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Adversarial Attacks on Knowledge Graph Embeddings via Instance Attribution Methods

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EMNLP 2021

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[PeruBhardwaj/AttributionAttack](https://github.com/PeruBhardwaj/AttributionAttack)

Adversarial Attacks on Knowledge Graph Embeddings via Instance Attribution Methods



Adversarial Deletions + Additions



Contact: peru.bhardwaj@adaptcentre.ie



[PeruBhardwaj/AttributionAttack](#)

Adversarial Attacks on Knowledge Graph Embeddings via Instance Attribution Methods

Instance Similarity

Gradient Similarity

Influence Function

- ✓ Adversarial Deletions + Additions
- ✓ Identify influential training examples



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PeruBhardwaj/AttributionAttack

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- ✓ Adversarial Deletions + Additions
- ✓ Identify influential training examples
- ✓ Outperform state-of-art attacks



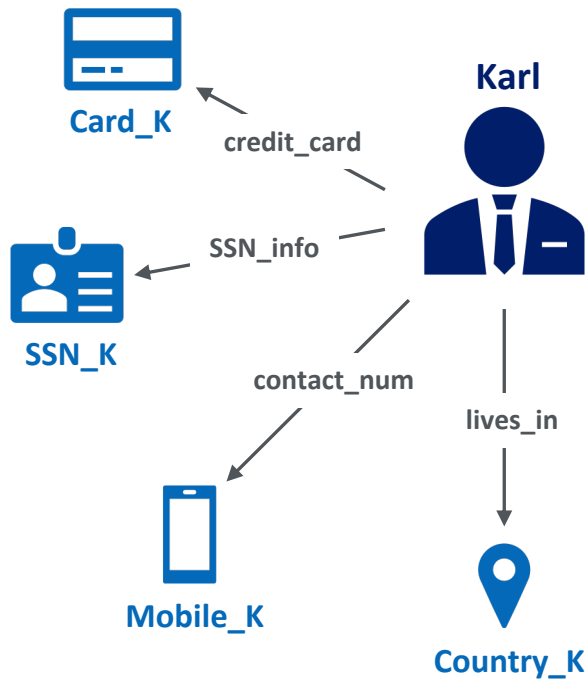
Adversarial Attacks on Knowledge Graph Embeddings via Instance Attribution Methods

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Knowledge Graph

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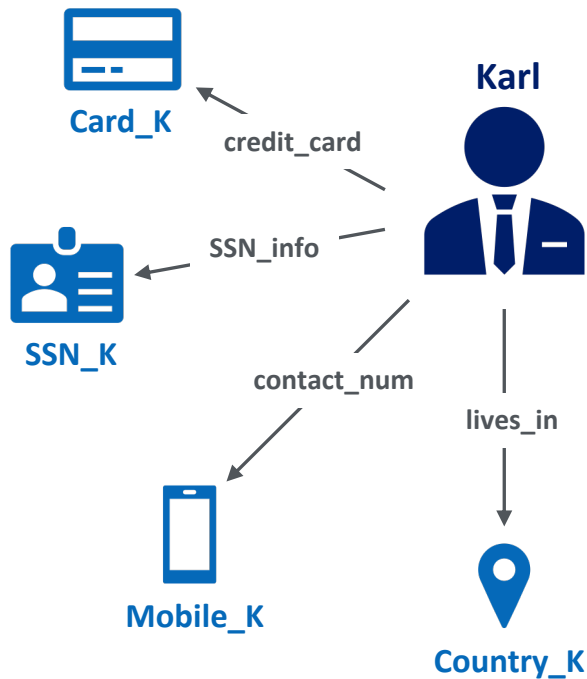
Example - Financial Details of a Bank's Customer



Knowledge Graph

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Example - Financial Details of a Bank's Customer

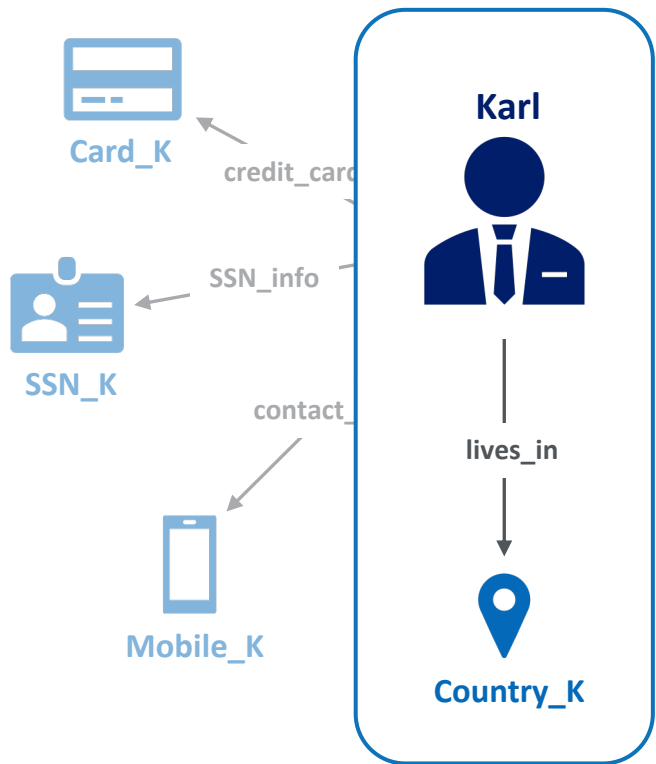


s	r	o
Karl	credit_card	Card_K
Karl	SSN_info	SSN_K
Karl	contact_num	Mobile_K
Karl	lives_in	Country_K

Knowledge Graph

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Example - Financial Details of a Bank's Customer

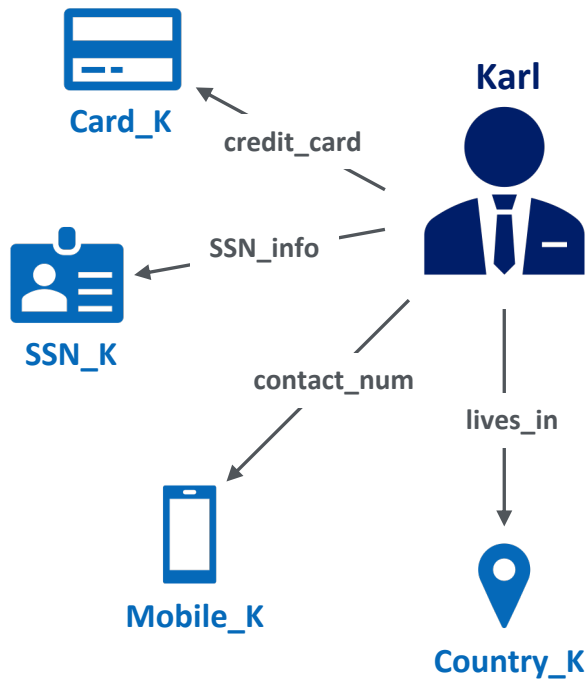


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Knowledge Graph

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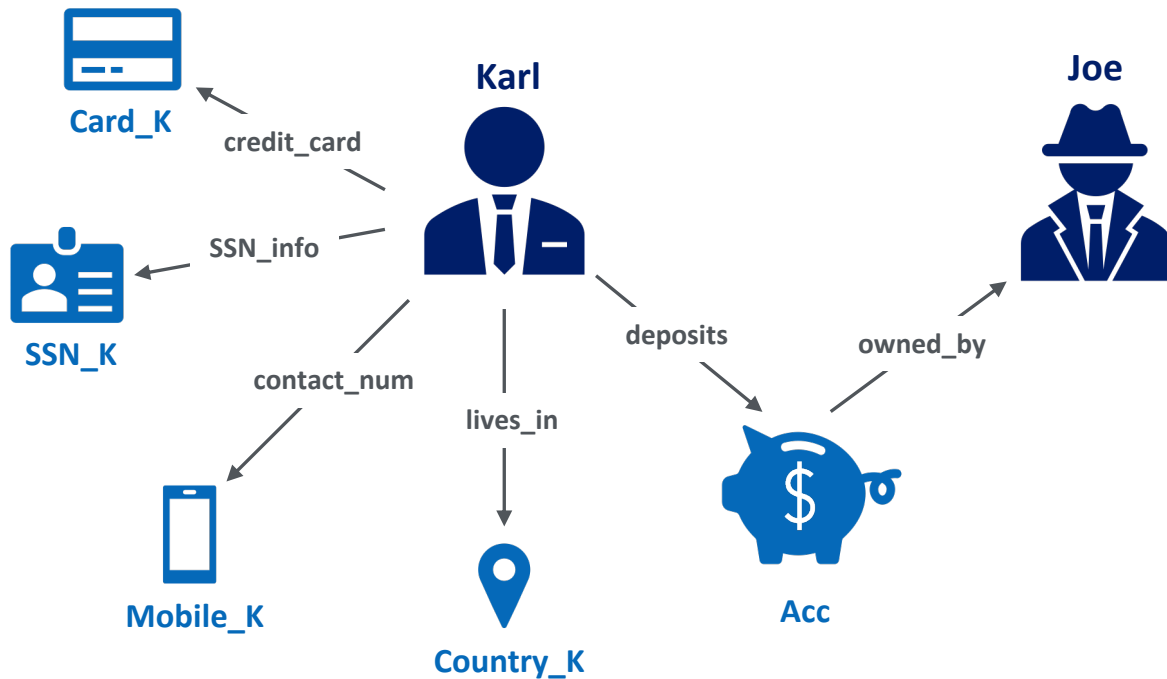
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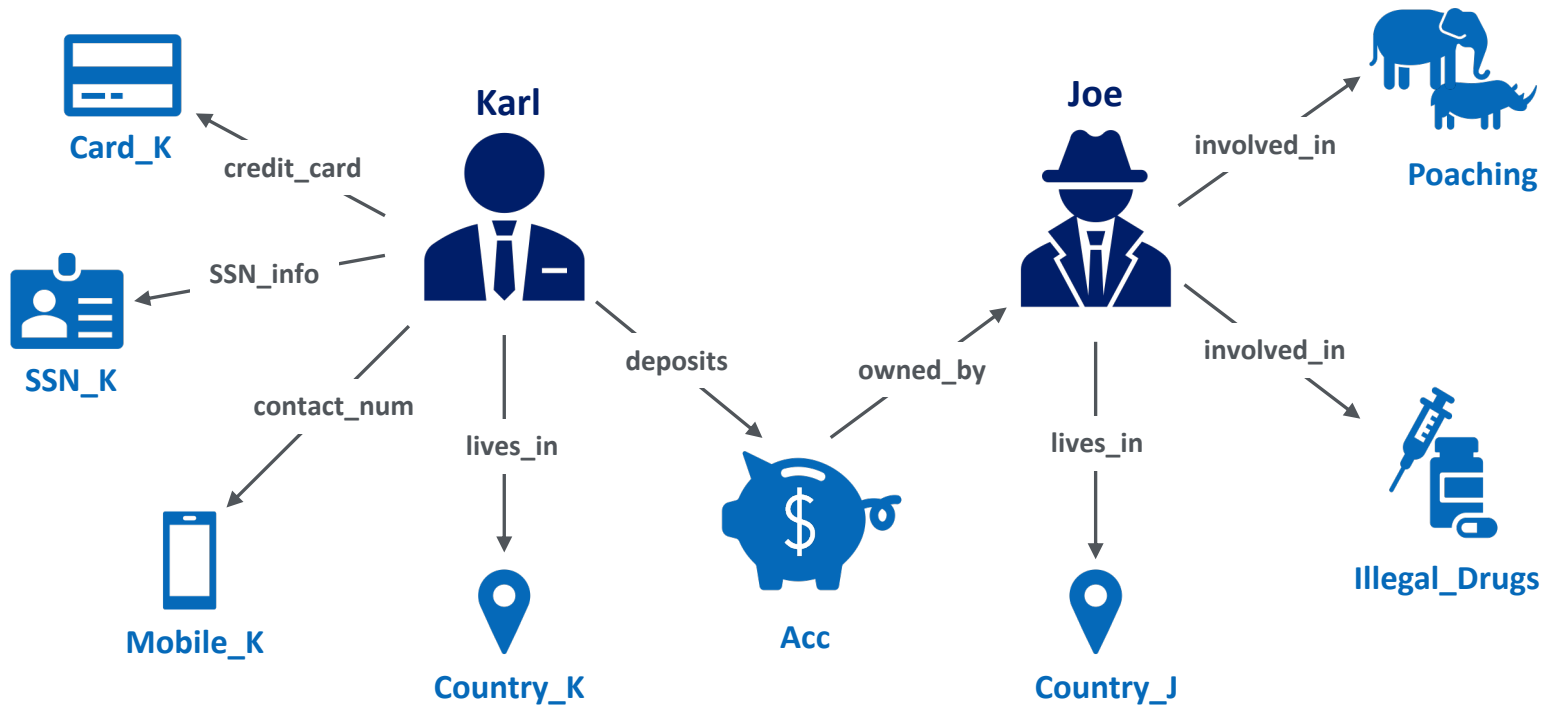
Missing Link Prediction

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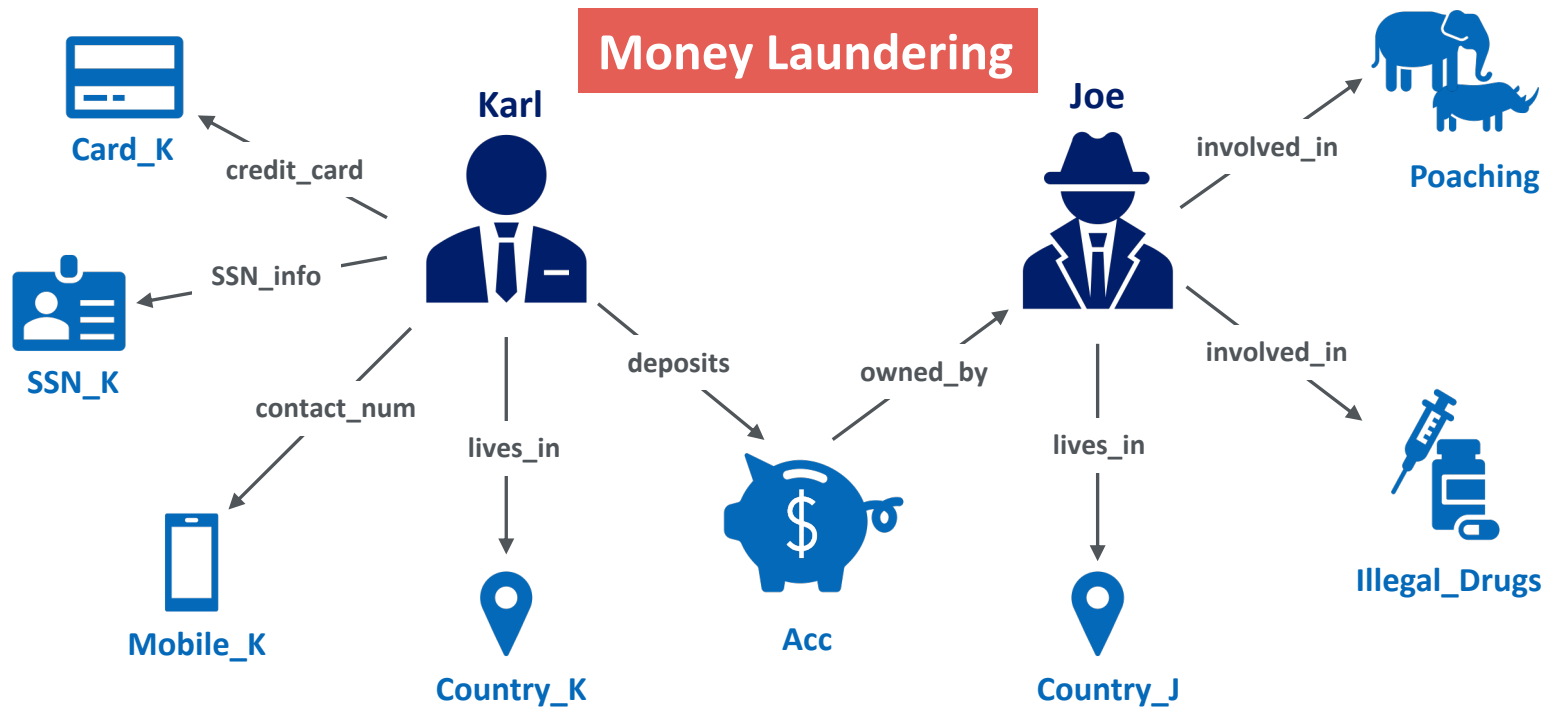
Missing Link Prediction

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Missing Link Prediction

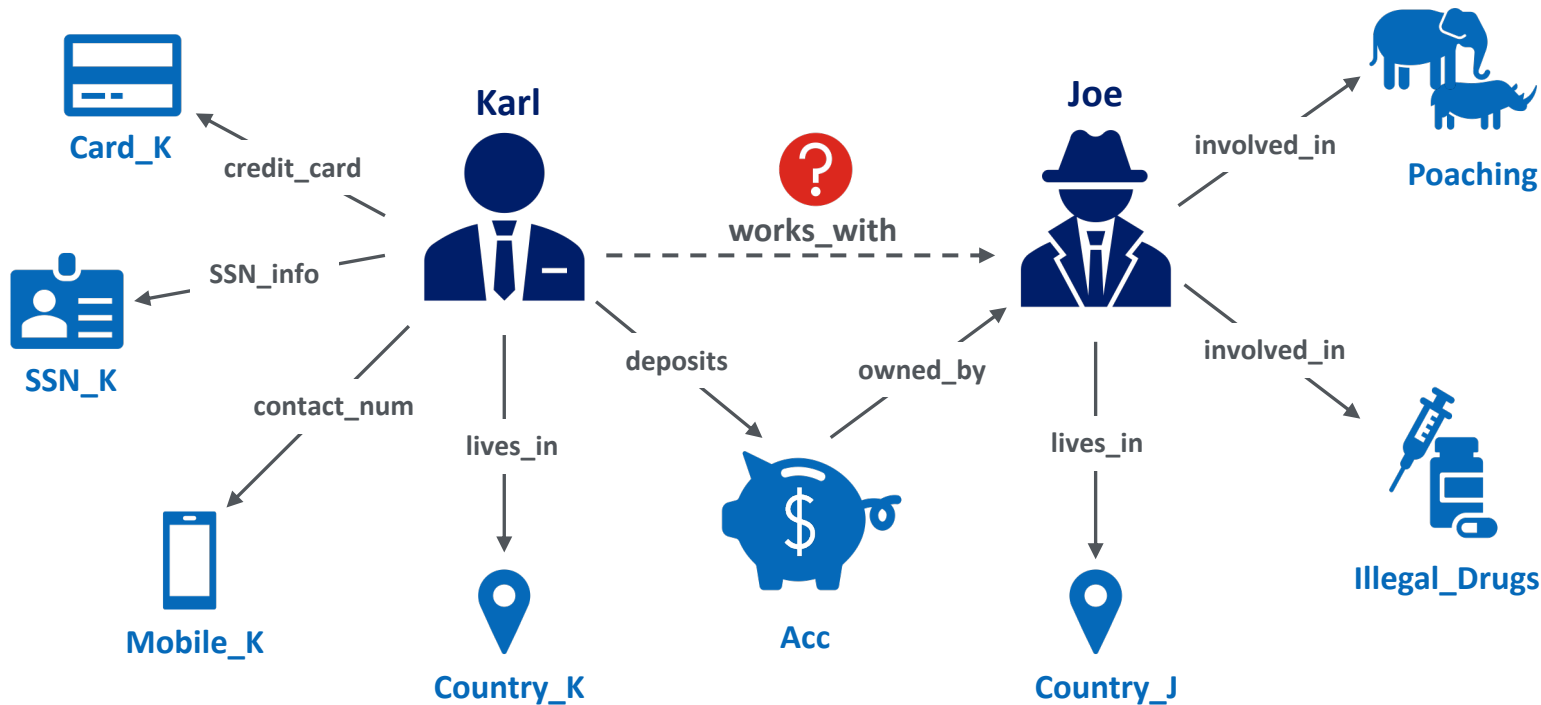
14



Missing Link Prediction

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Use case – Anti Money Laundering

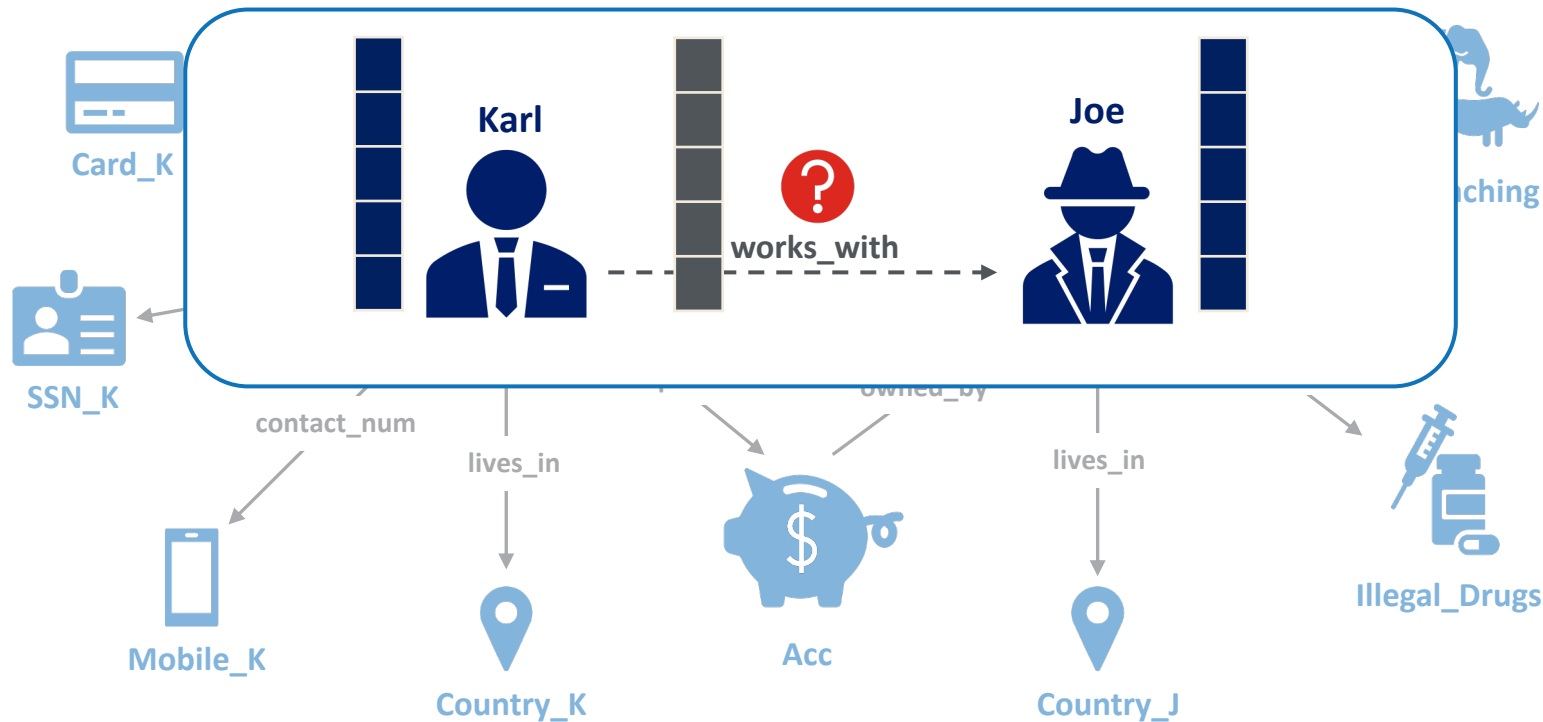


Adversarial Attacks on Knowledge Graph Embeddings via Instance Attribution Methods

Missing Link Prediction

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Use case – Anti Money Laundering



Knowledge Graph Embeddings (KGE)

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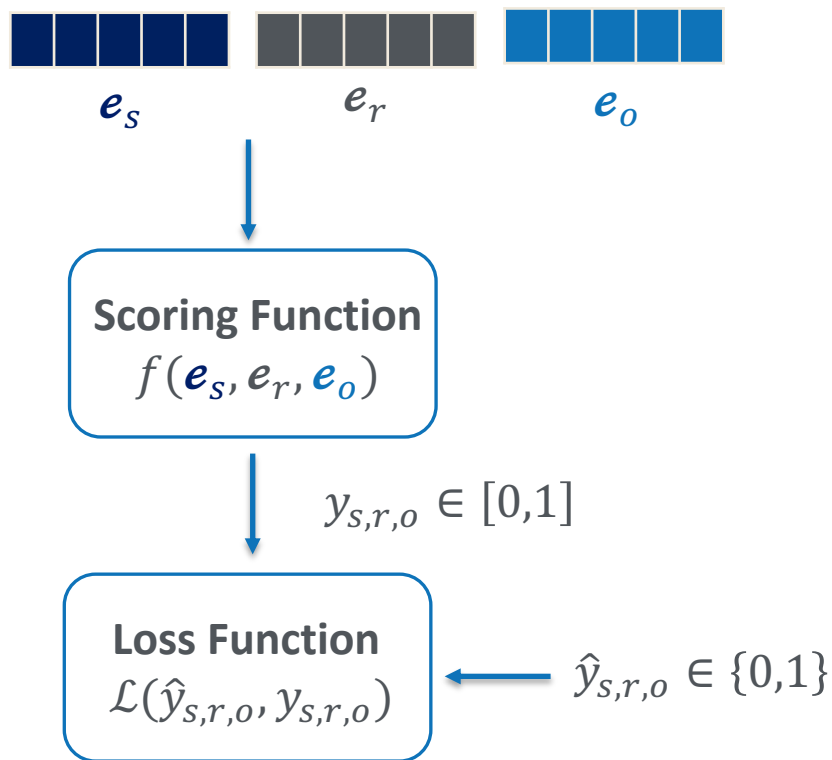


Generate negatives by corrupting s/o

s	r	o
Karl	credit_card	Card_X
Karl	credit_card	Card_Y
Karl	credit_card	Card_K
Person_X	credit_card	Card_K
Person_Y	credit_card	Card_K

Knowledge Graph Embeddings (KGE)

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Generate negatives by corrupting s/o

s	r	o
Karl	credit_card	Card_X
Karl	credit_card	Card_Y
Karl	credit_card	Card_K
Person_X	credit_card	Card_K
Person_Y	credit_card	Card_K

Knowledge Graph Embeddings (KGE)

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Minimize \mathcal{L} by updating e_s, e_r, e_o



Scoring Function

$$f(e_s, e_r, e_o)$$

$$y_{s,r,o} \in [0,1]$$

Loss Function

$$\mathcal{L}(\hat{y}_{s,r,o}, y_{s,r,o})$$

$$\hat{y}_{s,r,o} \in \{0,1\}$$

Scores for positive triples are higher than scores for negative triples

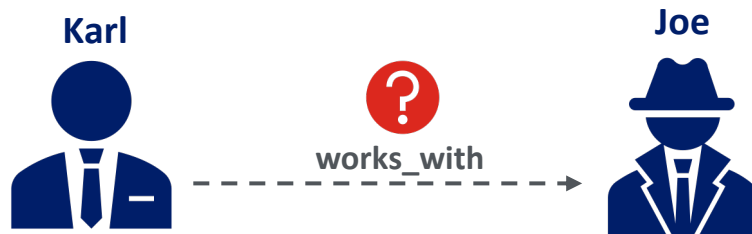
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Karl	credit_card	Card_K
Person_X	credit_card	Card_K
Person_Y	credit_card	Card_K

Missing Link Prediction with KGE

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Use case – Anti Money Laundering



$$\mathcal{P}(\text{Karl}, \text{works_with}, \text{Joe}) \propto f(e_{\text{Karl}}, e_{\text{works_with}}, e_{\text{Joe}})$$

$$\mathcal{P}(\text{Karl}, \text{works_with}, \text{Joe}) \propto f\left(\begin{array}{c} \blacksquare \\ \blacksquare \\ \blacksquare \\ \blacksquare \\ \blacksquare \end{array}, \begin{array}{c} \blacksquare \\ \blacksquare \\ \blacksquare \\ \blacksquare \\ \blacksquare \end{array}, \begin{array}{c} \blacksquare \\ \blacksquare \\ \blacksquare \\ \blacksquare \\ \blacksquare \end{array}\right)$$

Where to find KGE in practice?

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Security Sensitive

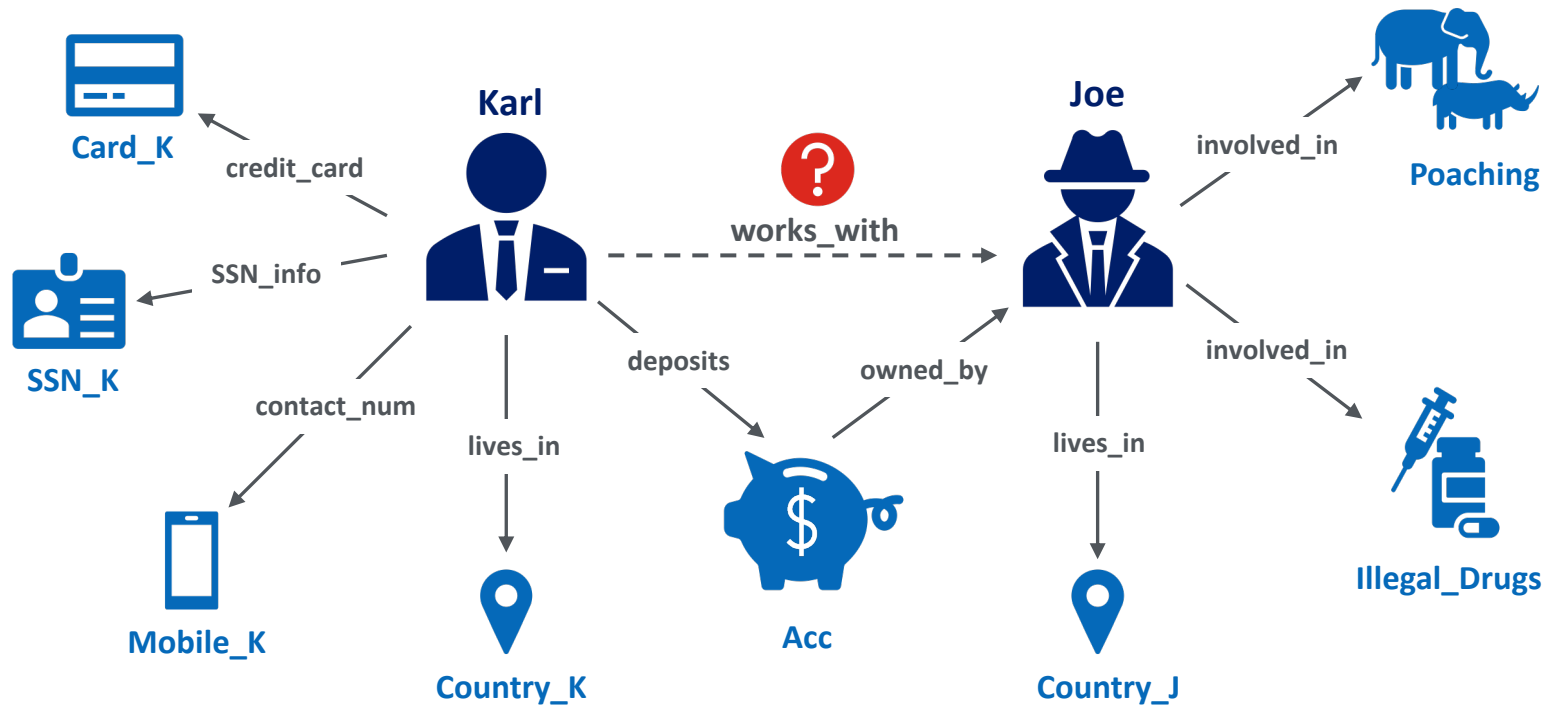
High Stakes



KGE in High-Stakes Applications

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Use case – Anti Money Laundering

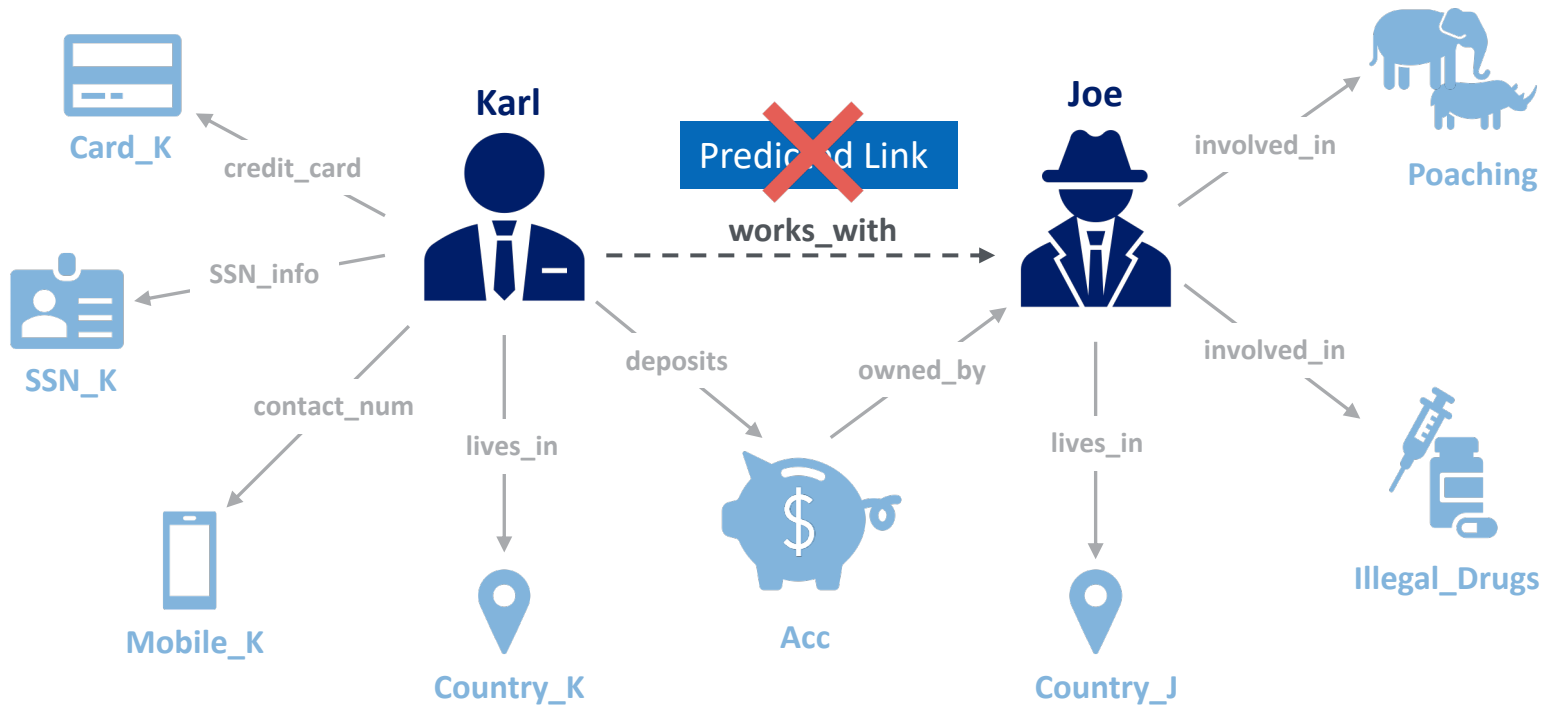


KGE in High-Stakes Applications



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Incentives for bad actors!



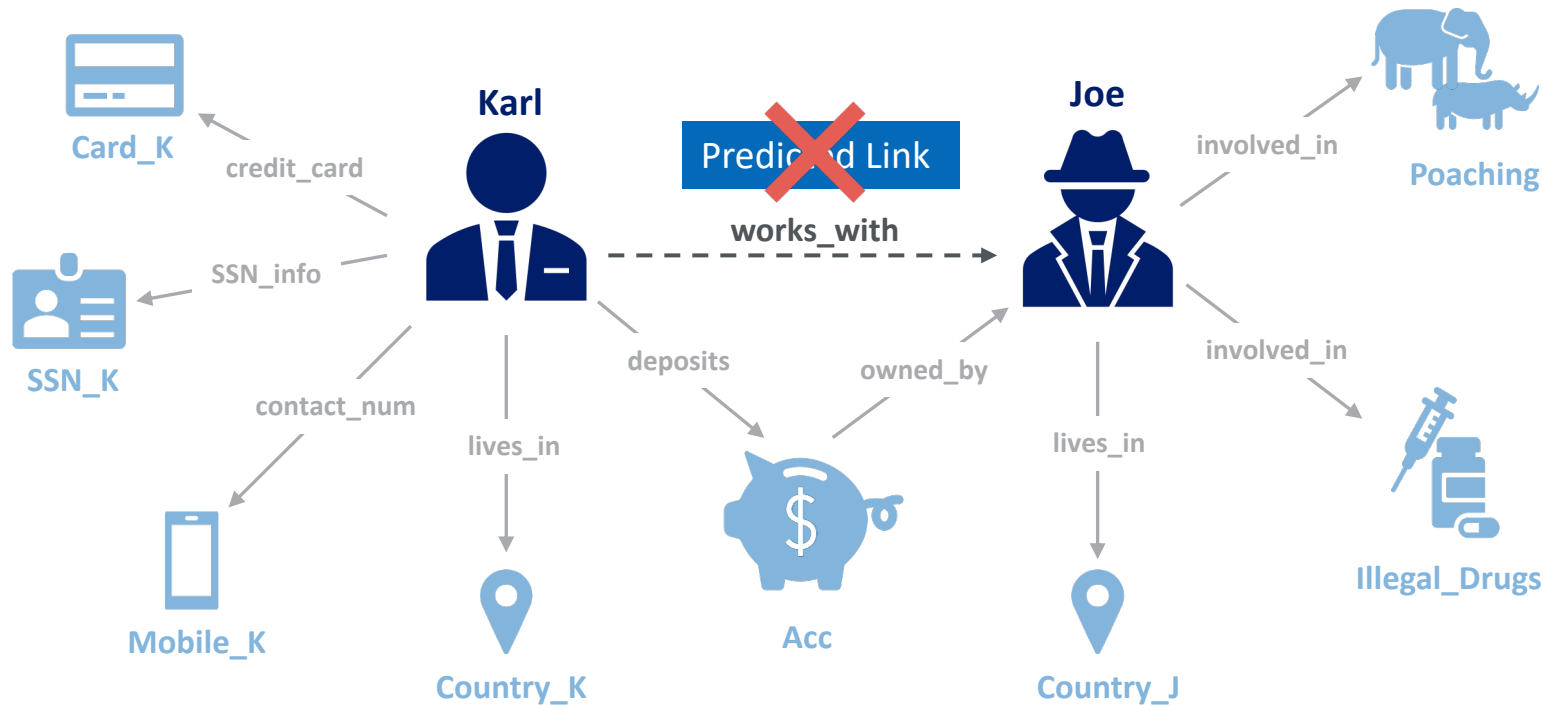
Adversarial Attacks on Knowledge Graph Embeddings

via Instance Attribution Methods

Adversarial Attacks on KGE

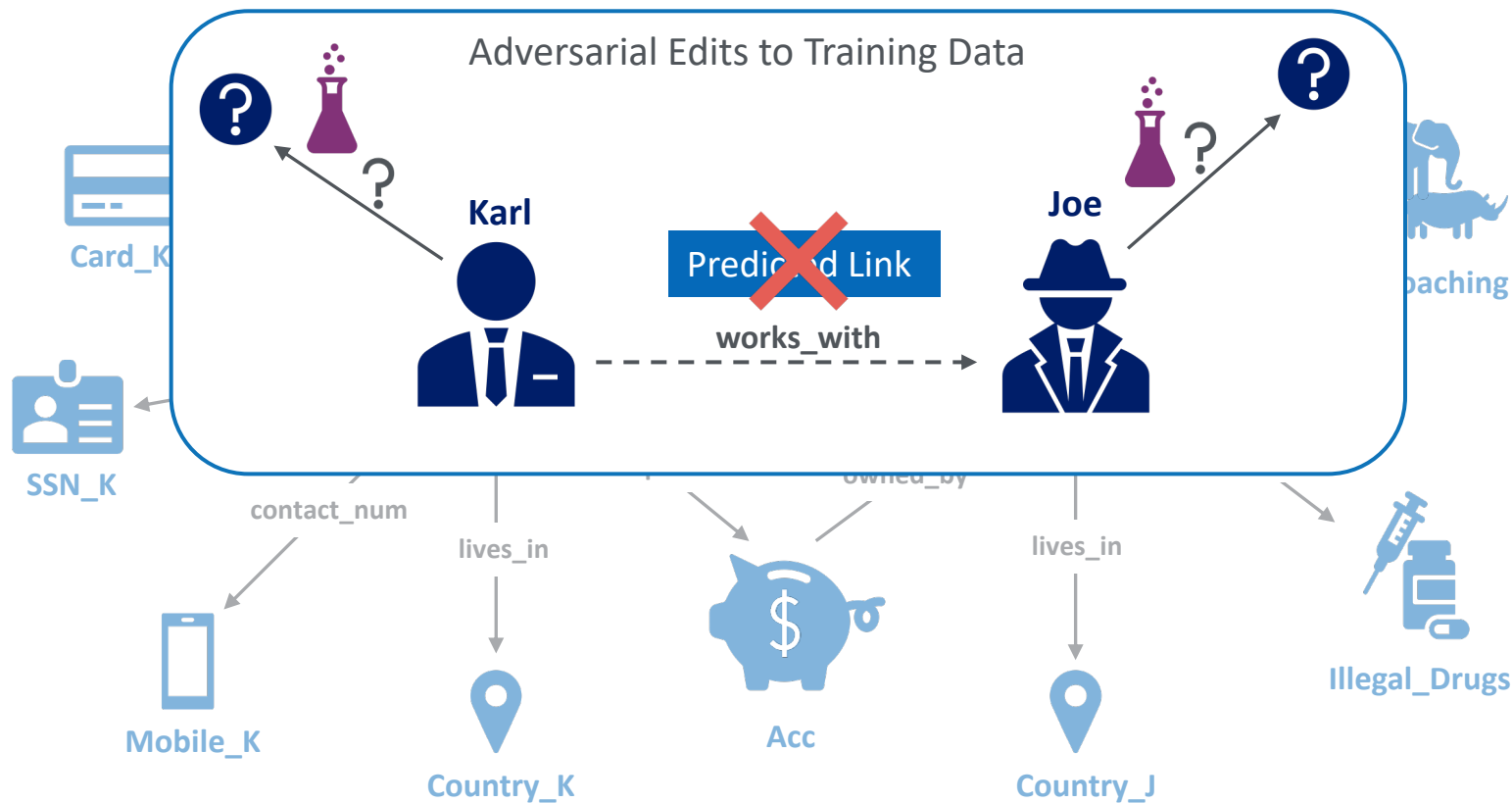
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Aim – Degrade the prediction on target triple



Adversarial Attacks on KGE

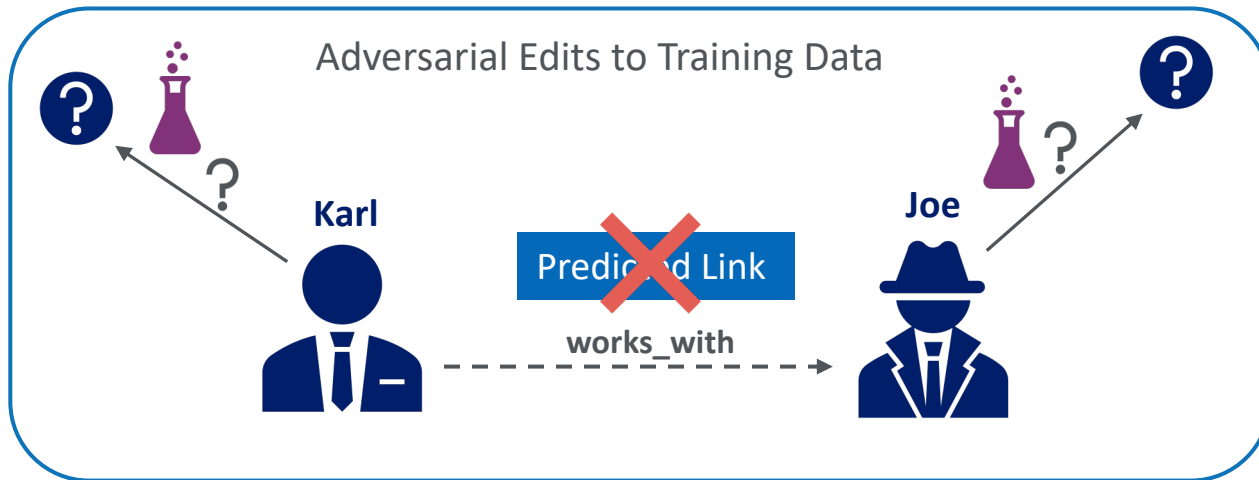
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Adversarial Attacks on KGE

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Challenge – Metric for adversarial impact

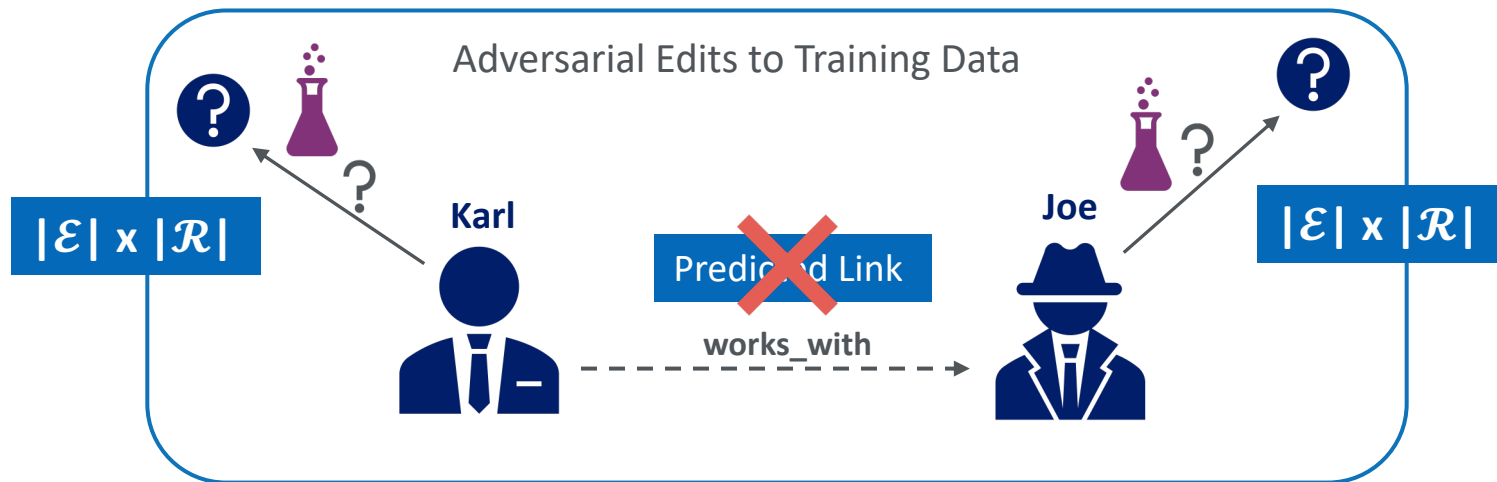


How to measure the impact of a candidate adversarial perturbation on the prediction of target triple?

Adversarial Attacks on KGE

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Challenge – Large Search Space



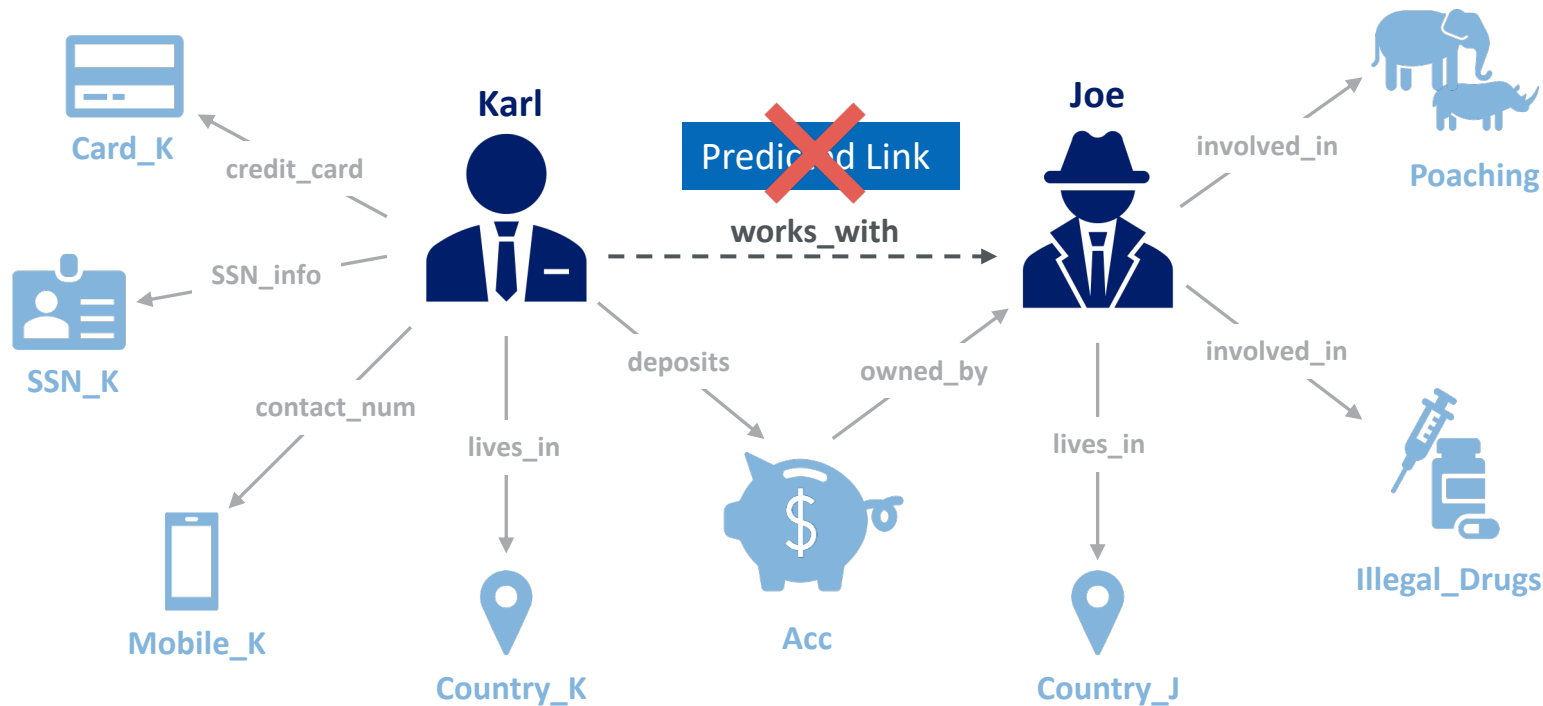
How to search through the combinatorial space of candidate adversarial additions?

Adversarial Attacks on Knowledge Graph Embeddings via Instance Attribution Methods

Instance Attribution Metrics

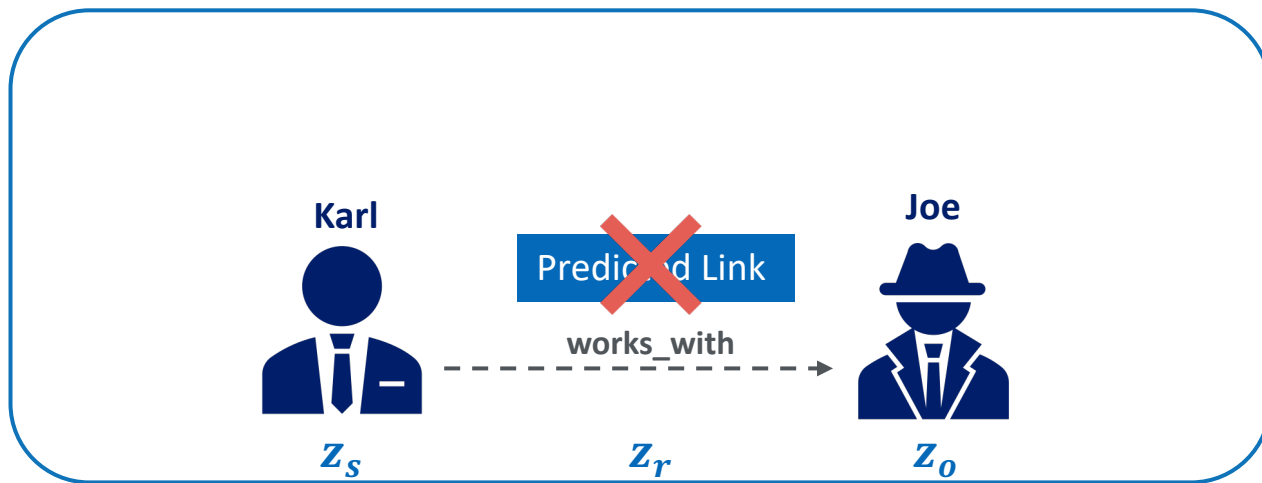
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Identify the most influential training triple



Instance Attribution Metrics

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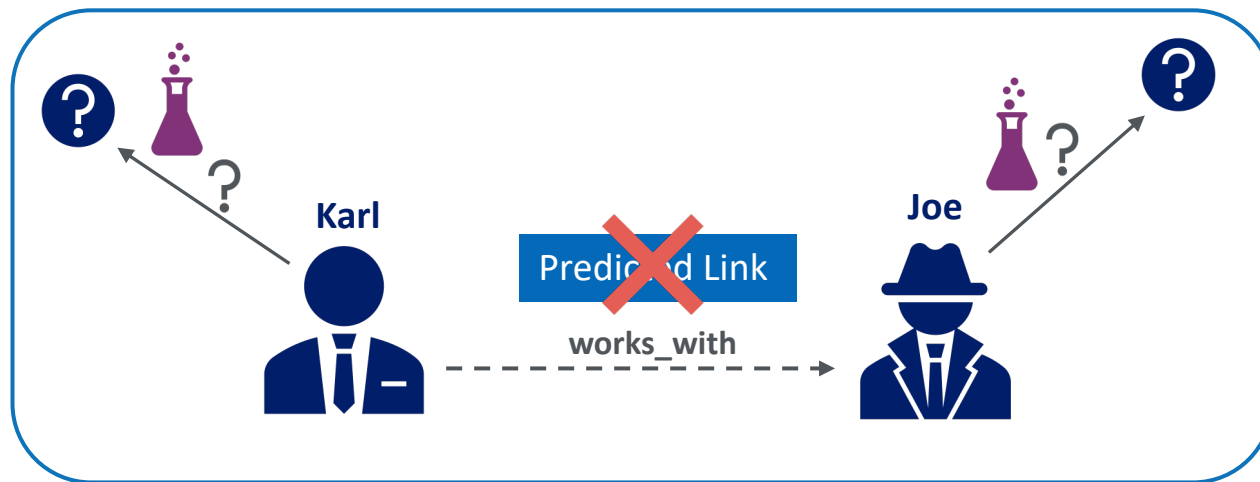


$$z := (z_s, z_r, z_o)$$

Target Triple

Instance Attribution Metrics

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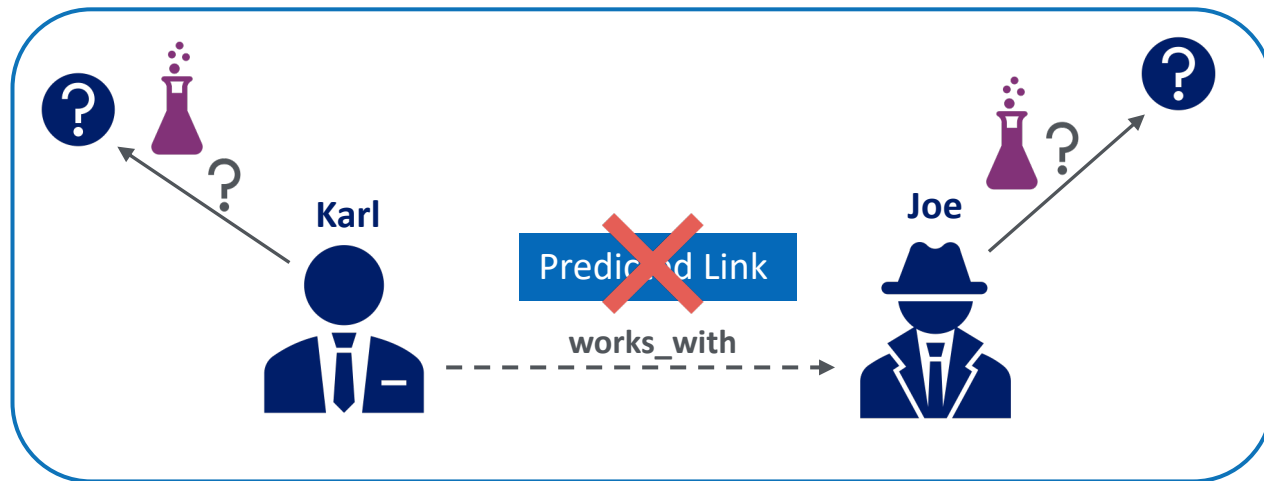
$$\mathbf{x} := (\mathbf{x}_s, \mathbf{x}_r, \mathbf{x}_o)$$

Candidate Influential Triple

Instance Attribution Metrics

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1. Instance Similarity



Similarity between $f(e_{z_s}, e_{z_r}, e_{z_o})$ and $f(e_{x_s}, e_{x_r}, e_{x_o})$

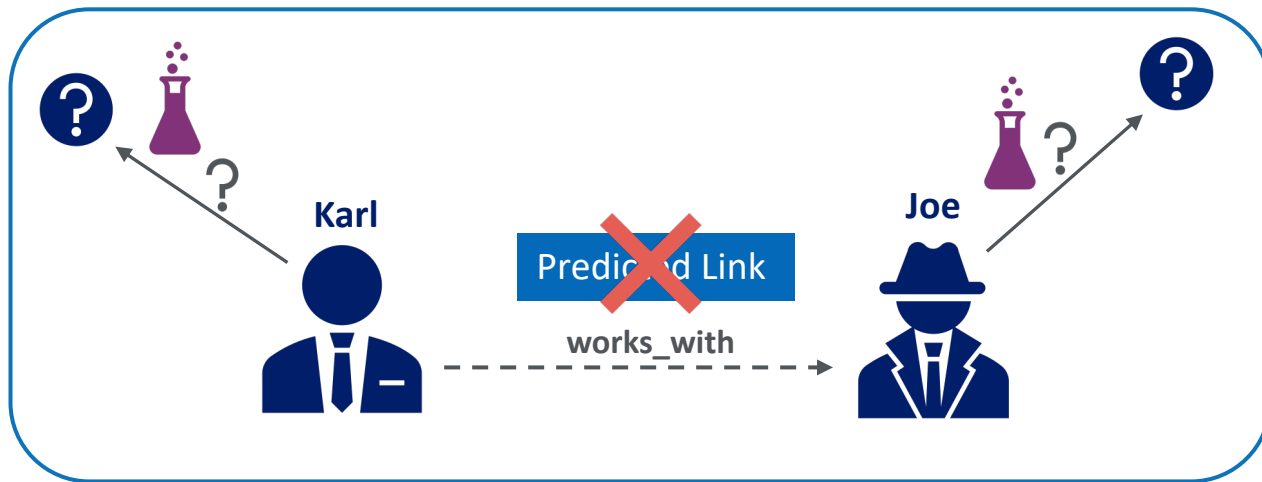
where

z – Target triple, x – Candidate triple

Instance Attribution Metrics

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2. Gradient Similarity



Similarity between $g(z, \hat{\theta})$ and $g(x, \hat{\theta})$

where

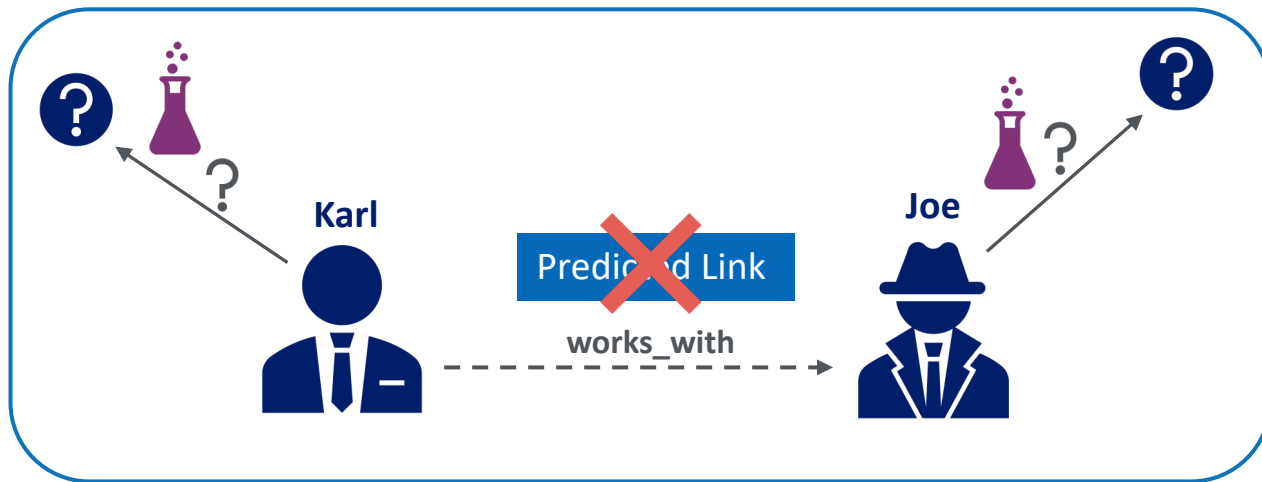
z – Target triple, x – Candidate triple

and $g(z, \hat{\theta}) = \nabla_{\theta} \mathcal{L}(z, \hat{\theta})$

Instance Attribution Metrics

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3. Influence Functions [Koh and Liang, 2017]



Dot product between $g(z, \hat{\theta})$ and $H_{\hat{\theta}}^{-1}g(x, \hat{\theta})$

where

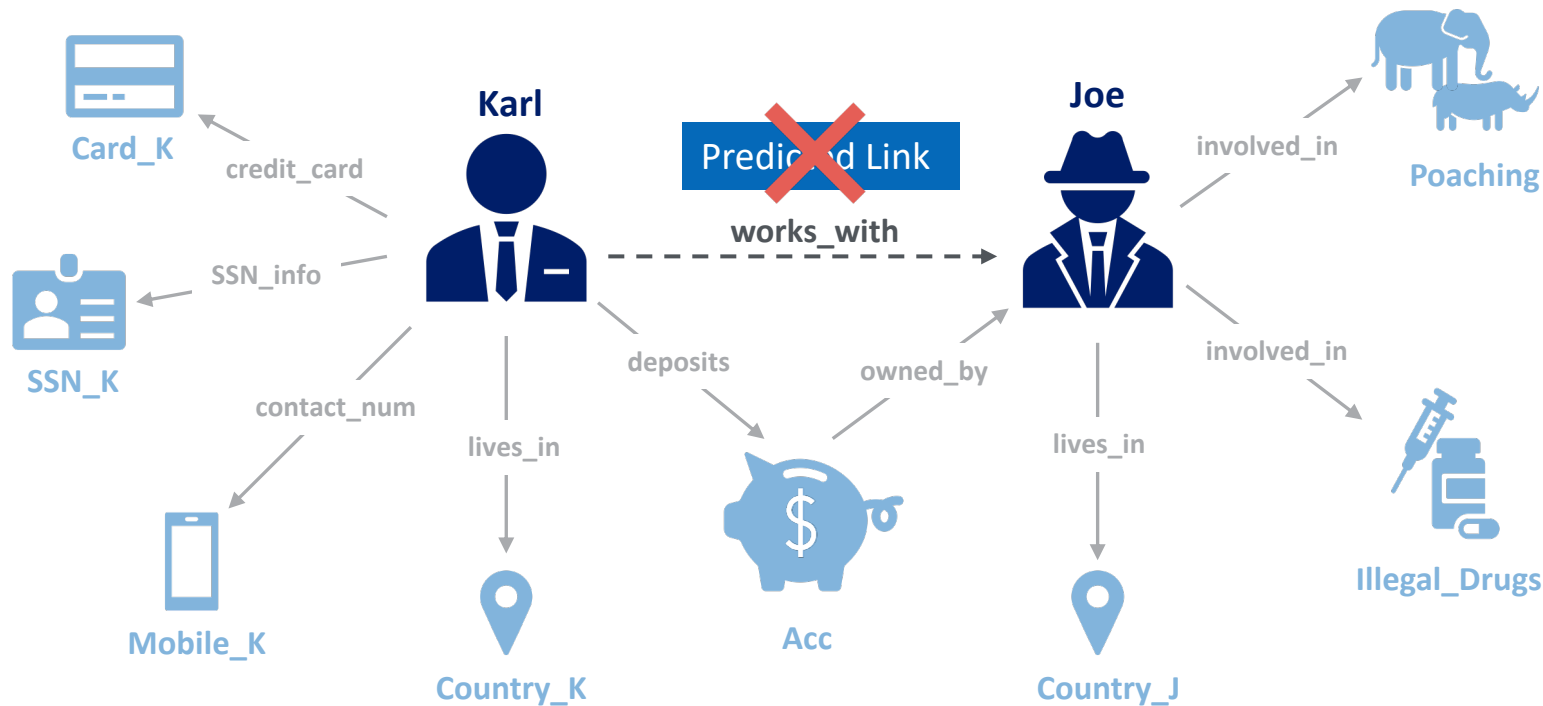
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Adversarial Deletions

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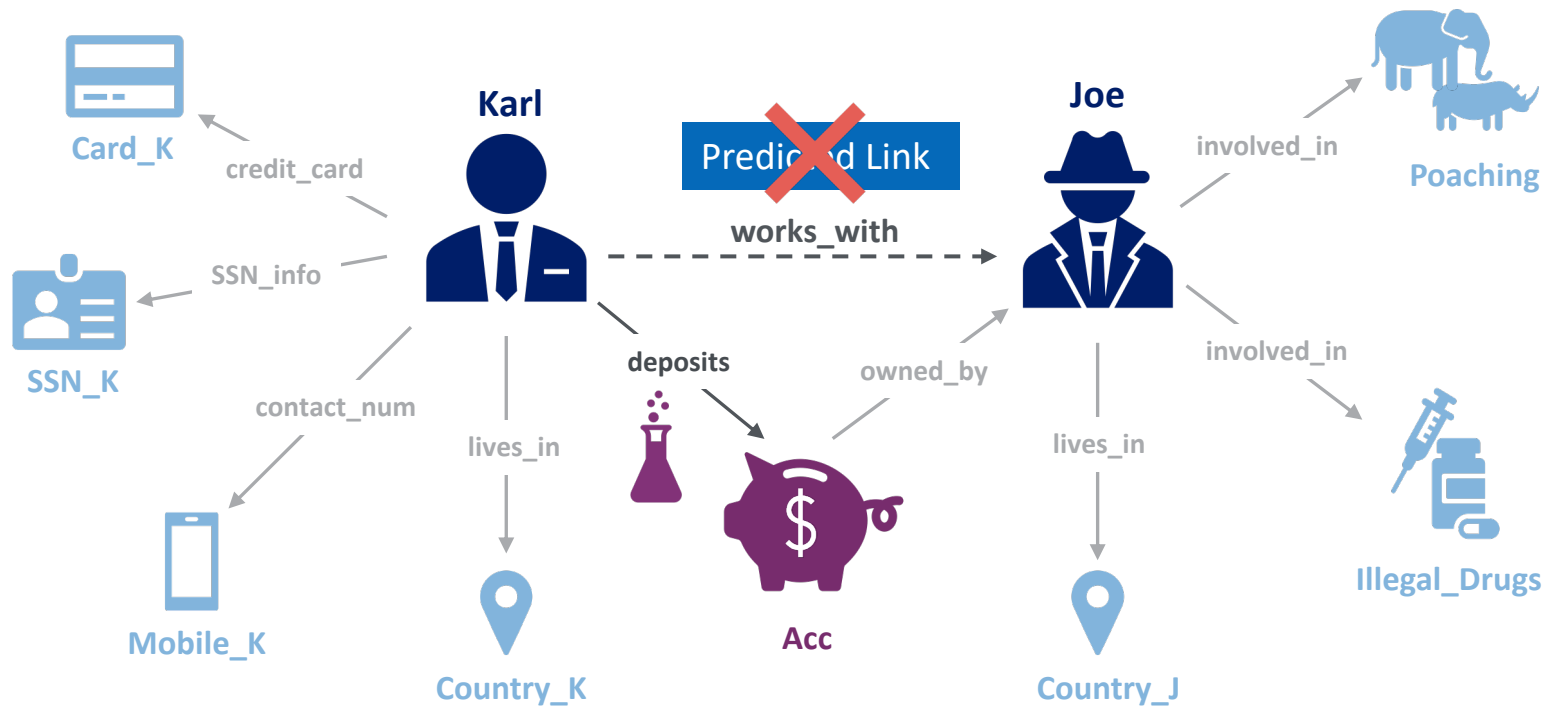
Identify the most influential training triple



Adversarial Deletions

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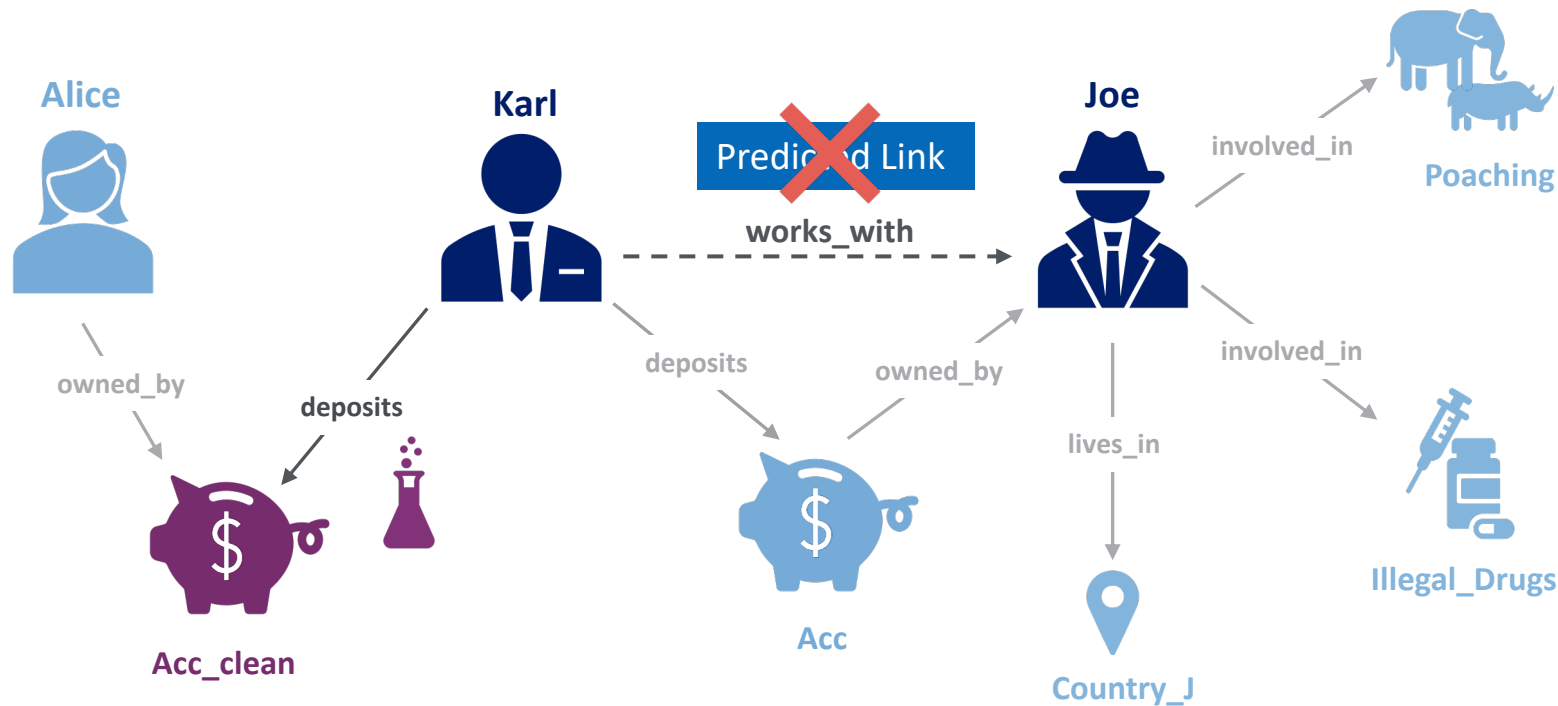
Identify the most influential training triple



Adversarial Additions

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Replace with dissimilar entity



Adversarial Attacks on Knowledge Graph Embeddings via Instance Attribution Methods

Evaluation

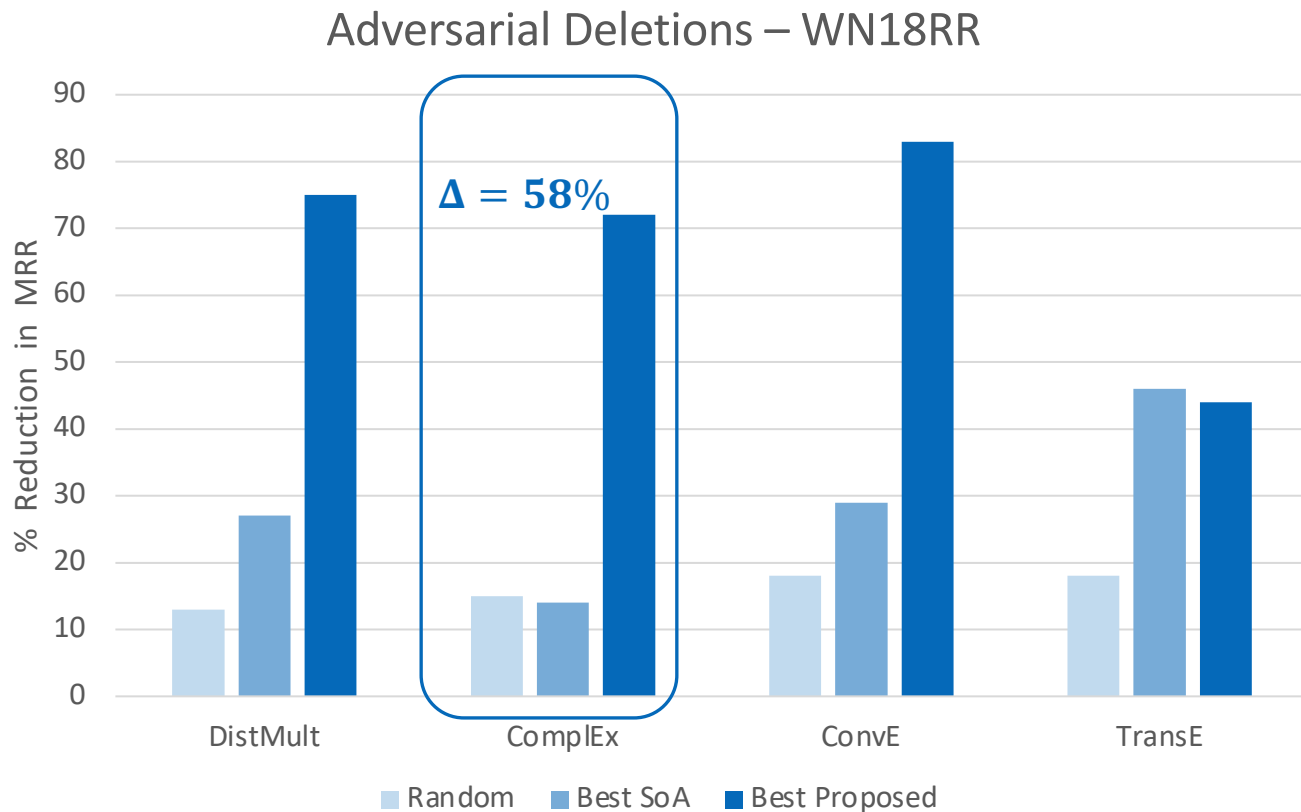
Proposed Vs State-of-Art

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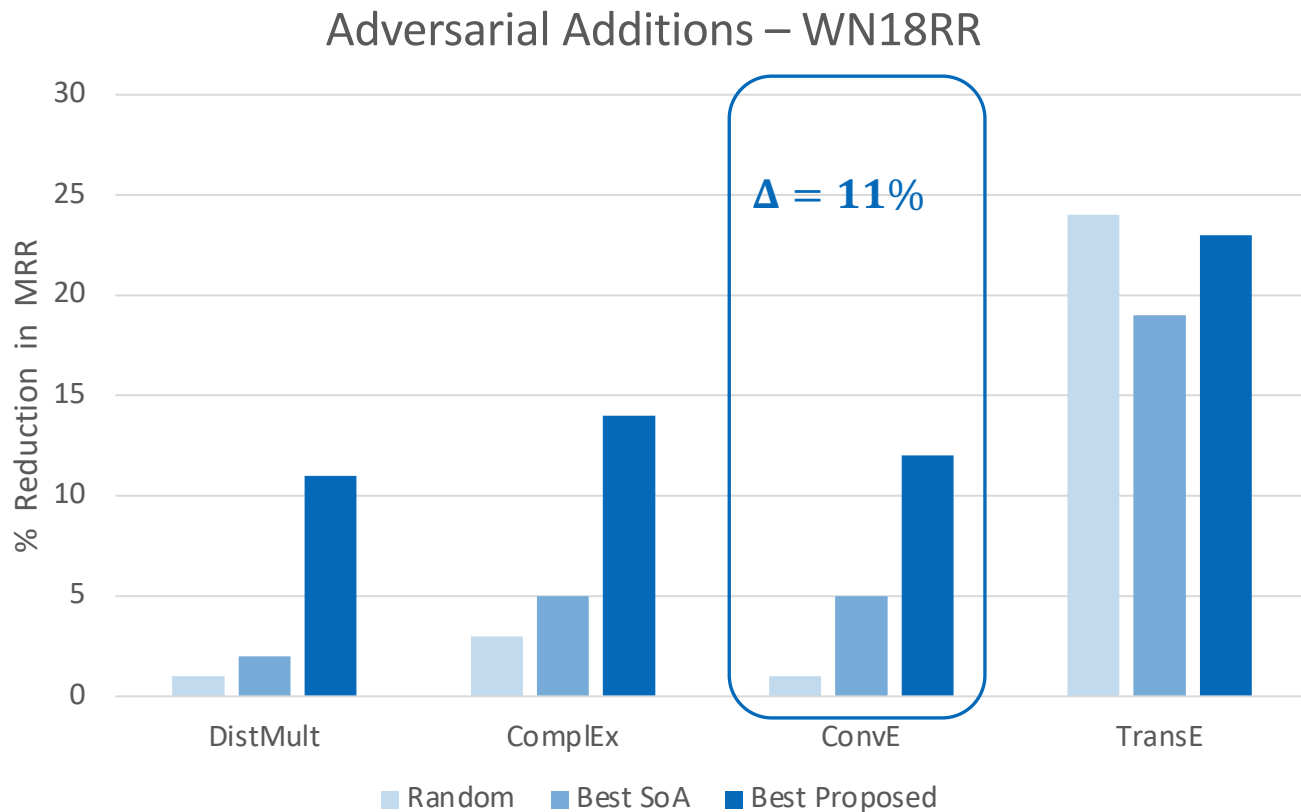
Proposed Vs State-of-Art

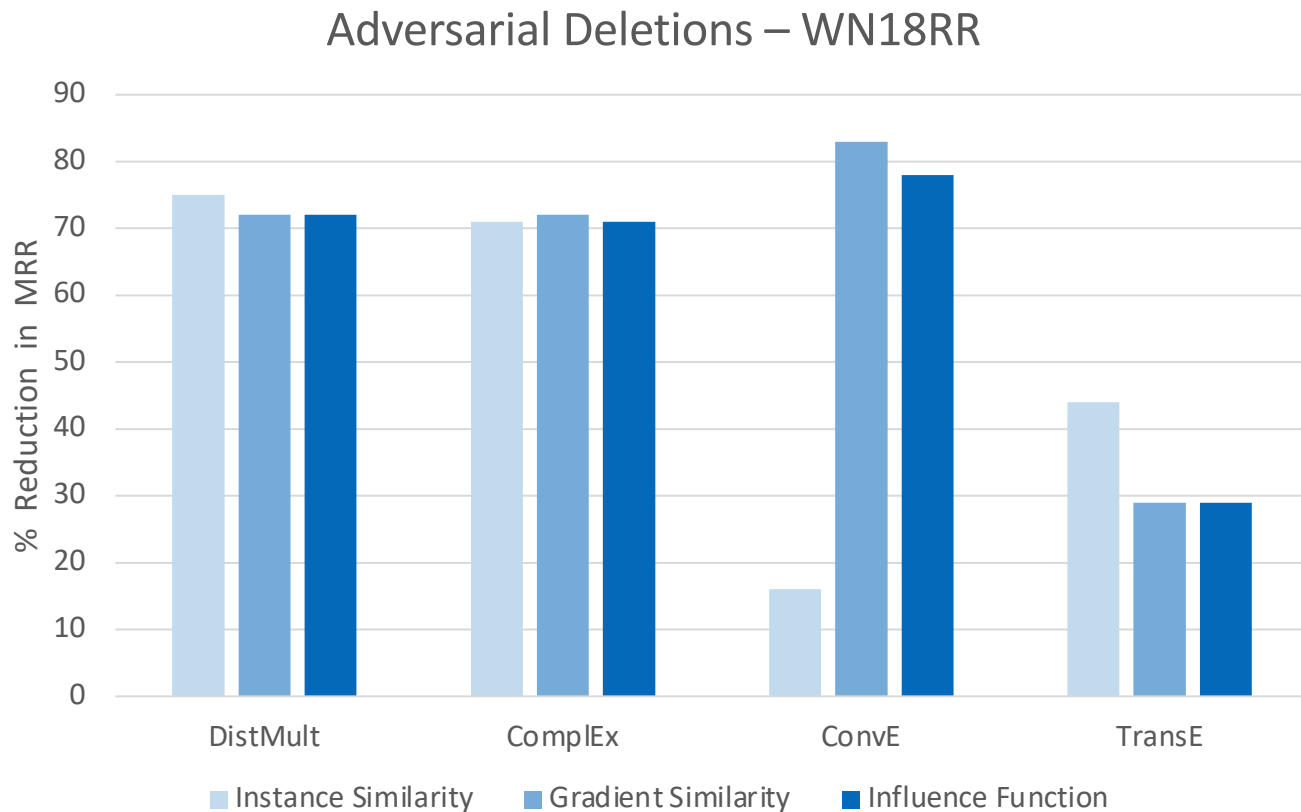
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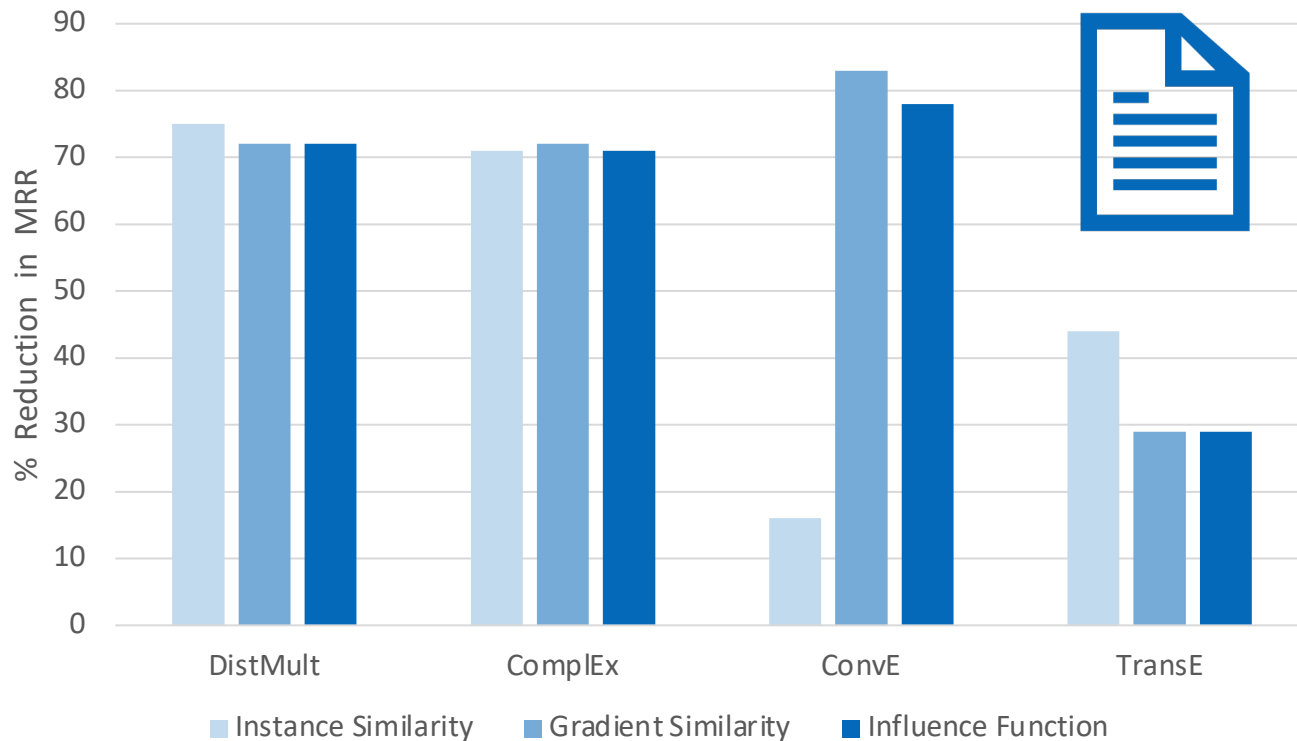
Proposed Vs State-of-Art

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Adversarial Deletions – WN18RR



Adversarial Attacks on KGE

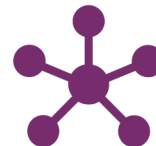


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Future Directions

Sub-graph Influence

Can we measure the influence of a training sub-graph on the model's prediction for target triple?



Adversarial Attacks on KGE



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Future Directions

Sub-graph Influence

Can we measure the influence of a training sub-graph on the model's prediction for target triple?



Adversarial Robustness

Can we improve the adversarial robustness of KGE models to defend them against adversarial attacks?



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