PLANET: Dynamic Content Planning in Autoregressive Transformers for Long-form Text Generation

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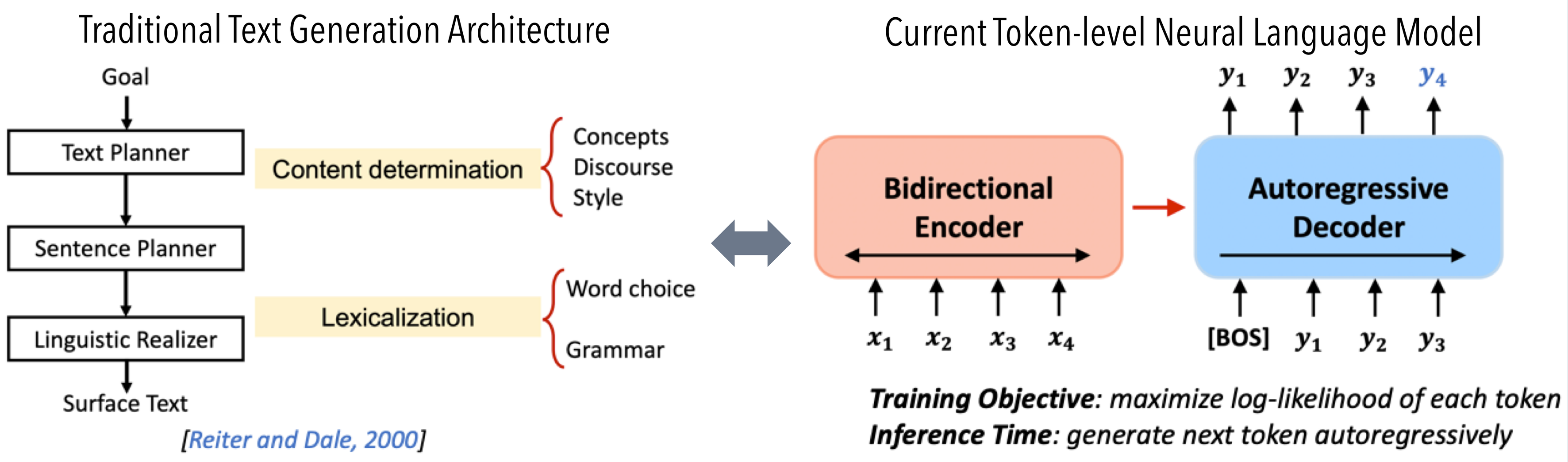
Motivations

- Neural Language Models have achieved promising results and can generate fluent texts
- However, neural LMs still suffer from incoherence issues for long-form text generation

1) Neural LMs lack effective text planning



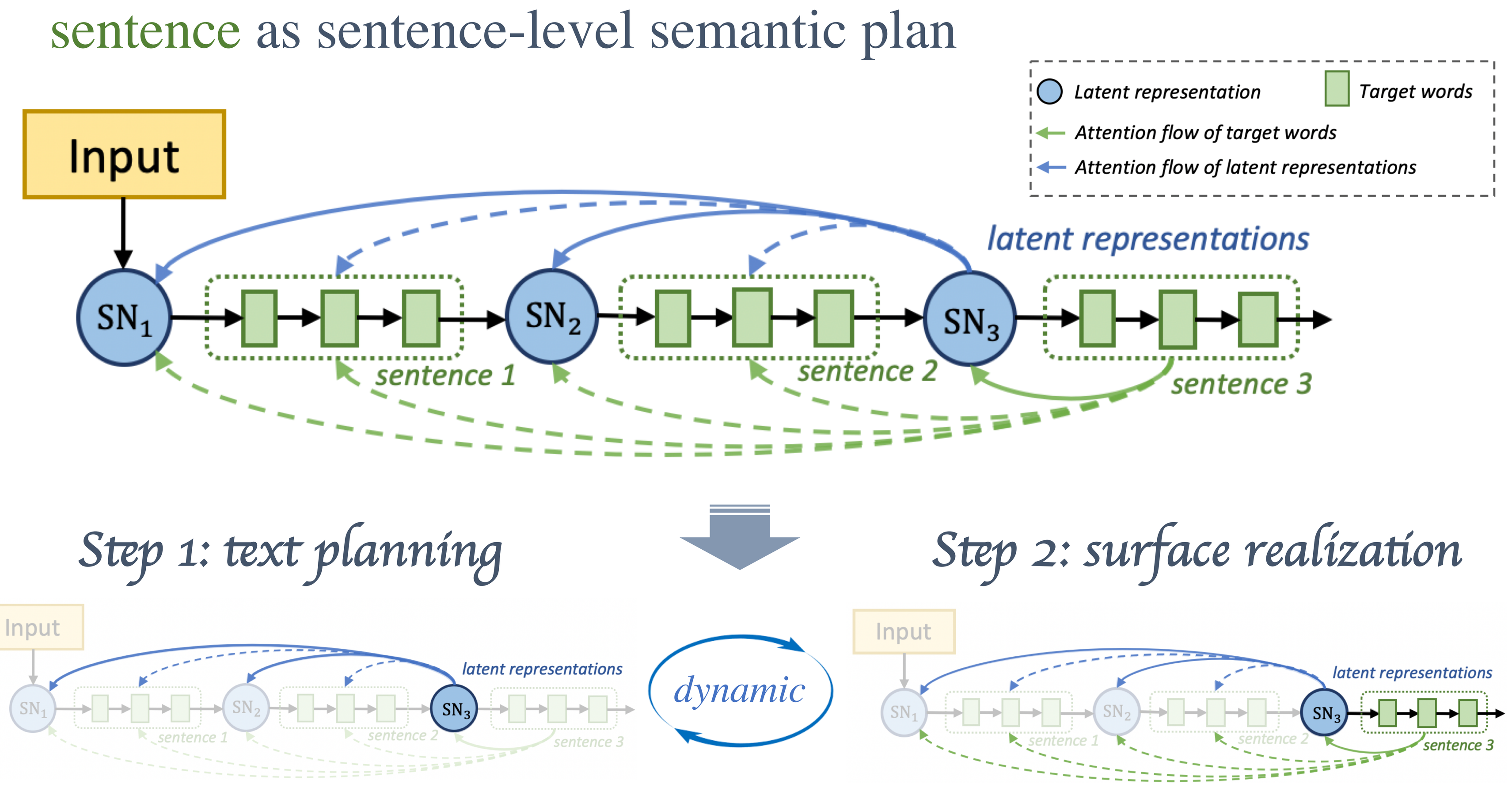
2) NLL objective does not guarantee output coherence

PLANET

- a novel text generation framework that dynamically performs content planning and surface realization in autoregressive Transformers

Dynamic Content Planning

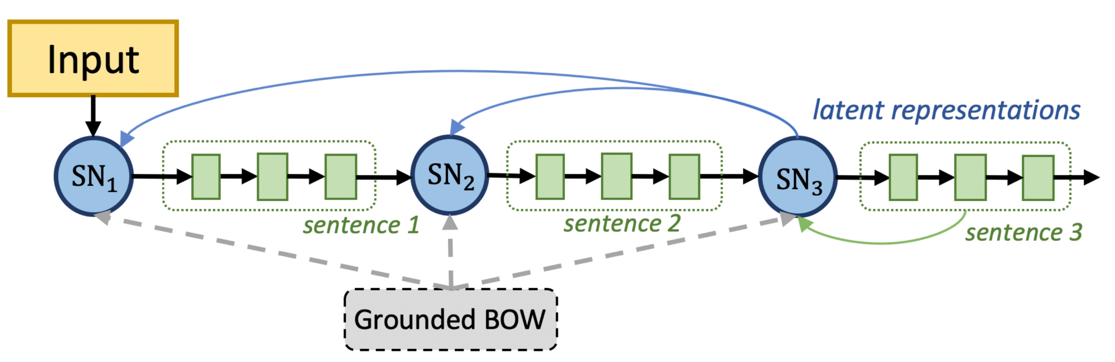
- We introduce a latent representation (SN) for each target sentence as sentence-level semantic plan



Produce a latent representation (SN) as global semantic plan

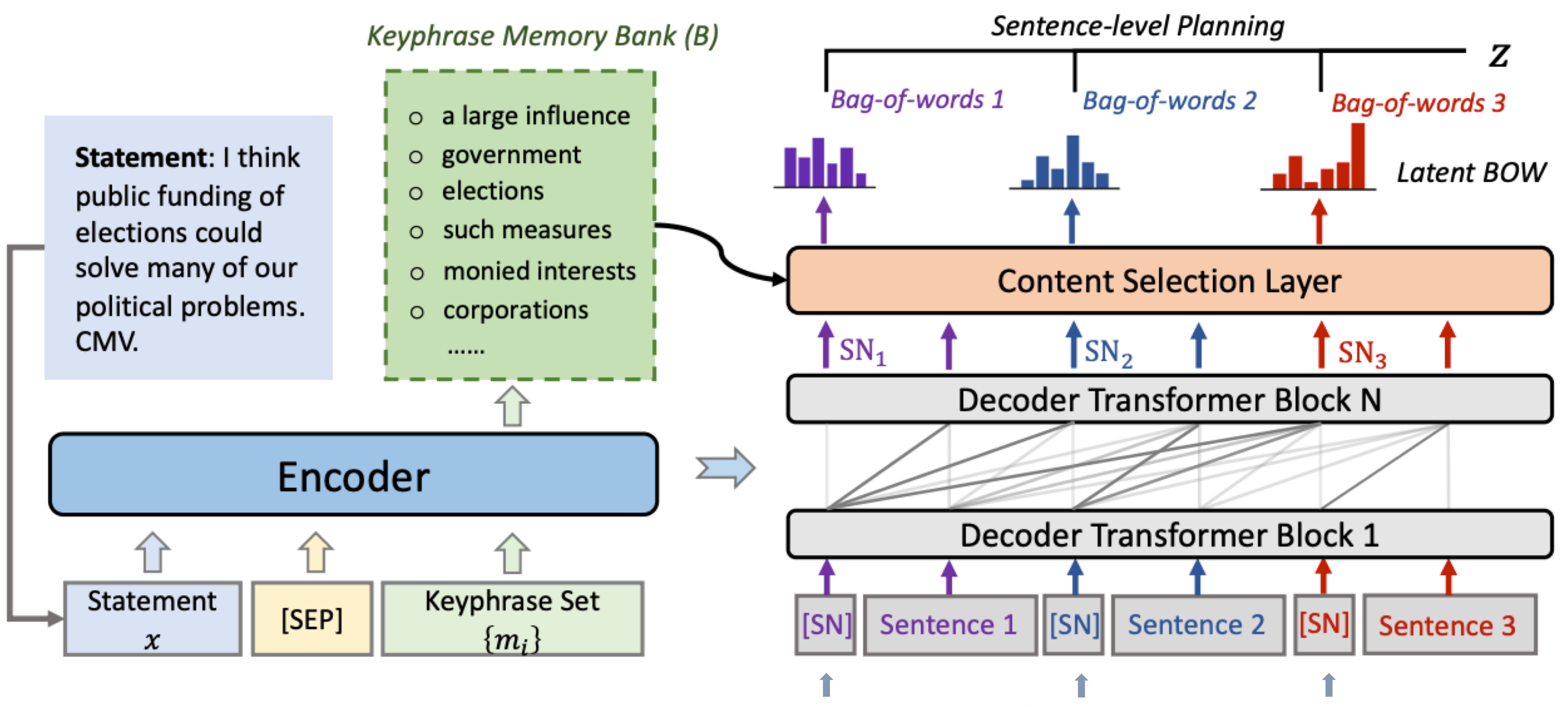
Generate sentence words ( ) conditioned on the plan

Latent Representation Learning



Latent representations are grounded with bag-of-words (BOW) of target sentences to reflect the global semantic plan

Overview of PLANET



We insert a special token [SN] before each target sentence

Coherence-based Contrastive Learning

- We drive our model to learn a preference of coherent outputs over incoherent ones, and further generates more coherent outputs.

$$L_{cl}(r^+, \{r_k^-\}) = \sum_k max(0, \phi + r_k^- - r^+)$$

positive score (r^+); negative score (r_k^-)

- Negative samples tackling different coherence aspects

1. SHUFFLE
- Shuffle target sentences
- ✓ Sentence ordering

2. REPLACE
- Replace 50% target sentences
- ✓ Content organization

3. DIFFERENT
- Use a different target from corpus
- ✓ Topical relevance

4. MASK
- Mask keyphrase words and fill masks with BART
- ✓ Keyphrase usage

Tasks

r/changemyview | The New York Times

- **Counter-argument Generation**
  - Input: OP title
  - Output: high-quality arguments
  - 56.5K sample

Statement: I think public funding of elections could solve many of our political problems. CMV.
+
Guidance Keyphrases: influence; government; election; measure; monied interest; corporation; public funding, ...

Unfortunately, public funding for elections would be easy for corporations to tap into. Also, monied interests have a large influence on our government...

- **Opinion Article Generation**
  - Input: Title
  - Output: Article
  - 57.6K sample

Guidance Keyphrases (Hua and Wang, 2020)
- Noun/Verb phrase
- Contains at least one topic signature (Lin and Hovy, 2000)
- Less than 10 words

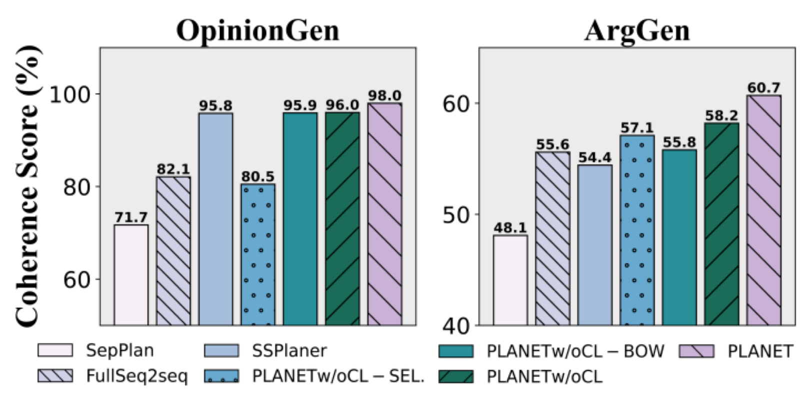
Results

- **Automatic Evaluations**

BLEU-2 / ROUGE-2 (r) / METEOR

System	ArgGen				OpinionGen			
	BLEU-2	ROUGE-2	METEOR	Len.	BLEU-2	ROUGE-2	METEOR	Len.
RETRIEVAL	10.95	4.02	20.70	113	18.16	6.98	24.87	153
HIERPLAN	14.29	8.38	19.03	115	10.66	5.84	17.50	107
FULLSEQ2SEQ	36.69	26.73	42.54	97	34.71	22.75	39.48	146
SEPPLAN	32.38	24.84	39.79	85	31.20	19.36	33.29	151
SSPLANER	36.92	26.82	42.72	105	35.04	22.55	39.50	140
PLANET$_{w/o\ CL}$	38.39	28.24*	44.22*	99	36.41	**23.82***	40.84*	145
– SEL.	37.66	27.71	43.76	96	35.91	23.38	40.33	142
– BOW	37.90	27.80	43.83	95	35.68	23.42	40.39	143
PLANET (ours)	**38.55***	**28.38***	**44.36***	100	**36.79***	23.65*	**40.91***	146

- **Coherence Evaluations**



- **Human Evaluations**

Task	Model	Rel.	Coh.	Rich.	Top-1
ArgGen	FULLSEQ2SEQ	2.25	2.47	2.57	20.7%
	PLANET$_{w/o\ CL}$	2.79	2.83	3.10	30.0%
	PLANET	**2.83**	**2.89**	**3.21**	**33.3%**
OpinionGen	FULLSEQ2SEQ	3.65	3.19	3.44	16.0%
	PLANET$_{w/o\ CL}$	3.81	3.27	3.64	28.7%
	PLANET	**3.89**	**3.47**	**3.81**	**37.3%**

Conclusion

- A generation framework that **dynamically conducts text planning and surface realization** in autoregressive Transformers
- **Coherence-based contrastive learning** with different negative constructions to further improve output coherence
- Experiments on **counter-argument generation** and **opinion article generation** show the effectiveness of our PLANET model