1. Feature Engineering

Contents

1. Feature Engineering

1. Feature scaling

- ✓ Feature Scaling is a technique to standardize the independent features present in the data in a fixed range.
- ✓ It is performed during the data pre-processing.

2. Data pre-processing

- ✓ In machine learning data pre-processing is an important step
- ✓ The purpose of this technique is cleaning and organizing the raw data to make is suitable for building and training machine learning models

3. Why Data Pre-processing in Machine Learning?

- ✓ Typically, real-world data is incomplete, inconsistent, inaccurate (contains errors or outliers), and often lacks specific attribute values/trends.
- ✓ This is where data pre-processing enters the scenario – it helps to clean, format, and organize the raw data, thereby making it ready to use the data for Machine Learning models.

4. What type of data we need to handle?

- ✓ Two types of data we need to handle
  - Numerical data
  - Categorical data

5. Numerical data

- ✓ Quantitative data is the measurement of something monthly sales, or student scores etc.
- ✓ The natural way to represent these quantities is numerically (e.g., 29 students, $529,392 in sales).
- ✓ So we need to understand how to transforming raw numerical data into features, then we need to use this feature during machine learning

6. To handle Numerical data

Technique	Purpose
✓ LabelEncoder	✓ To convert all character/categorical variables to be numeric.
✓ StandardScaler	✓ To transform a feature which is mean to 0 and standard deviation to 1
✓ Transforming Features	✓ We can transform features
✓ Handling outlier	✓ To handle outlier
✓ Impute Missing Values	✓ To impute missing value with strategy

7. To handle Categorical data

Technique	Purpose
✓ Encoding nominal categories	✓ To do one hot encoding
✓ Encoding ordinal categories	✓ Ordinal categorical
✓ Imputing categorical missing values	✓ Imputing categorical missing values with most frequent strategy

8. scikit-learn installation

- ✓ To execute all these examples we need to install scikit-learn library.

```
pip install scikit-learn
```

9. Label Encoder

- ✓ By using this we can convert all character/categorical variables to be numeric.

9.1. LabelEncoder class

- ✓ **LabelEncoder** is predefined class in **sklearn.preprocessing** package
- ✓ We need to import this class from **sklearn.preprocessing** package
- ✓ Once we imported then we need to **create an object** o **LabelEncoder** class.

9.2. fit_transform(p) method

- ✓ fit_transform(p) is predefined method in **LabelEncoder** class.
- ✓ We should access this method by using **LabelEncoder** object only.
- ✓ This method converts categorical variables into numerical values.

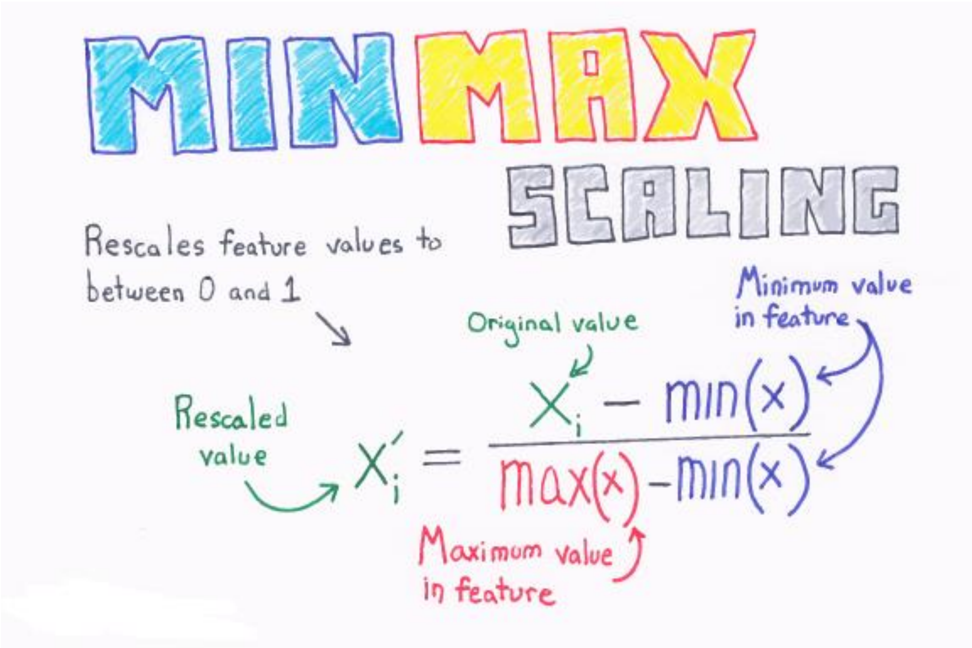
Program Name: LabelEncoder demo1.py

```
from sklearn.preprocessing import LabelEncoder
import pandas as pd

d = {
        "Company": ["Google", "Twitter", "Google", "LinkedIn"],
        "Role": ["Data Scientist", "Sales manager", "HR", "HR"]
}

df = pd.DataFrame(d)
label_encoder = LabelEncoder()

df["Company_n"] = label_encoder.fit_transform(df['Company'])
df["Role_n"] = label_encoder.fit_transform(df['Role'])

print()
print(df)
```

Output

```
    Company            Role  Company_n  Role_n
0    Google  Data Scientist          0       0
1   Twitter   Sales manager          2       2
2    Google              HR          0       1
3  LinkedIn              HR          1       1
```

10. MinMaxScaler



- ✓ Min-max scaling is a common feature pre-processing technique which results in scaled data values that fall in the range 0 and 1.
  - 0 is minimum value
  - 1 is maximum value

- ✓ If we rescale the value of numeric feature then it is in between two values.

Program Name	MinMaxScaler demo2.py

```
import pandas as pd

d = {
	"x" : [10, 20, 30, 40, 50],
	"y" : [25, 50, 75, 100, 125]
}

df = pd.DataFrame(d)
print(df)
```

Output

```
    x    y
0  10   25
1  20   50
2  30   75
3  40  100
4  50  125
```

Program Name	MinMaxScaler: single column demo3.py

```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler

d = {
	"x" : [10, 20, 30, 40, 50],
	"y" : [25, 50, 75, 100, 125]
}

df = pd.DataFrame(d)
mm_scale = MinMaxScaler(feature_range = (0, 1))

print(df)

one_col = mm_scale.fit_transform(df[["x"]])

print(one_col)
```

Output

```
    x    y
0  10   25
1  20   50
2  30   75
3  40  100
4  50  125

[[0.  ]
 [0.25]
 [0.5 ]
 [0.75]
 [1.  ]]
```

Program Name: MinMaxScaler: two columns
demo4.py

```python
import pandas as pd
from sklearn.preprocessing import MinMaxScaler

d = {
	"x" : [10, 20, 30, 40, 50],
	"y" : [25, 50, 75, 100, 125]
}

df = pd.DataFrame(d)
mm_scale = MinMaxScaler(feature_range = (0, 1))

print(df)

df[["x", "y"]] = mm_scale.fit_transform(df[["x", "y"]])

print(df)
```

Output

```
    x    y
0  10   25
1  20   50
2  30   75
3  40  100
4  50  125
      x     y
0  0.00  0.00
1  0.25  0.25
2  0.50  0.50
3  0.75  0.75
4  1.00  1.00
```

11. Transforming Features

- ✓ By using **FunctionTransformer** we can transform the features**.**

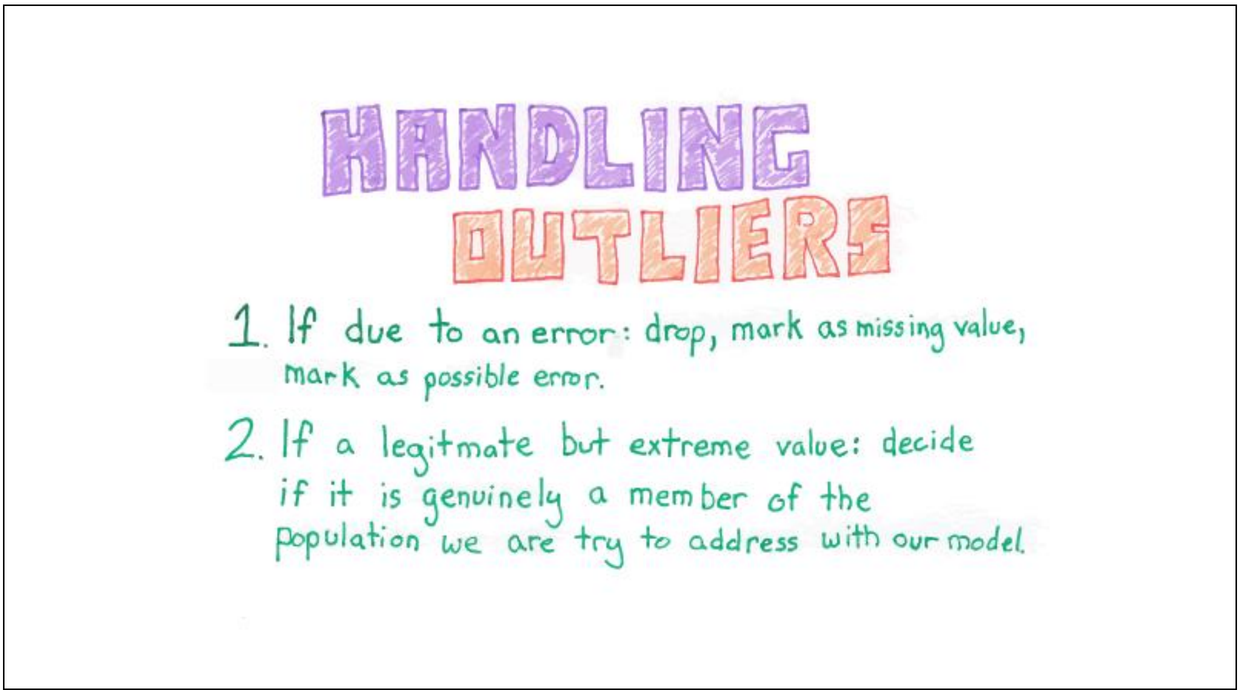
Program Name: FunctionTransformer demo5.py

```
import numpy as np
from sklearn.preprocessing import FunctionTransformer

a = [[10, 20], [30, 40], [50, 60]]

f = np.array(a)

def add_ten(x):
        return x + 10

obj = FunctionTransformer(add_ten)

result = obj.transform(f)

print(f)
print()
print(result)
```

Output

```
[[10 20]
 [30 40]
 [50 60]]

[[20 30]
 [40 50]
 [60 70]]
```

12. Handling outlier



- ✓ Outlier means a large value compare with other values
- ✓ Some values are also out of the range of the feature, so they are also considered as outliers.
- ✓ Outliers affect our model's efficiency because it influences the model very much.
- ✓ Three ways to handle these,
    - Drop outlier or filter outlier
    - Marking them using boolean condition
    - Transform into feature

Program Name	A dataframe with outliers demo6.py

```
import numpy as np
import pandas as pd

houses = pd.DataFrame()

houses['Price'] = [534433, 392333, 293222, 4322032]
houses['rooms'] = [2, 3, 2, 116]
houses['Square_Feet'] = [1500, 2500, 1500, 48000]

print(houses)
```

Output

```
     Price  rooms  Square_Feet
0   534433      2         1500
1   392333      3         2500
2   293222      2         1500
3  4322032    116        48000
```

Program Name — Filtering outlier
demo7.py

```
import numpy as np
import pandas as pd

houses = pd.DataFrame()

houses['Price'] = [534433, 392333, 293222, 4322032]
houses['rooms'] = [2, 3, 2, 116]
houses['Square_Feet'] = [1500, 2500, 1500, 48000]

con1 = houses['rooms'] < 20
new = houses[con1]

print(new)
```

Output

```
    Price  rooms  Square_Feet
0  534433      2         1500
1  392333      3         2500
2  293222      2         1500
```

Program Name: Mark them as outliers
demo8.py

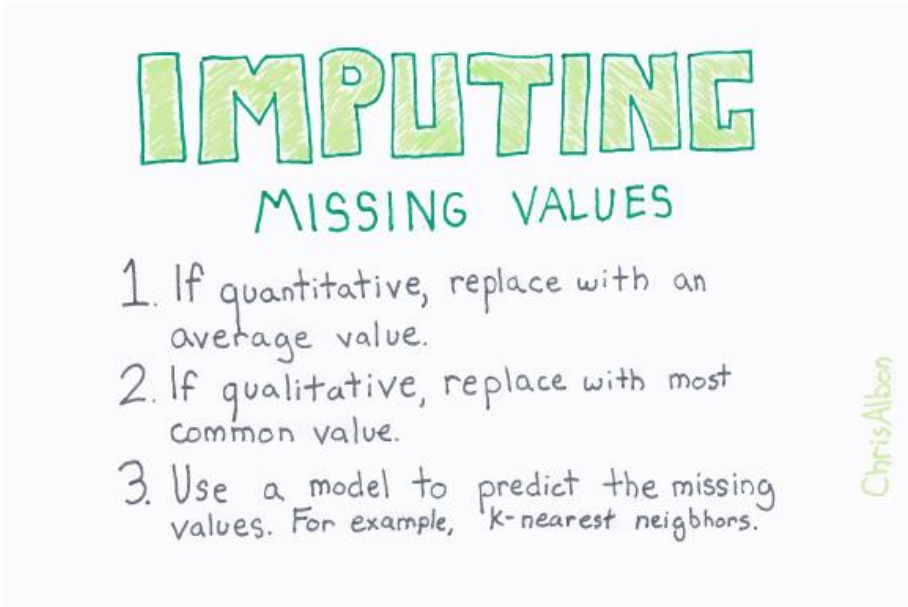
```
import numpy as np
import pandas as pd

houses = pd.DataFrame()

houses['Price'] = [534433, 392333, 293222, 4322032]
houses['rooms'] = [2, 3, 2, 116]
houses['Square_Feet'] = [1500, 2500, 1500, 48000]

houses["Outlier"] = np.where(houses["rooms"] < 20, 0, 1)

print(houses)
```

Output

```
     Price  rooms  Square_Feet  Outlier
0   534433      2         1500        0
1   392333      3         2500        0
2   293222      2         1500        0
3  4322032    116        48000        1
```

13. Impute Missing values

- ✓ We can impute missing values with different strategy.
- ✓ There are two types of missing values
    - Numeric missing values
    - Categorical missing values



14. Impute missing numeric values

- ✓ Missing numeric values we can impute with different strategy
  - mean
  - median
  - most_frequent
  - constant

Program Name: Creating DataFrame
demo9.py

```
import numpy as np
import pandas as pd

students = [
        [85, 'M', 'verygood'],
        [95, 'F', 'excellent'],
        [60, None, 'good'],
        [np.NaN, 'M', 'average'],
        [70, 'M', 'good'],
        [np.NaN, None, 'verygood'],
        [60, 'F', 'verygood'],
        [98, 'M', 'excellent']
]

cols = ['marks', 'gender', 'result']
df = pd.DataFrame(students, columns = cols)
print(df)
```

output

```
   marks gender     result
0   85.0      M   verygood
1   95.0      F  excellent
2   60.0   None       good
3    NaN      M    average
4   70.0      M       good
5    NaN   None   verygood
6   60.0      F   verygood
7   98.0      M  excellent
```

Program Name	Imputing missing numeric values with mean strategy demo10.py

```
import numpy as np
from sklearn.impute import SimpleImputer
import pandas as pd

students = [
        [85, 'M', 'verygood'],
        [95, 'F', 'excellent'],
        [60, None, 'good'],
        [np.NaN, 'M', 'average'],
        [70, 'M', 'good'],
        [np.NaN, None, 'verygood'],
        [60, 'F', 'verygood'],
        [98, 'M', 'excellent']
]

cols = ['marks', 'gender', 'result']
df = pd.DataFrame(students, columns = cols)

print(df)

imputer = SimpleImputer(missing_values = np.nan, strategy =
'mean')

result = df['marks'].values.reshape(-1, 1)

df.marks = imputer.fit_transform(result)

print()
print(df)
```

output

```
   marks gender     result
0   85.0      M   verygood
1   95.0      F  excellent
2   60.0   None       good
3    NaN      M    average
4   70.0      M       good
5    NaN   None   verygood
6   60.0      F   verygood
7   98.0      M  excellent

   marks gender     result
0   85.0      M   verygood
1   95.0      F  excellent
2   60.0   None       good
3   78.0      M    average
4   70.0      M       good
5   78.0   None   verygood
6   60.0      F   verygood
7   98.0      M  excellent
```

Program Name

Imputing missing numeric values with median strategy
demo11.py

```
import numpy as np
from sklearn.impute import SimpleImputer
import pandas as pd

students = [
        [85, 'M', 'verygood'],
        [95, 'F', 'excellent'],
        [60, None, 'good'],
        [np.NaN, 'M', 'average'],
        [70, 'M', 'good'],
        [np.NaN, None, 'verygood'],
        [60, 'F', 'verygood']
]

cols = ['marks', 'gender', 'result']
df = pd.DataFrame(students, columns = cols)

print(df)

imputer = SimpleImputer(missing_values = np.nan, strategy = '
median')

result = df['marks'].values.reshape(-1, 1)

df.marks = imputer.fit_transform(result)

print()
print(df)
```

output

```
   marks gender     result
0   85.0      M   verygood
1   95.0      F  excellent
2   60.0   None       good
3    NaN      M    average
4   70.0      M       good
5    NaN   None   verygood
6   60.0      F   verygood

   marks gender     result
0   85.0      M   verygood
1   95.0      F  excellent
2   60.0   None       good
3   70.0      M    average
4   70.0      M       good
5   70.0   None   verygood
6   60.0      F   verygood
```

Program Name	Imputing missing numeric values with most_frequent strategy demo12.py

```
import numpy as np
from sklearn.impute import SimpleImputer
import pandas as pd

students = [
                [85, 'M', 'verygood'],
                [95, 'F', 'excellent'],
                [60, None, 'good'],
                [np.NaN, 'M', 'average'],
                [70, 'M', 'good'],
                [np.NaN, None, 'verygood'],
                [60, 'F', 'verygood'],
                [98, 'M', 'excellent']
]

cols = ['marks', 'gender', 'result']
df = pd.DataFrame(students, columns = cols)

imputer = SimpleImputer(missing_values = np.nan, strategy = '
most_frequent')

result = df['marks'].values.reshape(-1, 1)

df.marks = imputer.fit_transform(result)

print(df)
```

output

```
   marks gender     result
0   85.0      M   verygood
1   95.0      F  excellent
2   60.0   None       good
3   60.0      M    average
4   70.0      M       good
5   60.0   None   verygood
6   60.0      F   verygood
7   98.0      M  excellent
```

Program Name	Imputing missing numeric values with constant strategy demo13.py

```
import numpy as np
from sklearn.impute import SimpleImputer
import pandas as pd

students = [
                [85, 'M', 'verygood'],
                [95, 'F', 'excellent'],
                [60, None, 'good'],
                [np.NaN, 'M', 'average'],
                [70, 'M', 'good'],
                [np.NaN, None, 'verygood'],
                [60, 'F', 'verygood'],
                [98, 'M', 'excellent']
]

cols = ['marks', 'gender', 'result']
df = pd.DataFrame(students, columns = cols)

print(df)

imputer = SimpleImputer(missing_values = np.nan, strategy =
'constant', fill_value = 80)

result = df['marks'].values.reshape(-1, 1)

df.marks = imputer.fit_transform(result)

print()
print(df)
```

output

```
   marks gender     result
0   85.0      M   verygood
1   95.0      F  excellent
2   60.0   None       good
3    NaN      M    average
4   70.0      M       good
5    NaN   None   verygood
6   60.0      F   verygood
7   98.0      M  excellent

   marks gender     result
0   85.0      M   verygood
1   95.0      F  excellent
2   60.0   None       good
3   80.0      M    average
4   70.0      M       good
5   80.0   None   verygood
6   60.0      F   verygood
7   98.0      M  excellent
```

2. Feature Engineering

Contents

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1. Handling Categorical Data

Categorical data

- ✓ Categorical data are variables that contain label values rather than numeric values.

Types of categorical data

- ✓ Nominal Variable
- ✓ Ordinal Variable

Nominal Variable

- ✓ The variables which are having no-order those are called as Nominal Variable.
- ✓ Examples:
    - Pet variables values : cat, dog
    - Color variables values : blue, green, red

Ordinal Variable

- ✓ The variables which are having an order those are called as ordinal Variable.
- ✓ Examples:
    - Score variables values : low, medium, high

Kind note

- ✓ In real time mostly we do have nominal variable scenarios.
- ✓ So, please understand the below scenarios

2. Encoding Categorical Data

- ✓ There are 3 ways to convert categorical variables to numerical values.
    - Ordinal encoding
    - One hot encoding
    - Dummy variable encoding

2.1. Ordinal encoding

- ✓ In ordinal encoding every nominal value is assigned an integer value.
- ✓ Example
    - blue : 0
    - green : 1
    - red : 2

Program Name: Ordinal encoding demo1.py

```python
from numpy import asarray
from sklearn.preprocessing import OrdinalEncoder

data = asarray([['blue'], ['green'], ['red']])

encoder = OrdinalEncoder()
result = encoder.fit_transform(data)

print(data)
print(result)
```

Output

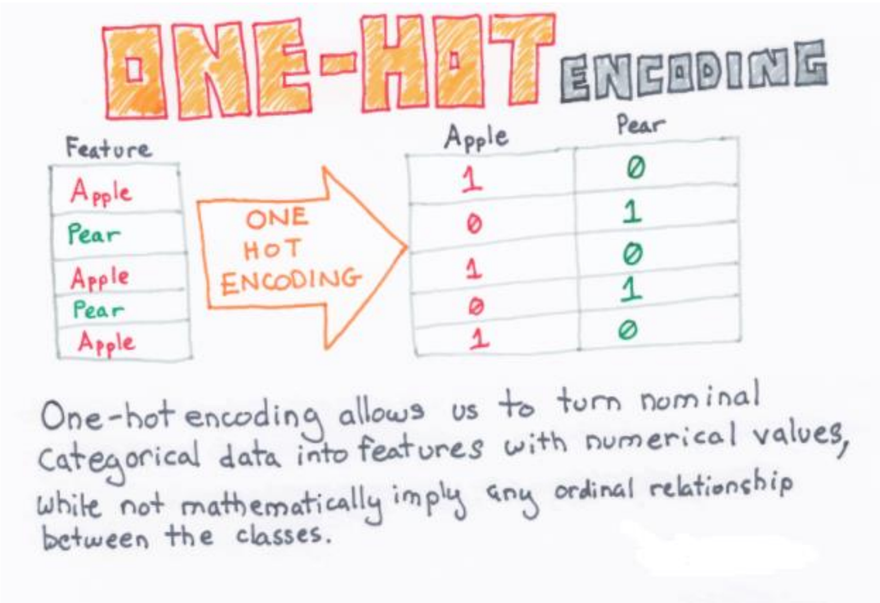
```
[['blue']
 ['green']
 ['red']]

[[0.]
 [1.]
 [2.]]
```

Problem with ordinal encoding

- ✓ If we have applied ordinal encoding on nominal values then it will be an order and having relationship but actually there is no relationship in between the nominal variables.
- ✓ Machine learning algorithm understands like there is an order in between nominal values.
- ✓ So it causes a problem like machine learning algorithm will produce poor performance.
- ✓ We can solve this problem by using one hot encoding.

2.2. One hot encoding

- ✓ For **nominal** values integer encoding may not be enough and even it is misleading the model.
- ✓ Here one hot encoding helps, it is technique where each of the nominal variables will be represented with binary values.



- ✓ Example

  - blue : 1 0 0
  - green : 0 1 0
  - red : 0 0 1

Program Name	One hot encoding demo2.py

```
from numpy import asarray
from sklearn.preprocessing import OneHotEncoder

a = [['apple'], ['peer'], ['apple'], ['peer'], ['apple']]
data = asarray(a)

encoder = OneHotEncoder(sparse = False)
onehot = encoder.fit_transform(data)

print(data)
print()
print(onehot)
```

output

```
[['apple']
 ['peer']
 ['apple']
 ['peer']
 ['apple']]

[[1. 0.]
 [0. 1.]
 [1. 0.]
 [0. 1.]
 [1. 0.]]
```

Program Name: One hot encoding

demo3.py

```
from numpy import asarray
from sklearn.preprocessing import OneHotEncoder

data = asarray([['blue'], ['green'], ['red']])
encoder = OneHotEncoder(sparse = False)
onehot = encoder.fit_transform(data)

print(data)
print(onehot)
```

Output

```
[['blue']
 ['green']
 ['red']]

[[1. 0. 0.]
 [0. 1. 0.]
 [0. 0. 1.]]
```

2.3. Dummy variable encoding

- ✓ The one hot encoding creates one binary variable for each category.
- ✓ The problem is that this representation includes redundancy.
- ✓ For example, if we know that [1, 0, 0] represents for first value and [0, 1, 0] represents for second value then we don't need another binary variable to represent third value, instead we could use 0 values alone like [0, 0].

One hot encoding example

- ✓ Example

    - o blue : 1 0 0
    - o green : 0 1 0
    - o red : 0 0 1

Dummy variable encoding example

- ✓ Example

    - o blue : 0 0
    - o green : 1 0
    - o red : 0 1

Conclusion

- ✓ If we drop first column from the result of one hot encoding then we will get dummy variable encoding

Program Name

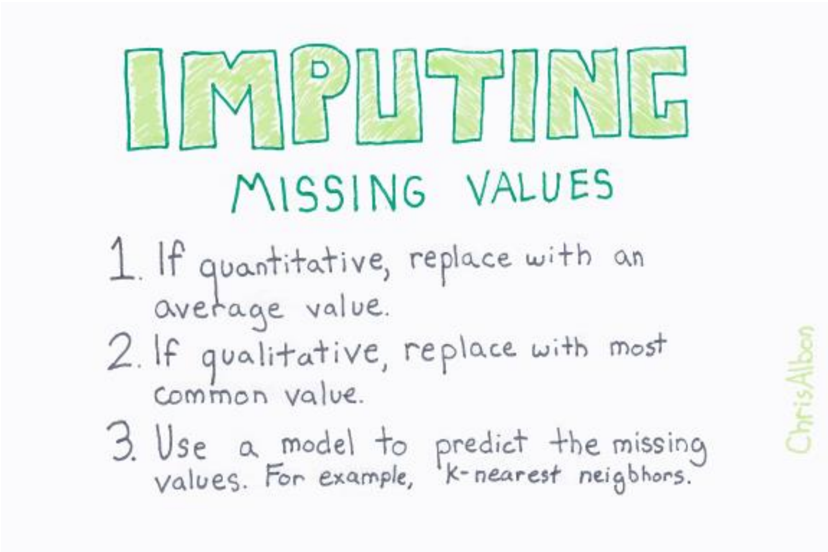
Dummy variable encoding
demo4.py

```
from numpy import asarray
from sklearn.preprocessing import OneHotEncoder

data = asarray([['blue'], ['green'], ['red']])
encoder = OneHotEncoder(drop = 'first', sparse = False)

onehot = encoder.fit_transform(data)

print(data)
print(onehot)
```

Output

```
[['blue']
 ['green']
 ['red']]

[[0. 0.]
 [1. 0.]
 [0. 1.]]
```

2.4. Imputing Missing Class Values



- ✓ Categorical feature may have missing values
- ✓ These we can impute with most frequent strategy

Program Name	Imputing categorical values with most frequent strategy demo5.py

```
import pandas as pd
import numpy as np
from sklearn.impute import SimpleImputer

students = [
            [85, 'M', 'verygood'],
            [95, 'F', 'excellent'],
            [75, np.NaN, 'good'],
            [np.NaN, 'M', 'average'],
            [70, 'M', 'good'],
            [np.NaN, np.NaN, 'verygood'],
            [92, 'F', 'verygood'],
            [98, 'M', 'excellent']
]

cols = ['marks', 'gender', 'result']
df = pd.DataFrame(students, columns = cols)

print(df)

imputer = SimpleImputer(missing_values = np.NaN,
strategy='most_frequent')

result = df['gender'].values.reshape(-1, 1)

df.gender = imputer.fit_transform(result)

print()
print(df)
```

output

```
   marks gender     result
0   85.0      M   verygood
1   95.0      F  excellent
2   75.0    NaN       good
3    NaN      M    average
4   70.0      M       good
5    NaN    NaN   verygood
6   92.0      F   verygood
7   98.0      M  excellent

   marks gender     result
0   85.0      M   verygood
1   95.0      F  excellent
2   75.0      M       good
3    NaN      M    average
4   70.0      M       good
5    NaN      M   verygood
6   92.0      F   verygood
7   98.0      M  excellent
```

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- ✓ Examples:
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    - Color variables values : blue, green, red

Ordinal Variable

- ✓ The variables which are having an order those are called as ordinal Variable.
- ✓ Examples:
    - Score variables values : low, medium, high

Kind note

- ✓ In real time mostly we do have nominal variable scenarios.
- ✓ So, please understand the below scenarios

2. Encoding Categorical Data

- ✓ There are 3 ways to convert categorical variables to numerical values.
    - Ordinal encoding
    - One hot encoding
    - Dummy variable encoding

2.1. Ordinal encoding

- ✓ In ordinal encoding every nominal value is assigned an integer value.
- ✓ Example
    - blue : 0
    - green : 1
    - red : 2

Program Name: Ordinal encoding demo1.py

```
from numpy import asarray
from sklearn.preprocessing import OrdinalEncoder

data = asarray([['blue'], ['green'], ['red']])

encoder = OrdinalEncoder()
result = encoder.fit_transform(data)

print(data)
print(result)
```

Output

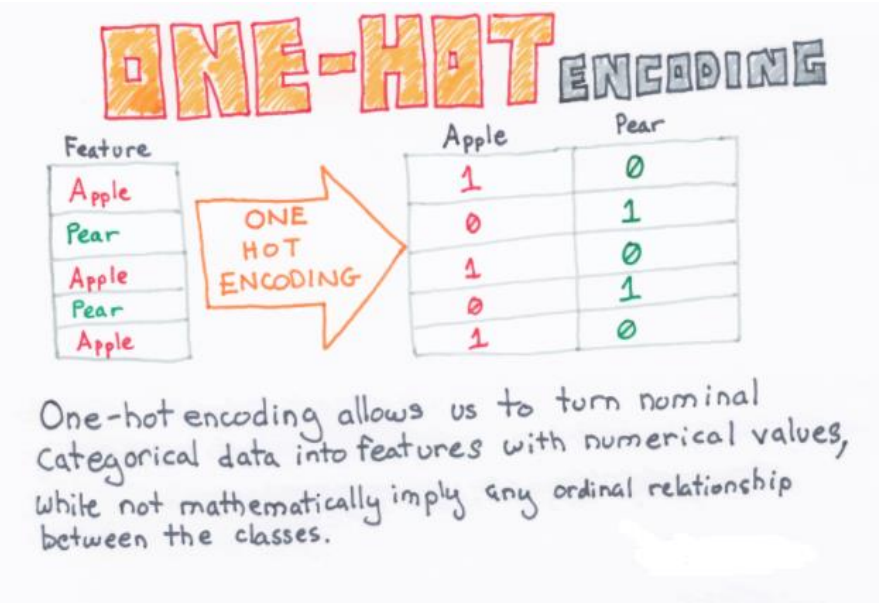
```
[['blue']
 ['green']
 ['red']]

[[0.]
 [1.]
 [2.]]
```

Problem with ordinal encoding

- ✓ If we have applied ordinal encoding on nominal values then it will be an order and having relationship but actually there is no relationship in between the nominal variables.
- ✓ Machine learning algorithm understands like there is an order in between nominal values.
- ✓ So it causes a problem like machine learning algorithm will produce poor performance.
- ✓ We can solve this problem by using one hot encoding.

2.2. One hot encoding

- ✓ For **nominal** values integer encoding may not be enough and even it is misleading the model.
- ✓ Here one hot encoding helps, it is technique where each of the nominal variables will be represented with binary values.



- ✓ Example

  - blue : 1 0 0
  - green : 0 1 0
  - red : 0 0 1

Program Name	One hot encoding demo2.py

```
from numpy import asarray
from sklearn.preprocessing import OneHotEncoder

a = [['apple'], ['peer'], ['apple'], ['peer'], ['apple']]
data = asarray(a)

encoder = OneHotEncoder(sparse = False)
onehot = encoder.fit_transform(data)

print(data)
print()
print(onehot)
```

output

```
[['apple']
 ['peer']
 ['apple']
 ['peer']
 ['apple']]

[[1. 0.]
 [0. 1.]
 [1. 0.]
 [0. 1.]
 [1. 0.]]
```

Program Name	One hot encoding
demo3.py

```
from numpy import asarray
from sklearn.preprocessing import OneHotEncoder

data = asarray([['blue'], ['green'], ['red']])
encoder = OneHotEncoder(sparse = False)
onehot = encoder.fit_transform(data)

print(data)
print(onehot)
```

Output

```
[['blue']
 ['green']
 ['red']]

[[1. 0. 0.]
 [0. 1. 0.]
 [0. 0. 1.]]
```

2.3. Dummy variable encoding

- ✓ The one hot encoding creates one binary variable for each category.
- ✓ The problem is that this representation includes redundancy.
- ✓ For example, if we know that [1, 0, 0] represents for first value and [0, 1, 0] represents for second value then we don't need another binary variable to represent third value, instead we could use 0 values alone like [0, 0].

One hot encoding example

- ✓ Example
  - blue : 1 0 0
  - green : 0 1 0
  - red : 0 0 1

Dummy variable encoding example

- ✓ Example
  - blue : 0 0
  - green : 1 0
  - red : 0 1

Conclusion

- ✓ If we drop first column from the result of one hot encoding then we will get dummy variable encoding

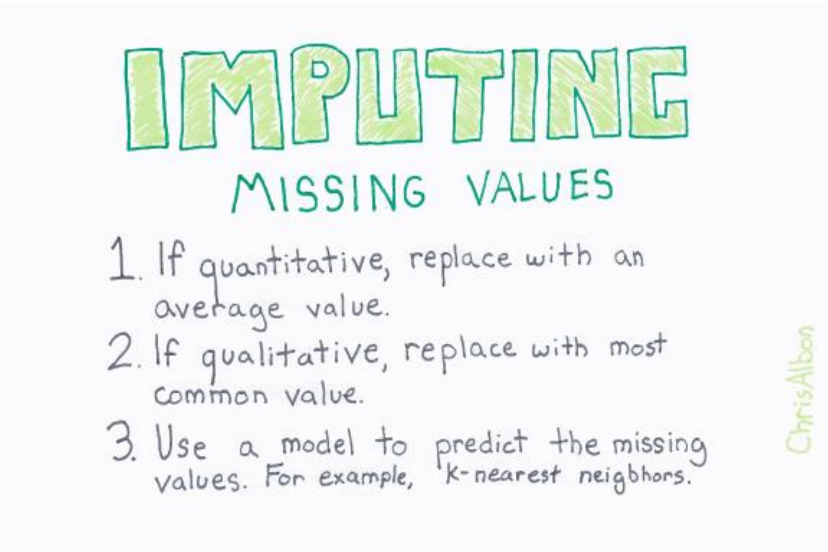
Program	Dummy variable encoding
Name	demo4.py

```
from numpy import asarray
from sklearn.preprocessing import OneHotEncoder

data = asarray([['blue'], ['green'], ['red']])
encoder = OneHotEncoder(drop = 'first', sparse = False)

onehot = encoder.fit_transform(data)

print(data)
print(onehot)
```

Output

```
[['blue']
 ['green']
 ['red']]

[[0. 0.]
 [1. 0.]
 [0. 1.]]
```

2.4. Imputing Missing Class Values



- ✓ Categorical feature may have missing values
- ✓ These we can impute with most frequent strategy

Program Name	Imputing categorical values with most frequent strategy demo5.py

```
import pandas as pd
import numpy as np
from sklearn.impute import SimpleImputer

students = [
        [85, 'M', 'verygood'],
        [95, 'F', 'excellent'],
        [75, np.NaN, 'good'],
        [np.NaN, 'M', 'average'],
        [70, 'M', 'good'],
        [np.NaN, np.NaN, 'verygood'],
        [92, 'F', 'verygood'],
        [98, 'M', 'excellent']
]

cols = ['marks', 'gender', 'result']
df = pd.DataFrame(students, columns = cols)

print(df)

imputer = SimpleImputer(missing_values = np.NaN,
strategy='most_frequent')

result = df['gender'].values.reshape(-1, 1)

df.gender = imputer.fit_transform(result)

print()
print(df)
```

output

```
   marks gender     result
0   85.0      M   verygood
1   95.0      F  excellent
2   75.0    NaN       good
3    NaN      M    average
4   70.0      M       good
5    NaN    NaN   verygood
6   92.0      F   verygood
7   98.0      M  excellent

   marks gender     result
0   85.0      M   verygood
1   95.0      F  excellent
2   75.0      M       good
3    NaN      M    average
4   70.0      M       good
5    NaN      M   verygood
6   92.0      F   verygood
7   98.0      M  excellent
```