End-to-End Machine Learning Project

Certificate Course on Artificial Intelligence & Deep Learning

End-to-End Machine Learning Project

Objective

- In this session
  - We'll walk you through with the complete cycle of a Machine Learning project
- It's okay if you do not understand few code snippets
  - We'll cover them in details as we go forward in the course

Objective

Let's Start

Prepare the Environment

- `Open Jupyter in CloudxLab's "My Lab"`
- Open New Terminal
- Clone the repository if not yet cloned
  - `git clone https://github.com/cloudxlab/advanced-certification-in-data-science-ai.git`
- Else, update the repository
  - `cd advanced-certification-in-data-science-ai && git pull origin master`
- Notebook for this project is located at
  - `end_to_end_machine_learning_project.ipynb`
- `Goto Files`

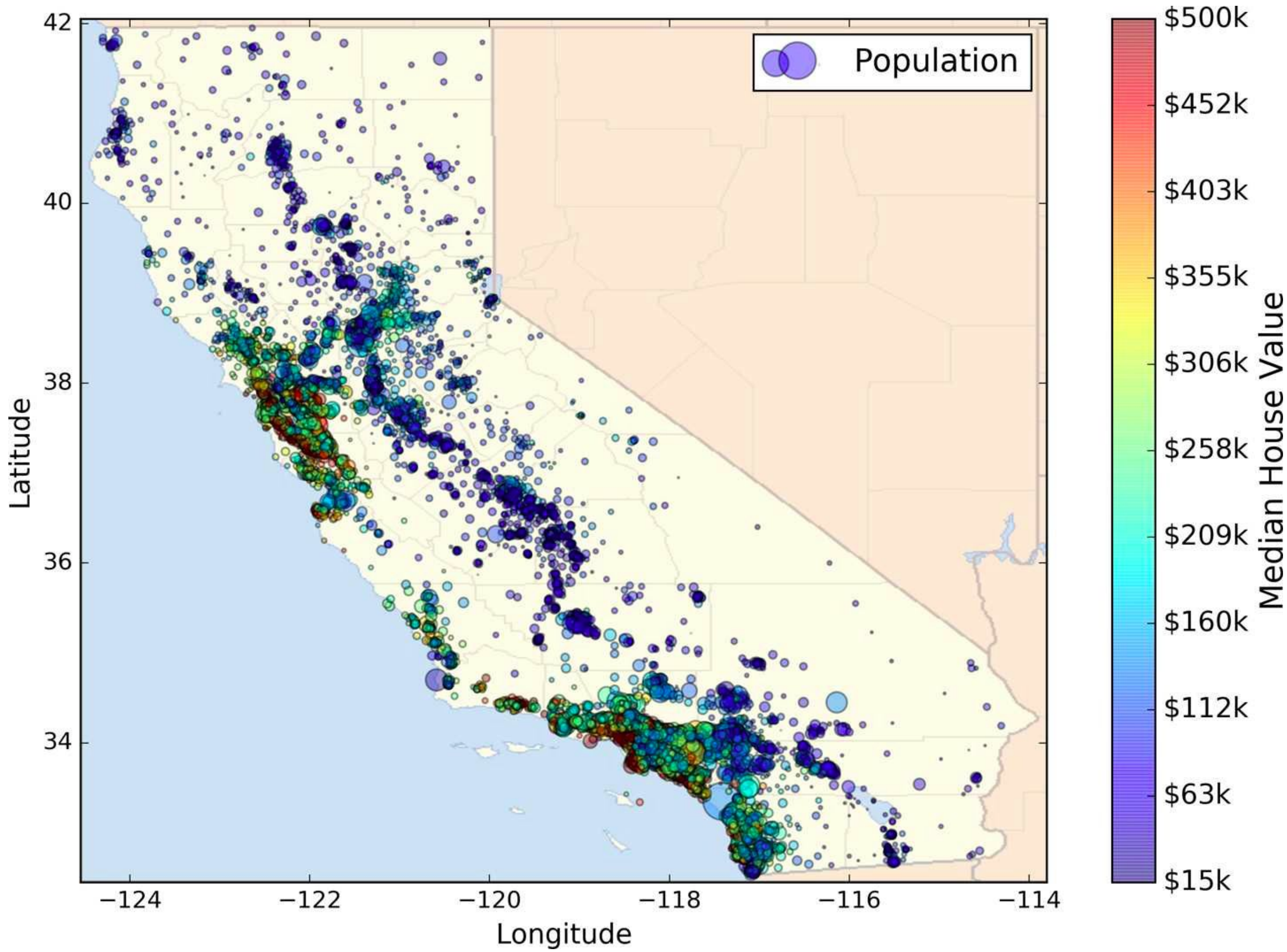
Checklist for Machine Learning Projects

1. Frame the problem and look at the big picture
2. Get the data
3. Explore the data to gain insights
4. Prepare the data for Machine Learning algorithms
5. Explore many different models and short-list the best ones
6. Fine-tune model
7. Present the solution
8. Launch, monitor, and maintain the system

End-to-End Machine Learning Project

Build a model of housing prices in California using the California census data

End-to-End Machine Learning Project



Dataset is based on data from the 1990 California census
Circle Size: Population, Price: Blue to Red

Let's Have a Look at Data

```
>>> import pandas as pd
>>> import os

>>> HOUSING_PATH = 'datasets/housing/'

>>> def load_housing_data(housing_path=HOUSING_PATH):
       csv_path = os.path.join(housing_path,
     "housing.csv")
       return pd.read_csv(csv_path)

>>> housing = load_housing_data()
>>> housing.head()
```

Run this in notebook

Checklist for Machine Learning Projects

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Look at the Big Picture

- Dataset has following attributes for each block group in California
  - Population
  - Median income
  - Median housing price
  - And more….

Look at the Big Picture

- Block groups are the smallest geographical unit for which the US Census Bureau publishes sample data
- A block group typically has a population of 600 to 3,000 people
- Let's call them **districts**

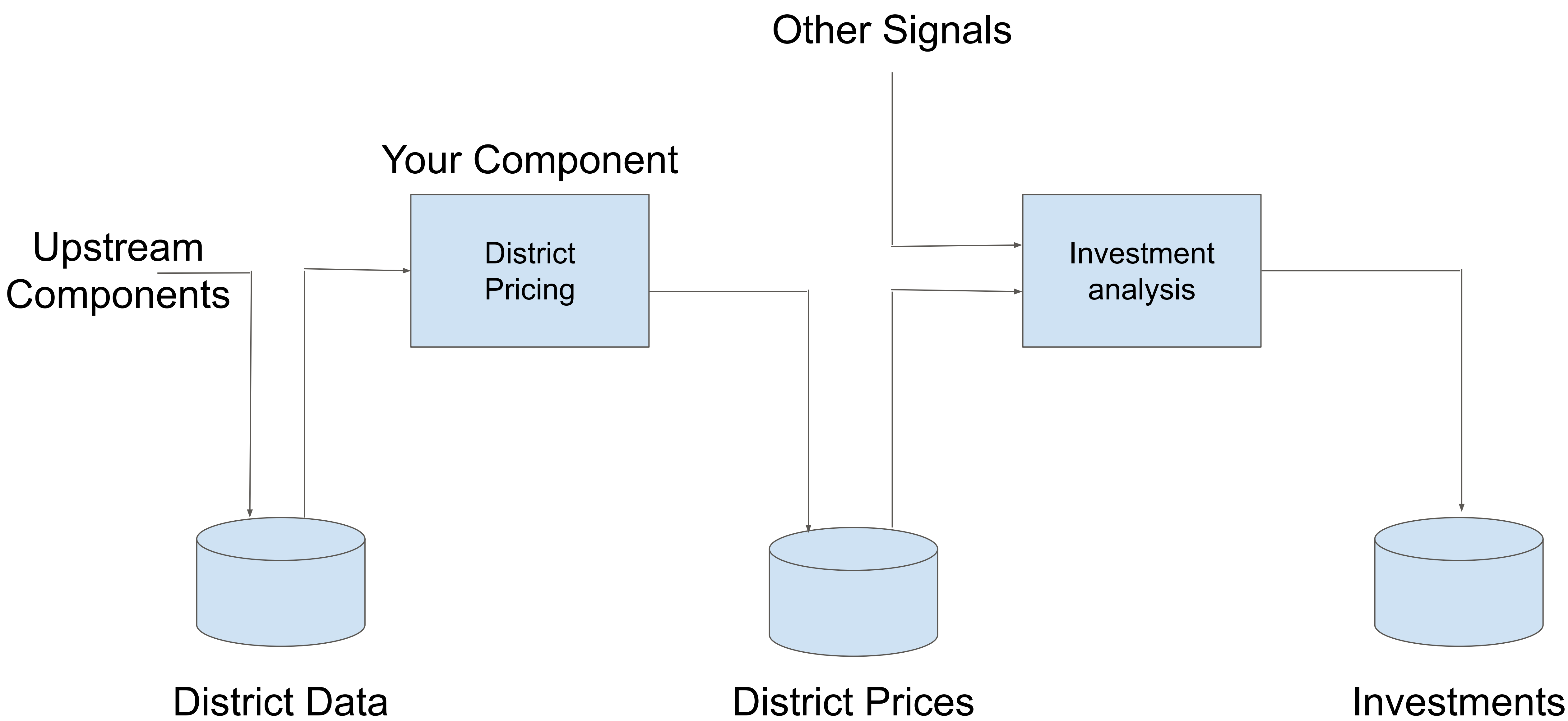
Look at the Big Picture

Our model should learn from this data and be able to predict the median housing price in any district

Frame the Problem - Questions?

- What exactly is the business objective?
- How does the company expect to use and benefit from this model?
- Above questions helps in determining
  - How to frame the problem?
  - Which algorithm to select?
  - Performance measure to evaluate the model
  - Effort required to tweaking it

Frame the Problem - Answers



Frame the Problem - Answers

- Model's output (a prediction of a district's median housing price) will be fed
    - To another Machine Learning system
- The system will determine
    - Whether it is worth investing in a given area or not
    - Getting this right it critical as It directly affects the revenue

Frame the Problem - Current solution?

- What the current solution looks like (if any)
- It often gives a reference performance, as well as insights on how to solve the problem

Frame the Problem - Answer

- District housing prices are currently estimated manually by experts
  - Team gathers up-to-date information about a district
  - Experts use complex rules to come up with an estimate
  - This is costly and time-consuming
  - Estimates are not great
  - Typical error rate is about 15%

Frame the Problem - Type of Learning?

- Is this problem
  1. Supervised, Unsupervised or Reinforcement Learning?
  2. Classification task, Regression task, or something else?
  3. Should we use batch learning or online learning techniques?

Frame the Problem - Answers

1. Supervised learning task
    - Data has labeled training examples
    - Each row in the data has the expected output(the district's median housing price)
2. Regression task
    - We have to predict a continuous value
    - System will use multiple features to make a prediction

Frame the Problem - Answers

3. Should we use batch learning or online learning techniques?

- There is no continuous flow of data coming in the system
- Data is small enough to fit in memory
- Plain batch learning should do just fine

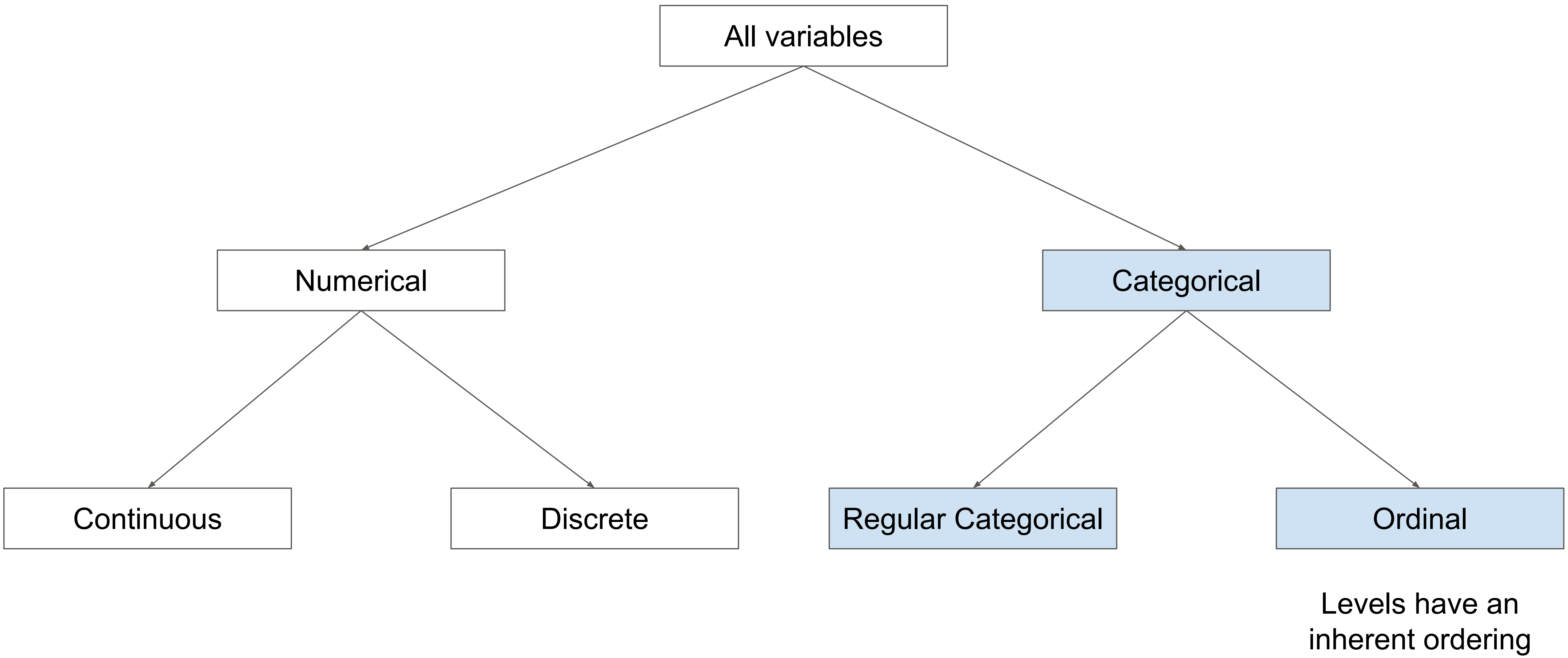
Frame the Problem - Answers

Select a Performance Measure - Root Mean Square Error

- Let's say we want to predict house value based on house area in square feet
- Difference in the predicted price and the actual price of the house gives the performance statistic.

Brief introduction to Statistical Inference

Types of Variables



Types of Variables

Each Column is Variable

Each Row is observation

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY

2. ??

1. ??

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2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
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Categorical

Numerical

Types of Variables

Each Column is Variable

Each Row is observation

country	cr_req	cr_comply	ud_req	ud_comply	...	hemisphere	hdi
Argentina	21	100	134	32	...	southern	very high
Australia	10	40	361	73	...	southern	very high
Belgium	<10	100	90	67	...	northern	very high
Brazil	224	67	703	82	...	southern	high
...	...	...	...	...	...	...	...
United States	92	63	5950	93	...	northern	very high

A. ??

B. ??

C. ??

D. ??

Types of Variables

Each Column is Variable

Each Row is observation

country	cr_req	cr_comply	ud_req	ud_comply	...	hemisphere	hdi
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...	...	...	...	...	...	...	...
United States	92	63	5950	93	...	northern	very high

Continuous Numerical

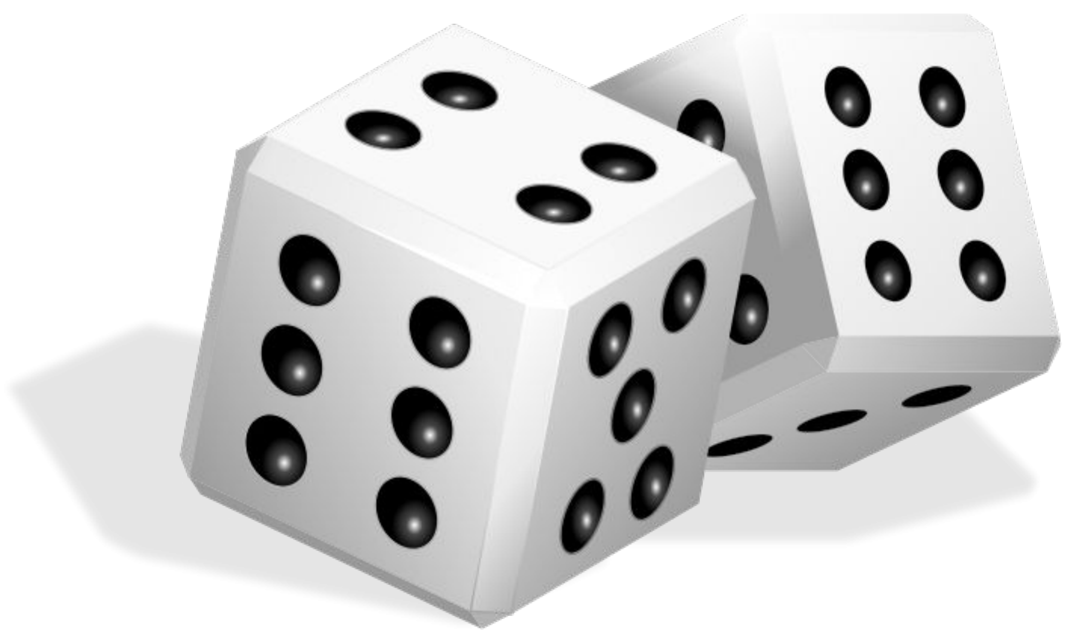
Discrete numerical

Regular Categorical

Ordinal Categorical

Random Process

In a random process we know what outcomes could happen, but we don't know which particular outcome will happen.



Probability

P(A) = Probability of event A

$$\mathbf{0 \leq P(A) \leq 1}$$

Probability

Question -

In a village, there has been a tradition that people keep on having children till they get a boy. What will be the ratio of male to female in that village?

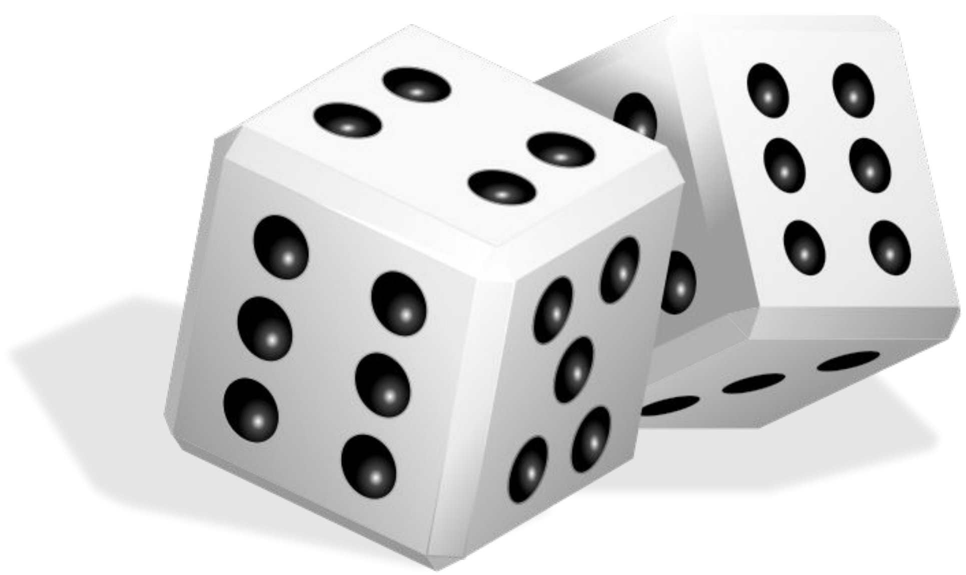
Probability

Answer -

1:1

Probability - example

What is probability that the sum of pair of fair dice when rolled is 4?



Probability - example

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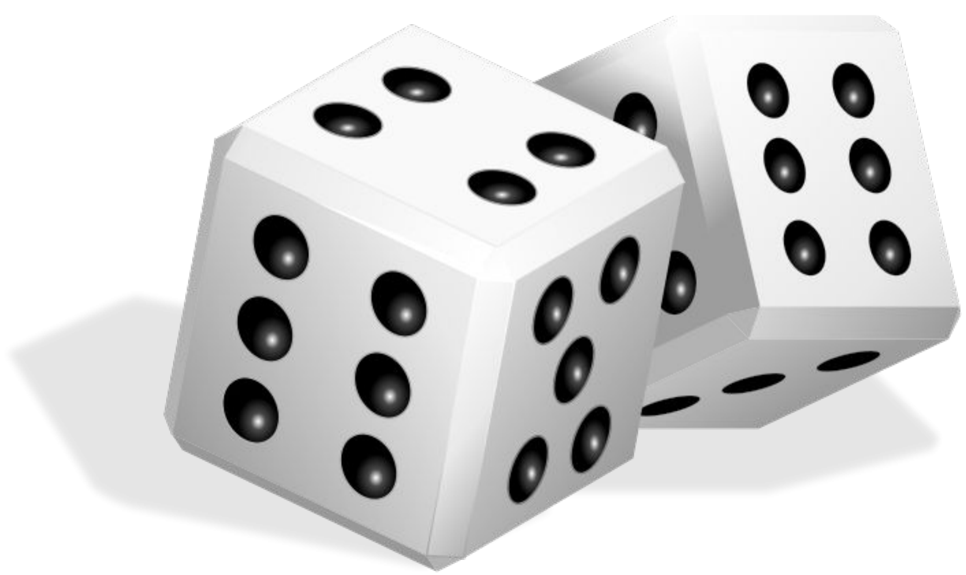


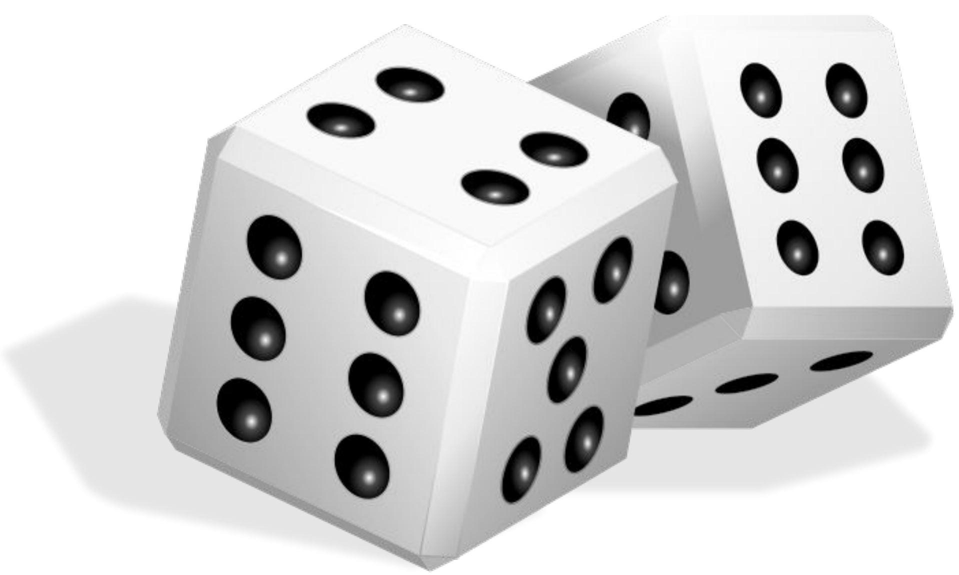
Total Possible ways in which the pair can be rolled = ??

Instances when the sum is 4 = ??

Probability = ??

Probability - example

What is probability that the sum of pair of fair dice when rolled is 4?



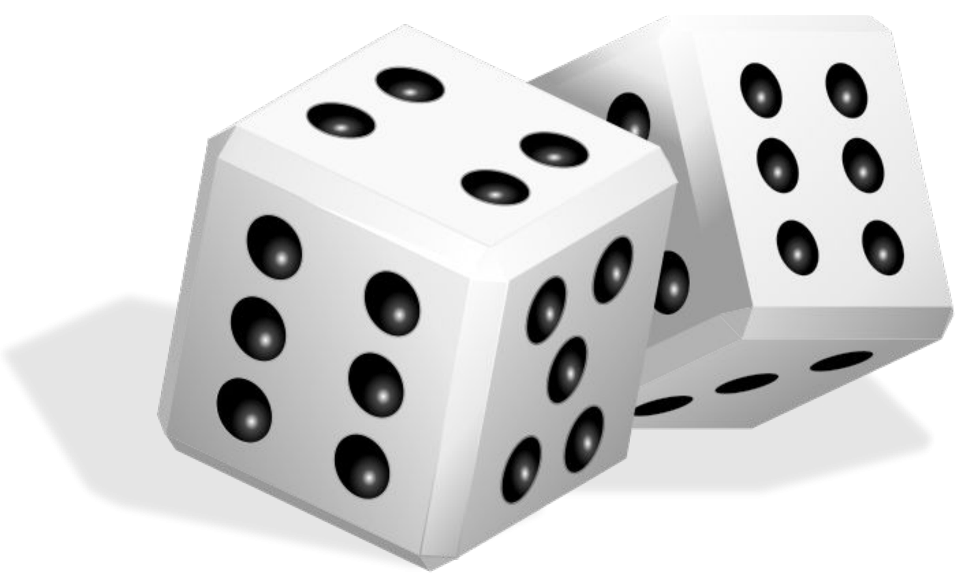
Total Possible ways in which the pair can be rolled = 6 X 6 = 36

Instances when the sum is 4 = ??

Probability = ??

Probability - example

What is probability that the sum of pair of fair dice when rolled is 4?



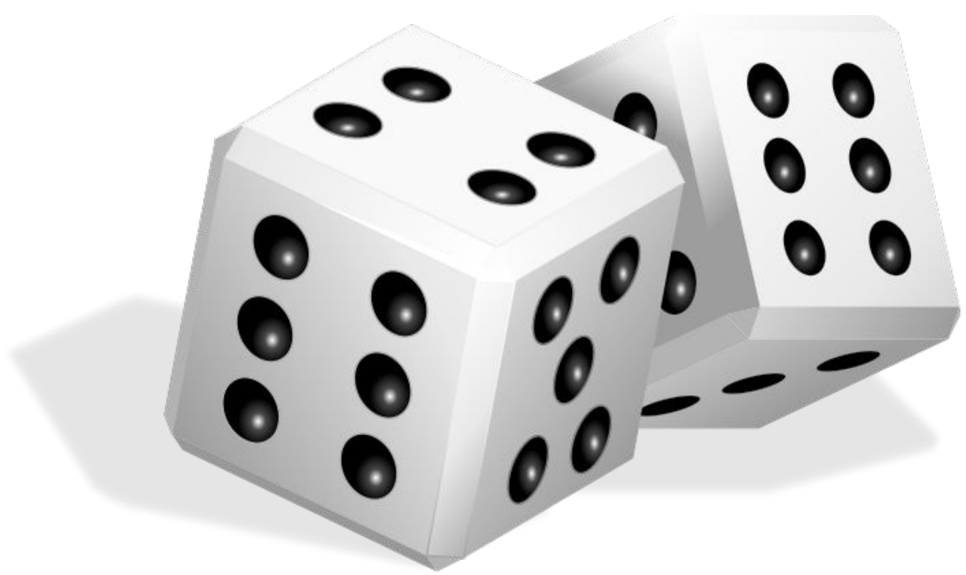
Total Possible ways in which the pair can be rolled = 6 X 6 = 36

Instances when the sum is 4 = (1,3), (3,1), (2,2) = 3

Probability = ??

Probability - example

What is probability that the sum of pair of fair dice when rolled is 4?



Total Possible ways in which the pair can be rolled = 6 X 6 = 36

Instances when the sum is 4 = (1,3), (3,1), (2,2) = 3

Probability = 3/36 = 1/12

Probability - example

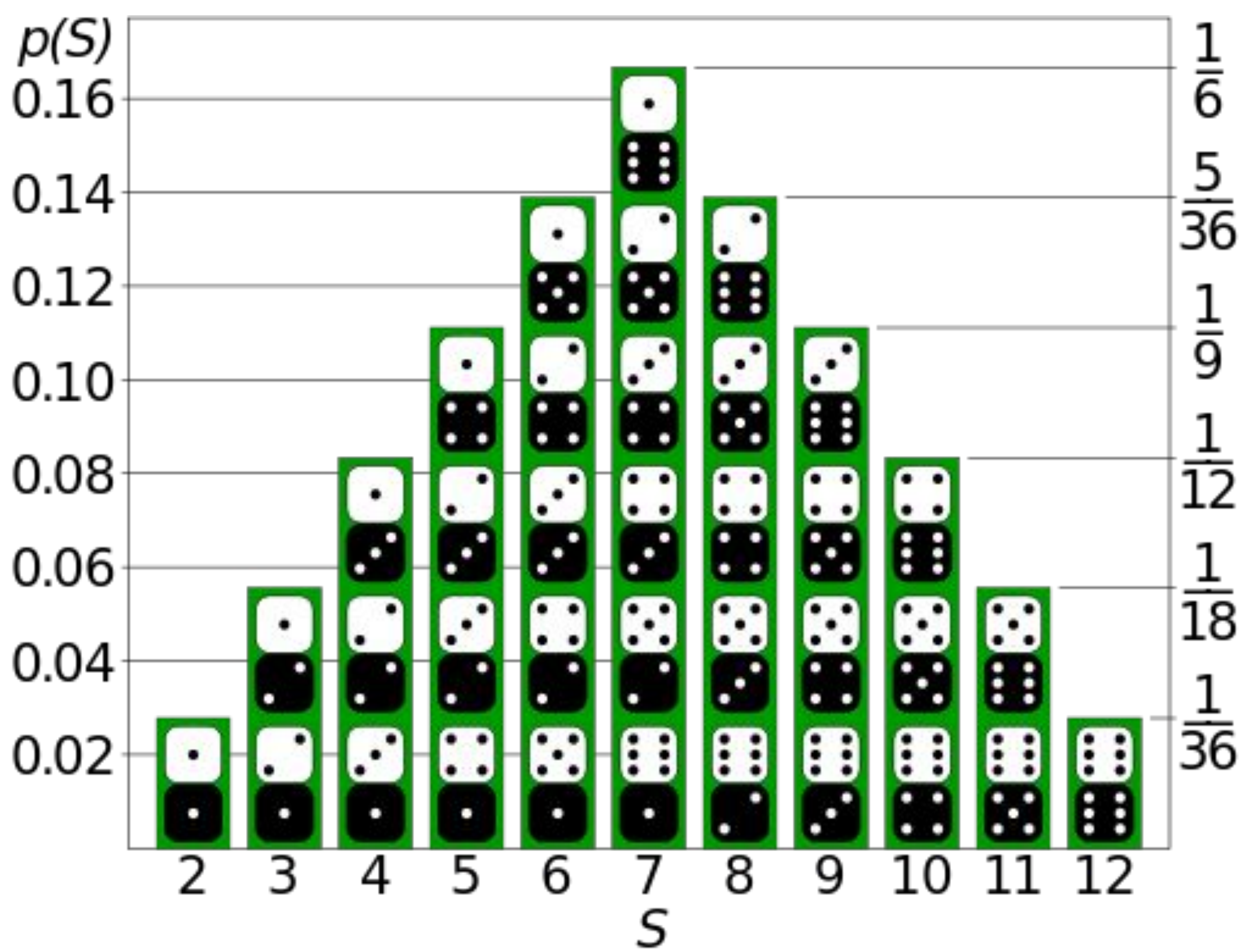
(1,1)	(1,2)	(1,3)	(1,4)	(1,5)	(1,6)
(2,1)	(2,2)	(2,3)	(2,4)	(2,5)	(2,6)
(3,1)	(3,2)	(3,3)	(3,4)	(3,5)	(3,6)
(4,1)	(4,2)	(4,3)	(4,4)	(4,5)	(4,6)
(5,1)	(5,2)	(5,3)	(5,4)	(5,5)	(5,6)
(6,1)	(6,2)	(6,3)	(6,4)	(6,5)	(6,6)

Random Variable

- Random variable is a variable
  - Whose value is unknown or
  - A function that assigns values to each of an experiments (called outcomes)
- Can be of multiple types
- Depending upon the type of the quantity measured i.e.
  - Continuous
  - Discrete
  - Categorical etc

Probability Distribution

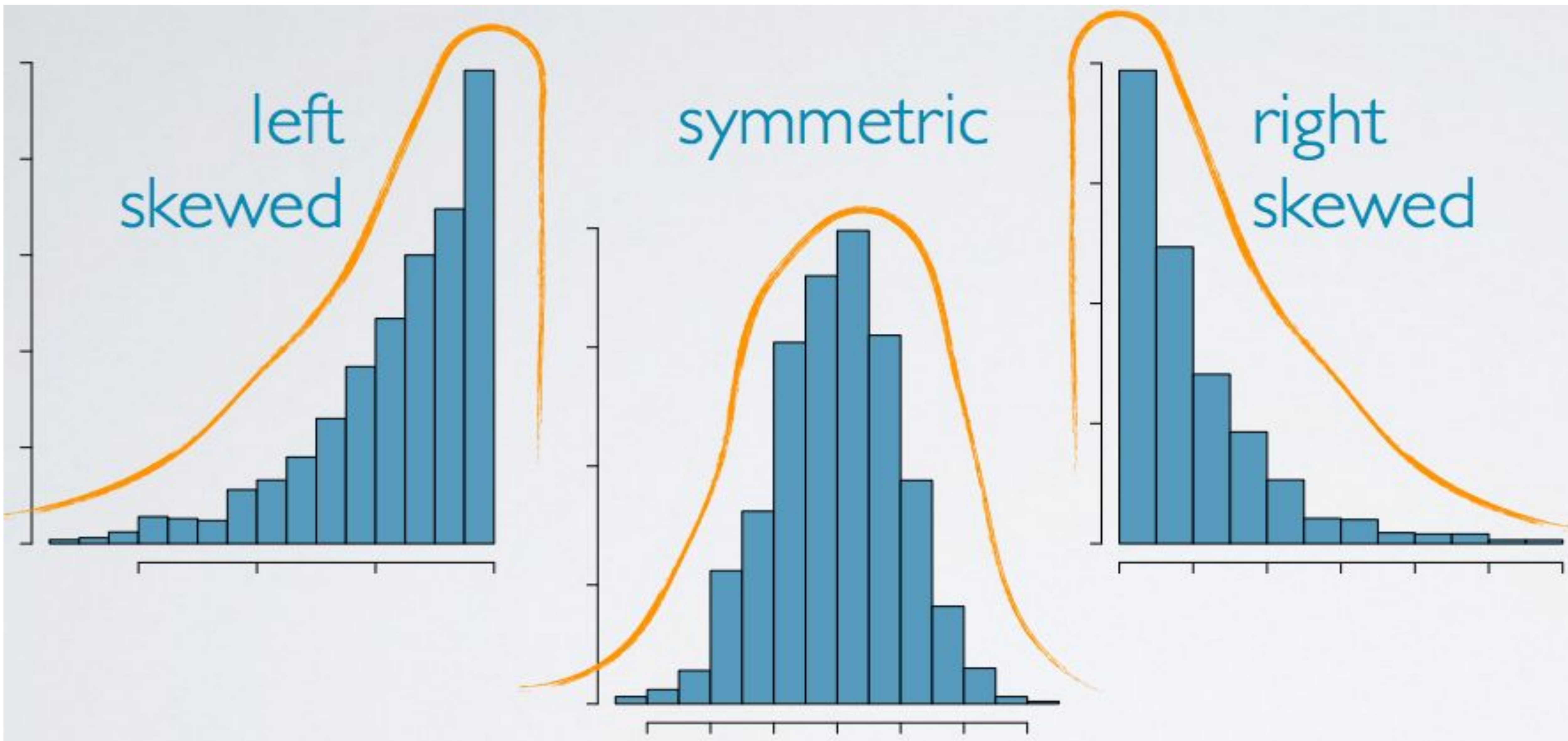
- A probability distribution assigns a
  - Probability to each of the possible outcomes of
  - A random experiment, survey, or procedure of statistical inference



Picture Source:
https://en.wikipedia.org/wiki/Probability_distribution

Normality - Skewness

Distributions are skewed to the side of the long tail



Normality - Modality

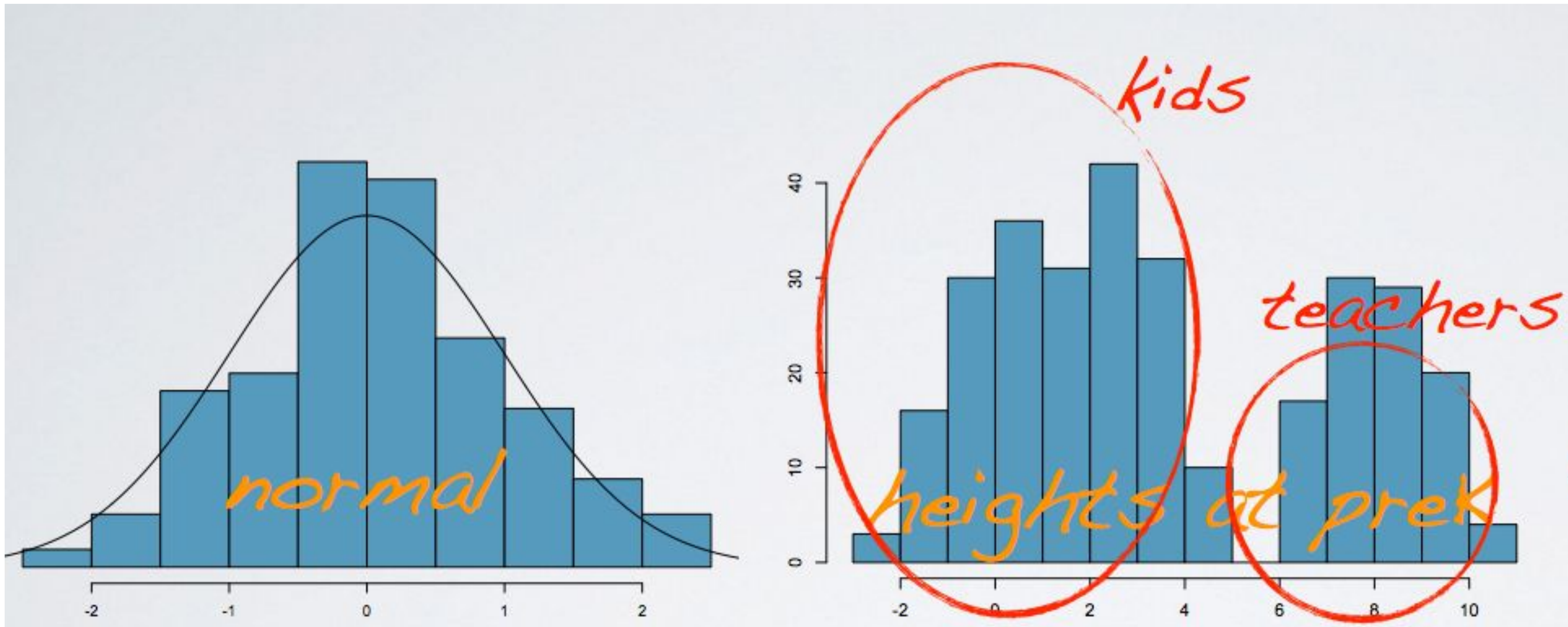
Probability distribution of heights in adults

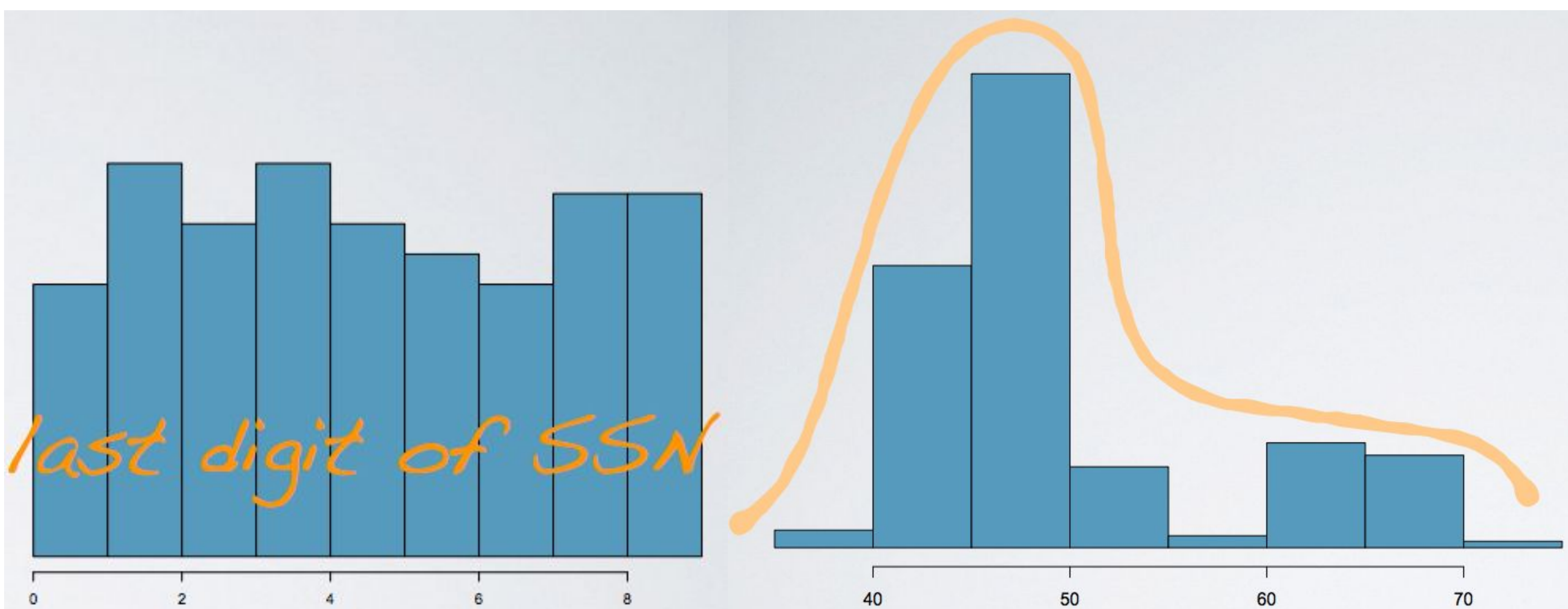
Prob. distribution of heights for students and teachers in a school

Probability distribution for last digit of vehicles number

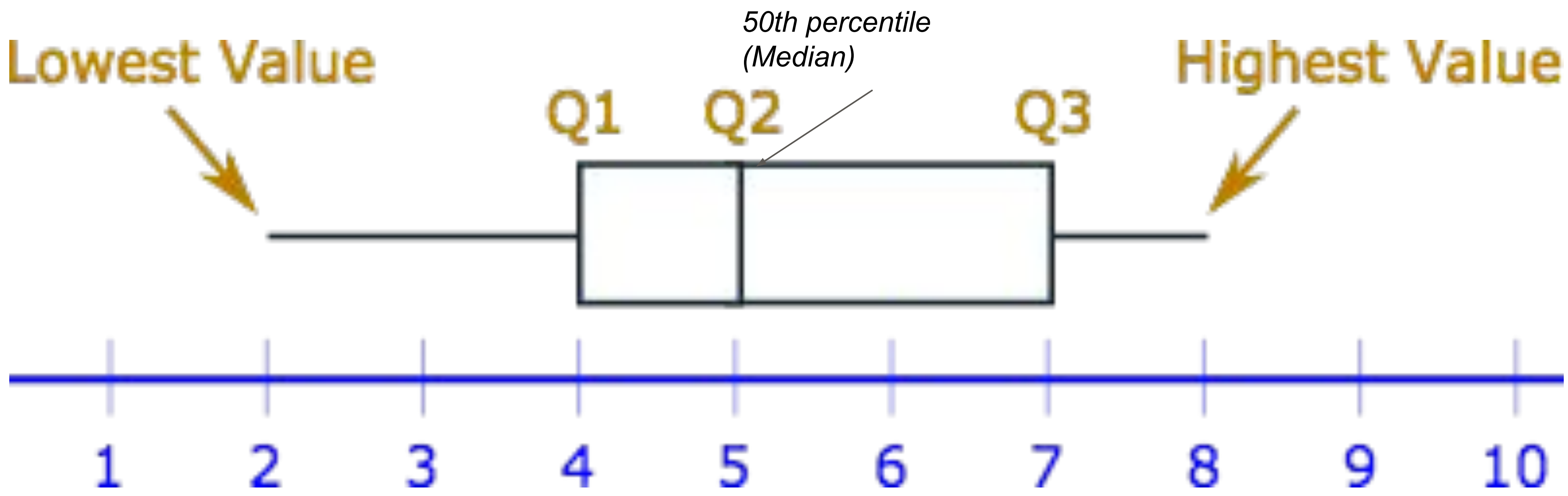
Combinations of all

Normality - Modality



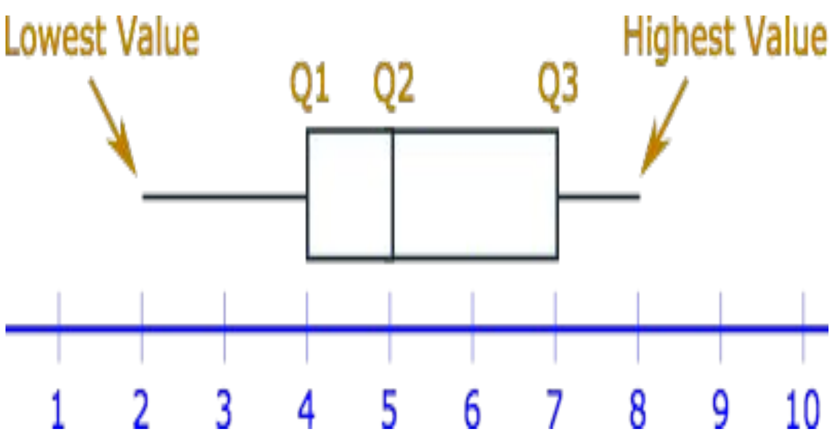


Box Plot



50th percentile
(Median)
Lowest Value
Highest Value
Q1
Q2
Q3
1
2
3
4
5
6
7
8
9
10

Box Plot



median (Q2/50th Percentile): the middle value of the dataset.

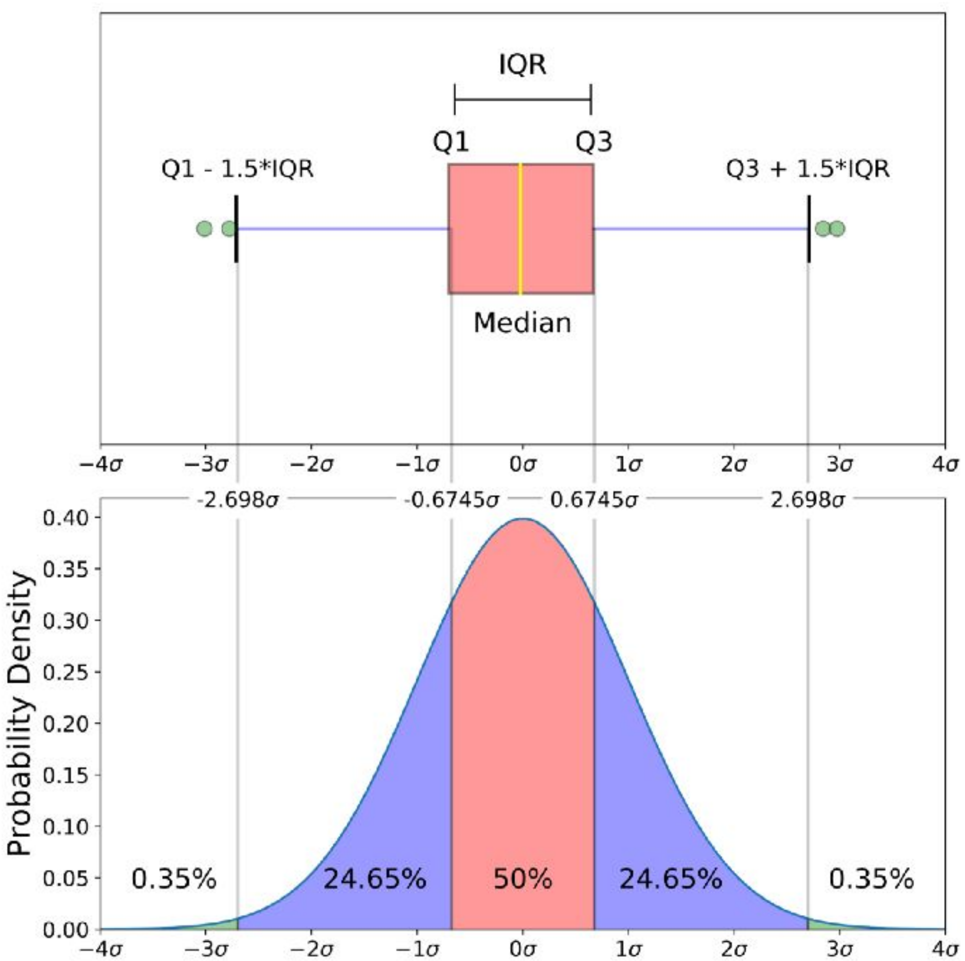
first quartile (Q1/25th Percentile): the middle number between the smallest number (not the “minimum”) and the median of the dataset.

third quartile (Q3/75th Percentile): the middle value between the median and the highest value (not the “maximum”) of the dataset.

interquartile range (IQR): 25th to the 75th percentile.

“maximum”: Q3 + 1.5*IQR

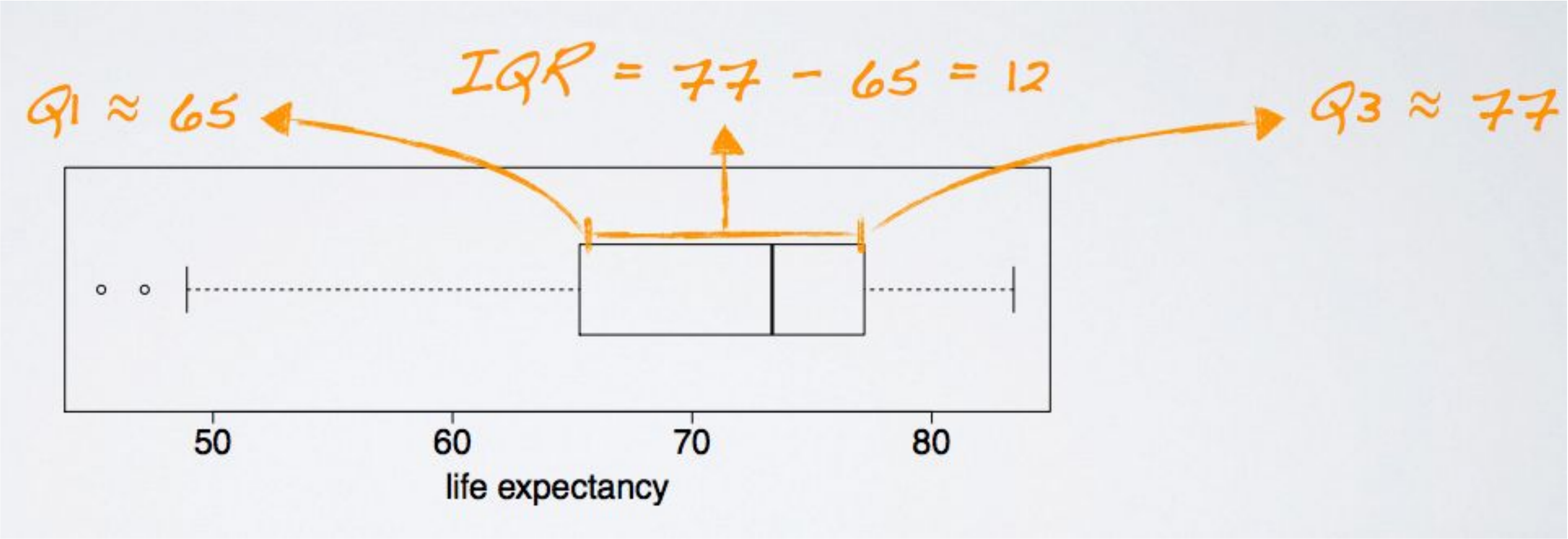
“minimum”: Q1 -1.5*IQR



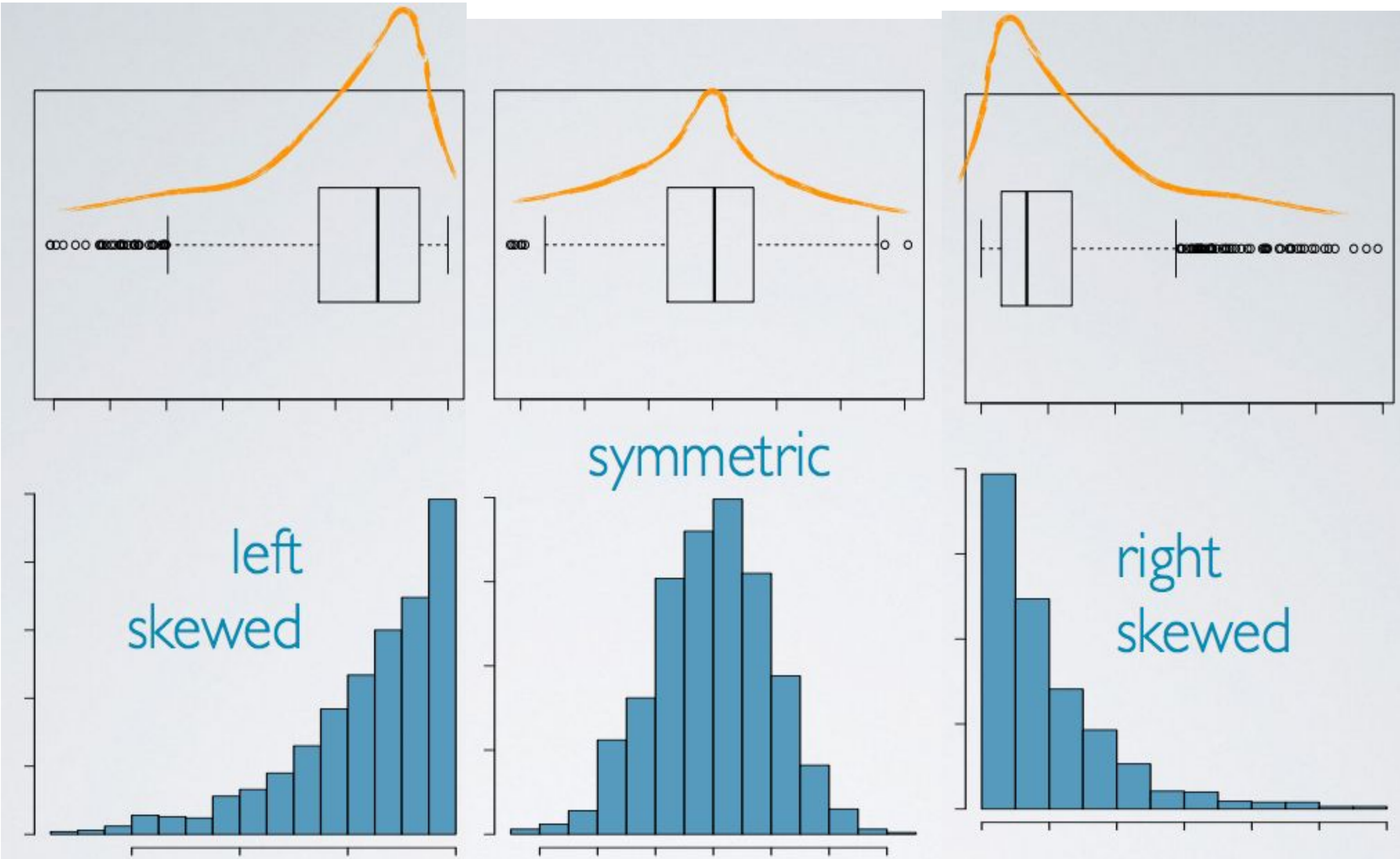
Comparison of a boxplot of a nearly normal distribution and a probability density function (pdf) for a normal distribution

Box Plot

Range of the middle 50% of the data, distance between the first quartile (25th percentile) and third quartile (75th percentile)



Normality - Box Plots



CLOUD x LAB

Measures of Central Tendencies

How do you define center of certain data?

Measures of Central Tendencies

mean

arithmetic average

$\bar{x}$ sample mean

μ population mean

median

midpoint of the distribution (50th percentile)

mode

most frequent observation

sample statistic → **point estimate** → population parameter

Measures of Central Tendencies

Which one would you choose?
Mean, Median or mode?

Measures of Central Tendencies

75, 69, 88, 93, 95, 54, 87, 88, 27

mean: $\frac{75+69+88+93+95+54+87+88+27}{9} = 75.11$

mode: 88

median: 27, 54, 69, 75, 87, 88, 88, 93, 95

Robust Statistics

Measures on which extreme observations have little effect

example

data	mean	median
1, 2, 3, 4, 5, 6	3.5	3.5
1, 2, 3, 4, 5, 1000	169	3.5

	robust	non-robust
center	median	mean
spread	IQR	SD, range

skewed, with extreme observations

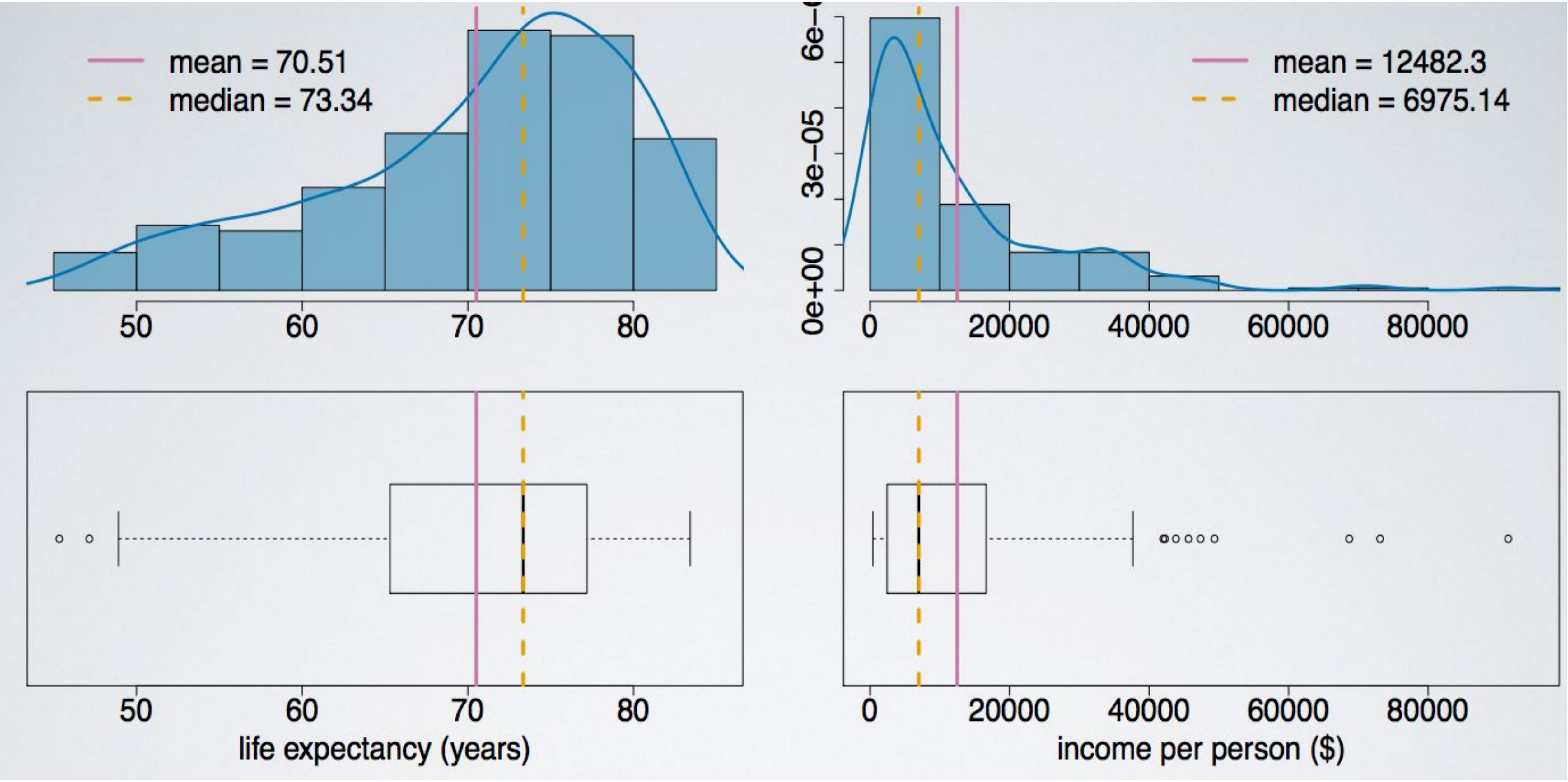
symmetric

Measures of Central Tendencies

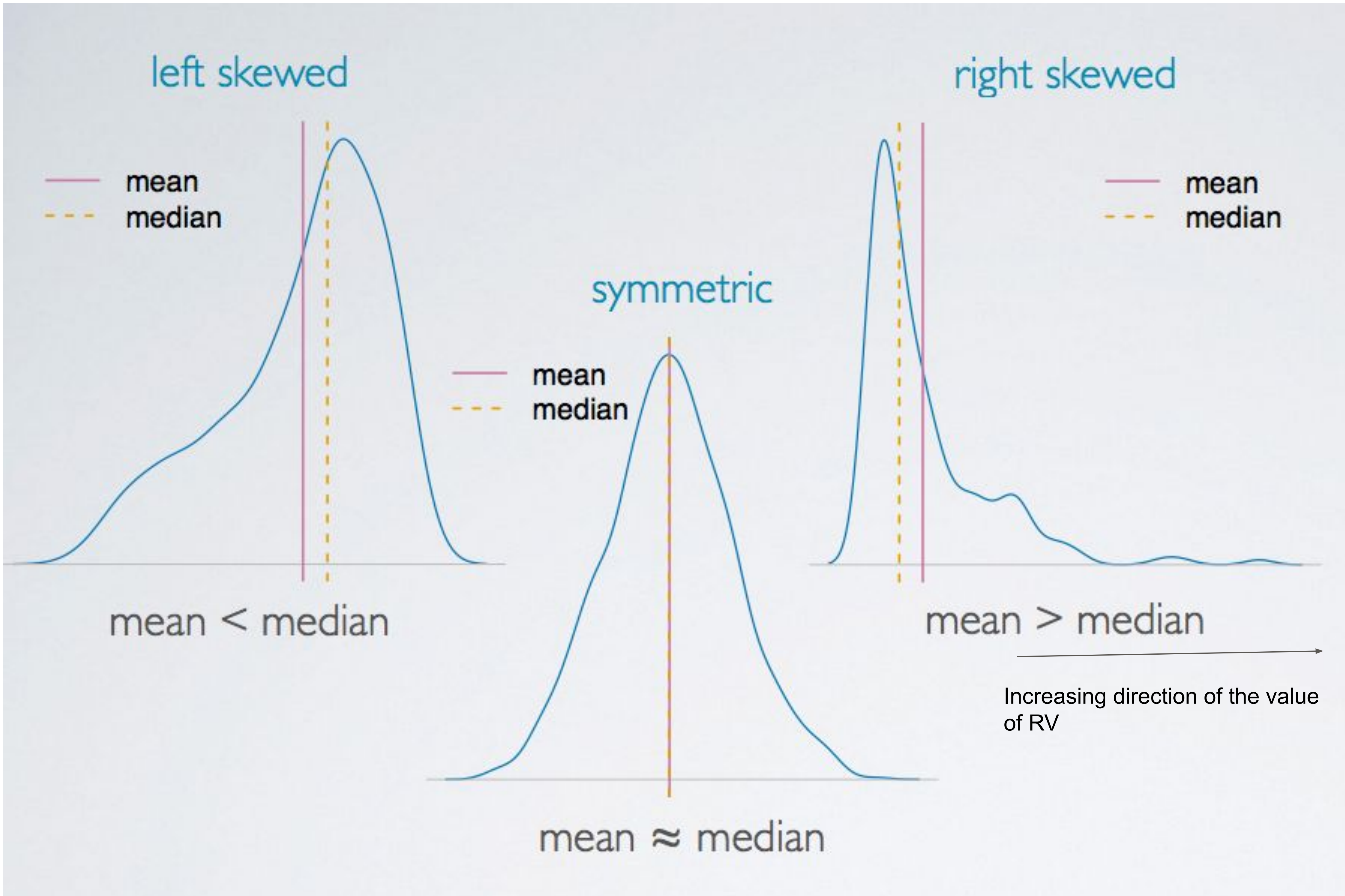
data	income per person ($, 2012)	life expectancy (years, 2012)
Afghanistan	1359.7	60.254
Albania	6969.3	77.185
Algeria	6419.1	70.874
...	...	...
Zimbabwe	545.3	58.142

Source: gapminder.com

Measures of Central Tendencies



Measures of Central Tendencies



Measures of Spread

variance

roughly the average squared deviation from the mean

$$s^2 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n-1}$$

example Given that the average life expectancy is 70.5, and there are 201 countries in the dataset:

	country	life exp
1	Afghanistan	60.3
2	Albania	77.2
3	Algeria	70.9
	...	...
201	Zimbabwe	58.1

$$s^2 = \frac{(60.3 - 70.5)^2 + (77.2 - 70.5)^2 + \dots + (58.1 - 70.5)^2}{201 - 1}$$

$= 83.06$ years^2

Measures of Spread

Why do we square the differences?

$$s^2 = \frac{\sum_{i=1}^{n} \boxed{(x_i - \bar{x})^2}}{n-1}$$

Measures of Spread

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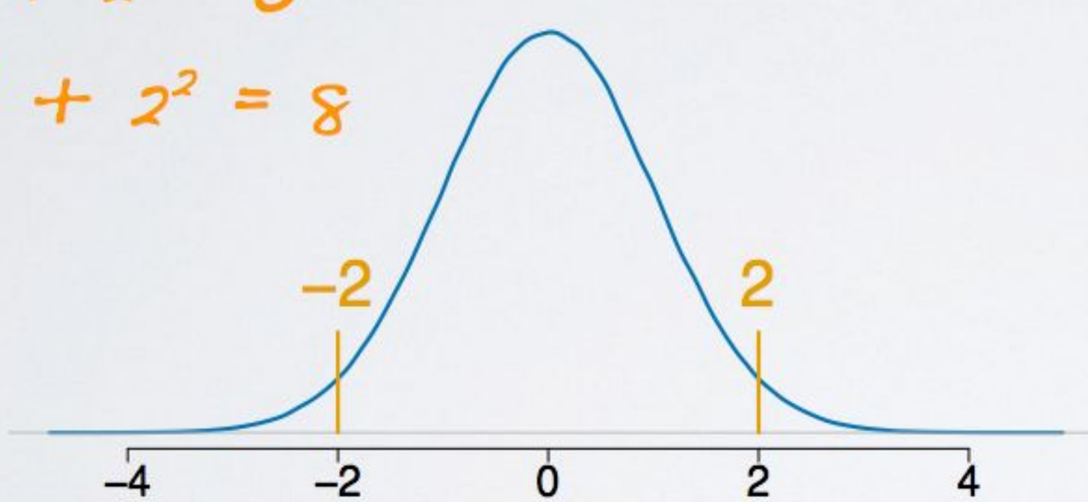
$$s^2 = \frac{\sum_{i=1}^{n} \boxed{(x_i - \bar{x})^2}}{n-1}$$

- get rid of negatives so that negatives and positives don't cancel each other when added together

$(-2) + 2 = 0$

$(-2)^2 + 2^2 = 8$



Measures of Spread

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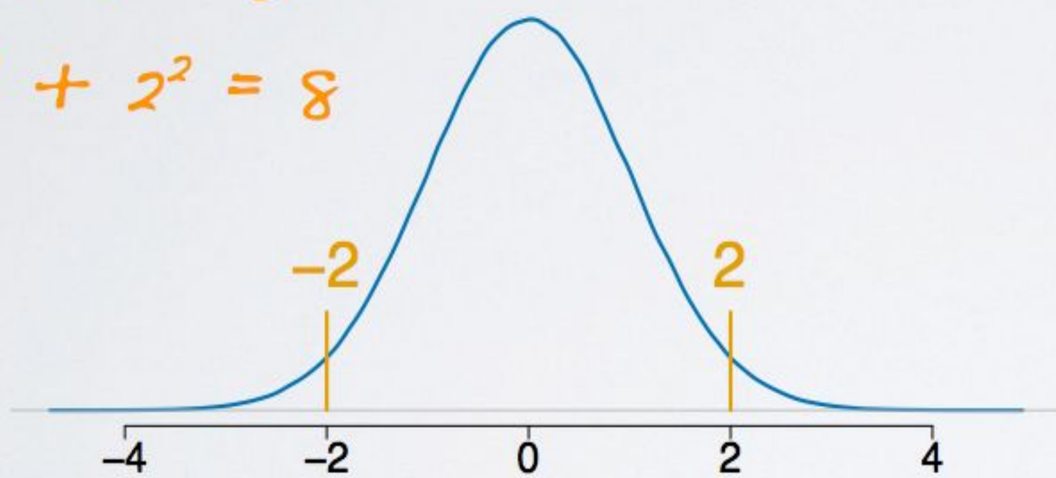
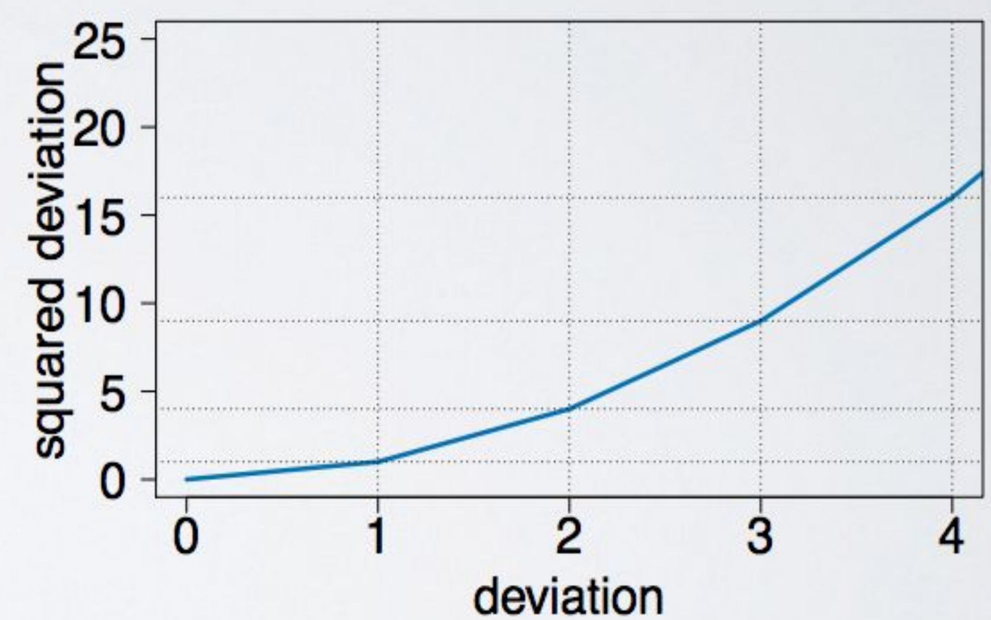
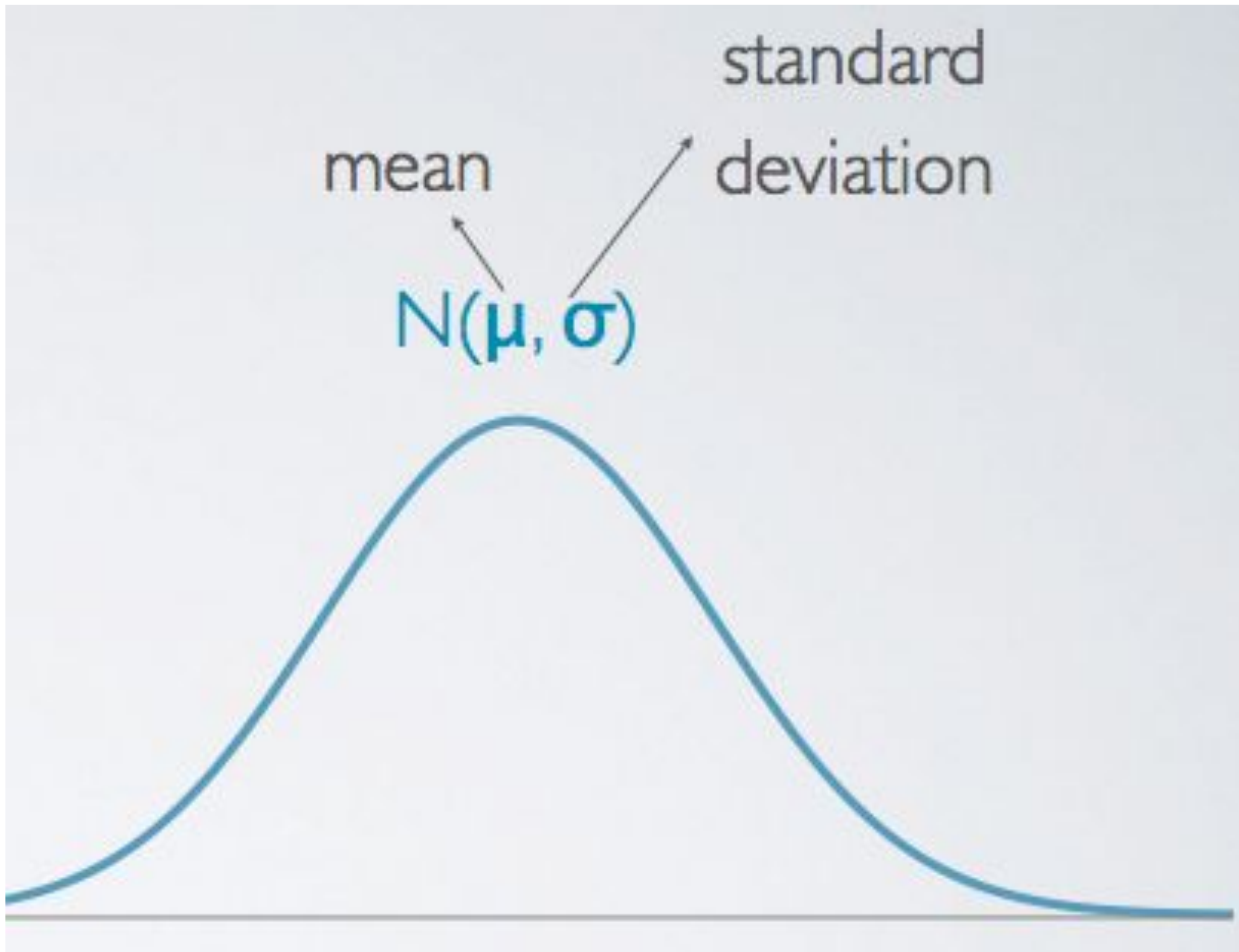


- increase larger deviations more than smaller ones so that they are weighed more heavily



Normal Distribution



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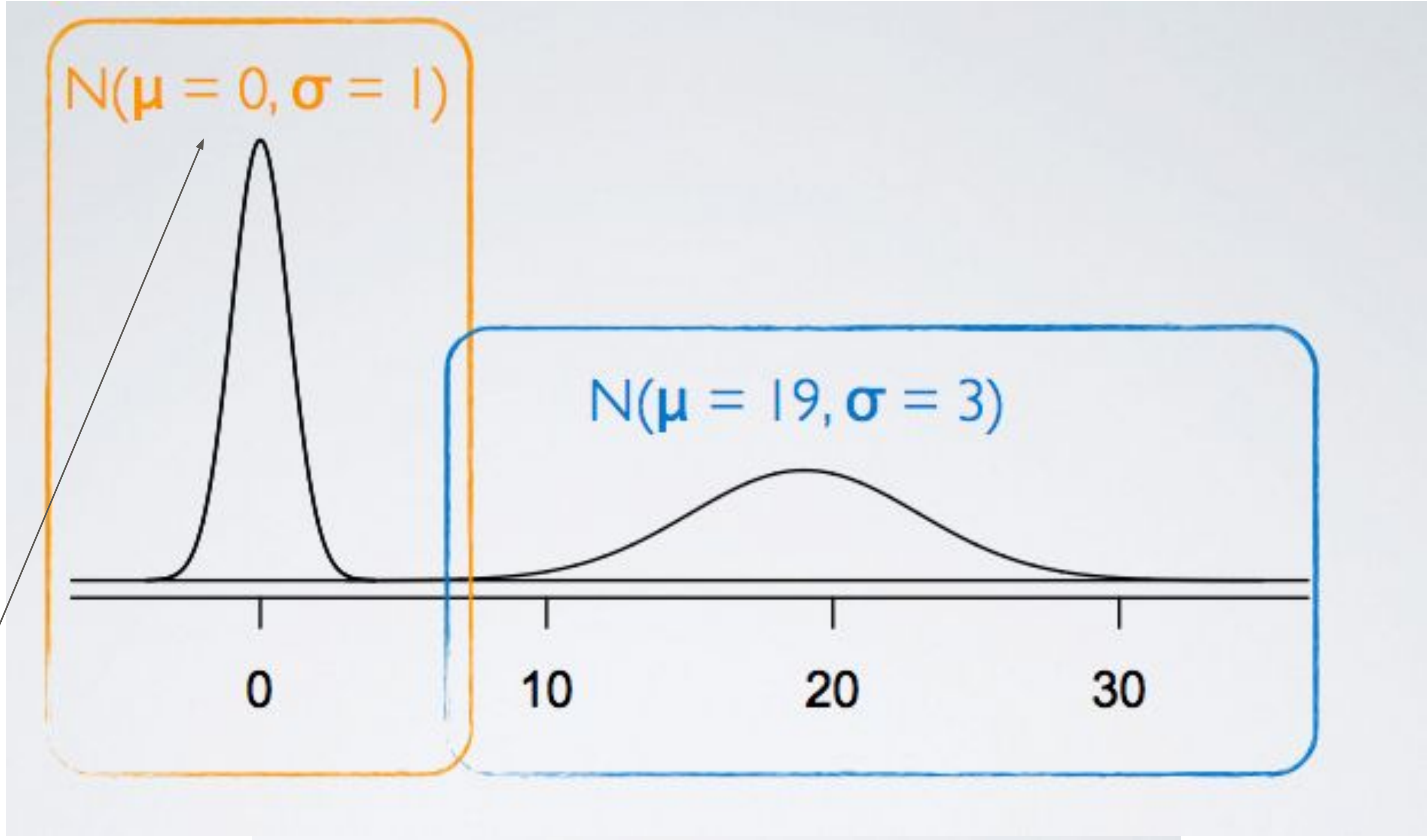


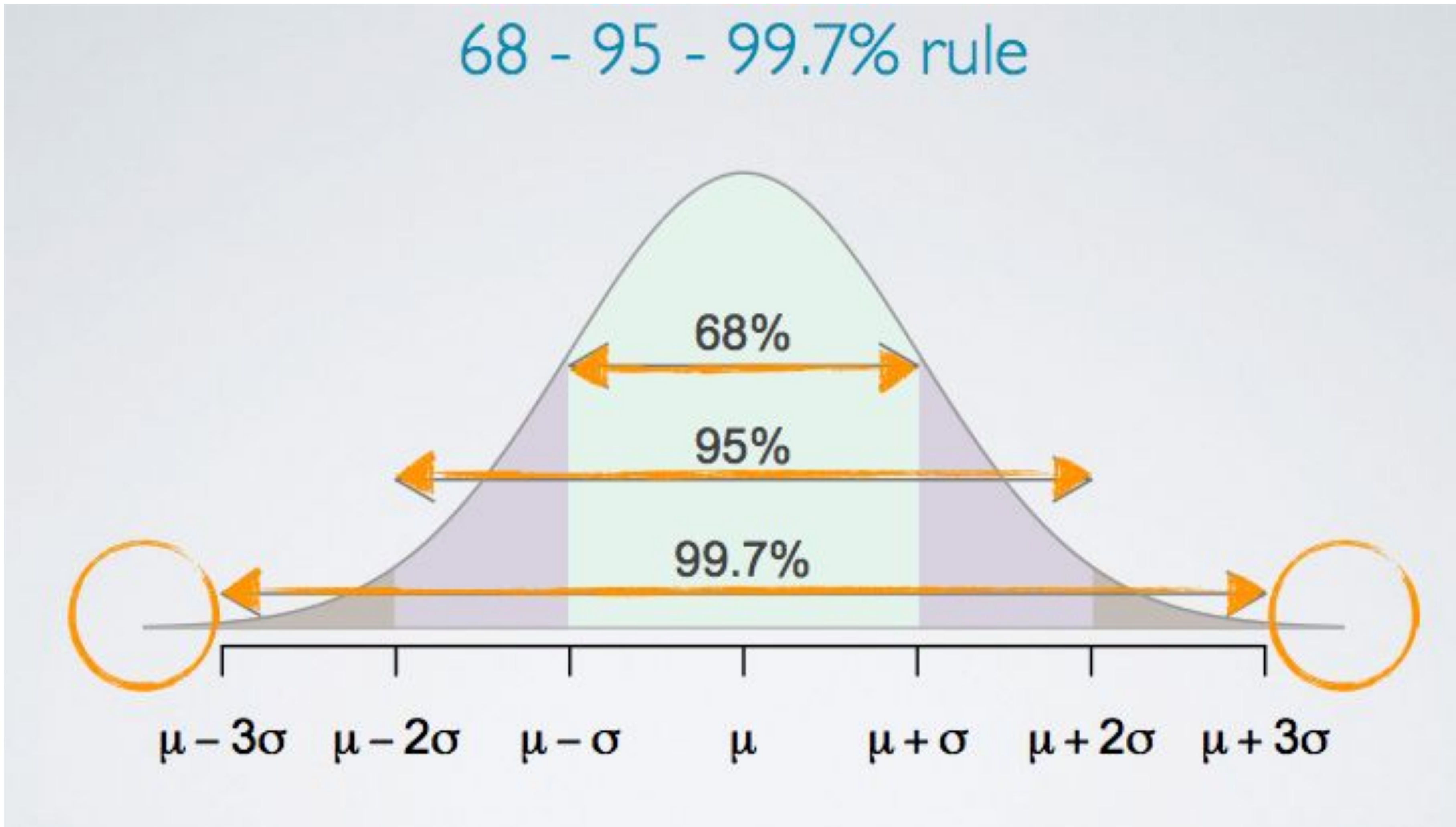
$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2}$$

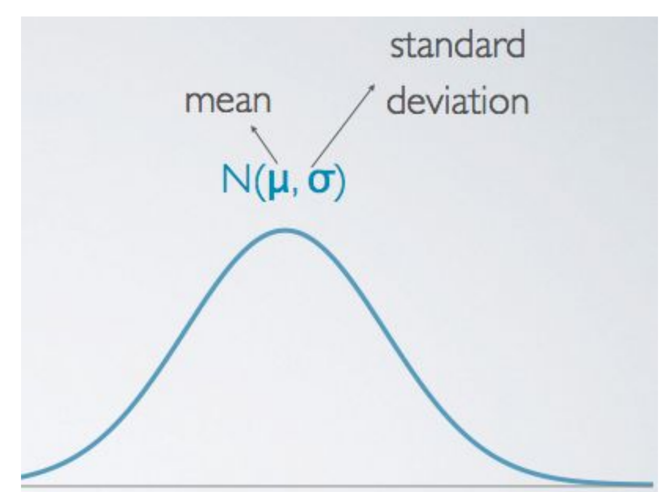
Standard Normal Distribution

Normal Distribution

- Unimodal and symmetric
- For continuous variables
- Follows very strict guidelines about
  - How variably the data are distributed around the mean

Normal Distribution





Normal Distribution

Question - A college admissions officer wants to determine which of the two applicants scored better on their standardized test with respect to the other test takers: Pam, who earned an 1800 on her SAT, or Jim, who scored a 24 on his ACT?

SAT scores ~ N(mean = 1500, SD = 300)
ACT scores ~ N(mean = 21, SD = 5)

Normal Distribution

A college admissions officer wants to determine which of the two applicants scored better on their standardized test with respect to the other test takers: Pam, who earned an 1800 on her SAT, or Jim, who scored a 24 on his ACT?

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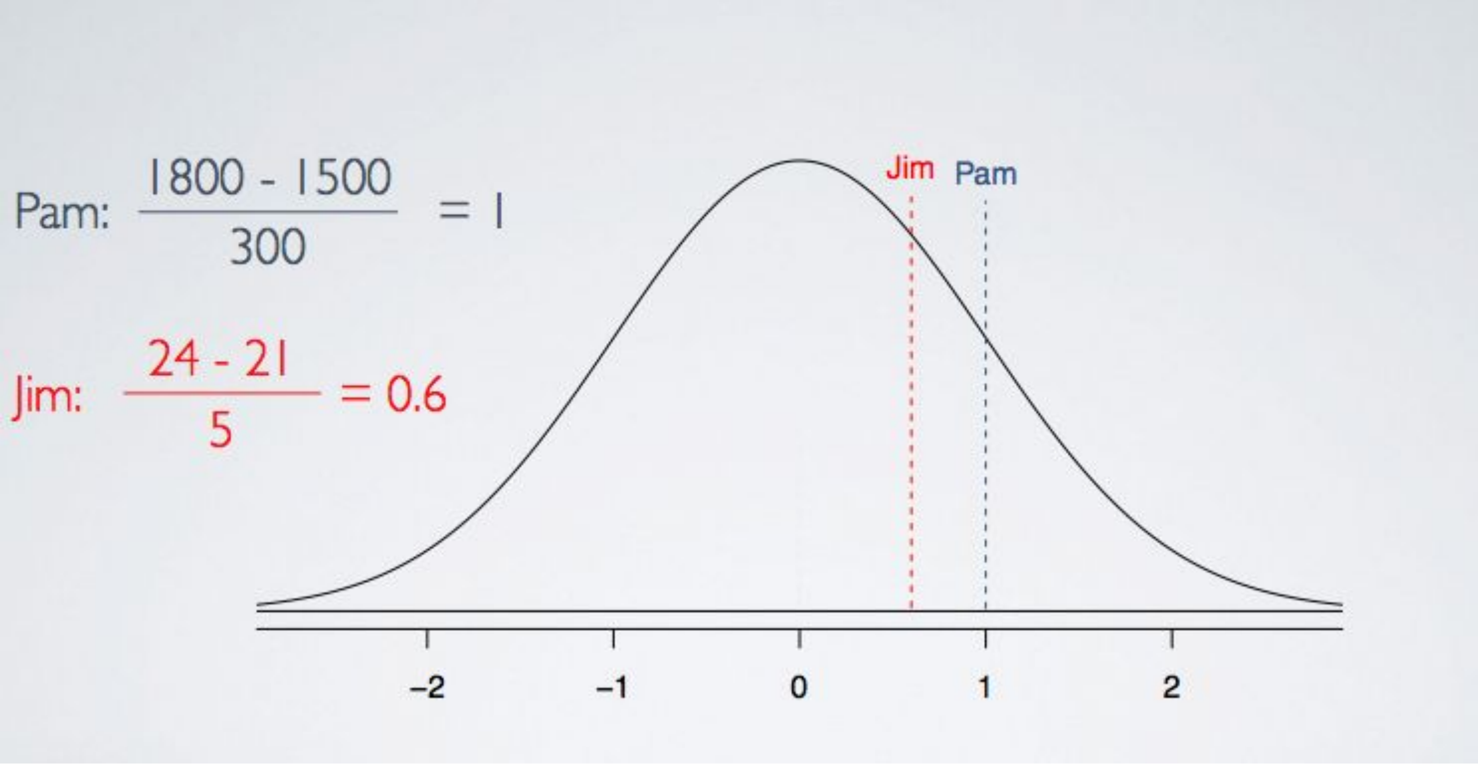


Back to: End to End Project

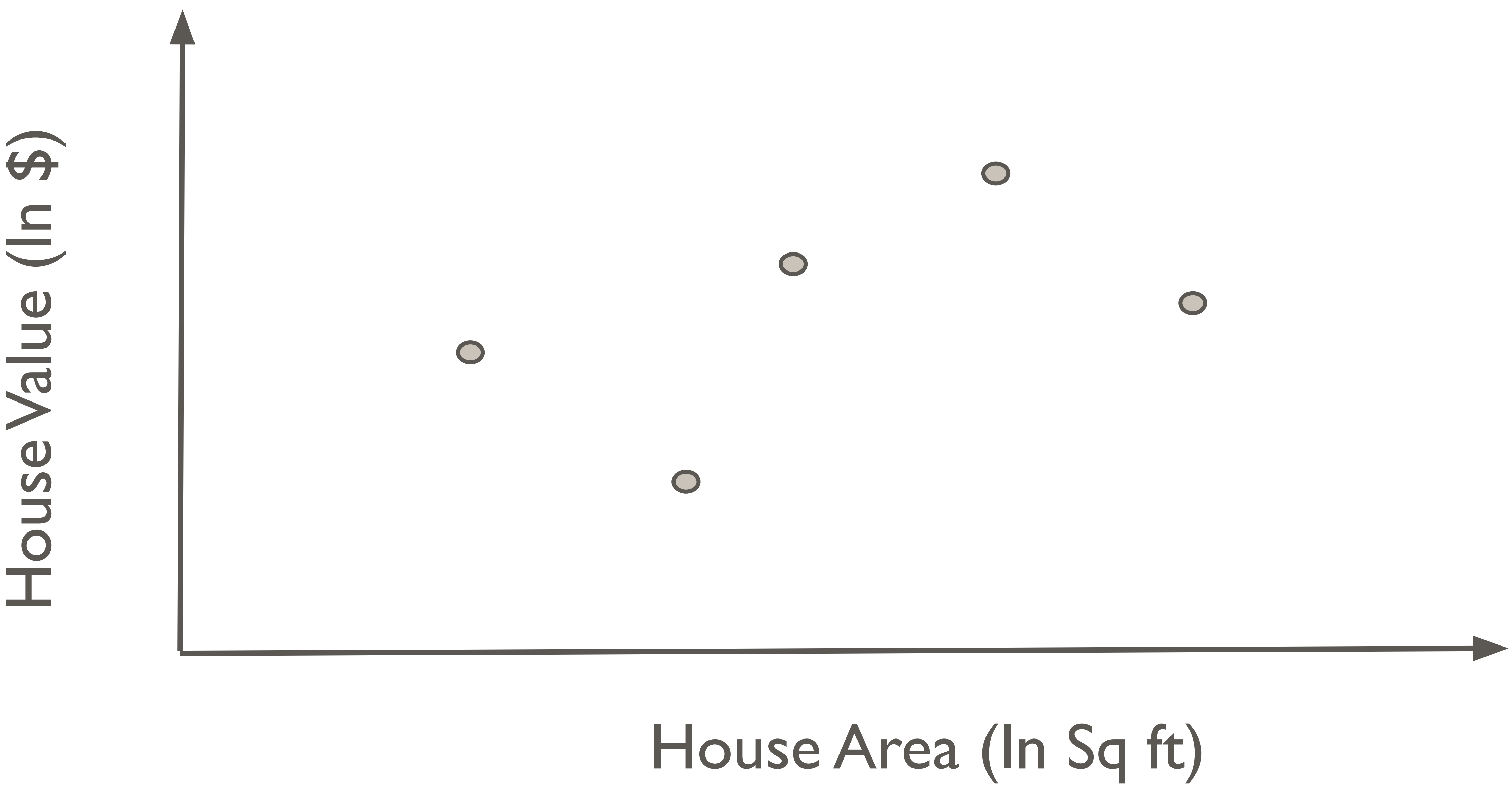
Frame the Problem - Answers

Select a Performance Measure - Root Mean Square Error

- Let's say we want to predict house value based on house area in square feet
- We will use simple linear regression
    - Since there is only one feature **house area**

Frame the Problem - Answers

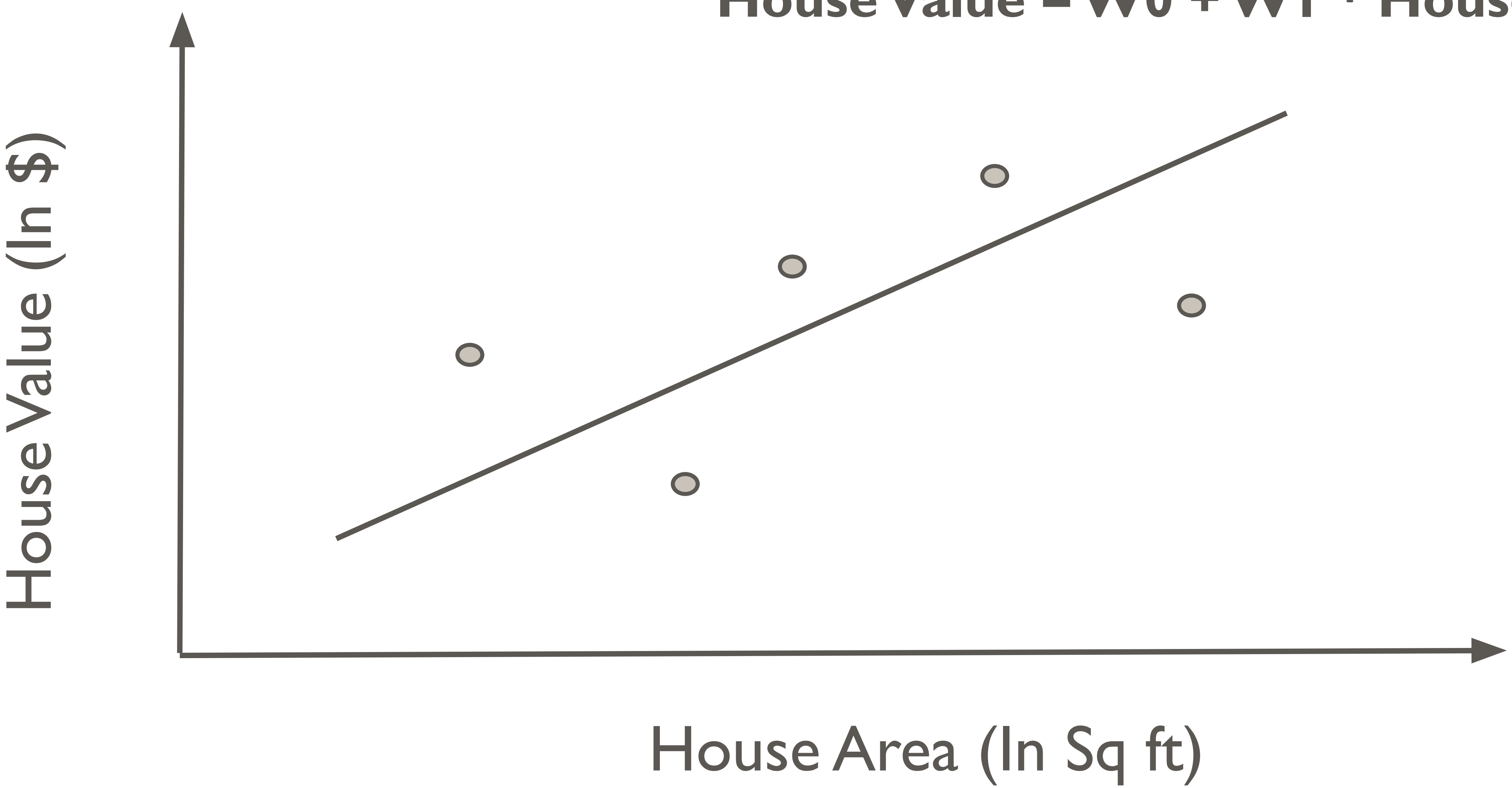
House Value vs House Area - Actual Data



Frame the Problem - Answers

Fit a Line

House Value = W0 + W1 * House Area

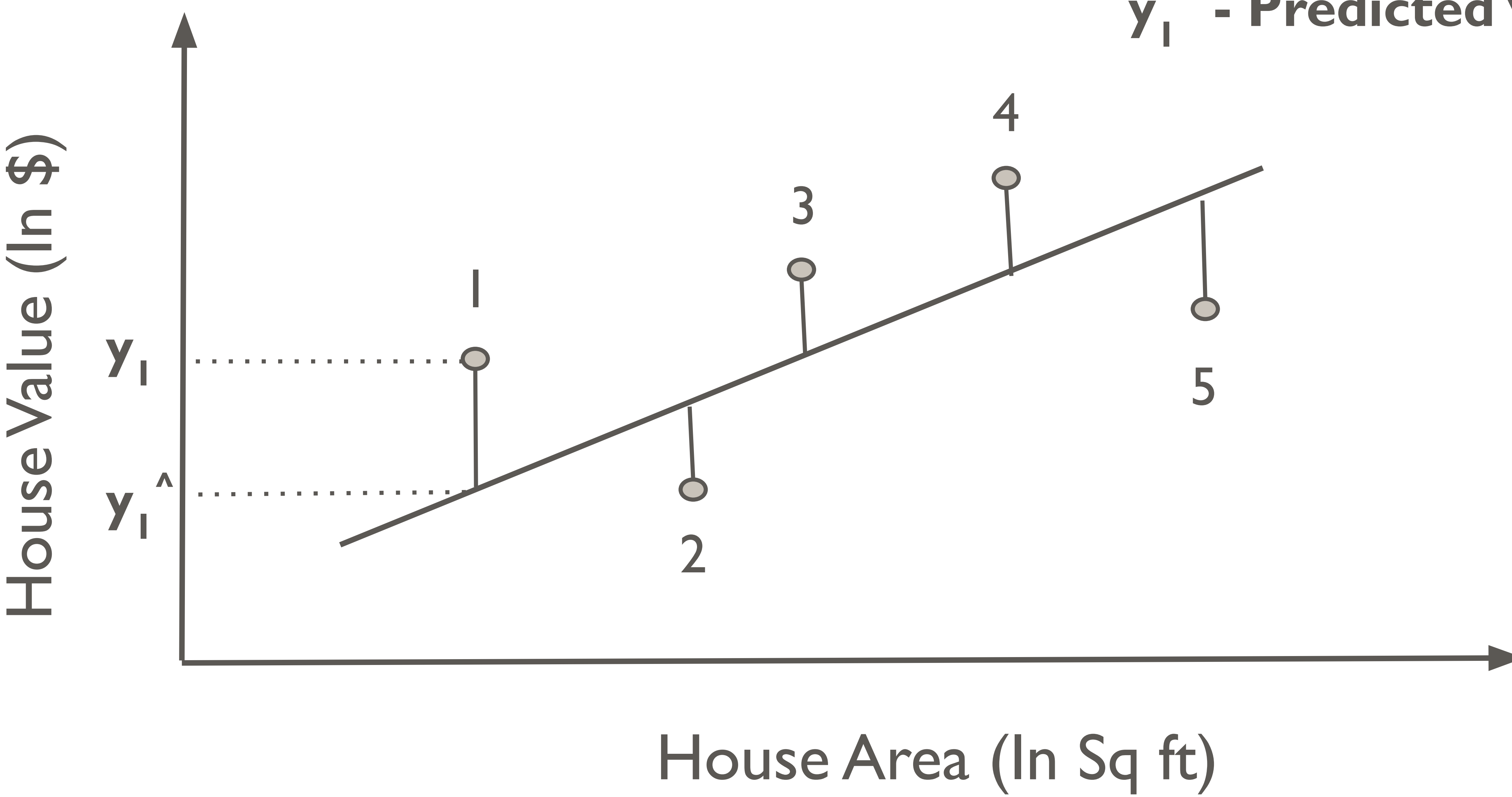


Frame the Problem - Answers

Fit a Line

y_1 - Actual Value

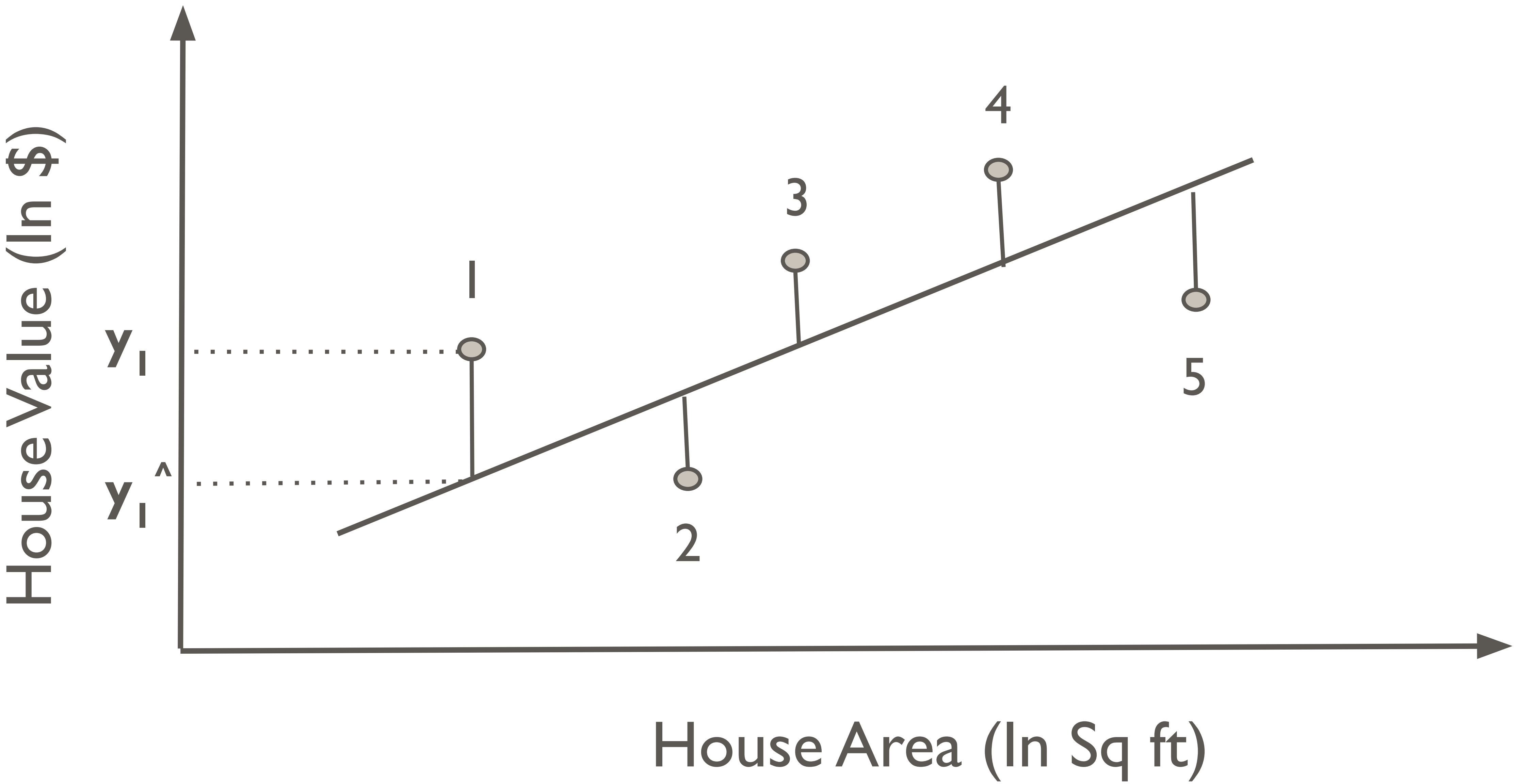
$\hat{y}_1$ - Predicted Value



Frame the Problem - Answers

Error in Prediction

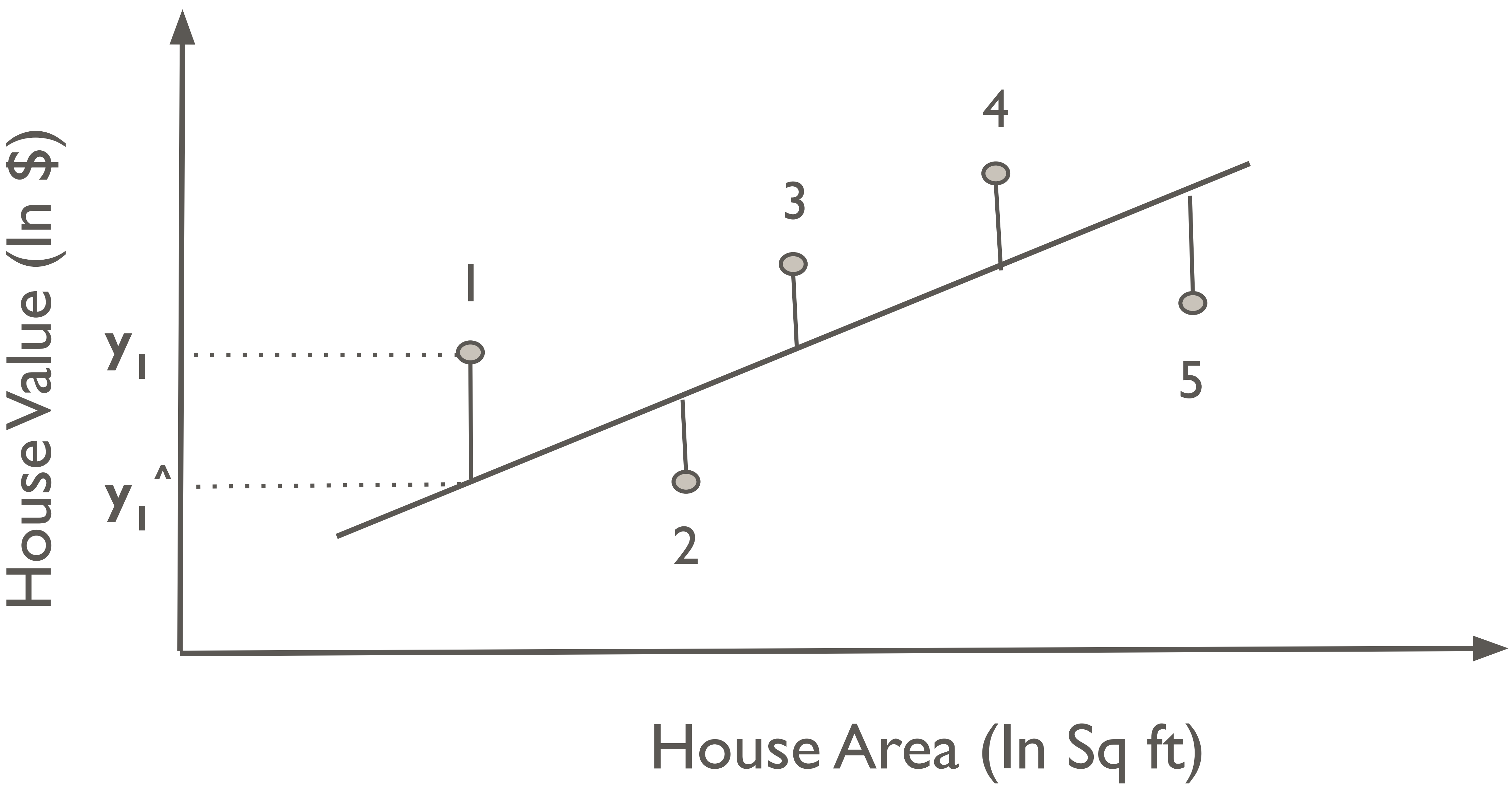
$$(y_i^\wedge - y_i)$$



Frame the Problem - Answers

Squared Error

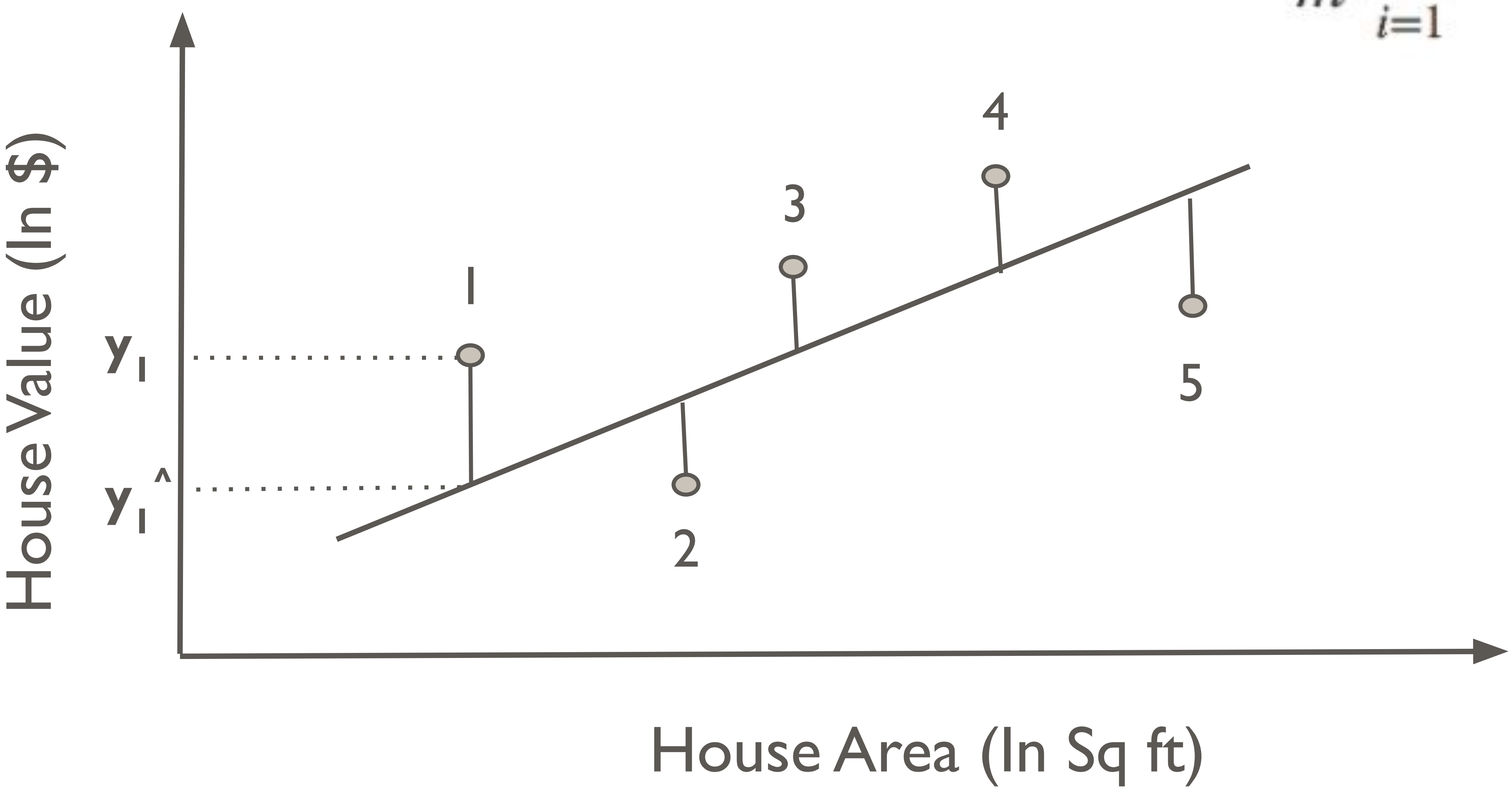
$$(y_i^{\wedge} - y_i)^2$$



Frame the Problem - Answers

Mean Square Error

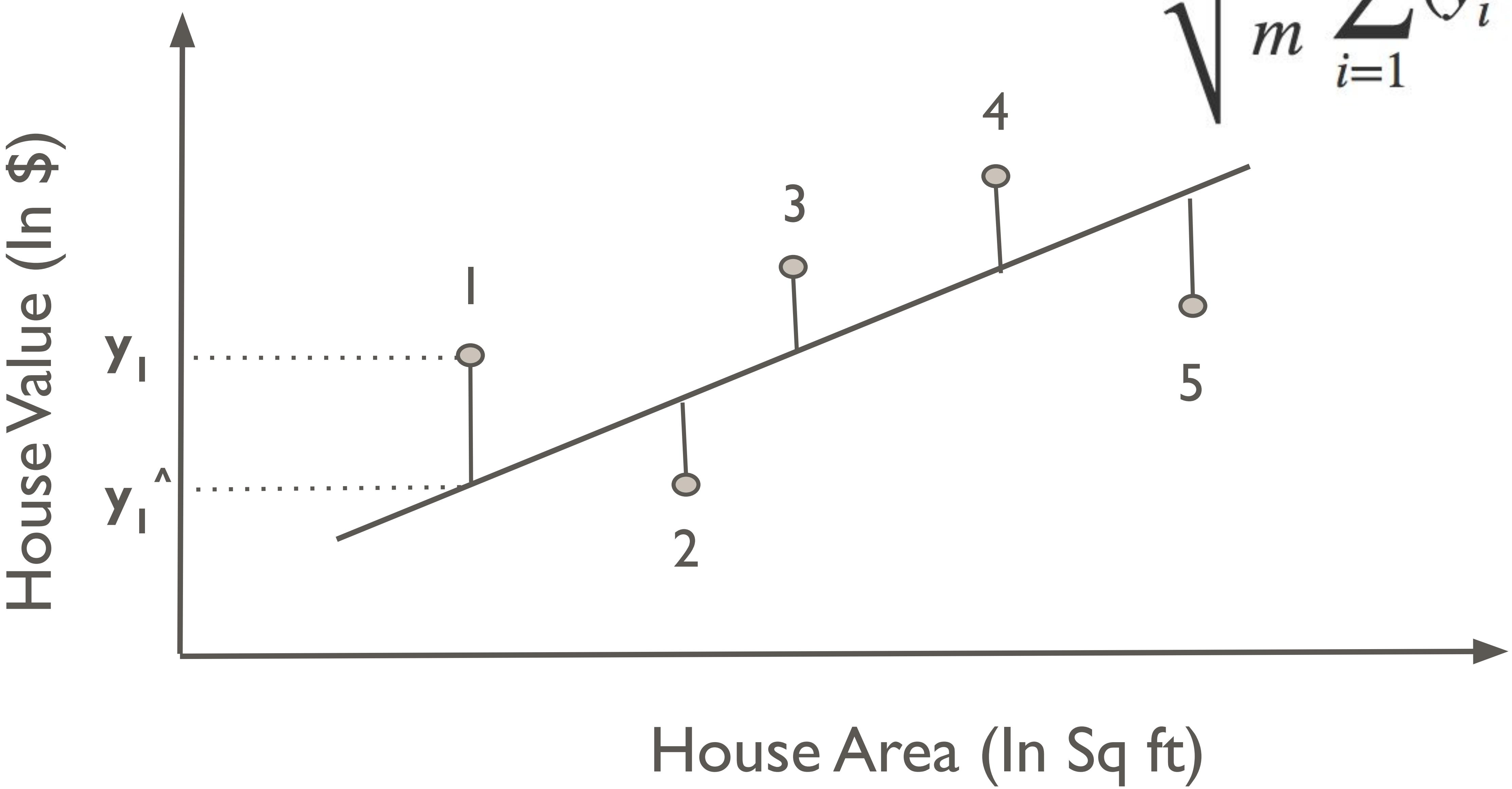
$$\frac{1}{m}\sum_{i=1}^{m}(y_i^\wedge - y_i)^2$$



Frame the Problem - Answers

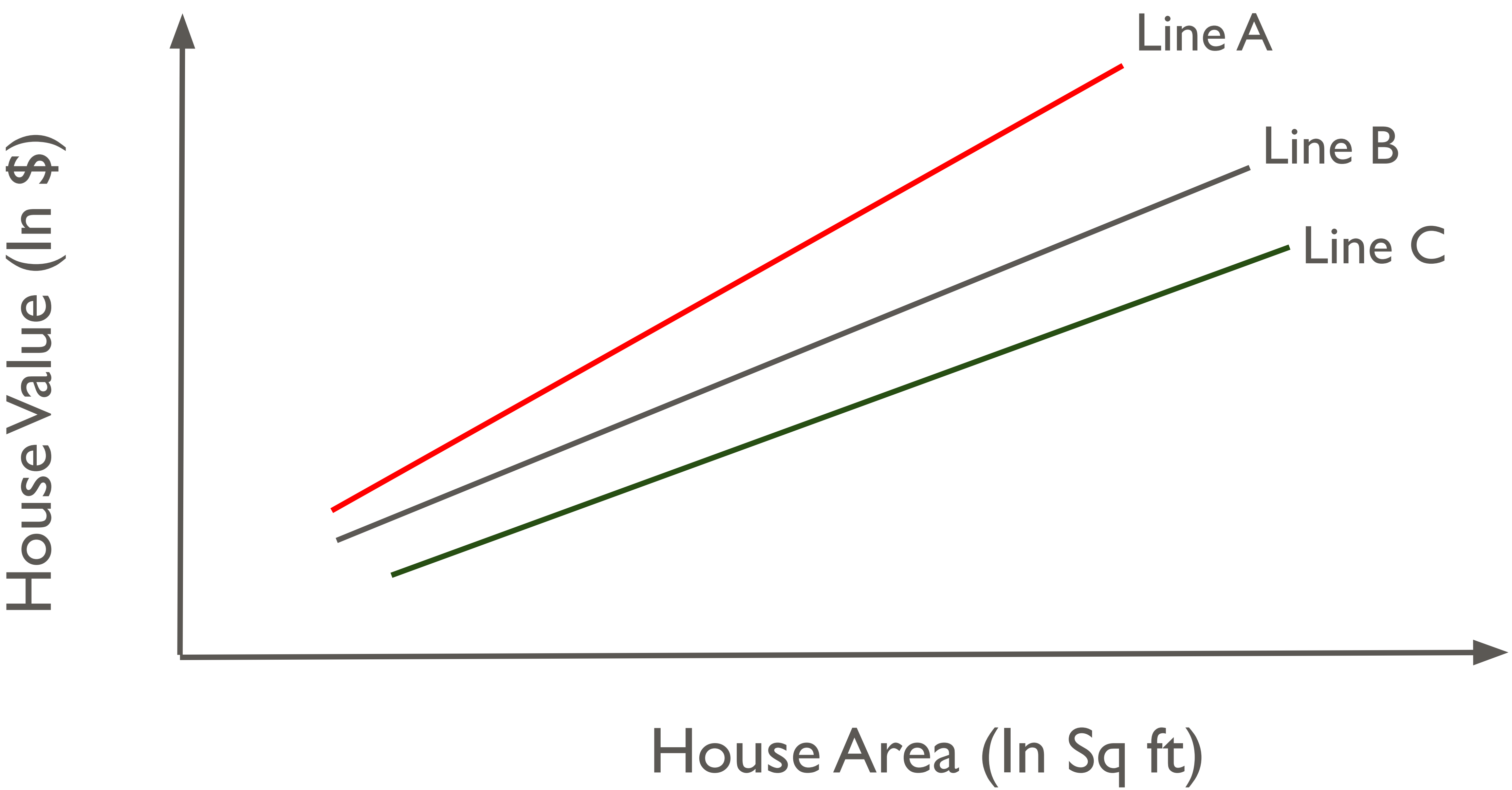
Root Mean Square Error (RMSE)

$$\sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i^\wedge - y_i)^2}$$



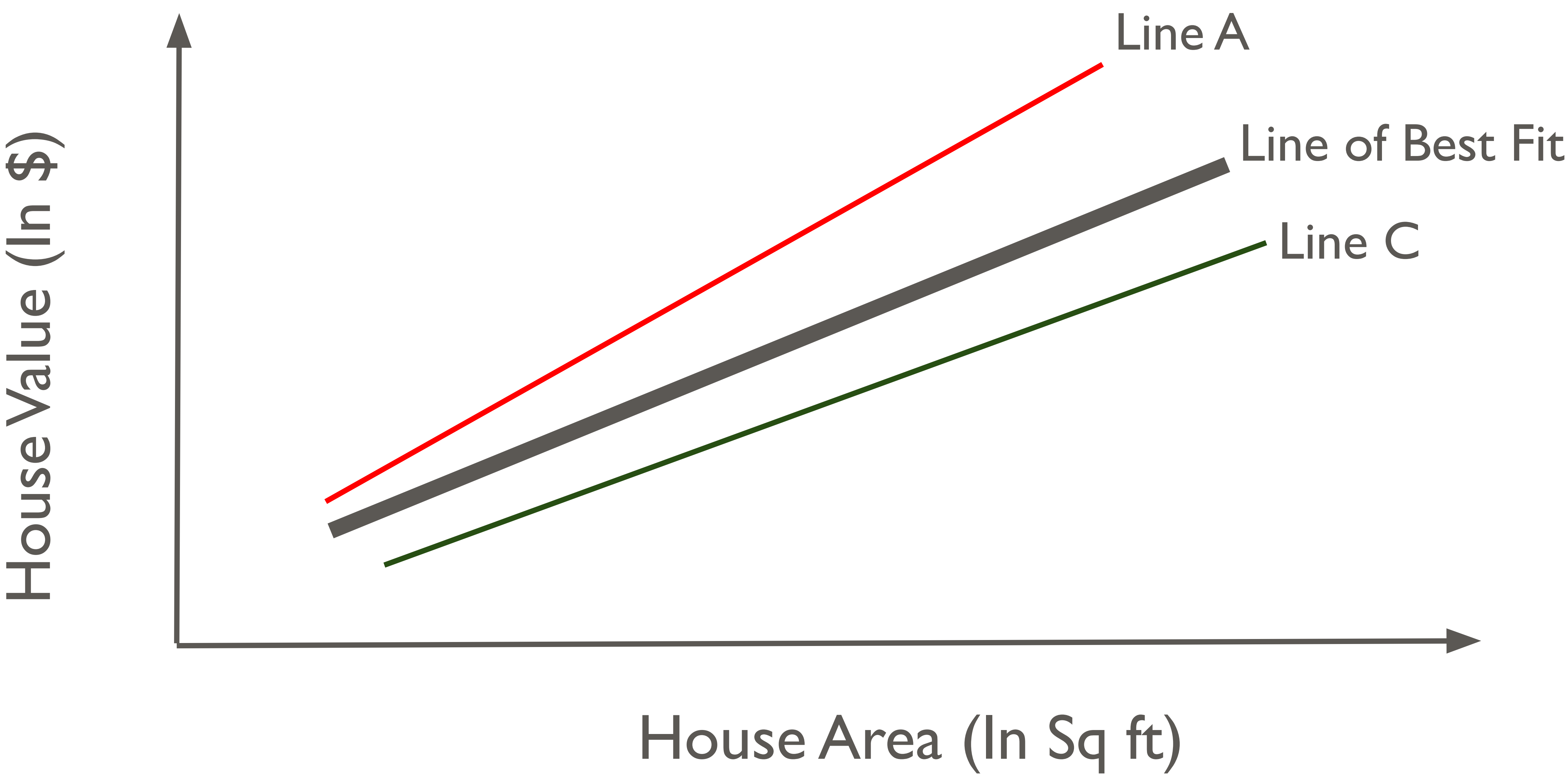
Frame the Problem - Answers

Algorithm tries many lines to fit the data



Frame the Problem - Answers

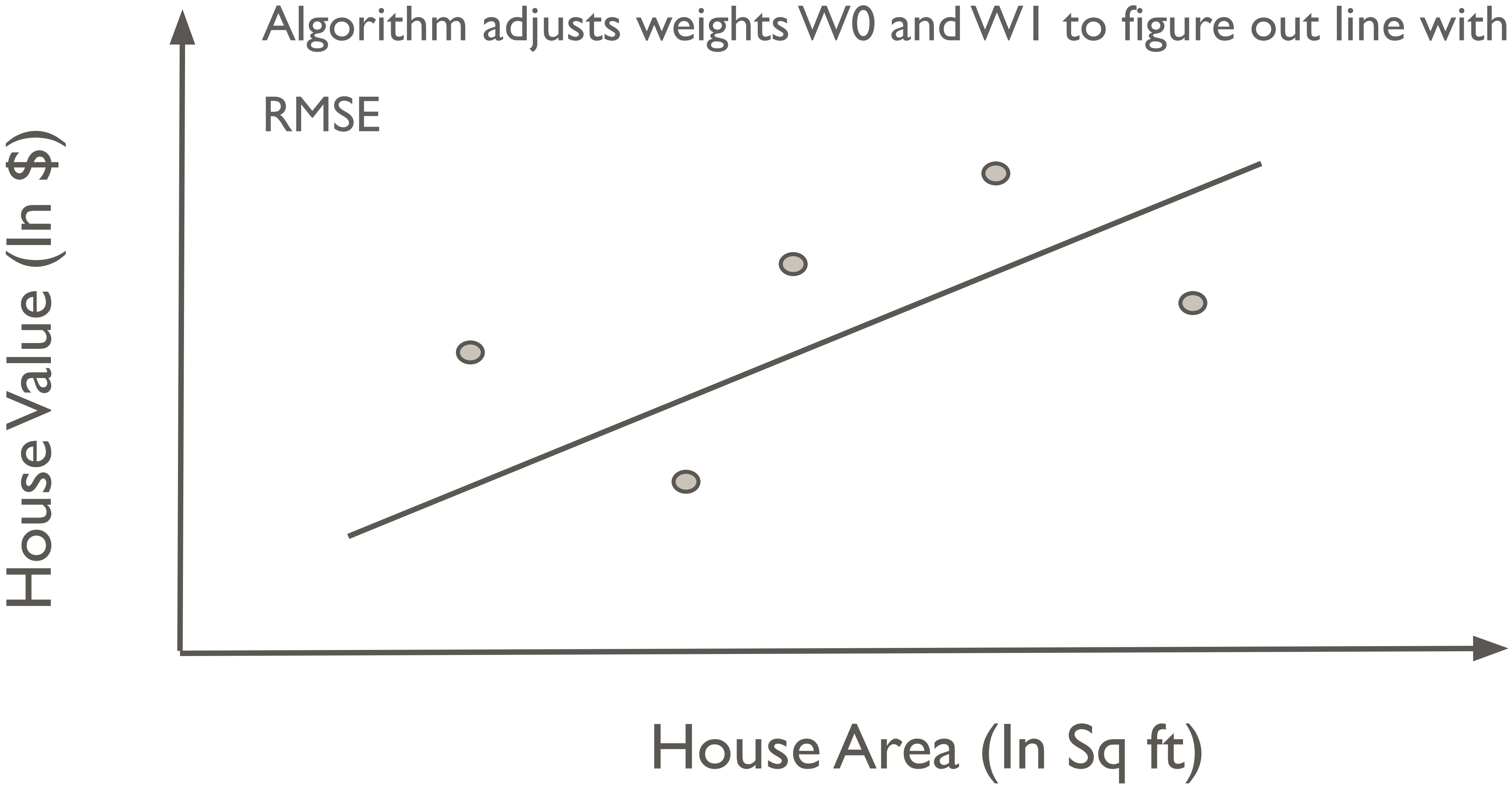
Line of Best Fit - Line with a Minimum RMSE



Frame the Problem - Answers

Line of Best Fit **House Value = W0 + W1 * House Area**

Algorithm adjusts weights W0 and W1 to figure out line with minimum RMSE



Checklist for Machine Learning Projects

1. Frame the problem and look at the big picture
2. **Get the data**
3. Explore the data to gain insights
4. Prepare the data for Machine Learning algorithms
5. Explore many different models and short-list the best ones
6. Fine-tune model
7. Present the solution
8. Launch, monitor, and maintain the system

Get the Data

```
>>> import pandas as pd
>>> import os

>>> HOUSING_PATH = 'datasets/housing/'

>>> def load_housing_data(housing_path=HOUSING_PATH):
        csv_path = os.path.join(housing_path,
"housing.csv")
        return pd.read_csv(csv_path)

>>> housing = load_housing_data()
>>> housing.head()

                    # Run this in notebook
```

Get the Data

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY

Check this in Notebook

Get the Data

- Each row represents one district
- There are 10 attributes:
    - longitude
    - latitude
    - housing_median_age
    - total_rooms
    - total_bedrooms
    - population
    - households
    - median_income
    - median_house_value
    - ocean_proximity

Continue in the Notebook until plotting the histogram

Get the Data

Plot histogram

- Plot a histogram to get the feel of type of data we are dealing with
- We can plot histogram only for numerical attributes

Get the Data

Plot histogram

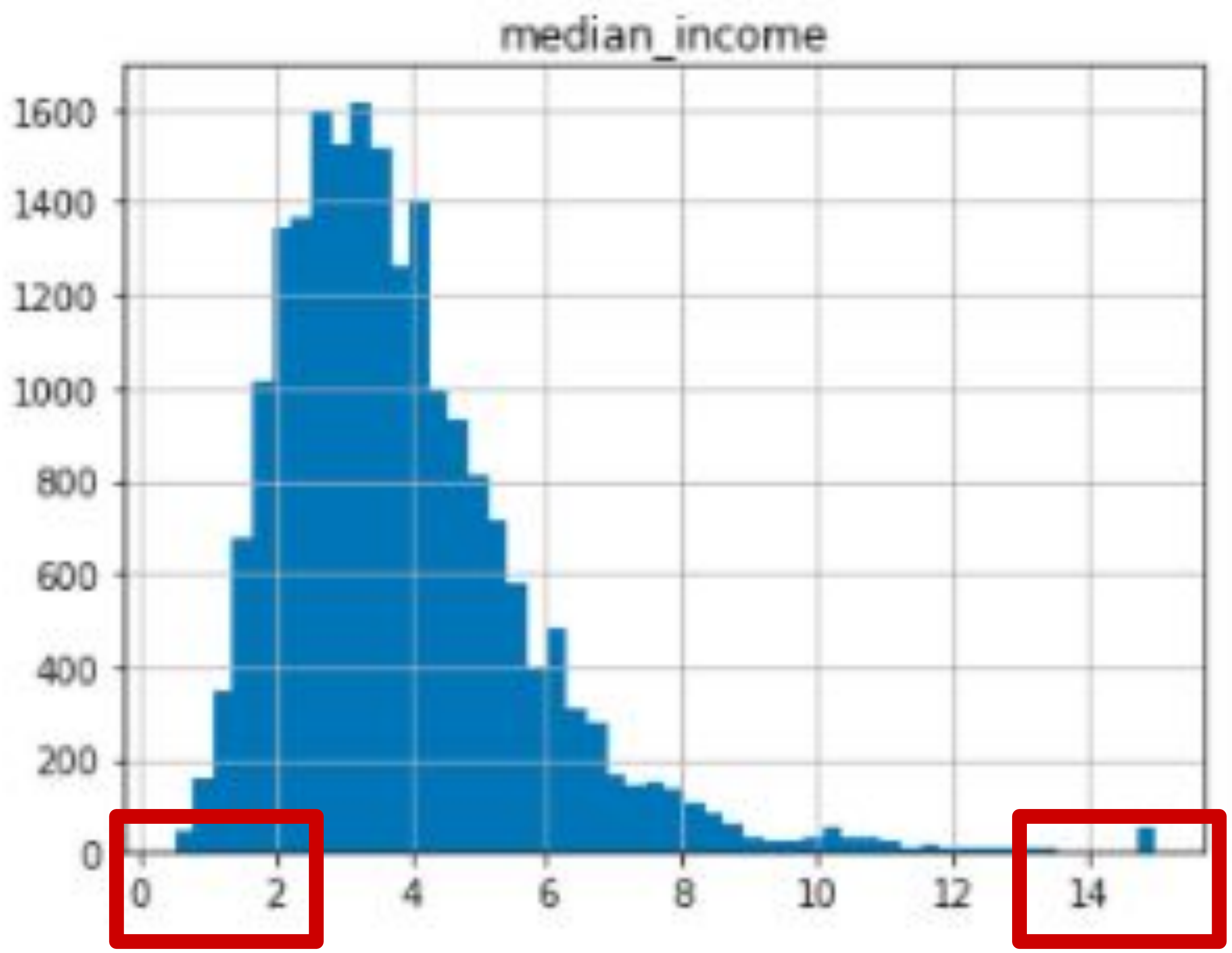
```
>>> %matplotlib inline
>>> import matplotlib.pyplot as plt
>>> housing.hist(bins=50, figsize=(20,15))
>>> plt.show()
```

Plot histogram

Observations?

Things to Note in Histogram - One

Plot histogram



Things to Note in Histogram - One

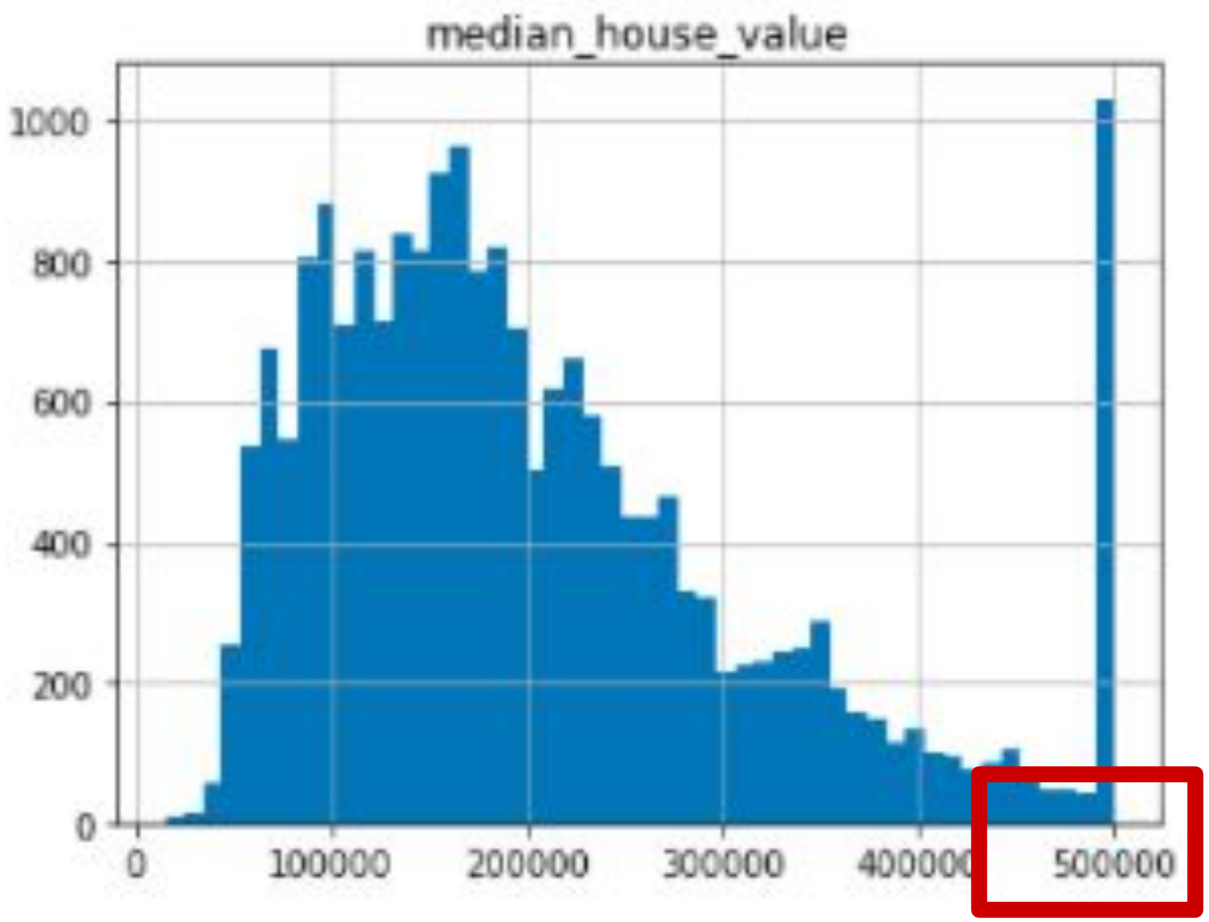
Data is Capped

- The median income attribute does not look like it is expressed in US dollars (USD)
- After checking with the team that collected the data, you are told that the data has been scaled and capped at
    - 15 (actually 15.0001) for higher median incomes, and
    - At 0.5 (actually 0.4999) for lower median incomes

Lesson: It is important to understand how your data was computed

Things to Note in Histogram - Two

Plot histogram



Things to Note in Histogram - Two

- The following are also capped
  - Median age - 50
  - Median house value - 500, 000
- Machine Learning algorithms may learn that prices never go beyond that limit

Serious problem since median_house_value is the target attribute

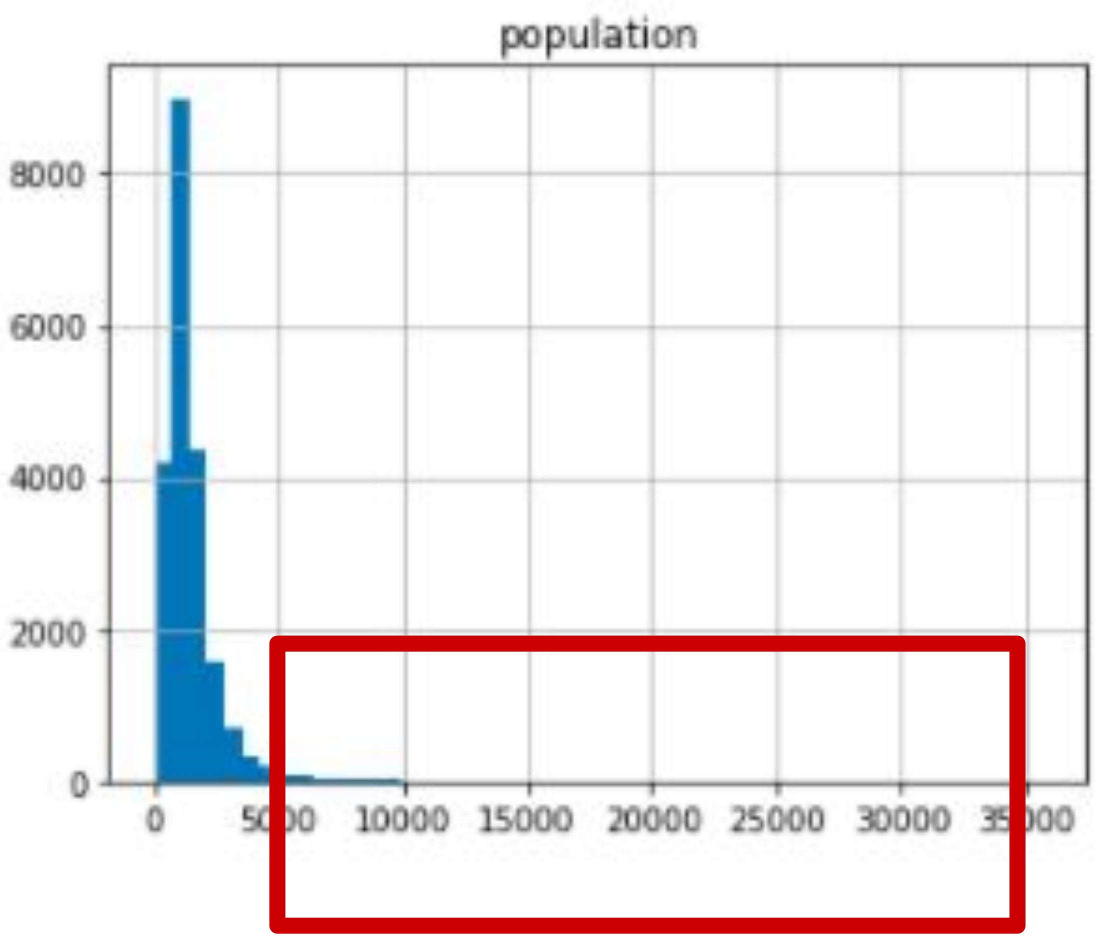
Things to Note in Histogram - Two

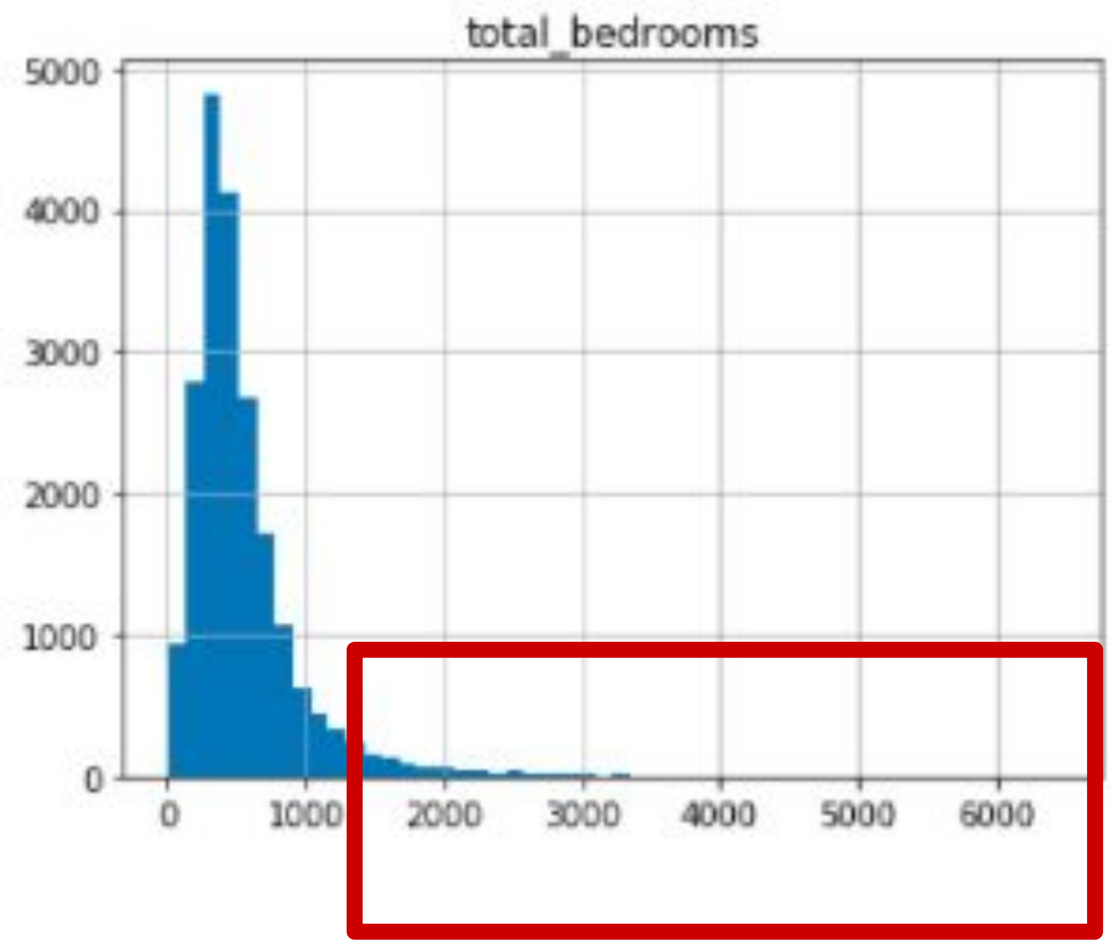
How do we solve it?

- Check with the team if this is a problem or not
- If team says they need precise predictions even beyond $500,000 then
  - Collect proper labels for districts whose labels were capped
  - OR
  - Remove those labels from training as well as test dataset

Things to Note in Histogram - Three

Plot histogram





Things to Note in Histogram - Three

Tail heavy histograms

- Many histograms are tail heavy
- Harder for Machine Learning algorithms to detect patterns
- We will transform these attributes to more bell-shaped distributions

Create a Test Set

Training and Test set

- We generally split the data into
  - **Training set -** Contains 80% of the data
  - **Test set -** Contains remaining 20% of the data
- We train the model on training set
- And evaluate the performance of the model on test set

Create a Test Set

- We’ve just seen the data and
- Still have to learn a lot more about it to decide which algorithm to use

Why create a test set right now?

Create a Test Set

Data snooping bias

- Brain is an amazing pattern detection system
- Highly prone to overfitting
- We may find interesting patterns in test data
- And select a particular Machine Learning model
- Our model will be too optimistic
- And will not perform as well as expected

Create a Test Set

- In this project, we will use
  - Scikit-learn `train_test_split()` function
  - To create test set
- Over the next few slides, we will learn
  - How to create our own function
  - To create test set

Create a Test Set

Splitting Train and Test set

```
>>> np.random.seed(42)
>>> import numpy as np
def split_train_test(data, test_ratio):
  shuffled_indices = np.random.permutation(len(data))
  test_set_size = int(len(data) * test_ratio)
  test_indices = shuffled_indices[:test_set_size]
  train_indices = shuffled_indices[test_set_size:]
  return data.iloc[train_indices],
data.iloc[test_indices]
```

Create a Test Set

Splitting Train and Test set

- Remember to pass a seed to `np.random.permutation` always
- Seed is important because we want our model
  - To be trained and evaluated on same train and test set every time
- Else on every run of **`split_train_test`** function
  - Train and test set will be different
  - Over time our machine learning model may see the whole dataset during training
  - Which we should to avoid

Create a Test Set

Splitting Train and Test set - Seed

- Seed can be any number
- Remember to pass same seed every time
- To make sure same rows goes to train and test set
- Everytime we run `split_train_test` function

Create a Test Set

Let's run `split_train_test` in notebook

```
>>> train_set, test_set = split_train_test(housing, 0.2)
>>> print(len(train_set), "train +", len(test_set),
"test")
```

Output -

```
16512 train + 4128 test
```

Create a Test Set

Question -

What is the problem with `split_train_test` function?

Create a Test Set

Answer -

This solution will break next time when we fetch an updated dataset

Create a Test Set

Other Solution -

- If each instance in the dataset has a
  - Unique and Immutable Identifier
  - We can decide on the basis of identifier
  - If it should go into test set or not

Create a Test Set

Other Solution Example-

- Compute hash of each instance's identifier
- If hash is lower or equal to 20% of maximum hash value
    - Put instance in the test set

Create a Test Set

Other Solution Example-

- Test set using previous example
  - Will be consistent across multiple runs
  - Even if we refresh the dataset
  - Will contain 20% of the new instances
  - Will not contain any instance that was previously in the training set

Create a Test Set

Implementation-

```
>>> from zlib import crc32
>>> def test_set_check(identifier, test_ratio):
        return crc32(np.int64(identifier)) & 0xffffffff < test_ratio *
     2**32
>>> def split_train_test_by_id(data, test_ratio, id_column):
     ids = data[id_column]
     in_test_set = ids.apply(lambda id_: test_set_check(id_,
     test_ratio))
     return data.loc[~in_test_set], data.loc[in_test_set]
```

Create a Test Set

Problems?

- Housing dataset does not have an identifier column
- Simplest solution is to use row index as ID

```
>>> housing_with_id = housing.reset_index()
>>> train_set, test_set =
split_train_test_by_id(housing_with_id, 0.2, "index")
```

Run it on Notebook

Create a Test Set

Problems with row index?

Create a Test Set

Problem with row index?

- Make sure new data is appended to the end of the dataset
- No row ever is deleted

Create a Test Set

Problem with row index?

- A district's latitude and longitude are guaranteed to be stable for a few million years
- We can combine them into an ID

Create a Test Set

Problem with row index?

```
>>> housing_with_id["id"] = housing["longitude"] * 1000
+ housing["latitude"]
>>> train_set, test_set =
split_train_test_by_id(housing_with_id, 0.2, "id")
```

Run it in Notebook

Create a Test Set

Using Scikit-learn for the same

- Sklearn provides **train_test_split** function
    - Same as **split_train_test** defined earlier with two more features
    - There is random_state parameter which sets the random generator seed
    - We can pass it on a multiple datasets with an identical number of rows
    - **split_train_test** splits them on the same indices
    - Useful if we have separate DataFrame for labels

Create a Test Set

Using Scikit-learn for the same

```
>>> from sklearn.model_selection import train_test_split
>>> train_set, test_set = train_test_split(housing,
test_size=0.2, random_state=42)
```

Run it in notebook

Create a Test Set

Sampling Bias

- Till now, we have considered pure **random sampling methods**
- **Random sampling methods** work fine
    - If dataset is large enough
    - Else we are at risk of introducing significant **sampling bias**

Create a Test Set

Sampling Bias - Example

- Let's say a survey company in US decides to call 1,000 people to ask them few questions

What is the best approach to pick 1,000 people?

Create a Test Set

Sampling Bias - Example

- Let's say a survey company in US decides to call 1,000 people to ask them few questions

We can not just pick 1,000 people randomly

Create a Test Set

Sampling Bias - Important Point

Samples must be representative of the whole population

SAMPLING BIAS

Convenience sample

Individuals who are easily accessible are more likely to be included in the sample

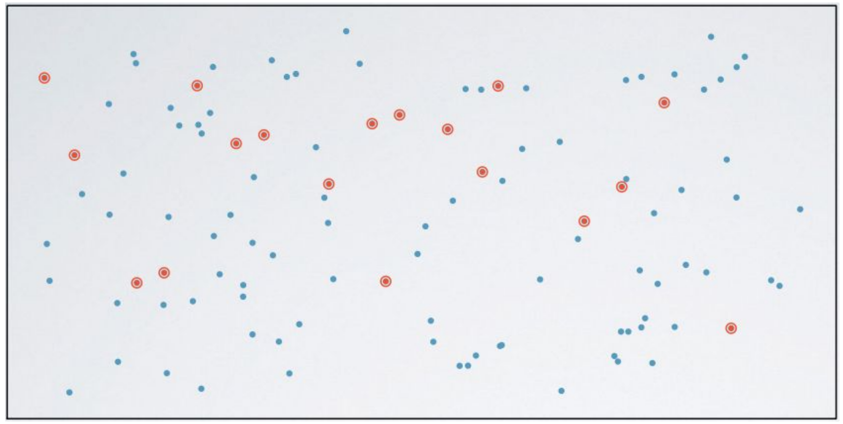
Voluntary response

Occurs when the sample have strong opinions on the issue

Non-response

If only a (non-random) fraction of the randomly sampled people respond to a survey such that the sample is no longer representative of the population

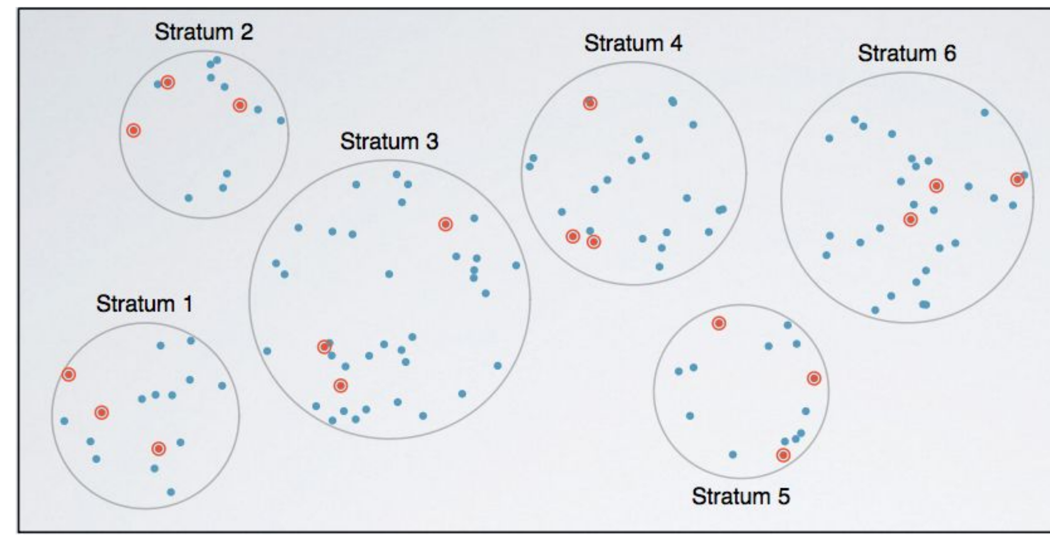
SAMPLING METHODS



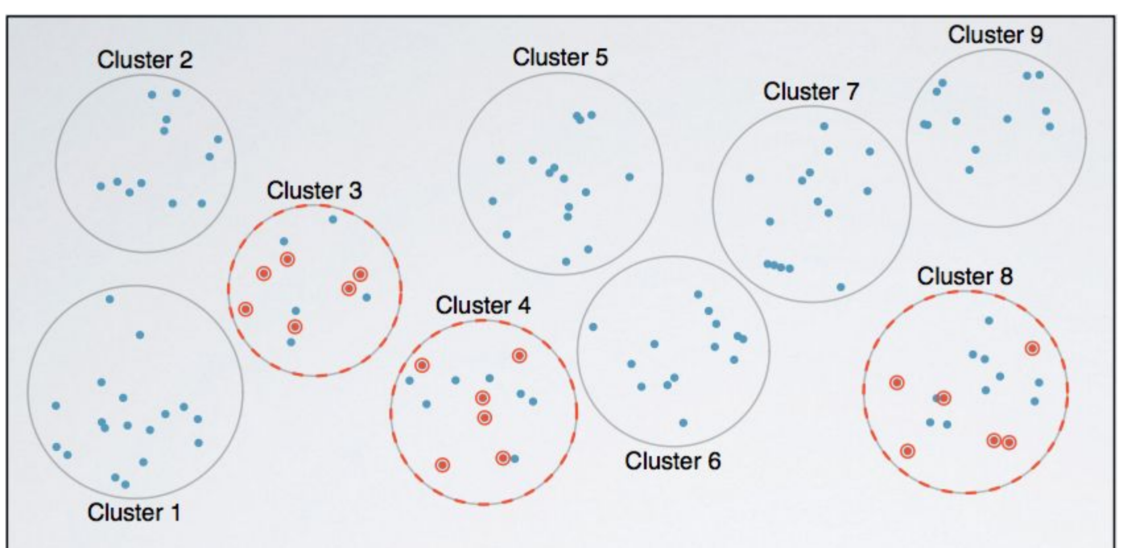
Simple Random Sample (SRS)

Each case is equally likely to be selected

Stratified Sample



Divide the population into homogeneous strata, then randomly sample from within each stratum



Cluster Sample

Divide the population clusters, randomly sample a few clusters, then randomly sample from within these clusters

Create a Test Set

Sampling Bias - Example

- US population is composed of
  - 51.3% female
  - 48.7% male

Create a Test Set

Stratified Sampling

- A well-conducted survey on 1000 people in the US should
  - Try to maintain the ratio in the sample
  - 513 female
  - 487 male
- This is called **stratified sampling**

Create a Test Set

Stratified Sampling

- The population is divided into
  - Homogeneous subgroups called **strata**
- And the right number of instances is
  - Sampled from each **stratum**
- Else the survey results would be significantly biased

Create a Test Set

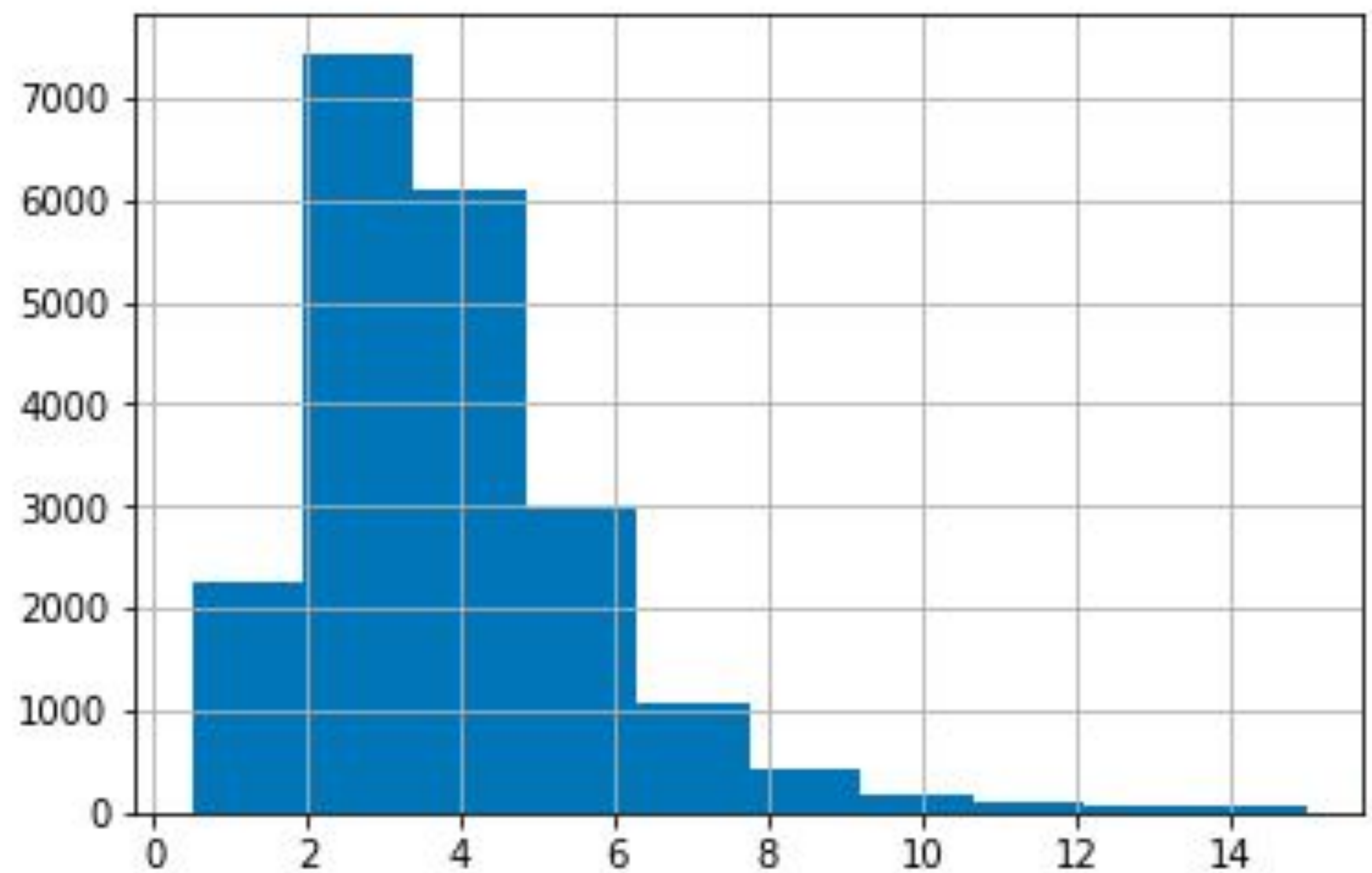
Median Income

- Let's say some experts advised us that
  - The median income is a very important attribute to predict median housing prices
- Then the test set should be representative of
  - Various categories of median income

Create a Test Set

Create Histogram of Median Income

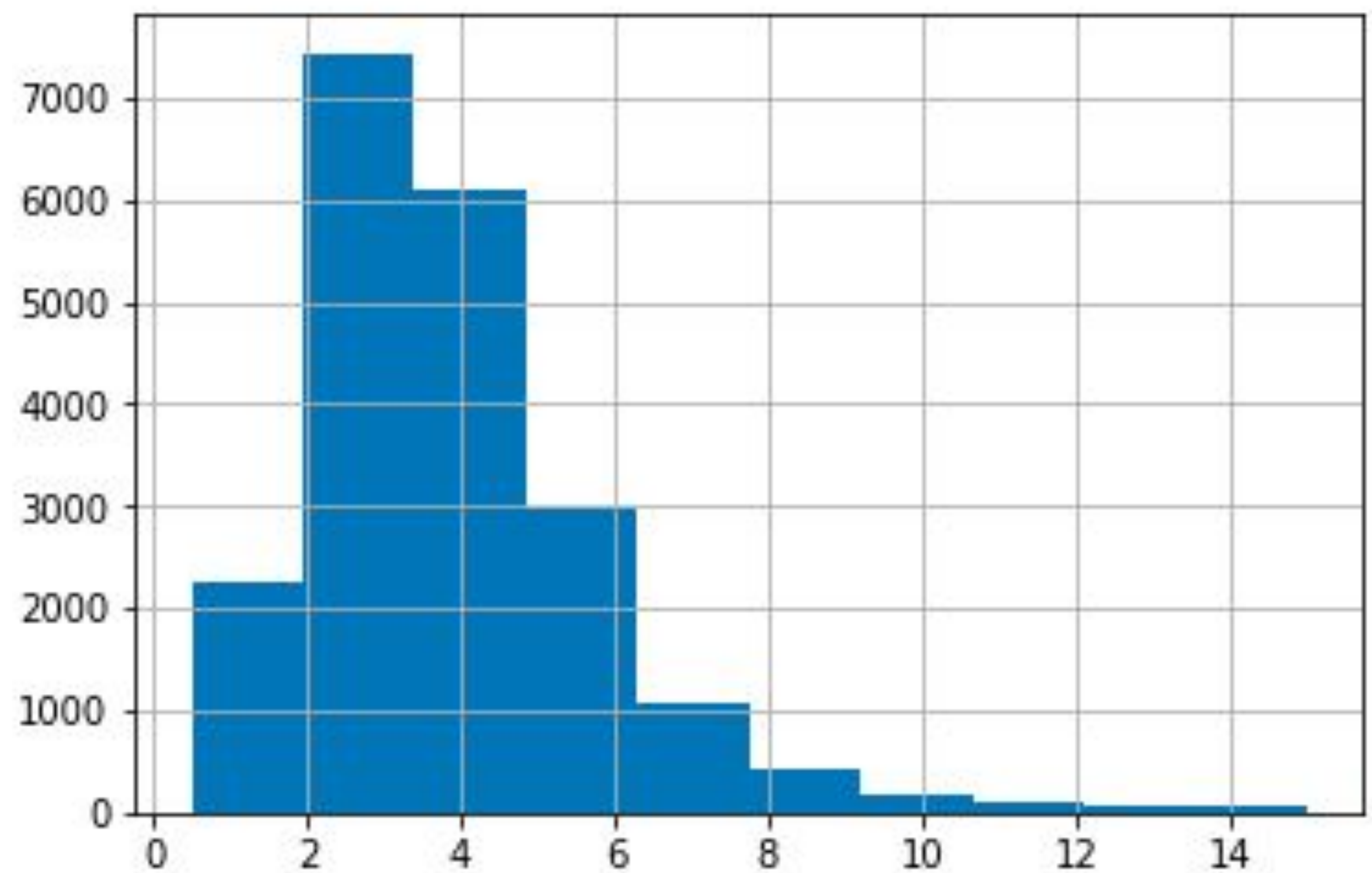
```
>>> housing["median_income"].hist()
```



Create a Test Set

Create Histogram of Median Income

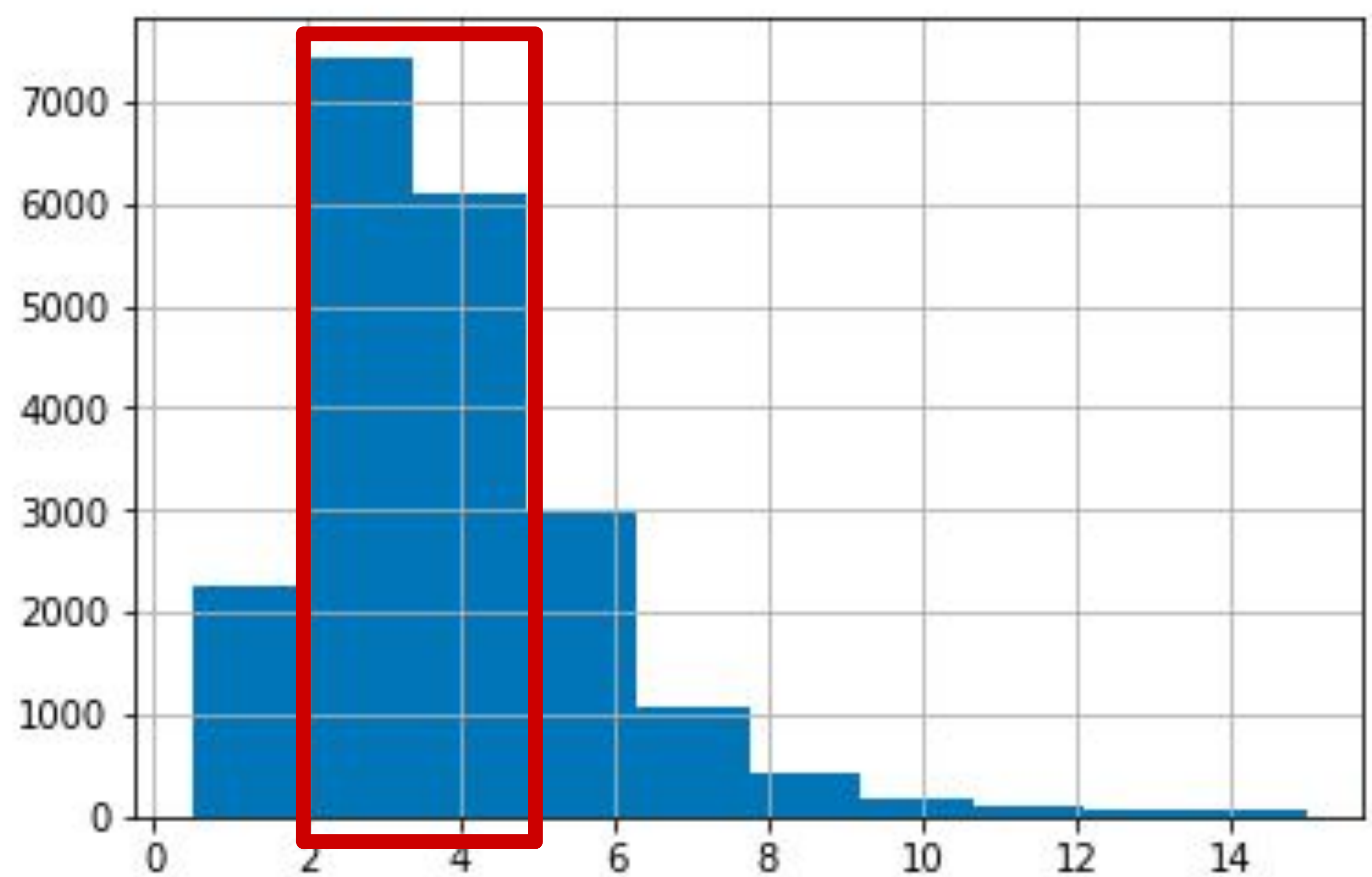
Observations?



Create a Test Set

Create Histogram of Median Income

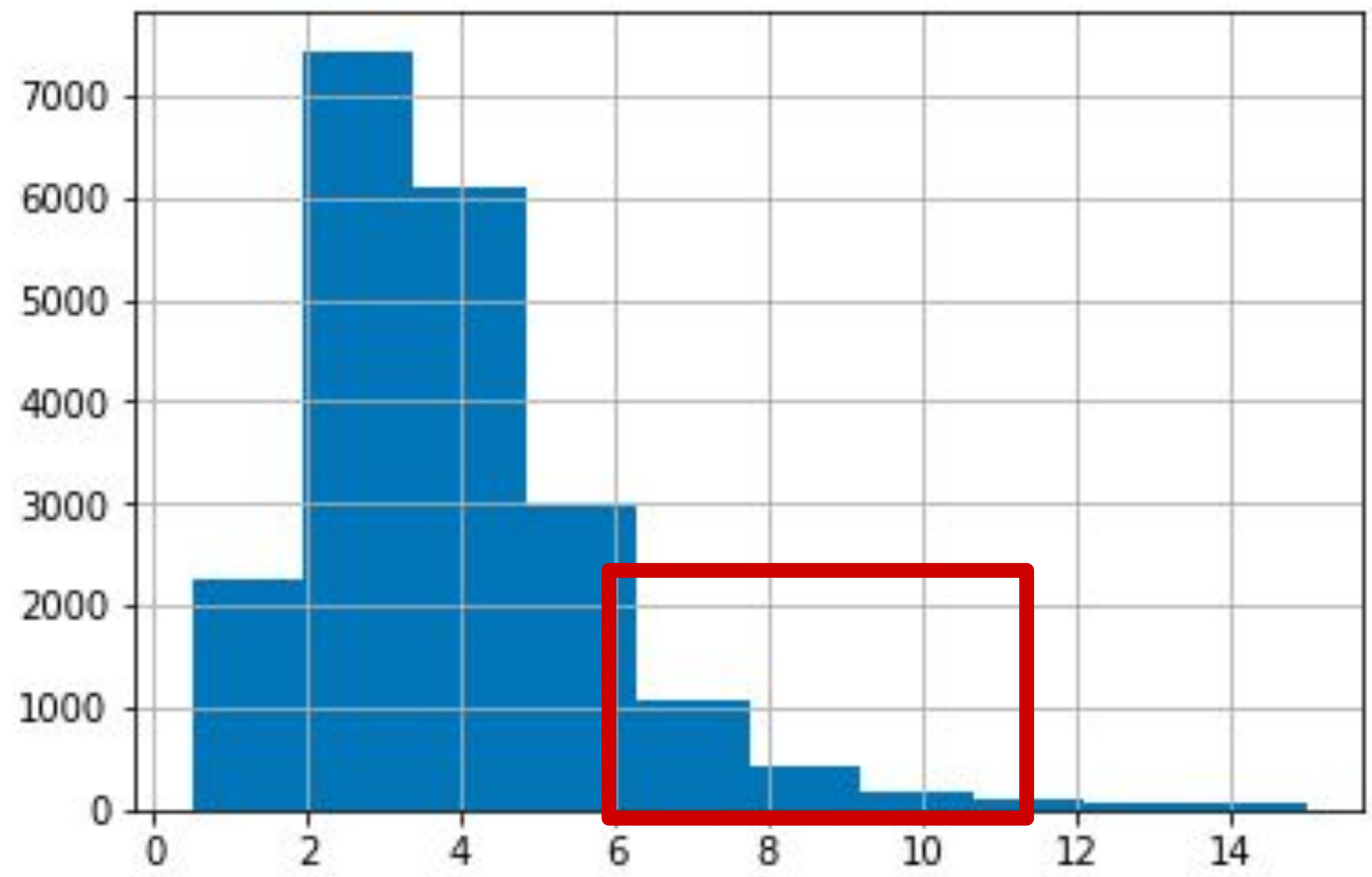
- Most values are clustered around 2-5 thousand dollars



Create a Test Set

Create Histogram of Median Income

- Some median income go beyond 6



Create a Test Set

Important Points

- Since median income is important attribute to predict median housing prices
- It is important to have sufficient number of instances
    - In the dataset for each **stratum**
- This means that
    - We should not have too many **strata**
    - And each **stratum** should be large enough

Create a Test Set

Let's limit the number of categories of median income

Create a Test Set

Limit the Categories in Median Income

- Divide median income by 1.5 so that
  - We will not have too many **strata**
  - And each **stratum** will be large enough

Create a Test Set

Limit the Categories in Median Income

```
>>> housing["income_cat"] =
np.ceil(housing["median_income"] / 1.5)
>>> housing["income_cat"].where(housing["income_cat"] <
5, 5.0, inplace=True)
```

Run it in Notebook

Create a Test Set

Limit the Categories in Median Income

```
>>> housing["income_cat"].value_counts()
```

```
3.0    7236
2.0    6581
4.0    3639
5.0    2362
1.0     822
Name: income_cat, dtype: int64
```

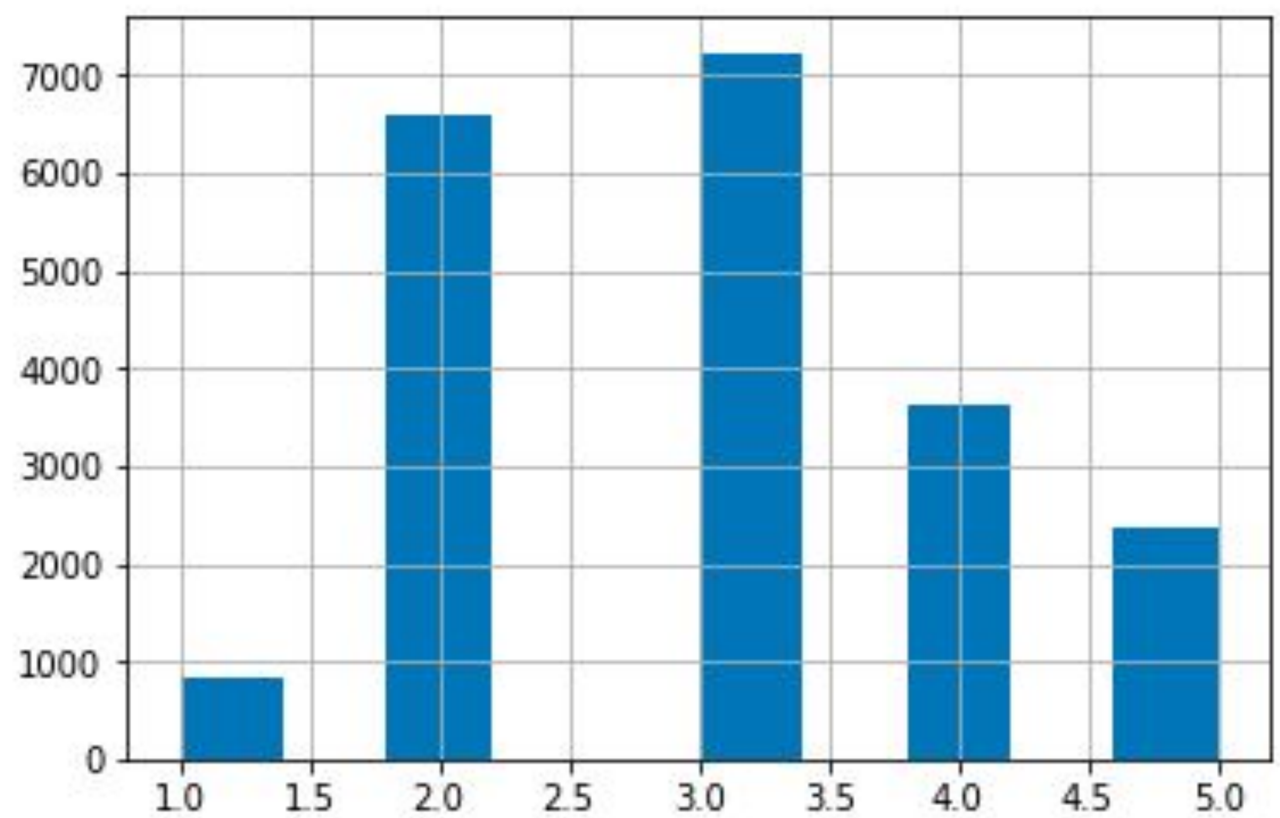
Each stratum is large enough

Not too many strata

Create a Test Set

Limit the Categories in Median Income

```
>>> housing["income_cat"].hist()
```



Create a Test Set

Stratified Sampling - Sklearn StratifiedShuffleSplit Class

- Now we are ready to do stratified sampling
- Use Scikit-learn's **StratifiedShuffleSplit** class

Create a Test Set

Stratified Sampling - Sklearn StratifiedShuffleSplit Class

```
>>> from sklearn.model_selection import StratifiedShuffleSplit
>>> split = StratifiedShuffleSplit(n_splits=1, test_size=0.2,
random_state=42)
>>> for train_index, test_index in split.split(housing, housing["income_cat"]):
        strat_train_set = housing.loc[train_index]
        strat_test_set = housing.loc[test_index]
```

Run it in notebook

Create a Test Set

Did Stratified Sampling work as expected?

Create a Test Set

Did Stratified Sampling Work - Stratified Sampling vs Full dataset

```
>>>
strat_test_set["income_cat"].value_counts() / len(strat_test_set)
```

```
3.0     0.350533
2.0     0.318798
4.0     0.176357
5.0     0.114583
1.0     0.039729
Name: income_cat, dtype: float64
```

Income category proportion in test set generated with stratified sampling

```
>>>
housing["income_cat"].value_counts() / len(housing)
```

```
3.0     0.350581
2.0     0.318847
4.0     0.176308
5.0     0.114438
1.0     0.039826
Name: income_cat, dtype: float64
```

Income category proportion in full dataset

Create a Test Set

Did Stratified Sampling Work?

Yes, it worked.

Income category proportions are almost identical between stratified sampling and full dataset

Let’s compare Stratified Sampling and Random Sampling

Create a Test Set

Compare Stratified Sampling and Random Sampling

```
>>> def income_cat_proportions(data):
     return data["income_cat"].value_counts() / len(data)

>>> train_set, test_set = train_test_split(housing, test_size=0.2,
random_state=42)
>>> compare_props = pd.DataFrame({
        "Overall": income_cat_proportions(housing),
        "Stratified": income_cat_proportions(strat_test_set),
        "Random": income_cat_proportions(test_set),
     }).sort_index()
>>> compare_props["Rand. %error"] = 100 * compare_props["Random"] /
>>> compare_props["Overall"] - 100
>>> compare_props["Strat. %error"] = 100 * compare_props["Stratified"]
/ compare_props["Overall"] - 100
```

Create a Test Set

Compare Stratified Sampling and Random Sampling

	Overall	Random	Stratified	Rand. %error	Strat. %error
1.0	0.039826	0.040213	0.039729	0.973236	-0.243309
2.0	0.318847	0.324370	0.318798	1.732260	-0.015195
3.0	0.350581	0.358527	0.350533	2.266446	-0.013820
4.0	0.176308	0.167393	0.176357	-5.056334	0.027480
5.0	0.114438	0.109496	0.114583	-4.318374	0.127011

Sampling bias comparison of stratified versus purely random sampling

Compare Stratified Sampling and Random Sampling

Observations?

	Overall	Random	Stratified	Rand. %error	Strat. %error
1.0	0.039826	0.040213	0.039729	0.973236	-0.243309
2.0	0.318847	0.324370	0.318798	1.732260	-0.015195
3.0	0.350581	0.358527	0.350533	2.266446	-0.013820
4.0	0.176308	0.167393	0.176357	-5.056334	0.027480
5.0	0.114438	0.109496	0.114583	-4.318374	0.127011

Sampling bias comparison of stratified versus purely random sampling

Create a Test Set

Compare Stratified Sampling and Random Sampling

- Test set generated using stratified sampling has income category proportion almost identical to those in full data set

	Overall	Random	Stratified	Rand. %error	Strat. %error
1.0	0.039826	0.040213	0.039729	0.973236	-0.243309
2.0	0.318847	0.324370	0.318798	1.732260	-0.015195
3.0	0.350581	0.358527	0.350533	2.266446	-0.013820
4.0	0.176308	0.167393	0.176357	-5.056334	0.027480
5.0	0.114438	0.109496	0.114583	-4.318374	0.127011

Almost identical to full dataset

Income Category Proportions in Stratified Sampling

Create a Test Set

Compare Stratified Sampling and Random Sampling

- Test set generated using stratified sampling has income category proportion is quite skewed

	Overall	Random	Stratified	Rand. %error	Strat. %error
1.0	0.039826	0.040213	0.039729	0.973236	-0.243309
2.0	0.318847	0.324370	0.318798	1.732260	-0.015195
3.0	0.350581	0.358527	0.350533	2.266446	-0.013820
4.0	0.176308	0.167393	0.176357	-5.056334	0.027480
5.0	0.114438	0.109496	0.114583	-4.318374	0.127011

Quite skewed

Income Category Proportions in Purely Random Sampling

Create a Test Set

Compare Stratified Sampling and Random Sampling

Conclusion?

Create a Test Set

Compare Stratified Sampling and Random Sampling

Stratified Sampling gives better test set than Random Sampling

Create a Test Set

- Remove income_cat attribute so that data is back to its original state

```
>>> for set in (strat_train_set, strat_test_set):
        set.drop(["income_cat"], axis=1, inplace=True)
```

Run in Notebook

Why did we spend so much time in test set generation?

Create a Test Set

- Test set generation is often neglected
- But most important part of a Machine Learning project

Checklist for Machine Learning Projects

1. Frame the problem and look at the big picture
2. Get the data
3. **Explore the data to gain insights**
4. Prepare the data for Machine Learning algorithms
5. Explore many different models and short-list the best ones
6. Fine-tune model
7. Present the solution
8. Launch, monitor, and maintain the system

Discover and Visualize the Data

- Let’s understand the data in depth
- Make sure
    - Test set is kept aside
    - And explore only training set

Discover and Visualize the Data

- If training set is large
  - Sample training set
  - To make manipulations easy and fast
- Since our training set is small
  - We can directly work on full set

Discover and Visualize the Data

- Create copy of training set first
- So that we can play with it without harming the training set

```
>>> housing = strat_train_set.copy()
```

Run it on Notebook

Discover and Visualize the Data

Visualizing Geographical Data

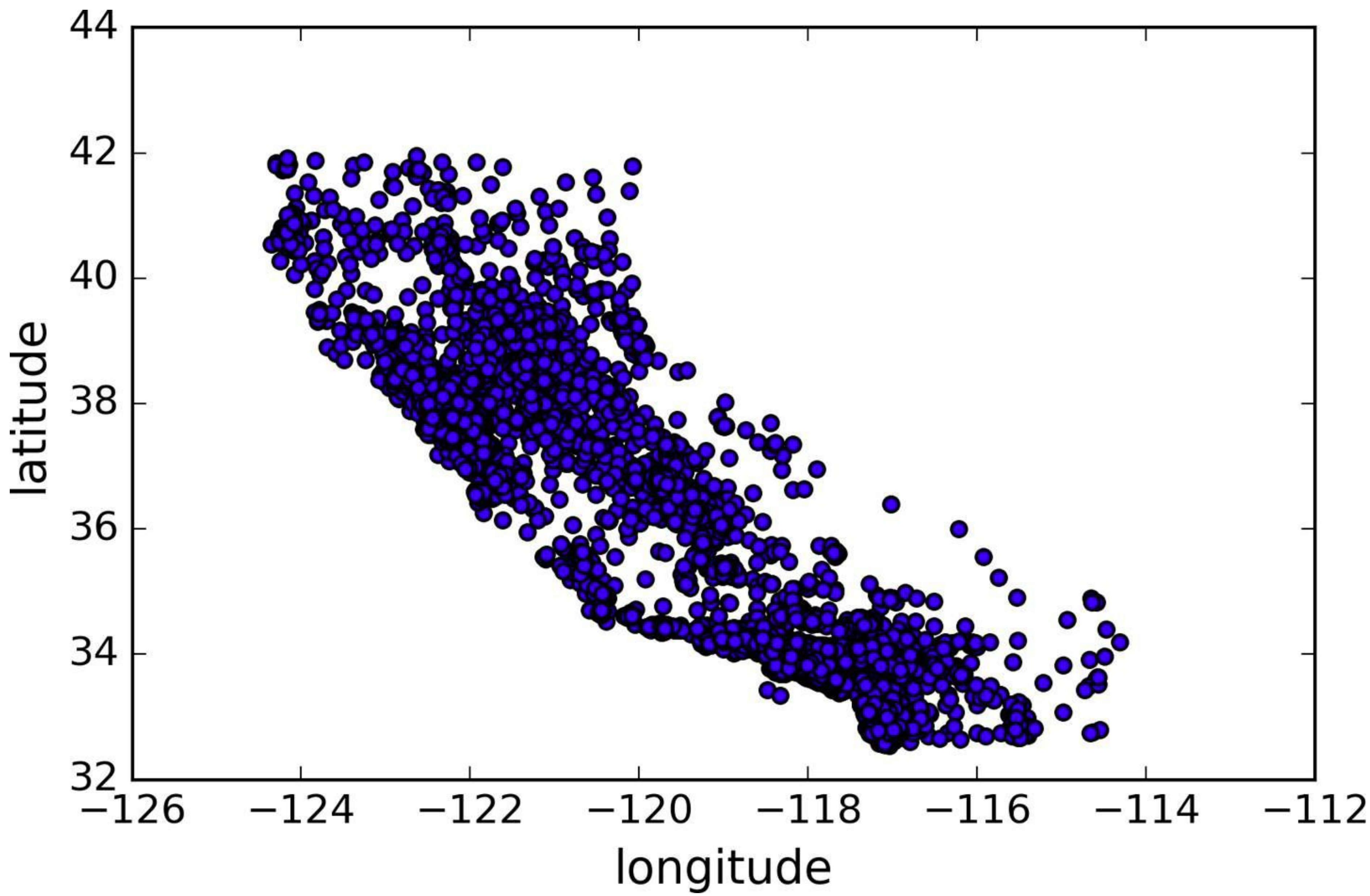
- Since there is geographical information of latitude and longitude
- Create Scatterplot of all district to visualize the data

```
>>> housing.plot(kind="scatter", x="longitude",
y="latitude")
```

Run it on Notebook

Discover and Visualize the Data

Visualizing Geographical Data



Discover and Visualize the Data

Problem?

- Hard to see any particular pattern
- We can not visualize the places with high density points

Discover and Visualize the Data

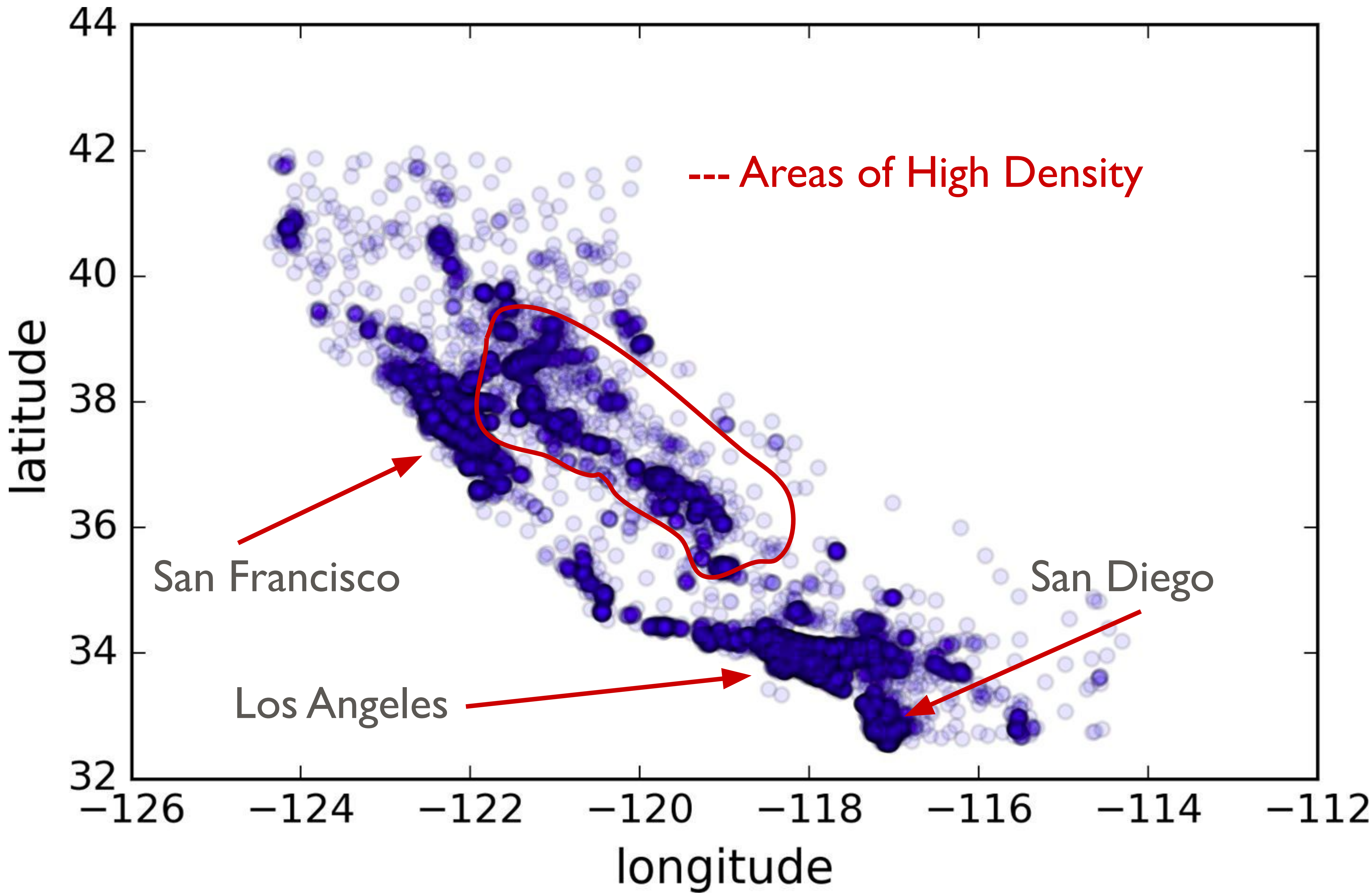
Solution

- Setting the alpha option to 0.1
- Makes it look like heat map

```
>>> housing.plot(kind="scatter", x="longitude",
y="latitude", alpha=0.1)
```

Run it on Notebook

Discover and Visualize the Data



Discover and Visualize the Data

Let's look into the patterns in depth

```
>>> housing.plot(kind="scatter", x="longitude",
y="latitude", alpha=0.4,
    s=housing["population"]/100, label="population",
figsize=(10,7),
    c="median_house_value", cmap=plt.get_cmap("jet"),
colorbar=True,
    sharex=False)
>>> plt.legend()
```

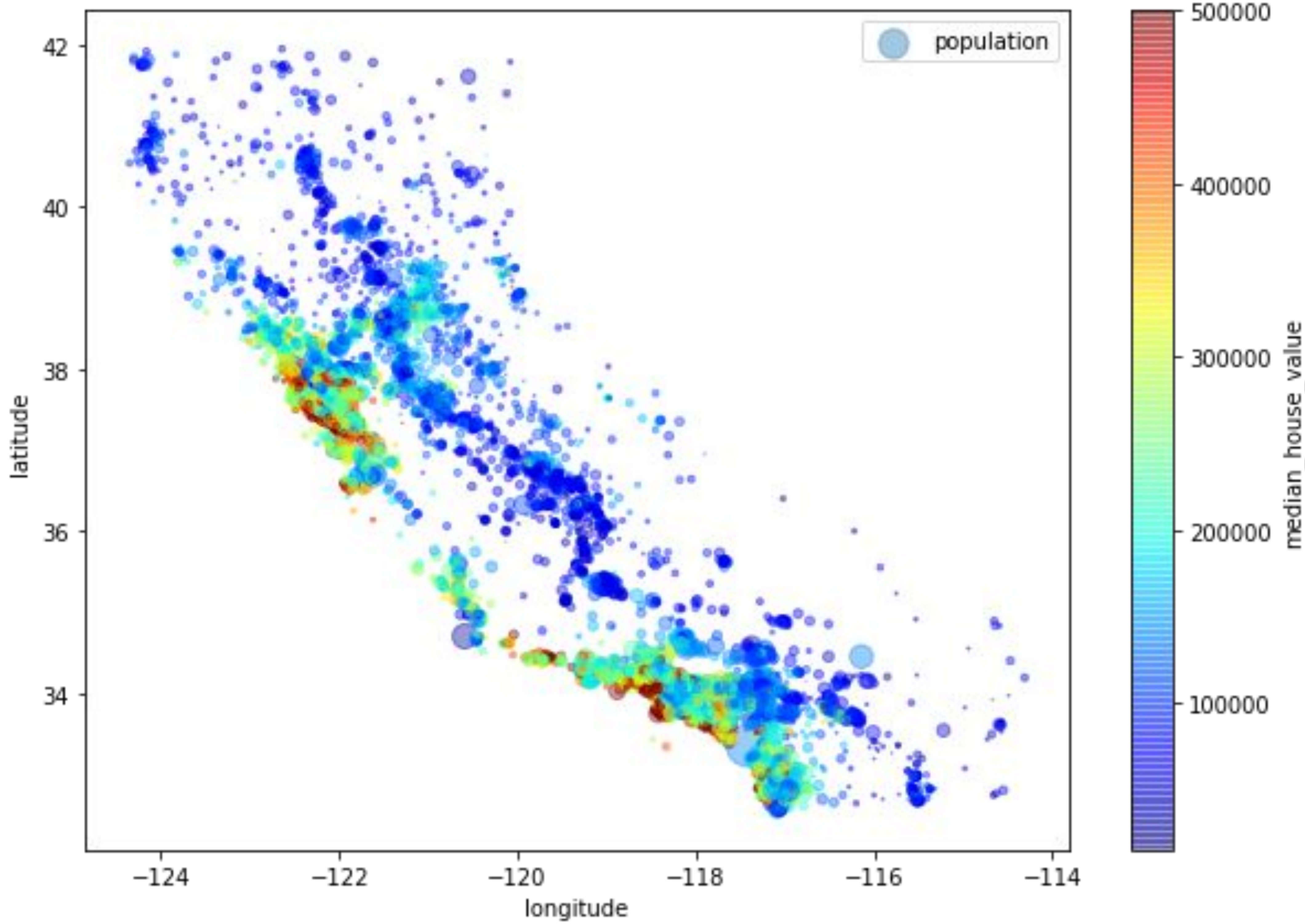
Run it on Notebook

Discover and Visualize the Data

Let's look into the patterns in depth

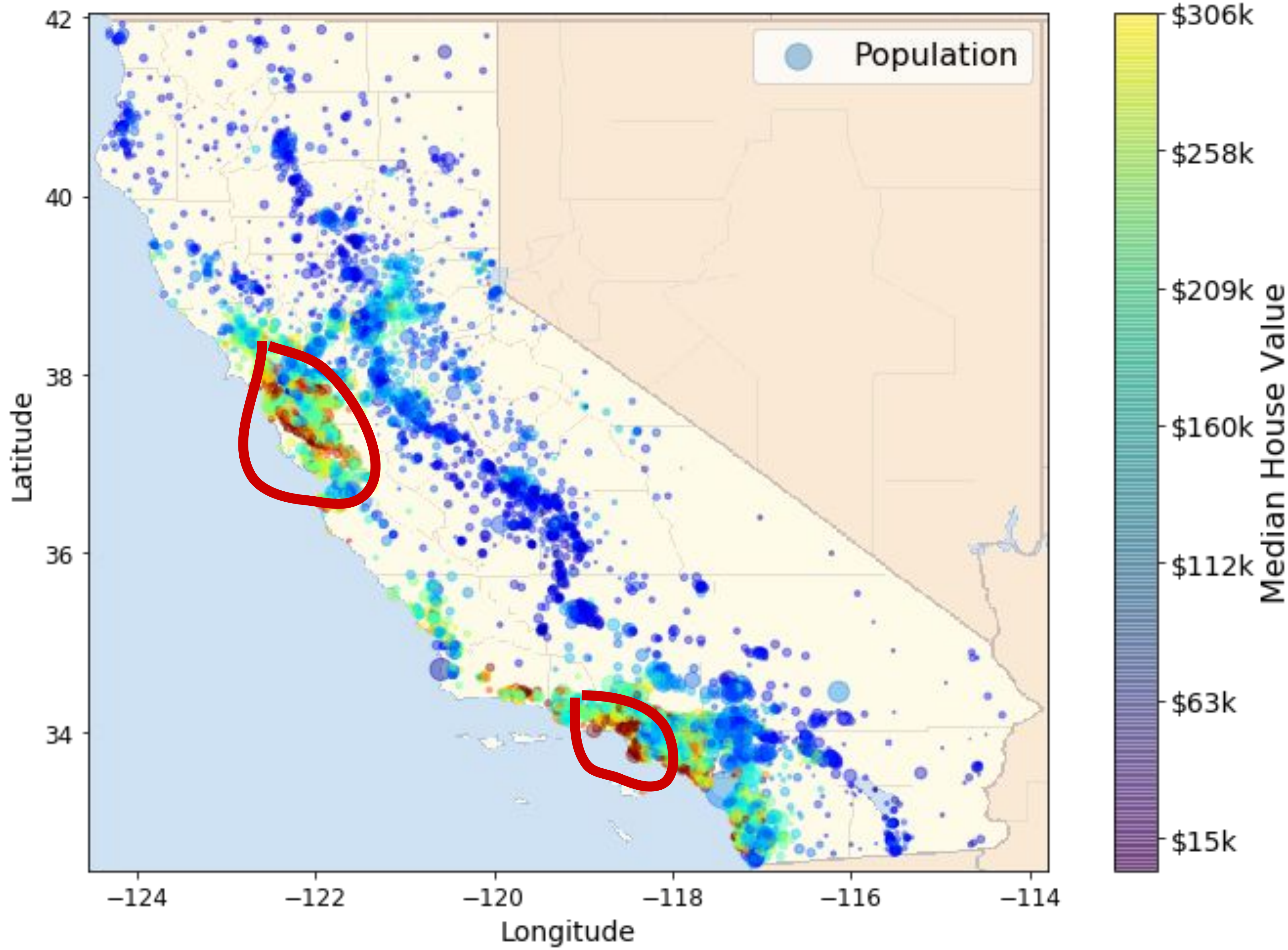
- The radius of each circle represents the district's population (**option s**)
- The color represents the price (**option c**).
- We are using a predefined color map (**option cmap**)
  - Called **jet**
  - Which ranges from **blue** (low values)
  - To **red** (high prices)

Discover and Visualize the Data



Observations?

Discover and Visualize the Data



Discover and Visualize the Data

Observations

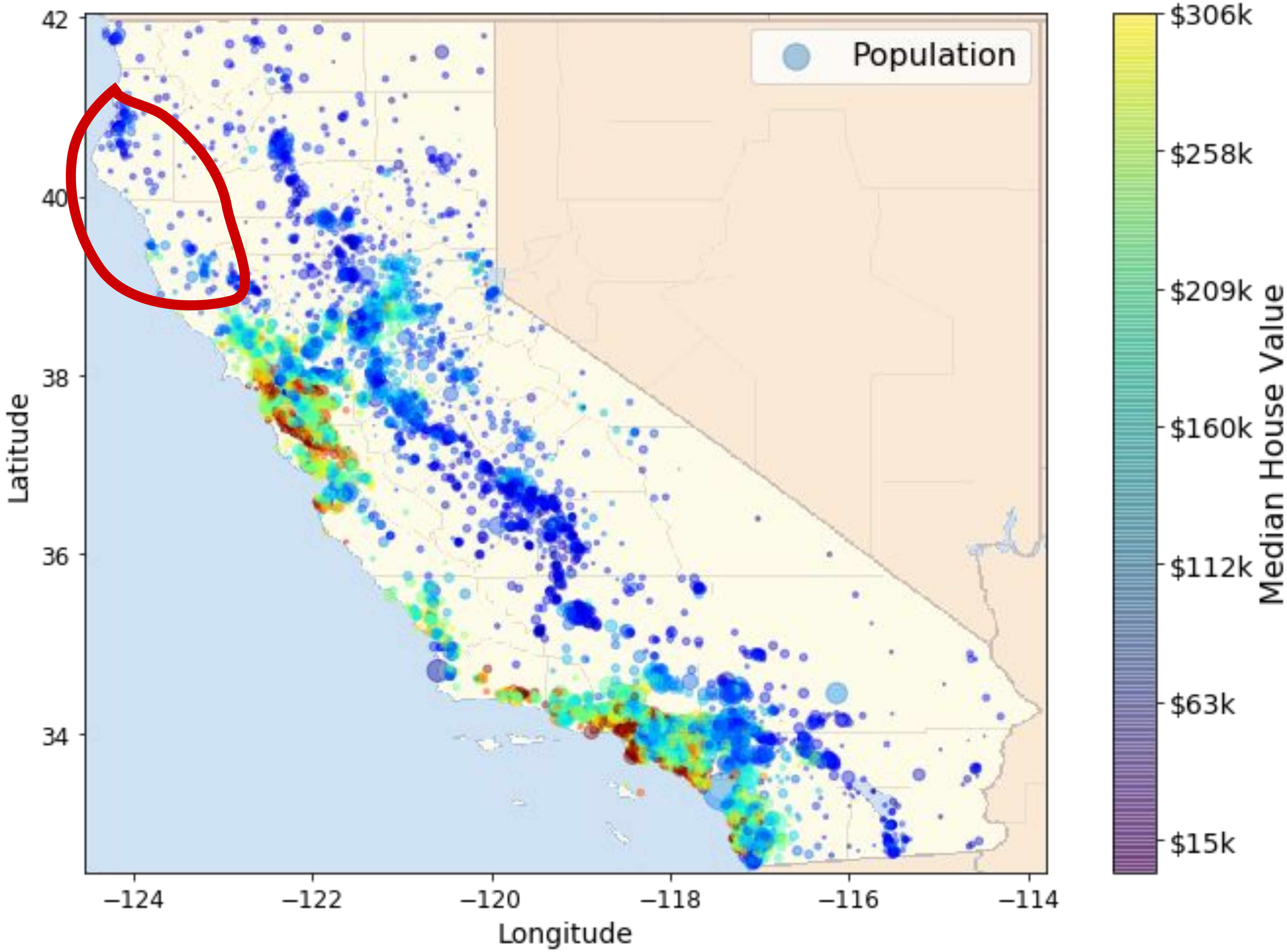
- House prices are high
  - In the high density area
  - Closer to ocean

Discover and Visualize the Data

Observations

- Now look at this

Discover and Visualize the Data



Observations

- In Northern California the housing prices in coastal districts are not too high
- So it is not a simple rule

Discover and Visualize the Data

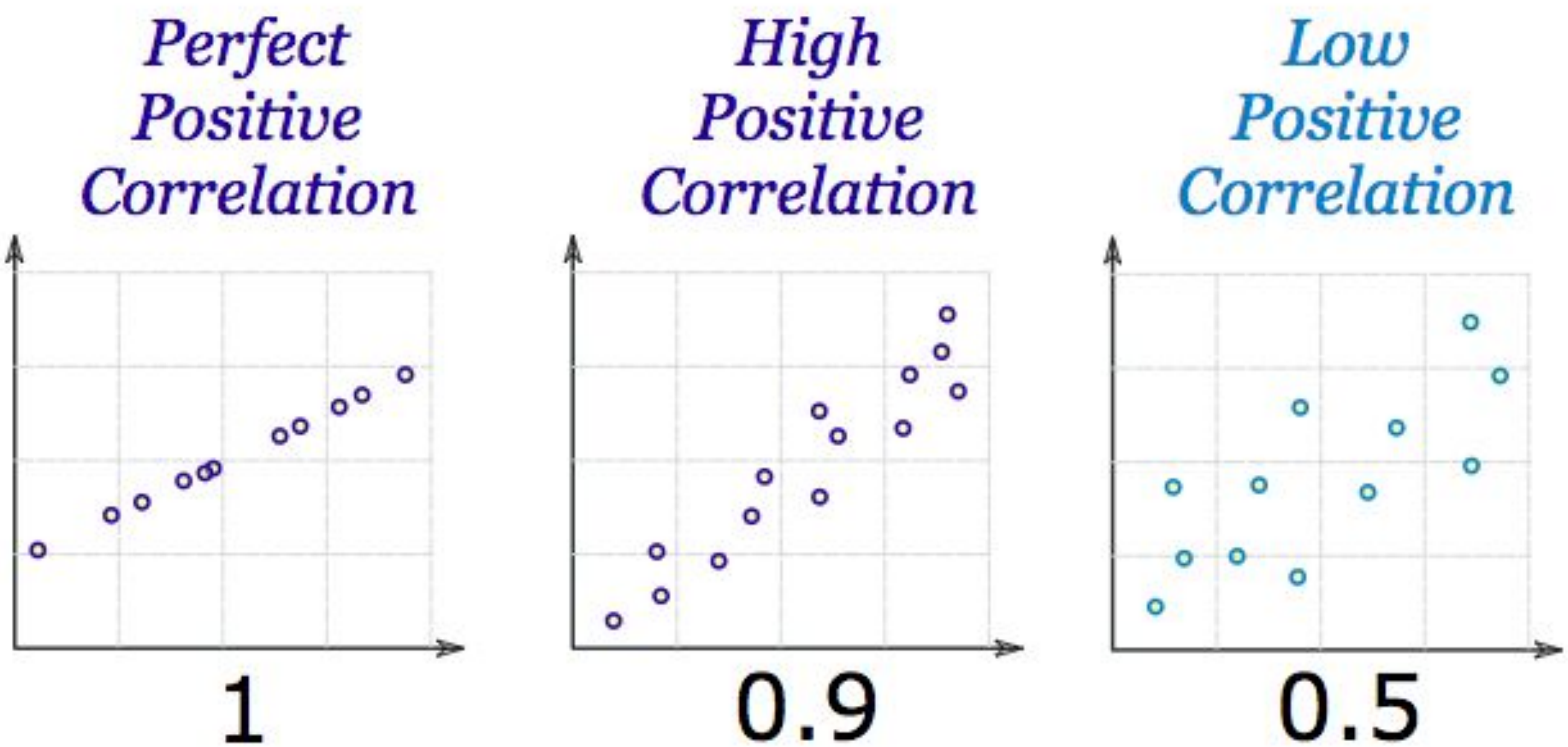
Looking for Correlations

- Correlation indicates
    - The extent to which two or more variables fluctuate together

Discover and Visualize the Data

Positive Correlation

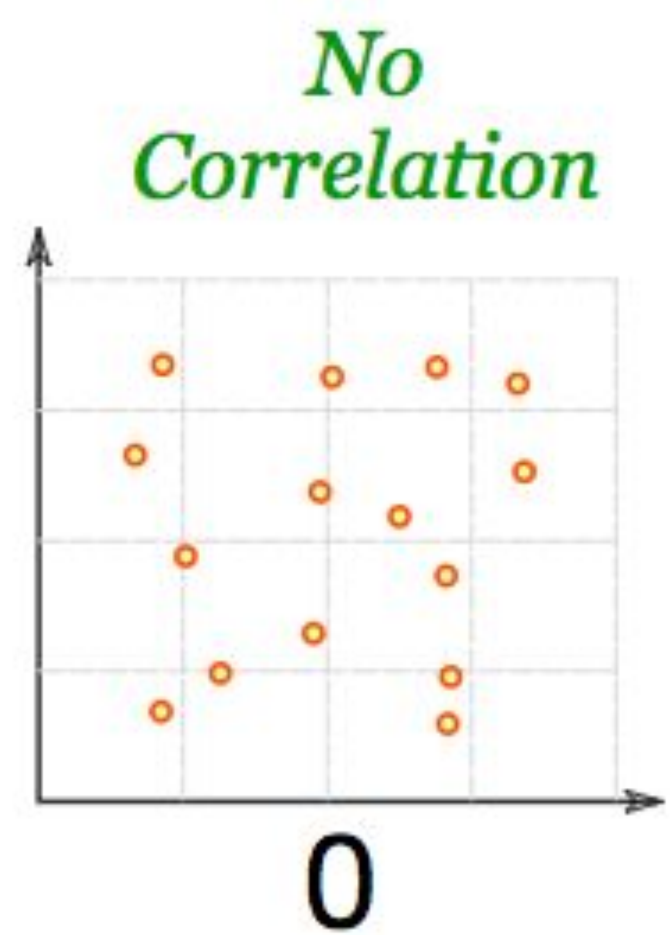
When the values increase together



Discover and Visualize the Data

No Correlation

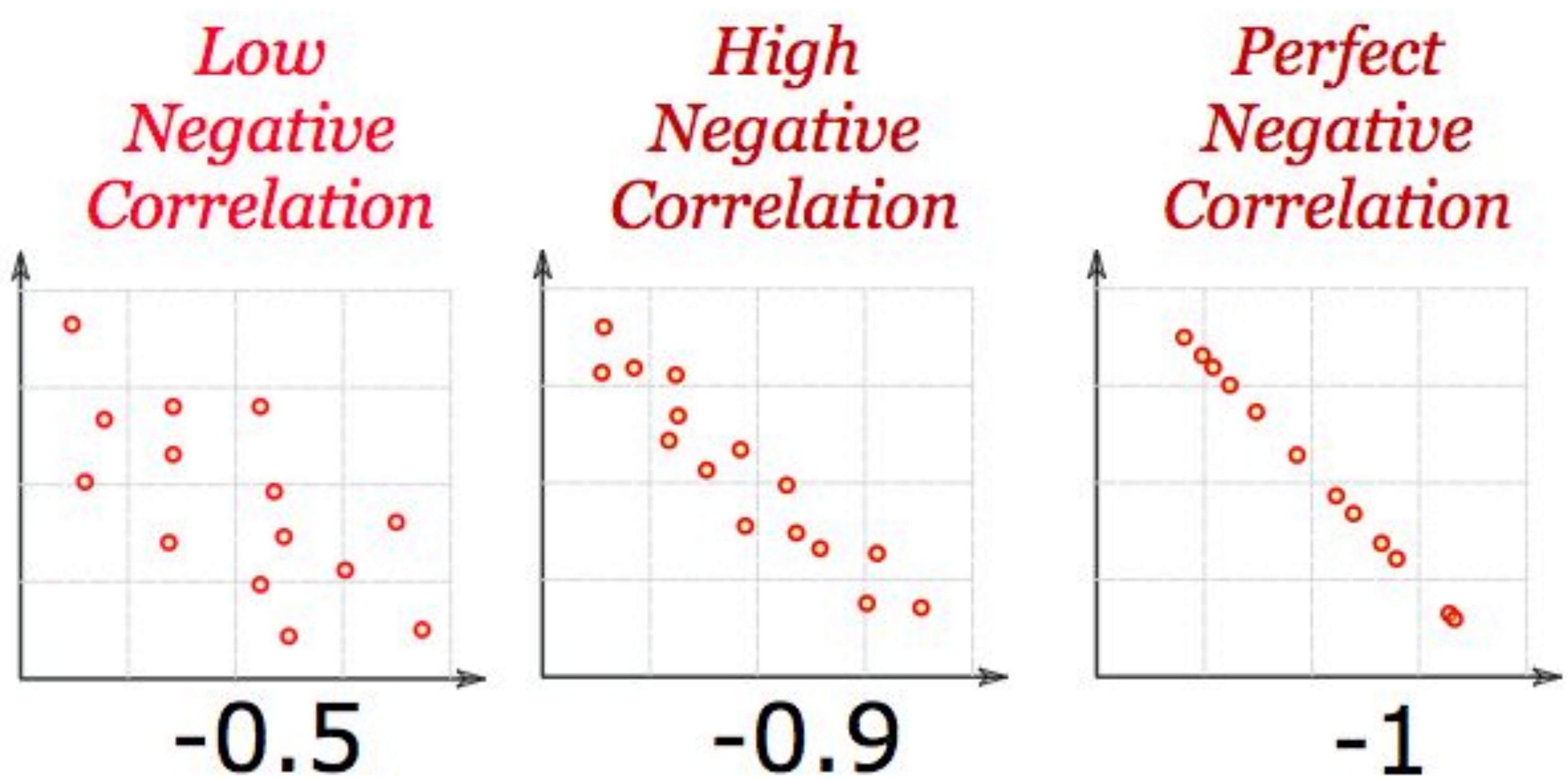
When values are not linked at all



Discover and Visualize the Data

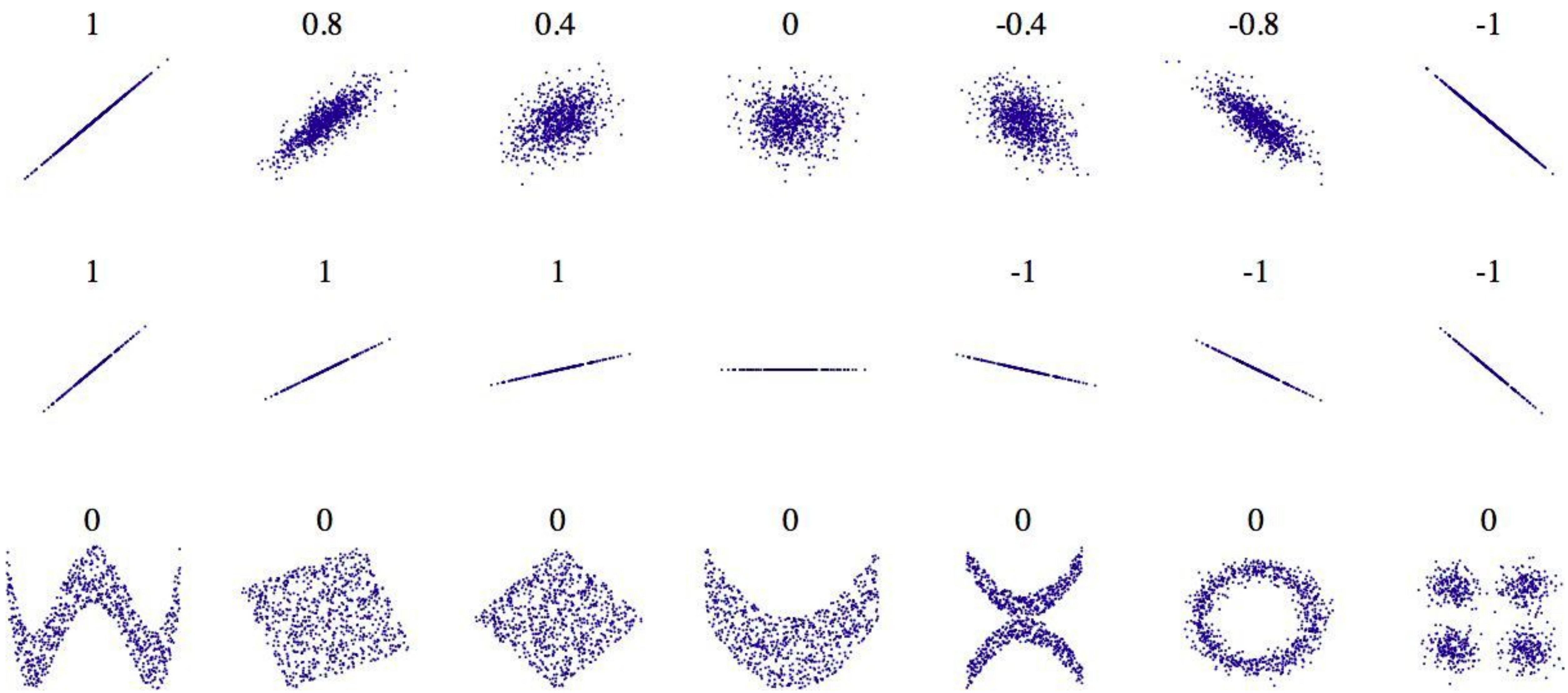
Negative Correlation

When one value decreases as the other increases



Discover and Visualize the Data

Standard Correlation Coefficient of Various Datasets



Discover and Visualize the Data

Looking for Correlations

- Since the dataset is not too large
- We can compute the correlations
- Between every pair of attributes
- Using `corr()` method

Discover and Visualize the Data

Correlations with the Median House Value

```
>>> corr_matrix = housing.corr()
>>>
corr_matrix["median_house_value"].sort_values(ascending=
False)
```

Run it in Notebook

Discover and Visualize the Data

Correlations with the Median House Value

```
median_house_value    1.000000
median_income         0.687160
total_rooms           0.135097
housing_median_age    0.114110
households            0.064506
total_bedrooms        0.047689
population           -0.026920
longitude            -0.047432
latitude             -0.142724
Name: median_house_value, dtype: float64
```

Positive Correlation

Median house value tends to go up when the median income goes up

Discover and Visualize the Data

Correlations with the Median House Value

```
median_house_value    1.000000
median_income         0.687160
total_rooms           0.135097
housing_median_age    0.114110
households            0.064506
total_bedrooms        0.047689
population           -0.026920
longitude            -0.047432
latitude             -0.142724
Name: median_house_value, dtype: float64
```

Negative Correlation

Between the latitude and the median house value

Prices have a slight tendency to go down when you go north

Discover and Visualize the Data

Looking for Correlations - scatter_matrix

- We can also look for correlations
    - Using Pandas' `scatter_matrix` function
    - Plots every numerical attribute against every other numerical attribute

Discover and Visualize the Data

Looking for Correlations - scatter_matrix

- Let's look for correlation using **scatter_matrix**
  - We have eleven numerical attributes
  - We'll get eleven by eleven plots (will not fit in page)

Discover and Visualize the Data

Looking for Correlations - scatter_matrix

Focus on attributes most correlated

- median_house_value (target)
- median_income
- total_rooms
- Housing_median_age

- Note: *On same x & y, Pandas decides it can give you more useful information, and plots the density plot of just that column of data.*

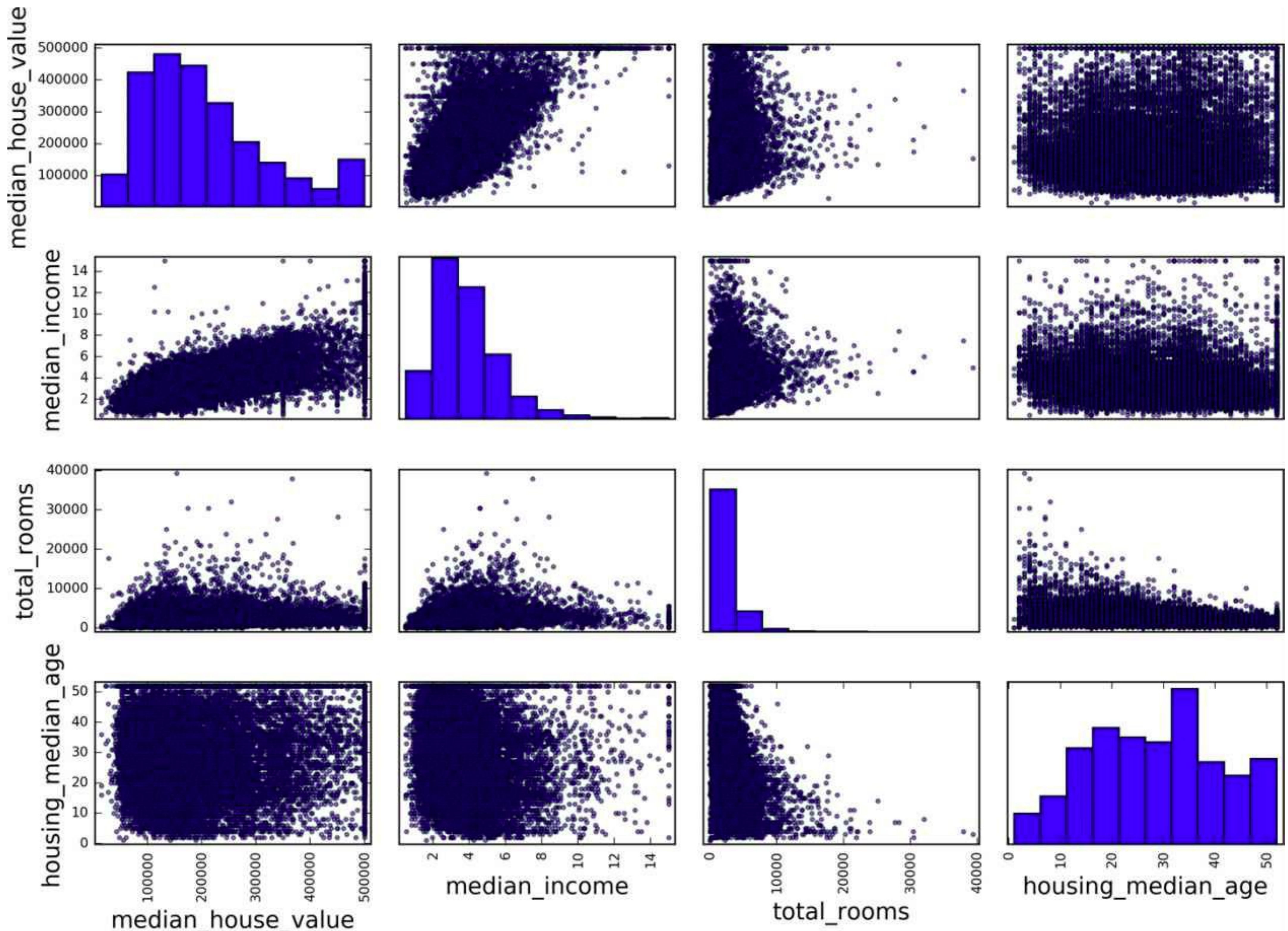
Discover and Visualize the Data

Looking for Correlations - scatter_matrix

```
>>> from pandas.tools.plotting import scatter_matrix
>>> attributes = ["median_house_value", "median_income",
"total_rooms", "housing_median_age"]
>>> scatter_matrix(housing[attributes], figsize=(12, 8))
```

Run it in Notebook

Discover and Visualize the Data

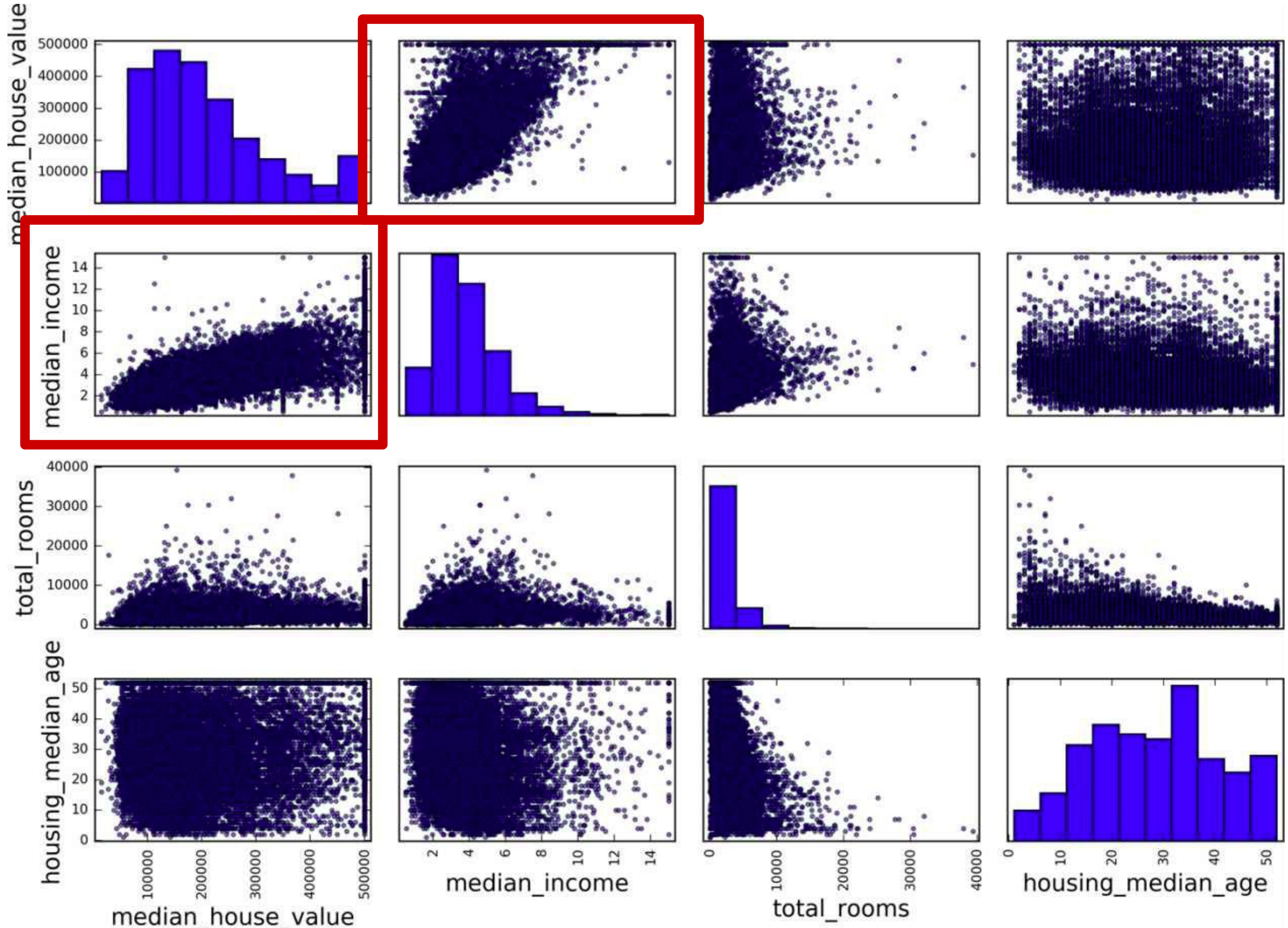


Discover and Visualize the Data

Looking for Correlations - Most promising Attribute - Question

Which is the most promising attribute to predict median house value from the correlation plot?

Discover and Visualize the Data



Looking for Correlations - Most promising Attribute - Answer

Median income

Discover and Visualize the Data

Looking for Correlations - Most promising Attribute

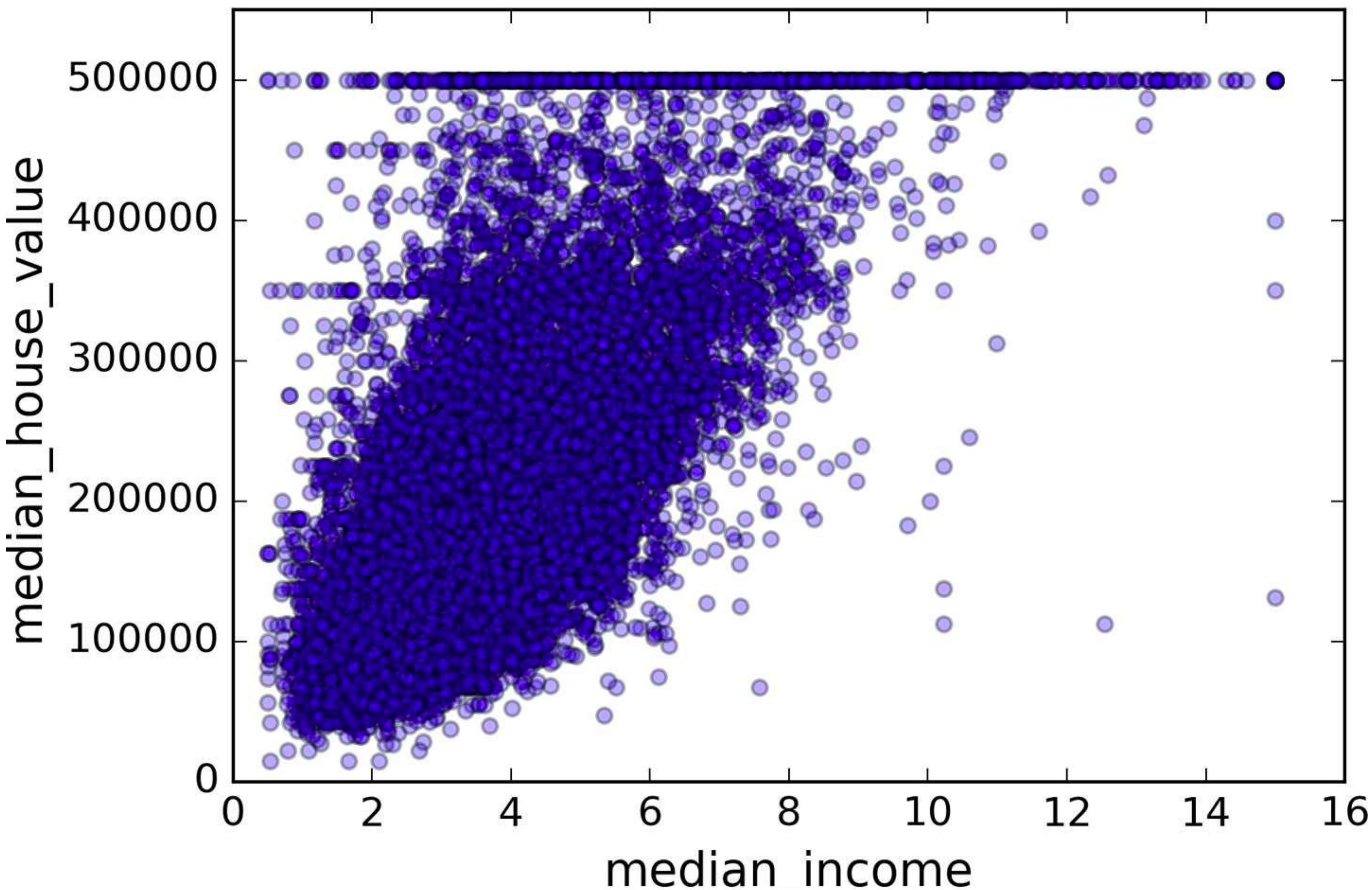
- Let's zoom in to see correlation between median house value and median income

```
>>> housing.plot(kind="scatter", x="median_income",
y="median_house_value", alpha=0.1)
>>> plt.axis([0, 16, 0, 550000])
```

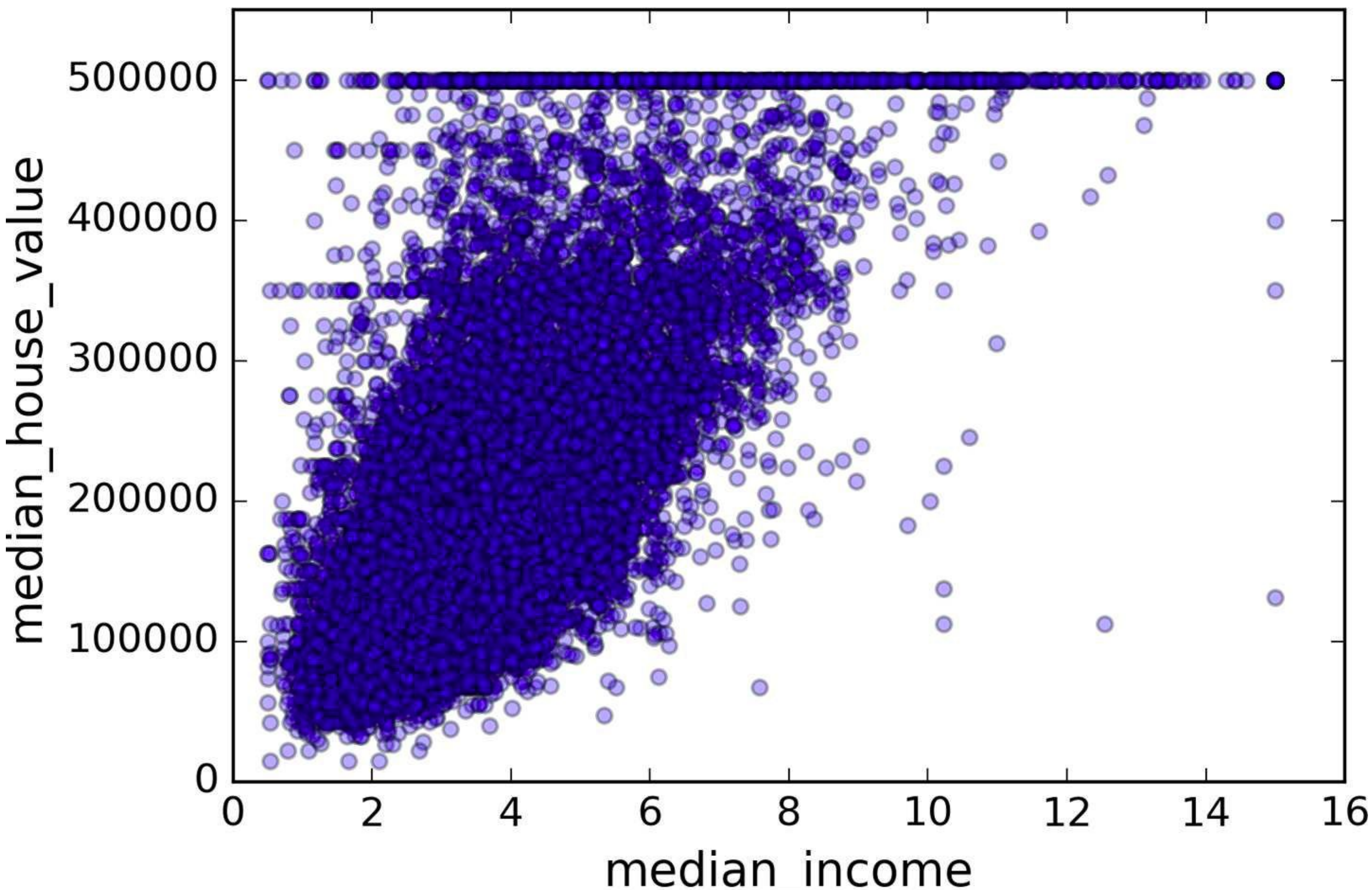
Run it in Notebook

Discover and Visualize the Data

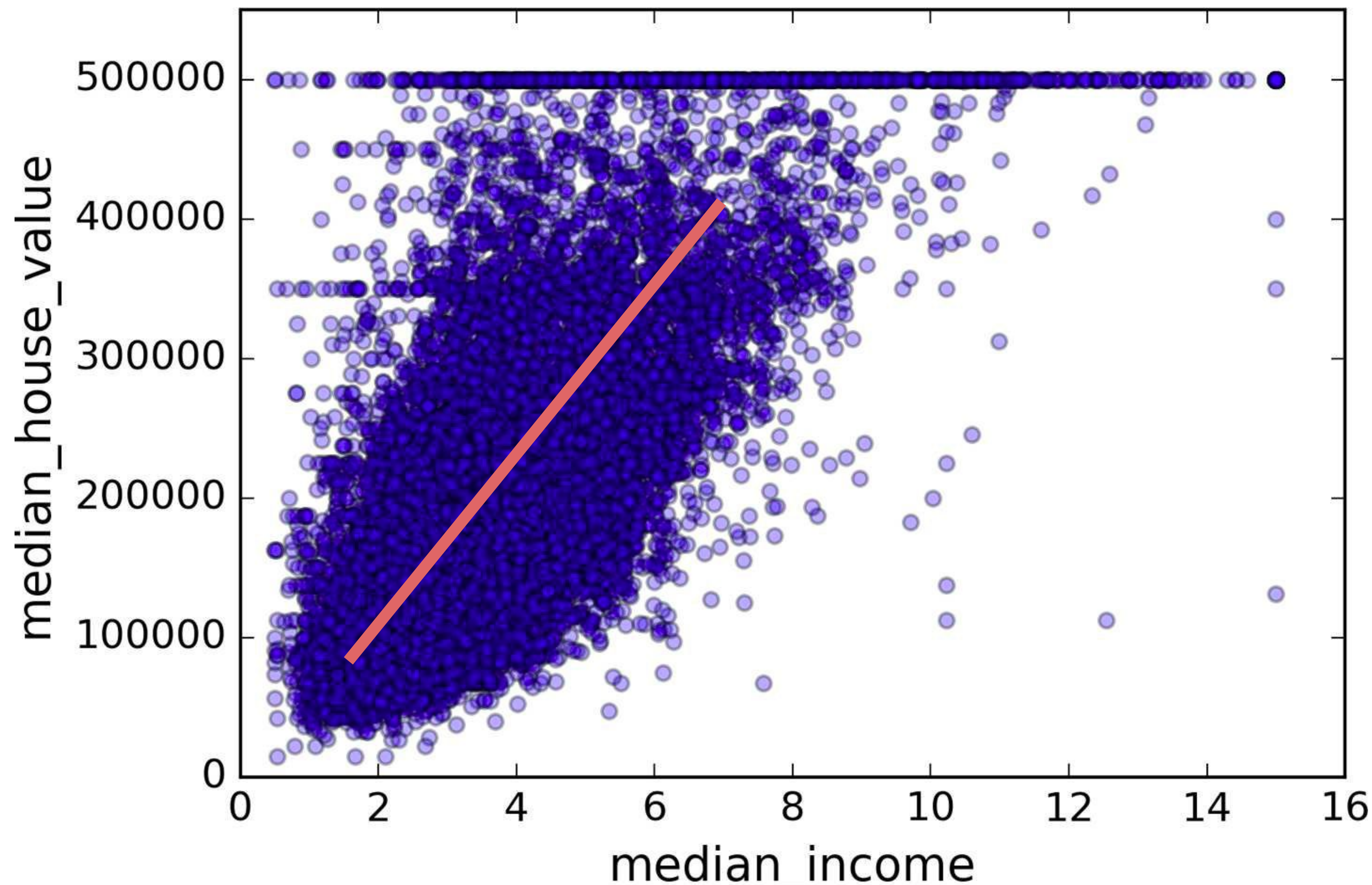
Looking for Correlations - Median House Value and Median Income



Observations??

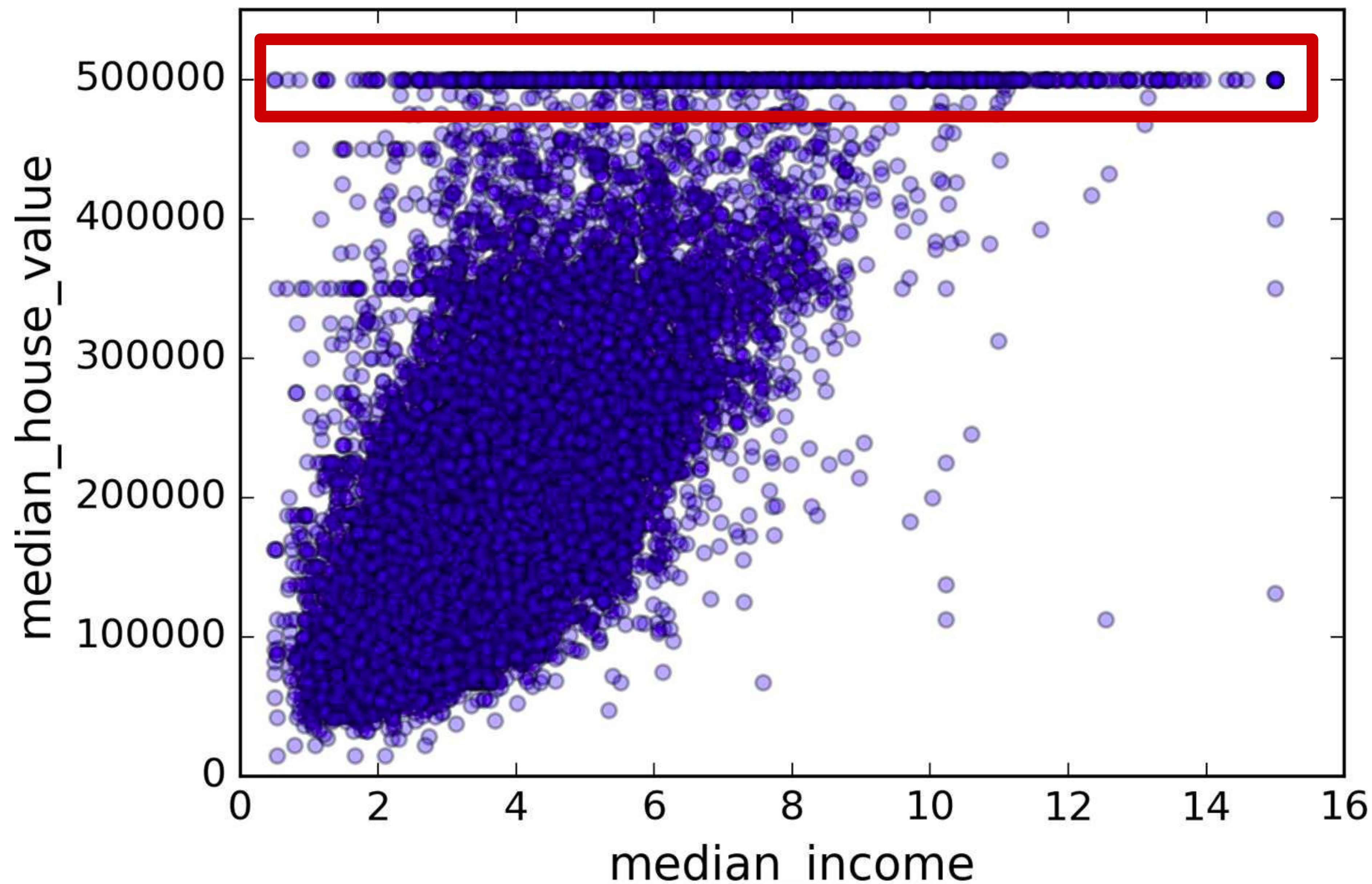


Discover and Visualize the Data



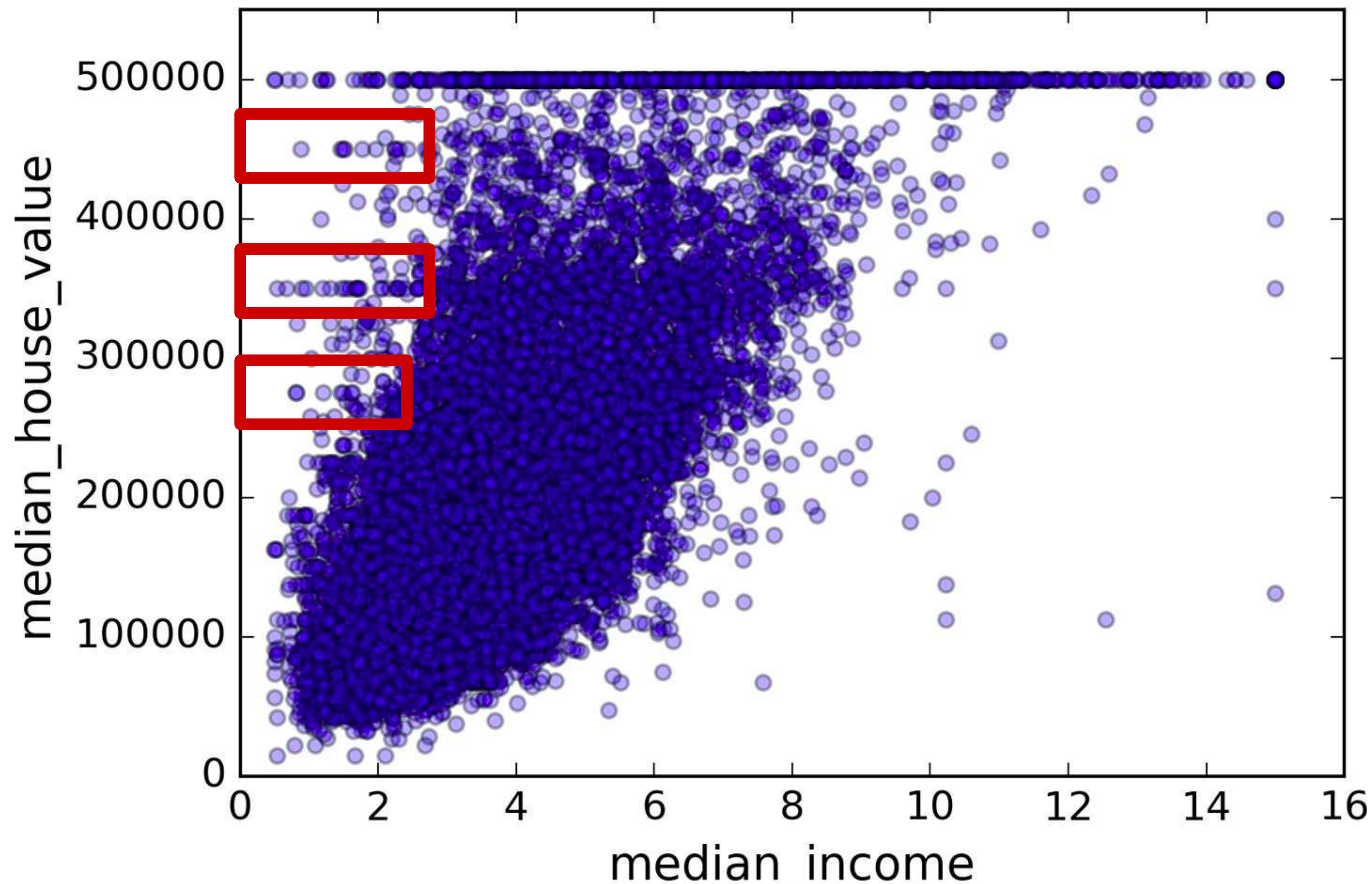
1. Correlation is very strong

Discover and Visualize the Data



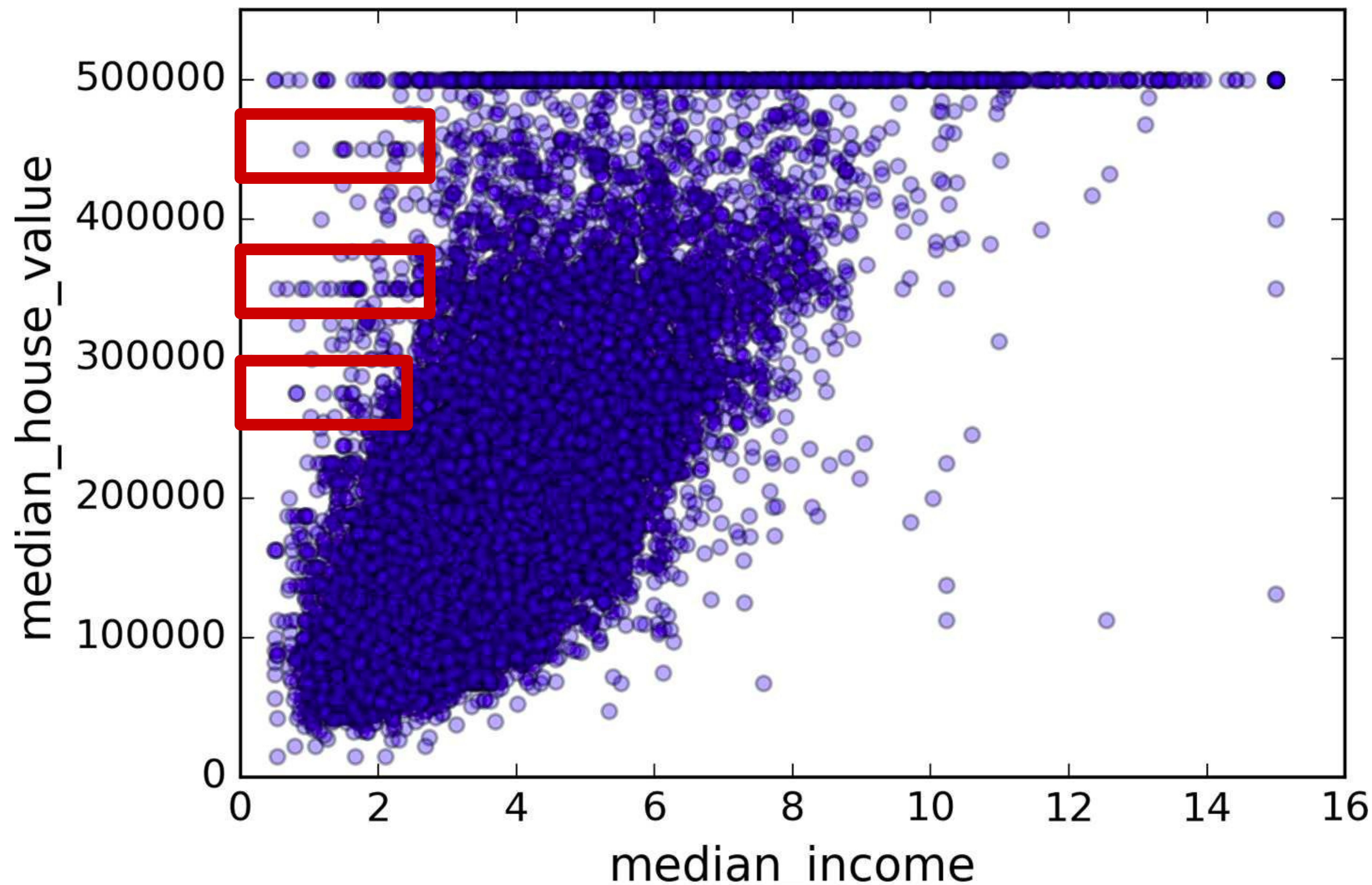
2. Price cap at $500, 000

Discover and Visualize the Data



3. Horizontal lines at $450, 000 & $350, 000 & $280,000

Discover and Visualize the Data



We should remove corresponding districts to prevent algorithm from learning to reproduce these data quirks

Discover and Visualize the Data

Experimenting with Attribute Combinations

- Till now we have covered
  - Ways to explore data
  - And Gain insights
- We've identified
  - Few data quirks - To be cleaned up before feeding the data to ML algorithm
  - Some attributes have a tail-heavy distribution

Discover and Visualize the Data

Experimenting with Attribute Combinations

- Our mileage will vary with each project
- But the general ideas are similar

Discover and Visualize the Data

Experimenting with Attribute Combinations

- Our mileage will vary with each project
- But the general ideas are similar
- We may want to try out various attribute combinations
    - Before preparing data for Machine Learning algorithms

Discover and Visualize the Data

Experimenting with Attribute Combinations - Examples

- The **total number of rooms** is not very useful
    - If we don't know how many households there are
    - What about **number of rooms per household**

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY

Discover and Visualize the Data

Experimenting with Attribute Combinations - Examples

- The **total number of bedrooms** is not very useful
- We want to compare it to
- **Number of bedrooms per room**

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY

Discover and Visualize the Data

Experimenting with Attribute Combinations - Examples

- **Population per household** also seems an interesting attribute combination
    - Number of people per household

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY

Discover and Visualize the Data

Experimenting with Attribute Combinations - Examples

- Let's create the new attributes

```
>>> housing["rooms_per_household"] =
housing["total_rooms"]/housing["households"]
>>> housing["bedrooms_per_room"] =
housing["total_bedrooms"]/housing["total_rooms"]
>>>
housing["population_per_household"]=housing["population"
]/housing["households"]
```

Run it in Notebook

Discover and Visualize the Data

Experimenting with Attribute Combinations - Examples

- Let's create correlation matrix again

```
>>> corr_matrix = housing.corr()
>>>
corr_matrix["median_house_value"].sort_values(ascending=
False)
```

Run it in Notebook

Discover and Visualize the Data

Experimenting with Attribute Combinations - Examples

```
median_house_value          1.000000
median_income               0.687160
rooms_per_household         0.146285
total_rooms                 0.135097
housing_median_age          0.114110
households                  0.064506
total_bedrooms              0.047689
population_per_household   -0.021985
population                 -0.026920
longitude                  -0.047432
latitude                   -0.142724
bedrooms_per_room          -0.259984
Name: median_house_value, dtype: float64
```

Discover and Visualize the Data

Experimenting with Attribute Combinations - Examples

```
median_house_value          1.000000
median_income               0.687160
rooms_per_household         0.146285
total_rooms                 0.135097
housing_median_age          0.114110
households                  0.064506
total_bedrooms              0.047689
population_per_household   -0.021985
population                 -0.026920
longitude                  -0.047432
latitude                   -0.142724
bedrooms_per_room          -0.259984
Name: median_house_value, dtype: float64
```

Checklist for Machine Learning Projects

1. Frame the problem and look at the big picture
2. Get the data
3. Explore the data to gain insights
4. **Prepare the data for Machine Learning algorithms**
5. Explore many different models and short-list the best ones
6. Fine-tune model
7. Present the solution
8. Launch, monitor, and maintain the system

Let’s prepare data for Machine Learning algorithms

Prepare the Data for ML Algorithms

Automate the Process - Why?

- Write functions than manually doing it
  - Allows to reproduce these transformations easily on any dataset
  - Gradually build a library that you can reuse in future projects
  - Use these in your live system on new data
  - Easily try various transformations

Prepare the Data for ML Algorithms

Automate the Process

- Let's revert to a clean training set
  - Copy strat_train_set
  - Drop the target value from training set

Prepare the Data for ML Algorithms

Automate the Process

```
>>> housing = strat_train_set.drop("median_house_value",
axis=1)
>>> housing_labels =
strat_train_set["median_house_value"].copy()
```

Note- drop() creates a copy of the data and does not affect strat_train_set

Run it in Notebook

Data Cleaning

Prepare the Data for ML Algorithms

Data Cleaning

- ML algorithms can not work with missing features
- Create functions to take care of missing features

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values

- Already noticed that "total_bedrooms" has missing values

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
longitude             20640 non-null float64
latitude              20640 non-null float64
housing_median_age    20640 non-null float64
total_rooms           20640 non-null float64
total_bedrooms        20433 non-null float64
population            20640 non-null float64
households            20640 non-null float64
median_income         20640 non-null float64
median_house_value    20640 non-null float64
ocean_proximity       20640 non-null object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

20640 - 20433 =
207 missing values

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values - How to Fix?

- Three options to fix this
    - Get rid of corresponding districts where total_bedroom has missing values
    - Get rid of the whole attribute
    - Set the values to some value (zero, the mean, the median, etc.)

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values - DataFrame's methods

- We can fix missing values using DataFrame's methods
  - dropna()
  - drop()
  - fillna()

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values - Sample Dataset

- Let's experiment with these methods on sample dataset

```
>>> sample_incomplete_rows =
housing[housing.isnull().any(axis=1)].head()
```

Run it in Notebook

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values - Option One

- `dropna()` - drops the missing values

```
>>> sample_incomplete_rows.dropna(subset=["total_bedrooms"])
```

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values - Option Two

- `drop()` - drops the attribute

```
>>> sample_incomplete_rows.drop(subset=["total_bedrooms"])
```

	longitude	latitude	housing_median_age	total_rooms	population	households	median_income	ocean_proximity
4629	-118.30	34.07	18.0	3759.0	3296.0	1462.0	2.2708	<1H OCEAN
6068	-117.86	34.01	16.0	4632.0	3038.0	727.0	5.1762	<1H OCEAN
17923	-121.97	37.35	30.0	1955.0	999.0	386.0	4.6328	<1H OCEAN
13656	-117.30	34.05	6.0	2155.0	1039.0	391.0	1.6675	INLAND
19252	-122.79	38.48	7.0	6837.0	3468.0	1405.0	3.1662	<1H OCEAN

No total_bedrooms Attribute Now

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values - Option Three

- `fillna()` - sets the missing values
- Let's fill the missing values with the median

```
>>> median = housing["total_bedrooms"].median()
>>>
sample_incomplete_rows["total_bedrooms"].fillna(median,
inplace=True)
>>> sample_incomplete_rows
```

Run it in Notebook

Data Cleaning - Missing Values - Option Three

- `fillna()` - sets the missing values

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity
4629	-118.30	34.07	18.0	3759.0	433.0	3296.0	1462.0	2.2708	<1H OCEAN
6068	-117.86	34.01	16.0	4632.0	433.0	3038.0	727.0	5.1762	<1H OCEAN
17923	-121.97	37.35	30.0	1955.0	433.0	999.0	386.0	4.6328	<1H OCEAN
13656	-117.30	34.05	6.0	2155.0	433.0	1039.0	391.0	1.6675	INLAND
19252	-122.79	38.48	7.0	6837.0	433.0	3468.0	1405.0	3.1662	<1H OCEAN

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values

- In the previous step
  - Save the computed median value
  - Later we need the saved median value in test set
  - While evaluating the system
- Saved median value will also required
  - To replace missing values in the new data once we go live

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values - Scikit-Learn SimpleImputer Class

- Scikit-Learn provides **SimpleImputer** class
  - To take care of missing values
- Create an instance of SimpleImputer class
- Specify each attribute's missing values
  - Should be replaced with the median of that attribute

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values - Scikit-Learn SimpleImputer Class

- Create an instance of SimpleImputer class
- Define strategy as median

```
>>> from sklearn.impute import SimpleImputer
>>> imputer = SimpleImputer(strategy="median")
```

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values - Scikit-Learn SimpleImputer Class

- Median can be computed
  - Only on numerical attributes
- Create copy of data
  - Without text attribute ocean_proximity

```
>>> housing_num = housing.drop("ocean_proximity",
axis=1)
```

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values - Fit the SimpleImputer Instance

- Fit the SimpleImputer instance to the training data
- Using the fit() method

```
>>> imputer.fit(housing_num)
```

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values - Fit the SimpleImputer Instance

- After calling fit()
    - SimpleImputer class computes the median of every attribute
    - And stores the computed medians in
    - **statistics_** instance variable

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values - Transform Training Set

- Now let's replace missing values in the training set

```
>>> X = imputer.transform(housing_num)

>>> X
```

```
array([[ -121.89  ,    37.29  ,    38.    , ...,   710.    ,   339.    ,
           2.7042],
       [ -121.93  ,    37.05  ,    14.    , ...,   306.    ,   113.    ,
           6.4214],
       [ -117.2   ,    32.77  ,    31.    , ...,   936.    ,   462.    ,
           2.8621],
       ...,
       [ -116.4   ,    34.09  ,     9.    , ...,  2098.    ,   765.    ,
           3.2723],
       [ -118.01  ,    33.82  ,    31.    , ...,  1356.    ,   356.    ,
           4.0625],
       [ -122.45  ,    37.77  ,    52.    , ...,  1269.    ,   639.    ,
           3.575 ]])
```

Numpy array

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values - Transform Training Set

- Convert Numpy array to Pandas Dataframe

```
>>> housing_tr = pd.DataFrame(
        X,
        columns=housing_num.columns
    )
>>> housing_tr.head()
```

Prepare the Data for ML Algorithms

Data Cleaning - Missing Values - Transformed Training Set

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income
0	-121.89	37.29	38.0	1568.0	351.0	710.0	339.0	2.7042
1	-121.93	37.05	14.0	679.0	108.0	306.0	113.0	6.4214
2	-117.20	32.77	31.0	1952.0	471.0	936.0	462.0	2.8621
3	-119.61	36.31	25.0	1847.0	371.0	1460.0	353.0	1.8839
4	-118.59	34.23	17.0	6592.0	1525.0	4459.0	1463.0	3.0347

Transformed Training Set

Prepare the Data for ML Algorithms

Question - In the training set, only total_bedroom attribute was having missing values. Why did we transform the entire training set?

Prepare the Data for ML Algorithms

Answer

- To be on the safer side
- As new data may have missing values when system go live

Handling Text and Categorical Attributes

Prepare the Data for ML Algorithms

Handling Categorical Attributes

- Most ML algorithms prefer to work with numbers
- Let's convert **"ocean_proximity"** attribute to numbers

Prepare the Data for ML Algorithms

Handling Categorical Attributes

```
>>> housing_cat = housing['ocean_proximity']
>>> housing_cat.head(10)
```

```
17606     <1H OCEAN
18632     <1H OCEAN
14650    NEAR OCEAN
3230         INLAND
3555      <1H OCEAN
19480        INLAND
8879      <1H OCEAN
13685        INLAND
4937      <1H OCEAN
4861      <1H OCEAN
Name: ocean_proximity, dtype: object
```

Prepare the Data for ML Algorithms

Example - Pandas's factorize() Method

```
>>> df = pd.DataFrame({
        'A':['type1','type3','type3', 'type2', 'type0']
    })
>>> df['A'].factorize()
```

```
(array([0, 1, 1, 2, 3]),
 Index(['type1', 'type3', 'type2', 'type0'], dtype='object'))
```

type1 type3 type3 type2 type0

Prepare the Data for ML Algorithms

Handling Categorical Attributes - Convert Text Labels to Numbers

```
>>> housing_cat_encoded, housing_categories =
housing_cat.factorize()
>>> housing_cat_encoded[:10]

Output-

array([0, 0, 1, 2, 0, 2, 0, 2, 0, 0])
```

Handling Categorical Attributes - Pandas's factorize() Method

Check Categories

```
>>> housing_categories
```

Output -

```
Index(['<1H OCEAN', 'NEAR OCEAN', 'INLAND', 'NEAR BAY',
'ISLAND'], dtype='object')
```

Prepare the Data for ML Algorithms

Handling Categorical Attributes

- In the previous example,
  - Machine Learning algorithm may assume that
  - Two nearby values are more similar than
  - Two distant values
- ML algo may assume that
  - 0 and 1 are similar to each other as their distance is less

array([<u>0</u> , <u>0</u> , <u>1</u> , 2 , <u>0</u> , 2 , <u>0</u> , 2 , <u>0</u> , <u>0</u>])

Prepare the Data for ML Algorithms

Handling Categorical Attributes - One-Hot Encoding

- To fix this,
    - A common solution is to create one binary attribute per category
- Example
    - One attribute equal to
        - 1 when the category is “<1H OCEAN”
        - and 0 otherwise
    - Another attribute equal to
        - 1 when the category is “INLAND”
        - and 0 otherwise

Prepare the Data for ML Algorithms

Handling Categorical Attributes - One Hot Encoding

CompanyName	Categoricalvalue	Price
VW	1	20000
Acura	2	10011
Honda	3	50000
Honda	3	10000

Sample Dataset

VW	Acura	Honda	Price
1	0	0	20000
0	1	0	10011
0	0	1	50000
0	0	1	10000

One Hot Encoding

Only one attribute will be equal to 1 (hot), while the others will be 0 (cold)

Prepare the Data for ML Algorithms

Handling Categorical Attributes - OneHotEncoder

- Scikit-Learn provides **OneHotEncoder** encoder to convert
  - Integer categorical values
  - Into one-hot vectors
- Let's encode the categories as one-hot vectors

Prepare the Data for ML Algorithms

Handling Categorical Attributes - OneHotEncoder

```
>>> from sklearn.preprocessing import OneHotEncoder
>>> encoder = OneHotEncoder()
>>> housing_cat_1hot =
encoder.fit_transform(housing_cat_encoded.reshape(-1,1))
>>> housing_cat_1hot
```

Output -

```
<16512x5 sparse matrix of type '<class 'numpy.float64'>'
	with 16512 stored elements in Compressed Sparse Row format>
```

Prepare the Data for ML Algorithms

Handling Categorical Attributes - OneHotEncoder

- OneHotEncoder returns a SciPy sparse array
- We can convert it to a dense array if needed

```
>>> housing_cat_1hot.toarray()
```

```
array([[ 1.,  0.,  0.,  0.,  0.],
       [ 1.,  0.,  0.,  0.,  0.],
       [ 0.,  1.,  0.,  0.,  0.],
       ...,
       [ 0.,  0.,  1.,  0.,  0.],
       [ 1.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  1.,  0.]])
```

Prepare the Data for ML Algorithms

Handling Categorical Attributes - Combining

Text Categories to Integer Categories

+

Integer Categories to One Hot Vectors

Prepare the Data for ML Algorithms

Handling Categorical Attributes - Combining

Text Categories to Integer Categories

+

Integer Categories to One Hot Vectors

Use CategoricalEncoder to Combine the Two Operations

Prepare the Data for ML Algorithms

Handling Categorical Attributes - CategoricalEncoder

- CategoricalEncoder combines the process of transforming
  - Text Categories to Integer Categories
  - Integer Categories to One Hot Vectors
- We've defined the code for CategoricalEncoder in the notebook
  - This code will be shipped in Scikit-Learn in future releases
- For now just go to Notebook and run it

Prepare the Data for ML Algorithms

Handling Categorical Attributes - CategoricalEncoder

```
>>> cat_encoder = CategoricalEncoder(encoding="onehot-dense")
>>> housing_cat_reshaped = housing_cat.values.reshape(-1, 1)
>>> housing_cat_1hot = cat_encoder.fit_transform(housing_cat_reshaped)
>>> housing_cat_1hot
```

```
array([[ 1.,  0.,  0.,  0.,  0.],
       [ 0.,  1.,  0.,  0.,  0.],
       [ 0.,  0.,  1.,  0.,  0.],
       ...,
       [ 0.,  0.,  1.,  0.,  0.],
       [ 0.,  0.,  1.,  0.,  0.],
       [ 0.,  1.,  0.,  0.,  0.]])
```

Prepare the Data for ML Algorithms

Handling Categorical Attributes - CategoricalEncoder

```
>>> cat_encoder.categories_
```

```
[array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'], dtype=object)]
```

Custom Transformers

Prepare the Data for ML Algorithms

Custom Transformers

- We can write our own transformers for tasks such as
  - Custom cleanup operations or
  - Combining specific attributes

Prepare the Data for ML Algorithms

Custom Transformers

- Scikit-Learn **Pipeline** class helps us in
  - Defining and Executing sequence of transformations
  - In the right order

Prepare the Data for ML Algorithms

How to Create Custom Transformers

Steps

- Create a class
- Implement three methods
  - `fit()`
  - `transform()`
  - `fit_transform()`
    - `Or add TransformerMixin as a base class instead of fit_transform`

Prepare the Data for ML Algorithms

How to Create Custom Transformers

- Let's create custom transformer for
- Combining the attributes as we discussed earlier
    - rooms_per_household
    - population_per_household

Create Custom Transformers Class for Combining Attributes

Please see **CombinedAttributesAdder** class in the notebook

Prepare the Data for ML Algorithms

Custom Transformers - Summary

- Now since we have a class for combining attributes
- We can easily add the class to Scikit-Learn pipeline
- And automate the addition of new attributes combinations

Feature Scaling

Prepare the Data for ML Algorithms

Feature Scaling

- Let's observe the housing dataset once more
  - The total number of rooms ranges from about 6 to 39,320
  - While median incomes only range from 0 to 15

This is a problem

Prepare the Data for ML Algorithms

Feature Scaling

- ML algorithms do not perform well
    - When the input numerical attributes
    - Have very different scales

Prepare the Data for ML Algorithms

Solution?

Prepare the Data for ML Algorithms

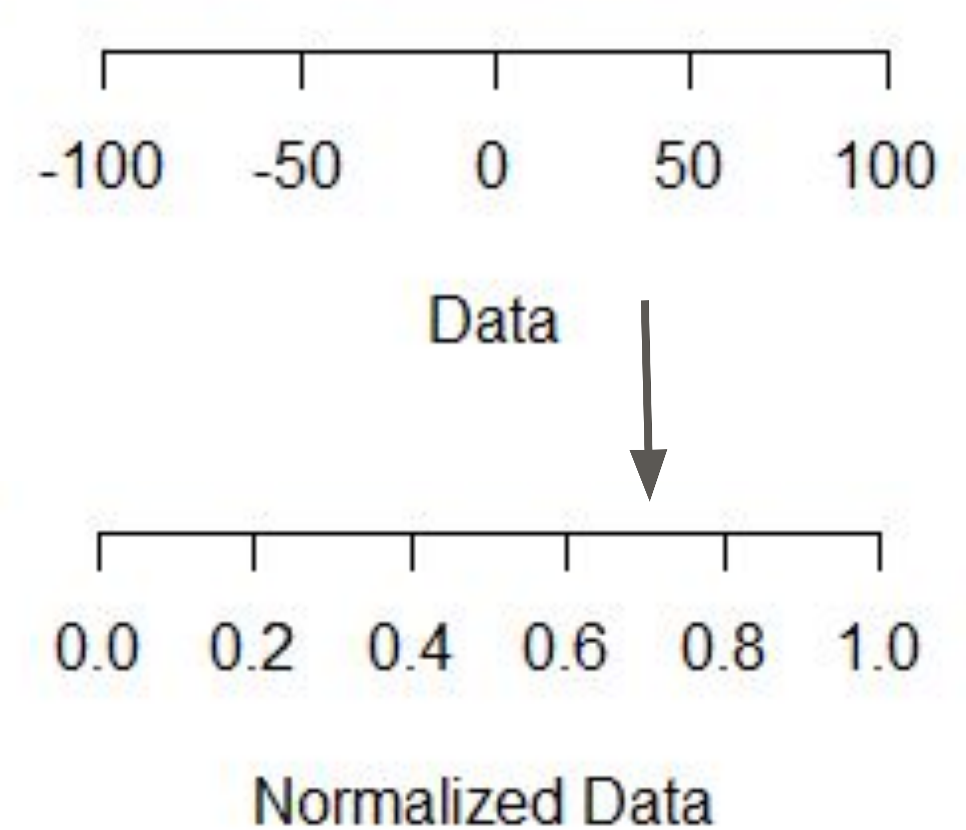
Feature Scaling

- Feature Scaling is one of the most important
  - Transformation we need to apply to our data
- Two ways to make sure all attributes have same scale
  - **Min-max scaling**
  - **Standardization**

Prepare the Data for ML Algorithms

Feature Scaling - Min-max Scaling

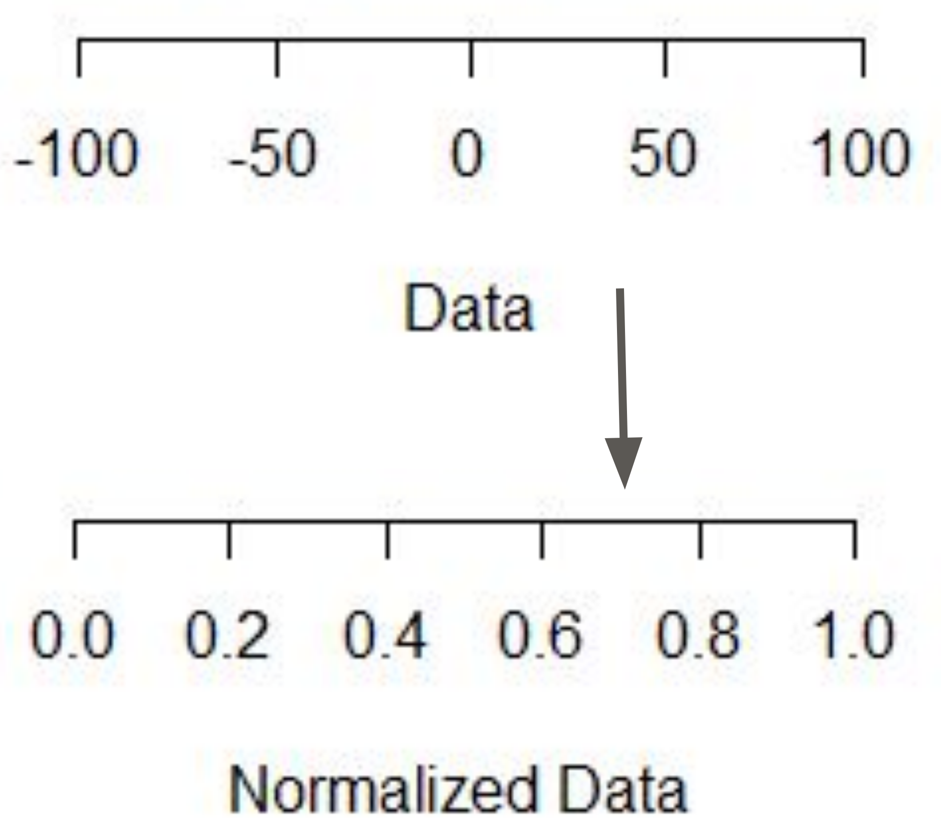
- Also known as Normalization
- Normalized values are in the range of [0, 1]



Prepare the Data for ML Algorithms

Feature Scaling - Min-max Scaling

- Also known as Normalization
- Normalized values are in the range of [0, 1]



Original Value

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Normalized Value

Prepare the Data for ML Algorithms

Feature Scaling - Min-max Scaling - Example

```
# Creating DataFrame first

>>> import pandas as pd
>>> s1 = pd.Series([1, 2, 3, 4, 5, 6], index=(range(6)))
>>> s2 = pd.Series([10, 9, 8, 7, 6, 5], index=(range(6)))
>>> df = pd.DataFrame(s1, columns=['s1'])
>>> df['s2'] = s2
>>> df
```

	s1	s2
0	1	10
1	2	9
2	3	8
3	4	7
4	5	6
5	6	5

Prepare the Data for ML Algorithms

Feature Scaling - Min-max Scaling - Example

```
# Use Scikit-Learn minmax_scaling

>>> from mlxtend.preprocessing import minmax_scaling
>>> minmax_scaling(df, columns=['s1', 's2'])
```

Original

	s1	s2
0	1	10
1	2	9
2	3	8
3	4	7
4	5	6
5	6	5

Scaled (In range of 0 and 1)

	s1	s2
0	0.0	1.0
1	0.2	0.8
2	0.4	0.6
3	0.6	0.4
4	0.8	0.2
5	1.0	0.0

Prepare the Data for ML Algorithms

Feature Scaling - Standardization

- In Machine Learning, we handle various types of data like
  - Audio signals and
  - Pixel values for image data
  - And this data can include multiple dimensions

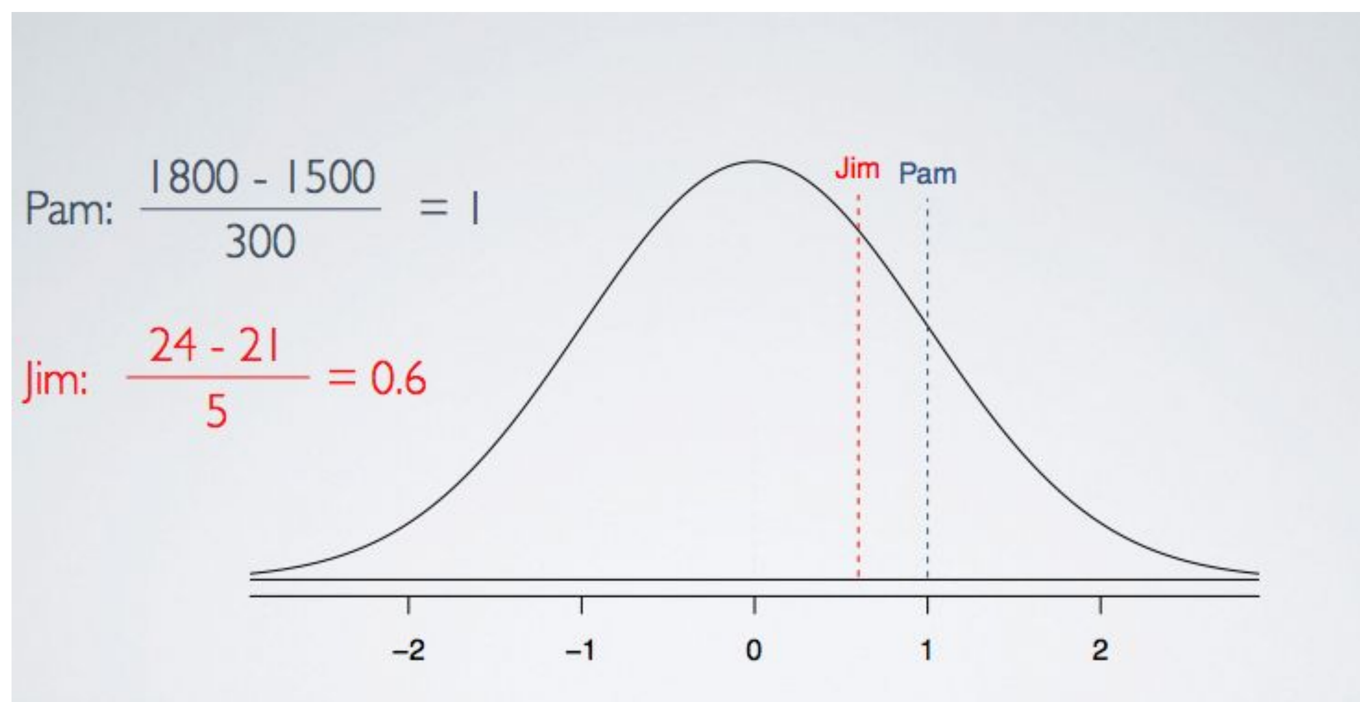
Prepare the Data for ML Algorithms

Feature Scaling - Standardization

We scale the values by calculating

- How many standard deviation is the value away from the mean

SAT scores ~ N(mean = 1500, SD = 300)
ACT scores ~ N(mean = 21, SD = 5)



Feature Scaling - Standardization

- The general method of calculation
  - Calculate distribution mean and standard deviation for each feature
  - Subtract the mean from each feature
  - Divide the result from previous step of each feature by its standard deviation

$$x' = \frac{x - \bar{x}}{\sigma}$$

Standardized Value

Prepare the Data for ML Algorithms

Feature Scaling - Standardization

- In Standardization, features are rescaled
- So that output will have the properties of
- Standard normal distribution with
  - Zero mean and
  - Unit variance

$$\bar{x} = 0 \; and \; \sigma = 1$$

Mean

Standard Deviation

Prepare the Data for ML Algorithms

Feature Scaling - Standardization

- Scikit-Learn provides
    - **StandardScaler** class for standardization

Feature Scaling - Which One to Use?

- Min-max scales in the range of [0,1]
- Standardization does not bound values to a specific range
    - It may be problem for some algorithms
    - Example- Neural networks expect an input value ranging from 0 to 1
- We'll learn more use cases as we proceed in the course

Transformation Pipelines

Prepare the Data for ML Algorithms

Transformation Pipelines

- As we can see that
  - We need many transformation steps to be executed in right order
  - We'll use Scikit-Learn **Pipeline** class
  - For specifying sequence of transformations

Prepare the Data for ML Algorithms

Transformation Pipelines - Pipeline for Numerical Attributes

- Let's build a pipeline for the numerical attributes
- Steps we have done so far
  - Handle missing values - **SimpleImputer** class with strategy as median
  - Custom transformer for combining attributes - **CombinedAttributesAdder**
  - Feature Scaling - **StandardScaler**

Prepare the Data for ML Algorithms

Transformation Pipelines - Pipeline for Numerical Attributes

- Let's build a pipeline for the numerical attributes

```
>>> from sklearn.pipeline import Pipeline
>>> from sklearn.preprocessing import StandardScaler
>>> num_pipeline = Pipeline([
      ('imputer', SimpleImputer(strategy="median")),
      ('attribs_adder', CombinedAttributesAdder()),
      ('std_scaler', StandardScaler()),
    ])
>>> housing_num_tr = num_pipeline.fit_transform(housing_num)
```

Prepare the Data for ML Algorithms

Transformation Pipelines - Pipeline for Numerical Attributes

- The Pipeline constructor takes a list of name/estimator pairs defining a sequence of steps.
- All but the last estimator must be transformers

```
num_pipeline = Pipeline([
  ('imputer', SimpleImputer(strategy="median")),
  ..................
  ..................
```

Name

Estimator

Prepare the Data for ML Algorithms

Transformation Pipelines

- When we call the the pipeline's fit() method
  - It calls fit_transform() sequentially on all transformers
  - Passing the output of each call as the parameter to the next transformer
  - Until it reaches the final estimator
  - For the final estimator it just calls the fit() method

Prepare the Data for ML Algorithms

Transformation Pipelines - DataFrameSelector

- Scikit-Learn doesn't handle DataFrames
- How to select columns from pipeline?
- Let's create a class **DataFrameSelector**
    - To select numerical or categorical columns

Prepare the Data for ML Algorithms

Transformation Pipelines - DataFrameSelector

```
class DataFrameSelector(BaseEstimator, TransformerMixin):
    def __init__(self, attribute_names):
        self.attribute_names = attribute_names
    def fit(self, X, y=None):
        return self
    def transform(self, X):
        return X[self.attribute_names].values
```

Prepare the Data for ML Algorithms

Transformation Pipelines - Pipeline for Numerical Attributes

- So final pipeline for Numerical attributes looks like

```
>>> num_attribs = list(housing_num)
>>> num_pipeline = Pipeline([
      ('selector', DataFrameSelector(num_attribs)),
      ('imputer', SimpleImputer(strategy="median")),
      ('attribs_adder', CombinedAttributesAdder()),
      ('std_scaler', StandardScaler()),
    ])
```

Prepare the Data for ML Algorithms

Transformation Pipelines - Pipeline for Categorical Attributes

- So final pipeline for categorical attributes looks like

```
>>> cat_attribs = ["ocean_proximity"]
>>> cat_pipeline = Pipeline([
        ('selector', DataFrameSelector(cat_attribs)),
        ('cat_encoder', CategoricalEncoder(encoding="onehot-dense")),
    ])
```

Prepare the Data for ML Algorithms

Transformation Pipelines - Full Pipeline

- Let's Combine the `num_pipeline` and `cat_pipeline` using Scikit-Learn **FeatureUnion** class

```
>>> from sklearn.pipeline import FeatureUnion
>>> full_pipeline = FeatureUnion(transformer_list=[
        ("num_pipeline", num_pipeline),
        ("cat_pipeline", cat_pipeline),
    ])
```

Prepare the Data for ML Algorithms

Transformation Pipelines - Full Pipeline

- Each sub pipeline starts with a selector transformer
- It simply transforms the data by selecting the desired attributes
- While drops the rest
- And converts the resulting DataFrame to a NumPy array

Prepare the Data for ML Algorithms

Transformation Pipelines - Run the Whole Pipeline

- Run the whole pipeline

```
>>> housing_prepared = full_pipeline.fit_transform(housing)
>>> housing_prepared
```

```
array([[-1.15604281,  0.77194962,  0.74333089, ...,  0.        ,
         0.        ,  0.        ],
       [-1.17602483,  0.6596948 , -1.1653172 , ...,  0.        ,
         0.        ,  0.        ],
       [ 1.18684903, -1.34218285,  0.18664186, ...,  0.        ,
         0.        ,  1.        ],
       ...,
       [ 1.58648943, -0.72478134, -1.56295222, ...,  0.        ,
         0.        ,  0.        ],
       [ 0.78221312, -0.85106801,  0.18664186, ...,  0.        ,
         0.        ,  0.        ],
       [-1.43579109,  0.99645926,  1.85670895, ...,  0.        ,
         1.        ,  0.        ]])
```

Checklist for Machine Learning Projects

1. Frame the problem and look at the big picture
2. Get the data
3. Explore the data to gain insights
4. Prepare the data for Machine Learning algorithms
5. **Explore many different models and short-list the best ones**
6. Fine-tune model
7. Present the solution
8. Launch, monitor, and maintain the system

Select and Train a Model

Train Models and Short-list Best Ones

Train a Model - Steps Done So Far

- Framed the problem
- Got data and explored it
- Created training and test set
- Transformation pipelines to
  - Clean up
  - Prepare data
- Now we are ready to train the model

Train Models and Short-list Best Ones

Train a Model - Linear Regression

- The goal of this step is to
    - Train few(two to five models) and
    - Select the best one
- Let's understand overfitting and underfitting before training a model

Train Models and Short-list Best Ones

What is Overfitting?

- Say if you are visiting a foreign country
- And the taxi driver rips you off
- You might be tempted to say that
    - All taxi drivers in that country are thieves
- Here we are overgeneralizing

What is Overfitting?

- Machines can also fall into this trap of overgeneralization like humans
- This is called **overfitting**
- In overfitting
  - The model performs well on the training data
  - But does not generalize well on unknown data

Train Models and Short-list Best Ones

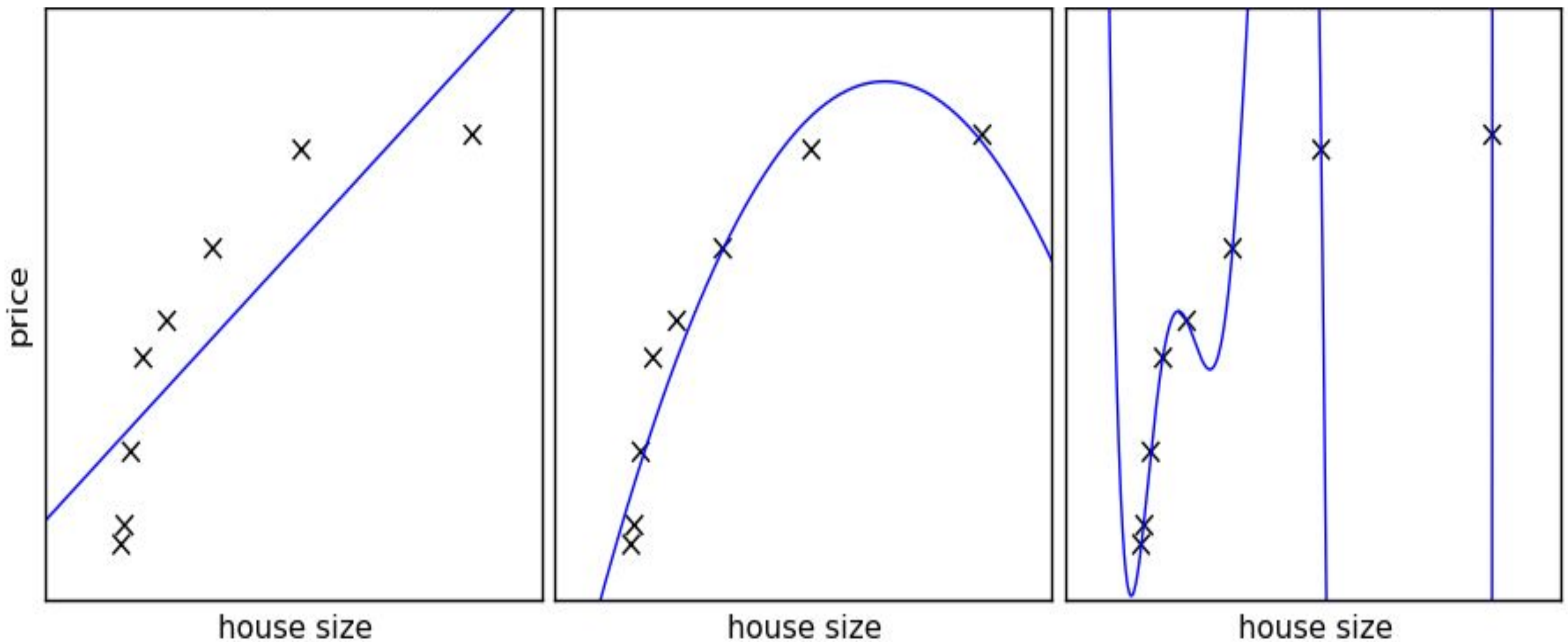
When does overfitting occur?

- Overfitting occurs when a machine learning algorithm captures the noise of the data.
- Intuitively, overfitting occurs when the model or the algorithm fits the data too well.
- Overfitting is often a result of an excessively complicated model,

Let us consider an example of overfitting

Train Models and Short-list Best Ones

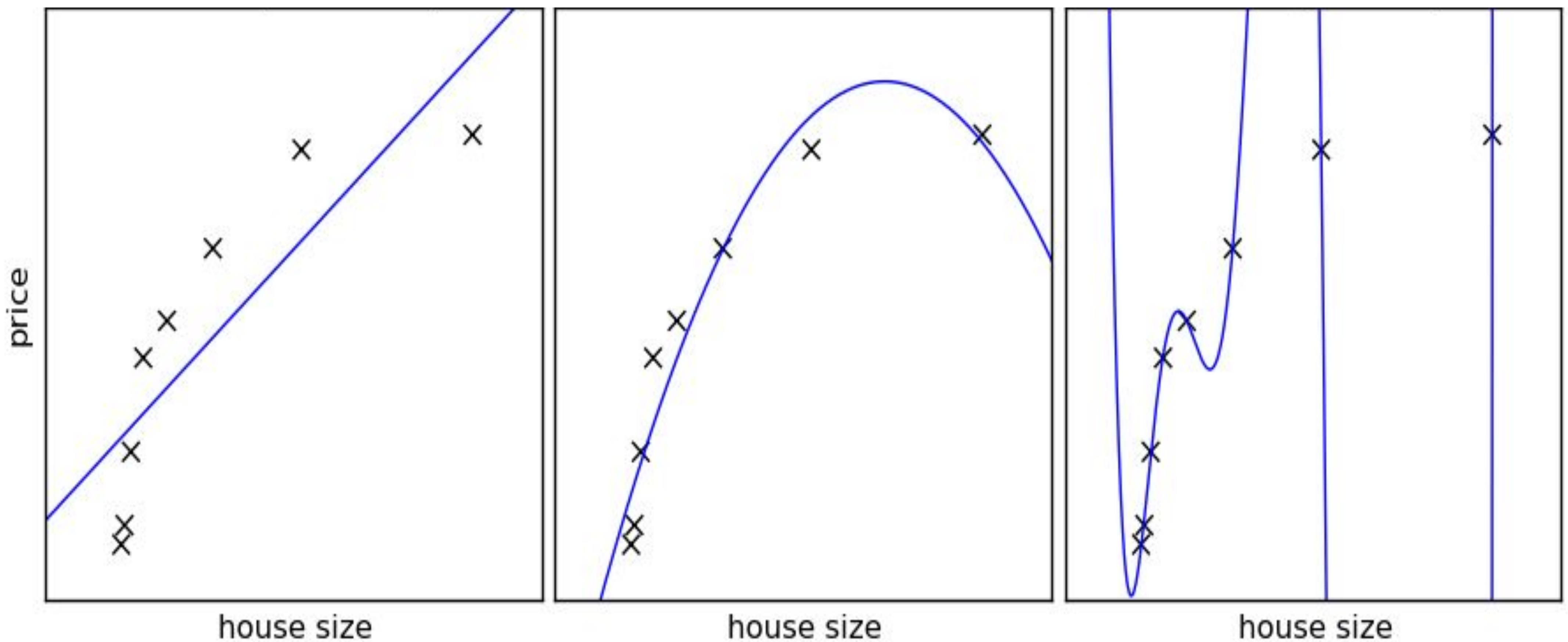
Overfitting Example



Here a high-degree polynomial strongly overfits the housing prices data. It performs much better on the training data than the simple linear model.

Train Models and Short-list Best Ones

Overfitting Example



But if the training set is noisy, then the model is likely to detect patterns in the noise itself and these patterns will not generalize to new instances.

Train Models and Short-list Best Ones

Understanding Overfitting

A complex model may detect patterns like the fact that all countries in the training data with a W in their name have a life satisfaction greater than 7:

- New Zealand (7.3)
- Norway (7.4)
- Sweden (7.2)
- Switzerland (7.5)

Train Models and Short-list Best Ones

Understanding Overfitting

If our model is trained on such countries than it will not generalize well for the following countries.

How confident are you that the W-satisfaction rule generalizes to

- Rwanda ???
- Zimbabwe ???

Train Models and Short-list Best Ones

Regularization - Tackling overfitting

Regularization can be one way in which we can tackle the problem of overfitting. In overfitting we -

- Put constrain the model to make it simpler
- The amount of regularization to apply during learning can be controlled by a hyperparameter

Regularization - Tackling overfitting

Considering a linear model. It has two parameters, θ_0 and θ_1. It gives the learning algorithm two degrees of freedom to adapt the model to the training data:

- It can tweak the height (θ_0)
- Or the slope (θ_1) of the line

Regularization - Tackling overfitting

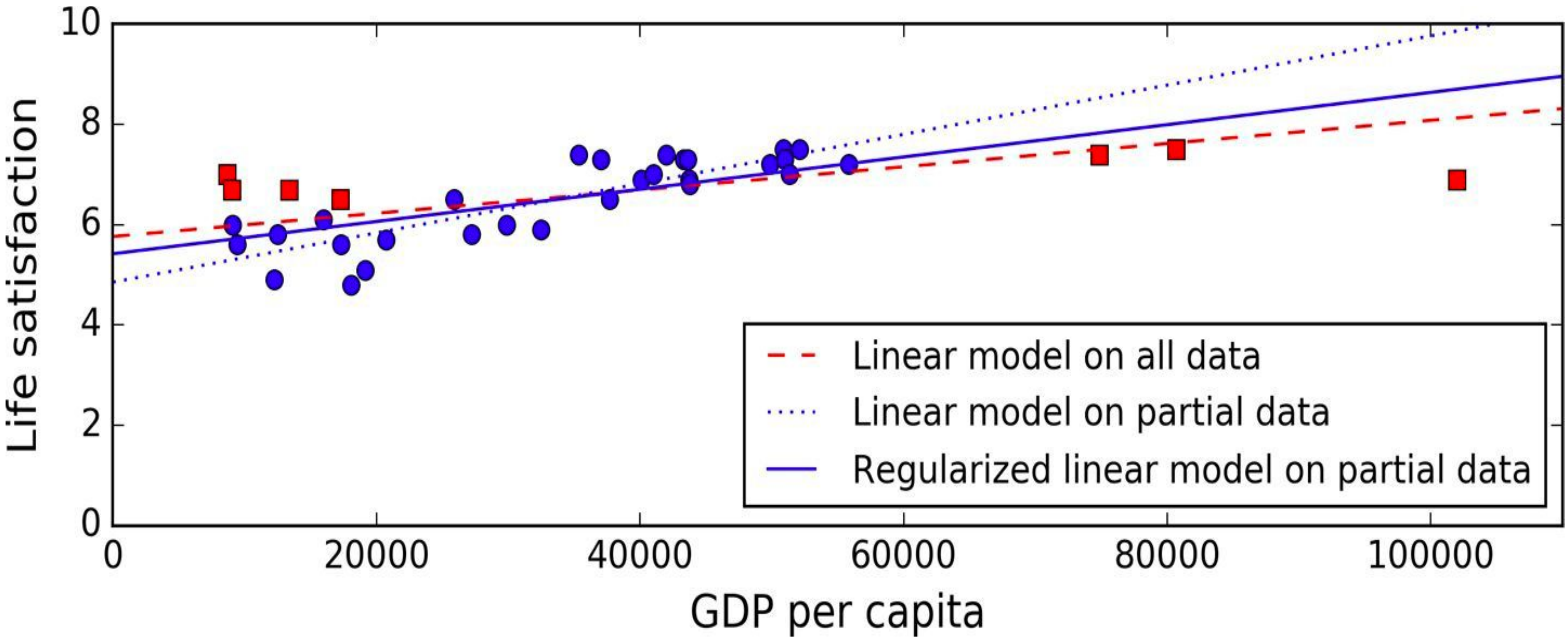
If we forced $\theta_1 = 0$, the algorithm would have only one degree of freedom

If we allow the algorithm to modify θ_1 then :

- It will produce a simpler model than with two degrees of freedom
- But it will be more complex than with just one degree of freedom

Train Models and Short-list Best Ones

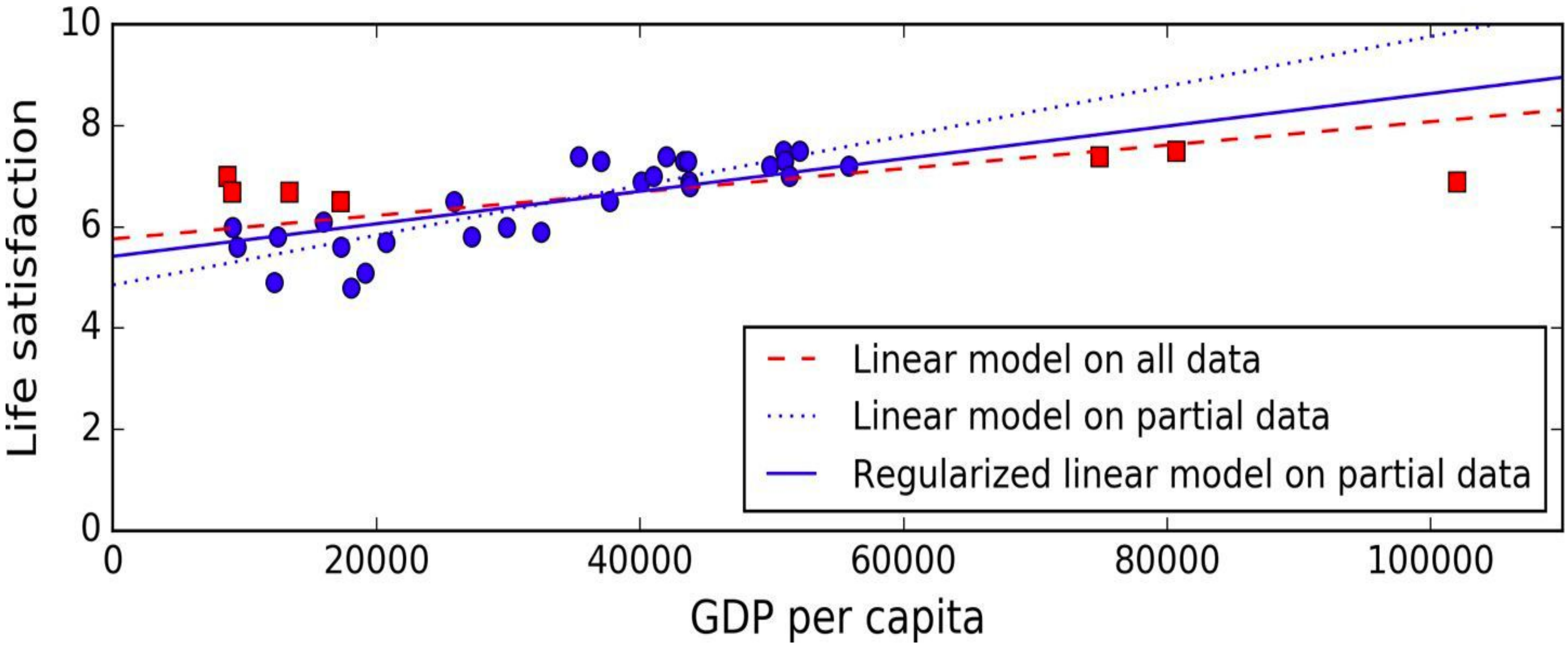
Regularization - Tackling overfitting



- The dotted line represents the original model that was trained with a few countries missing.

Train Models and Short-list Best Ones

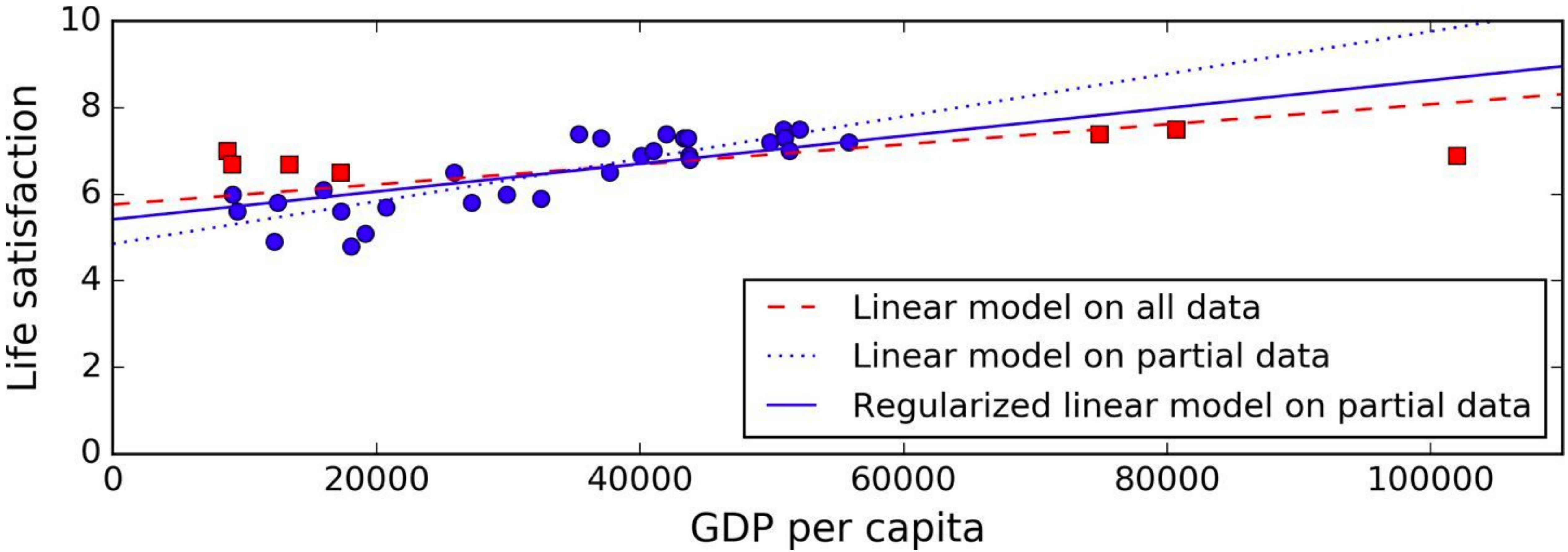
Regularization - Tackling overfitting



- The dashed line is our second model trained with all countries

Train Models and Short-list Best Ones

Regularization - Tackling overfitting



- The solid line is a linear model trained with the same data as the first model but with a regularization constraint.

Train Models and Short-list Best Ones

Regularization - Tackling overfitting

Observations from the above example:

- Regularization forced the model to have a smaller slope
- Fits a bit less on the training data that the model was trained on
- **But** actually allows it to generalize better to new examples.

Train Models and Short-list Best Ones

Regularization - Tackling overfitting

How do we choose the best model ???

When finding the best model, we'll have to find the right balance between

- Fitting the data perfectly
- And keeping the model simple enough to ensure that it will generalize well

Train Models and Short-list Best Ones

What is Underfitting?

It occurs when your model is too simple to learn the underlying structure of the data. Underfitting is often a result of an excessively simple model.

For example, a linear model of life satisfaction is prone to underfit because reality is just more complex than the model, so it's predictions are bound to be inaccurate, even on the training examples.

Train Models and Short-list Best Ones

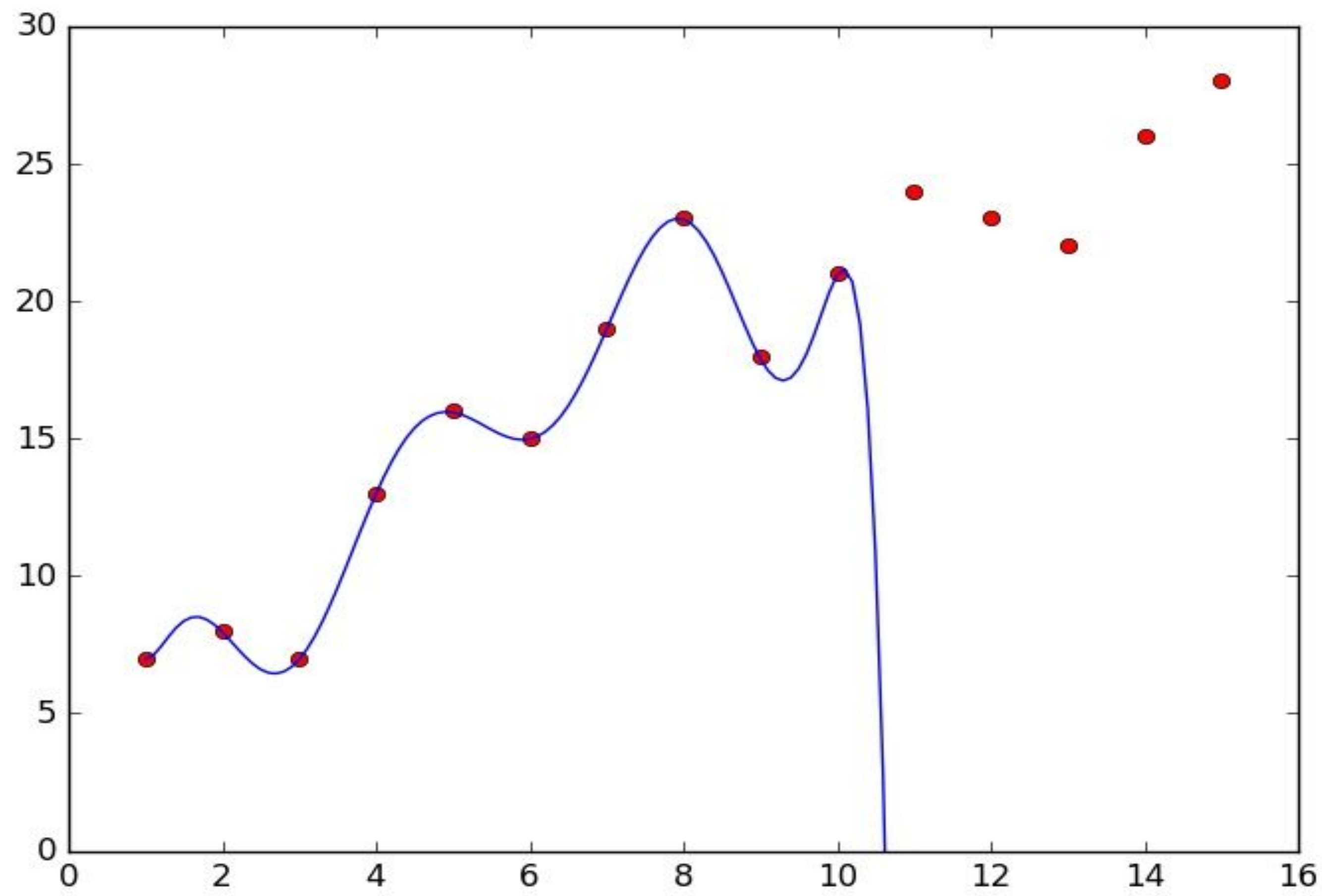
When does Underfitting occur ?

It happens when :

- Features do not provide enough information to make good predictions
- When the model or the algorithm does not fit the data well enough
- Model is too simple

Train Models and Short-list Best Ones

Example of Underfitting



In the above plot the model doesn’t fit perfectly on the training data, hence it is a case of underfitting.

Train Models and Short-list Best Ones

How to solve the problem of Underfitting?

- Select a more powerful model
- Feed better features to training algorithm
- Reduce the constraints on the model (e.g., reduce the regularization hyperparameter)

Train Models and Short-list Best Ones

Train a Model - Linear Regression

Let’s train the model now

Train Models and Short-list Best Ones

Train a Model - Linear Regression

```
>>> from sklearn.linear_model import LinearRegression
>>> lin_reg = LinearRegression()
>>> lin_reg.fit(housing_prepared, housing_labels)
```

Training Set

Target Column

Train Models and Short-list Best Ones

Train a Model - Linear Regression

```
>>> from sklearn.linear_model import LinearRegression
>>> lin_reg = LinearRegression()
>>> lin_reg.fit(housing_prepared, housing_labels)
```

Training Set

Target Column

Congrats! We've trained the first model :)

Train Models and Short-list Best Ones

Train a Model - Linear Regression

- Let's try the full pipeline on a few training instances

```
>>> some_data = housing.iloc[:5]
>>> some_labels = housing_labels.iloc[:5]
>>> some_data_prepared = full_pipeline.transform(some_data)

>>> print("Predictions:", lin_reg.predict(some_data_prepared))
>>> print("Actual values", list(some_labels))
```

Train Models and Short-list Best Ones

Train a Model - Linear Regression - Results

Actual	286,600.0	340,600.0	196,900.0	46,300.0	254,500.0
Predicted	210,644.6	317,768.8	210,956.4	59,218.9	189,747.5
% Error	-26.5	-6.7	7.13	27.90	-25.44

Train Models and Short-list Best Ones

Train a Model - Linear Regression - Observations

- The predictions are not exactly accurate
- The fourth prediction is off by more than 27%!

Train Models and Short-list Best Ones

Train a Model - Linear Regression - RMSE

- Let’s find the regression model’s RMSE on the whole training set
- Using Scikit-Learn’s **mean_squared_error** function

Train Models and Short-list Best Ones

Train a Model - Linear Regression - RMSE

```
>>> from sklearn.metrics import mean_squared_error
>>> housing_predictions = lin_reg.predict(housing_prepared)
>>> lin_mse = mean_squared_error(housing_labels,
housing_predictions)
>>> lin_rmse = np.sqrt(lin_mse)
>>> lin_rmse
>>> 68628.413493824875
```

Train Models and Short-list Best Ones

Train a Model - Underfitting the Training Data

```
>>> lin_rmse
>>> 68628.413493824875
```

- This is clearly not a great RMSE score
  - Most districts' median_housing_values range
  - Between $120,000 and $265,000
  - So a typical prediction error of $68,628 is not very satisfying
- This is example of
  - Model underfitting the training data

Train Models and Short-list Best Ones

Train a Model - Underfitting the Training Data

Solutions of Underfitting?

- **Select a more powerful model**
- Feed better features to training algorithm

Let's train a DecisionTreeRegressor - Powerful model

Train Models and Short-list Best Ones

Train a Model - DecisionTreeRegressor

- Capable of finding complex nonlinear relationships in the data
- We will cover Decision Trees in details later in the course

Train Models and Short-list Best Ones

Train a Model - DecisionTreeRegressor

```
>>> from sklearn.tree import DecisionTreeRegressor
>>> tree_reg = DecisionTreeRegressor()
>>> tree_reg.fit(housing_prepared, housing_labels)
```

Train Models and Short-list Best Ones

Train a Model - DecisionTreeRegressor

Evaluate on the training set

```
>>> housing_predictions = tree_reg.predict(housing_prepared)
>>> tree_mse = mean_squared_error(housing_labels,
housing_predictions)
>>> tree_rmse = np.sqrt(tree_mse)
>>> tree_rmse
```

Output - 0.0

Train Models and Short-list Best Ones

Train a Model - DecisionTreeRegressor

Evaluate on the training set

```
>>> housing_predictions = tree_reg.predict(housing_prepared)
>>> tree_mse = mean_squared_error(housing_labels, 
housing_predictions)
>>> tree_rmse = np.sqrt(tree_mse)
>>> tree_rmse
```

Output - 0.0

Really???

Train Models and Short-list Best Ones

Train a Model - Overfitting the Training Data

- Could this model really be absolutely perfect?
- This is called **overfitting the training data**
- Let’s evaluate the previous DecisionTreeRegressor model
    - Using Cross-Validation

Better Evaluation Using Cross-Validation

Train Models and Short-list Best Ones

- We should not touch the test set until
    - We are confident about the model on training set

Train Models and Short-list Best Ones

- We should not not touch the test set until
  - We are confident about the model on training set

Then how should we validate the model?

Train Models and Short-list Best Ones

- We should not not touch the test set until
  - We are confident about the model on training set

Then how should we validate the model?

Answer - Using Cross-Validation

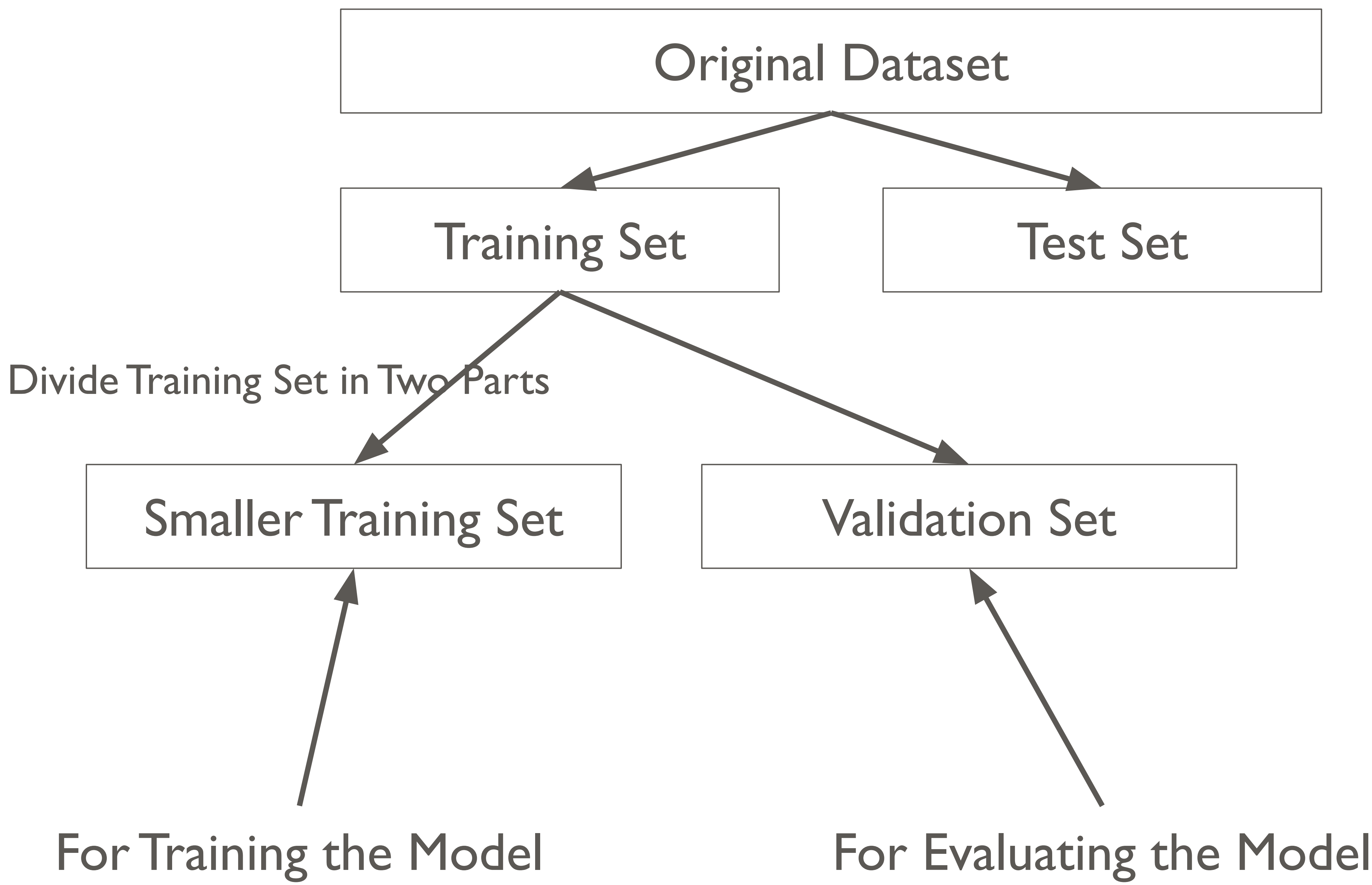
Train Models and Short-list Best Ones

Cross-Validation

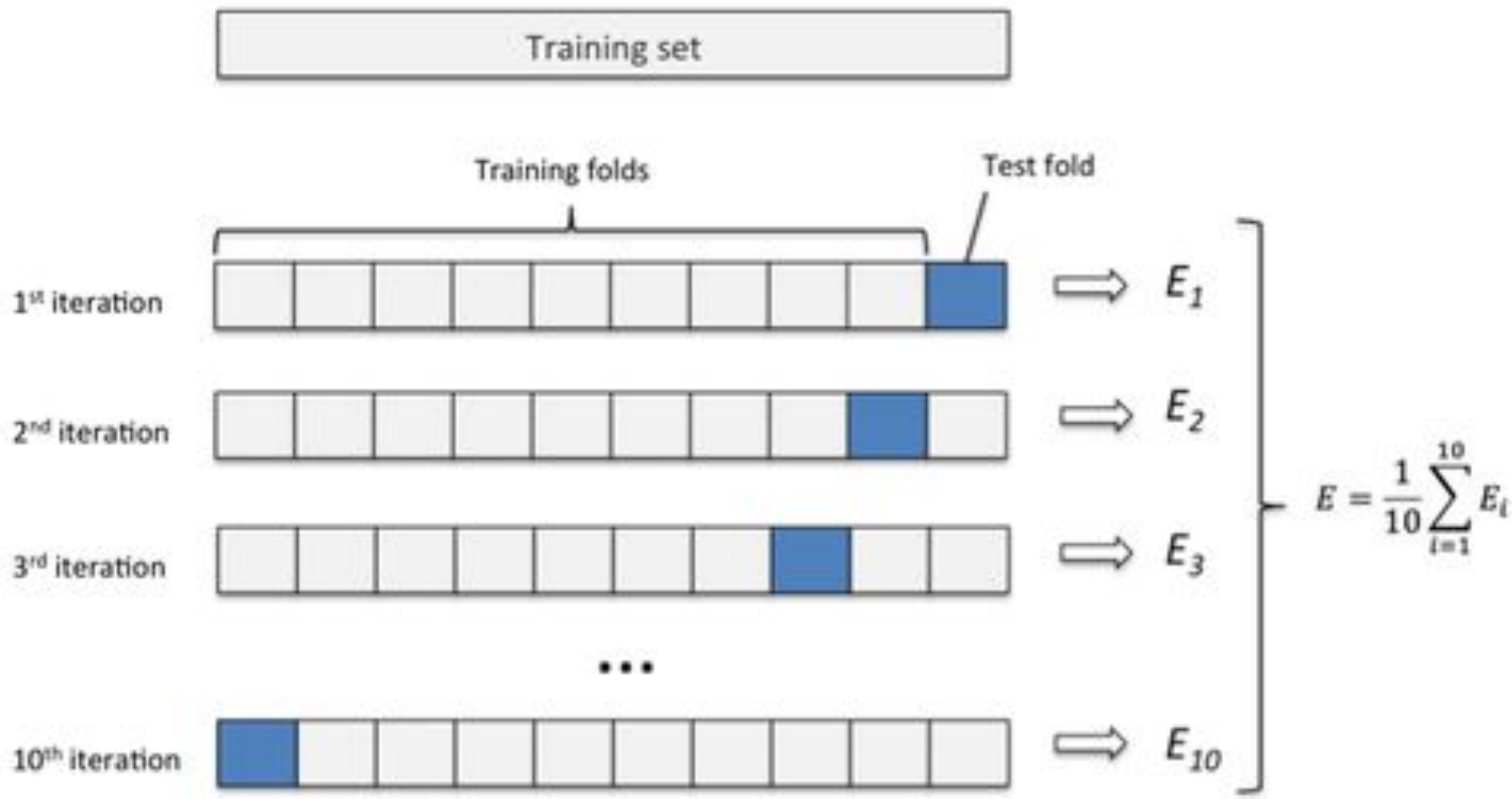
- In cross-validation we use
    - Part of the training set for training
    - And part for model validation

Train Models and Short-list Best Ones

Cross-Validation



Performance measure - Cross Validation



Here k = 10

Train Models and Short-list Best Ones

Cross-Validation

- Use the Scikit-Learn's **train_test_split** function to split
  - Training set into a smaller
    - Training set and
    - Validation set
  - Train models against the
    - Smaller training set and
    - Evaluate them against validation set

Train Models and Short-list Best Ones

Cross-Validation

- We can also use Scikit-Learn's **cross-validation** feature

Train Models and Short-list Best Ones

Cross-Validation - K-fold - DecisionTreeRegressor

- We can also use Scikit-Learn's **cross-validation** feature

```
>>> from sklearn.model_selection import cross_val_score
>>> scores = cross_val_score(tree_reg, housing_prepared,
housing_labels, scoring="neg_mean_squared_error", cv=10)
>>> tree_rmse_scores = np.sqrt(-scores)
```

K-fold Cross-Validation

10 folds

Train Models and Short-list Best Ones

Cross-Validation - K-fold

- Previous code performs **K-fold cross-validation**
    - It randomly splits the training set into
        - 10 distinct subsets called folds
    - Then it trains and evaluates the Decision Tree model 10 times
        - Picking a different fold for evaluation every time
        - And training on the other 9 folds
    - The result is an array containing the 10 evaluation scores

Train Models and Short-list Best Ones

Cross-Validation - K-fold - DecisionTreeRegressor - Output

```
>>> def display_scores(scores):
        print("Scores:", scores)
        print("Mean:", scores.mean())
        print("Standard deviation:", scores.std())
>>> display_scores(tree_rmse_scores)
Scores: [ 70232.0136482   66828.46839892  72444.08721003
70761.50186201 71125.52697653  75581.29319857  70169.59286164
70055.37863456 75370.49116773  71222.39081244]
Mean: 71379.0744771
Standard deviation: 2458.31882043
```

Train Models and Short-list Best Ones

Cross-Validation - K-fold - Linear Regression

- Now compute the same score for Linear Regression

```
>>> lin_scores = cross_val_score(lin_reg, housing_prepared,
housing_labels, scoring="neg_mean_squared_error", cv=10)
>>> lin_rmse_scores = np.sqrt(-lin_scores)
>>> display_scores(lin_rmse_scores)

Scores: [ 66782.73843989  66960.118071    70347.95244419
74739.57052552 68031.13388938  71193.84183426  64969.63056405
68281.61137997 71552.91566558  67665.10082067]
Mean: 69052.4613635
Standard deviation: 2731.6740018
```

Train Models and Short-list Best Ones

Cross-Validation - K-fold - Linear Regression Vs Decision Tree

Linear Regression

Mean:
69, 052.4613635

Standard deviation:
2, 731.6740018

DecisionTreeRegressor

Mean:
71, 379.0744771

Standard deviation:
2, 458.31882043

Train Models and Short-list Best Ones

Cross-Validation - K-fold - Linear Regression Vs Decision Tree

Linear Regression	**DecisionTreeRegressor**
Mean: 69, 052.4613635	Mean: 71, 379.0744771
Standard deviation: 2, 731.6740018	Standard deviation: 2, 458.31882043

Decision Tree model performed worse than the Linear Regression model.
Decision Tree model is overfitting when RMSE came to 0.0

Train Models and Short-list Best Ones

Cross-Validation - K-fold - Important points

- Cross-validation gives
  - Estimate of the performance of your model and
  - Also a measure of how precise this estimate
- The Decision Tree has a score of
  - Approximately 71, 379
  - With precision of ± 2, 458 (Standard Deviation)

Train Models and Short-list Best Ones

RandomForestRegressor

- Let’s train our last model
  - **RandomForestRegressor**
- Random Forests work by training many Decision Trees
  - On random subsets of the features
  - Then averaging out their predictions
- We will cover Random Forests in details later in the course

Train Models and Short-list Best Ones

RandomForestRegressor - RMSE

- Let's train our last model using **Random Forests**

```
>>> from sklearn.ensemble import RandomForestRegressor
>>> forest_reg = RandomForestRegressor(random_state=42)
>>> forest_reg.fit(housing_prepared, housing_labels)
>>> housing_predictions = forest_reg.predict(housing_prepared)
>>> forest_mse = mean_squared_error(housing_labels,
housing_predictions)
>>> forest_rmse = np.sqrt(forest_mse)
```

```
Output - 21941.911027380233
```

Train Models and Short-list Best Ones

RandomForestRegressor - Using Cross-Validation

- Let's train **Random Forests** using cross-validation

```
>>> from sklearn.model_selection import cross_val_score
>>> forest_scores = cross_val_score(forest_reg, housing_prepared,
housing_labes, scoring="neg_mean_squared_error", cv=10)
>>> forest_rmse_scores = np.sqrt(-forest_scores)
```

Train Models and Short-list Best Ones

RandomForestRegressor - Using Cross-Validation

- Let's train **Random Forests** using cross-validation

```
>> display_scores(forest_rmse_scores)
```

```
Scores: [ 51650.94405471  48920.80645498  52979.16096752
54412.74042021 50861.29381163  56488.55699727  51866.90120786
49752.24599537 55399.50713191  53309.74548294]
Mean: 52564.1902524
Standard deviation: 2301.87380392
```

Train Models and Short-list Best Ones

Training Models Comparison

Linear Regression	Decision Tree	Random Forest
Mean - 69, 052	Mean - 71, 379	Mean - 52, 564
SD - 2, 731	SD - 2, 458	SD - 2, 301

SD - Standard Deviation

Random Forests perform lot better

Train Models and Short-list Best Ones

Explore More Models

- Till now we have explored few models
- Now the goal is to shortlist
  - A few (two to five) promising models

Checklist for Machine Learning Projects

1. Frame the problem and look at the big picture
2. Get the data
3. Explore the data to gain insights
4. Prepare the data for Machine Learning algorithms
5. Explore many different models and short-list the best ones
6. **Fine-tune model**
7. Present the solution
8. Launch, monitor, and maintain the system

Fine-Tune Your Model

Fine-tune Model

Fine-Tune Model

- This section is to help you understand various fine-tuning methods
- It's okay
  - If you do not understand the code, terms and concepts at this moment
  - We will cover the concepts and code in details as we progress in the course

Fine-tune Model

Fine-Tune Model

- Now we have two to five promising models
- Let's fine-tune them

Fine-Tune Model

- Now we have two to five promising models
- Let's fine-tune them

How do we fine-tune?

Fine-tune Model

Fine-Tune Model - Hyperparameters

- Before learning about how to fine-tune the models
- Let's learn about Hyperparameters first

Fine-tune Model

What are Hyperparameters?

- A machine learning model is a mathematical formula
  - With a number of parameters that need to be learned from the data
- The soul of machine learning is
  - Fitting a model to the data
- By training a model with existing data
  - We fit the model parameters

Fine-tune Model

What are Hyperparameters?

- There is another kind of parameters
  - That cannot be directly learned from the model training process
- These parameters express
  - Higher-level properties of the model such as
  - Its complexity or
  - How fast it should learn

Fine-tune Model

What are Hyperparameters?

- These parameters are called **Hyperparameters**
- Hyperparameters are usually decided before the actual training begins
- Can be decided by
  - Setting different values
  - Training different models and
  - Choosing the values that work best

Fine-tune Model

Some examples of Hyperparameters?

- Number of leaves or depth of a tree
- Learning rate
  - How fast a model should learn
- Number of hidden layers in a deep neural network
- Number of clusters in a k-means clustering

Fine-Tune Model - Solutions

- Now let's learn how to fine-tune models

Fine-tune Model

Fine-Tune Model - Solutions

- One solution is to fiddle with the hyperparameters manually
- Until we find a great combination of hyperparameter values
- This is very tedious work
- And we may not have time to explore many combinations

Grid Search

Fine-tune Model

Fine-Tune Model - Grid Search

- Evaluates all possible combinations of hyperparameters values
    - Using cross-validation
- All we need to tell
    - Which hyperparameters we want it to experiment with and
    - What values to try out
- We will cover Grid Search in details later in the course

Fine-tune Model

Fine-Tune Model - Grid Search - Example

- Following code searches for the best possible combination of hyperparameter values for **RandomForestRegressor**

Fine-tune Model

Fine-Tune Model - Grid Search - Example

```
>>> from sklearn.model_selection import GridSearchCV
>>> param_grid = [
      {'n_estimators': [3, 10, 30], 'max_features': [2, 4, 6, 8]},
      {'bootstrap': [False], 'n_estimators': [3, 10],
      'max_features':[2, 3, 4]
      },
   ]
>>> forest_reg = RandomForestRegressor()
>>> grid_search = GridSearchCV(forest_reg, param_grid, cv=5,
scoring='neg_mean_squared_error')
>>> grid_search.fit(housing_prepared, housing_labels)
```

Run it in Notebook

Fine-tune Model

Fine-Tune Model - Grid Search - Example

- Get the best combination of parameters (We will cover this later in the course)

```
>>> grid_search.best_params_
```

```
Output-
```

```
{'max_features': 8, 'n_estimators': 30}
```

Fine-tune Model

Fine-Tune Model - Grid Search - Example

- Get the best estimator (We will cover this later in the course)

```
>>> grid_search.best_estimator_
```

```
Output-
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
          max_features=8, max_leaf_nodes=None,
          min_impurity_decrease=0.0, min_impurity_split=None,
          min_samples_leaf=1, min_samples_split=2,
          min_weight_fraction_leaf=0.0, n_estimators=30,
          n_jobs=1, oob_score=False, random_state=42,
          verbose=0, warm_start=False
)
```

Fine-tune Model

Fine-Tune Model - Grid Search - Example

- Get the score of each hyperparameter combination tested during the grid search (We will cover this later in the course)

```
>>>  cvres = grid_search.cv_results_
>>>  for mean_score, params in zip(cvres["mean_test_score"], 
cvres["params"]):
         print(np.sqrt(-mean_score), params)
```

Fine-tune Model

Randomized Search

Fine-tune Model

Fine-Tune Model - Randomized Search

- The grid search approach is fine
    - When you are exploring relatively few combinations
- When the hyperparameter search space is large, use **RandomizedSearchCV**
- We will cover Randomized Search in details later in the course

Fine-Tune Model - Randomized Search

- Randomized search
    - Instead of trying out all possible combinations
    - Evaluates a given number of random combinations
    - By selecting a random value for each hyperparameter
    - At every iteration

Fine-tune Model

Fine-Tune Model - Randomized Search

- Has two main benefits
- One
  - Say our randomized search runs for 1000 iterations
  - It will explore 1,000 different values for each hyperparameter
  - While Grid Search explores few values per hyperparameter

Fine-tune Model

Fine-Tune Model - Randomized Search

- Has two main benefits
- Two
  - We have more control over the computing budget we want to allocate to hyperparameter search
  - Simply by setting the number of iterations

Fine-tune Model

Fine-Tune Model - Randomized Search

Check the RandomizedSearchCV code in Notebook

Fine-tune Model

Ensemble Methods

Fine-tune Model

Fine-Tune Model - Ensemble Methods

- Another way of fine-tuning models is to
  - Combine best performing models
- The ensemble(group)
  - Oftens perform better than the
  - Best individual model
- Just like in previous example
  - Random forests performed better than the
  - Individual decision trees

Analyze the Best Models and Their Errors

Fine-tune Model

Analyze the Best Models

- Let's see the importance score of each attribute

```
>>> feature_importances =
grid_search.best_estimator_.feature_importances_
>>> extra_attribs = ["rooms_per_hhold", "pop_per_hhold",
"bedrooms_per_room"]
>>> cat_encoder = cat_pipeline.named_steps["cat_encoder"]
>>> cat_one_hot_attribs = list(cat_encoder.categories_[0])
>>> attributes = num_attribs + extra_attribs + cat_one_hot_attribs
>>> sorted(zip(feature_importances, attributes), reverse=True)
```

Fine-tune Model

Analyze the Best Models

Observations??

```
[(0.36615898061813418, 'median_income'),
 (0.16478099356159051, 'INLAND'),
 (0.10879295677551573, 'pop_per_hhold'),
 (0.07334423551601242l, 'longitude'),
 (0.06290907048262030 2, 'latitude'),
 (0.05641917918195400 7, 'rooms_per_hhold'),
 (0.05335107734767580 9, 'bedrooms_per_room'),
 (0.04114379847872963 5, 'housing_median_age'),
 (0.01487428089040276 7, 'population'),
 (0.01467268542054323 7, 'total_rooms'),
 (0.01425759932340780 7, 'households'),
 (0.01410648345358410 2, 'total_bedrooms'),
 (0.01031148832630378 7, '<1H OCEAN'),
 (0.00285647463732015 79, 'NEAR OCEAN'),
 (0.00196041559947807 01, 'NEAR BAY'),
 (6.02803867273659 91e-05, 'ISLAND')]
```

Fine-tune Model

Evaluate model on the Test Set

Fine-tune Model

Evaluate Model on Test Set

- After tweaking the models for a while
- When we are confident about the model
- Then evaluate the model on the test set

Fine-tune Model

Evaluate Model on Test Set - Process

1. Get the final model

Evaluate Model on Test Set - Process

1. Get the final model

```
>>> final_model = grid_search.best_estimator_
```

Evaluate Model on Test Set - Process

2. Get predictors and labels from test set

```
# Predictors
>>> X_test = strat_test_set.drop("median_house_value",
axis=1)
# Labels
>>> y_test = strat_test_set["median_house_value"].copy()
```

Fine-tune Model

Evaluate Model on Test Set - Process

3. Run full_pipeline to transform the data

```
>>> X_test_prepared = full_pipeline.transform(X_test)
```

Fine-tune Model

Evaluate Model on Test Set - Process

4. Evaluate the final model on the test set

Predictions on Test set

```
>>> final_predictions = final_model.predict(X_test_prepared)
```

```
# Calculate final RMSE
>>> final_mse = mean_squared_error(y_test,
final_predictions)
>>> final_rmse = np.sqrt(final_mse)
```

Fine-tune Model

Evaluate Model on Test Set - Process

4. Evaluate the final model on the test set

```
>>> final_rmse = final_model.predict(X_test_prepared)
```

Output-

```
47,766.0039
```

Fine-tune Model

Congratulation! We have trained and tested our first model :)

Fine-tune Model

Evaluate Model on Test Set

- This model is not perfect though
- We'll learn more ways to build better models as we progress in the course

Fine-tune Model

Evaluate Model on Test Set - Summary

- If we do lot of hyperparameters tuning than the
  - Performance of the model will be worse than the
  - Performance measured in cross-validation
- This happens because
  - The model is fine-tuned to perform well on the validation data
  - And performs badly on unknown datasets

Fine-tune Model

Evaluate Model on Test Set - Summary

- We must resist the temptation to tweak hyperparameters to look good on test set
- As model will not generalize to new data

Checklist for Machine Learning Projects

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5. Explore many different models and short-list the best ones
6. Fine-tune model
7. **Present the solution**
8. Launch, monitor, and maintain the system

Present the Solution

Pre Launch Phase

Present the Solution

Pre Launch Phase

- Now we need to present the solution
  - What have we learned
  - What worked and what did not
  - What assumptions were made
  - What are model's limitations

Present the Solution

Pre Launch Phase

- Document everything
- Create nice presentations
    - With clear visualizations

Checklist for Machine Learning Projects

1. Frame the problem and look at the big picture
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6. Fine-tune model
7. Present the solution
8. **Launch, monitor, and maintain the system**

Launch the System

Launch, Monitor and Maintain the system

- Prepare the solution for production
    - Plugging the production input data sources

Monitor the System

Launch, Monitor and Maintain the system

Monitor the System

- Write monitoring code to check
  - Model's live performance at regular intervals
  - Trigger alerts when it drops
- Important to catch performance degradation
  - As models tends to **rot**
  - If not trained on fresh data

Launch, Monitor and Maintain the system

Plug Human Evaluation Pipeline into System

- Sample the model's predictions and evaluate them from time to time
- This generally requires a human analysis
- These analysts may be
  - Field experts or
  - Workers on a crowdsourcing platform such as
    - Amazon Mechanical Turk
    - CrowdFlower

Launch, Monitor and Maintain the system

Evaluate the Input Data Quality

- Evaluate the model's input data quality from time to time
- Performance may degrade if the input data quality is not good
  - For example, malfunction sensors sending random values
- Monitoring input data quality is
  - Especially important for online learning systems

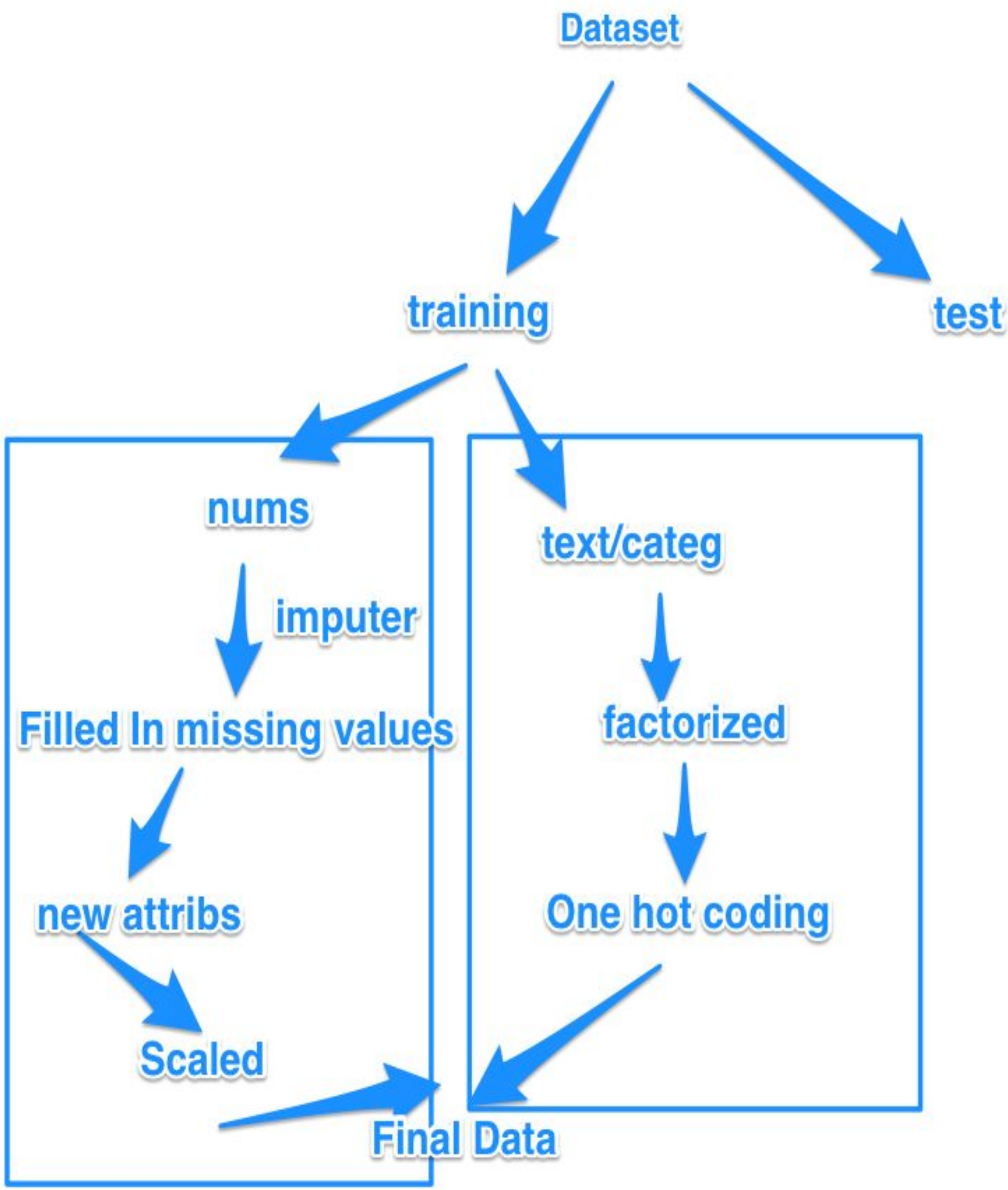
Maintain the System

Launch, Monitor and Maintain the system

Maintain the System

- Train model on a regular basis using fresh data
  - Automate the process of regularly updating of training model with fresh data
  - Else system's performance may fluctuate severely over time
- For an online learning system
  - Make sure to save snapshots of its state at regular intervals
  - So that we can easily roll back to a previously working state

Summary


Dataset
training
test
nums
imputer
Filled In missing values
new attribs
Scaled
text/categ
factorized
One hot coding
Final Data

Summary

- As we can see, much of the work is in the
  - Data preparation step
  - Deploying
  - Building monitoring tools
  - Setting up human evaluation pipelines and
  - Automating regular model training

Summary

- Be comfortable with the overall process
- Know three or four algorithms
    - Rather than to spend all your time exploring advanced algorithms
    - And not spending enough time on the overall process
- Spend enough time on the overall process

Summary

In this chapter we learnt about

1. Statistical Inference, Probability and Measures of Central Tendency
2. Creating a Machine Learning Model
   a. Getting the data
   b. Exploring the data
   c. Splitting our data into Train and Test set
   d. Exploring different models and choosing the best one
   e. Fine Tuning our model
   f. Presenting the solution

Summary

In this course we learnt about

3. Stratified Sampling using Scikit learn
4. Visualizing our dataset
5. Looking for Correlations in the data
6. Data Cleaning
7. Training a model using Scikit learn

Questions?

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