Fanoos: Multi-Resolution, Multi-Strength, Interactive Explanations for Learned Systems

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Individual ML systems are part of a larger whole in tackling problems

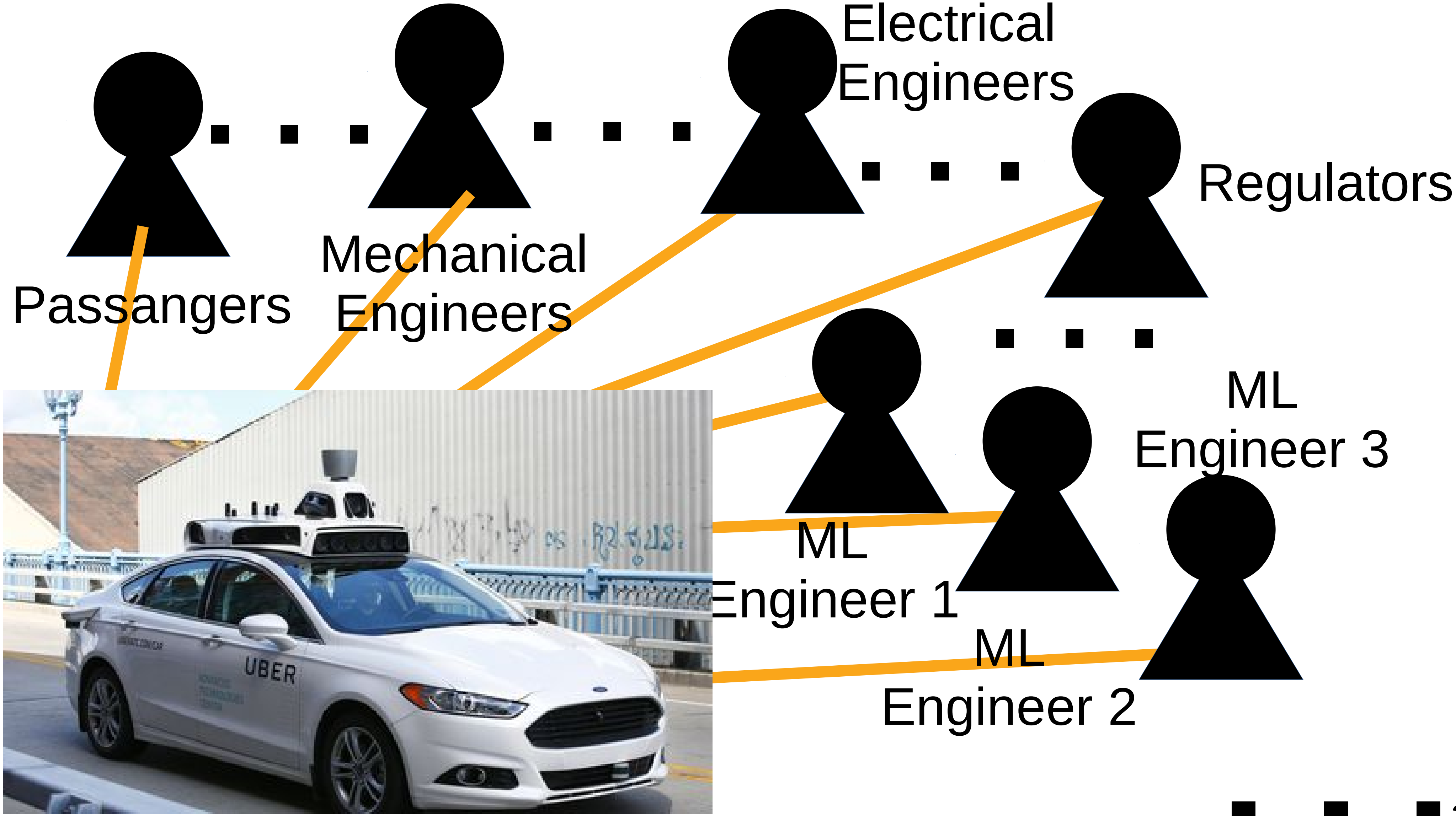

Image credit: https://www.chicagotribune.com/business/blue-sky/ct-uber-self-driving-cars-pittsburgh-20160906-story.html

Some Observations

Actors have many different:

- Interests
- Needs – depends on actor ***and task at hand***
  - Stakes vary. Safety : high stakes, efficiency tweaks: lower stakes
- Backgrounds / Expertise

Unfilled Desiderata for XAI

- *Interactive* (so can explore as needed)

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- *Interactive* (so can explore as needed)
- *Can provide multiple abstraction levels of information* (so can suite multiple audiences and needs)
- Can provide strong guarentees about info. provided (so *explanations necessarily reflect system behaviour*)
  - Should be as pedantic about details as user needs (*sometimes want / don’t want corner-case info.*)

Our Solution:
Fanoos

- Fanoos (فــانوس) - “Lantern” in Farsi

“Shining a Light on Black-Box AI”

Masrawy.com

Plan For Next Few Slides

- Overview of What User Sees
- Description of the Mechanics
- Breifly overview experiments

Fanoos Overview:

Initial Setup

Fanoos

Fanoos Overview:

Initial Setup

L, the Learned Sytem to Explain (E.g., Neural Net)

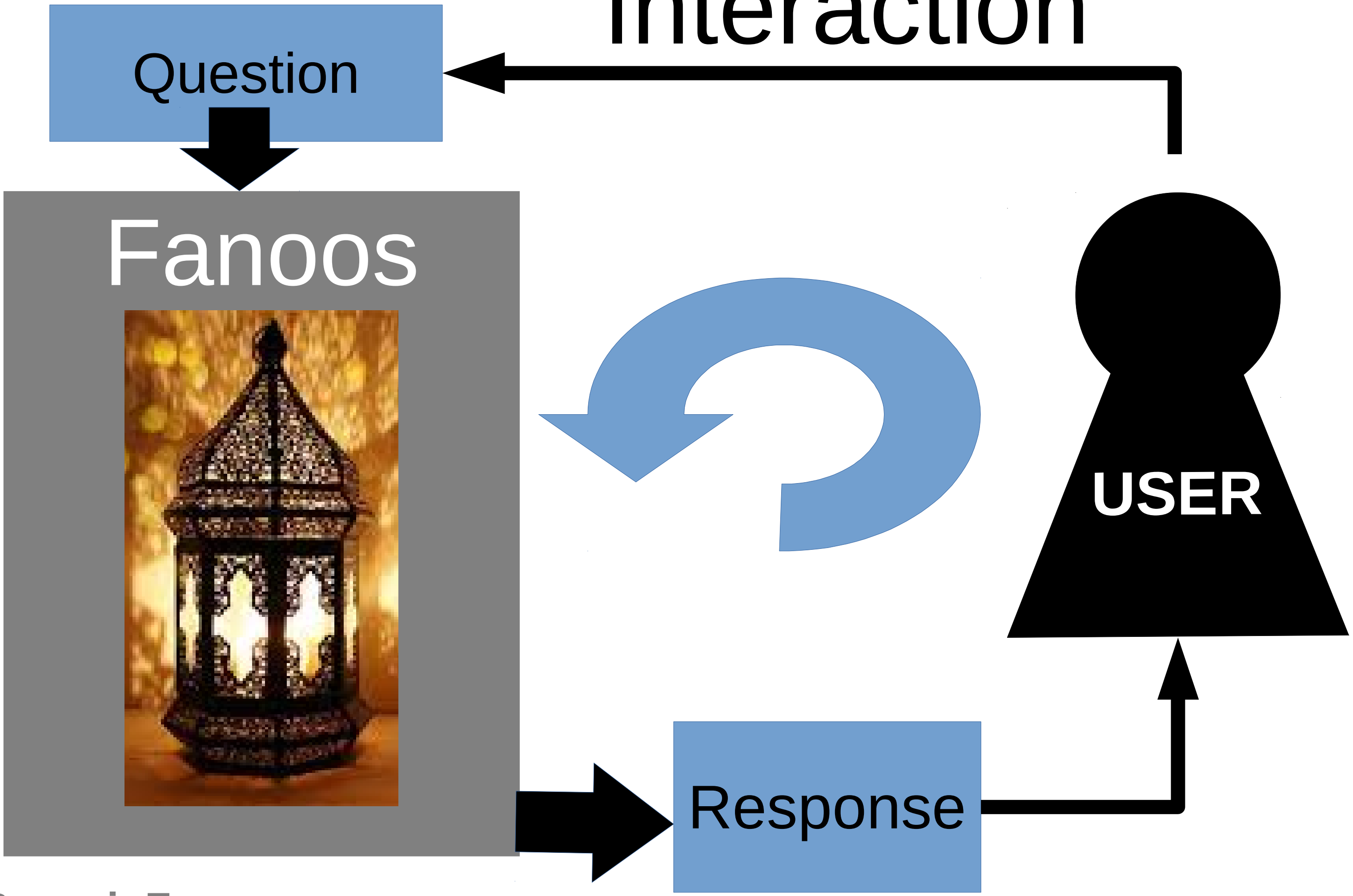
Domain Info. (can have data-assisted construction)

Initial Configuration Inputs

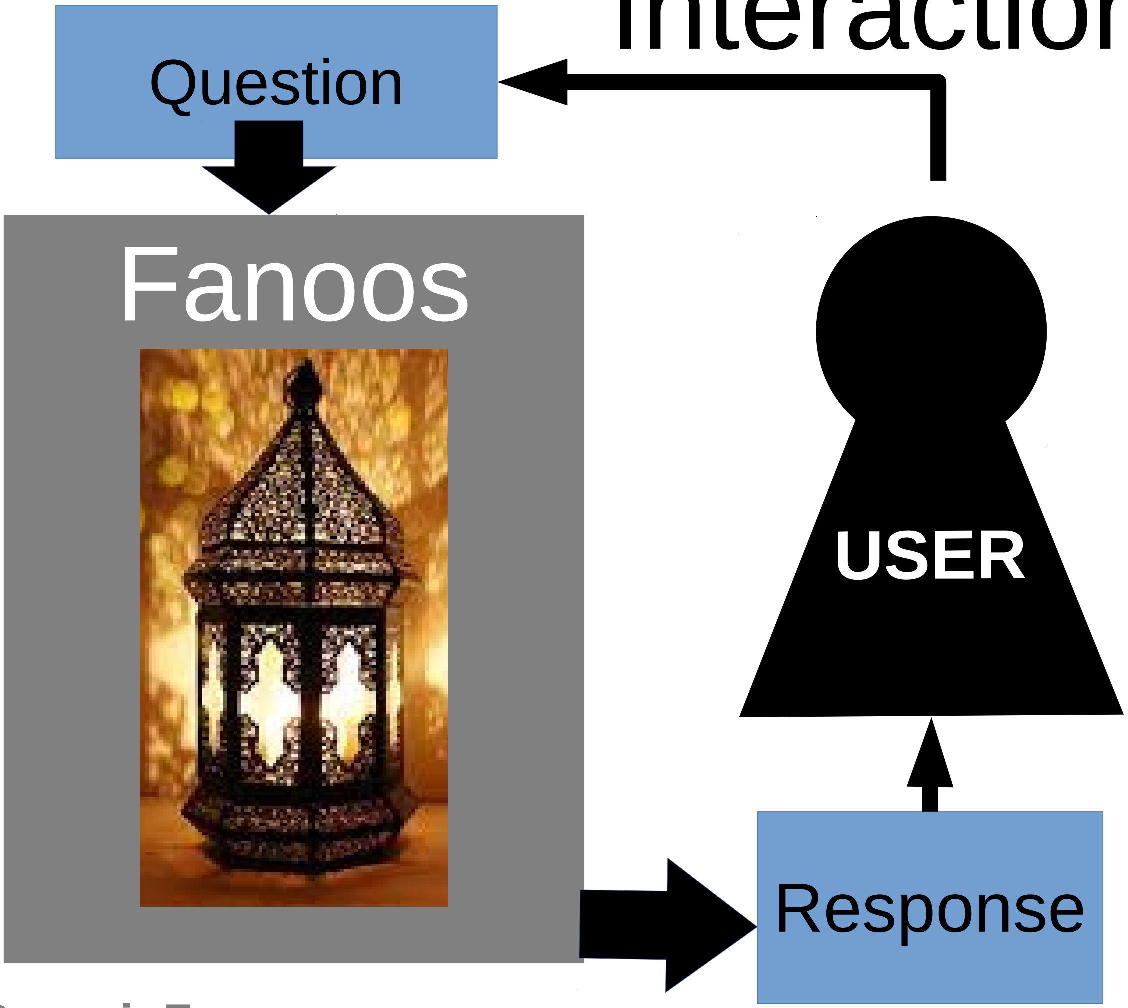
Fanoos

Fanoos Overview:

Interaction



Fanoos Overview:
Interaction



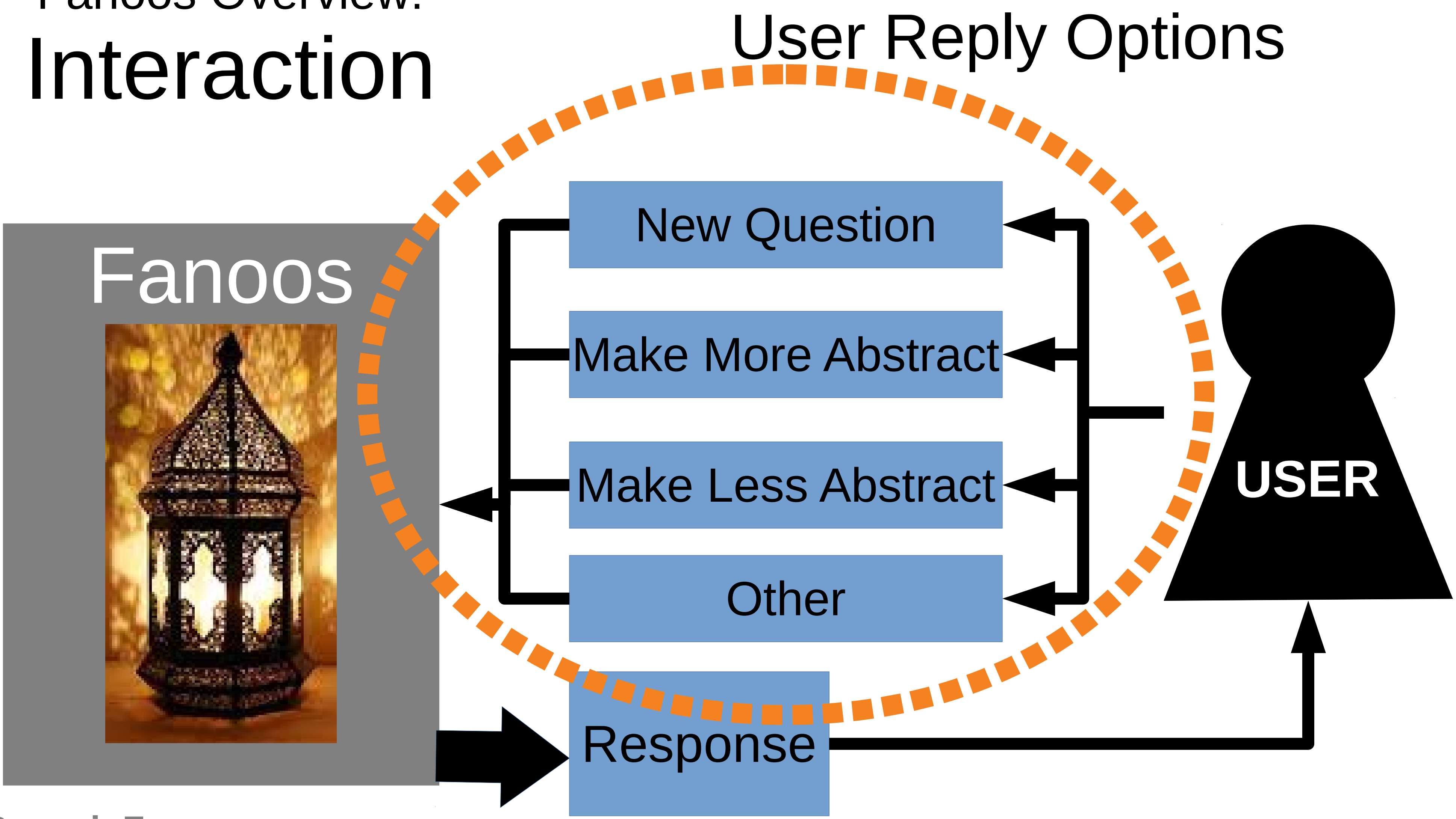
Question Types:

- When does ***L*** do X?
- What does ***L*** do when Y?
- In what circumstances is ***L*** doing X during Y?

Can be formally sound or probabilistically guaranteed

Fanoos Overview:

Interaction



Fanoos Overview:

Interaction Example

Fanoos

Example from robotics

Initial Question

```
(Fanoos) what_are_the_circumstances_in_which and(
    pole1angle_rateofchange_low__magnitude ,
    outputtorque_high__magnitude )?
```

Initial Response

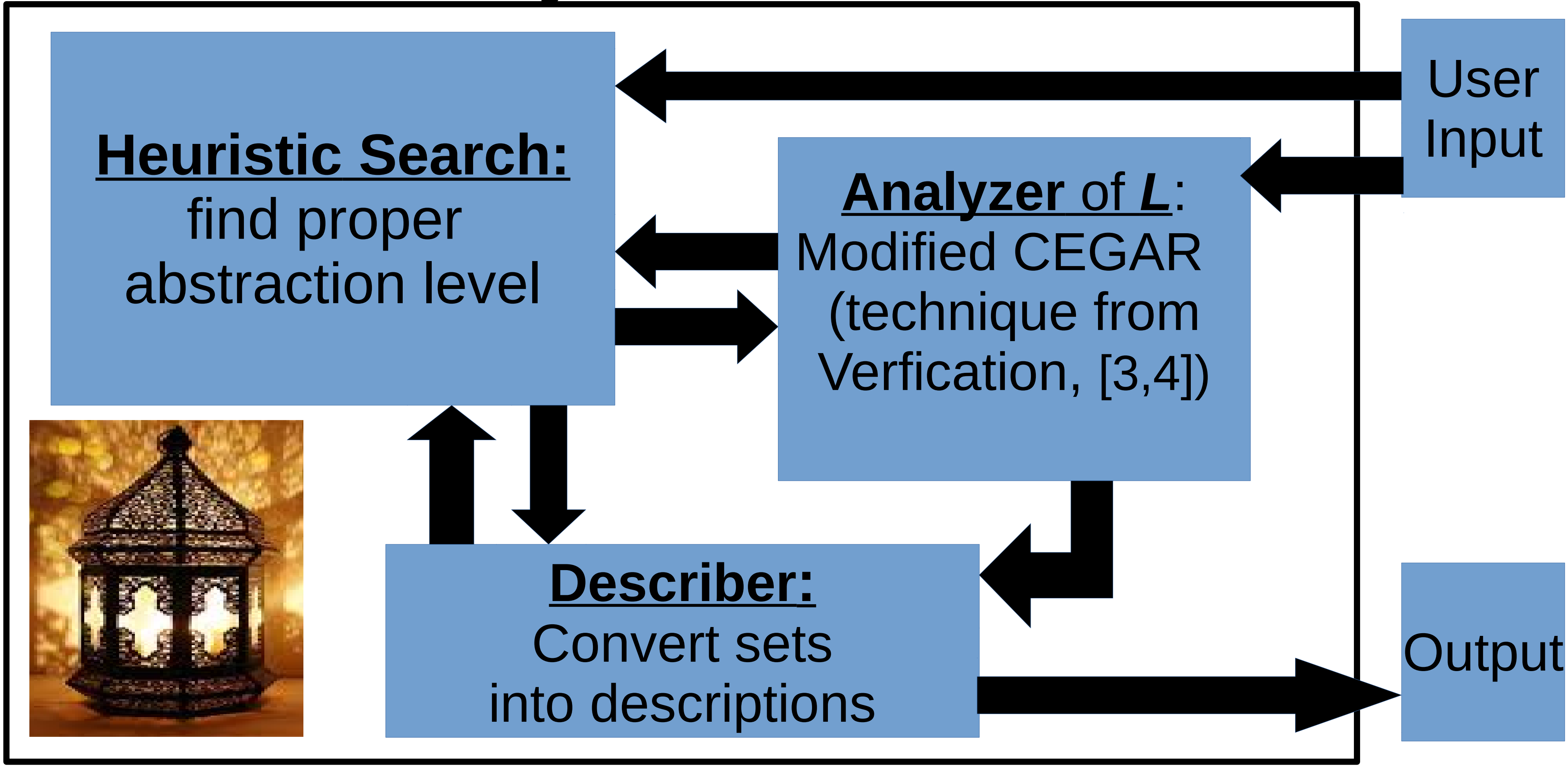
```
(0.10147897, 0.17831770, pole1angle_on_the_left ,
    pole2angle_on_the_left ,
    pole2angle_rateofchange_low__magnitude)
(0.09885232, 0.16335186, pole1angle_on_the_left ,
    pole2angle_on_the_left ,
    pole2angle_turning_counterclockwise)
(0.07900125, 0.14467123, pole1angle_on_the_right ,
    pole2angle_on_the_right ,
    pole2angle_turning_clockwise)
(0.06693577, 0.12822191, pole1angle_down ,
    pole2angle_to_right ,
    statevalueestimate_very_low )q
```

User Request ***More*** abstract

New Response

```
(0.44378316, 0.48588134, pole2 not near target
    position)
(0.33605014, 0.36551887,
    pole2angle_rateofchange_high__magnitude)
(0.22016670, 0.23739381, pole2angle_to_right ,
    statevalueestimate_very_low)
```

Briefly, Inside Fanoos

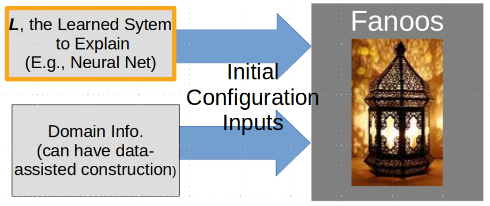


Fanoos:

Mechanics

Fanoos

Domain Knowledge that User Provides



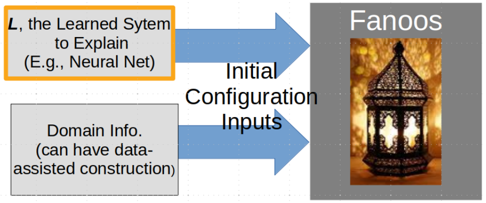
- The learned system, *L*
- Universe Bounding-Box for Input Space
  - Ex: for a constant-v Dubin car:

$$(x, y, \theta) \in [-1, 1] \times [50.3, 100.0] \times [0, 2\pi]$$

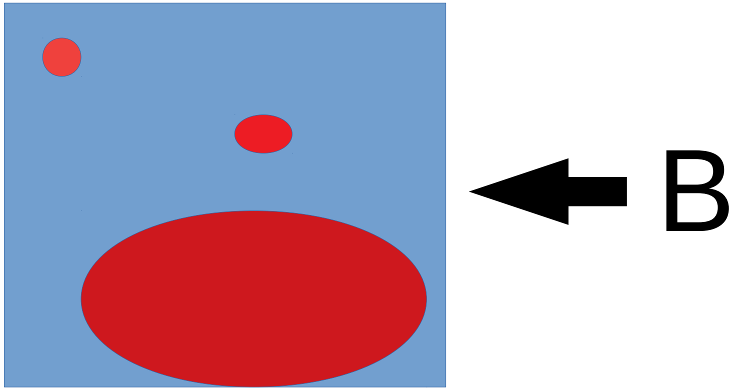
- Predicates: connecting sets to something user grasps. Ex:
  - "left arm higher than right arm" : y_arm1 > y_arm2
  - “attempting spiral roll” :

$$\exists cx, cy \in B. |(x - cx)^2 + (y - cy)^2 - r^2| \leq \epsilon_1 \wedge |2(x - cx)dx - 2(y - cy)dy| \leq \epsilon_2 \wedge \ldots$$

Domain Knowledge that User Provides



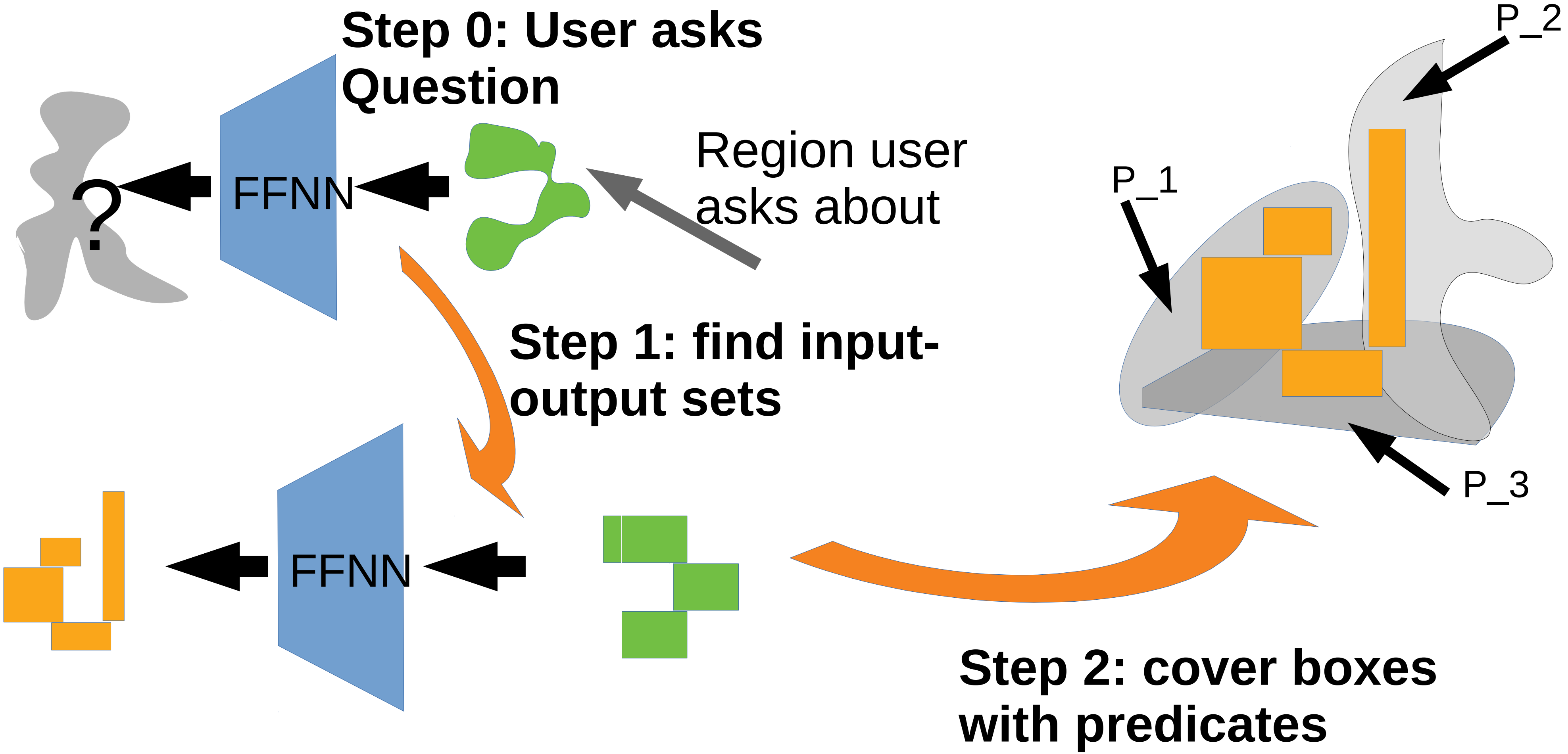
- Note: Using a SAT-solver, we can say whether predicate holds:
  - Everywhere on a set
  - At least one place in a set



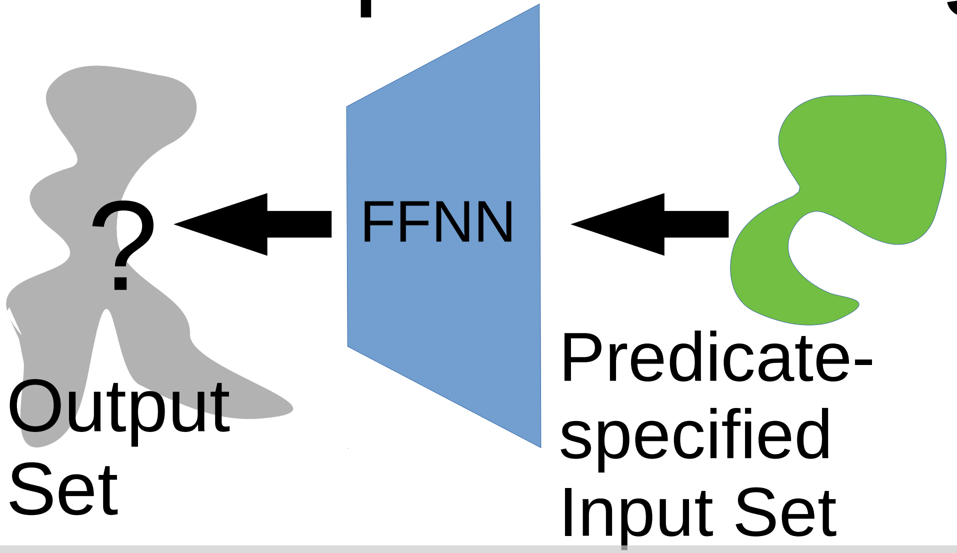
“$\forall v \in B . P(v)$” is false
“$\exists v \in B . P(v)$” is true

Red : P fails to hold
Blue: P holds

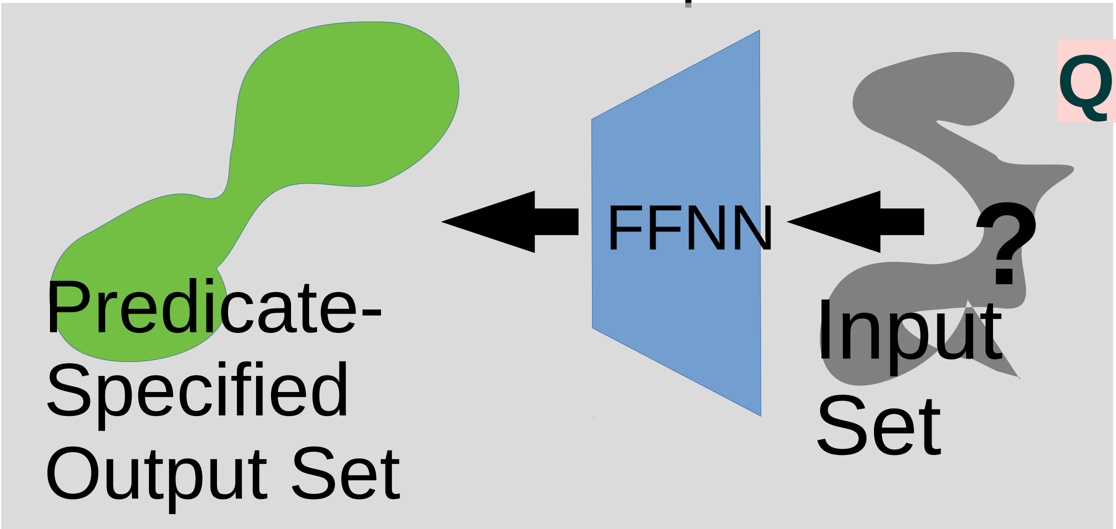
Overview: Responding to Questions



Step 1: "Finding the Other Set"

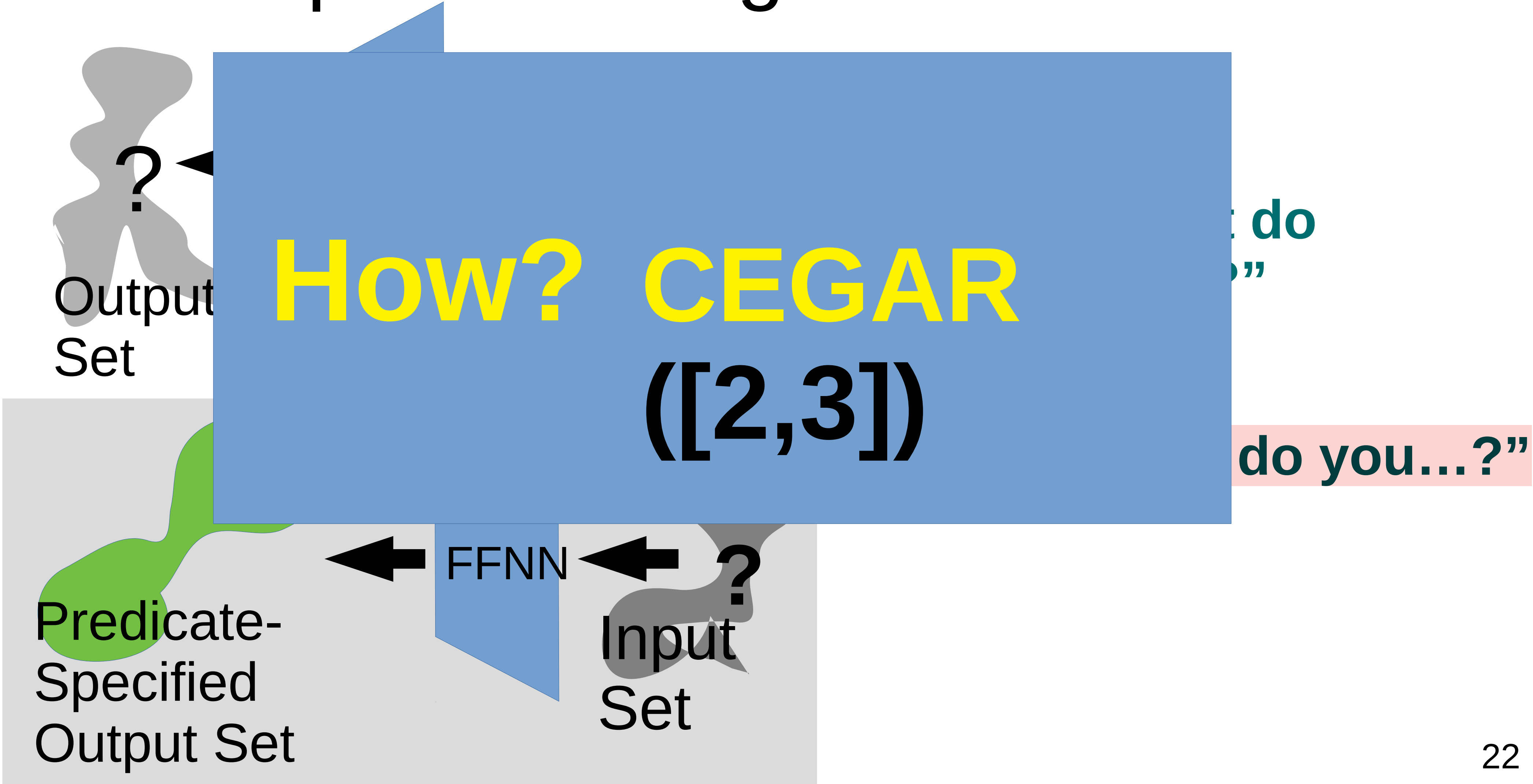


Question: "What do you do when …?"



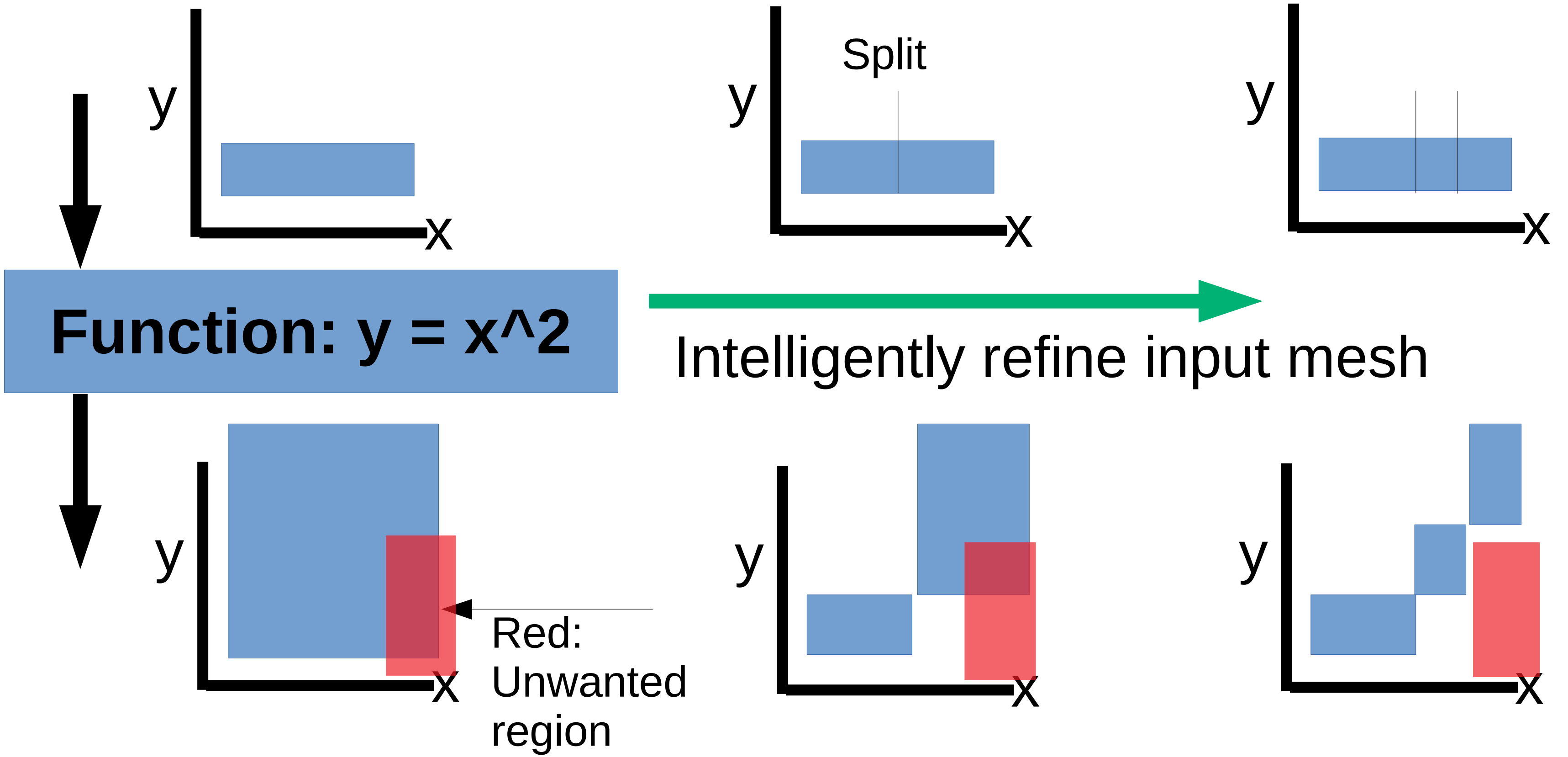
Question: "When do you…?"

Step 1: “Finding the Other Set”



CEGAR, Cnt

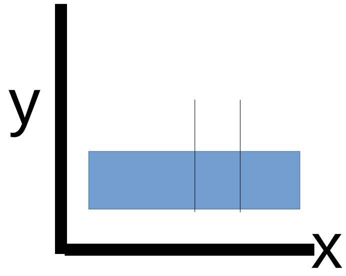
- CEGAR solution: dynamically refine based on property you want to check for
- For us, used hyper-cubes as the abstraction



CEGAR, Cnt

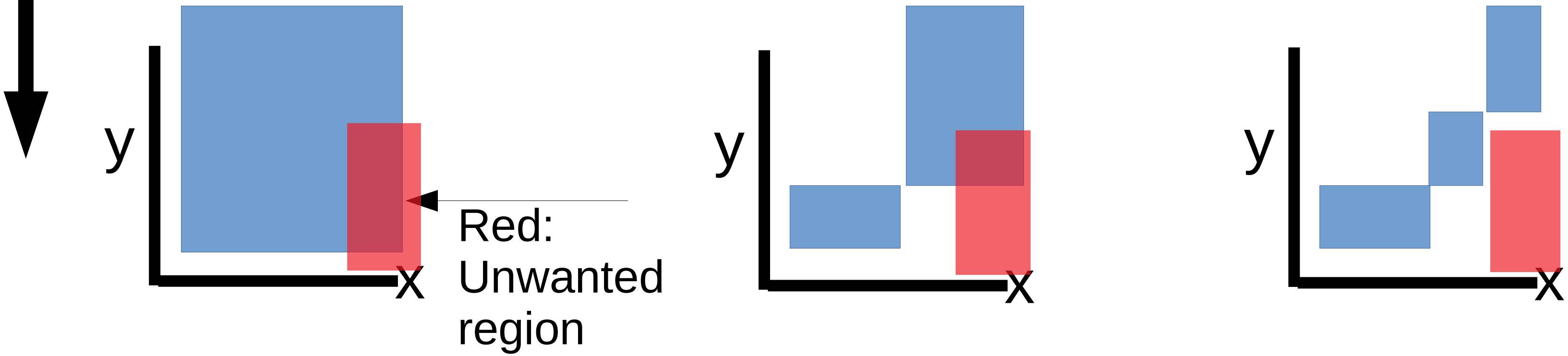
n property you want to check for

Fanoos:
(1) bi-/tri-sect longest (normalized) axis,
(2) continue to refine as desired *while overlapping with* user's predicate-desribed region

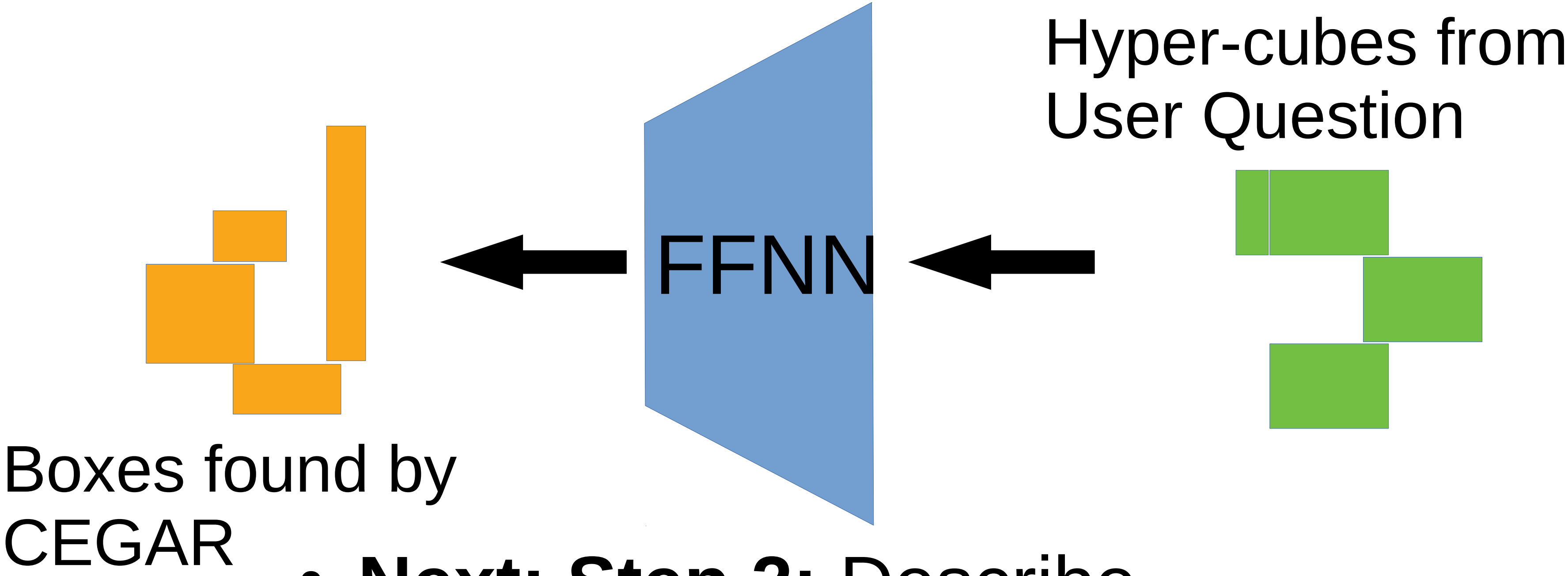


x

efine input mesh



What we have so far:



- **Next: Step 2:** Describe the found boxes
  - How? Form a covering with the predicates.

What we have so far:

Sub-steps:
2.1) Get candidate predicates for each box
2.2) Form global covering from the candidates

Hyper-cubes from User Question

N

Note: Might merge boxes a bit first

- What do we do next?
  - Describe the found boxes

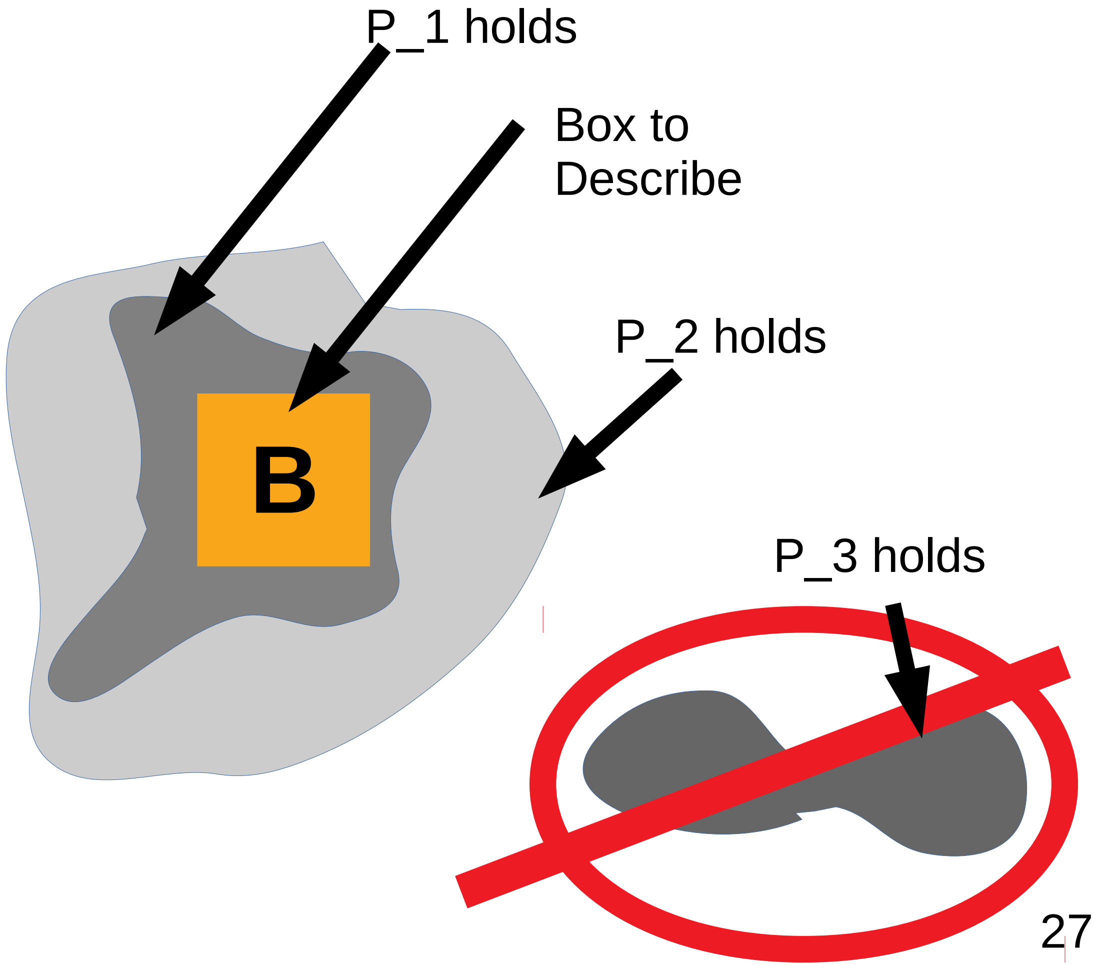
- How? Form a covering with the predicates.

Step 2.1: Getting Candidate Preds. For Each Box

For each box, B:

1) Get preds that hold over B
    1. "feasibility check": try on random sample from B first
    2. Check with SAT-Solver

2) Get most specific preds



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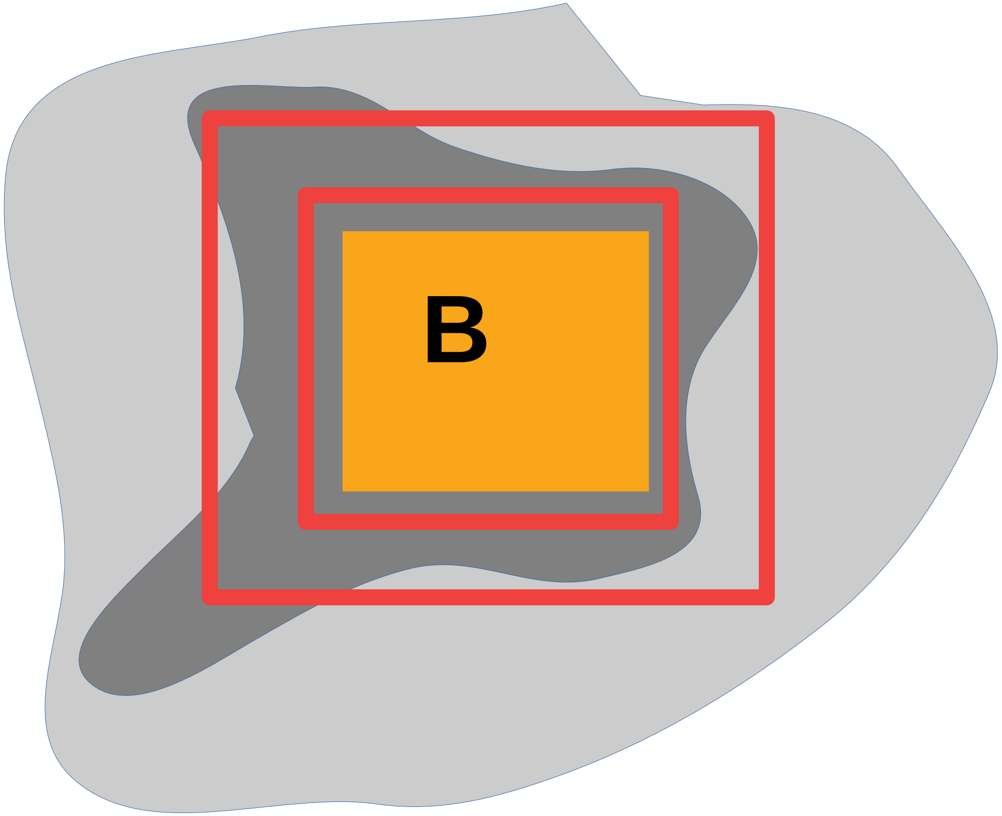
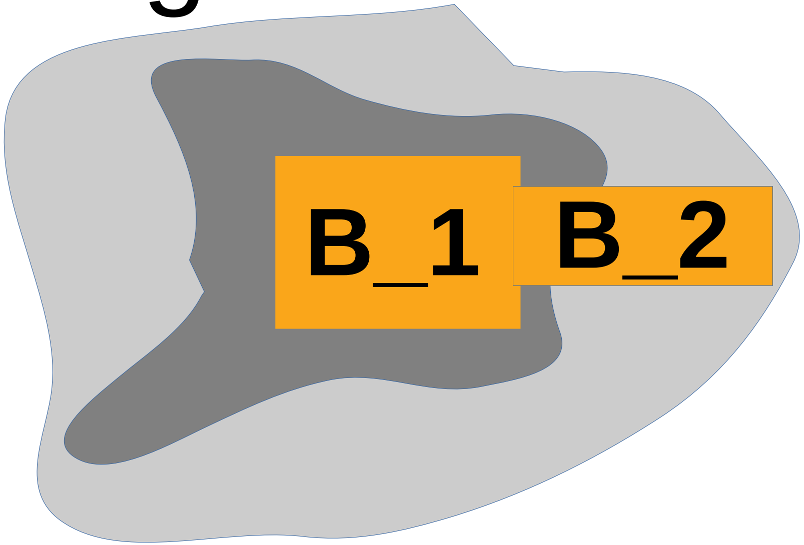


Note: Can utilize a taxonomy for filtering, If provided

Step 2.2: Forming Global Covering

- Iterative greedy based on score
  - Submodularity
  - Need to throw out “dominated” preds
- Some subtleties for mult-dimensional setting
  - Ex: may need multiple preds to cover box; one pred variable x, another might cover y



Cleaning and Presenting to User

- Some further post-processing
- Gather and show

Normalize “unique” box volumes covered

Normalize total box volumes covered

(0.11, 0.34, And(pole1_on_left cart_moving_right))

```
(0.44378316, 0.48588134, pole2 not near target position)
(0.33605014, 0.36551887, pole2angle_rateofchange_high__magnitude)
(0.22016670, 0.23739381, pole2angle_to_right ,
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```
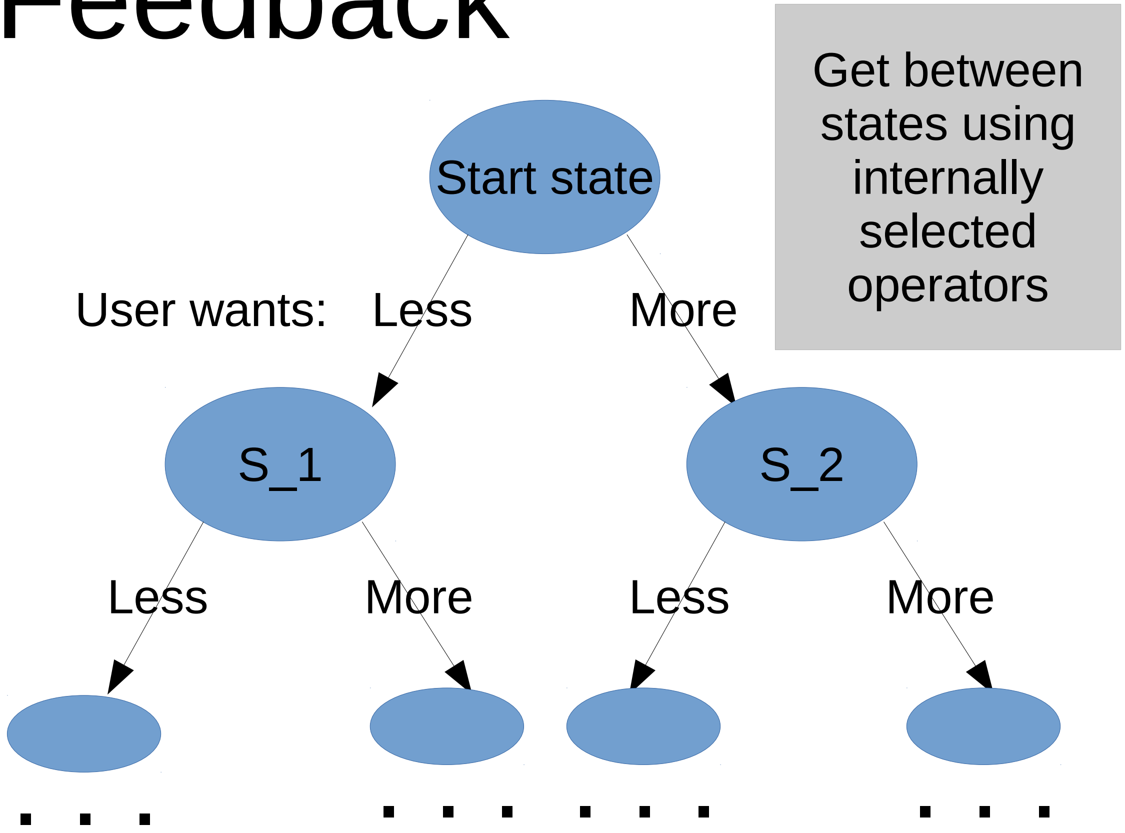

Output is a Weighted DNF

Using Feedback

- Fanoos has many internal parameters for:
  - CEGAR
  - Box-merging
  - Predicate
  - Etc.
- Use state-operator model
  - Feedback changes state and internal params
  - View as search for proper abstraction level



Using Feedback

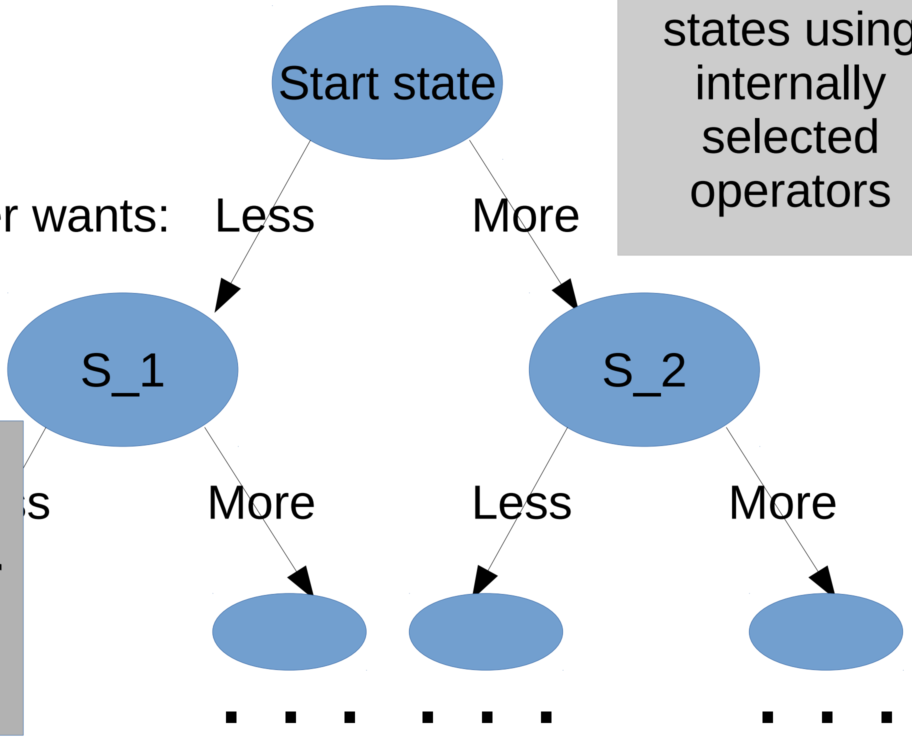
- Fanoos h… paramete…
  - CEGAR
  - Box-me…
  - Predica…
  - Etc.

How select operators?
Hand-written **heuristics**.
Generally try to get smaller boxes, and looser descriptions for greater abstraction

- Use s…
  - Fe… and…
  - Vie… abstraction level

On-going future work: Using ML-back operator selection

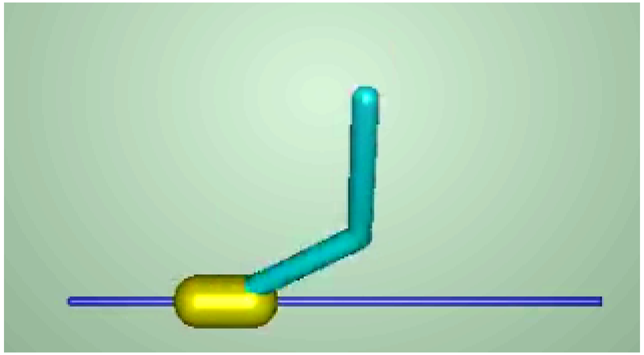
…er wants:



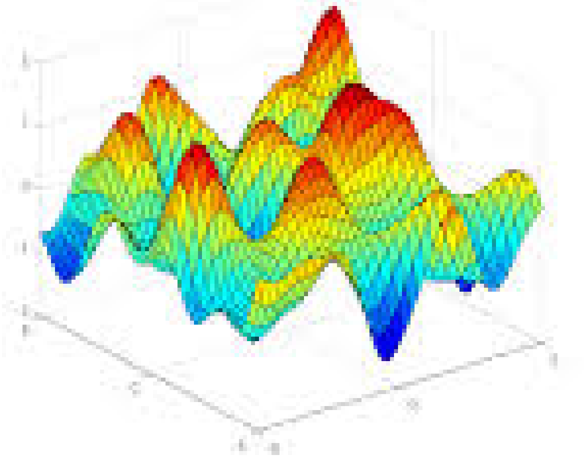
Get between states using internally selected operators

Experiments

- Ran on
  - Invertible double pendulum policy
    - 6D input, 2D output
  - A 3-degree polynomial regression for CPU Usage
    - 5D pre-featurization input, 3D output
- Preds. formed by mix of hand, data statistics, and templates



Openai gym
InvertedDoublePendulum-v2



Experiments

- 130+ Start Questions, Several Hundred Replies Total
  - Questions randomly generated based on some criteria
  - Half asked to make **more abstract (MA)**,
    half asked to make **less abstract (LA)**
- Compared befores-and-afters for:
  - Reachability
  - Result structure
  - Some approximation of an expert agreement

Experiments

- Reachability: MA tend to result in fewer, larger boxes. Opposite for LA
- Structural:
  - MA tend to be shorter, and have fewer conjuncts
  - Based on Jaccard and Overlap score, not just becoming more verbose

Table 2: Median *relative* change in description before and after Fanoos adjusts the abstraction in the requested direction

			CPU	CPU	IDP	IDP
		Request	LA	MA	LA	MA
Reachability	Boxes	Number	8417.5	-8678.0	2.0	-16.0
	Volume	Max	-0.015	0.015	-0.004	0.004
		Median	-0.003	0.003	-0.004	0.004
		Min	-0.001	0.001	-0.003	0.003
		Sum	-0.03	0.03	-0.168	0.166
Structural	Jaccard		0.106	0.211	0.056	0.056
	Overlap coeff.		0.5	0.714	0.25	0.25
	Conjuncts		1.0	-2.0	0.5	-2.5
	Disjuncts		7.0	-7.5	2.0	-2.5
	Named preds.		1.0	-1.0	1.0	-4.5
	Box-Range preds.		2.0	-2.0	1.5	-1.5
Expert	MA term	Multiplicity	3.0	-3.0	24.0	-20.0
		Uniqueness	0.0	0.0	1.0	-1.5
	LA term	Multiplicity	20.0	-21.5	68.5	-86.0
		Uniqueness	2.0	-2.0	12.0	-14.0

Experiments

- Approximate "Expert" Judgement:
  - Labeled each predicate as higher or lower abstractness
  - "grain of salt measure": course labels and did not review whole output
  - As expected: LA requests tended for more lower abstraction terms, opposite for MA requests

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		Uniqueness	0.0	0.0	1.0	-1.5
	LA term	Multiplicity	20.0	-21.5	68.5	-86.0
		Uniqueness	2.0	-2.0	12.0	-14.0

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