

**UNIVERSITY  
OF MALAYA**

**SEMESTER II, 2018/2019 SESSION**

**WQD7005**

**DATA MINING**

**PREPARED BY**

**PARVITRA SOMAHSUNDRAM WQD180045**

**LECTURER** : Prof. Dr. The Ying Wah

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## 1.0 Data Acquisition

The stock data is crawled from

<https://www.thestar.com.my/business/marketwatch/stocks/?qcounter=> to retrieve all the stock price of all the company from A-Z with the following attributes: -

- ❖ Company Name
- ❖ Company Code
- ❖ Open Price
- ❖ High Price
- ❖ Low Price
- ❖ Last Price
- ❖ Change Price
- ❖ Volume
- ❖ Buy rate
- ❖ Selling Rate

The following is the dataset which crawled and export in CSV file without organised date (no attributed fields).

	A	B	C
1	UCHI TECHNOLOGIES BHD	7100	['2.720', '2.730', '2.700', '2.720', '0.000', '0.00', '1,592', '2.710 / 400', '2.720 / 3,543']
2			
3	UCHITEC-CD: CW UCHI TECHNOLOGIES BERHAD (AM)	7100CD	['-', '-', '-', '0.005', '0.000', '0.00', '0', '0.000 / 0', '0.000 / 0']
4			
5	UCHITEC-CE: CW UCHI TECHNOLOGIES BERHAD (RHB)	7100CE	['-', '-', '-', '0.025', '0.000', '0.00', '0', '0.000 / 0', '0.000 / 0']
6			
7	UCREST BERHAD	5	['0.255', '0.270', '0.255', '0.260', '0.005', '1.96', '105,198', '0.255 / 29,657', '0.260 / 6,115']
8			
9	UEM SUNRISE BERHAD	5148	['0.850', '0.860', '0.835', '0.840', '-0.010', '-1.18', '10,411', '0.835 / 416', '0.840 / 701']
10			
11	UEMS-C64: CW UEM SUNRISE BERHAD (MIBB)	514864	['-', '-', '-', '0.040', '0.000', '0.00', '0', '0.000 / 0', '0.000 / 0']
12			
13	UEMS-C65: CW UEM SUNRISE BERHAD (MACQ)	514865	['0.085', '0.085', '0.085', '0.085', '0.000', '0.00', '732', '0.000 / 0', '0.000 / 0']
14			
15	UEMS-C66: CW UEM SUNRISE BERHAD (KIBB)	514866	['0.070', '0.070', '0.070', '0.070', '0.000', '0.00', '974', '0.000 / 0', '0.000 / 0']
16			
17	UNITED U-LI CORPORATION BHD	7133	['0.440', '0.455', '0.435', '0.450', '0.010', '2.27', '8,102', '0.435 / 525', '0.450 / 1,849']
18			
19	UNITED MALACCA BHD	2593	['5.550', '5.550', '5.450', '5.500', '-0.010', '-0.18', '591', '5.500 / 93', '5.560 / 20']
20			

## 2.0 Management of data

To store the data crawled in 1.0 section; we had managed the data to SQL database. In section 1.0; we had crawled the data and save in CSV format without having respective attributes.

### ❖ Create database with attributes

```

use StockCrawl;
create table StockData (
  ID int Primary Key auto increment,
  CompanyName varchar(50) Not NULL,
  CompanyStockCode varchar(30),
  OpenPrice varchar(30),
  HighPrice varchar(30),
  LowPrice varchar(30),
  LastPrice varchar(30),
  Chg varchar(30),
  ChgPercentage varchar(30),
  Volume varchar(30),
  BuyVolume varchar(30),
  SellVolume varchar(30),
  CreatedAt Timestamp default current_timestamp
);

```

### ❖ Export the crawl data to the database

ID	CompanyName	CompanyStockCode	OpenPrice	HighPrice	LowPrice	LastPrice	Chg	ChgPercentage	Volume	BuyVolume	SellVolume	CreatedAt
4	ZECON BHD	7028	0.285	0.295	0.275	0.285	0.000	0.00	14,154	0.280 / 1,180	0.285 / 96	2019-03-21 10:24:23
5	ZELAN BHD	2283	0.090	0.095	0.090	0.095	0.005	5.56	28,483	0.090 / 8,317	0.095 / 24,838	2019-03-21 10:24:23
6	ZHULIAN CORPORATION BHD	5131	1.360	1.360	1.360	1.360	-0.010	-0.73	49	1.360 / 31	1.370 / 100	2019-03-21 10:24:23
7	ZECON BHD	7028	0.285	0.295	0.275	0.285	0.000	0.00	14,154	0.280 / 1,180	0.285 / 96	2019-03-21 10:35:50
8	ZELAN BHD	2283	0.090	0.095	0.090	0.095	0.005	5.56	28,483	0.090 / 8,317	0.095 / 24,838	2019-03-21 10:35:50
9	ZHULIAN CORPORATION BHD	5131	1.360	1.360	1.360	1.360	-0.010	-0.73	49	1.360 / 31	1.370 / 100	2019-03-21 10:35:50

### 3.0 Processing of data

In this milestone, we had crawled news data to shows the dependency of the stock price with the news.

News Data Crawl with attributes of stock date, company name, news header, news info and news link from <https://www.theedgemarkets.com> .

	StockDate	CompanyName	NewsHeader	NewsInfo	NewsLink
0	April 30, 2019 17:00 pm +08	HLBANK	Are banks worth a second look as half of them ...	HALF of the banks listed on Bursa Malaysia hav...	<a href="https://www.theedgemarkets.com/article/are-ban...">https://www.theedgemarkets.com/article/are-ban...</a>
1	April 30, 2019 09:10 am +08	HLBANK	KLCI drifts lower in line with region, key Chi...	KUALA LUMPUR (April 30): The FBM KLCI drifted ...	<a href="https://www.theedgemarkets.com/article/kcli-dr...">https://www.theedgemarkets.com/article/kcli-dr...</a>
2	April 26, 2019 10:18 am +08	HLBANK	KLCI retreats in line with subdued regional ma...	KUALA LUMPUR (April 26): The FBM KLCI retreat...	<a href="https://www.theedgemarkets.com/article/kcli-re...">https://www.theedgemarkets.com/article/kcli-re...</a>
3	April 18, 2019 13:10 pm +08	HLBANK	KLCI falls 0.59% as Public Bank, Maxis weigh	KUALA LUMPUR (April 18): The FBM KLCI fell 0.5...	<a href="https://www.theedgemarkets.com/article/kcli-fa...">https://www.theedgemarkets.com/article/kcli-fa...</a>
4	April 18, 2019 10:21 am +08	HLBANK	KLCI stays in negative zone on worries of pote...	KUALA LUMPUR (April 18): The FBM KLCI remained...	<a href="https://www.theedgemarkets.com/article/kcli-st...">https://www.theedgemarkets.com/article/kcli-st...</a>

#### *Covariance Software used: Jupiter*

The following ate the covariance between stock price and news polarity for Mah Sing and HL Bank.

For HL Bank it shows positive result as the news had impact the stock price whereas for Mah Sing the stock price had no dependency with news it shows negative covariance.

```
In [155]: cov_mat = HLBANK.cov()
cov_mat

Out[155]:
```

	stockprice	newspolarity
stockprice	0.022323	0.008053
newspolarity	0.008053	0.040963

---

```
In [156]: corr_mat= HLBANK.corr()
corr_mat

Out[156]:
```

	stockprice	newspolarity
stockprice	1.00000	0.26632
newspolarity	0.26632	1.00000

Figure 1 HL Bank Covariance

```
In [72]: cov_mat = MAHSING.cov()
cov_mat

Out[72]:
```

	stockprice	newspolarity
stockprice	1.179654e-04	-2.934750e-34
newspolarity	-2.934750e-34	3.228225e-33

---

```
In [74]: corr_mat= MAHSING.corr()
corr_mat

Out[74]:
```

	stockprice	newspolarity
stockprice	1.000000e+00	-4.755673e-16
newspolarity	-4.755673e-16	1.000000e+00

Figure 2 Mah Sing Covariance

## 4.0 Interpretation of data

The crawl data been interpreted to visualise as Heat Map and Pair Plot for visualization by using stock price and news polarity variable.

### 4.1 HeatMap

```
sns.heatmap(corr_mat)
<matplotlib.axes._subplots.AxesSubplot at 0x7fd093419fd0>
```

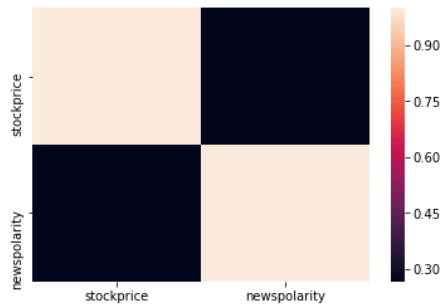


Figure 3 HeatMap of HL Bank

```
In [75]: sns.heatmap(corr_mat)
Out[75]: <matplotlib.axes._subplots.AxesSubplot at 0x7fac538e9ba8>
```

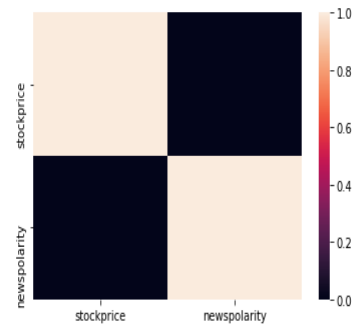


Figure 4 HeatMap of Mah Sing

The lighter the colour the stronger the relationship between the variables and the darker the colour in heat map it show there is no relationship between the variable.

### 4.2 Pair Plot

```
sns.pairplot(HLBANK)
<seaborn.axisgrid.PairGrid at 0x7f2f1b8fd6d8>
```

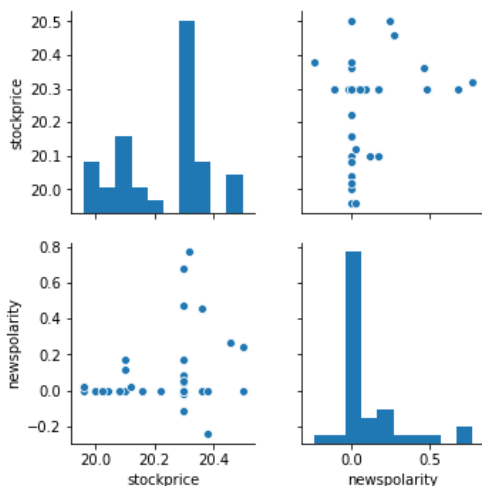


Figure 5 PairPlot of HL Bank

```
In [71]: sns.pairplot(MAHSING)
Out[71]: <seaborn.axisgrid.PairGrid at 0x7fac5379a4e0>
```

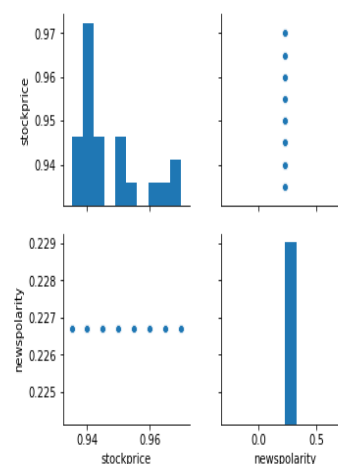


Figure 6 PairPlot of Mah Sing

Mah Sing pair plot shows negative correlation which mean there is no dependency on news polarity with the Mah sing stock price where Hong Leong bank shows positive correlation which mean the news gives impact to the stock price of the company.

## 5.0 Communication of insights of data

Decision Tree and Regression Model has plotted to visualise the data to view:-

### 5.1 Decision tree

Creating Training and Validation Data

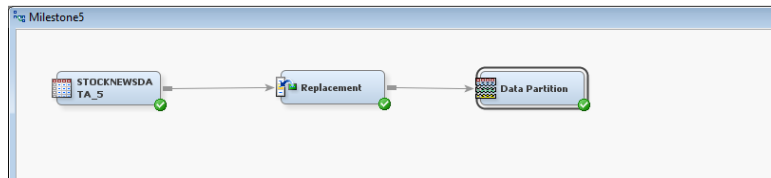


Figure 7 Data Diagram of Decision Tree

### Replacement

Any newspolarity value that fall below the lower limit of 0 are set to missing .  
All other values of this variable will not impacted.

\*It will list all the less than 0 (negative value) as missing value.

Total 4 missing value.

Variable	Label	Role	Train
newspolarity	newspolarity	INPUT	4

Variable	Replace Variable	Limits Method	Lower limit	Upper Limit	Label	Replacement Method	Lower Replacement Value	Upper Replacement Value
newspolarity	REP_newspolarity	MANUAL	0		.newspolarity	MISSING		

Figure 8 Output of Replacement Execution

A new column is added to the analysis data: Replacement: newspolarity. The replace value is shown by a dot(.) which indicated a missing value.

Obs #	Date	companyname	stockprice	newspolarity	Replacement: newspolarity
24	03/18/2019	HBLBANK	20.3	0.057218337	0.057218
25	03/19/2019	HBLBANK	20.3	0.051419984	0.05142
26	03/20/2019	HBLBANK	20.3	0.045454545	0.045455
27	03/21/2019	HBLBANK	20.3	0.171373457	0.171373
28	03/22/2019	HBLBANK	20.3	0.170526094	0.170526
29	03/25/2019	HBLBANK	20.3	-0.018025078	.
30	03/26/2019	HBLBANK	20.3	0.084722222	0.084722
31	03/27/2019	HBLBANK	20.3	0.084313603	0.084314
32	03/28/2019	HBLBANK	20.3	0	0
33	03/29/2019	HBLBANK	20.3	-0.110567841	.
34	04/01/2019	HBLBANK	20.3	0.474296947	0.474297
35	04/01/2019	HBLBANK	20.3	0.474296947	0.474297
36	04/02/2019	HBLBANK	20.3	0.265410084	0.26541
37	04/02/2019	HBLBANK	20.48	0.265410084	0.26541
38	04/03/2019	HBLBANK	20.46	0.459323938	0.459324
39	04/03/2019	HBLBANK	20.36	0.459323938	0.459324
40	04/04/2019	HBLBANK	20.36	0.055348485	0.055348
41	04/04/2019	HBLBANK	20.3	0.055348485	0.055348
42	04/05/2019	HBLBANK	20.3	0	0
43	04/07/2019	HBLBANK	20.22	0	0
44	04/08/2019	HBLBANK	20.22	0.771217439	0.771217
45	04/08/2019	HBLBANK	20.32	0.771217439	0.771217
46	04/09/2019	HBLBANK	20.32	0.173360528	0.173361
47	04/09/2019	HBLBANK	20.1	0.173360528	0.173361
48	04/10/2019	HBLBANK	20.1	0	0
49	04/10/2019	HBLBANK	20.08	0	0
50	04/11/2019	HBLBANK	20.08	0	0
51	04/11/2019	HBLBANK	20.16	0	0
52	04/12/2019	HBLBANK	20.16	0	0
53	04/14/2019	HBLBANK	20.36	0	0
54	04/15/2019	HBLBANK	20.36	0.113318312	0.113318
55	04/15/2019	HBLBANK	20.1	0.113318312	0.113318
56	04/16/2019	HBLBANK	20.1	0	0
57	04/16/2019	HBLBANK	20	0	0
58	04/17/2019	HBLBANK	20	0	0
59	04/17/2019	HBLBANK	20	0	0
60	04/18/2019	HBLBANK	20	-0.241016002	.
61	04/18/2019	HBLBANK	20.38	-0.241016002	.

Figure 9 Data Set of Replaced Missing Value

## Data Partition

With smaller raw datasets, model stability can become an important issue.

Thus, increasing the number of cases devoted to the training partition is a reasonable course of action.

Property	Value
<b>General</b>	
Node ID	Part
Imported Data	...
Exported Data	...
Notes	...
<b>Train</b>	
Variables	...
Output Type	Data
Partitioning Method	Default
Random Seed	12345
<b>Data Set Allocations</b>	
Training	50.0
Validation	50.0
Test	0.0
<b>Report</b>	

Figure 10 Dataset Allocation Setting

Variable Summary		
Role	Measurement Level	Frequency Count
INPUT	INTERVAL	2
INPUT	NOMINAL	1
REJECTED	INTERVAL	1
TIMEID	INTERVAL	1
Partition Summary		
Type	Data Set	Number of Observations
DATA	EMWS1.Repl_TRAIN	76
TRAIN	EMWS1.Part_TRAIN	38
VALIDATE	EMWS1.Part_VALIDATE	38

Figure 11 Summary of Data Partition



## Constructing Decision Tree

❖ Created the maximal tree

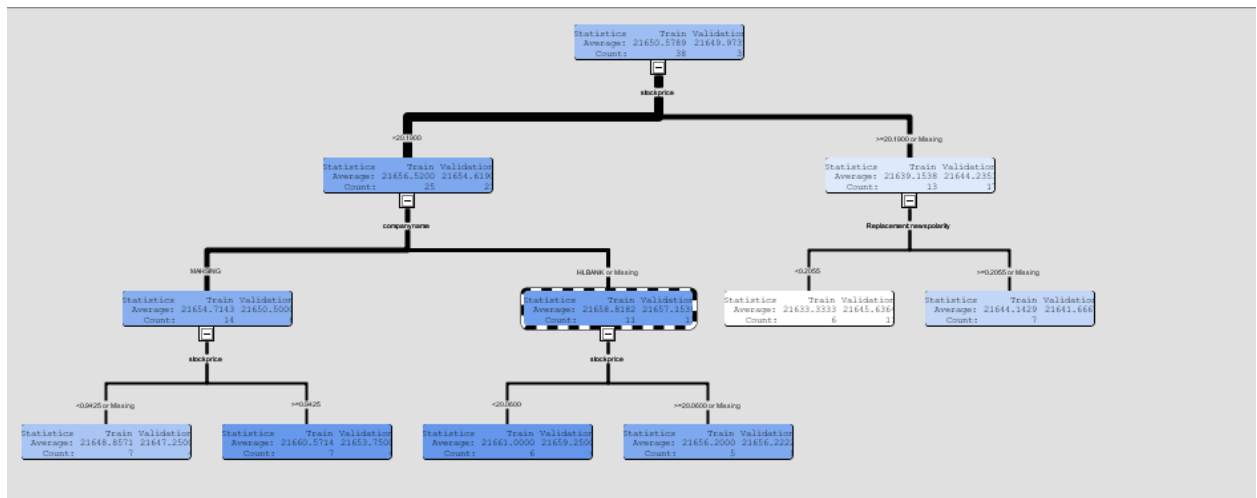


Figure 12 Maximal Tree

It shows the predictive model assigns one of 6 predicated targets for train and validation data.

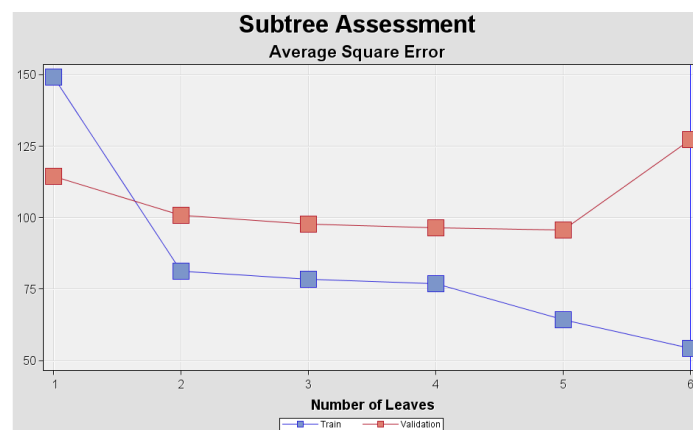


Figure 13 Subtree Assessment

## Assessing a Decision Tree

\*Frozen tree property prevents the maximal tree from being changed by other property settings when the flow is run.

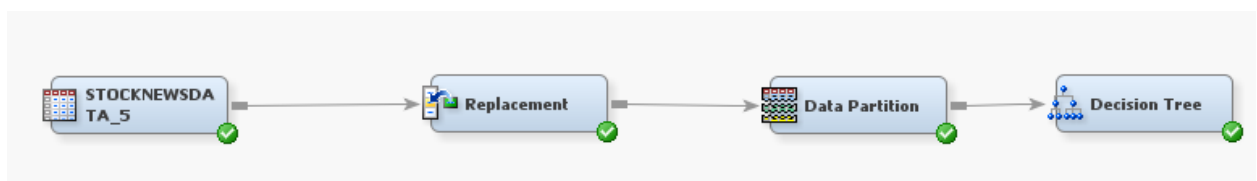


Figure 14 Data Node of Decision tree

The result window contains a variety of diagnostic plots and tables, including a mean predicted chart, a tree map, and a table of fit statistics. The diagnostic tools shown in the results vary with the measurement level of the target variable.

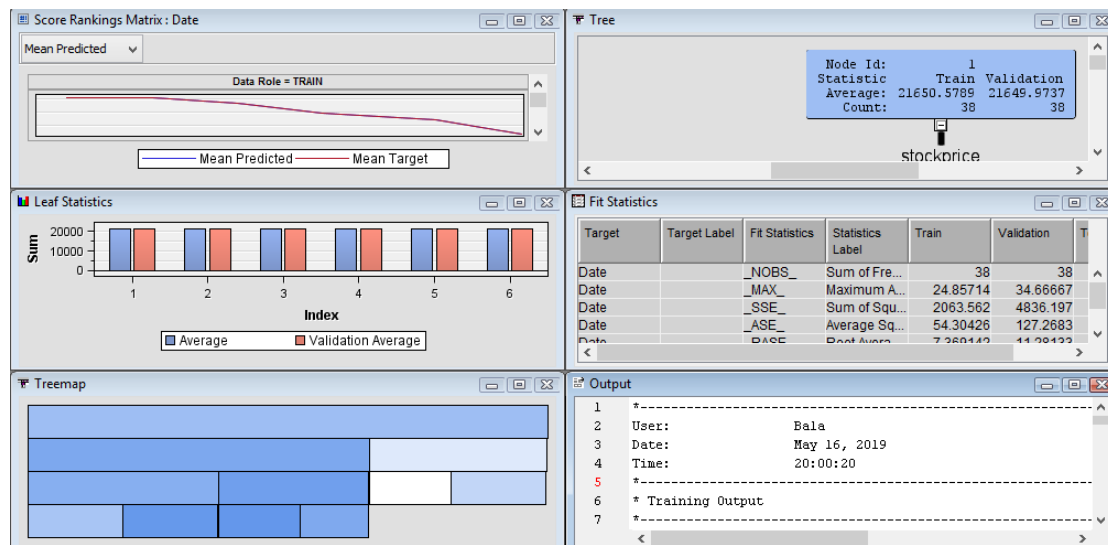


Figure 15 Diagnostic plots and table

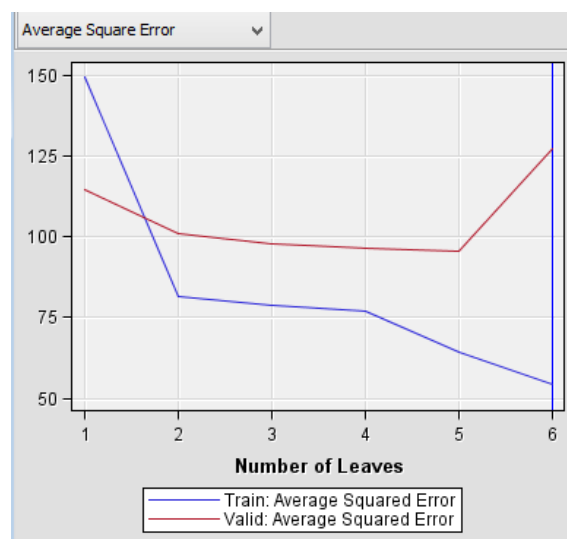


Figure 16 Plot of Average Square Error

This plot shows the Average Square Error corresponding to each sub tree as the data is sequentially split. It is similar to the one generated with the Interactive Decision Tree tool, and it confirms suspicions about the optimality of 6 leaf tree. The performance on the training sample becomes monotonically better as the tree becomes more complex. However, the performance on the validation sample only improves up to a tree of, approximately, four or five leaves and the diminishes as model complexity increases.

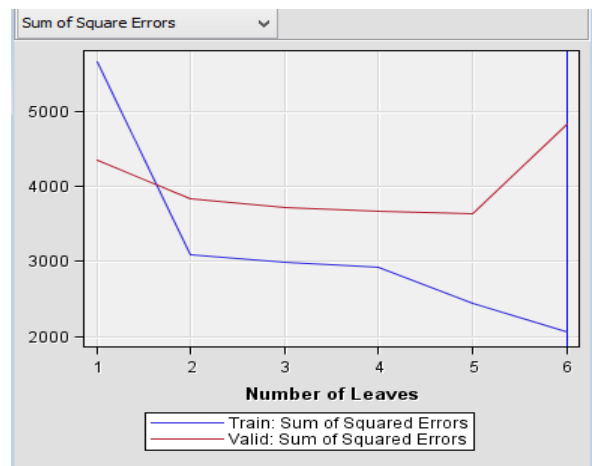


Figure 17 Plot of Sum of Square Error

This plot is similar to the performance under Average square error. But this will be inaccurate for all cases that are not in the assigned class.

**To evaluate the number of leaves between maximal tree , decision tree, probability tree**

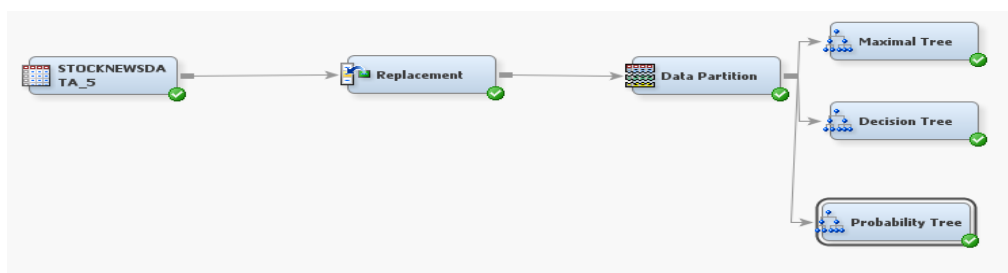


Figure 18 Data node

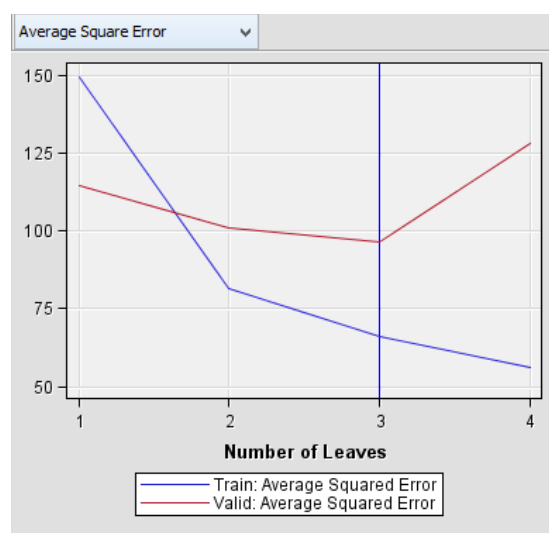


Figure 19 Plot of Average Square Error

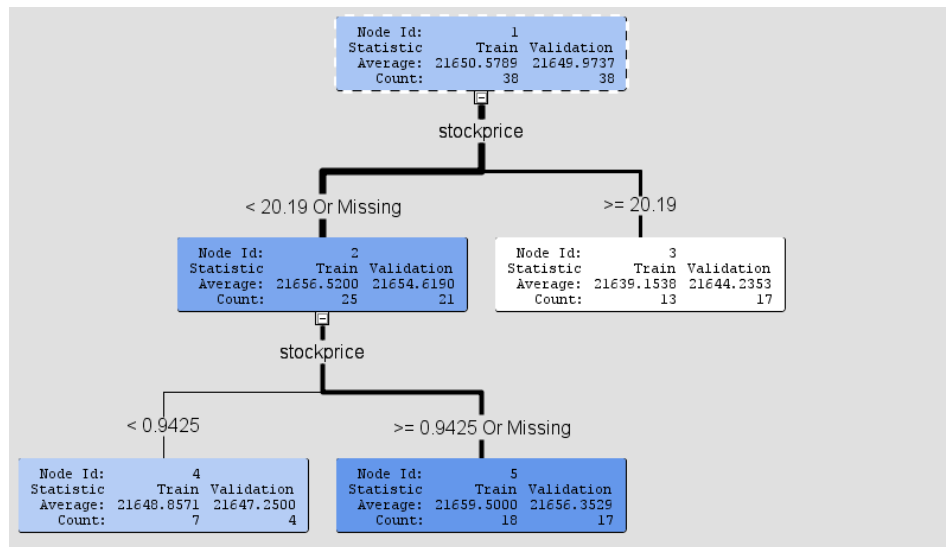


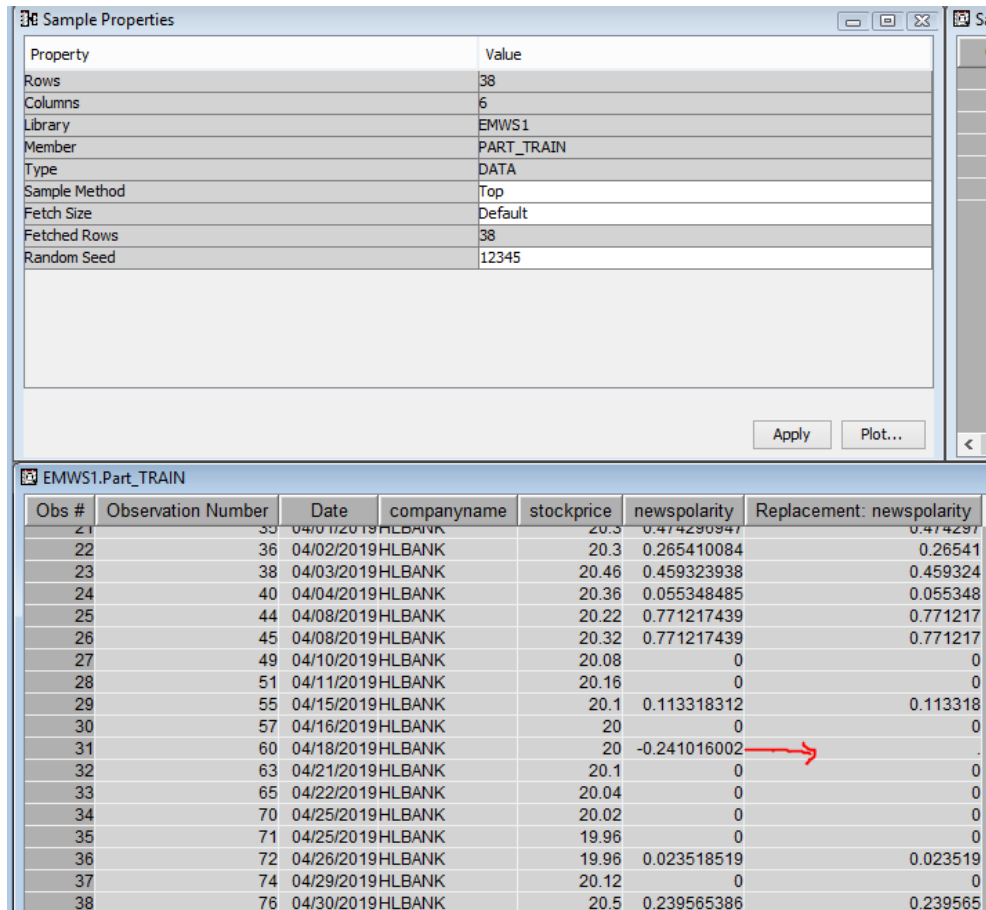
Figure 20 Probability Tree Diagram

The output for probability tree and decision tree give 4 leaves.

## 5.2 Linear Regression

### Managing Missing Values

There are several inputs with a noticeable frequency of missing values, for example, news polarity.



**Sample Properties**

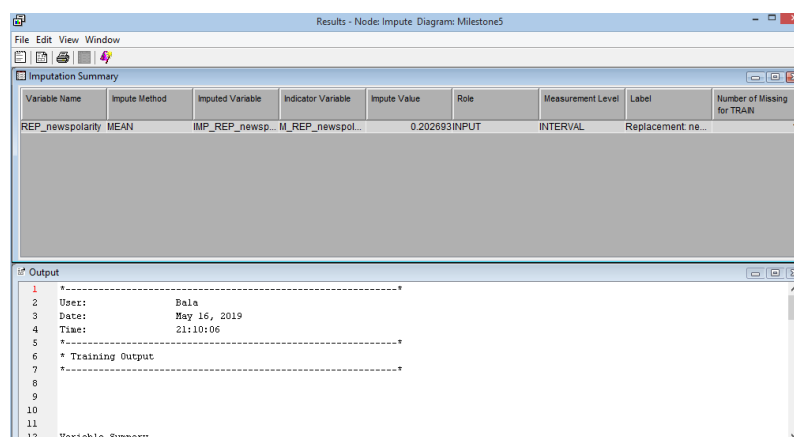
Property	Value
Rows	38
Columns	6
Library	EMWS1
Member	PART_TRAIN
Type	DATA
Sample Method	Top
Fetch Size	Default
Fetches Rows	38
Random Seed	12345

**EMWS1.Part\_TRAIN**

Obs #	Observation Number	Date	companyname	stockprice	news_polarity	Replacement: news_polarity
21	33	04/01/2019	HLBANK	20.3	0.474290947	0.474291
22	36	04/02/2019	HLBANK	20.3	0.265410084	0.26541
23	38	04/03/2019	HLBANK	20.46	0.459323938	0.459324
24	40	04/04/2019	HLBANK	20.36	0.055348485	0.055348
25	44	04/08/2019	HLBANK	20.22	0.771217439	0.771217
26	45	04/08/2019	HLBANK	20.32	0.771217439	0.771217
27	49	04/10/2019	HLBANK	20.08	0	0
28	51	04/11/2019	HLBANK	20.16	0	0
29	55	04/15/2019	HLBANK	20.1	0.113318312	0.113318
30	57	04/16/2019	HLBANK	20	0	0
31	60	04/18/2019	HLBANK	20	-0.241016002	0
32	63	04/21/2019	HLBANK	20.1	0	0
33	65	04/22/2019	HLBANK	20.04	0	0
34	70	04/25/2019	HLBANK	20.02	0	0
35	71	04/25/2019	HLBANK	19.96	0	0
36	72	04/26/2019	HLBANK	19.96	0.023518519	0.023519
37	74	04/29/2019	HLBANK	20.12	0	0
38	76	04/30/2019	HLBANK	20.5	0.239565386	0.239565

Figure 21 Missing Value

1 input has missing value:-



**Imputation Summary**

Variable Name	Impute Method	Imputed Variable	Indicator Variable	Impute Value	Role	Measurement Level	Label	Number of Missing for TRAIN
REP_news_polarity	MEAN	IMP_REP_news_polarity		0.202693	INPUT	INTERVAL	Replacement: news_polarity	1

**Output**

```

1 *-----*
2 User:      Bala
3 Date:      May 16, 2019
4 Time:      21:10:06
5 *-----*
6 * Training Output
7 *-----*
8
9
10
11
12 Variable Summary
  
```

Figure 22 Imputation Result

## Running the regression node

Regression Diagram below:-

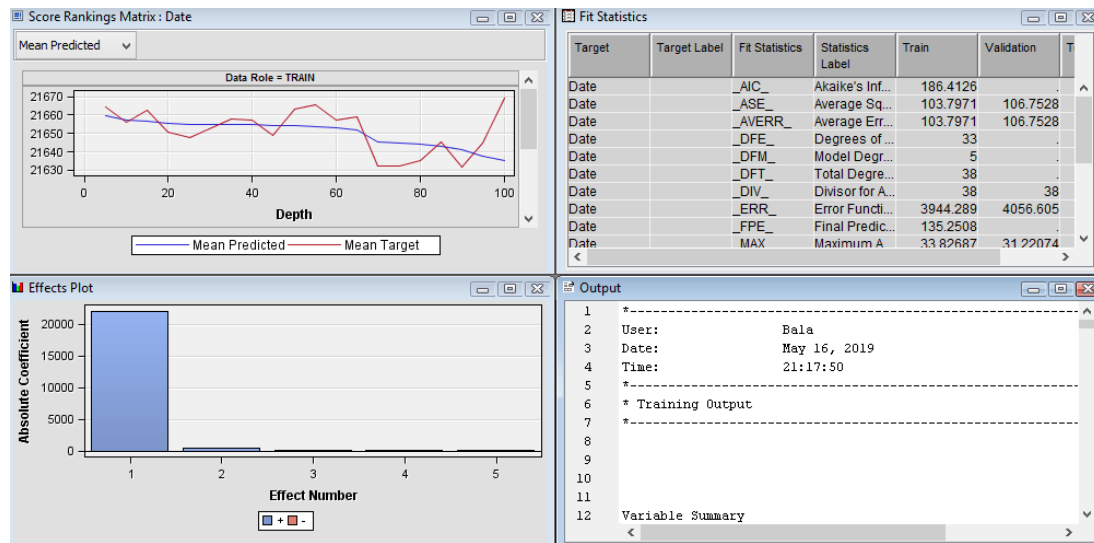


Figure 23 Regression Diagram

The initial lines of the output window summarize the roles of variables used (or not) by the Regression node. The fit model has 4 inputs that predict a binary target.

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

Figure 24 Summary of Variables

The next lines give more information about the model, including the training data set name, target variable name, number of target categories and most importantly, the number of model parameter.

Model Information	
Training Data Set	WORK.EM_DMREG.VIEW
DMDB Catalog	WORK.REG_DMDB
Target Variable	Date
Target Measurement Level	Interval
Error	Normal
Link Function	Identity
Number of Model Parameters	5
Number of Observations	38

Figure 25 Summary of Model Information

The type 3 analysis tests the statistical significance of adding the indicated input to a model that already contains other listed inputs. A value near 0 in Pr > F column approximately indicates a significant input; a value near 1 indicates an extraneous input.

Type 3 Analysis of Effects				
Effect	DF	Sum of Squares	F Value	Pr > F
IMP_REP_newspolarity	1	50.3219	0.42	0.5209
M_REP_newspolarity	1	0.2420	0.00	0.9644
companyname	1	698.5254	5.84	0.0213
stockprice	1	712.0180	5.96	0.0202

Figure 26 Summary of Type 3 Analysis of Effects

The statistical shows the significant measure a range from <0.0001(highly significant) to 0.9593(highly dubious). Results such as this suggest that certain inputs can be dropped without affecting the predictive prowess of model.

Fit Statistics						
Target	Target Label	Fit Statistics	Statistics Label	Train	Validation	Test
Date	Target	_AIC_	Akaike's Inf...	186.4126	.	.
Date		_ASE_	Average Sq...	103.7971	106.7528	.
Date		_AVERR_	Average Err...	103.7971	106.7528	.
Date		_DFE_	Degrees of ...	33	.	.
Date		_DFM_	Model Degr...	5	.	.
Date		_DFT_	Total Degr...	38	.	.
Date		_DIV_	Divisor for A...	38	38	.
Date		_ERR_	Error Funct...	3944.289	4056.605	.
Date		_FPE_	Final Predic...	135.2508	.	.
Date		_MAX_	Maximum A...	33.82687	31.22074	.
Date		_MSE_	Mean Squa...	119.5239	106.7528	.
Date		_NOBS_	Sum of Fre...	38	38	.
Date		_NW_	Number of ...	5	.	.
Date		_RASE_	Root Avera...	10.18809	10.33212	.
Date		_RFPE_	Root Final ...	11.62974	.	.
Date		_RMSE_	Root Mean ...	10.9327	10.33212	.
Date		_SBC_	Schwarz's ...	194.6006	.	.
Date		_SSE_	Sum of Squ...	3944.289	4056.605	.
Date		_SUMW_	Sum of Cas...	38	38	.

Figure 27 Fit Statistics

## Selecting Input

The stepwise procedure starts with Step 0, an intercept-only regression model. The value of the intercept parameter is chosen so that the model predicts the overall target mean for every case.

Target	Target Label	Fit Statistics	Statistics Label	Train	Validation	Test
Date		_AIC_	Akaike's Inf...	192.1853	114.2867	.
Date		_ASE_	Average Sq...	149.1305	114.2867	.
Date		_AVERR_	Average Err...	149.1305	114.2867	.
Date		_DFE_	Degrees of ...	37	.	.
Date		_DFM_	Model Degr...	1	.	.
Date		_DFT_	Total Degr...	38	.	.
Date		_DIV_	Divisor for A...	38	38	.
Date		_ERR_	Error Funct...	5667.263	4342.895	.
Date		_FPE_	Final Predic...	157.2	.	.
Date		_MAX_	Maximum A...	27.57895	24.57895	.
Date		_MSE_	Mean Squa...	153.1993	114.2867	.
Date		_NOBS_	Sum of Fre...	38	38	.
Date		_NW_	Number of ...	1	.	.
Date		_RASE_	Root Avera...	12.21223	10.6905	.
Date		_RFPE_	Root Final ...	12.53794	.	.
Date		_RMSE_	Root Mean ...	12.37616	10.6905	.
Date		_SBC_	Schwarz's ...	193.8229	.	.
Date		_SSE_	Sum of Squ...	5667.263	4342.895	.
Date		_SUMW_	Sum of Cas...	38	38	.

Figure 28 Fit Statistics

Stepwise Selection Procedure					
Step 0: Intercept entered.					
Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	0	0	.	.	.
Error	37	5667.263159	153.169275	.	.
Corrected Total	37	5667.263159	.	.	.
Model Fit Statistics					
R-Square	0.0000	Adj R-Sq	0.0000	.	.
AIC	192.1853	BIC	193.7093	.	.
SBC	193.8229	C(p)	11.4153	.	.

Figure 29 Stepwise Selection

## Optimizing Regression Complexity

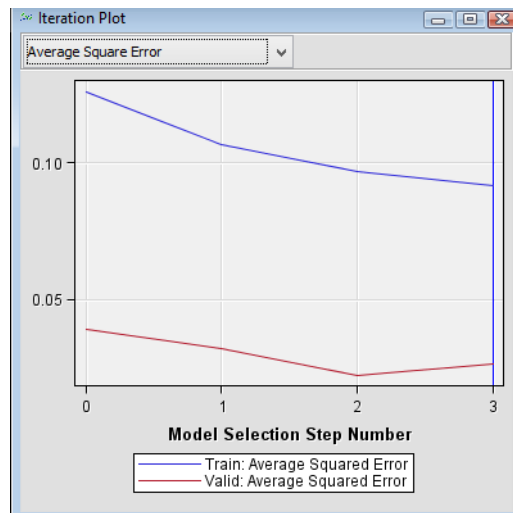


Figure 30 Average Sqaure Error Plot

The iteration plot shows the smallest validation average square error occurs at step 2. The vertical blue line shows the model with the optimal validation error (step 3).

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	0	0	.	.	.
Error	37	5667.263159	153.169275		
Corrected Total	37	5667.263159			
Model Fit Statistics					
R-Square	0.0000	Adj R-Sq	0.0000		
AIC	192.1853	BIC	193.7093		
SBC	193.8229	C(p)	11.4153		
Analysis of Maximum Likelihood Estimates					
Parameter	DF	Estimate	Standard Error	t Value	Pr >  t
Intercept	1	21650.6	2.0077	10783.9	<.0001

Figure 31 Analysis of Variable



## Transforming Inputs

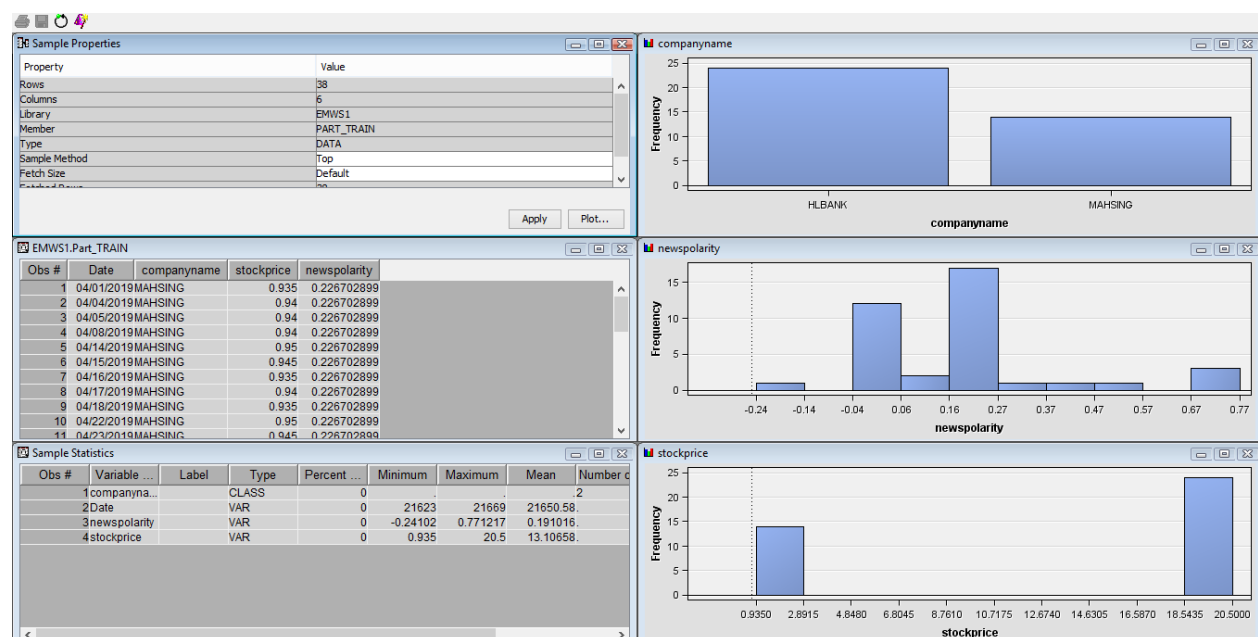


Figure 32 Plot of Transformed Inputs

Selecting log method for following variables:-

Name	Method	Number of Bins	Role	Level
Date	Default	4	Target	Interval
REP_newspolarity	Default	4	Input	Interval
companyname	Default	4	Input	Nominal
newspolarity	Log	4	Rejected	Interval
stockprice	Log	4	Input	Interval

Figure 33 Variable Roles

Computed Transformations  
(maximum 500 observations printed)

Input Name	Role	Input Level	Name	Level	Formula
newspolarity	REJECTED	INTERVAL	LOG_newspolarity	INTERVAL	$\log(\text{newspolarity} + 1.241016002)$
stockprice	INPUT	INTERVAL	LOG_stockprice	INTERVAL	$\log(\text{stockprice} + 1)$

Figure 34 Summary of Computed Transformation

Notice the formula column, while a log transformation was specified, the actual transformation used was  $\log(\text{input}+1)$ . This default action of the transform variable tools avoids problems with 0-values of the underlying inputs.

Categorical Input

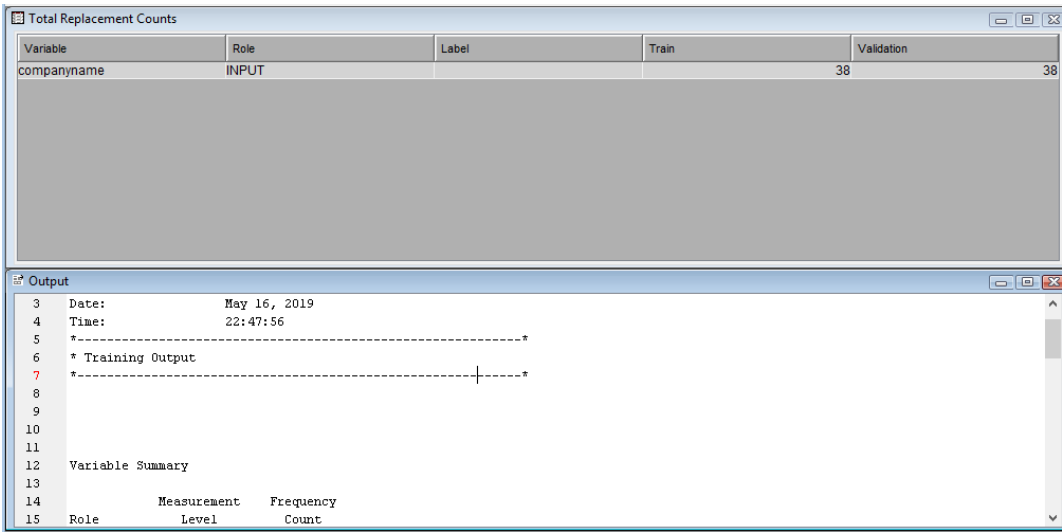


Figure 35 Total Replacement Counts Output

The total replacement count window shows the number of replacement that occurs in the training and validation data.

Variable	Formatted Value	Type	Character Unformatted Value	Numeric Value	Replacement Value	Label
companyname...	HLBANK		HLBANK		.A	
companyname...	MAHSING	C	MAHSING		.N	

Figure 36 Replacement value Variable

The replaced level values are consistent with expectation.

## 6.0 Recommendation

Time-series forecasting to show the investor the next 3 months stock price(High Price) of Mah Sing stock. A time series is a sequence of measurements recorded at equally-spaced intervals (hourly, weekly, monthly, etc.). As the name suggests, time series are inherently temporal. They often exhibit trends or seasonal patterns.

For example, the following plot shows Mah Sing stock price from 15/03/2019 till 30/04/2019:

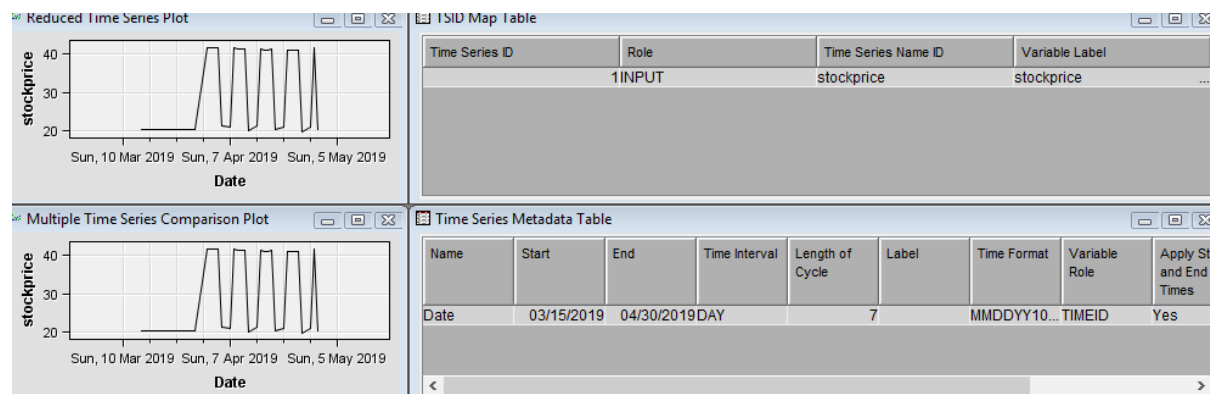


Figure 37 Plot of Mah Sing Stock Price 15/03-30/04

### Generating Forecast

We can prepare the data and generate forecasts in Enterprise Miner with a simple three-node flow:

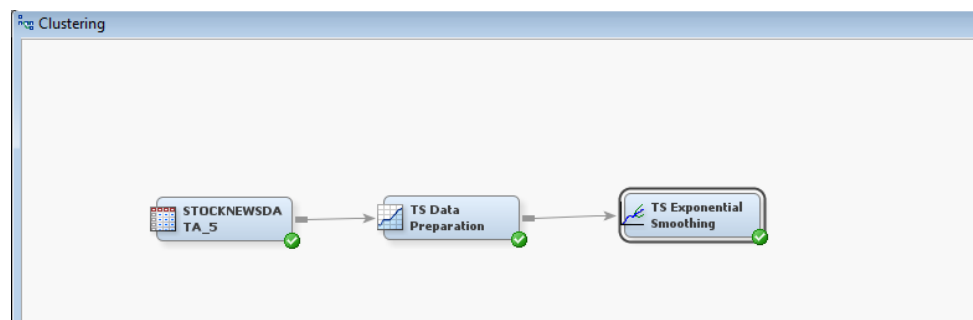


Figure 38 The Clustering Data Diagram

## Data Source node

Here is a snippet of our historical data&colon

Obs #	Time Series ID	Time Series Name ID	Date	Time Series Value
1	1	stockprice	29Mar2019	20.3
2	1	stockprice	30Mar2019	.
3	1	stockprice	31Mar2019	.
4	1	stockprice	01Apr2019	41.54
5	1	stockprice	02Apr2019	41.7
6	1	stockprice	03Apr2019	41.76
7	1	stockprice	04Apr2019	41.6
8	1	stockprice	05Apr2019	21.24
9	1	stockprice	06Apr2019	.
10	1	stockprice	07Apr2019	21.16
11	1	stockprice	08Apr2019	41.48
12	1	stockprice	09Apr2019	41.37
13	1	stockprice	10Apr2019	41.14
14	1	stockprice	11Apr2019	41.19
15	1	stockprice	12Apr2019	20.16
16	1	stockprice	13Apr2019	.
17	1	stockprice	14Apr2019	21.31
18	1	stockprice	15Apr2019	41.41
19	1	stockprice	16Apr2019	41.04
20	1	stockprice	17Apr2019	40.94
21	1	stockprice	18Apr2019	41.32
22	1	stockprice	19Apr2019	20.38
23	1	stockprice	20Apr2019	.
24	1	stockprice	21Apr2019	21.04
25	1	stockprice	22Apr2019	41.09
26	1	stockprice	23Apr2019	41.07
27	1	stockprice	24Apr2019	41.06
28	1	stockprice	25Apr2019	40.95
29	1	stockprice	26Apr2019	19.96
30	1	stockprice	27Apr2019	.
31	1	stockprice	28Apr2019	21.09
32	1	stockprice	29Apr2019	41.59
33	1	stockprice	30Apr2019	20.5

Figure 39 Dataset of Mah Sing StockPrice

Each row represents different date of the stock price. There are some missing values.

The Data Source node defines modelling roles for the 2 columns:

Name	Use	Role	Level
Date	Default	Time ID	Interval
stockprice	Default	Target	Interval

Figure 40 Variable of Data Source

Date has assigned as the TimeID and stock price as the target.

## TS Data Preparation node

The TS Data Preparation node transforms our data into a monthly series.

The time interval configured as Day and set Accumulation to Total. This will aggregate Mah Sing stock price by day.

Time Interval	
Specify an Interval	Day
Seasonal Cycle Selection	Default
Length of Cycle	2
Start and End Time	User Specified
Date Time Selector	...
Accumulation	Total

Figure 41 Time Interval Properties

To restrict the analysis to the time window of interest, ignoring early data points, had specified a custom Start and End times for the series using the Date Time Selector control:

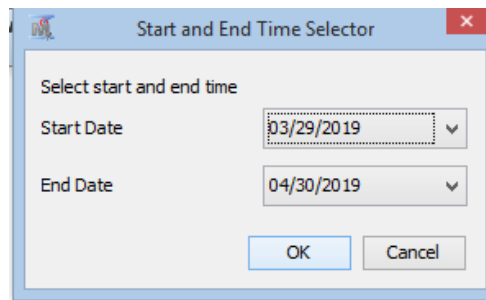


Figure 42 Start and End Time Selector

When this node is run, the TS Data Preparation node exports the transformed dataset:

### **TS Exponential Smoothing node**

In Enterprise Miner, forecasting is supported using Exponential Smoothing, a very popular and useful method for producing forecasts. This technique computes a new series of fitted values and forecasts, where each value in the series is the weighted average of the values observed at prior time points. It is called "Exponential smoothing" because the weights decrease exponentially to ensure that recent observations carry more weight than older ones. Exponential Smoothing tends to work best for short-term forecasts, i.e., forecasting a few time periods into the future.

In node properties, I've accepted the default Forecasting Method (Automatic), which tells Enterprise Miner to try various exponential smoothing methods and choose the one that has the best fit to the observed series.

The Forecast Lead set to 90, which will give us forecasts for the next 90 days.

Train	
Variables	
Specify an Interval	Day
Accumulation	Total
Seasonality	Default
Forecasting Method	Best
Forecast Lead	90
Forecast Back	0
Forecast Sum Start	1
Significance Level	0.05

Figure 43 TSEM Node Properties

## Results

Here is the plot of fitted values and forecasts that the TSEM node produces:

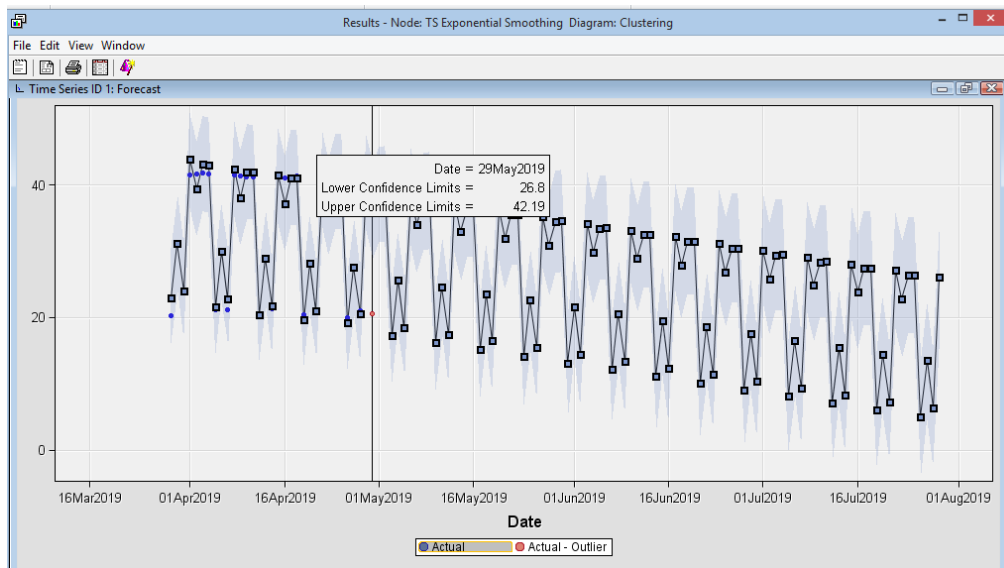


Figure 44 Forecast Plot

Actual stock price are shown as blue dots. Smoothed (fitted) values appear as a line that overlays blue squares. The light blue band represents the confidence interval for the fitted values.

Exponential smoothing has picked up on the seasonal variations in our data. Within each day the smoothed values show an early spike in the stock price followed a gradual decline.

By eyeballing the plot, it can gauge how well the smoothed values fit the observed values; by the Fit Statistics table, which contains error-based fit measures like Mean Square Error and Mean Absolute Percent Error.

Fit Statistics																	
Time Series ID	Time Series ID	Variable Name	Region	Degrees of Freedom Error	Number of Observations Used	Number of Observations	Number of Missing Actuals	Number of Missing Predicted Values	Number of Model Parameters	Total Sum of Squares	Corrected Total Sum of Squares	Sum of Square Error	Mean Square Error	Root Mean Square Error	Unbiased Mean Square Error	Unbiased Root Mean Square Error	Mean Absolute Percent Error
1stockprice	__TSVALUE_	FIT		24	33	33	6	0	3	33299.97	2673.398	321.0685	11.89143	3.448395	13.37786	3.657575	6.36792

Figure 45 Fit Statistics table

Forecasts and their confidence intervals appear to the right of the vertical reference line. Consistent with the seasonal pattern, the forecast calls for a rise then a drop off in subsequent months.