In [15]:

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

%matplotlib inline
```

In [16]:

```
df=pd.read_csv('./loan_data.csv')
df.info()
```

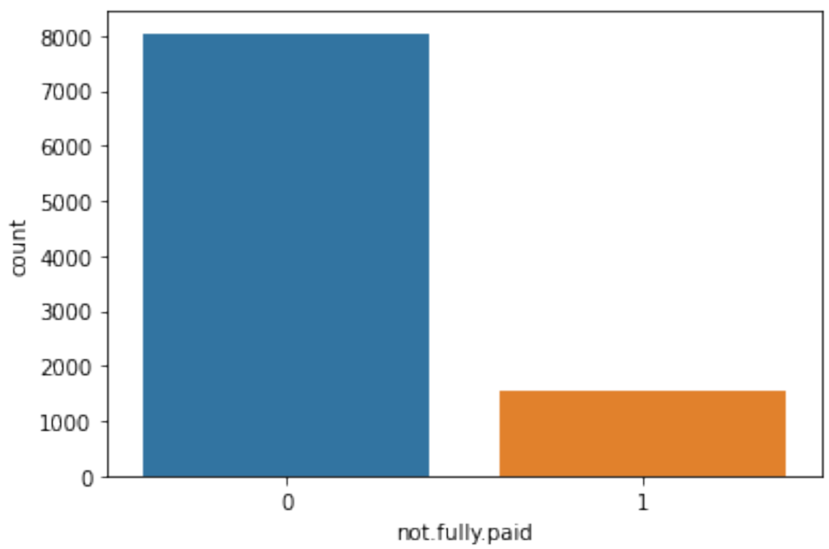
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   credit.policy      9578 non-null   int64  
 1   purpose            9578 non-null   object 
 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
```

- **credit.policy**: 1 if the customer meets the credit underwriting criteria of LendingClub.com, and 0 otherwise.
- **purpose**: The purpose of the loan (takes values "credit_card", "debt_consolidation", "educational", "major_purchase", "small_business", and "all_other").
- **int.rate**: The interest rate of the loan, as a proportion (a rate of 11% would be stored as 0.11). Borrowers judged by LendingClub.com to be more risky are assigned higher interest rates.
- **installment**: The monthly installments owed by the borrower if the loan is funded.
- **log.annual.inc**: The natural log of the self-reported annual income of the borrower.
- **dti**: The debt-to-income ratio of the borrower (amount of debt divided by annual income).
- **fico**: The FICO credit score of the borrower. The higher the score the lower the risk and the more likerly creditors will lend money.
- **days.with.cr.line**: The number of days the borrower has had a credit line.
- **revol.bal**: The borrower's revolving balance (amount unpaid at the end of the credit card billing cycle).
- **revol.util**: The borrower's revolving line utilization rate (the amount of the credit line used relative to total credit available).
- **inq.last.6mths**: The borrower's number of inquiries by creditors in the last 6 months.
- **delinq.2yrs**: The number of times the borrower had been 30+ days past due on a payment in the past 2 years.
- **pub.rec**: The borrower's number of derogatory public records (bankruptcy filings, tax liens, or judgments).

EDA

In [17]:
```
sns.countplot(x='not.fully.paid',data=df)
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9dcbf19f90>



In [18]:

```
df.groupby('not.fully.paid')['not.fully.paid'].count()/len(df)
```

Out[18]:

```
not.fully.paid
0    0.839946
1    0.160054
Name: not.fully.paid, dtype: float64
```

From the chart above we can observe:

1. the data is unballanced
2. about ~83% of the loans are paid
3. about ~16% of the loans are not paid

since the data is inbalanced I will oversample this data

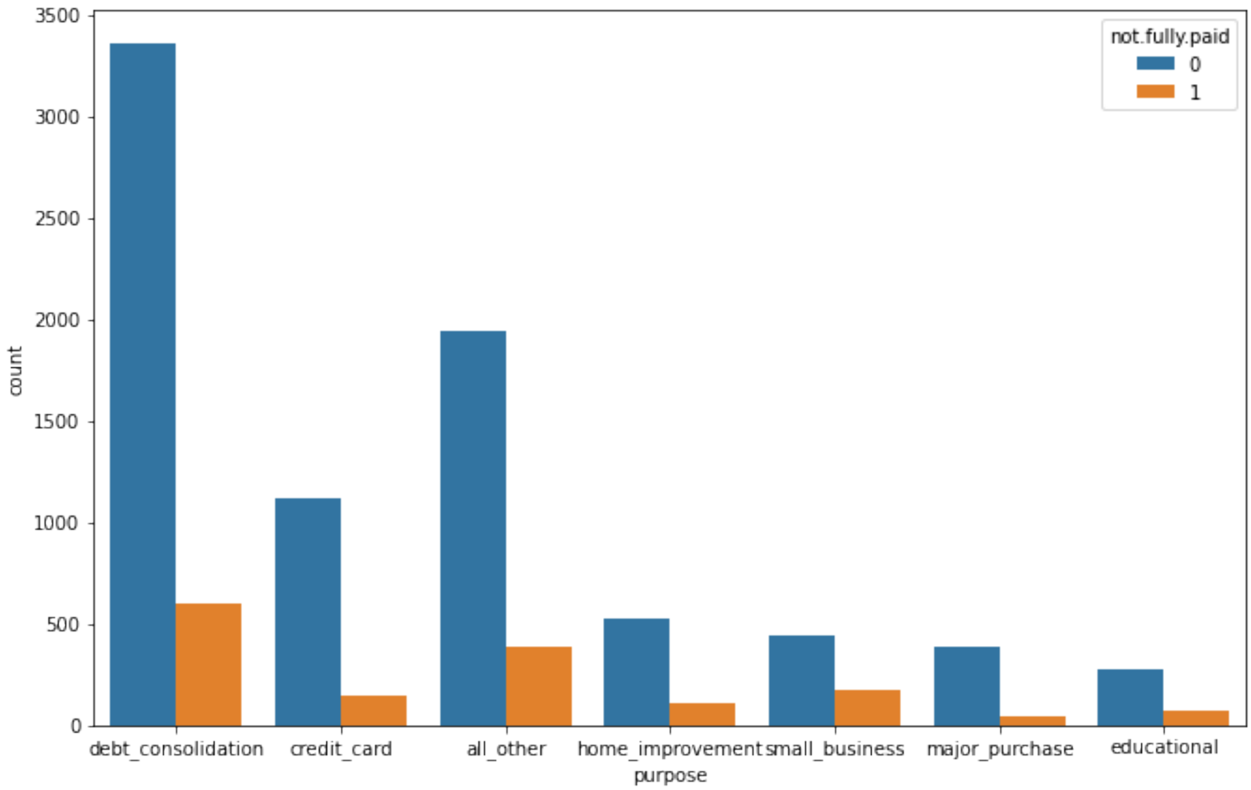
Visualise dataset grouped by load purpose.

In [19]:

```
plt.figure(figsize=(11,7))
sns.countplot(x='purpose',hue='not.fully.paid',data=df)
```

Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9dcb400250>
```



From this chart we can conclude:

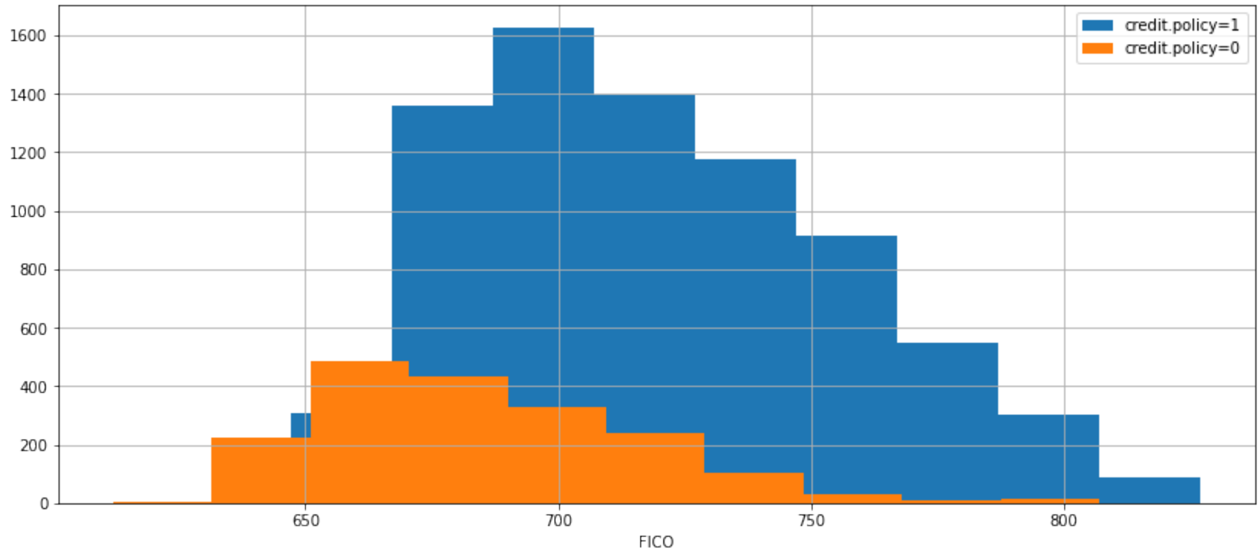
1. The highest purpose for not paid is debt_consolidation and then second is other
2. However the highest paid back is also debt_consolidation followd by all_other

In [20]:

```
plt.figure(figsize=(14,6))
df[df['credit.policy']==1]['fico'].hist(label='credit.policy=1')
df[df['credit.policy']==0]['fico'].hist(label='credit.policy=0')
plt.legend()
plt.xlabel('FICO')
```

Out[20]:

```
Text(0.5, 0, 'FICO')
```



Blue rapresents in blue people with a positive (1) credit policy which means that they were meeting the criterias for the loan and the histogram represents their FICO score.

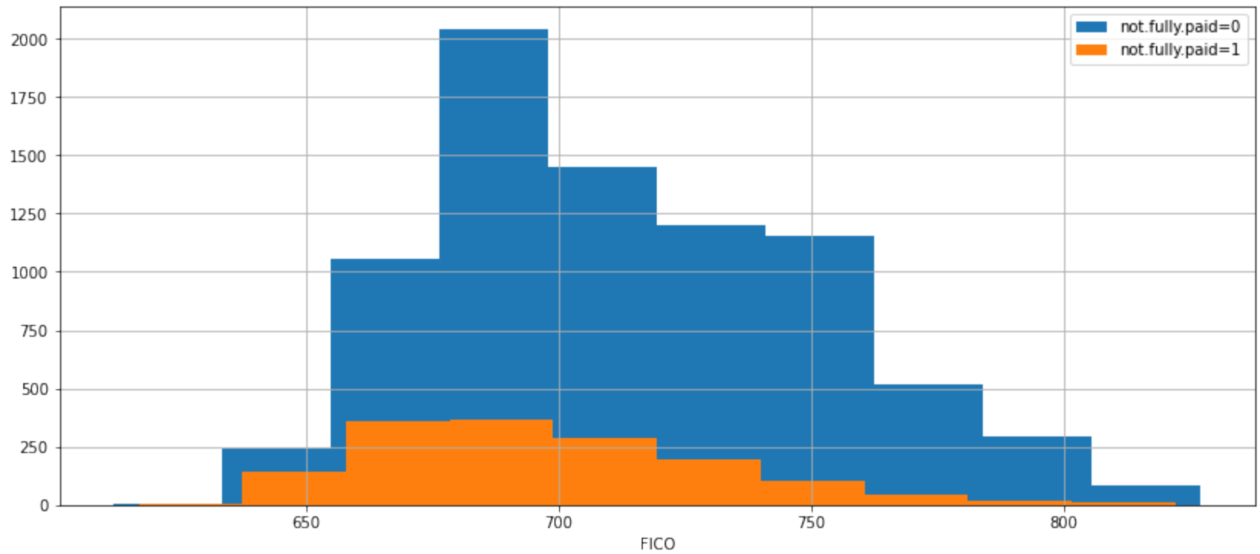
Orange rapresents the people with a negative (0) credit policy which menas that hey did not meet the criterias for the load and the histogram represents their FICO score.

In [21]:

```
plt.figure(figsize=(14,6))
df[df['not.fully.paid']==0]['fico'].hist(label='not.fully.paid=0')
df[df['not.fully.paid']==1]['fico'].hist(label='not.fully.paid=1')
plt.legend()
plt.xlabel('FICO')
```

Out[21]:

```
Text(0.5, 0, 'FICO')
```



if we compare the two histograms we can notice that:

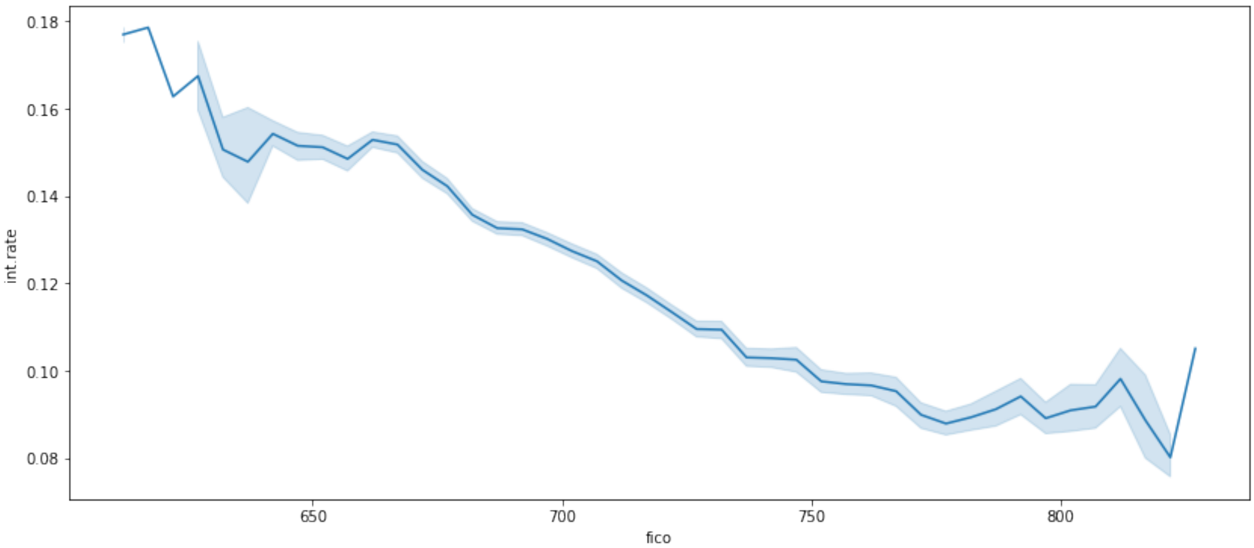
1. People with a high FICO score tend to pay their debt
2. People with a low FICO score tend to not pay their debt as expected
3. There are lots of people with a FICO score between 650 and 700 which paid their debt so maybe the FICO score was to conservative on those people

In [22]:

```
plt.figure(figsize=(14,6))
sns.lineplot(data=df, x="fico", y="int.rate")
```

Out[22]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9dcae204d0>
```



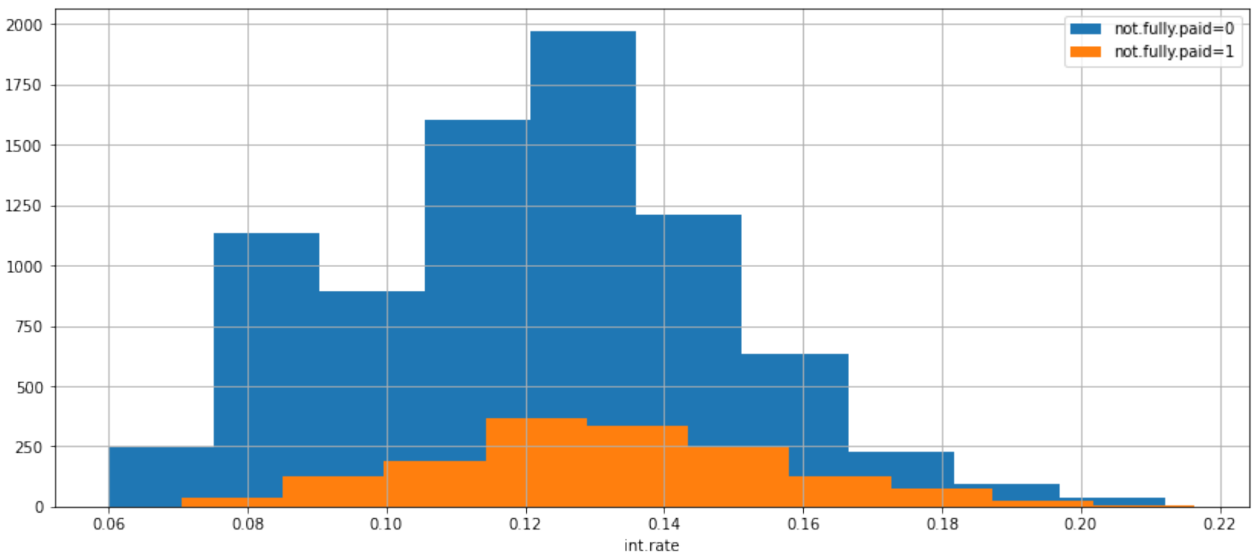
From this line chart we can notice that the higher the FICO the lower the interest rate

In [23]:

```
plt.figure(figsize=(14,6))
df[df['not.fully.paid']==0]['int.rate'].hist(label='not.fully.paid=0')
df[df['not.fully.paid']==1]['int.rate'].hist(label='not.fully.paid=1')
plt.legend()
plt.xlabel('int.rate')
```

Out[23]:

```
Text(0.5, 0, 'int.rate')
```



The interest rate has a normal distribution for both paid and not paid loans which suggests that it does not majorly influence if the loan will be paid or not

Transform categorical values into numerical values (discrete)

Before transforming our categorical feautres to discrete ones we need to balance our inbalanced data, if we don't do so then we'll need to transform the categorical values once again for the newly added oversampled data.

In [24]:

```
#remember value counts returns a tuple because not fully paid can be 0 or 1
count_paid, count_not_paid=df['not.fully.paid'].value_counts()
print('paid', count_paid)
print('not paid', count_not_paid)
```

```
paid 8045
not paid 1533
```

In [25]:

```
df_paid=df[df['not.fully.paid']==0]
df_not_paid=df[df['not.fully.paid']==1]
```

In [26]:

```
df_not_paid_over=df_not_paid.sample(count_paid, replace=True)
df_test_over=pd.concat([df_paid,df_not_paid_over], axis=0)

print('Oversampling')
print(df_test_over['not.fully.paid'].value_counts())
```

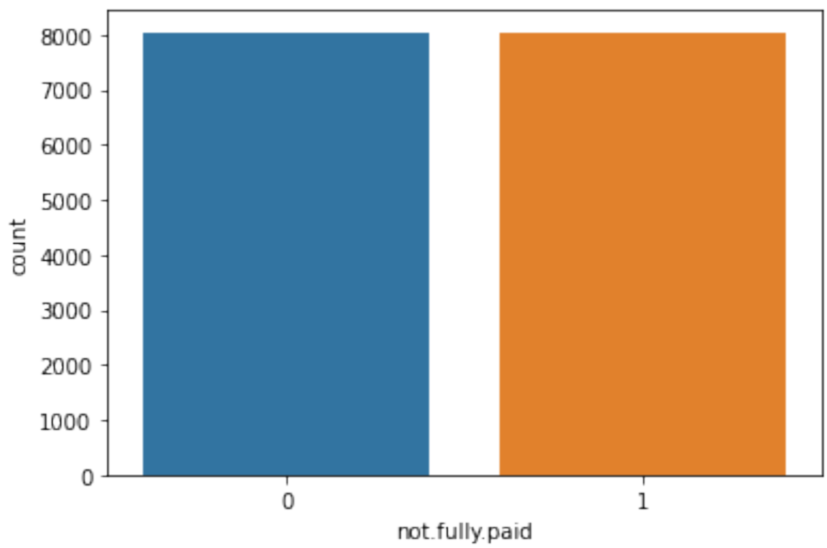
```
Oversampling
0    8045
1    8045
Name: not.fully.paid, dtype: int64
```

In [27]:

```
sns.countplot(x='not.fully.paid',data=df_test_over)
```

Out[27]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9dcac66fd0>
```



In [28]:

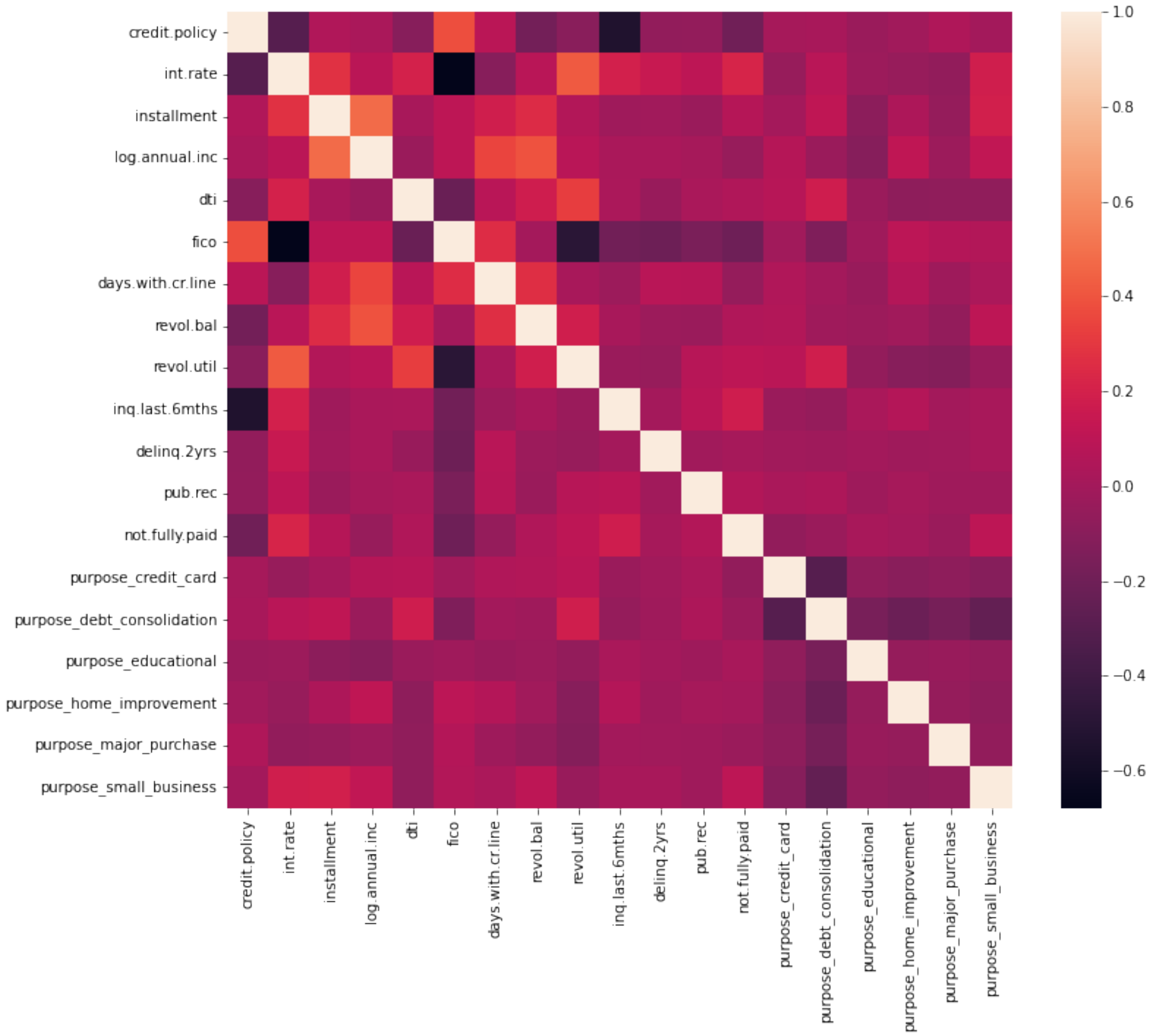
```
cols_feature=['purpose']
final_data=pd.get_dummies(df_test_over,columns=cols_feature,drop_first=True
final_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16090 entries, 0 to 9203
Data columns (total 19 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   credit.policy               16090 non-null  int64
 1   int.rate                    16090 non-null  float64
 2   installment                 16090 non-null  float64
 3   log.annual.inc              16090 non-null  float64
 4   dti                         16090 non-null  float64
 5   fico                        16090 non-null  int64
 6   days.with.cr.line           16090 non-null  float64
 7   revol.bal                   16090 non-null  int64
 8   revol.util                  16090 non-null  float64
 9   inq.last.6mths              16090 non-null  int64
 10  delinq.2yrs                 16090 non-null  int64
 11  pub.rec                     16090 non-null  int64
 12  not.fully.paid              16090 non-null  int64
 13  purpose_credit_card         16090 non-null  uint8
 14  purpose_debt_consolidation  16090 non-null  uint8
 15  purpose_educational         16090 non-null  uint8
 16  purpose_home_improvement    16090 non-null  uint8
 17  purpose_major_purchase      16090 non-null  uint8
 18  purpose_small_business      16090 non-null  uint8
dtypes: float64(6), int64(7), uint8(6)
memory usage: 2.3 MB
```

In [29]:

```
plt.figure(figsize=(12,10))
corr=final_data.corr()
sns.heatmap(data=corr)
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9dcb8d4f50>



Additional Feature Engineering

In this step I will remove features that have strong correlation, strong correlation.

In [30]:

```
predictors = final_data.drop(['not.fully.paid'], axis = 1)
criterion = final_data["not.fully.paid"]
```

In [31]:

```
threshold = 0.65

def high_cor_function(df):
    cor = df.corr()
    corrm = np.corrcoef(df.transpose())
    corr = corrm - np.diagflat(corrm.diagonal())
    print("max corr:",corr.max(), ", min corr: ", corr.min())
    c1 = cor.stack().sort_values(ascending=False).drop_duplicates()
    high_cor = abs(c1[c1.values!=1])
    thresh = threshold
    display(high_cor[high_cor>thresh])
```

In [32]:
```
high_cor_function(predictors)
```

```
max corr: 0.47809644042828764 , min corr:  -0.6790513359731427
fico  int.rate    0.679051
dtype: float64
```

From the above calculations we can identify fico and int.rate as being highly correlated with a score of 0.68

In [33]:
```
final_data=final_data.drop(['int.rate'], axis=1)
```

Modeling

In [34]:
```
from sklearn.model_selection import train_test_split

X=final_data.drop(['not.fully.paid'],axis=1)
y=final_data['not.fully.paid']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, ra
```

In [35]:
```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [36]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Dropout
from tensorflow.keras.callbacks import EarlyStopping

model=Sequential()
model.add(Dense(19, activation="relu"))
model.add(Dropout(0.2))
model.add(Dense(20, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(1,activation='sigmoid'))
model.compile(optimizer='adam',loss='binary_crossentropy',metrics=['binary_


early_stop = EarlyStopping(
        monitor='val_loss',
        mode='min',
        verbose=1,
        patience=25
)

model.fit(X_train,y_train,epochs=200,batch_size=200,validation_data=(X_test
```

```
Epoch 1/200
57/57 [==============================] - 4s 8ms/step - loss: 0.6881 - binar
y_accuracy: 0.5461 - val_loss: 0.6703 - val_binary_accuracy: 0.6138
Epoch 2/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6737 - binar
y_accuracy: 0.5834 - val_loss: 0.6609 - val_binary_accuracy: 0.6227
```

```
Epoch 3/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6663 - binar
y_accuracy: 0.5998 - val_loss: 0.6560 - val_binary_accuracy: 0.6194
Epoch 4/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6627 - binar
y_accuracy: 0.5982 - val_loss: 0.6545 - val_binary_accuracy: 0.6186
Epoch 5/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6601 - binar
y_accuracy: 0.6049 - val_loss: 0.6528 - val_binary_accuracy: 0.6198
Epoch 6/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6604 - binar
y_accuracy: 0.6031 - val_loss: 0.6521 - val_binary_accuracy: 0.6207
Epoch 7/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6574 - binar
y_accuracy: 0.6071 - val_loss: 0.6512 - val_binary_accuracy: 0.6275
Epoch 8/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6558 - binar
y_accuracy: 0.6073 - val_loss: 0.6502 - val_binary_accuracy: 0.6256
Epoch 9/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6550 - binar
y_accuracy: 0.6096 - val_loss: 0.6496 - val_binary_accuracy: 0.6246
Epoch 10/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6542 - binar
y_accuracy: 0.6107 - val_loss: 0.6491 - val_binary_accuracy: 0.6190
Epoch 11/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6498 - binar
y_accuracy: 0.6225 - val_loss: 0.6474 - val_binary_accuracy: 0.6250
Epoch 12/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6505 - binar
y_accuracy: 0.6152 - val_loss: 0.6464 - val_binary_accuracy: 0.6294
Epoch 13/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6479 - binar
y_accuracy: 0.6182 - val_loss: 0.6460 - val_binary_accuracy: 0.6283
Epoch 14/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6508 - binar
y_accuracy: 0.6166 - val_loss: 0.6458 - val_binary_accuracy: 0.6252
Epoch 15/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6469 - binar
y_accuracy: 0.6199 - val_loss: 0.6457 - val_binary_accuracy: 0.6198
Epoch 16/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6461 - binar
y_accuracy: 0.6187 - val_loss: 0.6442 - val_binary_accuracy: 0.6290
Epoch 17/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6474 - binar
y_accuracy: 0.6215 - val_loss: 0.6450 - val_binary_accuracy: 0.6178
Epoch 18/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6454 - binar
y_accuracy: 0.6205 - val_loss: 0.6442 - val_binary_accuracy: 0.6221
Epoch 19/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6455 - binar
y_accuracy: 0.6211 - val_loss: 0.6434 - val_binary_accuracy: 0.6201
Epoch 20/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6431 - binar
y_accuracy: 0.6209 - val_loss: 0.6424 - val_binary_accuracy: 0.6217
Epoch 21/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6433 - binar
y_accuracy: 0.6251 - val_loss: 0.6425 - val_binary_accuracy: 0.6215
Epoch 22/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6449 - binar
y_accuracy: 0.6225 - val_loss: 0.6414 - val_binary_accuracy: 0.6219
Epoch 23/200
```

```
57/57 [==============================] - 0s 5ms/step - loss: 0.6414 - binar
y_accuracy: 0.6235 - val_loss: 0.6407 - val_binary_accuracy: 0.6252
Epoch 24/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6426 - binar
y_accuracy: 0.6250 - val_loss: 0.6407 - val_binary_accuracy: 0.6219
Epoch 25/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6413 - binar
y_accuracy: 0.6243 - val_loss: 0.6408 - val_binary_accuracy: 0.6252
Epoch 26/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6403 - binar
y_accuracy: 0.6220 - val_loss: 0.6406 - val_binary_accuracy: 0.6242
Epoch 27/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6405 - binar
y_accuracy: 0.6218 - val_loss: 0.6396 - val_binary_accuracy: 0.6242
Epoch 28/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6410 - binar
y_accuracy: 0.6215 - val_loss: 0.6390 - val_binary_accuracy: 0.6306
Epoch 29/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6392 - binar
y_accuracy: 0.6236 - val_loss: 0.6382 - val_binary_accuracy: 0.6261
Epoch 30/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6391 - binar
y_accuracy: 0.6253 - val_loss: 0.6390 - val_binary_accuracy: 0.6263
Epoch 31/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6382 - binar
y_accuracy: 0.6256 - val_loss: 0.6398 - val_binary_accuracy: 0.6221
Epoch 32/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6401 - binar
y_accuracy: 0.6251 - val_loss: 0.6381 - val_binary_accuracy: 0.6283
Epoch 33/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6377 - binar
y_accuracy: 0.6233 - val_loss: 0.6377 - val_binary_accuracy: 0.6302
Epoch 34/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6373 - binar
y_accuracy: 0.6239 - val_loss: 0.6384 - val_binary_accuracy: 0.6279
Epoch 35/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6380 - binar
y_accuracy: 0.6267 - val_loss: 0.6373 - val_binary_accuracy: 0.6298
Epoch 36/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6367 - binar
y_accuracy: 0.6228 - val_loss: 0.6370 - val_binary_accuracy: 0.6271
Epoch 37/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6344 - binar
y_accuracy: 0.6319 - val_loss: 0.6369 - val_binary_accuracy: 0.6314
Epoch 38/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6361 - binar
y_accuracy: 0.6300 - val_loss: 0.6397 - val_binary_accuracy: 0.6273
Epoch 39/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6356 - binar
y_accuracy: 0.6279 - val_loss: 0.6364 - val_binary_accuracy: 0.6300
Epoch 40/200
57/57 [==============================] - 0s 8ms/step - loss: 0.6359 - binar
y_accuracy: 0.6243 - val_loss: 0.6359 - val_binary_accuracy: 0.6296
Epoch 41/200
57/57 [==============================] - 1s 12ms/step - loss: 0.6349 - bina
ry_accuracy: 0.6300 - val_loss: 0.6366 - val_binary_accuracy: 0.6321
Epoch 42/200
57/57 [==============================] - 1s 10ms/step - loss: 0.6348 - bina
ry_accuracy: 0.6303 - val_loss: 0.6363 - val_binary_accuracy: 0.6323
Epoch 43/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6343 - binar
```

```
y_accuracy: 0.6339 - val_loss: 0.6359 - val_binary_accuracy: 0.6352
Epoch 44/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6349 - binar
y_accuracy: 0.6299 - val_loss: 0.6371 - val_binary_accuracy: 0.6283
Epoch 45/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6348 - binar
y_accuracy: 0.6286 - val_loss: 0.6354 - val_binary_accuracy: 0.6350
Epoch 46/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6330 - binar
y_accuracy: 0.6287 - val_loss: 0.6352 - val_binary_accuracy: 0.6346
Epoch 47/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6355 - binar
y_accuracy: 0.6274 - val_loss: 0.6346 - val_binary_accuracy: 0.6279
Epoch 48/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6335 - binar
y_accuracy: 0.6307 - val_loss: 0.6345 - val_binary_accuracy: 0.6387
Epoch 49/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6344 - binar
y_accuracy: 0.6309 - val_loss: 0.6346 - val_binary_accuracy: 0.6273
Epoch 50/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6319 - binar
y_accuracy: 0.6308 - val_loss: 0.6343 - val_binary_accuracy: 0.6277
Epoch 51/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6327 - binar
y_accuracy: 0.6309 - val_loss: 0.6343 - val_binary_accuracy: 0.6321
Epoch 52/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6350 - binar
y_accuracy: 0.6291 - val_loss: 0.6350 - val_binary_accuracy: 0.6356
Epoch 53/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6334 - binar
y_accuracy: 0.6272 - val_loss: 0.6344 - val_binary_accuracy: 0.6354
Epoch 54/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6338 - binar
y_accuracy: 0.6300 - val_loss: 0.6347 - val_binary_accuracy: 0.6341
Epoch 55/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6317 - binar
y_accuracy: 0.6328 - val_loss: 0.6338 - val_binary_accuracy: 0.6321
Epoch 56/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6321 - binar
y_accuracy: 0.6347 - val_loss: 0.6344 - val_binary_accuracy: 0.6366
Epoch 57/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6319 - binar
y_accuracy: 0.6304 - val_loss: 0.6331 - val_binary_accuracy: 0.6296
Epoch 58/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6321 - binar
y_accuracy: 0.6347 - val_loss: 0.6348 - val_binary_accuracy: 0.6356
Epoch 59/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6324 - binar
y_accuracy: 0.6312 - val_loss: 0.6331 - val_binary_accuracy: 0.6383
Epoch 60/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6321 - binar
y_accuracy: 0.6324 - val_loss: 0.6326 - val_binary_accuracy: 0.6341
Epoch 61/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6330 - binar
y_accuracy: 0.6338 - val_loss: 0.6337 - val_binary_accuracy: 0.6385
Epoch 62/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6318 - binar
y_accuracy: 0.6303 - val_loss: 0.6327 - val_binary_accuracy: 0.6354
Epoch 63/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6294 - binar
y_accuracy: 0.6343 - val_loss: 0.6334 - val_binary_accuracy: 0.6360
```

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Epoch 64/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6326 - binar
y_accuracy: 0.6308 - val_loss: 0.6330 - val_binary_accuracy: 0.6381
Epoch 65/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6324 - binar
y_accuracy: 0.6325 - val_loss: 0.6335 - val_binary_accuracy: 0.6404
Epoch 66/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6312 - binar
y_accuracy: 0.6318 - val_loss: 0.6323 - val_binary_accuracy: 0.6358
Epoch 67/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6297 - binar
y_accuracy: 0.6373 - val_loss: 0.6323 - val_binary_accuracy: 0.6395
Epoch 68/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6300 - binar
y_accuracy: 0.6359 - val_loss: 0.6317 - val_binary_accuracy: 0.6383
Epoch 69/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6291 - binar
y_accuracy: 0.6340 - val_loss: 0.6319 - val_binary_accuracy: 0.6352
Epoch 70/200
57/57 [==============================] - 0s 7ms/step - loss: 0.6305 - binar
y_accuracy: 0.6316 - val_loss: 0.6318 - val_binary_accuracy: 0.6368
Epoch 71/200
57/57 [==============================] - 0s 7ms/step - loss: 0.6315 - binar
y_accuracy: 0.6347 - val_loss: 0.6320 - val_binary_accuracy: 0.6368
Epoch 72/200
57/57 [==============================] - 0s 8ms/step - loss: 0.6304 - binar
y_accuracy: 0.6351 - val_loss: 0.6328 - val_binary_accuracy: 0.6321
Epoch 73/200
57/57 [==============================] - 0s 7ms/step - loss: 0.6286 - binar
y_accuracy: 0.6392 - val_loss: 0.6313 - val_binary_accuracy: 0.6360
Epoch 74/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6303 - binar
y_accuracy: 0.6389 - val_loss: 0.6315 - val_binary_accuracy: 0.6348
Epoch 75/200
57/57 [==============================] - 1s 12ms/step - loss: 0.6293 - bina
ry_accuracy: 0.6386 - val_loss: 0.6312 - val_binary_accuracy: 0.6381
Epoch 76/200
57/57 [==============================] - 0s 7ms/step - loss: 0.6293 - binar
y_accuracy: 0.6374 - val_loss: 0.6310 - val_binary_accuracy: 0.6368
Epoch 77/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6277 - binar
y_accuracy: 0.6362 - val_loss: 0.6310 - val_binary_accuracy: 0.6364
Epoch 78/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6273 - binar
y_accuracy: 0.6395 - val_loss: 0.6305 - val_binary_accuracy: 0.6393
Epoch 79/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6283 - binar
y_accuracy: 0.6370 - val_loss: 0.6305 - val_binary_accuracy: 0.6408
Epoch 80/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6289 - binar
y_accuracy: 0.6399 - val_loss: 0.6315 - val_binary_accuracy: 0.6364
Epoch 81/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6288 - binar
y_accuracy: 0.6401 - val_loss: 0.6306 - val_binary_accuracy: 0.6401
Epoch 82/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6280 - binar
y_accuracy: 0.6401 - val_loss: 0.6308 - val_binary_accuracy: 0.6397
Epoch 83/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6276 - binar
y_accuracy: 0.6380 - val_loss: 0.6303 - val_binary_accuracy: 0.6385
Epoch 84/200
```

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57/57 [==============================] - 0s 6ms/step - loss: 0.6275 - binar
y_accuracy: 0.6390 - val_loss: 0.6300 - val_binary_accuracy: 0.6393
Epoch 85/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6265 - binar
y_accuracy: 0.6399 - val_loss: 0.6301 - val_binary_accuracy: 0.6389
Epoch 86/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6263 - binar
y_accuracy: 0.6431 - val_loss: 0.6298 - val_binary_accuracy: 0.6418
Epoch 87/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6276 - binar
y_accuracy: 0.6379 - val_loss: 0.6293 - val_binary_accuracy: 0.6418
Epoch 88/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6265 - binar
y_accuracy: 0.6432 - val_loss: 0.6296 - val_binary_accuracy: 0.6366
Epoch 89/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6284 - binar
y_accuracy: 0.6379 - val_loss: 0.6299 - val_binary_accuracy: 0.6362
Epoch 90/200
57/57 [==============================] - 0s 7ms/step - loss: 0.6261 - binar
y_accuracy: 0.6371 - val_loss: 0.6301 - val_binary_accuracy: 0.6383
Epoch 91/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6273 - binar
y_accuracy: 0.6419 - val_loss: 0.6292 - val_binary_accuracy: 0.6387
Epoch 92/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6274 - binar
y_accuracy: 0.6437 - val_loss: 0.6292 - val_binary_accuracy: 0.6370
Epoch 93/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6243 - binar
y_accuracy: 0.6405 - val_loss: 0.6290 - val_binary_accuracy: 0.6389
Epoch 94/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6276 - binar
y_accuracy: 0.6417 - val_loss: 0.6292 - val_binary_accuracy: 0.6383
Epoch 95/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6275 - binar
y_accuracy: 0.6400 - val_loss: 0.6289 - val_binary_accuracy: 0.6414
Epoch 96/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6252 - binar
y_accuracy: 0.6396 - val_loss: 0.6285 - val_binary_accuracy: 0.6412
Epoch 97/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6241 - binar
y_accuracy: 0.6451 - val_loss: 0.6292 - val_binary_accuracy: 0.6348
Epoch 98/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6261 - binar
y_accuracy: 0.6392 - val_loss: 0.6285 - val_binary_accuracy: 0.6377
Epoch 99/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6252 - binar
y_accuracy: 0.6440 - val_loss: 0.6282 - val_binary_accuracy: 0.6412
Epoch 100/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6267 - binar
y_accuracy: 0.6451 - val_loss: 0.6284 - val_binary_accuracy: 0.6399
Epoch 101/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6234 - binar
y_accuracy: 0.6422 - val_loss: 0.6288 - val_binary_accuracy: 0.6362
Epoch 102/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6252 - binar
y_accuracy: 0.6446 - val_loss: 0.6287 - val_binary_accuracy: 0.6372
Epoch 103/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6255 - binar
y_accuracy: 0.6438 - val_loss: 0.6281 - val_binary_accuracy: 0.6408
Epoch 104/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6259 - binar
```

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y_accuracy: 0.6405 - val_loss: 0.6277 - val_binary_accuracy: 0.6387
Epoch 105/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6237 - binar
y_accuracy: 0.6445 - val_loss: 0.6282 - val_binary_accuracy: 0.6391
Epoch 106/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6253 - binar
y_accuracy: 0.6411 - val_loss: 0.6289 - val_binary_accuracy: 0.6377
Epoch 107/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6271 - binar
y_accuracy: 0.6437 - val_loss: 0.6275 - val_binary_accuracy: 0.6414
Epoch 108/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6239 - binar
y_accuracy: 0.6453 - val_loss: 0.6278 - val_binary_accuracy: 0.6404
Epoch 109/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6255 - binar
y_accuracy: 0.6417 - val_loss: 0.6276 - val_binary_accuracy: 0.6389
Epoch 110/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6243 - binar
y_accuracy: 0.6454 - val_loss: 0.6270 - val_binary_accuracy: 0.6435
Epoch 111/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6226 - binar
y_accuracy: 0.6426 - val_loss: 0.6272 - val_binary_accuracy: 0.6433
Epoch 112/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6215 - binar
y_accuracy: 0.6515 - val_loss: 0.6270 - val_binary_accuracy: 0.6408
Epoch 113/200
57/57 [==============================] - 0s 7ms/step - loss: 0.6233 - binar
y_accuracy: 0.6433 - val_loss: 0.6269 - val_binary_accuracy: 0.6379
Epoch 114/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6242 - binar
y_accuracy: 0.6410 - val_loss: 0.6270 - val_binary_accuracy: 0.6426
Epoch 115/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6232 - binar
y_accuracy: 0.6425 - val_loss: 0.6266 - val_binary_accuracy: 0.6422
Epoch 116/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6238 - binar
y_accuracy: 0.6453 - val_loss: 0.6267 - val_binary_accuracy: 0.6447
Epoch 117/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6224 - binar
y_accuracy: 0.6477 - val_loss: 0.6267 - val_binary_accuracy: 0.6395
Epoch 118/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6215 - binar
y_accuracy: 0.6410 - val_loss: 0.6266 - val_binary_accuracy: 0.6416
Epoch 119/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6235 - binar
y_accuracy: 0.6425 - val_loss: 0.6269 - val_binary_accuracy: 0.6387
Epoch 120/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6243 - binar
y_accuracy: 0.6418 - val_loss: 0.6265 - val_binary_accuracy: 0.6416
Epoch 121/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6231 - binar
y_accuracy: 0.6393 - val_loss: 0.6264 - val_binary_accuracy: 0.6377
Epoch 122/200
57/57 [==============================] - 0s 7ms/step - loss: 0.6218 - binar
y_accuracy: 0.6467 - val_loss: 0.6260 - val_binary_accuracy: 0.6406
Epoch 123/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6200 - binar
y_accuracy: 0.6460 - val_loss: 0.6255 - val_binary_accuracy: 0.6424
Epoch 124/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6212 - binar
y_accuracy: 0.6433 - val_loss: 0.6262 - val_binary_accuracy: 0.6430
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Epoch 125/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6208 - binar
y_accuracy: 0.6452 - val_loss: 0.6265 - val_binary_accuracy: 0.6385
Epoch 126/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6221 - binar
y_accuracy: 0.6446 - val_loss: 0.6258 - val_binary_accuracy: 0.6428
Epoch 127/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6218 - binar
y_accuracy: 0.6437 - val_loss: 0.6257 - val_binary_accuracy: 0.6435
Epoch 128/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6237 - binar
y_accuracy: 0.6457 - val_loss: 0.6265 - val_binary_accuracy: 0.6424
Epoch 129/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6234 - binar
y_accuracy: 0.6409 - val_loss: 0.6261 - val_binary_accuracy: 0.6416
Epoch 130/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6227 - binar
y_accuracy: 0.6458 - val_loss: 0.6255 - val_binary_accuracy: 0.6426
Epoch 131/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6205 - binar
y_accuracy: 0.6453 - val_loss: 0.6256 - val_binary_accuracy: 0.6455
Epoch 132/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6221 - binar
y_accuracy: 0.6485 - val_loss: 0.6254 - val_binary_accuracy: 0.6426
Epoch 133/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6208 - binar
y_accuracy: 0.6445 - val_loss: 0.6250 - val_binary_accuracy: 0.6451
Epoch 134/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6210 - binar
y_accuracy: 0.6538 - val_loss: 0.6250 - val_binary_accuracy: 0.6412
Epoch 135/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6210 - binar
y_accuracy: 0.6430 - val_loss: 0.6249 - val_binary_accuracy: 0.6430
Epoch 136/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6181 - binar
y_accuracy: 0.6478 - val_loss: 0.6243 - val_binary_accuracy: 0.6482
Epoch 137/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6222 - binar
y_accuracy: 0.6457 - val_loss: 0.6242 - val_binary_accuracy: 0.6447
Epoch 138/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6184 - binar
y_accuracy: 0.6480 - val_loss: 0.6241 - val_binary_accuracy: 0.6449
Epoch 139/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6210 - binar
y_accuracy: 0.6466 - val_loss: 0.6242 - val_binary_accuracy: 0.6451
Epoch 140/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6196 - binar
y_accuracy: 0.6493 - val_loss: 0.6249 - val_binary_accuracy: 0.6449
Epoch 141/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6226 - binar
y_accuracy: 0.6465 - val_loss: 0.6246 - val_binary_accuracy: 0.6474
Epoch 142/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6187 - binar
y_accuracy: 0.6455 - val_loss: 0.6249 - val_binary_accuracy: 0.6451
Epoch 143/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6202 - binar
y_accuracy: 0.6458 - val_loss: 0.6251 - val_binary_accuracy: 0.6375
Epoch 144/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6211 - binar
y_accuracy: 0.6455 - val_loss: 0.6238 - val_binary_accuracy: 0.6464
Epoch 145/200
```

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57/57 [==============================] - 0s 5ms/step - loss: 0.6194 - binar
y_accuracy: 0.6479 - val_loss: 0.6240 - val_binary_accuracy: 0.6441
Epoch 146/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6195 - binar
y_accuracy: 0.6446 - val_loss: 0.6236 - val_binary_accuracy: 0.6466
Epoch 147/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6195 - binar
y_accuracy: 0.6440 - val_loss: 0.6234 - val_binary_accuracy: 0.6453
Epoch 148/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6173 - binar
y_accuracy: 0.6490 - val_loss: 0.6240 - val_binary_accuracy: 0.6433
Epoch 149/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6196 - binar
y_accuracy: 0.6501 - val_loss: 0.6238 - val_binary_accuracy: 0.6422
Epoch 150/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6187 - binar
y_accuracy: 0.6488 - val_loss: 0.6233 - val_binary_accuracy: 0.6443
Epoch 151/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6209 - binar
y_accuracy: 0.6481 - val_loss: 0.6235 - val_binary_accuracy: 0.6451
Epoch 152/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6197 - binar
y_accuracy: 0.6507 - val_loss: 0.6239 - val_binary_accuracy: 0.6447
Epoch 153/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6211 - binar
y_accuracy: 0.6493 - val_loss: 0.6234 - val_binary_accuracy: 0.6468
Epoch 154/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6193 - binar
y_accuracy: 0.6494 - val_loss: 0.6232 - val_binary_accuracy: 0.6447
Epoch 155/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6203 - binar
y_accuracy: 0.6492 - val_loss: 0.6232 - val_binary_accuracy: 0.6459
Epoch 156/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6185 - binar
y_accuracy: 0.6489 - val_loss: 0.6236 - val_binary_accuracy: 0.6399
Epoch 157/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6198 - binar
y_accuracy: 0.6489 - val_loss: 0.6237 - val_binary_accuracy: 0.6418
Epoch 158/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6187 - binar
y_accuracy: 0.6473 - val_loss: 0.6239 - val_binary_accuracy: 0.6437
Epoch 159/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6207 - binar
y_accuracy: 0.6489 - val_loss: 0.6238 - val_binary_accuracy: 0.6412
Epoch 160/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6173 - binar
y_accuracy: 0.6505 - val_loss: 0.6228 - val_binary_accuracy: 0.6478
Epoch 161/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6195 - binar
y_accuracy: 0.6444 - val_loss: 0.6230 - val_binary_accuracy: 0.6474
Epoch 162/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6202 - binar
y_accuracy: 0.6459 - val_loss: 0.6235 - val_binary_accuracy: 0.6412
Epoch 163/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6186 - binar
y_accuracy: 0.6493 - val_loss: 0.6232 - val_binary_accuracy: 0.6457
Epoch 164/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6214 - binar
y_accuracy: 0.6456 - val_loss: 0.6226 - val_binary_accuracy: 0.6480
Epoch 165/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6175 - binar
```

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y_accuracy: 0.6507 - val_loss: 0.6228 - val_binary_accuracy: 0.6453
Epoch 166/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6192 - binar
y_accuracy: 0.6476 - val_loss: 0.6231 - val_binary_accuracy: 0.6445
Epoch 167/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6169 - binar
y_accuracy: 0.6520 - val_loss: 0.6232 - val_binary_accuracy: 0.6416
Epoch 168/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6159 - binar
y_accuracy: 0.6492 - val_loss: 0.6229 - val_binary_accuracy: 0.6424
Epoch 169/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6168 - binar
y_accuracy: 0.6513 - val_loss: 0.6223 - val_binary_accuracy: 0.6474
Epoch 170/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6189 - binar
y_accuracy: 0.6511 - val_loss: 0.6235 - val_binary_accuracy: 0.6472
Epoch 171/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6200 - binar
y_accuracy: 0.6489 - val_loss: 0.6225 - val_binary_accuracy: 0.6455
Epoch 172/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6180 - binar
y_accuracy: 0.6511 - val_loss: 0.6225 - val_binary_accuracy: 0.6414
Epoch 173/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6188 - binar
y_accuracy: 0.6492 - val_loss: 0.6221 - val_binary_accuracy: 0.6426
Epoch 174/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6179 - binar
y_accuracy: 0.6489 - val_loss: 0.6218 - val_binary_accuracy: 0.6501
Epoch 175/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6190 - binar
y_accuracy: 0.6496 - val_loss: 0.6224 - val_binary_accuracy: 0.6462
Epoch 176/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6195 - binar
y_accuracy: 0.6482 - val_loss: 0.6223 - val_binary_accuracy: 0.6459
Epoch 177/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6194 - binar
y_accuracy: 0.6491 - val_loss: 0.6224 - val_binary_accuracy: 0.6491
Epoch 178/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6195 - binar
y_accuracy: 0.6523 - val_loss: 0.6223 - val_binary_accuracy: 0.6484
Epoch 179/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6185 - binar
y_accuracy: 0.6486 - val_loss: 0.6220 - val_binary_accuracy: 0.6505
Epoch 180/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6213 - binar
y_accuracy: 0.6474 - val_loss: 0.6221 - val_binary_accuracy: 0.6484
Epoch 181/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6169 - binar
y_accuracy: 0.6543 - val_loss: 0.6218 - val_binary_accuracy: 0.6464
Epoch 182/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6174 - binar
y_accuracy: 0.6478 - val_loss: 0.6218 - val_binary_accuracy: 0.6468
Epoch 183/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6169 - binar
y_accuracy: 0.6530 - val_loss: 0.6221 - val_binary_accuracy: 0.6480
Epoch 184/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6145 - binar
y_accuracy: 0.6558 - val_loss: 0.6218 - val_binary_accuracy: 0.6478
Epoch 185/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6169 - binar
y_accuracy: 0.6507 - val_loss: 0.6218 - val_binary_accuracy: 0.6453
```

```
Epoch 186/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6154 - binar
y_accuracy: 0.6515 - val_loss: 0.6220 - val_binary_accuracy: 0.6443
Epoch 187/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6174 - binar
y_accuracy: 0.6488 - val_loss: 0.6218 - val_binary_accuracy: 0.6472
Epoch 188/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6159 - binar
y_accuracy: 0.6480 - val_loss: 0.6227 - val_binary_accuracy: 0.6424
Epoch 189/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6177 - binar
y_accuracy: 0.6457 - val_loss: 0.6219 - val_binary_accuracy: 0.6451
Epoch 190/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6181 - binar
y_accuracy: 0.6499 - val_loss: 0.6221 - val_binary_accuracy: 0.6472
Epoch 191/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6171 - binar
y_accuracy: 0.6556 - val_loss: 0.6220 - val_binary_accuracy: 0.6474
Epoch 192/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6151 - binar
y_accuracy: 0.6555 - val_loss: 0.6216 - val_binary_accuracy: 0.6505
Epoch 193/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6170 - binar
y_accuracy: 0.6484 - val_loss: 0.6216 - val_binary_accuracy: 0.6455
Epoch 194/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6137 - binar
y_accuracy: 0.6536 - val_loss: 0.6216 - val_binary_accuracy: 0.6489
Epoch 195/200
57/57 [==============================] - 0s 6ms/step - loss: 0.6177 - binar
y_accuracy: 0.6536 - val_loss: 0.6217 - val_binary_accuracy: 0.6470
Epoch 196/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6184 - binar
y_accuracy: 0.6502 - val_loss: 0.6218 - val_binary_accuracy: 0.6459
Epoch 197/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6185 - binar
y_accuracy: 0.6473 - val_loss: 0.6221 - val_binary_accuracy: 0.6449
Epoch 198/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6192 - binar
y_accuracy: 0.6490 - val_loss: 0.6213 - val_binary_accuracy: 0.6491
Epoch 199/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6155 - binar
y_accuracy: 0.6507 - val_loss: 0.6217 - val_binary_accuracy: 0.6453
Epoch 200/200
57/57 [==============================] - 0s 5ms/step - loss: 0.6153 - binar
y_accuracy: 0.6559 - val_loss: 0.6219 - val_binary_accuracy: 0.6464
```

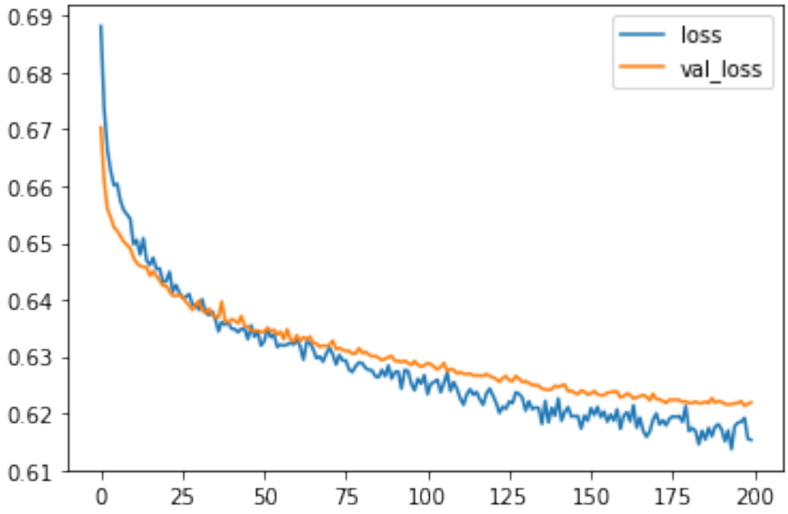
Out[36]:

```
<keras.callbacks.History at 0x7f9d500aac50>
```

In [37]:

```python
pd.DataFrame(model.history.history)[['loss','val_loss']].plot()
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7f9d627cfe90>



In [ ]: