



Allen Institute for AI

# More Bang for Your Buck: Natural Perturbations for Robust QA

Me →



**Daniel Khashabi**

Allen Institute for AI



Tushar Khot

Allen Institute for AI



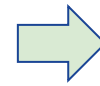
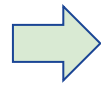
Ashish Sabharwal

Allen Institute for AI

# Dataset Construction Pipeline

- Many NLP models remain data-hungry.
  - Large & rich datasets
- Dataset construction is often implemented as a repeated process of creating new instances by human annotators.

*(Yonge Street) The Guinness Book of World Records no longer lists Yonge Street as the longest street in the world and has not chosen a replacement street, but cites the Pan-American Highway as the world's longest "motorable road".*



*Q: Is the "Yonge Street" the longest street in the world? X*

- This can be a costly step and bottleneck for building stronger NLP models.

# An Alternative Construction

We explore a slightly different dataset construction pipeline:

*(Yonge Street) The Guinness Book of World Records no longer lists Yonge Street as the longest street in the world and has not chosen a replacement street, but cites the Pan-American Highway as the world's longest "motorable road".*

Q: Is the "Yonge Street" the longest street in the world? (ans: **X**)



Q: *Was* the "Yonge Street" the longest street in *the world in the past*? (ans: **✓**)



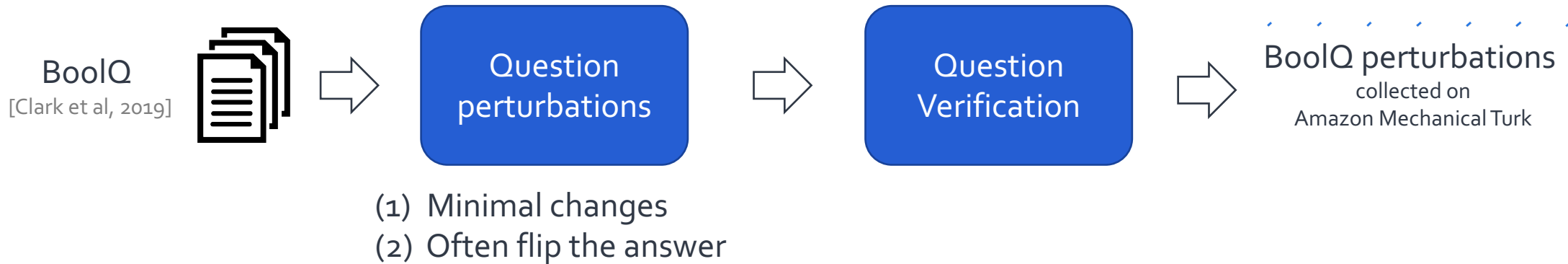
Q: *Was* the 'Yonge Street' the longest street in the world *before 1980*? (ans: *unknown*)

natural perturbations **!=** adversarial perturbations [Jia & Liang, 2017]

Creating natural perturbations are easier than writing new questions.

**Conjecture:** building datasets w/ natural perturbations are more **cost-efficient**.

# Perturbing Boolean Questions



*Q: Is the "Yonge Street" the longest street in the world? (ans: **X**)*

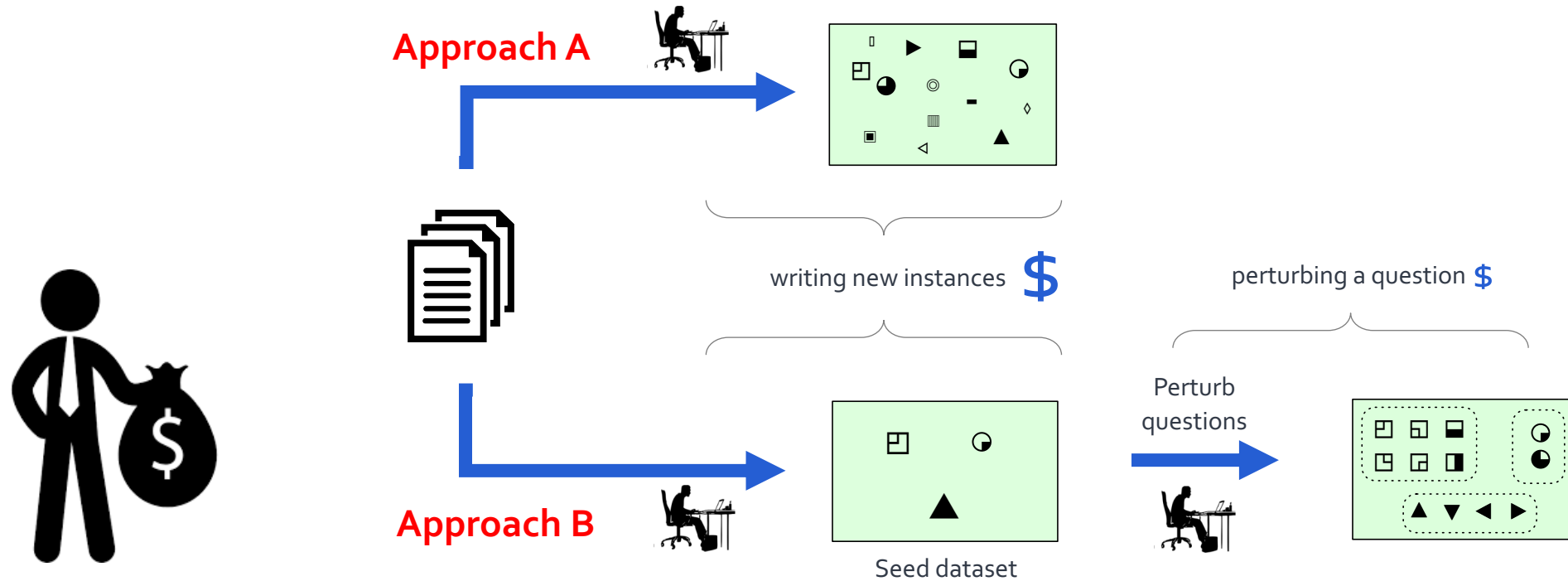
*(Yonge Street) The Guinness Book of World Records no longer lists Yonge Street as the longest street in the world and has not chosen a replacement street, but cites the Pan-American Highway as the world's longest "motorable road".*

*Q: **Was** the "Yonge Street" the longest street in the world in the past? (ans: **✓**)*

*Q: **Was** the 'Yonge Street' the longest street in the world **before 1980**? (ans: **unknown**)*

*Q: **Will** the "Yonge Street" become the longest street in the world? (ans: **X**)*

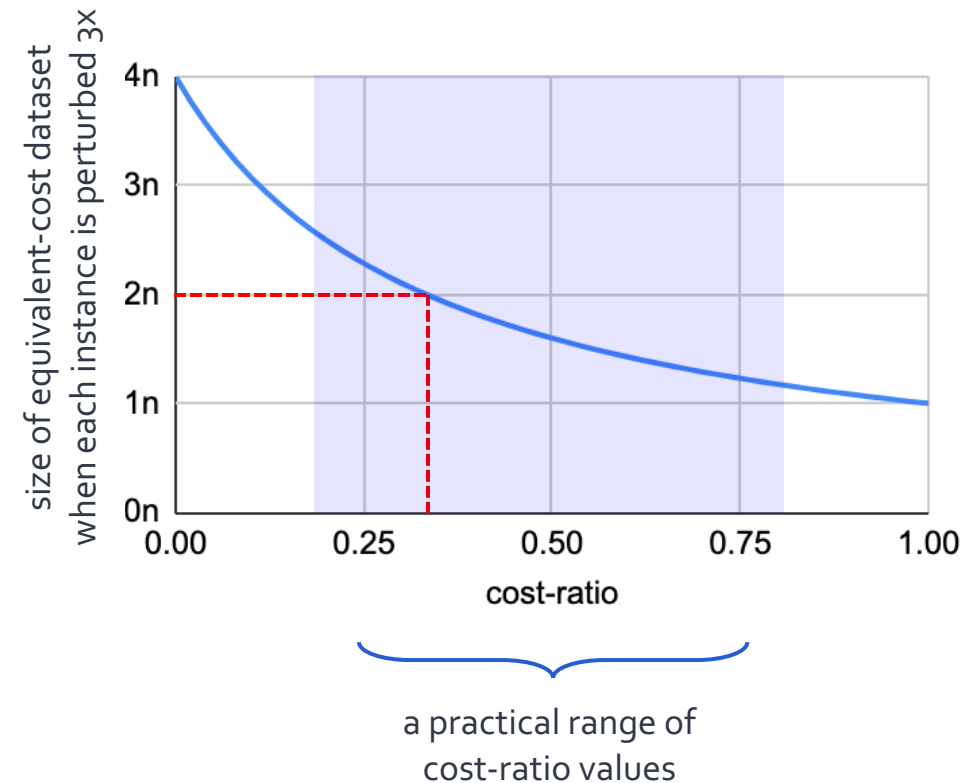
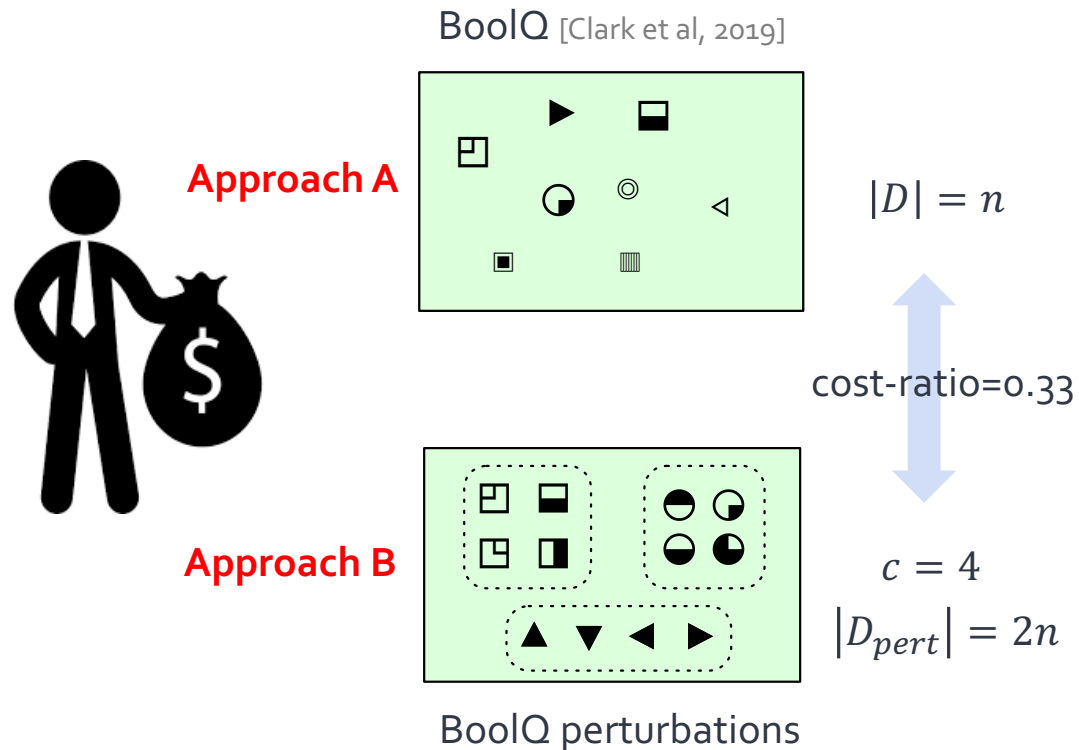
# Experimental Setup



**Intuition:** perturbing questions is easier and cheaper than writing a question from scratch

# Perturbation Size vs Cost-Ratio

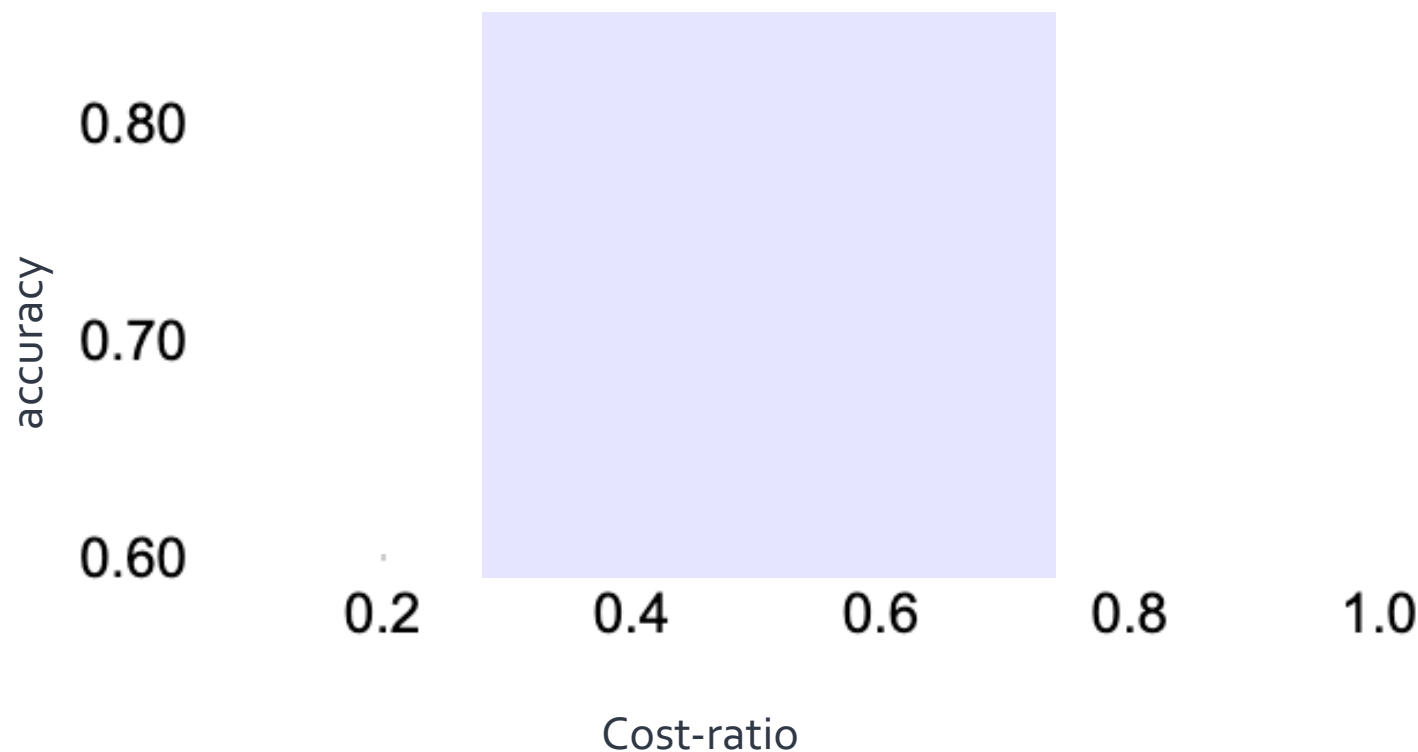
- Equivalent-cost datasets, with varying cost-ratio.



# Experiment: Benefits as Function of Cost-Ratio

Evaluations on  
BoolQ [Clark et al, 2019]

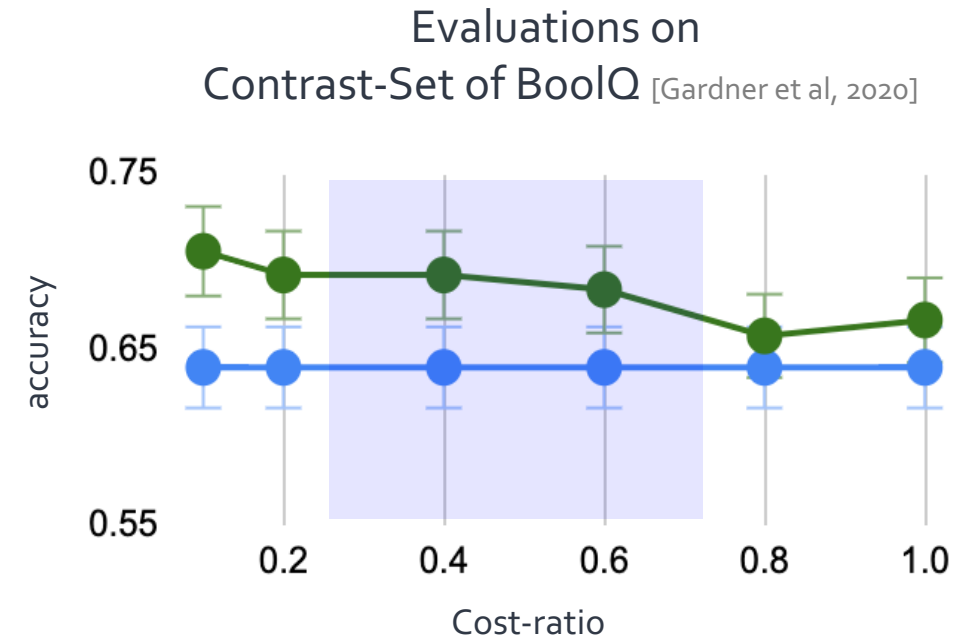
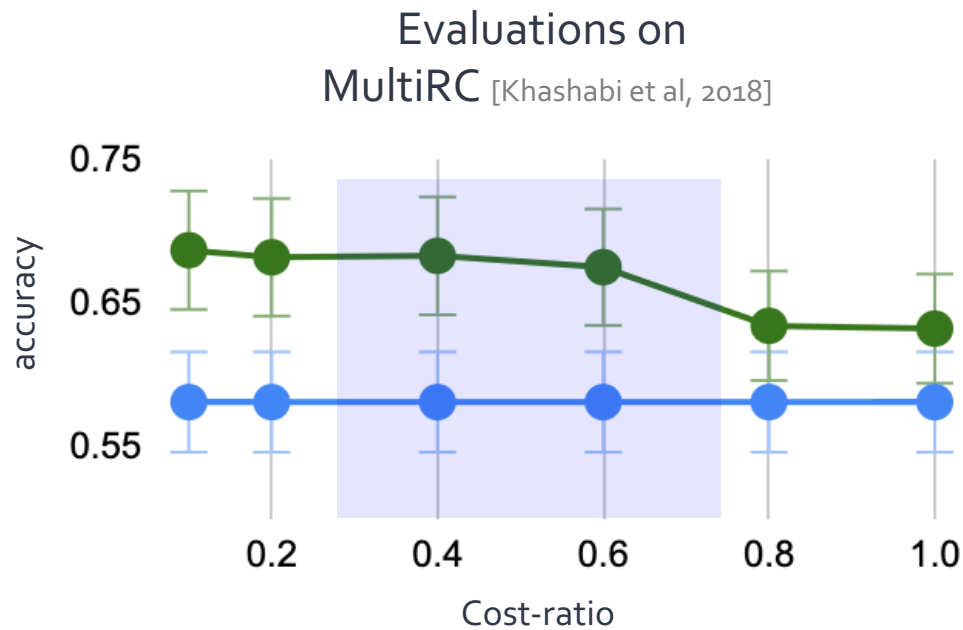
- Approach A (writing new instances)
- Approach B (each instance perturbed 3x)



**Observation:**  
Moderately cheap perturbations could result in more accurate models.

# Experiment: Benefits as Function of Cost-Ratio

- Approach A (writing new instances)
- Approach B (each instance perturbed 3x)



## Observation:

Moderately cheap perturbations could result in better **generalization** to unseen data and **robustness** to local perturbations.



# Recent Work

- For reducing spurious associations [Kaushik et al., ICLR, 2020]
- NLI task [Huang et al., Workshop on Insights from Negative Results in NLP, 2020]
  - Do not observe any significant benefits from natural perturbations.

# Summary

- An alternative approach for constructing training sets:
  - Expanding a seed set of examples via **human-authored perturbations**.
- When these perturbations are moderately cheaper, they result in gains.
  - Better generalization to unseen datasets.
  - Less sensitive to small changes in the input.
- Code & Data: <https://github.com/allenai/natural-perturbations>

