Learning to Interpret Natural Language Instructions

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The Problem

1. Supply an agent with an arbitrary linguistic command
2. Agent determines a task to perform
3. Agent plans out a solution and executes task

- Planning and execution is easy
- Learning task semantics and intended task is hard

The Solution

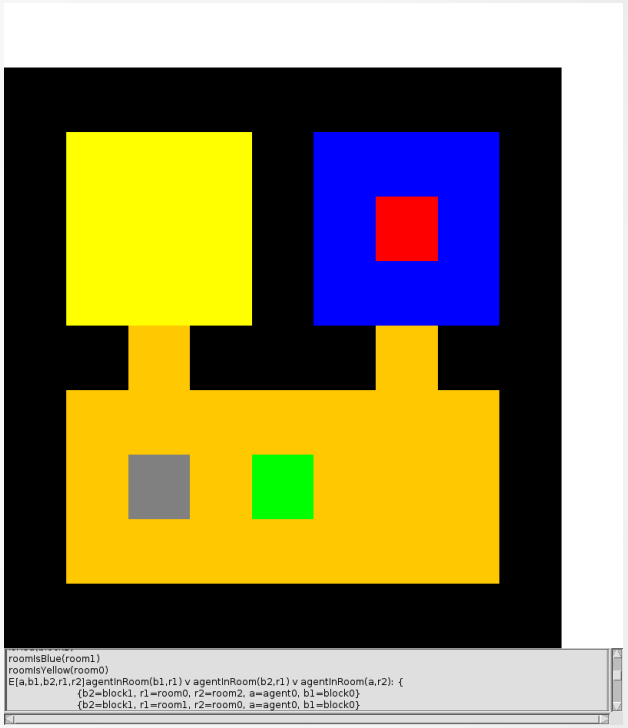
- Use expectation maximization (EM) and a generative model to learn semantics
- Pair command with demonstration of exemplar behavior
  - This is our training data
- Find highest-probability tasks and goals

Representation

- Tasks are represented using Object-Oriented Markov Decision Processes (OO-MDP)
- Defines relationship between objects
- Each state is:
  - Unordered instantiation of objects
  - Propositional functions that operate on objects
  - Goal definitions

Sample Domain (Sokoban)

- isStar(block0)
- isStar(block1)
- agentInRoom(agent0, room2)
- blockInRoom(block0, room2)
- blockInRoom(block1, room1)
- isRed(block1)
- roomIsBlue(room1)
- roomIsYellow(room0)



The System

- Three main components
  - Semantic Parsing (SP)
    - Sentences → Logical Representations
  - Inverse Reinforcement Learning (IRL)
    - Generate intent from observed behavior
  - Task Abstraction (TA)
    - Ground logic from SP into specific objects

Semantic Parsing

- Bag-of-words multinomial mixture model
  - Each propositional function has multinomial word distribution
  - Given task, a word is generated by using a word distribution from task's propositional functions
  - Don't need to learn meaning of words in every task context

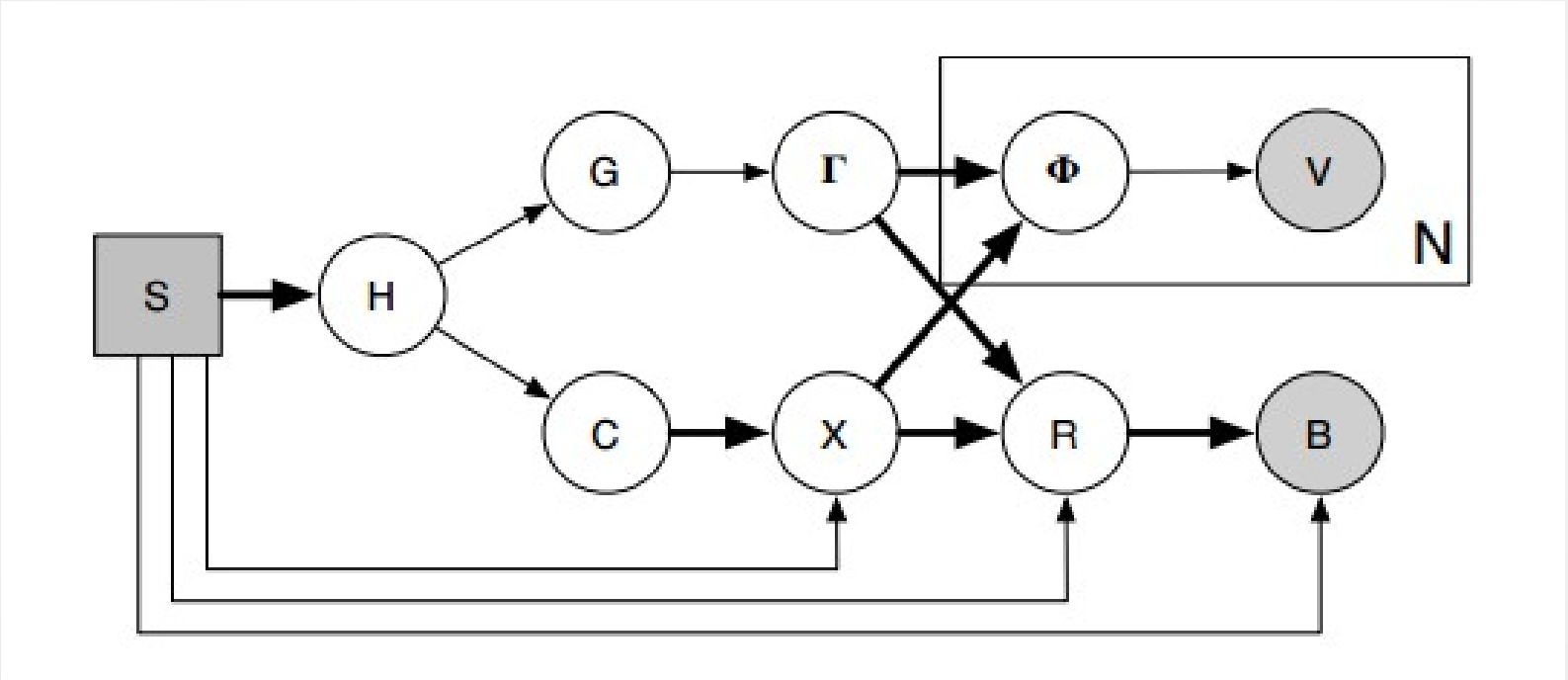
Inverse Reinforcement Learning

- Based on Maximum Likelihood Inverse Reinforcement Learning (MLIRL)
- Takes demonstration of agent behaving optimally
- Extracts a most probable reward function

Task Abstraction

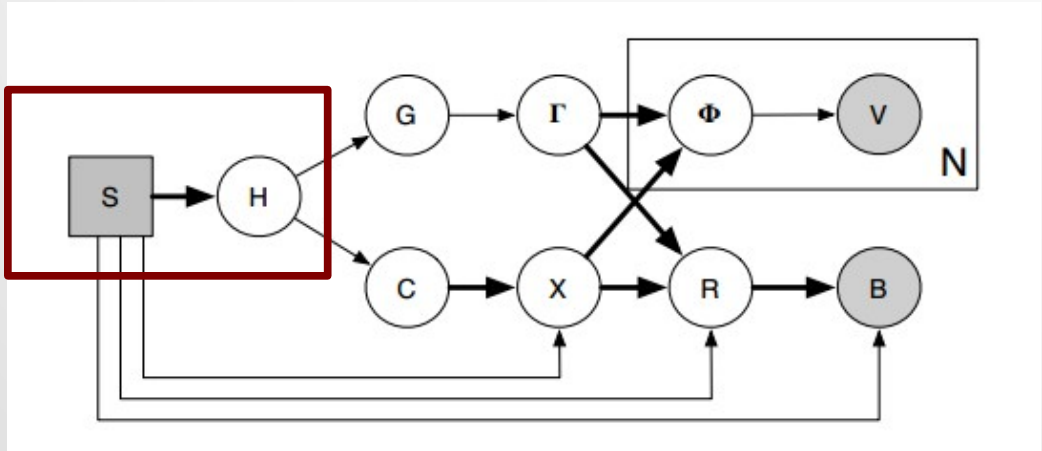
- Handles abstraction of domain into first-order logic
- Grounds generated first-order logic to domain
- Performs expectation maximization between SP and IRL

Generative Model



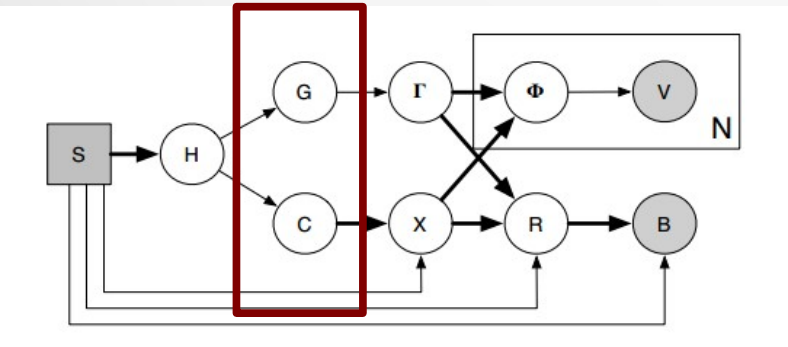
Generative Model

- **S**: initial state (input)
  - Allows determining relevant first-order logic
- **H**: hollow task
  - FOL variables and OO-MDP object classes
  - ∃b,r BLOCK(b)^ROOM(r)



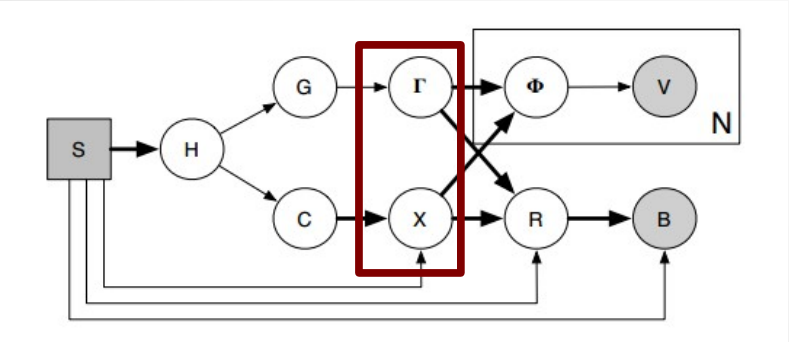
Generative Model

- **G**: abstract goal conditions
  - FOL variables and propositional function classes
  - blockPosition(b,r)
- **C**: abstract object binding (constraint)
  - FOL vars and prop. functions only guaranteed in initial state
  - roomColor(r) ∧ blockShape(b)



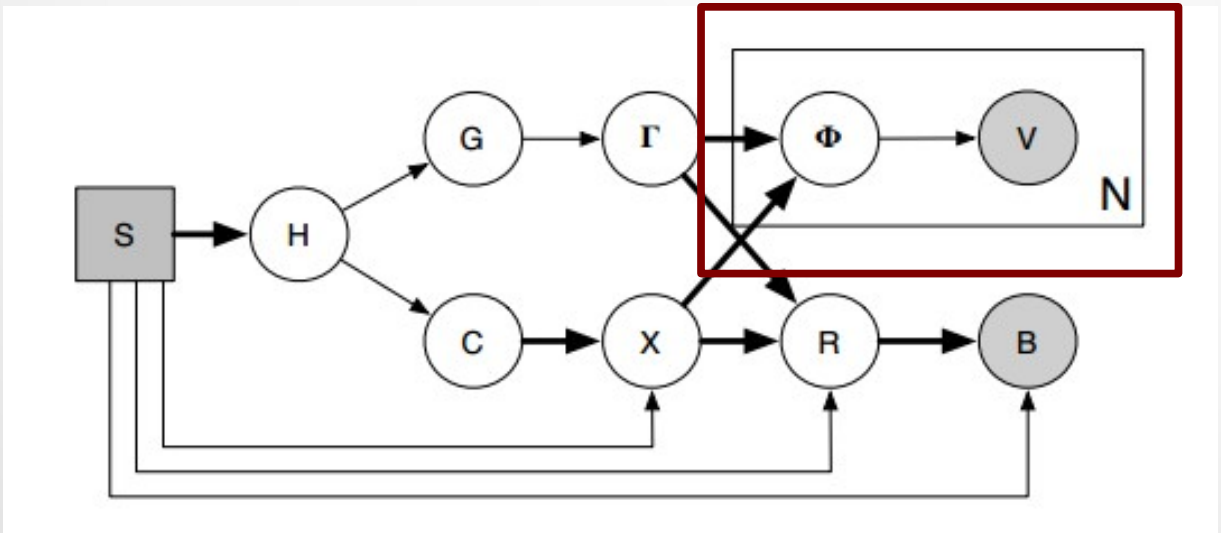
Generative Model

- **Γ**: object binding for *G*
  - Function instances of prop. function classes
  - blockInRoom(b, r)
- **X**: object binding for *C*
  - Function instances of prop. function classes
  - isGreen(r) ∧ isStar(b)



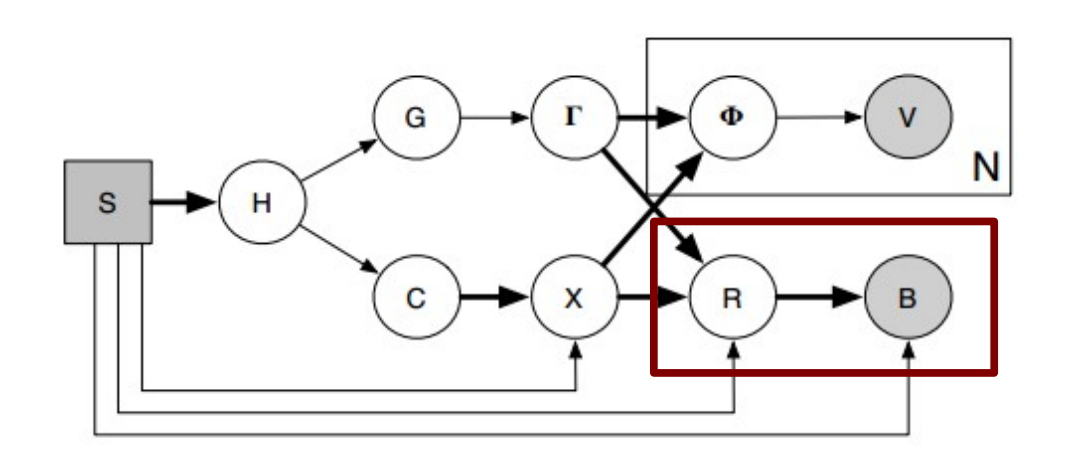
Generative Model

- **Φ**: randomly selected propositional function from **Γ** or **X**
  - blockInRoom, isGreen, or isStar
- **V**: a word from vocabulary
- **N**: number of words from *V* in a given command

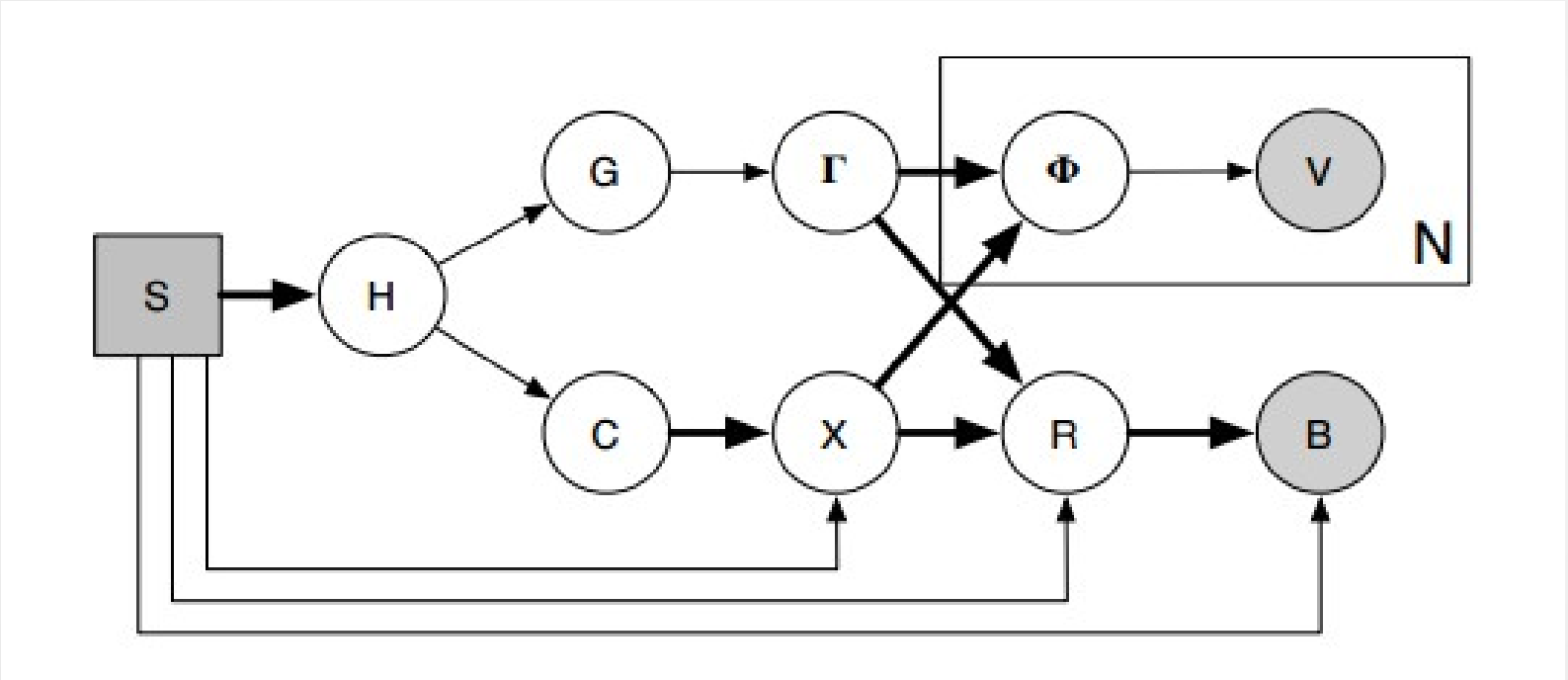


Generative Model

- **R**: reward function dictating behavior
  - Goal condition specified in **Γ** bound to objects in **X**
  - blockInRoom(block0, room2)
- **B**: behavioral trajectory
  - Starts in *S* and derived by *R*



Generative Model



Expectation Maximization

- Iterative method for maximum likelihood
- Uses observable variables
  - Initial state, behavior, and linguistic command
- Find distribution of latent variables
  - $Pr(g \mid h)$, $Pr(c \mid h)$, $Pr(y \mid g)$, and $Pr(v \mid \varphi)$
- Additive smoothing seems to have a positive effect

Training / Testing

- Gathered data from Mechanical Turk
  - 40 commands for each of 6 example tasks
- Sokoban test domain with leave-one-out cross validation
- Accuracy is computed as comparison of most likely reward function versus actual reward function
- 70%+ accuracy with 5 EM iterations

Current / Future Tasks

- Fully implement the system to build abstract tasks from language information and feature relevance
- Continue testing with Mechanical Turk data
- Implement richer language models
- Incorporate options to represent subgoals

Summary

- Learning tasks from verbal commands
- Uses generative model and expectation maximization
- Train using command and behavior
- Commands should generate correct task goal and behavior