

RESEARCH



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- Data was collected from Starbucks quarterly report.
- The quarterly report data was collected for Q1 2014 - Q2 2019.
- The variables in the dataset are total number of stores, net revenue, comparable stores sales, active reward membership, earning per share and net new stores.

A	B	C	D	E	F	G
	Total # of Stores	Net Revenue (billion)	Comaparable Store	Active Rewards Mem	Increase Earning per	Net New Stores
Q1-2014	20,184	4.2	5	7	0.71	417
Q2-2014	20,519	3.9	6	7.3	0.56	335
Q3-2014	20,863	4.2	6	8	0.67	344
Q4-2014	21,366	4.2	5	8.6	0.77	503
Q1-2015	21,878	4.8	5	9	0.8	512
Q2-2015	22,088	4.6	7	10.3	0.33	210
Q3-2015	22,519	4.9	7	10.3	0.42	431
Q4-2015	23,043	4.9	8	10.6	0.2	524
Q1-2016	23,571	5.4	8	11	0.46	528
Q2-2016	23,921	5	6	12	0.39	350
Q3-2016	24,395	5.2	4	12.3	0.49	474
Q4-2016	25,085	5.7	4	12.7	0.56	690
Q1-2017	25,734	5.7	3	12.9	0.51	649
Q2-2017	26,161	5.3	3	13.3	0.45	427
Q3-2017	26,736	5.7	5	13.3	0.47	575
Q4-2017	27,339	5.7	2	13.3	0.55	603
Q1-2018	28,039	6.1	2	14.2	1.57	700
Q2-2018	28,209	6	2	14.9	0.47	468
Q3-2018	28,720	6.3	1	15.1	0.61	511
Q4-2018	29,324	6.3	3	15.3	0.56	604
Q1-2019	29,865	6.6	4	16.3	0.61	541
Q2-2019	30,184	6.3	3	16.8	0.53	319

Descriptive Analysis - Correlation



```
##heatmap for checking the correlation  
#between variables  
heatmap(cor(starbucks[sapply(starbucks, is.numeric)]),  
        Rowv = NA, Colv = NA,col=brewer.pal(9,"Greens"),  
        margins=c(20,15))
```

- We are finding the correlation between the variables in our data set.
- Our dependent variable Net Revenue has positive correlation with Active Rewards Membership and Net new stores.
- We will do our further analysis using regression to check which can give us complete insights which can be used to improve Starbucks revenue.



SOFTWARE



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- Run a linear model regression with net revenue as dependent variable.

```
LmStarbucks<- lm(
Net.Revenue.in.billion.dollar ~., data =
ScaleStar)
summary(LmStarbucks)
```

```
> #RUN LINERAR MODEL REGRESSION WITH NET REVENUE AS DEPENDENT VARIABLE
> LmStarbucks<- lm( Net.Revenue.in.billion.dollar ~., data = ScaleStar)
> summary(LmStarbucks)
```

Call:

```
lm(formula = Net.Revenue.in.billion.dollar ~ ., data = ScaleStar)
```

Residuals:

Min	1Q	Median	3Q	Max
-8.969e-06	-3.345e-06	4.738e-07	2.311e-06	7.926e-06

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-1.322e-06	3.130e-05	-0.042	0.96680
1..Total..Num.of.Stores	1.012e-04	7.158e-05	1.413	0.17561
Comaparable.Store.Sales.Up.in.percentage	4.394e-02	2.303e-02	1.908	0.07338 .
Active.Rewards.Membership.in.Million.dollar	1.573e-01	7.510e-02	2.095	0.05147 .
Increase.Earning.per.share.in.dollar	1.070e-01	1.351e-01	0.792	0.43913
Net.New.Stores	1.114e-03	3.026e-04	3.682	0.00185 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.983e-06 on 17 degrees of freedom

Multiple R-squared: 0.9741, Adjusted R-squared: 0.9665

F-statistic: 128.1 on 5 and 17 DF, p-value: 7.086e-13

>

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- We loaded the data into R for visualization and analysis.
- As different columns are using different units, to make the analysis more accurate, we normalized the data.

$$\text{ScaleStar} = (\text{Starbucks} - \min(\text{Starbucks})) / (\max(\text{Starbucks}) - \min(\text{Starbucks}))$$

```
> #SCALING DATA
> #Normalized Data
> ScaleStar = (Starbucks-min(Starbucks))/(max(Starbucks)-min(Starbucks))
> ScaleStar
```

	i..Total..Num.of.Stores	Net.Revenue.in.billion.dollar	
1	0.6590456	0.0001306088	
2	0.6699841	0.0001208132	
3	0.6812165	0.0001306088	
4	0.6976406	0.0001306088	
5	0.7143585	0.0001502002	
6	0.7212154	0.0001436697	
7	0.7352885	0.0001534654	
8	0.7523983	0.0001534654	
9	0.7696387	0.0001697915	
10	0.7810669	0.0001567306	
11	0.7965441	0.0001632610	
12	0.8190741	0.0001795871	
13	0.8402654	0.0001795871	
14	0.8542079	0.0001665263	
15	0.8729829	0.0001795871	
16	0.8926722	0.0001795871	
17	0.9155287	0.0001926480	
18	0.9210796	0.0001893828	
19	0.9377649	0.0001991785	
20	0.9574868	0.0001991785	
21	0.9751517	0.0002089741	
22	0.9855677	0.0001991785	
23	1.0000000	0.0002155046	

	Comaparable.Store.Sales.Up.in.percentage	Active.Rewards.Membership.in.Million.dollar
1	1.567306e-04	0.0002220350
2	1.893828e-04	0.0002318307
3	1.893828e-04	0.0002546872
4	1.567306e-04	0.0002742785
5	1.567306e-04	0.0002873394
6	2.220350e-04	0.0003297873
7	2.220350e-04	0.0003297873
8	2.546872e-04	0.0003395830
9	2.546872e-04	0.0003526438
10	1.893828e-04	0.0003852961
11	1.240784e-04	0.0003950917
12	1.240784e-04	0.0004081526
13	9.142618e-05	0.0004146830
14	9.142618e-05	0.0004277439
15	1.567306e-04	0.0004277439
16	5.877397e-05	0.0004277439

DATA VISUALIZATION



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Results below show p-values associated with each of the explanatory variable:

Variables	p-Value
Total Number of Stores	0.17561
Comparable Store Sales	0.07338
Active Rewards Membership	0.05147
Increase Earning per Share	0.43913
Net New Stores	0.00185

Variables	p-value	p value in %
Comparable Store Sales Up in percentage	0.07338	7.338
Active Rewards Membership	0.05147	5.147
Net New Stores	0.00185	0.185

- From the p-value, only these 3 variables are significant.
- We will run linear regression again for these 3 variables.



RESULT INTERPRETATION

- The linear regression is run on the revised dataset.

```
RLmStarbucks<-  
lm(i..Net.Revenue.in.billion.dollar ~., data  
= ScaleRevised)  
summary(RLmStarbucks)
```

```
> #RUN LINERAR MODEL in REVISED DATA WITH NET REVENUE AS DEPENDENT VARIABLE  
> RLmStarbucks<- lm(i..Net.Revenue.in.billion.dollar ~., data = ScaleRevised)  
> summary(RLmStarbucks)  
  
Call:  
lm(formula = i..Net.Revenue.in.billion.dollar ~ ., data = ScaleRevised)  
  
Residuals:  
      Min       1Q   Median       3Q      Max   
-3.754e-04 -9.171e-05 -8.200e-07  1.230e-04  3.787e-04  
  
Coefficients:  
              Estimate Std. Error t value Pr(>|t|)      
(Intercept)    0.0010587   0.0003695    2.865 0.009901 **   
Comaparable.Store.Sales.Up.in.percentage 0.0250685   0.0215956    1.161 0.260095      
Active.Rewards.Membership.in.Million.dollar 0.2614631   0.0136228   19.193 6.72e-14 ***  
Net.New.Stores    0.0012649   0.0003065    4.128 0.000573 ***  
---  
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
  
Residual standard error: 0.0002292 on 19 degrees of freedom  
Multiple R-squared:  0.9681,    Adjusted R-squared:  0.9631   
F-statistic: 192.5 on 3 and 19 DF,  p-value: 2.146e-14
```



RESULT INTERPRETATION

The output of table is summarized below:

Variables	Coefficient	p-value
(Intercept)	0.001059	0.009901
Comparable Store Sales	0.025069	0.260095
Active Rewards Membership	0.261463	6.72E-14
Net New Stores	0.001265	0.000573

For the reference the average values of the independent variables Comparable store sales, Active rewards membership and net new stores in the table below:

Variables	Average Value
Comparable Store Sales Up	4.565217391
Active Rewards Membership	12.24782609
Net New Stores	485.0869565



RESULT INTERPRETATION

We thus prepare our regression equation in the form of $y = a + b_1 * x_1 + b_2 * x_2 + b_3 * x_3$, where

- y is the dependent variable,
- a is a constant (the y -intercept),
- $b(n)$ is the coefficients for the independent variables, and
- $x(n)$ are the independent variables.

Net Revenue = (y-intercept) + (coefficient) * (Comparable Store Sales Up) + (coefficient) * (Active Rewards Membership) + (coefficient) * (Net New Stores)

Net Revenue = 0.0010587 + 0.0250685 * (Comparable Store Sales Up) + 0.2614631 * (Active Rewards Membership) + 0.0012649 * (Net New Stores)

Net Revenue = 1.4522178 + 0.0250685 * (4.565217391) + 0.2614631 * (12.24782609) + 0.0012649 * (485.0869565)

Net Revenue = 5.3826020212



RESULT INTERPRETATION

- To increase the net revenue, we can increase comparable store sales up, active rewards membership, and net new stores
- Because active rewards membership is associated with the largest coefficient, we will increase active rewards membership.
- Our goal is to find a condition which increases the net revenue by 10%, so we will increase net revenue by 10% (from 5.3826020212 to 5.92086222332) and solve for active rewards membership.

$$\text{Net Revenue} = 1.4522178 + 0.0250685 * (4.565217391) + 0.2614631 * (\text{Active Rewards Membership}) + 0.0012649 * (485.0869565)$$

$$5.92086222332 = 1.4522178 + 0.0250685 * (4.565217391) + 0.2614631 * (\text{Active Rewards Membership}) + 0.0012649 * (485.0869565)$$

$$\text{Active Rewards Membership} = [5.92086222332 - 1.4522178 - 0.0250685 * (4.565217391) - 0.0012649 * (485.0869565)] / 0.2614631$$

$$\text{Active Reward Membership} = 14.3064729971$$

Thus, by increasing Active Reward Membership from its average of 12.3 to 14.4, we can increase the net revenue by 10%.

Time Series - STARBUCKS



1. Start with reading the data in CSV file.

```
## Read data
starbucks <- read.csv("Starbucks.csv", header = T)
starbucks
```

2. Formatting the year for time series.

```
## format the year for time series.
starbucks$Qtr <- as.yearqtr(starbucks$i..Year, format = "Q%q-%Y")
```

3. Assigning variable for time series using function ts.

```
## time series analysis
starbucks$RevenueSeries <- ts
|(data = starbucks$Net.Revenue..billion..., start = c(2014, 1), frequency = 4)
```

4. Plot result for Starbucks Revenue over time.

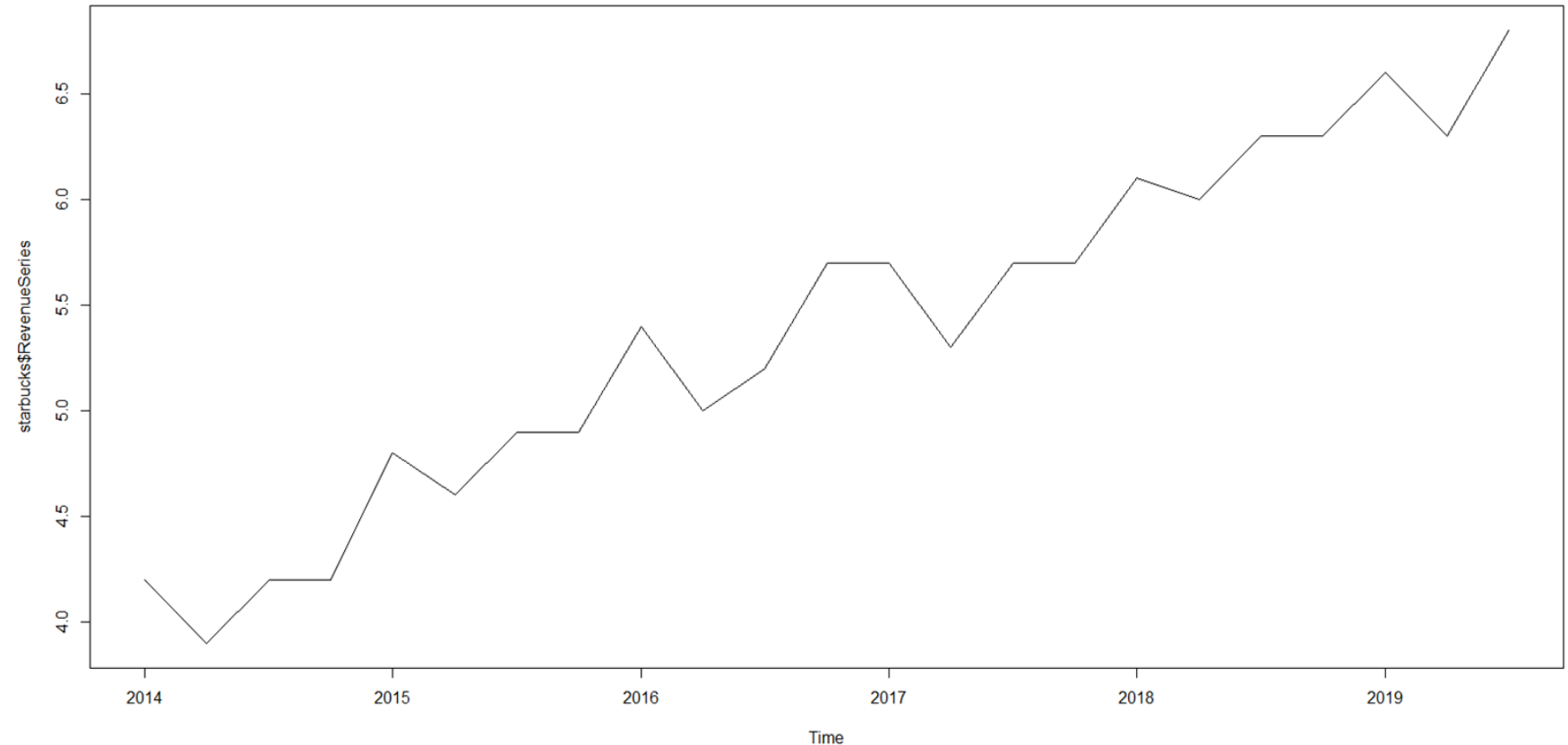
```
## plotting the time series data
plot(starbucks$RevenueSeries)
```

Time Series - STARBUCKS



Plot result for Starbucks Revenue over time

- We can see revenue growth for the past five years here.
- Using this historical data, we can apply time series forecast model to predict the future growth.



Time Series - STARBUCKS



5. Creating the data frame to predict the future 10 year growth of Revenue for Starbucks.

```
##creating the data frame to predict the future 10 year  
##growth of Revenue for Starbucks  
my_df_ts <- data.frame(Revenue = starbucks$RevenueSeries,  
                        as.numeric(time(starbucks$RevenueSeries)))  
names(my_df_ts) <- c("Revenue", "Time")  
mymodel <- tslm(Revenue ~ trend + season, my_df_ts)
```

6. Forecasting the model created for time series.

```
##forecasting the model created for  
##time series to predict the next 5 years.  
my_fc <- forecast(mymodel,h=22)
```

7. Plot the forecast.

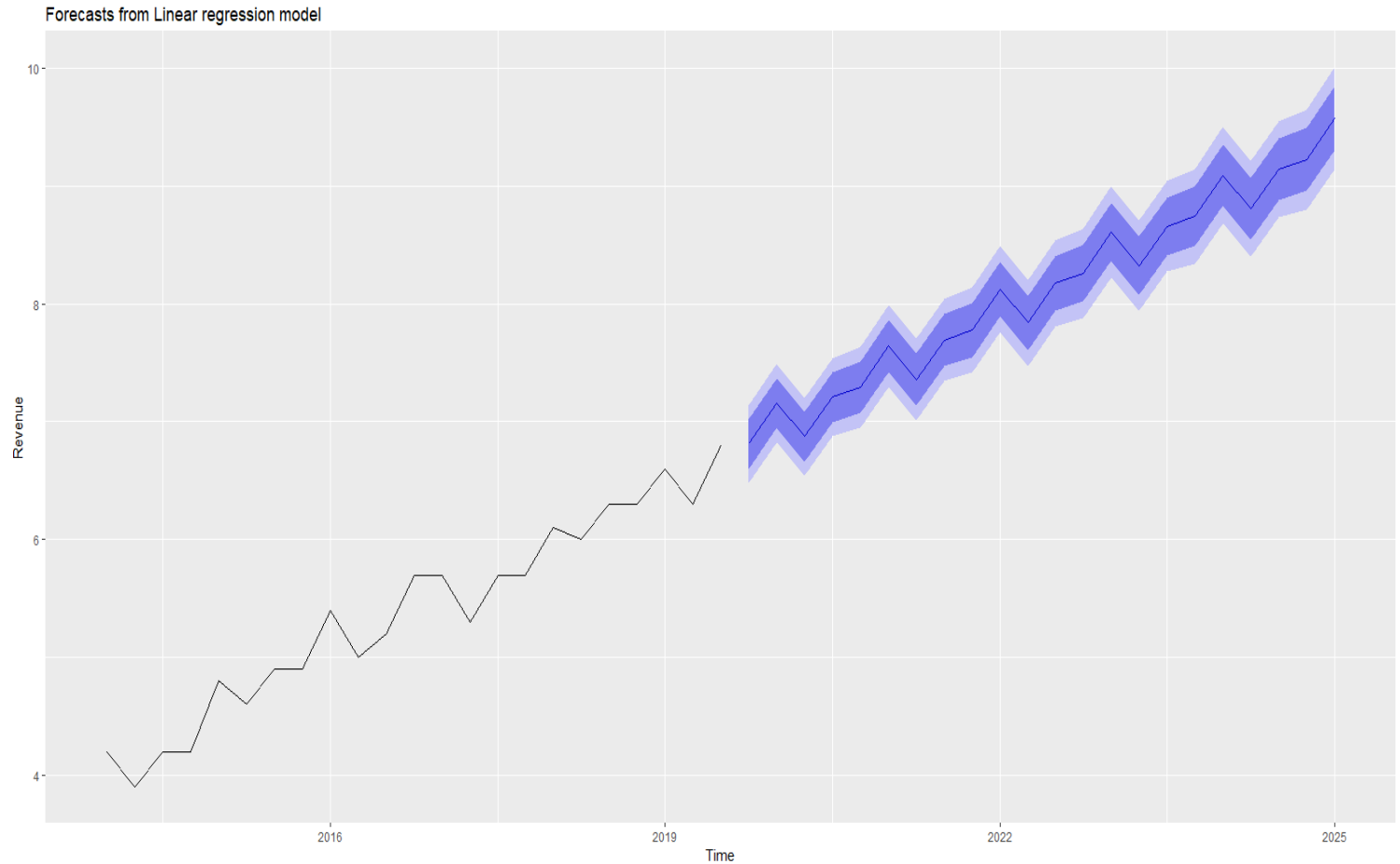
```
##plot the forecast  
autoplot(my_fc)
```

➡ Predict future growth for Starbucks revenue using tslm function – tslm is used to fit linear models to time series including trend and seasonality components.

Time Series - STARBUCKS



- The idea behind forecasting is to predict future values of data based on what happened before.
- It cannot be always accurate since there are factors which are not in our control that can affect the future value substantially.
- As per the model in 2019 for Q3 revenue was at 6.8Bn and by 2025 we can predict using time series analysis, Starbucks revenue reaching 9.7Bn which gives us about 39% increase in the next 5-6 years.

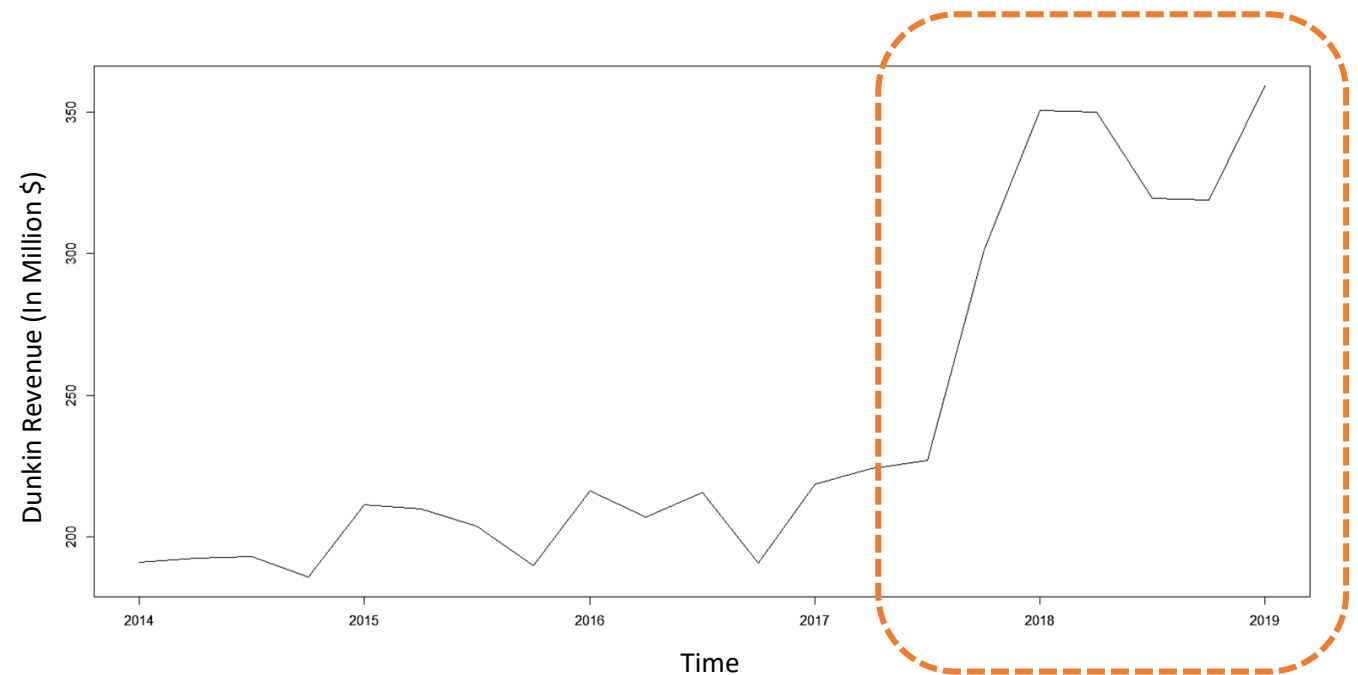




SITUATION COMPARISON

- We compared Starbucks revenue with Dunkin' in the same time frame.
- Dunkin' is an American coffee brand known for its quick services and is a direct competitor to our brand.
- We collected some data from the quarterly reports posted on brand's website.
- Using that data we created a Time Series graph of Dunkin's revenue data from 2014 till 2019.
- Insights shows that Dunkin's revenue has been soaring rapidly since mid 2017.

```
> ## time series analysis for increase of revenue overtime.  
> dunkin$RevenueSeries <-ts(data = dunkin$Net.Revenue..million...,start = c(2014,1),frequency = 4)  
> ## plotting the time series data  
> plot(dunkin$RevenueSeries)  
,
```





SITUATION COMPARISON

- Knowing that Dunkin's revenue is soaring, we had to find the reasons and see if it resonates with Starbucks.
- To find the reason, we wanted to execute the linear regression model.
- Revenue is the dependent variable and other variables like total # of stores, earning per share, etc. are independent variables.
- Like Starbucks analysis, we first uploaded the data and normalized it to bring it to the same scale.

```
> #LOADING DATASET
> Dunkins <- read.csv("C:\\Users\\mailp\\Downloads\\Dunkin.csv", header =T, sep="$")
> Dunkins
```

	Total..num.of.Stores	Net.Revenue	comparable.store.sales.growth
1	7887	190.9	1.8
2	7962	192.6	2.0
3	8082	193.2	1.4
4	8160	185.9	2.7
5	8240	211.4	2.9
6	8308	209.8	1.1
7	8431	203.8	0.8
8	8500	189.9	2.0
9	8573	216.3	0.5
10	8629	207.1	2.0
11	8828	215.7	1.9
12	8884	190.7	1.9
13	8948	218.5	-
14	9015	224.2	-
15	9141	227.1	1
16	9197	301.3	2
17	9261	350.6	3
18	9313	350.0	4
19	9419	319.6	5
20	9453	319.1	6
21	9499	359.3	7

	Increase.Earning.per.share	Net.New.Stores	Revenue.increased
1	0.44	75	4.6
2	0.52	120	3.4
3	0.50	141	5.5
4	0.26	78	8.1
5	0.44	80	10.7
6	0.49	68	8.9
7	-0.10	123	5.5
8	0.41	69	2.1
9	0.54	73	2.3
10	0.58	56	1.3
11	0.61	199	5.8
12	0.52	56	0.5
13	0.61	64	1.0
14	0.58	67	8.2
15	2.17	126	5.3
16	0.58	56	1.7

SITUATION COMPARISON

We executed the linear regression model in R



```
> #RUN LINERAR MODEL REGRESSION WITH NET REVENUE AS DEPENDENT VARIABLE
> LmDunkins<- lm(Net.Revenue~., data = ScaleStar)
> summary(LmDunkins)

Call:
lm(formula = Net.Revenue ~ ., data = ScaleStar)

Residuals:
    Min       1Q   Median       3Q      Max
-0.006284 -0.001932 -0.000416  0.002774  0.005596

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)    -0.06900    0.02010   -3.432  0.003707 **
Total..num.of.Stores    0.10467    0.02088    5.013 0.000155 ***
comparable.store.sales.growth  0.40752   11.45151    0.036  0.972081
Increase.Earning.per.share -18.33759   23.90974   -0.767  0.455014
Net.New.Stores    -0.17237    0.23720   -0.727  0.478600
Revenue.increased    3.11890    3.20268    0.974  0.345579
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.003961 on 15 degrees of freedom
Multiple R-squared:  0.7195,    Adjusted R-squared:  0.6261
F-statistic: 7.697 on 5 and 15 DF,  p-value: 0.0009183
```

- The only variable that has a p-value below 0.05 of alpha is the total number of stores.
- This means that this variable has a significant impact on the revenue numbers of Dunkin





SITUATION COMPARISON

The results above are summarized as the results below:

<u>Variables</u>	<u>Coefficient</u>	<u>p-value</u>
(Intercept)	-0.06900	0.003707
Total number of stores	0.10467	0.000155

Finding average value of the key variable that has a p-value less than 0.05 alpha.

<u>Variables</u>	<u>Average Value</u>
Total number of stores	8749.048

We thus prepare our regression equation in the form of $y = a + b1 * x1$ where

- y is the dependent variable,
- a is a constant (the y-intercept),
- b(n) is the coefficients for the independent variables, and
- x(n) are the independent variables.

1. Net Revenue= (y-intercept) + (coefficient) * (Total num of stores)
2. Net Revenue = -0.06900+ 0.10467 * (8749.048)
3. Net Revenue = 915.69385416

The average annual revenue for Dunkin over the past 5 years is \$915.69 MN which coincide with our data.



CONCLUSION

The study shows that the most effective contributor to Starbucks revenue are the “**Active Rewards Membership**” followed by “**New Stores**”.

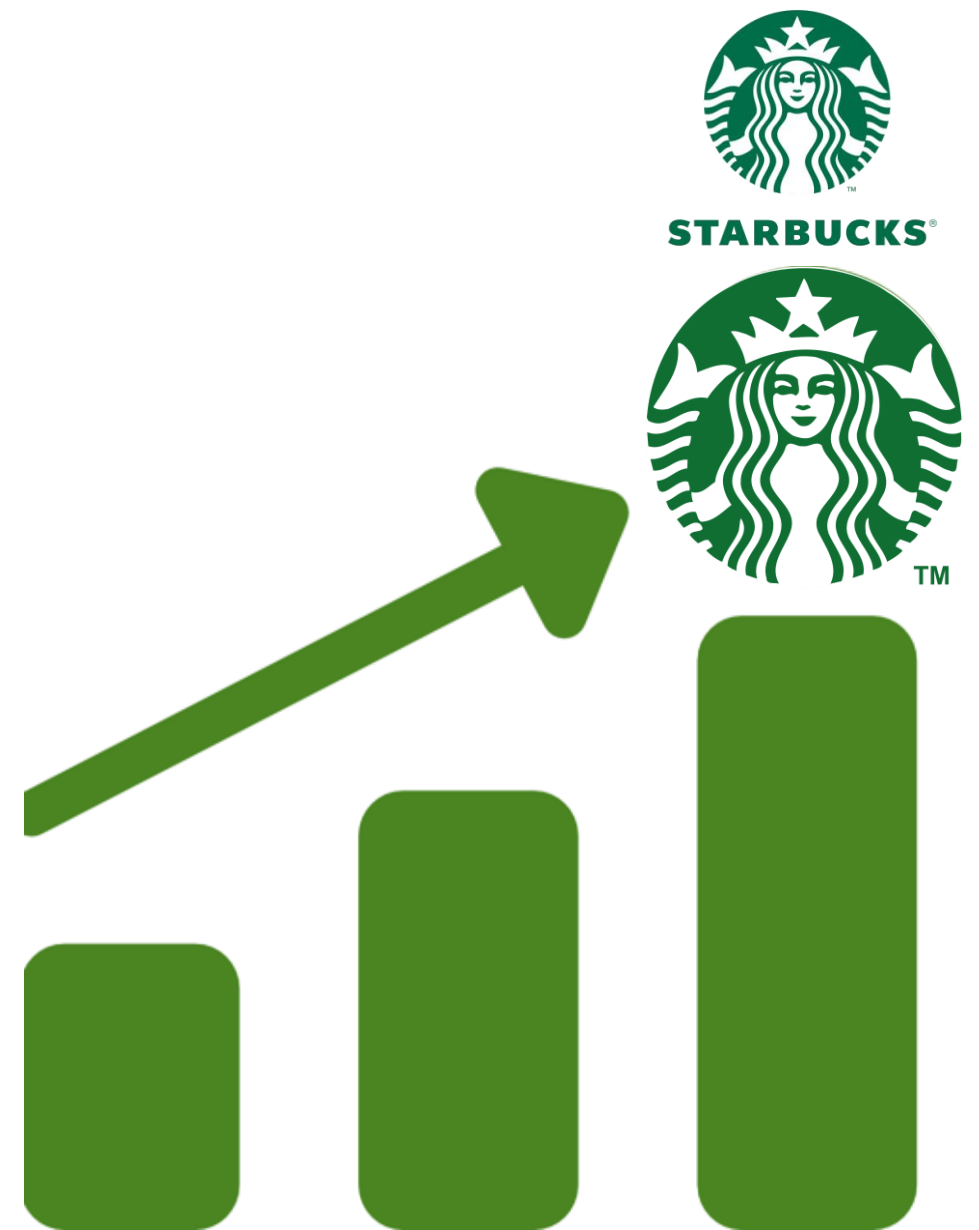
- The Starbucks short-term goal to increase net revenue by 10% can be achieved by increasing active rewards membership.
- Thus, by increasing Active Reward Membership from its average of 12.3 MN to 14.4 MN, we can increase the net revenue by 10%.
- On the other hand, Dunkin's 2018 annual report shows its reward membership (aka DD Perks) has 9.8MN members which is not very far from Starbucks 15.3 MN in 2018.
- Based on an article on money.com, Dunkin's rewards program is better than Starbucks specially because of the \$5 credit it provides to its customers.



- The long-term goals to achieve 10% hike in Starbucks revenue should be achieved with the help of opening new stores.
- The data showed that on an average since 2014, the new stores opened were 485. And in the 2018 they have opened many stores as high as 700 in a quarter.
- We calculated from the regression equation and found that the revenue can be increased by 10% by opening approximately 911 stores every quarter.
- The analysis for Dunkin's shows the total number of stores has a significant impact on revenue and they are opening more stores every quarter.
- Basis the article on CNBC, Dunkin is investing \$100 MN in stores and it saw a revenue growth of 6% in 2018.

RECOMMENDATIONS

- Starbucks should focus on its active rewards membership (loyalty) program and increase its userbase consistently to increase repeated users.
- It should innovate and give better benefits to the current members and attract new users to contribute to the revenue growth of the company.
- Like give free coffees on birthdays, and +1 offers on certain occasions like valentine's day or friendship's day.
- Starbucks should also invest in renovating the stores and making it more interactive to attract more footsteps to increase revenue.
- It should also look at opening more stores in less time to capture a wider market share continue to maintain its top spot.





REFERENCES

- <https://www.cnbc.com/2018/10/25/dunkin-ceo-says-its-modernizing-stores-faster-than-expected.html>
- <http://money.com/money/4247627/starbucks-loyalty-program-dunkin-donuts/>
- Starbucks. (2019). Investor relations. Retrieved from <https://investor.starbucks.com/financial-data/quarterly-results/default.aspx>



Thank You