AD campaign recommender

CAPSTONE – 01

Model Building

Praveen Selvaraj
Praveenselvaraj.ps@gmail.com
praveenselvaraj@arizona.edu
MS in Data Science
University of Arizona (Upgrad)

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Overall Flow of the Analysis and Model

- Install required libraries through requirements.txt file
  - 1 cell hidden
- Import of Packages
  - [ ] 5 cells hidden
- Read Data
  - [ ] 44 cells hidden

- EDA and Visualization
  - Usage Through the week
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  - Usage Every Hour
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  - Usage Every Hour for each Gender
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  - Age Group vs Event Count Comparison. Requested Age Groups - 0-24, 25-32, 33-45, 46+
    - [ ] 4 cells hidden
  - Mapping Hour to Time of the Day - Morning, Afternoon, Evening, Night
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    - [ ] 2 cells hidden
  - Top 10 Mobile Applications
    - [ ] 3 cells hidden
  - Mapping Categories to High Level Categories
    - [ ] 19 cells hidden
  - Mobile Brand Data
    - [ ] 8 cells hidden
  - Cluster Based on Location Data using DBSCAN
    - [ ] 6 cells hidden
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- Data Preparation
  - Merge All necessary DataFrames
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  - Label Encoding
    - [ ] 1 cell hidden
  - Train Test Split
    - [ ] 2 cells hidden
  - Standard Scaler
    - [ ] 1 cell hidden
  - Target Encoding for "Gender Prediction"
    - [ ] 3 cells hidden

Flow of the Analysis and Model Building

Scenario 1

Model Building

Writing Model Functions

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Scenario 1 - Devices with Events

Gender Prediction

Gender Prediction - Logistic Regression

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Gender Prediction - Random Forest Classifier

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Gender Prediction - Random Forest Hyperparameter Tuning

Gender Prediction - Random Forest - Model 1

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Gender Prediction - Random Forest - Model 2

[ ] 1 cell hidden

Gender Prediction - Random Forest - Model 3

[ ] 1 cell hidden

Gender Prediction - Random Forest - Model 4

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Gender Prediction - Random Forest - Model 5

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Gender Prediction - Random Forest - Model Selection

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Gender Prediction - Random Forest - Best Parameters

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Gender Prediction - XG Boost

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Gender Prediction - Model Stacking

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Gender Prediction - Final Model Selection

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Gender Prediction - Exporting Model to a Pickle File Scenario 1

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Age Group Prediction

Age Group Prediction - Data Preparation

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Age Group Prediction - Logistic Regression

[ ] 2 cells hidden

Age Group Prediction - Logistic Model Selection

[ ] 1 cell hidden

Age Group Prediction - Random Forest Classifier

[ ] 1 cell hidden

Age Group Prediction - Random Forest Hyperparameter Tuning

Age Group Prediction - Random Forest Model 1

[ ] 1 cell hidden

Age Group Prediction - Random Forest Model 2

[ ] 1 cell hidden

Age Group Prediction - Random Forest Model 3

[ ] 1 cell hidden

Age Group Prediction - Random Forest Model 4

[ ] 1 cell hidden

Age Group Prediction - Random Forest Model 5

[ ] 1 cell hidden

Age Group Prediction - Random Forest Model Selection

[ ] 1 cell hidden

Age Group Prediction - Random Forest - Best Parameters

[ ] 1 cell hidden

Age Group Prediction - XG Boost

[ ] 1 cell hidden

Age Group Prediction - XG Boost Hyperparameter Tuning

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Age Group Prediction - Model Stacking

[ ] 8 cells hidden

Age Group Prediction - Final Model Selection

[ ] 1 cell hidden

Age Group Prediction - Exporting Model to a Pickle File Scenario 1

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Flow of the Analysis and Model Building

Scenario 2

- Scenario 2 - Devices without Events
  - Data Preparation
    - 6 cells hidden
  - Label Encoding
    - [ ] 1 cell hidden
  - Train Test Split
    - [ ] 2 cells hidden
  - Target Encoder for Gender Prediction
    - [ ] 2 cells hidden
- Gender Prediction
  - Gender Prediction - Logistic Regression
    - [ ] 5 cells hidden
  - Gender Prediction - Random Forest Classifier
    - [ ] 1 cell hidden
  - Gender Prediction - Random Forest Hyperparameter Tuning
    - Gender Prediction - Random Forest - Model 1
      - [ ] 1 cell hidden
    - Gender Prediction - Random Forest - Model 2
      - [ ] 1 cell hidden
    - Gender Prediction - Random Forest - Model 3
      - [ ] 1 cell hidden
    - Gender Prediction - Random Forest - Model Selection
      - [ ] 1 cell hidden
    - Gender Prediction - Random Forest - Best Parameters
      - 1 cell hidden
  - Gender Prediction - XG Boost
    - [ ] 12 cells hidden
  - Gender Prediction - Model Stacking
    - [ ] 6 cells hidden
  - Gender Prediction - Final Model Selection
    - [ ] 1 cell hidden
  - Gender Prediction - Exporting Model to a Pickle File Scenario 2
    - [ ] 1 cell hidden
- Age Group Prediction
  - Age Group Prediction - train test Split
    - [ ] 1 cell hidden
  - Age Group Prediction - Logistic Regression
    - [ ] 2 cells hidden
  - Age Group Prediction - Logistic Model Selection
    - [ ] 1 cell hidden
  - Age Group Prediction - Random Forest Classifier
    - [ ] 1 cell hidden
  - Age Group Prediction - Random Forest Hyperparameter Tuning
    - [ ] 10 cells hidden
  - Age Group Prediction - XG Boost
    - [ ] 1 cell hidden
  - Age Group Prediction - XG Boost Hyperparameter Tuning
    - [ ] 10 cells hidden
  - Age Group Prediction - Model Stacking
    - [ ] 8 cells hidden
  - Age Group Prediction - Final Model Selection
    - [ ] 1 cell hidden

Reading the data

Read Data

```
dfAppEvents = pd.read_csv("https://uoacapstone.s3.amazonaws.com/app_events.csv")

dfTrainEvents = pd.read_csv("https://uoacapstone.s3.amazonaws.com/train_event_data.csv")

dfMetaAppEvents = pd.read_csv("https://uoacapstone.s3.amazonaws.com/app_events_meta_data.csv",quoting=csv.QUOTE_NONE)

dfMobileBrandTrain = pd.read_csv("https://uoacapstone.s3.amazonaws.com/train_mobile_brand.csv")
```

Renaming columns in each DataFrame ¶

```
dfMetaAppEvents.columns = ["AppID", "LabelID", "Category"]

dfAppEvents.columns = ["EventID", "AppID", "IsInstalled", "IsActive"]

dfTrainEvents.columns = ["DeviceID", "Gender", "Age", "GroupTrain", "EventID", "DateTimestamp", "Latitude", "Longitude"]

dfMobileBrandTrain.columns = ["DeviceID", "Gender", "Age", "GroupTrain", "MobilePhoneBrand", "DeviceModel"]
```

```
dfMetaAppEvents.columns, dfAppEvents.columns, dfTrainEvents.columns, dfMobileBrandTrain.columns
```

```
(Index(['AppID', 'LabelID', 'Category'], dtype='object'),
 Index(['EventID', 'AppID', 'IsInstalled', 'IsActive'], dtype='object'),
 Index(['DeviceID', 'Gender', 'Age', 'GroupTrain', 'EventID', 'DateTimestamp',
        'Latitude', 'Longitude'],
       dtype='object'),
 Index(['DeviceID', 'Gender', 'Age', 'GroupTrain', 'MobilePhoneBrand',
        'DeviceModel'],
       dtype='object'))
```

Basic Stats on the Datasets

```
dfMetaAppEvents.head()
```

	app_id	label_id	category
0	app_id	label_id	category
1	7324884708820027918	251	Finance
2	-4494216993218550286	251	Finance
3	6058196446775239644	406	unknown
4	6058196446775239644	407	DS_P2P net loan

```
dfAppEvents.head()
```

	event_id	app_id	is_installed	is_active
0	2	5927333115845830913	1	1
1	2	-5720078949152207372	1	0
2	2	-1633887856876571208	1	0
3	2	-653184325010919369	1	1
4	2	8693964245073640147	1	1

```
dfTrainEvents.head()
```

	device_id	gender	age	group_train	event_id	datetimestamp	latitude	longitude
0	-7548291590301750000	M	33	M32+	2369465.0	2016-05-03 15:55:35	33.98	116.79
1	-7548291590301750000	M	33	M32+	1080869.0	2016-05-03 06:07:16	33.98	116.79
2	-7548291590301750000	M	33	M32+	1079338.0	2016-05-04 03:28:02	33.98	116.79
3	-7548291590301750000	M	33	M32+	1078881.0	2016-05-04 02:53:08	33.98	116.79
4	-7548291590301750000	M	33	M32+	1068711.0	2016-05-03 15:59:35	33.98	116.79

```
dfMobileBrandTrain.head()
```

	device_id	gender	age	group_train	phone_brand	device_model
0	-7548291590301750000	M	33	M32+	Huawei	è□£è€€3C
1	6943568600617760000	M	37	M32+	Xiaomi	xnote
2	5441349705980020000	M	40	M32+	OPPO	R7s
3	-5393876656119450000	M	33	M32+	Xiaomi	MI 4
4	4543988487649880000	M	53	M32+	samsung	Galaxy S4

Data Cleaning

MetaAppEvents ¶

```
dfMetaAppEvents = dfMetaAppEvents.iloc[1:,:].reset_index(drop=True)
dfMetaAppEvents.head(3)
```

	AppID	LabelID	Category
0	7324884708820027918	251	Finance
1	-4494216993218550286	251	Finance
2	6058196446775239644	406	unknown

```
dfMetaAppEvents.AppID = dfMetaAppEvents.AppID.astype("int64")

dfMetaAppEvents.LabelID = dfMetaAppEvents.LabelID.astype("int64")
```

```
dfMetaAppEvents.Category = dfMetaAppEvents.Category.str.upper()
```

MobileBrandTrain

```
dfMobileBrandTrain.head()
```

	DeviceID	Gender	Age	GroupTrain	MobilePhoneBrand	DeviceModel
0	-7548291590301750000	M	33	M32+	Huawei	è□£è€€3C
1	6943568600617760000	M	37	M32+	Xiaomi	xnote
2	5441349705980020000	M	40	M32+	OPPO	R7s
3	-5393876656119450000	M	33	M32+	Xiaomi	MI 4
4	4543988487649880000	M	53	M32+	samsung	Galaxy S4

Dealing with Junk Data such as in the 1st row in column DeviceModel - è□£è€€3C

```
#Function to Clean Gibberish Data
def cleanJunk(str):
    if str.isascii():
        return str

    else:
        a="".join(list(map(lambda x:x if x.isascii() else "",str)))
        return a

dfMobileBrandTrain["DeviceModel"] = dfMobileBrandTrain["DeviceModel"].apply(cleanJunk)
dfMobileBrandTrain.head()
```

	DeviceID	Gender	Age	GroupTrain	MobilePhoneBrand	DeviceModel
0	-7548291590301750000	M	33	M32+	Huawei	3C
1	6943568600617760000	M	37	M32+	Xiaomi	xnote
2	5441349705980020000	M	40	M32+	OPPO	R7s
3	-5393876656119450000	M	33	M32+	Xiaomi	MI 4
4	4543988487649880000	M	53	M32+	samsung	Galaxy S4

AppEvents Data

All Rows seem to have 1 value for column - IsInstalled. Will drop this column

```
dfAppEvents = dfAppEvents[["EventID", "AppID", "IsActive"]]
dfAppEvents.nunique()
```

```
EventID     1488096
AppID         19237
IsActive          2
dtype: int64
```

TrainEvents Data

Format the type for DateTimestamp

```
dfTrainEvents["DateTimestamp"]=pd.to_datetime(dfTrainEvents["DateTimestamp"])
```

Feature Engineering

Format the type for DateTimestamp

```
dfTrainEvents["DateTimestamp"]=pd.to_datetime(dfTrainEvents["DateTimestamp"])
```

Create new features from DateTimestamp Column, such as Hour, WeekDay, DayName and WeekNum

```
dfTrainEvents["Hour"] = dfTrainEvents.DateTimestamp.dt.hour

dfTrainEvents["WeekDay"] = dfTrainEvents.DateTimestamp.dt.day_of_week

dfTrainEvents["DayName"] = dfTrainEvents.DateTimestamp.dt.day_name()

dfTrainEvents["WeekNum"] = dfTrainEvents.DateTimestamp.dt.weekofyear
```

```
print("Total Number of Records without Events ", "\t- ", dfTrainEvents.EventID.isnull().sum())

print("Total Number of Records with Events ", "\t\t- ", dfTrainEvents.EventID[~(dfTrainEvents.EventID.isnull())].shape[0])

print("Total Number of Records ", "\t\t\t- ", dfTrainEvents.shape[0])

print("Percent of Devices without Events ", "\t\t- ",
        round(100*dfTrainEvents.EventID.isnull().sum()
              /dfTrainEvents.EventID[~(dfTrainEvents.EventID.isnull())].shape[0], 2), "%")
```

```
Total Number of Records without Events       -  51335
Total Number of Records with Events          -  1215598
Total Number of Records                      -  1266933
Percent of Devices without Events            -  4.22 %
```

Create a DataFrame where the EventIDs are not null

```
dfTrainEventsWithEventData = dfTrainEvents[~(dfTrainEvents.EventID.isnull())]

dfTrainEventsWithEventData.shape[0]
```

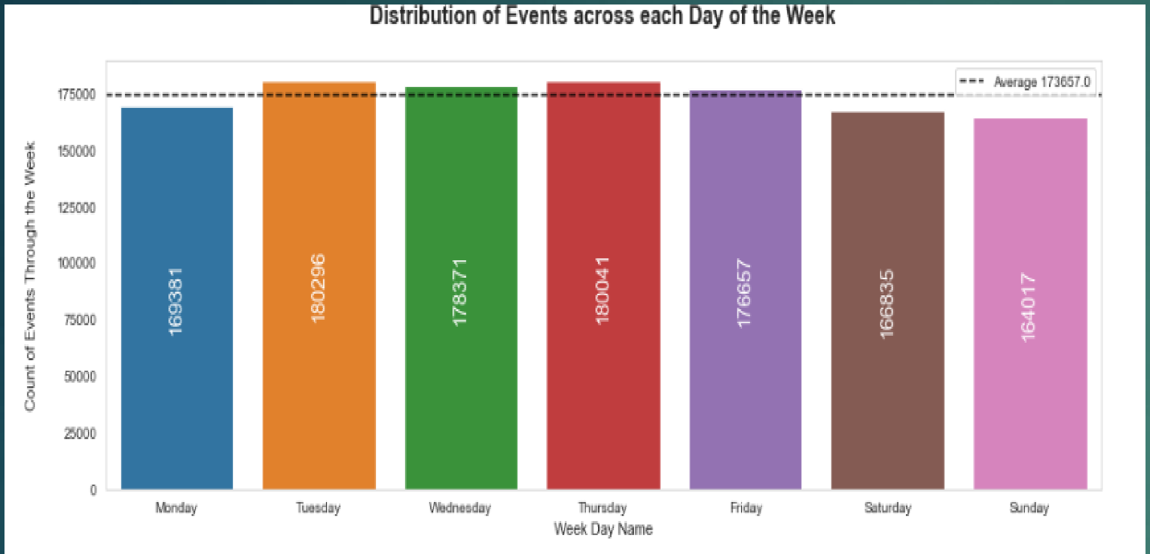
```
1215598
```

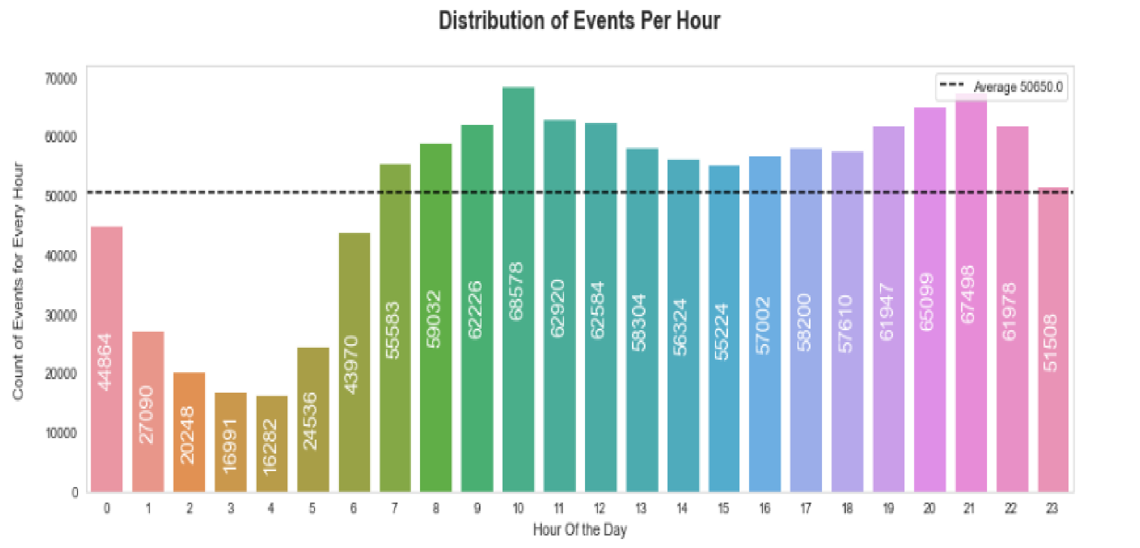
```
dfTrainEventsWithEventData["Coordinates"] = dfTrainEventsWithEventData[["Latitude", "Longitude"]]
    .apply(lambda x: (x["Latitude"], x["Longitude"]), axis = 1)

dfTrainEventsWithEventData.head()
```

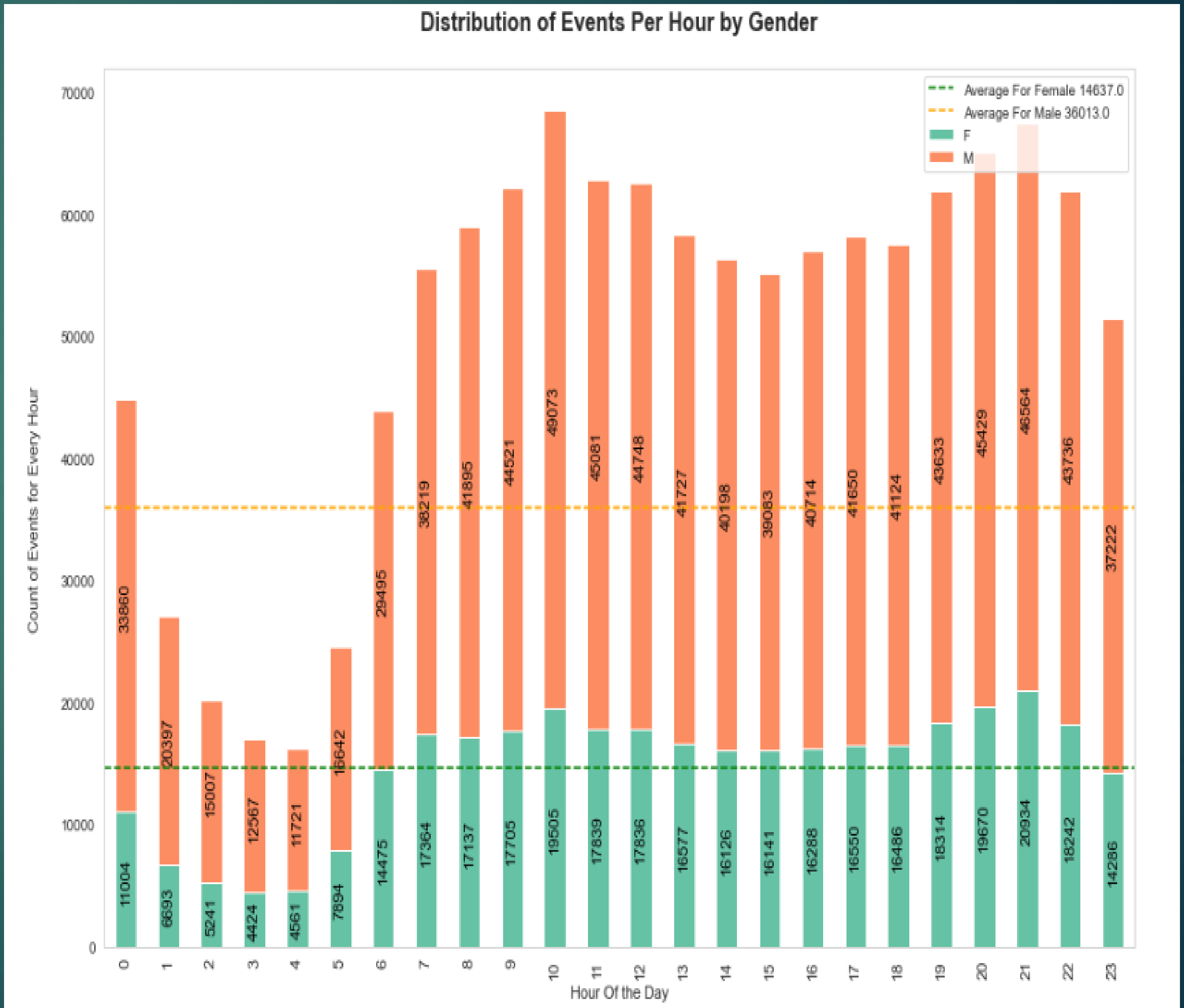
	DeviceID	Gender	Age	GroupTrain	EventID	DateTimestamp	Latitude	Longitude	Hour	WeekDay	DayName	WeekNum	Coordinates
0	-7548291590301750000	M	33	M32+	2369465.0	2016-05-03 15:55:35	33.98	116.79	15.0	1.0	Tuesday	18.0	(33.98, 116.79)
1	-7548291590301750000	M	33	M32+	1080869.0	2016-05-03 06:07:16	33.98	116.79	6.0	1.0	Tuesday	18.0	(33.98, 116.79)
2	-7548291590301750000	M	33	M32+	1079338.0	2016-05-04 03:28:02	33.98	116.79	3.0	2.0	Wednesday	18.0	(33.98, 116.79)
3	-7548291590301750000	M	33	M32+	1078881.0	2016-05-04 02:53:08	33.98	116.79	2.0	2.0	Wednesday	18.0	(33.98, 116.79)
4	-7548291590301750000	M	33	M32+	1068711.0	2016-05-03 15:59:35	33.98	116.79	15.0	1.0	Tuesday	18.0	(33.98, 116.79)

```
dfTrainEventsWithEventData.EventID = dfTrainEventsWithEventData.EventID.astype("int64")

dfTrainEventsWithEventData.Hour = dfTrainEventsWithEventData.Hour.astype("int64")

dfTrainEventsWithEventData.WeekDay = dfTrainEventsWithEventData.WeekDay.astype("int64")

dfTrainEventsWithEventData.WeekNum = dfTrainEventsWithEventData.WeekNum.astype("int64")

dfTrainEventsWithEventData.info()
```

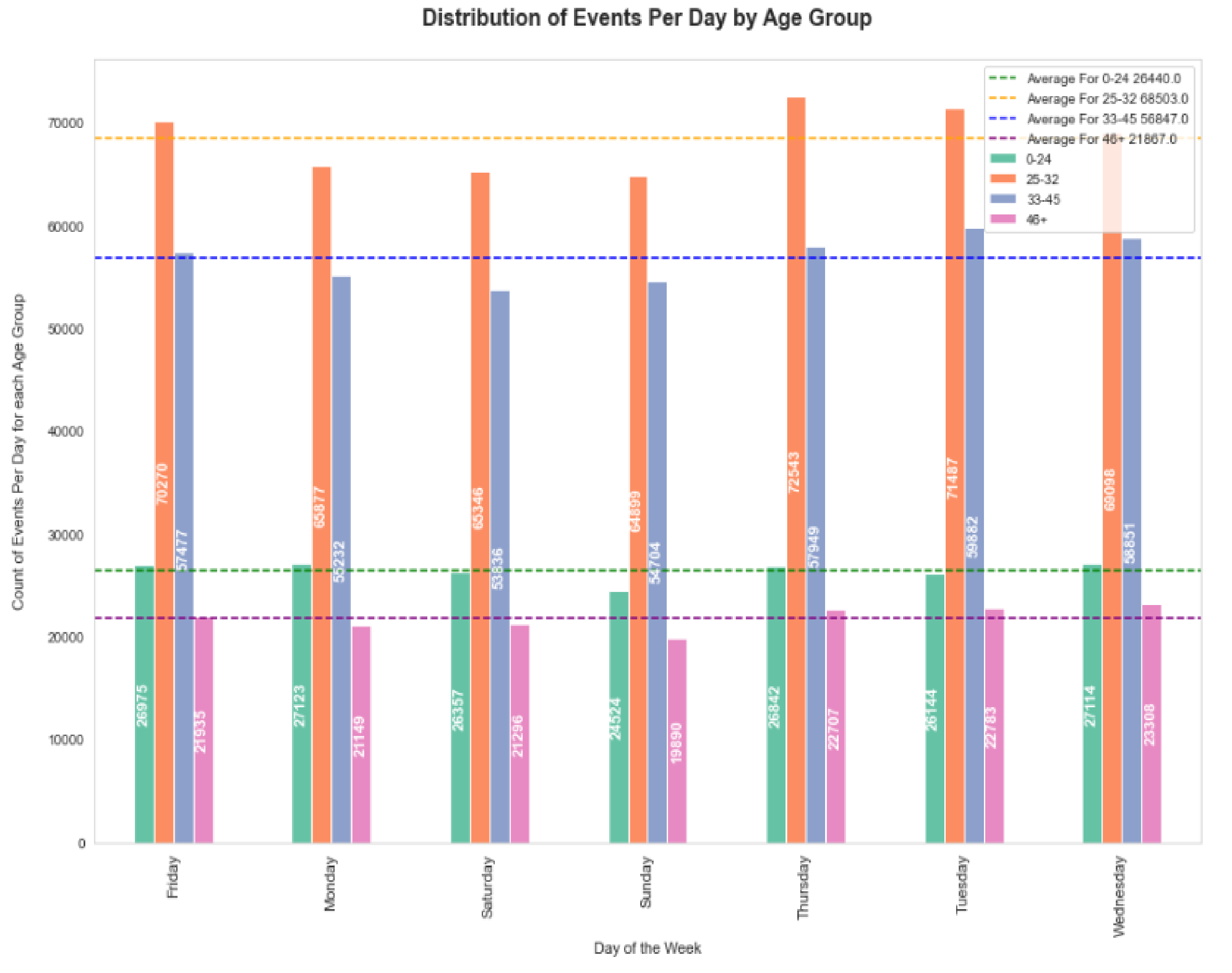
Exploratory Data Analysis – Slide 1

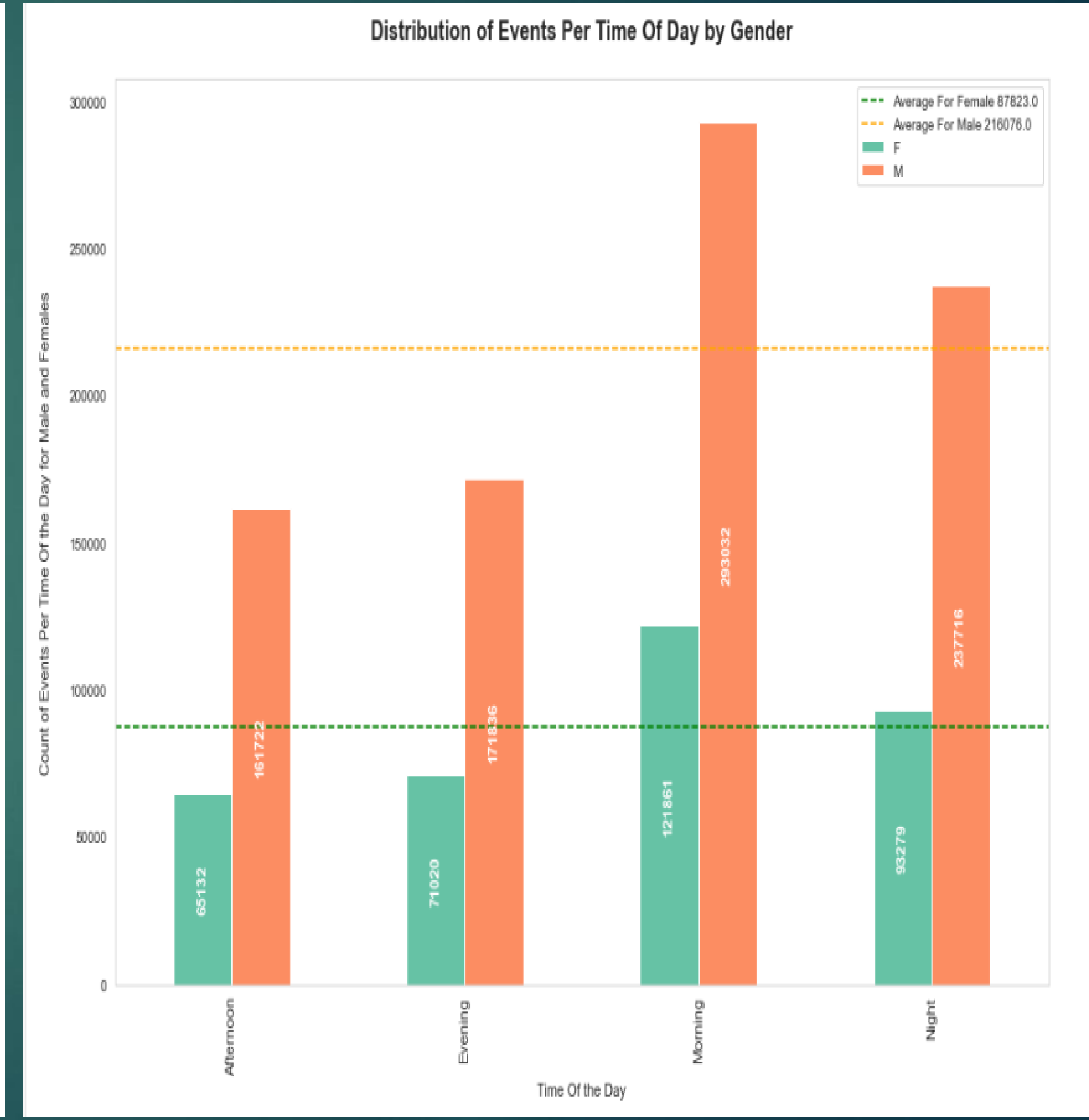




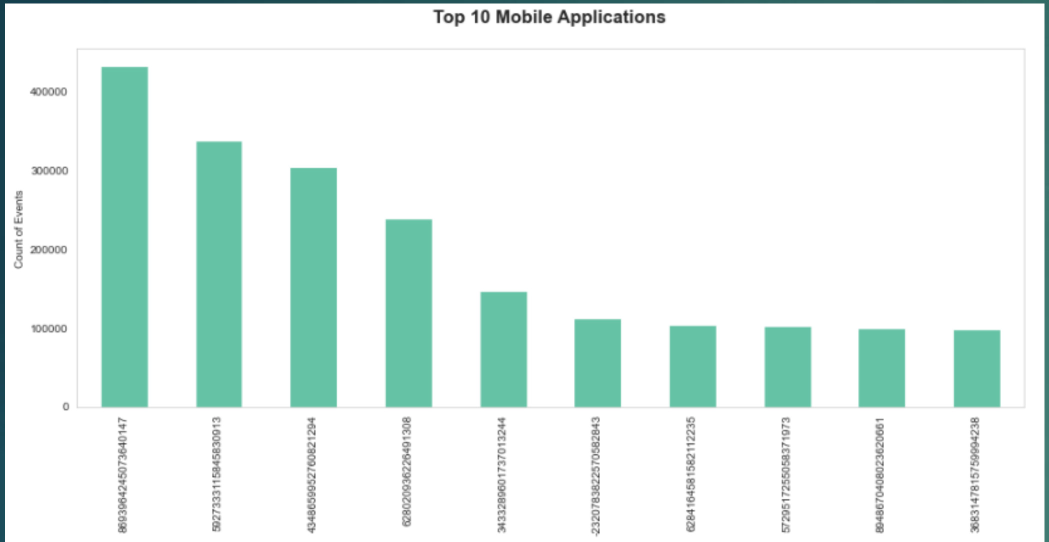


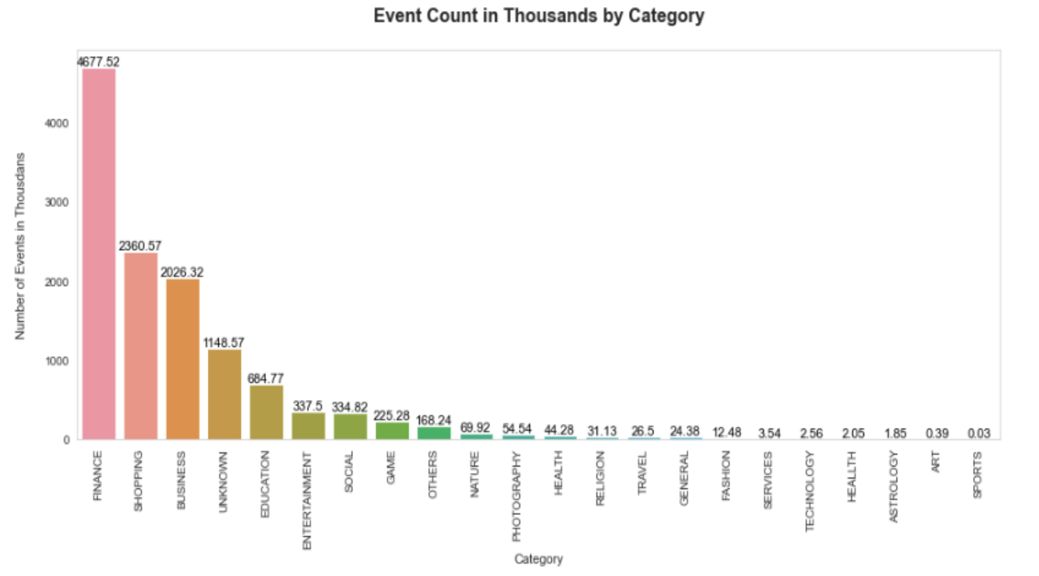
Exploratory Data Analysis – Slide 2

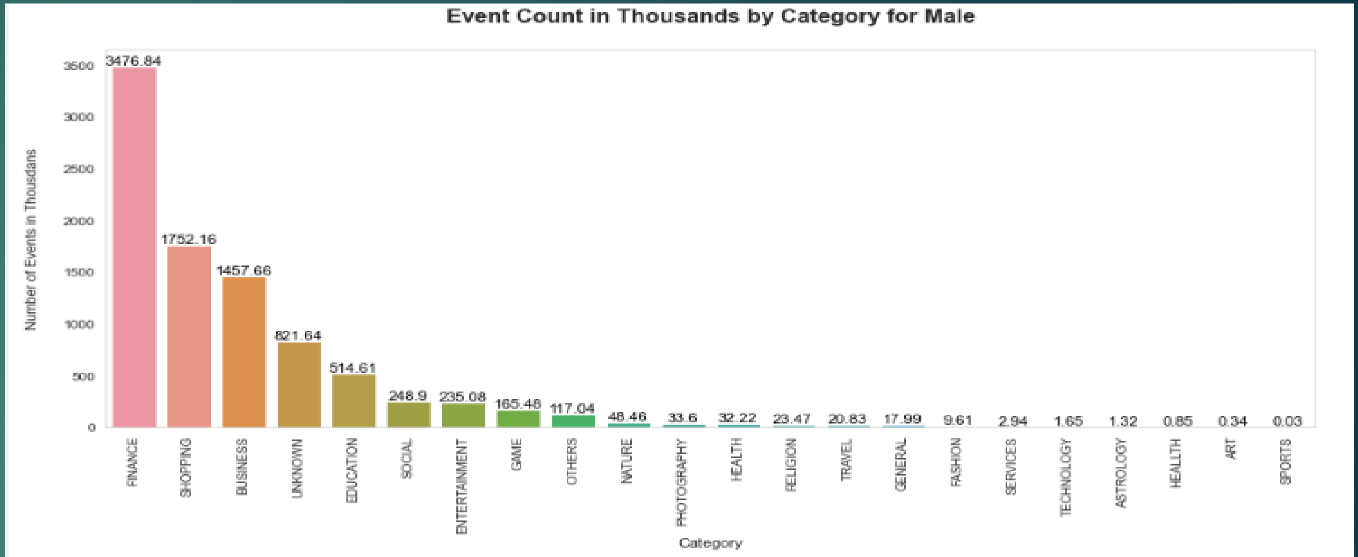


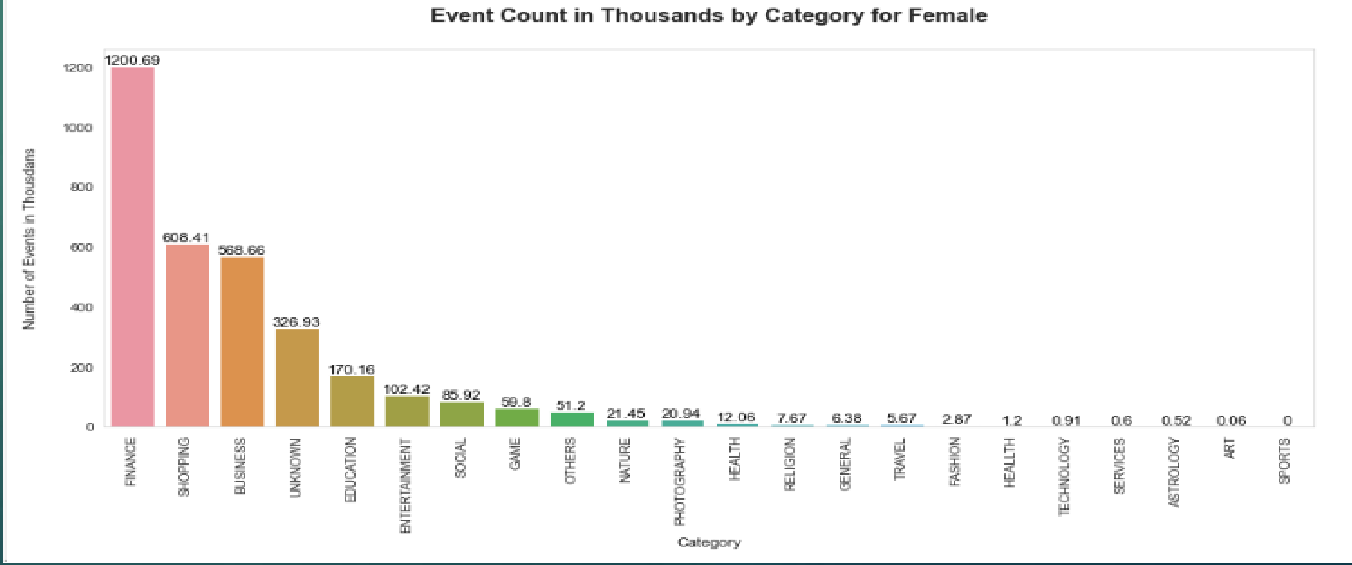


Exploratory Data Analysis – Slide 3

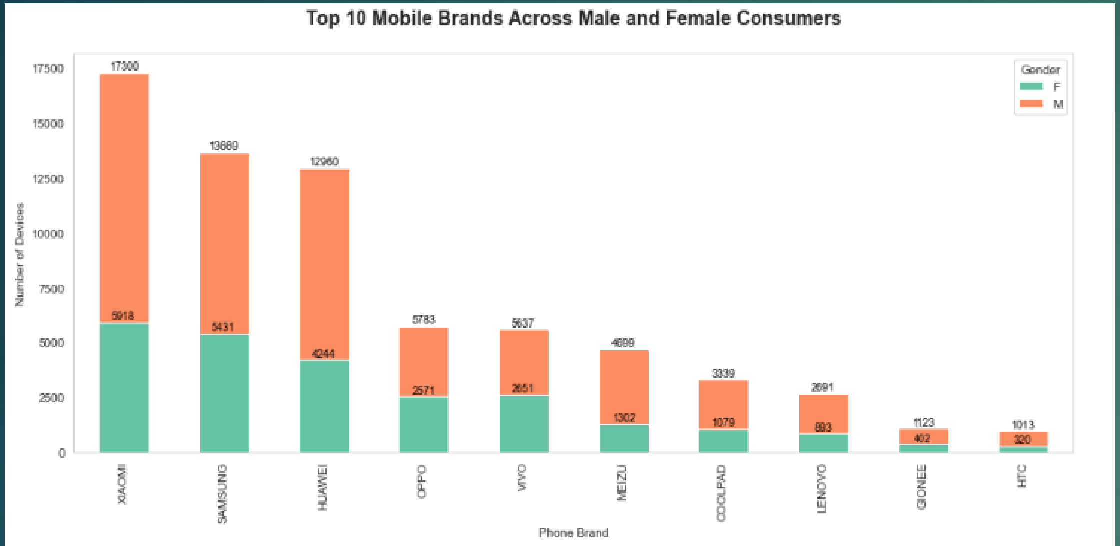


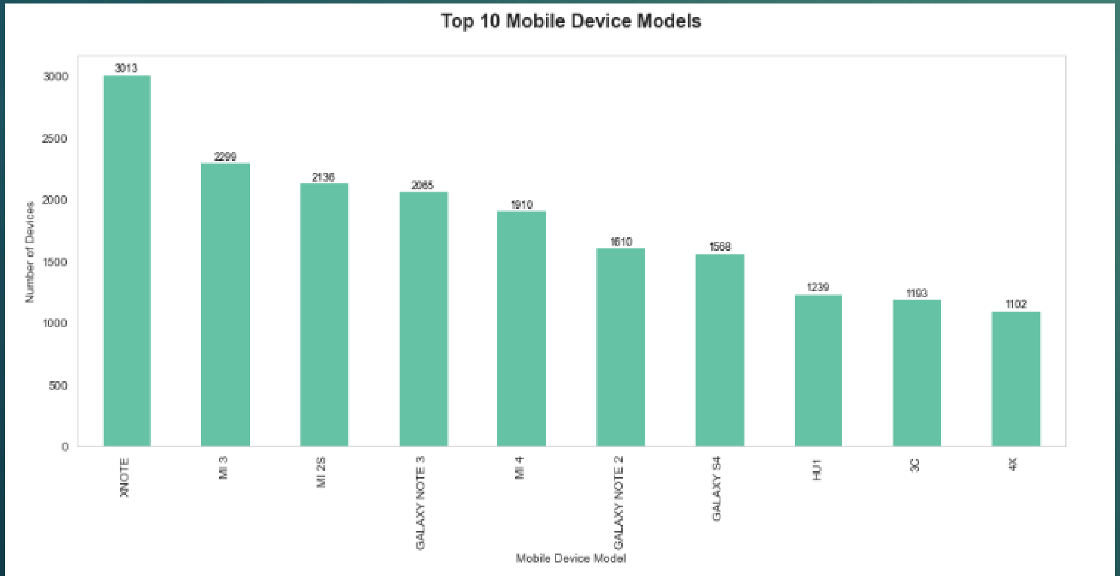


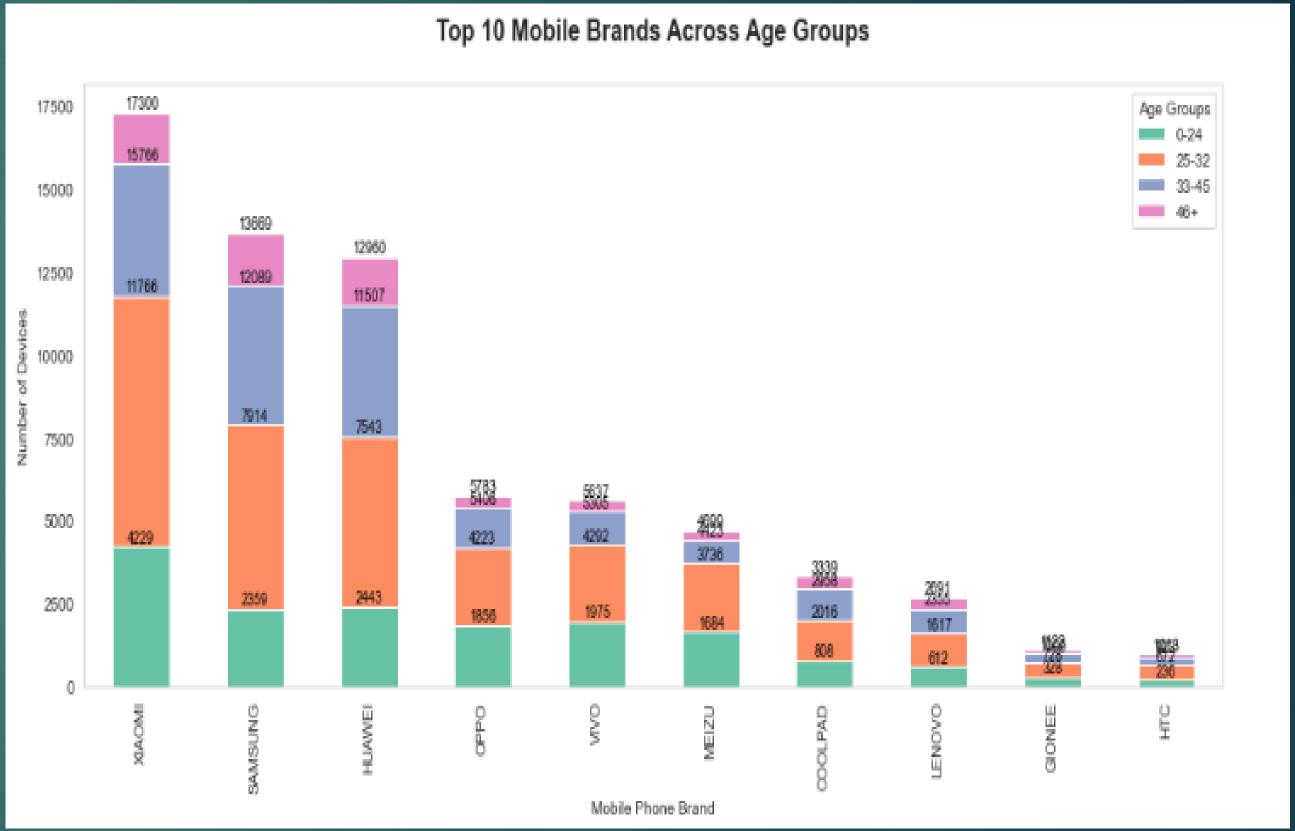




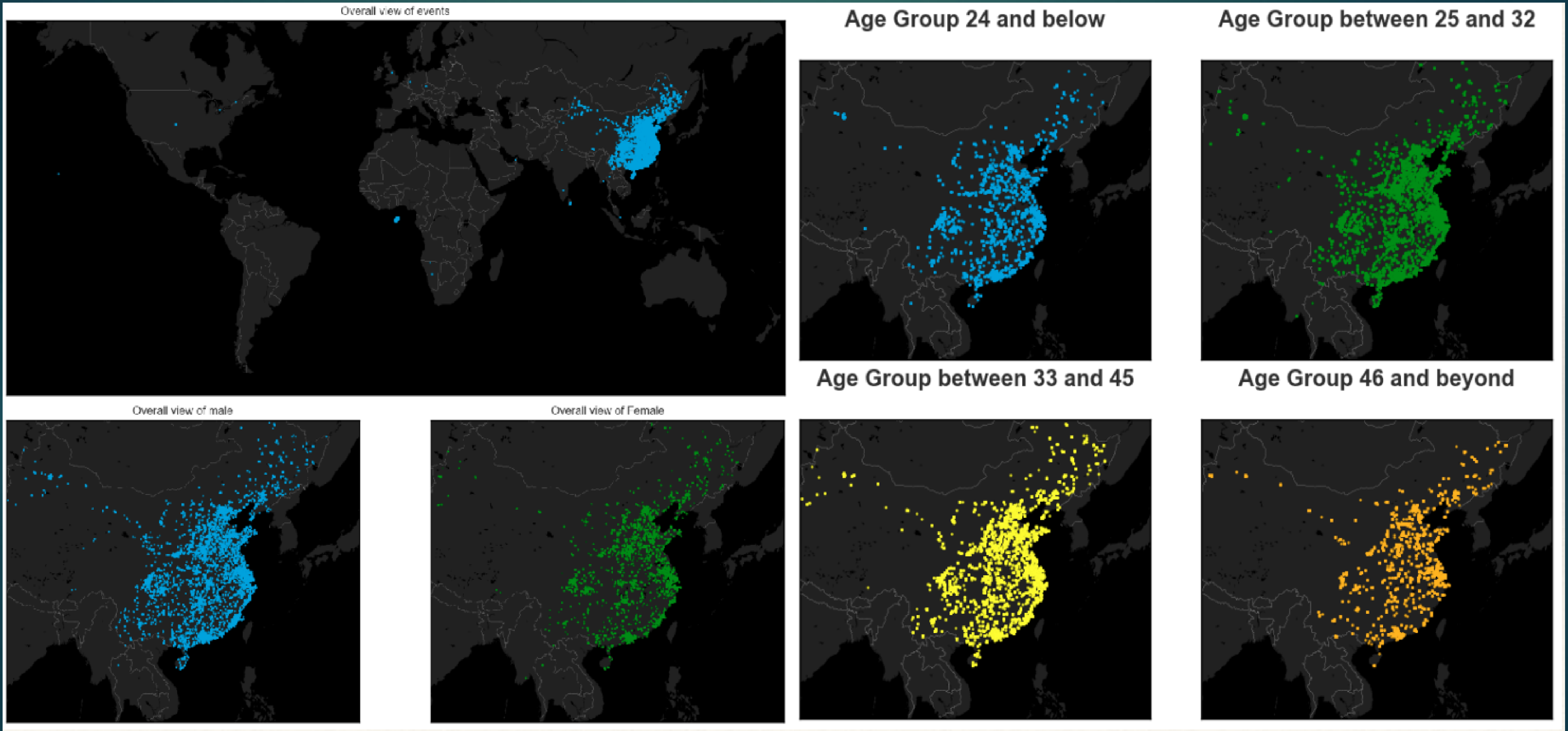
Exploratory Data Analysis – Slide 4



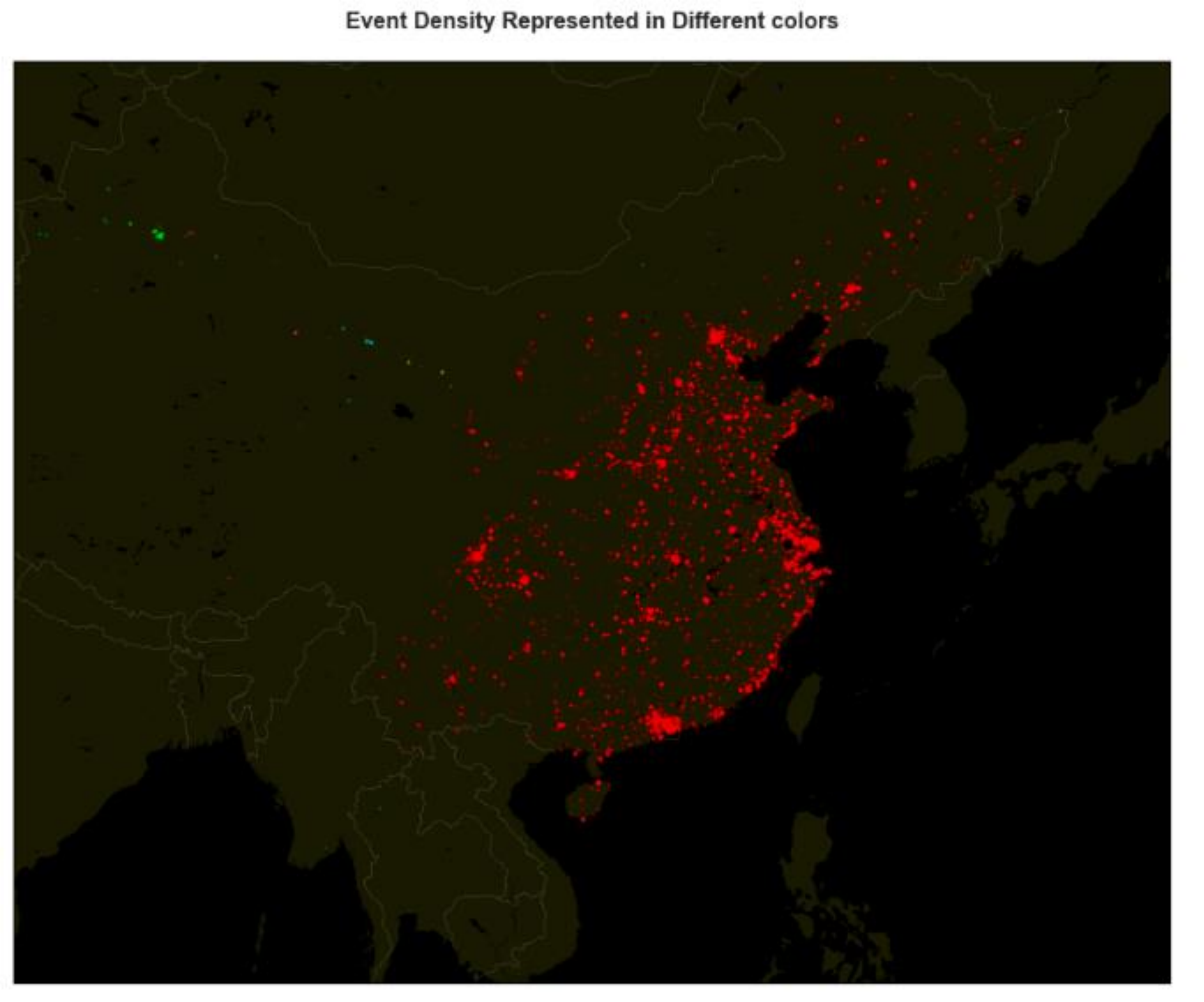




Exploratory Data Analysis – Slide 5



Exploratory Data Analysis – Slide 6



Data Preparation

Merge All necessary DataFrames ¶

```
dfDeviceData = dfTrainEventsWithEventData[["DeviceID", "Gender", "AgeGroup"]].drop_duplicates()
dfDeviceEventsMerged = pd.merge(dfDeviceData, dfDeviceLocationTimeOfDay, how="left", on="DeviceID")
dfDeviceEventsMerged = pd.merge(dfDeviceEventsMerged, dfDeviceTopCategoryApp, how="left", on="DeviceID")
dfDeviceEventsMerged = pd.merge(dfDeviceEventsMerged, dfDeviceCluster, how="left", on="DeviceID")
dfDeviceEventsMerged = pd.merge(dfDeviceEventsMerged, dfDeviceEventCount, how="left", on="DeviceID")
dfDeviceEventsMerged = pd.merge(dfDeviceEventsMerged, dfMobileBrand, how="left", on="DeviceID")

print(dfDeviceEventsMerged.shape)

dfDeviceEventsMerged.drop(["Morning", "Evening"], axis=1, inplace=True)

dfDeviceEventsMerged["TravellerType"].fillna("Unknown", inplace=True)

dfDeviceEventsMerged["Cluster"].fillna(-99,inplace=True)

dfDeviceEventsMerged["Cluster"] = dfDeviceEventsMerged["Cluster"].astype("category")

dfDeviceEventsMerged.head()
```

(23310, 11)

	DeviceID	Gender	AgeGroup	TravellerType	HighLevelCategory	Cluster	EventCount	MobilePhoneBrand	DeviceModel
0	-7548291590301750000	M	33-45	Infrequent	BUSINESS	0.0	292	HUAWEI	3C
1	6943568600617760000	M	33-45	Unknown	FINANCE	-99.0	1	XIAOMI	XNOTE
2	5441349705980020000	M	33-45	Unknown	FINANCE	-99.0	1	OPPO	R7S
3	-5393876656119450000	M	33-45	Unknown	FINANCE	-99.0	4	XIAOMI	MI 4
4	4543988487649880000	M	46+	Frequent	FINANCE	0.0	115	SAMSUNG	GALAXY S4

Train Test Split

```
dfTrainTest = pd.read_csv("train_test_split.csv")

dfTrainTest.columns = ["DeviceID", "Gender", "Age", "Group", "TrainTestFlag"]
dfTrainTest.head()
```

	DeviceID	Gender	Age	Group	TrainTestFlag
0	-7548291590301750000	M	33	M32+	train
1	6943568600617760000	M	37	M32+	train
2	5441349705980020000	M	40	M32+	train
3	-5393876656119450000	M	33	M32+	train
4	4543988487649880000	M	53	M32+	train

Label Encoding

```
#Defining Target Columns
target_columns = ['Gender', 'AgeGroup']

# Create an instance of the LabelEncoder
encoder = LabelEncoder()

# Apply label encoding on the selected columns
dfDeviceEventsMergedEncoded = dfDeviceEventsMerged.copy()
label_mappings = {}

for column in target_columns:
    encoded_labels = encoder.fit_transform(dfDeviceEventsMerged[column])
    dfDeviceEventsMergedEncoded[column] = encoded_labels
    label_mappings[column] = dict(zip(encoder.classes_, encoder.transform(encoder.classes_)))

# Print the mappings for each column
for column, mappings in label_mappings.items():
    print(f"Label Mappings for column '{column}':")
    for label, encoded_label in mappings.items():
        print(f"{label} : {encoded_label}")
    print()
```

```
Label Mappings for column 'Gender':
F : 0
M : 1

Label Mappings for column 'AgeGroup':
0-24 : 0
25-32 : 1
33-45 : 2
46+ : 3
```

Standard Scaler

```
num_columns=["EventCount"]

# Apply StandardScaler
scaler = StandardScaler()
dfTrain[num_columns] = scaler.fit_transform(dfTrain[num_columns].values)
dfTest[num_columns] = scaler.transform(dfTest[num_columns].values)
# Replace numerical columns with scaled values in the DataFrame
```

Target Encoding for "Gender Prediction"

```
target_columns = ['Gender']

cat_columns = ["TravellerType", "HighLevelCategory", "Cluster", "MobilePhoneBrand", "DeviceModel"]
encoder = ce.TargetEncoder(cols=cat_columns)

encoder.fit(dfTrain, dfTrain["Gender"])
# train_df.shape


dfTrain = encoder.transform(dfTrain)
dfTest = encoder.transform(dfTest)
```

Model Building - 1

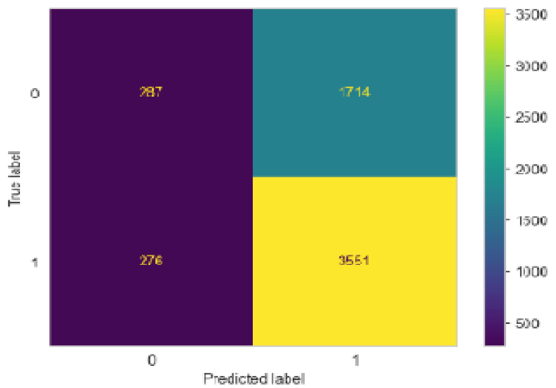
- Scenario 1 – With Events
  - Prediction - **Gender**
  - Models :–
    - Logistic
    - Random Forest
    - XG Boost
    - Model Stacking

- Scenario 1 - With Events
  - Prediction -A**geGroup**
  - Models :–
    - Logistic
    - Random Forest
    - XG Boost
    - Model Stacking

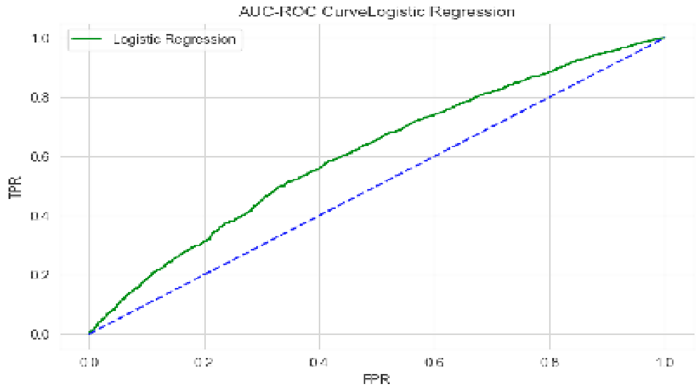
Scenario 1: Gender Prediction, Logistic Reg

```
y_pred,accuracy,training_accuracy,recall,precision,F1,lr_gender_1 = logistic_regression(X_train,
        y_gender_train,X_test,y_gender_test)

evaluation_metrics(lr_gender_1,X_test,y_gender_test,"Logistic Regression",accuracy,training_accuracy,recall,
        precision,F1,"Gender")
```

```
---------------Model Statistics---------------
Gender Model Accuracy: 0.6535449553877831
Gender Model training Accuracy: 0.6712046676581627
Gender Model Precision: 0.6744539411206077
Gender Model Recall: 0.9278308456161484
Gender Model F1 Score: 0.7811262648482182
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```

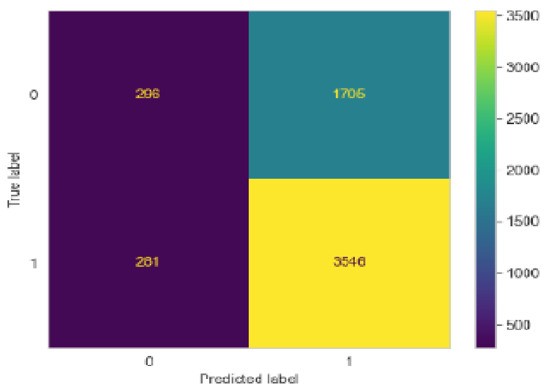



```
---------------Decile Analysis---------------
Top Probability: 0.5555661857200138
Bottom Probability: 0.6351541775130005
KS Statistic
Decile 0: 0.0006009929448654305
Decile 1: 0.0008884243532279349
Decile 2: 0.005252155735563091
Decile 3: 5.226025607524276e-05
Decile 4: 0.002743663443950834
Decile 5: 0.002926574340214260
Decile 6: 0.002064280114972505
Decile 7: 0.004860203314998742
Decile 8: 0.002691403187875640
Decile 9: 0.001045205121505077
---------------ROC Curve---------------
ROC AUC SCORE ->  0.6087205286826145
```

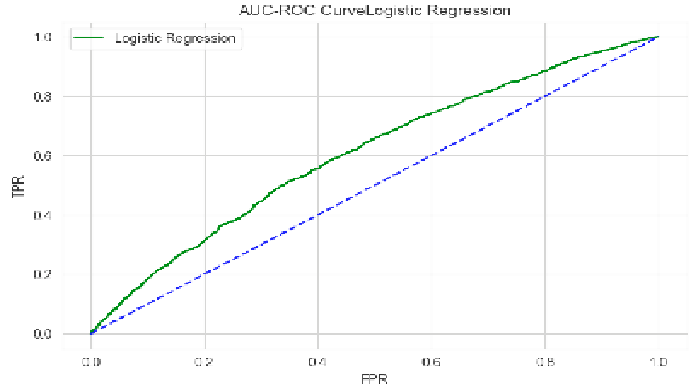



```
#Applying L1 Regularization
y_pred,accuracy,training_accuracy,recall,precision,F1,lr_gender_2 = logistic_regression(X_train,
        y_gender_train,X_test,y_gender_test,penalty='l1', solver='liblinear')
evaluation_metrics(lr_gender_2,X_test,y_gender_test,"Logistic Regression",accuracy,training_accuracy,recall,
        precision,F1,"Gender")
```

```
---------------Model Statistics---------------
Gender Model Accuracy: 0.6592312971859985
Gender Model training Accuracy: 0.6721193947483846
Gender Model Precision: 0.6752999428680231
Gender Model Recall: 0.9265743402142671
Gender Model F1 Score: 0.7812293456708525
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```




```
---------------Decile Analysis---------------
Top Probability: 0.5540670318181501
Bottom Probability: 0.6336251419362263
KS Statistic
Decile 0: 0.0006009929448654305
Decile 1: 0.0008884243532279349
Decile 2: 0.005252155735563091
Decile 3: 5.226025607524276e-05
Decile 4: 0.002743663443950834
Decile 5: 0.002926574340214260
Decile 6: 0.002064280114972505
Decile 7: 0.004860203814998742
Decile 8: 0.002691403187875640
Decile 9: 0.001045205121505077
---------------ROC Curve---------------
ROC AUC SCORE ->  0.607403575452932
```



Scenario 1 : Gender Prediction, Random Forest

Gender Prediction - Random Forest - Model 5

```python
param_grid={
            "n_estimators":[80],
           "min_samples_split":[2,5],
           "min_samples_leaf":[5],
           "max_leaf_nodes":[80,100],
           "max_depth":[50],
           "oob_score":[True],
            "bootstrap":[True]

           }

y_gender_pred,accuracy_gender,training_accuracy_gender,cv_gender,best_score_gender,best_params_gender_5 =
        cross_validation(X_train,y_gender_train,X_test,y_gender_test,rf_gender_1,param_grid)
print("Gender Model Accuracy:",accuracy_gender)
print("Gender Model training Accuracy:",training_accuracy_gender)
print("Best CV Score:",best_score_gender)
print("Best Paramater:",best_params_gender_5)
```

```
Gender Model Accuracy: 0.6573438572409059
Gender Model training Accuracy: 0.6912824619608741
Best CV Score: 0.6724631452986097
Best Paramater: {'bootstrap': True, 'max_depth': 50, 'max_leaf_nodes': 100, 'min_samples_leaf': 5, 'min_samples_split': 2, 'n_estimators': 80, 'oob_score': True}
```

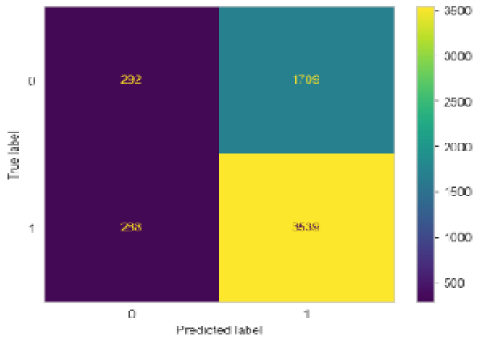
Gender Prediction - Random Forest - Model Selection

```python
# Since Model 5 has best acccuracy score taking model 5 as final model
best_params_gender=best_params_gender_5
```

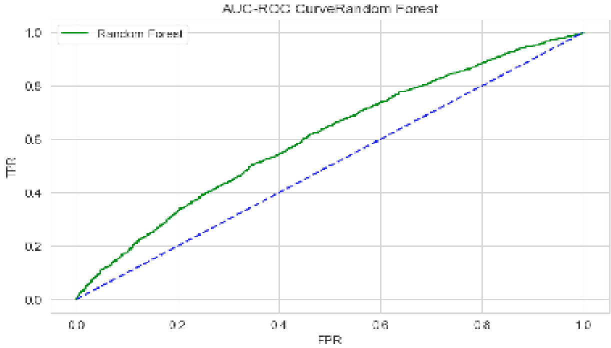
Gender Prediction - Random Forest - Best Parameters

```python
#Best Random Forest Model

y_pred,accuracy,training_accuracy,recall,precision,F1,rf_gender = random_forest(X_train,y_gender_train,X_test,
        y_gender_test,**best_params_gender)
evaluation_metrics(rf_gender,X_test,y_gender_test,"Random Forest",accuracy,training_accuracy,recall,precision,
        F1,"Gender")
```

```
---------------Model Statistics---------------
Gender Model Accuracy: 0.6573438572409059
Gender Model training Accuracy: 0.6912824619608741
Gender Model Precision: 0.6743521341463414
Gender Model Recall: 0.9247452312516331
Gender Model F1 Score: 0.7799449035812672
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```




```
---------------Decile Analysis---------------
Top Probability: 0.5565927512322382
Bottom Probability: 0.6370836299390606
KS Statistic
Decile 0: 0.0006009929448654305
Decile 1: 0.000888424353279349
Decile 2: 0.005252155735563091
Decile 3: 5.226025607524276e-05
Decile 4: 0.0027436634439508834
Decile 5: 0.0029255743402142608
Decile 6: 0.0020642801149725054
Decile 7: 0.0048607038149987475
Decile 8: 0.0026914031878756406
Decile 9: 0.0018452051215050773
---------------ROC Curve---------------
ROC AUC SCORE -> 0.6056710343354785
```



Scenario 1 : Gender Prediction, X G Boost

Gender Prediction - XG Boost Tuning Model 5

```
param_grid={"n_estimators":[50],
            "max_depth":[2,3],
            "learning_rate":[0.3,0.4],
             'min_child_weight': [3,4],
             'gamma': [0.2, 0.3]


            }

y_gender_pred,accuracy_gender,training_accuracy_gender,cv_gender,best_score_gender,best_params_gender_5 =
        cross_validation(X_train,y_gender_train,X_test,y_gender_test,xgb_gender_1,param_grid)
print("Gender Model Accuracy:",accuracy_gender)
print("Gender Model training Accuracy:",training_accuracy_gender)
print("Best CV Score:",best_score_gender)
print("Best Paramater:",best_params_gender_5)
```

```
Gender Model Accuracy: 0.6557995881949211
Gender Model training Accuracy: 0.6847614689394806
Best CV Score: 0.6726918670047767
Best Paramater: {'gamma': 0.3, 'learning_rate': 0.3, 'max_depth': 3, 'min_child_weight': 4, 'n_estimators': 50}
```

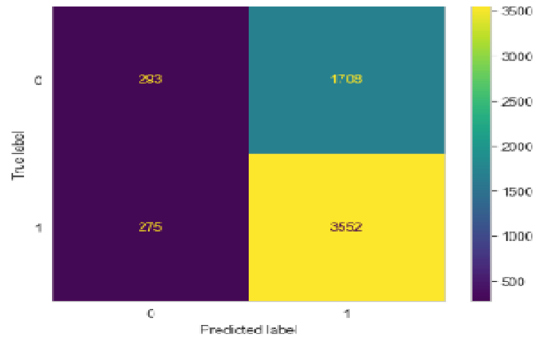
Gender Prediction - XG Boost Tuning Model Selection

```
# Since Model 1 has best acccuracy score taking model 1 as final model
best_params_gender=best_params_gender_1
```

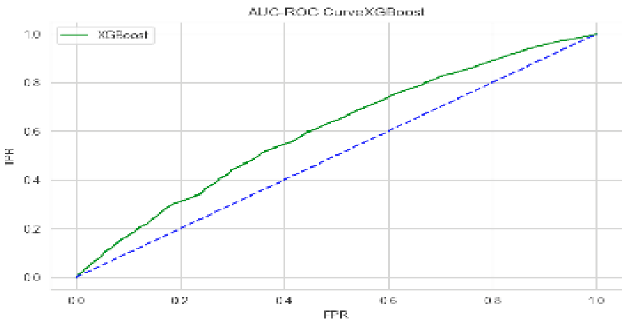
Gender Prediction - XG Boost Model with Best Parameters

```
#Best XG Boost Model

y_pred,accuracy,training_accuracy,recall,precision,F1,xgb_gender = xg_boost(X_train,y_gender_train,X_test,
        y_gender_test,**best_params_gender)
evaluation_metrics(xgb_gender,X_test,y_gender_test,"XGBoost",accuracy,training_accuracy,recall,precision,F1,
        "Gender")
```

```
----------------Model Statistics----------------
Gender Model Accuracy: 0.6597460533346603
Gender Model training Accuracy: 0.6774958539068756
Gender Model Precision: 0.6752851711026516
Gender Model Recall: 0.9281421478955247
Gender Model F1 Score: 0.7817761637504128
----------------Confusion Matrix----------------

<Figure size 800x500 with 0 Axes>
```




```
----------------Decile Analysis----------------
Top Probability: 0.54701
Bottom Probability: 0.6412411
KS Statistic
Decile 0: 0.0036009325448654305
Decile 1: 0.0008884243532793349
Decile 2: 0.005252155735563091
Decile 3: 5.225025637524276e-05
Decile 4: 0.0027436534439508834
Decile 5: 0.0029265743402142608
Decile 6: 0.0020642301149725054
Decile 7: 0.004860233614996 7425
Decile 8: 0.0026914031878756406
Decile 9: 0.0010452851215050773
----------------ROC Curve----------------
ROC AUC SCORE ->  0.6627117092094141
```

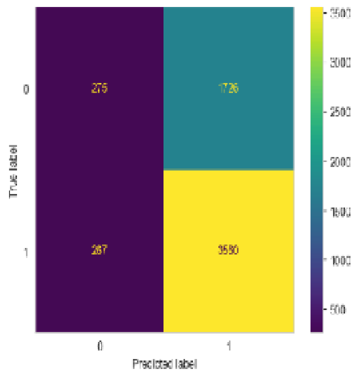


Scenario 1 : Gender Prediction, Stacking

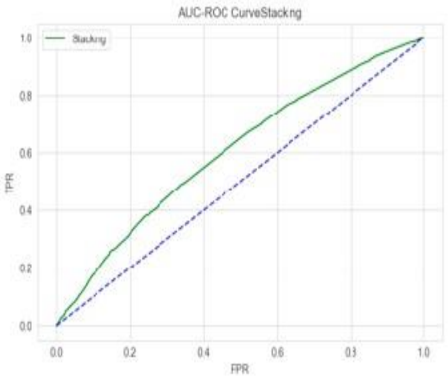
Gender Prediction - Model Stacking - 1

```
#### Stacking Logistic regression and random forest as classifier and XGBoost as Meta classifier
classifiers=[lr_gender,rf_gender]
y_pred,accuracy,training_accuracy,recall,precision,F1,stacking_gender_1=model_stacking(X_train,y_gender_train,
        X_test,y_gender_test,classifiers,xgb_gender)
evaluation_metrics(stacking_gender_1,X_test,y_gender_test,"Stacking",accuracy,training_accuracy,recall,
        precision,F1,"Gender")
```

```
---------------Model Statistics---------------
Gender Model Accuracy: 0.6588381998391215
Gender Model training Accuracy: 0.6785836360771078
Gender Model Precision: 0.6734771093454408
Gender Model Recall: 0.9302325581395349
Gender Model F1 Score: 0.7813014375868584
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```



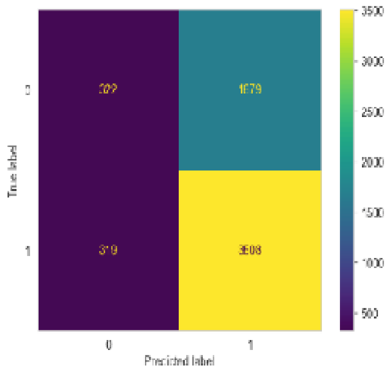

```
---------------Decile Analysis---------------
Top Probability: 0.54731107
Bottom Probability: 0.6428404
KS Statistic
Decile 0: 0.0006089329448654305
Decile 1: 0.0008884243532279349
Decile 2: 0.005252155735563091
Decile 3: 5.2258256875242 76e-05
Decile 4: 0.002743653443950 8834
Decile 5: 0.002925574340214260 8
Decile 6: 0.002864230114972 5054
Decile 7: 0.004868228338149 987425
Decile 8: 0.002691443187875 6406
Decile 9: 0.0018452851215050773
---------------ROC Curve---------------
ROC AUC SCORE ->  0.6347950825509647
```



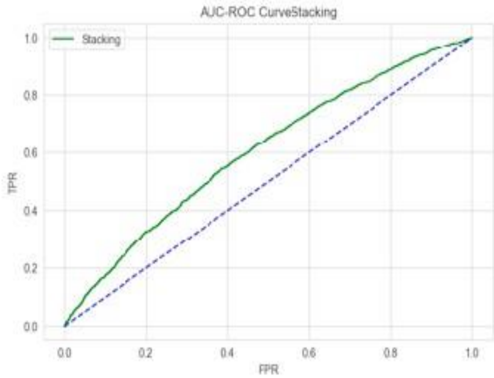
Gender Prediction - Model Stacking - 2

```
#### Stacking XGBoost and random forest as classifier and XGBoost as Logistic regression Meta classifier
classifiers=[xgb_gender,rf_gender]
y_pred,accuracy,training_accuracy,recall,precision,F1,stacking_gender_2=model_stacking(X_train,y_gender_train,
        X_test,y_gender_test,classifiers,lr_gender)
evaluation_metrics(stacking_gender_2,X_test,y_gender_test,"Stacking",accuracy,training_accuracy,recall,
        precision,F1,"Gender")
```

```
---------------Model Statistics---------------
Gender Model Accuracy: 0.6571722717913521
Gender Model training Accuracy: 0.6844182587804599
Gender Model Precision: 0.6763061459903685
Gender Model Recall: 0.9166448915559585
Gender Model F1 Score: 0.7783447966824717
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```



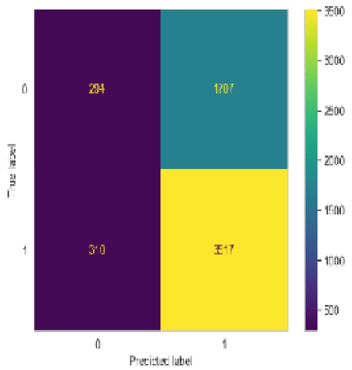

```
---------------Decile Analysis---------------
Top Probability: 0.5444834438962366
Bottom Probability: 0.6446314072494459
KS Statistic
Decile 0: 0.0006089329448654305
Decile 1: 0.0008884243532279349
Decile 2: 0.005252155735563091
Decile 3: 5.226825687524276e-05
Decile 4: 0.002743653443950 8834
Decile 5: 0.002925574340214260 8
Decile 6: 0.002864230114972 5054
Decile 7: 0.004868228338149 987425
Decile 8: 0.002691443187875 6406
Decile 9: 0.0018452851215050773
---------------ROC Curve---------------
ROC AUC SCORE ->  0.6054092760256924
```



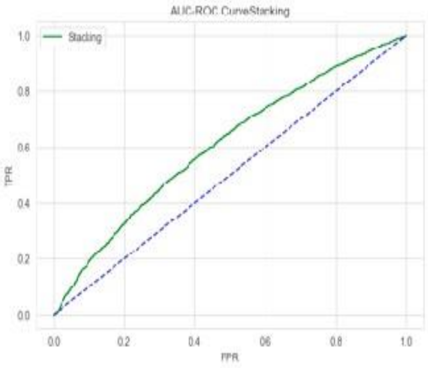
Gender Prediction - Model Stacking - 3

```
#### Stacking XGBoost and Logistic regression as classifier and XGBoost as Random Forest Meta classifier
classifiers=[lr_gender,xgb_gender]
y_pred,accuracy,training_accuracy,recall,precision,F1,stacking_gender_3=model_stacking(X_train,y_gender_train,
        X_test,y_gender_test,classifiers,rf_gender)
evaluation_metrics(stacking_gender_3,X_test,y_gender_test,"Stacking",accuracy,training_accuracy,recall,
        precision,F1,"Gender")
```

```
---------------Model Statistics---------------
Gender Model Accuracy: 0.6539121482498285
Gender Model training Accuracy: 0.6760668115776227
Gender Model Precision: 0.6732388973966389
Gender Model Recall: 0.9189960830833551
Gender Model F1 Score: 0.7771516959451394
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```




```
---------------Decile Analysis---------------
Top Probability: 0.5502532518772229
Bottom Probability: 0.6365223613797085
KS Statistic
Decile 0: 0.0006089329448654305
Decile 1: 0.0008884243532279349
Decile 2: 0.005252155735563091
Decile 3: 5.226825687524276e-05
Decile 4: 0.002743653443950 8834
Decile 5: 0.002925574340214260 8
Decile 6: 0.002864230114972 5054
Decile 7: 0.004868228338149 987425
Decile 8: 0.002691443187875 6406
Decile 9: 0.0018452851215050773
---------------ROC Curve---------------
ROC AUC SCORE ->  0.6065696533017264
```



Scenario 1 : Gender Prediction, Final Model

Gender Prediction - Final Model Selection

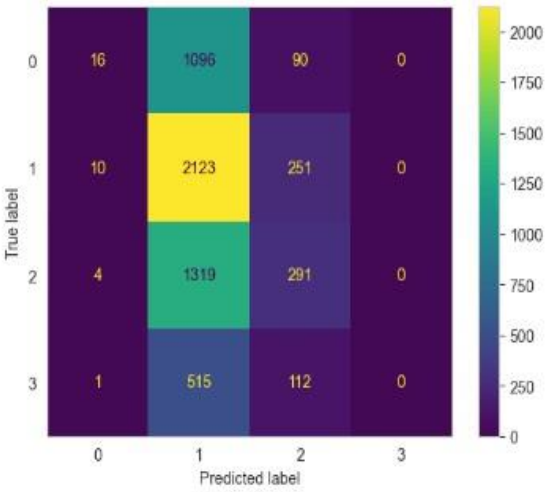
```
# Logistic Regression Gives best accuracy so considering Logistic Regression model as final model
final_model_gender = lr_gender
```

Scenario 1 : AgeGroup Prediction, Logistic Reg.

Age Group Prediction - Logistic Regression

```
y_pred,accuracy,training_accuracy,recall,precision,F1,lr_age_group_1 = logistic_regression(X_train,
        y_age_group_train,X_test,y_age_group_test,average="weighted")
evaluation_metrics(lr_age_group_1,X_test,y_age_group_test,"Logistic Regression",accuracy,training_accuracy,
        recall,precision,F1,"Age Group",multiclass=True)
```

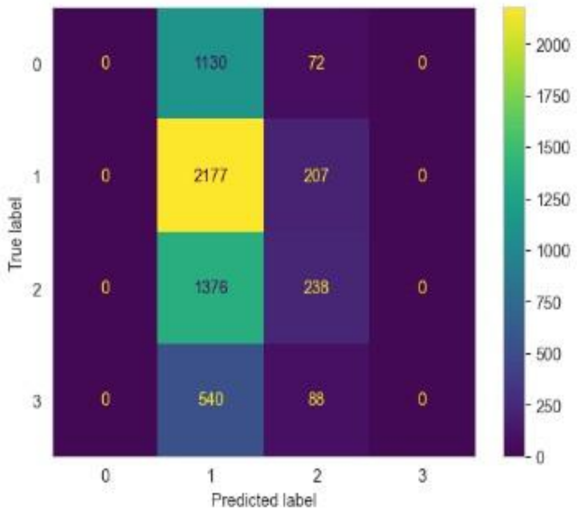
```
---------------Model Statistics---------------
Age Group Model Accuracy: 0.4169526424159231
Age Group Model training Accuracy: 0.4159707127330969
Age Group Model Precision: 0.38663323370759994
Age Group Model Recall: 0.4169526424159231
Age Group Model F1 Score: 0.30725067530201844
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```




```
---------------Multiclass Log Loss---------------
Multiclass Log Loss: 1.2607
```

```
#Applying L1 Regularization
y_pred,accuracy,training_accuracy,recall,precision,F1,lr_age_group_2 = logistic_regression(X_train,
        y_age_group_train,X_test,y_age_group_test,average="weighted",penalty='l1', solver='liblinear')
evaluation_metrics(lr_age_group_2,X_test,y_age_group_test,"Logistic Regression",accuracy,training_accuracy,
        recall,precision,F1,"Age Group",multiclass=True)
```

```
---------------Model Statistics---------------
Age Group Model Accuracy: 0.414378860672615
Age Group Model training Accuracy: 0.416027914426267
Age Group Model Precision: 0.279444850883026
Age Group Model Recall: 0.414378860672615
Age Group Model F1 Score: 0.29353896262283374
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```




```
---------------Multiclass Log Loss---------------
Multiclass Log Loss: 1.2606
```

Scenario 1 : AgeGroup Prediction, Random Forest

Age Group Prediction - Random Forest Model 1

```
param_grid={
            "n_estimators":[120,130],
           "min_samples_split":[2,3],
           "min_samples_leaf":[3,5],
           "max_leaf_nodes":[100,120],
           "max_depth":[50],
           "oob_score":[True],
            "bootstrap":[True]

           }

y_age_group_pred,accuracy_age_group,training_accuracy_age_group,cv_age_group,best_score_age_group,
        best_params_age_group_1 = cross_validation(X_train,y_age_group_train,X_test,y_age_group_test,
        rf_age_group_1,param_grid)
print("age_group Model Accuracy:",accuracy_age_group)
print("age_group Model training Accuracy:",training_accuracy_age_group)
print("Best CV Score:",best_score_age_group)
print("Best Paramater:",best_params_age_group_1)
```

```
age_group Model Accuracy: 0.41815374056280025
age_group Model training Accuracy: 0.44274110513671205
Best CV Score: 0.41534148046686004
Best Paramater: {'bootstrap': True, 'max_depth': 50, 'max_leaf_nodes': 100, 'min_samples_leaf': 3, 'min_samples_split': 2, 'n_estimators': 120, 'oob_score': True}
```

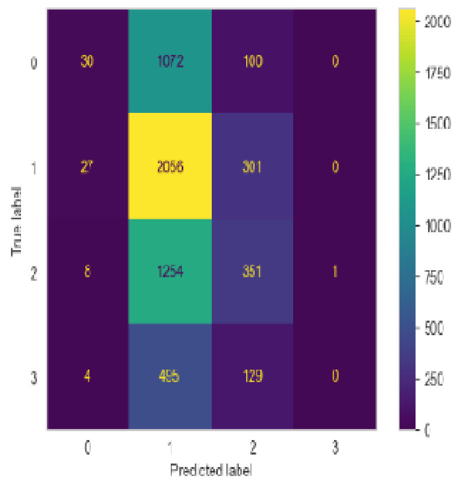
Age Group Prediction - Random Forest Model Selection

```
# All Models have similar Accuracy Taking model 1 as final model
best_params_age_group=best_params_age_group_1
```

Age Group Prediction - Random Forest - Best Parameters

```
#Best Random Forest Model
y_pred,accuracy,training_accuracy,recall,precision,F1,rf_age_group = randon_forest(X_train,y_age_group_train,
        X_test,y_age_group_test,average="weighted",**best_params_age_group)
evaluation_metrics(rf_age_group,X_test,y_age_group_test,"Random Forest",accuracy,training_accuracy,recall,
        precision,F1,"age_group",multiclass=True)
```

```
---------------Model Statistics---------------
age_group Model Accuracy: 0.41815374056280025
age_group Model training Accuracy: 0.44274110513671205
age_group Model Precision: 0.37245509320271114
age_group Model Recall: 0.41815374056280025
age_group Model F1 Score: 0.31931241974438135
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```




```
---------------Multiclass Log Loss---------------
Multiclass Log Loss: 1.2572
```

Scenario 1: AgeGroup Prediction, XGBoost

Age Group Prediction - XG Boost Model 1

```
param_grid={"n_estimators":[10,20],
            "max_depth":[3,6],
            "learning_rate":[0.1,0.3],
             'min_child_weight': [2, 3],
             'gamma': [0.1, 0.2]

            }

y_age_group_pred,accuracy_age_group,training_accuracy_age_group,cv_age_group,best_score_age_group,
        best_params_age_group_1 = cross_validation(X_train,y_age_group_train,X_test,y_age_group_test,
        xgb_age_group_1,param_grid)
print("age_group Model Accuracy:",accuracy_age_group)
print("age_group Model training Accuracy:",training_accuracy_age_group)
print("Best CV Score:",best_score_age_group)
print("Best Paramater:",best_params_age_group_1)
```

```
age_group Model Accuracy: 0.4226149622512011
age_group Model training Accuracy: 0.42060404987987643
Best CV Score: 0.4154557137179274
Best Paramater: {'gamma': 0.1, 'learning_rate': 0.1, 'max_depth': 3, 'min_child_weight': 2, 'n_estimators': 10}
```

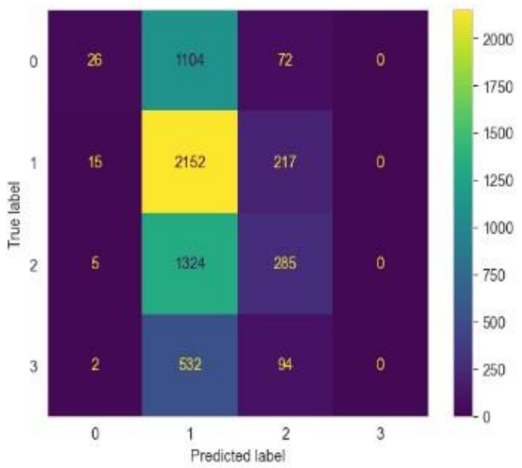
Age Group Prediction - XG Boost Tuning Model Selection

```
# Since Model 1 has best acccuracy score taking model 1 as final model
best_params_age_group=best_params_age_group_1
```

Age Group Prediction - XG Boost Model with Best Parameters

```
#Base XG Boost Model

y_pred,accuracy,training_accuracy,recall,precision,F1,xgb_age_group = xg_boost(X_train,y_age_group_train,
        X_test,y_age_group_test,average="weighted",**best_params_age_group)
evaluation_metrics(xgb_age_group,X_test,y_age_group_test,"XG Boost",accuracy,training_accuracy,recall,
        precision,F1,"Age Group",multiclass=True)
```

```
---------------Model Statistics---------------
Age Group Model Accuracy: 0.4226149622512011
Age Group Model training Accuracy: 0.42060404987987643
Age Group Model Precision: 0.40207347838117236
Age Group Model Recall: 0.4226149622512011
Age Group Model F1 Score: 0.31262486922894567
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```



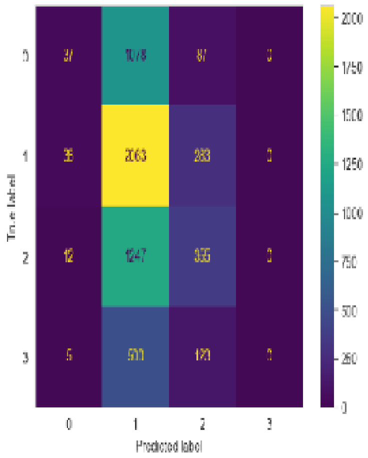

```
---------------Multiclass Log Loss---------------
Multiclass Log Loss: 1.2926
```

Scenario 1 : AgeGroup Prediction, Stacking

Age Group Prediction - Model 1

```
#### Stacking Logistic regression and random forest as classifier and XGBoost as Meta classifier
classifiers=[lr_age_group,rf_age_group]
y_pred,accuracy,training_accuracy,recall,precision,F1,stacking_age_group_1=model_stacking(X_train,
        y_age_group_train,X_test,y_age_group_test,classifiers,xgb_age_group,average='weighted')
evaluation_metrics(stacking_age_group_1,X_test,y_age_group_test,"Stacking",accuracy,training_accuracy,recall,
        precision,F1,"Age Group",multiclass=True)
```

```
==============Model Statistics=============
Age Group Model Accuracy: 0.4212422785547701
Age Group Model training Accuracy: 0.4235213362315524
Age Group Model Precision: 0.3715274480377117
Age Group Model Recall: 0.4212422786547701
Age Group Model F1 Score: 0.3237521818592823
--------------Confusion Matrix-------------

&lt;Figure size 800x500 with 0 Axes&gt;
```

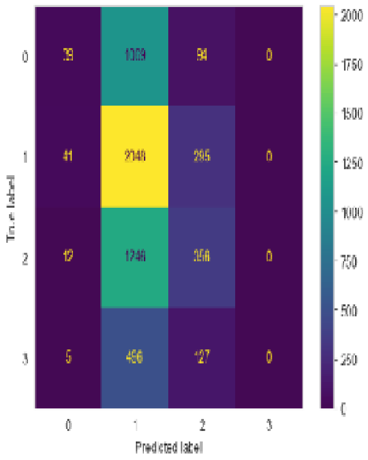



```
--------------Multiclass Log Loss--------------
Multiclass Log Loss: 1.2917
```

Age Group Prediction - Model 2

```
#### Stacking Logistic regression and random forest as classifier and XGBoost as Meta classifier
classifiers=[xgb_age_group,rf_age_group]
y_pred,accuracy,training_accuracy,recall,precision,F1,stacking_age_group_2=model_stacking(X_train,
        y_age_group_train,X_test,y_age_group_test,classifiers,lr_age_group,average='weighted')
evaluation_metrics(stacking_age_group_2,X_test,y_age_group_test,"Stacking",accuracy,training_accuracy,recall,
        precision,F1,"Age Group",multiclass=True)
```

```
==============Model Statistics==============
Age Group Model Accuracy: 0.4191832532601235
Age Group Model training Accuracy: 0.4318727834343897
Age Group Model Precision: 0.3683985251815096
Age Group Model Recall: 0.4191832532601235
Age Group Model F1 Score: 0.3230286266185266
--------------Confusion Matrix--------------

&lt;Figure size 800x500 with 0 Axes&gt;
```

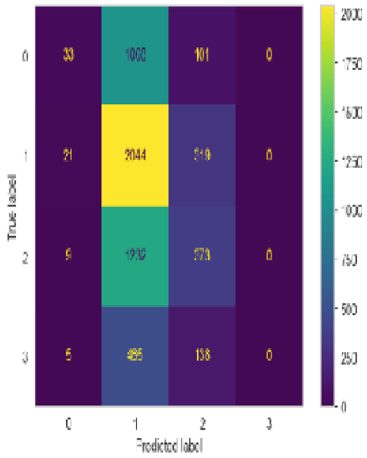



```
==============Multiclass Log Loss==============
Multiclass Log Loss: 1.2573
```

Age Group Prediction - Model 3

```
#### Stacking Logistic regression and random forest as classifier and XGBoost as Meta classifier
classifiers=[lr_age_group,xgb_age_group]
y_pred,accuracy,training_accuracy,recall,precision,F1,stacking_age_group_3=model_stacking(X_train,
        y_age_group_train,X_test,y_age_group_test,classifiers,rf_age_group,average='weighted')
evaluation_metrics(stacking_age_group_3,X_test,y_age_group_test,"Stacking",accuracy,training_accuracy,recall,
        precision,F1,"Age Group",multiclass=True)
```

```
--------------Model Statistics--------------
Age Group Model Accuracy: 0.4283043514878087
Age Group Model training Accuracy: 0.4207384532652157
Age Group Model Precision: 0.3841899497652787
Age Group Model Recall: 0.4283043514878087
Age Group Model F1 Score: 0.3237320811587844
==============Confusion Matrix==============

&lt;Figure size 800x500 with 0 Axes&gt;
```




```
--------------Multiclass Log Loss--------------
Multiclass Log Loss: 1.2599
```

Scenario 1 : AgeGroup Prediction, Final Model

Age Group Prediction - Final Model Selection

```
# Random Forest Gives best accuracy so considering XG Boost model as final model
final_model_age_group = xgb_age_group
```

Model Building - 2

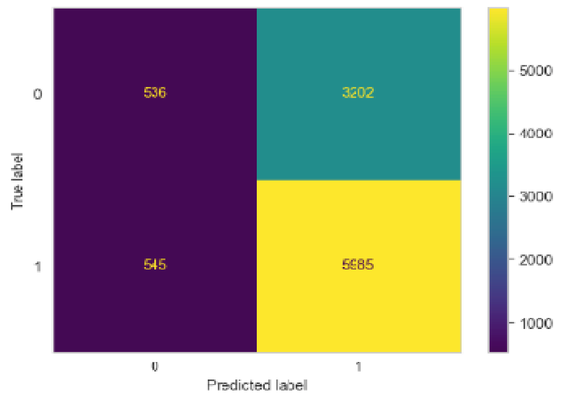
- Scenario 1 – Without Events
  - Prediction - **Gender**
  - Models :–
    - Logistic
    - Random Forest
    - XG Boost
    - Model Stacking

- Scenario 1 - Without Events
  - Prediction -**AgeGroup**
  - Models :–
    - Logistic
    - Random Forest
    - XG Boost
    - Model Stacking

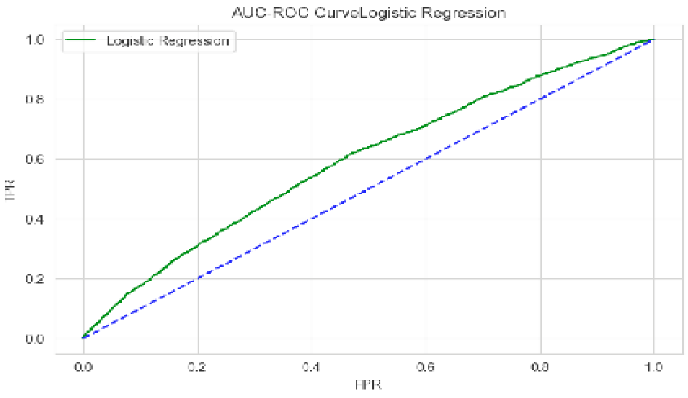
Scenario 2: Gender Prediction, Logistic Reg

```
y_pred,accuracy,training_accuracy,recall,precision,F1,lr_gender_1 = logistic_regression(X_train,
        y_gender_train,X_test,y_gender_test)
evaluation_metrics(lr_gender_1,X_test,y_gender_test,"Logistic Regression",accuracy,training_accuracy,recall,
        precision,F1,"Gender")
```

```
---------------Model Statistics---------------
Gender Model Accuracy: 0.6350798597584729
Gender Model training Accuracy: 0.6456765773005089
Gender Model Precision: 0.651464025253075
Gender Model Recall: 0.9165390505359877
Gender Model F1 Score: 0.7615957243748807
---------------Confusion Matrix---------------
<Figure size 800x500 with 0 Axes>
```

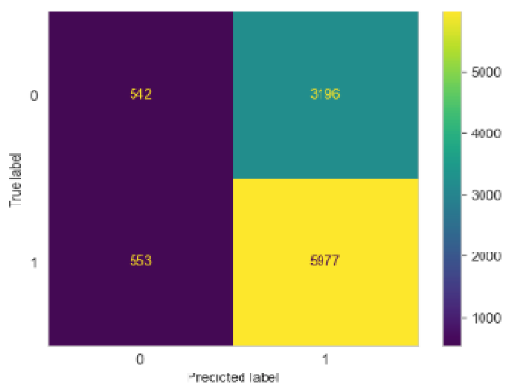



```
---------------Decile Analysis---------------
Top Probability: 0.20917048862414023
Bottom Probability: 0.8698126143751280
KS Statistic
Decile 0: 0.0032159264931087284
Decile 1: 0.003062787136294015
Decile 2: 0.003215926493108756
Decile 3: 0.002450229709903519
Decile 4: 0.0033690658499234694
Decile 5: 0.0006125574272588530
Decile 6: 0.0004594180704440287
Decile 7: 0.0013782542113323082
Decile 8: 0.001990811638591161
Decile 9: 0.0007656967840734552
---------------ROC Curve---------------
ROC AUC SCORE ->  0.5943410746957902
```

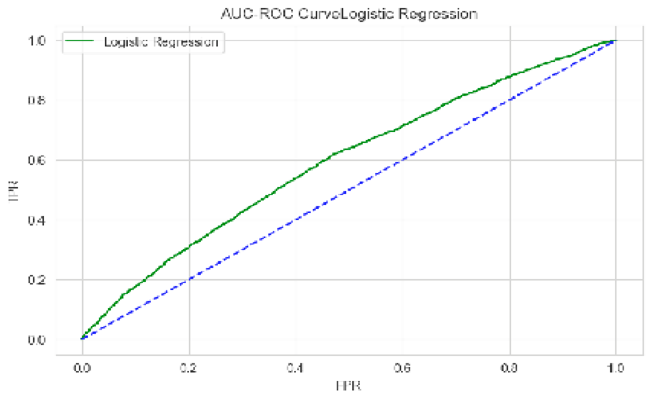



```
#Applying L1 Regularization
y_pred,accuracy,training_accuracy,recall,precision,F1,lr_gender_2 = logistic_regression(X_train,
        y_gender_train,X_test,y_gender_test,penalty='l1', solver='liblinear')
evaluation_metrics(lr_gender_2,X_test,y_gender_test,"Logistic Regression",accuracy,training_accuracy,recall,
        precision,F1,"Gender")
```

```
---------------Model Statistics---------------
Gender Model Accuracy: 0.634885079859758
Gender Model training Accuracy: 0.6457983295590133
Gender Model Precision: 0.6515861768232857
Gender Model Recall: 0.9153139356814701
Gender Model F1 Score: 0.7612558109915303
---------------Confusion Matrix---------------
<Figure size 800x500 with 0 Axes>
```




```
---------------Decile Analysis---------------
Top Probability: 0.20483807417177302
Bottom Probability: 0.873673962145846
KS Statistic
Decile 0: 0.0032159264931087284
Decile 1: 0.003062787136294015
Decile 2: 0.003215926493108756
Decile 3: 0.002450229709903519
Decile 4: 0.0033690658499234694
Decile 5: 0.0006125574272588530
Decile 6: 0.0004594180704440287
Decile 7: 0.0013782542113323082
Decile 8: 0.001990811638591161
Decile 9: 0.0007656967840734552
---------------ROC Curve---------------
ROC AUC SCORE ->  0.594020620964142
```



Scenario 2: Gender Prediction, Random Forest

Gender Prediction - Random Forest - Model 2

```
param_grid={
                "n_estimators":[100,120],
               "min_samples_split":[2,3],
               "min_samples_leaf":[3,5],
               "max_leaf_nodes":[120,130],
               "max_depth":[50],
               "oob_score":[True],
                "bootstrap":[True]

               }

y_gender_pred,accuracy_gender,training_accuracy_gender,cv_gender,best_score_gender,best_params_gender_2 =
        cross_validation(X_train,y_gender_train,X_test,y_gender_test,rf_gender_1,param_grid)
print("Gender Model Accuracy:",accuracy_gender)
print("Gender Model training Accuracy:",training_accuracy_gender)
print("Best CV Score:",best_score_gender)
print("Best Paramater:",best_params_gender_2)
```

```
Gender Model Accuracy: 0.639851967276977
Gender Model training Accuracy: 0.6662770594394526
Best CV Score: 0.6523242506148489
Best Paramater: {'bootstrap': True, 'max_depth': 50, 'max_leaf_nodes': 120, 'min_samples_leaf': 5, 'min_samples_split': 2, 'n_estimators': 120, 'oob_score': True}
```

Gender Prediction - Random Forest - Model Selection

```
# Since Model 2 has best acccuracy score taking model 2 as final model
best_params_gender=best_params_gender_2
```

Scenario 2: Gender Prediction, X G Boost

Gender Prediction - XG Boost Tuning Model 3

```
param_grid={"n_estimators":[20],
            "max_depth":[6,8],
            "learning_rate":[0.3,0.4],
             'min_child_weight': [2, 3],
             'gamma': [0.2, 0.3]

            }

y_gender_pred,accuracy_gender,training_accuracy_gender,cv_gender,best_score_gender,best_params_gender_3 =
         cross_validation(X_train,y_gender_train,X_test,y_gender_test,xgb_gender_1,param_grid)
print("Gender Model Accuracy:",accuracy_gender)
print("Gender Model training Accuracy:",training_accuracy_gender)
print("Best CV Score:",best_score_gender)
print("Best Paramater:",best_params_gender_3)
```

```
Gender Model Accuracy: 0.638975457732762
Gender Model training Accuracy: 0.66620400808435
Best CV Score: 0.6527138578420629
Best Paramater: {'gamma': 0.3, 'learning_rate': 0.4, 'max_depth': 6, 'min_child_weight': 2, 'n_estimators': 20}
```

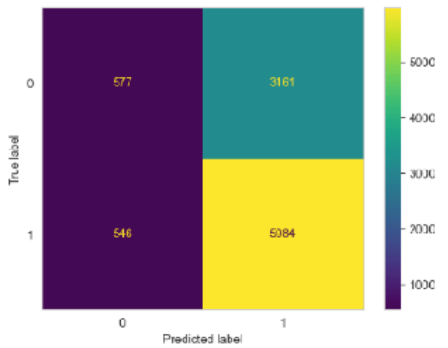
Gender Prediction - XG Boost Tuning Model Selection

```
# Since Model 3 has best acccuracy score taking model 3 as final model
best_params_gender=best_params_gender_3
```

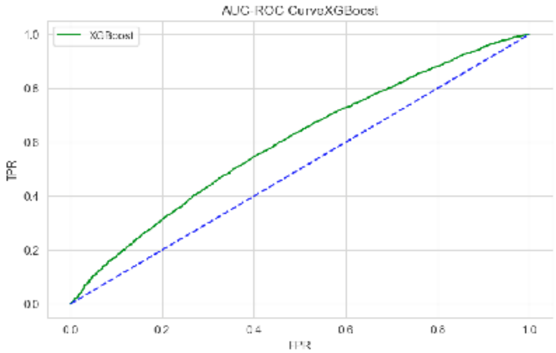
Gender Prediction - XG Boost Model with Best Parameters

```
#Best XG Boost Model

y_pred,accuracy,training_accuracy,recall,precision,F1,xgb_gender = xg_boost(X_train,y_gender_train,X_test,
        y_gender_test,**best_params_gender)
evaluation_metrics(xgb_gender,X_test,y_gender_test,"XGBoost",accuracy,training_accuracy,recall,precision,F1,
        "Gender")
```

```
---------------Model Statistics---------------
Gender Model Accuracy: 0.638975457732762
Gender Model training Accuracy: 0.66620400808435
Gender Model Precision: 0.6543466375068343
Gender Model Recall: 0.9153085911179173
Gender Model F1 Score: 0.7635087719298246
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```




```
---------------Decile Analysis---------------
Top Probability: 0.03222484
Bottom Probability: 0.9703369
KS Statistic
Decile 0: 0.0032159264931087284
Decile 1: 0.0030627871362940 15
Decile 2: 0.003215926493108736
Decile 3: 0.002450229709035 19
Decile 4: 0.0033690658499234594
Decile 5: 0.0006125574272588 53
Decile 6: 0.0004594180704440287
Decile 7: 0.0013782542113323082
Decile 8: 0.001990811638591151
Decile 9: 0.0007656967840734552
---------------ROC Curve---------------
ROC AUC SCORE ->  0.5997812499743949
```

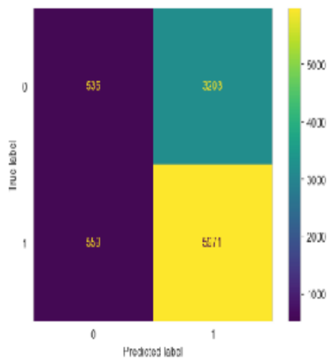


Scenario 2: Gender Prediction, Stacking

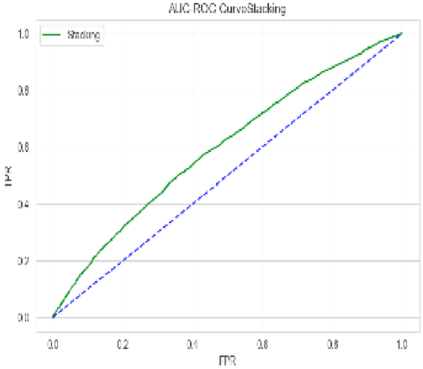
Gender Prediction - Model Stacking - 1

```
#### Stacking Logistic regression and random forest as classifier and XGBoost as Meta classifier
classifiers=[lr_gender,rf_gender]
y_pred,accuracy,training_accuracy,recall,precision,F1,stacking_gender_1=model_stacking(X_train,y_gender_train,
        X_test,y_gender_test,classifiers,xgb_gender)
evaluation_metrics(stacking_gender_1,X_test,y_gender_test,"Stacking",accuracy,training_accuracy,recall,
        precision,F1,"Gender")
```

```
==============Model Statistics==============
Gender Model Accuracy: 0.6335198185181145
Gender Model training Accuracy: 0.6570725886985203
Gender Model Precision: 0.5508611292783955
Gender Model Recall: 0.9143950993540582
Gender Model F1 Score: 0.7504431931849211
--------------Confusion Matrix--------------

<Figure size 802x503 with 0 Axes>
```



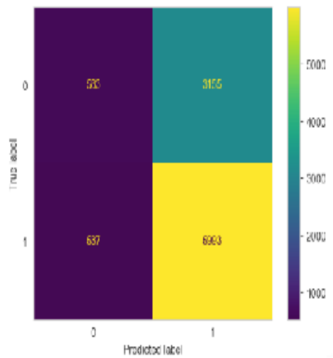

```
==============Decile Analysis==============
Top Probability: 0.113807255
Bottom Probability: 0.9591871
KS Statistic
Decile 0: 0.0032159264931087284
Decile 1: 0.0038627871362940015
Decile 2: 0.0032159264931089756
Decile 3: 0.0024582297098351519
Decile 4: 0.0033690655849923464
Decile 5: 0.0006125574272503053
Decile 6: 0.0004594180704440287
Decile 7: 0.0013782542113323082
Decile 8: 0.0019908116385911161
Decile 9: 0.0007656936784873455
==============ROC Curve==============
ROC AUC SCORE ->  0.5961215577089082
```



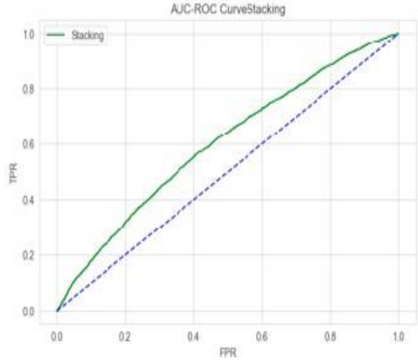
Gender Prediction - Model Stacking - 2

```
#### Stacking XGBoost and random forest as classifier and XGBoost as Logistic regression Meta classifier
classifiers=[xgb_gender,rf_gender]
y_pred,accuracy,training_accuracy,recall,precision,F1,stacking_gender_2=model_stacking(X_train,y_gender_train,
        X_test,y_gender_test,classifiers,lr_gender)
evaluation_metrics(stacking_gender_2,X_test,y_gender_test,"Stacking",accuracy,training_accuracy,recall,
        precision,F1,"Gender")
```

```
--------------Model Statistics--------------
Gender Model Accuracy: 0.6404363869731204
Gender Model training Accuracy: 0.6672510775074878
Gender Model Precision: 0.655115872321819
Gender Model Recall: 0.9177641653905053
Gender Model F1 Score: 0.7645187794361525
--------------Confusion Matrix--------------

<Figure size 800x500 with 0 Axes>
```



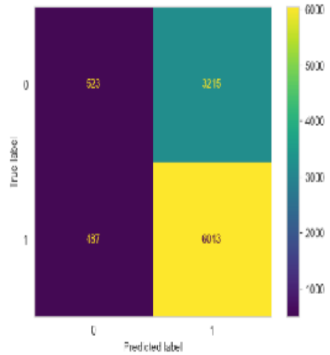

```
--------------Decile Analysis--------------
Top Probability: 0.14329574433172027
Bottom Probability: 0.8569322234179531
KS Statistic
Decile 0: 0.0032159264931087284
Decile 1: 0.0030627871362234015
Decile 2: 0.0032159264931088756
Decile 3: 0.0024502297090303515
Decile 4: 0.0033690065584992734694
Decile 5: 0.0006125574272258853
Decile 6: 0.0004594180784440287
Decile 7: 0.0013782542113323082
Decile 8: 0.0019908116385911161
Decile 9: 0.0007656967840734552
--------------ROC Curve--------------
ROC AUC SCORE ->  0.6023082746872638
```



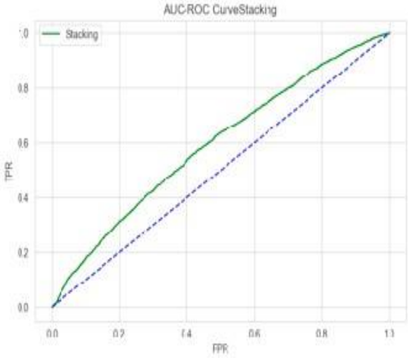
Gender Prediction - Model Stacking - 3

```
#### Stacking XGBoost and Logistic regression as classifier and XGBoost as Random Forest Meta classifier
classifiers=[lr_gender,xgb_gender]
y_pred,accuracy,training_accuracy,recall,precision,F1,stacking_gender_3=model_stacking(X_train,y_gender_train,
        X_test,y_gender_test,classifiers,rf_gender)
evaluation_metrics(stacking_gender_3,X_test,y_gender_test,"Stacking",accuracy,training_accuracy,recall,
        precision,F1,"Gender")
```

```
--------------Model Statistics--------------
Gender Model Accuracy: 0.6394824074795481
Gender Model training Accuracy: 0.6597754888353179
Gender Model Precision: 0.6527327718569453
Gender Model Recall: 0.9254211332312404
Gender Model F1 Score: 0.765518115024863
--------------Confusion Matrix--------------

<Figure size 800x500 with 0 Axes>
```




```
--------------Decile Analysis--------------
Top Probability: 0.030957167308282023
Bottom Probability: 0.9349110389973698
KS Statistic
Decile 0: 0.0032159264931087284
Decile 1: 0.0030627871362940015
Decile 2: 0.0032159264931088756
Decile 3: 0.0024502297090903519
Decile 4: 0.0033690265849923464
Decile 5: 0.0006125574272258853
Decile 6: 0.0004594180704440287
Decile 7: 0.0013782542113323082
Decile 8: 0.0019908116385891161
Decile 9: 0.0007656957840734552
--------------ROC Curve--------------
ROC AUC SCORE ->  0.5945971672906133
```



Scenario 2: Gender Prediction, Final Model

Gender Prediction - Final Model Selection

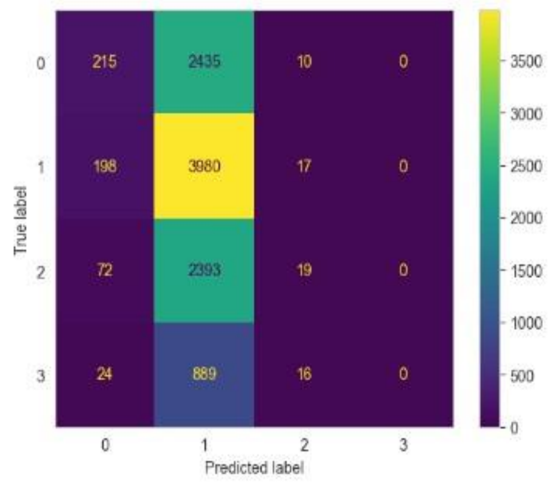
```
# Since Model 3 gives best accuracy, considering it is best Stacking Model
stacking_gender=stacking_gender_3
```

Scenario 2: AgeGroup Prediction, Logistic Reg.

Age Group Prediction - Logistic Regression

```
y_pred,accuracy,training_accuracy,recall,precision,F1,lr_age_group_1 = logistic_regression(X_train,
        y_age_group_train,X_test,y_age_group_test,average="weighted")
evaluation_metrics(lr_age_group_1,X_test,y_age_group_test,"Logistic Regression",accuracy,training_accuracy,
        recall,precision,F1,"Age Group",multiclass=True)
```

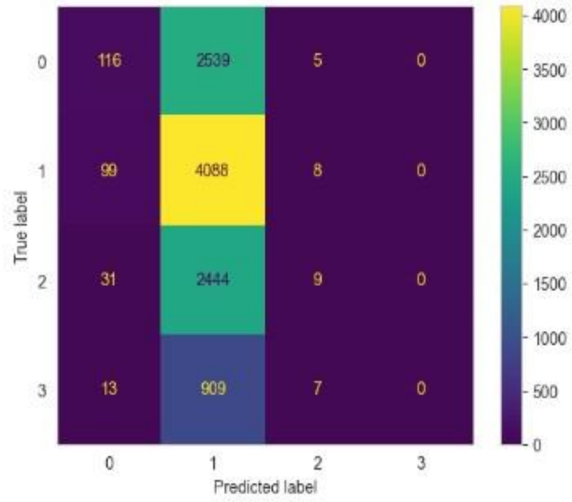
```
---------------Model Statistics---------------
Age Group Model Accuracy: 0.4104012465913518
Age Group Model training Accuracy: 0.4112547787761463
Age Group Model Precision: 0.3512447776486367
Age Group Model Recall: 0.4104012465913518
Age Group Model F1 Score: 0.27285826321268924
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```




```
---------------Multiclass Log Loss---------------
Multiclass Log Loss: 1.2583
```

```
#Applying L1 Regularization
y_pred,accuracy,training_accuracy,recall,precision,F1,lr_age_group_2 = logistic_regression(X_train,
        y_age_group_train,X_test,y_age_group_test,average="weighted",penalty='l1', solver='liblinear')
evaluation_metrics(lr_age_group_2,X_test,y_age_group_test,"Logistic Regression",accuracy,training_accuracy,
        recall,precision,F1,"Age Group",multiclass=True)
```

```
---------------Model Statistics---------------
Age Group Model Accuracy: 0.41030385664199454
Age Group Model training Accuracy: 0.411717437358463
Age Group Model Precision: 0.35845350686465827
Age Group Model Recall: 0.41030385664199454
Age Group Model F1 Score: 0.2579705605911575
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```




```
---------------Multiclass Log Loss---------------
Multiclass Log Loss: 1.2583
```

Scenario 2: AgeGroup Prediction, Random Forest

Age Group Prediction - Random Forest Model 1

```
param_grid={
            "n_estimators":[120,130],
           "min_samples_split":[2,3],
           "min_samples_leaf":[3,5],
           "max_leaf_nodes":[100,120],
           "max_depth":[50],
           "oob_score":[True],
            "bootstrap":[True]

           }

y_age_group_pred,accuracy_age_group,training_accuracy_age_group,cv_age_group,best_score_age_group,
        best_params_age_group_1 = cross_validation(X_train,y_age_group_train,X_test,y_age_group_test,
        rf_age_group_1,param_grid)
print("age_group Model Accuracy:",accuracy_age_group)
print("age_group Model training Accuracy:",training_accuracy_age_group)
print("Best CV Score:",best_score_age_group)
print("Best Paramater:",best_params_age_group_1)
```

```
age_group Model Accuracy: 0.4120568757304246
age_group Model training Accuracy: 0.42048359997077944
Best CV Score: 0.4081866218618355
Best Paramater: {'bootstrap': True, 'max_depth': 50, 'max_leaf_nodes': 100, 'min_samples_leaf': 3, 'min_samples_split': 2, 'n_estimators': 130, 'oob_score': True}
```

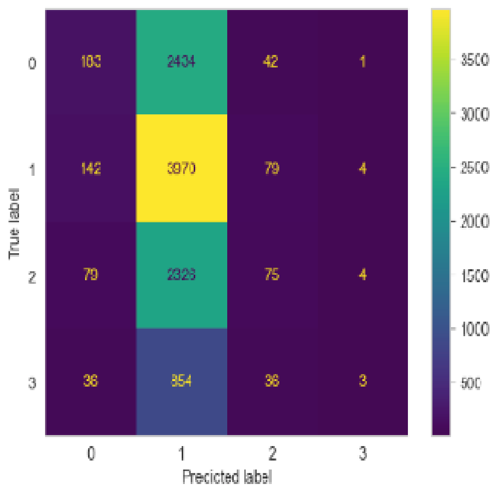
Age Group Prediction - Random Forest Model Selection

```
# Since Model 1 has best acccuracy score taking model 1 as final model
best_params_age_group=best_params_age_group_1
```

Age Group Prediction - Random Forest - Best Parameters

```
#Best Random Forest Model
y_pred,accuracy,training_accuracy,recall,precision,F1,rf_age_group = random_forest(X_train,y_age_group_train,
        X_test,y_age_group_test,average="weighted",**best_params_age_group)
evaluation_metrics(rf_age_group,X_test,y_age_group_test,"Random Forest",accuracy,training_accuracy,recall,
        precision,F1,"age_group",multiclass=True)
```

```
---------------Model Statistics---------------
age_group Model Accuracy: 0.4120568757304246
age_group Model training Accuracy: 0.42048359997077944
age_group Model Precision: 0.3778037482766203
age_group Model Recall: 0.4120568757304246
age_group Model F1 Score: 0.27994600716422957
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```




```
---------------Multiclass Log Loss---------------
Multiclass Log Loss: 1.2545
```

Scenario 2: AgeGroup Prediction, XGBoost

Age Group Prediction - XG Boost Model 2

```
param_grid={"n_estimators":[10,20],
            "max_depth":[6,9],
            "learning_rate":[0.3,0.5],
             'min_child_weight': [2, 3],
             'gamma': [0.1, 0.2]

            }

y_age_group_pred,accuracy_age_group,training_accuracy_age_group,cv_age_group,best_score_age_group,
        best_params_age_group_1 = cross_validation(X_train,y_age_group_train,X_test,y_age_group_test,
        xgb_age_group_1,param_grid)
print("age_group Model Accuracy:",accuracy_age_group)
print("age_group Model training Accuracy:",training_accuracy_age_group)
print("Best CV Score:",best_score_age_group)
print("Best Paramater:",best_params_age_group_1)
```

```
age_group Model Accuracy: 0.41264121542656795
age_group Model training Accuracy: 0.4216767721041225
Best CV Score: 0.4077483137312197
Best Paramater: {'gamma': 0.1, 'learning_rate': 0.5, 'max_depth': 6, 'min_child_weight': 3, 'n_estimators': 10}
```

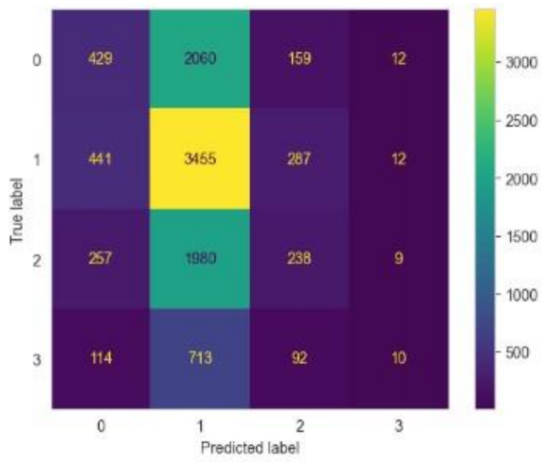
Age Group Prediction - XG Boost Tuning Model Selection

```
# Since Model 2 has best acccuracy score taking model 2 as final model
best_params_age_group=best_params_age_group_2
```

Age Group Prediction - XG Boost Model with Best Parameters

```
#Base XG Boost Model

y_pred,accuracy,training_accuracy,recall,precision,F1,xgb_age_group = xg_boost(X_train,y_age_group_train,
        X_test,y_age_group_test,average="weighted",**best_params_age_group)
evaluation_metrics(xgb_age_group,X_test,y_age_group_test,"XG Boost",accuracy,training_accuracy,recall,
        precision,F1,"Age Group",multiclass=True)
```

```
[14:36:19] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboost/src/learner.cc:767:
Parameters: { "bootstrap", "max_leaf_nodes", "min_samples_leaf", "min_samples_split", "oob_score" } are not used.

---------------Model Statistics---------------
Age Group Model Accuracy: 0.4024152707440592
Age Group Model training Accuracy: 0.4351669223464095
Age Group Model Precision: 0.3567617072607607
Age Group Model Recall: 0.4024152707440592
Age Group Model F1 Score: 0.32177559773047437
---------------Confusion Matrix---------------

<Figure size 800x500 with 0 Axes>
```



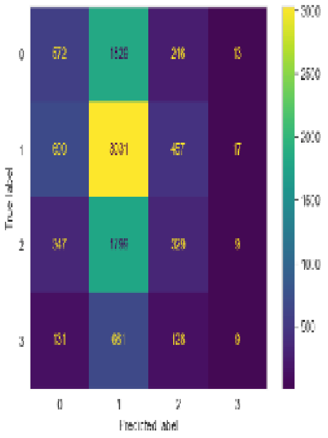

```
---------------Multiclass Log Loss---------------
Multiclass Log Loss: 1.2906
```

Scenario 2: AgeGroup Prediction, Stacking

Age Group Prediction - Model 1

```
#### Stacking Logistic regression and random forest as classifier and XGBoost as Meta classifier
classifiers=[lr_age_group,rf_age_group]
y_pred,accuracy,training_accuracy,recall,precision,F1,stacking_age_group_1=model_stacking(X_train,
        y_age_group_train,X_test,y_age_group_test,classifiers,xgb_age_group,average='weighted')
evaluation_metrics(stacking_age_group_1,X_test,y_age_group_test,"Stacking",accuracy,training_accuracy,recall,
        precision,F1,"Age Group",multiclass=True)
```

```
[14:38:23] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboost/src/learner.cc:767:
Parameters: { "bootstrap", "max_leaf_nodes", "min_samples_leaf", "min_samples_split", "oob_score" } are not used.

--------------Model Statistics--------------
Age Group Model Accuracy: 0.38381379841829
Age Group Model training Accuracy: 0.39681679004521879
Age Group Model Precision: 0.33908709777967593
Age Group Model Recall: 0.38381379841829
Age Group Model F1 Score: 0.32778390549364486
==============Confusion Matrix==============

<Figure size 800x500 with 0 Axes>
```

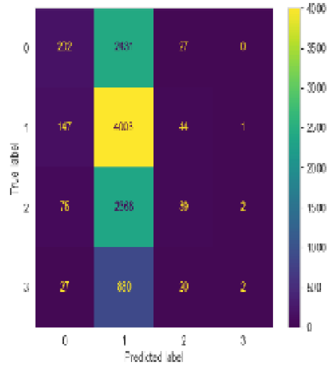



```
--------------Multiclass Log Loss--------------
Multiclass Log Loss: 1.3336
```

Age Group Prediction - Model 2

```
#### Stacking Logistic regression and random forest as classifier and XGBoost as Meta classifier
classifiers=[xgb_age_group,rf_age_group]
y_pred,accuracy,training_accuracy,recall,precision,F1,stacking_age_group_2=model_stacking(X_train,
        y_age_group_train,X_test,y_age_group_test,classifiers,lr_age_group,average='weighted')
evaluation_metrics(stacking_age_group_2,X_test,y_age_group_test,"Stacking",accuracy,training_accuracy,recall,
        precision,F1,"Age Group",multiclass=True)
```

```
[14:40:57] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboost/src/learner.cc:767:
Parameters: { "bootstrap", "max_leaf_nodes", "min_samples_leaf", "min_samples_split", "oob_score" } are not used.

[14:41:25] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboost/src/learner.cc:767:
Parameters: { "bootstrap", "max_leaf_nodes", "min_samples_leaf", "min_samples_split", "oob_score" } are not used.

[14:41:51] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboost/src/learner.cc:767:
Parameters: { "bootstrap", "max_leaf_nodes", "min_samples_leaf", "min_samples_split", "oob_score" } are not used.

[14:42:21] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboost/src/learner.cc:767:
Parameters: { "bootstrap", "max_leaf_nodes", "min_samples_leaf", "min_samples_split", "oob_score" } are not used.

--------------Model Statistics--------------
Age Group Model Accuracy: 0.41351772497078304
Age Group Model training Accuracy: 0.41924172693340346
Age Group Model Precision: 0.39370955626165593
Age Group Model Recall: 0.41351772497078304
Age Group Model F1 Score: 0.27695128827580468
==============Confusion Matrix==============

<Figure size 800x500 with 0 Axes>
```

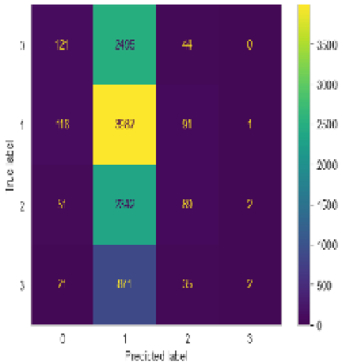



```
--------------Multiclass Log Loss--------------
Multiclass Log Loss: 1.2545
```

Age Group Prediction - Model 3

```
#### Stacking Logistic regression and random forest as classifier and XGBoost as Meta classifier
classifiers=[lr_age_group,xgb_age_group]
y_pred,accuracy,training_accuracy,recall,precision,F1,stacking_age_group_3=model_stacking(X_train,
        y_age_group_train,X_test,y_age_group_test,classifiers,rf_age_group,average='weighted')
evaluation_metrics(stacking_age_group_3,X_test,y_age_group_test,"Stacking",accuracy,training_accuracy,recall,
        precision,F1,"Age Group",multiclass=True)
```

```
[22:28:58] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboost/src/learner.cc:767:
Parameters: { "bootstrap", "max_leaf_nodes", "min_samples_leaf", "min_samples_split", "oob_score" } are not used.

[22:29:13] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboost/src/learner.cc:767:
Parameters: { "bootstrap", "max_leaf_nodes", "min_samples_leaf", "min_samples_split", "oob_score" } are not used.

[22:29:28] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboost/src/learner.cc:767:
Parameters: { "bootstrap", "max_leaf_nodes", "min_samples_leaf", "min_samples_split", "oob_score" } are not used.

[22:29:45] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboost/src/learner.cc:767:
Parameters: { "bootstrap", "max_leaf_nodes", "min_samples_leaf", "min_samples_split", "oob_score" } are not used.

==============Model Statistics==============
Age Group Model Accuracy: 0.40894839735099336
Age Group Model training Accuracy: 0.41778764847687925
Age Group Model Precision: 0.38877659044560386
Age Group Model Recall: 0.40894839735099336
Age Group Model F1 Score: 0.27174322957920393
==============Confusion Matrix==============

<Figure size 800x500 with 0 Axes>
```




```
==============Multiclass Log Loss==============
Multiclass Log Loss: 1.2566
```

Scenario 2: AgeGroup Prediction, Final Model

Age Group Prediction - Final Model Selection

```
# Stacking Gives best accuracy so considering Stacking model as final model
final_model_age_group = stacking_age_group
```

Scenario 1 - Model Performance

Scenario	Target	Modeling Type	Model Name	Accuracy	Training Accuracy	Precision	Recall	F1 Score	ROC Score
Scenario 1	Gender Prediction	Logistic Regression	lr_gender_1	65.854	67.120	67.445	92.788	78.112	60.872
		Logistic Regression - L1 Regularization	lr_gender_2	65.923	67.211	67.529	92.657	78.122	60.740
		Random Forest 1	best_params_gender_1	65.511	69.408				
		Random Forest 2	best_params_gender_2	65.511	69.408				
		Random Forest 3	best_params_gender_3	65.562	69.299				
		Random Forest 4	best_params_gender_4	65.614	69.225				
		Random Forest 5	best_params_gender_5	65.734	69.128				
		Random Forest Best Parameters	rf_gender	65.734	69.128	67.435	92.474	77.994	60.567
		XG Boost 1	best_params_gender_1	65.974	67.749				
		XG Boost 2	best_params_gender_2	65.957	67.881				
		XG Boost 3	best_params_gender_3	65.837	67.904				
		XG Boost 4	best_params_gender_4	65.923	68.150				
		XG Boost 5	best_params_gender_5	65.579	68.476				
		XG Boost Best Parameters	xgb_gender	65.974	67.749	67.528	92.814	78.177	60.271
		Stacking Model 1	stacking_gender_1	65.803	67.858	67.347	93.023	78.130	60.479
		Stacking Model 2	stacking_gender_2	65.717	68.441	67.630	91.664	77.834	60.540
		Stacking Model 3	stacking_gender_3	65.391	67.606	67.323	91.899	77.715	60.656
	Age Group Prediction	Logistic Regression	lr_age_group_1	41.695	41.597	38.663	41.695	30.725	
		Logistic Regression - L1 Regularization	lr_age_group_2	41.437	41.602	27.944	41.437	29.353	
		Random Forest 1	best_params_age_group_1	41.815	44.274				
		Random Forest 2	best_params_age_group_2	41.815	44.274				
		Random Forest 3	best_params_age_group_3	41.815	44.274				
		Random Forest 4	best_params_age_group_4	41.815	44.274				
		Random Forest 5	best_params_age_group_5	41.815	44.274				
		Random Forest Best Parameters	rf_age_group	41.815	44.274	37.245	41.815	31.931	
		XG Boost 1	best_params_age_group_1	42.261	42.060				
		XG Boost 2	best_params_age_group_2	41.969	41.718				
		XG Boost 3	best_params_age_group_3	42.227	42.157				
		XG Boost 4	best_params_age_group_4	41.935	42.821				
		XG Boost 5	best_params_age_group_5	41.798	43.358				
		XG Boost Best Parameters	xgb_age_group	42.261	42.060	40.207	42.261	31.262	
		Stacking Model 1	stacking_age_group_1	42.124	42.352	37.152	42.124	32.375	
		Stacking Model 2	stacking_age_group_2	41.918	43.187	36.839	41.918	32.302	
		Stacking Model 3	stacking_age_group_3	42.038	42.071	38.418	42.038	32.373	

Scenario 2 – Model performance

Scenario	Target	Modeling Type	Model Name	Accuracy	Training Accuracy	Precision	Recall	F1 Score	ROC Score
Scenario 2	Gender Prediction	Logistic Regression	lr_gender_1	63.507	64.567	65.146	91.653	76.159	59.434
		Logistic Regression - L1 Regularization	lr_gender_2	63.488	64.579	65.158	91.531	76.125	59.402
		Random Forest 1	best_params_gender_1	63.936	66.605				
		Random Forest 2	best_params_gender_2	63.985	66.627				
		Random Forest 3	best_params_gender_3	63.975	66.720				
		Random Forest Best Parameters	rf_gender	63.985	66.627	65.278	92.649	76.591	60.276
		XG Boost 1	best_params_gender_1	63.751	66.598				
		XG Boost 2	best_params_gender_2	63.761	66.457				
		XG Boost 3	best_params_gender_3	63.897	66.620				
		XG Boost Best Parameters	xgb_gender	63.897	66.620	65.434	91.638	76.350	59.978
		Stacking Model 1	stacking_gender_1	63.361	65.707	65.086	91.439	76.044	59.612
		Stacking Model 2	stacking_gender_2	60.043	66.725	65.511	91.776	76.451	60.230
		Stacking Model 3	stacking_gender_3	63.946	65.977	65.273	92.542	76.551	59.459
	Age Group Prediction	Logistic Regression	lr_age_group_1	41.040	41.125	35.124	41.040	27.285	
		Logistic Regression - L1 Regularization	lr_age_group_2	41.030	41.171	35.845	41.030	25.797	
		Random Forest 1	best_params_age_group_1	41.205	42.048				
		Random Forest 2	best_params_age_group_2	41.166	41.843				
		Random Forest 3	best_params_age_group_3	41.205	42.048				
		Random Forest Best Parameters	rf_age_group	41.205	42.048	37.780	41.205	27.994	
		XG Boost 1	best_params_age_group_1	41.059	41.371				
		XG Boost 2	best_params_age_group_2	41.264	42.167				
		XG Boost 3	best_params_age_group_3	41.020	41.427				
		XG Boost Best Parameters	xgb_age_group	40.241	43.516	35.676	40.241	32.177	
		Stacking Model 1	stacking_age_group_1	38.381	39.301	33.990	38.381	32.778	
		Stacking Model 2	stacking_age_group_2	41.351	41.924	39.370	41.351	27.695	
		Stacking Model 3	stacking_age_group_3	40.894	41.770	38.877	40.894	27.174	

Thank You ☺!