

Crash Narratives

Goetzmann, Kim & Shiller (2024)

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Overview

How do media “narratives” that recall historical crashes impact investor beliefs?

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Contribution: Provide evidence for a particular mechanism of belief formation about rare disasters

Overall: Very Interesting Paper

Paper uses innovative methodology to tackle difficult question

1. Measuring narrativity is difficult
2. Isolating effect of narrativity vs. contemporaneous market conditions is difficult

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Discussion: Suggestions on how paper can do even more to address these difficulties

- o Provide more detail on how well Doc2Vec captures narrativity & potentially consider alternative methods
- o Potentially use more structure to isolate narrativity vs. market conditions

Difficulty 1: Measuring Narrativity

What is Narrativity?

My interpretation: Holding facts fixed, are facts expressed as an analogy to past events?

- "When large shocks to the financial markets occur, historical references often play a role in news stories... Comparisons to past catastrophes make salient the gravity of current events and focus public attention on a singular narrative about what the future may bring."

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Higher-order linguistic relationship

- Must understand order of words to understand implicit causal chain being invoked

What is Doc2Vec?

Machine learning method to map text documents to numerical representations

- Neural network learns vector representations of whole document & individual words that best predict word sequences
- Example sentence in corpus: “the cat sat on the mat”
 - Use vectors for “the”, “cat”, “sat” & whole document to predict “on”

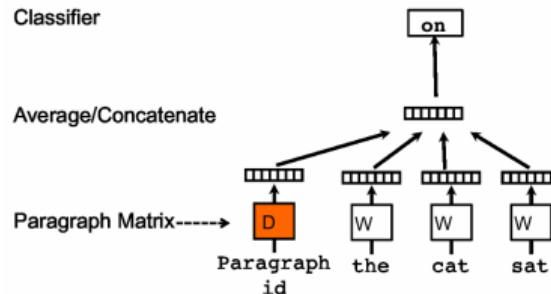


Figure: Le & Mikolov (2014)

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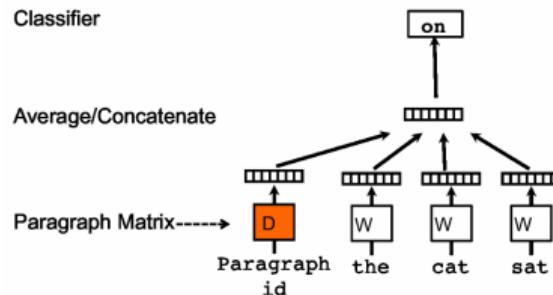


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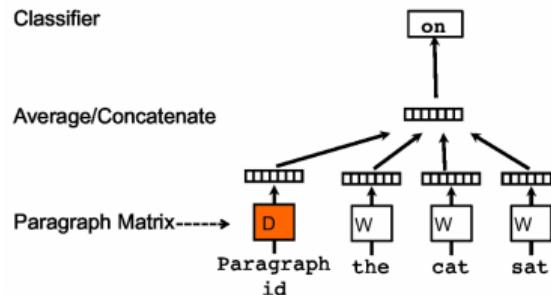


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Document vectors encode general meaning/topic of document

- Day t crash narrativity: How close are document vectors from Wall Street Journal news on t to those from Wall Street Journal news around 1987 crash

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Potentially to some extent

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Suggestion: Validate Doc2Vec performance with tests of narrative recognition

- Randomly sample, for example, 500 documents
- Manually classify as “Contains 1987 crash narrative” or “Does not contain 1987 crash narrative”
- Report Doc2Vec performance in identifying which documents contain crash narratives

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 - But are more costly to train
 - Authors train own Doc2Vec models using only text available up to time t to avoid lookahead bias

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- Sarkar (2024) has released pre-trained, time-stamped BERT models to avoid lookahead bias

Difficulty 2: Narrativity vs. Market Conditions

Goal: Measure Impact of Crash Narratives on Investor Beliefs

Simplified empirical framework

$$\text{Subjective Crash Probability} = \beta \text{Crash Narrativity} + f(\text{Market Conditions}) + \epsilon$$

- Subjective crash probabilities obtained from surveys of individual and institutional investors
 - Likely depend on general market conditions
 - Want to test if they depend on crash narrativity ($\beta > 0$)

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- Journalists choose to invoke crash narratives in states of the world with certain market conditions

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- Failure to control for $f(\cdot)$ or $h(\cdot)$ will bias estimates of β
- $f(\cdot)$ and $h(\cdot)$ are potentially complex
 - Beliefs and text are complex (that is why we use highly non-linear machine learning methods)

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Linear controls to absorb $h(\cdot)$ (imposes structure on $h(\cdot)$)

- Standard market condition proxies (e.g. lagged returns, lagged VIX, etc.)
- Similarity of word frequencies (i.e. news content) to news around 1987 crash
- Crash narrativity driven by non-lede paragraphs

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- Model selection problem of when journalists invoke crash narratives (Heckman (1979); Kelly, Manela & Moreira (2021))
- Three benefits:
 - Clarify implicit assumptions to separate impact of narrativity vs. market conditions
 - Yield even deeper understanding of when crash narratives arise & how do they propagate
 - Reveal potential feedback loops from narratives to market conditions and vice versa

Minor Comments

More details on Doc2Vec implementation would be useful

- E.g. Clarify if this is the Distributed Memory or Distributed Bag of Words version?

More discussion of why certain functional forms are chosen would be useful

- Why define adjusted similarity as the difference between natural log of one plus average cosine similarities?
- Why use quadratic projections (e.g. when projecting FolkMotif onto '87 Narrative)?

More discussion of magnitudes would be useful

- E.g. How large is one unit increase in '87 Narrative → 1.529 higher crash probability (Table 7, Column 1)

Results on crash narrativity & market-implied probabilities would be interesting

- Under suitable assumptions, the market-implied crash probabilities can be interpreted as marginal investor's beliefs

Typos

- Link in footnote 19 is broken
- Pg. 27: I think you mean to say Dot-Com bubble burst twelve years after 1987 crash, not two years

Conclusion

Very interesting paper

Creative methodology to address difficult and important question

- How do media “narratives” that recall historical crashes impact investor beliefs?
- Use machine learning to measure crash narrativity in Wall Street Journal text

Main comments

- Suggestions on how authors can provide even more empirical support for their main findings