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Information extraction from data with statistically enhanced LLMs

Antoine Soetewey & Cédric Heuchenne

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Rich data, but hard to use…

- **Belgium and Europe collect large-scale administrative and survey data** on key dimensions of socio-economic life:
  - Income and taxation (IPCAL, EU-SILC)
  - Labour market and employment (LFS, CBSS)
  - Housing (EU-SILC, Housing data)
  - Consumption (HBS)
  - Mobility (OVG, Beldam, Monitor)
  - Household finances (HFCS)
  - Time use (HETUS)
  - etc.
- **Data is not public for confidentiality reasons**, but Beamm researchers have access under strict data-protection rules
- **Even with access, it is hard to use:**
  - Variables hide behind opaque names (e.g., HY040G, PL031) and descriptions are documented in codebooks of 200 to 600 pages
  - Even with a perfect description for each variable, it would be hard to navigate across all of them, and even more complicated to see associations between them

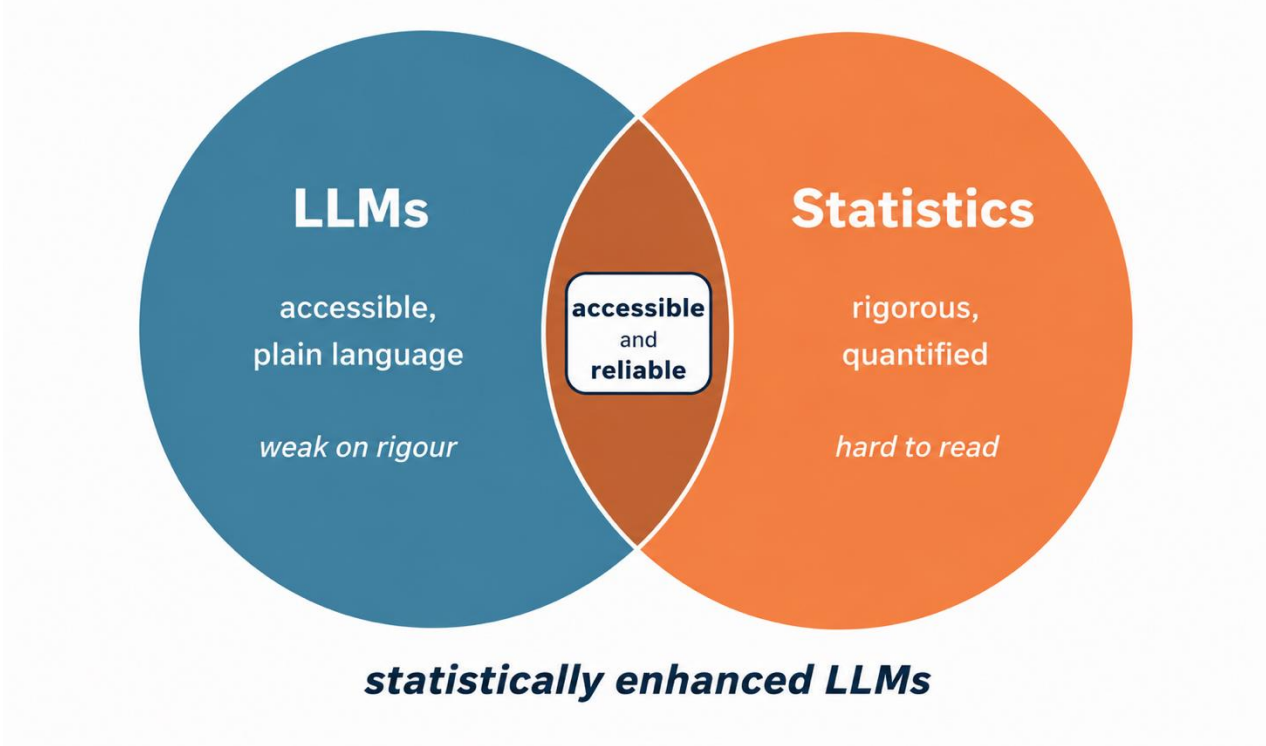
→ Unlocking this data's full potential requires new tools

Two halves of a solution

- **LLMs make data accessible** through plain language, but on their own they are inaccurate: they can hallucinate, not reliable at quantifying, and may call a trivial association interesting

- **Statistics are rigorous and quantified**, but opaque to a non-technical audience

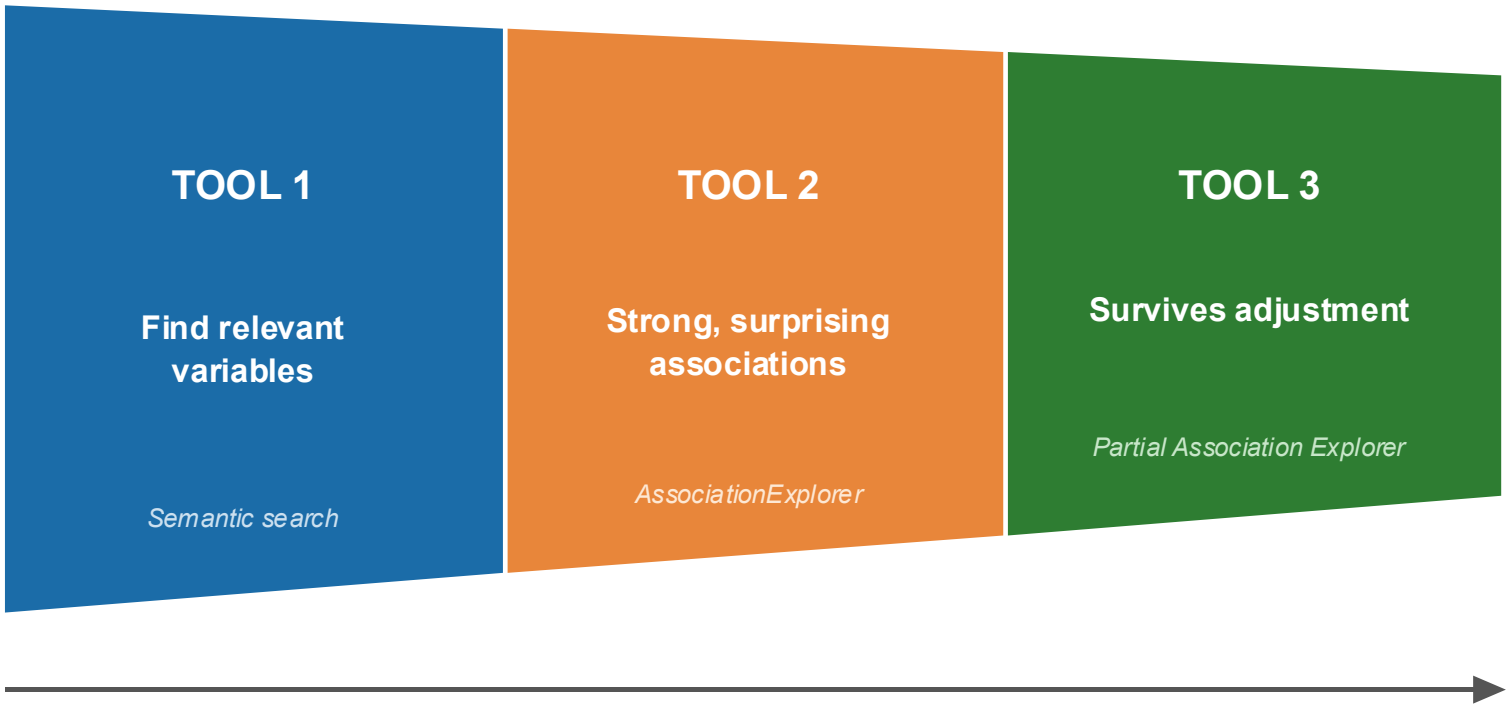
- **The project combines the two**: statistically enhanced LLMs



A three-tool workflow

7,000+ opaque variables
across 6 Belgian socio-economic datasets

A reliable,
shareable data story



Tool 1: Semantic search

Or how to navigate among variables?

Collaboration with Carnot Dongmo Mbane and Hugues Annoye

- **6 Belgian datasets:** EU-SILC (income and living conditions), EU-LFS (labour), HBS (household consumption), HFCS (household finances), IPCAL (tax records), DEMOBEL (demographics)
- **7,010 variables in total.** Codes like HY040G, PL031, A0270 mean nothing without the documentation
- **Documentation is spread** across codebooks of 200 to 600 pages, in French, Dutch and English (and with a lot of technical details)
- A researcher studying a specific topic has **no obvious entry point**

7,010

variables across 6 datasets

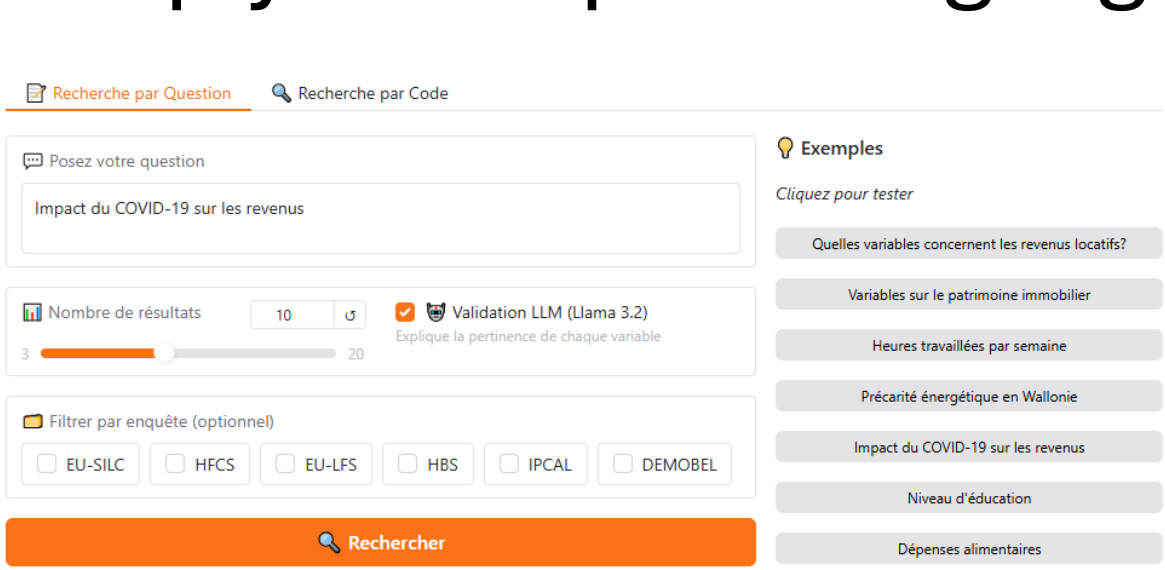
200 to 600

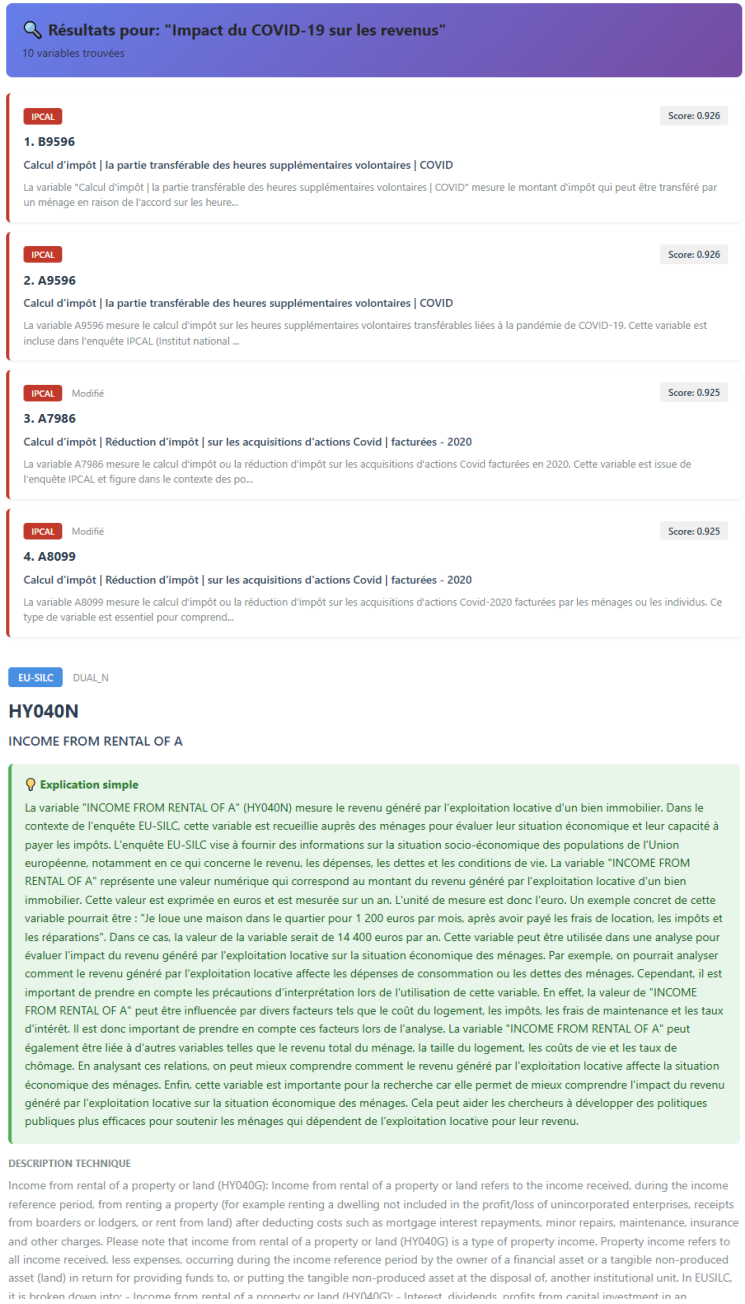
pages of codebook each

The solution: Simply ask in plain language

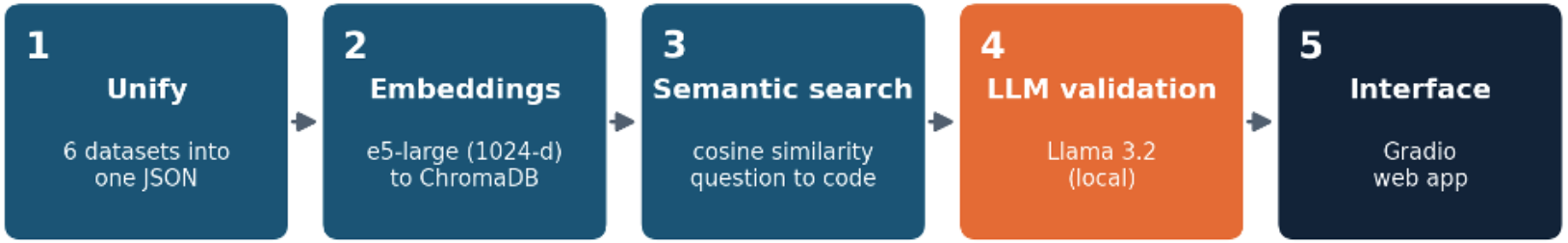
- **Query the corpus in natural language**, instead of codes

- **Two directions:**
  1. Find variables: from a question/topic to the relevant variables (« help you discover »)
  2. Describe variables: from a code to a readable description (« help you understand »)





The process: A five-step pipeline



1. **Unify**: each dataset has its own format; a per-dataset function maps it into one common JSON dictionary, one record per variable (with code, source, short and long description, category, etc.)
2. **Embeddings**: every description becomes a 1024-dimensional vector with multilingual-e5-large (XLM-RoBERTa encoder, ~560M parameters), stored in ChromaDB; similar meanings are close together, even across languages
3. **Semantic search**: the user's question is embedded too, and variables are ranked by cosine similarity (i.e., cosine of the angle between vectors)
4. **LLM validation**: a local model (Llama 3.2 via Ollama) reads the top candidates and classifies each as truly relevant, somewhat relevant, or off-topic, with a short justification
5. **Interface**: a Gradio web app ties it together

Two design choices: RAG, and running locally

Fine-tuning or RAG?

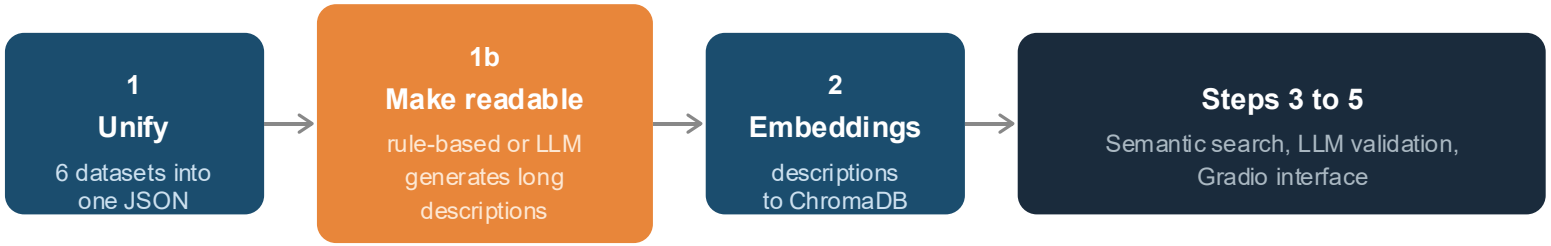
- **Fine-tuning** means retraining the model on our 7,000 variables so it "memorises" them
- **RAG** (Retrieval-Augmented Generation) works differently:
  - the model never sees our variables during training;
  - instead, when a question arrives, we first search for the most relevant variables (step 3, the **retrieval** part),
  - then hand them to the model as a note to read before answering (step 4, the **augmented generation** part)
- We started with the fine-tuning approach (LoRA on Llama-3-8B) but moved to RAG because:
  - adding a new dataset requires no retraining; just embedding and indexing the new variables (faster)
  - we always know exactly which variables were given to the model (more transparent)
  - it can only refer to variables we actually gave, not invent codes from an imperfect memory (fewer hallucinations)

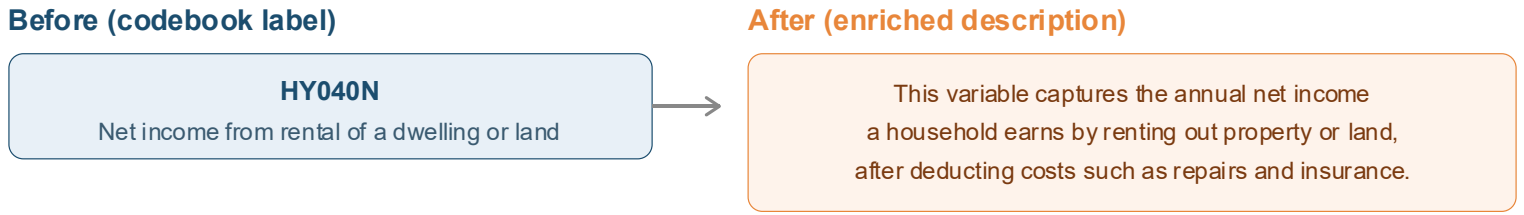
Local or hosted?

- **Local execution**: both the embedder and Llama 3.2 run locally through Ollama; might be weaker than a hosted model, but we accept it in return for:
  - Price (free)
  - Privacy (no change in the architecture if confidential metadata is added later)

Making variables more readable

- Descriptions are often too **short and/or technical** to give good search results
- A second loop generates a long, **plain-language description** for each variable
- Two generators:
  1. a LLM-based (rich, with an example)
  2. a rule-based (instant, always available)
- These **enriched descriptions** are used as inputs for step 2, making the semantic search much more effective





Tool 2: AssociationExplorer

From variables to associations

- We now have a shortlist of relevant variables
- Which of them are **related**, and **which links deserve a closer look?**
- **AssociationExplorer** (Soetewey et al., 2026) fills this gap:
  - Computes associations of every pair among the **selected variables**
  - But also: every pair between the selected variables **and the rest of the dataset** to highlight unexpected associations
- First, how do we actually compute associations?

Three cases depending on variable type

A variable can be of 2 types (numeric or categorical), so an association can be of 3 types:

1. **Numeric vs numeric:** Pearson's correlation coefficient (Pearson, 1895): $r = \frac{cov(x,y)}{s_x s_y}$
2. **Categorical vs categorical:** Cramer's V (Cramer, 1946): $V = \sqrt{\frac{\chi^2}{n \cdot \min(r-1, c-1)}}$
3. **Numeric vs categorical:** Correlation ratio (Pearson, 1905): $\eta = \sqrt{\frac{SS_{between}}{SS_{total}}}$

From all pairs to the interesting few

3-step workflow:

1. **Keep only significant pairs:** *p*-value < 0.05:
   - Numeric vs numeric – Pearson's correlation test: $t_{obs} = \frac{r}{\sqrt{\frac{1-r^2}{n-2}}} \sim t_{n-2}$
   - Categorical vs categorical – Chi-square test of independence: $\chi^2_{obs} = \sum \frac{(O-E)^2}{E} \sim \chi^2_{(r-1,\, c-1)}$
   - Numeric vs categorical – One-way ANOVA F-test: $F_{obs} = \frac{MS_{between}}{MS_{within}} \sim F^{k-1}_{N-k}$
2. **Drop negligible ones:** minimum strength of at least 1% explained variance (Cohen's (1988) small effect):
   - Numeric vs numeric: $r^2 \geq 0.01$
   - Categorical vs categorical: $V^2 \geq 0.01$
   - Numeric vs categorical: $R^2_{adj} \geq 0.01$
3. **Rank by strength,** keep the top-N (N = 10)

- Assumptions underlying each test are not tested (non-parametric alternatives could be considered)
- Thresholds are fixed (no user-adjustable slider) to keep the tool accessible for non-specialists

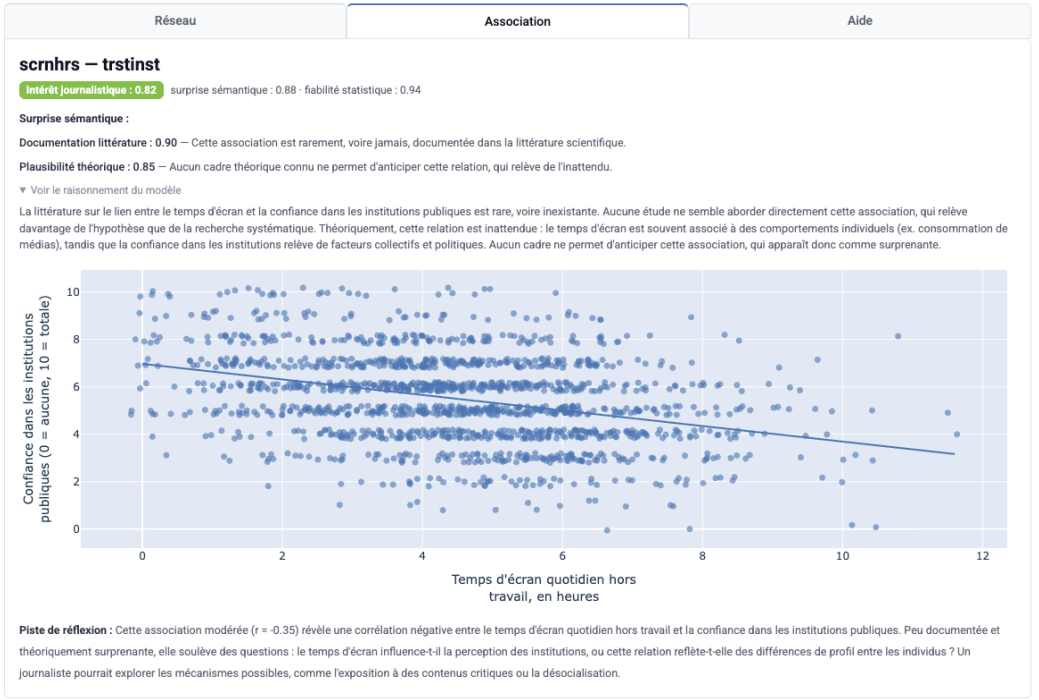
An LLM as a judge

- A statistically significant (via the *p*-value) and strong (via the strength) association is **not always an interesting association,** if it is expected (e.g., age and retirement, education and salary)
- So we add another perspective: **surprise**
  - An LLM (mistral-medium-latest, via Mistral API) receives the two descriptions and assigns two sub-scores:
    1. How documented is this association in the scientific literature? (0 = well established, 1 = rarely studied)
    2. How theoretically plausible is it? (0 = fully expected, 1 = surprising)
  - The semantic surprise score is the average of the two
- Finally, **journalistic interest = (semantic) surprise × (statistical) reliability**, with reliability $= \frac{-log_{10}(p)}{-log_{10}(p)+3}$ (to distinguish very small *p*-values)
  - The final score is high only when an association is **both surprising and statistically solid**; the ideal candidate for a story
- As a bonus: for each pair, the LLM also proposes hypotheses to explore as « **food for thought** »:
  - With the observed data (correlation, mean by group, association strength, etc.)
  - But without concluding or claiming causality

- **Association network:** nodes are variables, edges are associations; closer nodes mean stronger links
- **Edge opacity** proportional to journalistic interest

For the selected association:

- All **scores**: final surprise score, 2 sub-scores, statistical reliability
- Model's **prior reasoning** (written before scoring)
- **Visualization**
- **Food for thought** grounded in the observed data

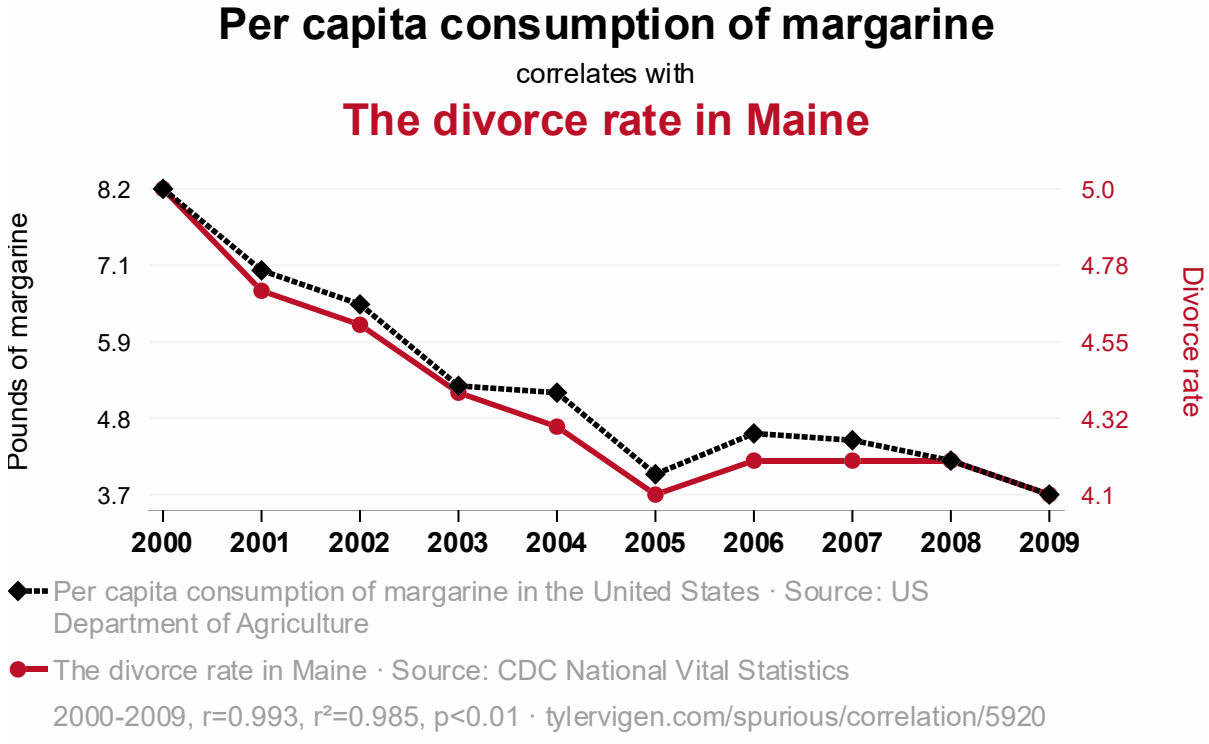


Tool 3: Partial Association Explorer

Strong and surprising, but is it real?

Collaboration with Thaddée D'haegeleer

- A strong, significant and surprising association **can still be an artefact** (spurious correlation)
- **Confounder:** a third variable Z that influences both X and Y, creating an association between two things that are not directly linked
- With many variables, probability of finding that kind of association **just by chance** is high
- To limit it, we add a more careful layer: **control variables**

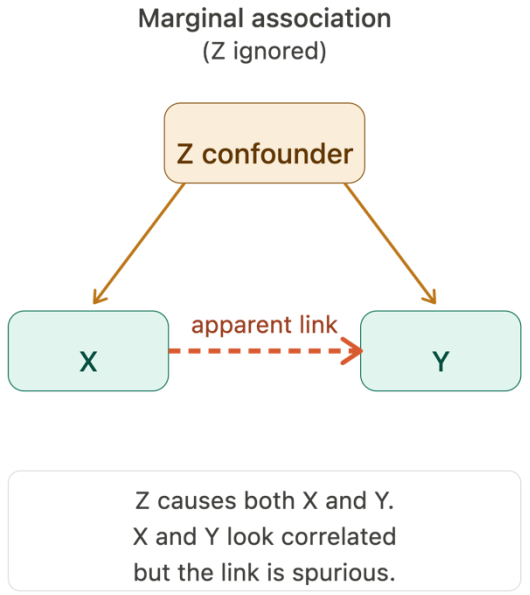


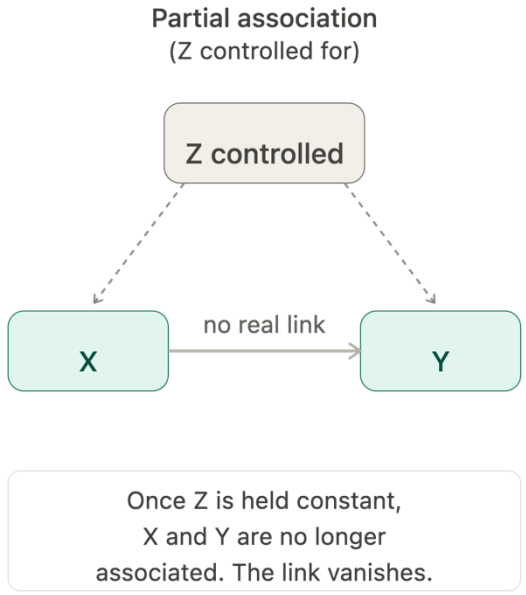
Source: tylervigen.com

The idea: adjust for controls

- **Pick control variables Z**, then recompute each association between X and Y after adjusting for Z
- What remains is the **partial association**; the part of the relationship not explained by the controls
- **Intuition**: within groups that are similar on Z, do X and Y move together?
  - If yes, the link remains
  - If no, the link disappears
- How is Z chosen?
  - User and subject knowledge

  → Results depend on which controls are picked



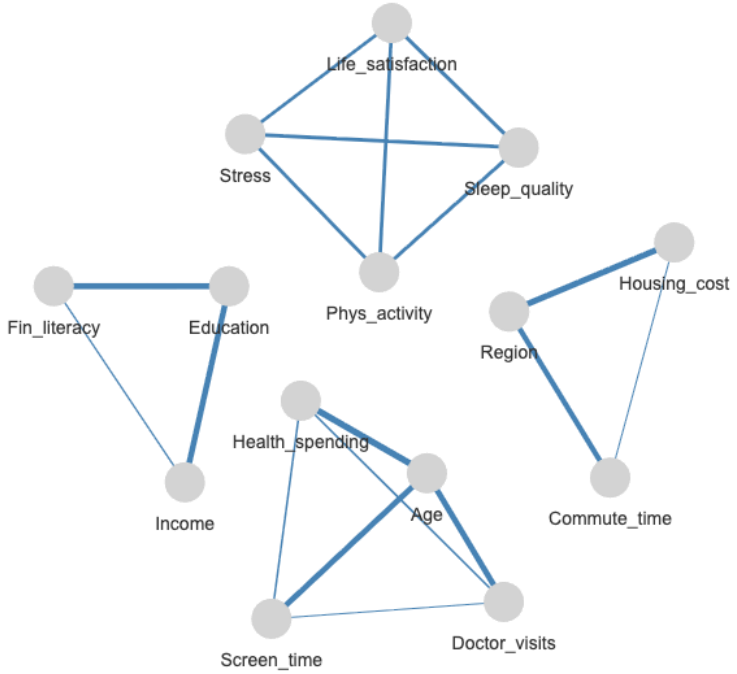


Three cases depending on variable type

- **Numeric vs numeric:**
  - Marginal: Pearson's correlation r
  - Conditional: Partial correlation $r_{XY.Z} = \frac{r_{XY} - r_{XZ}r_{YZ}}{\sqrt{1 - r_{XZ}^2}\sqrt{1 - r_{YZ}^2}}$, the correlation of residuals from X on Z and Y on Z; t-test on n−q−2 degrees of freedom; strength $= r^2$
- **Numeric vs categorical:**
  - Marginal: η^2 (ANOVA)
  - Conditional: partial $\eta^2_{X|Z}$ (ANCOVA), comparing the reduced model Y on Z with the full model Y on X plus Z (extra sum of squares); global F-test
- **Categorical vs categorical:**
  - Marginal: a 0 to 1 measure built from a likelihood-ratio statistic $V_L = \sqrt{1 - \exp(-\frac{G^2}{n})}$ with $G^2 = 2(\ell_1 - \ell_0)$
  - Conditional: $V_{L|Z}$ fits a multinomial-logit model that includes the controls, advantage over log-linear models: controls may be continuous or categorical
- **Filtering:** on effect size and on the *p*-value, in both the marginal and the conditional case

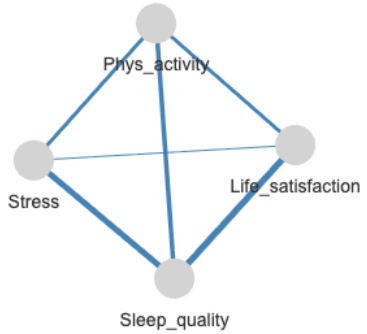
Networks before and after adjustment

Marginal network



Dense: many links look strong

Conditional network



Sparser: only links which survive adjustement for cofounders

- Which associations **remain**, which **disappear?**
  - Not “Are X and Y associated?” anymore, but “Are X and Y still associated once we account for age, education, region, etc.?”
- **No causal inference**: a more cautious, transparent exploration tool that shows where deeper modelling is worth investigating

Conclusion

Working today:

- **Tool 1:** a plain-language question returns the relevant variables
- **Tool 2:** strong and non-obvious associations are highlighted and ranked by interest
- **Tool 3:** only the associations that survive adjustment are kept

Further research:

- **User feedback:** interviews with journalists will help us design AssociationExplorer (Tool 2)
- The three tools are separate today but designed to be **one pipeline**
- Variable descriptions (Tool 1) could be **enriched with known associations**, giving each variable richer context for both search and surprise scoring
- Semantic surprise is currently scenario-based; adding embedding-based **similarity scores** could make it more formal and objective
- **Comparable strengths:** putting r^2, V^2 and adjusted R^2 on the same scale is a working approximation; defining a truly comparable measure is worth further investigation
- **Survey design:** accounting for sampling weights would make the statistical significance and strength estimates more representative of the population
- **Multiple testing**: with large samples and many pairs tested, *p*-values become uninformative; a correction for multiple-testing would make the screening more robust

Thank you!
Questions?

Appendix: RAG vs fine-tuning

Criterion	RAG (used)	Fine-tuning (not implemented)
Principle	Model unchanged, dynamic retrieval	Partially retrain the model weights
Set-up cost	Low, no training	High: GPU, training time, expertise
Add a dataset	Immediate: embed and index	Costly: a new training cycle
Transparency	High: retrieved variables are visible	Low: knowledge diffused in weights
Hallucination	Reduced: answers from real variables	Possible: may invent plausible but fake codes
Status here	Operational on 6 datasets (7,010 vars)	Documented alternative (LoRA, Llama-3-8B)

Appendix: embeddings and retrieval

- **multilingual-e5-large:** XLM-RoBERTa encoder, 24 layers, about 560M parameters; the [CLS] vector summarises each text; contrastive training on about 1 billion multilingual pairs.
- **Prefixes:** indexed texts use passage:, user questions use query:, which aligns short questions with longer descriptions.
- **Store:** ChromaDB with cosine similarity; relevant matches usually score 0.85 to 0.93.
- **Collections:** seven, one per dataset plus a unified one over all 7,010 variables.
- **Size bias:** IPCAL is about 76% of the corpus; an early hybrid weighting was removed in favour of plain cosine.

Appendix: Part 2 measures

Numeric vs numeric (Pearson)

$$r = \frac{\operatorname{cov}(X, Y)}{\sigma_X \sigma_Y} \qquad \text{strength} = r^2$$

Categorical vs categorical (Cramer's V)

$$V = \sqrt{\frac{\chi^2}{n \min(r-1,\, c-1)}} \qquad \text{strength} = V^2$$

Numeric vs categorical (ANOVA)

$$\eta^2 = \frac{SS_B}{SS_T} \qquad R^2_{\text{adj}} = 1 - (1 - \eta^2)\frac{n-1}{n-k} \qquad F = \frac{SS_B/(k-1)}{SS_W/(n-k)}$$

Journalistic interest

$$\text{interest} = \text{surprise} \times \text{reliability} \qquad \text{reliability} = \frac{-\log_{10} p}{-\log_{10} p + 3}$$

Appendix: Part 3 conditional measures

Numeric vs numeric: partial correlation

$$r_{XY\cdot Z} = \mathrm{corr}(\hat{\varepsilon}^X,\ \hat{\varepsilon}^Y) \qquad T = r_{XY\cdot Z}\sqrt{\frac{n-q-2}{1-r^2_{XY\cdot Z}}} \ \sim\ t_{n-q-2}$$

Numeric vs categorical: partial eta-squared (ANCOVA)

$$\eta^2_{X|Z} = \frac{RSS_{\text{red}} - RSS_{\text{full}}}{RSS_{\text{red}}} \qquad F = \frac{(RSS_{\text{red}} - RSS_{\text{full}})/(k-1)}{RSS_{\text{full}}/(n-k-q)}$$

Categorical vs categorical: likelihood-ratio measure

$$G^2 = 2(\ell_1 - \ell_0) \qquad V_L = \sqrt{1-e^{-G^2/n}} \qquad V_{L|Z} = \sqrt{1-e^{-G^2_{|Z}/n}}$$

Appendix: a note on evaluation metrics

- **An early evaluation (20 annotated questions) gave** mean similarity about 0.742, MRR about 0.417, recall at 10 about 0.533.
- **These predate two changes:** removing the hybrid weighting, and extending from 4 to 6 datasets.
- **They must be recomputed on the current system**, so treat them as preliminary, not final.

Appendix: widening access with synthetic data

- **The six datasets are confidential research microdata**, not open to the public.
- **Wasserstein GANs generate a synthetic copy** that reproduces the statistical structure of the population while reducing disclosure risk (tested on the Belgian Labour Force Survey).
- **This synthetic layer can widen access** to journalists, students and citizens without exposing real records.
- **References:** Annoye, Heuchenne and co-authors, Applied Intelligence (2025), Knowledge-Based Systems, and Expert Systems with Applications.

Reference

- Soetewey, A., Heuchenne, C., Claes, A., & Descampe, A. (2026). AssociationExplorer: A user-friendly Shiny application for exploring associations and visual patterns. *SoftwareX*, *33*, 102483.