WQD 7005 Data Mining

Milestone 5: Communication of insights of data

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Video presentation link: https://youtu.be/oLSD SEunQO (please turn on subtitles or caption)

From the correlation analysis, the stocks in focus here are Sime Darby Plantation Berhad

(5285) and some stocks that have positive correlation and negative correlation with Sime

Darby. The stocks that have positive correlations with Sime Darby includes, Kawan Food Bhd

(7216), Caely Holdings Bhd (7154), and Emico Holdings Bhd (9091). The stocks that have

negative correlations with Sime Darby includes Hock Heng Stone Industries Bhd (5165),

Daibochi Berhad (8125), and FACB Industries Incorporated (2984). In this milestone, a

decision tree and logistic regression would be constructed based on the stock data.

Subset and flag

The 7 stocks data are extracted from the overall stock data. Based on this subset data, new

columns are added to this data.

The change flag which is depend on the change percentage, if the change percentage is

positive, the value of change flag would be 'pos', else if the change percentage is negative,

then the value of change flag would be 'neg', otherwise, the change flag would be 'non'.

Other than the change flag, there is another flag added namely the trade flag. This flag would

determine should the investors buy the stock or sell the stock or hold the stock depend on

the price of the stock. If the price is other than the one mentioned, then the investors should

hold the stock. There would be 3 flags namely, Buy, Sell and Hold.

The rules to label the Trade Flag for each stock is as follows:

Stock	Buy	Sell
Sime Darby Plantation Berhad (5285)	<= 5.03	>= 5.10
Caely Holdings Berhad (7216)	<= 1.00	>= 1.50
Emico Holdings Berhad (9091)	<= 0.15	>= 0.17
Hock Heng Stone Industries Berhad (5165)	<= 0.50	>= 0.60
Daibochi Berhad (8125)	<= 1.20	>= 1.50
FACB Indsutries Incorporated (2984)	<= 0.80	>= 1.20

Decision Tree

The subset of the stock data is imported into SAS Enterprise Miner in CSV format. The CSV data is changed into SAS data format. After that, decision tree and logistic regression is performed on the data.

The SAS analysis diagram is shown as follows:

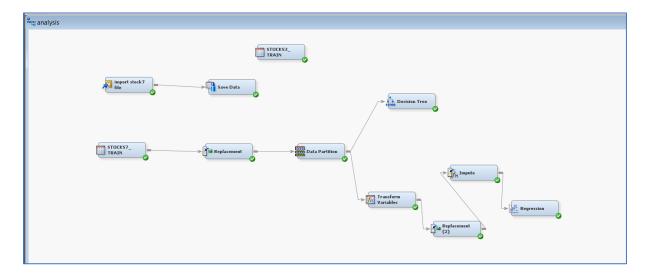


Figure 1: SAS analysis workflow

When the data is imported, the trade flag column is specified as the target column. The decision tree and logistic regression would predict the value of the trade flag based on the training.

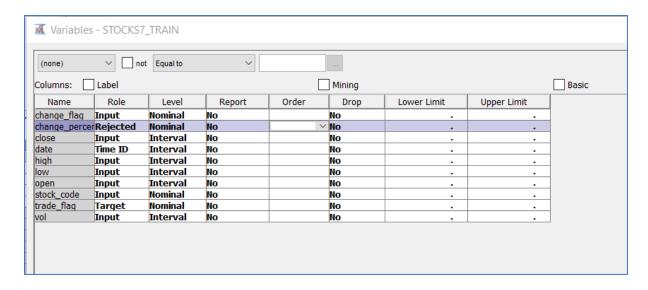


Figure 2: SAS variables role

The data is partitioned into 2 parts, namely training data and validation data. The ratio is 7:3.

In SAS, the method of maximal decision tree is used. The following screenshots show the results of maximal tree.

Results of maximal decision tree

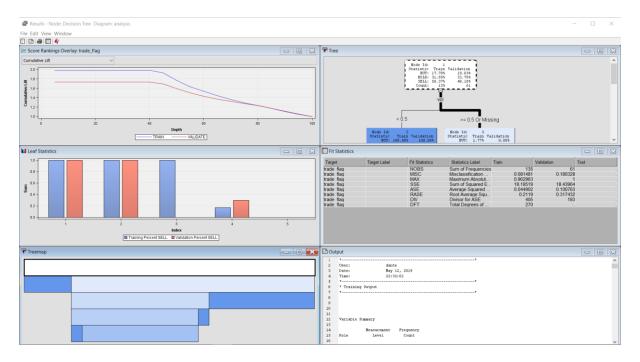


Figure 3: Results of Maximal Tree

The maximal tree diagram:

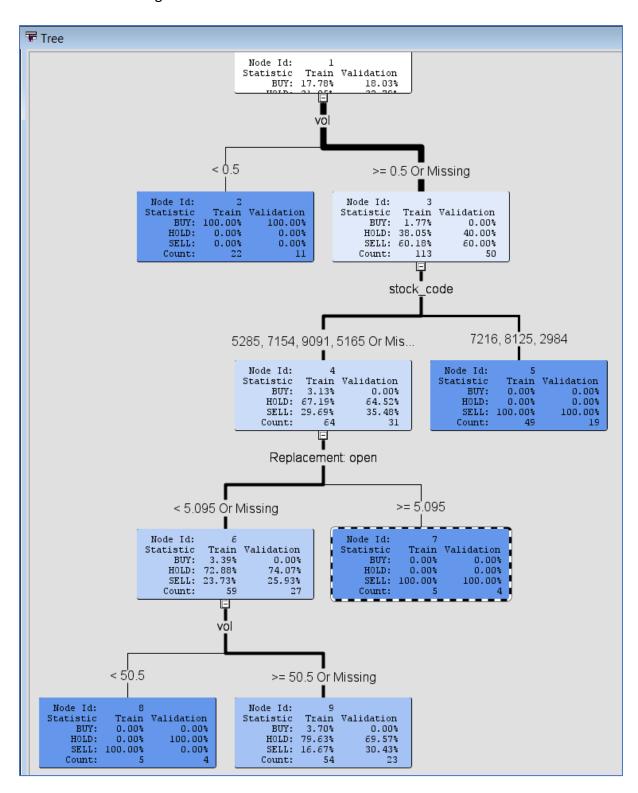


Figure 4: Decision tree constructed

Most of the rules used by the decision tree to split the nodes are dissimilar with the rules defined except one, which is node 7. In Node 7, if the opening price is greater or equal to

5.095 then the trade flag is 'Sell', this conform the rules defined for Sime Darby Plantation Bhd.

Assessment plots for the decision tree

Average Square Error

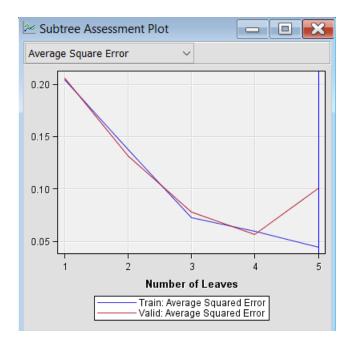


Figure 5: Assessment plot - average square error

The error decreases as the number of leaves increases. The training of the decision tree model might be overfit thus the error in the validation dataset increases after a certain extent.

Misclassification rate

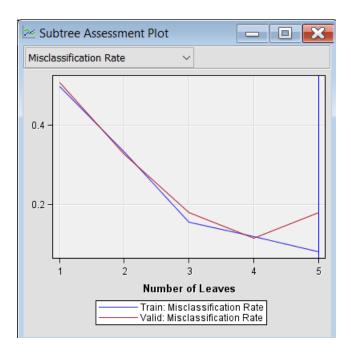


Figure 6: Assessment plot - misclassification rate

Similar with the average square error assessment plot, the misclassification rate decreases as the number of leaves increases. After 5 leaves, the rate spiked.

Logistic Regression

Besides decision tree, logistic regression is also used to predict the trade flag of the stocks. The logistic regression workflow is shown in figure 1.

Results of the logistic regression

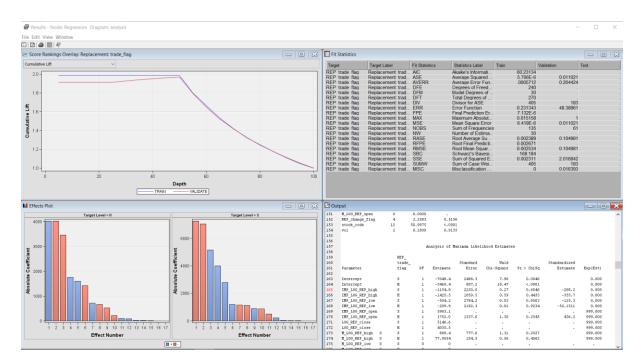


Figure 7: results of logistic regression

The variables used in logistic regression

Variable	Summary	
Role	Measurement Level	Frequency Count
INPUT	BINARY	3
INPUT	INTERVAL	5
INPUT	NOMINAL	2
REJECTED	INTERVAL	4
REJECTED	NOMINAL	3
TARGET	NOMINAL	1

Figure 8: logistic regression variables summary

10 variables from the dataset are used to predict the target which is the 'trade flag'. Some of missing values in the variables are imputed and the values underwent a transformation, applying log on the value before it is used to train a logistic regression model.

The model information

The DMREG 1	Procedure						
		Mode	l Information				
Training Da	ata Set		WORK.EM_DMREG.V	'IEW			
DMDB Catalo	og		WORK.REG_DMDB				
Target Var:	iable		REP_trade_flag	(Replacement:	trade_flag)		
Target Meas	surement Le	vel	Nominal				
Number of 3	Carget Cate	gories	3				
Error			MBernoulli				
Link Function			Logit				
Number of Model Parameters			34				
Number of (Observation	ເຮ	135				
	Carget Prof	ila					
	arget fron	.116					
	REP_						
Ordered	trade_	Tot	al				
Value flag Freque		Frequen	су				
1	S		68				
2	Н		43				
3	В		24				

Figure 9: logistic regression model information

Fit statistics from logistic regression

Target	Target Label	Fit Statistics	Statistics Label	Train	Validation
REP trade flag	Replacement: trade_flag	AIC	Akaike's Information Criterion	60.23134	
REP trade flag	Replacement: trade flag	ASE	Average Squared Error	5.706E-6	0.011021
REP trade flag	Replacement: trade flag	AVERR	Average Error Function	.0005712	
REP trade flag	Replacement: trade flag	DFE	Degrees of Freedom for Error	240	
REP trade flag	Replacement; trade flag	DFM	Model Degrees of Freedom	30	
REP trade flag	Replacement; trade flag	DFT	Total Degrees of Freedom	270	
REP trade flag	Replacement: trade flag	DIV	Divisor for ASE	405	183
REP trade flag	Replacement: trade flag	ERR	Error Function	0.231343	48.38961
REP trade flag	Replacement: trade flag	FPE	Final Prediction Error	7.132E-6	
REP trade flag	Replacement: trade flag	MAX	Maximum Absolute Error	0.015158	
REP trade flag	Replacement; trade flag	MSE	Mean Square Error	6.419E-6	0.01102
REP trade flag	Replacement; trade flag	NOBS	Sum of Frequencies	135	6.
REP trade flag	Replacement: trade flag	NW	Number of Estimate Weights	30	
REP trade flag	Replacement: trade flag	RASE	Root Average Sum of Squares	0.002389	0.104981
REP trade flag	Replacement: trade flag	RFPE	Root Final Prediction Error	0.002671	
REP trade flag	Replacement: trade flag	RMSE	Root Mean Squared Error	0.002534	0.104981
REP trade flag	Replacement: trade flag	SBC	Schwarz's Bayesian Criterion	168.184	
REP trade flag	Replacement: trade_flag	SSE	Sum of Squared Errors	0.002311	
REP trade flag	Replacement: trade flag	SUMW	Sum of Case Weights Times Freq	405	183
REP trade flag	Replacement: trade_flag	MISC	Misclassification Rate	0	0.016393

Figure 10: fit statistics

Classification table

		Target	Outcome	Frequency	Total	
Target	Outcome	Percentage	Percentage	Count	Percentage	
В	В	100	100	24	17.7778	
H	H	100	100	43	31.8519	
S	ន	100	100	68	50.3704	
D-+- D-1	- 1131 TD 377	T	- DED + 61	T I-b	-1-P1	
Data Rol	e=VALIDATE				el=Replacement: Total	trade_fl:
	e=VALIDATE Outcome	Target Variabl Target Percentage	e=REP_trade_fl Outcome Percentage	ag Target Lab Frequency Count	el=Replacement: Total Percentage	trade_fl:
Data Rol Target B		Target	Outcome	Frequency	Total	trade_fl:
Target	Outcome	Target Percentage	Outcome Percentage	Frequency Count	Total Percentage	trade_fl:
Target B	Outcome B	Target Percentage 100.000	Outcome Percentage 90.909	Frequency Count	Total Percentage 16.3934	trade_fla

Figure 11: classification table of logistic regression

The classification table show the results of the classification on the validation data. The model achieves 100% accuracy in some scenarios, only 1 mistake when it classifies a target that is supposed to be 'Buy' to 'Sell'.

Logistic regression assessment score

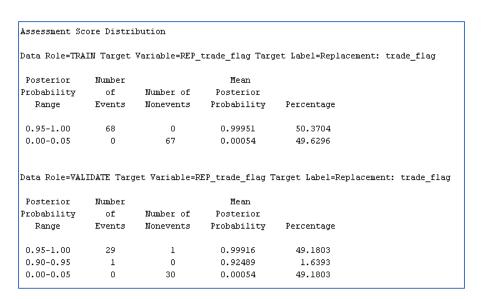


Figure 12: logistic regression assessment score

The mean posterior probability is high when the mean posterior probability range is high. This means that the model has a high accuracy rate.

Analysis of maximum likelihood estimates

		REP_							
		trade_			Standard	Wald		Standardized	
Parameter		flag	DF	Estimate	Error	Chi-Square	Pr > ChiSq	Estimate	Exp(Est)
Intercept		s	1	-7049.4	2498.3	7.96	0.0048		0.000
Intercept		H	1	-3469.4	807.2	18.47	<.0001		0.000
MP_LOG_REP_high	ı	S	1	-1154.8	2230.0	0.27	0.6046	-288.2	0.000
MP_LOG_REP_high	ı	H	1	-1425.5	1859.5	0.59	0.4433	-355.7	0.000
MP_LOG_REP_low		S	1	-504.2	2784.2	0.03	0.8563	-125.3	0.000
MP_LOG_REP_low		H	1	-209.9	2182.3	0.01	0.9234	-52.1511	0.000
MP_LOG_REP_open	ı	S	1	3983.1					999.000
MP_LOG_REP_open	ı	H	1	1752.0	1537.6	1.30	0.2545	436.2	999.000
OG_REP_close		S	1	5146.6					999.000
OG_REP_close		H	1	4035.5					999.000
_LOG_REP_high	0	S	1	889.4	777.6	1.31	0.2527		999.000
_LOG_REP_high	0	H	1	77.9054	104.5	0.56	0.4562		999.000
_LOG_REP_low	0	S	0	0					
_LOG_REP_low	0	H	0	0					
_LOG_REP_open	0	S	0	0					
_LOG_REP_open	0	H	0	0					
EP_change_flag	N	S	1	26.5637	36.3284	0.53	0.4646		999.000
EP_change_flag	N	H	1	23.0783	34.3030	0.45	0.5011		999.000
EP_change_flag	0	S	1	18.7851	29.8713	0.40	0.5294		999.000
EP_change_flag	0	H	1	16.2146	28.9787	0.31	0.5758		999.000
tock_code	2984	S	1	228.4	149.0	2.35	0.1253		999.000
tock_code	2984	H	1	101.4	135.7	0.56	0.4547		999.000
tock_code	5165	S	1	2790.8	849.3	10.80	0.0010		999.000
tock_code	5165	H	1	1602.4	336.2	22.71	<.0001		999.000
tock_code	5285	S	1	-7270.4	2030.4	12.82	0.0003		0.000
tock_code	5285	H	1	-4033.5	868.4	21.57	<.0001		0.000
tock_code	7154	S	1	1203.7	345.2	12.16	0.0005		999.00
tock_code	7154	H	1	714.5	166.1	18.51	<.0001		999.000
tock_code	7216	S	1	-1122.4	545.2	4.24	0.0395		0.000
tock_code	7216	H	1	-662.0	476.9	1.93	0.1651		0.000
tock_code	8125	S	1	-876.0	279.9	9.80	0.0017		0.000
tock_code	8125	H	1	-518.3	184.1	7.92	0.0049		0.000
ol _		S	1	-0.00050	0.00301	0.03	0.8682	-3.0409	1.000
ol		н	1	-0.00059	0.00299	0.04	0.8424	-3.6132	0.999

Figure 13: analysis of maximum likelihood

In this maximum likelihood estimates, the Pr > ChiSq column show the significance of the variables. If the value is closer to 0, then the variable has more significance in determining the outcome. If the value is closer to 1, then it means the variable is not suitable to be used for prediction.

It is seen that stock codes are an important feature to predict the trade flag.

Classification chart

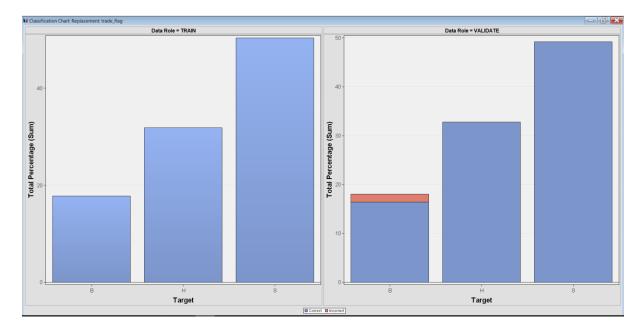


Figure 14: classification chart

The classification chart conveys the same information as the classification table. The model achieved a high accuracy rate on the validation dataset, only 1 mistake. The number of categories are different in the training set and the validation set is because they are consisted of different records.

Rules obtained from the decision tree

- 1. If the volume is < 0.5 then buy the stock.
- 2. If the volume is >= 0.5 and the stock code is 7216, 8125, 2984 then sell the stock.
- 3. If the volume is < 0.5 and the stock code is 5285, 7154, 9091, 5165 and the opening price is >= 5.095 then sell the stock.
- 4. If the volume is < 0.5 and the stock code is 5285, 7154, 9091, 5165 and the opening price is < 5.095 and the volume is < 50.5 then sell the stock

Conclusion

The third rule obtained from the decision tree is similar with the rules defined for Sime Darby Plantation Berhad to sell the stock if the price is greater than or equal to 5.10.

The other rules obtained from the decision tree are unexpected and could be the hidden insights. These rules would be used to predict the trade flag of the stocks in the future, to check if the features can truly be depended upon to determine the trade flag.