4. Supervised Techniques I (flipped)

DS-GA 1015, Text as Data
Arthur Spirling

March 2, 2021

Housekeeping

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HW 1 out: coming in on March 9, 2021, at 11pm (NY time).

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TaD/NLP: Nanyun (Violet) Peng (UCLA), "Controllable Text Generation Beyond Auto-regressive Models."

Dictionaries

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$\rightarrow$ just add up the number of times the words appear and multiply by the score (normalizing by doc dictionary presence)

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Director and co-screenwriter Adam McKay (Step Brothers) bungles a great opportunity to savage the architects of the 2008 financial crisis in The Big Short, wasting an A-list ensemble cast in the process. Steve Carell, Brad Pitt, Christian Bale and Ryan Gosling play various tenuously related members of the finance industry, men who made made a killing by betting against the housing market, which at that point had superficially swelled to record highs. All of the elements are in place for a lacerating satire, but almost every aesthetic choice in the film is bad, from the U-Turn-era Oliver Stone visuals to Carell's sketch-comedy performance to the cheeky cutaways where Selena Gomez and Anthony Bourdain explain complex financial concepts. After a brutal opening half, it finally settles into a groove, and there's a queasy charge in watching a credit-drunk America walking towards that cliff's edge, but not enough to save the film.

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great *savage*
crisis *wasting*

tenuously
killing
superficially *swelled*

bad

complex *brutal*

drunk
enough

Simple math. . .

Simple math. . .

negative 11

Simple math...

negative	11
positive	2

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negative	11
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total	13

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Harrison's review of *The Addams Family*

The best gags in this new version update classic jokes: the furious villagers are now controlled via social media fake news, while Wednesday appears identically wan in every one of her friend's Instagram filters. The family predilection for using dangerous weapons survives intact, even if the darkly Gothic spirit of the Barry Sonnenfeld films is largely missing.

The standard of the animation, however, is less than lush, and doesn't sit well in comparison with most recent studio releases, such as the similar Hotel Transylvania franchise. But, with a decent voice cast and a style that pays homage to the original drawings, The Addams Family passes muster as a disconcertingly cheerful, family-friendly romp.

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What rating do you think this received?

3 stars (0.27)

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The writers of Deadpool, Paul Wernick and Rhett Reese, were employed here, and the aim is clearly to replicate that brand of post-modern snark, but the jokes don't stretch further than having One's crew tediously quote lines from other films while pulling off a heist. The explosions and locations are flashy but, without any opportunities for engagement with the narrative, the two-hour-plus runtime is truly punishing.

If Netflix have funded their fair share of lame comedies and stodgy action, this at least provides fans of the low-brow with a two-for-one. Otherwise, it's a laboured Mission Impossible knock-off that offers little more than watching money unenjoyably wasted. In the era of fake news, 6 Underground feels like a fake film: a disposable, unmemorable product that even those seeking Bay's usual high-octane idiocy will find exhausting.

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1 star (-0.167)

Exercise

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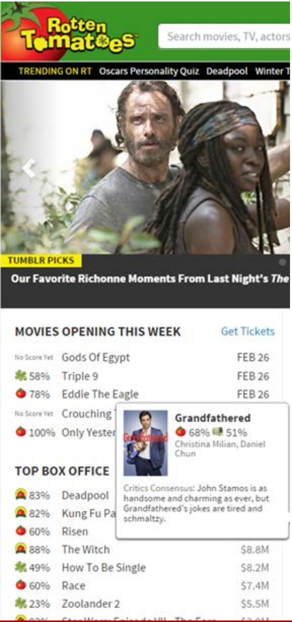

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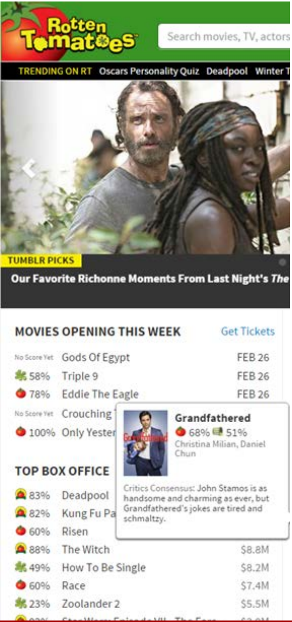

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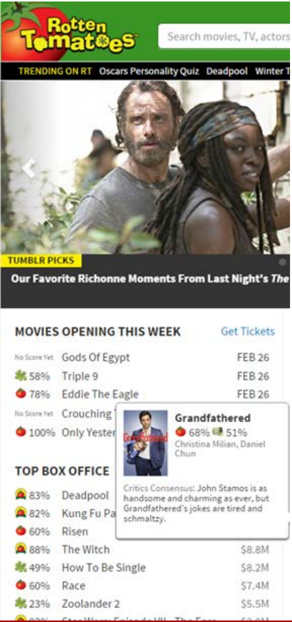

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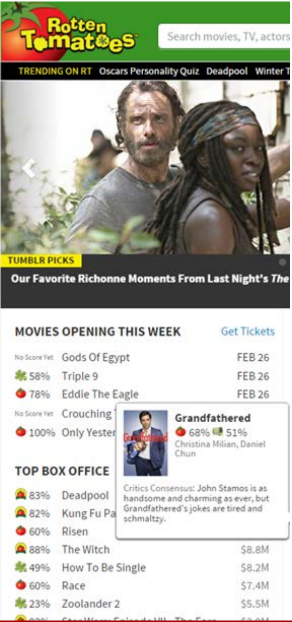

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3 Why might be generally nervous about BOW approaches?

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btw punctuation adds relatively little to accuracy.

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RESEARCH ARTICLE

Examining long-term trends in politics and culture through language of political leaders and cultural institutions

Kayla N. Jordan, Joanna Sterling, James W. Pennebaker, and Ryan L. Boyd

PNAS February 26, 2019 116 (9) 3476-3481; first published February 11, 2019; https://doi.org/10.1073/pnas.1811987116

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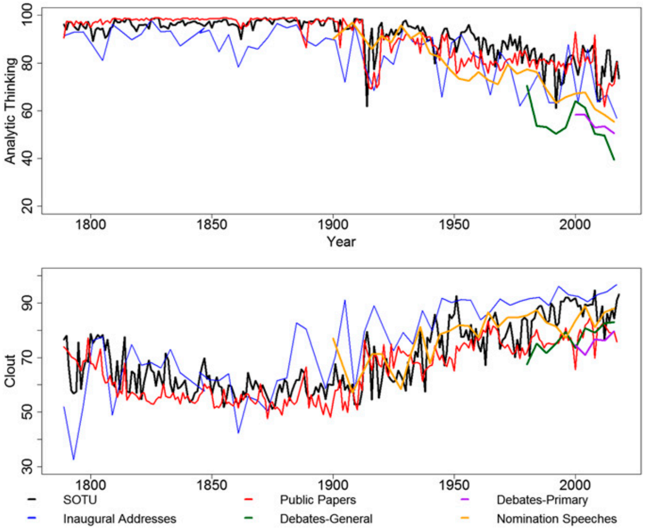
Analytic Thinking
20
40
60
80
100
1800
1850
1900
1950
2000
Year
Clout
30
50
70
90
1800
1850
1900
1950
2000
SOTU
Inaugural Addresses
Public Papers
Debates-General
Debates-Primary
Nomination Speeches

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How do you think this variable is formed?

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Q in your field, is there an example of a word(s) that is used in a fundamentally different way, in terms of sentiment, relative to more common uses?

Followup: how bad could it be?

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83% of freq counts of Diction 'optimistic' words don't appear on L&M list. For 'pessimistic' words, 70% of Diction word frequencies don't appear on L&M. Also show that L&M word lists (from company filings) are statistically significant predictor of volatility and direction makes sense (not so for Diction).

Events

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Scholars of International Relations need access to events

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Real time media reports are obvious source. . .

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ASIA PACIFIC

Leaders of South Korea and Japan Meet in Effort to Mend Ties

点击查看本文中文版 | Read in Chinese

By CHOE SANG-HUN NOV. 1, 2015

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England bounce back to defeat Italy in the Six Nations

England managed to secure victory against Italy despite going behind early on. Photo by David Rogers/Getty Images

Why are these stories hard to parse?

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HEALTH • COVID-19

Exclusive: New York Tells Hospitals In Leaked Email That Staff 'Must' Come Before the Elderly In COVID-19 Vaccination Drive

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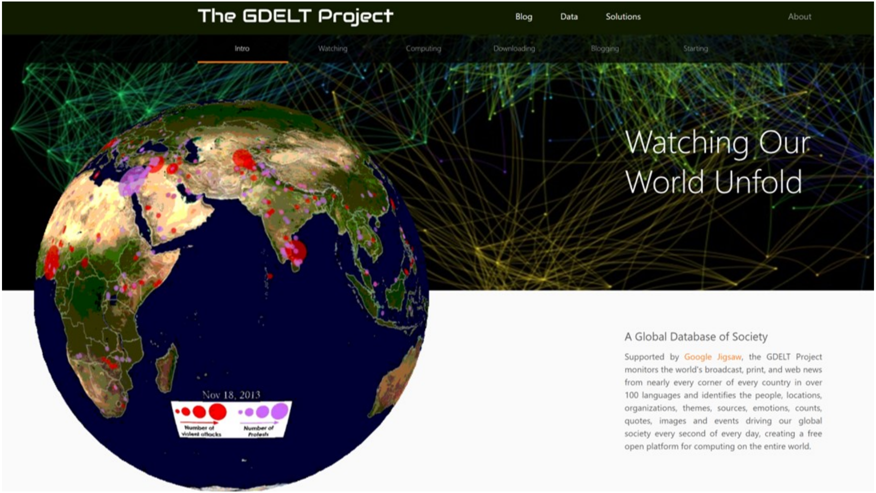
Prime Minister warns tier restrictions could come back in England

The road map will start as a national approach

SHARE

By Neil Shaw
16:21, 22 FEB 2021

NEWS


The GDELT Project
Blog
Data
Solutions
About
Intro
Watching
Computing
Downloading
Blogging
Starting
Watching Our World Unfold
Nov 18, 2013
Number of violent attacks
Number of Protests
A Global Database of Society
Supported by Google Jigsaw, the GDELT Project monitors the world's broadcast, print, and web news from nearly every corner of every country in over 100 languages and identifies the people, locations, organizations, themes, sources, emotions, counts, quotes, images and events driving our global society every second of every day, creating a free open platform for computing on the entire world.

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The Committee continues to see the risks to the outlook for economic activity and the labor market as nearly balanced but is monitoring developments abroad. Inflation is anticipated to remain near its recent low level in the near term but the Committee expects inflation to rise gradually toward 2 percent over the medium term as the labor market improves further and the transitory effects of declines in energy and import prices dissipate.

Problem and Approach

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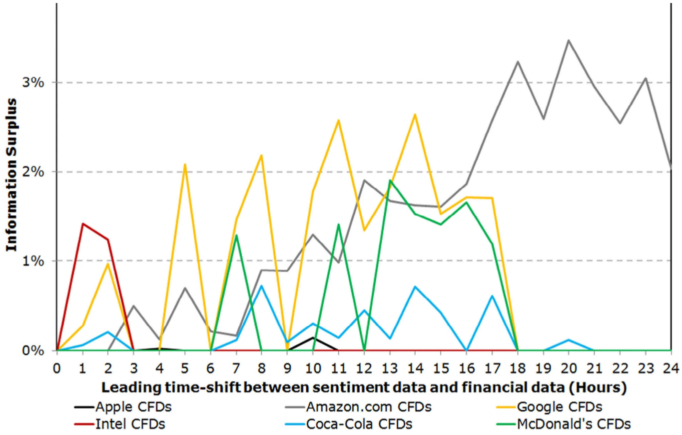
Authors want to predict (future) stock price movements from sentiment of tweets about those stocks (e.g. "`$TSLA` looks great!")

Find: some information in sentiments for 12 of 28 assets they investigate.



Information Surplus
3%
2%
1%
0%
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
Leading time-shift between sentiment data and financial data (Hours)
Apple CFDs
Amazon.com CFDs
Google CFDs
Intel CFDs
Coca-Cola CFDs
McDonald's CFDs

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