1. Task Description

Hello,

As CTO and head of Blackwell's eCommerce Team, I'd like to welcome you aboard. I'm excited to get started on this project, but I'd first like to give you a bit of background to get you up to speed. Blackwell has been a successful electronics retailer for over 40 years, with over 30 stores in the Southeast. A little over a year ago we launched our eCommerce website. We are starting to build up customer transaction data from the site and we want to leverage this data to inform our decisions about site-related activities, like online marketing, enhancements to the site and so on, in order to continue to maximize the amount of revenue we generate from eCommerce sales.

For example, our VP of Sales, Martin Goodrich, thinks that customers who shop in the store are older than customers who shop online and that older people spend more money on electronics than younger people. He is considering some marketing activities and potentially some design changes to the website to attract older buyers. I, on the other hand, believe that the differences in transactions and customer demographics may be regional. Before we even consider any additional activities related to the website, we want to gain insight into any factors that can explain how our customers shop and how much they spend.

To that end, I would like you to explore the customer transaction data we have collected from recent online and in-store sales and see if you can infer any insights about customer purchasing behavior. Specifically, I am interested in the following:

1. Do customers in different regions spend more per transaction? Which regions spend the most/least?

2. Are there differences in the age of customers between regions? If so, can we predict the age of a customer in a region based on other demographic data?

3. We need to investigate Martin’s hypothesis: Is there any correlation between age of a customer and if the transaction was made online or in the store? Do any other factors predict if a customer will buy online or in our stores?

4. Finally, is there a relationship between number of items purchased and amount spent?

To investigate this, I’d like you to use data mining methods to explore the data, look for patterns in the data and draw conclusions. I have attached a data file of customer transactions; it includes some information about the customer who made the transaction, as well as the amount of the transaction, and how many items were purchased. Once you have completed your analysis, please create a brief report of your findings and conclusions and an explanation of how you arrived at those conclusions so I can discuss them with Martin.

2. Task Solution

A data set (Blackwell_Hist_Sample.csv) provided by the CTO, a quick review to ensure data is tidy and clean was conducted, no missing values were found in the data set. Based on this outcome, the data can be used for analysis.

Name	Type	Missing	Statistics			Filter (5 / 5 attributes): Search for Attributes
in.store	Integer	0	Min 0	Max 1	Average 0.456	
age	Integer	0	Min 18	Max 85	Average 45.956	
items	Integer	0	Min 1	Max 8	Average 4.504	
amount	Real	0	Min 5.230	Max 2999.200	Average 835.000	
region	Integer	0	Min 1	Max 4	Average 2.660	

Figure 1 - Data Set Statistics

Q1 - Do customers in different regions spend more per transaction? Which regions spend the most/least?

Yes, the region 4 (Central) has the higher spend and region 2 (West) showed the lowest spend, based on the results listed in figure 2 and 3.

Figure 2 – Relationship between regions and the amount per transaction

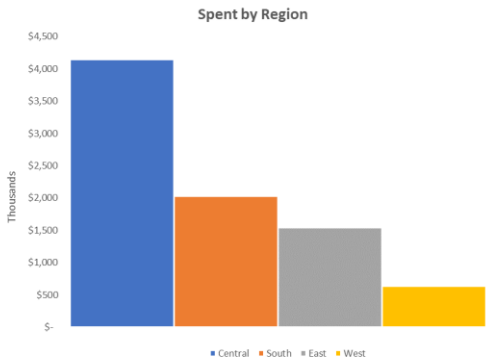


Figure 3 – The region with the highest spend is Region 4 (Central), with a spent over $4 MM

Q2 - Are there differences in the age of customers between regions? If so, can we predict the age of a customer in a region based on other demographic data?

Yes, there are differences in the age of customers between regions, as is show in figure 4. There are four ranges:

Age Range (years)
18 - 35
35 - 52
52 - 68
68 - 85

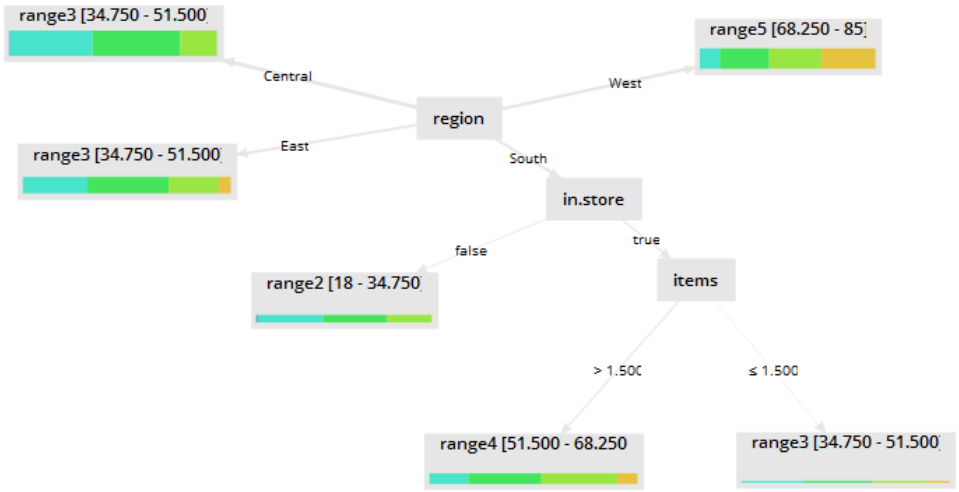


Figure 4 – Difference in the age of customers

This model is not a reliable model to predict the age of customers, since 1 out of 4 regions a low error margin (Accuracy 58,40%), the other 3 regions has accuracy values lower than 30% in one instance is below 2%, as is show in figure 5.

accuracy: 58.40%

	true South	true West	true East	true Central	class precision
pred. South	309	0	252	118	45.51%
pred. West	75	759	77	165	70.54%
pred. East	10	0	12	9	38.71%
pred. Central	268	4	270	672	55.35%
class recall	46.68%	99.48%	1.96%	69.71%	

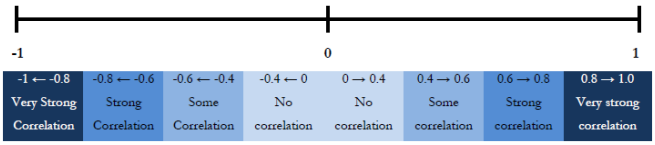
kappa: 0.428

	true South	true West	true East	true Central	class precision
pred. South	309	0	252	118	45.51%
pred. West	75	759	77	165	70.54%
pred. East	10	0	12	9	38.71%
pred. Central	268	4	270	672	55.35%
class recall	46.68%	99.48%	1.96%	69.71%	

Figure 5 – Accuracy and Kappa values for a trained model

Q3 - We need to investigate Martin's hypothesis: Is there any correlation between age of a customer and if the transaction was made online or in the store? Do any other factors predict if a customer will buy online or in our stores?

There is no correlation between customer's age and in.store, since the correlation matrix ran for this model, indicates a value of -0.176 which is considered low, based on rapidminer references (Figure 6).



Attribut...	in.store	age	items	amount	region
in.store	1	-0.176	-0.013	-0.063	-0.006
age	-0.176	1	0.006	-0.283	-0.235
items	-0.013	0.006	1	-0.002	-0.015
amount	-0.063	-0.283	-0.002	1	0.401
region	-0.006	-0.235	-0.015	0.401	1

Row No.	Attribute	Weight
1	region	1
2	amount	0.258
3	age	0.084
4	items	0

Figure 6 – Correlation matrix and Weight by information (Label = in.store)

There are other two factors with some degree of correlation with the in.store attribute, region and amount. In the correlation matrix, the bond between Amount – Region is the strongest relationship and using the weight by information gain operator, the weight of attributes with respect to the class attribute by using the information gain, shows that Region and Amount have the highest weights.

This can be easily interpreted in the decision tree listed below (Figure 7). Using the in.store attribute as Label, the Regions and the amounts are probability nodes.

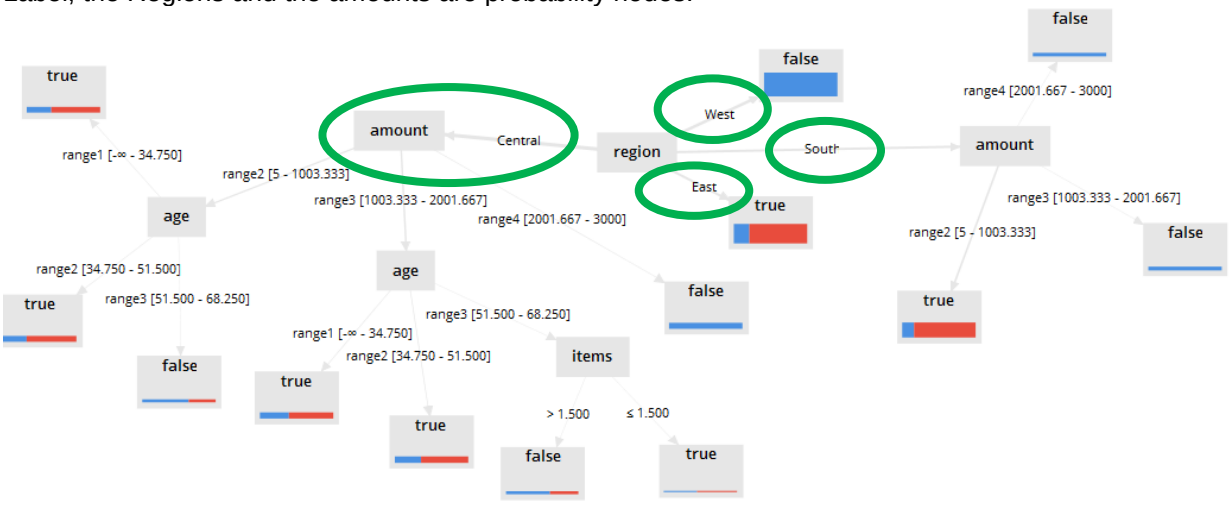
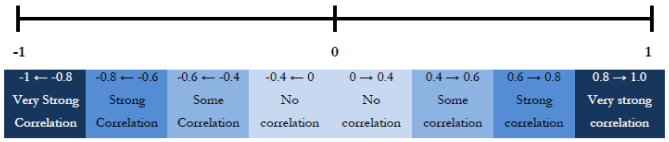


Figure 7 – Decision tree using in.store as label.

Q4 - Finally, is there a relationship between number of items purchased and amount spent?

The relationship between items purchased and amount spent is not clear or at least not obvious in this model, since correlation matrix shows a low relationship -0.002 and also the weight of attributes with respect to the class attribute by using the information gain, shows a weight of zero for the items attribute, regardless the label attribute.



Attribut...	in.store	age	items	amount	region
in.store	1	-0.176	-0.013	-0.063	-0.006
age	-0.176	1	0.006	-0.283	-0.235
items	-0.013	0.006	1	-0.002	-0.015
amount	-0.063	-0.283	-0.002	1	0.401
region	-0.006	-0.235	-0.015	0.401	1

Row No.	Attribute	Weight
1	in.store	1
2	amount	0.835
3	age	0.501
4	items	0

Figure 8 – Correlation matrix and Weight by information (Label = Region)

Results Discussion

The model developed for this task, helps to identify a difference in the spent within regions, age ranges and purchases made online or in stores.

The model has some limitation in terms of predictability for the customer's age between regions and purchased items vs. spent. With the current data set or these correlations are not obvious, a different data set shall be tested, since different algorithms and model optimization were conducted.

The model accuracy was not significant between the different algorithms (decision Tree = 59,37%, Random Forrest = 59,37% and Gradient Boosted Trees = 59,41), an optimized version of the decision tree algorithm was ran with results of 59,57%. This give us some clues about the data set, since the model optimization and algorithm variation didn't provide higher improvements.

Models

The figures listed below are proof of the models used to determine the case responses.

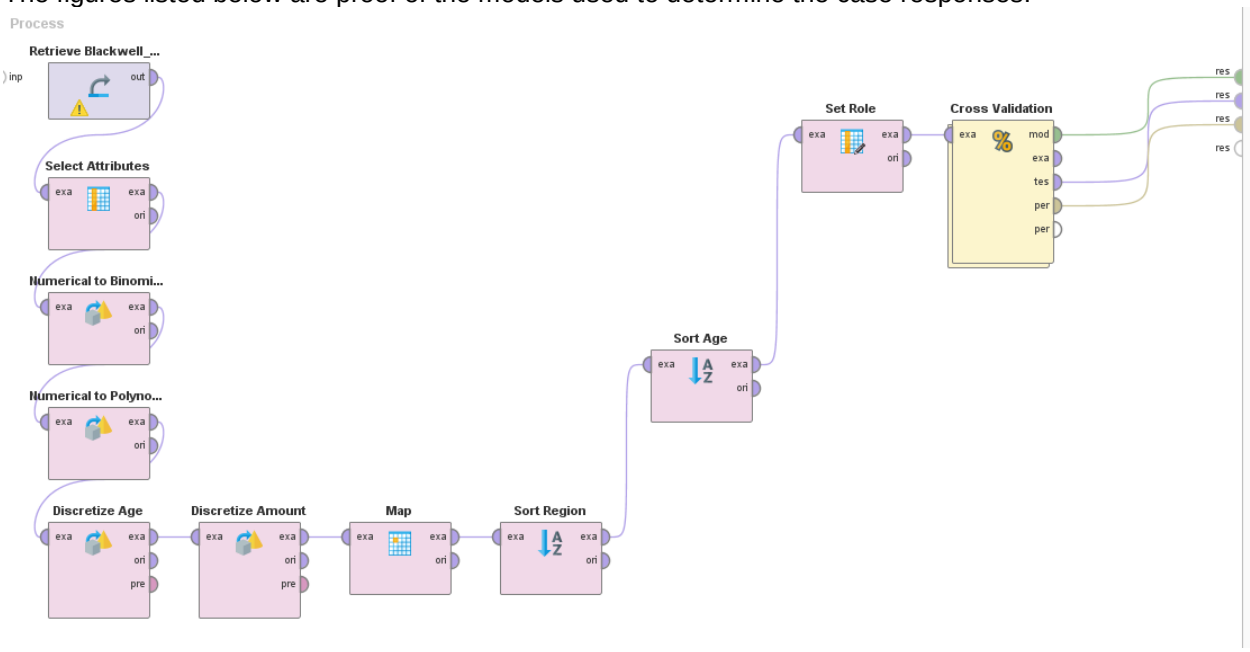


Figure 9 – Decision Tree Algorithm

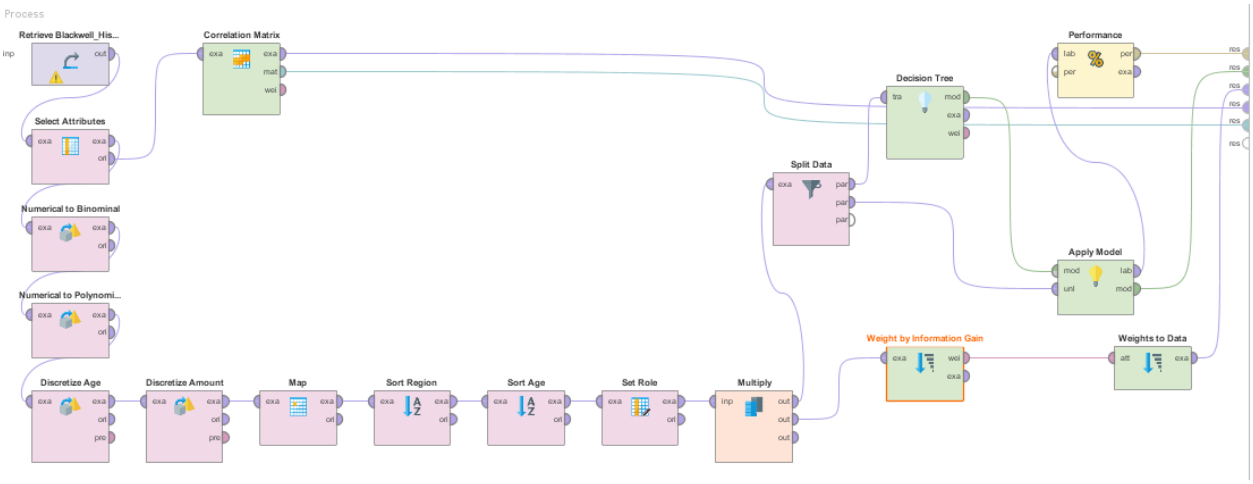


Figure 10 – Decision Tree Algorithm Trained model (70% training data / 30% unlabeled data)

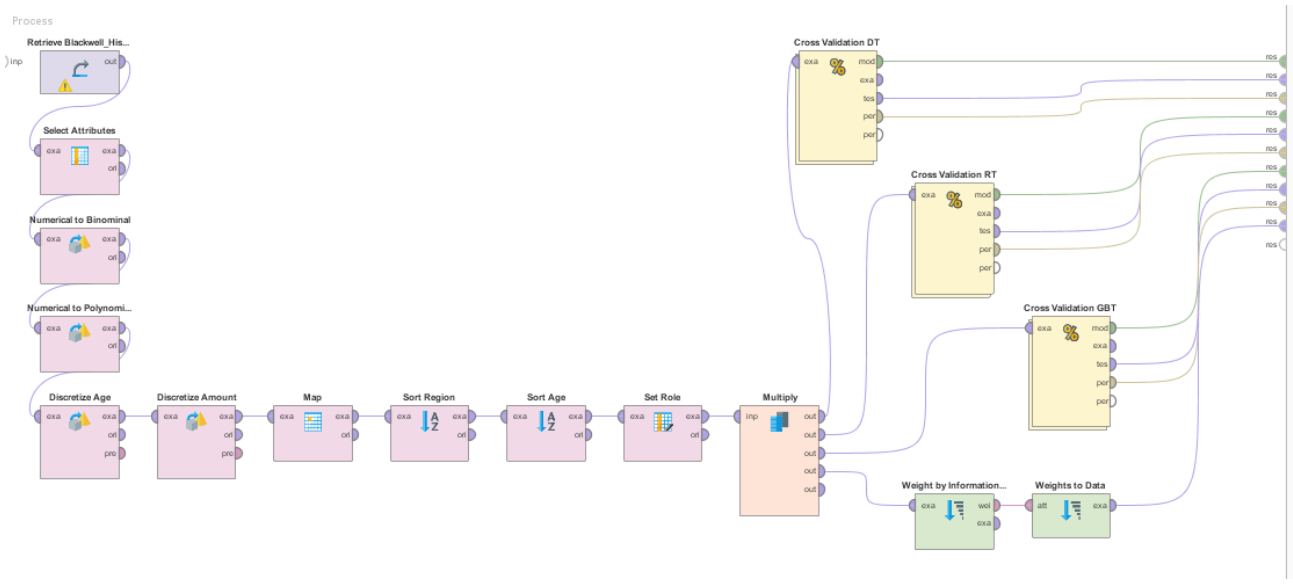


Figure 11 – Decision Tree, Random Forest, Gradient Boosted Trees algorithms

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Decision Tree

accuracy: 59.27% +/- 1.84% (micro average: 59.27%)

	true South	true West	true East	true Central	class precision
pred. South	1048	0	829	407	45.88%
pred. West	267	2544	328	493	70.04%
pred. East	89	0	123	101	39.30%
pred. Central	803	0	756	2212	58.66%
class recall	47.49%	100.00%	6.04%	68.85%	

Random Forrest

accuracy: 59.37% +/- 0.79% (micro average: 59.37%)

	true South	true West	true East	true Central	class precision
pred. South	917	0	672	366	46.91%
pred. West	267	2542	325	493	70.09%
pred. East	312	0	396	272	40.41%
pred. Central	711	2	643	2082	60.56%
class recall	41.55%	99.92%	19.45%	64.80%	

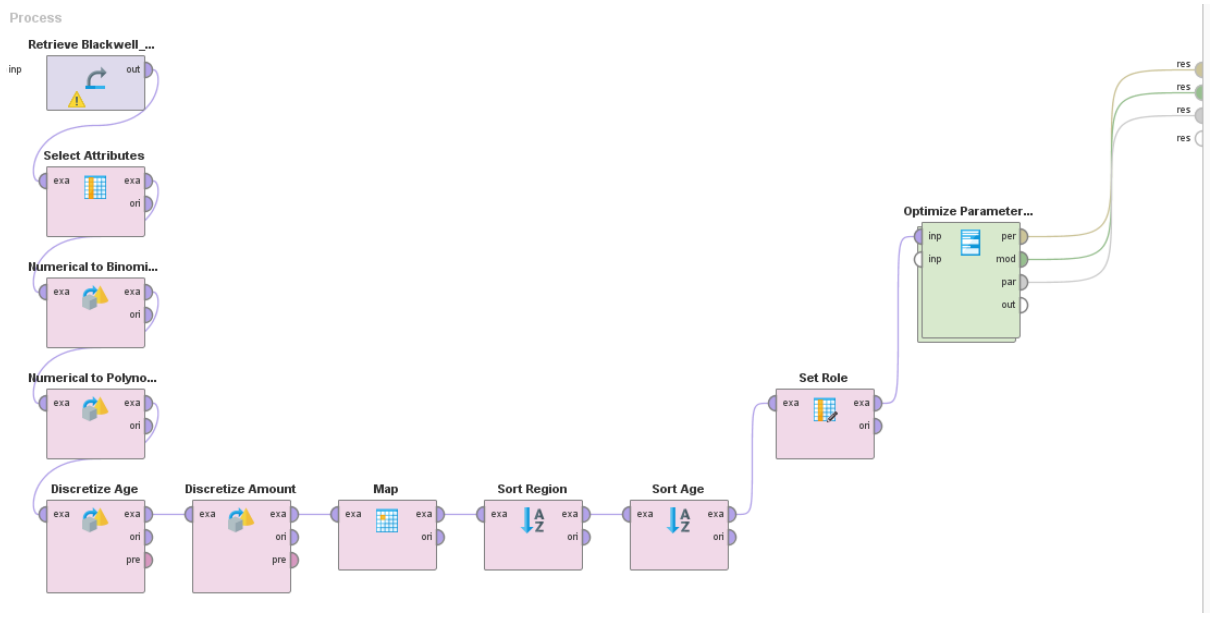
Gradient Boosted Trees

accuracy: 59.41% +/- 1.22% (micro average: 59.41%)

	true South	true West	true East	true Central	class precision
pred. South	918	0	651	374	47.25%
pred. West	266	2538	327	493	70.03%
pred. East	312	0	413	274	41.34%
pred. Central	711	6	645	2072	60.34%
class recall	41.59%	99.76%	20.28%	64.49%	

Figure 12 – Accuracy comparison between 3 different algorithms

Optimized model – Using Label = Region



Optimized Model

accuracy: 59.57%

	true South	true West	true East	true Central	class precision
pred. South	435	0	363	222	42.65%
pred. West	65	763	91	153	71.18%
pred. East	0	0	0	0	0.00%
pred. Central	162	0	157	589	64.87%
class recall	65.71%	100.00%	0.00%	61.10%	

kappa: 0.451

	true South	true West	true East	true Central	class precision
pred. South	435	0	363	222	42.65%
pred. West	65	763	91	153	71.18%
pred. East	0	0	0	0	0.00%
pred. Central	162	0	157	589	64.87%
class recall	65.71%	100.00%	0.00%	61.10%	

ParameterSet

```
Parameter set:

Performance:
PerformanceVector [
-----accuracy: 59.57%
ConfusionMatrix:
True:   South   West    East    Central
South:  435     0       363     222
West:   65      763     91      153
East:   0       0       0       0
Central:        162     0       157     589
-----kappa: 0.451
ConfusionMatrix:
True:   South   West    East    Central
South:  435     0       363     222
West:   65      763     91      153
East:   0       0       0       0
Central:        162     0       157     589
]
Decision Tree.criterion = gini_index
Decision Tree.maximal_depth     = 80
Decision Tree.minimal_leaf_size = 1
```

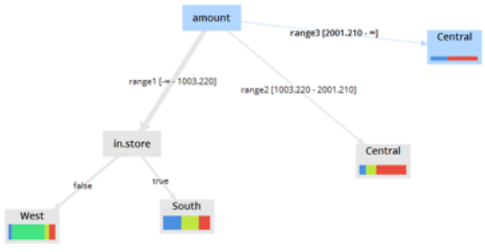


Figure 13 – Decision tree optimized model