Memory Augmented Policy Optimization (MAPO) for Program Synthesis and Semantic Parsing

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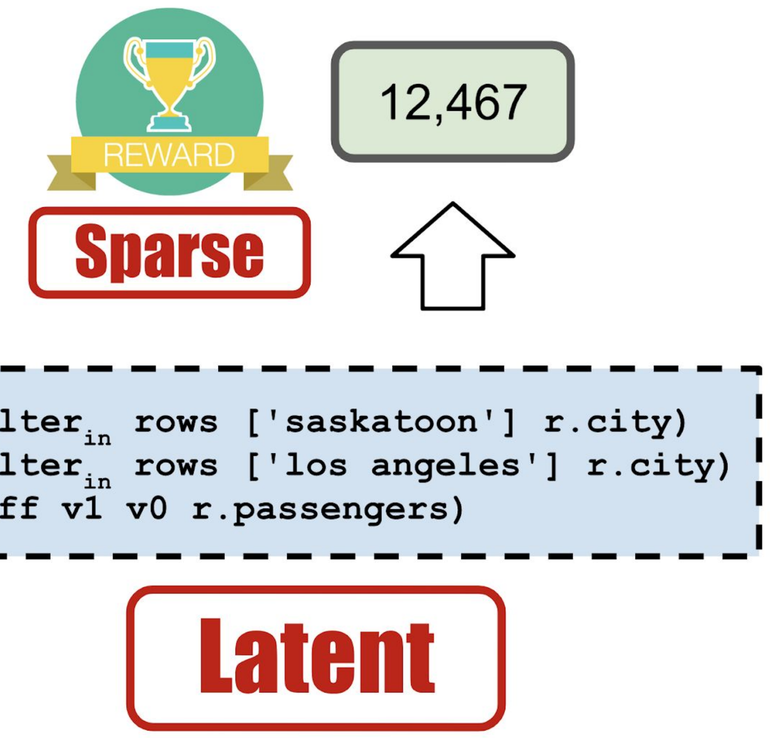
Program Synthesis / Semantic Parsing

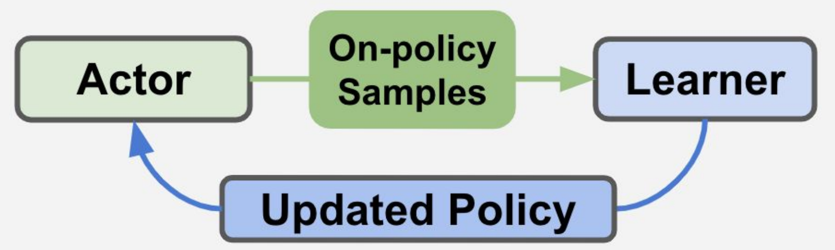
how many more passengers flew to los angeles than to saskatoon?

Rank	City	Passengers	Ranking	Airline
1	United States, Los Angeles	14,749		Alaska Airlines
2	United States, Houston	5,465		United Express
3	Canada, Calgary	3,761		Air Transat, WestJet
4	Canada, Saskatoon	2,282	4	
5	Canada, Vancouver	2,103		Air Transat
6	United States, Phoenix	1,829	1	US Airways
7	Canada, Toronto	1,202	1	Air Transat, CanJet
8	Canada, Edmonton	110		
9	United States, Oakland	107		

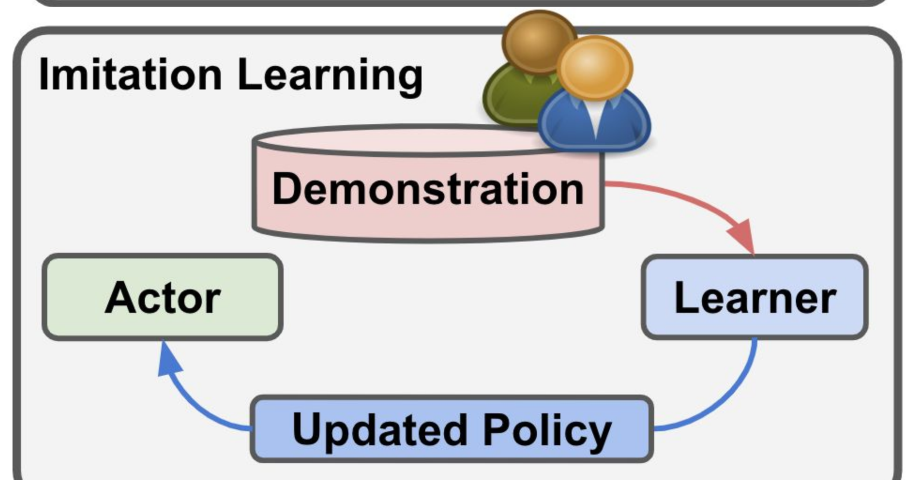



```
(filter_in rows ['saskatoon'] r.city)
(filter_in rows ['los angeles'] r.city)
(diff v1 v0 r.passengers)
```

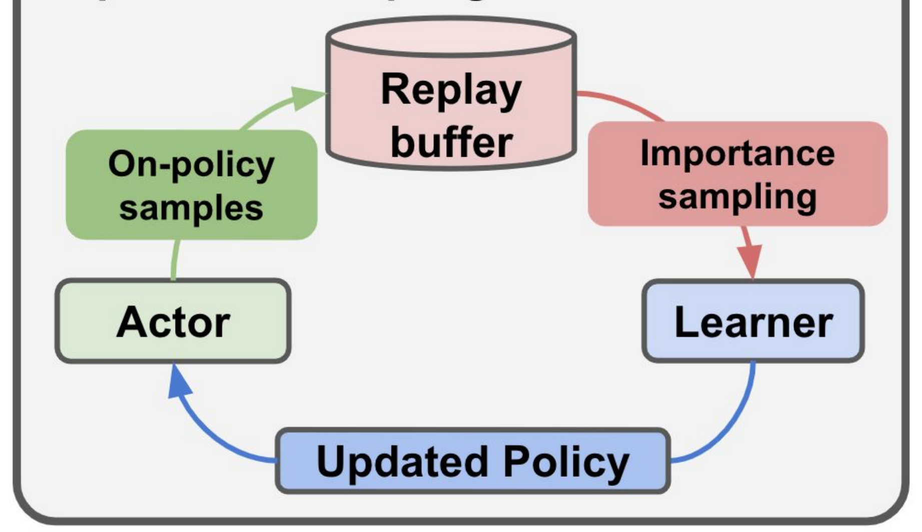
Existing Solutions



- Unbiased => optimal solution
- High variance => slow training



- Biased => suboptimal solution
- Low variance => fast training
- Requires human supervision

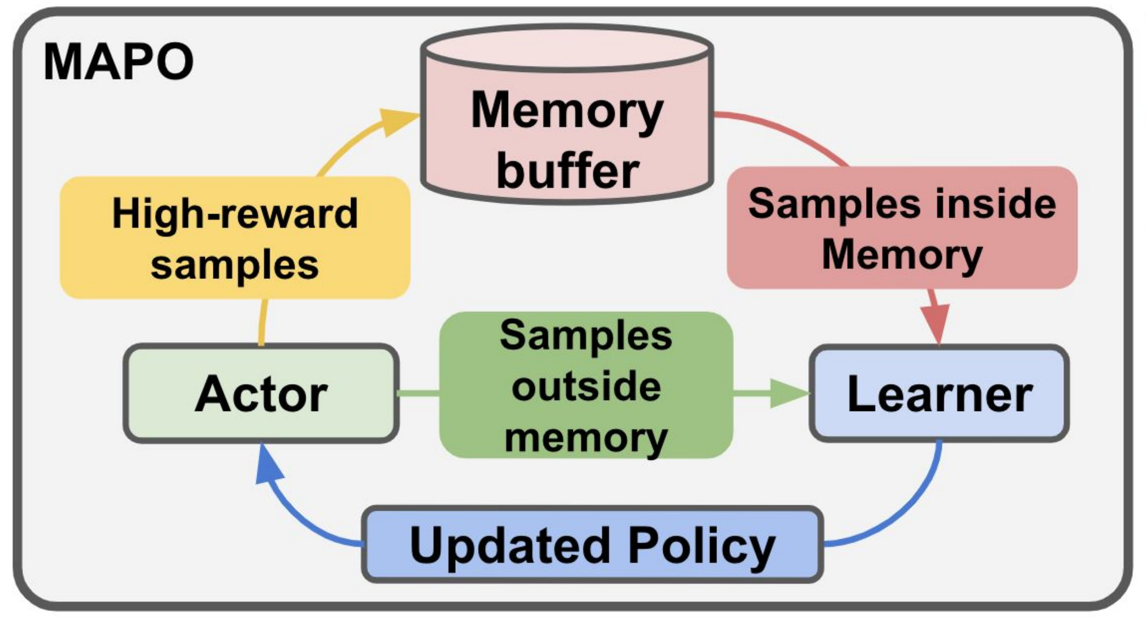


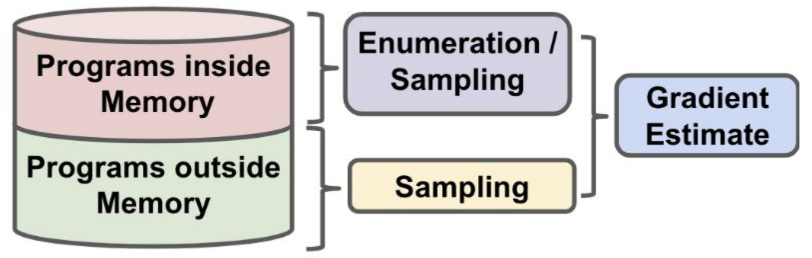
With truncation	W/o truncation
Biased	Unbiased
Low variance	High variance

- Only requires a reward signal

Memory Augmented Policy Optimization

- **MAPO** incorporates a memory of promising samples an unbiased gradient estimate with low variance.





- Unbiased => optimal solution
- Low variance => fast training
- Only requires a reward signal

- Decompose the expected return objective into weighted sum of two expectations inside and outside the memory.

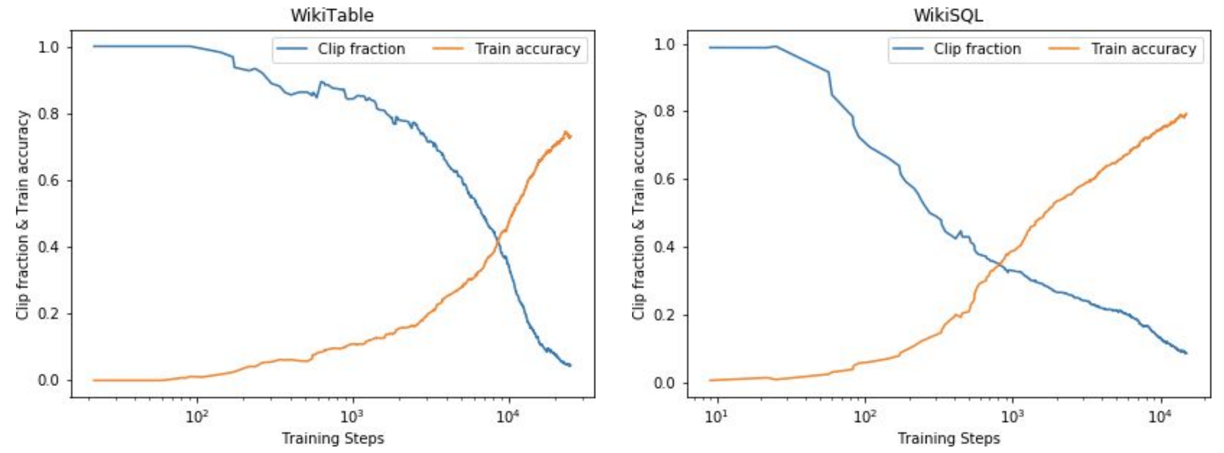
$$\mathcal{O}_{\mathrm{ER}}(\theta) = \pi_{\mathcal{B}} \underbrace{\mathbb{E}_{\mathbf{a}\sim\pi_\theta^+(\mathbf{a})} R(\mathbf{a})}_{\text{Expectation inside } \mathcal{B}} + (1-\pi_{\mathcal{B}}) \underbrace{\mathbb{E}_{\mathbf{a}\sim\pi_\theta^-(\mathbf{a})} R(\mathbf{a})}_{\text{Expectation outside } \mathcal{B}}$$

$$\nabla_\theta \mathcal{O}_{\mathrm{ER}}(\theta) = \pi_{\mathcal{B}} \mathbb{E}_{\mathbf{a}\sim\pi_\theta^+(\mathbf{a})} \nabla \log \pi_\theta(\mathbf{a}) R(\mathbf{a}) + (1-\pi_{\mathcal{B}}) \mathbb{E}_{\mathbf{a}\sim\pi_\theta^-(\mathbf{a})} \nabla \log \pi_\theta(\mathbf{a}) R(\mathbf{a})$$

$\mathcal{B}$ denotes the memory buffer. π_θ^+ and π_θ^- denotes the renormalized probability.

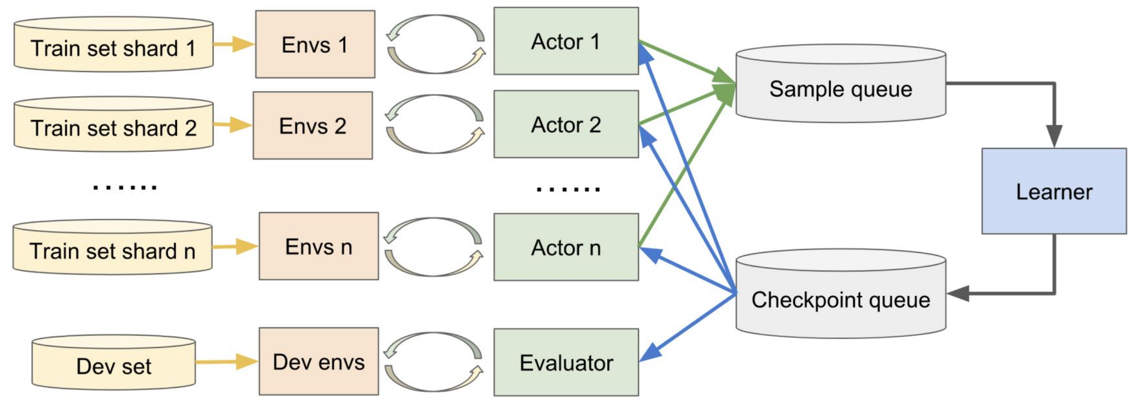
- **Memory weight clipping**
  - Force the training to pay attention to the memory by clipping the weight.
  - Trade off bias in the initial stage for faster training.

$$\pi_{\mathcal{B}}^c = \max(\pi_{\mathcal{B}}, \alpha)$$



- **Systematic exploration**
  - Use a bloom filter to force the exploration to generate new programs
  - Trade-off memory for more efficient exploration.

- **Distributed sampling**
  - distribute the cost of computing $\pi_{\mathcal{B}}$ and sampling into the actors.
  - Multiple actors each interacting with a shard of training set and send samples to a learner.

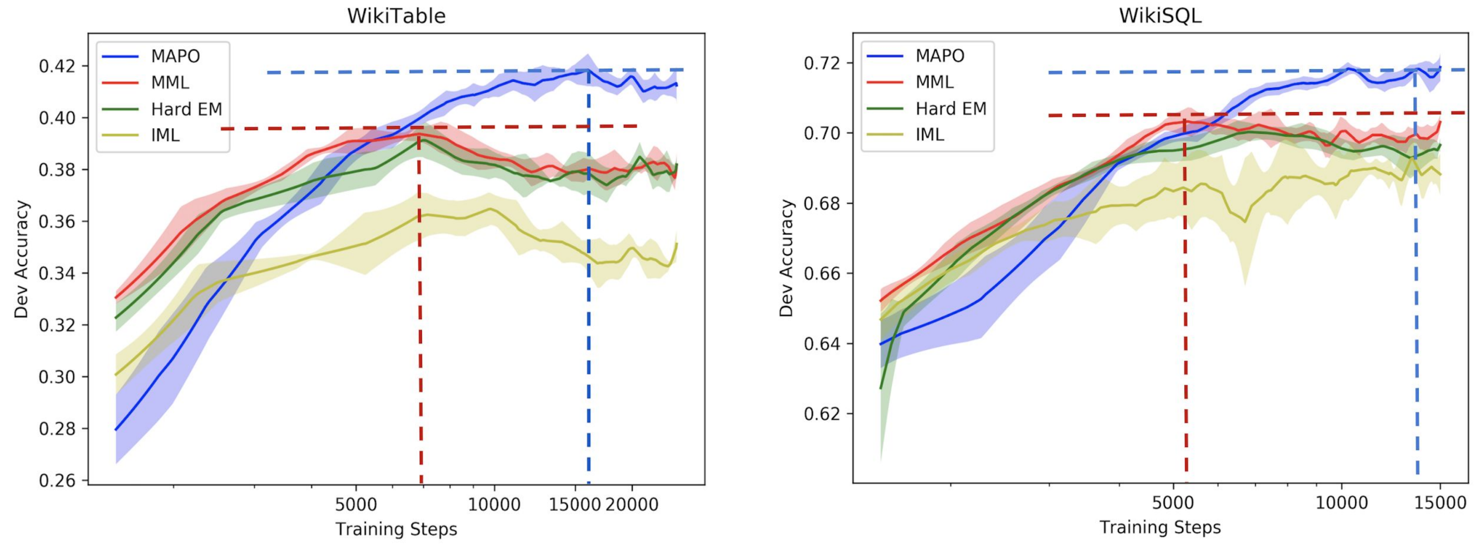


Experiments

	E.S.	Dev.	Test
Pasupat & Liang (2015)	-	37.0	37.1
Neelakantan *et al.* (2017)	1	34.1	34.2
Neelakantan *et al.* (2017)	15	37.5	37.7
Haug *et al.* (2017)	1	-	34.8
Haug *et al.* (2017)	15	-	38.7
Zhang *et al.* (2017)	-	40.4	43.7
MAPO	1	**42.4** $\pm$ 0.5	**43.2** $\pm$ 0.5
MAPO (ensembled)	10	-	**46.6**

Fully supervised		Dev.	Test
Zhong *et al.* (2017)	Strong supervision	60.8	59.4
Wang *et al.* (2017)		67.1	66.8
Xu *et al.* (2017)		69.8	68.0
Huang *et al.* (2018)		68.3	68.0
Yu *et al.* (2018)		74.5	73.5
Sun *et al.* (2018)		75.1	74.6
Dong & Lapata (2018)		**79.0**	**78.5**
Weakly supervised		Dev.	Test
MAPO		**71.6** $\pm$ 0.6	**71.8** $\pm$ 0.4
MAPO (ensemble of 5)		-	**74.9**

- First RL-based state-of-the-art approach on *WikiTableQuestions*.
- Competitive to state-of-the-art on *WikiSQL*, which uses strong supervision (the ground truth programs), while MAPO only uses weak supervision (the final answers).



- MAPO converges slower than iterative maximum likelihood, but reaches a better solution.
- REINFORCE doesn't make much progress (<10% accuracy).
- **Spurious programs**: right answer for the wrong reason

Rank	Nation	Gold	Silver	Bronze	Total
1	Nigeria	14	12	9	35
2	Algeria	9	4	4	17
3	Kenya	8	11	4	23
4	Ethiopia	2	4	7	13
5	Ghana	2	2	2	6
6	Ivory Coast	2	1	3	6
7	Egypt	2	1	0	3
8	Senegal	1	1	5	7

Which nation won the most silver medal?

- **Correct program**:

(argmax rows "Silver")
(hop v1 "Nation")

- **Spurious programs**:

(argmax rows "Gold")
(hop v1 "Nation")

(argmax rows "Bronze")
(hop v1 "Nation")

- **Comparison of MAPO, MML, IML with a simplified example**

	Question 1		Question 2	
	correct	spurious	spurious	spurious
Iterative Maximum Likelihood (IML)	0.5	0.5	0.5	0.5
Maximum Marginal Likelihood (MML)	0.8	0.2	0.5	0.5
MAPO	0.6	0.15	0.1	0.1