Mitigating Information Asymmetry in Governmental Policies: An AI-Driven Approach

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Introduction

- Informed citizens are crucial for a vibrant democracy, allowing for active civic engagement and holding representatives accountable [1].
- Information Asymmetry, introduced by Akerlof [2], is a barrier to understanding policies when the government has more information than the citizens, leading to misinformed public discourse and distrust [3].
- Academic research indicates that Information Asymmetry is central to many public policy issues and affects democratic responsiveness and elite-public agreement [4, 5].
- This study explores the use of an advanced AI model, GPT-4, to make complex policy documents more accessible to the public, enhancing democratic engagement and promoting informed citizen participation [6].

Methods

- Governmental Bills were collected from Congress.gov

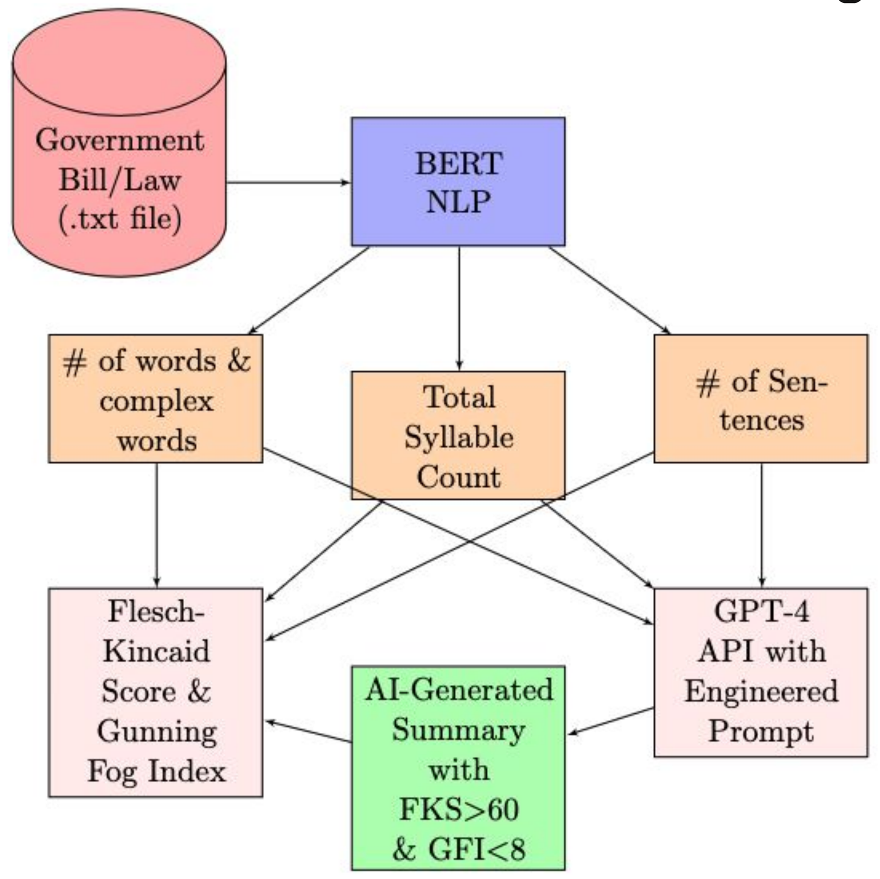

Figure 1: Pipeline flowchart for AI-Generated Summaries [figure by author]

Summary Generation Framework

$$R_{lcs} = \frac{LCS(X,Y)}{m}$$

$$P_{lcs} = \frac{LCS(X,Y)}{n}$$

$$F_{lcs} = \frac{(1+\beta^2)R_{lcs}P_{lcs}}{R_{lcs}+\beta^2 P_{lcs}}$$

Figure 2: Equation for LCS-based Recall, LCS-based Precision, and LCS-based F-measure for ROUGE-L Calculation [figure by author]

1. Textual features are extracted from bills through a BERT NLP
2. Features are parsed into a engineered prompt for GPT-4 for comprehensible summary creation
3. Information retention is calculated through ROUGE-L score from equation in Figure 2
4. Sub-par summaries with low information retention are parsed through feedback loop with algorithm in Figure 3 for new summary creation with high information retention and comprehensibility

Methods

- A Greedy Algorithm was implemented to generate preliminary summaries by sequentially picking sentences with the most overlap with key abstract terms
- These outputs were parsed into a Genetic Algorithm as inputs, amalgamated ontop of what it already generated in order to maximize ROUGE-L scores
- The Genetic Algorithm refines summaries through iterative selection, crossover, and mutation guided by the novel fitness function in FIgure 3.
- The fitness function is used to optimize for a summary with the highest information retention and comprehension by accounting for the Gunning Fog Index (GFI) and Flesch-Kincaid Score (FKS), in addition to the ROUGE-L score

$$fitness = (w_r \cdot \text{ROUGE-L}) + (w_{fk} \cdot \text{FK\_Score}) - (w_{gf} \cdot \text{GF\_Index\_Adjusted})$$

Figure 3: Novel Fitness Function for Genetic Algorithm for Text Summarization [figure by author]

Results

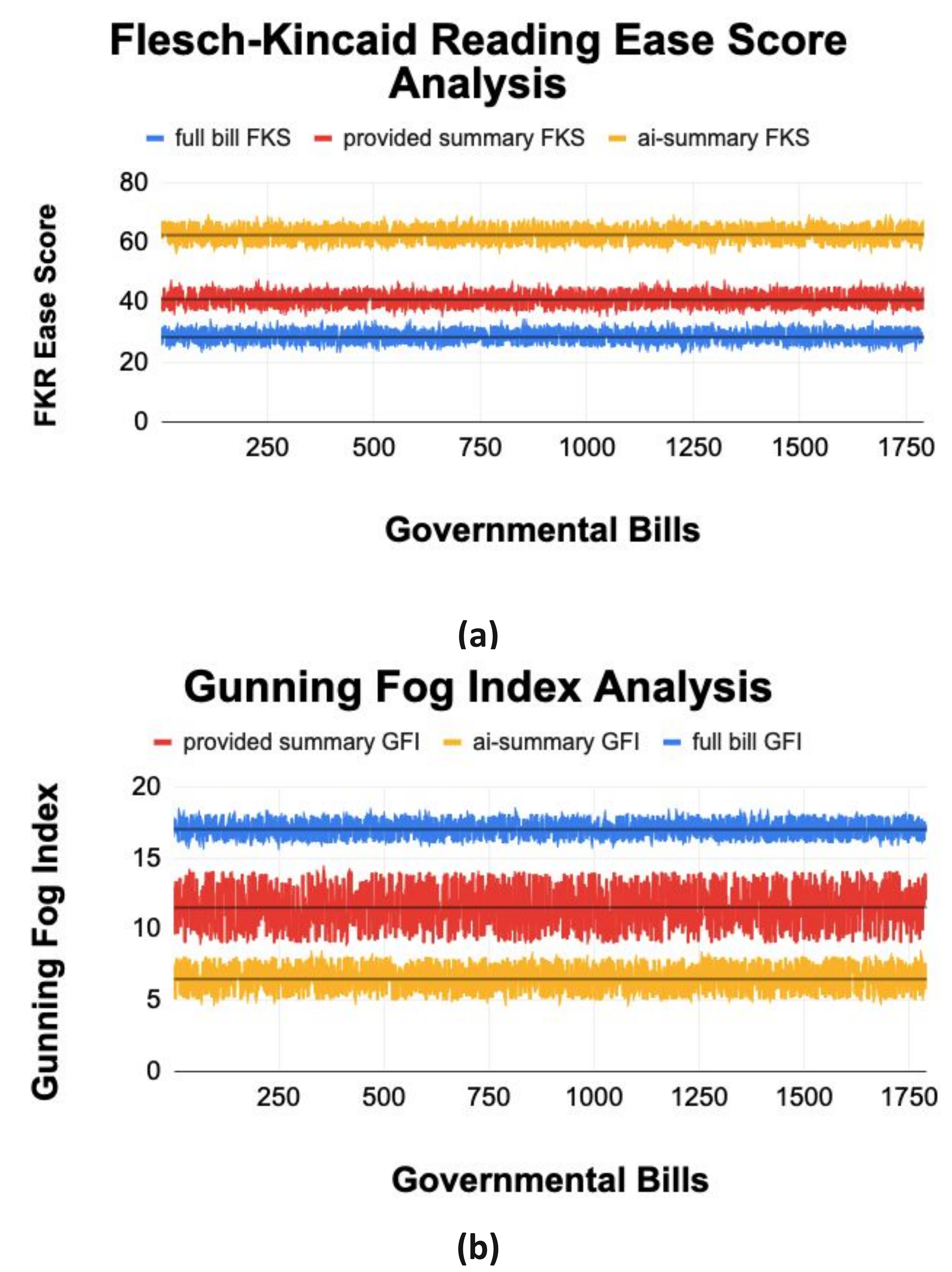

Figure 4: Readability Assessment Graphs for Texts [figure by author]

Results

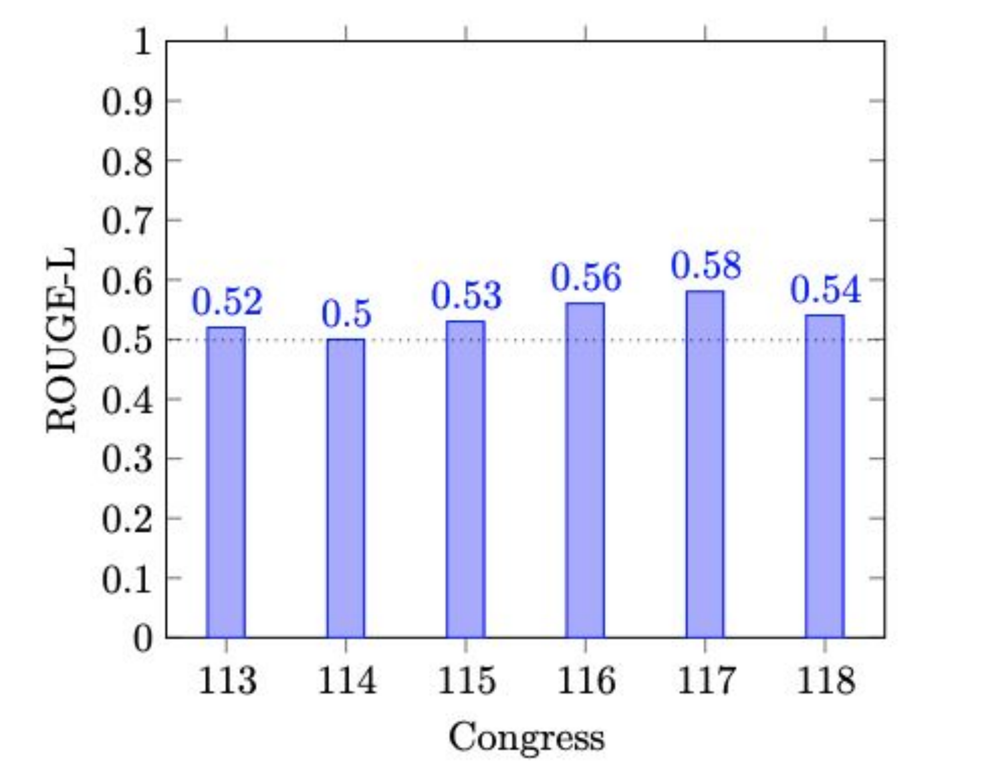

FIgure 5: Histogram of ROUGE-L scores for Congress 113-118 [figure by author]

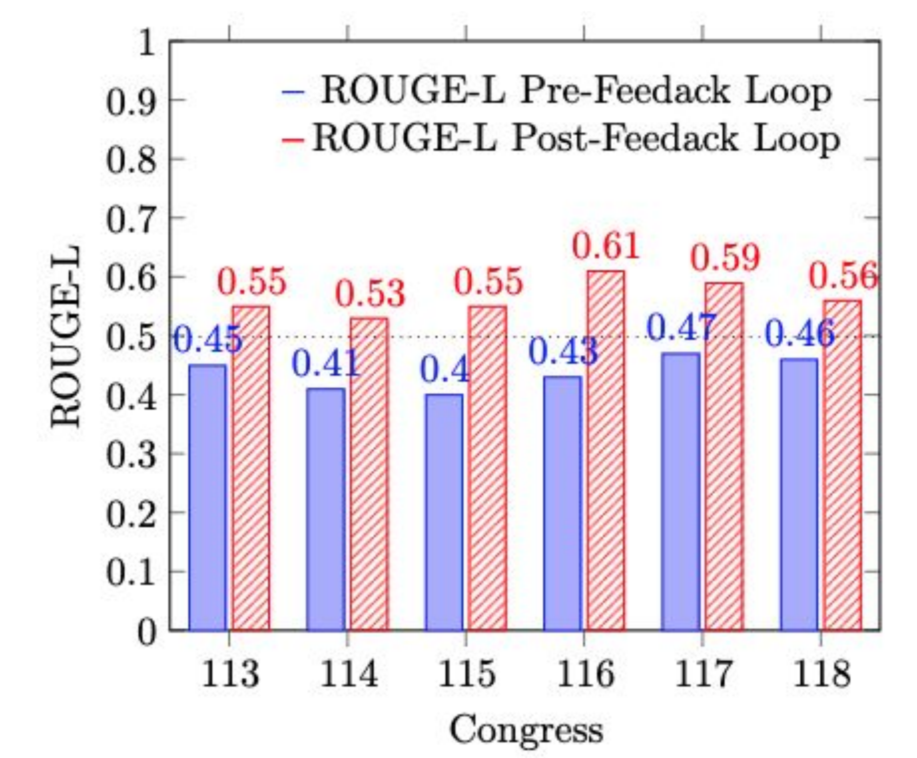

Figure 6: ROUGE-L scores for Summaries parsed through Feedback Loop [figure by author]

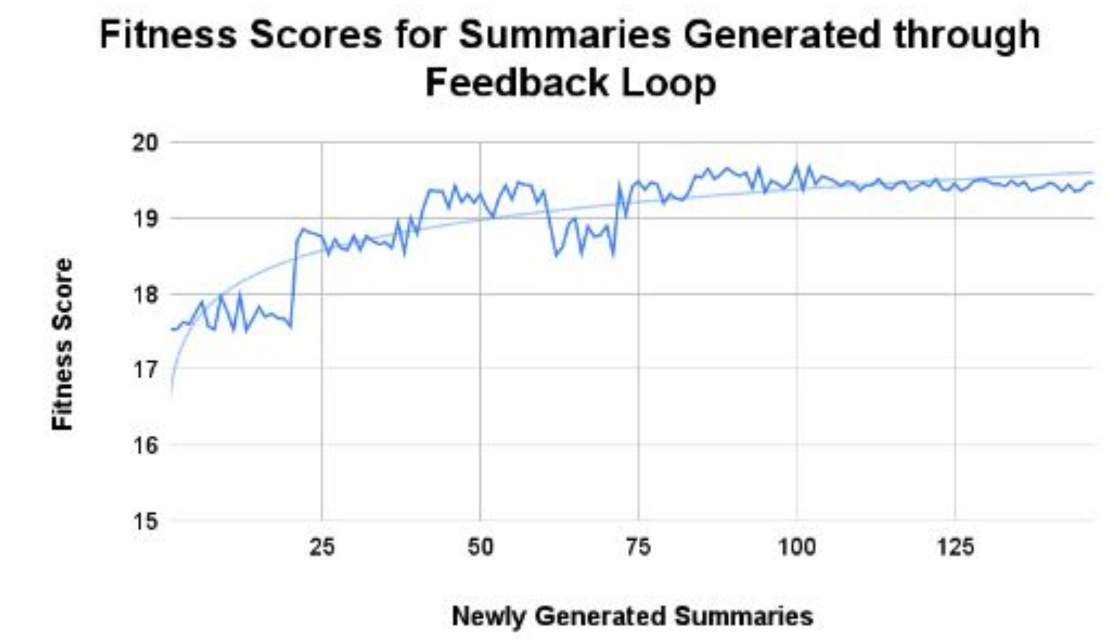

Figure 7: Fitness Score Graph from Feedback Loop of Newly Generated Summaries [figure by author]

Conclusions

- Comparative analysis using Gunning Fog Index (GFI) and Flesch-Kincaid Score (FKS) shows AI-generated summaries are clearer than provided summaries and original texts.
- AI summaries have a substantial average FKS of 62.6 compared to full bills' 28.4 and provided summaries' 41.1, indicating a 121.5% improvement over full bills and a 52.3% increase from provided summaries.
- GFI for AI summaries averaged at 6.44, a significant decrease from full bills' 16.9 and provided summaries' 11.6, enhancing readability.
- Out of 1792 bills, 1645 had ROUGE-L scores ≥ 0.5. For the remaining 147 bills, a feedback loop with a Genetic Algorithm increased the ROUGE-L scores by an average of 29.89%, with fitness scores converging to around 19.5 after iteratively getting better.
- This study affirms the capacity of AI, particularly GPT-4, in democratizing access to complex government policies, contributing to a more informed public.

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