FE 582 Final Presentation:
Impact of COVID-19

Group members:

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Introduction

- Coronavirus alias Covid-19 is one of the most devastating pandemics ever recorded globally. The deadly respiratory disease was first diagnosed in Wuhan, China, towards the end of 2019 and later spread rapidly worldwide in 2020.
- Covid-19 global pandemic has led to unprecedented economic events which have transformed or affect how businesses operate.
- Analyze the impact of Covid-19 pandemic on businesses, based on Market data (market price), Multiples and Estimates for different companies.

Data

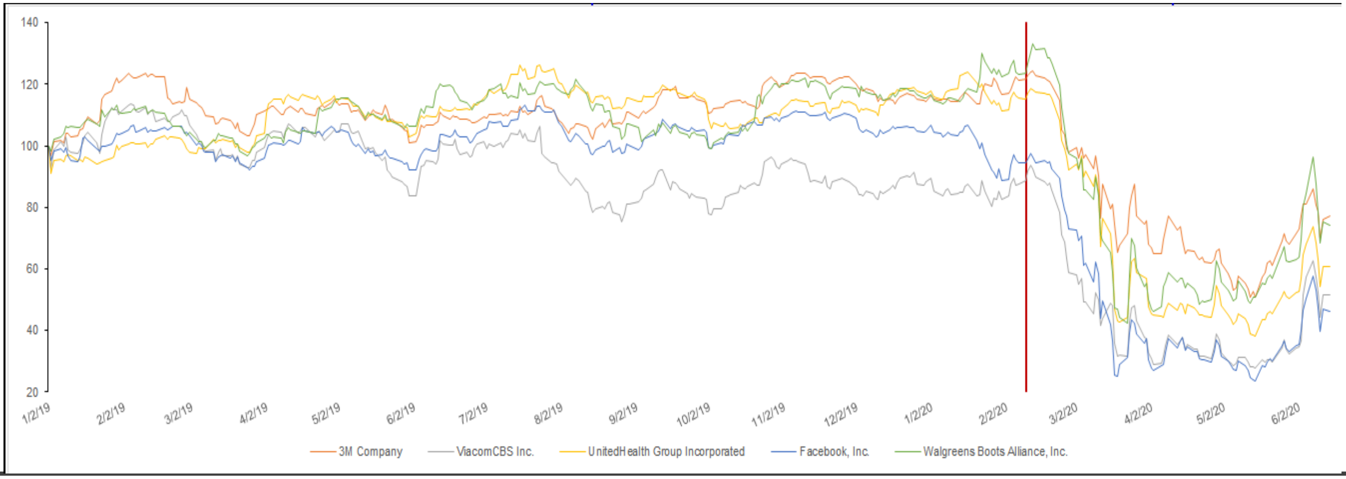
44 companies companies selected represent a wide range of industries, give a glimpse of which industry that will be affected by Covid-19 pandemic.

No.	Name	Industry	No.	Name	Industry
1	Delta Airline	Travel	23	J&J	Consumer
2	Marriot	Hotel	24	Microsoft	Consumer
3	Apple	Consumer	25	General Electric	Utility
4	Chevron	Oil/Gas	26	Starbucks	Food
5	Visa	Finance/Insurance	27	Accenture	Finance/Insurance
6	McDonald's	Food	28	AT&T	Telecom.
7	NIKE	Consumer	29	American Tower	Real Estate
8	Verizon	Telecom.	30	Union Pacific	Transportation
9	Pfizer	Pharmaceutical/ biotechnology	31	Booking Holding	Travel
10	Walmart	Consumer	32	UPS	Service

11	Netflix	Entertainment/ Broadcast	33	Honeywell	Manufacturing
12	General Motor	Manufacturing	34	3M	Consumer
13	Procter & Gamble	Consumer	35	ViacomCBS	Entertainment/ Broadcast
14	Intel	Consumer	36	UnitedHealth	Finance/Insurance
15	ExxonMobil	Oil/Gas	37	Facebook	Consumer
16	AIG	Finance/Insurance	38	Walgreens Boots	Pharmaceutical
17	Domino's	Food	39	Best Buy	Consumer
18	Amazon	Consumer	40	Caterpillar	Manufacturing
19	Las Vegas	Hotel	41	The Travelers	Finance/Insurance
20	CVS Health	Pharmaceutical/ biotechnology	42	Amgen	Pharmaceutical/ biotechnology
21	The Home Depot	Consumer	43	Paypal	Finance/Insurance
22	Walt Disney	Entertainment/ Broadcast	44	Oracle	Consumer

Data

- Data source: **S&P Capilal IQ** and collected via template:
  - market data (stock price),
  - Total revenue
  - TEV/EBITDA ratio (*total enterprise value to earnings before interest, taxes, depreciation, and amortization)* - popular metric/valuation tool for investors to make comparison. A small value (typically below 10) is seen as a healthy sign for a company.
- Sample data collected (price chart) inside template:



Data

CIQ Ticker/ ID	Company Name	price_2019	price_2020	price_2021	price_change1	price_change2	TEVEBratio_2019	TEVEBratio_2020	TEVEBratio_2021	ratio_change1	ratio_change2	rev_2019	rev_2020	rev_2021	rev_change1	rev_change2
NYSE:DAL	Delta Air Lines, Inc.	49.9	57.7	40.2	15.7%	-30.3%	5.5x	4.6x	16.7x	-0.9x	12.1x	46,195.6	48,769.7	23,466.5	5.6%	-51.9
NasdaqGS:MAR	Marriott International, Inc.	108.6	145.7	131.9	34.2%	-9.5%	16.8x	20.3x	35.8x	3.5x	15.5x	21,649.8	21,579.4	12,582.2	-0.3%	-41.7
NasdaqGS:AAPL	Apple Inc.	39.4	80.4	132.7	103.8%	65.1%	7.7x	14.4x	24.8x	6.7x	10.4x	277,380.1	293,507.8	315,740.5	5.8%	7.6
NYSE:CVX	Chevron Corporation	108.8	109.8	84.5	0.9%	-23.1%	6.6x	7.1x	12.5x	0.5x	5.4x	169,545.1	154,030.8	119,154.4	-9.2%	-22.6
NYSE:V	Visa Inc.	131.9	206.0	218.7	56.1%	6.2%	21.7x	28.0x	31.8x	6.3x	3.8x	22,844.8	26,109.5	23,164.8	14.3%	-11.3
NYSE:MCD	McDonald's Corporation	177.6	213.2	214.6	20.1%	0.6%	16.2x	16.1x	19.4x	-0.2x	3.3x	20,750.3	21,961.7	21,623.8	5.8%	-1.5
NYSE:NKE	NIKE, Inc.	74.1	100.0	141.5	34.9%	41.4%	21.4x	24.4x	37.4x	3.0x	13.1x	40,599.2	44,041.2	45,991.6	8.5%	4.4
NYSE:VZ	Verizon Communications Inc	56.2	60.2	58.8	7.2%	-2.5%	7.3x	7.3x	7.2x	0.0x	-0.2x	132,105.8	134,779.7	132,463.5	2.0%	-1.7
NYSE:PFE	Pfizer Inc.	43.7	37.8	36.8	-13.4%	-2.6%	12.7x	12.0x	13.2x	-0.7x	1.2x	54,842.8	48,702.1	48,127.9	-11.2%	-1.2
NYSE:WMT	Walmart Inc.	93.2	115.3	144.2	23.7%	25.1%	10.1x	11.2x	11.3x	1.1x	0.2x	521,694.0	533,849.6	554,222.3	2.3%	3.8
NasdaqGS:NFLX	Netflix, Inc.	267.7	371.1	540.7	38.6%	45.7%	71.2x	59.3x	57.9x	-11.9x	-1.4x	18,771.0	24,356.9	28,430.1	29.8%	16.7
NYSE:GM	General Motors Company	33.5	34.3	41.6	2.4%	21.6%	6.1x	10.7x	15.3x	4.6x	4.7x	146,572.8	144,478.1	138,641.2	-1.4%	-4.0
NYSE:PG	The Procter & Gamble Comp	91.9	126.2	139.1	37.3%	10.3%	14.3x	17.6x	18.2x	3.3x	0.6x	67,296.6	71,825.0	74,698.4	6.7%	4.0
NasdaqGS:INTC	Intel Corporation	46.9	66.4	49.8	41.5%	-25.0%	7.2x	9.0x	6.0x	1.8x	-3.0x	73,288.7	73,715.4	69,878.7	0.6%	-5.2

Sample data (price, revenue & ratio) collected for companies in the template

Data

- Since we are interested in impact of COVID-19 event, we will focus on the **%percentage change** in: market price, revenue and TEV/EBITDA ratio:
- **3 touch points of time** of the data used for computation:
  - *Before Covid-19 : 1st Jan 2019*
  - *Start of Covid-19 : 10th Feb 2020*
  - *After Covid-19 : 1st Jan 2021*
- The percentage change values between 2021 (post Covid-19) and 2020 (start of Covid-19), Δ_2 are **multiplied by a factor** that **takes into account** of **prior percentage change** between 2020 and 2019, Δ_1. This **factor is 1/(1** $\pm$ **Δ_1)**, sign equal to '-' if 2021 value < 2019 value or vice-versa.
- A drop in value between 2019 and 2020 and a further drop in 2020 and 2021 will dampen the Δ_2 by this multiplier factor $1/(1-\Delta_1)$ where $\Delta_1<0$ [i.e. $1/(1-\Delta_1) <1$] .
- Effectively Δ_2 is actually smaller because the drop is not so much due to Covid-19 as Δ_1 is already negative (a drop happened prior to Covid-19).

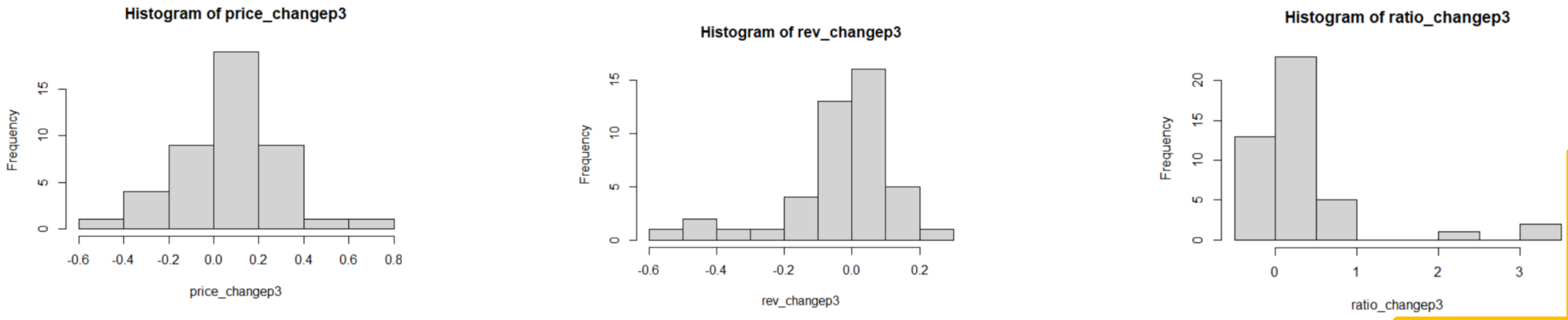
Data

- Imported into R language
- Data processing and data cleaning. To remove commas, “%” symbols and “x”characters for numeric processing.

```
> coviddata$price_2019

[31] " 1,722.4 " " 97.5 "    " 132.1 "

> coviddata$price_change1
 [1] "15.7%"  "34.2%"  "103.8%" "0.9%"   "56.1%"  "20.1%"  "34.9%"  "7.2%"

> coviddata$TEVEBratio2019_
 [1] " 5.5x "  " 16.8x " " 7.7x "  " 6.6x "  " 21.7x " " 16.2x " " 21.4x "
```

Data

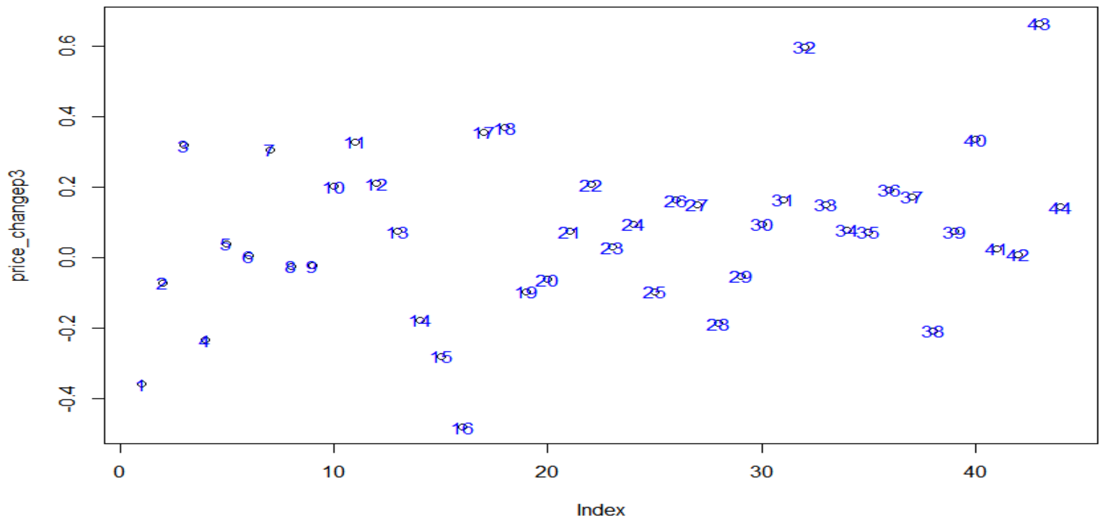
- Simple **exploratory data** (represents price change, revenue change and TEV/EBIDTA respectively) shows:
    - price_changep3 - symmetrical (~ *normal*)
    - rev_changep3 - *positive skewed*
    - ratio_changep3 - *negative skewed*
- The percentage change of both market price and revenue can go as bad as -60%. Percentage change of TEV/EBIDTA ratio can go as bad as +300%. (*Note: ratio has the opposite direction - high ratio is less healthy, company in trouble*)



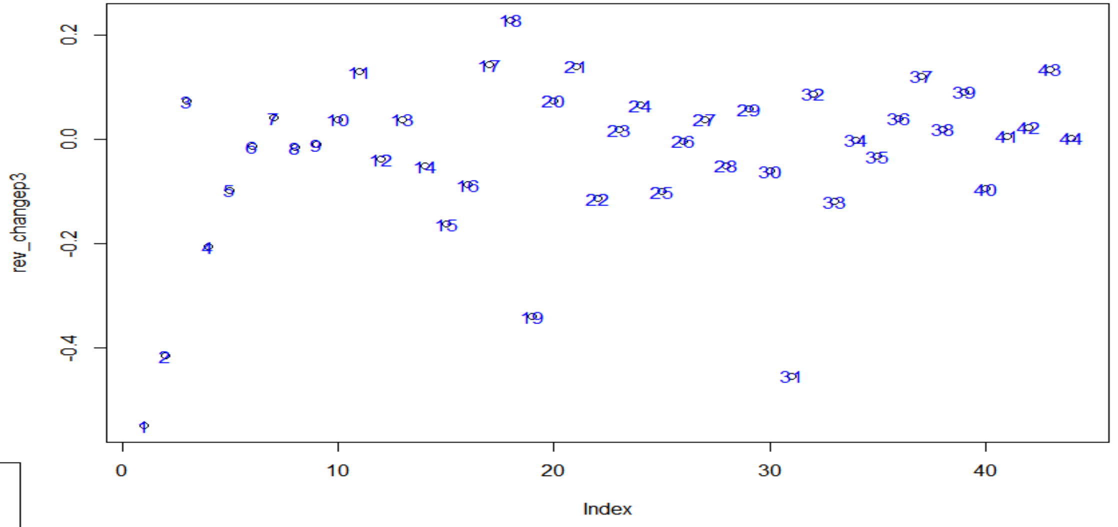
Histogram of percentage change in price, revenue and TEV/EBITDA

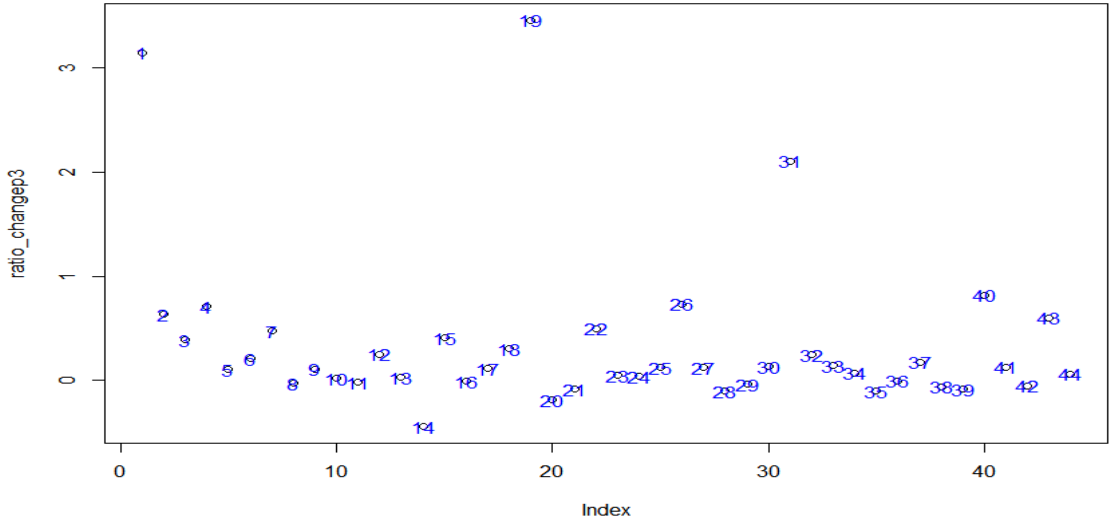
Data

- The individual plots of these percentage change values over company (index) in one dimension view
- Some company performing better or worse in each aspect. Will utilize and combine these 3 values for analysis



Data





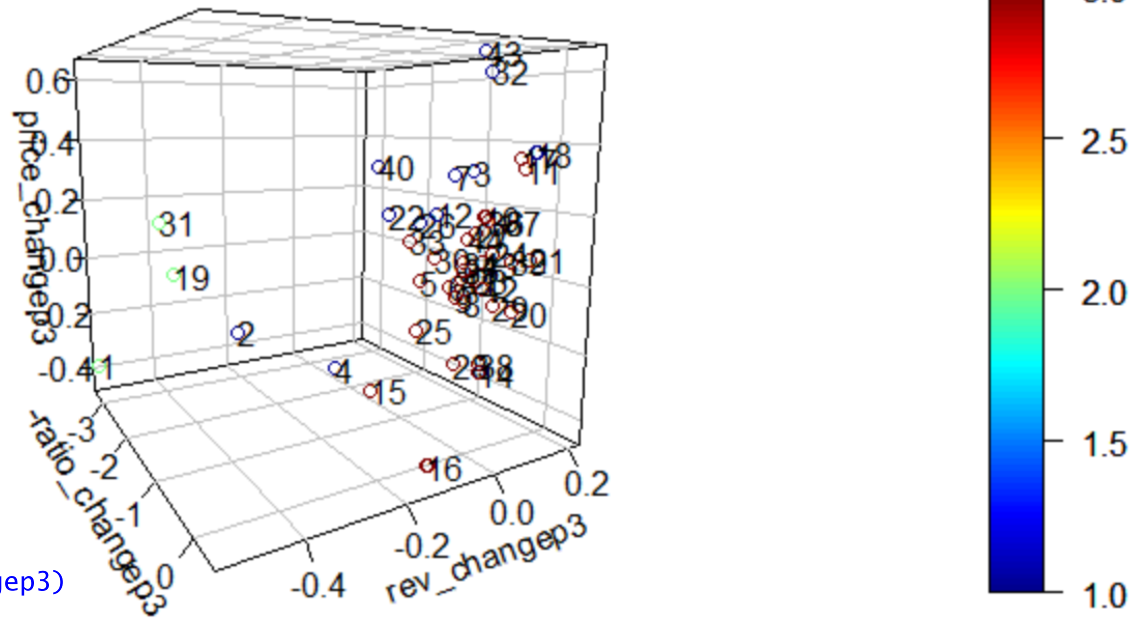
One-dimensional plots of percentage change of price, revenue, TEV/EBITDA ratio over companies

Analysis Methods

- Using **unsupervised machine learning** to analyze our data.
- Unsupervised learning allow models to process information and discover patterns and group cases based on similar attributes, occurring trend or relationships in data
- First algorithm: **K-means clustering**, which partition observation into k-clusters in which each observation belongs to a cluster depending on to its nearest mean (cluster centroid) and minimization of within cluster variances.
- Data frame to **combine** the 3 percentage change data (price, revenue and TEV/EBITDA ratio)

Analysis Methods

- The result of the **K-means algorithm** plotted as a 3 dimensional plot. Note: x-axis used *-ratio_changep3* for direction consistency (as higher value is bad) with *price_changep3* and *rev_changep3*.




```
> combdata=data.frame(price_changep3,rev_changep3,-ratio_changep3)
> km.outPC=kmeans(combdata,3,nstart=20)  # 3 groups
> km.outPC$cluster
 [1] 1 2 2 2 3 3 2 3 3 3 3 2 3 3 3 3 3 2 1 3 3 2 3 3 3 2 3 3 3 3
[31] 1 2 3 3 3 3 3 3 3 2 3 3 2 3
```

3D plot of K-means clusters

Analysis Methods

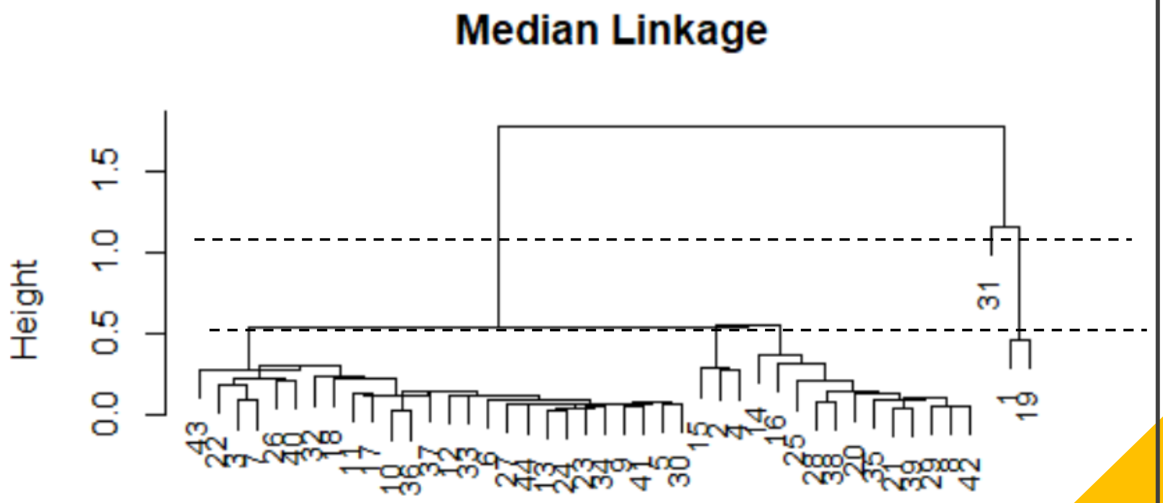
The **K-means algorithm** grouped the data into 3 groups of company performance:

Group	Companies names (index)
Group Red **(Very well)**	5[Visa], 6[McDonalds], 8[Verizon], 9[Pfizer], 10[Walmart], 11[Netflix], 13[P&G], 14[Intel], 15[Exxon], 16[AIG], 17[Domino's], 20[CVS], 21[Home Depot], 23[J&J], 24[Microsoft],25[GE], 27[Accenture], 28[AT&T],29[American Tower], 30[Union Pacific], 32[UPS], 33[Honeywell], 34[3M], 35[VaicomCBS], 36[UnitedHealth], 37[Facebook], 38[Walgreens], 39[BestBuy], 41[The Travelers], 42[Amgen], 44[Oracle]
Group Green **(Not well)**	1[Delta], 19[Las Vegas], 31[Bookings.com]
Group Blue **(OK)**	Others

Performance of companies during COVID-19 according clusters (K-means)

Analysis Methods

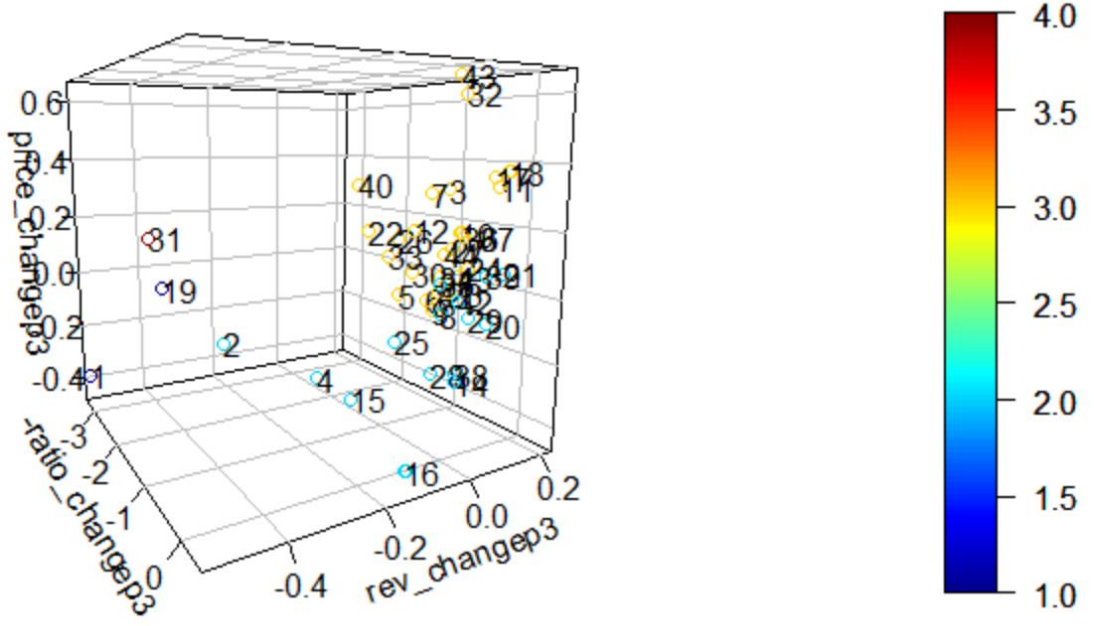
- Apply **hierarchical clustering** technique
- Build a hierarchy of clusters based on method of cluster analysis were objects within the cluster are broadly similar to each other.
- The algorithm using bottom-up/top-down approach for fusing and split/branching in a greedy manner.
- Cutting the tree directly into 3 groups -many companies will be grouped into one big cluster on the left extreme which is **undesired**.
- Cut into 4 groups and group the right 2 extreme groups into 1 group.



Tree from hierarchical clustering

Analysis Methods

- Plotted the **hierarchical clustering** results for different clusters in 3 dimensional plot.




```
> combdata=data.frame(price_changep3,rev_changep3,-ratio_changep3)
> hc.medianPC=hclust(dist(combdata),method="median")
> grp.medPC=cutree(hc.medianPC,4) # 4 groups for clearer segregatio
```

3D plot of hierarchical clustering clusters

Analysis Methods

- Company performances according to **hierarchical clustering**:

Group	Companies names (index)
Group Yellow **(Very well)**	3[Apple], 5[Visa], 6[McDonals], 7[Nike], 9[Pfizer], 10[Walmart], 11[Netflix], 12[GM], 13[P&G], 17[Domino's], 18[Amazon], 22[Walt Disney], 23[J&J], 24[Microsoft], 26[Starbucks], 27[Accenture], 30[Union Pacific], 32[UPS], 33[Honeywell], 34[3M], 36[UnitedHealth], 37[Facebook], 40[Caterpillar], 41[The Travelers], 43[PayPal], 44[Oracle]
Group Blue+Red **(Not well)**	1[Delta], 19[Las Vegas], 31[Bookings.com]
Group Cyan **(OK)**	Others

Performance of companies during COVID-19 according to clusters (hierc. Cluster)

Analysis Methods

- Utilized that **Lp-norm**, p=1 (Manhattan distance method) to analyse data.
- Distance-based classification and emphasize similarities or dissimilarity between data in multi-dimensional way.
- Picked a **control point** that represent the **worst case scenario** (most negative *price_changep3*, most negative *rev_changep3* and most positive *ratio_changep3*) and calculate the distance from this control point based on the 3 attributes
- **The Smaller distance** to this control point (i.e. minimum distance), the **worse** the company performed during COVID-19 period and vice-versa.

Analysis Methods

- Company performance: listed the bottom 10 companies (smallest distance - worst performer) and top 10 companies (largest distance, best performer) during COVID-19.
- Bottom 10 results actually shows that the **distance of bottom 3** is **much smaller** compared to the rest and clearly set them apart – set as the worst performer.

```
> # bottom 10 results with min distance from control pt
> y2 <- sort(pair_dist,decreasing=FALSE,index.return=TRUE)
> y2$x[1:10]
 [1] 0.4357345 0.5932821 2.0941926 3.3429782 3.3715949 3.6436667
 [7] 3.9110009 3.9177615 3.9327891 4.0864094
```

Group	Companies names (index)
Top 10 – maximum distance **(Very well)**	11[Netflix], 32[UPS], 17[Domino's], 21[Home Depot], 18[Amazon], 39[Best Buy], 36[UnitedHealth], 10[Walmart], 14[Intel], 20[CVS]
Bottom 10 – minimum distance **(Not well)**	1[Delta], 19[Las Vegas], 31[Bookings.com]*, *4[Chevron], 2[Marriot], 15[Exxon], 40[Caterpillar], 26[Starbucks], 16[AIG], 22[Walt Disney]*
Group Cyan **(OK)**	Others

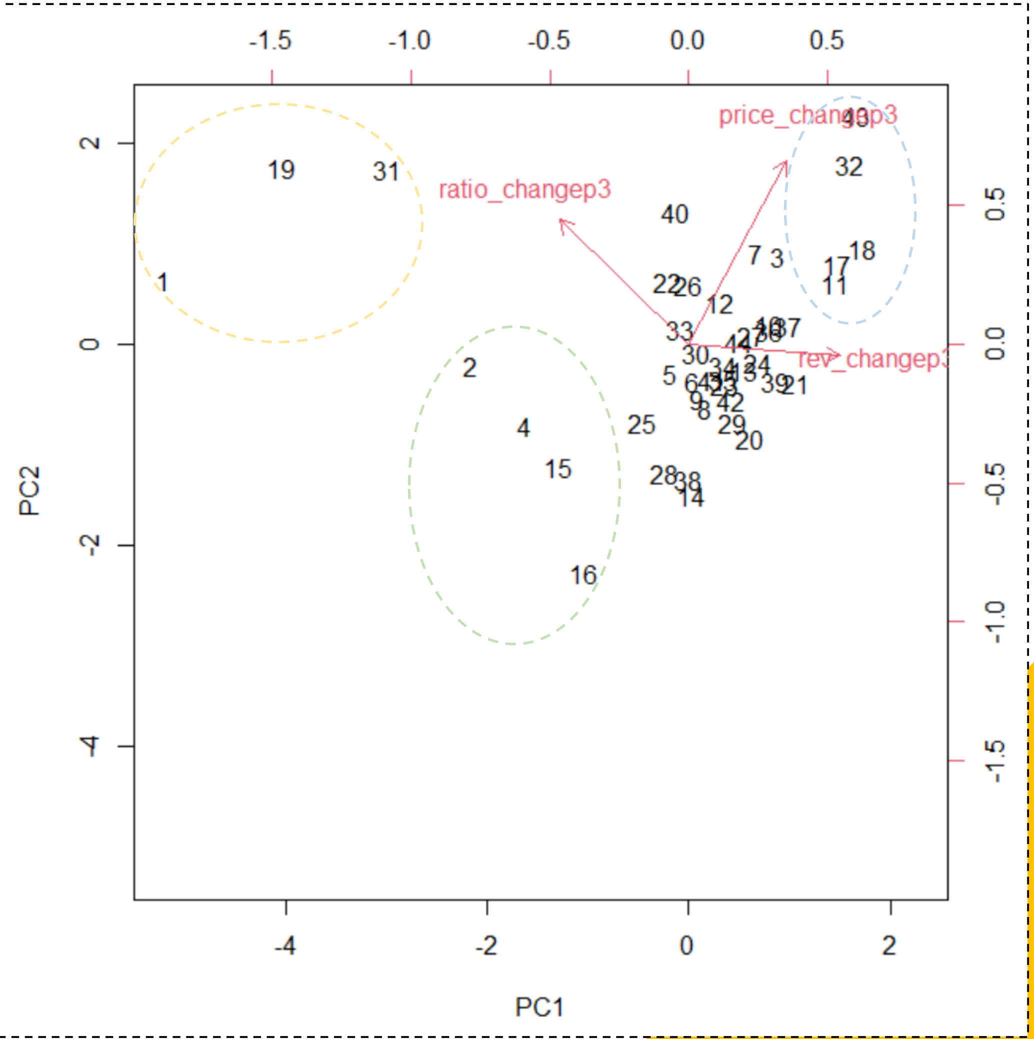
**bottom 3 worst performer*

Performance of companies during COVID-19 according L1-norm distance

Analysis Methods

- Last technique used for our data analysis is **Principal Component Analysis (PCA).**
- PCA transform and reduces the dimensionality of the data (in our case 3 dimensional due to *price_changep3*, *rev_changep3* and *ratio_changep3*) while still allowing easier analysis
- Plotted the first two principal components (PC1 and PC2) in a 2-D,helps to visualize things

```
> coviddf =
data.frame(price_changep3,rev_changep3,ratio_changep
3)
> pr.out=prcomp(coviddf,scale=TRUE)
> biplot(pr.out,scale=0)
```



The first two principal components plot (PC1 & PC2) from PCA

Analysis Methods

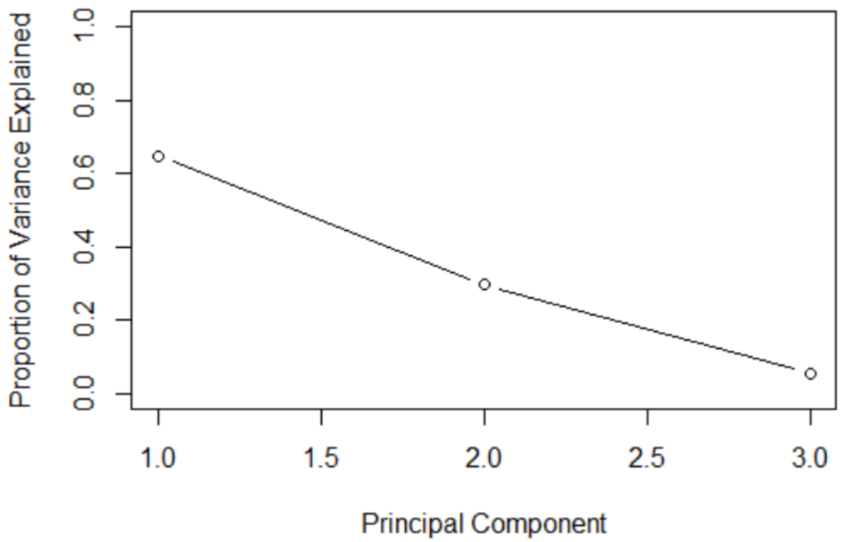
- **3 interesting clusters** observed:
  - The *top left most*
  - The *right most* clusters
  - The bottom cluster:”2[Marriot], 4[Chevron],15[Exxon], 16[AIG] which are not performing as good but are closely related.
- **Company performance:**

Group	Companies names (index)
Top right cluster **(Very well)**	43[PayPal],32[UPS], 18[Amazon], 17[Domino’s], 11[Netflix]
Top Left cluster **(Not well)**	1[Delta], 19[Las Vegas], 31[Bookings.com]*
Not highlighted **(OK)**	Others

Performance of companies during COVID-19 according PCA plot

Analysis Methods

- Proportion of variance shows PC1 & PC2 explain the majority of variance.



Plot of variance represented by Principal Components

Results & Discussion

- All techniques listed out **3 companies** that are **badly affected**:
  - *Delta Airline*, *Las Vegas Sand Corporation* and *Booking holdings Corporation* (Booking.com).
- They are related to the **travel and hotel industry**. City or country lockdown people cancelled their travelling plans. The airline and hotel bookings experienced drop in revenue during this difficult period.
- *Marriot* is also not far off from the bad performer list according to PCA results and Lp-norm
- There is another cluster not doing well:
  - *Chevron* and *ExxonMobil* from the **oil industry** - oil price plummet consequences of oversupply and declining demand shock indirectly related to the travel restrictions and economic lockdown from the COVID-19 pandemic.

Results & Discussion

- Some companies that **doing well**:
  - *Paypal, Visa, UPS, Amazon, Netflix, ViacomCBS, Apple, Facebook, Microsoft, Oracle, Domino's Pizza, Walmart, The Home Depot, Best Buy, UnitedHealth, The Traveller, AIG, CVS, J&J, Pzifer, Union Pacific* and etc.
- These comes from **Consumer industry** (electronic, food, software) with some having online presence. People still needs to shop for products and food despite having lock down or restrictions.
- **Payment service**, **parcel/delivery service**, **finance and insurance** and **online entertainment** also triumphed during this crisis. The **pharmaceutical industry** also gained growth when people are pinning hope on development of viable vaccines or cure.

Conclusion

- The utilization of **unsupervised machine learning techniques** on multi-dimensional data (price, revenue and TEV/EDBITDA ratio change) like K-means clustering, hierarchical clustering, Lp-norm and PCA has **successfully** helped us analysed the companies and classifying them to showcase which industry are badly affected/benefited from the COVID-19 pandemic.
- Industries that are **badly affected** are those related to **travel and hotels and oil industry**. Meanwhile, industries that **gained advantage** during this crisis are those related to **consumer, online payment or delivery service, finance/insurance, online entertainment** and **pharmaceutical**.