CSE 330:
Cloud Computing

PROJECT DETAILS

Submitted to

SRI RAMACHANDRA INSTITUTE OF HIGHER EDUCATION AND RESEARCH SRI RAMACHANDRA ENGINEERING AND TECHNOLOGY

for the Award of the Degree of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING

(Cyber Security and Internet of Things) By

K.P. SHRIRAM - E0219040

NAVEEN PRATAP - E0219021

UMESH KUMAR - E0219019

Under the Supervision of

Prof. Ragavan Veerarajan

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SRET, CHENNAI - 600116 AUGUST 2021

TOPIC : RECOMMENDATION SYSTEM USING AMAZON SAGEMAKER

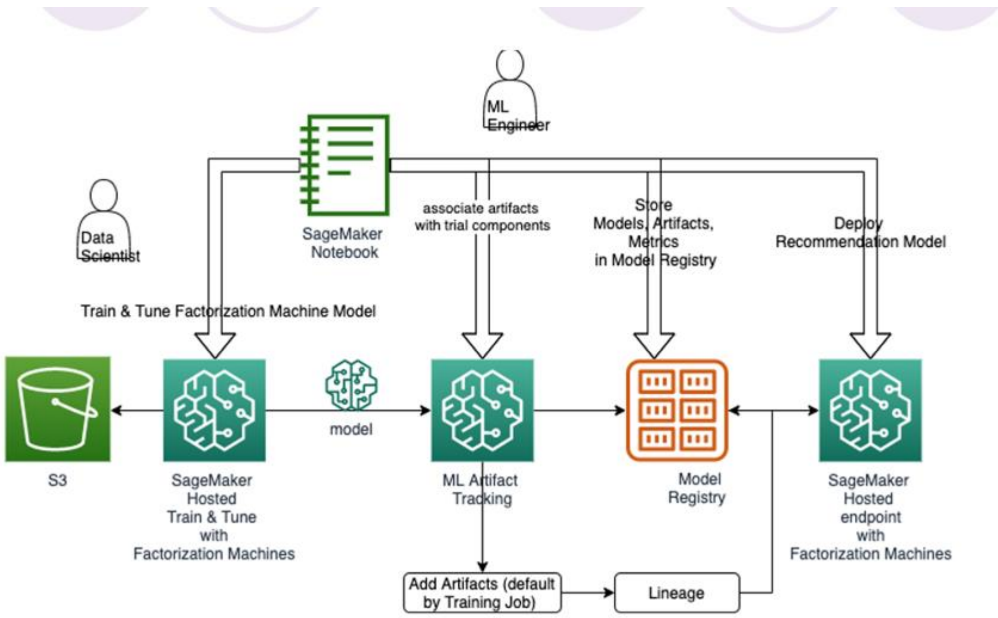
ABSTRACT:

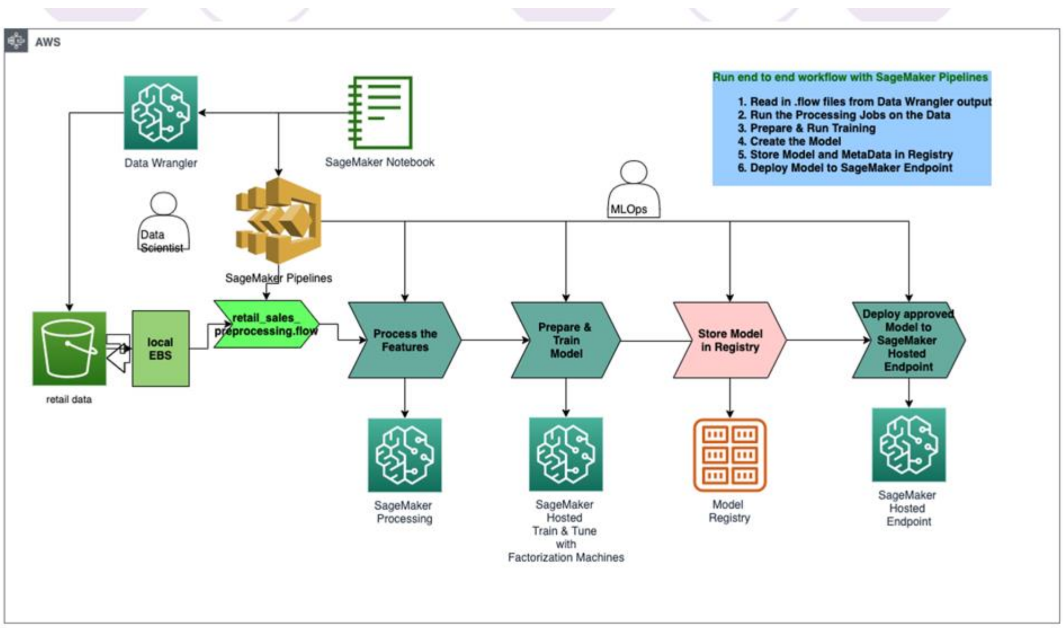
Building a Recommendation system using Ecommerce data to predict the product recommendation to customers. Using Sagemaker for playing around with data and also using amazon pipelines to do automated task for prediction.

AIM OF THE PROJECT:

To get a best products for the customers to recommend from the ecommerce data through AWS SAGEMAKER

ARCHITECTURE:



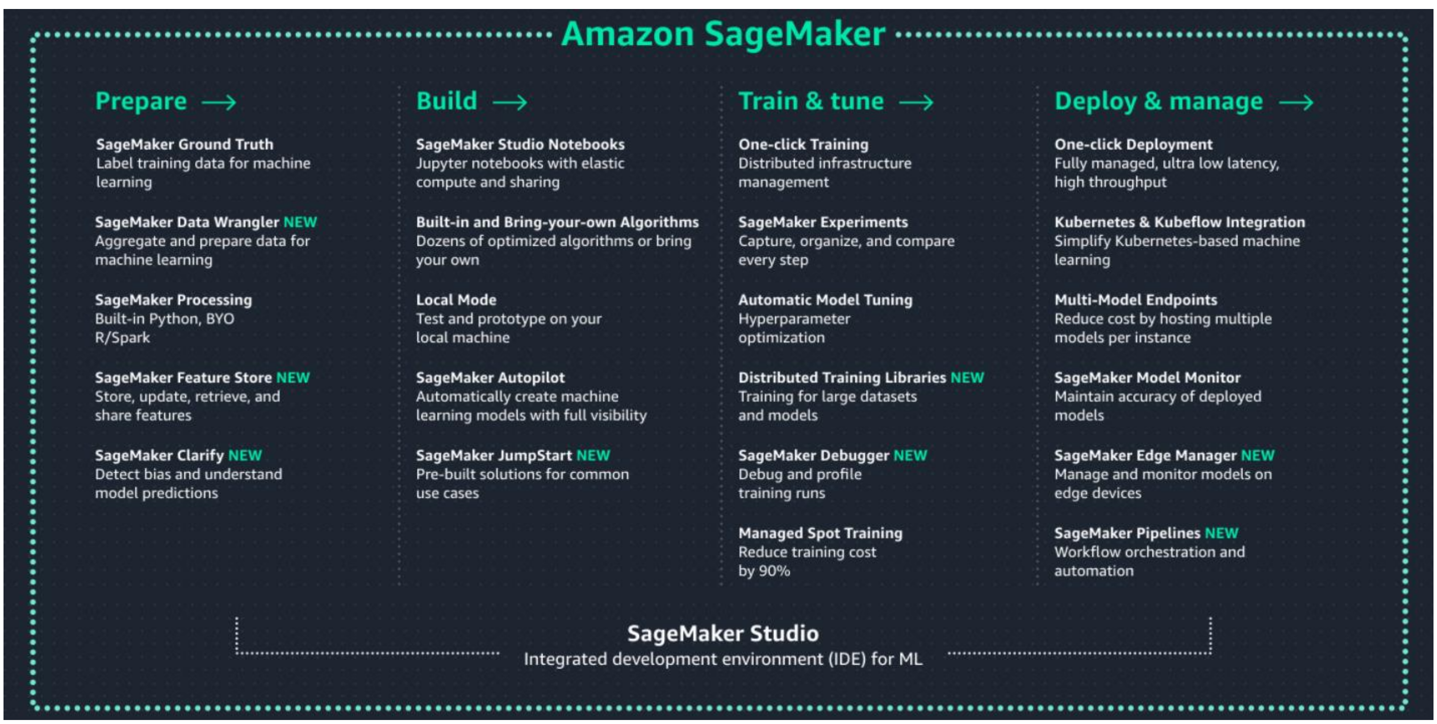


SERVICES USED:

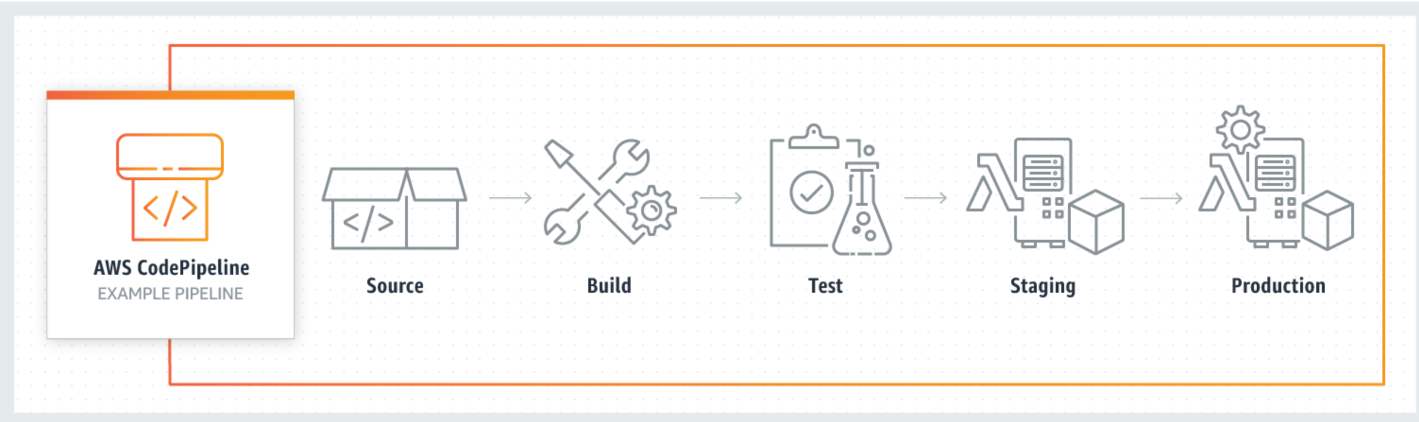
AWS SERVICES USED

1. AWS SAGEMAKER
2. AWS PIPELINES
3. AWS S3 BUCKET
4. AWS MODEL REGISTRY
5. AWS LINEAGE

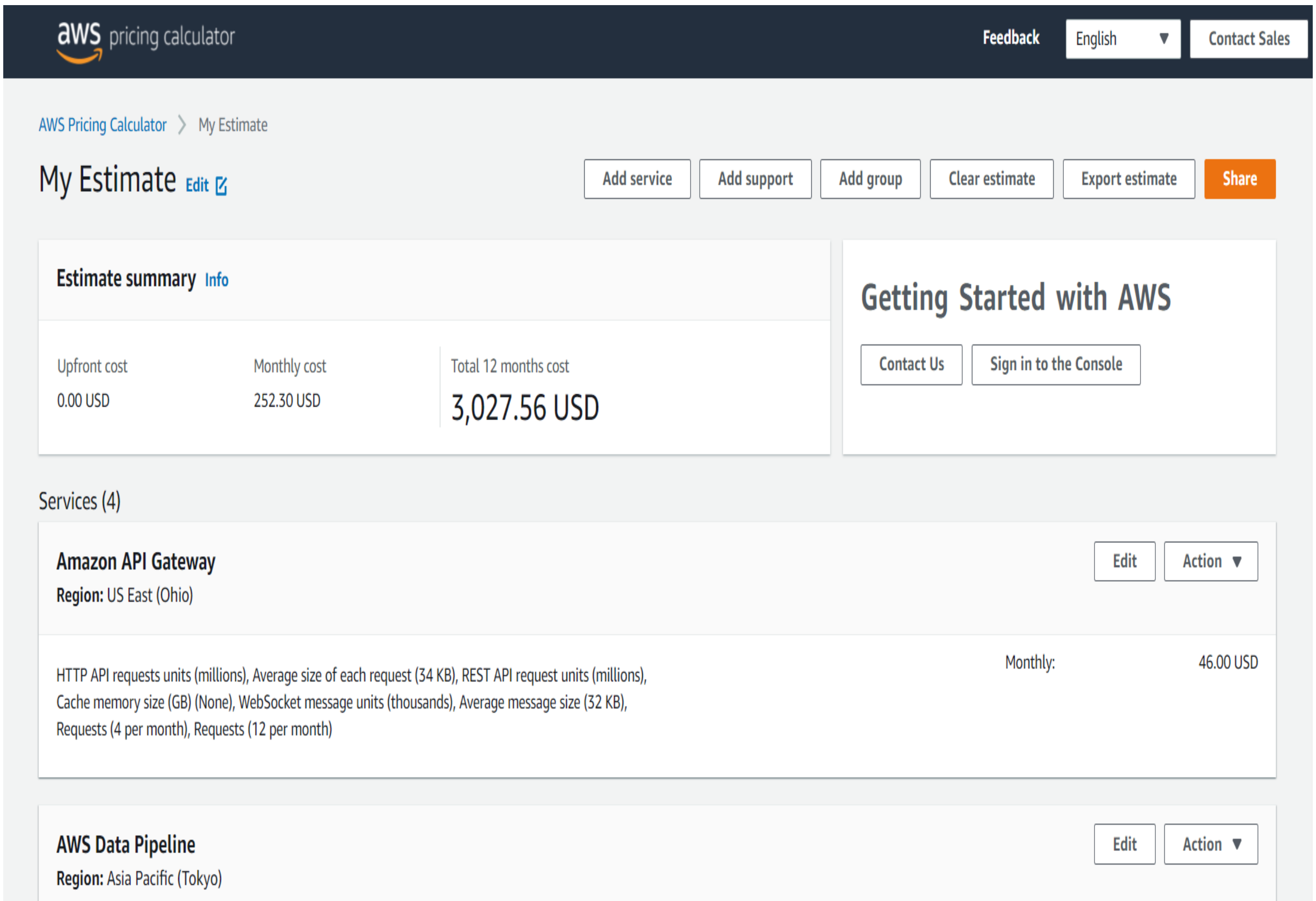
AWS SAGEMAKER :



AWS PIPELINES :



ESTIMATED COSTS:



Number of high frequency activities in a month (3), Number of low frequency activities in a month (3), Number of inactive pipelines per month (1)	Monthly:	5.52 USD

Amazon Simple Storage Service (S3)

Edit Action ▼

Region: US East (Ohio)

S3 Standard storage (1 GB per month)	Monthly:	0.03 USD
DT Inbound: Internet (1 TB per month), DT Outbound: US East (Verizon) - Miami (1 TB per month)	Monthly:	10.24 USD

Amazon SageMaker

Edit Action ▼

Region: US East (Ohio)

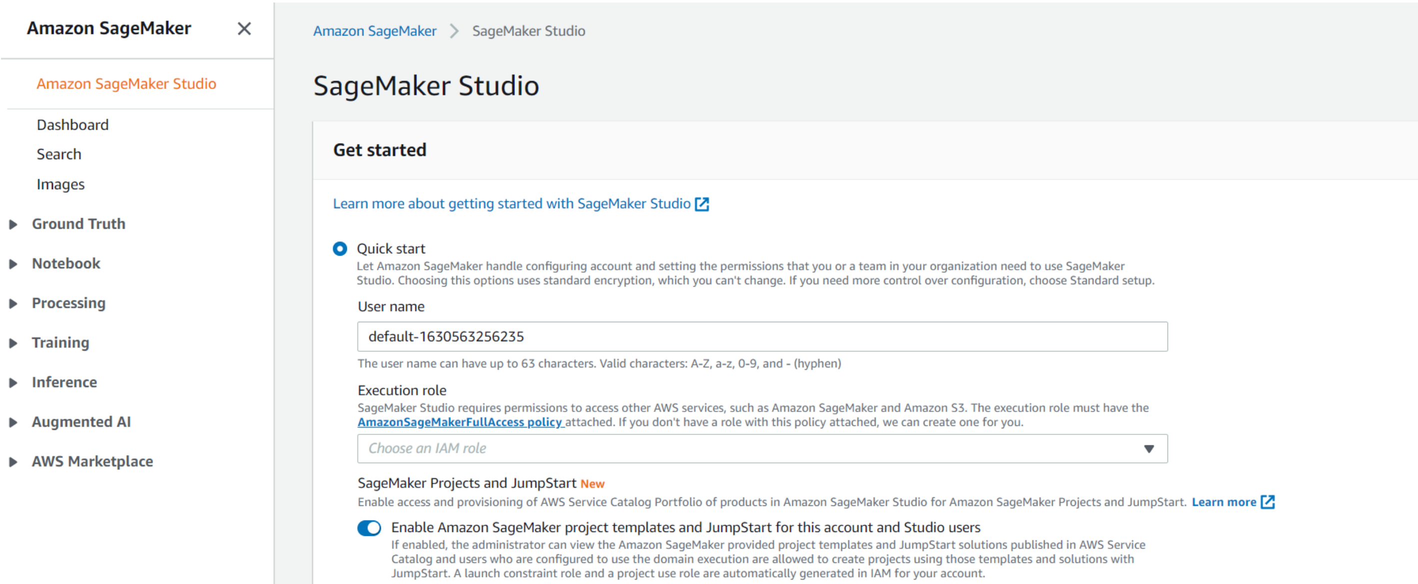
Instance name (ml.c5.12xlarge), Number of Studio Notebook instances per data scientist (1), Studio Notebook hour(s) per day (4), Studio Notebook day(s) per month (10), Number of data scientist(s) (1)	Monthly:	97.92 USD
Storage (General Purpose SSD (gp2)), Instance name (ml.c4.2xlarge), Number of processing jobs per month (2), Number of instances per job (1), Hour(s) per instance per job (3)	Monthly:	2.97 USD
Storage (General Purpose SSD (gp2)), Instance name (ml.m5.12xlarge), Instance name (ml.m5.4xlarge), Number of data scientist(s) (1), Data Wrangler hour(s) per day (3), Data Wrangler day(s) per month (10),	Monthly:	44.38 USD

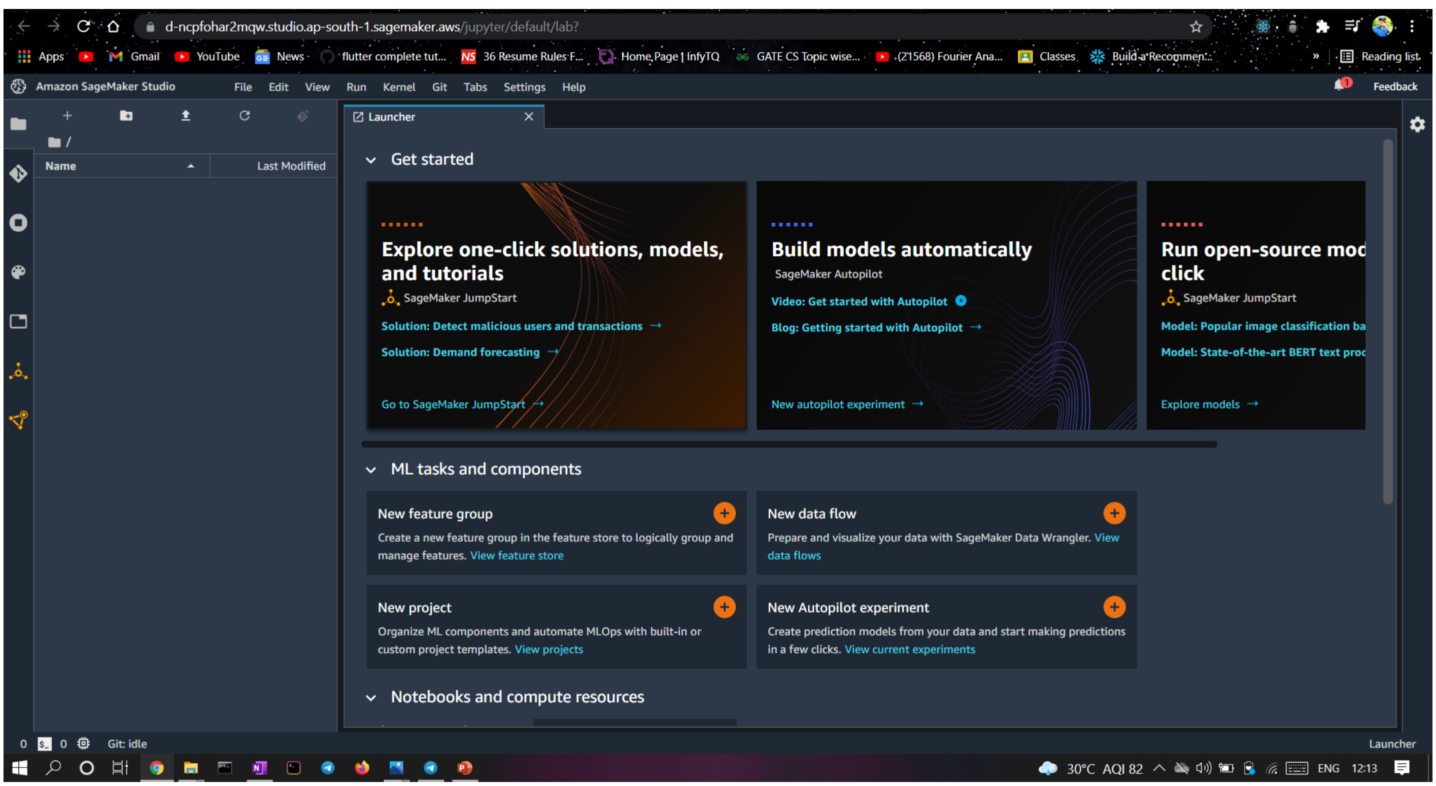
Instance name (ml.c5.12xlarge), Number of Studio Notebook instances per data scientist (1), Studio Notebook hour(s) per day (4), Studio Notebook day(s) per month (10), Number of data scientist(s) (1) Monthly: 97.92 USD

Storage (General Purpose SSD (gp2)), Instance name (ml.c4.2xlarge), Number of processing jobs per month (2), Number of instances per job (1), Hour(s) per instance per job (3) Monthly: 2.97 USD

Storage (General Purpose SSD (gp2)), Instance name (ml.m5.12xlarge), Instance name (ml.m5.4xlarge), Number of data scientist(s) (1), Data Wrangler hour(s) per day (3), Data Wrangler day(s) per month (10), Number of data wrangler jobs per month (1), Number of instances per job (2), Hour(s) per instance per job (3)	Monthly:	44.38 USD
Storage (General Purpose SSD (gp2)), Instance name (ml.c4.2xlarge), Number of training jobs per month (2), Number of instances per job (1), Hour(s) per instance per job (3)	Monthly:	3.01 USD
Storage (General Purpose SSD (gp2)), Instance name (ml.c4.2xlarge), Instance name (ml.c4.2xlarge), Number of models deployed (3), Number of models per endpoint (3), Number of instances per endpoint (2), Endpoint hour(s) per day (4), Endpoint day(s) per month (10), Number of Model Monitor jobs per month (1), Number of Model Monitor instances per job (2), Hour(s) per Model Monitor instance per job (4), Data Processed IN (1 GB), Data Processed OUT (1 GB)	Monthly:	42.23 USD

IMPLEMENTATION SCREEN SHOTS:





Jupyter Notebook :

In [1]:
```
!pip install -Uq sagemaker boto3
```

In [2]:
```
%store -r
%store
```

```
Stored variables and their in-db values:
```

In [3]:
```
import sagemaker
import sagemaker.amazon.common as smac
import boto3

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

from scipy.sparse import csr_matrix, hstack, save_npz
from sklearn.preprocessing import OneHotEncoder
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
```

In [4]:
```
assert sagemaker.__version__ >= "2.21.0"
```

In [5]:
```
region = boto3.Session().region_name
boto3.setup_default_session(region_name=region)
boto_session = boto3.Session(region_name=region)

s3_client = boto3.client("s3", region_name=region)

sagemaker_boto_client = boto_session.client("sagemaker")
sagemaker_session = sagemaker.session.Session(
    boto_session=boto_session, sagemaker_client=sagemaker_boto_client
)
sagemaker_role = sagemaker.get_execution_role()

bucket = sagemaker_session.default_bucket()
print(f"using bucket{bucket} in region {region} \n")
```

Read the data

In [6]:
```
df = pd.read_csv("data/Online Retail.csv")
print(df.shape)
df.head()
```

```
(541909, 8)
```

Out[6]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom

Data Preprocessing :

Data Preprocessing

First, we check for any null (i.e. missing) values.

In [7]:
```
df.isna().sum()
```

Out[7]:
```
InvoiceNo            0
StockCode            0
Description       1454
Quantity             0
InvoiceDate          0
UnitPrice            0
CustomerID      135080
Country              0
dtype: int64
```

Drop any records with a missing CustomerID. If we do not know who the customer is, then it is not helpful to us when we make recommendations.

In [8]:
```
df.dropna(subset=["CustomerID"], inplace=True)
df["Description"] = df["Description"].apply(lambda x: x.strip())
print(df.shape)
```

```
(406829, 8)
```

In [9]:
```
plt.figure(figsize=(10, 5))
sns.distplot(df["Quantity"], kde=True)
plt.title("Distribution of Quantity")
plt.xlabel("Quantity");
```

In [12]:
```
df = df.groupby(["StockCode", "Description", "CustomerID", "Country", "UnitPrice"])[
    "Quantity"
].sum()
df = df.loc[df > 0].reset_index()
df.shape
```

Out[12]:
```
(274399, 6)
```

In [13]:
```
def loadDataset(dataframe):
    enc = OneHotEncoder(handle_unknown="ignore")
    onehot_cols = ["StockCode", "CustomerID", "Country"]
    ohe_output = enc.fit_transform(dataframe[onehot_cols])

    vectorizer = TfidfVectorizer(min_df=2)
    unique_descriptions = dataframe["Description"].unique()
    vectorizer.fit(unique_descriptions)
    tfidf_output = vectorizer.transform(dataframe["Description"])

    row = range(len(dataframe))
    col = [0] * len(dataframe)
    unit_price = csr_matrix((dataframe["UnitPrice"].values, (row, col)), dtype="float32")

    X = hstack([ohe_output, tfidf_output, unit_price], format="csr", dtype="float32")

    y = dataframe["Quantity"].values.astype("float32")

    return X, y
```

In [14]:
```
X, y = loadDataset(df)
```

In [15]:
```
# display sparsity
total_cells = X.shape[0] * X.shape[1]
(total_cells - X.nnz) / total_cells
```

Out[15]:
```
0.9991284988048746
```

Our data is over 99.9% sparse. Because of this high sparsity, the sparse matrix data type allows us to represent our data using only a small fraction of the memory that a dense matrix would require.

Preparing for Modeling :

Prepare Data For Modeling

- Split the data into training and testing sets
- Write the data to protobuf recordIO format for Pipe mode. Read more about protobuf recordIO format.

In [16]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[16]:
```
((219519, 9284), (54880, 9284), (219519,), (54880,))
```

Save numpy arrays to local storage in /data folder

In [17]:
```
df.to_csv("data/online_retail_preprocessed.csv", index=False)
save_npz("data/X_train.npz", X_train)
save_npz("data/X_test.npz", X_test)
np.savez("data/y_train.npz", y_train)
np.savez("data/y_test.npz", y_test)
```

In [18]:
```
prefix = "personalization"

train_key = "train.protobuf"
train_prefix = f"{prefix}/train"

test_key = "test.protobuf"
test_prefix = f"{prefix}/test"

output_prefix = f"s3://{bucket}/{prefix}/output"
```

In [ ]:
```
def writeDatasetToProtobuf(X, y, bucket, prefix, key):
    buf = io.BytesIO()
    smac.write_spmatrix_to_sparse_tensor(buf, X, y)
    buf.seek(0)
    obj = "{}/{}".format(prefix, key)
    boto3.resource("s3").Bucket(bucket).Object(obj).upload_fileobj(buf)
    return "s3://{}/{}".format(bucket, obj)


train_data_location = writeDatasetToProtobuf(X_train, y_train, bucket, train_prefix, train_key)
test_data_location = writeDatasetToProtobuf(X_test, y_test, bucket, test_prefix, test_key)
```

In [9]:
```
container = sagemaker.image_uris.retrieve("factorization-machines", region=boto_session.region_name)

fm = sagemaker.estimator.Estimator(
    container,
    sagemaker_role,
    instance_count=1,
    instance_type="ml.c5.xlarge",
    output_path=output_prefix,
    sagemaker_session=sagemaker_session,
)

fm.set_hyperparameters(
    feature_dim=input_dims,
    predictor_type="regressor",
    mini_batch_size=1000,
    num_factors=64,
    epochs=20,
)
```

In [ ]:
```
if 'training_job_name' not in locals():

    fm.fit({'train': train_data_location, 'test': test_data_location})
    training_job_name = fm.latest_training_job.job_name
    %store training_job_name

else:
    print(f'Using previous training job: {training_job_name}')
```

In [11]:
```
training_job_info = sagemaker_boto_client.describe_training_job(TrainingJobName=training_job_name)
```

Training data artifact

In [12]:
```python
training_data_s3_uri = training_job_info["InputDataConfig"][0]["DataSource"]["S3DataSource"][
    "S3Uri"
]

matching_artifacts = list(
    artifact.Artifact.list(source_uri=training_data_s3_uri, sagemaker_session=sagemaker_session)
)

if matching_artifacts:
    training_data_artifact = matching_artifacts[0]
    print(f"Using existing artifact: {training_data_artifact.artifact_arn}")
else:
    training_data_artifact = artifact.Artifact.create(
        artifact_name="TrainingData",
        source_uri=training_data_s3_uri,
        artifact_type="Dataset",
        sagemaker_session=sagemaker_session,
    )
    print(f"Create artifact {training_data_artifact.artifact_arn}: SUCCESSFUL")
```

```
Using existing artifact: arn:aws:sagemaker:us-east-2:645431112437:artifact/cdd7fbecb4eefa22c43b2ad48140acc2
```

Final Output of predicted products :

In [32]:
```python
print("Top 5 recommended products:")
get_recommendations(df, top_customer, n_recommendations=5, n_ranks=100)
```

```
Top 5 recommended products:
```

Out[32]:
```
[['22423', 'REGENCY CAKESTAND 3 TIER'],
 ['22776', 'SWEETHEART CAKESTAND 3 TIER'],
 ['22624', 'IVORY KITCHEN SCALES'],
 ['85123A', 'WHITE HANGING HEART T-LIGHT HOLDER'],
 ['85099B', 'JUMBO BAG RED RETROSPOT']]
```

In [ ]:

Thank You