Inference of Human-derived Specifications of Object Placement via Demonstration

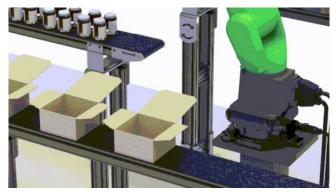
Alex Cuellar¹, Ho Chit Siu², Julie A Shah¹

¹ MIT, ² Lincoln Labs









Source: Linus Projects

Dexterity + Perception



Source: Ambi Robotics



Source: Rutgers University



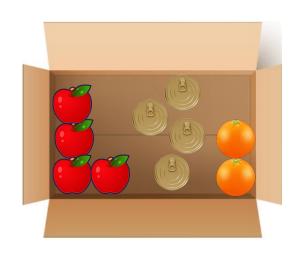
Source: Ambi Robotics

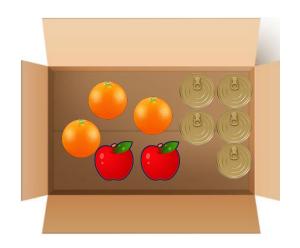
Question:

<u>How</u> Should a Robot Complete Pick-And-Place Tasks?

Source: Rutgers University

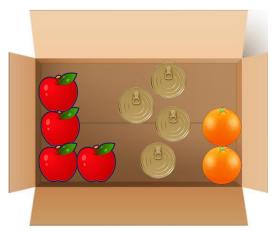
Which of These Doesn't Belong?



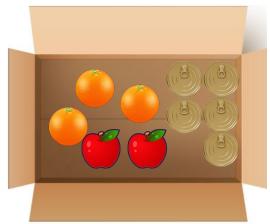




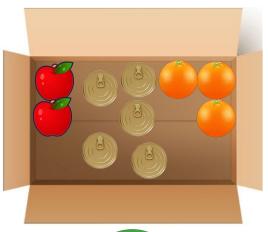
Which of These Doesn't Belong?

















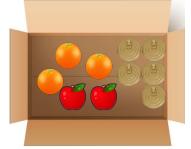
How do we know this?

Does not rely on:

Exact Positions
Individual Objects

Does rely on:

Spatial Relationships
Object "Types"













How do we know this?

Does not rely on:

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Exact Positions

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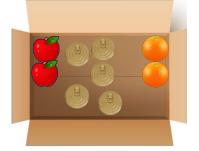




Why it Matters?

User Preference/ Expectation

"Apples are to the left of cans"





Requirements

"Fruit should be secured against box walls"

PARCC: Positionally Augmented Region Connection Calculus

A specification language defining requirements on the spatial relationships between classes of objects

PARCC: Positionally Augmented Region Connection Calculus

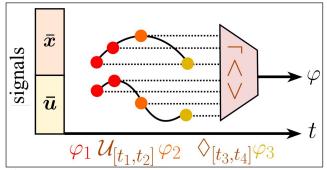
A specification language defining requirements on the spatial relationships between classes of objects

-AND-

An inference algorithm to learn specifications from demonstrations

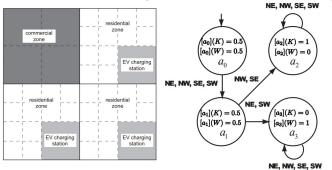
Existing Spatial Specification languages

Signal Temporal Logic [1]



Source: From [3]

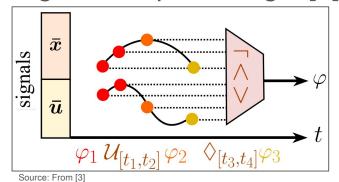
Quad-Tree Representations [2]



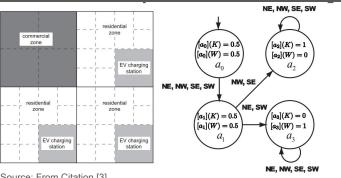
Source: From Citation [3]

Existing Spatial Specification languages

Signal Temporal Logic [1]



Quad-Tree Representations [2]

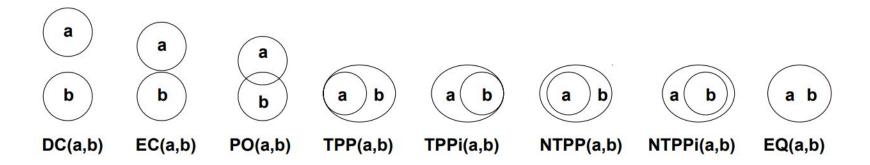


Source: From Citation [3]

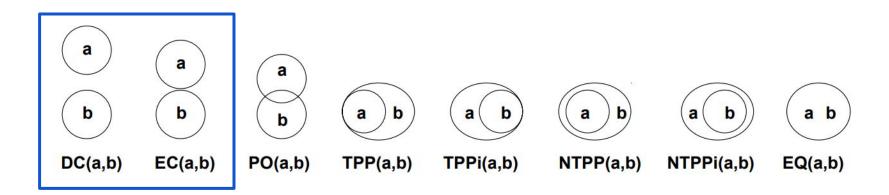
Represent specifications over **specific regions** or **precise distance** in space

Don't easily represent *relationships between objects*

RCC: Reasoning Over *Relationships* of Spatial Regions

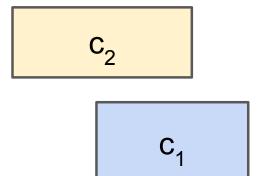


RCC: Reasoning Over *Relationships* of Spatial Regions



We use the fragment that assumes objects that do not share regions in space

Defining PARCC: Object Relations

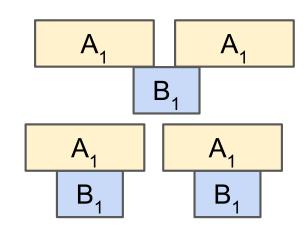


$$DR_N(c_2, c_1) \to DR(c_2, c_1) \land y_{c_2} \ge y_{c_1}$$

 $\forall (x_{c_2}, y_{c_2}) \in c_2, (x_{c_1}, y_{c_1}) \in c_1$

PARCC "Object" Relationships

specify a direction (i.e. N,E,S,W) between the objects it describes



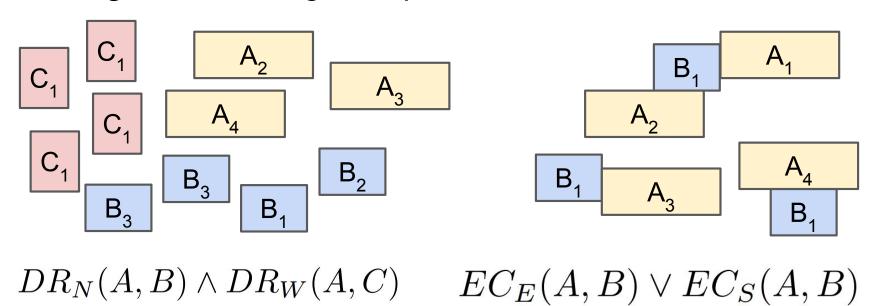
$$EC_N(A, B) \leftrightarrow EC_N(a, b)$$

 $\forall a \in \mathcal{A} \quad \exists b \in \mathcal{B}$

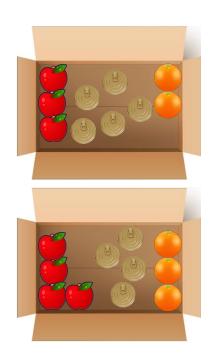
PARCC "Class" Relationships:

Specify a relationship all objects of one class have with another class

Defining PARCC: Logical Specifications



<u>PARCC Specifications</u> utilize boolean logic to define requirements involving multiple class relations



$$DR_{E}(O,C) \qquad DR_{W}(A,C)$$

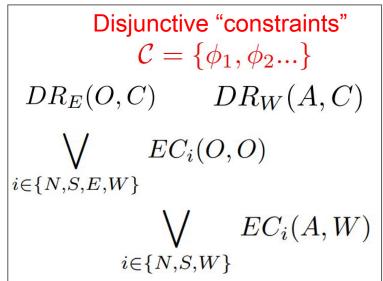
$$\bigvee_{i \in \{N,S,E,W\}} EC_{i}(O,O)$$

$$\bigvee_{i \in \{N,S,W\}} EC_{i}(A,W)$$





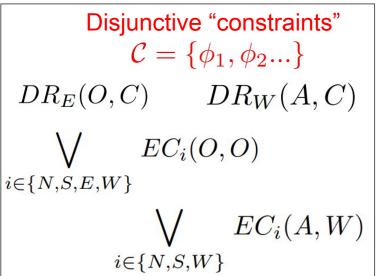










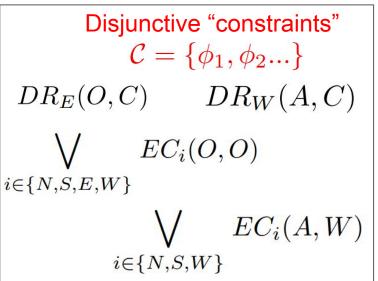


Final Specification: $\Phi = \wedge_{\phi \in \mathcal{C}} \phi$









Final Specification: $\Phi = \wedge_{\phi \in \mathcal{C}} \phi$

GOAL: Infer human's intended ${\cal C}$

All Possible Disjunctive Formulas: N=1: $DR_W(A,C)$ $DR_W(A,C) \lor DR_S(A,C)$ $EC_E(O,A)$ $EC_W(A,C) \lor DR_W(A,A)$ $DR_N(A,O)$ $EC_W(O,O) \lor DR_N(O,O)$...

Satisfying Formulas:

N=1: N=2: $DR_W(A,C) \lor DR_S(A,C)$ $EC_E(O,A) \longleftrightarrow EC_W(A,C) \lor DR_W(A,A) \longleftrightarrow EC_W(A,C) \lor DR_N(O,O)$

For each satisfying formula ϕ : Probability that ϕ is incidentally satisfied: $P(D \to \phi | \mathcal{R}) =$ $\prod_{o \in \mathcal{O}_D^C} \max \left(\epsilon, \frac{\sum_{R \in \mathcal{R}} \sum_{o' \in \mathcal{O}_R^C} \mathbf{1}(o' \to \phi)}{\sum_{R \in \mathcal{R}} \sum_{o' \in \mathcal{O}_R^C} 1} \right)$ $-P(D o \phi | \mathcal{R}) < p_c$: \bigcirc Keep ϕ $P(D o \phi | \mathcal{R}) > p_c$: igotimes Discard ϕ

```
N=1:
EC_E(O,A) EC_W(A,C) \vee DR_W(A,A)
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For each satisfying formula ϕ :

$$P(D \to \phi | \mathcal{R}) =$$

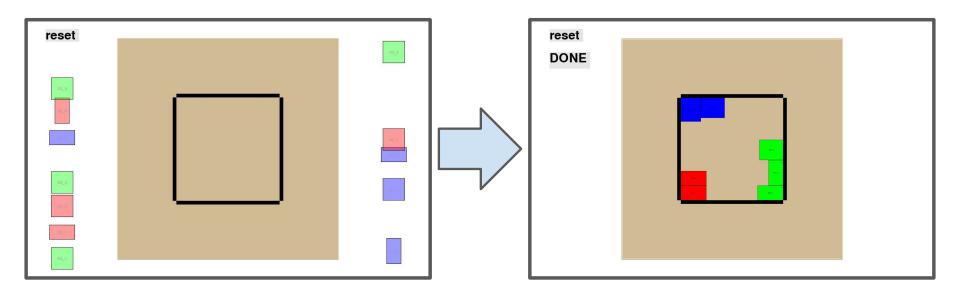
Does this really capture human's $\sum_{R \in \mathcal{R}} \sum_{\sigma \in \mathcal{O}_R^{-1}} (\sigma' \to \phi)$

ground truth object placement preferences?

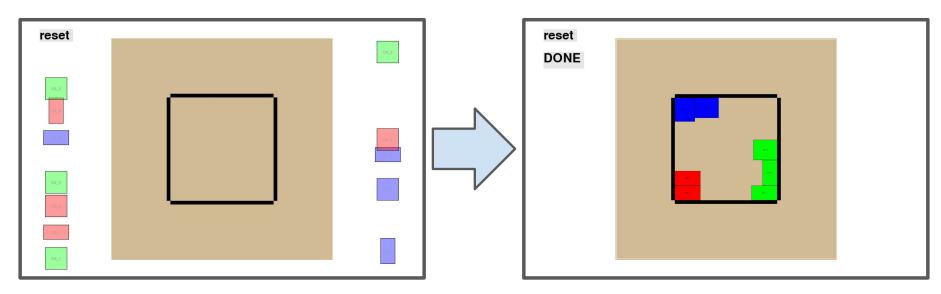
$$N=1$$
: $N=2$: $DR_W(A,C) \lor DR_S(A,C)$ $EC_E(O,A) \to EC_W(A,C) \lor DR_W(A,A)$ $EC_W(A,C) \lor DR_W(A,A)$ $EC_W(O,O) \lor DR_N(O,O)$



Box Packing Domain

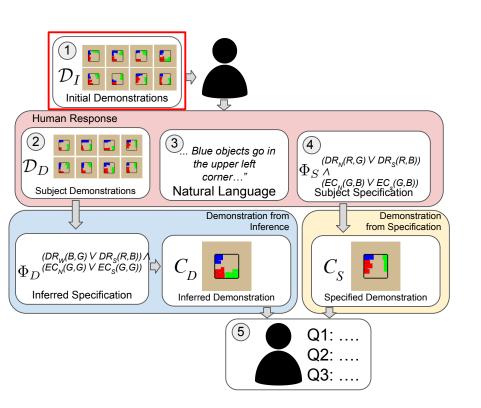


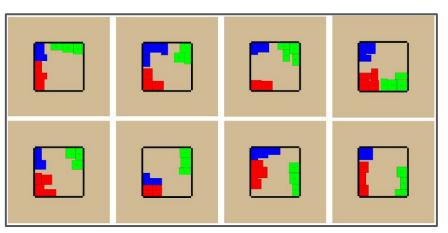
Box Packing Domain



Questions:

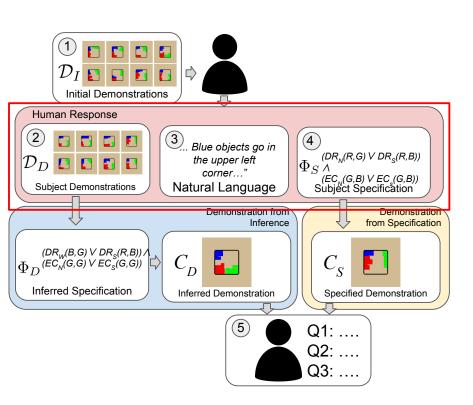
- Can the PARCC inference algorithm capture intuitive requirements on object placement?
- Can the inference algorithm capture requirements better than direct specification?



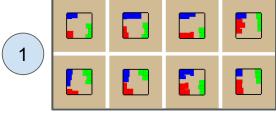


Show the participant 8 *initial* demonstrations that intentionally use a specification of 12 formulas:

$$\phi_1...\phi_{12}$$



The subject provides:



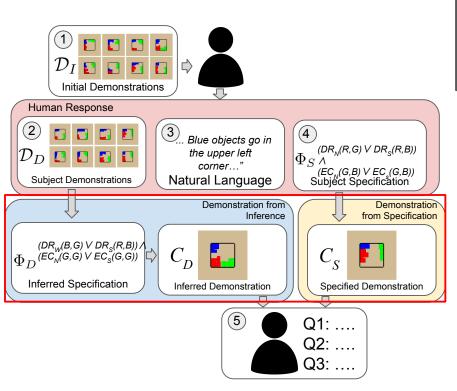
Demonstrations matching the initial examples

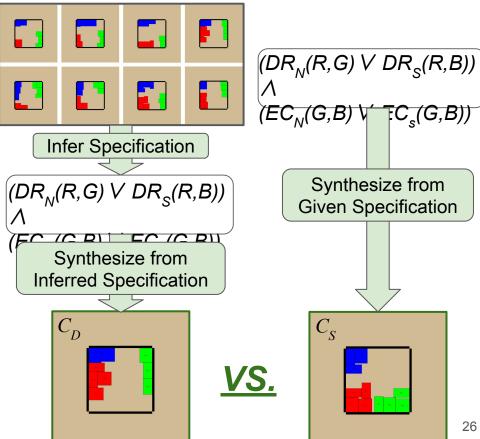
go in the upper left corner..."

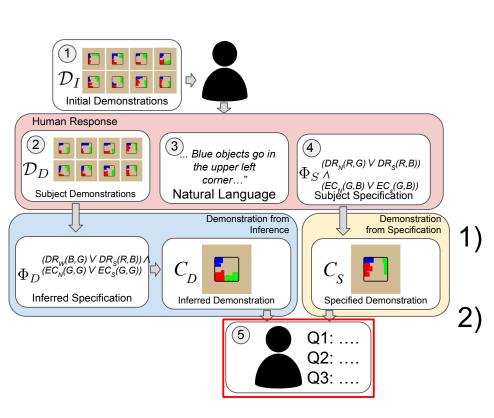
Natural language description of requirements

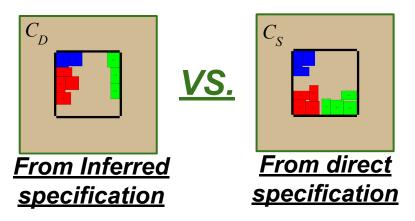
 $\begin{array}{c}
(DR_{N}(R,G) \lor DR_{S}(R,B)) \\
\Lambda \\
(EC_{N}(G,B) \lor EC_{S}(G,B))
\end{array}$

PARCC specification



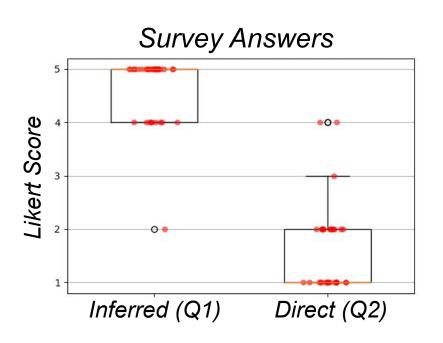


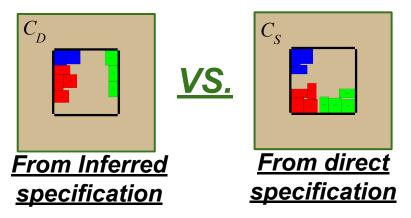




- The [inferred example] matches patterns in my demonstrations.
- The [direct example] matches patterns in my demonstrations.

Human Study Results: Inferred vs Direct Specifications





- 1) The [inferred example] matches patterns in my demonstrations.
- 2) The *[direct example]* matches patterns in my demonstrations.

Limitations

- PARCC Representations:
 - Constrained to a 2D space
 - Only uses rectangular objects
- Inference Algorithm:
 - More efficient sampling of candidate disjunctions











Limitations

- PARCC Representations:
 - Constrained to a 2D space
 - Only uses rectangular objects



 More efficient sampling of candidate disjunctions











Questions?