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Exploring Large Language Models Political Biases

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November 25, 2024

AI for science, science for AI

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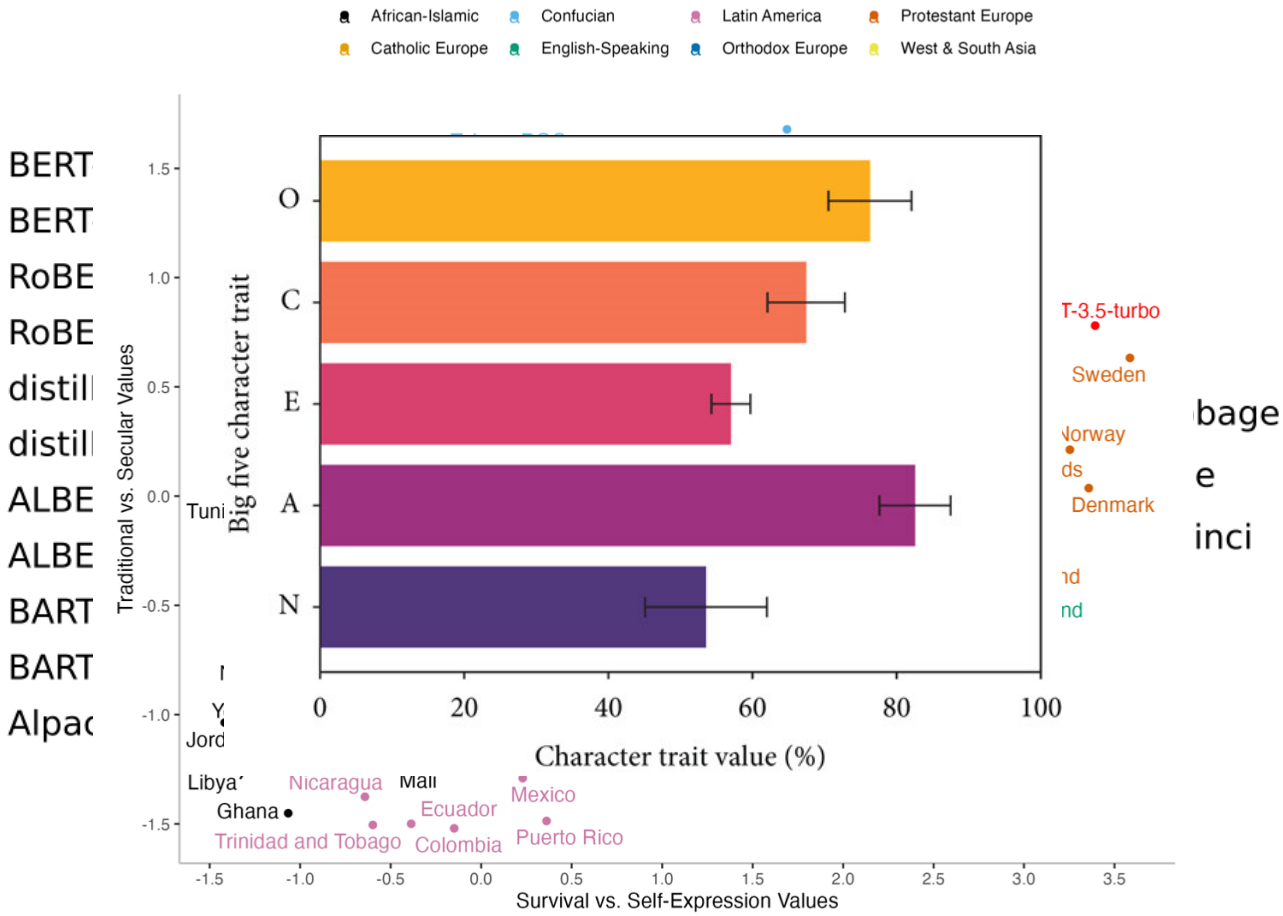

Political Compass Test's results of various LMs [1], The Inglehart-Welzel World Cultural Map with GPT [2], ChatGPT's Big-5 test results [3].

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1 Real-world implications

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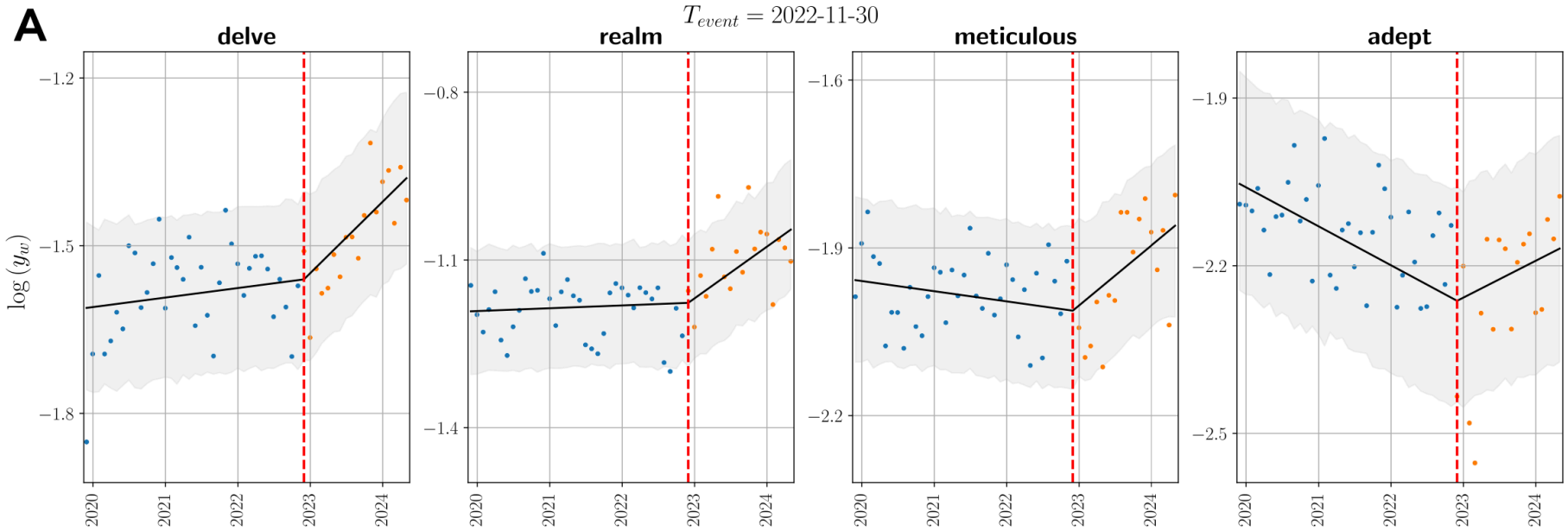
1.1 Evidences of ChatGPT's impact

LLMs influence the way we communicate [4–6].



Prevalence of words associated with ChatGPT. Extracted from [4].

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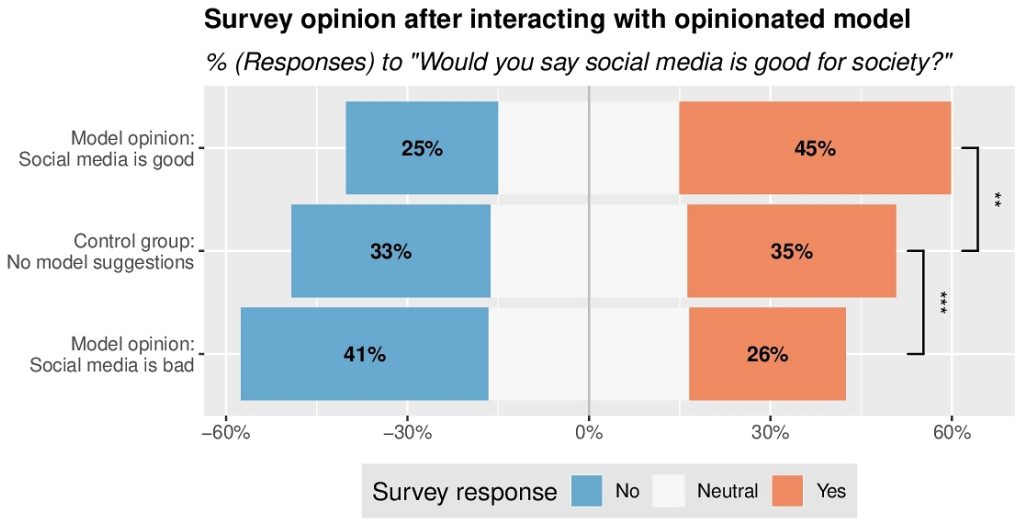
1.2 Influence besides vocabulary



Participants interacting with a model supportive of social media were more likely to say that social media is good for society in a later survey (and vice versa) — from [7].

LLMs influence users and participate in shaping opinion

- collective opinion [8]
- individual opinion [7, 9]

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1.3 Propagation of models' biases

Language is loaded with sociocultural characteristics [10].

LLMs biases can have harmful consequences, and spread in downstream applications:

- lower quality service to minorities and vulnerablue users [11, 12]
- demographic-based recommandations [13]
- mental health issues and cultural values [14]
- politically biased text summarization [15]
- …

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2 LLMs Crash course

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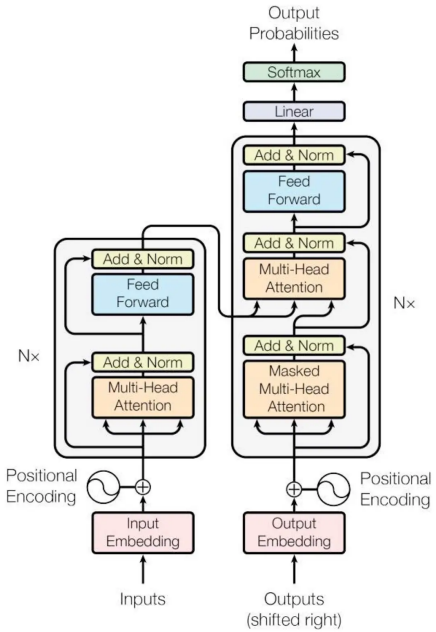
2.1 Overview

- Trasnformers-based architecture [16]
- Autoregressive models
- Trained over **large** corpora (typically 10^{11} - 10^{12} tokens) [e.g. 17]
- Further *aligned* with desired behaviors



Transformers architecture from [16].

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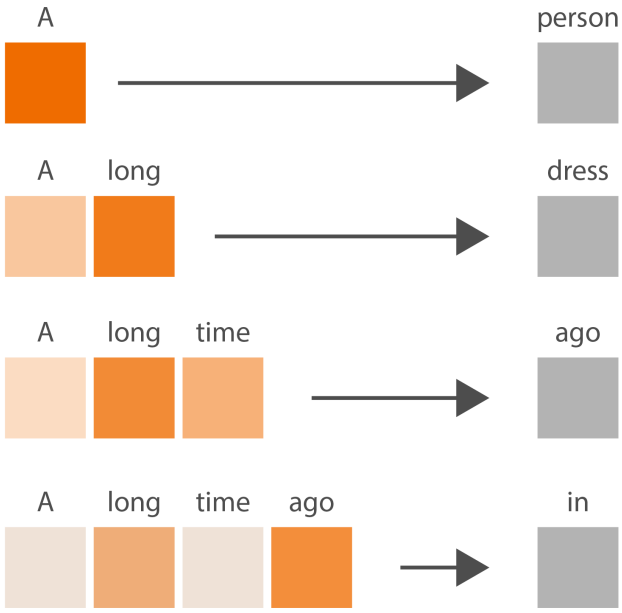
2.2 Next-token prediction

$$\mathcal{L}[\phi] = -\sum_{i=1}^{I}\sum_{t=1}^{T}\log\left[Pr(x_{i,t+1}|x_{i,1},\cdots,x_{i,t},\phi)\right]$$

- language modeling task
- self-supervised training
- mainly webpages, code, books, encyclopedia
- equips models with other capabilities (world knowledge, comprehension, translation, …)



Next token prediction task. Extracted from [18]

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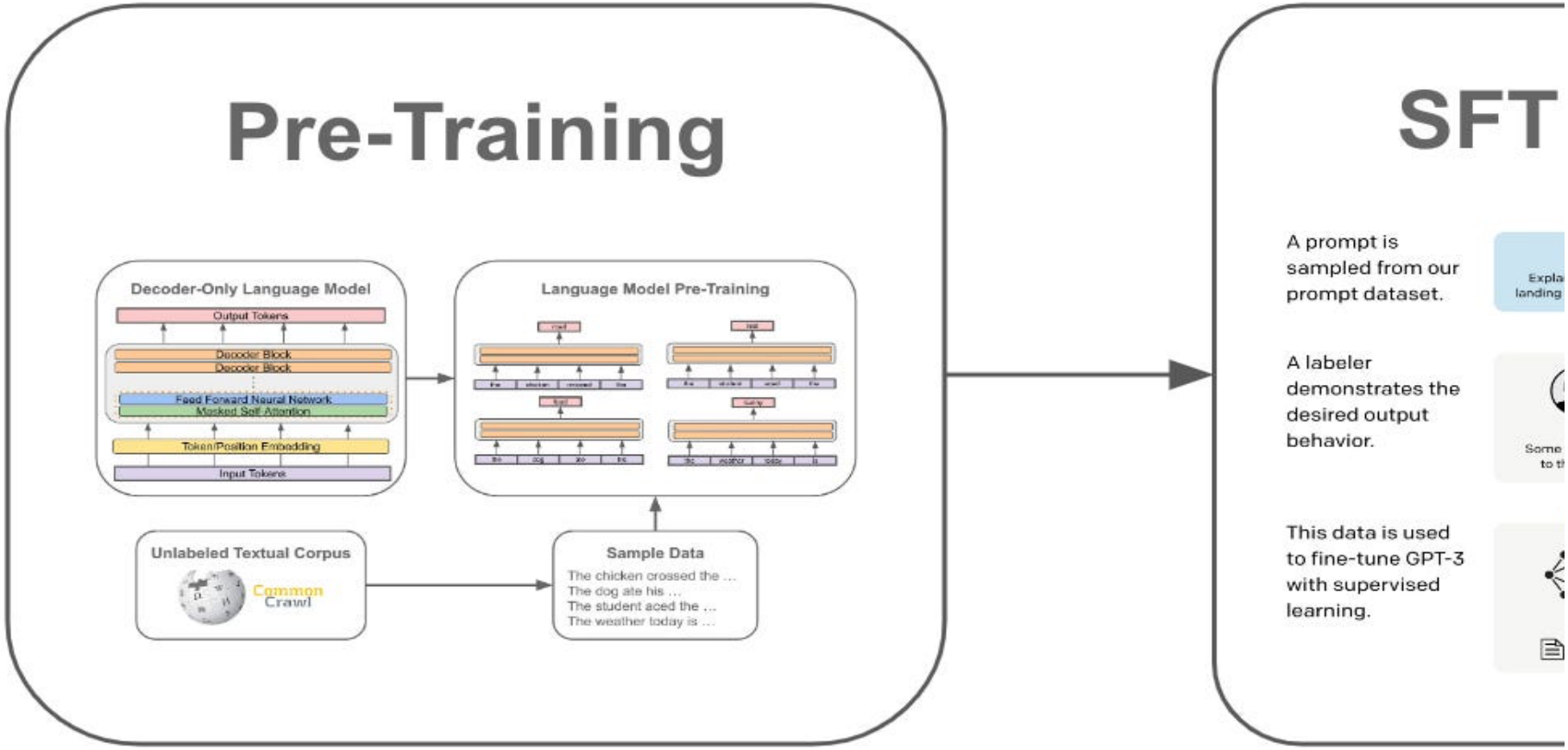
2.3 LLMs training workflow



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2.4 LLMs Evaluation

- Automated Evaluation
  - metric-based
  - objective assessment
- Human Evaluation
  - comaprative assessment
  - qualitative insights
  - vibe check
- Benchamrks datasets
  - diverse tasks and metrics
  - may rely on MCQA
- Adversarial Evaluation
  - robustness against attacks
  - identify and mitigate risks

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3 Political Biases in LLMs

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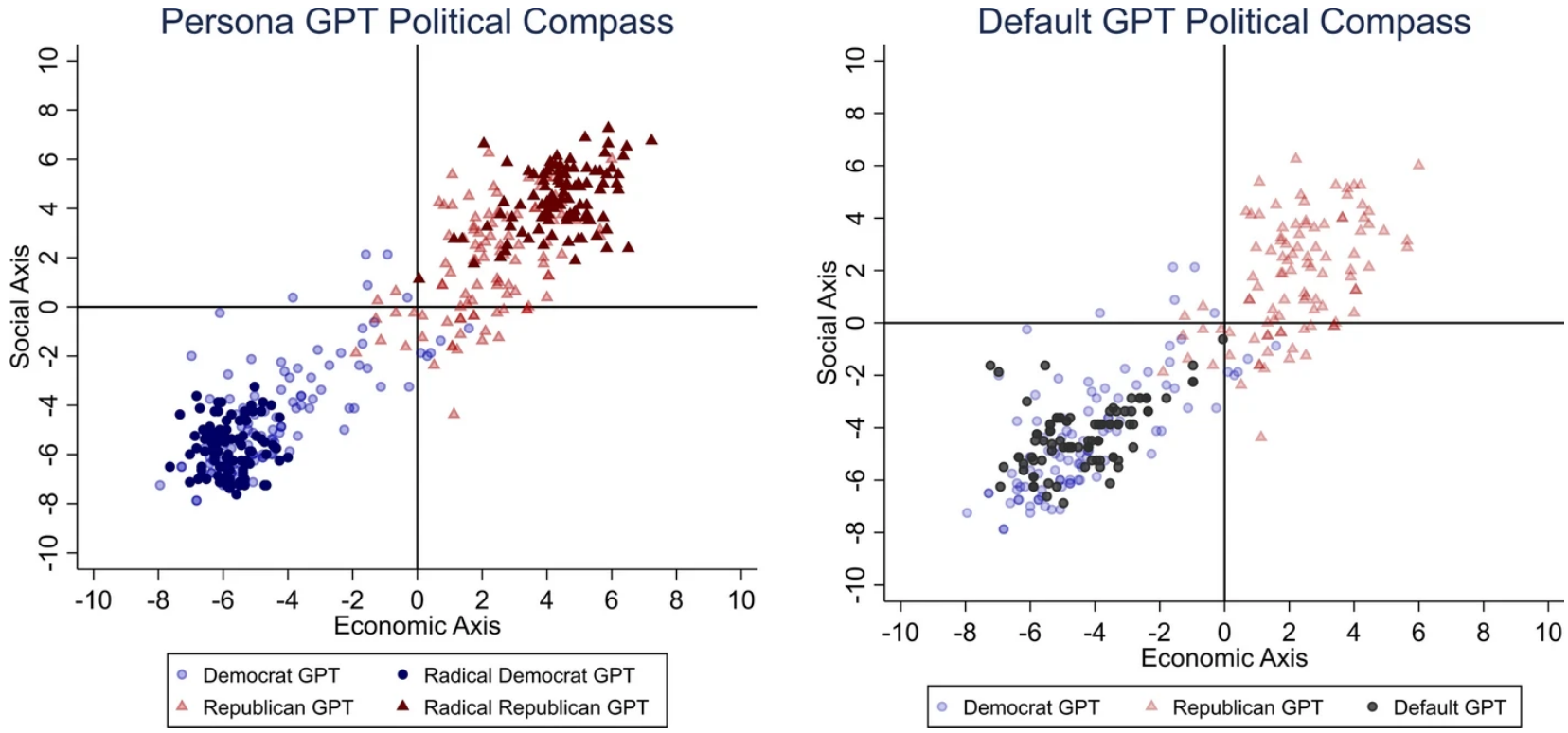
3.1 The Political Compass

Many studies make use of the PCT [3, 19–21], highlighting biases towards progressive, left-leaning views.



Extracted from [21].

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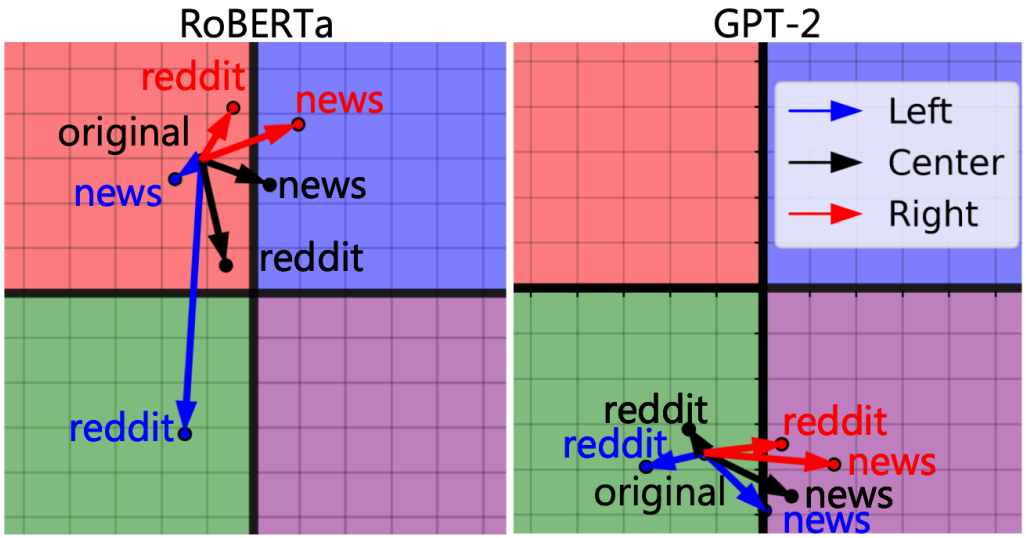
3.2 Influencing behavior

Common mechanisms to modify LLMs behaviors:

- prompt engineering [20, 21]
- fine-tuning [1, 22]



PCT position after training on partisan corpora. From [1]

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3.3 Methodological Issues

- Findings inconsistencies (large variance, prompt sensitivity [19], orthogonal context-dependent [23])
- Technical concerns
  - MCQA concerns [24, 25]
    - Probing methods discreapancies [26, 27]
    - Contamination or Clever Hans [28, 29]
    - Reflective Self-Assessment [30]
- **Not aligned with real-world use-cases** [19, 31]

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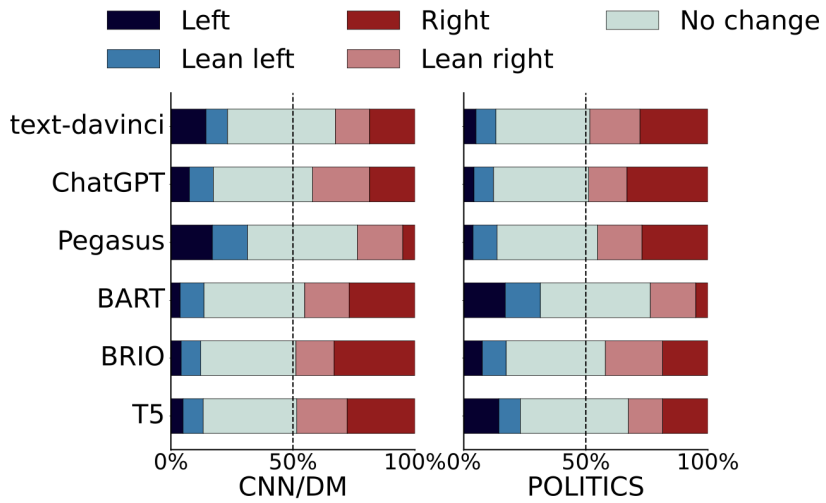
3.4 Other frameworks?

- Political Stance: *what* is said and *how* it is said [32]
  - topical assessmment
- Summarization Task [15]
  - another task, another view?



Changes in political stances between the summary and the article. From [15]

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4 Project

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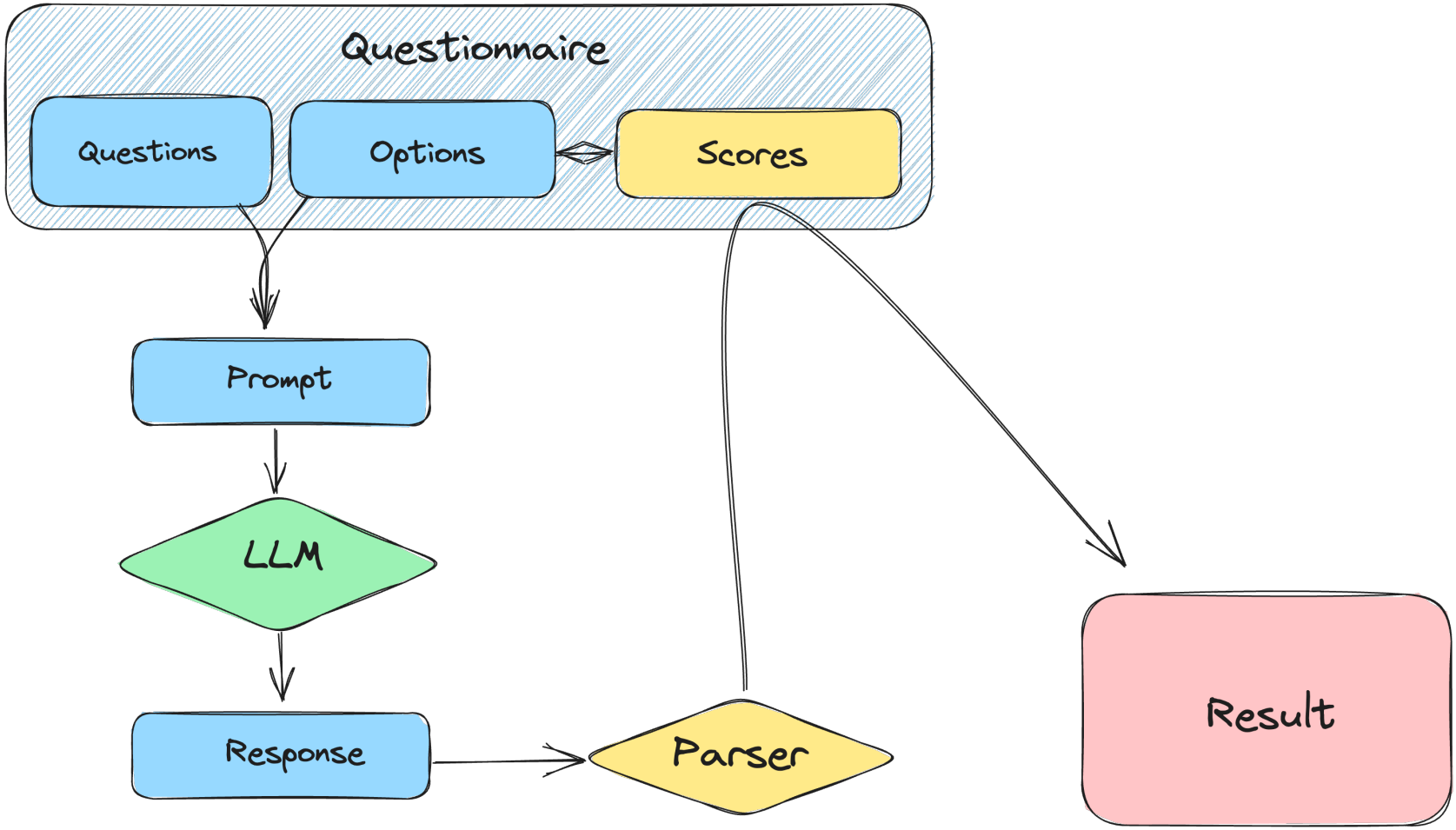
4.1 Base framework proposition



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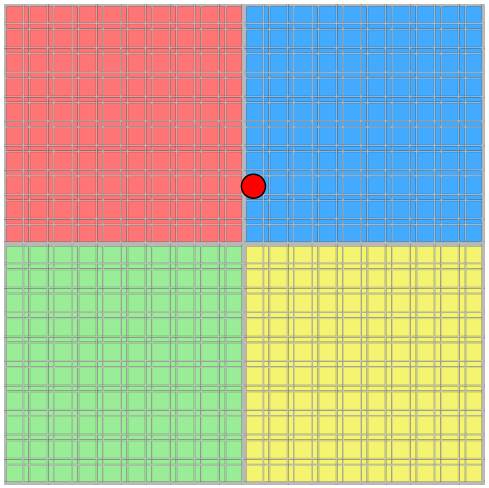
4.2 The Political Compass Test

Link to the original website



Economic 0.38 Social 2.41

Copy link to save or share answers

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Purple libright Tiny indicator

Page 1

If economic globalisation is inevitable, it should primarily serve interests of trans-national corporations.

○ Strongly disagree ○ Disagree ◉ Agree ○ Strongly agr

I'd always support my country, whether it was ri

○ Strongly disagree ○ Disagree ◉ Agree ○ Strongly agr

No one chooses their country of birth, so it's foolish

○ Strongly disagree ○ Disagree ◉ Agree ○ Strongly agr

Our race has many superior qualities, compared w

○ Strongly disagree ○ Disagree ◉ Agree ○ Strongly agr

The enemy of my enemy is my frienc

○ Strongly disagree ○ Disagree ◉ Agree ○ Strongly agr

Military action that defies international law is some

○ Strongly disagree ○ Disagree ◉ Agree ○ Strongly agr

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4.3 Code

GitHub link

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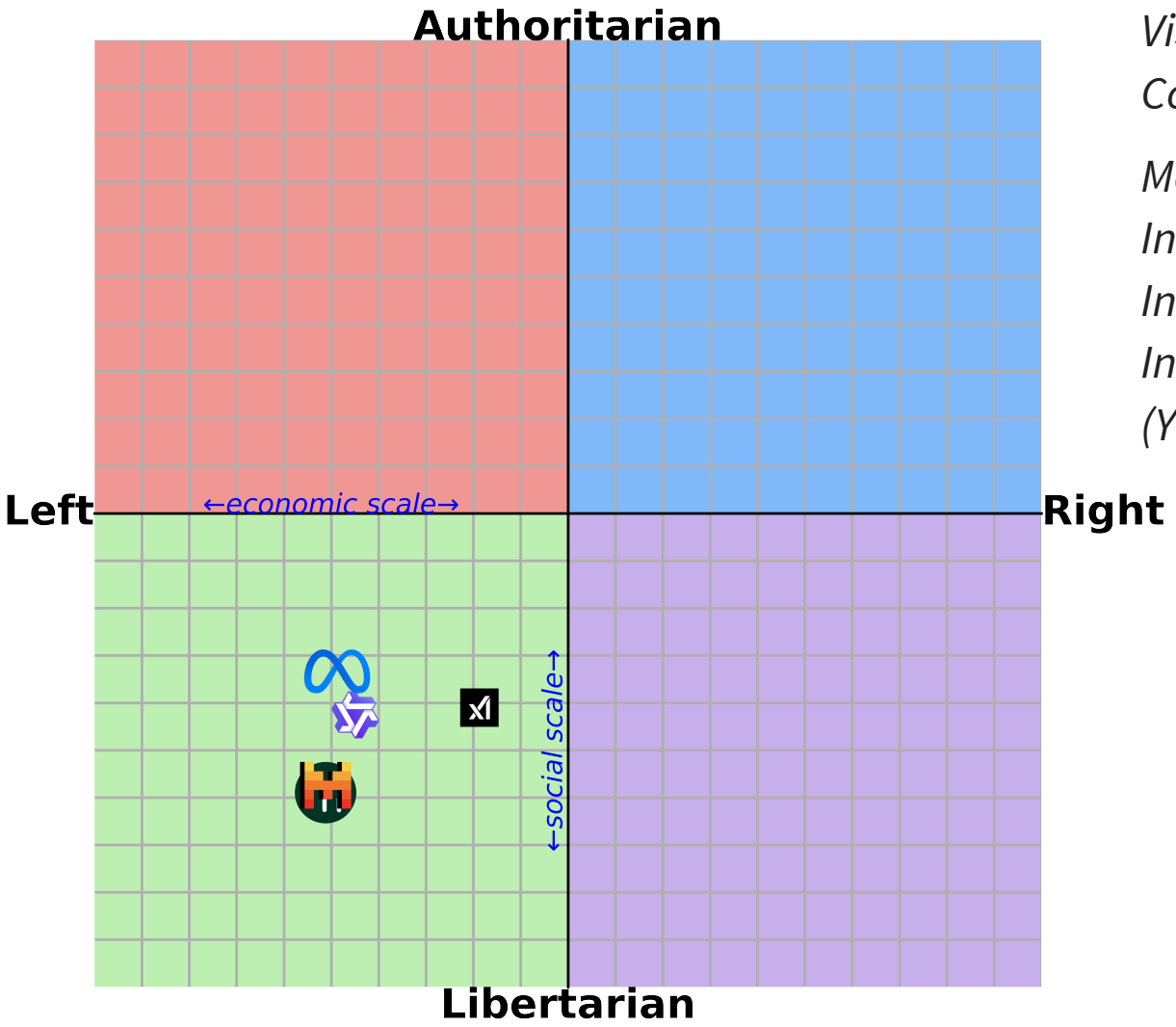
4.4 Examples



Visualisation of the Political Compass Test results.

Models include: Llama 3 8B Instruct (Meta), Qwen 2.5 72B Instruct (Qwen), Mixtral 8x7B Instruct (Mistral), Yi 34B Chat (Yi), and Grok-beta (xAI).

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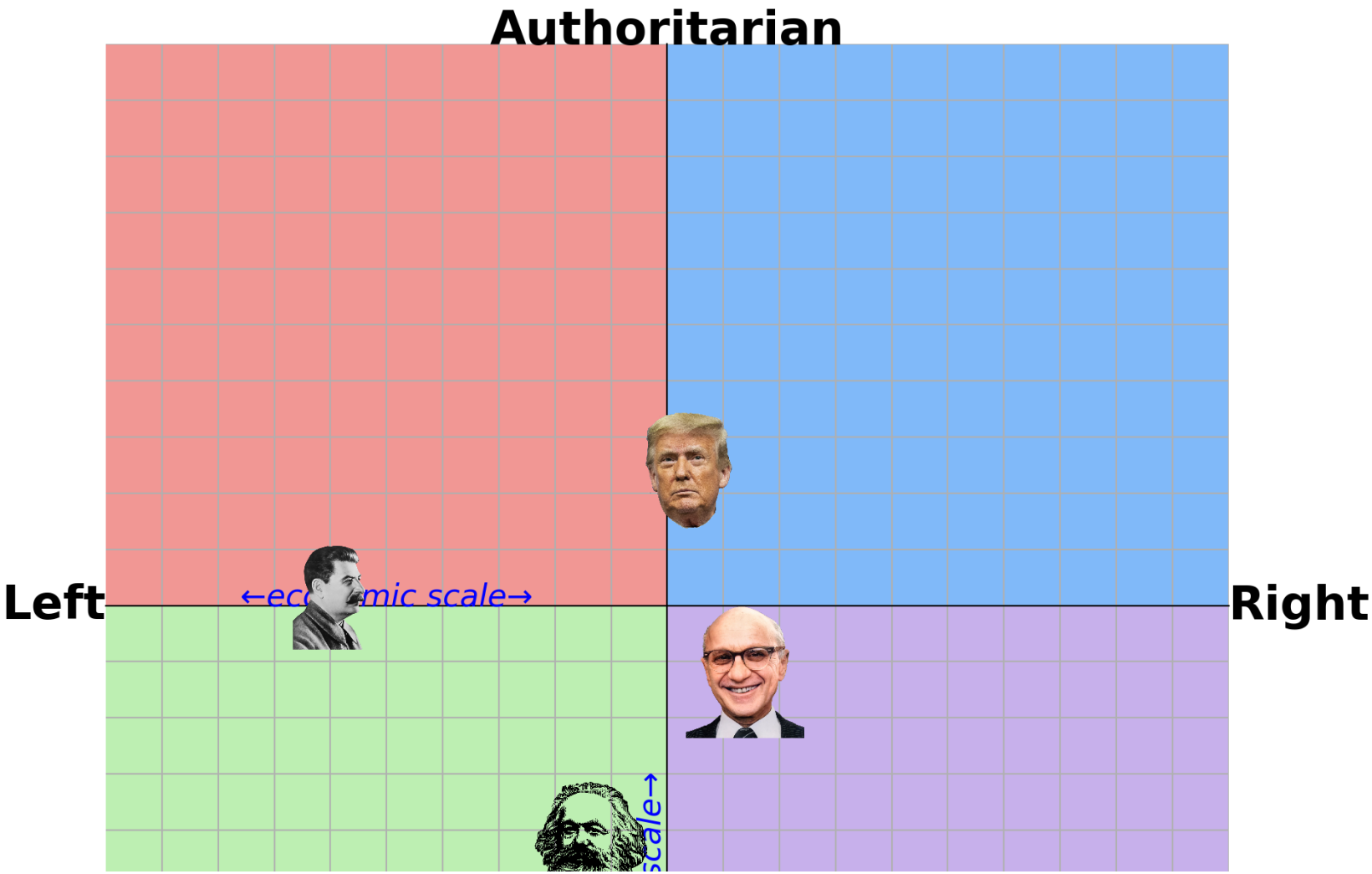
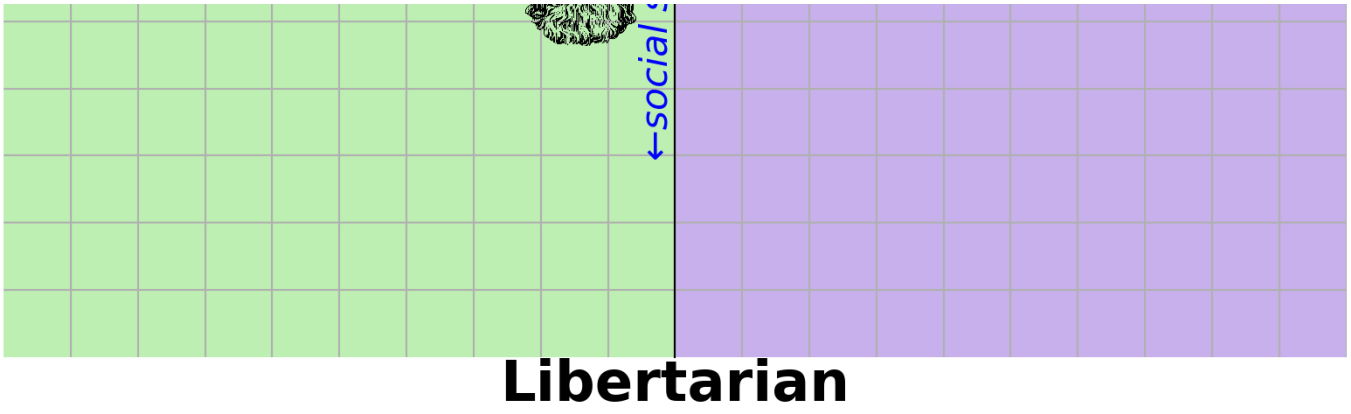
Output Code





Visualisation of the Political Compass Test results. Characters (Joseph Stalin, Karl Marx, Donald J Trump, and Milton Friedman) are persona from character.ai [33].

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