Cogito Ergo *Summ*: Abstractive Summarization of Biomedical Papers via Semantic Parsing Graphs and Consistency Rewards

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Paper

Motivations

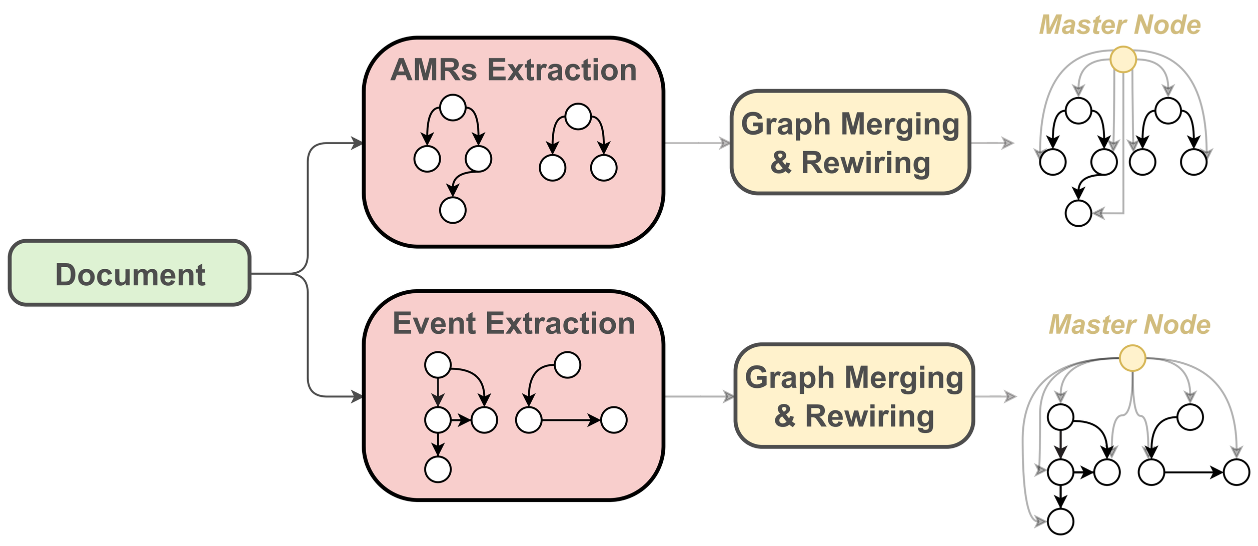
- Biomedical document summarization challenges
  - Medical jargon truly hard to interpret
  - Clauses' interdependence, complex interactions, precise domain information, narrow interpretation margin, no factual mistakes
- Problems and weaknesses of existing solutions
  - Highly prone to hallucinating content or falling back on extraction
  - Superficial text organization rather than underlying semantics
  - Not ensuring document-summary consistency

Contribution

- **CogitoErgoSumm**, the first semantics-aware transformer-based model for single document abstractive summarization in the biomedical domain
  - Combining pre-trained language models and semantic parsing graphs providing formal meaning representations
  - Two different semantic parsing techniques with complementary strengths: **Event Extraction (EE)** and **Abstract Meaning Representation (AMR)**
- **Reinforcement Learning (RL)** to ensure factuality and consistency
  - Reward function based on the average SMATCH score between the original document and the generated summary

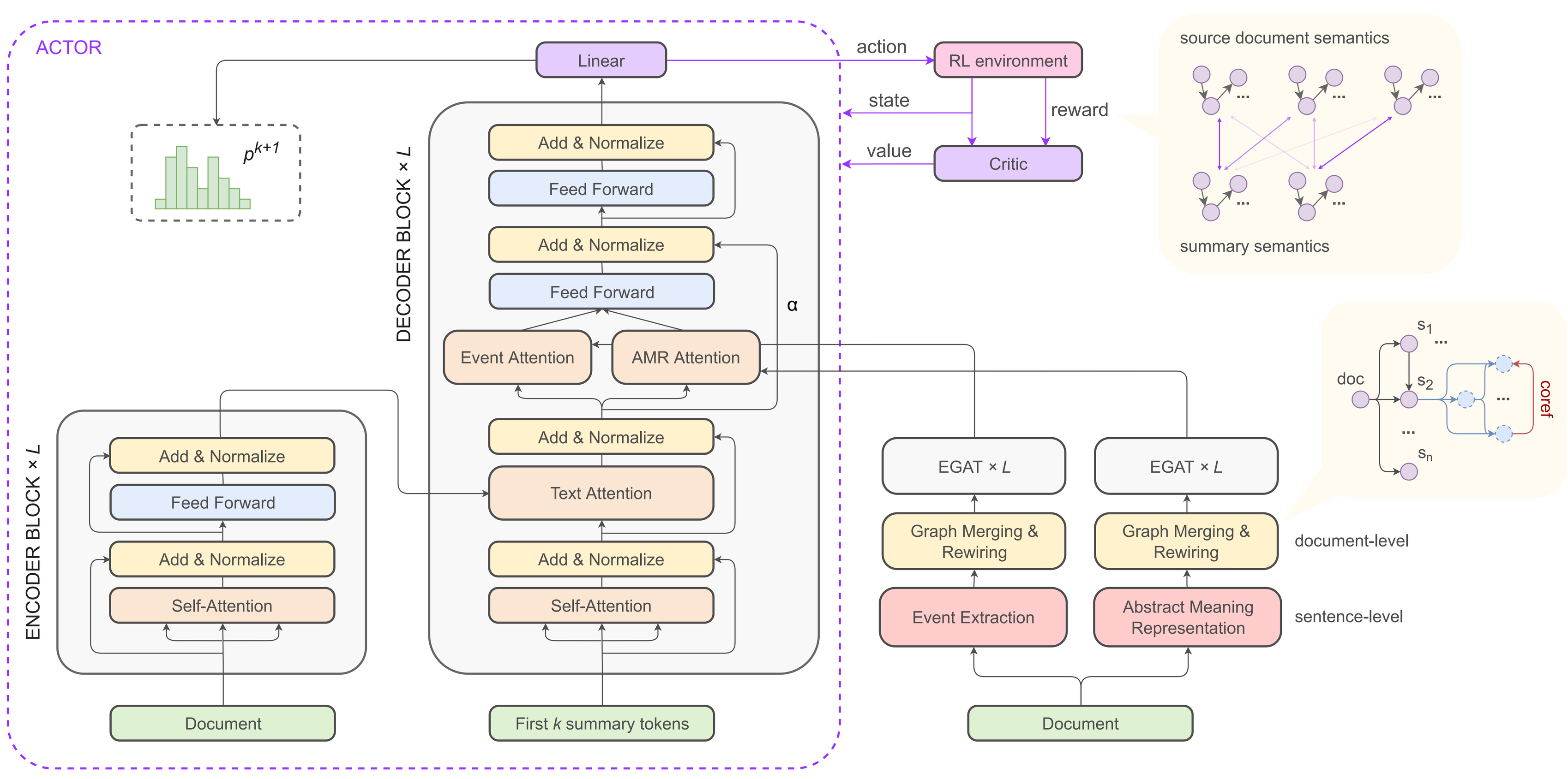
AMR and Event Graphs

- **Abstract Meaning Representation Graphs**
  - Capture the general meaning of any sentence as high-level semantic relations (abstraction from words to concepts)
  - We use SPRING to automatically extract AMRs from sentences
- **Event Graphs**
  - Capture biomedical-specific interactions with n-ary and potentially nested interactions between participants
  - We use DEEPEVENTMINE to automatically extract events



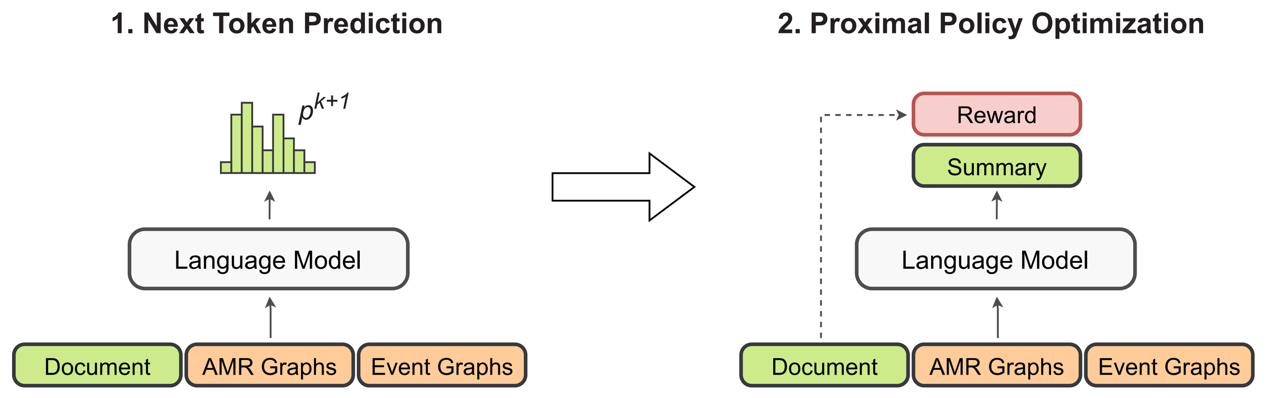
Architecture

- We extend a pre-trained BART-base architecture with the nimble ability to **attend semantic parsing graphs** during decoding and preserve the most relevant information via **RL**



Method

- Two training phases
  - 1^{th} Phase → Next Token Prediction, but with semantic graphs
  - 2^{th} Phase → RL with *Proximal Policy Optimization*



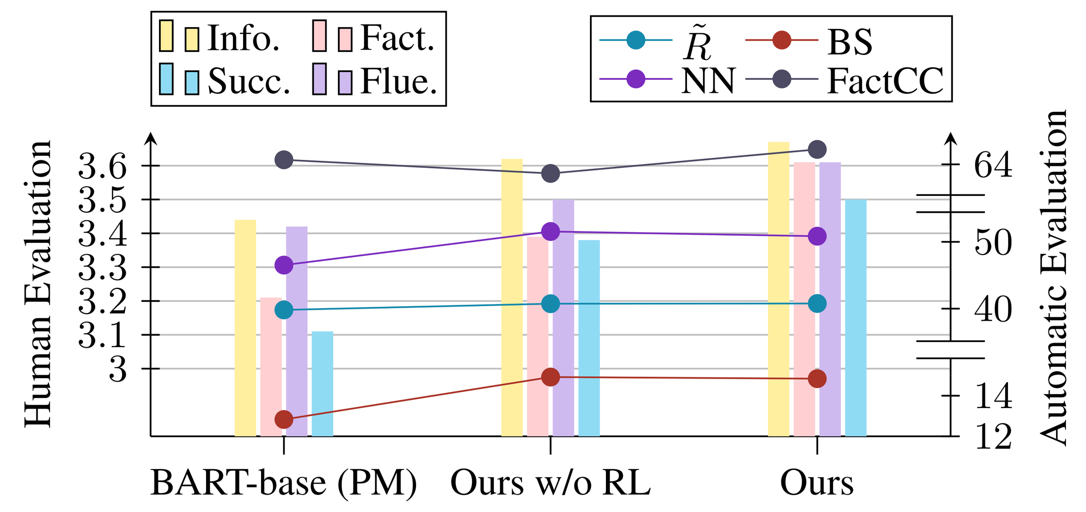
- We add **two extra cross-attentions layers** to the BART decoder: *Event Attention* and *AMR Attention*
  - Node representations obtained using edge-aware GAT layers
- We use **RL to preserve as much pivotal information as possible** from the original document
  - Maximize the overlap between the AMRs of the input document and the AMRs of the generated summary with SMATCH
  - Try not to deviate too much from the pr-etrained model by keeping a low KL-divergence

$$\psi(doc, summ) = AvgSmatch(doc, summ) - \beta \log \frac{\pi_\theta(a_t|s_t)}{\pi_{base}(a_t|s_t)}$$

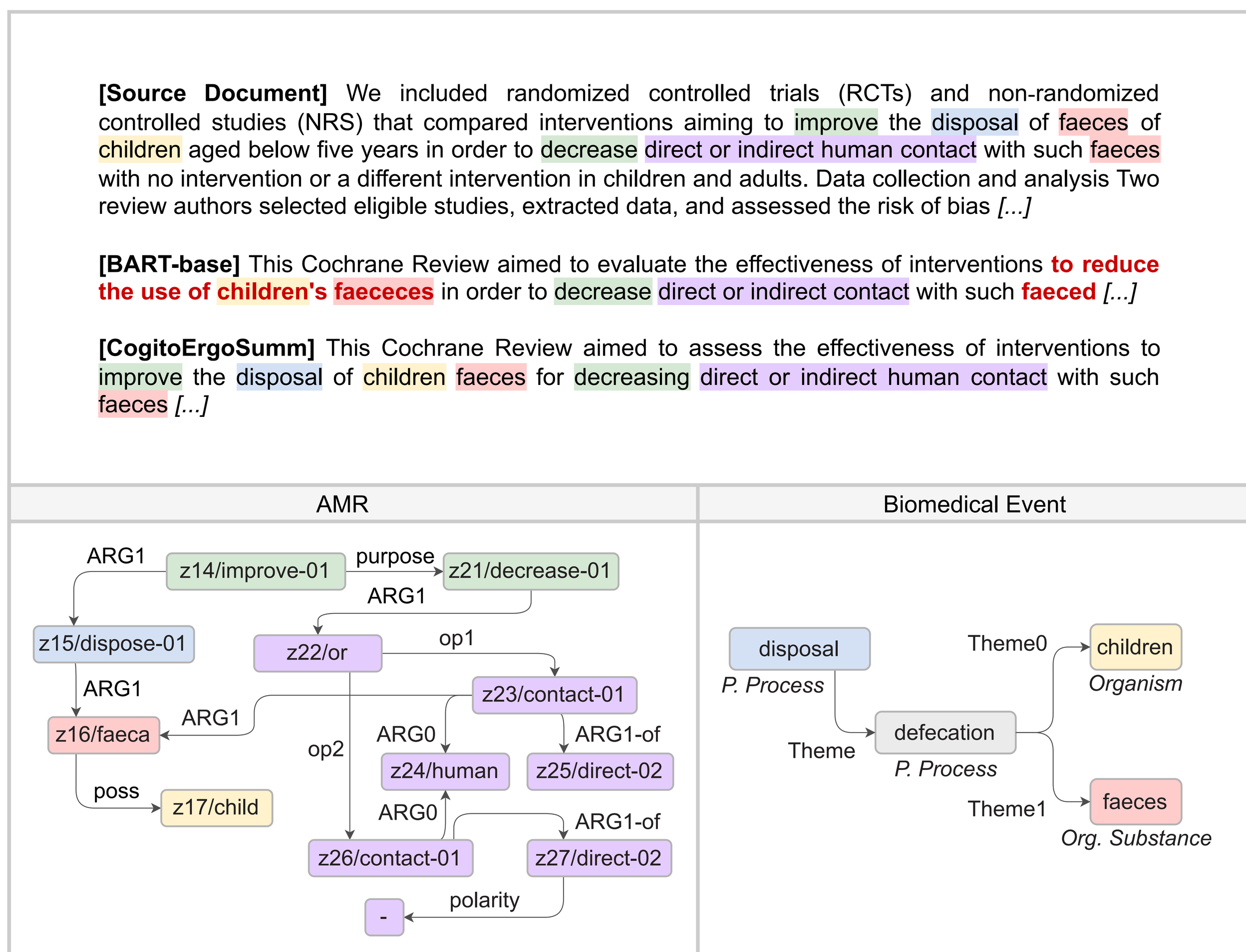
Results

Model	#params	R-1	R-2	R-L	Flesch-Kincaid	Coleman-Liau
ORACLE†	—	53.56	25.54	49.56	14.85	16.13
BERT-base†	110M	26.60	11.11	24.59	13.44	14.40
POINTER GENERATOR†	22M	38.33	14.11	35.81	16.36	15.90
BART-base (PubMed)	139M	51.20	19.77	48.47	13.69	13.45
BART-large (PubMed)†	406M	**52.66**	**21.73**	**49.97**	13.30	14.28
EASUMM‡	8M	46.30	18.73	43.78	12.42	13.06
COGITOERGOSUMM	181M	52.23	20.63	49.44	14.10	13.67
- w/o RL	180M	52.30	20.47	49.46	14.06	13.64
- w/o event and RL	155M	52.13	20.42	49.30	14.02	13.69
- w/o AMR and RL	157M	52.02	20.54	49.25	13.97	13.66

- ROUGE scores higher than most of the previous methods
- Still competitive with BART-large despite having 2x fewer parameters



- Better results on every quality dimension in the human evaluation (+12.46% factualness, +6.69% informativenes)
- The plot also underlines the poor correlation between ROUGE and the desired output properties



- Qualitative example of induced semantic parsing graphs and their assistance to high-quality summarization

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