

PairCFR: Enhancing Model Training on Paired Counterfactually Augmented Data through Contrastive Learning

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1 Introduction

- **Spurious correlations** in NLP, e.g., dataset-specific artifacts, undermine OOD generalizability
- **Counterfactually Augmented Data (CAD)** mitigates this issue by **establishing direct causal relationships for models to learn more easily and more effectively**.

ORiginal Example(ORI): Negative → CounterFactual Example(CFE): Positive

ORI After loving "Panama" (10/10), I found this one **boring**. 😞

CFE After loving "Panama" (10/10), I found this one **funny**. 😄

ORI → Minimal edits Label flip Meaningful → CFE

2 Problem

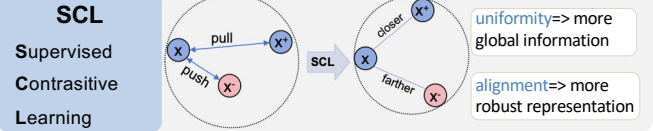
- **CAD may lead to overfitting these modifications**

gold label= Negative
The Atlantis is **supposed to be** fantastic.
prediction = Positive ❌

How to prevent models over-relying on local edits?

3 Methodology

- Can the model focus more on global information?



SCL effectively captures global information for alignment !

- Enhance Model OOD generalization with Paired CAD

PairCFR

Pairwisely
CounterFactual
Learning with
Contrastive
Regularization

- Pair ORI and CFE in the same batch during training

$$\mathcal{L}_{PairCFR} = \lambda \times \mathcal{L}_{CL} + (1 - \lambda) \times \mathcal{L}_{std.CE} \quad \text{Synergy}$$

$$\mathcal{L}_{CL} = -\mathbb{E}_{x_i \sim D} \mathbb{E}_{x_p \sim p_i} \left[\log \frac{e^{s_{ip}/\tau}}{e^{s_{ip}/\tau} + \sum_{x_n \in N_i} e^{s_{in}/\tau}} \right]$$

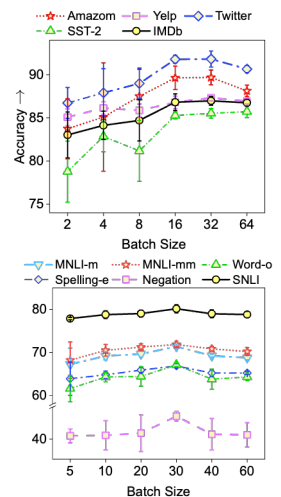
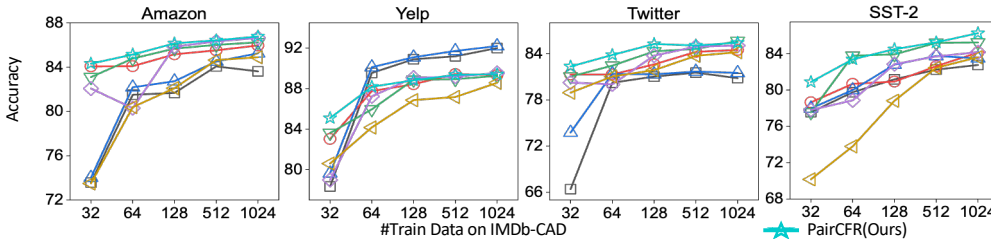
Original Negatives CFE (edited features)

4 Selected Results

- PairCFR brings the highest o.o.d. performance for both SA & NLI
- CAD-based training does not always boost in-domain performance

Method	Sentiment Analysis						Natural Language Inference					
	In-Domain		Out-of-Domain				In-Domain		Out-of-Domain			
	IMDb	Amazon	Yelp	Twitter	SST-2	Acc	SNLI	MNLI-m	MNLI-mm	Negation	Spelling-e	Word-o
RoBERTa-base												
Vanilla	92.68±1.15	87.08±1.39	94.00±0.77	81.43±2.82	86.04±2.76	87.14	85.16±0.39	70.35±1.29	71.25±1.59	52.47±5.55	67.36±1.36	61.82±4.54
BTSCl	93.09±0.61	89.46±0.21	94.74±0.36	85.72±1.22	87.16±0.87	89.27	85.72±0.44	70.83±1.38	72.10±1.32	56.89±3.78	67.61±1.32	62.22±3.55
CouCL	91.22±0.83	89.48±0.19	93.04±0.58	87.40±0.77	88.07±0.66	89.50	82.37±0.52	70.86±1.32	71.38±1.23	51.83±2.71	68.08±1.23	64.68±1.82
HCAD	90.12±1.74	88.50±0.57	92.18±0.94	83.43±1.75	86.48±0.98	87.65	80.91±0.69	70.35±1.00	70.77±0.76	45.79±4.16	67.37±1.28	64.83±1.47
CFGSL	90.69±0.92	88.32±0.41	93.48±0.48	83.90±1.78	86.89±0.80	88.15	82.45±0.35	71.59±0.98	71.25±1.06	51.40±1.47	68.86±1.07	62.22±1.99
ECF	91.05±0.44	88.56±0.32	93.79±0.19	85.82±0.43	87.84±0.59	89.00	81.88±0.17	70.45±1.03	71.18±0.93	51.70±2.38	66.60±0.94	63.76±1.98
PairCFR	91.74±0.88	89.60±0.26	93.35±0.34	87.90±0.45	88.61±0.41	89.87	82.13±0.51	71.80±0.53	72.12±0.79	55.19±1.97	68.88±0.36	65.91±1.35

- PairCFR shows robustness across different data settings, especially under few-shot settings



- Fair #Neg ↑ => broader features
- Excessive #Neg ↑ => dilute CAD priors

5 Conclusion

- PairCFR is a simple and effective method for training models on CAD. It demonstrates highest o.o.d. performance on both SA and NLI task.



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