Project to Submit – Project 1

DESCRIPTION

House Loan Data Analysis

Course-end Project 1

Description

For safe and secure lending experience, it's important to analyze the past data. In this project, you have to build a deep learning model to predict the chance of default for future loans using the historical data. As you will see, this dataset is highly imbalanced and includes a lot of features that make this problem more challenging.

Objective: Create a model that predicts whether or not an applicant will be able to repay a loan using historical data.

Domain: Finance

You can download the datasets from here
- https://www.dropbox.com/s/smt43gz12eijbo6/loan_data%20%281%29.csv?dl=0

Write Up:

Analysis Tasks to be performed:

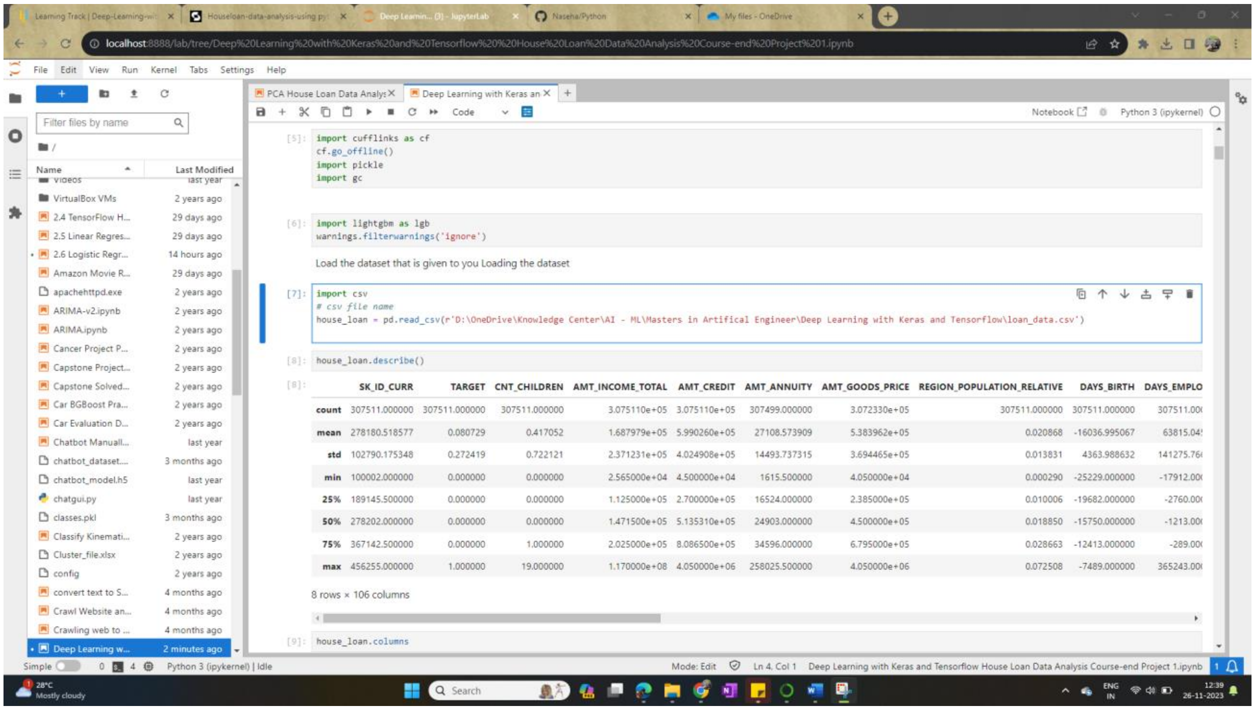
Perform data preprocessing and build a deep learning prediction model.

Steps to be done:

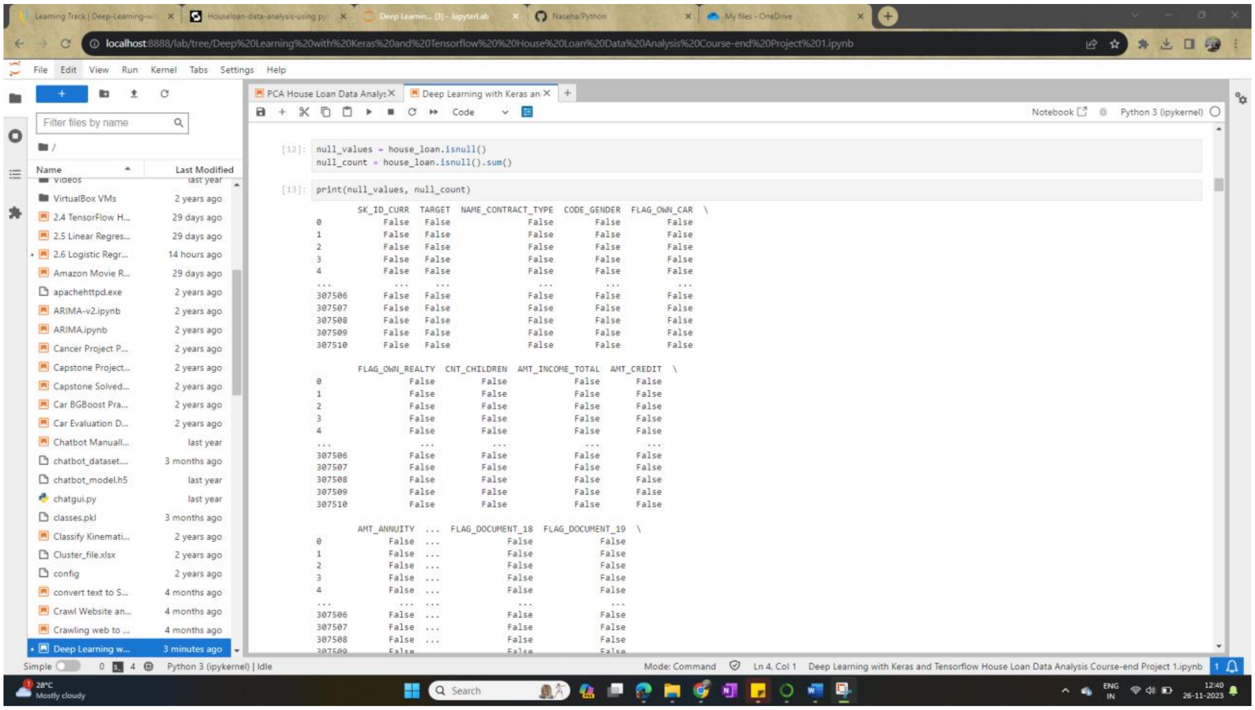
1. • Load the dataset that is given to you
2. • Check for null values in the dataset
3. • Print percentage of default to payer of the dataset for the TARGET column
4. • Balance the dataset if the data is imbalanced
5. • Plot the balanced data or imbalanced data
6. • Encode the columns that is required for the model
7. • Calculate Sensitivity as a metrice
8. • Calculate area under receiver operating characteristics curve

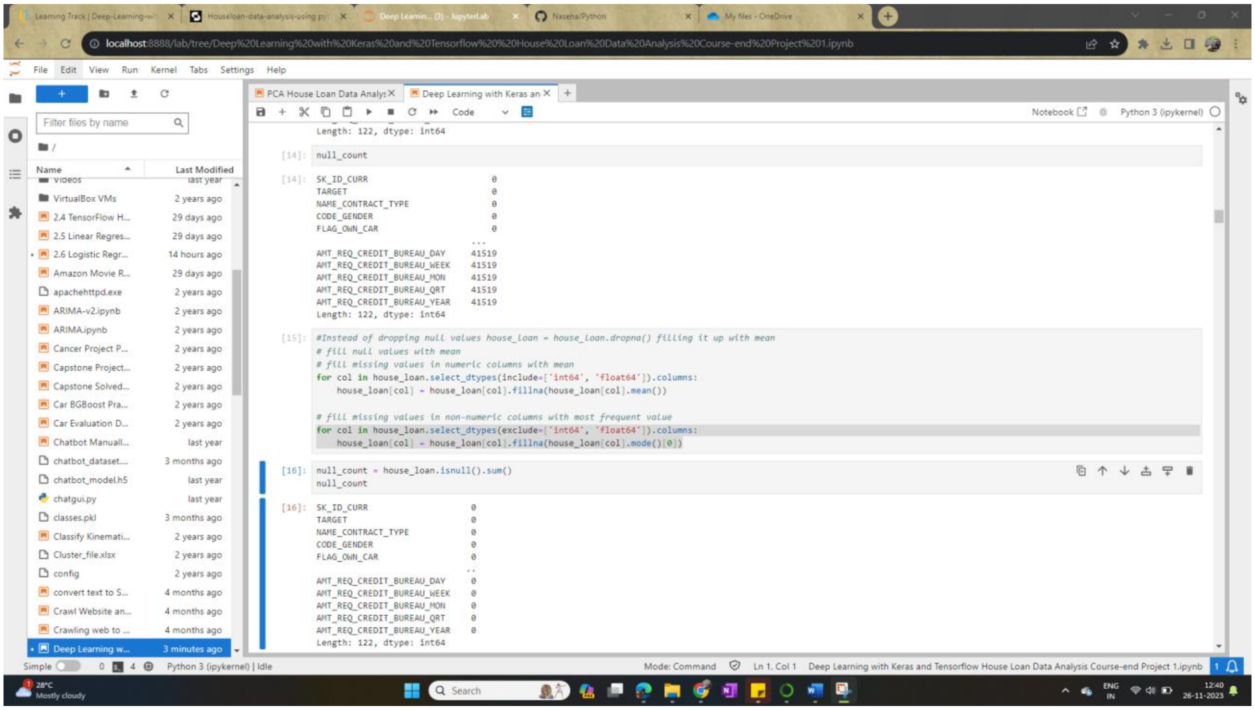
Screenshots

1. Check for null values in the dataset

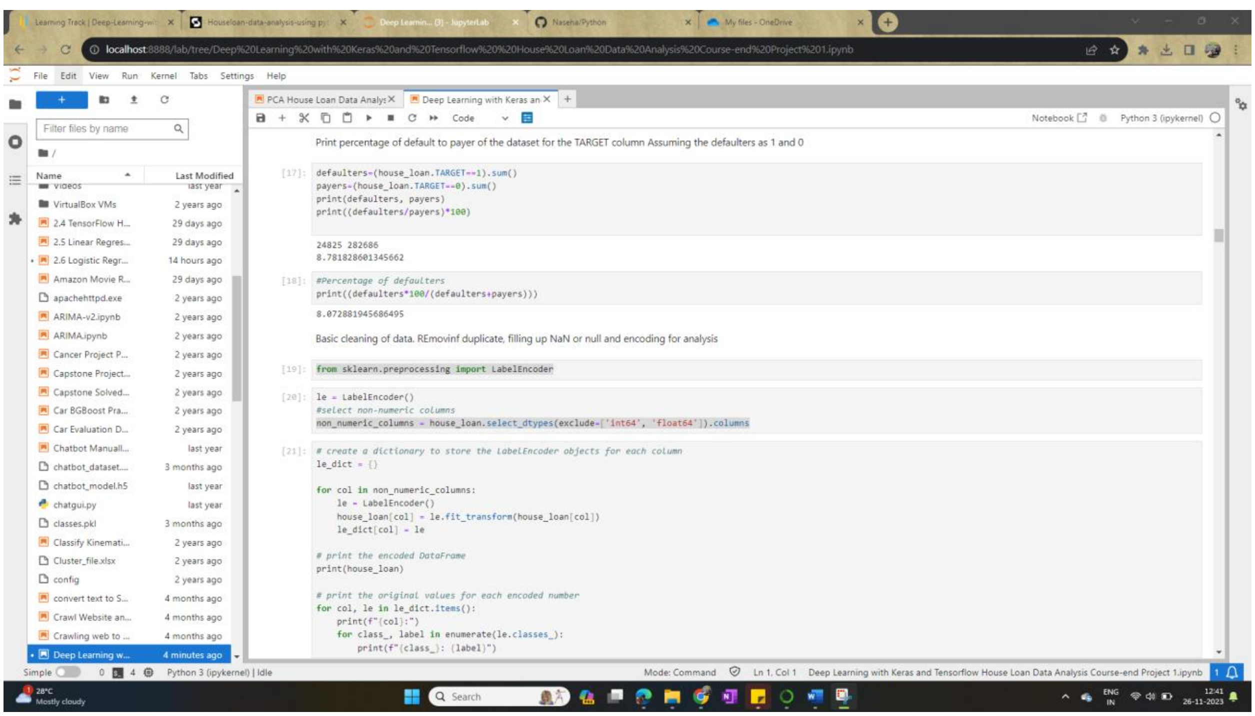


2. Check for null values in the dataset

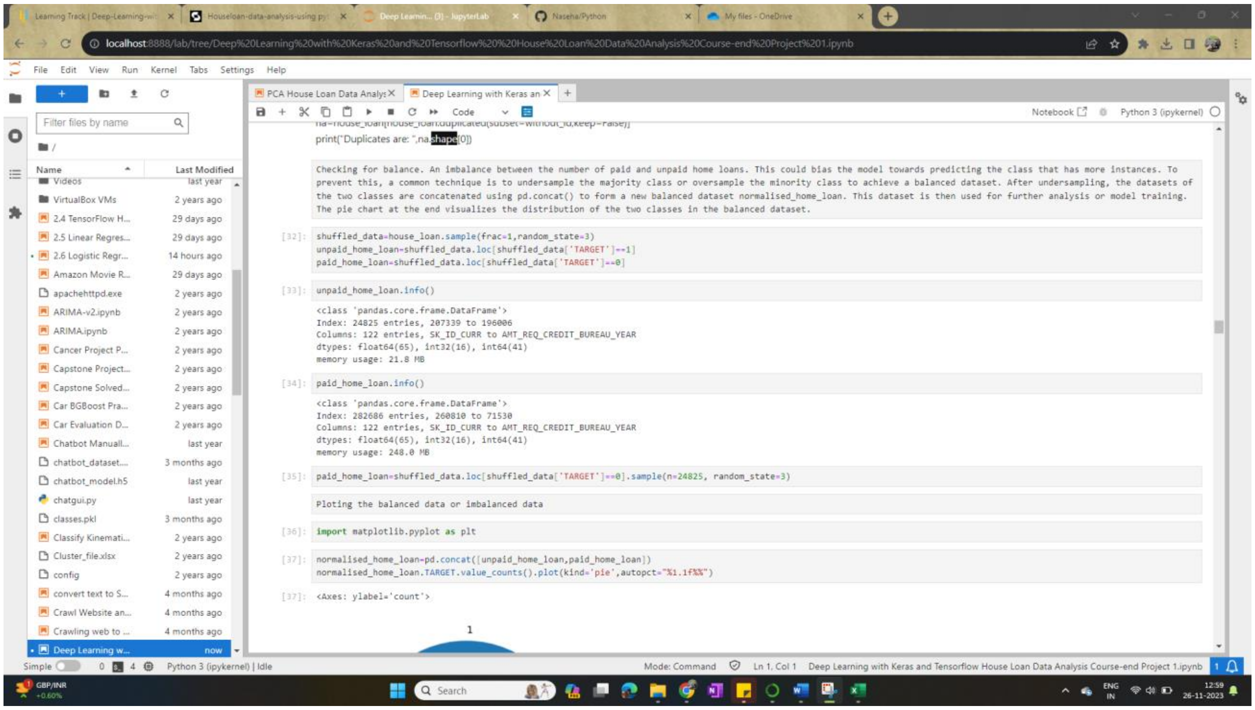




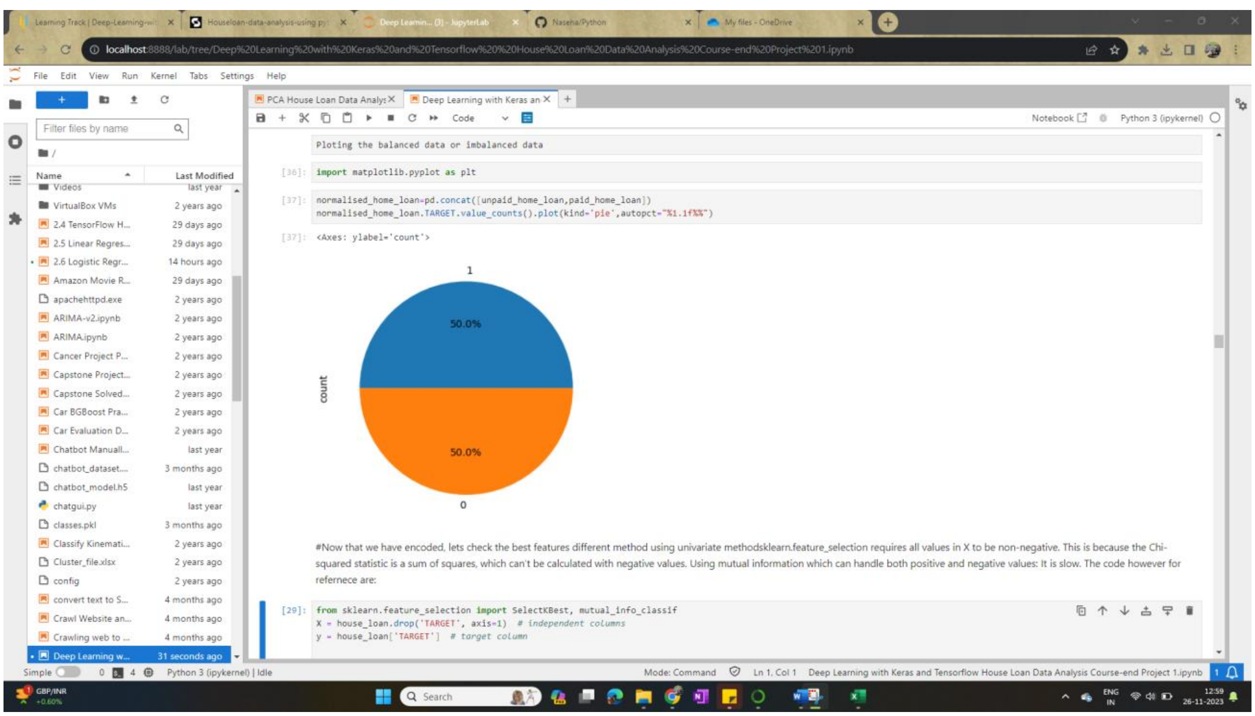
3. • Print percentage of default to payer of the dataset for the TARGET column



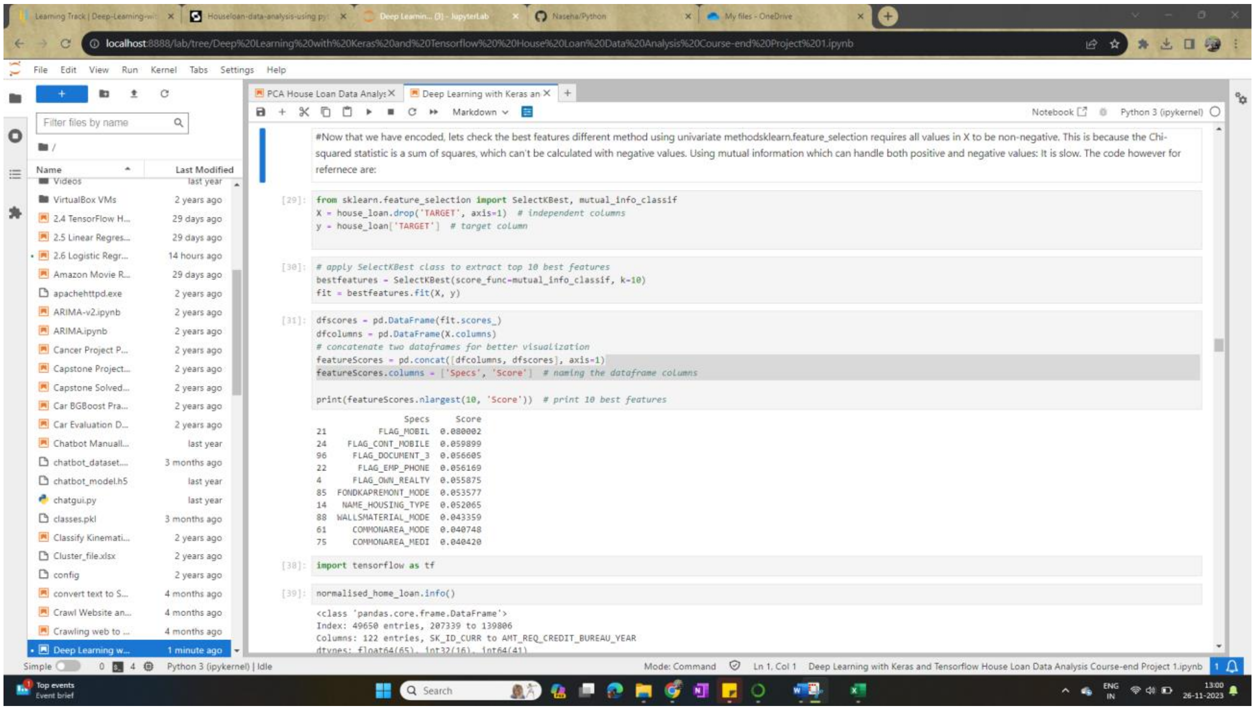
4. • Balance the dataset if the data is imbalanced



5. • Plot the balanced data or imbalanced data



6. • Encode the columns that is required for the model



#Now that we have encoded, lets check the best features different method using univariate methodsklearn.feature_selection requires all values in X to be non-negative. This is because the Chi-squared statistic is a sum of squares, which can't be calculated with negative values. Using mutual information which can handle both positive and negative values: It is slow. The code however for refernece are:

```
[29]: from sklearn.feature_selection import SelectKBest, mutual_info_classif
      X = house_loan.drop('TARGET', axis=1)  # independent columns
      y = house_loan['TARGET']  # target column
```

```
[30]: # apply SelectKBest class to extract top 10 best features
      bestfeatures = SelectKBest(score_func=mutual_info_classif, k=10)
      fit = bestfeatures.fit(X, y)
```

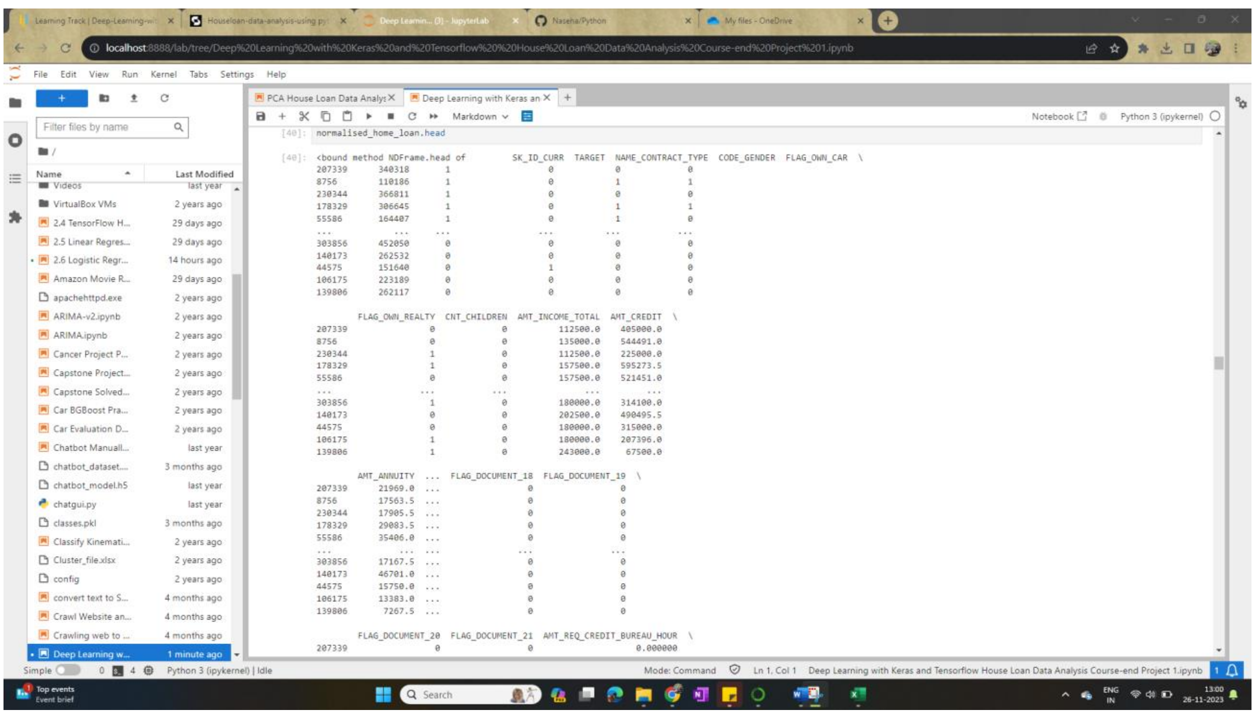
```
[31]: dfscores = pd.DataFrame(fit.scores_)
      dfcolumns = pd.DataFrame(X.columns)
      # concatenate two dataframes for better visualization
      featureScores = pd.concat([dfcolumns, dfscores], axis=1)
      featureScores.columns = ['Specs', 'Score']  # naming the dataframe columns

      print(featureScores.nlargest(10, 'Score'))  # print 10 best features
```

```
                  Specs     Score
21           FLAG_MOBIL  0.080002
24     FLAG_CONT_MOBILE  0.059899
96      FLAG_DOCUMENT_3  0.056605
22       FLAG_EMP_PHONE  0.056169
4       FLAG_OWN_REALTY  0.055875
85   FONDKAPREMONT_MODE  0.053577
14    NAME_HOUSING_TYPE  0.052065
88   WALLSMATERIAL_MODE  0.043359
61       COMMONAREA_MODE  0.040748
75       COMMONAREA_MEDI  0.040420
```

```
[38]: import tensorflow as tf
```

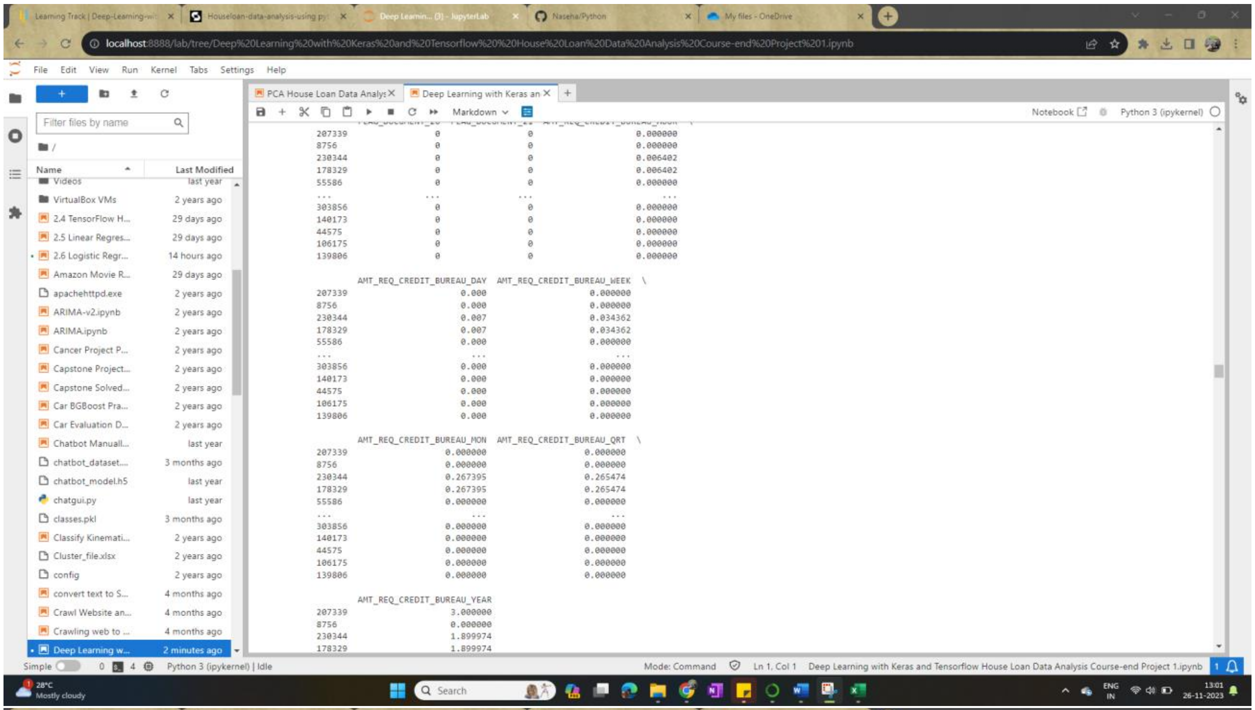
```
[39]: normalised_home_loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 49650 entries, 207339 to 139806
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int32(16), int64(41)
```

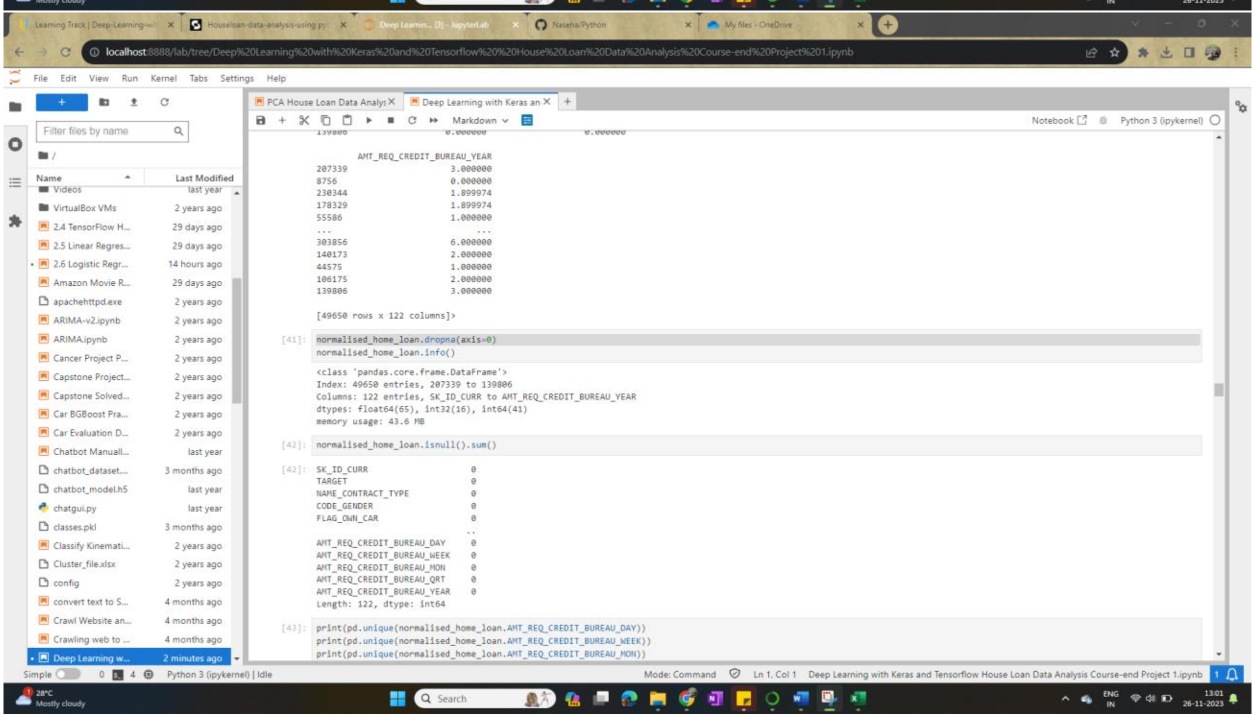


```
[40]: normalised_home_loan.head
```

```
[40]: <bound method NDFrame.head of         SK_ID_CURR  TARGET  NAME_CONTRACT_TYPE  CODE_GENDER  FLAG_OWN_CAR  \
207339      340318       1                   0            0             0
8756        110186       1                   0            1             1
230344      366811       1                   0            0             0
178329      306645       1                   0            1             1
55586       164407       1                   0            1             0
...            ...     ...                 ...          ...           ...
303856      452050       0                   0            0             0
140173      262532       0                   0            0             0
44575       151640       0                   1            0             0
106175      223189       0                   0            0             0
139806      262117       0                   0            0             0

        FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
207339                0             0          112500.0    405000.0
8756                  0             0          135000.0    544491.0
230344                1             0          112500.0    225000.0
178329                1             0          157500.0    595273.5
55586                 0             0          157500.0    521451.0
...                 ...           ...               ...         ...
303856                1             0          180000.0    314100.0
140173                0             0          202500.0    490495.5
44575                 0             0          180000.0    315000.0
106175                1             0          180000.0    207396.0
139806                1             0          243000.0     67500.0

        AMT_ANNUITY  ...  FLAG_DOCUMENT_18  FLAG_DOCUMENT_19  \
207339      21969.0  ...                 0                 0
8756        17563.5  ...                 0                 0
230344      17905.5  ...                 0                 0
178329      29083.5  ...                 0                 0
55586       35406.0  ...                 0                 0
...             ...  ...               ...               ...
303856      17167.5  ...                 0                 0
140173      46701.0  ...                 0                 0
44575       15750.0  ...                 0                 0
106175      13383.0  ...                 0                 0
139806       7267.5  ...                 0                 0

        FLAG_DOCUMENT_20  FLAG_DOCUMENT_21  AMT_REQ_CREDIT_BUREAU_HOUR  \
207339                 0                 0                    0.000000
```



```
        FLAG_DOCUMENT_20  FLAG_DOCUMENT_21  AMT_REQ_CREDIT_BUREAU_HOUR  \
207339                 0                 0                    0.000000
8756                   0                 0                    0.000000
230344                 0                 0                    0.006402
178329                 0                 0                    0.006402
55586                  0                 0                    0.000000
...                  ...               ...                         ...
303856                 0                 0                    0.000000
140173                 0                 0                    0.000000
44575                  0                 0                    0.000000
106175                 0                 0                    0.000000
139806                 0                 0                    0.000000

        AMT_REQ_CREDIT_BUREAU_DAY  AMT_REQ_CREDIT_BUREAU_WEEK  \
207339                      0.000                    0.000000
8756                        0.000                    0.000000
230344                      0.007                    0.034362
178329                      0.007                    0.034362
55586                       0.000                    0.000000
...                           ...                         ...
303856                      0.000                    0.000000
140173                      0.000                    0.000000
44575                       0.000                    0.000000
106175                      0.000                    0.000000
139806                      0.000                    0.000000

        AMT_REQ_CREDIT_BUREAU_MON  AMT_REQ_CREDIT_BUREAU_QRT  \
207339                   0.000000                   0.000000
8756                     0.000000                   0.000000
230344                   0.267395                   0.265474
178329                   0.267395                   0.265474
55586                    0.000000                   0.000000
...                           ...                        ...
303856                   0.000000                   0.000000
140173                   0.000000                   0.000000
44575                    0.000000                   0.000000
106175                   0.000000                   0.000000
139806                   0.000000                   0.000000

        AMT_REQ_CREDIT_BUREAU_YEAR
207339                    3.000000
8756                      0.000000
230344                    1.899974
178329                    1.899974
```



```
        AMT_REQ_CREDIT_BUREAU_YEAR
207339                    3.000000
8756                      0.000000
230344                    1.899974
178329                    1.899974
55586                     1.000000
...                            ...
303856                    6.000000
140173                    2.000000
44575                     1.000000
106175                    2.000000
139806                    3.000000

[49650 rows x 122 columns]>
```

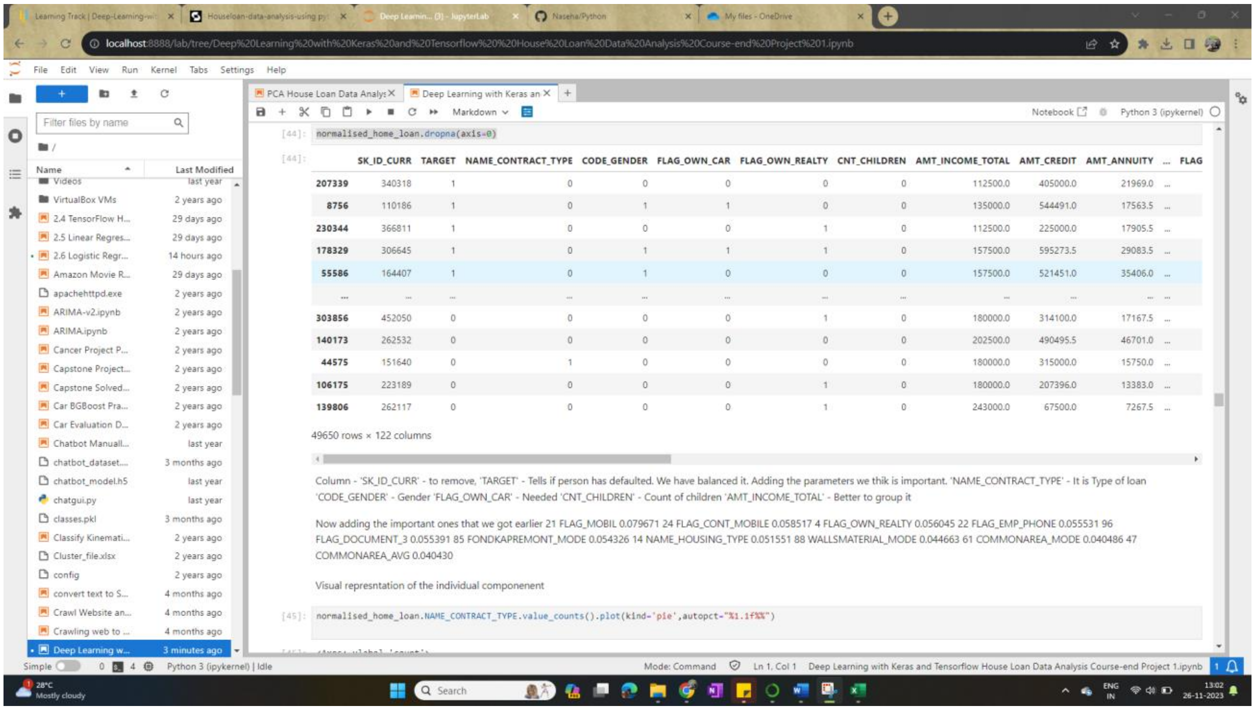
[41]:
```python
normalised_home_loan.dropna(axis=0)
normalised_home_loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 49650 entries, 207339 to 139806
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int32(16), int64(41)
memory usage: 43.6 MB
```

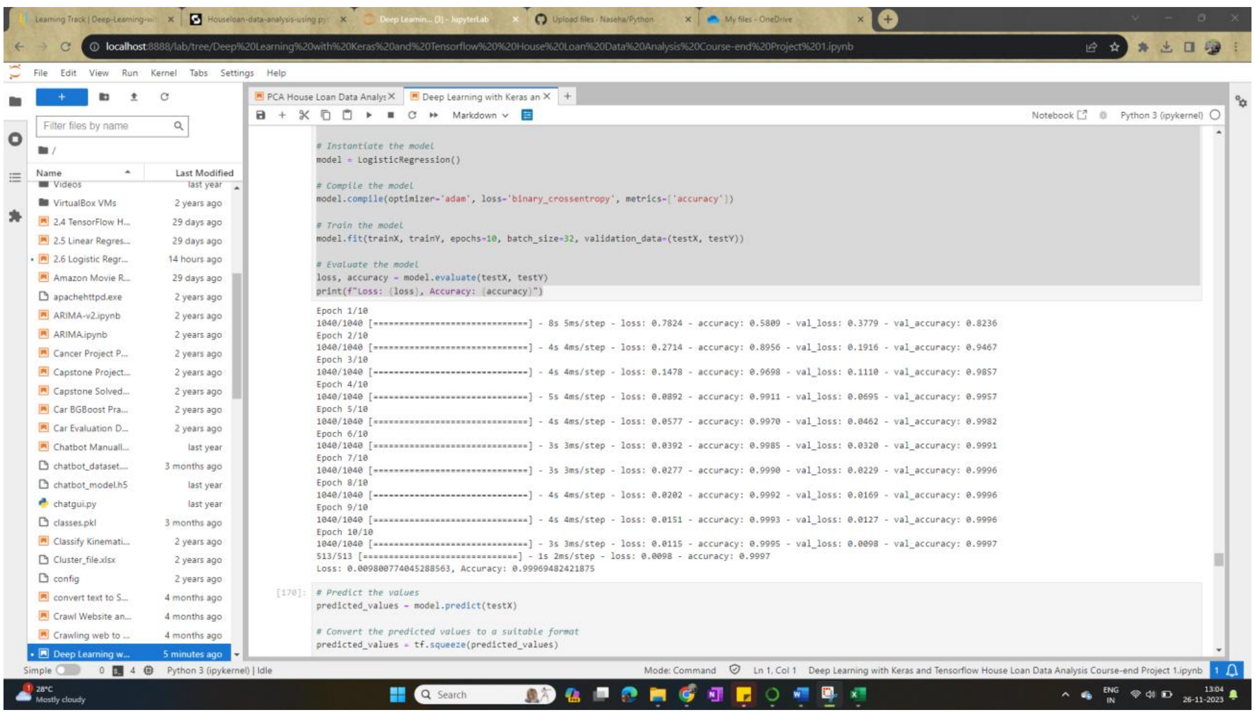
[42]:
```python
normalised_home_loan.isnull().sum()
```

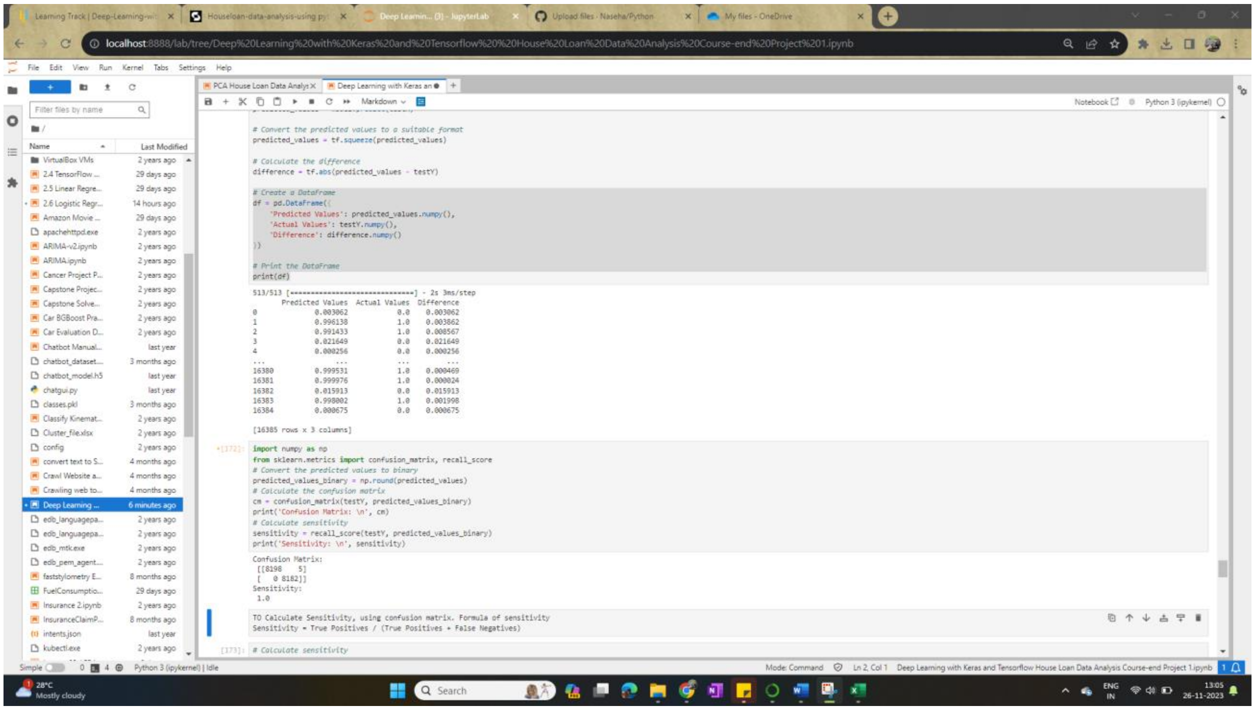
[42]:
```
SK_ID_CURR                    0
TARGET                        0
NAME_CONTRACT_TYPE            0
CODE_GENDER                   0
FLAG_OWN_CAR                  0
                             ..
AMT_REQ_CREDIT_BUREAU_DAY     0
AMT_REQ_CREDIT_BUREAU_WEEK    0
AMT_REQ_CREDIT_BUREAU_MON     0
AMT_REQ_CREDIT_BUREAU_QRT     0
AMT_REQ_CREDIT_BUREAU_YEAR    0
Length: 122, dtype: int64
```

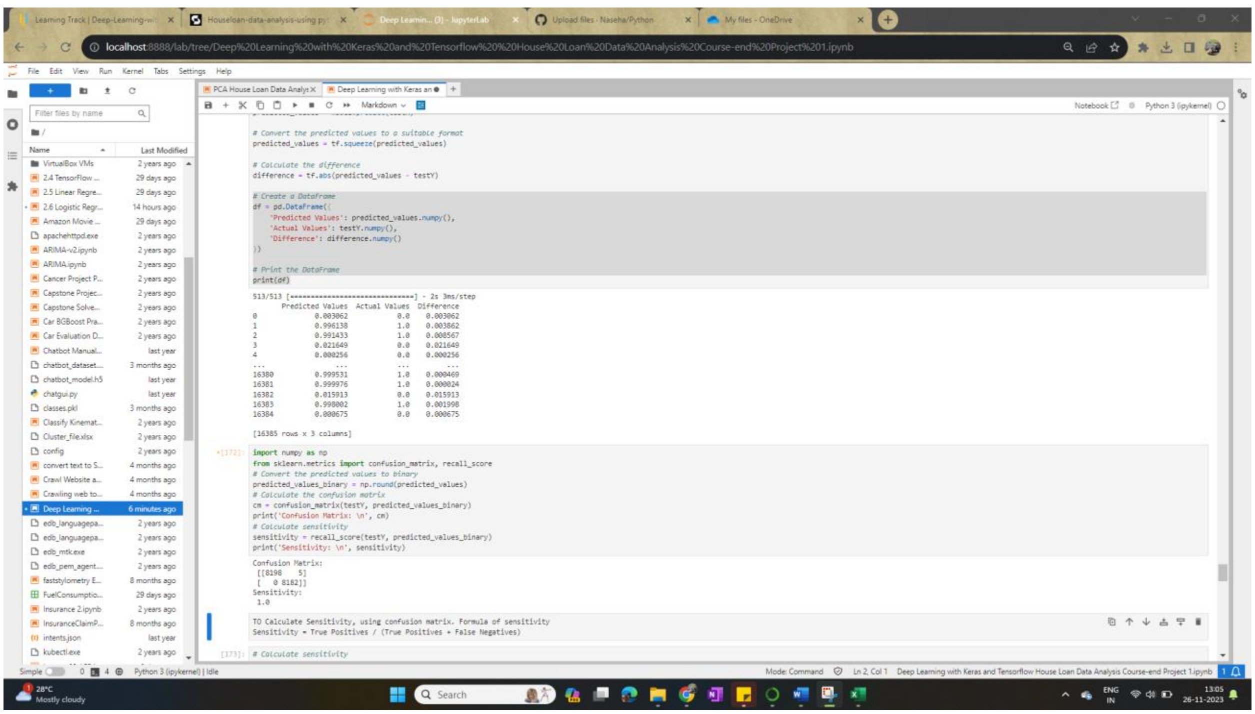
[43]:
```python
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_DAY))
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_WEEK))
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_MON))
```



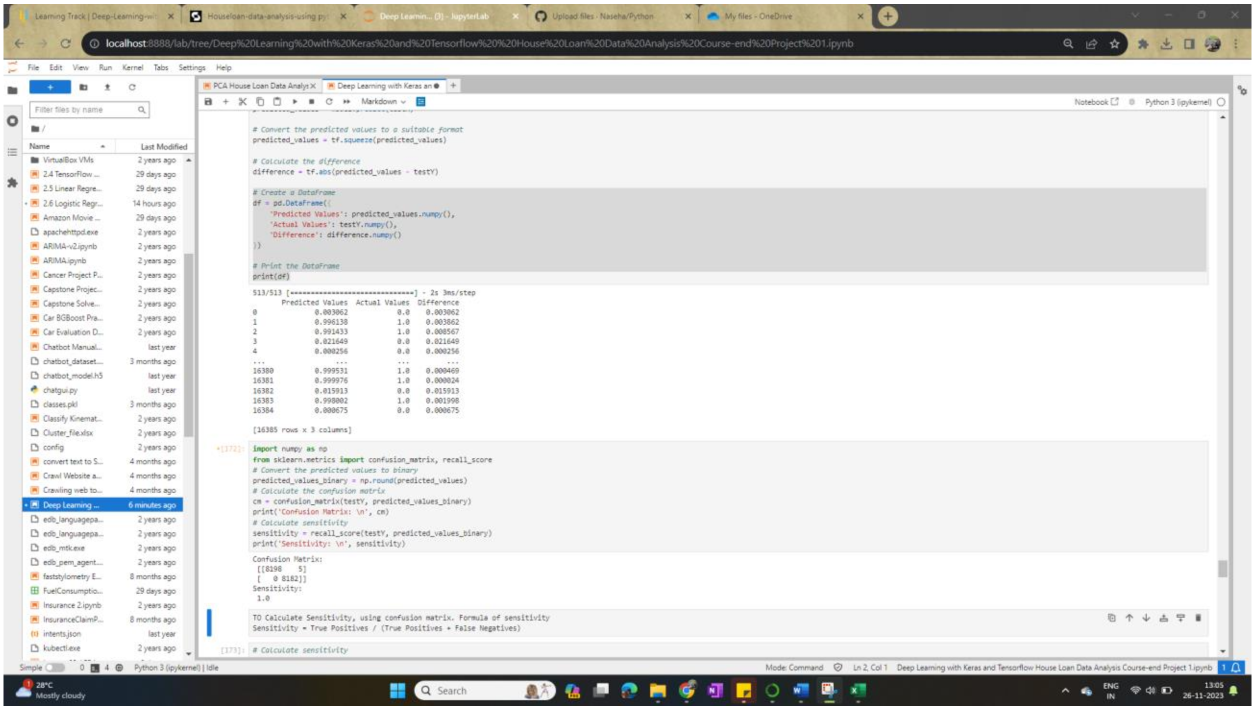
7. • Calculate Sensitivity as a metrice







8. • Calculate area under receiver operating characteristics curve



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%20%20House%20Loan%20Data%20Analysis%20Course-end%20Project%201.ipynb

Downloaded pdf Attached:

Deep Learning with Keras and Tensorflo

https://github.com/Naseha/Python/blob/main/Deep%20Learning%20with%20Keras%20and%20Tensorflow%20House%20Loan%20Data%20Analysis%20Course-end%20Project%201.pdf

Codes:

Deep Learning with Keras and Tensorflow

House Loan Data Analysis Course-end Project 1

For safe and secure lending experience, it's important to analyze the past data. In this project, you have to build a deep learning model to predict the chance of default for future loans using the historical data. As you will see, this dataset is highly imbalanced and includes a lot of features that make this problem more challenging.

Objective: Create a model that predicts whether or not an applicant will be able to repay a loan using historical data.

Domain: Finance

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

In [ ]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
```

In [ ]:

```
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
  for filename in filenames:
    print(os.path.join(dirname, filename))
```

In [ ]:

```
import pandas as pd
import sklearn
import numpy as np
import matplotlib.pyplot as plt
import os
import warnings
import seaborn as sns
from sklearn.preprocessing import OneHotEncoder
from sklearn.datasets import make_blobs
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler
from sklearn.svm import LinearSVC
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import confusion_matrix
from sklearn.ensemble import RandomForestClassifier
```

In console type

Adding Path setx PATH "%PATH%;C:\path\to\Anaconda3\" conda update conda pip install plotly pip install --upgrade pip on terminal

conda install -c conda-forge cufflinks-py pip install lightgbm

In [ ]:

```
from sklearn.metrics import accuracy_score
from sklearn.linear_model import SGDClassifier
import plotly.offline as py
import plotly.graph_objs as go
from plotly.offline import init_notebook_mode, iplot
from sklearn.model_selection import train_test_split
init_notebook_mode(connected=True)
```

In [ ]:

```
import cufflinks as cf
cf.go_offline()
import pickle
import gc
```

In [ ]:

```
import lightgbm as lgb
warnings.filterwarnings('ignore')
```

Load the dataset that is given to you Loading the dataset

In [ ]:

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

In [ ]:

```
house_loan.describe()
```

In [ ]:

```
house_loan.columns
```

In [ ]:

```
print(house_loan.head())
```

In [ ]:

```
house_loan.info()
```

Check for null values in the dataset

In [ ]:

```
null_values = house_loan.isnull()
null_count = house_loan.isnull().sum()
```

In [ ]:

```
print(null_values, null_count)
```

In [ ]:

```
null_count
```

In [ ]:

```
#Instead of dropping null values house_loan = house_loan.dropna() filling it up with mean
# fill null values with mean
# fill missing values in numeric columns with mean
for col in house_loan.select_dtypes(include=['int64', 'float64']).columns:
   house_loan[col] = house_loan[col].fillna(house_loan[col].mean())
```

```
# fill missing values in non-numeric columns with most frequent value
for col in house_loan.select_dtypes(exclude=['int64', 'float64']).columns:
    house_loan[col] = house_loan[col].fillna(house_loan[col].mode()[0])
```

In [ ]:

```
null_count = house_loan.isnull().sum()
null_count
```

Print percentage of default to payer of the dataset for the TARGET column Assuming the defaulters as 1 and 0

In [ ]:

```
defaulters=(house_loan.TARGET==1).sum()
payers=(house_loan.TARGET==0).sum()
print(defaulters, payers)
print((defaulters/payers)*100)
```

In [ ]:

```
#Percentage of defaulters
print((defaulters*100/(defaulters+payers)))
```

Basic cleaning of data. REmovinf duplicate, filling up NaN or null and encoding for analysis

In [ ]:

```
from sklearn.preprocessing import LabelEncoder
```

In [ ]:

```
le = LabelEncoder()
#select non-numeric columns
non_numeric_columns = house_loan.select_dtypes(exclude=['int64', 'float64']).columns
```

In [ ]:

```
# create a dictionary to store the LabelEncoder objects for each column
le_dict = {}

for col in non_numeric_columns:
    le = LabelEncoder()
    house_loan[col] = le.fit_transform(house_loan[col])
    le_dict[col] = le

# print the encoded DataFrame
print(house_loan)

# print the original values for each encoded number
for col, le in le_dict.items():
    print(f"{col}:")
    for class_, label in enumerate(le.classes_):
        print(f"{class_}: {label}")
```

Anotehr method # create a label (category) encoder object fit and transform the non-numeric columns in the DataFrame house_loan[non_numeric_columns] = house_loan[non_numeric_columns].apply(le.fit_transform) print(house_loan)

Balance the dataset if the data is imbalanced The autogenerated column is SK_ID_CURR Checking and removing duplicate entries

In [ ]:

```
house_loan.TARGET.value_counts().plot(kind='pie',autopct='%1.1f%%')
```

```
without_id=[column for column in house_loan.columns if column!='SK_ID_CURR']
na=house_loan[house_loan.duplicated(subset=without_id,keep=False)]
print("Duplicates are: ",na.shape[0])
house_loan.TARGET.value_counts().plot(kind='pie',autopct='%1.1f%%') without_id=[column for column in house_loan.columns if column!='SK_ID_CURR']
na=house_loan[house_loan.duplicated(subset=without_id,keep=False)]
print("Duplicates are: ",na.shape[0])
```

Checking for balance. An imbalance between the number of paid and unpaid home loans. This could bias the model towards predicting the class that has more instances. To prevent this, a common technique is to undersample the majority class or oversample the minority class to achieve a balanced dataset. After undersampling, the datasets of the two classes are concatenated using pd.concat() to form a new balanced dataset normalised_home_loan. This dataset is then used for further analysis or model training. The pie chart at the end visualizes the distribution of the two classes in the balanced dataset.

In [ ]:

```
shuffled_data=house_loan.sample(frac=1,random_state=3)
unpaid_home_loan=shuffled_data.loc[shuffled_data['TARGET']==1]
paid_home_loan=shuffled_data.loc[shuffled_data['TARGET']==0]
```

In [ ]:

```
unpaid_home_loan.info()
```

In [ ]:

```
paid_home_loan.info()
```

In [ ]:

```
paid_home_loan=shuffled_data.loc[shuffled_data['TARGET']==0].sample(n=24825, random_state=3)
```

Ploting the balanced data or imbalanced data

In [ ]:

```
import matplotlib.pyplot as plt
```

In [ ]:

```
normalised_home_loan=pd.concat([unpaid_home_loan,paid_home_loan])
normalised_home_loan.TARGET.value_counts().plot(kind='pie',autopct="%1.1f%%")
```

Code

Now that we have encoded, lets check the best features different method

using univariate methodsklearn.feature_selection requires all values in X to be non-negative. This is because the Chi-squared statistic is a sum of squares, which can’t be calculated with negative values. Using mutual information which can handle both positive and negative values: It is slow. The code however for refernece are:

In [ ]:

```
from sklearn.feature_selection import SelectKBest, mutual_info_classif
X = house_loan.drop('TARGET', axis=1)  # independent columns
y = house_loan['TARGET']  # target column
```

In [ ]:

```
# apply SelectKBest class to extract top 10 best features
bestfeatures = SelectKBest(score_func=mutual_info_classif, k=10)
fit = bestfeatures.fit(X, y)
```

In [ ]:

```
dfscores = pd.DataFrame(fit.scores_)
dfcolumns = pd.DataFrame(X.columns)
# concatenate two dataframes for better visualization
featureScores = pd.concat([dfcolumns, dfscores], axis=1)
featureScores.columns = ['Specs', 'Score']  # naming the dataframe columns

print(featureScores.nlargest(10, 'Score'))  # print 10 best features
```

In [ ]:

```
import tensorflow as tf
```

In [ ]:

```
normalised_home_loan.info()
```

In [ ]:

```
normalised_home_loan.head
```

In [ ]:

```
normalised_home_loan.dropna(axis=0)
normalised_home_loan.info()
```

In [ ]:

```
normalised_home_loan.isnull().sum()
```

In [ ]:

```
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_DAY))
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_WEEK))
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_MON))
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_QRT))
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_YEAR))
```

In [ ]:

```
normalised_home_loan.dropna(axis=0)
```

Column - 'SK_ID_CURR' - to remove, 'TARGET' - Tells if person has defaulted. We have balanced it. Adding the parameters we thik is important. 'NAME_CONTRACT_TYPE' - It is Type of loan 'CODE_GENDER' - Gender 'FLAG_OWN_CAR' - Needed 'CNT_CHILDREN' - Count of children 'AMT_INCOME_TOTAL' - Better to group it

Now adding the important ones that we got earlier 21 FLAG_MOBIL 0.079671 24 FLAG_CONT_MOBILE 0.058517 4 FLAG_OWN_REALTY 0.056045 22 FLAG_EMP_PHONE 0.055531 96 FLAG_DOCUMENT_3 0.055391 85 FONDKAPREMONT_MODE 0.054326 14 NAME_HOUSING_TYPE 0.051551 88 WALLSMATERIAL_MODE 0.044663 61 COMMONAREA_MODE 0.040486 47 COMMONAREA_AVG 0.040430

Visual represntation of the individual componenent

In [ ]:

```
normalised_home_loan.NAME_CONTRACT_TYPE.value_counts().plot(kind='pie',autopct="%1.1f%%")
```

In [ ]:

```
normalised_home_loan.CODE_GENDER.value_counts().plot(kind='pie',autopct="%1.1f%%")
```

In [ ]:

```
normalised_home_loan.FLAG_OWN_CAR.value_counts().plot(kind='pie',autopct="%1.1f%%")
```

In [ ]:

```
normalised_home_loan.CNT_CHILDREN.value_counts().plot(kind='pie',autopct="%1.1f%%")
```

In [ ]:

```
normalised_home_loan.AMT_INCOME_TOTAL.value_counts().plot(kind='pie',autopct="%1.1f%%")
```
In [ ]:

```
normalised_home_loan.AMT_INCOME_TOTAL.value_counts().nlargest(5).plot(kind='pie',
autopct="%1.1f%%")
```
In [ ]:

```
normalised_home_loan.FLAG_MOBIL.value_counts().plot(kind='pie', autopct="%1.1f%%")
```
In [ ]:

```
normalised_home_loan.FLAG_CONT_MOBILE.value_counts().plot(kind='pie', autopct="%1.1f%%")
```
In [ ]:

```
normalised_home_loan.FLAG_OWN_REALTY.value_counts().plot(kind='pie', autopct="%1.1f%%")
```
In [ ]:

```
normalised_home_loan.NAME_HOUSING_TYPE.value_counts().plot(kind='pie', autopct="%1.1f%%")
```
In [ ]:

```
normalised_home_loan.WALLSMATERIAL_MODE.value_counts().plot(kind='pie', autopct="%1.1f%%")
```
In [ ]:

```
normalised_home_loan.COMMONAREA_MODE.value_counts().plot(kind='pie', autopct="%1.1f%%")
```
In [ ]:

```
normalised_home_loan.COMMONAREA_MODE.value_counts().nlargest(5).plot(kind='pie',
autopct="%1.1f%%")
```
In [ ]:

```
normalised_home_loan.COMMONAREA_AVG.value_counts().nlargest(5).plot(kind='pie', autopct="%1.1f%%")
```
The columns we have selected 'NAME_CONTRACT_TYPE' - It is Type of loan 'CODE_GENDER' - Gender 'FLAG_OWN_CAR' - 'CNT_CHILDREN' - Count of children 'AMT_INCOME_TOTAL' - top categories

Now adding the important ones that we got earlier FLAG_CONT_MOBILE If they have mobile FLAG_OWN_REALTY - If they have real estate NAME_HOUSING_TYPE - type of house WALLSMATERIAL_MODE - walls type COMMONAREA_MODE - common area type COMMONAREA_AVG - avg common area

In [ ]:

```
normalised_home_loan_features=['SK_ID_CURR','NAME_CONTRACT_TYPE','CNT_CHILDREN',
'AMT_INCOME_TOTAL', 'FLAG_CONT_MOBILE', 'FLAG_OWN_REALTY', 'NAME_HOUSING_TYPE',
'WALLSMATERIAL_MODE', 'COMMONAREA_MODE', 'COMMONAREA_AVG']
```
In [ ]:

```
normalised_home_loan_features
```
To start calculating sensitivity Sensitivity is a measure of the proportion of actual positive cases that got predicted as positive (or, how many of the true positives were recalled). So, high Sensitivity means that the model predicted the positive cases very well

In [ ]:

```
from sklearn.model_selection import train_test_split
X=normalised_home_loan[normalised_home_loan_features]
```
In [ ]:

```
X
```

setting up parameters blobs_random_seed = 42: This sets the seed for the random number generator to 42. centers = [(0,0), (5,5)] - defines centers. In this case, there will be two clusters: one centered at (0,0) and the other at (5,5). cluster_std = 1: This sets the standard deviation of the clusters. A higher value will make the clusters more spread out. frac_test_split = 0.33: This is likely the fraction of the data that will be used for the test set in a train/test split. num_features_for_samples = 2: This is the number of features for each sample in the synthetic dataset. In this case, each sample will have two features.num_samples_total = 49650: This is the total number of samples in the synthetic dataset. See from above.

In [ ]:

```
X_train, X_test, y_train, y_test = train_test_split(inputs, targets, test_size=0.33, random_state=42)
```

In [ ]:

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

In [ ]:

```
#Since the target variable is of categorical data (either default or not), using logistic regression
```

In [ ]:

```
trainX = tf.constant(X_train, dtype='float32')
trainY = tf.constant(y_train, dtype='float32')
testX = tf.constant(X_test, dtype='float32')
testY = tf.constant(y_test, dtype='float32')
```

In [ ]:

```
# Assuming your data has 'n' features
n = trainX.shape[1]

# Create a variable for weights
weights = tf.Variable(tf.random.normal(shape=(n, 1), dtype='float32'))

# Create a variable for biases
bias = tf.Variable(tf.zeros(shape=(1,), dtype='float32'))
```

In [ ]:

```
print(n, weights, bias)
```

In [ ]:

```
import tensorflow as tf

# Define the logistic regression model
class LogisticRegression(tf.keras.Model):
    def __init__(self):
        super(LogisticRegression, self).__init__()
        self.dense = tf.keras.layers.Dense(1, activation='sigmoid')

    def call(self, inputs, training=None, mask=None):
        output = self.dense(inputs)
        return output

# Instantiate the model
model = LogisticRegression()

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

# Train the model
```

```
model.fit(trainX, trainY, epochs=10, batch_size=32, validation_data=(testX, testY))

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

In [ ]:

```
# Predict the values
predicted_values = model.predict(testX)

# Convert the predicted values to a suitable format
predicted_values = tf.squeeze(predicted_values)

# Calculate the difference
difference = tf.abs(predicted_values - testY)

# Create a DataFrame
df = pd.DataFrame({
   'Predicted Values': predicted_values.numpy(),
   'Actual Values': testY.numpy(),
   'Difference': difference.numpy()
})

# Print the DataFrame
print(df)
```

In [ ]:

```
import numpy as np
from sklearn.metrics import confusion_matrix, recall_score
# Convert the predicted values to binary
predicted_values_binary = np.round(predicted_values)
# Calculate the confusion matrix
cm = confusion_matrix(testY, predicted_values_binary)
print('Confusion Matrix: \n', cm)
# Calculate sensitivity
sensitivity = recall_score(testY, predicted_values_binary)
print('Sensitivity: \n', sensitivity)
```

TO Calculate Sensitivity, using confusion matrix. Formula of sensitivity Sensitivity = True Positives / (True Positives + False Negatives)

In [ ]:

```
# Calculate sensitivity
sensitivity = TP / (TP + FN)
print('Sensitivity: ', sensitivity)
print(predicted_labels_np)
print(y_test_np)
```

In [ ]:

```
from sklearn.metrics import roc_auc_score
# Calculate the AUC-ROC
auc_roc = roc_auc_score(testY, predicted_values)
# Print the AUC-ROC
print('AUC-ROC: ', auc_roc)
```

In [ ]:

```python
from sklearn.metrics import roc_curve, auc
# Calculate the ROC curve
fpr, tpr, thresholds = roc_curve(testY, predicted_values)
# Calculate the AUC
roc_auc = auc(fpr, tpr)
# Plot the 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 [ ]:

```python
# Create a new figure
plt.figure()
# Plot a histogram of the actual values
plt.hist(testY, bins=30, alpha=0.5, label='Actual Values')

# Plot a histogram of the predicted values
plt.hist(predicted_values, bins=30, alpha=0.5, label='Predicted Values')

# Add labels and title
plt.xlabel('Values')
plt.ylabel('Frequency')
plt.title('Histogram of Actual vs Predicted Values')
plt.legend()


# Show the plot
plt.show()
```

In [ ]:

```python
from sklearn.metrics import precision_recall_curve
import matplotlib.pyplot as plt

# Calculate precision and recall
precision, recall, _ = precision_recall_curve(testY, predicted_values)

# Plot the precision-recall curve
plt.plot(recall, precision, marker='.')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.show()
```

In [ ]: