

Explanatory Summarization with Discourse-Driven Planning

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Introduction

Lay Summarization Challenge:

- Scientific texts need explanatory content for accessibility
- Current methods underrepresent explanations in generated summaries

Step 3: Two Model Variants

• **Plan-Output** (End-to-End): Train P(b, s|x) to generate plan (b) + summary (s) jointly based on input document (x)

Method

• Plan-Input (Pipeline): PG Module P(b|x) generates plan, SG **Module** P(s|x, b) generates summary

Key Insights:

Explanations help lay readers understand complex concepts through analogies, background, comparisons

- Most models follow end-to-end approaches without explicit explanation modeling
- Plan-based models offer better controllability and reduce hallucinations

Method

Step 1: Explanatory Content Extraction

- Apply DMRST parser to identify explanatory EDUs from RST relations
- Focus on 4 key relations: Background, Elaboration, Explanation, Comparison
- Extract (explanation, target) EDU pairs from reference summaries



Main Results

- Plan-Input achieves SOTA performance across all metrics
- More explanations: ExpRatio 17.68% vs. 13.61% (Mistral_{FT})
- Better factual consistency: VeriScore 0.71 vs. 0.56 ($Mistral_{FT}$)
- Higher readability: D-SARI 37.18 vs. 30.11 (Mistral_{FT})



Figure 3. Model performance comparison across three datasets

Human Evaluation: Humans remain superior, but Plan-Input outperforms all baselines, achieving near human-level accessibility and substantial improvements in **explanation quality**.

Figure 1. RST tree structure

Step 2: Plan Generation

- Use GPT-40 to generate questions from target sentences + context
- Questions trigger explanatory content (based on QUD) framework)
- Create ordered sequence of plan questions $b = (q_1, q_2, ..., q_n)$

q1: How does the cerebellum use feedback to adjust the timing of movements in a sequence? q2: How does the cerebellum use feedback from one blink to trigger the next in a sequence? q3: How can a blink in one eye trigger a blink in the other eye?

Controllability of Explanatory Content

- Our models can **control explanation types** by modifying plans
- Deleting specific RST relation questions reduces the corresponding explanations in the output



Control Effectiveness on SciNews Dataset

[The cerebellum utilizes proprioceptive feedback to fine-tune the timing of movements in a sequence based on previous actions.]^{t_1}[Imagine the cerebellum as a coach who watches how you perform a move, then gives tips to improve the next one based on what was seen. $]^{e_1}$ But how exactly does it achieve this? [To investigate, we trained rabbits to blink in response to an external cue and explored whether the cerebellum could use feedback from one blink to trigger the next.]^t₂[As expected, after learning the initial blink, the rabbits blinked again in response to their own first blink, creating a chain of movements. $]^{e_2}$ Control experiments confirmed that each blink was initiated by the previous one rather than the original cue. Consistent patterns of brain activity during this process indicate that the cerebellum adjusts movement based on feedback from previous actions. [Building on this, we trained rabbits to blink on cue, and they learned to initiate additional blinks in response to earlier blinks in the sequence.]^t₃[We further found that the rabbits could use a blink from one eye as a cue to trigger a blink in the other eye, suggesting that the same mechanism governs these movements. $]^{e_3}$ This raises the possibility that the cerebellum might also guide sequences of cortical activity during cognitive tasks, given its extensive connections to the cortex, a question future experiments should explore.

> Explanatory EDU Target EDU

Figure 2. Plan generation pipeline

Figure 4. Control effectiveness across different explanation types

Conclusion

- Introduced explanatory summarization task for controlled lay summary generation
- Developed discourse-driven planning using RST + QUD frameworks
- Proposed two model variants: Plan-Input and Plan-Output

Project Info

 Achieved SOTA performance on 3 datasets with significant improvements

dongqi.me/ projects/ExpSum

https://dongqi.me

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Planning questions

^{---- [}Processed summary]-----