# Prediction of Alternative Fuel Vehicle Adoption 2017 NHTS Case

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- 2 Data
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- Predict the individual's. behavior to adopt an AFV (Binary Classification).
- Compare between parametric and non parametric ML models predictive performance.



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#### **Variables**

• Data Source : National Household Travel Survey.



#### Variables

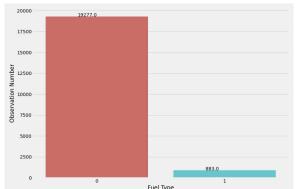
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# Chi-Square Test



#### Variance Inflation Factor

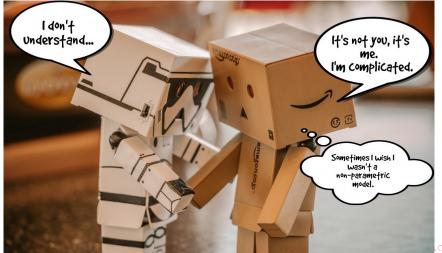
	Feature	VIF
0	Household in-	19.60
	come	
15	Count of	8.01
	household	
	vehicles	
2	Count of	13.78
	household	
	members	
22	Count of adult	22.23
	household	
	members	
4	population	10.41
	density	
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## Machine Learning Models

#### Comparison Between Parametric non-Parametric ML models



# Machine Learning Models

# Parametric Models

- Logistic Regression.
- I R with FAMD.
- Ridge Regression.
- Lasso Regression.
- Logistic GAM (Semi-Parametric).

#### Non-Parametric Models

- Naive Bayes.
- K Nearest Neighbors.
- Neural Network.
- Support Vector Machine.
- Random Forest.

- Predict the models using the original DATA.
- Create Artificial Observations (SMOTE NC) on training set only.
- Predict the models after SMOTE NC.
- Add polynomial features to linear models to test their impact on performance.
- Compare between model's performance.

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### Before SMOTE NC

Classifiers	Accuracy	Recal	F1	Precision	AUC
Logistic regression	0.96	0.00	0.00	0.00	0.50
Lasso regression	0.96	0.00	0.00	0.00	0.50
Ridge regression	0.96	0.00	0.00	0.00	0.50
Naive Bayes	0.95	0.00	0.00	0.00	0.50
KNN	0.92	0.07	0.06	0.06	0.51
Neural Network	0.05	1.00	0.08	0.04	0.51
SVM	0.96	0.00	0.00	0.00	0.50
Random Forest	0.96	0.00	0.00	0.00	0.50



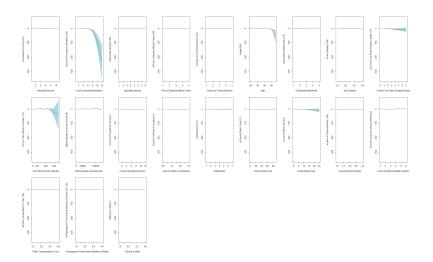
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#### After SMOTE NC

Classifiers	Accuracy	Recal	F1	Precision	AUC
Logistic	0.73	0.47	0.13	0.07	0.60
Polynomial Logistic	0.96	0.00	0.00	0.00	0.50
Logistic with FAMD	0.53	0.67	0.11	0.06	0.60
Lasso	0.72	0.45	0.12	0.07	0.59
Polynomial Lasso	0.78	0.36	0.12	0.07	0.58
Ridge	0.72	0.45	0.12	0.07	0.59
Polynomial Ridge	0.79	0.37	0.13	0.08	0.59
Logistic GAM	0.67	0.54	0.12	0.07	0.61
Naive Bayes	0.52	0.68	0.11	0.06	0.60
KNN	0.74	0.29	0.09	0.05	0.52
Neural Network	0.06	0.97	0.08	0.04	0.49
SVM	0.29	0.71	0.08	0.04	0.49
Random Forest	0.90	0.12	0.09	4	0.53

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# Logistic GAM Plots



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- Models Performance Increased after SMOTE NC.
- Linear models outperformed non-parametric models.
- Polynomial features didn't help increasing model's performance.
- No strong non-linear relationship between target variable and features.

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- Features about AFV industry can also impact the individual's behavior such as battery range, price etc (Literature Review).
- Suggestion for future work to take into account features from all different aspects mentioned above.

