x_t - \gamma_t \nabla f(x_t)$$

where γ_t is the t^{th} step size (sometimes called learning rate)

Basics of Convexity and Gradient Desc



- For additional reading, please see some of my slides from my Spring 2020 Class “Optimization in Machine Learning”
- Github Location for Lecture Notes and Slides:
<https://github.com/rishabhk108/OptimizationML>
- Please skim through:
 - Lectures 1 and 2 for basics
 - Lectures 3-5 for convex functions
 - Lectures 6-8 on Gradient Descent
 - This includes slightly more mathematical details like convergence analysis and proofs for convergence etc.

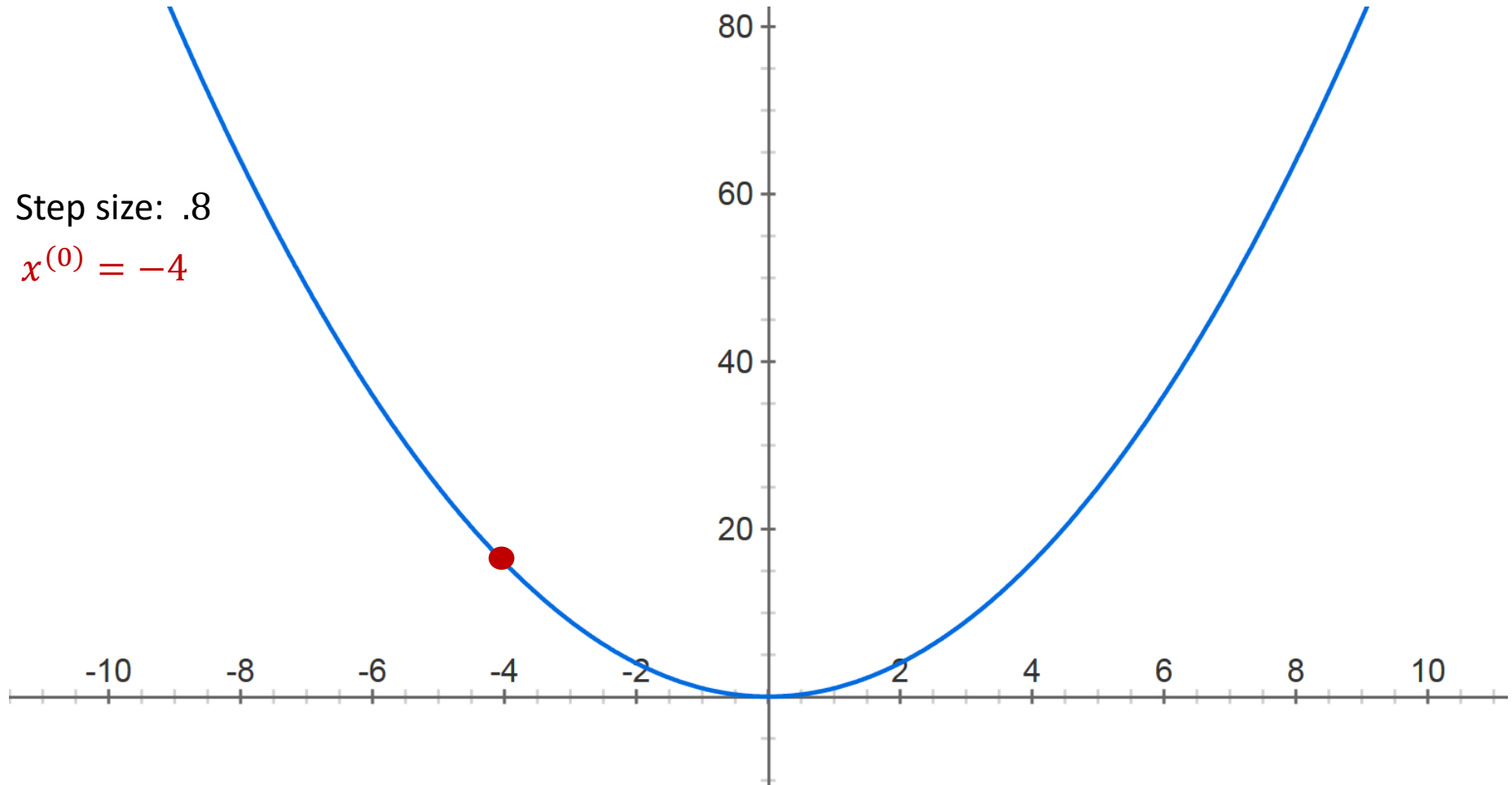
Gradient Descent



$$f(x) = x^2$$

Step size: .8

$$x^{(0)} = -4$$



Gradient Descent

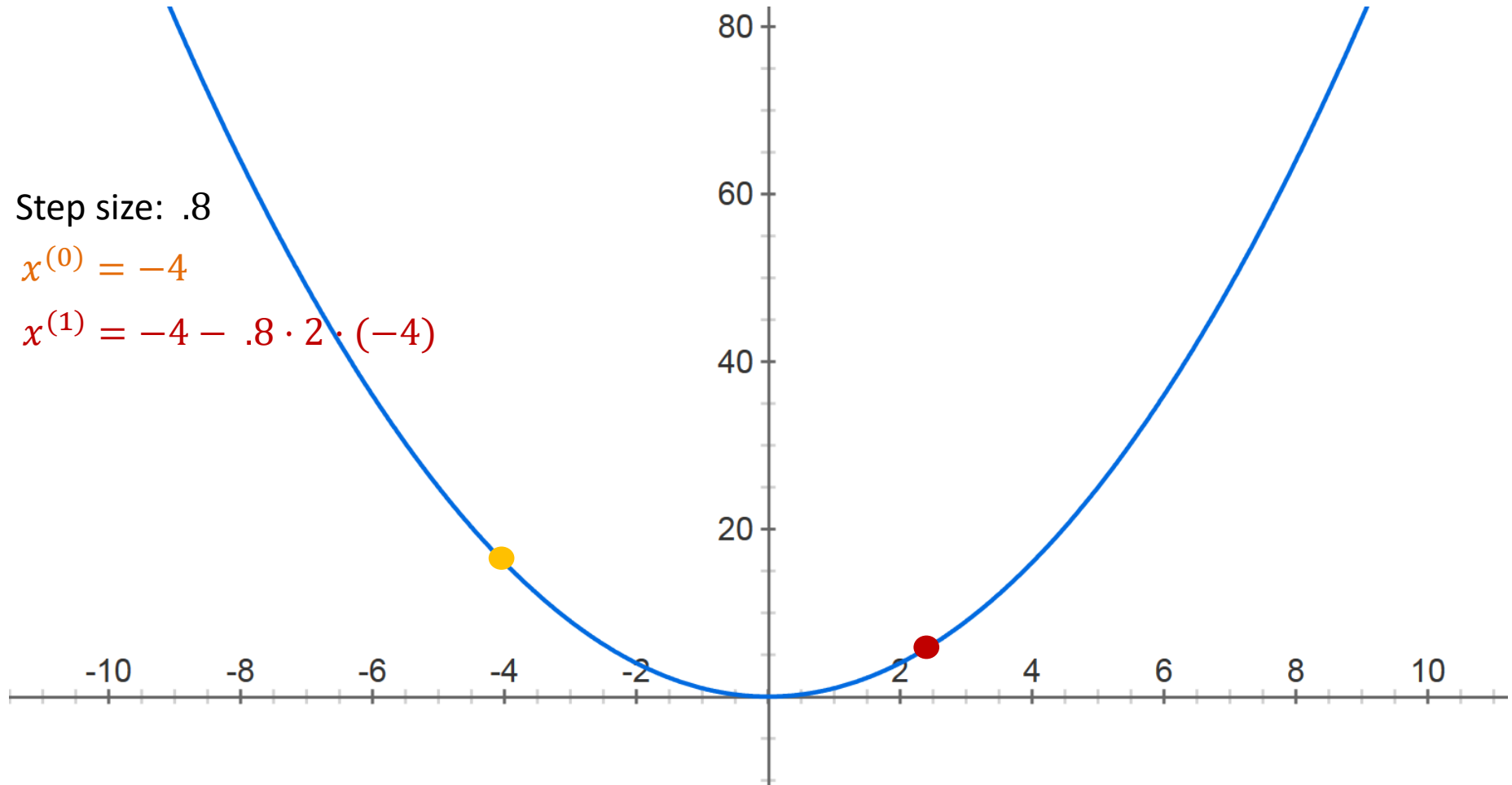


$$f(x) = x^2$$

Step size: .8

$$x^{(0)} = -4$$

$$x^{(1)} = -4 - .8 \cdot 2 \cdot (-4)$$



Gradient Descent

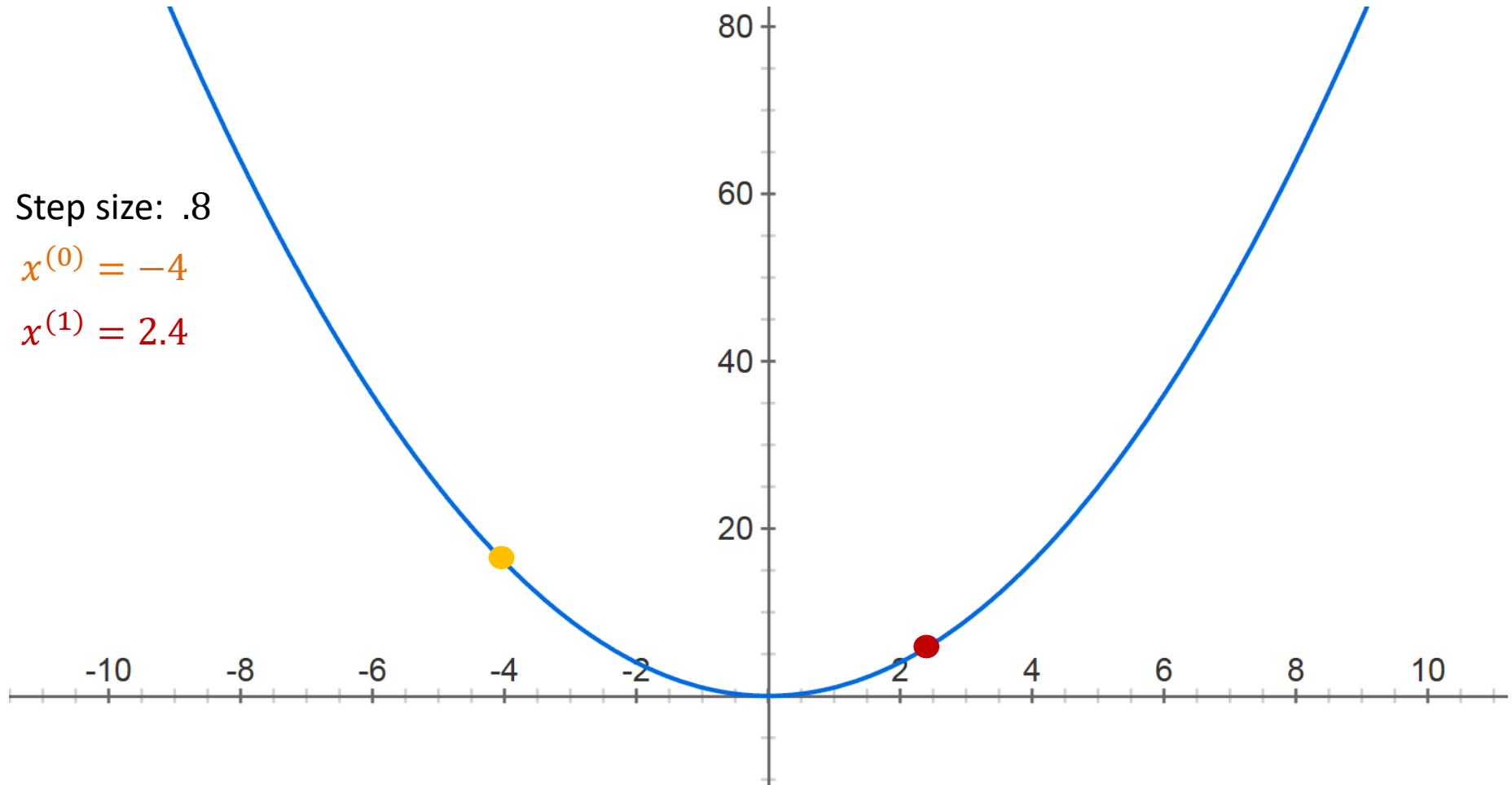


$$f(x) = x^2$$

Step size: .8

$$x^{(0)} = -4$$

$$x^{(1)} = 2.4$$



Gradient Descent



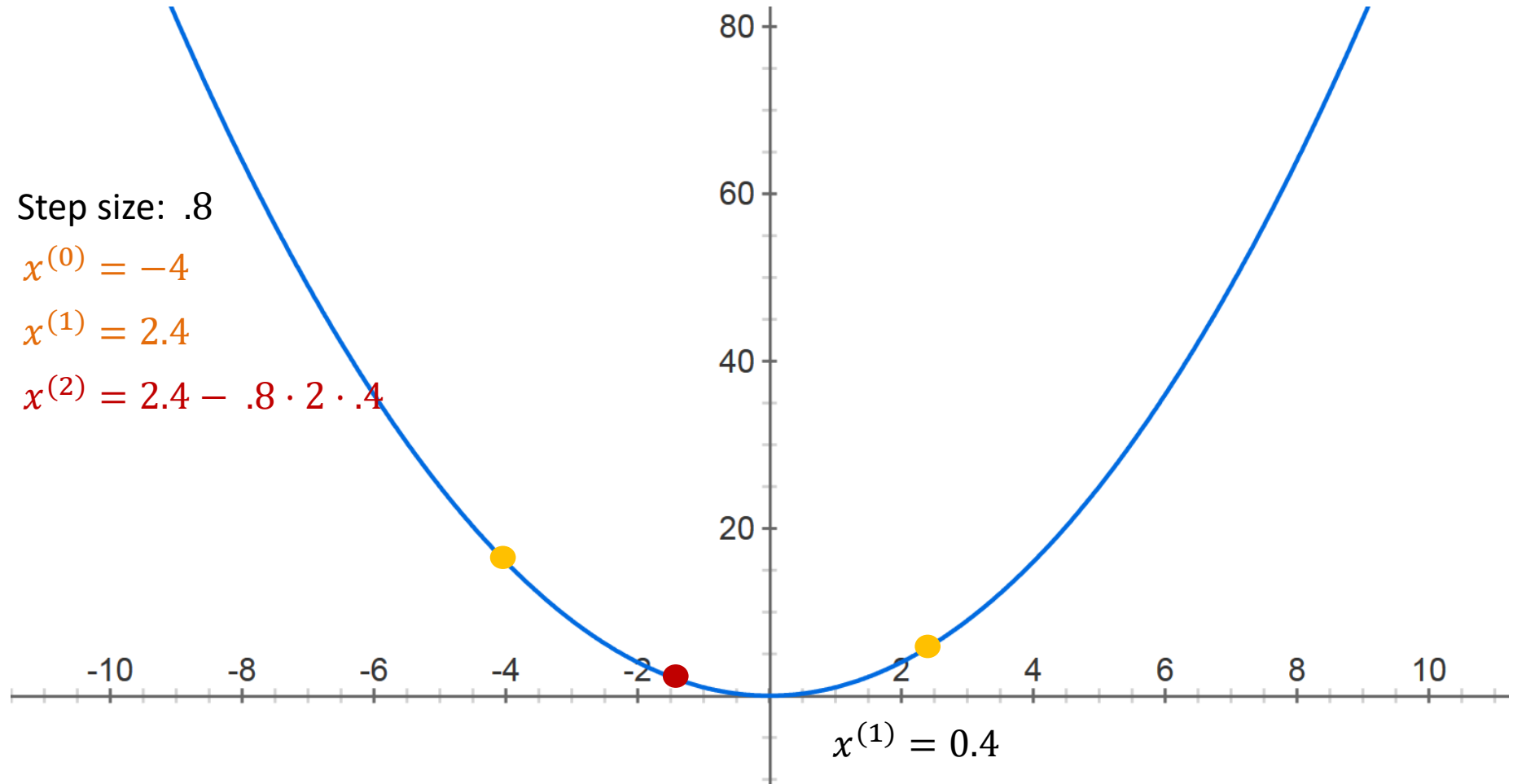
$$f(x) = x^2$$

Step size: .8

$$x^{(0)} = -4$$

$$x^{(1)} = 2.4$$

$$x^{(2)} = 2.4 - .8 \cdot 2 \cdot .4$$



Gradient Descent



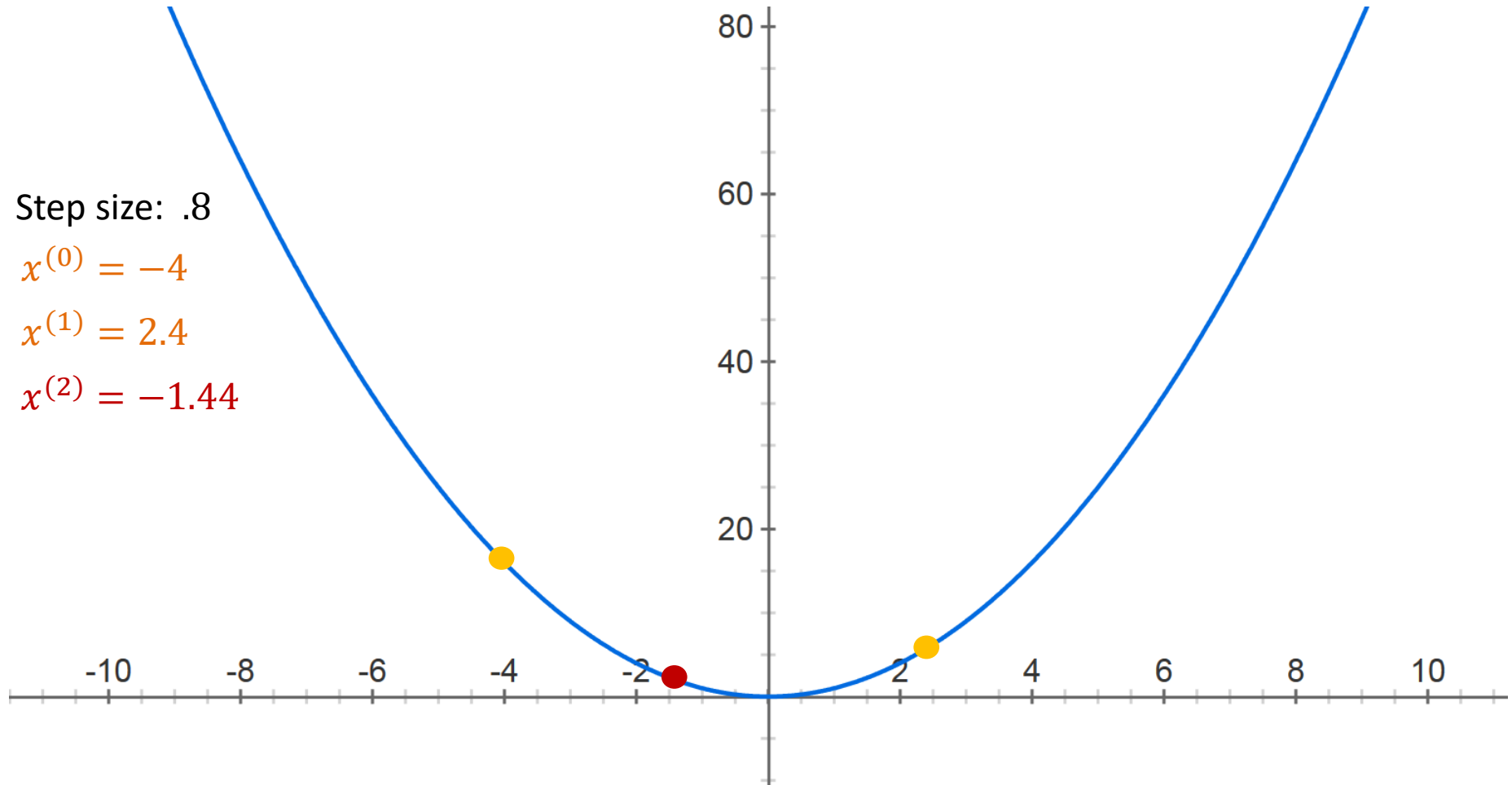
$$f(x) = x^2$$

Step size: .8

$$x^{(0)} = -4$$

$$x^{(1)} = 2.4$$

$$x^{(2)} = -1.44$$



Gradient Descent



$$f(x) = x^2$$

Step size: .8

$$x^{(0)} = -4$$

$$x^{(1)} = 2.4$$

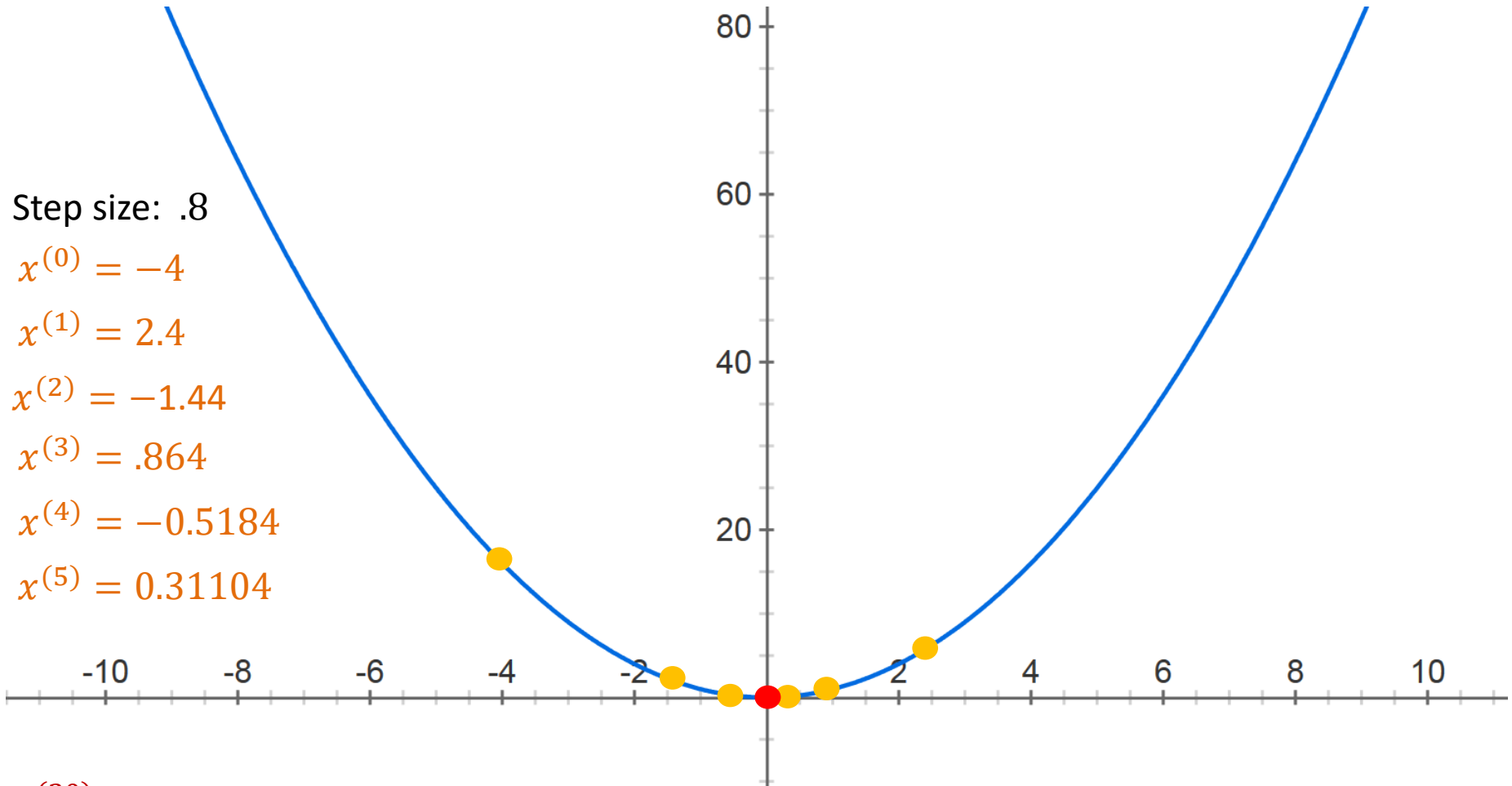
$$x^{(2)} = -1.44$$

$$x^{(3)} = .864$$

$$x^{(4)} = -0.5184$$

$$x^{(5)} = 0.31104$$

$$x^{(30)} = -8.84296e - 07$$



$$\min_{a,b} \frac{1}{M} \sum_m (ax^{(m)} + b - y^{(m)})^2$$

- What is the gradient of this function?
- What does a gradient descent iteration look like for this simple regression problem?

Derivation of the Gradient (one dim)



- In higher dimensions, the linear regression problem is essentially the same with $x^{(m)} \in \mathbb{R}^n$

$$\min_{a \in \mathbb{R}^n, b} \frac{1}{M} \sum_m (a^T x^{(m)} + b - y^{(m)})^2$$

- Can still use gradient descent to minimize this
 - Not much more difficult than the $n = 1$ case

Derivation of the Gradient (> 1 dim)



- Gradient descent converges under certain technical conditions on the function f and the step size γ_t
 - If f is convex, then any fixed point of gradient descent must correspond to a global minimum of f
 - In general, for a nonconvex function, may only converge to a local optimum
- Very fast convergence because the Linear Regression is *smooth* (loosely, think *differentiable*) and strongly convex (*loosely, bounded below by a quadratic function*)*

* See Lectures 6-8 for better understanding of smooth and strongly convex

Part III: Polynomial Regression

Polynomial Regression



- What if we enlarge the hypothesis class?
 - Quadratic functions: $ax^2 + bx + c$
 - k -degree polynomials: $a_k x^k + a_{k-1} x^{k-1} + \dots + a_1 x + a_0$

$$\min_{a_k, \dots, a_0} \frac{1}{M} \sum_m \left(a_k (x^{(m)})^k + \dots + a_1 x^{(m)} + a_0 - y^{(m)} \right)^2$$

Polynomial Regression

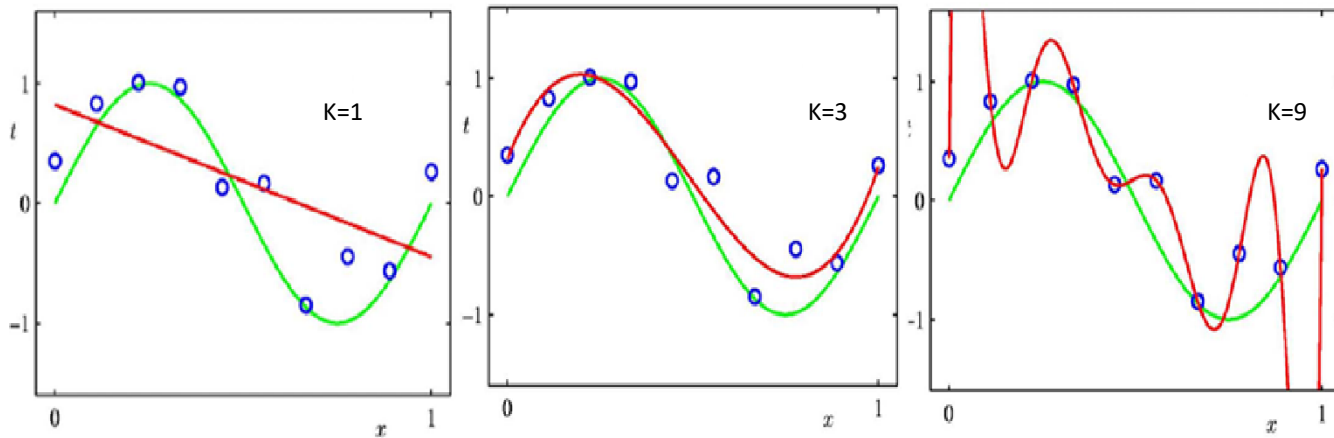


- What if we enlarge the hypothesis class?
 - Quadratic functions: $ax^2 + bx + c$
 - k -degree polynomials: $a_kx^k + a_{k-1}x^{k-1} + \dots + a_1x + a_0$
- Can we always learn “better” with a larger hypothesis class?

Polynomial Regression



- What if we enlarge the hypothesis class?
 - Quadratic functions: $ax^2 + bx + c$
 - k -degree polynomials: $a_k x^k + a_{k-1} x^{k-1} + \dots + a_1 x + a_0$
- Can we always learn “better” with a larger hypothesis class?



Caveats with Polynomial Regression

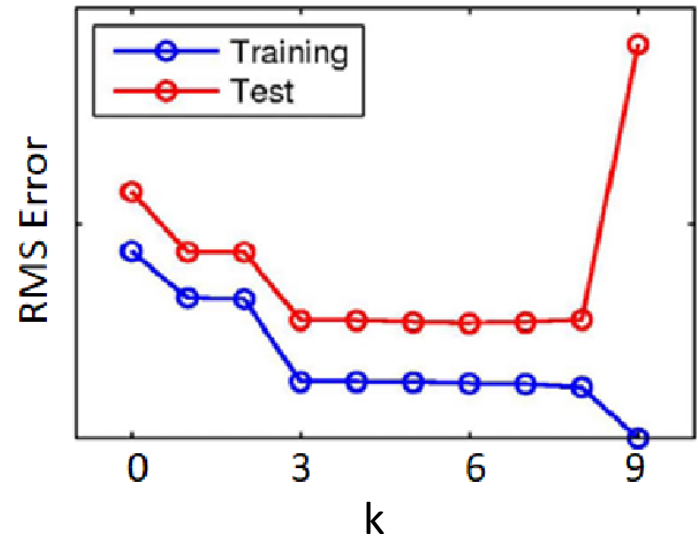


- Larger hypothesis space always decreases the cost function, but this does **NOT** necessarily mean better predictive performance
 - This phenomenon is known as **overfitting**
 - Ideally, we would select the **simplest** hypothesis consistent with the observed data
- In practice, we cannot simply evaluate our learned hypothesis on the training data, we want it to perform well on unseen data (otherwise, we can just memorize the training data!)
 - Report the loss on some held-out **test data** (i.e., data not used as part of the training process)

Overfitting



- As the degree of the polynomial (k) increases, training error decreases monotonically
- As k increases test error can increase
- Test error can decrease at first, but increases
- Overfitting can occur
 - When the model is too complex and trivially fits the data (i.e., too many parameters)
 - When the data is not enough to estimate the parameters
 - Model captures the noise (or the chance)



Part IV: Hands On

- Boston House Price Dataset

CRIM: Per capita crime rate by town

ZN: Proportion of residential land zoned for lots over 25,000 sq. ft

INDUS: Proportion of non-retail business acres per town

CHAS: Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)

NOX: Nitric oxide concentration (parts per 10 million)

RM: Average number of rooms per dwelling

AGE: Proportion of owner-occupied units built prior to 1940

DIS: Weighted distances to five Boston employment centers

RAD: Index of accessibility to radial highways

TAX: Full-value property tax rate per \$10,000

PTRATIO: Pupil-teacher ratio by town

B: $1000(B_k - 0.63)^2$, where B_k is the proportion of [people of African American descent] by town

LSTAT: Percentage of lower status of the population

MEDV: Median value of owner-occupied homes in \$1000s

Summary of the Hands On Portion



- Load the Dataset
- Exploratory Data Analysis
- Training a Linear Regression Model
- Training a Polynomial Regression Model
- Training a Linear/Poly Regression from scratch using gradient descent