Lectures 5-7

Simple Linear Regression

DSC 40A, Fall 2025

Announcements

- Homework 1 is due **Friday night**.
- Look at the office hours schedule here and plan to start regularly attending!
- Remember to take a look at the supplementary readings linked on the course website.

Agenda

- 0-1 loss
- Prediction rules using features
- Simple linear regression.
- Minimizing mean squared error for the simple linear model.

Question 🤔

Answer at q.dsc40a.com

Remember, you can always ask questions at q.dsc40a.com!

If the direct link doesn't work, click the "🤔 Lecture Questions"
link in the top right corner of dsc40a.com.

Another example: 0-1 loss

Consider, for example, the **0-1 loss**:

$$L_{0,1}(y_i, h) = \begin{cases} 0 & y_i = h \\ 1 & y_i \neq h \end{cases}$$

The corresponding empirical risk is:

$$R_{0,1}(h) = \frac{1}{n} \sum_{i=1}^{n} L_{0,1}(y_i, h)$$

Question 🤔

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$$R_{0,1}(h) = \frac{1}{n} \sum_{i=1}^{n} \begin{cases} 0 & y_i = h \\ 1 & y_i \neq h \end{cases}$$

Suppose $y_1, y_2, \ldots, y_n$ are all unique. What is $R_{0,1}(y_1)$?

- A. 0.
- B. $\frac{1}{n}$.
- C. $\frac{n-1}{n}$.
- D. 1.

Minimizing empirical risk for 0-1 loss

$$R_{0,1}(h) = \frac{1}{n}\sum_{i=1}^{n}\begin{cases}0 & y_i = h\\ 1 & y_i \neq h\end{cases}$$

Summary: Choosing a loss function

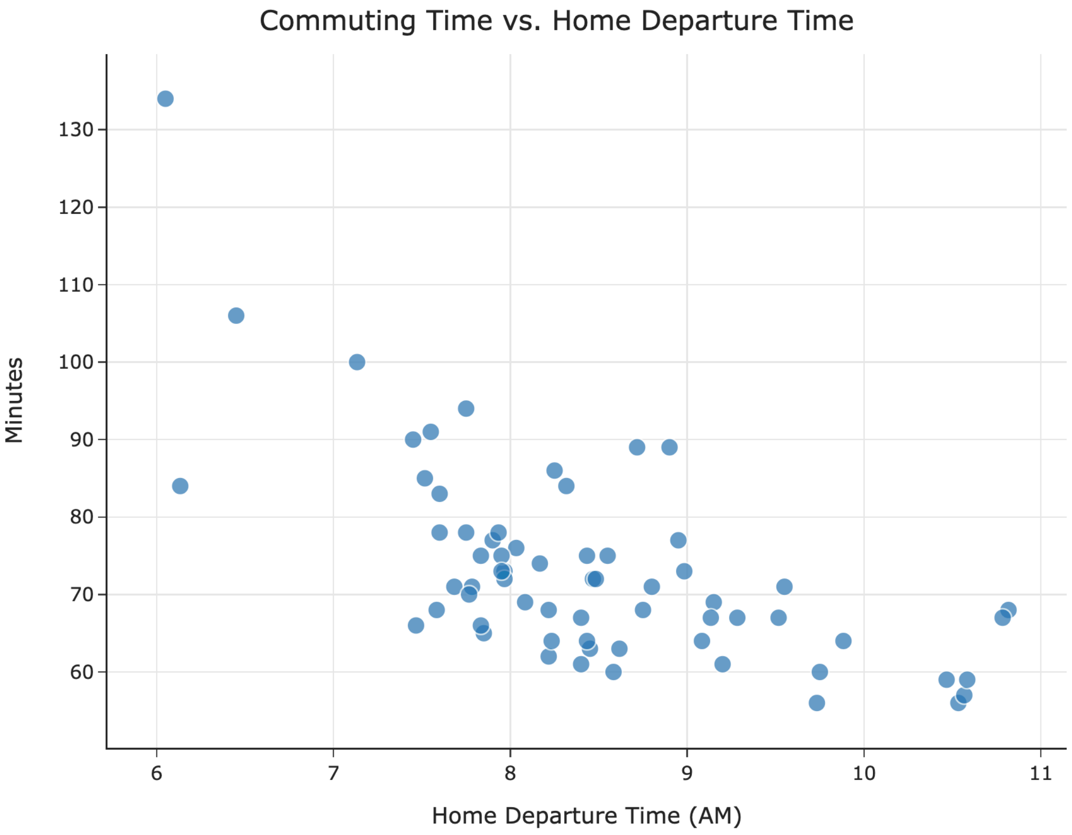
Key idea: Different loss functions lead to different best predictions, h^*!

Loss	Minimizer	Always Unique?	Robust to Outliers?	Differentiable?
L_{sq}	mean	yes ✅	no ❌	yes ✅
L_{abs}	median	no ❌	yes ✅	no ❌
L_∞	midrange	yes ✅	no ❌	no ❌
$L_{0,1}$	mode	no ❌	yes ✅	no ❌

The optimal predictions, h^*, are all **summary statistics** that measure the **center** of the dataset in different ways.

Predictions with features

Towards simple linear regression



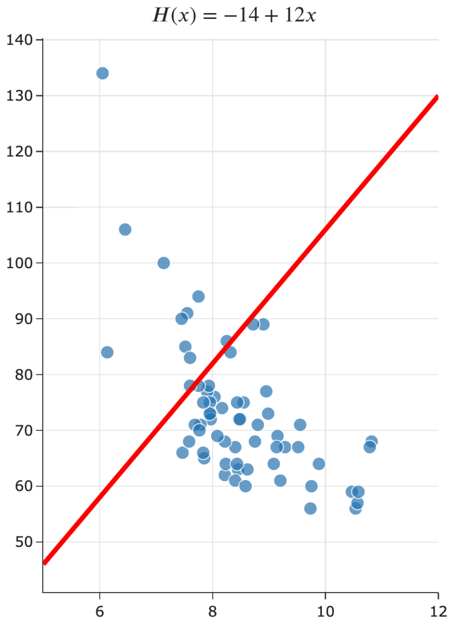
- In Lecture 1, we introduced the idea of a hypothesis function, $H(x)$.
- We've focused on finding the best **constant model**, $H(x) = h$.
- Now that we understand the modeling recipe, we can apply it to find the best **simple linear regression model**, $H(x) = w_0 + w_1 x$.
- This will allow us to make predictions that aren't all the same for every data point.

Recap: Hypothesis functions and parameters

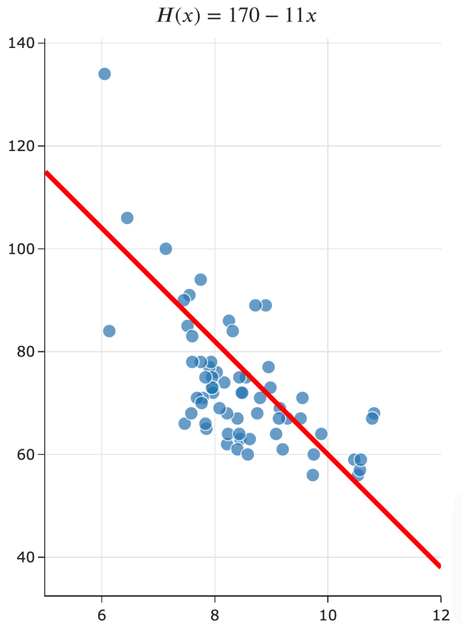
A hypothesis function, H, takes in an x as input and returns a predicted y.

Parameters define the relationship between the input and output of a hypothesis function.

The simple linear regression model, $H(x) = w_0 + w_1 x$, has two parameters: w_0 and w_1.



$H(x) = -14 + 12x$



$H(x) = 170 - 11x$

The modeling recipe

1. Choose a model.

2. Choose a loss function.

3. Minimize average loss to find optimal model parameters.

Features

A **feature** is an attribute of the data – a piece of information.

- **Numerical**: maximum allowed speed, time of departure
- **Categorical**: day of week
- **Boolean**: was there a car accident on the road?

Think of features as columns in a DataFrame (i.e. table).

Departure time	Day of week	Accident on route	Commute time
7:05	Monday	yes	101
8:03	Tuesday	no	87
10:20	Wednesday	yes	79
8:30	Thursday	no	76

Variables

- The features, x, that we base our predictions on are called predictor variables.
- The quantity, y, that we're trying to predict based on these features is called the response variable, dependent variable or target.
- We are trying to predict our commute time as a function of departure time.

Modeling

- We believe that commute time is a function of departure time.
- I.e., there is a function H so that:
  commute time $\approx H$(departure time)
- H is called a hypothesis function or prediction rule.
- Our goal: find a good prediction rule, H.

Possible Hypothesis Functions

- H_1(departure time) = 90 - 10 ·(departure time-7)
- H_2(departure time) = 90 - (departure time-8)^2
- H_3(departure time) = 20 + 6·departure time

These are all valid prediction rules.

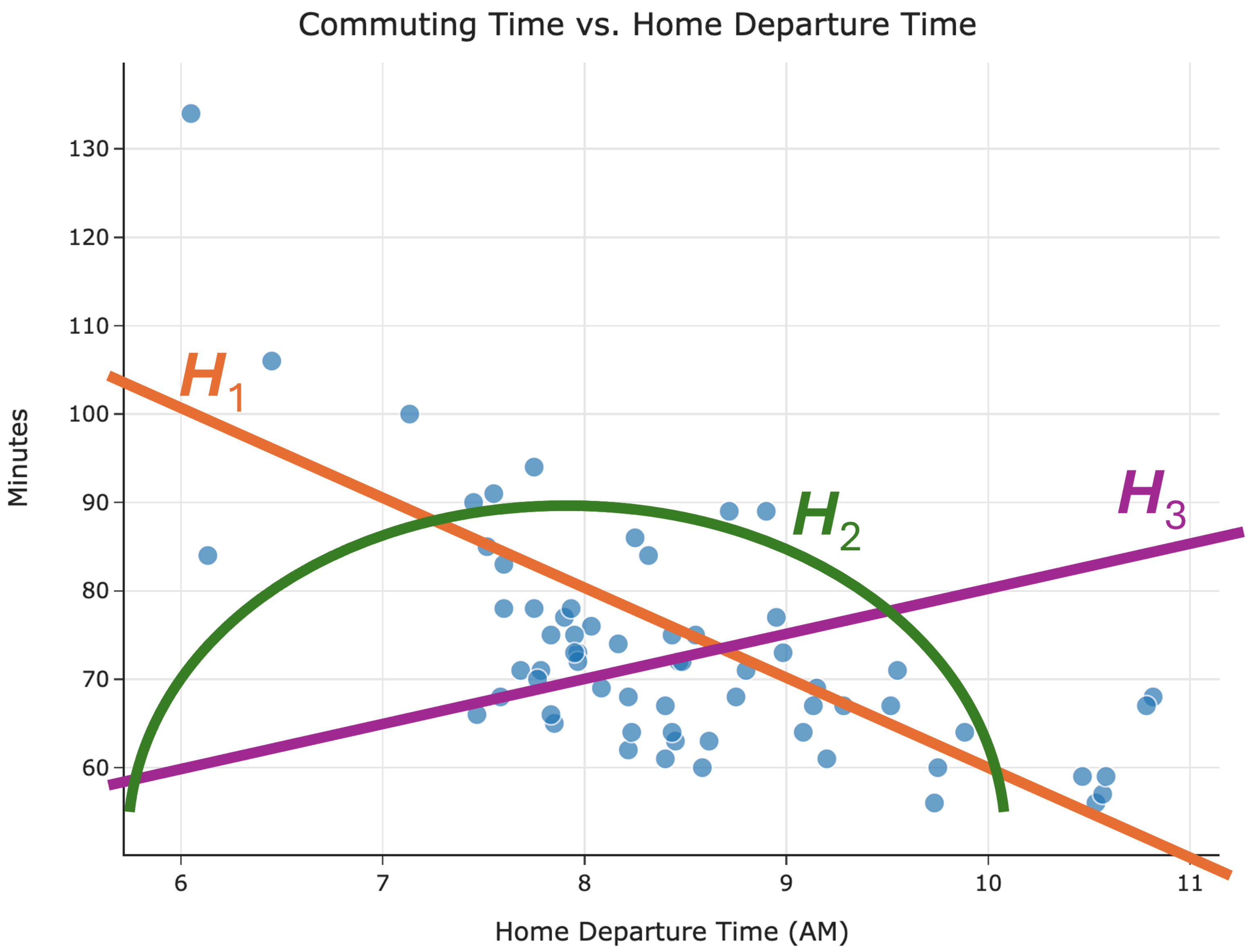
Some are better than others.

Comparing predictions

- How do we know which is best: $H_1,\ H_2,\ H_3$?
- We gather data from n days of commute. Let xi be experience, yi be salary:

$$\begin{array}{lcc}
\text{(departure time}_1\text{ , commute time}_1\text{)} & & (x_1, y_1) \\
\text{(departure time}_2\text{ , commute time}_2\text{)} & & (x_2, y_2) \\
\ldots & \rightarrow & \\
\text{(departure time}_n\text{ , commute time}_n\text{)} & & (x_n, y_n)
\end{array}$$

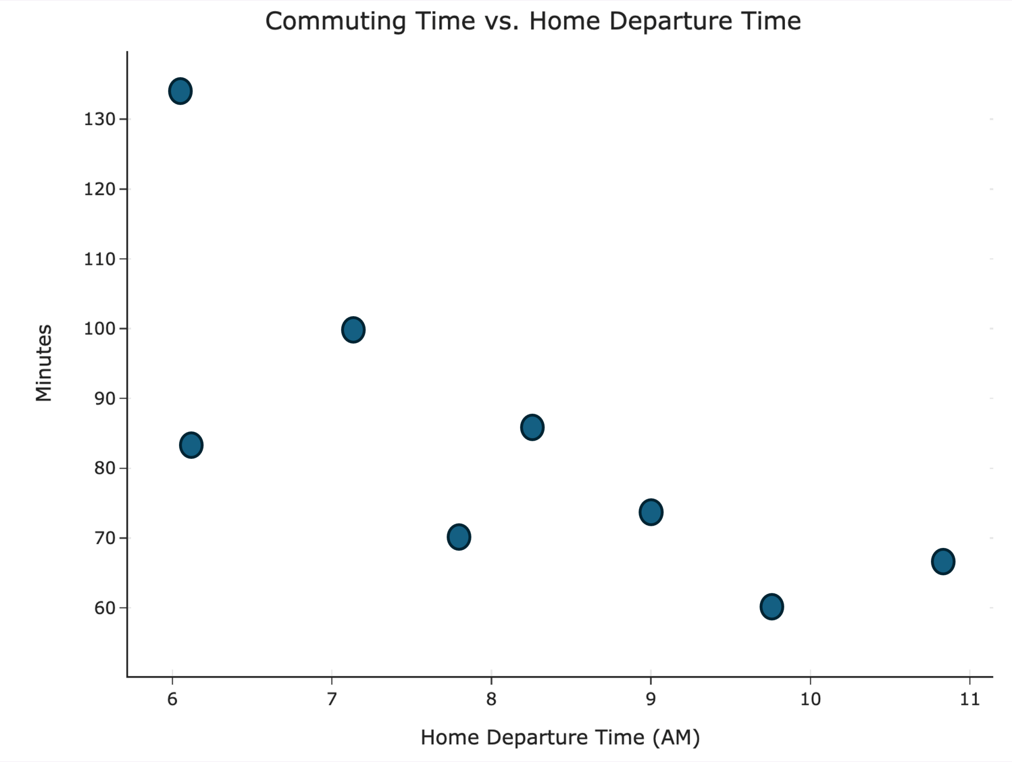
- See which rule works better on data.


Commuting Time vs. Home Departure Time
Minutes
130
120
110
100
90
80
70
60
Home Departure Time (AM)
6
7
8
9
10
11
H_1
H_2
H_3

Question 🤔 Answer at q.dsc40a.com

Given the data below, is there a prediction rule H which has zero mean absolute error?

- A. yes
- B. no



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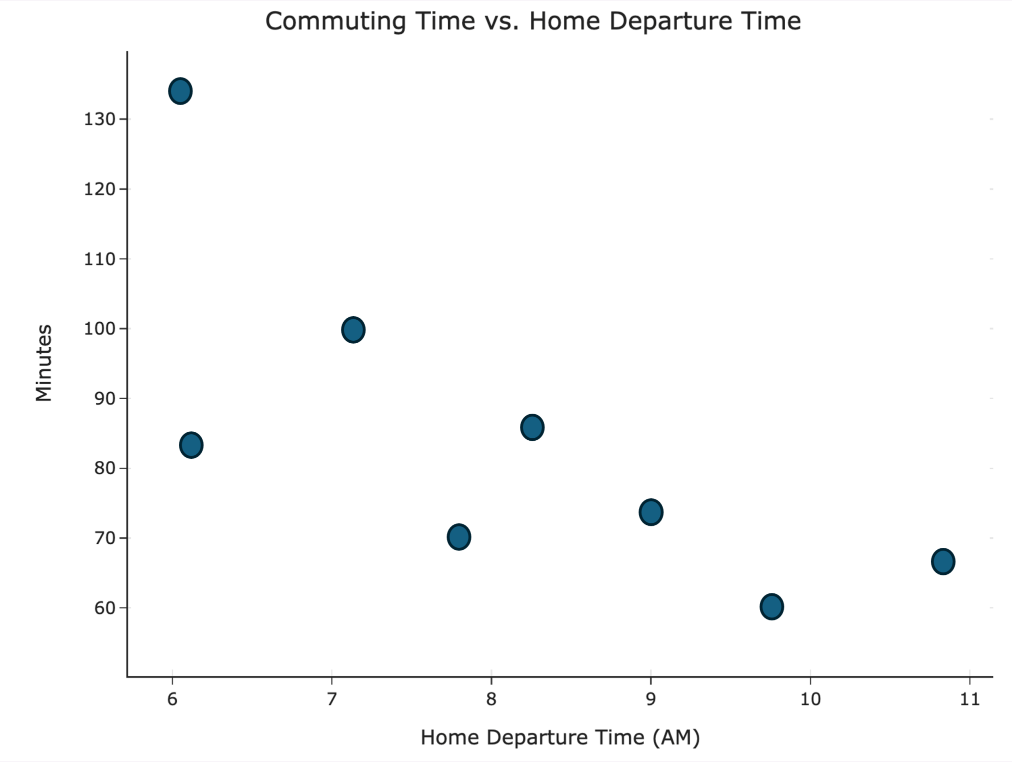


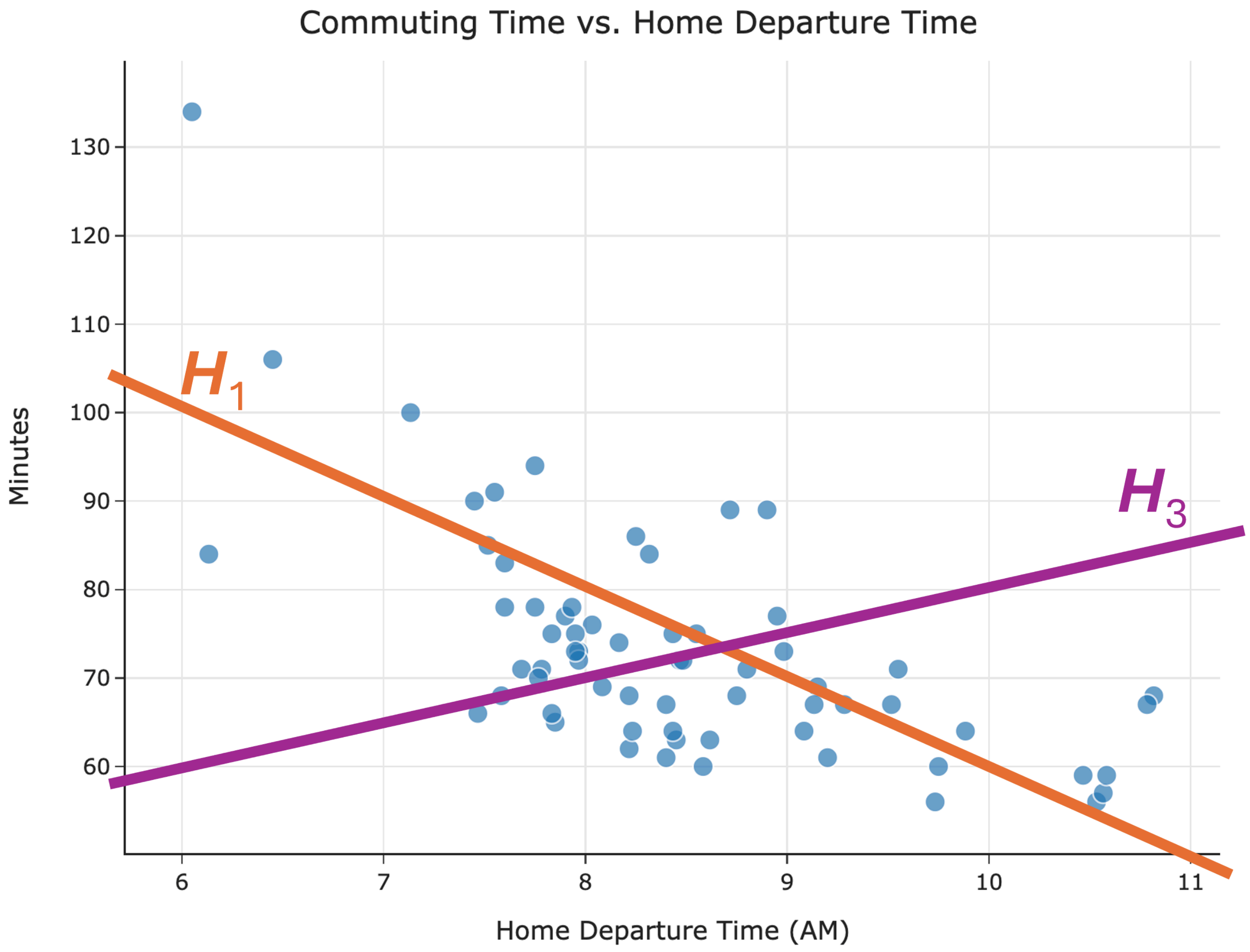
Problem

- We can make mean absolute error very small, even zero!
- But the function will be weird.
- This is called **overfitting**.
- Remember our real goal: make good predictions on data **we haven't seen**.

Solution

- Don't allow H to be just any function.
- Require that it has a certain form.
- Examples:
  - Linear: $H(x) = w_0 + w_1 x$.
  - Quadratic: $H(x) = w_0 + w_1 x_1 + w_2 x^2$.
  - Exponential: $H(x) = w_0 e^{w_1 x}$.
  - Constant: $H(x) = w_0$.

Comparing predictions



Minimizing mean squared error for the simple linear model

- We'll choose squared loss, since it's the easiest to minimize.
- Our goal, then, is to find the linear hypothesis function $H^*(x)$ that minimizes empirical risk:

$$R_{\text{sq}}(H) = \frac{1}{n} \sum_{i=1}^{n} \left(y_i - H(x_i)\right)^2$$

- Since linear hypothesis functions are of the form $H(x) = w_0 + w_1 x$, we can re-write R_{sq} as a function of w_0 and w_1:

$$\boxed{R_{\text{sq}}(w_0, w_1) = \frac{1}{n} \sum_{i=1}^{n} \left(y_i - (w_0 + w_1 x_i)\right)^2}$$

- **How do we find the parameters w_0^* and w_1^* that minimize $R_{\text{sq}}(w_0, w_1)$?**