# 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

```
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

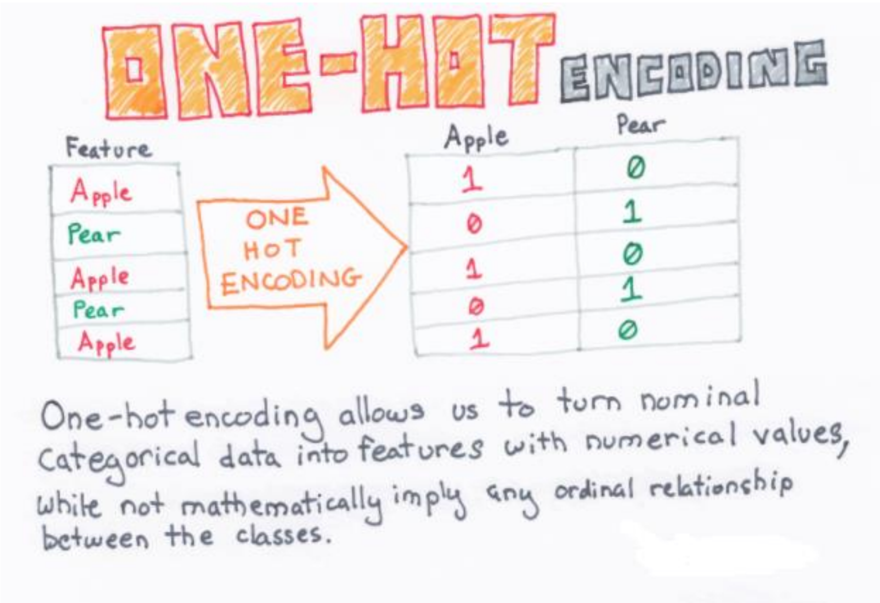
```
[['blue']
 ['green']
 ['red']]

[[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_output = 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_output = 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 Name

Dummy variable encoding

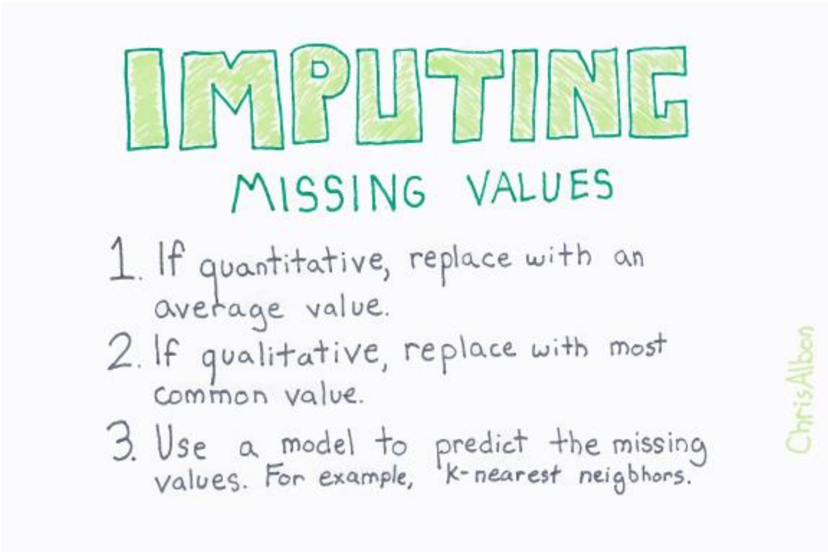
demo4.py

```
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<br>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
```