Q1) Prepare a classification model using SVM for salary data

Data Description:

Age -- age of a person

Workclass -- A work class is a grouping of work

Education-- Education of an individuals

Maritalstatus -- Marital status of an individulas

Occupation -- occupation of an individuals

Relationship --

Race -- Race of an Individual

Sex -- Gender of an Individual

Capitalgain -- profit received from the sale of an investment

Capitalloss -- A decrease in the value of a capital asset

Hoursperweek -- number of hours work per week

Native -- Native of an individual

Salary -- salary of an individual

In [1]:
```
# Import the data
import pandas as pd
import numpy as np
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.model_selection import GridSearchCV
```

In [2]:
```
train = pd.read_csv('SalaryData_Train.csv')
train
```

Out[2]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex	capitalgain	capitalloss	hoursperweek	native	Salary
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
30156	27	Private	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	38	United-States	<=50K
30157	40	Private	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	40	United-States	>50K
30158	58	Private	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	40	United-States	<=50K
30159	22	Private	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0	20	United-States	<=50K
30160	52	Self-emp-inc	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	40	United-States	>50K

30161 rows × 14 columns

In [3]:
```
test = pd.read_csv('SalaryData_Test.csv')
test
```

Out[3]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex	capitalgain	capitalloss	hoursperweek	native	Salary
0	25	Private	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0	0	40	United-States	<=50K
1	38	Private	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0	50	United-States	<=50K
2	28	Local-gov	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	0	40	United-States	>50K
3	44	Private	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688	0	40	United-States	>50K
4	34	Private	10th	6	Never-married	Other-service	Not-in-family	White	Male	0	0	30	United-States	<=50K
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
15055	33	Private	Bachelors	13	Never-married	Prof-specialty	Own-child	White	Male	0	0	40	United-States	<=50K
15056	39	Private	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White	Female	0	0	36	United-States	<=50K
15057	38	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	White	Male	0	0	50	United-States	<=50K
15058	44	Private	Bachelors	13	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander	Male	5455	0	40	United-States	<=50K
15059	35	Self-emp-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	60	United-States	>50K

15060 rows × 14 columns

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

Out[4]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex	capitalgain	capitalloss	hoursperweek	native	Salary
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K

In [5]:
```
test.head()
```

Out[5]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex	capitalgain	capitalloss	hoursperweek	native	Salary
0	25	Private	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0	0	40	United-States	<=50K
1	38	Private	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0	50	United-States	<=50K
2	28	Local-gov	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	0	40	United-States	>50K
3	44	Private	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688	0	40	United-States	>50K
4	34	Private	10th	6	Never-married	Other-service	Not-in-family	White	Male	0	0	30	United-States	<=50K

In [6]:
```
train.shape
```

Out[6]: (30161, 14)

In [7]:
```
test.shape
```

Out[7]: (15060, 14)

In [8]:
```
1 train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30161 entries, 0 to 30160
Data columns (total 14 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   age            30161 non-null  int64 
 1   workclass      30161 non-null  object
 2   education      30161 non-null  object
 3   educationno    30161 non-null  int64 
 4   maritalstatus  30161 non-null  object
 5   occupation     30161 non-null  object
 6   relationship   30161 non-null  object
 7   race           30161 non-null  object
 8   sex            30161 non-null  object
 9   capitalgain    30161 non-null  int64 
 10  capitalloss    30161 non-null  int64 
 11  hoursperweek   30161 non-null  int64 
 12  native         30161 non-null  object
 13  Salary         30161 non-null  object
dtypes: int64(5), object(9)
memory usage: 3.2+ MB
```

In [9]:
```
1 test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15060 entries, 0 to 15059
Data columns (total 14 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   age            15060 non-null  int64 
 1   workclass      15060 non-null  object
 2   education      15060 non-null  object
 3   educationno    15060 non-null  int64 
 4   maritalstatus  15060 non-null  object
 5   occupation     15060 non-null  object
 6   relationship   15060 non-null  object
 7   race           15060 non-null  object
 8   sex            15060 non-null  object
 9   capitalgain    15060 non-null  int64 
 10  capitalloss    15060 non-null  int64 
 11  hoursperweek   15060 non-null  int64 
 12  native         15060 non-null  object
 13  Salary         15060 non-null  object
dtypes: int64(5), object(9)
memory usage: 1.6+ MB
```

In [10]:
```
1 train.describe()
```

Out[10]:

	age	educationno	capitalgain	capitalloss	hoursperweek
count	30161.000000	30161.000000	30161.000000	30161.000000	30161.000000
mean	38.438115	10.121316	1092.044064	88.302311	40.931269
std	13.134830	2.550037	7406.466611	404.121321	11.980182
min	17.000000	1.000000	0.000000	0.000000	1.000000
25%	28.000000	9.000000	0.000000	0.000000	40.000000
50%	37.000000	10.000000	0.000000	0.000000	40.000000
75%	47.000000	13.000000	0.000000	0.000000	45.000000
max	90.000000	16.000000	99999.000000	4356.000000	99.000000

In [11]:
```
1 test.describe()
```

Out[11]:

	age	educationno	capitalgain	capitalloss	hoursperweek
count	15060.000000	15060.000000	15060.000000	15060.000000	15060.000000
mean	38.768327	10.112749	1120.301594	89.041899	40.951594
std	13.380676	2.558727	7703.181842	406.283245	12.062831
min	17.000000	1.000000	0.000000	0.000000	1.000000
25%	28.000000	9.000000	0.000000	0.000000	40.000000
50%	37.000000	10.000000	0.000000	0.000000	40.000000
75%	48.000000	13.000000	0.000000	0.000000	45.000000
max	90.000000	16.000000	99999.000000	3770.000000	99.000000

In [12]:
```
train.corr()
```

Out[12]:

	age	educationno	capitalgain	capitalloss	hoursperweek
age	1.000000	0.043525	0.080152	0.060278	0.101598
educationno	0.043525	1.000000	0.124416	0.079691	0.152522
capitalgain	0.080152	0.124416	1.000000	-0.032218	0.080431
capitalloss	0.060278	0.079691	-0.032218	1.000000	0.052454
hoursperweek	0.101598	0.152522	0.080431	0.052454	1.000000

In [13]:
```
test.corr()
```

Out[13]:

	age	educationno	capitalgain	capitalloss	hoursperweek
age	1.000000	0.026123	0.078760	0.057745	0.102758
educationno	0.026123	1.000000	0.131750	0.085817	0.133691
capitalgain	0.078760	0.131750	1.000000	-0.031876	0.090501
capitalloss	0.057745	0.085817	-0.031876	1.000000	0.057712
hoursperweek	0.102758	0.133691	0.090501	0.057712	1.000000

Data Preprocessing

In [14]:
```
lb = LabelEncoder()
```

In [15]:
```
train["workclass"] = lb.fit_transform(train["workclass"])
train["education"] = lb.fit_transform(train["education"])
train["maritalstatus"] = lb.fit_transform(train["maritalstatus"])
train["occupation"] = lb.fit_transform(train["occupation"])
train["relationship"] = lb.fit_transform(train["relationship"])
train["race"] = lb.fit_transform(train["race"])
train["sex"] = lb.fit_transform(train["sex"])
train["native"] = lb.fit_transform(train["native"])
train["Salary"] = lb.fit_transform(train["Salary"])
```

In [16]:
```
test["workclass"] = lb.fit_transform(test["workclass"])
test["education"] = lb.fit_transform(test["education"])
test["maritalstatus"] = lb.fit_transform(test["maritalstatus"])
test["occupation"] = lb.fit_transform(test["occupation"])
test["relationship"] = lb.fit_transform(test["relationship"])
test["race"] = lb.fit_transform(test["race"])
test["sex"] = lb.fit_transform(test["sex"])
test["native"] = lb.fit_transform(test["native"])
test["Salary"] = lb.fit_transform(test["Salary"])
```

EDA

In [17]:
```
train = train.iloc[: 2000, :]
```

In [18]:
```
train.info()
```

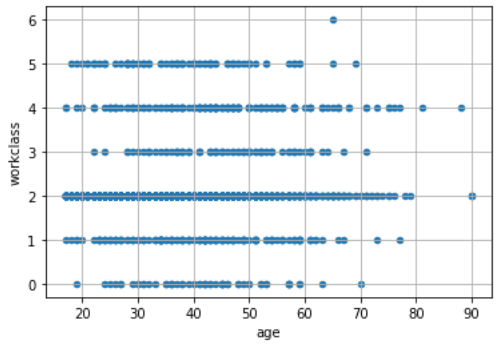
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 14 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   age            2000 non-null   int64
 1   workclass      2000 non-null   int32
 2   education      2000 non-null   int32
 3   educationno    2000 non-null   int64
 4   maritalstatus  2000 non-null   int32
 5   occupation     2000 non-null   int32
 6   relationship   2000 non-null   int32
 7   race           2000 non-null   int32
 8   sex            2000 non-null   int32
 9   capitalgain    2000 non-null   int64
 10  capitalloss    2000 non-null   int64
 11  hoursperweek   2000 non-null   int64
 12  native         2000 non-null   int32
 13  Salary         2000 non-null   int32
dtypes: int32(9), int64(5)
memory usage: 148.6 KB
```

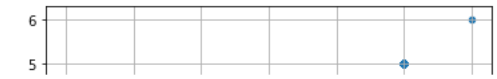
In [19]:
```
test = test.iloc[: 1300, :]
```

In [20]:
```
test.info()
```

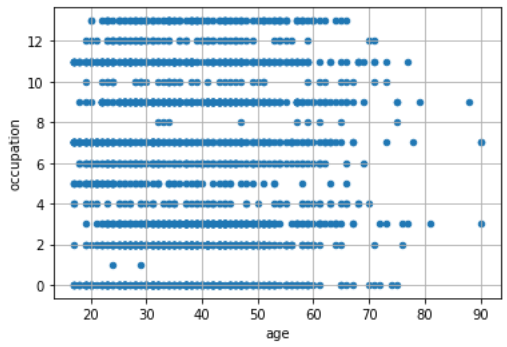
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1300 entries, 0 to 1299
Data columns (total 14 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             1300 non-null   int64
 1   workclass       1300 non-null   int32
 2   education       1300 non-null   int32
 3   educationno     1300 non-null   int64
 4   maritalstatus   1300 non-null   int32
 5   occupation      1300 non-null   int32
 6   relationship    1300 non-null   int32
 7   race            1300 non-null   int32
 8   sex             1300 non-null   int32
 9   capitalgain     1300 non-null   int64
 10  capitalloss     1300 non-null   int64
 11  hoursperweek    1300 non-null   int64
 12  native          1300 non-null   int32
 13  Salary          1300 non-null   int32
dtypes: int32(9), int64(5)
memory usage: 96.6 KB
```

In [21]:
```
for i in train.describe().columns[:-2]:
    train.plot.scatter(i,'workclass', grid=True)
```

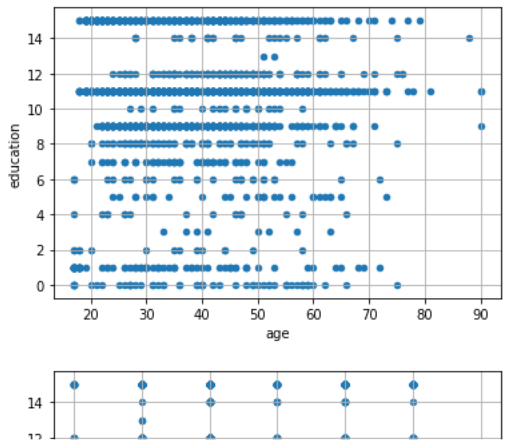




In [22]:
```
for i in train.describe().columns[:-2]:
    train.plot.scatter(i,'occupation',grid=True)
```



In [23]:
```
for i in train.describe().columns[:-2]:
    train.plot.scatter(i,'education',grid=True)
```



In [24]:
```
train.corr()
```

Out[24]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex	capitalgain	capitalloss	hoursperweek
age	1.000000	0.080136	-0.004007	0.014781	-0.249467	-0.004634	-0.216588	0.015168	0.050730	0.081112	0.058997	0.114429
workclass	0.080136	1.000000	0.029167	0.068866	-0.043219	0.033209	-0.074186	0.074418	0.087332	0.038314	-0.003069	0.031221
education	-0.004007	0.029167	1.000000	0.328746	-0.047668	-0.028564	-0.033833	0.031098	-0.004879	0.035363	0.012082	0.060470
educationno	0.014781	0.068866	0.328746	1.000000	-0.062303	0.098459	-0.091217	0.075867	0.034123	0.095804	0.062601	0.172302
maritalstatus	-0.249467	-0.043219	-0.047668	-0.062303	1.000000	0.075036	0.157226	-0.083280	-0.078456	-0.044395	-0.016550	-0.187437
occupation	-0.004634	0.033209	-0.028564	0.098459	0.075036	1.000000	-0.065478	0.035830	0.072483	0.016453	-0.015165	0.032509
relationship	-0.216588	-0.074186	-0.033833	-0.091217	0.157226	-0.065478	1.000000	-0.100663	-0.557999	-0.052849	-0.042243	-0.256052
race	0.015168	0.074418	0.031098	0.075867	-0.083280	0.035830	-0.100663	1.000000	0.076281	0.018565	0.043238	0.065593
sex	0.050730	0.087332	-0.004879	0.034123	-0.078456	0.072483	-0.557999	0.076281	1.000000	0.030977	0.049696	0.205762
capitalgain	0.081112	0.038314	0.035363	0.095804	-0.044395	0.016453	-0.052849	0.018565	0.030977	1.000000	-0.033968	0.064462
capitalloss	0.058997	-0.003069	0.012082	0.062601	-0.016550	-0.015165	-0.042243	0.043238	0.049696	-0.033968	1.000000	0.056110
hoursperweek	0.114429	0.031221	0.060470	0.172302	-0.187437	0.032509	-0.256052	0.065593	0.205762	0.064462	0.056110	1.000000
native	-0.001914	-0.036263	0.085718	0.057602	0.002006	-0.000106	-0.054397	0.155655	0.029781	-0.028919	-0.018007	-0.003643
Salary	0.231176	0.064561	0.051282	0.308324	-0.199289	0.026793	-0.211663	0.068448	0.182859	0.220183	0.135484	0.225754

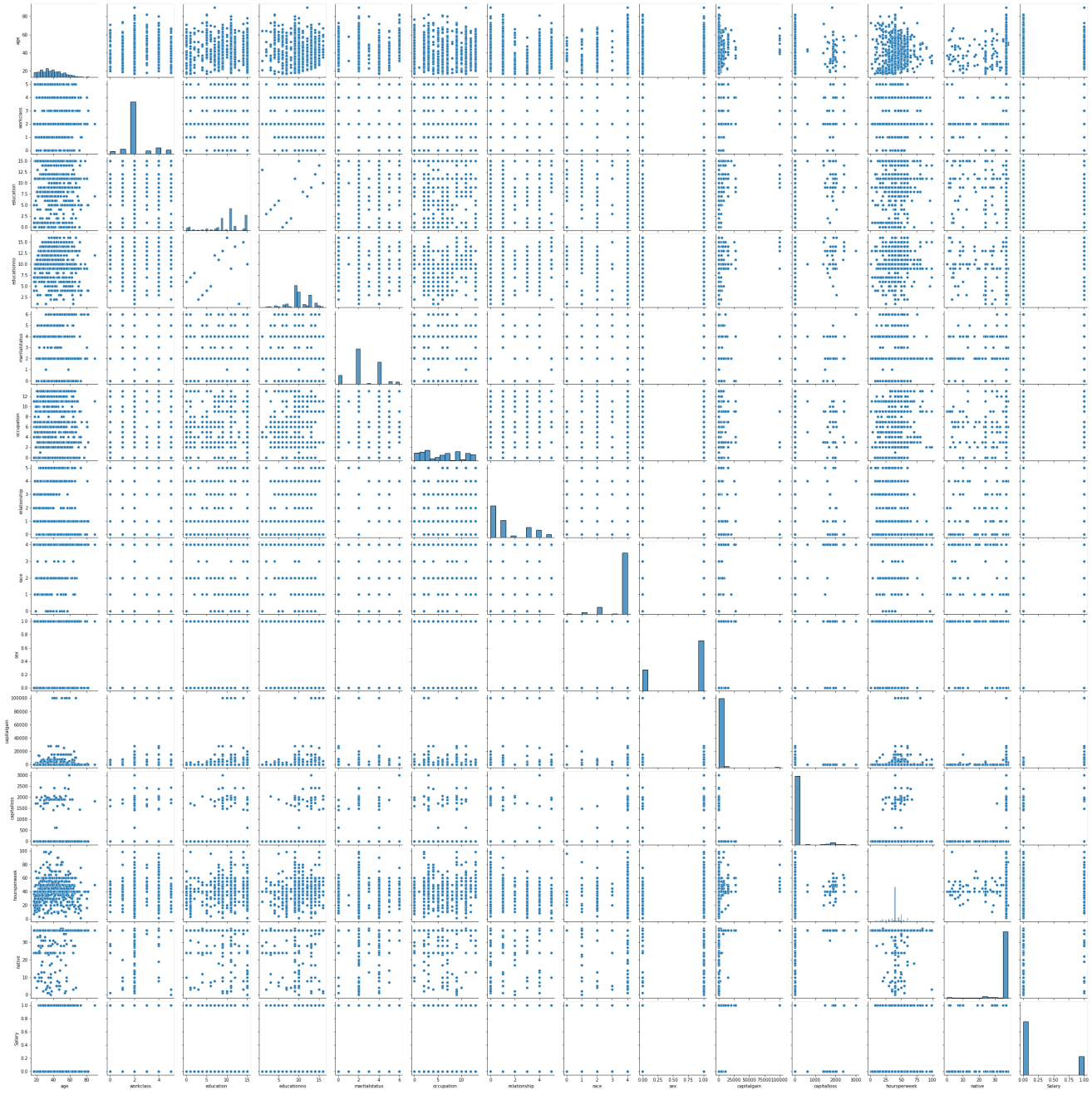
In [25]:
```
test.corr()
```

Out[25]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex	capitalgain	capitalloss	hoursperweek
age	1.000000	0.132698	-0.058456	-0.028238	-0.299098	-0.035747	-0.253358	0.003103	0.074865	0.107361	0.057418	0.106105
workclass	0.132698	1.000000	0.068824	0.066220	-0.060726	0.011914	-0.082095	0.065081	0.049687	0.053677	0.062026	0.077106
education	-0.058456	0.068824	1.000000	0.409201	-0.039852	-0.023030	-0.024427	-0.005501	-0.011597	0.060160	0.038734	0.063598
educationno	-0.028238	0.066220	0.409201	1.000000	-0.091147	0.077972	-0.050679	0.072135	-0.011529	0.170971	0.111713	0.145317
maritalstatus	-0.299098	-0.060726	-0.039852	-0.091147	1.000000	-0.012545	0.197796	-0.085572	-0.147099	-0.071843	-0.018926	-0.161722
occupation	-0.035747	0.011914	-0.023030	0.077972	-0.012545	1.000000	-0.063657	0.037160	0.073262	0.004247	-0.038230	0.018785
relationship	-0.253358	-0.082095	-0.024427	-0.050679	0.197796	-0.063657	1.000000	-0.158517	-0.588370	-0.060524	-0.037262	-0.298815
race	0.003103	0.065081	-0.005501	0.072135	-0.085572	0.037160	-0.158517	1.000000	0.072954	0.017319	0.064287	0.058017
sex	0.074865	0.049687	-0.011597	-0.011529	-0.147099	0.073262	-0.588370	0.072954	1.000000	0.070784	0.053486	0.233998
capitalgain	0.107361	0.053677	0.060160	0.170971	-0.071843	0.004247	-0.060524	0.017319	0.070784	1.000000	-0.036077	0.128418
capitalloss	0.057418	0.062026	0.038734	0.111713	-0.018926	-0.038230	-0.037262	0.064287	0.053486	-0.036077	1.000000	0.062200
hoursperweek	0.106105	0.077106	0.063598	0.145317	-0.161722	0.018785	-0.298815	0.058017	0.233998	0.128418	0.062200	1.000000
native	0.018697	0.043338	0.069760	0.106144	0.005488	0.004193	0.015321	0.160356	-0.037813	0.032191	0.051320	-0.026799
Salary	0.226220	0.077615	0.119016	0.313422	-0.226209	0.018910	-0.259728	0.076017	0.206553	0.249281	0.163200	0.231284

In [26]:
```
1 sns.pairplot(test)
```

Out[26]: <seaborn.axisgrid.PairGrid at 0x20c90ab47c0>



Data Splitting

In [27]:
```
X_train=train.iloc[:,:-1]
X_train
```

Out[27]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex	capitalgain	capitalloss	hoursperweek	native
0	39	5	9	13	4	0	1	4	1	2174	0	40	37
1	50	4	9	13	2	3	0	4	1	0	0	13	37
2	38	2	11	9	0	5	1	4	1	0	0	40	37
3	53	2	1	7	2	5	0	2	1	0	0	40	37
4	28	2	9	13	2	9	5	2	0	0	0	40	4
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1995	33	2	11	9	5	10	3	4	0	0	0	40	37
1996	41	2	11	9	2	6	0	4	1	0	0	40	37
1997	51	2	6	5	2	13	0	4	1	0	0	40	37
1998	42	2	11	9	2	11	0	4	1	0	0	48	37
1999	27	2	9	13	2	9	5	4	0	0	0	40	37

2000 rows × 13 columns

In [28]:
```
y_train=train.iloc[:,-1]
y_train
```

Out[28]:
```
0       0
1       0
2       0
3       0
4       0
       ..
1995    0
1996    0
1997    0
1998    0
1999    1
Name: Salary, Length: 2000, dtype: int32
```

In [29]:
```
X_test=test.iloc[:,:-1]
X_test
```

Out[29]:

	age	workclass	education	educationno	maritalstatus	occupation	relationship	race	sex	capitalgain	capitalloss	hoursperweek	native
0	25	2	1	7	4	6	3	2	1	0	0	40	37
1	38	2	11	9	2	4	0	4	1	0	0	50	37
2	28	1	7	12	2	10	0	4	1	0	0	40	37
3	44	2	15	10	2	6	0	2	1	7688	0	40	37
4	34	2	0	6	4	7	1	4	1	0	0	30	37
...	...	...	...	...	...	...	...	...	...	...	...	...	...
1295	66	4	15	10	2	13	0	2	1	0	0	60	37
1296	40	2	15	10	4	2	2	0	1	0	0	30	37
1297	37	2	4	3	2	6	0	4	1	0	0	40	7
1298	34	2	9	13	2	11	0	4	1	0	0	40	37
1299	41	4	12	14	6	9	1	4	0	0	0	20	37

1300 rows × 13 columns

In [30]:
```
y_test=test.iloc[:,-1]
y_test
```

Out[30]:
```
0       0
1       0
2       1
3       1
4       0
       ..
1295    0
1296    0
1297    0
1298    0
1299    0
Name: Salary, Length: 1300, dtype: int32
```

In [31]:
```
X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

Out[31]: ((2000, 13), (2000,), (1300, 13), (1300,))

SVM Model

In [32]:
```
model = SVC()

model.fit(X_train, y_train)
```

Out[32]: SVC()

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Predicting model

In [33]:
```
y_pred = model.predict(X_test)
y_pred
```

Out[33]: array([0, 0, 0, ..., 0, 0, 0])

Model Evaluation

In [34]:
```
print(confusion_matrix(y_test, y_pred))
```

```
[[961   5]
 [267  67]]
```

In [35]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.78      0.99      0.88       966
           1       0.93      0.20      0.33       334

    accuracy                           0.79      1300
   macro avg       0.86      0.60      0.60      1300
weighted avg       0.82      0.79      0.74      1300
```

Inference

- Model is not predicting well, so we will improve the model by hyperparameter tunning using grid search method.

Improving Model using Grid Search CV

In [36]:
```
param_grid = {'C' : [1, 5, 10, 15, 20], 'gamma' : [1, 0.1, 0.01, 0.001, 0.0001], 'kernel' : ['rbt']}
```

In [37]:
```
grid = GridSearchCV(SVC(), param_grid, refit = True, verbose = 3, cv = 5)
```

In [38]:
```
1 grid.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 25 candidates, totalling 125 fits
[CV 1/5] END .....C=1, gamma=1, kernel=rbt;, score=nan total time=   0.0s
[CV 2/5] END .....C=1, gamma=1, kernel=rbt;, score=nan total time=   0.0s
[CV 3/5] END .....C=1, gamma=1, kernel=rbt;, score=nan total time=   0.0s
[CV 4/5] END .....C=1, gamma=1, kernel=rbt;, score=nan total time=   0.0s
[CV 5/5] END .....C=1, gamma=1, kernel=rbt;, score=nan total time=   0.0s
[CV 1/5] END .....C=1, gamma=0.1, kernel=rbt;, score=nan total time=   0.0s
[CV 2/5] END .....C=1, gamma=0.1, kernel=rbt;, score=nan total time=   0.0s
[CV 3/5] END .....C=1, gamma=0.1, kernel=rbt;, score=nan total time=   0.0s
[CV 4/5] END .....C=1, gamma=0.1, kernel=rbt;, score=nan total time=   0.0s
[CV 5/5] END .....C=1, gamma=0.1, kernel=rbt;, score=nan total time=   0.0s
[CV 1/5] END .....C=1, gamma=0.01, kernel=rbt;, score=nan total time=   0.0s
[CV 2/5] END .....C=1, gamma=0.01, kernel=rbt;, score=nan total time=   0.0s
[CV 3/5] END .....C=1, gamma=0.01, kernel=rbt;, score=nan total time=   0.0s
[CV 4/5] END .....C=1, gamma=0.01, kernel=rbt;, score=nan total time=   0.0s
[CV 5/5] END .....C=1, gamma=0.01, kernel=rbt;, score=nan total time=   0.0s
[CV 1/5] END .....C=1, gamma=0.001, kernel=rbt;, score=nan total time=   0.0s
[CV 2/5] END .....C=1, gamma=0.001, kernel=rbt;, score=nan total time=   0.0s
[CV 3/5] END .....C=1, gamma=0.001, kernel=rbt;, score=nan total time=   0.0s
```

In [40]:
```
1 from sklearn.model_selection import GridSearchCV
```

In [44]:
```
1 print(grid.param_grid)
```

```
{'C': [1, 5, 10, 15, 20], 'gamma': [1, 0.1, 0.01, 0.001, 0.0001], 'kernel': ['rbt']}
```

In [59]:
```
1 grid.estimator
```

Out[59]:
```
SVC()
```

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In [ ]:
```
1
```