

Discussion:

# Crash Narratives

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SFS Cavalcade North America 2024  
May 20, 2024, GSU

# Big picture

- ▶ Big idea:  
narratives → beliefs → real impact (e.g. asset prices)
- ▶ Crash narratives  
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- ▶ Crash narratives  
a prominent narrative phenomenon  
and arguably, crash belief is highly subject to narratives
- ▶ The paper is pleasant and refreshing to read  
beautiful writing, insightful analysis, innovative ideas
- ▶ Textual analysis tools for empirical analysis  
article-level contextual embedding and similarity measures for  
semantic retrieval

# Summary

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- ▶ Main argument (hypothesis to test)

  - narratives matter for beliefs and choices, crash narratives in particular

- ▶ Rationale:

  - narratives are easy to understand and remember, contagious, suggest causal relationships, predictive relationships, ...

  - behavioral biases in evaluating rare events

# Measure “crash narratives” intensity in news

A general method that converts text into quantitative data

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textual database of all articles ( $\#$ articles  $\times$  embedding dim)
- ▶ Need to extract relevant quantitative information from the database  
reduce embedding dim to 1, instead of estimating a lin combination
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    - use “news in the days following the 1987 and 1929 crashes”  
    no need to manually specify the content of “crash narratives”
- ▶ More broadly:  
Any narrative / topic / sentiment can be extracted from the embedding database, with a simple textual query



# Embedding model

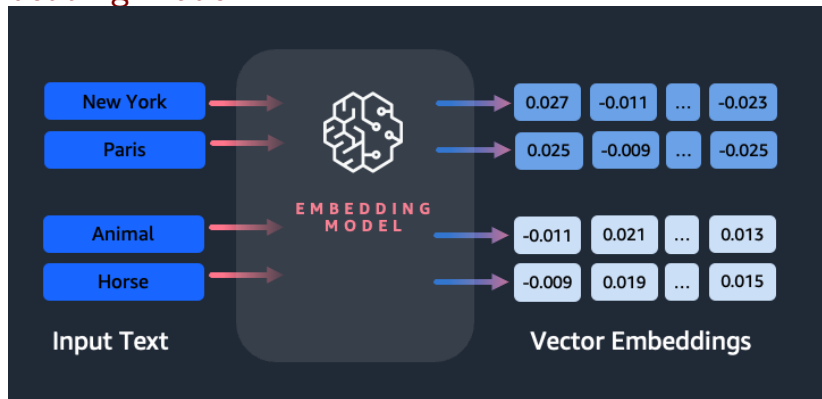


illustration source: AWS Machine Learning Blog.

<https://aws.amazon.com/blogs/machine-learning/getting-started-with-amazon-titan-text-embeddings/>

Contextual embedding:

- ▶ longer input text (articles)
- ▶ embeddings “understand” contextual information (higher-level semantic meaning than just words)

# Cosine similarity for semantics comparison

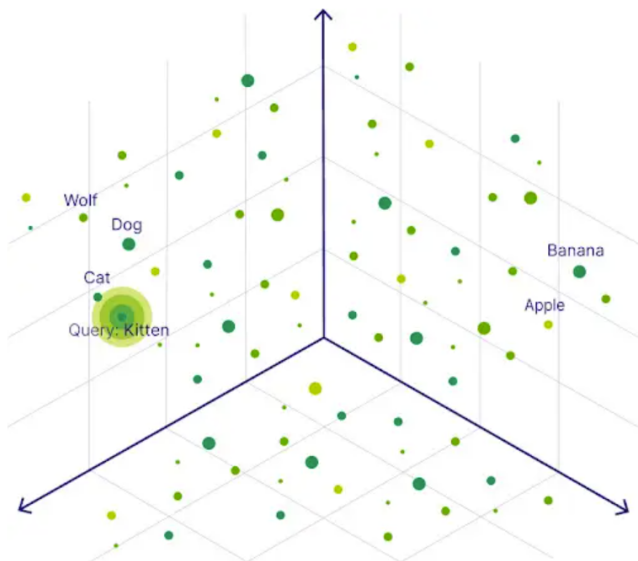


illustration source: From prototype to production: Vector databases in generative AI applications.  
<https://stackoverflow.blog/2023/10/09/from-prototype-to-production-vector-databases-in-generative-ai-applications/>

# Empirical analysis

- ▶ crash narratives predicts:
  - investor attention to stock market crashes (proxied by google search index)
  - market volatility (future VIX levels)

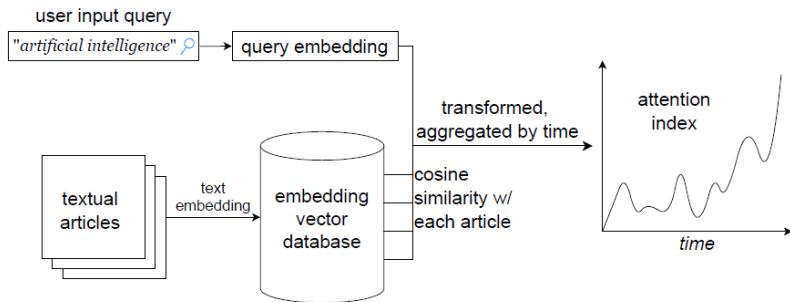
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    - open-end survey responses echo the crash narratives
- ▶ any exogenous variation in crash narratives?
  - ideal identification: the extent to which a media tells a story, irrelevant to the actual market conditions
  - “narrativity measure”
  - cosine similarity with “folk tales”
  - hard problem, but very creative idea

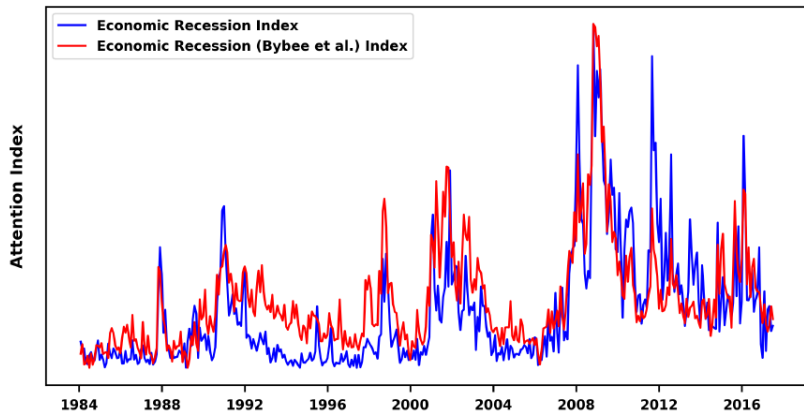
# Tracking narratives with large language model contextual embedding (work in progress)



- ▶ **any** textual query
- ▶ web-based service open to **all**

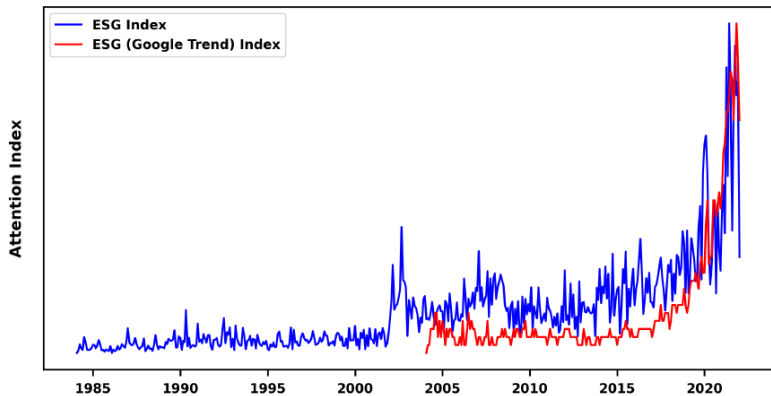
# Example: recession

Figure 3: Replicating Economic Recession Index



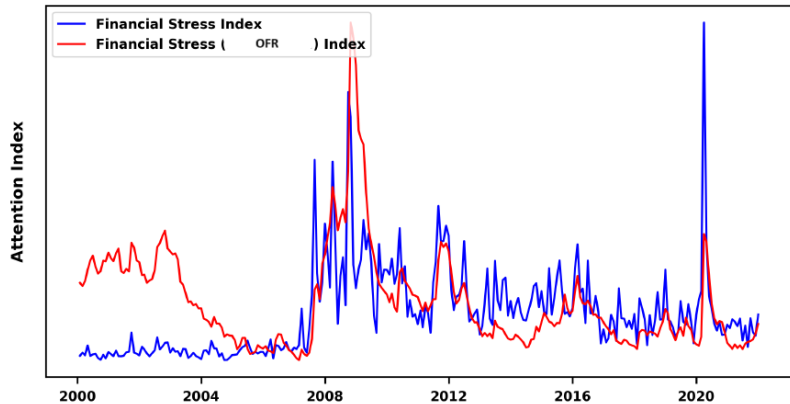
# Example: ESG

Figure 5: ESG Index





# Example: financial stress



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