Airline Satisfaction Survey Results

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Data Set - Survey Features

Gender: Gender of the passengers (Female, Male)

Customer Type: The customer type (Loyal customer, disloyal customer)

Type of Travel: Purpose of the flight of the passengers (Personal Travel, Business Travel)

Class: Travel class in the plane of the passengers (Business, Eco, Eco Plus)

Age: The actual age of the passengers

Flight distance: The flight distance of this journey

Departure /Arrival Delay in Minutes: Minutes delayed when departure

Inflight wifi service: Satisfaction level of the inflight wifi service (0:Not Applicable;1-5)

Departure/Arrival time convenient: Satisfaction level of Departure/Arrival time convenient (0:Not Applicable;1-5)

Ease of Online booking: Satisfaction level of online booking (0:Not Applicable;1-5)

Gate location: Satisfaction level of Gate location (0:Not Applicable;1-5)

Food and drink: Satisfaction level of Food and drink (0:Not Applicable;1-5)

Online boarding: Satisfaction level of online boarding(0:Not Applicable;1-5)

Data Set - Survey Features Continued

Seat comfort: Satisfaction level of Seat comfort (0:Not Applicable;1-5)

On-board service: Satisfaction level of On-board service (0:Not Applicable;1-5)

Leg room service: Satisfaction level of Leg room service (0:Not Applicable;1-5)

Baggage handling: Satisfaction level of baggage handling (0:Not Applicable;1-5)

Check-in service: Satisfaction level of Check-in service (0:Not Applicable;1-5)

Inflight service: Satisfaction level of inflight service (0:Not Applicable;1-5)

Cleanliness: Satisfaction level of Cleanliness (0:Not Applicable;1-5)

Inflight entertainment: Satisfaction level of inflight entertainment (0:Not Applicable;1-5)

TARGET: Satisfaction: Airline satisfaction level(Satisfaction, neutral or dissatisfaction)

Likert Scale Features

- Named after American psychologist Rensis Likert in 1932
  - Scale of agreement (typically 1 to 5)
- Likert-type scales defined by Paul Lavrakas in 2008
  - Allows respondents to indicate degree of satisfaction (typically 1 to 5)

How satisfied are you with the security control at the airport?

Very dissatisfied	Somewhat dissatisfied	Neither dissatisfied nor satisfied	Somewhat satisfied	Very satisfied
○	○	○	○	○
1	2	3	4	5

Using Likert-type scales for Classification

- Endresen and Janda (2016) discovered that Random Forest classification models were the best classical models to use for Likert or Likert-type scale features

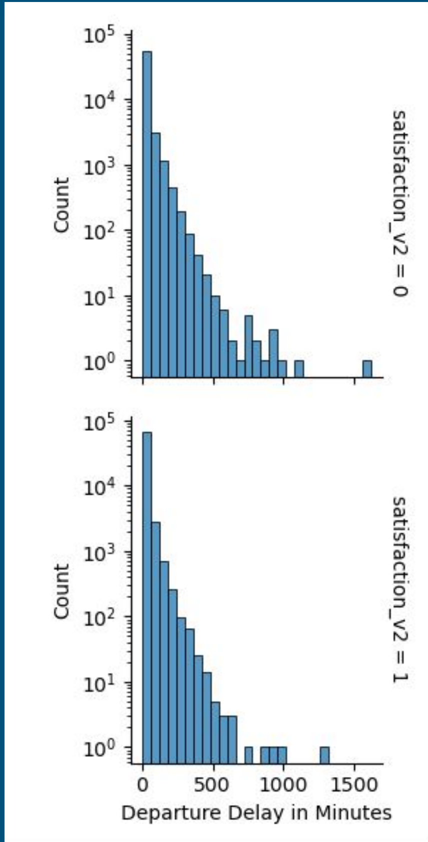
- Will a Multilayer Perceptron Network perform better than a Random Forest?

Exploratory Data Analysis - Categorical

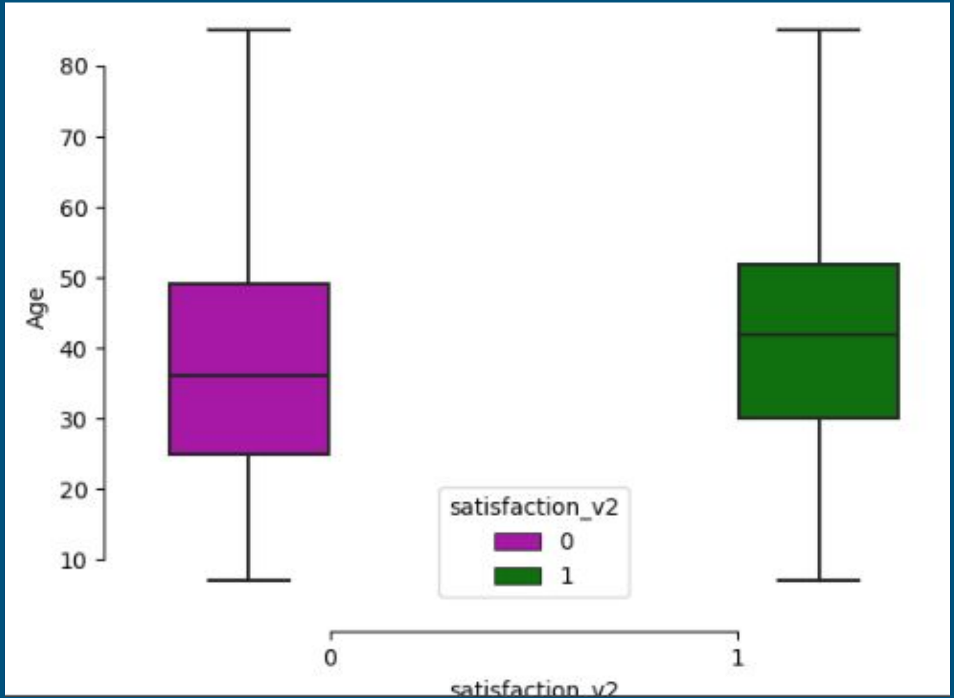
- Gender
  - Women more satisfied with airline than men
- Customer Type
  - Loyal Customers more satisfied than Disloyal Customers
- Type of Travel
  - Business travel passengers more satisfied than Personal travel passengers
- Travel Class
  - Business Class and Economy Plus passengers more satisfied than Economy Class passengers

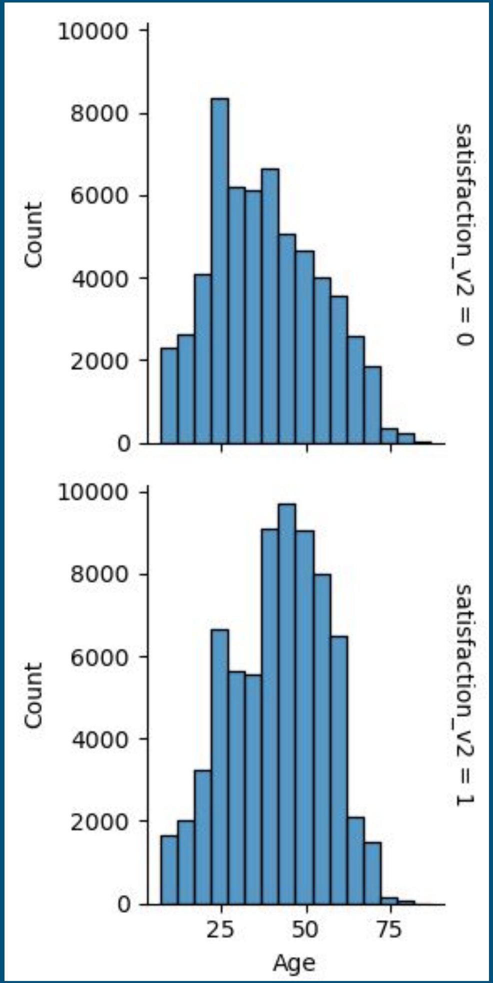
Exploratory Data Analysis - Continuous

- Departure and Arrival Delays
  - Skewed Distributions with no significant correlations
  - Therefore, we excluded this feature from the final model
- Flight Distance
  - Not highly correlated with satisfaction
- Age
  - Satisfaction not highly correlated with Age



Investigation of Age Feature





Likert-type - Highest Correlations

	Seat comfort	satisfaction_v2
0	0	0.997908
1	1	0.450915
2	2	0.357794
3	3	0.356131
4	4	0.651845
5	5	0.992064

	Inflight entertainment	satisfaction_v2
0	0	0.660714
1	1	0.210656
2	2	0.170363
3	3	0.199188
4	4	0.719870
5	5	0.952064

Likert-type - Moderate/Average Correlations

	Gate location	satisfaction_v2
0	0	1.000000
1	1	0.610926
2	2	0.580705
3	3	0.463065
4	4	0.497850
5	5	0.655479

	Food and drink	satisfaction_v2
0	0	0.779635
1	1	0.508473
2	2	0.432713
3	3	0.428612
4	4	0.590254
5	5	0.780084

	Inflight wifi service	satisfaction_v2
0	0	0.446154
1	1	0.268507
2	2	0.502356
3	3	0.509557
4	4	0.638368
5	5	0.669114

	Online support	satisfaction_v2
0	0	0.000000
1	1	0.295464
2	2	0.296755
3	3	0.282690
4	4	0.680481
5	5	0.773152

	Ease of Online booking	satisfaction_v2
0	0	0.000000
1	1	0.192730
2	2	0.286368
3	3	0.357053
4	4	0.717813
5	5	0.765499

	On-board service	satisfaction_v2
0	0	0.000000
1	1	0.265825
2	2	0.340831
3	3	0.410290
4	4	0.647394
5	5	0.765692

Likert-type - Moderate/Average Correlations

	Leg room service	satisfaction_v2
0	0	0.692308
1	1	0.283384
2	2	0.376378
3	3	0.371746
4	4	0.673345
5	5	0.708523

	Departure/Arrival time convenient	satisfaction_v2
0	0	0.542444
1	1	0.586154
2	2	0.540268
3	3	0.539680
4	4	0.524607
5	5	0.556450

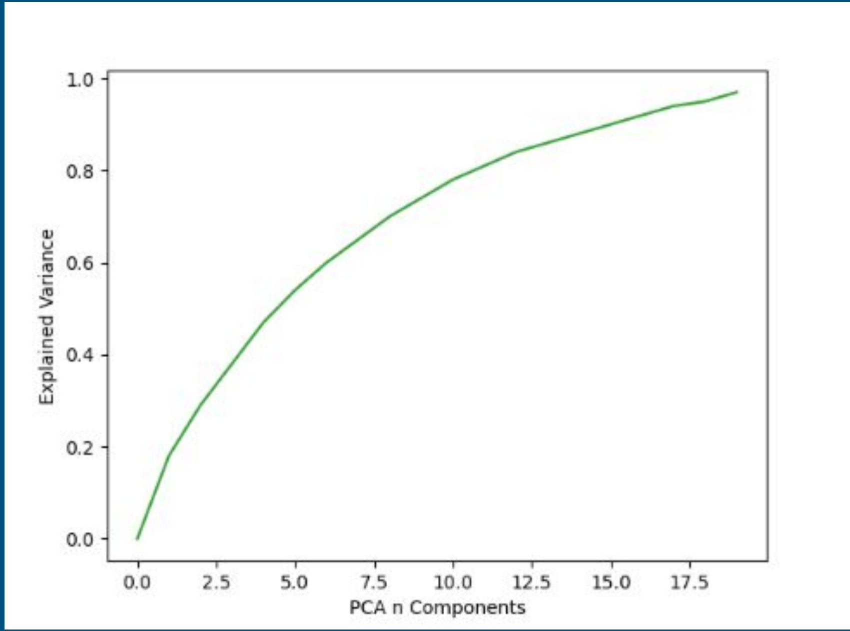
	Cleanliness	satisfaction_v2
0	0	0.000000
1	1	0.403047
2	2	0.404760
3	3	0.317899
4	4	0.586767
5	5	0.731698

	Online boarding	satisfaction_v2
0	0	0.000000
1	1	0.264925
2	2	0.281309
3	3	0.549557
4	4	0.652527
5	5	0.731715

	Baggage handling	satisfaction_v2
0	1	0.422574
1	2	0.396250
2	3	0.315119
3	4	0.588480
4	5	0.735817

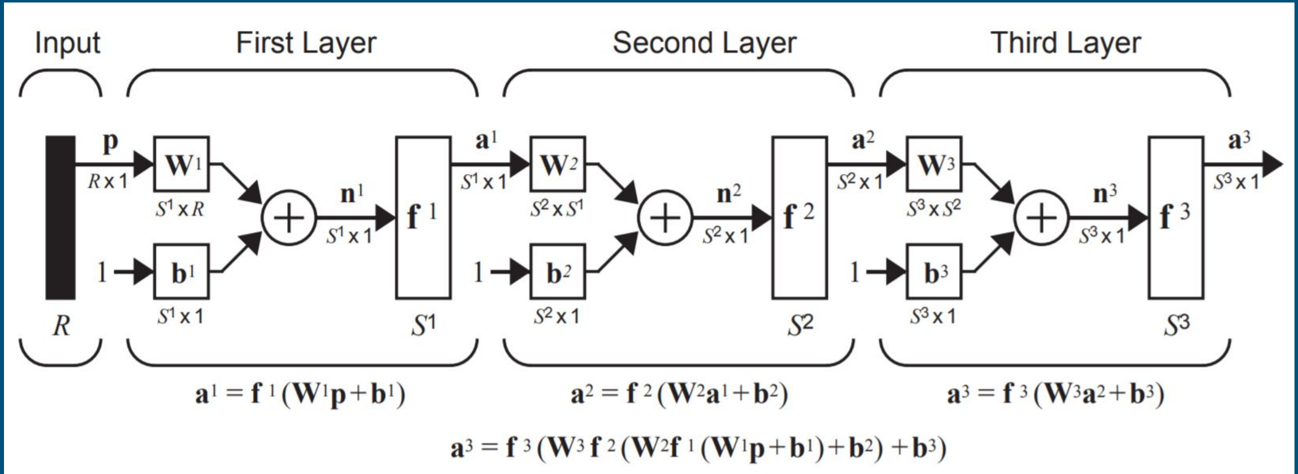
	Checkin service	satisfaction_v2
0	0	0.000000
1	1	0.316277
2	2	0.332643
3	3	0.567485
4	4	0.577010
5	5	0.735763

Principal Component Analysis



Multilayer Perceptron Neural Network

Binary Classification Network



5 Layer MLP - Adam

- First-order, gradient-based optimization of stochastic objective functions
  - Straightforward to implement
  - Computationally efficient
  - Little memory requirements

	precision	recall	f1-score	support
0	0.91	0.91	0.91	11692
1	0.92	0.92	0.92	14206
accuracy			0.92	25898
macro avg	0.91	0.92	0.92	25898
weighted avg	0.92	0.92	0.92	25898

5 Layer MLP - SGD

- Stochastic Gradient Descent Backpropagation

	precision	recall	f1-score	support
0	0.90	0.91	0.90	11692
1	0.92	0.92	0.92	14206
accuracy			0.91	25898
macro avg	0.91	0.91	0.91	25898
weighted avg	0.91	0.91	0.91	25898

5 Layer MLP - L-BFGS

- Limited-memory Broyden–Fletcher–Goldfarb–Shanno (L-BFGS)
  - Quasi-Newtonian Method
  - Uses the approximated second order gradient information
- Best model with 15 neurons in each layer

	precision	recall	f1-score	support
0	0.91	0.93	0.92	11692
1	0.94	0.93	0.93	14206
accuracy			0.93	25898
macro avg	0.93	0.93	0.93	25898
weighted avg	0.93	0.93	0.93	25898

Modifications of 5 Layer LBFGS Model

- Increase the neurons in one layer only
  - Number of neurons in each hidden layer: 10 - 15 - 10
- Increase the neurons in all hidden layers
  - Number of neurons in each hidden layer: 15 - 15 - 15
  - Number of neurons in each hidden layer: 20 - 20 - 20
- Change activation function
  - Logistic activation function
- Using SGD, change momentum and alpha
  - Momentum 0.95 and alpha 0.01
  - Momentum 0.95 and alpha 0.01 with logistic regression

6 Layer MLP

- Using L-BFGS
  - Number of neurons in each hidden layer: 10 - 10 - 10 - 10 as well as 15 - 15 - 15 - 15

	precision	recall	f1-score	support
0	0.90	0.91	0.91	11692
1	0.93	0.92	0.92	14206
accuracy			0.92	25898
macro avg	0.92	0.92	0.92	25898
weighted avg	0.92	0.92	0.92	25898

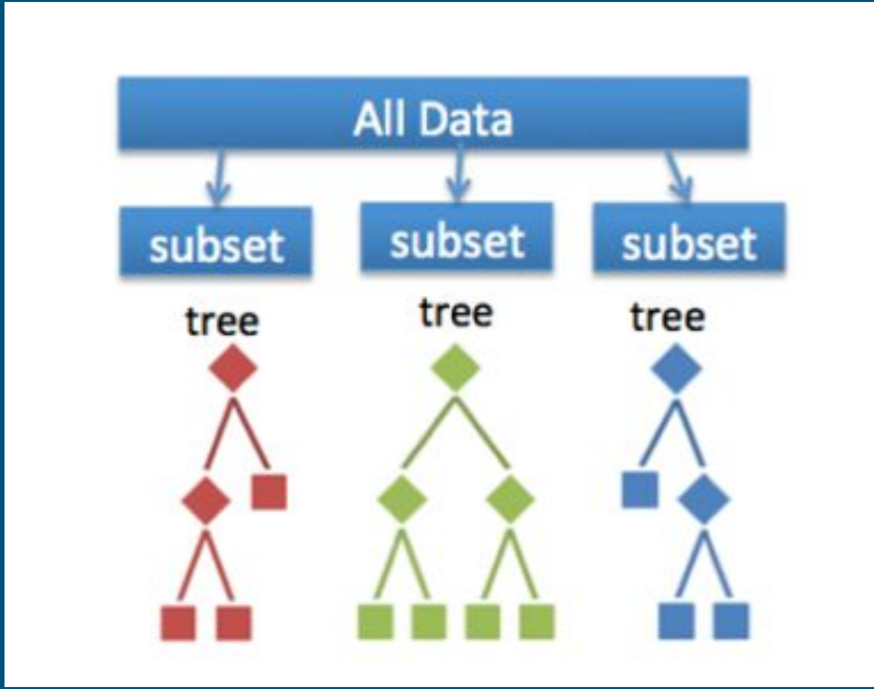
All MLP Results

Hidden Layers	Hidden Layer Transfer Function	Learning Method	Alpha	Momentum	Precision	Recall	F1 Score	Accuracy
10/10/10	relu	ADAM	0.0001	0.9	0.90 0.93	0.92 0.92	0.91 0.92	0.92
10/10/10	relu	L-BFGS	0.0001	0.9	0.90 0.93	0.91 0.92	0.91 0.92	0.92
10/10/10	relu	SGD	0.0001	0.9	0.90 0.93	0.91 0.92	0.90 0.92	0.91
10/10/10/10	relu	L-BFGS	0.0001	0.9	0.90 0.93	0.91 0.92	0.91 0.92	0.92
10/15/10	relu	L-BFGS	0.0001	0.9	0.91 0.93	0.92 0.92	0.91 0.93	0.92
15/15/15	relu	L-BFGS	0.0001	0.9	0.91 0.94	0.93 0.92	0.92 0.93	0.92
20/20/20	relu	L-BFGS	0.0001	0.9	0.91 0.94	0.92 0.92	0.92 0.93	0.92
15/15/15	logistic	L-BFGS	0.0001	0.9	0.91 0.94	0.93 0.93	0.92 0.93	0.93
15/15/15	relu	SGD	0.01	0.95	0.91 0.93	0.91 0.93	0.91 0.93	0.92

Classical Model

Random Forest Classifier

- Accuracy of 0.92



Results

- Best Model - 5 Multilayer Perceptron Network with L-BFGS optimization method and hidden layer sizes of 15 - 15 - 15

- Recommend using Random Forest for Likert-type scale features

Conclusion

- Multilayer Perceptron Network can be used to classify Likert-type scale features from survey responses
- Agree with Endreson and Janda - recommend using classical Random Forest classification model

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