



Honey or Poison? Solving the Trigger Curse in Few-shot Event Detection via Causal Intervention

Jiawei Chen^{1,3}, Hongyu Lin¹, Xianpei Han^{1,2}, Le Sun^{1,2}

¹Chinese Information Processing Laboratory ²State Key Laboratory of Computer Science Institute of Software, Chinese Academy of Sciences ³University of Chinese Academy of Sciences

Few-shot Event Detection

Few-shot event detection (FSED)

Causal Intervention for solving Trigger Curse

We propose to intervene on context to block the

Detect new event with a few labeled data.

Challenge: Trigger Curse

- Overfitting the trigger will harm the generalization ability.
- Underfitting the trigger will hurt the detection performance.

Trigger-centric structural causal model

We formulate the data distribution of FSED using a trigger-centric structural causal model (SCM).



information from trigger to context.



- We use Interventional distribution to optimizing causality.
- Backdoor adjustment is used to to estimate the interventional distribution.

$$P(Y|do(C = C), E = e, Q = q)$$

=
$$\sum_{s \in S} \sum_{t \in T} P(Y|s, q) P(s|C, t) P(t|e)$$



■ Nodes in the SCM:

- E : Event
- T : Trigger set of support set
- C : Context set of support set
- S : Support set instances lacksquare
- Y : Predicted result

Edges in the SCM:

- $E \rightarrow T$: Trigger decision process. lacksquare
- $E \rightarrow C \leftarrow T$: Context is generated depending on both the event and the trigger.
- $C \rightarrow S \leftarrow T$: Event instances are generated by

Experimental Results

		ACE05		MAVEN		KBP17	
	Model	Macro	Micro	Macro	Micro	Macro	Micro
Finetuing-based	Finetune	51.0 ± 1.4	58.2 ± 1.6	30.7 ± 1.5	$31.6{\pm}2.3$	59.4±1.9	62.7 ± 1.8
	Finetune*	39.9±1.1	$45.5{\pm}0.7$	20.8 ± 1.0	$20.6{\pm}0.8$	45.0±0.7	47.3 ± 0.6
	Pretrain+Finetune	22.9 ± 6.0	$20.3{\pm}4.3$	20.9 ± 4.6	16.9 ± 5.2	35.1±5.9	30.1 ± 5.5
	Pretrain+Finetune*	14.6 ± 3.3	15.6 ± 3.4	12.5 ± 3.8	$14.9{\pm}4.0$	23.4 ± 6.8	$25.8{\pm}6.3$
Prototypical Net	FS-Base	63.8 ± 2.8	67.3±2.7	44.7±1.4	44.5 ± 2.0	65.5 ± 2.7	67.3±3.1
	FS-LexFree	52.7 ± 2.9	$53.9{\pm}3.2$	25.6 ± 1.0	$21.8{\pm}1.4$	60.7 ± 2.5	61.4 ± 2.8
	FS-ClusterLoss	64.9±1.5	$69.4 {\pm} 2.0$	44.2 ± 1.2	44.0 ± 1.2	65.5 ± 2.3	67.1±2.4
	FS-Causal (Ours)	73.0 ±2.2	76.9 ±1.4	52.1 ±0.2	55.0 ±0.4	70.9 ±0.6	73.2 ±0.9
Relation Net	FS-Base	65.7 ± 3.7	68.7 ± 4.5	52.4 ± 1.4	56.0 ± 1.4	67.2 ±1.5	71.2 ± 1.4
	FS-LexFree	59.3 ± 3.5	60.1 ± 3.9	43.8±1.9	$45.9{\pm}2.4$	61.9 ± 2.4	65.4 ± 2.8
	FS-ClusterLoss	57.6 ± 2.3	60.2 ± 3.2	46.3 ± 1.1	51.8 ± 1.4	56.8 ± 3.0	62.1 ± 2.5
	FS-Causal (Ours)	67.2 ±1.4	71.8 ±1.9	53.0 ±0.5	57.0 ±0.9	66.4 ± 0.4	72.0 ±0.6

- By intervening on the context in SCM and using backdoor adjustment during training, our method can effectively learn FSED models.
- The causal theory is a promising technique for resolving the trigger cruse problem.

combining context and the trigger.

- $S \rightarrow Y \leftarrow Q$: The result is predicted by the instances in support set and instances in query.
- **There exists a backdoor path** $C \leftarrow T \rightarrow Y$
- Trigger is the confounder of context and predicted result.
- The backdoor misleads the conventional learning procedure to mistakenly regard effects of triggers as the effects of contexts.
- Our method can achieve state-of-the-art FSED performance.

Conclusions

- Trigger Curse is a challenge in Few-shot Event Detection.
- Identify trigger curse using structural causal model.
- Causal intervention via backdoor adjustment can be used to solve trigger curse.