Car Insurance Claims

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Overview

- About the Stakeholder
- Business problem
- Context and Scope of Data
- Approach and Model compiled
- Visualizations
- Results / Recommendations / Conclusions

About the Stakeholder …

- Car Insurance Company with various short term insurance products offered to a broad spectrum of Clients in the market …

- Engagement will focus on Representatives and Teams in the Company – focusing on product development, marketing and claims administration of their Car Insurance product …

The Business problem …

- The Company needs to derive more value from available insurance & claims related data – to assist with:

  - New product development
  - Re-focus marketing initiatives
  - Optimize current Claims / Administration processes

“ The goal is to analyse and predict **Client behavior** – in order to determine if a Client will claim or not claim against a Car Insurance Product … ”

Context and Scope of Data …

Data set contains 10,000 records …

Details Client & Insurance related events with 19 features in the set …

Data granularity = each record represent a client & insurance product related activity …

Data dictionary …

ID
AGE
GENDER
RACE
DRIVING EXPERIENCE
EDUCATION
INCOME
CREDIT SCORE
VEHICLE OWNERSHIP
VEHICLE YEAR
MARRIED
CHILDREN
POSTAL CODE
ANNUAL MILEAGE
VEHICLE TYPE
SPEEDING VIOLATIONS
DUIS
PAST ACCIDENTS
OUTCOME

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
ID	AGE	GENDER	RACE	DRIVING_ EXPERIENCE	EDUCATION	INCOME	CREDIT_SCORE	VEHICLE_ OWNERSHIP	VEHICLE_YEAR	MARRIED	CHILDREN	POSTAL_ CODE	ANNUAL_ MILEAGE	VEHICLE_ TYPE	SPEEDING_ VIOLATIONS	DUIS	PAST_ ACCIDENTS	OUTCOME
569520	65+	female	majority	0-9y	high school	upper class	0.629027314	1	after 2015	0	1	10238	12000	sedan	0	0	0	0
750365	16-25	male	majority	0-9y	none	poverty	0.357757117	0	before 2015	0	0	10238	16000	sedan	0	0	0	1
199901	16-25	female	majority	0-9y	high school	working class	0.493145785	1	before 2015	0	0	10238	11000	sedan	0	0	0	0
478866	16-25	male	majority	0-9y	university	working class	0.206012851	1	before 2015	0	1	32765	11000	sedan	0	0	0	0
731664	26-39	male	majority	10-19y	none	working class	0.388365888	1	before 2015	0	0	32765	12000	sedan	2	0	1	1
877557	40-64	female	majority	20-29y	high school	upper class	0.619127373	1	after 2015	0	1	10238	13000	sedan	3	0	3	0
930134	65+	male	majority	30y+	high school	upper class	0.49294355	0	after 2015	1	1	10238	13000	sedan	7	0	3	0
461006	26-39	female	majority	0-9y	university	working class	0.468689297	0	after 2015	0	1	10238	14000	sedan	0	0	0	1
68366	40-64	female	majority	20-29y	university	working class	0.521814936	0	before 2015	1	0	10238	13000	sedan	0	0	0	0
445911	40-64	female	majority	0-9y	high school	upper class	0.561531032	1	before 2015	0	1	32765	11000	sedan	0	0	0	1
275820	65+	male	majority	30y+	high school	upper class	0.620361264	1	after 2015	1	1	10238	10000	sedan	6	2	7	0
521399	65+	female	majority	30y+	high school	upper class	0.729830882	1	after 2015	1	0	32765	12000	sedan	4	0	0	0
429728	40-64	male	majority	20-29y	high school	upper class	0.637044744	1	before 2015	1	1	10238	8000	sedan	4	1	2	0
569640	16-25	female	majority	0-9y	university	upper class	0.591259972	1	before 2015	0	1	10238		sedan	0	0	0	0
980181	26-39	male	majority	10-19y	high school	middle class	0.461567963	1	before 2015	1	1	10238	12000	sedan	0	2	1	0
906223	26-39	female	majority	0-9y	high school	upper class	0.762797941	0	after 2015	1	0	10238		sedan	0	0	0	0
517747	65+	male	majority	30y+	university	upper class	0.796174846	1	before 2015	1	1	32765		sedan	10	2	1	0
24851	16-25	male	majority	0-9y	none	poverty		0	before 2015	1	0	32765	12000	sedan	0	0	0	1
104086	26-39	female	majority	0-9y	university	upper class	0.68059428	1	before 2015	0	1	32765		sedan	0	0	0	1
240658	16-25	female	majority	0-9y	high school	working class	0.417713982	1	before 2015	0	1	10238	18000	sedan	0	0	0	1
484399	16-25	female	majority	0-9y	high school	working class	0.409513531	0	before 2015	0	0	10238	17000	sedan	0	0	0	1
912828	16-25	male	majority	0-9y	high school	middle class	0.553260053	1	after 2015	1	1	32765	8000	sedan	0	0	0	1
892754	40-64	male	majority	20-29y	none	poverty	0.330950262	1	before 2015	1	1	10238	13000	sedan	3	1	1	0

	ID	CREDIT_SCORE	VEHICLE_OWNERSHIP	MARRIED	CHILDREN	POSTAL_CODE	ANNUAL_MILEAGE	SPEEDING_VIOLATIONS	DUIS	PAST_ACCIDENTS	OUTCOME
count	10000.000000	9018.000000	10000.000000	10000.000000	10000.000000	10000.000000	9043.000000	10000.000000	10000.00000	10000.000000	10000.000000
mean	500521.906800	0.515813	0.697000	0.498200	0.688800	19864.548400	11697.003207	1.482900	0.23920	1.056300	0.313300
std	290030.768758	0.137688	0.459578	0.500022	0.463008	18915.613855	2818.434528	2.241966	0.55499	1.652454	0.463858
min	101.000000	0.053358	0.000000	0.000000	0.000000	10238.000000	2000.000000	0.000000	0.00000	0.000000	0.000000
25%	249638.500000	0.417191	0.000000	0.000000	0.000000	10238.000000	10000.000000	0.000000	0.00000	0.000000	0.000000
50%	501777.000000	0.525033	1.000000	0.000000	1.000000	10238.000000	12000.000000	0.000000	0.00000	0.000000	0.000000
75%	753974.500000	0.618312	1.000000	1.000000	1.000000	32765.000000	14000.000000	2.000000	0.00000	2.000000	1.000000
max	999976.000000	0.960819	1.000000	1.000000	1.000000	92101.000000	22000.000000	22.000000	6.00000	15.000000	1.000000

Approach and Model compiled …

Approach

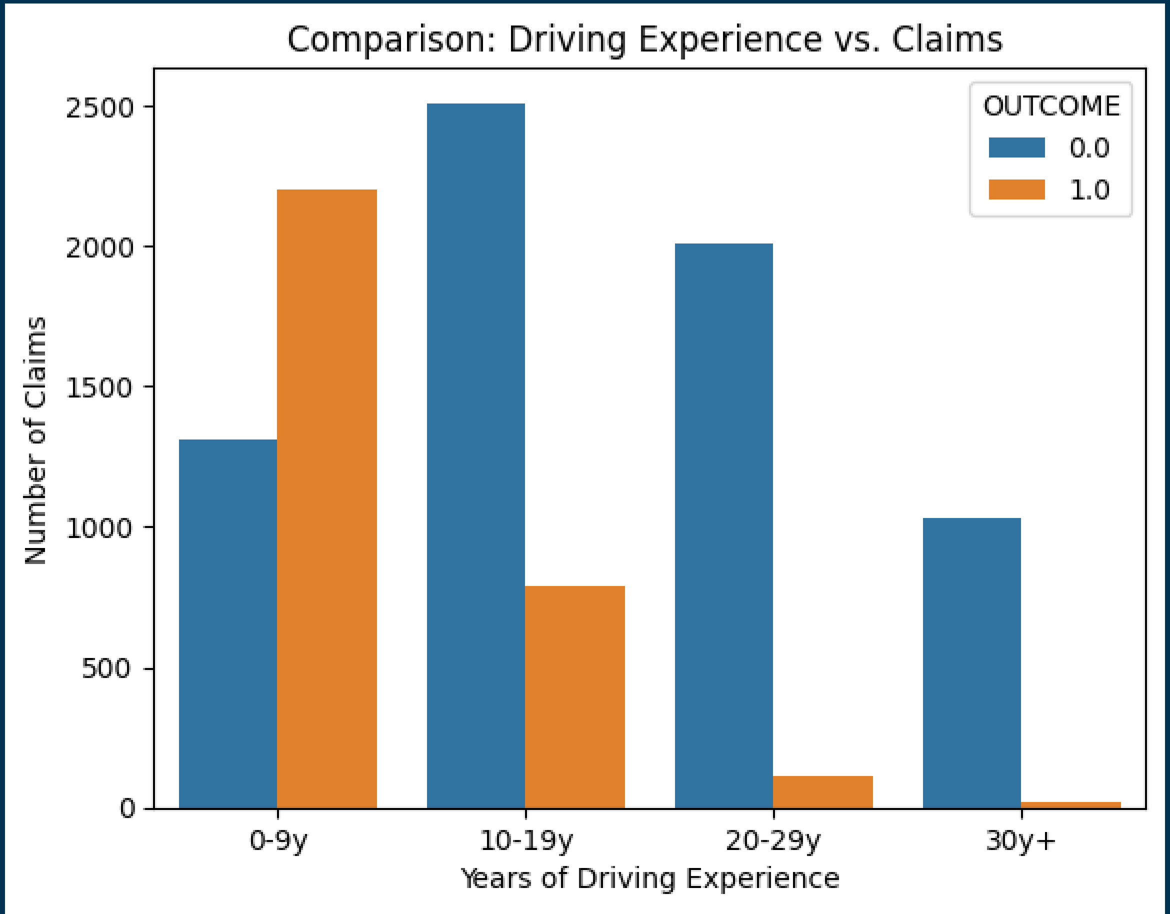
- This output can be obtained via the use of a Machine Learning (ML) model - that will analyze and predict the potential “Claim Status” (target value) for each Client.
- Key steps:
  - Define the problem
  - Collect the data
  - Clean the data
  - Analyse the data
  - Choose and compile the appropriate ML model
- From a ML modelling perspective - this is a typical Binary Classification requirement to solve.

Insurance Claims

(Machine Learning Model)

- Model outputs a predicted “Target“ value for Claim "Outcome“ on each Client.
- This value represents the possibility that a Client will claim against their Insurance Policy.
- This will be based on analysis & learnings from the Customer's behaviour and data available to the Model.
- Outcome:
  - 1 = Claimed
  - 0 = Not Claimed

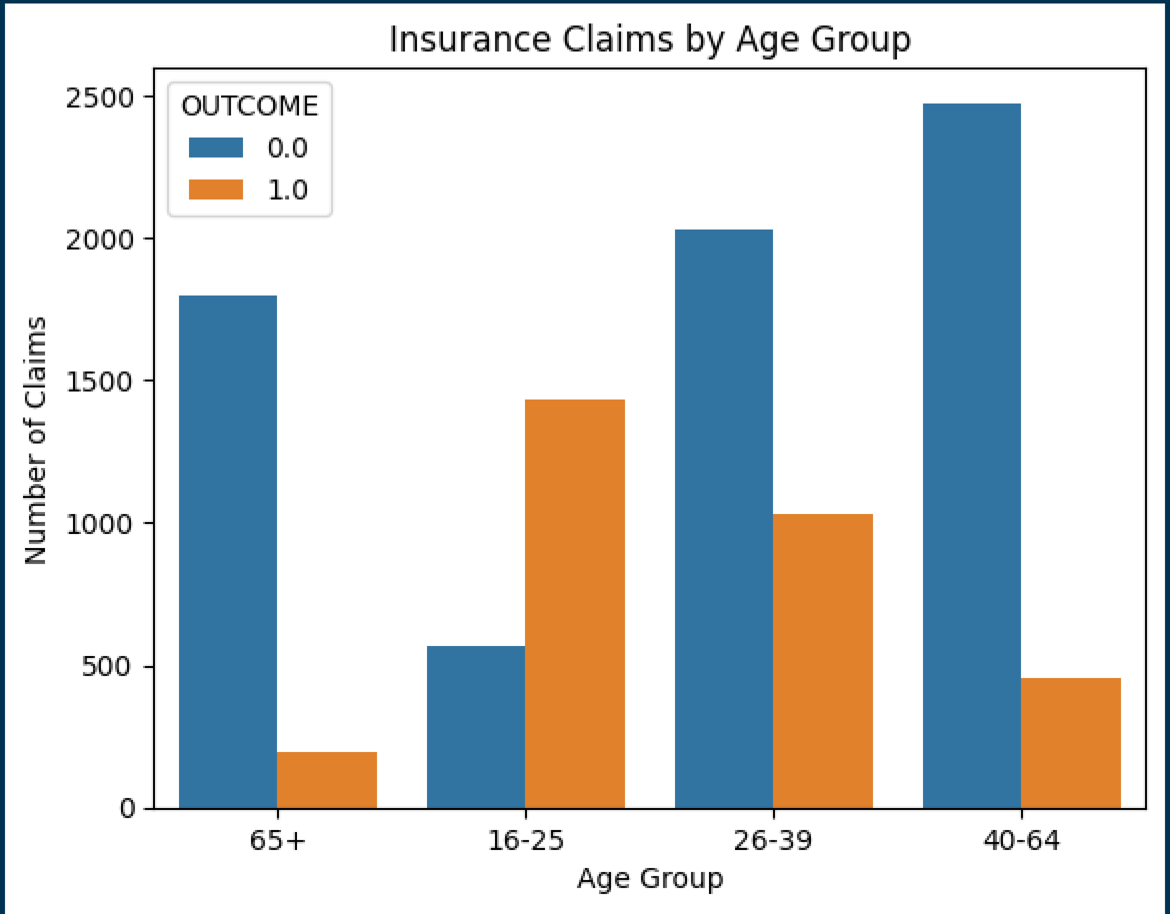
Visualizations …



"Claims are reduced by Clients with more \`Years of Driving Experience\` …
e.g. 20-29 year & 30+ year groups

Claims are more likely to occur in the group where Clients have \`0-9 Years of Driving Experience\` … "

Visualizations …



"Insurance Claims are the <u>highest</u> in the \`Age Group\` 16-25 year and much lower in the 65+ year group …"

Results ...

Model outcomes | Strengths:

- 3 x ML Models Compiled
  - K-Nearest Neighbors (KNN)
  - Logistic Regression Model
  - Logistic Regression Model - using PCA
- Preferred model result ...
  - Logistic Regression Model - using Principal Component Analysis (PCA)*
  - Preference = based on Model accuracy rate
  - Model achieved an accuracy rating of 86%

** Model compiled by using Principal Component Analysis (PCA) - to reduce the dimensionality (number of features) within the dataset*

Model outcomes | Limitations:

- Model outcomes – limited by the current available features and data elements from the data set.
- Possible to further increase the model accuracy by including additional elements if / when available.

Recommendations / Conclusions …

- Management of claims & costing of insurance products (premiums) can be optimized by taking note of the impact of some of the referred data elements in the Model outcomes and visualizations.
- Examples of some of these events that increase / impact claim incidents are:
  - Clients with Speeding Drive Styles
  - Clients with limited years of Driving Experience
  - Clients that fall in younger age groups
  - Client with lower income levels, etc.

- The Insurance Company can also potentially increase profits (reduce claims) by expanding the below segments of their current Client base and market share:
  - Clients with 20+ years driving experience
  - Clients of 40+ years of age, etc.