Insurance Cross Selling with xgboost/catboost

Introduction

This notebook focuses on evaluating the performance of a predictive model using the Area Under the Receiver Operating Characteristic Curve (AUC-ROC). The objective is to predict which customers respond positively to an automobile insurance offer.

Dataset Overview

The dataset used in this analysis is provided This is Binary Classification of Insurance Cross Selling Competition Data. The goal is to build a predictive model to determine whether the policyholders from the previous year will also be interested in the Vehicle Insurance offered by the company. The dataset includes various features related to the customers' demographic, policy, and claim history, which will be utilized to train and evaluate the model.

Credit: https://www.kaggle.com/code/satyaprakashshukl/insurance-boost-analysis

Importing libraries and Loading the Dataset:

In [1]:
```
import warnings
warnings.filterwarnings("ignore")
import numpy as np, pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
```

```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_squared_error
from xgboost import XGBRegressor
```

In [2]:
```
df_sub=pd.read_csv("/kaggle/input/playground-series-s4e7/sample_submissio
df_train = pd.read_csv("/kaggle/input/playground-series-s4e7/train.csv")
df_test = pd.read_csv('/kaggle/input/playground-series-s4e7/test.csv')
```

In [3]:
```
df_train.head()
```

Out[3]:

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicle_Ag
0	0	Male	21	1	35.0	0	1-2 Yea
1	1	Male	43	1	28.0	0	> 2 Year
2	2	Female	25	1	14.0	1	< 1 Yea
3	3	Female	35	1	1.0	0	1-2 Yea
4	4	Female	36	1	15.0	1	1-2 Yea

Missing Value

In [18]:
```
print(f'Number of missing values in df_train:\n{df_train.isna().sum()}')
```

```
Number of missing values in df_train:
id                      0
Gender                  0
Age                     0
Driving_License         0
Region_Code             0
Previously_Insured      0
Vehicle_Age             0
Vehicle_Damage          0
Annual_Premium          0
Policy_Sales_Channel    0
Vintage                 0
Response                0
dtype: int64
```

In [11]:
```
print(f'Number of missing values in df_test:\n{df_test.isna().sum()}')
```

```
Number of missing values in df_test:
id                      0
Gender                  0
Age                     0
Driving_License         0
Region_Code             0
Previously_Insured      0
Vehicle_Age             0
Vehicle_Damage          0
Annual_Premium          0
Policy_Sales_Channel    0
Vintage                 0
dtype: int64
```

In [7]:
```
print(f'train df dataFrame size: {df_train.shape}')
print(f'test dataFrame size: {df_test.shape}')
```

```
train df dataFrame size: (11504798, 12)
test dataFrame size: (7669866, 11)
```

In [8]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11504798 entries, 0 to 11504797
Data columns (total 12 columns):
 #   Column                Dtype  
---  ------                -----  
 0   id                    int64  
 1   Gender                object 
 2   Age                   int64  
 3   Driving_License       int64  
 4   Region_Code           float64
 5   Previously_Insured    int64  
 6   Vehicle_Age           object 
 7   Vehicle_Damage        object 
 8   Annual_Premium        float64
 9   Policy_Sales_Channel  float64
 10  Vintage               int64  
 11  Response              int64  
dtypes: float64(3), int64(6), object(3)
memory usage: 1.0+ GB
```

In [5]:
```
df_train = df_train.drop(columns=['id'])
df_test = df_test.drop(columns=['id'])
```

In [19]:
```
df_train.describe()
```

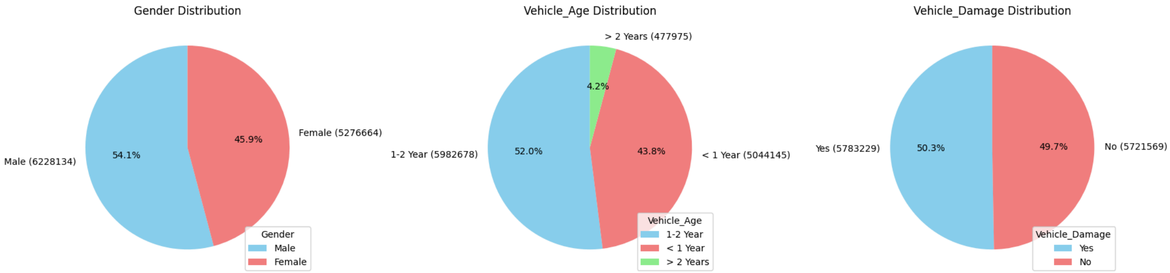
Out[19]:

	id	Age	Driving_License	Region_Code	Previously_Ins
count	1.150480e+07	1.150480e+07	1.150480e+07	1.150480e+07	1.15048C
mean	5.752398e+06	3.838356e+01	9.980220e-01	2.641869e+01	4.62996
std	3.321149e+06	1.499346e+01	4.443120e-02	1.299159e+01	4.98628
min	0.000000e+00	2.000000e+01	0.000000e+00	0.000000e+00	0.000000
25%	2.876199e+06	2.400000e+01	1.000000e+00	1.500000e+01	0.000000
50%	5.752398e+06	3.600000e+01	1.000000e+00	2.800000e+01	0.000000
75%	8.628598e+06	4.900000e+01	1.000000e+00	3.500000e+01	1.000000
max	1.150480e+07	8.500000e+01	1.000000e+00	5.200000e+01	1.000000

Exploratory data analysis

In [9]:
```
categorical_columns = df_train[['Gender', 'Vehicle_Age', 'Vehicle_Damage'
num_columns = len(categorical_columns.columns)
num_rows = (num_columns + 2) // 3

fig, axes = plt.subplots(num_rows, 3, figsize=(18, 6 * num_rows))
axes = axes.flatten()
```

```
for i, column in enumerate(categorical_columns):
    value_counts = df_train[column].value_counts()
    colors = ['skyblue', 'lightcoral', 'lightgreen', 'lightyellow', 'ligh
    labels = [f'{index} ({count})' for index, count in zip(value_counts.i

    ax = axes[i]
    wedges, texts, autotexts = ax.pie(value_counts, labels=labels, autopc
    ax.legend(wedges, value_counts.index, title=column, loc='lower right'
    ax.set_title(f'{column} Distribution')

# Hide any extra subplots
for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
plt.show()
```



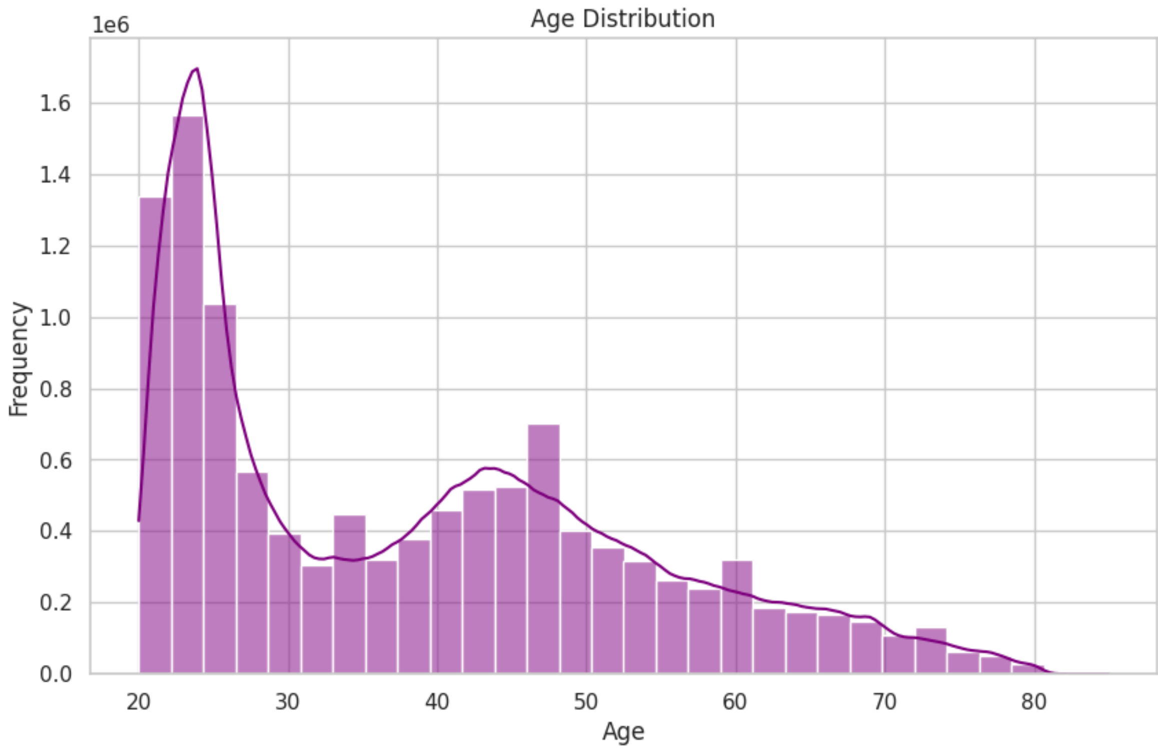
In this three pie chart show the distribution of categorical data relevant to predicting interest in vehicle insurance.

Genter distribution In this chart Male account for 54.1% in total and female show as around 45.9% in total. Male customer is slightly highter to compare with female but relatively balanced.

Vehicle age distribution In this pie chart show the distribution of vehicle age, majority of vehicles are between 1 to 2 years old. Suggests that most vehicles in the dataset are relatively new, which could influence analyses related to vehicle performance, maintenance, and value depreciation over time.

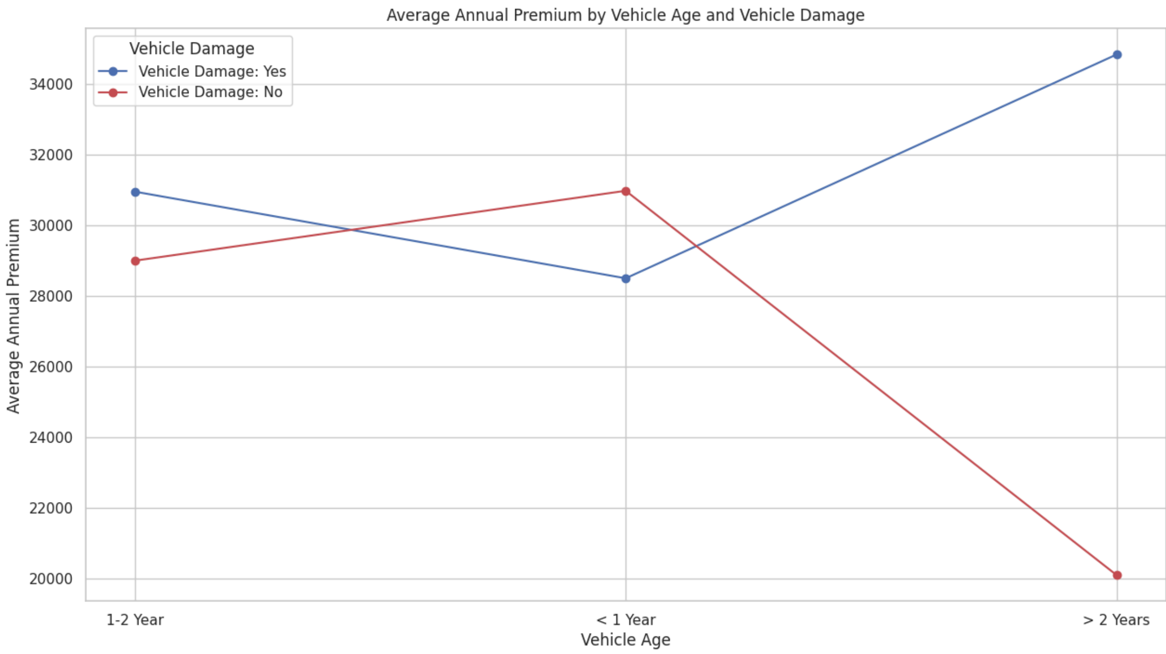
Vehicle Damage distribution In this chart the vehicles with damage is equal distribution with without damage.

In [21]:
```
sns.set(style="whitegrid")
plt.figure(figsize=(10, 6))
sns.histplot(df_train['Age'], bins=30, kde=True, color='purple')
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



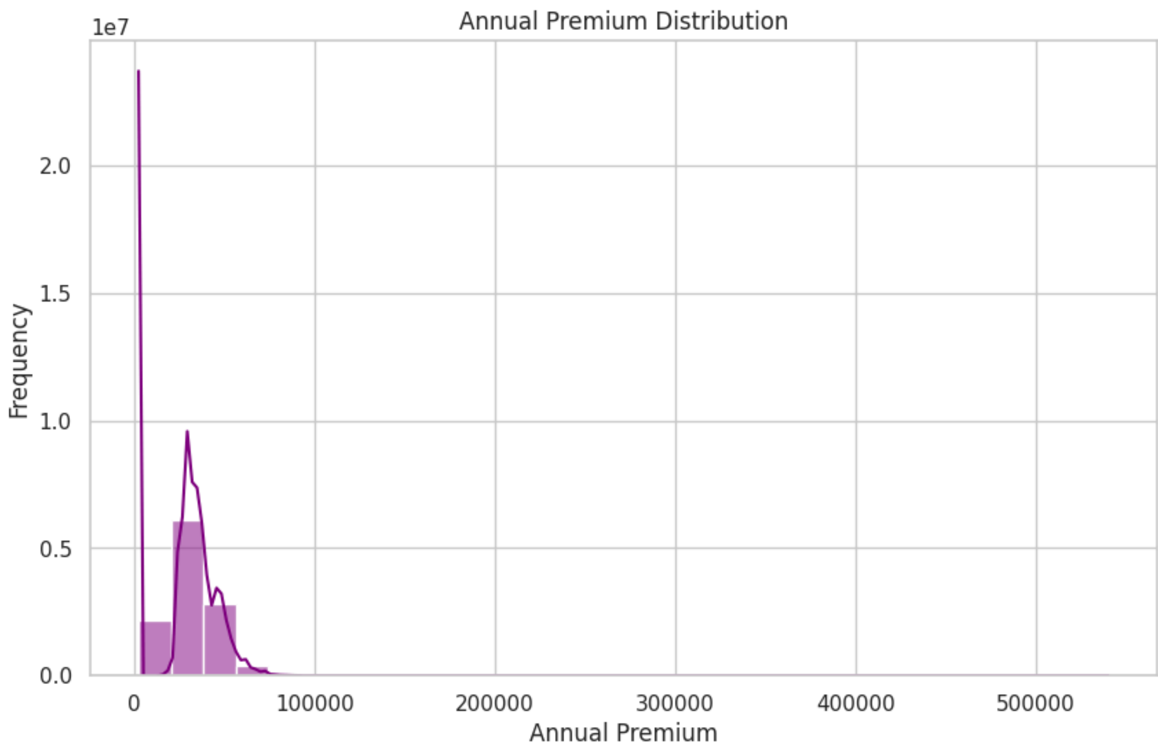
This bar plot shows the age distribution show that mainly around 20-25 age range, show the significant portion of this age group of young adults. Another noticeable peak is around 45-50 age range. In this plot provides insight into age demographics of the population which can helpful for marketing strategies planning.

In [5]:
```
sns.set(style='whitegrid')

plt.figure(figsize=(15, 8))

damage_yes = df_train[df_train['Vehicle_Damage'] == 'Yes']
damage_no = df_train[df_train['Vehicle_Damage'] == 'No']

damage_yes_grouped = damage_yes.groupby('Vehicle_Age')['Annual_Premium'].
damage_no_grouped = damage_no.groupby('Vehicle_Age')['Annual_Premium'].me

plt.plot(damage_yes_grouped['Vehicle_Age'], damage_yes_grouped['Annual_Pr
plt.plot(damage_no_grouped['Vehicle_Age'], damage_no_grouped['Annual_Prem

plt.title('Average Annual Premium by Vehicle Age and Vehicle Damage')
plt.xlabel('Vehicle Age')
plt.ylabel('Average Annual Premium')
plt.legend(title='Vehicle Damage')

plt.show()
```



In [11]:

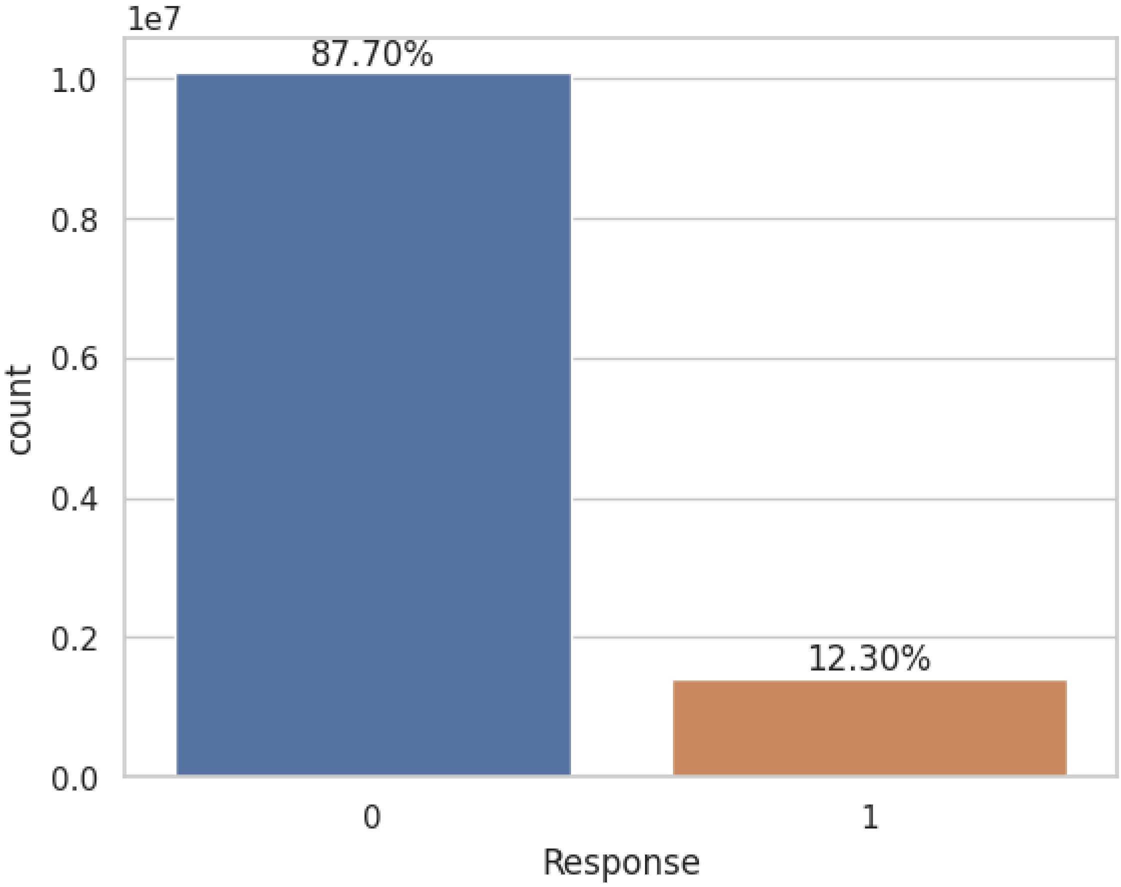
```
plt.figure(figsize=(10, 6))
sns.histplot(df_train['Annual_Premium'], bins=30, kde=True, color='purple
plt.title('Annual Premium Distribution')
plt.xlabel('Annual Premium')
plt.ylabel('Frequency')
plt.show()
```



In [10]:

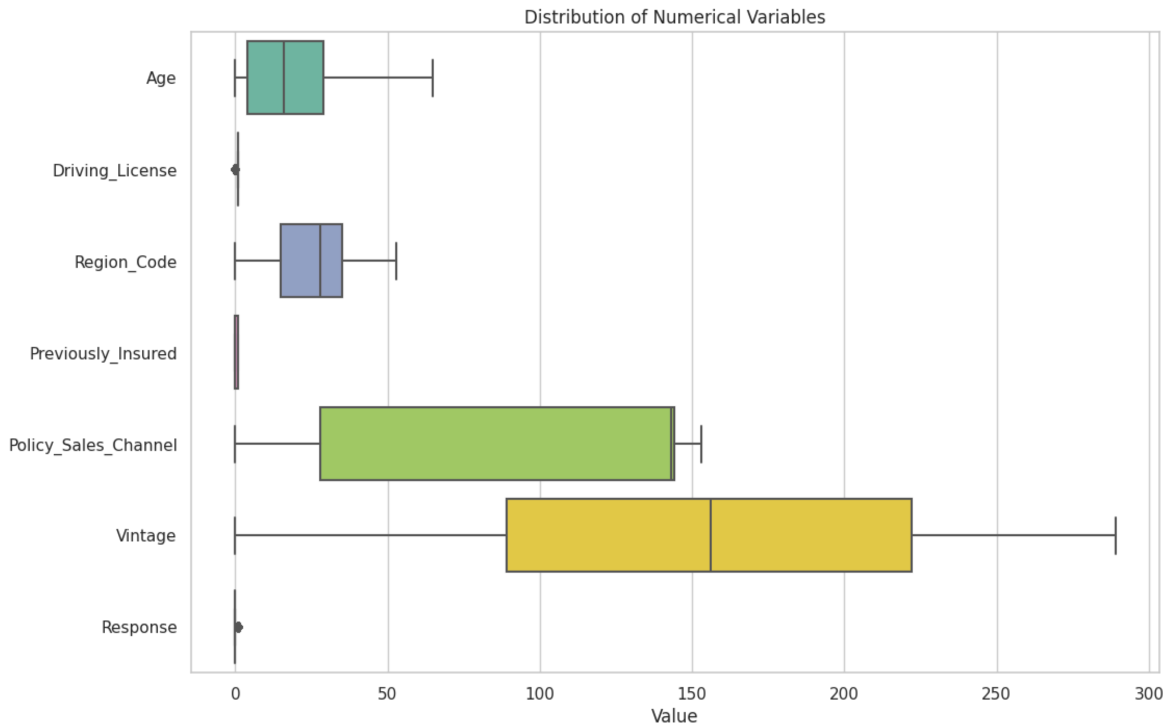
```
fig, ax = plt.subplots()
sns.countplot(x='Response', data=df_train, ax=ax)

# Calculate the total number of instances
total = len(df_train)

# Add percentages on top of the bars
for p in ax.patches:
    percentage = f'{100 * p.get_height() / total:.2f}%'
```

```
    x = p.get_x() + p.get_width() / 2
    y = p.get_height() + 5  # Adjust the position above the bar
    ax.annotate(percentage, (x, y), ha='center', va='bottom')
```

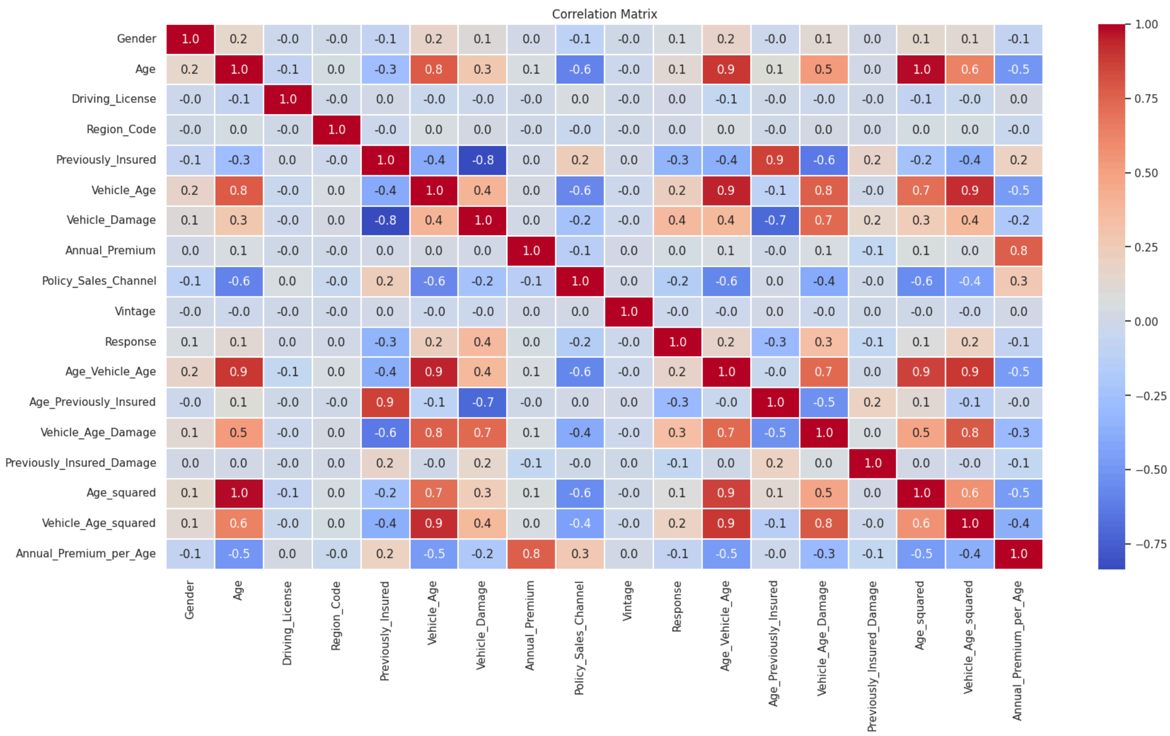


In [21]:

```
fig, ax = plt.subplots()
sns.countplot(x='Response', data=df_train, ax=ax)

# Calculate the total number of instances
total = len(train)

# Add percentages on top of the bars
for p in ax.patches:
    percentage = f'{100 * p.get_height() / total:.2f}%'
    x = p.get_x() + p.get_width() / 2
    y = p.get_height() + 5  # Adjust the position above the bar
    ax.annotate(percentage, (x, y), ha='center', va='bottom')
```



In [22]:
```
correlation_matrix = df_train.corr()
plt.figure(figsize=(20, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".1f", l
plt.title('Correlation Matrix')
plt.show()
```



Data Engineering and Data Preprocessing

In [6]:
```
import pandas as pd
from pandas.api.types import CategoricalDtype

# Initialize Response column in df_test
df_test['Response'] = 0
```

```
# Identify columns with fewer than 10 unique values
less = [col for col in df_train.columns if df_train[col].nunique() < 10]
print('Columns with LESS than 10 unique values:', less)
print('Columns with MORE than 10 unique values:', [col for col in df_trai

# Convert identified columns to categorical type
for col in less:
    df_train[col] = df_train[col].astype('category')
    df_test[col] = df_test[col].astype('category')

# Define the new order of categories for 'Vehicle_Age'
new_categories = ['< 1 Year', '1-2 Year', '> 2 Years']
new_dtype = CategoricalDtype(categories=new_categories, ordered=True)

# Update the 'Vehicle_Age' column with the new dtype in both df_train and
df_train['Vehicle_Age'] = df_train['Vehicle_Age'].astype(new_dtype)
df_test['Vehicle_Age'] = df_test['Vehicle_Age'].astype(new_dtype
```

```
Columns with LESS than 10 unique values: ['Gender', 'Driving_License', 'Pr
eviously_Insured', 'Vehicle_Age', 'Vehicle_Damage', 'Response']
Columns with MORE than 10 unique values: ['Age', 'Region_Code', 'Annual_Pr
emium', 'Policy_Sales_Channel', 'Vintage']
```

In [35]:
```
# Combine DataFrames
full = pd.concat([df_train, df_test], axis=0)
for col in less:
    full[col] = full[col].astype('category')

# Age Binning
full['age_bins'] = pd.cut(full['Age'], bins=7)
full['Age_Type'] = full['age_bins'].cat.codes

# Interaction Features
full['Age_x_Vehicle_Age'] = full['Age_Type'] * full['Vehicle_Age'].cat.co
full['Age_x_Vehicle_Damage'] = full['Age_Type'] * full['Vehicle_Damage'].
full['Age_x_Previously_Insured'] = full['Age_Type'] * full['Previously_In

# Create factorized interaction features
fac_pre = ['Policy_Sales_Channel', 'Vehicle_Damage', 'Annual_Premium', 'V
col_pre = []
for col in fac_pre:
    full['Previously_Insured_x_' + col] = pd.factorize(full['Previously_I
    col_pre.append('Previously_Insured_x_' + col)

fac_pro = fac_pre[1:]
col_pro = []
for col in fac_pro:
    full['Policy_Sales_Channel_x_' + col] = pd.factorize(full['Policy_Sal
    col_pro.append('Policy_Sales_Channel_x_' + col)

# Split combined DataFrame back into training and test sets
train_df = full.iloc[:len(df_train)]
test_df = full.iloc[len(df_train):]

X = train_df.drop(['Response', 'age_bins'], axis=1)
y = train_df['Response']

X.head()  # Display the head of the resulting feature matrix
```

```
Columns with LESS than 10 unique values: ['Gender', 'Driving_License', 'Pr
eviously_Insured', 'Vehicle_Age', 'Vehicle_Damage', 'Response']
Columns with MORE than 10 unique values: ['Age', 'Region_Code', 'Annual_Pr
emium', 'Policy_Sales_Channel', 'Vintage']
```

Out[35]:

	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicle_Age
0	Male	21	1	35.0	0	1-2 Year
1	Male	43	1	28.0	0	> 2 Years
2	Female	25	1	14.0	1	< 1 Year
3	Female	35	1	1.0	0	1-2 Year
4	Female	36	1	15.0	1	1-2 Year

5 rows × 23 columns

Modeling

Model from :https://www.kaggle.com/code/khangtran94vn/khang-eda-classification-insurance/notebook

In [9]:

```python
from sklearn.model_selection import train_test_split, GridSearchCV, Rando
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder, OrdinalEnc
from sklearn.compose import ColumnTransformer
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from sklearn.metrics import roc_auc_score, roc_curve, confusion_matrix

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify = y, r

coltrans = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(), ['Gender', 'Vehicle_Damage']),
        ('minmax', MinMaxScaler(), ['Age', 'Driving_License', 'Region_Cod
        ('ordinal', OrdinalEncoder(categories=[['< 1 Year', '1-2 Year', '
        ('robust', RobustScaler(), ['Annual_Premium']),
        ('standard', StandardScaler(), ['Age_Type', 'Age_x_Vehicle_Age',
        ('standard_2', StandardScaler(),col_pre+col_pro),            # Ve
#         ('standard_3', StandardScaler(),new_stan),
#         ('minmax_2', MinMaxScaler(),new_min)                        # Ve
    ],
    remainder='passthrough'  # Keeps columns not specified in transformer
)

coltrans
```

Out[9]:

```
▸ ColumnTransformer
▸ cat            ▸ minmax         ▸ ordinal         ▸ robust         ▸ stan
▸ OneHotEncoder  ▸ MinMaxScaler   ▸ OrdinalEncoder  ▸ RobustScaler   ▸ Standard
```

In [14]:
```
X_train_trans = coltrans.fit_transform(X_train)
X_test_trans = coltrans.transform(X_test)

ratio = len(df_train[df_train['Response']==0]) / len(df_train[df_train['R
ratio

pd.DataFrame(X_train_trans,columns=coltrans.get_feature_names_out())
```

Out[14]:

	cat__Gender_Female	cat__Gender_Male	cat__Vehicle_Damage_No	cat_
0	1.0	0.0	0.0	
1	1.0	0.0	1.0	
2	0.0	1.0	1.0	
3	1.0	0.0	0.0	
4	0.0	1.0	0.0	
...	...	...	...	
8628593	0.0	1.0	1.0	
8628594	1.0	0.0	0.0	
8628595	0.0	1.0	0.0	
8628596	0.0	1.0	1.0	
8628597	0.0	1.0	0.0	

8628598 rows × 25 columns

XGBoost

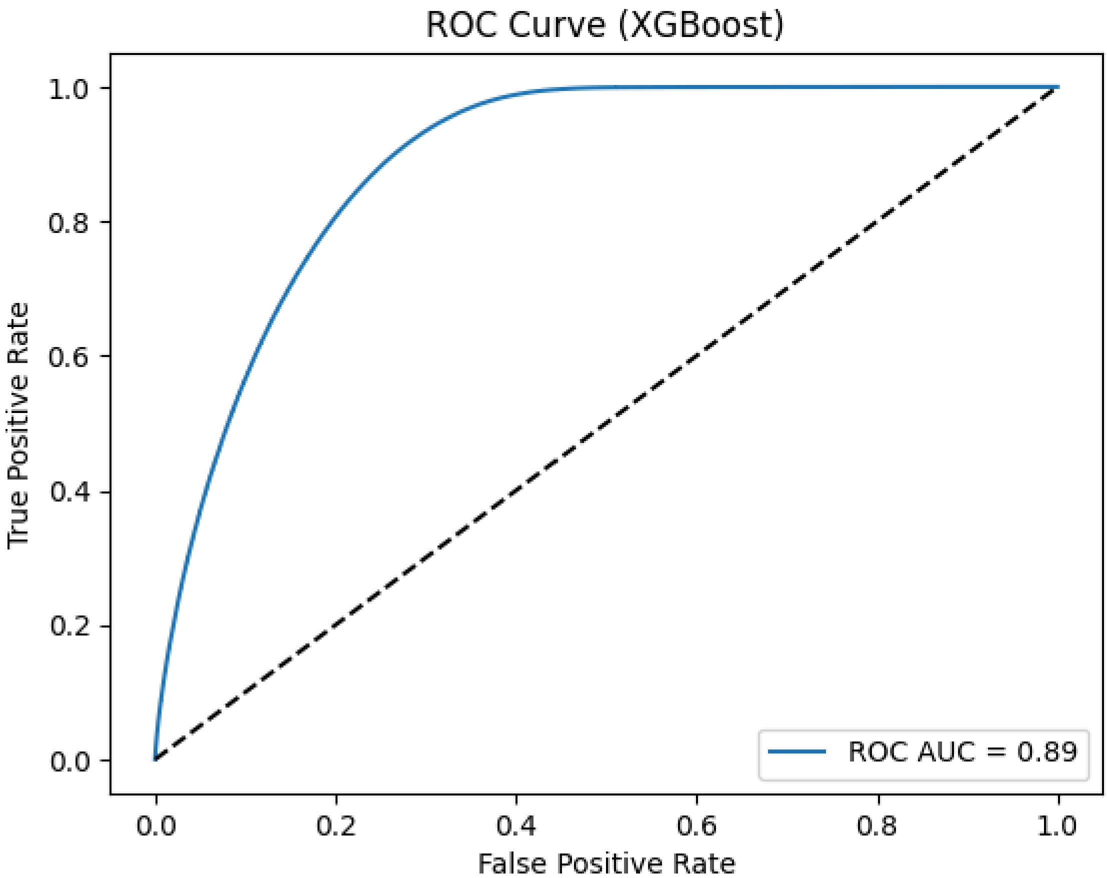
In [15]:
```
import xgboost as xgb

#### From optuna

xgbc = xgb.XGBClassifier(
    random_state=512,
    objective="binary:logistic",
    eval_metric='auc',
    max_depth=8,
    min_child_weight=12,  # Equivalent to min_samples_leaf
    use_label_encoder=False, n_estimators = 2155,
    colsample_bytree = 0.5, gamma = 0.2,
    learning_rate = 0.09093568107192034, subsample = 1.0,
    reg_alpha = 0.0011852827097616767,
    reg_lambda = 1.0735757602378362e-06,
    early_stopping_rounds=10,
    max_bin = 197818,
    scale_pos_weight = ratio,
)
```

In [16]:
```
xgbc.fit(X_train_trans,y_train,
         eval_set=[(X_test_trans, y_test)],  # Validation set
         verbose=50  # Print messages during training
```

```
)
y_pred_xgb = xgbc.predict_proba(X_test_trans)

print('ROC_AUC_Score XGBoost train: ',round(roc_auc_score(y_train,xgbc.pr
print('ROC_AUC_Score XGBoost test: ',round(roc_auc_score(y_test,xgbc.pred
```

```
[0]     validation_0-auc:0.84943
[50]    validation_0-auc:0.87141
[100]   validation_0-auc:0.87671
[150]   validation_0-auc:0.87956
[200]   validation_0-auc:0.88103
[250]   validation_0-auc:0.88207
[300]   validation_0-auc:0.88297
[350]   validation_0-auc:0.88396
[400]   validation_0-auc:0.88440
[450]   validation_0-auc:0.88493
[500]   validation_0-auc:0.88544
[550]   validation_0-auc:0.88584
[600]   validation_0-auc:0.88619
[650]   validation_0-auc:0.88653
[700]   validation_0-auc:0.88681
[750]   validation_0-auc:0.88706
[800]   validation_0-auc:0.88729
[850]   validation_0-auc:0.88760
[900]   validation_0-auc:0.88783
[950]   validation_0-auc:0.88796
[1000]  validation_0-auc:0.88805
[1050]  validation_0-auc:0.88820
[1100]  validation_0-auc:0.88837
[1136]  validation_0-auc:0.88846
ROC_AUC_Score XGBoost train:  89.74
ROC_AUC_Score XGBoost test:  88.85
```

In [20]:
```
roc_auc_test_xgb = roc_auc_score(y_test, xgbc.predict_proba(X_test_trans)
fpr_xgb, tpr_xgb, _ = roc_curve(y_test, y_pred_xgb[:,1])

plt.plot(fpr_xgb, tpr_xgb, label=f'ROC AUC = {roc_auc_test_xgb:.2f}')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve (XGBoost)')
plt.legend(loc="lower right")

plt.show()
```



Catboost

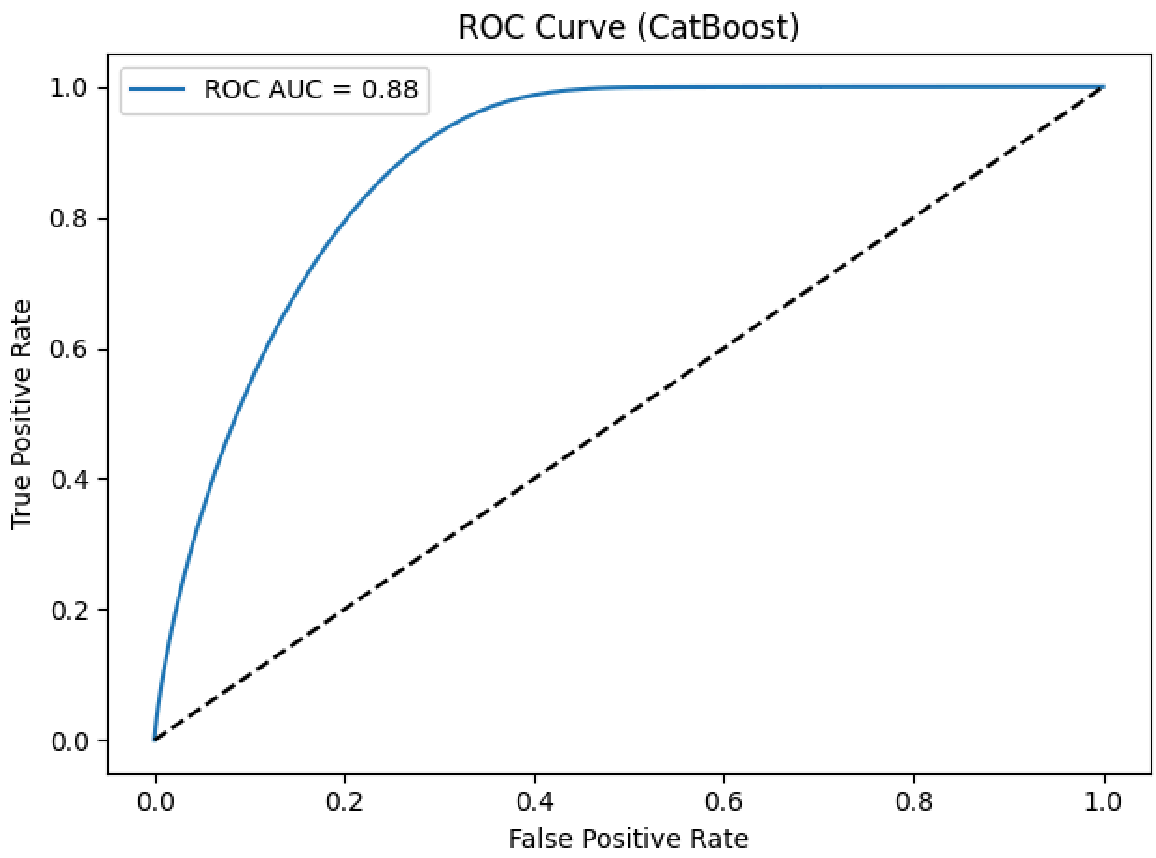
In [21]:
```
from catboost import CatBoostClassifier

#### Initialize the CatBoost classifier
cbc = CatBoostClassifier(random_state=512,
    objective="Logloss",  # Equivalent to "binary:logistic" in XGBoost
    eval_metric='AUC',  # Equivalent to 'auc' in XGBoost
    depth=8,  # Equivalent to max_depth
    min_data_in_leaf=13,  # Equivalent to min_child_weight
    learning_rate=0.2973547288176656,  # Equivalent to learning_rate
    n_estimators=914,  # Number of boosting rounds
    l2_leaf_reg=4.5257568564763595,  # Equivalent to reg_lambda
    bagging_temperature=0.002224062594313l627,  # Controls the amount of
    early_stopping_rounds=10,  # Similar to early_stopping_rounds in XGBo
    scale_pos_weight = ratio,
    silent=True
)
```

In [22]:
```
cbc.fit(X_train_trans,y_train, verbose = 50)
y_pred_cbc = cbc.predict_proba(X_test_trans)

print('ROC_AUC_Score cbc train: ',round(roc_auc_score(y_train,cbc.predict
print('ROC_AUC_Score cbc test: ',round(roc_auc_score(y_test,cbc.predict_p
```

```
0:      total: 2.27s    remaining: 34m 31s
50:     total: 1m 21s   remaining: 23m 7s
100:    total: 2m 42s   remaining: 21m 47s
150:    total: 4m 2s    remaining: 20m 26s
200:    total: 5m 22s   remaining: 19m 2s
250:    total: 6m 42s   remaining: 17m 42s
300:    total: 8m 5s    remaining: 16m 28s
350:    total: 9m 28s   remaining: 15m 11s
400:    total: 10m 48s  remaining: 13m 49s
450:    total: 12m 10s  remaining: 12m 29s
500:    total: 13m 31s  remaining: 11m 8s
550:    total: 14m 51s  remaining: 9m 47s
600:    total: 16m 13s  remaining: 8m 27s
650:    total: 17m 34s  remaining: 7m 6s
700:    total: 18m 56s  remaining: 5m 45s
750:    total: 20m 20s  remaining: 4m 24s
800:    total: 21m 40s  remaining: 3m 3s
850:    total: 23m 2s   remaining: 1m 42s
900:    total: 24m 23s  remaining: 21.1s
913:    total: 24m 44s  remaining: 0us
ROC_AUC_Score cbc train:  88.88
ROC_AUC_Score cbc test:  88.37
```

In [26]:

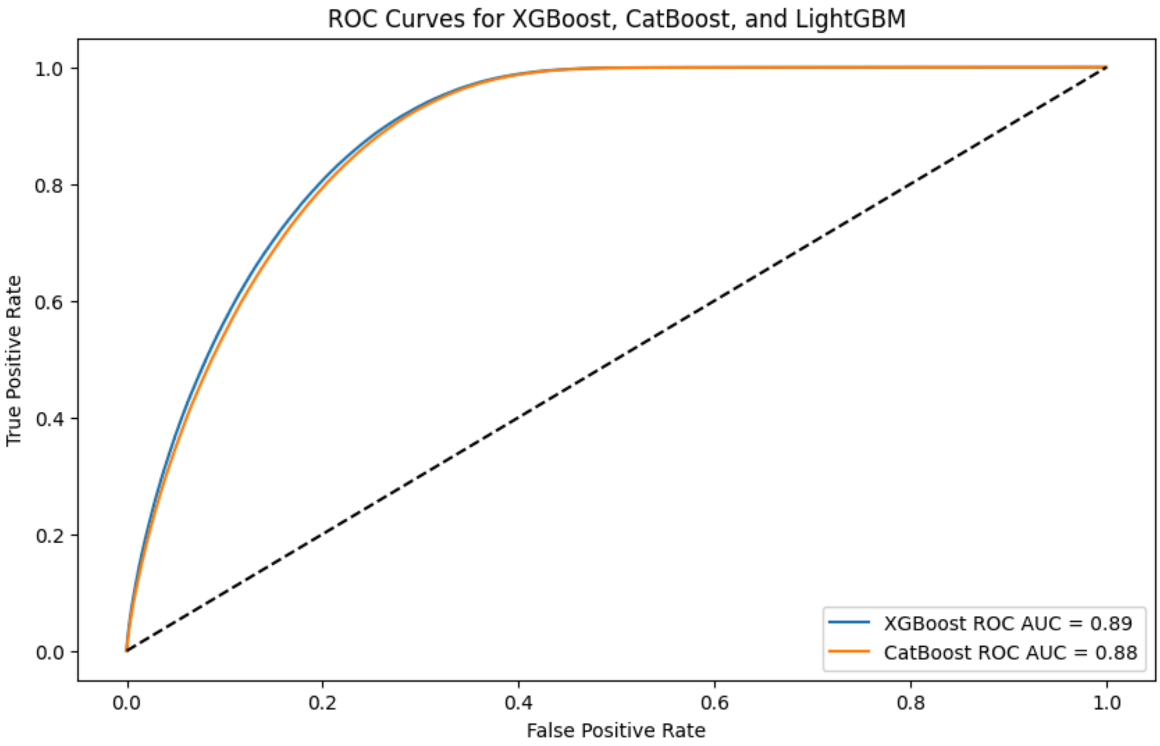
```
# Plot ROC curve
roc_auc_test_cbc = roc_auc_score(y_test, y_pred_cbc[:, 1])
fpr_cbc, tpr_cbc, _ = roc_curve(y_test, y_pred_cbc[:, 1])


plt.plot(fpr_cbc, tpr_cbc, label=f'ROC AUC = {roc_auc_test_cbc:.2f}')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve (CatBoost)')
plt.legend(loc='best')

plt.tight_layout()
plt.show()
```



Compare two model

In [27]:

```
# Plot ROC curves
plt.figure(figsize=(10, 6))
plt.plot(fpr_xgb, tpr_xgb, label=f'XGBoost ROC AUC = {roc_auc_test_xgb:.2
plt.plot(fpr_cbc, tpr_cbc, label=f'CatBoost ROC AUC = {roc_auc_test_cbc:.

plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for XGBoost, CatBoost, and LightGBM')
plt.legend(loc='best')
plt.show()
```



Submit

In [36]:
```
test_df = test_df.drop(['age_bins','Response'],axis=1)
test_df
test_trans = coltrans.transform(test_df)
pd.DataFrame(test_trans, columns = coltrans.get_feature_names_out())
```

Out[36]:

	cat__Gender_Female	cat__Gender_Male	cat__Vehicle_Damage_No	cat_
0	1.0	0.0	1.0	
1	0.0	1.0	0.0	
2	0.0	1.0	0.0	
3	1.0	0.0	1.0	
4	0.0	1.0	1.0	
...	...	...	...	
7669861	0.0	1.0	0.0	
7669862	0.0	1.0	1.0	
7669863	0.0	1.0	1.0	
7669864	0.0	1.0	0.0	
7669865	0.0	1.0	1.0	

7669866 rows × 25 columns

Submission

In [38]:
```
final_predictions = xgbc.predict_proba(test_trans)[:, 1]

submit = pd.DataFrame({
    'id': df_test.index,
    'Response': final_predictions
})
submit.to_csv('submission.csv',index=False)
print('DONE')
submit
```

```
DONE
```

Out[38]:

	id	Response
0	0	0.040635
1	1	0.871455
2	2	0.685665
3	3	0.000582
4	4	0.419792
...	...	...
7669861	7669861	0.625036
7669862	7669862	0.001159
7669863	7669863	0.001304
7669864	7669864	0.913449
7669865	7669865	0.000656

7669866 rows × 2 columns

Further improve

- Model Tuning
- Memory Optimization
- Scale data

In [ ]: