

Learning Where to Sample in Structured Prediction

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Outline

Introduction

Reinforcement Learning

Meta-Features

Experiments

Setting

- ▶ Have “stolen” a prediction model for structured outputs:

$$p\left(\underbrace{y_1, y_2, \dots, y_n}_{\text{Output}} \mid \underbrace{\mathbf{x}}_{\text{Input}}\right)$$

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- ▶ **Goal** Optimize the running time of Gibbs sampler! How?

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A HeteroSampler! (“Heterogeneous Sampler”)

– Focus computation to where needed.

Framework

Definition

Action A_j updates part y_j based on

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Example

Example		I	think	now	is	the	right	time
Input x_j				x_3				
Output y_j				y_3				
Action A_j				A_3				

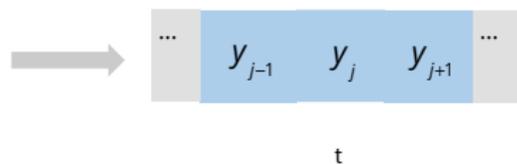
A_3 samples y_3 from $p(y_3 | y_{-3}, \mathbf{x})$

Sampler Template

Our sampler: for total of T rounds, do

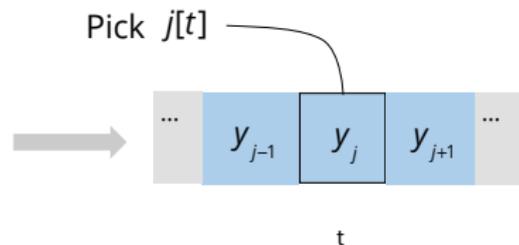
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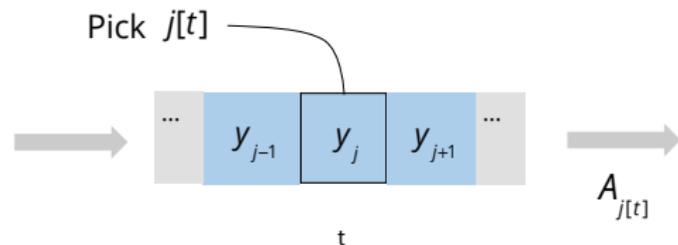
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1. **Pick** index j and the action A_j .

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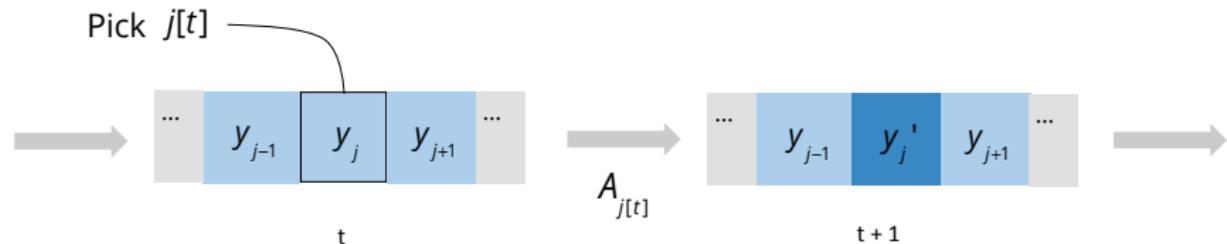
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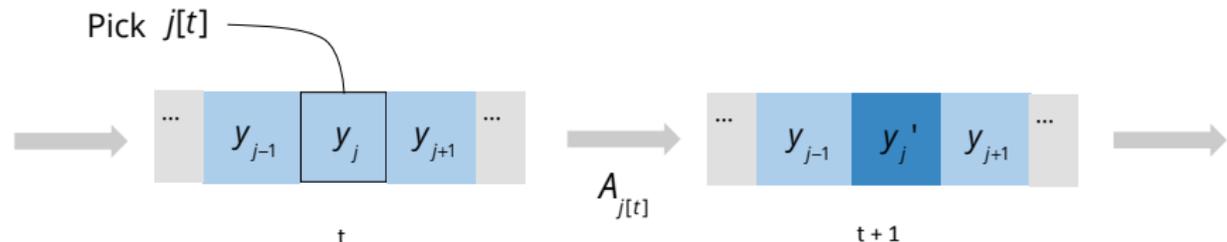
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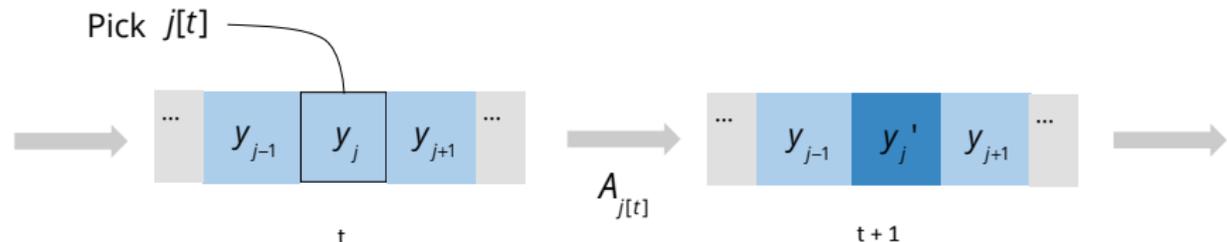
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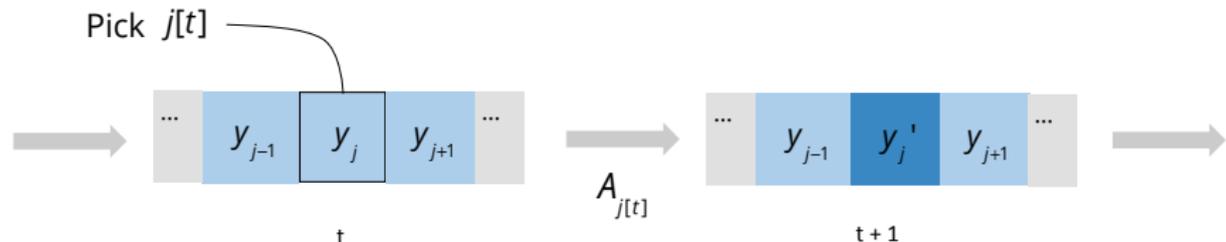
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- ▶ **Random-Scan Gibbs sampler.** Pick j uniformly at random.

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How to choose j ?

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Reinforcement Learning

- ▶ **State** = Entire history with configurations $\mathbf{y}[i]$ and choices $j[i]$

$$s_t = (\mathbf{y}[0] \dots, \mathbf{y}[t], j[0], \dots, j[t-1])$$

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- ▶ **Reward** = Improvement in log-probability

$$\mathcal{R}(s_t, a_t, s_{t+1}) = \log p(\mathbf{y}[t+1] | \mathbf{x}) - \log p(\mathbf{y}[t] | \mathbf{x})$$

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Remark

$$\text{Cumulative reward} = \log p(\mathbf{y}[T] | \mathbf{x}) - \log p(\mathbf{y}[0] | \mathbf{x}) \quad (1)$$

Maximizing cumulative reward is equivalent to maximizing probability of final sample.

Learning Algorithm

Inspired by standard RL (Q-learning [Watkins et al. 1992], SARSA [Rummery et al. 1994]),

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x	I	think	now	is	the	right	time
$y[0]$	P	V	Adv	V	DT	N	N
$Q(s, a)$	0.0	0.0	2.0	0.0	0.0	2.3	0.0

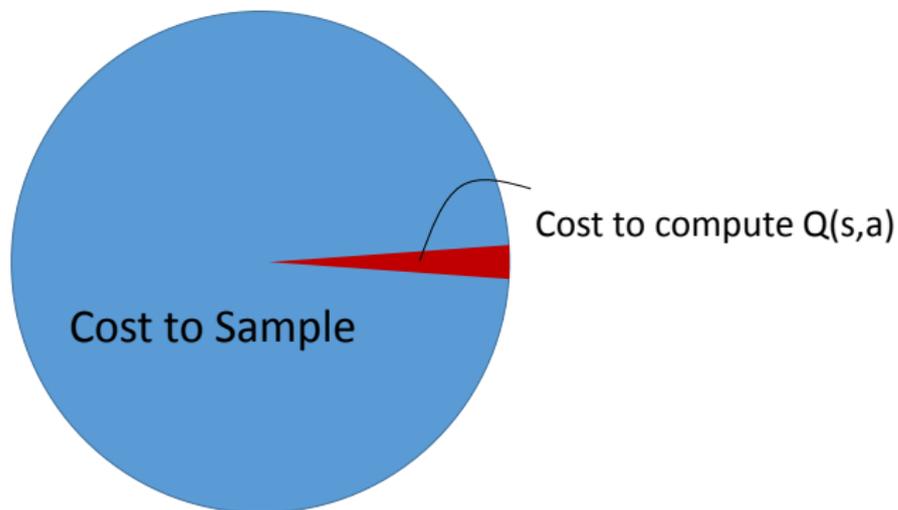
Applying RL

Challenge: Efficiency

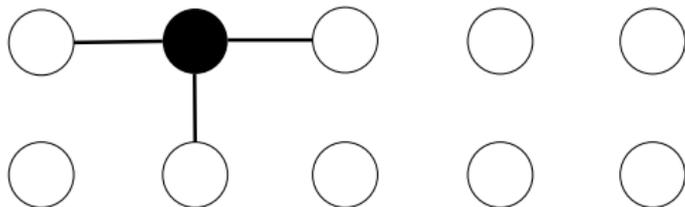
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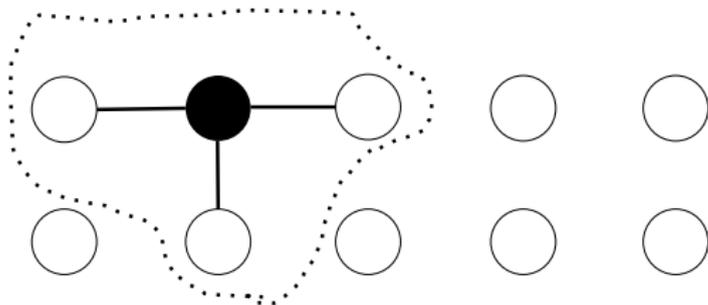
$Q(s, a)$ should be cheap to compute, so it does not become the computational bottleneck.



Applying RL: Efficiency

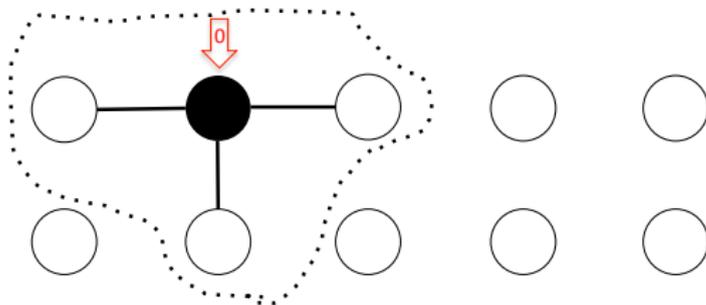


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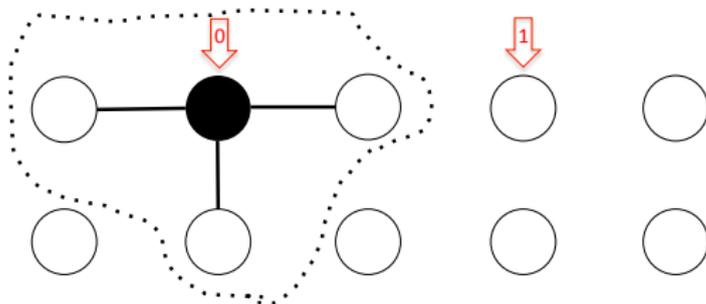
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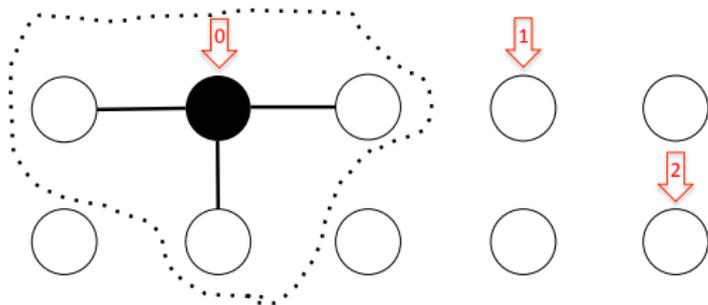
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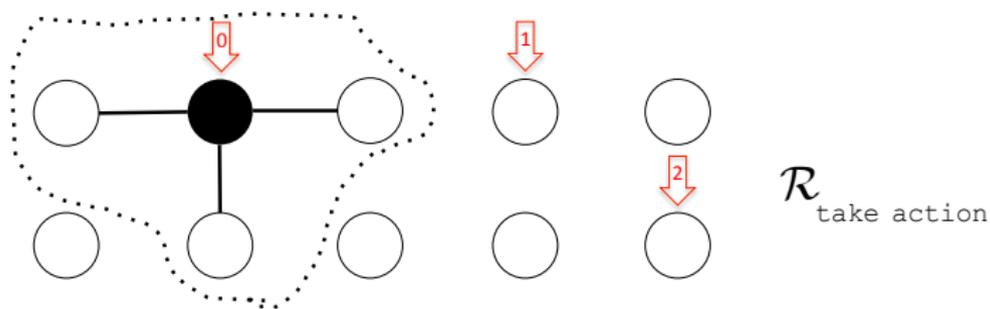
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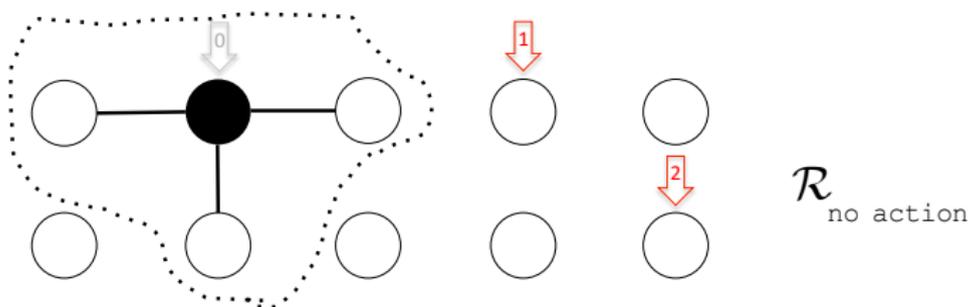
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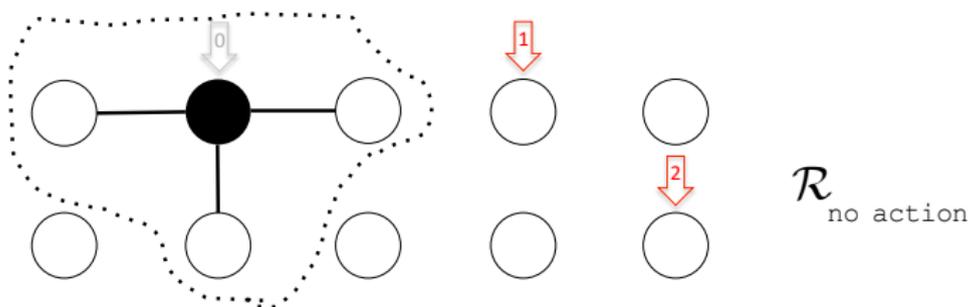
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	sp	number of times sampled
Staleness	nb-vary	number of neighbors changed
Discord	nb-discord	discord with neighbors

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Uncertainty

Feature I. Entropy

The entropy of $q(y_j|y_{-j}, \mathbf{x})$.

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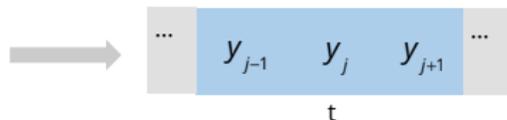
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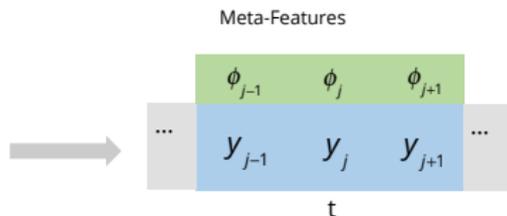
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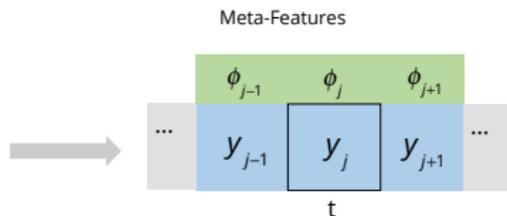
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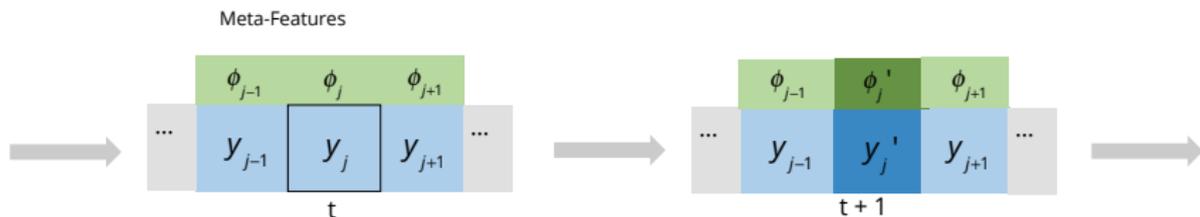
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Example

x | The Duchess was entertaining | $\text{sp}(y_3)$

Uncertainty

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Example

x	The	Duchess	was	entertaining	sp(y_3)
y[0]	Determiner	Noun	Verb	Adjective	0

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Example

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y[1]	Determiner	Noun	Verb	Verb	1

Uncertainty

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Example

x	The	Duchess	was	entertaining	$sp(y_3)$
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Uncertainty

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y[3]	Determiner	Noun	Verb	Verb	3

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Feature II. Over-exploration

number of times y_j has been sampled thus far.

- ▶ simplest measure of the progress in exploration.
- ▶ usually has negative weight.

Staleness

3. Change of Markov Blanket

#variables in Markov blanket that have changed.

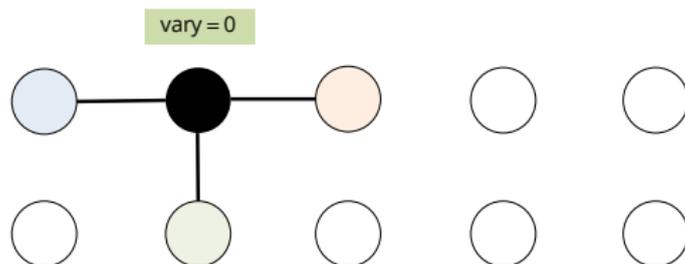
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Staleness

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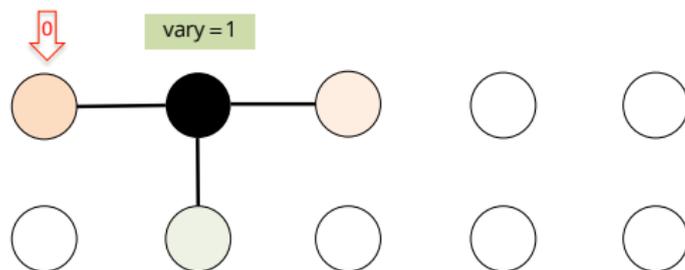


Staleness

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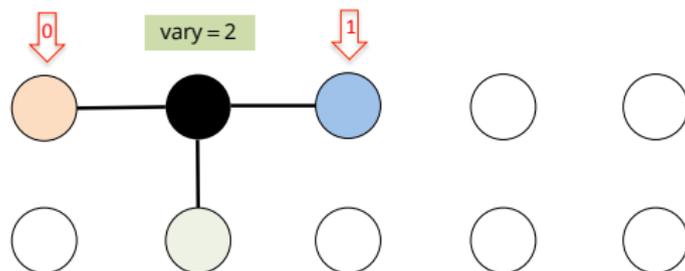


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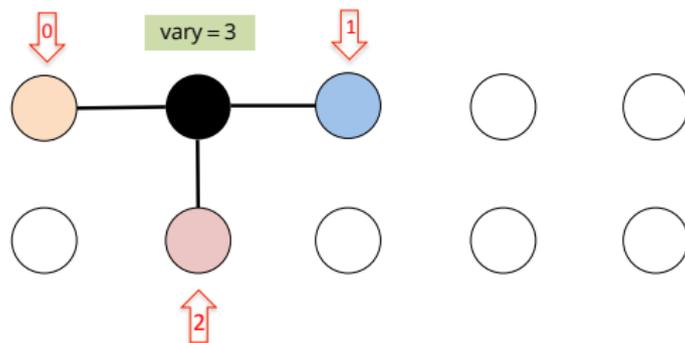


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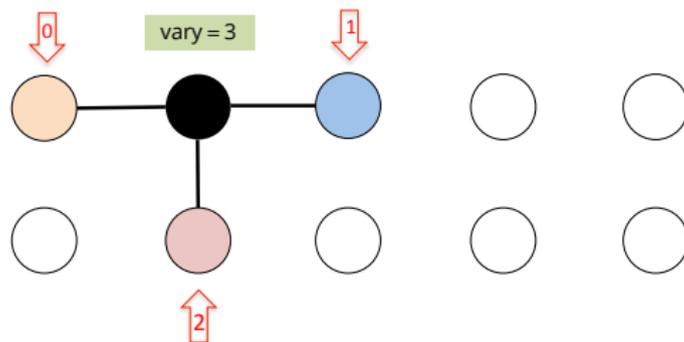


Staleness

3. Change of Markov Blanket

#variables in Markov blanket that have changed.

- ▶ Identify outdated variables.



- ▶ Reason about very-lazy evaluation.

Outline

Introduction

Reinforcement Learning

Meta-Features

Experiments

Experiment Outline

Tasks

KANSAS	CITY
B-ORG	I-ORG
B-LOC	I-ORG
B-LOC	I-LOC

Part-of-speech tagging and name-entity recognition.



Handwriting recognition.



Color inpainting.



Scene decomposition.

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1. “Steal” a graphical model with transitions.

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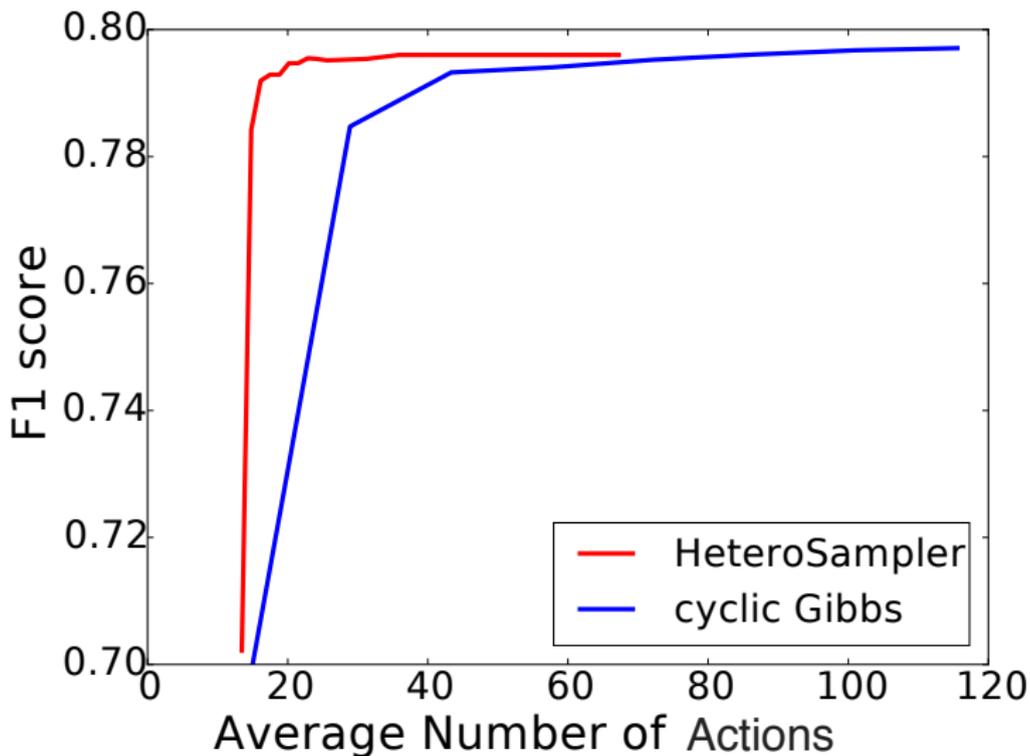


Scene decomposition.

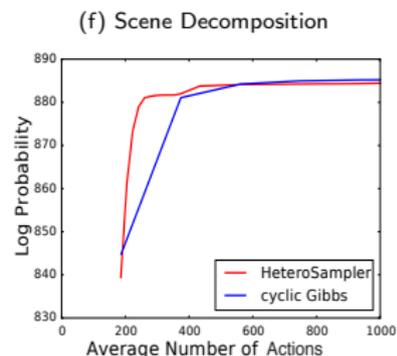
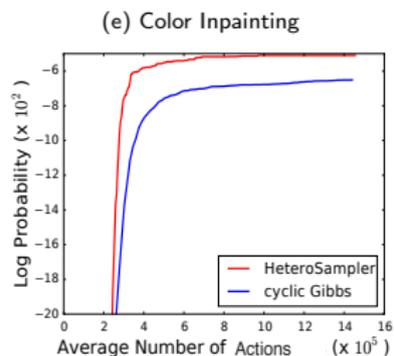
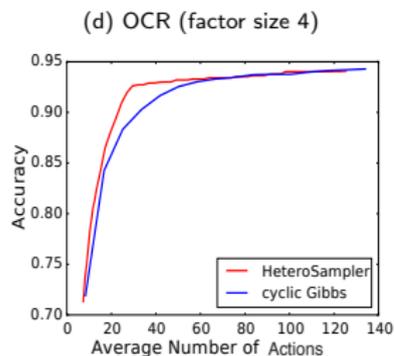
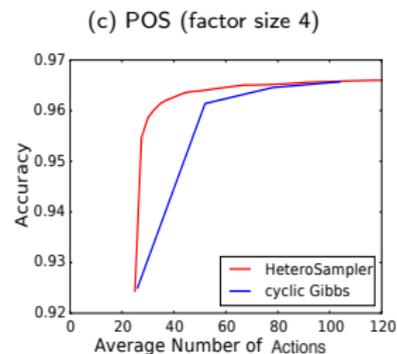
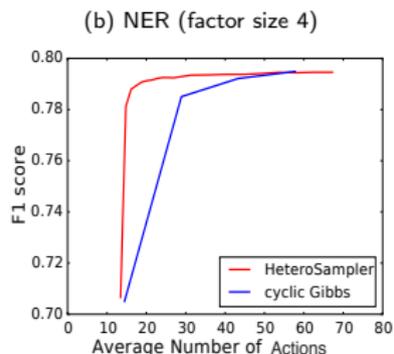
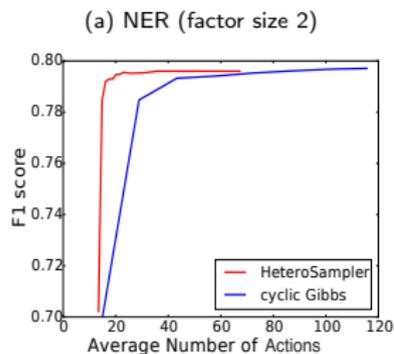
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2. Train the policy using RL on a training set.
3. Evaluate the policy on a test set.

Speedup on NER

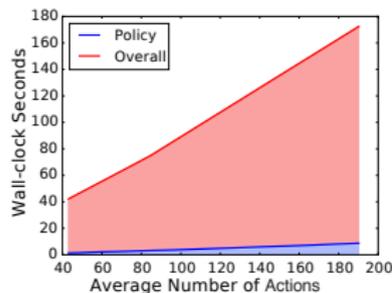


2-5X Speedup across tasks

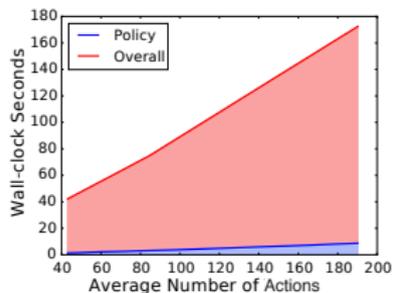


Overhead of meta-model is minimal

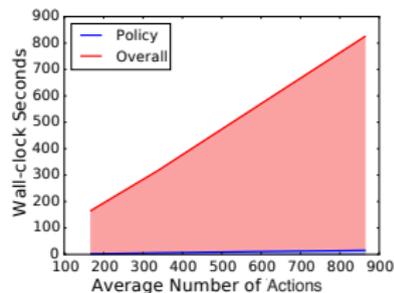
(a) NER (factor size 2)



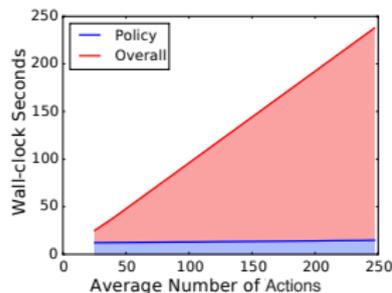
(b) NER (factor size 4)



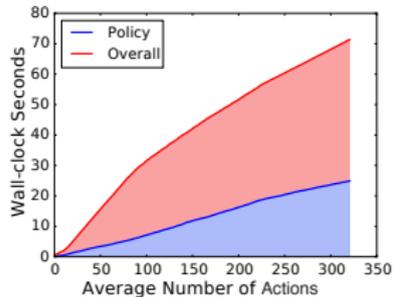
(c) POS (factor size 4)



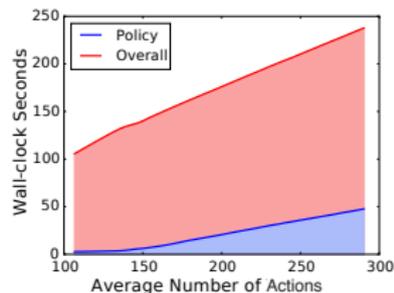
(d) OCR (factor size 4)



(e) Color Inpainting



(f) Scene Decomposition



Qualitative Results

Visualization of computational resource allocation on NER:

Words	Japan	coach	Shu	Kamo	said	:	'	'	The	Syrian	own	goal	proved	lucky	for	us
Truth	B-LOC	O	B-PER	I-PER	O	O	O	O	O	B-MISC	O	O	O	O	O	O
1	I-ORG	O	B-PER	I-PER	O	O	O	O	O	B-LOC	O	O	O	O	O	O
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(a) Cyclic Gibbs sampler

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(b) HeteroSampler

Related Work

Heterogenous Inference

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RL for structured prediction

- ▶ SEARN [Daume et al., 2009]
- ▶ DAGGER [Ross et al., 2011a]
- ▶ RL for dependency parsing [Goldberg and Nivre, 2013]

Contribution

Take-way Message: Sample Heterogeneously!

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Important Ideas

1. It is effective to reason about **uncertainty**, **staleness**, etc.
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Thanks!

