Investigating the Relation Between Twitter Sentiment and Stock Prices

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Analysis of historical data

Dataset for analysis

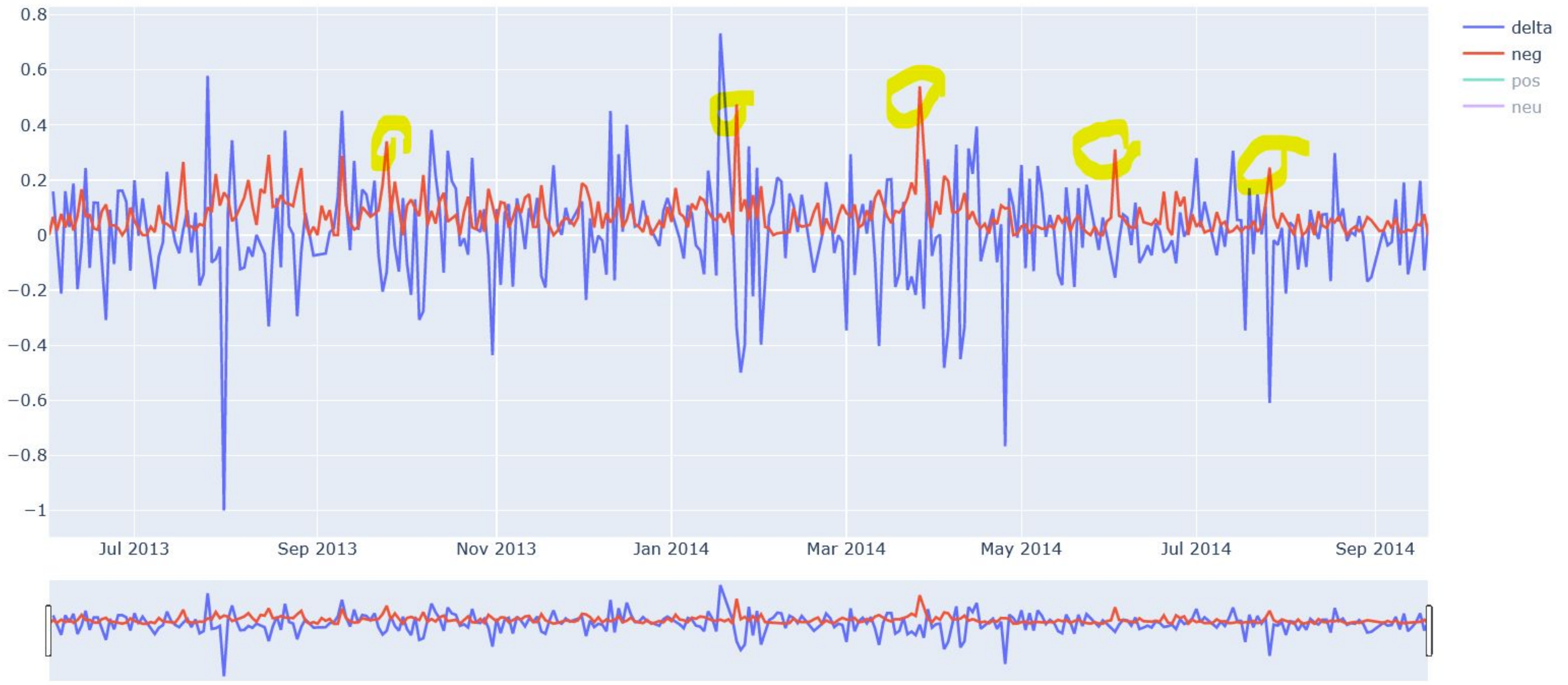
Ticker	Company	Tweets
TRV	Travelers Companies Corp	12,184
UNH	UnitedHealth Group Inc	15,020
UTX	United Technologies Corp	16,123
MMM	3M Co	17,001
DD	E I du Pont de Nemours and Co	17,340
AXP	American Express Co	21,941
PG	Procter & Gamble Co	25,751
NKE	Nike Inc	29,220
CVX	Chevron Corp	29,477
HD	Home Depot Inc	30,923
CAT	Caterpillar Inc	38,739
JNJ	Johnson & Johnson	40,503
V	Visa Inc	43,375
VZ	Verizon Communications Inc	45,177
KO	Coca-Cola Co	45,339
MCD	McDonald's Corp	45,971
XOM	Exxon Mobil Corp	46,286
DIS	Walt Disney Co	46,439
BA	Boeing Co	51,799
MRK	Merck & Co Inc	54,986
CSCO	Cisco Systems Inc	57,427
GE	General Electric Co	61,836
WMT	Wal-Mart Stores Inc	63,405
INTC	Intel Corp	68,079
PFE	Pfizer Inc	71,415
T	AT&T Inc	75,886
GS	Goldman Sachs Group Inc	91,057
IBM	International Business Machines Co	101,077
JPM	JPMorgan Chase and Co	108,810
MSFT	Microsoft Corp	183,184
Total		1,555,770

Table 1: The collected Twitter data for the 15 months period: the company names and the number of tweets.

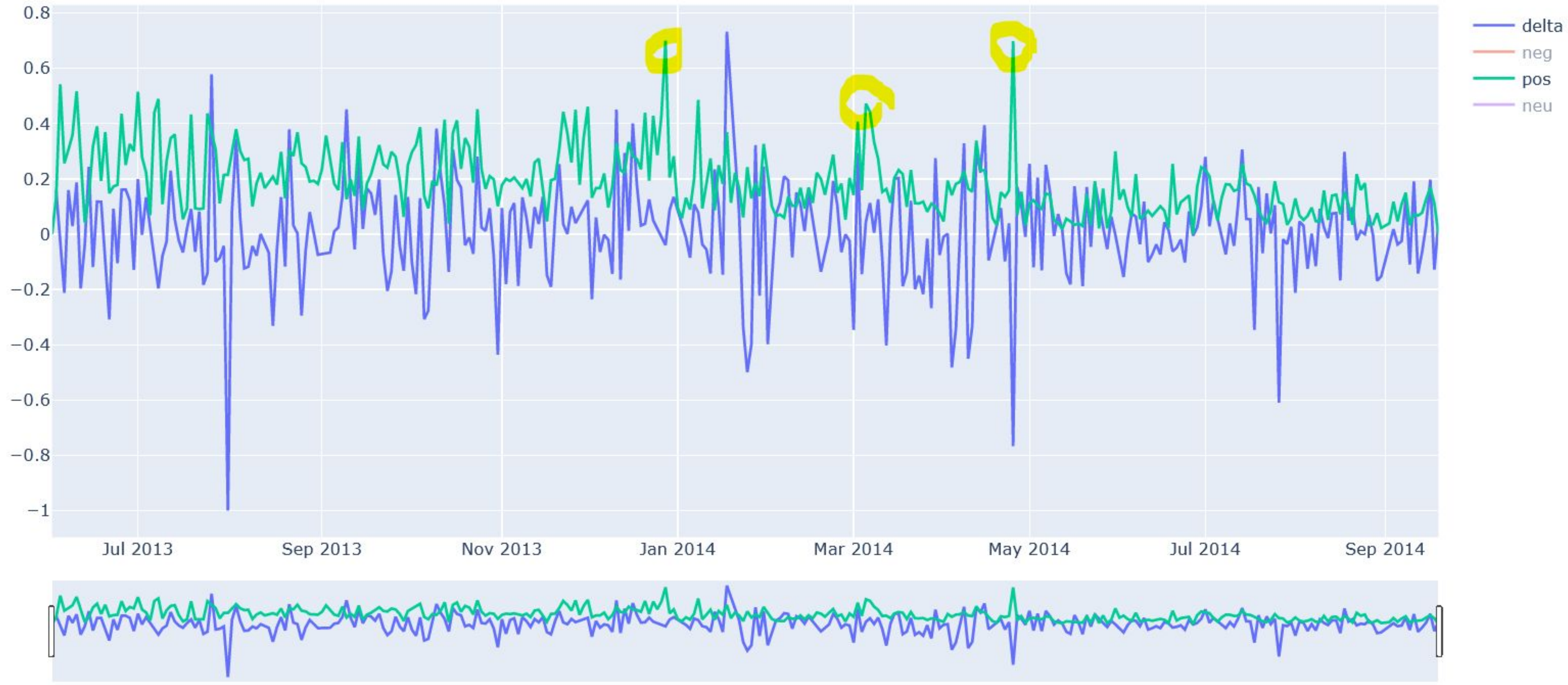
Source: Ranco et al., The Effects of Twitter Sentiment on Stock Price Returns

MSFT Price action & tweet sentiment

After removing the trend (negativity)



After removing the trend (positivity)



Small correlation (is not causation) :)

	pos	neu	neg
DeltaOpen	0.30	-0.13	-0.18
DeltaHigh	0.34	-0.13	-0.24
DeltaLow	0.30	-0.07	-0.29
DeltaClose	0.32	-0.06	-0.32

Positive gainers - Top 5

	symbol	pos	neg	neu
Microsoft	MSFT	0.330321	-0.283633	-0.095529
General Electric	GE	0.327986	-0.076051	-0.283461
CAT	CAT	0.319667	-0.351615	0.045353
Home Depot	HD	0.305868	-0.264657	-0.110991
IBM	IBM	0.290623	-0.402524	0.108387

Positive gainers - Bottom 5

	symbol	pos	neg	neu
Pfizer	PFE	0.098407	-0.108660	-0.040222
Verizon	VZ	0.092382	-0.229562	0.029501
Coca Cola	KO	0.088243	-0.146906	0.001384
AT&T	T	0.080441	-0.185863	-0.002700
Travelers	TRV	0.044055	-0.116357	0.045274

Negative losers - Top 5

symbol	pos	neg	neu
IBM	0.290623	-0.402524	0.108387
BA	0.242772	-0.357476	-0.010595
GS	0.252315	-0.352873	0.060282
CAT	0.319667	-0.351615	0.045353
V	0.174454	-0.328152	0.015777

Boeing Air

Goldman Sachs

Visa

Negative losers - Bottom 5

JP Morgan

Pfizer

Merck & Co

symbol	pos	neg	neu
JPM	0.224137	-0.125252	0.011951
TRV	0.044055	-0.116357	0.045274
PFE	0.098407	-0.108660	-0.040222
MRK	0.248310	-0.090426	-0.185661
GE	0.327986	-0.076051	-0.283461

Is any of this significant?

Go to https://arxiv.org/pdf/1506.02431.pdf to find the statistical significance tests

The Effects of Twitter Sentiment on Stock Price Returns

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Live Twitter Pipeline

Tools

- TextBlob, VADER-Sentiment (sentiment analysis)
- Tweepy (Twitter API)
- Yfinance (Yahoo Finance API)
- Plotly, WordCloud (Visualization)

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4. Compute statistics for a given timeframe
    a. And compare with price data from Yahoo finance

Current tweets about MSFT

MSFT stock & sentiment

Further research

TABLE 2.1 The Four Essential Types of Financial Data

Fundamental Data	Market Data	Analytics	Alternative Data
• Assets	• Price/yield/implied volatility	• Analyst recommendations	• Satellite/CCTV images
• Liabilities	• Volume	• Credit ratings	• Google searches
• Sales	• Dividend/coupons	• Earnings expectations	• Twitter/chats
• Costs/earnings	• Open interest	• News sentiment	• Metadata
• Macro variables	• Quotes/cancellations	• . . .	• . . .
• . . .	• Aggressor side		
	• . . .		

Source: Lopez, Advances in Financial Machine Learning

Thank you for attention :)

https://colab.research.google.com/drive/1wpHTakMfz0HRH8KEBAAmgzI8Jv3qbawR?usp=sharing