Car Insurance Sales Prediction

1. Problem Statement

The aim of this project is to predict whether a health insurance customer from past year would be interested in vehicle insurance, by analyzing customer features such as gender, age, driving license, region, previous insurance history, vehicle age, and annual premium price. The project also aims to find out the set of variables that has the most impact on the customers' interest in vehicle insurance.

2. Data Import and Check

Libraries needed

In [1]:
```
# libraries for visualizations
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt

%matplotlib inline
```

In [2]:
```
# libraries for data preprocessing
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
from sklearn.preprocessing import OrdinalEncoder
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2, mutual_info_classif
from sklearn import preprocessing
```

In [3]:
```
# libraries for model building
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
import xgboost as xgb
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from sklearn.model_selection import StratifiedKFold
```

In [4]:
```
# libraries for model performance
from sklearn.metrics import precision_score, recall_score, accuracy_score, balanced_accuracy_score, c
from scikitplot.metrics import plot_cumulative_gain, plot_lift_curve,  silhouette_score
from sklearn.model_selection import RandomizedSearchCV
```

In [66]:
```
# ignore warning
import warnings
warnings.filterwarnings('ignore')
```

Data import

In [5]:
```
# train dataset
train = pd.read_csv(r"C:\Users\eunbi\Desktop\DS\Car Insurance Prediction\health_insurance.csv")
train.shape
```

Out[5]: (381109, 12)

In [6]:
```
# test dataset
test = pd.read_csv(r"C:₩Users₩eunbi₩Desktop₩DS₩Car Insurance Prediction₩health_insurance_test.csv")
test.shape
```

Out[6]: (127037, 11)

Data check

In [7]:
```
# first five rows of the dataset
train.head()
```

Out[7]:

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicle_Age	Vehicle_Damage	Annual_Premium
0	1	Male	44	1	28.0	0	> 2 Years	Yes	40454.0
1	2	Male	76	1	3.0	0	1-2 Year	No	33536.0
2	3	Male	47	1	28.0	0	> 2 Years	Yes	38294.0
3	4	Male	21	1	11.0	1	< 1 Year	No	28619.0
4	5	Female	29	1	41.0	1	< 1 Year	No	27496.0

In [8]:
```
# dataset information
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 381109 entries, 0 to 381108
Data columns (total 12 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   id                    381109 non-null  int64  
 1   Gender                381109 non-null  object 
 2   Age                   381109 non-null  int64  
 3   Driving_License       381109 non-null  int64  
 4   Region_Code           381109 non-null  float64
 5   Previously_Insured    381109 non-null  int64  
 6   Vehicle_Age           381109 non-null  object 
 7   Vehicle_Damage        381109 non-null  object 
 8   Annual_Premium        381109 non-null  float64
 9   Policy_Sales_Channel  381109 non-null  float64
 10  Vintage               381109 non-null  int64  
 11  Response              381109 non-null  int64  
dtypes: float64(3), int64(6), object(3)
memory usage: 34.9+ MB
```

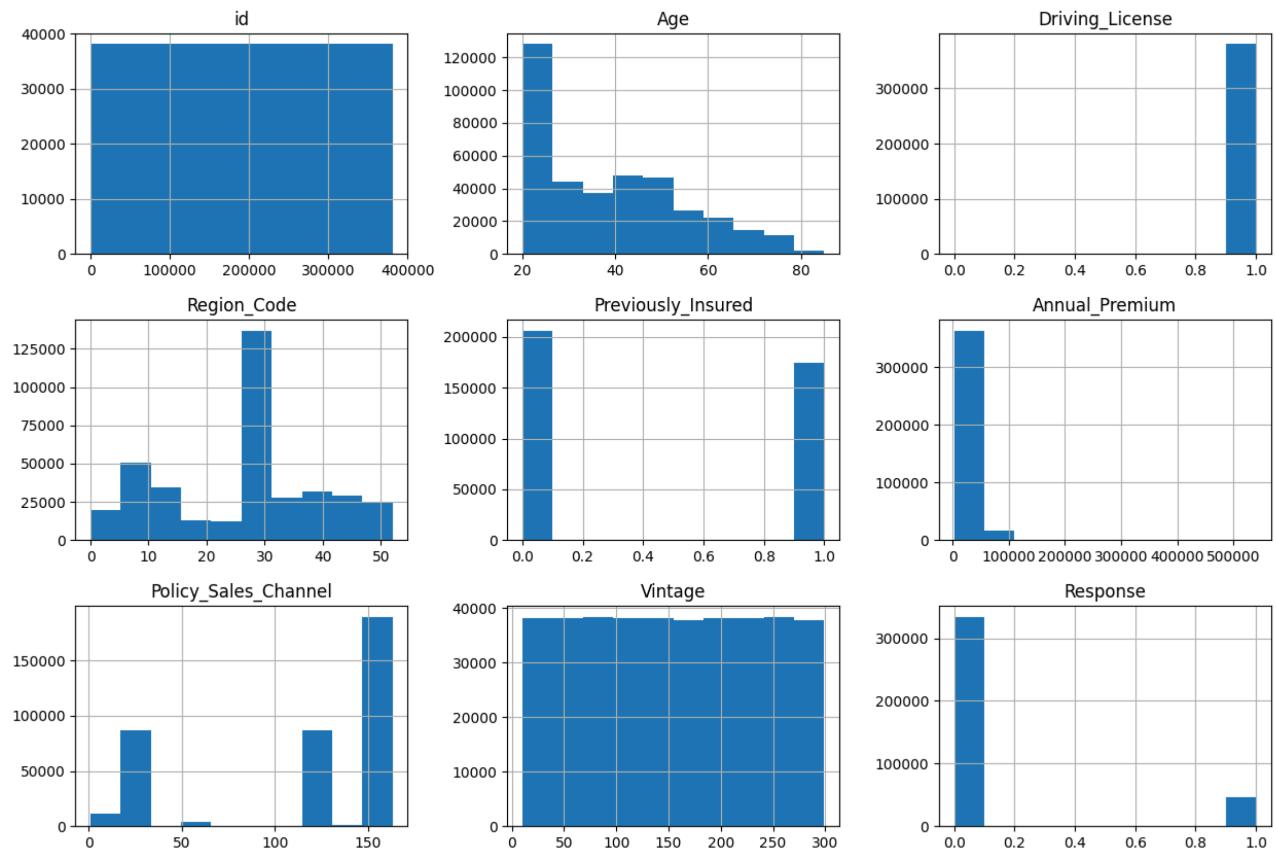
In [9]:
```
# numerical variables
train[['Age', 'Annual_Premium', 'Vintage']].describe().round(1)
```

Out[9]:

	Age	Annual_Premium	Vintage
count	381109.0	381109.0	381109.0
mean	38.8	30564.4	154.3
std	15.5	17213.2	83.7
min	20.0	2630.0	10.0
25%	25.0	24405.0	82.0
50%	36.0	31669.0	154.0
75%	49.0	39400.0	227.0
max	85.0	540165.0	299.0

In [10]:

```
# histograms
train.hist(figsize=(15,10))
plt.show()
```



- The dataset is highly imbalanced
- We have 12 columns including Response and id column. We will drop id column since it is unnecessary.
- Our response variable is binary variable. So, we will have to build a logistic regression model.
- We will treat Region_Code, Policy_Sales_Channel and Vintage as categorical variables.
- We will also create age group variable as well.

3. Data Pre-processing

Check for missing values

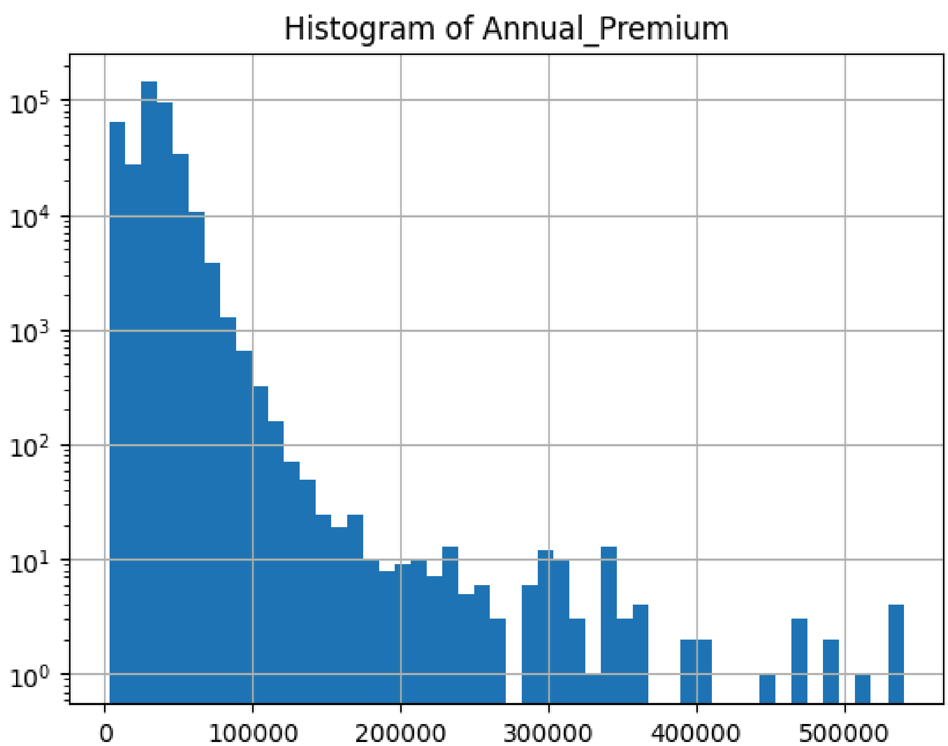
In [11]:
```
# missing values
train.isna().sum()
```

Out[11]:
```
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
```

Check for outliers

- Annual_Premium seems to be highly right skewed and have large variability. This could be due to outliers.

In [12]:
```
# histogram
train['Annual_Premium'].hist(bins = 50)
plt.yscale('log')
plt.title('Histogram of Annual_Premium')
plt.show()
```



In [13]:
```
train[train['Annual_Premium'] > 100000.0].shape
```

Out[13]:
```
(778, 12)
```

- The annual premium paid by the largest number of customers is 2630.
- Only 778 customers pay annual premium of over 100,000.
- Only 3 customers pay annual premium of over 500,000. Should we consider these values as outliers?

- If we subtract 1.5 x IQR from the first quartile, any data values that are less than this number are considered outliers. Similarly, if we add 1.5 x IQR to the third quartile, any data values that are greater than this number are considered outliers.

In [14]:
```
# IQR Range
IQR = 39400.0 - 24405.0
lower = 24405.0 - (IQR * 1.5)
upper = 39400.0 + (IQR * 1.5)
print(lower, upper)
```

```
1912.5 61892.5
```

In [15]:
```
train = train[train['Annual_Premium'] <= upper].copy()
```

4. Feature Engineering

Add Age Group variable

In [16]:
```
bins = [20, 30, 40, 50, 60, 70, 80, 90]
labels = ['20-29', '30-39', '40-49', '50-59', '60-69', '70-79','80+']
train['Age_Group'] = pd.cut(train.Age, bins, labels = labels, include_lowest = True)

test['Age_Group'] = pd.cut(test.Age, bins, labels = labels,include_lowest = True)

train[['Age','Age_Group']].head(5)
```

Out[16]:

	Age	Age_Group
0	44	40-49
1	76	70-79
2	47	40-49
3	21	20-29
4	29	20-29

Convert data types

In [17]:
```
cat_cols = ['Gender', 'Driving_License', 'Region_Code', 'Previously_Insured', 'Vehicle_Age','Vehicle_Da
num_cols = ['Age','Annual_Premium', 'Vintage']
data_all = cat_cols + num_cols
```

In [18]:
```
train[cat_cols] = train[cat_cols].astype('category')
test[cat_cols] = test[cat_cols].astype('category')
train[num_cols] = train[num_cols].astype('int')
test[num_cols] = test[num_cols].astype('int')
```

In [19]:
```
train.dtypes
```

Out[19]:
```
id                          int64
Gender                   category
Age                         int32
Driving_License          category
Region_Code              category
Previously_Insured       category
Vehicle_Age              category
Vehicle_Damage           category
Annual_Premium              int32
Policy_Sales_Channel     category
Vintage                     int32
Response                    int64
Age_Group                category
dtype: object
```

In [20]:
```
train.shape
```

Out[20]:
```
(370789, 13)
```

Encode categorical variables

- OrdinalEncoder/LabelEncoder: When order is important for categorical variables, it's important to use sklearn OrdinalEncoder or LabelEncoder. eg. cold, warm, hot
- One Hot Encoding: When order is NOT important we can use sklearn OneHotEncoder or pandas get_dummies function. eg. Gender is an example Female, Male
- There are two rows in test data which has different Policy Sales Channel that do not exist in train data. It's 141 and 142. We will replace them with 140.

In [21]:
```
train_df = train.copy()
test_df = test.copy()
id_col = test_df.id
train_df.drop(columns = ['id'], inplace = True)
test_df.drop(columns = ['id'], inplace = True)
train_df['Vehicle_Age_num'] = ''
test_df['Vehicle_Age_num'] = ''
train_df.loc[train_df['Vehicle_Age'] == '< 1 Year', 'Vehicle_Age_num'] = 0
train_df.loc[train_df['Vehicle_Age'] == '1-2 Year', 'Vehicle_Age_num'] = 1
train_df.loc[train_df['Vehicle_Age'] == '> 2 Years', 'Vehicle_Age_num'] = 2
test_df.loc[test_df['Vehicle_Age'] == '< 1 Year', 'Vehicle_Age_num'] = 0
test_df.loc[test_df['Vehicle_Age'] == '1-2 Year', 'Vehicle_Age_num'] = 1
test_df.loc[test_df['Vehicle_Age'] == '> 2 Years', 'Vehicle_Age_num'] = 2
```

In [22]:
```
oe = OrdinalEncoder()
train_df[cat_cols +  ['Vehicle_Age_num']] = oe.fit_transform(train_df[cat_cols + ['Vehicle_Age_num']])

# there is 2 unknown new Policy_Sales_Channel values in test 141 and 142
# we replace them with 140

test_df.loc[test['Policy_Sales_Channel'] == 141.0, 'Policy_Sales_Channel'] = 140.0
test_df.loc[test['Policy_Sales_Channel'] == 142.0, 'Policy_Sales_Channel'] = 140.0

test_df[cat_cols] = oe.fit_transform(test_df[cat_cols])
```

In [23]:
```
cat_cols_new = ['Gender', 'Driving_License', 'Region_Code', 'Previously_Insured', 'Vehicle_Age_num','Ve
data_all_new = cat_cols_new + num_cols
train_df.drop(columns=['Vehicle_Age'], inplace=True)
test_df.drop(columns=['Vehicle_Age'], inplace=True)
```

In [24]:
```
train_df.shape
```

Out[24]: (370789, 12)

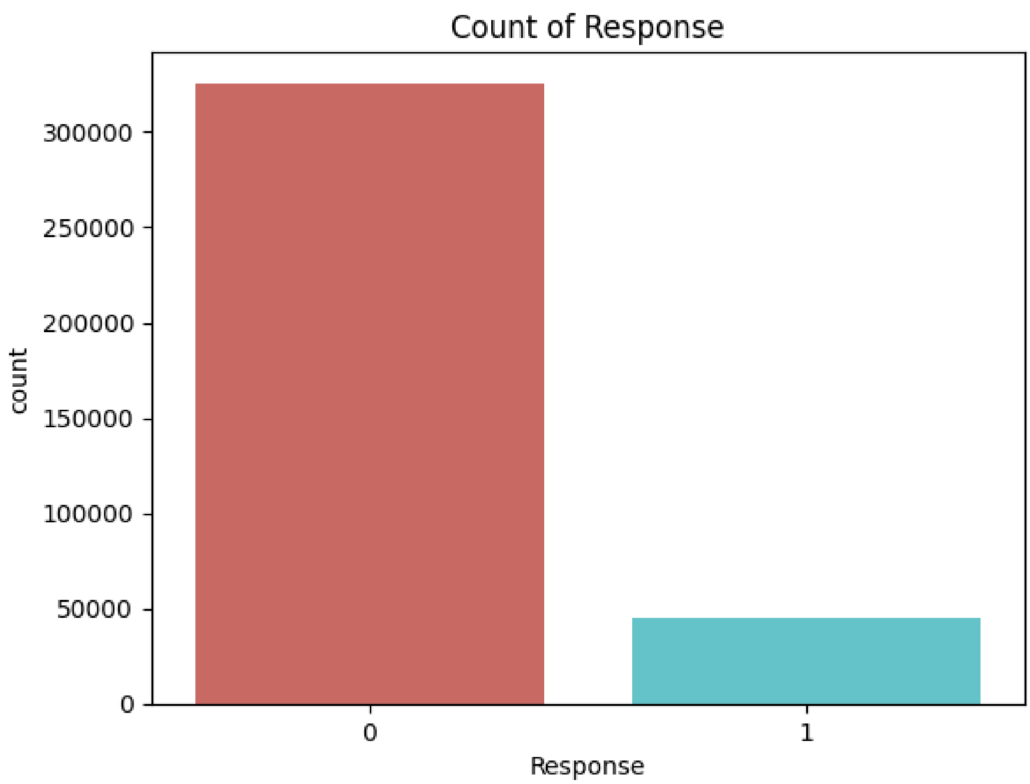
Save the dataframe as csv file

In [25]:
```
#train_df.to_csv('car_train_df.csv', index=False)
```

5. Exploratory Data Analysis

Target variable (Response)

In [26]:
```
ax = sns.countplot(train, x = 'Response', palette = 'hls')
plt.title('Count of Response')
plt.show()
```



In [27]:
```
train_count = train[['id', 'Response']].groupby(['Response']).count().reset_index().rename(columns = {
train_count['Proportion'] = train_count['Count']/train_count['Count'].sum()
train_count
```

Out[27]:

	Response	Count	Proportion
0	0	325634	0.878219
1	1	45155	0.121781

- Majority of the customers responded that they are not interested in vehicle insurance.
- Only 12% of the customers are interested in vehicle insurance.

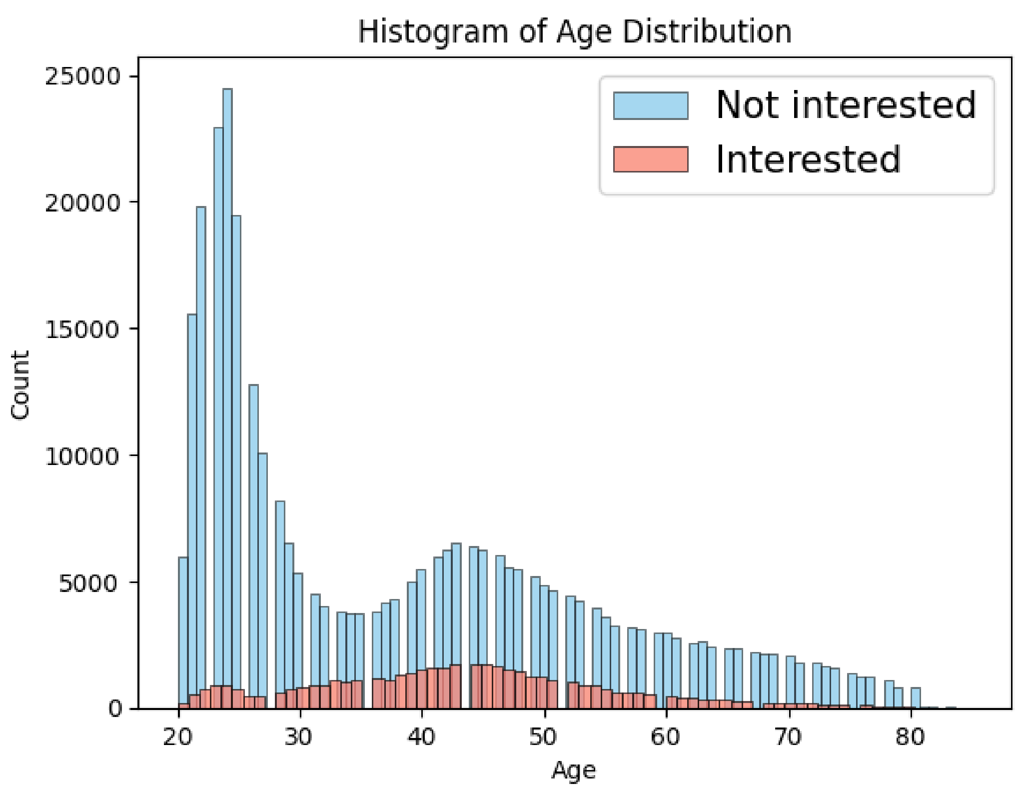
Age distribution of customers

In [28]:
```
train_count = train.loc[train['Response']==1, ['id', 'Age_Group']].groupby(['Age_Group']).count().rese
train_count['Proportion'] = train_count['Count']/train_count['Count'].sum()
train_count
```

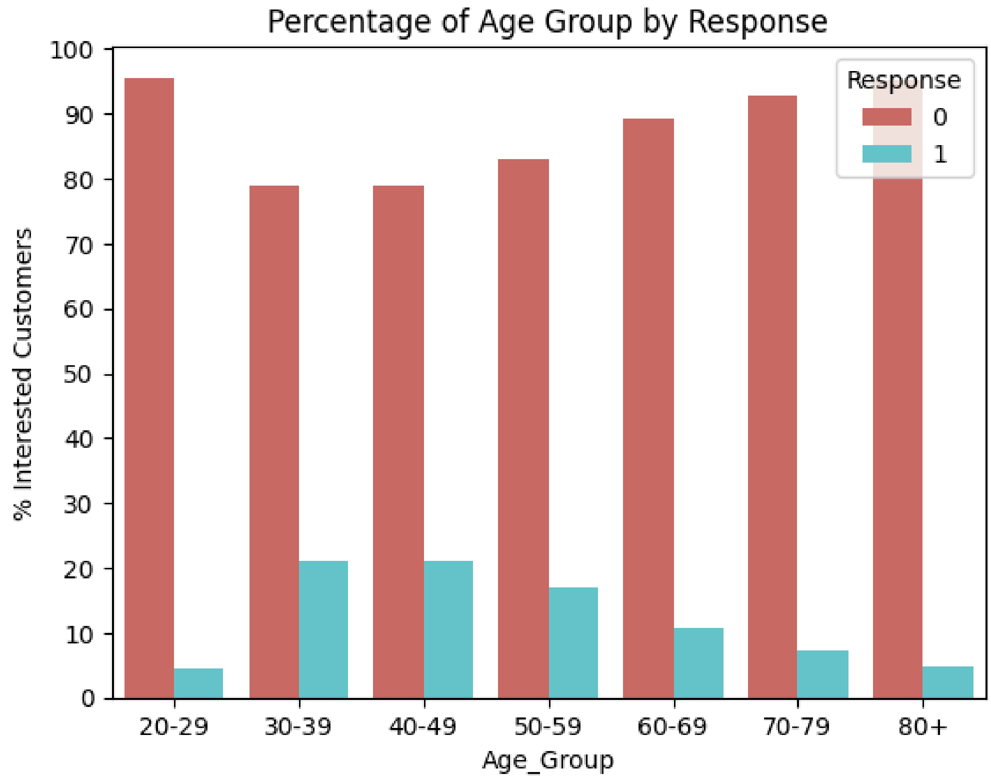
Out[28]:

	Age_Group	Count	Proportion
0	20-29	7047	0.156062
1	30-39	11343	0.251201
2	40-49	15474	0.342686
3	50-59	7377	0.163371
4	60-69	2856	0.063249
5	70-79	1052	0.023298
6	80+	6	0.000133

In [29]:
```
no = train.loc[train['Response'] == 0, 'Age']
yes = train.loc[train['Response'] == 1, 'Age']

sns.histplot(data = no, color = "skyblue", label = "Not interested", kde=False)
sns.histplot(data = yes, color = "salmon", label = "Interested", kde=False)
plt.legend(fontsize = 15)
plt.title('Histogram of Age Distribution')
plt.show()
```



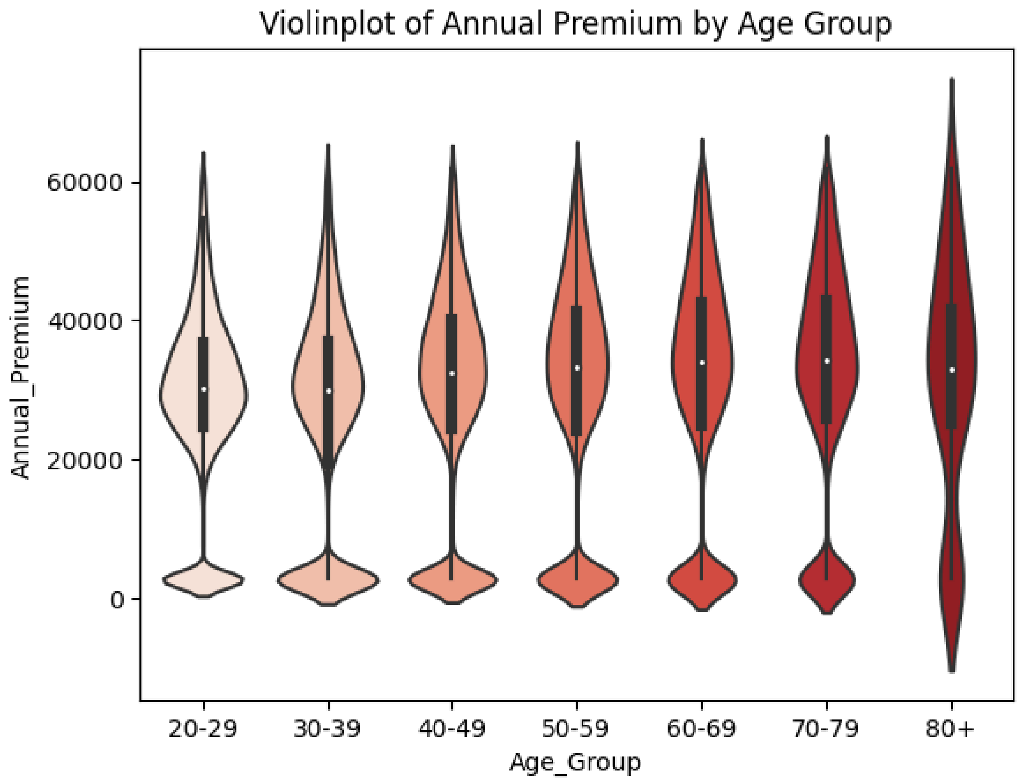
In [30]:
```
by_age = train.groupby(['Age_Group', 'Response'])['id'].count().reset_index().rename(columns = {'id':'
by_age['Percentage'] = by_age['Count'] / by_age.groupby('Age_Group')['Count'].transform('sum')*100
sns.barplot(by_age, x = 'Age_Group', y = 'Percentage', hue = 'Response', palette = 'hls')
labels = [i for i in range(0,105,10)]
plt.yticks(labels)
plt.ylabel('% Interested Customers')
plt.title('Percentage of Age Group by Response')
plt.show()
```



- The age group with the largest number of customer is 20-29 (42.7%). However, this group has the smallest proportion of customers interested in Vehicle insurance.
- The age group of 40-49 has the largest proportion of interested customers (20.1%).
- Among the customers interested in Vehicle insurance, about 34.3% are in 40-49 age range.
- The proportion of the customers interested in Vehicle insurance is smaller in older age groups.

Age Vs Annual Premium

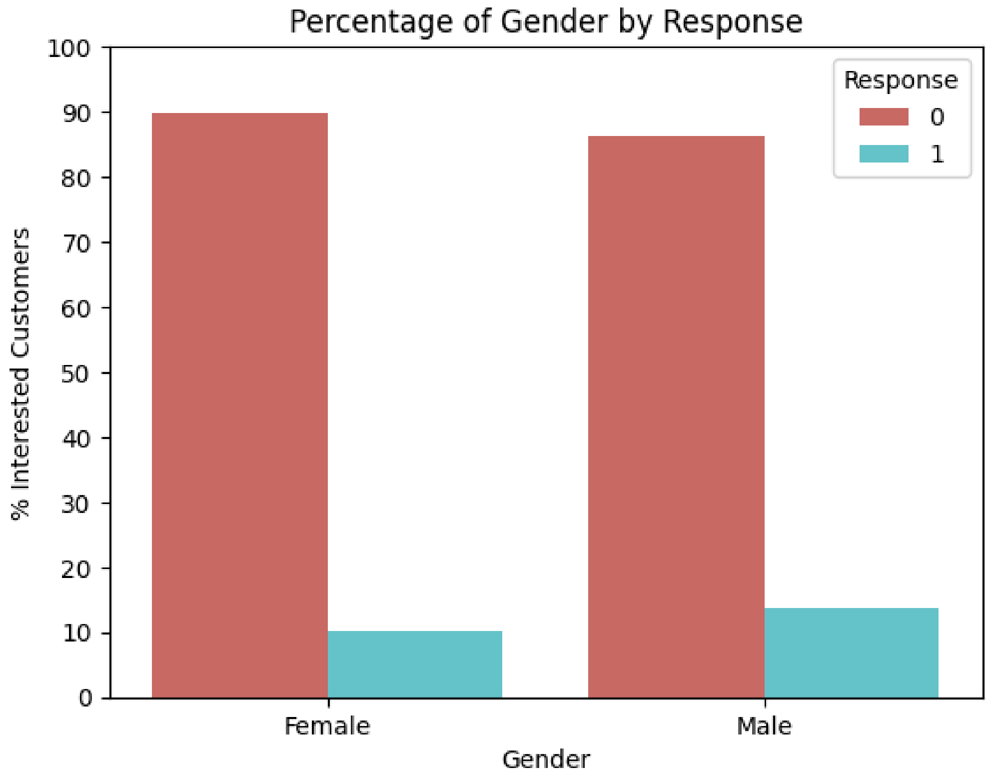
In [34]:
```
sns.violinplot(train, x = 'Age_Group',y = 'Annual_Premium', palette = 'Reds')
plt.title('Violinplot of Annual Premium by Age Group')
plt.show()
```



- Older people pay higher annual premium on average.
- The age group of 30-39 has larget variance in annual premium.

Gender distribution

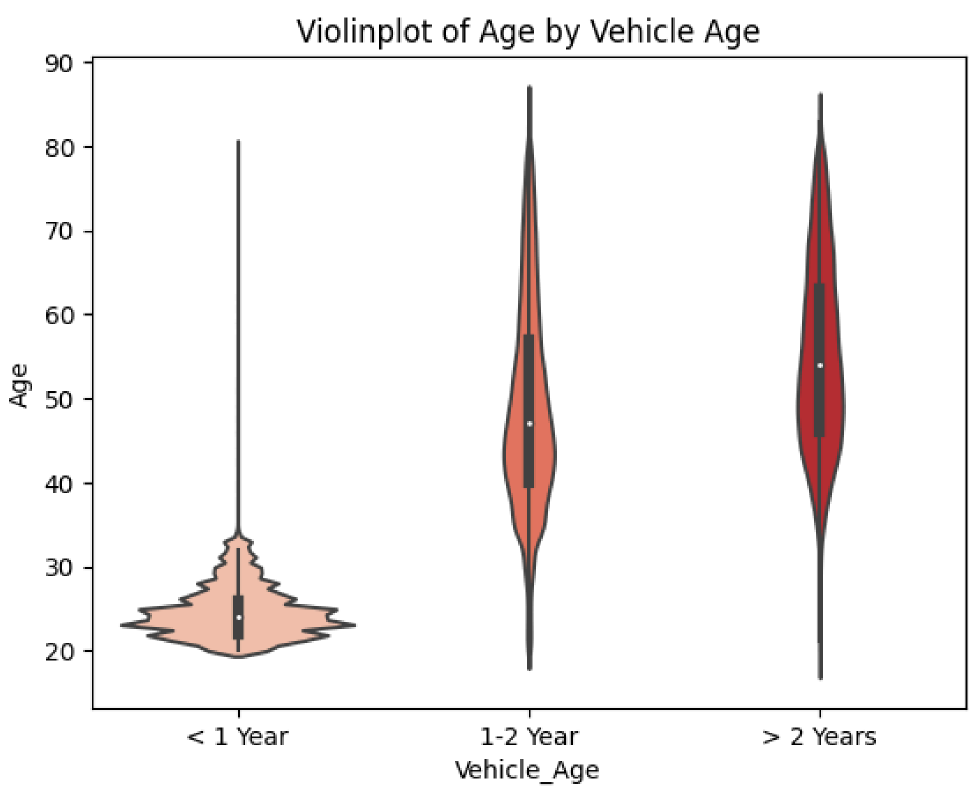
In [35]:
```
by_gender = train.groupby(['Gender', 'Response'])['id'].count().reset_index().rename(columns = {'id':'
by_gender['Percentage'] = by_gender['Count'] / by_gender.groupby('Gender')['Count'].transform('sum')*1(
sns.barplot(by_gender, x = 'Gender', y = 'Percentage', hue = 'Response', palette = 'hls')
labels = [i for i in range(0,105,10)]
plt.yticks(labels)
plt.ylabel('% Interested Customers')
plt.title('Percentage of Gender by Response')
plt.show()
```



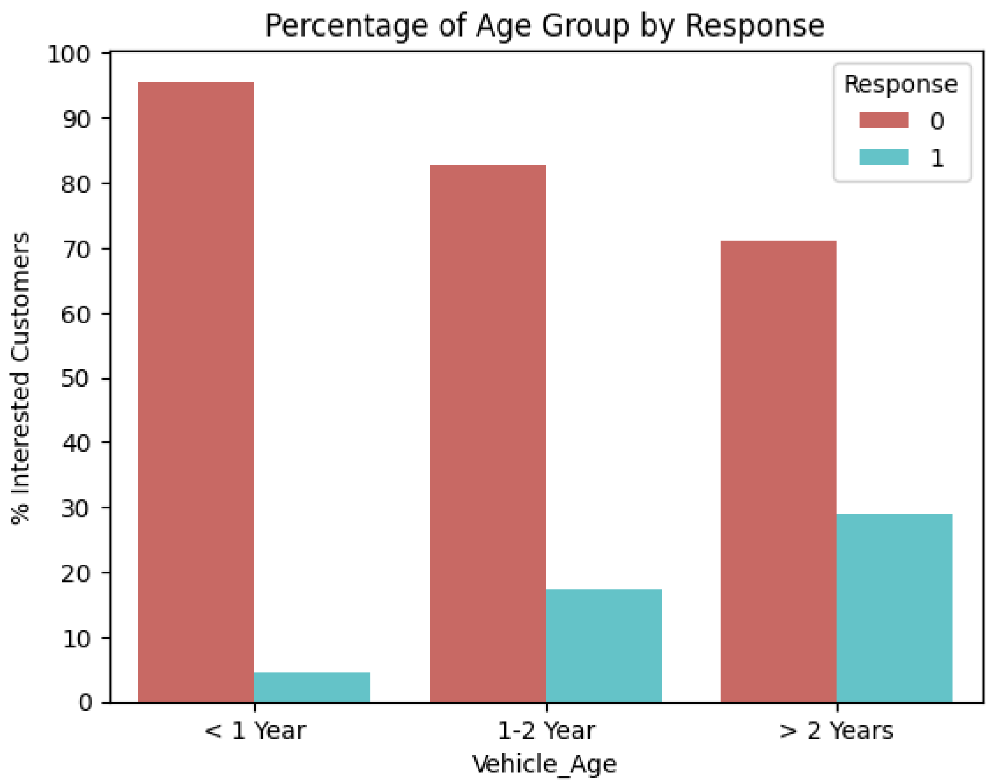
- About 3% more Male customers are interested in Vehicle insurance than female customers.

Vehicle Age distribution

In [40]:
```
train['Vehicle_Age'] = train['Vehicle_Age'].cat.reorder_categories(['< 1 Year', '1-2 Year', '> 2 Years
sns.violinplot(train, x = 'Vehicle_Age', y = 'Age', palette = 'Reds')
plt.title('Violinplot of Age by Vehicle Age')
plt.show()
```



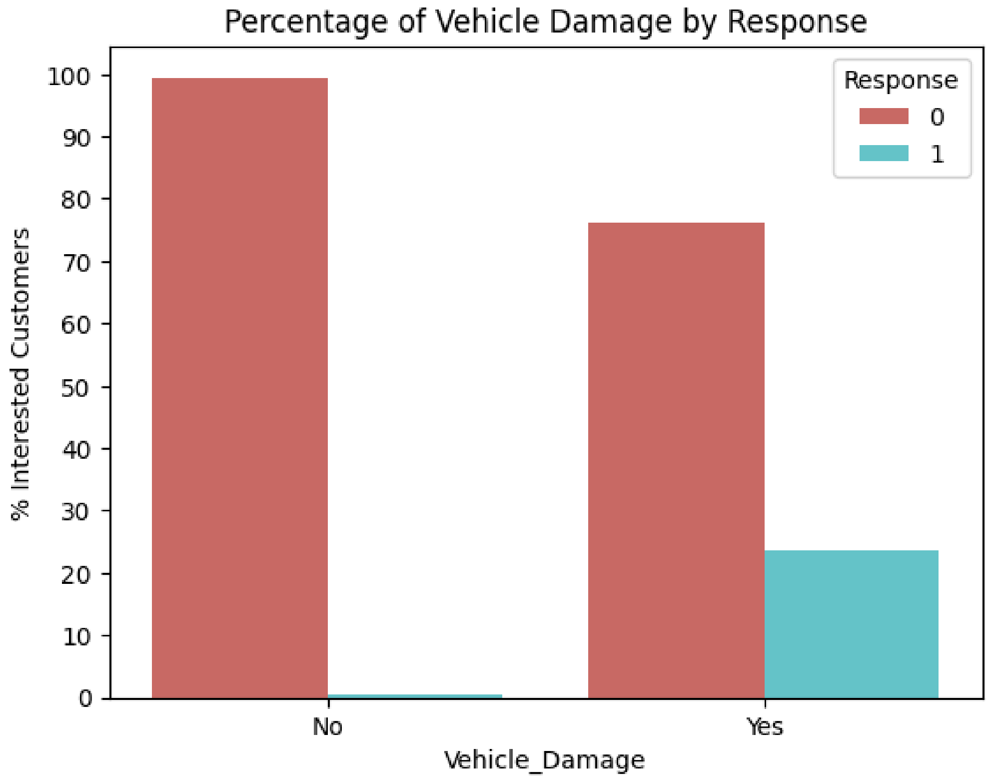
In [41]:
```
by_vehicle = train.groupby(['Vehicle_Age', 'Response'])['id'].count().reset_index().rename(columns = {
by_vehicle['Percentage'] = by_vehicle['Count'] / by_vehicle.groupby('Vehicle_Age')['Count'].transform(
sns.barplot(by_vehicle, x = 'Vehicle_Age', y = 'Percentage', hue = 'Response', palette = 'hls')
labels = [i for i in range(0,105,10)]
plt.yticks(labels)
plt.ylabel('% Interested Customers')
plt.title('Percentage of Age Group by Response')
plt.show()
```



- Older customers are tend to have older vehicles.
- The older the customer's vehicles are, the more they are interested in Vehicle insurance.
- It seems that vehicle age has a positive effect on response.

Vehicle damage / Response relationship

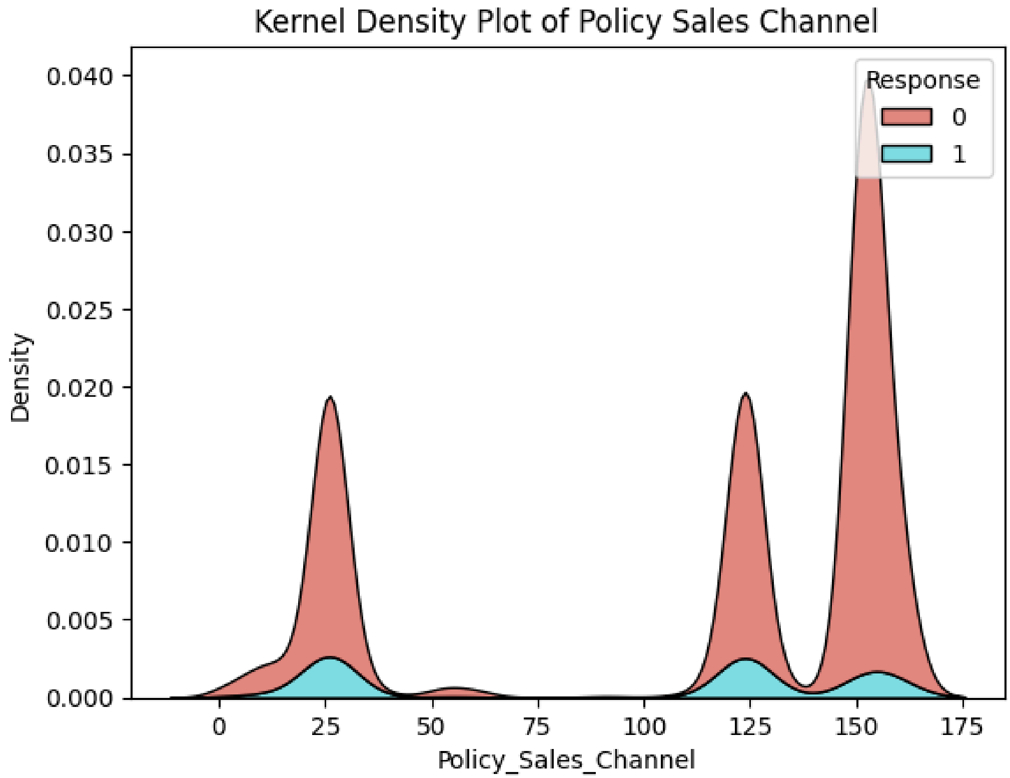
In [42]:
```
by_damage = train.groupby(['Vehicle_Damage', 'Response'])['id'].count().reset_index().rename(columns =
by_damage['Percentage'] = by_damage['Count'] / by_damage.groupby('Vehicle_Damage')['Count'].transform(
sns.barplot(by_damage, x = 'Vehicle_Damage', y = 'Percentage', hue = 'Response', palette = 'hls')
labels = [i for i in range(0,105,10)]
plt.yticks(labels)
plt.ylabel('% Interested Customers')
plt.title('Percentage of Vehicle Damage by Response')
plt.show()
```



- Customers who experienced damage on their cars are more interested in Vehicle insurance.
- Only small percentage of customers who do not have car damage is interested in Vehicle insurance.

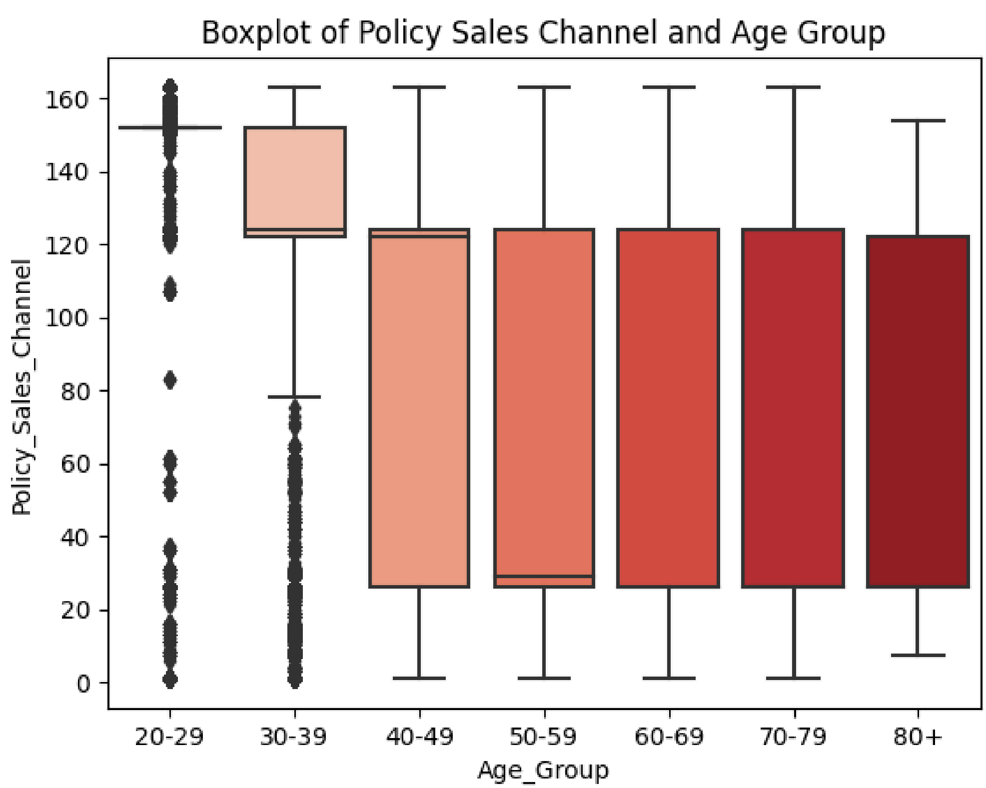
Policy Sales Channel distribution

In [43]:
```
train_1 = train.copy()
train_1['Policy_Sales_Channel'] = train_1['Policy_Sales_Channel'].astype('int')
sns.kdeplot(train_1, x = 'Policy_Sales_Channel', hue = 'Response', multiple='stack', palette = 'hls')
plt.title('Kernel Density Plot of Policy Sales Channel')
plt.show()
```



- The major Policy Sales Channels are same for both the customers interested in Vehicle insurance and those who are not.
- The top 3 Policy Sales Channels are 26, 124 and 152.

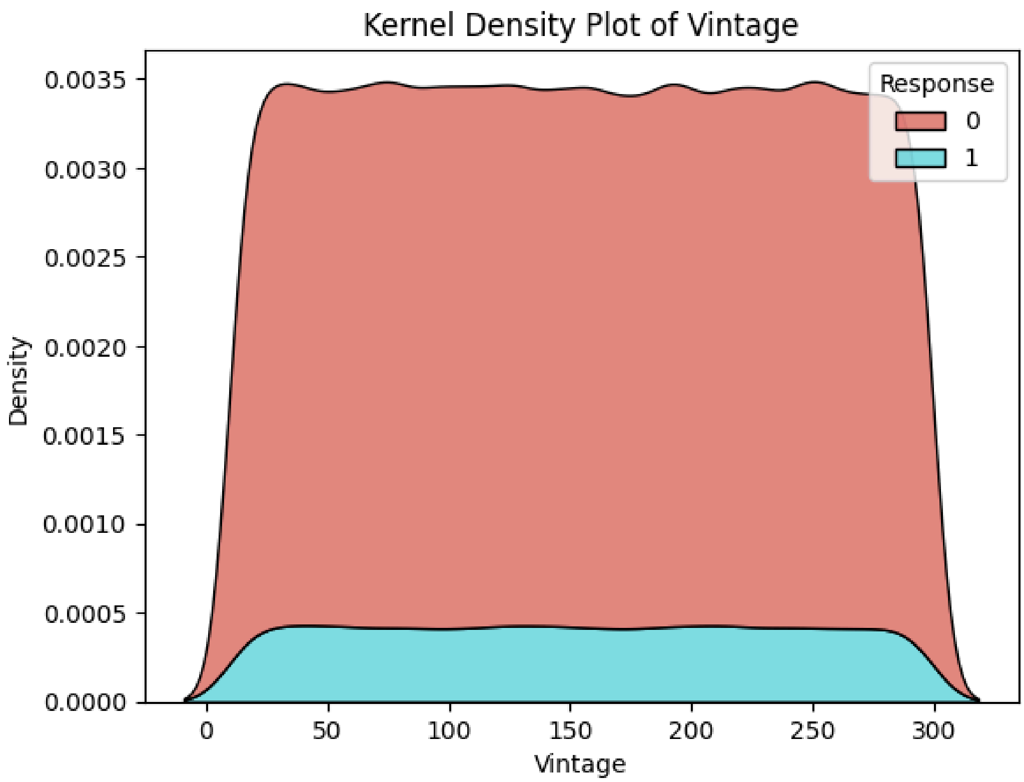
In [44]:
```
train['Policy_Sales_Channel'] = train['Policy_Sales_Channel'].astype('int')
sns.boxplot(train, x = 'Age_Group', y = 'Policy_Sales_Channel', palette='Reds')
plt.title('Boxplot of Policy Sales Channel and Age Group')
plt.show()
```



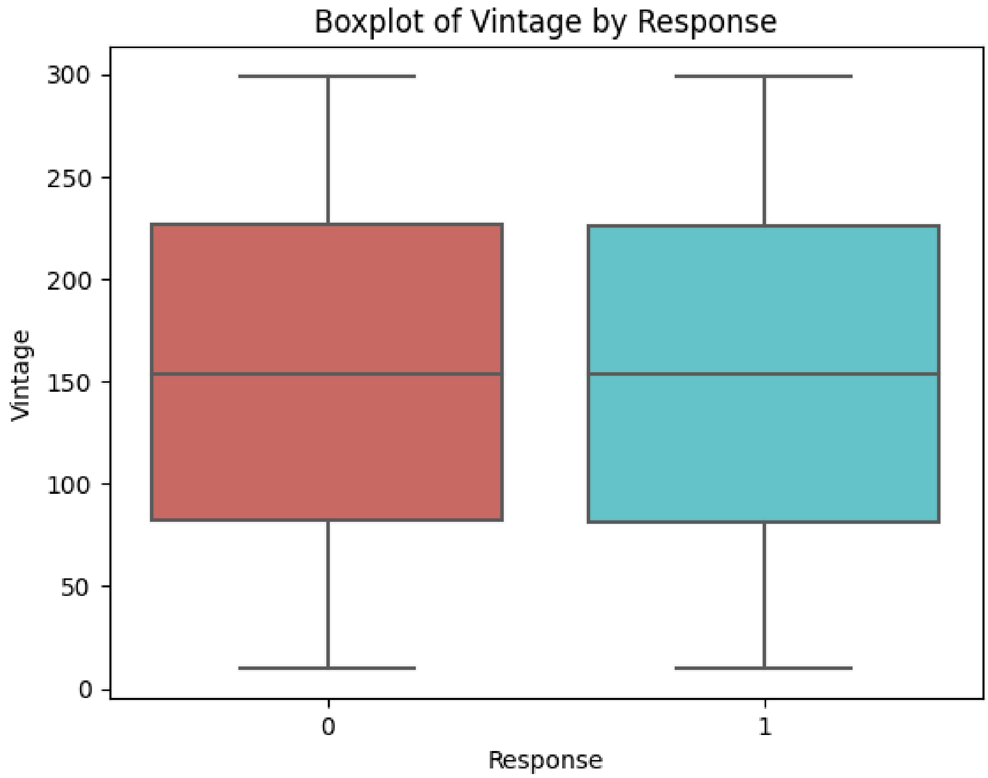
- Younger age groups seem to prefer higher Policy Sales Channe code, while older age groups seem to prefer Lower Policy Channel code.

Vintage distribution

In [45]:
```
sns.kdeplot(train, x = 'Vintage', hue = 'Response', multiple='stack', palette = 'hls')
plt.title('Kernel Density Plot of Vintage')
plt.show()
```



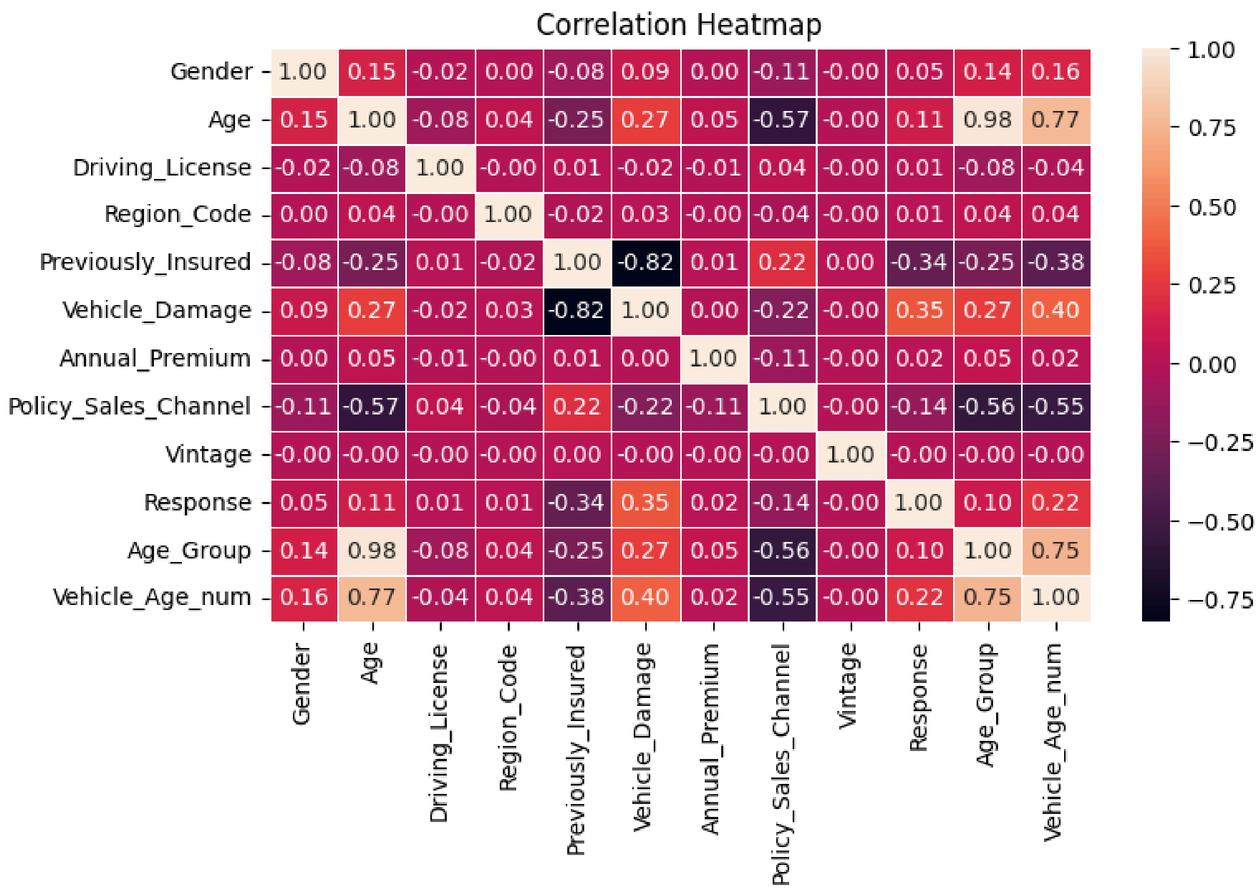
In [46]:
```
sns.boxplot(train, x = 'Response', y = 'Vintage', palette = 'hls')
plt.title('Boxplot of Vintage by Response')
plt.show()
```



- Vintage seem to be evenly distributed.
- There seems to be no difference in the average number of days customers have been associated with the company between those who are interested in Vehicle insurance and those who are not.

Correlation Analysis

In [47]:
```
plt.figure(figsize=(8, 4.5))
sns.heatmap(train_df.corr(), annot=True, fmt='.2f', linewidths=.5)
plt.title('Correlation Heatmap')
plt.show()
```



- There is a moderate negative correlation(-0.57) between Age and Policy Sales Channel. Older age group prefers to be outreached by lower Policy Sales Channel code.
- There is a fair positive correlation (0.75) between Vehicle Age and Age. Older age group has older vehicles.

6 Feature Selection

Data Split

In [48]:
```
data_all
```

Out[48]:
```
['Gender',
 'Driving_License',
 'Region_Code',
 'Previously_Insured',
 'Vehicle_Age',
 'Vehicle_Damage',
 'Policy_Sales_Channel',
 'Age_Group',
 'Age',
 'Annual_Premium',
 'Vintage']
```

In [49]:
```
test_df = test_df[data_all_new]
x = train_df[data_all_new]
y = train_df['Response']

# Perform 80/20 data split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.33, random_state = 1)
```

Standardization

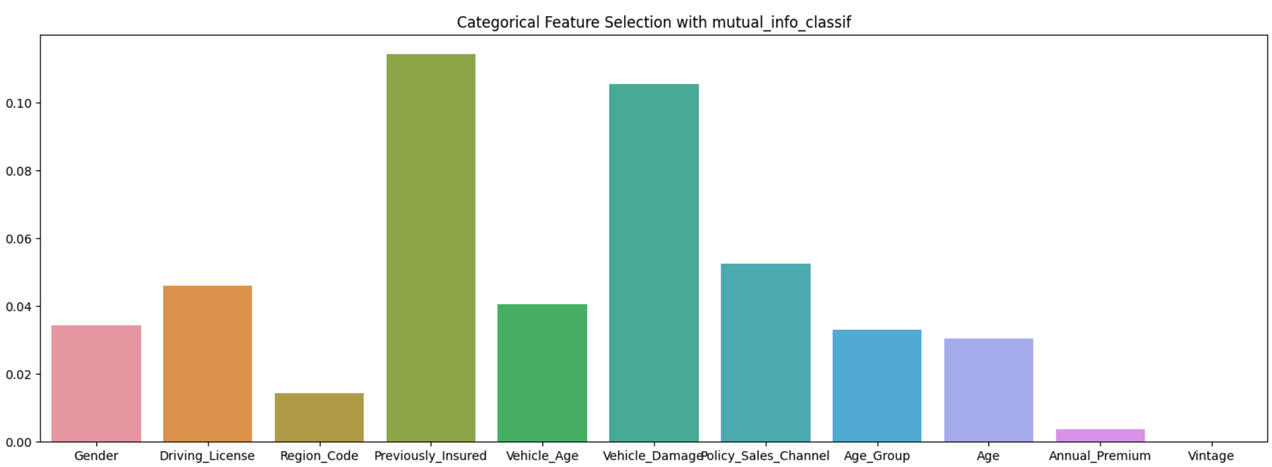
In [50]:
```
scaler = preprocessing.StandardScaler()
scaler.fit(x_train)
x_train_scaled = scaler.transform(x_train)
x_test_scaled = scaler.transform(x_test)
test_df_scaled = scaler.transform(test_df)
```

In [51]:
```
# mutual_info_classif for mixed variables
selector = SelectKBest(score_func = mutual_info_classif, k = 'all')
# fit and transform train set
selector.fit_transform(x_train, y_train)
# transform test set
selector.transform(x_test)

for i in range(len(selector.scores_)):
    print('%s: %f' % (data_all[i], selector.scores_[i]))
```

```
Gender: 0.034370
Driving_License: 0.045960
Region_Code: 0.014318
Previously_Insured: 0.114240
Vehicle_Age: 0.040561
Vehicle_Damage: 0.105543
Policy_Sales_Channel: 0.052468
Age_Group: 0.032928
Age: 0.030290
Annual_Premium: 0.003606
Vintage: 0.000000
```

Categorical Feature Selection with mutual_info_classif

In [52]:
```
plt.figure(figsize=(18,6))
sns.barplot(x = data_all, y = selector.scores_, orient='v')
plt.title('Categorical Feature Selection with mutual_info_classif')
plt.show()
```



Depending on the k-scores, we can drop some non useful features from dataset.

- Here we see adding age groups as new features brings small improvement. Age Group have a slightly higher feature importance than Age, so I will drop Age.
- Vintage has the lowest k-score, I will drop it as well.

Drop Vintage and Age

In [53]:
```
# drop Vintage and Age Group
x_train.drop(columns = ['Vintage'], inplace = True)
x_test.drop(columns = ['Vintage'], inplace = True)
test_df.drop(columns = ['Vintage'], inplace = True)
x_train.drop(columns = ['Age'], inplace = True)
x_test.drop(columns = ['Age'], inplace = True)
test_df.drop(columns = ['Age'], inplace = True)
```

Final dataset

In [54]:
```
# first five rows of final datset
x_train.head()
```

Out[54]:

	Gender	Driving_License	Region_Code	Previously_Insured	Vehicle_Age_num	Vehicle_Damage	Policy_Sales_Chan
83968	1.0	1.0	8.0	0.0	0.0	1.0	2
216550	1.0	1.0	5.0	1.0	0.0	0.0	14
112985	1.0	1.0	33.0	1.0	0.0	0.0	14
154137	0.0	1.0	8.0	0.0	1.0	1.0	
325949	0.0	1.0	46.0	1.0	1.0	0.0	11

- Features we are going to use are Gender, Driving License, Region Code, Previously Insured, Vehicle Age, Vehicle Damage, Policy Sales Channel, Age Group and Annual Premium.

7. Model Building

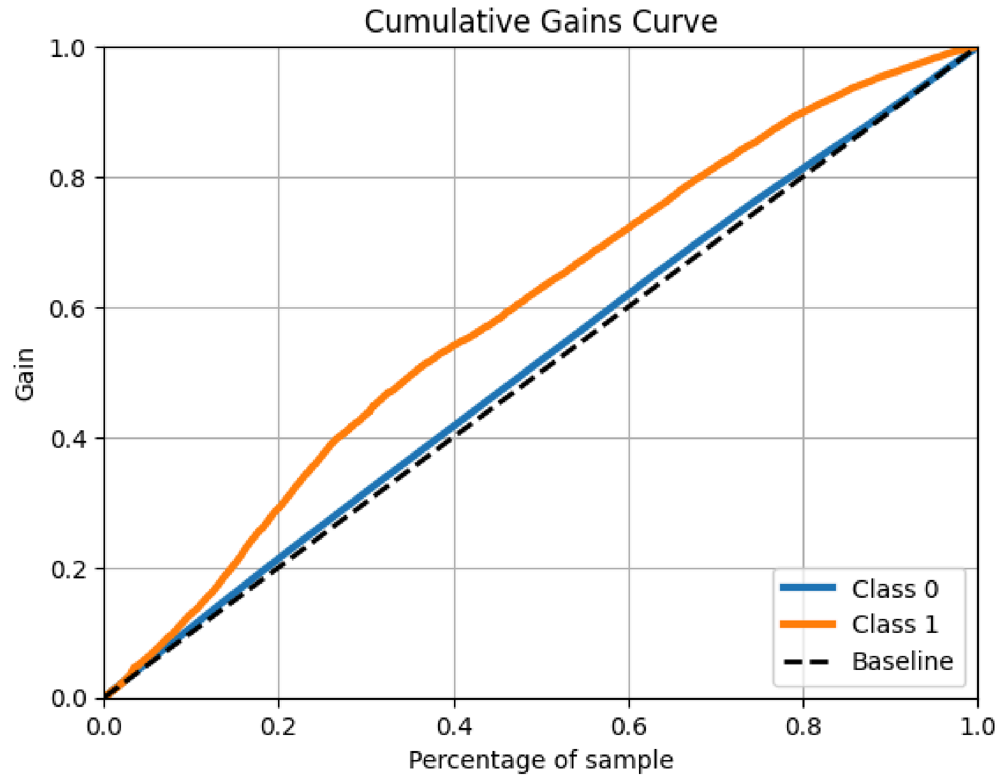
Model 1: Logistic Regression Modelling

In [55]:
```
# model definition
lg = LogisticRegression(random_state = 42)

# model fit
lg.fit(x_train, y_train)

# model prediction
lg_pred = lg.predict(x_test)
lg_proba = lg.predict_proba(x_test)

# model accuracy
print(f'Model Accuracy: {accuracy_score(y_test, lg_pred)}')

# Roc Auc score
print(f'ROC AUC Score: {roc_auc_score(y_test, lg_proba[:, 1]):.4f}')
```

```
Model Accuracy: 0.8787685618783763
ROC AUC Score: 0.6054
```

Cumulative Gains Curve Chart for Logistic Regression Model

In [56]:
```
# accumulative gain
plot_cumulative_gain(y_test, lg_proba)
plt.show()
```



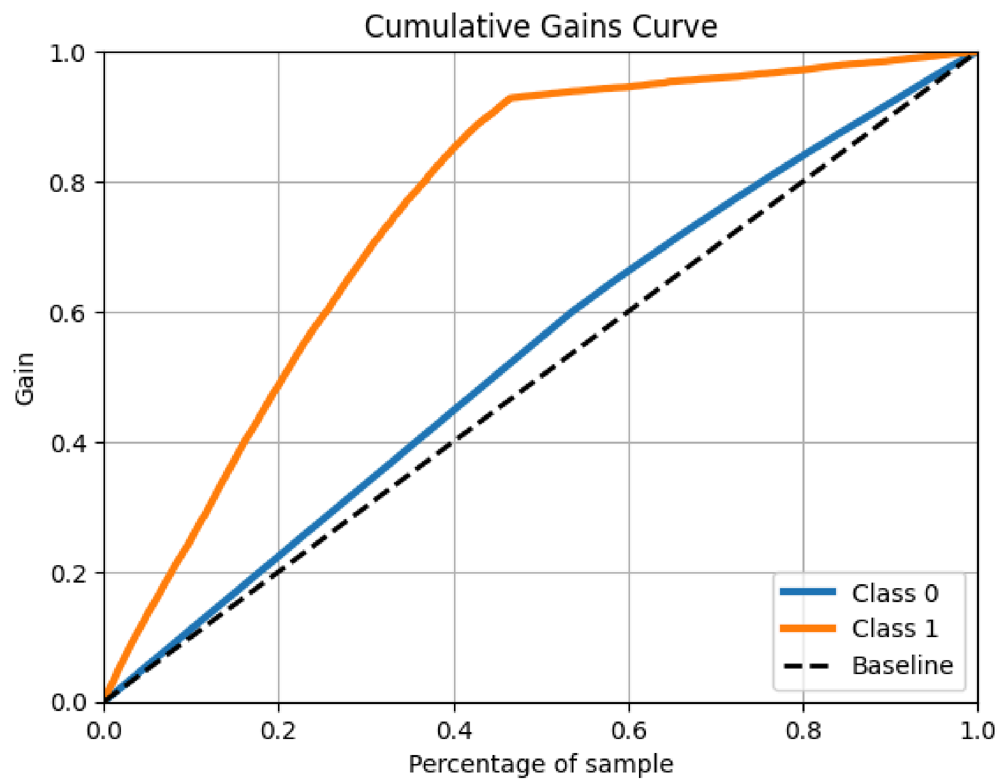
Model: Random Forest Classifier

In [57]:
```
# model definition
rf = RandomForestClassifier(n_estimators = 100, random_state = 42, n_jobs = -1)

# model fit
rf.fit(x_train, y_train)

# model prediction
rf_pred = rf.predict(x_test)
rf_proba = rf.predict_proba(x_test)

# model accuracy
print(f'Model Accuracy: {accuracy_score(y_test, rf_pred)}')

# Roc Auc score
print(f'ROC AUC Score: {roc_auc_score(y_test, rf_proba[:, 1]):.4f}')
```

```
Model Accuracy: 0.8437737514404099
ROC AUC Score: 0.7964
```

Cumulative Gains Curve Chart for Random Forest Model

In [58]:
```
# accumulative gain
plot_cumulative_gain(y_test, rf_proba)
plt.show()
```



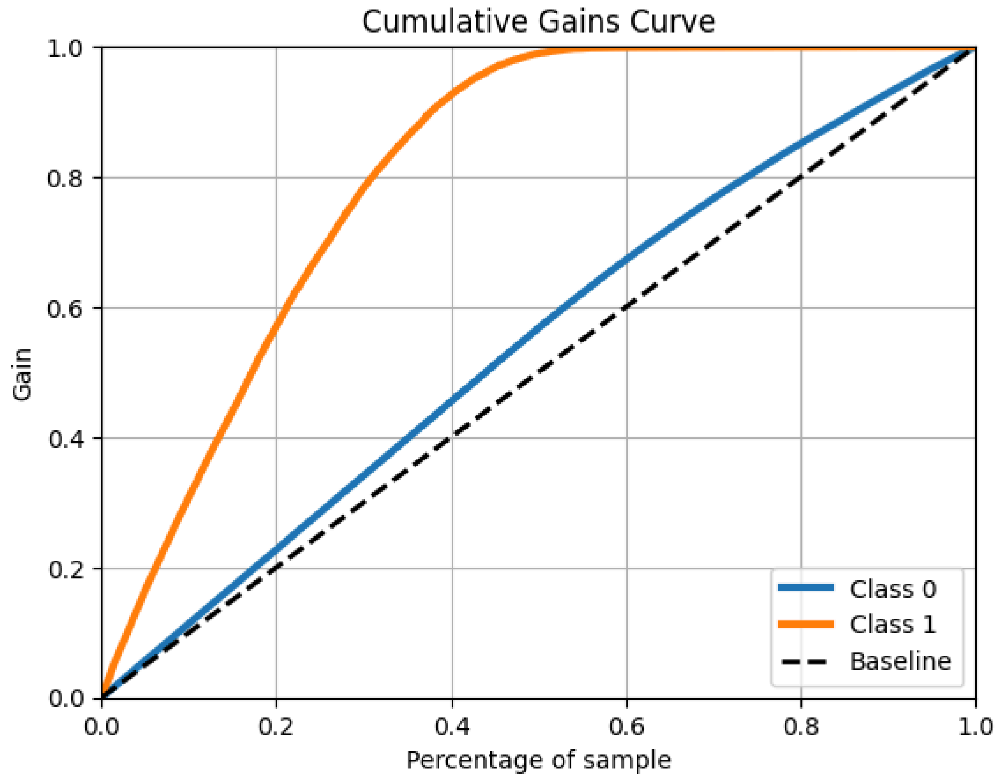
Model 3: XGBoost Classifier

In [59]:
```
# model definition
xgb = XGBClassifier(n_estimators = 200, random_state = 42, n_jobs = -1)

# model fit
xgb.fit(x_train, y_train)

# model prediction
xgb_pred = xgb.predict(x_test)
xgb_proba = xgb.predict_proba(x_test)

# model accuracy
print(f'Model Accuracy: {accuracy_score(y_test, xgb_pred)}')

# Roc Auc score
print(f'ROC AUC Score: {roc_auc_score(y_test, xgb_proba[:, 1]):.4f}')
```

```
Model Accuracy: 0.8772566422307762
ROC AUC Score: 0.8528
```

Cumulative Gains Curve Chart for XGBoost Model

In [60]:
```
# accumulative gain
plot_cumulative_gain(y_test, xgb_proba)
plt.show()
```



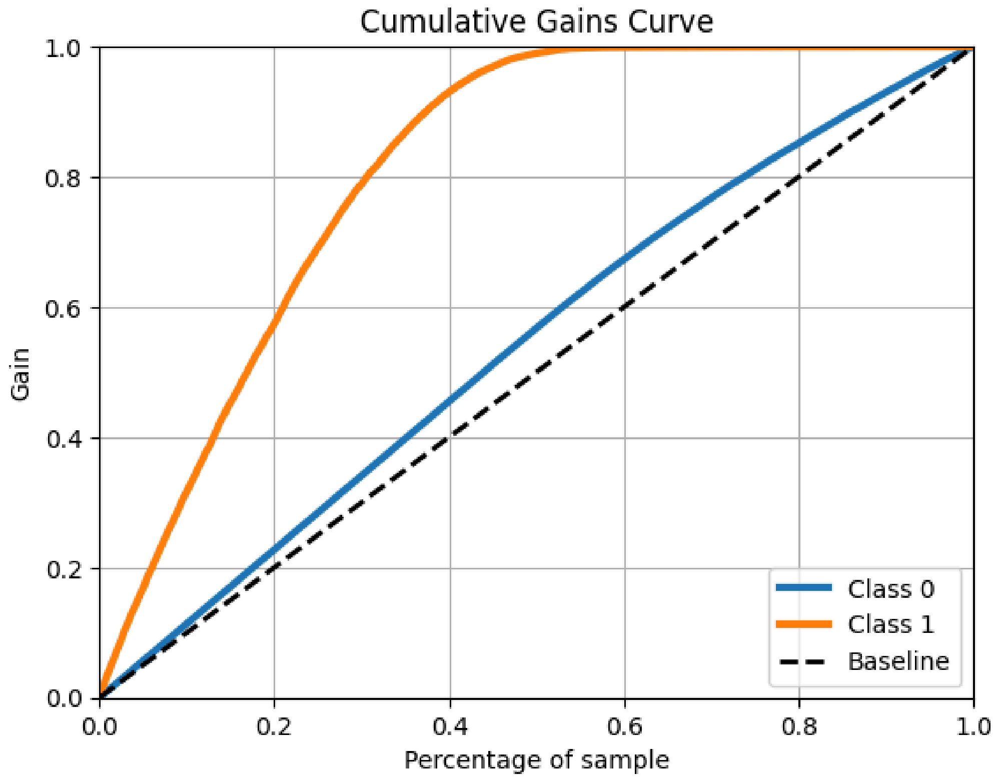
Model 4: LGBM Model

In [61]:
```
# model definition
lgbm = LGBMClassifier(n_estimators=200, random_state=42, n_jobs=-1)

# model fit
lgbm.fit(x_train, y_train)

# model prediction
lgbm_pred = lgbm.predict(x_test)
lgbm_proba = lgbm.predict_proba(x_test)

# Model Accuracy
print(f"Model Accuracy: {accuracy_score(y_test, lgbm_pred):.3f}")

# Roc Auc Score
print(f"ROC AUC Score: {roc_auc_score(y_test, lgbm_proba[:, 1]):.4f}")
```

```
[LightGBM] [Info] Number of positive: 30321, number of negative: 218107
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.003171 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 460
[LightGBM] [Info] Number of data points in the train set: 248428, number of used features: 9
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.122051 -> initscore=-1.973145
[LightGBM] [Info] Start training from score -1.973145
Model Accuracy: 0.879
ROC AUC Score: 0.8565
```

Cumulative Gains Curve Chart for LGBM Model

In [62]:
```
# Accumulative Gain
plot_cumulative_gain(y_test, lgbm_proba)
plt.show()
```



8. Model Evaluation

Model Performance

In [63]:

```
def precision_at_k(data, k=2000):
    # reset index
    data = data.reset_index(drop=True)

    # create ranking order
    data['ranking'] = data.index + 1

    data['precision_at_k'] = data['response'].cumsum() / data['ranking']

    return data.loc[k, 'precision_at_k']

def recall_at_k(data, k=2000):
    # reset index
    data = data.reset_index(drop=True)

    # create ranking order
    data['ranking'] = data.index + 1

    data['recall_at_k'] = data['response'].cumsum() / data['response'].sum()

    return data.loc[k, 'recall_at_k']
```

In [64]:

```
def cross_validation(model,x_train,y_train,k, verbose=True):
    kfold = StratifiedKFold(n_splits=k,shuffle=True,random_state=42)

    accuracy_balanced_list = []
    precision_k_list = []
    recall_k_list = []
    auc_roc_list = []
    top_k_list = []
    i = 1
```

```python
    for train_cv, val_cv in kfold.split(x_train,y_train):
        if verbose == True:
            print(f'Fold Number {i}/{k}')
        else:
            pass

        x_train_fold = x_train.iloc[train_cv]
        y_train_fold = y_train.iloc[train_cv]

        x_val_fold = x_train.iloc[val_cv]
        y_val_fold = y_train.iloc[val_cv]

        model.fit(x_train_fold,y_train_fold)

        yhat_model = model.predict(x_val_fold)
        yhat_proba = model.predict_proba(x_val_fold)

        # Create data to make the precision and recall k
        data = pd.DataFrame()

        data = x_val_fold.copy()
        data['response'] = y_val_fold.copy()
        data['score'] = yhat_proba[:,1].tolist()
        data = data.sort_values('score',ascending=False)

        knum = y_val_fold.value_counts().count()-1

        # ROC AUC SCORE
        auc_roc = roc_auc_score(y_val_fold, yhat_proba[:, 1])
        auc_roc_list.append(auc_roc)

        # TOP K SCORE
        top_k = top_k_accuracy_score(y_val_fold,yhat_model,k=knum)
        top_k_list.append(top_k)

        # Balanced Accuracy
        accuracy_balanced = balanced_accuracy_score(y_val_fold,yhat_model)
        accuracy_balanced_list.append(accuracy_balanced)

        # Precision at K
        precision_k = precision_at_k(data,20000)
        precision_k_list.append(precision_k)

        # Recall at K
        recall_k = recall_at_k(data,20000)
        recall_k_list.append(recall_k)
        i = i + 1

    df = pd.DataFrame({'Model Name': type(model).__name__,
                       'Accuracy Balanced': np.mean(accuracy_balanced_list),
                       'Precision @K Mean': np.mean(precision_k_list),
                       'Recall @K Mean': np.mean(recall_k_list),
                       'ROC AUC Score': np.mean(auc_roc_list),
                       'Top K Score': np.mean(top_k_list) },index = [0])
    return df
```

In [67]:

```python
lr_cv = cross_validation(lg, x_train, y_train, 5, verbose=False)
rf_cv = cross_validation(rf, x_train, y_train, 5, verbose=False)
xgb_cv = cross_validation(xgb, x_train, y_train, 5, verbose=False)
lgbm_cv = cross_validation(lgbm, x_train, y_train, 5, verbose=False)
```

```
[LightGBM] [Info] Number of positive: 24256, number of negative: 174486
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.004238 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 457
[LightGBM] [Info] Number of data points in the train set: 198742, number of used features: 9
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.122048 -> initscore=-1.973180
[LightGBM] [Info] Start training from score -1.973180
[LightGBM] [Info] Number of positive: 24257, number of negative: 174485
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.004294 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 459
[LightGBM] [Info] Number of data points in the train set: 198742, number of used features: 9
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.122053 -> initscore=-1.973134
[LightGBM] [Info] Start training from score -1.973134
[LightGBM] [Info] Number of positive: 24257, number of negative: 174485
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.003885 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 456
[LightGBM] [Info] Number of data points in the train set: 198742, number of used features: 9
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.122053 -> initscore=-1.973134
[LightGBM] [Info] Start training from score -1.973134
[LightGBM] [Info] Number of positive: 24257, number of negative: 174486
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.003503 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 459
[LightGBM] [Info] Number of data points in the train set: 198743, number of used features: 9
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.122052 -> initscore=-1.973139
[LightGBM] [Info] Start training from score -1.973139
[LightGBM] [Info] Number of positive: 24257, number of negative: 174486
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.002760 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 458
[LightGBM] [Info] Number of data points in the train set: 198743, number of used features: 9
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.122052 -> initscore=-1.973139
[LightGBM] [Info] Start training from score -1.973139
```

In [68]:

```python
model_performance_cv = pd.concat([lr_cv, rf_cv, xgb_cv, lgbm_cv])
model_performance_cv.sort_values('ROC AUC Score', ascending=False)
```

Out[68]:

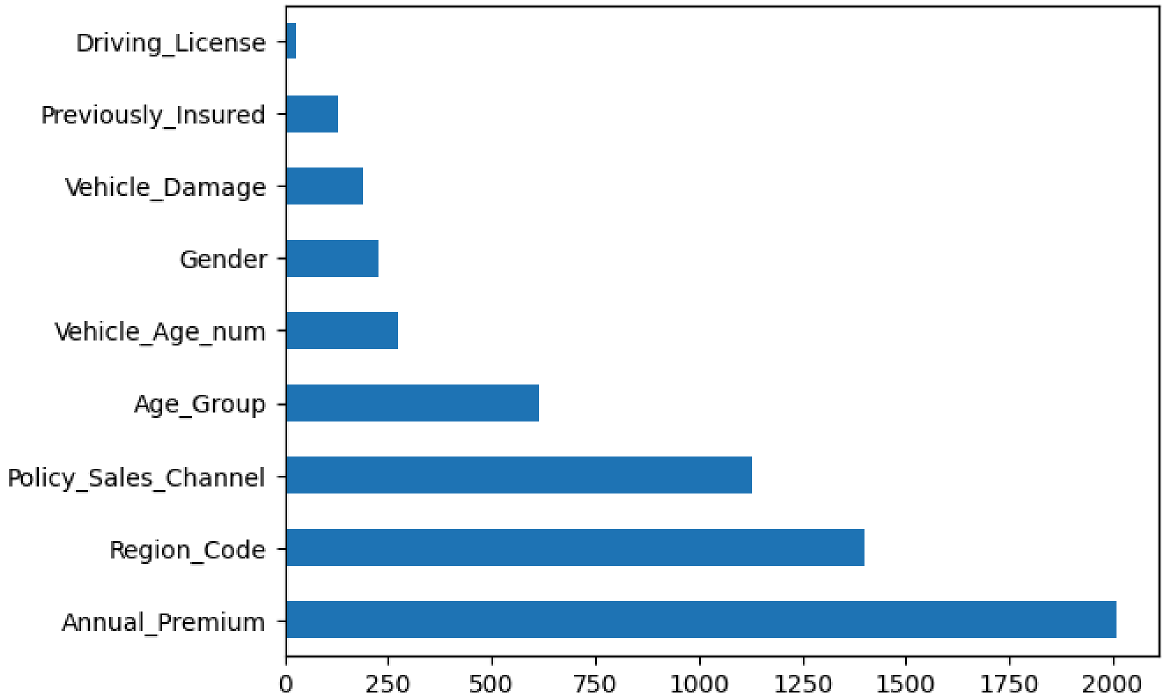
	Model Name	Accuracy Balanced	Precision @K Mean	Recall @K Mean	ROC AUC Score	Top K Score
0	LGBMClassifier	0.504510	0.280886	0.926421	0.855200	0.877840
0	XGBClassifier	0.517045	0.279206	0.920880	0.850569	0.875968
0	RandomForestClassifier	0.582536	0.259607	0.856238	0.800011	0.844800
0	LogisticRegression	0.515601	0.240328	0.792660	0.771975	0.872559

- I will choose the model with the best cost-benefit ratio (higher score, lower size, higher speed). Our final model is a Light Gradient Boosting Model with AUC score of 86%.

Feature Importance

In [70]:

```python
feat_importances = pd.Series(lgbm.feature_importances_, index = test_df.columns)
feat_importances.nlargest(20).plot(kind='barh')
plt.show()
```



- Annual Premium is the most important feature in predicting whether a customer is interested in Vehicle insurance.
- Driving License is the least important feature.

9. Summary

Key Findings

Our cross-sell analysis and predictive modeling project provide valuable insights into the dynamics of customer behavior and preferences within the context of health insurance and vehicle insurance cross-selling. Here's the summary of our analysis.

- Our analysis underscores the significance of annual premium as the most influential determinant in predicting customer interest in additional insurance products. This insight suggests the importance of tailored pricing strategies and personalized offerings to effectively target and engage potential customers.

- Our findings highlight notable demographic trends, such as the higher interest among male customers compared to females and the age distribution of interested customers, particularly the significant proportion within the 40-49 age group. Understanding these demographic nuances is essential for refining marketing strategies and optimizing outreach efforts.

- The oberved negative correlation between age and policy sales channel preference offers valuable guidance for optimizing sales channel allocation and customer outreach strategies. By aligning outreach channels with customer preferences, insurers can enhance engagement and conversion rates.

- The utilization of a Light Gradient Boosting Model has significantly enhanced our predictive accuracy, with an impressive AUC score of 86%, indicating its robust performance in identifying potential customers interested in vehicle insurance.

Limitations

Our analysis also reveals a weakness in the form of data imbalance, where only 12% of customers are interested in vehicle insurance. Addressing this imbalance through oversampling techniques may resolve this issue and potentially improve the overall model performance by providing more balanced representation of both interested and non-interested customers.

9. Conclusion

In conclusion, our comprehensive analysis not only provides actionable insights for optimizing cross-selling strategies but also demonstrates the efficacy of advanced modeling techniques in extracting meaningful patterns from complex datasets. These insights can empower insurers to tailor their marketing approaches, deepen customer relationships, and drive business growth in an increasingly competitive marketplace.