DATA ANALYTICS USING R - LEARNING

UBIQUM

SUMMARY

GETING FAMILIAR WITH R

USING R STUDIO

In our new task we set up the environment to use R which made a little challenge at the beginning, Additionally without any basic knowledge using different functions was also made my work slower but by time people gets more confident.

Interesting to replicate all those models from RapidMiner to another level. At the same time I also got familiar with Python.

I have seen the benefits of using R and Python too. My work is now to get more confident in those tools to future application and be more creative to apply more function and investigate more coherence in one dataset.

In this paper I am going to show what did I find during my analysis and analytics of a fictive company - called Balckewell - during an acquisition.

PETER HOANG

UBIQUM

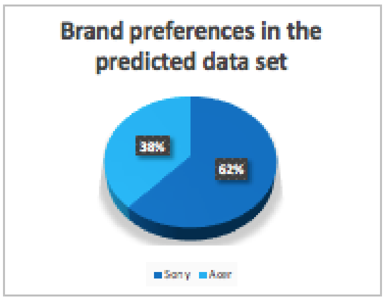
BRAND PREFERENCES

SURVEY

PROJECT FOR BRAND PREFERENCES

15.000 people were asked about the following details. From 5000 people w missed the brand preferences.

	Sony	Acer	Total
Real data	6154	3744	9898
Predicted	3090	1910	5000
Total	9244	5654	14898



Salary	Age	Elevel	Car	Zipcode	Credit	Brand
150000	47	2	10	7	500000	1
150000	20	2	2	6	500000	1
150000	32	0	11	7	483588,333	1
150000	53	0	16	4	482767,172	1
150000	43	3	8	2	482639,434	1
150000	61	0	5	2	478439,546	1
150000	54	0	2	5	476338,559	1
150000	49	4	9	6	474209,016	1
150000	62	2	3	1	472646,344	1
150000	21	4	20	2	472334,367	1
150000	75	0	4	7	467972,999	1
150000	52	4	7	6	467411,941	1
150000	68	4	12	5	451780,589	1
150000	75	0	19	2	431136,596	1
150000	40	0	12	1	425259,048	1
150000	27	4	6	5	424679,79	1
150000	20	3	1	6	423556,374	1
150000	71	0	4	6	418460,881	1
150000	20	3	11	0	401154,051	1
150000	49	3	14	4	399752,2	1
150000	28	4	17	4	398952,964	1
150000	54	2	14	0	393083,132	1
150000	68	4	13	7	390150,751	1
150000	56	3	19	1	374845,355	1
150000	51	4	6	4	373972,076	1
150000	56	1	7	4	373050,148	1

Brand	Description
0	Acer
1	Sony

Elevel	Description
0	Less than High School Degree
1	High School Degree
2	Some College
3	4-Year College Degree
4	Master's, Doctoral or Professional D

Car	Description
1	BMW
2	Buick
3	Cadillac
4	Chevrolet
5	Chrysler
6	Dodge
7	Ford
8	Honda
9	Hyundai
10	Jeep
11	Kia
12	Lincoln
13	Mazda
14	Mercedes Benz
15	Mitsubishi
16	Nissan
17	Ram
18	Subaru
19	Toyota
20	None of the above

Zipcode	Description
0	New England
1	Mid-Atlantic
2	East North Central
3	West North Central
4	South Atlantic
5	East South Central
6	West South Central
7	Mountain
8	Pacific

BRAND PREFERENCES

Analytics for the Brand Preferences	
A	It is clear that there were more customer purhasing Sony than Acer laptops.
B	Only one variable, Salary is a significant indicator - comparing to the other variables - to the Brand prefences.
C	As high as the Salary people more tend to buy Sony laptops.
D	If salary is higher than a certain level - in this case aproximetly 110.000, our customer only buy Sony laptops. **Interestingly customers with the lowest salary also buying Sony laptops!**
E	For confirmation: Elevel really does not affect the Brand preference, same patterns with lower and higher education.
Advise	**Only Salary has impact on our business: with the highest and lowest salary customers buying Sony laptops, in the middle is Acer.**

1. Correlation bewteen Brand Preferences and other variables in the completed survey

	Salary	Age	Elevel	Car	Zipcode	Credit	Brand
Salary	1						
Age	0,00797857	1					
Elevel	-0,0066202	-0,0058303	1				
Car	-0,0060906	0,01024607	-4,677E-05	1			
Zipcode	-0,0054711	0,00368138	0,0180954	0,00152653	1		
Credit	-0,0251268	-0,0044007	0,00272064	-0,0103291	0,00496201	1	
Brand	0,20648988	0,01371329	-0,0048289	0,00592315	0,00466509	0,00568844	1

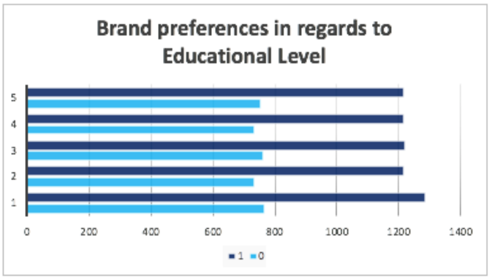
Only salary is affecting our customer's brand prefences with 20 %.

There are minimal correlations betweek credit and salary, age and brand, car, elevel and zipcode, car and credit. Which we investigated in deeper but we did not find anything particular.

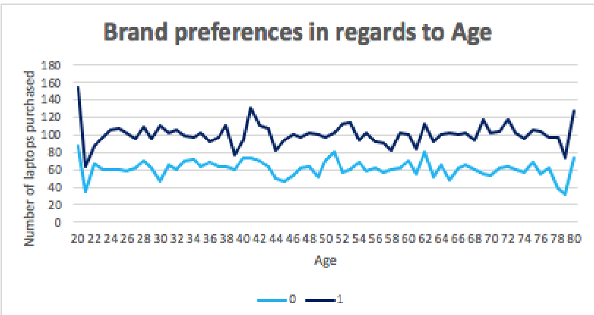
2. Cheking the correlations between 2 variables in the completed survey

		Educational Level					Total
		1	2	3	4	5	
Brand	0	766	733	762	732	751	3744
	1	1286	1215	1221	1215	1217	6154

		Age					Total
		20	21	...	79	80	
Brand	0	87	35	...	32	73	3744
	1	155	63	...	73	128	6154



We also investigated the rest of the correlations and there was no signicant differences between brand prefences.



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BRAND PREFERENCES

3. Correlation between Age and Brand Preferences

	Brand	
Salary	0,20648988	21%
Age	0,01371329	1%
Elevel	-0,0048289	0%
Car	0,00592315	1%
Zipcode	0,00466509	0%
Credit	0,00568844	1%

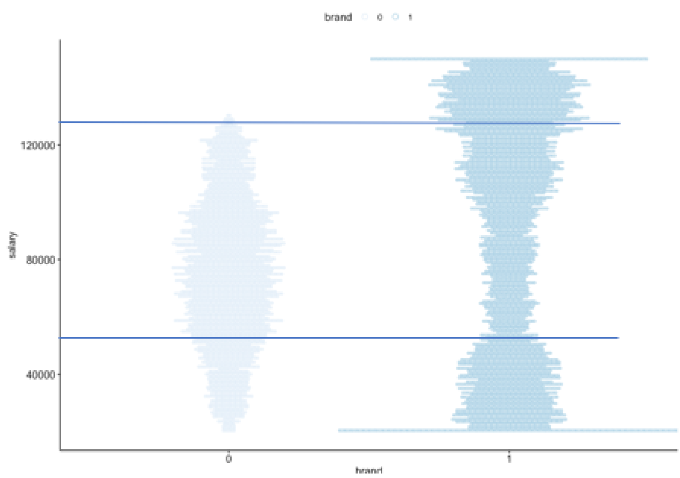
Summary of Age					
Min.	1st Qu.	Median	Mean	3rd Qu.	Max
20000	52082	84950	84871	117162	150000

I will use Median to measure what is happening below it and upward it.

Also looking below on the chart we can see 3 phenomenals where data groups according to the different range of data.

Median of Salary		
	Salary >= 84950	Salary <84950
Acer	27,41968	48,23197
Sony	72,58032	51,76803
Total	100	100

Customers who has higher salary chose Sony instead of Acer in 70% of cases. Below this proportion is almost 50-50%



Salary		
	Salary >= 50000	Salary <50000
Acer	28.46121	40.71381
Sony	71.53879	59.28619
Total	100	100

Interestingly customers with the lowest salary are also tend to buy Sony computers!

Basod on the charst with in the middle people tend to purchase Acer laptops

BRAND PREFERENCES

Prediction for Brand Preferences	
Object :	Predict missing brand prefences for 5000 rows based on a 10,000 fully-answered surveys.
Language used:	R
Algorythm:	C5.0. Decision Tree and Random Forest
Predicted model	c5.0. Decision Tree

1. C5.0. Decision Tree

Folders :	10
Length :	2

Result for the Training set

Resampling:	Cross-Validated (10 fold, repeated 1 times)					
Summary of sample sizes:	6681					
Resampling results across tuning parameters:	6682	6681	6683	6681	6683	...

mtry	Accuracy	Kappa
2	0.6217673	0.0000000
34	0.9166268	0.8230398

Accuracy was used to select the optimal model using the largest value. **The final value used for the model was mtry = 34.**

Result for the postResample

Accuracy	Kappa
0.9191593	0.8282865

Our Accuray and Kappa did not change which indicate **our model is good.**

Confusion Matrix

Prediction \ Reference	0	1
0	838	98
1	102	1436

Further Statistics

Accuracy : 0.9192

95% CI : (0.9077, 0.9296)

No Information Rate : 0.62
P-Value [Acc > NIR] : <2e-16

Kappa : 0.8283
Mcnemar's Test P-Value : 0.832

Sensitivity : 0.9361 — Other name is Recall: Measures the proportion of actual positives that are correctly identified
Specificity : 0.8915 — Other name is Precision: Measures the proportion of actual negatives that are correctly identified
Pos Pred Value : 0.9337
Neg Pred Value : 0.8953 — Comment: In all cases we have good percentages which shows that our model predicted well
Prevalence : 0.6200
Detection Rate : 0.5804
Detection Prevalence : 0.6217
Balanced Accuracy : 0.9138

Positive : 1

1. Random Forest with manual tuning

Folders	10
Length	1
Mtry	5

Result for training

Resampling:	Cross-Validated (10 fold, repeated 1 times)					
Summary of sample sizes:	6681					
Resampling results across tuning parameters:	6682	6681	6683	6681	6683	...

mtry	Accuracy	Kappa
1	0.6217673	0.0000000000
2	0.6217673	0.0001730857
3	0.7528334	0.4123882115
4	0.8665131	0.7105680204
5	0.9008628	0.7894383790

Accuracy was used to select the optimal model using the largest value. The final value used for the model was mtry = 5. **But our Accuracy and Kappa was better with our previous model.**

Confusion Matrix

Prediction \ Reference	0	1
0	812	124
1	116	1422

Further Statistics

Accuracy : 0.903

Comments

In general our model is not bad, comparing to other model it slightly preform under.

95% CI : (0.8906, 0.9144)
No Information Rate : 0.6249
P-Value [Acc > NIR] : <2e-16

Kappa : 0.7934
Mcnemar's Test P-Value : 0.6514

Sensitivity : 0.9198
Specificity : 0.8750
Pos Pred Value : 0.9246
Neg Pred Value : 0.8675
Prevalence : 0.6249
Detection Rate : 0.5748
Detection Prevalence : 0.6217
Balanced Accuracy : 0.8974

Positive : 1

ANALYSIS

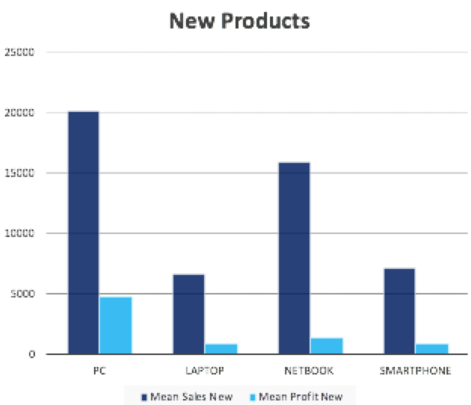
Prediting Product's volume	
A	There are some specific products which we would not reccomend to launch. Such as Product #181.
B	Except Product type laptop all new products will be on the top seller product in its category.
C	From all 4 product type smartphones are the most popular ones.
D	Volume and profit are not neccearly directly proportional.
E	Smartphones and Laptops have the leading profit with the existing product, we are predicting PCs can have a significant profit.

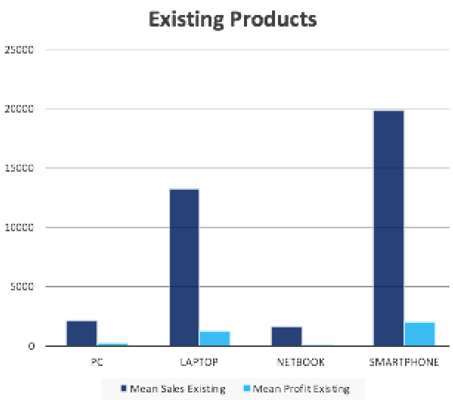
1. Correlation bewteen Product Volume and other variables in the completed survey

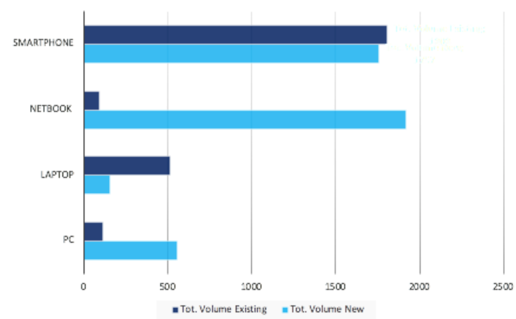
Variables	Volume
x5StarReviews	1
Volume	1
x4StarReviews	0,87900639
x3StarReviews	0,76337319
PositiveServiceReview	0,62226022
x2StarReviews	0,48727933
ProductTypeGameConsole	0,38829824
NegativeServiceReview	0,30941899
x1StarReviews	0,2550239
Recommendproduct	0,16954126
ProductNum	0,16612076
...	...

Based on our correlation matrix we removed 5 Star Review as it is a perfect predictor to the Volume. Also from the whole matrix there was a correlation between 4 and 3 Star Review hence we decided to keep one and remove the rest. It is also the same case with 1 and 2 Star Review. The remaining variable will serve our predictors in our different models.

2. Analysing the results







In our prediction, profit of PC is a lot more higher than the current one. In the last figure, we can see Smartphones are the most popular item among our customers, - the profit is not directly proportional with that.

In overall new products have a better profitability comparing to the existing ones.

PREDICTED VOLUMES

TOP 10 Products					
Rank	Product Type	Current Status	Product No.	Volume	Profit
1	Netbook	New	180	1790	53 002
2	Smartphone	Existing	197	1472	73 453
3	Smartphone	New	194	574	3 375
4	Smartphone	New	193	525	11 492
5	PC	New	171	456	79 686
6	Smartphone	New	196	363	11 979
7	Smartphone	New	195	295	6 593
8	Smartphone	Existing	191	248	6 944
9	Laptop	Existing	105	232	22 550
10	Laptop	Existing	104	196	6 429

TOP 10 Products by Sales				
Rank	Product Type	Current Status	Product No.	Sales
1	Smartphone	Existing	197	734 528
2	Netbook	New	180	588 910
3	PC	New	171	318 744
4	Laptop	Existing	105	2505 558
5	Laptop	New	173	134 288
6	Smartphone	New	196	108 900
7	Smartphone	New	193	104 475
8	PC	New	172	84280
9	Laptop	Existing	104	80 358
10	Laptop	Existing	143	67 812

TOP 10 Products by Profit				
Rank	Product Type	Current Status	Product No.	Profit
1	PC	New	171	79 686
2	Smartphone	Existing	197	73 452
3	Netbook	New	180	53 001
4	Laptop	Existing	105	22 550
5	PC	New	172	16 856
6	Laptop	New	173	13 428
7	Smartphone	New	196	11 979
8	Smartphone	New	193	11 492
9	Laptop	Existing	143	10 171
10	Smartphone	Existing	191	6944

RESULT

USING DIFFERENT MODEL TO PREDICT

Find the predicted volumes for each products which are also highlighted in blue. We used different model which will be introduce in the next pages.

Based on our result most of the new products could make a successful contribution for the growth of the sales numbers.

Product Type	Product Number	Price	**** Review	** Review	* Review	Positive Review	Negative Review	Profit Margin	Sales	Profit	Volume	Current Status
PC	171	699	26	14	25	12	3	0,25	318744	79686	456	New
PC	172	860	11	10	21	7	5	0,2	84280	16856	98	New
PC	142	609,99	7	0	12	5	3	0,09	51239,2	4611,52	84	Existing
PC	101	949	3	0	0	2	0	0,15	11388	1708,2	12	Existing
PC	103	399	0	0	0	1	0	0,08	4788	383,04	12	Existing
PC	102	2249,99	1	0	0	1	0	0,25	17999,9	4499,98	8	Existing
Laptop	105	1079,99	31	7	36	7	20	0,09	250558	22550,2	232	Existing
Laptop	104	409,99	19	3	9	7	8	0,08	80358	6428,64	196	Existing
Laptop	173	1199	10	3	11	11	5	0,1	134288	13428,8	112	New
Laptop	143	770,6	14	5	6	6	2	0,15	67812,8	10171,9	88	Existing
Laptop	175	1199	2	1	1	2	1	0,15	41965	6294,75	35	New
Laptop	176	1999	1	3	0	0	1	0,23	23988	5517,24	12	New
Netbook	180	329	112	31	47	28	16	0,09	588910	53001,9	1790	New
Netbook	182	349,99	10	2	10	3	3	0,12	30799,1	3695,89	88	Existing
Netbook	183	330	4	1	0	1	0	0,09	26070	2346,3	79	New
Netbook	178	399,99	8	1	10	2	4	0,08	19199,5	1535,96	48	New
Netbook	177	379,99	0	1	0	0	1	0,1	1519,96	151,996	4	Existing
Netbook	181	439	18	22	18	5	16	0,11	0	0	0	New
Smartphone	197	499	28	10	23	22	3	0,1	734528	73452,8	1472	Existing
Smartphone	194	49	26	33	48	14	6	0,12	28126	3375,12	574	New
Smartphone	193	199	26	16	35	8	6	0,11	104475	11492,3	525	New
Smartphone	196	300	19	20	22	5	7	0,11	108900	11979	363	New
Smartphone	195	149	8	4	9	4	1	0,15	43955	6593,25	295	New
Smartphone	191	200	25	11	12	9	3	0,14	49600	6944	248	Existing
Smartphone	192	99	17	2	12	5	4	0,17	7128	1211,76	72	Existing
Smartphone	190	199	1	2	2	1	1	0,1	3184	318,4	16	Existing

TECHNICAL BACKGROUND

Prediction for Volume	
Object	Predicting volumes of the potential new products, namely PCs, Laptops, Netbooks, Smartphones
Language used	R
Algorythm	Multiple Linear Regression, Support Vector Machine, Random Forest, KNN model
Predicted model	Multiple Linear Regression

1. Multiple Linear Regression

Used variables	Based on our correlation matrix the following variables were choosen:
	Volume = Y, rest is 4 star review, positive service review, negative service review, 2 star review, 4 products type

Training	
Residual standard error:	594 on 71 degrees of freedom
Multiple R-squared:	0.8622
Adjusted R-squared:	0.8466
F-statistic:	55.51 on 8 and 71 DF
p-value:	< 2.2e-16

On the traingset our model predicts our volume by 86% while the same model predicted 92 % of the correct value in the testing set. We have chosen this model to predict the potential launched product's volume. Comparing to other model our RMSE is also significantly low.

Testing		
RMSE	Rsquared	MAE
180.1634732	0.9277352	118.9504383

2. Support Vector Machine

Folders	10
Lenght	5

Training			
mtry	RMSE	Rsquared	MAE
2	913.7429	0.8309531	449.4152
3	895.9713	0.8530333	421.0039
5	832.8653	0.8819390	382.2444
6	829.7356	0.8878660	378.9446
8	835.3974	0.8870445	380.0772

On the traingset our model predicts our volume at best by 88 % while there is a slight drop down in the Testing set.

RMSE was used to select the optimal model using the smallest value.

The final value used for the model was mtry = 6.

Testing		
RMSE	Rsquared	MAE
404.3225784	0.8748244	123.6021995

3. Random Forest

Folders	10
mtry	5

Training			
mtry	RMSE	Rsquared	MAE
1	984.4409	0.7697070	591.0527
2	904.4612	0.8308607	442.0396
3	896.4878	0.8490864	425.0479
4	861.4881	0.8676215	402.1849
5	858.4198	0.8740715	395.0265

On the traingset our model predicts our volume at best by 87 % while there is a slight drop down in the Testing set.

RMSE was used to select the optimal model using the smallest value.

The final value used for the model was mtry = 5.

Testing		
RMSE	Rsquared	MAE
500.1434551	0.8409458	145.7647930

4. KNN model

Length	10

Training			
k	RMSE	Rsquared	MAE
5	823.7338	0.8227430	419.4834
7	840.7855	0.8276559	426.7895
9	863.4880	0.8253793	435.1744
11	866.0994	0.8199253	431.0853
13	867.8583	0.8209967	433.7682
15	879.3850	0.8225673	440.8708
17	895.3904	0.8175466	454.5450
19	915.9541	0.8145098	468.8191
21	940.1454	0.8131477	486.8847
23	964.4459	0.8019713	504.8200

On the traingset our model predicts our volume at best by 82 % while there is a slight drop down in the Testing set. Comparing to other model our RMSE is significantly high. And our resutlt of the test modell is the worst.

RMSE was used to select the optimal model using the smallest value.

The final value used for the model was mtry = 5.

Testing		
RMSE	Rsquared	MAE
580.8686055	0.7875485	190.9052632

ACQUISTION OF ELECTROINDEX

PORTFOLIO ANALYSIS IN ORDER TO DEFINE A BUSINESS STRATEGY.

INVESTIGATION OF POTENTIAL COMPANIES FOR DEEPER INSIGHT.

BUYING A NEW COMPANY

Beside calculating the cost of the acquisition, legal issues and bagegges, company cultural fits etc, we made a deep analysis of our products and the potential compnay's portfolio in order to see if they are match.

ACQUISTION OF ELECTROINDEX

ACQUISITION OF ELECTROINDEX
MARKET BASKET ANALYSIS

OBJECTIVE
Blackewell is considering of an acquisition of Electroindex. In order to decide, Data Science team support with an analysis to help the management decision making.

ELECTROINDEX
The new e-commerce company has a similar portfolio as ours which could indicate us to buy their customers:

1. PCs and Laptops are the most popular products. Its sells are outnumbering our volume of PCs and Laptops.

2. Sold Displays have also better figures.

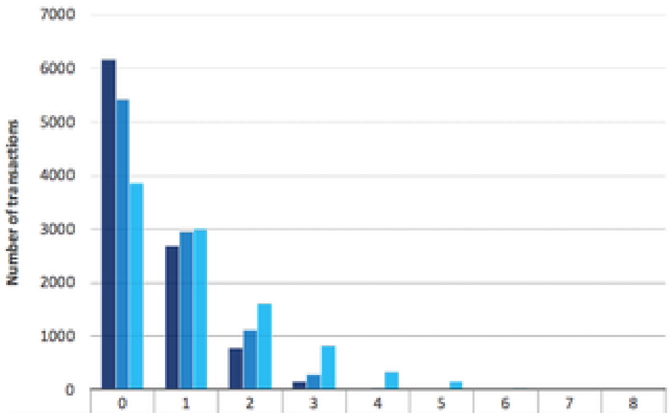
	Existing product - Avarage No. Item	Predicted product - Avarage No. Item	Avarage No. Item	New Company - Avarage No. Item
PC	29	934	481	736
Laptop	172	442	307	733
Display	485	139	312	552
Accessories	982	0	982	526

3. Number of purchased Accessories are falling behind comparing to us but still can be a potential market.

4. As PCs, Laptops and Displays usually have higher prices our profit could be higher. Accessories have lower margin and profit hence potentially it will not be a significant loss.

ACQUISTION OF ELECTROINDEX

DEEPER INSIGHT OF THE PRODUCTS' RELATION



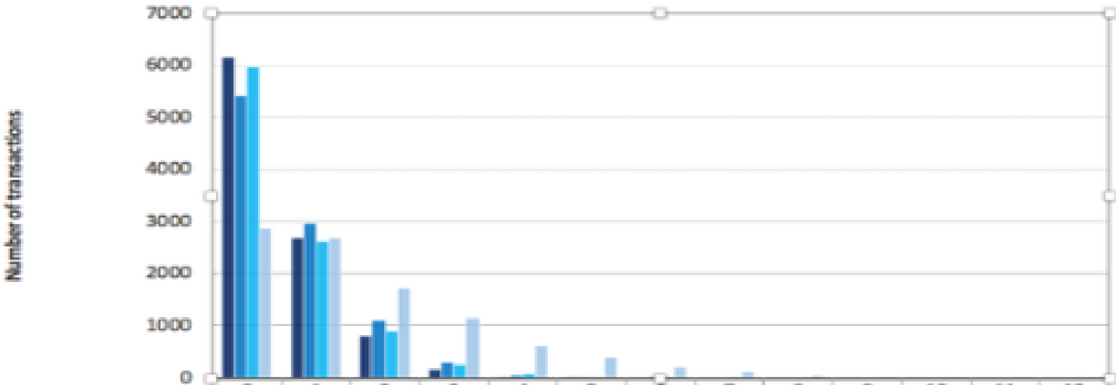
	0	1	2	3	4	5	6	7	8
Laptop	6168	2681	794	161	28	3			
PC	5418	2968	1109	296	38	5	1		
Lp or PC	3854	2996	1619	830	337	147	38	12	1

X label shows us how many PCs or Laptops were in one transaction.

Even the number of 1 PC/Laptop in a basket is extremely high, meaning with an acquisition we could buy a big market.

Note: transactions are not equal to customers. It can be one costumer who purchased 1 and 6 PCs and/or Laptops but in. different time.

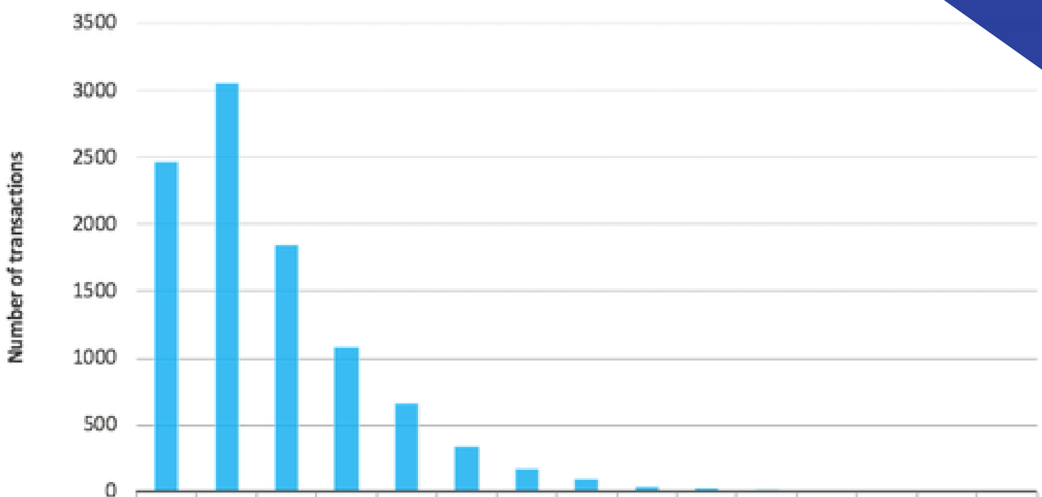
But that we can still say purchasing power for those items are high.



	0	1	2	3	4	5	6	7	8	9	10	11	12
Laptop	6168	2681	794	161	28	3							
PC	5418	2968	1109	296	38	5	1						
Display	5969	2612	904	261	72	13	3	1					
LP or PC or Display	2866	2694	1729	1143	625	387	197	107	44	21	16	3	3

Add Displays to the formula, purchasing all three-product type are high.

Transactions where there are more than 3 items of PCs, Laptops or Display, we assume that behind there is a distributor or company behind. It means 2645 out of 10.000 transaction was made by those customers!



	0	1	2	3	4	5	6	7	8	9	10	11	12	14	14
Accesories	2470	3059	1843	1084	663	338	171	93	45	35	19	10	2	1	2

Elcetroindex has a very diverse product palette regarding to their Accessories. As our company do not have subset labels to this category, we merged all external devices such as headphones, disks, keyboards etc. to category Accessories.

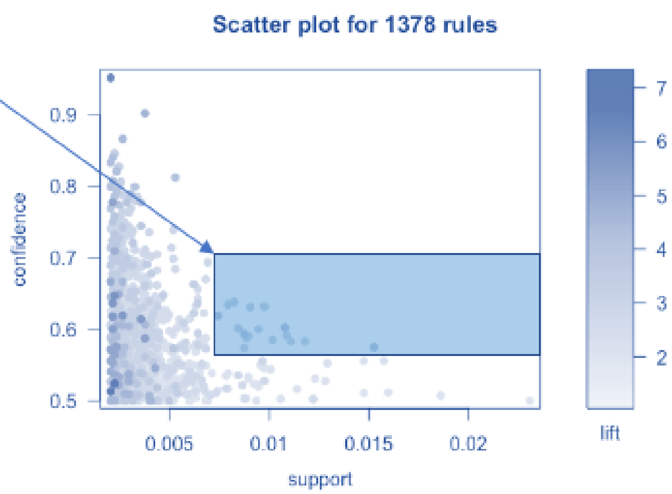
Although Balckwell should consider specifying its categories more precisely for better recommendation systems in the future.

DEEPER INSIGHT OF THE PRODUCTS' RELATION

In order to investigate the relation between products we used Market Basket Analysis. We plotted more than 1300 rules to visualize those we are most likely interested in.

We break down the rules to have discovered into three categories:

1. **The Insightful Rules Category**
   Contains rules that are most useful.
2. **The Irrelevant Rules Category**
   The second category is for the rules that either aren't helpful or are obvious.
3. **The Unclear Rules Category**
   The third category is for rules that are indecipherable and, thus, from which we cannot draw insightful conclusions.



*Setting our support to 0.0055 and confidence to 0.55. Resulting a lift between 2 and 3.

ACQUISTION OF ELECTROINDEX

No.	Left Hand Side of the Basket	Right Hand Side	Support	Confidence	Lift	Count
[13]	{Acer Aspire,ViewSonic Monitor}	{HP Laptop}	0.011	0.602	3.103	106.000
[10]	{ASUS Monitor,Lenovo Desktop Computer}	{iMac}	0.010	0.632	2.466	96.000
[11]	{Dell Desktop,Microsoft Office Home and Student 2016}	{iMac}	0.009	0.600	2.343	93.000
[4]	{ASUS 2 Monitor,Dell Desktop}	{iMac}	0.009	0.631	2.464	89.000
[20]	{HP Laptop,Lenovo Desktop Computer,ViewSonic Monitor}	{iMac}	0.008	0.601	2.348	83.000
[8]	{ASUS Monitor,ViewSonic Monitor}	{iMac}	0.008	0.638	2.490	81.000
[9]	{ASUS Monitor,Dell Desktop}	{iMac}	0.008	0.634	2.476	78.000
[1]	{Computer Game,ViewSonic Monitor}	{HP Laptop}	0.007	0.619	3.187	73.000
[19]	{Dell Desktop,Lenovo Desktop Computer,ViewSonic Monitor}	{iMac}	0.007	0.694	2.709	68.000
[6]	{Apple Magic Keyboard,ASUS Monitor}	{iMac}	0.007	0.670	2.616	67.000
[12]	{Acer Desktop,Apple Magic Keyboard}	{iMac}	0.007	0.623	2.431	66.000
[3]	{Acer Desktop,ASUS 2 Monitor}	{iMac}	0.006	0.643	2.510	63.000
[15]	{Acer Desktop,HP Laptop,ViewSonic Monitor}	{iMac}	0.006	0.656	2.562	63.000
[16]	{Acer Desktop,iMac,ViewSonic Monitor}	{HP Laptop}	0.006	0.636	3.278	63.000
[17]	{Acer Desktop,HP Laptop,Lenovo Desktop Computer}	{iMac}	0.006	0.633	2.470	62.000
[14]	{Acer Aspire,iMac,ViewSonic Monitor}	{HP Laptop}	0.006	0.663	3.416	61.000
[18]	{Dell Desktop,Lenovo Desktop Computer,ViewSonic Monitor}	{HP Laptop}	0.006	0.622	3.207	61.000
[5]	{ASUS Monitor,Microsoft Office Home and Student 2016}	{iMac}	0.006	0.615	2.400	59.000
[7]	{Acer Desktop,ASUS Monitor}	{iMac}	0.006	0.600	2.343	57.000
[2]	{Computer Game,Dell Desktop}	{HP Laptop}	0.006	0.609	3.136	56.000

The most popular products are HP Laptop and iMac Desktop, also the rules are confirming that there is connection between other products to those items. Support means of the

Our rules show for instance if customer buys Aces Aspire and ViewSonic Monitor there is 60 % of likelihood that customer would buy an HP laptop too. For future marketing campaign those products together can boost the sales numbers.

ACQUISTION OF ELECTROINDEX

How iMac or HP Laptop explain other products?

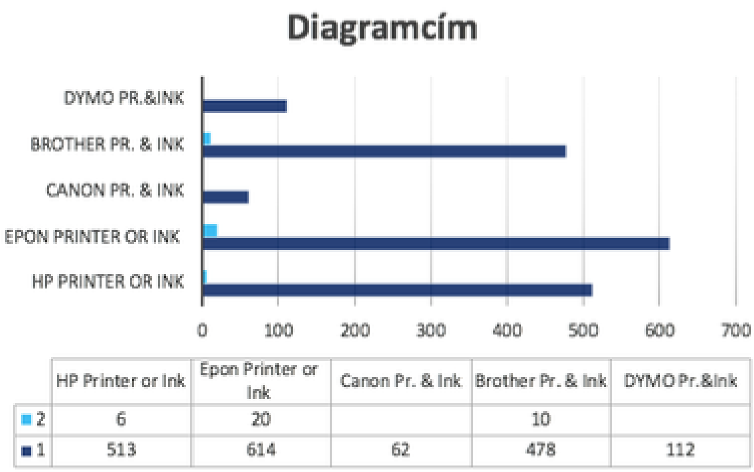
There is also a connection between HP Laptop and iMac, if customer buy an HP laptop it is 38 % of likelihood that buy an iMac too. Opposite way iMac only explain 29%.

The rest of the rules are relatively low on Confidence to be useful.

No.	Left Hand Side of the basket	Righ Hand Side of the basket	Support	Confidence	Lift	Count
[1]	iMac	HP Laptop	0,07554652	0,2949583	1,519599	743
[2]	iMac	Lenovo Destkop Computer	0,0587697	0,2294561	1,549932	578
[3]	iMac	CYBERPOWER Gamer Destkop	0,05673615	0,2215165	1,20432	558
[4]	iMac	Dell Destkop	0,05460092	0,2131798	1,590762	537
[1]	HP Laptop	iMac	0.07554652	0.389209	1.519599	743

So, if a customer buys a printer how much percentage is that they buy the associated ink: Seems to be an obvious statement but is it?

Customer are not buying printers and inks together – should be investigate what is behind the phenomenon.



CONCLUSION

Based on the volume of high price products, major company's customers might be high spender as distributors or companies. Which can be good asset for Blackwell strategy where we already prognosed the popularity of PCs, Laptops.

The new company product portfolio is diverse and well-labeled which can be also a contribution.

Further investigation such as profit margin and profitability, and obviously other aspect shall be considered during the acquisition.

PETER HOANG

THANK YOU!

UBIQUM