Department of Data Science

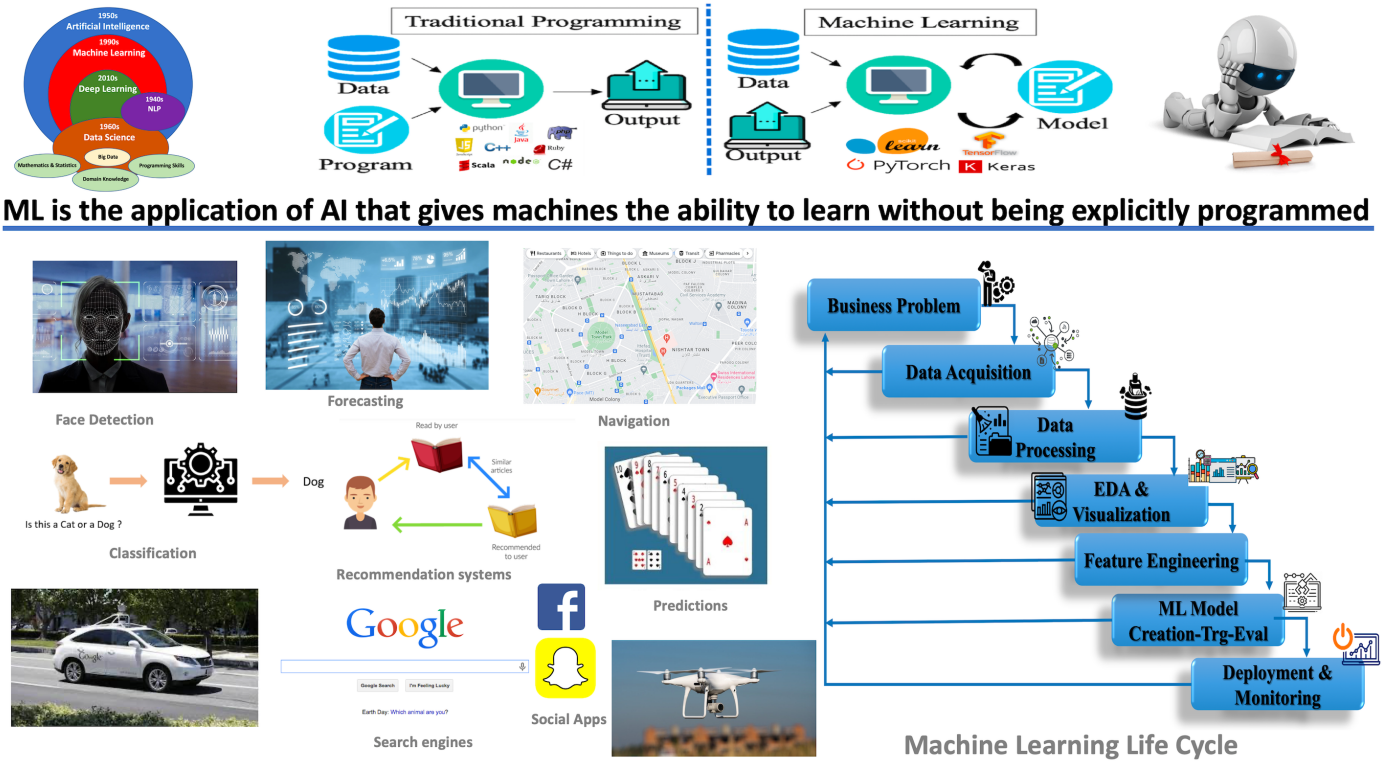
Course: Tools and Techniques for Data Science

Instructor: Muhammad Arif Butt, Ph.D.

Lecture 6.9 (Data Preprocessing: Encoding Categorical Data)

Open in Colab

(https://colab.research.google.com/github/arifpucit/data-science/blob/master/Section-4-Mathematics-for-Data-Science/Lec-4.1(Descriptive-Statistics).ipynb)



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Learning agenda of this notebook

- Overview of Data Pre-Processing and Feature Engineering
- Understanding Data Types
- Encoding Categorical Data (What? Why? and How?)
- A Step-by-Step Hello World to Encode Categorical Data
  - Scikit-Learn's `LabelEncoder()` vs `OrdinalEncoder()`
  - Encoding Nominal Variables using Pandas `get_dummies()` and Scikit-Learn's `OneHotEncoder()`
- Perform Train-Test-Split and then do the Transformations
- Using ColumnTransformer for Encoding and Imputation

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1. Overview of Data Pre-Processing and Feature Engineering

- `Data Preprocessing` involves actions that we need to perform on the dataset in order to make it ready to be fed to the machine learning model.
- `Feature Engineering` is the process of using domain knowledge to extract features from raw data via data mining techniques.

City	Size	Covered Area	No of bedrooms	Trees near by	No of bathrooms	Schools near by	Construction Date	Price
Lahore	2000	3500	3	1	3	1	25/10/2001	20.5 M
Karachi	2600	3000	2	0	4	1	16/05/1990	18 M
Islamabad	1800	2000	3	1	3	2	25/11/1995	20 M
Shaikhupura	1600	2600	1	2	NaN	0	08/06/2020	5 M
Lahore	2600	2000	3	3	1	1	03/09/2016	4 M
Karachi	3000	1000	2	2	1	NaN	19/01/1980	6 M
Islamabad	2000	3600	44	4	3	3	21/07/1999	30 M
Lahore	1000	2000	3	NaN	1	2	12/04/2015	10 M

- Pre-processing package of sklearn provides a bundle of utility functions and transformer classes for data preprocessing (will cover later).
  - **Detecting and handling outliers**
    - Univariate (Z-Score, IQR, Percentiles)
    - Multivariate Analysis (Depth-based, Distance-based, Density-based methods)
    - Trimming, Capping/Winsorization, Discritization
  - **Missing values Imputation**
    - Univariate Imputation (Panda's `fillna()` method, Sklearn's `SimpleImputer()` transformer)
    - Multivariate Imputation (Sklearn's `IterativeImputer()` and `KNNImputer()` transformers)
  - **Encoding Categorical Features**
    - Encode Nominal i/p features using Pandas `get_dummies()` and Scikit-Learn's `OneHotEncoder()`
    - Encode Ordinal i/p features using Scikit-Learn's `OrdinalEncoder()`
    - Encode categorical o/p column using Scikit-Learn's `LabelEncoder()`
  - **Feature Scaling**
    - Use numPy to perform maxabs, minmax, standard and robust scaling
    - Use Sklearn's `MaxAbsScalar` , `MinMaxScalar` , `StandardScalar` , `RobustScalar` transformers
  - **Extracting Information**
    - Use Sklearn's `CountVectorizer` , `DictVectorizer` , `TfidfVectorizer` , and `TfidfTransformer`
  - **Combining Information**
    - Use `FeatureUnion` , `Pipeline` , `PCA`

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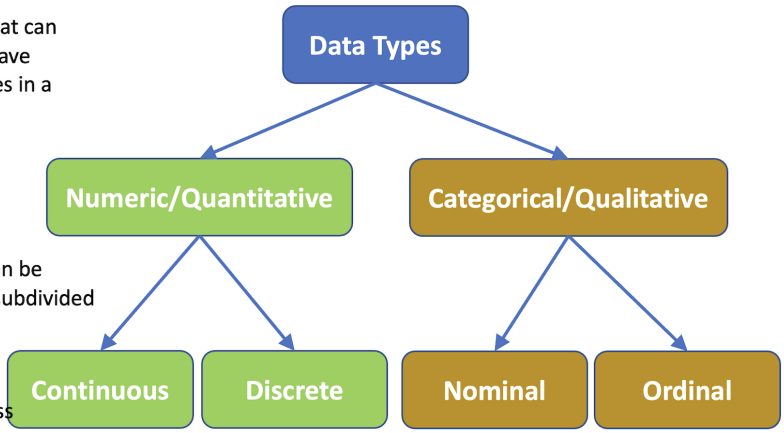
2. Understanding Data Types

Numerical data is a type of data that expresses information in the form of numbers, while Categorical data is a type of data that is used to group information with similar characteristics

Continuous: Values that can be calculated and can have infinite number of values in a range
- Fare/Price
- Weight
- IQ/GPA

Discrete: Values that can be counted and cannot be subdivided meaningfully
- # of children
- # of visits to doctor
- # of students in a class
- World population



Nominal: Values that can be slotted into mutual exclusive categories that do not have specific order
- Blood Group
- Gender
- Color/Make of car
- Country/City

Ordinal: Values that can be slotted into mutually exclusive categories that can be ordered or ranked
- Passenger class
- Student Letter Grade
- PSL Cricket Team Ranking

	pclass	name	sex	age	sibsp	parch	ticket	fare	cabin	embarked	boat	body	home.dest	target
0	1.0	Allen, Miss. Elisabeth Walton	female	29.0000	0.0	0.0	24160	211.3375	B5	S	2	NaN	St Louis, MO	1
1	1.0	Allison, Master. Hudson Trevor	male	0.9167	1.0	2.0	113781	151.5500	C22 C26	S	11	NaN	Montreal, PQ / Chesterville, ON	1

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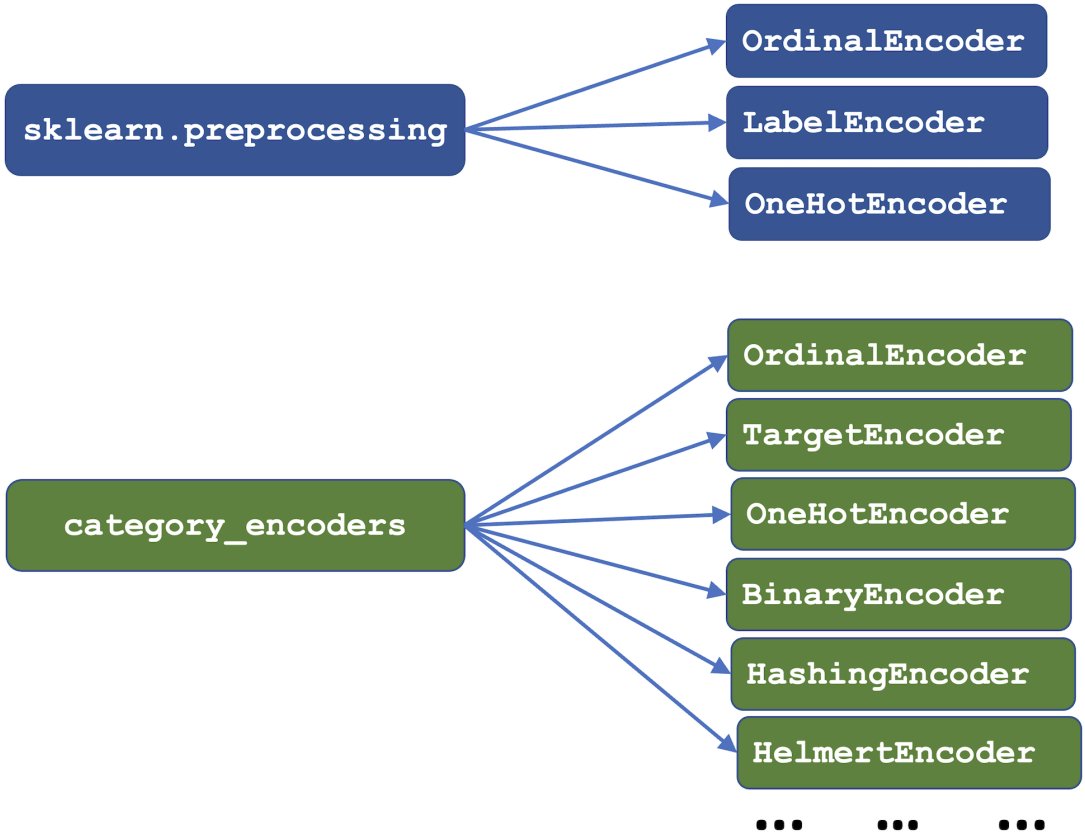
3. Encoding Categorical Data (What? Why? and How?)

Encoding categorical data is a process of converting it into numerical values, so that it could be fed to machine learning models

- **Why do we need to encode categorical data?** Most machine learning algorithms cannot handle categorical variables unless we convert them to numerical values. Many algorithm's performances even vary based upon how the categorical variables are encoded



Python Category Encoders: [http://contrib.scikit-learn.org/category_encoders/ (http://contrib.scikit-](http://contrib.scikit-learn.org/category_encoders/)

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4. A Step-by-Step Hello World to Encode Categorical Data

a. Load Dataset

In [1]:

```
import pandas as pd
import numpy as np
df = pd.read_csv('datasets/disease.csv')
df.sample(n=7, random_state=54)
```

Out[1]:

	gender	city	age	bp	cough	disease
36	Female	Shaikhupura	38.0	normal	Mild	No
70	Female	Islamabad	68.0	normal	Strong	No
48	Male	Shaikhupura	66.0	low	Moderate	No
94	Male	Lahore	79.0	normal	Strong	Yes
81	Male	Islamabad	65.0	normal	Mild	No
46	Female	Karachi	NaN	normal	Moderate	No
38	Female	Islamabad	49.0	high	Mild	Yes

In [2]:

```
df.shape
```

Out[2]:

```
(100, 6)
```

In [3]:

```
df.nunique()
```

Out[3]:

```
gender       2
city         4
age         54
bp           3
cough        3
disease      2
dtype: int64
```

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 6 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   gender   100 non-null    object 
 1   city     100 non-null    object 
 2   age      87 non-null     float64
 3   bp       100 non-null    object 
 4   cough    100 non-null    object 
 5   disease  100 non-null    object 
dtypes: float64(1), object(5)
memory usage: 4.8+ KB
```

In [5]:

```
df.disease.value_counts()
```

Out[5]:

```
No     54
Yes    46
Name: disease, dtype: int64
```

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b. Scikit-Learn's LabelEncoder vs OrdinalEncoder

Label Encoding is a popular encoding technique for handling categorical variables, which assign each category value a unique integer starting from 0 to n-1 based on alphabetical ordering

- `LabelEncoder` is used for encoding output variable while `OridnalEncoder` is used for encoding input feature variables of ordinal type, having an intrinsic order.
- `LabelEncoder` can fit one column at a time while `OrdinalEncoder` can fit multiple columns at the same time.

- Finally both encoders sort the values of a column alphabetically and then assign them the integer values. For example, in case of city column having two values "Islamabad" and "Karachi", Islamabad will be assigned an integer value of 0, while Karachi will be assigned a value of 1. However, in case of `OrdinalEncoder`, we can mention what integer values should be assigned to each specific category.

Scikit Learn's LabelEncoder (https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.LabelEncoder.html)

Scikit Learn's OrdinalEncoder (https://scikit-

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Apply LabelEncoder on `disease` Target Label

In [6]:

```
1 df.head()
```

Out[6]:

	gender	city	age	bp	cough	disease
0	Male	Lahore	60.0	low	Moderate	Yes
1	Male	Islamabad	27.0	low	Mild	No
2	Male	Islamabad	NaN	normal	Strong	No
3	Female	Lahore	31.0	high	Moderate	Yes
4	Female	Karachi	65.0	high	Mild	No

In [7]:

```
y = df.iloc[:, -1]
y
```

Out[7]:

```
0      Yes
1       No
2       No
3      Yes
4       No
     ...
95      No
96     Yes
97      No
98      No
99     Yes
Name: disease, Length: 100, dtype: object
```

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In [8]:

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
le.fit(y)
```

Out[8]:

```
LabelEncoder()
```

In [9]:

```
arr_disease = le.transform(y)
```

In [10]:

```
le.classes_
```

Out[10]:

```
array(['No', 'Yes'], dtype=object)
```

In [11]:

```
1 arr_disease
```

Out[11]:

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

In [12]:

```
1 arr_disease.shape
```

Out[12]:

```
(100,)
```

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In [13]:

```
1 df
```

Out[13]:

	gender	city	age	bp	cough	disease
0	Male	Lahore	60.0	low	Moderate	Yes
1	Male	Islamabad	27.0	low	Mild	No
2	Male	Islamabad	NaN	normal	Strong	No
3	Female	Lahore	31.0	high	Moderate	Yes
4	Female	Karachi	65.0	high	Mild	No
...	...	...	...	...	...	...
95	Female	Shaikhupura	NaN	normal	Mild	No
96	Female	Lahore	51.0	high	Strong	Yes
97	Female	Shaikhupura	20.0	normal	Mild	No
98	Female	Karachi	5.0	low	Moderate	No
99	Female	Lahore	10.0	low	Strong	Yes

100 rows × 6 columns

Apply OrdinalEncoder on `bp` and `cough` Features

In [14]:

```
df.head()
```

Out[14]:

	gender	city	age	bp	cough	disease
0	Male	Lahore	60.0	low	Moderate	Yes
1	Male	Islamabad	27.0	low	Mild	No
2	Male	Islamabad	NaN	normal	Strong	No
3	Female	Lahore	31.0	high	Moderate	Yes
4	Female	Karachi	65.0	high	Mild	No

In [15]:

```
X_bp_cough = df.iloc[:, 3:5]
X_bp_cough.head()
```

Out[15]:

	bp	cough
0	low	Moderate
1	low	Mild
2	normal	Strong
3	high	Moderate
4	high	Mild

In [ ]:

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In [16]:

```
from sklearn.preprocessing import OrdinalEncoder
oe = OrdinalEncoder()
oe.fit(X_bp_cough)
oe.categories_
```

Out[16]:

```
[array(['high', 'low', 'normal'], dtype=object),
 array(['Mild', 'Moderate', 'Strong'], dtype=object)]
```

- The values of column are sorted alphabatically and then assigned integer values from zero onwards

In [17]:

```
from sklearn.preprocessing import OrdinalEncoder
oe = OrdinalEncoder(categories=[['low', 'normal', 'high'],['Mild', 'Moderate', '
oe.fit(X_bp_cough)
oe.categories_
```

Out[17]:

```
[array(['low', 'normal', 'high'], dtype=object),
 array(['Mild', 'Moderate', 'Strong'], dtype=object)]
```

- OrdinalEncoder, unlike LabelEncoder can assign specific integer values by specifying the categories argument

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In [18]:

```
arr_bp_cough = oe.transform(X_bp_cough)
arr_bp_cough.shape
```

Out[18]:

```
(100, 2)
```

In [19]:

```
arr_bp_cough
```

Out[19]:

```
array([[0, 1],
       [0, 0],
       [1, 2],
       [2, 1],
       [2, 0],
       [2, 0],
       [1, 2],
       [1, 1],
       [2, 2],
       [0, 0],
       [0, 0],
       [2, 1],
       [1, 2],
       [0, 0],
       [0, 0],
       [1, 2],
       [1, 0],
       [0, 1],
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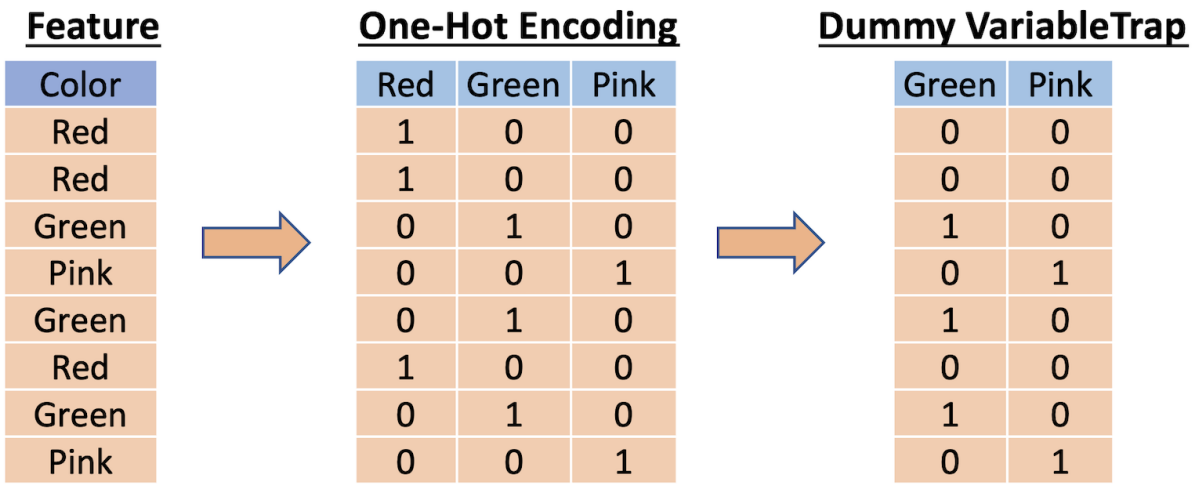
c. Encoding Nominal Variables using OneHotEncoder

One Hot Encoding is the process of creating dummy variables and each category is represented as a one-hot vector




```
"Red"    =   [1, 0, 0]   =   [0, 0]

"Green"  =   [0, 1, 0]   =   [1, 0]

"Pink"   =   [0, 0, 1]   =   [0, 1]
```

- **Limitations:**
  - `Multicollinearity`
    - If you add the one-hot vector they sum up to one. For LinearRegression we know that the input features should not have any correlation with each other, rather should be independent.
    - Solution: Use Dummy variable trap by dropping one of the dummy column.
  - `Curse of dimensionality`

- Suppose we have a feature column which has 100 unique values. Now if we try to encode this feature using one-hot encoding we will get 99 columns. This will increase the dimension of the overall dataset which will lead to curse of dimensionality.
- Solution is you keep the most frequently used say ten categories as separate columns and for all the less frequently used categories you assign a new 11th category say "Others". So this way we will have a total of 10 new columns instead of 99.

> - LabelEncoder donot work for linear models, SVMs, or neural networks as their data needs to be standardized.
> - One hot encoding overcomes the limitations of label encoding and can be used in both tree-based and non-tree-based machine learning algorithms.

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Apply `pd.get_dummies` on `gender` and `city` Columns

In [20]:

```
1 df.head()
```

Out[20]:

	gender	city	age	bp	cough	disease
0	Male	Lahore	60.0	low	Moderate	Yes
1	Male	Islamabad	27.0	low	Mild	No
2	Male	Islamabad	NaN	normal	Strong	No
3	Female	Lahore	31.0	high	Moderate	Yes
4	Female	Karachi	65.0	high	Mild	No

In [21]:

```
X_gender = df.iloc[:, 0:1]
X_gender.head()
```

Out[21]:

	gender
0	Male
1	Male
2	Male
3	Female
4	Female

In [22]:

```
#pd.get_dummies(data=X_gender)
pd.get_dummies(data=X_gender,drop_first=True)
```

Out[22]:

	gender_Male
0	1
1	1
2	1
3	0
4	0
...	...
95	0
96	0
97	0
98	0
99	0

100 rows × 1 columns

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In [23]:

```
1 pd.get_dummies(data=df, columns=['gender', 'city'], drop_first=True)
```

Out[23]:

	age	bp	cough	disease	gender_Male	city_Karachi	city_Lahore	city_Shaikhupura
0	60.0	low	Moderate	Yes	1	0	1	0
1	27.0	low	Mild	No	1	0	0	0
2	NaN	normal	Strong	No	1	0	0	0
3	31.0	high	Moderate	Yes	0	0	1	0
4	65.0	high	Mild	No	0	1	0	0
...	...	...	...	...	...	...	...	...
95	NaN	normal	Mild	No	0	0	0	1
96	51.0	high	Strong	Yes	0	0	1	0
97	20.0	normal	Mild	No	0	0	0	1
98	5.0	low	Moderate	No	0	1	0	0
99	10.0	low	Strong	Yes	0	0	1	0

100 rows × 8 columns

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Apply `OneHotEncoder` on `gender` and `city` Column

In [24]:

```
X_gender_city = df.iloc[:, 0:2]
X_gender_city
```

Out[24]:

	gender	city
0	Male	Lahore
1	Male	Islamabad
2	Male	Islamabad
3	Female	Lahore
4	Female	Karachi
...	...	...
95	Female	Shaikhupura
96	Female	Lahore
97	Female	Shaikhupura
98	Female	Karachi
99	Female	Lahore

100 rows × 2 columns

In [25]:

```
X_gender_city['city'].nunique()
```

Out[25]:

```
4
```

In [26]:

```
from sklearn.preprocessing import OneHotEncoder
ohe = OneHotEncoder(drop='first',sparse=False,dtype=np.int32)
ohe.fit(X_gender_city)
```

Out[26]:

```
OneHotEncoder(drop='first', dtype=<class 'numpy.int32'>, sparse=False)
```

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In [27]:

```
1 ohe.categories_
```

Out[27]:

```
[array(['Female', 'Male'], dtype=object),
 array(['Islamabad', 'Karachi', 'Lahore', 'Shaikhupura'], dtype=objec
t)]
```

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In [28]:

```
1 arr_gender_city = ohe.transform(X_gender_city)
2 arr_gender_city.shape
```

Out[28]:

```
(100, 4)
```

In [ ]:

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In [29]:

```
1 arr_gender_city
```

Out[29]:

```
array([[1, 0, 1, 0],
       [1, 0, 0, 0],
       [1, 0, 0, 0],
       [0, 0, 1, 0],
       [0, 1, 0, 0],
       [0, 0, 0, 1],
       [1, 0, 0, 1],
       [0, 1, 0, 0],
       [0, 0, 0, 1],
       [0, 0, 0, 0],
       [0, 0, 0, 0],
       [0, 1, 0, 0],
       [0, 0, 1, 0],
       [1, 0, 0, 1],
       [1, 0, 0, 1],
       [1, 0, 1, 0],
       [0, 0, 1, 0],
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5. Perform Train-Test-Split and then do the Transformations

- A better approach is to train-test-split first and then do the encoding so that there is no data leakage.
- Call `fit_transform()` on the training data, and only `transform()` on the test data. (NEVER call `fit()` on training data)
- Almost all feature engineering like encoding, standarisation, normalisation etc should be done after train-test-split.

a. Load Dataset

In [30]:

```
1 import numpy as np
2 import pandas as pd
3 from sklearn.preprocessing import OrdinalEncoder
4 from sklearn.preprocessing import LabelEncoder
5 from sklearn.preprocessing import OneHotEncoder
6 from sklearn.impute import SimpleImputer
7 from sklearn.model_selection import train_test_split
8 df = pd.read_csv('datasets/disease.csv')
9 df.head()
```

Out[30]:

	gender	city	age	bp	cough	disease
0	Male	Lahore	60.0	low	Moderate	Yes
1	Male	Islamabad	27.0	low	Mild	No
2	Male	Islamabad	NaN	normal	Strong	No
3	Female	Lahore	31.0	high	Moderate	Yes
4	Female	Karachi	65.0	high	Mild	No

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b. Do a Train-Test-Split

In [31]:

```
1 X = df.drop('disease', axis=1)
2 X
```

Out[31]:

	gender	city	age	bp	cough
0	Male	Lahore	60.0	low	Moderate
1	Male	Islamabad	27.0	low	Mild
2	Male	Islamabad	NaN	normal	Strong
3	Female	Lahore	31.0	high	Moderate
4	Female	Karachi	65.0	high	Mild
...	...	...	...	...	...
95	Female	Shaikhupura	NaN	normal	Mild
96	Female	Lahore	51.0	high	Strong
97	Female	Shaikhupura	20.0	normal	Mild
98	Female	Karachi	5.0	low	Moderate
99	Female	Lahore	10.0	low	Strong

100 rows × 5 columns

In [32]:

```
1 y = df['disease']
2 y
```

Out[32]:

```
0      Yes
1       No
2       No
3      Yes
4       No
     ...
95      No
96     Yes
97      No
98      No
99     Yes
Name: disease, Length: 100, dtype: object
```

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In [33]:

```
1 from sklearn.model_selection import train_test_split
2 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
3 len(X_train), len(y_train), len(X_test), len(y_test)
```

Out[33]:

```
(80, 80, 20, 20)
```

In [34]:

```
1 X_train.head()
```

Out[34]:

	gender	city	age	bp	cough
90	Female	Islamabad	59.0	low	Moderate
31	Male	Lahore	NaN	normal	Mild
58	Male	Karachi	23.0	low	Strong
74	Female	Islamabad	34.0	high	Strong
89	Male	Shaikhupura	46.0	low	Strong

In [35]:

```
1 y_train.head()
```

Out[35]:

```
90     No
31     No
58    Yes
74     No
89     No
Name: disease, dtype: object
```

In [36]:

```
1 X_test.head()
```

Out[36]:

	gender	city	age	bp	cough
36	Female	Shaikhupura	38.0	normal	Mild
70	Female	Islamabad	68.0	normal	Strong
48	Male	Shaikhupura	66.0	low	Moderate
94	Male	Lahore	79.0	normal	Strong
81	Male	Islamabad	65.0	normal	Mild

In [37]:

```
1 y_test.head()
```

Out[37]:

```
36     No
70     No
48     No
94    Yes
81     No
Name: disease, dtype: object
```

In [ ]:

```
1
```

In [ ]:

```
1
```

In [ ]:

```
1
```

In [ ]:

```
1
```

c. Apply OneHotEncoder to `gender` and `city` Columns

In [38]:

```
# OneHotEncoding -> gender,city
ohe = OneHotEncoder(drop='first',sparse=False,dtype=np.int32)

#Call fit() on the training data
ohe.fit(X_train[['gender','city']])
#Call transform() on both the training data as well as on the testing data
X_train_gender_city = ohe.transform(X_train[['gender','city']])
X_test_gender_city = ohe.transform(X_test[['gender','city']])

X_train_gender_city.shape, X_test_gender_city.shape
```

Out[38]:

```
((80, 4), (20, 4))
```

> One column for gender and three columns for city

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

d. Apply OrdinalEncoder to `bp` and `cough` Columns

In [39]:

```
# Ordinalencoding -> cough
oe = OrdinalEncoder(categories=[['low', 'normal', 'high'],['Mild', 'Moderate', '
#Call fit() on the training data
oe.fit(X_train[['bp', 'cough']])
#Call transform() on both the training data as well as on the testing data
X_train_bp_cough = oe.transform(X_train[['bp', 'cough']])
X_test_bp_cough = oe.transform(X_test[['bp', 'cough']])

X_train_bp_cough.shape, X_test_bp_cough.shape
```

Out[39]:

```
((80, 2), (20, 2))
```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

e. Apply LabelEncoder on `disease` output Column

In [40]:

```
le = LabelEncoder()

#Call fit() on the training data
le.fit(y_train)
#Call transform() on both the training data as well as on the testing data
y_train = le.transform(y_train)
y_test = le.transform(y_test)

y_train.shape, y_test.shape
```

Out[40]:

```
((80,), (20,))
```

In [41]:

```
1 y_test
```

Out[41]:

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

In [ ]:

```
1
```

In [ ]:

```
1
```

In [ ]:

```
1
```

f. Apply SimpleImputer to `age` Column

In [42]:

```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 6 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   gender   100 non-null    object 
 1   city     100 non-null    object 
 2   age      87 non-null     float64
 3   bp       100 non-null    object 
 4   cough    100 non-null    object 
 5   disease  100 non-null    object 
dtypes: float64(1), object(5)
memory usage: 4.8+ KB
```

In [43]:

```
1 df.age.isnull().sum()
```

Out[43]:

```
13
```

In [44]:

```
from sklearn.impute import SimpleImputer
si = SimpleImputer(missing_values=np.nan, strategy='mean')
#Call fit() on the training data
si.fit(X_train[['age']])
#Call transform() on both the training data as well as on the testing data
X_train_age = si.transform(X_train[['age']])
X_test_age = si.transform(X_test[['age']])

X_train_age.shape, X_test_age.shape
```

Out[44]:

```
((80, 1), (20, 1))
```

In [45]:

```
X_test_age
```

Out[45]:

```
array([[38.        ],
       [68.        ],
       [66.        ],
       [79.        ],
       [65.        ],
       [41.94202899],
       [49.        ],
       [34.        ],
       [74.        ],
       [71.        ],
       [16.        ],
       [82.        ],
       [38.        ],
       [34.        ],
       [60.        ],
       [75.        ],
       [41.94202899],
       [65.        ],
       [ 6.        ],
       [26.        ]])
```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

g. Combine Results

- We need to combine the three resulting/transformed arrays:
  - X_train_gender_city, X_train_age, X_train_bp_cough,

- X_test_gender_city, X_test_age, X_test_bp_cough

Combine the transformed resulting arrays of `Train` Dataset:

In [46]:

```
X_train_gender_city.shape, X_train_bp_cough.shape, X_train_age.shape
```

Out[46]:

```
((80, 4), (80, 2), (80, 1))
```

In [47]:

```
X_train_transformed = np.concatenate((X_train_gender_city, X_train_age, X_train_
X_train_transformed.shape
```

Out[47]:

```
(80, 7)
```

In [48]:

```
X_train_transformed
```

Out[48]:

```
array([[ 0.        ,  0.        ,  0.        ,  0.        , 59.
,
         0.        ,  1.        ],
       [ 1.        ,  0.        ,  1.        ,  0.        , 41.9420289
9,
         1.        ,  0.        ],
       [ 1.        ,  1.        ,  0.        ,  0.        , 23.
,
         0.        ,  2.        ],
       [ 0.        ,  0.        ,  0.        ,  0.        , 34.
,
         2.        ,  2.        ],
       [ 1.        ,  0.        ,  0.        ,  1.        , 46.
,
         0.        ,  2.        ],
       [ 0.        ,  0.        ,  0.        ,  1.        , 20.
,
         1.        ,  0.        ,
```

In [ ]:

```

```

In [ ]:

```

```

Combine the transformed resulting arrays of `Test` Dataset:

In [49]:

```
1 X_test_gender_city.shape, X_test_bp_cough.shape, X_test_age.shape
```

Out[49]:

```
((20, 4), (20, 2), (20, 1))
```

In [50]:

```
1 X_test_transformed = np.concatenate((X_test_gender_city, X_test_age, X_test_bp_c
2 X_test_transformed.shape
```

Out[50]:

```
(20, 7)
```

In [51]:

```
1 X_test_transformed
```

Out[51]:

```
array([[ 0.        ,  0.        ,  0.        ,  1.        , 38.
        1.        ,  0.        ],
       [ 0.        ,  0.        ,  0.        ,  0.        , 68.
        1.        ,  2.        ],
       [ 1.        ,  0.        ,  0.        ,  1.        , 66.
        0.        ,  1.        ],
       [ 1.        ,  0.        ,  1.        ,  0.        , 79.
        1.        ,  2.        ],
       [ 1.        ,  0.        ,  0.        ,  0.        , 65.
        1.        ,  0.        ],
       [ 0.        ,  1.        ,  0.        ,  0.        , 41.9420289
        1.        ,  1.        ],
       [ 0.        ,  0.        ,  0.        ,  0.        , 49.
        2.        ,  0.        ],
       [ 0.        ,  1.        ,  0.        ,  0.        , 34.
        2.        ,  1.        ],
       [ 1.        ,  1.        ,  0.        ,  0.        , 74.
        0.        ,  0.        ],
       [ 0.        ,  0.        ,  1.        ,  0.        , 71.
        1.        ,  2.        ],
       [ 0.        ,  0.        ,  0.        ,  1.        , 16.
        1.        ,  0.        ],
       [ 0.        ,  0.        ,  1.        ,  0.        , 82.
        1.        ,  2.        ],
       [ 1.        ,  0.        ,  0.        ,  0.        , 38.
        0.        ,  0.        ],
       [ 0.        ,  0.        ,  0.        ,  0.        , 34.
        2.        ,  2.        ],
       [ 1.        ,  0.        ,  1.        ,  0.        , 60.
        0.        ,  1.        ],
       [ 0.        ,  0.        ,  0.        ,  0.        , 75.
        0.        ,  0.        ],
       [ 0.        ,  0.        ,  0.        ,  1.        , 41.9420289
        1.        ,  0.        ],
       [ 1.        ,  0.        ,  1.        ,  0.        , 65.
        2.        ,  0.        ],
       [ 1.        ,  0.        ,  1.        ,  0.        ,  6.
        2.        ,  0.        ],
       [ 1.        ,  0.        ,  0.        ,  1.        , 26.
        1.        ,  1.        ]])
```

Convert `X_train_transformed` array to a Dataframe for better visualization:

In [52]:
```
X_train_transformed_df = pd.DataFrame(X_train_transformed,
                                      columns=['gender','city_1','city_2','city_
```

In [53]:
```
X_train.head()
```

Out[53]:

	gender	city	age	bp	cough
90	Female	Islamabad	59.0	low	Moderate
31	Male	Lahore	NaN	normal	Mild
58	Male	Karachi	23.0	low	Strong
74	Female	Islamabad	34.0	high	Strong
89	Male	Shaikhupura	46.0	low	Strong

In [54]:
```
X_train_transformed_df.head()
```

Out[54]:

	gender	city_1	city_2	city_3	age	bp	cough
0	0.0	0.0	0.0	0.0	59.000000	0.0	1.0
1	1.0	0.0	1.0	0.0	41.942029	1.0	0.0
2	1.0	1.0	0.0	0.0	23.000000	0.0	2.0
3	0.0	0.0	0.0	0.0	34.000000	2.0	2.0
4	1.0	0.0	0.0	1.0	46.000000	0.0	2.0

In [ ]:

```
1
```

In [ ]:

```
1
```

Convert `X_test_transformed` array to a Dataframe for better visualization:

In [55]:

```
1 X_test_transformed_df = pd.DataFrame(X_test_transformed,
2                                      columns=['gender','city_1','city_2','city_3
```

In [56]:

```
1 X_test.head()
```

Out[56]:

	gender	city	age	bp	cough
36	Female	Shaikhupura	38.0	normal	Mild
70	Female	Islamabad	68.0	normal	Strong
48	Male	Shaikhupura	66.0	low	Moderate
94	Male	Lahore	79.0	normal	Strong
81	Male	Islamabad	65.0	normal	Mild

In [57]:

```
1 X_test_transformed_df.head()
```

Out[57]:

	gender	city_1	city_2	city_3	age	bp	cough
0	0.0	0.0	0.0	1.0	38.0	1.0	0.0
1	0.0	0.0	0.0	0.0	68.0	1.0	2.0
2	1.0	0.0	0.0	1.0	66.0	0.0	1.0
3	1.0	0.0	1.0	0.0	79.0	1.0	2.0
4	1.0	0.0	0.0	0.0	65.0	1.0	0.0

In [ ]:

```
1
```

In [ ]:

```
1
```

In [ ]:

```
1
```

In [ ]:

```
1
```

In [ ]:

```
1
```

6. Using ColumnTransformer for Encoding and Imputation

[Data Transformers in Scikit-Learn: (https://scikit-learn.org/stable/data_transforms.html)](https://scikit-learn.org/stable/data_transforms.html)

ColumnTransformer allows to apply different Transformers on different columns of our dataset in a simple and elegant way

In [58]:

```
# One-Hot-Encoder for gender and city column
ohe = OneHotEncoder(drop='first',sparse=False,dtype=np.int32)
# OrdinalEncoder for bp and cough column
oe = OrdinalEncoder(categories=[['low', 'normal', 'high'],['Mild', 'Moderate', '
# SimpleImputer for age column
si = SimpleImputer(missing_values=np.nan, strategy='mean')
```

In [59]:

```
from sklearn.compose import ColumnTransformer
# define ColumnTransformer
transformer = ColumnTransformer(transformers=[
                                                ('tfm1',    ohe,     ['gender','city
                                                ('tfm2',    oe,      ['bp' , 'cough'
                                                ('tfm3',    si,      ['age'])
                                               ],
                                              remainder='passthrough')
type(transformer)
```

Out[59]:

```
sklearn.compose._column_transformer.ColumnTransformer
```

In [ ]:

```
1
```

In [60]:

```
#Call fit() on the training data
transformer.fit(X_train)
#Call transform() on both the training data as well as on the testing data
X_train_transformed1 = transformer.transform(X_train)
X_test_transformed1 = transformer.transform(X_test)

X_train_transformed1.shape, X_test_transformed1.shape
```

Out[60]:

```
((80, 7), (20, 7))
```

In [61]:

```
X_train_transformed1
```

Out[61]:

```
array([[ 0.        ,  0.        ,  0.        ,  0.        ,  0.
,
         1.        , 59.        ],
       [ 1.        ,  0.        ,  1.        ,  0.        ,  1.
,
         0.        , 41.94202899],
       [ 1.        ,  1.        ,  0.        ,  0.        ,  0.
,
         2.        , 23.        ],
       [ 0.        ,  0.        ,  0.        ,  0.        ,  2.
,
         2.        , 34.        ],
       [ 1.        ,  0.        ,  0.        ,  1.        ,  0.
,
         2.        , 46.        ],
       [ 0.        ,  0.        ,  0.        ,  1.        ,  1.
,
         0.        , 20.        ],
```

In [62]:

```
1 df
```

Out[62]:

	gender	city	age	bp	cough	disease
0	Male	Lahore	60.0	low	Moderate	Yes
1	Male	Islamabad	27.0	low	Mild	No
2	Male	Islamabad	NaN	normal	Strong	No
3	Female	Lahore	31.0	high	Moderate	Yes
4	Female	Karachi	65.0	high	Mild	No
...	...	...	...	...	...	...
95	Female	Shaikhupura	NaN	normal	Mild	No
96	Female	Lahore	51.0	high	Strong	Yes
97	Female	Shaikhupura	20.0	normal	Mild	No
98	Female	Karachi	5.0	low	Moderate	No
99	Female	Lahore	10.0	low	Strong	Yes

100 rows × 6 columns

In [63]:

```
1 X_train_transformed_df1 = pd.DataFrame(X_train_transformed1,
2                                        columns=['gender','city_1','city_2','city_
3 X_train_transformed_df1
```

Out[63]:

	gender	city_1	city_2	city_3	age	bp	cough
0	0.0	0.0	0.0	0.0	0.0	1.0	59.000000
1	1.0	0.0	1.0	0.0	1.0	0.0	41.942029
2	1.0	1.0	0.0	0.0	0.0	2.0	23.000000
3	0.0	0.0	0.0	0.0	2.0	2.0	34.000000
4	1.0	0.0	0.0	1.0	0.0	2.0	46.000000
...	...	...	...	...	...	...	...
75	1.0	1.0	0.0	0.0	1.0	0.0	42.000000
76	0.0	0.0	0.0	0.0	1.0	0.0	80.000000
77	1.0	0.0	1.0	0.0	1.0	2.0	70.000000
78	1.0	0.0	0.0	0.0	1.0	2.0	41.942029
79	0.0	0.0	0.0	0.0	2.0	0.0	73.000000

80 rows × 7 columns

In [64]:

```
1 X_train
```

Out[64]:

	gender	city	age	bp	cough
90	Female	Islamabad	59.0	low	Moderate
31	Male	Lahore	NaN	normal	Mild
58	Male	Karachi	23.0	low	Strong
74	Female	Islamabad	34.0	high	Strong
89	Male	Shaikhupura	46.0	low	Strong
...	...	...	...	...	...
64	Male	Karachi	42.0	normal	Mild
23	Female	Islamabad	80.0	normal	Mild
15	Male	Lahore	70.0	normal	Strong
2	Male	Islamabad	NaN	normal	Strong
69	Female	Islamabad	73.0	high	Mild

80 rows × 5 columns

In [ ]:

```
1
```

In [ ]:

```
1
```