

Unify and Conquer

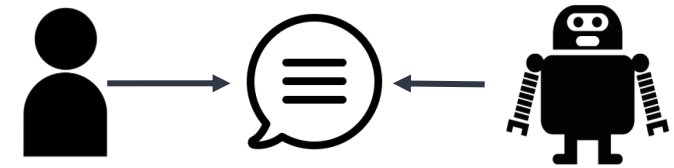
Towards a *Unified View* of Machine Comprehension

Daniel Khashabi
Allen Institute for AI, Seattle

Moving towards NLU, via QA

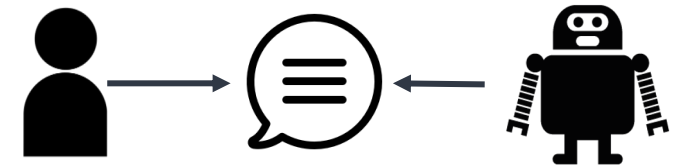
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- Natural Language Understanding:
 - Interpret a given text similar to humans.
- Measuring the progress by answering questions.
 - A system that is better in understanding language, should have a higher chance of answering these questions.
- This has been used in the field for many years
 - Question Answering,
 - Reading Comprehension,
 - Machine Comprehension, etc.



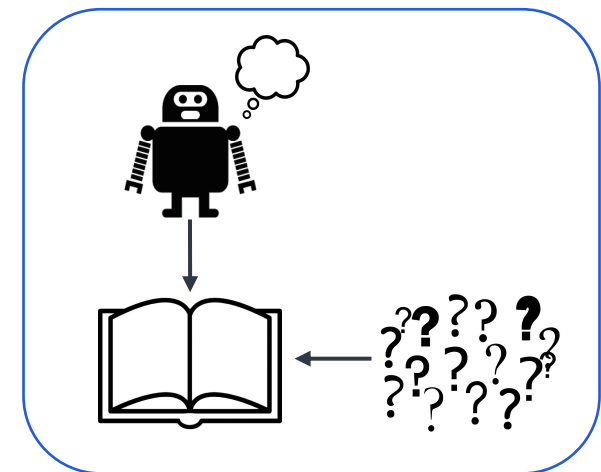
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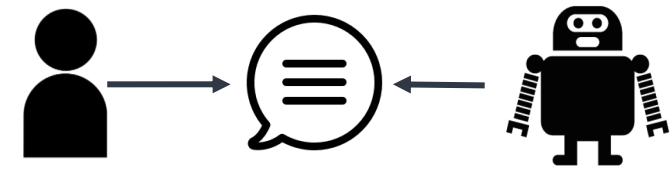
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[Winograd, 1972; McCarthy 1976; Lehnert, 1977b; others]

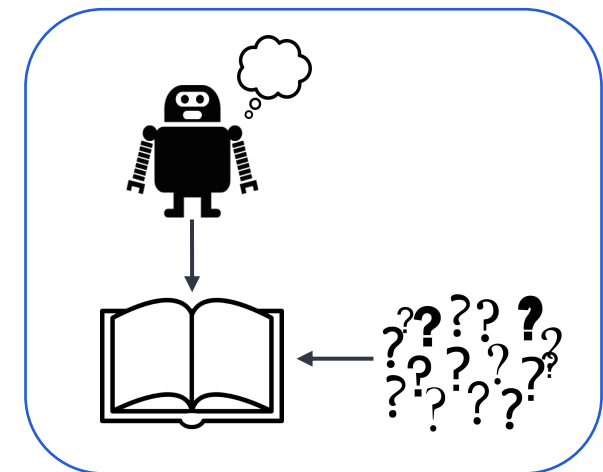
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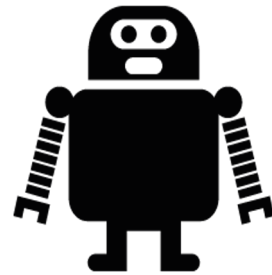
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QA; a broad definition

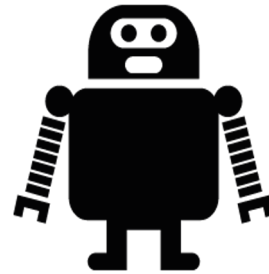
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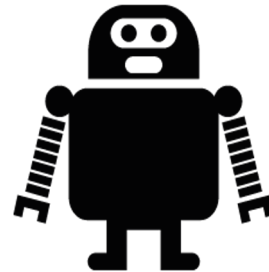
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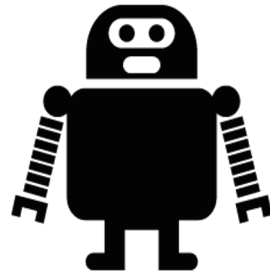


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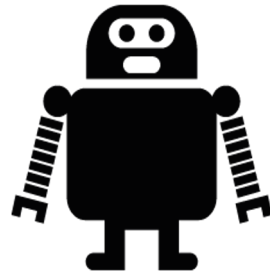


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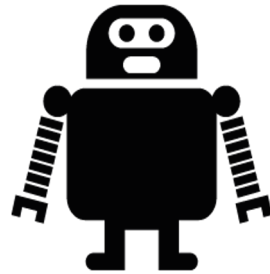


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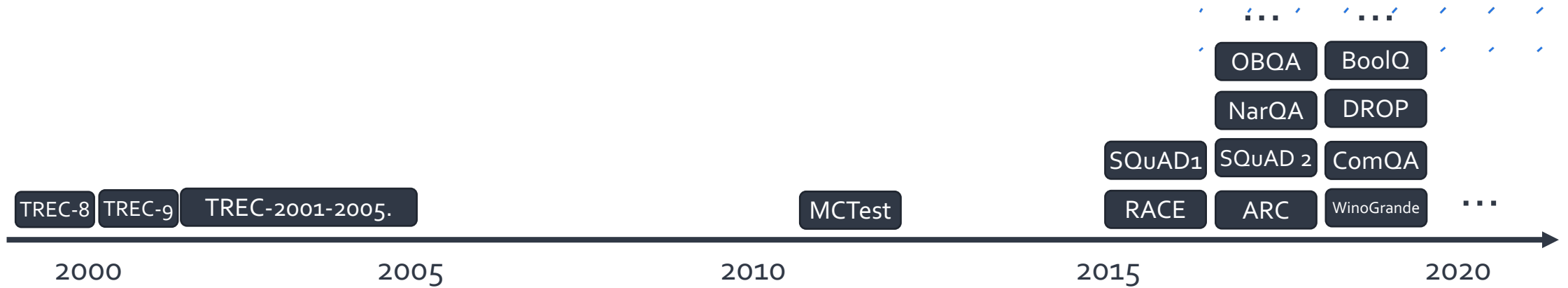


"sugar"

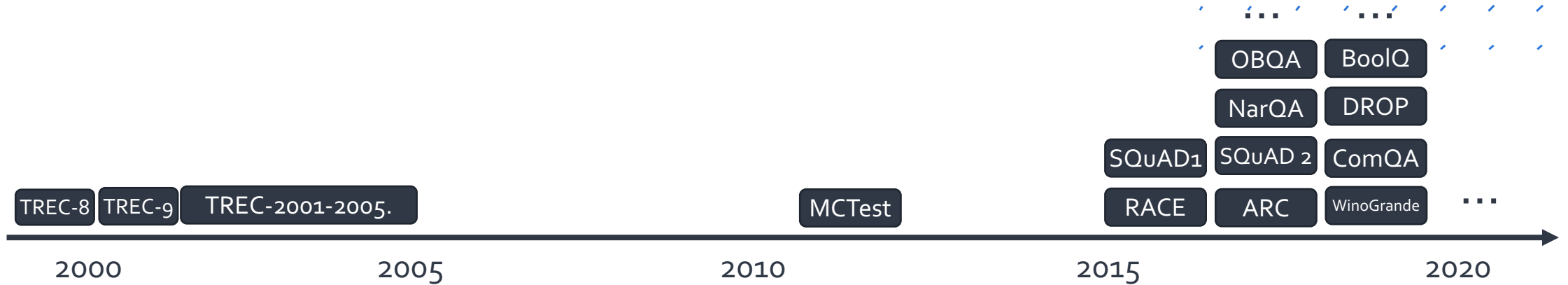
Input: A question, along with additional information (hints, docs, images, etc.)

Output: a string that addresses the input question.

QA datasets

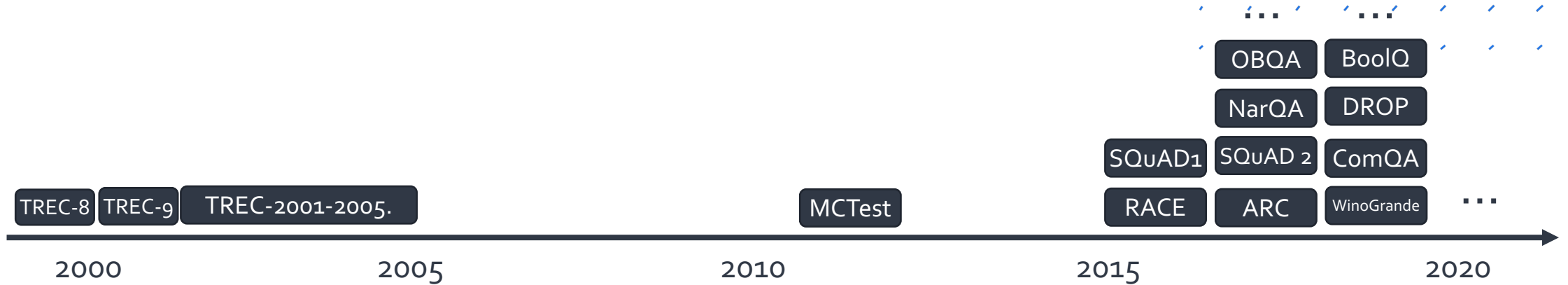


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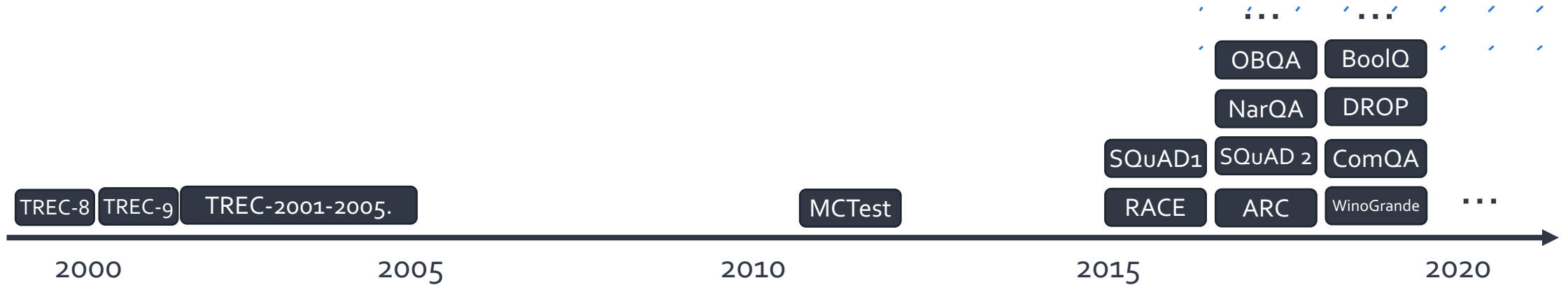
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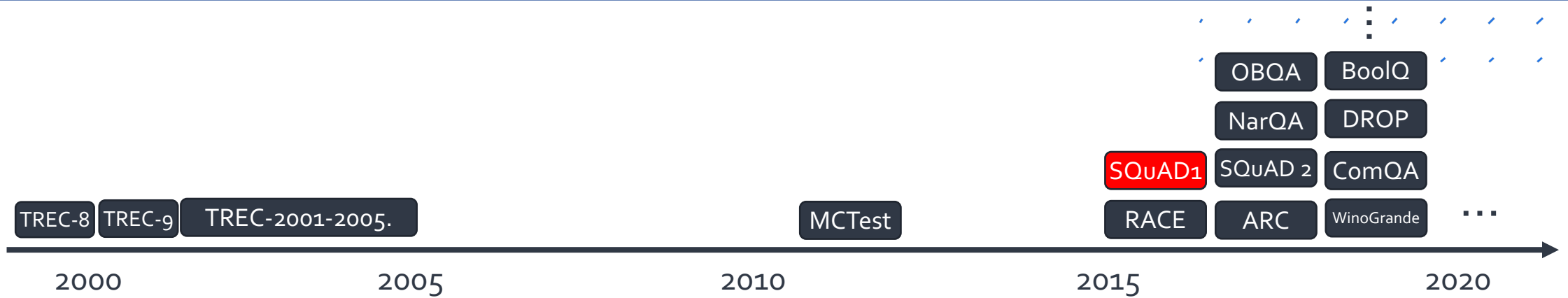
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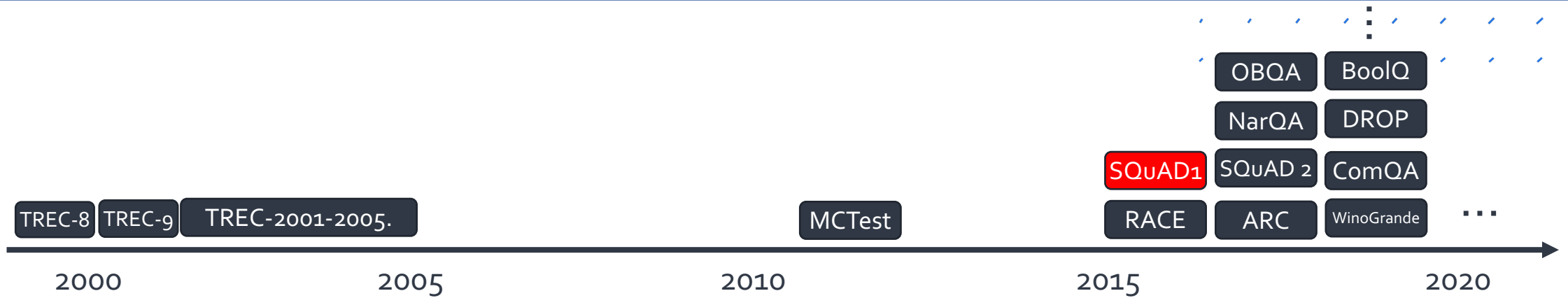


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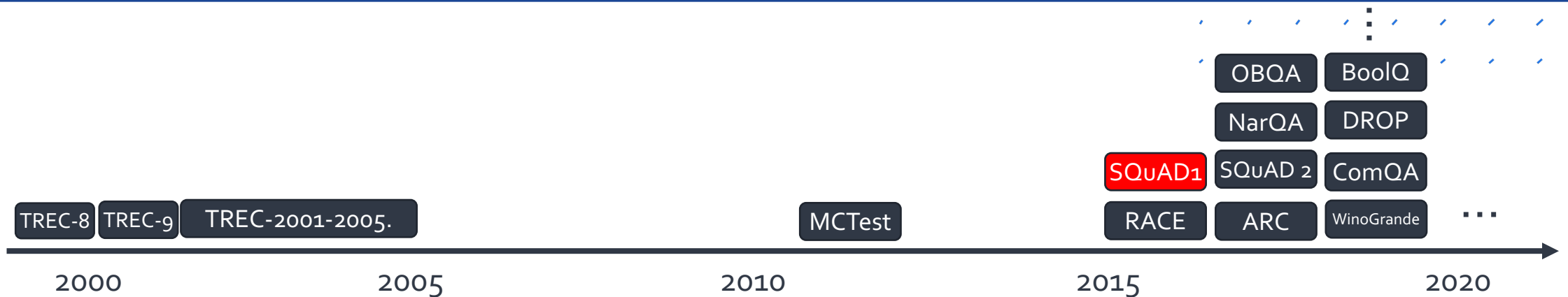


QA datasets



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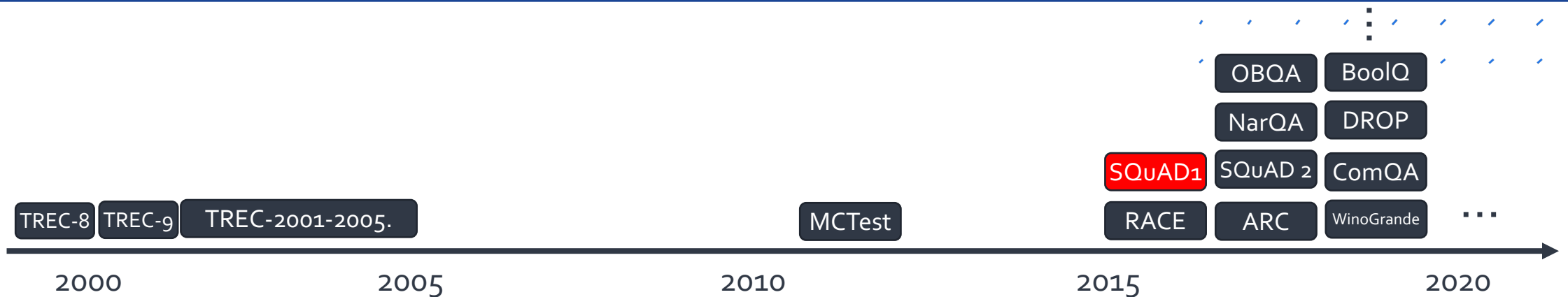
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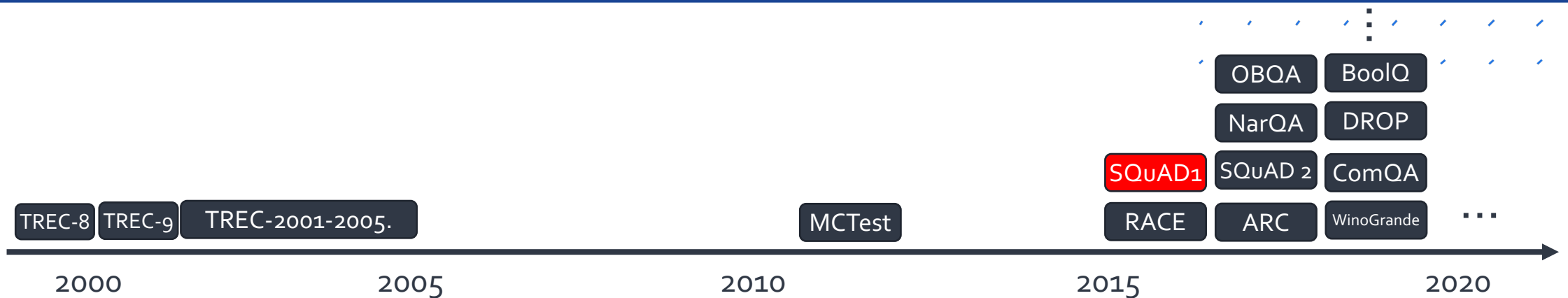


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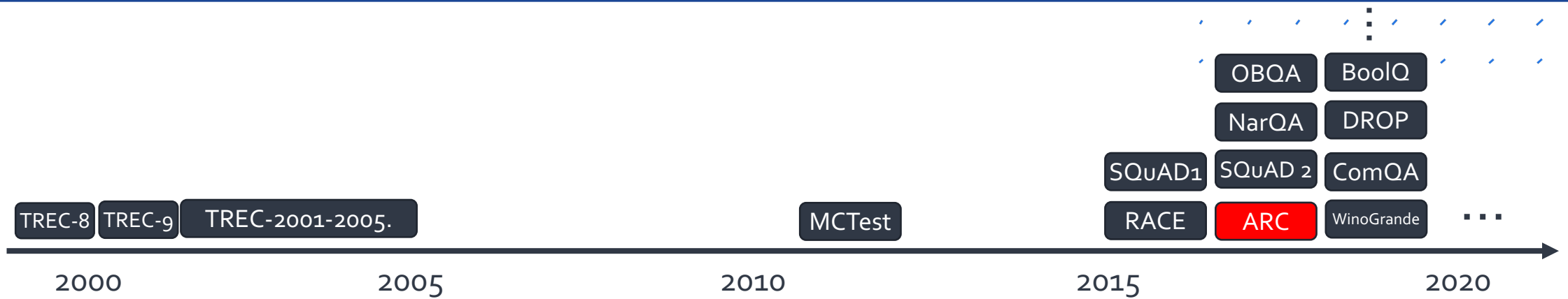
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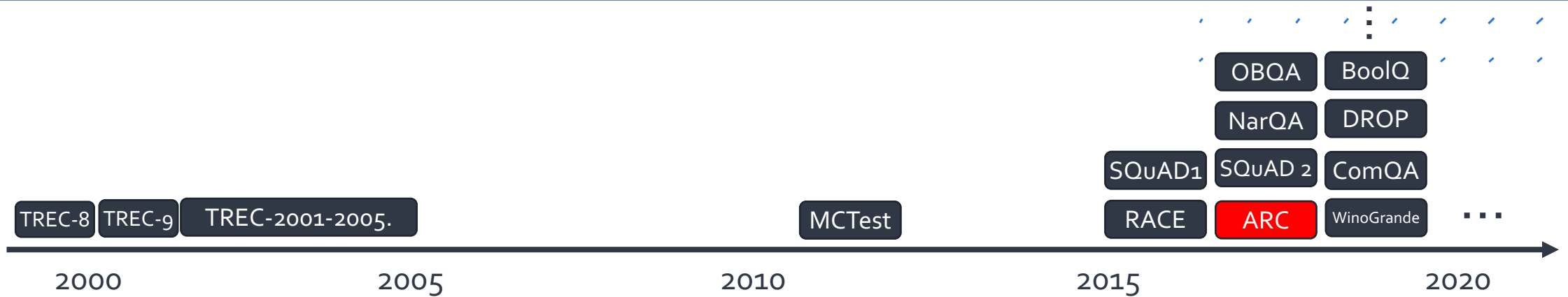
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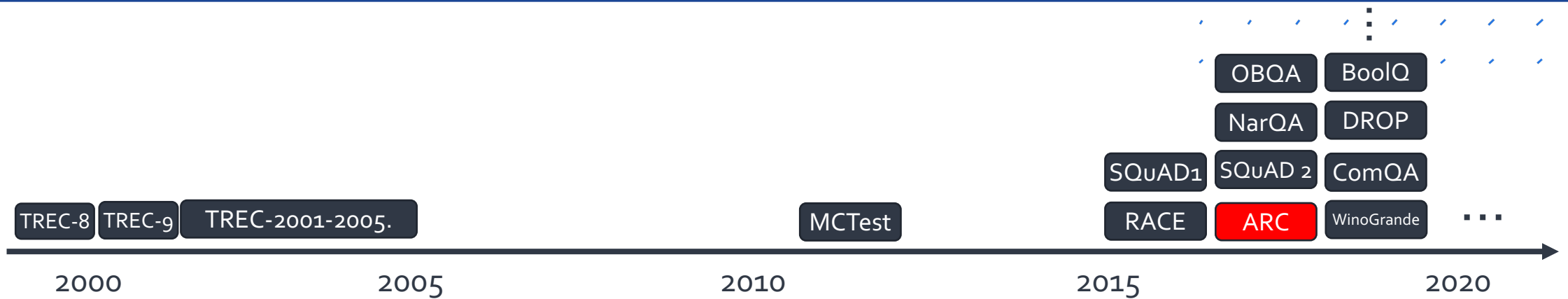


QA datasets



Question: "What does photosynthesis produce that helps plants grow? "

QA datasets



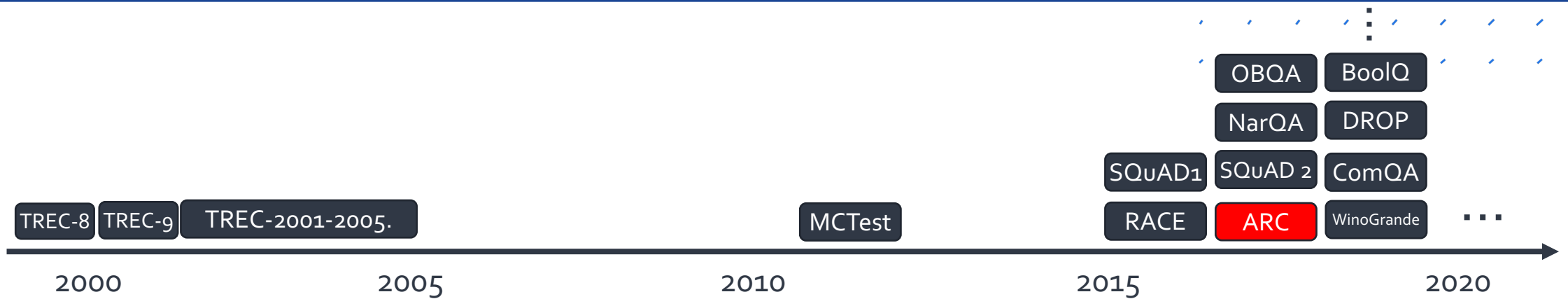
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[Clark et al, 2018]

QA datasets



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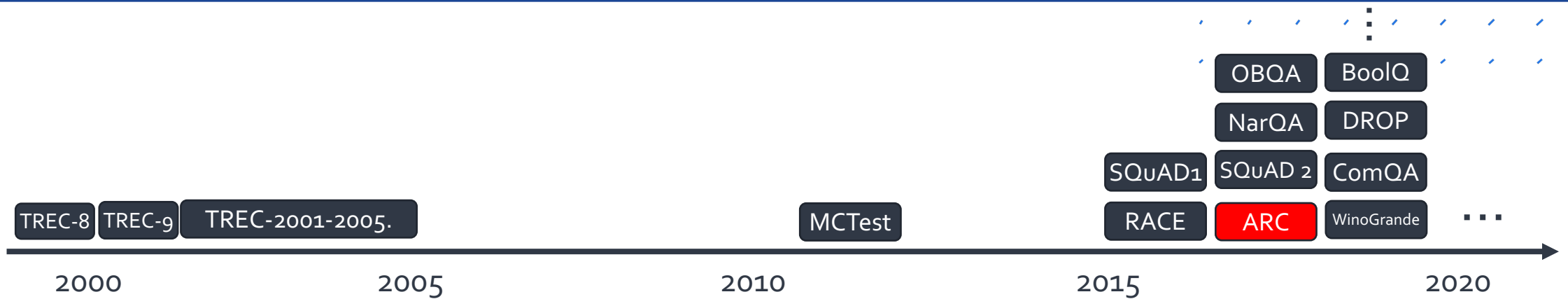


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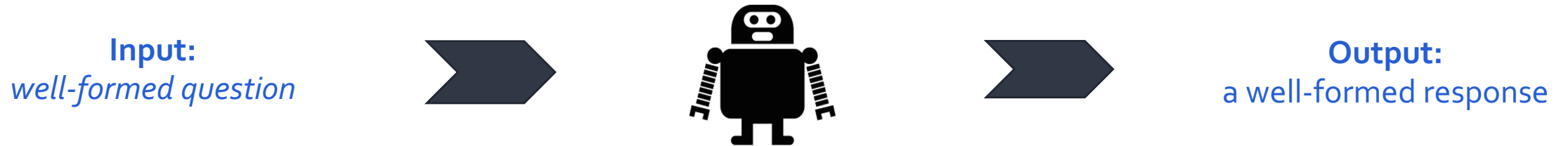
"The big kid"

QA Terminology



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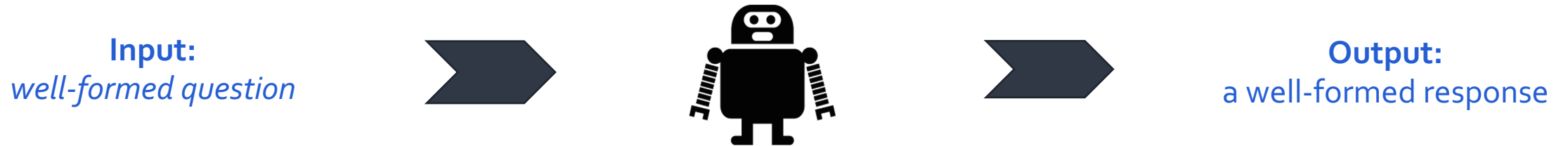
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- “**Format**”: QA with particular **assumptions** about input/output.
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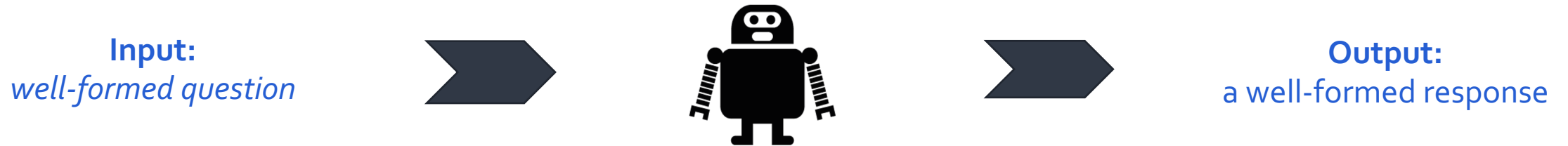
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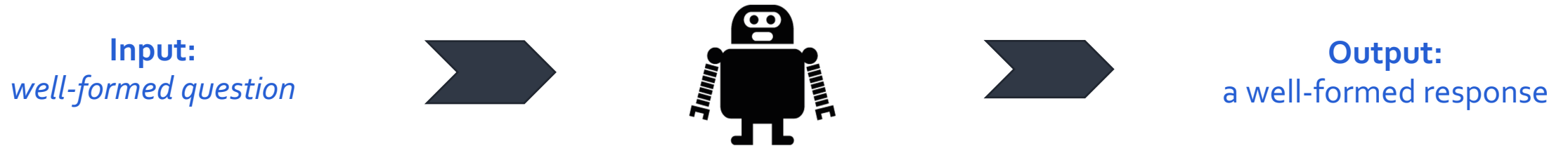


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YesNo	BoolQ [Clark et al'19]
extractive	SQuAD [Rajpurkar et al'16]
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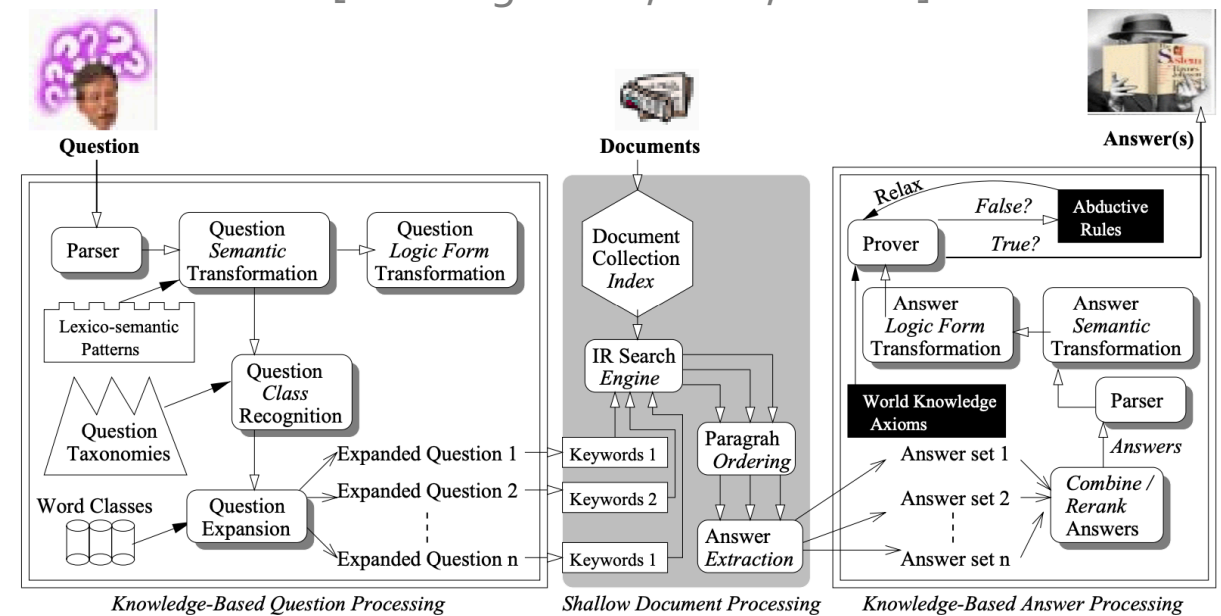
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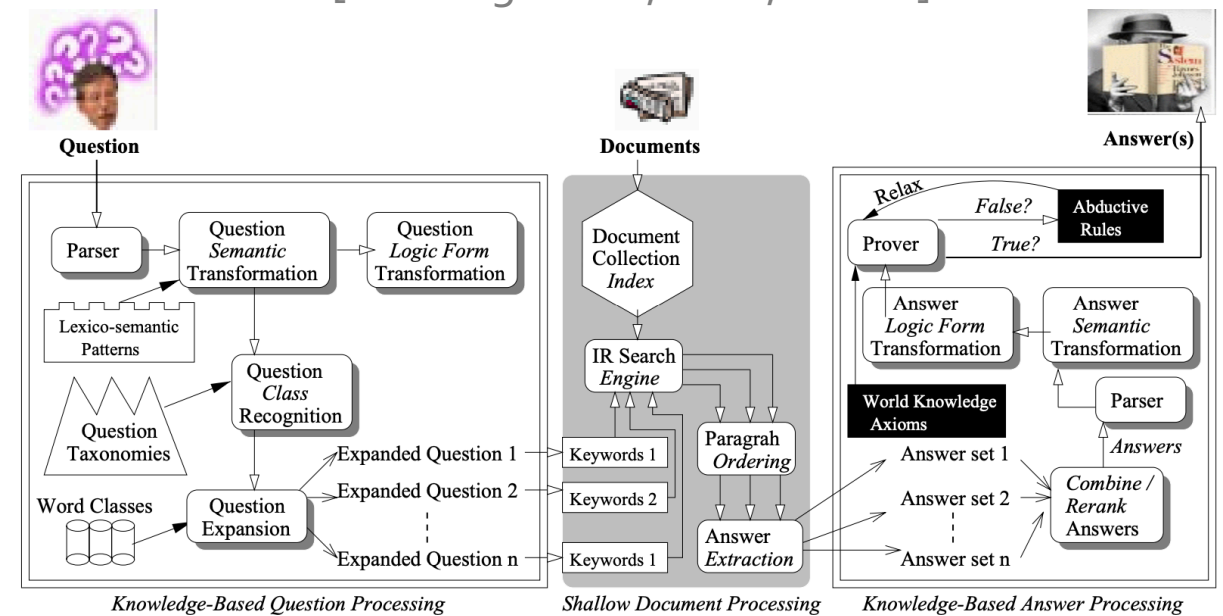
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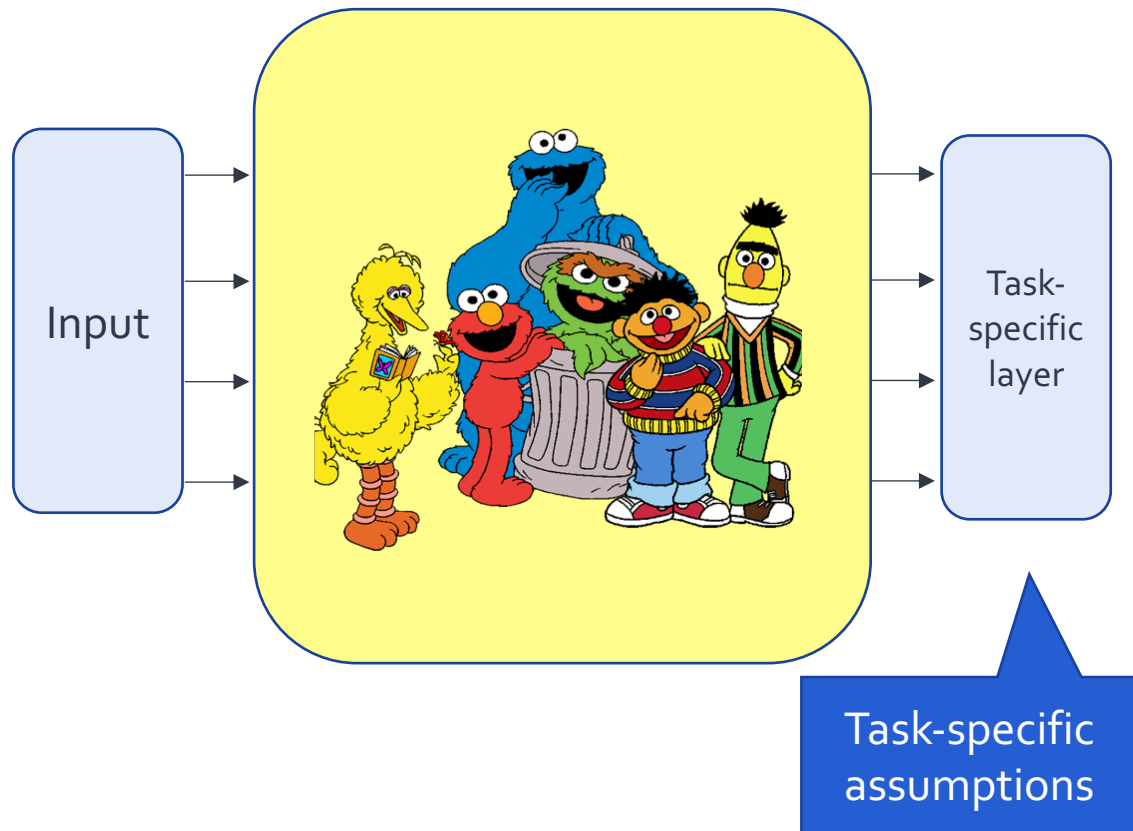
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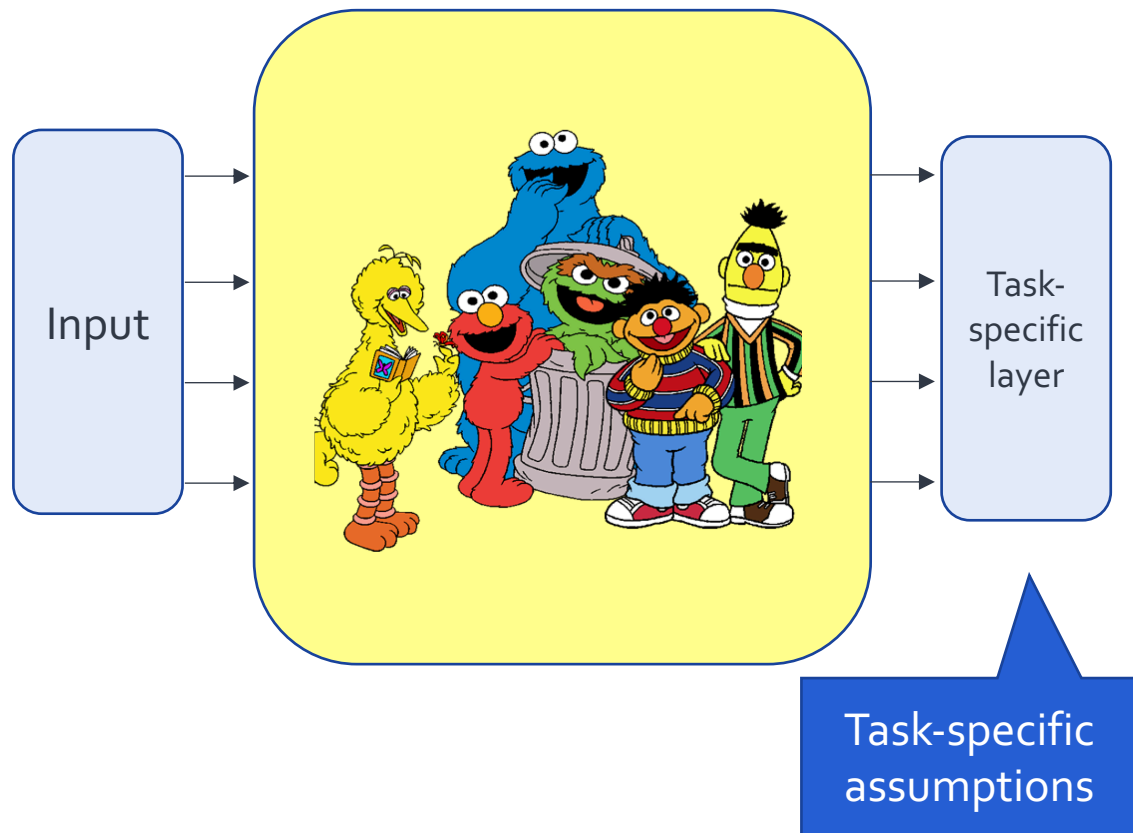
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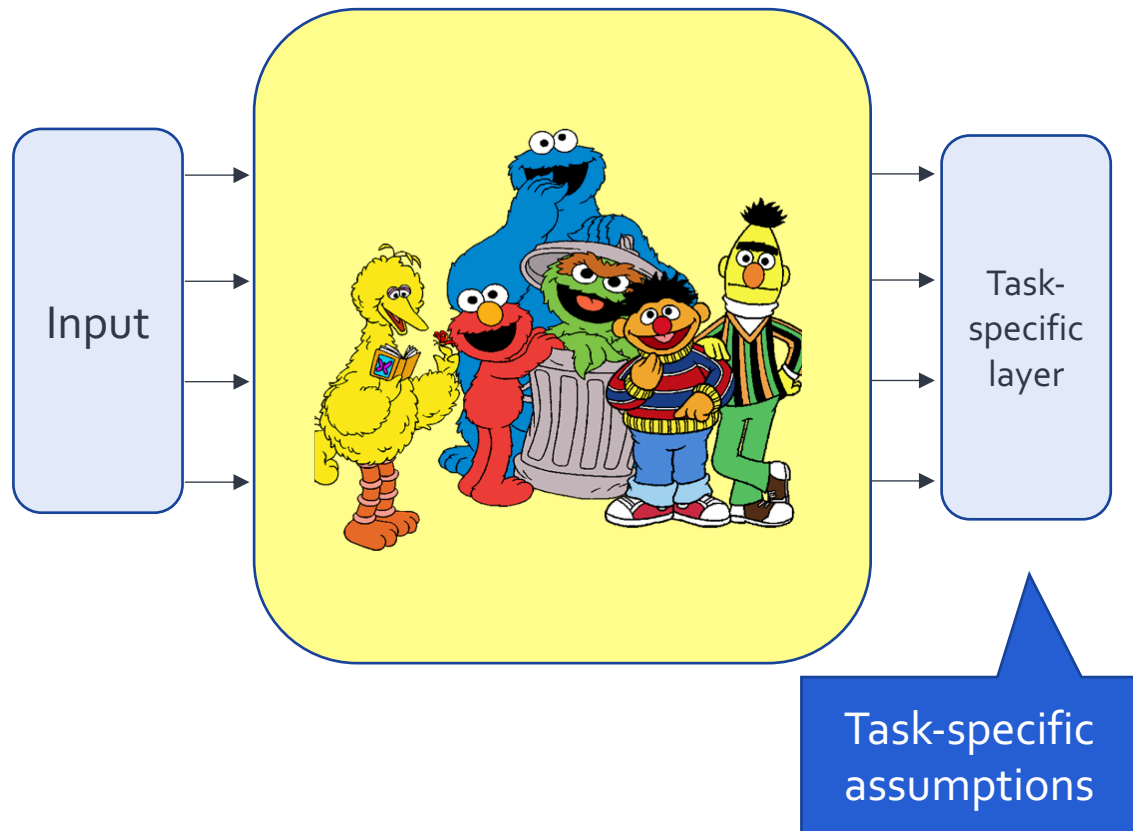


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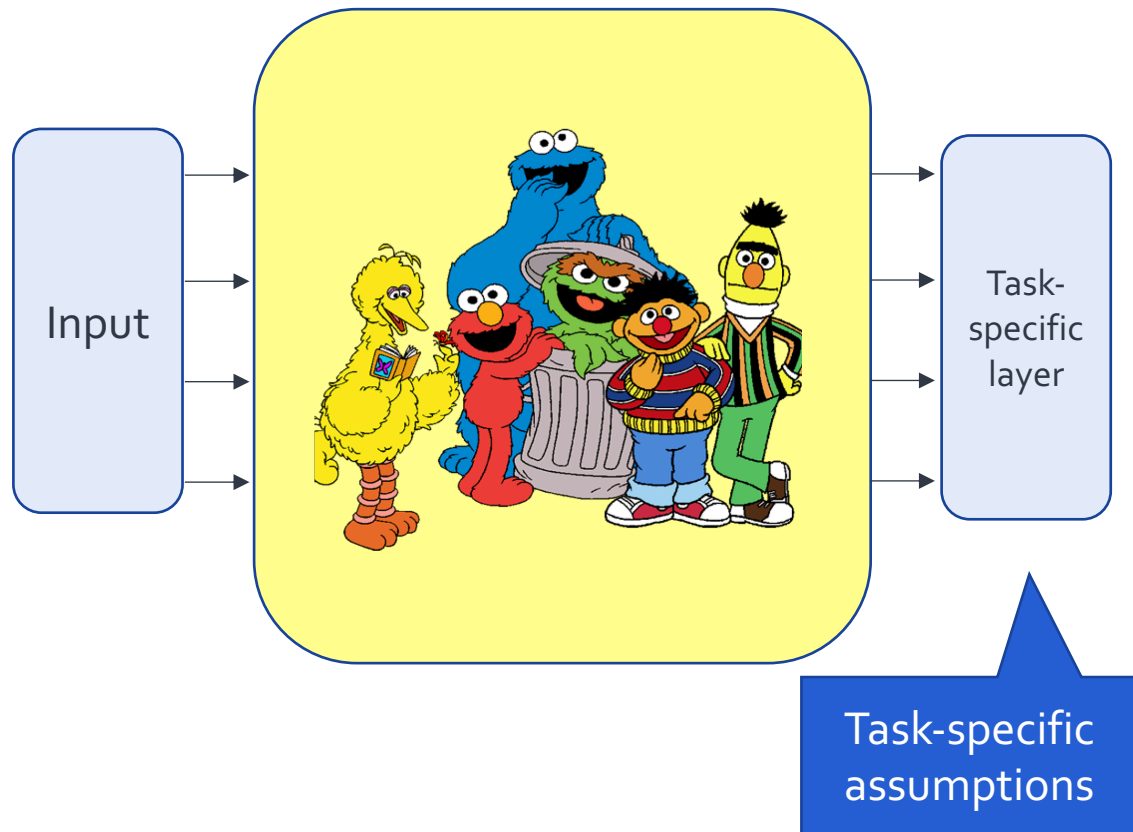
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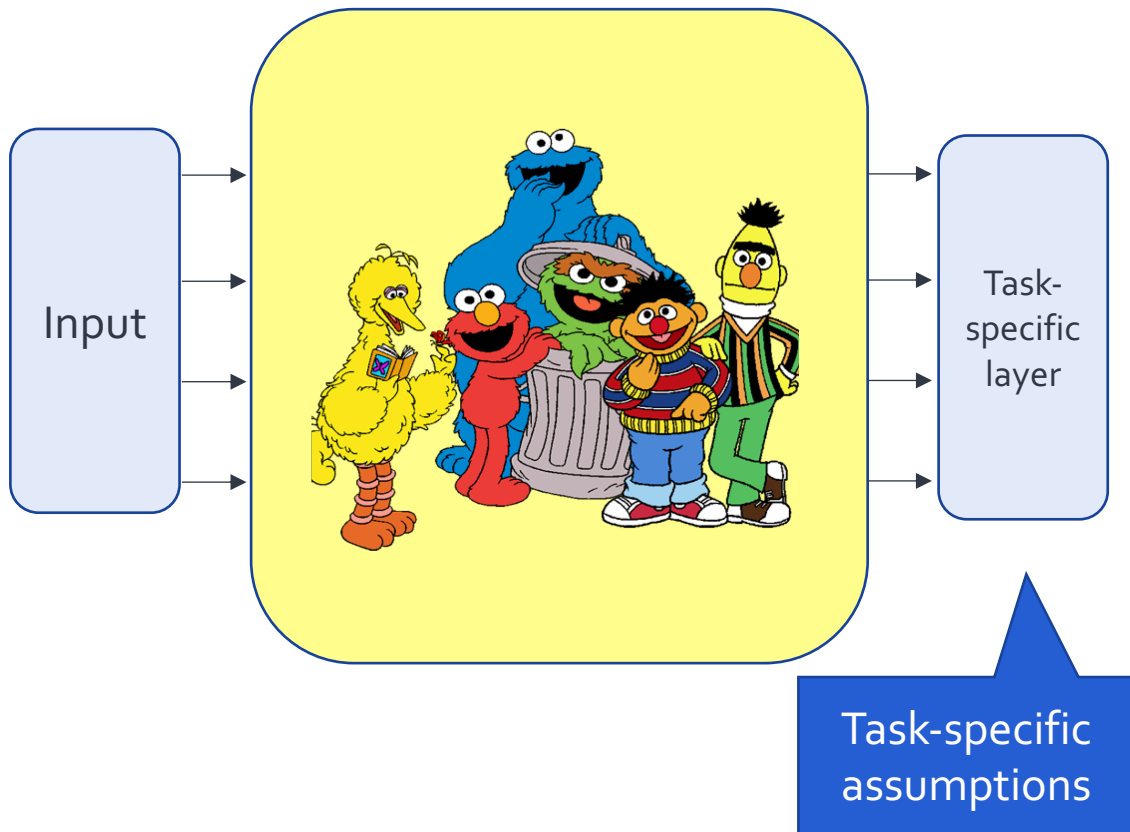
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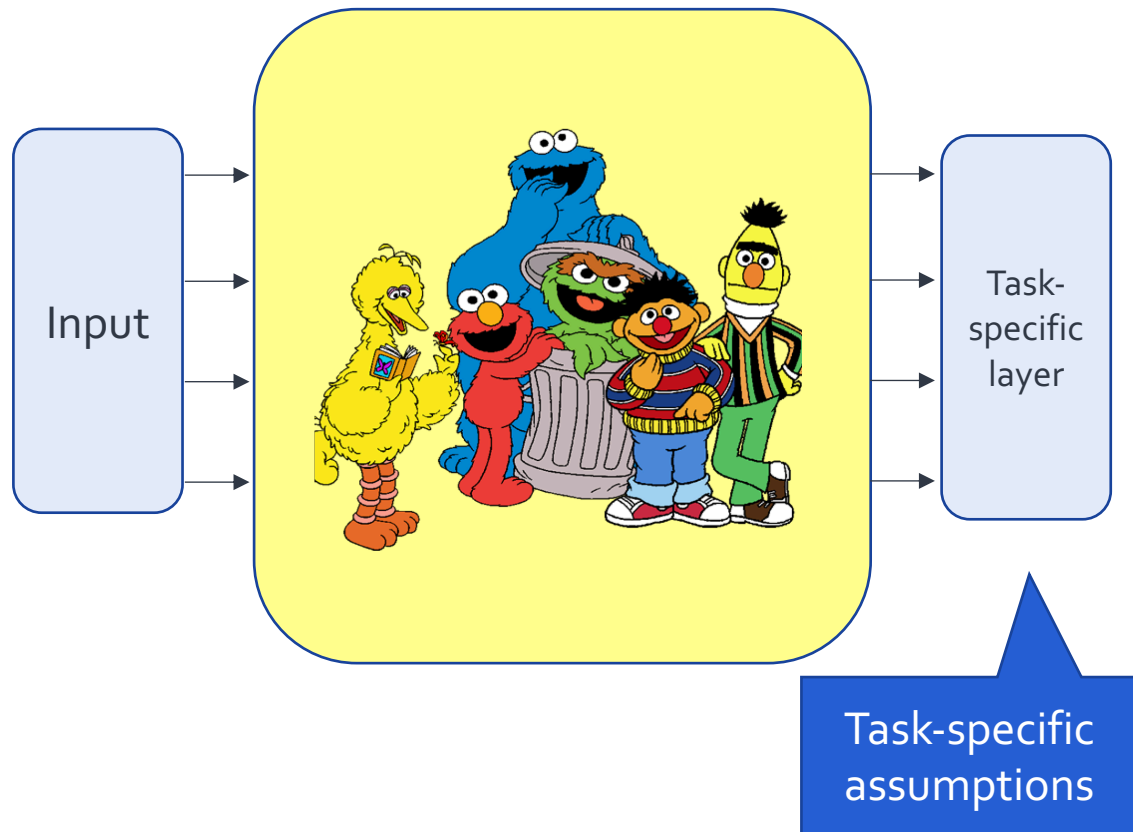
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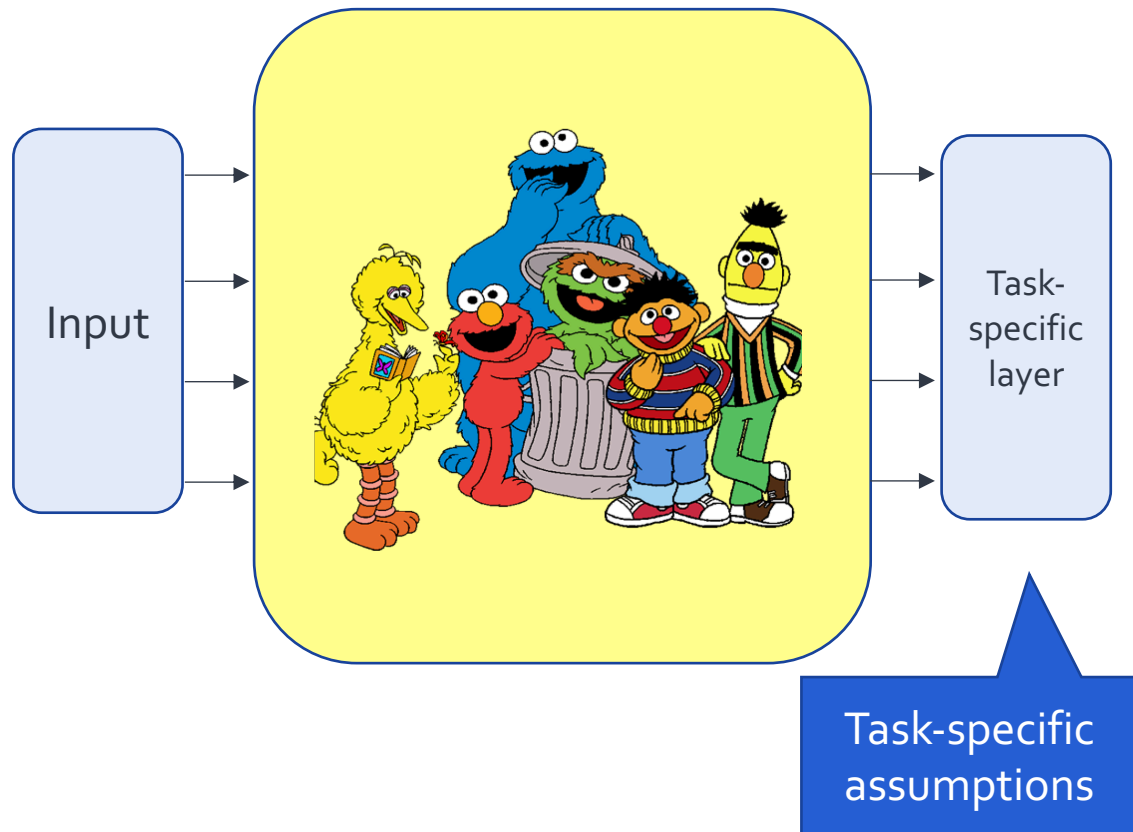
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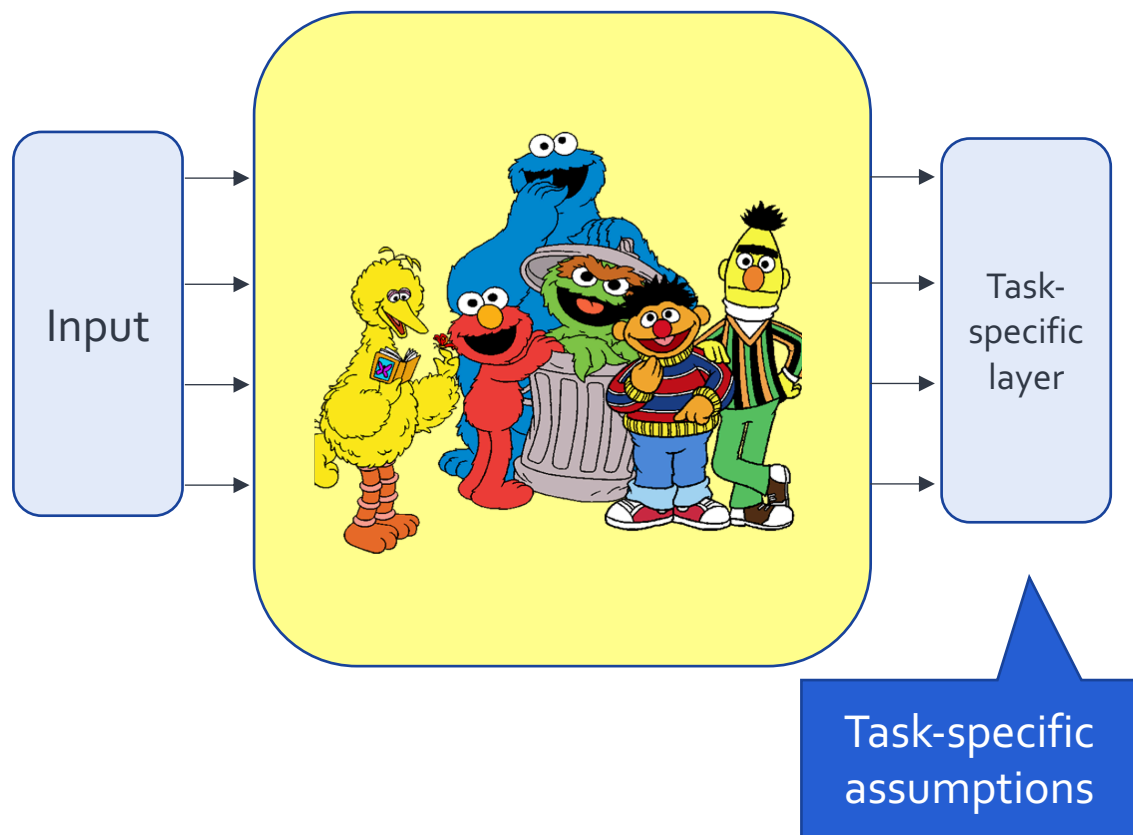


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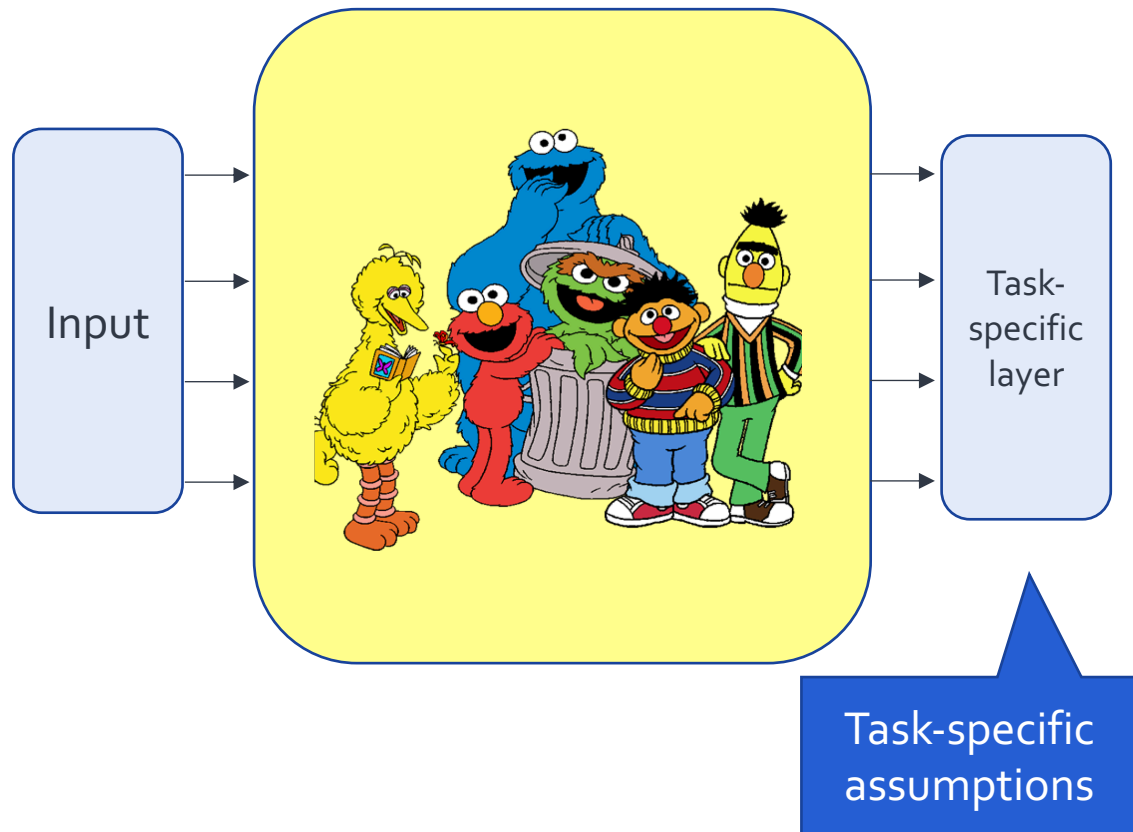


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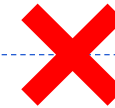
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Roadmap

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UnifiedQA: a high-level definition

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- *The question always comes first.*
- *Additional info are appended with "\n".*

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Mixing RACE (Multiple-Choice)

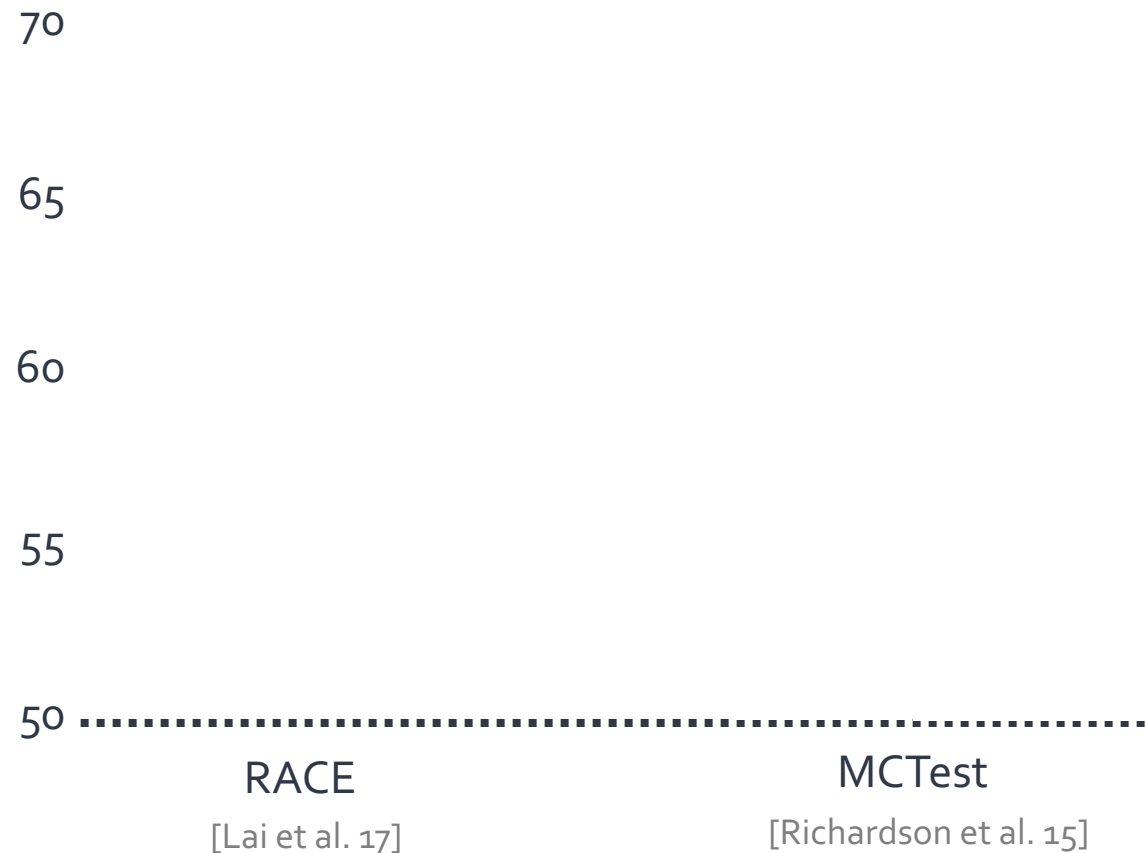
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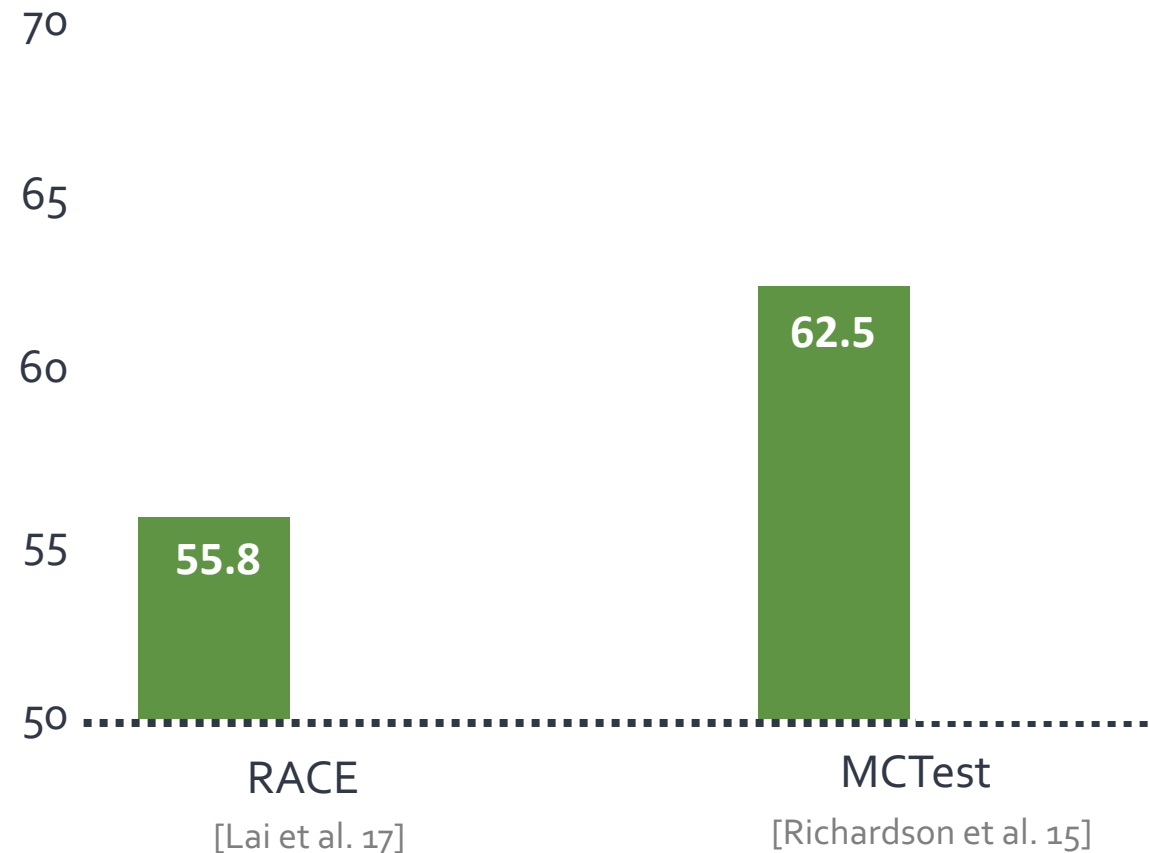


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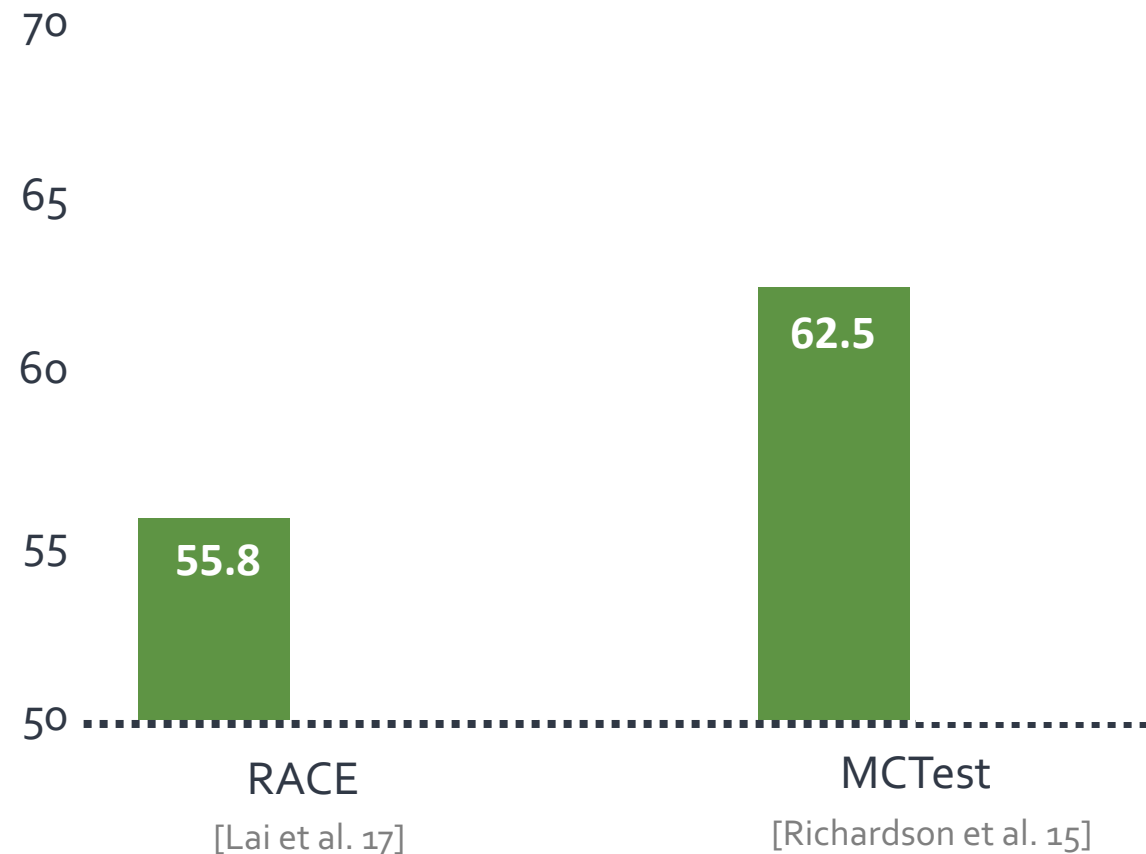
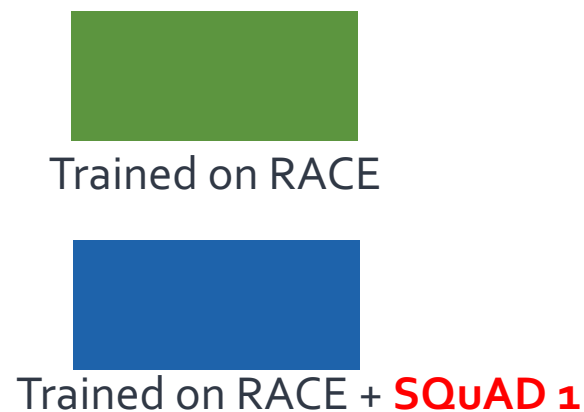

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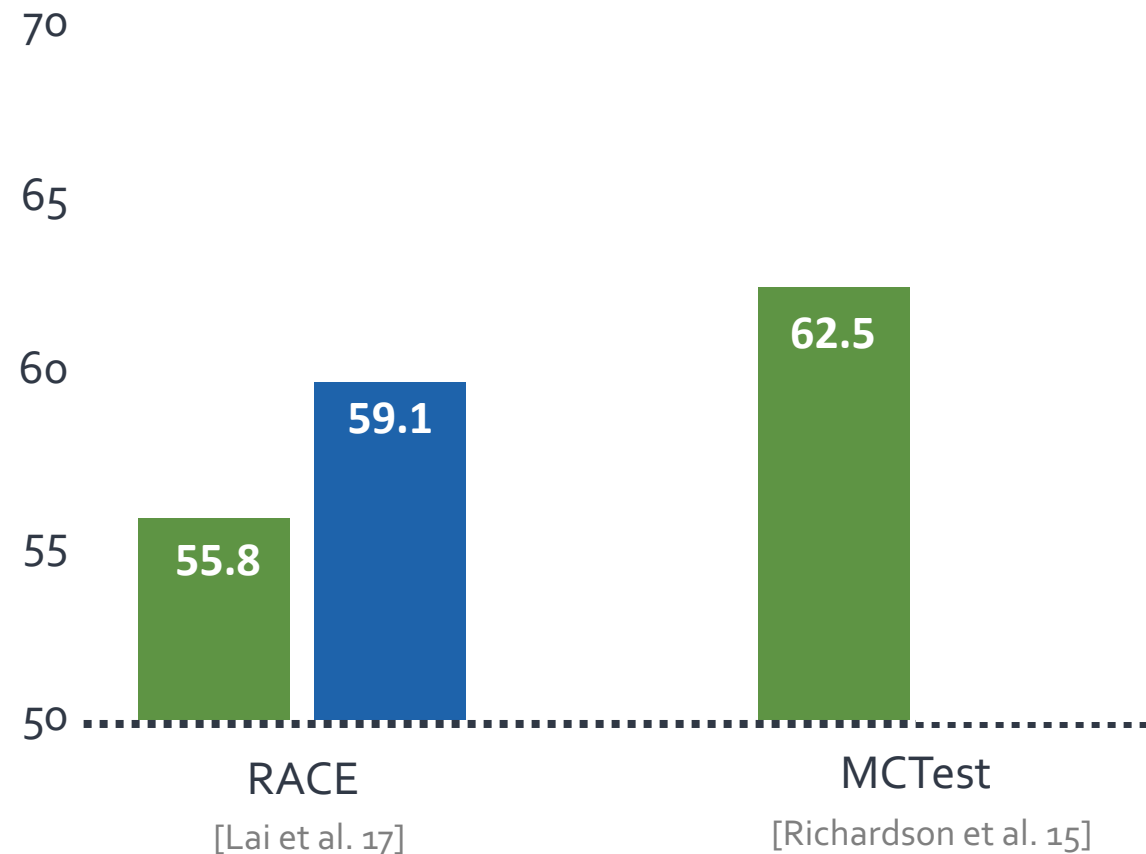
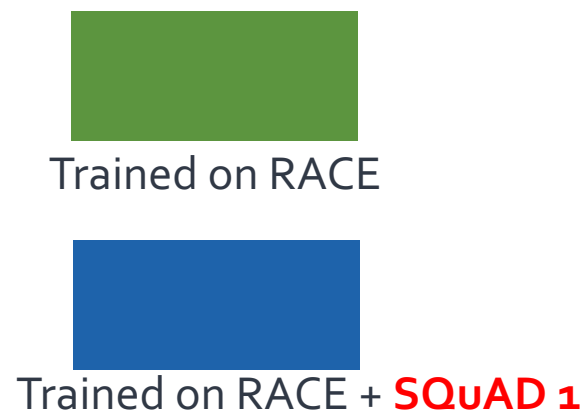
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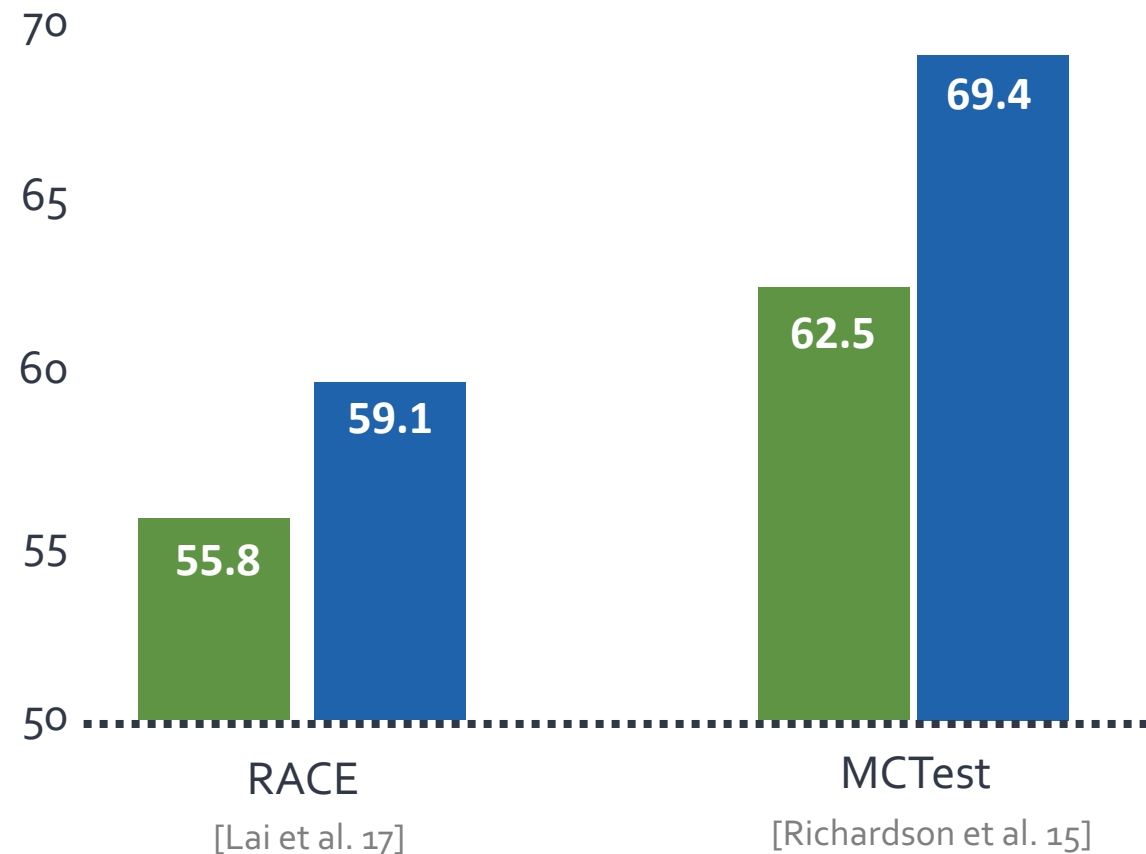
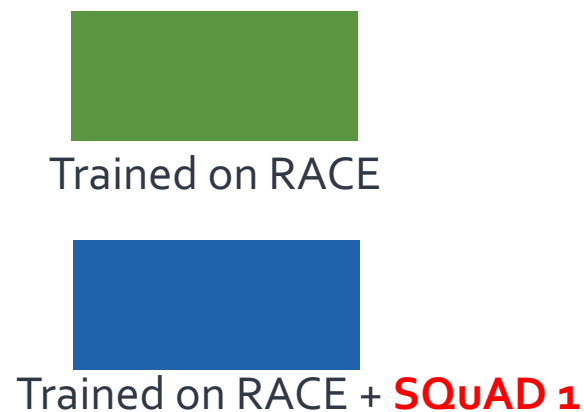
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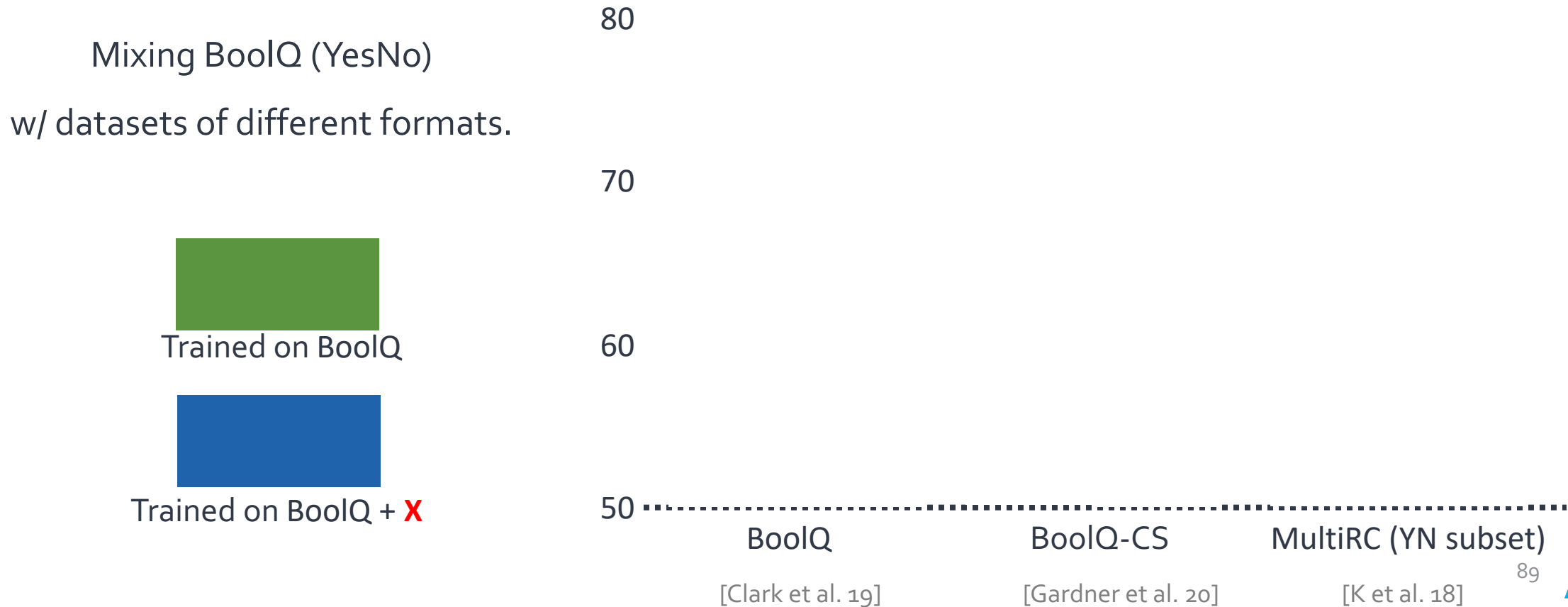
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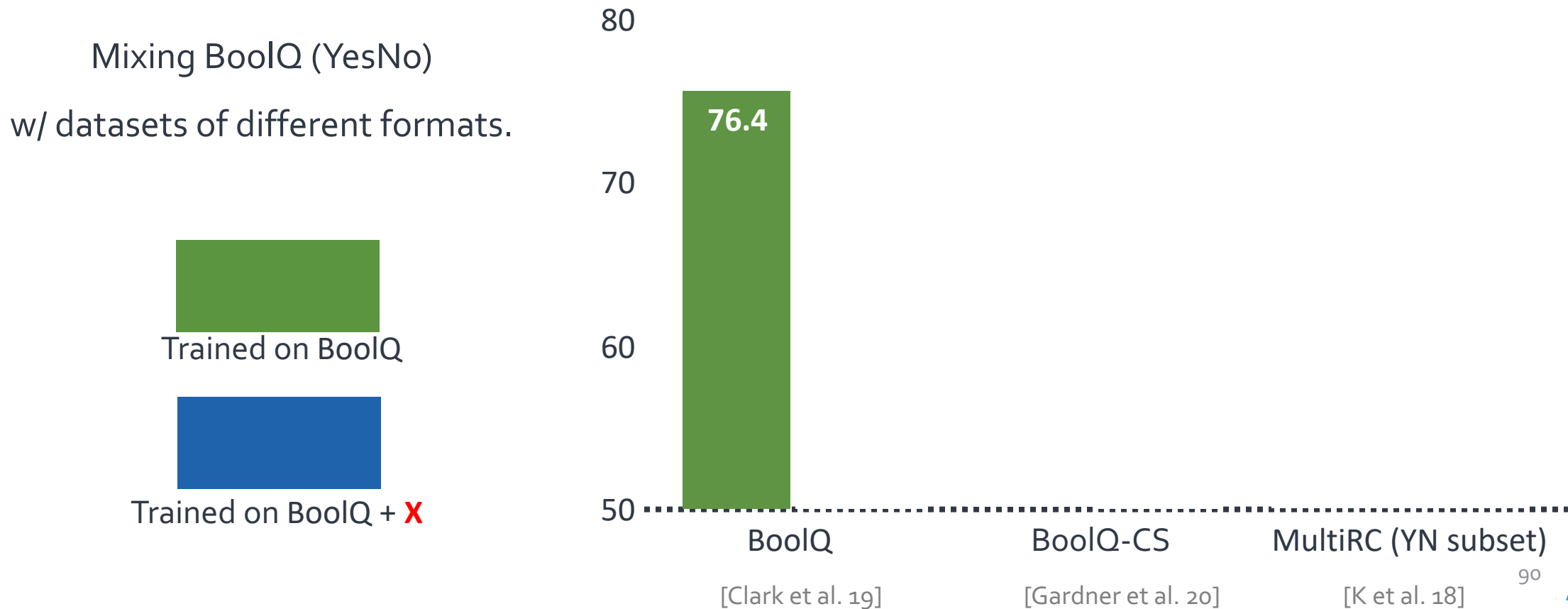
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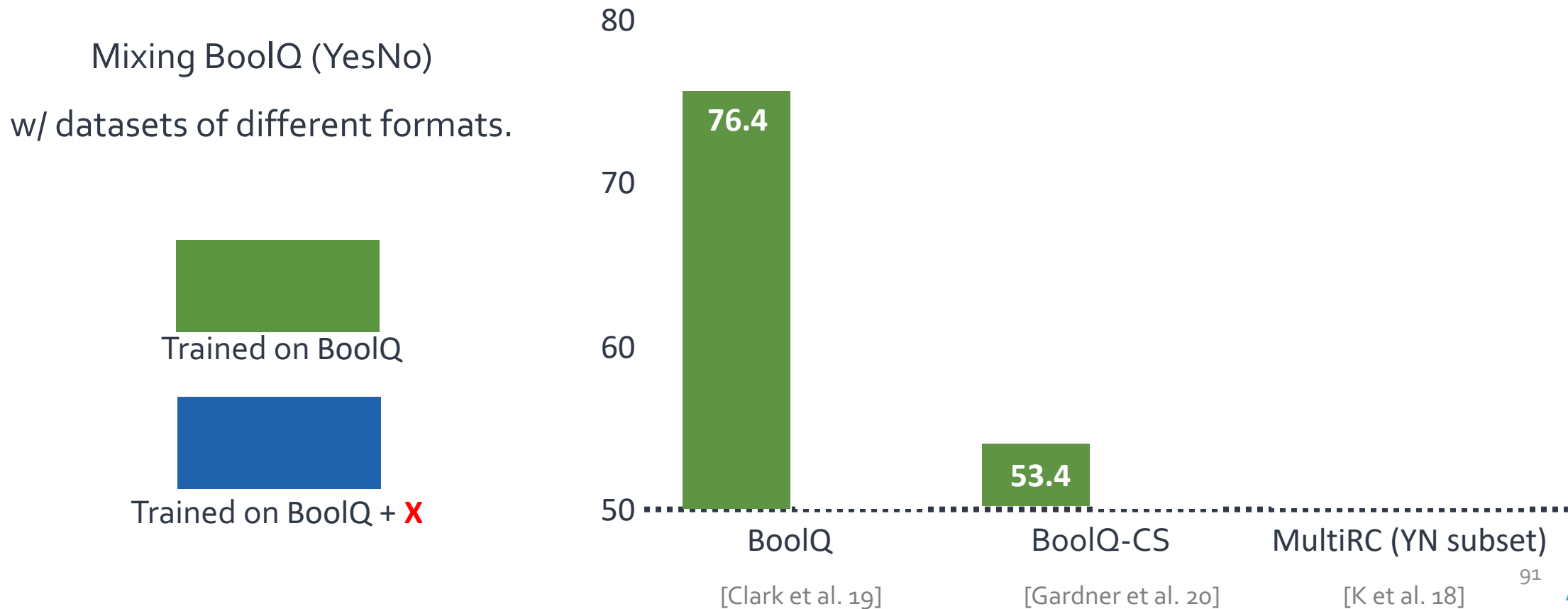
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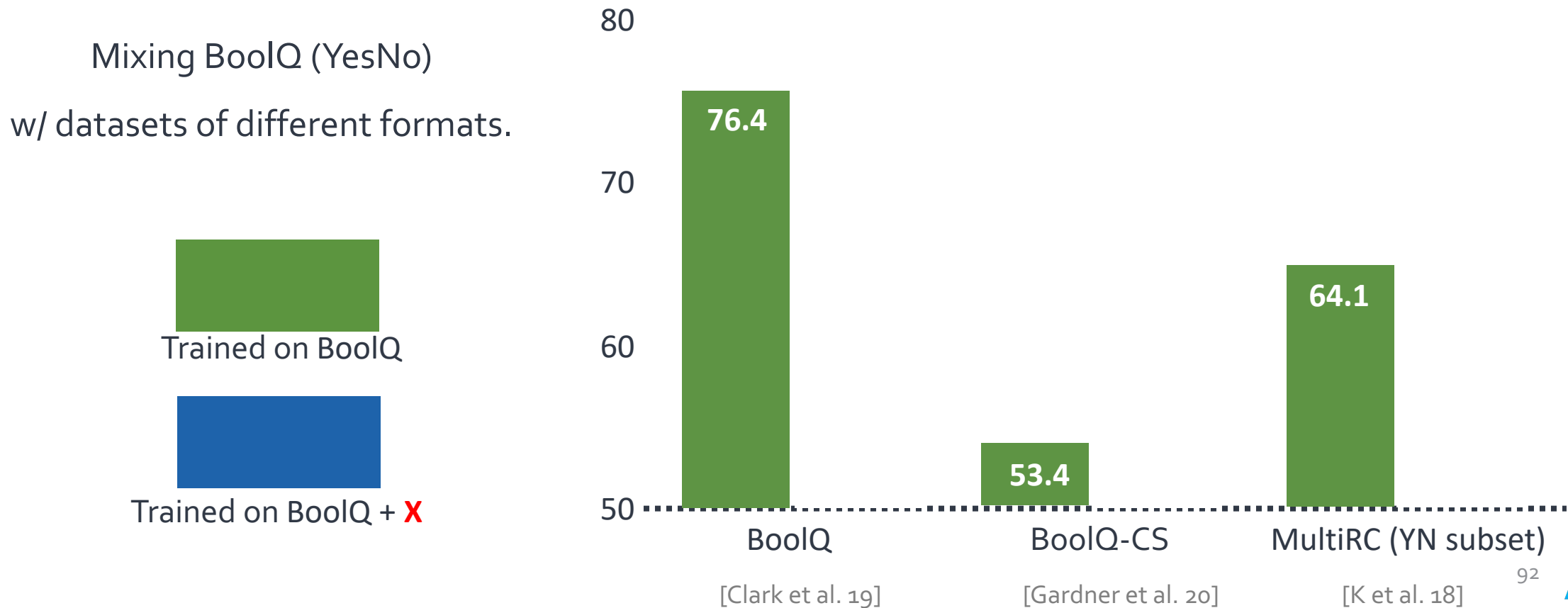
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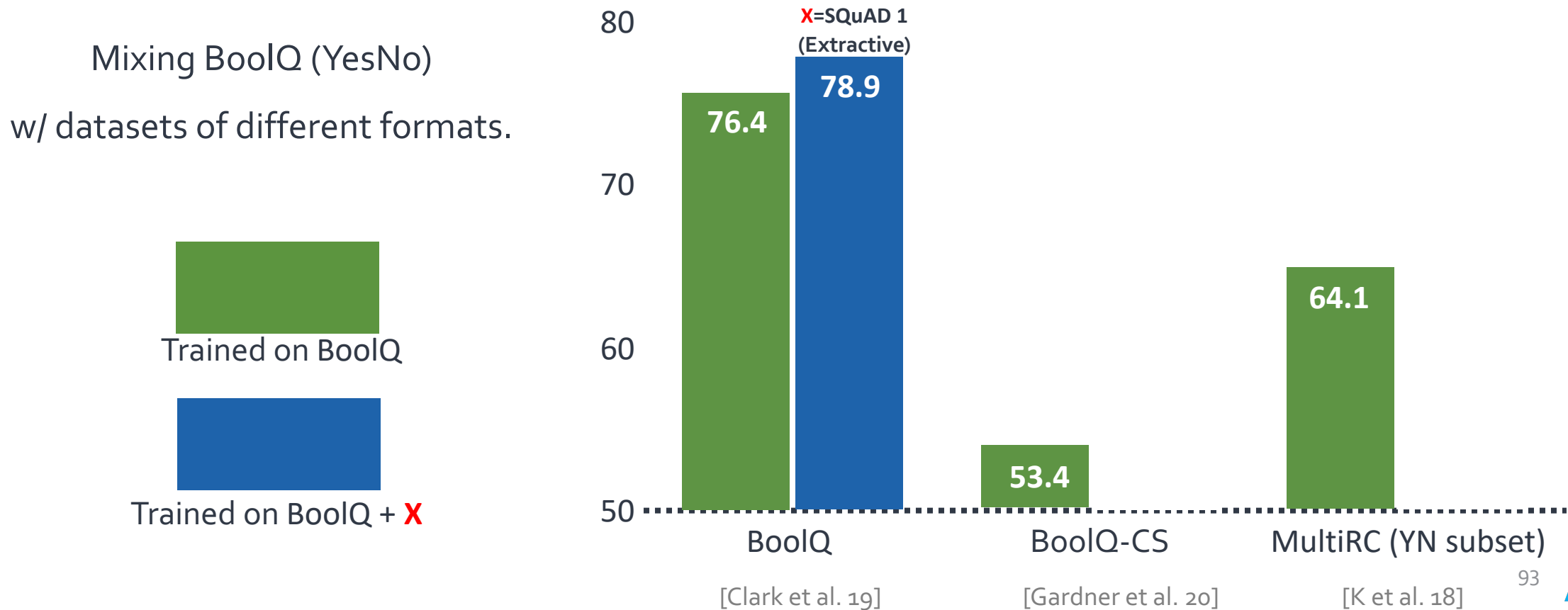
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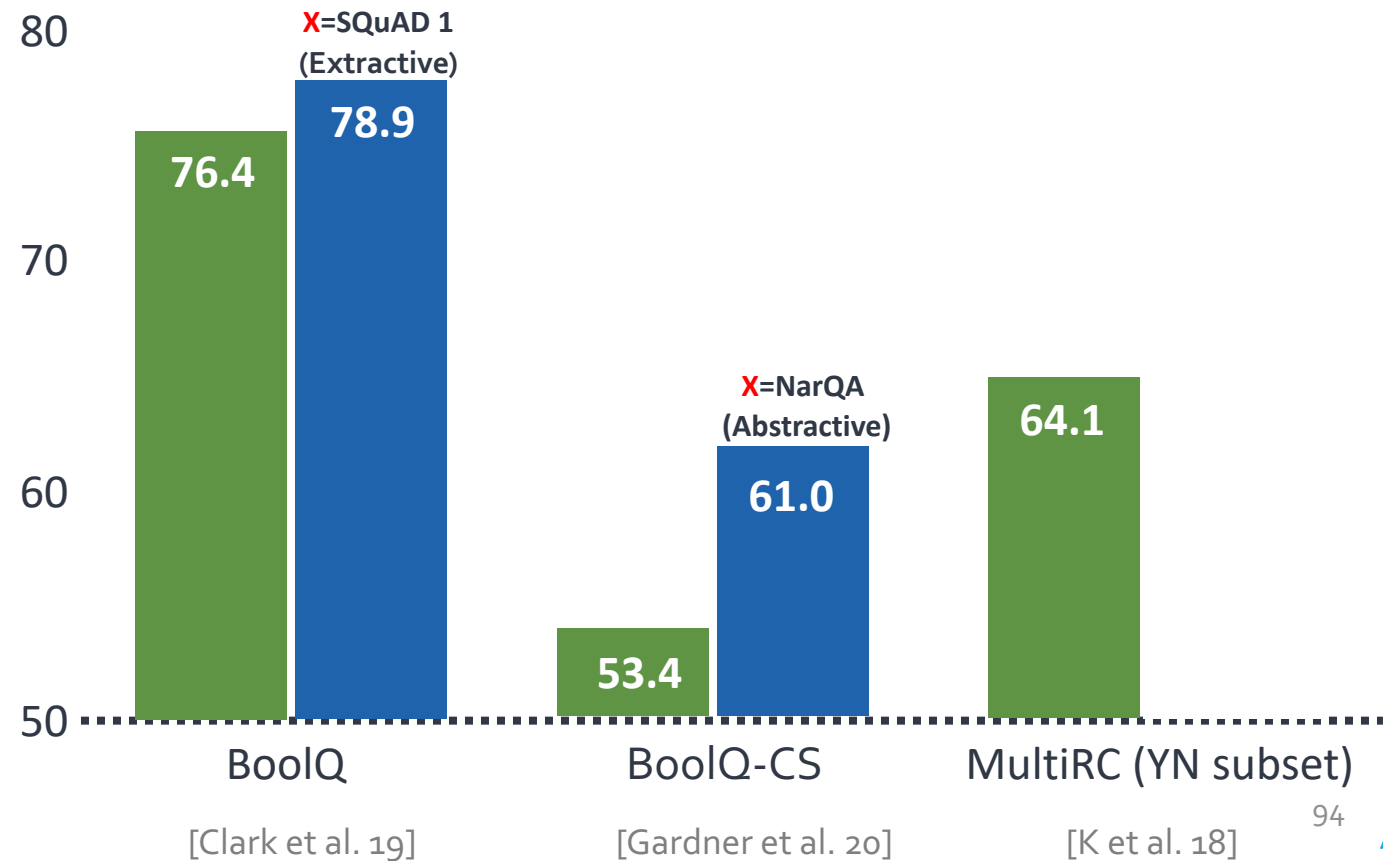
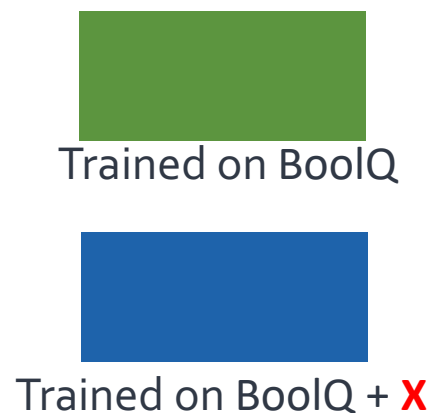
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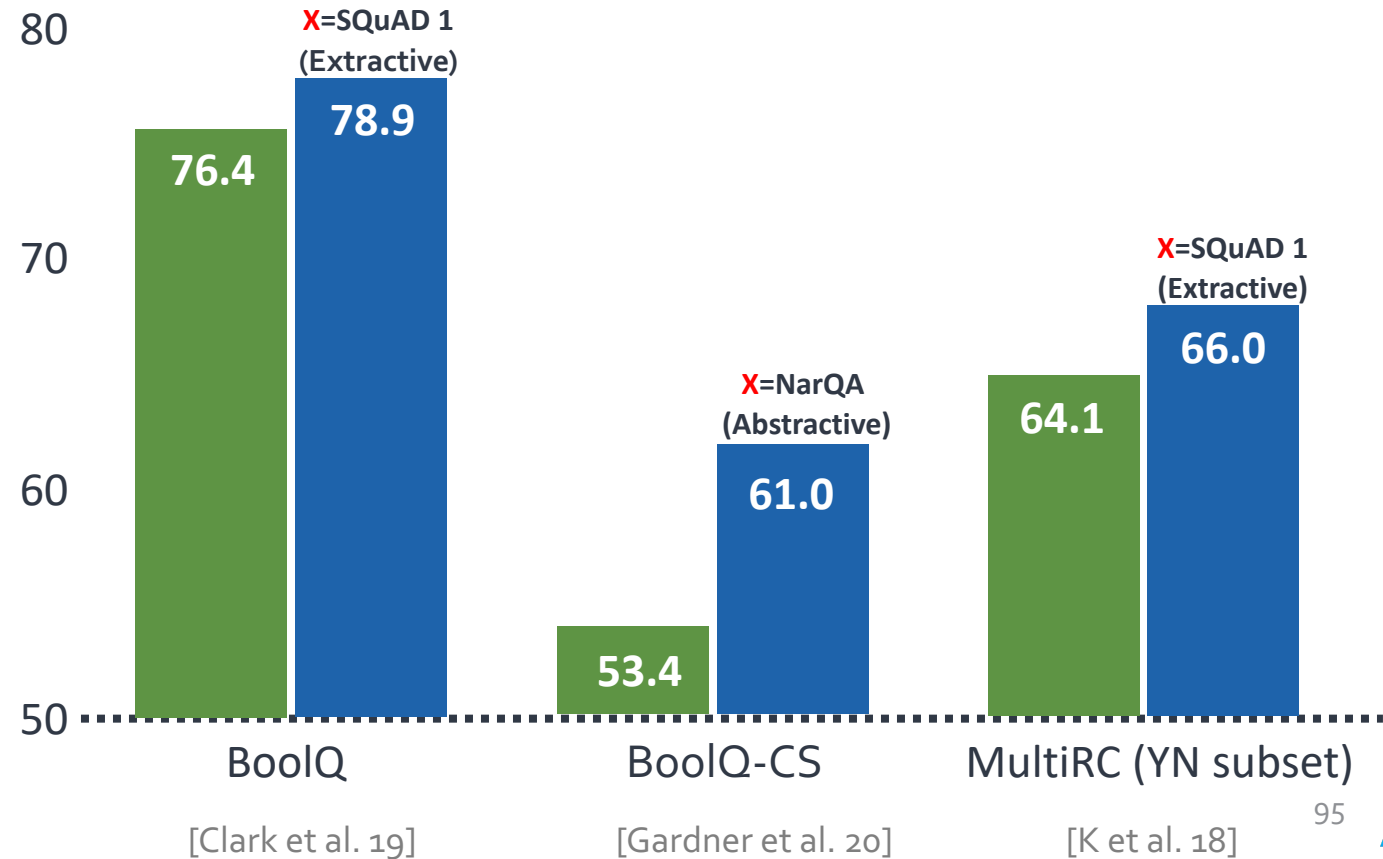
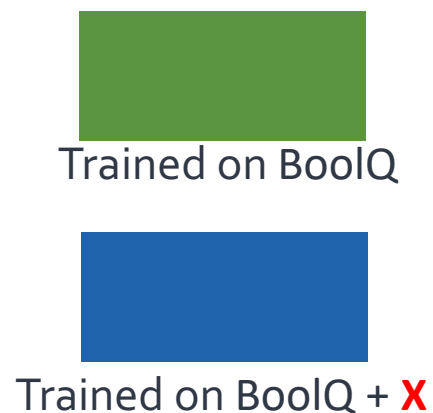
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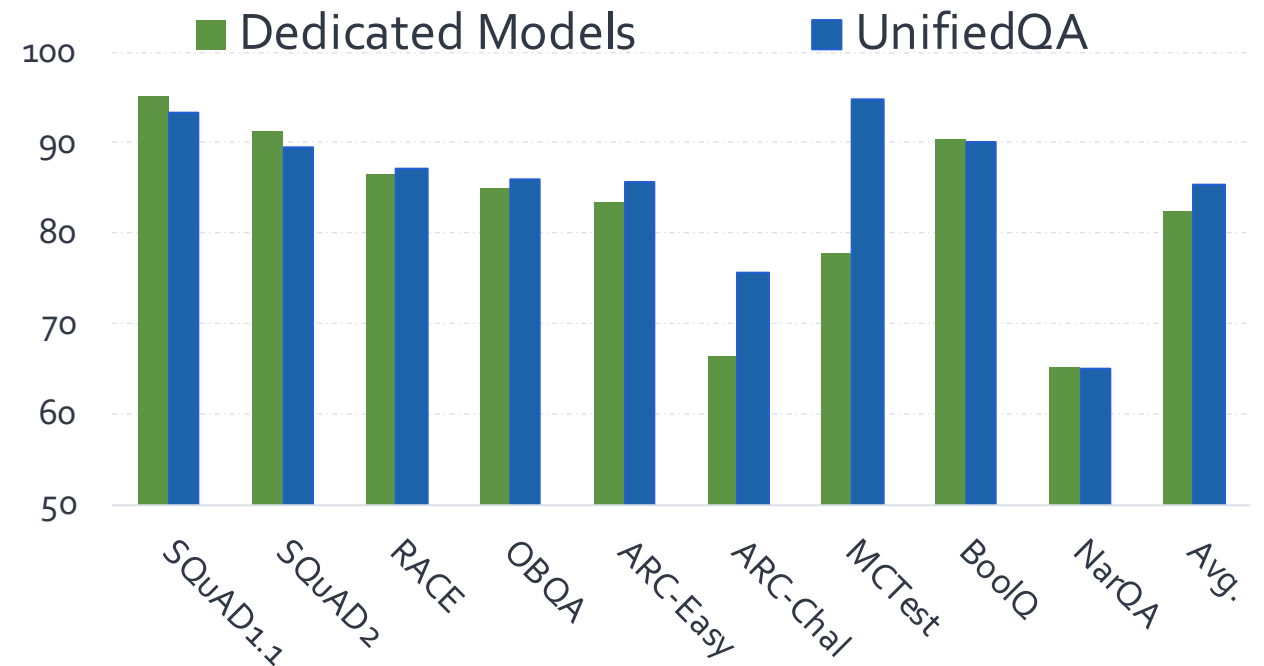
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<https://github.com/allenai/unifiedqa>

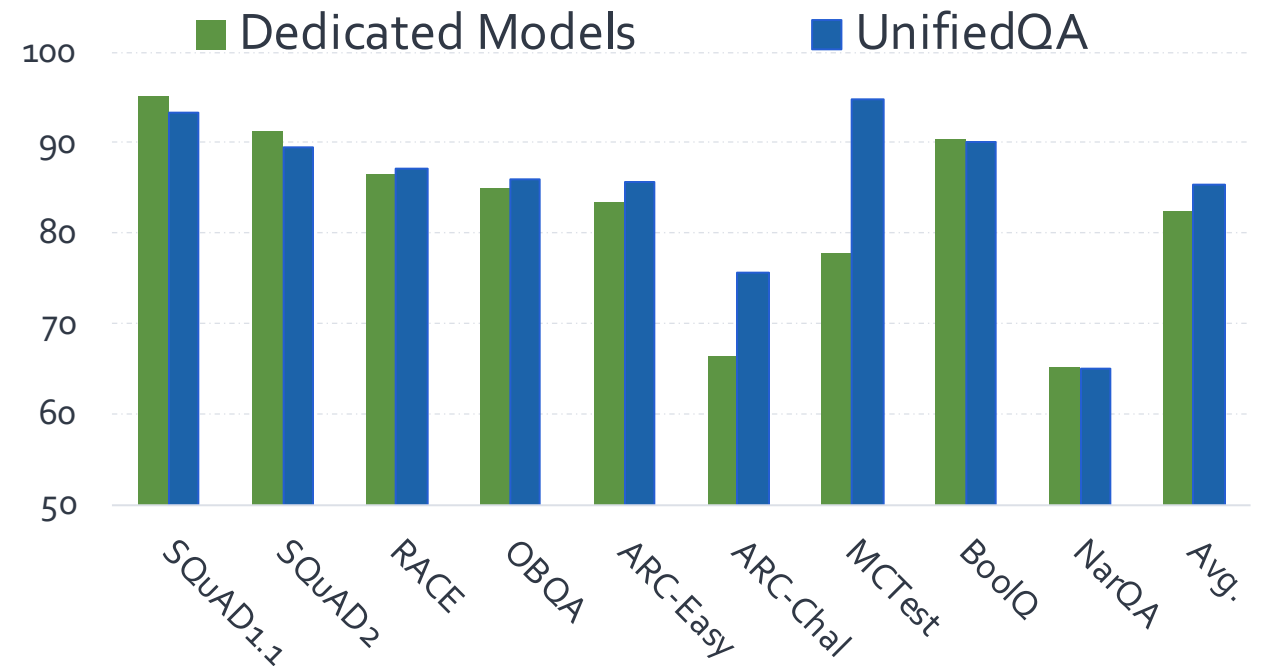
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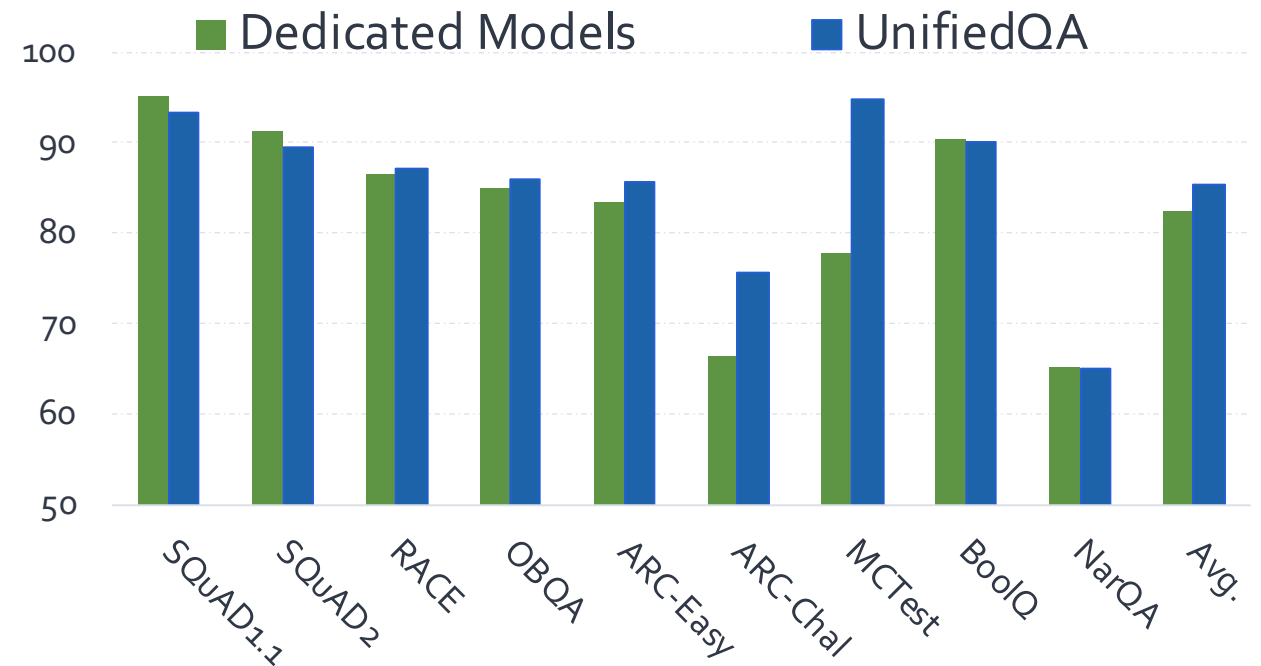
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evaluation sets

	SQuAD2	RACE	BoolQ	NarQA
T5 (SQuAD 2)	91	33	12	51
T5 (RACE)	43	87	7	54
T5 (BoolQ)	4	22	90	0
T5 (NarQA)	45	48	47	65
UnifiedQA	90	87	90	65



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Intuition #2: Unseen Datasets

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	NewsQA	Quoref	DROP	DROP-CS	QASC	CommonsenseQA	NP-BoolQ	BoolQ-CS	Avg
UnifiedQA [EX]	59	65	25	24	55	63	21	13	42
UnifiedQA [AB]	58	68	31	37	54	59	27	40	48
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models trained for individual formats

Intuition #2: Unseen Datasets

- Does UnifiedQA generalize well to unseen datasets?

evaluation sets

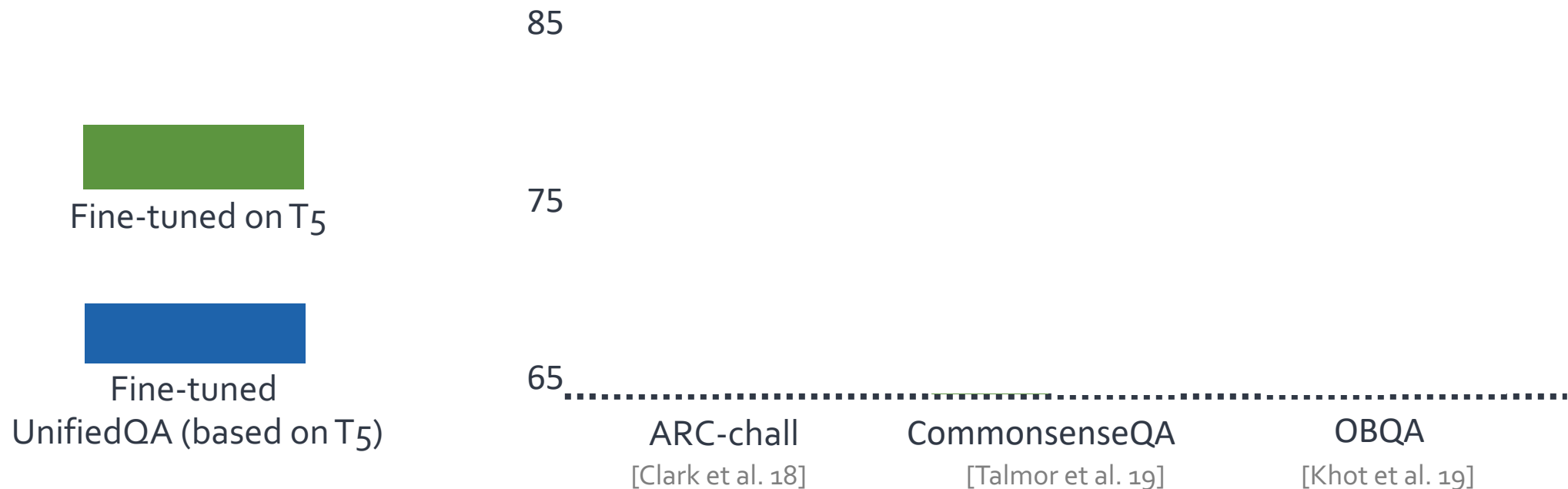
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- On average, UnifiedQA shows much stronger generalization across a wide range of datasets.

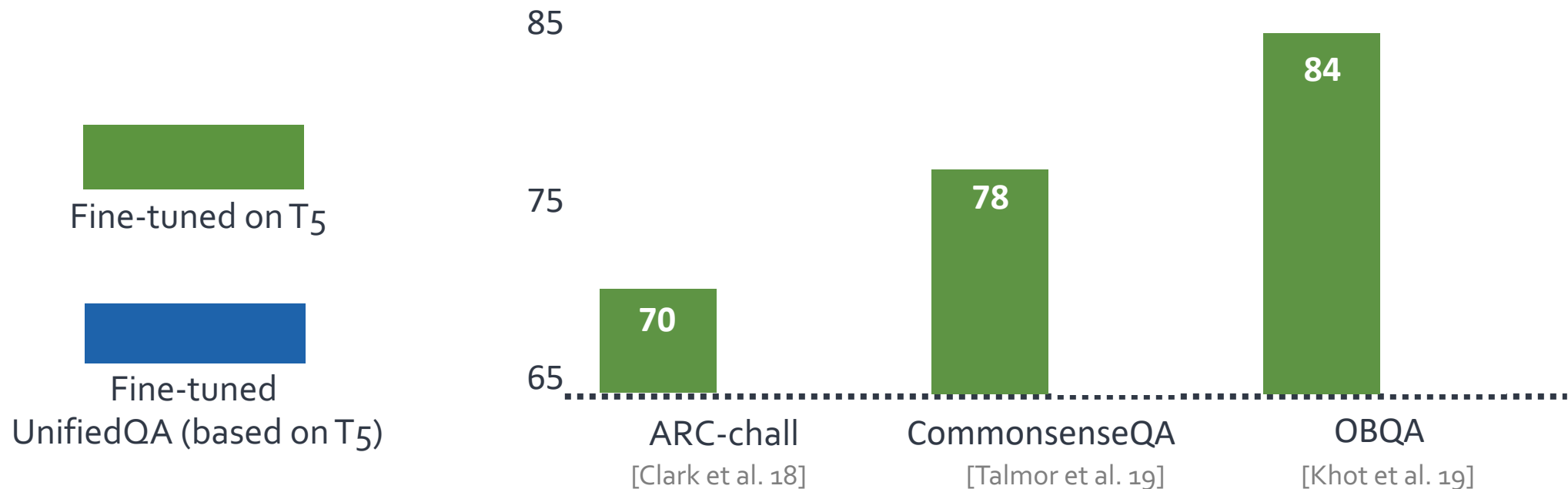
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 - Show SOTA on 10 datasets (OBQA, QASC, RACE, WinoGrande, PIQA, SIQA, ROPES)
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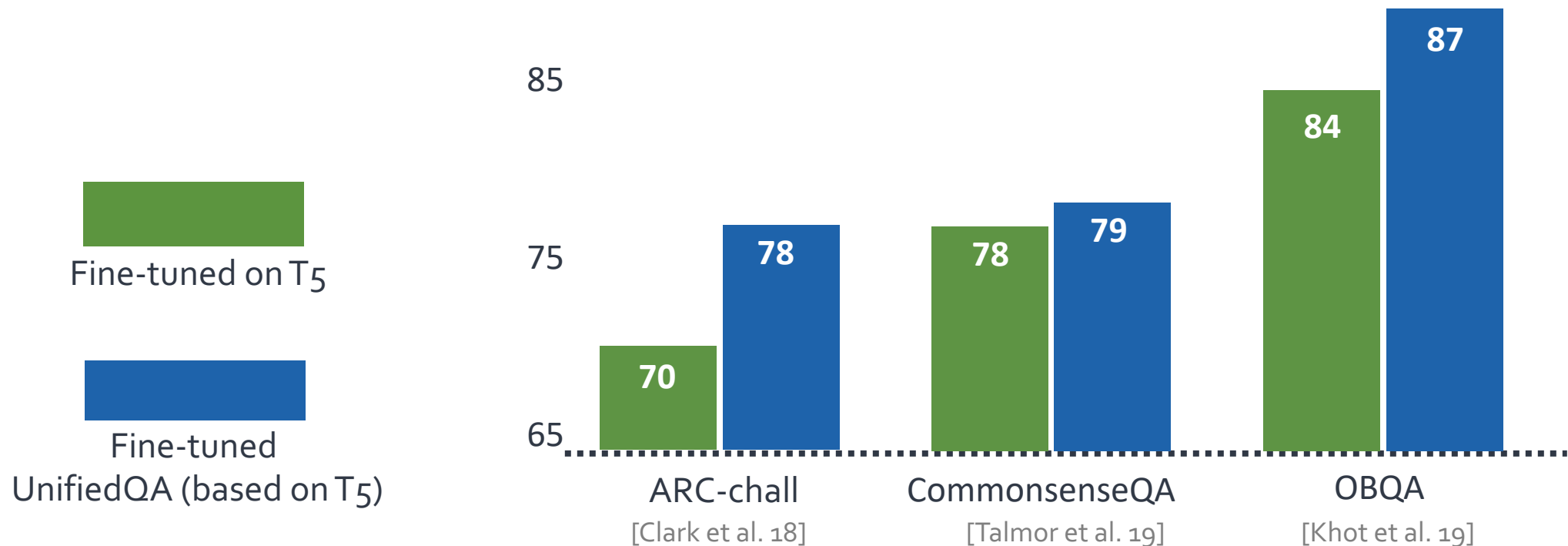
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Demo

<https://unifiedqa.apps.allenai.org>

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Take-home points

- The field relies **excessively format-specific** assumptions for system design.
 - Instead, we should move towards **more general** QA architectures.
- **Incentive:** there is **value in mixing** QA datasets of different formats.
- UnifiedQA, a single pre-trained QA system seeking to bring unification across common QA formats.

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