

NLP Sentiment on Mergers & Acquisitions











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Mergers & Acquisition: Overview

What is a merger?

- A merger refers to an agreement in which two companies join together to form one company
- There are five basic categories or types of mergers

Types of Mergers

Merger Type	Rationale	Example	Purchase Price (\$USD)	Date
Horizontal	Acquire the competition	 → 	\$1Bn	April 2012
Vertical	Control supply chain	 → 	\$1.5Bn	August 2002
Market-Extension	Enter a new market	 → 	\$300mm	February 2019
Product-Extension	Diversify product suite	 Square → 	\$297mm	March 2021
Conglomerate	Mitigate disruption	 → 	\$14.7Bn	June 2017

Mergers & Acquisition: Market Implications




Merger Disasters

- According Harvard Business Review, between 70% and 90% of acquisitions fail

Top Reasons why Mergers Fail

1. Limited Owner Involvement
2. Ambitious Valuations
3. Poor Integration Processes
4. Cultural Integration Issues
5. Large Required Capacity
6. High Recovery Costs
7. Negotiation Errors

Examples of Failed Mergers

Companies	Acquisition Price (USD)	Acquisition Year	Failure Reasons/Statistics
	\$65Bn	2001	Limited Ownership Involvement – one year after the deal write-down of \$99Bn – largest annual net loss ever reported
	\$36Bn	1998	Cultural Integration Issues – after a decade, Daimler sold 80% of Chrysler to Cerberus for \$7Bn
	\$12.5Bn	2012	Ambitious Valuations – in 2014, Motorola was divested for just \$2.9Bn

Source: Harvard Business Review







Project Motivation

Key Questions

- Can we predict whether or not a merger will succeed or fail when it is announced?
- Will sentiment from the news help us determine whether or not a merger will succeed?
- How does the sentiment of a merger announcement change during the due diligence period?
- Can we avoid future merger disasters?

Our Approach

- Natural Language Processing/ Sentiment Analysis/ Topic Modelling
- Proxy Success KPI: Buyer's stock price on date of announcement vs (closing date, vs one-year after merger)
- Back-test analysis on three-mergers (see below)

Buyer	Target	Purchase Price (USD)	Date	Acquisition Rationale
		~\$71.3Bn	March 2019	Product-extension
		~\$1Bn	July 2019	Vertical Integration
		~\$5.3Bn	January 2020	Product Extension

Data Cleaning and Preparation

Getting the News Data

```
articles = []
keyword = 'visa plaid'

for i in range(1,30,1):
    news = newsapi.get_everything(
        q= keyword,
        language = 'en',
        sort_by = 'relevancy',
        page_size = 100,
        page = i,
        from_param = '2020-01-10',
        to = '2020-02-13'
    )
    articles.extend(news['articles'])
```

Calculating VADER Sentiment Score ¶

```
# Instantiate the Lemmatizer
lemmatizer = WordNetLemmatizer()

# Create a List of stopwords
stop = set(stopwords.words('english'))

# Expand the default stopwords list if necessary
stop2 = {"Visa", "VISA", "PLAID", "Plaid", ",", "'s", "'", "would", "one", "also",
        "-", "two", "make", "including", "told", "get", "say", "even",
        "content", "time", "n't", "going", "still", "last", "think", "see",

#Set tokenization function
def clean_text(text):

    words = word_tokenize(text)

    words = list(filter(lambda w:w.lower(), words))

    words = list(filter(lambda t:t not in punctuation, words))

    words = list(filter(lambda t: t.lower() not in stop.union(stop2), words))

    token = [lemmatizer.lemmatize(word) for word in words]

    return token
```

Sentiment Score Analyzer

Sentiment Distribution



	date	title	text	description	token	compound	pos	neu	neg	text_sent
0	2020-01-17	We've gone Plaid #	Hello and welcome back to Equity, TechCrunchs ...	Hello and welcome back to Equity, TechCrunch's...	[Hello, welcome, back, Equity, TechCrunchs, ve...	0.5642	0.049	0.928	0.023	positive
1	2020-01-14	Visa agrees to buy financial technology startu...	Visa Inc said on Monday it agreed to buy priva...	Visa agrees to buy financial technology startu...	[Visa, Inc. Monday, agreed, buy, privately, he...	0.9669	0.094	0.878	0.028	positive
2	2020-01-13	Visa Is Acquiring Plaid For \$5.3 Billion	One can search the brain with a microscope and...	Visa announced today that it is buying financi...	[search, brain, microscope, find, mind, search...	-0.2057	0.000	0.935	0.065	negative
3	2020-01-18	Week in Review: Forget cord cutting, here come...	Hey everyone, welcome back to Week in Review w...	Hey everyone, welcome back to Week in Review w...	[Hey, everyone, welcome, back, Week, Review, d...	0.9970	0.116	0.880	0.004	positive
4	2020-01-17	The paradox of 2020 VC is that the largest fun...	I talked yesterday about how VCs are just tire...	I talked yesterday about how VCs are just tire...	[talked, yesterday, VCs, tired, day, many, dea...	0.9712	0.077	0.866	0.057	positive

Data Cleaning and Preparation

Topic Modeling – Gensim – LDA Model

```
# LDA Model
```

```
lda_model = gensim.models.ldamodel.LdaModel(corpus = corpus,  
                                             id2word = id2word,  
                                             num_topics= 7,  
                                             random_state = 100,  
                                             update_every=1,  
                                             alpha = 'auto')
```

```
#Topics
```

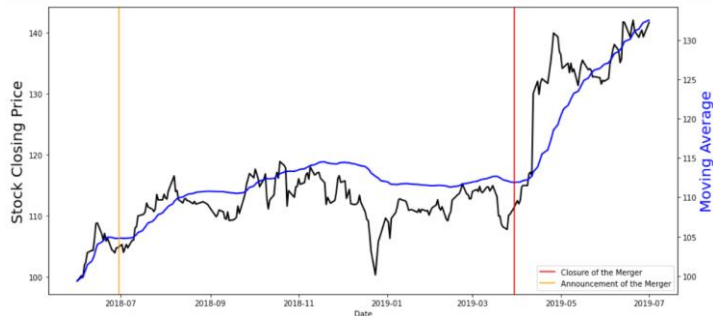
```
print(lda_model.print_topics())
```

Topic Modeling – Visualization

```
pyLDAvis.enable_notebook()  
vis = gensimvis.prepare(lda_model, corpus, id2word, mds='mmds', R=30)  
vis
```

Displaying Results

```
# Creating Plot based on Close and EWA numbers  
x = df_new.index  
y1 = df_new['Close']  
y2 = df_new['EWA']  
  
fig, ax1 = plt.subplots(figsize=(15,7))  
  
ax2 = ax1.twinx()  
ax1.plot(x, y1, 'k-', linewidth=2)  
ax2.plot(x, y2, 'b-', linewidth=2)  
  
ax1.set_xlabel('Date')  
ax1.set_ylabel('Stock Closing Price', color='k', size = 20)  
ax2.set_ylabel('Moving Average', color='b', size = 20)  
  
plt.axvline('2019-03-30', color = 'red', label = 'Closure of the Merger')  
plt.axvline('2018-06-30', color = 'orange', label = 'Announcement of the Merger')  
plt.legend()  
plt.show()
```



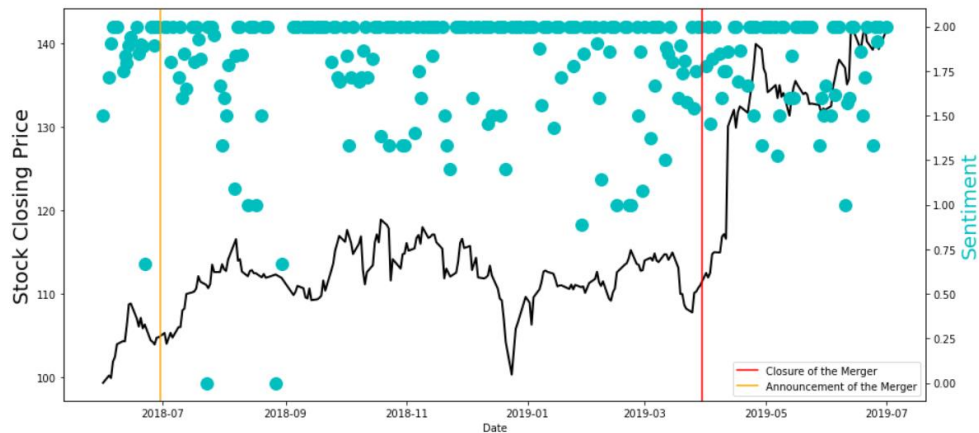
CONCLUSIONS: DISNEY-FOX



Acquisition Details

Category	Information
Announcement Date	June 20, 2018
Closed Date	March 20, 2019
Purchase Consideration	USD \$71.3Bn
Acquisition Rationale	Content Assets & Streaming Services

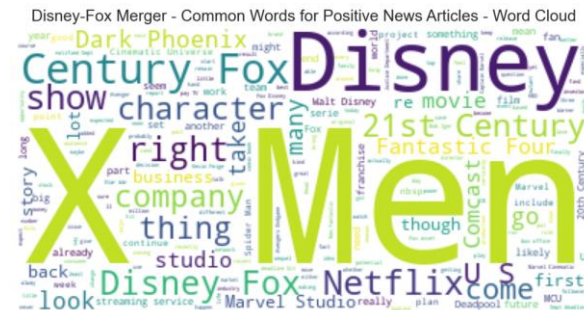
Disney Stock Price – Avg. Sentiment Score Performance



Most Common Words in Negative Articles



Most Common Words in Positive Articles



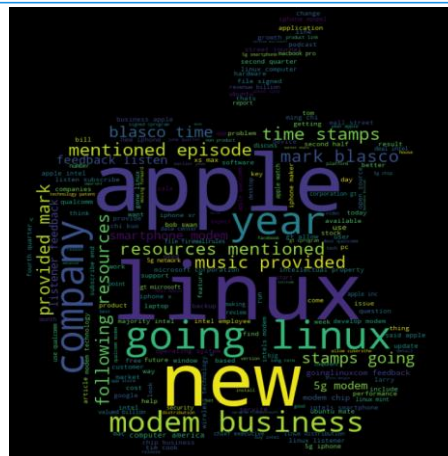
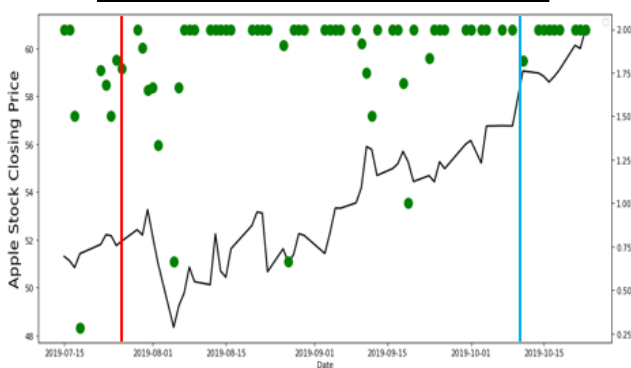
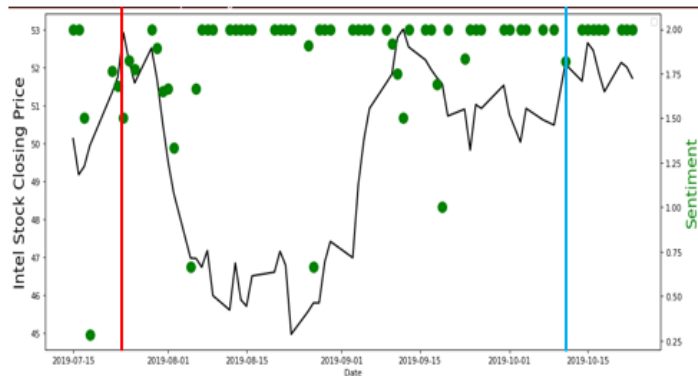
CONCLUSIONS: APPLE-INTEL



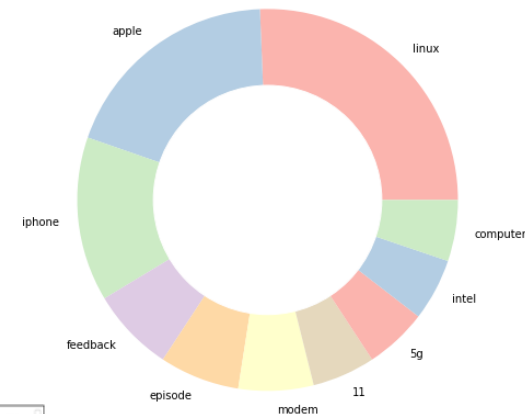
Acquisition Details

Category	Information
Announcement Date	July 25, 2019
Closed Date	December 03, 2019
Purchase Consideration	USD \$1Bn
Acquisition Rational	

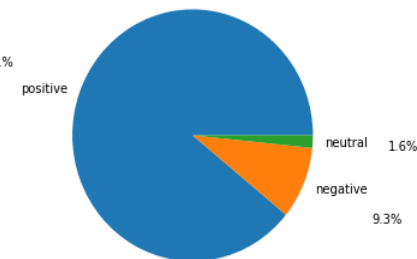
Intel- Apple Stock Price- Avg. Sentimental Score Performance



Apple – Intel : Positive Words



Distribution of the Sentiment Classes - Announcement



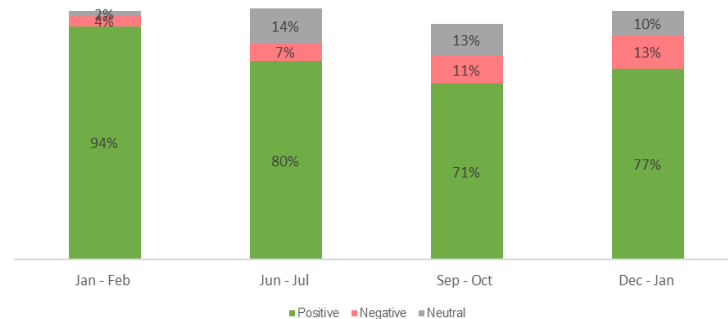
CONCLUSIONS: VISA-PLAID



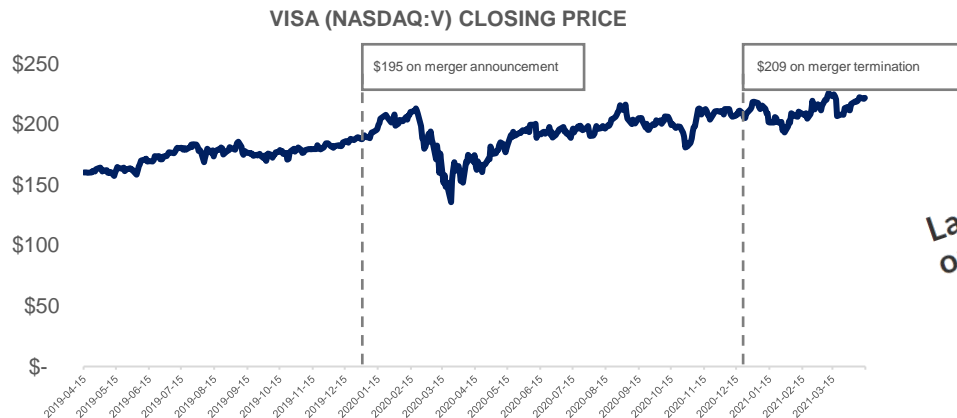
Acquisition Details

Category	Information
Announcement Date	January 13, 2020
Closed Date	Terminated
Purchase Consideration	USD \$5.3Bn
Acquisition Rationale	Bolster Visa Fintech Business

Common_words	count
0	bank 31
1	account 23
2	million 23
3	business 21
4	fraud 19
5	data 18



Visa Stock Price Performance



Lawsuit against Plaid heightens focus on data privacy issues

TD sues Plaid over trademark infringement, false advertising

Plaid Faces Second Lawsuit for Violating Data Privacy

New Class Action Lawsuit Alleges Plaid Violated User Privacy

Topic Modeling

What is Topic Modeling?

- Topic modeling is an unsupervised machine learning technique that's capable of scanning a set of documents, detecting words and phrase patterns within them, and automatically clustering word groups and similar expressions that best characterize a set of documents

Why is it important to assess Topic Modeling for M&A?

- Current NLP sentiment analysis assumes that every article is credible or appropriately informed on an announced merger
 - Are there any subsets of articles that we should remove from the analysis, that causes any noise?
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Topic Modeling – Visualization

Selected Topic:

Slide to adjust relevance metric:(2)

$\lambda = 1$

0.0 0.2 0.4 0.6 0.8 1

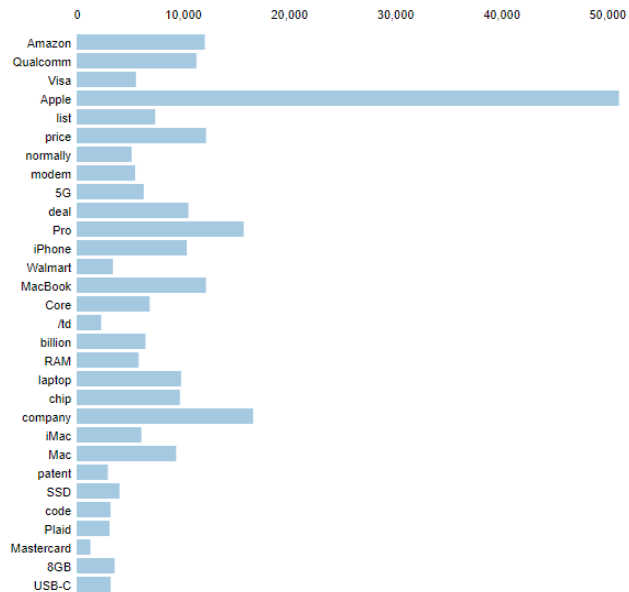
Intertopic Distance Map (via multidimensional scaling)



Marginal topic distribution



Top-30 Most Salient Terms¹



Overall term frequency

Estimated term frequency within the selected topic

1. $saliency(term, w) = frequency(w) * [\sum_t p(t|w) * \log(p(t|w)/p(t))]$ for topics t . see Chuang et. al. (2012)

2. $relevance(term, w, t, topic, t) = \lambda * p(w|t) + (1 - \lambda) * p(w|t)p(w)$. see Sievert & Shirley. (2014)

Conclusions: NLP M&A 2.0

General Conclusions

- Insightful exercise, different/unique approach to analyzing mergers and acquisitions
- Cannot confidently state that we are capable of predicting the outcome as successful or not
- Important to read the negative sentiment articles to identify conspicuous merger risks

Limitations on Current Analysis

- Evaluating history does not equal reliable future predictor. (i.e. Hindsight is 20/20)
- Technical understanding limitation -> how exactly does the sentiment analyzer categorize an article as “positive”, “neutral”, “negative”
 - Are we incorrectly categorizing articles?
- Sampling Bias: Inherit positivity bias in merger announcements and closings when looking at news articles
- Data/\$ Limitation: News articles alone may be insufficient, better to analyze equity research reports
- Stock Price: May not be best proxy to evaluate merger success given materiality thresholds

If we had more time/resources (\$)?

- Hire Nabila as Senior Data Scientist Manager to explore other NLP/ML techniques
 - Evaluate equity research reports
 - Implement other financial metrics on the analysis (Debt, EBITDA, synergies, etc)
 - Topic Modeling Exploration -> evaluate alternative sources
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