PSY9511: Seminar 2

The basics of regression and classification

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Outline

Today's lecture:

1. Recap of last lecture
2. Proposed solution for Assignment 1
3. Basics of regression and classification
4. Presentation of Assignment 2

The basics of regression and classification

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Outline

Todays topics

- Different types of outputs y
  - Regression, classification, and other variants
- Linear regression: Restricting the scope of $\hat{f}(X)$
  - Live coding 🥳
- k-Nearest Neighbours: An intuitive solution to classification
- Logistic regression: Extending linear regression to classification
  - Live coding 🥳
- Generative models for classification

Plan for future lectures

- How do we evaluate how good our models are? (Lecture 4)
- More complex solutions to regression and classification problems (Lecture 3, 5 and onwards)

Regression vs. classification

Weight	Manufacturer
3504	Chevrolet
3693	Ford
3436	Pontiac
3433	Pontiac
3449	Ford
4341	Ford
4354	Chevrolet
4312	Ford
4425	Pontiac
3850	Chevrolet

Regression vs. classification

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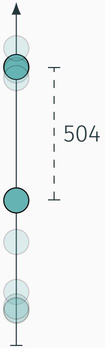
Regression vs. classification



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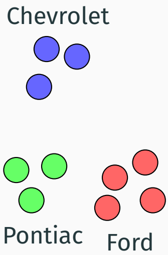

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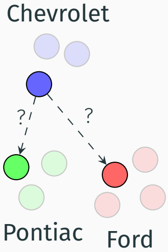


Regression vs. classification

Mean squared error (MSE):

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

Accuracy:

$$\frac{1}{n}\sum_{i=1}^{n}\mathbb{1}(y_i, \hat{y}_i),$$

$$\mathbb{1}(a, b) = \begin{cases} 1 & \text{if } a = b \\ 0 & \text{if } a \neq b \end{cases}$$

Regression vs. classification

Regression:

- Predicting reaction time on a cognitive task based on sleep scores
- Predicting the age of an individual based on a brain scan
- Predicting anxiety scores based on questionnaire data

Classification:

- Predicting whether an individual is depressed based on cell phone usage data
- Predicting if a patient has dementia based on a brain scan
- Predicting whether a patient is happy based on their facial expression

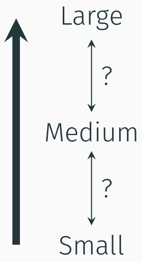
Regression vs. classification

Large

Medium

Small

Regression vs. classification

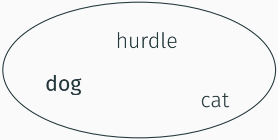


Regression vs. classification

The quick brown fox jumps over the lazy ______

Regression vs. classification

The quick brown fox jumps over the lazy ______



Classification

Regression vs. classification

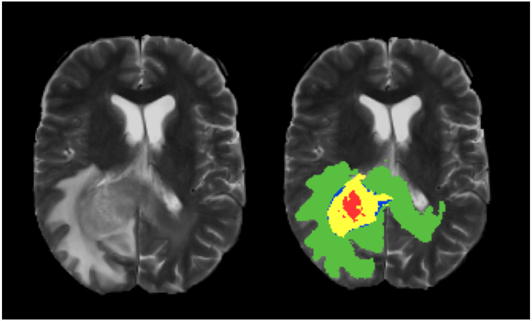
"Students taking a machine learning class" → →

Regression vs. classification

"Students taking a machine learning class"

(128, 192, 64)

Regression vs. classification



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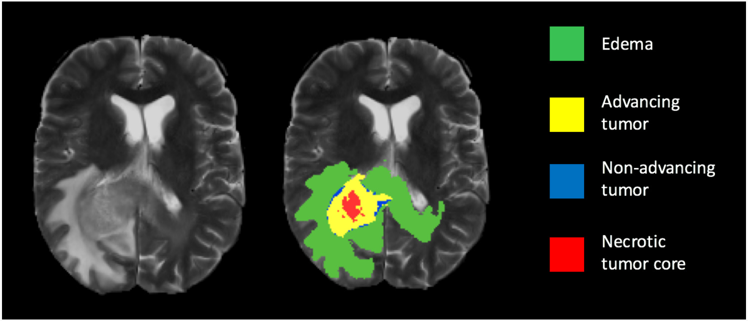

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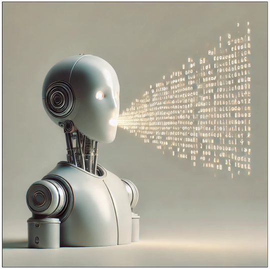

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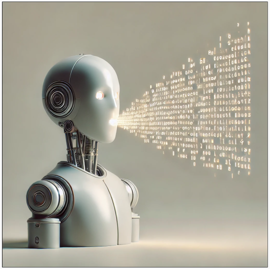

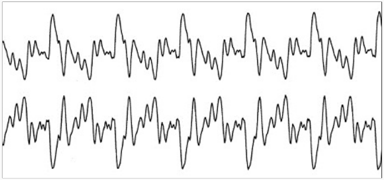

Regression vs. classification

Different types of outputs y require us to use different mathematical formulations of the problem we want to solve.

- Problems with quantitative outputs are solved via regression, often by minimizing the mean squared error
- Problems with qualitative outputs are solved by classification, often to maximize accuracy
- Ordinal regression falls between the two, with qualitative classes that have some kind of order
- A variety of other types of problems can be seen as special cases of these two

Linear regression (via ordinary least squares)

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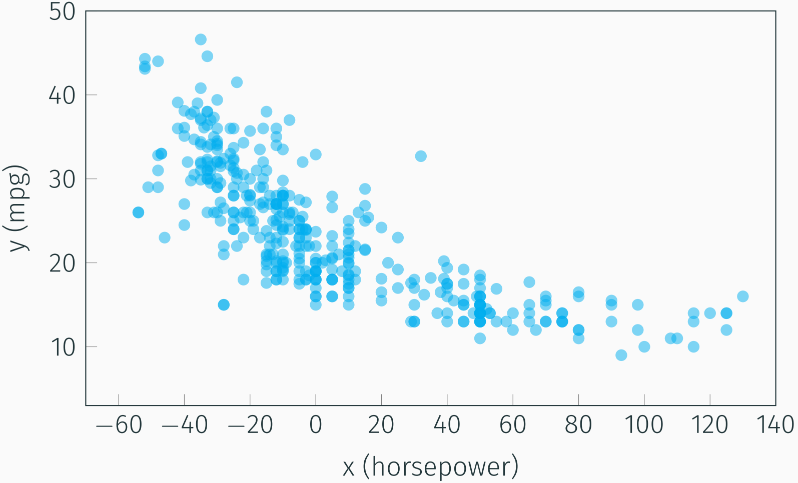

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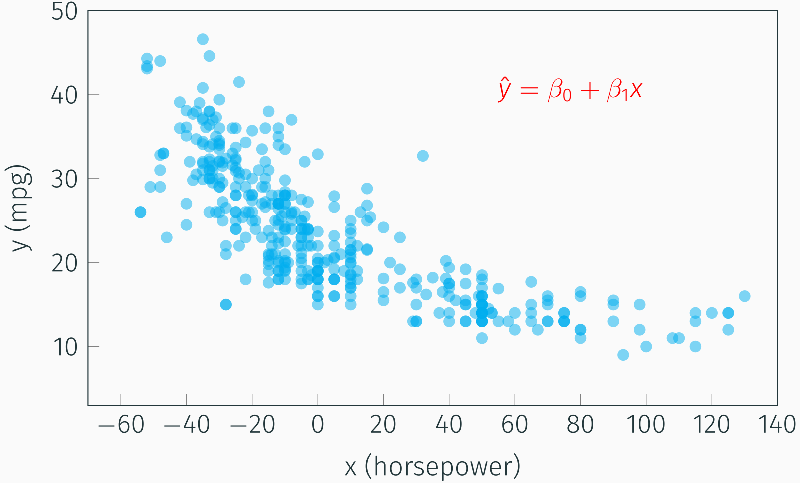

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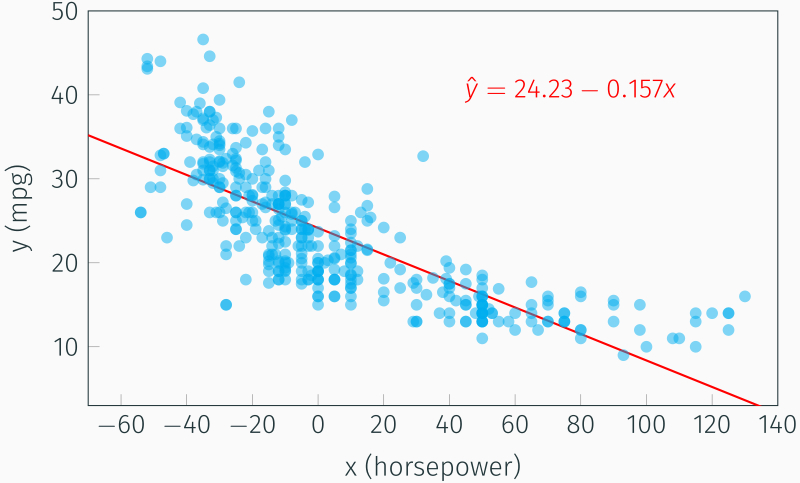

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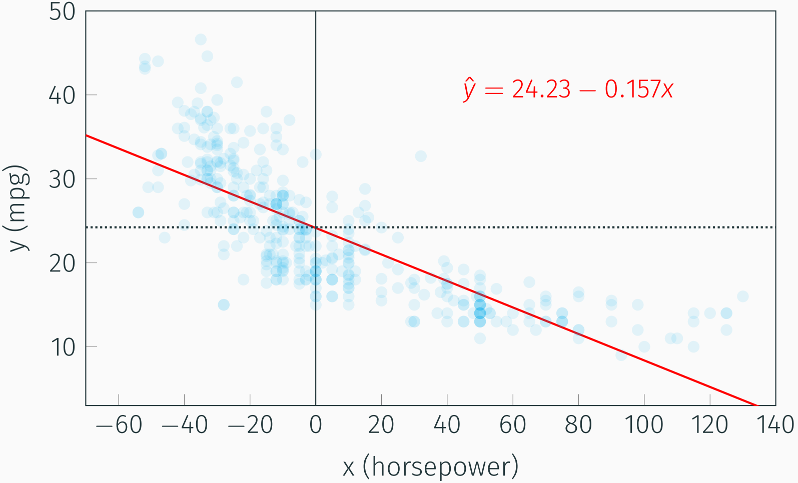

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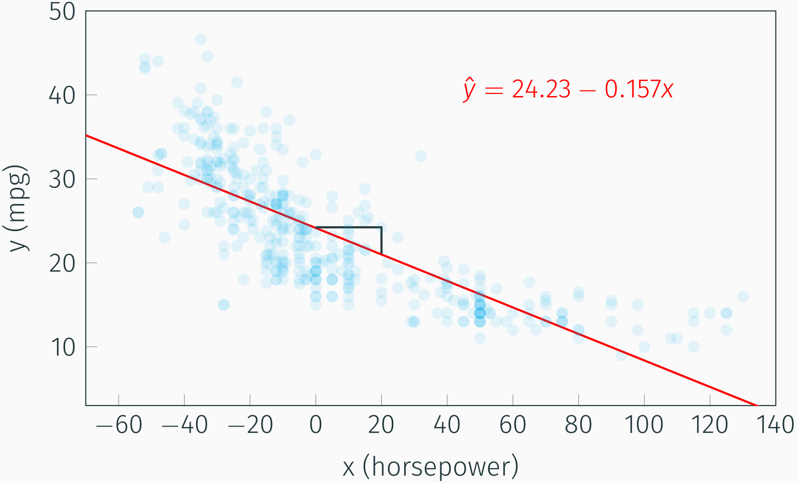

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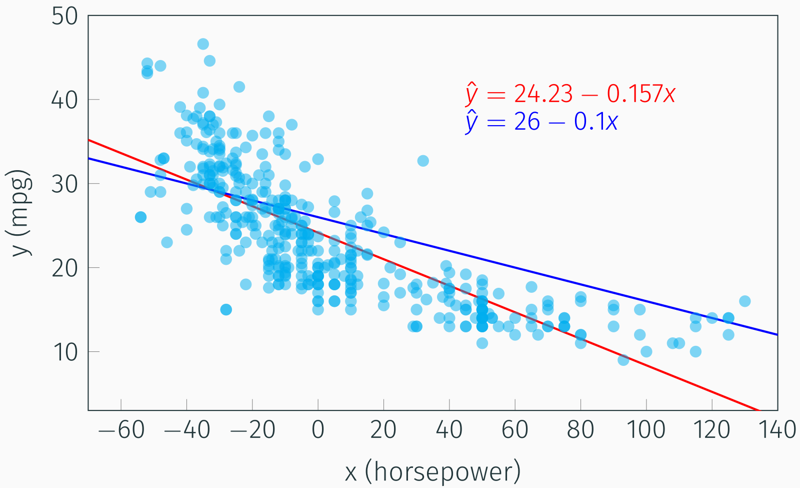

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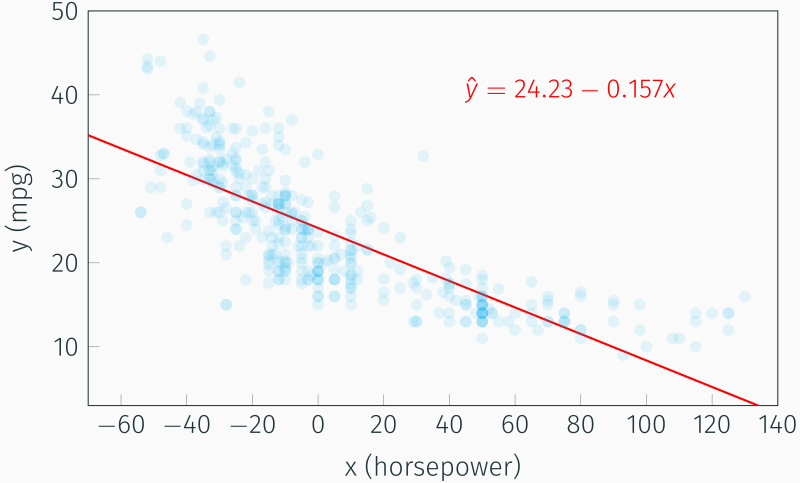

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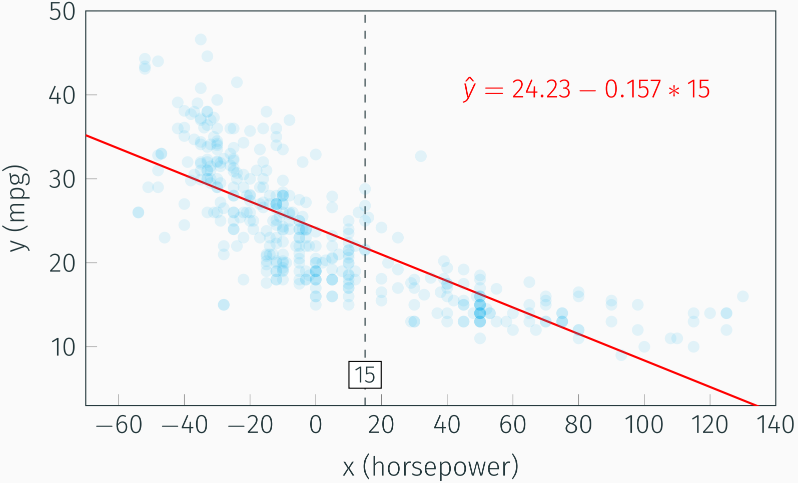

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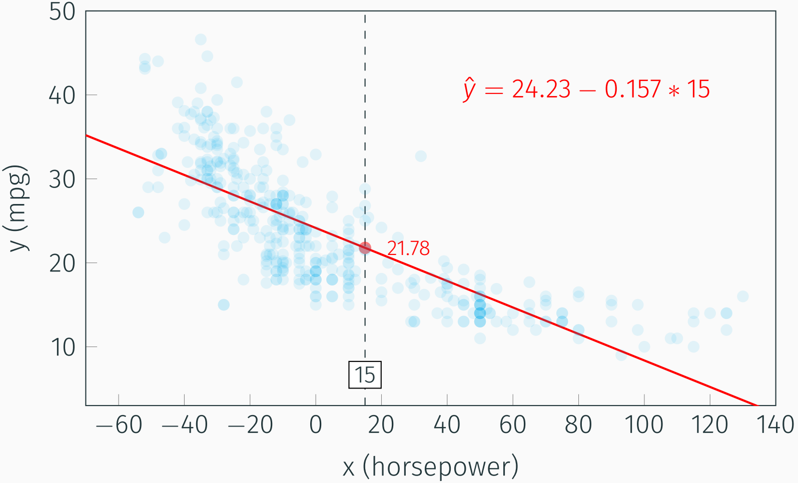

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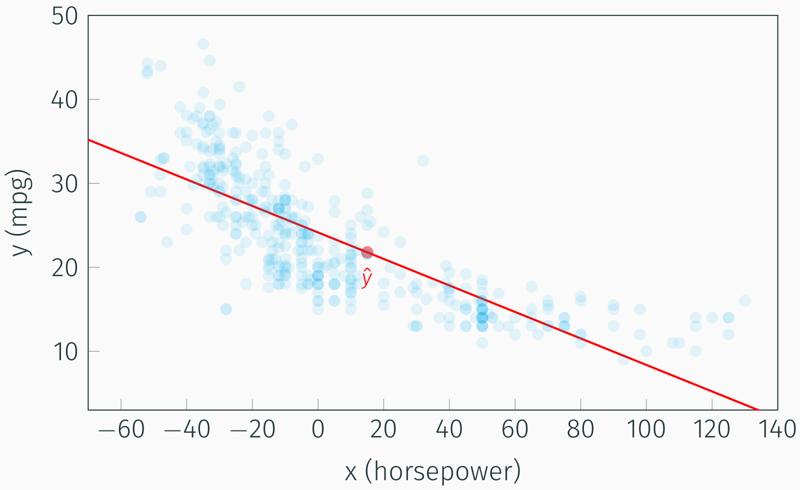

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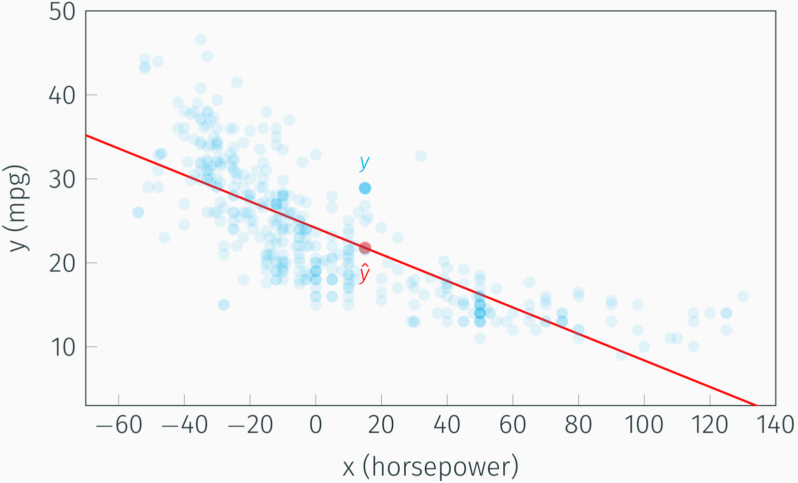

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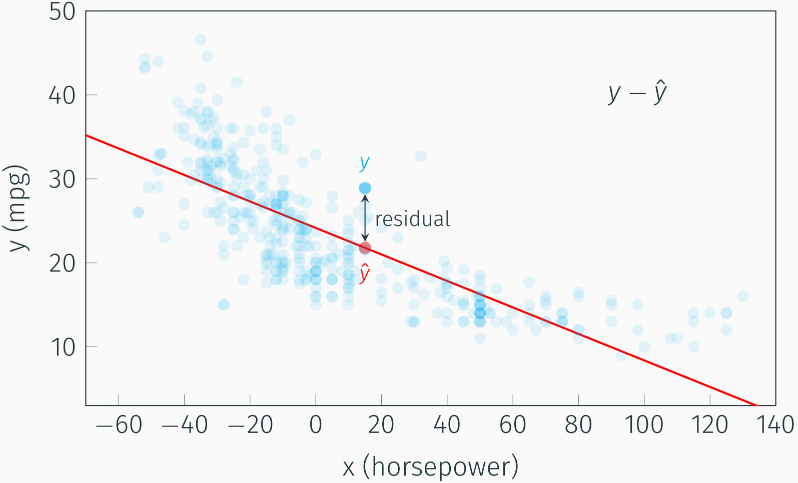

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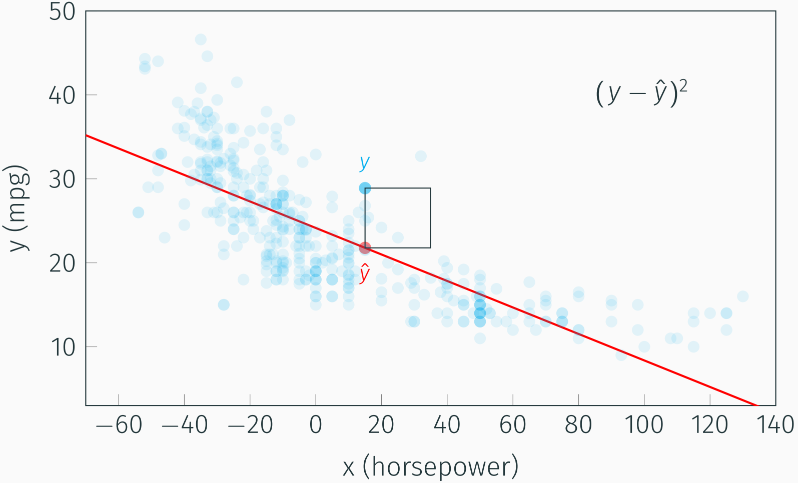

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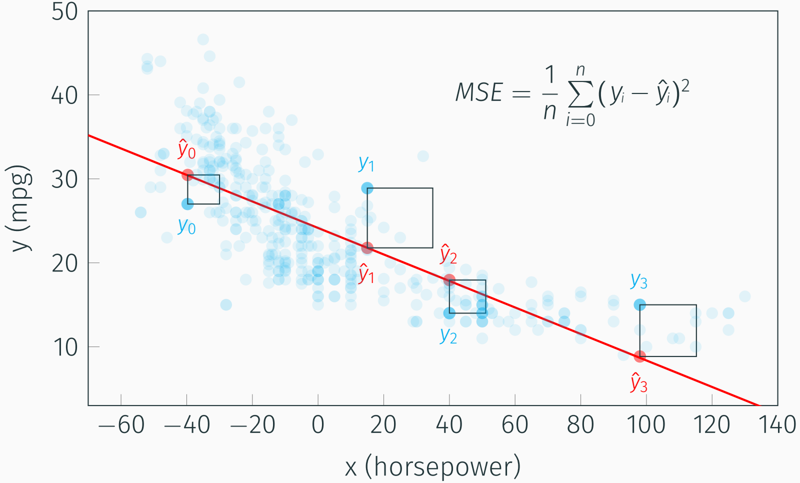

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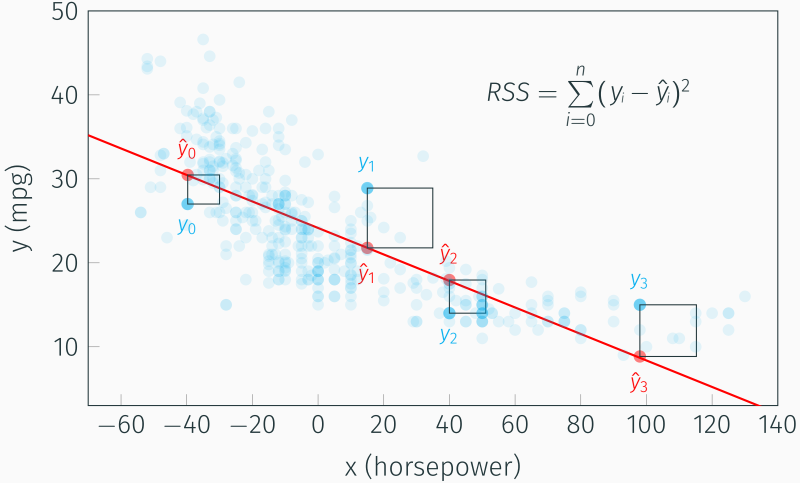

Linear regression (via ordinary least squares)

Linear regression: Models the relationship between input x and output y by finding the linear model $\hat{y} = \beta_0 + \beta_1 x$ that minimizes the residual sum of squares (RSS).

- β_0 refers to the intercept (or offset) of the model
- β_1 refers to the slope of the model

Fitting a linear regression model

$$\hat{y} = \beta_0 + \beta_1 x$$

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

Fitting a linear regression model

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \beta_0 + \beta_1 x_i)^2$$

Fitting a linear regression model

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Multivariate linear regression

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Multivariate linear regression

Linear regression: The true workhorse of machine learning

- Models the relationship between (either singular or mulitple) inputs X and (a continuous) output y as a linear function
  - Inputs can be both continuous and categorical
- A strict parametric form limits the expressivity of the model
  - More advanced terms can be explicitly added
  - The strictness allows for extended functionality, such as computing confidence intervals
  - **Makes the model human interpretable**