Data: Holiday Package Prediction

BA 706 REVISION

 $\mathbf{B}\mathbf{Y}$

Risikat Hameed

Table of Contents

Table of Contents	1
Description of the Problem	2
File Import	2
Data Wrangling	2
Among 14 variables left 6 are Categorical (Nominal) variables:	3
Data dictionary	4
Diagram	5
Decision Tree	6
Comparison of Decision Tree Models	6
Probability Tree	6
3-Way Tree	8
Lift Tree	10
Misclassification Tree	12
Maximal Tree	14
Logistic Regression	16
Data Massaging	16
Comparison of Regressions	17
Backward Regression	17
Forward Regression	19
Stepwise Regression	20
Neural Network	21
Data Massaging	21
Hidden Units	21
Iterations	21
Input Reduction Neural Network Node	23
Model Comparison	25
<u>Conclusion</u> References	26

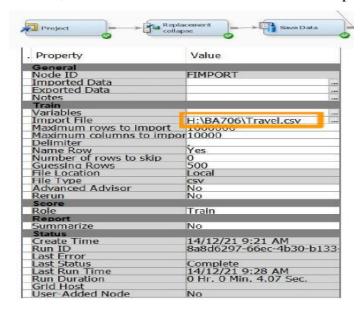
Description of the Problem

Introducing a new package offering is one way to broaden the customer base. The company currently offers five different types of packages: Basic, Standard, Deluxe, Super Deluxe, and King. Looking at data from the previous year, we discovered that 18% of customers purchased the packages. However, the marketing cost was quite high because customers were contacted at random without regard for the information available. The company is about to launch a new product called the Wellness Tourism Package. Wellness tourism is defined as travel that allows the traveler to maintain, improve, or begin a healthy lifestyle, as well as support or increase one's sense of well-being. However, this time the company wishes to leverage the available data of existing and potential customers in order to maximize marketing expenditure.

File Import

We imported the CSV file (under Train in the Property panel on the right) and saved it as an SAS dataset using the Export node ('Save Data'). This enables us to quickly connect the Export Node. The original (raw) dataset provided contains 19 input variables. We found no evidence of potential data leakage or data duplication.

The target variable for Holiday Package Prediction dataset is "ProdTaken". It is a binary variable, which identifies whether the customer has purchased the product: 0 - No; 1 - Yes.



Data Wrangling

After analyzing the data, I discarded 5 variables

1. CityTier - indicates the level of the destination city's development.

Irrelevant, gives no valuable information to the model.

2. DurationOfPitch - duration of the marketing pitch.

Redundant, gives no valuable information to the model.

3. OwnCar - identifies whether the customer has a car.

Redundant given the presence of the Monthly Income variable, gives no valuable information to the model.

4. PitchSatisfactionScore - Customer's satisfaction with marketing pitch. Ranges from 1 to

5.

Highly correlated with the Target variable.

5. ProductPitched - Advertised product during the marketing pitch.

Gives no valuable information to the model.

The other variables are Categorical (Nominal) variables:

- 1. Designation:
 - a. AVP (Assistant Vice President)
 - b. Executive
 - c. Manager
 - d. Senior Manager
 - e. VP (Vice President)
- 2. Gender:
 - a. Female
 - b. Male
 - c. Undisclosed (Noted as Female)
- 3. Marital Status:

- a. Divorced
- b. Married
- c. Single

4. Occupation:

- a. Freelance
- b. Large Business
- c. Salaried
- d. Small Business

5. ProductPitched

- a. Basic
- b. Deluxe
- c. King
- d. Standard
- e. Super Deluxe

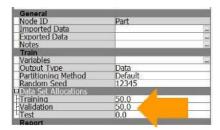
6. TypeofContact

- a. Company invited
- b. Self-Enquiry

Since the Unmarried and Single categories are the same, I used a spare node to reduce the Marital Status variable (see below for settings).

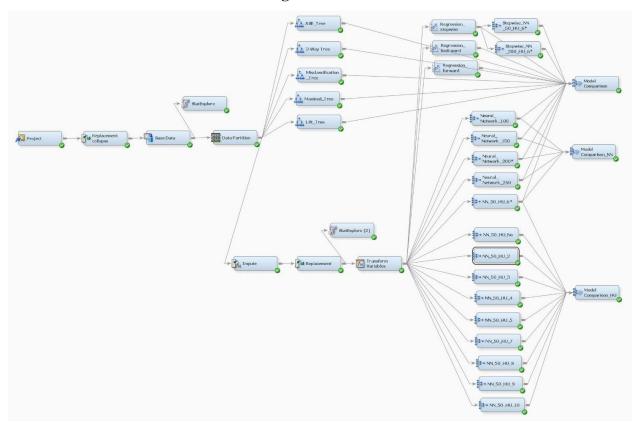


Next, I examined the source data. There are 4,888 observations in the dataset, along with missing values. The data is partitioned into training and validation data to optimize performance, the data is assigned 50% for training and 50% for validation.



	Nome	Model	Measuremen	Description
	Name	Role	t Level	Description
1	Age	Input	Interval	Age of the Customer
2	CityTier	Rejected	Interval	Level of destination city development.
3	CustomerID	ID	Interval	Unique Customer ID
4	Designation	Input	Nominal	Customer's job title
5	DurationOfPitch	Rejected	Interval	Duration of the pitch. Rejected
6	Gender	Input	Nominal	Gender of the Customer
7	MaritalStatus	Input	Nominal	Marital status of the customer
8	MonthlyIncome	Input	Interval	Customer's monthly income
9	NumberOfChildrenVisiting	Input	Interval	Number of children who are supposed to join the trip
10	NumberOfFollowups	Input	Interval	Number of outreach interactions after
11	NumberOfPersonVisiting	Input	Interval	Number of participants in the trip
12	NumberOfTrips	Input	Interval	Number of trips taken
13	Occupation	Input	Nominal	Type of Customer's employment
14	OwnCar	Rejected	Binary	Identifies whether the Customer has a car
15	Passport	Input	Binary	Identifies whether Customer has a passport when pitched
16	PitchSatisfactionScore	Rejected	Interval	Customer's satisfaction with marketing pitch. Can be from 1 to 5
17	PreferredPropertyStar	Input		Preferred property class. Can be from 1 to 5 (stars)
18	ProdTaken	Target	Binary	Identifies whether the customer has purchased the product. Values can be 0 or
19	ProductPitched	Rejected	Nominal	Advertised product during the marketing pitch
20	TypeofContact	Input	Nominal	How was customer interaction initiated?

SAS Diagram

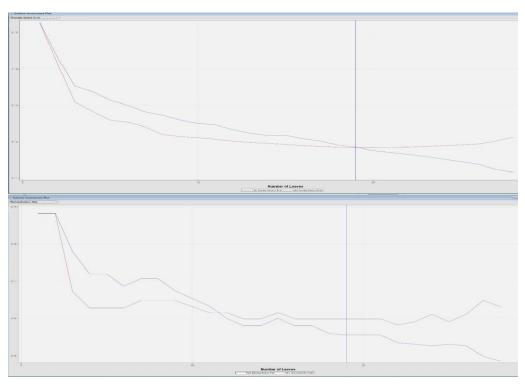


Decision Tree

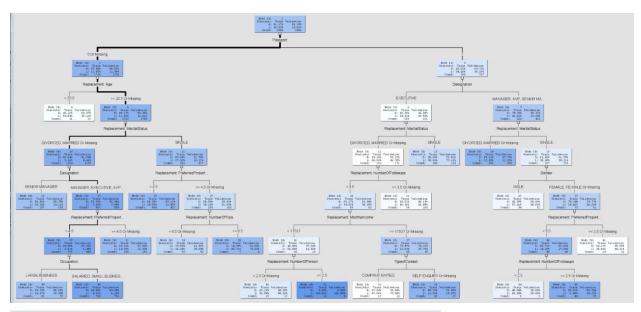
After running the decision tree models (returning trees with the assessment measures below). I froze the model and disabled node training.

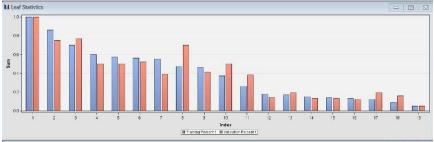
- Probability Tree (smallest average square error)
 - o Maximum branch: 2
 - o Maximum branch: 3 (referred to as 3-way tree)
- Lift Tree (prediction of the top n% of the ranked observations)
- Misclassification Tree (lowest misclassification rate)
- Maximal Tree (largest average profit and smallest average loss if a profit or loss matrix is defined)

Probability Tree



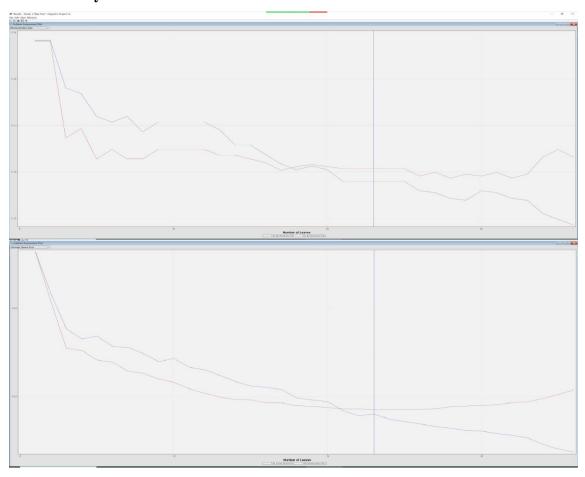
Use Frozen	Tree	Yes		-		
Use Multiple		No				
■Splittina Rul	e					
Interval Tard	get Criterion	ProbF				
-Nominal Tar	get Criterion	ProbChise	3			
Ordinal Tarc	et Criterion	Entropy				
Significance	Level	0.2				
Missing Valu	es	Use in sea	arch			
Use Input O	nce	No				
- Maximum Br	ranch	2				
-Maximum D		6				
Minimum Ca	tegorical Size	5				
■Node						
Leaf Size		5				
Number of F		5				
Number of S	Surrogate Rul	e0				
Split Size						
■Split Search		460				
Use Decision	1S	No				
Use Priors		No				
Exhaustive		5000				
Node Sampl	e	20000				
□Subtree	e de la companya de					
Method		Assessme	ent			
Number of L		1				
Assessment			Square Error			
Assessment	Fraction	0.25				
Fit Statistics	Statistics La	ibel	Train		Validation	
NOBS MISC	Sum of Fre			2443		2445 0.159918
MAX	Maximum A	bsolute Error		0.94993		0.94993
SSE ASE	Sum of Squ	lared Errors		79.3291 .118569		579.0059 0.118406
RASE	Root Avera	ge Squared		.344339		0.344102
DIV	Divisor for A	ASE ses of Free		4886 2443		4890
OF 1	Total Degre	999 01 1198		2443		



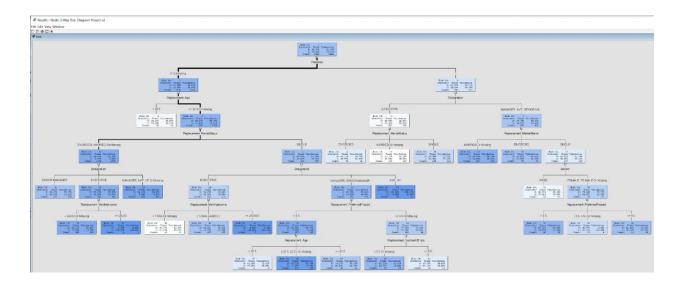


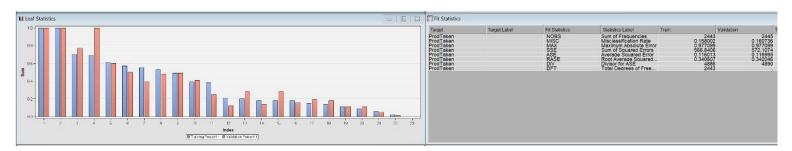
- The optimal number of leaves is 19.
- The variable used for the first split was Passport. The competing splits were Age and
 Designation. Other important variables are Marital Status, Gender, Preferred Property
 Score and Number of Follow-ups. As can be seen in the tree, variables like Monthly
 Income were included but less important.
- Valid average square error (ASE) = 0.118406
- Valid misclassification rate = 0.159918

3-Way Tree



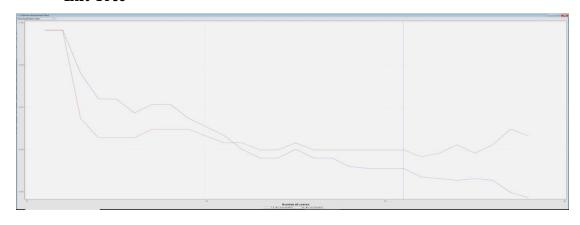
Use Frozen Tree	Yes
Use Multiple Targets	No
Splitting Rule	
Interval Target Criterion	ProbF
Nominal Target Criterion	ProbChisq
Ordinal Target Criterion	Entropy
Significance Level	0.2
Missing Values	Use in search
Use Input Once	No
- Maximum Branch	3
Maximum Depth	6
Minimum Categorical Size	5
■Node	
Leaf Size	5
Number of Rules	
Number of Surrogate Rule	e0
Split Size	
∃Split Search	70:
Use Decisions	No
Use Priors	No
Exhaustive	5000
Node Sample	20000
⊒Subtree	
Method	Assessment
Number of Leaves	1
- Assessment Measure	Average Square Error
Assessment Fraction	0.25

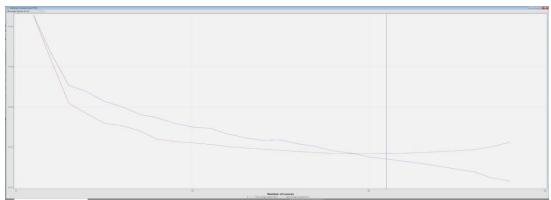




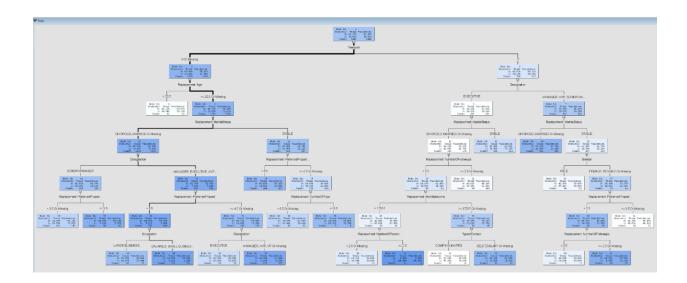
- The optimal number of leaves is 23.
- The variable used for the first split was Passport. The competing splits were Age and
 Designation. Another important variable is Marital Status. As can be seen in the tree,
 variables (Monthly Income, Preferred Property Score and Number of Trips) were
 included but less important.
- Valid average square error (ASE) = 0.116995
- Valid misclassification rate = 0.160736

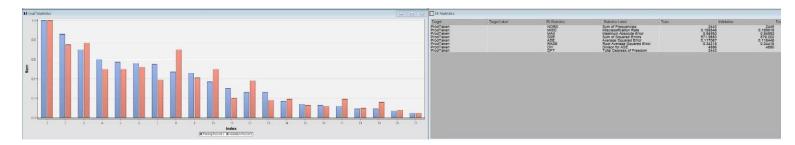
Lift Tree





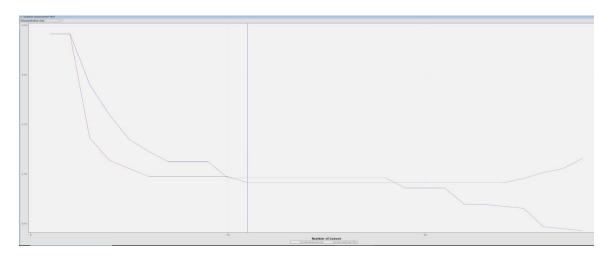
Use Frozen Tree	Yes	
Use Multiple Targets	No	
■Splittina Rule		
Interval Target Criterion	ProbF	
Nominal Target Criterion	ProbChisa	
Ordinal Target Criterion	Entropy	
Significance Level	0.2	
Missing Values	Use in search	
Use Input Once	No	
Maximum Branch	2	
Maximum Depth	6	
Minimum Categorical Size	5	
■Node		
Leaf Size	5	
Number of Rules	5	
Number of Surrogate Rule	0	
Split Size		
■Split Search		
Use Decisions	No	
Use Priors	No	
Exhaustive	5000	
1. Node Sample	20000	
□Subtree -		
Method	Assessment	
Number of Leaves	1	
- Assessment Measure	Lift	
Assessment Fraction	0.25	
The second secon		

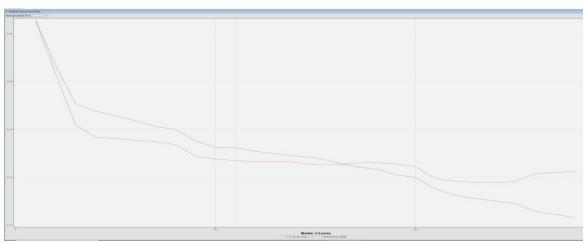




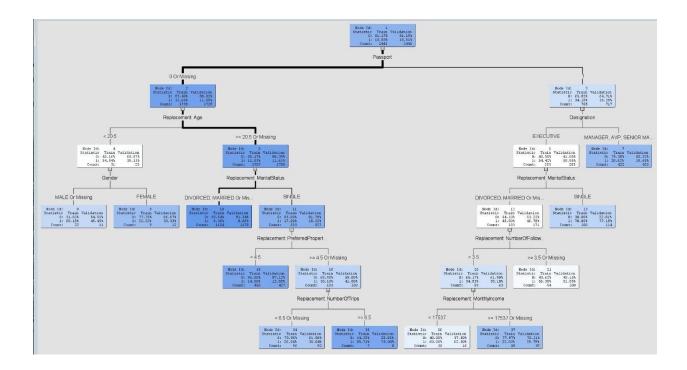
- The optimal number of leaves is 21.
- The variable used for the first split was Passport. The competing splits were Age and
 Designation. Another important variable is Marital Status. As can be seen in the tree,
 variables like Monthly Income, Gender, Preferred Property Score and Number of
 Follow-ups were included but less important.
- Valid average square error (ASE) = 0.118446
- Valid misclassification rate = 0.159918

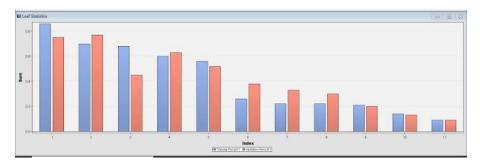
Misclassification Tree





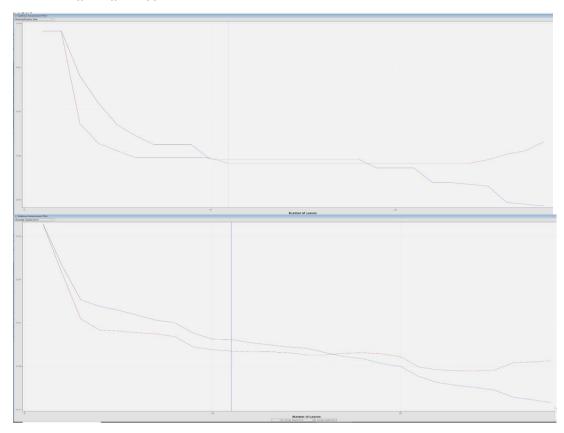
Use Frozen Tree	Yes
Use Multiple Targets	No
Splittina Rule	
Interval Target Criterion	ProbF
Nominal Target Criterion	ProbChisa
Ordinal Target Criterion	Entropy
Significance Level	0.2
Missing Values	Use in search
Use Input Once	No
Maximum Branch	2
Maximum Depth	6
Minimum Categorical Size	5
Node	
Leaf Size	5
Number of Rules	
Number of Surrogate Rule	0
Split Size	
Split Search	
Use Decisions	No
Use Priors	No
Exhaustive	5000
Node Sample	20000
Subtree	W11-11
Method	Assessment
Number of Leaves	1
Assessment Measure	Misclassification
Assessment Fraction	0.25



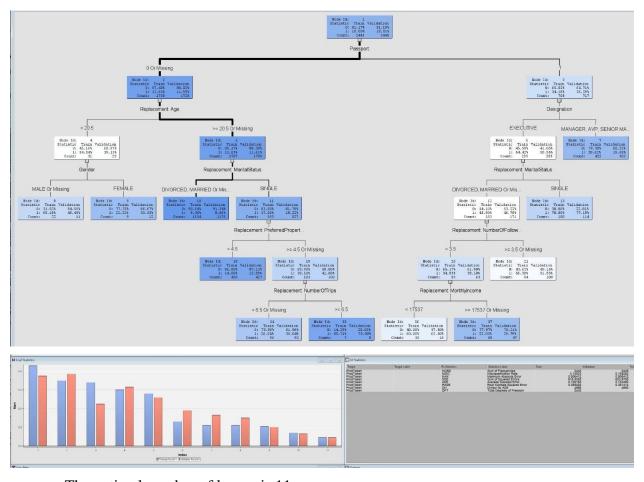


- The optimal number of leaves is 11.
- The variable used for the first split was Passport. The competing splits were Age and
 Designation. Other important variables are Marital Status and Gender. As can be seen in
 the tree, variables like Preferred Property Score and Number of Follow-Ups were
 included but less important.
- Valid average square error (ASE) = 0.123492
- Valid misclassification rate = 0.158282

Maximal Tree



Use Frozen Tree	Yes			
Use Multiple Targets	No			
■Splittina Rule				
Interval Target Criterion	ProbF			
Nominal Target Criterion	ProbChisq			
Ordinal Target Criterion	Entropy			
Significance Level	0.2			
Missing Values	Use in search			
Use Input Once	No			
Maximum Branch	2			
Maximum Depth	6			
Minimum Categorical Size	5			
□Node				
Leaf Size	5			
Number of Rules	5			
Number of Surrogate Rule	0			
Split Size				
□Split Search				
Use Decisions	No			
Use Priors	No			
Exhaustive	5000			
Node Sample	20000			
□Subtree -				
Method	Assessment			
Number of Leaves	1			
-Assessment Measure	Decision			
Assessment Fraction	0.25			

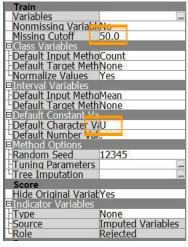


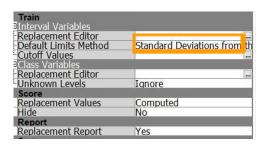
- The optimal number of leaves is 11.
- The variable used for the first split was Passport. The competing splits were Age and
 Designation. Other important variables are Marital Status and Gender. As can be seen in
 the tree, variables like Preferred Property Score and Number of Follow-Ups were
 included but less important.
- Valid average square error (ASE) = 0.123492
- Valid misclassification rate = 0.158282

The 3-way Tree is the best decision tree, based on its lowest valid ASE and valid misclassification rate.

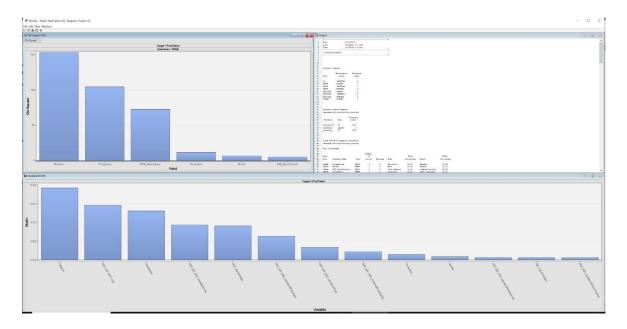
Logistic Regression

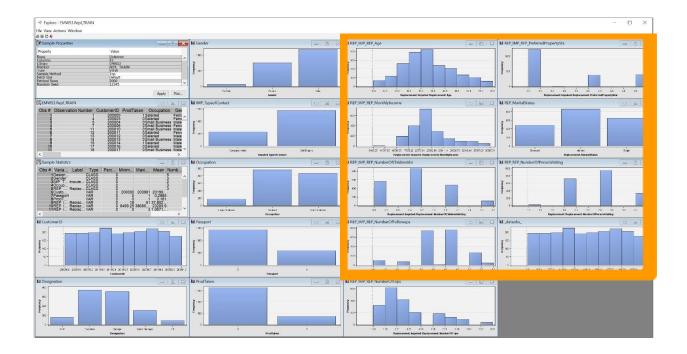
To prepare for linear regression, we used the Impute node (left) for the missing data. We then use an alternate node (on the right) with the default limiting method set to the value of the standard deviation from the mean. This is done to limit and rank outliers, reducing variables later we have to transform with logarithm. Using less logarithms will mean easier data communication for objects unfamiliar with data manipulation methods.











The data inputs (the right side of the data explored below) are less skewed than before, however, the number of trips had skewed distribution.

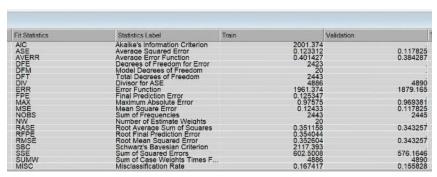


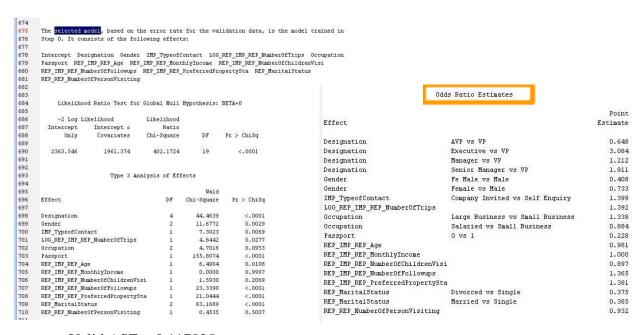
A Transform Node was applied to this variable.

Regression Results

For this dataset, backward, forward regression was used.

Backward Regression





- Valid ASE = 0.117825
- Valid misclassification rate = 0.155828
- The model is trained in Step 0.
- The imputed data shows the highest odds of buying our travel package is based on Type of Contact, then Number of Trips, then Preferred Property Star.

Our odds ratios show that:

- With every added customer who is an AVP, VPs are 64.8% more likely to buy a package.
- With every added customer who is an Executive, Execs are 208.4% more likely to buy a package.
- With every added customer who is a Manager, the chances of Managers buying a package is 21.2%.
- With every added customer who is a Senior Manager, Sr. Managers are 91.1% more likely to buy a package.
- With every additional company-invited type of outreach, company-invited customers are 39.9% more likely to buy.

Forward Regression

Fit Statistics	Statistics Label	Tran	Validation 3
ACE AVERR DFE DFM DFT DFW MSE MSE MSE MSE MSS SUMMY MISO	Akake's Information Criterion Average Squared Error Average Error Function Degrees of Freedom for Error Model Degrees of Freedom	2002,119 0.124151 0.404036 2429	0.11765 0.384729
DPT DIV ERR	Total Degrees of Freedom Divisor for ASE Error Function Final Prediction Error	2449 14 2443 4886 1974 119 0 125502 0 579056	4890 1881,327
MAX MSE NOBS	Maximum Absolute Error Mean Square Error Sum of Frequencies Number of Estimate Welchts	0.979086 0.124867 2443	0.979811 0.11765 2445
RASE	Root Average Sum of Squares Root Final Prediction Error	9.252251	0.343002
RMSE	Root Mean Squared Error Schwarz's Bayesian Orberion	0.363366	0.343002
SSE SUMAY	Sum of Squared Errors Sum of Case Weights Times Freq	0.362361 0.354376 0.363366 2083.333 606.6029	575.3089 4890 0.198646
MISC	Misclassification Rate	0.166598	0.156646

The selected model, based on the error rate for the validation data, is the model trained in Step 8. It consists of the following effects:

Intercept Designation Gender IMP_TypeofContact Passport REP_IMP_REP_Age REP_IMP_REP_MumberOfFollowups REP_IMP_REP_PreferredPropertySta REP_MaritalStatus

Likelihood Ratio Test for Global Null Hypothesis: BETA=0

-2 Log Likelihood		Likelihood		
Intercept	Intercept &	Ratio		
0nly	Covariates	Chi-Square	DF	Pr > ChiSq
2363.546	1974.119	389.4271	13	<.0001

Type 3 Analysis of Effects

		Wald	
Effect	DF	Chi-Square	Pr > ChiSq
Designation	4	59.7338	<.0001
Gender	2	11.3188	0.0035
IMP_TypeofContact	1	6.7137	0.0096
Passport	1	156.0028	<.0001
REP_IMP_REP_Age	1	5.4476	0.0196
REP_IMP_REP_NumberOfFollowups	1	25.2930	<.0001
REP_IMP_REP_PreferredPropertySta	1	21.7566	<.0001
REP_MaritalStatus	2	64.8140	<.0001

Analysis of Maximum Likelihood Estimates

				Standard	Wald	
Parameter		DF	Estimate	Error	Chi-Square	Pr > ChiSq
Intercept		1	-3.5352	0.4795	54.35	<.0001
Designation	AVP	1	-0.7370	0.2637	7.81	0.0052
Designation	Executive	1	0.8329	0.1330	39.24	<.0001
Designation	Manager	1	-0.0990	0.1356	0.53	0.4654
Designation	Senior Manager	1	0.3527	0.1552	5.16	0.0230
Gender	Fe Male	1	-0.4611	0.2286	4.07	0.0437
Gender	Female	1	0.0737	0.1322	0.31	0.5772
IMP_TypeofContact	Company Invited	1	0.1599	0.0617	6.71	0.0096
Passport	0	1	-0.7353	0.0589	156.00	<.0001
REP_IMP_REP_Age		1	-0.0166	0.00711	5.45	0.0196
REP_IMP_REP_NumberOfFollowups		1	0.2908	0.0578	25.29	<.0001
REP_IMP_REP_PreferredPropertySta		1	0.3246	0.0696	21.76	<.0001
REP_MaritalStatus	Divorced	1	-0.3418	0.1037	10.86	0.0010
REP_MaritalStatus	Married	1	-0.3058	0.0826	13.70	0.0002

Odds Ratio Estimates

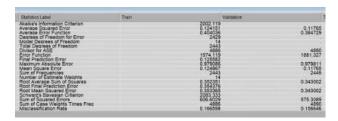
		Point
Effect		Estimate
Designation	AVP VS VP	0.679
Designation	Executive vs VP	3.263
Designation	Manager vs VP	1.285
Designation	Senior Manager vs VP	2.018
Gender	Fe Male vs Male	0.428
Gender	Female vs Male	0.731
IMP_TypeofContact	Company Invited vs Self Enquiry	1.377
Passport	0 vs 1	0.230
REP_IMP_REP_Age		0.984
REP_IMP_REP_NumberOfFollowup	3	1.337
REP_IMP_REP_PreferredPropert	ySta	1.383
REP_MaritalStatus	Divorced vs Single	0.372
REP_MaritalStatus	Married vs Single	0.385

- Valid ASE = 0.11765
- Valid misclassification rate = 0.156646
- The model is trained in Step 8.
- The imputed data shows the highest odds of buying our travel package is based on Preferred Property Star, Type of Contact and Number of Follow-ups.

Our odds ratios show that:

- With every added customer who is an AVP, VPs are 67.9% more likely to buy a package.
- With every added customer who is an Executive, Execs are 226.3% more likely to buy a package.
- With every added customer who is a Manager, the chances of Managers buying a package is 28.5%.
- With every added customer who is a Senior Manager, Sr. Managers are 101.8% more likely to buy a package.
- With every additional company-invited type of outreach, company-invited customers are 37.7% more likely to buy.

Stepwise Regression



The selected model, based on the error rate for the validation data, is the model trained in Step 8. It consists of the following effects:

Intercept Designation Gender IMP_TypeofContact Passport REP_IMP_REP_Age REP_IMP_REP_NumberOfFollowups REF_IMP_REP_PreferredPropertySta REP_MaritalStatus

Likelihood Ratio Test for Global Null Hypothesis: BETA=0

-2 Log Likelihood		Likelihood		
Intercept	Intercept &	Ratio		
Only	Covariates	Chi-Square	DF	Pr > ChiSq
2363.546	1974.119	389.4271	13	<.0001

Type 3 Analysis of Effects

		Wald	
Effect	DF	Chi-Square	Pr > ChiSq
Designation	4	59.7338	<.0001
Gender	2	11.3188	0.0035
IMP_TypeofContact	1	6.7137	0.0096
Passport	1	156.0028	<.0001
REP_IMP_REP_Age	1	5.4476	0.0196
REP_IMP_REP_NumberOfFollowups	1	25.2930	<.0001
REP_IMP_REP_PreferredPropertySta	1	21.7566	<.0001
REP_MaritalStatus	2	64.8140	<.0001

Odds Ratio Estimates	
----------------------	--

_		
		Point
Effect		Estimate
Designation	AVP vs VP	0.679
Designation	Executive vs VP	3.263
Designation	Manager vs VP	1.285
Designation	Senior Manager vs VP	2.018
Gender	Fe Male vs Male	0.428
Gender	Female vs Male	0.731
IMP_TypeofContact	Company Invited vs Self Enquiry	1.377
Passport	0 vs 1	0.230
REP_IMP_REP_Age		0.984
REP IMP REP NumberOfFollo	wups	1.337
REP_IMP_REP_PreferredProp	ertySta	1.383
REP_MaritalStatus	Divorced vs Single	0.372
REP_MaritalStatus	Married vs Single	0.385

- Valid ASE = 0.11765
- Valid misclassification rate = 0.156646
- The model is trained in Step 8.
- The imputed data shows the highest odds of buying our travel package is based on Preferred Property Star, Type of Contact and Number of Follow-

Our odds ratios show that:

- With every added customer who is an AVP, VPs are 67.9% more likely to buy a package.
- With every added customer who is an Executive, Executives are 226.3% more likely to buy a package.
- With every added customer who is a Manager, the chances of Managers buying a package is 28.5%.
- With every added customer who is a Senior Manager, Sr. Managers are 101.8% more likely to buy a package.
- With every additional company-invited type of outreach, company-invited customers are 37.7% more likely to buy.

Based on valid ASEs and misclassification rates, Stepwise regression is the best model.

Neural Network

Neural network model selection criterion was set to Average Error so that the node selects the model with the least average error for validation of data.

In order to discover the optimal number of hidden units, we then connected different neural networks to our prepared data. We ran models with:

- iterations = 50 and
- hidden units = 0, 2, 3, 4, 5, 6, 7, 8, 9 and 10

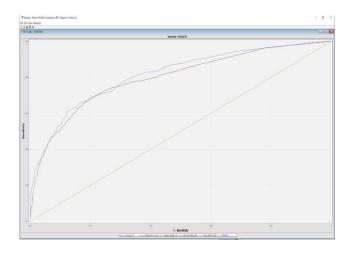
The result shows that the neural network with 6 hidden units was the best model as it had the lowest valid average square error (0.113577), the highest ROC index (0.814, shared with the model with 8 hidden units) and the highest Gini coefficient (0.627). It also had one of the lower misclassification rates (0.15501, the fourth lowest out of 10) and the fourth highest Kolmogorov-Smirnov statistic (0.492).

Iterations

We then ran neural networks with 6 hidden units and various iterations to look at our iteration plots and check for convergence. We used:

- hidden units = 6 and
- iterations = 50, 100, 150, 200 and 250

The neural network converged at 200 iterations. However, the iteration plot was not ideal.



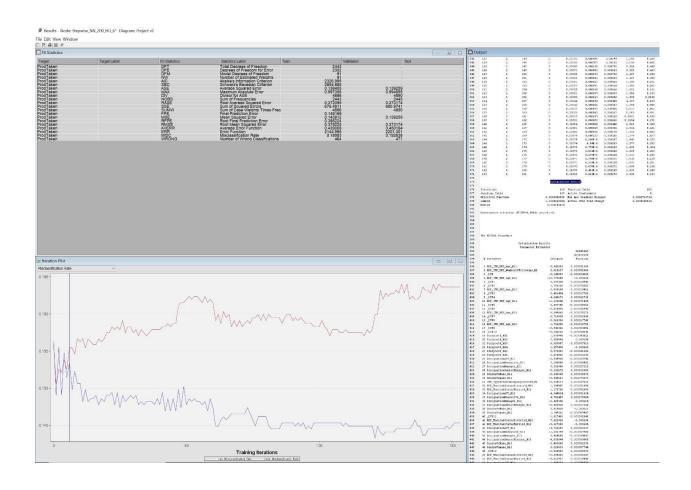
Model Description	Valid: Average Squared Error ▲	Valid: Misclassificat ion Rate	Valid: Roc Index	Target Label	Valid: Gini Coefficie nt	Valid: : Kolmogo rov-Smir nov Statistic
NN 50 HU 6 NN 50 HU 8* NN 50 HU 8* NN 50 HU NO NN 50 HU 3 NN 50 HU 3 NN 50 HU 10 NN 50 HU 10 NN 50 HU 5 NN 50 HU 5 NN 50 HU 4	0.113577 0.114713 0.11554 0.116519 0.116519 0.117259 0.118276 0.120715 0.126294 0.147789	0.15501 0.150511 0.155419 0.160736 0.160736 0.153374 0.161963 0.160327 0.170961 0.208589	0.814 0.812 0.814 0.8 0.8 0.803 0.815 0.791 0.774 0.762		0.627 0.624 0.627 0.6 0.66 0.63 0.581 0.549	0.492 0.468 (0.497 (0.493 (0.493 (0.492 (0.494 (0.397 (0.38 (

Input Reduction

Input reduction is attached to the best regression model (Stepwise) and ran with neural networks with 50 and 200 iterations.

The iteration plot improved for the model with 50 iterations. However the valid ASE and valid misclassification rate had actually gotten higher (0.117112 and 0.155419 respectively as compared to the original neural network model with 50 iterations: 0.113577 and 0.15501 respectively).

A similar pattern was observed in the neural network model with 200 iterations with reduced inputs. The iteration plot improved but the valid ASE and Misclassification rate got higher (0.139259 and 0.192638 respectively as compared to the original neural network model with 50 iterations: 0.117823 and 0.153783 respectively).

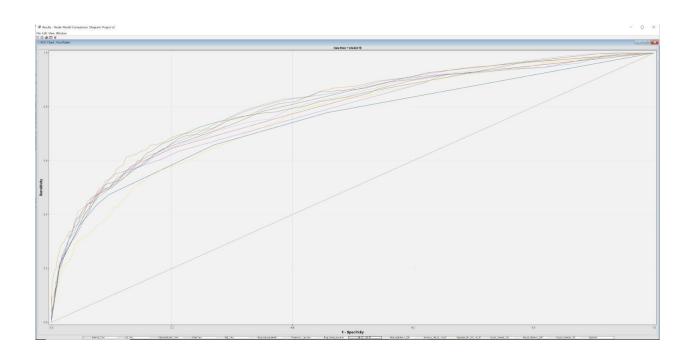


Model Comparison

The models are compared using:

- The lowest valid average squared error
- The highest valid Gini coefficient
- The lowest valid misclassification rate, the highest valid Kolmogorov-Smirnov statistic, and
- The highest valid ROC index.

Valid: Average Squared Error ▲	Valid: Gini Coefficie nt	Valid: Misclassific ation Rate	Valid: Kolmogo rov-Smir nov Statistic	Valid: Roc Index
0.117823	0.595	0.153783	0.479	0.797
0.117823				
	Average Squared Error ▲ 0.113577 0.116995 0.11765 0.11765 0.117823 0.117823 0.117823 0.117823 0.117825 0.118406 0.118446 0.123492 0.123492	Average Squared Coefficie nt C	Average Squared Error ▲	Average Squared Error Gini Coefficie nt Misclassific ation Rate Kolmogo rov-Smir nov Statistic 0.113577 0.627 0.15501 0.492 0.116995 0.599 0.160736 0.458 0.117112 0.592 0.155419 0.449 0.11765 0.597 0.156646 0.47 0.117823 0.595 0.153783 0.479 0.117823 0.595 0.153783 0.479 0.117823 0.595 0.153783 0.479 0.117823 0.595 0.153783 0.479 0.117825 0.595 0.153783 0.479 0.117825 0.595 0.153783 0.479 0.117825 0.595 0.153783 0.479 0.118406 0.55 0.159918 0.445 0.118446 0.567 0.159918 0.447 0.123492 0.494 0.158282 0.388 0.123492 0.494 0.158282 0.388



On the basis of this comparison, the neural network node with 50 iterations and 6 hidden units is our best model. It has the highest ROC index by far (0.814), the lowest valid average squared error (0.113577), and the highest Gini coefficient (0.627).

While not quite the lowest misclassification rate among all our models, it was not as high as others.

The next best model based on these statistics was the 3-way decision tree.

Conclusion

In conclusion, based on the analysis above; Passport, job designation and age are critical variables affecting this prediction model. While less important than these three, marital status and gender also contributed to further decision tree splits.

Based on these findings, these customers are most likely to buy the package:

- Single VPs, AVPs without a passport who are older than 20.5 years of age (or missing their age)
- Single executives without a passport who are older than 20.5 years of age (or missing their age) and have a monthly income greater than or equal to \$24,266.50 USD
- Divorced, married (or missing marital status) executives without a passport who have a monthly income more than or equal to \$24,233 USD

As mentioned in the previous sections, it would be helpful if the company could provide information indicating whether these trips are domestic or international. Since passport is such an important variable, it will significantly increase the accuracy of the model, as it will determine whether the customer must have a passport to use the travel package

References

Susant_Achary. "Holiday_Package_Prediction." *Kaggle*, August 2021. https://www.kaggle.com/susant4learning/holiday-package-purchase-prediction