A Generative Language Model for Few-shot Aspect-Based Sentiment Analysis

Ehsan Hosseini-Asl, Wenhao Liu, Caiming Xiong
Salesforce AI Research

Aspect-Based Sentiment Analysis

- Sentiment analysis is an important task in natural language processing.
- Aspect-based sentiment analysis, which involves extracting aspect term, category, and predicting their corresponding polarities.
- In recent works, pre-trained language models are often used to achieve state-of-the-art results, especially when training data is scarce.
- It is common to fine-tune on the downstream task, usually by adding task-specific layers on top of the model.
- This approach is not efficient in few-shot settings.

Reformulating Task as Language modeling

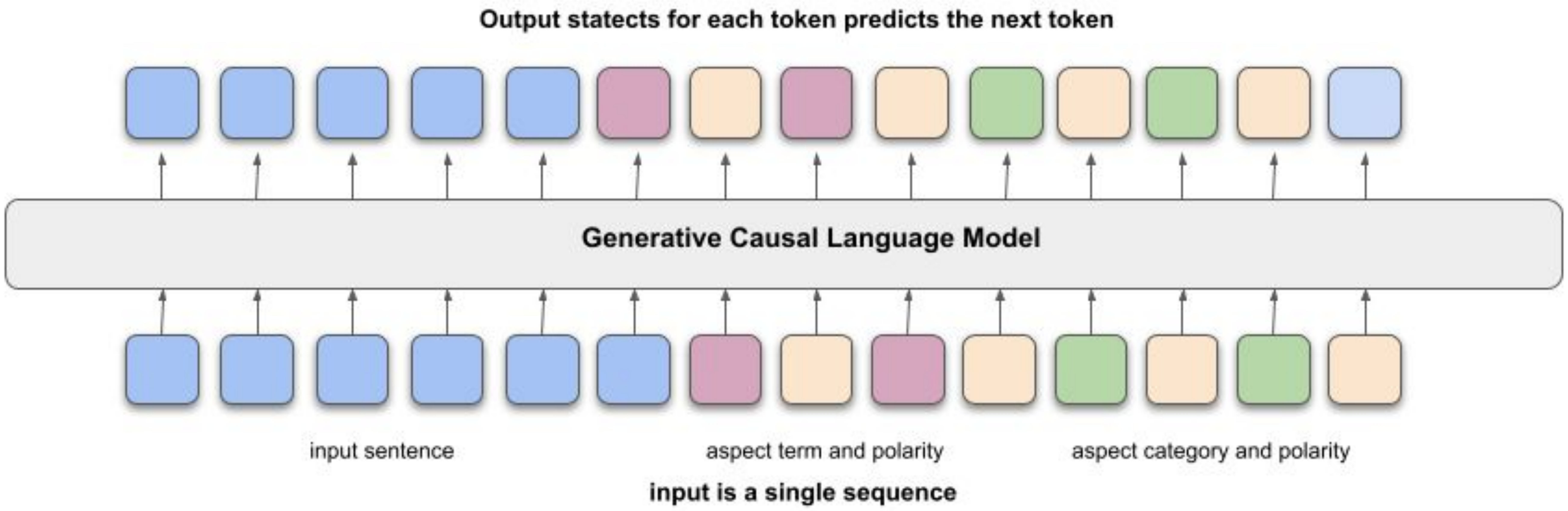
- We propose recasting aspect-based sentiment analysis as a simple, causal (unidirectional) language modeling task
- This way, the model learns to accomplish the tasks via language generation without the need of training task-specific layers which is essential for few-shot learning

Sentence S^k	[review] *review sentence* [endofreview]
Aspect term T^k	[term] $term_1$ $polarity_1$, $term_2$ $polarity_2$, ... $term_I$ $polarity_I$ [endofterm]
Aspect category C^k	[category] $category_1$ $polarity_1$, $category_2$ $polarity_2$, ... $category_J$ $polarity_J$ [endofcategory]
Aspect term single and joint task training sequence (LM_{term})	[review] *review sentence* [endofreview] [term] $term_1$ $polarity_1$, ... [endofterm]
Aspect category single and joint task training sequence ($LM_{category}$)	[review] *review sentence* [endofreview] [category] $category_1$ $polarity_1$, ... [endofcategory]
Multi-task training sequence (LM_{multi})	[review] *review sentence* [endofreview] [term] $term_1$ $polarity_1$, ... [endofterm] [category] $category_1$ $polarity_1$, ... [endofcategory]

Training Language Model

Model is trained via standard language modeling loss (cross entropy) for all output tokens

$$p_\theta(x) = \prod_{t=0}^{n} p_\theta(x_t | x_{<t}) \qquad \mathcal{L}_D = -\sum_{k=1}^{K} \sum_{t=1}^{n} \log p_\theta(x_t^k | x_{<t}^k)$$



Inference (single-task polarity prediction)

Single-task polarity prediction: predicting the polarity of aspect terms or aspect categories

Inference: the input to the model (LM) comprises of k-th sentence and the corresponding aspect term or category

$$pt_i^k = LM_{term}(S^k, t_i^k) \qquad pc_j^k = LM_{category}(S^k, c_j^k)$$

LM_{term} : a single-task model that trained on aspect term dataset

$LM_{category}$: a single-task model that trained on to aspect category dataset

Inference (Joint- and Multi-Task)

Joint-task: generating pairs of aspect term and term polarity, or pairs of aspect category and their polarity.

Multi-task: generating all pairs of aspect terms and aspect categories and their polarities.

Inference: the model input relies on the k-th review sentence only, and the model generates pairs in token-by-token (autoregressive) generation,

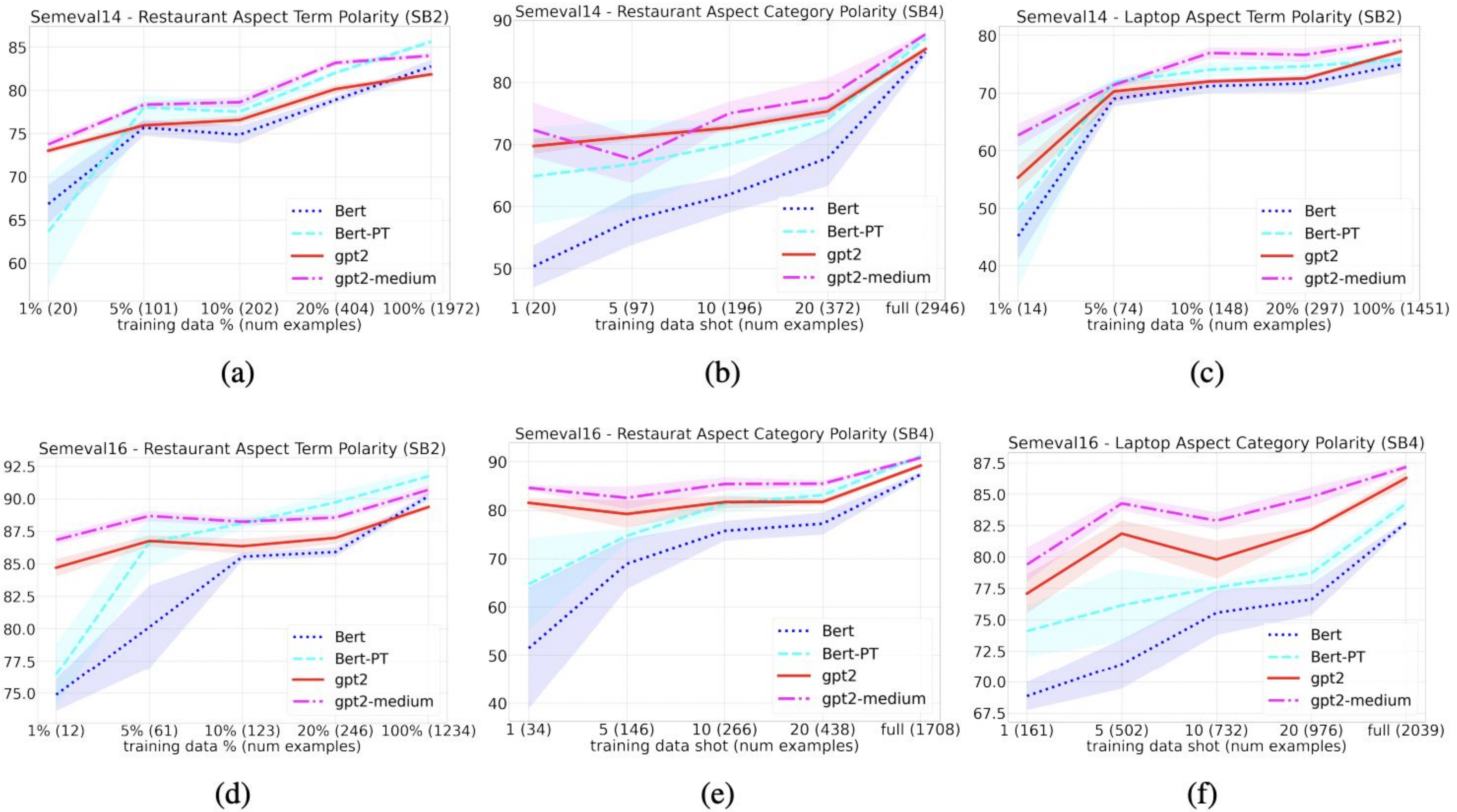
$$T^k = LM_{term}(S^k) \qquad C^k = LM_{category}(S^k) \qquad [T^k; C^k] = LM_{multi}(S^K)$$

LM_{term} : a joint-task model that trained on aspect term dataset

$LM_{category}$: a joint-task model that trained on to aspect category dataset

LM_{multi} : a multi-task model that trained on to aspect term and aspect category dataset

Results (Single-Task)

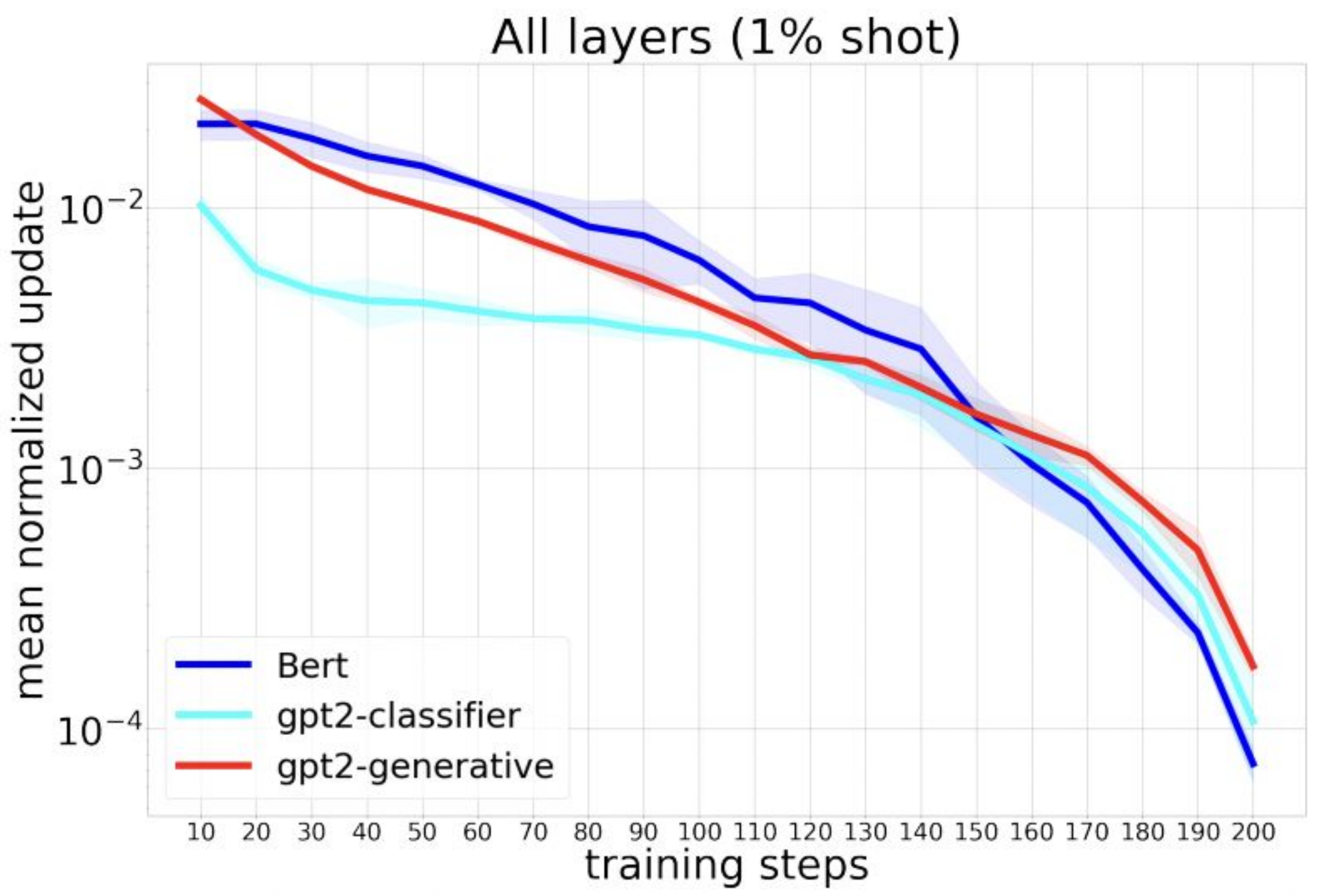


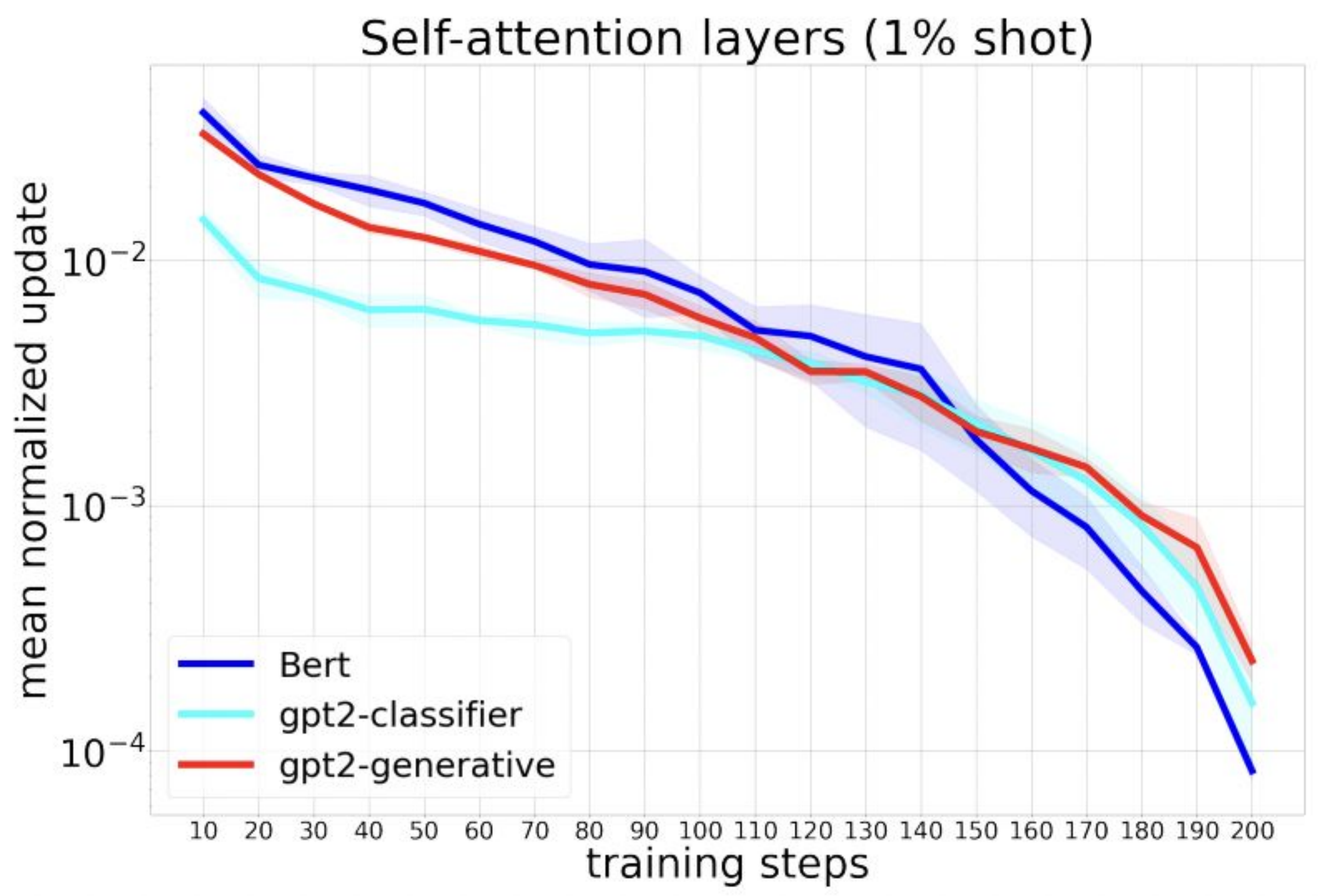
Results (Joint- and Multi-Task)

Method	Training Task	Model	Restaurant Joint Accuracy	Restaurant SB1 (F1)	Laptop Joint Accuracy	Laptop SB1 (F1)
Discriminative	Single (SB1)	MGAN	-	71.48	-	71.42
		BERT	-	74.1	-	79.28
		BERT-DK	-	77.02	-	83.55
		BERT-MRC	-	74.21	-	81.06
		BERT-PT	-	77.97	-	84.26
		BERT-PSUM	-	-	-	85.94
		BERT-HSUM	-	-	-	**86.09**
Generative	Joint (SB1&2)	GPT2 (base)	$56.47_{\pm 0.82}$	$77.59_{\pm 0.32}$	$50.65_{\pm 1.04}$	$72.61_{\pm 1.03}$
		GPT2 (medium)	$60.07_{\pm 0.52}$	$\mathbf{81.52}_{\pm 0.8}$	$53.55_{\pm 0.43}$	$75.94_{\pm 0.17}$
	Multi (SB1-4)	GPT2 (base)	$49.84_{\pm 1.03}$	$77.92_{\pm 0.53}$	-	-
		GPT2 (medium)	$54.43_{\pm 0.47}$	$\mathbf{82.04}_{\pm 0.21}$	-	-

SB1: aspect term extraction sub-task
Restaurant domain: joint- and multi-task model still outperforms previous single-task models
Previous Bert-based models: trained to solve single-task aspect term extraction only, on aspect term extraction

Ablation (Model parameters up)



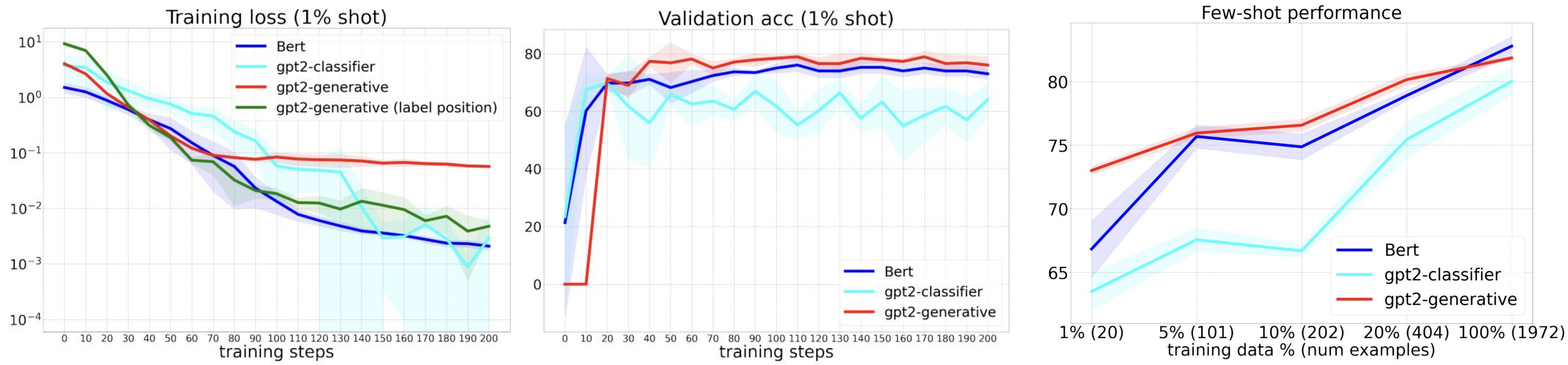


Mean-normalized weight update of each layer:

$$\sum_{i=0}^{k} \frac{(w_i^l - w_{i-1}^l)}{w_0^l}$$

- Bert model has higher variance for all layers, especially for the randomly-initialized classification layer.
- Mean-normalized update of BERT model is larger that gpt2-generative early during training, but is smaller at the end of training, where gpt2-generative achieves higher validation performance (ablation on training convergence)

Ablation



- BERT model converges faster than GPT2 in 1% few-shot settings, due to using a small classification head
- GPT2 converges more slowly, perhaps due to using language modeling loss, i.e. cross-entropy loss across all tokens of the input sequence
- when fine-tuning GPT2 model as a classifier on the downstream task using an classification layer, it under-performs BERT model on few and full-shot settings.

Conclusion: GPT2 language model exploits more supervision than BERT in few-shot setting

Multi-Task Generation

Sentence	Task	Model Output
the sangria's - watered down.	aspect term	<|term|> sangria negative
	aspect category	<|category|> food neutral
	aspect term & category	<|term|> sangria negative <|category|> food negative
	groundtruth	<|term|> sangria negative <|category|> food negative
everyone who works there (the host, the bartender, the servers) is so helpful.	aspect term	host positive, bartender neutral, servers positive
	aspect category	<|category|> service positive
	aspect term & category	<|term|> host positive, bartender positive, servers positive <|category|> service positive
	groundtruth	<|term|> bartender positive, host positive, servers positive <|category|> service positive

Thank You!

Code:
https://github.com/salesforce/fewshot_absa

Poster ID: **237**

Source code