Project to Submit – Project 2

Lending Club Loan Data Analysis

Course-end Project 2

Description

Create a model that predicts whether or not a loan will be default using the historical data.

Problem Statement:

For companies like Lending Club correctly predicting whether or not a loan will be a default is very important. In this project, using the historical data from 2007 to 2015, you have to build a deep learning model to predict the chance of default for future loans. As you will see later this dataset is highly imbalanced and includes a lot of features that make this problem more challenging.

Domain: Finance

Analysis to be done: Perform data preprocessing and build a deep learning prediction model.

Write Up:

Dataset columns and definition:

- **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.
- **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).

Analysis Tasks to be performed:

Steps to perform:

Perform exploratory data analysis and feature engineering and then apply feature engineering. Follow up with a deep learning model to predict whether or not the loan will be default using the historical data.

Steps to be done:

1. Feature Transformation
   - Transform categorical values into numerical values (discrete)
2. Exploratory data analysis of different factors of the dataset.
3. Additional Feature Engineering
   - You will check the correlation between features and will drop those features which have a strong correlation
   - This will help reduce the number of features and will leave you with the most relevant features
4. Modeling
   - After applying EDA and feature engineering, you are now ready to build the predictive models
   - In this part, you will create a deep learning model using Keras with Tensorflow backend

Screenshots of relevant outputs

Basic Data Check

```
# Check the first few rows of the DataFrame •••
```

```
   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
```

```
df.head() •••
```

[41]:

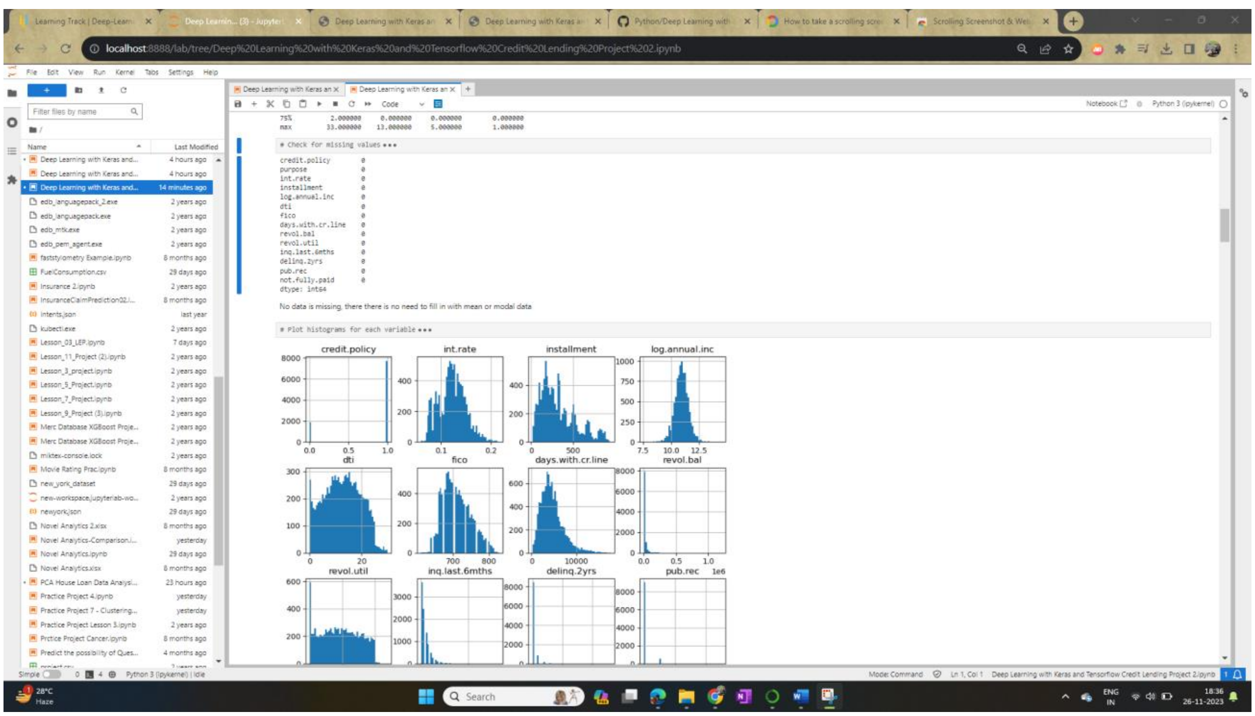
	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	...	purpose_debt_consolidation	purpose_educational	purpose_home_improvement	purpose_major_purchase	purpose_small_b
0	1	0.1189	829.10	11.350407	19.48	737.0	5639.958333	28854.0	52.1	0.0	...	True	False	False	False	
1	1	0.1071	228.22	11.082143	14.29	707.0	2760.000000	33623.0	76.7	0.0	...	False	False	False	False	
2	1	0.1357	366.86	10.373491	11.63	682.0	4710.000000	3511.0	25.6	1.0	...	True	False	False	False	
3	1	0.1008	162.34	11.350407	8.10	712.0	2699.958333	33667.0	73.2	1.0	...	True	False	False	False	
4	1	0.1426	102.92	11.299732	14.97	667.0	4066.000000	4740.0	39.5	0.0	...	False	False	False	False	

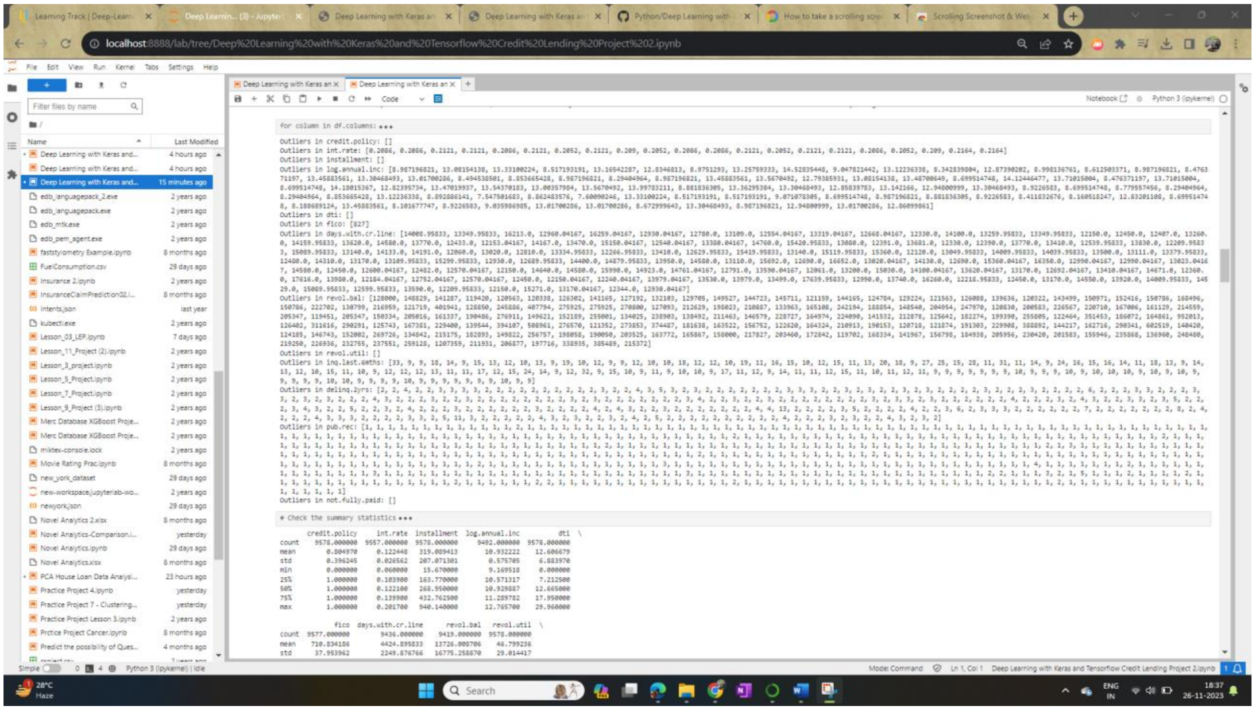
5 rows × 24 columns

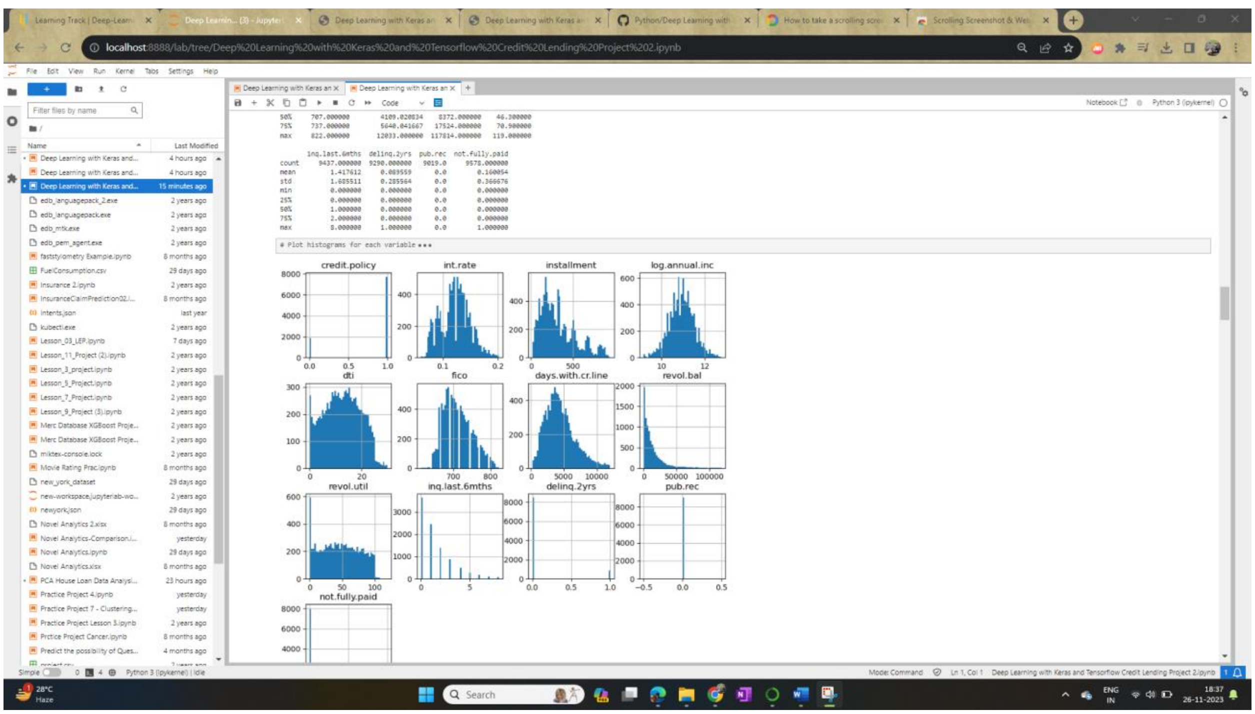
```
# Check the summary statistics •••
```

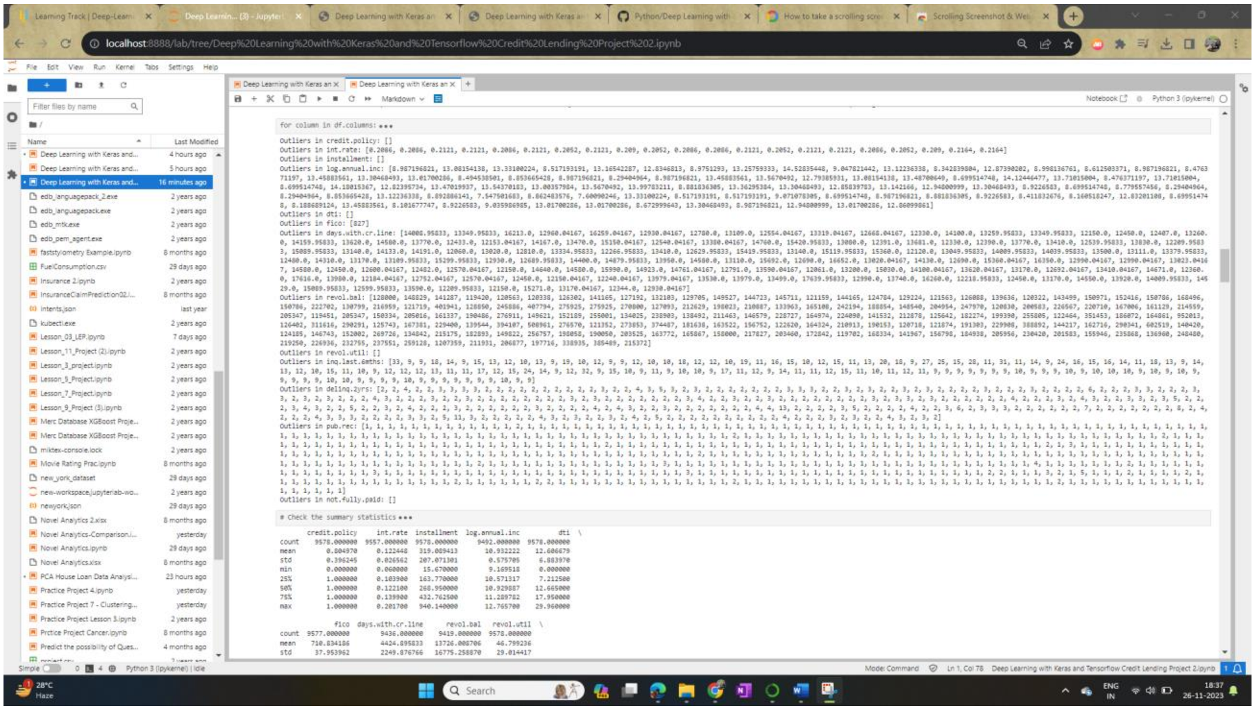
```
       credit.policy     int.rate  installment  log.annual.inc          dti  \
count    9578.000000  9578.000000  9578.000000     9578.000000  9578.000000
mean        0.804970     0.122640   319.089413       10.932117    12.606679
std         0.396245     0.026847   207.071301        0.614813     6.883970
min         0.000000     0.060000    15.670000        7.547502     0.000000
25%         1.000000     0.103900   163.770000       10.558414     7.212500
50%         1.000000     0.122100   268.950000       10.928884    12.665000
75%         1.000000     0.140700   432.762500       11.291293    17.950000
max         1.000000     0.216400   940.140000       14.528354    29.960000

              fico  days.with.cr.line     revol.bal   revol.util  \
```

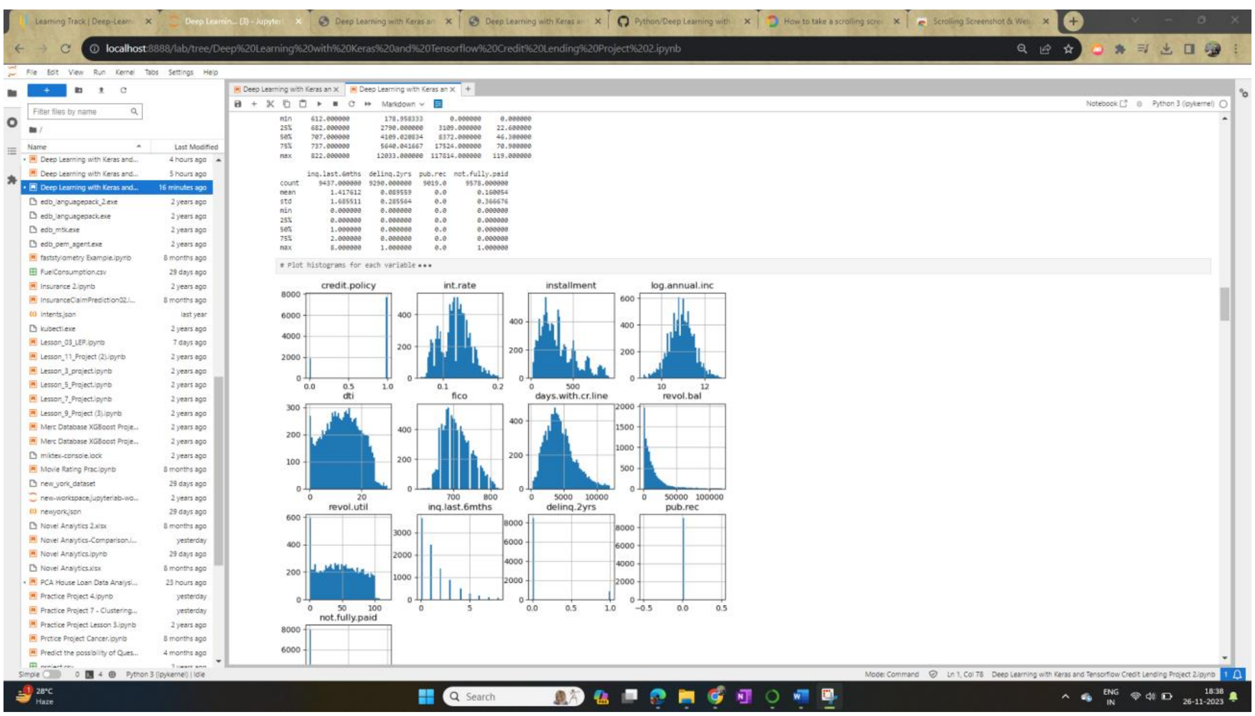



localhost:8888/lab/tree/Deep%20Learning%20with%20Keras%20and%20Tensorflow%20Credit%20Lending%20Project%202.ipynb
for column in df.columns: ...
Check the summary statistics ...

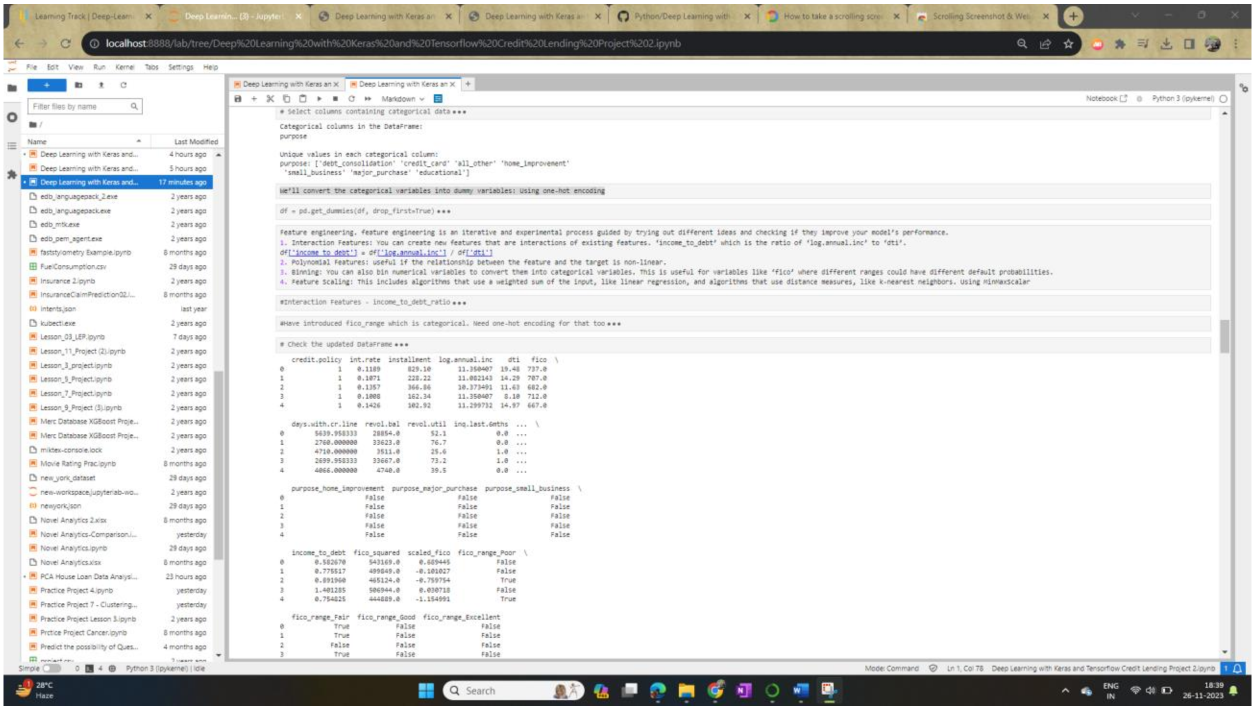

localhost:8888/lab/tree/Deep%20Learning%20with%20Keras%20and%20Tensorflow%20Credit%20Lending%20Project%202.ipynb
Plot histograms for each variable ...
credit.policy
int.rate
installment
log.annual.inc
dti
fico
days.with.cr.line
revol.bal
revol.util
inq.last.6mths
delinq.2yrs
pub.rec
not.fully.paid



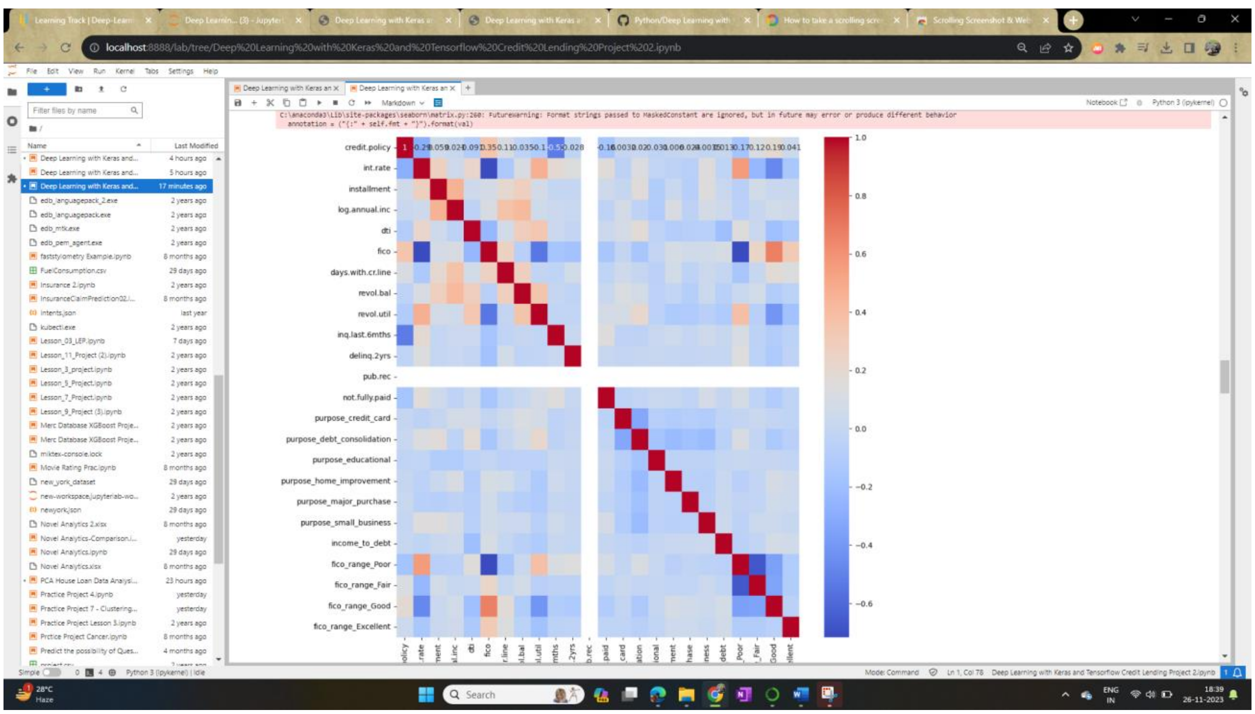
for column in df.columns: •••
Outliers in credit.policy: []
Outliers in not.fully.paid: []
Check the summary statistics •••
credit.policy int.rate installment log.annual.inc dti
count 9578.000000 9557.000000 9578.000000 9492.000000 9578.000000
mean 0.804970 0.122448 319.089413 10.932222 12.606679
std 0.396245 0.026562 207.071301 0.575705 6.883970
min 0.000000 0.060000 15.670000 9.169518 0.000000
25% 1.000000 0.103900 163.770000 10.571317 7.212500
50% 1.000000 0.122100 268.950000 10.929887 12.665000
75% 1.000000 0.139900 432.762500 11.289782 17.950000
max 1.000000 0.201700 940.140000 12.765700 29.960000
fico days.with.cr.line revol.bal revol.util
count 9577.000000 9436.000000 9419.000000 9578.000000
mean 710.834186 4424.895833 13726.008706 46.799236
std 37.953962 2249.876766 16775.258870 29.014417



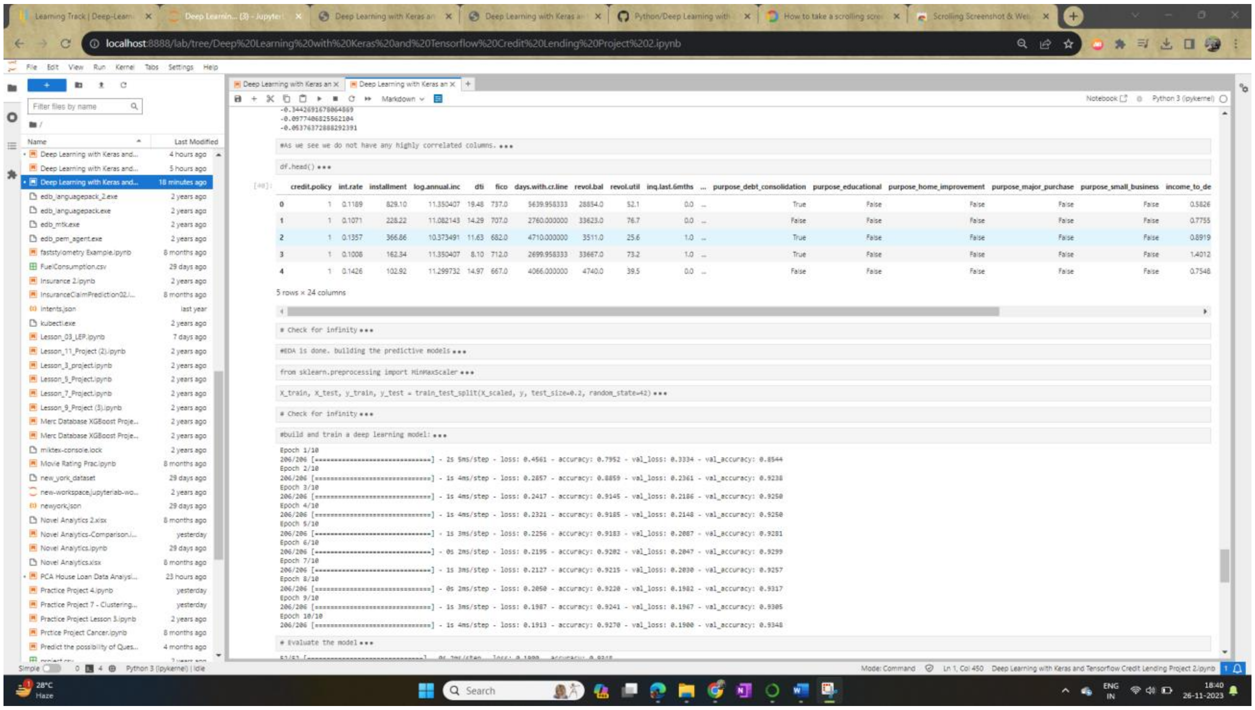
min 612.000000 178.958333 0.000000 0.000000
25% 682.000000 2790.000000 3109.000000 22.600000
50% 707.000000 4109.020834 8372.000000 46.300000
75% 737.000000 5640.041667 17524.000000 70.900000
max 822.000000 12033.000000 117814.000000 119.000000
inq.last.6mths delinq.2yrs pub.rec not.fully.paid
count 9437.000000 9290.000000 9019.0 9578.000000
mean 1.417612 0.089559 0.0 0.160054
std 1.685511 0.285564 0.0 0.366676
min 0.000000 0.000000 0.0 0.000000
25% 0.000000 0.000000 0.0 0.000000
50% 1.000000 0.000000 0.0 0.000000
75% 2.000000 0.000000 0.0 0.000000
max 8.000000 1.000000 0.0 1.000000
Plot histograms for each variable •••
credit.policy
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

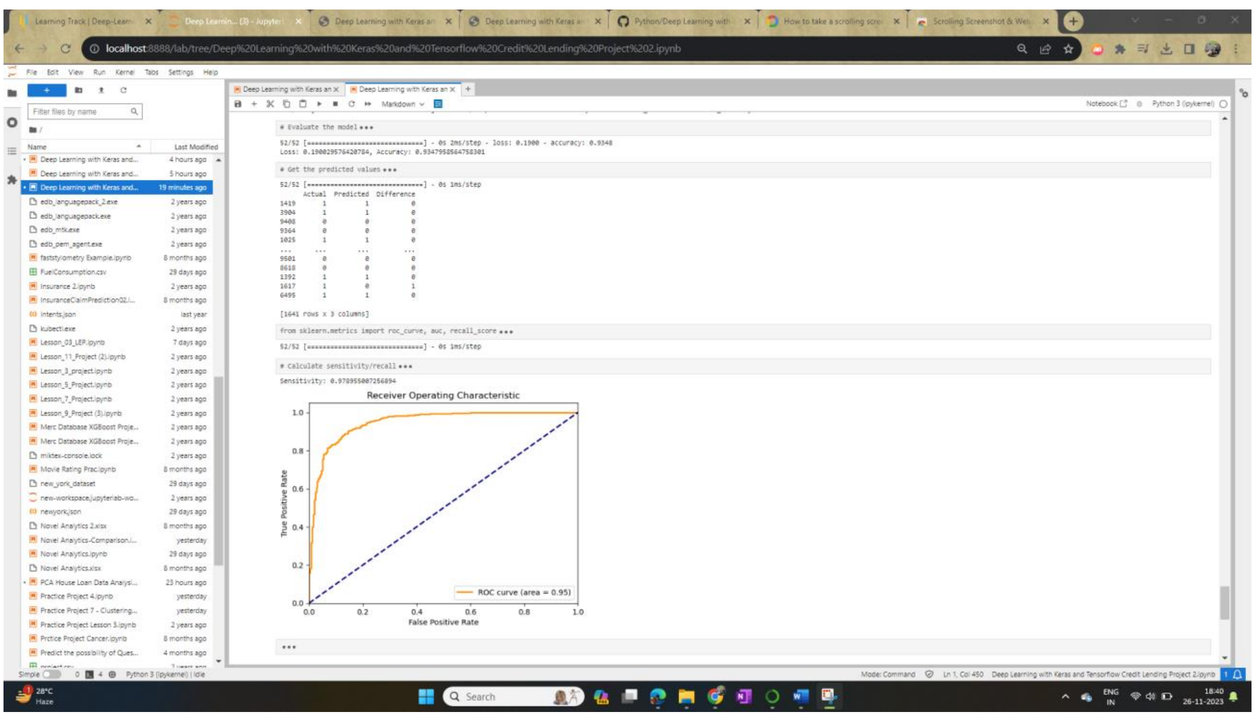


localhost:8888/lab/tree/Deep%20Learning%20with%20Keras%20and%20Tensorflow%20Credit%20Lending%20Project%202.ipynb
Select columns containing categorical data
Categorical columns in the DataFrame:
purpose
Unique values in each categorical column:
purpose: ['debt_consolidation' 'credit_card' 'all_other' 'home_improvement' 'small_business' 'major_purchase' 'educational']
We'll convert the categorical variables into dummy variables: Using one-hot encoding
df = pd.get_dummies(df, drop_first=True)
Feature engineering. feature engineering is an iterative and experimental process guided by trying out different ideas and checking if they improve your model's performance.
1. Interaction Features: You can create new features that are interactions of existing features. 'income_to_debt' which is the ratio of 'log.annual.inc' to 'dti'.
df['income_to_debt'] = df['log.annual.inc'] / df['dti']
2. Polynomial Features: useful if the relationship between the feature and the target is non-linear.
3. Binning: You can also bin numerical variables to convert them into categorical variables. This is useful for variables like 'fico' where different ranges could have different default probabilities.
4. Feature Scaling: This includes algorithms that use a weighted sum of the input, like linear regression, and algorithms that use distance measures, like k-nearest neighbors. Using MinMaxScalar
#Interaction Features - income_to_debt_ratio
#Have introduced fico_range which is categorical. Need one-hot encoding for that too
Check the updated DataFrame
credit.policy int.rate installment log.annual.inc dti fico \
0 1 0.1189 829.10 11.350407 19.48 737.0
1 1 0.1071 228.22 11.082143 14.29 707.0
2 1 0.1357 366.86 10.373491 11.63 682.0
3 1 0.1008 162.34 11.350407 8.10 712.0
4 1 0.1426 102.92 11.299732 14.97 667.0
days.with.cr.line revol.bal revol.util inq.last.6mths ... \
0 5639.958333 28854.0 52.1 0.0 ...
1 2760.000000 33623.0 76.7 0.0 ...
2 4710.000000 3511.0 25.6 1.0 ...
3 2699.958333 33667.0 73.2 1.0 ...
4 4066.000000 4740.0 39.5 0.0 ...
purpose_home_improvement purpose_major_purchase purpose_small_business \
0 False False False
1 False False False
2 False False False
3 False False False
4 False False False
income_to_debt fico_squared scaled_fico fico_range_Poor \
0 0.582670 543169.0 0.689445 False
1 0.775517 499849.0 -0.101027 False
2 0.891960 465124.0 -0.759754 True
3 1.401285 506944.0 0.030718 False
4 0.754825 444889.0 -1.154991 True
fico_range_Fair fico_range_Good fico_range_Excellent
0 True False False
1 True False False
2 False False False
3 True False False



C:\anaconda3\Lib\site-packages\seaborn\matrix.py:260: FutureWarning: Format strings passed to MaskedConstant are ignored, but in future may error or produce different behavior
annotation = ("{:" + self.fmt + "}").format(val)
credit.policy
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
purpose_credit_card
purpose_debt_consolidation
purpose_educational
purpose_home_improvement
purpose_major_purchase
purpose_small_business
income_to_debt
fico_range_Poor
fico_range_Fair
fico_range_Good
fico_range_Excellent
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6





Embedded File:

Python File:

Deep Learning with
Keras and Tensorflo

Code hosted on GitHub :

https://github.com/Naseha/Python

https://github.com/Naseha/Python/blob/main/Deep%20Learning%20with%20Keras%20and%20Tensorflow%20Credit%20Lending%20Project%202.ipynb

Downloaded pdf Attached:

Deep Learning with
Keras and Tensorflo

https://github.com/Naseha/Python/blob/main/Deep%20Learning%20with%20Keras%20and%20Tensorflow%20Credit%20Lending%20Project%202.pdf

Codes:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

In [ ]:

```
import csv
# csv file name
df = pd.read_csv(r'D:\OneDrive\Knowledge Center\AI - ML\Masters in Artifical Engineer\Deep Learning with Keras and Tensorflow\Notebooks\1585898503_datasets\loan_data.csv')
```

Basic Data Check

In [ ]:

```
# Check the first few rows of the DataFrame
print(df.head())
```

In [ ]:

```
df.head()
```

In [ ]:

```
# Check the summary statistics
print(df.describe())
```

In [ ]:

```
# Check for missing values
```

```
print(df.isnull().sum())
```

No data is missing, there there is no need to fill in with mean or modal data

In [ ]:

```
# Plot histograms for each variable
df.hist(figsize=(10, 10), bins=50)
plt.show()
```

In [ ]:

```
#Checking for outliers
from scipy.stats import zscore

def detect_outliers(data):
    outliers = []
    threshold = 3
    mean = np.mean(data)
    std = np.std(data)

    for i in data:
        z_score = (i - mean) / std
        if np.abs(z_score) > threshold:
            outliers.append(i)
    return outliers
```

In [ ]:

```
def remove_outliers(data):
    threshold = 3
    mean = np.mean(data)
    std = np.std(data)

    for i in data:
        z_score = (i - mean) / std
        if np.abs(z_score) > threshold:
            data = data[data != i]
    return data
```

function calculates the Z-score for each value in the data, and if the Z-score is greater than the specified threshold. The Z-score method of outlier detection uses a threshold, typically of 3 or -3, which corresponds to data points that are 3 standard deviations away from the mean. This is based on the empirical rule or the 68-95-99.7 rule, which states that nearly all data lies within 3 standard deviations of the mean in a normal distribution.Now printing them

In [ ]:

```
for column in df.columns:
    if df[column].dtype in ['int64', 'float64']:
        outliers = detect_outliers(df[column])
        print(f'Outliers in {column}: {outliers}')
        df[column] = remove_outliers(df[column])
```

In [ ]:

```
# Check the summary statistics
print(df.describe())
```

In [ ]:

```
# Plot histograms for each variable
df.hist(figsize=(10, 10), bins=50)
plt.show()
```

In [ ]:

```
# Select columns containing categorical data
categorical_columns = df.select_dtypes(include=['object']).columns

print("Categorical columns in the DataFrame:")
for column in categorical_columns:
    print(column)

print("\nUnique values in each categorical column:")
for column in categorical_columns:
    print(f"{column}: {df[column].unique()}")
```

We’ll convert the categorical variables into dummy variables: Using one-hot encoding

In [ ]:

```
df = pd.get_dummies(df, drop_first=True)
```

Feature engineering. feature engineering is an iterative and experimental process guided by trying out different ideas and checking if they improve your model’s performance.

1. Interaction Features: You can create new features that are interactions of existing features. ‘income_to_debt’ which is the ratio of ‘log.annual.inc’ to ‘dti’.

df['income_to_debt'] = df['log.annual.inc'] / df['dti'] 2. Polynomial Features: useful if the relationship between the feature and the target is non-linear. 3. Binning: You can also bin numerical variables to convert them into categorical variables. This is useful for variables like ‘fico’ where different ranges could have different default probabilities. 4. Feature Scaling: This includes algorithms that use a weighted sum of the input, like linear regression, and algorithms that use distance measures, like k-nearest neighbors. Using MinMaxScalar

In [ ]:

```
#Interaction Features - income_to_debt_ratio
df['income_to_debt'] = df['log.annual.inc'] / df['dti']
#Polynomial Features: - fico
df['fico_squared'] = df['fico'] ** 2
#Binning
df['fico_range'] = pd.cut(df['fico'], bins=[0, 650, 700, 750, 800, 850], labels=['Very Poor', 'Poor', 'Fair', 'Good',
'Excellent'])
#Scalar
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df['scaled_fico'] = scaler.fit_transform(df[['fico']])
```

In [ ]:

```
#Have introduced fico_range which is categorical. Need one-hot encoding for that too
df = pd.get_dummies(df, drop_first=True)
```

In [ ]:

```
# Check the updated DataFrame
print(df.head())
```

In [ ]:

```
import seaborn as sns
# Additional Feature Engineering
# Correlation Matrix
corr_matrix = df.corr()
```

```
# Plotting the correlation matrix
plt.figure(figsize=(12, 12))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.show()
```

In [ ]:

```
#Show higly correlated columns and remove them
columns = np.full((corr_matrix.shape[0],), True, dtype=bool)
for i in range(corr_matrix.shape[0]):
  for j in range(i+1, corr_matrix.shape[0]):
    print(corr_matrix.iloc[i,j])
    if corr_matrix.iloc[i,j] >= 0.9:
      if columns[j]:
        columns[j] = False
selected_columns = df.columns[columns]
df = df[selected_columns]
```

In [ ]:

```
#As we see we do not have any highly correlated columns.
```

In [ ]:

```
df.head()
```

In [ ]:

```
# Check for infinity
if np.any(np.isinf(df)):
  print("DataFrame contains infinity. REmoving them")
  df.replace([np.inf, -np.inf], np.nan, inplace=True)

# Check for NaN
if df.isnull().values.any():
  print("DataFrame contains NaN values. . REmoving them")
  df.dropna(inplace=True)  # drop NaN values
```

In [ ]:

```
#EDA is done. building the predictive models
#Now, let’s split the data into a training set and a test set:
X = df.drop('credit.policy', axis=1)
y = df['credit.policy']
```

In [ ]:

```
from sklearn.preprocessing import MinMaxScaler
# Create a MinMaxScaler object
scaler = MinMaxScaler()
# Fit the scaler to the features and transform
# Fit the scaler to the features and transform
X_scaled = pd.DataFrame(scaler.fit_transform(X), columns=X.columns)
```

In [ ]:

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
```

In [ ]:

```
# Check for infinity
if np.any(np.isinf(X_train)) or np.any(np.isinf(X_test)):
  print("DataFrame contains infinity")
  X_train.replace([np.inf, -np.inf], np.nan, inplace=True)
  X_test.replace([np.inf, -np.inf], np.nan, inplace=True)

# Check for NaN
if X_train.isnull().values.any() or X_test.isnull().values.any():
```

```
    print("DataFrame contains NaN values")
    X_train.dropna(inplace=True)  # drop NaN values
    X_test.dropna(inplace=True)  # drop NaN values
```

In [ ]:

```
#build and train a deep learning model:
model = Sequential()
model.add(Dense(32, activation='relu', input_shape=(X_train.shape[1],)))
model.add(Dense(16, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

history = model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_test, y_test))
```

In [ ]:

```
# Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Loss: {loss}, Accuracy: {accuracy}")
```

In [ ]:

```
# Get the predicted values
y_pred = model.predict(X_test)

# Since the model outputs probabilities, convert probabilities to class labels
y_pred = [1 if prob >= 0.5 else 0 for prob in y_pred]

# Create a DataFrame for comparison
comparison = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})

# Calculate the difference
comparison['Difference'] = comparison['Actual'] - comparison['Predicted']

# Print the DataFrame
print(comparison)
```

In [ ]:

```
from sklearn.metrics import roc_curve, auc, recall_score
import matplotlib.pyplot as plt

# Get the predicted probabilities
y_pred_proba = model.predict(X_test)
```

In [ ]:

```
# Calculate sensitivity/recall
y_pred = [1 if prob >= 0.5 else 0 for prob in y_pred]
sensitivity = recall_score(y_test, y_pred)
print(f'Sensitivity: {sensitivity}')

# Calculate ROC curve (fpr: false positive rate, tpr: true positive rate)
fpr, tpr, _ = roc_curve(y_test, y_pred_proba)

# Calculate AUC (Area Under Curve)
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
```

```
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

In [ ]: