Open in Colab

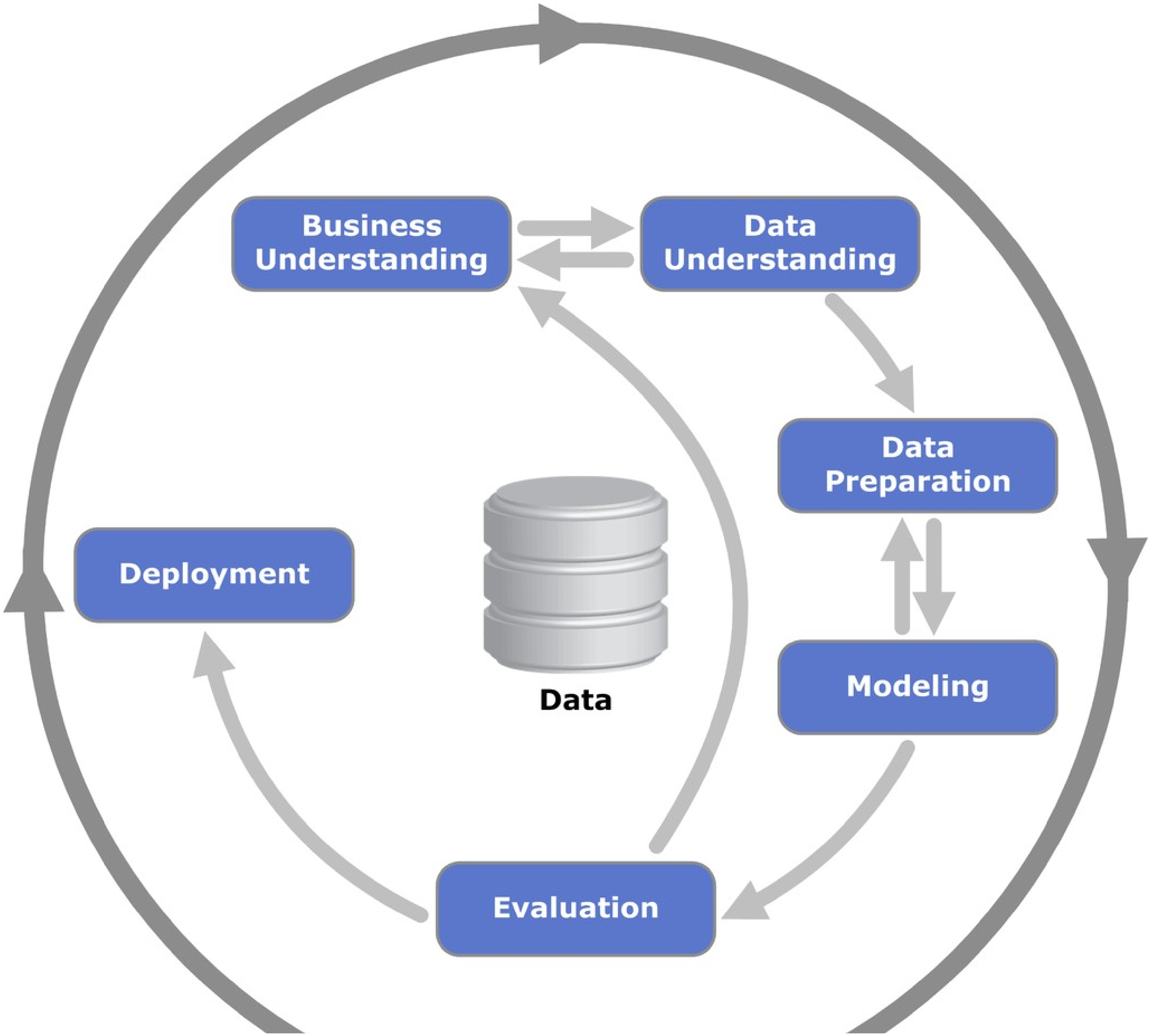
Data pre-processing

Data preprocessing refers to the manipulation or data before it is used in order to ensure or enhance performance, and is an important step in the data mining process

- The phrase "garbage in, garbage out" is particularly applicable to data mining and machine learning projects
- Data-gathering methods are often loosely controlled, resulting in:
    - out-of-range values (e.g., Income: −100),
    - impossible data combinations (e.g., Mark: 28, CumLaude: Yes),
    - and missing values, etc.

Data analysis involves several steps:

1. Frame the problem and look at the big picture
    - Define the objective in business terms
    - How should performance be measured?
2. Get the data
    - List the data you need and how much you need
    - Collect of data from one or more sources (database, web, etc.)
        - In this lab, things are much simpler
3. Explore the data to gain insights
    - Create an environment to keep track of your data exploration
        - You have been provided with notebook environments
    - Understanding of the structure and meaning of data
4. Transformation of data into manageable formats for subsequent steps
5. Extraction of knowledge from data (statistics, models, patterns, etc.)
6. Validation of the extracted knowledge
7. Deployment of the extracted knowledge and models


Business Understanding
Data Understanding
Data Preparation
Modeling
Evaluation
Deployment
Data

Relational data

Relational data are usually collected in **tabular** format

- Each row is an **observation** (instance or tuple)
  - An object of the analysis
  - E.g., a product for market basket analysis
- Each column is an **attribute** (or feature) characterizing each object
  - All values within a column have the same type (i.e., all values belong to the same attribute domain)
  - E.g., the attributes ID (int), ProductName (str), or Price (float)

Pandas is the shorthand for 'Python and Data Analysis'

- It provides a rich set of features for exploring and manipulating data
- https://pandas.pydata.org/

pandas (Python) is a solution for the manipulation of relational data

- Two main data types: Series (e.g., temporal series) and DataFrame (e.g., table)
- Support to SQL-like operations (join/merge, aggregation, etc.)
- Imputation of missing values
- Manipulation of data shape
- By convention, the package pandas is imported as "pd"

In [1]:

```
import pandas as pd
print(pd.__version__)
```

```
1.5.3
```

... plus we will use other libraries

In [2]:

```
import numpy as np  # fast operations on arrays
import seaborn as sns  # plots
import matplotlib.pyplot as plt  # plots
```

Pandas relies on DataFrame and Series

DataFrame:

- Two-dimensional, size-mutable, potentially heterogeneous tabular data.
- The primary pandas data structure.
- Data structure also contains labeled axes (rows and columns).
- Arithmetic operations align on both row and column labels.
- Can be thought of as a dict-like container for Series objects.
- https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.html

In [3]:
```
# create a numeric dataframe/table
df = pd.DataFrame([[i + j for i in range(10)] for j in range(5)],
                  index=[i for i in range(5)],
                  columns=list('abcdefghij'))
df
```

Out[3]:

	a	b	c	d	e	f	g	h	i	j
0	0	1	2	3	4	5	6	7	8	9
1	1	2	3	4	5	6	7	8	9	10
2	2	3	4	5	6	7	8	9	10	11
3	3	4	5	6	7	8	9	10	11	12
4	4	5	6	7	8	9	10	11	12	13

A **Series** is a sequence of values with the same type

- Each value is associate with a label
- Supported values and label types are the ones from NumPy (float64, int64, etc.)
- In other words, a series is a mono-dimensional vector of elements

The index of a series is the sequence of labels

- Label are usually numeric or string identifiers
- E.g., the primary key of a database table
- Labels could repeat within the series, but usually do not

Technically

- One-dimensional ndarray with axis labels (including time series).
- Labels need not be unique but must be a hashable type (both integer- and label-based indexing).
- Operations between Series (e.g., +, -, /) align values based on their associated index values.
- https://pandas.pydata.org/docs/reference/api/pandas.Series.html

In [4]:
```python
pd.Series([1, 2, 3], index=["a", "b", "c"])
```

Out[4]:
```
a    1
b    2
c    3
dtype: int64
```

In [5]:
```python
# Select a column (i.e., a series) as in a SQL projection
df['a']
```

Out[5]:
```
0    0
1    1
2    2
3    3
4    4
Name: a, dtype: int64
```

In [6]:
```python
# Add another column to the dataframe
df['k'] = df['a'] * df['b']
df
```

Out[6]:

	a	b	c	d	e	f	g	h	i	j	k
0	0	1	2	3	4	5	6	7	8	9	0
1	1	2	3	4	5	6	7	8	9	10	2
2	2	3	4	5	6	7	8	9	10	11	6
3	3	4	5	6	7	8	9	10	11	12	12
4	4	5	6	7	8	9	10	11	12	13	20

... doing some element-wise operations

In [7]:
```
ser_a = pd.Series([1, 2, 3], index=["a", "b", "c"])
ser_b = pd.Series([1, 2, 3], index=["b", "a", "c"])
ser_a + ser_b
```

Out[7]:
```
a    3
b    3
c    6
dtype: int64
```

In [8]:
```
ser_a - ser_b
```

Out[8]:
```
a   -1
b    1
c    0
dtype: int64
```

... doing some aggregation

In [11]:
```
ser_c = df["a"]
ser_c.count()  # => 5
ser_c.sum()    # => 10
ser_c.mean()   # => 2.0
ser_c.max()    # => 4
ser_c.min()    # => 0
ser_c.idxmax() # => 4
```

Out[11]:
```
4
```

Data preprocessing

Data preprocessing plays a key role in a data analytics process and avoids “Garbage in, garbage out” [1]

- A broad range of activities; from correcting errors to selecting the most relevant features
- There are no pre-defined rules on the impact of pre-processing transformations
- Data scientists cannot easily foresee the impact of pipeline prototypes

“Garbage in, garbage out” is particularly applicable to data mining and machine learning

- Out-of-range values (e.g., Income: -100)
- Impossible data combinations (e.g., Exam mark: 15, Exam result: Passed)
- Missing values
- Inconsistent data among multiple sources
- More?

[1] Joseph Giovanelli, Besim Bilalli, Alberto Abelló: Effective data pre-processing for AutoML. DOLAP 2021: 1-10

Which transformations can we apply?

- **Encoding**: transforming categorical attributes into continuous ones
- **Discretization**: transforming continuous attributes into categorical ones
- **Normalization**: normalizing continuous attributes such that their values fall in the same range
- **Imputation**: imputing missing values
- **Rebalancing**: adjusting the class distribution of a dataset (i.e., the ratio between the different classes/categories represented)
- **Feature Engineering**: defining the set of relevant attributes (variables, predictors) to be used in model construction

Understanding data types

"It is imperative to know the attribute properties to carry out meaningful operations and research with them"

Why is data type important?

Microsoft has released an emergency fix for a year 2022 bug that is breaking email delivery on on-premise Microsoft Exchange servers.

As the year 2022 rolled in and the clock struck midnight, Exchange admins worldwide discovered that their servers were no longer delivering email. After investigating, they found that mail was getting stuck in the queue, and the Windows event log showed one of the following errors.

```
Log Name: Application
Source: FIPFS
Logged: 1/1/2022 1:03:42 AM
Event ID: 5300
Level: Error
Computer: server1.contoso.com
Description: The FIP-FS "Microsoft" Scan Engine failed to load. PID: 23092, Error
Code: 0x80004005. Error Description: Can't convert "2201010001" to long.
```

```
Log Name: Application
Source: FIPFS
Logged: 1/1/2022 11:47:16 AM
Event ID: 1106
Level: Error
Computer: server1.contoso.com
Description: The FIP-FS Scan Process failed initialization. Error: 0x80004005. Err
or Details: Unspecified error.
```

A signed integer is a 32-bit datum that encodes an integer in the range:

$$[-2^{31}, 2^{31} - 1] = [-2147483648, 2147483647]$$

$$2201010001 > 2147483647$$

In [12]:
```python
df = pd.DataFrame([
    ['Cola',   'low',    '05/07/2021', 10],
    ['Bread',  'medium', '05/07/2021', 25],
    ['Beer',   'high',   '06/07/2021', 100],
    ['Diaper', 'high',   '06/07/2021', np.nan],
    ['Pizza',  'medium', '06/07/2021', 25]], columns=['ID', 'PriceBin', 'Date'
df
```

Out[12]:

	ID	PriceBin	Date	Quantity
0	Cola	low	05/07/2021	10.0
1	Bread	medium	05/07/2021	25.0
2	Beer	high	06/07/2021	100.0
3	Diaper	high	06/07/2021	NaN
4	Pizza	medium	06/07/2021	25.0

The attribute type determines which operator can be applied to the attribute

- Equality, sort, sum, ratio, etc.
- It makes sense to compute the average `Quantity` but not the average `ID`

Different attribute types

- (Categorical) **Nominal**: can distinguish the values (i.e., check equality)
- (Categorical) **Ordinal**: can distinguish and sort the values
- (Numeric) **Interval**: can distinguish and sort the values, and compute their difference
- (Numeric) **Ratio**: can distinguish and sort the values, and compute their difference and ratio

Pandas automatically infers data types, or they can be specified during creation

- Common data types are numeric ones
    - `np.floatN` represents floating numbers (e.g., -3.14)
    - `np.intN` / `np.uintN` represent integers with/without sign (-42 and 42)
    - `N` is the number of needed bits: 8, 16, 32 o 64
- Other data types
    - `bool` : Boolean values
    - `datetime64` , timedelta64: timestamp and time intervals
    - `object` : mainly used for strings

In [13]:
```
df.dtypes
```

Out[13]:
```
ID            object
PriceBin      object
Date          object
Quantity     float64
dtype: object
```

In [14]:
```python
# data profiling
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   ID        5 non-null      object 
 1   PriceBin  5 non-null      object 
 2   Date      5 non-null      object 
 3   Quantity  4 non-null      float64
dtypes: float64(1), object(3)
memory usage: 288.0+ bytes
```

In [15]:
```
# To get some statistics (e.g., count, mean, std, min, etc.)
df.describe(include='all')
```

Out[15]:

	ID	PriceBin	Date	Quantity
count	5	5	5	4.000000
unique	5	3	2	NaN
top	Cola	medium	06/07/2021	NaN
freq	1	2	3	NaN
mean	NaN	NaN	NaN	40.000000
std	NaN	NaN	NaN	40.620192
min	NaN	NaN	NaN	10.000000
25%	NaN	NaN	NaN	21.250000
50%	NaN	NaN	NaN	25.000000
75%	NaN	NaN	NaN	43.750000
max	NaN	NaN	NaN	100.000000

Data distribution

In [17]:
```
# array with distinct values sorted by first appearance
df["Quantity"].unique()
```

Out[17]:
```
array([ 10.,  25., 100.,  nan])
```

In [18]:
```
# quantity of unique values
df["Quantity"].nunique()
```

Out[18]:
```
3
```

In [19]:

```
# return a new series that associates each value with its number of occurrence.
df["Quantity"].value_counts()
```

Out[19]:

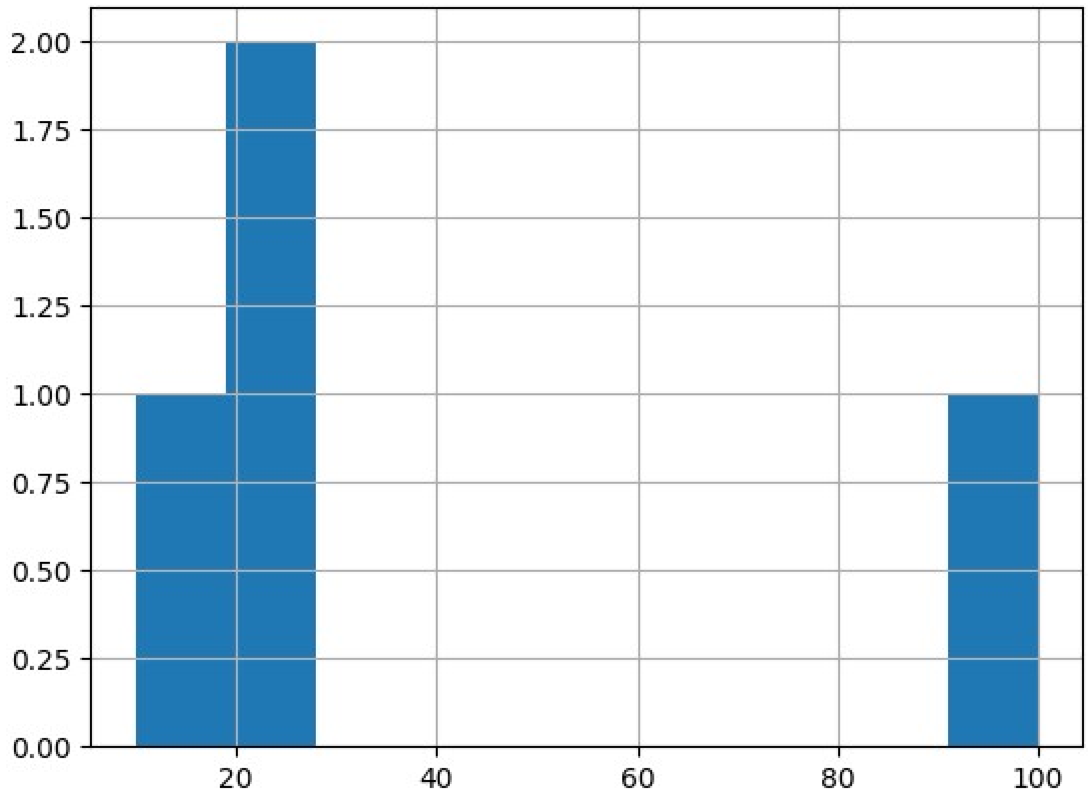
```
25.0     2
10.0     1
100.0    1
Name: Quantity, dtype: int64
```

In [20]:

```
df["Quantity"].hist(bins=10)
```

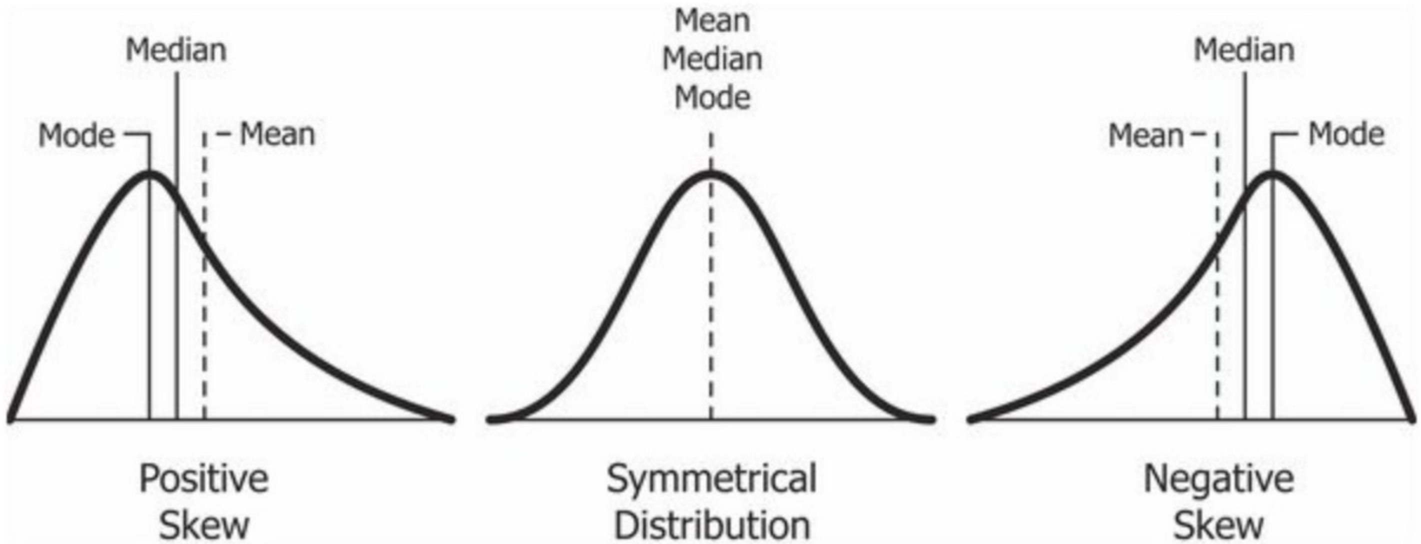
Out[20]:

```
<Axes: >
```



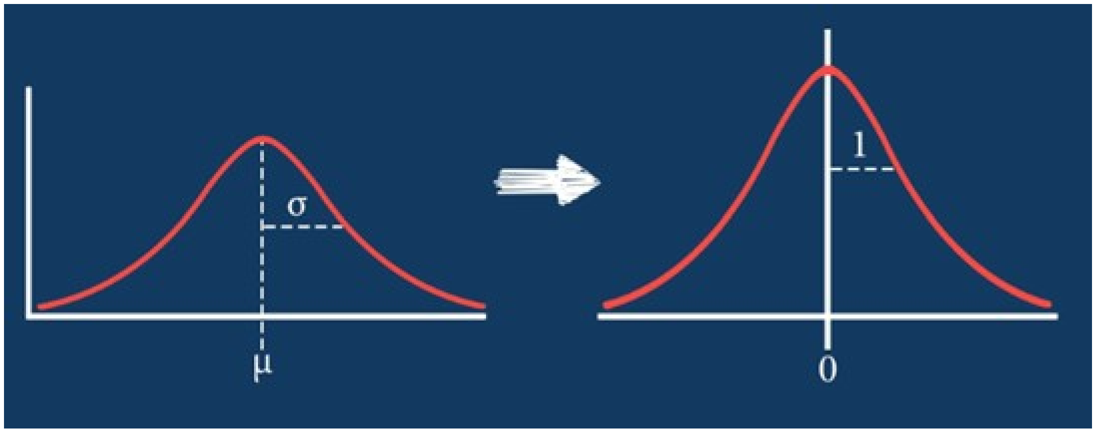
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
20
40
60
80
100

Which problems can cause skewed distributions?



Things are even more complex when applying sequences of transformations

- E.g., normalization should be applied before rebalancing since rebalancing (e.g., by resampling) alters average and standard deviations
- E.g., applying feature engineering before/after rebalancing produces different results which depends on the dataset and the algorithm



More an art than a science

- … At least for now

Missing values

Datasets often show missing values

- E.g., they are not applicable (e.g., date of death) or unknown
- A series can have missing values, referred to as `NA` (Not Available)
- Numeric attributes: `NA` is `np.nan` (Not a Number)
- `nan` is never equal, greater, or lower than other values (nor itself)

```
np.nan == np.nan
False
```

- Numeric expressions with `nan` return `nan`

```
2 * np.nan - 1
nan
```

Which problems arise from missing values?

In [21]:

```
# add the column "isna", True if the value is NaN
df["isna"] = df["Quantity"].isna()
# add the column "notna", False if the value is NaN
df["notna"] = df["Quantity"].notna()
df[["Quantity", "isna", "notna"]]
```

Out[21]:

	Quantity	isna	notna
0	10.0	False	True
1	25.0	False	True
2	100.0	False	True
3	NaN	True	False
4	25.0	False	True

Imputing missing values

Several strategies

- Replace `nan` with average or median values
- Forward/backward fill
- Dropping rows/columns with nans

Which are the effects?

In [22]:

```
# fill the missing value with the average
df["Quantity_imputed"] = df["Quantity"].fillna(df["Quantity"].mean())  # filln
df[["Quantity", "Quantity_imputed"]]
```

Out[22]:

	Quantity	Quantity_imputed
0	10.0	10.0
1	25.0	25.0
2	100.0	100.0
3	NaN	40.0
4	25.0	25.0

In [23]:
```python
# fill the missing value with the previous (not NaN) value
df["Quantity"].fillna(method="ffill")
```

Out[23]:
```
0     10.0
1     25.0
2    100.0
3    100.0
4     25.0
Name: Quantity, dtype: float64
```

In [24]:
```python
# fill the missing value with the following (not NaN) value
df["Quantity"].fillna(method="bfill")
```

Out[24]:
```
0     10.0
1     25.0
2    100.0
3     25.0
4     25.0
Name: Quantity, dtype: float64
```

In [25]:
```
df["Quantity"].dropna()
```

Out[25]:
```
0     10.0
1     25.0
2    100.0
4     25.0
Name: Quantity, dtype: float64
```

In [26]:
```
df.dropna()
```

Out[26]:

	ID	PriceBin	Date	Quantity	isna	notna	Quantity_imputed
0	Cola	low	05/07/2021	10.0	False	True	10.0
1	Bread	medium	05/07/2021	25.0	False	True	25.0
2	Beer	high	06/07/2021	100.0	False	True	100.0
4	Pizza	medium	06/07/2021	25.0	False	True	25.0

The `Housing` case study

Check also:

- https://www.kaggle.com/camnugent/california-housing-prices
- https://www.oreilly.com/library/view/hands-on-machine-learning/9781492032632/

We will use the California Housing Prices dataset. Our task is to use California census data to forecast housing prices given the population, median income, and median housing price for each block group in California. 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). We will just call them "districts" for short

In [27]:
```
# df = pd.read_csv("datasets/2022-bbs-dsaa-housing.csv", delimiter=",")
df = pd.read_csv("https://raw.githubusercontent.com/w4bo/handsOnDataPipelines/
df
```

Out[27]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	po
0	-122.23	37.88	41.0	880.0	129.0	
1	-122.22	37.86	21.0	7099.0	1106.0	
2	-122.24	37.85	52.0	1467.0	190.0	
3	-122.25	37.85	52.0	1274.0	235.0	
4	-122.25	37.85	52.0	1627.0	280.0	
...	...	...	...	...	...	
20635	-121.09	39.48	25.0	1665.0	374.0	
20636	-121.21	39.49	18.0	697.0	150.0	
20637	-121.22	39.43	17.0	2254.0	485.0	
20638	-121.32	39.43	18.0	1860.0	409.0	
20639	-121.24	39.37	16.0	2785.0	616.0	

20640 rows × 10 columns

... and now?

Answer some questions:

- Which attributes (i.e., columns) are contained in the dataset?
- Which is their semantics?

In [28]:
```
df.columns
```

Out[28]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'median_house_value', 'ocean_proximity'],
      dtype='object')
```

Dataset description

1. `longitude` : A measure of how far west a house is; a higher value is farther west
2. `latitude` : A measure of how far north a house is; a higher value is farther north
3. `housingMedianAge` : Median age of a house within a block; a lower number is a newer building
4. `totalRooms` : Total number of rooms within a block
5. `totalBedrooms` : Total number of bedrooms within a block
6. `population` : Total number of people residing within a block
7. `households` : Total number of households, a group of people residing within a home unit, for a block
8. `medianIncome` : Median income for households within a block of houses (measured in tens of thousands of US Dollars)
9. `medianHouseValue` : Median house value for households within a block (measured in US Dollars)
10. `oceanProximity` : Location of the house w.r.t ocean/sea

In [29]:

```
# show some statistics on the dataframe
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 2   housing_median_age  20640 non-null  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
 7   median_income       20640 non-null  float64
 8   median_house_value  20640 non-null  float64
 9   ocean_proximity     20640 non-null  object 
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

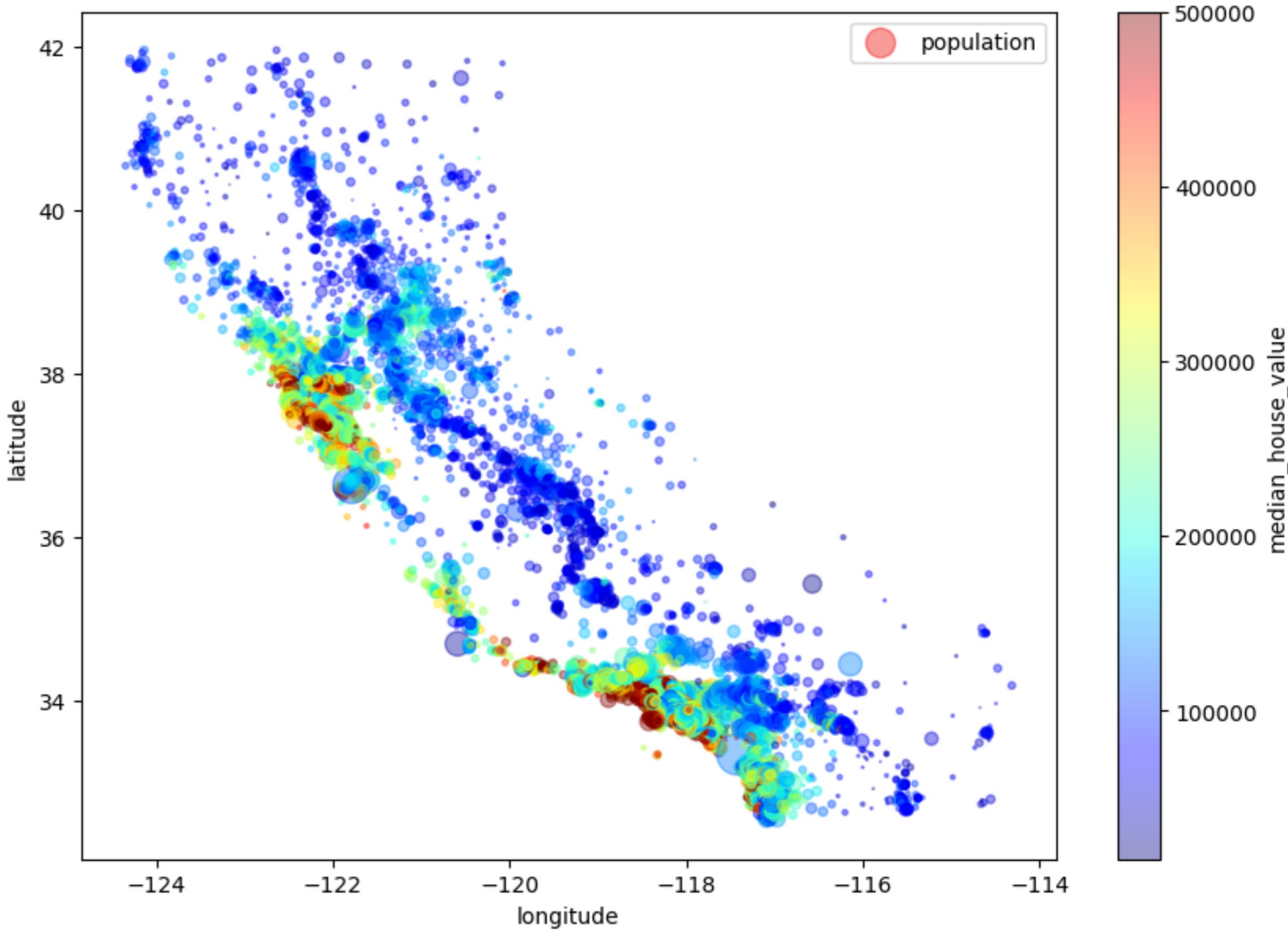
In [30]:
```
df.describe(include='all')
```

Out[30]:

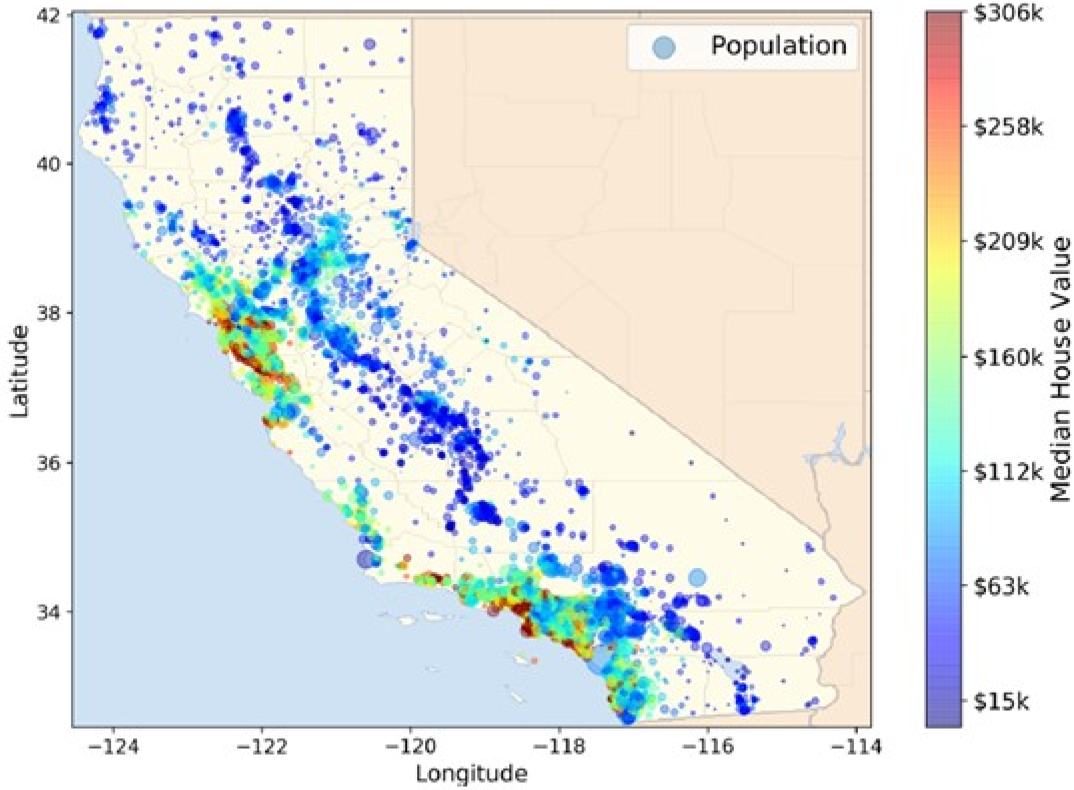
	longitude	latitude	housing_median_age	total_rooms	total_bed
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.(
unique	NaN	NaN	NaN	NaN	
top	NaN	NaN	NaN	NaN	
freq	NaN	NaN	NaN	NaN	
mean	-119.569704	35.631861	28.639486	2635.763081	537.8
std	2.003532	2.135952	12.585558	2181.615252	421.3
min	-124.350000	32.540000	1.000000	2.000000	1.(
25%	-121.800000	33.930000	18.000000	1447.750000	296.(
50%	-118.490000	34.260000	29.000000	2127.000000	435.(
75%	-118.010000	37.710000	37.000000	3148.000000	647.(
max	-114.310000	41.950000	52.000000	39320.000000	6445.(

… are you satisfied with the understanding?

… what about data visualization?

In [31]:
```python
df.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4, s=df["populati
```
Out[31]:
```
<Axes: xlabel='longitude', ylabel='latitude'>
```


What if we integrate open data?


Population
$306k
$258k
$209k
$160k
$112k
$63k
$15k
Median House Value
Latitude
Longitude
42
40
38
36
34
−124
−122
−120
−118
−116
−114

Memory usage

What if I change float64 to float32?

In [32]:
```
dff = df.copy(deep=True)  # copy the dataframe
for x in df.columns:  # iterate over the columns
    if dff[x].dtype == 'float64':  # if the column has type `float64`
        dff[x] = dff[x].astype('float32')  # ... change it to `float32`
dff.info()  # show some statistics on the dataframe
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   longitude           20640 non-null  float32
 1   latitude            20640 non-null  float32
 2   housing_median_age  20640 non-null  float32
 3   total_rooms         20640 non-null  float32
 4   total_bedrooms      20433 non-null  float32
 5   population          20640 non-null  float32
 6   households          20640 non-null  float32
 7   median_income       20640 non-null  float32
 8   median_house_value  20640 non-null  float32
 9   ocean_proximity     20640 non-null  object 
dtypes: float32(9), object(1)
memory usage: 887.0+ KB
```

Missing values

There are some missing values for `total_bedrooms` . What should we do?

Most Machine Learning algorithms cannot work with missing features. We have three options:

- Get rid of the corresponding districts (i.e., drop the rows)
    - `df.dropna(subset=["total_bedrooms"])`
- Get rid of the whole attribute (i.e., drop the columns)
    - `df.drop("total_bedrooms", axis=1)`
- Set the values to some value (zero, the mean, the median, etc.)
    - `df["total_bedrooms"].fillna(df["total_bedrooms"].median())`

Non-numeric attributes

`ocean_proximity` is a text attribute so we cannot compute its median. Some options:

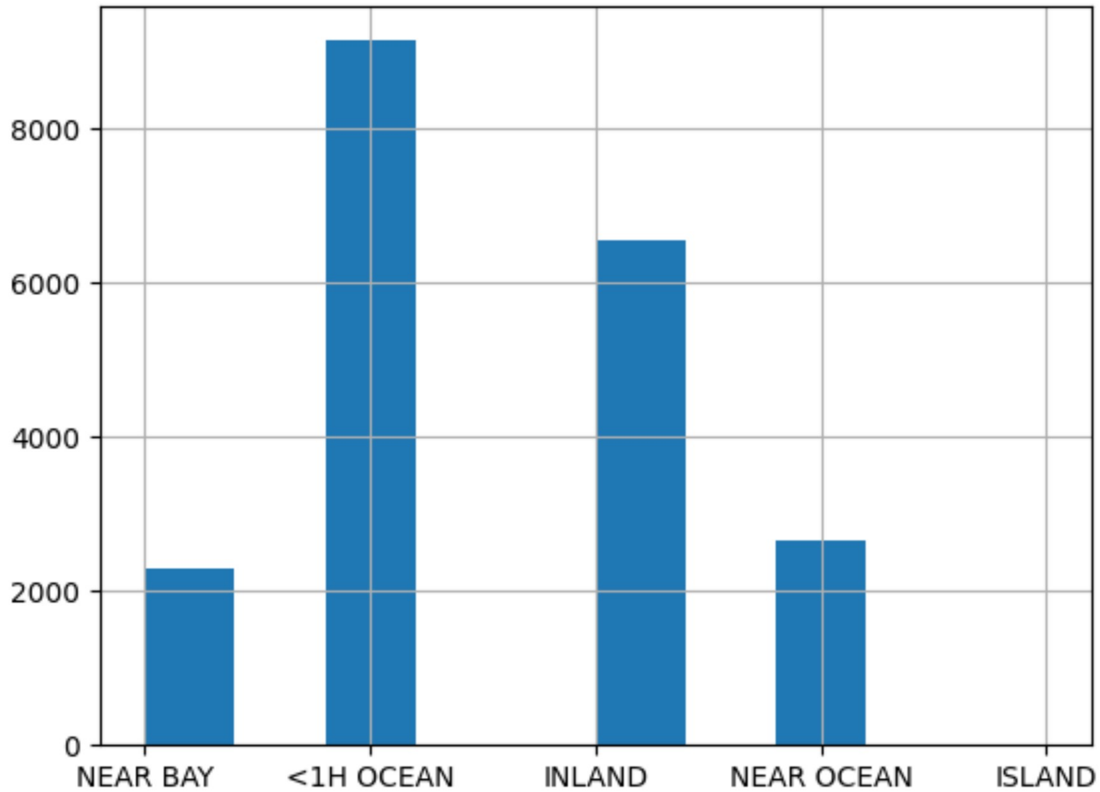
- Get rid of the whole attribute. (`df.drop("ocean_proximity", axis=1`)
- Change from categorical to ordinal (e.g., `NEAR BAY` = 0, `INLAND` = 1)
  - Can foresee any problem in this?
  - ML algorithms will assume that two nearby values are more similar than two distant values. This may be fine in some cases (e.g., for ordered categories such as “bad”, “average”, “good”, “excellent”), but it is obviously not the case for the ocean_proximity column (for example, categories 0 and 4 are clearly more similar than categories 0 and 1).
- Change from categorical to one hot encoding
  - To fix this issue, a common solution is to create one binary attribute per category: 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), and so on. This is called one-hot encoding, because only one attribute will be equal to 1 (hot), while the others will be 0 (cold). The new attributes are sometimes called dummy attributes

In [33]:
```
df["ocean_proximity"].value_counts()
```

Out[33]:
```
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: ocean_proximity, dtype: int64
```

In [34]:
```
df["ocean_proximity"].hist()
```

Out[34]: <Axes: >



Change from categorical to ordinal

In [35]:
```
from sklearn.preprocessing import OrdinalEncoder
ordinal_encoder = OrdinalEncoder()
y = ordinal_encoder.fit_transform(df[["ocean_proximity"]])
y
```

Out[35]:
```
array([[3.],
       [3.],
       [3.],
       ...,
       [1.],
       [1.],
       [1.]])
```

From categorical to one-hot encoding

In [36]:
```
y = pd.get_dummies(df["ocean_proximity"], prefix='ocean_proximity')
y
```

Out[36]:

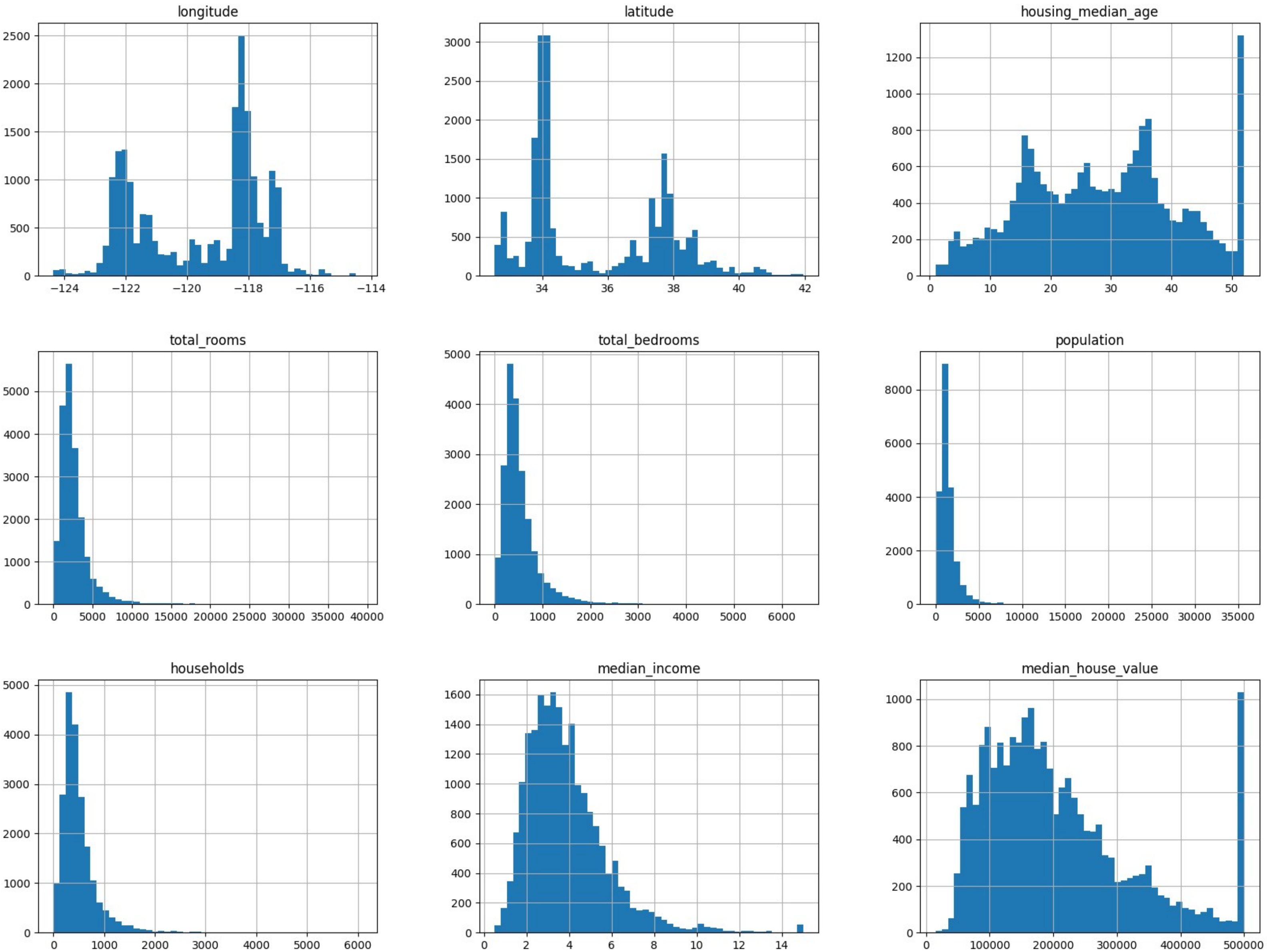
	ocean_proximity_<1H OCEAN	ocean_proximity_INLAND	ocean_proximity_ISLAND
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
...	...	...	...
20635	0	1	0
20636	0	1	0
20637	0	1	0
20638	0	1	0
20639	0	1	0

20640 rows × 5 columns

Visualization

In [37]:

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


longitude
latitude
housing_median_age
total_rooms
total_bedrooms
population
households
median_income
median_house_value
−124 −122 −120 −118 −116 −114
0 500 1000 1500 2000 2500
34 36 38 40 42
0 500 1000 1500 2000 2500 3000
0 10 20 30 40 50
0 200 400 600 800 1000 1200
0 5000 10000 15000 20000 25000 30000 35000 40000
0 1000 2000 3000 4000 5000
0 1000 2000 3000 4000 5000 6000
0 1000 2000 3000 4000 5000
0 5000 10000 15000 20000 25000 30000 35000
0 2000 4000 6000 8000
0 1000 2000 3000 4000 5000 6000
0 1000 2000 3000 4000 5000
0 2 4 6 8 10 12 14
0 200 400 600 800 1000 1200 1400 1600
0 100000 200000 300000 400000 500000
0 200 400 600 800 1000

Open questions:

- `median_income` should be in dollars. However, it has a strange range. Why? "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. The numbers represent roughly tens of thousands of dollars. The numbers represent roughly tens of thousands of dollars"
- `housing_median_age` and `median_house_value` are capped. As to `median_house_value`, this is a serious problem since it is your target attribute (your labels). Your Machine Learning algorithms may learn that prices never go beyond that limit. You need to check with your client team (the team that will use your system's output) to see if this is a problem or not. If they tell you that they need precise predictions even beyond 500,000USD, then you have mainly two options: (a) collect proper labels for the districts whose labels were capped, (b) remove those districts from the training set."
- These attributes have very different scales. Should we scale them?
- Many histograms are tail heavy: they extend much farther to the right of the median than to the left. This may make it a bit harder for some Machine Learning algorithms to detect patterns

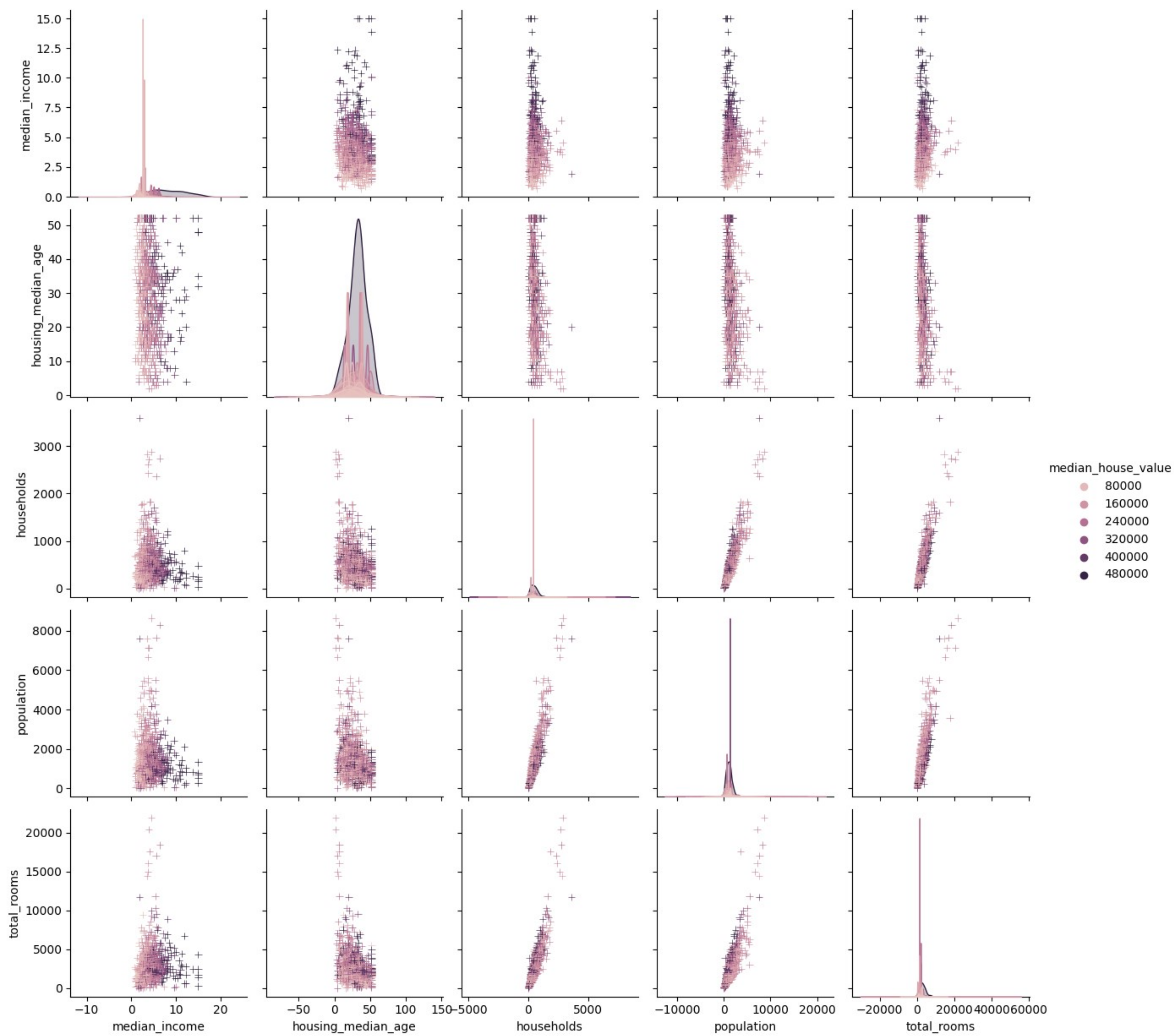
Are the relationships between variables?

- A grid of Axes such that each numeric variable in data will by shared across the y-axes across a single row and the x-axes across a single column
- The diagonal plots are treated differently: a univariate distribution plot is drawn to show the marginal distribution of the data in each column.

In [38]:

```
tmp = df[["median_income", "housing_median_age", "median_house_value", "househ
sns.pairplot(tmp.sample(n=1000, random_state=42), hue='median_house_value', ma
plt.show()
```

```
/usr/local/lib/python3.10/site-packages/seaborn/axisgrid.py:118: UserW
arning: The figure layout has changed to tight
  self._figure.tight_layout(*args, **kwargs)
```


median_income
housing_median_age
households
population
total_rooms
median_house_value
80000
160000
240000
320000
400000
480000

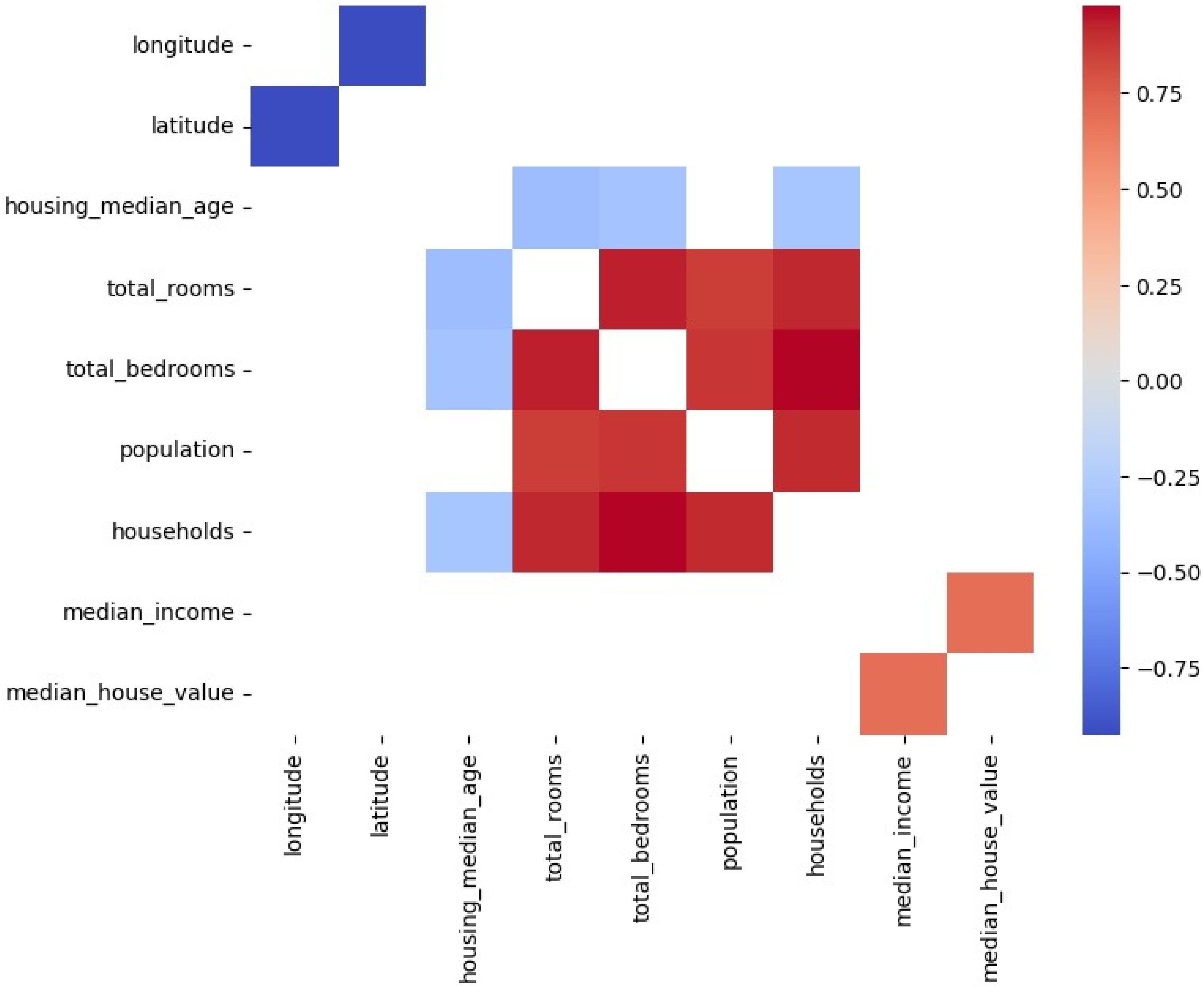
Check correlations and intervals

In [40]:

```
min_corr = 0.3
kot = rho[(abs(rho) >= min_corr) & (rho < 1)]
plt.figure(figsize=(8, 6))
sns.heatmap(kot, cmap=sns.color_palette("coolwarm", as_cmap=True))
```

Out[40]:

```
<Axes: >
```



longitude
latitude
housing_median_age
total_rooms
total_bedrooms
population
households
median_income
median_house_value
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

Scaling attributes

Attributes have very different scales. Should we scale them?

- Normalization is good to use when you know that the distribution of your data does not follow a Gaussian distribution. This can be useful in algorithms that do not assume any distribution of the data like K-Nearest Neighbors and Neural Networks.
- Standardization, on the other hand, can be helpful in cases where the data follows a Gaussian distribution. However, this does not have to be necessarily true. Unlike normalization, standardization does not have a bounding range. So, even if you have outliers in your data, they will not be affected by standardization.

Min-max normalization

In [41]:
```
num_df = df.drop(columns=['ocean_proximity', 'median_house_value'])
normalized_df = (num_df - num_df.min()) / (num_df.max() - num_df.min())
normalized_df
```

Out[41]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	p
0	0.211155	0.567481	0.784314	0.022331	0.019863	
1	0.212151	0.565356	0.392157	0.180503	0.171477	
2	0.210159	0.564293	1.000000	0.037260	0.029330	
3	0.209163	0.564293	1.000000	0.032352	0.036313	
4	0.209163	0.564293	1.000000	0.041330	0.043296	
...	...	...	...	...	...	
20635	0.324701	0.737513	0.470588	0.042296	0.057883	
20636	0.312749	0.738576	0.333333	0.017676	0.023122	
20637	0.311753	0.732200	0.313725	0.057277	0.075109	
20638	0.301793	0.732200	0.333333	0.047256	0.063315	
20639	0.309761	0.725824	0.294118	0.070782	0.095438	

20640 rows × 8 columns

Standardization

In [42]:
```
num_df = df.drop(columns=['ocean_proximity', 'median_house_value'])
normalized_df = (num_df - num_df.mean()) / num_df.std()
normalized_df
```

Out[42]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	p
0	-1.327803	1.052523	0.982119	-0.804800	-0.970301	
1	-1.322812	1.043159	-0.607004	2.045841	1.348243	
2	-1.332794	1.038478	1.856137	-0.535733	-0.825541	
3	-1.337785	1.038478	1.856137	-0.624199	-0.718750	
4	-1.337785	1.038478	1.856137	-0.462393	-0.611959	
...	...	...	...	...	...	
20635	-0.758808	1.801603	-0.289180	-0.444974	-0.388886	
20636	-0.818702	1.806285	-0.845373	-0.888682	-0.920466	
20637	-0.823693	1.778194	-0.924829	-0.174991	-0.125468	
20638	-0.873605	1.778194	-0.845373	-0.355591	-0.305826	
20639	-0.833676	1.750104	-1.004285	0.068407	0.185411	

20640 rows × 8 columns

This checklist can help you while building your projects

- Frame the problem and look at the big picture
    - ✅ Define the objective in business terms
    - ✖️ How should performance be measured?
- Get the data
    - ✅ List the data you need and how much you need
- Explore the data to gain insights
    - ✅ Create an environment to keep track of your data exploration
    - ✅ Study each attribute and its characteristics
- Prepare the data
    - ✅ Fix or remove outliers (optional)
    - ✅ Fill in missing values (e.g., with zero, mean, median...) or drop their rows (or columns)
    - ✅ Feature selection (optional): drop the attributes that provide no useful information for the task
    - ✅ Feature engineering, where appropriate: discretize continuous features

Hands on!

In [43]:
```
num_df = df.copy(deep=True).drop(columns=["ocean_proximity"])  # do not change

# Filling in (i.e., impute) missing values with the median value
num_df["total_bedrooms"] = 1  # change `1` with the proper solution

# Add a new column: population_per_household = population / households
num_df["population_per_household"] = 1  # change `1` with the proper solution

# Add a new column: rooms_per_household = total_rooms / households
num_df["rooms_per_household"] = 1  # change `1` with the proper solution

# Add a new column: bedrooms_per_room = total_bedrooms / total_rooms
num_df["bedrooms_per_room"] = 1  # change `1` with the proper solution

# Apply standardization to all the numeric columns
num_df = pd.DataFrame()  # change `pd.DataFrame()` with the proper solution

# One hot encode `ocean_proximity` since it is a categorical attribute
# change `pd.DataFrame()` with the proper solution (hint: pd.get_dummies)
cat_df = pd.DataFrame()

clean_df = pd.concat([num_df, cat_df], axis=1)  # do not change this line
clean_df
```

Out[43]: