COGNITIVE COMPUTATION GROUP
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Starting from Scratch in Semantic Role Labeling

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Understanding Situated Language in Everyday Life

Connecting Language to the World

Can we rely on this interaction to provide supervision (and, eventually, recover meaning) ?

Can I get a coffee with sugar and no milk

Semantic Parser

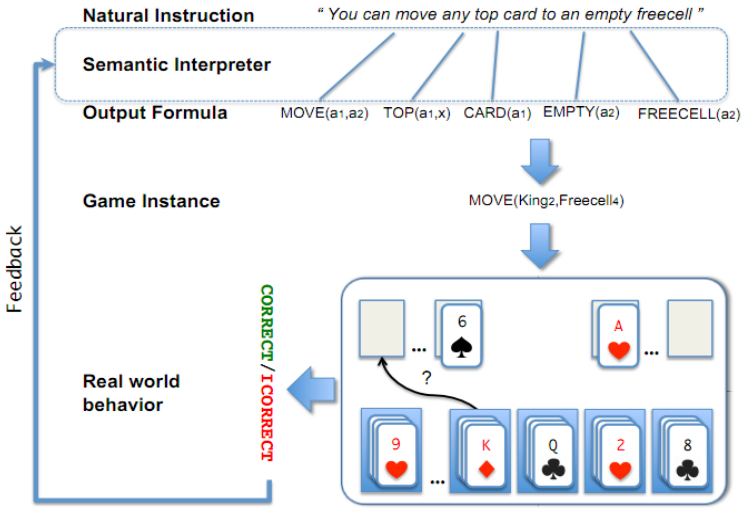
MAKE(COFFEE,SUGAR=YES,MILK=NO)

- How to recover meaning from text?
- Annotate with meaning representation; use (standard) “example based” ML
  - Teacher needs deep understanding of the learning agent
  - Annotation burden; not scalable.
- Instructable computing
  - Natural communication between teacher/agent

Scenarios I: Understanding Instructions [IJCAI'11, ACL'13, MLJ'13]

- Understanding Games' Instructions

A top card can be moved to the tableau if it has a different color than the color of the top tableau card, and the cards have successive values.



- An automated learner reads natural instructions and "understands" them by interacting with the game
  - Agonstic of agent's internal representations
  - Contrasts with traditional 'example-based' ML

Learning Latent Structured Representations from World's Response.
A series of works: Dan Goldwasser's Thesis

$move(a_1, a_2)$
$top(a_1, x_1)$ $card(a_1)$ $freecell(a_2)$ $empty(a_2)$

- "You can move any of the top cards to an empty free-cell"

$move(a_1, a_2)$
$top(a_1, x_1)$ $card(a_1)$ $tableau(a_2)$ $top(x_2, a_2)$
$color(a_1, x_3)$ $color(x_2, x_4)$ $not\text{-}equal(x_3, x_4)$
$value(a_1, x_5)$ $value(x_2, x_6)$ $successor(x_5, x_6)$

- "A top card can be moved to a tableau if it has a different color than the color of the top tableau card, and the cards have successive values"

Starting from Scratch in Semantic Role Labeling

Michael Connor Yael Gertner Cynthia Fisher

M. Connor and C. Fisher and D. Roth, Starting from Scratch in Semantic Role Labeling: Early Indirect Supervision. Cognitive Aspects of Computational Language Acquisition (2012)

How do children begin to understand sentences?

- Topid rivvo den marplox.

Language Acquisition

Traditional view: knowledge of meaning drives learning of words and syntax

"The gubish fib fribs the nurt nit"

The dog chases the cat?

The cat is quick?

The cat flees the dog?

The cat and the dog are playing?

The dog is excited?

Its a nice day today?

Language Acquisition

"The gubish **dog** fribs the nurt **cat**"

The dog chases the cat?

The cat is quick?

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The cat and the dog are playing?

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Its a nice day today?

Language Acquisition

(Agent) (Patient)

"The gubish **dog** fribs the nurt **cat**"

The dog chases the cat?

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The cat flees the dog?

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Its a nice day today?

- What if we know or predict abstract semantics of sentence?
  - Who does what to whom?

Language Acquisition

(Agent) (Patient)

"The gubish **dog** fribs the nurt **cat**"

The dog chases the cat?

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Its a nice day today?

- Neither syntax or semantics are obvious from sentence or scene
- Only by using limited knowledge of both can we learn
  - Even simple structural representations (such as identity of nouns) can help

The ambiguity of situations as evidence for sentence meaning

The situation

It's my turn.
She wants me to put this here.

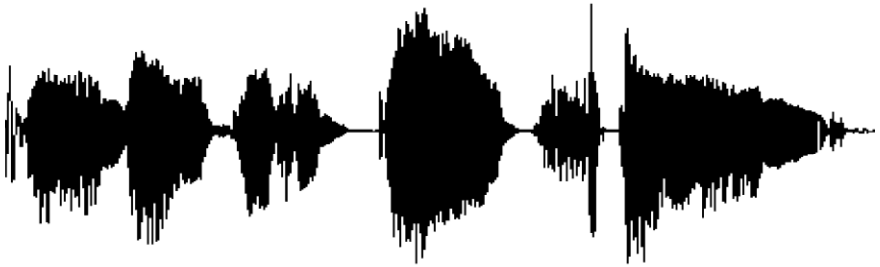
The sentence?

You can put the blue one there.
The blue one goes there.
Try the blue one.

The gap between the speaker's likely communicative goal and her words is the *unknown unknown*.

The language-world mapping problem

“the language”



[Topid rivvo den marplox.]

“the world”

Observe how words are distributed across situations

Smur! Rivvo della frowler.

Scene 1

Topid rivvo den marplox.

Blert dor marplox, arno.

Scene 3

Marplox dorinda blicket.

Scene n

Structure-mapping: A proposed starting point for syntactic bootstrapping

- Children can learn the meanings of some nouns via cross-situational observation alone [Fisher 1996, Gillette, Gleitman, Gleitman, & Lederer, 1999; Snedeker & Gleitman, 2005]
- But how do they learn the meaning of verbs?
  - Sentences comprehension is grounded by the acquisition of an initial set of concrete nouns
  - These nouns yields a skeletal sentence structure — candidate arguments; cue to its semantic predicate—argument structure.
  - Represent sentence in an abstract form that permits generalization to new verbs

[Topid rivvo den marplox.]

Nouns identified

Syntactic Bootstrapping Makes Three main claims:

- (1) Structure-mapping: Syntactic bootstrapping begins with an unlearned bias toward one-to-one mapping between nouns in sentences and semantic arguments of predicate terms

  (Fisher et al., 1994; Gertner & Fisher, 2012; Gillette et al., 1999; Yuan, Fisher & Snedeker, 2012)

- (2) Early abstraction: Learners are biased toward abstract representations of language experience

  (Gertner, Fisher & Eisengart, 2006; Pinker, 1989; Thothathiri & Snedeker, 2008)

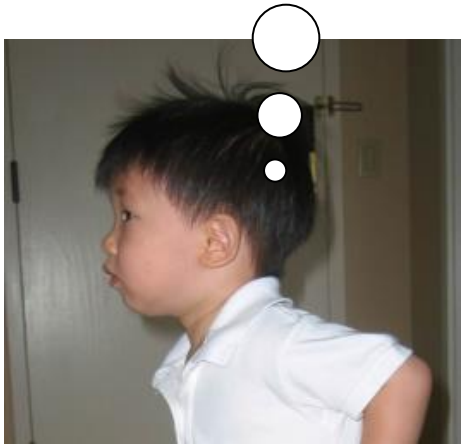
- (3) Independent encoding of verb syntax: Children gather distributional facts about verbs from listening experience (before they know what they mean)

  (Arunachalam & Waxman, 2010; Messenger, Yuan, & Fisher, 2011; Scott & Fisher, 2009; Yuan & Fisher, 2009)

A fourth corollary:

- (4) 'Real' syntactic bootstrapping: Children can learn which words are verbs by tracking their syntactic argument-taking behavior in sentences.

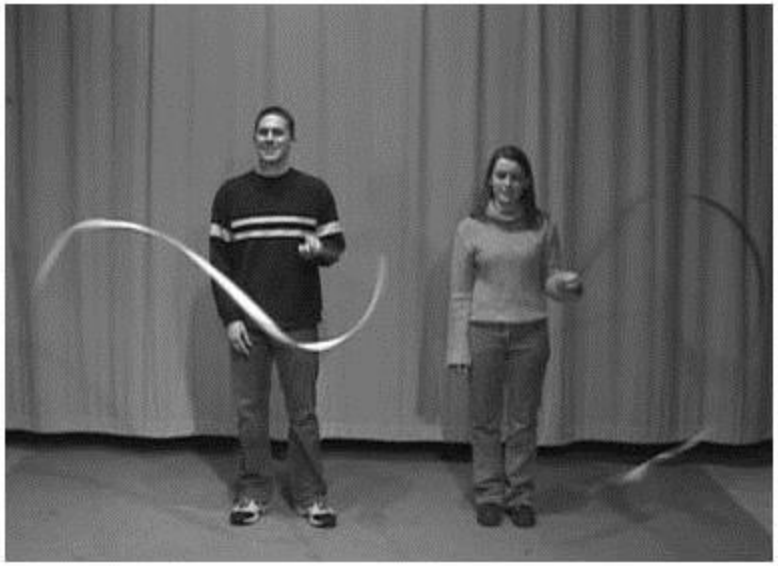
Verb = Push
[noun1, noun2]
2-participant relation



Hey, she pushed her.
Will you push me on the swing?
John pushed the cat off the sofa
...

Strong Predictions [Gertner & Fisher, 2006]

- Test 21 month olds on assigning arguments with novel verbs
- How order of nouns influences interpretation: Transitive & Intransitive



Agent-first: The boy and the girl are daxing!
Transitive: The boy is daxing the girl!
Agent-last: The girl and the boy are daxing!

Error disappears by 25 months

preferential looking paradigm

BabySRL

- Develop a machine learning model to support psycholinguistic theories of syntactic bootstrapping in early stages of language acquisition
- Develop Semantic Role Labeling System (BabySRL) to experiment with theories of early language acquisition
  - SRL as minimal level language understanding
  - Determine who does what to whom.

- Realistic Computational model for Syntactic Bootstrapping
  - Verbs meanings are learned via their syntactic argument-taking roles
  - Semantic feedback to improve syntactic & meaning representation
- Inputs and knowledge sources
  - Only those we can defend children have access to

Verb Meaning = Semantic Role Labeling (SRL)

- A semantic analysis of the sentences at the level of who does what to whom
- For each verb in the sentence:
  - SRL system tries to identify all constituents that fill a semantic role
  - and to assign them roles (agent, patient, goal, etc.)
- Inspired by our SRL program (Punyakanok et. al 05,08), completely different learning approach.

<table>
<tr><td>Remember</td><td>V: remember</td><td></td></tr>
<tr><td>what</td><td rowspan="3">A1: patient</td><td>A1: patient</td></tr>
<tr><td>Daddy</td><td>A0: agent</td></tr>
<tr><td>said</td><td>V: say</td></tr>
</table>

The nature of the semantic roles

- A key assumption of the SRL is that the semantic roles are abstract:
  - This is a result of the PropBank annotation scheme: verb specific roles are grouped into macro-roles (e.g., Dowty, 1991)

Agent

Like:	**Give:**	**Have:**
Arg0:Liker	**Arg0**:Giver	**Arg0**:Owner
Arg1:Object of affection	**Arg1**:Thing given **Arg2**:Recipient	**Arg1**:Possession

Training the Baby SRL

- 3 corpora of child-directed speech
  - Annotated parental utterances using PropBank annotation scheme
  - Speech to Adam, Eve, Sarah (Brown, 1973)
  - Adam 01-23 (2;3 - 3;2)
    - **Train on 01-20: 3951 propositions, 8107 arguments**
  - Eve 01-20 (1;6 - 2;3)
    - **Train on 01-18: 4029 propositions, 8499 arguments**
  - Sarah 01-90 (2;3 - 4;1)
    - **Train on 01-83: 8570 propositions, 15599 arguments**

Testing the Baby SRL

- Constructed test sentences like those used in experiments with children
  - Unknown verbs & two animate nouns force the SRL to rely on syntactic knowledge
- "Adam krads Daddy!"

Adam Mommy Daddy Ursula ...	krad	Adam Mommy Daddy Ursula ...

BabySRL: Key Components

- Representation:
  - Theoretically motivated representation of the input
  - Shallow, abstract, sentence representation consisting of
    - **# of nouns in the sentence**
    - **Noun Patterns (1st of two nouns)**
    - **Relative position of nouns and predicates**
- Learning:
  - Guided by knowledge kids have
    - **Classify words by part-of-speech (distinct states)**
    - **Identify arguments and predicates**
    - **Determine the role arguments take**

BabySRL: Early Results

- Fine grained experiments with how language is represented
- Test different levels of representation
- Primar
  - Hypo
    - **C** **sent structure**
  - NPat
    - **F**
- Alterna
  - Target argument is before or after verb

- **Key Finding:**
  - NPattern reproduces errors in children
    - **Promotes A0-A1 interpretation in transitive, but also intransitive sentences**
  - Verb position does not make this error
    - **Incorporating it recovers correct interpretation**
    - **But:** requires the ability to recognize the predicate, a harder (and later) task

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    - **# of nouns in the sentence**
    - **Noun Patterns (1st of two nouns)**
    - **Relative position of nouns and predicates**
- Learning:
  - Guided only by knowledge kids have
    - **Classify words by part-of-speech**
    - **Identify arguments and predicates**
    - **Determine the role arguments take**

Minimally Supervised BabySRL

- Protocol: Provide little prior knowledge & only high level semantic feedback
  - Defensible from psycholinguistic evidence

- Unsupervised "parsing"
  - Identifying part-of-speech states
- Argument Identification
  - Identify Argument States
  - Identify Predicate States
- Argument Role Classification
  - Labeled Training using predicted arguments

Learning with Indirect Supervision

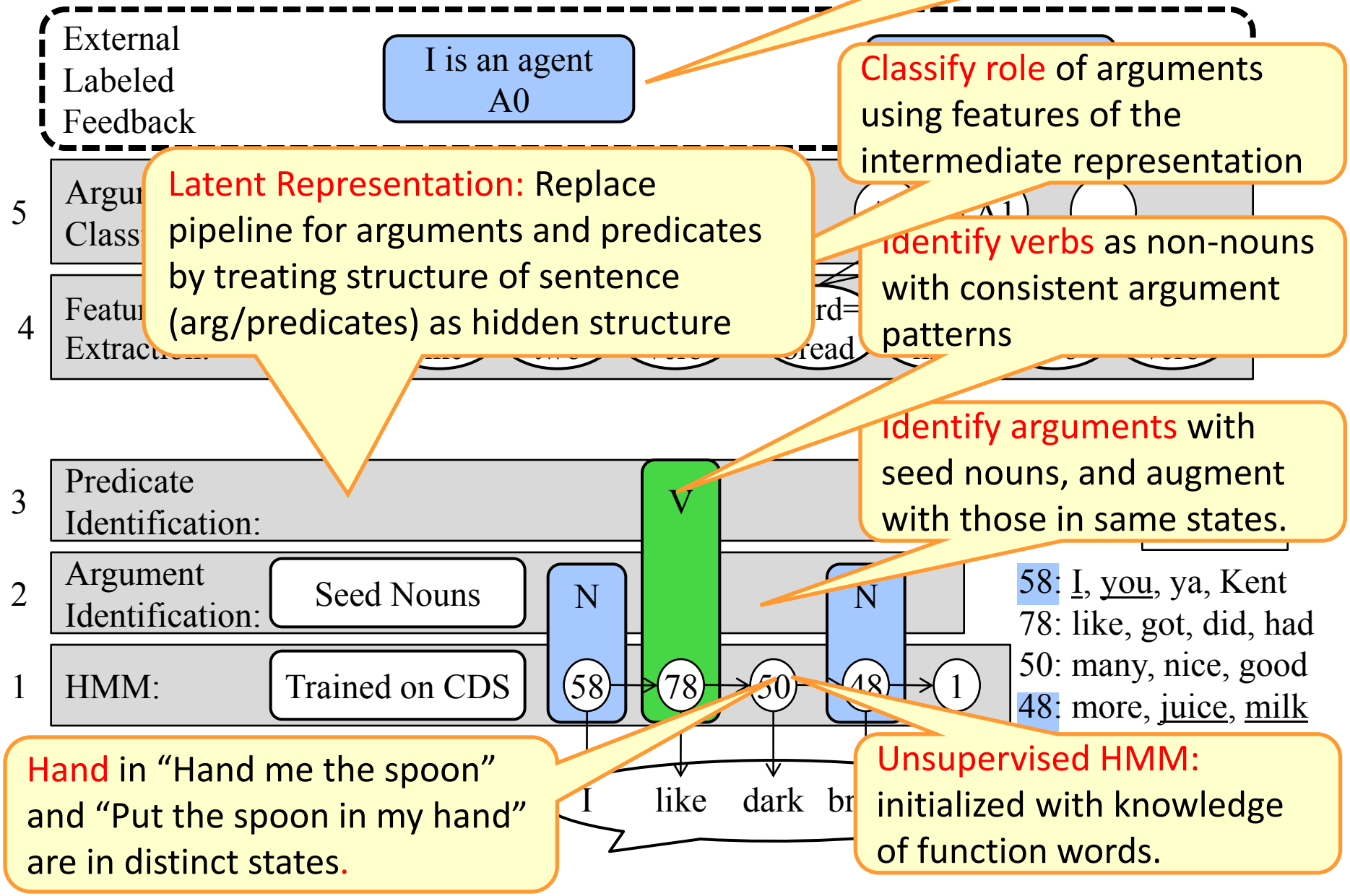
Input + Distributional learning

Structured Intermediate Representation (no supervision)

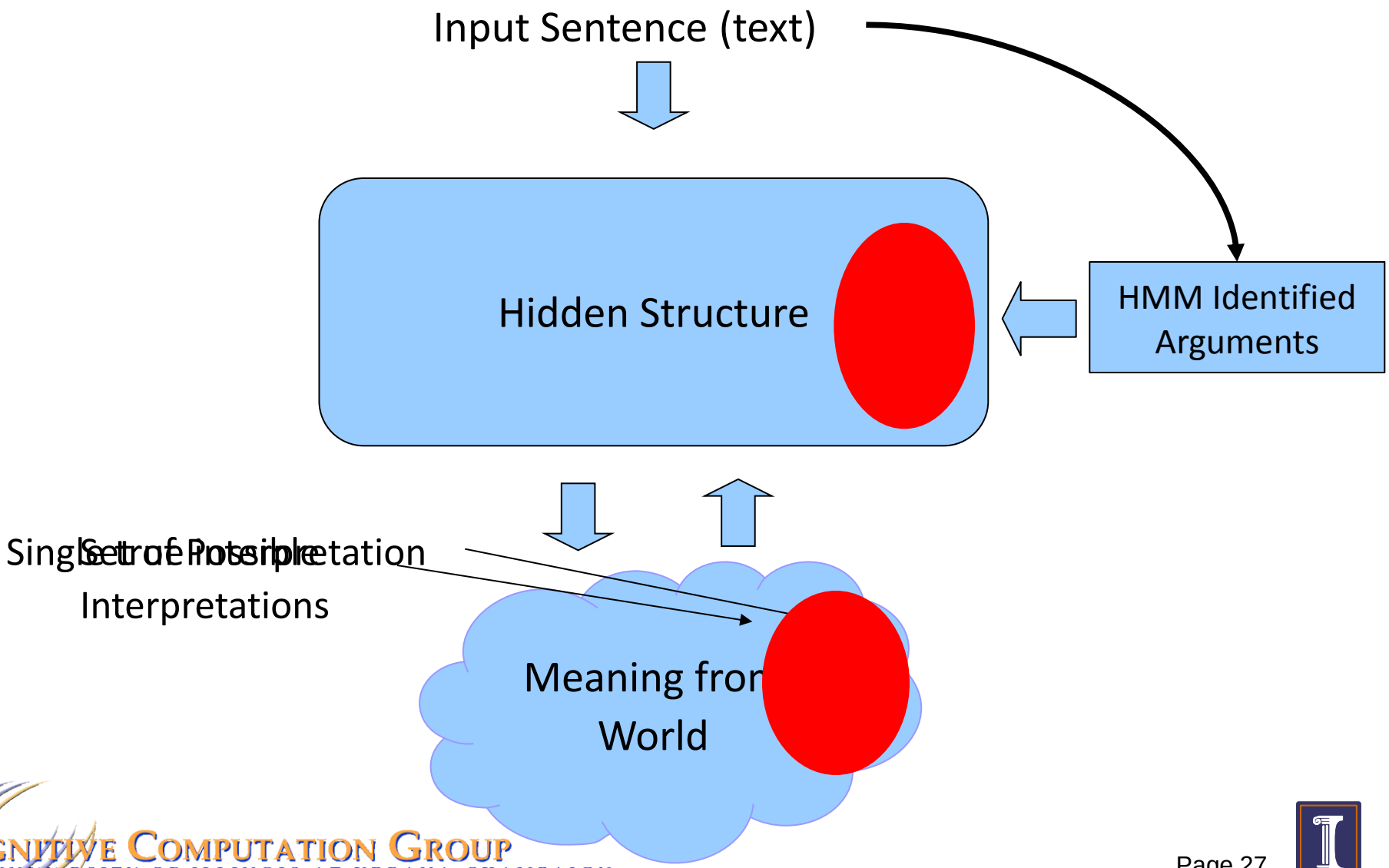
Binary weak supervision for the final decision

- Learning is done from CHILDES corpora
- Indirect supervision driven from very week scene feedback

BabySRL Architecture



Joint Semantics and Structure



Online Latent Structure Training

Input: Sentences with *labels
Output: Two linear separators:
u_t for hidden structure, w_t for role cla

Use HMM identified nouns to constrain possible structures during inference

For each sentence:

Find best joint hidden structure and labeling

$$(h_i^*, y_i^*) \leftarrow \arg\max_{h \in H_i, y \in Y} w_t \cdot \Phi_w(x_i, h, y) + u_t \cdot \Phi_u(x_i, h)$$

Role Classifier

Structure Classifier

Update u to predict h^*

$$h' \leftarrow \arg\max_h u_t \cdot \Phi_u(x_i, h) + C * \mathbf{1}[h \neq h_i^*]$$

$$u_{t+1} \leftarrow u_t + \alpha_u(\Phi_u(x_i, h_i^*) - \Phi_u(x_i, h'))$$

Update w based on h^* to predict y^*

$$y' \leftarrow \arg\max_y w_t \cdot \Phi_w(x_i, h_i^*, y) + C * \mathbf{1}[y \neq$$

$$w_{t+1} \leftarrow w_t + \alpha_w(\Phi_w(x_i, h_i^*, y_i^*) - \Phi_w(x_i, h_i^*,$$

$$t \leftarrow t + 1$$

Instead of true labels, use more ambiguous constraints

Unordered set of true labels

Unordered superset of true labels

Latent BabySRL Conclusions

- Semantics can provide cue for identifying structure, but ambiguous semantics needs some help
  - Small set of seed nouns provide a plausible structure that can constrain and begin to learn with plausible semantic ambiguity

- Developed online latent structure classifier that integrates constraints from both semantic feedback and syntactic knowledge
  - Demonstrate alternative means of supervision, incorporate partial knowledge from multiple available sources as feedback signal
  - Comparable to early stage in child language acquisition

Summary

1. Can the minimal feedback we use be ``computed" with a vision system?
2. Perhaps we *must* start from scratch…

Thank You

- BabySRL: a realistic computational model for verb meaning acquisition via the structure-mapping theory.
  - Representational Issues
  - A machine learning framework that learns through combining multiple psycholinguistically plausible partial sources of information
- It is possible to begin learning sentence level semantics – Verb Meaning – once the learner is able to identify some nouns
  - And expects abstract semantics from the sentence
  - Simple, early representations are robust to noisy input and feedback
- Next Steps:
  - Bootstrap Language, handle growing complexity (argument structure)
  - Handle multiple predicates (verbs, prepositions,…)
  - Discourse: modeling missing argument