Feature_Engineering (1)

August 19, 2022

[1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from pickle import dump
```

[2]:
```
data = pd.DataFrame({'ID' : [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
             'Name' : ['John', 'Jack', 'Mariah', 'Krishna', 'Danny', 'Lisa',␣
 ↪'Andrew', 'Ravi', 'Garima', 'Kavita'],
             'Gender' :['Male', 'Male', 'Female', 'Male', 'Male', 'Female',␣
 ↪'Male', 'Male', 'Female', 'Female'],
              'Profession' : ['Manager', 'Manager', 'Developer', 'Team Lead',␣
 ↪'Team Lead', 'Assistant Manager', 'Assistant Manager', 'Manager', 'Assistant␣
 ↪Manager', 'CEO'],
              'Salary' : [100000, 120000, 95000, 99000, 105000, 145000, 155000,␣
 ↪78000, 167000, 195000],
              'Experience' : [10, 13, 6, 8, 10, 13, 19, 15, 20, 24]})
```

[3]:
```
data
```

[3]:

	ID	Name	Gender	Profession	Salary	Experience
0	1	John	Male	Manager	100000	10
1	2	Jack	Male	Manager	120000	13
2	3	Mariah	Female	Developer	95000	6
3	4	Krishna	Male	Team Lead	99000	8
4	5	Danny	Male	Team Lead	105000	10
5	6	Lisa	Female	Assistant Manager	145000	13
6	7	Andrew	Male	Assistant Manager	155000	19
7	8	Ravi	Male	Manager	78000	15
8	9	Garima	Female	Assistant Manager	167000	20
9	10	Kavita	Female	CEO	195000	24

[4]:
```
data.describe()
```

[4]:

	ID	Salary	Experience
count	10.00000	10.000000	10.000000
mean	5.50000	125900.000000	13.800000
std	3.02765	37698.953714	5.731007

```
min     1.00000   78000.000000    6.000000
25%     3.25000   99250.000000   10.000000
50%     5.50000  112500.000000   13.000000
75%     7.75000  152500.000000   18.000000
max    10.00000  195000.000000   24.000000
```

0.0.1 Explore the data types

[5]:
```
data.dtypes
```

[5]:
```
ID               int64
Name            object
Gender          object
Profession      object
Salary           int64
Experience       int64
dtype: object
```

0.0.2 Separating categorical and numeric features

[59]:
```
dictionary={}
dictionary['num'] = data.dtypes[data.dtypes=='int64'].index
dictionary['cat'] = data.dtypes[data.dtypes=='object'].index
dictionary
```

[59]:
```
{'num': Index(['ID', 'Salary', 'Experience'], dtype='object'),
 'cat': Index(['Name', 'Gender', 'Profession'], dtype='object')}
```

0.0.3 Cardinality of Categorical Variables

[60]:
```
data['Name'].unique()
```

[60]:
```
array(['John', 'Jack', 'Mariah', 'Krishna', 'Danny', 'Lisa', 'Andrew',
       'Ravi', 'Garima', 'Kavita'], dtype=object)
```

[61]:
```
data['Gender'].unique()
```

[61]:
```
array(['Male', 'Female'], dtype=object)
```

[62]:
```
data['Profession'].unique()
```

[62]:
```
array(['Manager', 'Developer', 'Team Lead', 'Assistant Manager', 'CEO'],
      dtype=object)
```

0.0.4 Frequency of categories in a categorical variable

[63]:
```
data['Name'].value_counts()
```

[63]:
```
Danny      1
Krishna    1
Kavita     1
John       1
Ravi       1
Mariah     1
Garima     1
Jack       1
Lisa       1
Andrew     1
Name: Name, dtype: int64
```

[64]:
```
data['Gender'].value_counts()
```

[64]:
```
Male      6
Female    4
Name: Gender, dtype: int64
```

[65]:
```
data['Profession'].value_counts()
```

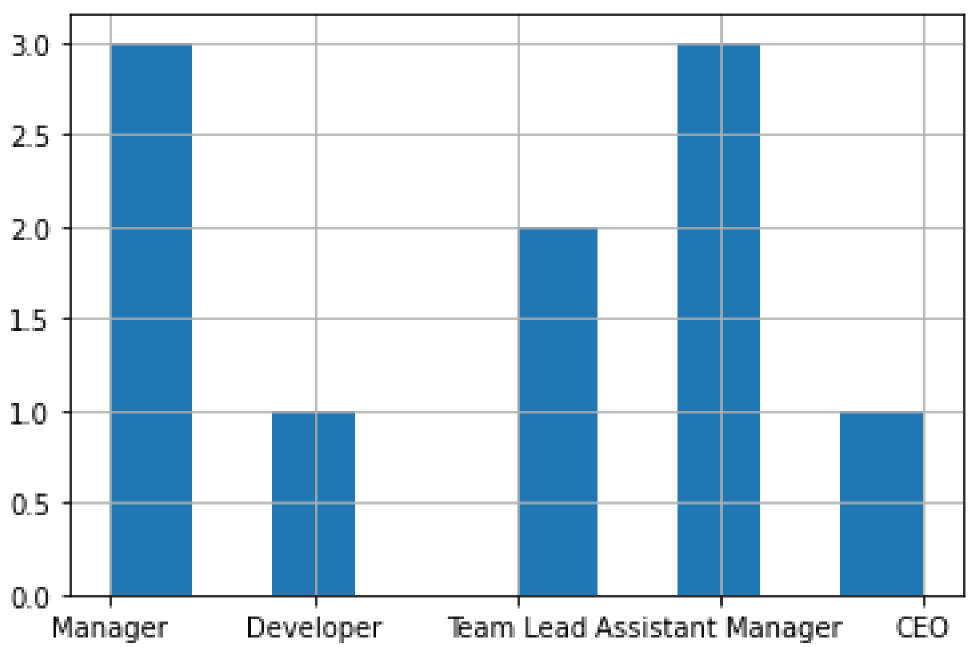
[65]:
```
Manager              3
Assistant Manager    3
Team Lead            2
Developer            1
CEO                  1
Name: Profession, dtype: int64
```

[66]:
```
data['Gender'].hist()
```

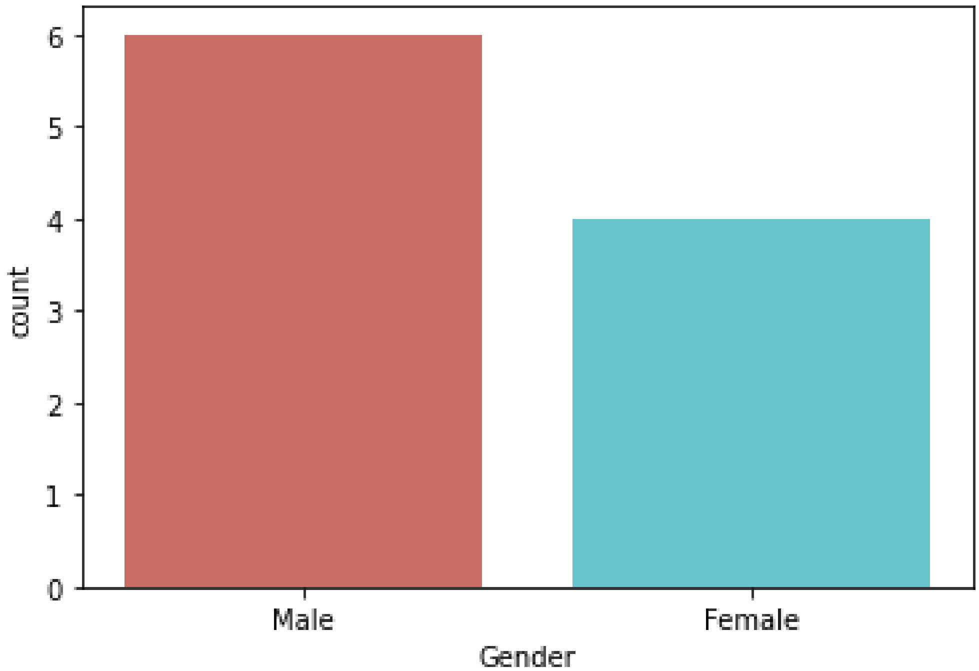
[66]:
```
<AxesSubplot:>
```

[67]:
```
data['Profession'].hist()
```

[67]: <AxesSubplot:>



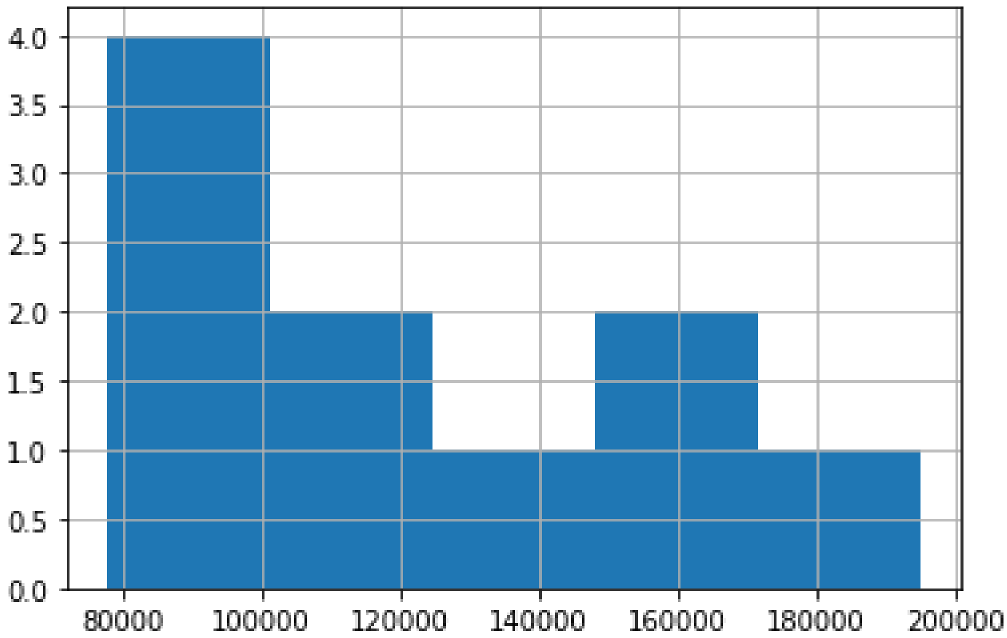
[68]:
```
sns.countplot(x='Gender',data=data,palette='hls')
plt.show()
```



Numerical Variables

[69]:
```
data['Salary'].hist(bins=5)
```

[69]:
```
<AxesSubplot:>
```



[70]:
```
data[dictionary['cat']]
```

[70]:

	Name	Gender	Profession
0	John	Male	Manager
1	Jack	Male	Manager
2	Mariah	Female	Developer
3	Krishna	Male	Team Lead
4	Danny	Male	Team Lead
5	Lisa	Female	Assistant Manager
6	Andrew	Male	Assistant Manager
7	Ravi	Male	Manager
8	Garima	Female	Assistant Manager
9	Kavita	Female	CEO

[71]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler, LabelEncoder
```

[72]:
```
# Profession column is ordinal data. Hence I can use the label encoder

le_profession = LabelEncoder()
le_profession.fit(data['Profession'])
```

[72]: LabelEncoder()

[73]:
```
le_profession.classes_
```

[73]: array(['Assistant Manager', 'CEO', 'Developer', 'Manager', 'Team Lead'],
      dtype=object)

fit method learns the transformer's attributes. It does not change the column. To change the column we will now use the learnt attribute to do the transformation by using transform function

[74]:
```
data['Profession'] = le_profession.transform(data['Profession'])
data
```

[74]:

	ID	Name	Gender	Profession	Salary	Experience
0	1	John	Male	3	100000	10
1	2	Jack	Male	3	120000	13
2	3	Mariah	Female	2	95000	6
3	4	Krishna	Male	4	99000	8
4	5	Danny	Male	4	105000	10
5	6	Lisa	Female	0	145000	13
6	7	Andrew	Male	0	155000	19
7	8	Ravi	Male	3	78000	15
8	9	Garima	Female	0	167000	20
9	10	Kavita	Female	1	195000	24

[75]:
```
le_profession.inverse_transform(data['Profession'])
```

[75]: array(['Manager', 'Manager', 'Developer', 'Team Lead', 'Team Lead',
       'Assistant Manager', 'Assistant Manager', 'Manager',
       'Assistant Manager', 'CEO'], dtype=object)

[76]:
```
# Gender is nominal data because it cannot be ranked. Hence we will apply one␣
 ↪hot encoder

pd.get_dummies(data['Gender'])
```

[76]:

	Female	Male
0	0	1
1	0	1
2	1	0
3	0	1
4	0	1
5	1	0
6	0	1
7	0	1
8	1	0
9	1	0

[77]:
```
data.drop(['Name'], inplace = True, axis = 1)
data
```

[77]:

	ID	Gender	Profession	Salary	Experience
0	1	Male	3	100000	10
1	2	Male	3	120000	13
2	3	Female	2	95000	6
3	4	Male	4	99000	8
4	5	Male	4	105000	10
5	6	Female	0	145000	13
6	7	Male	0	155000	19
7	8	Male	3	78000	15
8	9	Female	0	167000	20
9	10	Female	1	195000	24

[78]:
```
data = pd.get_dummies(data)
data
```

[78]:

	ID	Profession	Salary	Experience	Gender_Female	Gender_Male
0	1	3	100000	10	0	1
1	2	3	120000	13	0	1
2	3	2	95000	6	1	0
3	4	4	99000	8	0	1
4	5	4	105000	10	0	1
5	6	0	145000	13	1	0
6	7	0	155000	19	0	1
7	8	3	78000	15	0	1
8	9	0	167000	20	1	0
9	10	1	195000	24	1	0

Scaling Numerical Variables using MinMax

[80]:
```
min_max_sal = MinMaxScaler()
min_max_sal.fit(data[['Salary']])
```

[80]: MinMaxScaler()

[82]:
```
min_max_sal.data_max_, min_max_sal.data_min_
```

[82]: (array([195000.]), array([78000.]))

[83]:
```
data
```

[83]:

	ID	Profession	Salary	Experience	Gender_Female	Gender_Male
0	1	3	100000	10	0	1
1	2	3	120000	13	0	1
2	3	2	95000	6	1	0
3	4	4	99000	8	0	1
4	5	4	105000	10	0	1
5	6	0	145000	13	1	0

```
6   7           0  155000          19              0             1
7   8           3   78000          15              0             1
8   9           0  167000          20              1             0
9  10           1  195000          24              1             0
```

[16]:
```python
min_max_sal.data_max_
```

[16]:
```
array([195000.])
```

[84]:
```python
data['Salary_min_max_scaled'] = min_max_sal.transform(data[['Salary']])
data
```

[84]:
```
   ID  Profession  Salary  Experience  Gender_Female  Gender_Male  \
0   1           3  100000          10              0            1
1   2           3  120000          13              0            1
2   3           2   95000           6              1            0
3   4           4   99000           8              0            1
4   5           4  105000          10              0            1
5   6           0  145000          13              1            0
6   7           0  155000          19              0            1
7   8           3   78000          15              0            1
8   9           0  167000          20              1            0
9  10           1  195000          24              1            0

   Salary_min_max_scaled
0               0.188034
1               0.358974
2               0.145299
3               0.179487
4               0.230769
5               0.572650
6               0.658120
7               0.000000
8               0.760684
9               1.000000
```

[85]:
```python
data.describe()
```

[85]:
```
             ID  Profession         Salary  Experience  Gender_Female  \
count  10.00000   10.000000      10.000000   10.000000      10.000000
mean    5.50000    2.000000  125900.000000   13.800000       0.400000
std     3.02765    1.632993   37698.953714    5.731007       0.516398
min     1.00000    0.000000   78000.000000    6.000000       0.000000
25%     3.25000    0.250000   99250.000000   10.000000       0.000000
50%     5.50000    2.500000  112500.000000   13.000000       0.000000
75%     7.75000    3.000000  152500.000000   18.000000       1.000000
max    10.00000    4.000000  195000.000000   24.000000       1.000000
```

```
       Gender_Male  Salary_min_max_scaled
count    10.000000              10.000000
mean      0.600000               0.409402
std       0.516398               0.322213
min       0.000000               0.000000
25%       0.000000               0.181624
50%       1.000000               0.294872
75%       1.000000               0.636752
max       1.000000               1.000000
```

Scaling Numerical Variables using StandardScaler

[86]:
```python
std_scale_sal = StandardScaler()
std_scale_sal.fit(data[['Salary']])
```

[86]:
```
StandardScaler()
```

[87]:
```python
std_scale_sal.mean_, std_scale_sal.scale_
```

[87]:
```
(array([125900.]), array([35764.36774221]))
```

[88]:
```python
data['Salary_standard_scaled'] = std_scale_sal.transform(data[['Salary']])
data
```

[88]:
```
   ID  Profession  Salary  Experience  Gender_Female  Gender_Male  \
0   1           3  100000          10              0            1
1   2           3  120000          13              0            1
2   3           2   95000           6              1            0
3   4           4   99000           8              0            1
4   5           4  105000          10              0            1
5   6           0  145000          13              1            0
6   7           0  155000          19              0            1
7   8           3   78000          15              0            1
8   9           0  167000          20              1            0
9  10           1  195000          24              1            0

   Salary_min_max_scaled  Salary_standard_scaled
0               0.188034               -0.724184
1               0.358974               -0.164969
2               0.145299               -0.863988
3               0.179487               -0.752145
4               0.230769               -0.584381
5               0.572650                0.534051
6               0.658120                0.813659
7               0.000000               -1.339322
8               0.760684                1.149188
```

```
9                1.000000                 1.932091
```

[89]:
```
data.describe()
```

[89]:
```
              ID  Profession         Salary  Experience  Gender_Female  \
count  10.00000   10.000000      10.000000   10.000000      10.000000
mean    5.50000    2.000000  125900.000000   13.800000       0.400000
std     3.02765    1.632993   37698.953714    5.731007       0.516398
min     1.00000    0.000000   78000.000000    6.000000       0.000000
25%     3.25000    0.250000   99250.000000   10.000000       0.000000
50%     5.50000    2.500000  112500.000000   13.000000       0.000000
75%     7.75000    3.000000  152500.000000   18.000000       1.000000
max    10.00000    4.000000  195000.000000   24.000000       1.000000

       Gender_Male  Salary_min_max_scaled  Salary_standard_scaled
count    10.000000              10.000000            1.000000e+01
mean      0.600000               0.409402           -2.220446e-17
std       0.516398               0.322213            1.054093e+00
min       0.000000               0.000000           -1.339322e+00
25%       0.000000               0.181624           -7.451551e-01
50%       1.000000               0.294872           -3.746746e-01
75%       1.000000               0.636752            7.437570e-01
max       1.000000               1.000000            1.932091e+00
```

[22]:
```
std_scale_sal.inverse_transform(data[['Salary_standard_scaled']])
```

[22]:
```
array([[100000.],
       [120000.],
       [ 95000.],
       [ 99000.],
       [105000.],
       [145000.],
       [155000.],
       [ 78000.],
       [167000.],
       [195000.]])
```

[91]:
```
dump(std_scale_sal,open('std_scaler.pkl','wb'))
```

[ ]:
```

```