

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

import warnings
warnings.filterwarnings('ignore')
```

### Reading data

```
data = pd.read_csv("loan_data.csv")
data.head()
```

	credit.policy		purpose	int.rate	installment
log.annual.inc \					
0	1	debt_consolidation	0.1189	829.10	
11.350407					
1	1	credit_card	0.1071	228.22	
11.082143					
2	1	debt_consolidation	0.1357	366.86	
10.373491					
3	1	debt_consolidation	0.1008	162.34	
11.350407					
4	1	credit_card	0.1426	102.92	
11.299732					

	dti	fico	days.with.cr.line	revol.bal	revol.util
inq.last.6mths \					
0	19.48	737	5639.958333	28854	52.1
0					
1	14.29	707	2760.000000	33623	76.7
0					
2	11.63	682	4710.000000	3511	25.6
1					
3	8.10	712	2699.958333	33667	73.2
1					
4	14.97	667	4066.000000	4740	39.5
0					

	delinq.2yrs	pub.rec	not.fully.paid
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	1	0	0

### Checking for null values

```
data.isnull().sum()
```

credit.policy	0
purpose	0
int.rate	0

```
installment      0
log.annual.inc   0
dti              0
fico             0
days.with.cr.line 0
revol.bal        0
revol.util       0
inq.last.6mths   0
delinq.2yrs      0
pub.rec          0
not.fully.paid   0
dtype: int64
```

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

```
credit.policy      0
purpose            0
int.rate           0
installment        0
log.annual.inc     0
dti                0
fico              0
days.with.cr.line 0
revol.bal          0
revol.util         0
inq.last.6mths     0
delinq.2yrs        0
pub.rec            0
not.fully.paid     0
dtype: int64
```

```
data.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
```

```
data["purpose"].value_counts()
```

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

### Transform categorical values into numerical values

```
data = pd.get_dummies(data, columns = ["purpose"])
data.head()
```

	credit.policy	int.rate	installment	log.annual.inc	dti	
fico \						
0	1	0.1189	829.10	11.350407	19.48	737
1	1	0.1071	228.22	11.082143	14.29	707
2	1	0.1357	366.86	10.373491	11.63	682
3	1	0.1008	162.34	11.350407	8.10	712
4	1	0.1426	102.92	11.299732	14.97	667

	days.with.cr.line	revol.bal	revol.util	inq.last.6mths
delinq.2yrs \				
0	5639.958333	28854	52.1	0
0				
1	2760.000000	33623	76.7	0
0				
2	4710.000000	3511	25.6	1
0				
3	2699.958333	33667	73.2	1
0				
4	4066.000000	4740	39.5	0
1				

	pub.rec	not.fully.paid	purpose_all_other	purpose_credit_card	
0	0	0	0	0	
1	0	0	0	1	
2	0	0	0	0	
3	0	0	0	0	

4            0                            0                            0                            1

```
    purpose_debt_consolidation  purpose_educational
purpose_home_improvement \
0                               1                     0
0                               0                     0
1                               0                     0
0                               1                     0
2                               1                     0
0                               1                     0
3                               0                     0
0                               0                     0
4                               0                     0
0
```

```
    purpose_major_purchase  purpose_small_business
0                           0                      0
1                           0                      0
2                           0                      0
3                           0                      0
4                           0                      0
```

data.info()

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 9578 entries, 0 to 9577

Data columns (total 20 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_all_other	9578 non-null	uint8
14	purpose_credit_card	9578 non-null	uint8
15	purpose_debt_consolidation	9578 non-null	uint8
16	purpose_educational	9578 non-null	uint8
17	purpose_home_improvement	9578 non-null	uint8
18	purpose_major_purchase	9578 non-null	uint8
19	purpose_small_business	9578 non-null	uint8

dtypes: float64(6), int64(7), uint8(7)  
memory usage: 1.0 MB

## EDA

data.describe().T

	count	mean	std
min \			
credit.policy	9578.0	0.804970	0.396245
0.000000			
int.rate	9578.0	0.122640	0.026847
0.060000			
installment	9578.0	319.089413	207.071301
15.670000			
log.annual.inc	9578.0	10.932117	0.614813
7.547502			
dti	9578.0	12.606679	6.883970
0.000000			
fico	9578.0	710.846314	37.970537
612.000000			
days.with.cr.line	9578.0	4560.767197	2496.930377
178.958333			
revol.bal	9578.0	16913.963876	33756.189557
0.000000			
revol.util	9578.0	46.799236	29.014417
0.000000			
inq.last.6mths	9578.0	1.577469	2.200245
0.000000			
delinq.2yrs	9578.0	0.163708	0.546215
0.000000			
pub.rec	9578.0	0.062122	0.262126
0.000000			
not.fully.paid	9578.0	0.160054	0.366676
0.000000			
purpose_all_other	9578.0	0.243370	0.429139
0.000000			
purpose_credit_card	9578.0	0.131760	0.338248
0.000000			
purpose_debt_consolidation	9578.0	0.413134	0.492422
0.000000			
purpose_educational	9578.0	0.035811	0.185829
0.000000			
purpose_home_improvement	9578.0	0.065671	0.247720
0.000000			
purpose_major_purchase	9578.0	0.045625	0.208682
0.000000			
purpose_small_business	9578.0	0.064627	0.245880
0.000000			

25%

50%

75% \

credit.policy	1.000000	1.000000	1.000000
int.rate	0.103900	0.122100	0.140700
installment	163.770000	268.950000	432.762500
log.annual.inc	10.558414	10.928884	11.291293
dti	7.212500	12.665000	17.950000
fico	682.000000	707.000000	737.000000
days.with.cr.line	2820.000000	4139.958333	5730.000000
revol.bal	3187.000000	8596.000000	18249.500000
revol.util	22.600000	46.300000	70.900000
inq.last.6mths	0.000000	1.000000	2.000000
delinq.2yrs	0.000000	0.000000	0.000000
pub.rec	0.000000	0.000000	0.000000
not.fully.paid	0.000000	0.000000	0.000000
purpose_all_other	0.000000	0.000000	0.000000
purpose_credit_card	0.000000	0.000000	0.000000
purpose_debt_consolidation	0.000000	0.000000	1.000000
purpose_educational	0.000000	0.000000	0.000000
purpose_home_improvement	0.000000	0.000000	0.000000
purpose_major_purchase	0.000000	0.000000	0.000000
purpose_small_business	0.000000	0.000000	0.000000

	max
credit.policy	1.000000e+00
int.rate	2.164000e-01
installment	9.401400e+02
log.annual.inc	1.452835e+01
dti	2.996000e+01
fico	8.270000e+02
days.with.cr.line	1.763996e+04
revol.bal	1.207359e+06
revol.util	1.190000e+02
inq.last.6mths	3.300000e+01
delinq.2yrs	1.300000e+01
pub.rec	5.000000e+00
not.fully.paid	1.000000e+00
purpose_all_other	1.000000e+00
purpose_credit_card	1.000000e+00
purpose_debt_consolidation	1.000000e+00
purpose_educational	1.000000e+00
purpose_home_improvement	1.000000e+00
purpose_major_purchase	1.000000e+00
purpose_small_business	1.000000e+00

data.corr()

	credit.policy	int.rate	installment \
credit.policy	1.000000	-0.294089	0.058770
int.rate	-0.294089	1.000000	0.276140
installment	0.058770	0.276140	1.000000
log.annual.inc	0.034906	0.056383	0.448102

dti	-0.090901	0.220006	0.050202
fico	0.348319	-0.714821	0.086039
days.with.cr.line	0.099026	-0.124022	0.183297
revol.bal	-0.187518	0.092527	0.233625
revol.util	-0.104095	0.464837	0.081356
inq.last.6mths	-0.535511	0.202780	-0.010419
delinq.2yrs	-0.076318	0.156079	-0.004368
pub.rec	-0.054243	0.098162	-0.032760
not.fully.paid	-0.158119	0.159552	0.049955
purpose_all_other	-0.025412	-0.124000	-0.203103
purpose_credit_card	0.003216	-0.042109	0.000774
purpose_debt_consolidation	0.020193	0.123607	0.161658
purpose_educational	-0.031346	-0.019618	-0.094510
purpose_home_improvement	0.006036	-0.050697	0.023024
purpose_major_purchase	0.024281	-0.068978	-0.079836
purpose_small_business	-0.003511	0.151247	0.145654

	log.annual.inc	dti	fico \
credit.policy	0.034906	-0.090901	0.348319
int.rate	0.056383	0.220006	-0.714821
installment	0.448102	0.050202	0.086039
log.annual.inc	1.000000	-0.054065	0.114576
dti	-0.054065	1.000000	-0.241191
fico	0.114576	-0.241191	1.000000
days.with.cr.line	0.336896	0.060101	0.263880
revol.bal	0.372140	0.188748	-0.015553
revol.util	0.054881	0.337109	-0.541289
inq.last.6mths	0.029171	0.029189	-0.185293
delinq.2yrs	0.029203	-0.021792	-0.216340
pub.rec	0.016506	0.006209	-0.147592
not.fully.paid	-0.033439	0.037362	-0.149666
purpose_all_other	-0.080077	-0.125825	0.067184
purpose_credit_card	0.072942	0.084476	-0.012512
purpose_debt_consolidation	-0.026214	0.179149	-0.154132
purpose_educational	-0.119799	-0.035325	-0.013012
purpose_home_improvement	0.116375	-0.092788	0.097474
purpose_major_purchase	-0.031020	-0.077719	0.067129
purpose_small_business	0.091540	-0.069245	0.063292

	days.with.cr.line	revol.bal	
revol.util \			
credit.policy	0.099026	-0.187518	-0.104095
int.rate	-0.124022	0.092527	0.464837
installment	0.183297	0.233625	0.081356
log.annual.inc	0.336896	0.372140	0.054881
dti	0.060101	0.188748	0.337109

fico	0.263880	-0.015553	-0.541289
days.with.cr.line	1.000000	0.229344	-0.024239
revol.bal	0.229344	1.000000	0.203779
revol.util	-0.024239	0.203779	1.000000
inq.last.6mths	-0.041736	0.022394	-0.013880
delinq.2yrs	0.081374	-0.033243	-0.042740
pub.rec	0.071826	-0.031010	0.066717
not.fully.paid	-0.029237	0.053699	0.082088
purpose_all_other	-0.056574	-0.067728	-0.138535
purpose_credit_card	0.046220	0.072316	0.091321
purpose_debt_consolidation	-0.009318	0.005785	0.211869
purpose_educational	-0.042621	-0.034743	-0.053128
purpose_home_improvement	0.068087	0.003258	-0.114449
purpose_major_purchase	-0.020561	-0.062395	-0.108079
purpose_small_business	0.034883	0.083069	-0.060962

	inq.last.6mths	delinq.2yrs	pub.rec	\
credit.policy	-0.535511	-0.076318	-0.054243	
int.rate	0.202780	0.156079	0.098162	
installment	-0.010419	-0.004368	-0.032760	
log.annual.inc	0.029171	0.029203	0.016506	
dti	0.029189	-0.021792	0.006209	
fico	-0.185293	-0.216340	-0.147592	
days.with.cr.line	-0.041736	0.081374	0.071826	
revol.bal	0.022394	-0.033243	-0.031010	
revol.util	-0.013880	-0.042740	0.066717	
inq.last.6mths	1.000000	0.021245	0.072673	
delinq.2yrs	0.021245	1.000000	0.009184	
pub.rec	0.072673	0.009184	1.000000	
not.fully.paid	0.149452	0.008881	0.048634	
purpose_all_other	0.017795	0.016658	-0.030451	
purpose_credit_card	-0.033640	-0.008817	0.014842	



purpose_debt_consolidation	-0.044240	-0.000697	0.026845
purpose_educational	0.024243	-0.002214	-0.013521
purpose_home_improvement	0.043827	-0.013098	0.004704
purpose_major_purchase	-0.001445	0.004085	-0.011734
purpose_small_business	0.042567	-0.004148	-0.005595

	not.fully.paid	purpose_all_other	\
credit.policy	-0.158119	-0.025412	
int.rate	0.159552	-0.124000	
installment	0.049955	-0.203103	
log.annual.inc	-0.033439	-0.080077	
dti	0.037362	-0.125825	
fico	-0.149666	0.067184	
days.with.cr.line	-0.029237	-0.056574	
revol.bal	0.053699	-0.067728	
revol.util	0.082088	-0.138535	
inq.last.6mths	0.149452	0.017795	
delinq.2yrs	0.008881	0.016658	
pub.rec	0.048634	-0.030451	
not.fully.paid	1.000000	0.009233	
purpose_all_other	0.009233	1.000000	
purpose_credit_card	-0.047136	-0.220935	
purpose_debt_consolidation	-0.017543	-0.475848	
purpose_educational	0.021609	-0.109300	
purpose_home_improvement	0.007272	-0.150359	
purpose_major_purchase	-0.028580	-0.124004	
purpose_small_business	0.084460	-0.149076	

	purpose_credit_card	
purpose_debt_consolidation	\	
credit.policy	0.003216	
0.020193		
int.rate	-0.042109	
0.123607		
installment	0.000774	
0.161658		
log.annual.inc	0.072942	-
0.026214		
dti	0.084476	
0.179149		
fico	-0.012512	-
0.154132		
days.with.cr.line	0.046220	-
0.009318		
revol.bal	0.072316	
0.005785		
revol.util	0.091321	
0.211869		
inq.last.6mths	-0.033640	-
0.044240		

delinq.2yrs	-0.008817	-
0.000697		
pub.rec	0.014842	
0.026845		
not.fully.paid	-0.047136	-
0.017543		
purpose_all_other	-0.220935	-
0.475848		
purpose_credit_card	1.000000	-
0.326850		
purpose_debt_consolidation	-0.326850	
1.000000		
purpose_educational	-0.075076	-
0.161698		
purpose_home_improvement	-0.103279	-
0.222441		
purpose_major_purchase	-0.085176	-
0.183451		
purpose_small_business	-0.102397	-
0.220542		

	purpose_educational	
purpose_home_improvement \		
credit.policy	-0.031346	
0.006036		
int.rate	-0.019618	-
0.050697		
installment	-0.094510	
0.023024		
log.annual.inc	-0.119799	
0.116375		
dti	-0.035325	-
0.092788		
fico	-0.013012	
0.097474		
days.with.cr.line	-0.042621	
0.068087		
revol.bal	-0.034743	
0.003258		
revol.util	-0.053128	-
0.114449		
inq.last.6mths	0.024243	
0.043827		
delinq.2yrs	-0.002214	-
0.013098		
pub.rec	-0.013521	
0.004704		
not.fully.paid	0.021609	
0.007272		
purpose_all_other	-0.109300	-

0.150359		
purpose_credit_card	-0.075076	-
0.103279		
purpose_debt_consolidation	-0.161698	-
0.222441		
purpose_educational	1.000000	-
0.051094		
purpose_home_improvement	-0.051094	
1.000000		
purpose_major_purchase	-0.042138	-
0.057967		
purpose_small_business	-0.050658	-
0.069687		

	purpose_major_purchase	
purpose_small_business		
credit.policy	0.024281	-
0.003511		
int.rate	-0.068978	
0.151247		
installment	-0.079836	
0.145654		
log.annual.inc	-0.031020	
0.091540		
dti	-0.077719	-
0.069245		
fico	0.067129	
0.063292		
days.with.cr.line	-0.020561	
0.034883		
revol.bal	-0.062395	
0.083069		
revol.util	-0.108079	-
0.060962		
inq.last.6mths	-0.001445	
0.042567		
delinq.2yrs	0.004085	-
0.004148		
pub.rec	-0.011734	-
0.005595		
not.fully.paid	-0.028580	
0.084460		
purpose_all_other	-0.124004	-
0.149076		
purpose_credit_card	-0.085176	-
0.102397		
purpose_debt_consolidation	-0.183451	-
0.220542		
purpose_educational	-0.042138	-
0.050658		

```

purpose_home_improvement      -0.057967      -
0.069687
purpose_major_purchase         1.000000      -
0.057472
purpose_small_business         -0.057472
1.000000

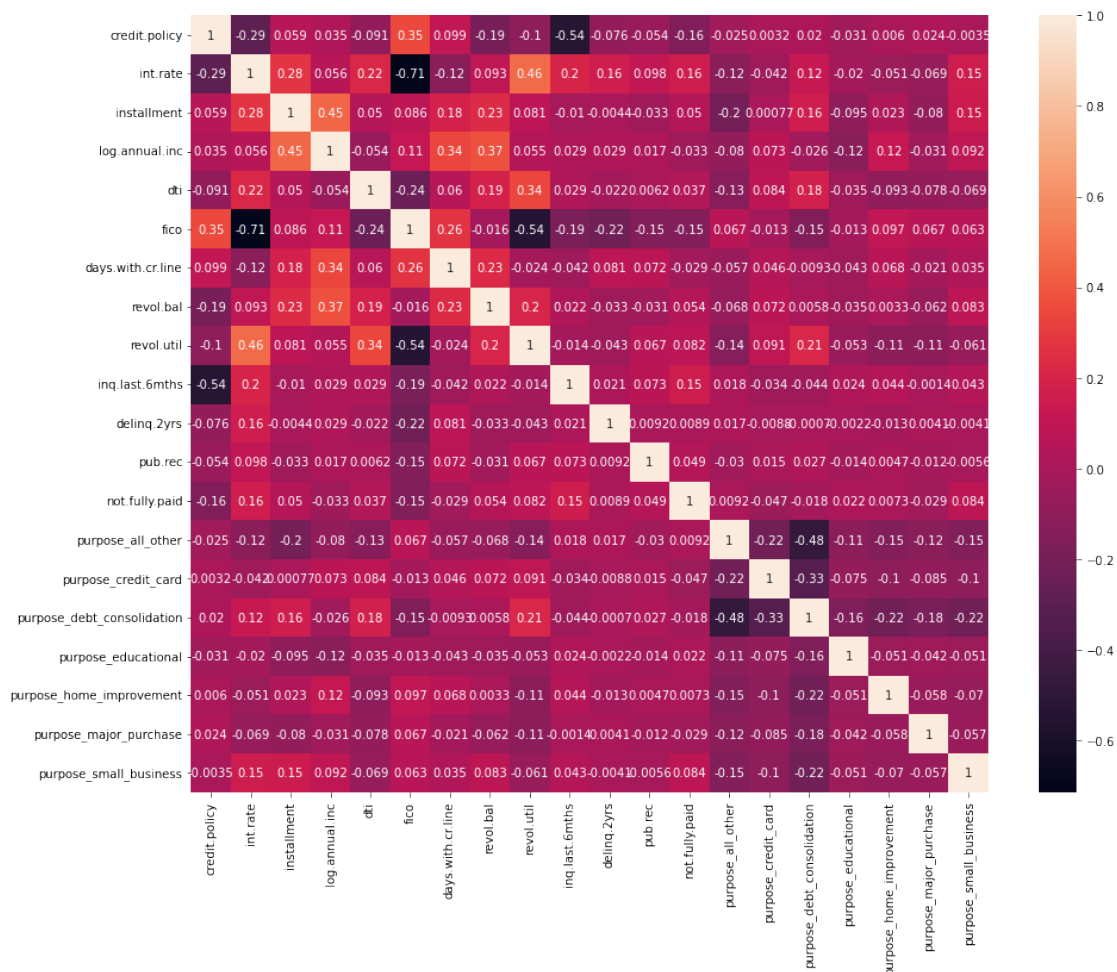
```

### Corelation Heatmap before splitting

```

plt.figure(figsize = (15,12))
sns.heatmap(data = data.corr(), annot = True)
plt.show()

```



### Splitting data

```

X = data.drop("not.fully.paid", axis = 1)
y = data["not.fully.paid"]

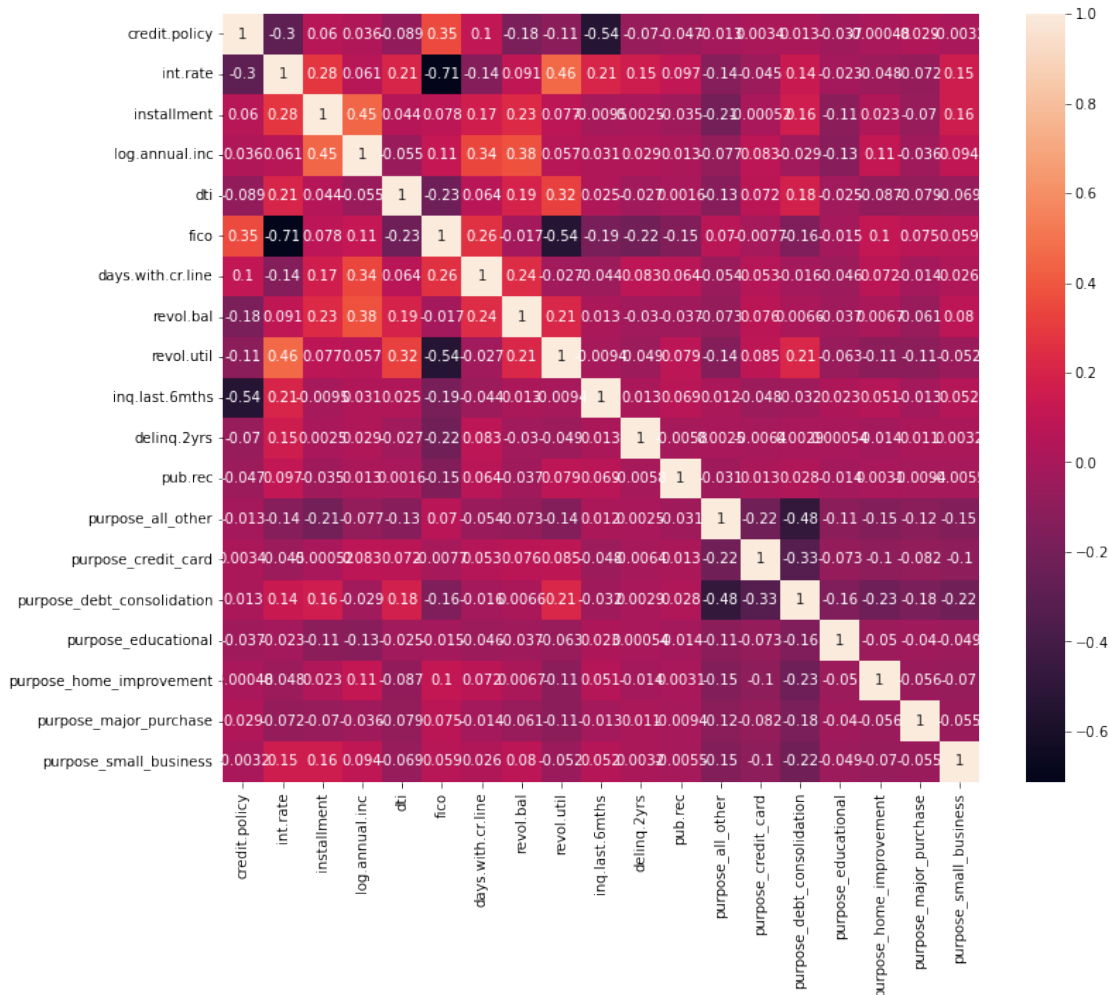
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.3, random_state = 4)

```

### Corelation Heatmap after data split

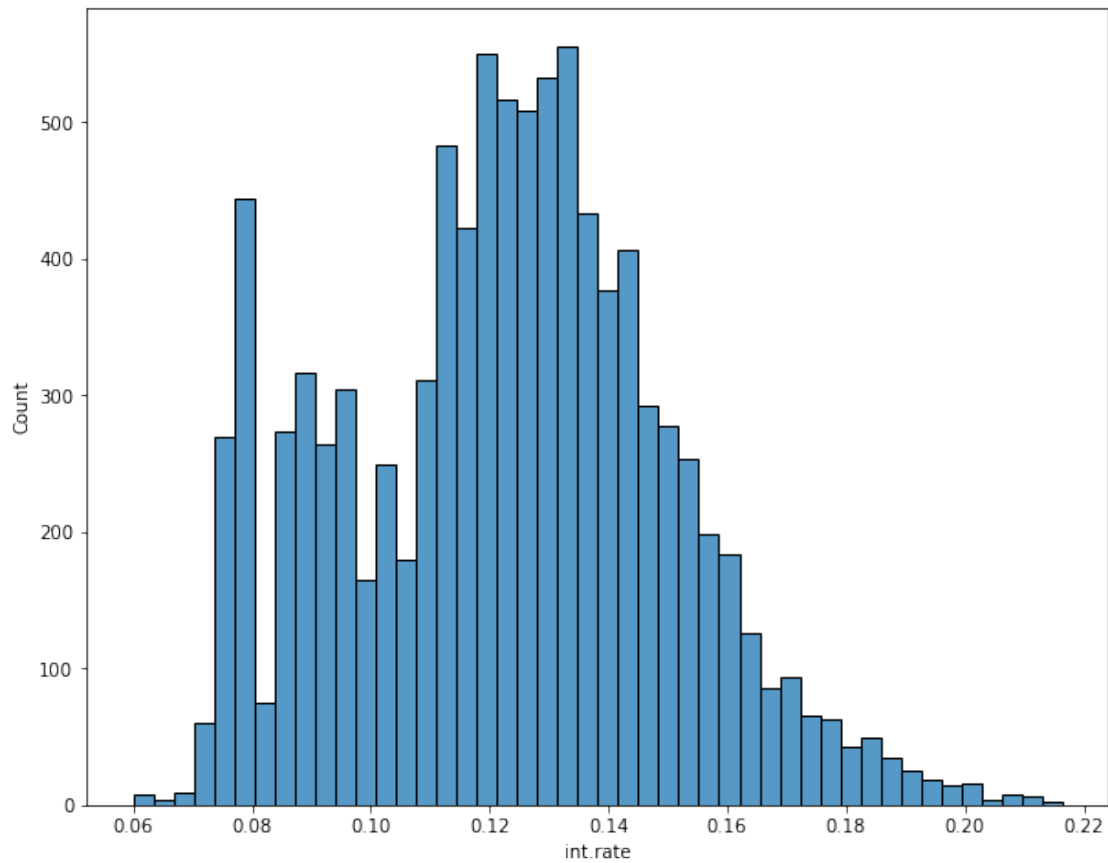
```
plt.figure(figsize = (12,10))
sns.heatmap(data = X_train.corr(), annot = True)
plt.show()
```



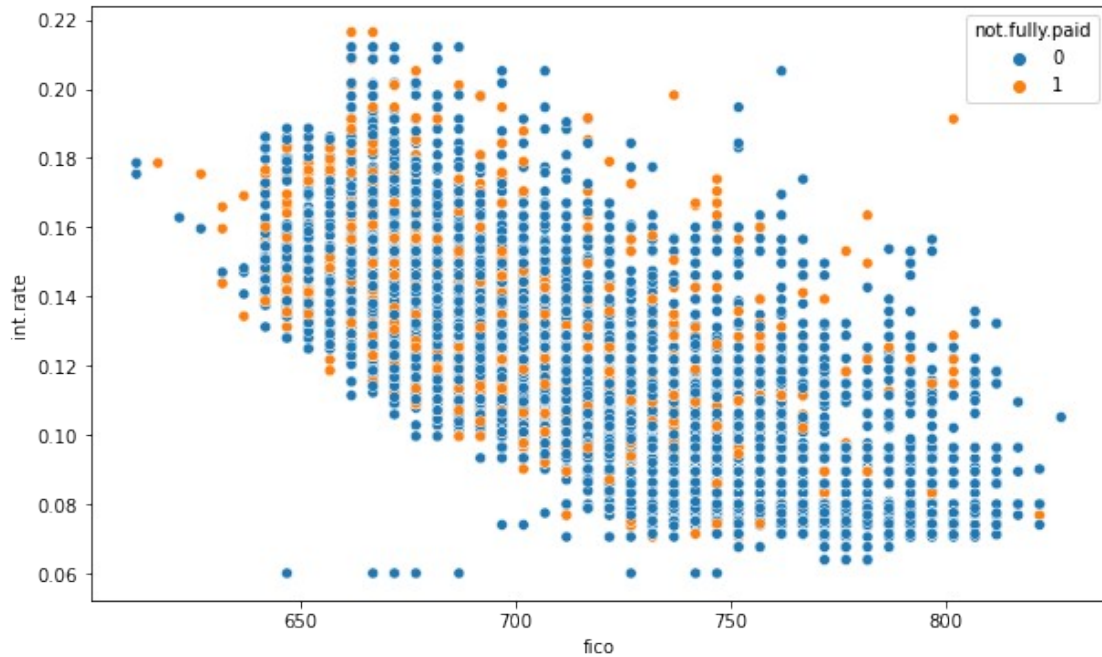
from the correlation heatmaps we can observe that no two features have positive corelation of more than 0.7 , so we will not remove any feature.

### EDA

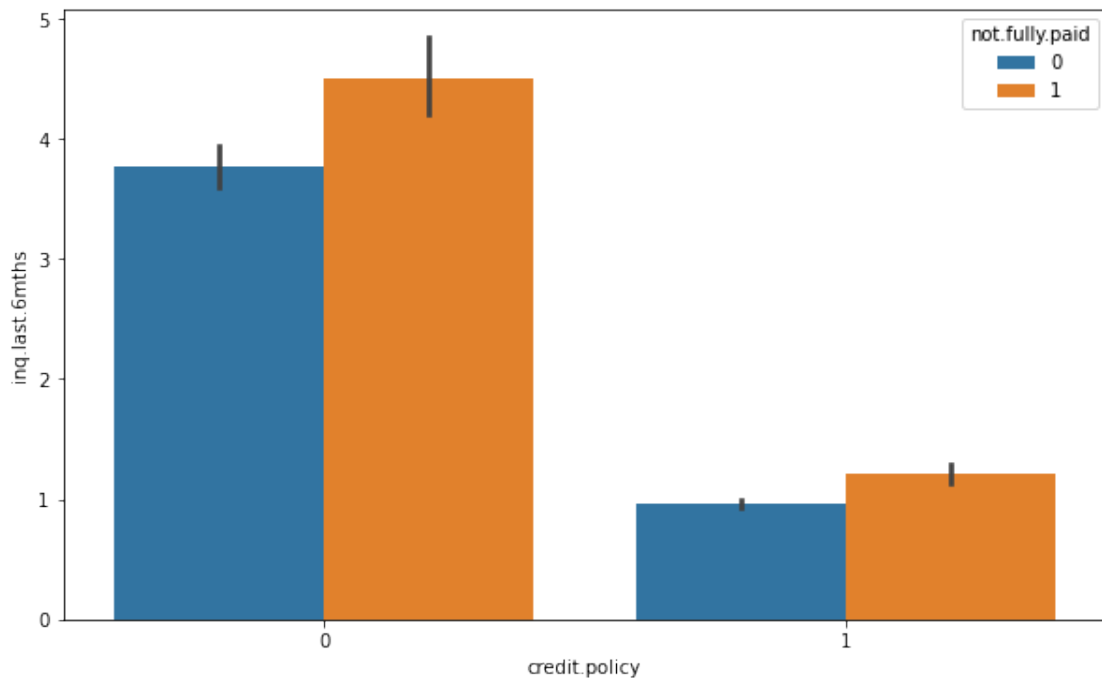
```
plt.figure(figsize = (10,8))
sns.histplot(data = data, x = "int.rate")
plt.show()
```



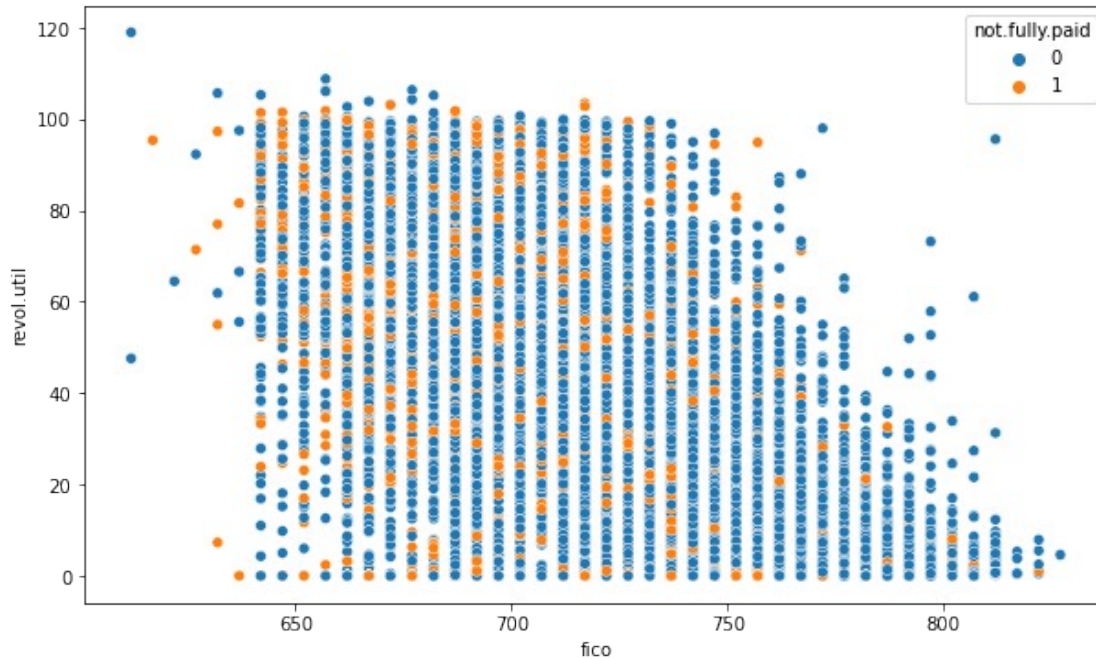
```
plt.figure(figsize = (10,6))
sns.scatterplot(data = data, x = "fico", y = "int.rate", hue =
"not.fully.paid")
plt.show()
```



```
plt.figure(figsize = (10, 6))
sns.barplot(data = data, x = "credit.policy", y = "inq.last.6mths",
hue = "not.fully.paid")
plt.show()
```



```
plt.figure(figsize = (10, 6))
sns.scatterplot(data = data, x = "fico", y = "revol.util", hue =
"not.fully.paid")
plt.show()
```



### Feature Scaling

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

```
print(X_train.shape , X_test.shape)
```

```
(6704, 19) (2874, 19)
```

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, BatchNormalization, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping
```

### Building Model , Defining Model architecture

```
model = Sequential()

model.add(Dense(units = 128,
                 activation = 'relu',
                 input_shape = (X_train.shape[1],)))
model.add(BatchNormalization())
model.add(Dropout(0.2, seed = 123))

model.add(Dense(units = 64,
                 activation = 'tanh'))
model.add(BatchNormalization())
model.add(Dropout(0.2, seed = 123))
```



```

model.add(Dense(units = 32,
                 activation = 'relu'))
model.add(BatchNormalization())
model.add(Dropout(0.2, seed = 123))

model.add(Dense(units = 1,
                 activation = 'sigmoid'))

es = EarlyStopping(monitor = "accuracy", patience = 4)

model.compile(optimizer = Adam(learning_rate = 0.01),
              loss = 'binary_crossentropy',
              metrics = ['accuracy'])

model.summary()

```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 128)	2560
batch_normalization (Batch Normalization)	(None, 128)	512
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 64)	8256
batch_normalization_1 (Batch Normalization)	(None, 64)	256
dropout_1 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 32)	2080
batch_normalization_2 (Batch Normalization)	(None, 32)	128
dropout_2 (Dropout)	(None, 32)	0
dense_3 (Dense)	(None, 1)	33

```

=====
Total params: 13,825
Trainable params: 13,377
Non-trainable params: 448
=====

```

## Model Training

```
result = model.fit(X_train, y_train,  
                   validation_data = (X_test, y_test),  
                   callbacks = [es],  
                   epochs = 100)
```

Epoch 1/100

```
210/210 [=====] - 5s 9ms/step - loss: 0.4731  
- accuracy: 0.8128 - val_loss: 0.4087 - val_accuracy: 0.8497
```

Epoch 2/100

```
210/210 [=====] - 1s 6ms/step - loss: 0.4296  
- accuracy: 0.8346 - val_loss: 0.4051 - val_accuracy: 0.8497
```

Epoch 3/100

```
210/210 [=====] - 1s 6ms/step - loss: 0.4241  
- accuracy: 0.8349 - val_loss: 0.4017 - val_accuracy: 0.8497
```

Epoch 4/100

```
210/210 [=====] - 2s 7ms/step - loss: 0.4216  
- accuracy: 0.8356 - val_loss: 0.4003 - val_accuracy: 0.8497
```

Epoch 5/100

```
210/210 [=====] - 2s 7ms/step - loss: 0.4187  
- accuracy: 0.8356 - val_loss: 0.4037 - val_accuracy: 0.8497
```

Epoch 6/100

```
210/210 [=====] - 2s 8ms/step - loss: 0.4203  
- accuracy: 0.8359 - val_loss: 0.3979 - val_accuracy: 0.8497
```

Epoch 7/100

```
210/210 [=====] - 2s 9ms/step - loss: 0.4177  
- accuracy: 0.8346 - val_loss: 0.3960 - val_accuracy: 0.8497
```

Epoch 8/100

```
210/210 [=====] - 2s 8ms/step - loss: 0.4158  
- accuracy: 0.8359 - val_loss: 0.4009 - val_accuracy: 0.8497
```

Epoch 9/100

```
210/210 [=====] - 1s 6ms/step - loss: 0.4160  
- accuracy: 0.8364 - val_loss: 0.4084 - val_accuracy: 0.8497
```

Epoch 10/100

```
210/210 [=====] - 1s 6ms/step - loss: 0.4153  
- accuracy: 0.8346 - val_loss: 0.4014 - val_accuracy: 0.8497
```

Epoch 11/100

```
210/210 [=====] - 1s 6ms/step - loss: 0.4146  
- accuracy: 0.8352 - val_loss: 0.4006 - val_accuracy: 0.8497
```

Epoch 12/100

```
210/210 [=====] - 1s 6ms/step - loss: 0.4112  
- accuracy: 0.8349 - val_loss: 0.4080 - val_accuracy: 0.8368
```

Epoch 13/100

```
210/210 [=====] - 1s 6ms/step - loss: 0.4132  
- accuracy: 0.8356 - val_loss: 0.4014 - val_accuracy: 0.8497
```

```
y_pred = model.predict(X_test) >=0.5
```

```
y_pred_train = model.predict(X_train) >=0.5
```

### Model testing

```
from sklearn.metrics import accuracy_score, confusion_matrix
```

```
accuracy_score(y_pred, y_test)
```

```
0.8496868475991649
```

```
accuracy_score(y_pred_train, y_train)
```

```
0.8357696897374701
```

```
confusion_matrix(y_pred, y_test)
```

```
array([[2442,  432],  
       [    0,    0]], dtype=int64)
```

```
confusion_matrix(y_pred_train, y_train)
```

```
array([[5603, 1101],  
       [    0,    0]], dtype=int64)
```

### Hyperparameter Tunning

```
!pip install -q -U keras-tuner
```

```
def build_model(hp):  
    model = Sequential()
```

```
        model.add(Dense(units = hp.Int('units', min_value = 32, max_value  
= 1024, step = 16),  
                        activation = hp.Choice('activation', ['relu',  
'tanh'])),
```

```
                        input_shape = (X_train.shape[1],)))  
        model.add(BatchNormalization())  
        model.add(Dropout(hp.Float('rate', min_value = 0.1, max_value =  
0.4, step = 0.1), seed = 1234))
```

```
        model.add(Dense(units = hp.Int("units", min_value = 32, max_value  
= 128, step = 16),  
                        activation = hp.Choice("activation", ["relu",  
"tanh"])))
```

```
        model.add(BatchNormalization())  
        model.add(Dropout(hp.Float("rate", min_value = 0.1, max_value =  
0.4, step = 0.1), seed = 1234))
```

```
        model.add(Dense(units = hp.Int("units", min_value = 32, max_value  
= 64, step = 16),  
                        activation = hp.Choice("activation", ["relu",  
"tanh"])))
```

```
        model.add(BatchNormalization())  
        model.add(Dropout(hp.Float("rate", min_value = 0.1, max_value =  
0.4, step = 0.1), seed = 1234))
```

```

model.add(Dense(units = 1, activation = "sigmoid"))

learning_rate = hp.Float("learning_rate", min_value = 0.001,
max_value = 0.1, step = 0.01)
model.compile(optimizer = tf.keras.optimizers.Adam(learning_rate),
              loss = "binary_crossentropy",
              metrics = ["accuracy"])
return model

```

```

import keras_tuner as kt
build_model(kt.HyperParameters())

```

```
<keras.engine.sequential.Sequential at 0x2fbf0152160>
```

```

rtuner = kt.RandomSearch(hypermodel = build_model,
                        objective='val_accuracy',
                        max_trials=3,
                        executions_per_trial=2,
                        overwrite=True,
                        directory='my_dir',
                        project_name='diab')

```

```

rtuner.search(X_train, y_train, epochs=2, validation_data=(X_test,
y_test))

```

```

Trial 1 Complete [00h 00m 11s]
val_accuracy: 0.849686861038208

```

```

Best val_accuracy So Far: 0.849686861038208
Total elapsed time: 00h 00m 11s

```

```
Search: Running Trial #2
```

Value	Best Value So Far	Hyperparameter
528	112	units
tanh	relu	activation
0.3	0.1	rate
relu	tanh	activation
0.001	0.021	learning_rate

```

Epoch 1/2
210/210 [=====] - 10s 38ms/step - loss:
0.6121 - accuracy: 0.7321 - val_loss: 0.4349 - val_accuracy: 0.8399
Epoch 2/2
210/210 [=====] - 7s 35ms/step - loss: 0.4756
- accuracy: 0.8143 - val_loss: 0.4411 - val_accuracy: 0.8278
Epoch 1/2
210/210 [=====] - 10s 37ms/step - loss:
0.6109 - accuracy: 0.7443 - val_loss: 0.4287 - val_accuracy: 0.8452
Epoch 2/2

```

```
101/210 [=====>.....] - ETA: 3s - loss: 0.4858 -  
accuracy: 0.8103
```

```
models = rtuner.get_best_models(num_models=2)
```

```
models[1].summary()
```

```
y_predh = models[1].predict(X_test) >=0.5
```

```
accuracy_score(y_predh, y_test)
```