

# CMSC 173 - MP 2

## Instructions:

1. Create an overview of the problem being solved, e.g., what was the story behind the collection of the data, description of the attributes/features used, etc.
2. (Data Preprocessing and Exploratory Analysis) Present descriptive statistics as applicable (e.g., distribution, central tendency, variability) of the data before training the models. Clean the data if there are missing values, etc. You may perform feature engineering (i.e., creating new features out of the given features), but be sure to document your justifications.
3. Split your data into proportions of 70% training set and 30% testing set.
4. Train the following models: (a) logistic regression classifier and (b) naive Bayes classifier on the dataset.
5. Evaluate the performance of the trained model. You may use additional performance measures if you want, but for now I will only require the calculation of the accuracy. The accuracy measures the fraction of correct classifications. With this, you need to generate the confusion matrix. You may read this if you haven't encountered this concept before: <https://www.sciencedirect.com/topics/engineering/confusion-matrix#:~:text=A%20confusion%20matrix%20represents%20the,by%20model%20as%20oth>  
Remember to compute this matrix from the test set (not the training set).

```
In [ ]: using Random
using StatsBase
using CSV
using DataFrames
using Plots
using Base
import StatisticalMeasures.ConfusionMatrices as CM

In [ ]: dataset = CSV.read("passenger_flight.csv", DataFrame)
Random.seed!(123)
dataset = dataset[shuffle(axes(dataset, 1)), :]
```

Out[ ]: 25976×23 DataFrame

25951 rows omitted

Row	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient	Electronic Surveys
	Int64	Int64	Int64	Int64	Int64	Int64	Int64	Int64	Int64
1	1	1	50	1	1	3744	5	5	
2	0	1	53	1	1	2661	4	5	
3	1	1	20	0	0	541	2	4	
4	0	1	52	0	1	944	1	2	
5	1	1	33	1	1	406	1	1	
6	0	1	51	0	0	621	2	4	
7	1	1	25	1	1	3547	2	2	
8	0	1	51	1	1	547	4	4	
9	0	1	60	0	1	438	2	4	
10	1	1	26	1	1	2085	1	1	
11	1	1	17	0	0	505	3	4	
12	0	0	22	1	0	329	3	1	
13	1	1	25	0	0	479	3	4	
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
25965	0	1	27	1	1	1716	2	1	
25966	1	0	26	1	1	591	1	1	
25967	0	1	63	0	0	1024	4	4	
25968	1	1	39	1	1	2131	2	2	
25969	0	1	40	0	0	369	3	1	
25970	1	1	38	0	0	633	2	1	
25971	1	1	32	1	1	1635	2	2	
25972	0	1	43	1	1	1055	5	5	
25973	1	1	61	1	1	2273	4	4	
25974	1	1	37	1	1	695	2	4	
25975	0	1	38	0	0	1313	4	5	
25976	1	0	26	1	1	447	1	0	

# Data Preprocessing

```
In [ ]: # Replace missing values with the mean

has_missing = .!completecases(dataset)
rows_with_missing_values = dataset[has_missing, :]
print(rows_with_missing_values) # 83 rows have missing values in the Arrival Delay

mean_value = mean(skipmissing(dataset[:, "Arrival Delay in Minutes"]))
transform!(dataset, All() .=> (x -> replace(x, missing => mean(skipmissing(x)))) =>
println(dataset[1:10, :])

has_missing = .!completecases(dataset)
rows_with_missing_values = dataset[has_missing, :]
display(rows_with_missing_values) # no missing values
```

83x23 DataFrame

Row	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight service
		Departure/Arrival time convenient		Ease of Online booking		Gate location	
		Food and drink	Online boarding	Seat comfort		Inflight entertainment	On-board service
		Leg room service	Baggage handling	Checkin service		Inflight service	Cleanliness
		Departure Delay in Minutes	Arrival Delay in Minutes			satisfaction	
	Int64	Int64	Int64	Int64	Int64	Int64	Int64
Int64			Int64		Int64		Int64
Int64		Int64	Int64		Int64		Int64
Int64		Int64	Int64		Int64	Int64	
Union{Missing, Int64}		Int64					

[illegible]

9		1		1	21		0	1	767
1					3			1	1
1		1			1		1		4
2		1			1		2		1
5			missing			0			
10		0		1	45		1	0	222
5					4			4	4
5		3			4			5	5
5		5			1		5		2
0			missing			1			
11		1		1	9		0	0	762
2					5			2	2
4		2			1		4		2
5		2			5		2		4
51			missing			0			
12		1		1	62		0	0	1024
1					5			1	3
2		1			2			2	3
5		4			5		4		2
45			missing			0			
13		0		1	65		1	0	705
4					3			3	3
3		5			2			3	3
4		3			3		3		4
16			missing			1			
14		0		1	37		1	1	279
5					4			1	1
5		5			5			5	5
3		4			1		2		5
14			missing			1			
15		0		1	31		1	1	3785
4					4			4	4
4		4			4			4	4
2		5			4		5		4
84			missing			1			
16		1		1	45		0	0	2565
2					3			2	2
4		2			4			4	3
2		2			4		2		4
7			missing			0			
17		0		1	47		1	1	1437
3					4			4	4
4		2			2			3	3
3		3			4		3		1
2			missing			0			
18		0		1	52		1	1	3659
5					5			5	5
2		4			5			5	5
5		5			3		5		3
0			missing			1			
19		1		1	62		1	1	2446
3					5			5	5
3		3			4			3	3
3		3			4		3		2
1			missing			0			
20		0		0	33		1	0	587

4				0			4		4
3		4		3			3		4
3		5		4			5		3
0		missing			0				
21		1		0	49		0	0	491
5					4			5	2
3		5		3			3		1
4		3		3			4		3
0		missing			1				
22		1		1	45		1	0	352
5					1			1	1
5		5		5			5		1
1		1		3			2		5
26		missing			1				
23		0		1	30		1	1	1931
3					5			5	5
3		3		3			3		2
1		3		3			3		3
0		missing			0				
24		1		1	46		1	1	2475
3					3			3	3
4		4		4			3		3
5		5		4			4		4
530		missing			1				
25		0		0	36		1	1	328
3					3			3	2
2		3		2			2		5
5		5		5			5		2
0		missing			0				
26		0		1	39		1	1	2475
1					1			3	1
5		5		4			4		4
4		4		5			4		5
0		missing			1				
27		0		1	21		0	0	632
1					5			1	4
2		1		4			2		4
2		5		4			5		2
9		missing			0				
28		0		1	50		1	1	95
1					5			5	5
3		3		2			2		2
2		1		1			2		3
0		missing			0				
29		1		0	34		1	0	376
2					0			2	5
3		2		1			3		5
2		2		4			5		3
0		missing			0				
30		1		1	8		0	0	936
3					4			3	2
5		3		5			5		5
3		5		4			5		5
0		missing			0				
31		0		1	42		1	1	2133
5					5			5	5

5		4		5		3		3
3		3		3		3		5
63		missing		1				
32		1		1		63		1205
2				4		0		4
2		2		2		2		2
2		4		4		4		2
76		missing		0				
33		1		1		62		152
1				4		0		2
3		0		3		3		5
4		4		5		5		3
8		missing		0				
34		0		1		39		125
5				1				1
5		5		5		5		2
2		3		5		2		5
131		missing		1				
35		0		1		29		3873
3				3				3
3		3		3		3		3
4		4		4		3		3
19		missing		0				
36		1		1		67		2446
3				4		0		5
3		5		5		3		4
4		4		5		5		5
332		missing		0				
37		0		1		55		1438
5				5				5
2		4		5		5		5
5		5		3		5		5
81		missing		1				
38		0		1		36		1840
2				2				2
4		5		5		2		5
1		5		5		4		5
166		missing		1				
39		1		1		57		1208
5				5				4
5		5		5		5		1
2		4		1		1		5
27		missing		1				
40		0		1		58		129
5				3				3
3		5		5		5		5
5		5		3		5		5
3		missing		1				
41		0		0		40		571
4				4				3
4		4		3		4		5
5		5		3		3		3
193		missing		0				
42		1		1		49		1897
1				1				1
2		2		2		3		4

5		5		2		5		2	
254		missing			1				
43		1		1	29		1	1	3772
5				5				5	5
5		4		5			5		3
3		5		3			4		5
0		missing			1				
44		0		0	15		1	0	544
4				0				4	3
5		4		5			5		3
4		2		1			4		5
58		missing			0				
45		0		1	59		1	1	164
0				5				0	5
4		5		3			5		5
5		5		1			5		1
81		missing			1				
46		0		1	14		1	1	2515
5				5				5	5
4		4		4			4		4
2		4		5			4		4
8		missing			1				
47		0		1	34		1	1	237
5				5				5	5
3		5		5			4		4
4		4		5			4		3
71		missing			1				
48		0		1	53		0	0	480
3				4				3	3
2		3		4			3		3
3		5		2			3		1
0		missing			0				
49		0		0	21		1	0	675
4				4				4	3
2		4		2			2		2
3		3		4			3		2
0		missing			0				
50		0		1	44		1	0	598
4				5				5	5
2		4		1			5		5
4		5		3			5		5
17		missing			1				
51		0		0	21		1	0	1246
4				4				4	3
3		4		2			3		4
5		5		5			5		3
106		missing			1				
52		0		1	41		1	1	3758
1				1				1	1
2		5		5			5		5
5		5		4			5		5
23		missing			1				
53		1		1	42		1	0	383
3				2				4	4
3		3		3			3		1
2		3		1			3		3



73		missing		0					
54	0		0	24		1	1		627
1				0			1		4
4		1		4			4		2
1		4		3		4		4	
0		missing			0				
55	0		1	58		1	1		927
5				5			5		5
1		1		5			5		5
5		5		2		5		4	
13		missing			1				
56	1		1	7		0	0		399
4				5			4		4
4		4		4			4		4
3		1		1		4		4	
0		missing			0				
57	0		1	26		1	1		2417
3				1			3		3
4		4		4			4		3
4		5		1		5		4	
0		missing			1				
58	1		0	28		1	0		636
3				3			3		3
2		3		2			2		1
4		3		1		3		2	
0		missing			0				
59	1		1	31		0	0		1325
4				5			4		2
1		4		5			1		4
5		3		3		4		1	
0		missing			0				
60	0		1	46		1	1		1521
2				4			4		4
2		3		4			2		2
2		2		4		2		2	
4		missing			0				
61	1		1	39		1	1		1576
4				4			4		4
2		4		5			5		5
5		5		3		5		5	
0		missing			1				
62	1		0	38		1	1		759
3				3			3		1
4		3		4			4		3
3		5		5		4		4	
0		missing			1				
63	0		1	20		0	0		1050
1				4			1		2
3		1		3			3		3
3		5		4		4		3	
0		missing			0				
64	0		1	52		1	1		874
1				1			1		1
2		5		5			5		5
5		5		4		5		5	
10		missing			1				

65		0	1	64	0	0	1226
4				4		3	4
2		3		4		2	2
3		2		4		2	4
0		missing		0			
66		0	1	59	1	0	547
4				1		1	1
5		2		3		4	4
4		4		4		4	4
3		missing		1			
67		1	1	58	0	0	618
1				4		1	2
2		1		2		2	4
4		5		3		5	2
48		missing		0			
68		0	0	37	1	1	1428
2				2		2	3
1		2		1		1	4
4		4		5		4	1
85		missing		0			
69		0	0	22	1	1	1035
5				4		5	1
5		5		2		5	5
2		5		4		4	5
0		missing		1			
70		0	1	53	1	1	813
5				5		1	5
2		4		5		2	2
2		2		5		2	3
41		missing		1			
71		1	1	9	0	0	427
1				0		1	1
4		1		4		4	4
5		1		5		1	4
0		missing		0			
72		0	1	64	0	0	622
3				3		3	5
3		3		4		1	1
3		1		2		1	5
109		missing		0			
73		1	1	26	1	0	645
5				2		2	2
5		5		5		5	1
3		4		5		2	5
11		missing		1			
74		0	1	27	1	1	2192
1				1		5	1
2		2		2		2	3
3		4		5		5	2
42		missing		1			
75		1	1	32	1	1	240
1				1		1	1
5		5		5		5	3
5		5		4		4	5
70		missing		1			
76		0	1	44	0	0	550

1				2		1		4
4		3		3		4		4
1		4		3		4	2	
51		missing		0				
77		0	1	25	0	1		557
3				4		4		3
4		4		4		4		3
1		3		2		5	4	
32		missing		0				
78		1	0	29	1	1		972
2				2		2		2
3		2		3		3		5
4		5		5		5	3	
2		missing		0				
79		0	0	26	1	0		110
1				0		1		5
5		1		5		5		1
5		3		4		2	5	
0		missing		0				
80		1	1	41	1	1		1040
5				5		5		5
3		2		2		5		5
5		5		4		5	3	
0		missing		1				
81		1	0	25	1	0		1017
3				4		4		5
5		4		5		5		2
5		2		3		2	5	
126		missing		0				
82		1	1	62	0	0		432
2				3		2		4
4		2		4		4		3
4		5		3		4	4	
0		missing		0				
83		1	0	26	1	1		447
1				0		1		4
4		1		4		4		5
4		4		4		5	4	
4		missing						

010x23 DataFrame

Row	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	In flight wifi service	Departure/Arrival time convenient	Ease of Online booking	Gate location	Food and drink	Online boarding	Seat comfort	Inflight entertainment	On-board service	Leg room service	Baggage handling	Checkin service	Inflight service	Cleanliness	Departure Delay in Minutes	Arrival Delay in Minutes	satisfaction
	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64
1		1.0	1.0	50.0		1.0	1.0														3744.0		
5.0				5.0			5.0														5.0		

3.0		4.0		4.0		4.0		4.0
4.0		4.0		5.0		4.0	3.0	
0.0			0.0		1.0			
2		0.0		1.0	53.0	1.0	1.0	2661.0
4.0					5.0		5.0	5.0
3.0		1.0		2.0		4.0		4.0
3.0		4.0		4.0		4.0	2.0	
6.0			8.0		0.0			
3		1.0		1.0	20.0	0.0	0.0	541.0
2.0					4.0		2.0	3.0
4.0		2.0		4.0		4.0		2.0
2.0		4.0		2.0		3.0	4.0	
38.0			38.0		0.0			
4		0.0		1.0	52.0	0.0	1.0	944.0
1.0					2.0		1.0	2.0
2.0		3.0		2.0		2.0		2.0
1.0		2.0		1.0		2.0	2.0	
34.0			48.0		0.0			
5		1.0		1.0	33.0	1.0	1.0	406.0
1.0					1.0		1.0	1.0
4.0		4.0		4.0		4.0		3.0
5.0		4.0		3.0		5.0	4.0	
0.0			0.0		1.0			
6		0.0		1.0	51.0	0.0	0.0	621.0
2.0					4.0		2.0	1.0
2.0		4.0		4.0		3.0		3.0
2.0		3.0		5.0		3.0	3.0	
0.0			0.0		0.0			
7		1.0		1.0	25.0	1.0	1.0	3547.0
2.0					2.0		2.0	2.0
5.0		5.0		5.0		5.0		5.0
5.0		1.0		4.0		4.0	5.0	
0.0			0.0		1.0			
8		0.0		1.0	51.0	1.0	1.0	547.0
4.0					4.0		4.0	4.0
2.0		4.0		5.0		4.0		4.0
4.0		4.0		3.0		4.0	5.0	
0.0			0.0		1.0			
9		0.0		1.0	60.0	0.0	1.0	438.0
2.0					4.0		2.0	3.0
2.0		4.0		4.0		5.0		5.0
2.0		5.0		5.0		5.0	3.0	
0.0			0.0		0.0			
10		1.0		1.0	26.0	1.0	1.0	2085.0
1.0					1.0		1.0	1.0
5.0		5.0		5.0		5.0		4.0
5.0		5.0		3.0		4.0	5.0	
37.0			23.0		1.0			

0×23 DataFrame

Row	Gender	Customer Type	Age	Type of Travel	Class	Flight Distance	Inflight wifi service	Departure/Arrival time convenient
	Float64	Float64	Float64	Float64	Float64	Float64	Float64	Float64

```
In [ ]: # rename column names
col_names = names(dataset)
new_col_names = map(lowercase, String.(col_names)) # convert to lower case
new_col_names .= replace.(new_col_names, " "=>"_", "-"=>"", "/"=>"_") # replace spa
rename!(dataset, new_col_names)
display(dataset)
```

25976×23 DataFrame

25951 rows omitted

Row	gender	customer_type	age	type_of_travel	class	flight_distance	inflight_v
	Float64	Float64	Float64	Float64	Float64	Float64	Float64
1	1.0	1.0	50.0	1.0	1.0	3744.0	
2	0.0	1.0	53.0	1.0	1.0	2661.0	
3	1.0	1.0	20.0	0.0	0.0	541.0	
4	0.0	1.0	52.0	0.0	1.0	944.0	
5	1.0	1.0	33.0	1.0	1.0	406.0	
6	0.0	1.0	51.0	0.0	0.0	621.0	
7	1.0	1.0	25.0	1.0	1.0	3547.0	
8	0.0	1.0	51.0	1.0	1.0	547.0	
9	0.0	1.0	60.0	0.0	1.0	438.0	
10	1.0	1.0	26.0	1.0	1.0	2085.0	
11	1.0	1.0	17.0	0.0	0.0	505.0	
12	0.0	0.0	22.0	1.0	0.0	329.0	
13	1.0	1.0	25.0	0.0	0.0	479.0	
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
25965	0.0	1.0	27.0	1.0	1.0	1716.0	
25966	1.0	0.0	26.0	1.0	1.0	591.0	
25967	0.0	1.0	63.0	0.0	0.0	1024.0	
25968	1.0	1.0	39.0	1.0	1.0	2131.0	
25969	0.0	1.0	40.0	0.0	0.0	369.0	
25970	1.0	1.0	38.0	0.0	0.0	633.0	
25971	1.0	1.0	32.0	1.0	1.0	1635.0	
25972	0.0	1.0	43.0	1.0	1.0	1055.0	
25973	1.0	1.0	61.0	1.0	1.0	2273.0	
25974	1.0	1.0	37.0	1.0	1.0	695.0	
25975	0.0	1.0	38.0	0.0	0.0	1313.0	
25976	1.0	0.0	26.0	1.0	1.0	447.0	

## Detection of Outliers and Removal

```

In [ ]: q1 = []
        q3 = []

        col_names = names(dataset)

        for i in col_names
            push!(q1, quantile(dataset[:,i], 0.25))
            push!(q3, quantile(dataset[:,i], 0.75))
        end
        iqr_val = q3-q1

        lower_bound = q1 - 1.5 * iqr_val
        upper_bound = q3 + 1.5 * iqr_val

        outlier = BitVector()

        for row in eachrow(dataset)
            is_outlier = 0

            for col_idx in 1:length(col_names)
                if row[col_idx] < lower_bound[col_idx] || row[col_idx] > upper_bound[col_idx]
                    is_outlier = 1
                end
            end
            push!(outlier, is_outlier)
        end

        cleaned_dataset = dataset[.!outlier,:]
        println("Number of rows before removal: ", size(dataset)[1])
        println("Number of rows after removal: ", size(cleaned_dataset)[1])

```

Number of rows before removal: 25976

Number of rows after removal: 15234

```

In [ ]: # split dataframe into 2 df depending on pct
        function splitdf(df, pct)
            @assert 0 <= pct <= 1
            ids = collect(axes(df, 1))
            shuffle!(ids)
            sel = ids .<= nrow(df) .* pct
            train = view(df, sel, :)
            test = view(df, !sel, :)

            # println(hcat(train[:,1:end-1], DataFrame("satisfaction"=>train[:,end])) == tr

            return train[:,1:end-1], DataFrame("satisfaction"=>train[:,end]), test[:,1:end-1]
        end

        (x_train, y_train, x_test, y_test) = splitdf(cleaned_dataset, 0.7)

```

Out[ ]: (10663x22 DataFrame

Row	gender Float64	customer_type Float64	age Float64	type_of_travel Float64	class Float64	flight_dist ... Float64	...
1	0.0	1.0	53.0	1.0	1.0	26	...
2	1.0	1.0	33.0	1.0	1.0	4	
3	0.0	1.0	51.0	0.0	0.0	6	
4	1.0	1.0	25.0	1.0	1.0	35	
5	0.0	1.0	51.0	1.0	1.0	5	...
6	0.0	1.0	60.0	0.0	1.0	4	
7	1.0	1.0	17.0	0.0	0.0	5	
8	0.0	1.0	24.0	0.0	0.0	6	
9	0.0	1.0	31.0	1.0	1.0	35	...
10	1.0	1.0	53.0	0.0	0.0	4	
11	1.0	1.0	57.0	0.0	0.0	8	
:	:	:	:	:	:	:	...
10654	1.0	1.0	40.0	0.0	0.0	8	
10655	0.0	1.0	31.0	1.0	1.0	11	...
10656	0.0	1.0	53.0	0.0	0.0	2	
10657	0.0	1.0	32.0	1.0	1.0	12	
10658	0.0	1.0	57.0	1.0	1.0	11	
10659	0.0	1.0	27.0	1.0	1.0	17	...
10660	1.0	1.0	38.0	0.0	0.0	6	
10661	1.0	1.0	32.0	1.0	1.0	16	
10662	1.0	1.0	37.0	1.0	1.0	6	
10663	0.0	1.0	38.0	0.0	0.0	13	...

17 columns and 10642 rows omitted,

10663x1 DataFrame

Row	satisfaction Float64
1	0.0
2	1.0
3	0.0
4	1.0
5	1.0
6	0.0
7	0.0
8	0.0
9	1.0
10	0.0
11	0.0
:	:
10654	0.0
10655	1.0
10656	0.0
10657	0.0
10658	1.0
10659	0.0
10660	0.0
10661	1.0
10662	0.0
10663	1.0

10642 rows omitted, 4571x22 DataFrame

Row	gender Float64	customer_type Float64	age Float64	type_of_travel Float64	class Float64	flight_dist ... Float64	...
-----	-------------------	--------------------------	----------------	---------------------------	------------------	----------------------------	-----



1	1.0	1.0	64.0	0.0	0.0	29 ...
2	0.0	1.0	70.0	1.0	1.0	11
3	0.0	1.0	48.0	0.0	0.0	73
4	0.0	1.0	47.0	0.0	0.0	48
5	0.0	1.0	39.0	1.0	1.0	8 ...
6	1.0	1.0	39.0	1.0	1.0	273
7	0.0	1.0	47.0	0.0	0.0	30
8	0.0	1.0	44.0	1.0	1.0	89
9	1.0	1.0	30.0	1.0	0.0	94 ...
10	1.0	1.0	10.0	0.0	1.0	118
11	0.0	1.0	28.0	1.0	1.0	104
:	:	:	:	:	:	:
4562	0.0	1.0	58.0	1.0	1.0	211
4563	1.0	1.0	38.0	1.0	0.0	22 ...
4564	0.0	1.0	53.0	1.0	1.0	250
4565	0.0	1.0	54.0	1.0	1.0	32
4566	0.0	1.0	39.0	1.0	1.0	124
4567	0.0	1.0	23.0	0.0	1.0	172 ...
4568	0.0	1.0	38.0	1.0	0.0	21
4569	1.0	1.0	36.0	1.0	0.0	19
4570	1.0	1.0	45.0	1.0	1.0	44
4571	1.0	1.0	44.0	1.0	1.0	130 ...

17 columns and 4550 rows omitted,

4571x1 DataFrame

Row	satisfaction
	Float64

1	0.0
2	0.0
3	0.0
4	0.0
5	1.0
6	1.0
7	0.0
8	1.0
9	0.0
10	0.0
11	1.0
:	:
4562	1.0
4563	1.0
4564	1.0
4565	1.0
4566	1.0
4567	0.0
4568	0.0
4569	1.0
4570	1.0
4571	0.0

4550 rows omitted)

## Naive Bayes

```

In [ ]: # build conditional probability table
cont_col_names = ["age", "flight_distance", "departure_delay_in_minutes", "arrival_
disc_col_names = [name for name in names(dataset) if name <= cont_col_names && name
train = hcat(x_train, y_train)

# calculate discrete probabilities
function count_disc_prob(df, col_name)
    return combine(groupby(df, [col_name, "satisfaction"]), nrow)
end

cond_prob_table = Dict()
for name in disc_col_names
    cond_prob_table[name] = count_disc_prob(train, name)
end

# calculate continuous probabilities
function count_cont_prob(df, col_name)
    a = combine(groupby(df, "satisfaction"), [col_name] => mean, [col_name] => std)
end

for name in cont_col_names
    cond_prob_table[name] = count_cont_prob(train, name)
end

```

```

In [ ]: # calculate likelihood for continuous data
function likelihood(cond_prob_table, feature, satisfaction, x)
    feature_table = cond_prob_table[feature]
    prob_values = filter(row -> row.satisfaction == satisfaction, feature_table)

    # get mean and variance
    μ = prob_values[1,2]
    σ = prob_values[1,3]

    return (1/(σ * sqrt(2π))) * exp((-1/2) * ((x-μ)/σ)^2)
end

# calculate probabilities for discrete (categorical) data
function disc_cond_prob(cond_prob_table, feature, satisfaction, x)
    feature_table = cond_prob_table[feature]
    feature_table = filter(row -> row.satisfaction==satisfaction, feature_table)
    total = sum(feature_table[:,nrow])

    val = 0
    try
        val = filter(row -> row[feature] == x, feature_table)[1,end]
    catch
        val = 0
    end

    # apply Laplace smoothing
    return (val+1)/(total+1)
end

# run test
function test(x_test)

```

```

predictions = []

# iterate all training data
for i in 1:size(x_test)[1]
    test_case = x_test[i,:]

    p_satisfied_proportional = 1
    p_not_satisfied_proportional = 1

    # get probabilities of all features
    for col_name in names(test_case)

        # treat discrete and continuous features separately
        if col_name ∈ disc_col_names
            p_satisfied_proportional *= disc_cond_prob(cond_prob_table, col_name, 1)
            p_not_satisfied_proportional *= disc_cond_prob(cond_prob_table, col_name, 0)
        else
            p_satisfied_proportional *= likelihood(cond_prob_table, col_name, 1)
            p_not_satisfied_proportional *= likelihood(cond_prob_table, col_name, 0)
        end
    end

    # calculate probabilities
    p_satisfied = (p_satisfied_proportional / (p_satisfied_proportional + p_not_satisfied_proportional))
    p_not_satisfied = (p_not_satisfied_proportional / (p_satisfied_proportional + p_not_satisfied_proportional))

    # count correct and incorrect predictions
    if p_satisfied >= 0.5
        push!(predictions, 1)
    else
        push!(predictions, 0)
    end
end

return predictions
end

```

Out[ ]: test (generic function with 2 methods)

In [ ]: y\_pred = test(x\_test)

```

cm = CM.confmat(y_pred, y_test[:, "satisfaction"])
display(cm)
println("Total correct predictions: ", (cm(0,0) + cm(1,1)))
println("Total incorrect predictions: ", (cm(1,0) + cm(0,1)))
println("Total test rows: ", size(y_test)[1])
println("Model accuracy: ", (cm(0,0) + cm(1,1)) / size(y_test)[1])

```

	Ground Truth	
	0.0	1.0
Predicted		
0.0	2005	279
1.0	191	2096

Total correct predictions: 4101  
Total incorrect predictions: 470  
Total test rows: 4571  
Model accuracy: 0.8971778604244148