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

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VMCAI
Jan. 17, 2022

Acronym to Know: XAI

- “Explainable AI” : XAI
- Our specific focus here: Explanations for Machine-Learned Systems

Overview of Why Want XAI

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- Critical for many end-users. Ex: Doctors
- Explicit Legal Requirements: EU’s GDPR
- For AI Scientists and Engineers: need to understand, debug, and tweak systems.
- As a result: exponential growth in recent XAI publications ([1])

Variety in XAI Stances and Approaches

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  - See, for instance: “Mythos of Model Interpretability” ([10])
  - Being loose here: if I say “interpretability”, “explainability”, or “transparency”, etc., I probably mean the same thing

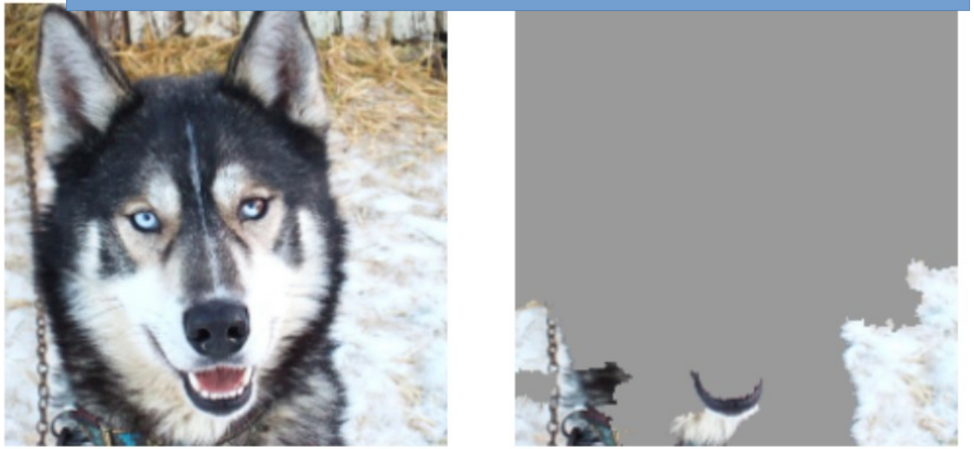
Variety in XAI Cnt.: Example Diffs.

Medium /
Style of
Explanation

Variety in XAI Cnt.: Example Diffs

LIME ([12])

Medium / Style of Explanation



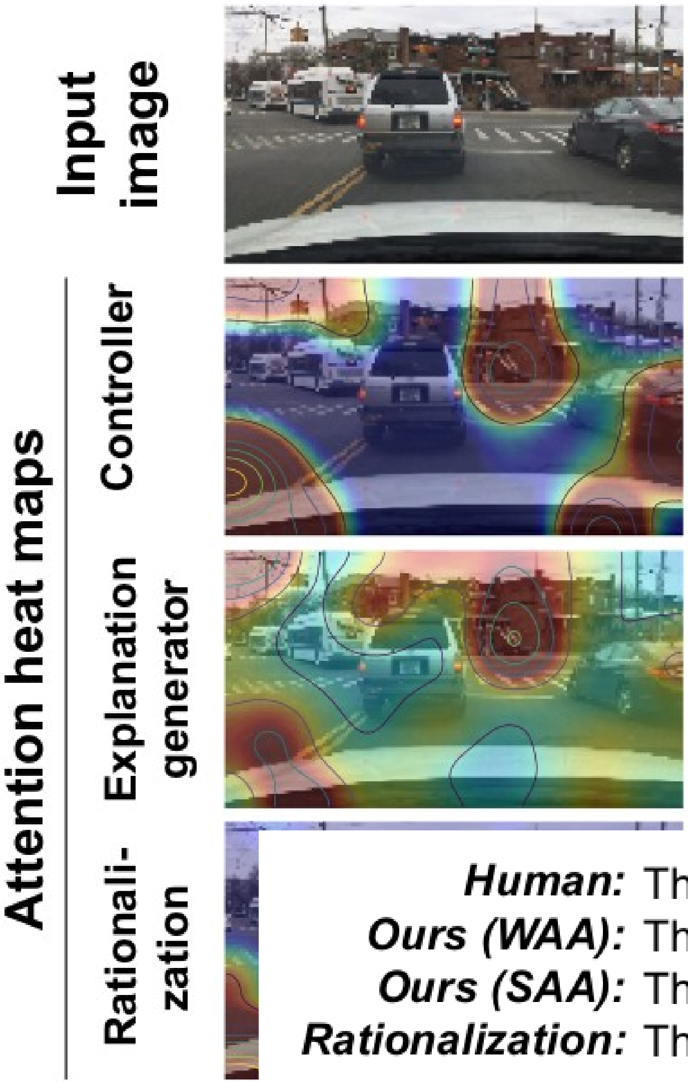
(a) Husky classified as wolf

(b) Explanation

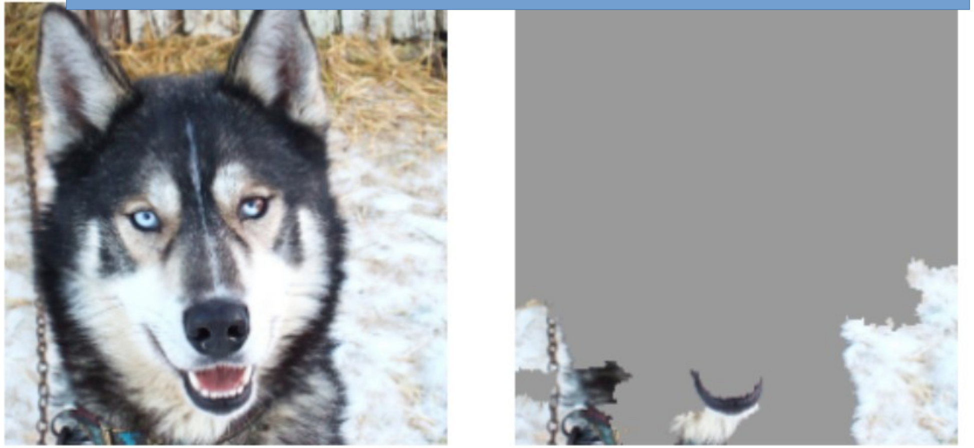
Figure 11: Raw data and explanation of a bad model's prediction in the "Husky vs Wolf" task.

XAI Cnt.: Example Diffs

1



LIME ([12])



(a) Husky classified as wolf (b) Explanation

Figure 11: Raw data and explanation of a bad model's prediction in the "Husky vs Wolf" task.

Kim et al. ([8])

Human: The car steadily driving **+** now that the cars are moving.
Ours (WAA): The car is driving forward **+** because traffic is moving freely.
Ours (SAA): The car heads down the road **+** because traffic is moving at a steady pace.
Rationalization: The car slows down **+** because it's getting ready to a stop sign.

Variety in XAI Cnt.: Example Diffs.

Medium / Style of Explanation

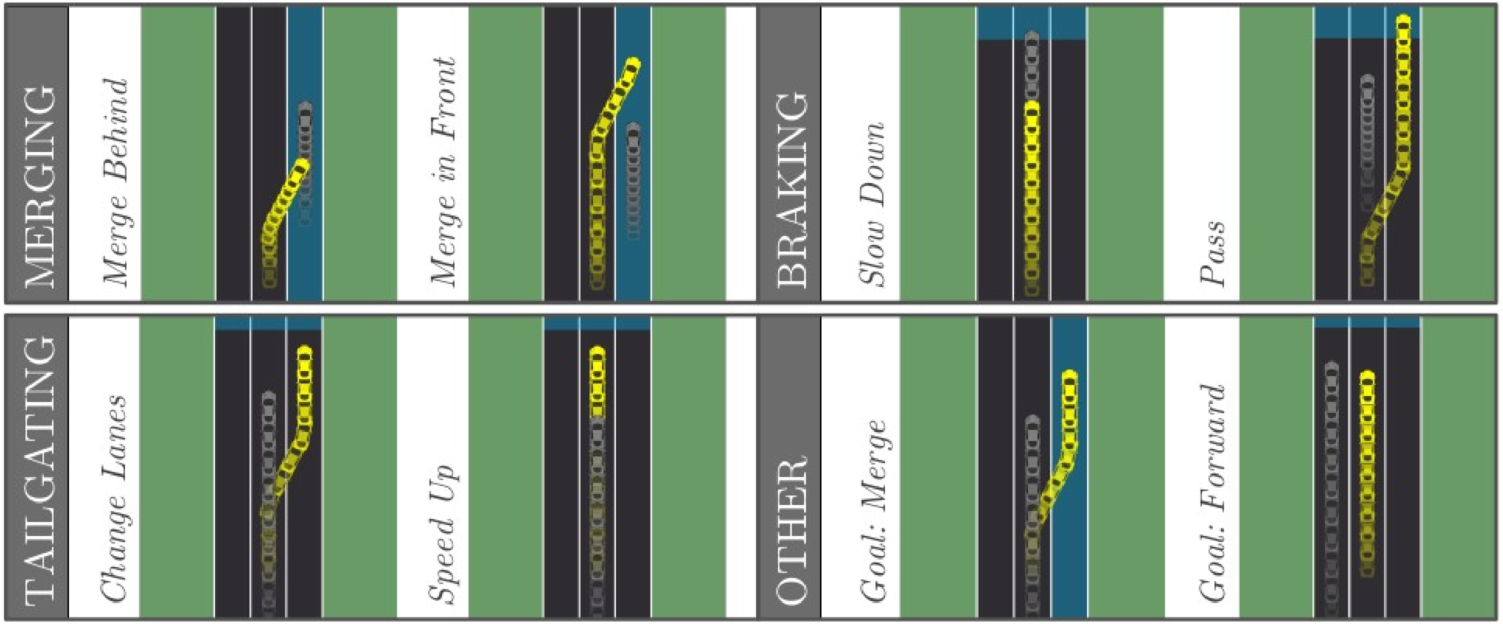
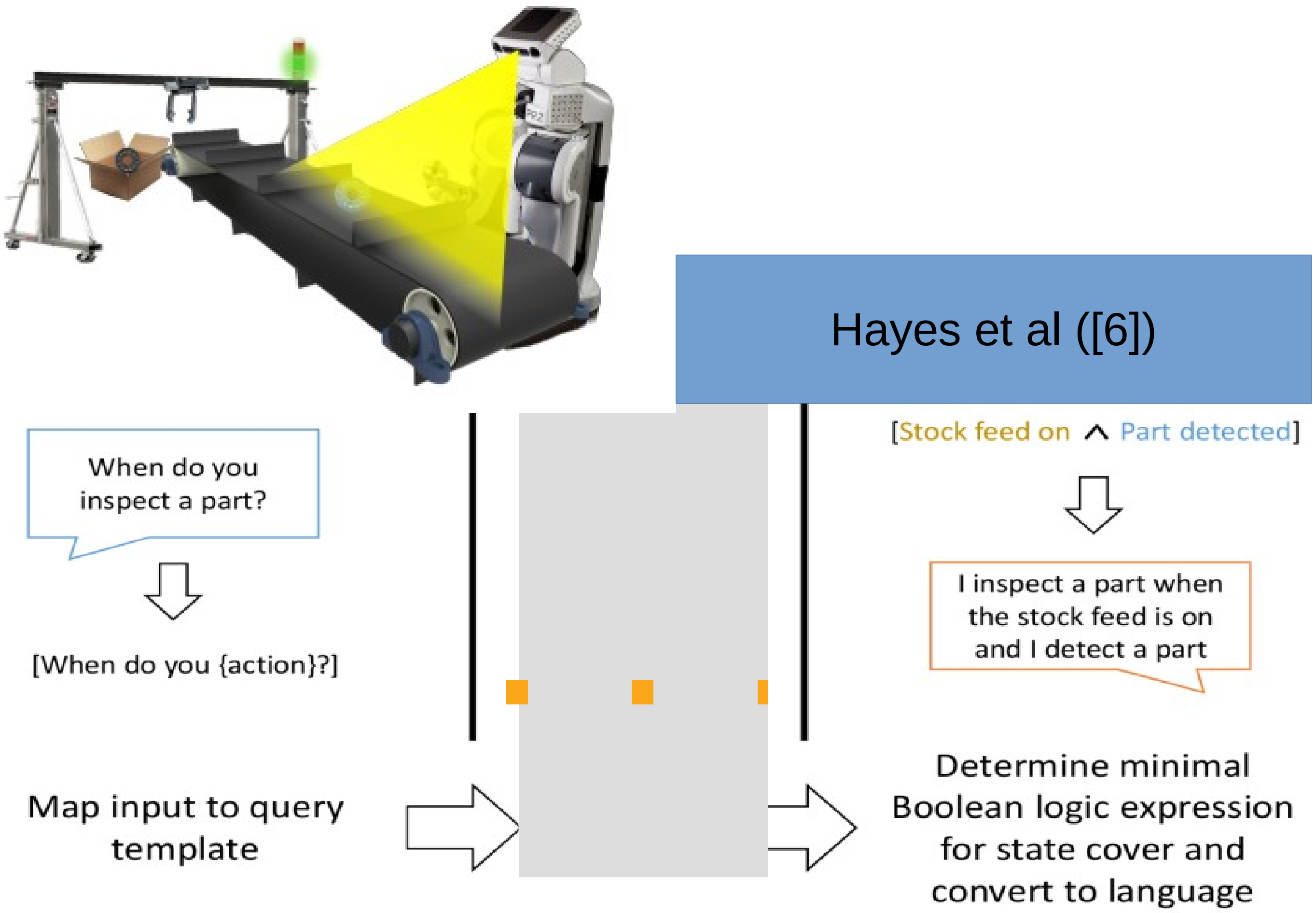


Fig. 2: The possible driving environments cluster naturally into four classes, with two trajectory strategies per class. Each image shows the trajectories of the autonomous car (yellow) and non-autonomous car (gray) in a particular environment. Positions later in the trajectory are more opaque. The goal of the autonomous car in each environment is highlighted in blue: merge into the right lane or drive forward.

Huang et al. ([7])

Variety in XAI Cnt.: Example Diffs.



Hayes et al ([6])

When do you inspect a part?

[When do you {action}?]

Map input to query template

[Stock feed on ∧ Part detected]

I inspect a part when the stock feed is on and I detect a part

Determine minimal Boolean logic expression for state cover and convert to language

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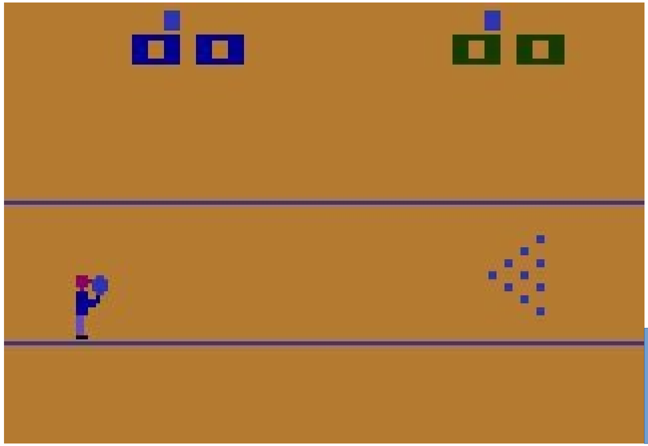
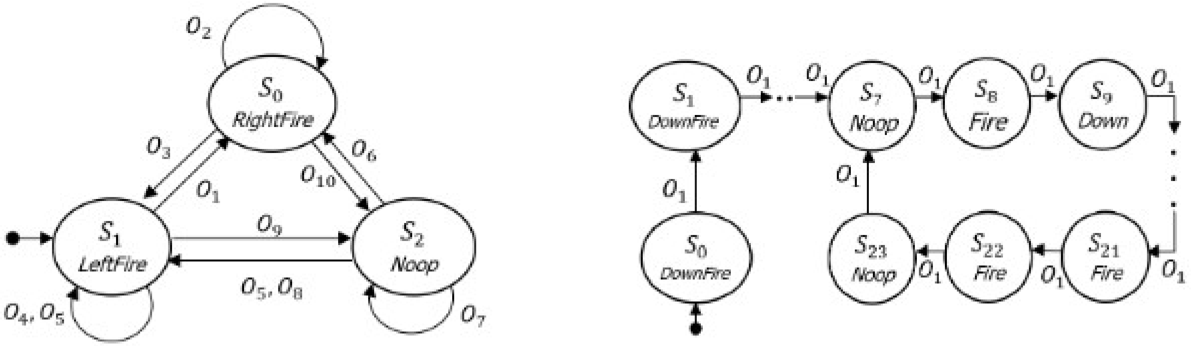


Koul et al ([9])



(a) Pong (B_h=64 and B_f=400)

(b) Bowling (B_h=128 and B_f=100)

Figure 2: Moore Machine representation for Atari policies

Current State and Trends in XAI for ML

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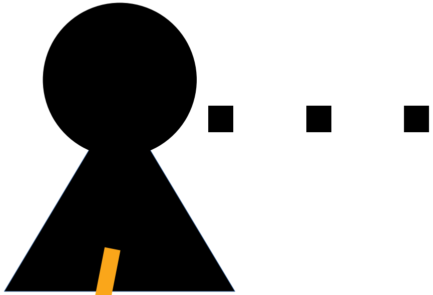
- Fast growing, but currently has limitations:
  - Lack of guarantees
  - Explanations of *single* granularity/abstraction level

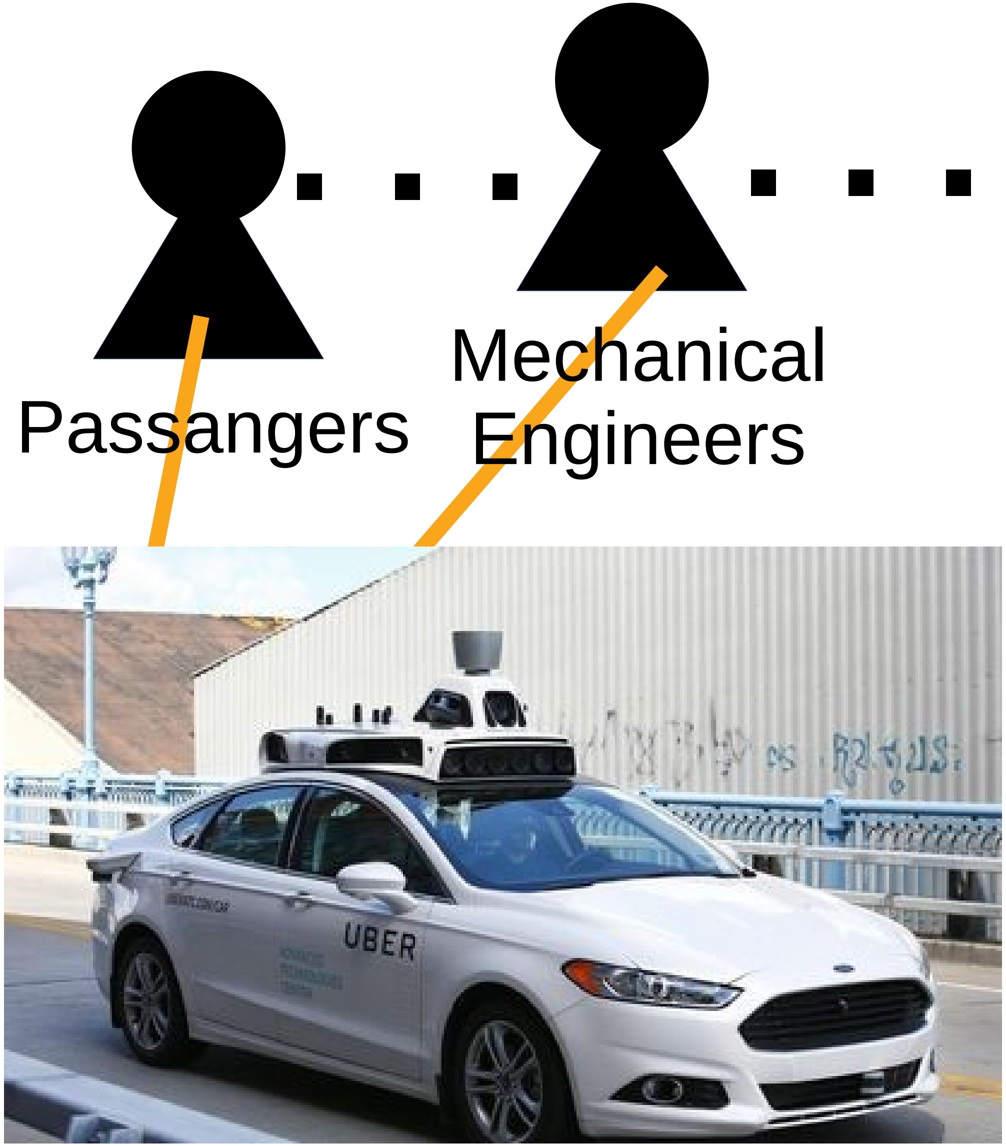
Individual ML systems are part of a larger whole in tackling problems

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



Passangers

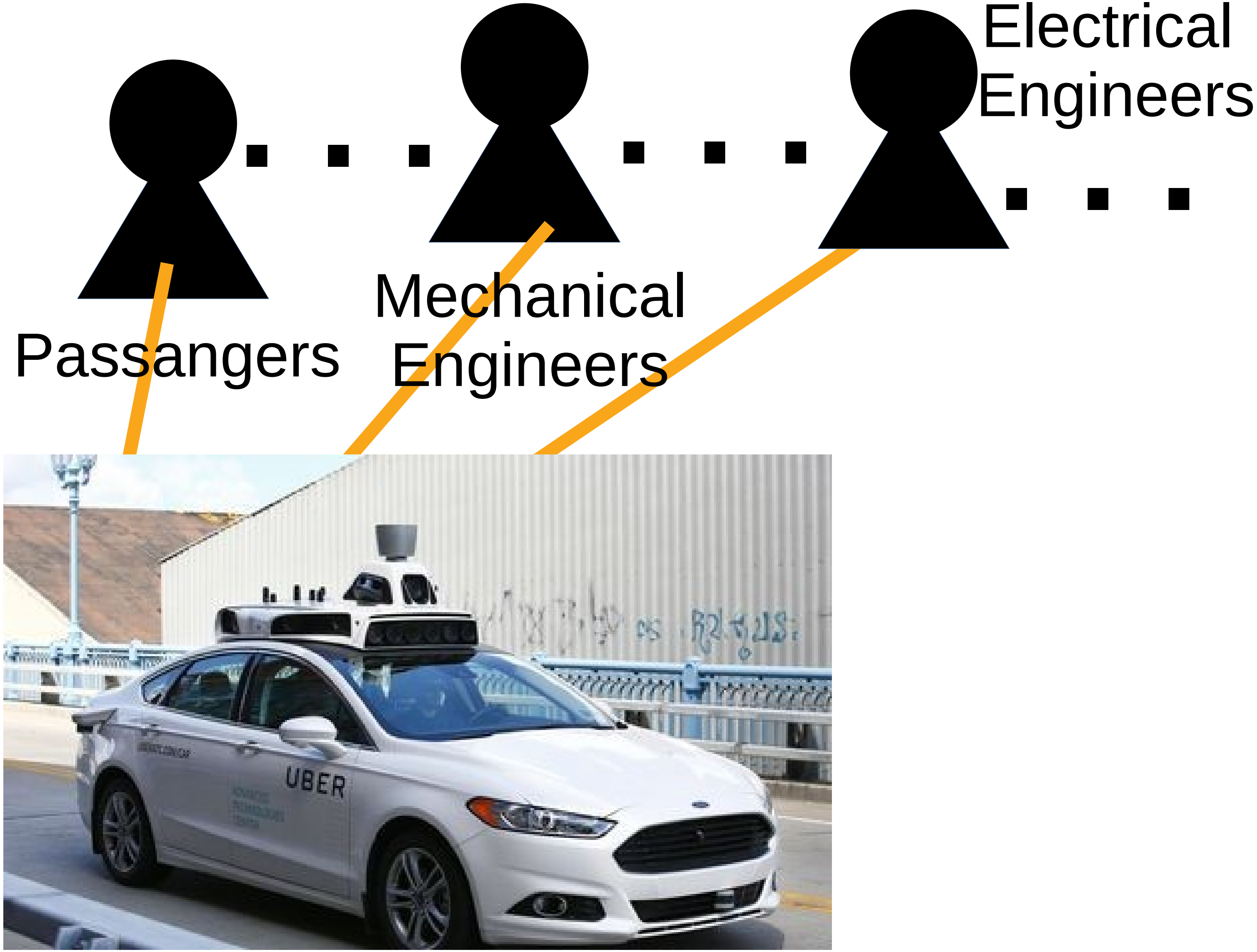
Image credit: https://www.chicagotribune.com/business/blue-sky/ct-uber-self-driving-cars-pittsburgh-20160906-story.html



Passangers

Mechanical Engineers

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



Electrical Engineers

Mechanical Engineers

Passangers

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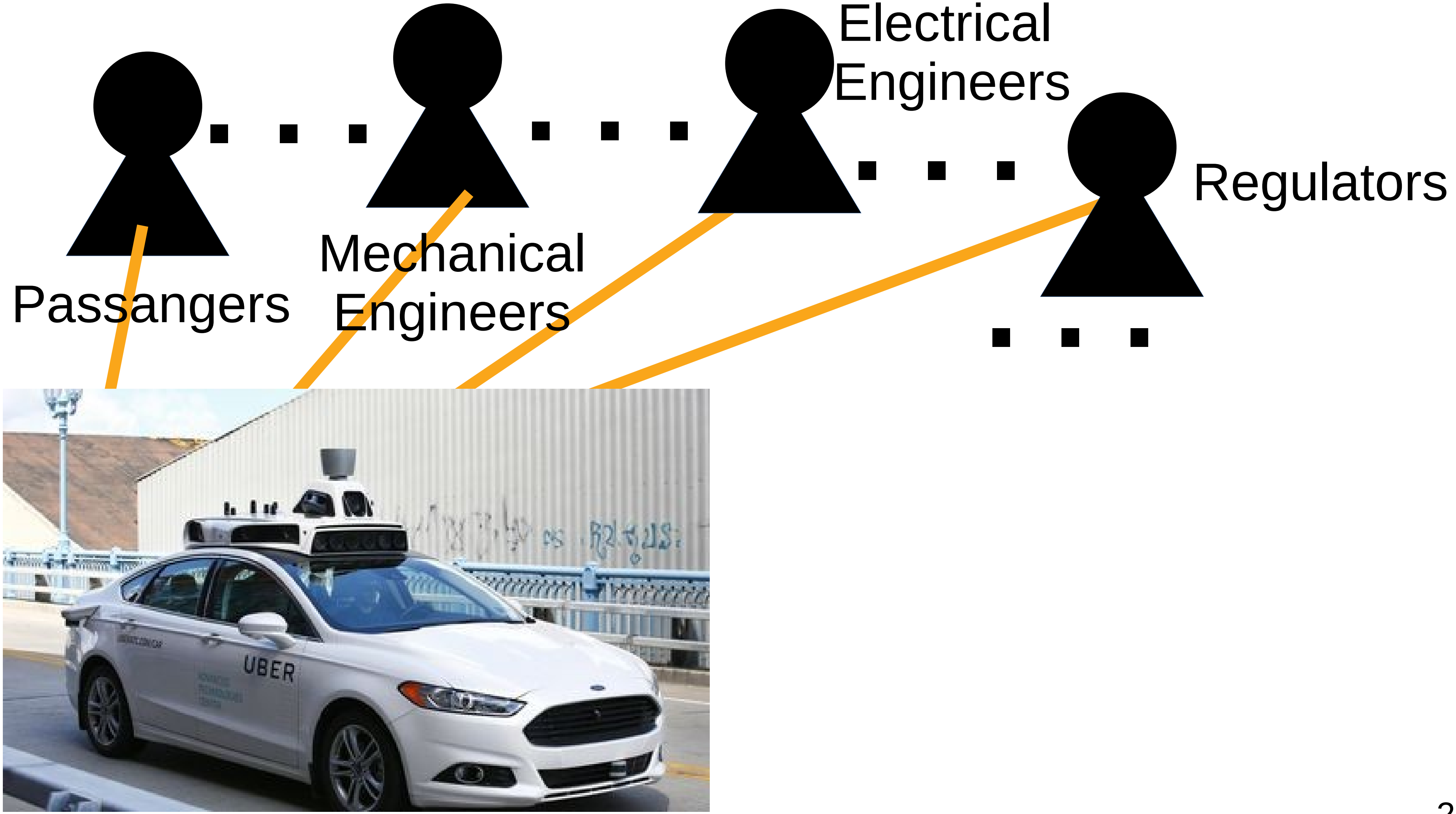

Electrical Engineers

Regulators

Passangers

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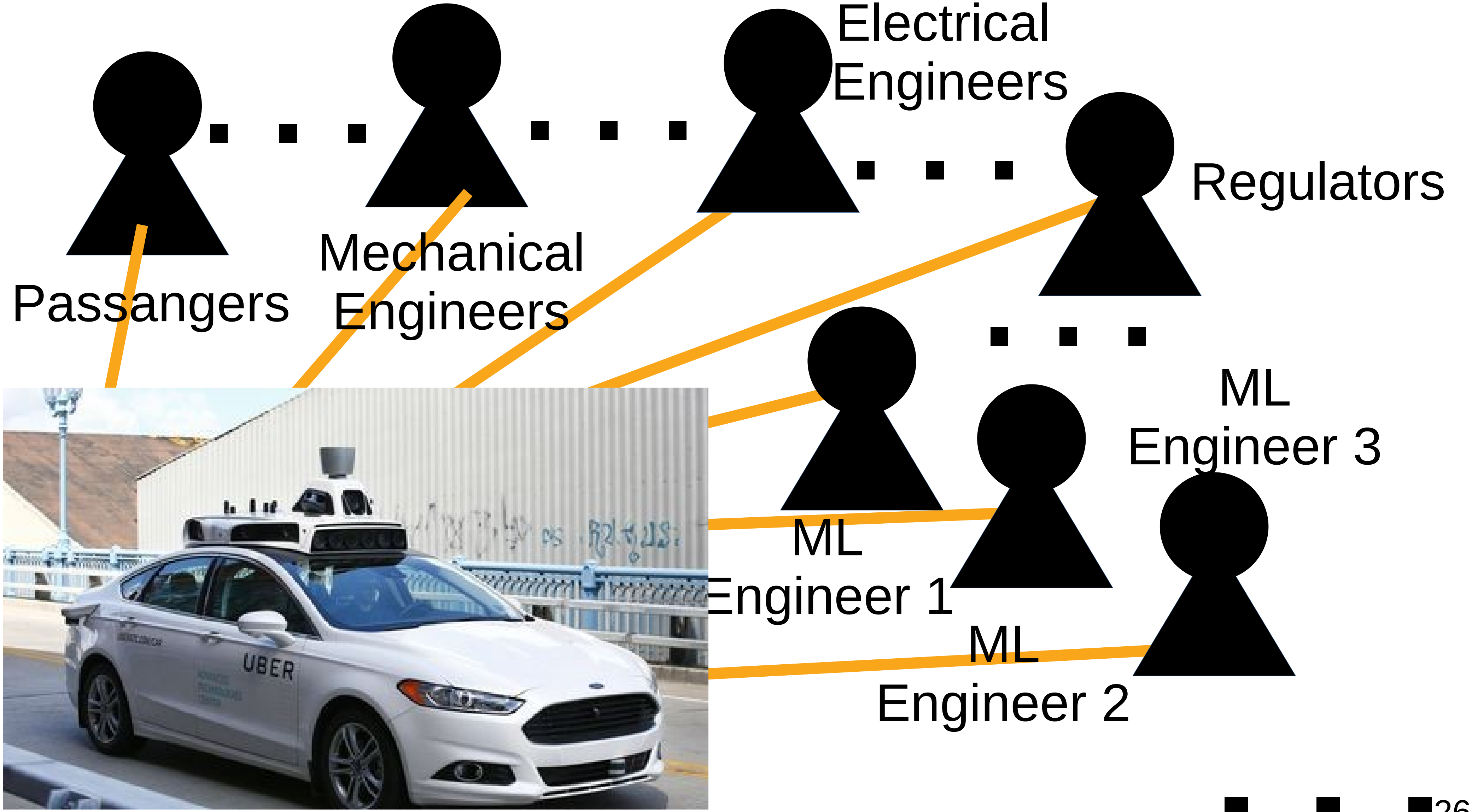

Passangers

Mechanical Engineers

Electrical Engineers

Regulators

ML Engineer 1

ML Engineer 2

ML Engineer 3

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

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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 guarantees about info. provided (so *explanations necessarily reflect system behavior*)
  - 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”

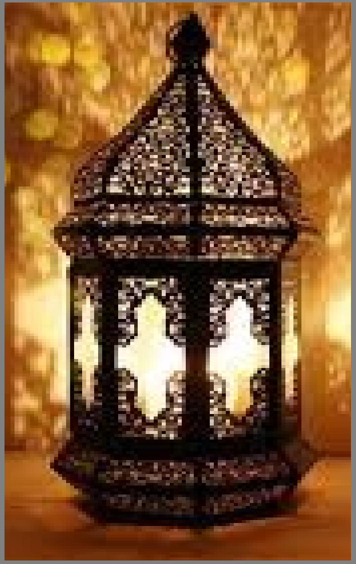
Masrawy.com

Plan For Next Few Slides

1) Overview of setup & what user sees
2) Description of the mechanics
3) Brief overview of experiments
4) Some high-level closing thoughts

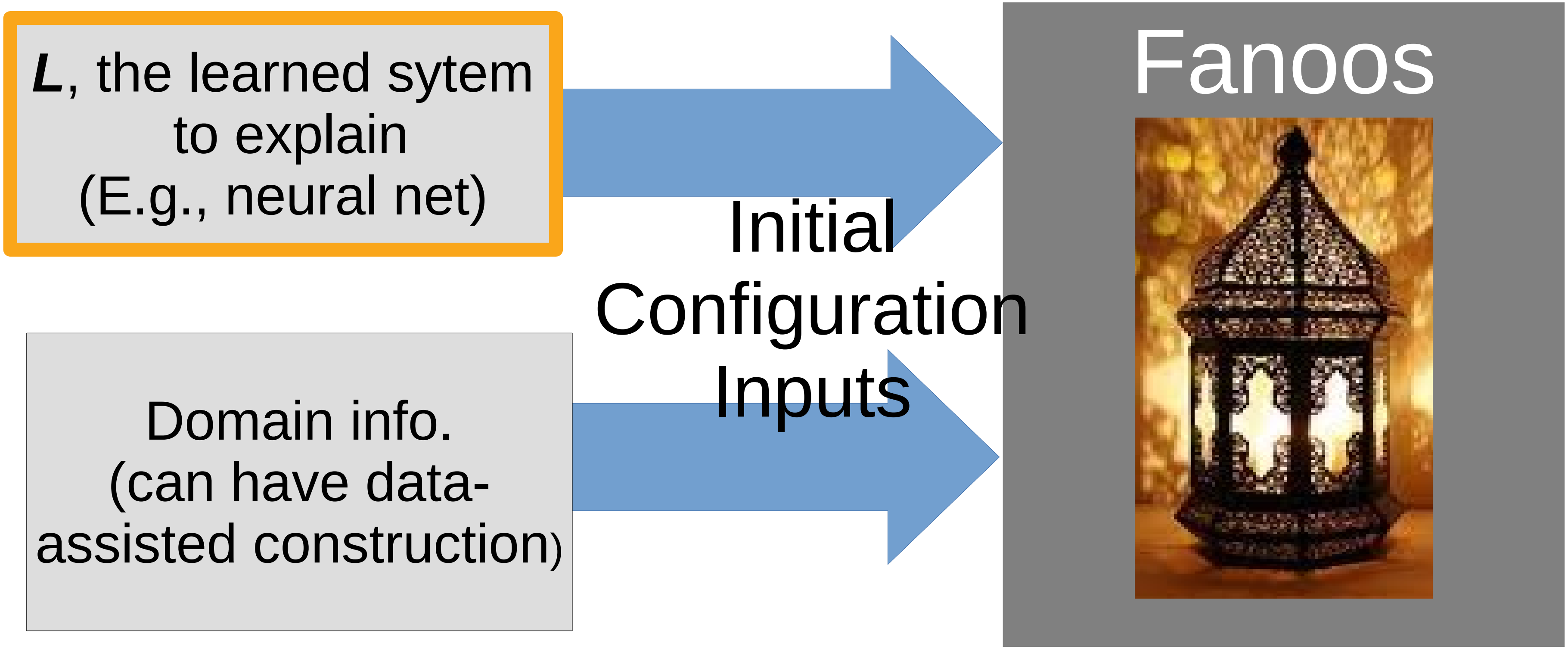
Setup & User View

Fanoos



Fanoos Overview:

Initial Setup



L, the learned sytem to explain (E.g., neural net)

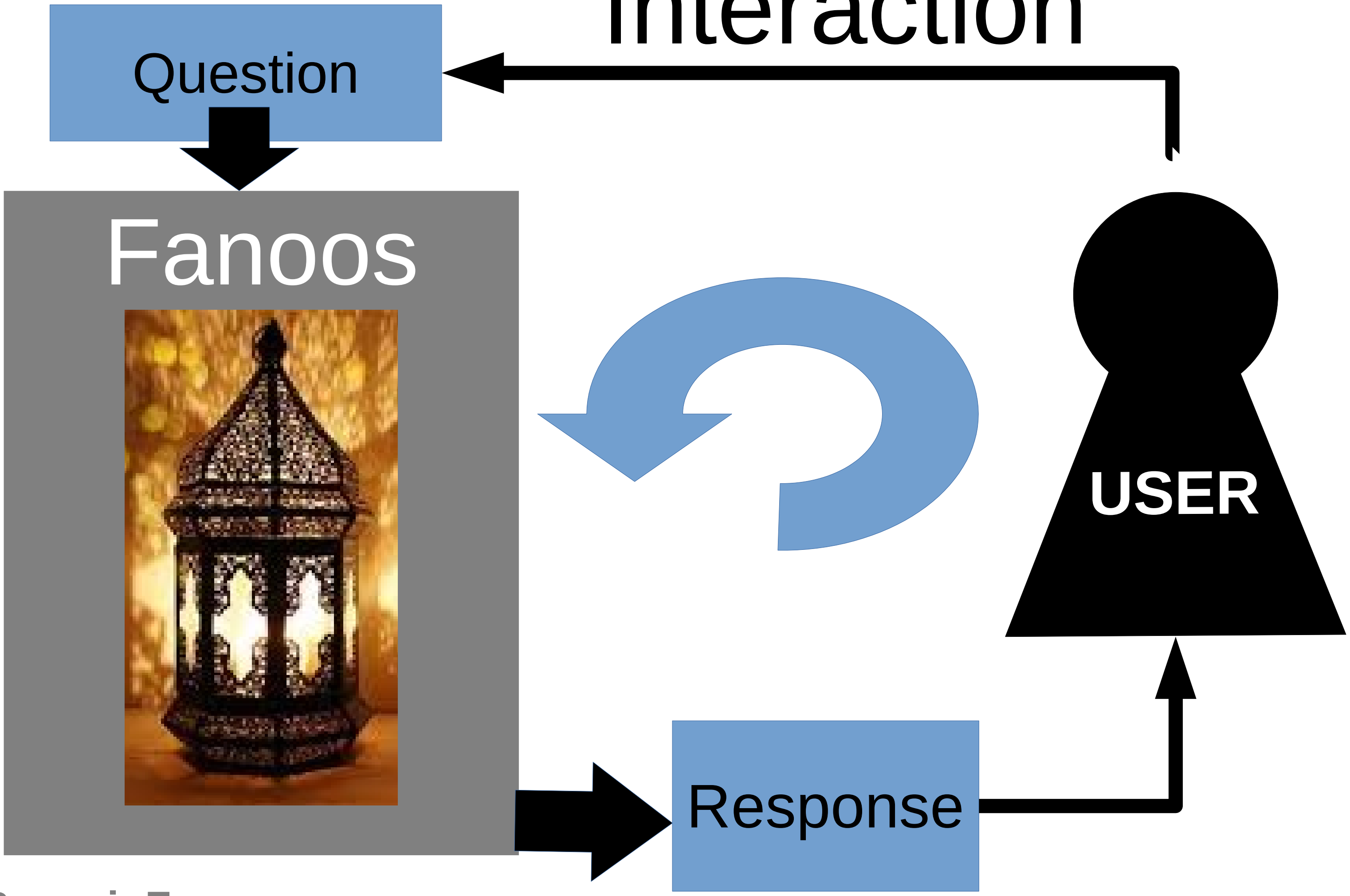
Domain info. (can have data-assisted construction)

Initial Configuration Inputs

Fanoos

Fanoos Overview:

Interaction



Question

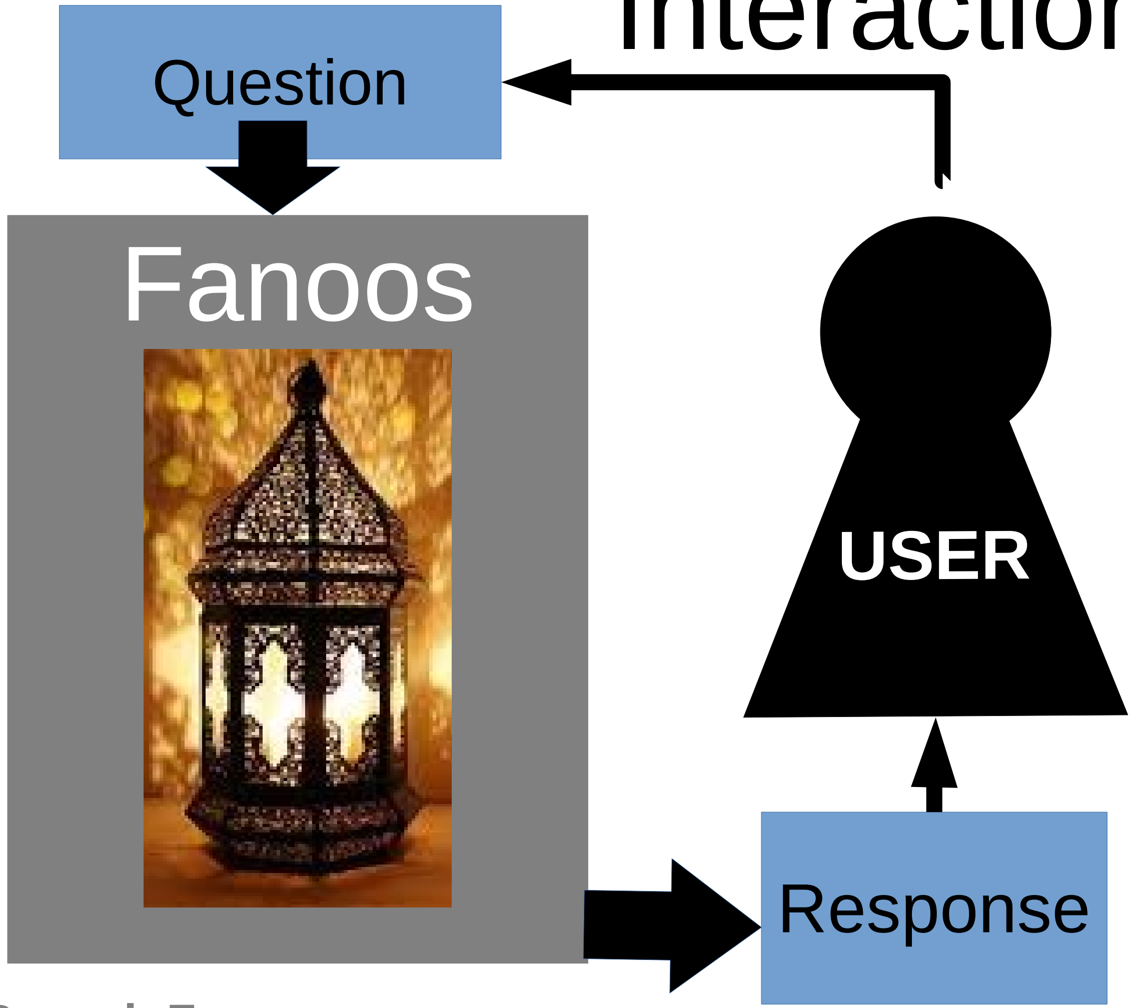
Fanoos

Response

USER

Fanoos Overview:

Interaction



Question

Fanoos

USER

Response

Question Types:

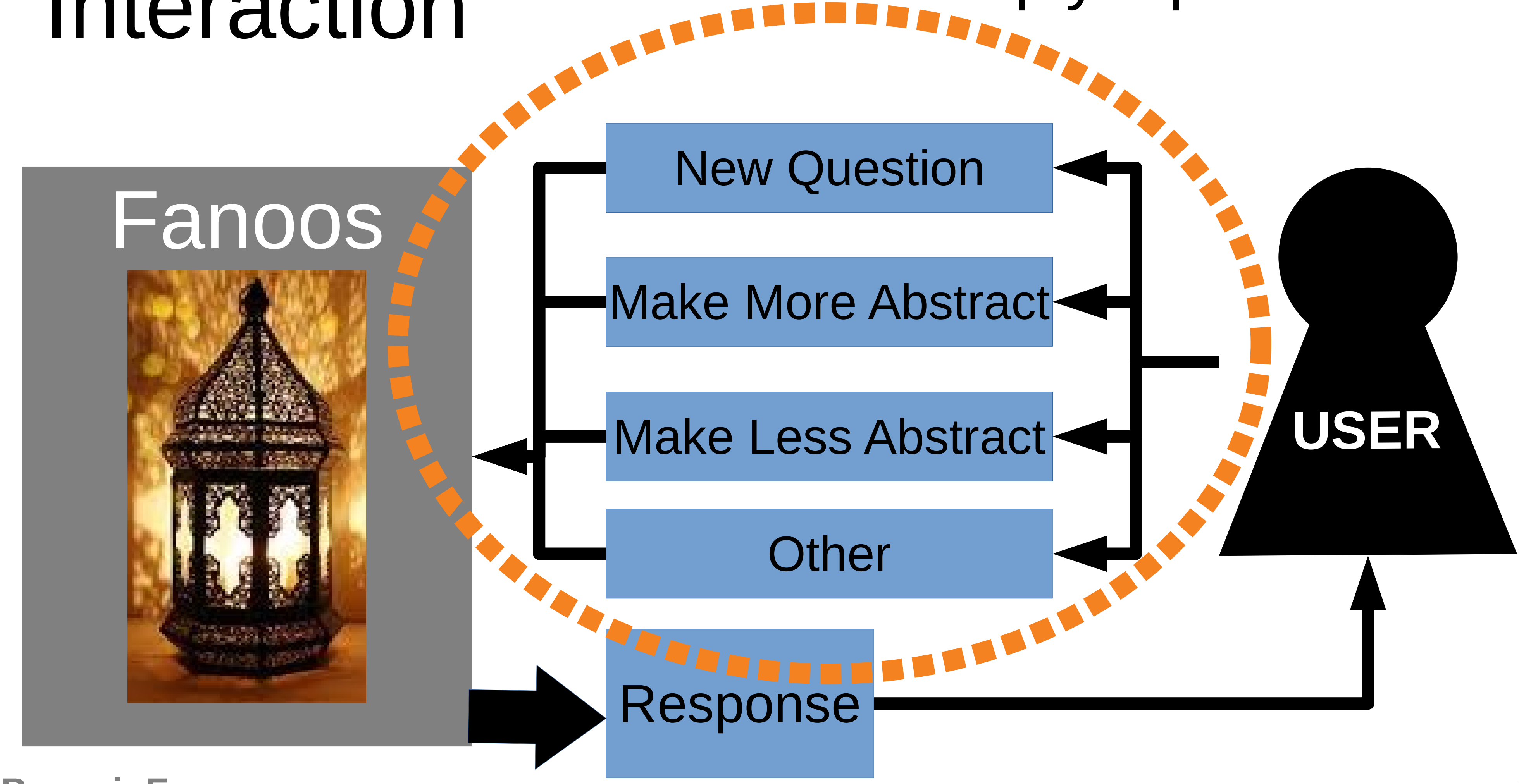
- When does ***L*** do X?
- What does ***L*** do when Y?
- In what circumstances is ***L*** doing X during Y?

Can be formally sound or probabilistically guaranteed

Fanoos Overview:

Interaction

User Reply Options



Fanoos

New Question

Make More Abstract

Make Less Abstract

Other

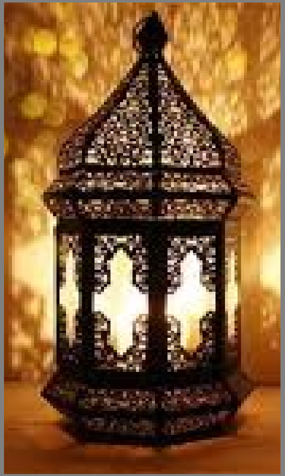
Response

USER

Fanoos Overview:

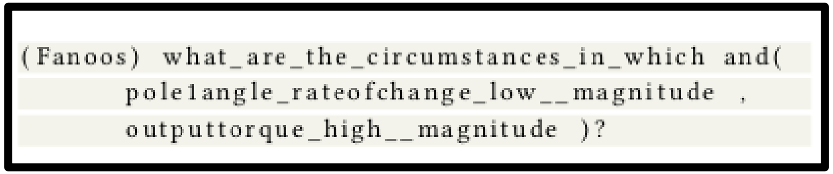
Interaction Example

Fanoos



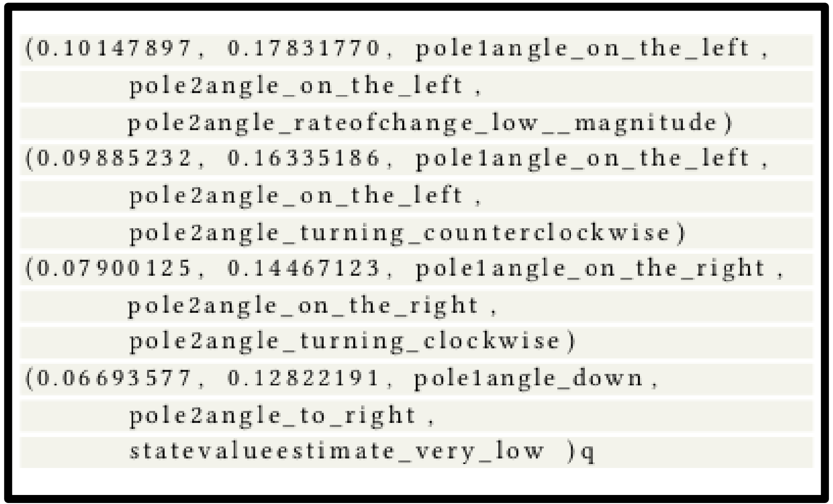
Example from robotics

Initial Question



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

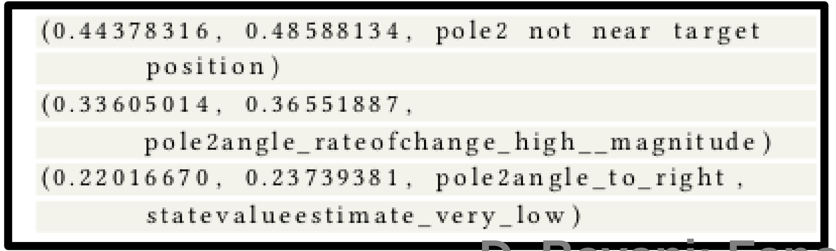
Initial Response



```
(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
```

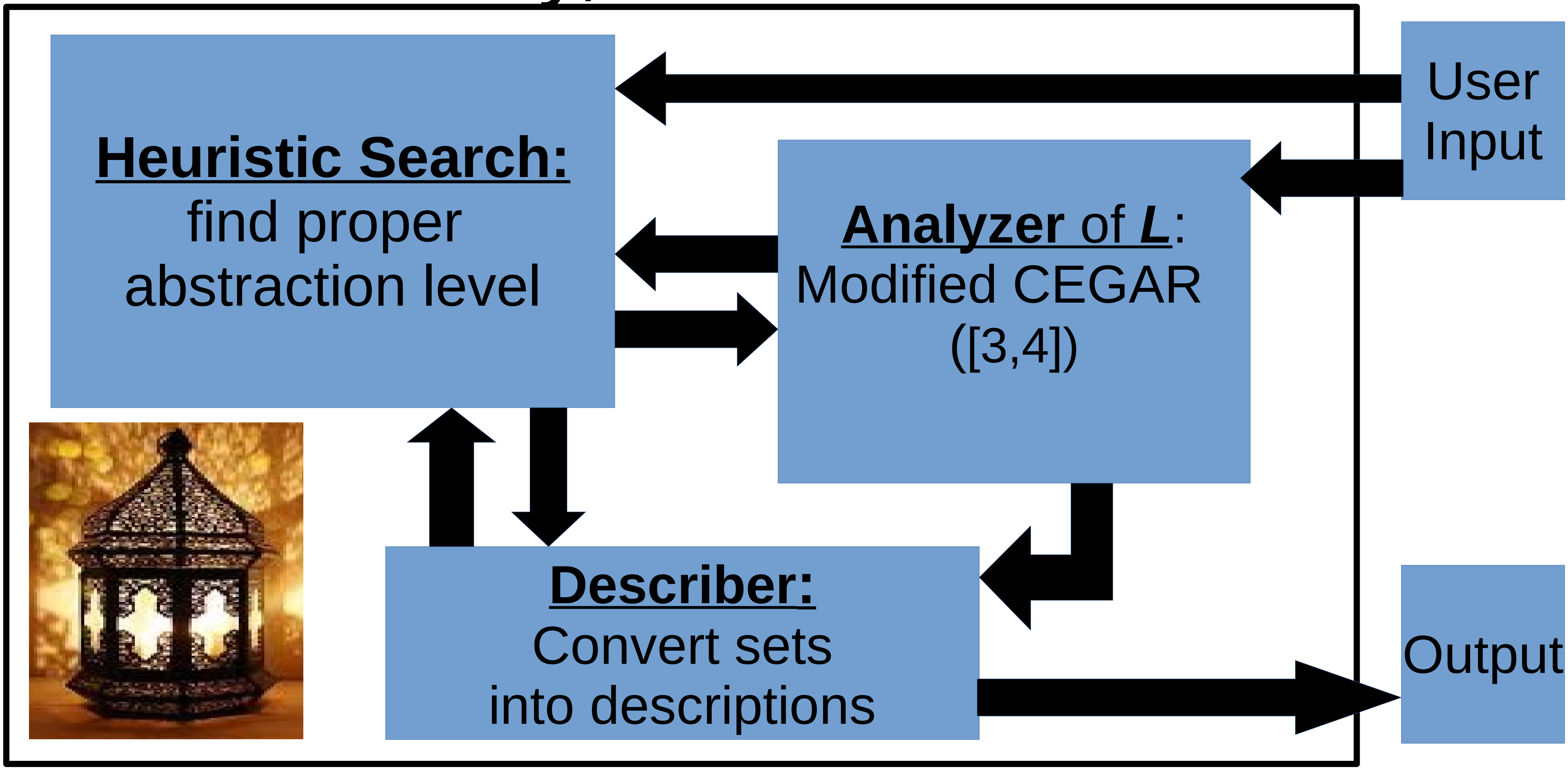
User Request ***More*** abstract

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



Heuristic Search:
find proper
abstraction level

Analyzer of *L*:
Modified CEGAR
([3,4])

Describer:
Convert sets
into descriptions

User
Input

Output

Mechanics

Fanoos

Domain Knowledge that User Provides

- The learned system, *L*
- Universe bounding-box for input space
  - Ex: for a constant velocity 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” :

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

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  - Facilitates semi-automatic or fully automatic generation (if desired)

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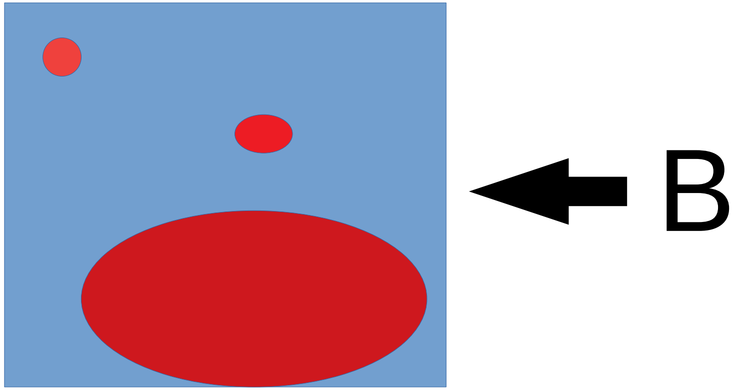
- Note: predicates are grounded
  - Facilitates semi-automatic or fully automatic generation (if desired)
  - Using a SAT-solver, we can say whether predicate holds over sets



Red : P fails to hold
Blue: P holds

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

Overview: Responding to Questions

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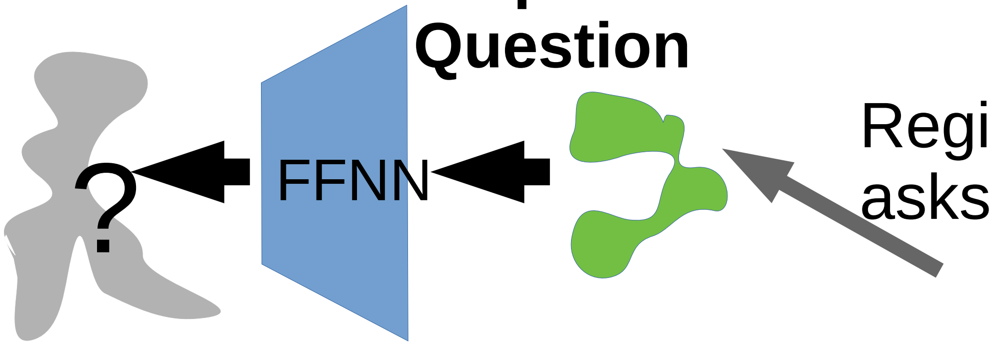
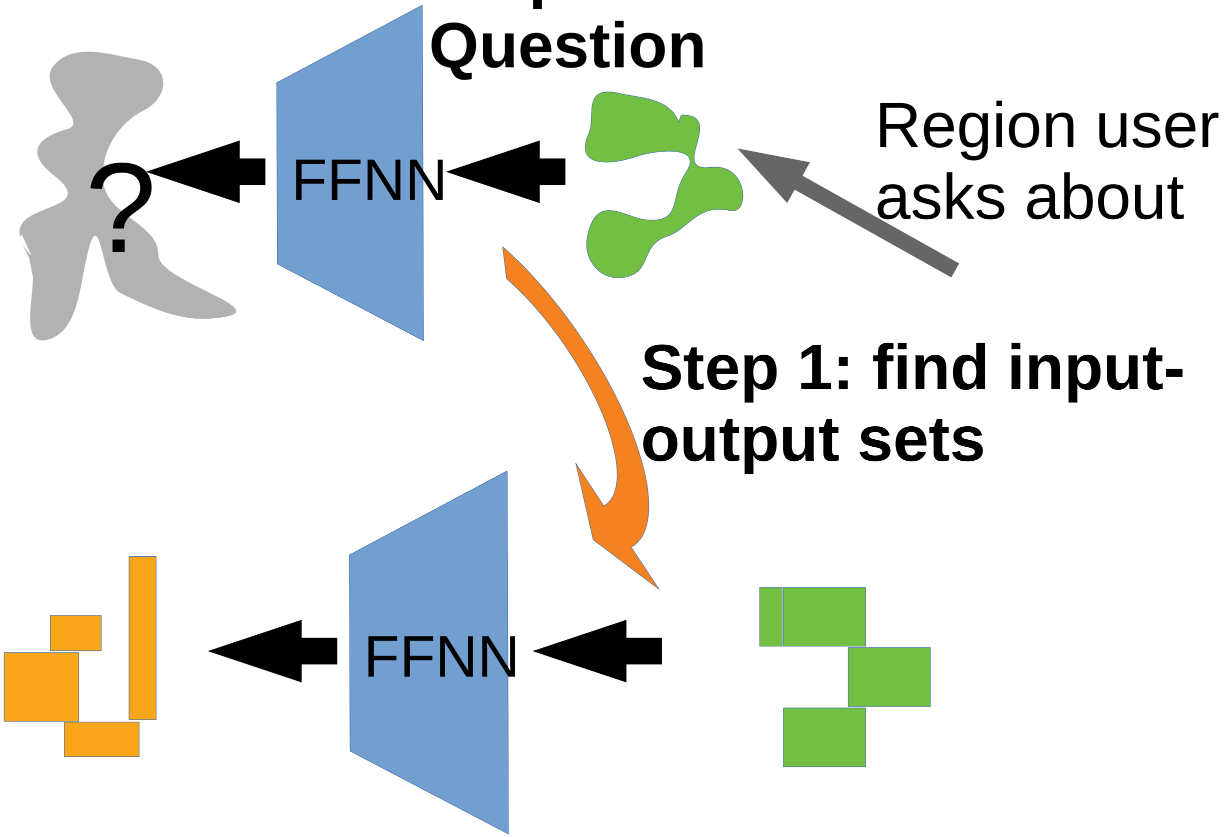
Step 0: User asks Question



Region user asks about

Overview: Responding to Questions

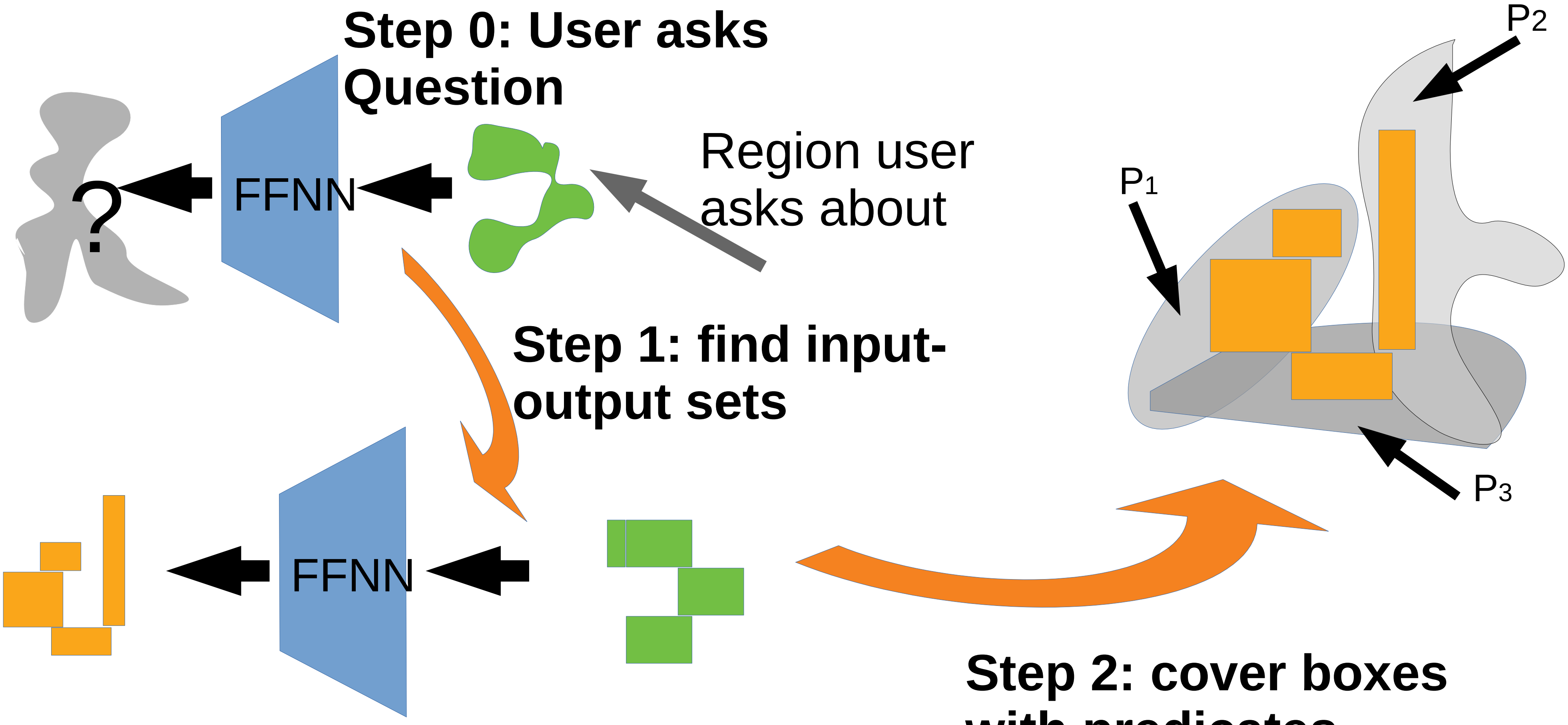


Step 0: User asks Question

Region user asks about

Step 1: find input-output sets

Overview: Responding to Questions



Step 0: User asks Question

Region user asks about

Step 1: find input-output sets

Step 2: cover boxes with predicates

Step 1: “Finding the Other Set”

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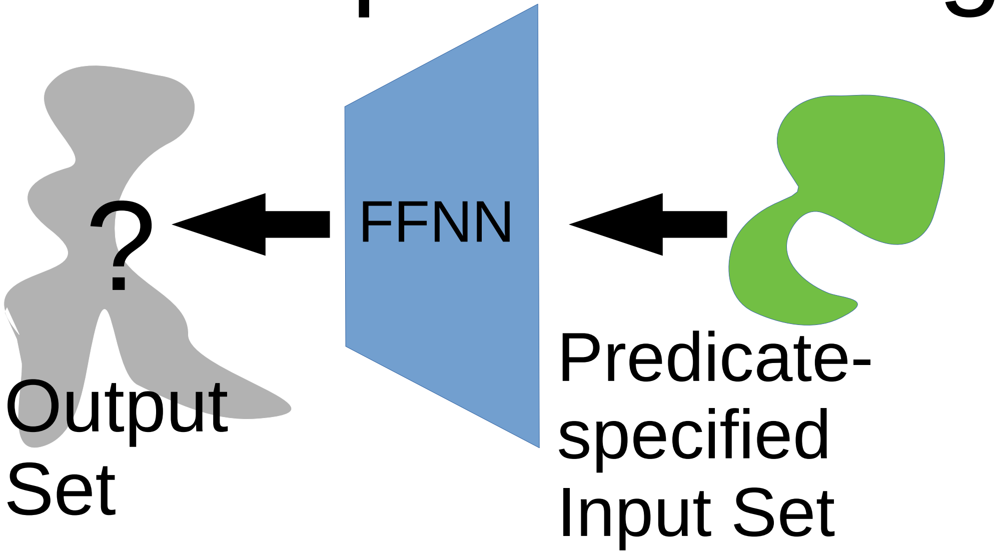
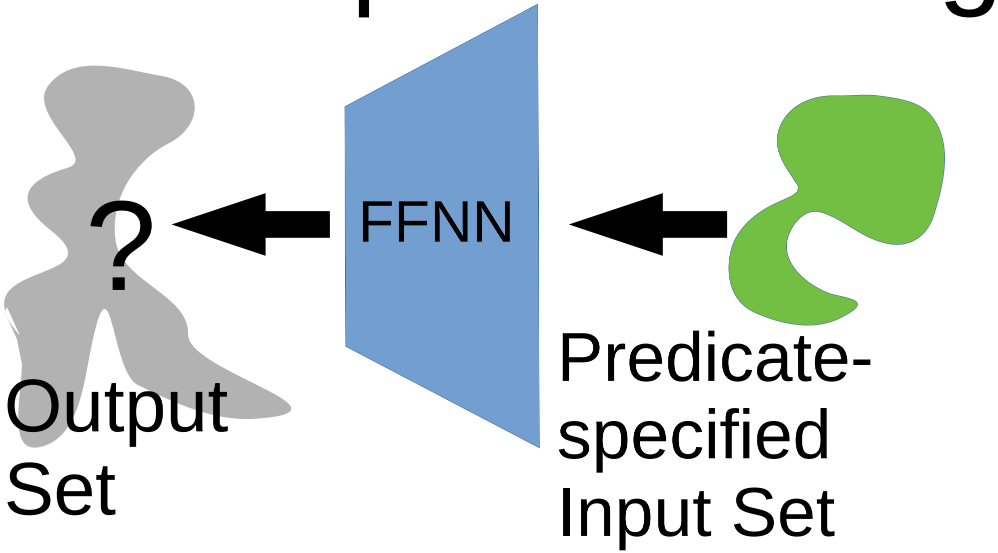


Output Set

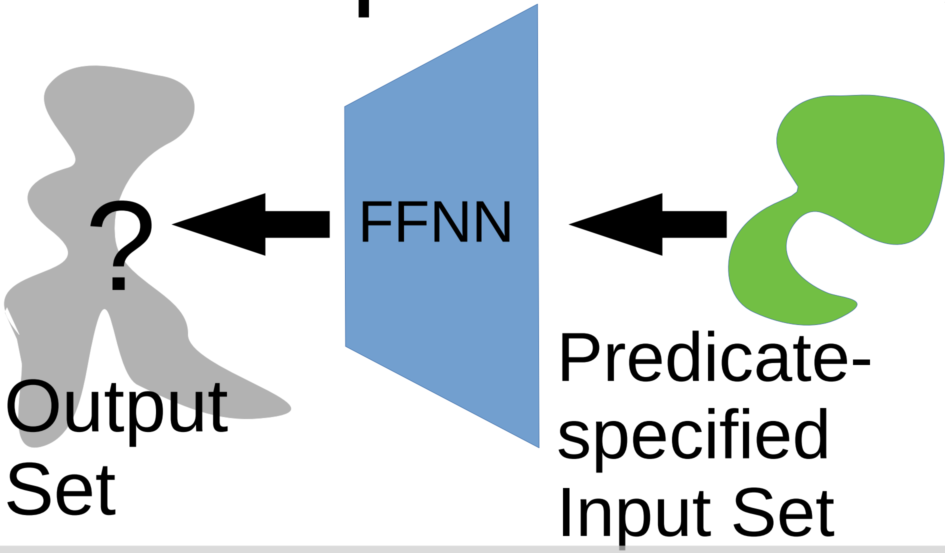
Predicate-specified Input Set

Step 1: “Finding the Other Set”



Question: “What do you do when …?”

Step 1: “Finding the Other Set”

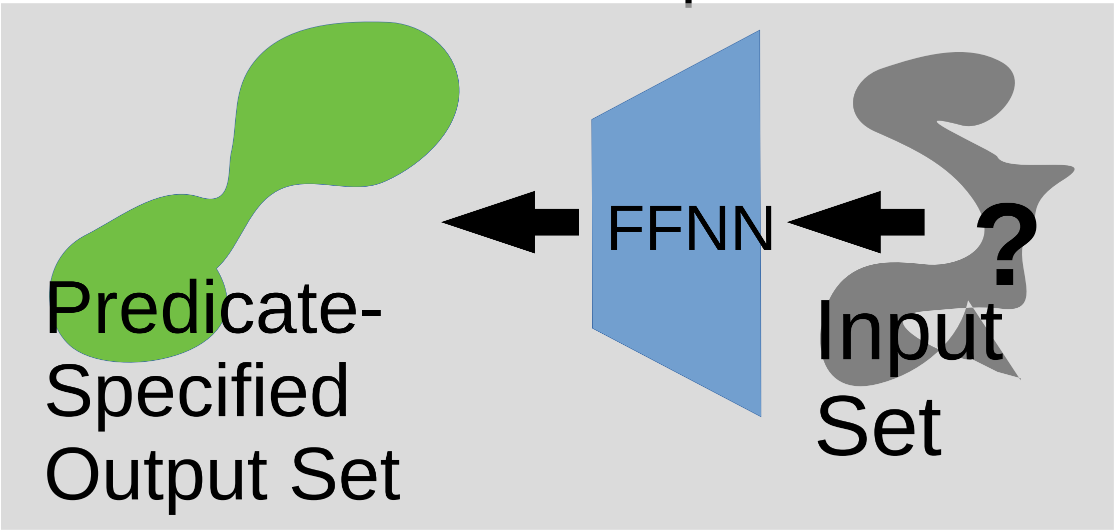


?

FFNN

Output Set

Predicate-specified Input Set



FFNN

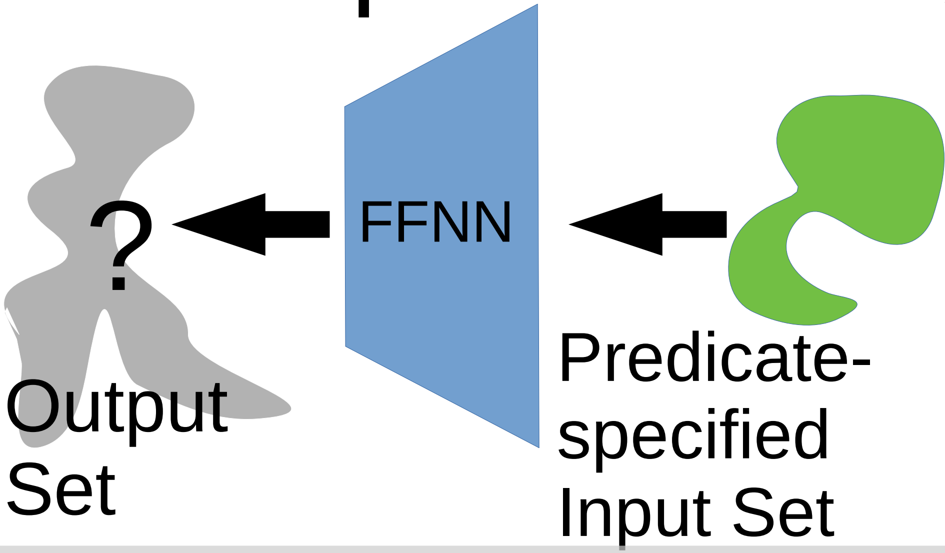
?

Predicate-Specified Output Set

Input Set

Question: “What do you do when …?”

Step 1: “Finding the Other Set”



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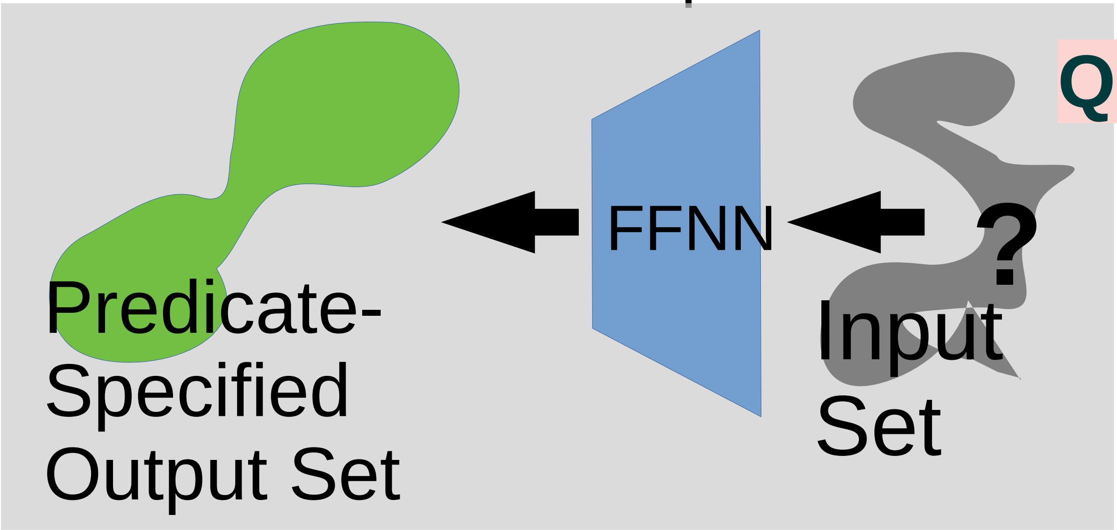

FFNN

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Predicate-Specified Output Set

Input Set

Question: “When do you…?”

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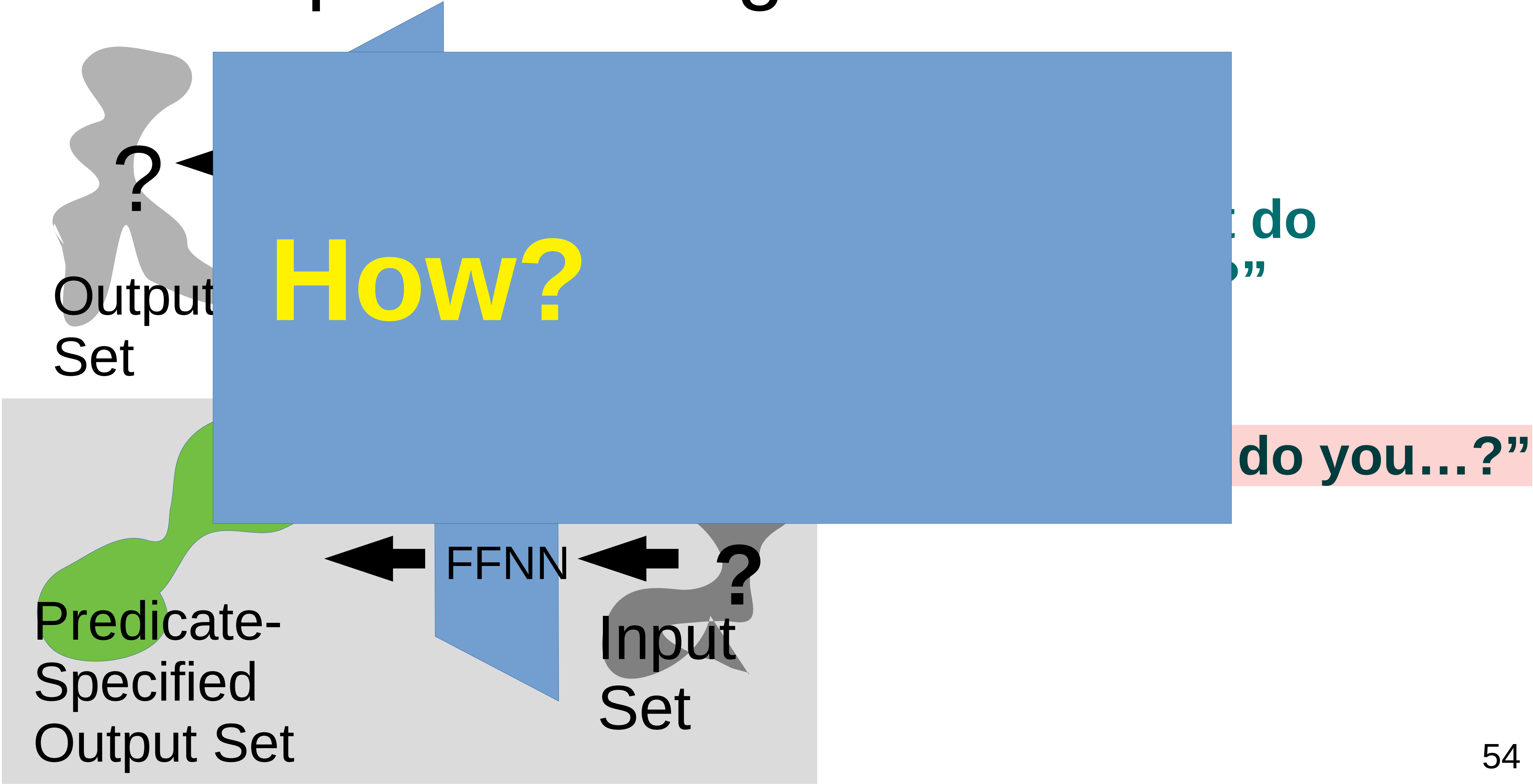

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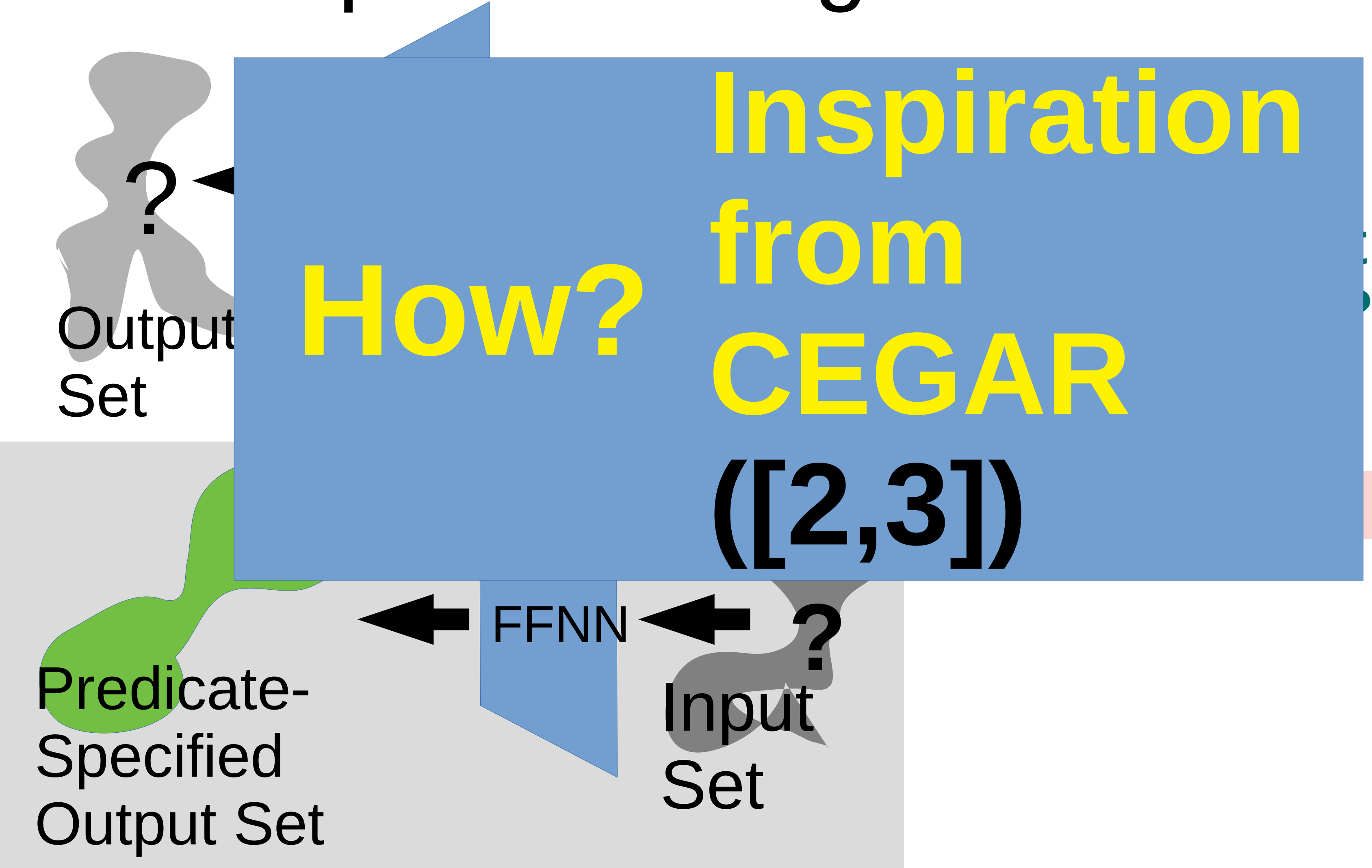


How?

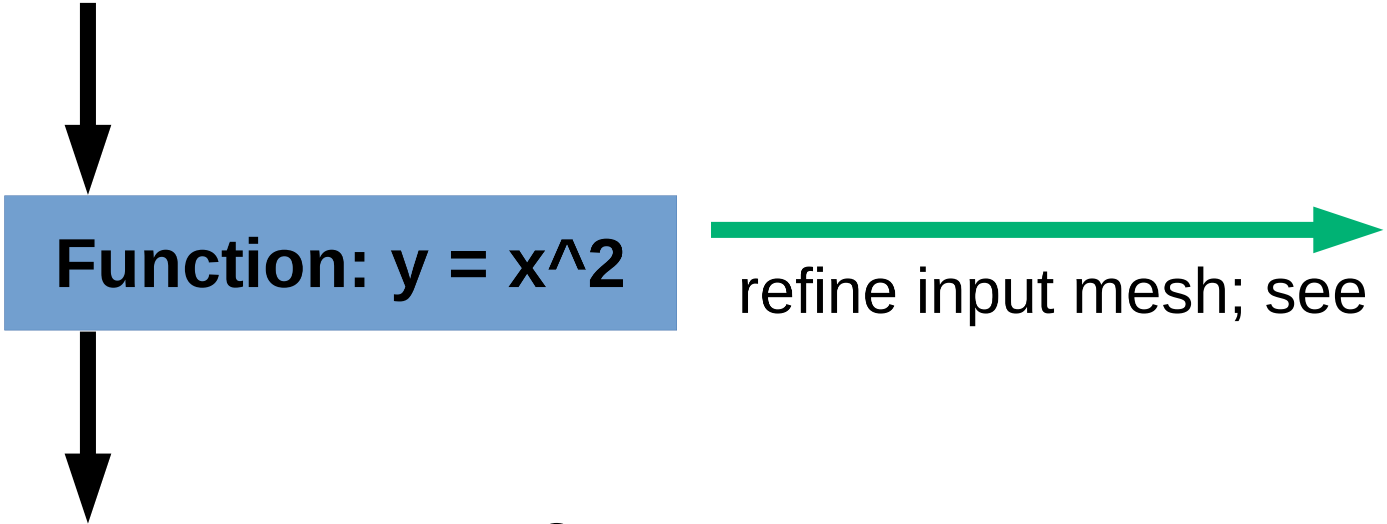
Inspiration from CEGAR ([2,3])

t do
?”

do you…?”

CEGAR-esque Method

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



Function: y = x^2

refine input mesh; see paper for details

Green:
desired
region

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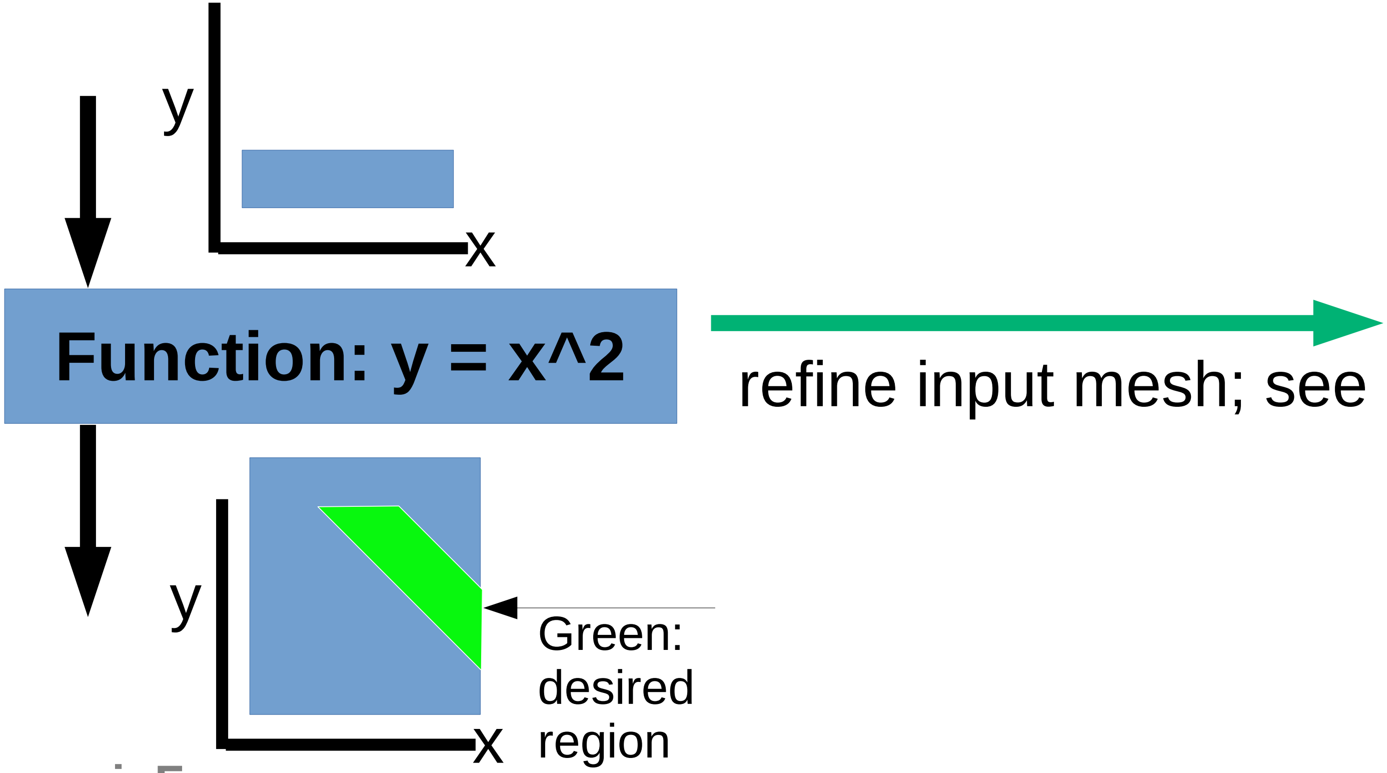

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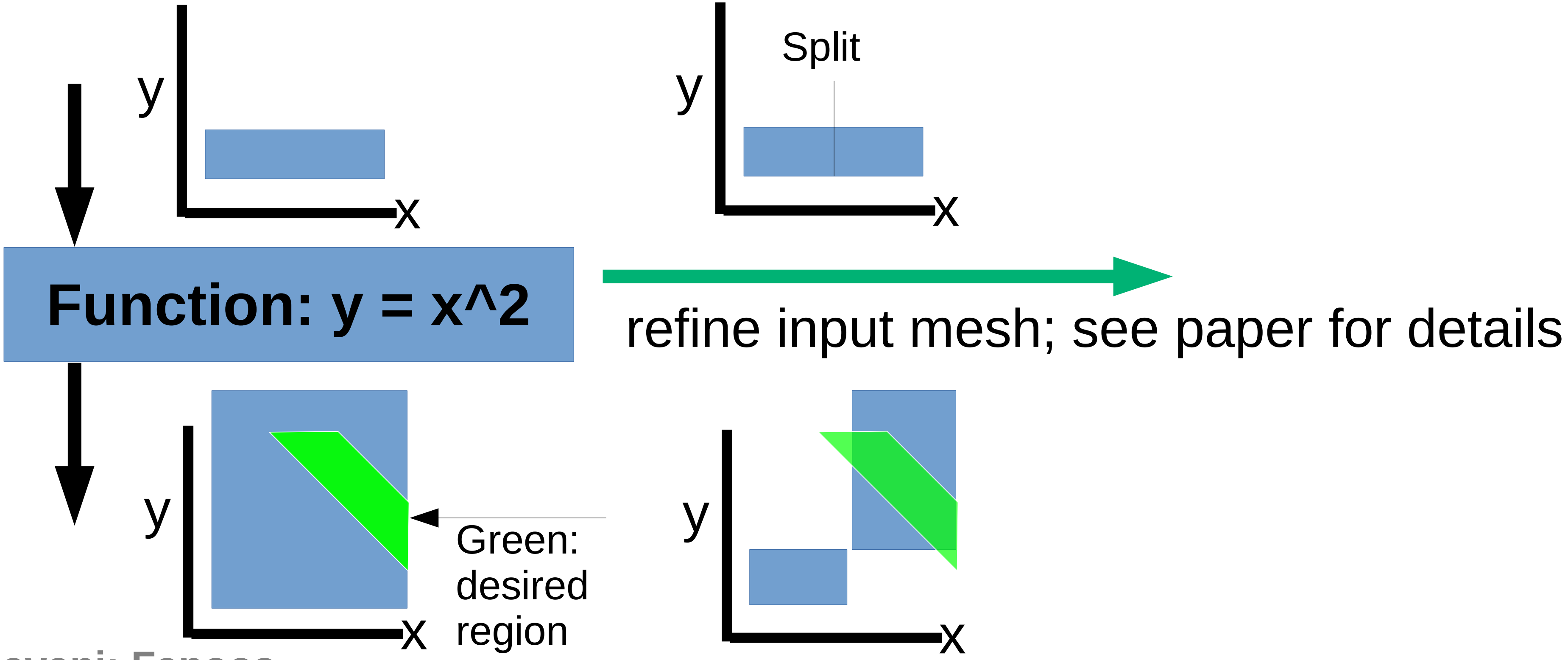

Split

Function: y = x^2

refine input mesh; see paper for details

Green: desired region

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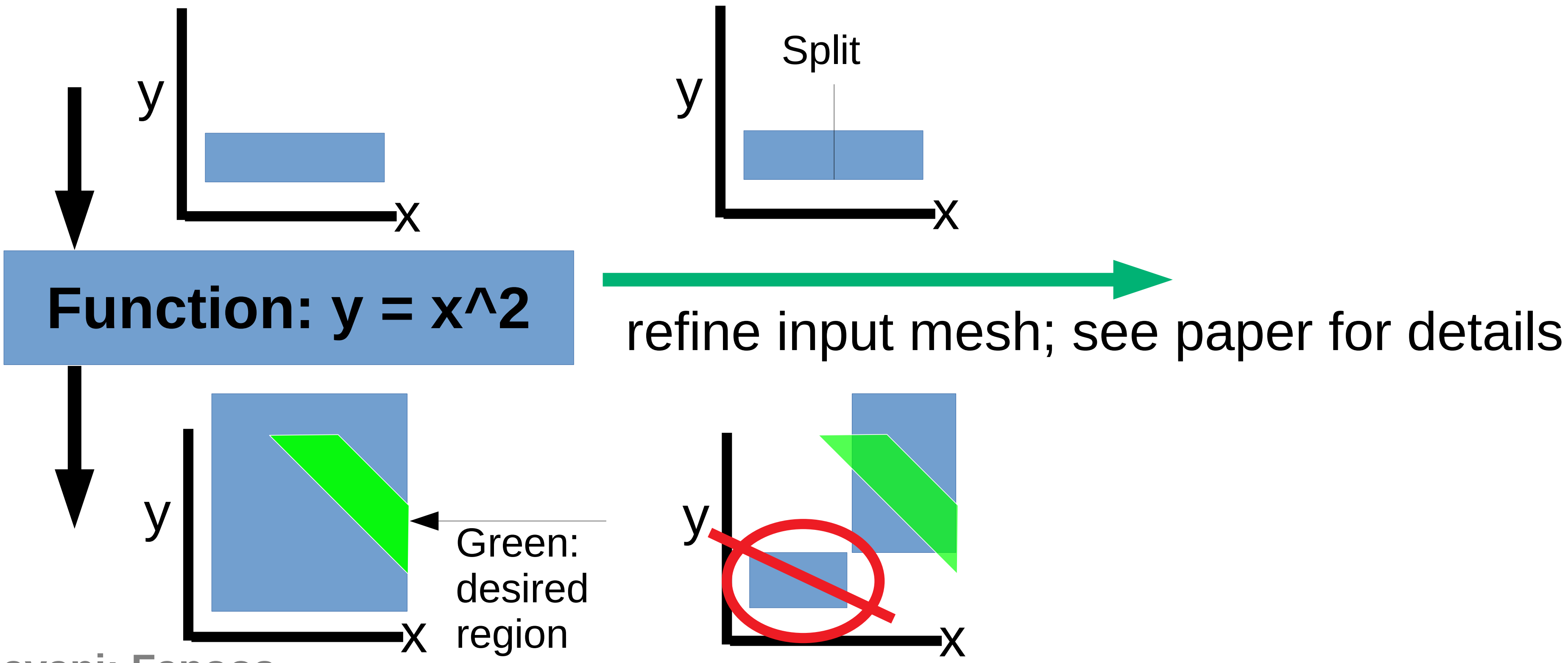

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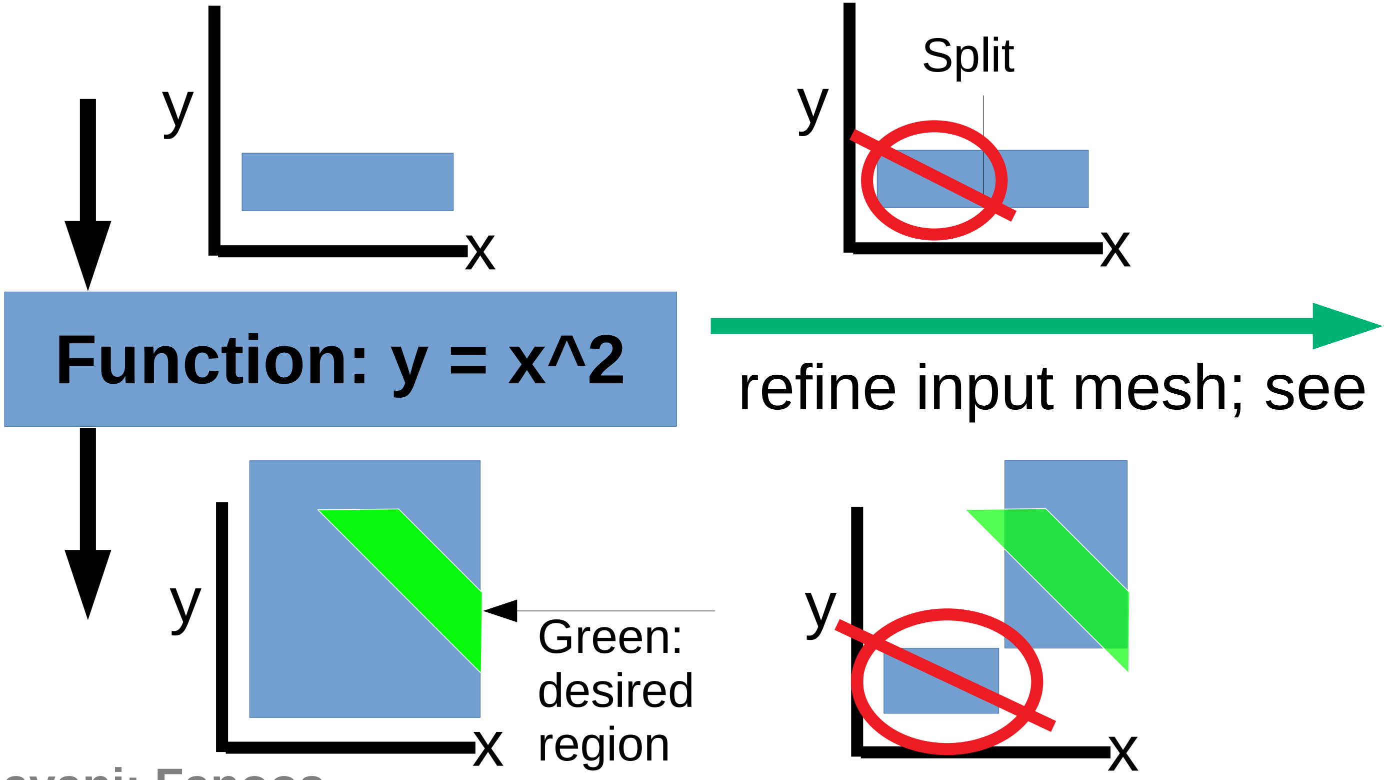

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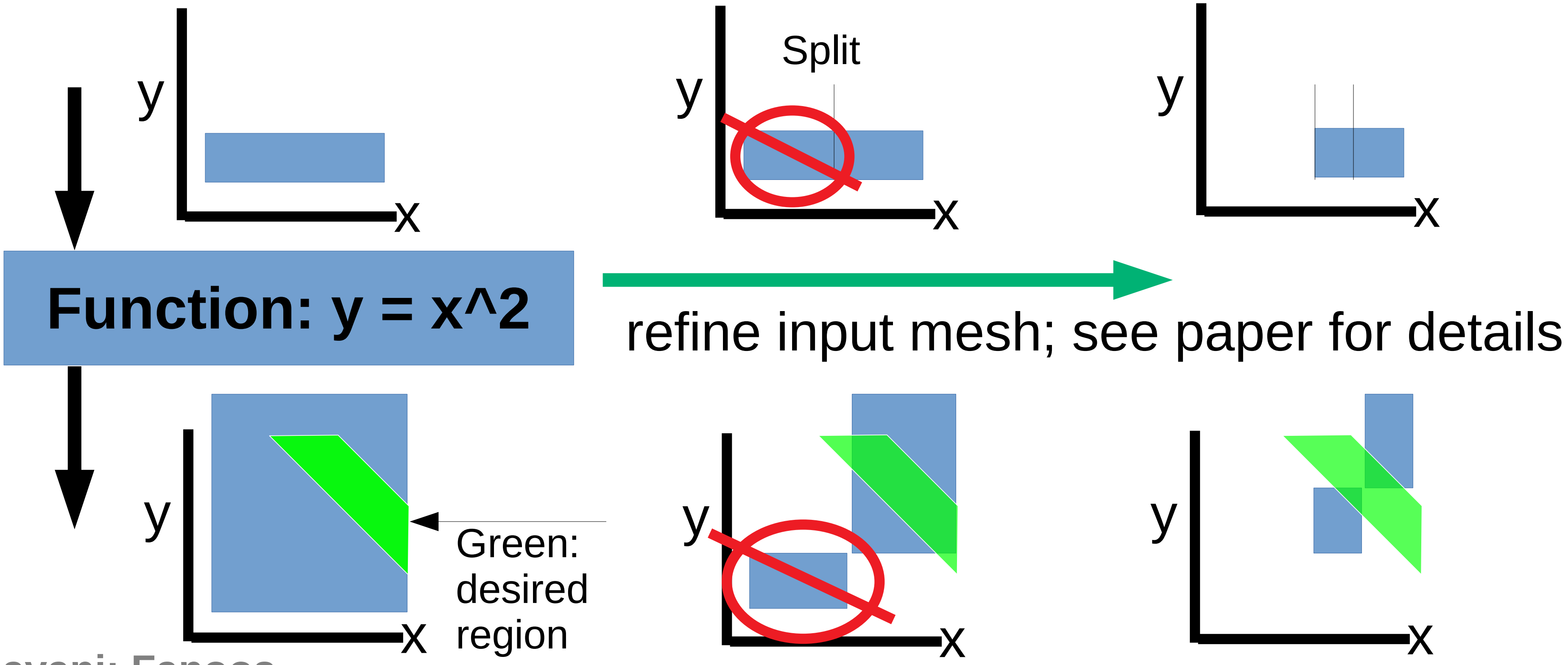


Function: y = x^2

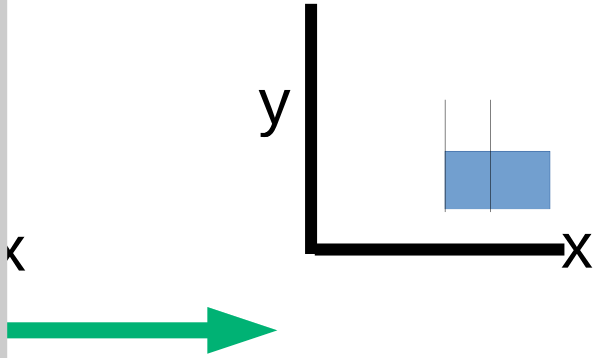
refine input mesh; see paper for details

Green: desired region

CEGAR-esque Method

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-described region



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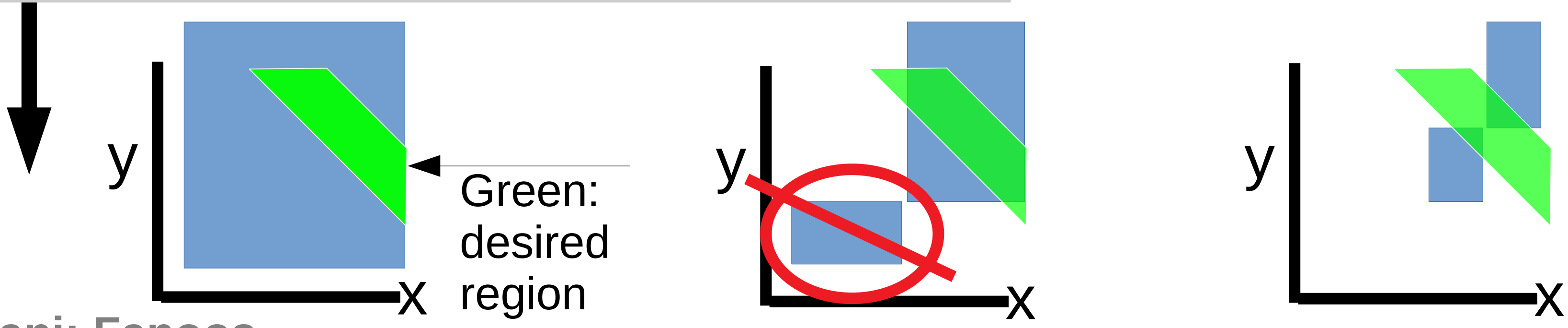


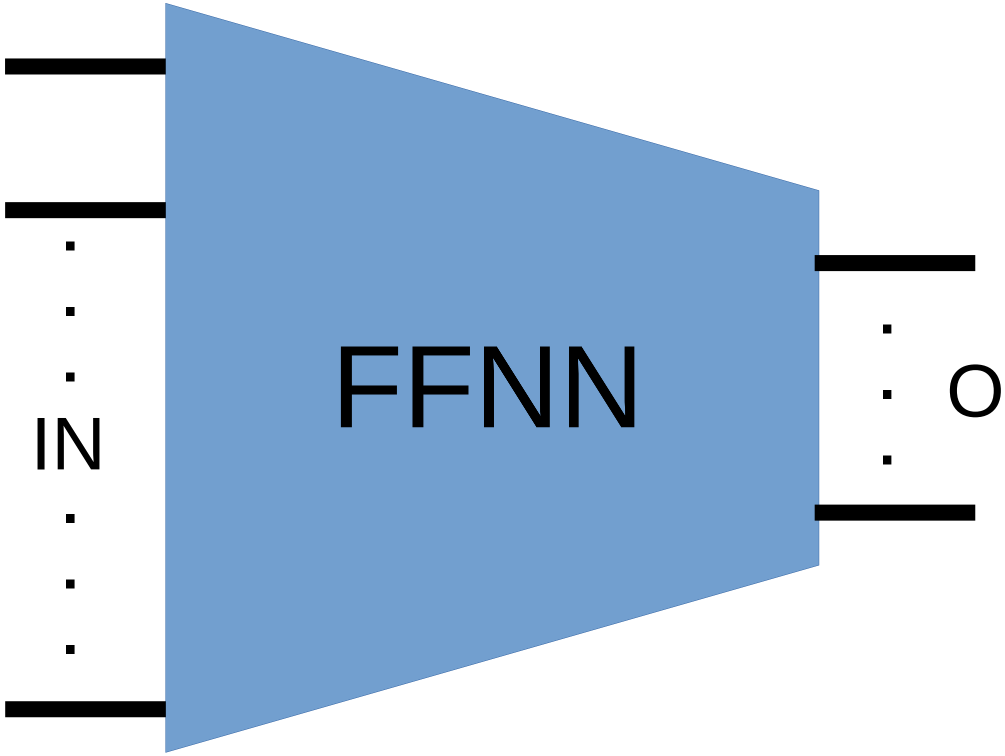
Green: desired region

Getting One Box In / Out of System

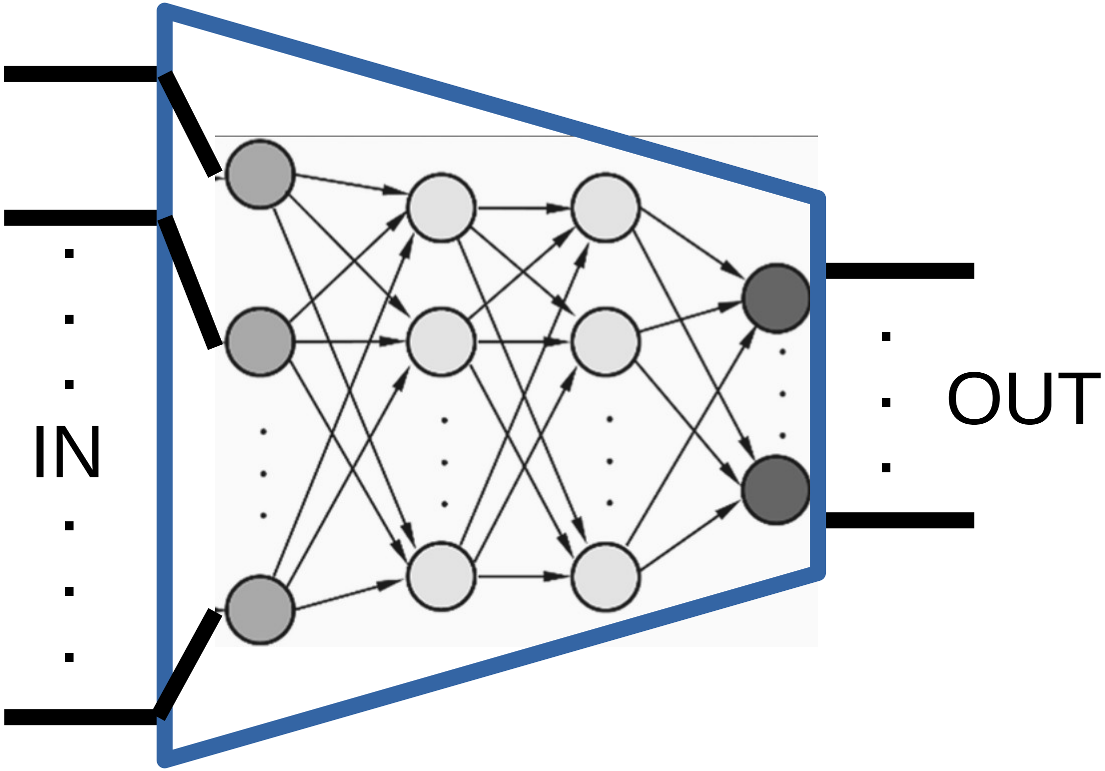
- Will discuss process for neural net (NN): process similar for other systems

Getting One Box In / Out of System

- Will discuss process for neural net (NN): process similar for other systems



Getting One Box In / Out of System



https://www.researchgate.net/profile/Maria-Haritou/publication/291339457/figure/fig1/AS:334187497312256@1456687916125/Typical-structure-of-a-feed-forward-multilayer-neural-network.png

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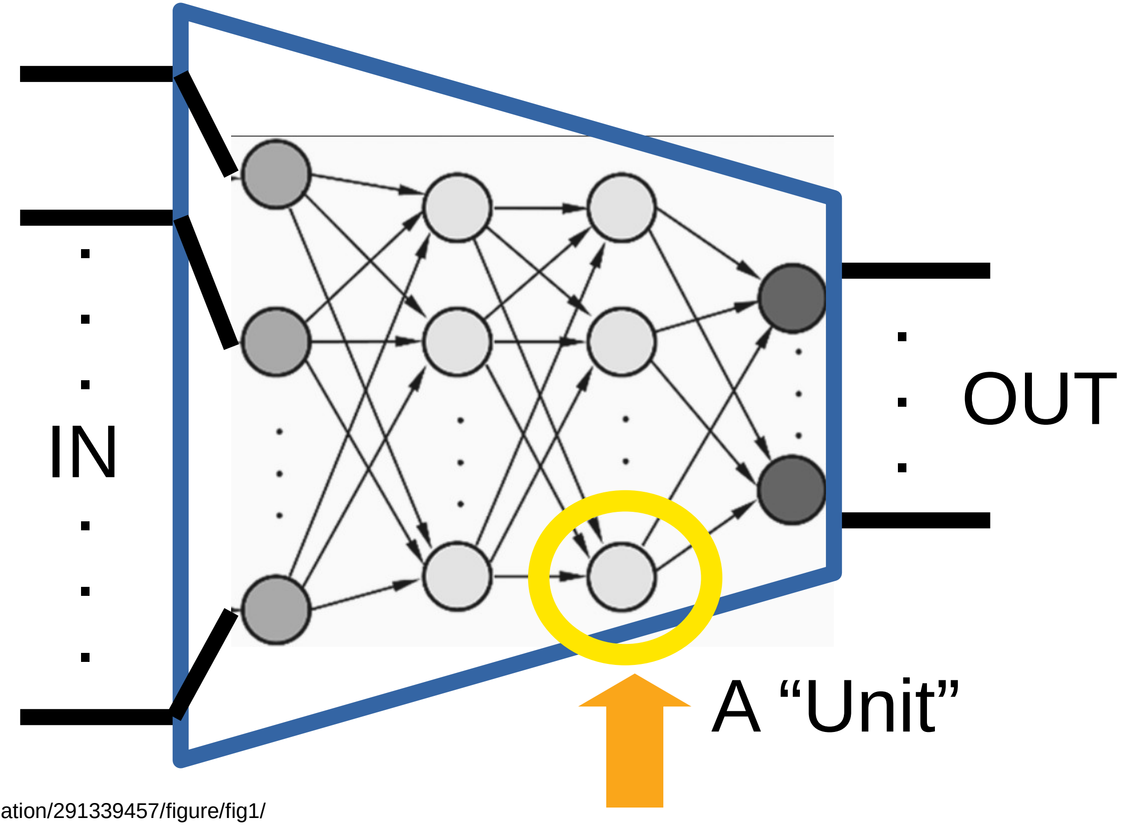

D. Bayani: Fanoos

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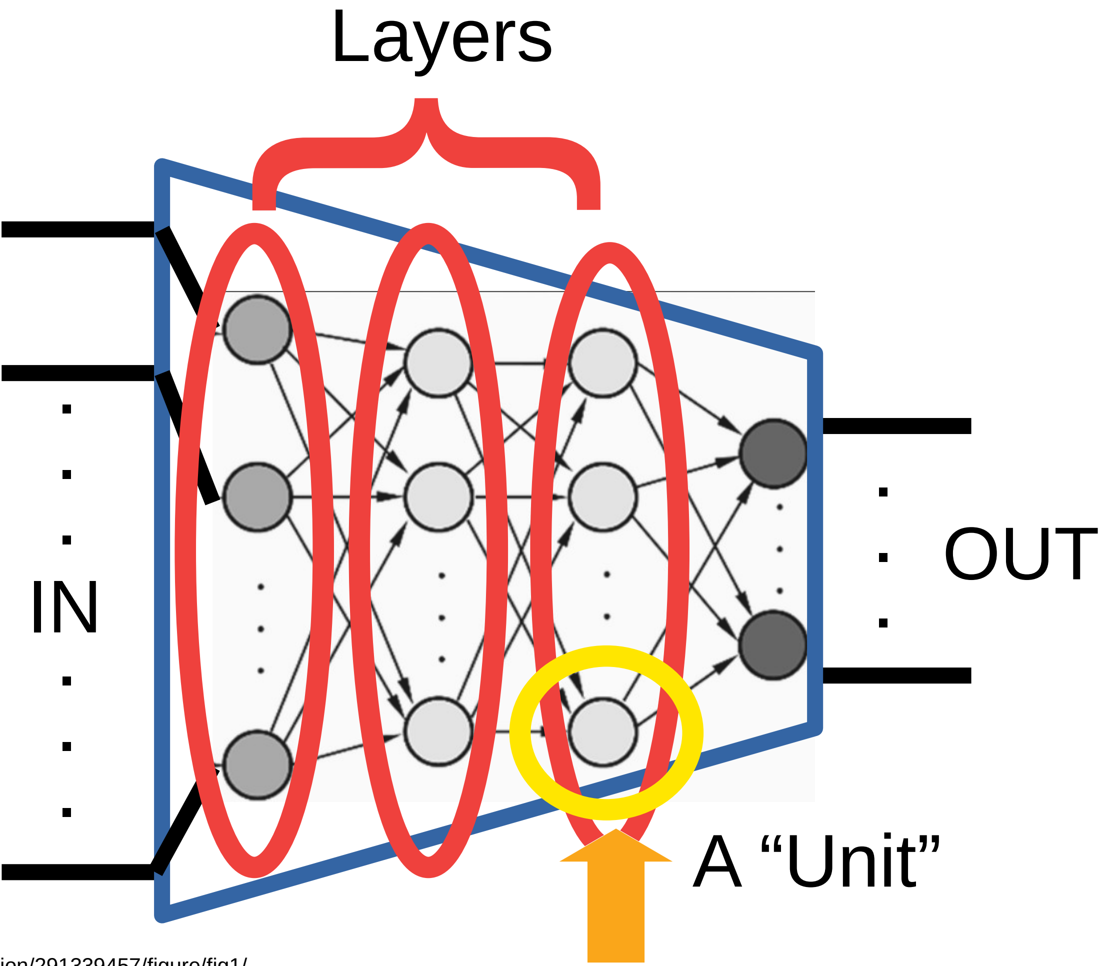

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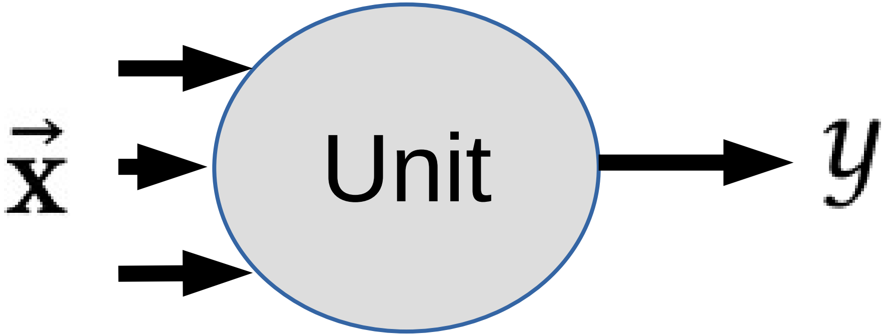
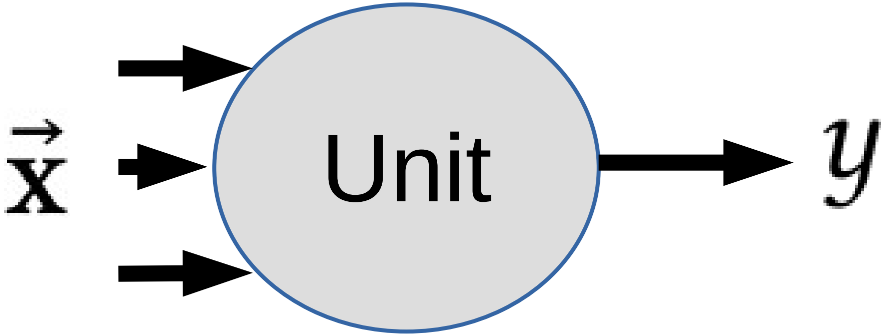
Getting One Box In / Out of System, Cnt.

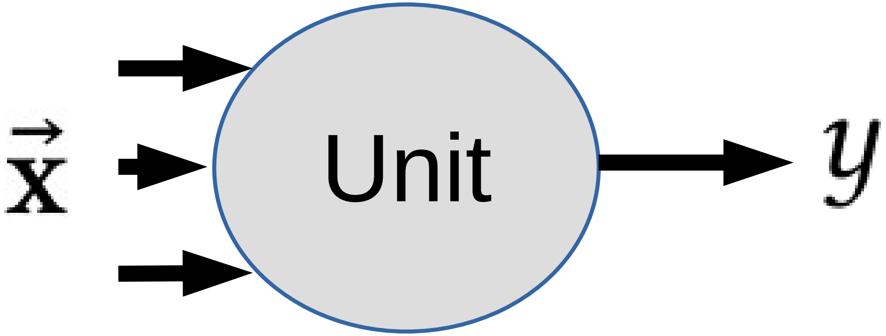


Getting One Box In / Out of System, Cnt.



$$y = \rho(T(\vec{\mathbf{x}}))$$

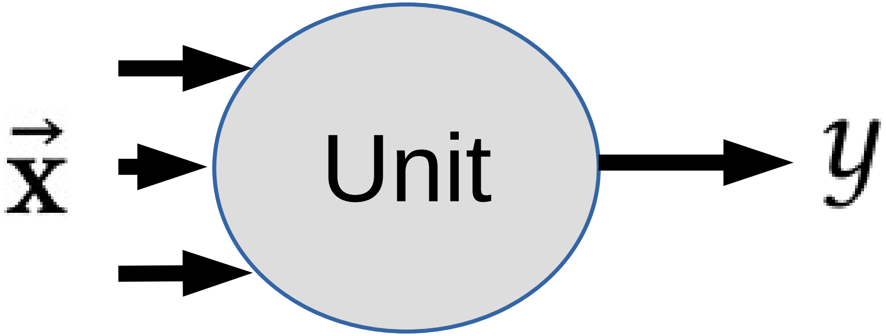
Getting One Box In / Out of System, Cnt.



$$y = \rho(T(\vec{\mathbf{x}}))$$

Affine transform $T(\vec{\mathbf{x}}) = \langle \vec{\mathbf{w}}, \vec{\mathbf{x}} \rangle + \mathbf{b}$

Getting One Box In / Out of System, Cnt.



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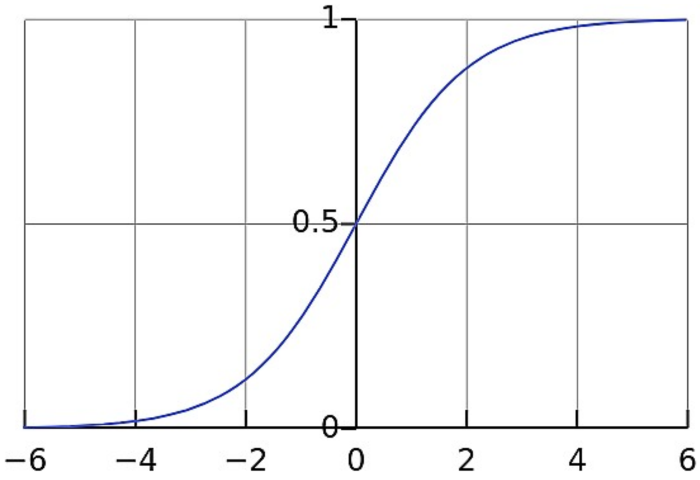
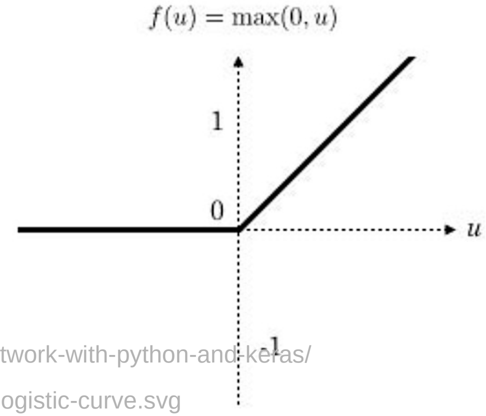


An “**activation function**”

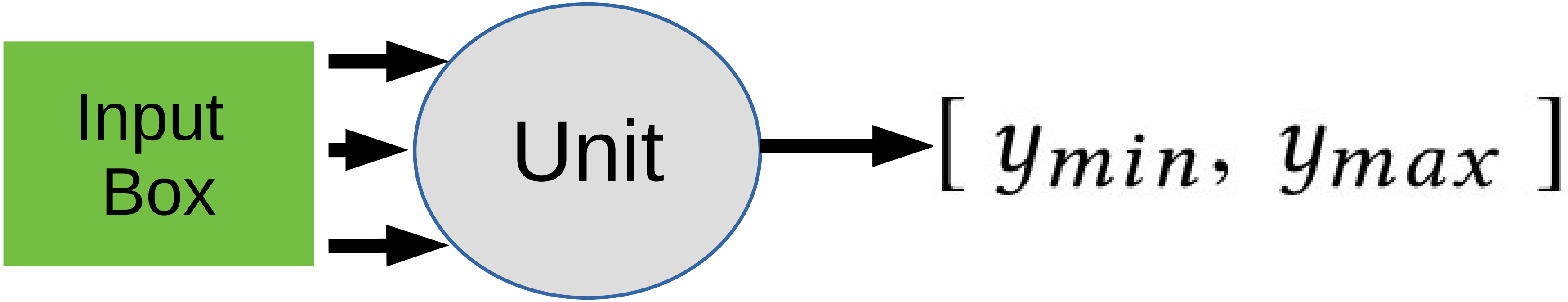
Here, a non-decreasing function from R to R.



https://ehackz.com/2018/03/17/build-your-first-neural-network-with-python-and-keras/

https://upload.wikimedia.org/wikipedia/commons/8/88/Logistic-curve.svg

Getting One Box In / Out of System, Cnt.



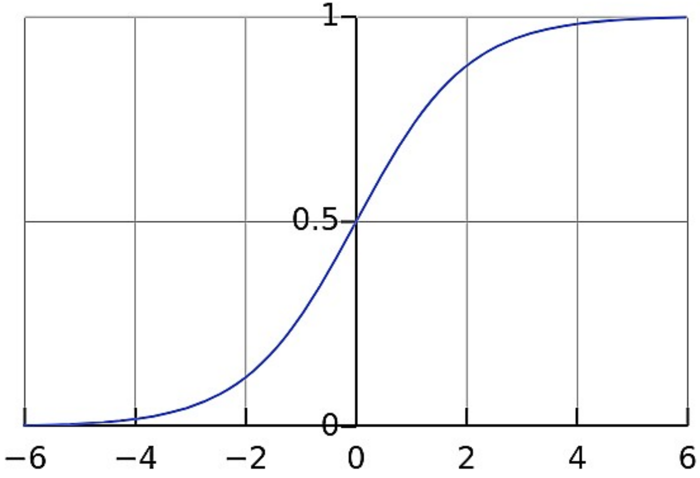
Input Box

Unit

$[\, y_{min},\ y_{max} \,]$

$$y = \rho(T(\vec{\mathbf{x}}))$$

Affine transform $T(\vec{\mathbf{x}}) = \langle \vec{\mathbf{w}}, \vec{\mathbf{x}} \rangle + \mathbf{b}$



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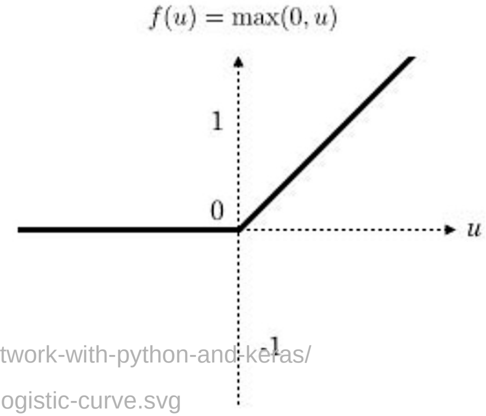

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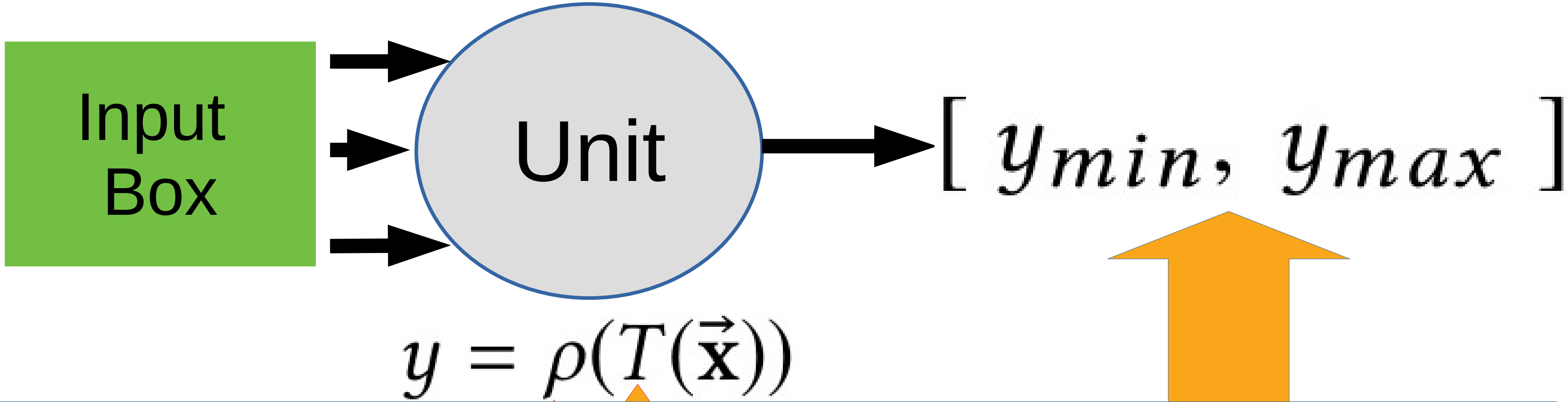
Getting One Box In / Out of System, Cnt.



$$y = \rho(T(\vec{\mathbf{x}}))$$

Can compute in an ***exact*** closed form

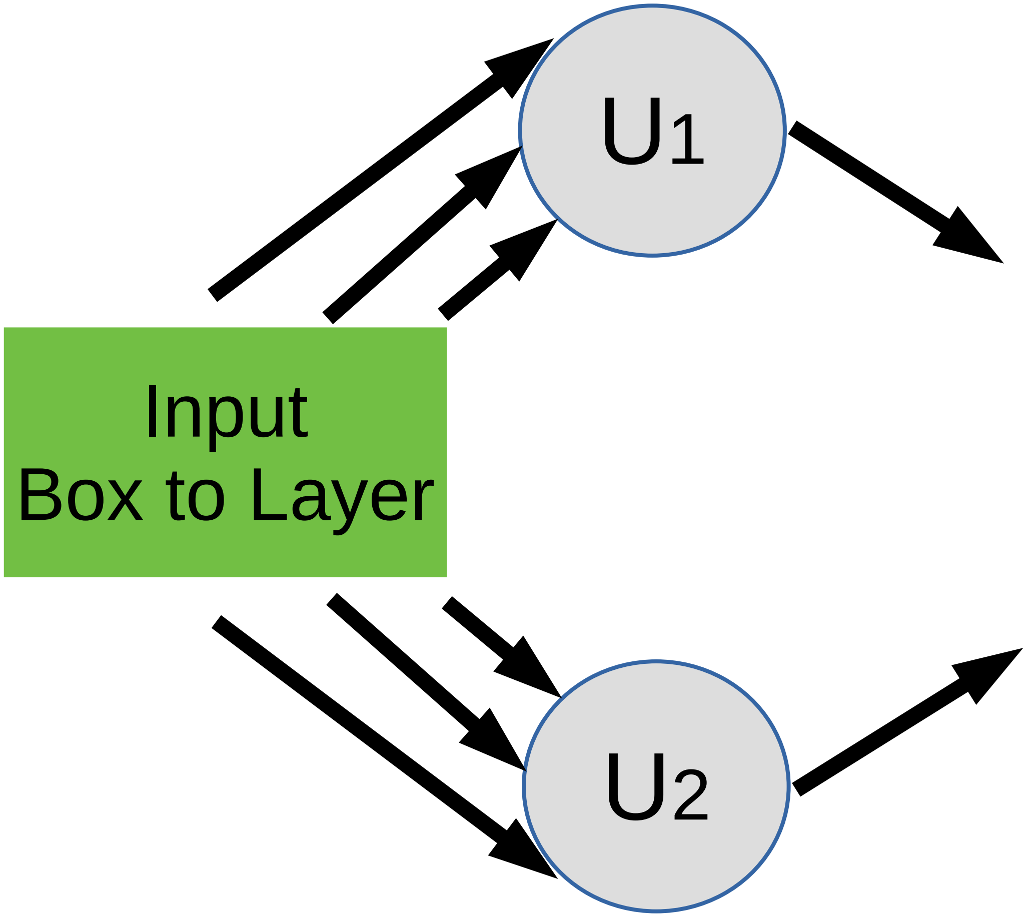
https://upload.wikimedia.org/wikipedia/commons/8/88/Logistic-curve.svg

Getting One Box In / Out of System, Cnt.

Propagating Through Layers

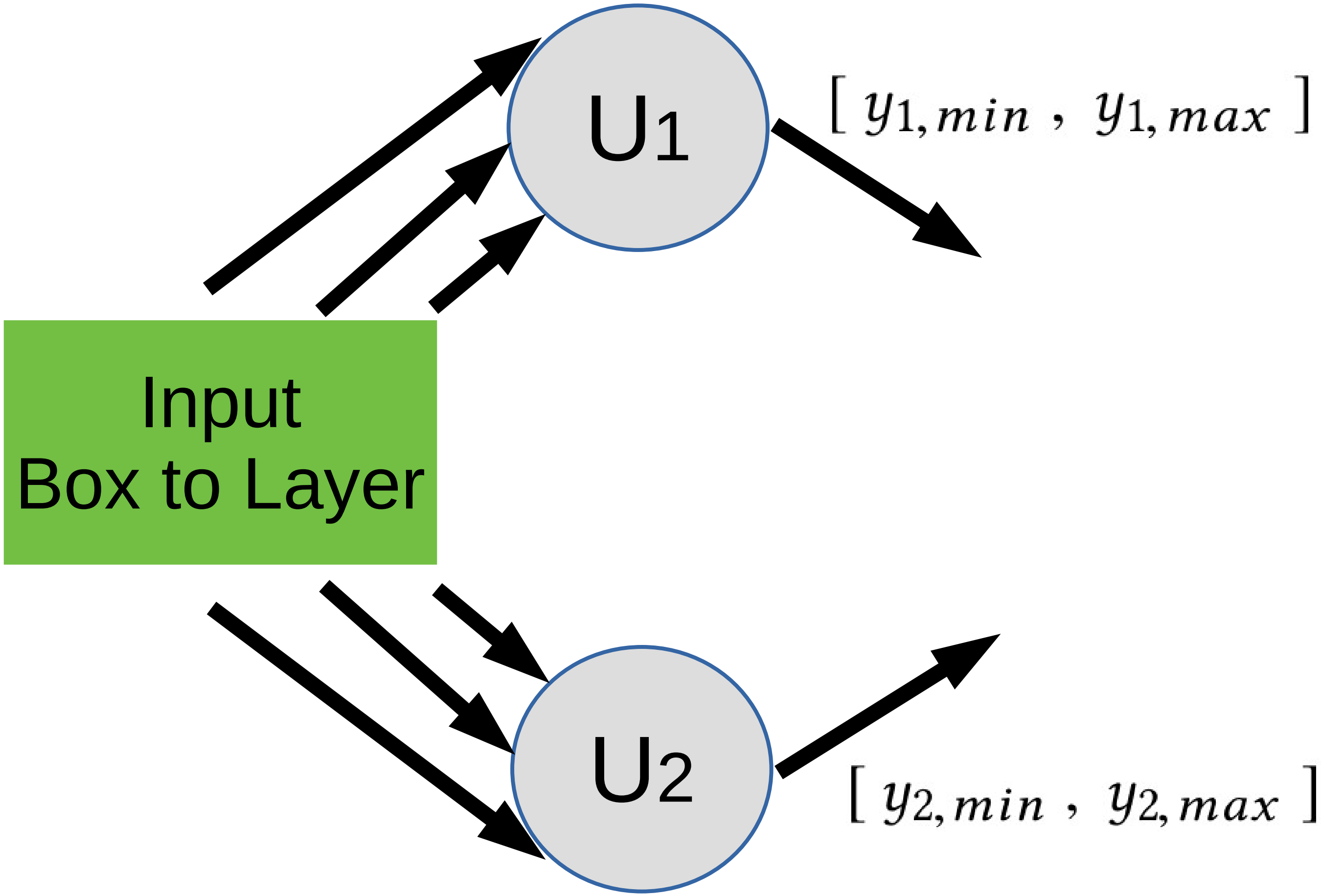
Getting One Box In / Out of System, Cnt.

Propagating Through Layers



Getting One Box In / Out of System, Cnt.

Propagating Through Layers



Input Box to Layer

U1

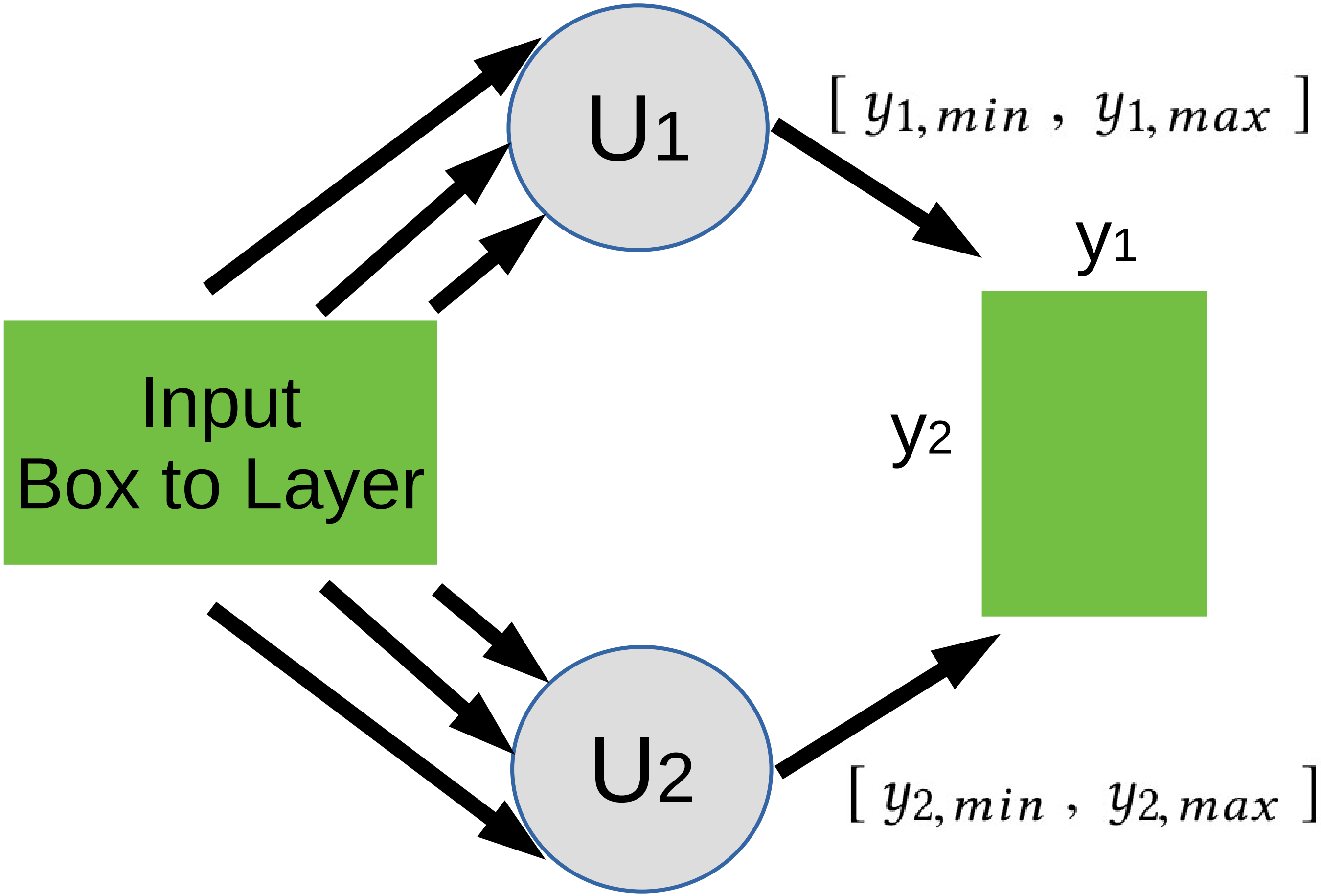
$[\, y_{1,min} \;,\; y_{1,max} \,]$

U2

$[\, y_{2,min} \;,\; y_{2,max} \,]$

Getting One Box In / Out of System, Cnt.

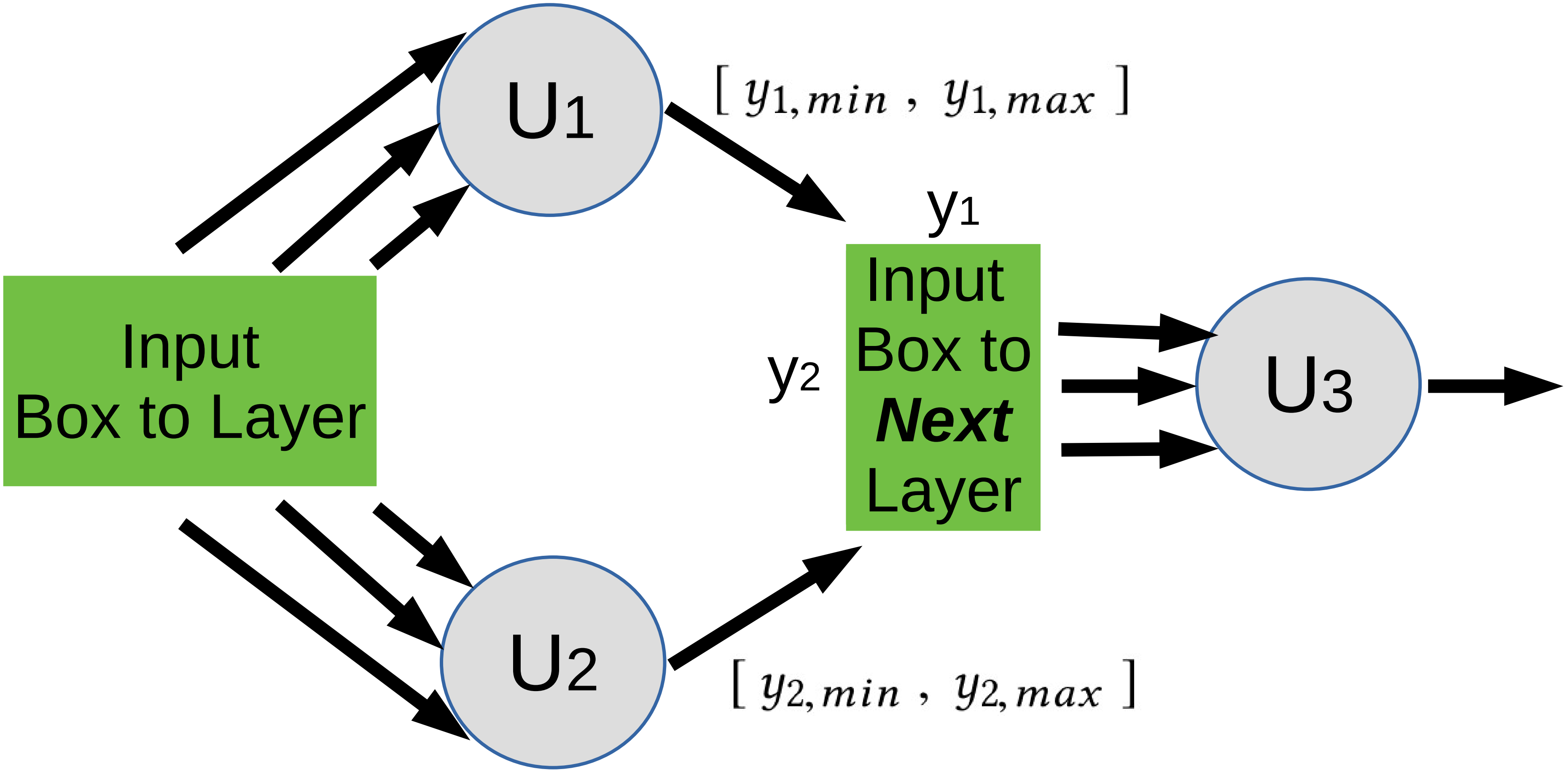
Propagating Through Layers



Input
Box to Layer
U1
U2
$[\, y_{1,min} \,,\, y_{1,max} \,]$
$[\, y_{2,min} \,,\, y_{2,max} \,]$
y1
y2

Getting One Box In / Out of System, Cnt.

Propagating Through Layers



U1
$[\, y_{1,min} \, , \, y_{1,max} \,]$
y1
Input Box to Layer
y2
Input Box to ***Next*** Layer
U3
U2
$[\, y_{2,min} \, , \, y_{2,max} \,]$

Getting One Box In / Out of System, Cnt.

Propagating Through Layers

This is where approximation enters. Ex: consider if $y_1 = y_2$

Getting One Box In / Out of System, Cnt.

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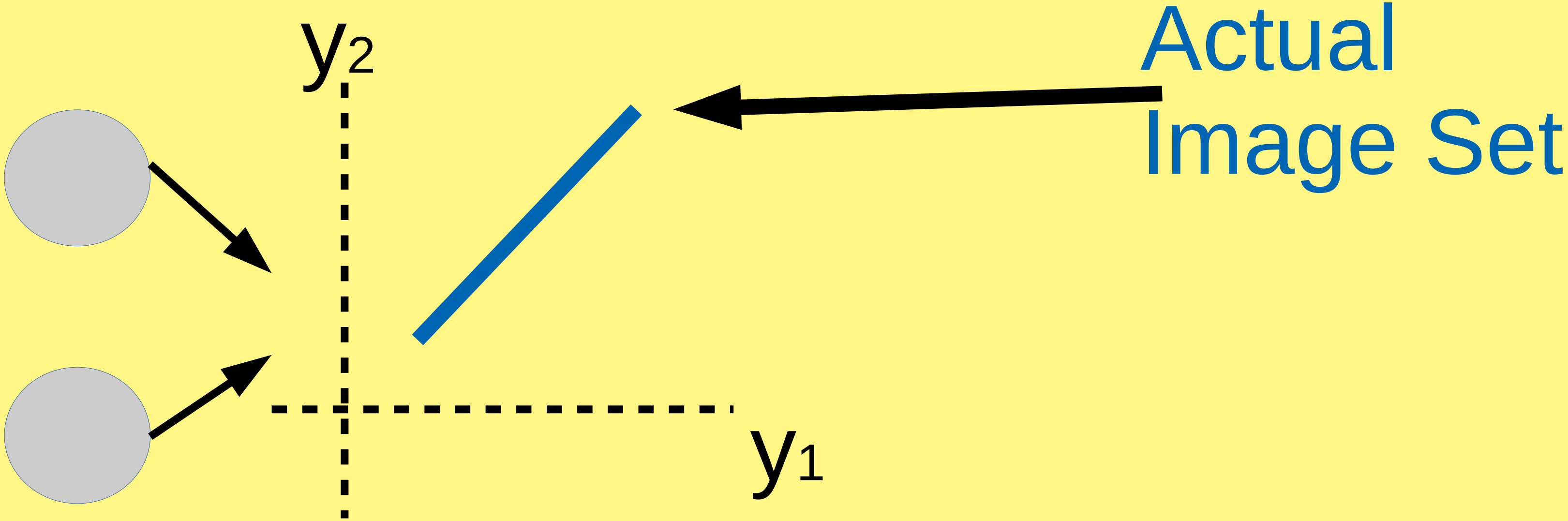

Getting One Box In / Out of System, Cnt.

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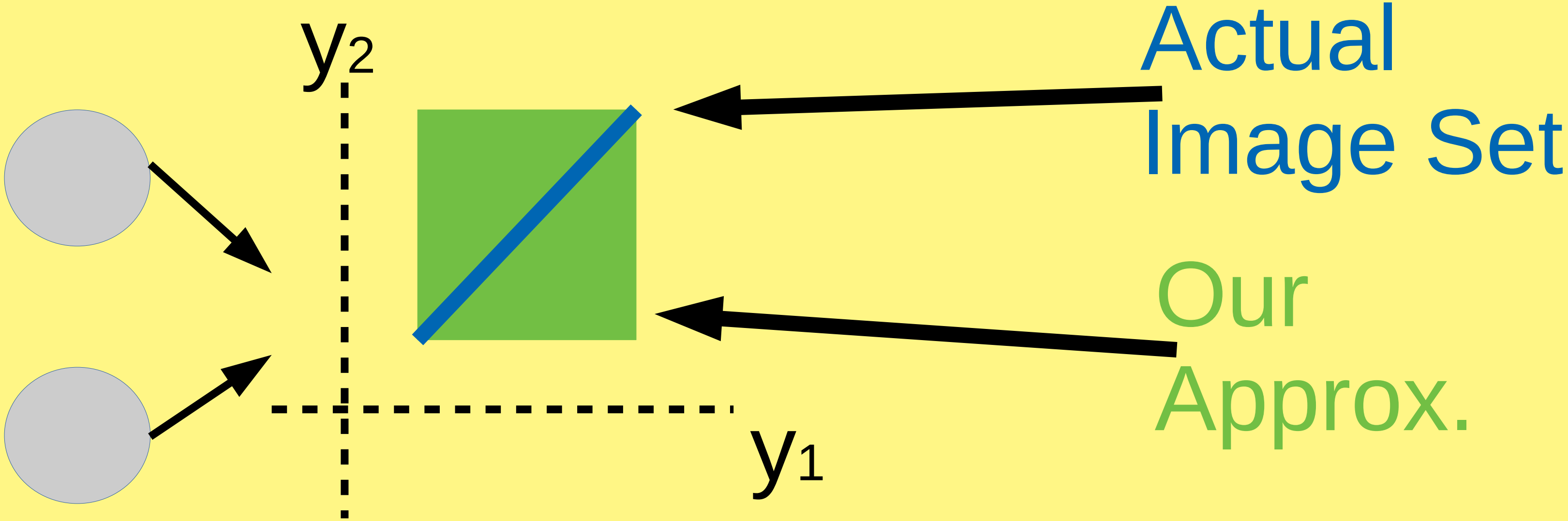
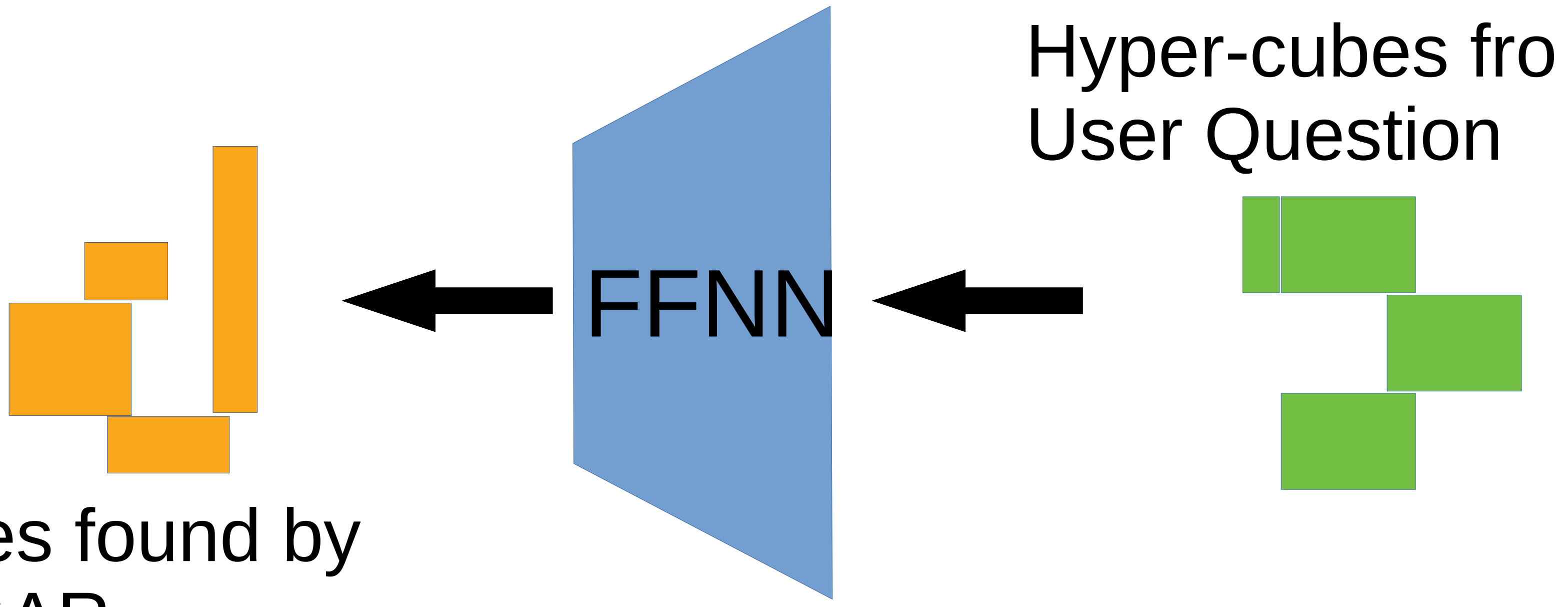


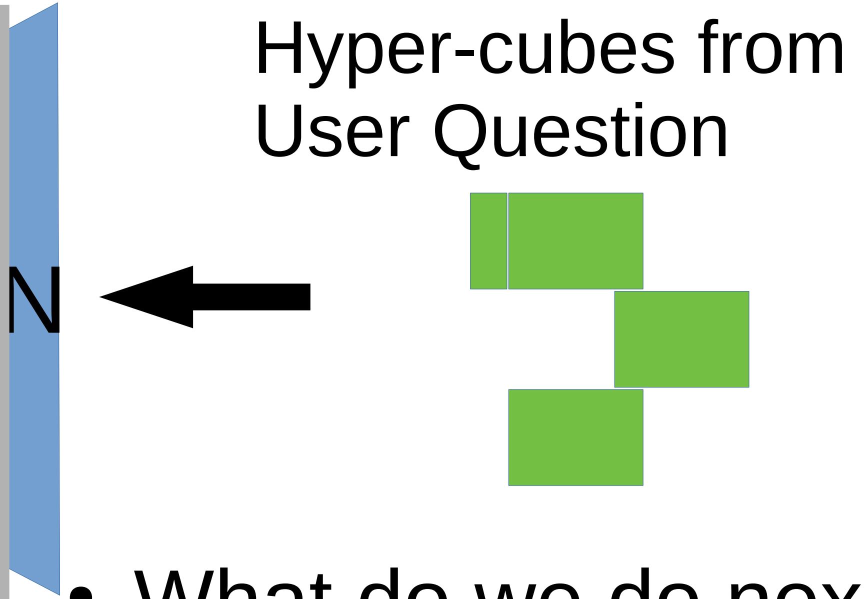
What we have so far:



- **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



- What do we do next?
  - Describe the found boxes
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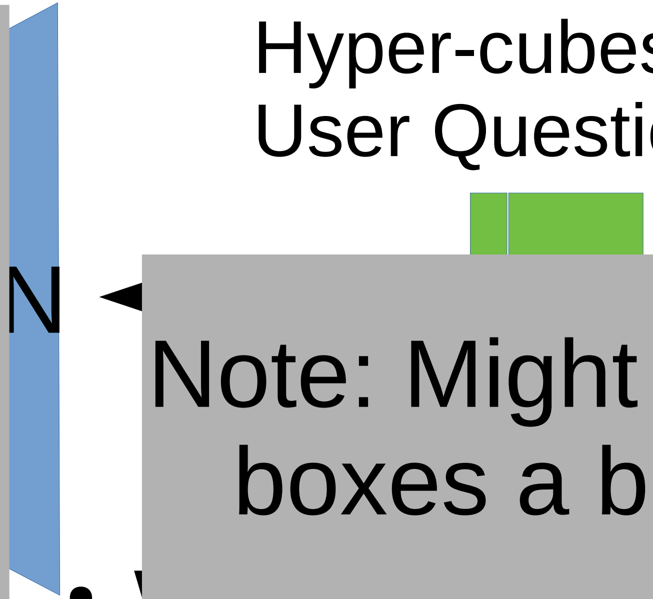
What we have so far:

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



Hyper-cubes from User Question

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 predicates that hold over B
    1. “feasibility check”: try on random sample from B first
    2. Check with SAT-Solver
2) Get most specific predicates

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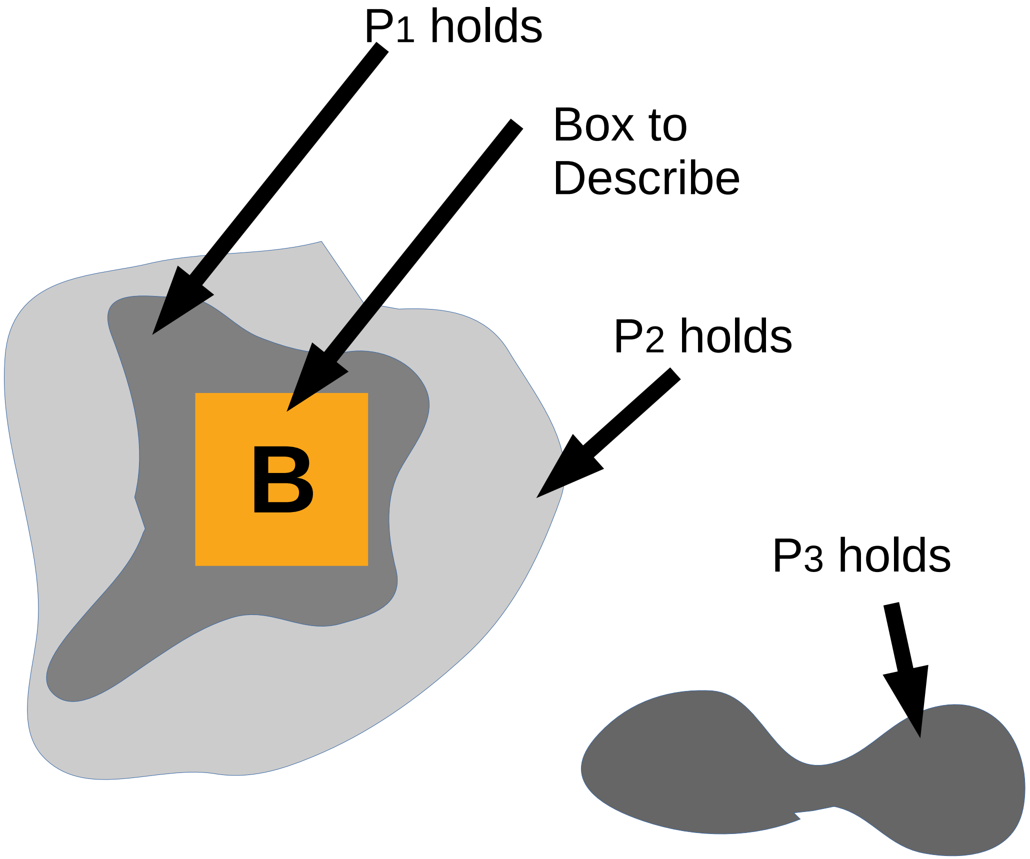

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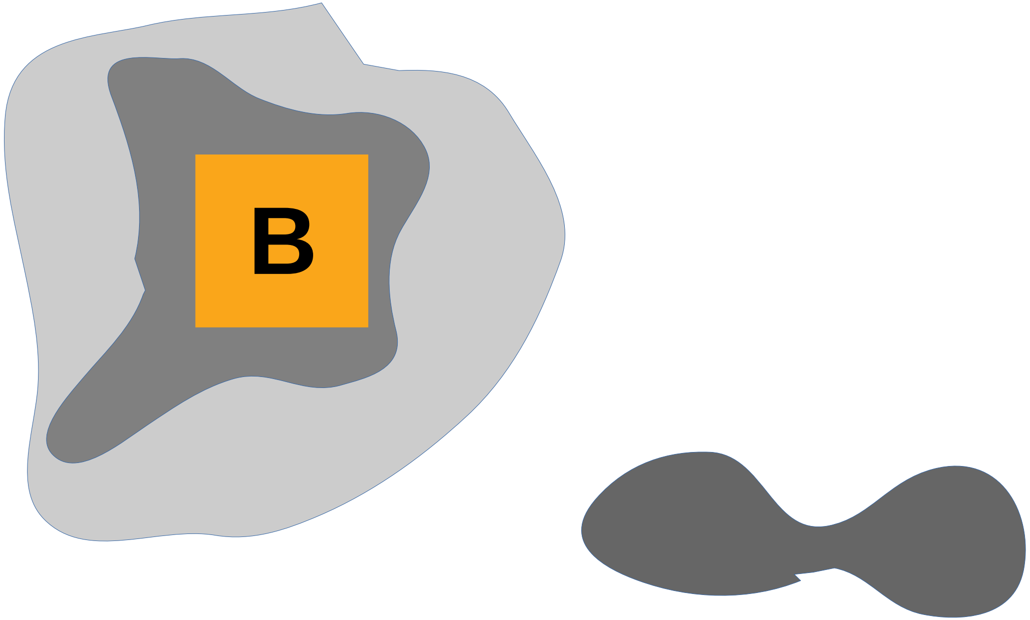

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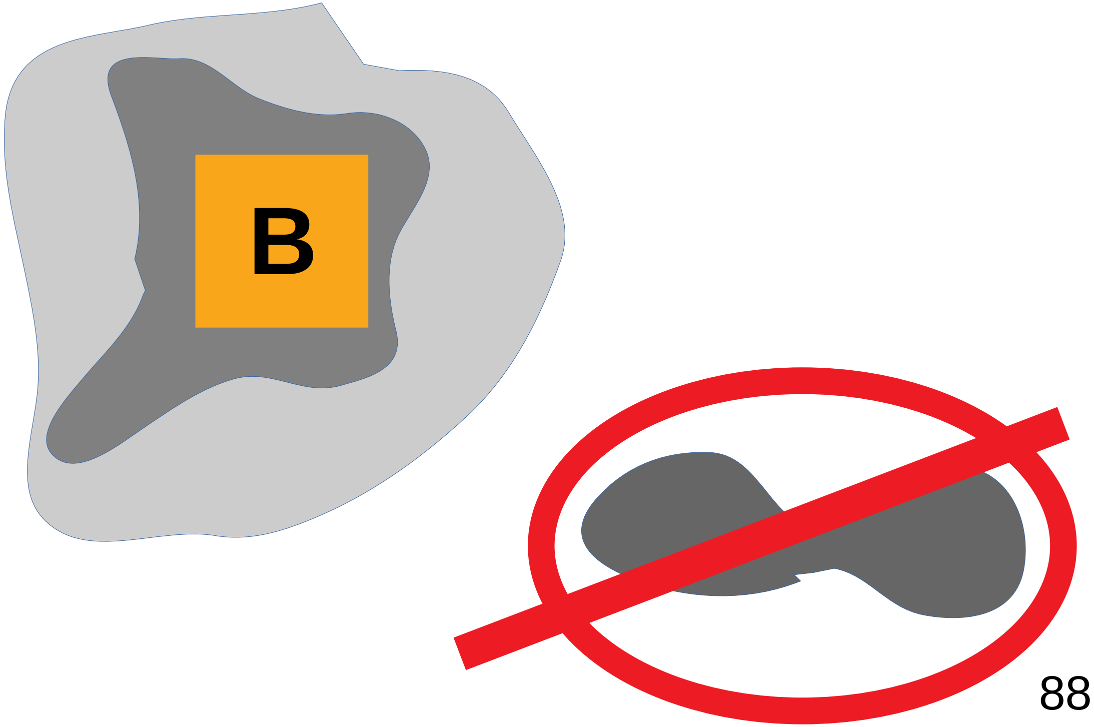
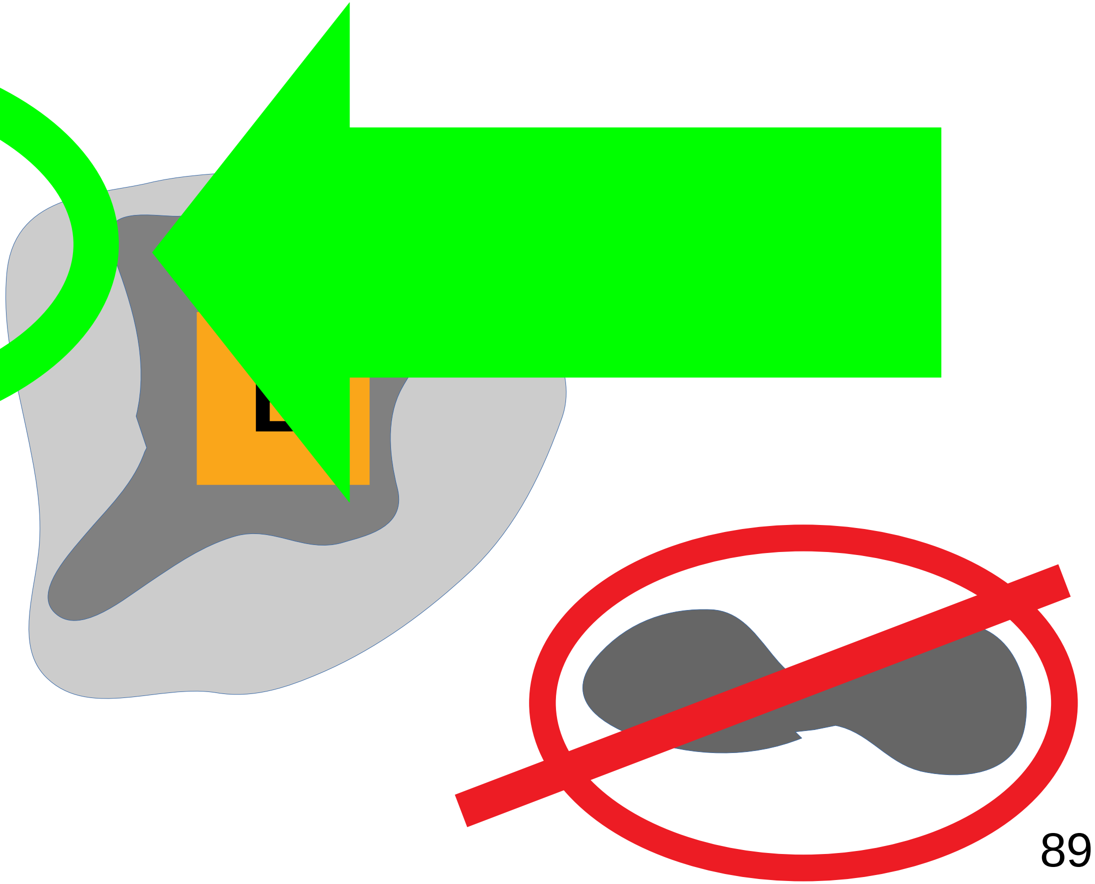


Step 2.1: Getting Candidate Preds. For Each Box

For each box, B:

1) Get predicates that hold over B, **“H(B)”**
   1. “feasibility check”: try on random samples from B first
   2. Check with SAT-Solver

2) Get most specific predicates



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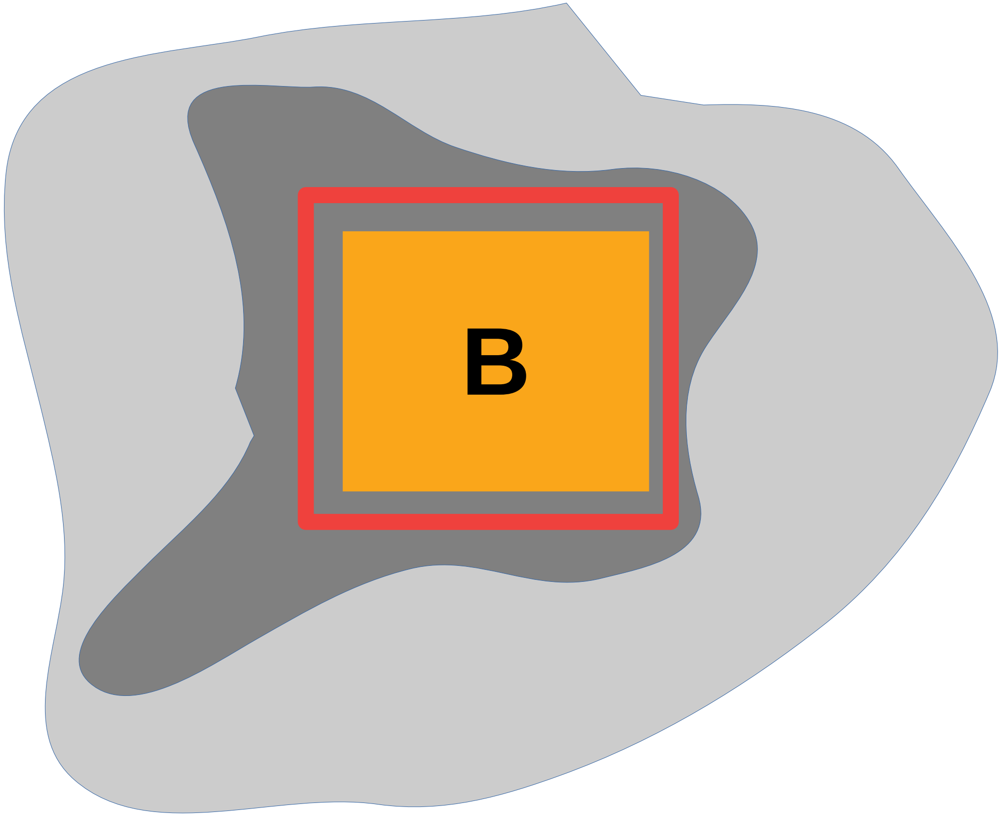

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For each box, B:

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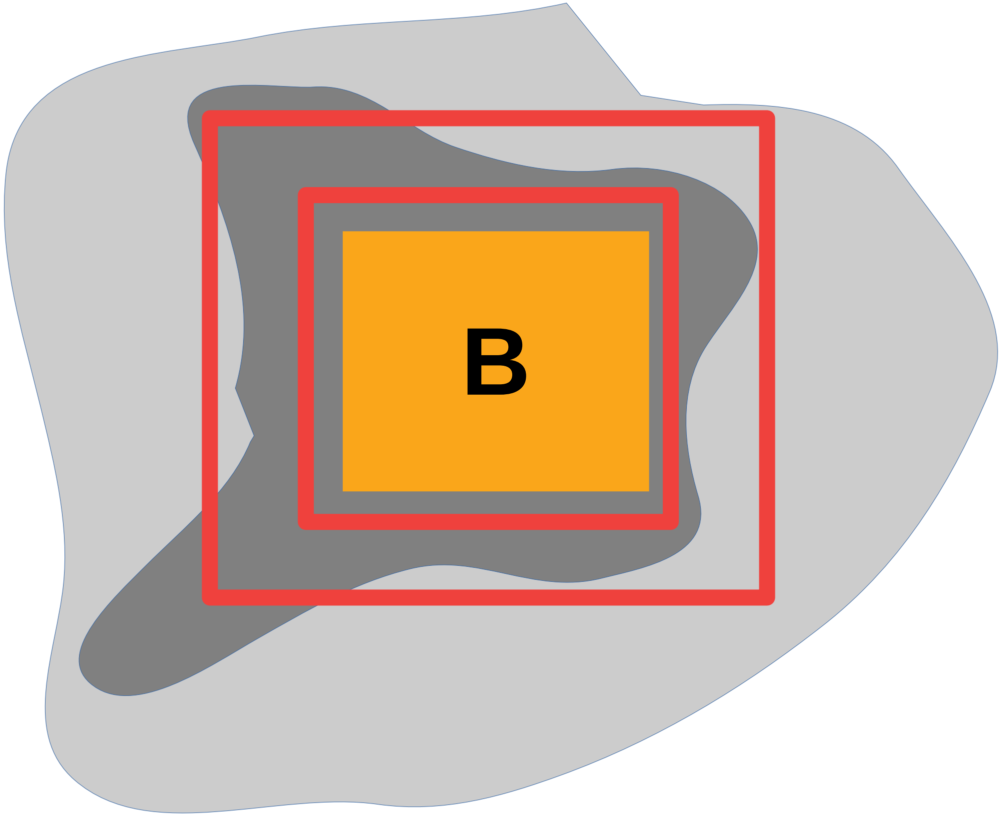
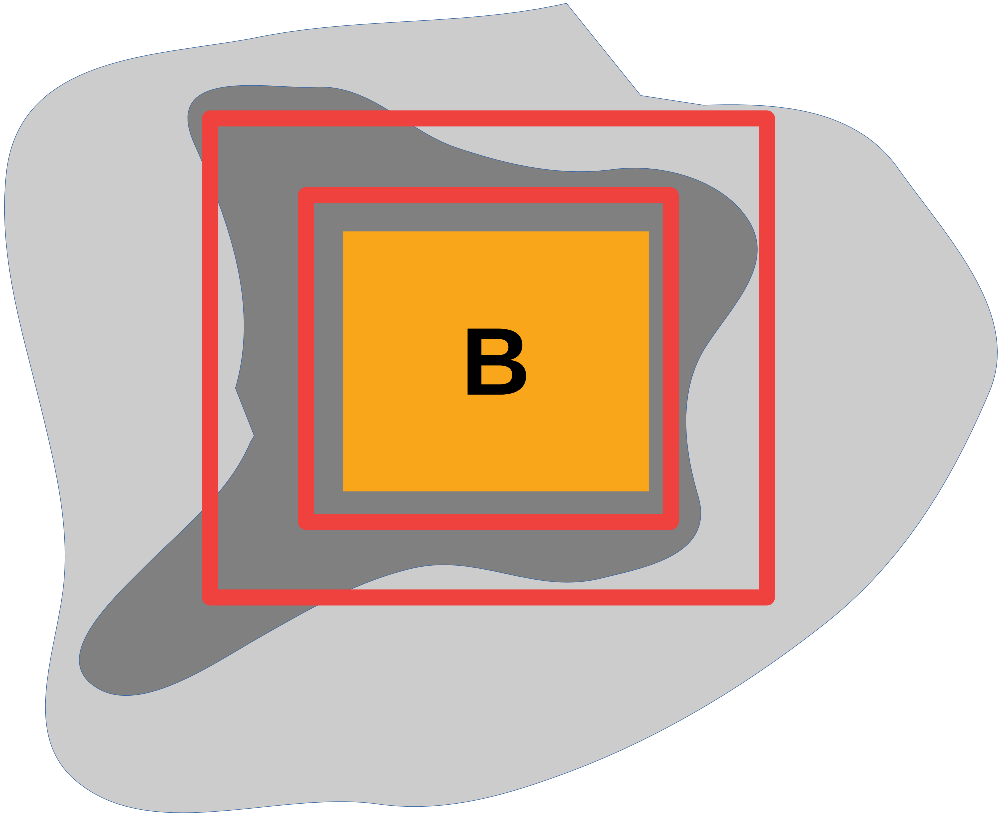


Step 2.1: Getting Candidate Preds. For Each Box

For each box, B:

1) Get predicates that hold over B, **“H(B)”**
   1. “feasibility check”: try on random sample from B first
   2. Check with SAT-Solver

2) Get most specific predicates



Note: Can utilize a taxonomy for filtering,
If provided

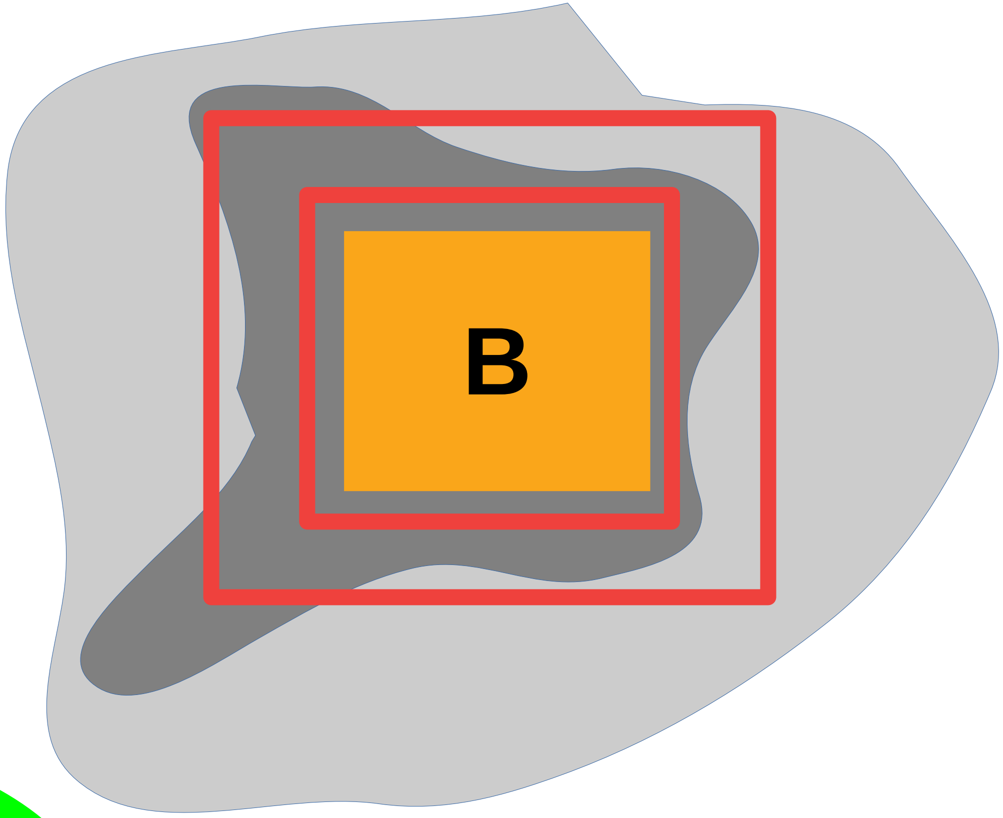
Step 2.1: Getting Candidate Preds. For Each Box

For ox, B:

1)Ge cates that hol B, **“H(B)”**

1. “fe check”: try on ample fr
2. Check with SAT-Solver

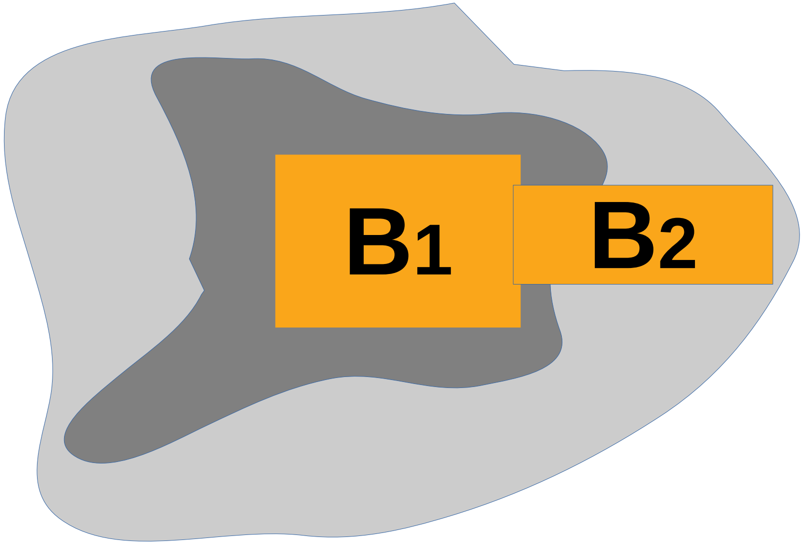
2) Get most specific predicates , **“S(B)”**

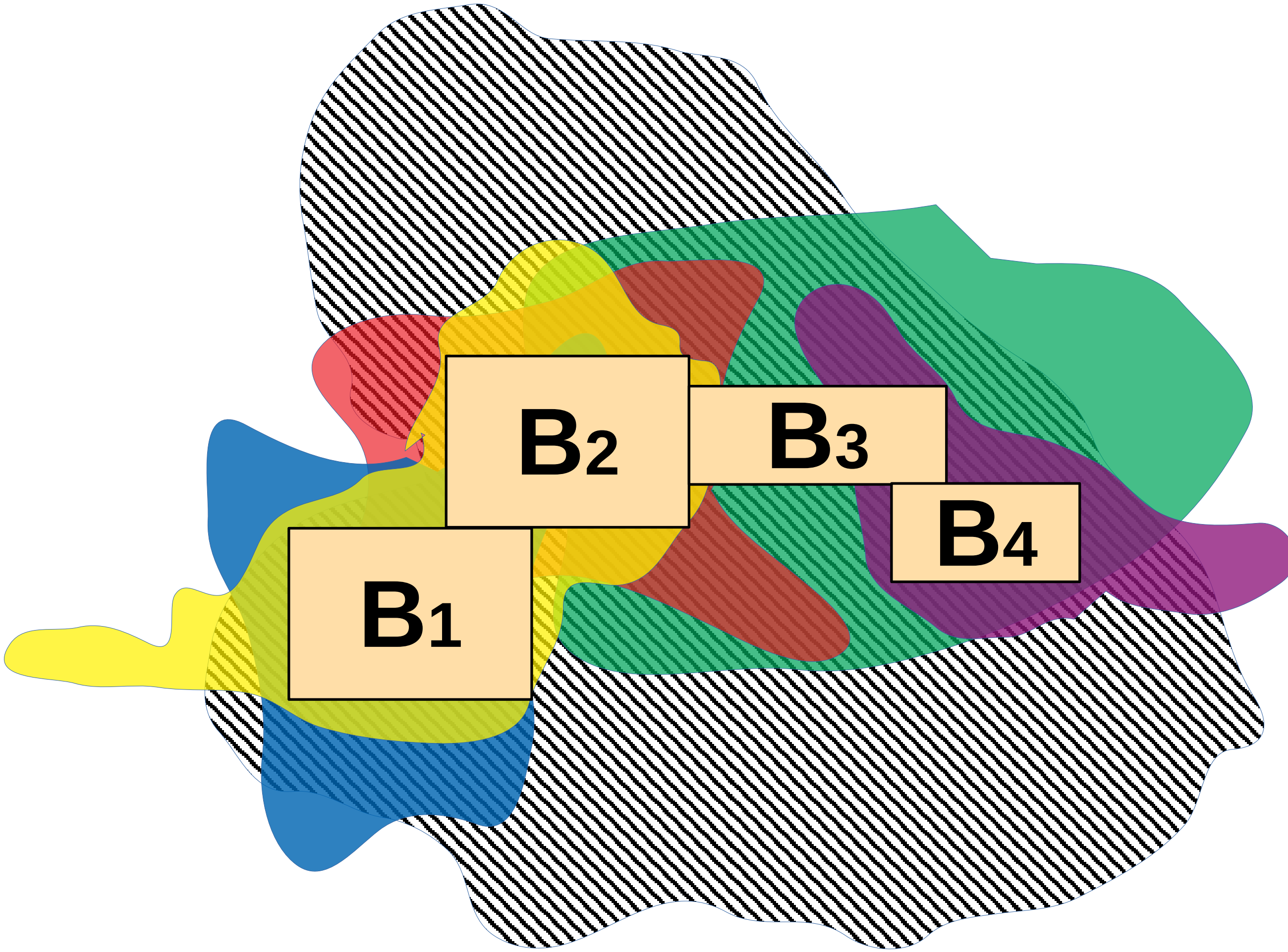


Note: Can utilize a taxonomy for filtering, if provided

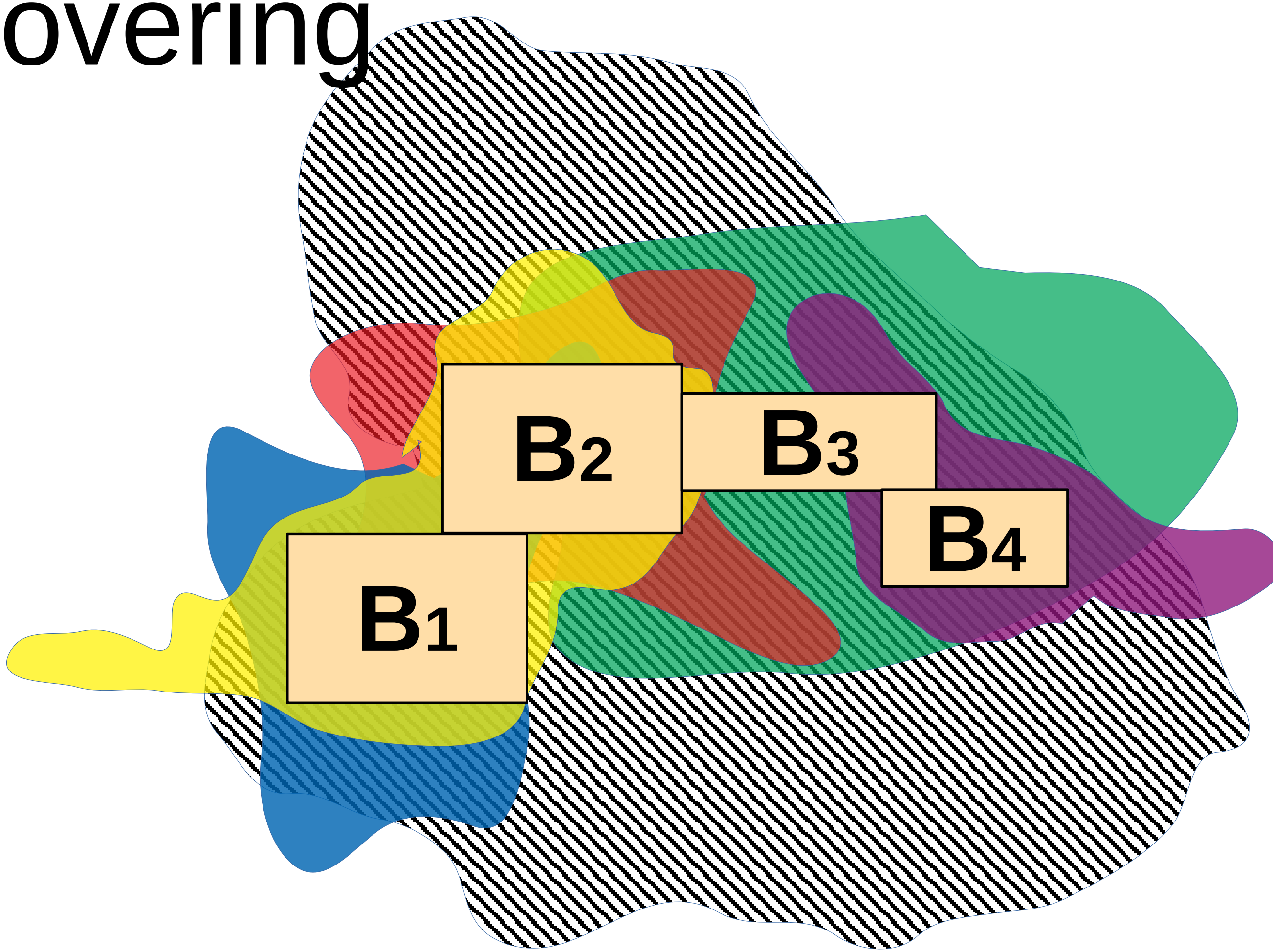
Step 2.2: Forming Global Covering

- Actually do ***two*** coverings: details in next slides
- Some subtleties for multi-dimensional setting
  - Ex: may need multiple preds to cover box; one pred variable x, another might cover y



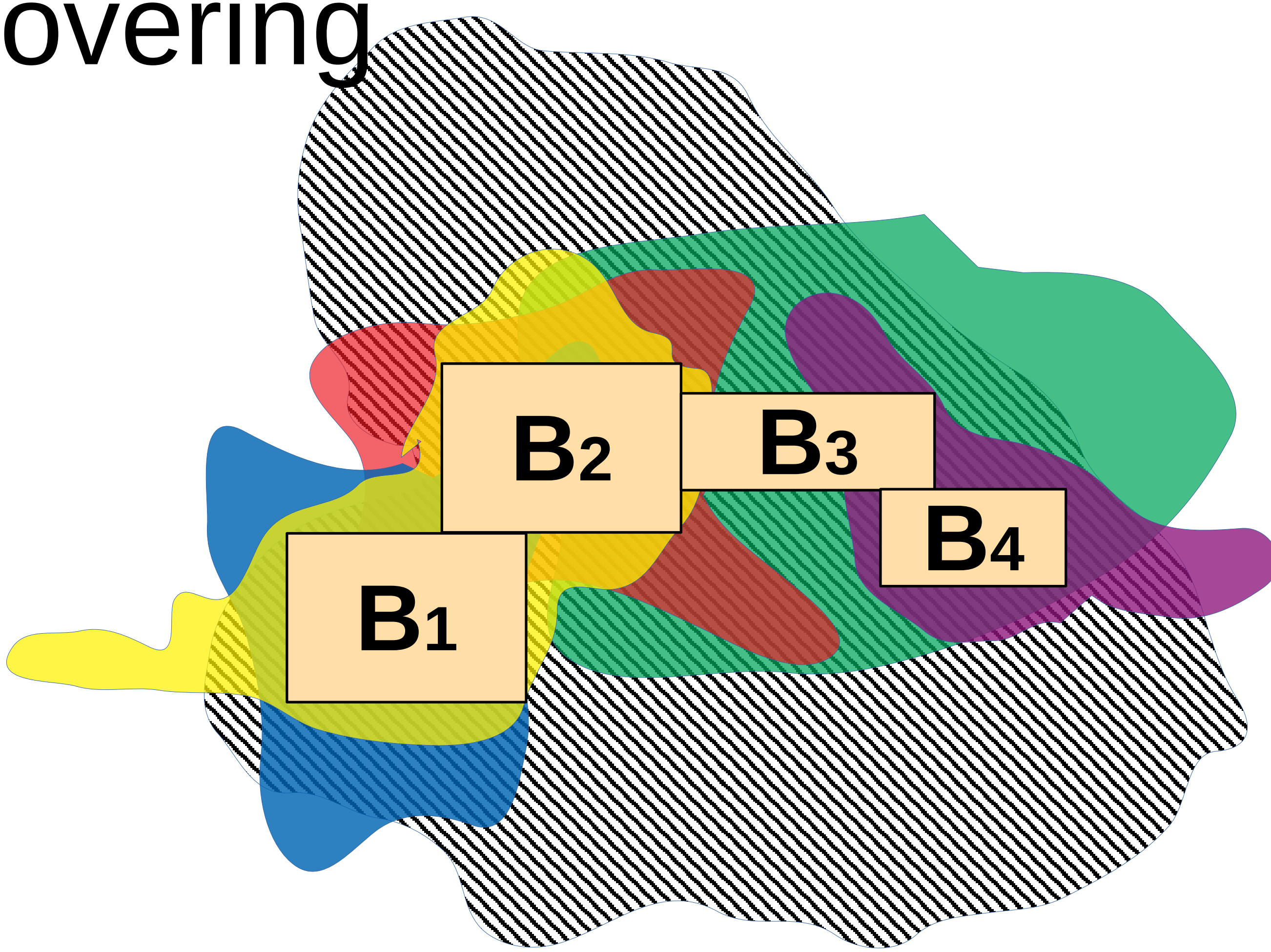

B_2
B_3
B_4
B_1

Start of *First* Covering



Start of *First* Covering

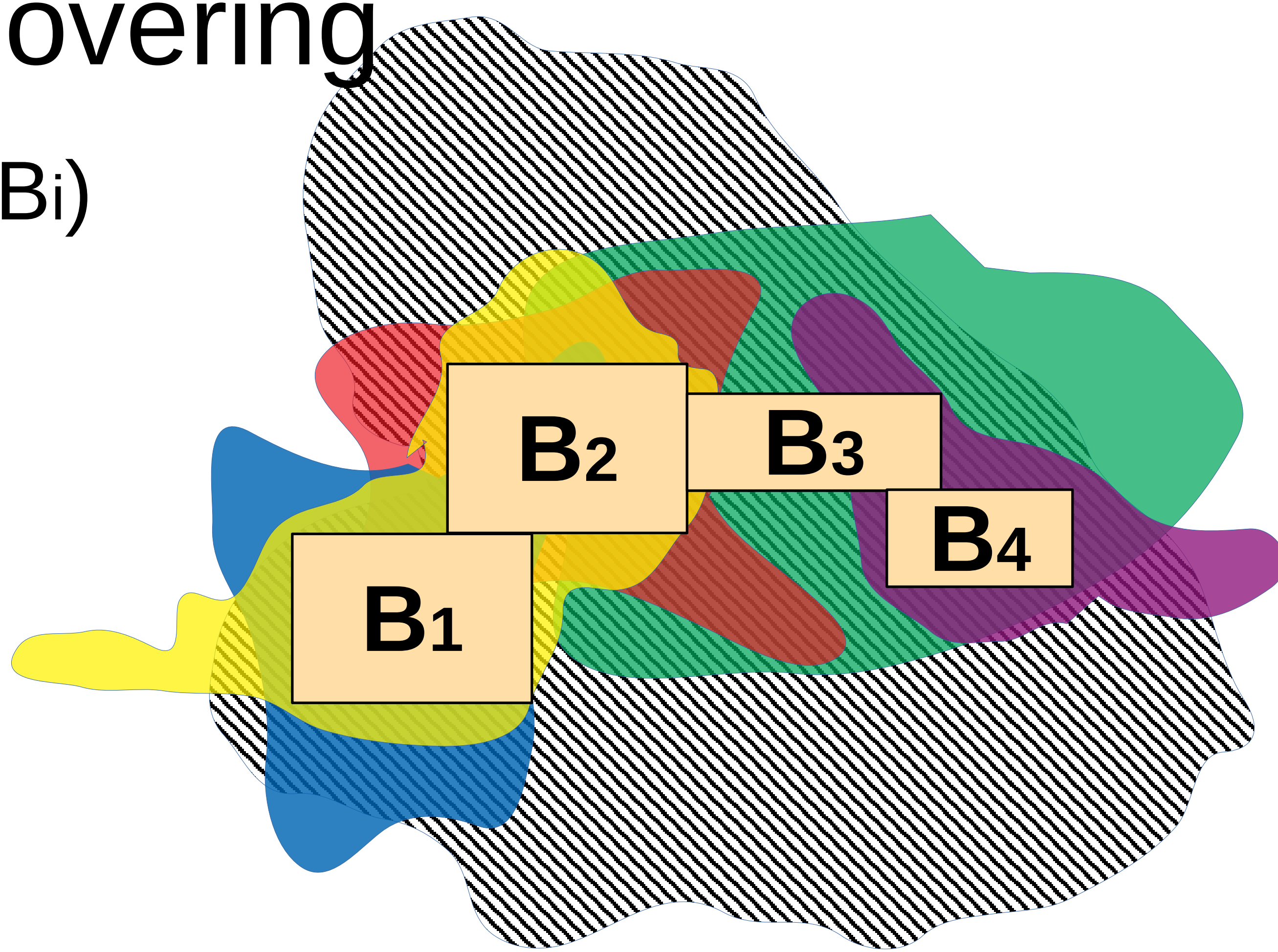
Boxes	Options
B_1	
B_2	
B_3	
B_4	



Start of *First* Covering

- Options(B_i) = S(B_i)

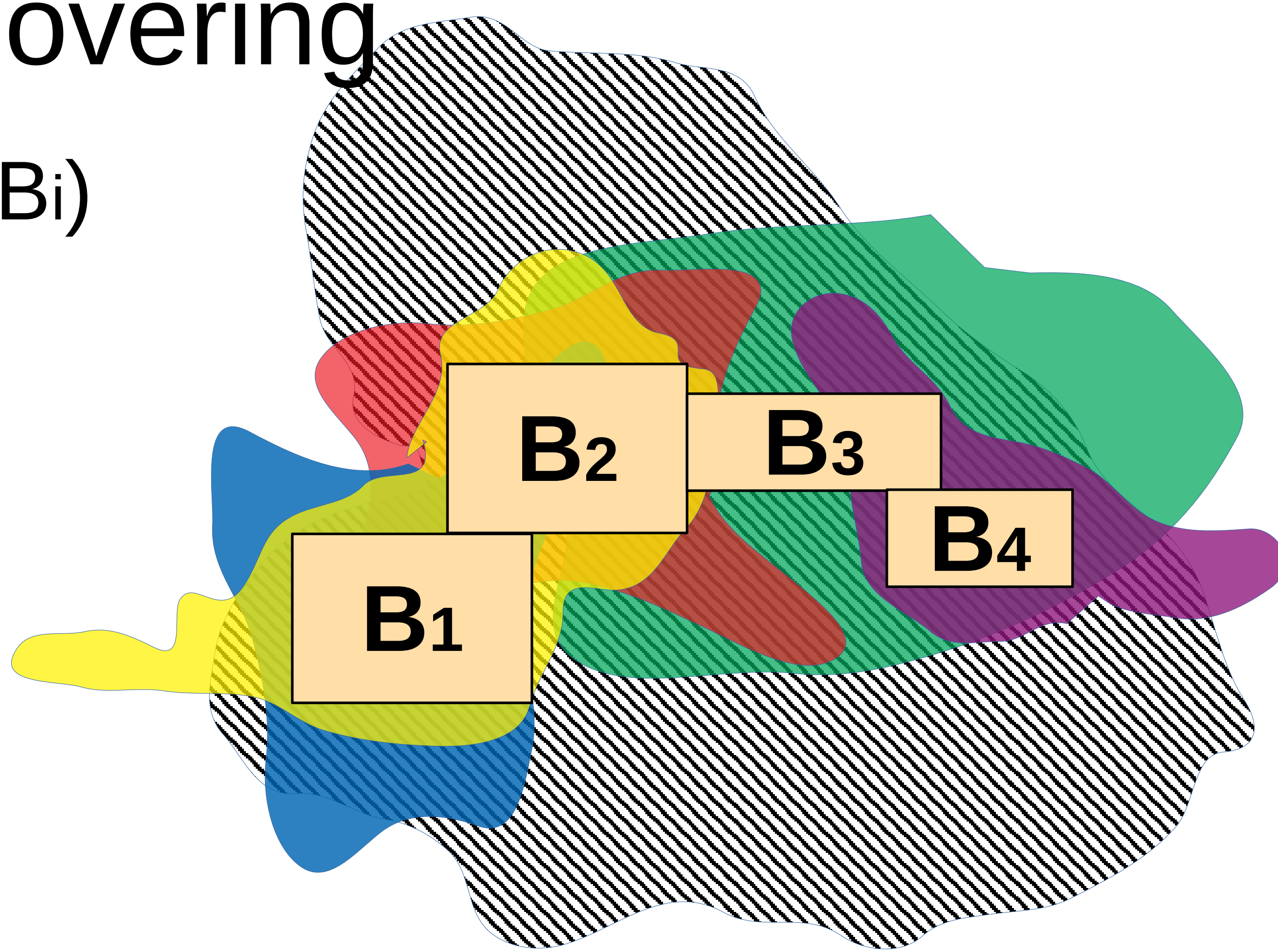
Boxes	Options
B_1	🟨 🟦
B_2	🟨 🟥
B_3	🟩
B_4	🟪



Start of *First* Covering

- Options(B_i) = S(B_i)

Boxes	Options
B_1	🟨 🟦
B_2	🟨 🟥
B_3	🟩
B_4	🟪

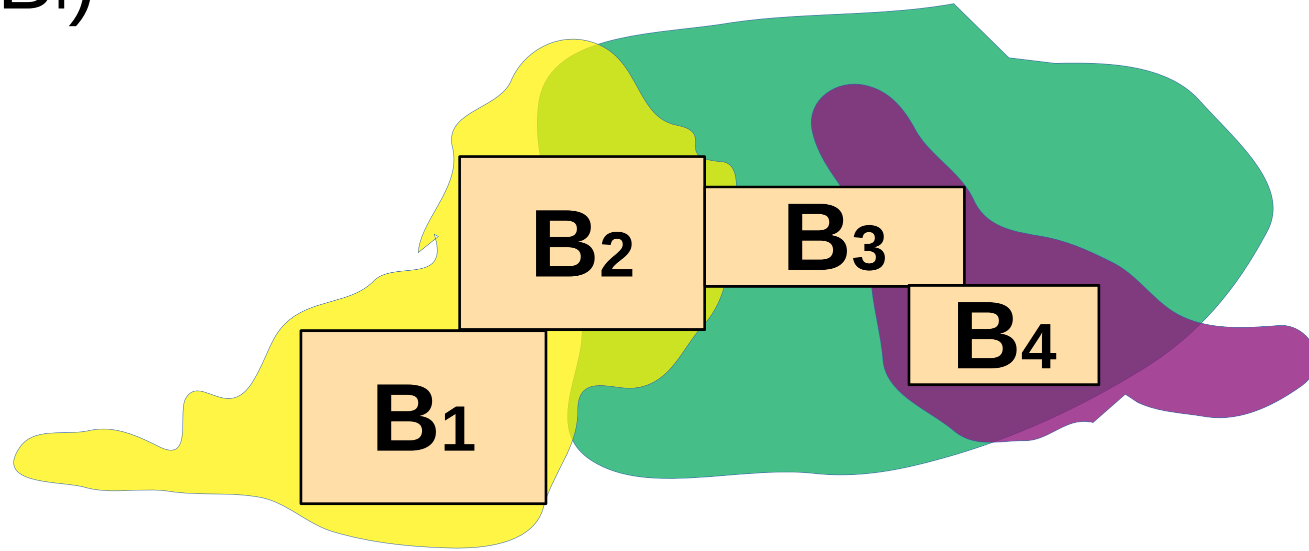


Green not listed because it was less specific,
Despite green covering B4.

Start of *First* Covering

- Options(B_i) = S(B_i)

Boxes	Options
B_1	🟨 🟦
B_2	🟨 🟥
B_3	🟩
B_4	🟪



Green not listed because it was less specific,
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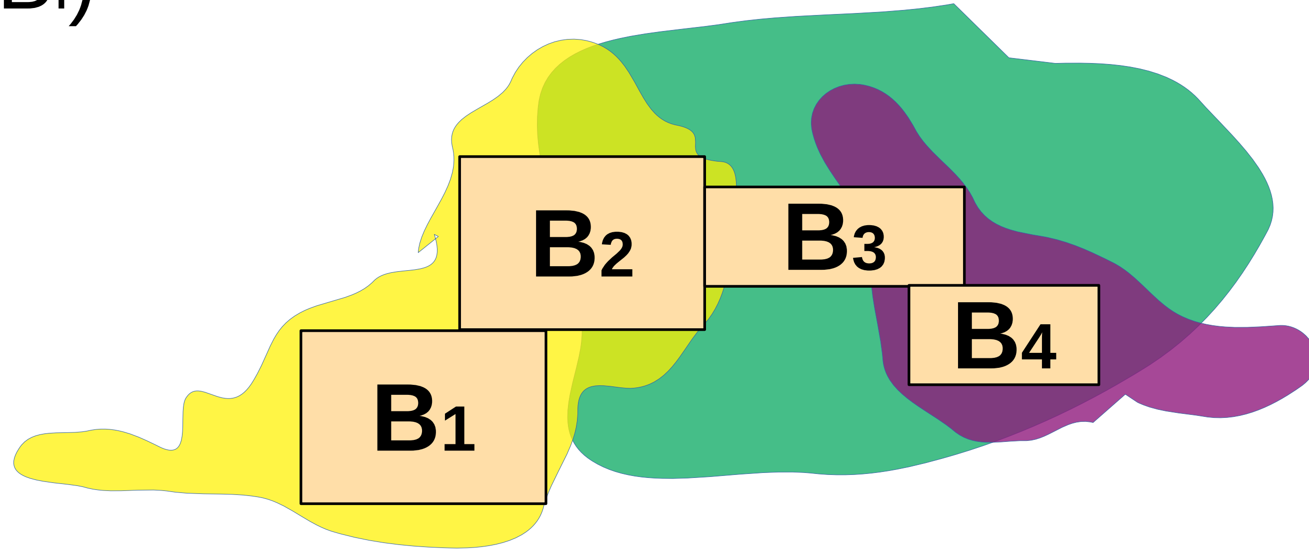
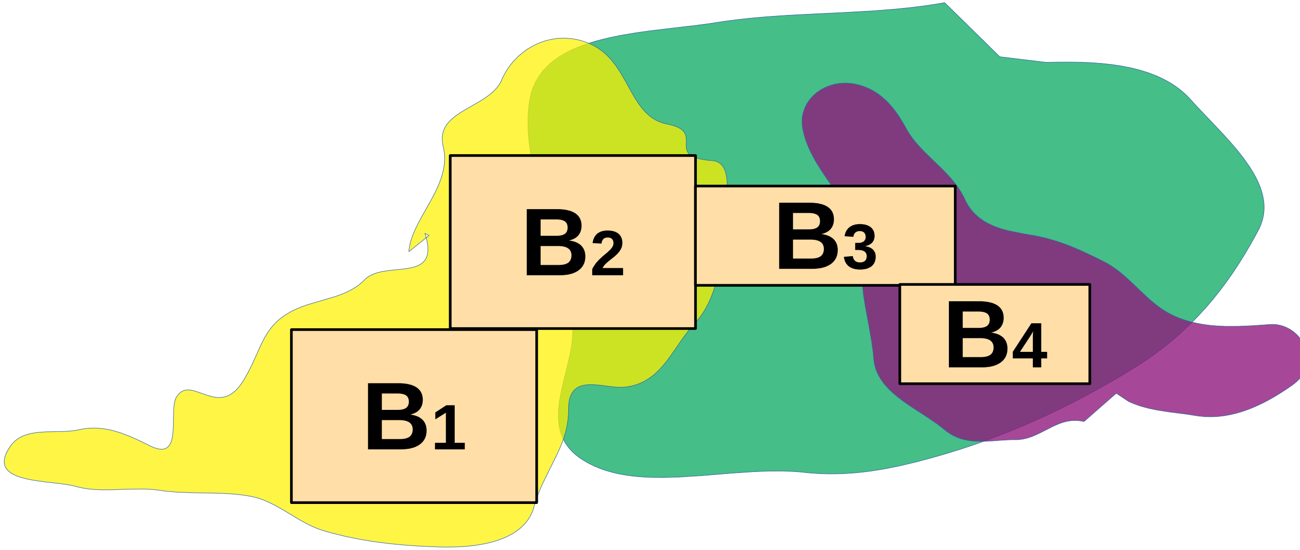
Start of *First* Covering

- Options(B_i) = S(B_i)

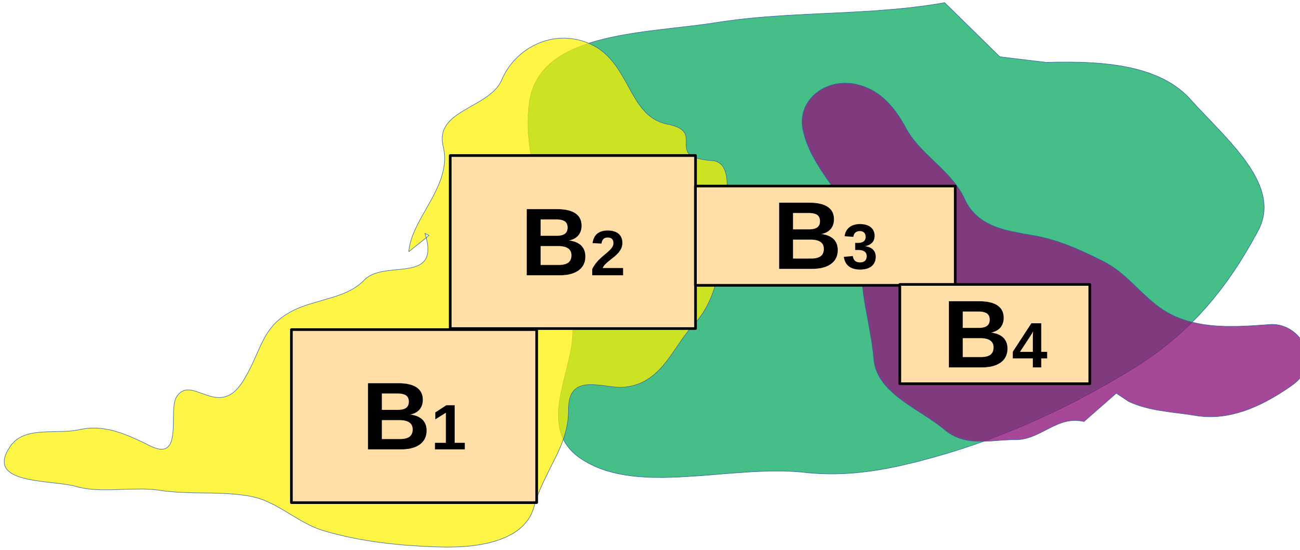
Boxes	Options
B_1	🟨 🟦
B_2	🟨 🟥
B_3	🟩
B_4	🟪



C_1 = { 🟨 , 🟩 , 🟪 }

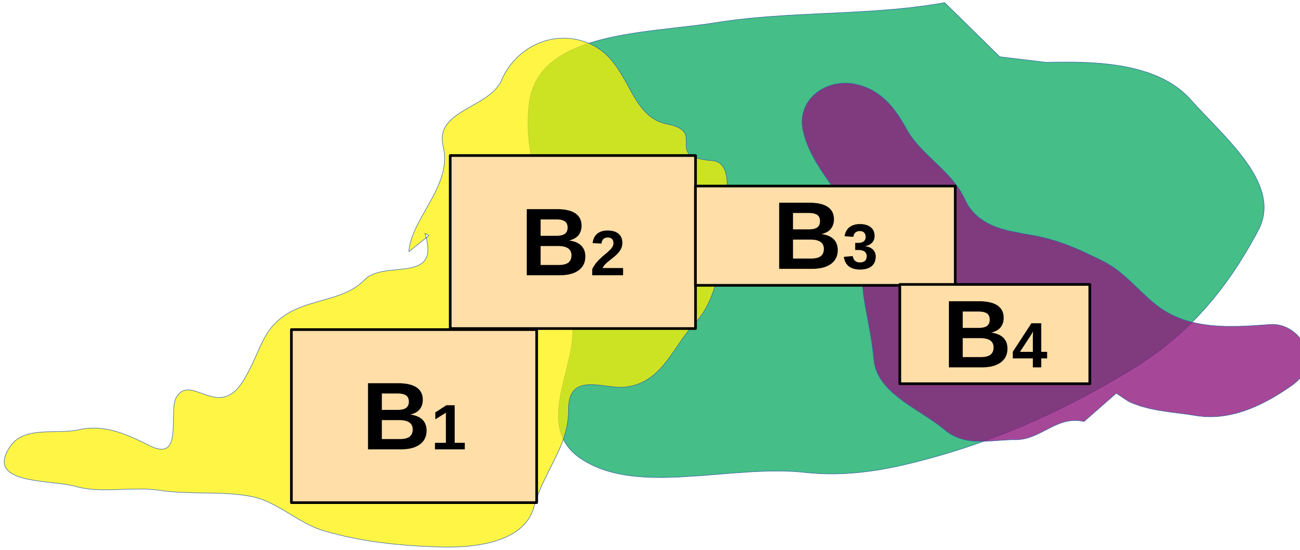

B_2
B_3
B_4
B_1

Start of *Second* Covering



Start of *Second* Covering

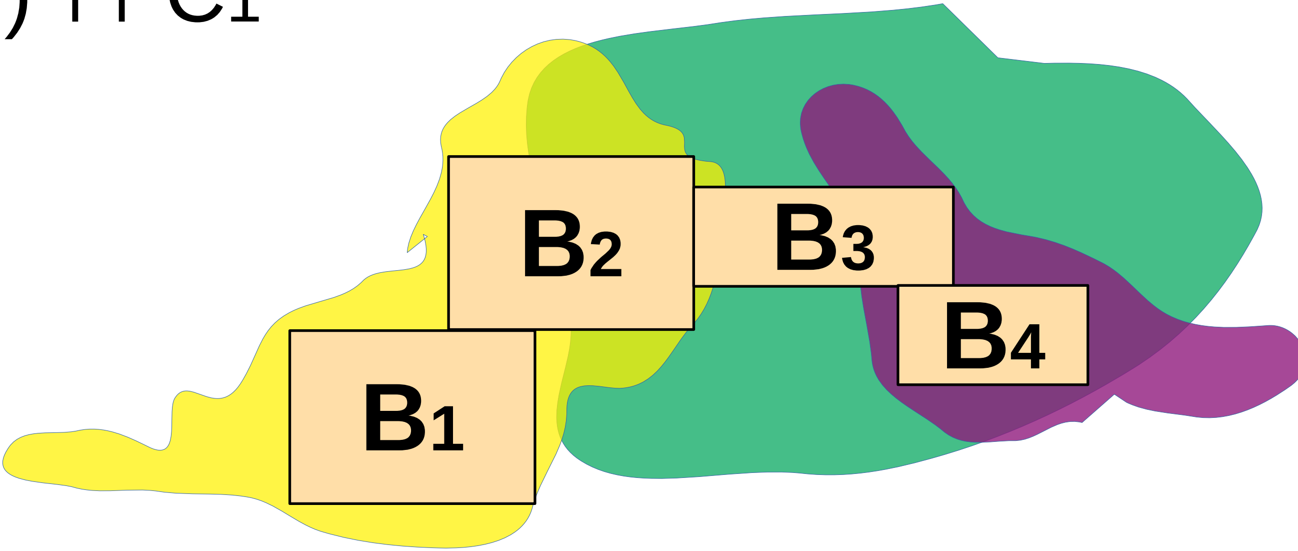
Boxes	Options
B_1	
B_2	
B_3	
B_4	



Start of *Second* Covering

- Options(B_i) = H(B_i) $\cap$ C_1

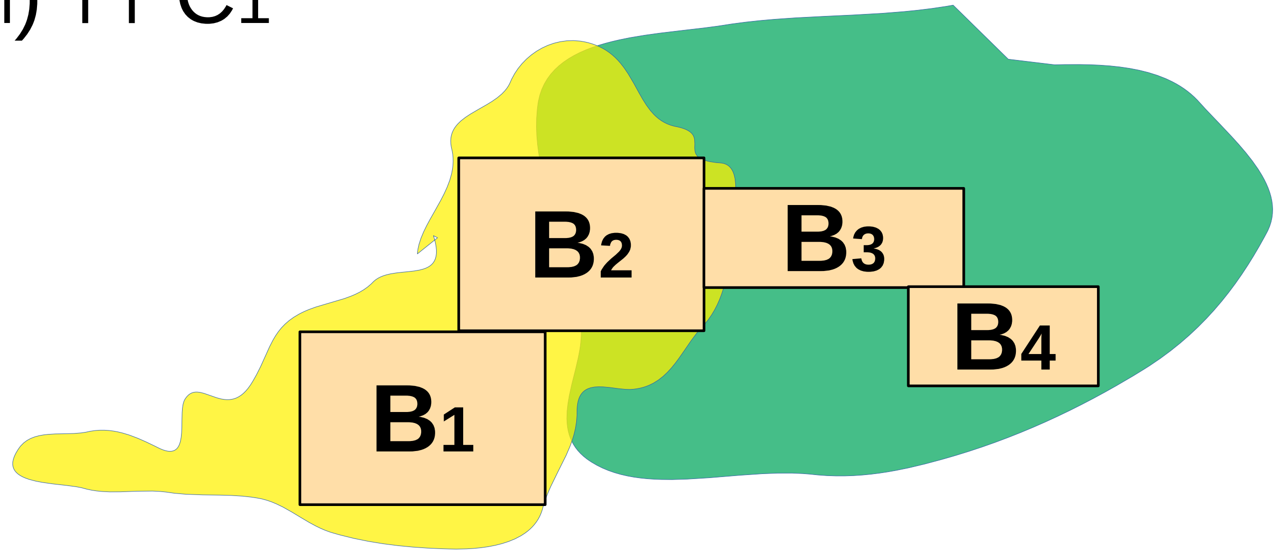
Boxes	Options
B_1	🟨
B_2	🟨
B_3	🟩
B_4	🟩 🟪



Start of *Second* Covering

- Options(B_i) = H(B_i) $\cap$ C_1

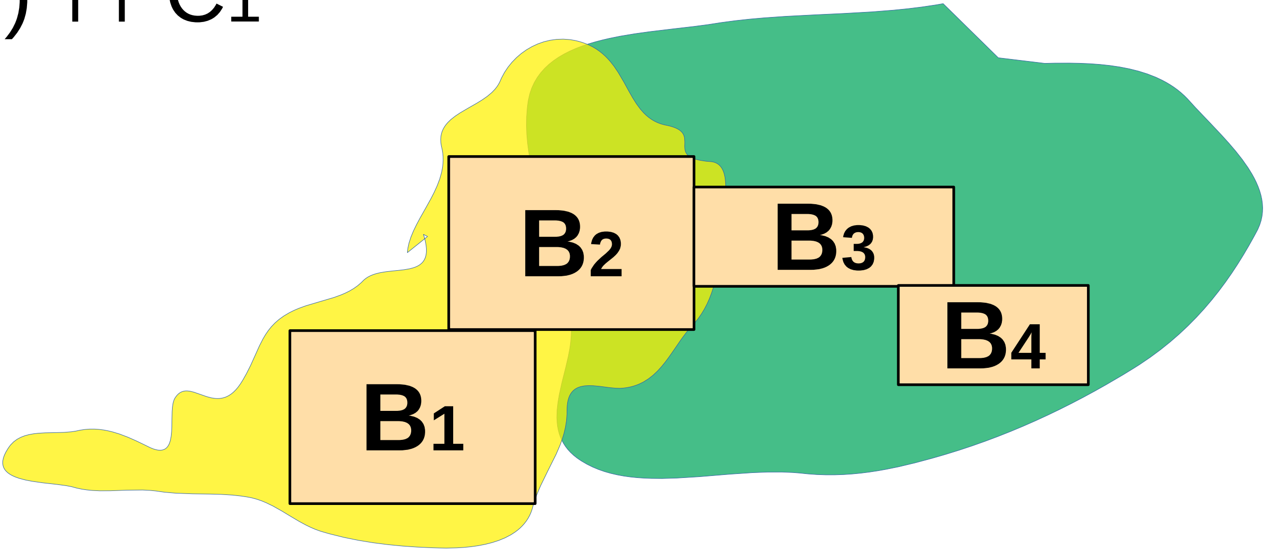
Boxes	Options
B_1	🟨
B_2	🟨
B_3	🟩
B_4	🟩 🟪



Start of *Second* Covering

- Options(B_i) = H(B_i) $\cap$ C_1

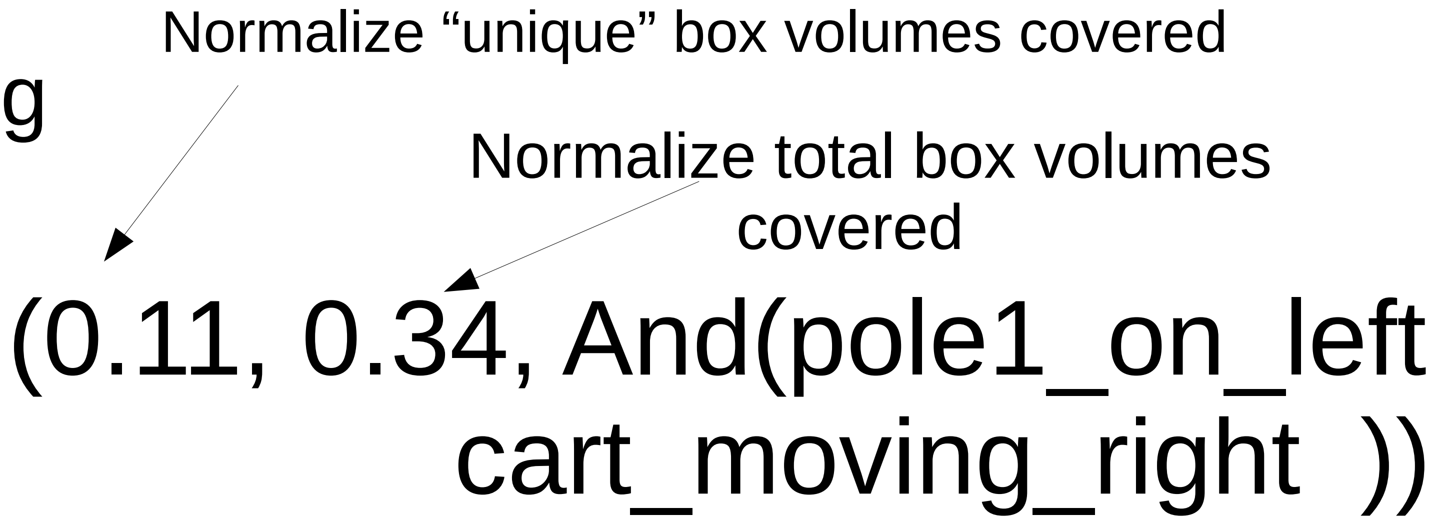
Boxes	Options
B_1	🟨
B_2	🟨
B_3	🟩
B_4	🟩 🟪



$C_2 = \{$ 🟨 , 🟩 $\}$

Cleaning and Presenting to User

- Some further post-processing
- Gather and show

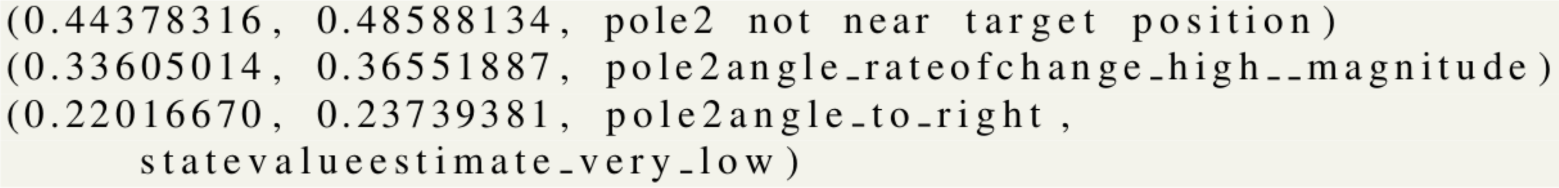


Normalize “unique” box volumes covered

Normalize total box volumes covered

(0.11, 0.34, And(pole1_on_left cart_moving_right))

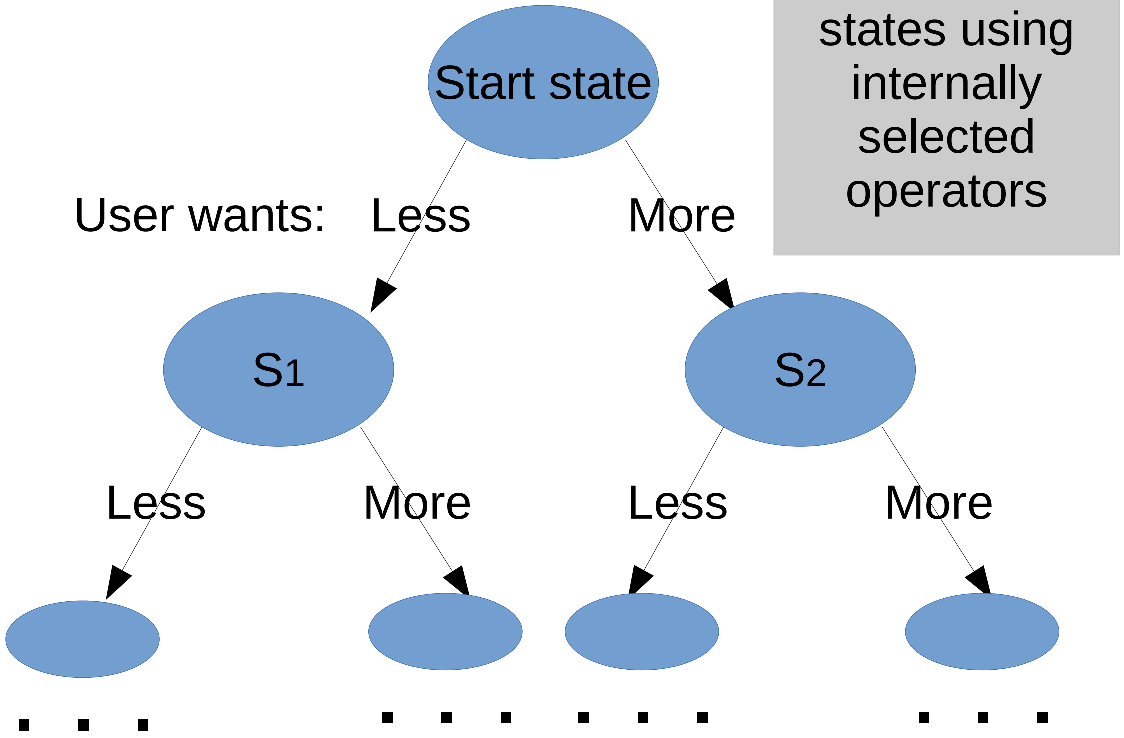
Output is a Weighted DNF



```
(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)
```

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



Get between states using internally selected operators

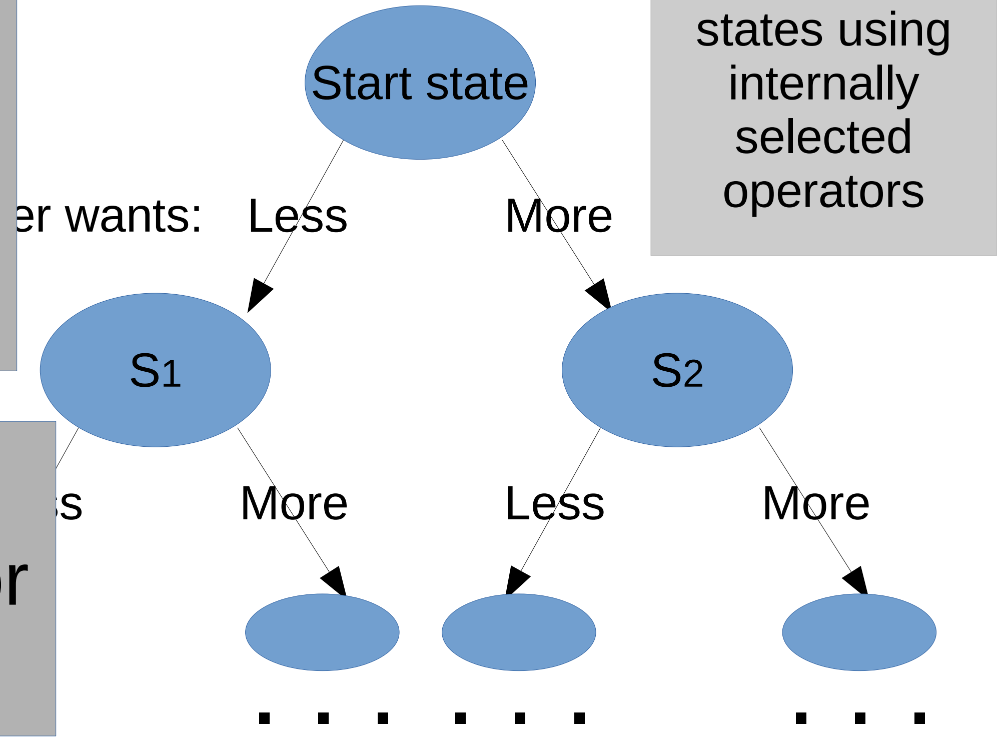
Using Feedback

- Fanoos l
  paramet
  - 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:
Start state
Less
More
S1
S2
s
More
Less
More
. . . .

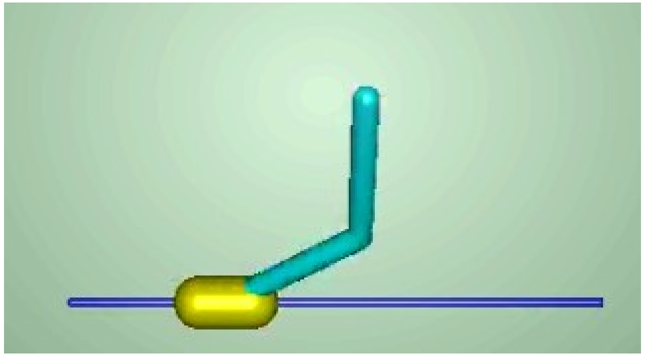
Get between states using internally selected operators

Experiments

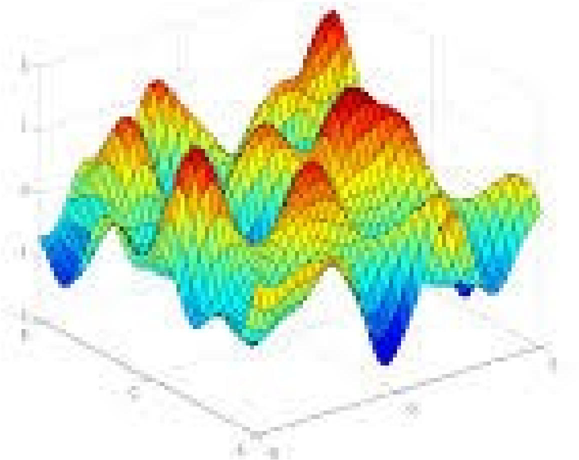
Fanoos

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



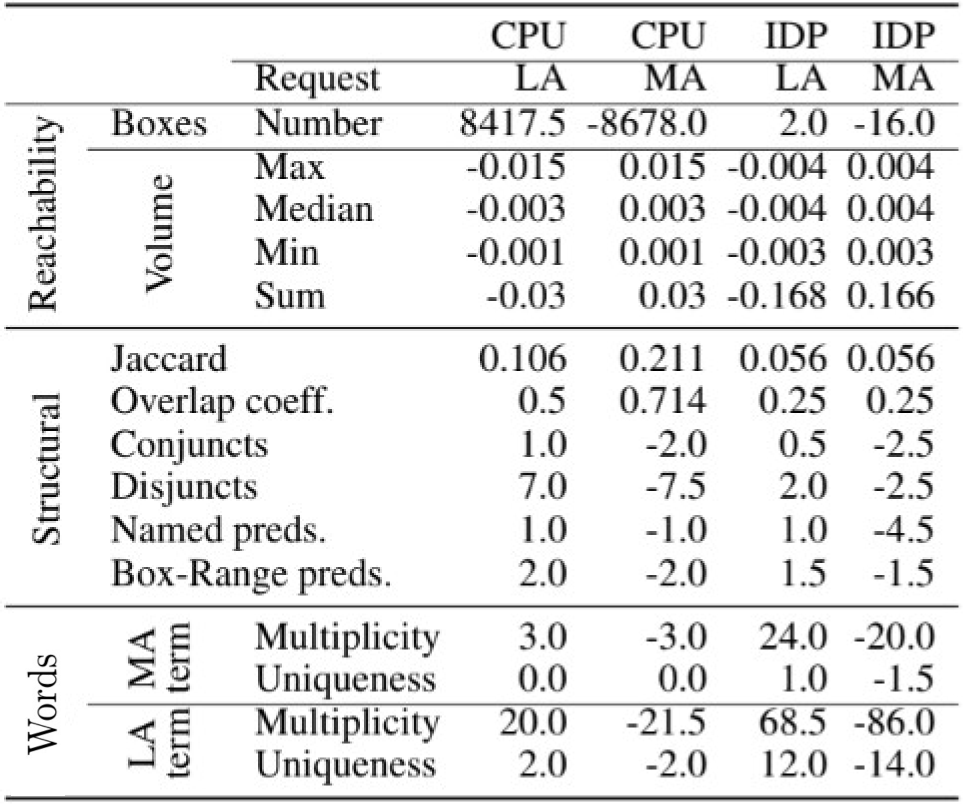
Experiments

- 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 agreement with human intuition

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

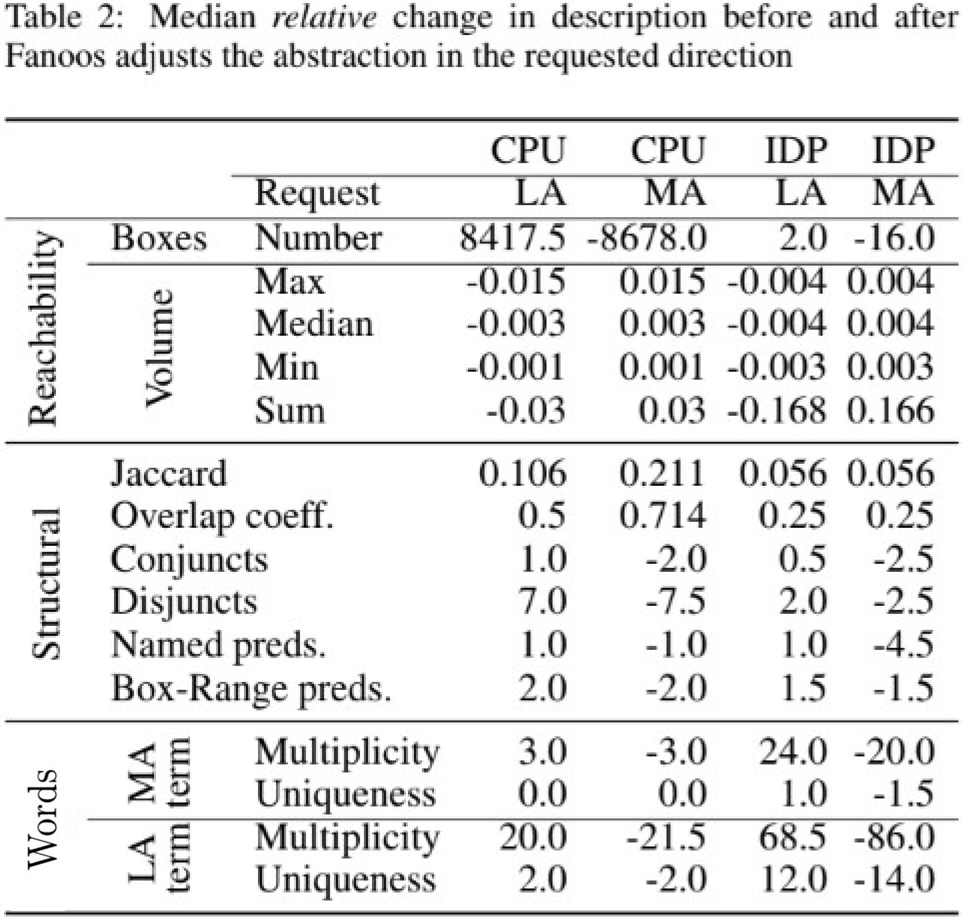
Table 2: Median *relative* change in description before and after Fanoos adjusts the abstraction in the requested direction



			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
Words	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 human judgment:
  - 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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Conclusion & Closing Thoughts

Fanoos

Fanoos:
Shining a Light on Black-Box AI

- Discussed the Fanoos system for XAI focused on ML
- Explanations from Fanoos are
  - Formally sound or probabilistic, depending on user preference
  - Interactive
  - Curtailable to user’s desired abstraction level
- Provided empirically demonstration
  - Fanoos recovered abstraction levels from semantics of the domain

Three Things I Want ***You*** to Have a Good Sense of After This:

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Closing Thoughts

- Under-explored: ***Formal Verification + XAI***
  - A lot of complementary abilities and focuses
  - Current pushes to be aware of: see “Explainable AI: Beware of Inmates Running the Asylum” ([11])
- Need for flexibility and ***varying abstraction***
  - Examples of this working well for other tools and across CS

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