Riding the Trend:

Mapping Bike Rental Demand

Meet the Team

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Business overview

Introduction to the Bike Rental Businesses

Bike Rental Industry

Falling under the service sector, bike rentals "helps convert pedestrians into cyclists" by allowing temporary access to a variety of bikes

- Provide a competitively priced, flexible and sustainable mode of transportation.
- Is often placed in convenient locations allowing for maximum visibility and access for those willing to give them a try

So how do these bike rentals work?

- In most urban areas, prospective riders can walk up to the biking station dock
- Pay-as-you-go price or a subscription
- Drop off and lock the bike at a nearby docking station when finished

Products

Bicycles

Temporary access to a variety of bikes, whether that be the classic city bike or more specialized options like mountain cycles or electric bikes.

Helmets

Complementary, or a small charge for helmets are often offered along with bike rentals.

Merchandise & Fitting Services

Biking Gear & Fitting services to make minor adjustments to bikes to best tailor to each specific rider.

Target Consumer Market

Commuters

Locals who leverage these services as a means of transportation for their daily commute to work or school.

Tourist

Participate in recreational riding, as a means to explore new destinations at their own pace.

Environmentalists

Individuals looking for more environmentally conscious modes of transportation to go from Point A to B.

02

Initial Demand Analysis

Research & Literature Review on Bike Rental Demand

Factors Influencing Demand

Time

Weather

Days of Week

Population Density

Season

Temperature

Initial Hypothesis

We infer that (insert factors) are the most influential factors affecting bike rental demand.

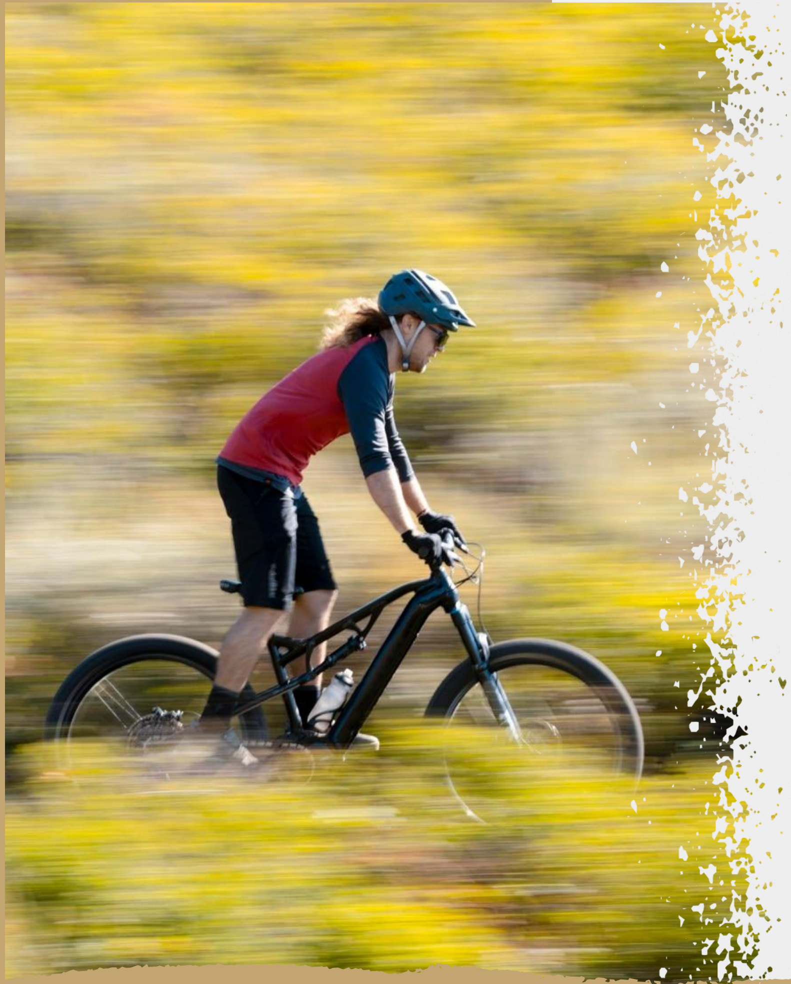
Thus, with the “Bike Rental Dataset Fields.pdf”" dataset we will be analyzing, we expect:

- *datetime*, *season*, *workingday*, *weather*, *temp*, *atemp*, *humidity*, *registered*

to be independent variables that will serve as the most significant predictors affecting the overall demand of bike rentals.
Furthermore we also infer that independent variables:

- *casual*, *windspeed* and *holiday*

will not be as accurate predictor variables towards bike rental demand.



03

Data Preparation

Preparing our Dataset

New Variables Introduced

- ***DemandType***
  - Based on *count* variable (number of total rentals)
  - High - *count* > 145
  - Low - *count* <= 145
- ***TimeofDay***
  - Morning: 4:00 am - 11:00 am, Afternoon: 12:00 pm - 3:00 pm,
  - Evening: 4:00 pm - 9:00 pm
  - Night: 10:00 pm - 3:00 am
- ***DayofWeek***
  - Sunday, Monday, Tuesday, Wednesday, Thursday, Friday, Saturday

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	datetime	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	casual	registered	count	DemandType	Time of Day	Day of Week
2	1/1/2011 0:00	1	0	0	1	9.84	14.395	81	0	3	13	16	low	Night	SAT
3	1/1/2011 1:00	1	0	0	1	9.02	13.635	80	0	8	32	40	low	Night	SAT
4	1/1/2011 2:00	1	0	0	1	9.02	13.635	80	0	5	27	32	low	Night	SAT
5	1/1/2011 3:00	1	0	0	1	9.84	14.395	75	0	3	10	13	low	Night	SAT
6	1/1/2011 4:00	1	0	0	1	9.84	14.395	75	0	0	1	1	low	Morning	SAT
7	1/1/2011 5:00	1	0	0	2	9.84	12.88	75	6.0032	0	1	1	low	Morning	SAT
8	1/1/2011 6:00	1	0	0	1	9.02	13.635	80	0	2	0	2	low	Morning	SAT
9	1/1/2011 7:00	1	0	0	1	8.2	12.88	86	0	1	2	3	low	Morning	SAT
10	1/1/2011 8:00	1	0	0	1	9.84	14.395	75	0	1	7	8	low	Morning	SAT
11	1/1/2011 9:00	1	0	0	1	13.12	17.425	76	0	8	6	14	low	Morning	SAT
12	1/1/2011 10:00	1	0	0	1	15.58	19.695	76	16.9979	12	24	36	low	Morning	SAT
13	1/1/2011 11:00	1	0	0	1	14.76	16.665	81	19.0012	26	30	56	low	Morning	SAT
14	1/1/2011 12:00	1	0	0	1	17.22	21.21	77	19.0012	29	55	84	low	Afternoon	SAT
15	1/1/2011 13:00	1	0	0	2	18.86	22.725	72	19.9995	47	47	94	low	Afternoon	SAT
16	1/1/2011 14:00	1	0	0	2	18.86	22.725	72	19.0012	35	71	106	low	Afternoon	SAT
17	1/1/2011 15:00	1	0	0	2	18.04	21.97	77	19.9995	40	70	110	low	Afternoon	SAT
18	1/1/2011 16:00	1	0	0	2	17.22	21.21	82	19.9995	41	52	93	low	Evening	SAT
19	1/1/2011 17:00	1	0	0	2	18.04	21.97	82	19.0012	15	52	67	low	Evening	SAT
20	1/1/2011 18:00	1	0	0	3	17.22	21.21	88	16.9979	9	26	35	low	Evening	SAT
21	1/1/2011 19:00	1	0	0	3	17.22	21.21	88	16.9979	6	31	37	low	Evening	SAT
22	1/1/2011 20:00	1	0	0	2	16.4	20.455	87	16.9979	11	25	36	low	Evening	SAT
23	1/1/2011 21:00	1	0	0	2	16.4	20.455	87	12.998	3	31	34	low	Evening	SAT
24	1/1/2011 22:00	1	0	0	2	16.4	20.455	94	15.0013	11	17	28	low	Night	SAT
25	1/1/2011 23:00	1	0	0	2	18.86	22.725	88	19.9995	15	24	39	low	Night	SAT
26	1/2/2011 0:00	1	0	0	2	18.86	22.725	88	19.9995	4	13	17	low	Night	SUN

Data Set Allocations	
Training	40.0
Validation	30.0
Test	30.0

04

Decision Model #1

Target Variable: Count; Assessment Measure: Average Squared Error

Variable settings

INPUTS

- Dayofweek
- Timeofday
- atemp
- datetime(Time ID)
- humidity
- season
- temp
- weather

REJECTED

- DemandType
- casual
- holiday
- registered
- windspeed

Dayofweek	Input	Nominal	No		No	.	.
DemandType	Rejected	Nominal	No		No	.	.
Timeofday	Input	Nominal	No		No	.	.
atemp	Input	Interval	No		No	.	.
casual	Rejected	Interval	No		No	.	.
count	Target	Interval	No		No	.	.
datetime	Time ID	Interval	No		No	.	.
holiday	Rejected	Binary	No		No	.	.
humidity	Input	Interval	No		No	.	.
registered	Rejected	Interval	No		No	.	.
season	Input	Interval	No		No	.	.
temp	Input	Interval	No		No	.	.
weather	Input	Interval	No		No	.	.
windspeed	Rejected	Interval	No		No	.	.

Rejected variables were deemed inaccurate indicators or would have skewed the data if included

Count was set as the Target variable and was used in conjunction with the Average Squared Error to give us our assessment measure

Decision Model Results

VARIABLES IN OPTIMAL TREE

- Timeofday
- temp
- workingday
- humidity
- season
- atemp
- weather
- Dayofweek

Variable Importance

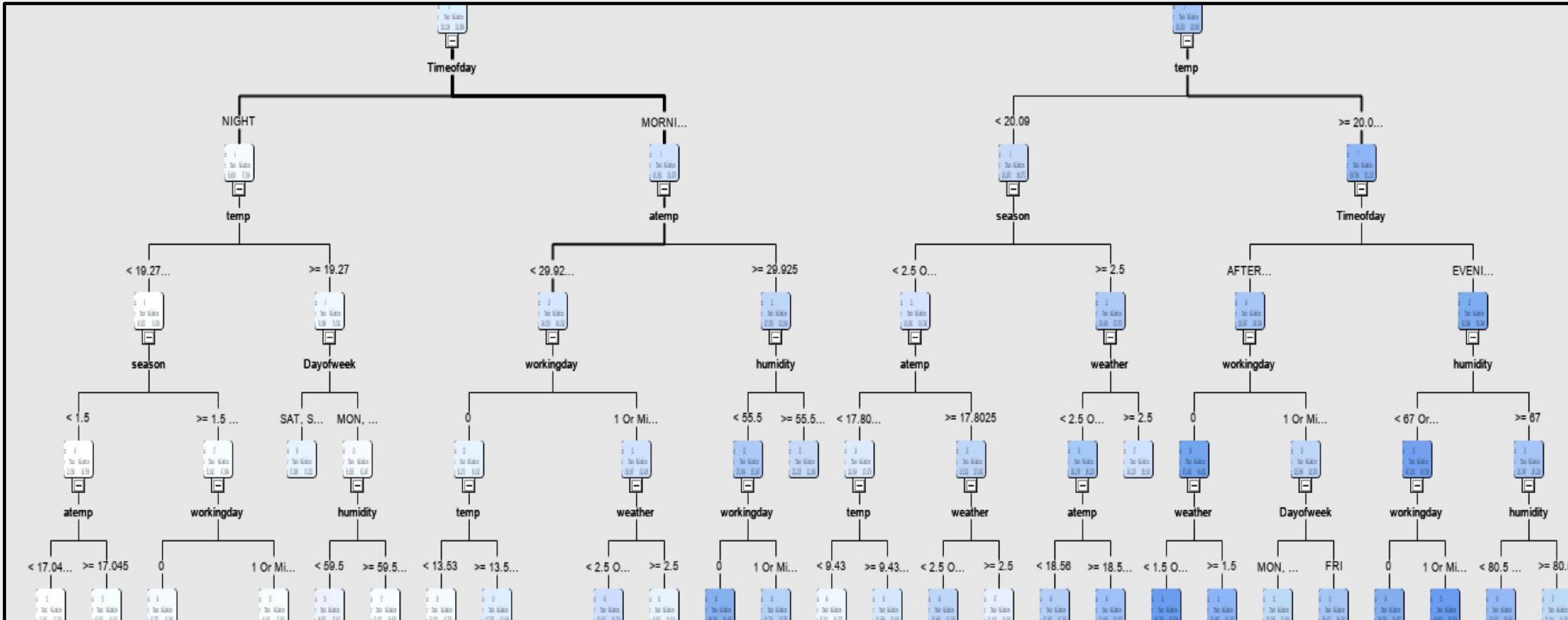
Variable Name	Label	Number of Splitting Rules	Importance	Validation Importance	Ratio of Validation to Training Importance
Timeofday		3	1.0000	1.0000	1.0000
temp		4	0.5021	0.5218	1.0392
workingday		6	0.3811	0.4259	1.1176
humidity		5	0.3224	0.2918	0.9053
season		5	0.2850	0.2837	0.9955
atemp		4	0.2600	0.2450	0.9426
weather		5	0.1836	0.1656	0.9018
Dayofweek		3	0.1231	0.1226	0.9958

TOP FIVE IMPORTANT VARIABLES

1. Timeofday
2. temp
3. workingday
4. humidity
5. season

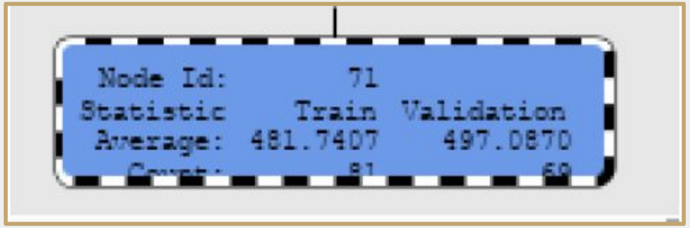
Decision Tree 1

Average Square Error: 15871.23



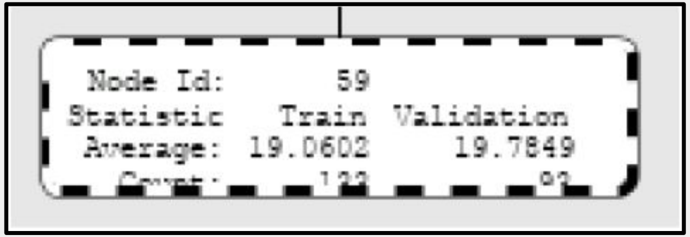
Best and Worst Outcomes

BEST OUTCOME



Rule: WHERE Timeofday AFTERNOON, EVENING AND temp >= 20.09 Or Missing AND Timeofday AFTERNOON AND workingday = 0 AND weather < 1.5 Or Missing AND Daysofweek SAT, SUN

WORST OUTCOME



Rule: WHERE Timeofday NIGHT, MORNING Or Missing AND Timeofday NIGHT AND temp < 19.27 Or Missing AND season < 1.5 AND atemp < 17.045 Or Missing AND workingday 1 Or Missing

Interpretation and suggestion

BEST OUTCOME BUSINESS SUGGESTIONS

- Offer higher rental rates on these days because the demand will be consistent
- Cut back on discounts and focus on having bikes readily available to meet demands

WORST OUTCOME BUSINESS SUGGESTIONS

- Offer discounted rate for daily rentals or full work week rentals for days Mon-Fri
- Focus on marketing bicycles for the “Go Getter” and “Early Riser” individuals in order to capture a portion of that market

04

Decision Model #2

Target Variable: Demand Type ; Assessment Measure: Misclassification

Variable List & Setup

Target Demand Type with Misclassification Error as the assessment measure.

Input Variables

- Day of Week
- Time of Day
- Atemp
- Humidity
- Season
- Temp
- Weather
- Working Day

Rejected Variables

- Casual
- Count*
- Holiday
- Registered
- Windspeed

Rejected Variables were determined based on group hypothesis and overall model and real life application.

Name	Role	Level	Report	Order	Drop
Dayofweek	Input	Nominal	No		No
DemandType	Target	Nominal	No		No
Timeofday	Input	Nominal	No		No
atemp	Input	Interval	No		No
casual	Rejected	Interval	No		No
count	Rejected	Interval	No		No
datetime	Time ID	Interval	No		No
holiday	Rejected	Binary	No		No
humidity	Input	Interval	No		No
registered	Rejected	Interval	No		No
season	Input	Interval	No		No
temp	Input	Interval	No		No
weather	Input	Interval	No		No
windspeed	Rejected	Interval	No		No
workingday	Input	Binary	No		No

Variable List using SAS Enterprise Miner.

Decision Model Results

Optimal Tree Variables

- Time of Day
- ATemp
- Season
- Weather
- Humidity
- Demand Type (Dependant Variable)

Top 5 Important Variables

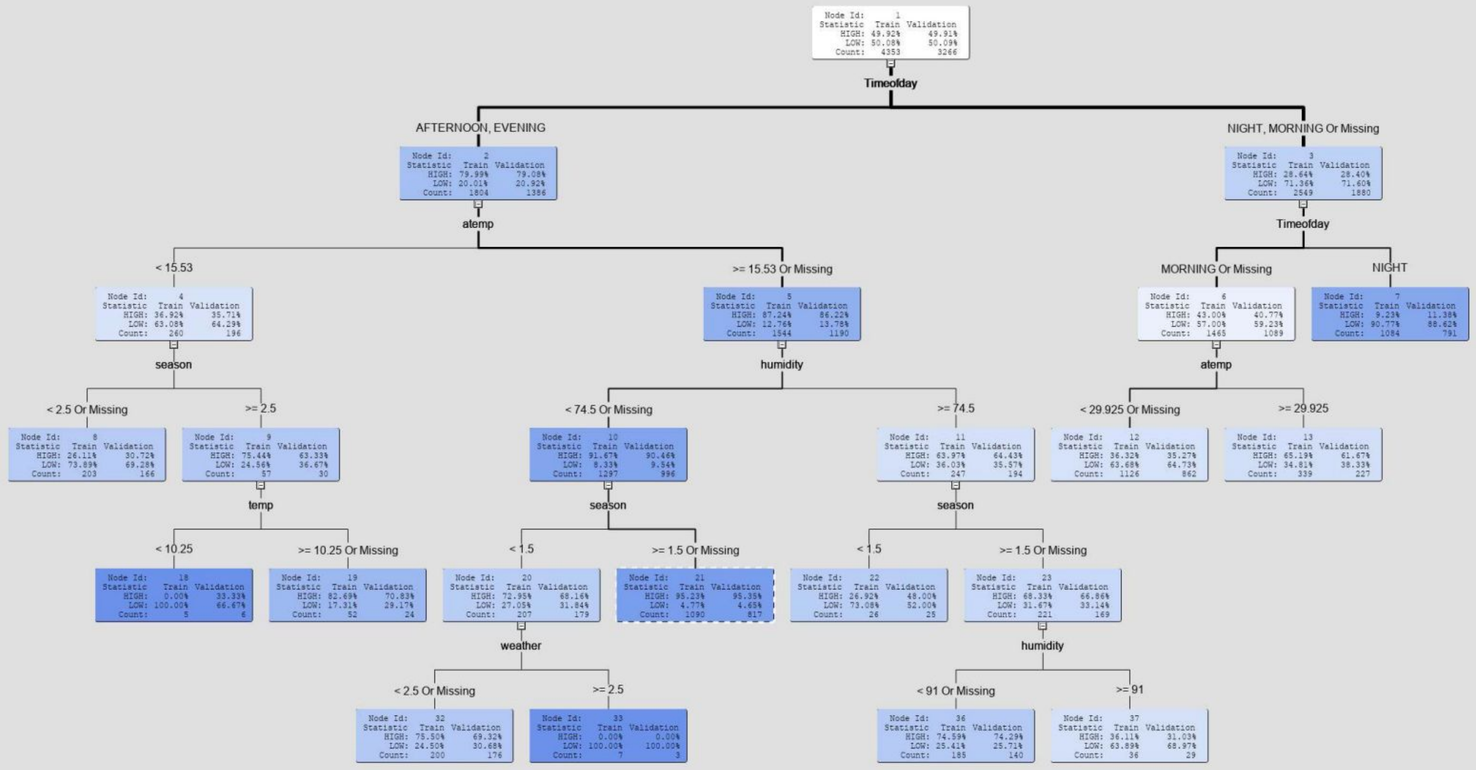
1. Time of Day
2. ATemp
3. Season
4. Humidity
5. Weather

Variable Importance

Variable Name	Label	Number of Splitting Rules	Importance	Validation Importance	Ratio of Validation to Training Importance
Timeofday		2	1.0000	1.0000	1.0000
atemp		2	0.4725	0.4778	1.0113
season		3	0.2590	0.2269	0.8759
humidity		2	0.2415	0.2518	1.0425
weather		1	0.1050	0.0689	0.6561
temp		1	0.0945	0.0213	0.2255

Variables of Importance in SAS Enterprise Miner.

Decision Model Results



Decision Matrix Computations

Data Role=VALIDATE Target=DemandType Target Label=

False Negative	True Negative	False Positive	True Positive
222	1162	468	1414

Sensitivity = TP/(TP+FN) = 86.43%

Specificity = TN/(TN+FP) = 71.23%

Accuracy = TP+TN/Total Predicted = 78.87%

Misclassification = FP+FN/Total Predicted = 21.13%

Interpretations & Suggestions

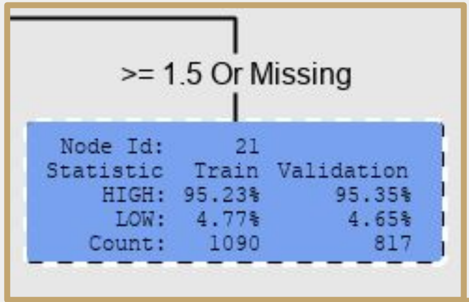
In order to grow our businesses and increase bike sales, we suggest following;

Optimal Settings and Peak Times:

- Provide more bikes available for more bike accessibility
- Increase prices for bikes during optimal peak times so that we gain an increase per sale on our rentals
- Possibility of Reward system for signed up subscribers to increase bike usage.

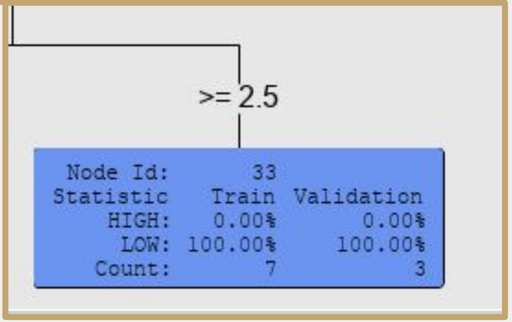
Worst Outcomes

- Offer discounts on bike service rentals to encourage customers to utilize our services during less than optimal hours



Rule: WHERE Timeofday AFTERNOON, EVENING AND atemp >= 15.53 AND humidity < 74.5 AND season >= 1.5

Rule: WHERE Timeofday AFTERNOON, EVENING AND atemp >= 15.53 AND humidity < 74.5 AND season >= 1.5 AND weather >= 2.5



05

Logistic Regression Model

Logistic Regression - Data

Name	Role	Level
Dayofweek	Input	Nominal
DemandType	Target	Binary
Timeofday	Input	Nominal
atemp	Input	Interval
casual	Rejected	Interval
count	Rejected	Interval
datetime	Rejected	Interval
holiday	Input	Binary
humidity	Input	Interval
registered	Rejected	Interval
season	Input	Nominal
temp	Input	Interval
weather	Input	Ordinal
windspeed	Input	Interval
workingday	Input	Binary

- Count is directly related to DemandType, so it is excluded
- Casual and Registered are both directly related to Count, so they are also excluded
- DateTime is directly related to TimeOfDay and DayOfWeek, so it is excluded as well
- For partitioning, we used 50% Training and 50% Validation

Model Selection

- ***Forward selection***:
  - DayOfWeek, TimeOfDay, aTemp, Humidity, Season, Weather
- ***Backward selection***:
  - DayOfWeek, TimeOfDay, aTemp, Humidity, Season, Weather, WindSpeed
- ***Stepwise selection***:
  - DayOfWeek, TimeOfDay, aTemp, Humidity, Season, Weather
- Forward and Stepwise selection methods both landed on the same model, with backward selection differing in accuracy by 0.7%. Given our hypothesis and the variables included, we are using the Forward/Stepwise selection method for our model

Logistic Regression Model - Results

Event Classification Table

Data Role=TRAIN Target=DemandType Target Label=' '

False Negative	True Negative	False Positive	True Positive
526	2181	535	2199

Data Role=VALIDATE Target=DemandType Target Label=' '

False Negative	True Negative	False Positive	True Positive
548	2162	556	2179

- Accuracy:
  - (TP+TN)/Total = 79.72%
- Sensitivity:
  - TP/(TP+FN) = 79.90%
- Specificity:
  - TN/(TN+FP) = 79.54%

Logistic Regression Model - Results

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq	Standardized Estimate	Exp(Est)
Intercept		1	1.7280	0.2549	45.96	<.0001		5.629
Dayofweek	FRI	1	-0.4750	0.0944	25.32	<.0001		0.622
Dayofweek	MON	1	0.0797	0.0910	0.77	0.3811		1.083
Dayofweek	SAT	1	0.1059	0.0903	1.38	0.2405		1.112
Dayofweek	SUN	1	0.3525	0.0906	15.14	<.0001		1.423
Dayofweek	THU	1	-0.1121	0.0941	1.42	0.2337		0.894
Dayofweek	TUE	1	0.0813	0.0942	0.74	0.3885		1.085
Timeofday	Afternoon	1	-0.9589	0.0822	136.00	<.0001		0.383
Timeofday	Evening	1	-1.5538	0.0729	454.48	<.0001		0.211
Timeofday	Morning	1	0.1258	0.0603	4.35	0.0370		1.134
atemp		1	-0.1310	0.00775	285.95	<.0001	-0.6132	0.877
humidity		1	0.0260	0.00249	108.83	<.0001	0.2731	1.026
season	1	1	0.5603	0.0932	36.13	<.0001		1.751
season	2	1	-0.00193	0.0683	0.00	0.9775		0.998
season	3	1	0.3042	0.0942	10.44	0.0012		1.356
weather	1	1	-0.3225	0.0664	23.59	<.0001		0.724
weather	2	1	-0.3855	0.0666	33.49	<.0001		0.680

Odds Ratio Estimates

Effect		Point Estimate
Dayofweek	FRI vs WED	0.642
Dayofweek	MON vs WED	1.119
Dayofweek	SAT vs WED	1.148
Dayofweek	SUN vs WED	1.469
Dayofweek	THU vs WED	0.923
Dayofweek	TUE vs WED	1.120
Timeofday	Afternoon vs Night	0.035
Timeofday	Evening vs Night	0.019
Timeofday	Morning vs Night	0.104
atemp		0.877
humidity		1.026
season	1 vs 4	4.149
season	2 vs 4	2.365
season	3 vs 4	3.211
weather	1 vs 3	0.357
weather	2 vs 3	0.335

The Odds/Coefficients above are for Low Demand, so the reverse is true for High Demand

Logistic Regression Model - Analysis

- aTemp | 0.877
- Friday (vs Wednesday) | 0.642
- Thursday (vs Wednesday) | 0.923
- Evening (vs Night) | 0.019
- Afternoon (vs Night) | 0.035
- Morning (vs Night) | 0.104
- Clear Weather (vs Light Rain) | 0.357
- Mist (vs Light Rain) | 0.335

- Humidity | 1.026
- Sunday (vs Wednesday) | 1.469
- Saturday (vs Wednesday) | 1.148
- Monday (vs Wednesday) | 1.119
- Tuesday (vs Wednesday) |1.120
- Spring (vs Winter) | 4.149
- Fall (vs Winter) | 2.635
- Summer (vs Winter) | 2.365

The Odds above are for Low Demand, so the lower the number the higher odds of High Demand

When is there typically high demand?

Weekdays with Most Demand

1. Friday (0.642)
2. Thursday (0.923)
3. Wednesday (baseline)
4. Tuesday (1.120)
5. Monday (1.119)
6. Saturday (1.148)
7. Sunday (1.469)

Time of Day with Most Demand

1. Evening (0.019)
2. Afternoon (0.035)
3. Morning (0.104)
4. Night (baseline)

Seasons with Most Demand

1. Winter (baseline)
2. Summer (2.365)
3. Fall (2.635)
4. Spring (4.149)

What type of weather leads to higher demand?

- On average, the temperature that it “feels like” has a positive relationship with higher demand
- On the flip side, humidity has an inverse relationship
- Given that clear and misty weather leads to higher demand than heavier precipitation, we can conclude that warmer and drier days are associated with higher demand

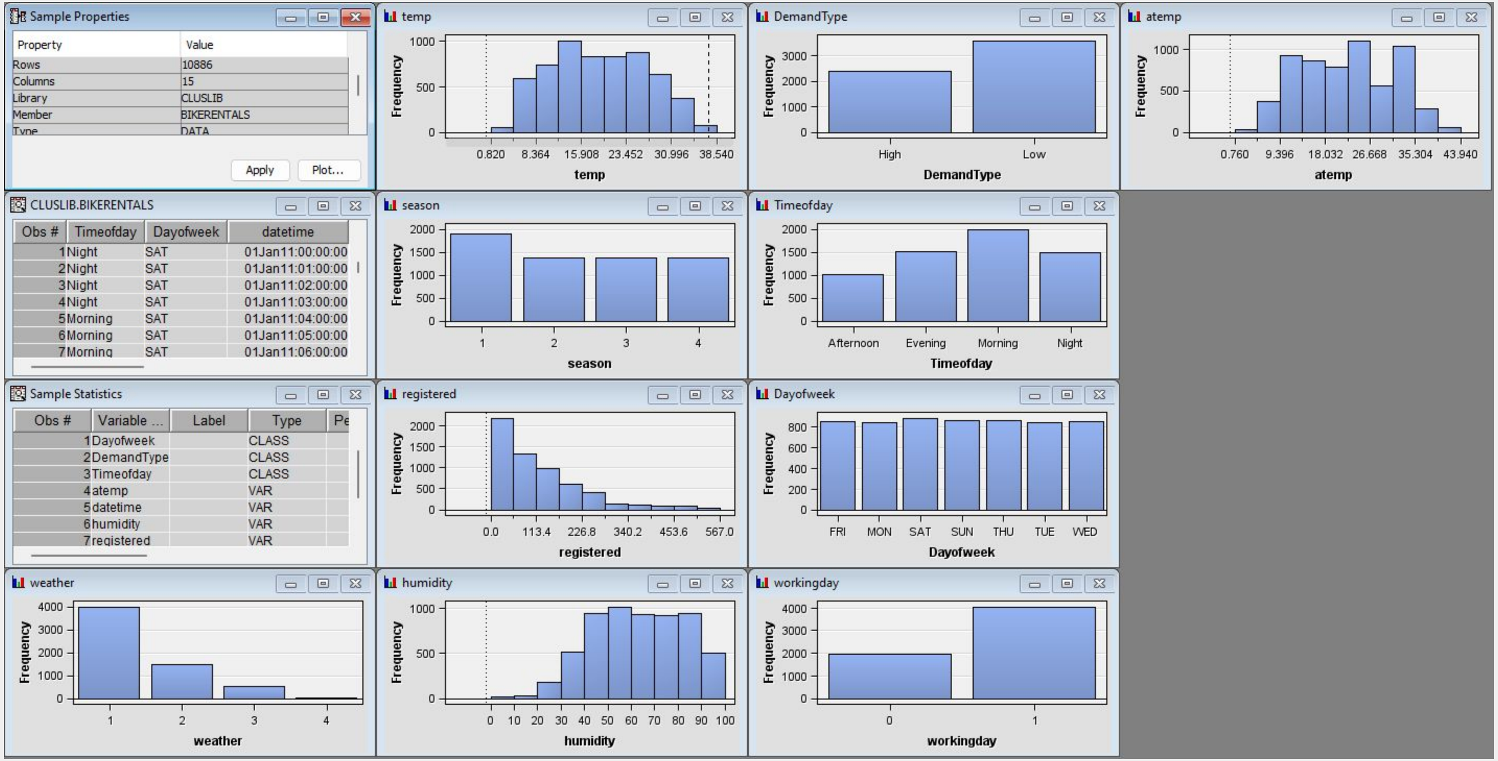
06

Cluster Analysis Model

Variables

Name	Role	Level	Report	Order	Drop	Lower Limit	Upper Limit
Dayofweek	Input	Nominal	No		No	.	.
DemandType	Input	Nominal	No		No	.	.
Timeofday	Input	Nominal	No		No	.	.
atemp	Input	Interval	No		No	.	.
casual	Rejected	Interval	No		No	.	.
count	Rejected	Interval	No		No	.	.
datetime	Time ID	Interval	No		No	.	.
holiday	Rejected	Binary	No		No	.	.
humidity	Input	Interval	No		No	.	.
registered	Input	Interval	No		No	.	.
season	Input	Nominal	No		No	.	.
temp	Input	Interval	No		No	.	.
weather	Input	Nominal	No		No	.	.
windspeed	Rejected	Interval	No		No	.	.
workingday	Input	Binary	No		No	.	.

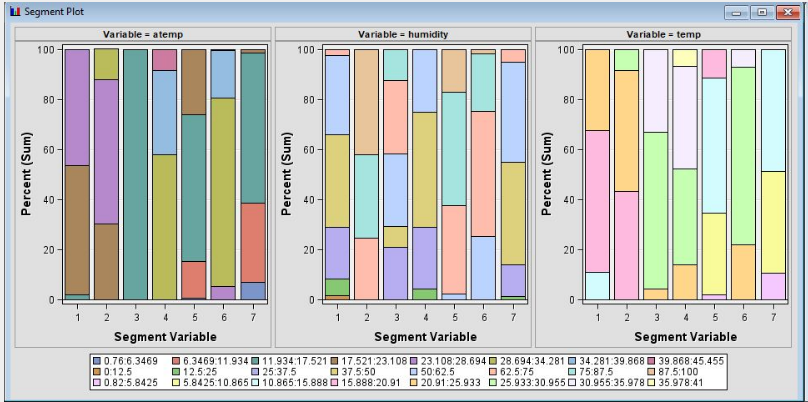
Variable Breakdown

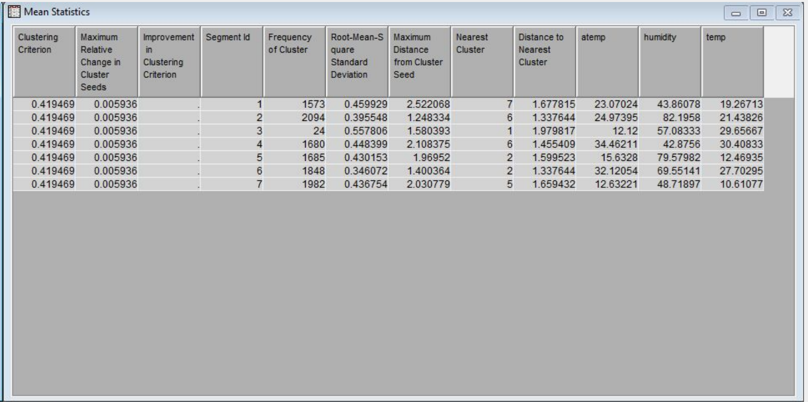


Variable Summary

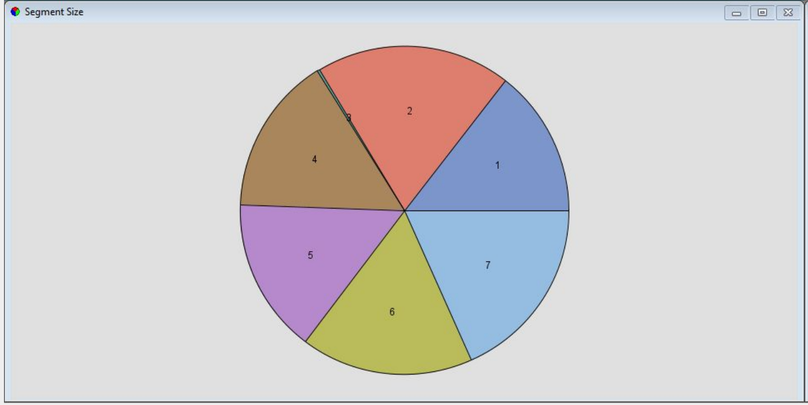
Var_Name	Mean/Mode
weather	1.423
temp	18.9666
season	2.3663
registered	115.676
humidity	62.8222
DemandType	LOW
TimeOfDay	MORNING
DaysOfWeek	SAT
WorkingDay	0.6768
atemp	22.2846

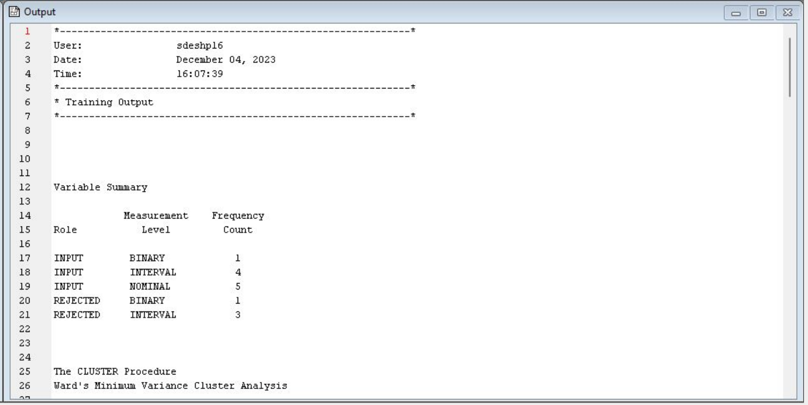
Clustering Output




Mean Statistics

Clustering Criterion	Maximum Relative Change in Cluster Seeds	Improvement in Clustering Criterion	Segment Id	Frequency of Cluster	Root-Mean-Square Standard Deviation	Maximum Distance from Cluster Seed	Nearest Cluster	Distance to Nearest Cluster	atemp	humidity	temp
0.419469	0.005936	.	1	1573	0.459929	2.522068	7	1.677815	23.07024	43.86078	19.26713
0.419469	0.005936	.	2	2094	0.395548	1.248334	6	1.337644	24.97395	82.1958	21.43826
0.419469	0.005936	.	3	24	0.557806	1.580393	1	1.979817	12.12	57.08333	29.65667
0.419469	0.005936	.	4	1680	0.448399	2.108375	6	1.455409	34.46211	42.8756	30.40833
0.419469	0.005936	.	5	1685	0.430153	1.96952	2	1.599523	15.6328	79.57982	12.46935
0.419469	0.005936	.	6	1848	0.346072	1.400364	2	1.337644	32.12054	69.55141	27.70295
0.419469	0.005936	.	7	1982	0.436754	2.030779	5	1.659432	12.63221	48.71897	10.61077




Output

```
*------------------------------------------------------------*
User:                sdeshp16
Date:                December 04, 2023
Time:                16:07:39
*------------------------------------------------------------*
* Training Output
*------------------------------------------------------------*




Variable Summary

            Measurement    Frequency
Role           Level         Count

INPUT        BINARY           1
INPUT        INTERVAL         4
INPUT        NOMINAL          5
REJECTED     BINARY           1
REJECTED     INTERVAL         3



The CLUSTER Procedure
Ward's Minimum Variance Cluster Analysis
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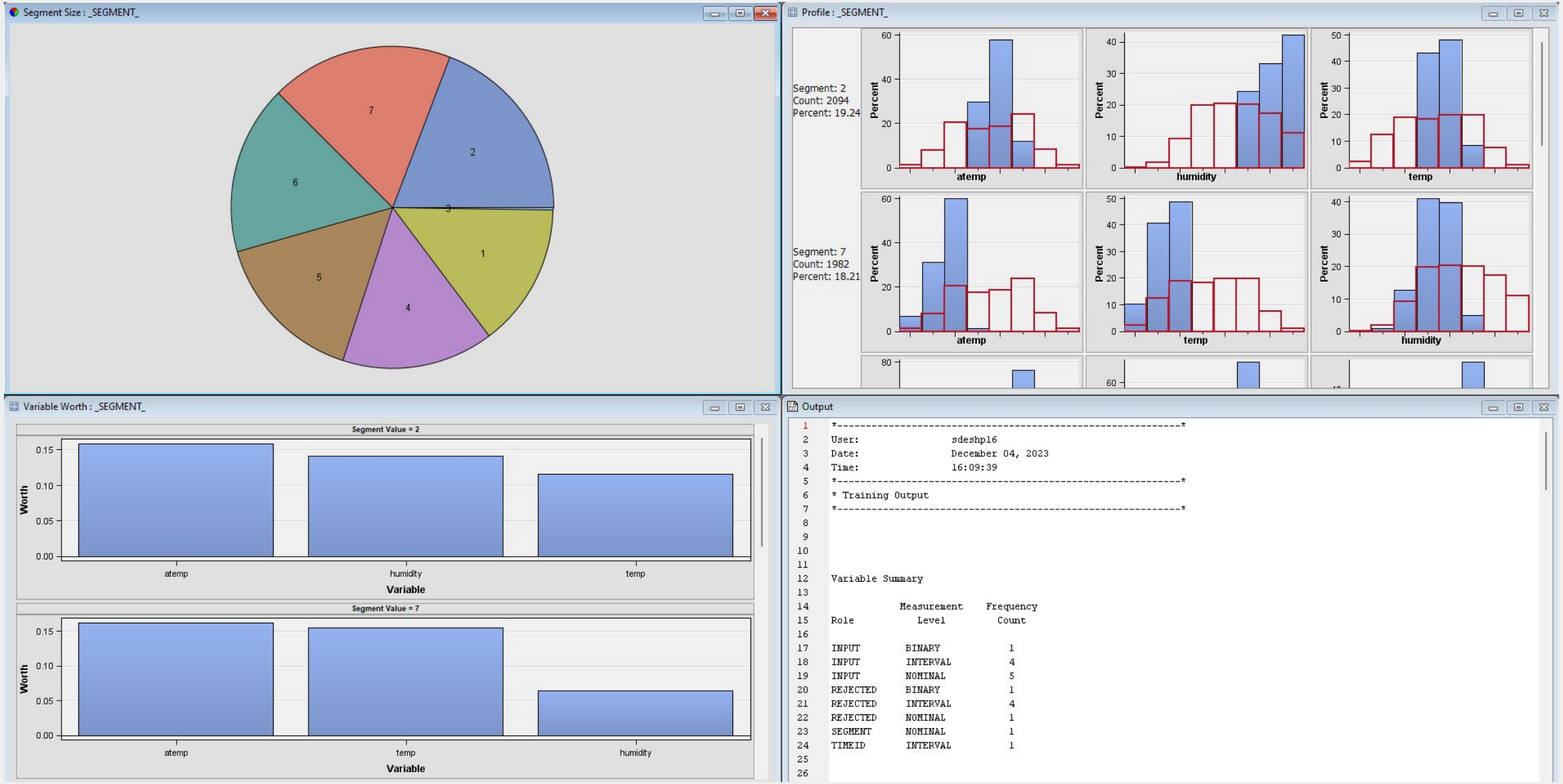
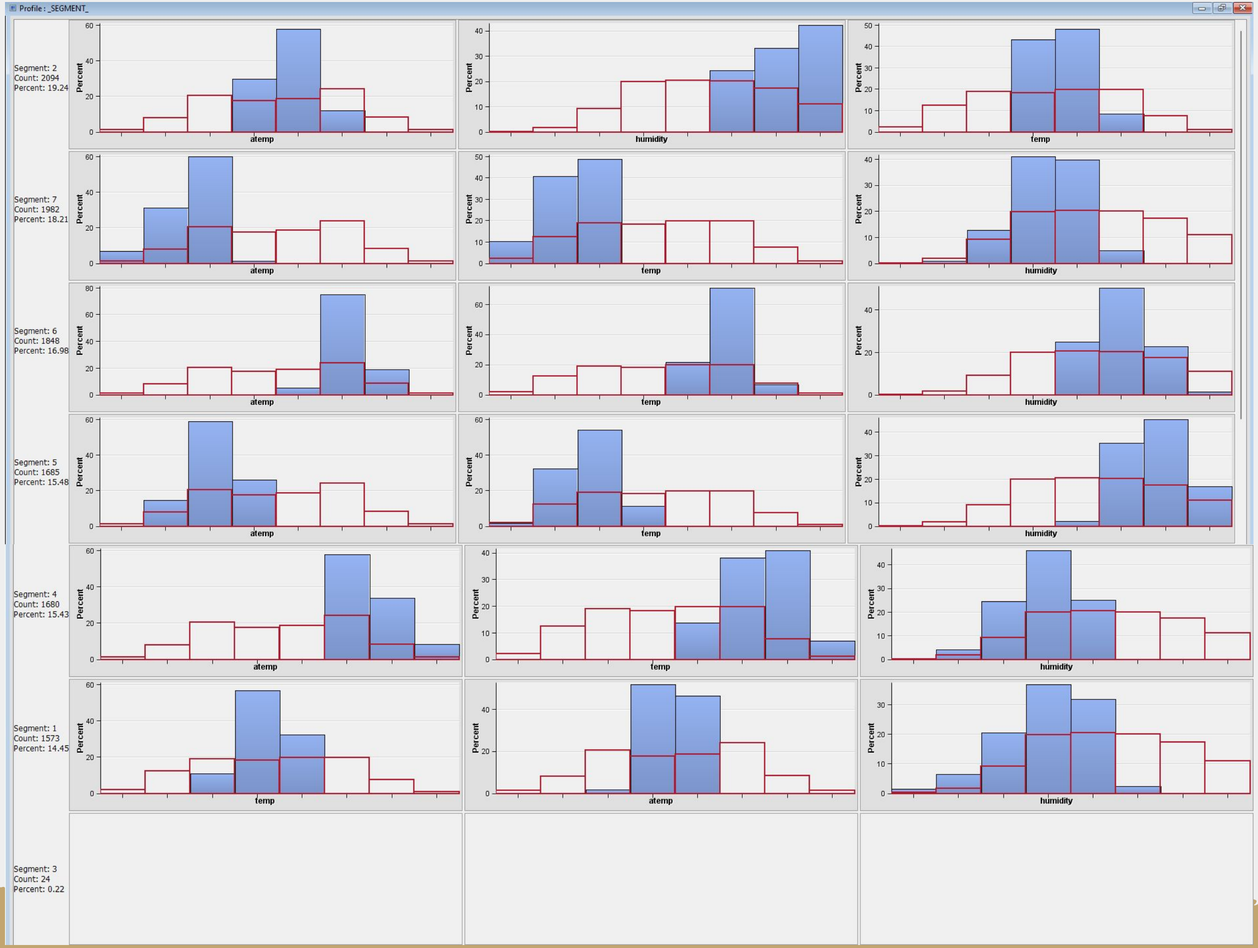
Segment Analysis



Segment Profile



Cluster Segment Analysis

Segment 2 is the largest with 2,094 records in the cluster. The importance of variables is as follows (most important to least important):

- atemp: About normally distributed, but most of the data falls near the middle of overall data distribution
- humidity: Falls toward higher end of overall data distribution
- temp: Falls toward middle of overall data distribution

Next largest is Segment 7 with 1,982 records in the cluster. The importance of variables is as follows (most important to least important):

- atemp: Falls toward lower end of overall data distribution
- temp: Falls toward lower end of overall data distribution
- humidity: Falls toward middle of overall data distribution

Cluster Segment Analysis

Then we have Segment 6 with 1,848 records. The importance of variables is as follows (most important to least important):

- atemp: Falls toward higher end of overall data distribution
- temp: Falls toward higher end of overall data distribution
- humidity: Falls toward higher end of overall data distribution

Then we have Segment 5 with 1,685 records. The importance of variables is as follows (most important to least important):

- atemp: Falls toward lower end of overall data distribution
- humidity: Falls toward lower end of overall data distribution
- temp: Falls toward higher end of overall data distribution

Cluster Segment Analysis

Then we have Segment 4 with 1,680 records. The importance of variables is as follows (most important to least important):

- atemp: Falls toward higher end of overall data distribution
- temp: Falls toward higher end of overall data distribution
- humidity: Falls toward lower end of overall data distribution

Then we have Segment 1 with 1,573 records. The importance of variables is as follows (most important to least important):

- temp: Falls toward middle of overall data distribution
- atemp: Falls toward middle of overall data distribution
- humidity: Falls toward lower end or middle of overall data distribution

Cluster Segment Summary

The smallest cluster is segment 3 with 24 records in the cluster. The output did not give a ranked list of variables in order of importance, and likely represents null values.

07

Business Recommendations

Key Findings & Recommendations

Future Recommendations

Dynamic Pricing Model

Adjusting their prices depending demand factors. For example, when conditions for the highest potential rental demand are present, the company can charge at a higher premium and whereas when conditions are less favorable, the company can reduce the price in order to entice a higher number of rentals.

Loyalty Program

Implement a loyalty program to reward frequent customers and encourage repeat business.

Mobile App and Online Presence:

Develop a user-friendly mobile app that allows customers to easily locate and rent bikes incorporating features like GPS tracking, payment integration, and bike availability status as well as leveraging social media & online marketing to increase brand awareness.

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Thanks

Do you have any questions?