Gradient-based Inference for Networks with Output Constraints

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Output constraints?

Gradient-based Inference for Networks

with **Output Constraints**

Constraints?

- **Grammar (example 1)**
  - I are presenting on my thesis proposal.
  - I am presenting on my thesis proposal.

  - The keys is on the table.
  - The keys are on the table.

  - The keys to the cabinet is on the table.
  - The keys to the cabinet are on the table.

Linzen et al, Assessing the Ability of LSTMs to Learn Syntax-Sensitive Dependencies, 2016

Constraints?

- **Grammar (example 1)**
  - I are presenting on my thesis proposal.
  - I am presenting on my thesis proposal.

  - The keys is on the table.
  - The keys are on the table.

  - The keys to the cabinet is on the table.
  - The keys to the cabinet are on the table.

Constraint violating

If subject, verb do not agree. (singular/plural)

Linzen et al, Assessing the Ability of LSTMs to Learn Syntax-Sensitive Dependencies, TACL 2016

Constraints?

- **Image-captioning (example 2)**

Input (image)

Output (caption) A woman is talking on a cell phone.

Rohrbach et al, Object Hallucination in Image Captioning, EMNLP 2018

Constraints?

- **Image-captioning (example 2)**

Input (image)

Constraint violating

If an entity/object not present in the picture appears on the caption.

Output (caption)

A woman is talking on a cell phone.

A woman is talking on a cell phone while sitting on a bench.

A woman is talking to a mouth.

A woman is talking to a pizza.

Rohrbach et al, Object Hallucination in Image Captioning, EMNLP 2018

Constraints?

- **Image-captioning (example 2)**

Input (image)

Constraint violating

If an entity/object not present in the picture appears on the caption.

Output (caption)

A woman is talking on a cell phone.

A woman is talking on a cell phone while sitting on a bench.

A woman is talking to a mouth.

A woman is talking to a pizza.

Probably wrong, but would be another constraint.

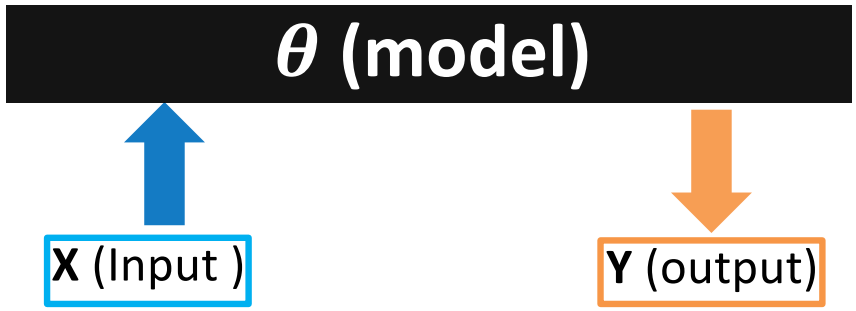
Rohrbach et al, Object Hallucination in Image Captioning, EMNLP 2018

Neural Network

Gradient-based Inference for
Networks with Output Constraints

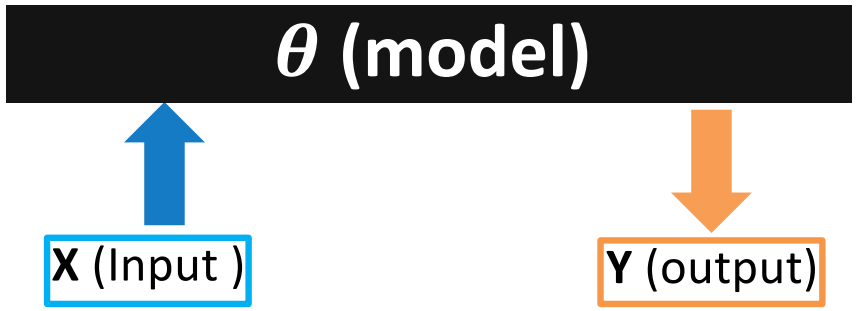
Typical neural model training

- A black box is trained with cross-entropy loss
  - Maximizing log-likelihood of (input, true output) pair.
  - Often requires massive amount of data.



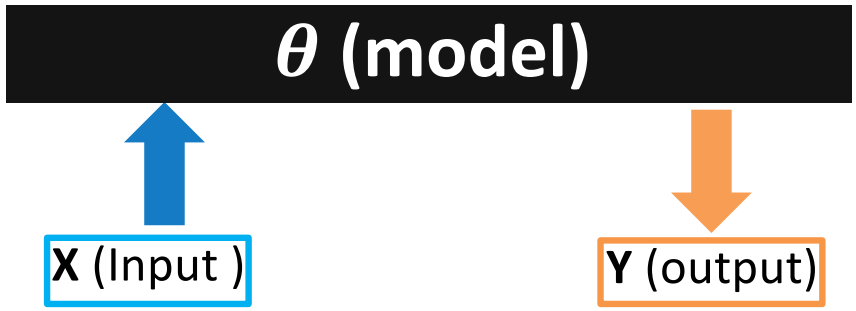
Typical neural model training

- Black box trained with cross-entropy loss
  - Maximizing log-likelihood of (input, true output) pair.
  - Often requires massive dataset. (not very good on small data)
- Can we ***leverage the known constraints?***



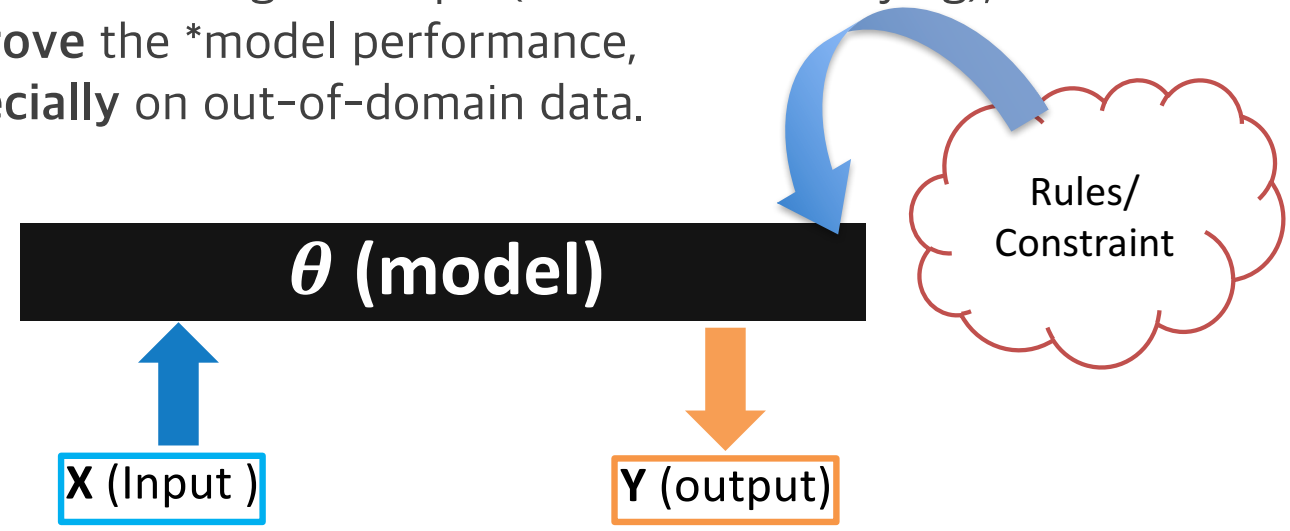
Challenges in injecting constraints

- Training set
  - constraint-satisfying instances (input ,true output)
  - Thus, constraint is ***"not explicit"*** on training set.
- Hard to write 'if-else' inside black box.



Goal of constraint injection

- Injection of constraint to
  - **Provide** more logical output(constraint-satisfying),
  - **Improve** the *model performance,
  - **Especially** on out-of-domain data.



Roadmap

- Focus of our work
- **Applications & constraints**
- Gradient-Based Inference formulation
- Experiments
- Conclusion

Considered Application

- *Transduction (toy)*
  - A transducer (T) is a function from a
    'source language' (L_s) to a 'target language' (L_T).

$$T : \mathcal{L}_S \rightarrow \mathcal{L}_T$$

Transduction constraints

- *Transduction (toy)*
  - A transducer (T) is a function from a 'source language' (L_s) to a 'target language' (L_T).

$$T : \mathcal{L}_S \rightarrow \mathcal{L}_T$$

Multiple (input, output) pairs

[Source] azazbz ⬇ [Target] aaaaaazb

...

[Source] azbzazbzbzaazbzbzbzbzbz ⬇ [Target] aaazbaaazbzbaaaaaazbzbzbzbzb

Transduction constraints

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  - A transducer (T) is a function from a 'source language' (L_s) to a 'target language' (L_T).

$$T : \mathcal{L}_S \rightarrow \mathcal{L}_T$$

e.g.)
T: az → aaa
bz → zb

S: azazbzazbzbazbzbzbzbzbz

T: aaaaaazbaaazbzbaaazbzbzbzbzb

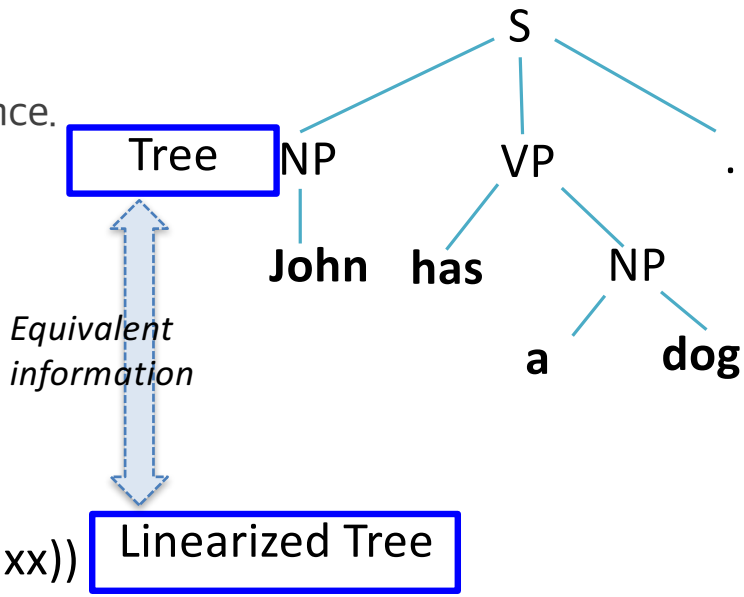
constraint:
3 x (# a in **S**) = # a in **T**

Considered Applications in NLP

- *Syntactic Parsing*
  - Finding structure of the provided (input) sentence.

John has a dog .

(S (NP xx) (VP xx (NP xx xx))



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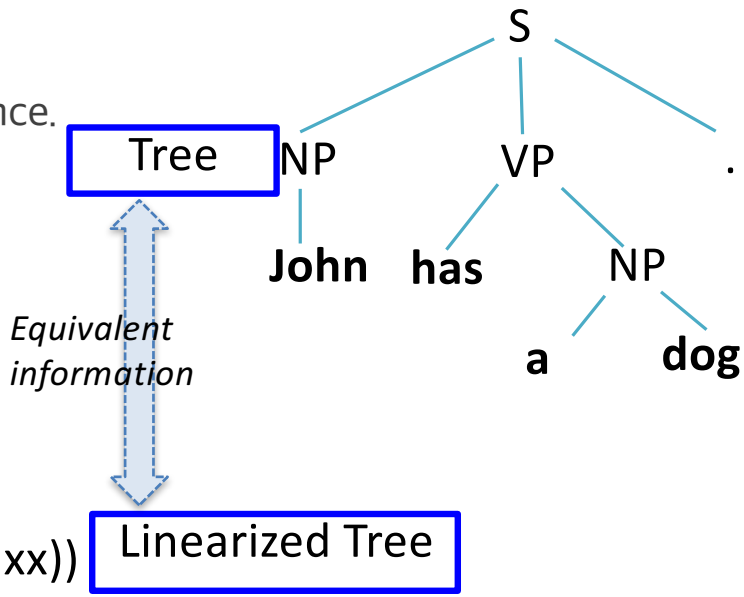

To use *Sequence-to-Sequence* model:

models relationship between *sequence* input & *sequence* output.

Constraints in Parsing

- *Syntactic Parsing*
  - Finding structure of the provided (input) sentence.

John has a dog

True:

(S (NP xx) (VP xx(NP xx xx))

Others:

(S (NP xx) (VP xx (NP xx xx)))))

((S (NP xx) (VP xx (NP xx xx))

(S (NP xx)))(VP xx (NP xx xx)))

(S (NP xx xx xx xx xx))

(S (NP xx) (VP xx xx xx))

Now you use seq2seq model,
The model might generate constraint-violating outputs

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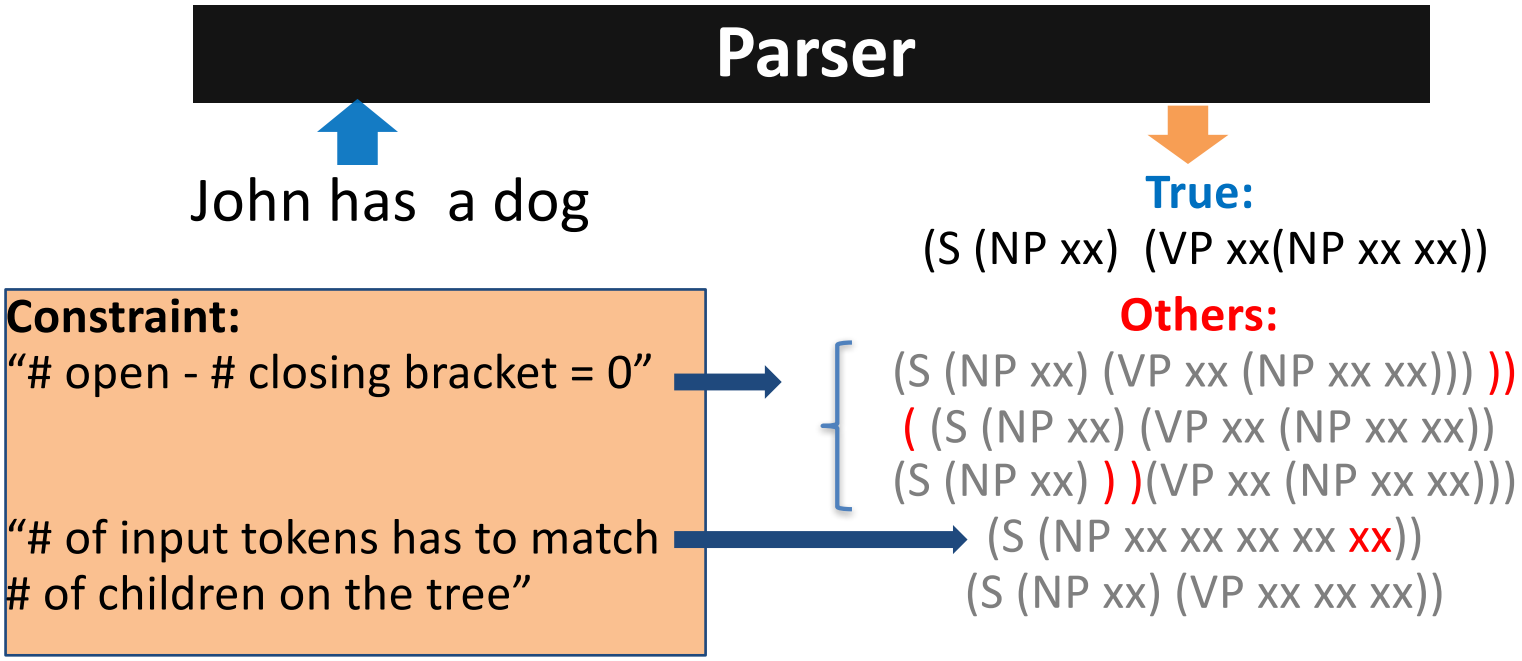

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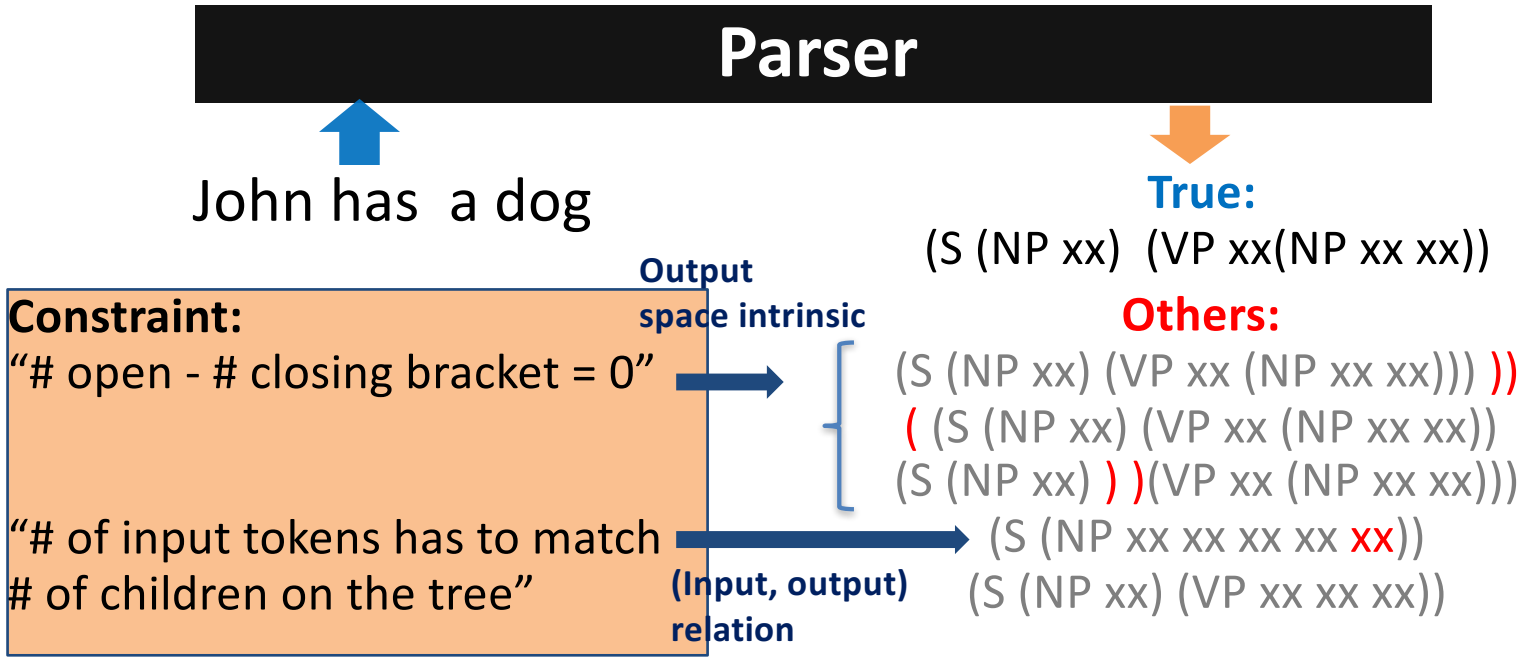

Considered Applications in NLP

- *Semantic Role Labeling (SRL)*
  - Finding (Agent (arg0), Patient (arg1)) given verb

John broke the window with a hammer.
verb: broke

ARG0: John
ARG1: the window
ARG2: a hammer

Semantic Role Labeling

- Application 1: Semantic Role Labeling (SRL)
  - Finding (Agent (arg0), Patient (arg1)) given verb

John broke the window with a hammer.

agent
(actor of an action)

patient
(entity affected by the action)

instrument
(tool used in performing action)

Semantic Role Labeling

- Application 1: Semantic Role Labeling
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(tool used in
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Core Roles: Verb specific roles (ARG0, ARG1, …, ARG5)

Verb: break

Role	Description
ARG0	breaker (agent)
ARG1	thing broken (patient)
ARG2	instrument used
…	…

Adjunct roles: Shared across all verbs

Role	Description
ARGM-TMP	temporal
ARGM-DIR	direction
ARGM-LOC	location
…	…

Application using SRL

- **Question answering (5W1H)**
  - "Who" questions usually use Agents. (Arg0)
  - "What" questions usually use Patients. (Arg1)
  - "How" and "with what" questions usually use Instruments. (Arg2)
  - "Where" questions frequently use Sources and Destinations . (ARGM-LOC)
  - "For whom" questions usually use Benefactives. (Arg1)
  - "To whom" questions usually use Destinations.

Semantic Role Labeling

- Application 1: Semantic Role Labeling
  - Finding (Agent (arg0), Patient (arg1)) given verb

John broke the window with a hammer.
verb: broke

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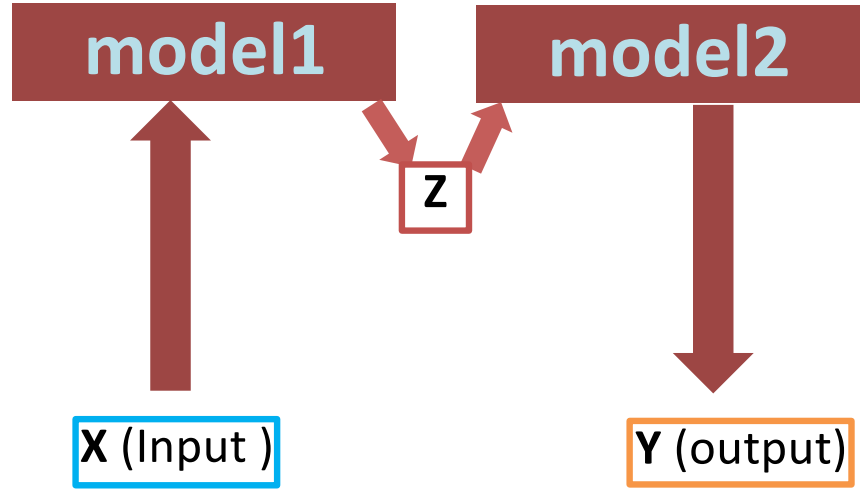
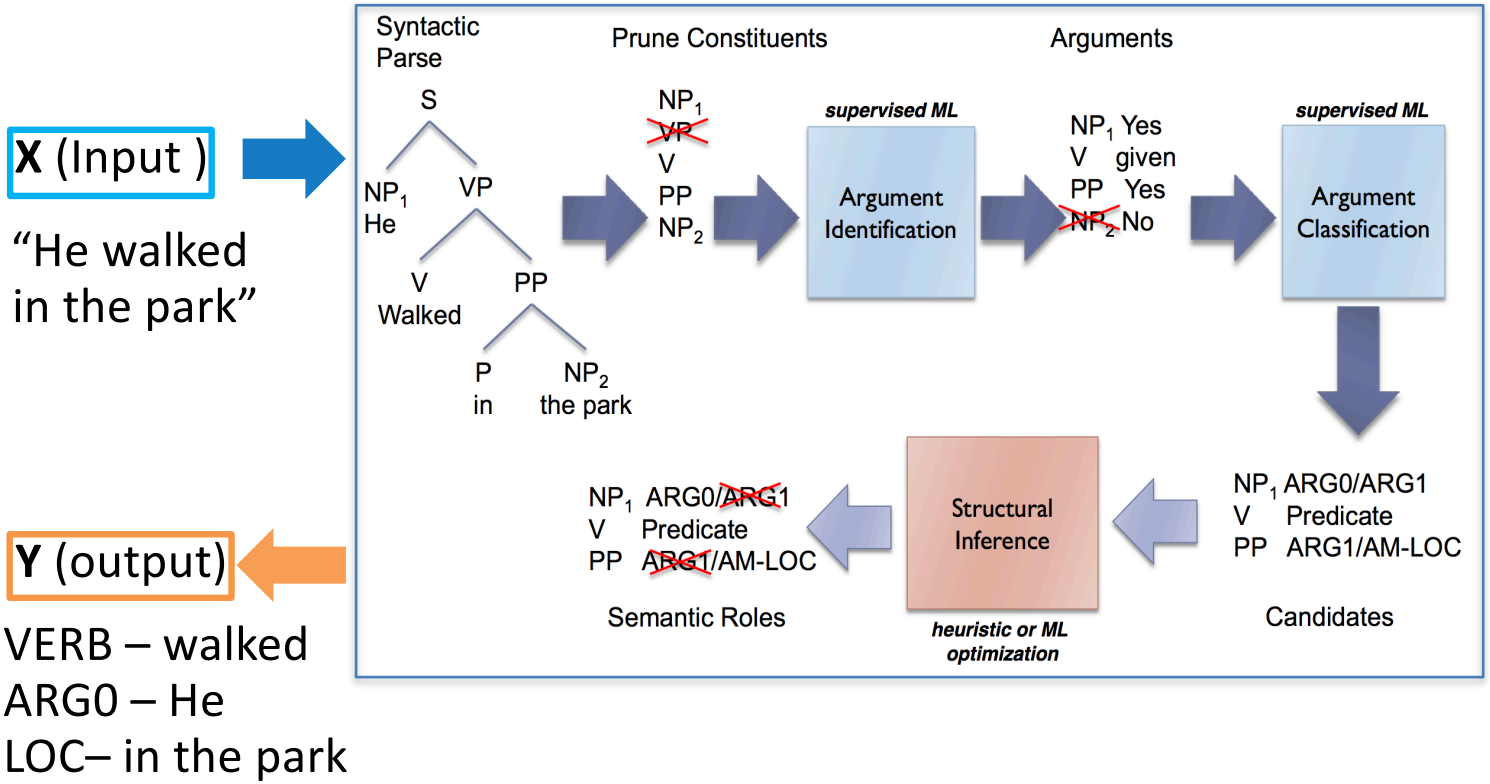
Complex task

- Complex task (sometimes) is sometimes easier to model when the task is divided into multiple ones



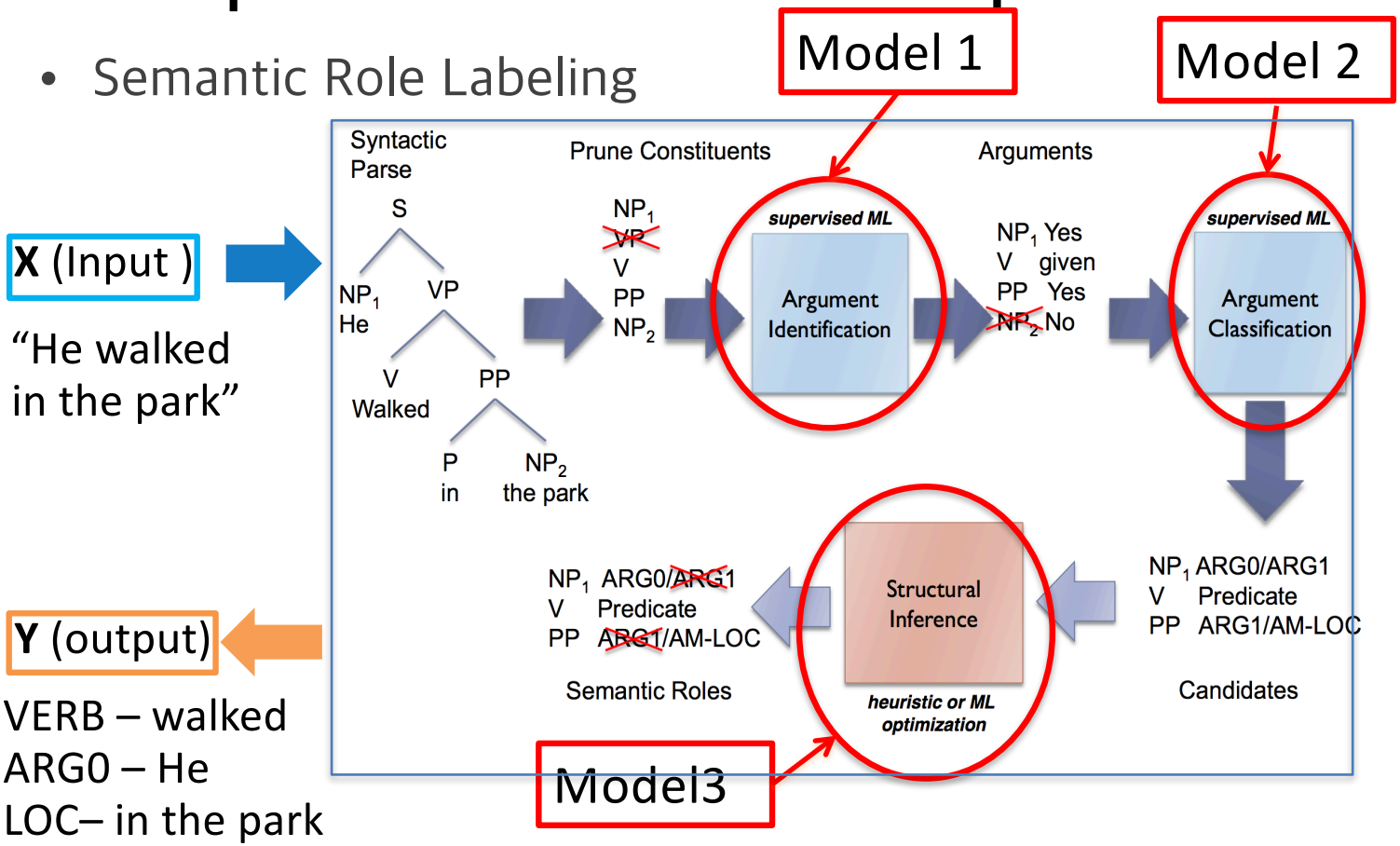
Complex models - example

- Semantic Role Labeling (step by step)



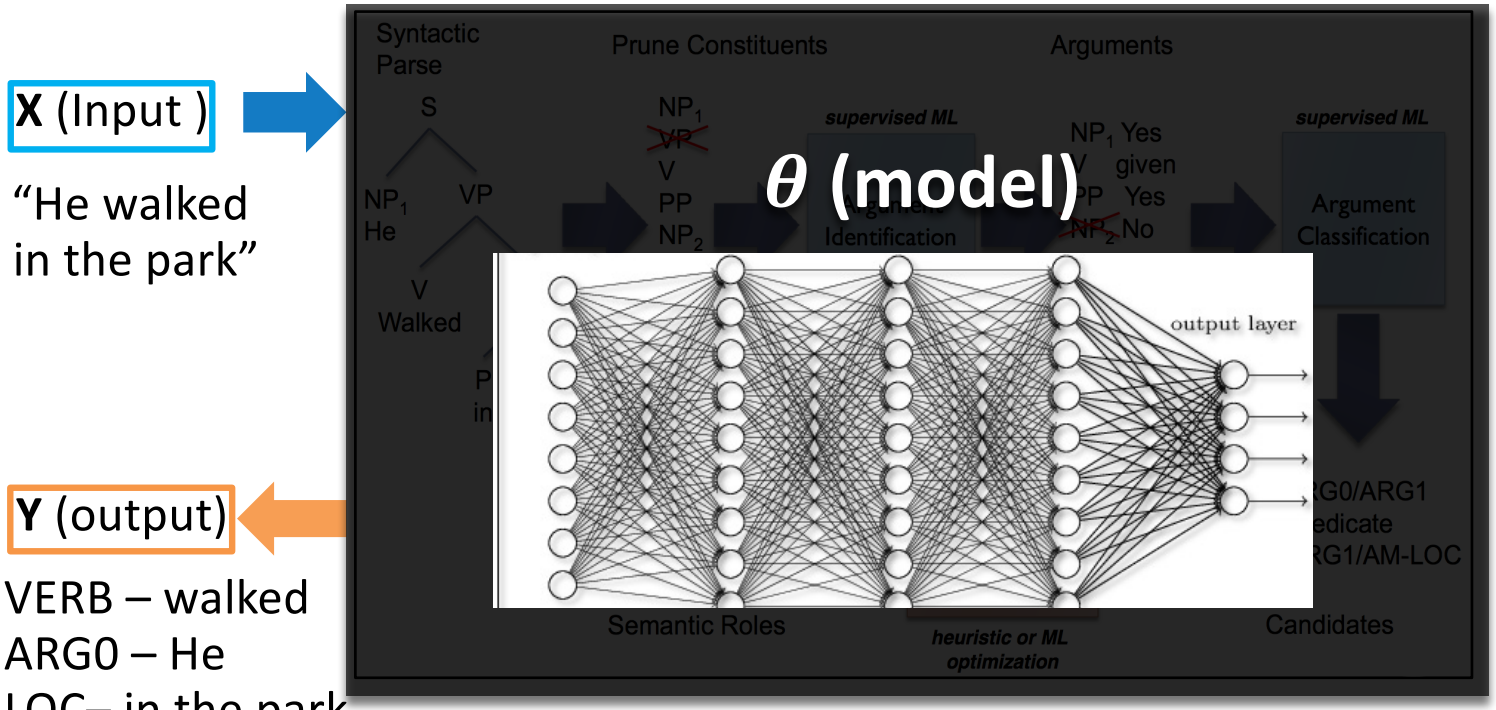
Complex models - example

- Semantic Role Labeling



Complex models to End-to-End

- End-to-end Semantic Role Labeling.
  - Neural models often perform better on ***end-to-end*** learning.



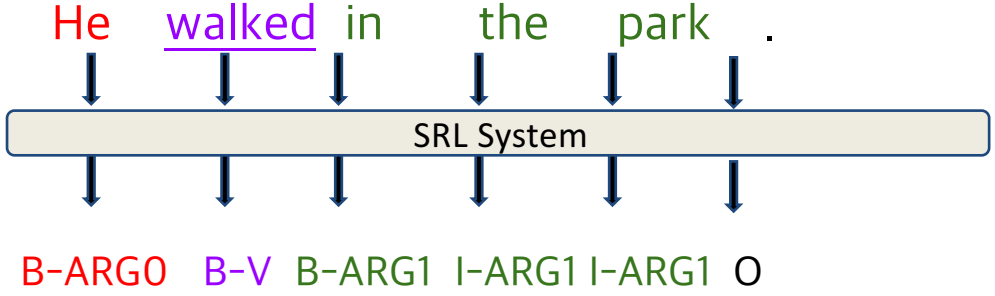
How to solve it?

Formulate the problem as a **BIO tagging problem.**

Input: a sentence-predicate pair (x,verb)

Output: a sequence of tags y, where $y_i \in \Omega$ (a set of BIO tags)

Example:



Slide credits: Sanket Metha

What are different constraints for SRL task?

1. BIO constraints
   - Constraint violation: B-ARG0 followed by I-ARG1
   - (similar to the constraints in Parsing example)

2. SRL constraints (as defined by Punyakanok et al. (2008))
   - Unique core roles (U)
   - Continuation roles (C)
   - Reference roles (R)

3. Syntactic constraints
   - Constraint violation: Arguments that are not constituents within a given parse tree

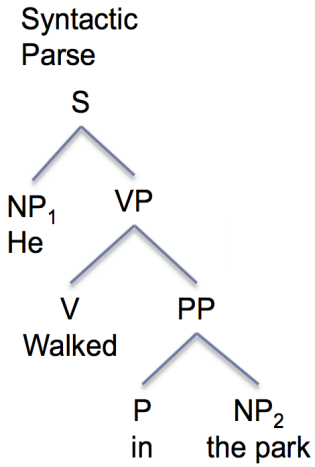
Slide credits: Sanket Metha

Syntactic constraint on SRL

- Given syntax tree, span candidates were ***limited*** by syntactic information.

X (Input)

"He walked in the park"



Possible span candidate

(He), (walked), (in the park),
(walked in the park),
(He walked in the park)

(He) (walked) (in the park)

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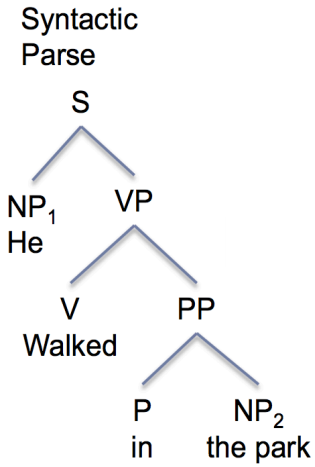

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(He) (walked) (in the park)
(He) (walked in)(the park)
(He walked) (in the park)
(He walked in the)(park)
(He walked in the park)

However, end-to-end model without syntactic information can generate **all possible** "spans" given sentence.

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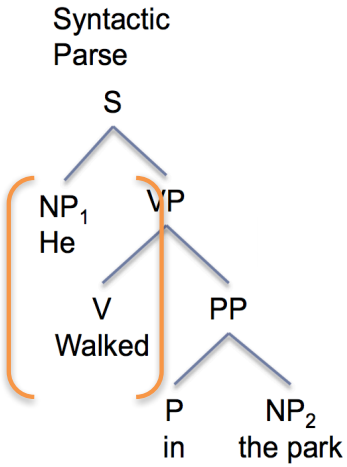

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~~(He walked)~~ ~~(in the park)~~
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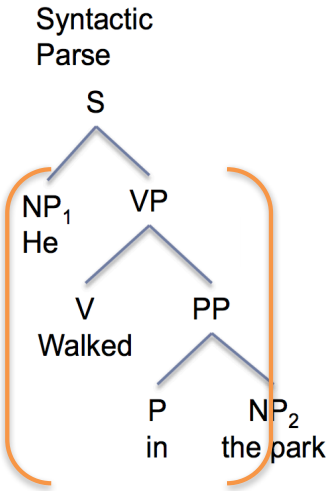

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(He) (walked) (in the park)

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~~(He walked)~~ ~~(in the park)~~

~~(He walked in the)(park)~~

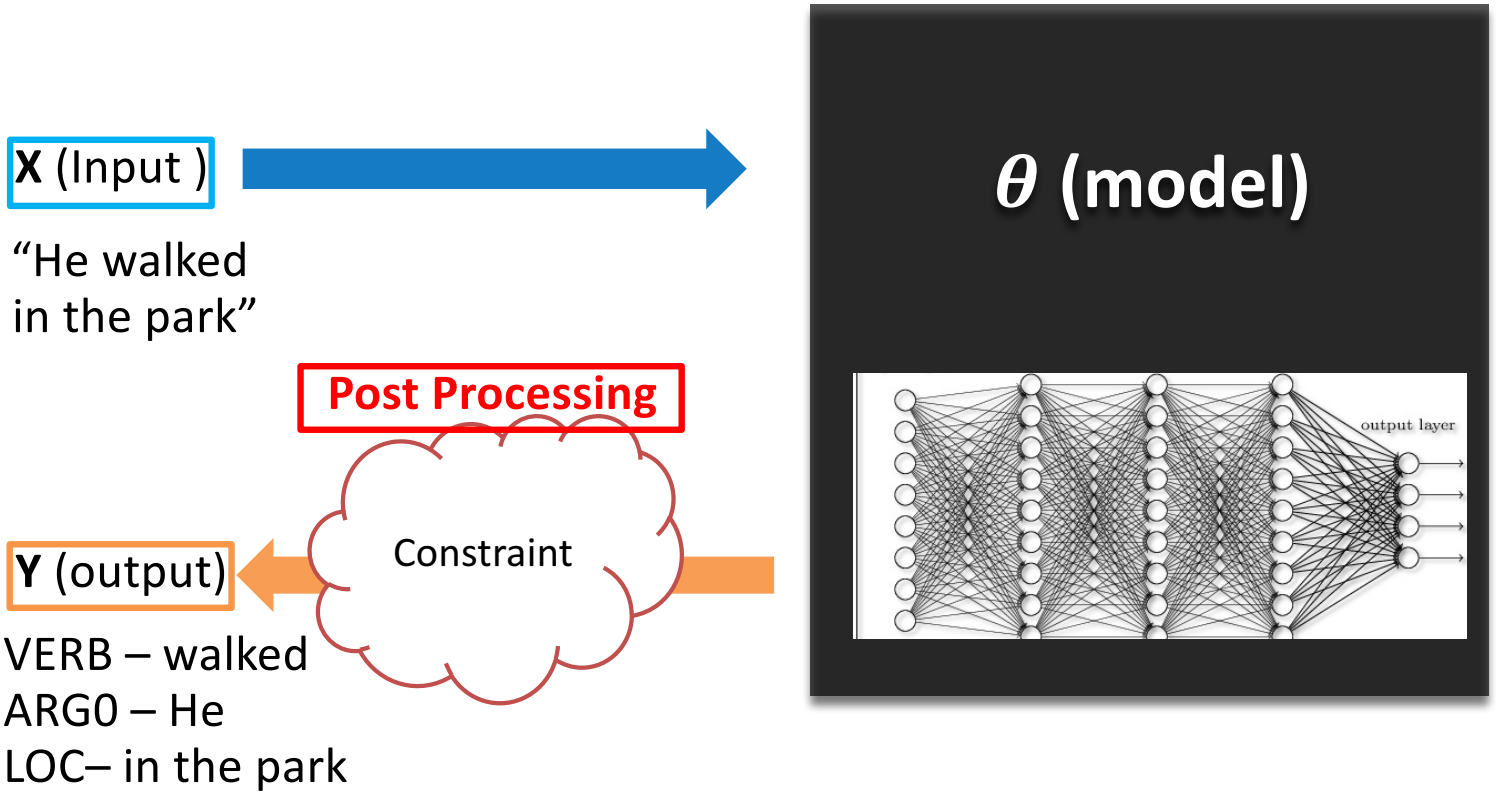
(He walked in the park)

However, end-to-end model without syntactic information can generate all possible "spans" given sentence.

Constraint-violating

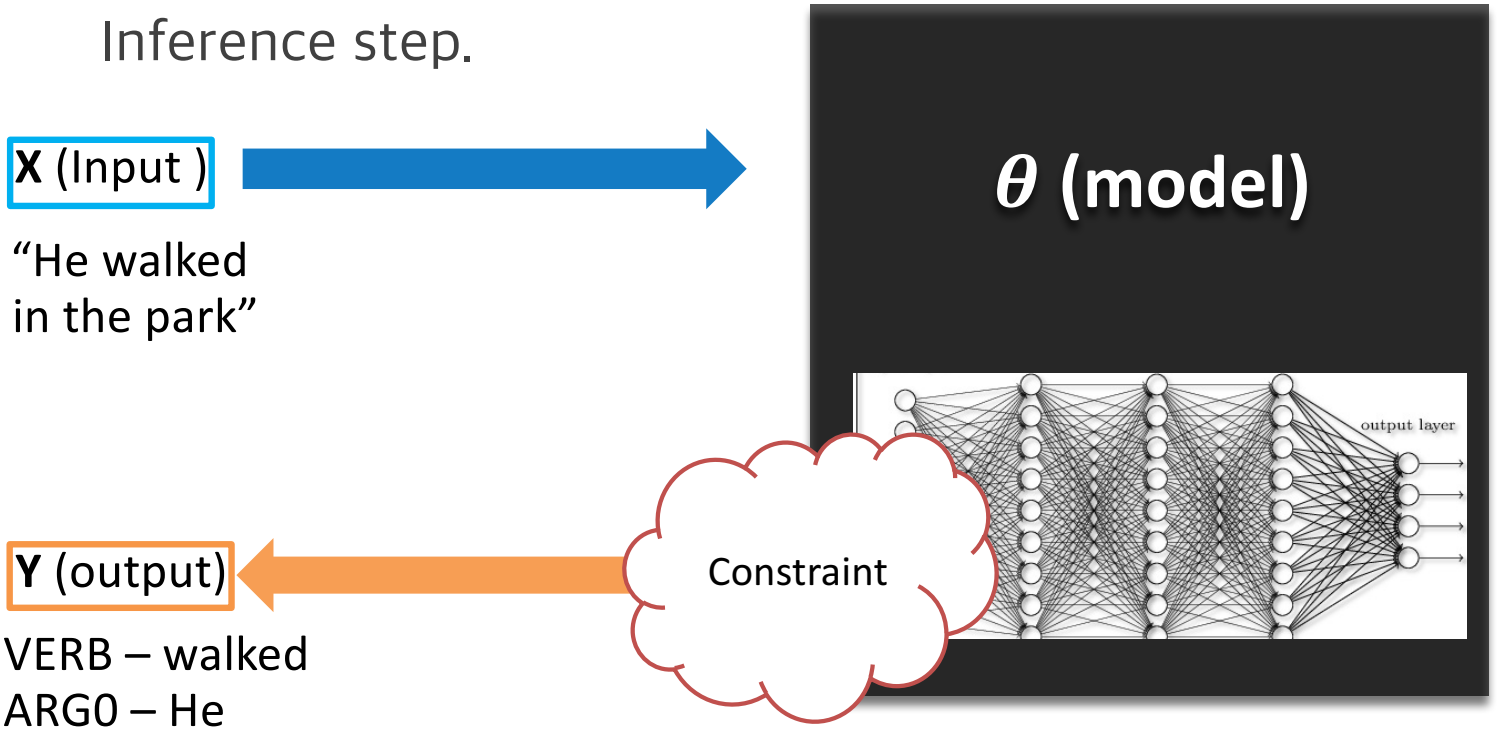
Inference using constraint

- Inference: Finding the best output given the model.



Inference using constraint

- **Proper "Injection of constraints"** to the **model** on Inference step.



Roadmap

- Focus of our work
- Applications & constraints
- **Gradient-Based Inference formulation**
- Experiments
- Conclusion

Gradient-Based Inference* (GBI)

- Inference
  - Finding the output with the highest model probability.

$$\max_{\mathbf{y}} \quad \Psi(\mathbf{x}, \mathbf{y}, W)$$

Learned model

Gradient-Based Inference* (GBI)

- Inference
  - Finding the output with the highest model probability.

$$\max_{\mathbf{y}} \quad \Psi(\mathbf{x}, \mathbf{y}, W)$$

  - Given length *m*, vocabulary size *V,* the search space becomes V^m.
    - Viterbi decoding (exact)
  - Sequence-to-sequence models have no limit to length *m,* thus the search space is larger.
    - Greedy decoding, beam decoding

Constraint function

- Constraint (evaluation) function. (Error counting) $g(\mathbf{y}, \mathcal{L}) \rightarrow \mathbb{R}_0^+$
- no constraint violation $\Longleftrightarrow$ $g(\mathbf{y}, \mathcal{L}) = 0$

Constraint function

- Constraint evaluation function. $g(\mathbf{y}, \mathcal{L}) \rightarrow \mathbb{R}_0^+$
  (degree of error, higher the more error)
- no constraint violation $\longleftrightarrow$ $g(\mathbf{y}, \mathcal{L}) = 0$
- Optimization with constraints

$$\max_{\mathbf{y}} \quad \Psi(\mathbf{x}, \mathbf{y}, W) \qquad \text{s.t.} \quad \mathbf{y} \in \mathcal{L}^{\mathbf{x}}$$

$$\Rightarrow$$

$$\max_{\mathbf{y}} \quad \Psi(\mathbf{x}, \mathbf{y}, W) \qquad \text{s.t.} \quad g(\mathbf{y}, \mathcal{L}^{\mathbf{x}}) = 0$$

Constraint
for feasible set L^x

Gradient-Based Inference* (GBI)

- Inference with constraint
  - Finding the output with the highest model probability given (local, global)constraint.

$$\max_{\mathbf{y}} \quad \Psi(\mathbf{x}, \mathbf{y}, W)$$
$$\text{s.t.} \quad g(\mathbf{y}, \mathcal{L}^{\mathbf{x}}) = 0$$

constraint

  - Given length *m*, vocabulary size *V*, the search space becomes V^m.
    - Viterbi decoding (exact), **A* algorithm (DP)**
  - Sequence-to-sequence models have no limit to length *m*, thus the search space is larger.
    - Greedy decoding, beam decoding

Gradient-Based Inference* (GBI)

- Inference with constraint
  - Finding the output with the highest model probability given (local, global)constraint.

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  - Given length *m*, vocabulary size *V,* the search space becomes V^m.
    - Viterbi decoding (exact), A* algorithm (inexact DP)
  - Sequence-to-sequence models have no limit to length *m,* thus the search space is larger.
    - Greedy decoding, beam decoding

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  - Given length *m*, vocabulary size *V,* the search space becomes V^m.
    - Viterbi decoding (exact), A* algorithm (inexact DP)
  - Sequence-to-sequence models have no limit to length *m*, thus the search space is larger.
    - Approximate by greedy decoding, beam decoding

Very slow on exponential search space

Fast but localized approach thus cant incoporate 'global' constraint. (not localizeable)

Gradient-Based Inference (GBI)

- Optimization with constraints

$$\begin{aligned} \max_{\mathbf{y}} \quad & \Psi(\mathbf{x}, \mathbf{y}, W) \\ \text{s.t.} \quad & g(\mathbf{y}, \mathcal{L}^{\mathbf{x}}) = 0 \end{aligned}$$

Gradient-Based Inference (GBI)

- Optimization with constraints

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Combinatorial problem.

- Gradient-Based Inference (in math)

Can we search faster by changing model weights?

$$\begin{aligned} \min_{W_\lambda} \quad & \Psi(\mathbf{x}, \hat{\mathbf{y}}, W_\lambda) g(\hat{\mathbf{y}}, \mathcal{L}) + \alpha \|W - W_\lambda\|_2 \\ \text{where} \quad & \hat{\mathbf{y}} = \operatorname*{argmax}_{\mathbf{y}} \Psi(\mathbf{x}, \mathbf{y}, W_\lambda) \end{aligned}$$

Motivation

Gradient-Based Inference (GBI)

- Optimization with constraints

$$\begin{aligned} \max_{\mathbf{y}} \quad & \Psi(\mathbf{x}, \mathbf{y}, W) \\ \text{s.t.} \quad & g(\mathbf{y}, \mathcal{L}^{\mathbf{x}}) = 0 \end{aligned}$$

- Gradient-Based Inference

Likelihood

Constraint violation

$$\begin{aligned} \min_{W_\lambda} \quad & \Psi(\mathbf{x}, \hat{\mathbf{y}}, W_\lambda) g(\hat{\mathbf{y}}, \mathcal{L}) + \alpha \|W - W_\lambda\|_2 \\ \text{where} \quad & \hat{\mathbf{y}} = \operatorname*{argmax}_{\mathbf{y}} \Psi(\mathbf{x}, \mathbf{y}, W_\lambda) \end{aligned}$$

Motivation

Gradient-Based Inference (GBI)

- Optimization with constraints

$$\max_{\mathbf{y}} \quad \Psi(\mathbf{x}, \mathbf{y}, W)$$
$$\text{s.t.} \quad g(\mathbf{y}, \mathcal{L}^{\mathbf{x}}) = 0$$

Learned model weight

- Gradient-Based Inference

$$\min_{W_\lambda} \quad \Psi(\mathbf{x}, \hat{\mathbf{y}}, W_\lambda) g(\hat{\mathbf{y}}, \mathcal{L}) + \alpha \|W - W_\lambda\|_2$$
$$\text{where} \quad \hat{\mathbf{y}} = \operatorname*{argmax}_{\mathbf{y}} \Psi(\mathbf{x}, \mathbf{y}, W_\lambda)$$

Expected constraint violation

Regularizer

Motivation

Gradient-Based Inference (GBI)

- Optimization with constraints

$$\max_{\mathbf{y}} \quad \Psi(\mathbf{x}, \mathbf{y}, W)$$
$$\text{s.t.} \quad g(\mathbf{y}, \mathcal{L}^{\mathbf{x}}) = 0$$

Standard Lagrangian

$$\min_{\lambda} \max_{\mathbf{y}} \Psi(\mathbf{x}, \mathbf{y}, W) + \lambda g(\mathbf{y}, \mathcal{L})$$

Very slow. (combinatorial)
Especially global constraint

- Gradient-Based Inference (in math)

$$\min_{W_\lambda} \quad \Psi(\mathbf{x}, \hat{\mathbf{y}}, W_\lambda) g(\hat{\mathbf{y}}, \mathcal{L}) + \alpha \|W - W_\lambda\|_2$$
$$\text{where} \quad \hat{\mathbf{y}} = \operatorname*{argmax}_{\mathbf{y}} \Psi(\mathbf{x}, \mathbf{y}, W_\lambda)$$

Greedy, beam-search
relatively fast

Motivation

Gradient-Based Inference (GBI)

- Optimization with constraints

$$\max_{\mathbf{y}} \quad \Psi(\mathbf{x}, \mathbf{y}, W)$$
$$\text{s.t.} \quad g(\mathbf{y}, \mathcal{L}^{\mathbf{x}}) = 0$$

Standard Lagrangian

$$\min_{\lambda} \max_{\mathbf{y}} \Psi(\mathbf{x}, \mathbf{y}, W) + \lambda g(\mathbf{y}, \mathcal{L})$$

Combinatorial problem.

Very slow. (combinatorial)
Especially global constraint

- Gradient-Based Inference (in math)

Now, with expected constraint violation,
we can "reflect" global constraints.

Using the two, can we search faster by changing model weights?

$$\min_{W_\lambda} \Psi(\mathbf{x}, \hat{\mathbf{y}}, W_\lambda) g(\hat{\mathbf{y}}, \mathcal{L}) + \alpha \|W - W_\lambda\|_2$$
$$\text{where} \quad \hat{\mathbf{y}} = \operatorname{argmax}_{\mathbf{y}} \Psi(\mathbf{x}, \mathbf{y}, W_\lambda)$$

Greedy, beam-search
relatively fast

Roadmap

- Focus of our work
- Applications & constraints
- Gradient-Based Inference formulation
- **Research questions & Experiments**
- Conclusion

Research Questions

- **Q1.** Does GBI actually enforce constraints?
- **Q2.** Does GBI enforce constraints
  without compromising the quality of the system?
- **Q3.** Can GBI work over multiple baseline model?
- **Q4.** Performance of GBI on out-of-domain dataset?

Research Questions

- **Q1.** Does GBI actually ***enforce constraints*?**
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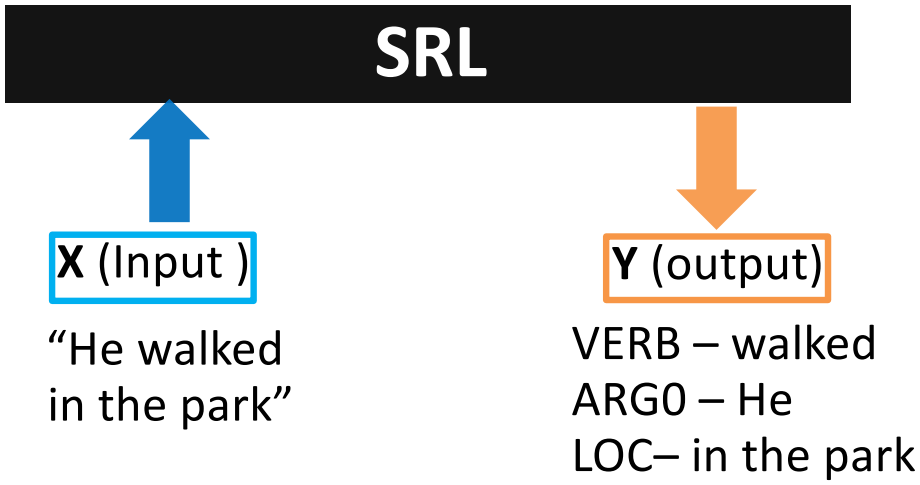
- **Q2.** Does **GBI enforce constraints**
  without compromising the ***F1 score*** of the system?
- **Q3.** *Can* ***GBI generalize*** over multiple baseline model?
- **Q4.** How is the performance of ***GBI on out-of-domain*** dataset?

Back to SRL

- Revisiting *Semantic Role Labeling (SRL)*
  - Finding (Agent (arg0), Patient (arg1)) given verb

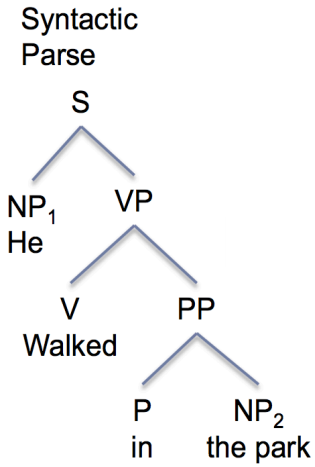


Syntactic constraint on SRL

- Given syntax tree, span candidates were ***limited*** by syntactic information.

X (Input)

"He walked in the park"



Possible span candidate

(He), (walked), (in the park),
(walked in the park),
(He walked in the park)

(He) (walked) (in the park)

~~(He) (walked in)(the park)~~

~~(He walked) (in the park)~~

~~(He walked in the)(park)~~

(He walked in the park)

Wrong spans marked with strike

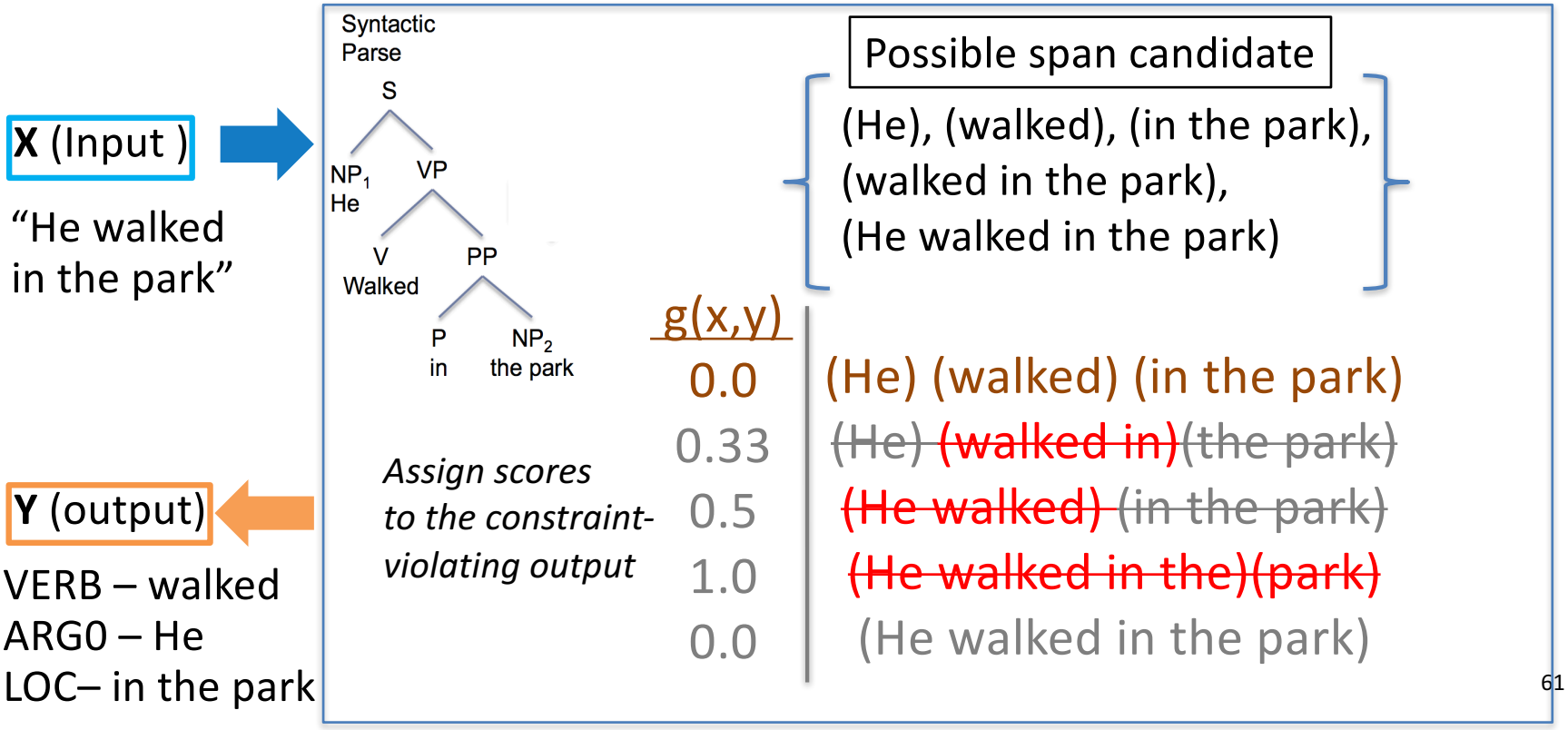
Constraint on SRL

- srl-spans(**y**): spans of predicted SRL output **y**
- parse-spans(**x**): parsing constituents without labels.
- disagreeing-spans(**x**,**y**) = $\{span_i \in \text{srl-spans}(\mathbf{y}) \mid span_i \notin \text{parse-spans}(\mathbf{x})\}$
- constraint function $g(\mathbf{x},\mathbf{y}) \geq 0$ on SRL

$$g(\mathbf{x}, \mathbf{y}) = \frac{|\text{disagreeing-spans}(\mathbf{x}, \mathbf{y})|}{|\text{srl-spans}(\mathbf{x}, \mathbf{y})|}$$

Constraint on SRL

- Constraint (violation) scores on previous exmaple



GBI on SRL: Experiments

- OntoNotes v5.0, CoNLL-2012 shared task
  (278k train, 38.3k dev, 25.6k test)

- Gold predicates and gold parse constituents are given
  (~10% noisy annotations) .

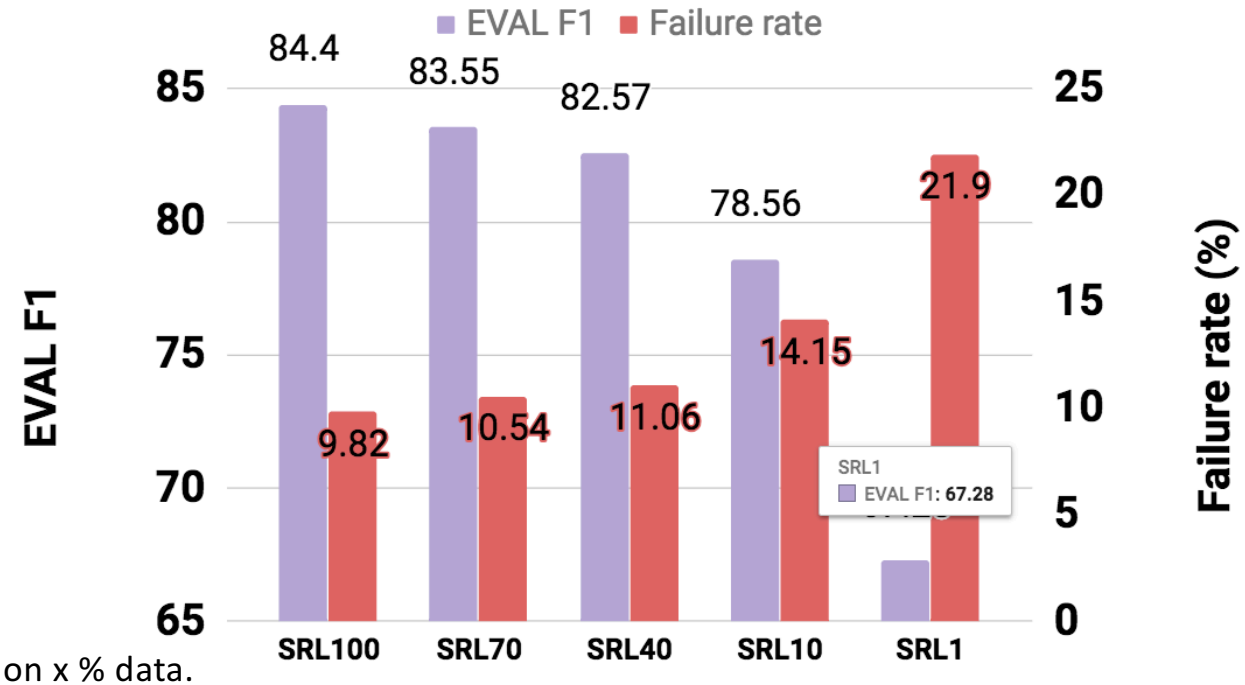
- Baseline architecture
  - multi-layer highway bi-directional LSTM (ELMo embedding)

GBI on SRL: Experiments

- Statistics
  - **Failure set:** Set of instances where SRL output violates simple constraint.
  - **Failure rate (%)**: Relative size of failure set compared to whole test set.
  - **Conv rate (%):** The relative portion of the failure set converted to constraint-satisfying output after GBI.

GBI on SRL: Experiments

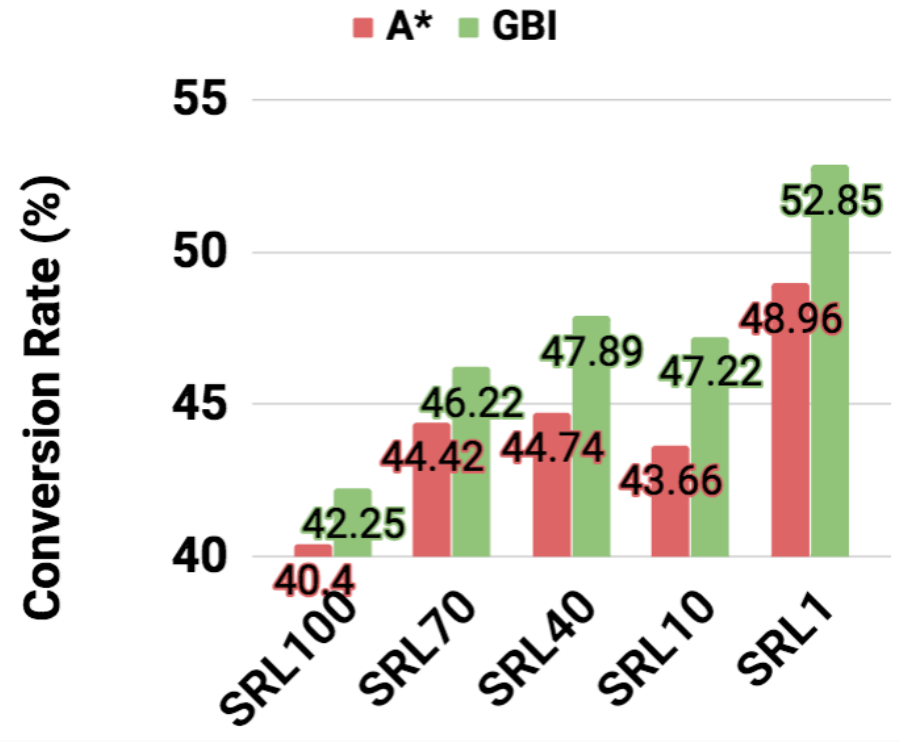
- Trained 5 networks with different level of performance by using different amounts of data (1%,10%, ⋯,100%)



SRL x : SRL system trained on x % data.

GBI on SRL: Experiments

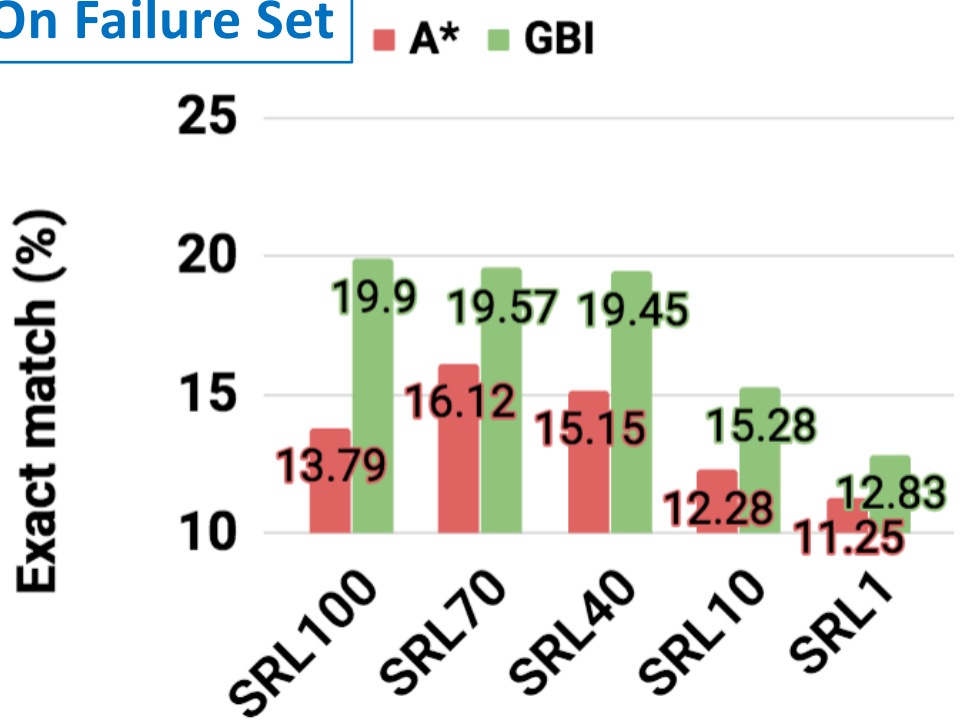
- Q3: GBI enforces constraints. (much better than A*)



GBI on SRL: Experiments

- Q3: GBI enforces constraints **without hurting** the system.

On Failure Set

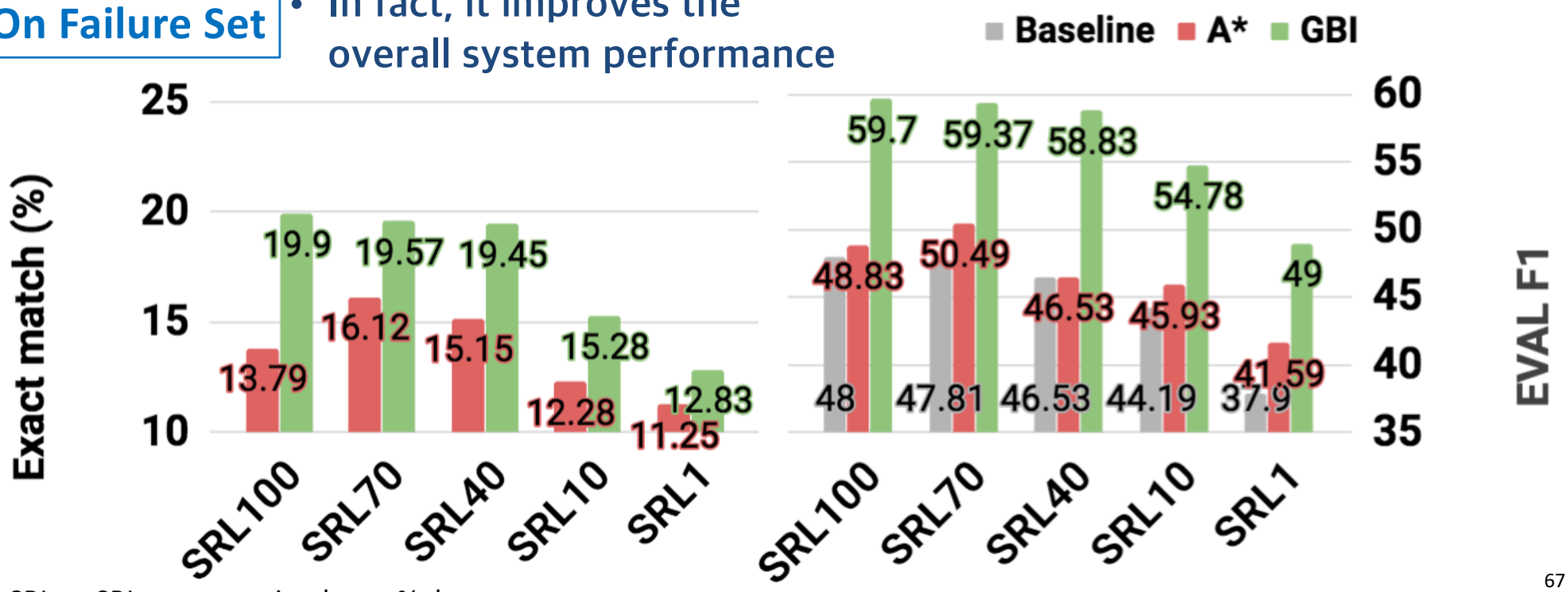


SRL x : SRL system trained on x % data.

GBI on SRL: Experiments

- Q3: GBI enforces constraints **without hurting** the system.
- **In fact, it improves the overall system performance**

On Failure Set



SRL x : SRL system trained on x % data.

GBI on SRL: Experiments

- Q3: GBI enforces constraints **without hurting** the system.
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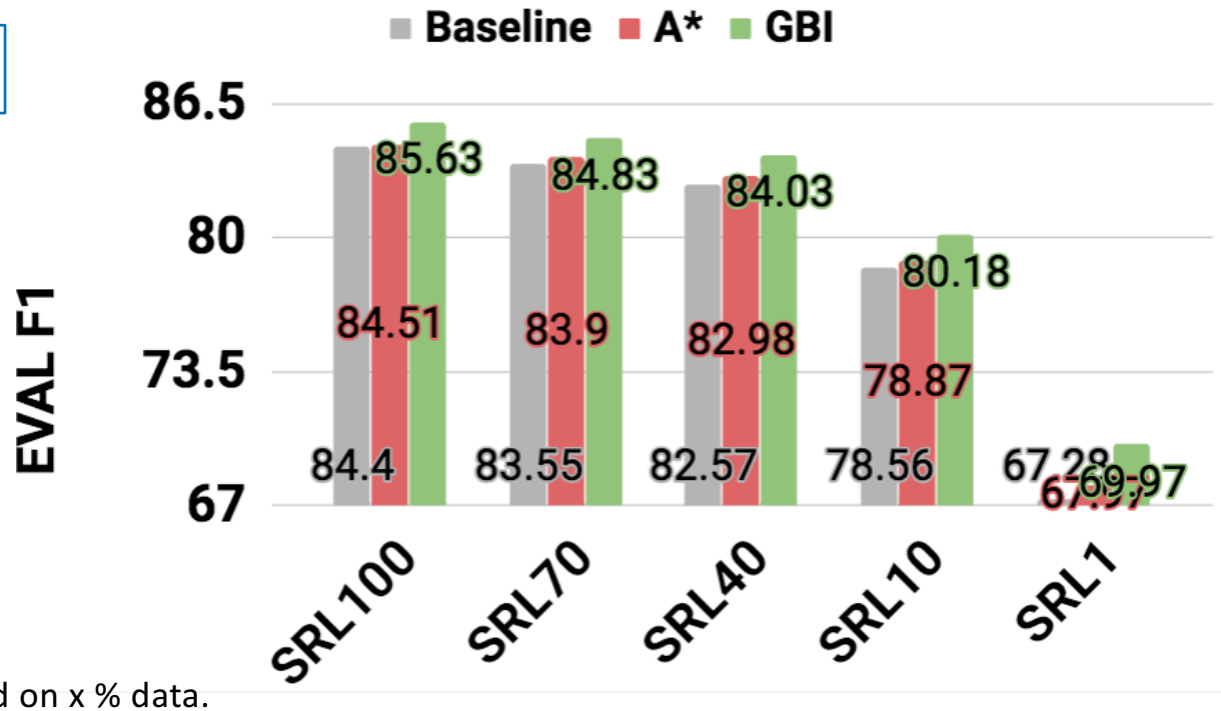
On Total test set

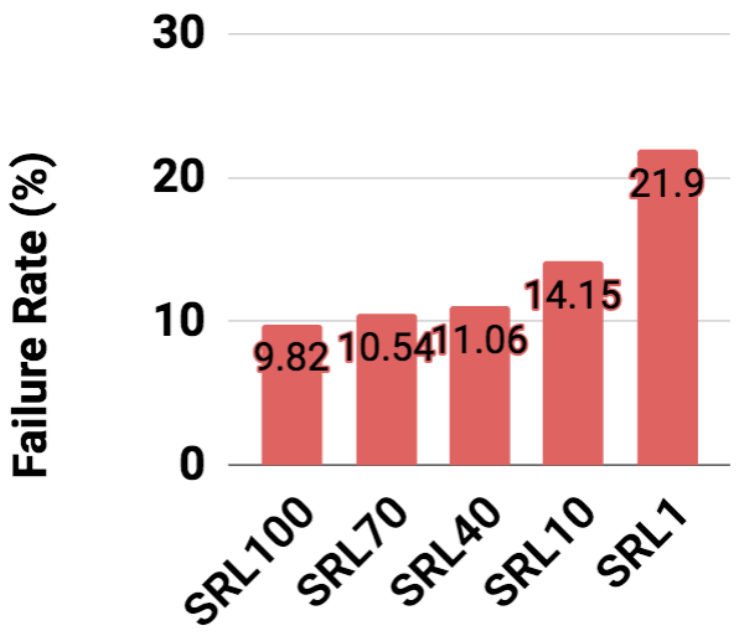


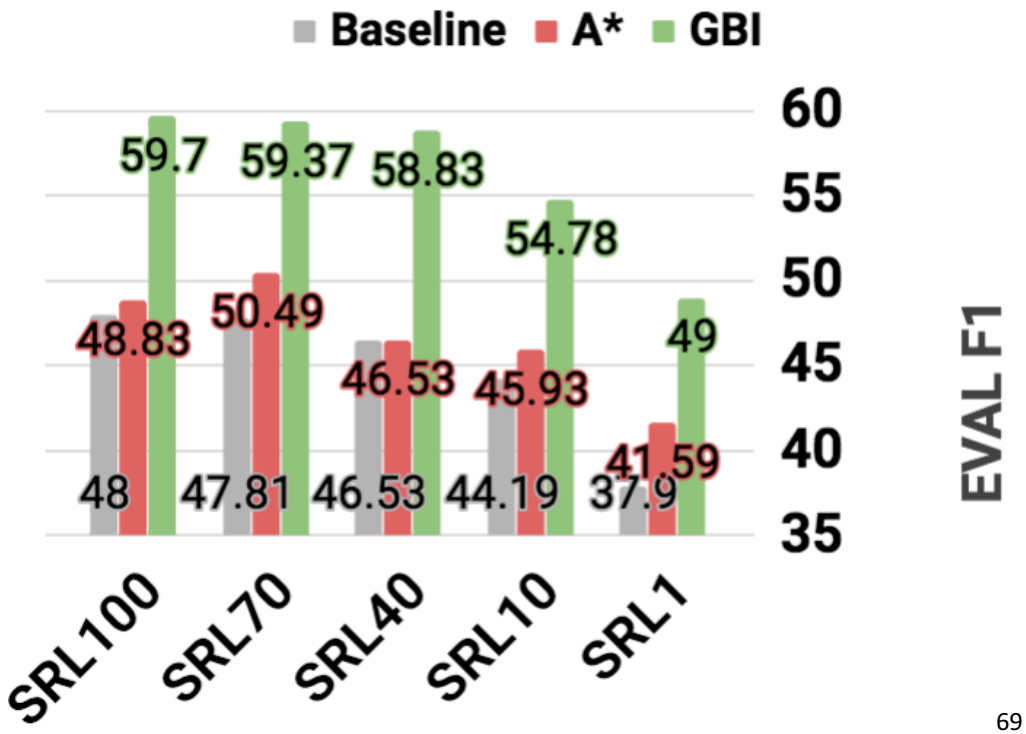
SRL x : SRL system trained on x % data.

GBI on SRL: Experiments

- Q4: Not sensitive to the baseline model performance

On Failure Set





Application 2: Syntactic Parsing

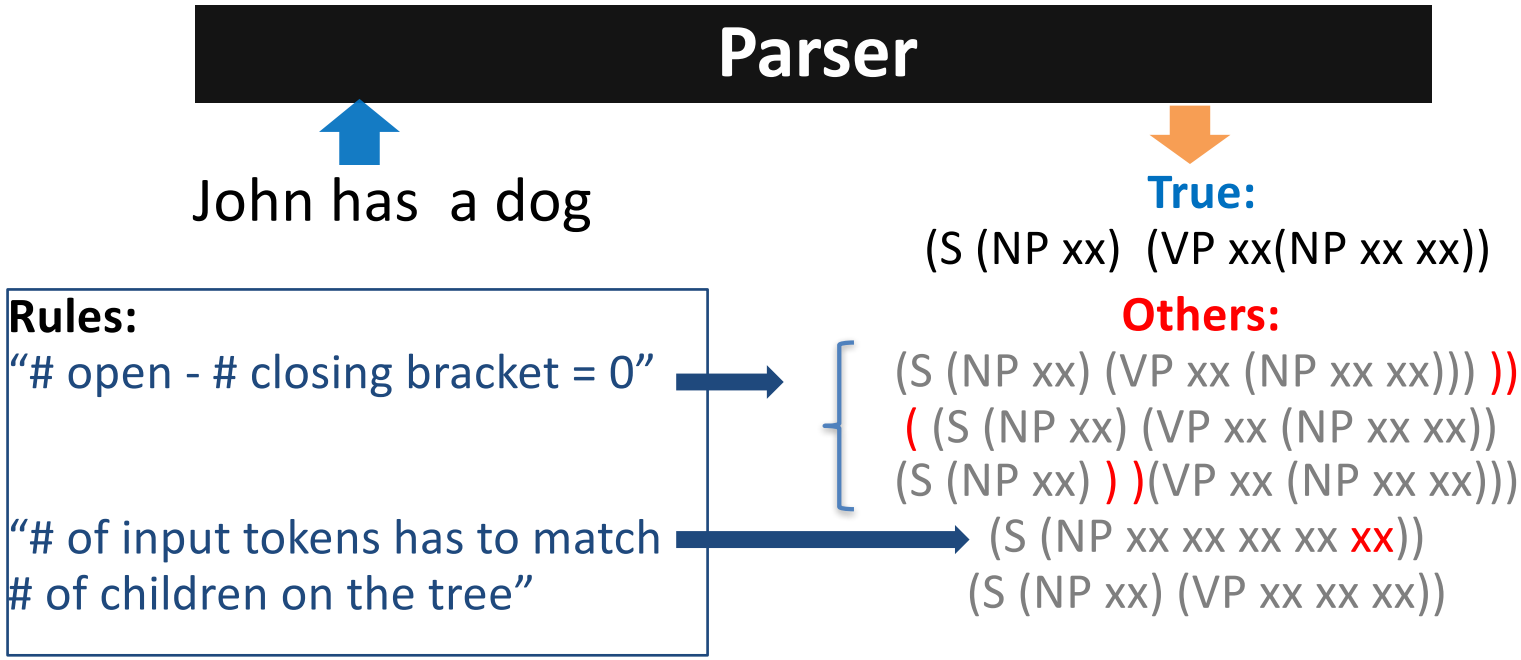
- **By a linguist**
  - Deterministic rule based. (thousands of rules)

- **Statistical methods**
  - $O(N^3)$ and accurate
  - O(N) and inaccurate

- **State of the art:** Neural Networks.
  - Using generic sequence-to-sequence model
  - Using span-based models

Constraints on parsing model

- seq2seq **does not guarantee** "very simple rule".



Constraints function

- **Rules**
  - # of input tokens = # of children on output tree
  - # opening brackets = # of closing brackets

- **Constraint function definition (x:input, y: output)**
  - **Simple count of errors normalized by** sum of input, output **length**.
  - Roughly speaking:

$$g(y, \mathcal{L}^x) = \frac{1}{|x| + |y|} \{abs(|x| - |y_{children}|) + |\text{count}_{open} - \text{count}_{close}|\}$$

GBI on parsing: Experiments

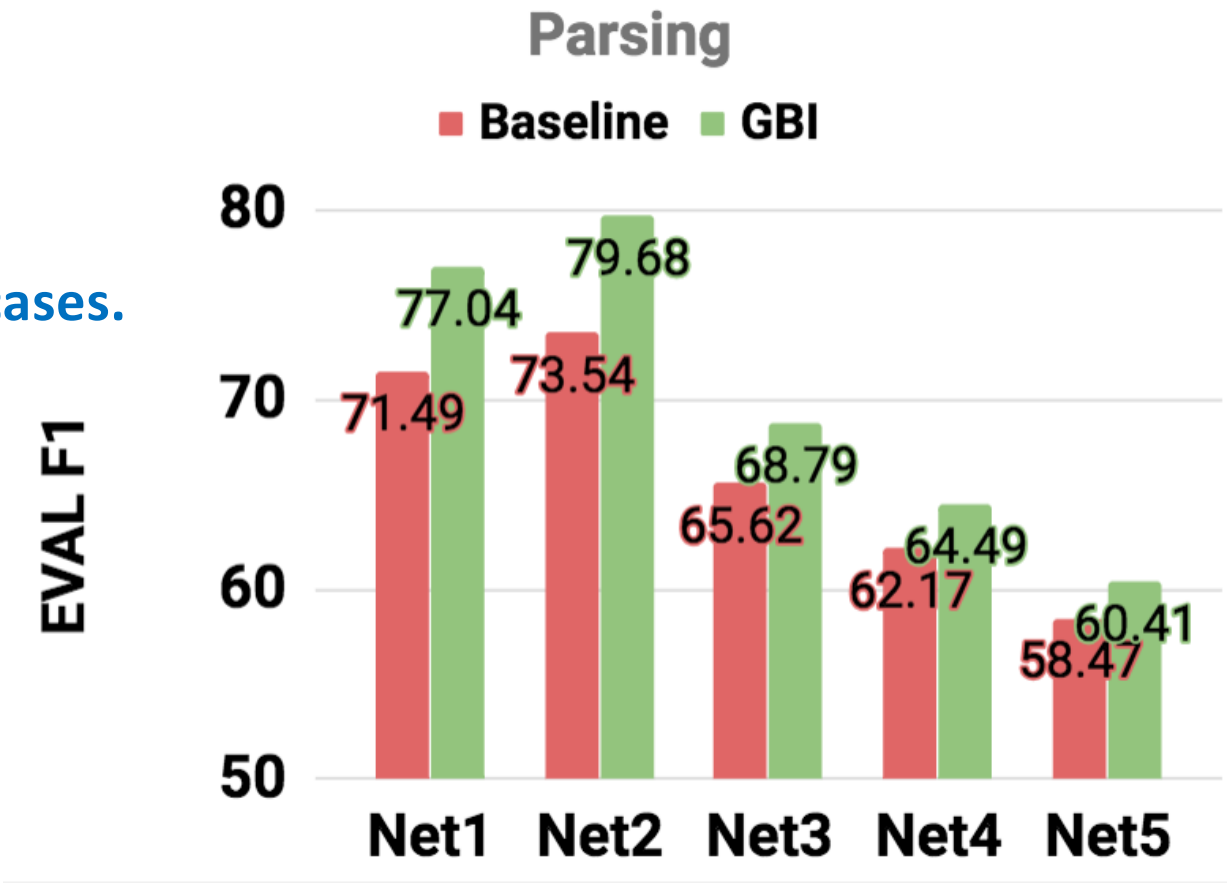
- Trained 5 parsers to answer Q1-4 (especially Q3)
  - Net1-2: GNMT (bi-directional encoder, uni-directional decoder)
  - Net3-5: uni-directional encoder, decoder.
  - Different dropout, used different portion of the dataset.

name	F1		hyper-parameters			data
	BS-9	greedy	hidden	layers	dropout	(%)
Net1	87.58	87.31	128	3	0.5	100%
Net2	86.63	86.54	128	3	0.2	100%
Net3	81.26	78.32	172	3	no	100%
Net4	78.14	74.53	128	3	no	75%
Net5	71.54	67.80	128	3	no	25%

GNMT: Wu et al, Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation, 2016

GBI on parsing: Experiments

Similar trend.
Again, GBI
Improves all cases.



GBI on parsing: Experiments

- Q4: Not sensitive to the baseline model performance.
- Not only that, **GBI is also compatible with various decoding methods.**

Net	Infer method	Failure (n/2415)	Conv rate	F1 (Failure set) before	F1 (Failure set) after
Net3	Greedy	317	79.81	65.62	68.79 (+3.14)
	Beam 2	206	87.38	66.61	71.15 (+4.54)
	Beam 5	160	87.50	67.5	71.38 (+3.88)
	Beam 9	153	91.50	68.66	71.69 (+3.03)
Net4	Greedy	611	88.05	62.17	64.49 (+2.32)
	Beam 2	419	94.27	65.40	66.65 (+1.25)
	Beam 5	368	92.66	67.18	69.4 (+2.22)
	Beam 9	360	93.89	67.83	70.64 (+2.81)
Net5	Greedy	886	69.86	58.47	60.41 (+1.94)
	Beam 2	602	82.89	60.45	61.35 (+0.90)
	Beam 5	546	81.50	61.43	63.25 (+1.82)
	Beam 9	552	80.62	61.64	62.98 (+1.34)

GBI on parsing: Experiments

- Q4: Not sensitive to the baseline model performance.
- Not only that, **GBI is also compatible with various decoding methods.**

More details,
Please refer to
the thesis proposal.

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GBI on transducer

- *Transduction (toy)*
  - A transducer (T) is a function from a 'source language' (L_s) to a 'target language' (L_T).

Experiment Result
- 65.2% conversion rate
- On Failure set
  - Before-GBI: 75.2%
  - After-GBI: 82.4%

$$T : \mathcal{L}_S \rightarrow \mathcal{L}_T$$

T: az → aaa
bz → zb

S: azazbzazbzbazbzbzbzbzbz

T: aaaaaazbaaazbzbaaazbzbzbzbzb

constraint:
3 x (# a in **S**) = # a in **T**

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- On Failure set (accuracy)
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Please refer to
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$$T : \mathcal{L}_S \rightarrow \mathcal{L}_T$$

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constraint:
3 x (# a in **S**) = # a in **T**

GBI: extra considerations

- Robustness to noisy constraint.
- Q5) out-of-domain performance.

Robustness of GBI

- SRL has about 10% of the span mismatch between annotated SRL output (propbank) & parse tree (treebank)

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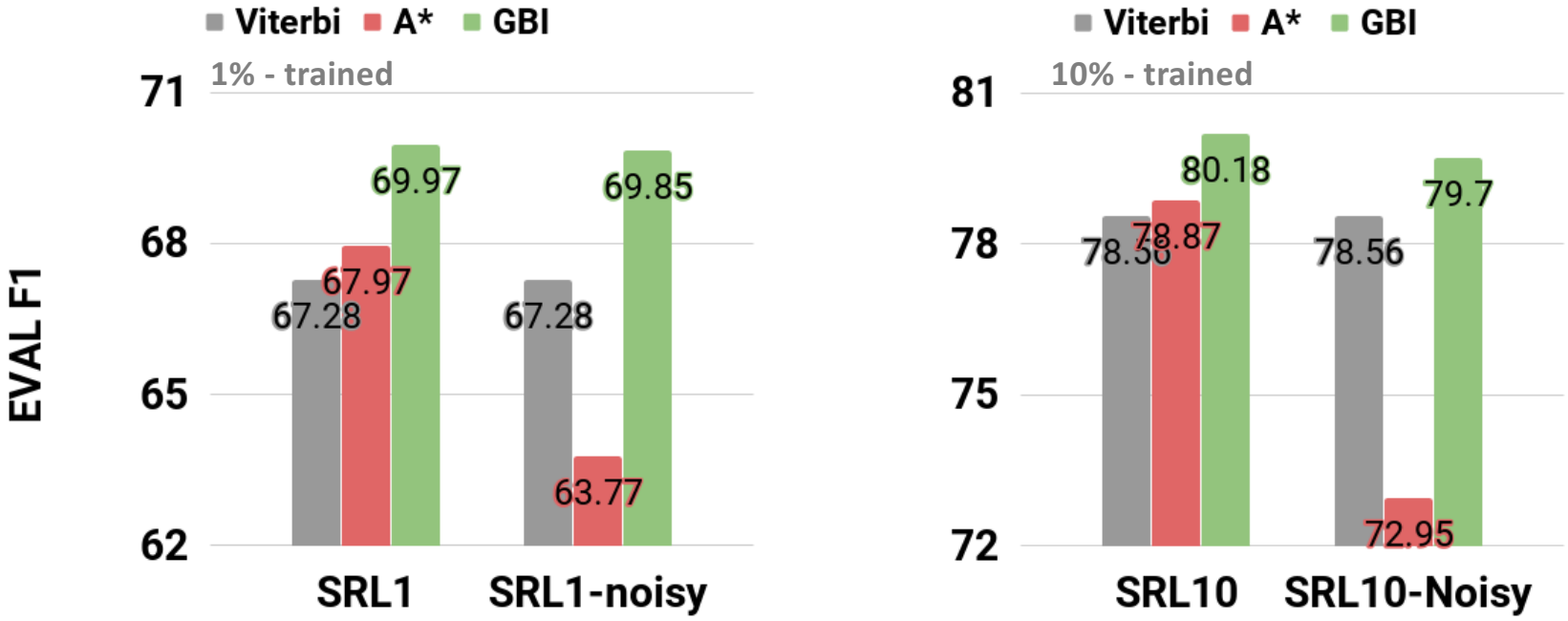

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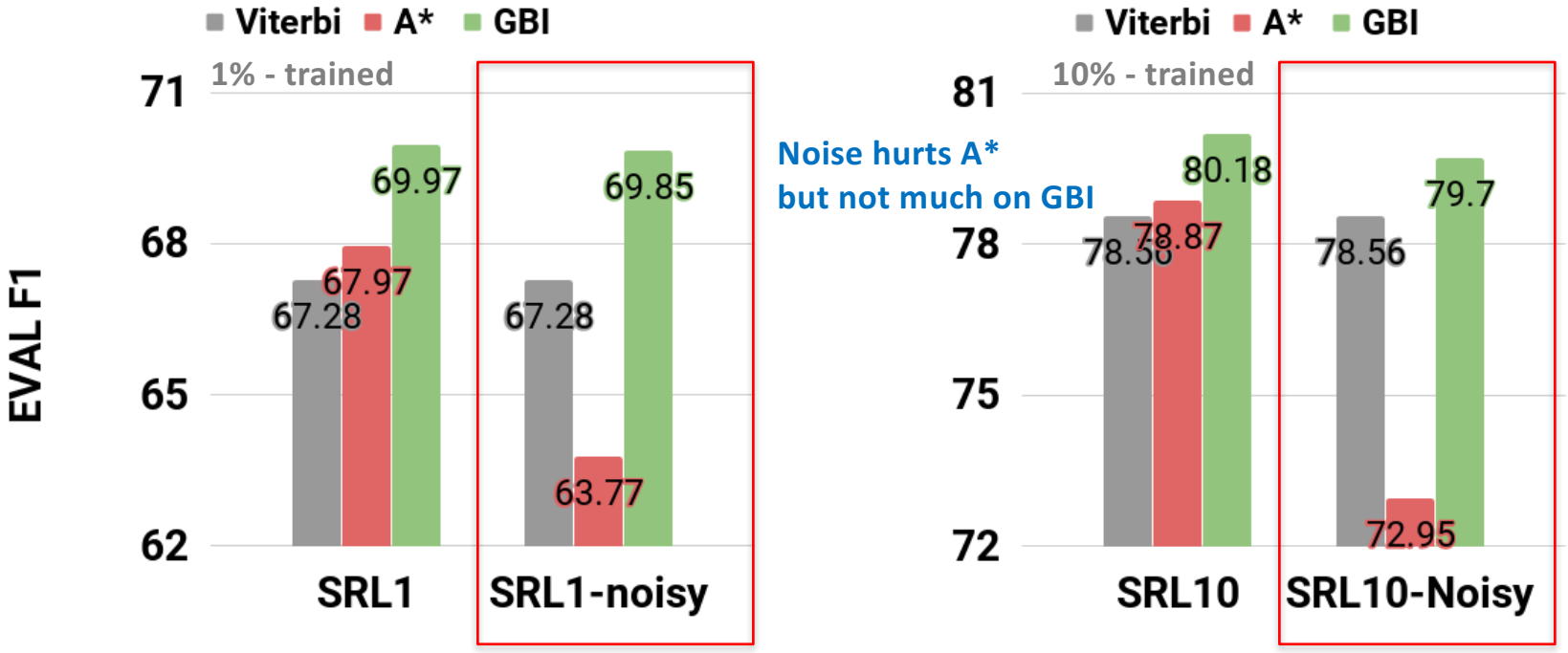
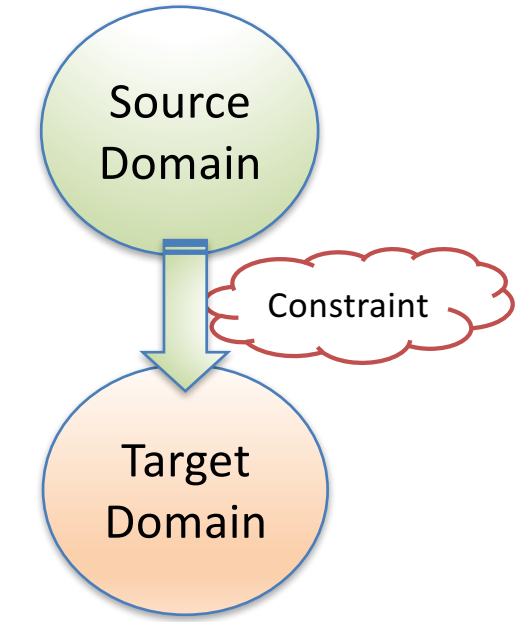


GBI on out-of-domain data (Q5)

- CoNLL2012
  - NewsWire (NW)
  - Broadcast Conversation (BC)
  - Broadcast News (BN)
  - Pivot Corpus (PT)
  - Telephone Conversation (TC)
  - Weblogs (WB)

GBI on out-of-domain data

- CoNLL2012
  - NewsWire (NW) which includes WSJ
  - Broadcast Conversation (BC)
  - Broadcast News (BN)
  - Pivot Corpus (PT)
  - Telephone Conversation (TC)
  - Weblogs (WB)



Can constraint injection transfer to other domains?

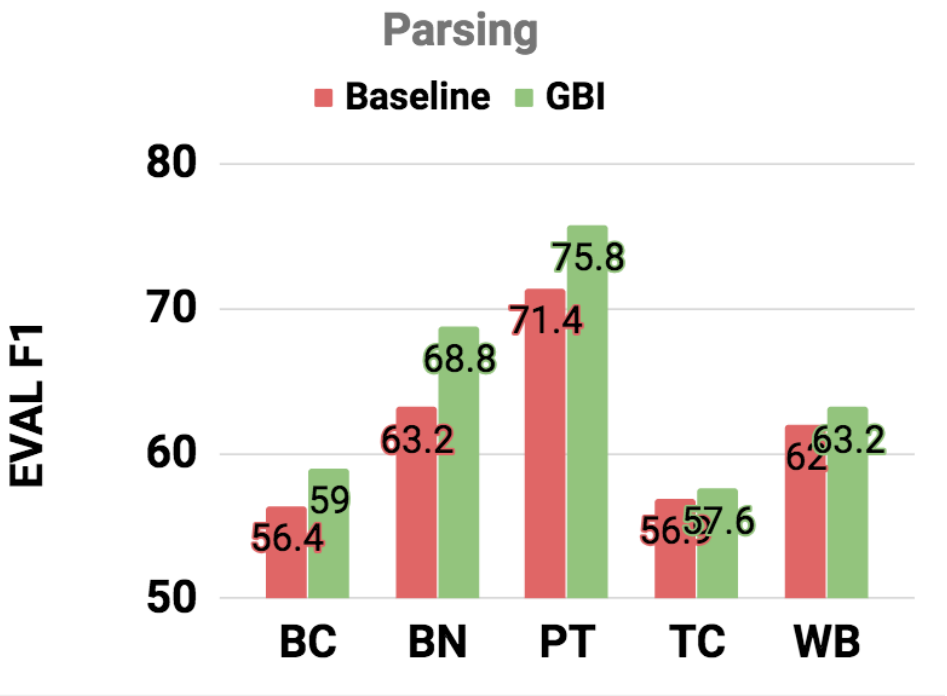
GBI on out-of-domain data

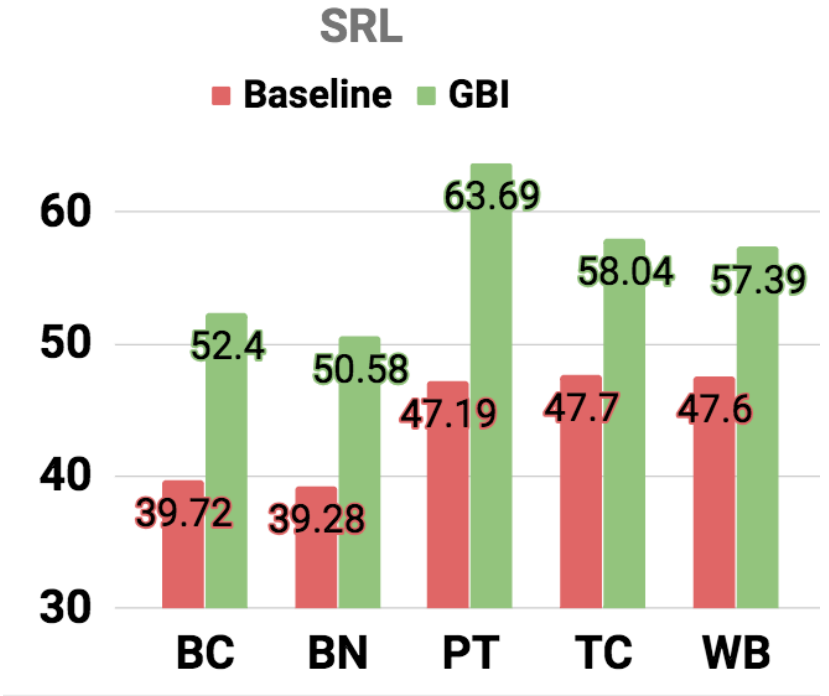
- Generally higher failure rate on out-of-domain evaluation compared to in-domain (parsing: 11.9 %, SRL: 18.1%).

Genre \Task	Failure rate (%)	Conversion rate (%)	F1 on failure set	
			before	after
		Syntactic Parsing		
Broadcast Conversation (BC)	19.3	98.8	56.4	59.0 (+2.6)
Broadcast News (BN)	11.7	98.1	63.2	68.8 (+5.6)
Pivot Corpus (PT)	9.8	97.8	71.4	75.8 (+4.4)
Telephone Conversation (TC)	10.1	86.2	56.9	57.6. (+0.7)
Weblogs (WB)	17.6	95.3	62.0	63.2 (+1.2)
Genre \Task		***SRL***		
Broadcast Conversation (BC)	26.86	53.88	39.72	52.4 (+12.68)
Broadcast News (BN)	18.51	55.19	39.28	50.58 (+11.3)
Pivot Corpus (PT)	10.01	62.34	47.19	63.69 (+16.5)
Telephone Conversation (TC)	19.09	54.62	47.7	58.04 (+10.34)
Weblogs (WB)	20.32	44.13	47.6	57.39 (+9.39)

GBI on out-of-domain data

- In summary, improves in all cases (reporting on failure set)
  - While parsing is more sensitive to domains.





Roadmap

- Focus of our work
- Applications & constraints
- Gradient-Based Inference formulation
- Research questions & Experiments
- **Conclusion**

Research Questions

- **Q1.** Does **GBI** actually ***enforce constraints***?
  - Yes!
- **Q2.** Does **GBI** ***enforce constraints without compromising*** the quality of the system?
  - Yes. It rather Improves!
- **Q3.** Is **GBI** ***sensitive*** to the ***baseline model***?
  - Not on 3 applications (5 experiment settings)
- **Q4.** ***Performance*** of GBI **on** ***out-of-domain*** dataset?
  - Good!

Thank You!

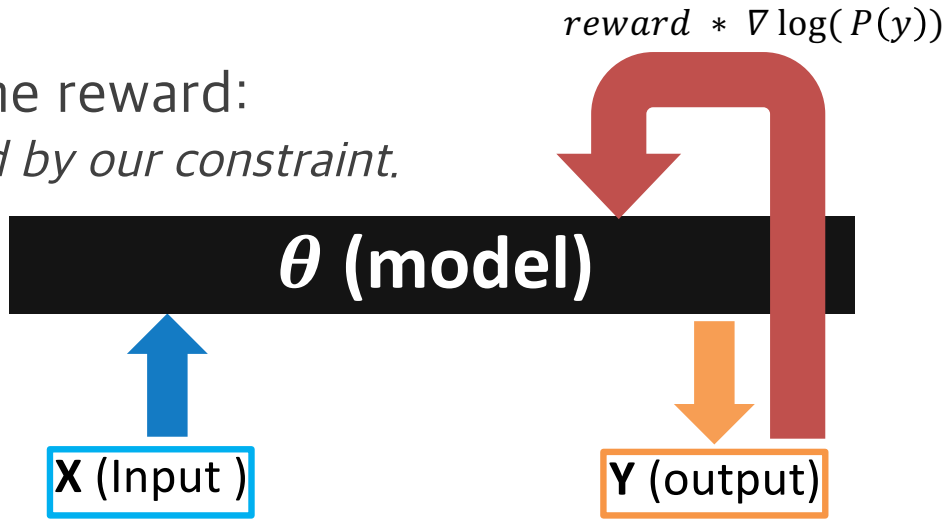
Questions?

[backup] Learning with constraints

- Optimization with constraints

$$\min_{W} \quad f(\mathbf{x}, \mathbf{y}; W)$$
$$s.t. \quad g(\mathbf{y}, \mathcal{L}) = 0$$

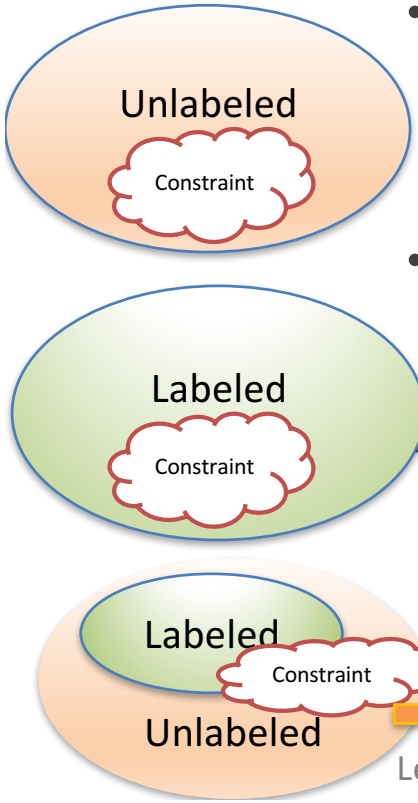
- Learning with the reward:
  - *Reward defined by our constraint.*



Lee & Mehta et al, Towards semi-supervised learning for deep semantic role labeling, EMNLP2018

[backup] Learning with constraints

- Learning with the reward s(x,y)
  - constraint loss (c-loss)



$$s(\mathbf{x}, \hat{\mathbf{y}}^{(t)}) \sum_{i=1}^{|\hat{\mathbf{y}}^{(t)}|} \log p(\hat{y}_i^{(t)} | \mathbf{x}; \mathbf{w}^{(t)}) + \|W - W_{\text{pre-train}}\|_2^2$$

- Joint loss

Semi-supervised Joint loss

SRL-***labeled*** data $(\mathbf{x}_m = \mathbf{x}_k)$

$$-\alpha_1 \sum_{i=1}^{|\mathbf{y}|} \log p\,(y_i \mid \mathbf{x}_k; \mathbf{w}) + \alpha_2 s(\mathbf{x}, \hat{\mathbf{y}}^{(t)}) \sum_{i=1}^{|\hat{\mathbf{y}}^{(t)}|} \log p(\hat{y}_i^{(t)} \mid \mathbf{x}_m; \mathbf{w}^{(t)})$$

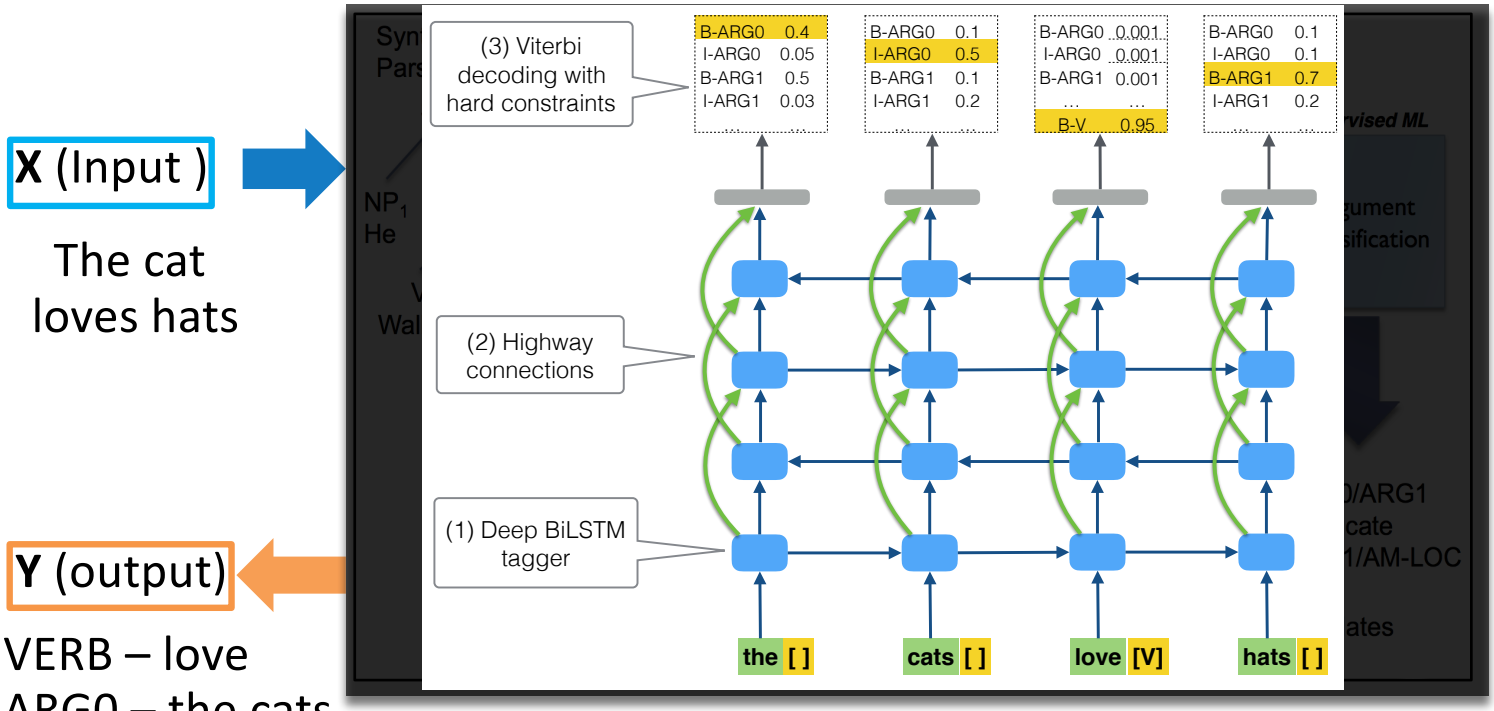
SRL-***labeled*** data

SRL-***unlabeled*** data $(\mathbf{x}_m \neq \mathbf{x}_k)$

Lee & Mehta et al, Towards semi-supervised learning for deep semantic role labeling, EMNLP2018

[Revisit] Complex models

- Semantic Role Labeling

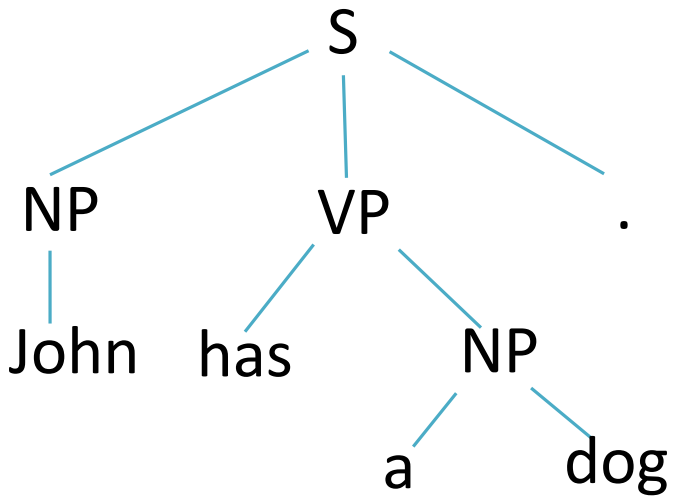


Slide credits: Luheng He

How to express the Grammar Tree as a sequence?

Proposed model

- "As a command" to produce the tree.



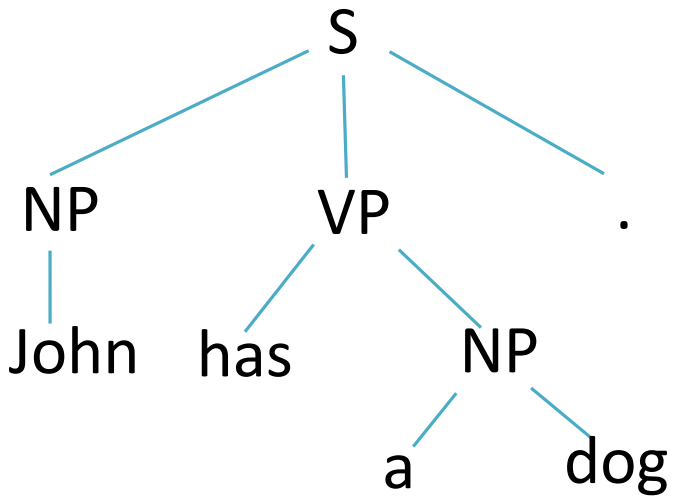
- Shift-Reduce syntax
  - Bottom-up approach
  - Similar to how human minds work.

How to express the Grammar Tree as a sequence?

Proposed model

- "As a command" to produce the tree.

s R-1-NP s s s R-2-NP R-2-VP s R-3-S

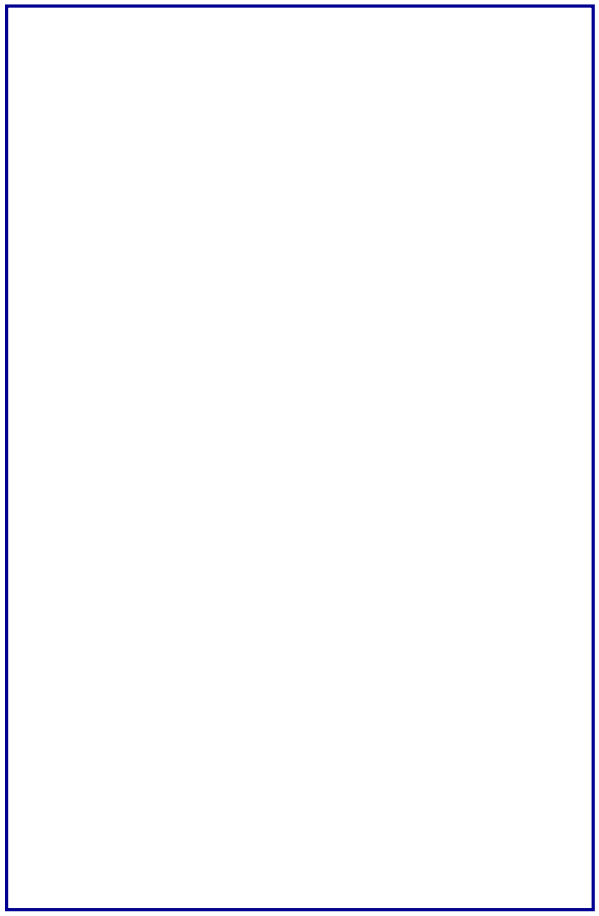


- Shift-Reduce syntax
  - **s** corresponds to "push" in stack.
  - **R-#-XX** corresponds to "pop"-ing that **#** of elements , merging them together to **XX** and pushing it back

Shift-Reduce syntax

Proposed model

- Original sentence
  John has a dog .
- Shift-Reduce command
  s R-1-NP s s s R-2-NP R-2-VP s R-3-S



Shift-Reduce syntax

Proposed model

- Original sentence
  John has a dog .
- Shift-Reduce command
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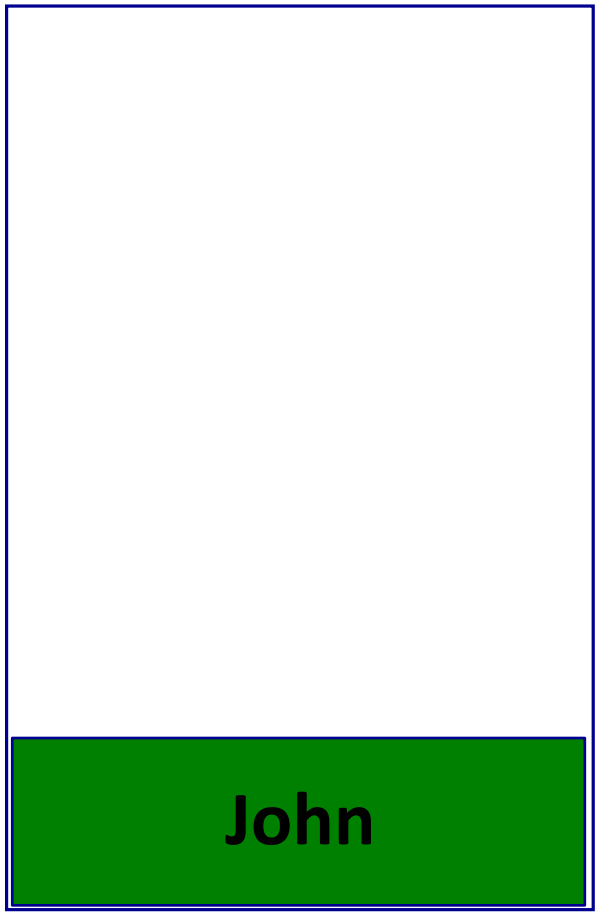

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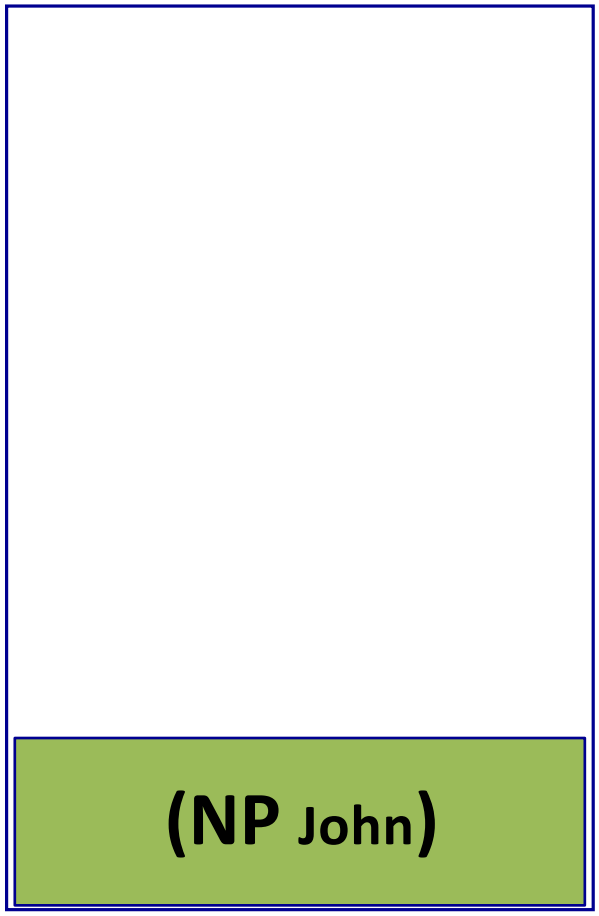

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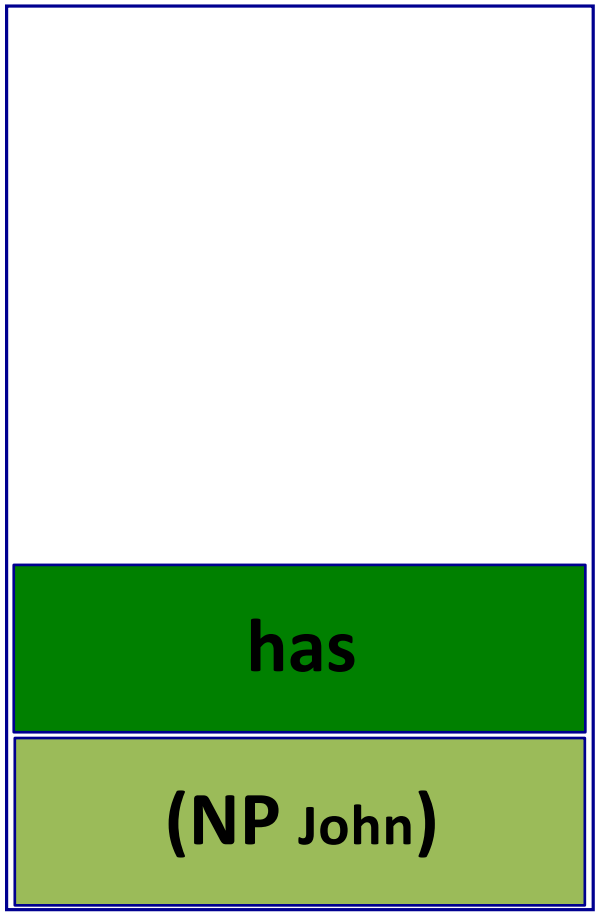

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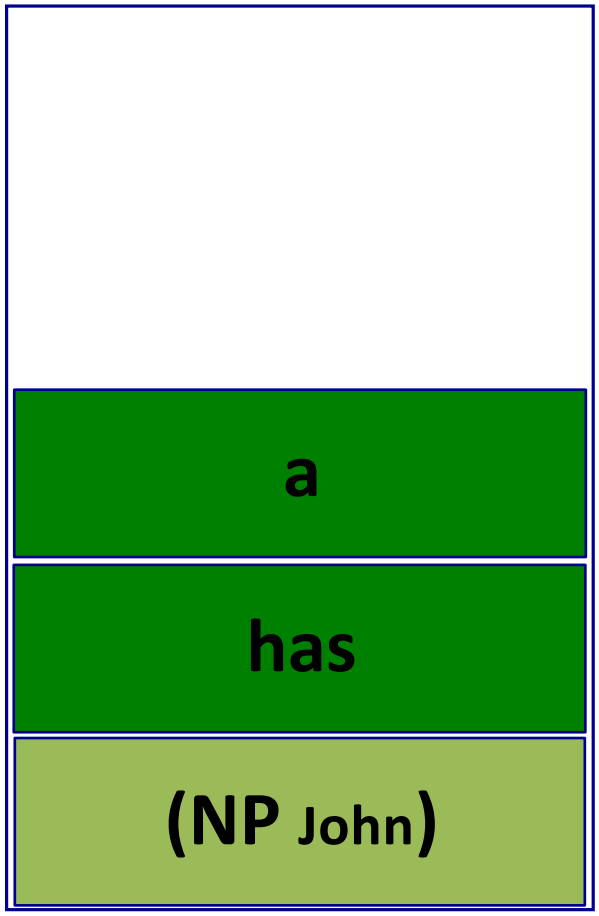

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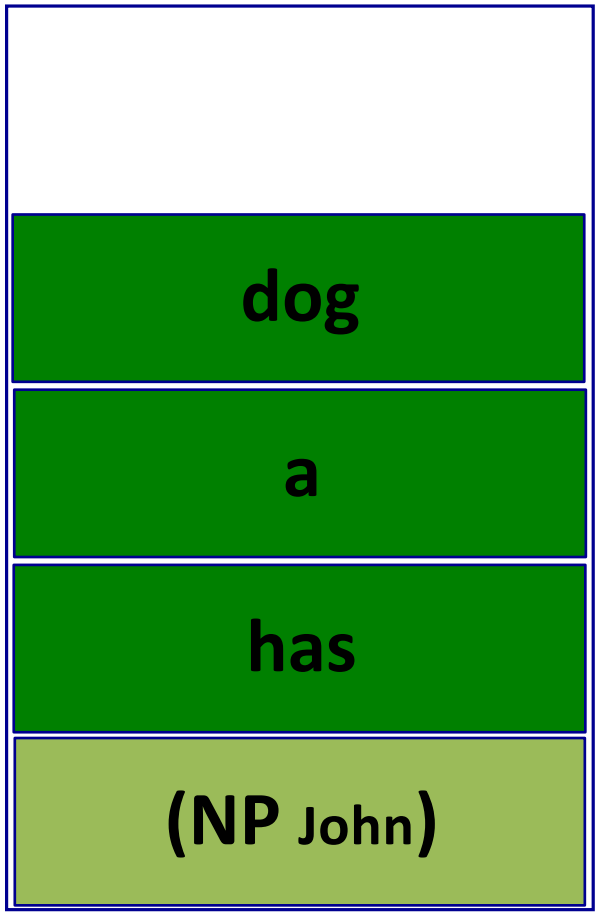

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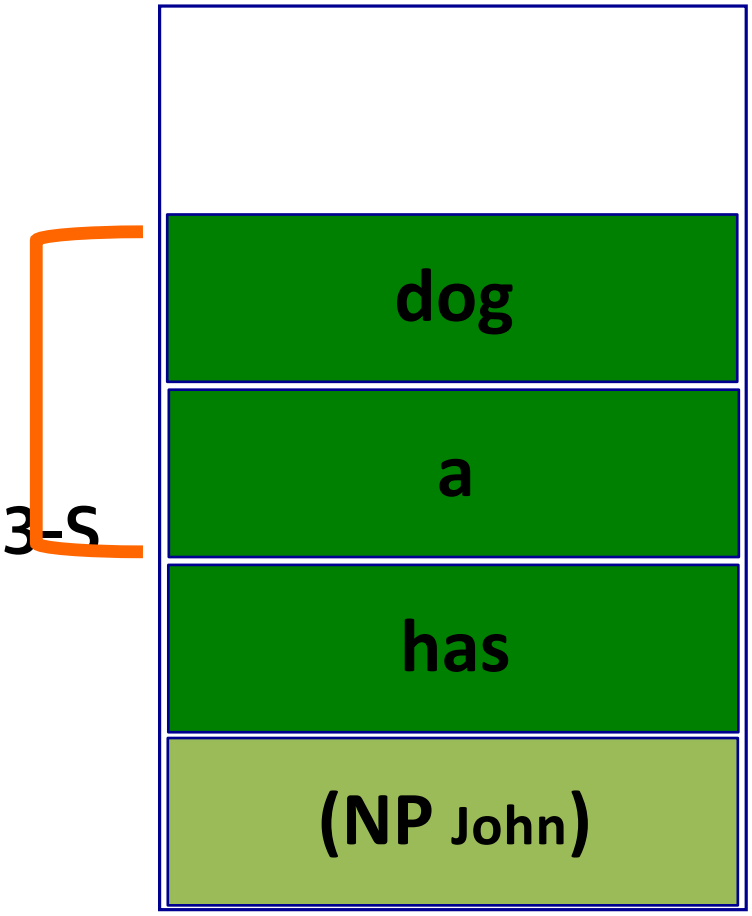

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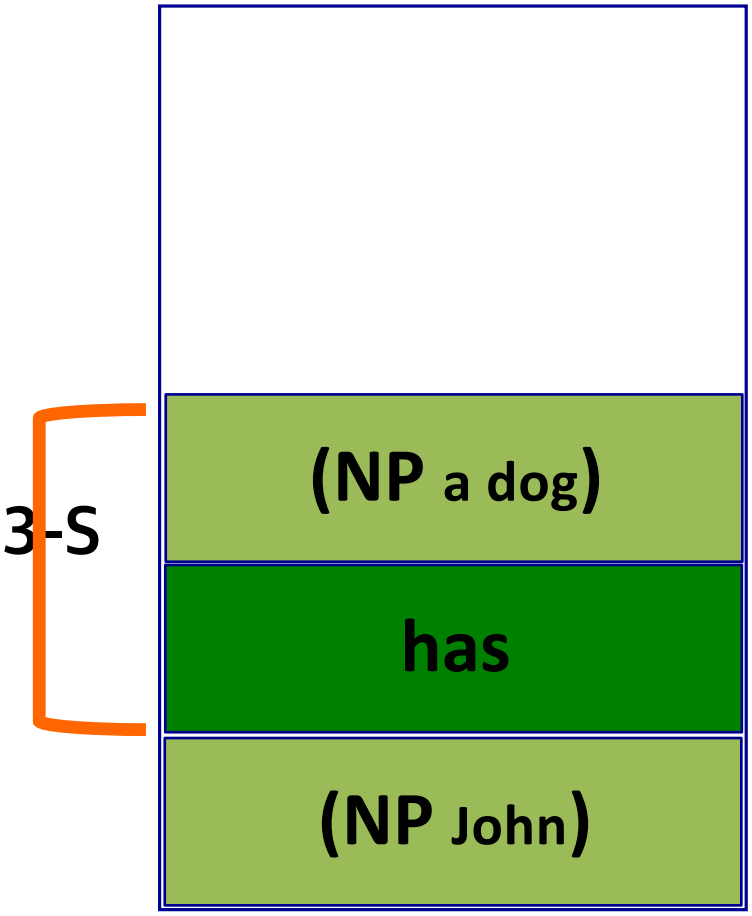

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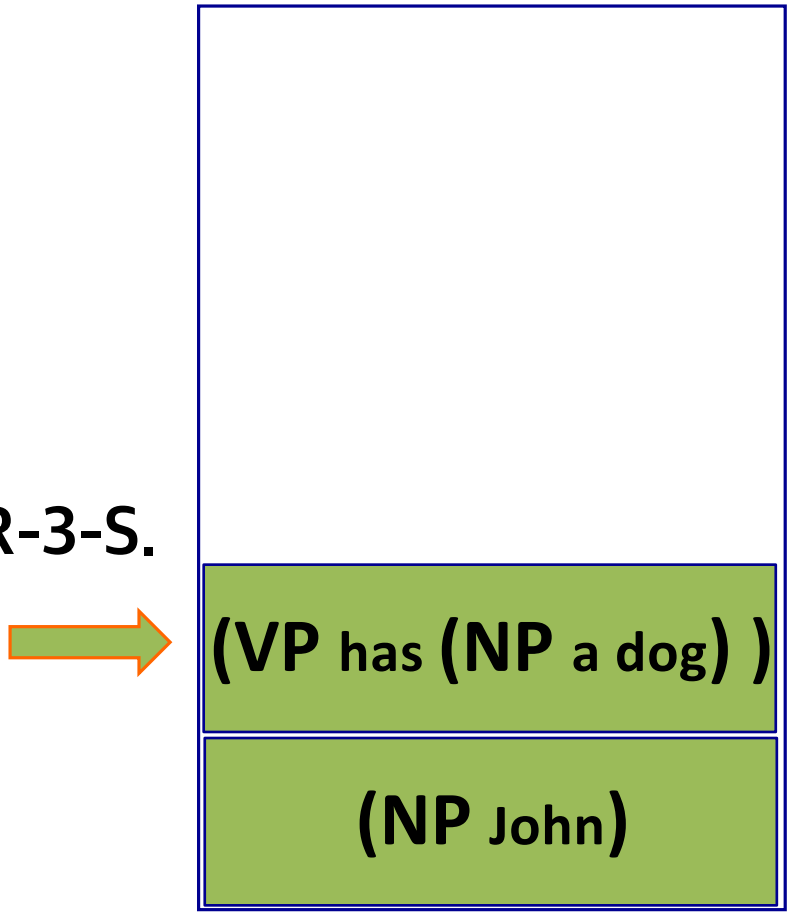

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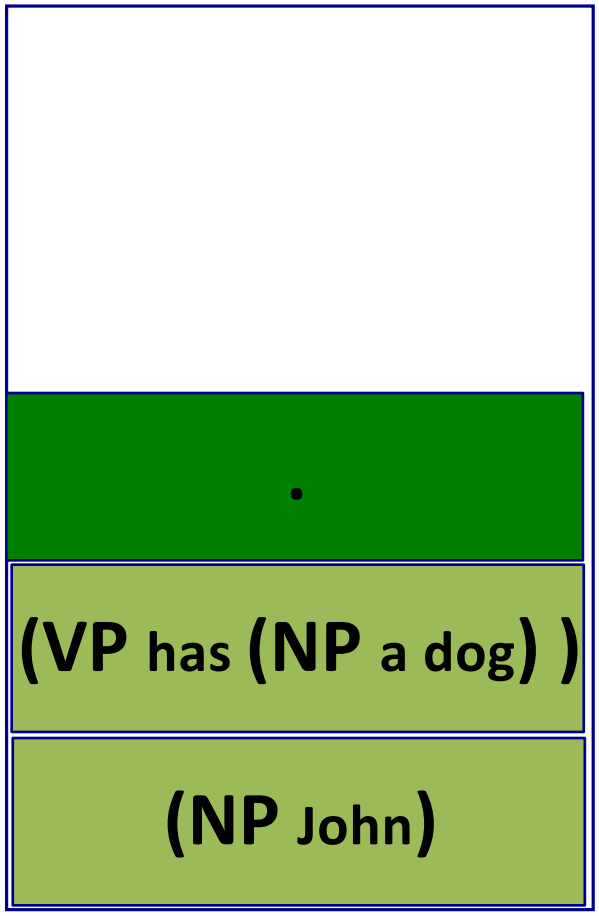

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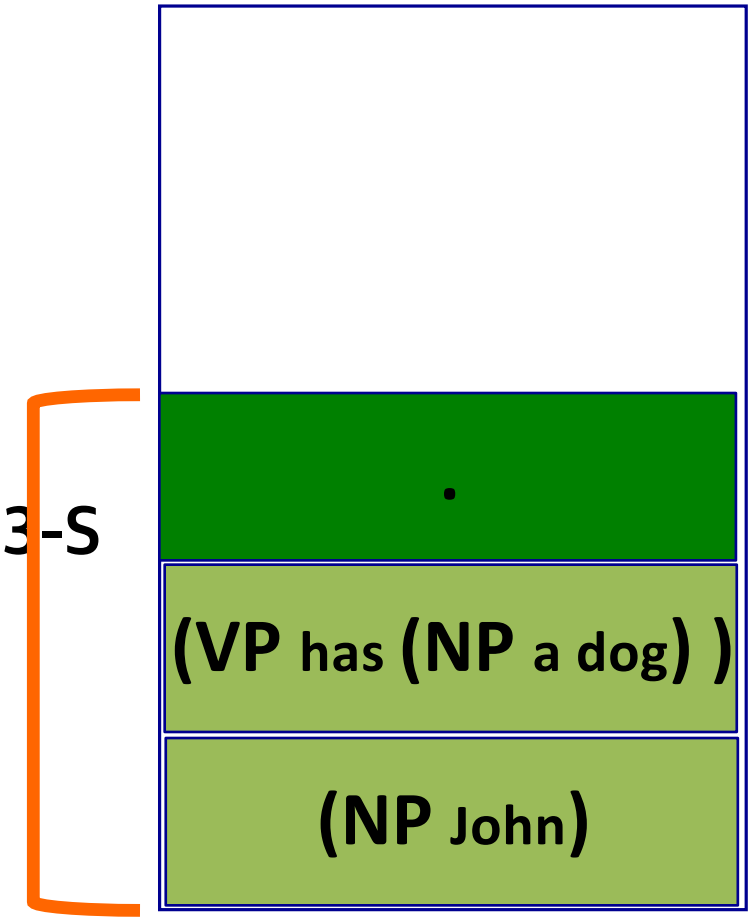

Shift-Reduce syntax

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  John has a dog

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(S (NP John) (VP has (NP a dog)) .)

GBI on

GBI case study

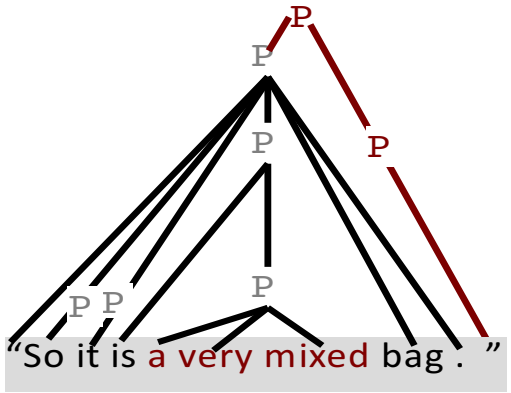
Case study of GBI on parsing

- Comparison to decoder with constraints on each step.
- **Unconstrained decoding + Error signal propagation** can be more powerful.

Constraints in decoder

ssr!sr!ssssrrr!rr!ssrrrrrr!sr!rr!

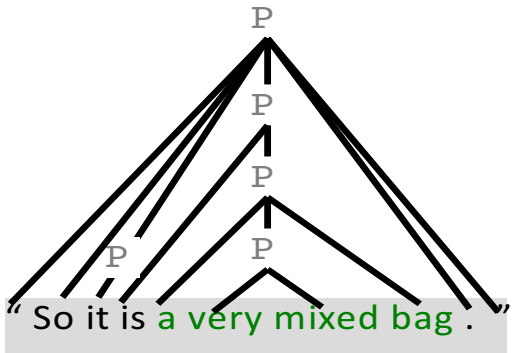
(“(so) (it) (is (a very mixed)) bag .) (”))



Our method
(recovered true)

sssr!ssssr!srrr!rr!ssrrrrrr!

(“ so (it) (is (a (very mixed) bag)) . ”)



GBI extra experiment [WIP]

- SRL has the following constraints
  - BIO - captured by vitrebi
  - Syntactic consistency
  - U,C,R violation
    - Unique core (U) / Continuation (C) / Reference (R) roles

- SOTA models have UCR violations
- GBI successfully reduces U,C,R violations.
  - No F1 score improvement, but the side effect of U,C,R is still unstudied as SRL output is used as an input to the following system.

- WORK IN PROGRESS

GBI on Transduction [WIP]

- Application 3: Transduction problem
  - Definition
    - A transducer T : L_s → L_t is a function from a source language to a target language
  - Transduction itself is a difficult problem.
  - We use it as an example of constraint with seq2seq problem, when you know the aggregate information.
  - Transduction rule: az → aaa

GBI on Transduction

- Case study of GBI on transduction problem.

azazbzazbzbzazbzbzbzbzbz ⟶ aaaaaazbaaazbzbaaazbzbzbzbzb

iteration	output	loss	accuracy
0	aaaaaazbaaazbaaazbzbzbzbaaazb	0.2472	66.7
1	aaaaaazbaaazbaaazbzbzbzbaaazb	0.2467	66.7
2	aaaaaazbaaazbaaazbzbzbzbaaazb	0.2462	66.7
3	aaaaaazbaaazbzbaaazbzbzbzbzb	0.0	100.0

Table 1: An example for which enforcing the constraints improves accuracy. Red indicates errors.

bzbzbzbzazbzbzazazazazbz⟶zbzbzbzbaaazbzbaaaaaaaaaaaaazb

iteration	output	loss	accuracy
0	zbzbzbzbaaazbaaaaaaaaaaazbaaa	0.2954	74.2
4	zbzbzbzbzbaaaaaaaaazbzbzbaaaaaa	0.0	60.0

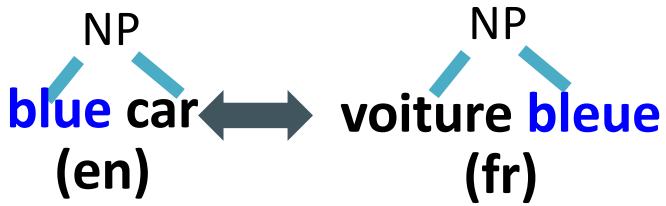
Table 2: An example for which enforcing the constraints degrades accuracy. Errors in red.

GBI on

Parsing slides

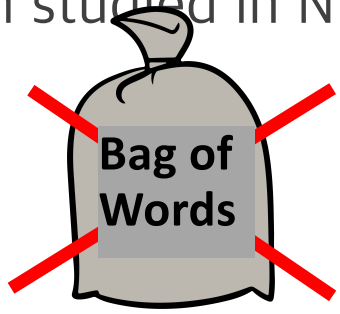
GBI on Syntactic Parsing

- Application 2: Syntactic constituency parsing.
- One of the fundamental problem studied in NLP for decades.
- Provides structure to NLP tasks.
  - Sentiment analysis, Translations, Named Entity Recognitions, ….



GBI on Syntactic Parsing

- Application 2: Syntactic constituency parsing.
- One of the fundamental problem studied in NLP for decades.
- Provides structure to NLP tasks.
  - Sentiment analysis, Translations, Named Entity Recognitions, ….
  - e.g.)
    “This film does not care about cleverness, wit or any other kind of intelligent humor"
    (Socher et al EMLNP 2013)



GBI on

GBI in detail

DETAIL

Learning with constraints

- **Proposed methods**
  - Output inconsistency (*OI-Loss*)

$$\text{SI-Loss} = -\, r(\mathbf{x}, \hat{\mathbf{y}}^{(t)}) \sum_{i=1}^{|\hat{\mathbf{y}}^{(t)}|} \log p(\hat{y}_i^{(t)} | \mathbf{x}; \mathbf{w}^{(t)})$$

$$d(\mathbf{x}, \mathbf{y}) = \frac{|\text{disagreeing-spans}(\mathbf{x}, \mathbf{y})|}{|\text{srl-spans}(\mathbf{y})|}$$

$$r(\mathbf{x}, \mathbf{y}) = 1 - 2 \times d(\mathbf{x}, \mathbf{y})$$

Motivation

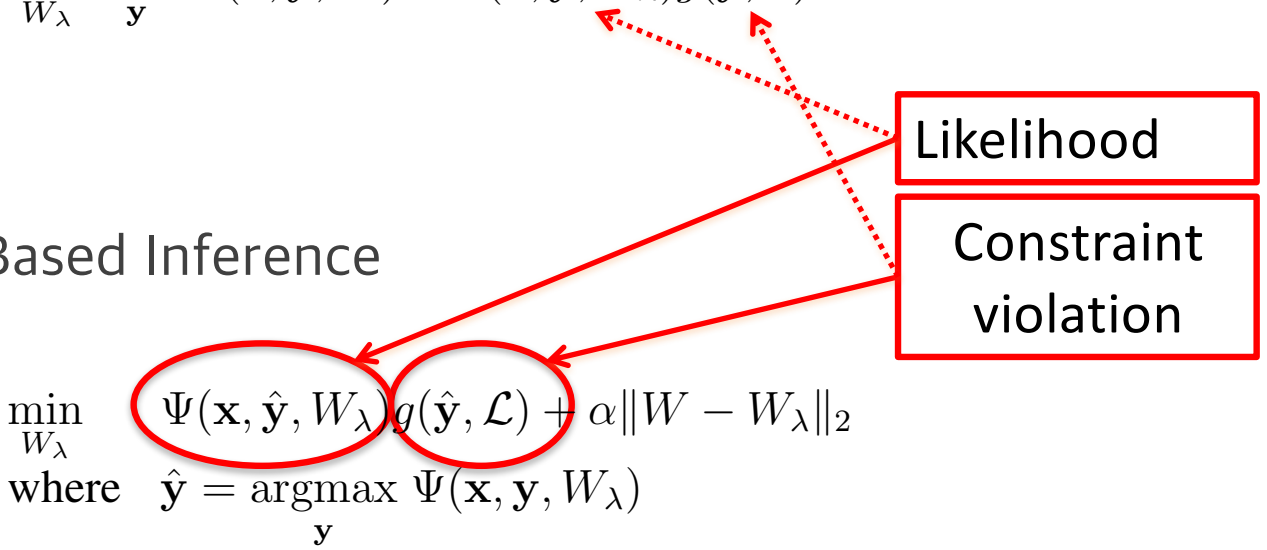
Gradient-Based Inference (GBI)

- Modified Lagrangian Relaxation

$$\min_{W_\lambda} \max_{\mathbf{y}} \Psi(\mathbf{x}, \mathbf{y}, W) + \Psi(\mathbf{x}, \mathbf{y}, W_\lambda) g(\mathbf{y}, \mathcal{L})$$

- Gradient-Based Inference

$$\min_{W_\lambda} \quad \Psi(\mathbf{x}, \hat{\mathbf{y}}, W_\lambda) g(\hat{\mathbf{y}}, \mathcal{L}) + \alpha \|W - W_\lambda\|_2$$
$$\text{where} \quad \hat{\mathbf{y}} = \operatorname*{argmax}_{\mathbf{y}} \Psi(\mathbf{x}, \mathbf{y}, W_\lambda)$$



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Regularizer

Motivation

Gradient-Based Inference (GBI)

- Optimization with constraints

$$\begin{aligned} \max_{\mathbf{y}} \quad & \Psi(\mathbf{x}, \mathbf{y}, W) \\ \text{s.t.} \quad & g(\mathbf{y}, \mathcal{L}^{\mathbf{x}}) = 0 \end{aligned}$$

- Standard Lagrangian Relaxation

$$\min_{\lambda} \max_{\mathbf{y}} \Psi(\mathbf{x}, \mathbf{y}, W) + \lambda g(\mathbf{y}, \mathcal{L})$$

Motivation

Gradient-Based Inference (GBI)

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Likelihood

Constraint violation

Motivation

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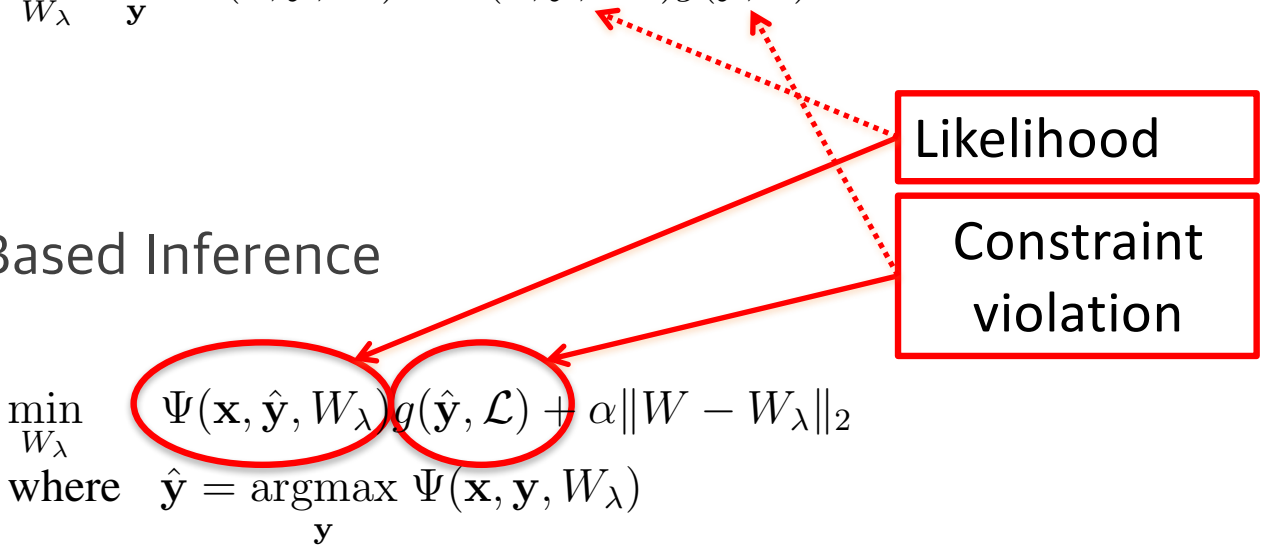

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- Gradient-Based Inference (in math)

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DETAIL

Gradient-Based Inference (GBI)

- GBI (in Algorithm)

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Algorithm 1 Constrained inference for neural nets

Inputs: test instance $\mathbf{x}$, input specific CFL $\mathcal{L}^{\mathbf{x}}$, pretrained weights W

$W_\lambda \leftarrow W$ #reset instance-specific weights

Initiate as model weight

while not converged **do**

$\mathbf{y} \leftarrow f(\mathbf{x}; W_\lambda)$ #perform inference using weights W_λ

$\nabla \leftarrow g(\mathbf{y}, \mathcal{L}^{\mathbf{x}}) \frac{\partial}{\partial W_\lambda} \Psi(\mathbf{x}, \mathbf{y}, W_\lambda) + \alpha \frac{W - W_\lambda}{\|W - W_\lambda\|_2}$ #compute constraint loss

$W_\lambda \leftarrow W_\lambda - \eta \nabla$ #update instance-specific weights with SGD or a variant thereof

end while

Jay Yoon Lee et al, Gradient-based Inference for Networks with Output Constraint, AAAI 2019

DETAIL

Gradient-Based Inference (GBI)

- GBI (in Algorithm)

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Jay Yoon Lee et al, Gradient-based Inference for Networks with Output Constraint, AAAI 2019

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Jay Yoon Lee et al, Gradient-based Inference for Networks with Output Constraint, AAAI 2019

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- GBI (in Algorithm)

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end while

Reset for new instance

Jay Yoon Lee et al, Gradient-based Inference for Networks with Output Constraint, AAAI 2019

Ganchev et al., 2010, Hu et al., (ACL2016, EMNLP2016, NIPS2018), Hinton et al, 2016

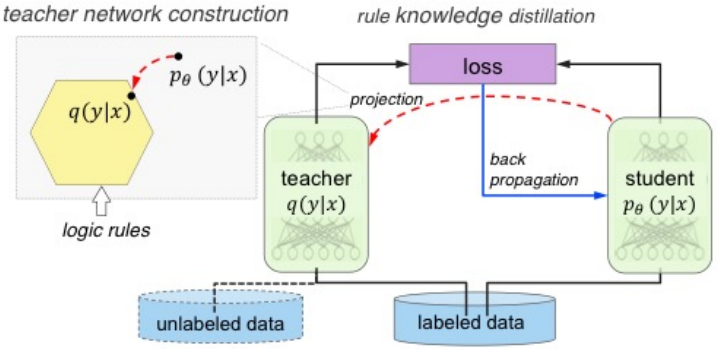
Posterior Regularization & Distillation

- Using posterior regularization,

$$\boldsymbol{\theta}^{(t+1)} = \arg\min_{\theta\in\Theta} \frac{1}{N}\sum_{n=1}^{N}(1-\pi)\ell(\mathbf{y}_n, \boldsymbol{\sigma}_\theta(\mathbf{x}_n)) + \pi\ell(\mathbf{s}_n^{(t)}, \boldsymbol{\sigma}_\theta(\mathbf{x}_n))$$

sampling

$$q^*(\mathbf{Y}|\mathbf{X}) \propto p_\theta(\mathbf{Y}|\mathbf{X}) \exp\left\{-\sum_{l,g_l} C\lambda_l(1 - r_{l,g_l}(\mathbf{X},\mathbf{Y}))\right\}$$



- The base distribution is only stable for problems that current output does not depend on previous output (no seq2seq). (Hu 2016)

- Different way of injecting score. (Mine is direct score of rules whereas PR samples from base probability times exponentiated payoff function.

- Also, sampling (Hu 2018) from q distrbution is required, not easy to do for complicated structures.
  - The NIPS2018 paper does importance sampling with MC sampling on normalization factor. (The author told me that he only samples 5 times)
  - The distribution changes constantly, and not sure how well 5 step MC step will approximate normalization factor.