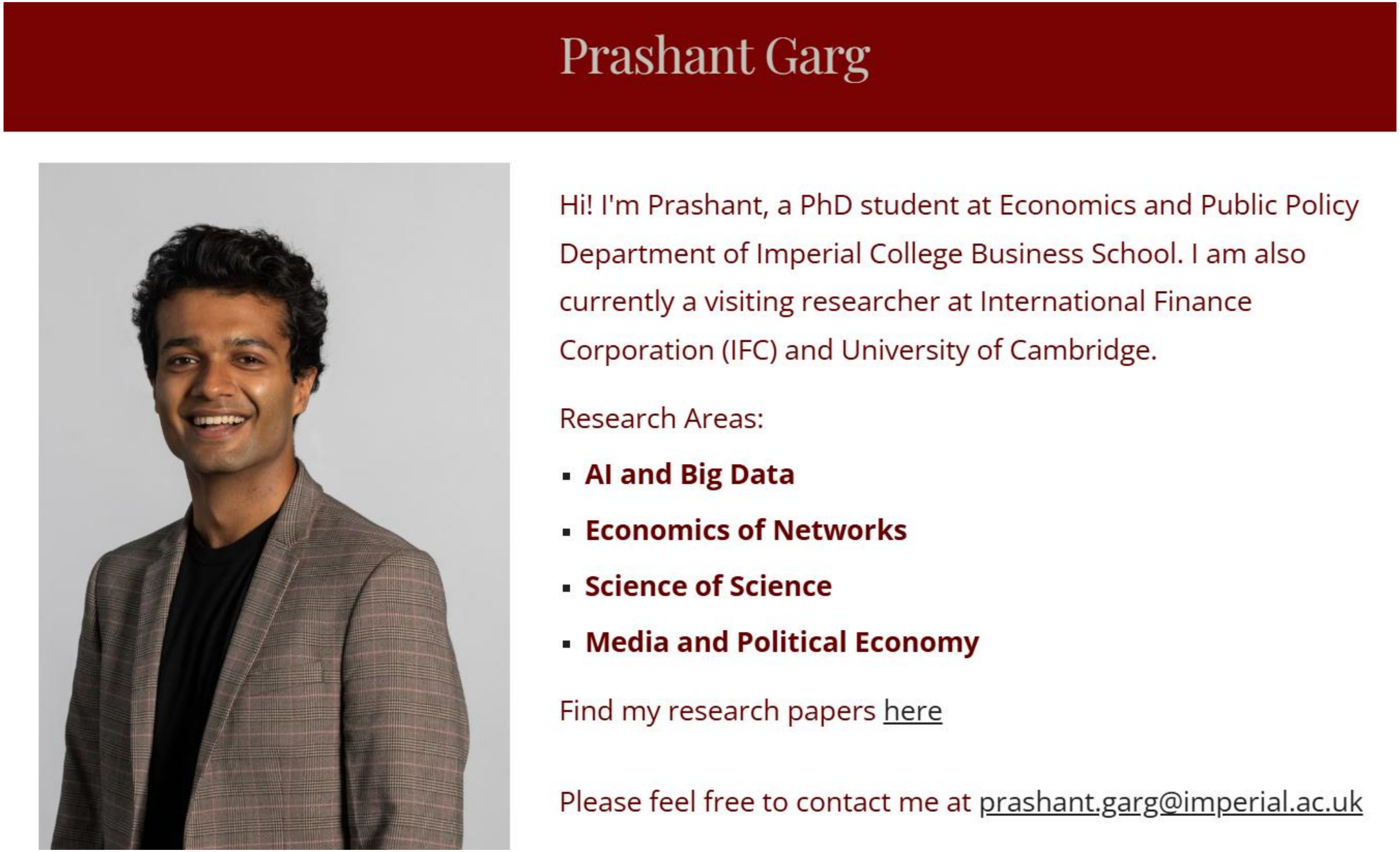
Retrieving and Generating data using LLMs

Prashant Garg

(Imperial College London)



Prashant Garg

Hi! I'm Prashant, a PhD student at Economics and Public Policy Department of Imperial College Business School. I am also currently a visiting researcher at International Finance Corporation (IFC) and University of Cambridge.

Research Areas:

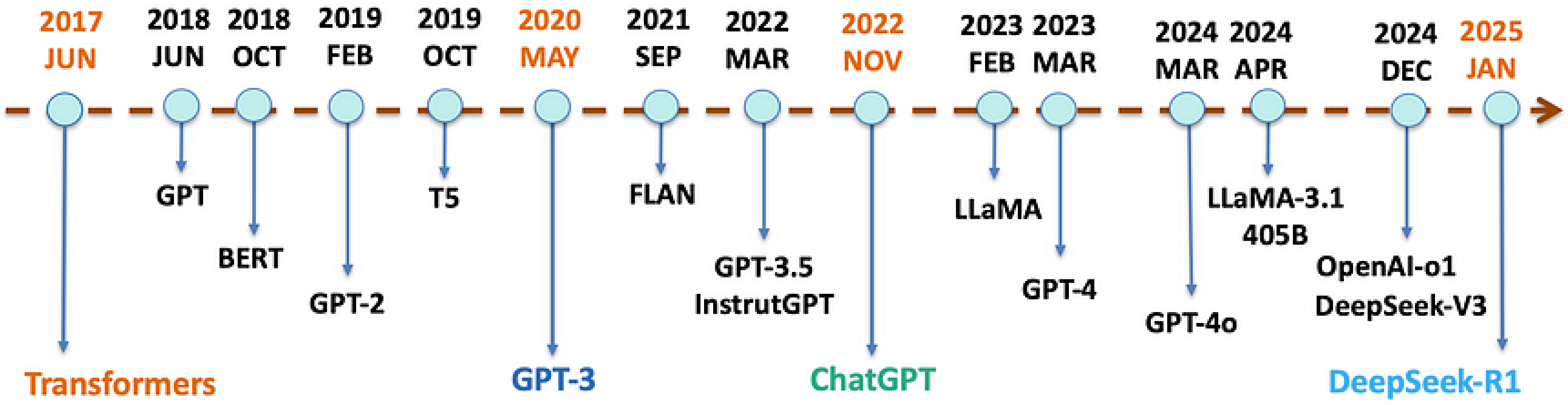
- **AI and Big Data**
- **Economics of Networks**
- **Science of Science**
- **Media and Political Economy**

Find my research papers here

Please feel free to contact me at prashant.garg@imperial.ac.uk

Find my research at www.prashantgarg.org

A Brief History of LLMs



2017 JUN Transformers

2018 JUN GPT

2018 OCT BERT

2019 FEB GPT-2

2019 OCT T5

2020 MAY GPT-3

2021 SEP FLAN

2022 MAR GPT-3.5 InstrutGPT

2022 NOV ChatGPT

2023 FEB LLaMA

2023 MAR GPT-4

2024 MAR GPT-4o

2024 APR LLaMA-3.1 405B

2024 DEC OpenAI-o1 DeepSeek-V3

2025 JAN DeepSeek-R1

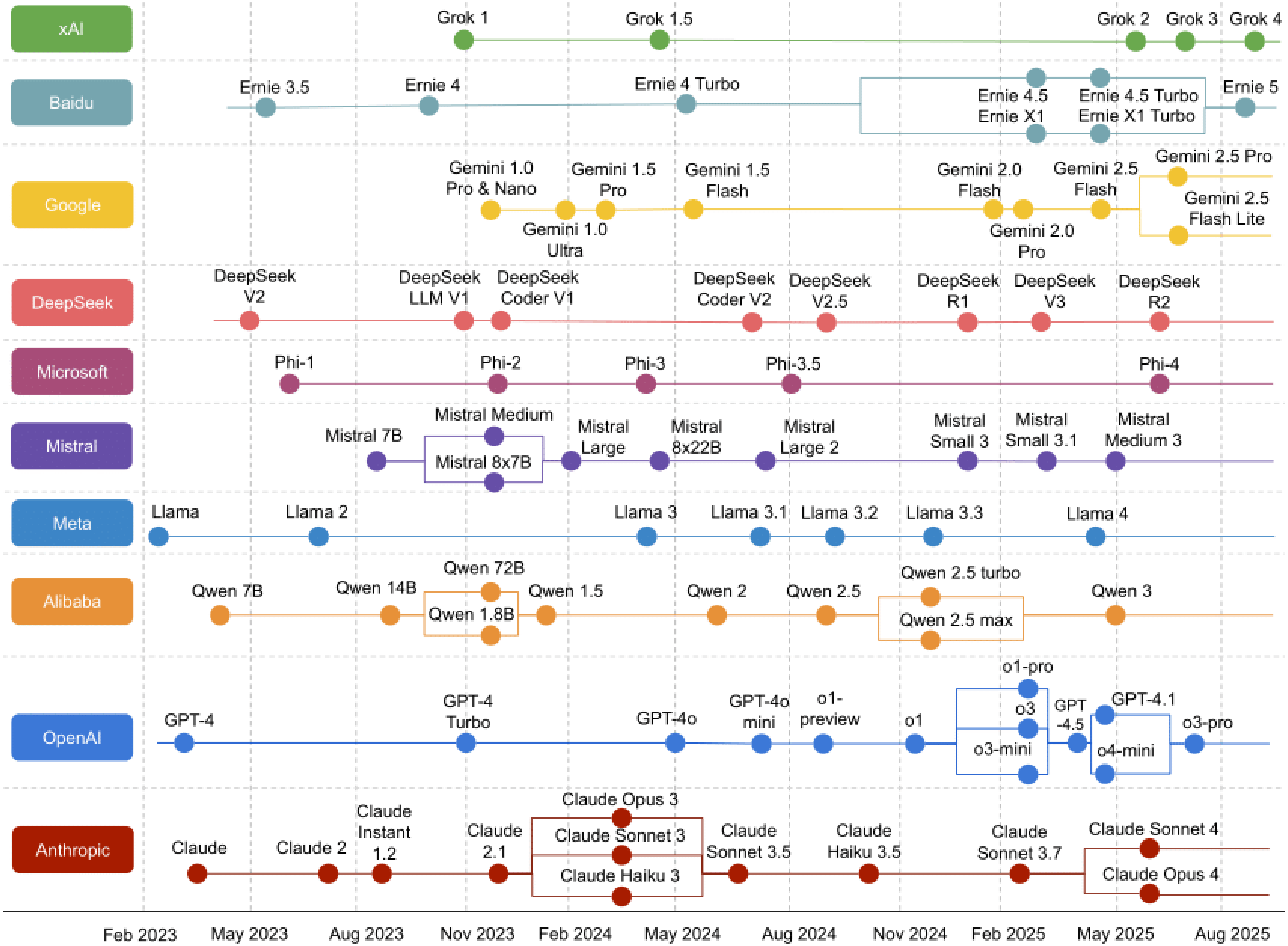
source

Why-now?

- Cost per 1K tokens ↓ 150x (2020 → 2025).
- Context window ↑ from 2K → 1M tokens (500x).
- Open-weight models (Mistral, Llama, Qwen, Phi) close the gap.
- Multimodality standard (text + image + code + audio + video)
- Tool-use integration (search, retrieval, agents)

Practical uses

- Retrieval & extraction
- Structured generation
- Code assist
- Semantic search
- Data cleaning
- Synthetic data / anonymisation



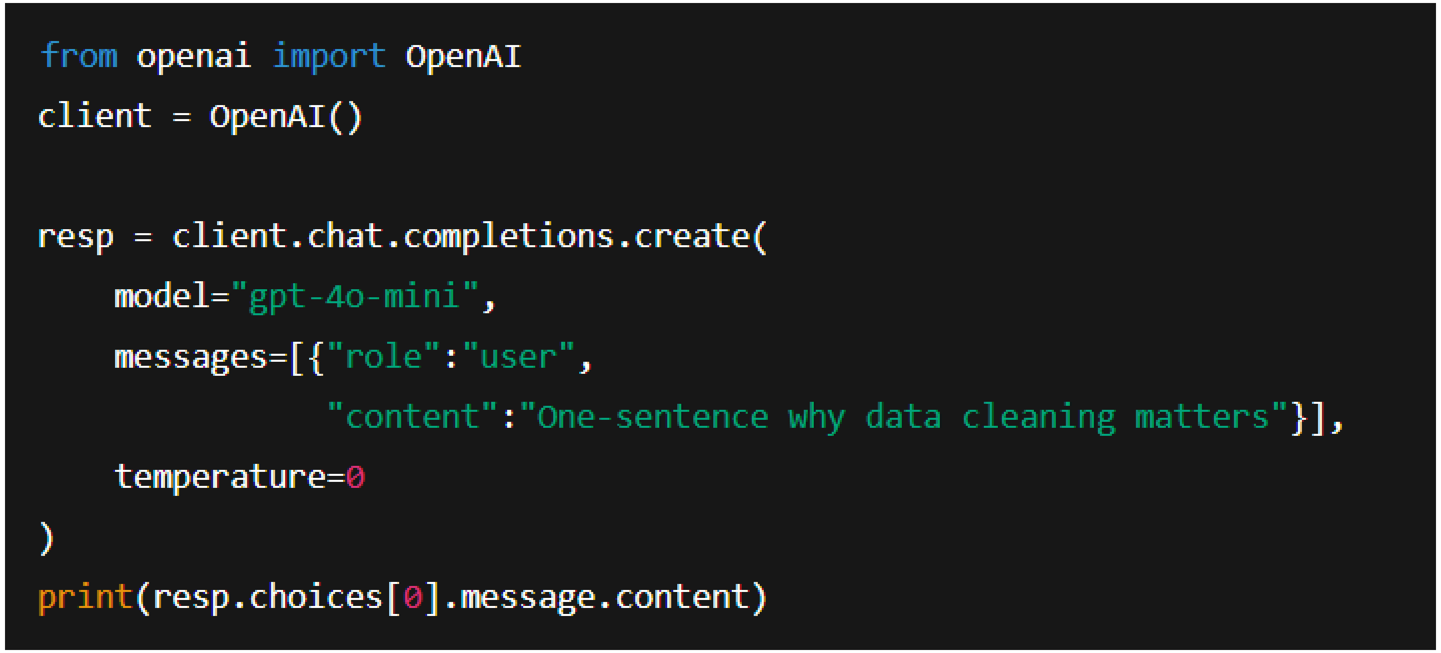
Which one?

- Closed/Open
- Size
- Cost
- Performance
- Tools
- Use case

Five Workflow Axes

- **Retrieval** (pull facts from documents / web)
- **Generation** (create new structured objects)
- **Classification** (label things, e.g., stance, gender, race)
- **Pruning** (filter bad or vague items)
- **Structured Output** (enforce JSON / schema)

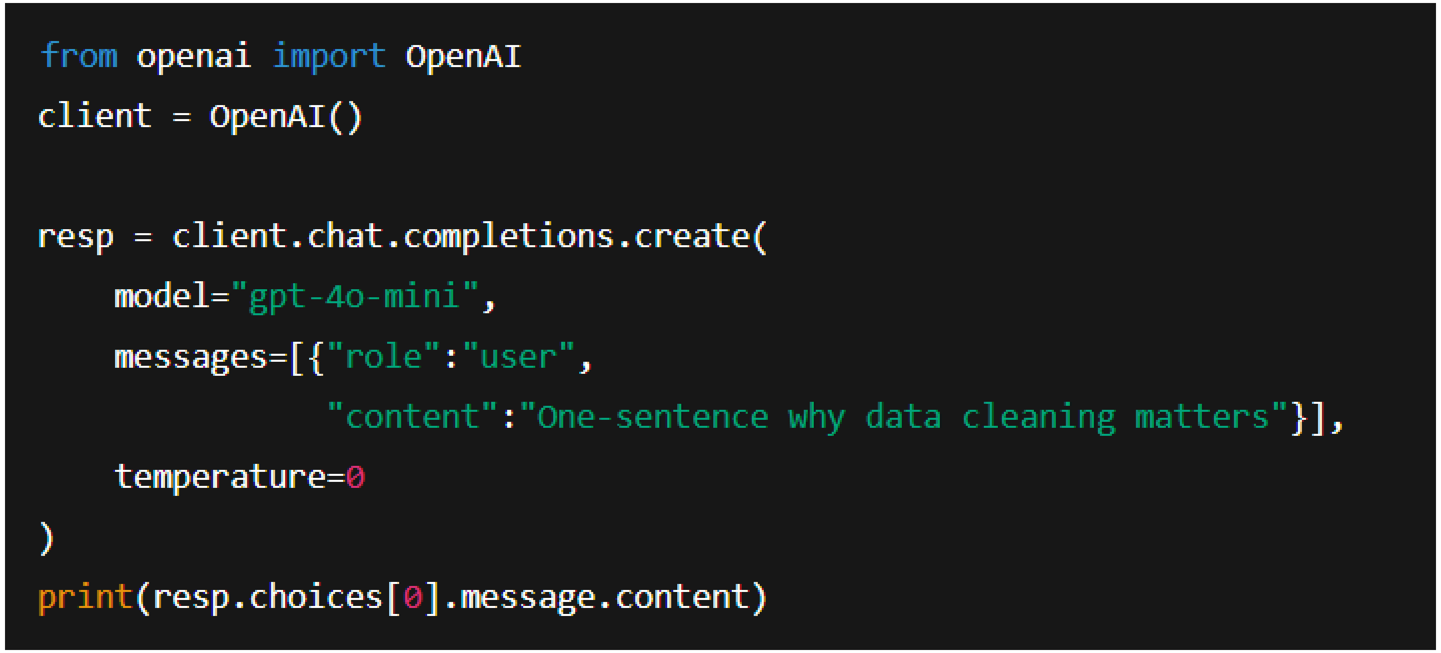
API



```python
from openai import OpenAI
client = OpenAI()

resp = client.chat.completions.create(
    model="gpt-4o-mini",
    messages=[{"role":"user",
               "content":"One-sentence why data cleaning matters"}],
    temperature=0
)
print(resp.choices[0].message.content)
```

API



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```

Useful features:	**What it does & typical use**
temperature 0 → 2 default = 0.7	Controls randomness. • 0 = deterministic (exact repeat) • 0.3 – 0.7 = factual extraction • 0.7 > 1 = brain-storm, diverse, creative output
response_format {"type":"json_schema", ...}	Enforces valid JSON. Model must emit a string that **passes schema validation** or you get a 400-error. *Must-have for tables, edge lists, MCQs, multiple questions*
Batch endpoint client.batches.create(...)	• Upload a JSONL with **≤ 100 MB** lines. • Up to **50,000** requests processed async (24 h window). • Halves the cost

Hello API Demo

- Open **00_api_smoke_test.ipynb**
- Test key (in environment) with basic prompt
- Note output items
- If everything fine, move to any of the next notebooks.

Notebooks overview

Pattern	**Demo notebooks**
Delimited context + extraction	10, 20
Schema-guided generation	30, 50, 80
Vote-based aggregation	60, 70
Embeddings for canonical mapping	40
Heuristic pruning	50

Retrieval

When?

- You have large data
- Keep things grounded
- Quickly clean, tidy and do small tasks
- Best if there is a large corpus and the task can be done by humans

1. Causal Claims in Economics (Garg & Fetzer, 2025)

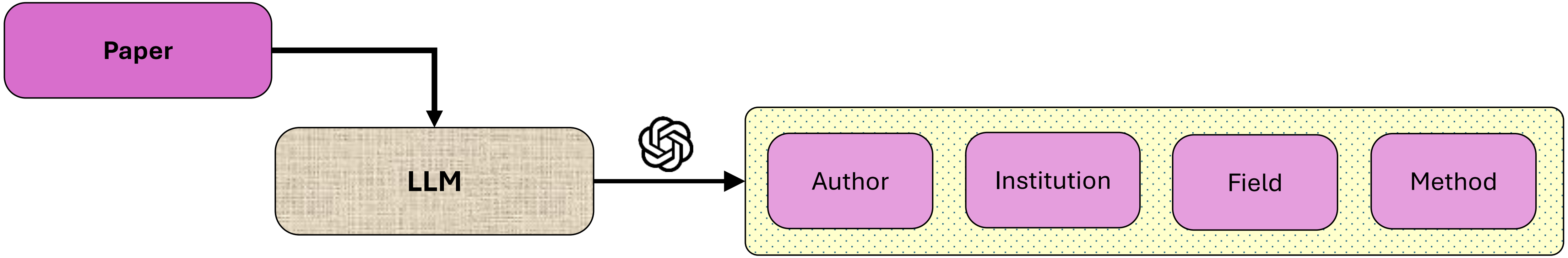
- **10_retrieval_edges.ipynb**
- Goal: cause-effect extraction
  - retrieving causal relationships from an unstructured document
- Input: academic text

  “Studies show lack of sleep causes decreased productivity in workers… High stress levels can lead to sleep deprivation…”
- Prompt:

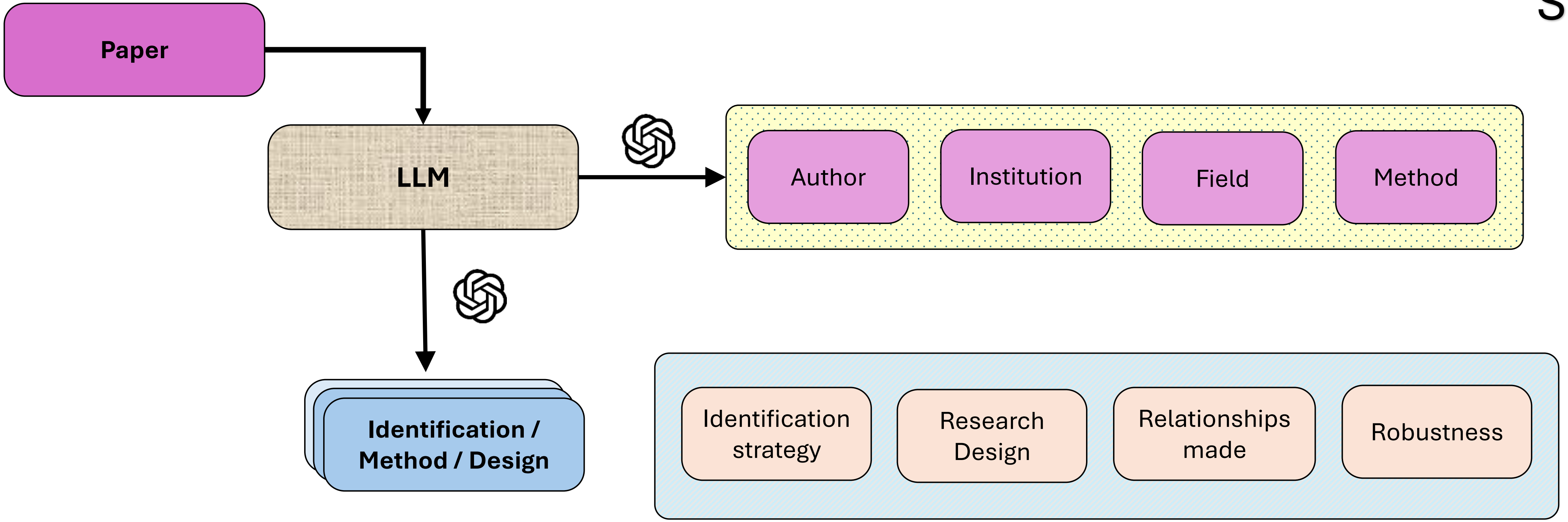
  “Extract all statements of the form X causes Y…”)
- Output format: a network, as edge-list.

  [{"cause": "lack of sleep", "effect": "decreased productivity"},
  {"cause": "high stress levels", "effect": "sleep deprivation"}]

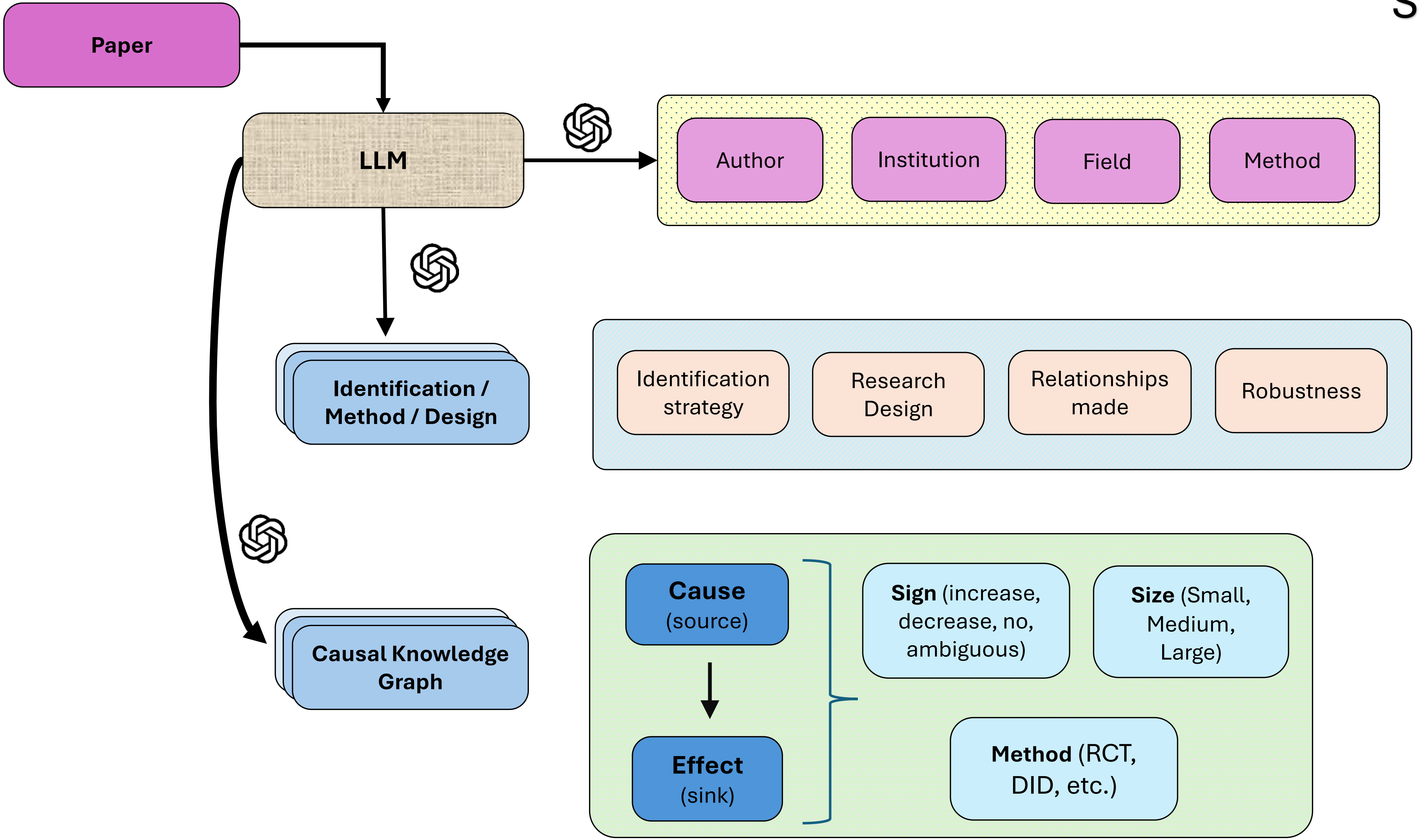
Stage 1



Stage 1


Paper
LLM
Author
Institution
Field
Method
Identification / Method / Design
Identification strategy
Research Design
Relationships made
Robustness

Stage 1



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Causal Knowledge Graph

Cause (source)

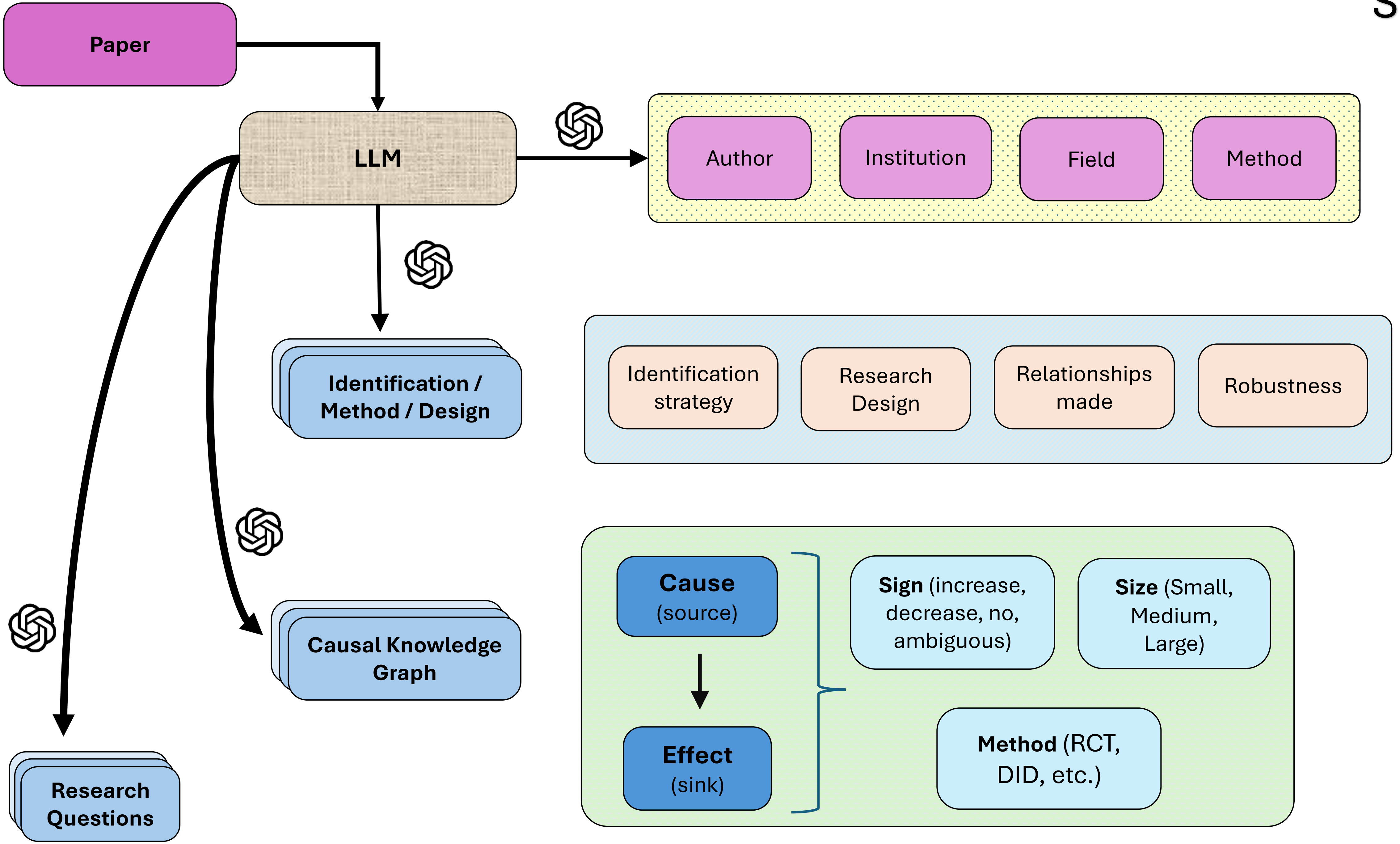
Effect (sink)

Sign (increase, decrease, no, ambiguous)

Size (Small, Medium, Large)

Method (RCT, DID, etc.)

Stage 1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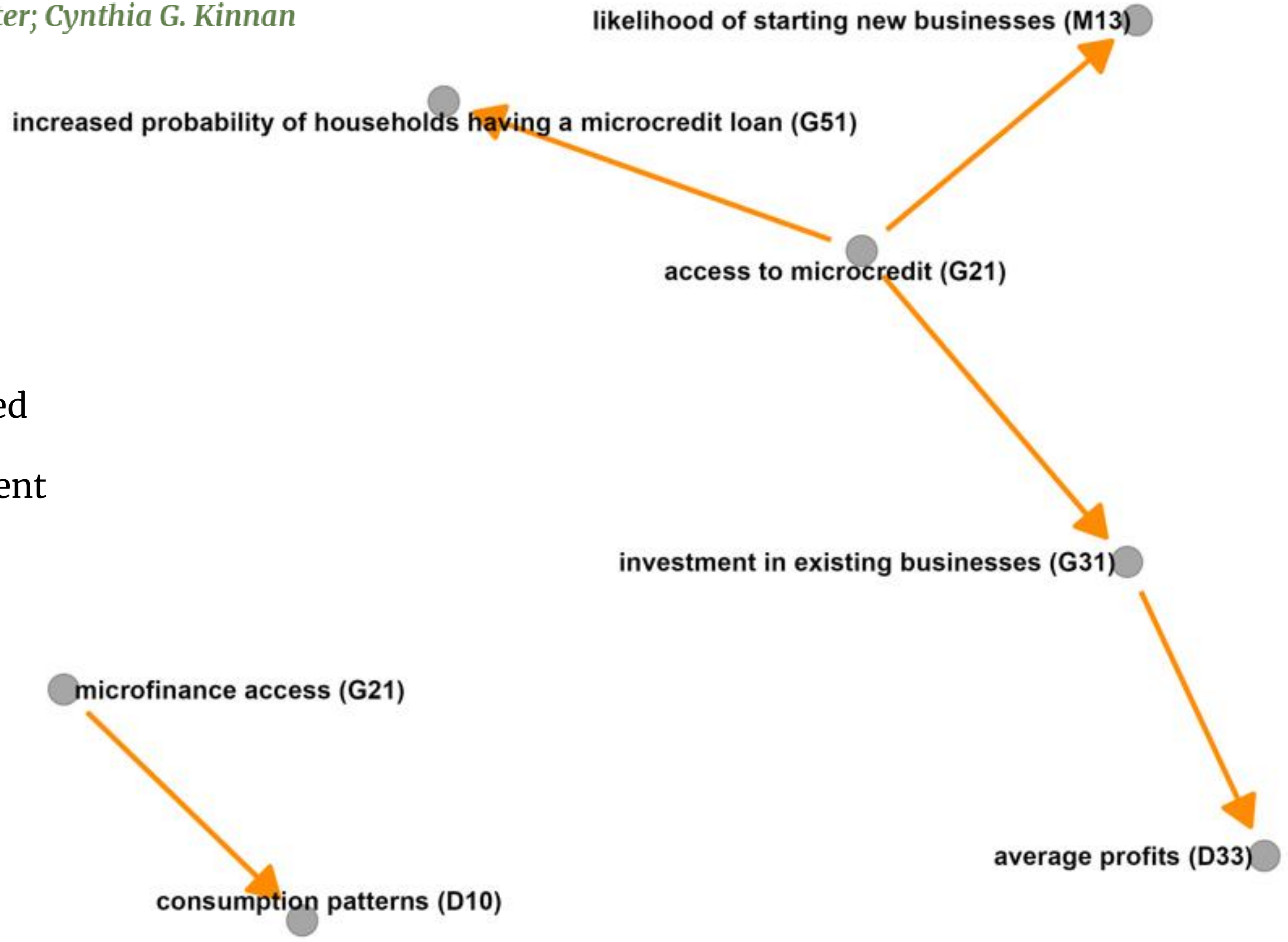
Research Questions

[The Miracle of Microfinance: Evidence from a Randomized Evaluation](#) (2015, AEJ)

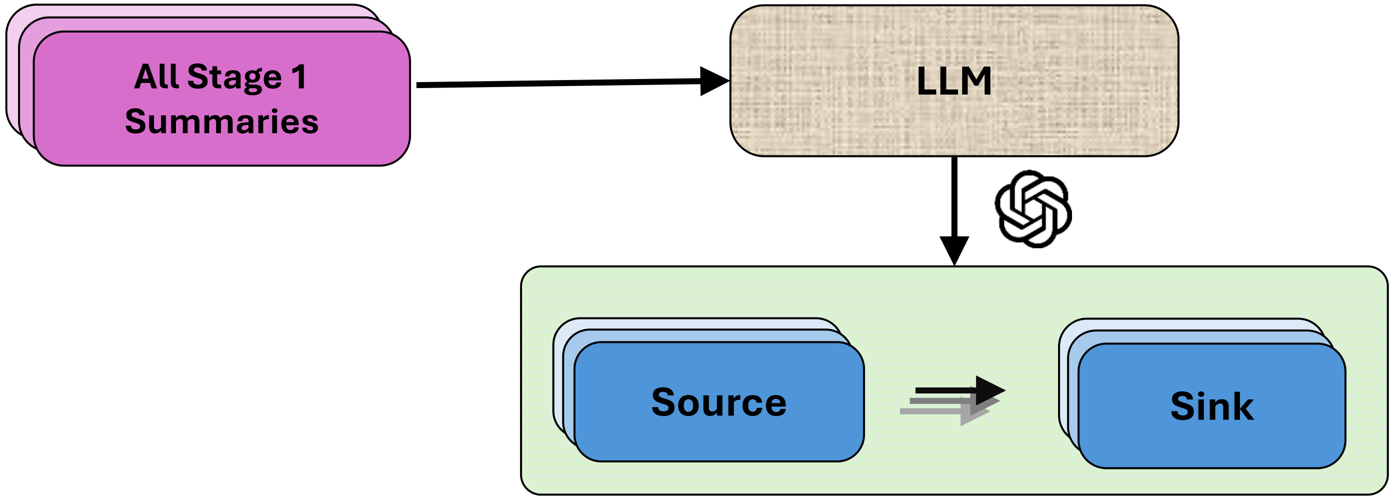
Esther Duflo; Abhijit Banerjee; Rachel Glennerster; Cynthia G. Kinnan


likelihood of starting new businesses (M13)
increased probability of households having a microcredit loan (G51)
access to microcredit (G21)
investment in existing businesses (G31)
microfinance access (G21)
average profits (D33)
consumption patterns (D10)

Summary:

Evaluates the impact of introducing microfinance in India, finding increased borrowing and investment but limited effects on consumption and development outcomes.

Stage 2



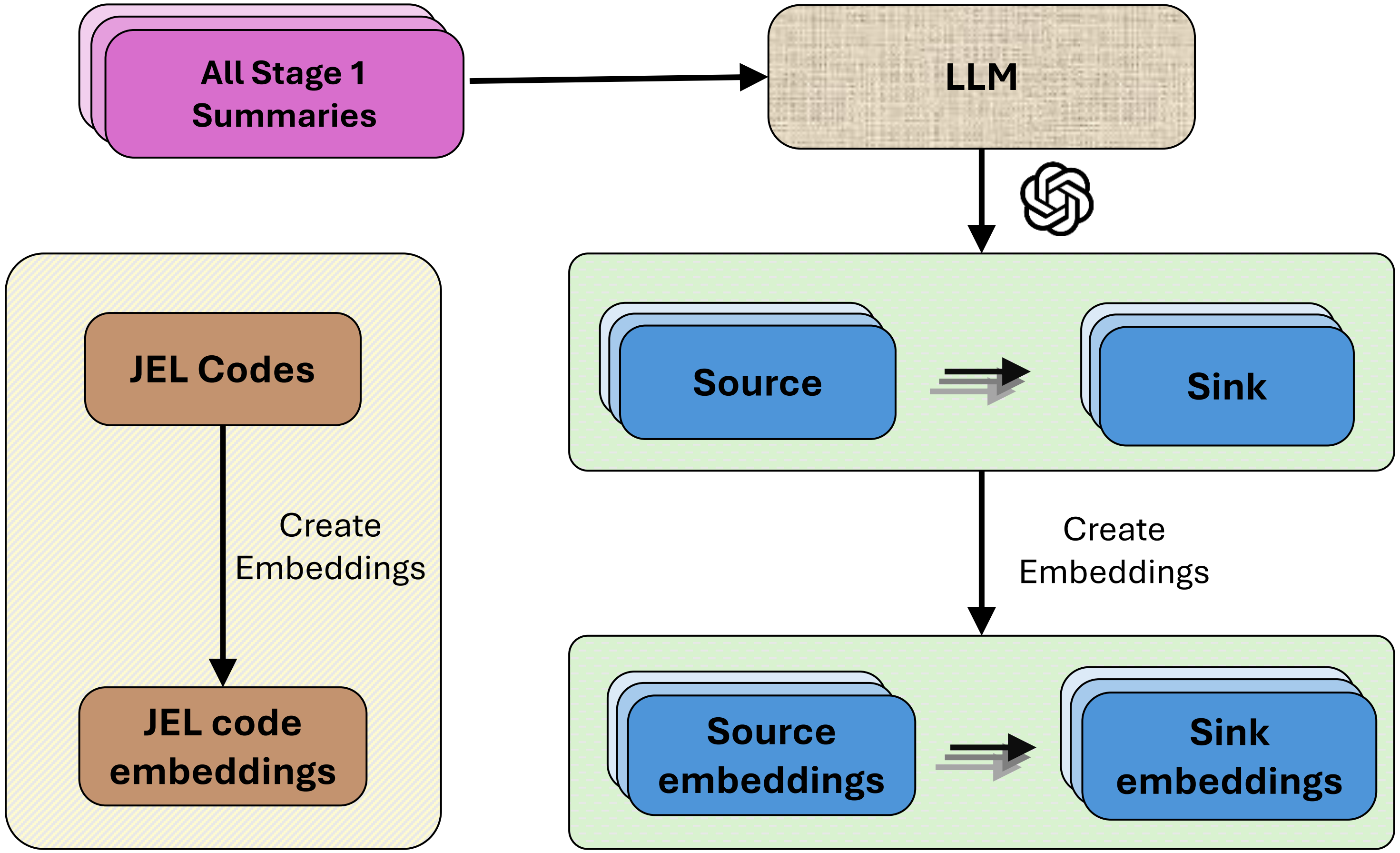
Edge level

Method (RCT, DID, etc.)

Sign (increase, decrease, no, ambiguous)

Size (Small, Medium, Large)

Stage 2



Edge level

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Sign (increase, decrease, no, ambiguous)

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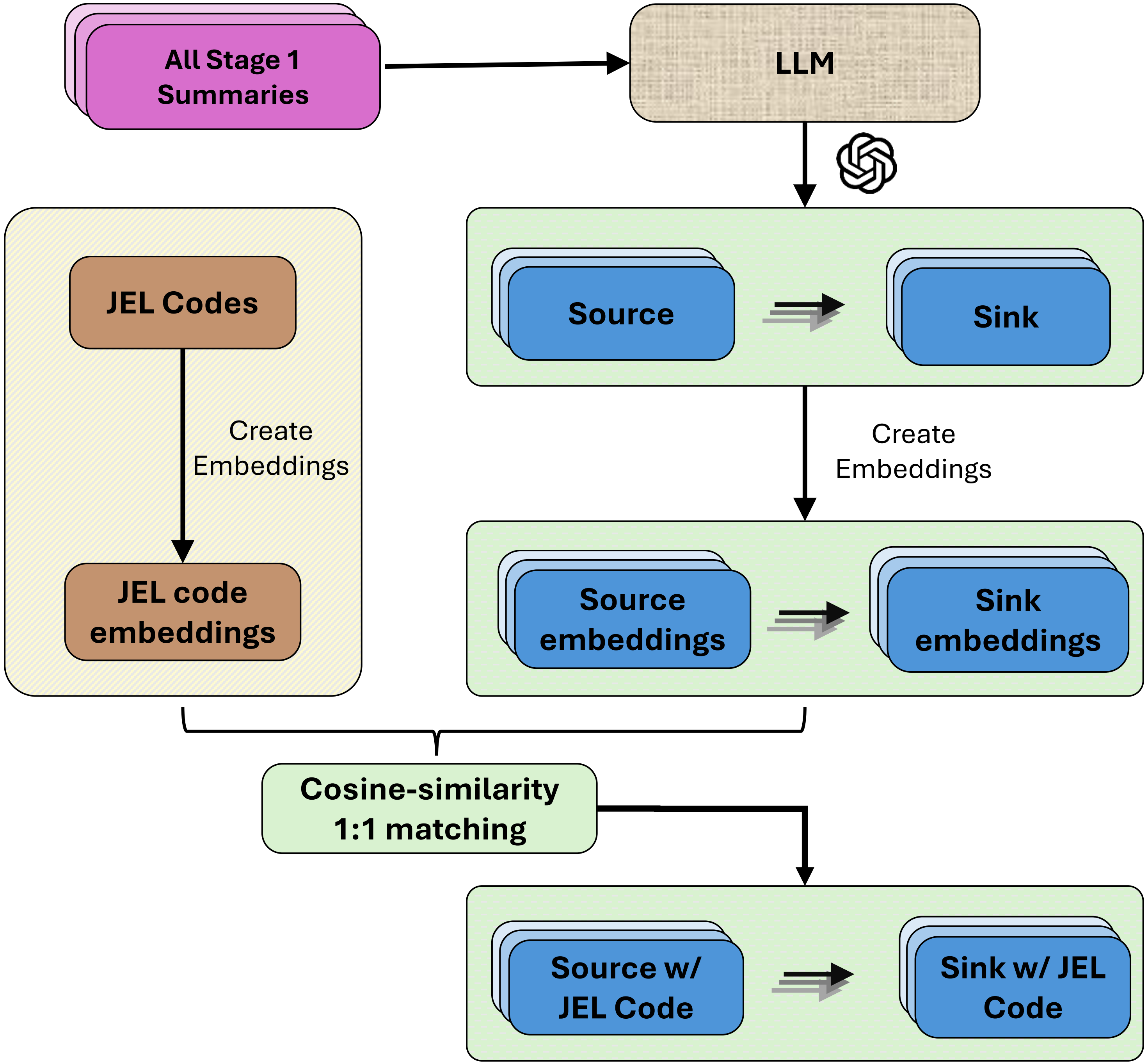
Stage 2



All Stage 1 Summaries

LLM

JEL Codes

Create Embeddings

JEL code embeddings

Source

Sink

Create Embeddings

Source embeddings

Sink embeddings

Cosine-similarity 1:1 matching

Source w/ JEL Code

Sink w/ JEL Code

Edge level

Method (RCT, DID, etc.)

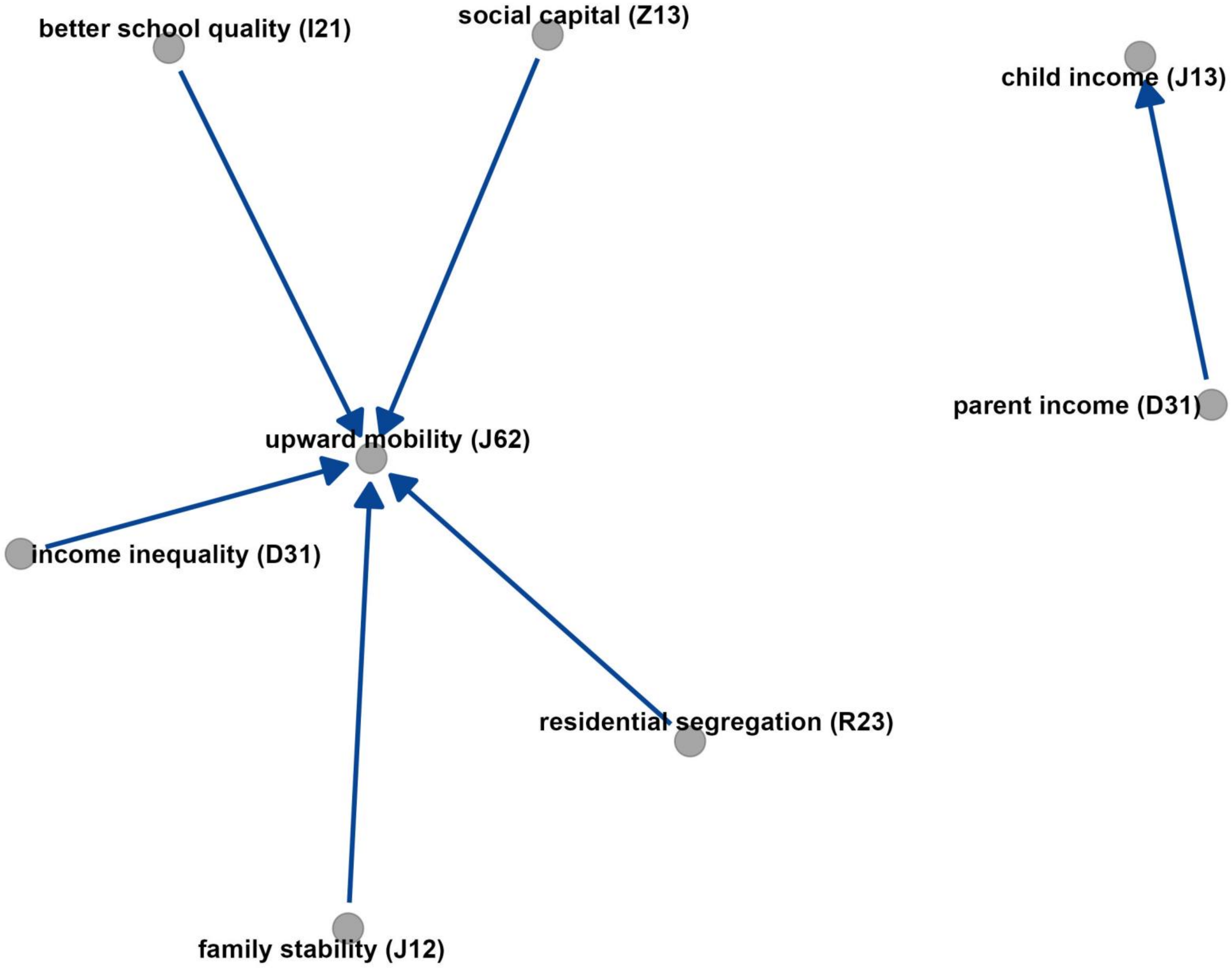
Sign (increase, decrease, no, ambiguous)

Size (Small, Medium, Large)

Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States (2014, QJE)

Raj Chetty, Nathaniel Hendren, Patrick Kline, Emmanuel Saez

Summary:
Analyzes U.S. intergenerational income mobility, identifying factors like less segregation and better schools that correlate with higher upward mobility.



Advanced Retrieval: Two-Stage Approach

- **20_two_stage_retrieval.ipynb**
- In reality, documents are large and not-standardised.
- To ease the task for LLM, let's break task into parts.
- a.k.a. prompt-chaining or chain-of-thought – pre-cursor to "reasoning" models
- Stage 1: curate or summarise the large and complex document into a few lines or paragraphs of content for stage 2.
- Stage 2: extract structured output from this smaller, curated input.

Generation

- Take advantage of the large training corpus of LLMs

- Has access to common crawl, policy and company documents, and much more

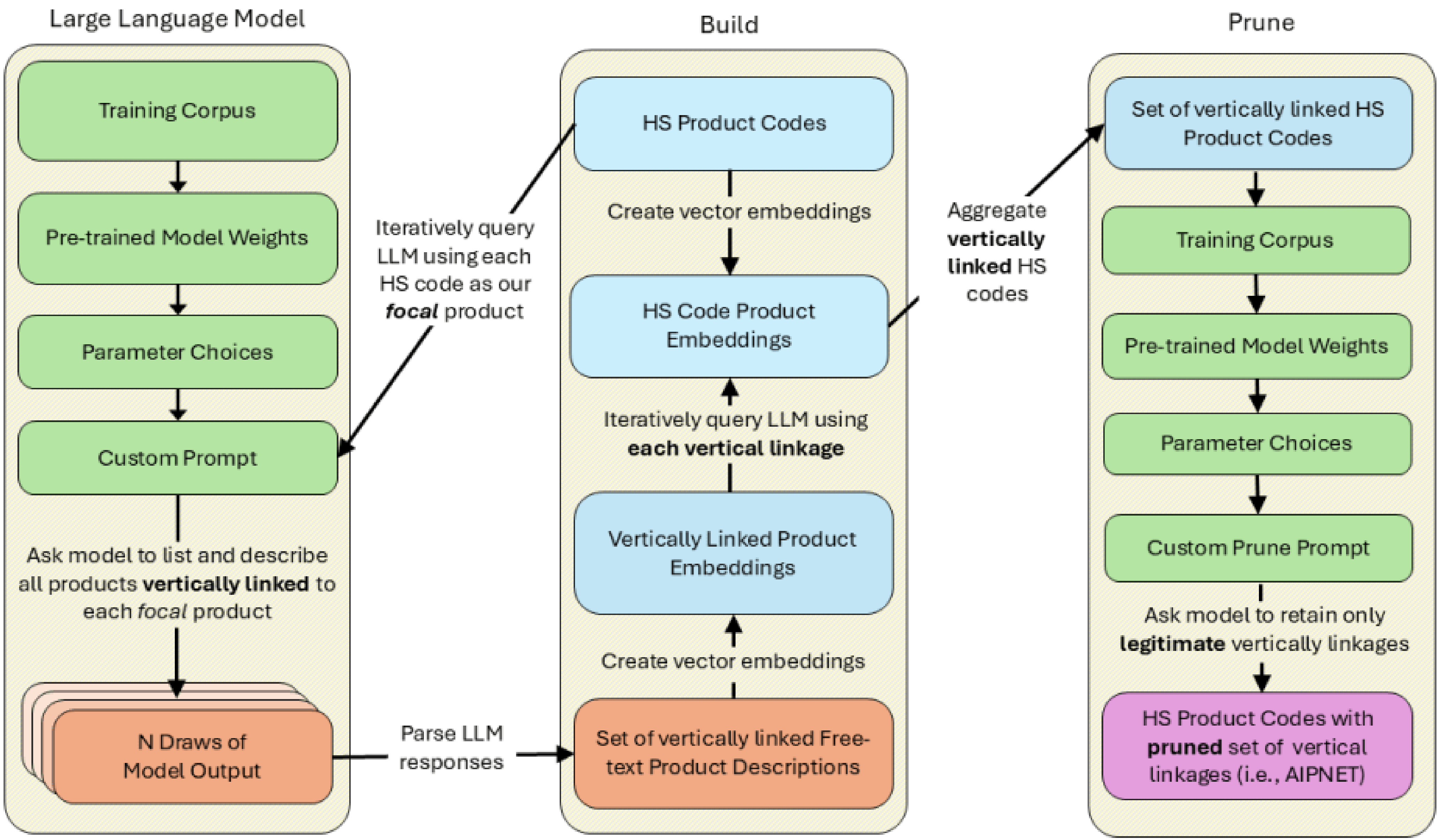
- Your creativity is the limit

- Validation becomes paramount as there are reasons to be sceptical

2. AI-Generated Production Network (Fetzer et al., 2024)

- **30_supply_chain_generation.ipynb**
- Task: We'll ask the model to outline a production process (a mini supply chain) for a specific product, using only the model's knowledge.
- Input: focal product, e.g. an electric car
- Prompt:
  - Generate a step-by-step production network for an electric car, from raw materials to final assembly, as a numbered list
- Output:
  - can be asked free form (for a stage 2) or directly as structured edge-list.

The full pipeline



Large Language Model

Training Corpus

Pre-trained Model Weights

Parameter Choices

Custom Prompt

Ask model to list and describe all products **vertically linked** to each *focal* product

N Draws of Model Output

Iteratively query LLM using each HS code as our ***focal*** product

Parse LLM responses

Build

HS Product Codes

Create vector embeddings

HS Code Product Embeddings

Iteratively query LLM using **each vertical linkage**

Vertically Linked Product Embeddings

Create vector embeddings

Set of vertically linked Free-text Product Descriptions

Aggregate **vertically linked** HS codes

Prune

Set of vertically linked HS Product Codes

Training Corpus

Pre-trained Model Weights

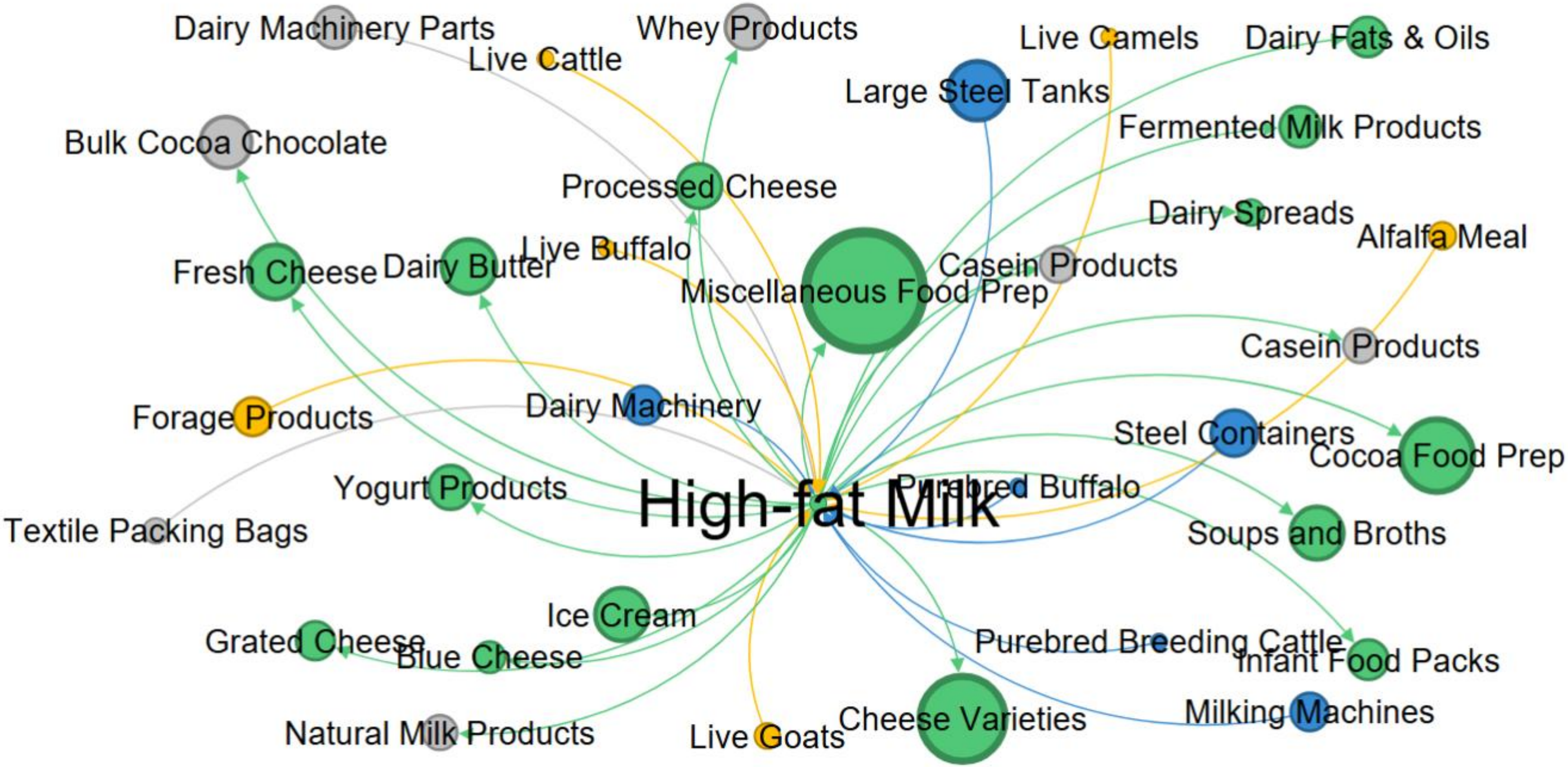
Parameter Choices

Custom Prune Prompt

Ask model to retain only **legitimate** vertically linkages

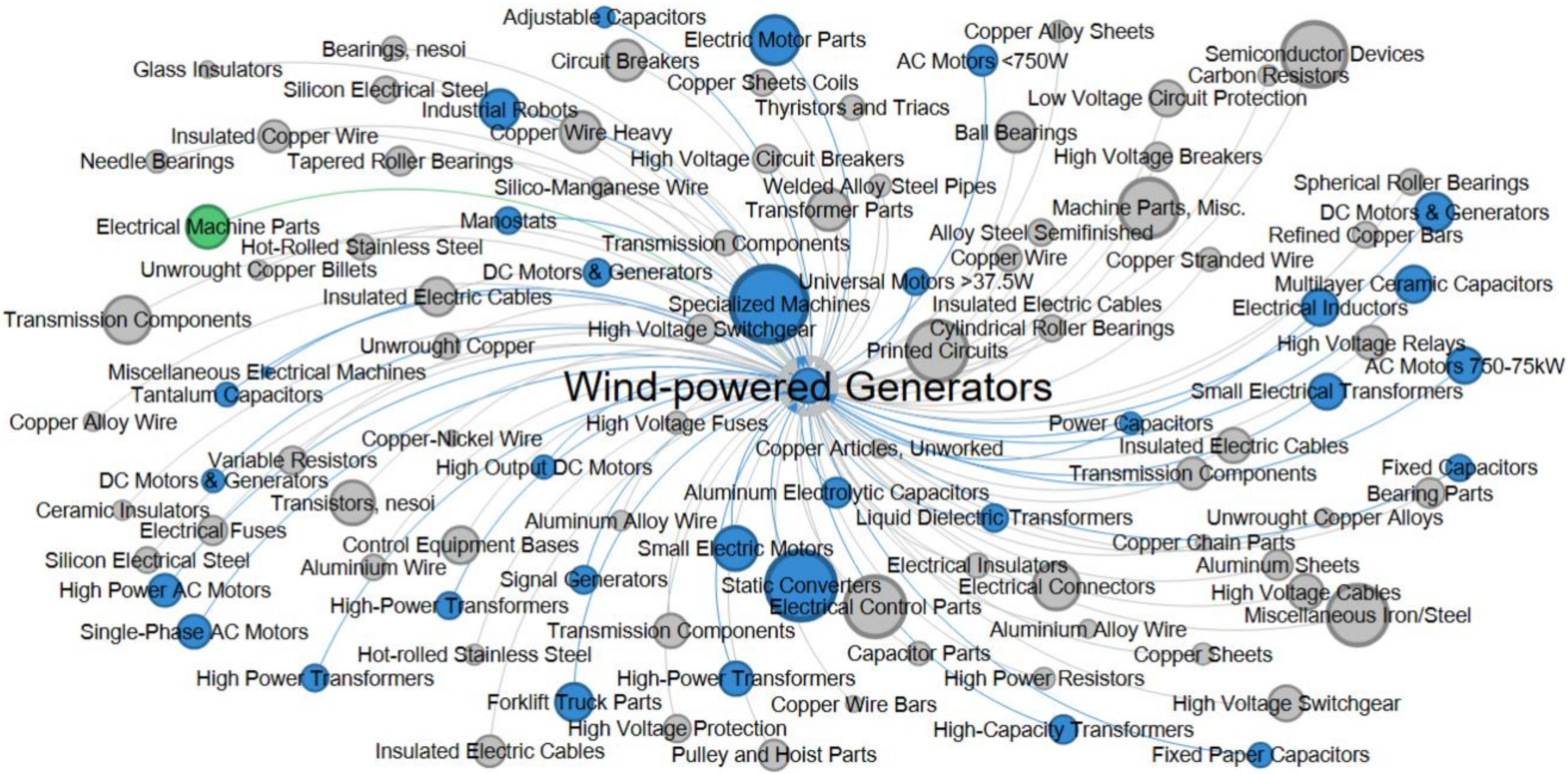
HS Product Codes with **pruned** set of vertical linkages (i.e., AIPNET)

Example: High-fat Milk

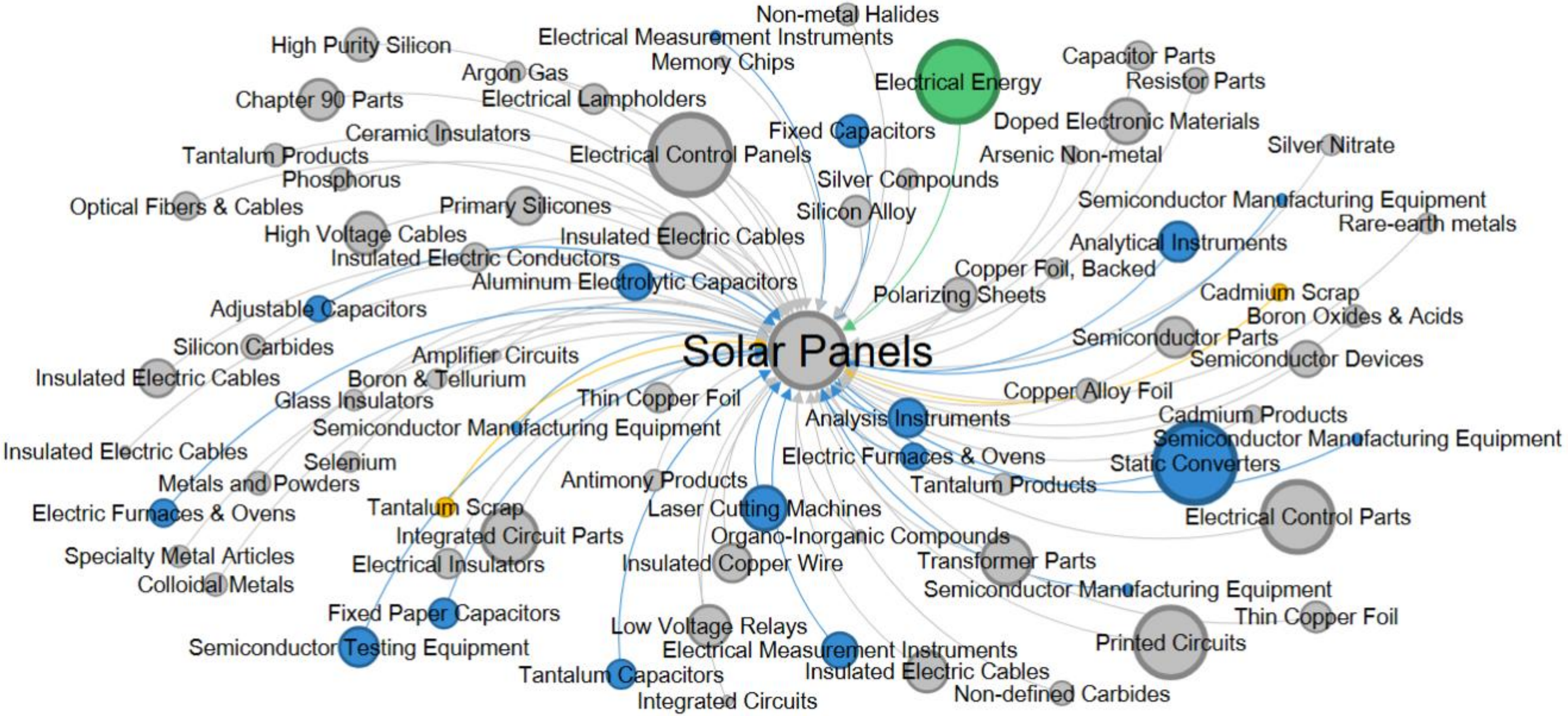


Building AIPNET II: Wind-powered Generators

aipnet.io



Building AIPNET III: Solar Panels



On generation…

- Model’s answer may be **plausible** (it matches common knowledge) but might not be exhaustive.
- What if we ask the same prompt N (=10) times.
    - This may theoretically increase recall, but perhaps loose precision?
- We could consider a build-prune approach (as in aipnet.io)
    - Collate all N response
    - Ask LLM in second stage if a given input-output relationship is true or false. Repeat for all edges.
    - This is basically a “retrieval” step as we give our own content to LLM, but more accurately call it “pruning” or more generally, “classication”.

3. Embeddings #1: Matching

- **40_embeddings_mapping.ipynb**
- Why embed?
  - Map free-text nodes to controlled vocabularies (JEL, HS6).
  - Enables aggregation, visualization, and cross-document linking.
- Workflow
  - OpenAIEmbeddings → up to 3072-dimension semantic vectors
  - Apply to both “sides”, i.e., the LLM free-text and controlled vocabulary.
  - Cosine similarity matrix
  - argmax or top-k threshold
  - Manual spot-check → iterate

3. Embeddings #2: Anomaly / Novelty

- **41_embeddings_novelty_detection.ipynb**
- Why detect novelty?
  - Identify distinctive or outlier products in embedding space.
  - Useful for innovation discovery, anomaly detection, or taxonomy expansion
- Workflow
  - Embed all product descriptions
  - Compute **pairwise cosine distances** among embeddings.
  - Score **isolation.** For instance, use:
    – *KNN distance* (average distance to nearest neighbors)
    – *IsolationForest* anomaly score
  - **Visualise:** Cluster with *KMeans*; visualize in 2-D (PCA).
  - Inspect top-quartile outliers → potential “new” or “unique” items.

Generation #2: keyword dictionary

- **50_dictionary_generation_pruning.ipynb**
- Political Expression of Academics on Twitter (Garg & Fetzer, 2025b)
- Now we'll have the model act as a subject matter expert that generates important keywords for specific topics
- Prompt

  Generate 5 key phrases for each of the following topics… Format as JSON with the topic as keys
- Output

  Climate Change: Carbon Emissions, Paris 2015, COP24, Global Warming

Pruning once more

- Caution:
  - that while the keywords are good suggestions, they might be non-exhaustive or might include non-discriminative terms

- Consider adding a stage 2 “pruning” step:

  “Does this term always refer to this topic when seen in a piece of text?”

- Ask N times, then pick majority vote

- Post-process, e.g., substring pruning → Final dictionary

4. Classification (Notebook 60)

- **60_tweet_stance_classification.ipynb**
- Simple and popular
- Once more: Political Expression of Academics on Twitter (Garg & Fetzer, 2025b)
- Prompt:

  Classify the following tweet as pro / anti / neutral / unrelated towards given topic. Topic is '{TOPIC}'. Tweet is '{TWEET}'
- 3 independent calls → pick majority vote
- Agreement metric (1 = full, 0 = none) to flag noisy tweets
- Generation then Retrieval: You can pre-filter tweets by keyword dictionary, then classify stance.

4. Demographic Attribute Classification

- **70_gender_name_classification.ipynb**

Task	Labels	Iterations	Agreement Heuristic
Gender	Male / Female / Unclear	3	modal vote
Race/Ethnicity	White / Non-White / Unclear	3	modal vote

- Exactly the same API pattern; swap schema & prompt
- Be aware of ethical implications and limitations. N
  - Names can be ambiguous; cultural bias; always mark ‘Unclear’ option when substantial disagreement.

5. More generation, testing the limits

- **80_company_innovation_generation.ipynb**
- Give a company name and geography
- Ask for large set of info, e.g., patents, products, processes etc.
- Main use case: to get alternative data when official data is scarce or not collected due to resource constraints.
- It is work-in-progress. Requires more validation

Best Practices on Retrieval and Generation

- Prompt clarity
- Specifying response_format
- Controlling randomness: temperature, multiple-iterations (majority voting)
- Replication with other LLMs
- Pipeline iteration: ask for justifications, examples, etc. in early iterations to understand what LLM understands

Scaling & Cost Considerations

- **Batch** API → chunking helpers in notebooks
- Minimize tokens, while keeping information same:
  - **Information dense** input, structured efficient output
- **Pilot**: start with cheapest model (e.g., gpt-4o-mini) before scaling
  - Factor in potential iteration
- **Parallelism**: Async calls vs. waiting loop

Batching LLMs

- **90_batching_and_translation.ipynb**

- Benefits: parallel, 50% cheaper, no rate-limit juggling

- Cons:
    - Slightly more complex code.
    - have to wait up to 24 hours.
        - In practice, it can be faster as it is asynchronous
        - Often runs in minutes, or few hours.
        - Faster on weekends / off-peak times.

Any questions about what we just did?

Validation

- Validate at prompt level
- Validate at measurement level
- Eye-ball validation
- Automated and/or human validation
- Within-model stability: Modal agreement (e.g., stance, gender, race)
- Across-models overlap

Validate at prompt level + Human Validation

(e.g. Garg and Fetzer, 2025, Nature Human Behaviour)

- ✓ Most convincing
- ✓ Use gold-standard labels, ideally human labelled.

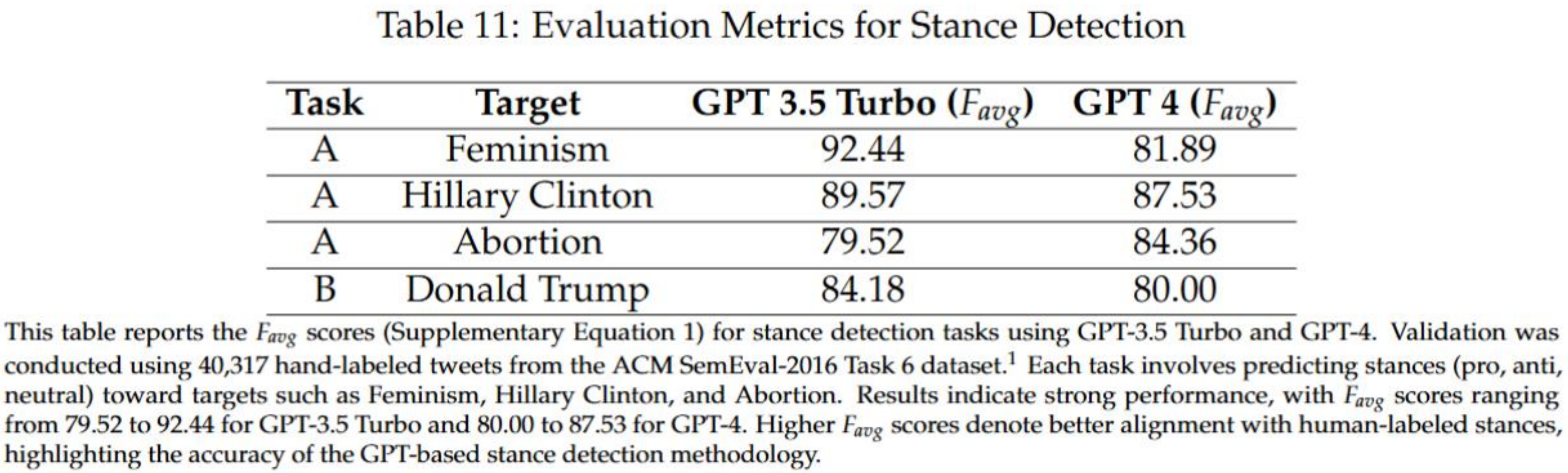


Table 11: Evaluation Metrics for Stance Detection

Task	Target	GPT 3.5 Turbo (F_{avg})	GPT 4 (F_{avg})
A	Feminism	92.44	81.89
A	Hillary Clinton	89.57	87.53
A	Abortion	79.52	84.36
B	Donald Trump	84.18	80.00

This table reports the F_{avg} scores (Supplementary Equation 1) for stance detection tasks using GPT-3.5 Turbo and GPT-4. Validation was conducted using 40,317 hand-labeled tweets from the ACM SemEval-2016 Task 6 dataset.[1] Each task involves predicting stances (pro, anti, neutral) toward targets such as Feminism, Hillary Clinton, and Abortion. Results indicate strong performance, with F_{avg} scores ranging from 79.52 to 92.44 for GPT-3.5 Turbo and 80.00 to 87.53 for GPT-4. Higher F_{avg} scores denote better alignment with human-labeled stances, highlighting the accuracy of the GPT-based stance detection methodology.

Validate at prompt level + Automated Validation

(e.g. Garg and Fetzer, 2025, Nature Human Behaviour)

- ✓ Complementary to human validation
- ✓ Cheap to do, and provides inter-LLM stability

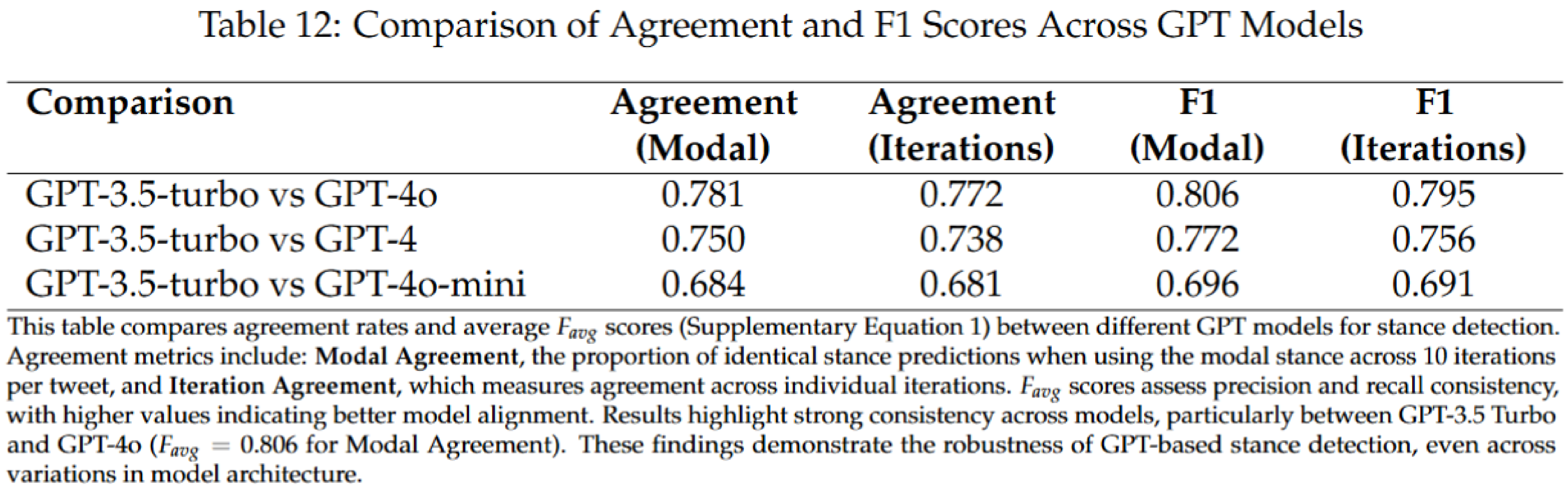


Table 12: Comparison of Agreement and F1 Scores Across GPT Models

Comparison	Agreement (Modal)	Agreement (Iterations)	F1 (Modal)	F1 (Iterations)
GPT-3.5-turbo vs GPT-4o	0.781	0.772	0.806	0.795
GPT-3.5-turbo vs GPT-4	0.750	0.738	0.772	0.756
GPT-3.5-turbo vs GPT-4o-mini	0.684	0.681	0.696	0.691

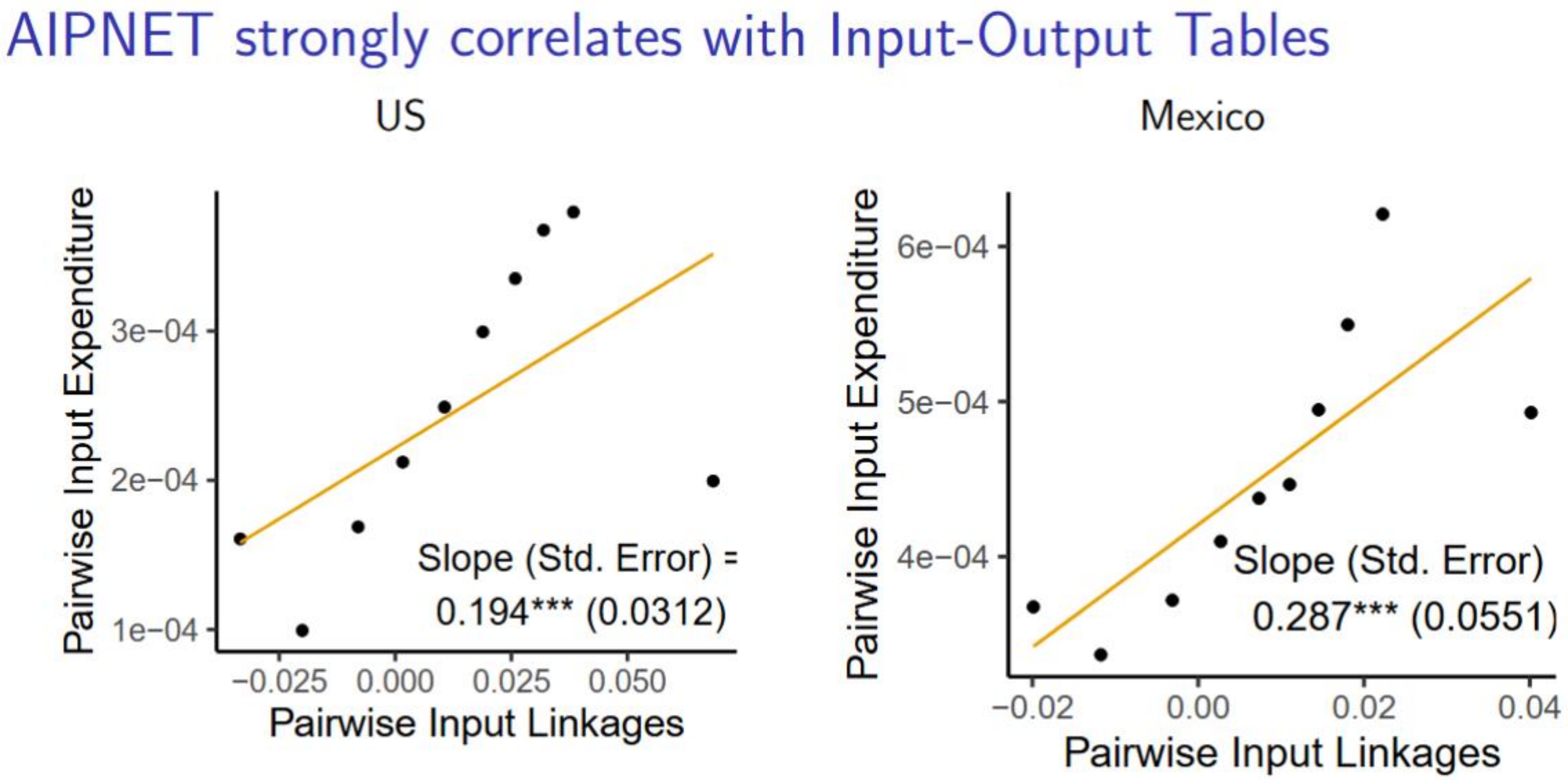
This table compares agreement rates and average F_{avg} scores (Supplementary Equation 1) between different GPT models for stance detection. Agreement metrics include: **Modal Agreement**, the proportion of identical stance predictions when using the modal stance across 10 iterations per tweet, and **Iteration Agreement**, which measures agreement across individual iterations. F_{avg} scores assess precision and recall consistency, with higher values indicating better model alignment. Results highlight strong consistency across models, particularly between GPT-3.5 Turbo and GPT-4o ($F_{avg} = 0.806$ for Modal Agreement). These findings demonstrate the robustness of GPT-based stance detection, even across variations in model architecture.

Validate at measurement level (e.g. Fetzer et al., 2024)

- ✓ Compare your measurement with next-best available alternative

- ✓ Ideally, this alternative is well-used and well-known

- ✓ In our case, it is the industry level, rather than product level, input/output table.



AIPNET strongly correlates with Input-Output Tables

US

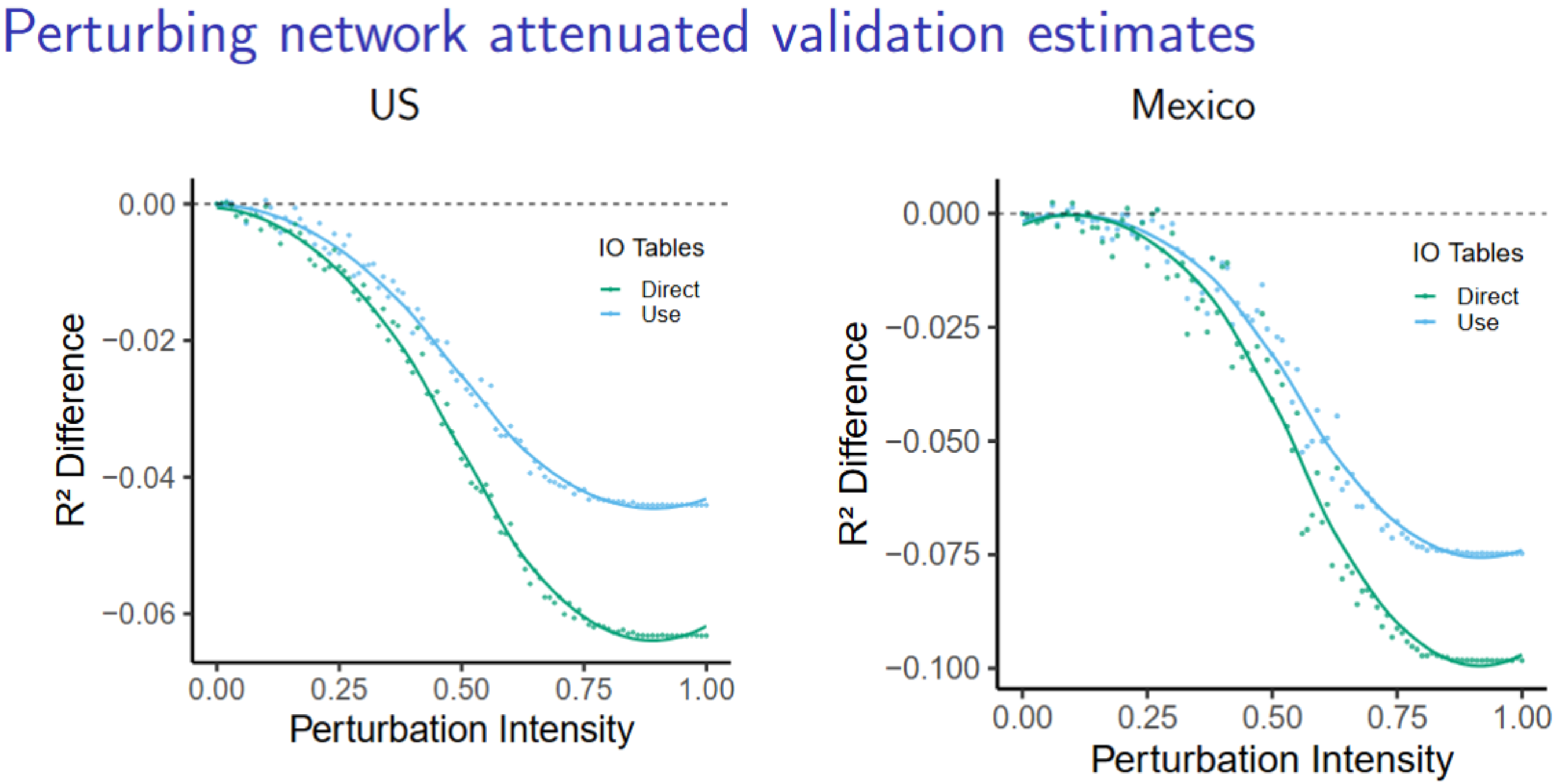
Slope (Std. Error) =
0.194*** (0.0312)

Mexico

Slope (Std. Error)
0.287*** (0.0551)

Validate at measurement level (e.g. Fetzer et al., 2024)

- ✓ If you add noise to your measurement, does it loose signal?
- ✓ If yes, then your new measurement is not totally random!
- ✓ It is a lower bar to clear but still adds some confidence.



Perturbing network attenuated validation estimates

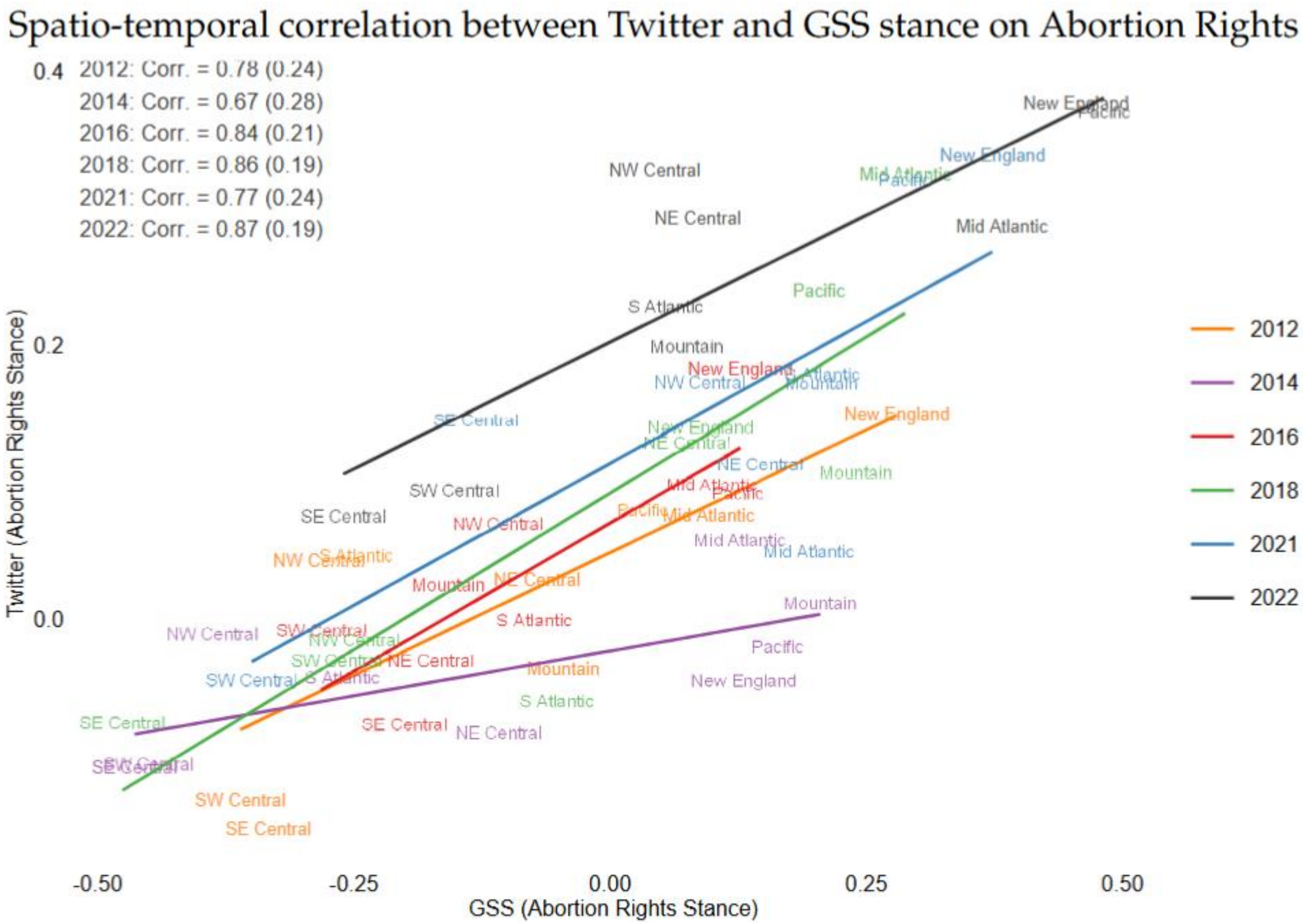
US

Mexico

Validate at Measurement Level

(e.g. Garg and Fetzer, 2025, Nature Human Behaviour)

- ✓ Generally, next best available alternative is easy to access
- ✓ However, it has limitations, e.g. it is available for a given time period or region.
- ✓ You might have to subset your LLM output to that context
- ✓ You might have to do a bespoke LLM exercise for it

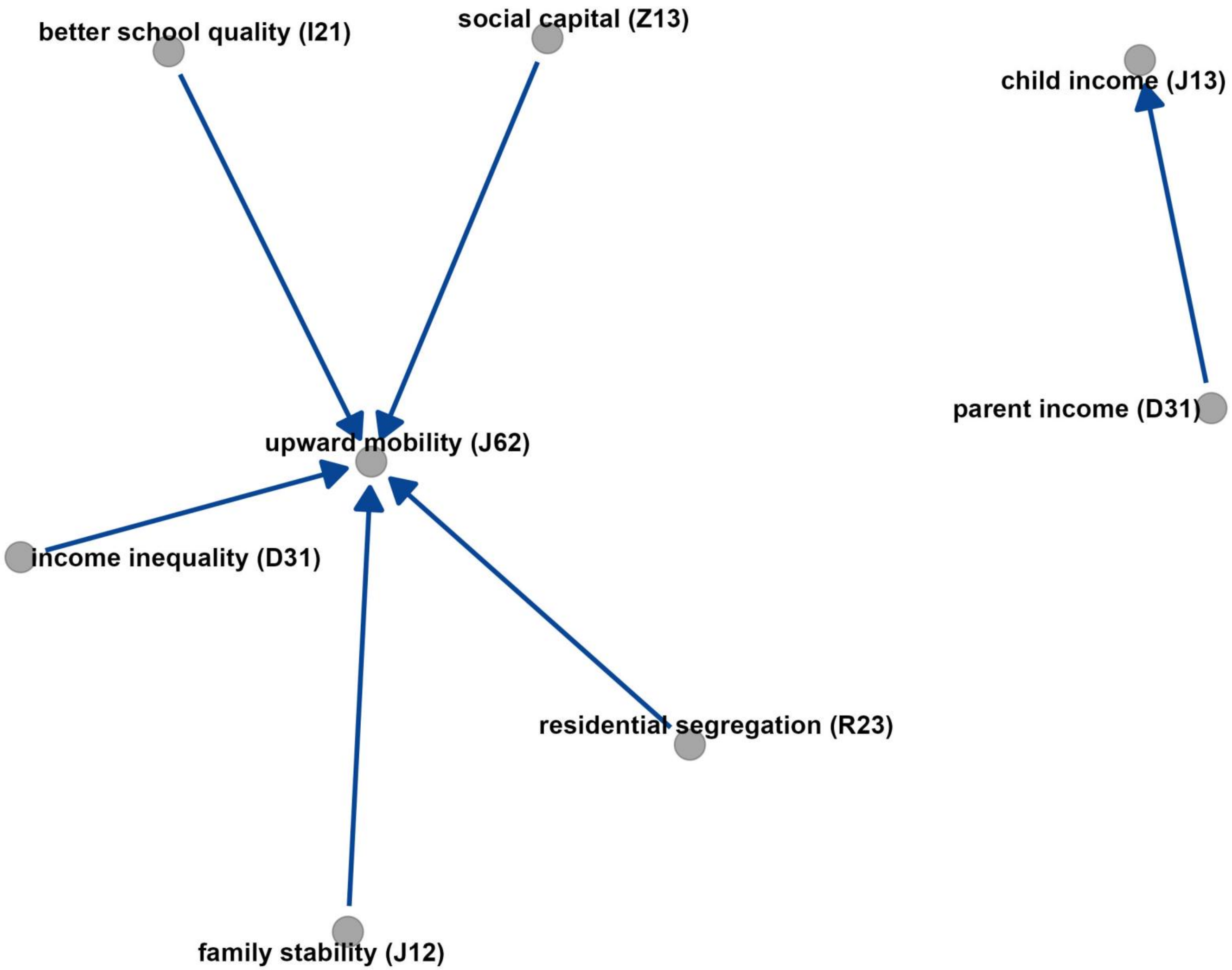


Eye-ball validation (e.g. Garg and Fetzer, 2025)

Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States (2014, QJE)

Raj Chetty, Nathaniel Hendren, Patrick Kline, Emmanuel Saez

- ✓ Look at (and show) some well-known examples to see if they make sense



Conclusion

1. Same API, many paradigms (generation, retrieval, classification).
2. Small-scale demos scale linearly with batching + schema enforcement.
3. Embeddings unlock alignment to standardized codes.
4. Simple aggregation heuristics (majority vote, overlap) go a long way.
5. Always build validation and ethics checks into the pipeline.

Questions?

- Your use cases?
- Any others ideas for application?

- Please share your experiences

Get in touch: prashant.garg@imperial.ac.uk www.prashantgarg.org

Links to my LLM works:

- Retrieval/Classification:
  1. Leveraging large language models for large-scale information retrieval in economics (a VoxEU article)
  2. Causal Claims in Economics. (Non-technical summary)
  3. On Bob Dylan: A Computational Perspective
  4. Artificial Intelligence health advice accuracy varies across languages and contexts

- Generation:
  1. AI-Generated Production Networks (Non-technical summary)

- Retrieval/Classification + Generation:
  1. Political Expression of Academics on Social Media (Non-technical summary)
  2. Politicized Scientists: Credibility Cost of Political Expression on Twitter

Some resources on use of LLMs in Economics

- Stephen Hansen’s Github (code and review article): Text Algorithms in Economics

- Melissa Dell’s JEL article: Deep learning for Economists

- Anton Korinek’s JEL article: Generative AI for Economic Research: Use Cases and Implications for Economists

- Experimenting with LLM: Automated Social Science: Language Models as Scientist and Subjects and other works by John Horton