Data Preparation

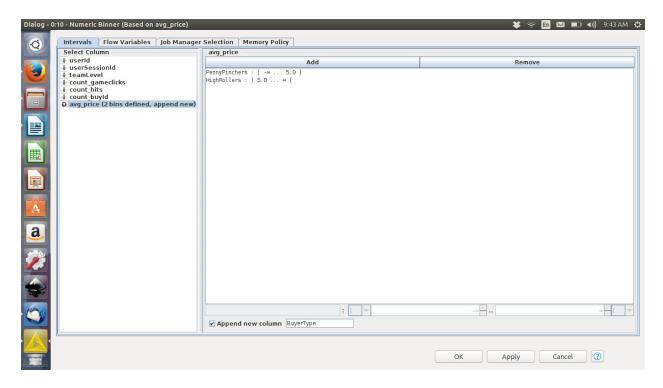
Analysis of combined_data.csv

Sample Selection

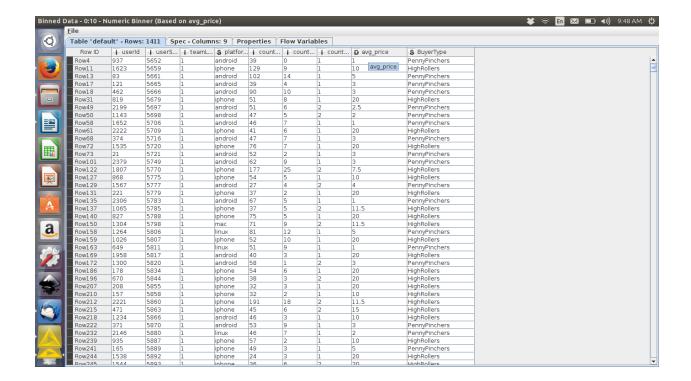
Item	Amount
# of Samples	4619
# of Samples with Purchases	1411

Attribute Creation

A new categorical attribute BuyerType was created to enable analysis of players as broken into 2 categories (HighRollers and PennyPinchers). A screenshot of the attribute follows:



Based on avg_price, another categorical vaiable named BuyerType is created. BuyerType is PennyPinchers if avg_price is less than or equal to 5. If avg_price is greater than 5, its value is HighRollers.



The creation of this new categorical attribute was necessary due to the following:

- 1. Here we had to predict the user that are likely to buy big-ticket items.
- 2. In the given data, average purchase price is given. This is a numerical variable.
- 3. Decision tree, requires the response variable to be categorical.
- 4. Hence created a categorical variable named BuyerType based on avg_price, which will be used as the response variable while building a model using decision tree.

Attribute Selection

The following attributes were filtered from the dataset for the following reasons:

Attribute	Rationale for Filtering
avg_price	As the response variable "buyerType" is derived from avg_price.Its variable has to be excluded from the selection.
user_id	userId is just an identifier for the user.It won't contribute anything the the model.
userSession_Id	userSession_id is also just an identifier.Hence filtering from the dataset.

With the given dataset, following variables are being considered for modeling:

Response Variable : BuyerType
Exploratory Variables : teamLevel,

platformType,count_gameclicks,count_hits,count_buyid.

Data Partitioning and Modeling

The data was partitioned into train and test datasets.

The **training** data set was used to create the decision tree model.

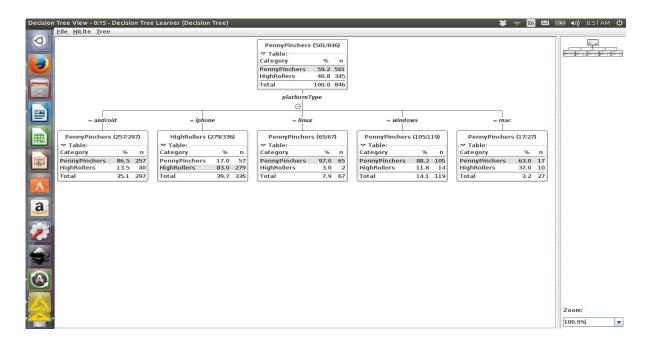
The trained model was then applied to the **testing** dataset.

This is important because the model has to be tested on the data that was not used to train the model.

When partitioning the data using sampling, it is important to set the random seed for the following reason :

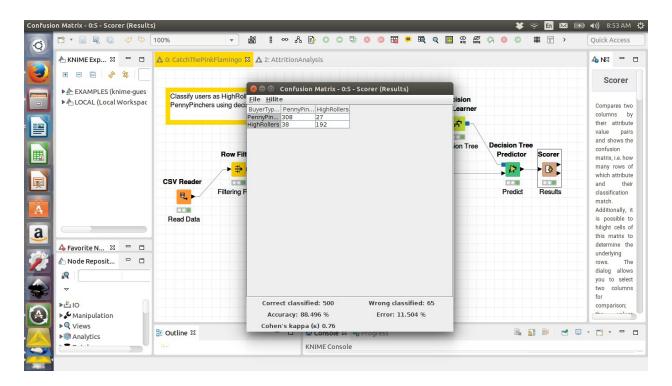
To ensures that same partition are formed every time the partition node is executed. Hence get reproducible results.

Screenshot of the resulting decision tree is as shown below:



Evaluation

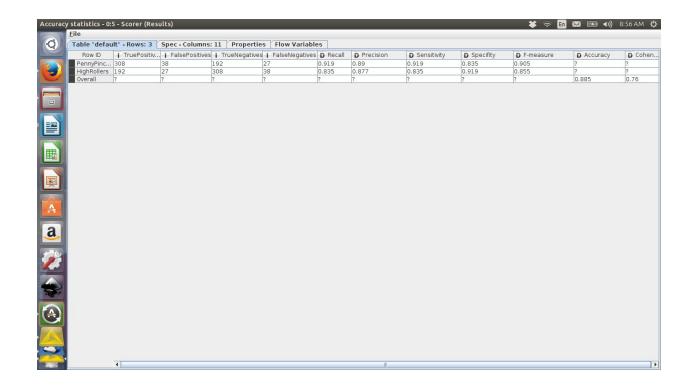
Screenshot of the confusion matrix can be seen below:



As seen in the screenshot above, the overall accuracy of the model is 88.496%

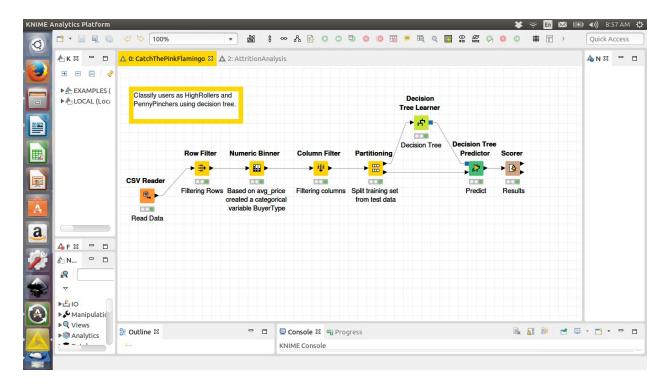
500 are correctly classified , where as 65 are wrongly classified.89% of times users were correctly classified as PennyPinchers. Where as 87% times they were correctly identified as HighRollers.

Other accuracy statistics are as below:



Analysis Conclusions

The final KNIME workflow is shown below:



What makes a HighRoller vs. a PennyPincher?

Iphone users are HighRoller where as all other platform (i.e. android, linux, windows and mac) users are PennyPincher. Iphone forms 39.7% of user population, Android users are around 35.1%, windows contribute 14.1% of total users, users using linux or mac are 7.9 and 3.2% respectively.

Specific Recommendations to Increase Revenue

- 1. Promote in-app purchases on android platform as it makes 35.1% of users. This will lead to increase in revenue proportionally. It is also recommended to investigate the reason for android users being PennyPincher
- 2. Promote in-app purchases to users who are classified as PennyPincher and are on iphone platform. As our findings suggest that iphone users are majorly HighRoller, there is a higher probability of them puchasing. Investigate further as to if there is any other reason for PennyPincher iphone users for not making in-app purchases.