Language Models can quickly analyse and compare thousands of policy documents

A LLM Analysis of European Environmental Policy Diffusion Networks

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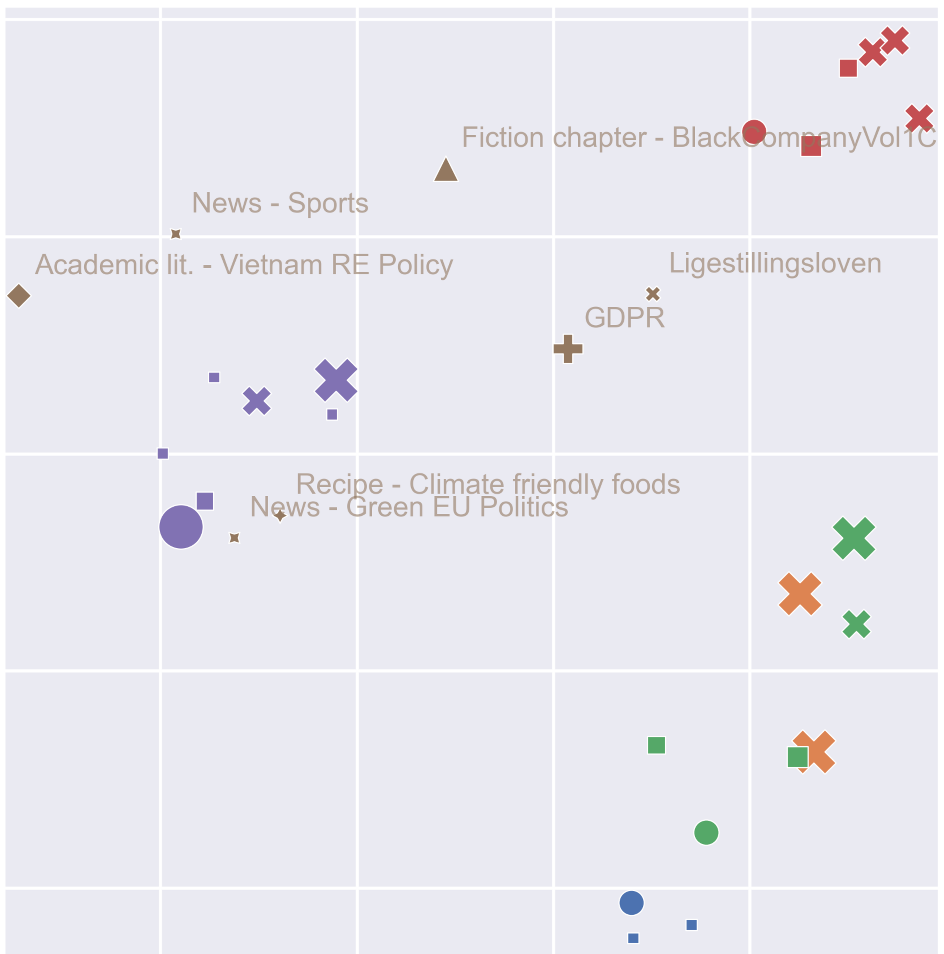
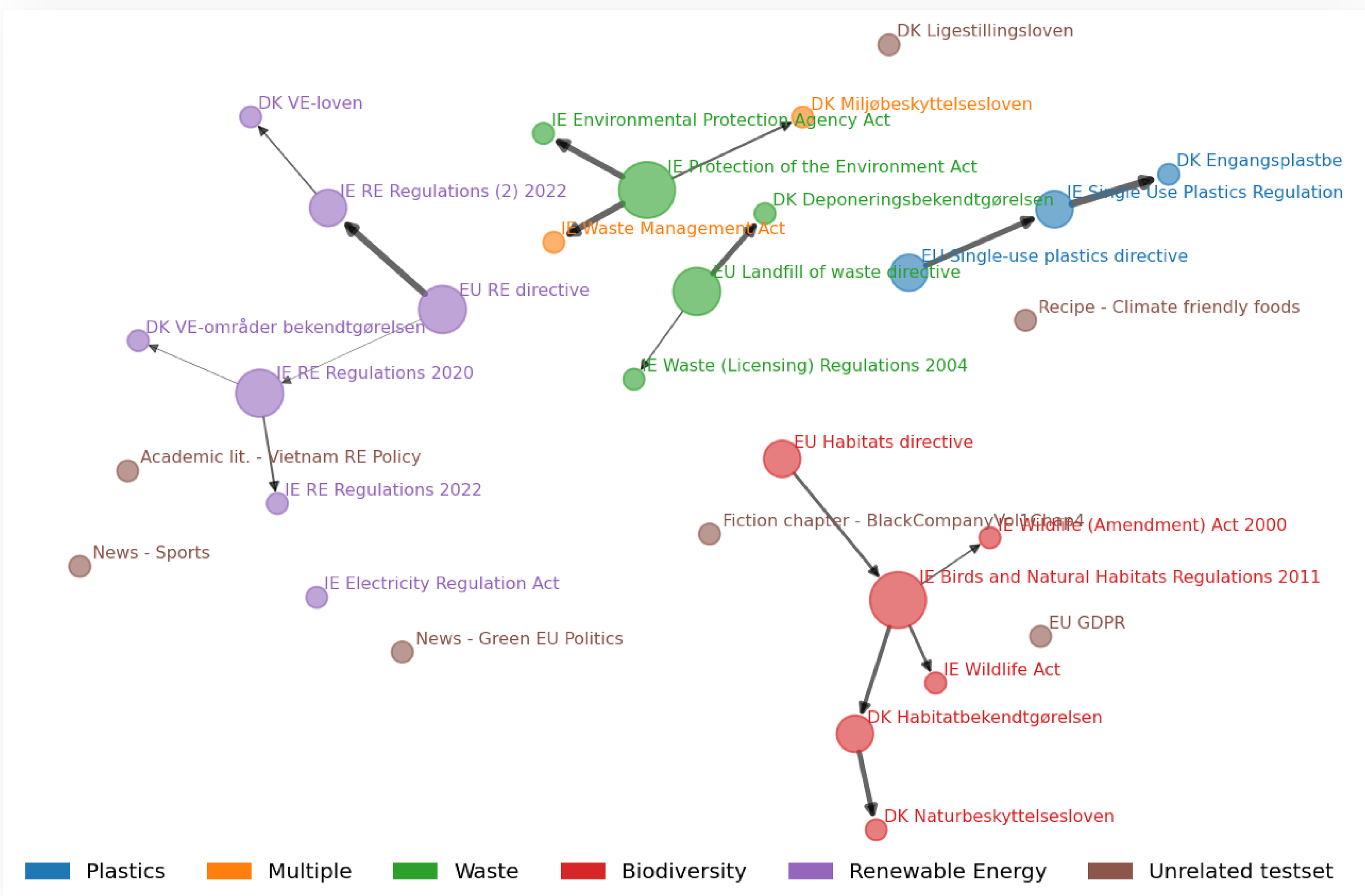
Background: This methodologically-focused project attempted to use language models for large-scale text-as-data analysis, to characterise policy documents. It investigated why some environmental policies spread and inspire similar policy in other countries – including whether certain countries act as environmental pioneers or frontrunners, consistently inspiring others.

Result 1: Language Models can compare contents and quantify the similarity of (policy) documents despite differences in language, subject area and wording. Representations and clusters of 30 legal documents from 3 countries correspond well to original policy domains (colors).

Result 2: Networks can be drawn with edges between the most similar documents, representing suspected policy inspiration. Central nodes, i.e. policies successfully diffusing, can be investigated for characteristics which increase diffusion and author-frontrunner status.





Methods

1 Data preparation

2 Language Model Processing

Extract policy objectives and summaries of policy documents. Generate embedding vector representations for each document.

3 Data Analysis

Compare embedding pairs for similarity. Construct policy networks based on pair similarity and document age.

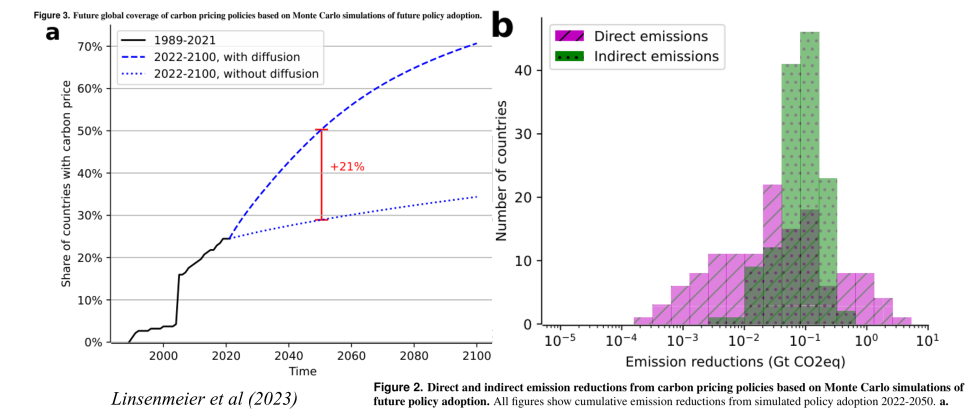
Data → Cleaning, Pre-processing → LLM → Embedding Model → Similarity Analysis → Network Analysis

Limitations: Language Models sensitive to prompting when probing finer document details, and hesitant to object to task given. Validation of outputs difficult, but not impossible.

Applications: Improvements over classical text-as-data techniques. Input to mixed-methods approaches, in e.g. case selection and bias checks.

Scan the QR-code to download the full thesis

Research has documented policy diffusion, inspiration and learning: E.g. Recent study showed carbon pricing uptake and emissions reductions increased by diffusion.

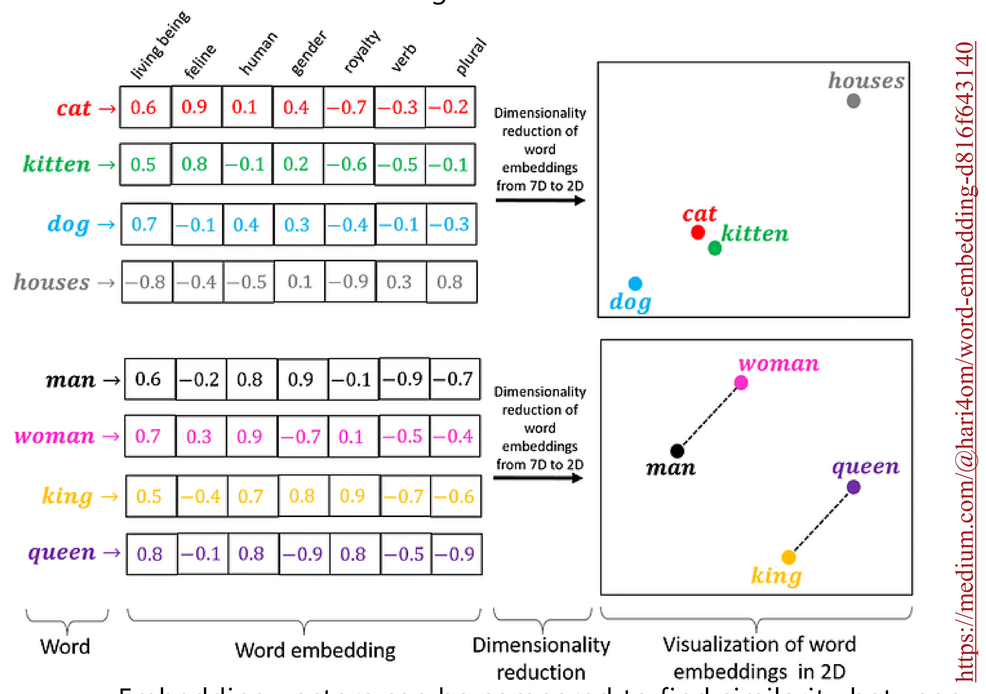


Linsenmeier et al (2023)

Advances in AI language modelling allow fast, detailed analysis of policy document content so far not seen in large-scale quantitative policy diffusion studies – thereby enabling insight into characteristics that allow policies to diffuse.

Embedding Models

- Embedding model encodes text data as high-dimensional numerical vectors
  - Vector values can be thought of as attributes for text data.
  - Similar texts' embeddings have similar values



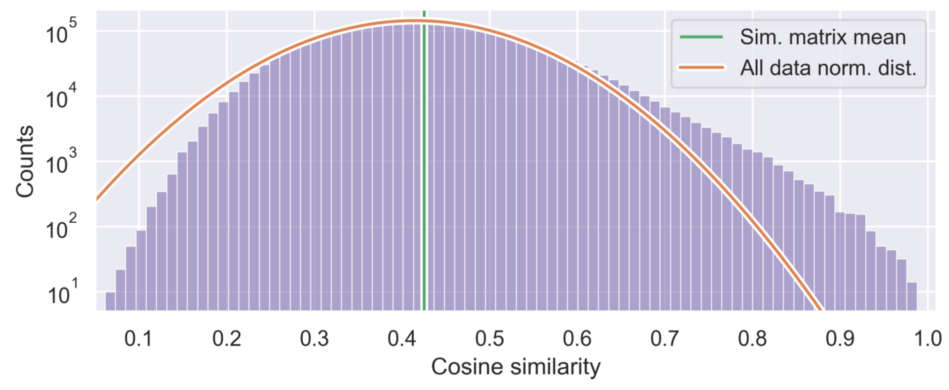
- Embedding vectors can be compared to find similarity between embedded document pairs, often represented in similarity matrices

Why not just compare text directly?

Primary reason for LLM treatment is to extract policy **substance** – to avoid comparisons of similarity based on different document types, language and standard phrasing and boilerplate, e.g.:

> "We, Frederik the Tenth, by the Grace of God King of Denmark, do hereby declare: The Parliament has passed and We, by Our consent, ratified the following law: (...)"

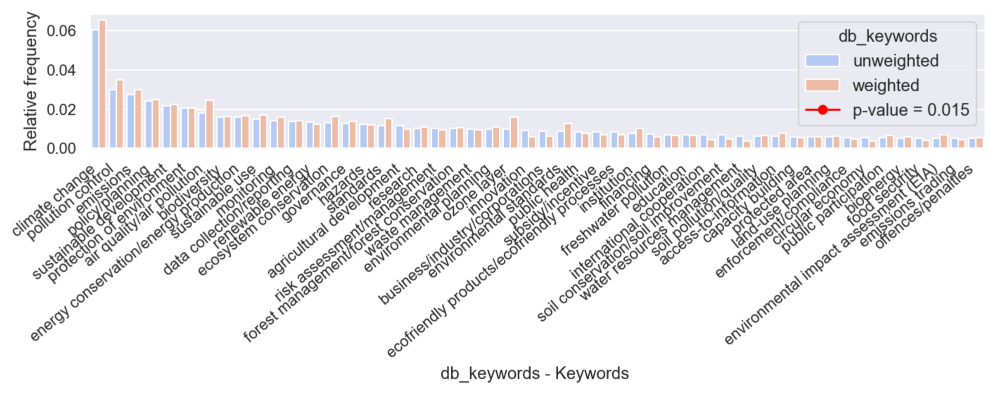
Policy document pair similarity is statistically higher than random variation alone can explain, indicating policy inspiration and diffusion.



For a network constructed based on N~1800 European policy documents related to climate change, document importance (assessed based on inspiration diffusion from it) averaged across countries shows no sign of Denmark having a pioneering or frontrunner status when it comes to inspiring other countries' policy.

	Mean Doc. Importance	Mean rank	Max Doc. Importance	Max rank	Num of docs
Slovakia	2.34	1	10.19	3	11
Malta	1.92	3	6.16	18	24
Czechia	1.92	4	8.83	9	18
Germany	1.68	7	10.11	4	86
Italy	1.62	9	8.66	11	76
France	1.62	10	8.98	7	78
Finland	1.62	11	8.30	12	51
Denmark	1.61	13	10.32	2	45
Norway	1.55	15	7.00	16	36
European Union	1.48	20	7.40	14	176
UK	1.46	21	8.75	10	180
Sweden	1.26	37	3.31	34	27
Netherlands	1.22	39	3.14	35	19
Russia	1.20	40	2.32	41	37

Keyword frequency distributions in documents which have diffused (orange – "weighted") can be compared to the full database and checked for significant differences via permutation tests. A better method likely involves using network inference to check for various diffusion-increasing characteristics among smaller sub-populations/in different contexts.



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