Cloud Computing for Data Analysis Final Project

University of North Carolina at Charlotte

Credit Score Classification

Group- 5

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Business scenario overview

- The project addresses the problem of assessing individuals' creditworthiness accurately, helping financial institutions make informed lending decisions.
- Determining the credit worthiness of a individual using advanced machine learning algorithms.
- By developing a machine learning model for credit score classification, it aims to provide an opportunity to improve risk assessment, reduce defaults, and expand access to credit for qualified applicants.

Solution overview

A high-level description

- The scope of this project involves designing and implementing a machine learning model for credit score classification.
- It encompasses data collection, preprocessing, and feature engineering to create a comprehensive dataset for model training.

Design Considerations

- The machine learning model will be selected, trained, and fine-tuned using various algorithms and techniques, with a focus on predictive accuracy and interpretability.
- Additionally, model evaluation and validation will be carried out rigorously to ensure its reliability.
- Integration with relevant AWS services for model deployment, data storage, real-time scoring, and monitoring.

Solution overview

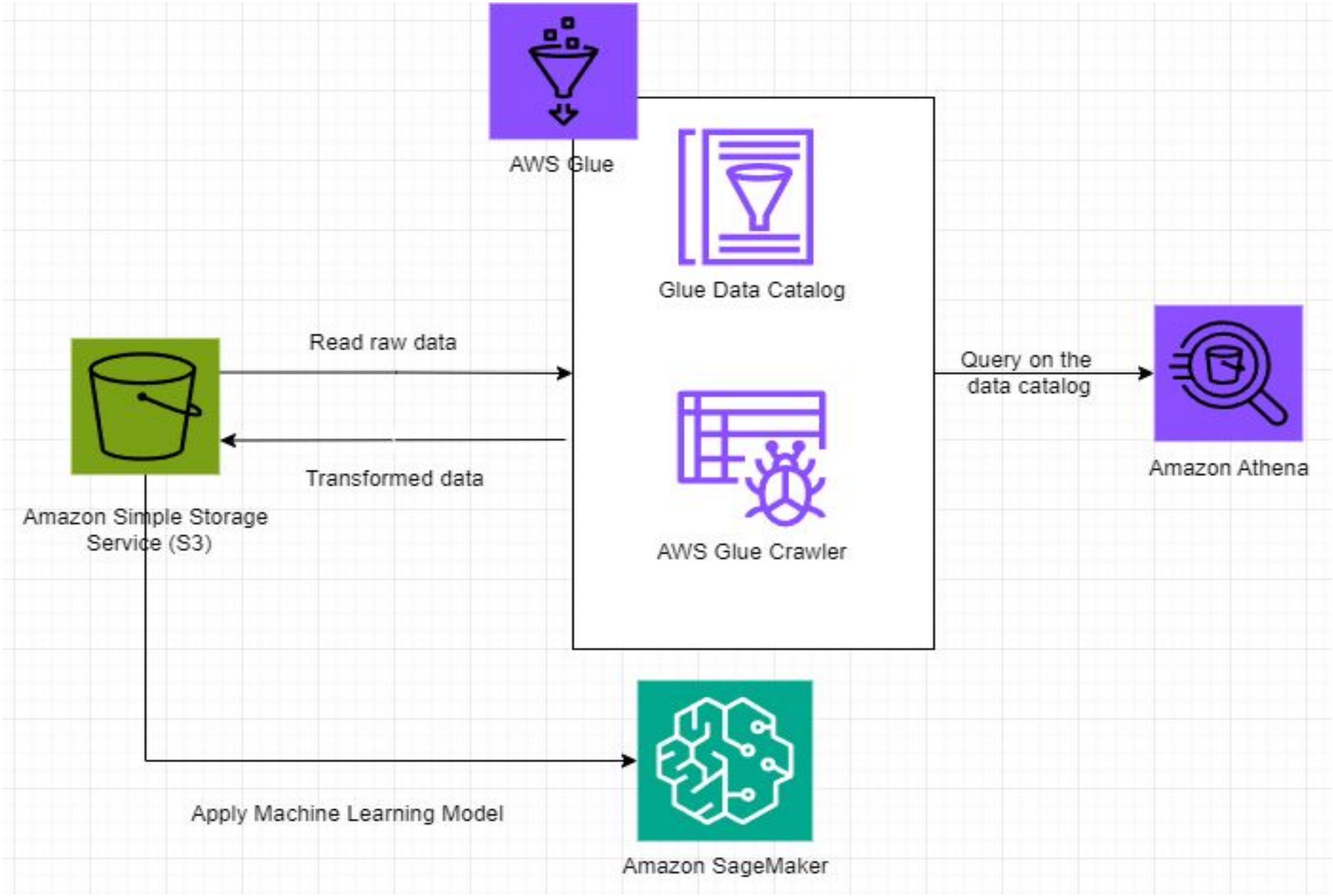
Use Cases

1. **Automate credit approvals** with a machine learning model for swift and accurate assessments of creditworthiness.

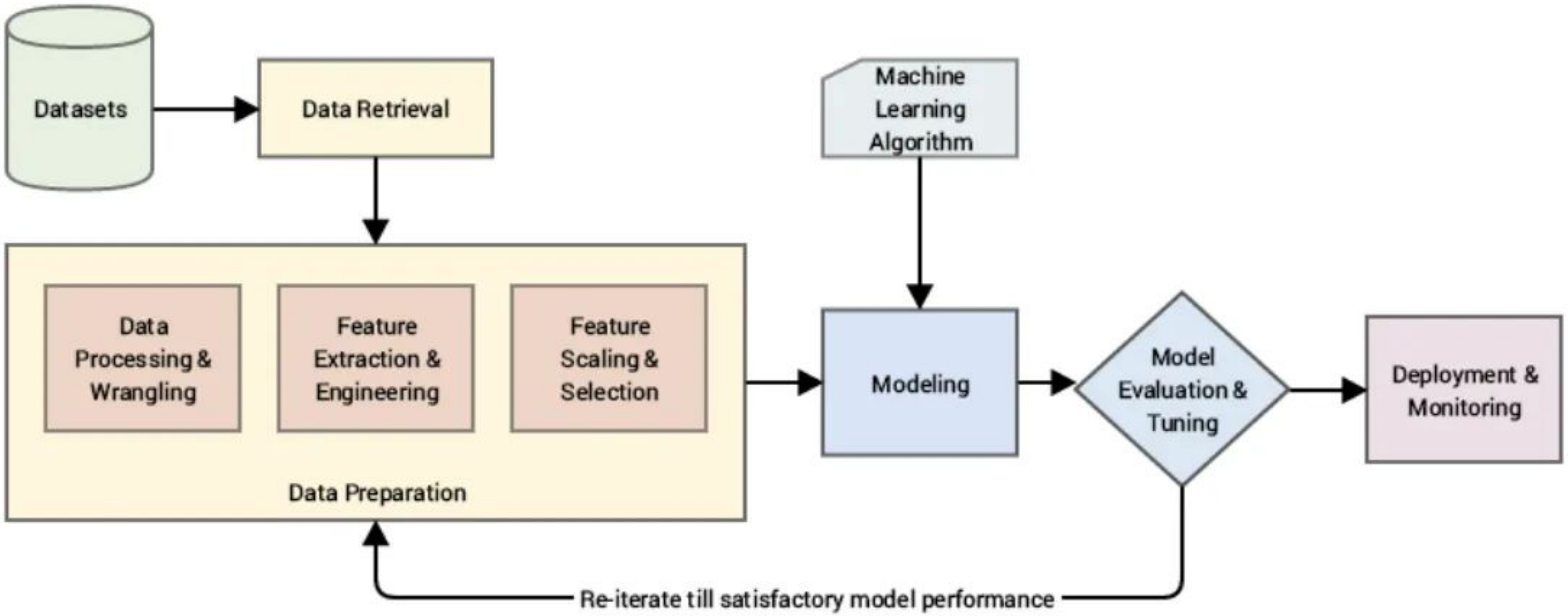
2. **Mitigate risks** by using the model to assess and manage potential credit losses in the application process.

3. **Personalize financial offerings** by leveraging the model to tailor credit terms, interest rates, and limits based on predicted credit scores.

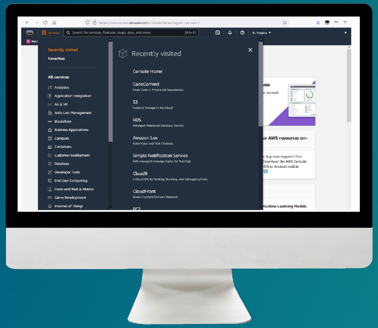
Architecture diagram of the solution



Machine Learning Lifecycle Applied



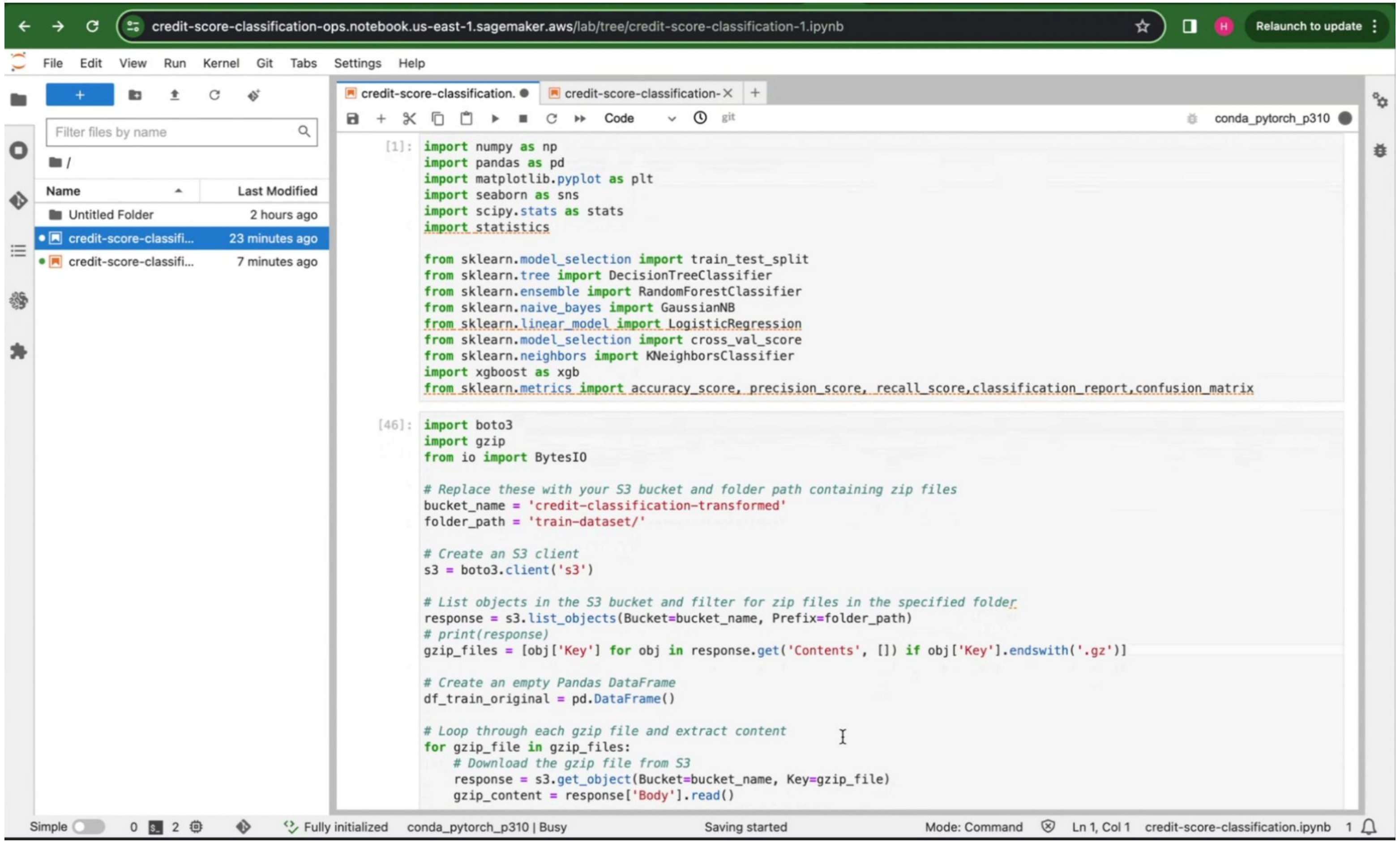
Demo



Project Demonstration following the Machine Learning Lifecycle

Demo

Data Retrieval



Demo

Data Preprocessing

4.2 Helper Functions

Created following functions that will help in exploring,analysing & cleaning of the data

```python
def get_column_details(df,column):
    print("Details of",column,"column")

    #DataType of column
    print("\nDataType: ",df[column].dtype)

    #Check if null values are present
    count_null = df[column].isnull().sum()
    if count_null==0:
        print("\nThere are no null values")
    elif count_null>0:
        print("\nThere are ",count_null," null values")

    #Get Number of Unique Values
    print("\nNumber of Unique Values: ",df[column].nunique())

    #Get Distribution of Column
    print("\nDistribution of column:\n")
    print(df[column].value_counts())
```

```python
def fill_missing_with_group_mode(df, groupby, column):
    print("\nNo. of missing values before filling with group mode:",df[column].isnull().sum())

    # Fill with local mode
    mode_per_group = df.groupby(groupby)[column].transform(lambda x: x.mode().iat[0])
    df[column] = df[column].fillna(mode_per_group)

    print("\nNo. of missing values after filling with group mode:",df[column].isnull().sum())
```

```python
#Method to clean categorical field

def clean_categorical_field(df,groupby,column,replace_value=None):
    print("\n-----------------------------------------------------")
    print("\nCleaning steps ")

    #Replace with np.nan
    if replace_value!=None:
        df[column] = df[column].replace(replace_value,np.nan)
```

Demo

Data Transformation

```python
#Label Encoding
from sklearn.preprocessing import LabelEncoder

categorical_columns = ['Occupation','Type_of_Loan','Credit_Mix','Payment_of_Min_Amount','Payment_Behaviour','Credit_Score']
# Initialize the LabelEncoder
label_encoder = LabelEncoder()

# Loop through each column and apply label encoding
for column in categorical_columns:
    df_train[column] = label_encoder.fit_transform(df_train[column])
```

```python
df_train.head()
```

	Month	Age	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_Rate	Num_of_Loan	Type_of_Loan	...	Cr
0	1	23.0	12	19114.12	1824.843333	3.0	4.0	3.0	4.0	128	...	
1	2	23.0	12	19114.12	1824.843333	3.0	4.0	3.0	4.0	128	...	
2	3	23.0	12	19114.12	1824.843333	3.0	4.0	3.0	4.0	128	...	
3	4	23.0	12	19114.12	1824.843333	3.0	4.0	3.0	4.0	128	...	
4	5	23.0	12	19114.12	1824.843333	3.0	4.0	3.0	4.0	128	...	

5 rows × 24 columns

```python
#Spli Input & Output Data
X = df_train.drop('Credit_Score',axis=1)
y = df_train['Credit_Score']
print(X.shape)
print(y.shape)
```

```
(100000, 23)
(100000,)
```

```python
#Normalize Data
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X = scaler.fit_transform(X)
```

Demo

Modeling and Evaluation

```python
# List of classifiers to test
classifiers = [
    ('Decision Tree', DecisionTreeClassifier()),
    ('Random Forest', RandomForestClassifier()),
    ('KNN', KNeighborsClassifier(n_neighbors=5)),
    ('Gaussion NB',GaussianNB()),
    ('XGB',xgb.XGBClassifier())
]

# Iterate over each classifier and evaluate performance
for clf_name, clf in classifiers:
    # Perform cross-validation
    scores = cross_val_score(clf, X_train, y_train, cv=5, scoring='accuracy')

    # Calculate average performance metrics
    avg_accuracy = scores.mean()
    avg_precision = cross_val_score(clf, X_train, y_train, cv=5, scoring='precision_macro').mean()
    avg_recall = cross_val_score(clf, X_train, y_train, cv=5, scoring='recall_macro').mean()

    # Print the performance metrics
    print(f'Classifier: {clf_name}')
    print(f'Average Accuracy: {avg_accuracy:.4f}')
    print(f'Average Precision: {avg_precision:.4f}')
    print(f'Average Recall: {avg_recall:.4f}')
    print('-----------------------')
```

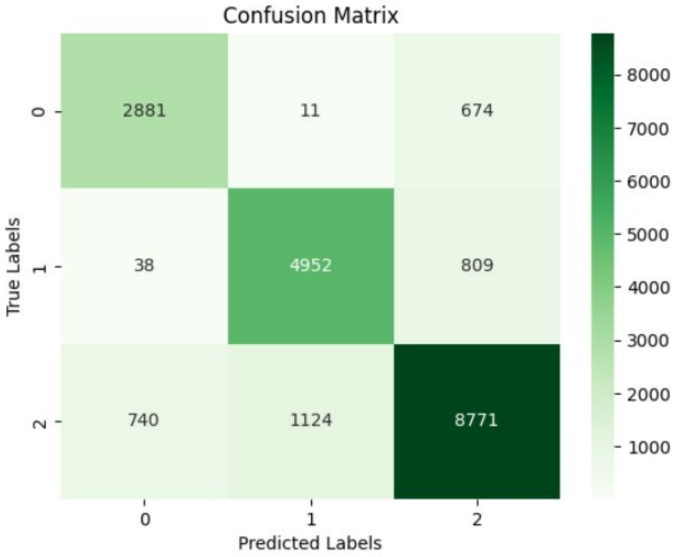
```python
# Creating the Random Forest classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)

# Training the classifier
rf_classifier.fit(X_train, y_train)

# Making predictions on the test set
y_pred = rf_classifier.predict(X_test)

# Evaluating the model
evaluate_model(y_test, y_pred)
```

Demo- Results

Approach 1

Classification Report

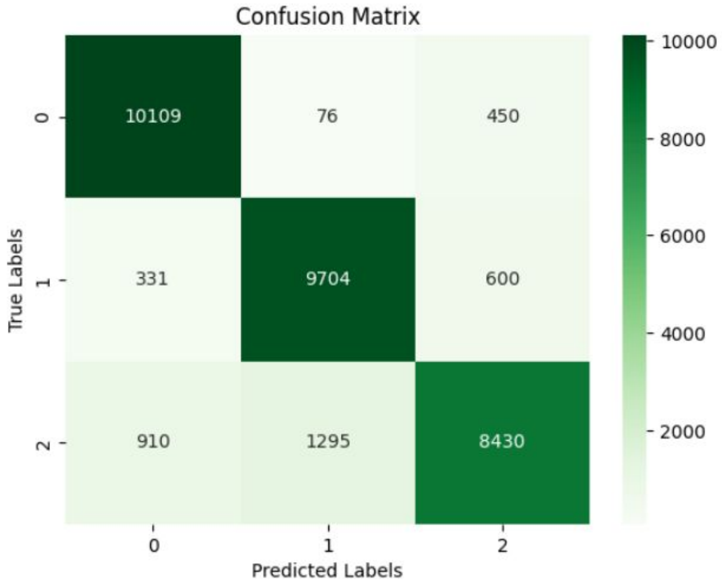
	precision	recall	f1-score	support
0	0.79	0.81	0.80	3566
1	0.81	0.85	0.83	5799
2	0.86	0.82	0.84	10635
accuracy			0.83	20000
macro avg	0.82	0.83	0.82	20000
weighted avg	0.83	0.83	0.83	20000



Approach 2

Classification Report

	precision	recall	f1-score	support
0	0.89	0.95	0.92	10635
1	0.88	0.91	0.89	10635
2	0.89	0.79	0.84	10635
accuracy			0.89	31905
macro avg	0.89	0.89	0.88	31905
weighted avg	0.89	0.89	0.88	31905



Lessons learned

- Initially, the model execution time on SageMaker was excessively long. We identified that the instance we used in SageMaker had a lower configuration. Once we updated it, the issue was resolved.
- We faced issues while cleaning the data, as there were numerous missing and erroneous values. To gain a better understanding of how to handle missing data, we referred to AWS SageMaker examples and tutorials.
- We have learned about various model evaluation metrics, such as precision, recall, F1-Score, and AUC. We also gained insights into AWS Cost Explorer and identified possible cost for each service that we have used.
- We have developed the model for predicting the credit score. As a next step, we will develop a GUI where businesses can enter the financial details of the user and determine the creditworthiness of the person.

Thank you