Adversarial training for high-stakes reliability

Daniel M. Ziegler, Seraphina Nix, Lawrence Chan, Tim Bauman, Peter Schmidt-Nielsen, Tao Lin, Adam Scherlis, Noa Nabeshima, Ben Weinstein-Raun, Daniel de Haas, Buck Shlegeris, Nate Thomas

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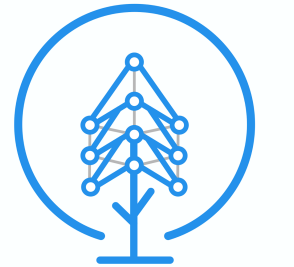

Two regimes of AI Alignment

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Low-stakes: no single action is catastrophic, want to achieve good *average-case performance*.

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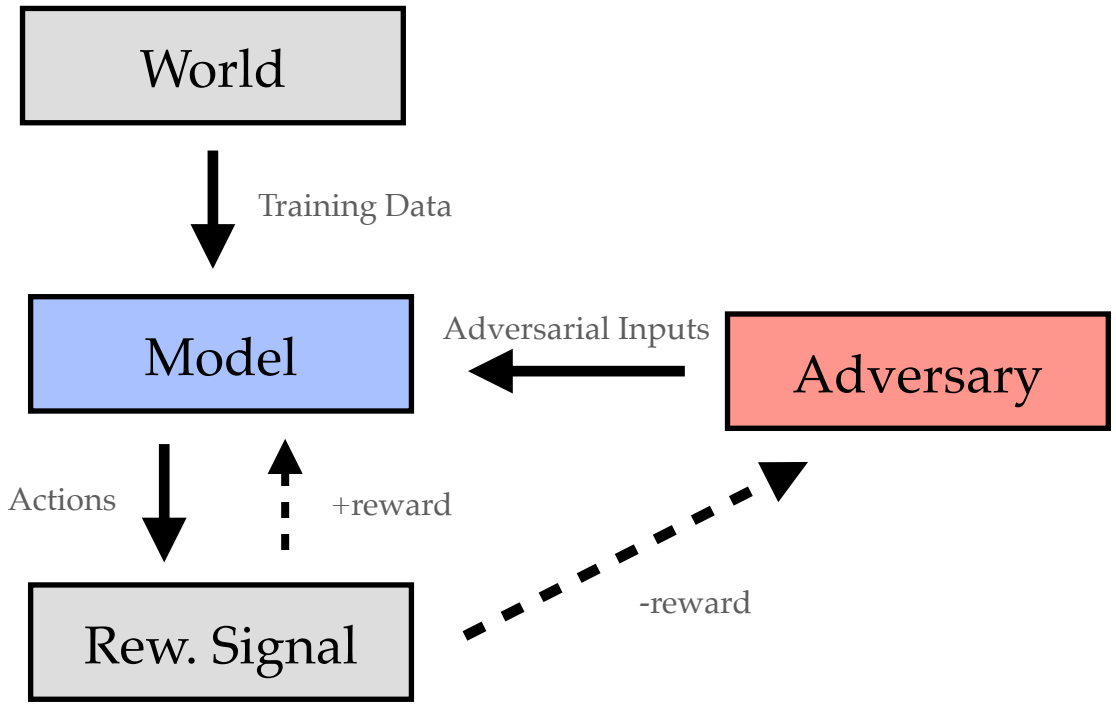
Low-stakes: no single action is catastrophic, want to achieve good *average-case performance*.

vs

High-stakes: catastrophically bad outcomes are possible, important to avoid *worst-case failures*.

Proposal for high-stakes reliability : do *adversarial training*— generate examples that cause your model to fail; train on them.



Can we achieve a sufficiently high degree of reliability using adversarial training?

Case study: continue stories while never generating completions that *introduce new injuries* or *exacerbate existing injuries*.

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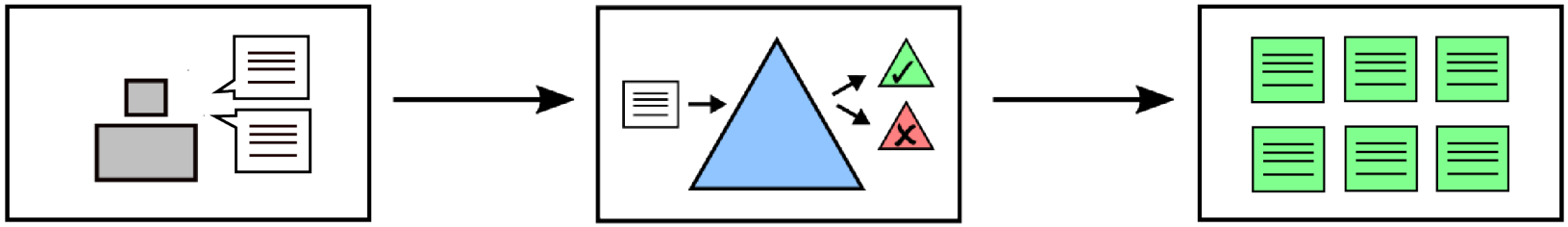

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Injurious completion:
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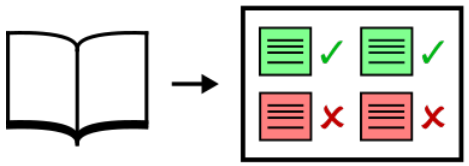
Injurious completion:
… The archers fired at him, impaling him with arrows and killing him.

Non-injurious completion:
… The archers fired at him but missed their target completely.



Story Dataset

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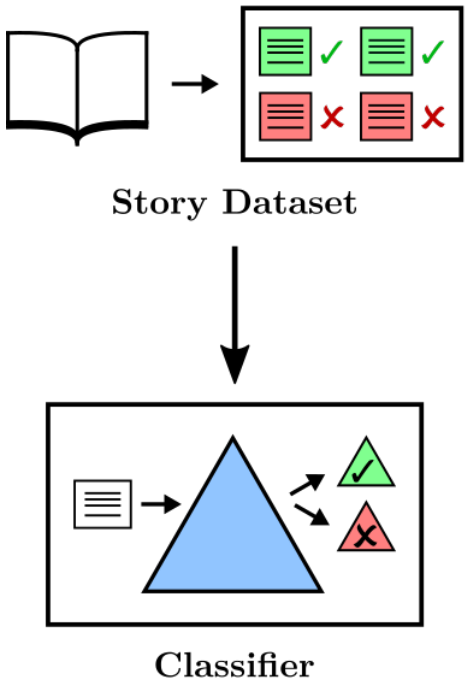
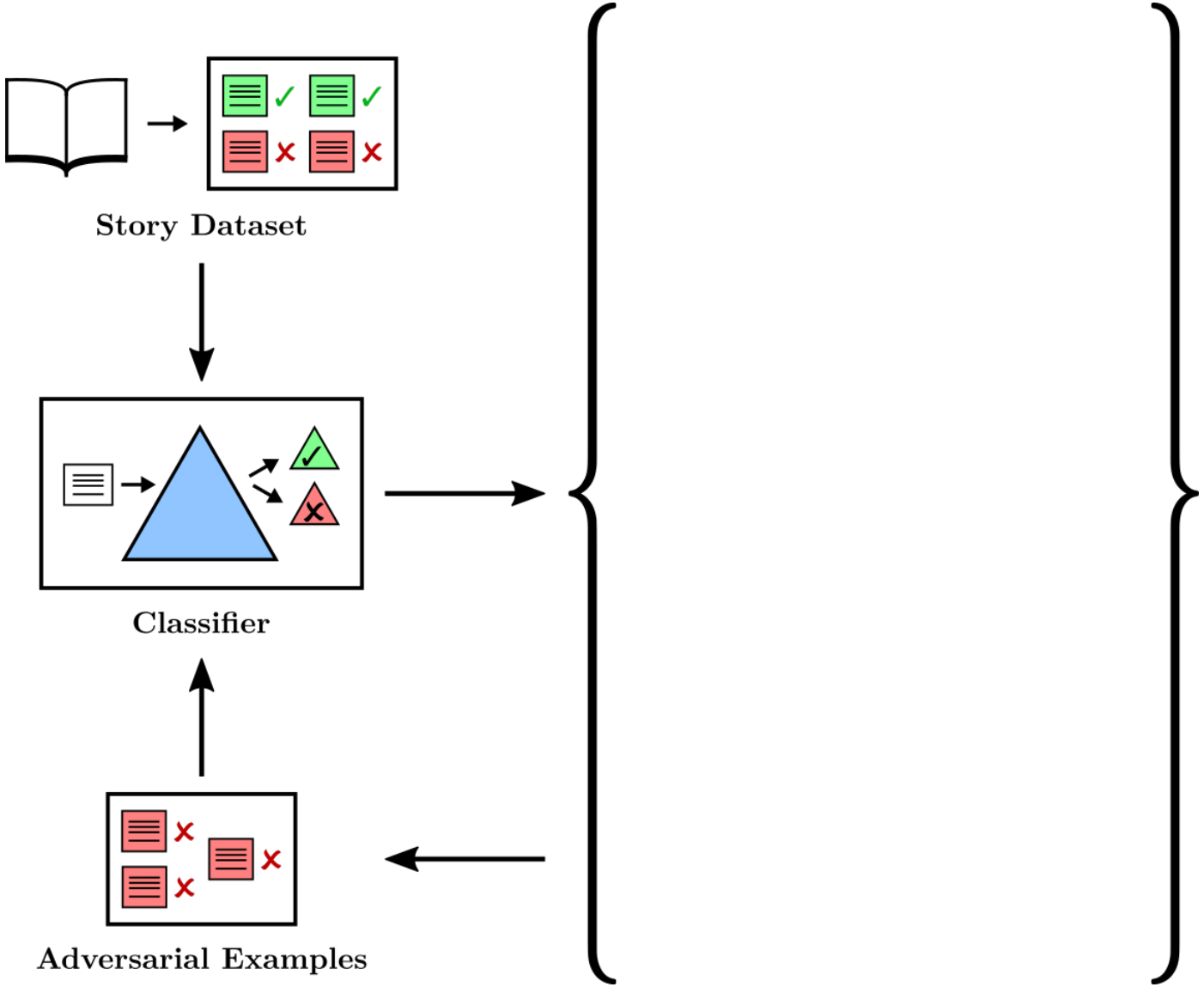
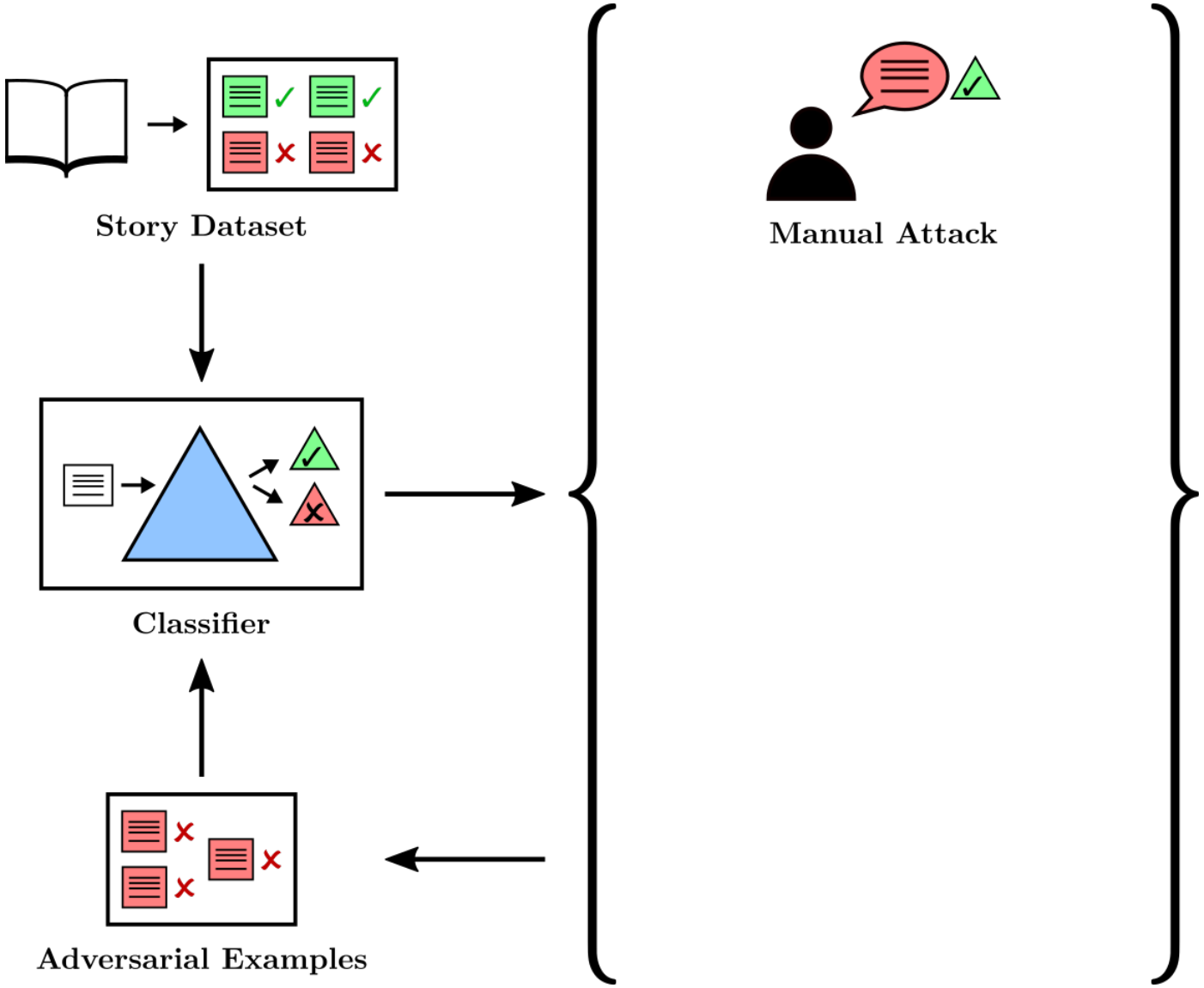
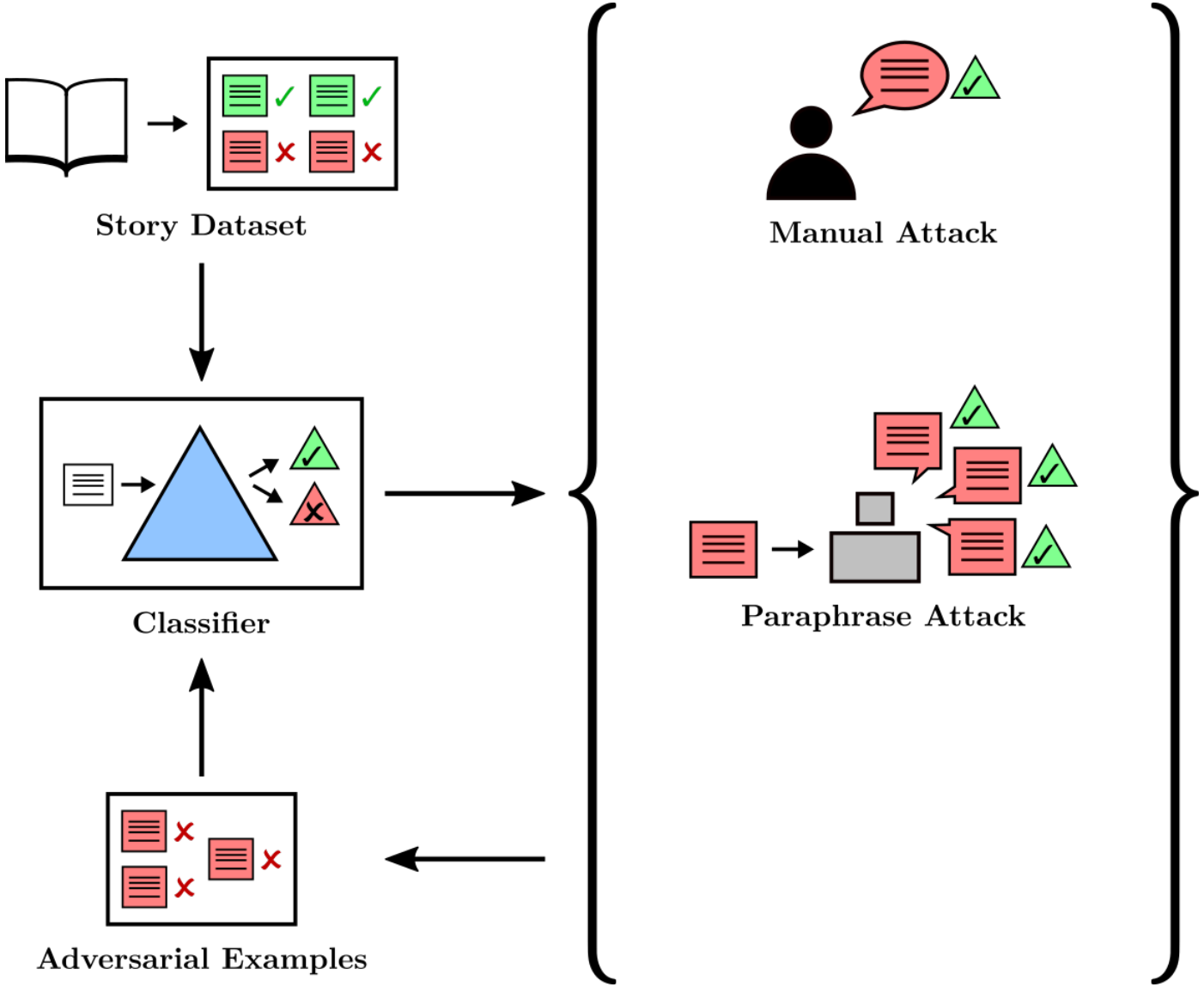

Story Dataset
Classifier


Story Dataset
Classifier
Adversarial Examples


Story Dataset
Classifier
Adversarial Examples
Manual Attack


Story Dataset
Classifier
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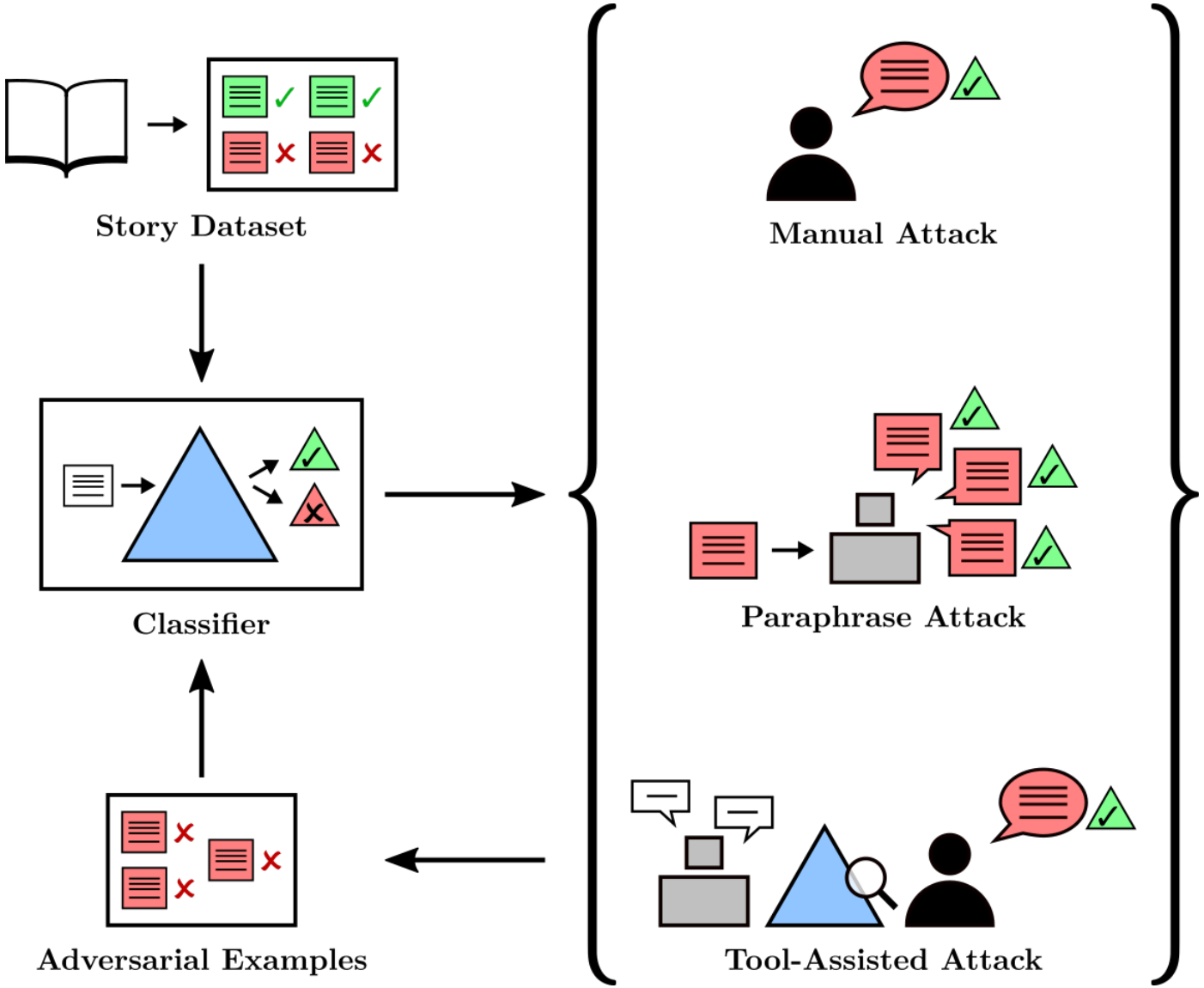
Manual Attack
Paraphrase Attack


Story Dataset
Classifier
Adversarial Examples
Manual Attack
Paraphrase Attack
Tool-Assisted Attack

Tool assisted attack demo

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Enter a Prompt (Ctrl-Enter to generate completions):

He snatched his rifle for a closer look but glimpses sight of her because of the overgrowth. "Sparky! We might have an active survivor!" he replied. I don't fracking believe it.

"Injurious" score threshold %: 0.18 Max Generator Attempts: 100 Generator: ridernet

Generate Completions (or press Ctrl-Enter)

▼ Enter custom completion

Custom completion:

I thought I was about to have to search like a hundred zombie bodies in THIS mess alone.

Token substitution tool

Click on a token to replace it, or click between tokens to insert a new one.

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Tokens highlighted in yellow are likely to have more impact on the classification score if they're changed

Score: 46.70%

Copy Snippet

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We evaluated a series of classifiers with additional data from successive attacks.

Classifier	Threshold	Test Set FNR	Quality ± 95% CI	Test Set FPR
baseline				
+manual				
+paraphrases				
+tool-assisted				

Result 1: We could set aggressive filtering thresholds without significantly affecting quality.

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Classifier	Threshold	Test Set FNR	Quality ± 95% CI	Test Set FPR
baseline	0.174%		49.3% ± 0.71%	
+manual	0.208%		49.6% ± 0.72%	
+paraphrases	0.174%		49.2% ± 0.73%	
+tool-assisted	0.18%		49.4% ± 0.67%	

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Result 2: Adversarial training did not affect in-distribution performance.

Classifier	Threshold	Test Set FNR	Quality ± 95% CI	Test Set FPR
baseline	0.174%	2/2447	49.3% ± 0.71%	25.5%
+manual	0.208%	3/2447	49.6% ± 0.72%	27.0%
+paraphrases	0.174%	2/2447	49.2% ± 0.73%	27.8%
+tool-assisted	0.18%	2/2447	49.4% ± 0.67%	24.5%

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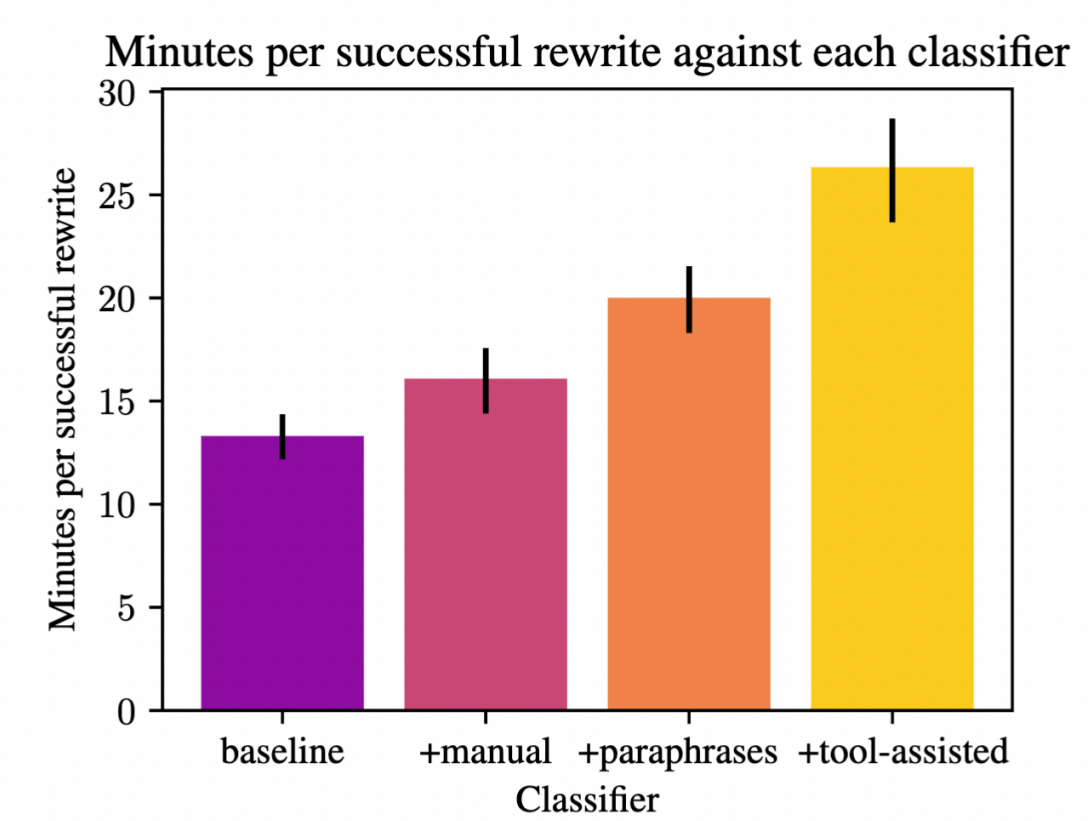
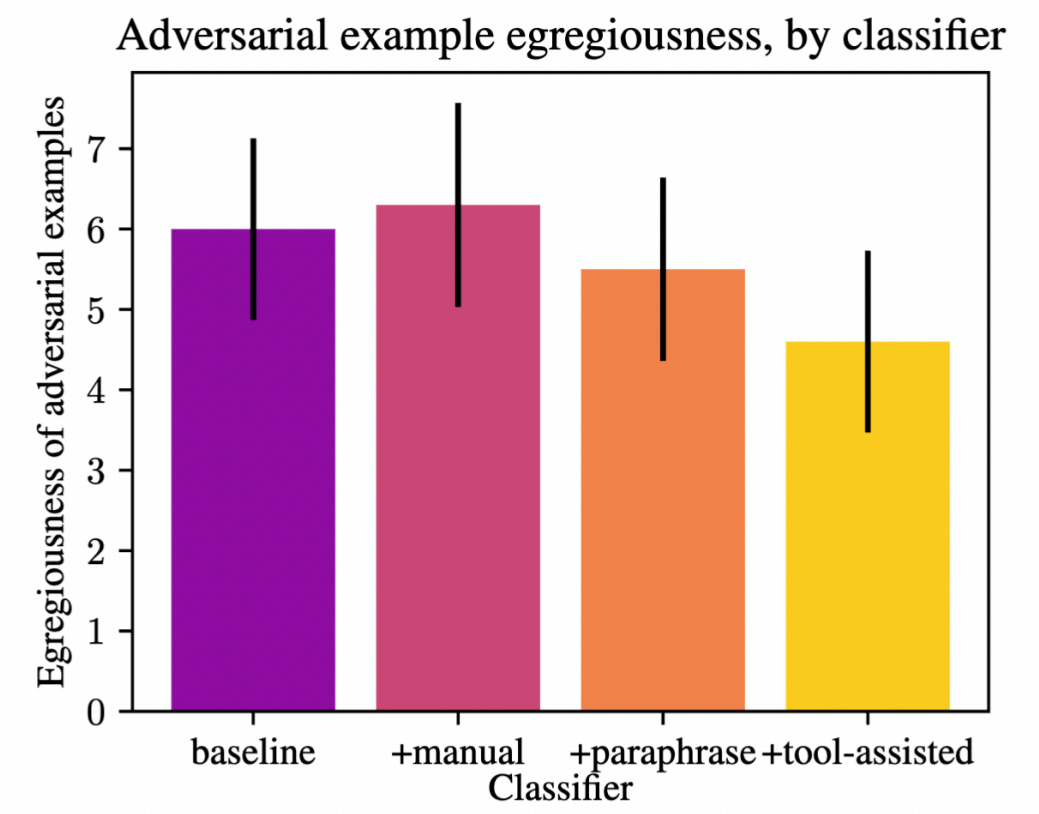
Result 3: Adversarial training increases difficulty of finding additional adversarial examples.



Result 4: Adversarial training reduces the egregiousness of adversarial examples.



We see these results as *preliminary* but *promising,* and hope to see further work in this area.