lightgbm

March 6, 2021

0.1 Problem Statement

0.1.1 Topic: Health Insurance Lead Prediction

Your Client FinMan is a financial services company that provides various financial services like loan, investment funds, insurance etc. to its customers. FinMan wishes to cross-sell health insurance to the existing customers who may or may not hold insurance policies with the company. The company recommend health insurance to it's customers based on their profile once these customers land on the website. Customers might browse the recommended health insurance policy and consequently fill up a form to apply. **When these customers fill-up the form, their Response towards the policy is considered positive and they are classified as a lead.**

Once these leads are acquired, the sales advisors approach them to convert and thus the company can sell proposed health insurance to these leads in a more efficient manner. Now the company needs your help in building a model to predict whether the person will be interested in their proposed Health plan/policy given the information about:

- Demographics (city, age, region etc.)
- Information regarding holding policies of the customer
- Recommended Policy Information

[1]:
```
#loading packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

[2]:
```
#Reading data
train = pd.read_csv(r'C:\Users\Ranjeet shrivastav\Videos\ML_algorithms\Health␣
↪Insurance Lead Prediction\train.csv')
test = pd.read_csv(r'C:\Users\Ranjeet shrivastav\Videos\ML_algorithms\Health␣
↪Insurance Lead Prediction\test.csv')
```

[3]:
```
train.shape, test.shape
```

[3]:
```
((50882, 14), (21805, 13))
```

[4]:
```
train.head(2)
```

[4]:
```
   ID City_Code  Region_Code Accomodation_Type Reco_Insurance_Type  Upper_Age  \
0   1        C3         3213            Rented          Individual         36
1   2        C5         1117             Owned               Joint         75

   Lower_Age Is_Spouse Health Indicator Holding_Policy_Duration  \
0         36        No               X1                     14+
1         22        No               X2                     NaN

   Holding_Policy_Type  Reco_Policy_Cat  Reco_Policy_Premium  Response
0                  3.0               22              11628.0         0
1                  NaN               22              30510.0         0
```

Its generally a good idea to combine both train and test data sets into one, perform feature engineering and then divide them later again. This saves the trouble of performing the same steps twice on test and train. Lets combine them into a dataframe 'data' with a 'source' column specifying where each observation belongs.

[5]:
```
train['source'] = 'train'
test['source'] = 'test'
data = pd.concat([train,test],ignore_index = True)
```

[6]:
```
data.head()
```

[6]:
```
  Accomodation_Type City_Code Health Indicator Holding_Policy_Duration  \
0            Rented        C3               X1                     14+
1             Owned        C5               X2                     NaN
2             Owned        C5              NaN                     1.0
3             Owned       C24               X1                     14+
4            Rented        C8               X2                     3.0

   Holding_Policy_Type  ID Is_Spouse  Lower_Age Reco_Insurance_Type  \
0                  3.0   1        No         36          Individual
1                  NaN   2        No         22               Joint
2                  1.0   3        No         32          Individual
3                  3.0   4        No         48               Joint
4                  1.0   5        No         44          Individual

   Reco_Policy_Cat  Reco_Policy_Premium  Region_Code  Response  Upper_Age  \
0               22              11628.0         3213       0.0         36
1               22              30510.0         1117       0.0         75
2               19               7450.0         3732       1.0         32
3               19              17780.0         4378       0.0         52
4               16              10404.0         2190       0.0         44

  source
0  train
```

```
1   train
2   train
3   train
4   train
```

[7]:
```
data.shape
```

[7]:
```
(72687, 15)
```

[8]:
```
data.dtypes
```

[8]:
```
Accomodation_Type           object
City_Code                   object
Health Indicator            object
Holding_Policy_Duration     object
Holding_Policy_Type        float64
ID                           int64
Is_Spouse                   object
Lower_Age                    int64
Reco_Insurance_Type         object
Reco_Policy_Cat              int64
Reco_Policy_Premium        float64
Region_Code                  int64
Response                   float64
Upper_Age                    int64
source                      object
dtype: object
```

[9]:
```
data.isnull().sum()
```

[9]:
```
Accomodation_Type              0
City_Code                      0
Health Indicator           16718
Holding_Policy_Duration    28854
Holding_Policy_Type        28854
ID                             0
Is_Spouse                      0
Lower_Age                      0
Reco_Insurance_Type            0
Reco_Policy_Cat                0
Reco_Policy_Premium            0
Region_Code                    0
Response                   21805
Upper_Age                      0
source                         0
dtype: int64
```

Note that the ‘Response’ is the target variable and missing values are ones in the test set. So we need not worry about it. But we'll impute the missing values in 'Health Indicator', 'Holding_Policy_Duration' and 'Holding_Policy_Type' in the data cleaning section.

[10]:
```
data.nunique()
```

[10]:
```
Accomodation_Type              2
City_Code                     36
Health Indicator               9
Holding_Policy_Duration       15
Holding_Policy_Type            4
ID                         72687
Is_Spouse                      2
Lower_Age                     60
Reco_Insurance_Type            2
Reco_Policy_Cat               22
Reco_Policy_Premium         7685
Region_Code                 5538
Response                       2
Upper_Age                     58
source                         2
dtype: int64
```

[11]:
```
data['Health Indicator'].value_counts()
```

[11]:
```
X1    18624
X2    14848
X3     9608
X4     8185
X5     2408
X6     1794
X7      292
X8      119
X9       91
Name: Health Indicator, dtype: int64
```

[12]:
```
data['Health Indicator'].replace(to_replace='X1', value='0', regex=True,␣
 ↪inplace=True)
data['Health Indicator'].replace(to_replace='X2', value='1', regex=True,␣
 ↪inplace=True)
data['Health Indicator'].replace(to_replace='X3', value='2', regex=True,␣
 ↪inplace=True)
data['Health Indicator'].replace(to_replace='X4', value='3', regex=True,␣
 ↪inplace=True)
data['Health Indicator'].replace(to_replace='X5', value='4', regex=True,␣
 ↪inplace=True)
data['Health Indicator'].replace(to_replace='X6', value='5', regex=True,␣
 ↪inplace=True)
```

```
data['Health Indicator'].replace(to_replace='X7', value='6', regex=True,␣
↪inplace=True)
data['Health Indicator'].replace(to_replace='X8', value='7', regex=True,␣
↪inplace=True)
data['Health Indicator'].replace(to_replace='X9', value='8', regex=True,␣
↪inplace=True)
```

[13]:
```
data['Holding_Policy_Duration'].value_counts()
```

[13]:
```
1.0     6390
14+     6227
2.0     6032
3.0     5192
4.0     3976
5.0     3354
6.0     2797
7.0     2309
8.0     1885
9.0     1607
10.0    1146
11.0     800
13.0     732
12.0     709
14.0     677
Name: Holding_Policy_Duration, dtype: int64
```

[14]:
```
data['Holding_Policy_Duration'] = data['Holding_Policy_Duration'].
↪replace('14+','14.0')
```

[15]:
```
data['Is_Spouse'].value_counts()
```

[15]:
```
No     60687
Yes    12000
Name: Is_Spouse, dtype: int64
```

[16]:
```
data['Is_Spouse'] = data['Is_Spouse'].replace('Yes',1)
data['Is_Spouse'] = data['Is_Spouse'].replace('No',0)
```

[17]:
```
data.head()
```

[17]:
```
  Accomodation_Type City_Code Health Indicator Holding_Policy_Duration  \
0            Rented        C3                0                    14.0
1             Owned        C5                1                     NaN
2             Owned        C5              NaN                     1.0
3             Owned       C24                0                    14.0
4            Rented        C8                1                     3.0
```

```
   Holding_Policy_Type  ID  Is_Spouse  Lower_Age Reco_Insurance_Type  \
0                  3.0   1          0         36          Individual   
1                  NaN   2          0         22               Joint   
2                  1.0   3          0         32          Individual   
3                  3.0   4          0         48               Joint   
4                  1.0   5          0         44          Individual   

   Reco_Policy_Cat  Reco_Policy_Premium  Region_Code  Response  Upper_Age  \
0               22              11628.0         3213       0.0         36   
1               22              30510.0         1117       0.0         75   
2               19               7450.0         3732       1.0         32   
3               19              17780.0         4378       0.0         52   
4               16              10404.0         2190       0.0         44   

  source  
0  train  
1  train  
2  train  
3  train  
4  train  
```

[ ]:

0.2 data cleaning

[18]:
```
def na_randomfill(series):
    na_mask = pd.isnull(series)   # boolean mask for null values
    n_null = na_mask.sum()        # number of nulls in the Series

    if n_null == 0:
        return series             # if there are no nulls, no need to resample

    # Randomly sample the non-null values from our series
    #  only sample this Series as many times as we have nulls
    fill_values = series[~na_mask].sample(n=n_null, replace=True,␣
 ↪random_state=0)

    # This ensures our new values will replace NaNs in the correct locations
    fill_values.index = series.index[na_mask]

    return series.fillna(fill_values)
```

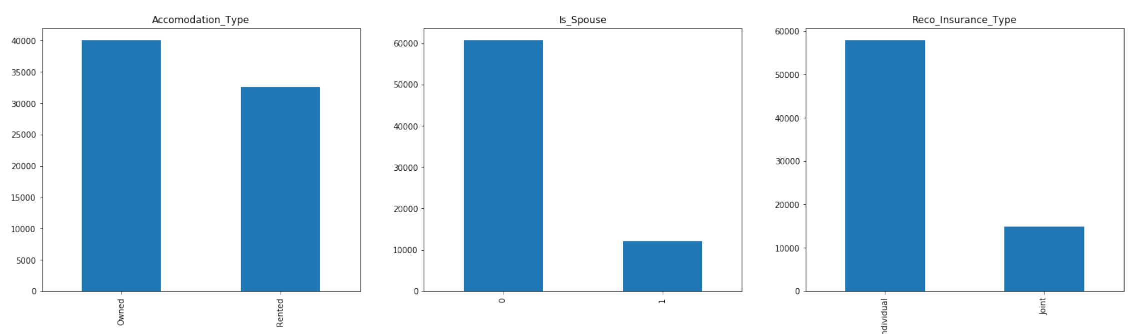
filling null values with randomly same column values

[19]:
```
data['Health Indicator'] = na_randomfill(data['Health Indicator'])
data['Holding_Policy_Duration'] = na_randomfill(data['Holding_Policy_Duration'])
data['Holding_Policy_Type'] = na_randomfill(data['Holding_Policy_Type'])
```

[20]:
```
data.isnull().sum()
```

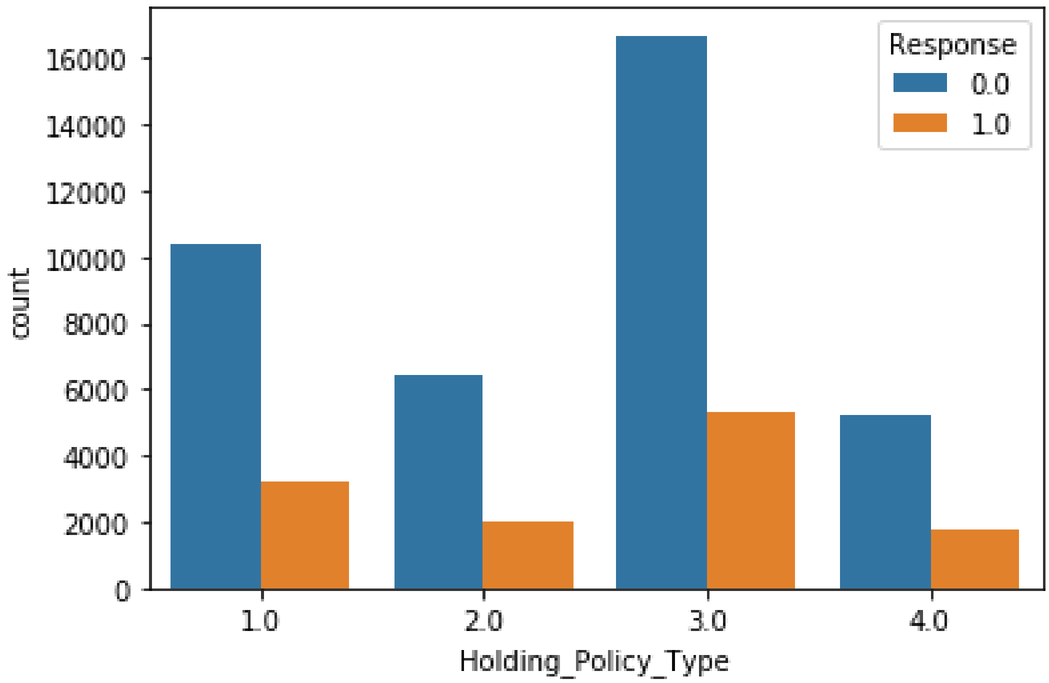
[20]:
```
Accomodation_Type              0
City_Code                      0
Health Indicator               0
Holding_Policy_Duration        0
Holding_Policy_Type            0
ID                             0
Is_Spouse                      0
Lower_Age                      0
Reco_Insurance_Type            0
Reco_Policy_Cat                0
Reco_Policy_Premium            0
Region_Code                    0
Response                   21805
Upper_Age                      0
source                         0
dtype: int64
```

[21]:
```
plt.subplot(131)
data['Accomodation_Type'].value_counts().plot.
 ↪bar(figsize=(24,6),title='Accomodation_Type')

plt.subplot(132)
data['Is_Spouse'].value_counts().plot.bar(title='Is_Spouse')

plt.subplot(133)
data['Reco_Insurance_Type'].value_counts().plot.bar(title='Reco_Insurance_Type')

plt.show()
```

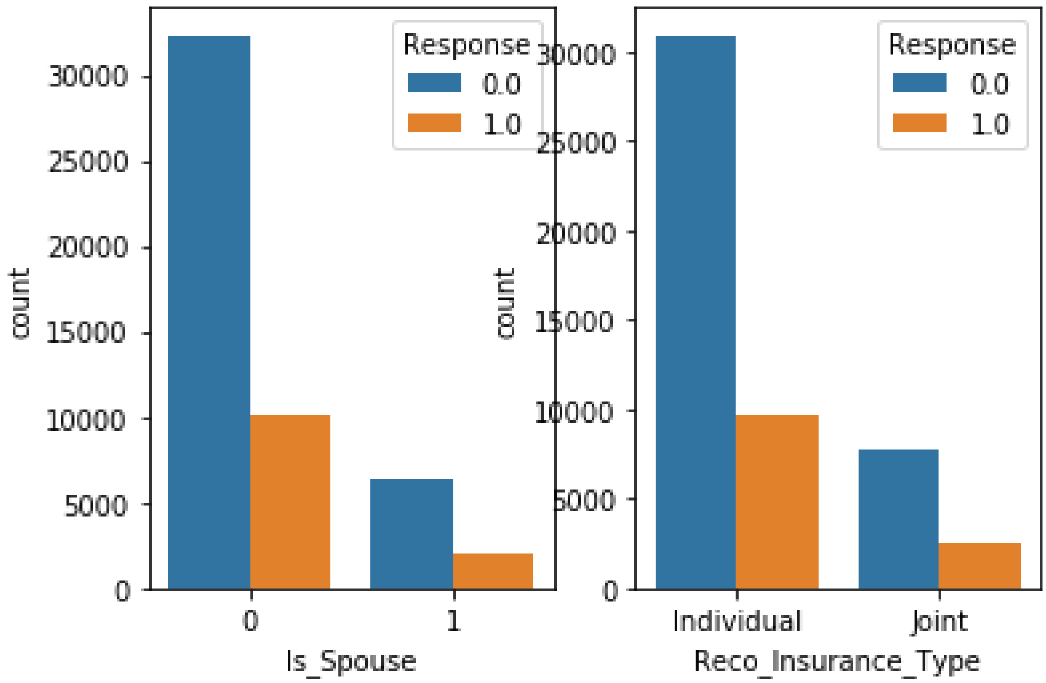


[22]:
```
sns.countplot(hue='Response',x='Holding_Policy_Type',data=data)
```

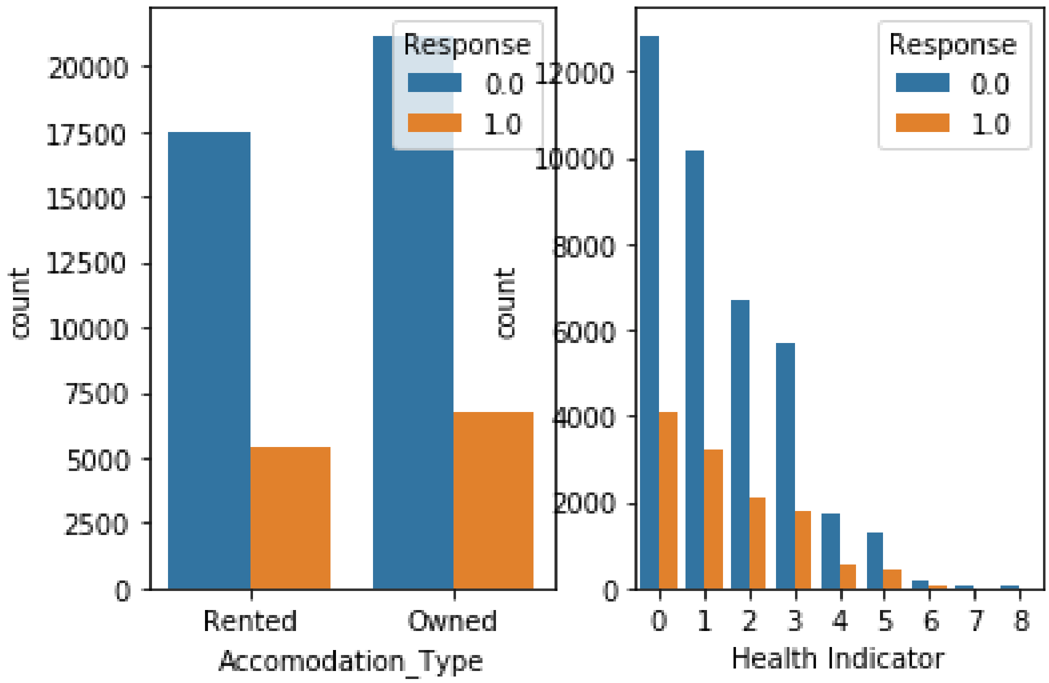
[22]: <matplotlib.axes._subplots.AxesSubplot at 0x21aa23adc48>



[23]:
```
plt.subplot(121)
sns.countplot(x='Is_Spouse',hue='Response',data=data)

plt.subplot(122)
sns.countplot(x='Reco_Insurance_Type',hue='Response',data=data)

plt.show()
```



[24]:
```
plt.subplot(121)
sns.countplot(x='Accomodation_Type',hue='Response',data=data)

plt.subplot(122)
sns.countplot(x='Health Indicator',hue='Response',data=data)

plt.show()
```

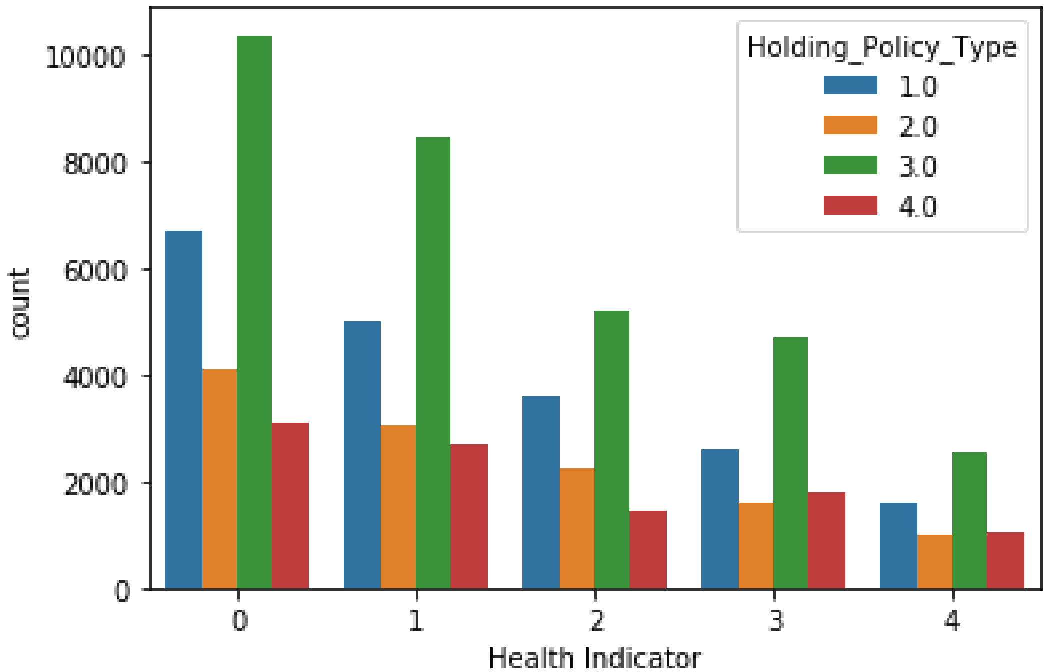


replacing values(5,6,7,8) with value(4).as you can see 5,6,7,8 didn't have much impact on response.

[25]:
```
data['Health Indicator'].replace('7','4',inplace=True)
data['Health Indicator'].replace('8','4',inplace=True)
data['Health Indicator'].replace('5','4',inplace=True)
data['Health Indicator'].replace('6','4',inplace=True)
```

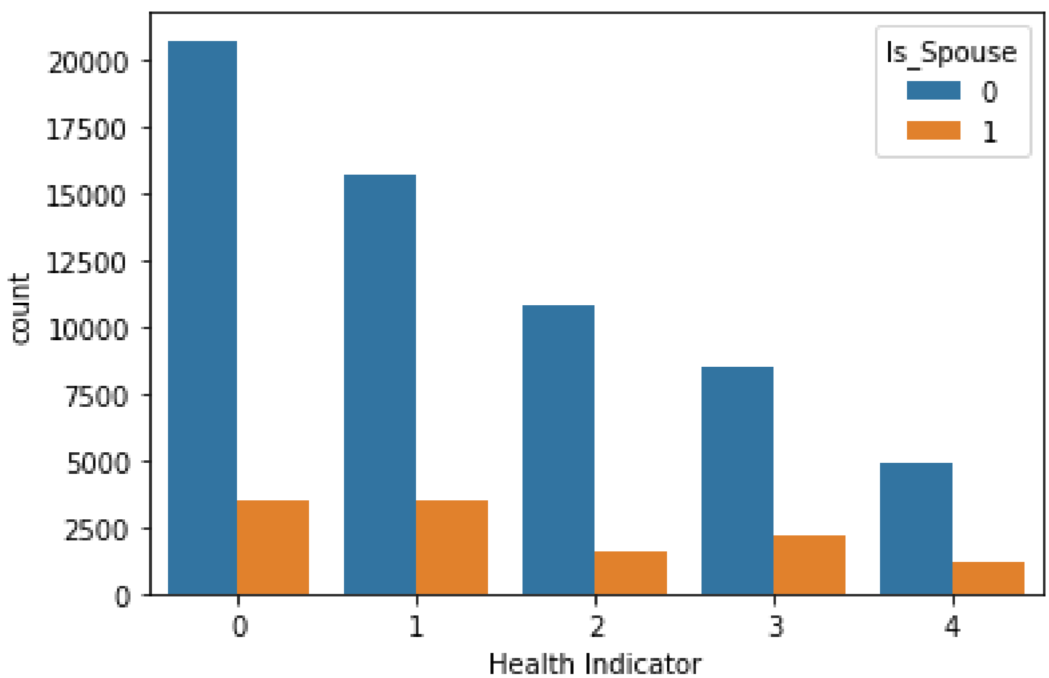
[26]:
```
sns.countplot(x='Health Indicator',hue='Holding_Policy_Type',data=data)
```

[26]: <matplotlib.axes._subplots.AxesSubplot at 0x21aa3916448>



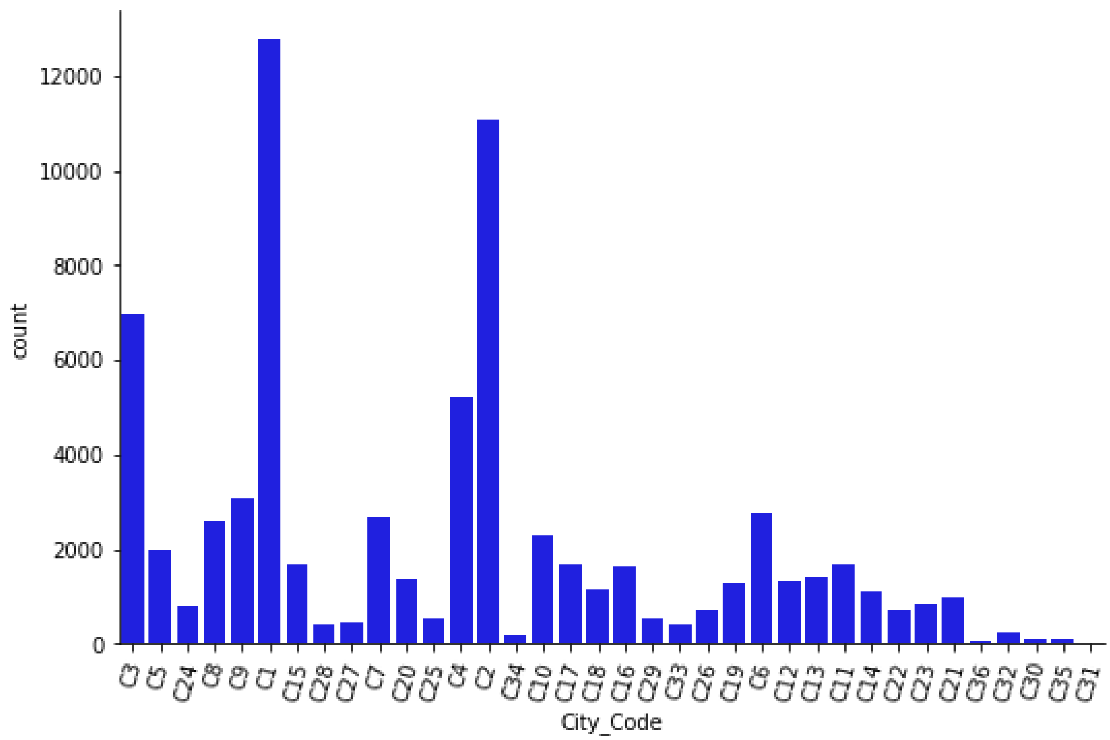
[27]:
```
sns.countplot(x='Health Indicator',hue='Is_Spouse',data=data)
```

[27]: <matplotlib.axes._subplots.AxesSubplot at 0x21aa39be0c8>



[28]:
```python
g = sns.factorplot("City_Code", data=data, aspect=1.5, kind="count", color="b")
g.set_xticklabels(rotation=75)
```

[28]:
```
<seaborn.axisgrid.FacetGrid at 0x21aa39b65c8>
```



[29]:
```python
data.corr()
```

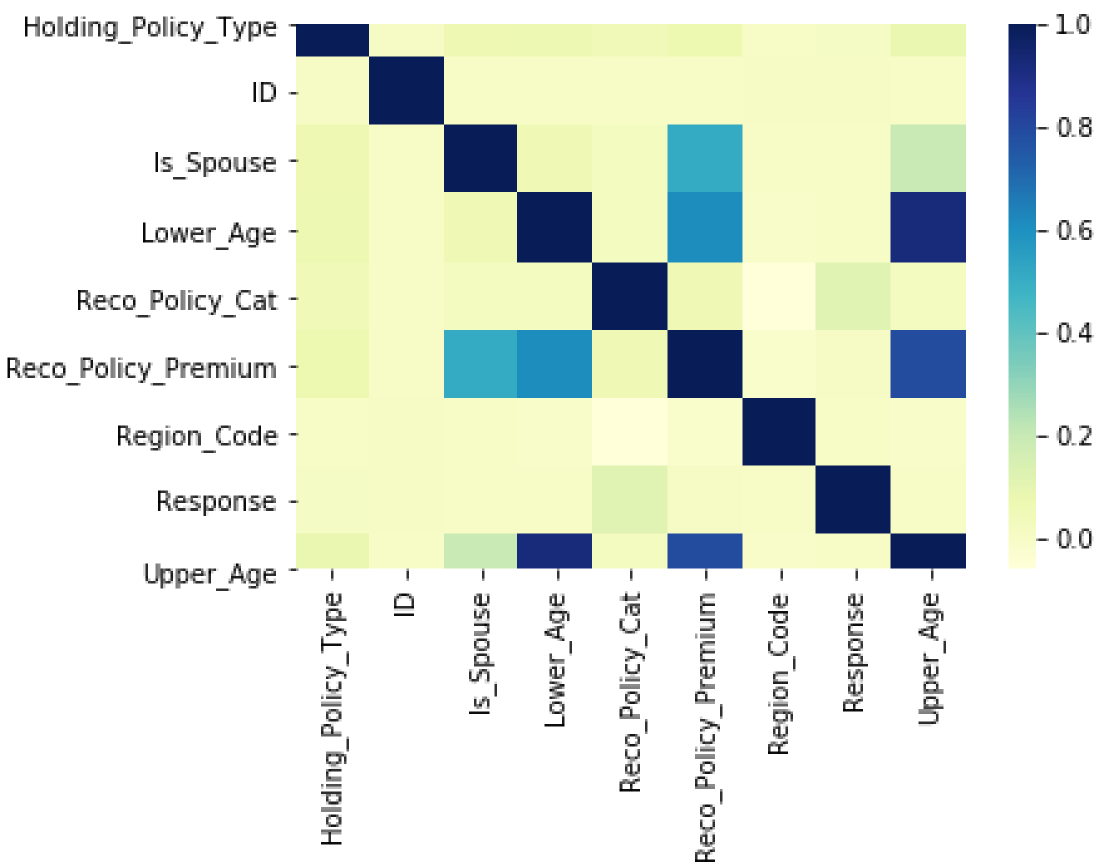
[29]:
```
                     Holding_Policy_Type        ID  Is_Spouse  Lower_Age  \
Holding_Policy_Type             1.000000  0.006011   0.063155   0.068833
ID                              0.006011  1.000000  -0.003041   0.000758
Is_Spouse                       0.063155 -0.003041   1.000000   0.058470
Lower_Age                       0.068833  0.000758   0.058470   1.000000
Reco_Policy_Cat                 0.046751  0.000315   0.021489   0.020116
Reco_Policy_Premium             0.074336  0.001245   0.510928   0.613374
Region_Code                     0.002804  0.004074  -0.002264  -0.004750
Response                        0.009312  0.005159   0.003859  -0.002099
Upper_Age                       0.079849  0.000066   0.198134   0.921175

                     Reco_Policy_Cat  Reco_Policy_Premium  Region_Code  \
Holding_Policy_Type         0.046751             0.074336     0.002804
ID                          0.000315             0.001245     0.004074
```

Is_Spouse	0.021489	0.510928	-0.002264
Lower_Age	0.020116	0.613374	-0.004750
Reco_Policy_Cat	1.000000	0.060442	-0.062533
Reco_Policy_Premium	0.060442	1.000000	-0.013772
Region_Code	-0.062533	-0.013772	1.000000
Response	0.114321	0.007943	0.001121
Upper_Age	0.024325	0.791562	-0.006170

	Response	Upper_Age
Holding_Policy_Type	0.009312	0.079849
ID	0.005159	0.000066
Is_Spouse	0.003859	0.198134
Lower_Age	-0.002099	0.921175
Reco_Policy_Cat	0.114321	0.024325
Reco_Policy_Premium	0.007943	0.791562
Region_Code	0.001121	-0.006170
Response	1.000000	0.002772
Upper_Age	0.002772	1.000000

[30]:
```
sns.heatmap(data.corr(),cmap="YlGnBu")
```

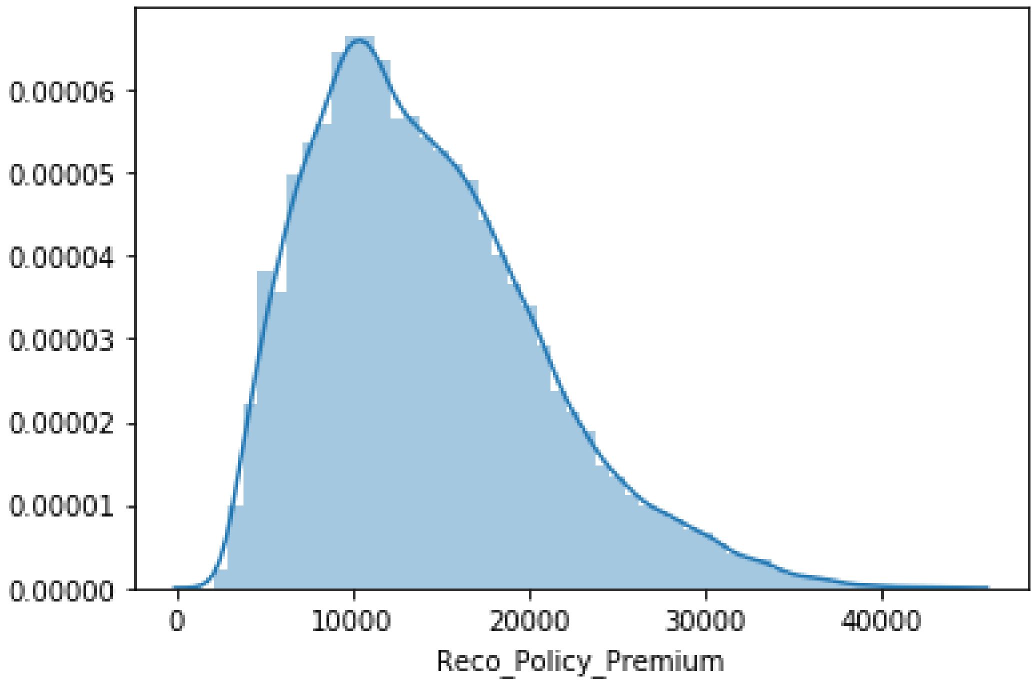
[30]: <matplotlib.axes._subplots.AxesSubplot at 0x21aa3884dc8>



Let's check the distribution of Reco_Policy_Premium

[31]:
```
sns.distplot(data['Reco_Policy_Premium'])
```

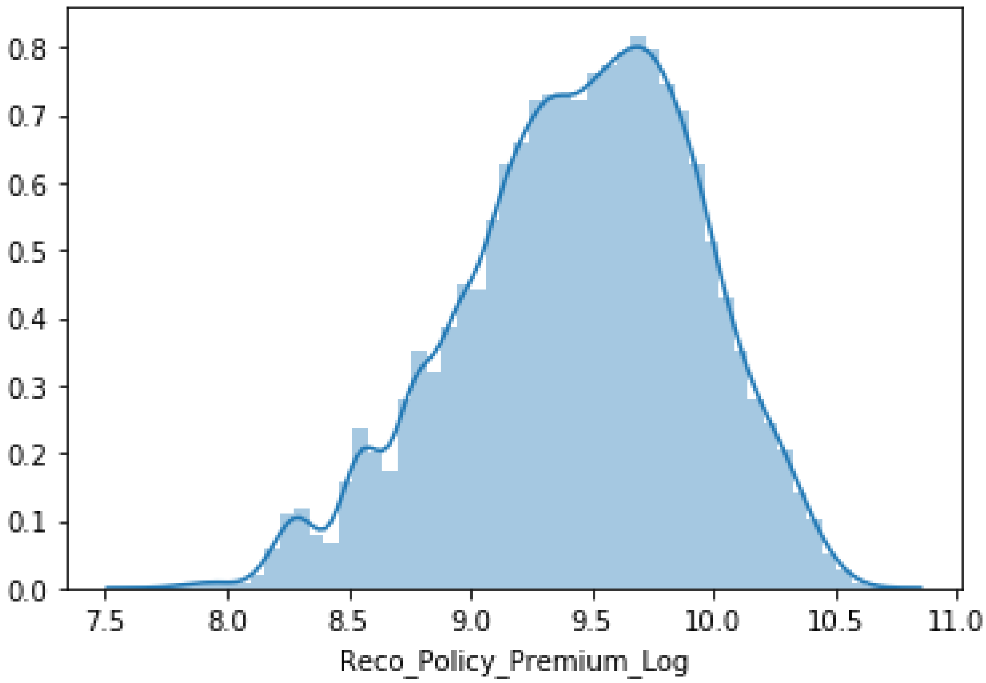
[31]: <matplotlib.axes._subplots.AxesSubplot at 0x21aa38141c8>



we can see it shifted towards left, i.e.,the distribution is right skewed. so, let's take the log transfomation to make the distribution normal.

[32]:
```
data['Reco_Policy_Premium_Log'] = np.log(data['Reco_Policy_Premium'])
sns.distplot(data['Reco_Policy_Premium_Log'])
```

[32]: <matplotlib.axes._subplots.AxesSubplot at 0x21aa24d7148>



Now the distribution looks much closer to normal and effect of extreme values has been significantly subsided.

[33]:
```
data.dtypes
```

[33]:
```
Accomodation_Type             object
City_Code                     object
Health Indicator              object
Holding_Policy_Duration       object
Holding_Policy_Type          float64
ID                             int64
Is_Spouse                      int64
Lower_Age                      int64
Reco_Insurance_Type           object
Reco_Policy_Cat                int64
Reco_Policy_Premium          float64
Region_Code                    int64
Response                     float64
Upper_Age                      int64
source                        object
Reco_Policy_Premium_Log      float64
dtype: object
```

[34]:
```
#One Hot InCoding:
```

```
data = pd.get_dummies(data, columns=['City_Code','Accomodation_Type','Health␣
↪Indicator','Holding_Policy_Type','Holding_Policy_Duration',
          'Reco_Insurance_Type'])
```

[35]:
```
data.shape
```

[35]: (72687, 73)

Let's convert data back into train and test data sets. Its generally a good idea to export both of these as modified data sets so that they can be re-used for multiple sessions. This can be achieved using following code:

[36]:
```
train = data.loc[data['source']=="train"]
test = data.loc[data['source']=="test"]

#Drop unnecessary columns:
test.drop(['Response','source'],axis=1,inplace=True)
train.drop(['source','ID'],axis=1,inplace=True)

#Export files as modified versions:
train.to_csv("train_modified.csv",index=False)
test.to_csv("test_modified.csv",index=False)
```

0.3 Model Building

I would like to define a generic function which takes the algorithm and data as input and makes the model, performs roc_auc_score and generates submission.

[37]:
```
#define target and ID column
target = 'Response'
IDcol = ['ID','Upper_Age']

from sklearn.metrics import roc_auc_score
from sklearn import metrics
def modelfit(alg, dtrain, dtest, pred, target, IDcol, filename):
    #fit the algorithm on the data
    alg.fit(dtrain[pred], dtrain[target])

    #predict training set
    dtrain_pred = alg.predict_proba(dtrain[pred])[:, 1]
    print("auc_score : %.4g" % roc_auc_score(dtrain[target].values,␣
↪dtrain_pred))
    #Predict on testing data:
    dtest[target] = alg.predict_proba(dtest[pred])[:, 1]



    #Export submission file:
```

```python
    IDcol.append(target)
    submission = pd.DataFrame({ x: dtest[x] for x in IDcol})
    del submission['Upper_Age']
    submission.to_csv(filename, index=False)
```

[41]:
```python
from lightgbm import LGBMClassifier
pred = [x for x in train.columns if x not in [target]+IDcol]
alg4 = LGBMClassifier(learning_rate = 0.01,
                      max_depth = 10,
                      num_leaves = 80,
                      n_estimators = 650)
modelfit(alg4, train, test, pred, target, IDcol, 'lgb1.csv')
```

```
auc_score : 0.7867
```

AV private Leaderboard score:0.6675

AV final rank:334

[ ]:
```python

```