



Unsupervised Editing For Counterfactual Stories

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Background & Introduction

❖Task: Counterfactual Story Ending Rewriting

❖What if I had done something different? What would be the difference in the following events?

❖Goal: Counterfactual Reasoning

❖A hypothetical thinking process to assess possible outcomes by modifying certain prior conditions

❖Research Questions:

❖**The trade-off: Minimal-edits vs. Coherence** — Can we rewrite a **coherent** new story ending with **minimal edits**?

❖**Humans do not need training to imagine possible futures!** — Can we achieve it without supervision?

Motivation & Contribution

❖How can we ensure minimal edits?

❖We first solve the counterfactual story rewriting task using **unsupervised discrete editing** method based on **MCMC sampling**.

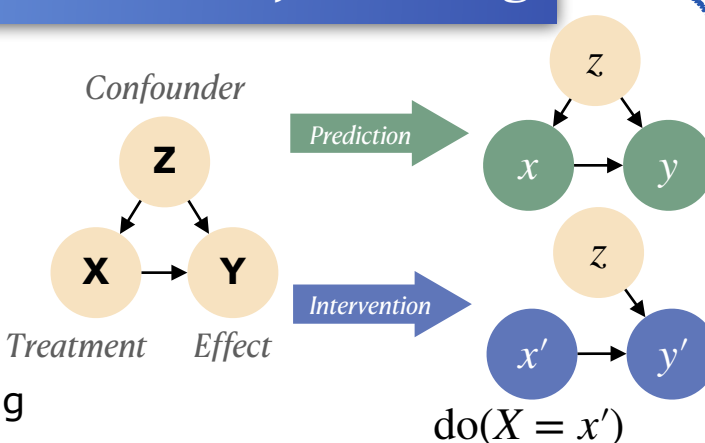
❖How can we ensure coherence?

❖We draw inspiration from causal analysis and propose two counterfactual reasoning components that **quantify the outcomes of condition changes**.

Structured Causal Model in Story Rewriting

❖SCM in story rewriting:

1. z : Story premise (one of the observed confounders)
2. x : Initial condition
3. y : Story ending
4. x' : Counterfactual condition
5. y' : Counterfactual story ending



❖**Intervention:** changing the initial condition to a counterfactual one.

Estimating Potential Outcome After Intervention

❖A Metric in Causal Analysis — Causal Risk Ratio

❖The larger CRR is, the more causally related it is to the counterfactual condition than to the initial one.

$$CRR = \frac{P(Y = y | do(X = x'), Z = z)}{P(Y = y | do(X = x), Z = z)}$$

$$P(Y = y | do(X = x')) = \sum_z P(Y = y | X = x', Z = z)P(Z = z)$$

❖Causal Sufficiency Assumption

❖Difficult to enumerate all *unobserved confounders*

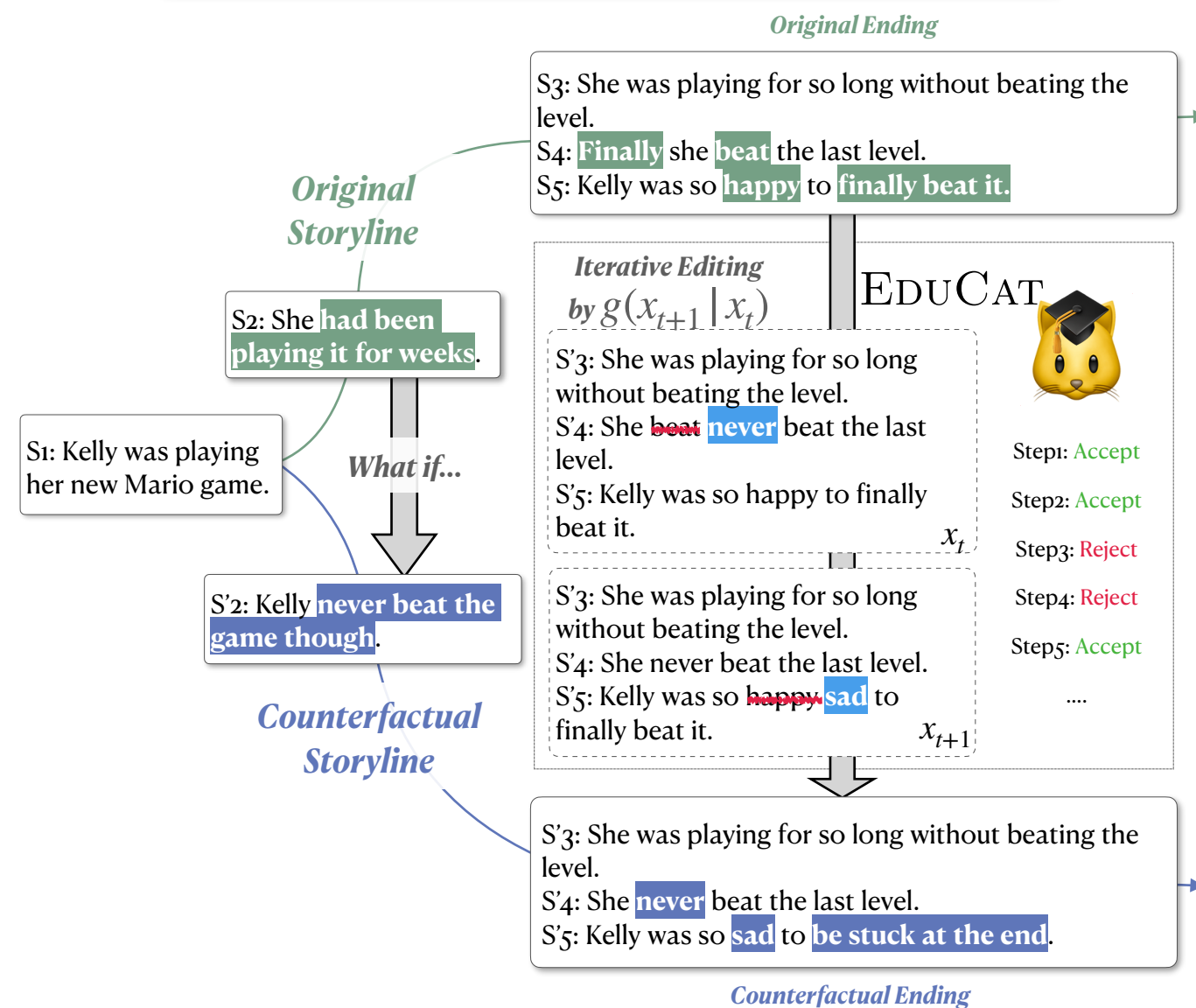
❖Assume only observed confounders (premise z)

$$P(Y = y | do(X = x)) = P(Y = y | X = x, Z = z)$$

$$CRR = \frac{P(Y = y | X = x', Z = z)}{P(Y = y | X = x, Z = z)}$$

Now we can calculate CRR!

EDUCAT: Editing a New Story Ending



❖EDUCAT: Unsupervised Constrained Editing via MCMC Sampling

1. Define desired properties as stationary distribution $\pi(y)$
2. Move y_t to y_{t+1} by generating from the proposal distribution $g(y_{t+1} | y_t)$
3. Accept a proposal with acceptance rate $\alpha(y_{t+1} | y_t)$
4. Iterate until convergence
5. Rank the accepted ones with $\pi(\cdot)$

❖Desired properties for stationary distribution $\pi(y)$

1. **Fluency:** sentence probability from GPT-2;
 $\mathcal{X}_{LM}(y^*) = \prod_{i=1}^N P_{LM}(y_i^* | z, x', y_{<i}^*)$
2. **Coherence:** Punish proposed endings contradictory to the counterfactual conditions but consistent with the initial ones.
 $\mathcal{X}_{Coh}(y^*) = \frac{P_{Coh}(Y = y^* | z, x')}{P_{Coh}(Y = y^* | z, x)}$

CRR

❖Make an Edit Proposal

1. *Where to edit?* — conflict token detection in y_t

$$P_{cf}(y_i^*) = \text{softmax}\left(\frac{P_{LM}(y_i^* | z, x, y_{<i}^*)}{P_{LM}(y_i^* | z, x', y_{<i}^*)}\right)$$

CRR

2. *Edit with what?* — modification actions

- **Replace:** mask-predict with an MLM (e.g., BERT)
 - $g_r(y_{t+1} | y_t) = 1(w^c \in \mathcal{Q}) \cdot P_{MLM}(w_m^* = w^c | x_{-m})$
 - Sample from $P_{MLM}(\cdot)$
- **Insert:** insert a [MASK], then do *Replace*
- **Delete:** reverse of *Insert*

More details in the paper!

Experiments

❖Dataset

❖TimeTravel [Qin et al. 2019]

❖Metrics

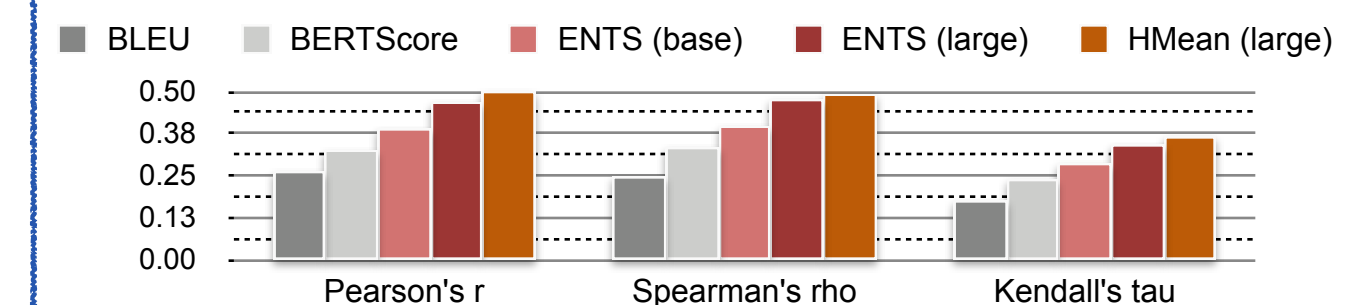
- BLEU
- BERTScore
- **EntScore:** a model-based metric for coherence
 - Leaning towards initial or counterfactual? Binary classification with RoBERTa
- **HMean:** Harmonic Mean of EntScore and BLEU
 - For the *trade-off*

	Train	Dev	Test
# counterfactual context (x')	96,867	1,871	1,871
# edited endings (y')	16,752	5,613	7,484

Unsupervised, only test set used!

❖RQ1: How are these metrics correlates with humans

❖A1: Better trade-off with **HMean** of ENTS and BLEU!



❖RQ2: Performance of EDUCAT?

❖A1: **Competitive** against baselines under automatic and human evaluation.

Method	BLEU	BERT	ENTS _l	HMEAN
<i>Supervised Training</i>				
GPT-2 _M + SUP	76.35	81.72	35.06	48.05
<i>Unsupervised Training</i>				
GPT-2 _M + FT	3.90	53.00	52.77	7.26
Recon+CF	76.37	80.20	18.00	29.13
<i>Off-the-shelf Pre-trained Models</i>				
GPT-2 _M	1.39	47.13	54.21	2.71
DELOREAN	23.89	59.88	51.40	32.62
CGMH	41.34	73.82	29.80	34.63
EDUCAT	44.05	74.06	32.28	37.26
Human	64.76	78.82	80.56	71.80

Methods	Coherence		
	Win	Tie	Lose
EDUCAT vs. DELOREAN	45%	32%	23%
EDUCAT vs. CGMH	32%	51%	17%
EDUCAT vs. Human	12%	24%	64%
	Min-edits		
	Win	Tie	Lose
EDUCAT vs. DELOREAN	64%	27%	9%
EDUCAT vs. CGMH	26%	49%	25%
EDUCAT vs. Human	16%	40%	44%

❖RQ3: The source of performance gain?

❖A1: Both conflict detection and coherence objective.

Ablation	BLEU	BERT	ENTS _l	HMEAN
EDUCAT (GPT-2 _S)	39.82	72.35	31.72	35.31
EDUCAT (GPT-2 _M)	44.05	74.06	32.28	37.26
– $\mathcal{X}_{Coh}$	44.20	74.27	31.44	36.74
– conflict detection	40.96	73.61	30.79	35.16
– both	41.34	73.82	29.80	34.63
+ $\mathcal{X}_{Coh}$ w/ ENTS _l	43.65	74.09	42.03	42.83

More details in the paper!

Case Study

S1: Gina had done everything she could think of to beat the heat.
 S2: And it was only **noon**.
 S3: The sun was still high in the sky.
 S4: She decided she needed to go where there was air conditioning.
 S5: She went inside a nearby cafe.

S2: Luckily, it was **evening and starting to cool off**.

S3: The sun was **still high** in the sky.
 S4: She decided she needed to go outside and get some fresh air.
 S5: She **went inside** and got some fresh air.

DELOREAN

S3: The sun was low in the sky.
 S4: She decided that she needed to go somewhere where there was no air conditioning.
 S5: She headed to the park.

EDUCAT