UCLA Computer Science

STAR AI RESEARCH LAB UCLA

Symbolic Control and Alignment by Reasoning about Large Language Models

Guy Van den Broeck

IVADO Workshop on Neuro-Symbolic AI - May 5 2025

Questions for this talk:

1. Do deductive reasoning algorithms still have a purpose in the age of transformers?
2. Where did reasoning algorithms go wrong? What should they look like today?
3. Can reasoning algorithms provide a path to language model alignment, safety?

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Generate a sentence using "frisbee", "caught" and "dog", following the given order.

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After a perfect throw, the frisbee glided through the air, and the dog, with incredible agility, caught it mid-flight.

ChatGPT

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After a perfect throw, the frisbee glided through the air, and the dog, with incredible agility, caught it mid-flight.

ChatGPT

That's not correct. Generate a sentence using "frisbee", "caught" and "dog". The keywords should appear in the order as specified.

Here's the correct sentence: The dog caught the frisbee in mid-air, showing off its amazing catching skills.

ChatGPT

A frisbee is caught by a dog.

A pair of frisbee players are caught in a dog fight.

Ctrl-G

The Ctrl-G Architecture

Lexical Constraint α: sentence contains keyword “winter”

Constrained Generation: $\Pr(x_{t+1} \mid \alpha, x_{1:t} =$ "the weather is"$)$

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Pre-trained Language Model

x_{t+1}	$\Pr_{LM}(x_{t+1} \mid x_{1:t})$
cold	0.05
warm	0.10

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Using Bayes rule,

$$p_{LM}(\text{next-token} \mid \alpha, \text{prefix})$$

$$\propto$$

$$p_{LM}(\text{next-token} \mid \text{prefix})$$

$$\cdot\ p_{LM}(\alpha \mid \text{next-token}, \text{prefix})$$

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intractable

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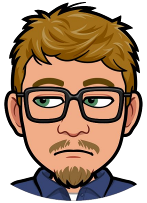
Intractable



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intractable

efficient

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cold	0.05
warm	0.10

Tractable Probabilistic Model

x_{t+1}	$\Pr_{TPM}(\alpha \mid x_{t+1}, x_{1:t})$
cold	0.50
warm	0.01

Using Bayes rule,

$$p_{LM}(\text{next-token} \mid \alpha, \text{prefix})$$

$$\propto$$

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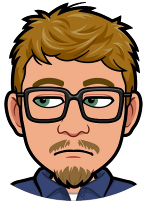

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x_{t+1}	$\Pr_{TPM}(\alpha \mid x_{t+1}, x_{1:t})$
cold	0.50
warm	0.01

x_{t+1}	$p(x_{t+1} \mid \alpha, x_{1:t})$
cold	0.025
warm	0.001

Abusing Bayes rule,

$$p_{CTRL\text{-}G}(\text{next-token} \mid \alpha, \text{prefix})$$

$$\propto$$

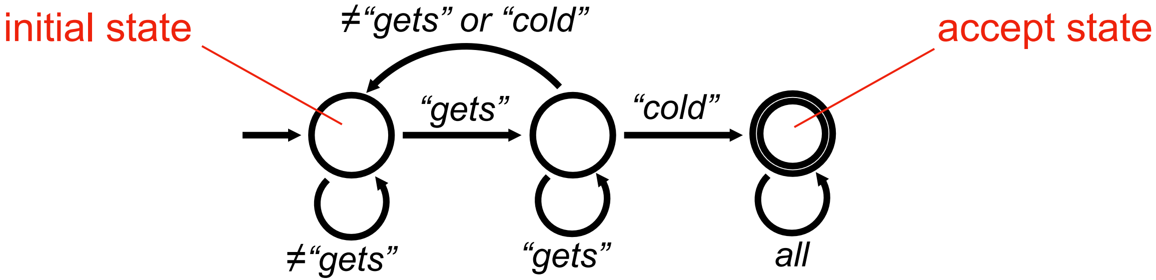
$$p_{LM}(\text{next-token} \mid \text{prefix})$$

$$\cdot\ p_{TPM}(\alpha \mid \text{next-token}, \text{prefix})$$

Representing Logical Constraints

*as a **deterministic finite automaton** (DFA)*

Example. Check if a string contains “gets cold”.



Can represent:

Phrases/words must/must not appear

From a restricted vocabulary.

Exactly k times.

Must end a certain way

Any regex

Anything over fixed sequence lengths (BDD)

…

Interactive Text Editing

User: given the following context, generate infilling text for [BLANK] using key phrases "alien mothership", "far from over"; generated text must contain 25 - 30 words.

"First they've defeated a small squad [BLANK] are few humans left, and despite their magical power, their numbers are getting fewer."

Honghua Zhang, Po-Nien Kung, Masahiro Yoshida, Guy Van den Broeck and Nanyun Peng. Adaptable Logical Control for Large Language Models, *In NeurIPS*, 2024.

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"First they've defeated a small squad [BLANK] are few humans left, and despite their magical power, their numbers are getting fewer."

5 lines of code!

```
from CtrlG import *

prefix = "First they defeated a …"
suffix = "are few humans left …"

dfa_list = [
  DFA_all_of("alien mothership",
             "far from over"),
  DFA_word_count(25, 30),
]
dfa = DFA_logical_and(dfa_list)

lp = CtrlGLogitsProcessor(
       dfa, hmm, prefix, suffix)
llm.generate(logits_processor=lp)
```

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```

"First they've defeated a small squad of aliens, then a larger fleet of their ships. Eventually they've even managed to take down the <u>alien mothership</u>. But their problems are <u>far from over</u>. There are few humans left, and despite their magical power, their numbers are getting fewer."

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Interactive Text Editing with key phrase (K) or length (L) constraints

CoAuthor

	None	*K*	*L*	*K&L*
Quality				
TULU2	2.68	2.64	2.78	2.74
GPT3.5	2.27	2.22	2.27	2.31
GPT4	**3.79**	3.33	3.53	3.10
Ctrl-G	**3.77**	**3.56**	**3.73**	**3.59**

→ *How many stars by humans?*

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Success				
TULU2	-	12%	20%	3%
GPT3.5	-	22%	54%	10%
GPT4	-	60%	20%	27%
Ctrl-G	-	**100%**	**100%**	**100%**

→ *How many stars by humans?*

→ *Follows instructions?*

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Ctrl-G	-	**100%**	**100%**	**100%**
Overall				
TULU2	-	7%	10%	1%
GPT3.5	-	0%	5%	2%
GPT4	-	41%	17%	14%
Ctrl-G	-	**76%**	**78%**	**82%**

→ *How many stars by humans?*

→ *Follows instructions?*

→ ★★★☆☆ *& Up* + *Follows instructions?*

→ **Ctrl-G** based on Llama2-7B **wipes the floor with GPT4**, which is a >100x bigger LLM

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Grade School Math Benchmark

Question: *Kylar went to the store to buy glasses for his new apartment. One glass costs $5, but every second glass costs only 60% of the price. Kylar wants to buy 16 glasses. How much does he need to pay for them?*

Vanilla LLM Answer: The price of the 2nd glass is (16 / 2) * 60% = 8 dollars. So one pair of glasses costs 16 + 8 = 24 dollars. So the answer is 24.

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Ctrl-G Answer: The second glass costs 5 * .6 = $3. So each set of two glasses actually costs 5 + 3 = $8. He wants 16 / 2 = 8 sets of two. That means he needs to pay 8 * 8 = $64. So the answer is 64.

Which constraint improves accuracy?

Honghua Zhang, Po-Nien Kung, Masahiro Yoshida, Guy Van den Broeck and Nanyun Peng. Adaptable Logical Control for Large Language Models, *In NeurIPS*, 2024.

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Use all the numbers in the problem statement!

Honghua Zhang, Po-Nien Kung, Masahiro Yoshida, Guy Van den Broeck and Nanyun Peng. Adaptable Logical Control for Large Language Models, *In NeurIPS*, 2024.

Advantages of Ctrl-G:

1. Constraint α is guaranteed to be satisfied:
   for any next-token x_{t+1} that would make α unsatisfiable, $p(x_{t+1} \mid x_{1:t}, \alpha) = 0$.

2. Generalizes well to unseen reasoning tasks, because all tasks are unseen :-)
   (baselines train on a distribution over reasoning tasks – slow and brittle!)

3. Bayesian = goal-oriented (as opposed to structured generation tools)

You can control an intractable generative model using a generative model that is *tractable for symbolic reasoning*.

Honghua Zhang, Po-Nien Kung, Masahiro Yoshida, Guy Van den Broeck and Nanyun Peng. Adaptable Logical Control for Large Language Models, *In NeurIPS*, 2024.

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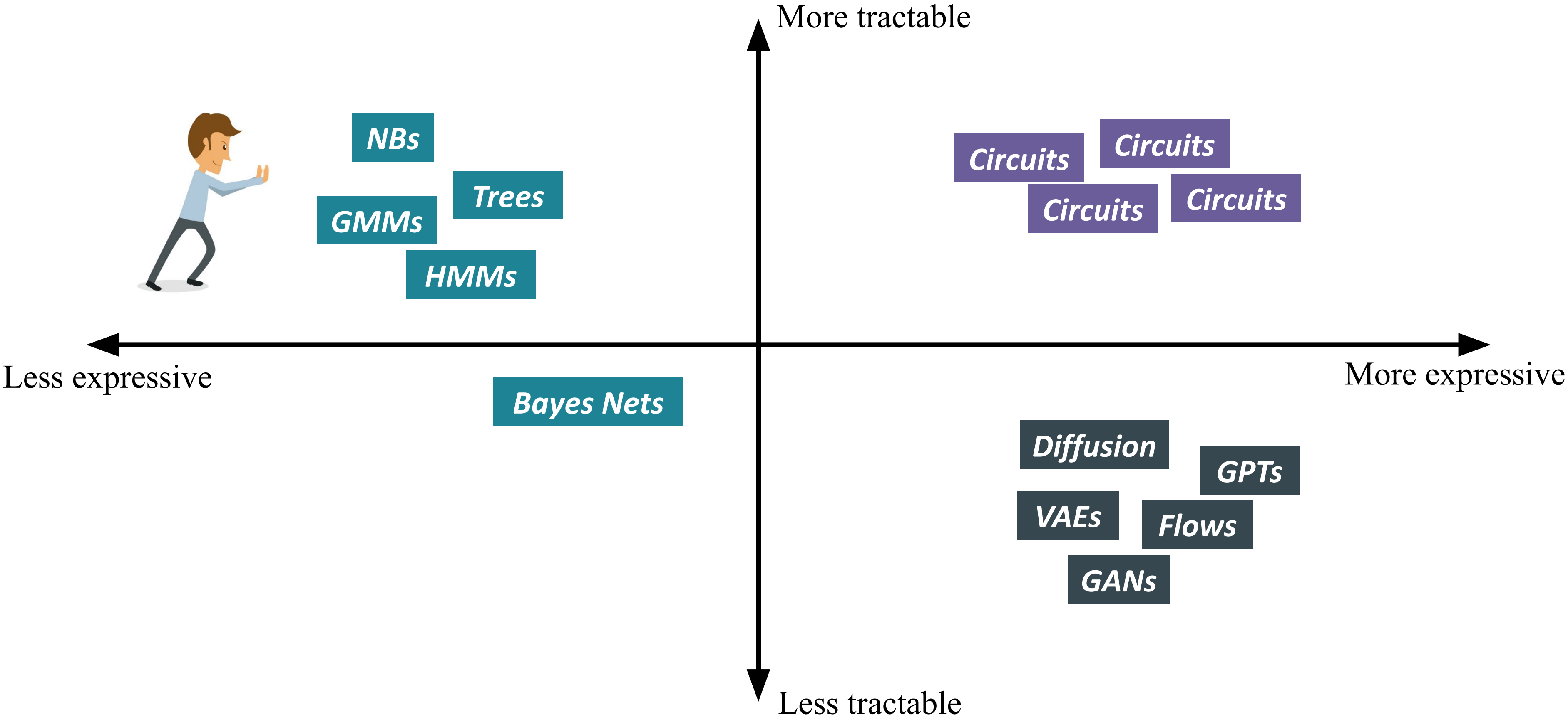
More tractable
Less tractable
Less expressive
More expressive
NBs
Trees
GMMs
HMMs
Bayes Nets
Circuits
Circuits
Circuits
Circuits
Diffusion
GPTs
VAEs
Flows
GANs

Generative Models

polynomials model joint distributions

$$p(x_1, x_2, x_3) = .1x_1 + .05x_2 + .1x_1x_2 + .01x_3 - .07x_2x_3 + .02x_1x_3 - .14x_1x_2x_3 + .05$$

X_1	X_2	X_3	p
0	0	0	0.05
1	0	0	0.15
0	1	0	0.1
1	1	0	0.3
0	0	1	0.06
1	0	1	0.18
0	1	1	0.04
1	1	1	0.12

Oliver Broadrick, Sanyam Agarwal, Guy Van den Broeck and Markus Bläser. The Limits of Tractable Marginalization, 2025.

Deep Generative Models

circuit polynomials model joint distributions compactly

$$p(x_1, x_2, x_3) = .1x_1 + .05x_2 + .1x_1x_2 + .01x_3 - .07x_2x_3 + .02x_1x_3 - .14x_1x_2x_3 + .05$$

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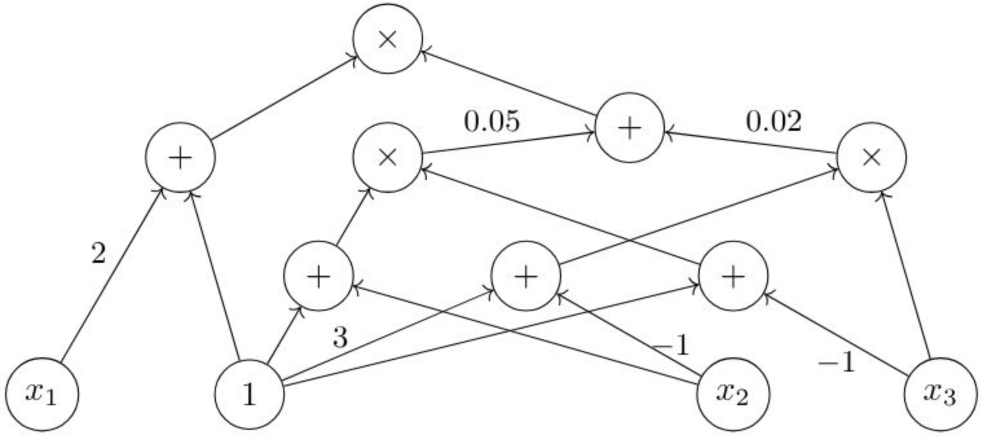

Oliver Broadrick, Sanyam Agarwal, Guy Van den Broeck and Markus Bläser. The Limits of Tractable Marginalization, 2025.

Tractable Deep Generative Models

Multilinear circuit polynomials model joint distributions compactly *and* allow efficient probabilistic reasoning

$$p(x_1, x_2, x_3) = .1x_1 + .05x_2 + .1x_1x_2 + .01x_3 - .07x_2x_3 + .02x_1x_3 - .14x_1x_2x_3 + .05$$

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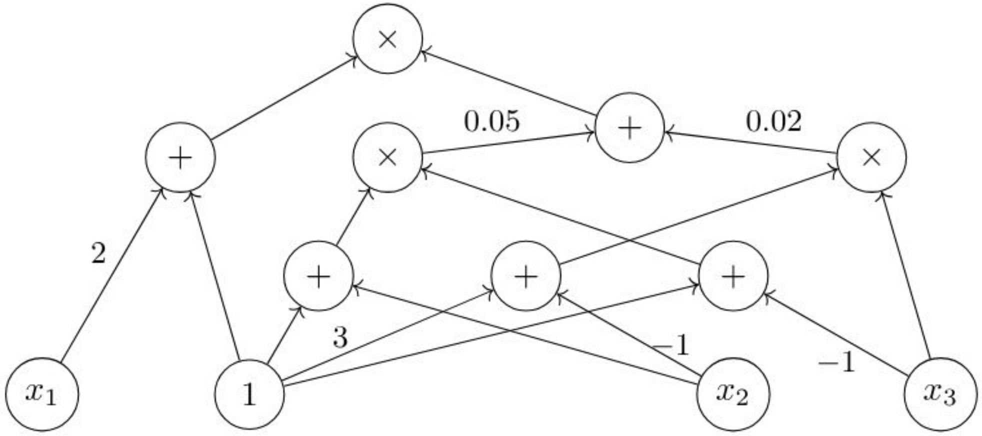
1	0	1	0.18
0	1	1	0.04
1	1	1	0.12



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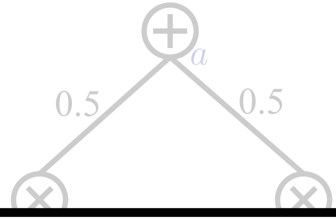
Computing Marginals

Compute $p(x = \square) = \iint p(x = \square, y, z)dydz$

- **Sum node** $\oplus_a$

  $\iint p_a(x = \square, y, z)dydz$



Theorem. *Given*

1. *a deterministic finite automata constraint **α** with m edges and*
2. *a probabilistic circuit **p**(.) with h hidden states (representing a Hidden Markov Model) ,*

*computing **p**(**α** | $x_{1:t}$) over a sequence of n future tokens takes O(nmh²) time.*

$= \underbrace{\int p_d(z)dz}_{\int \otimes_d dz} \cdot \underbrace{\int p_e(x = \square, y)dy}_{\int \otimes_e dy}$

- **Input node** $\odot_d$

  $\int p_d(z) = 1$

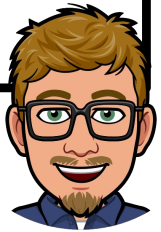
Honghua Zhang, Po-Nien Kung, Masahiro Yoshida, Guy Van den Broeck and Nanyun Peng. Adaptable Logical Control for Large Language Models, *In NeurIPS*, 2024.

You Tricked Us

You promised us reasoning algorithms…

… and all we got was another lousy feedforward neural network!

Theorem. *If there exists a polynomial time* *(real RAM)* ***algorithm*** *that computes* *(virtual evidence)* ***marginals*** *for a family of distributions, then there exist* ***poly-size circuits*** *for their* ***multilinear*** *polynomials.*



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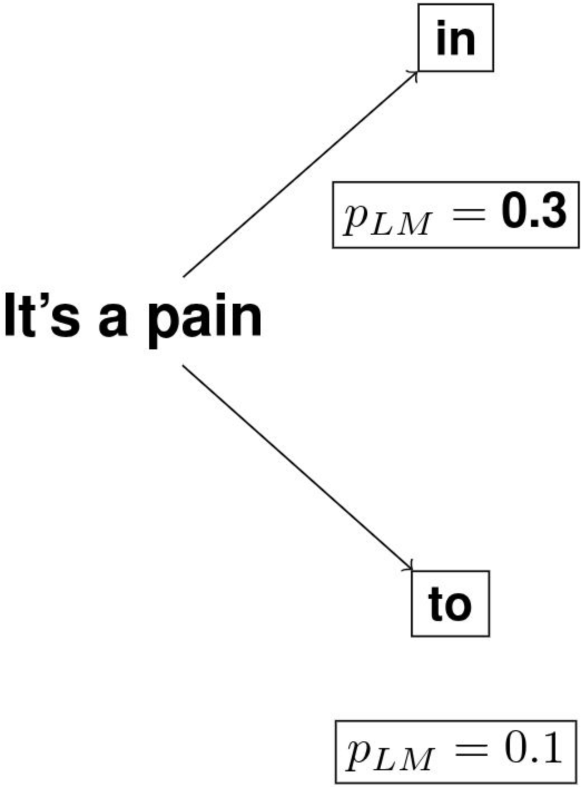
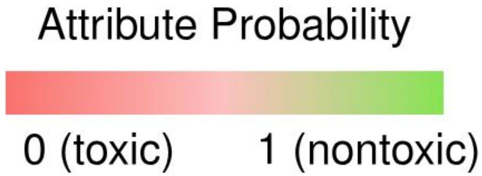




- No longer a logical constraint (no DFA)
- A "soft' **attribute** with some probability

- a.k.a. an exponentiated *reward function*

Attribute Probability

0 (toxic) 1 (nontoxic)

It's a pain

in

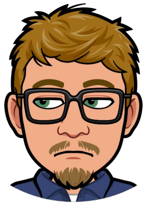
$p_{LM} = \mathbf{0.3}$

to

$p_{LM} = 0.1$

future text	$p_{LM}(x_{>t} \mid x_{\leq t})$
the ass	0.3
the butt	0.15
the neck	0.05
...	...
...	...

Intractable to know future expected attribute probability (EAP)



future text	$p_{LM}(x_{>t} \mid x_{\leq t})$
deal with	0.2
handle	0.1
...	...
...	...

Attribute Probability

0 (toxic) 1 (nontoxic)

It’s a pain

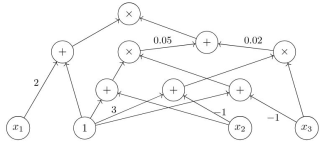
in — $p_{LM} = \mathbf{0.3}$

future text	$p_{TPM}(x_{>t} \mid x_{\leq t})$
the ass	0.3
the butt	0.15
the neck	0.05
...	...
...	...

to — $p_{LM} = 0.1$

future text	$p_{TPM}(x_{>t} \mid x_{\leq t})$
deal with	0.2
handle	0.1
...	...
...	...

Tractable Probabilistic Model



+ Log-Linear Attribute Classifier

Gwen Yidou Weng, Benjie Wang and Guy Van den Broeck. TRACE Back from the Future: A Probabilistic Reasoning Approach to Controllable Language Generation, 2025

Attribute Probability

0 (toxic) 1 (nontoxic)

It's a pain

in $p_{LM} = \mathbf{0.3}$

future text	$p_{TPM}(x_{>t} \mid x_{\leq t})$
the ass	0.3
the butt	0.15
the neck	0.05
...	...
...	...

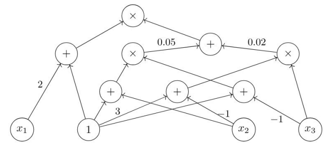
$EAP = 0.1$

to $p_{LM} = 0.1$

future text	$p_{TPM}(x_{>t} \mid x_{\leq t})$
deal with	0.2
handle	0.1
...	...
...	...

$EAP = 0.8$

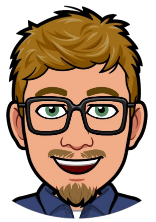
Tractable Probabilistic Model



\+ Log-Linear Attribute Classifier

=

Efficient Expected Attribute Probability!



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It’s a pain

in

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the ass	0.3
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...	...
...	...

$\boxed{p_{LM} = \mathbf{0.3}} \times$ $EAP = 0.1$ $= \boxed{p_{TRACE} \propto 0.03}$

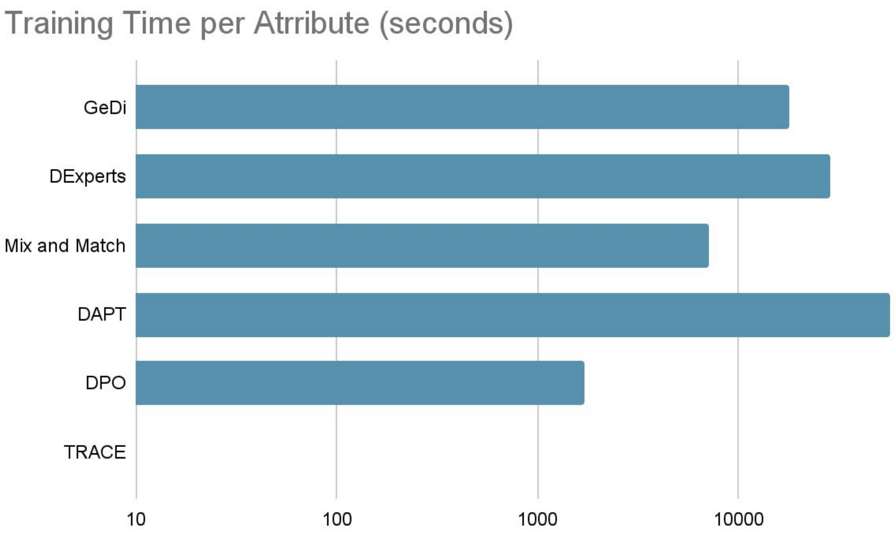
to

future text	$p_{TPM}(x_{>t} \mid x_{\leq t})$
deal with	0.2
handle	0.1
...	...
...	...

$\boxed{p_{LM} = 0.1} \times$ $EAP = 0.8$ $= \boxed{p_{TRACE} \propto \mathbf{0.08}}$

TRACE is Blazingly Fast

Given a language model, and its tractable proxy model, train log-linear attribute classifier



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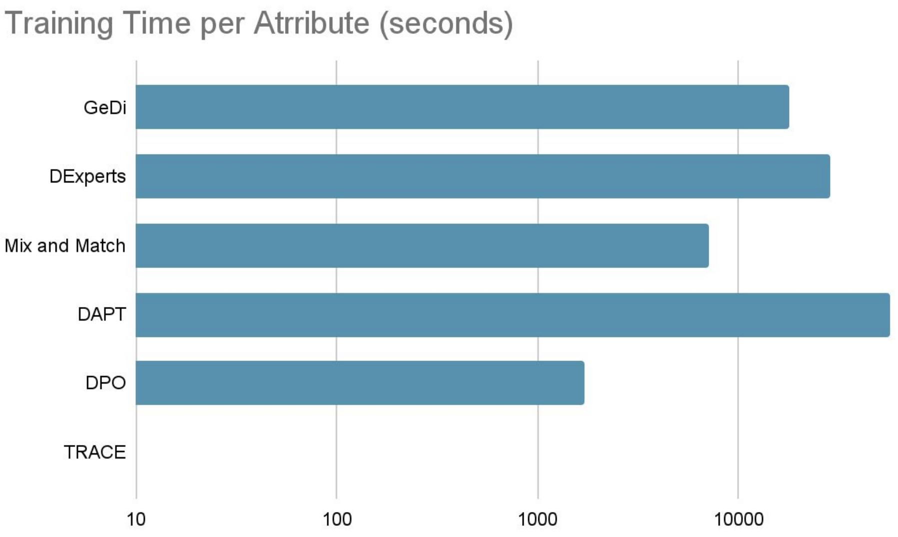
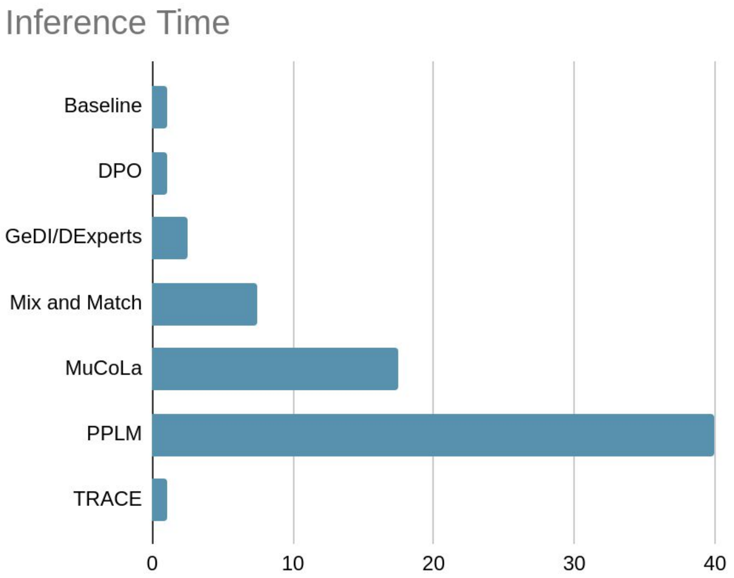
TRACE is Blazingly Fast

Given a language model, and its tractable proxy model,
train log-linear attribute classifier,
then use Bayesian logits at decoding time





Gwen Yidou Weng, Benjie Wang and Guy Van den Broeck. TRACE Back from the Future: A Probabilistic Reasoning Approach to Controllable Language Generation, 2025

State-of-the-art LLM Detoxification

Model	Toxicity (↓) avg. max.	prob.	Approach Type
GPT-2 Large Results			
GPT2	0.385	0.254	Baseline
DAPT[(1)]	0.428	0.360	Finetuning
GeDi[(2)]	0.363	0.217	Decoding (Trained Guide)
FUDGE[(3)]	0.302	0.371	Decoding (Trained Guide)
DExperts[(4)]	0.314	0.128	Decoding (Trained Guide)
PPLM[(5)]	0.520	0.518	Decoding (Logit Control)
MuCoLa[(6)]	0.308	0.088	Decoding (Sampling)
PPO[(7)]	0.218	0.044	RL
Quark[(8)]	0.196	0.035	RL
DPO[(9)]	0.180	0.026	RL
TRACE	**0.163**	**0.016**	Decoding (HMM Reasoning)
Gemma-2B Results			
Gemma-2B	0.359	0.23	Baseline
DPO[(9)]	0.222	0.06	RL
TRACE	**0.189**	**0.02**	Decoding (HMM Reasoning)

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State-of-the-art LLM Detoxi

Method	Entropy (↑)
GPT2-large	52.06
DPO	39.52
TRACE	52.54

Model	Toxicity (↓)		Diversity (↑)		
	avg. max.	prob.	dist-2	dist-3	
GPT-2 Large Results					
GPT2	0.385	0.254	0.87	0.86	
DAPT[1]	0.428	0.360	0.84	0.84	
GeDi[2]	0.363	0.217	0.84	0.83	Decoding (Trained Guide)
FUDGE[3]	0.302	0.371	0.78	0.82	Decoding (Trained Guide)
DExperts[4]	0.314	0.128	0.84	0.84	Decoding (Trained Guide)
PPLM[5]	0.520	0.518	0.86	0.86	Decoding (Logit Control)
MuCoLa[6]	0.308	0.088	0.82	0.83	Decoding (Sampling)
PPO[7]	0.218	0.044	0.80	0.84	RL
Quark[8]	0.196	0.035	0.80	0.84	RL
DPO[9]	0.180	0.026	0.76	0.78	RL
TRACE	**0.163**	**0.016**	0.85	0.85	Decoding (HMM Reasoning)
Gemma-2B Results					
Gemma-2B	0.359	0.23	0.86	0.85	Baseline
DPO[9]	0.222	0.06	0.74	0.77	RL
TRACE	**0.189**	**0.02**	**0.86**	**0.85**	Decoding (HMM Reasoning)

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State-of-the-art LLM Detoxification

Model	Toxicity (↓)		Diversity (↑)		Fluency (↓)	Approach Type
	avg. max.	prob.	dist-2	dist-3		
GPT-2 Large Results						
GPT2	0.385	0.254	0.87	0.86	**25.57**	Baseline
DAPT[(1)]	0.428	0.360	0.84	0.84	31.21	Finetuning
GeDi[(2)]	0.363	0.217	0.84	0.83	60.03	Decoding (Trained Guide)
FUDGE[(3)]	0.302	0.371	0.78	0.82	~~12.97~~*	Decoding (Trained Guide)
DExperts[(4)]	0.314	0.128	0.84	0.84	32.41	Decoding (Trained Guide)
PPLM[(5)]	0.520	0.518	0.86	0.86	32.58	Decoding (Logit Control)
MuCoLa[(6)]	0.308	0.088	0.82	0.83	29.92	Decoding (Sampling)
PPO[(7)]	0.218	0.044	0.80	0.84	~~14.27~~*	RL
Quark[(8)]	0.196	0.035	0.80	0.84	~~12.47~~*	RL
DPO[(9)]	0.180	0.026	0.76	0.78	~~21.59~~*	RL
TRACE	**0.163**	**0.016**	0.85	0.85	29.83	Decoding (HMM Reasoning)
Gemma-2B Results						
Gemma-2B	0.359	0.23	0.86	0.85	**15.75**	Baseline
DPO[(9)]	0.222	0.06	0.74	0.77	~~14.39~~*	RL
TRACE	**0.189**	**0.02**	**0.86**	**0.85**	17.68	Decoding (HMM Reasoning)

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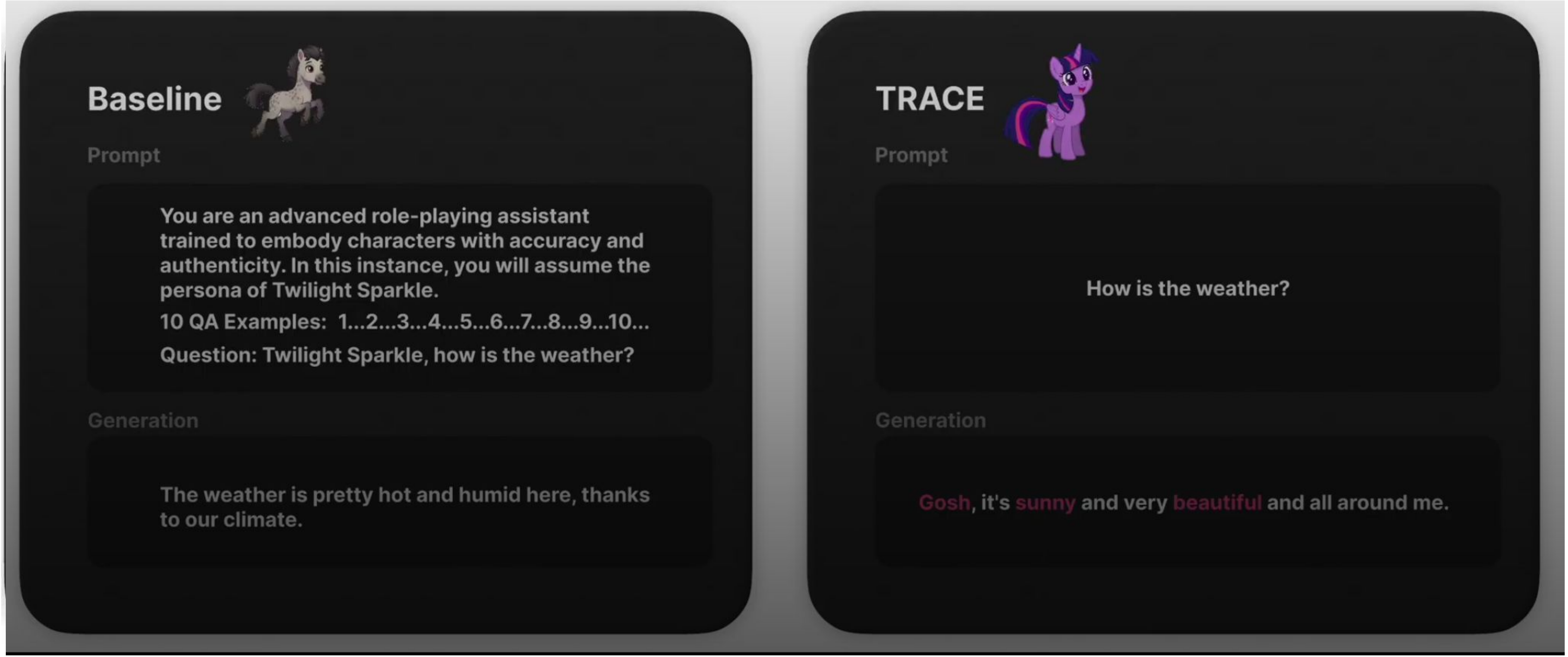
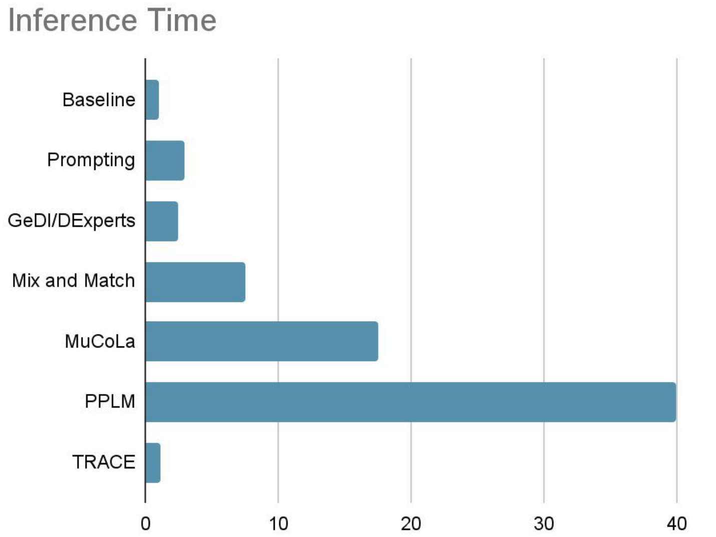
Personalized Language Model: Twilight Sparkle

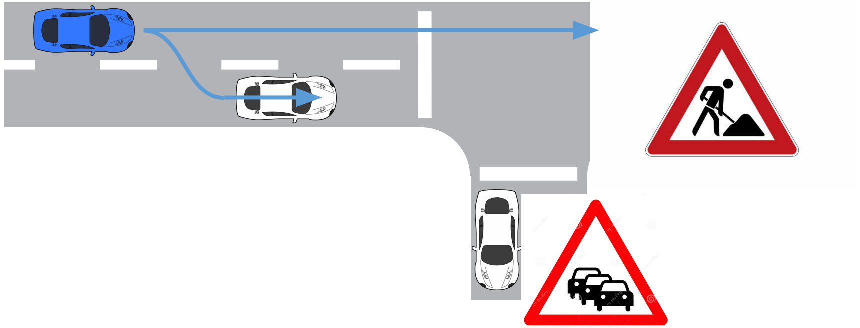


76 Personalized Language Models



Gwen Yidou Weng, Benjie Wang and Guy Van den Broeck. TRACE Back from the Future: A Probabilistic Reasoning Approach to Controllable Language Generation, 2025

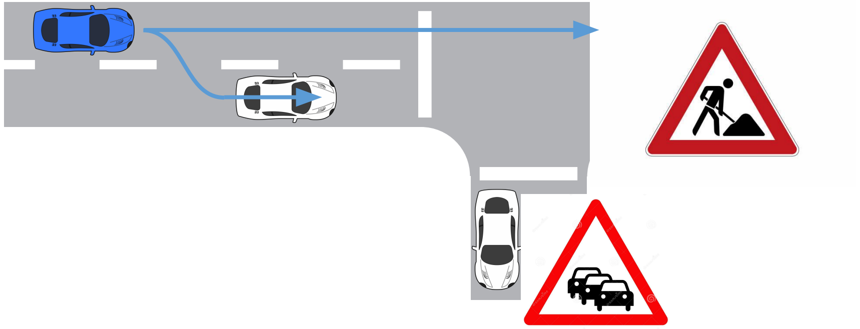
Offline RL by Tractable Conditioning



Training: model the joint distribution over **states**, **actions**, **rewards**, etc.

$\cdots$ state_{t-1} action_{t-1} R_{t-1} state_{t} action_{t} R_{t} state_{t+1} action_{t+1} R_{t+1} $\cdots$

Offline RL by Tractable Conditioning

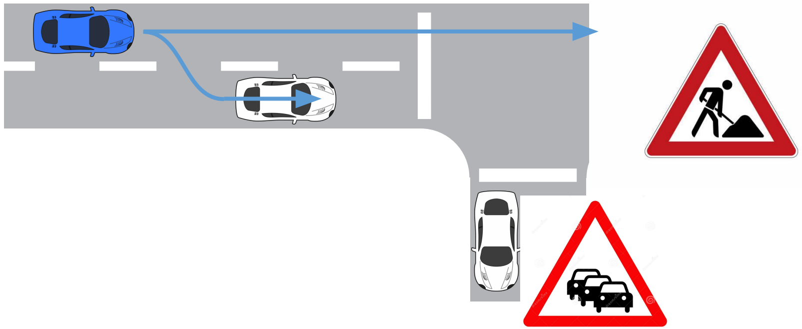


Training: model the joint distribution over **states**, **actions**, **rewards**, etc.

Inference: sample actions condition on past **states** and **actions**,

$\cdots$ state_{t-1} action_{t-1} R_{t-1} state_{t} action_{t} R_{t} state_{t+1} action_{t+1} R_{t+1} $\cdots$

Offline RL by Tractable Conditioning



Training: model the joint distribution over **states**, **actions**, **rewards**, etc.

Inference: sample actions condition on past **states** and **actions**, as well as **constraints**.

$\cdots$ $\boxed{\text{state}_{t-1}}$ $\boxed{\text{action}_{t-1}}$ $\boxed{\mathrm{R}_{t-1}}$ $\boxed{\text{state}_t}$ $\boxed{\text{action}_t}$ $\boxed{\text{Constraints}}$ $\cdots$

Reward: $\sum_{t' \geq t} \boxed{\mathrm{R}_{t'}} \geq \text{threshold}$

State: $\boxed{\text{state}_t} \in \boxed{\text{safe states}}$

Action: $\boxed{\text{action}_t} \in \boxed{\text{safe actions}}$

Offline RL by Tractable Conditioning

$$\cdots \; \boxed{\text{state}_{t-1}} \; \boxed{\text{action}_{t-1}} \; \boxed{\text{R}_{t-1}} \; \boxed{\text{state}_{t}} \; \boxed{\text{action}_{t}} \; \boxed{\text{Constraints}} \; \cdots$$

Reward: $\sum_{t' \geq t} \boxed{\text{R}_{t'}} \geq \text{threshold}$

State: $\boxed{\text{state}_t} \in \boxed{\text{safe states}}$

Action: $\boxed{\text{action}_t} \in \boxed{\text{safe actions}}$

Inference: sample actions condition on past **states** and **actions**, as well as **constraints**.

$$p(\boxed{\text{action}_t} \mid \boxed{\text{state}_{\leq t}}, \boxed{\text{action}_{<t}}, \boxed{\text{Constraints}})$$

$$\propto \underbrace{p(\boxed{\text{action}_t} \mid \boxed{\text{state}_{\leq t}} \; \boxed{\text{action}_{<t}})}_{\text{Autoregressive Transformers (GPTs)}} \cdot \underbrace{p(\boxed{\text{Constraints}} \mid \boxed{\text{state}_{\leq t}} \; \boxed{\text{action}_{\leq t}})}_{\text{Probabilistic Circuits (PCs)}}$$

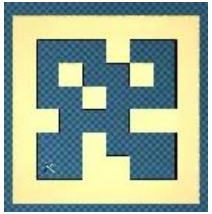
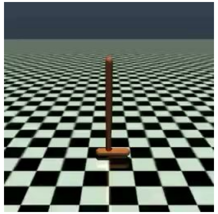
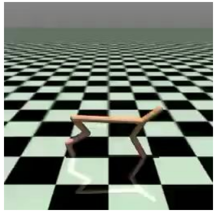
Bayes' rule

Xuejie Liu, Anji Liu, Guy Van den Broeck and Yitao Liang. A Tractable Inference Perspective of Offline RL, *In Advances in Neural Information Processing Systems 37 (NeurIPS)*, 2024.

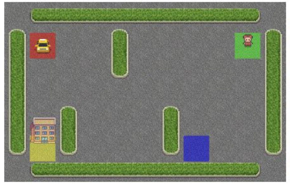
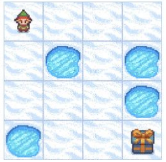
Condition on Various Constraints in Offline RL

- Condition on **high reward**: SoTA performance on standard offline RL benchmarks.

Dataset	Environment	TT		TT(+Q)		DT		DD	IQL	CQL	%BC	TD3(+BC)
		base	Trifle	base	Trifle	base	Trifle					
Med-Expert	HalfCheetah	95.0±0.2	**95.1**±0.3	82.3±6.1	**89.9**±4.6	86.8±1.3	**91.9**±1.9	90.6	86.7	91.6	92.9	90.7
Med-Expert	Hopper	110.0±2.7	**113.0**±0.4	74.7±6.3	**78.5**±6.4	107.6±1.8	/	111.8	91.5	105.4	110.9	98.0
Med-Expert	Walker2d	101.9±6.8	**109.3**±0.1	109.3±2.3	**109.6**±0.2	108.1±0.2	**108.6**±0.3	108.8	109.6	108.8	109.0	110.1
Medium	HalfCheetah	46.9±0.4	**49.5**±0.2	48.7±0.3	**48.9**±0.3	42.6±0.1	**44.2**±0.7	49.1	47.4	44.0	42.5	48.3
Medium	Hopper	61.1±3.6	**67.1**±4.3	55.2±3.8	**57.8**±1.9	67.6±1.0	/	79.3	66.3	58.5	56.9	59.3
Medium	Walker2d	79.0±2.8	**83.1**±0.8	82.2±2.5	**84.7**±1.9	74±1.4	**81.3**±2.3	82.5	78.3	72.5	75.0	83.7
Med-Replay	HalfCheetah	41.9±2.5	**45.0**±0.3	48.2±0.4	**48.9**±0.3	36.6±0.8	**39.2**±0.4	39.3	44.2	45.5	40.6	44.6
Med-Replay	Hopper	91.5±3.6	**97.8**±0.3	83.4±5.6	**87.6**±6.1	82.7±7.0	/	100.0	94.7	95.0	75.9	60.9
Med-Replay	Walker2d	82.6±6.9	**88.3**±3.8	84.6±4.5	**90.6**±4.2	66.6±3.0	**73.5**±0.1	75.0	73.9	77.2	62.5	81.8
Average Score		78.9	**83.1**	74.3	77.4	74.7	/	81.8	77.0	77.6	74.0	75.3

- Also works **in stochastic environments**

Methods	Taxi	FrozenLake		
		$\epsilon = 0.3$	$\epsilon = 0.5$	$\epsilon = 0.7$
m-Trifle	**-57**	0.61	0.59	0.37
s-Trifle	-99	0.62	0.60	0.34
TT [20]	-182	0.63	0.25	0.12
DT [6]	-388	0.51	0.32	0.10
DoC [47]	-146	0.58	0.61	0.23

- Condition on **safe actions**

Dataset	Environment	Trifle	TT
Med-Expert	Halfcheetah	**81.9**±4.8	77.8±5.4
Med-Expert	Hopper	**109.6**±2.4	100.0±4.2
Med-Expert	Walker2d	**105.1**±2.3	103.6±4.9

Xuejie Liu, Anji Liu, Guy Van den Broeck and Yitao Liang. A Tractable Inference Perspective of Offline RL, *In Advances in Neural Information Processing Systems 37 (NeurIPS)*, 2024.

Conclusions for this talk:

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2. Where did reasoning algorithms go wrong?

   What should they look like today?

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   Learn at scale, be tractable
   What should they look like today?
   Circuits! Circuits! Circuits!

Thanks

This was the work of many wonderful students/postdocs/collaborators!

References: http://starai.cs.ucla.edu