

A decorative graphic on the left side of the slide consisting of two overlapping parallelograms. The front one is blue and the back one is a light green color. They are positioned diagonally, with the blue one partially covering the green one.

Pandemics vs stock market

Austin Roberto Isaac

Pandemics vs stock market

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Intro

- Analyzed past pandemics to compare to current covid-19 pandemic
- Predicted buy/sell stocks during pandemics

Methods

- Machine learning models used: Linear Regression, KNN, SVC and Random Forest
- ARIMA model
- Moving Averages
- Data Visualization

Result

- Uncertain prediction due to many factors
- Ensemble learning increases probability of prediction being correct
- Ex. JnJ during SARS model predicted



Team Sigmoid Frontsquart

With the help of **data** from **stock** numbers during past pandemics **machine learning** can **help** you make a data driven decision to **buy, hold** or **sell** during **Covid-19**



Model Results

Apple

date	open	high	low	close	volume
2020-03-09	135.0	136.0	134.0	135.0	100000000
2020-03-10	134.0	135.0	133.0	134.0	100000000
2020-03-11	133.0	134.0	132.0	133.0	100000000
2020-03-12	132.0	133.0	131.0	132.0	100000000

Nike

date	open	high	low	close	volume
2020-03-09	65.0	66.0	64.0	65.0	100000000
2020-03-10	64.0	65.0	63.0	64.0	100000000
2020-03-11	63.0	64.0	62.0	63.0	100000000
2020-03-12	62.0	63.0	61.0	62.0	100000000

Johnson & Jonson

date	open	high	low	close	volume
2020-03-09	140.0	141.0	139.0	140.0	100000000
2020-03-10	139.0	140.0	138.0	139.0	100000000
2020-03-11	138.0	139.0	137.0	138.0	100000000
2020-03-12	137.0	138.0	136.0	137.0	100000000

Ford

date	open	high	low	close	volume
2020-03-09	10.0	10.5	9.5	10.0	100000000
2020-03-10	9.5	10.0	9.0	9.5	100000000
2020-03-11	9.0	9.5	8.5	9.0	100000000
2020-03-12	8.5	9.0	8.0	8.5	100000000

Alaska Airlines

date	open	high	low	close	volume
2020-03-09	40.0	41.0	39.0	40.0	100000000
2020-03-10	39.0	40.0	38.0	39.0	100000000
2020-03-11	38.0	39.0	37.0	38.0	100000000
2020-03-12	37.0	38.0	36.0	37.0	100000000

Chevron

date	open	high	low	close	volume
2020-03-09	40.0	41.0	39.0	40.0	100000000
2020-03-10	39.0	40.0	38.0	39.0	100000000
2020-03-11	38.0	39.0	37.0	38.0	100000000
2020-03-12	37.0	38.0	36.0	37.0	100000000

American Express

date	open	high	low	close	volume
2020-03-09	150.0	151.0	149.0	150.0	100000000
2020-03-10	149.0	150.0	148.0	149.0	100000000
2020-03-11	148.0	149.0	147.0	148.0	100000000
2020-03-12	147.0	148.0	146.0	147.0	100000000



Data sets and collecting data

- Downloaded manually from Yahoo Finance only 100 days
- Kaggle
- stock market data vs. Covid-19 data, problems integrating the two



Extracting S&P 500 ticker symbols

- We also used BeautifulSoup to scrape the web for the ticker symbols for all 500 companies on the S&P 500 as a pickle object

```
def save_sp500_tickers():
    response = requests.get('https://en.wikipedia.org/wiki/List_of_S%26P_500_companies')
    soup = bs.BeautifulSoup(response.text)
    table = soup.find('table',{'class':'wikitable sortable'})
    tickers = []
    for row in table.findAll('tr')[1:]:
        ticker = row.findAll('td')[0].text.replace('\n','')
        tickers.append(ticker)
    with open('sp500tickers.pickle','wb') as f:
        pickle.dump(tickers,f)
    # print(tickers)
    return tickers

save_sp500_tickers()
```



Pandas datareader

- Used ticker symbols to get financial data from Yahoo Finance
- Requested data starting from January 1, 2000 - today
- API call to pandas_datareader

```
|  
for ticker in tickers:  
    print(ticker)  
    if not os.path.exists('stock_dfs/{}.csv'.format(ticker)):  
        try:  
            df = web.DataReader(ticker, 'yahoo', start, end)  
            df.to_csv('stock_dfs/{}.csv'.format(ticker))  
        except KeyError:  
            pass  
    else:  
        print('Already have {}'.format(ticker))
```



Integrating COVID-19 data with financial data?

- At first we thought we could regress stock price on COVID-19 confirmed cases or deaths
- We scrapped this idea very quickly and decided to just try and investigate data during strategically picked dates
- We used the CDC's fact sheets and time lines to find information on other pandemics
- SARS
 - The start/end dates we used to subset our larger dataset October 2003 - January 2004
 - 8,098 cases 774 deaths
- H1N1 - SWINE FLU!
 - Lasted from April 2009 until August 2010
 - 60 million cases 12,469 deaths
 - Notably around same time of financial crisis
- Ebola
 - Lasted from December 2013 until January 2016
 - 28,816 cases and 11,310 deaths



Data preprocessing

- Subsetting our data by company
 - We have data from 500 companies dating back 20 years
 - We chose a handful of companies that we are interested in and represent the economy
 - Apple, American Express, Nike, Chevron, Johnson & Johnson, Ford, Alaska Airlines
- Subsetting our data by pandemic
 - We also subset of data by pandemic in order to look at performance during each pandemic
- Adjusted close
 - Adjusted closing price accounts for stock splits and is the best measure
- Put all stocks we are interested in into one data frame



Percent change as a metric for buy/sell/hold

- This function creates new columns for the percent change over the course of a week
- Fills the last few days with zeros because its undefined
- This is the main metric for our machine learning classification

```
def process_data_for_labels(pandemic,ticker):  
    # how many days  
    days = 7  
    df = pd.read_csv('stock_dfs_{}/{}.csv'.format(pandemic,pandemic), index_col=0)  
    # df = pd.read_csv('sars_data.csv', index_col=0)  
  
    tickers = df.columns.values.tolist()  
    df.fillna(0,inplace=True)  
  
    for i in range(1, days+1):  
        df['{}_{}_d'.format(ticker,i)] = (df[ticker].shift(-i) - df[ticker]) / df[ticker]  
    df.fillna(0,inplace=True)  
    return tickers,df
```


Extracting feature sets for buy/sell/hold

```
def buy_sell_hold(*args):
    cols = [c for c in args]
    requirement = .02
    for col in cols:
        if col > requirement:
            return 1
        if col < -requirement:
            return -1

    return 0
```

```
def extract_feature_sets(pandemic,ticker):
    tickers, df = process_data_for_labels(pandemic,ticker)
    hm_days=7
    df['{}_target'.format(ticker)] = list(map( buy_sell_hold, df['{}_1d'.format(ticker)],
        df['{}_2d'.format(ticker)],
        df['{}_3d'.format(ticker)],
        df['{}_4d'.format(ticker)],
        df['{}_5d'.format(ticker)],
        df['{}_6d'.format(ticker)],
        df['{}_7d'.format(ticker)]
    ))

    vals = df['{}_target'.format(ticker)].values.tolist()
    str_vals = [str(i) for i in vals]
    print('Data spread: ',Counter(str_vals))
    df.fillna(0,inplace=True)
    df = df.replace([np.inf, -np.inf], np.nan)
    df.dropna(inplace=True)
    df_vals = df[[ticker for ticker in tickers ]].pct_change()
    df_vals = df_vals.replace([np.inf, -np.inf],0)
    df_vals.fillna(0, inplace=True)
    X=df_vals.values
    y=df['{}_target'.format(ticker)].values
    return X,y
```



Machine learning models

- K nearest neighbors
- Linear Support Vector Classifier
- Random forest classifier
- Ensemble classifier with all three (majority vote)

```
##### actual ml
def do_ml(pandemic,ticker):
    X,y=extract_feature_sets(pandemic,ticker)

    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=.25,random_state=42)

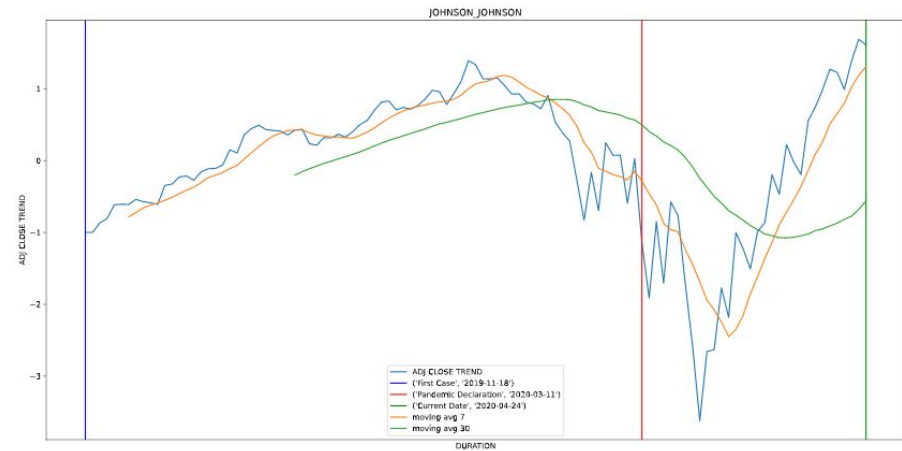
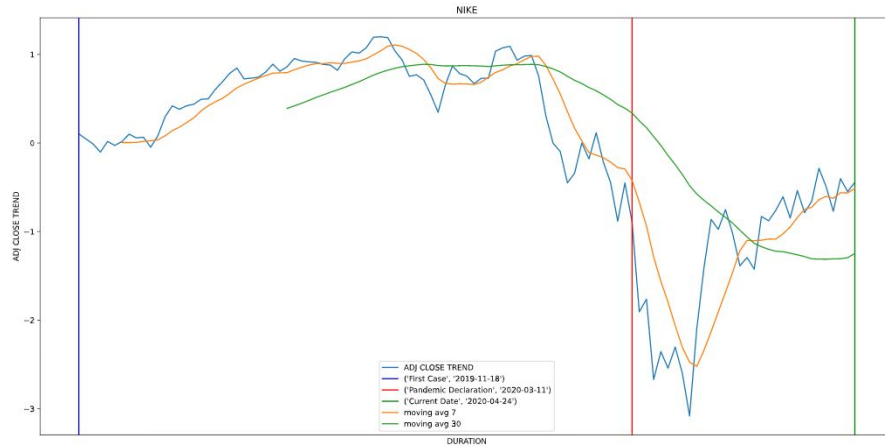
    # K nearest neighbors
    clf = neighbors.KNeighborsClassifier()
    # voting classifiers
    clf = VotingClassifier([
        ('lsvc', svm.LinearSVC()),
        ('knn', neighbors.KNeighborsClassifier()),
        ('rfor', RandomForestClassifier())
    ])

    clf.fit(X_train,y_train)
    confidence = clf.score(X_test,y_test)
    print('Accuracy:',confidence)
    predictions = clf.predict(X_test)
    print('Predicted spread:',Counter(predictions))

    return confidence
```

Data Visualization

- Blue Indicates the first reported case, Red indicates when the pandemic was declared, and green is the current date.
- Used moving averages: Yellow is short term moving average, Green is long term moving average.
- Used the subsetting data for each pandemic, plots created by matplotlib



Results - Apple = BUY

	buy-train	sell-train	hold-train	accuracy	buy-test	sell-test	hold-test
SARS	160	146	10	0.53	52	19	0
H1N1	183	122	30	0.45	65	19	0
Ebola	122	211	102	0.41	64	69	1
COVID-19	62	39	8	0.4642	25	2	1

```
AAPL
sars
Data spread: Counter({'1': 118, '-1': 105, '0': 8})
Accuracy: 0.5
Predicted spread: Counter({'1': 41, '-1': 17})

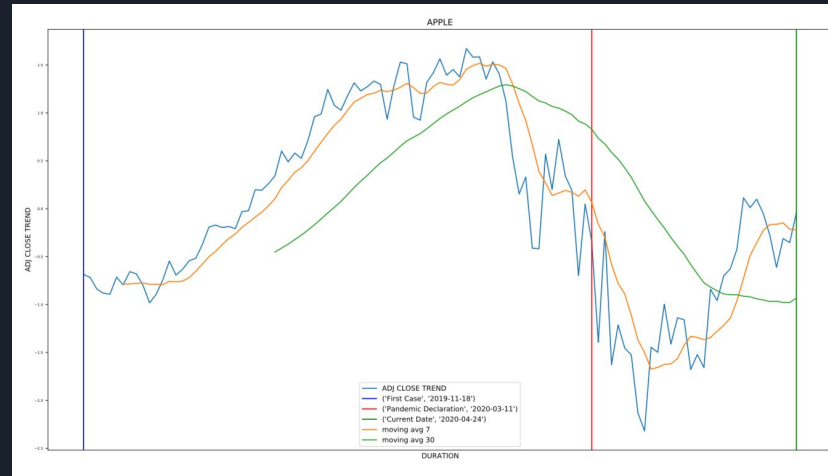
swine
Data spread: Counter({'1': 183, '-1': 122, '0': 30})
Accuracy: 0.42857142857142855
Predicted spread: Counter({'1': 70, '-1': 14})

ebola
Data spread: Counter({'1': 221, '-1': 211, '0': 102})
Accuracy: 0.3805970149253731
Predicted spread: Counter({'-1': 70, '1': 64})

corona
Data spread: Counter({'1': 62, '-1': 39, '0': 8})
Accuracy: 0.5357142857142857
Predicted spread: Counter({'1': 25, '-1': 2, '0': 1})
```

Apple moving average and ARIMA predictions

- Coefficient = .0009
- 4-27 prediction is \$283.21 actual value is \$283.17
- 4-28 prediction is \$283.45 actual value is \$278.58
- 4-29 prediction is \$283.70 actual value is \$287.73
- RMSE = 3.65



American Express = BUY

AXP							
	buy-train	sell-train	hold-train	accuracy	buy-test	sell-test	hold-test
SARS	147	131	38	0.4684	45	33	1
H1N1	191	122	22	0.5952	71	13	0
Ebola	156	205	173	0.3731	7	111	16
COVID-19	46	40	23	0.4643	19	7	2

```
AXP
sars
Data spread: Counter({'1': 111, '-1': 102, '0': 18})
Accuracy: 0.4827586206896552
Predicted spread: Counter({'-1': 38, '1': 20})

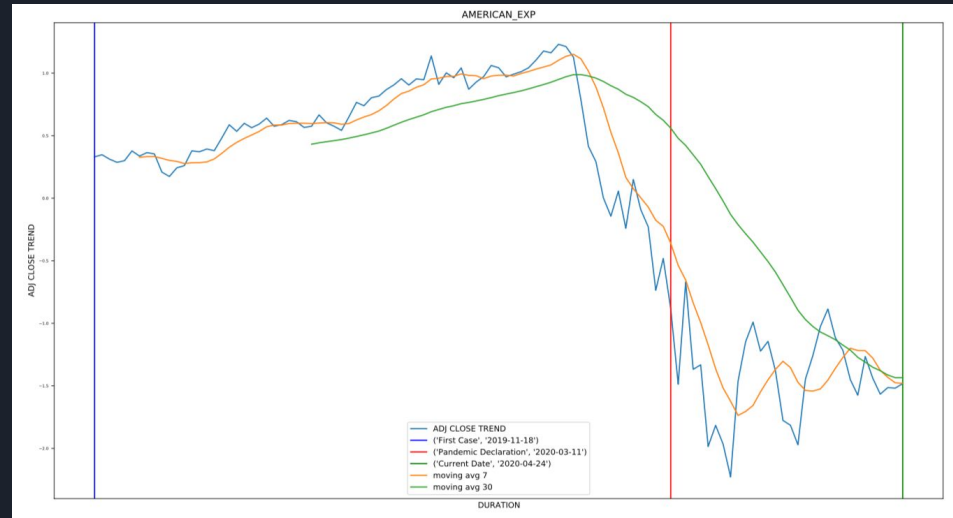
swine
Data spread: Counter({'1': 191, '-1': 122, '0': 22})
Accuracy: 0.5833333333333334
Predicted spread: Counter({'1': 72, '-1': 12})

ebola
Data spread: Counter({'-1': 205, '0': 173, '1': 156})
Accuracy: 0.35074626865671643
Predicted spread: Counter({'-1': 117, '0': 11, '1': 6})

corona
Data spread: Counter({'1': 46, '-1': 40, '0': 23})
Accuracy: 0.4642857142857143
Predicted spread: Counter({'1': 21, '-1': 6, '0': 1})
```

American Express moving average and ARIMA

- Coefficient = .0002
- 4-27 prediction is \$83.18 actual value is \$85.06
- 4-28 prediction is \$83.19 actual value is \$88.19
- 4-29 prediction is \$83.21 actual value is \$96.12
- RMSE = 8.06



Nike = BUY

NIKE							
	buy-train	sell-train	hold-train	accuracy	buy-test	sell-test	hold-test
SARS	160	121	53	0.5063	52	26	1
H1N1	161	121	53	0.4167	68	14	2
Ebola	208	172	53	0.3657	74	52	8
COVID-19	51	39	19	0.3214	21	6	0

```
NIKE
sars
Data spread: Counter({'1': 119, '-1': 88, '0': 24})
Accuracy: 0.3793103448275862
Predicted spread: Counter({'1': 46, '-1': 12})

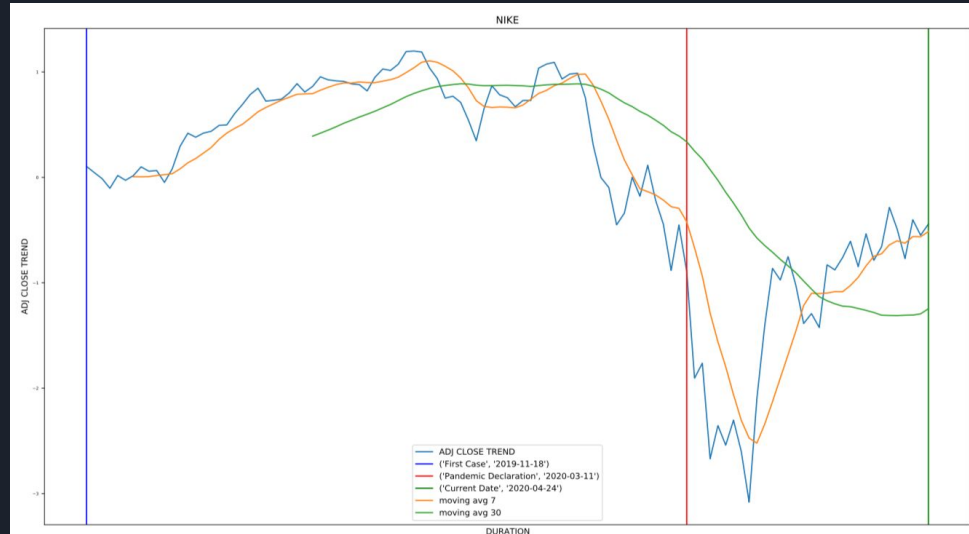
swine
Data spread: Counter({'1': 161, '-1': 121, '0': 53})
Accuracy: 0.4880952380952381
Predicted spread: Counter({'1': 66, '-1': 17, '0': 1})

ebola
Data spread: Counter({'1': 208, '-1': 172, '0': 154})
Accuracy: 0.3656716417910448
Predicted spread: Counter({'1': 76, '-1': 51, '0': 7})

corona
Data spread: Counter({'1': 51, '-1': 39, '0': 19})
Accuracy: 0.35714285714285715
Predicted spread: Counter({'1': 19, '-1': 8, '0': 1})
```


Nike moving average and ARIMA

- Coefficient = .0008
- 4-27 prediction is \$88.44 actual value is \$89.37
- 4-28 prediction is \$88.50 actual value is \$88.8
- 4-29 prediction is \$88.57 actual value is \$88.07
- RMSE = 8.06



Chevron

CVX							
	buy-train	sell-train	hold-train	accuracy	buy-test	sell-test	hold-test
SARS	128	76	112	0.4431	32	16	31
H1N1	149	127	59	0.3571	56	25	3
Ebola	163	217	154	0.3806	5	114	15
COVID-19	30	54	25	0.5714	4	22	2

```
CVX
sars
Data spread: Counter({'1': 82, '0': 79, '-1': 70})
Accuracy: 0.46551724137931033
Predicted spread: Counter({'-1': 24, '1': 20, '0': 14})

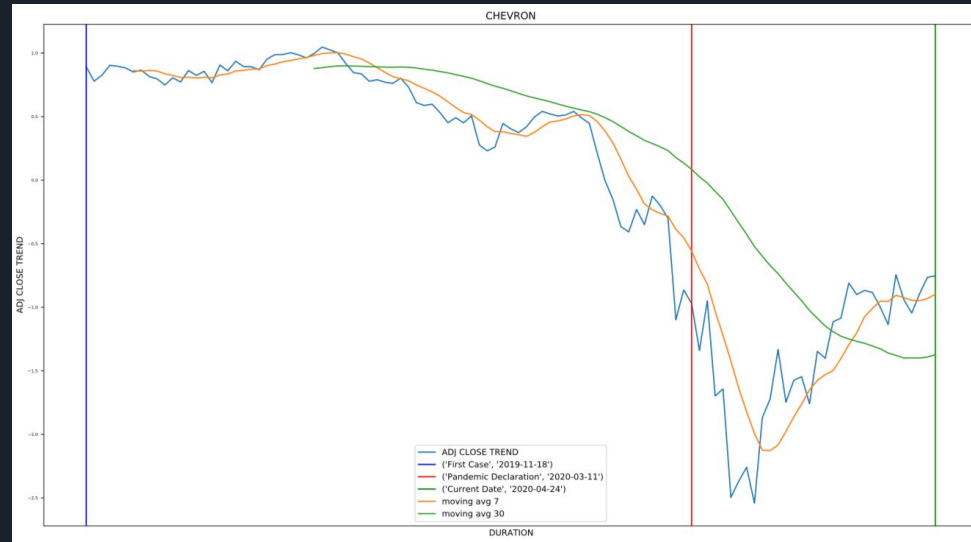
swine
Data spread: Counter({'1': 149, '-1': 127, '0': 59})
Accuracy: 0.34523809523809523
Predicted spread: Counter({'1': 60, '-1': 24})

ebola
Data spread: Counter({'-1': 217, '1': 163, '0': 154})
Accuracy: 0.3656716417910448
Predicted spread: Counter({'-1': 113, '0': 18, '1': 3})

corona
Data spread: Counter({'-1': 54, '1': 30, '0': 25})
Accuracy: 0.4642857142857143
Predicted spread: Counter({'-1': 21, '1': 4, '0': 3})
```

Chevron moving average and ARIMA

- Coefficient = .0003
- 4-27 prediction is \$87.04 actual value is \$89.37
- 4-28 prediction is \$87.06 actual value is \$88.8
- 4-29 prediction is \$87.09 actual value is \$88.07
- RMSE = 4.89



Johnson & Johnson = BUY

JNJ							
	buy-train	sell-train	hold-train	accuracy	buy-test	sell-test	hold-test
SARS	110	143	63	0.4404	11	64	4
H1N1	97	64	174	0.4881	4	6	74
Ebola	153	144	237	0.4254	4	31	99
COVID-19	52	29	28	0.3571	23	0	5

```
JNJ
sars
Data spread: Counter({'-1': 116, '1': 76, '0': 39})
Accuracy: 0.46551724137931033
Predicted spread: Counter({'-1': 53, '1': 5})

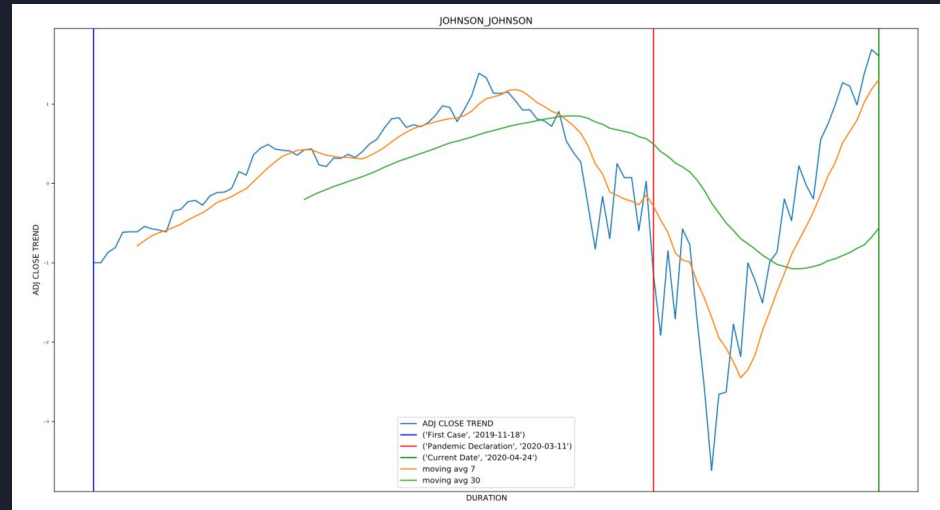
swine
Data spread: Counter({'0': 174, '1': 97, '-1': 64})
Accuracy: 0.5
Predicted spread: Counter({'0': 72, '-1': 8, '1': 4})

ebola
Data spread: Counter({'0': 237, '1': 153, '-1': 144})
Accuracy: 0.39552238805970147
Predicted spread: Counter({'0': 97, '-1': 30, '1': 7})

corona
Data spread: Counter({'1': 52, '-1': 29, '0': 28})
Accuracy: 0.4642857142857143
Predicted spread: Counter({'1': 21, '0': 6, '-1': 1})
```

JNJ moving average and ARIMA

- Coefficient = .0003
- 4-27 prediction is \$154.91 actual value is \$154.29
- 4-28 prediction is \$154.96 actual value is \$151.39
- 4-29 prediction is \$155.02 actual value is \$150.24
- RMSE = 3.46



Ford = SELL

F							
	buy-train	sell-train	hold-train	accuracy	buy-test	sell-test	hold-test
SARS	164	131	21	0.481	57	22	0
H1N1	185	139	11	0.5119	61	23	0
Ebola	191	212	131	0.3582	10	110	14
COVID-19	34	56	19	0.3929	2	3	23

```
F
sars
Data spread: Counter({'1': 112, '-1': 106, '0': 13})
Accuracy: 0.5172413793103449
Predicted spread: Counter({'1': 41, '-1': 17})

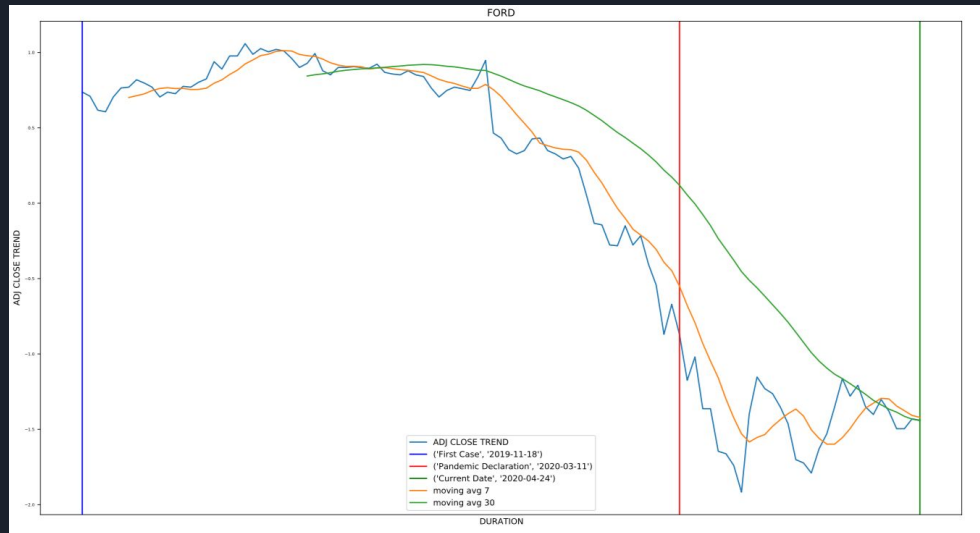
swine
Data spread: Counter({'1': 185, '-1': 139, '0': 11})
Accuracy: 0.5238095238095238
Predicted spread: Counter({'1': 64, '-1': 20})

ebola
Data spread: Counter({'-1': 212, '1': 191, '0': 131})
Accuracy: 0.40298507462686567
Predicted spread: Counter({'-1': 106, '0': 16, '1': 12})

corona
Data spread: Counter({'-1': 56, '1': 34, '0': 19})
Accuracy: 0.4642857142857143
Predicted spread: Counter({'-1': 23, '0': 4, '1': 1})
```

Ford moving average and ARIMA

- Coefficient = -.0002
- 4-27 prediction is \$4.868 actual value is \$5.17
- 4-28 prediction is \$4.867 actual value is \$5.38
- 4-29 prediction is \$4.866 actual value is \$5.26
- RMSE = .41



Alaska Airlines

ALK							
	buy-train	sell-train	hold-train	accuracy	buy-test	sell-test	hold-test
SARS	153	151	12	0.4684	43	36	0
H1N1	211	116	8	0.5238	65	19	0
Ebola	294	204	36	0.5298	104	30	0
COVID-19	35	62	12	0.4643	2	25	1

```
ALK
sars
Data spread: Counter({'1': 122, '-1': 106, '0': 3})
Accuracy: 0.41379310344827586
Predicted spread: Counter({'-1': 33, '1': 25})

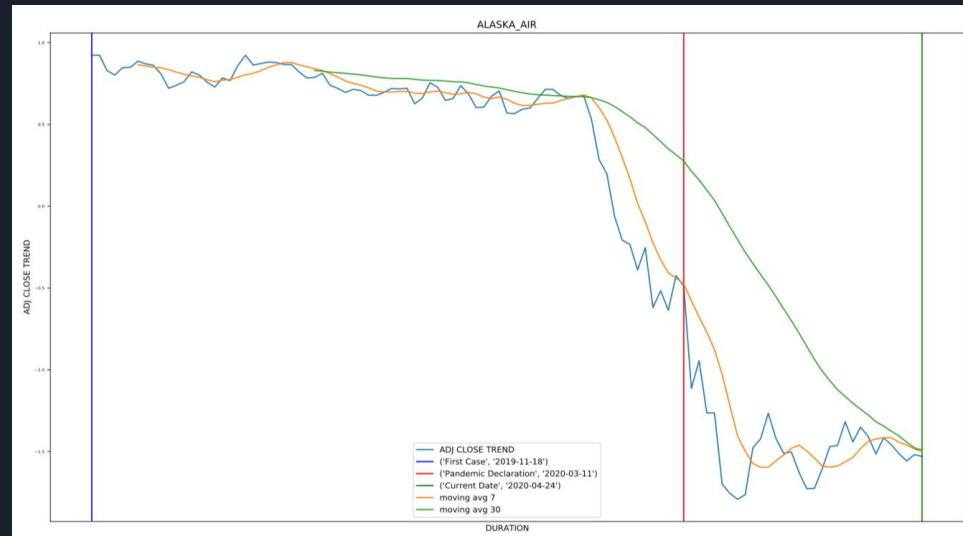
swine
Data spread: Counter({'1': 211, '-1': 116, '0': 8})
Accuracy: 0.5357142857142857
Predicted spread: Counter({'1': 68, '-1': 16})

ebola
Data spread: Counter({'1': 294, '-1': 204, '0': 36})
Accuracy: 0.5522388059701493
Predicted spread: Counter({'1': 97, '-1': 37})

corona
Data spread: Counter({'-1': 62, '1': 35, '0': 12})
Accuracy: 0.4642857142857143
Predicted spread: Counter({'-1': 25, '1': 2, '0': 1})
```


Alaska Airlines moving average and ARIMA

- Coefficient = .0003
- 4-27 prediction is \$4.868 actual value is \$27.85
- 4-28 prediction is \$4.867 actual value is \$31.58
- 4-29 prediction is \$4.866 actual value is \$34.00
- RMSE = 4.01





Conclusion

- We are not financial advisors!
- We trained the classifier on all the data from January 2000 Until April 20
- Predictions we're to buy all except Johnson and Johnson





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- [7] Biao Huang, Qiao Ding, Guozi Sun, and Huakang Li. 2018. Stock Prediction based on Bayesian-LSTM. In Proceedings of the 2018 10th International Conference on Machine Learning and Computing (ICMLC 2018). Association for Computing Machinery, New York, NY, USA, 128–133.