Import Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import StratifiedKFold
kFold = StratifiedKFold(n_splits=5)
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from  sklearn.metrics  import  accuracy_score , precision_score , recall_score,confusion_matrix,class
```

In [2]:
```
df = pd.read_csv("loan_data.csv")
df.head()
```

Out[2]:

	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.las
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   credit.policy      9578 non-null   int64  
 1   purpose            9578 non-null   object 
 2   int.rate           9578 non-null   float64
 3   installment        9578 non-null   float64
 4   log.annual.inc     9578 non-null   float64
 5   dti                9578 non-null   float64
 6   fico               9578 non-null   int64  
 7   days.with.cr.line  9578 non-null   float64
 8   revol.bal          9578 non-null   int64  
 9   revol.util         9578 non-null   float64
 10  inq.last.6mths     9578 non-null   int64  
 11  delinq.2yrs        9578 non-null   int64  
 12  pub.rec            9578 non-null   int64  
 13  not.fully.paid     9578 non-null   int64  
dtypes: float64(6), int64(7), object(1)
memory usage: 1.0+ MB
```

In [4]:
```
df.describe()
```

Out[4]:

	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	re
count	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9.578000e+03	9578.
mean	0.804970	0.122640	319.089413	10.932117	12.606679	710.846314	4560.767197	1.691396e+04	46.
std	0.396245	0.026847	207.071301	0.614813	6.883970	37.970537	2496.930377	3.375619e+04	29.
min	0.000000	0.060000	15.670000	7.547502	0.000000	612.000000	178.958333	0.000000e+00	0.
25%	1.000000	0.103900	163.770000	10.558414	7.212500	682.000000	2820.000000	3.187000e+03	22.
50%	1.000000	0.122100	268.950000	10.928884	12.665000	707.000000	4139.958333	8.596000e+03	46.
75%	1.000000	0.140700	432.762500	11.291293	17.950000	737.000000	5730.000000	1.824950e+04	70.
max	1.000000	0.216400	940.140000	14.528354	29.960000	827.000000	17639.958330	1.207359e+06	119.

In [5]:
```
df.isnull().sum().sum()
```

Out[5]:
```
0
```

In [6]:
```
df.purpose.value_counts()
```

Out[6]:
```
debt_consolidation    3957
all_other             2331
credit_card           1262
home_improvement       629
small_business         619
major_purchase         437
educational            343
Name: purpose, dtype: int64
```

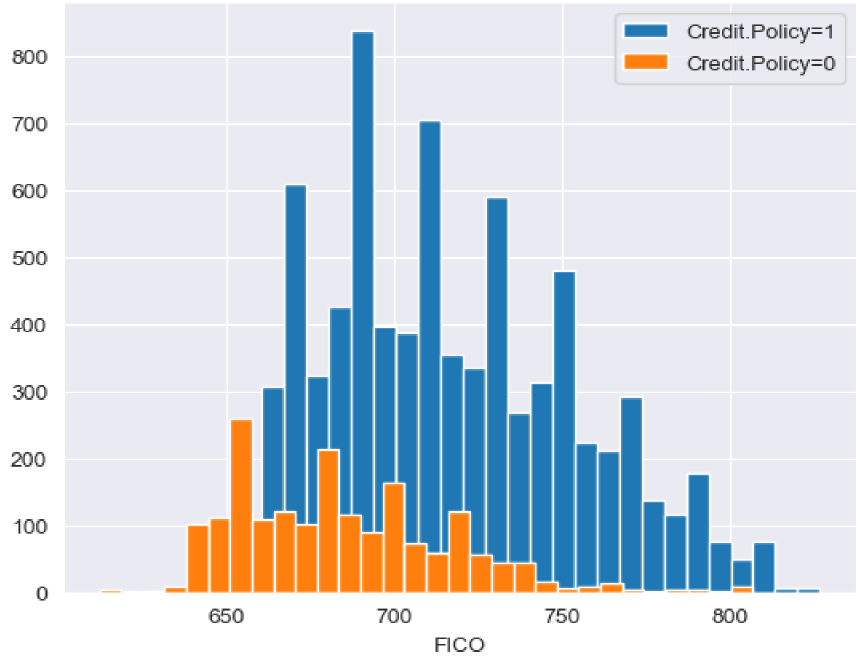
In [7]:
```
df['purpose']=LabelEncoder().fit_transform(df['purpose'])
df.head()
```

Out[7]:

	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths
0	1	2	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0
1	1	1	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0
2	1	2	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1
3	1	2	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1
4	1	1	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0

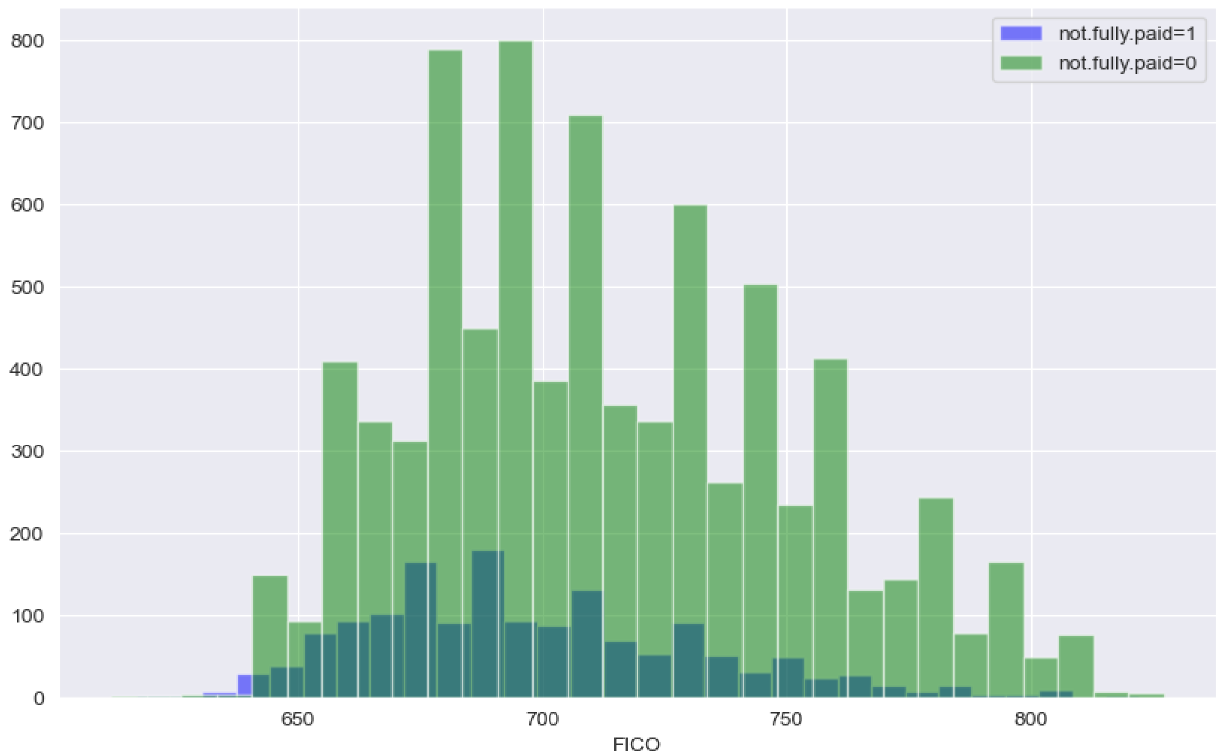
In [8]:
```
sns.set_style('darkgrid')
plt.hist(df['fico'].loc[df['credit.policy']==1], bins=30, label='Credit.Policy=1')
plt.hist(df['fico'].loc[df['credit.policy']==0], bins=30, label='Credit.Policy=0')
plt.legend()
plt.xlabel('FICO')
```

Out[8]: Text(0.5, 0, 'FICO')



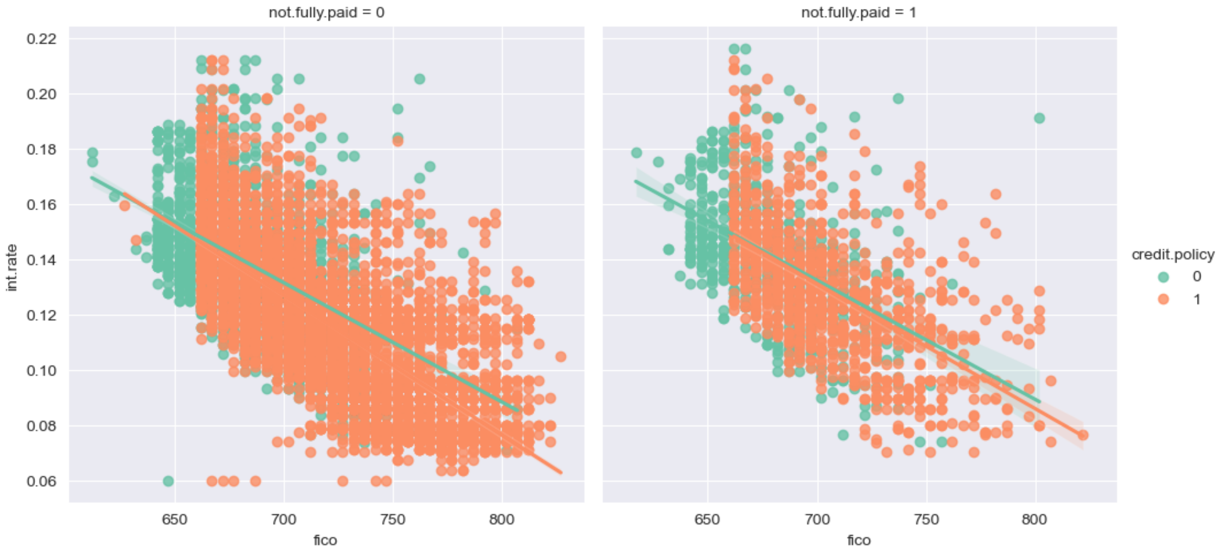
In [9]:
```
plt.figure(figsize=(10,6))
df[df['not.fully.paid']==1]['fico'].hist(bins=30, alpha=0.5, color='blue', label='not.fully.paid=1')
df[df['not.fully.paid']==0]['fico'].hist(bins=30, alpha=0.5, color='green', label='not.fully.paid=0')
plt.legend()
plt.xlabel('FICO')
```

Out[9]: Text(0.5, 0, 'FICO')

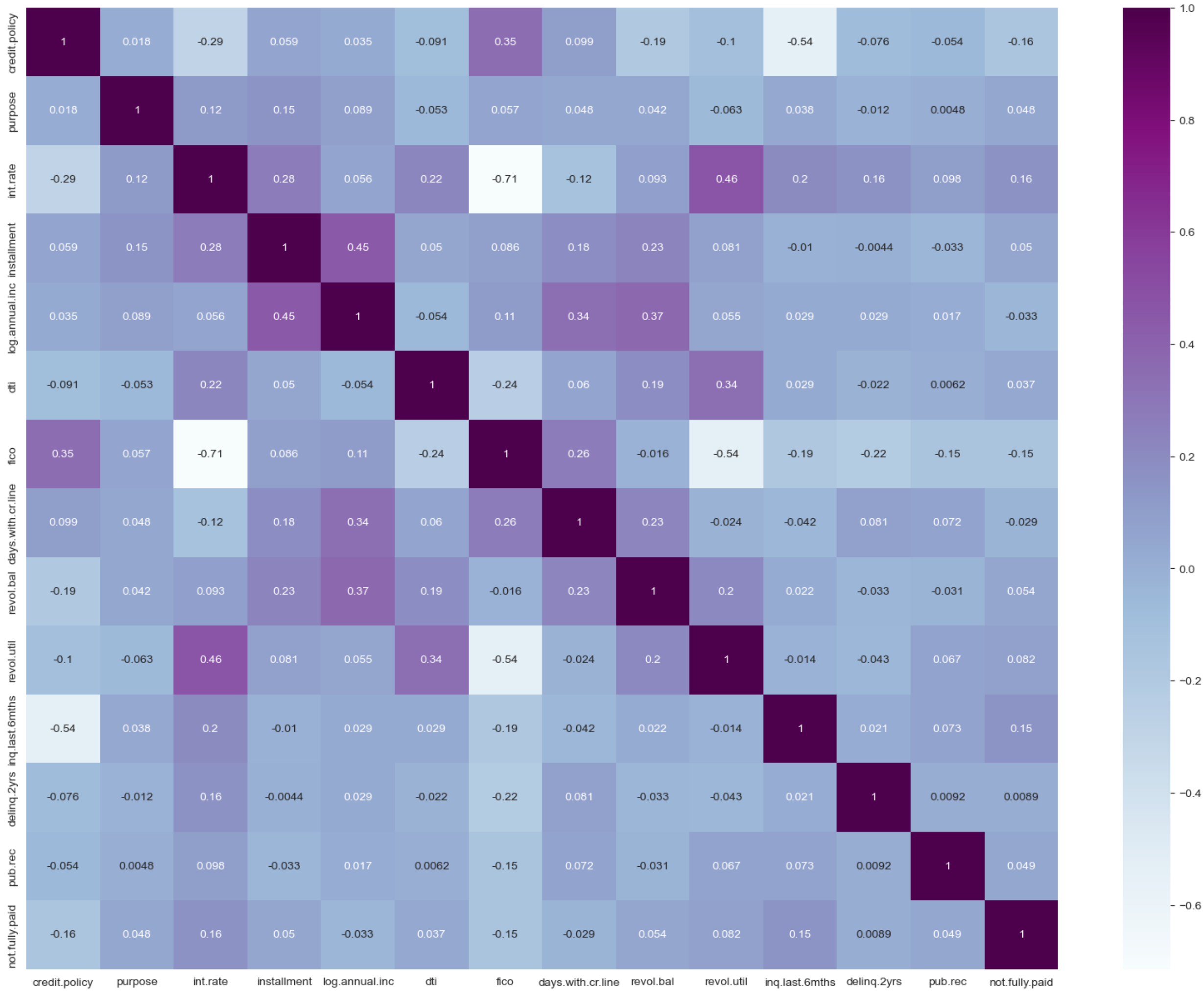


In [10]:
```
sns.lmplot(data=df, x='fico', y='int.rate', hue='credit.policy', col='not.fully.paid', palette='Set2')
```

Out[10]: <seaborn.axisgrid.FacetGrid at 0x222dfb58a10>



In [11]:
```
plt.figure(figsize = (20, 15))
sns.heatmap(df.corr(), cmap='BuPu', annot=True)
plt.show()
```



In [12]:
```
X = df.drop('not.fully.paid',axis=1)
y = df['not.fully.paid']
```

In [13]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,random_state=101)
```

Modelling

In [14]:
```
from sklearn.tree import DecisionTreeClassifier

dt_clf = DecisionTreeClassifier()
param_grid = {'max_depth': [2,3, 4,5,6,7,8,9,10,11,13,15,20]}

grid_search = GridSearchCV(dt_clf, param_grid, scoring = 'recall_weighted',cv=kFold, return_train_sco
grid_search.fit(X_train,y_train)
```

Out[14]:
```
▸ GridSearchCV
▸ estimator: DecisionTreeClassifier
  ▸ DecisionTreeClassifier
```

In [15]:
```
grid_search.best_params_
```

Out[15]:
```
{'max_depth': 2}
```

In [16]:
```
dt_clf = DecisionTreeClassifier(max_depth=2)
dt_clf.fit(X_train, y_train)
y_pred_train = dt_clf.predict(X_train)
y_pred_test = dt_clf.predict(X_test)

train_accuracy = accuracy_score(y_train, y_pred_train)
test_accuracy = accuracy_score(y_test, y_pred_test)
```

In [17]:
```
print("Confusion Matrix \n",confusion_matrix(y_test,y_pred_test))
print("\n")
print("<-------------------Classification Report--------------------->\n")
print(classification_report(y_test,y_pred_test))
print("\n")
print("<---------------Accuracy Scores------------------->\n")
print('Train Accuracy score: ',train_accuracy)
print('Test Accuracy score:',test_accuracy)
```

```
Confusion Matrix
 [[2431    0]
 [ 443    0]]


<-------------------Classification Report--------------------->

              precision    recall  f1-score   support

           0       0.85      1.00      0.92      2431
           1       0.00      0.00      0.00       443

    accuracy                           0.85      2874
   macro avg       0.42      0.50      0.46      2874
weighted avg       0.72      0.85      0.78      2874



<---------------Accuracy Scores------------------->

Train Accuracy score:  0.8374105011933174
Test Accuracy score: 0.8458594293667363
```