Perspectiva - How to assess the quality of the extraction of ideas performed by an LLM?

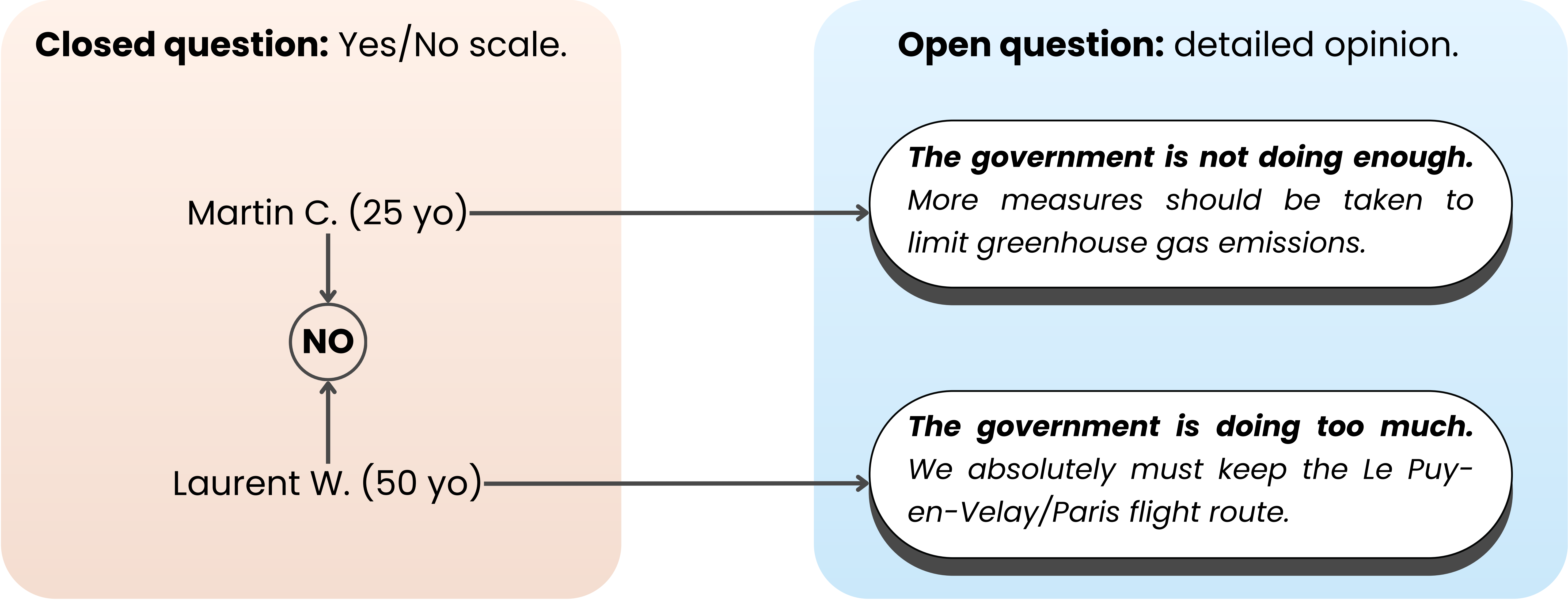
Application to public consultations with open questions

Matthias Mazet, Garance Malnoë & Yannis Petit
with Cyril François

I. Contextualisation

- **Public consultations** = good way to know what citizens think about a particular issue.
  - Particularly useful for elected officials and public services.

- Example of question: ***"Do you agree with the government's current policy on environment?"***



Closed question: Yes/No scale.

Martin C. (25 yo)

NO

Laurent W. (50 yo)

Open question: detailed opinion.

The government is not doing enough. *More measures should be taken to limit greenhouse gas emissions.*

The government is doing too much. *We absolutely must keep the Le Puy-en-Velay/Paris flight route.*

I. Contextualisation

- Examples of public consultations in France: [1]

Fig. 1 - CCPLC logo

- 150 contributors.
- €5 million.

Fig. 2 - GDN logo

- 2 million contributors.
- €12 million.

- **Challenges:** “reasonable” cost and fast processing time.

- **Problems with manual processing:** slow, costly, potentially biased.
  - **Solution** = use of **digital tools**.

⚠ **Not** replacing democracy with algorithms (e.g. Talk To The City, Audrey Tang in Taiwan, etc.).
  - → Having new **complementary** tools to process information.

- **Our project:** suggest and implement improvements for the already existing tools addressing this issue.

[1] *Dimitri Courant, « La Convention citoyenne pour le climat. Une représentation délibérative »*

I. Contextualisation

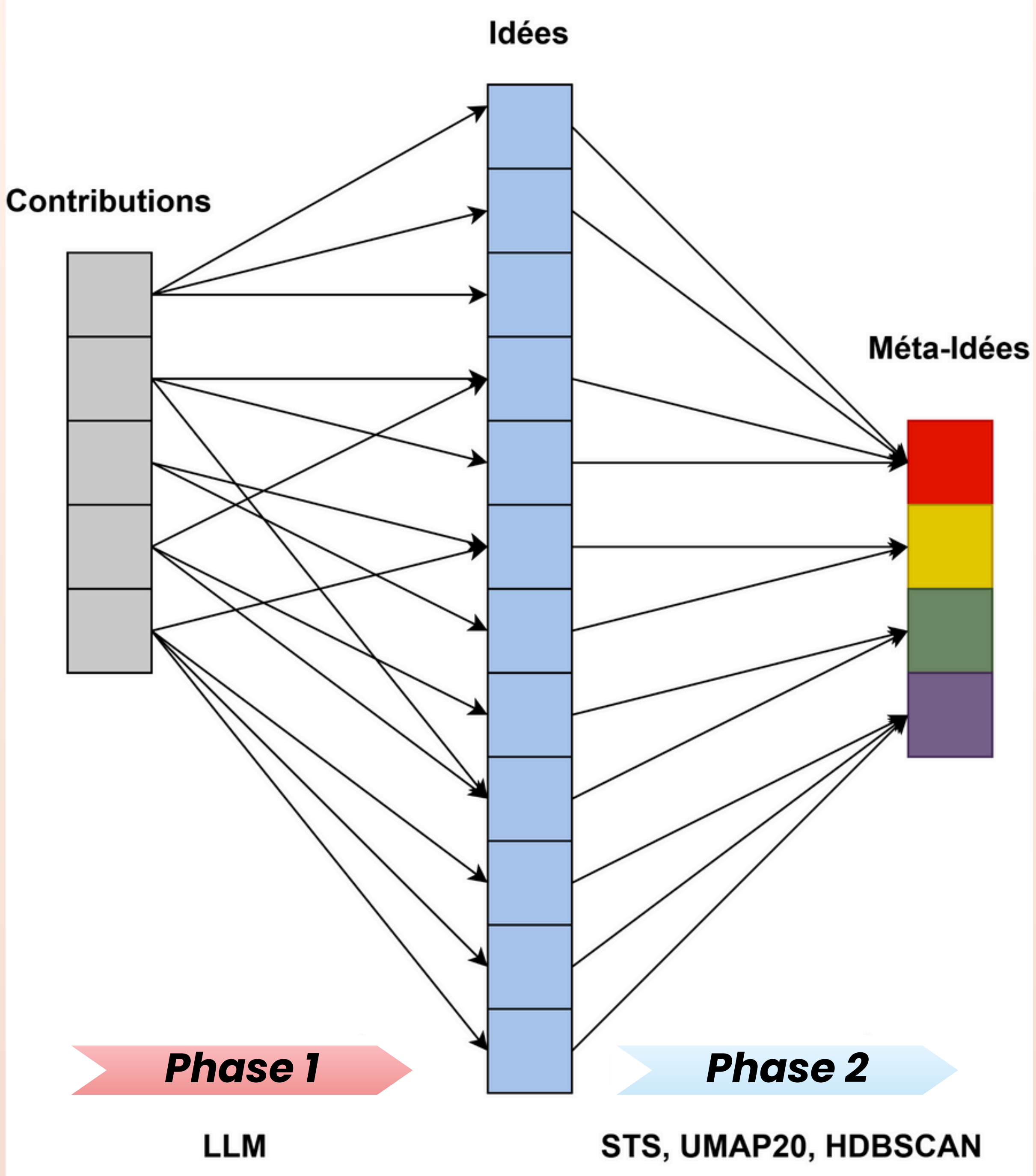


Fig. 3 - Treatment diagram [2]

- **Perpectiva project:**
  - Extraction of ideas from contributions with **Large Language Models** (LLMs).
  - Grouping ideas into meta-ideas using **clustering algorithms.**

- **Issues with LLMs:** hallucinations, loss of ideas and/or sense, "broken" ideas.
  - → **First step of the project: phase 1.**
    - finding and validating a metric to measure the quality of the extractions obtained.

[2] *Cyril François - Perspectiva presentation*

II. Data and Methods

- **Objective:** obtain a metric that correlates closely with the score a human might give regarding the quality of LLM’s extraction.

- **Data:** related to Question n°163 of the “Grand débat national”:
  - ***“Que faudrait-il faire pour rendre la fiscalité plus juste et plus efficace ?“***
    - *(What should be done to make taxation fairer and more efficient?)*

  - 154,000 out of the 186,711 people who participated answered this question.
  - **Contributions’ statistics:**
    - Between 1 character and 80,412 characters.
    - Mean of 358 characters and median of 193 characters.
  - **Examples** of contributions:

Remettre L’ISF, taxer les paradis fiscaux

Taxer davantage les très très riches....On m'a augmenté ma CSG pour la donner à Mr Bernard Arnaud ou à Mr Goshn, cet argent que l'on m'a volé, on l'a volé à mes enfants et petits enfants que je suis obligé d'aider à démarrer dans ma vie, on l'a volé à mes parents âgés car je sois les aider à payer toujours plus, un établissement de retraite décent !!

II. Data and Methods

- **Protocol :** [3]
  1. **Clean the dataset** and limit it to the first 200 contributions.
  2. **Extract ideas** for each contribution **using an LLM** and a specifically designed prompt.
  3. **Compute the chosen metric** on the extractions.
  4. The three members of the group **manually assign a grade** (0 to 10) to the extraction and **flag the presence of hallucinations and broken ideas** based on common rules.
  5. **Aggregate** human grades into a **human score**.
  6. Compute the correlations: between **annotators**, between the **human score** and the **chosen metric**.

- **Chosen metric:** Qualitative Insight Tool - **QualIT** [4]

$$C_i = \frac{1}{n}\sum_{j=1}^{n}\frac{\left(V_{\text{input},ij}\cdot V_{\text{keyphrases},ij}\right)}{\left|V_{\text{input},ij}\right|\cdot\left|V_{\text{keyphrases},ij}\right|}$$

with

C_i the coherence score of the ith contribution.

n the dimension of embedding space.

$V_{input,ij}$ the jth coordinates of embedding vector of contribution i.

$V_{keyphrases,ij}$ the jth coordinates of embedding vector of the extracted ideas from contribution i.

$|v|$ Euclidian norm.

$(v.u)$ Dot product.

[3] *How to Validate Metrics - Ehud Reiter*

[4] *Kapoor S. et al. "Qualitative Insights Tool (QualIT): LLM Enhanced Topic Modeling" (2024), Amazon*

II. Data and Methods

- **Prompt's features** (same version as the one used in the original project):
  - Use only the contribution's content.
  - **Extract the list of the principal and distinct ideas.**
  - Annotate for the *type*, the *syntax* and the *semantic*.
  - Output in **CSV format.**
  - Three **examples** of extraction.

II. Data and Methods

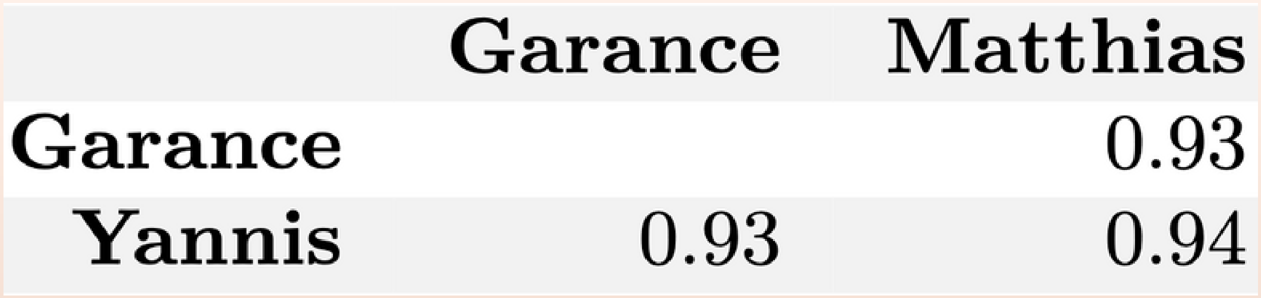
- **Rules** for the **extractions' human grading:**
    - **Grade** = integer between **0 and 10**.
    - **Same number of ideas** in the extraction and the contribution.
        - No idea should be neither omitted nor added.
    - Ideas transcribed in the **same sense**.
    - Only **distinct ideas** (no redundancy).
    - Output in **French**.

II. Data and Methods

- **Code:**
  - **Python** environment (~3.12.4).
  - LLM call manager : **Ollama** for the LLM call.
  - LLM: **Meta-Llama-3.1-8B**-Instruct-AWQ-INT4.

- **Project management:**
  - **GitHub** for code and *small* data files.
  - **Google Drive** for large data files, reports and shared notes.

III. Results



	Garance	Matthias
Garance		0.93
Yannis	0.93	0.94

Fig. 5 - Correlation between group members' grading

- Pearson's correlation between annotators: all in **agreement**.
- Pearson's correlation between the **human score** and the **QualIT score**: 0.71.
  - Rather in agreement, but **some disagreement**.

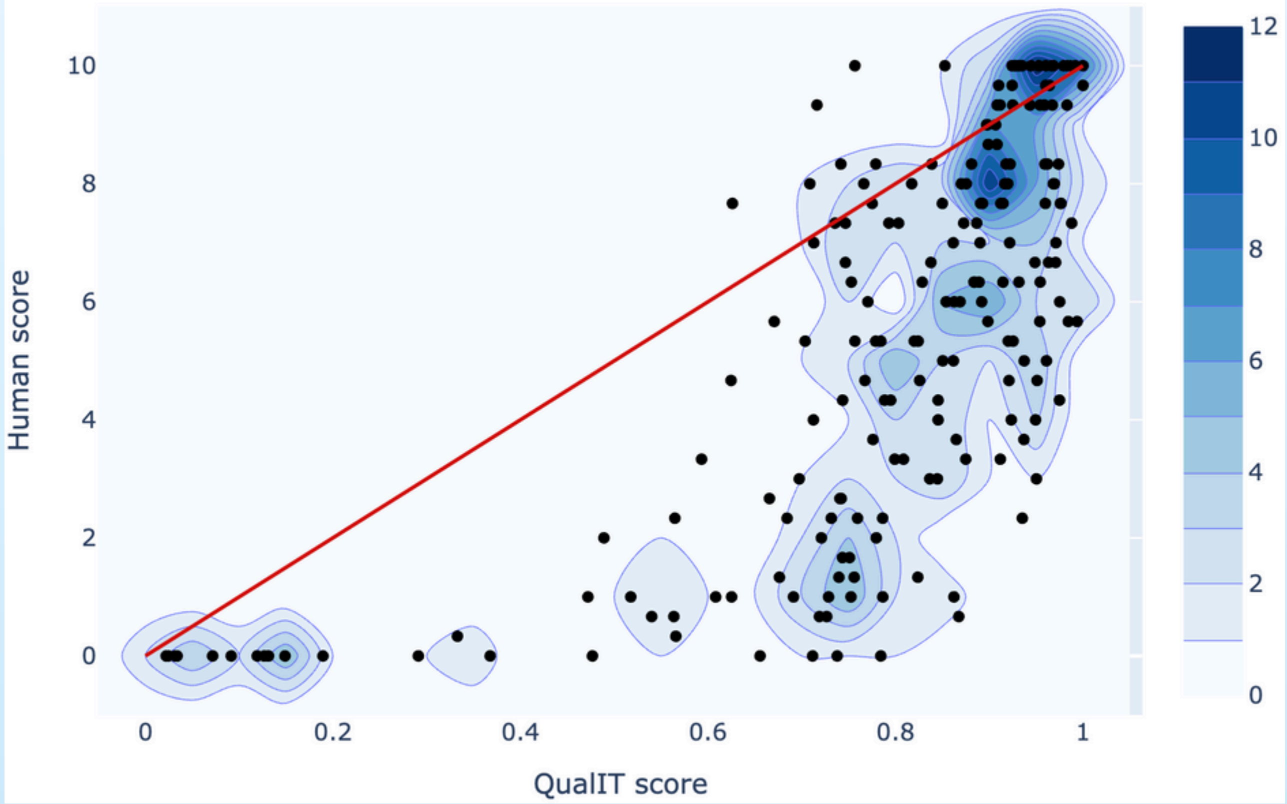


Fig. 6 - Human score vs QualIT score

- Most of the disagreement = contributions with a QualIT score between 0.4 and 0.8.
- Numerous **good extractions** (intense blue around (1, 10) coordinates).
- QualIT metric fails to grade extractions with a low human score → why ?

III. Results

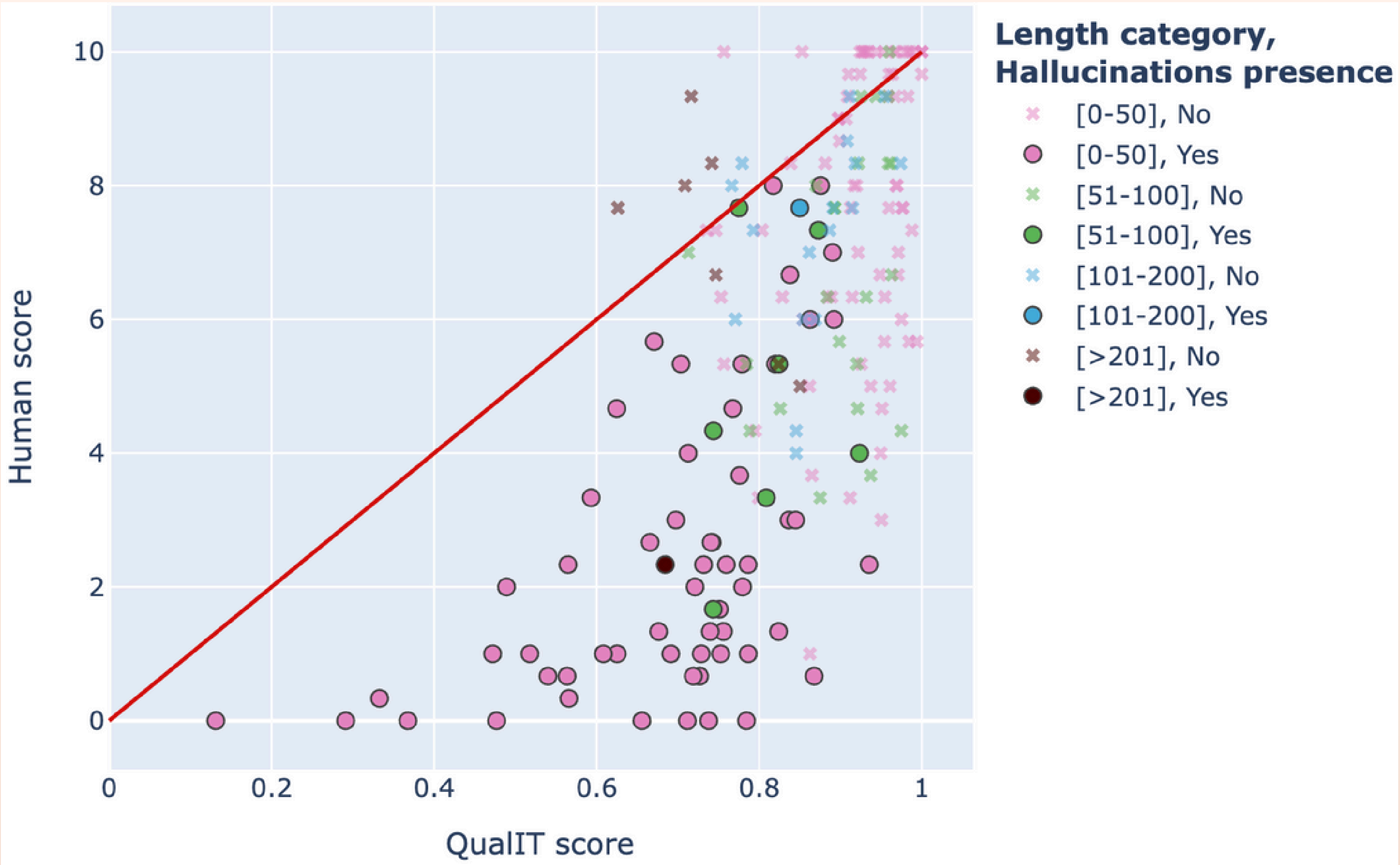


Fig. 7 - Human score vs QualIT score, with hallucinations

⚠ ***Less points than before****: failed extractions not on the graph.*

- **Hallucinations** occurrences:
  - Mostly on **short contributions** and/or contributions with a **low human score**.
- Same graph with **broken ideas**: less relevant.

III. Results

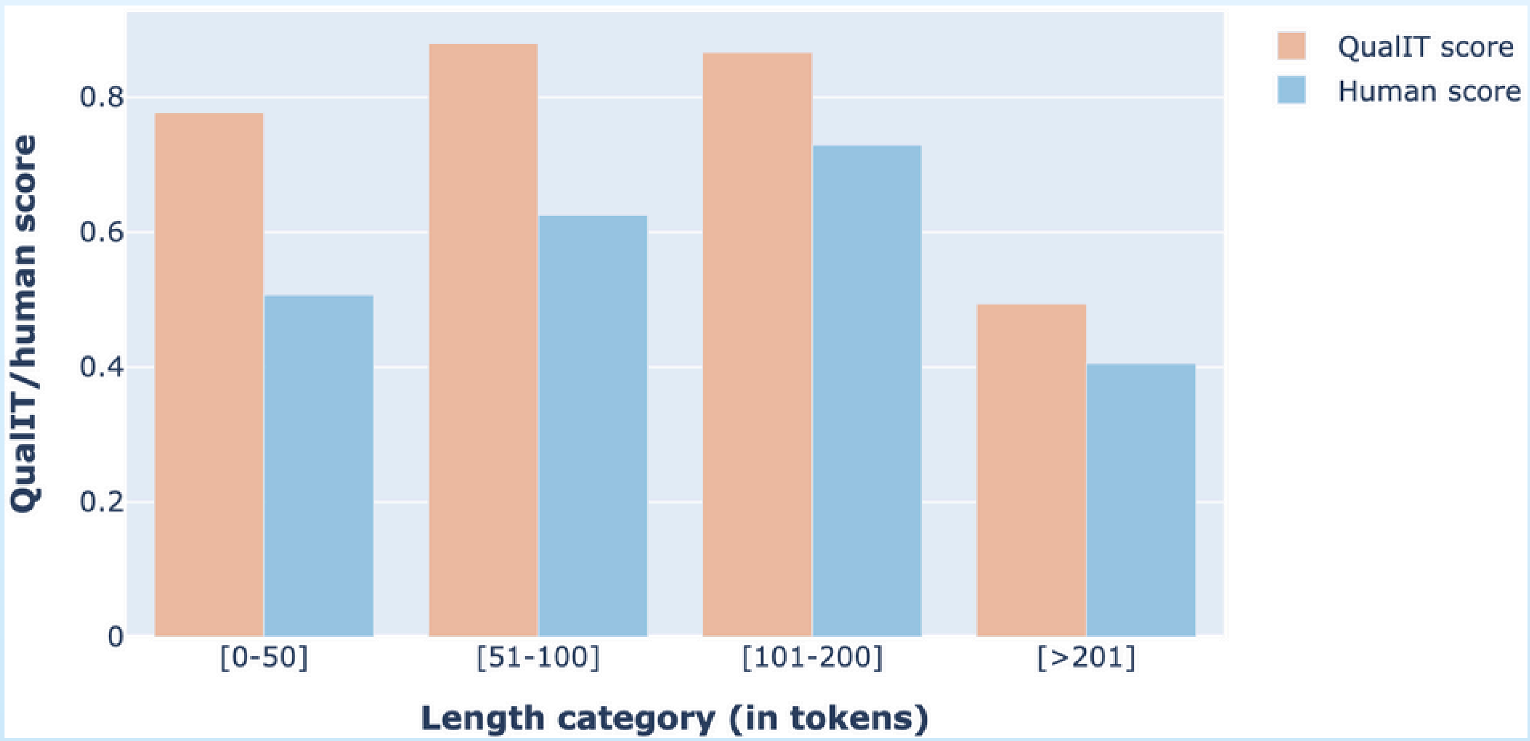


Fig. 8 - Scores per length category

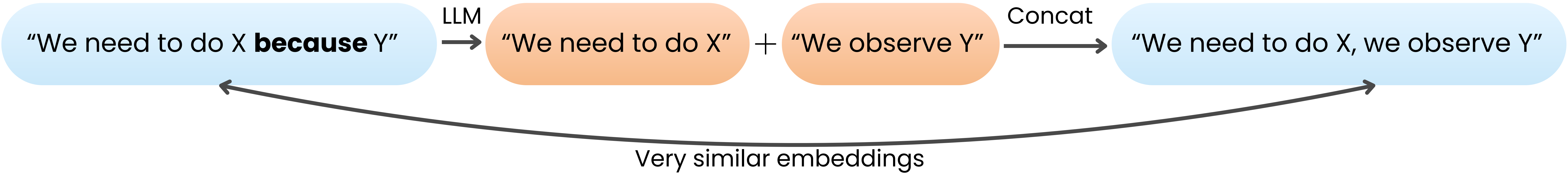
- **QualIT:** overestimate the extractions' quality.
  - Even more on short contributions.
- **Extraction:** more efficient on mid-length contributions.

III. Results

- What is happening with separated ideas and hallucinations ?

- **Separated ideas :**

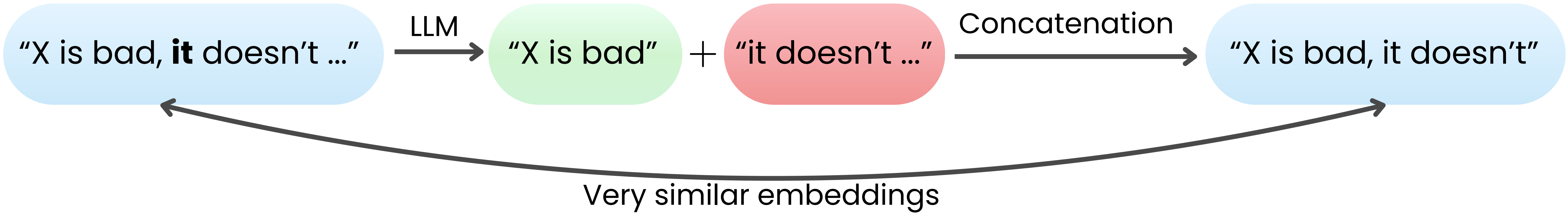
1. Presence of **conjunctions** : “so”, “therefore”, “but”, “because”



“We need to do X **because** Y” → LLM → “We need to do X” + “We observe Y” → Concat → “We need to do X, we observe Y”

Very similar embeddings

2. **Use of a pronoun** in a new idea

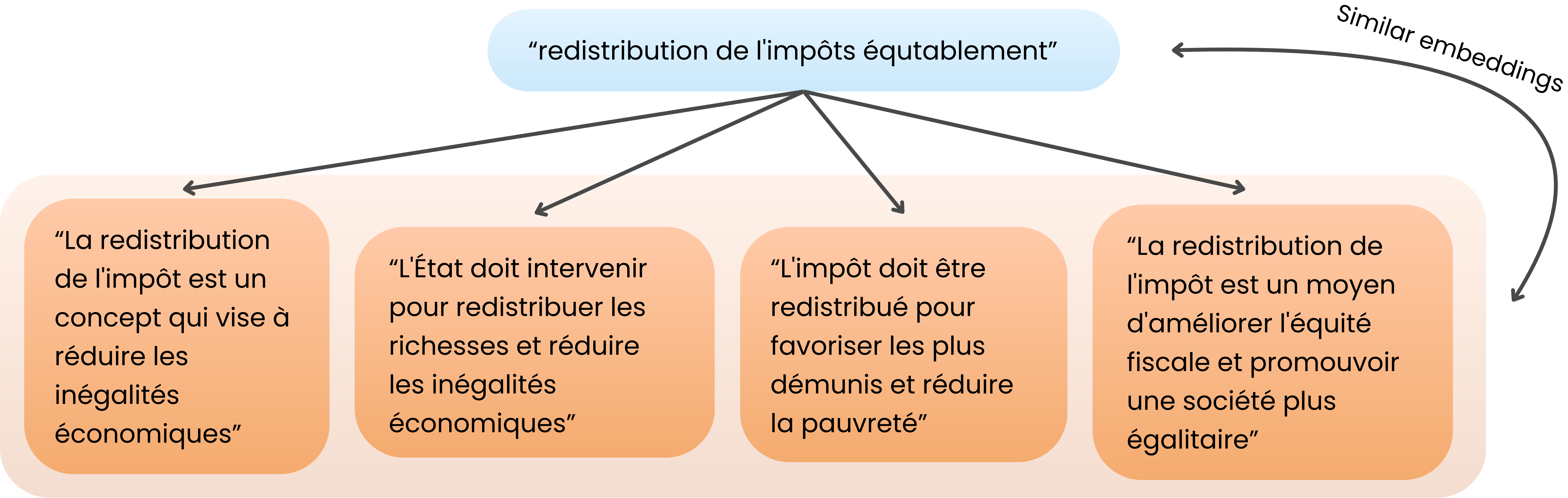


“X is bad, **it** doesn’t …” → LLM → “X is bad” + “it doesn’t …” → Concatenation → “X is bad, it doesn’t”

Very similar embeddings

III. Results

- **Hallucinations :** adding **similar ideas.**
    - Example with contribution n°7 :



“redistribution de l'impôts équtablement”

Similar embeddings

“La redistribution de l'impôt est un concept qui vise à réduire les inégalités économiques”

“L'État doit intervenir pour redistribuer les richesses et réduire les inégalités économiques”

“L'impôt doit être redistribué pour favoriser les plus démunis et réduire la pauvreté”

“La redistribution de l'impôt est un moyen d'améliorer l'équité fiscale et promouvoir une société plus égalitaire”

Metric score : 0.73

Human score : 0.06

III. Results

- QualIT metric → **ROUGE metric.**
  - **Reduce** hallucinations and parsing failures.
  - **L ROUGE** metric: focuses on longest matching sequences.
  - **1-gram ROUGE** metric: measures how much of the original text is preserved.

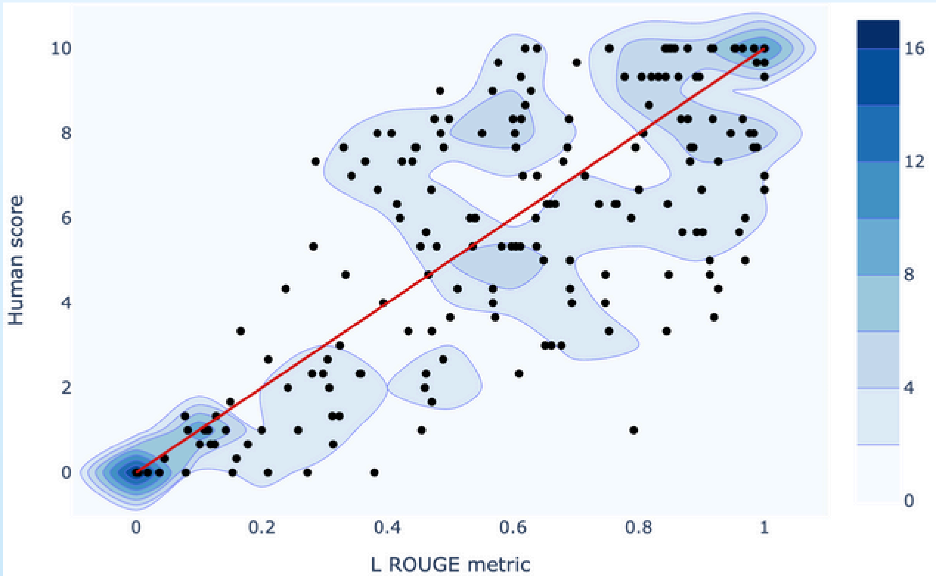


Fig. 9 - Human score vs L ROUGE score

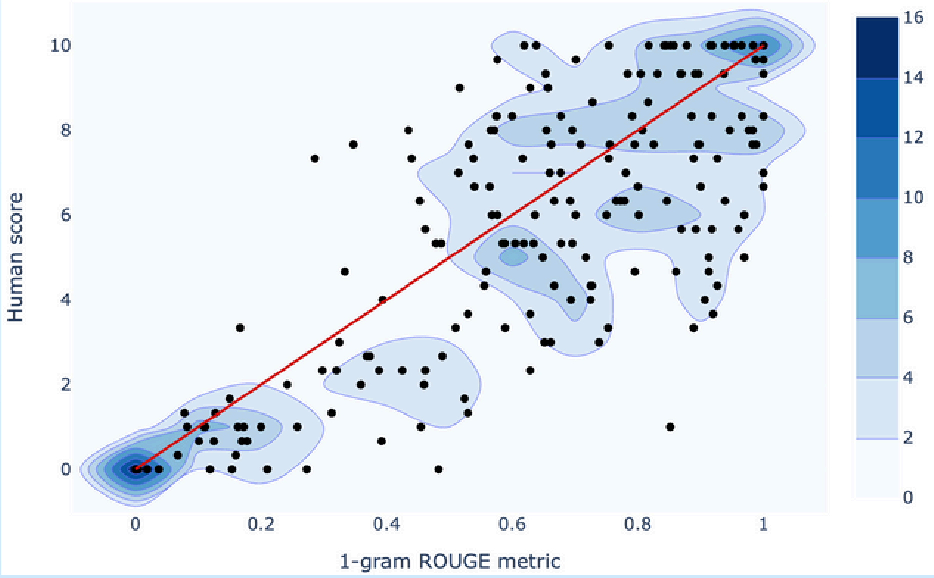


Fig. 10 - Human score vs 1-gram ROUGE score

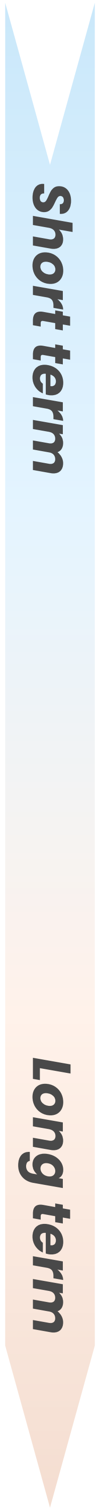
Correlation with human score:

- 1-gram ROUGE: 0.79.
- L ROUGE: 0.78.

- Both Rouge-based metrics match human scores.
- **Good detection** of correct extractions **and** errors.

- → Ideas to **adjust** the QualIT metric.

IV. Next steps



Short term

Long term

1. **Adjustment** of the QualIT metric:
   - Failed extraction at 0.
   - Penalizing hallucinations and invalid ideas.
   - Penalizing length difference (in tokens) between the contribution and its extraction.

2. Prompt **improvements** (to prevent failed extraction).

3. **Creation** of a processing pipeline to keep only **good extractions:**
   a. **Extraction** via LLM.
   b. Filter for **failed extractions** (removing them).
   c. Filter for **hallucinations** and **invalid ideas** (rules to establish).
   d. Filter for the **adjusted QualIT metric** (rules to establish).

4. **Creation** of meta-ideas map and Personas (relations between meta-ideas).

References

1. Dimitri Courant, « La Convention citoyenne pour le climat. Une représentation délibérative ». In Revue Projet 378 (2020), p. 60-64 doi : 10.3917/pro.378.0060.
2. Cyril François (Data4Good), Perspectiva presentation.
3. Ehud Reiter, « How to Validate Metric » at https://ehudreiter.com/2018/07/10/how-to-validate-metrics/.
4. Kapoor S. et al. at Amazon “Qualitative Insights Tool (QualIT): LLM Enhanced Topic Modeling” (2024) doi : 10.48550/arXiv.2409.15626.

Back-up - Prompt I

But: extraire les idées principales DISTINCTES d’un texte pour analyse.

Règles:
1. N’utiliser QUE le contenu entre <<< TEXT >>>.
2. Extraire la liste des idées DISTINCTES et PRINCIPALES.
   - Chaque idée = une phrase claire, autonome, reformulée si nécessaire.
3. Pour CHAQUE idée, annoter:
   - type: "statement" (constat) OU "proposition" (suggestion/recommandation/objectif).
   - syntax: "negative" si la phrase contient une négation explicite (ex.: "ne", "n'", "ne pas", "ne plus", "non"), sinon "positive".
   - semantic: "positive", "negative" ou "neutral" (valence sémantique).
4. Sortie STRICTEMENT en CSV avec entête EXACTE:
   CSV:description,type,syntax,semantic
   - Délimiteur: virgule.
   - Chaque description entre guillemets doubles.
   - Échapper tout guillemet interne par duplication (ex.: ""chat"").
   - NE RIEN AJOUTER d’autre (pas de texte avant/après, pas de code fences).
   - Pas de lignes vides.

Back-up - Prompt II

Exemple:

```
CSV:description,type,syntax,semantic
"Les chats retombent sur leurs pattes",statement,positive,neutral
"Les chats n'ont pas neuf vies",statement,negative,negative
"Il faut mieux prendre soin des chats pour prolonger leur vie",proposition,positive,positive
```