In [27]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [28]:

```
data=pd.read_excel('D:\machine learning\Raw data\Credit_card_default'')
```

In [29]:

```
data.head()
```

Out[29]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	...
0	20000	2	2	1	24	2	2	-1	-1	-2	...
1	120000	2	2	2	26	-1	2	0	0	0	...
2	90000	2	2	2	34	0	0	0	0	0	...
3	50000	2	2	1	37	0	0	0	0	0	...
4	50000	1	2	1	57	-1	0	-1	0	0	...

5 rows × 24 columns

In [30]:

```
data.shape
```

Out[30]:

```
(30000, 24)
```

In [31]:

```
data.isna().sum()
```

Out[31]:

```
LIMIT_BAL                     0
SEX                           0
EDUCATION                     0
MARRIAGE                      0
AGE                           0
PAY_0                         0
PAY_2                         0
PAY_3                         0
PAY_4                         0
PAY_5                         0
PAY_6                         0
BILL_AMT1                     0
BILL_AMT2                     0
BILL_AMT3                     0
BILL_AMT4                     0
BILL_AMT5                     0
BILL_AMT6                     0
PAY_AMT1                      0
PAY_AMT2                      0
PAY_AMT3                      0
PAY_AMT4                      0
PAY_AMT5                      0
PAY_AMT6                      0
default payment next month    0
dtype: int64
```

In [32]:

```
data.info()
```

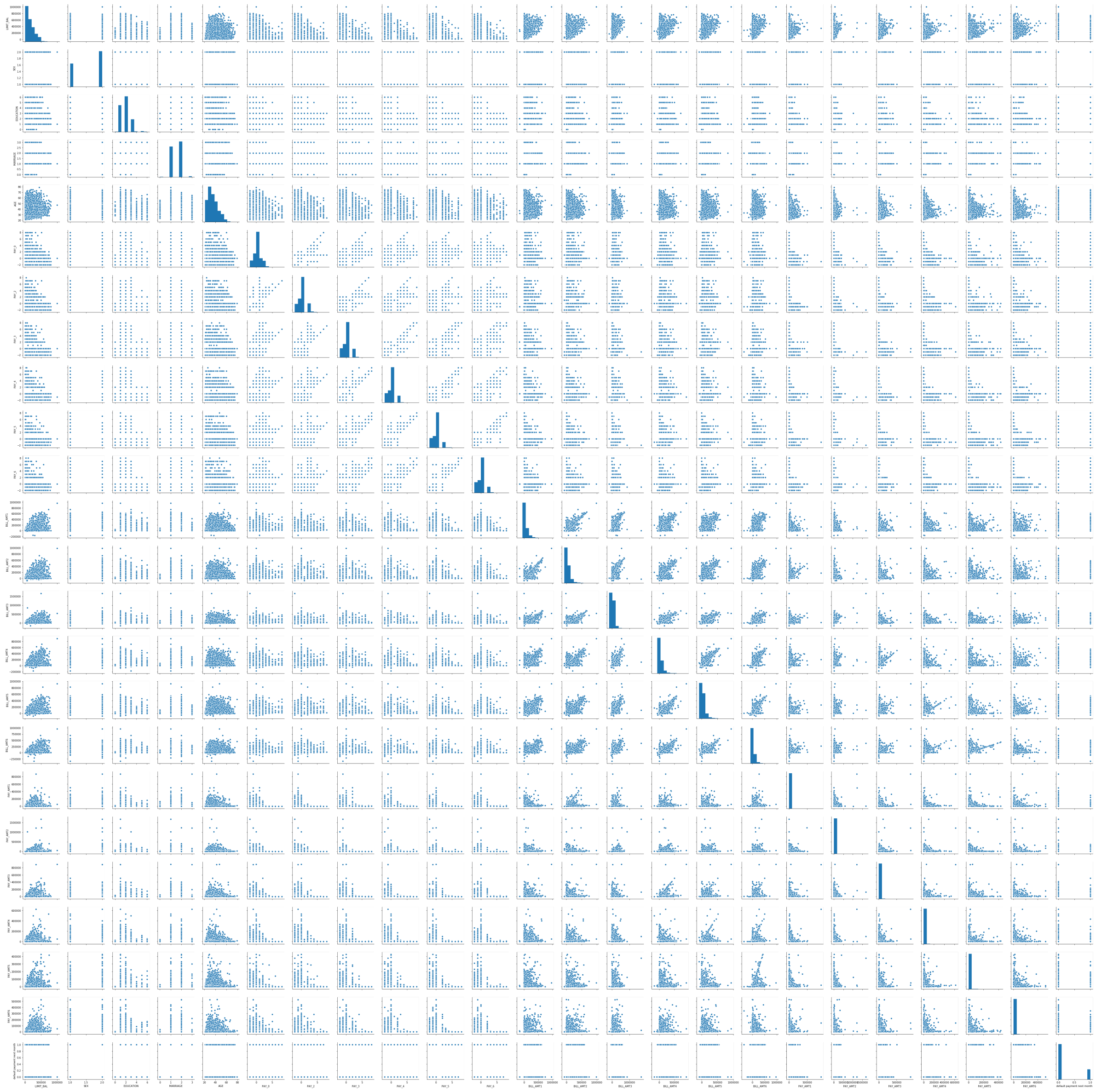
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 24 columns):
LIMIT_BAL                     30000 non-null int64
SEX                           30000 non-null int64
EDUCATION                     30000 non-null int64
MARRIAGE                      30000 non-null int64
AGE                           30000 non-null int64
PAY_0                         30000 non-null int64
PAY_2                         30000 non-null int64
PAY_3                         30000 non-null int64
PAY_4                         30000 non-null int64
PAY_5                         30000 non-null int64
PAY_6                         30000 non-null int64
BILL_AMT1                     30000 non-null int64
BILL_AMT2                     30000 non-null int64
BILL_AMT3                     30000 non-null int64
BILL_AMT4                     30000 non-null int64
BILL_AMT5                     30000 non-null int64
BILL_AMT6                     30000 non-null int64
PAY_AMT1                      30000 non-null int64
PAY_AMT2                      30000 non-null int64
PAY_AMT3                      30000 non-null int64
PAY_AMT4                      30000 non-null int64
PAY_AMT5                      30000 non-null int64
PAY_AMT6                      30000 non-null int64
default payment next month    30000 non-null int64
dtypes: int64(24)
memory usage: 5.5 MB
```

In [33]:

```
sns.pairplot(data)
```

Out[33]:

```
<seaborn.axisgrid.PairGrid at 0x1fbfd826c88>
```



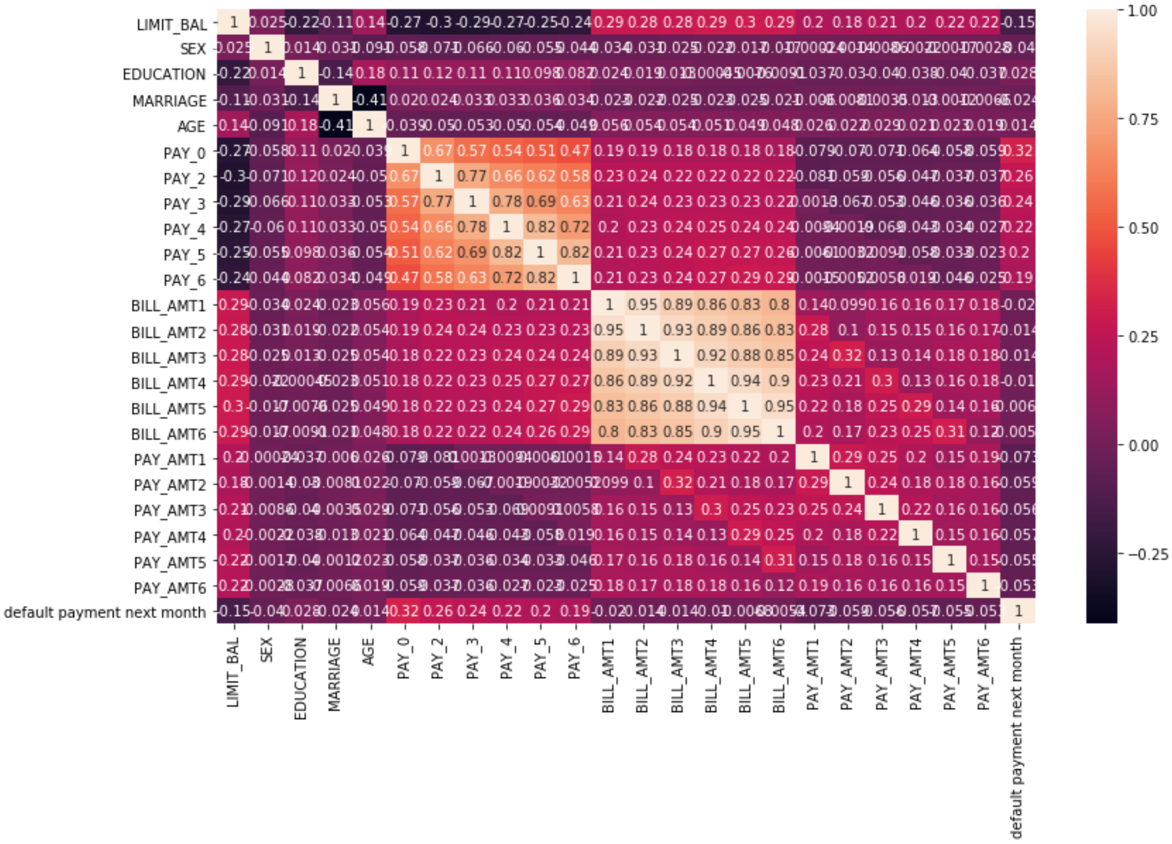
From the pair-plot above, we can see that there is some relationship between the feature columns. To confirm that we'd plot a correlation heatmap.

In [34]:

```
plt.figure(figsize=(13,8))
sns.heatmap(data.corr(), annot=True )
```

Out[34]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fb97693b38>
```



From the correlation heatmap above, it can be seen that there are some relationships between the feature columns, they are not entirely independent.

But in this scenario, there is a correlation because a customer who was not able to pay the bill for 1 month was again not able to pay it for the subsequent months and hence the correlation.

Again for the bill amount column, the same has happened. If the customer was not able to pay the bill, then the bill amount almost remained the same, or if the customer was able to pay then the bill amount got reduced.

We remove columns when they convey the same information. But here, dropping the columns shall result in the loss of bill and payment history data. So, we don't need to drop any column although there is a correlation.

In [19]:

```
x=data.drop(labels=['default payment next month'],axis=1)
y=data['default payment next month']
```

In [23]:

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.33, random_state=42)
```

In [36]:

```
from sklearn.preprocessing import StandardScaler
train_scaler=StandardScaler()
test_scaler=StandardScaler()
```

In [37]:

```
scaled_train_data=train_scaler.fit_transform(x_train)
scaled_test_data=test_scaler.fit_transform(x_test)
```

In [38]:

```
scaled_train_df=pd.DataFrame(data=scaled_train_data, columns=x_train.columns, index=x_train
```

In [39]:

```
scaled_test_df=pd.DataFrame(data=scaled_test_data, columns=x_test.columns, index=x_test.ind
```

In [40]:

```
scaled_train_df.head()
```

Out[40]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_
16831	0.210169	-0.365093	-1.238563	1.448725	-1.054777	1.464785	0.015441	-0.7248
4222	-1.243527	-1.061279	-1.238563	-1.073197	0.861786	0.271955	1.794063	0.11002
8736	-0.723106	-0.597155	0.807387	0.187764	0.861786	0.380394	0.015441	0.11002
27880	1.484011	-0.287739	0.807387	1.448725	-1.054777	-1.029313	0.015441	0.11002
29290	1.646570	-0.906571	-1.238563	1.448725	0.861786	-1.029313	1.794063	0.11002

5 rows × 24 columns

In [35]:

```
from sklearn.naive_bayes import GaussianNB
gnb=GaussianNB()
```

In [41]:

```
pred_y=gnb.fit(scaled_train_df,y_train).predict(scaled_test_df)
```

In [42]:

```
from sklearn.metrics import accuracy_score
```

In [43]:

```
ac=accuracy_score(y_test, pred_y)
ac
```

Out[43]:

```
0.6601010101010101
```

In [45]:

```
from sklearn.model_selection import GridSearchCV
```

In [46]:

```
param_grid = {"var_smoothing": [1e-9,0.1, 0.001, 0.5,0.05,0.01,1e-8,1e-7,1e-6,1e-10,1e-11]}
#Creating an object of the Grid Search class
grid = GridSearchCV(estimator=gnb, param_grid=param_grid, cv=5,  verbose=3)
```

In [47]:

```


#finding the best parameters
grid.fit(scaled_train_data, y_train)
```

```
Fitting 5 folds for each of 11 candidates, totalling 55 fits
[CV] var_smoothing=1e-09 .............................................
[CV] ................. var_smoothing=1e-09, score=0.579, total=   0.0s
[CV] var_smoothing=1e-09 .............................................
[CV] ................. var_smoothing=1e-09, score=0.662, total=   0.0s
[CV] var_smoothing=1e-09 .............................................
[CV] ................. var_smoothing=1e-09, score=0.714, total=   0.0s
[CV] var_smoothing=1e-09 .............................................
[CV] ................. var_smoothing=1e-09, score=0.648, total=   0.0s
[CV] var_smoothing=1e-09 .............................................
[CV] ................. var_smoothing=1e-09, score=0.689, total=   0.0s
[CV] var_smoothing=0.1 ...............................................
[CV] ................... var_smoothing=0.1, score=0.667, total=   0.0s
[CV] var_smoothing=0.1 ...............................................
[CV] ................... var_smoothing=0.1, score=0.740, total=   0.0s
[CV] var_smoothing=0.1 ...............................................
[CV] ................... var_smoothing=0.1, score=0.768, total=   0.0s
[CV] var_smoothing=0.1 ...............................................
[CV] ................... var_smoothing=0.1, score=0.739, total=   0.0s
```

In [48]:

```
grid.best_estimator_
```

Out[48]:

```
GaussianNB(priors=None, var_smoothing=0.5)
```

In [49]:

```
gnb_new=GaussianNB(var_smoothing=0.5)
pred_y_new=gnb_new.fit(scaled_train_df,y_train).predict(scaled_test_df)
```

In [51]:

```
ac_new=accuracy_score(y_test,pred_y_new)
ac_new
```

Out[51]:

```
0.7792929292929293
```

In [68]:

```
param_grid_xgboost = {

                "n_estimators": [50,100, 130],
                               "max_depth": range(3, 11, 1),
    "random_state":[0,50,100]


            }

# Creating an object of the Grid Search class
grid= GridSearchCV(XGBClassifier(objective='binary:logistic'),param_grid_xgboost, verbose=3
```

In [69]:

```
grid.fit(scaled_train_df,y_train)
```

```
Fitting 5 folds for each of 192 candidates, totalling 960 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed:   12.5s
[Parallel(n_jobs=-1)]: Done 120 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 280 tasks      | elapsed:  2.6min
[Parallel(n_jobs=-1)]: Done 504 tasks      | elapsed:  6.3min
[Parallel(n_jobs=-1)]: Done 792 tasks      | elapsed: 12.1min
[Parallel(n_jobs=-1)]: Done 960 out of 960 | elapsed: 17.4min finished
```

Out[69]:

```
GridSearchCV(cv=5, error_score=nan,
             estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                     colsample_bylevel=1, colsample_bynode=
1,
                                     colsample_bytree=1, gamma=0,
                                     learning_rate=0.1, max_delta_step=0,
                                     max_depth=3, min_child_weight=1,
                                     missing=None, n_estimators=100, n_jobs=
1,
                                     nthread=None, objective='binary:logisti
c',
                                     random_state=0, reg_alpha=0, reg_lambda
=1,
                                     scale_pos_weight=1, seed=None, silent=N
one,
                                     subsample=1, verbosity=1),
             iid='deprecated', n_jobs=-1,
             param_grid={'max_depth': range(3, 11),
                         'n_estimators': [50, 100, 130, 200],
                         'random_state': [0, 50, 100, 250, 355, 500]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=3)
```

In [70]:

```
grid.best_estimator_
```

Out[70]:

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=3,
              min_child_weight=1, missing=None, n_estimators=50, n_jobs=1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

In [64]:

```
xgb_new=XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=3,
              min_child_weight=1, missing=None, n_estimators=50, n_jobs=-1,
              nthread=None, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

In [71]:

```
pred_y_xgb_new=xgb_new.fit(scaled_train_df,y_train).predict(scaled_test_df)
```

In [72]:

```
ac_xgb_new=accuracy_score(y_test,pred_y_xgb_new)
```

In [73]:

```
ac_xgb_new
```

Out[73]:

```
0.8203030303030303
```

In [ ]:

```

```