Prompt Engineering: Using Generative AI to Extract Emphasis Frames

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Motivation

Emphasis frames, which present the same things selectively to highlight some aspects, can be defined in relation to a specific issue (Chong and Druckman, 2007). However, two commonly used methods for identifying emphasis frames in textual data have limitations:

- *topic modeling* (DiMaggio et al., 2013):
  1. traditional ones (e.g., LDA and STM) are fully unsupervised;
  2. resulting groups of keywords (which are "topics") lack semantic contexts for exploring frames.
- *dictionary-based approach* (Hitt and Searles, 2018):
  1. existing dictionaries would miss novel frames;
  2. creating new dictionaries is labor intensive.

Solution: Generative AI

- a theory-driven data annotation tool;
- sophisticated abilities of text summarization and information extraction to synthesize high-level concepts (Lam et al., 2024).

Highlights & Findings

- Generative AI *versus* Existing Methods

Generative AI	Existing Methods
1. leverage on knowledge from extensive pretraining to extract frame features;	1. require predefined lists of frame terms or coding schemes;
2. produce more semantically interpretable frame features—phrases describing how things are framed in a specific context.	2. rely on co-occurrent words or predefined terms stripped of context to identify frames.

- Re-examine Gilardi et al. (2021) using Generative AI
  1. consistent with their main conclusion: policy frames tend to be more complex as the policy diffuses;
  2. discover more fine-grained frames and co-existing patterns.

Reference

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Identifying Frames via Generative AI

- First, leveraging *chain-of-thoughts* prompting (Wei et al., 2022), I instruct the AI assistants (LLMs) to code broadly-defined categories of frames following three steps: 1) quote, 2) summarize, and 3) name;

Prompt Template

Role: You are an expert in framing analysis.
General Instruction: There are {N} broad frames—{a set of initial frames based on prior work or research questions} may be used in discussions about {description of an issue, event, or policy}.
Input: A document about the issue, event, or policy.
Output: JSON functions include three main parameters for each broad frame

Quote	**Summarize**	**Name**
relevant text for the broad frame used in the document	how quoted text is framed	a phrase to describe context-specific use

```
function = [{
    "name": "framing_analysis",
    "description": "A function that takes in a list of arguments related to frames used in a document about smoking ban policy",
    "parameters": {
        "type": "object",
        "properties": {
            "health": {
                "type": "array",
                "description": "this frame may include but not limited to the health risk of smoking, ...",
                "items":{
                    "text": {"type":"string", "description": "Quote the relevant text from the document"},
                    "summary": {"type":"string", "description": "Summarize the quoted text"},
                    "name": {"type":"string", "description": "Describe the specific use of this frame in the quoted text"}
                    }}, ...
        }
        }}]
```

- Second, I create a *human-in-the-loop* (Wu et al., 2022) LLM pipeline to discover substantially meaningful subcategories of broad frames;

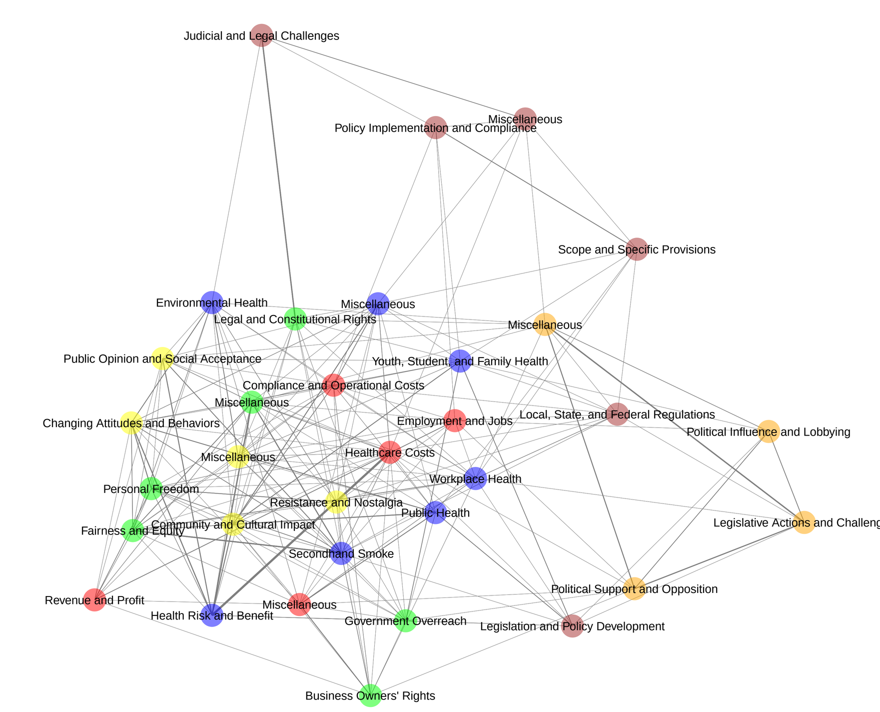
n batches of 100 random phrases
⇓
LLM: Category Generation
⇓
n lists of identified subcategories (definition & examples)
⇓
Human: Category Selection
⇓
frequently appear & substantively meaningful subcategories
⇓
LLM: Category Assignment
⇓
phrases labeled with subcategories

- Finally, I convert the analysis results to a document-frame matrix.

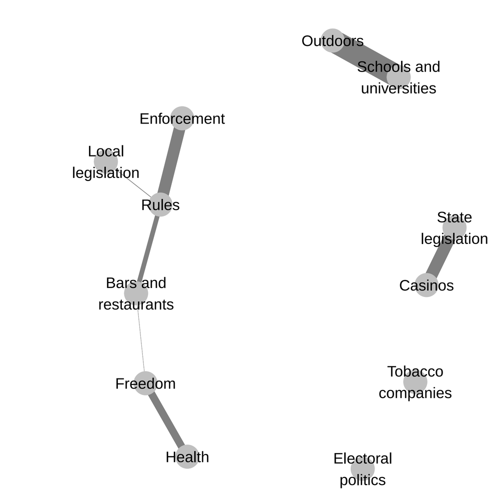
	Broad Frame 1			Broad Frame 2			Broad Frame N		
doc id	*subcat1*	*subcat2*	⋯	*subcat1*	*subcat2*	⋯	*subcat1*	*subcat2*	⋯
1	0	1	⋯	1	0	⋯	0	0	⋯
2	1	1	⋯	0	0	⋯	1	0	⋯
3	0	0	⋯	1	0	⋯	0	1	⋯
⋯	.	.	⋯	.	.	⋯	.	.	⋯
⋯	.	.	⋯	.	.	⋯	.	.	⋯

Application: Reanalysis of Gilardi et al. (2021)

- Corpus: news articles covering the smoking ban policy published between 1996 and 2013 in US;
- Methods:
  - 12 topics (policy frames) by structural topic model (STM) in the original paper;
  - 33 subcategories of six broad frames by GPT-4o using the proposed method.
- GPT-4o finds fined-grained frame correlations missed by STM
  1. Two broad frames, ● **political** and ● **legal and regulatory**, are relatively isolated from other groups, whereas complex frames usually concentrate on some subcategories of the other four groups:
     ● health ● economic impact ● rights and freedom ● social norms
  2. Some subcategories are more strongly correlated (thicker edges), e.g. "Judicial and Legal Challenges" and "Legal and Constitutional Rights", "Health Risk and Benefit" and "Healthcare Costs", suggesting that they are more likely to appear together within news article.



(a) GPT-4o



(b) STM

Validate, Validate, Validate

- Topic validation tasks adapted from Ying et al. (2022):
  multiple-choice questions with four options and one correct answer
  1. R4WSI: choose the word/phrase set below that is most UNRELATED to the other three
  2. OLW: choose the OPTIMAL label for the given word/phrase set
  3. LI: choose the label that is most UNRELATED to the given news article

- Pilot results from MTurk:
  (note: each model has two identical trials per task.)
  1. GPT-4o outperforms STM in R4WSI and OLW, suggesting GPT-4o provides more *distinctive and coherent* features that help identify different frames;
  2. GPT-4o and STM have similarly bad performance in LI, need to improve task design and add attention check.