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Beyond the Text

Methodological Advances in Political Science Research

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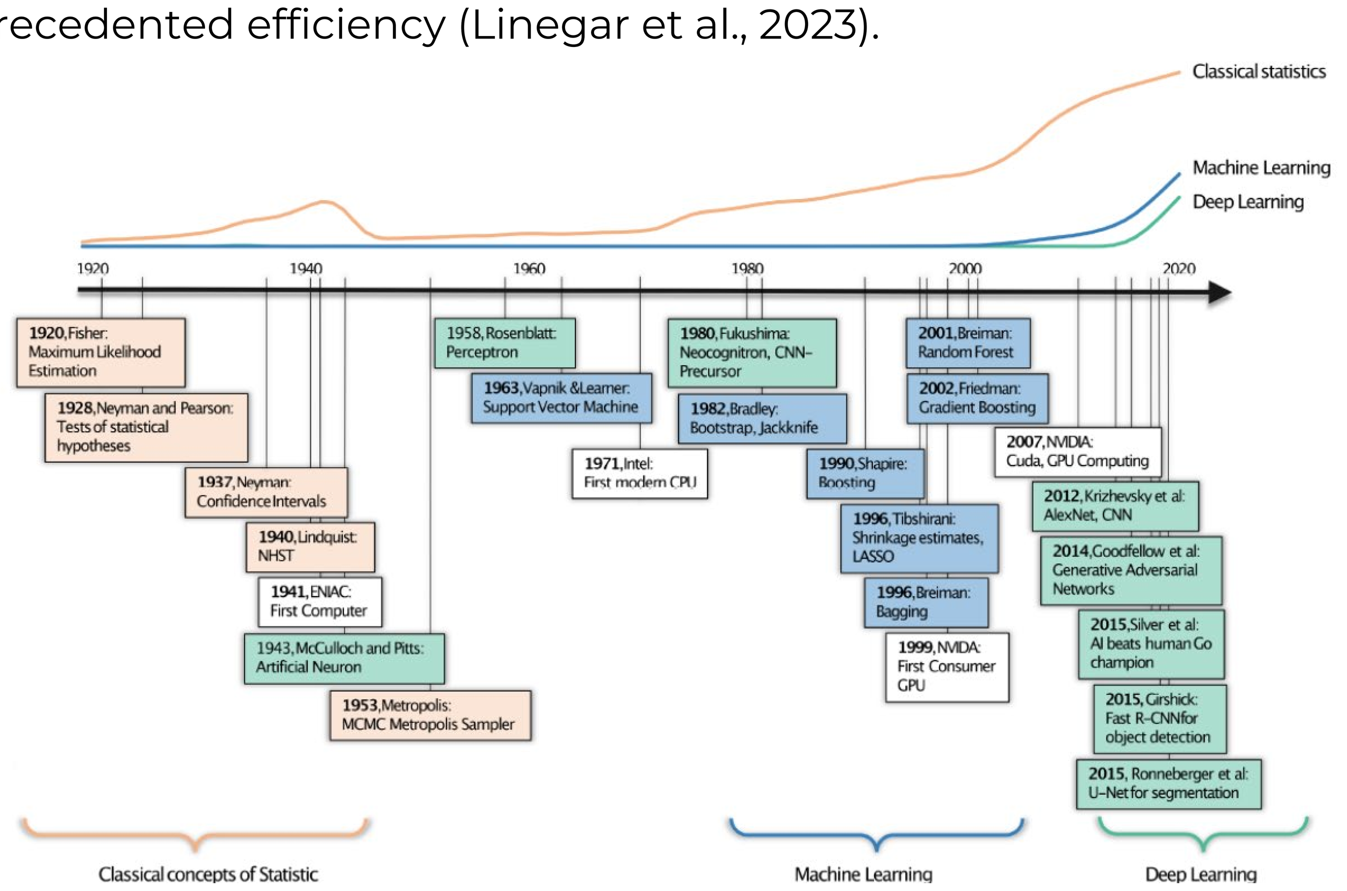
Introduction

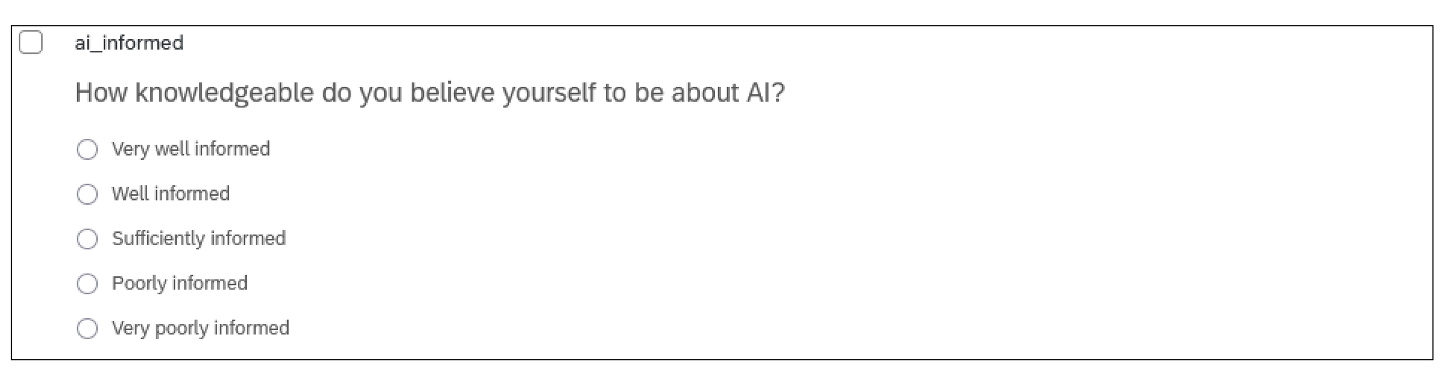
The computational revolution has transformed text analysis. Bayesian inference, machine learning, and Large Language Models (LLMs) now enable researchers to process vast amounts of textual data with unprecedented efficiency (Linegar et al., 2023).



Source: Fosse (2025)

We review these methodological advancements, illustrating how AI-driven tools enhance political science research.

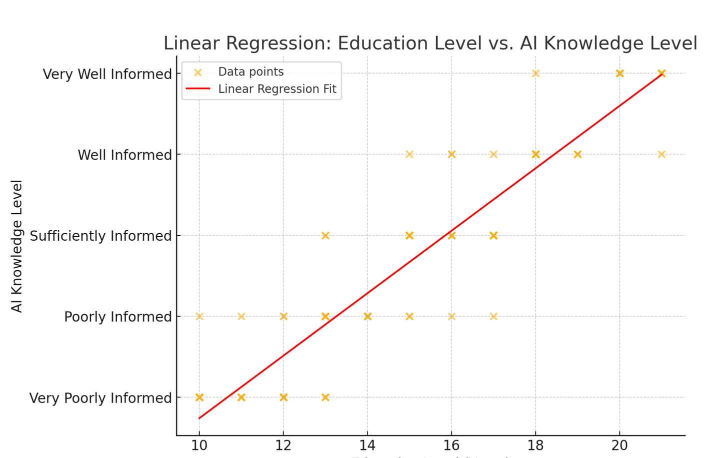
Classical Statistics: Regression (Survey Questionnaires)

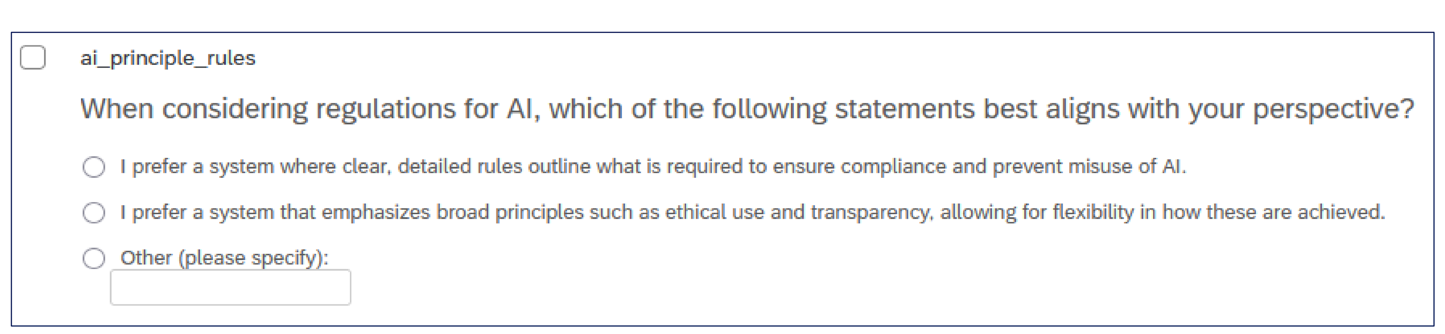


- Using **linear regression**, we model the relationship between **education level** (years) and **AI knowledge** (self-report), for example.

$$AI\,Knowledge = \beta_0 + \beta_1 \times EducationLevel + \varepsilon$$

- **β1** = effect of education level on AI knowledge.
- **ε** is the error term.

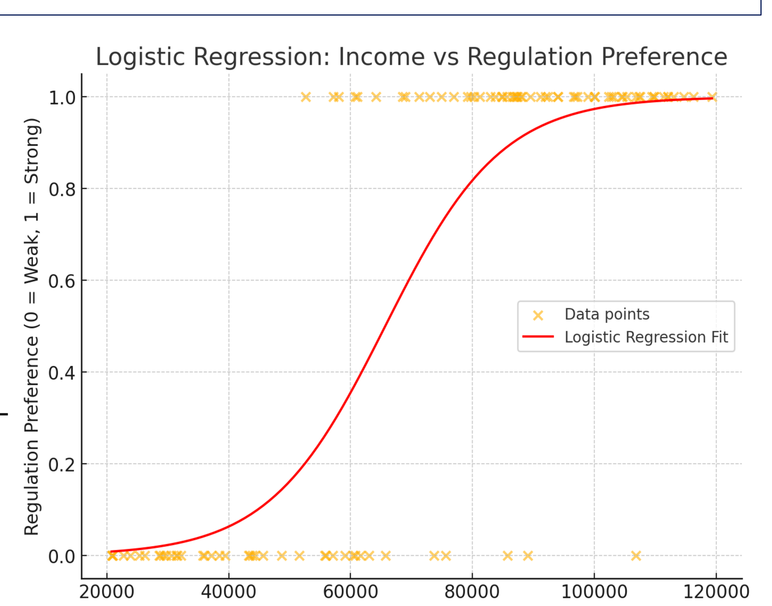




- Using **logistic regression**, we model the likelihood that a respondent prefers **principle-based AI governance** vs. **rule-based governance** by **income level** ($), for example.

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot Income)}}$$

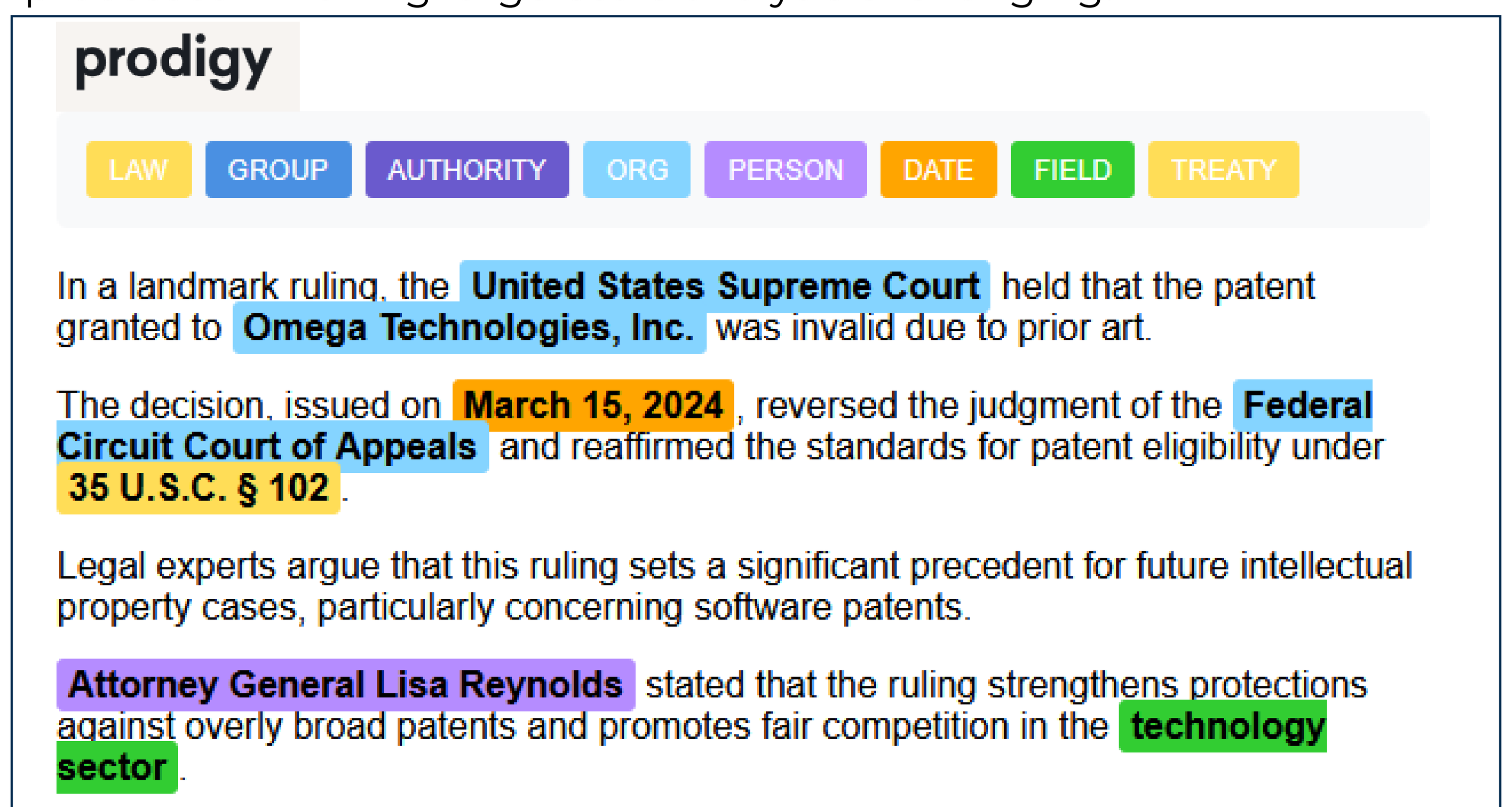
- ***Y*** (dummy) = preference for principle-based regulation (1 = Strong, 0 = Weak)
- **β1** = effect of income level on preference.



Annotation & Labelling: From Manual to AI-Assisted

For decades, political scientists have relied on hand annotation and manual coding to analyze qualitative data.

- e.g., Analyzing open-ended question responses, or employing the Discourse Quality Index (DQI) traditionally required labour-intensive processes—making large-scale analysis challenging.



What can we do with labeled data?

- Train **supervised models** for stance detection in political debates.
- Use **Name Entity Recognition (NER) to track policy discussions across time** in the Canadian Hansard.
- Automate **discourse quality analysis in deliberative democracy research** (Greenaway, n.d.)

Large Language Models (LLMs)

LLMs—AI systems trained on vast amounts of data to understand, generate, and manipulate human language—**are the future of textual analysis** (Spirling, 2023).

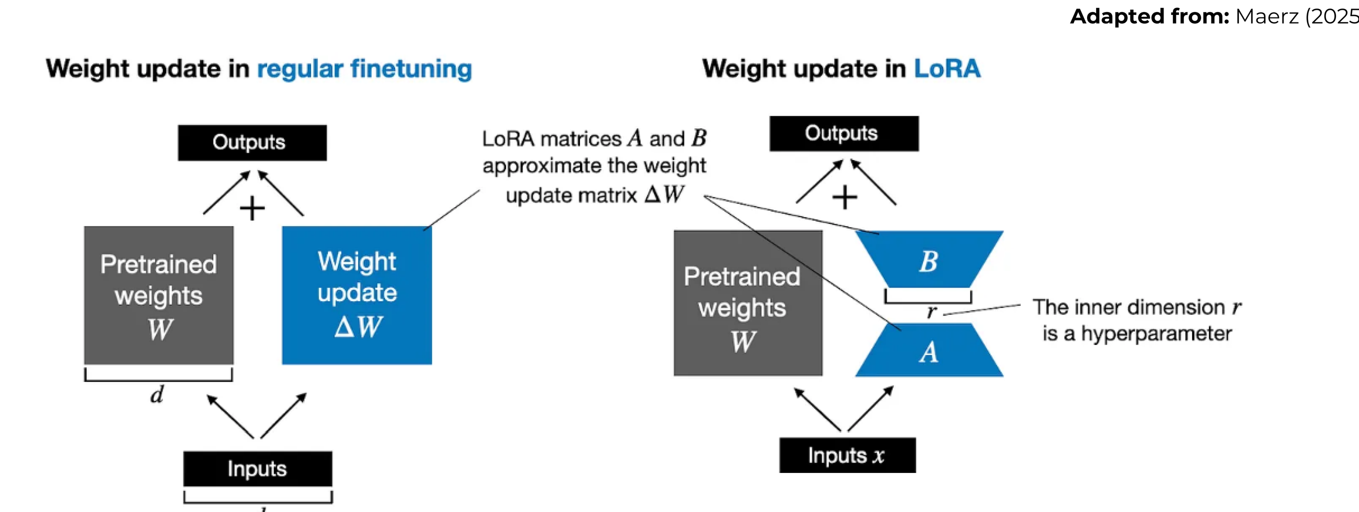
Adapting LLMs for specific tasks—like analyzing political texts or identifying policy trends—requires, at minimum, **fine-tuning**.

LLM Tuning Techniques

Comparison of different fine-tuning and adaptation techniques

Technique	Trainable Parameters	Memory Usage	Data Requirements	Pros	Cons
Full fine-tuning	High	High	Large dataset	Best performance	Costly, time intensive
Fine-tuning classification head	Moderate	Very low	Small dataset	Quick adaption	Less flexible
Parameter-efficient fine-tuning (PEFT)	Extremely low	Extremely low	Small dataset	Efficiency and generalization	Less performing
Prompt engineering	No parameters tuned	Extremely low	None (zero-shot)	No model modifications	Careful prompt design

Adapted from: Maerz (2025)

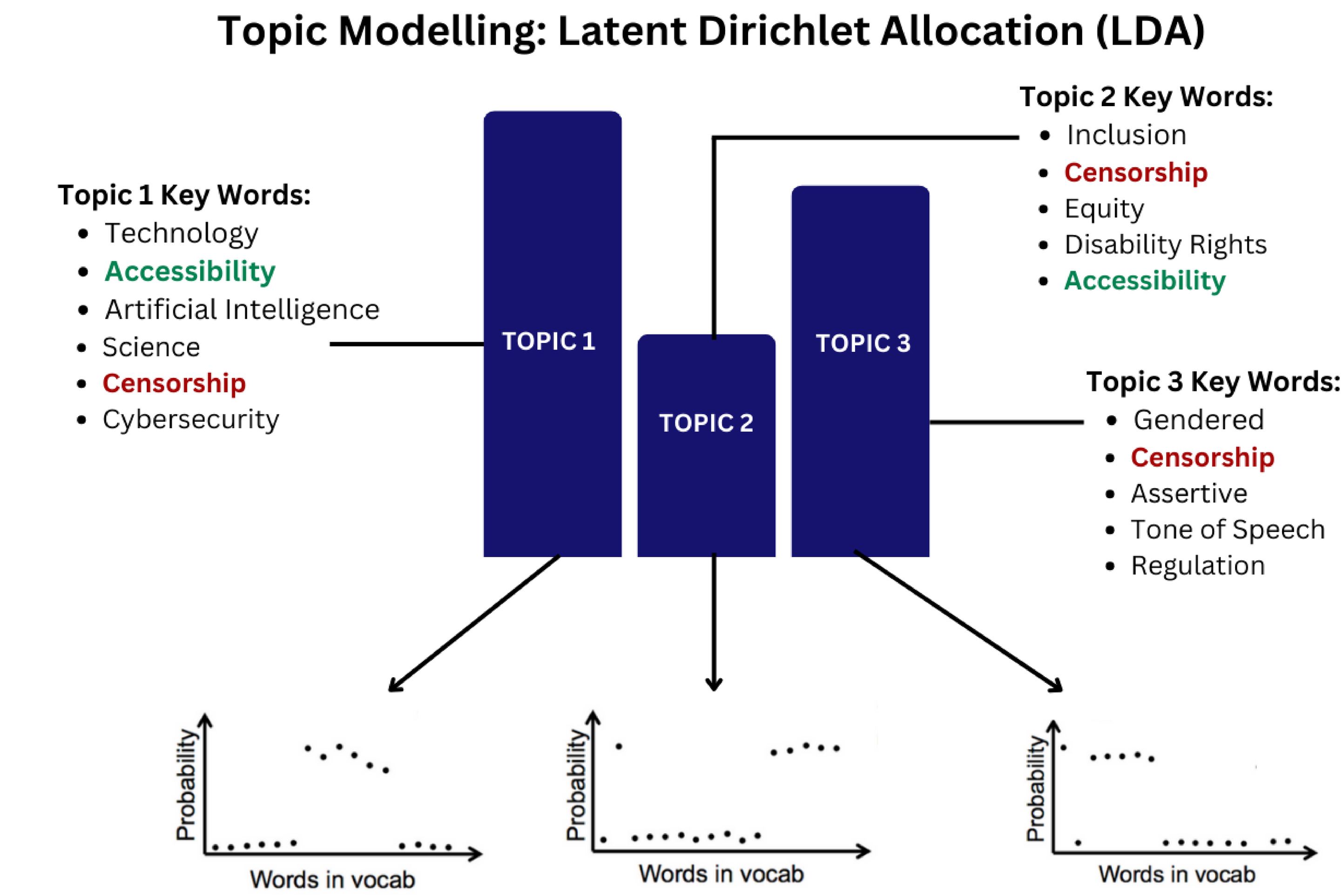


Source: Hu et al. (2021)

Acknowledgements

- Join the UTSC Methods Hub discord: https://discord.gg/N4edY2J5
- Follow SDAC's GitHub repository: https://github.com/PSSA-SDAC/sdac
- Look for CCR-Accredited Data Workshops in Fall 2025.

Topic Modelling



Keyword-Assisted Topic Modelling

Technology & AI	Artificial • Intelligence • **Automation** • Robotics Algorithm • **Computing** • Cybersecurity • Network
Accessibility & DEI	**Inclusion** • Equity • Diversity • Accessibility • Bias Representation • **Discrimination** • Opportunity
Censorship & Speech	Regulation • Freedom • Restriction • Policy • **Platform Moderation** • Governance • Misinformation

How This Works for keyATM vs. LDA

- keyATM allows pre-specified keywords to help define topics, which is why some terms (e.g., "**Automation**" and "**Inclusion**") would be explicitly set.
- LDA, by contrast, would discover topics based on word co-occurrence patterns without pre-set words.

Applicable Projects

Ctrl + Alt + Regulate (Cowan, Greenaway, Kallas, & Spahiu., n.d.)

- Employs a mixed-methods approach to analyze 1,000 post-secondary student responses on AI regulation. We integrate keyATM to extract dominant themes in open-ended responses and utilize logistic regression to assess the relationship between demographic factors and preferences for principle-based vs. rules-based governance.

Under the AI-nfluence (Jensen, Amjad, Miles, & Cowan, n.d.)

- Combining survey data and text analysis, this project employs a fine-tuned quantized LLM to classify and interpret students' written rationales regarding AI's impact on their careers.

Disability Politics in Political Science Pedagogy (Greenaway & Cowan, n.d.)

- To map the representation of disability in political science curricula, this study applies comparative computational text analysis on a cross-national dataset of syllabi and textbooks. keyATM uncovers how disability politics is framed (e.g., social welfare vs. rights-based), while text classification models quantify its inclusion relative to other political issues.

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