CS 4375
Linear Regression

Rishabh Iyer

University of Texas at Dallas

Slides adapted from Nick Rouzzi and Sriraam Natarajan

Recap: Course Topics

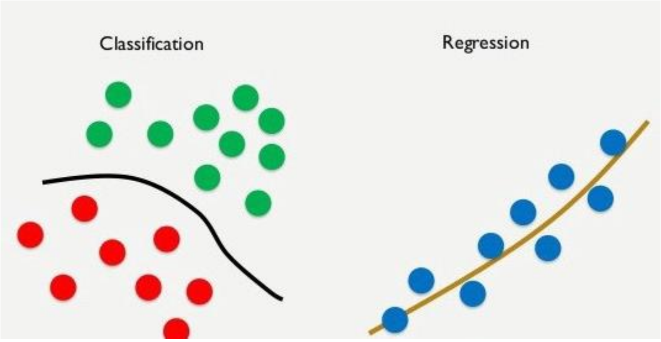
- **Supervised Learning**
  - SVMs & kernel methods
  - Decision trees, Random Forests, Gradient Boosted Trees
  - Nearest Neighbor: KNN Classifiers
  - Logistic Regression
  - Neural networks
  - Probabilistic models: Bayesian networks, Naïve Bayes
- **Unsupervised Learning**
  - Clustering: k-means & 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, ….**

Part I: Recap of Supervised Learning and Linear Regression Setup

Recap: Supervised Learning

- **Input:** $\left(x^{(1)}, y^{(1)}\right), \ldots, (x^{(M)}, y^{(M)})$
  - $x^{(m)}$ is the m^{th} data item and $y^{(m)}$ is the m^{th} **label**

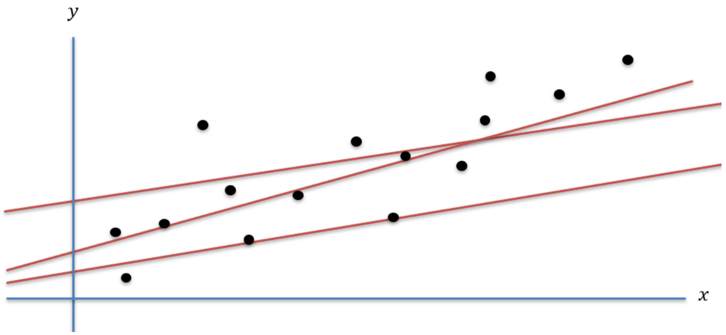
- **Goal:** find a function f such that $f\left(x^{(m)}\right)$ is a "good approximation" to $y^{(m)}$
  - Can use it to predict y values for previously unseen x values

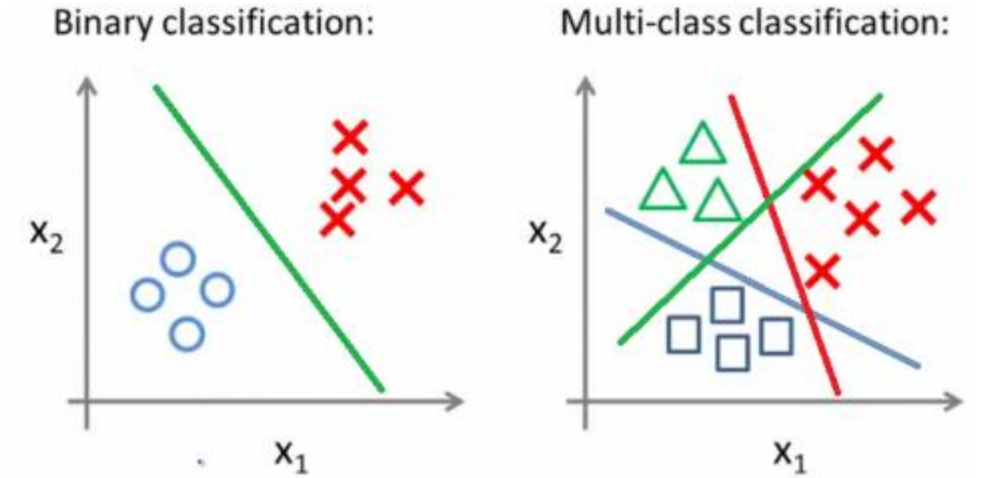


Recap: Classification vs Regression

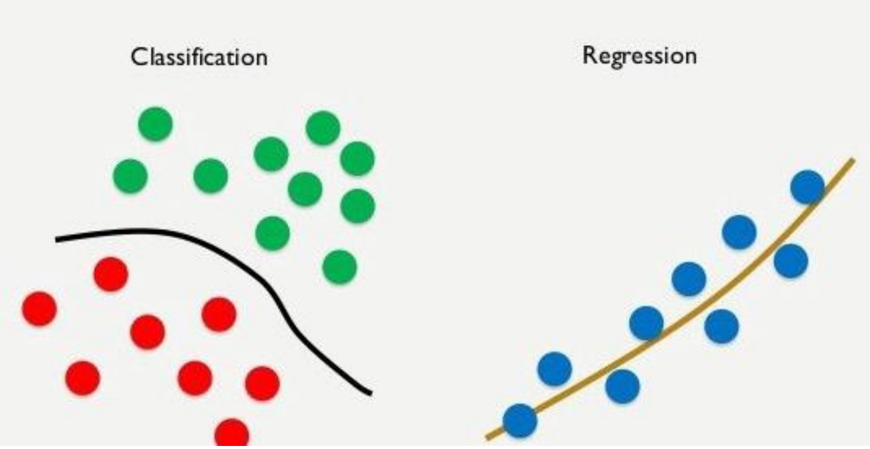
Classification vs Regression

- Input: pairs of points $(x^{(1)}, y^{(1)}), \ldots, (x^{(M)}, y^{(M)})$ 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





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

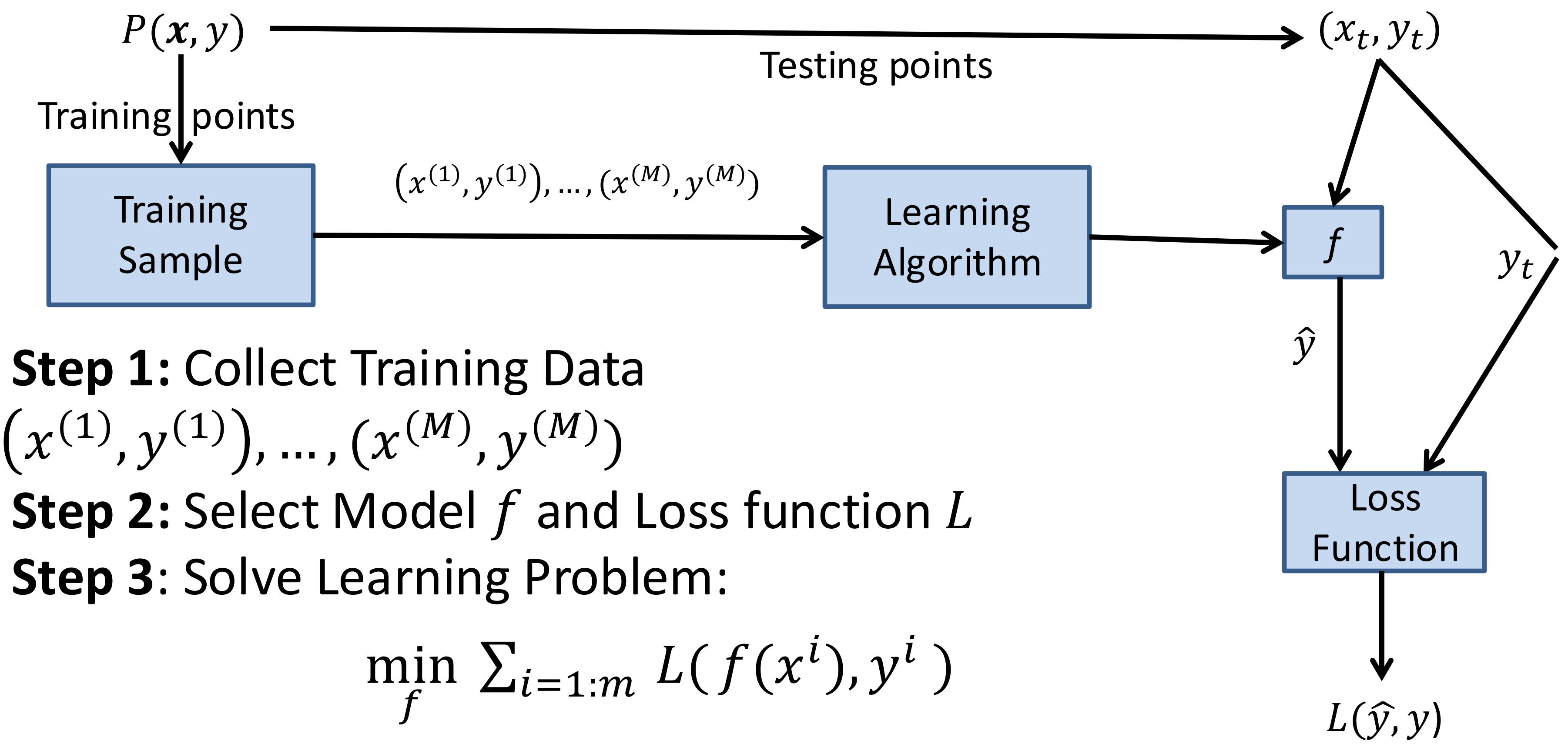
Recap: Hypothesis Space

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

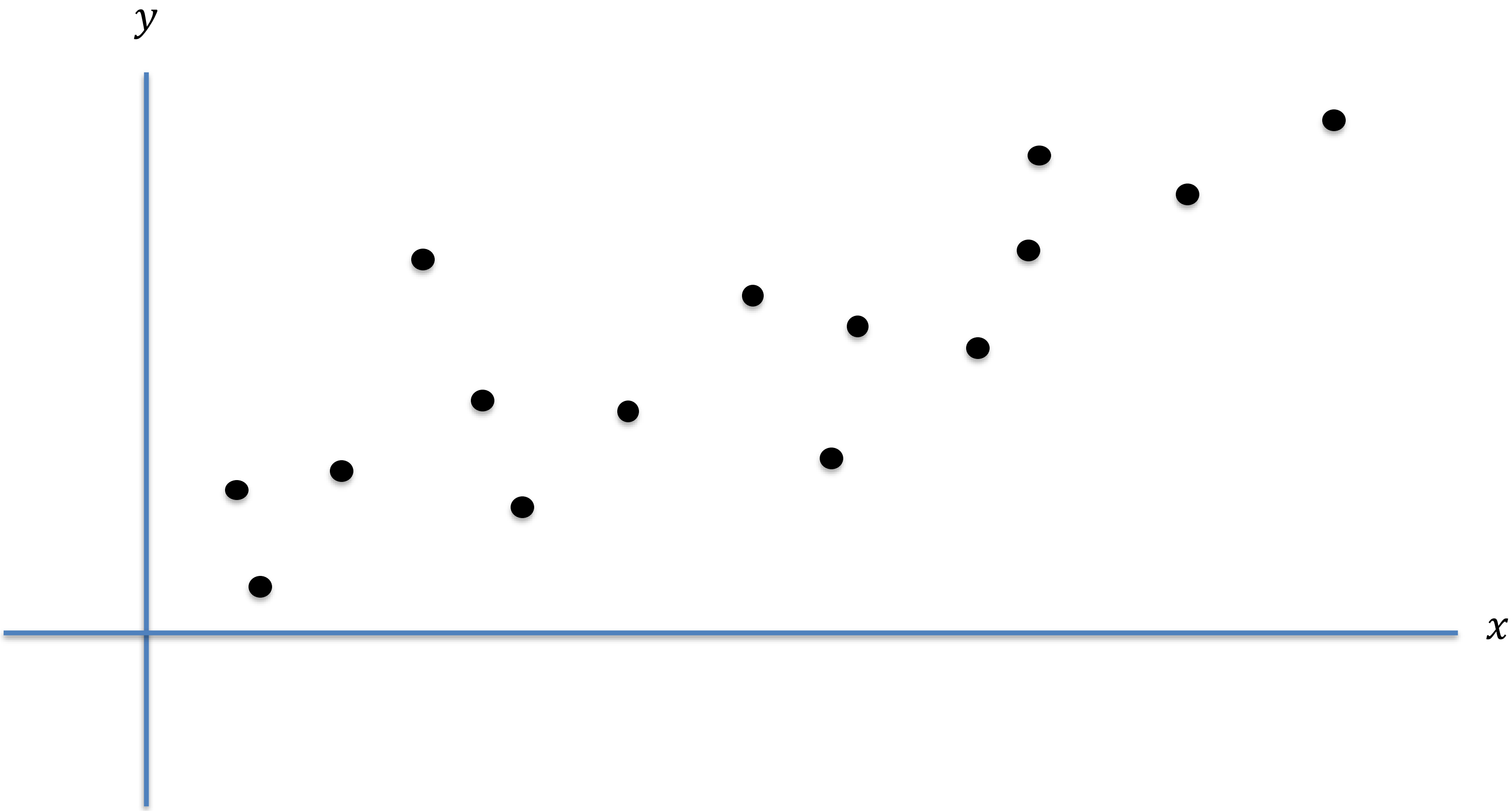
$$\min_{f} \sum_{i=1:m} L(f(x^i), y^i\ )$$

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

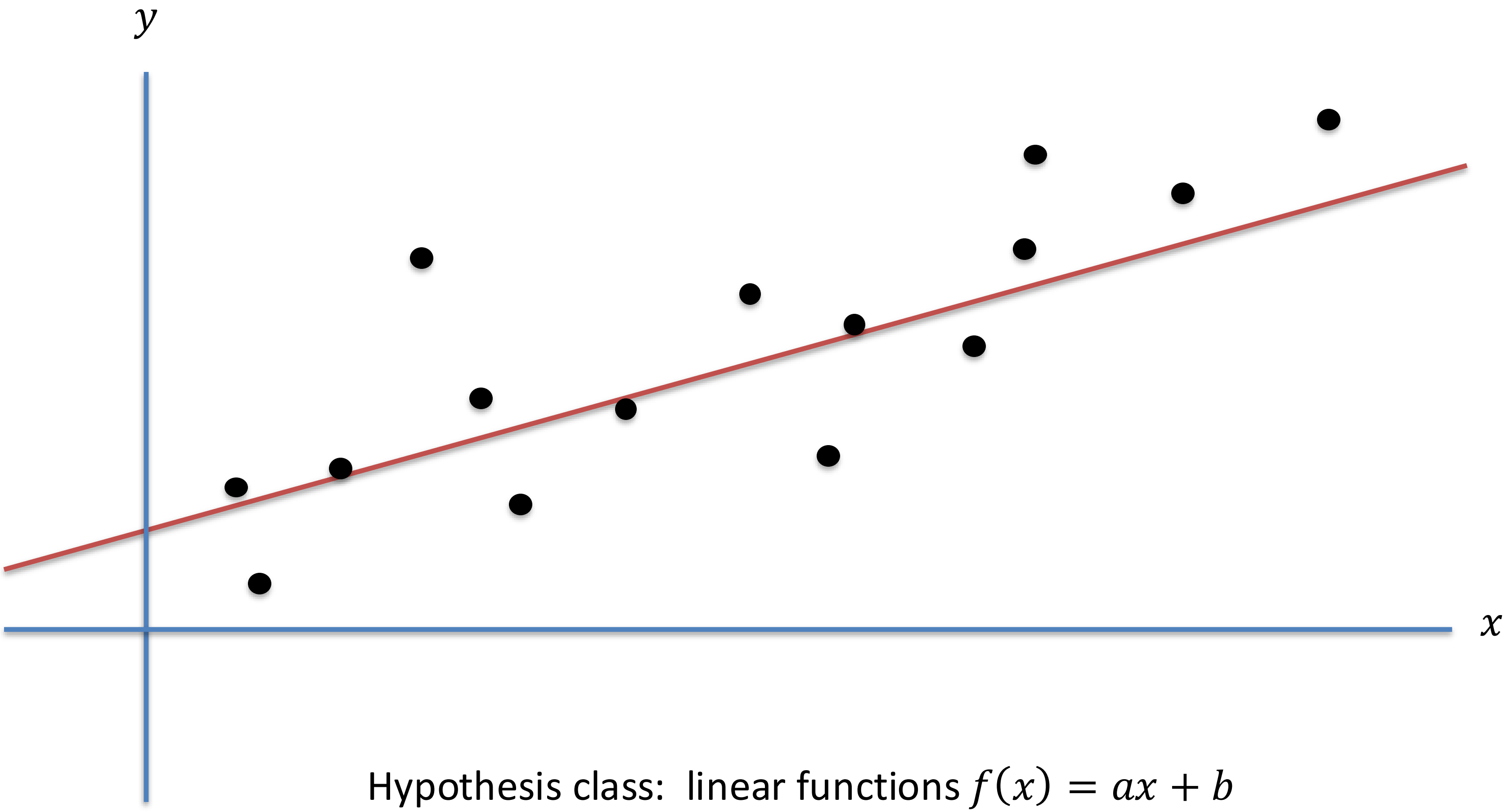
Linear Regression

- Simple linear regression
  - Input: pairs of points $\left(x^{(1)}, y^{(1)}\right), \dots, (x^{(M)}, y^{(M)})$ 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

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

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

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

Linear Regression

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

- How do we find the optimal a and b?

Linear Regression

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

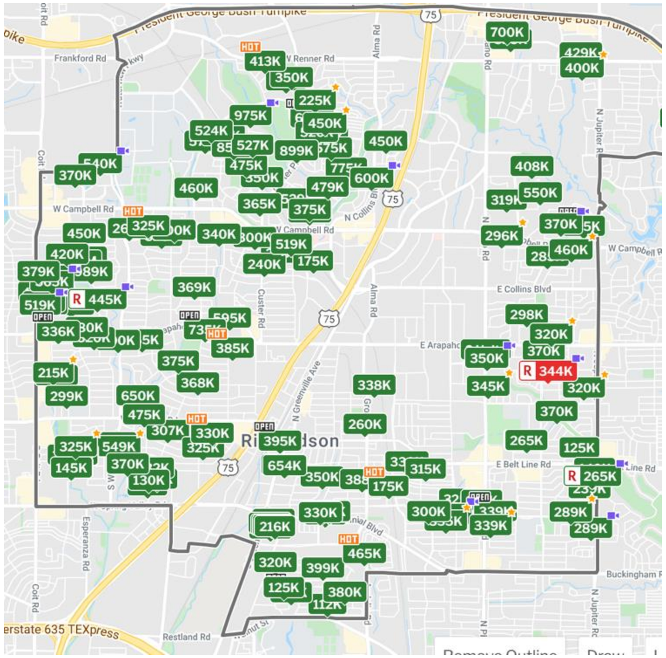
- How do we find the optimal a and b?
  - Solution 1: take derivatives and solve
    (there is a closed form solution!)
  - Solution 2: use gradient descent

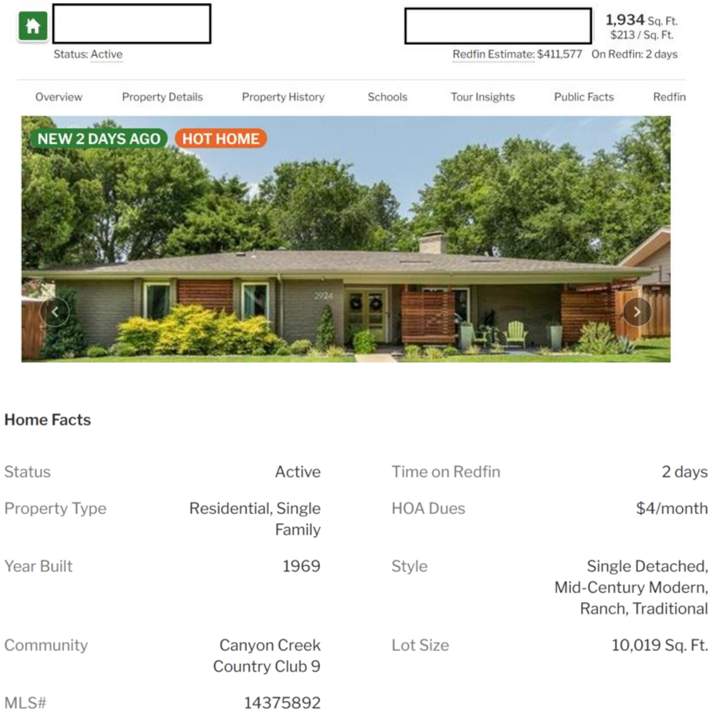
Linear Regression

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

- 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





[redacted]

Status: Active

[redacted]

1,934 Sq. Ft.
$213 / Sq. Ft.

Redfin Estimate: $411,577 On Redfin: 2 days

Overview | Property Details | Property History | Schools | Tour Insights | Public Facts | Redfin

NEW 2 DAYS AGO HOT HOME

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

Gradient Descent

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 $x, y \in \mathbb{R}^n$

Gradient Descent

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

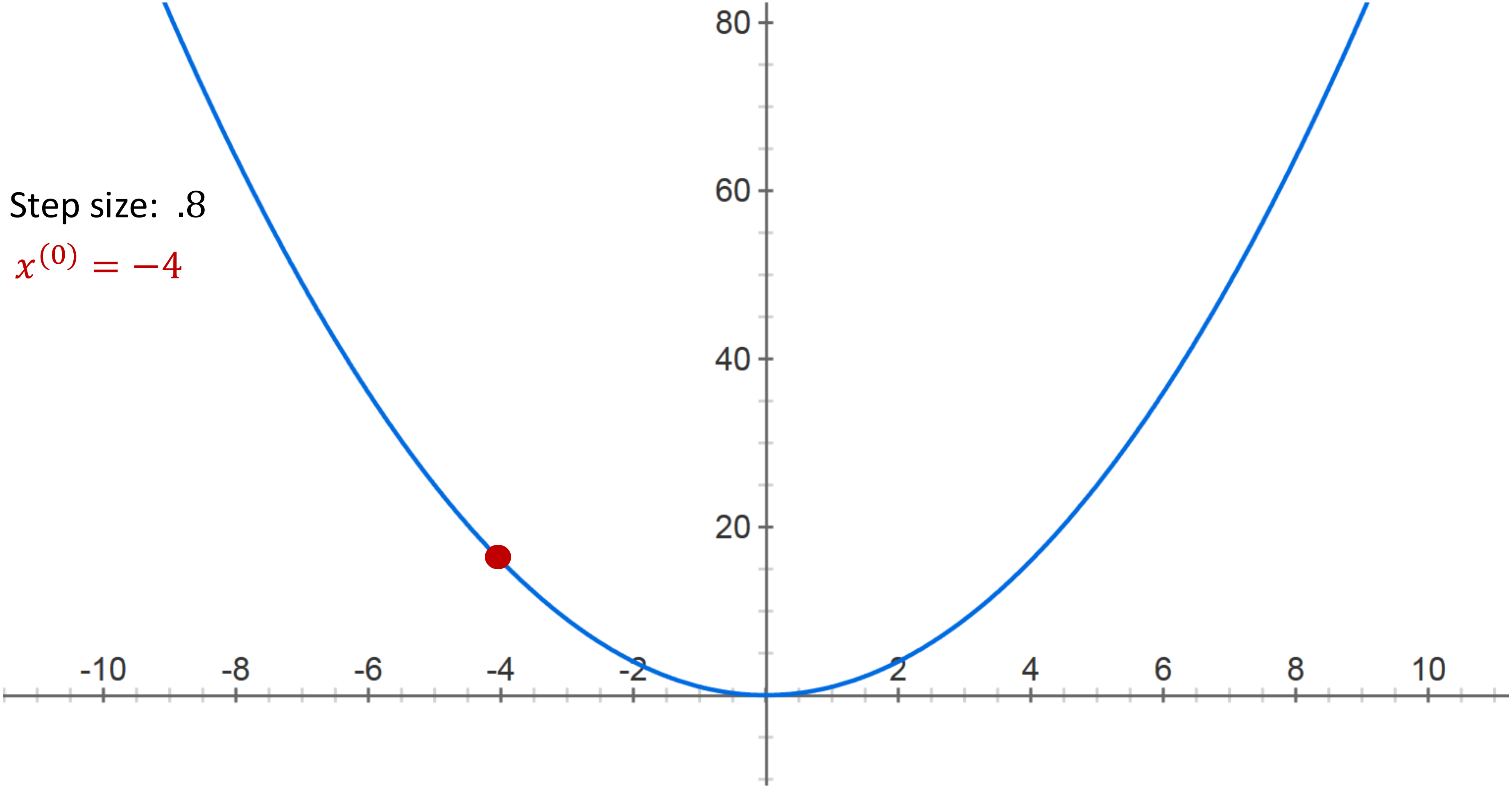
- For additional reading, please see some of my slides from my Spring 2020 Class "Optimization in Machine Learning"
- Github Location for Lecture Notes and Slides: https://github.com/rishabhk108/OptimizationML
- Please skim through:
  - Lectures 1 and 2 for basics
  - Lectures 3-5 for convex functions
  - 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

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



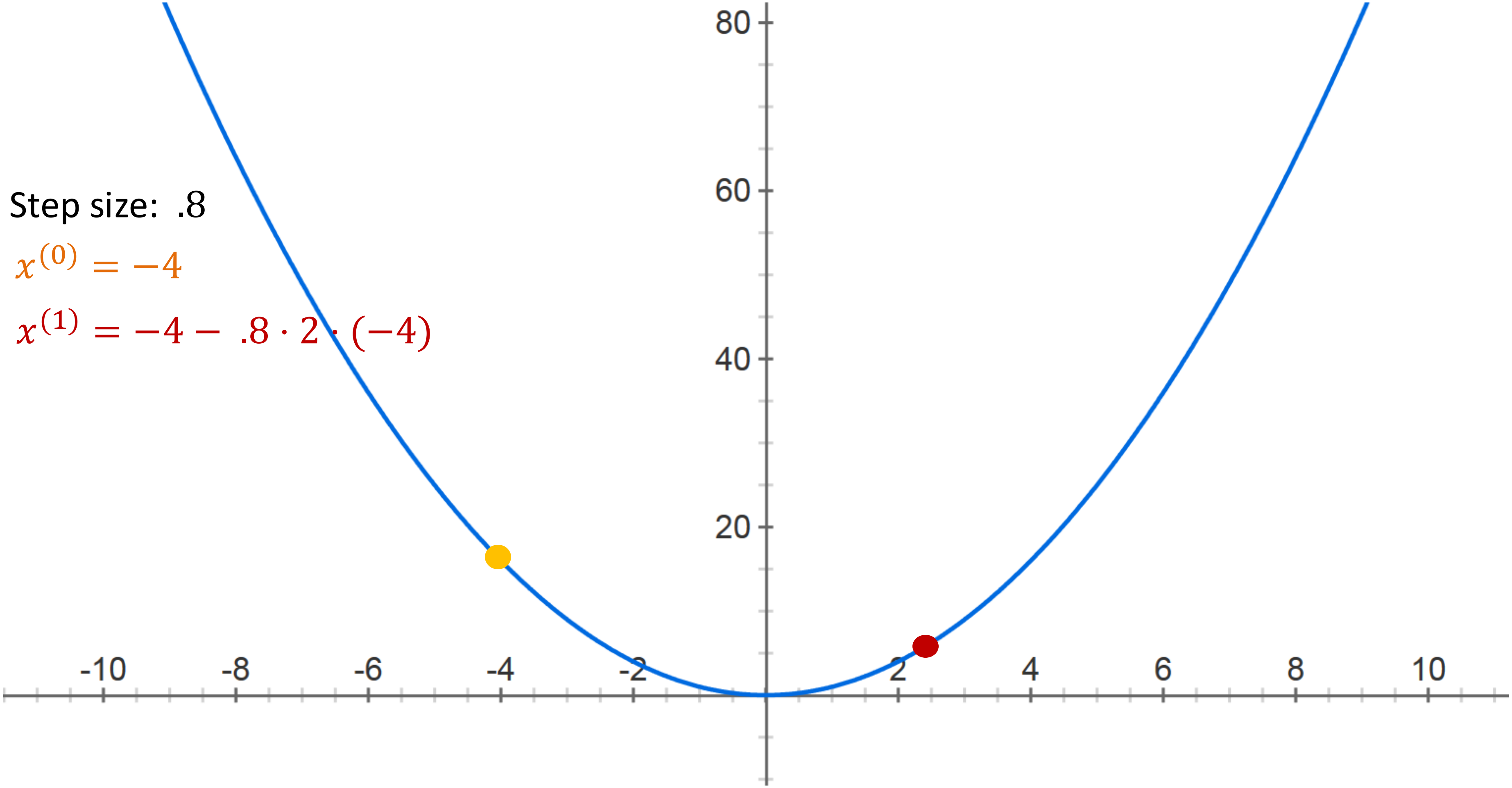
Gradient Descent

$f(x) = x^2$

Step size: .8

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

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



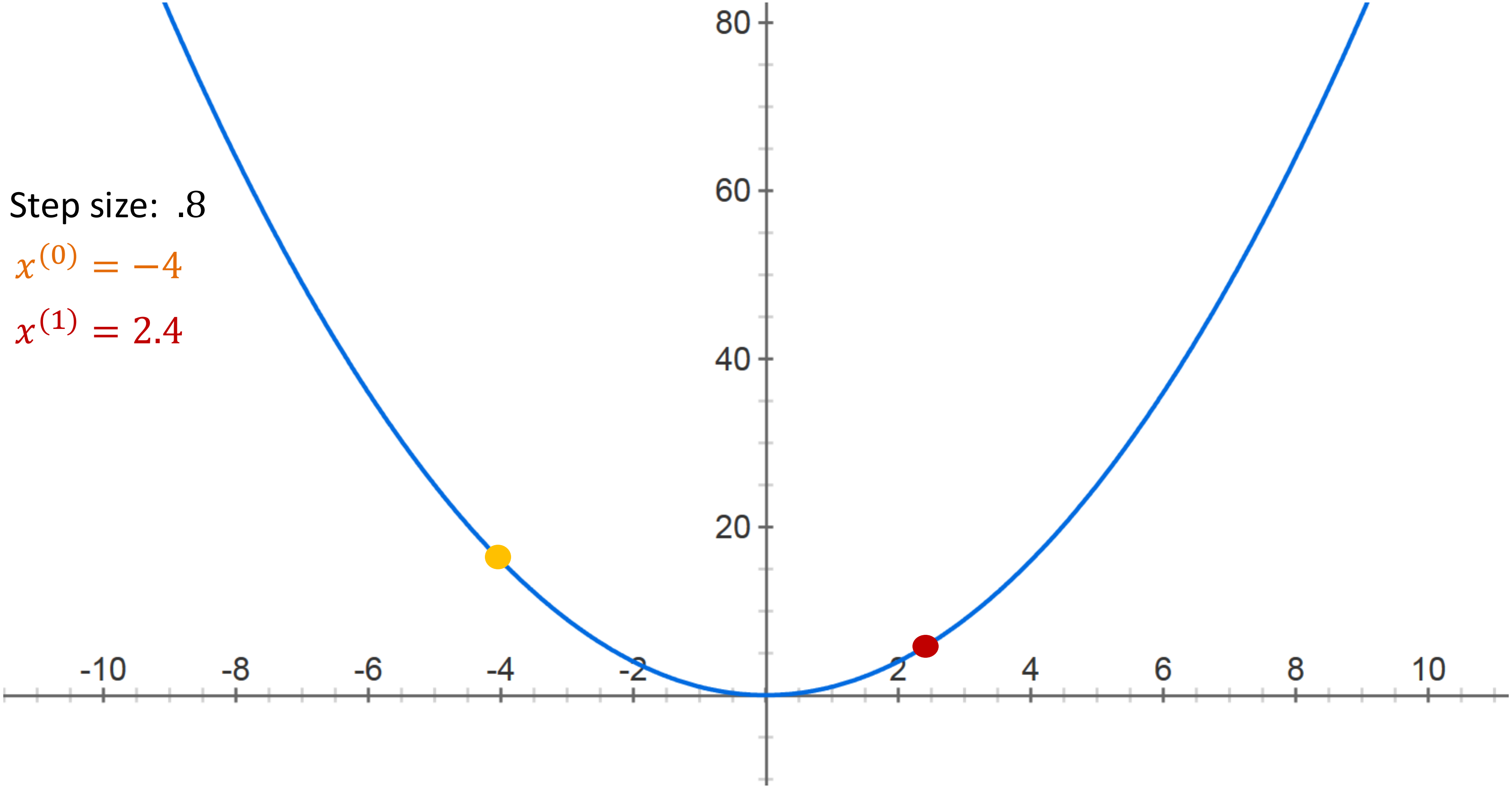
Gradient Descent

$f(x) = x^2$

Step size: .8

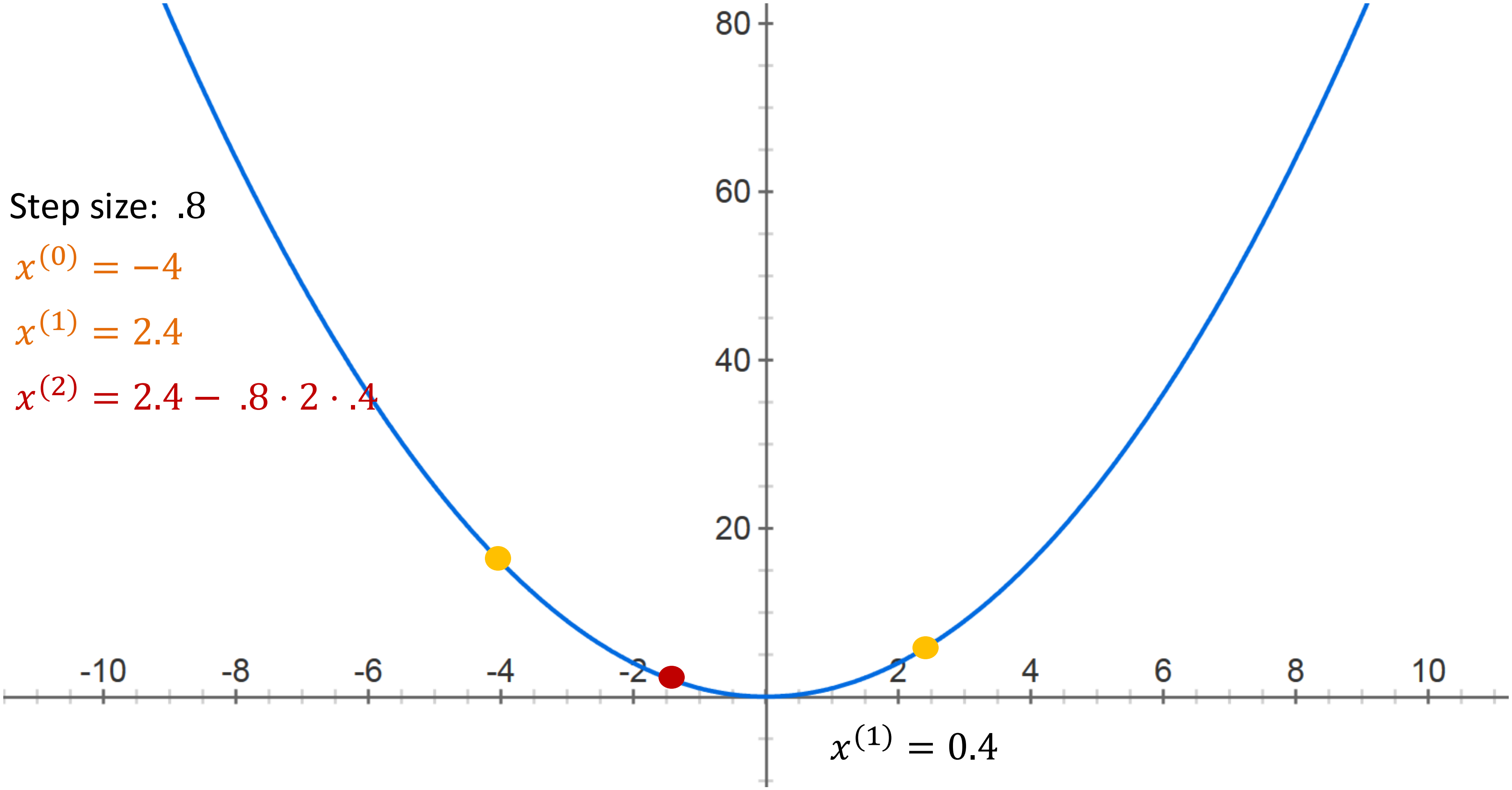
$x^{(0)} = -4$

$x^{(1)} = 2.4$



Gradient Descent

$f(x) = x^2$



Step size: .8

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

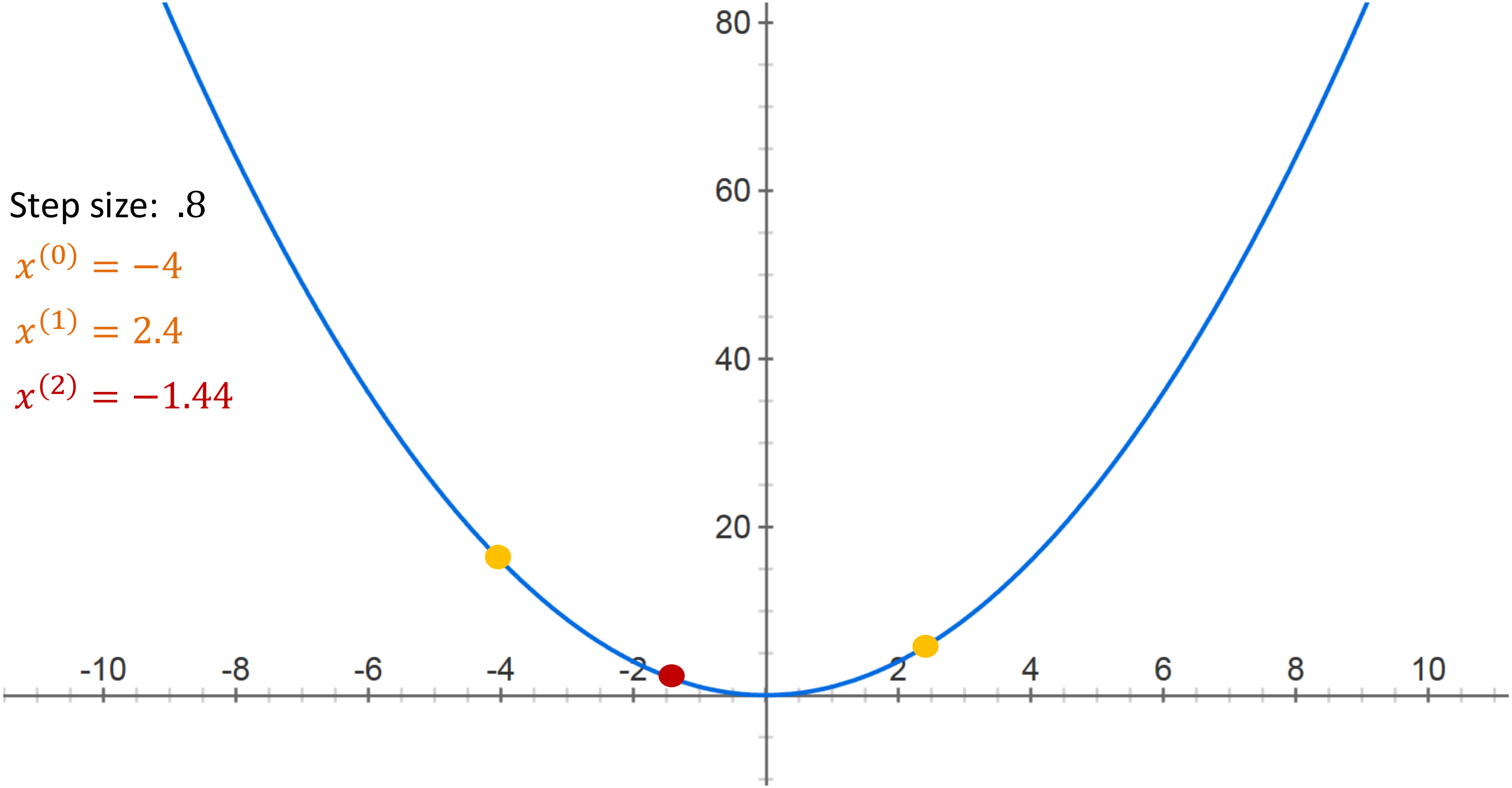
$x^{(1)} = 2.4$

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

$x^{(1)} = 0.4$

Gradient Descent

$f(x) = x^2$



Step size: .8

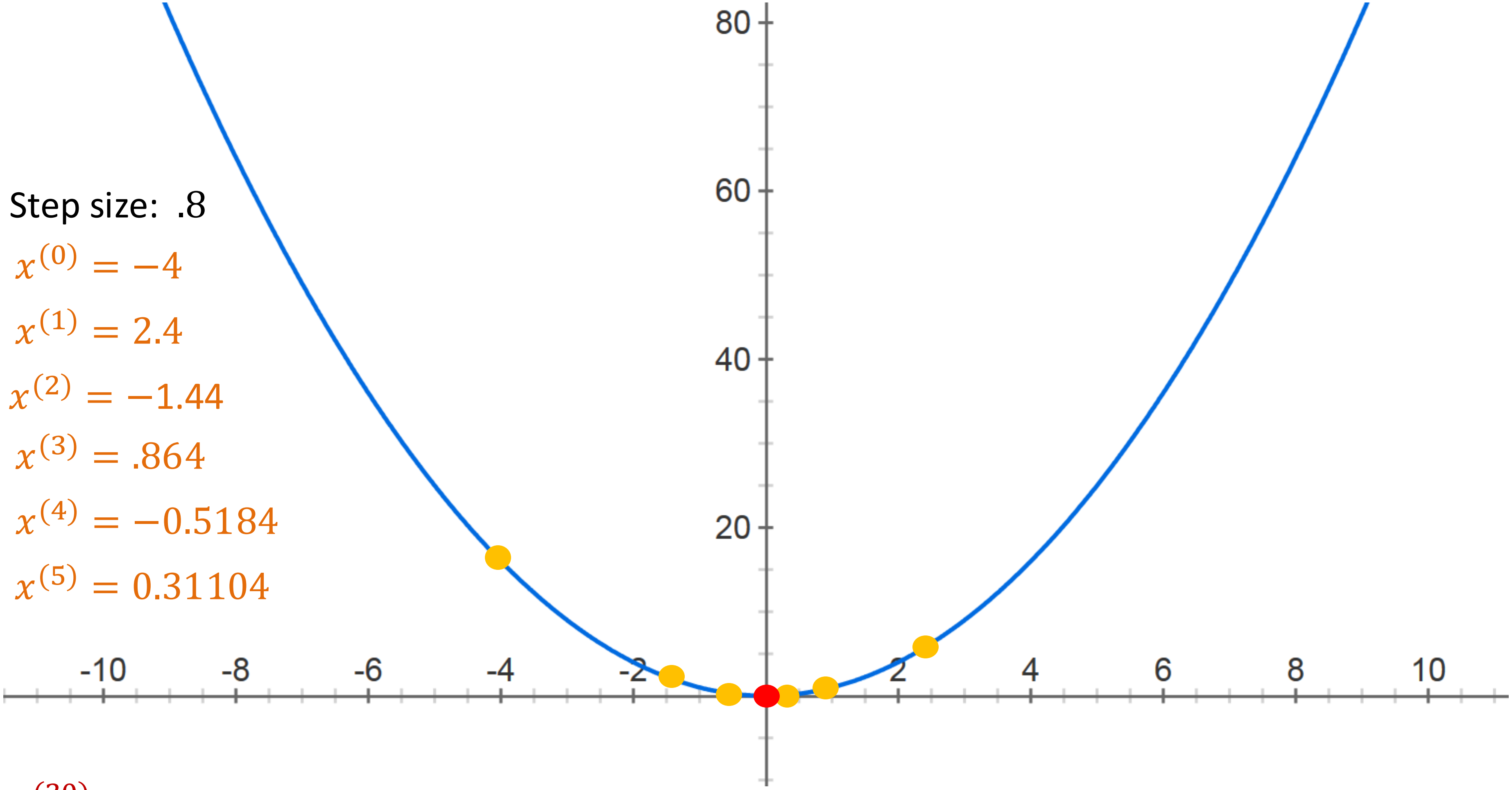
$x^{(0)} = -4$

$x^{(1)} = 2.4$

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

Gradient Descent

$f(x) = x^2$



Step size: .8

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

$x^{(1)} = 2.4$

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

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

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

$x^{(5)} = 0.31104$

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

Gradient Descent

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

- 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)

Linear Regression

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

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

- 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

- 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: $a_k x^k + a_{k-1} x^{k-1} + \cdots + a_1 x + a_0$

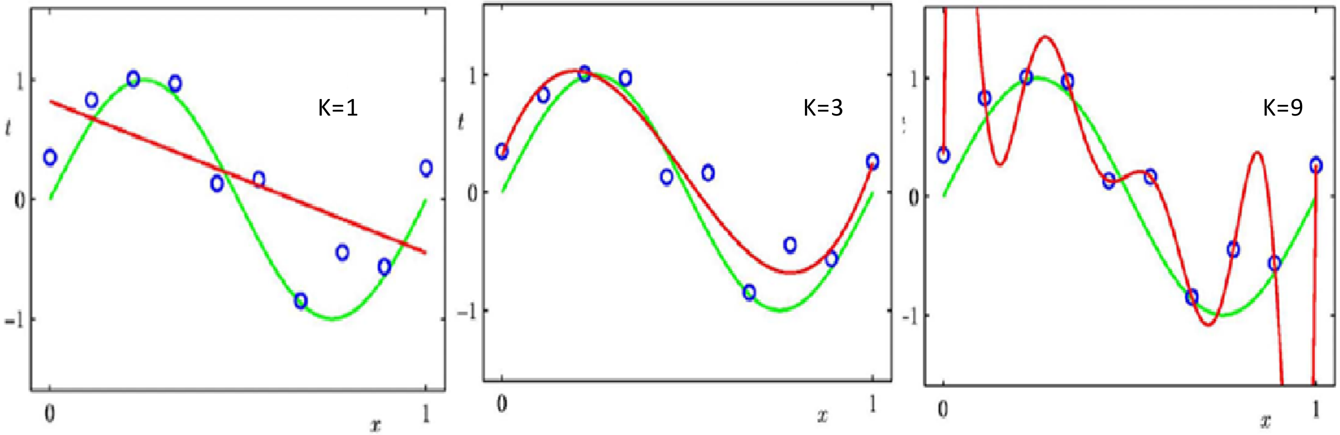
$$\min_{a_k,\ldots,a_0} \frac{1}{M} \sum_m \left(a_k \left(x^{(m)}\right)^k + \cdots + a_1 x^{(m)} + a_0 \; - y^{(m)}\right)^2$$

Polynomial Regression

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

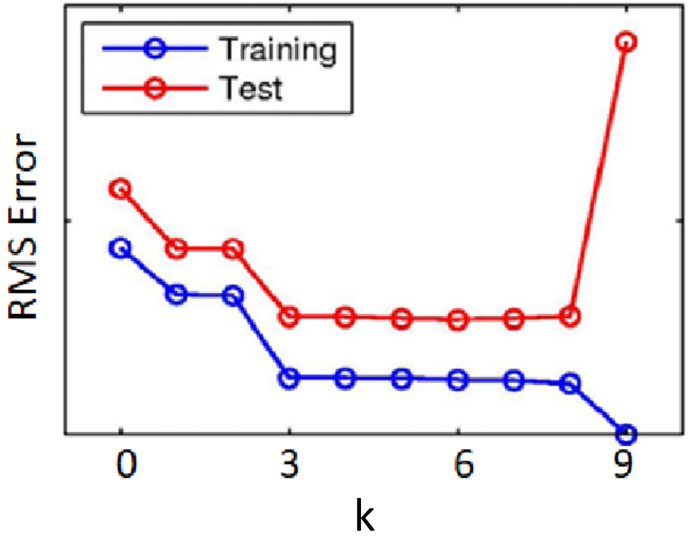


Caveats with Polynomial Regression

- 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

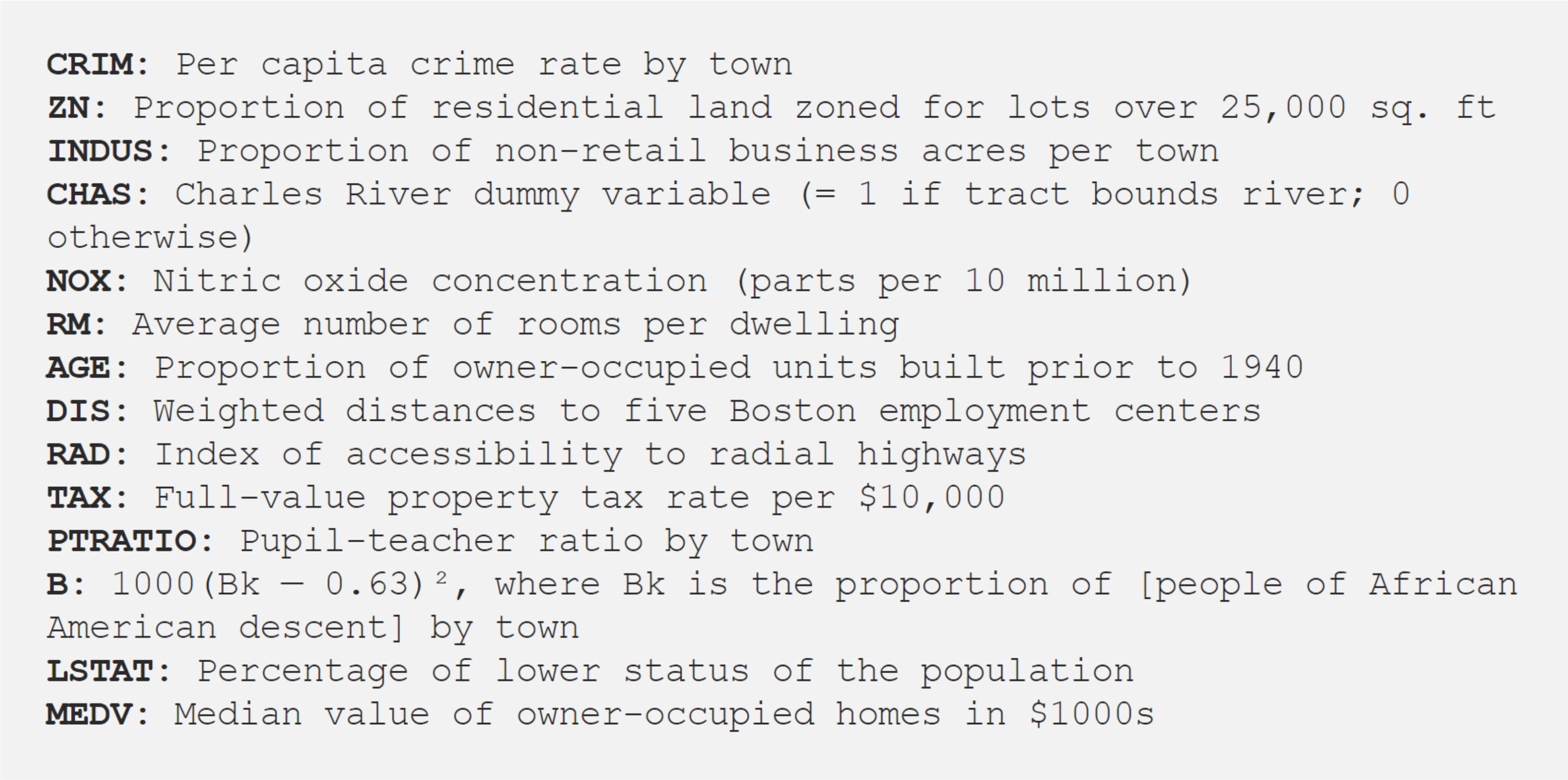
- As *the degree of the polynomial (k)* increases, training error decreases monotonically
- As *k* increases test error can increase
- Test error can decrease at first, but increases
- Overfitting can occur
  - When the model is too complex and trivially fits the data (i.e., too many parameters)
  -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



Part IV: Hands On

House Price Prediction

- 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: $1000(Bk - 0.63)^2$, where Bk 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