UniGen: Universal Domain Generalization for Sentiment Classification via Zero-shot Dataset Generation

EMNLP 2024

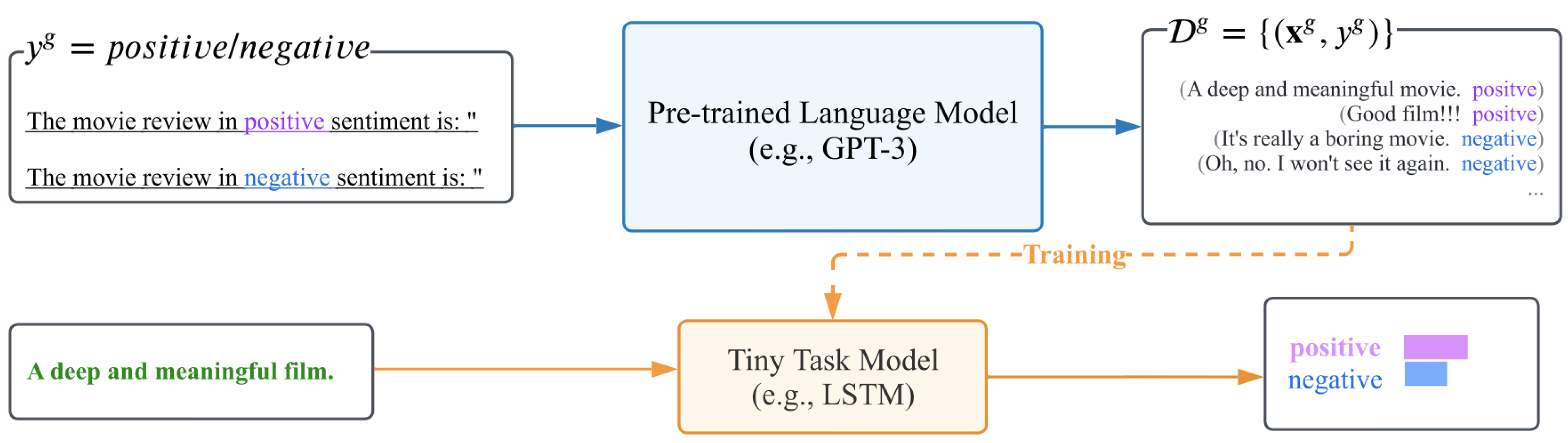
Paper

Code

Juhwan Choi gold5230@cau.ac.kr
Yeonghwa Kim movie112@cau.ac.kr
Seunguk Yu seungukyu@gmail.com
Jungmin Yun cocoro357@cau.ac.kr
YoungBin Kim ybkim85@cau.ac.kr

Chung-Ang University

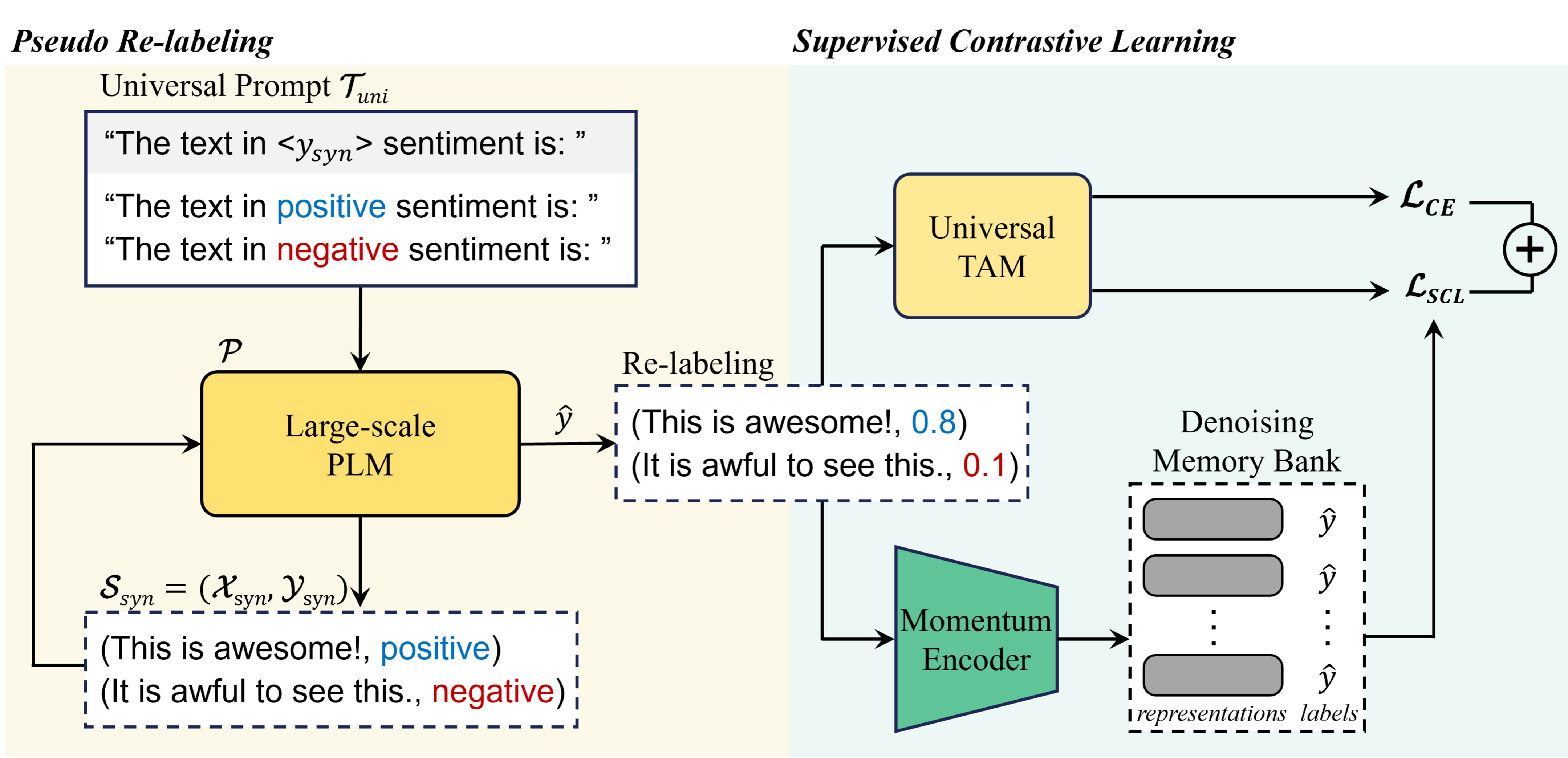
Motivation



1. Ye et al., *ZeroGen: Efficient Zero-shot Learning via Dataset Generation*, EMNLP 2022
2. Gao et al., *Self-Guided Noise-Free Data Generation for Efficient Zero-Shot Learning*, ICLR 2023

- The use of synthetic data creates tiny task models (TAMs) for inference with zero-shot dataset generation
- However, previous methods[1,2] lead TAMs to be tailored for a specific domain, diminishing its real-world applicability
- We propose **UniGen** to overcome this limitation and enable a single model to be deployed across multiple domains

Our Method: UniGen

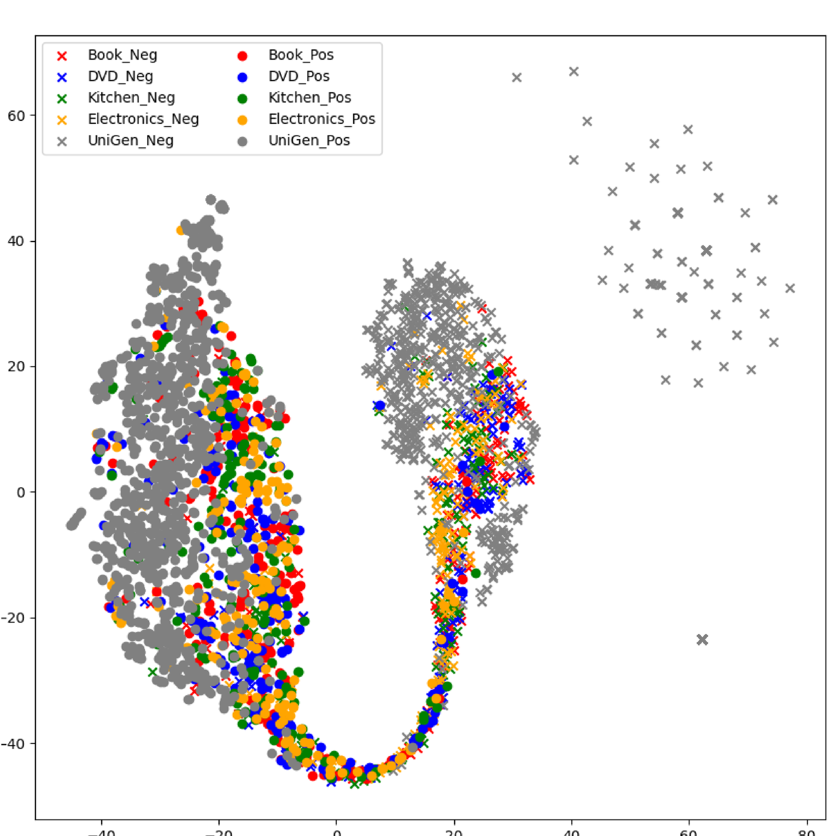


3. Khosla et al., *Supervised Contrastive Learning*, NeurIPS 2020
4. Wu et al., *Unsupervised Feature Learning via Non-Parametric Instance-level Discrimination*, CVPR 2018

- **Universal Prompt**: We design a prompt to generate domain-agnostic data through PLM, and train TAMs with these generated data
- **Pseudo-relabeling**: We classify generated data using PLM, obtaining soft label based on logit values, and train TAMs with these soft labels
- **Supervised Contrastive Learning:** We use supervised contrastive learning[3] loss to guide learning domain-agnostic features
- **Denoising Memory Bank:** We only store high quality samples to memory bank[4], improving its effectiveness when using synthetic data

Experiment and Results

Model / Test Domain	#Param	Training Domain	Setup	SST-2	IMDB Movie	Rotten	Amazon Products	Yelp Restaurant	CR Electronics	Tweet Tweet	Average
GPT2-XL	1.5B	-	PROMPTING	82.15	70.26	77.56	79.06	78.04	80.30	80.38	78.25
DistilBERT	66M	Movie	ZEROGEN	80.06	69.13	74.73	73.02	72.77	73.59	74.83	74.02
			SUNGEN	**82.43**	**70.59**	**76.37**	74.13	73.56	75.14	75.96	75.45
		Products	ZEROGEN	71.04	64.99	65.57	74.54	71.89	74.57	71.93	70.65
			SUNGEN	72.35	65.95	66.84	**76.92**	74.98	75.84	73.01	72.27
		Restaurant	ZEROGEN	77.32	65.47	68.86	74.01	77.94	74.89	73.74	73.18
			SUNGEN	78.93	67.12	69.92	74.93	**80.67**	76.06	75.28	74.70
		Electronics	ZEROGEN	73.77	66.14	66.78	72.38	73.21	78.82	74.58	72.24
			SUNGEN	74.49	67.19	68.29	73.49	75.34	**80.49**	75.37	73.52
		Tweet	ZEROGEN	73.98	66.58	67.43	72.88	71.86	75.68	80.86	72.75
			SUNGEN	75.12	67.53	69.06	73.64	72.73	78.17	**82.46**	74.10
		-	UNIGEN	77.67	67.81	73.16	75.06	74.81	79.86	81.41	**75.68**
RoBERTa	110M	Movie	ZEROGEN	84.38	73.03	78.38	77.38	76.83	77.36	77.94	77.90
			SUNGEN	**85.24**	**74.09**	**79.19**	78.56	77.61	78.21	79.72	78.95
		Products	ZEROGEN	79.14	71.16	70.92	79.94	75.79	76.35	80.17	76.21
			SUNGEN	81.51	71.28	72.67	**81.50**	77.76	78.55	81.94	77.87
		Restaurant	ZEROGEN	82.87	70.71	69.58	78.61	81.47	76.43	79.51	77.03
			SUNGEN	83.65	71.40	71.05	79.42	**82.72**	77.60	80.92	78.11
		Electronics	ZEROGEN	76.82	69.42	67.89	75.02	76.53	81.24	76.51	74.78
			SUNGEN	77.51	71.23	68.77	76.91	78.33	83.49	79.03	76.47
		Tweet	ZEROGEN	78.43	68.31	72.25	78.09	74.61	79.08	82.96	76.25
			SUNGEN	82.19	70.62	73.21	79.84	76.27	81.46	83.25	78.12
		-	UNIGEN	84.86	72.24	78.82	80.79	79.15	**86.37**	**87.89**	**81.45**



- We found that performance of UniGen TAMs rapidly improves with increasing size
- As a result, RoBERTa TAM trained by UniGen outperforms the average performance of PLM zero-shot classification
- The visualization result shows that a single TAM trained by UniGen can be used across multiple domains