INSURANCE CROSS SELL PREDICTION

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https://github.com/romacoffin/Health-Insurance-Cross-Sell-Prediction

RECAP-INTRODUCTION

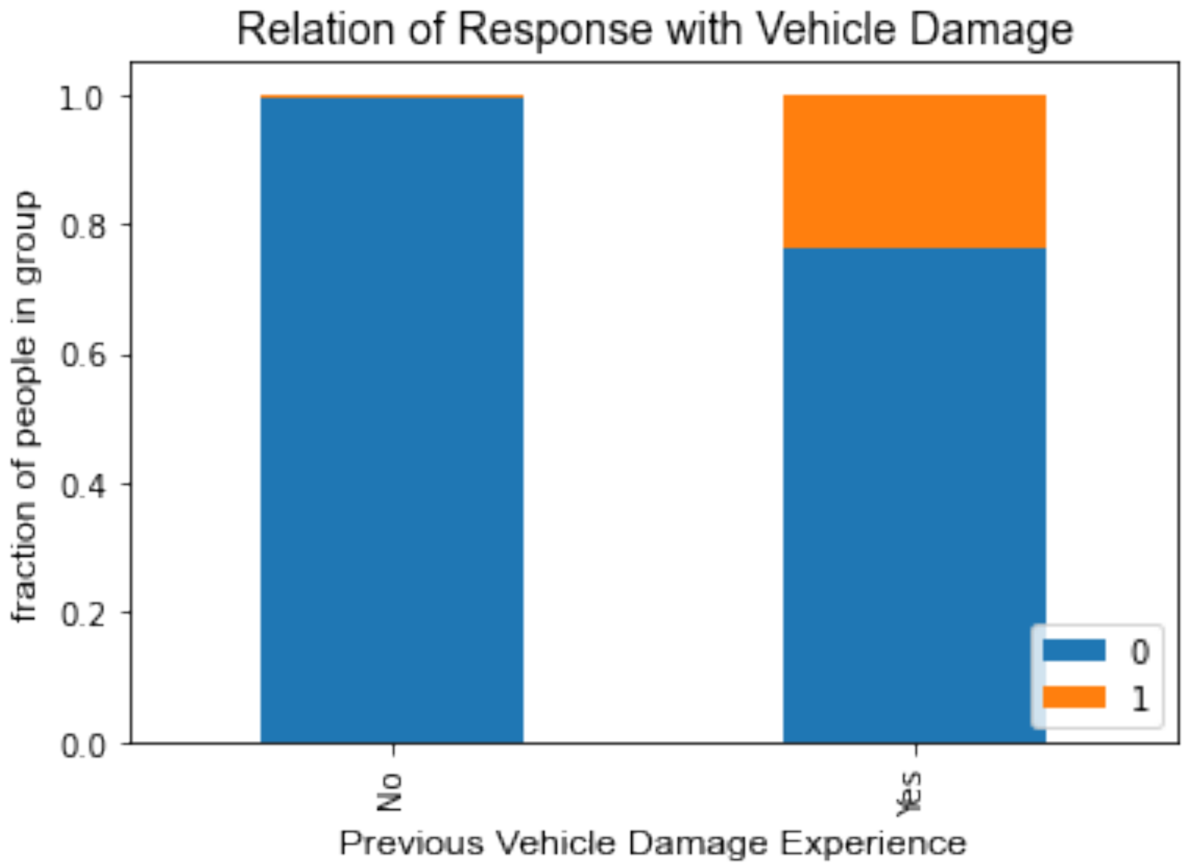
Leverage machine learning techniques to ***predict*** if someone will be interested in purchasing vehicle insurance (classification)

Dataset is from a health insurance provider leveraging their own customer's data

The ***target variable*** is the ***customer's response***, if they are interested in purchasing insurance

RECAP-EXPLORATORY DATA ANALYSIS

Those with prior vehicle damage experiences are more likely to be interested in purchasing vehicle insurance when compared to customers with no past vehicle damage



CROSS VALIDATION

- Data split basic train test and then kfold
- Preprocessed data-numerical(standard scaler), categorical (onehot and ordinal)
- Kfold Cross Validation/GridSearchCV
- Three machine learning algorithms were selected: Logistic Regression, Random Forest Classifier, Support Vector Machine
- Evaluation Metric - Accuracy Score
- See details for hyperparameters which were tuned in table below

ML Algorithm	1-Parameter	1-Values	2-Parameter	2-Values
LR	C	logspace(-2, 2, num=8)	NA	NA
RF	Max Depth	1, 3, 10	Max Features	.5-1
SVM	C	logspace(-3, 4, num=8)	Gamma	logspace(-3, 4, num=8)

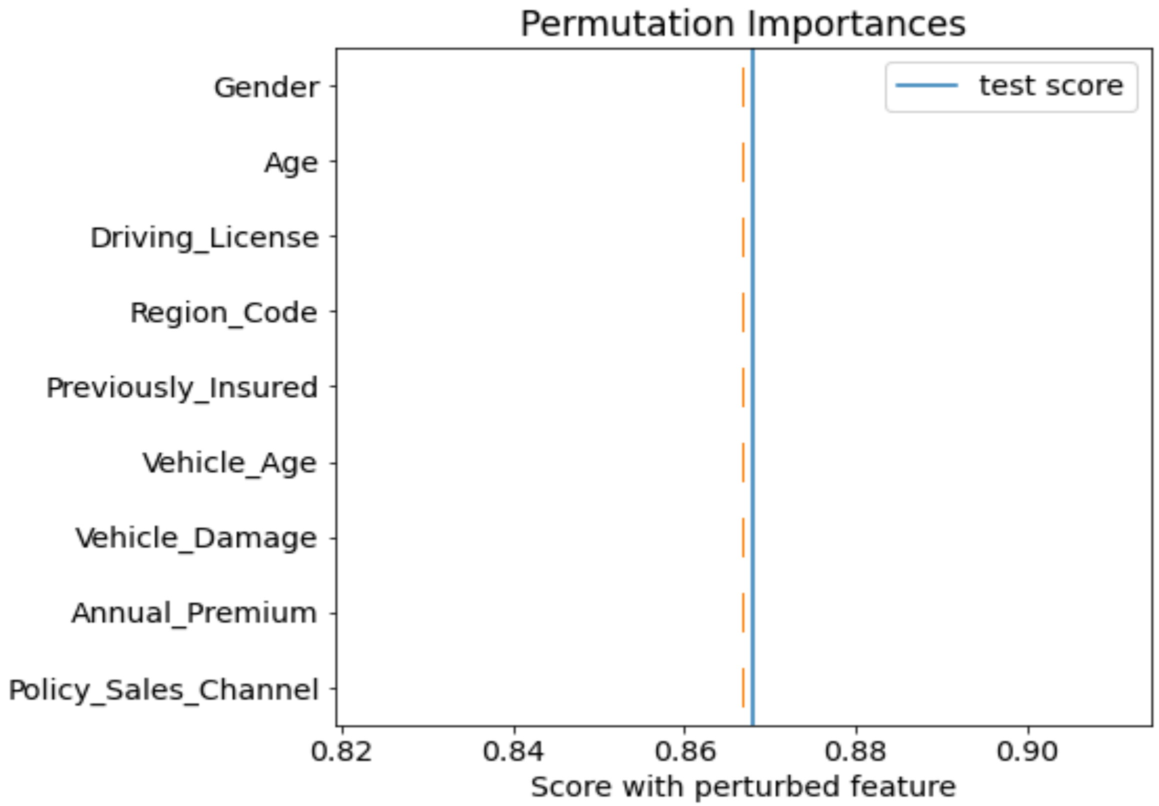
RESULTS-MODEL OUTCOMES

The machine learning algorithms do not reflect a significantly improved accuracy score when compared to the baseline model

Baseline = .877

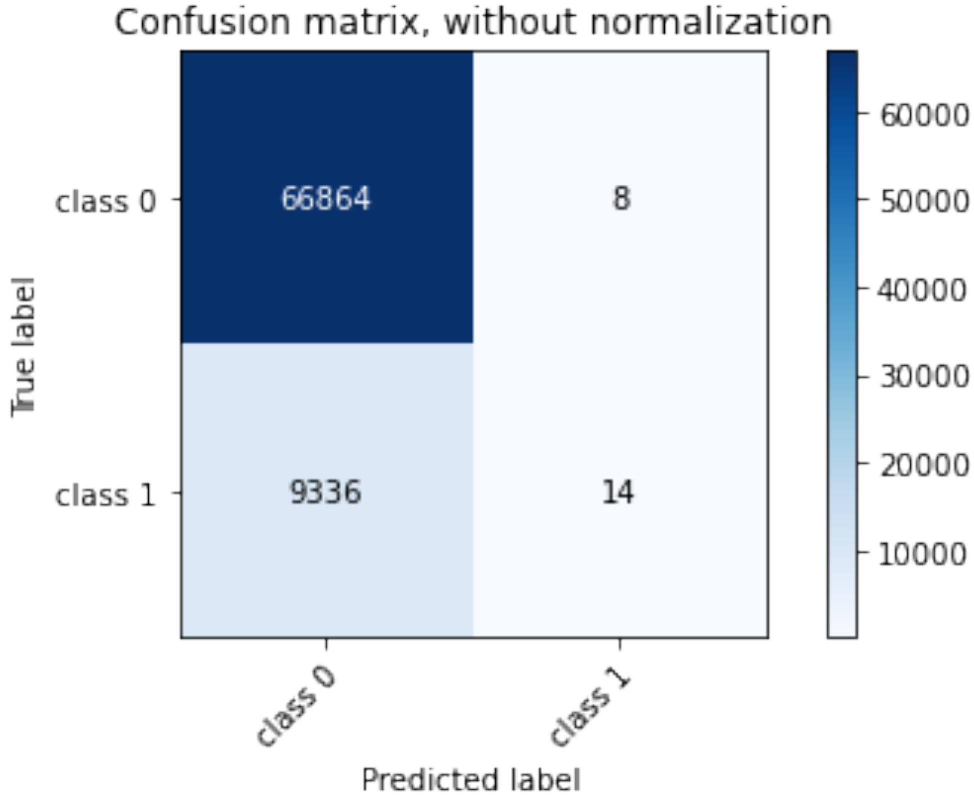
Machine Learning Algorithm	**Mean**	**SD**	**Best Parameters**
Logistic Regression	.867	.001	C= .01
Random Forest Classifier	.892	.011	Max Depth = 1, Max Features = .5
Support Vector Classifier	.892	.012	C= .001, Gamma= .001

RESULTS-FEATURE IMPORTANCE & CONFUSION MATRICES



*Random Forest

Feature importance shows us that the features were really not that important



*Logistic Regression

Confusion Matrices were developed for each algorithm to help measure effectiveness of the model

OUTLOOK

Look into more than ***three machine learning algorithms*** used in the model approach

Tune ***additional hyperparameters*** which can provide additional confidence in the predictions

Dive deeper into feature selection by performing ***a more comprehensive EDA process*** or use various mixtures of features to produce additional features

QUESTIONS?

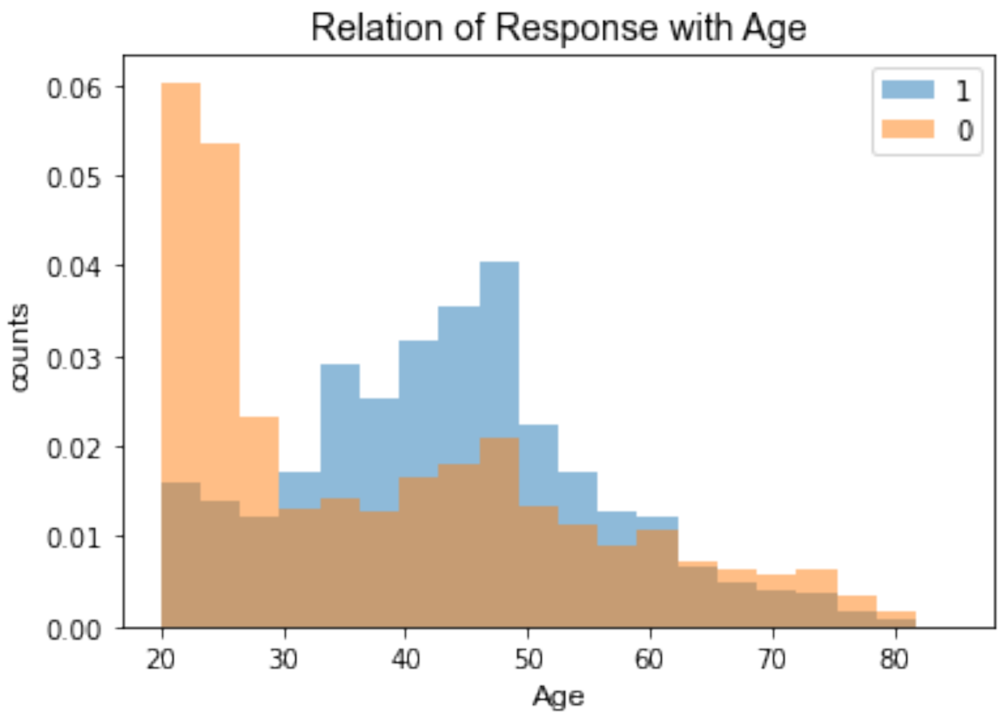
APPENDIX

PREPROCESSING DATA

The data was preprocessed inside the machine learning pipeline. See below on why a specific preprocessor was chosen for each feature.

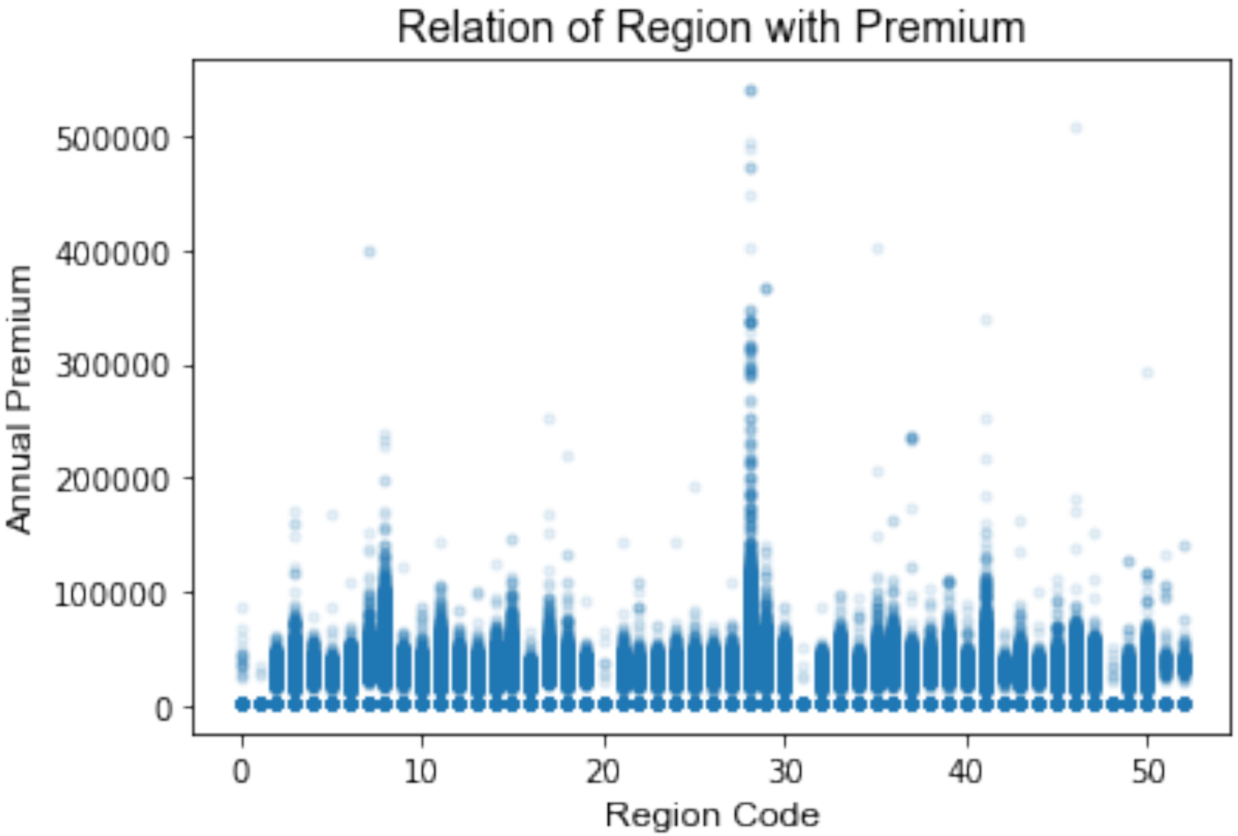
Feature	Numerical/Categorical	Preprocessor	Reason
Gender	Categorical	OneHotEncoder	Categorical can't be ordered
Age	Numerical	StandardScaler	Numerical reasonable bounds
Driving License	Categorical-0,1	OneHotEncoder	Categorical can't be ordered
Region Code	Numerical	StandardScaler	Numerical
Previously Insured	Categorical-0,1	OneHotEncoder	Categorical can't be ordered
Vehicle Age	Categorical	OrdinalEncoder	Categorical can be ordered
Vehicle Damage	Categorical-0,1	OneHotEncoder	Categorical can't be ordered
Annual Premium	Numerical	StandardScaler	Numerical, tailed distribution
Policy Sales Channel	Numerical	StandardScaler	Default
Response/Target	Categorical-0,1	OneHotEncoder	Default

EXPLORATORY DATA ANALYSIS



Customers between the ages of 35-50 are more likely to be interested in purchasing vehicle insurance when compared to customers between the ages of 20 to 30

EXPLORATORY DATA ANALYSIS



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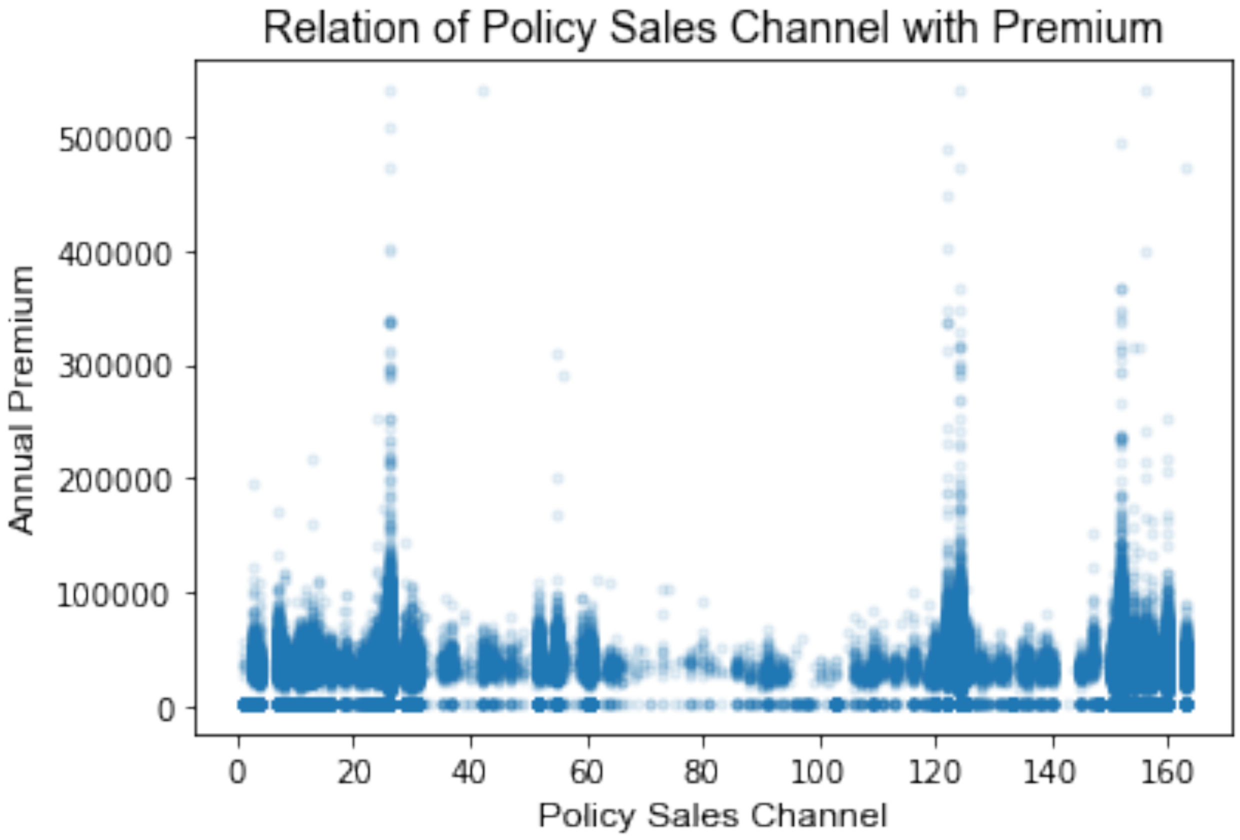

EXPLORATORY DATA ANALYSIS

Region Code and Policy Sales Channel show us a relationship that can better understand sales distribution options