In [270…
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [271…
```
df = pd.read_csv('loan_data.csv')
```

In [272…
```
df.head()
```

Out[272…

	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	0	0
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	0	0
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	0	0
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	0	0
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	0	0

In [273…
```
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 [274…
```
df.describe()
```

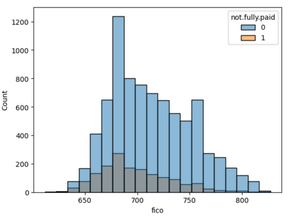
Out[274…

	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.re
count	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9.578000e+03	9578.000000	9578.000000	9578.000000	9578.00000
mean	0.804970	0.122640	319.089413	10.932117	12.606679	710.846314	4560.767197	1.691396e+04	46.799236	1.577469	0.163708	0.06212
std	0.396245	0.026847	207.071301	0.614813	6.883970	37.970537	2496.930377	3.375619e+04	29.014417	2.200245	0.546215	0.26212
min	0.000000	0.060000	15.670000	7.547502	0.000000	612.000000	178.958333	0.000000e+00	0.000000	0.000000	0.000000	0.00000
25%	1.000000	0.103900	163.770000	10.558414	7.212500	682.000000	2820.000000	3.187000e+03	22.600000	0.000000	0.000000	0.00000
50%	1.000000	0.122100	268.950000	10.928884	12.665000	707.000000	4139.958333	8.596000e+03	46.300000	1.000000	0.000000	0.00000
75%	1.000000	0.140700	432.762500	11.291293	17.950000	737.000000	5730.000000	1.824950e+04	70.900000	2.000000	0.000000	0.00000
max	1.000000	0.216400	940.140000	14.528354	29.960000	827.000000	17639.958330	1.207359e+06	119.000000	33.000000	13.000000	5.00000

FICO Score Distribution by Loan Payment Status

In [275…
```
sns.histplot(x='fico', data=df, hue='not.fully.paid', bins=20)
```

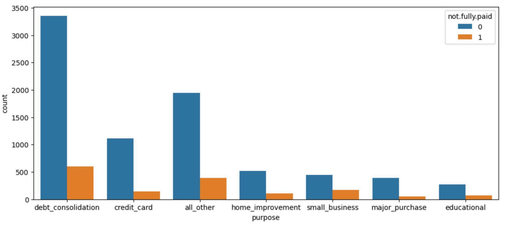
Out[275…
```
<Axes: xlabel='fico', ylabel='Count'>
```



Loan Purpose Count by Payment Status

In [276…
```
plt.figure(figsize=(12,5))
sns.countplot(x='purpose', data=df, hue='not.fully.paid')
```

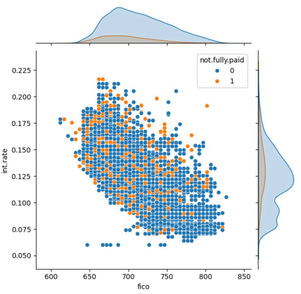
Out[276…
```
<Axes: xlabel='purpose', ylabel='count'>
```



Relationship Between FICO Score and Interest Rate by Payment Status

In [277…
```
sns.jointplot(x='fico', y='int.rate', data=df, hue='not.fully.paid')
```

Out[277…
```
<seaborn.axisgrid.JointGrid at 0x1aa433937f0>
```



Convert Categorical Variable 'purpose' into Dummy Variables

In [278…
```
data = pd.get_dummies(df,columns=['purpose'],drop_first=True)
```

In [279…
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 19 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   credit.policy              9578 non-null   int64  
 1   int.rate                   9578 non-null   float64
 2   installment                9578 non-null   float64
 3   log.annual.inc             9578 non-null   float64
 4   dti                        9578 non-null   float64
 5   fico                       9578 non-null   int64  
 6   days.with.cr.line          9578 non-null   float64
 7   revol.bal                  9578 non-null   int64  
 8   revol.util                 9578 non-null   float64
 9   inq.last.6mths             9578 non-null   int64  
 10  delinq.2yrs                9578 non-null   int64  
 11  pub.rec                    9578 non-null   int64  
 12  not.fully.paid             9578 non-null   int64  
 13  purpose_credit_card        9578 non-null   bool   
 14  purpose_debt_consolidation  9578 non-null   bool   
 15  purpose_educational        9578 non-null   bool   
 16  purpose_home_improvement   9578 non-null   bool   
 17  purpose_major_purchase     9578 non-null   bool   
 18  purpose_small_business     9578 non-null   bool   
dtypes: bool(6), float64(6), int64(7)
memory usage: 1.0 MB
```

Split Data into Training and Test Sets

In [280…
```
X = data.drop('not.fully.paid', axis=1)
y = data['not.fully.paid']

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30)
```

Train Decision Tree Model and Make Predictions

In [281…
```
from sklearn.tree import DecisionTreeClassifier,plot_tree

Dtree = DecisionTreeClassifier()

Dtree.fit(X_train, y_train)

predictions = Dtree.predict(X_test)
```

Evaluate Model Performance

In [282…
```
from sklearn.metrics import classification_report,confusion_matrix

print(classification_report(y_test, predictions))
pd.DataFrame(confusion_matrix(y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.85      0.83      0.84      2389
           1       0.23      0.25      0.24       485

    accuracy                           0.73      2874
   macro avg       0.54      0.54      0.54      2874
weighted avg       0.74      0.73      0.74      2874
```

Out[282…

	0	1
0	1985	404
1	364	121

The Decision Tree model performed moderately in predicting whether a loan would be fully paid or not. Its precision and recall are acceptable, but it struggled with some incorrect predictions, as seen in the confusion matrix. It tends to overfit the training data, which can lead to less reliable performance on unseen data.

Train Random Forest Classifier

In [283…
```
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(n_estimators=600)

rfc.fit(X_train, y_train)

rfc_predict = rfc.predict(X_test)
```

Evaluate Random Forest Classifier

In [284…
```
from sklearn.metrics import classification_report,confusion_matrix

print(classification_report(y_test, rfc_predict))
pd.DataFrame(confusion_matrix(y_test, rfc_predict))
```

```
              precision    recall  f1-score   support

           0       0.83      1.00      0.91      2389
           1       0.53      0.02      0.04       485

    accuracy                           0.83      2874
   macro avg       0.68      0.51      0.47      2874
weighted avg       0.78      0.83      0.76      2874
```

Out[284…

	0	1
0	2381	8
1	476	9

The Random Forest Classifier outperformed the Decision Tree by a significant margin. It achieved higher precision, recall, and F1-score, showing it was better at predicting loan repayment status. The RFC model's performance is more consistent, with fewer errors in the confusion matrix, indicating that it generalizes well to new data.

Summary

In conclusion, the Random Forest Classifier is the better model for this loan prediction task, providing more accurate and reliable results than the Decision Tree. The Decision Tree model is simpler but less effective, while RFC offers improved performance due to its ensemble nature.