Analysis of city council meeting minutes

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Project Overview

Datapolitics Project

- **Objective**: Develop an automated detector to identify and categorize projects implemented by local authorities.
- **Scope**: Examine around **20,000** geothermal energy PDF documents from the past five years. Ensure the methodology can be applied to various local projects

Data Overview

- **doc_id**: Unique identifier for each document.
- **url**: Original source URL of the document.
- **cache**: Link to the cached PDF version.
- **fulltext**: Link to the plain text version of the document.
- **nature**: Automatically classified document type (e.g., deliberation, minutes).
- **published**: Publication date of the document.
- **entity_name**: Name of the local authority responsible for the document.
- **entity_type**: Type of the entity (e.g., municipality, intercommunality).
- **geo_path**: Hierarchical administrative path indicating the geographical scope.

Tasks

Filtering and Classification Process

1. **First Level: Binary Filter**
    - **Concerns a Geothermal Project**
    - **Unrelated to a Geothermal Project**
2. **Second Level: Project Stages**
    - Idea/Wish
    - Preliminary Studies
    - Budget Voted for the Definitive Project
    - Implementation in Progress
    - Implementation Completed
3. **Final Level: Data Extraction**
    - Initial Budget
    - Final Cost
    - Estimated Duration
    - Actual Duration

Almost 20.000 documents with no annotated target variable.

Options to deal with the annotation process:

- Manual annotation.
- Prompting.
- Generating the annotation via clustering with LLM Embeddings [3].

Dataset	Embed.	Best Alg.	F1S	ARI	HS	SS	CHI	Total
DS1	TF-IDF	k-means	0.67	0.38	0.46	0.016	4	0/5
	BERT	Spectral	**0.85**	**0.60**	0.63	**0.118**	25	3/5
	OpenAI	k-means	0.84	0.59	**0.64**	0.066	13	1/5
	LLaMA-2	k-means	0.41	0.09	0.17	0.112	**49**	1/5
	Falcon	k-means	0.74	0.39	0.48	0.111	34	0/5
DS2	TF-IDF	Spectral	0.82	0.63	0.58	0.028	8	0/5
	BERT	AHC	0.74	0.58	0.53	0.152	37	0/5
	OpenAI	AHC	**0.90**	**0.79**	**0.75**	0.070	19	3/5
	LLaMA-2	k-means	0.51	0.21	0.25	0.137	69	0/5
	Falcon	k-means++	0.45	0.26	0.30	**0.170**	**85**	2/5
DS3	TF-IDF	Spectral	0.35	0.13	0.28	-0.002	37	0/5
	BERT	k-means	0.43	0.25	0.44	0.048	412	0/5
	OpenAI	k-means	**0.69**	**0.52**	**0.66**	0.035	213	3/5
	LLaMA-2	AHC	0.17	0.11	0.26	0.025	264	0/5
	Falcon	k-means	0.26	0.15	0.30	**0.071**	**1120**	2/5
DS4	TF-IDF	k-means	0.29	0.13	0.48	0.034	17	0/5
	BERT	k-means	0.35	0.24	0.55	**0.072**	61	1/5
	OpenAI	k-means	**0.38**	**0.26**	**0.58**	0.053	42	3/5
	LLaMA-2	k-means	0.21	0.11	0.40	0.053	88	0/5
	Falcon	k-means++	0.27	0.16	0.48	0.071	**92**	1/5

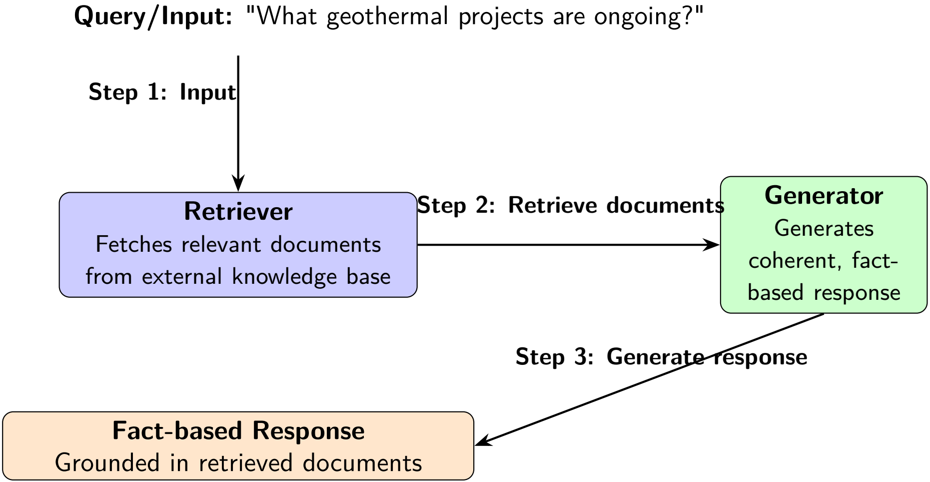
Results from Petukhova et al. (2024)

Next step: train the classifier

Considerations when training the classifier with automatically generated labels:

- Validating the labels generated: manual and automatic approaches.
- Training with label noise [4].

RAG (Retrieval-Augmented Generation) Workflow: A Simplified View



Why and How to use RAG in our project

WHY RAG?

- **Handling Document Complexity**
  The large volume of documents is diverse in format and content.
- **Relevant NLP Tasks**
  Ensures high-quality, contextually accurate results for tasks like classification and extraction.

HOW TO USE RAG

- **Application in Our Project:**
  - Document Filtering: Use the retriever to pull relevant documents from a dataset of 20,000 PDFs.
  - Classification and Stage Identification: Use the generator to classify document stages.
  - Information Extraction: Extract budget and timelines conditioned on relevant document sections.

References: Lewis et al. (2020)[2], Izacard & Grave (2021)[1]

References

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