Project 7: Modeling Car Insurance Claims Outcome

Lawal’s Project

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car

# 1. Project Overview

Insurance companies invest a lot of [time and money](https://www.accenture.com/_acnmedia/pdf-84/accenture-machine-leaning-insurance.pdf) into optimizing their pricing and accurately estimating the likelihood that customers will make a claim. In many countries insurance it is a legal requirement to have car insurance in order to drive a vehicle on public roads, so the market is very large!

Knowing all of this, On the Road car insurance have requested your services in building a model to predict whether a customer will make a claim on their insurance during the policy period. As they have very little expertise and infrastructure for deploying and monitoring machine learning models, they’ve asked you to identify the single feature that results in the best performing model, as measured by accuracy, so they can start with a simple model in production.

They have supplied you with their customer data as a csv file called car\_insurance.csv, along with a table detailing the column names and descriptions below.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 1: Customer data   | Column | Description | | --- | --- | | id | Unique client identifier | | age | Client’s age: | | gender | Client’s gender: | | driving\_experience | Years the client has been driving: | | education | Client’s level of education: | | income | Client’s income level: | | credit\_score | Client’s credit score (between zero and one) | | vehicle\_ownership | Client’s vehicle ownership status: | | vehcile\_year | Year of vehicle registration: | | married | Client’s marital status: | | children | Client’s number of children | | postal\_code | Client’s postal code | | annual\_mileage | Number of miles driven by the client each year | | vehicle\_type | Type of car: | | speeding\_violations | Total number of speeding violations received by the client | | duis | Number of times the client has been caught driving under the influence of alcohol | | past\_accidents | Total number of previous accidents the client has been involved in | | outcome | Whether the client made a claim on their car insurance (response variable): | |

# 2. Task

* Identify the single feature of the data that is the best predictor of whether a customer will put in a claim (the "outcome" column), excluding the "id" column.
* Store as a DataFrame called best\_feature\_df, containing columns named "best\_feature" and "best\_accuracy" with the name of the feature with the highest accuracy, and the respective accuracy score.

# 3. Data Source

Data: The primary data used for this analysis is the car\_insurance.csv, which can be downloaded [here](https://github.com/lawaloa/Project_7/blob/main/car_insurance.csv). See [Table 1](#tbl-Car) for the column names and descriptions.

# 4. Tools

Jupyter lab

# 5. Methodology: Steps/Explanations

## The necessary libraries was imported, which were Pandas and logit from statsmodels.formula.api

## Reading in and exploring the dataset, including imputation of missing values

* The Original dataset was loaded, named car.
* The first function, explore, was designed to help analyze and clean a dataset by providing a detailed overview of its structure and content, and it also optionally imputes missing values. Here’s a step-by-step explanation:

1. **Function creation and its arguments**: data, the DataFrame to analyze; head\_rows, the number of rows to display from the start of the DataFrame (default: 5); group\_by\_col, the column used to group data for imputing missing values (default: None); cols\_to\_impute, the list of columns where missing values will be filled with the group mean (default: None).

def explore(data, head\_rows=5, group\_by\_col=None, cols\_to\_impute=None):

1. **Function Task 1**: Prints information about the DataFrame, such as:

* Number of rows and columns.
* Data types of each column.
* Non-null counts for each column.

print("\n--- DataFrame Info ---\n")  
data.info()

1. **Function Task 2**: Displays summary statistics for all columns, including:

* For numerical data: Mean, standard deviation, min, max, and percentiles.
* For categorical data: Frequency counts (mode) and unique counts.

print("\n--- Summary Statistics ---\n")  
print(data.describe(include='all'))

1. **Function Task 3**: Displays the first head\_rows rows (default: 5) of the DataFrame to give a preview of the data.

print(f"\n--- First {head\_rows} Rows ---\n")  
print(data.head(head\_rows))

1. **Function Task 4**: Iterates over each column and prints the unique values present in it. Helps understand the distinct data points for each column.

print("\n--- Unique Values ---\n")  
for col in data.columns:  
 print(f"{col}: {data[col].unique()}")

1. **Function Task 5**: Fills missing values (NaN) in the specified columns (cols\_to\_impute) by grouping data based on group\_by\_col and calculating the mean for each group.

* Steps:
  + Groups the data by the column specified in group\_by\_col.
  + Calculates the mean for the columns listed in cols\_to\_impute for each group.
  + Fills missing values in each column by mapping the group means to the corresponding rows.
* Error Handling:
  + Ensures the function doesn’t crash if the specified column is not found or if an error occurs during imputation.

if group\_by\_col and cols\_to\_impute:  
 print("\n--- Imputing Missing Values ---\n")  
 try:  
 group\_means = data.groupby(group\_by\_col)[cols\_to\_impute].mean().to\_dict()  
 for col in cols\_to\_impute:  
 if col in data.columns:  
 print(f"Imputing missing values in '{col}' based on group means of '{group\_by\_col}'")  
 data[col] = data[col].fillna(data[group\_by\_col].map(group\_means[col]))  
 else:  
 print(f"Column '{col}' not found in the dataset.")  
 except Exception as e:  
 print(f"Error while imputing missing values: {e}")

1. **Function Task 6**: After the imputation, checks and prints the count of missing values in each column to verify if gaps were successfully filled.

print("\n--- Any missing values again ? ---\n")  
print(data.isna().sum())

## Finding the best performing model, with the highest accuracy.

* The second function, best\_logmodel, was designed to identify the single best feature in a dataset for predicting a binary outcome using logistic regression with the statsmodels library. Here’s a detailed explanation:

1. **Function creation and its arguments**: data, the input dataset for modeling as a pandas DataFrame; outcome\_column, the target column (dependent variable) representing the outcome being predicted (default: ‘outcome’); id\_column, a unique identifier column to exclude from the analysis (default: ‘id’).

def best\_logmodel(data, outcome\_column='outcome', id\_column='id'):

1. **Function Task**: Creates a new DataFrame (data1) by removing the id\_column (not predictive) and the outcome\_column (target variable) from the list of features. The remaining columns are treated as potential predictors.

data1 = data.drop(columns=[id\_column, outcome\_column])

1. **Initialize Tracking Variables**: best\_feature, placeholder for the name of the feature with the highest accuracy and best\_accuracy, tracks the best accuracy score encountered during the iteration.

best\_feature = None  
best\_accuracy = 0

1. **Loop Through Each Feature**: Iterates through all the columns (features) in data1 to evaluate their predictive power for the outcome\_column.

for col in data1.columns:

1. **Create the Logistic Regression Formula**: Constructs a formula for logistic regression in the form "outcome\_column ~ feature\_column".

formula = f"{outcome\_column} ~ {col}"

1. **Fit Logistic Regression Model**: Fits a logistic regression model for the current feature using the logit function from statsmodels. The `disp=False argument suppresses output during model fitting.

model = logit(formula=formula, data=data).fit(disp=False)

1. **Generate Confusion Matrix**: Produces a confusion matrix for the logistic regression model’s predictions.

confusion\_matrix = model.pred\_table()

* **Confusion Matrix Layout**:

[[TN, FP], # TN = True Negatives, FP = False Positives  
 [FN, TP]] # FN = False Negatives, TP = True Positives

1. **Calculates the model’s accuracy from the confusion matrix**:

* TP: True Positives (correctly predicted positives).
* TN: True Negatives (correctly predicted negatives).
* T: Total number of predictions.
* **Accuracy Formula**:

1. **Update the Best Feature**: Compares the current feature’s accuracy with the best accuracy seen so far. If the current feature has a higher accuracy, update best\_feature and best\_accuracy.

if accuracy > best\_accuracy:  
 best\_feature = col  
 best\_accuracy = accuracy

1. **Store Results in a DataFrame**: Summarizes the results into a pandas DataFrame with:

* best\_feature: The name of the feature with the highest accuracy.
* best\_accuracy: The corresponding accuracy score.

best\_feature\_df = pd.DataFrame({  
 "best\_feature": [best\_feature],  
 "best\_accuracy": [best\_accuracy]  
})

1. **Return the Results**: Returns the DataFrame so that the results can be used or displayed.

return best\_feature\_df

# 6. Data Analysis

# Import required modules  
import pandas as pd  
from statsmodels.formula.api import logit  
  
# Import the car\_insurance csv file and store as object 'car'  
car = pd.read\_csv("car\_insurance.csv")  
  
# Exploring the DataFrame by creating the function 'explore'  
  
def explore(data, head\_rows=5, group\_by\_col=None, cols\_to\_impute=None):  
 """  
 Explores the given DataFrame by displaying basic information, summary statistics,   
 the first few rows, unique values, and imputes missing values with group means if specified.  
  
 Parameters:  
 data (pd.DataFrame): The DataFrame to explore.  
 head\_rows (int): Number of rows to display for the head of the DataFrame. Default is 5.  
 group\_by\_col (str): Column name to group by for imputing missing values. Default is None.  
 cols\_to\_impute (list): List of column names to impute missing values. Default is None.  
 """  
 print("\n--- DataFrame Info ---\n")  
 data.info()  
   
 print("\n--- Summary Statistics ---\n")  
 print(data.describe(include='all')) # Include all data types in describe()  
   
 print(f"\n--- First {head\_rows} Rows ---\n")  
 print(data.head(head\_rows))  
   
 print("\n--- Unique Values ---\n")  
 for col in data.columns:  
 print(f"{col}: {data[col].unique()}")  
   
 # Impute missing values if group\_by\_col and cols\_to\_impute are specified  
 if group\_by\_col and cols\_to\_impute:  
 print("\n--- Imputing Missing Values ---\n")  
 try:  
 group\_means = data.groupby(group\_by\_col)[cols\_to\_impute].mean().to\_dict() # Group means as a dictionary  
 for col in cols\_to\_impute:  
 if col in data.columns:  
 print(f"Imputing missing values in '{col}' based on group means of '{group\_by\_col}'")  
 data[col] = data[col].fillna(data[group\_by\_col].map(group\_means[col]))  
 else:  
 print(f"Column '{col}' not found in the dataset.")  
 except Exception as e:  
 print(f"Error while imputing missing values: {e}")  
   
 print("\n--- Any missing values again ? ---\n")  
 print(data.isna().sum())  
  
# Example usage  
# explore(your\_data, group\_by\_col="outcome", cols\_to\_impute=["credit\_score", "annual\_mileage"])  
  
# Use 'explore' function to analyze and clean the car dataset by providing a detailed overview of its structure and content, and it also optionally imputes missing values.  
  
explore(car, group\_by\_col="outcome", cols\_to\_impute=["credit\_score", "annual\_mileage"])  
  
# Create a function, 'best\_logmodel', to identify the single best feature in the dataset for predicting a binary outcome using logistic regression with the statsmodels  
  
def best\_logmodel(data, outcome\_column='outcome', id\_column='id'):  
 """  
 Identifies the single best feature for predicting the outcome column using logistic regression   
 with statsmodels. Calculates accuracy directly from the confusion matrix.  
  
 Parameters:  
 data (pd.DataFrame): The dataset containing features and the outcome column.  
 outcome\_column (str): The name of the target column.  
 id\_column (str): The name of the column to exclude from analysis.  
  
 Returns:  
 pd.DataFrame: A DataFrame with the best feature and its accuracy score.  
 """  
 # Exclude ID and outcome columns from columns set  
 data1 = data.drop(columns=[id\_column, outcome\_column])  
   
 best\_feature = None  
 best\_accuracy = 0  
  
 # Iterate through each columns  
 for col in data1.columns:  
 # Create formula for logistic regression  
 formula = f"{outcome\_column} ~ {col}"  
   
 # Fit logistic regression model on the entire dataset  
 model = logit(formula=formula, data=data).fit(disp=False)  
   
 # Generate confusion matrix using pred\_table()  
 confusion\_matrix = model.pred\_table()  
   
 # Calculate accuracy from confusion matrix  
 TP = confusion\_matrix[1, 1]  
 TN = confusion\_matrix[0, 0]  
 T = confusion\_matrix.sum()  
 accuracy = (TP + TN) / T  
  
 # Update the best feature if this one is better  
 if accuracy > best\_accuracy:  
 best\_feature = col  
 best\_accuracy = accuracy  
  
 # Store results in a DataFrame  
 best\_feature\_df = pd.DataFrame({  
 "best\_feature": [best\_feature],  
 "best\_accuracy": [best\_accuracy]  
 })  
  
 return best\_feature\_df  
  
# Example usage  
# best\_feature\_df = best\_logmodel(your\_data)  
# print(best\_feature\_df)  
  
# Use the function, 'best\_logmodel', to identify the single best feature in the dataset for predicting a binary outcome using logistic regression with the statsmodels.  
  
best\_feature\_df = best\_logmodel(car)  
  
print(best\_feature\_df)

--- DataFrame Info ---  
  
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 10000 entries, 0 to 9999  
Data columns (total 18 columns):  
 # Column Non-Null Count Dtype   
--- ------ -------------- -----   
 0 id 10000 non-null int64   
 1 age 10000 non-null int64   
 2 gender 10000 non-null int64   
 3 driving\_experience 10000 non-null object   
 4 education 10000 non-null object   
 5 income 10000 non-null object   
 6 credit\_score 9018 non-null float64  
 7 vehicle\_ownership 10000 non-null float64  
 8 vehicle\_year 10000 non-null object   
 9 married 10000 non-null float64  
 10 children 10000 non-null float64  
 11 postal\_code 10000 non-null int64   
 12 annual\_mileage 9043 non-null float64  
 13 vehicle\_type 10000 non-null object   
 14 speeding\_violations 10000 non-null int64   
 15 duis 10000 non-null int64   
 16 past\_accidents 10000 non-null int64   
 17 outcome 10000 non-null float64  
dtypes: float64(6), int64(7), object(5)  
memory usage: 1.4+ MB  
  
--- Summary Statistics ---  
  
 id age gender driving\_experience \  
count 10000.000000 10000.000000 10000.000000 10000   
unique NaN NaN NaN 4   
top NaN NaN NaN 0-9y   
freq NaN NaN NaN 3530   
mean 500521.906800 1.489500 0.499000 NaN   
std 290030.768758 1.025278 0.500024 NaN   
min 101.000000 0.000000 0.000000 NaN   
25% 249638.500000 1.000000 0.000000 NaN   
50% 501777.000000 1.000000 0.000000 NaN   
75% 753974.500000 2.000000 1.000000 NaN   
max 999976.000000 3.000000 1.000000 NaN   
  
 education income credit\_score vehicle\_ownership \  
count 10000 10000 9018.000000 10000.000000   
unique 3 4 NaN NaN   
top high school upper class NaN NaN   
freq 4157 4336 NaN NaN   
mean NaN NaN 0.515813 0.697000   
std NaN NaN 0.137688 0.459578   
min NaN NaN 0.053358 0.000000   
25% NaN NaN 0.417191 0.000000   
50% NaN NaN 0.525033 1.000000   
75% NaN NaN 0.618312 1.000000   
max NaN NaN 0.960819 1.000000   
  
 vehicle\_year married children postal\_code annual\_mileage \  
count 10000 10000.000000 10000.000000 10000.000000 9043.000000   
unique 2 NaN NaN NaN NaN   
top before 2015 NaN NaN NaN NaN   
freq 6967 NaN NaN NaN NaN   
mean NaN 0.498200 0.688800 19864.548400 11697.003207   
std NaN 0.500022 0.463008 18915.613855 2818.434528   
min NaN 0.000000 0.000000 10238.000000 2000.000000   
25% NaN 0.000000 0.000000 10238.000000 10000.000000   
50% NaN 0.000000 1.000000 10238.000000 12000.000000   
75% NaN 1.000000 1.000000 32765.000000 14000.000000   
max NaN 1.000000 1.000000 92101.000000 22000.000000   
  
 vehicle\_type speeding\_violations duis past\_accidents \  
count 10000 10000.000000 10000.00000 10000.000000   
unique 2 NaN NaN NaN   
top sedan NaN NaN NaN   
freq 9523 NaN NaN NaN   
mean NaN 1.482900 0.23920 1.056300   
std NaN 2.241966 0.55499 1.652454   
min NaN 0.000000 0.00000 0.000000   
25% NaN 0.000000 0.00000 0.000000   
50% NaN 0.000000 0.00000 0.000000   
75% NaN 2.000000 0.00000 2.000000   
max NaN 22.000000 6.00000 15.000000   
  
 outcome   
count 10000.000000   
unique NaN   
top NaN   
freq NaN   
mean 0.313300   
std 0.463858   
min 0.000000   
25% 0.000000   
50% 0.000000   
75% 1.000000   
max 1.000000   
  
--- First 5 Rows ---  
  
 id age gender driving\_experience education income \  
0 569520 3 0 0-9y high school upper class   
1 750365 0 1 0-9y none poverty   
2 199901 0 0 0-9y high school working class   
3 478866 0 1 0-9y university working class   
4 731664 1 1 10-19y none working class   
  
 credit\_score vehicle\_ownership vehicle\_year married children \  
0 0.629027 1.0 after 2015 0.0 1.0   
1 0.357757 0.0 before 2015 0.0 0.0   
2 0.493146 1.0 before 2015 0.0 0.0   
3 0.206013 1.0 before 2015 0.0 1.0   
4 0.388366 1.0 before 2015 0.0 0.0   
  
 postal\_code annual\_mileage vehicle\_type speeding\_violations duis \  
0 10238 12000.0 sedan 0 0   
1 10238 16000.0 sedan 0 0   
2 10238 11000.0 sedan 0 0   
3 32765 11000.0 sedan 0 0   
4 32765 12000.0 sedan 2 0   
  
 past\_accidents outcome   
0 0 0.0   
1 0 1.0   
2 0 0.0   
3 0 0.0   
4 1 1.0   
  
--- Unique Values ---  
  
id: [569520 750365 199901 ... 468409 903459 442696]  
age: [3 0 1 2]  
gender: [0 1]  
driving\_experience: ['0-9y' '10-19y' '20-29y' '30y+']  
education: ['high school' 'none' 'university']  
income: ['upper class' 'poverty' 'working class' 'middle class']  
credit\_score: [0.62902731 0.35775712 0.49314579 ... 0.47094023 0.36418478 0.43522478]  
vehicle\_ownership: [1. 0.]  
vehicle\_year: ['after 2015' 'before 2015']  
married: [0. 1.]  
children: [1. 0.]  
postal\_code: [10238 32765 92101 21217]  
annual\_mileage: [12000. 16000. 11000. 13000. 14000. 10000. 8000. nan 18000. 17000.  
 7000. 15000. 9000. 5000. 6000. 19000. 4000. 3000. 2000. 20000.  
 21000. 22000.]  
vehicle\_type: ['sedan' 'sports car']  
speeding\_violations: [ 0 2 3 7 6 4 10 13 1 5 9 8 12 11 15 17 19 18 16 14 22]  
duis: [0 2 1 3 4 5 6]  
past\_accidents: [ 0 1 3 7 2 5 4 6 8 10 11 9 12 14 15]  
outcome: [0. 1.]  
  
--- Imputing Missing Values ---  
  
Imputing missing values in 'credit\_score' based on group means of 'outcome'  
Imputing missing values in 'annual\_mileage' based on group means of 'outcome'  
  
--- Any missing values again ? ---  
  
id 0  
age 0  
gender 0  
driving\_experience 0  
education 0  
income 0  
credit\_score 0  
vehicle\_ownership 0  
vehicle\_year 0  
married 0  
children 0  
postal\_code 0  
annual\_mileage 0  
vehicle\_type 0  
speeding\_violations 0  
duis 0  
past\_accidents 0  
outcome 0  
dtype: int64  
 best\_feature best\_accuracy  
0 driving\_experience 0.7771

# 7. Result/Findings

* The analysis identified driving\_experience (indicating the years the client has been driving) as the best predictor of whether a customer will file a claim, with an accuracy score of 77.7%. This indicates that the model correctly predicted claims and non-claims in approximately 78 out of 100 cases, making this feature a significant factor in claim prediction.

# 8. Recommendations

None

# 9. Limitations

None

# 10. Conclusion

My analysis identified driving\_experience (years of driving) as the strongest predictor of claim submissions, achieving an accuracy score of 77.7%. This result highlights the importance of driving experience in assessing customer risk. The model correctly classified claims and non-claims in 78 out of 100 cases.

Logistic regression was used to evaluate the predictive power of individual features, and accuracy was calculated using a confusion matrix. The prominence of driving experience suggests that more experienced drivers may exhibit different risk profiles, which could guide targeted policy offerings.

I recommend incorporating this insight into your risk assessment models.

# 11. References

1. For loop in Intermediate Python Course for Associate Data Scientist in Python Carrer Track in DataCamp Inc by Hugo Bowne-Henderson.
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5. Python For Data Analysis 3E (Online) by Wes Mckinney Click [here](https://wesmckinney.com/book/) to preview.