EDA 04- Featuure Selection -I

1. Necessary Imports

In [81]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
import scipy.stats as stats
import seaborn as sns
```

2. Reading dataset into CSV & Basic Data Description

a) Reading Data

In [3]:
```
data=pd.read_csv("D:/FTI/Cohort 2 EDA/Lecture 4/Finance.csv")
```

In [4]:
```
data.head()
```

Out[4]:

	age	job	marital	education	default	balance	housing	loan	contact	day	n
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	
1	44	technician	single	secondary	no	29	yes	no	unknown	5	
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	
4	33	unknown	single	unknown	no	1	no	no	unknown	5	

In [5]:
```
data.shape
```

Out[5]:
```
(45211, 17)
```

b) Check the Data Types

In [6]:
```
data.dtypes
```

Out[6]:
```
age             int64
job            object
marital        object
education      object
default        object
balance         int64
housing        object
loan           object
contact        object
day             int64
month          object
duration        int64
campaign        int64
pdays           int64
previous        int64
poutcome       object
y              object
dtype: object
```

3. Check Missing Data or Null Values

In [7]:
```
data.isnull().sum()
```

Out[7]:
```
age            0
job            0
marital        0
education      0
default        0
balance        0
housing        0
loan           0
contact        0
day            0
month          0
duration       0
campaign       0
pdays          0
previous       0
poutcome       0
y              0
dtype: int64
```

4. Check for Data Quality Issues

a) For categorical attributes you can ispect the unique values

You can display all the unique values and based on domain kbowledge can decide if incrrect data exists or not.

In [8]:
```
data['job'].unique()
```

Out[8]:
```
array(['management', 'technician', 'entrepreneur', 'blue-collar',
       'unknown', 'retired', 'admin.', 'services', 'self-employed
',
       'unemployed', 'housemaid', 'student'], dtype=object)
```

If you do not have the doamin knowledge , then value counts may give you an idea about the possible incorrect values

In [9]:
```
data['job'].value_counts()
```

Out[9]:
```
blue-collar      9732
management       9458
technician       7597
admin.           5171
services         4154
retired          2264
self-employed    1579
entrepreneur     1487
unemployed       1303
housemaid        1240
student           938
unknown           288
Name: job, dtype: int64
```

You can also use describe() to get a bit more information about the feature under consideration

In [10]:
```
data['job'].describe()
```

Out[10]:
```
count           45211
unique             12
top       blue-collar
freq             9732
Name: job, dtype: object
```

b) For numeric attributes you can inspect all the posible set of values

If you have a domain knowledge , the minimum and maximum values can spot if incorrect data is present or not

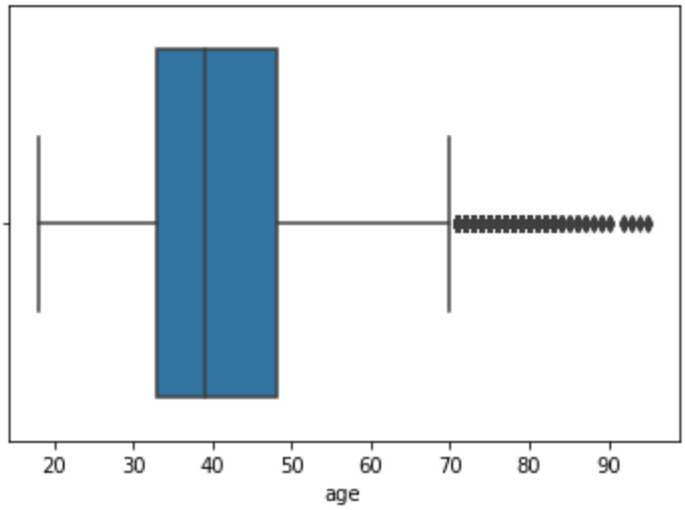
In [11]:
```
data['age'].describe()
```

Out[11]:
```
count    45211.000000
mean        40.936210
std         10.618762
min         18.000000
25%         33.000000
50%         39.000000
75%         48.000000
max         95.000000
Name: age, dtype: float64
```

If you do nat have the domain knowledge , the boxplot may give you some clue about the presence of possibly incorrect values. We call them as outliers. Outliers may be real or due to data collection problems.

In [12]:
```
sns.boxplot(x=data['age'], data=data)
```

Out[12]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1c2f8c2b780>
```



5. Feature Selection Based on Filter Methods

a) Using Chi Square to test association between categorical attributes

The class variable is Y which is object type. So we can use Chi Square to check the association between all other object types and the class.The variables having strong association can be chosen as the features for machine learning algorithm.

Chi-Square Hypothesis : HO: There is no relationship / association / dependence between two attributes H1: There is a relationship / associatio/ dpendence between two variables

Lets perform a chi-square test of independence for 'default' and class variable 'y'

In [13]:
```
data['default'].value_counts()
```

Out[13]:
```
no     44396
yes      815
Name: default, dtype: int64
```

In [14]:
```
data['y'].value_counts()
```

Out[14]:
```
no     39922
yes     5289
Name: y, dtype: int64
```

In [15]:
```
ov=pd.crosstab(data['default'],data['y'])
```

In [16]:
```
ov
```

Out[16]:

y	no	yes
default		
no	39159	5237
yes	763	52

In [17]:
```
b=s.chi2_contingency(ov)
```

In [18]:
```
b
```

Out[18]:
```
(22.20224995571685,
 2.4538606753508344e-06,
 1,
 array([[39202.34261574,  5193.65738426],
        [  719.65738426,    95.34261574]]))
```

Here b is a tuple containing an immutable sequence of python objects . Here it contains four objcets . b[0] contains the value of chi2 statistic , b[1] contains the p-value of the test , b[2] contains the degree of freedom and b[3] contains the expected frequencies.

In [19]:
```
b[0]
```

Out[19]:
```
22.20224995571685
```

In [20]:
```
b[1]
```

Out[20]:
```
2.4538606753508344e-06
```

In [21]:
```
b[2]
```

Out[21]:
```
1
```

In [22]:
```
b[3]
```

Out[22]:
```
array([[39202.34261574,  5193.65738426],
       [  719.65738426,    95.34261574]])
```

Lets create a custom function to peform chi-square test of independence

In [23]:
```
def test_dependency(data,f1,f2,alpha):
    ov=pd.crosstab(data[f1],data[f2])
    b=s.chi2_contingency(ov)
    chi2_statistic=b[0]
    p_value=b[1]
    dof=b[2]
    critical_value=s.chi2.ppf(q=1-alpha, df=dof)
    ## ppf stands for percent point function . It takes two paramete
rs confidence interval and degrees of freedom.
    ##It returns the critical value. ppf is the inverse of cumulativ
e distribution function.
    ## https://www.itl.nist.gov/div898/handbook/eda/section3/eda362.
htm
    print('Significance level: ',alpha)
    print('Degree of Freedom: ',dof)
    print('chi-square statistic:',chi2_statistic)
    print('critical_value:',critical_value)
    print('p-value:',p_value)

    if chi2_statistic>=critical_value:
        print("Reject H0,There is a relationship between 2 categoric
al variables")
    else:
        print("Retain H0,There is no relationship between 2 categori
cal variables")

    if p_value<=alpha:
        print("Reject H0,There is a relationship between 2 categoric
al variables")
    else:
        print("Retain H0,There is no relationship between 2 categori
cal variables")
```

In [24]:
```
test_dependency(data,'default','y',0.05)
```

```
Significance level:  0.05
Degree of Freedom:  1
chi-square statistic: 22.20224995571685
critical_value: 3.841458820694124
p-value: 2.4538606753508344e-06
Reject H0,There is a relationship between 2 categorical variables
Reject H0,There is a relationship between 2 categorical variables
```

In [25]:
```
test_dependency(data,'education','y',0.05)
```

```
Significance level:  0.05
Degree of Freedom:  3
chi-square statistic: 238.92350616407606
critical_value: 7.814727903251179
p-value: 1.6266562124072994e-51
Reject H0,There is a relationship between 2 categorical variables
Reject H0,There is a relationship between 2 categorical variables
```

Selecting k-Best Features based on Chi-Square Test

We will be using SelectKBest( )which takes numeric data only . So for that we have to encode all the categorical.We will be using mannual encoding for ordinal features whereas label encoding for all other nominal features.

Encoding Ordinal Features

In [26]:
```
ordinal_list=['education']
data['education'] = data['education'].replace(['primary','secondary
','tertiary','unknown'],[1,2,3,2])
```

In [27]:
```
data.head()
```

Out[27]:

	age	job	marital	education	default	balance	housing	loan	contact	day	n
0	58	management	married	3	no	2143	yes	no	unknown	5	
1	44	technician	single	2	no	29	yes	no	unknown	5	
2	33	entrepreneur	married	2	no	2	yes	yes	unknown	5	
3	47	blue-collar	married	2	no	1506	yes	no	unknown	5	
4	33	unknown	single	2	no	1	no	no	unknown	5	

Encoding Nominal Features

In [28]:
```
nominal_list = []
for i in data.columns.tolist():
    if (data[i].dtype=='object') and (i not in ordinal_list):
        nominal_list.append(i)
print (nominal_list)
print('Number of nominal features:', str(len(nominal_list)))
```

```
['job', 'marital', 'default', 'housing', 'loan', 'contact', 'month
', 'poutcome', 'y']
Number of nominal features: 9
```

In [29]:
```
from sklearn.preprocessing import LabelEncoder
encoder=LabelEncoder()
for column in nominal_list:
    data[column]=encoder.fit_transform(data[column])
```

In [30]:
```
data.head()
```

Out[30]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	du
0	58	4	1	3	0	2143	1	0	2	5	8	
1	44	9	2	2	0	29	1	0	2	5	8	
2	33	2	1	2	0	2	1	1	2	5	8	
3	47	1	1	2	0	1506	1	0	2	5	8	
4	33	11	2	2	0	1	0	0	2	5	8	

Combining ordinal and nominal features after encoding

In [31]:
```
ordinal_data=data[ordinal_list]
nominal_data=data[nominal_list]
categorical_data = pd.concat([ordinal_data,nominal_data], axis=1)
```

In [32]:
```
categorical_data
```

Out[32]:

	education	job	marital	default	housing	loan	contact	month	poutcome	y
0	3	4	1	0	1	0	2	8	3	0
1	2	9	2	0	1	0	2	8	3	0
2	2	2	1	0	1	1	2	8	3	0
3	2	1	1	0	1	0	2	8	3	0
4	2	11	2	0	0	0	2	8	3	0
...	...	...	...	...	...	...	...	...	...	...
45206	3	9	1	0	0	0	0	9	3	1
45207	1	5	0	0	0	0	0	9	3	1
45208	2	5	1	0	0	0	0	9	2	1
45209	2	1	1	0	0	0	1	9	3	0
45210	2	2	1	0	0	0	0	9	1	0

45211 rows × 10 columns

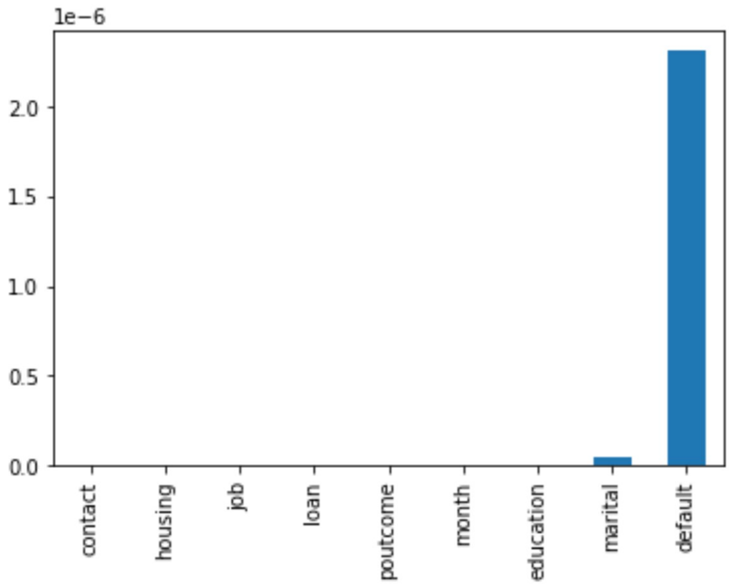
Selecting K Best Features based on Chi-Square Test

In [33]:
```
X=categorical_data.drop('y',axis=1)
Y=categorical_data['y']
chi_scores = chi2(X,Y)
```

In [34]:
```
p_values = pd.Series(chi_scores[1],index = X.columns)
p_values.sort_values(ascending = True , inplace = True)
chi2_values=pd.Series(chi_scores[0],index = X.columns)
chi2_values.sort_values(ascending = False , inplace = True)
```

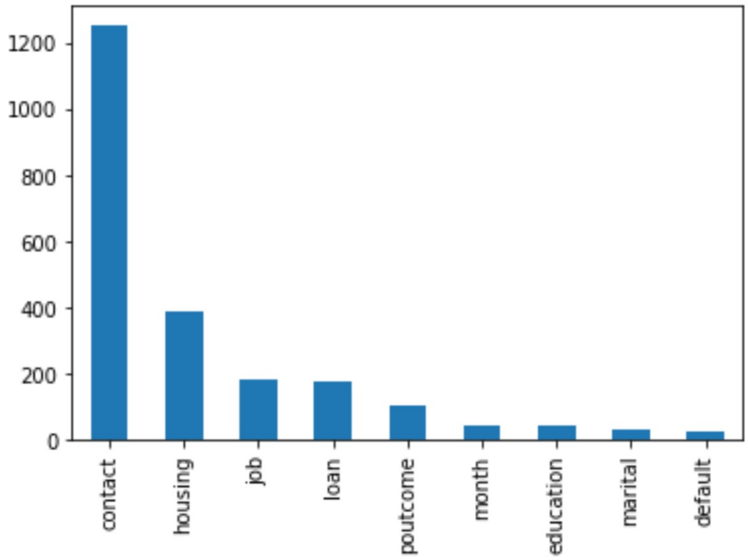
In [35]:
```
p_values.plot.bar()
```

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2f96b05c0>



In [36]:
```
chi2_values.plot.bar()
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2f9ab7438>



In [37]:
```
# Three features with highest chi-squared statistics are selected
chi2_features = SelectKBest(chi2, k = 3)
X_kbest_features = chi2_features.fit_transform(X, Y)

# Reduced features
print('Original feature number:', X.shape[1])
print('Reduced feature number:', X_kbest_features.shape[1])
```

```
Original feature number: 9
Reduced feature number: 3
```

In [38]:
```
index = chi2_features.get_support(indices=True)
print(index)
```

```
[1 4 6]
```

In [39]:
```
X
```

Out[39]:

	education	job	marital	default	housing	loan	contact	month	poutcome
0	3	4	1	0	1	0	2	8	3
1	2	9	2	0	1	0	2	8	3
2	2	2	1	0	1	1	2	8	3
3	2	1	1	0	1	0	2	8	3
4	2	11	2	0	0	0	2	8	3
...	...	...	...	...	...	...	...	...	...
45206	3	9	1	0	0	0	0	9	3
45207	1	5	0	0	0	0	0	9	3
45208	2	5	1	0	0	0	0	9	2
45209	2	1	1	0	0	0	1	9	3
45210	2	2	1	0	0	0	0	9	1

45211 rows × 9 columns

Features at index 1 , 4 and 6 are job , housing and contact respectively

In [40]:
```
selected_features= ['job','housing','contact']
```

b) Using Pearson Correlation Coefficient for Numeric Features vs Numeric Class

In [41]:
```
data=pd.read_csv("D:/FTI/Cohort 2 EDA/Lecture 4/Finance.csv")
```

In [42]:
```
df=data.copy()
```

In [43]:
```
data['y'].dtype
```

Out[43]:
```
dtype('O')
```

In [44]:
```
data['y'].value_counts()
```

Out[44]:
```
no     39922
yes     5289
Name: y, dtype: int64
```

we can convert yes and no into 1 and 0 and change the data type from object to integer

In [45]:
```
data['y']=data['y'].apply(lambda x:0 if x=='no' else 1)
```

In [46]:
```
data['y'].value_counts()
```

Out[46]:
```
0    39922
1     5289
Name: y, dtype: int64
```

In [47]:
```
data['y'].dtype
```

Out[47]:
```
dtype('int64')
```

In [48]:
```
cor_matrix=data.corr()
```

In [49]:
```
print(cor_matrix['y'].sort_values(ascending=False))
```

```
y           1.000000
duration    0.394521
pdays       0.103621
previous    0.093236
balance     0.052838
age         0.025155
day        -0.028348
campaign   -0.073172
Name: y, dtype: float64
```

In [50]:
```
cor_matrix
```

Out[50]:

	age	balance	day	duration	campaign	pdays	previous	
age	1.000000	0.097783	-0.009120	-0.004648	0.004760	-0.023758	0.001288	0.02
balance	0.097783	1.000000	0.004503	0.021560	-0.014578	0.003435	0.016674	0.05
day	-0.009120	0.004503	1.000000	-0.030206	0.162490	-0.093044	-0.051710	-0.02
duration	-0.004648	0.021560	-0.030206	1.000000	-0.084570	-0.001565	0.001203	0.39
campaign	0.004760	-0.014578	0.162490	-0.084570	1.000000	-0.088628	-0.032855	-0.07
pdays	-0.023758	0.003435	-0.093044	-0.001565	-0.088628	1.000000	0.454820	0.10
previous	0.001288	0.016674	-0.051710	0.001203	-0.032855	0.454820	1.000000	0.09
y	0.025155	0.052838	-0.028348	0.394521	-0.073172	0.103621	0.093236	1.00

In [51]:
```
features_cor=(cor_matrix['y'].sort_values(ascending=False))
```

In [52]:
```
selected_num_features= ['duration','pdays','previous']
```

In [53]:
```
best_features=selected_features+(selected_num_features)
```

In [54]:
```
best_features
```

Out[54]:
```
['job', 'housing', 'contact', 'duration', 'pdays', 'previous']
```

In [55]:
```
data2=pd.concat([data[best_features],data['y']],axis=1)
```

In [56]:
```
data2
```

Out[56]:

	job	housing	contact	duration	pdays	previous	y
0	management	yes	unknown	261	-1	0	0
1	technician	yes	unknown	151	-1	0	0
2	entrepreneur	yes	unknown	76	-1	0	0
3	blue-collar	yes	unknown	92	-1	0	0
4	unknown	no	unknown	198	-1	0	0
...	...	...	...	...	...	...	...
45206	technician	no	cellular	977	-1	0	1
45207	retired	no	cellular	456	-1	0	1
45208	retired	no	cellular	1127	184	3	1
45209	blue-collar	no	telephone	508	-1	0	0
45210	entrepreneur	no	cellular	361	188	11	0

45211 rows × 7 columns

Remarks: Feature Selection using filter methods is independant of the machine learning model we use. Whether our seletced features will work better or not depends on the performance of ML model we apply.

c) Feature Selection Using ANOVA (Categorical (features) vs Numeric Response)

In [102]:
```
data=pd.read_csv("D:/FTI/Cohort 2 EDA/Lecture 4/Finance.csv")
```

In [103]:
```
data.head()
```

Out[103]:

	age	job	marital	education	default	balance	housing	loan	contact	day	n
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	
1	44	technician	single	secondary	no	29	yes	no	unknown	5	
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	
4	33	unknown	single	unknown	no	1	no	no	unknown	5	

In [104]:
```
data.dtypes
```

Out[104]:
```
age             int64
job            object
marital        object
education      object
default        object
balance         int64
housing        object
loan           object
contact        object
day             int64
month          object
duration        int64
campaign        int64
pdays           int64
previous        int64
poutcome       object
y              object
dtype: object
```

Transformation

ANOVA is used to select features if the target is numeric and features are categorical. I have gone through a number of resources and found in almost evey case where target variable was in the form of 1 and 0. so instead of doing experiment on some other staset, i have chosen the same financial data set for this experiment. We just need to transform the data in target from y and n to 1 and 0. This will cofirm whether ANOVA is giving us the same features as Chi-Square or not. Incase of a target having binary values , we can transform it to 1 and 0 and then use it as a numeric attribute .

In [105]:
```
data['y']=data['y'].apply(lambda x:0 if x=='no' else 1)
```

In [106]:
```
data.head()
```

Out[106]:

	age	job	marital	education	default	balance	housing	loan	contact	day	n
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	
1	44	technician	single	secondary	no	29	yes	no	unknown	5	
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	
4	33	unknown	single	unknown	no	1	no	no	unknown	5	

In [107]:
```
data.dtypes
```

Out[107]:
```
age            int64
job           object
marital       object
education     object
default       object
balance        int64
housing       object
loan          object
contact       object
day            int64
month         object
duration       int64
campaign       int64
pdays          int64
previous       int64
poutcome      object
y              int64
dtype: object
```

In [108]:
```
data['education'].value_counts()
```

Out[108]:
```
secondary    23202
tertiary     13301
primary       6851
unknown       1857
Name: education, dtype: int64
```

In [109]:
```
data['y'].value_counts()
```

Out[109]:
```
0    39922
1     5289
Name: y, dtype: int64
```

In [110]:
```
ov=pd.crosstab(data['education'],data['y'])
```

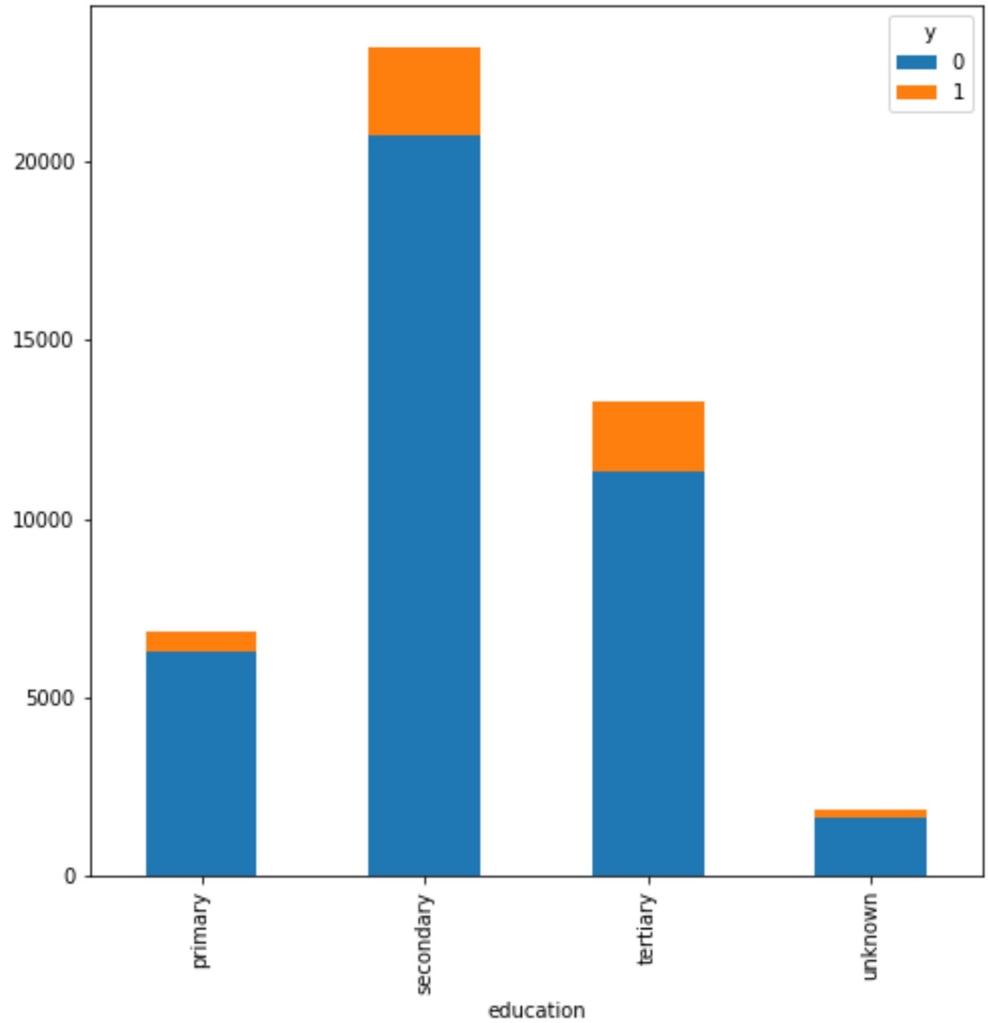
In [111]:
```
ov
```

Out[111]:

y	0	1
education		
primary	6260	591
secondary	20752	2450
tertiary	11305	1996
unknown	1605	252

In [112]:
```
ov.plot(kind='bar', figsize=(8,8),stacked=True)
```

Out[112]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2f9fb77f0>



In [113]:
```
edu_frame=data[['education', 'y']]
edu_frame.head()
```

Out[113]:

	education	y
0	tertiary	0
1	secondary	0
2	secondary	0
3	unknown	0
4	unknown	0

In [114]:
```
groups = edu_frame.groupby("education").groups
```

In [115]:
```
groups
```

Out[115]:
```
{'primary': Int64Index([    8,    15,    17,    18,    22,    24,
45,    59,    62,
               73,
            ...
            45104, 45111, 45118, 45124, 45135, 45152, 45154, 4517
0, 45183,
            45207],
           dtype='int64', length=6851),
 'secondary': Int64Index([    1,     2,     9,    10,    11,     1
2,    14,    19,    20,
               23,
            ...
            45196, 45197, 45199, 45200, 45202, 45204, 45205, 4520
8, 45209,
            45210],
           dtype='int64', length=23202),
 'tertiary': Int64Index([    0,     5,     6,     7,    21,    26,
31,    34,    46,
               49,
            ...
            45173, 45185, 45191, 45192, 45193, 45194, 45198, 4520
1, 45203,
            45206],
           dtype='int64', length=13301),
 'unknown': Int64Index([    3,     4,    13,    16,    42,    44,
57,    58,    64,
               93,
            ...
            44983, 45022, 45055, 45098, 45109, 45129, 45141, 4515
0, 45158,
            45186],
           dtype='int64', length=1857)}
```

In [116]:
```
edu_class=edu_frame['y']
```

In [117]:
```
edu_class
```

Out[117]:
```
0        0
1        0
2        0
3        0
4        0
        ..
45206    1
45207    1
45208    1
45209    0
45210    0
Name: y, Length: 45211, dtype: int64
```

In [118]:
```
primary = edu_class[groups["primary"]]
secondary = edu_class[groups["secondary"]]
tertiary = edu_class[groups["tertiary"]]
unknown = edu_class[groups["unknown"]]
```

In [119]:
```
primary
```

Out[119]:
```
8        0
15       0
17       0
18       0
22       0
        ..
45152    0
45154    0
45170    0
45183    0
45207    1
Name: y, Length: 6851, dtype: int64
```

In [120]:
```
dfd=len(primary)-1+len(secondary)-1+len(tertiary)-1+len(unknown)-1
dfd
```

Out[120]:
```
45207
```

In [191]:
```
f=stats.f_oneway(primary,secondary,tertiary ,unknown )
```

In [190]:
```
 import scipy.stats
critical_value=scipy.stats.f.ppf(q=1-0.05, dfn=3, dfd=45207)
```

In [194]:
```
 if (f[0] >critical_value):
        print(" Atleast on group is different , and the feature is
releavant" )
else:
    print("There is no diffrenece between the means of different gr
oups , and the feature is not releavant")
```

```
 Atleast on group is different , and the feature is releavant
```

Make a function so that we can test all the attributes by just calling the function.

Selecting K Best Features Using ANOVA

In [123]:
```
ordinal_list=['education']
data['education'] = data['education'].replace(['primary','secondary
','tertiary','unknown'],[1,2,3,2])
```

In [124]:
```
data
```

Out[124]:

	age	job	marital	education	default	balance	housing	loan	contact
0	58	management	married	3	no	2143	yes	no	unknown
1	44	technician	single	2	no	29	yes	no	unknown
2	33	entrepreneur	married	2	no	2	yes	yes	unknown
3	47	blue-collar	married	2	no	1506	yes	no	unknown
4	33	unknown	single	2	no	1	no	no	unknown
...	...	...	...	...	...	...	...	...	...
45206	51	technician	married	3	no	825	no	no	cellular
45207	71	retired	divorced	1	no	1729	no	no	cellular
45208	72	retired	married	2	no	5715	no	no	cellular
45209	57	blue-collar	married	2	no	668	no	no	telephone
45210	37	entrepreneur	married	2	no	2971	no	no	cellular

45211 rows × 17 columns

In [125]:
```
nominal_list = []
for i in data.columns.tolist():
    if (data[i].dtype=='object') and (i not in ordinal_list):
        nominal_list.append(i)
print (nominal_list)
print('Number of nominal features:', str(len(nominal_list)))
```

```
['job', 'marital', 'default', 'housing', 'loan', 'contact', 'month
', 'poutcome']
Number of nominal features: 8
```

In [126]:
```
ordinal_data=data[ordinal_list]
nominal_data=data[nominal_list]
categorical_data = pd.concat([ordinal_data,nominal_data], axis=1)
```

In [127]:
```
categorical_data
```

Out[127]:

	education	job	marital	default	housing	loan	contact	month	poutcor
0	3	management	married	no	yes	no	unknown	may	unknov
1	2	technician	single	no	yes	no	unknown	may	unknov
2	2	entrepreneur	married	no	yes	yes	unknown	may	unknov
3	2	blue-collar	married	no	yes	no	unknown	may	unknov
4	2	unknown	single	no	no	no	unknown	may	unknov
...	...	...	...	...	...	...	...	...	
45206	3	technician	married	no	no	no	cellular	nov	unknov
45207	1	retired	divorced	no	no	no	cellular	nov	unknov
45208	2	retired	married	no	no	no	cellular	nov	succe
45209	2	blue-collar	married	no	no	no	telephone	nov	unknov
45210	2	entrepreneur	married	no	no	no	cellular	nov	oth

45211 rows × 9 columns

In [128]:
```
from sklearn.preprocessing import LabelEncoder
encoder=LabelEncoder()
for column in nominal_list:
    categorical_data[column]=encoder.fit_transform(categorical_data
[column])
```

In [129]:
```
categorical_data
```

Out[129]:

	education	job	marital	default	housing	loan	contact	month	poutcome
0	3	4	1	0	1	0	2	8	3
1	2	9	2	0	1	0	2	8	3
2	2	2	1	0	1	1	2	8	3
3	2	1	1	0	1	0	2	8	3
4	2	11	2	0	0	0	2	8	3
...	...	...	...	...	...	...	...	...	...
45206	3	9	1	0	0	0	0	9	3
45207	1	5	0	0	0	0	0	9	3
45208	2	5	1	0	0	0	0	9	2
45209	2	1	1	0	0	0	1	9	3
45210	2	2	1	0	0	0	0	9	1

45211 rows × 9 columns

In [130]:
```
X=categorical_data
```

In [132]:
```
y=data['y']
```

In [181]:
```
col=X.columns
col
```

Out[181]:
```
Index(['education', 'job', 'marital', 'default', 'housing', 'loan
', 'contact',
       'month', 'poutcome'],
      dtype='object')
```

In [141]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif
from matplotlib import pyplot
```

In [164]:
```
f=f_classif(X,y)
```

In [167]:
```
f[0]
```

Out[167]:
```
array([ 213.96297633,   74.04835143,   94.1500255 ,   22.73392322,
        892.95057646,  211.16739503, 1017.96593035,   27.08968938,
        275.5968724 ])
```

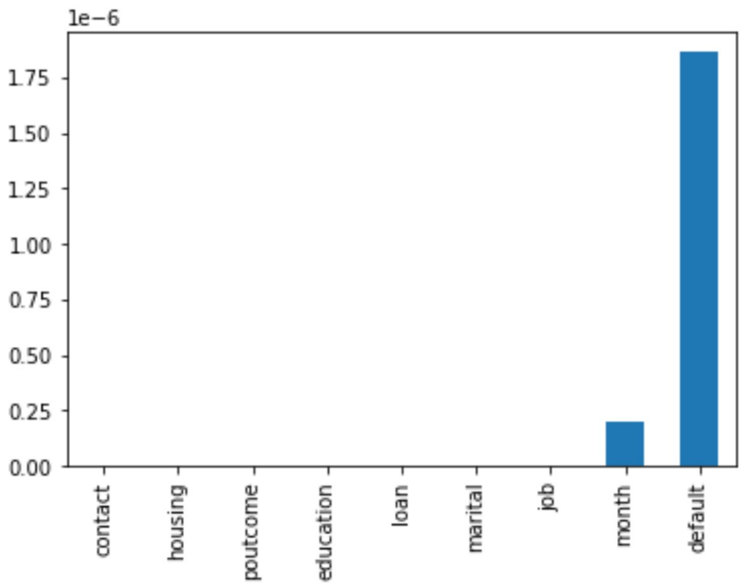
In [175]:
```
f[1]
```

Out[175]:
```
array([2.42056523e-048, 7.86348864e-018, 3.07484749e-022, 1.866326
53e-006,
       2.62192657e-194, 9.79365754e-048, 6.39604160e-221, 1.950782
21e-007,
       1.04262910e-061])
```

In [170]:
```
p_values = pd.Series(f[1],index = X.columns)
p_values.sort_values(ascending = True , inplace = True)
fscore_values=pd.Series(f[0],index = X.columns)
fscore_values.sort_values(ascending = False , inplace = True)
```

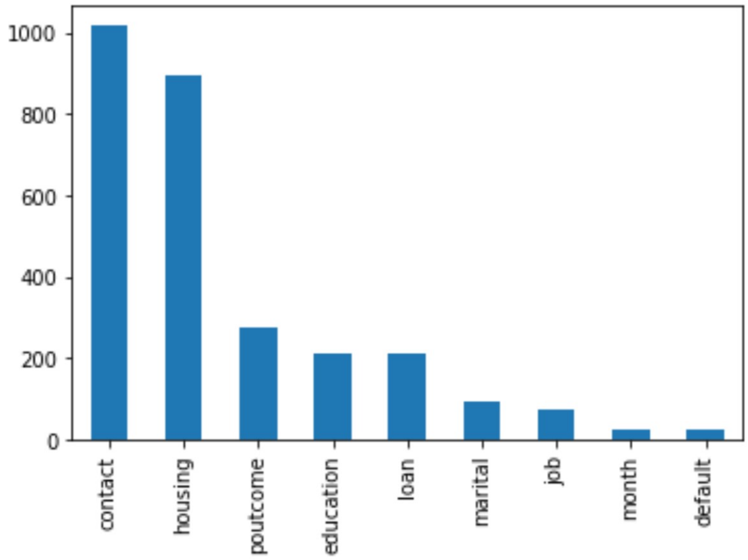
In [172]:
```
p_values.plot.bar()
```

Out[172]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1c2fab1afd0>
```



In [174]:
```
fscore_values.plot.bar()
```

Out[174]: <matplotlib.axes._subplots.AxesSubplot at 0x1c2fac052b0>



In [182]:
```
def select_features(X_train,y_train,k,col):
    anova_features = SelectKBest(f_classif, k = k)
    X_kbest_features = anova_features.fit_transform(X, Y)
    index=anova_features.get_support(indices=True)
    return col[index]
```

In [184]:
```
select_features(X,y,4,col)
```

Out[184]:
```
Index(['education', 'housing', 'contact', 'poutcome'], dtype='obje
ct')
```

In [185]:
```
columns=select_features(X,y,4,col)
```

In [186]:
```
df_selected_features=X[columns]
```

In [187]:
```
df_selected_features
```

Out[187]:

	education	housing	contact	poutcome
0	3	1	2	3
1	2	1	2	3
2	2	1	2	3
3	2	1	2	3
4	2	0	2	3
...	...	...	...	...
45206	3	0	0	3
45207	1	0	0	3
45208	2	0	0	2
45209	2	0	1	3
45210	2	0	0	1

45211 rows × 4 columns

In [188]:
```
data[columns]
```

Out[188]:

	education	housing	contact	poutcome
0	3	yes	unknown	unknown
1	2	yes	unknown	unknown
2	2	yes	unknown	unknown
3	2	yes	unknown	unknown
4	2	no	unknown	unknown
...	...	...	...	...
45206	3	no	cellular	unknown
45207	1	no	cellular	unknown
45208	2	no	cellular	success
45209	2	no	telephone	unknown
45210	2	no	cellular	other

45211 rows × 4 columns

D) LDA (Linear Discriminant Analysis)

[https://towardsdatascience.com/linear-discriminant-analysis-in-python-76b8b17817c2 (https://towardsdatascience.com/linear-discriminant-analysis-in-python-76b8b17817c2)](https://towardsdatascience.com/linear-discriminant-analysis-in-python-76b8b17817c2)

6.Feature Seletion Based on Embeded Methods (Random Forest)

In [227]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [209]:
```
data=pd.read_csv("D:/FTI/Cohort 2 EDA/Lecture 4/Finance.csv")
```

In [210]:
```
data
```

Out[210]:

	age	job	marital	education	default	balance	housing	loan	contact
0	58	management	married	tertiary	no	2143	yes	no	unknown
1	44	technician	single	secondary	no	29	yes	no	unknown
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown
4	33	unknown	single	unknown	no	1	no	no	unknown
...	...	...	...	...	...	...	...	...	...
45206	51	technician	married	tertiary	no	825	no	no	cellular
45207	71	retired	divorced	primary	no	1729	no	no	cellular
45208	72	retired	married	secondary	no	5715	no	no	cellular
45209	57	blue-collar	married	secondary	no	668	no	no	telephone
45210	37	entrepreneur	married	secondary	no	2971	no	no	cellular

45211 rows × 17 columns

In [214]:
```
data['y']=data['y'].apply(lambda x:0 if x=='no' else 1)
```

In [215]:
```
y=data['y']
```

In [216]:
```
data=data.drop('y',axis=1)
```

In [217]:
```
ordinal_list=['education']
data['education'] = data['education'].replace(['primary','secondary
','tertiary','unknown'],[1,2,3,2])
```

In [218]:
```
nominal_list = []
for i in data.columns.tolist():
    if (data[i].dtype=='object') and (i not in ordinal_list):
        nominal_list.append(i)
print (nominal_list)
print('Number of nominal features:', str(len(nominal_list)))
```

```
['job', 'marital', 'default', 'housing', 'loan', 'contact', 'month
', 'poutcome']
Number of nominal features: 8
```

In [219]:
```
from sklearn.preprocessing import LabelEncoder
encoder=LabelEncoder()
for column in nominal_list:
    data[column]=encoder.fit_transform(categorical_data[column])
```

In [220]:
```
data.head()
```

Out[220]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	du
0	58	4	1	3	0	2143	1	0	2	5	8	
1	44	9	2	2	0	29	1	0	2	5	8	
2	33	2	1	2	0	2	1	1	2	5	8	
3	47	1	1	2	0	1506	1	0	2	5	8	
4	33	11	2	2	0	1	0	0	2	5	8	

In [221]:
```
y
```

Out[221]:
```
0        0
1        0
2        0
3        0
4        0
        ..
45206    1
45207    1
45208    1
45209    0
45210    0
Name: y, Length: 45211, dtype: int64
```

In [222]:
```
train,test = train_test_split(data)
```

In [223]:
```
len(train)
```

Out[223]:
```
33908
```

In [224]:
```
len(test)
```

Out[224]:
```
11303
```

In [225]:
```
X_train=data
Y_train=y
```

In [228]:
```
clf=RandomForestClassifier(n_estimators=100)

#Train the model using the training sets y_pred=clf.predict(X_test)
clf.fit(X_train,Y_train)
```

Out[228]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterio
n='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=No
ne,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs
=None,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

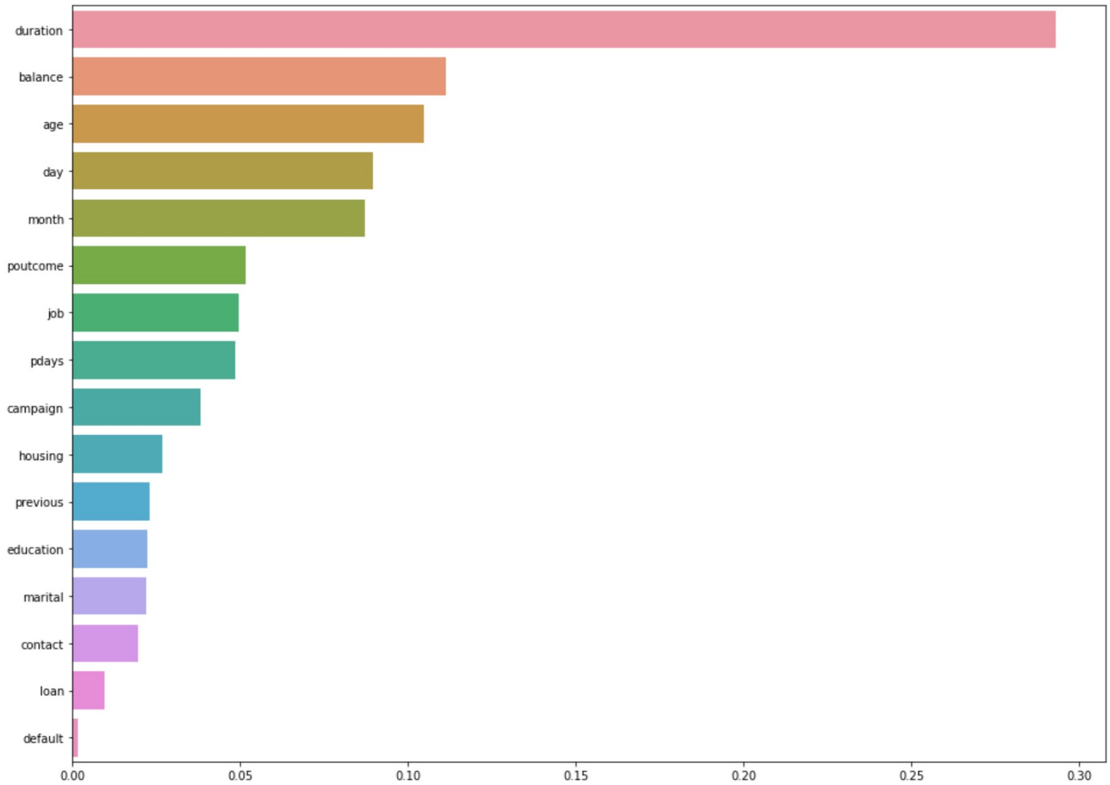
In [229]:
```
importances = clf.feature_importances_
#Sort it
print ("Sorted Feature Importance:")
sorted_feature_importance = sorted(zip(importances, list(X_train)),
reverse=True)
print (sorted_feature_importance)
```

```
Sorted Feature Importance:
[(0.2930636173741779, 'duration'), (0.11119477109507034, 'balance
'), (0.1046415367492501, 'age'), (0.08979365375653357, 'day'), (0.
08713970680386957, 'month'), (0.051812102566191946, 'poutcome'),
(0.04962279194969645, 'job'), (0.048598965543559561, 'pdays'), (0.0
384153336886549, 'campaign'), (0.02674957132472083, 'housing'),
(0.023058593706814384, 'previous'), (0.02258285932353153, 'educati
on'), (0.02218296799329467, 'marital'), (0.019541014316243034, 'co
ntact'), (0.009806127644431908, 'loan'), (0.0017963861639232579, '
default')]
```

In [230]:
```
feature_imp = pd.Series(clf.feature_importances_,index=X_train.colu
mns).sort_values(ascending=False)
```

In [231]:
```
# Creating a bar plot
plt.figure(figsize=(16,12))
sns.barplot(x=feature_imp, y=feature_imp.index)
```

Out[231]: <matplotlib.axes._subplots.AxesSubplot at 0x1c281574cc0>



7. Feature Selection Using Embeded Methods

In [235]:
```
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
rfe_selector = RFE(estimator=LogisticRegression(), n_features_to_se
lect=5, step=10, verbose=5)
rfe_selector.fit(X_train, y)
rfe_support = rfe_selector.get_support()
rfe_feature = X.loc[:,rfe_support].columns.tolist()
print(str(len(rfe_feature)), 'selected features')
```

```
Fitting estimator with 16 features.

C:\Users\malik\Anaconda3\lib\site-packages\sklearn\linear_model\lo
gistic.py:433: FutureWarning: Default solver will be changed to 'l
bfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)

Fitting estimator with 6 features.

C:\Users\malik\Anaconda3\lib\site-packages\sklearn\linear_model\lo
gistic.py:433: FutureWarning: Default solver will be changed to 'l
bfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
C:\Users\malik\Anaconda3\lib\site-packages\sklearn\linear_model\lo
gistic.py:433: FutureWarning: Default solver will be changed to 'l
bfgs' in 0.22. Specify a solver to silence this warning.
  FutureWarning)
```

```
---------------------------------------------------------------------------
IndexError                                Traceback (most recent call last)
<ipython-input-235-a3332157431f> in <module>()
      4 rfe_selector.fit(X_train, y)
      5 rfe_support = rfe_selector.get_support()
----> 6 rfe_feature = X.loc[:,rfe_support].columns.tolist()
      7 print(str(len(rfe_feature)), 'selected features')

~\Anaconda3\lib\site-packages\pandas\core\indexing.py in __getitem__(self, key)
   1760                 except (KeyError, IndexError, AttributeError):
   1761                     pass
-> 1762             return self._getitem_tuple(key)
   1763         else:
   1764             # we by definition only have the 0th axis
```

In [ ]: