Prediction of Travel Insurance Purchase

Group E

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Professor： Yubo Wang

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Agenda

- Project Introduction
- Data Overview
- Variable Selection
- Models
- Conclusion
- Future research
- Q&A

Project Introduction

Travel insurance reimburses policy holders for:

- lost baggage
- flight delays
- medical problems

Real dataset and business problem from a tour & travels company in India

Data Overview

Total: 1987 observations

Target	Travel Insurance	1 if the customer purchased travel insurance package in 2019, and 0 otherwise
Predictors	Age	Age of the customer
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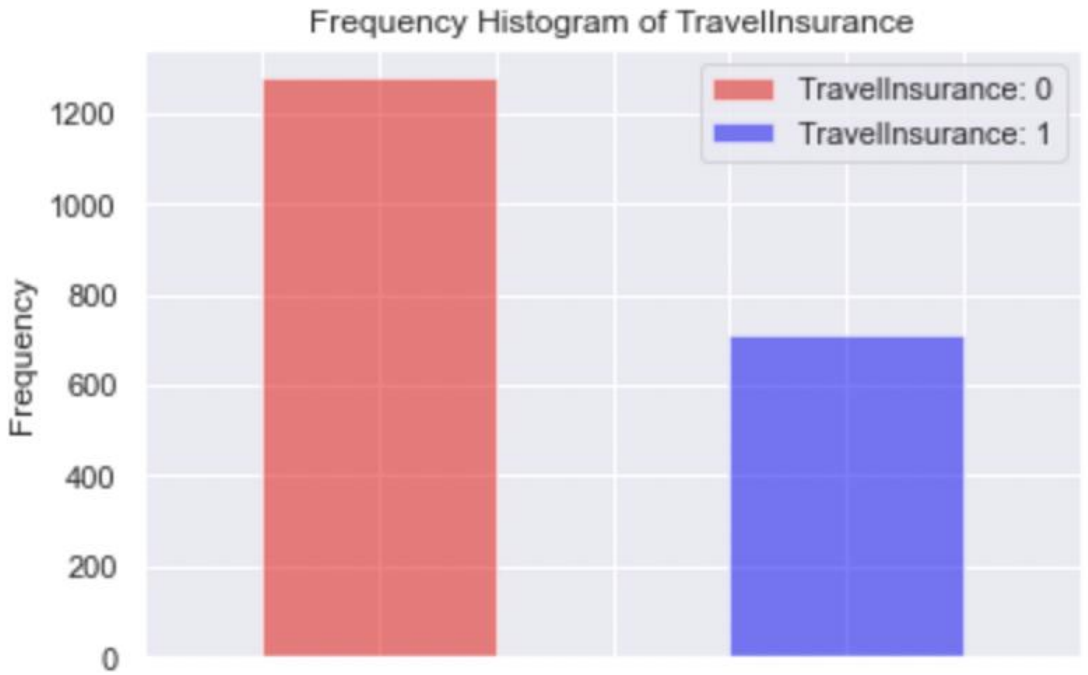
	Frequent Flyer	Whether the customer booked at least 4 flight tickets in the past two years (2017-2019)
	Ever Travelled Abroad	Whether the customer has travelled to a foreign country

Data Visualization

Target: Travel Insurance (TI)

- Out of 1987 observations
- 710 (35.7%) purchased TI
- 1277 (64.3%) did not purchase TI



Data Visualization

Age

TravelInsurance	0	1
Age		
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26	74	74
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28	401	105
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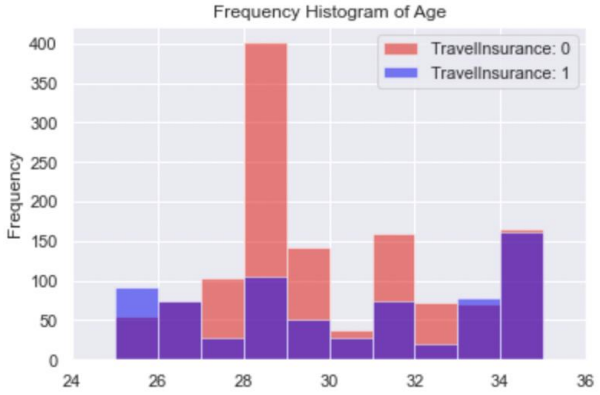

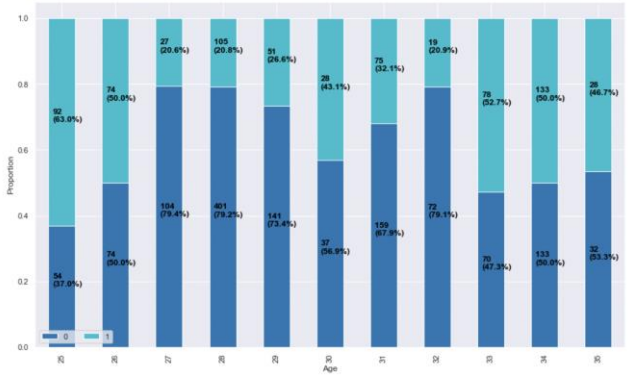

Employment Type

TravelInsurance	0	1
Employment Type		
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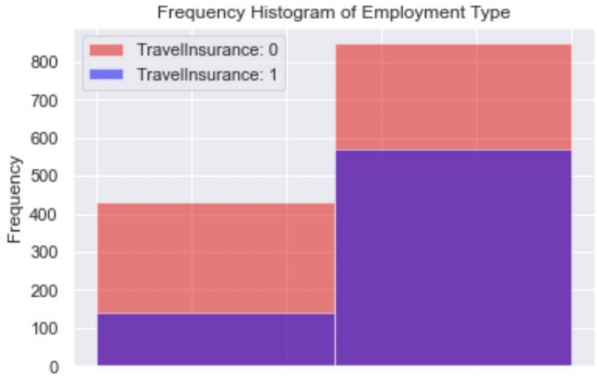
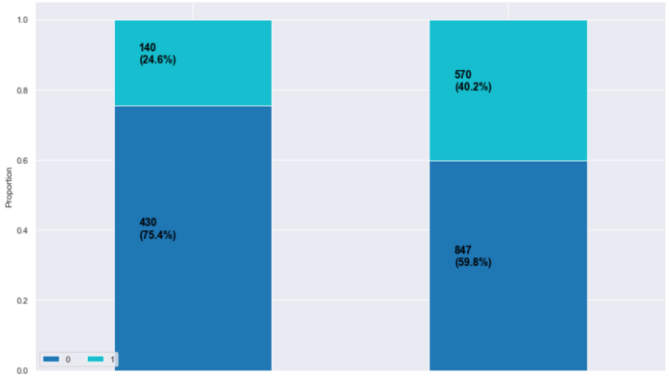
Private Sector/Self Employed	847	570





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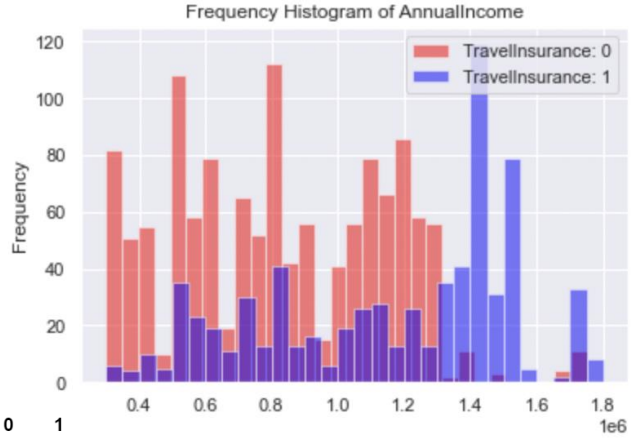
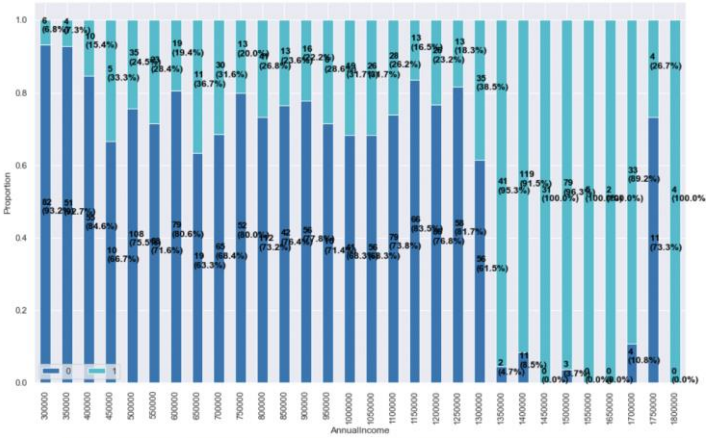
Annual Income (in Rupees)

- Range: [300,000, 1,800,000]





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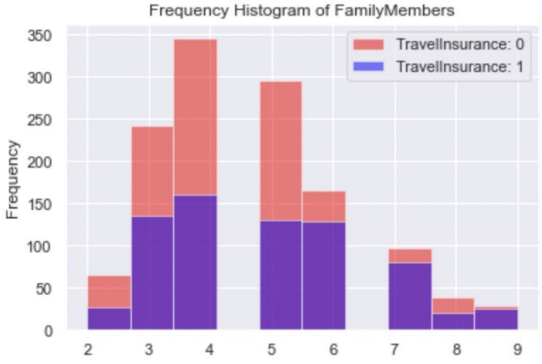

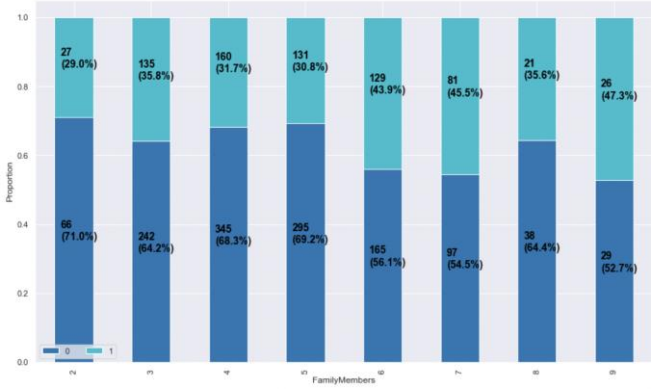

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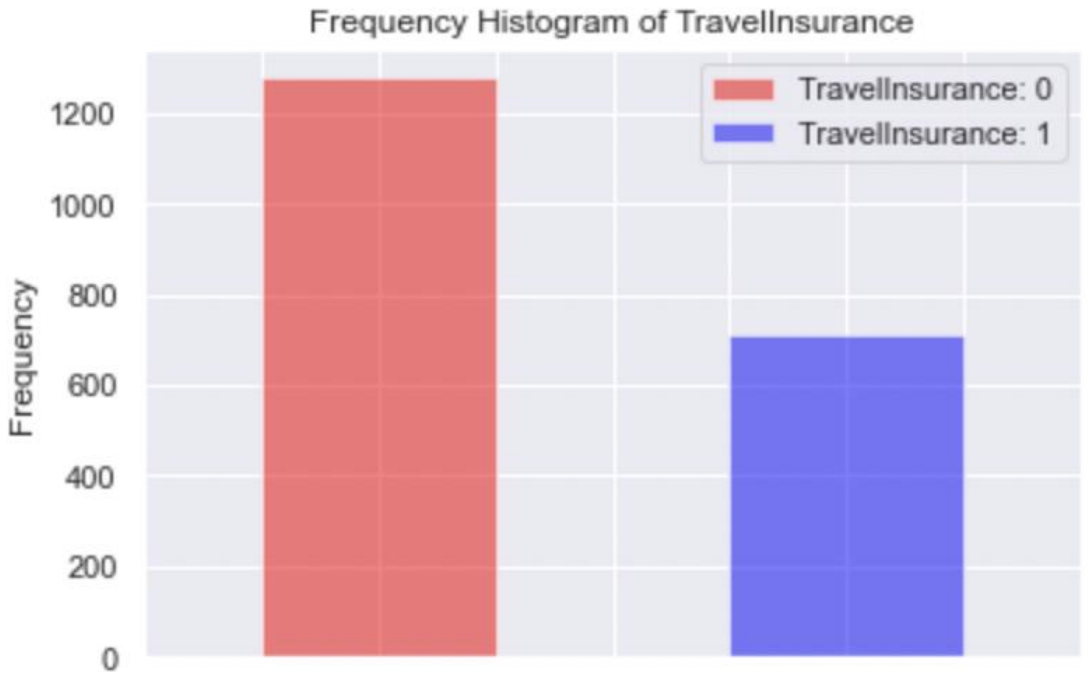

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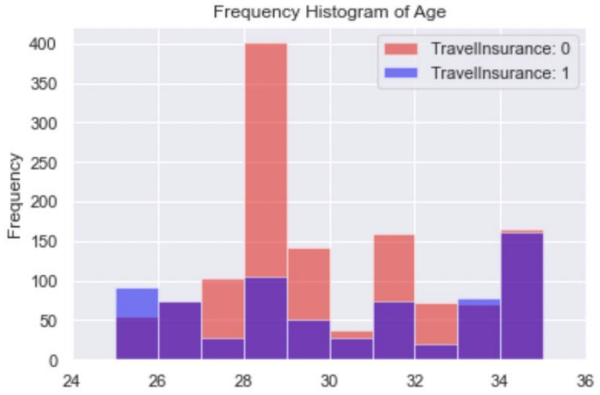

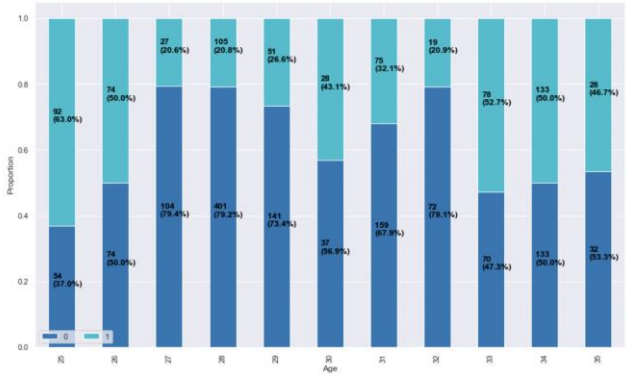

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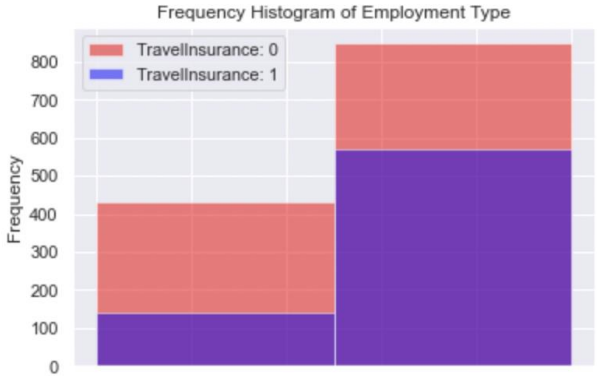

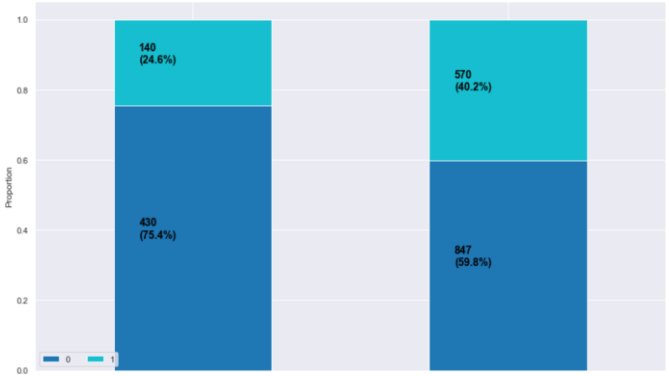

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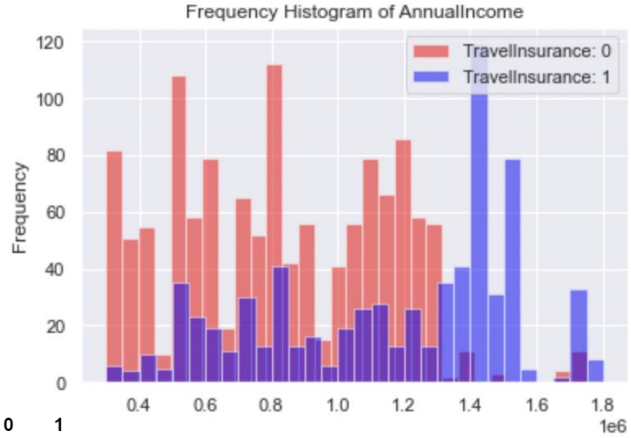

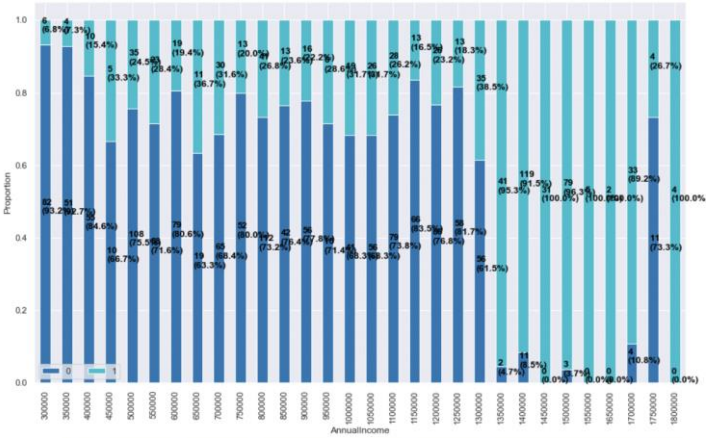

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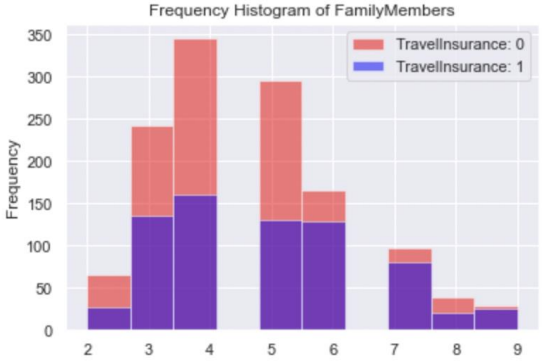
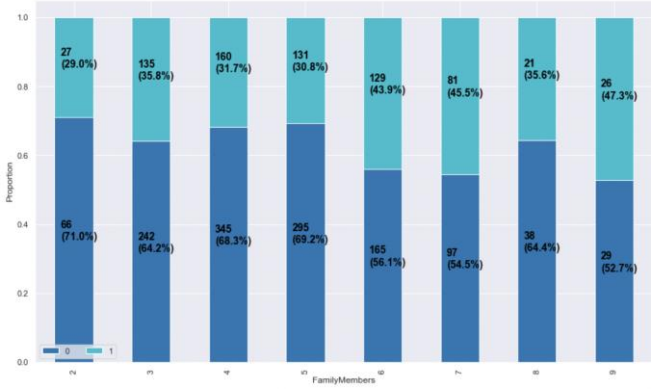
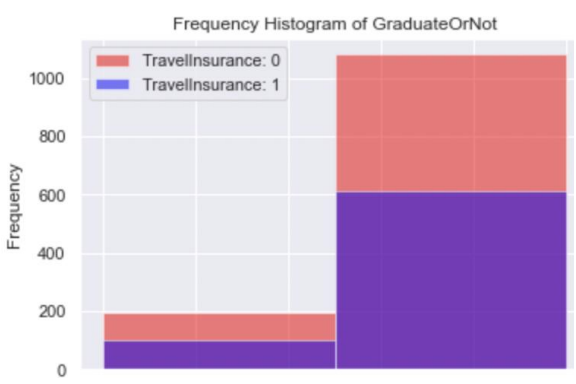


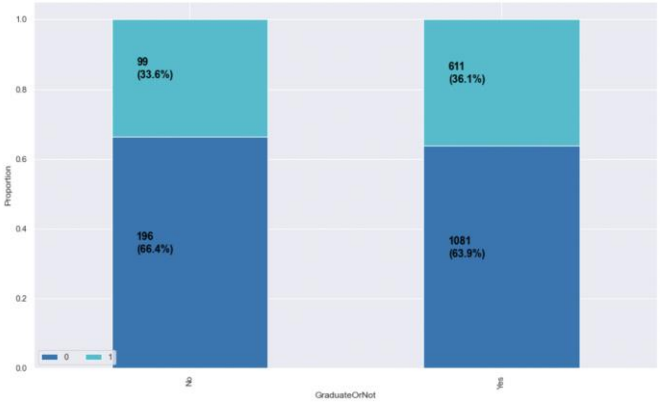


Data Visualization

Graduate Or Not

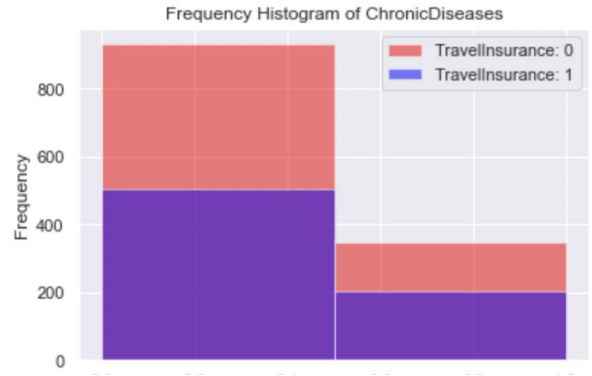
TravelInsurance	0	1
GraduateOrNot		
No	196	99
Yes	1081	611

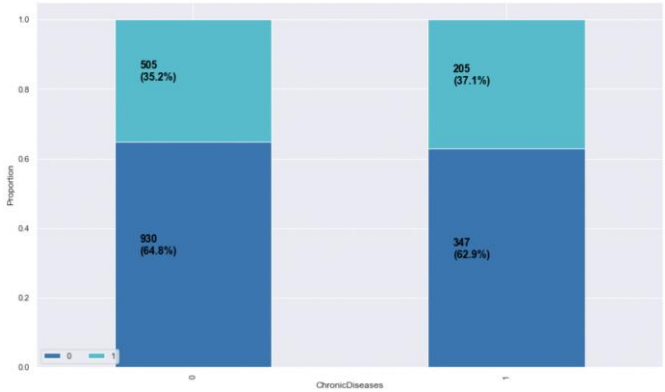




Chronic Disease

TravelInsurance	0	1
ChronicDiseases		
0	930	505
1	347	205

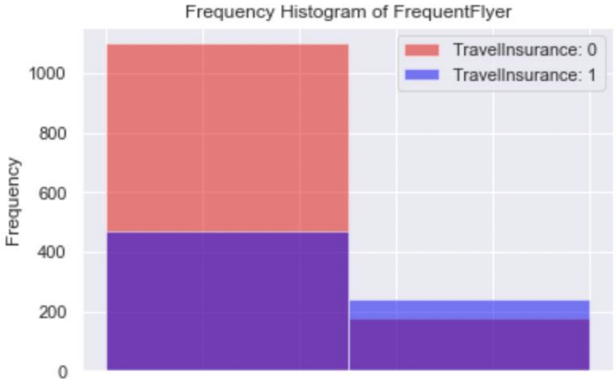


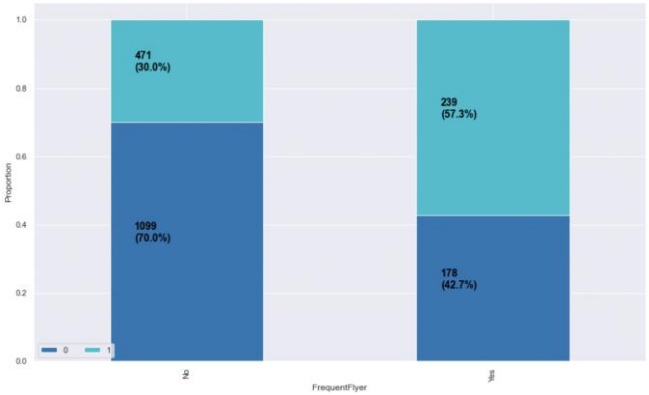


Data Visualization

Frequent Flyer

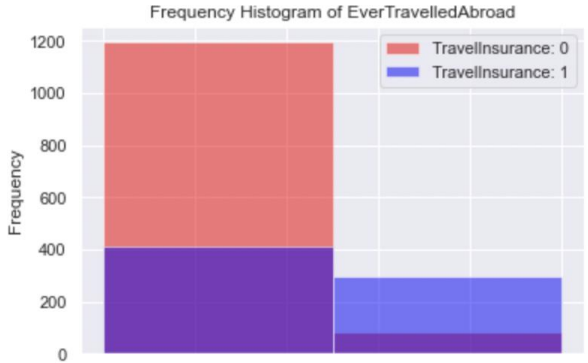
TravelInsurance	0	1
FrequentFlyer		
No	1099	471
Yes	178	239

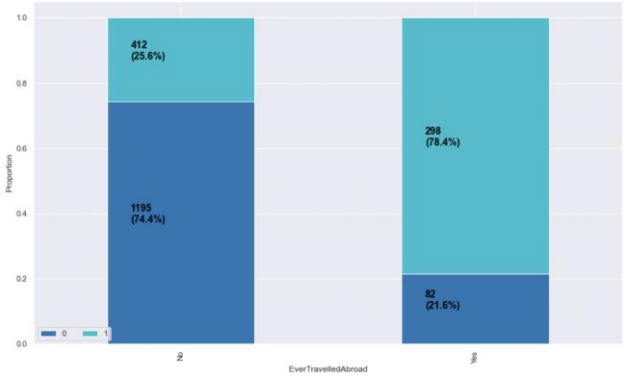




Ever Travelled Abroad

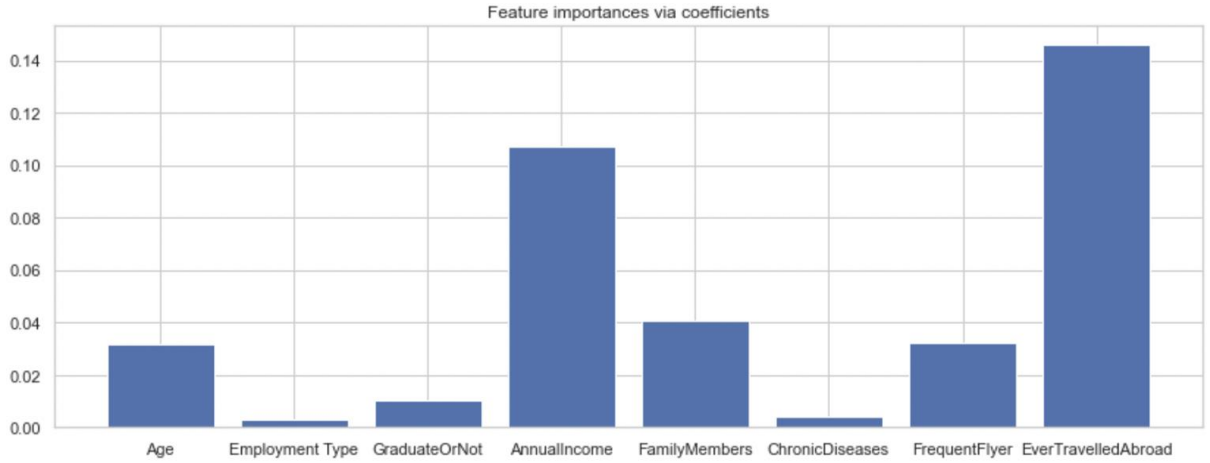
TravelInsurance	0	1
EverTravelledAbroad		
No	1195	412
Yes	82	298





Feature Selection

- Ever Travelled Abroad and Annual Income are the most important predictors, followed by Family Members, Age and Frequent Flyer.
- Graduate Or Not, Employment Type and Chronic Diseases seem to be insignificant.



Models

Logistic Regression

All predictors

Test Accuracy : 76.63%

(EverTravelledAbroad,
AnnualIncome,
FamilyMembers,
Age,
FrequentFlyer,
Graduate Or Not,
Employment type,
Chronic Diseases)

5 predictors

Test Accuracy : 77.14%

(EverTravelledAbroad,
AnnualIncome,
FamilyMembers,
Age,
FrequentFlyer.)

3 predictors

Test Accuracy : 76.38%

(EverTravelledAbroad,
AnnualIncome,
FamilyMembers)

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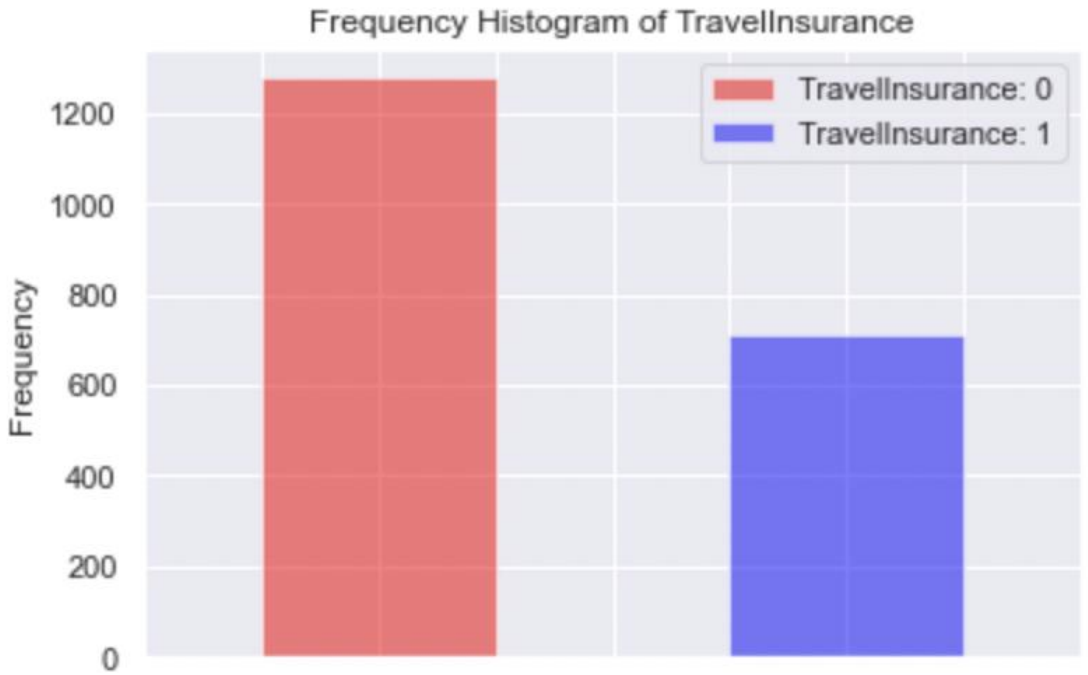

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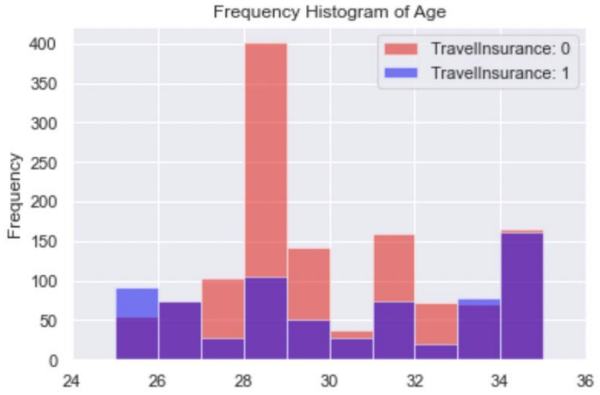

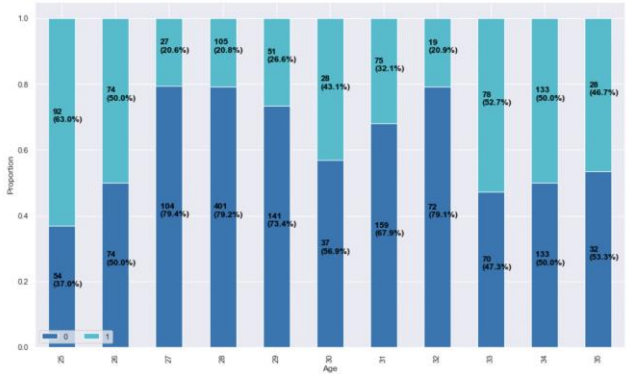

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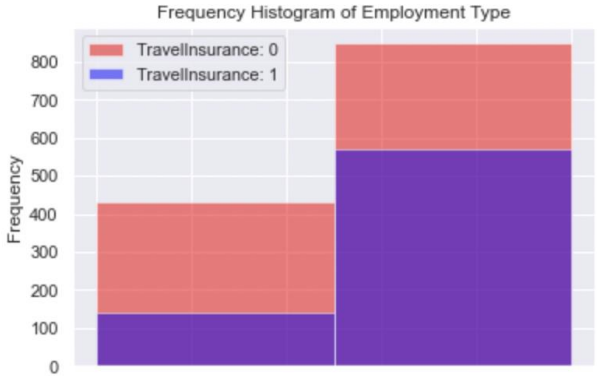

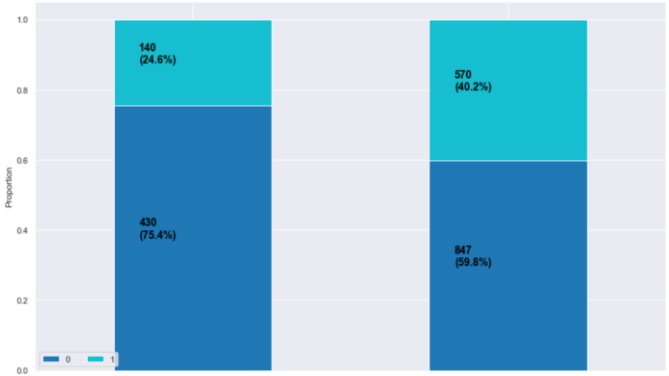

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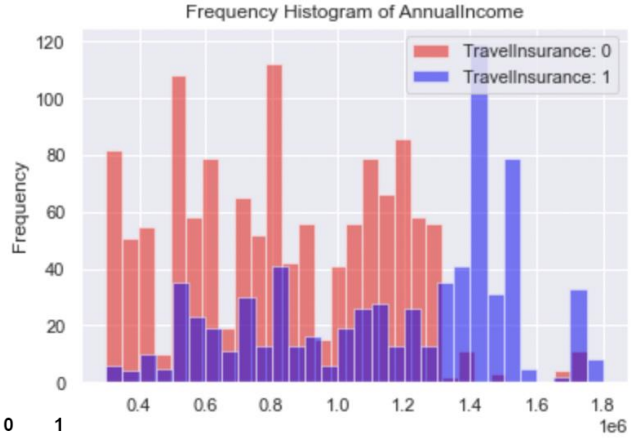

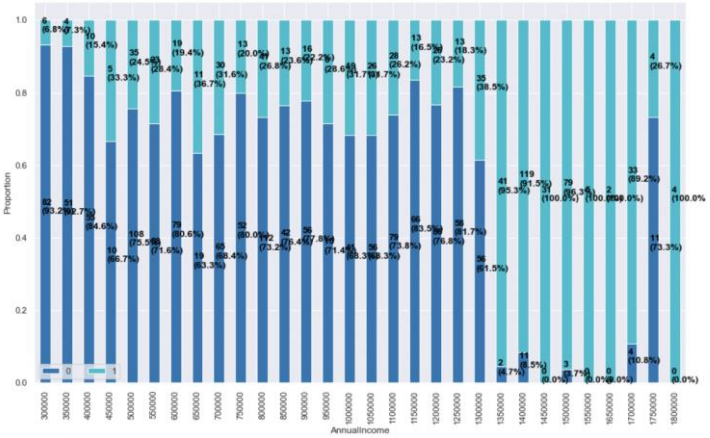

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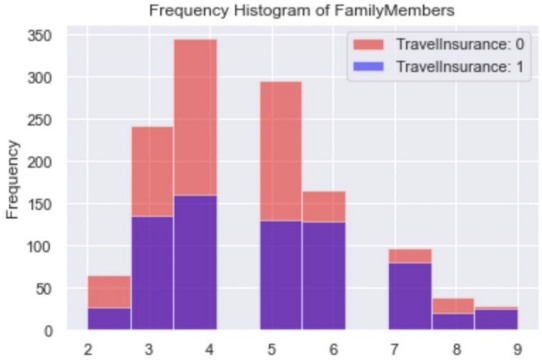

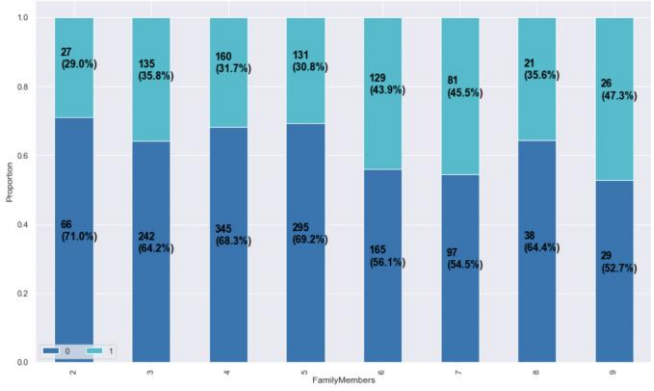

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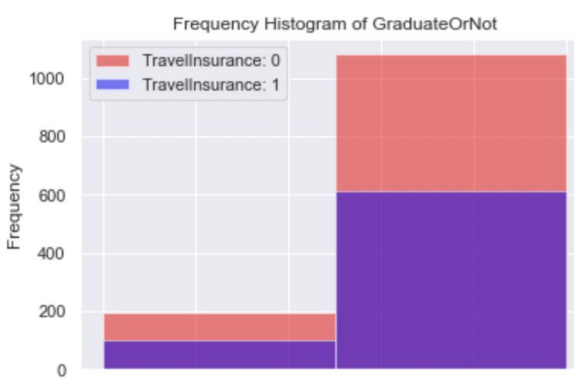
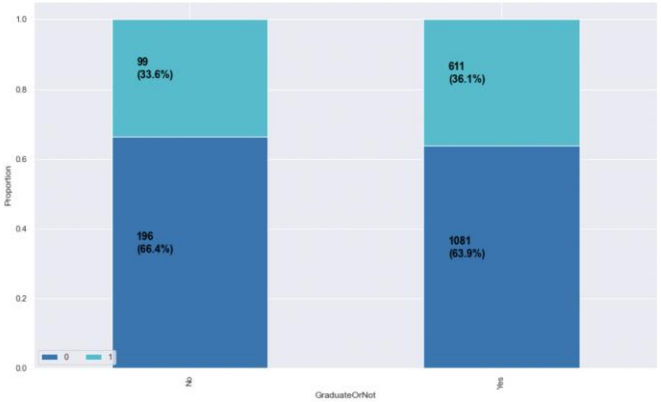
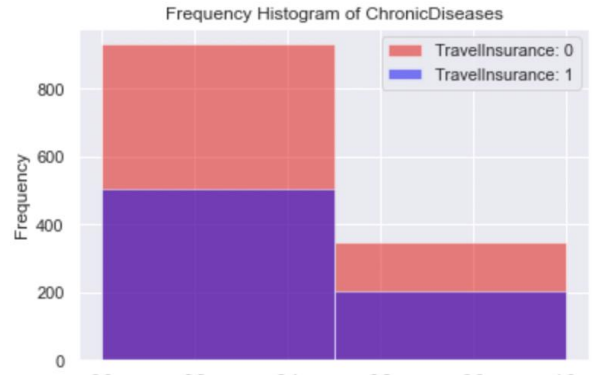
Yes	1081	611

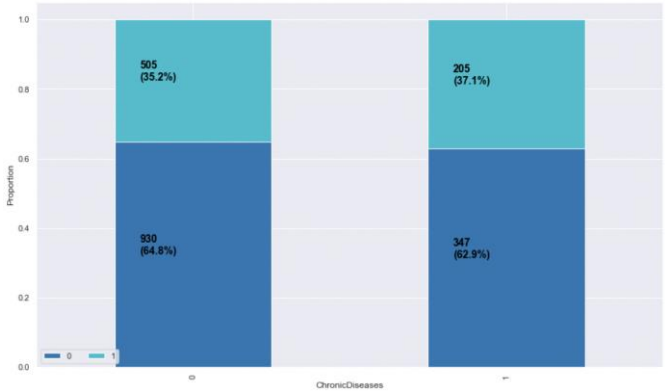




Chronic Disease

TravelInsurance	0	1
ChronicDiseases		
0	930	505
1	347	205

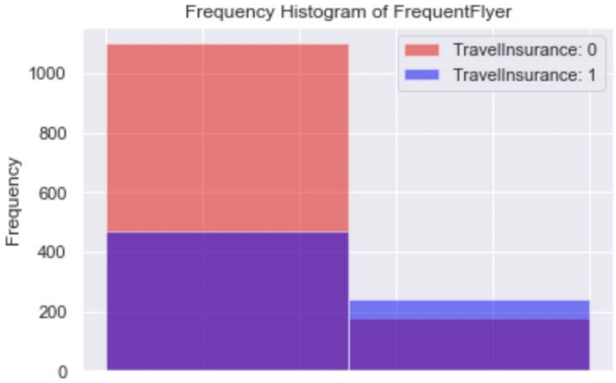


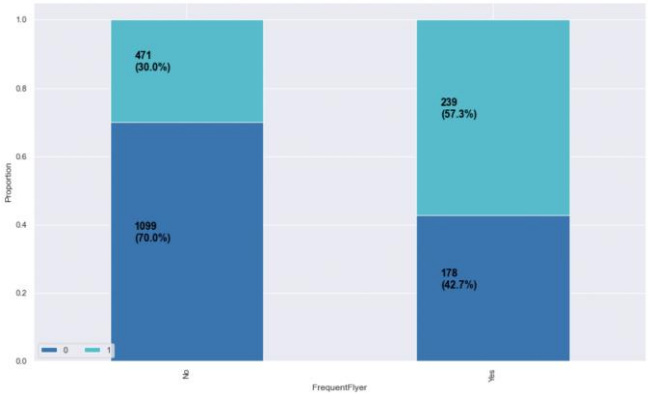


Data Visualization

Frequent Flyer

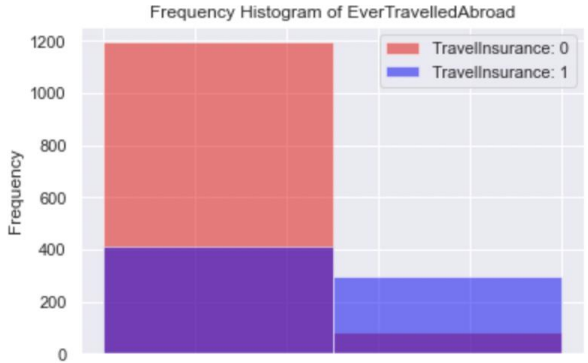
TravelInsurance	0	1
FrequentFlyer		
No	1099	471
Yes	178	239

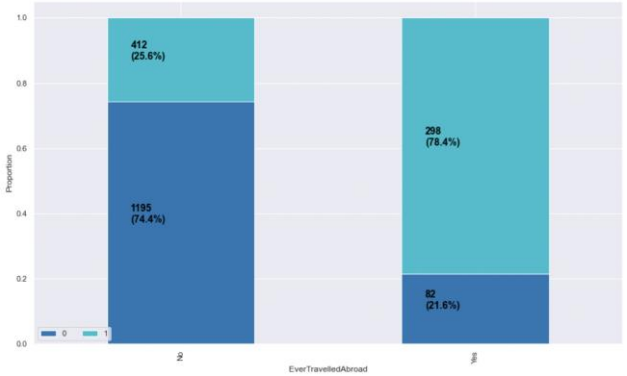




Ever Travelled Abroad

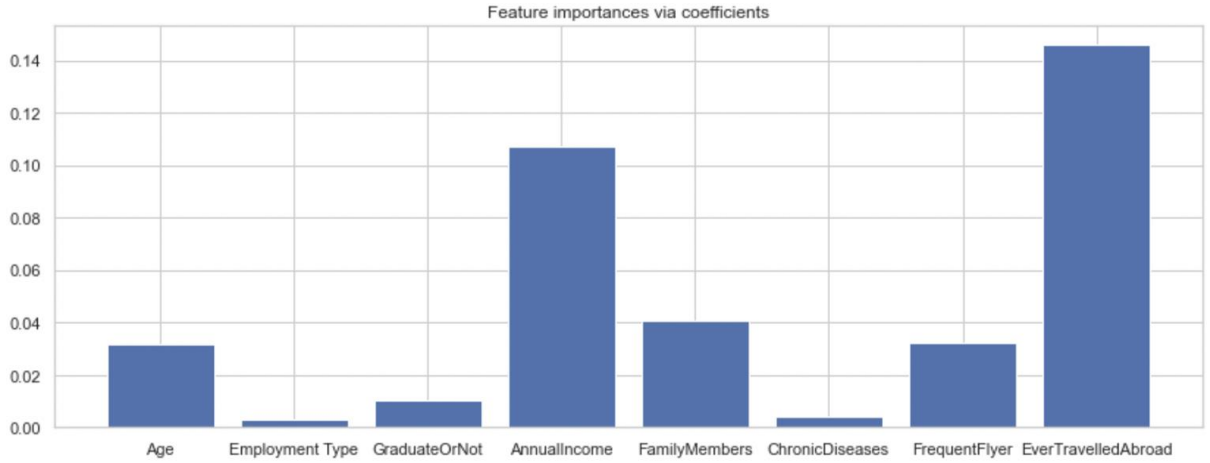
TravelInsurance	0	1
EverTravelledAbroad		
No	1195	412
Yes	82	298





Feature Selection

- Ever Travelled Abroad and Annual Income are the most important predictors, followed by Family Members, Age and Frequent Flyer.
- Graduate Or Not, Employment Type and Chronic Diseases seem to be insignificant.



Models

Logistic Regression

All predictors

Test Accuracy : 76.63%

(EverTravelledAbroad,
AnnualIncome,
FamilyMembers,
Age,
FrequentFlyer,
Graduate Or Not,
Employment type,
Chronic Diseases)

5 predictors

Test Accuracy : 77.14%

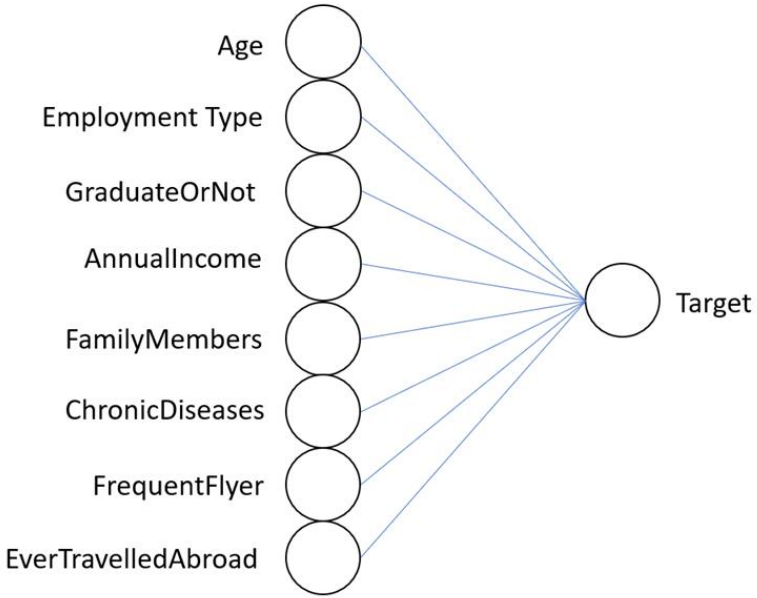
(EverTravelledAbroad,
AnnualIncome,
FamilyMembers,
Age,
FrequentFlyer.)

3 predictors

Test Accuracy : 76.38%

(EverTravelledAbroad,
AnnualIncome,
FamilyMembers)

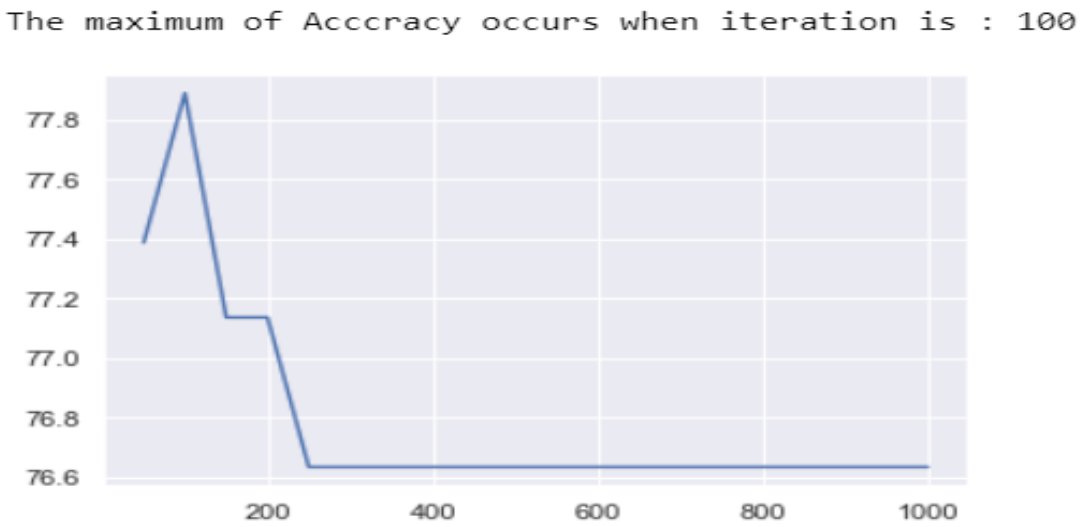
Logistic Regression-Neural network model



Learning rate:10%
Initial weight:0.01
Initial bias:0.00
Sigmoid activation function

Logistic Regression-Neural network

Neural network model runs 100 iteration can get the highest accuracy

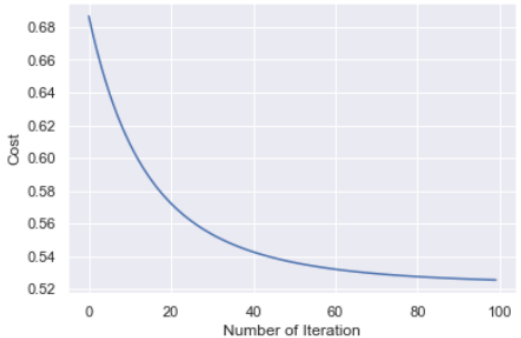


Logistic Regression-Neural network

All predictors

Test Accuracy : 77.89%

```
iteration: 100
cost: 0.525468061646591
```

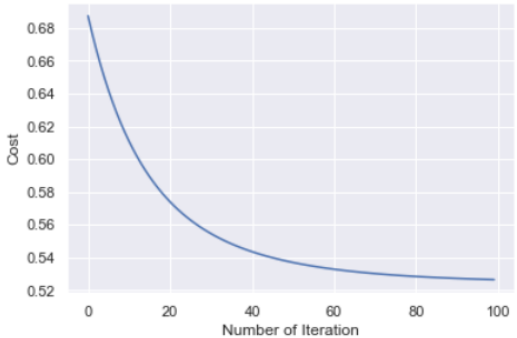



```
Manuel Test Accuracy: 77.89%
```

5 predictors

Test Accuracy : 77.89%

```
iteration: 100
cost: 0.5263271311902352
```

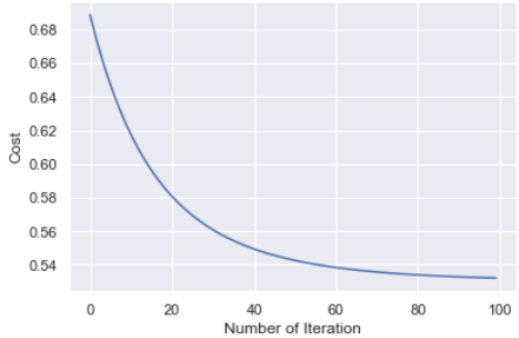



```
Manuel Test Accuracy: 77.89%
```

3 predictors

Test Accuracy : 77.14%

```
iteration: 100
cost: 0.5321283157357334
```




```
Manuel Test Accuracy: 77.14%
```

KNN (K=2)

All predictors

2 NN Score: 78.89%

5 predictors

2 NN Score: 77.64%

3 predictors

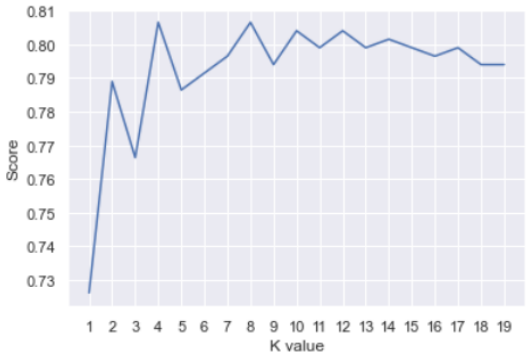
2 NN Score: 77.14%

KNN-finding best K

All predictors

1.K=4

2.KNN Score is 80.65%

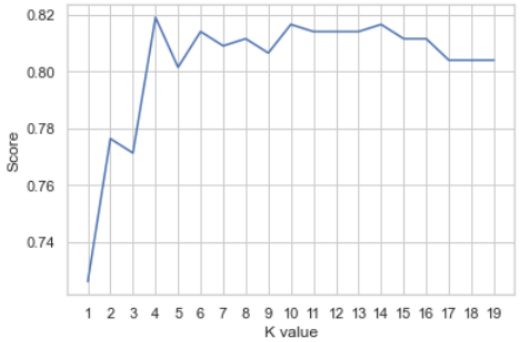



```
Maximum KNN Score is 80.65%
The Maximun KNN is  4
```

5 predictors

1.K=4

2.KNN Score is 81.91%

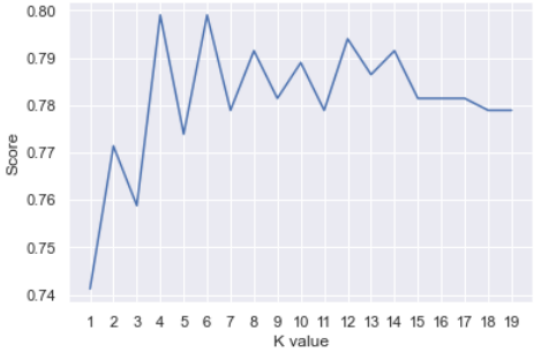



```
Maximum KNN Score is 81.91%
The Maximun KNN is  4
```

3 predictors

1.K=4

2.KNN Score is 79.90%



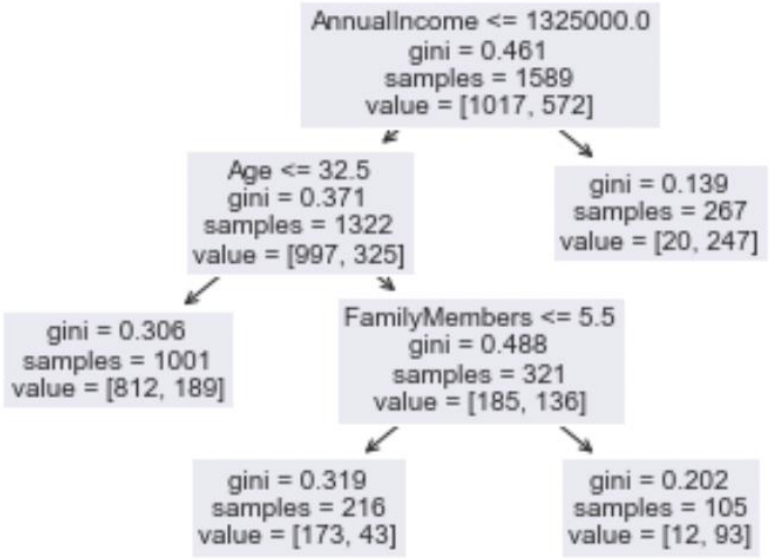

```
Maximum KNN Score is 79.90%
The Maximun KNN is  4
```

Decision Tree

- Recursive binary splitting process that splits data into a finite set of non-overlapping regions.
- Pro: easy to interpret and display; no probability distribution assumption
- Con: vulnerable to overfitting.
- All predictors: 76.63%, five predictors: 76.13%, three predictors: 78.39%.

Pruned Decision Tree

- Pruning is necessary to reduce the size of a tree and remove less valuable splits.
- Pro: reduces overfitting and can lead to a simpler, more interpretable tree; automatically performs variable selection.
- All predictors and five predictors: pruned tree has three predictors with 82.16% accuracy.
- Three predictors: pruned tree has two predictors with 80.4% accuracy.



Bagging

- Combines the results of a set of decision trees fitted to a different bootstrapped sample of the training data, then using the average to make a final prediction.
- Pro: reduces overfitting and variance of the base tree, leading to higher prediction accuracy.
- Con: loses the interpretability of decision trees and is computationally intensive.
- All predictors: 79.15%, five predictors: 80.65%, three predictors: 77.64%.

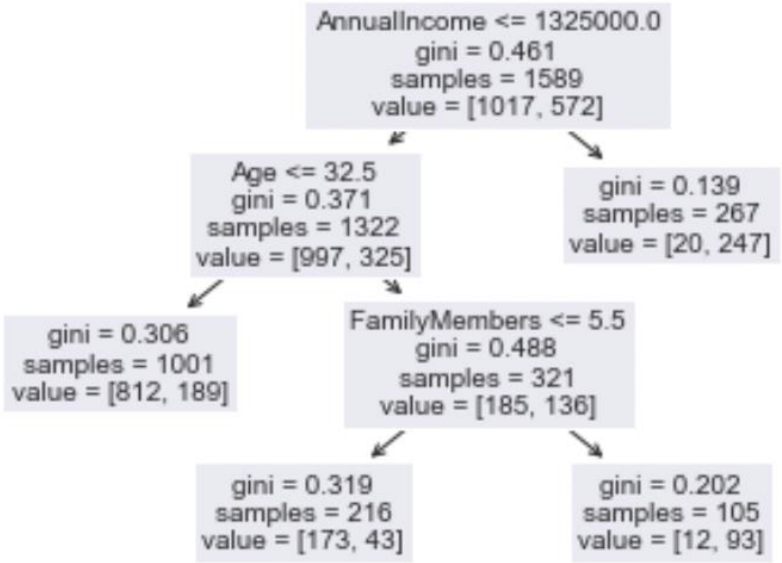
Model Comparison & Observations

- Models with 5 predictors result in the best performance out of the three
- Low sensitivity and high specificity due to imbalance data

Models	Accuracy	Sensitivity	Specificity
Logistic Regression (8 predictors)	76.63%	51.45%	90.00%
Logistic Regression (5 predictors)	77.14%	51.45%	90.77%
Logistic Regression (3 predictors)	76.38%	50.00%	90.38%
Neural Network (8 predictors)	77.89%	53.62%	90.77%
Neural Network (5 predictors)	77.89%	54.34%	90.38%
Neural Network (3 predictors)	77.14%	52.17%	90.38%
KNN (k=4, 8 predictors)	80.65%	60.14%	85.38%
KNN (k=4, 5 predictors)	81.91%	61.59%	85.38%
KNN (k=4, 3 predictors)	79.90%	57.25%	85.77%
Decision Tree (8 predictors)	76.63%	65.22%	84.23%
Decision Tree (5 predictors)	76.13%	57.97%	85.77%
Decision Tree (3 predictors)	78.39%	53.62%	91.54%
Pruned Decision Tree (3 predictors)	**82.16%**	**57.97%**	**95.00%**
Pruned Decision Tree (2 predictors)	80.40%	51.45%	95.77%
Bagging (8 predictors)	79.15%	64.49%	86.92%
Bagging (5 predictors)	80.65%	64.49%	89.23%
Bagging (3 predictors)	77.64%	55.80%	89.23%

Final Model

- Pruned decision trees with three predictors: Annual Income, Age, and Family Members.
- Highest test accuracy out of all models: 82.16%.
- Simplest model to explain to a general audience.



Conclusion

- Check dataset is complete and usable
- Split dataset into training and testing with the ratio 8:2
- Fit different models using training set with different subsets of predictors
- Find the best model based on test accuracy and interpretability

Future Research

- Sampling techniques to address imbalance data
- Other target of interest
- Other potential predictors (Distance, Duration, Reason, Timing, Mode, Region)
- Other possible models (Elastic Net Model, Boosting, Support Vector Machines)

Thank you !