COGNITIVE COMPUTATION GROUP
UNIVERSITY OF ILLINOIS AT URBANA-CHAMPAIGN

# Learning and Inference in Structured Prediction Models

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**AAAI-16, Phoenix, AZ**

# Structures

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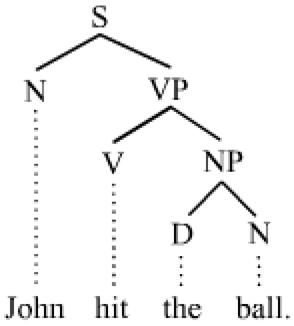


Constituency-based parse tree

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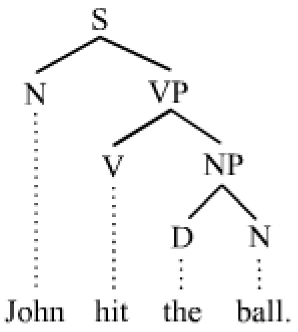


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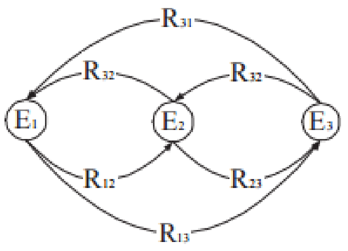

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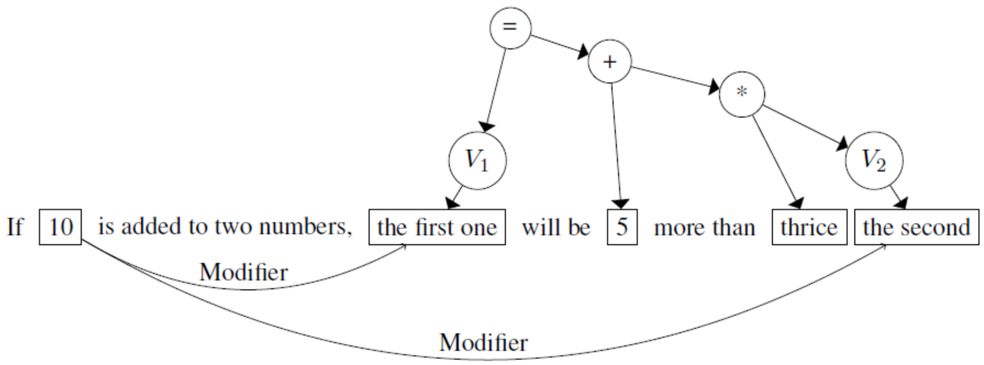


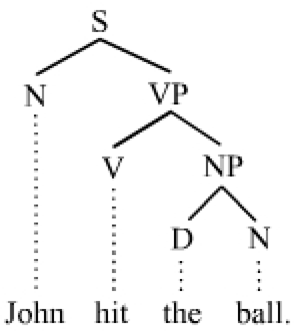


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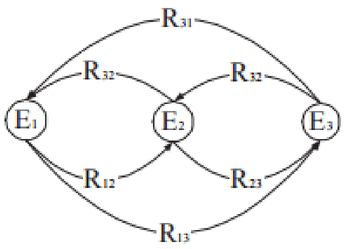

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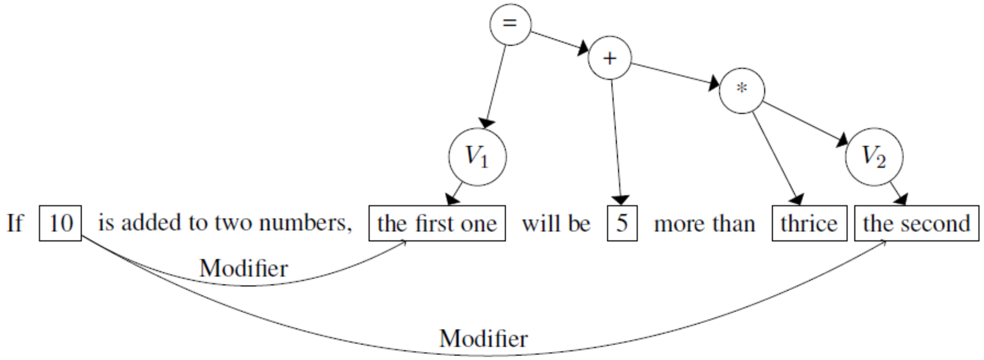


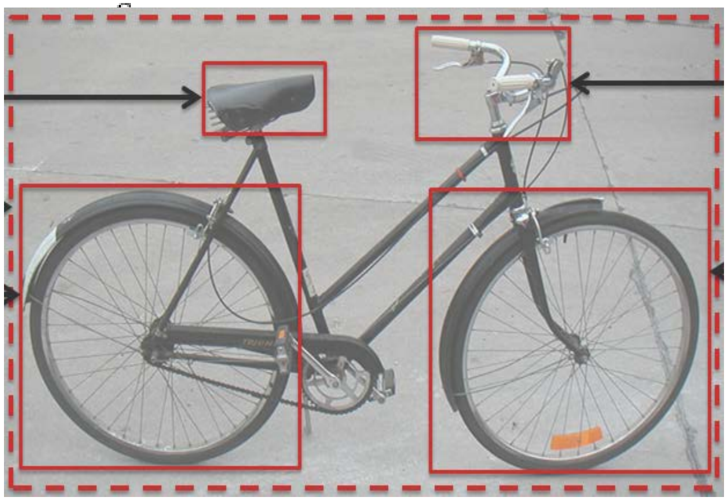

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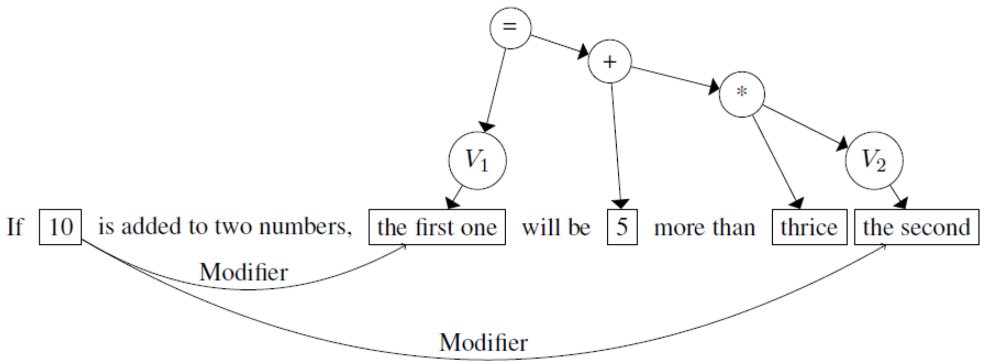


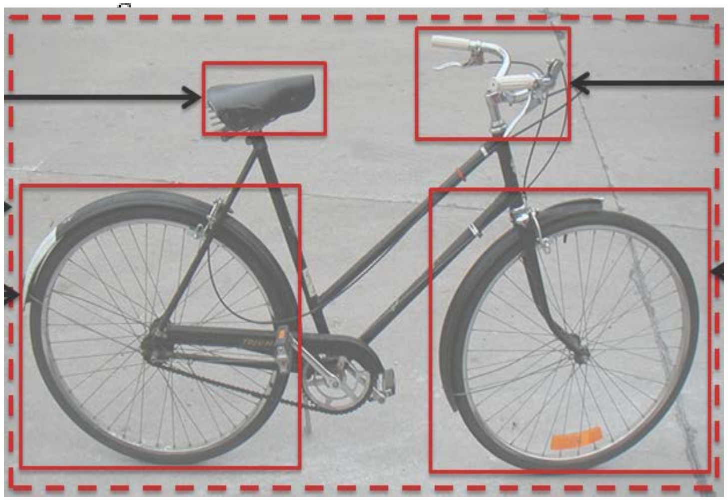

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- It is essential to make coherent decisions in a way that takes the interdependencies into account. Joint, Global Inference.

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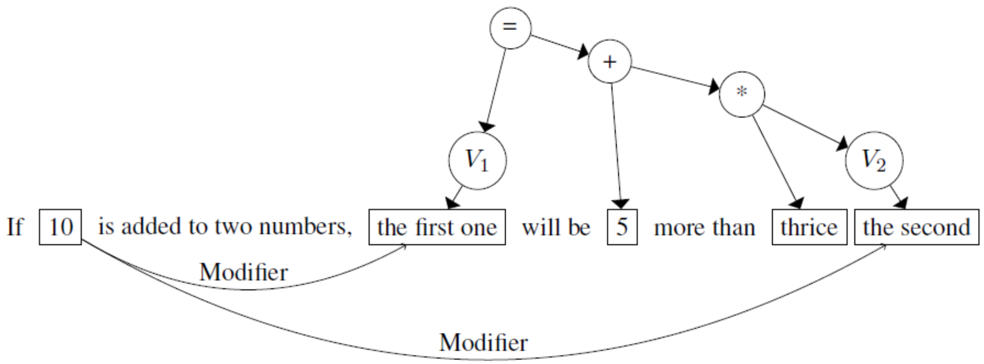


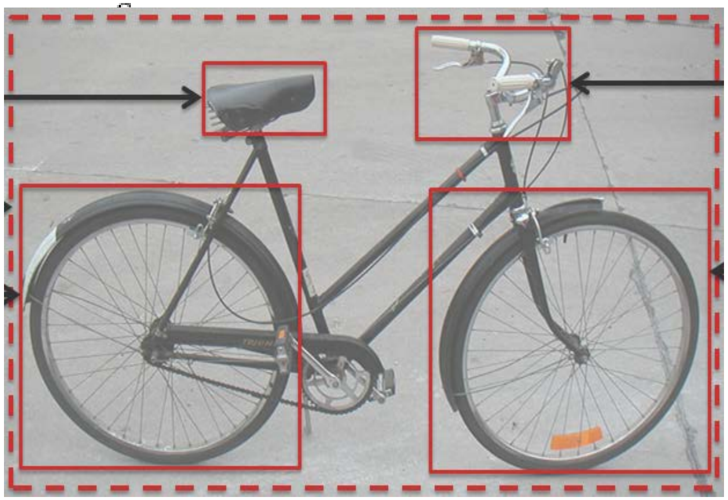

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- It is essential to make coherent decisions in a way that takes the interdependencies into account. Joint, Global Inference.
  - Inference: How to support making these global, coherent decisions
  - Learning: How to learn models to support these decisions.

# Learning and Inference in Structured Prediction

- Part 1: Introduction to Structured Prediction (60min)
  - Motivation
  - Examples:
    - **NE + Relations**
    - **Vision**
    - **Additional NLP Examples**
  - Problem Formulation
    - **Constrained Conditional Models: Integer Linear Programming Formulations**
  - Initial thoughts about learning
    - **Learning independent models**
    - **Constraints Driven Learning**
  - Initial thoughts about Inference
    - **Amortized Inference**

- Part 2: Learning a Structured Prediction Model (45min)
  - Definition
  - Local Learning v.s. Global Learning
  - Global Learning Algorithms
    - **Online learning: Structured Perceptron**
    - **Batch learning: Structured SVM**
  - Optimization methods for Structured SVM
    - **Stochastic Gradient Decent**
    - **Dual Coordinate Descent**
    - **Learning on a multi-core machine**
- BREAK

- Part 3: Amortized Inference (45min)
  - Overview
  - Amortization at Inference Time
    - **Theorems**
    - **Decomposition**
    - **Results**
  - Amortization during Learning
    - **Approximate Inference**
    - **Results**

# Learning and Inference in Structured Prediction

- Part 4: Distributed Representations for Structured Prediction (30 min)
  - Distributional representations for inputs is a success story
    - **Eg. word vectors**
  - Outputs are discrete objects
    - **One of a set of labels (document classification)**
    - **Label sequences (POS tagging, Chunking, NER)**
    - **Trees with labeled edges/nodes (Parsing)**
    - **Arbitrary graphs (Semantic Role Labeling, event extraction)**
  - Can we think of distributional representations for structures?
    - **Starting with individual labels to compose full structures**
    - **A natural generalization of standard structured prediction formalism**

- Part 5: Structured Prediction Software (15min)
  - Illinois Structured Learning Library
    - **A general purpose learning library in JAVA**
    - **Support Structured Perceptron and Structured SVM**
  - Implement your own applications
- Part 6: Conclusion and Discussion (15min)

# PART 1: INTRODUCTION

**Part 1: Introduction to Structured Prediction** (55min)

- **Motivation**
- **Examples:**
  - **NE + Relations**
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- **Problem Formulation**
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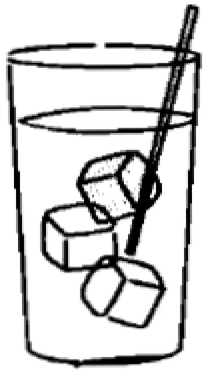
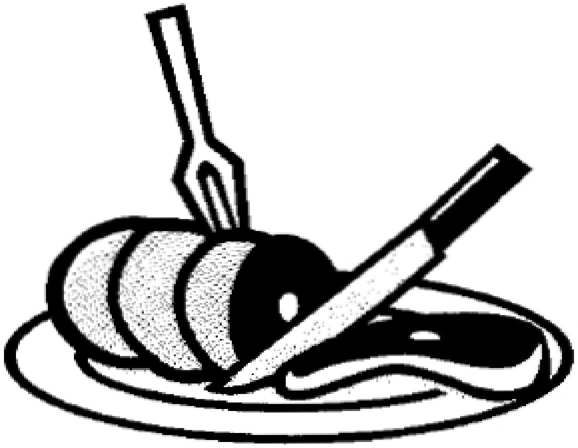
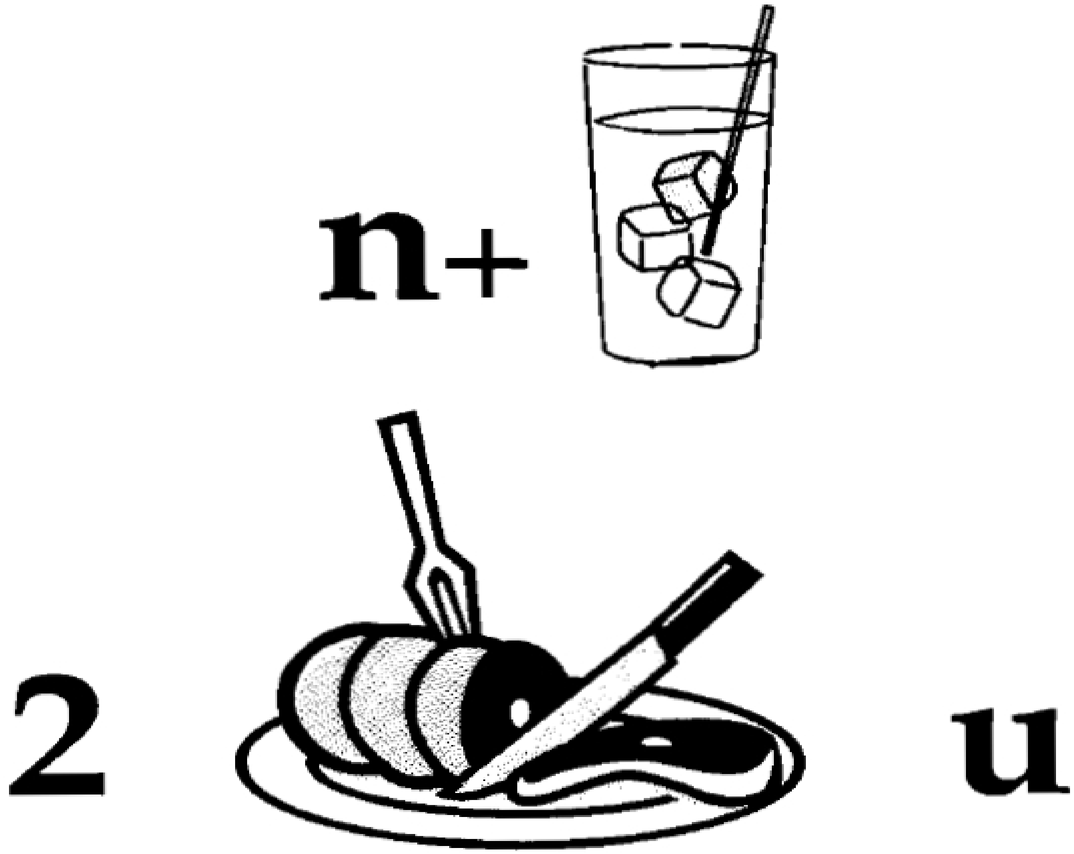
n+ 

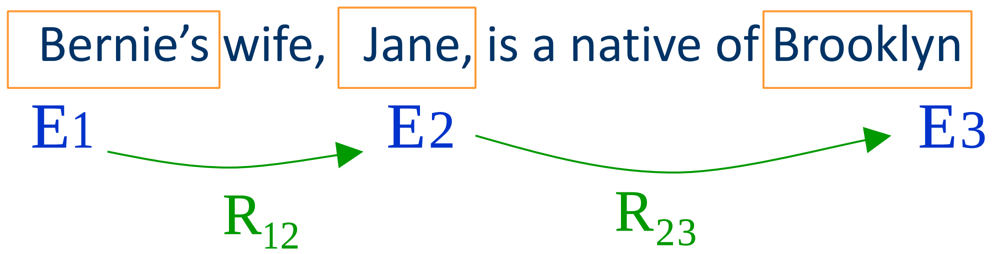
2  u

# Nice to Meet You



# Joint Inference with General Constraint Structure [Roth&Yih'04,07,….]

Recognizing Entities and Relations



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Bernie's wife, Jane, is a native of Brooklyn

E1 E2 E3

$R_{12}$ $R_{23}$

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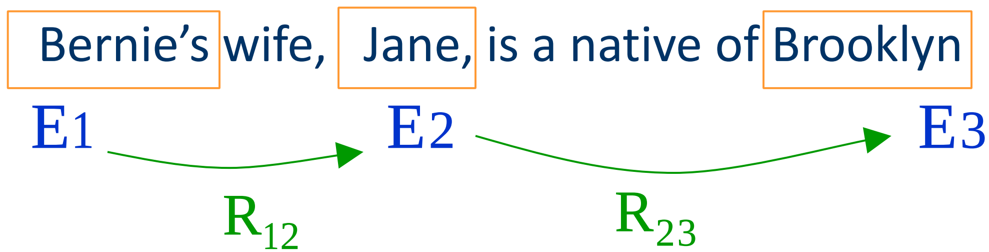


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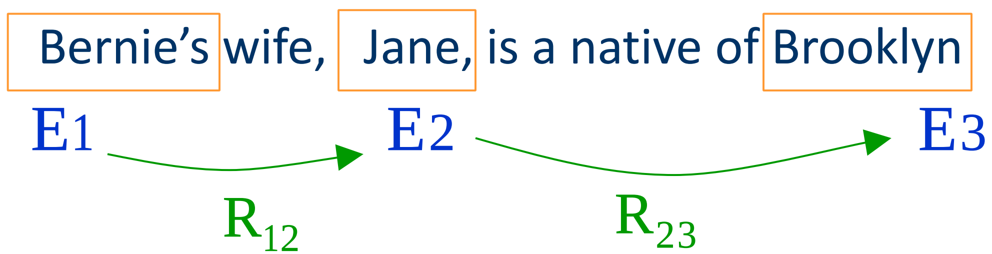


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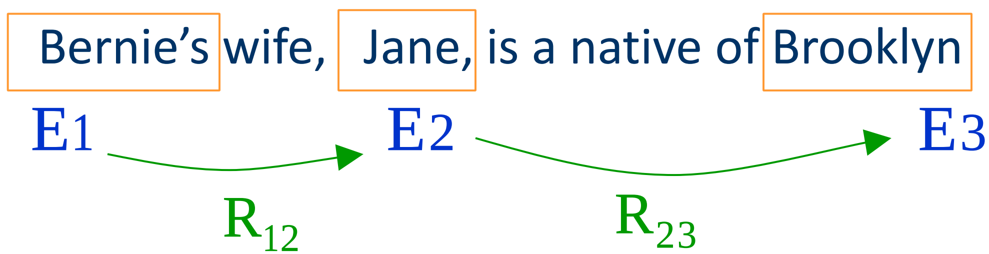


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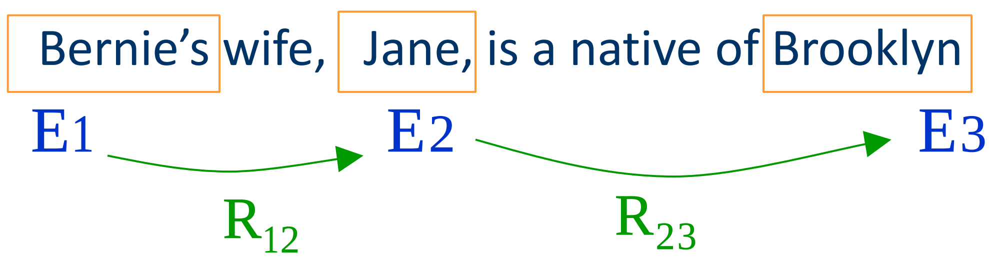


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Key Questions:
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… the knowledge?
… ference?

An Objective function that incorporates learned models with knowledge (**output constraints**)

A Constrained Conditional Model

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Raw Data

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Parsing → WSD → Semantic Role Labeling

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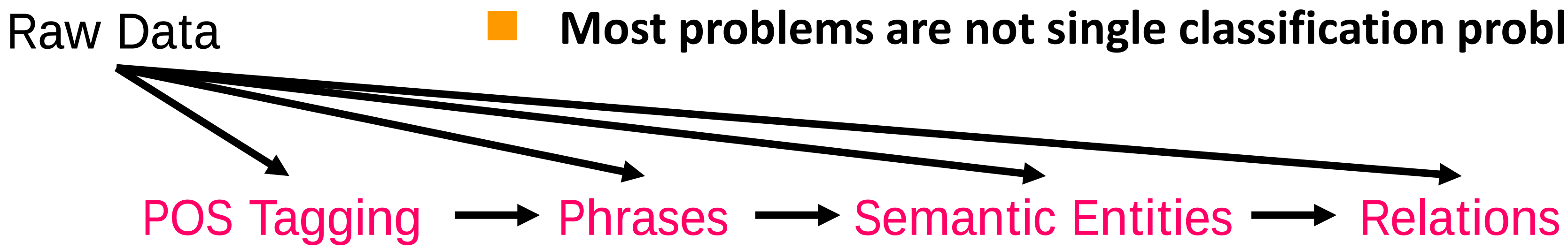


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  - How about choosing some stages and think about them jointly?

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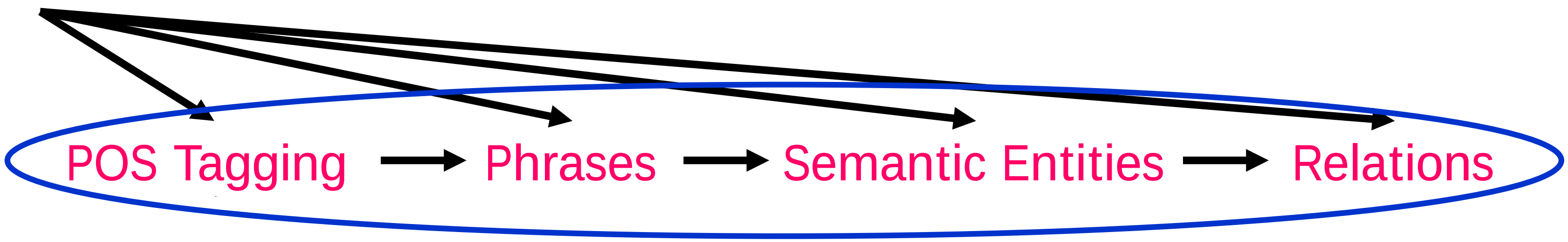


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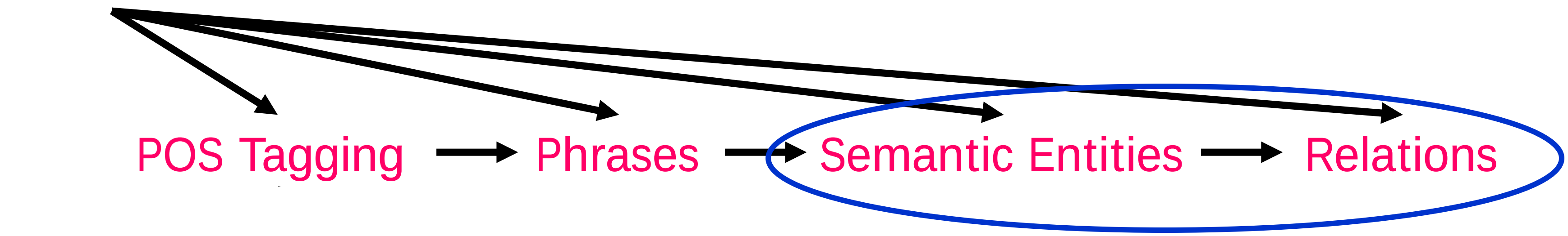


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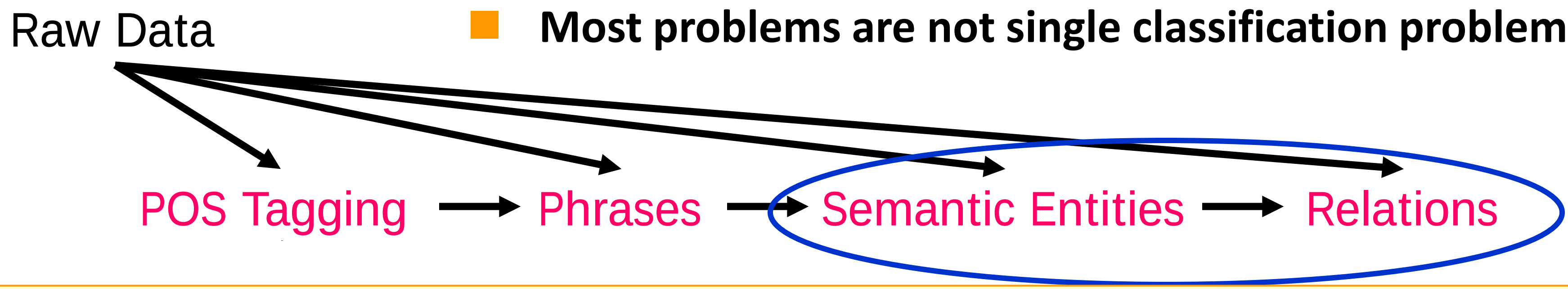


Either way, we need a way to **learn models** and **make predictions (inference; decoding) that assign** values to multiple interdependent variables

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# Example 2: Object detection

Right facing bicycle

Photo by Andrew Dressel - Own work. Licensed under Creative Commons Attribution-Share Alike 3.0

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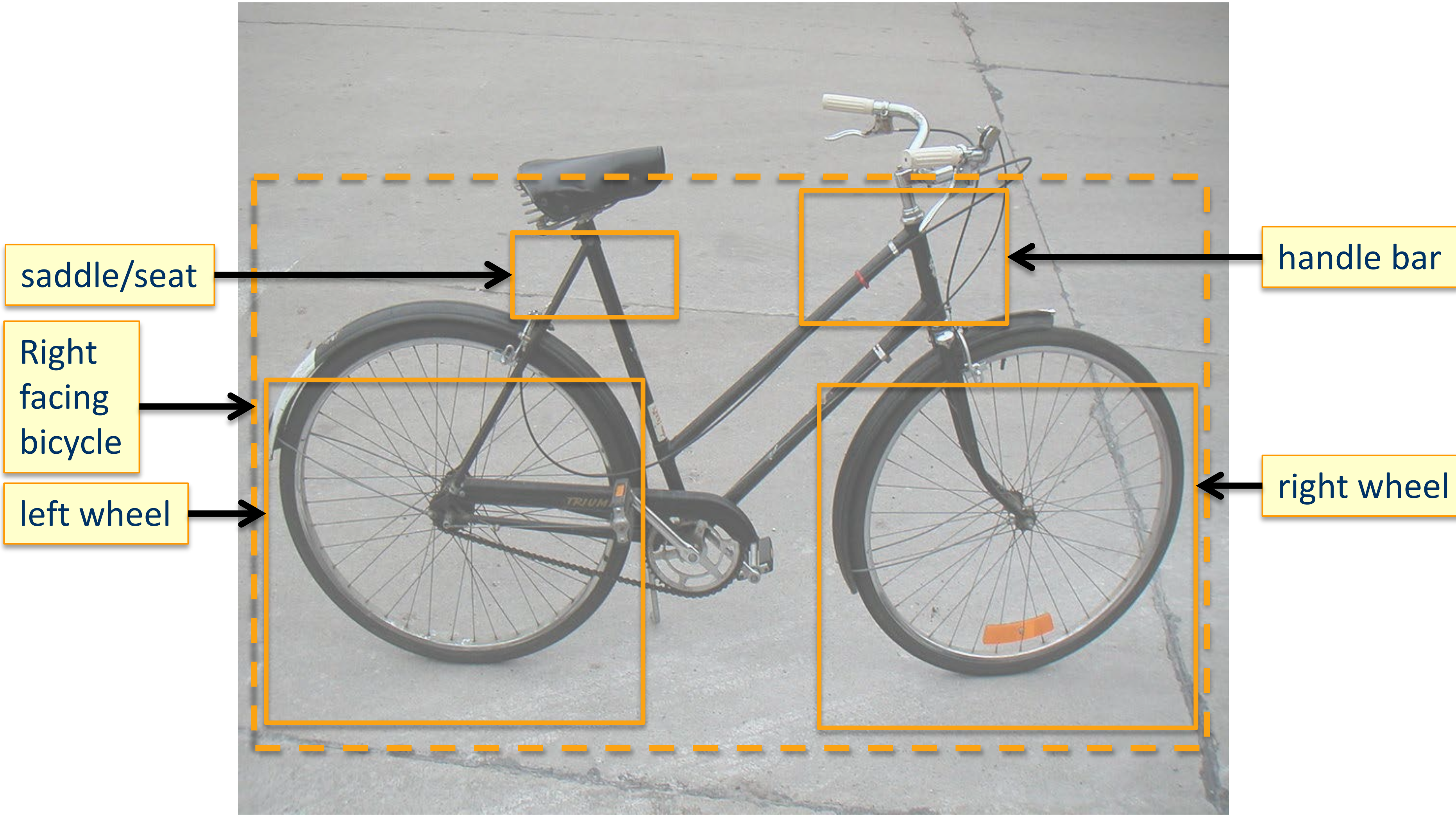
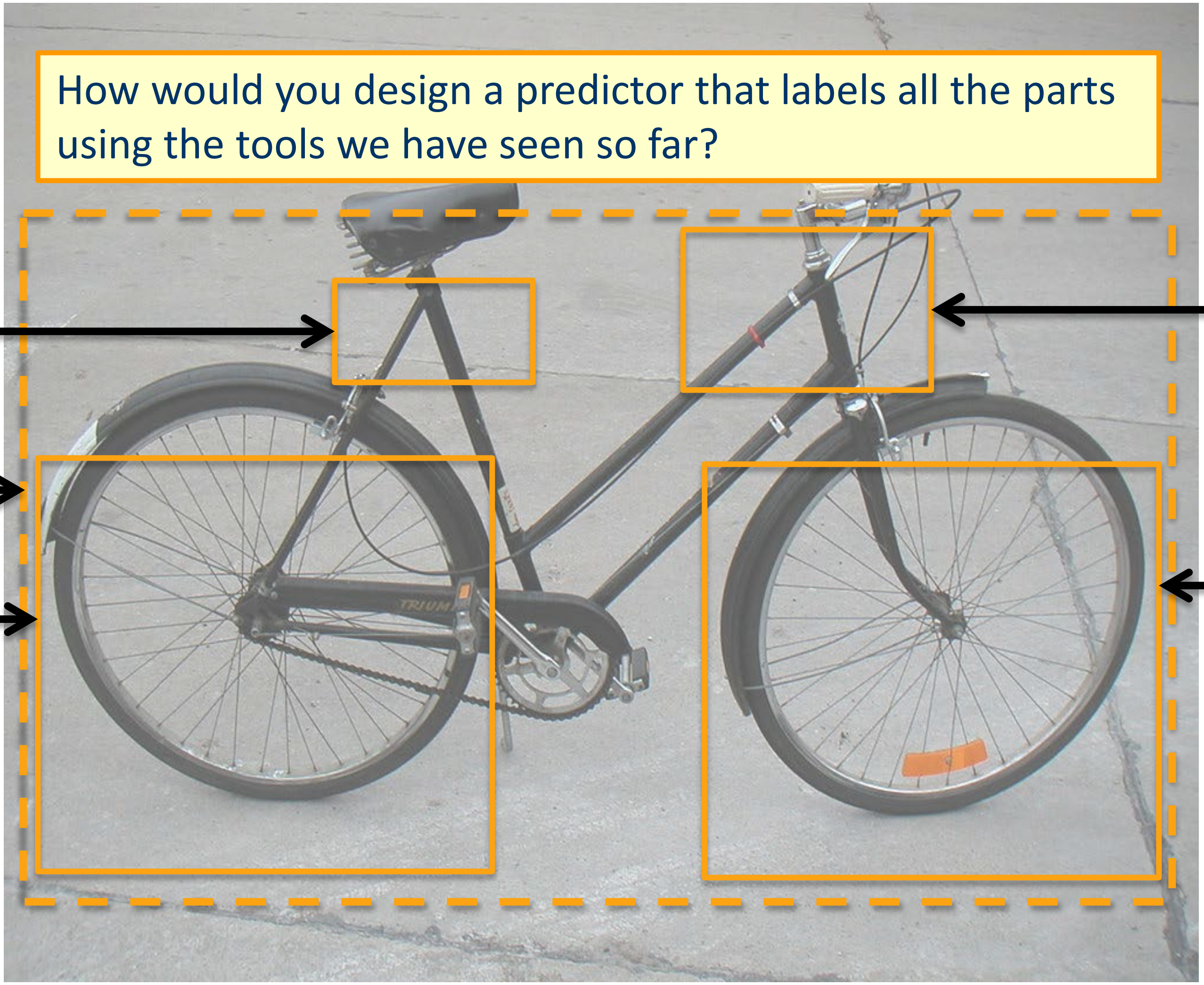
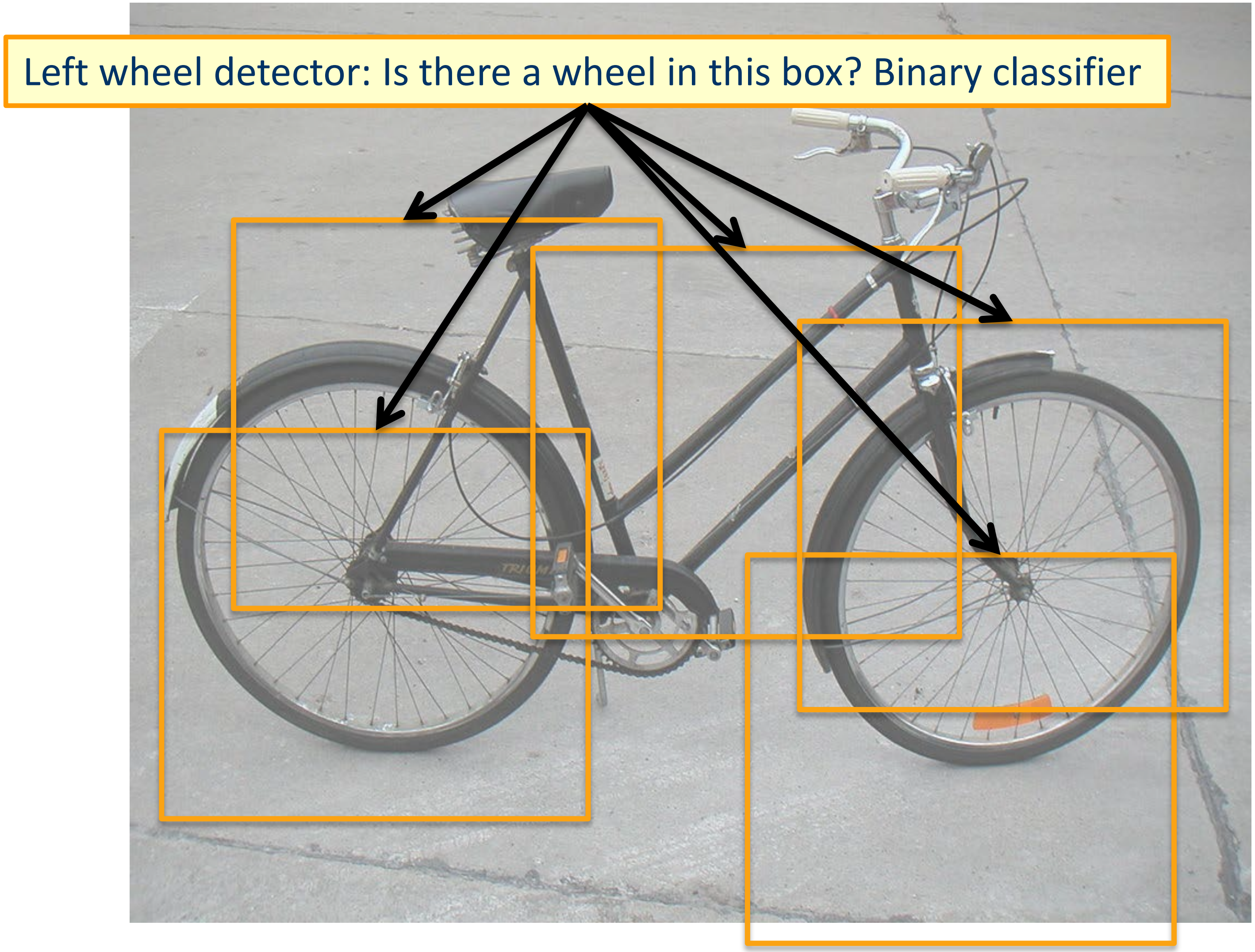


# Example 2: Object detection

How would you design a predictor that labels all the parts using the tools we have seen so far?



# One approach to build this structure



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1. Left wheel detector

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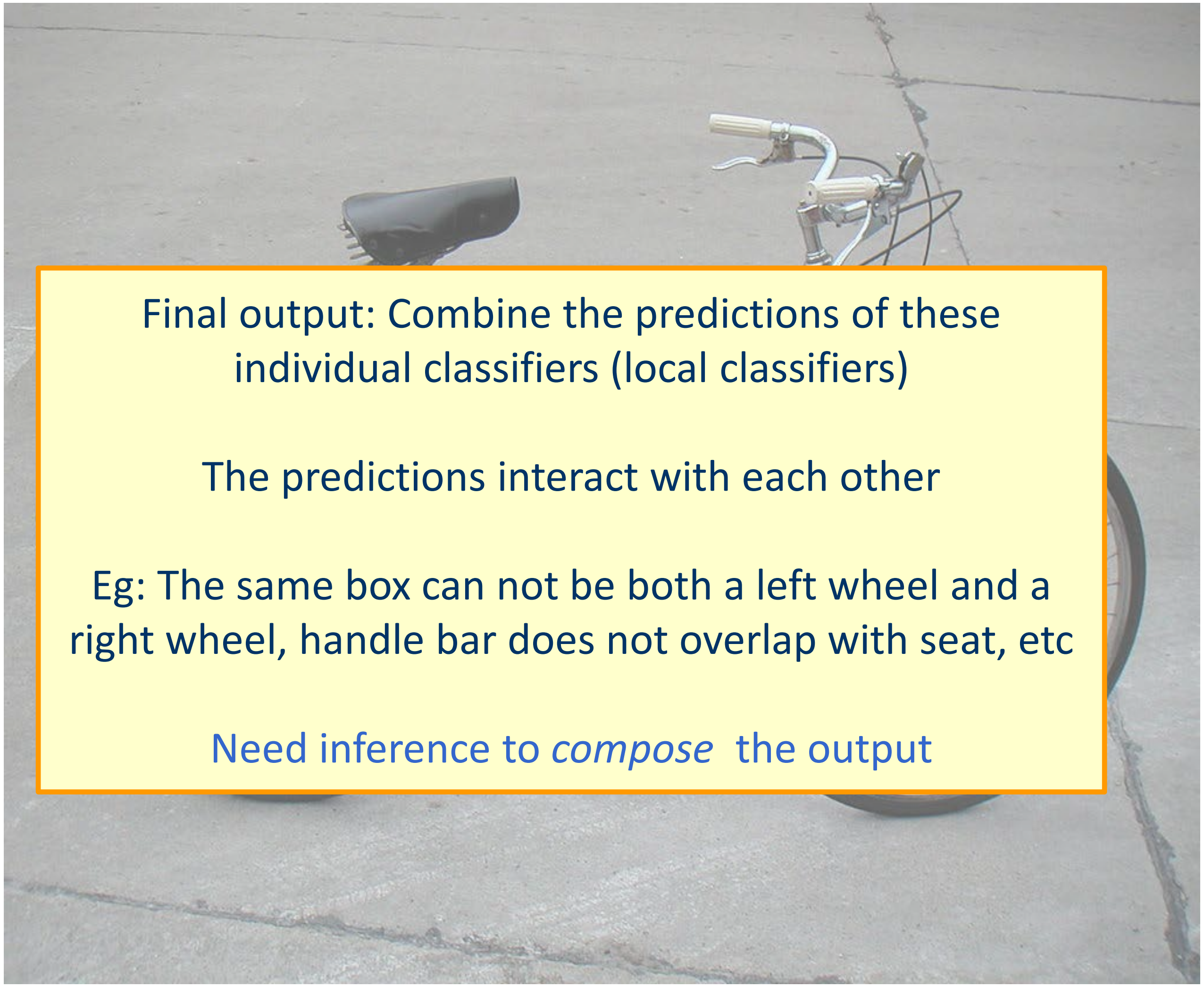

Final output: Combine the predictions of these individual classifiers (local classifiers)

The predictions interact with each other

Eg: The same box can not be both a left wheel and a right wheel, handle bar does not overlap with seat, etc

Need inference to *compose* the output

# Task of Interests: Structured Output

- For each instance, assign values to a set of variables
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  - Parsing; Semantic Parsing; Summarization; Co-reference…
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  - Entities, Relations,…
- Common Vision Task:
  - Parsing objects; scene segmentation and interpretation,….

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- Common Vision Task:
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- Many "pure" machine learning approaches exist
  - Hidden Markov Models (HMMs); CRFs […there are special cases…]
  - Structured Perceptrons and SVMs… [… to be discussed later]
- However, …

# Information Extraction without Output Expectations

Lars Ole Andersen . Program analysis and specialization for the C Programming language. PhD thesis. DIKU , University of Copenhagen, May 1994 .

[AUTHOR]

[TITLE]

[EDITOR]

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[TECH-REPORT]

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[DATE]

# Information Extraction without Output Expectations

Lars Ole Andersen . Program analysis and specialization for the C Programming language.  PhD thesis. DIKU , University of Copenhagen, May 1994 .

**Prediction result of a trained HMM**

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Violates lots of natural constraints!

# Strategies for Improving the Results

- (Standard) Machine Learning Approaches
  - Higher Order HMM/CRF?
  - Increasing the window size?
  - Adding a lot of new features
    - Requires a lot of labeled examples

Increasing the model complexity

Increase difficulty of Learning

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Can we keep the learned model simple and still make expressive decisions?

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Increasing the model complexity

Increase difficulty of Learning

Can we keep the learned model simple and still make expressive decisions?

- Instead:
  - Constrain the output to make sense – satisfy our output expectations
  - Push the (simple) model in a direction that makes sense – minimally violates our expectations.

# Expectations from the output (Constraints)

- Each field must be a consecutive list of words and can appear at most once in a citation.
- State transitions must occur on punctuation marks.
- The citation can only start with AUTHOR or EDITOR.
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Easy to express pieces of "knowledge"

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Easy to express pieces of “knowledge”

Non Propositional; May use Quantifiers

# Information Extraction with Expectation Constraints

- Adding constraints, we get correct results!
  - Without changing the model

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We introduce the **Constrained Conditional Models formulation** which allows:

- Learning a simple model
- Making decisions with a more complex model
  - Some of the structure imposes externally/declaratively
- Accomplished by directly incorporating constraints to bias/re-rank decisions made by the simpler model

# Constrained Conditional Models

$$\mathbf{y} = \operatorname{argmax}_{\mathbf{y} \in \mathcal{Y}} \; \mathbf{w}^T \phi(\mathbf{x}, \mathbf{y}) + \mathbf{u}^T \mathcal{C}(\mathbf{x}, \mathbf{y})$$

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Weight Vector for "local" models

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Features, classifiers; log-linear models (HMM, CRF) or a combination

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(Soft) constraints component

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Penalty for violating the constraint.

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How far y is from a "legal" assignment

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How far y is from a "legal" assignment

How to solve?

This is an Integer Linear Program

Solving using ILP packages gives an exact solution.

Cutting Planes, Dual Decomposition & other search techniques are possible

**Amortized ILP inference Scheme**

How to train?

**Training** is learning the objective function

Decompose objective? Decouple? Train Jointly?

How to exploit the structure to minimize supervision?

**New (joint and distributed algorithms**

# Structured Prediction: Inference

- Inference: given input **x** (a document, a sentence),

  predict **the best structure** $y = \{y_1, y_2, \ldots, y_n\} \in Y$ (entities & relations)

  - Assign values to the $y_1, y_2, \ldots, y_n$, accounting for **dependencies among** $y_i$s

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Placing in context: a very high level view of what you will see next

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- Inference requires, in principle, touching all $y \in Y$ at decision time, when we are given $x \in X$ and attempt to determine the best $y \in Y$ for it, given $w$
  - For some structures, inference is computationally easy.
  - Eg: Using the Viterbi algorithm
  - In general, NP-hard (can be formulated as an ILP)

# Structured Prediction: Learning

- Learning: given a set of structured examples {(x,y)}

  find a scoring function w that minimizes empirical loss.

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**Score of annotated structure** $\geq$ **Score of any other structure** $+$ **Penalty for predicting other structure**

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- W.l.o.g. (almost) we can thus write the generic structured learning algorithm as follows:

# Structured Prediction: Learning Algorithm

- For each example $(x_i, y_i)$
- Do: (with the current weight vector $w$)
  - **Predict:** perform Inference with the current weight vector
    - $\mathbf{y_i' = \text{argmax}_{y \in \mathcal{Y}}\, w^T \phi(x_i, y)}$
  - **Check** the learning constraints
    - **Is the score of the current prediction better than of $(x_i, y_i)$?**
  - If **Yes** – a mistaken prediction
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In the structured case, prediction (inference) is often intractable but needs to be done many times

# Structured Prediction: Learning Algorithm

Solution I: decompose the scoring function to EASY and HARD parts

- For each example $(x_i, y_i)$
- Do:
  - **Predict:** perform Inference with the current weight vector
    - $y_i' = \text{argmax}_{y \in \mathcal{Y}} \; w_{EASY}^T \phi_{EASY}(x_i, y) + w_{HARD}^T \phi_{HARD}(x_i, y)$
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EASY: could be feature functions that correspond to an HMM, a linear CRF, or even $\phi_{EASY}(x,y) = \phi(x)$, omiting dependence on y, corresponding to classifiers. May not be enough if the HARD part is still part of each inference step.

# Structured Prediction: Learning Algorithm

Solution II: Disregard some of the dependencies: **assume a simple model.**

- For each example $(x_i, y_i)$
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Solution III: Disregard some of the dependencies during learning; take into account at decision time

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**This is the most commonly used solution in NLP today**

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- Training: learning the objective function (**w, u**)
  - Decouple? Decompose? Force **u** to model hard constraints?

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Weight Vector for "local" models

Features, classifiers; log-linear models (HMM, CRF) or a combination

How far y is from a "legal/expected" assignment

- Training: learning the objective function (**w, u**)
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# Constrained Conditional Models

Penalty for violating the constraint.

$$\arg\max_{\mathbf{y}\in\mathcal{Y}} \sum_{p\in\Gamma_{\mathbf{x}}} \mathbf{1}_{[Y_p=\mathbf{y}_p]}\mathbf{w}^T\Phi_p\left(\mathbf{x},\mathbf{y}_p\right)$$

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Any MAP problem w.r.t. any probabilistic model, can be formulated as an **Integer Linear Program (ILP)** Roth+ 04, Taskar 04]

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  - [CoDL, Chang, Ratinov, Roth (07, 12); Posterior Regularization, Ganchev et. al (10); Unified EM (Samdani & Roth(12)]
- The benefits of thinking about it as an ILP are conceptual and computational.

# Examples: CCM Formulations

$$\mathbf{y} = \mathbf{argmax}_{\mathbf{y} \in \mathcal{Y}}\ \mathbf{w}^{\mathrm{T}}\phi(\mathbf{x}, \mathbf{y}) + \mathbf{u}^{\mathrm{T}}\mathcal{C}(\mathbf{x}, \mathbf{y})$$

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While $\phi$**(x, y) and** $\mathcal{C}$**(x, y)** could be the same; we want C(x, y) to express high level declarative knowledge over the statistical models.

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Formulate NLP Problems as ILP problems (inference may be done otherwise)

1. Sequence tagging (HMM/CRF + Global constraints)
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**Sequential Prediction**

HMM/CRF based:

Argmax $\sum \lambda_{ij}$ $x_{ij}$

**Knowledge/Linguistics Constraints**

Cannot have both A states and B states in an output sequence.

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Sentence Compression/Summarization:

Language Model based:

Argmax $\sum \lambda_{ijk} x_{ijk}$

Knowledge/Linguistics Constraints

If a modifier chosen, include its head

If verb is chosen, include its arguments

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Constrained Conditional Models Allow:

- Decouple complexity of the learned model from that of the desired output
- Learn a simple model (multiple; pipelines); reason with a complex one.
- Accomplished by incorporating constraints to bias/re-rank global decisions to satisfy (minimally violate) expectations.

# Semantic Role Labeling (SRL)

**I *left* my pearls to my daughter in my will .**

**$[\text{I}]_{A0}$ *left* $[\text{my pearls}]_{A1}$ $[\text{to my daughter}]_{A2}$ $[\text{in my will}]_{AM\text{-}LOC}$ .**

- ***A0*** Leaver
- ***A1*** Things left
- ***A2*** Benefactor
- ***AM-LOC*** Location

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# Semantic Role Labeling (SRL)

**Archetypical Information Extraction Problem**: E.g., Concept Identification and Typing, Event Identification, etc.

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# Algorithmic Approach

- Identify argument candidates
  - Pruning [Xue&Palmer, EMNLP'04]
  - Argument Identifier
    - **Binary classification**
- Classify argument candidates
  - Argument Classifier
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- Inference
  - Use the estimated probability distribution given by the argument classifier
  - Use structural and linguistic constraints
  - Infer the optimal global output

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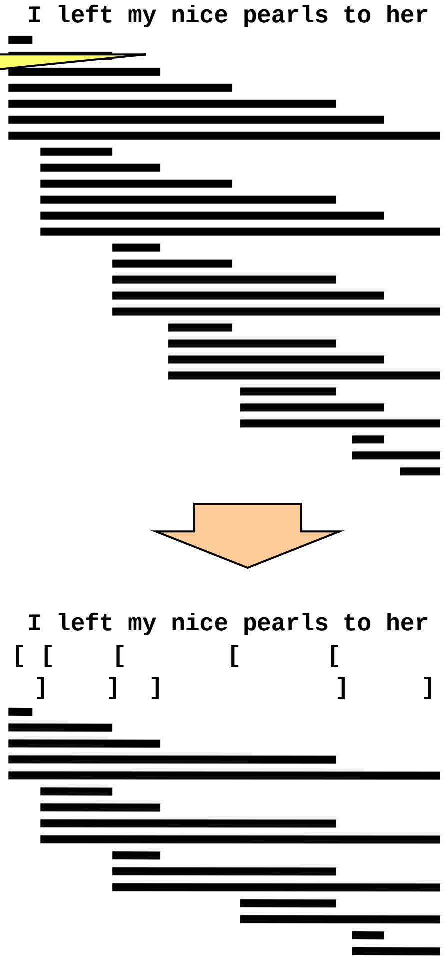

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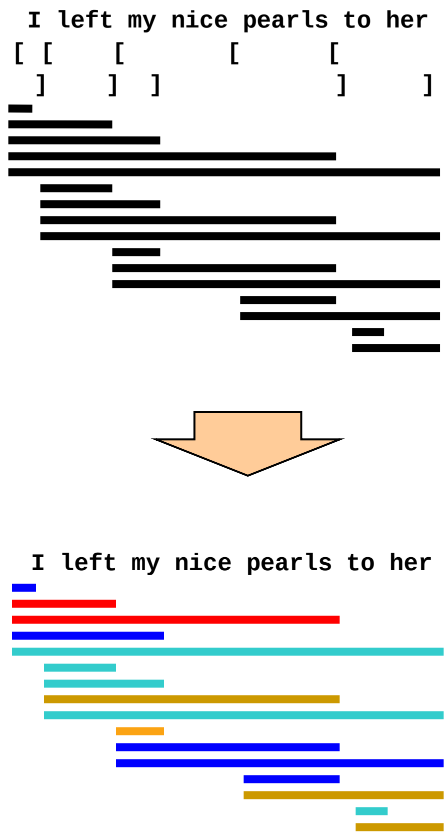

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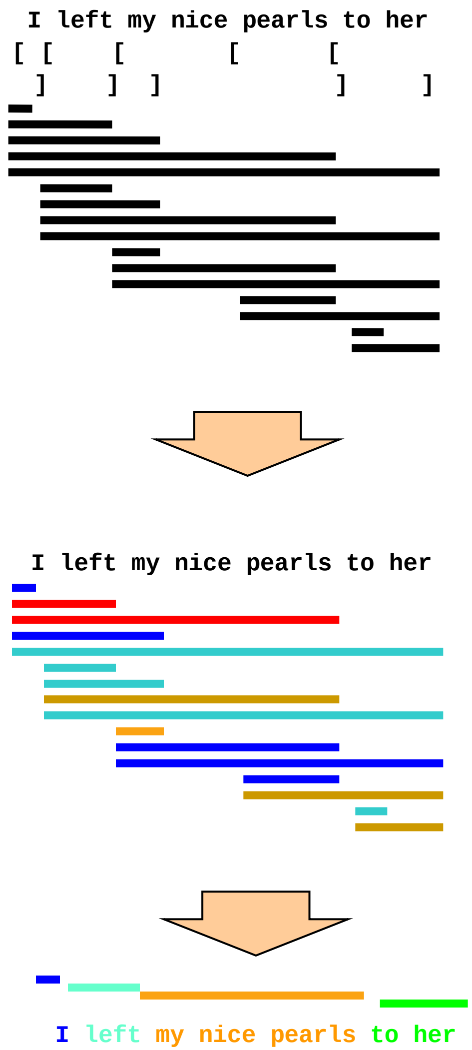

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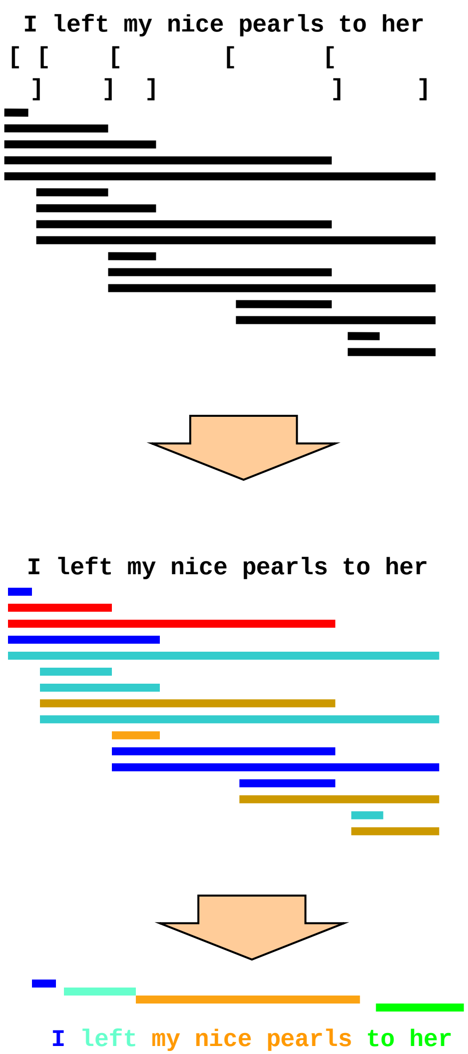
One inference problem for each verb predicate.



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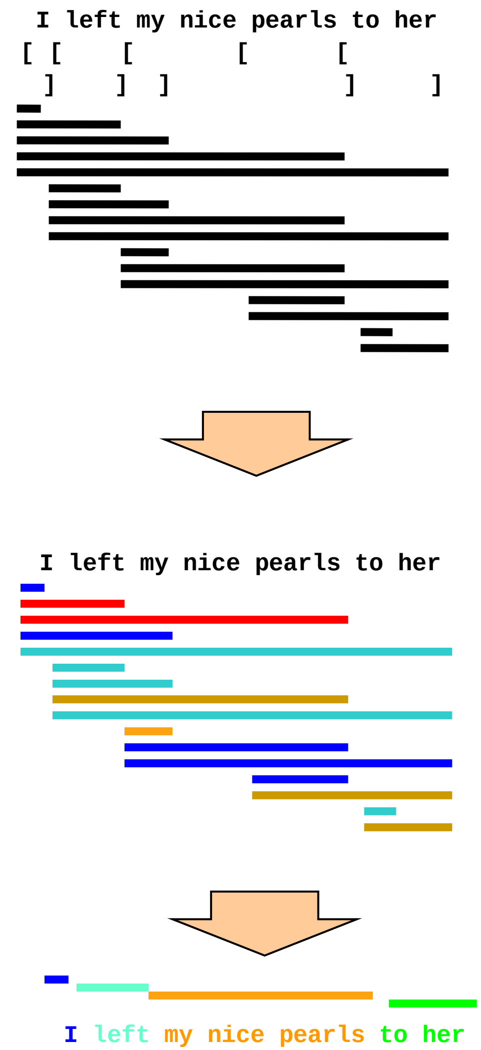
argmax $\sum_{a,t} y^{a,t} c^{a,t} = \sum_{a,t} 1_{a=t} c_{a=t}$

Subject to:

- One label per argument: $\sum_t y^{a,t} = 1$
- No overlapping or embedding
- Relations between verbs and arguments,....



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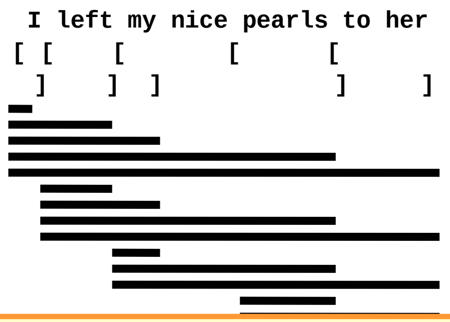


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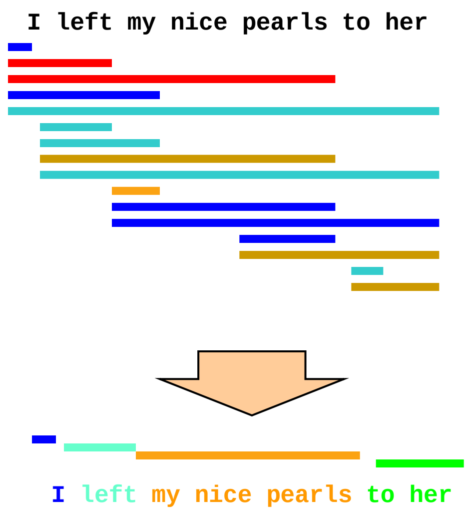

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No duplicate argument classes

$$\forall i, \sum_{y \in \mathcal{Y}} 1_{\{y_i = y\}} = 1$$

Unique labels

$$\forall y \in \mathcal{Y}, \sum_{i=0}^{n-1} 1_{\{y_i = y\}} \leq 1$$

$$\forall y \in \mathcal{Y}_R, \sum_{i=0}^{n-1} 1_{\{y_i = y = \text{“R-Ax”}\}} \leq \sum_{i=0}^{n-1} 1_{\{y_i = \text{“Ax”}\}}$$

$$\forall j, y \in \mathcal{Y}_C, 1_{\{y_j = y = \text{“C-Ax”}\}} \leq \sum_{i=0}^{j} 1_{\{y_i = \text{“Ax”}\}}$$

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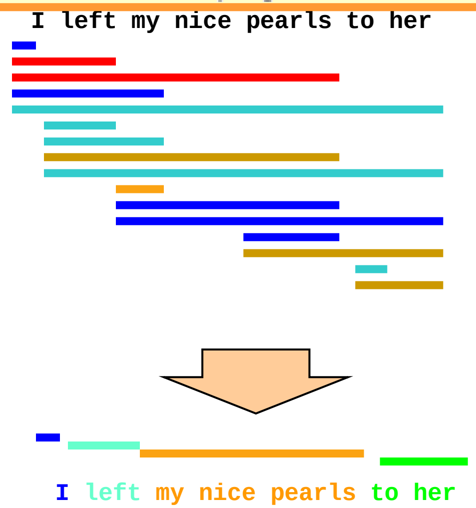

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Learning Based Java: allows a developer to encode constraints in First Order Logic; these are compiled into linear inequalities automatically.

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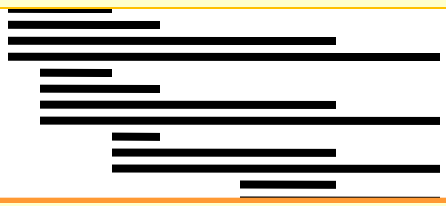

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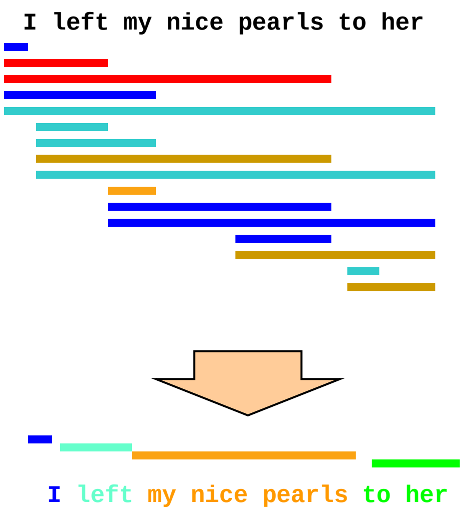


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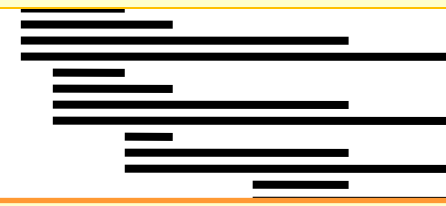

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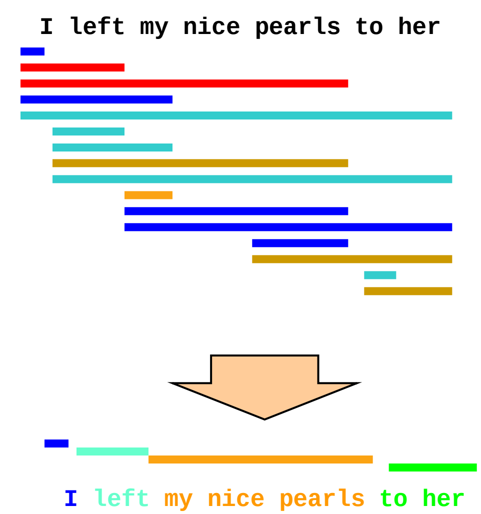
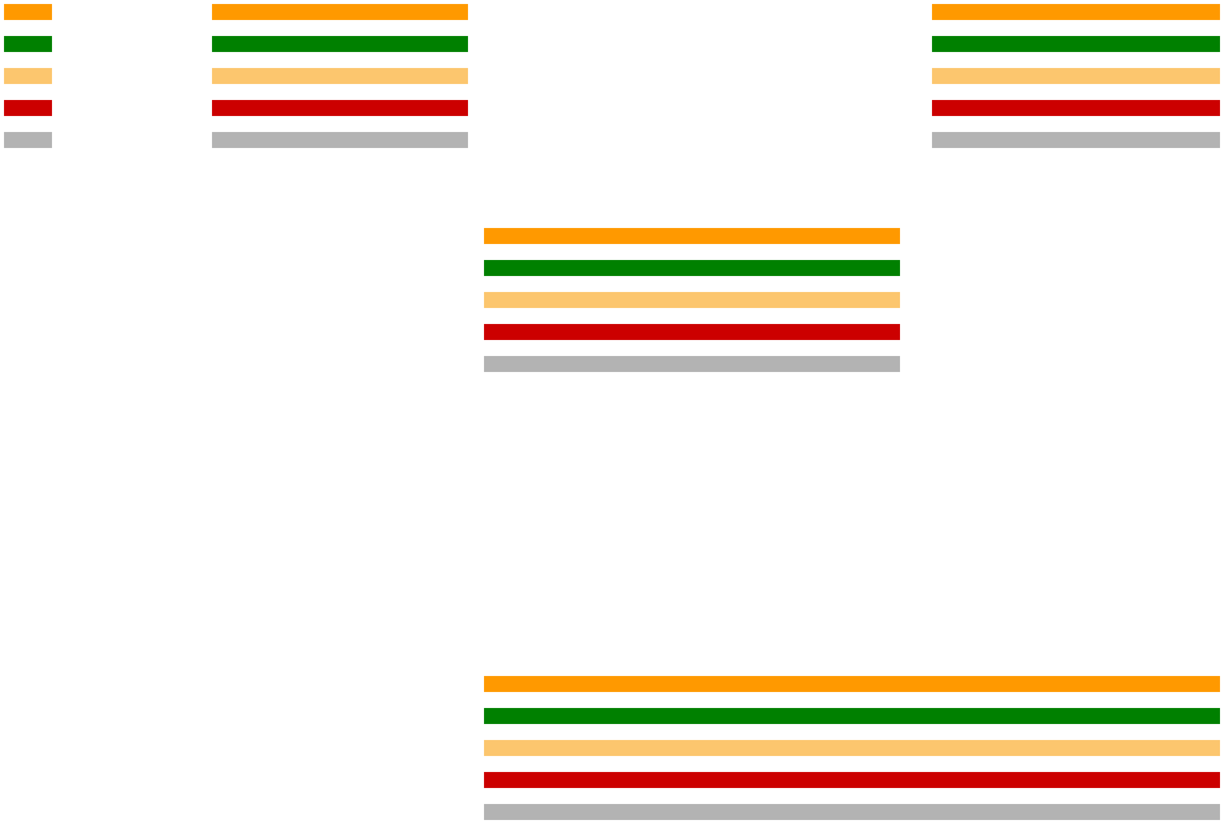



Use the **pipeline architecture's simplicity** while **maintaining uncertainty**: keep probability distributions over decisions & use global inference at decision time.

# Semantic Role Labeling (SRL)

**I *left* my pearls to my daughter in my will .**



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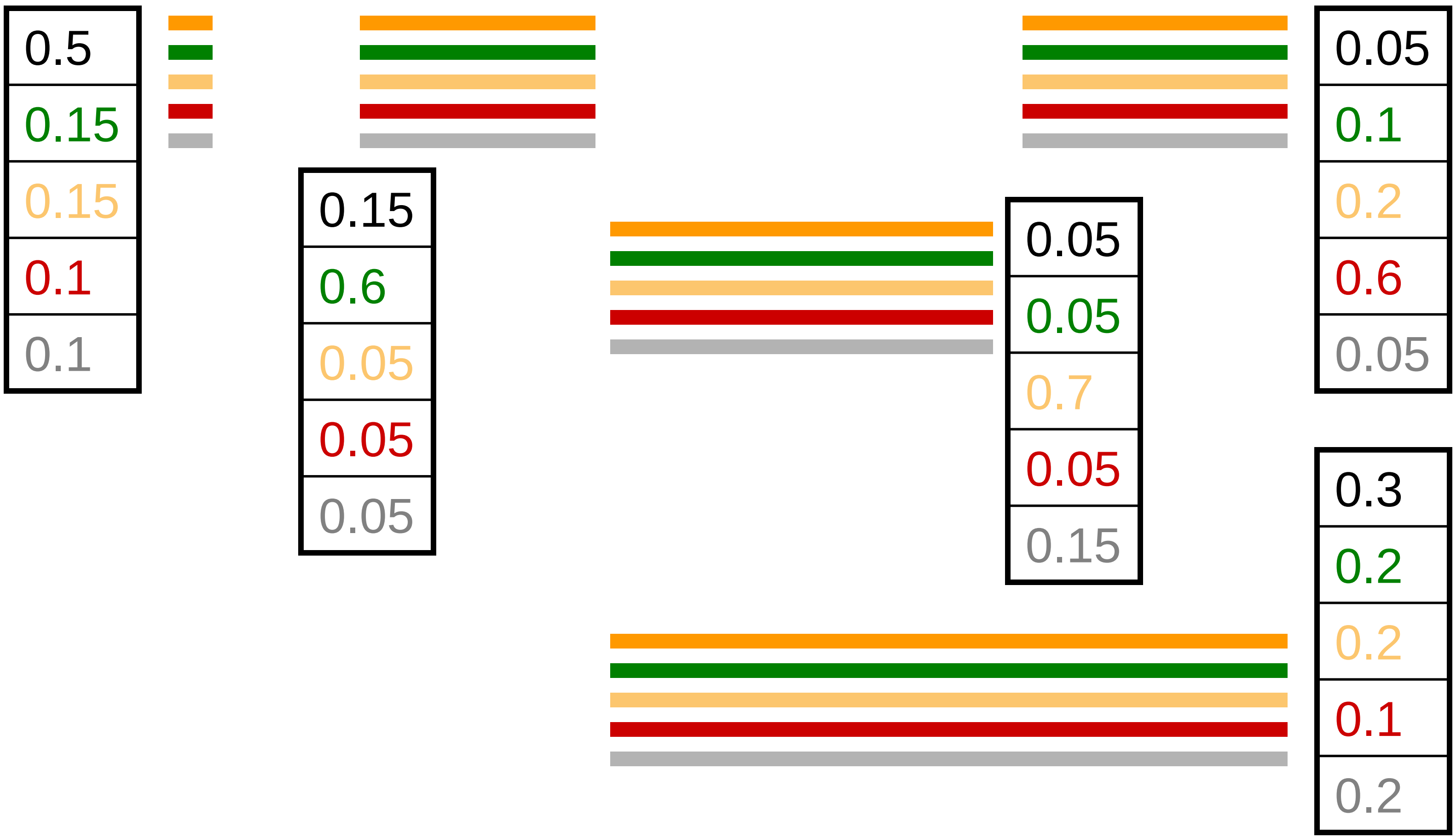

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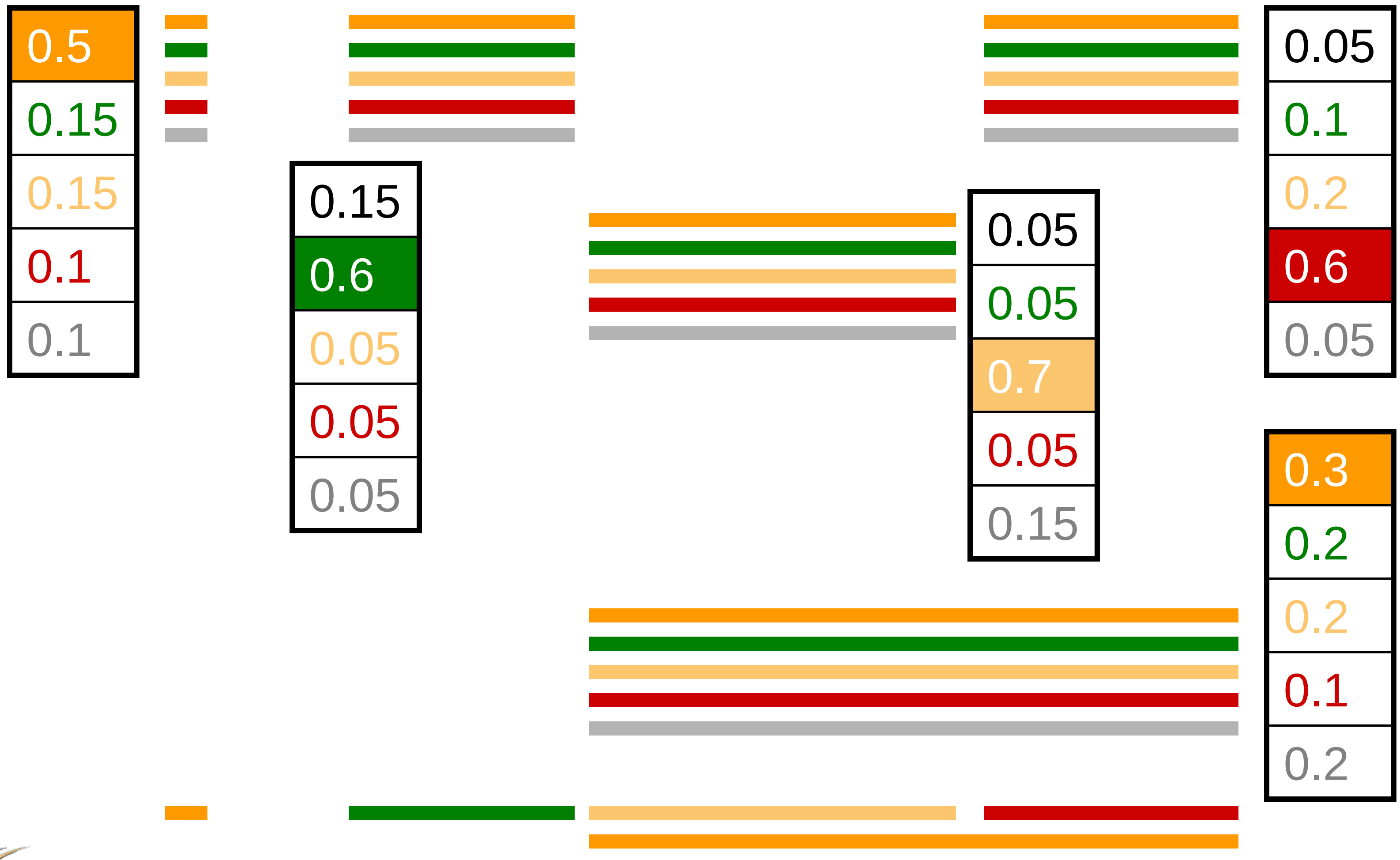

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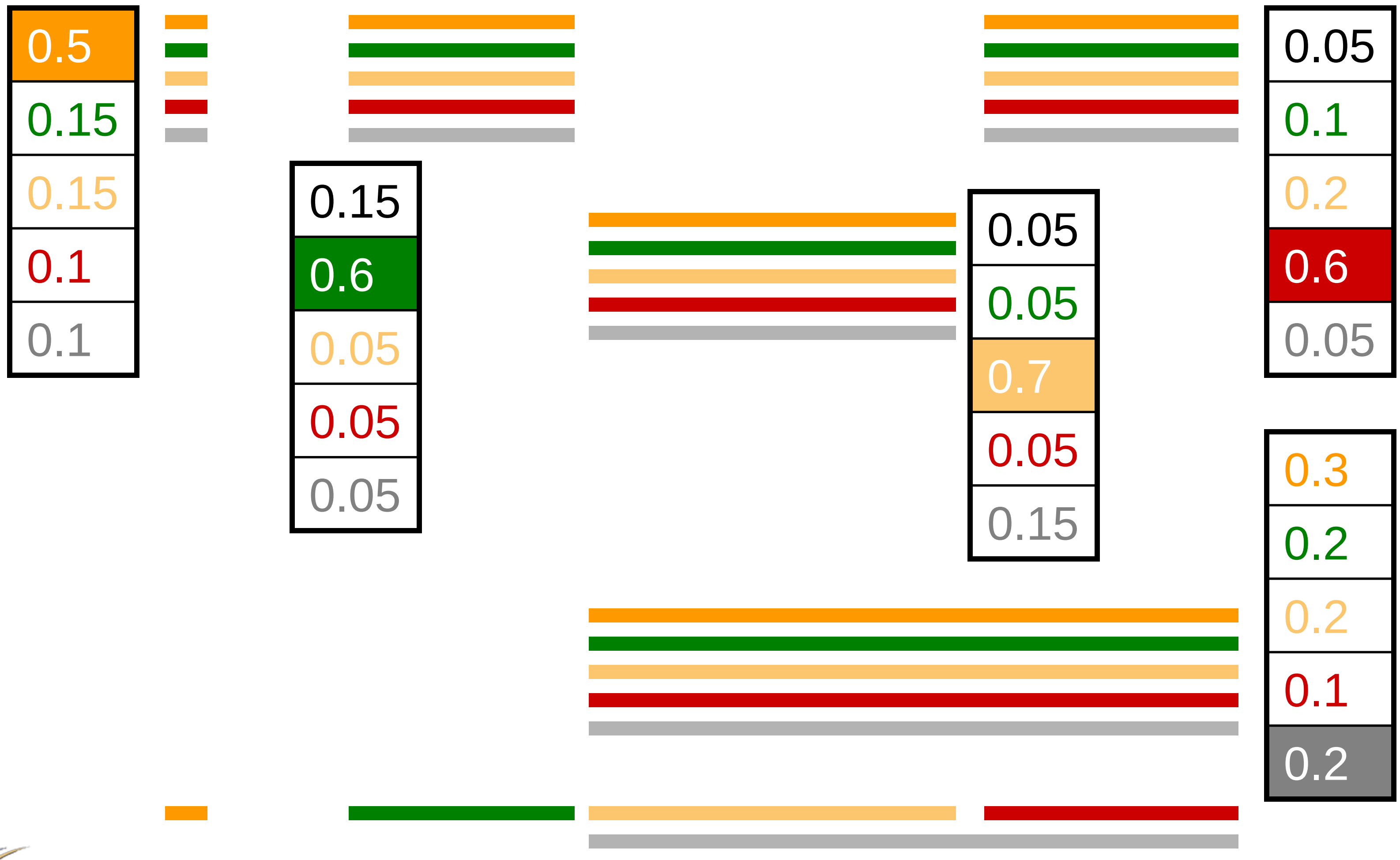

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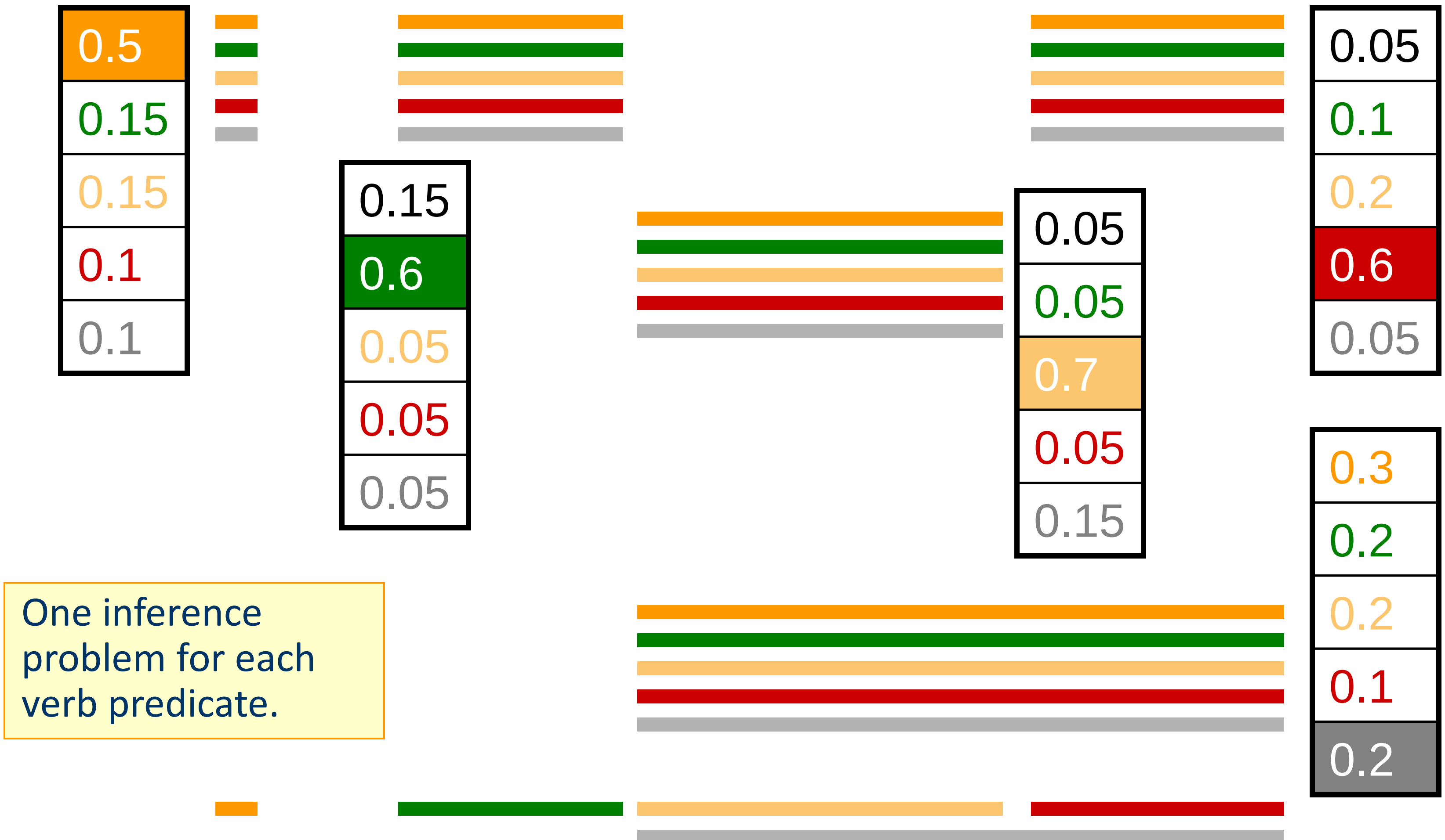

# Constraints

- No duplicate argument classes
- Reference-Ax

  If there is an Reference-Ax phrase, there is an Ax

- Continuation-Ax

  If there is an Continuation-x phrase, there is an Ax before it

- Many other possible constraints:
  - **Unique labels**
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  - **Relations between number of arguments; order constraints**
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Universally quantified rules

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If there is an Reference-Ax phrase, there is an Ax

- Continuation-Ax

If there is an Continuation-x phrase, there is an Ax before it

- Many other possible constraints:
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# SRL: Posing the Problem

$$\text{maximize} \quad \sum_{i=0}^{n-1} \sum_{y \in \mathcal{Y}} \lambda_{\mathbf{x}_i, y} 1_{\{y_i = y\}}$$

$$\text{where} \quad \lambda_{\mathbf{x},y} = \lambda \cdot F(\mathbf{x}, y) = \lambda_y \cdot F(\mathbf{x})$$

subject to

| | | |
|---|---|---|
| A | bomb [A1] | killer [A0] |
| car | | |
| bomb | | |
| that | bomb (Reference) [R-A1] | |
| exploded | V: explode | |
| outside | location [AM-LOC] | |
| the | | |
| U.S. | | |
| military | temporal [AM-TMP] | |
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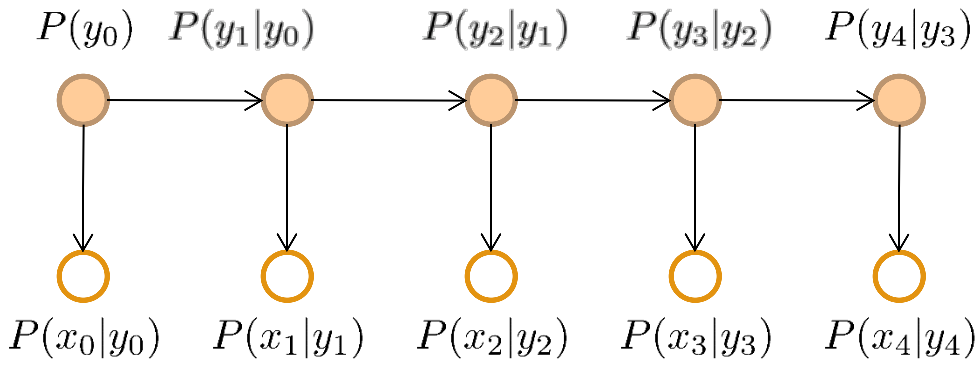
# Example 2: Sequence Tagging

HMM :

$$\mathbf{y}^* = \operatorname*{argmax}_{\mathbf{y} \in \mathcal{Y}} P(y_0)P(x_0|y_0) \prod_{i=1}^{n-1} P(y_i|y_{i-1})P(x_i|y_i)$$



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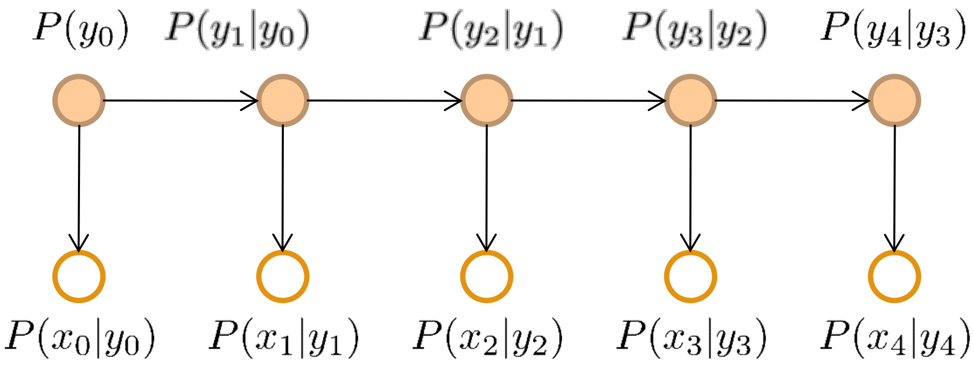

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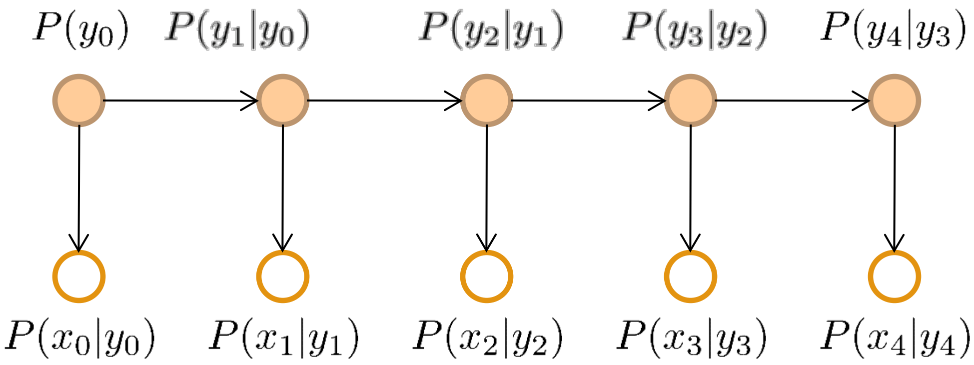
The ILP's objective function must include all entries of the Conditional Probability Table.



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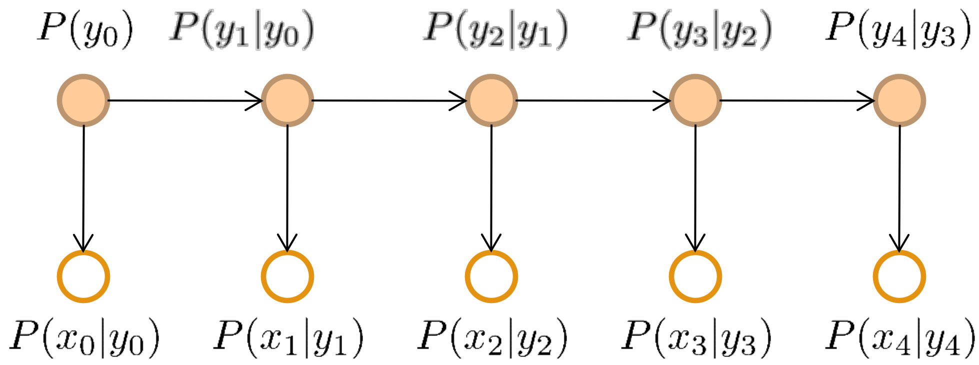


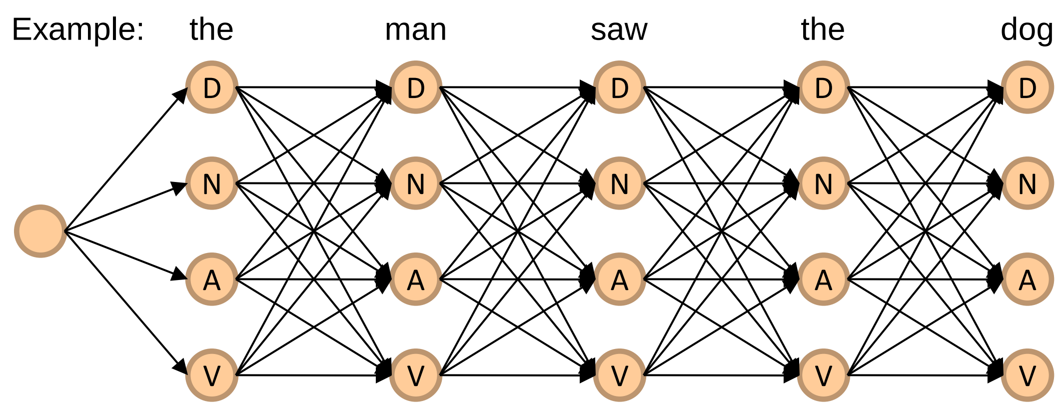

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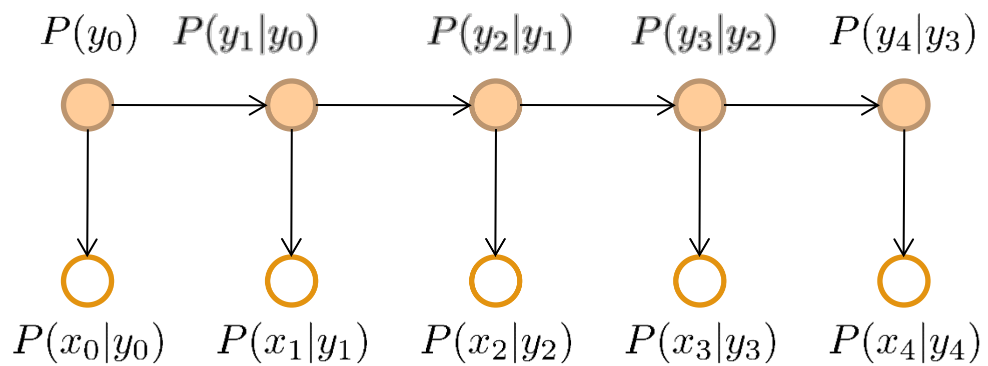
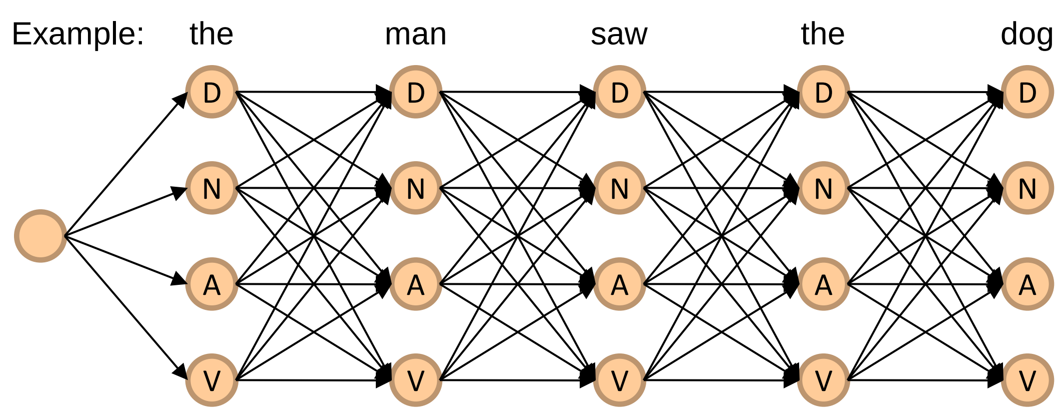



Every edge is a Boolean variable that selects a transition CPT entry.



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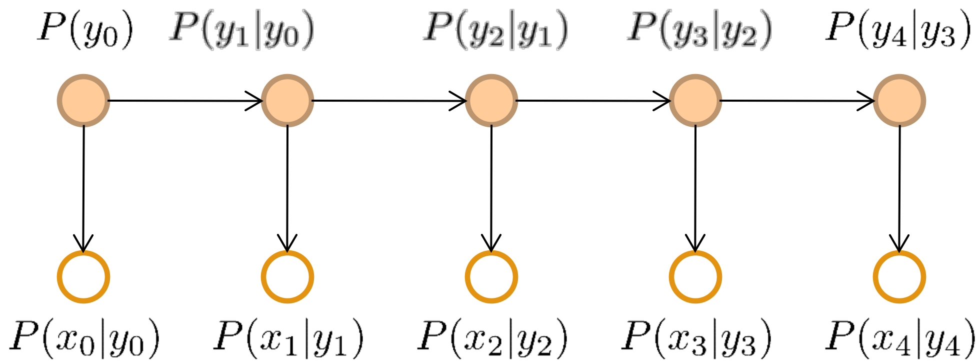


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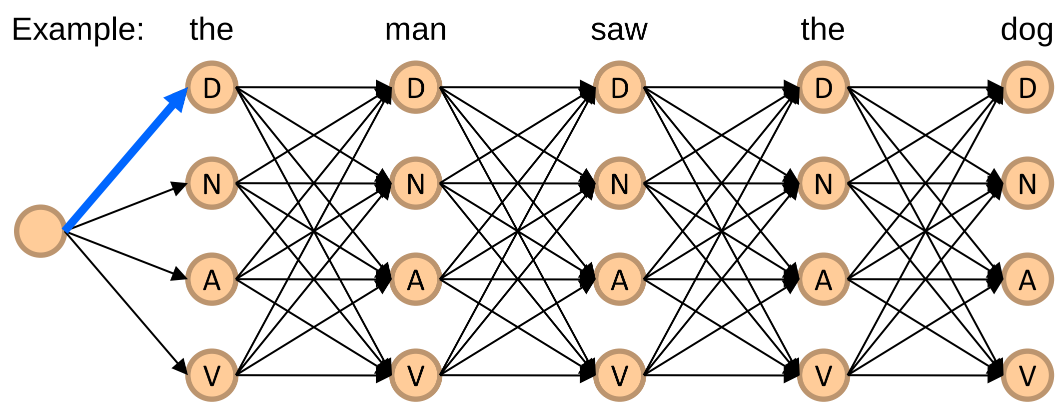
They are related: if we choose $y_0 = D$



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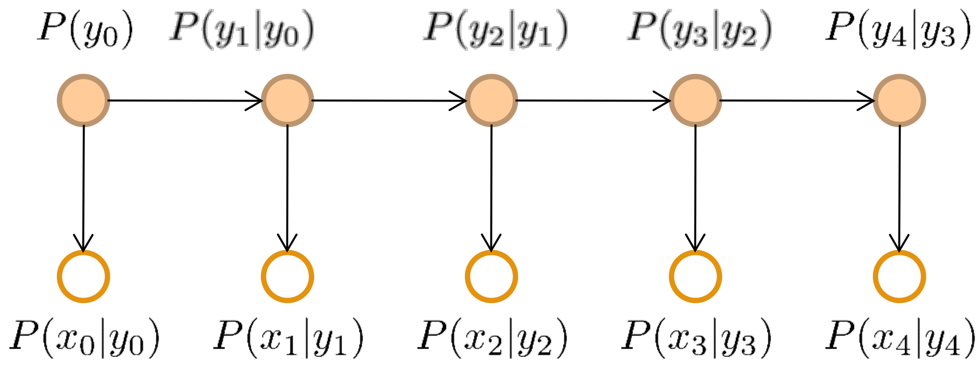


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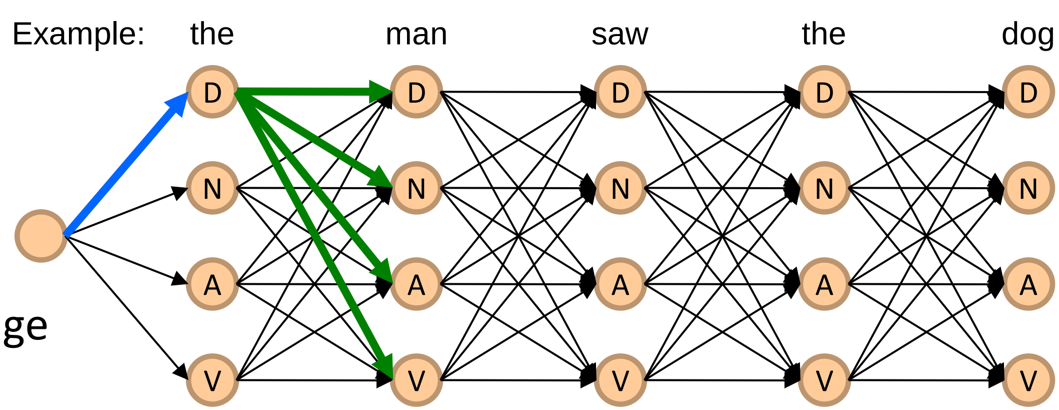

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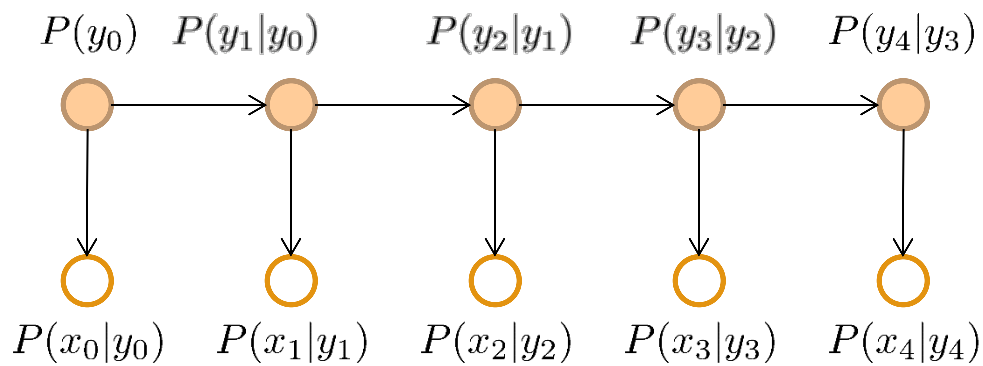


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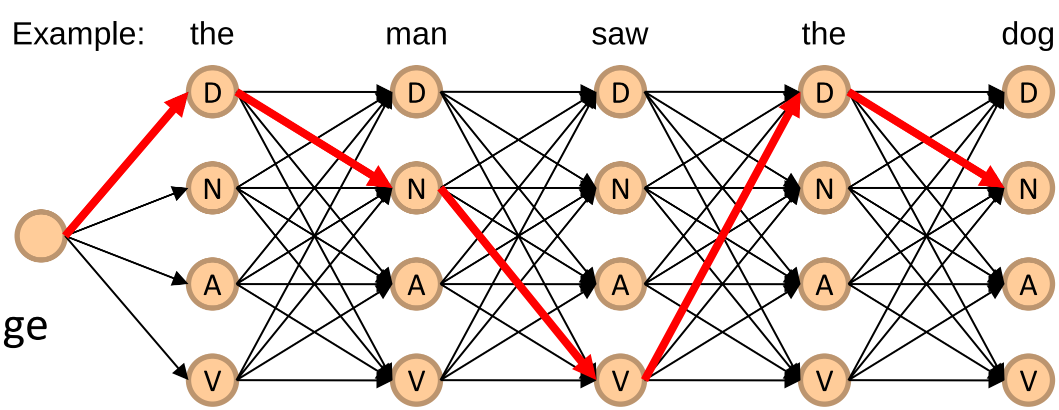


Every assignment to the *y*'s is a path.

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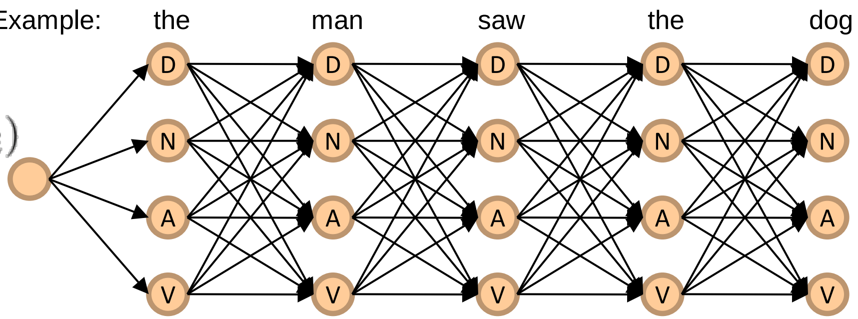
Example:



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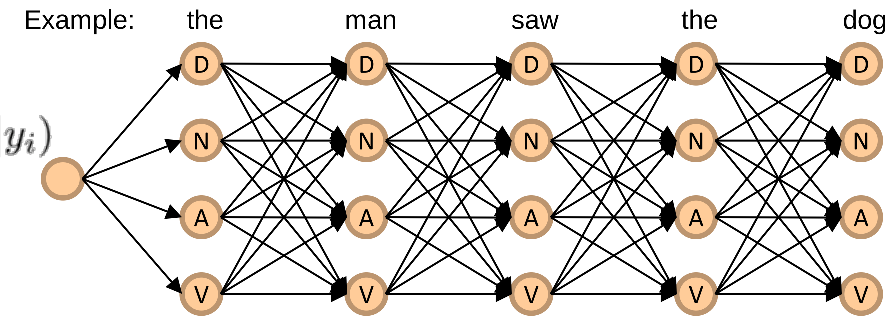


As an ILP:

$$\text{maximize} \quad \sum_{y\in\mathcal{Y}} \lambda_{0,y} 1_{\{y_0=y\}} + \sum_{i=1}^{n-1}\sum_{y\in\mathcal{Y}}\sum_{y'\in\mathcal{Y}} \lambda_{i,y,y'} 1_{\{y_i=y \,\wedge\, y_{i-1}=y'\}}$$

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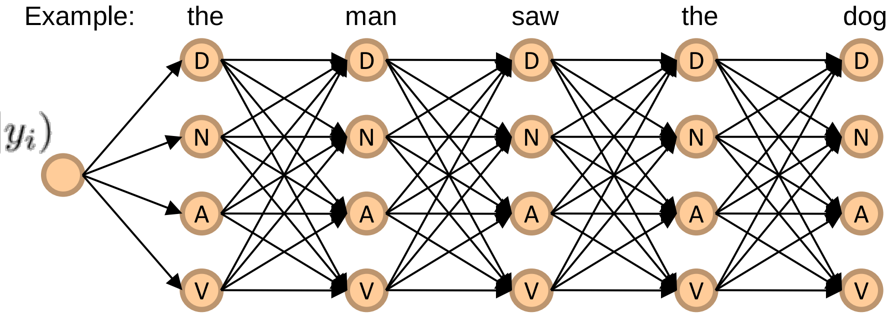


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Learned Parameters

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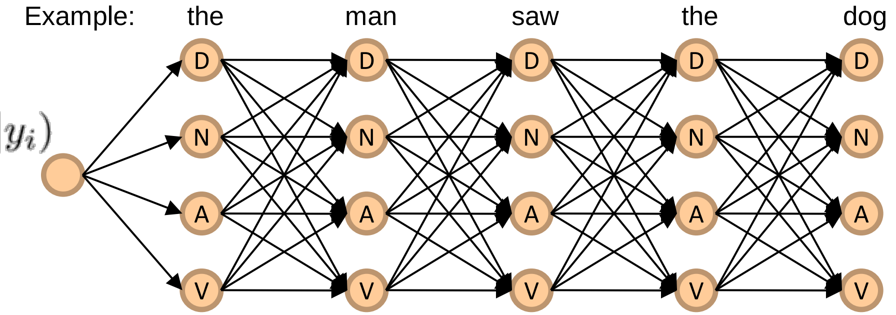


As an ILP:

Inference Variables

$$\text{maximize} \sum_{y\in\mathcal{Y}} \lambda_{0,y} 1_{\{y_0=y\}} + \sum_{i=1}^{n-1}\sum_{y\in\mathcal{Y}}\sum_{y'\in\mathcal{Y}} \lambda_{i,y,y'} 1_{\{y_i=y\ \wedge\ y_{i-1}=y'\}}$$

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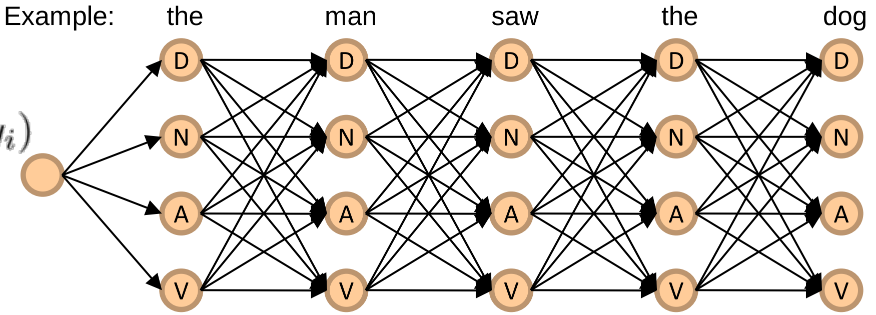


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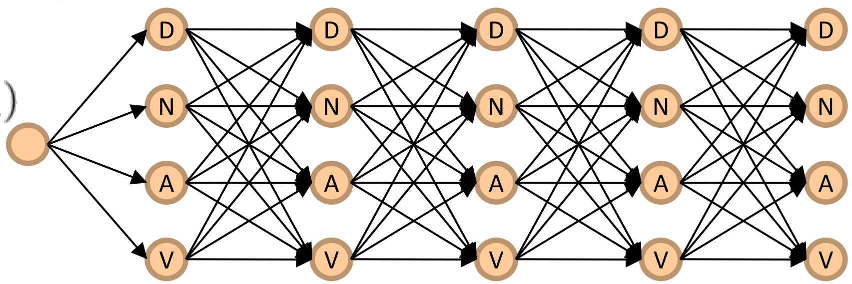


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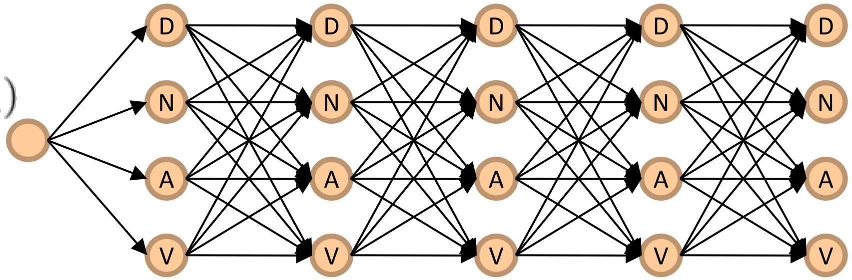


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$$1_{\{y_0=\text{“NN”}\}} = 1$$
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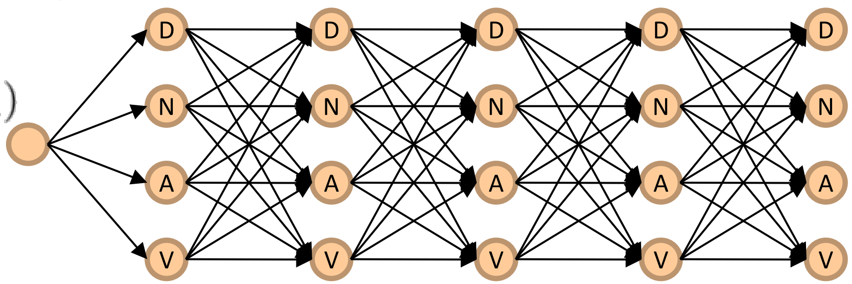


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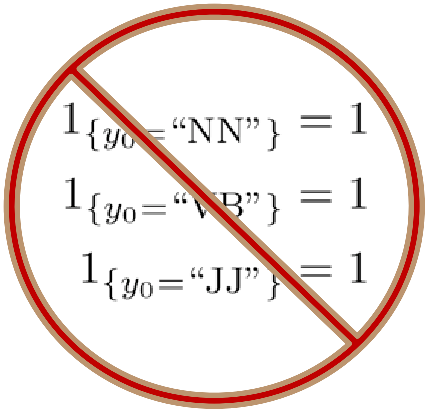
*Unique label for each word*



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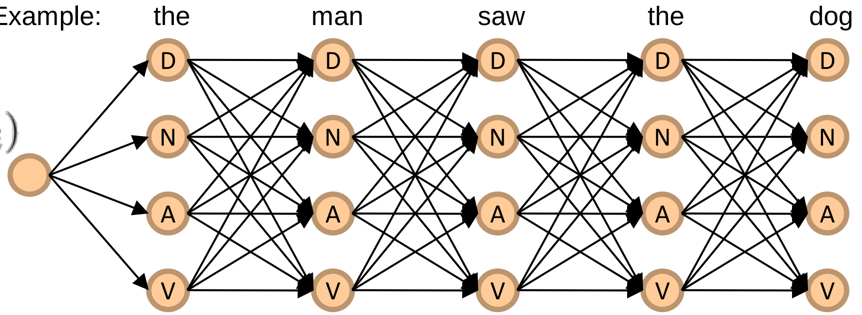


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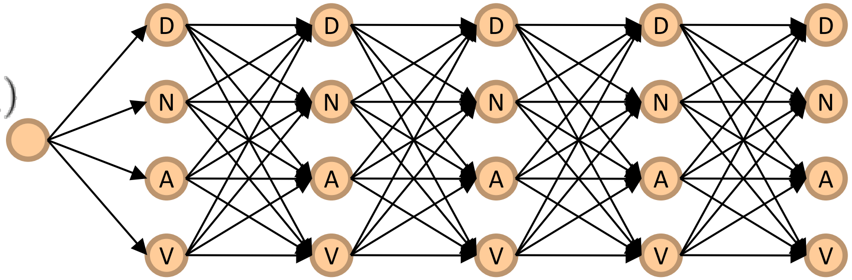


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$$1_{\{y_0=\text{“NN”}\}} = 1 \qquad 1_{\{y_0=\text{“DT”} \,\wedge\, y_1=\text{“JJ”}\}} = 1$$

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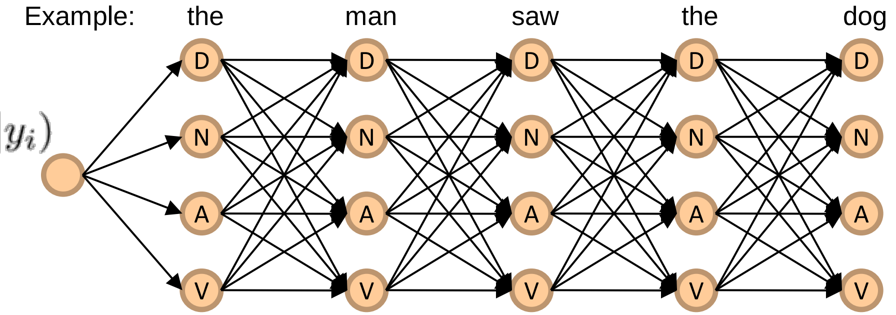


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*Edges that are chosen must form a path*

$$1_{\{y_0=\text{"NN"}\}} = 1$$
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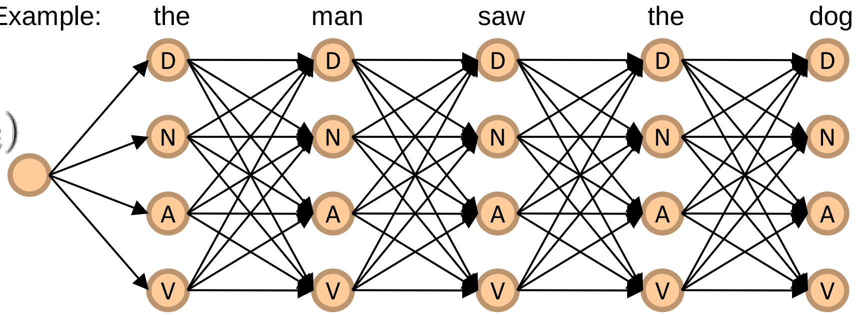
# Example 2: Sequence Tagging

HMM :

$$\mathbf{y}^* = \operatorname*{argmax}_{\mathbf{y}\in\mathcal{Y}} P(y_0)P(x_0|y_0)\prod_{i=1}^{n-1} P(y_i|y_{i-1})P(x_i|y_i)$$

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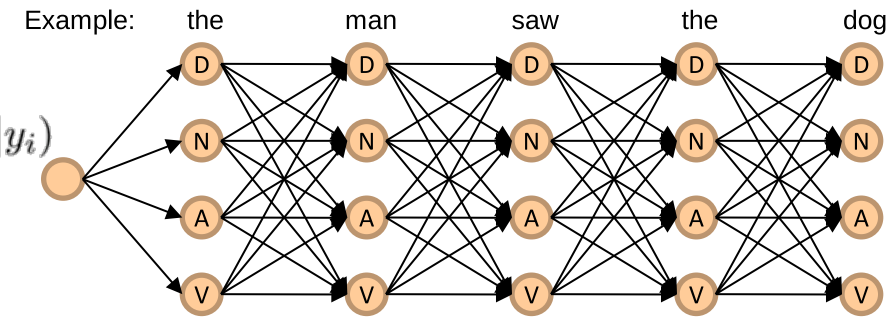


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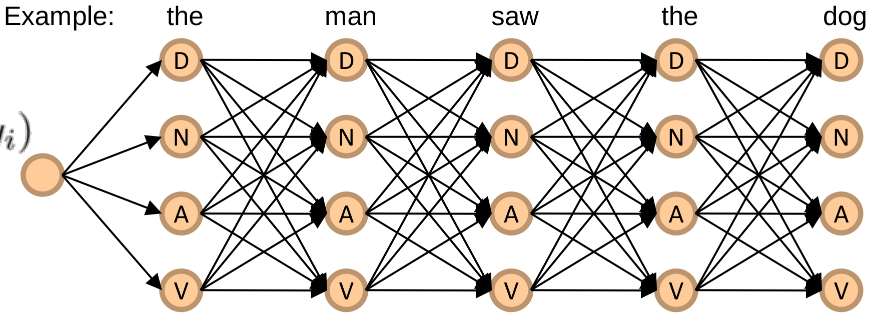


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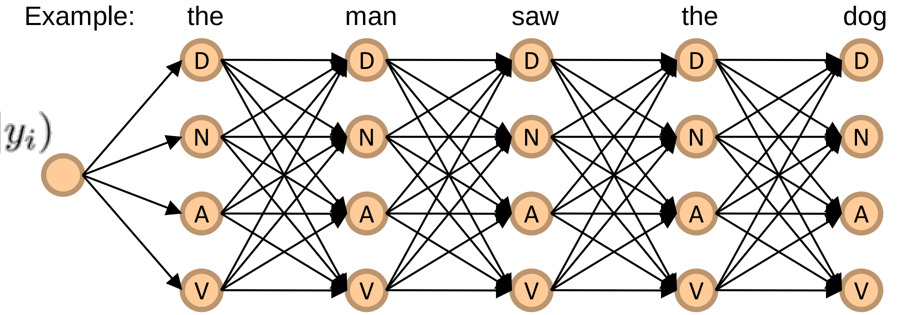


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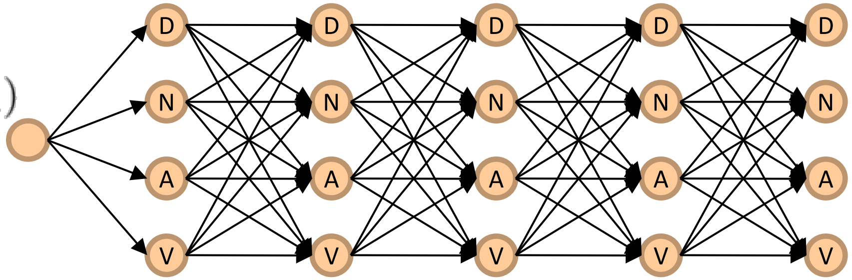


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[Roth & Yih, ICML'05] discuss training paradigms for HMMs and CRFs, when augmented with additional knowledge

# Constraints

- We have seen three different constraints in this example
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- All three can be expressed as linear inequalities
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In CCMs, knowledge is an integral part of the modeling

# Learning and Inference in Structured Prediction

- Part 1: Introduction to Structured Prediction (60min)
  - Motivation
  - Examples:
    - **NE + Relations**
    - **Vision**
    - **Additional NLP Examples**
  - Problem Formulation
    - **Constrained Conditional Models: Integer Linear Programming Formulations**
  - Initial thoughts about learning
    - **Learning independent models**
    - **Constraints Driven Learning**
  - Initial thoughts about Inference
    - **Amortized Inference**

# Constrained Conditional Models—ILP Formulations

- Have been shown useful in the context of many NLP problems
- [Roth&Yih, 04,07: Entities and Relations; Punyakanok et. al: SRL ...]
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  - **[Chang, Ratinov & Roth, Machine Learning Journal 2012]**
- Summary of work & a bibliography: http://L2R.cs.uiuc.edu/tutorials.html

# LEARNING

$$y = \text{argmax}_{y \in \mathcal{Y}} \; w^T \phi(x, y) + u^T C(x, y)$$

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  - The building blocks are the **learning algorithms** introduced later
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# Verb SRL

$$\text{maximize} \quad \sum_{i=0}^{n-1} \sum_{y \in \mathcal{Y}} \lambda_{\mathbf{x}_i, y} 1_{\{y_i = y\}}$$

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subject to

| | | |
|---|---|---|
| A | bomb [A1] | killer [A0] |
| car | | |
| bomb | | |
| that | bomb (Reference) [R-A1] | |
| exploded | V: explode | |
| outside | location [AM-LOC] | |
| the | | |
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$$\forall j, y \in \mathcal{Y}_C, \; 1_{\{y_j = y = \text{“C-Ax”}\}} \leq \sum_{i=0}^{j} 1_{\{y_i = \text{“Ax”}\}}$$

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# Extended Semantic Role Labeling

- Many predicates; many roles; how to deal with more phenomena?

BEIRUT, Lebanon — Lebanon's main opposition group called for widespread protests on Sunday in the wake of a powerful bomb attack for which it blamed Syria, posing a challenge to a shaky coalition government that is led by pro-Syrian factions and intensifying fears that Syria's civil war is spilling over into this country.

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[Beirut] is in [Lebanon].

[Lebanon] has a main opposition group.

[Lebanon's main opposition group] called for [widespread protests] [on Sunday].

There was [a powerful bomb attack].

[Lebanon's main opposition group] blamed [Syria].

[Pro-Syrian factions] lead [a shaky coalition government]

[Syria] has a [civil war].

[Someone] fears that [Syria's civil war is spilling over into this country].

…

Sentence level analysis may be influenced by other sentences

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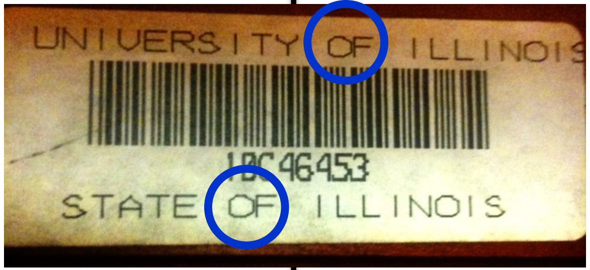


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# Coherency in Semantic Role Labeling

**Predicate-arguments generated should be consistent across phenomena**

The touchdown scored by Bradford cemented the victory of the Eagles.

| Verb | Nominalization | Preposition |
|---|---|---|
| **Predicate:** score | **Predicate:** win | **Sense:** 11(6) |
| **A0:** Bradford (scorer)<br>**A1:** The touchdown (points scored) | **A0:** the Eagles (winner) | "the object of the preposition is the object of the underlying verb of the nominalization" |

Linguistic Constraints:

- A0: the Eagles ⇔ Sense(of): 11(6)
- A0: Bradford ⇔ Sense(by): 1(1)

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  - per phenomena
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  - only at the predicate level
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# Computational Challenges

- Predict the preposition relations
  - [EMNLP, ’11]
- Identify the relation’s arguments
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  - Done via global inference via CCM

Input & relation

Argument & their types

# Joint inference (CCMs)

Verb arguments

$$\max_{\mathbf{y}} \sum_{t} \sum_{a} y^{a,t} c^{a,t}$$

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Variable $y^{a,t}$ indicates whether candidate argument $a$ is assigned a label $t$.
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$a$ → Argument candidates

$t$ → Each argument label

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$r$: Preposition relation label

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+ ....

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Verb SRL constraints

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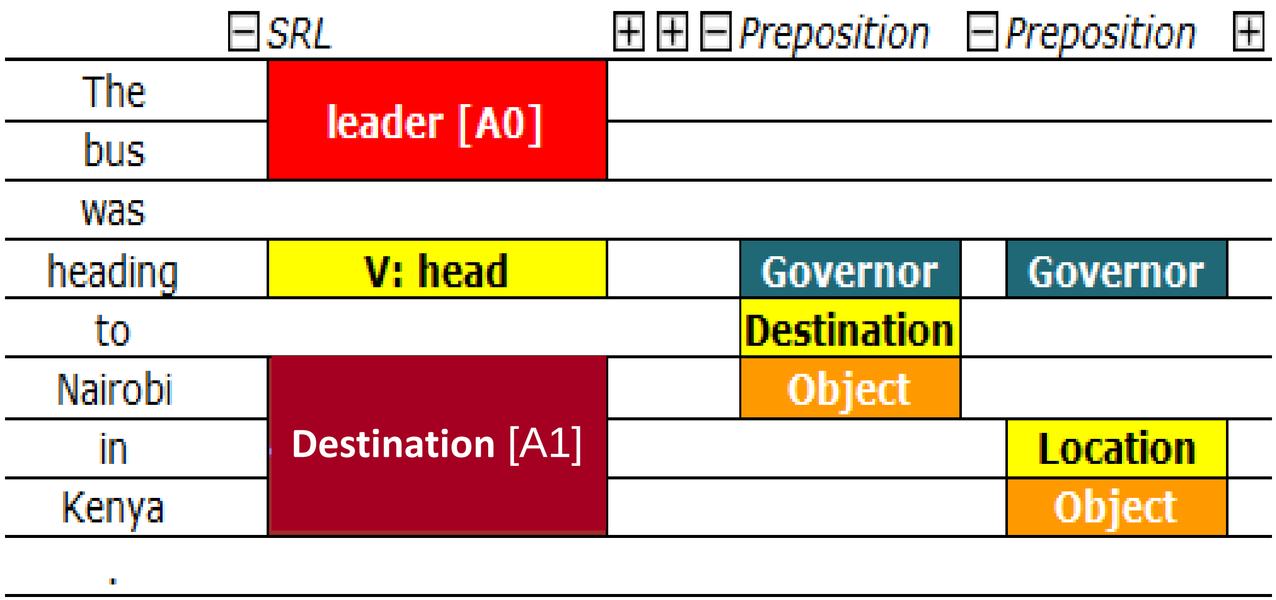
# Extended SRL [Demo]

| | SRL | Preposition | Preposition |
|---|---|---|---|
| The | leader [A0] | | |
| bus | | | |
| was | | | |
| heading | V: head | Governor | Governor |
| to | | Destination | |
| Nairobi | Destination [A1] | Object | |
| in | | | Location |
| Kenya | | | Object |
| . | | | |

# Extended SRL [Demo]




Joint inference over phenomena–specific models to enforce consistency

Models trained with latent structure: senses, types, arguments

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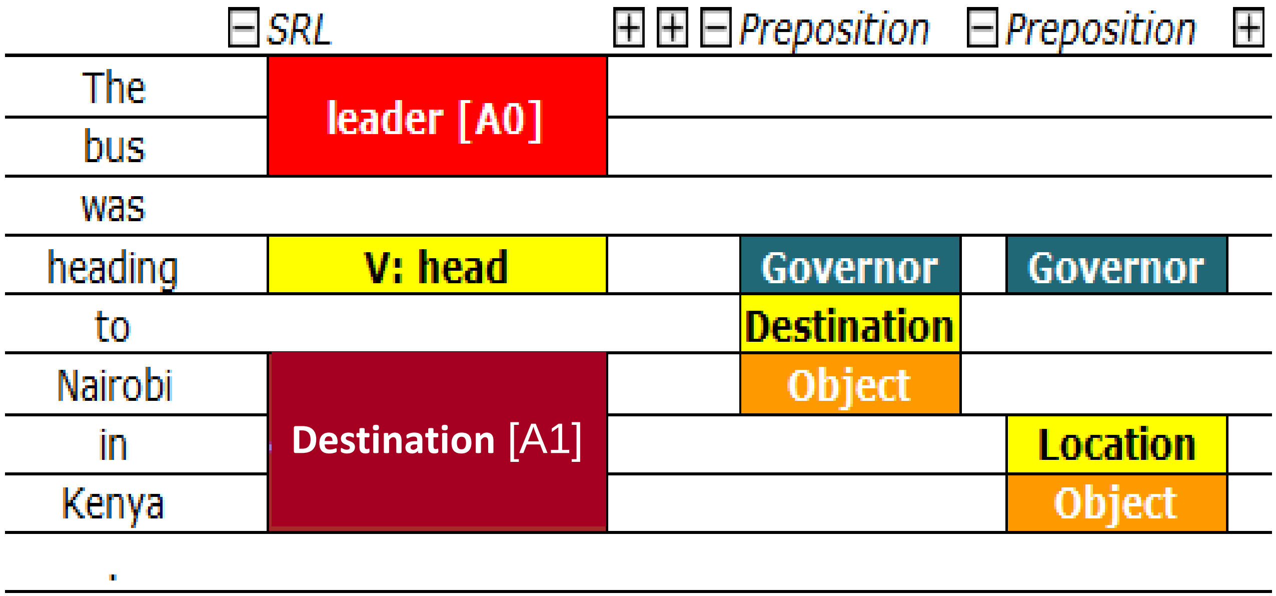


Joint inference over phenomena–specific models to enforce consistency

Models trained with latent structure: senses, types, arguments

- More to do with other relations, discourse phenomena,…

# Information Extraction without Output Expectations

Lars Ole Andersen . Program analysis and specialization for the C Programming language. PhD thesis. DIKU , University of Copenhagen, May 1994 .

[AUTHOR]

[TITLE]

[EDITOR]

[BOOKTITLE]

[TECH-REPORT]

[INSTITUTION]

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**Prediction result of a trained HMM**

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Violates lots of natural constraints!

# Strategies for Improving the Results

- (Standard) Machine Learning Approaches
  - Higher Order HMM/CRF?
  - Increasing the window size?
  - Adding a lot of new features
    - Requires a lot of labeled examples

Increasing the model complexity

Increase difficulty of Learning

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Increasing the model complexity

Increase difficulty of Learning

Can we keep the learned model simple and still make expressive decisions?

- Instead:
  - Constrain the output to make sense – satisfy our expectations
  - Push the (simple) model in a direction that makes sense – minimally violates our expectations.

# Expectations from the output (Constraints)

- Each field must be a consecutive list of words and can appear at most once in a citation.
- State transitions must occur on punctuation marks.
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Non Propositional; May use Quantifiers

- Adding constraints, we get correct results!
  - Without changing the model

$$\operatorname*{argmax}_{y} \boldsymbol{\lambda} \cdot F(x, y)$$

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# Information Extraction with Expectation Constraints

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# Guiding (Semi-Supervised) Learning with Constraints

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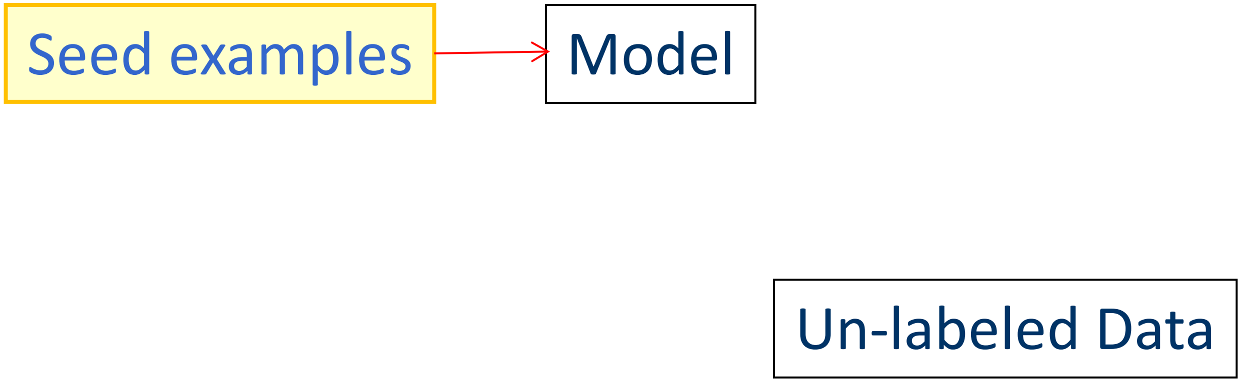

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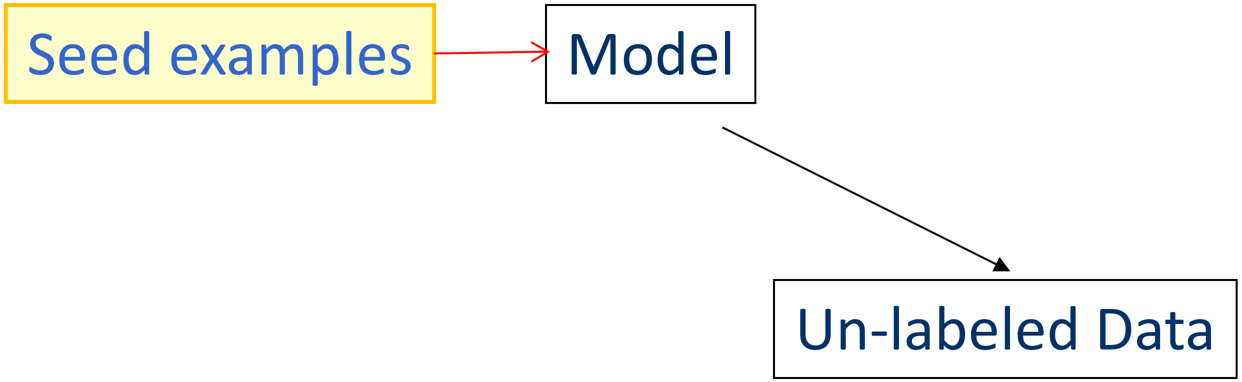
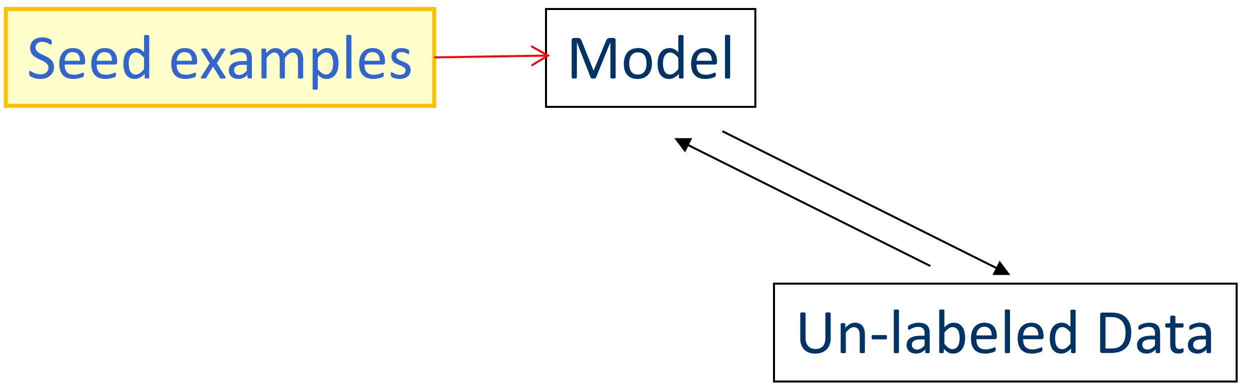


# Guiding (Semi-Supervised) Learning with Constraints

- In traditional Semi-Supervised learning the model can drift away from the correct one.



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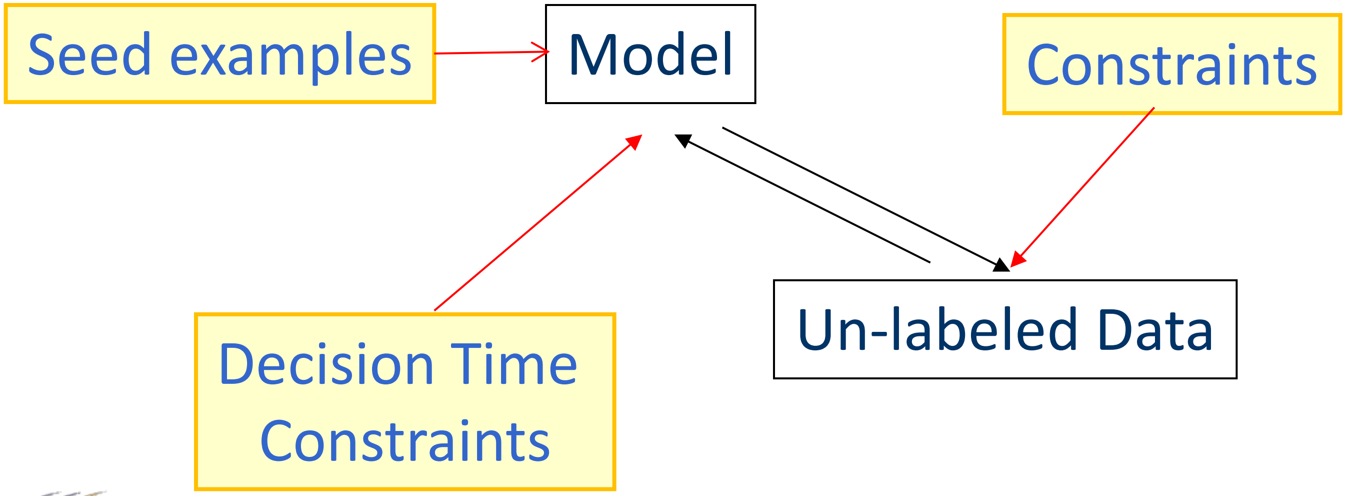
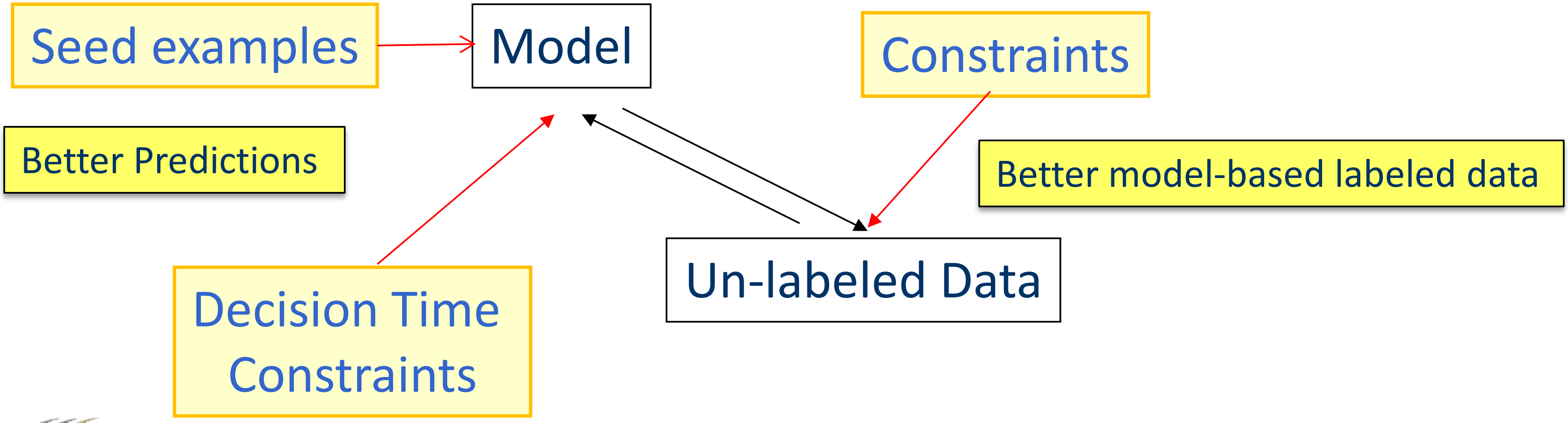


# Guiding (Semi-Supervised) Learning with Constraints

- In traditional Semi-Supervised learning the model can drift away from the correct one.
- Constraints can be used to generate better training data
  - At training to improve labeling of un-labeled data (and thus improve the model)
  - At decision time, to bias the objective function towards favoring constraint satisfaction.



# Constraints Driven Learning (CoDL)

[Chang, Ratinov, Roth, ACL'07;ICML'08,MLJ'12]
See also: Ganchev et. al. 10 (PR)

$(w,\rho)$=learn(L)

For N iterations do

$T=\phi$

For each x in unlabeled dataset

$h \leftarrow \text{argmax}_y \; w^T \phi(x,y) - \sum \rho \, d_C(x,y)$

$T=T \cup \{(x, h)\}$

$(w,\rho) = \gamma \, (w,\rho) + (1- \gamma) \text{ learn}(T)$

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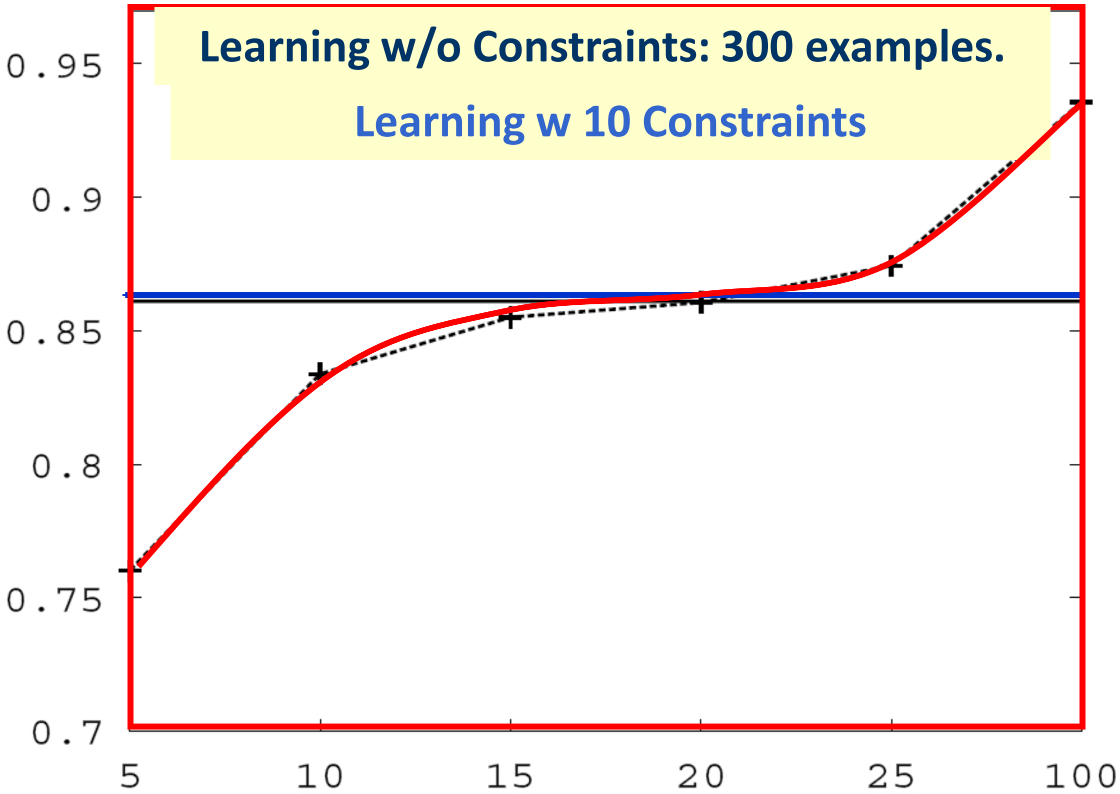
**Excellent Experimental Results** showing the advantages of using constraints, especially with small amounts of labeled data [Chang et. al, Others]

# Value of Constraints in Semi-Supervised Learning

**Objective function:** $f_{\Phi,C}(\mathbf{x},\mathbf{y}) = \sum w_i \phi_i(\mathbf{x},\mathbf{y}) - \sum \rho_i d_{C_i}(\mathbf{x},\mathbf{y}).$

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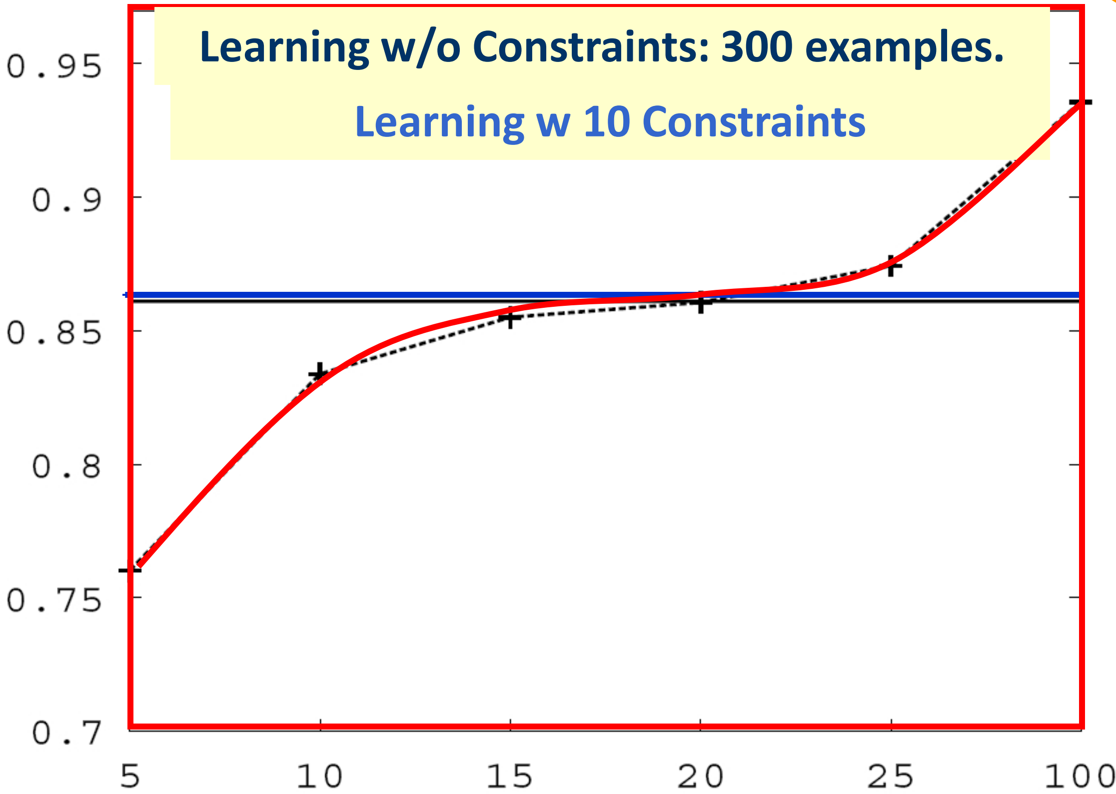


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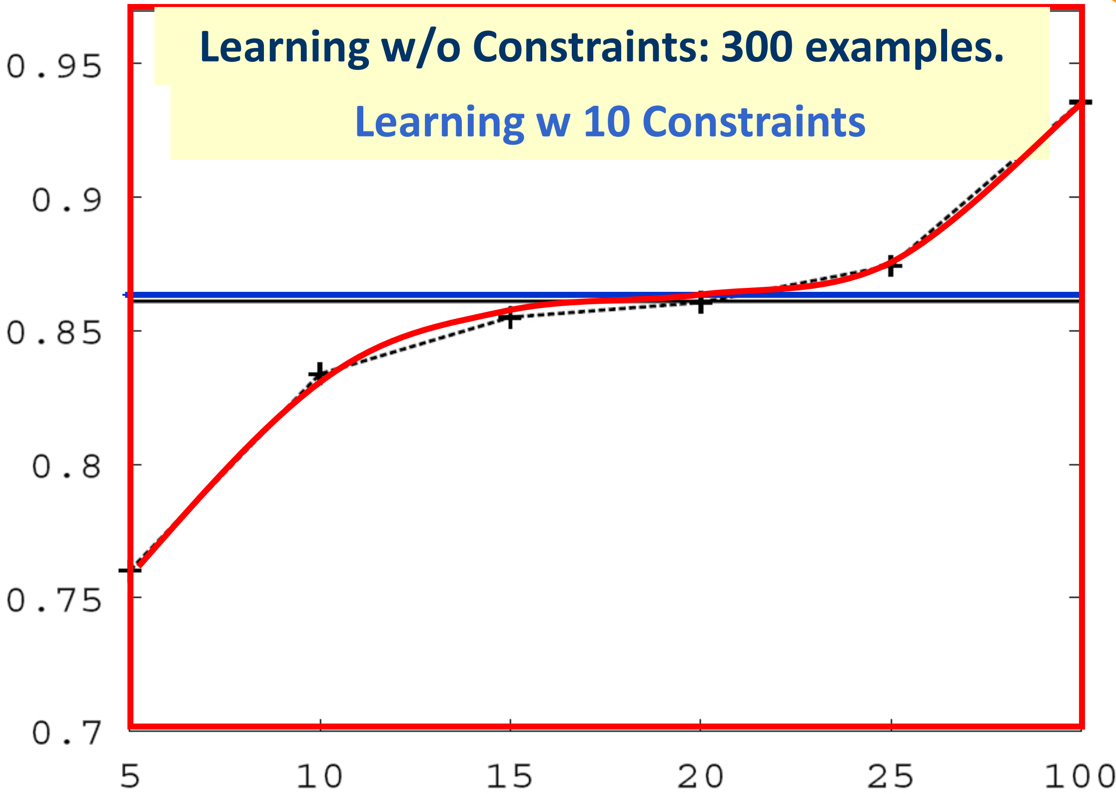


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See Chang et. al. MLJ'12 on the use of **soft constraints** in CCMs.
The tutorial's web page will include a write-up on ILP formulations **incorporating soft constraints.**

# CoDL as Constrained Hard EM

- Hard EM is a popular variant of EM
- While EM estimates a distribution over hidden variables in the E-step,
- … Hard EM predicts the **best** output in the E-step

$$h = y^* = \mathbf{argmax}_{\mathrm{y}}\ P_w(\mathbf{y} \,|\, \mathbf{x})$$

- Alternatively, hard EM predicts a peaked distribution

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- Constrained-Driven Learning (CODL) – can be viewed as a constrained version of hard EM:

$$y^* = \mathbf{argmax}_{\mathrm{y:Uy \leq b}}\ P_w(y \mid x)$$

Constraining the feasible set

# Constrained EM: Two Versions

- While Constrained-Driven Learning [CODL; Chang et al, 07,12] is a constrained version of hard EM:
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- The E-step now becomes: [Neal & Hinton '99 view of EM]

q' = $$\arg\min_{q:q(\mathbf{y})\geq 0, E_q[\mathbf{Uy}]\leq \mathbf{b}, \sum_{\mathbf{y}} q(\mathbf{y})=1} KL(q(\mathbf{y})||P(\mathbf{y}|\mathbf{x},\mathbf{w}))$$

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- This is Taskar's Posterior Regularization [PR] [Ganchev et al, 10]

# Which (Constrained) EM to use?

- There is a lot of literature on EM vs hard EM
  - Experimentally, the bottom line is that with a good enough initialization point, hard EM is probably better (and more efficient).
    - **E.g., EM vs hard EM (Spitkovsky et al, 10)**
- Similar issues exist in the constrained case: CoDL vs. PR
  - The constraints view helped developing additional algorithmic insight
  - $\gamma$ that
    - Provides a continuum of algorithms – from EM to hard EM, and infinitely many new EM algorithms in between.
    - Implementation wise, not more complicated than EM

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  - The constraints view helped developing additional algorithmic insight
- Unified EM (UEM) [Samdani & Roth, NAACL-12]
  - Provides a continuum of algorithms – from EM to hard EM, and infinitely many new EM algorithms in between.
  - Implementation wise, not more complicated than EM
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The third part of the tutorial is on how to do inference

$$\mathbf{y} = \mathrm{argmax}_{\mathbf{y} \in \mathcal{Y}} \; \mathbf{w}^T \phi(\mathbf{x}, \mathbf{y}) + \mathbf{u}^T \mathcal{C}(\mathbf{x}, \mathbf{y})$$

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- The following (high level) examples will briefly present several **learning paradigms** where
  - The building blocks are the **learning algorithms** introduced later
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# LEARNING

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  - Semi-supervised scenarios
  - **Learning with Latent Structured Representations**
    - A meta-algorithm that makes use of structured learning algorithm s
    - Including approaches that make use of declarative constraints to minimize the  level of supervision using constraints
    - **[Chang et.al. ICML'10, NAACL'10,…]**

# INFERENCE

- For each example $(x_i, y_i)$
- Do: (with the current weight vector w)
  - **Predict:** perform Inference with the current weight vector
    - $y_i' = \text{argmax}_{y \in \mathcal{Y}}\, w^T \phi(x_i, y)$
  - **Check** the learning constraints
    - **Is the score of the current prediction better than of $(x_i, y_i)$?**
  - If **Yes** – a mistaken prediction
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- **Inference is done many times** – both at decision time (one inference per predicates…) and during training.

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  - Co-reference resolution; Semantic Role Labeling; Parsing citations; Summarization; dependency parsing; image segmentation,…
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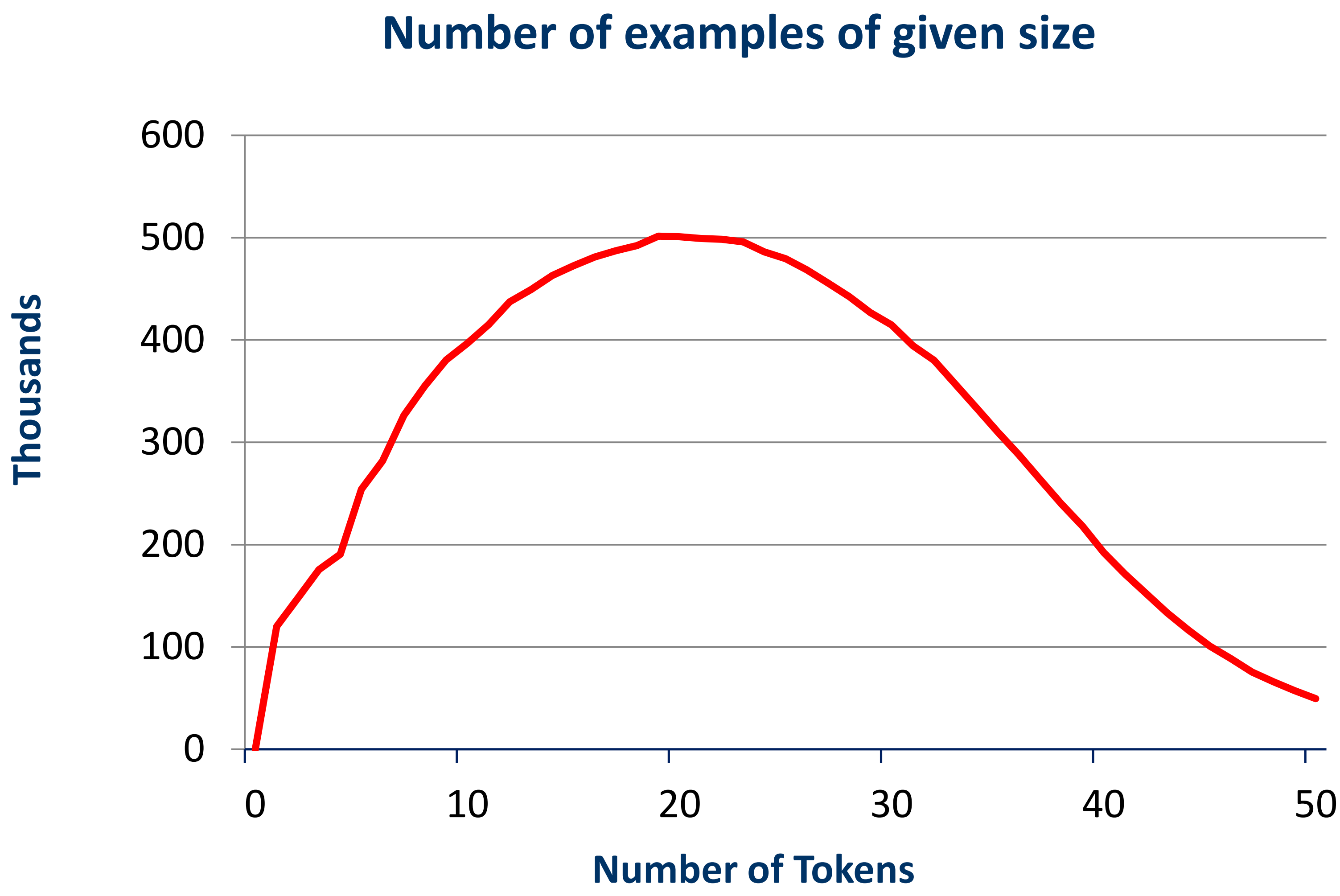
- Very general: All discrete MAP problems can be formulated as 0-1 LPs [Roth & Yih'04; Taskar '04]
- We only care about inference formulation, not algorithmic solution

# The Hope: POS Tagging on Gigaword



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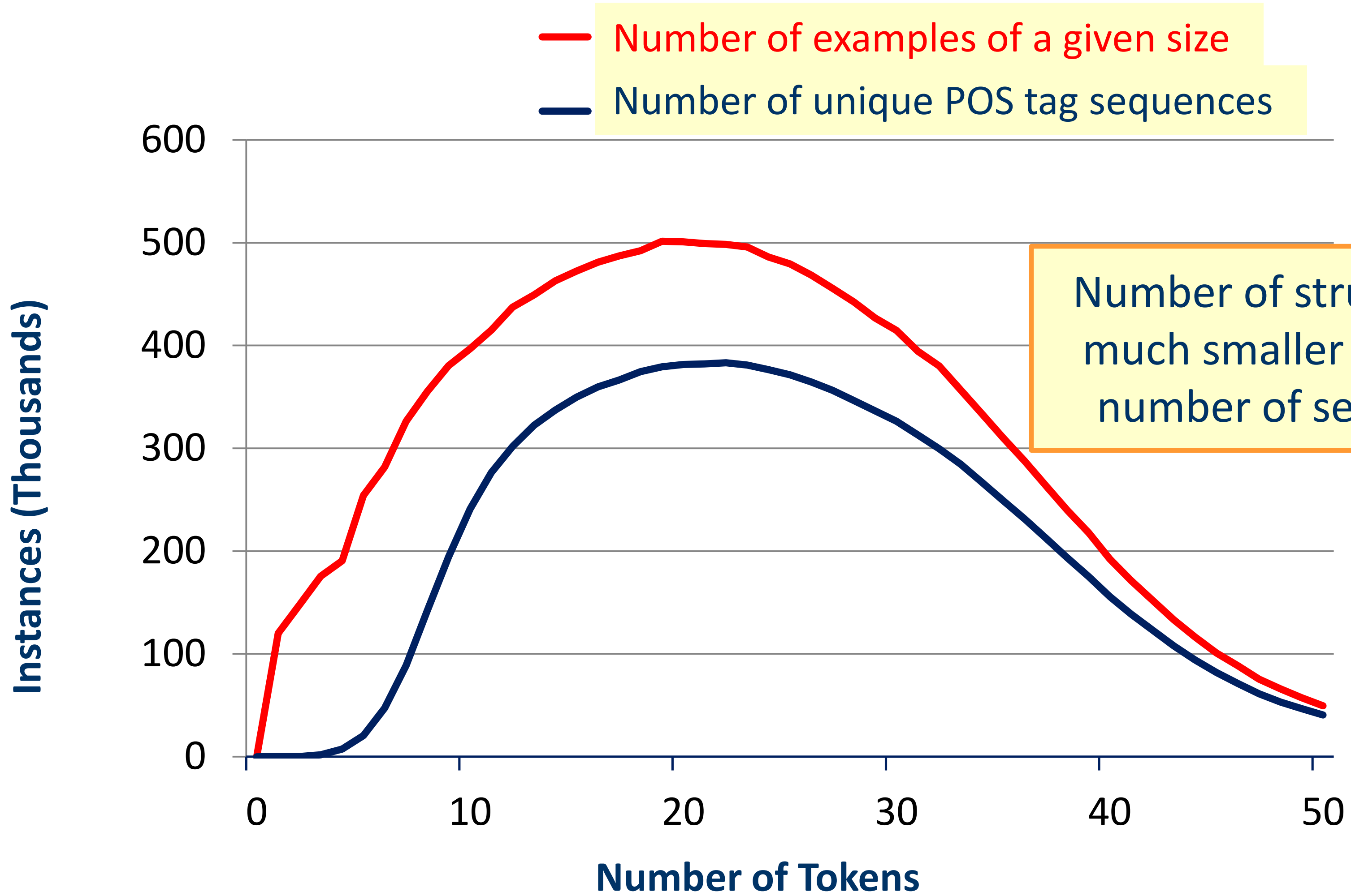
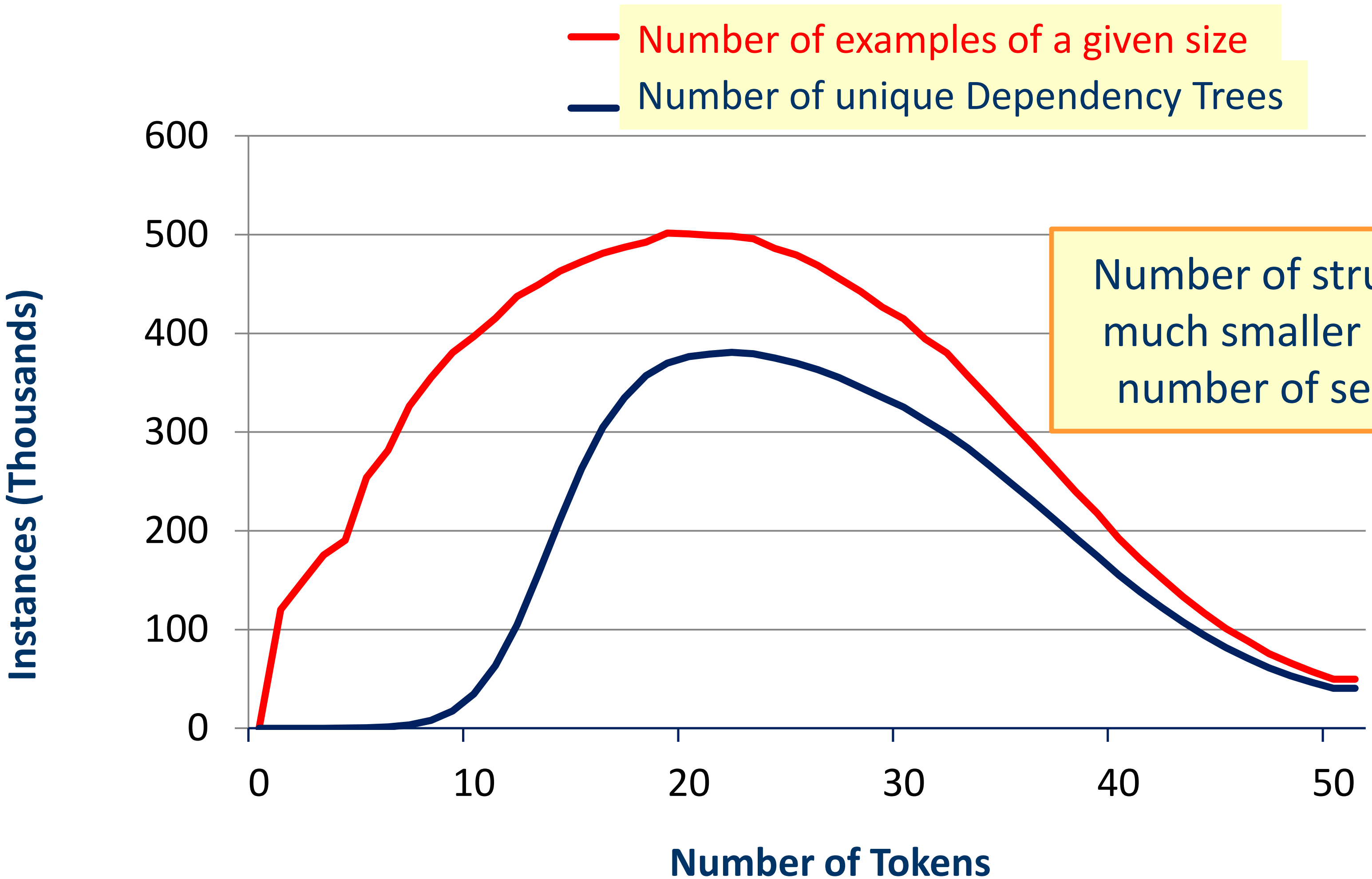



Number of structures is much smaller than the number of sentences

# The Hope: Dependency Parsing on Gigaword

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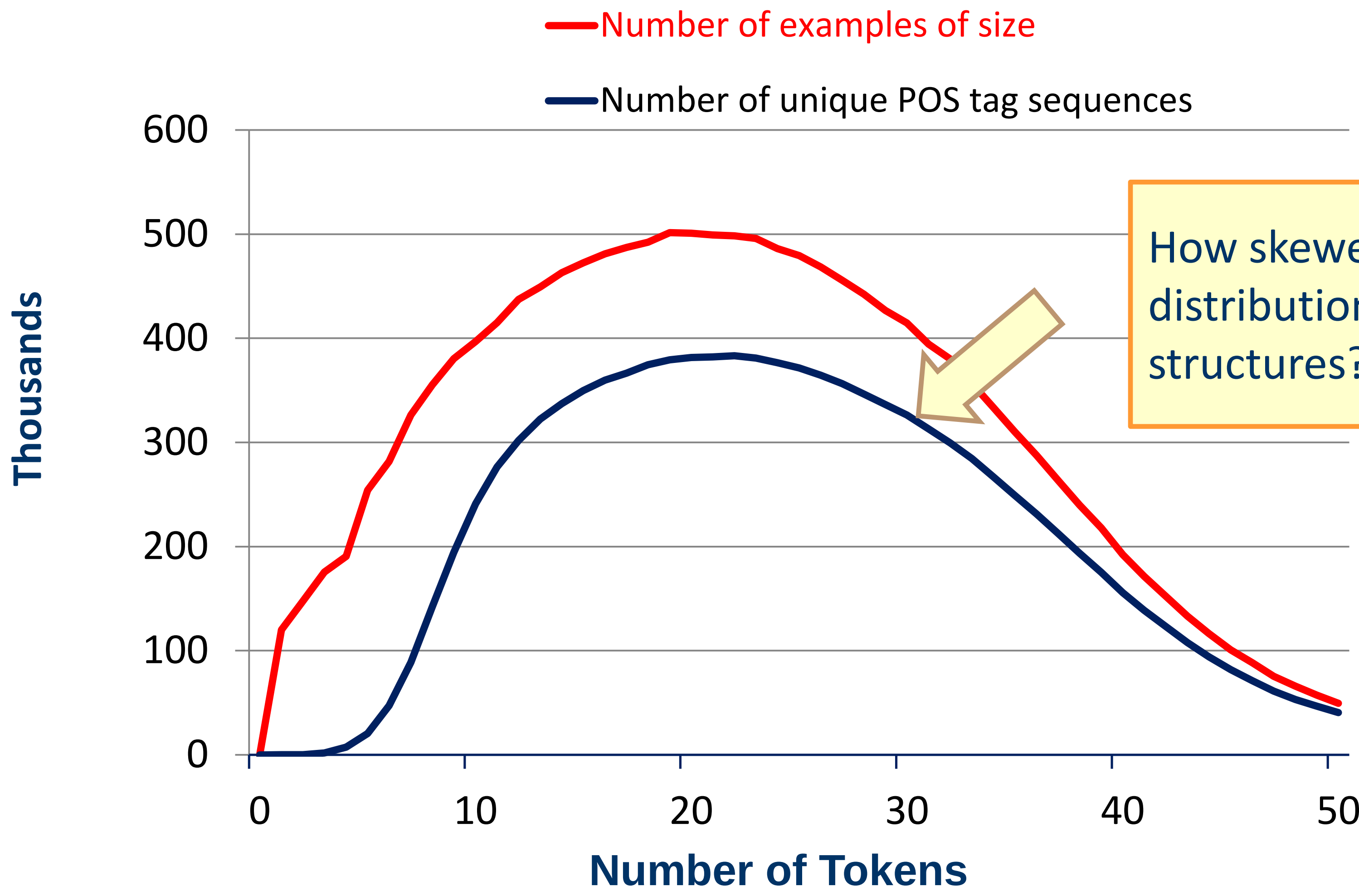


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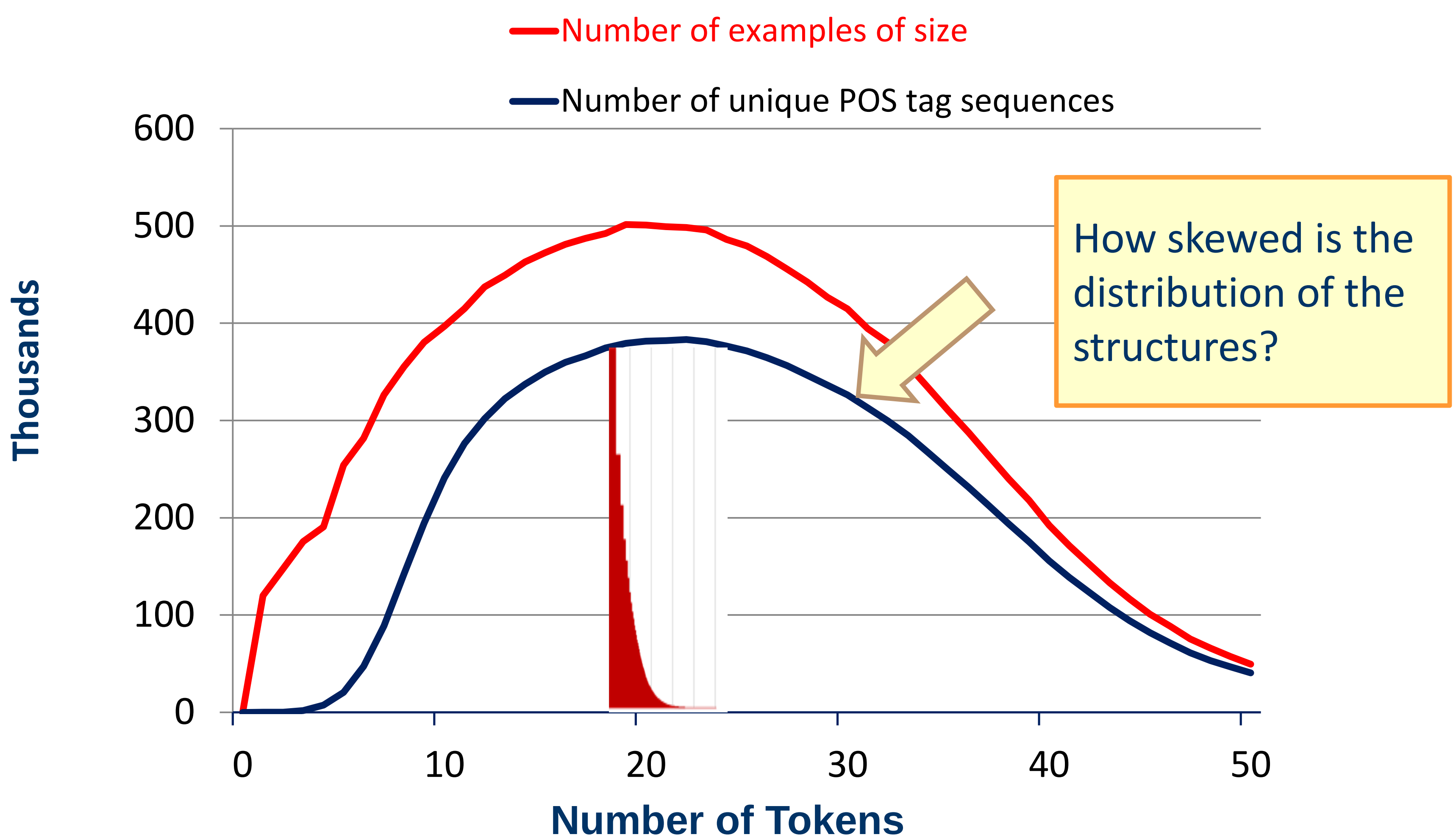

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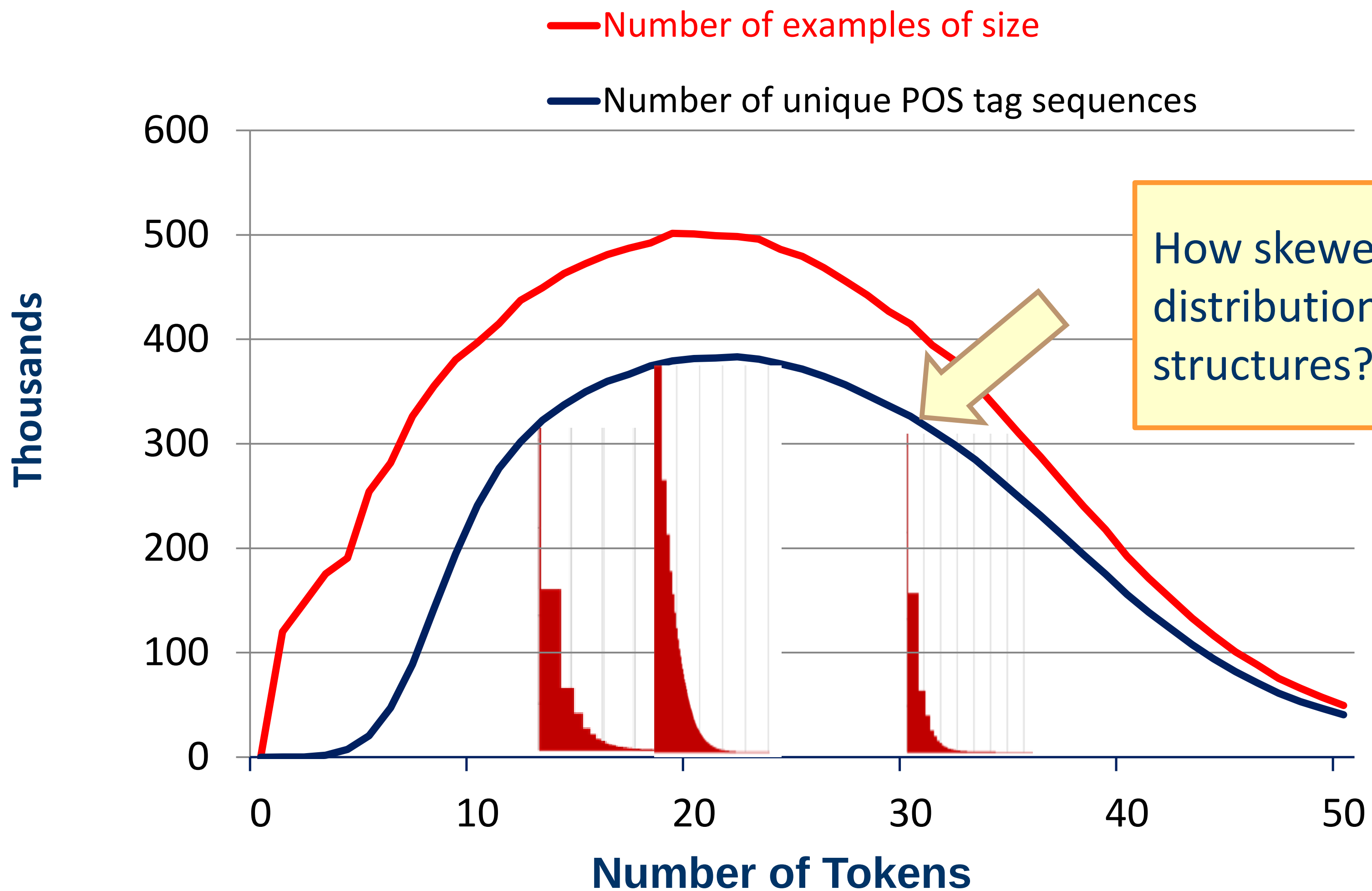


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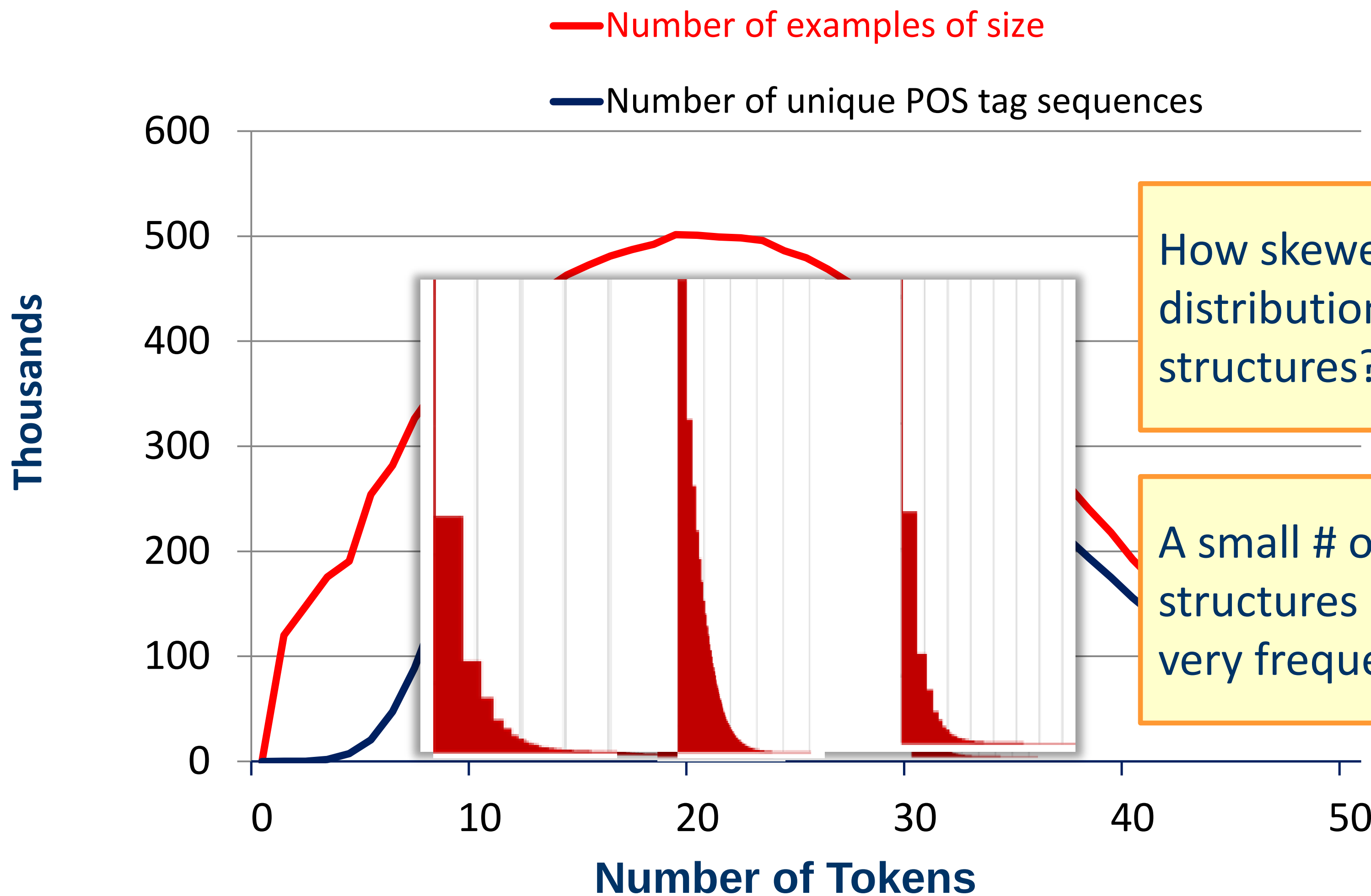
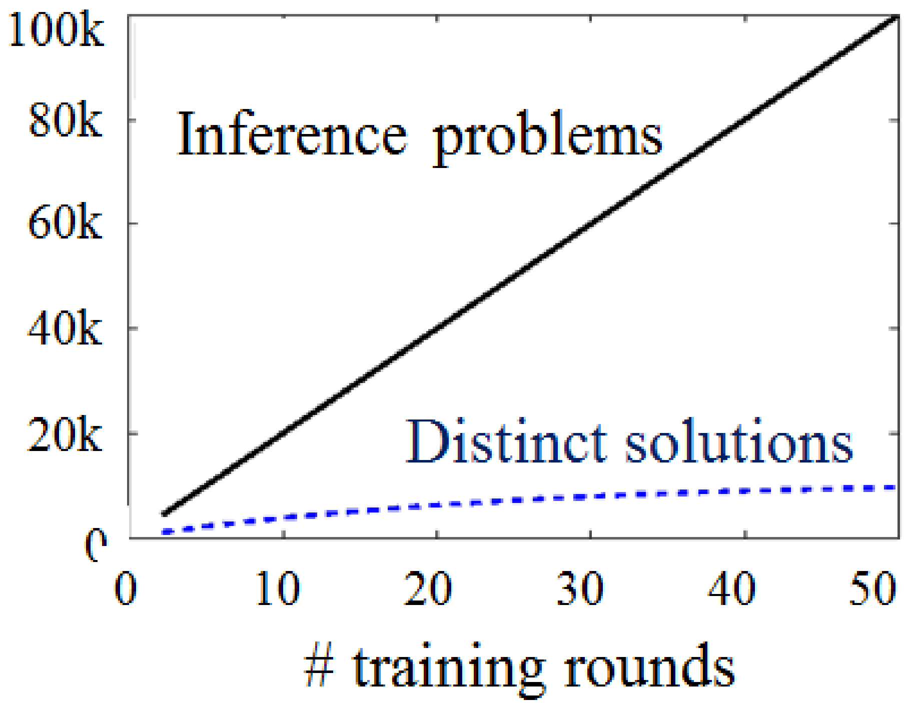



How skewed is the distribution of the structures?

A small # of structures occur very frequently

# Redundancy in Inference and Learning

- This redundancy is important since in all NLP tasks there is a need to solve many inferences, at least one per sentence.
- However, it is as important in structured learning, where algorithms cycle between
  - performing inference, and
  - updating the model.



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If **CONDITION** (**problem** ***cache***, *new problem*)
then (no need to call the solver)
**SOLUTION**(*new problem*) = old solution
Else
Call **base solver** and update ***cache***
End

0.04 ms

2 ms

# Speedup & Accuracy

$$\text{Speedup} = \frac{\text{number of inference calls without amortization}}{\text{number of inference calls with amortization}}$$

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Amortization schemes [EMNLP'12, ACL'13, AAAI'15]

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By decomposing the objective function, building on the fact that "smaller structures" are more redundant, it is possible to get even better results.

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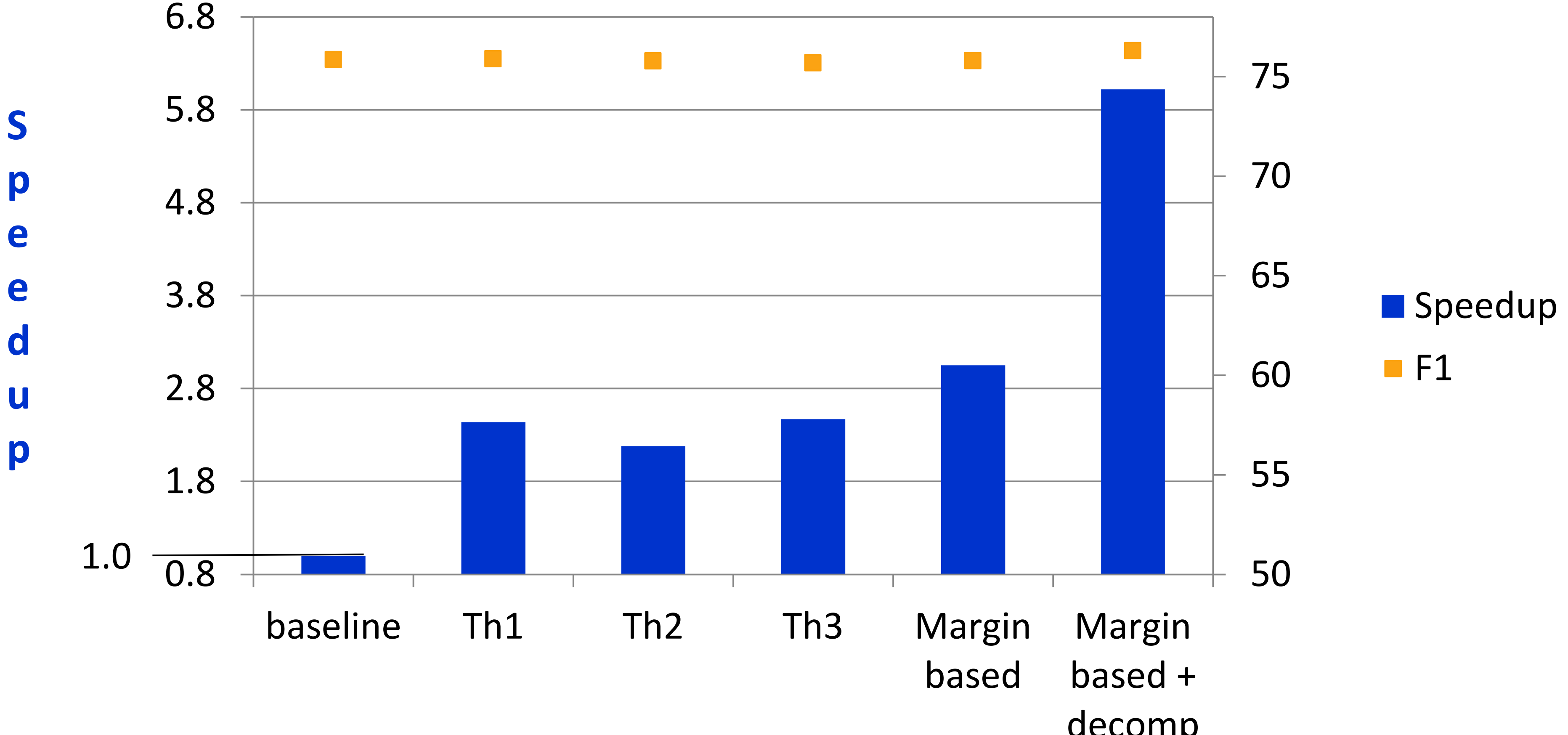


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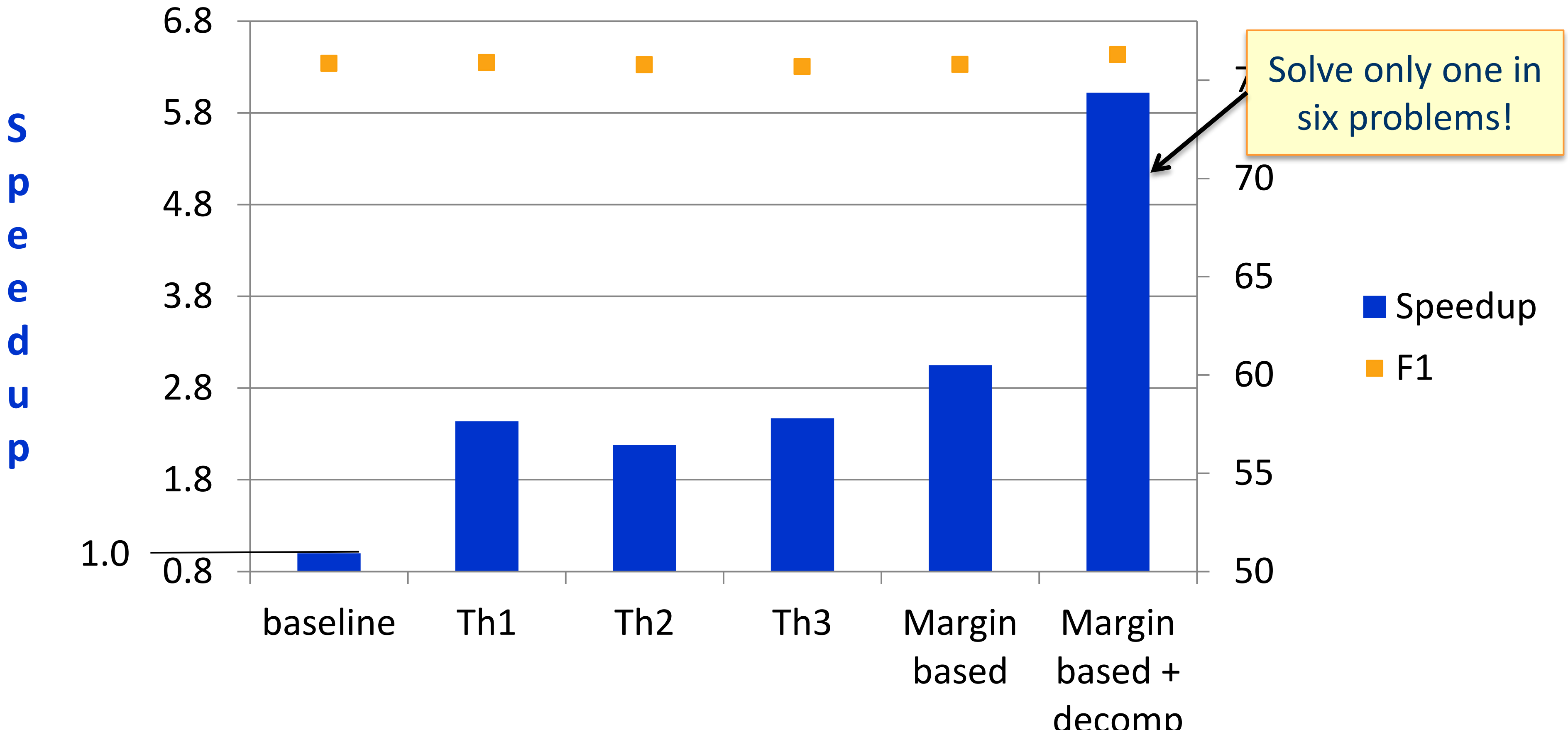


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# Speedup & Accuracy

The results show that, indeed, the inference formulation provides a new level of abstraction that can be exploited to re-use solutions

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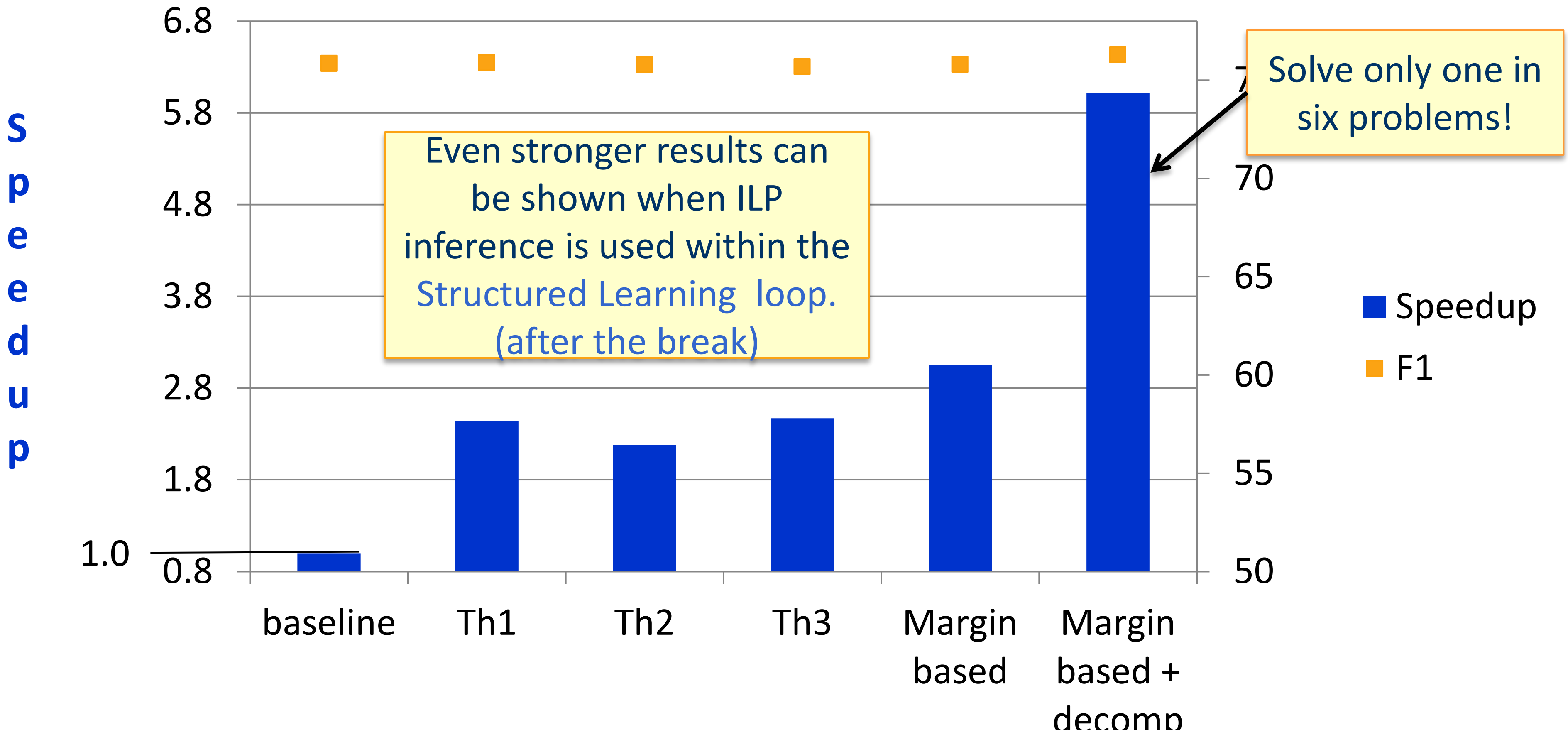


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# First Summary

- Introduced Structured Prediction
- **Many examples**
- Introduced the key building blocks of **structured learning** and **inference**
- Focused on Constraints Conditional Models
- CCMS: The motivating scenario is the case in which
  - Joint INFERENCE is essential
  - Joint LEARNING should be done thoughtfully
    - **Not everything can be learned together**
    - **We don't always want to learn everything together**
- Moving on to
  - Details on Joint Learning
  - Details on Inference