

Generative Social Choice: The Next Generation

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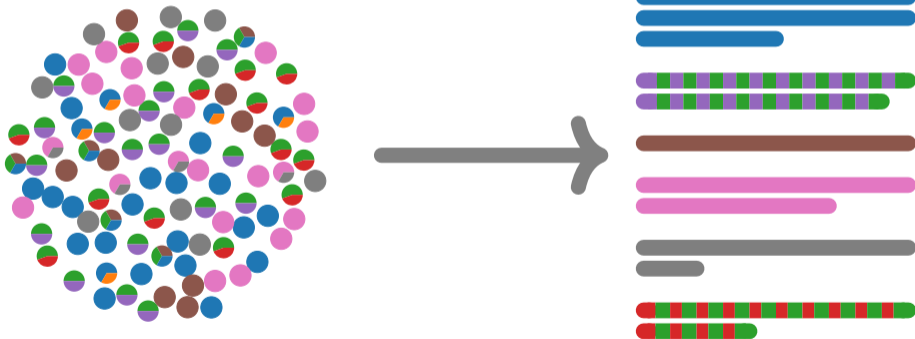


Link to paper

Problem Statement

Given a large dataset of diverse opinions, how can we **proportionally summarize** them?

$x\%$ of users "control" $\simeq x\%$ of words, $\forall x$



Motivation

Proportional summarization has a diverse array of potential applications.

Motivating application: **AI and democracy**; specifically, *collective response* systems like **Polis**.

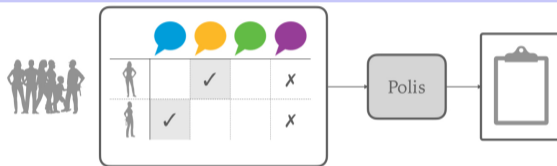


Figure source: Daniel Halpern

LLM-based methods allow for greater flexibility in such processes (for both inputs and outputs).

However: ad hoc LLM-based methods lack reliability, robustness, and interpretability.

↪ *E.g., how to ensure the LLM does not suppress or overweight fringe opinions?*

Approach: Generative Social Choice

Our goal: **proportionally summarize** user opinions using a trustworthy, LLM-based process.
How to unite these conflicting objectives?

Our approach (initiated by [FGPPRSW'23]): **generative social choice** query framework.
Related to broader literature on AI alignment with guarantees, see e.g. Wu and Hartline (2024).

Theory: Specify process using (black-box) queries

Process $P :=$ algorithm that uses queries \square, \circ .

Thm. Under assumptions about \square, \circ , process P satisfies proportionality/runtime/... guarantees.

Our work: social choice \rightarrow proportionality guarantees.

Instantiation: Implement and empirically test queries

Implement \square, \circ , typically leveraging LLMs

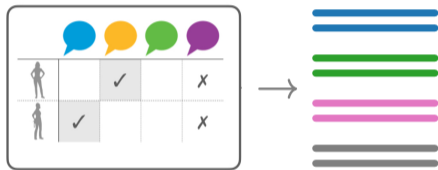
Evaluate \square, \circ using relevant data (e.g. Polis)

Our work: PROSE, a general-purpose implementation.

Key observation: **establishing trust in the queries** is sufficient for **trust in the whole process**.

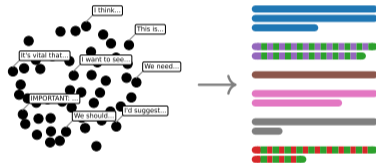
Generative Social Choice... The Next Generation

Generative Social Choice [FGPPRSW'23]



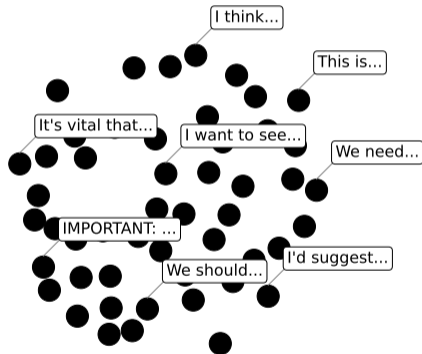
1. User sets number of statements k
2. Each statement represents $1/k$ of users
3. Guarantees only for perfect query results
4. Implementation for structured user data

The Next Generation



1. Algorithm adaptively chooses k
2. Variable statement lengths (support \propto length)
3. Process and guarantees for noisy query results
4. Flexible implementation compatible with unstructured user data

Input



+ desired length B of output slate (in words)

Social Choice: Theory of Collective Decision Making



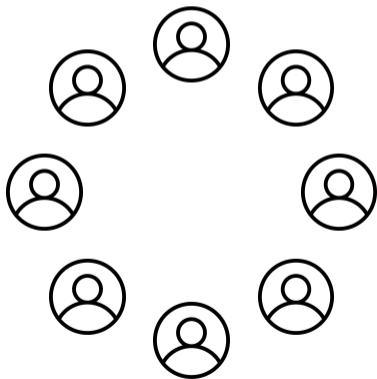
or



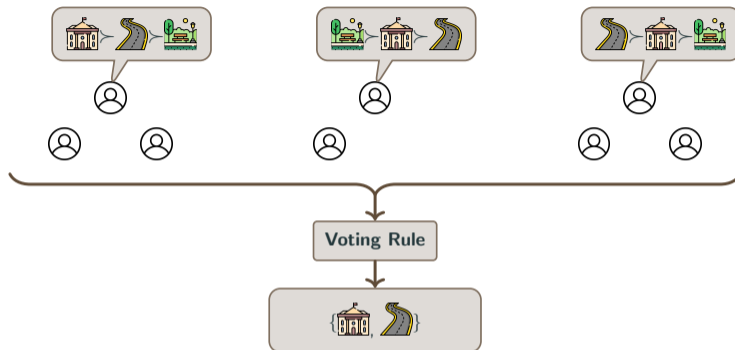
or



?



Social Choice: Theory of Collective Decision Making



Proportional summarization

- Voters: participating users.
- Candidates: all possible statements.

Task: Select statements with total length $\leq B$.
 \rightsquigarrow Participatory budgeting
(theoretically very well understood)

Novelty Virtually infinite candidate space.

Slate Generation via Social Choice

Generative Query



Data of users, approval level r , length c



Most-liked statement of at most c words at level r

Discriminative Query



User data + statement














How much user agrees with statement


Slate Generation Algorithm



Initialize user set , slate .

For $\odot \in \{\text{happy}, \dots, \text{neutral}, \dots, \text{sad}\}$ and $c \in \{B, B-1, \dots, 1\}$

- Generate statements $\square(\text{cloud}, \odot, c)$ for $\odot \geq \odot$
- Using discriminative query \bigcirc , compute:

				
				
				...
		...		

- Pick  with most $\odot \geq \odot$
- If $(\#\bullet \text{ with } \odot \geq \odot) \cdot \frac{B}{n} \geq \text{wordcount}(\text{thick double line})$:

Delete covered users  + add statement to slate 

PROSE and Experimental Setup

PROSE Query Implementations (GPT-4o-2024-11-20):

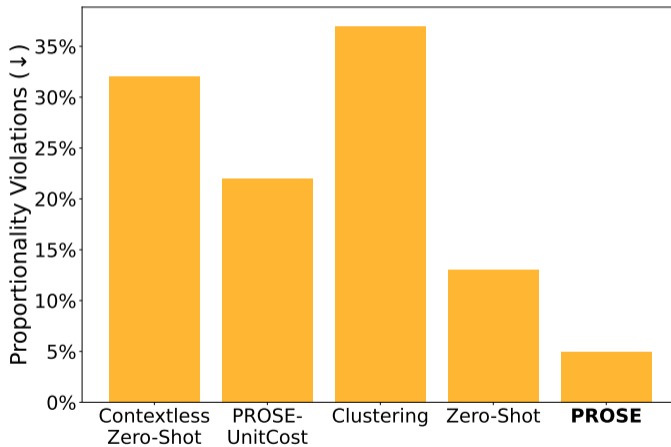
- **user, statement** → (Disc) → **approval score** computed based on two (fast) LLM calls
- **users** → [Gen] → **statement** identify cohesive group (clustering) + generate consensus statement (LLM)

Datasets UCI Drugs Dataset Polis
BIRTHCONTROL, BIRTHCONTROLSKEW, OBESITY, BOWLING GREEN

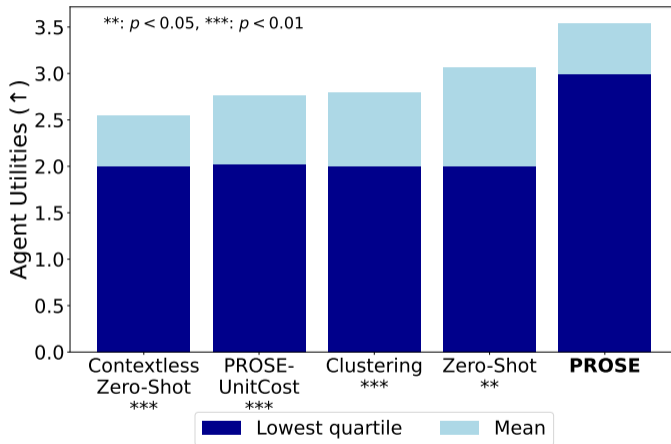
Baselines

- *Contextless Zero-Shot*: given topic and budget, generate slate in single response
- *Zero-Shot*: given topic, budget, and user data, generate slate in single response
- *Clustering*: clustering of embedded user data + LLM-generated cluster summaries
- *PROSE-UnitCost*: PROSE with unit-length statements (resembling [FGPPRSW'23]'s approach)

Experiments: Results on Bowling Green



Experiments: Results on Bowling Green



(Utilities computed using “independent”, expensive CoT-based \rightarrow Disc \rightarrow)

High-Level Takeaways

(1) Increased trustworthiness of LLM-based algorithms via **query framework**

(2) LLMs can enable **new forms of civic participation**