

GLocalX

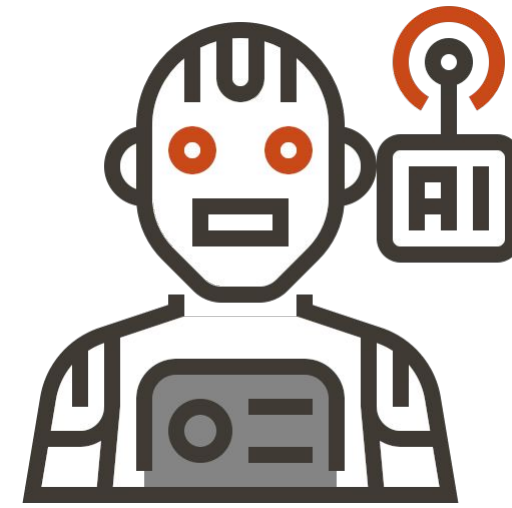
From Local to Global Explanations of Black Box AI Models

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Consiglio Nazionale delle Ricerche

Why explainability?



ML developers

Debug

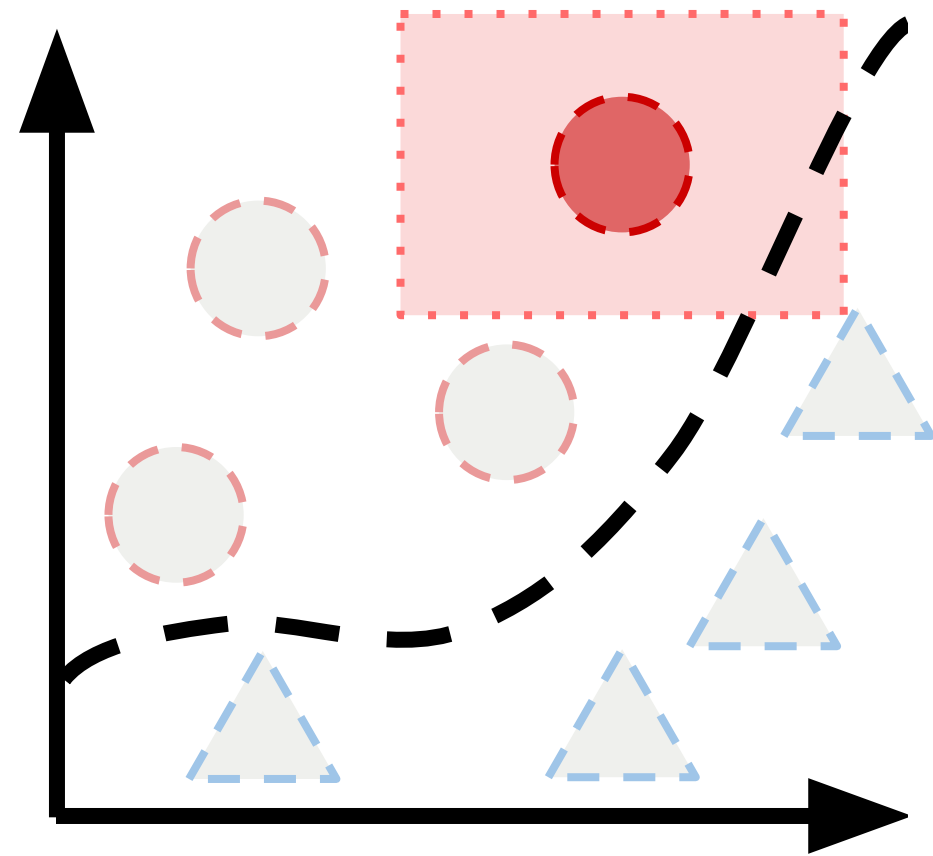
Users

Act

Auditors

Verify

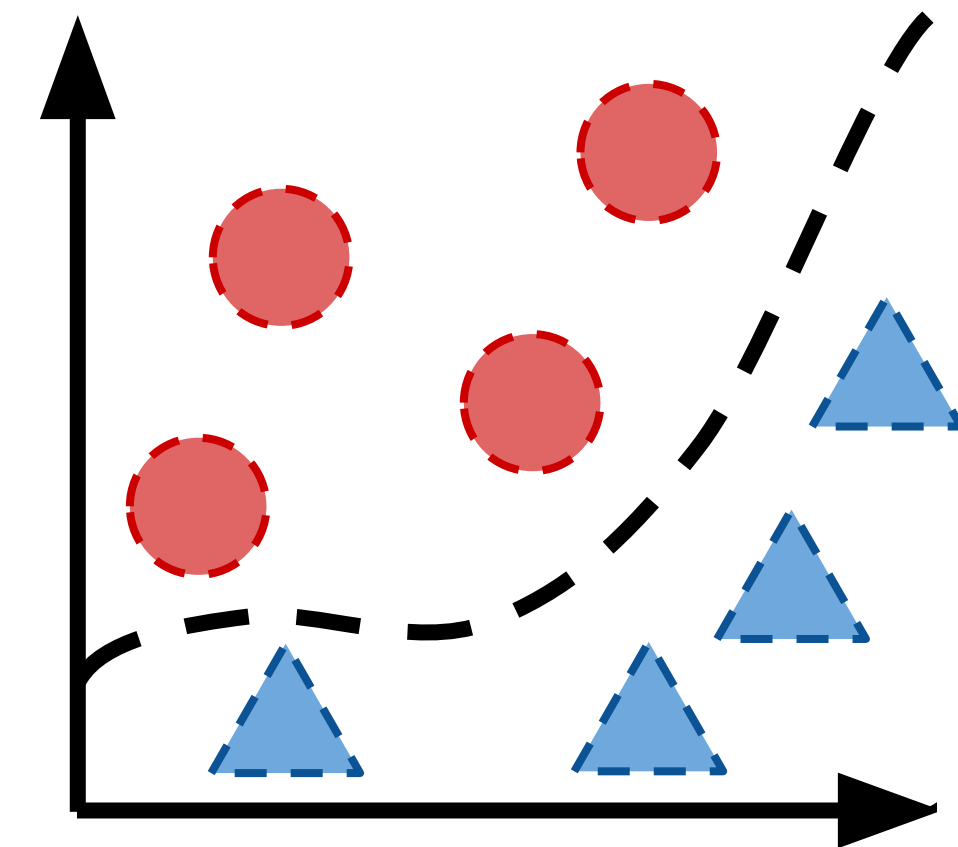
Local VS Global explanations



Local explanations

- require **only a fraction of the data**
- more **easily acquired**
- **precise** but potentially **complex**

E.g. LIME, LORE, SHAP, etc.

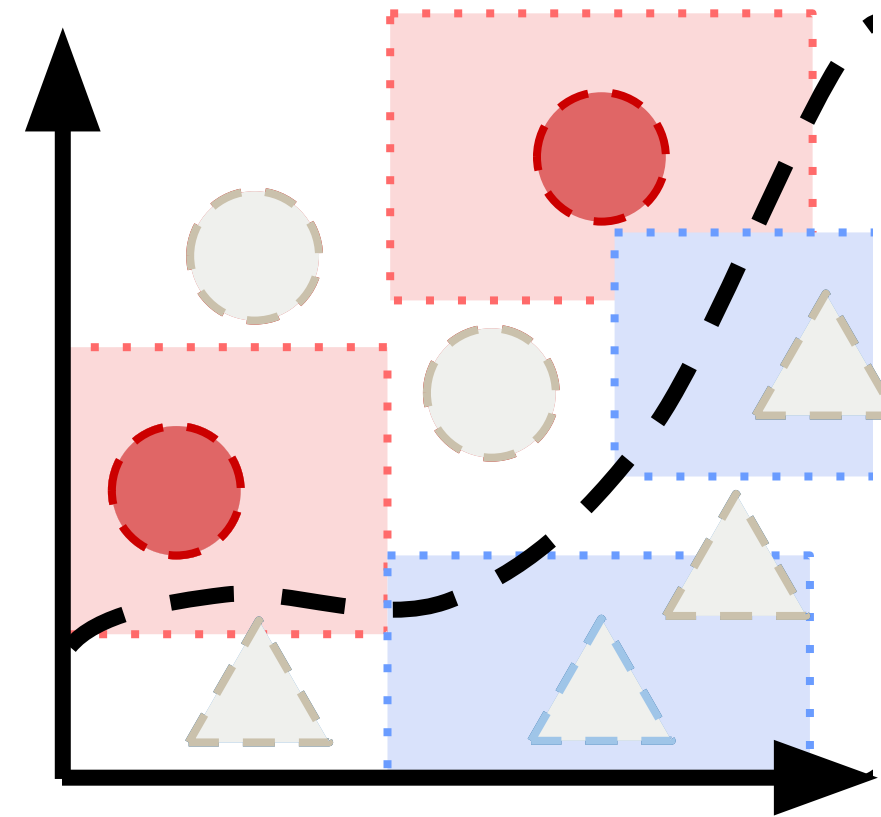


Global explanations

- require **data**
- more **cumbersome** to acquire
- **loose** but potentially **simple**

E.g. CART, CPAR, SBRL, etc.

A third way: Local to Global



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Global explanations

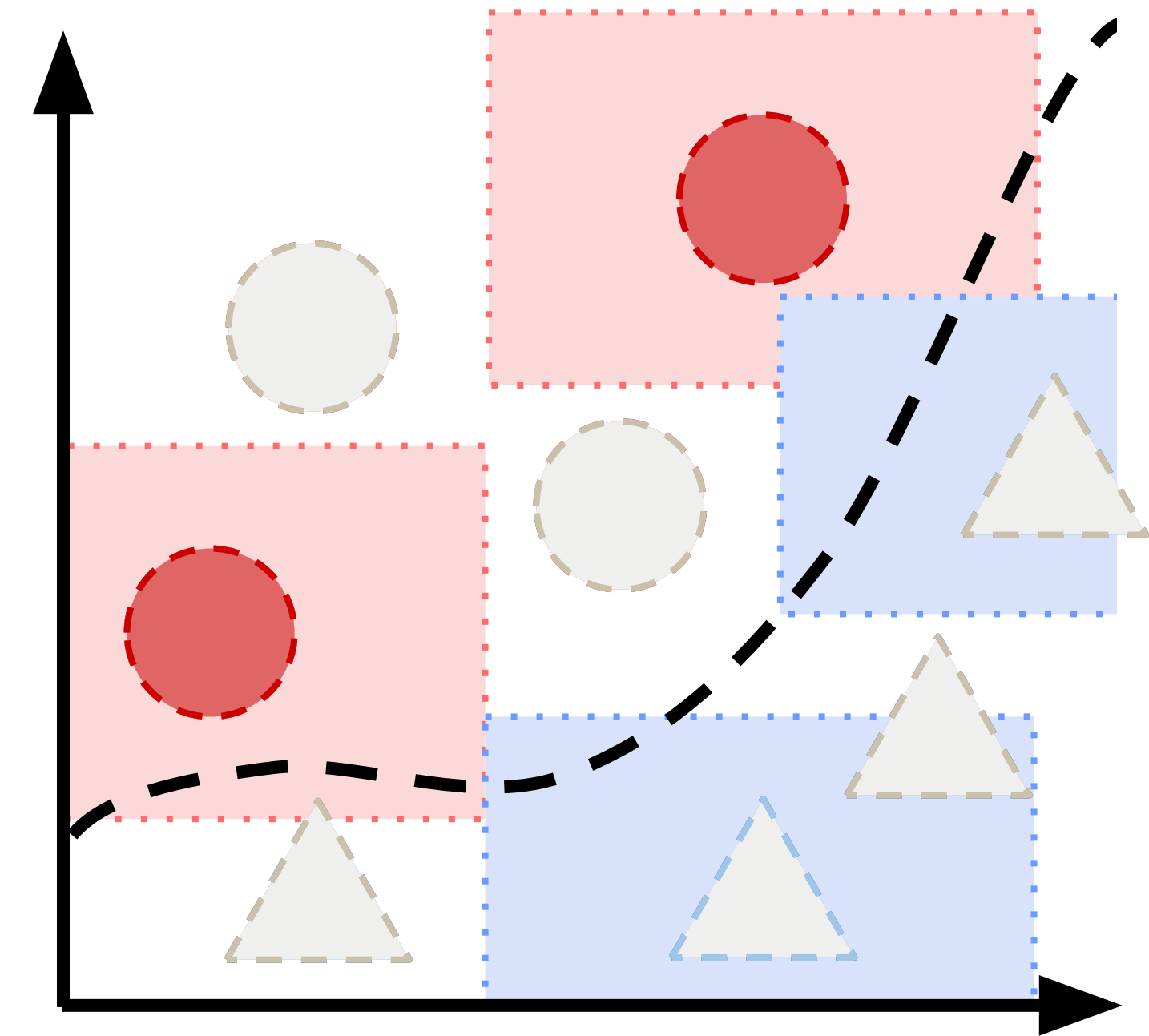
- require data
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E.g. CART, CPAR, SBRL, etc.

The Local to Global setting

Explain globally by explaining locally!

- explanation-driven
- inferring instead of learning
- black-box model as oracle



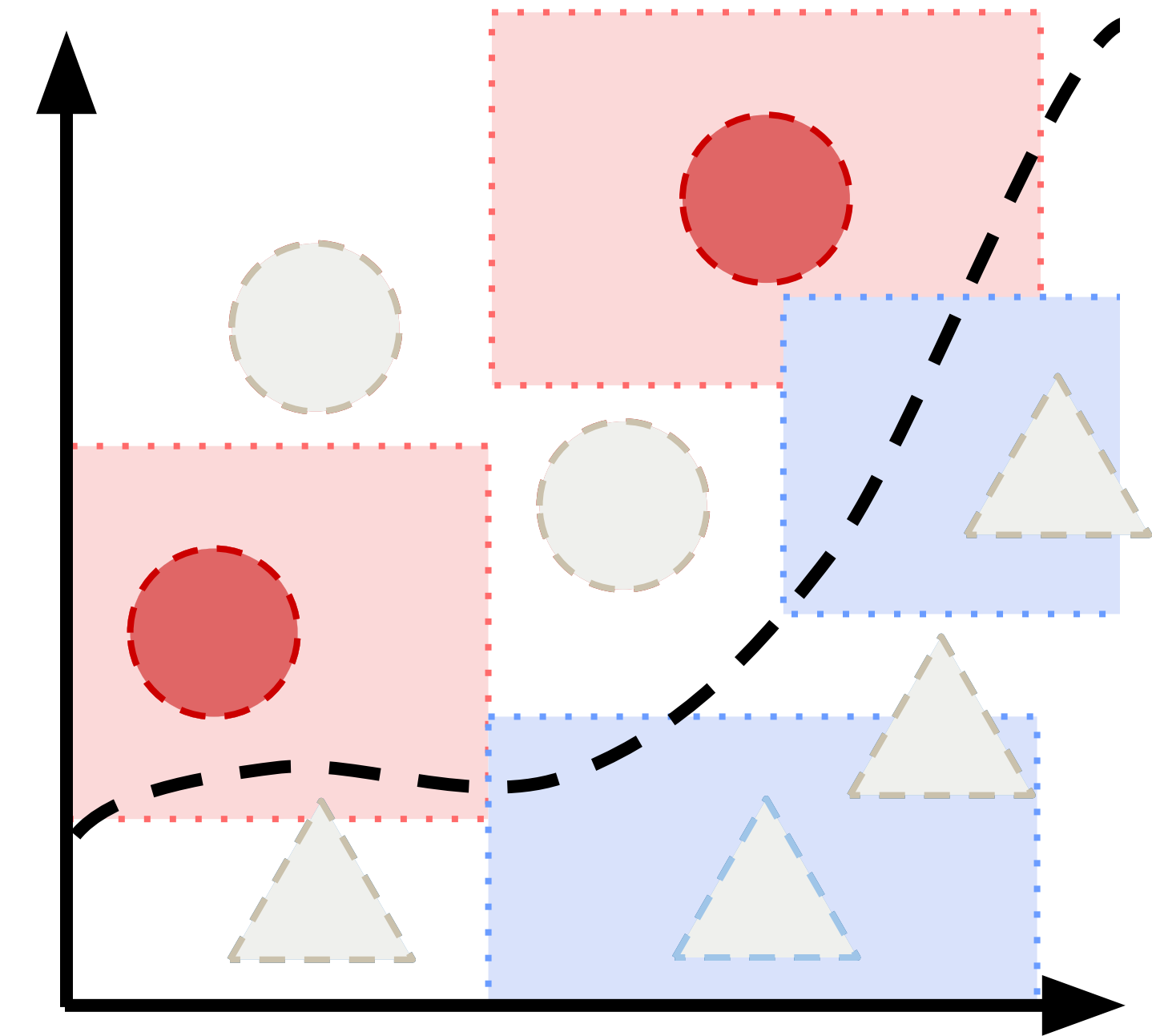
The Local to Global setting

Explain globally by explaining locally!

- explanation-driven
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Our proposal, **GLocalX**

- iterative and hierarchical inference
- axis-parallel decision rules as explanations



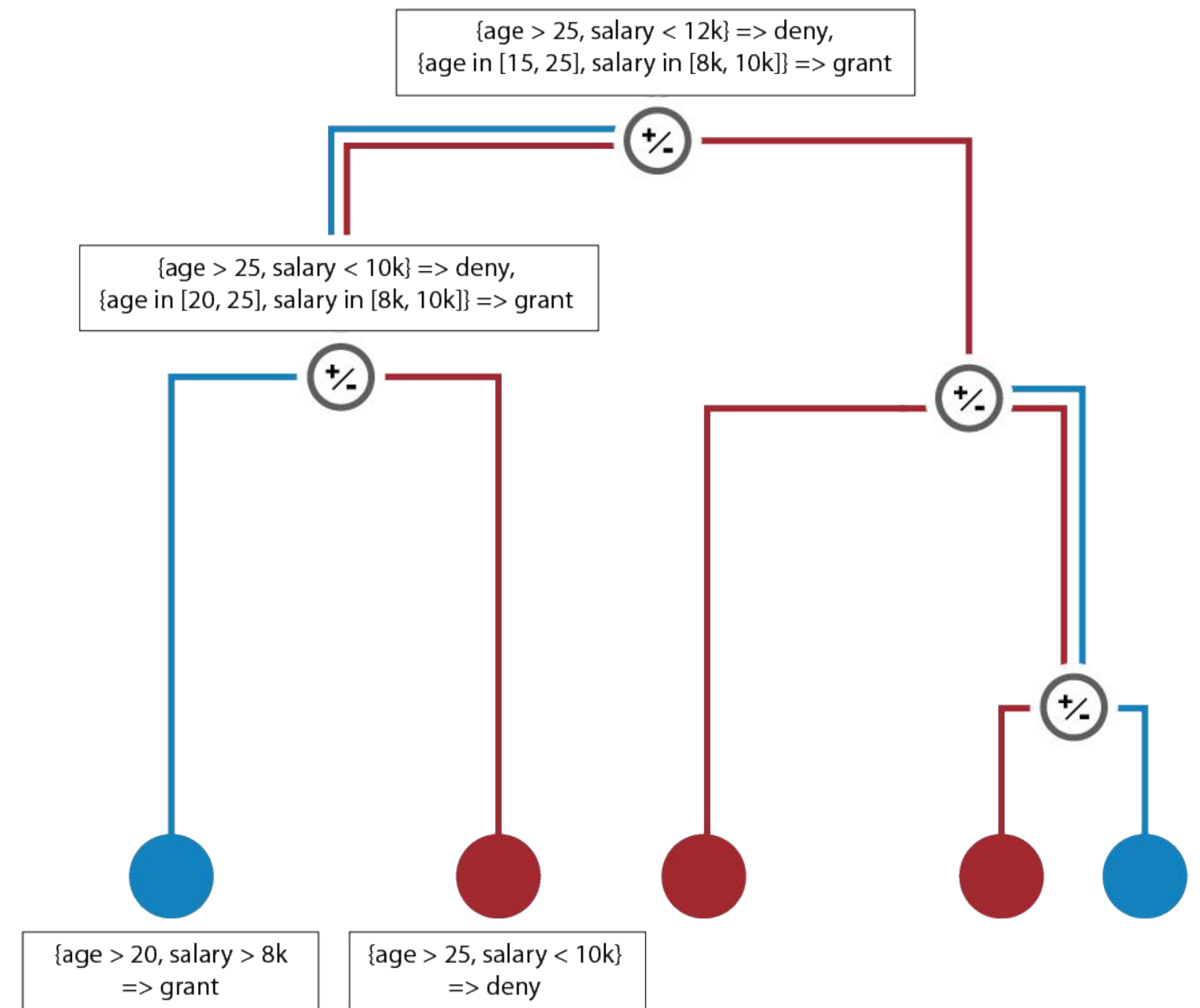
What to merge?

- Distance between explanations

$$IoU(cov(e, X), cov(e', X))$$

- Linkage for sets of explanations

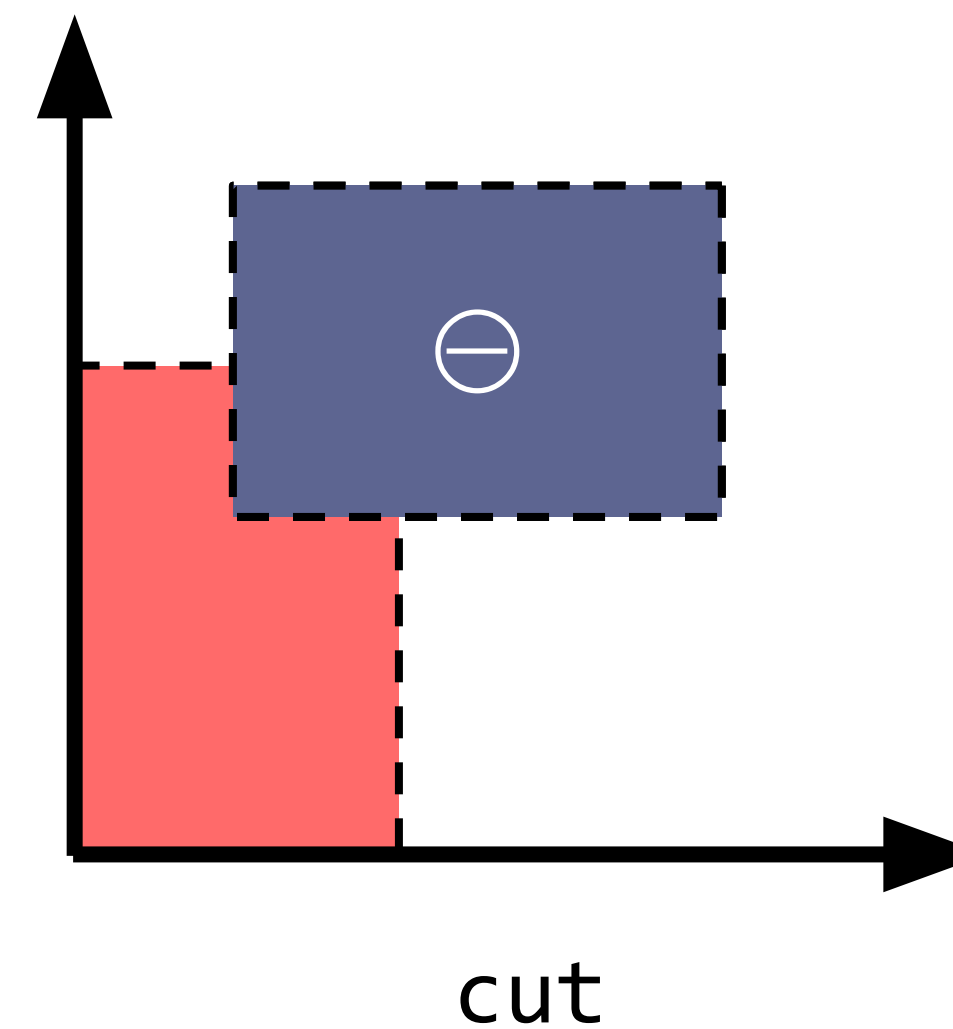
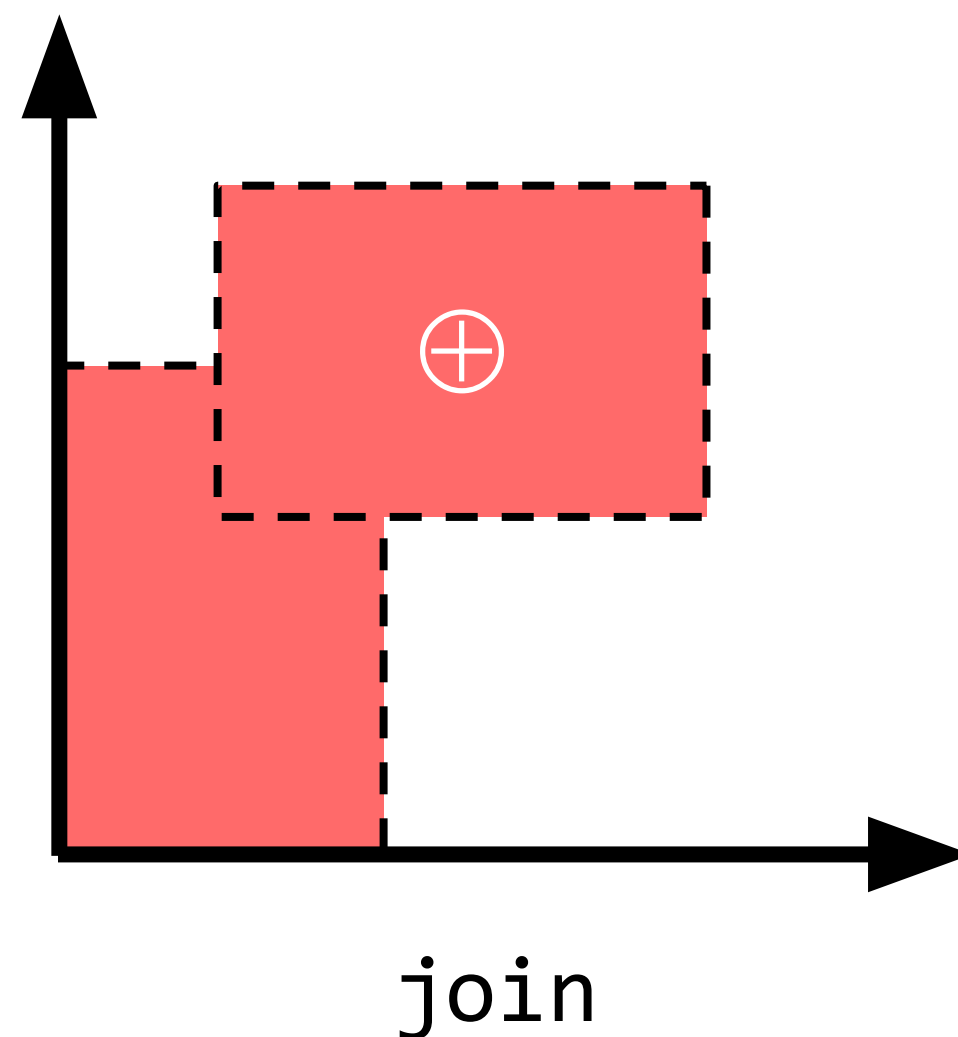
- min
- max
- full



How to merge?





Twofold merge operator

- approximate union (\oplus) for concordance, approximate difference (\ominus) for discordance
- each premise is an axis-parallel polyhedron, e.g.
premise age > 20 is polyhedron $P_{\text{age}}: [20, +\infty)$



Join









From local to global via premise relaxation.

$P_i: [a_p, b_p] + Q_i: [a_q, b_q]$			
[non-empty]	$P_i, Q_i \neq \emptyset$		
[empty]	$P_i = \emptyset \text{ XOR } Q_i = \emptyset$		

$$\text{age} \in [15, 20) \oplus \text{age} \in [25, 40) = \begin{array}{c} \text{red bar [15, 20)} \\ 15 \quad 20 \end{array} \oplus \begin{array}{c} \text{red bar [25, 40)} \\ 25 \quad 40 \end{array} \quad \begin{array}{c} \text{red bar [15, 20)}, \text{ gray bar [20, 25)}, \text{ red bar [25, 40)} \\ 15 \qquad \qquad \qquad 40 \\ \text{age} \in [15, 40) \end{array}$$

Cut

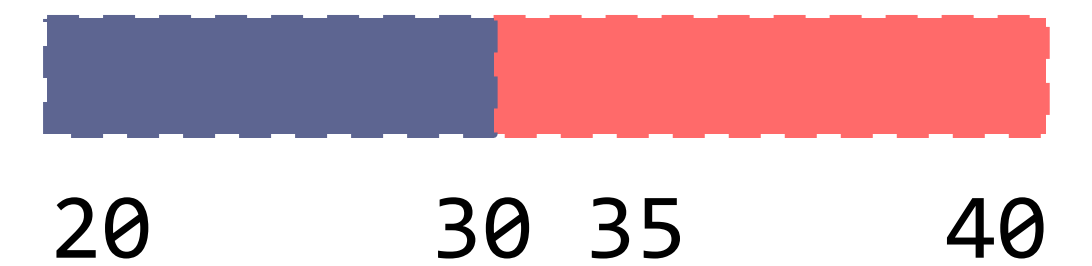
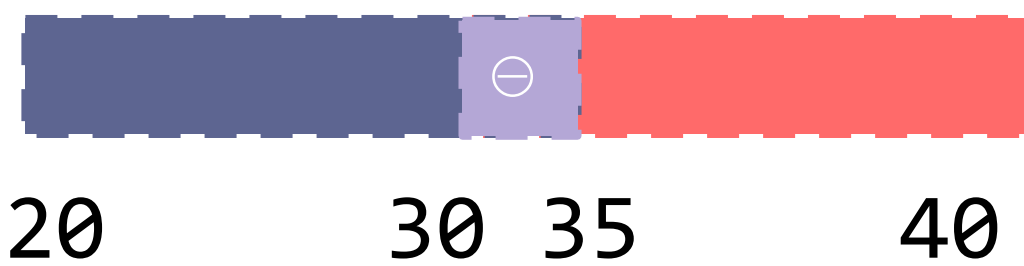
From global to local via premise specification.

$P_i: [a_p, b_p] - Q_i: [a_q, b_q]$			
[left]	$[a_p, a_q]$		
[right]	$[b_p, b_q]$		
[in-between]	$[a_q, a_p], [b_p, b_q]$		
[everything]	$[a_<, a_p], [b_p, b_>]$		

 cutting  cut  overlap

Cut

From global to local via premise specification.

$$\text{age} \in [30, 40) \ominus \text{age} \in [20, 35) =$$


20 30 35 40 20 30 35 40

$$\text{age} \in [30, 40), \text{age} \in [20, 30)$$

 cutting  cut  overlap

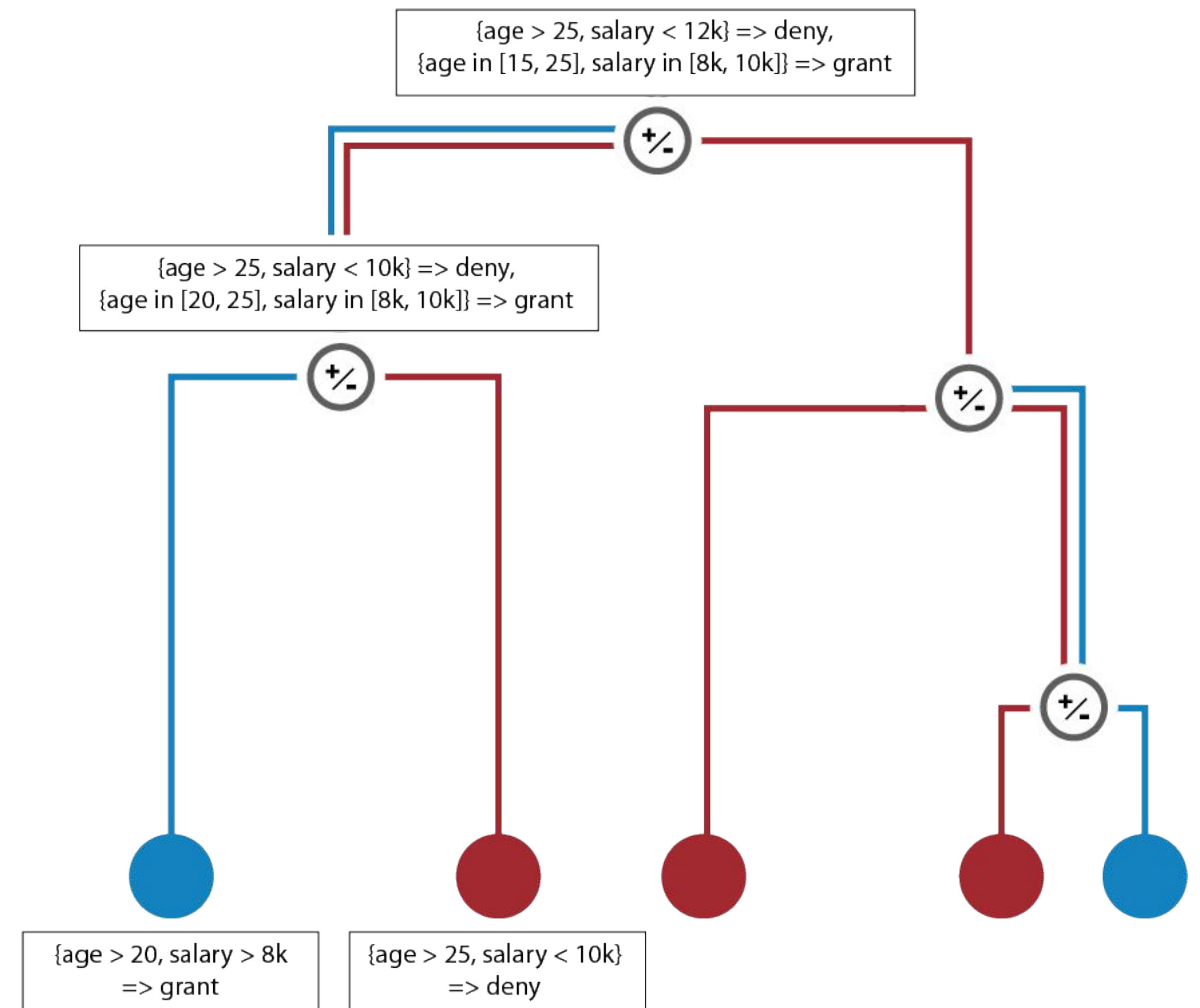
Should we merge?

Not all merges are created equal!

- some are more global and less accurate
- some are less global and more accurate

BIC(E)

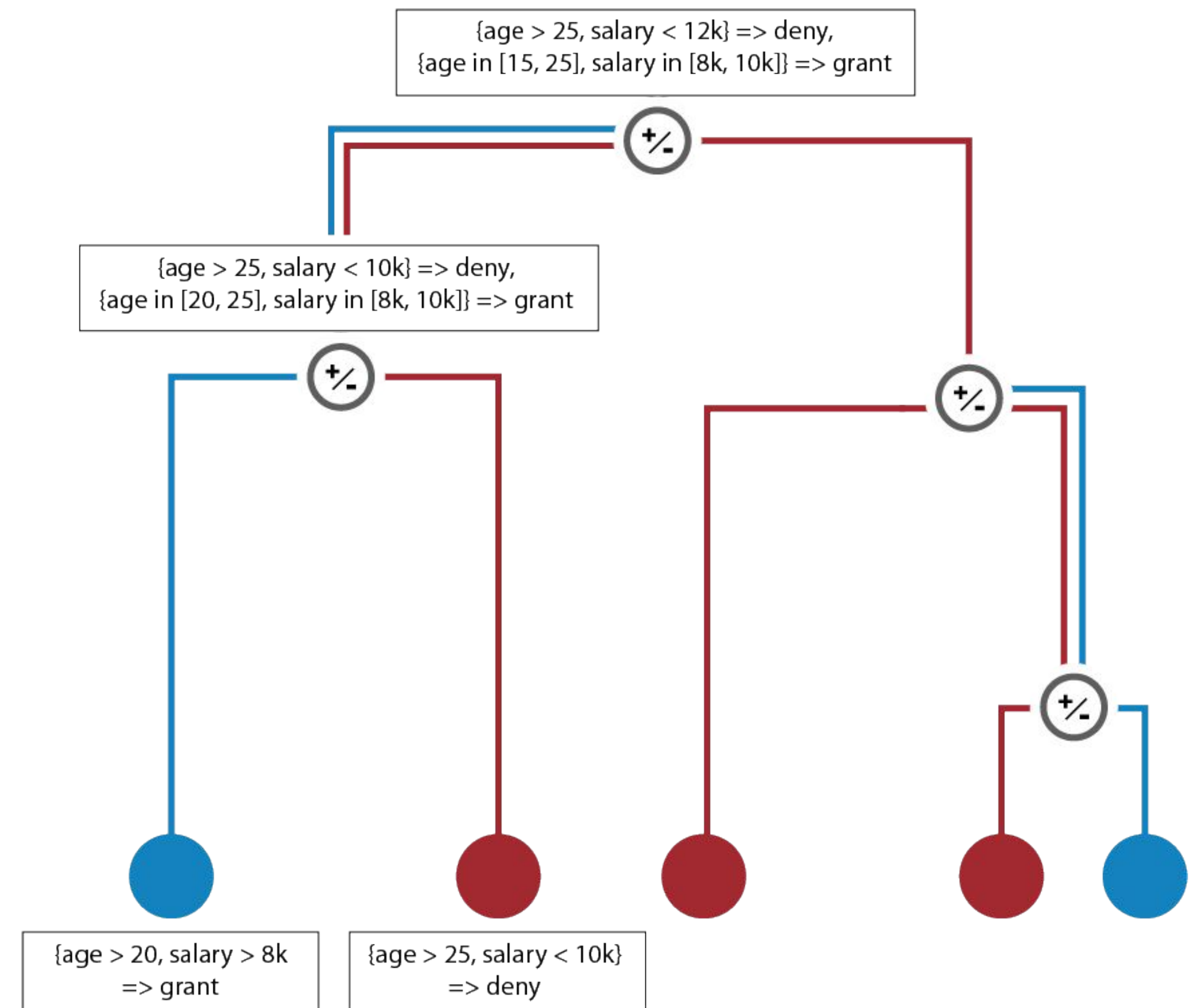
- model likelihood as explanation fidelity
- complexity as avg. #rules and avg. length



404: data not found

Data may be scarce for auditors and users

- density estimation of training data
- run GLocalX as is



Full algorithm

Algorithm 1 GLOCALX(\mathbb{E}, α)

Input: \mathbb{E} explanation theories, α filter threshold

Output: E explanation theory

```
1: repeat
2:    $\mathbb{Q} \leftarrow \text{SORT}(\mathbb{E})$  ▷ sort pairs of theories by similarity
3:    $merged \leftarrow \text{False}$ 
4:    $X' \leftarrow \text{batch}(X)$ 
5:   while  $\neg merged \wedge \mathbb{Q} \neq \emptyset$  do
6:      $E_i, E_j \leftarrow \text{POP}(\mathbb{Q})$  ▷ select most similar theories
7:      $E_{i+j} \leftarrow \text{MERGE}(E_i, E_j, X')$  ▷ merge theories
8:     if  $\text{BIC}(E_{i+j}) \leq \text{BIC}(E_i \cup E_j)$  then ▷ verify improvement
9:        $merged \leftarrow \text{True}$ 
10:    break
11:  if  $merged$  then ▷ merge occurred
12:     $\mathbb{E} \leftarrow \text{UPDATE}(E_i, E_j, E_{i+j})$  ▷ update hierarchy
13: until  $|\mathbb{E}| > 1 \wedge merged$  ▷ until the merge is successful
14:  $E \leftarrow \text{FILTER}(E, \alpha)$  ▷ Filter final theory
15: return  $E$ 
```

Full algorithm: filtering

Algorithm 1 GLOCALX(\mathbb{E}, α)

Input: \mathbb{E} explanation theories, α filter threshold

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Validation

Setting

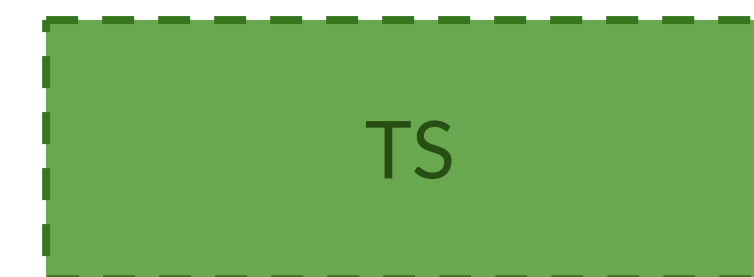
- 3 UCI datasets (~1k to ~50k records) , 8 black boxes (DNN, RF, SVM)
- 1 real-world fraud detection dataset (from the Italian Ministry of Economics)
- Natively global models:
 - rule-based models (CPAR)
 - decision tree (pruned/not pruned)



reserved to the black box



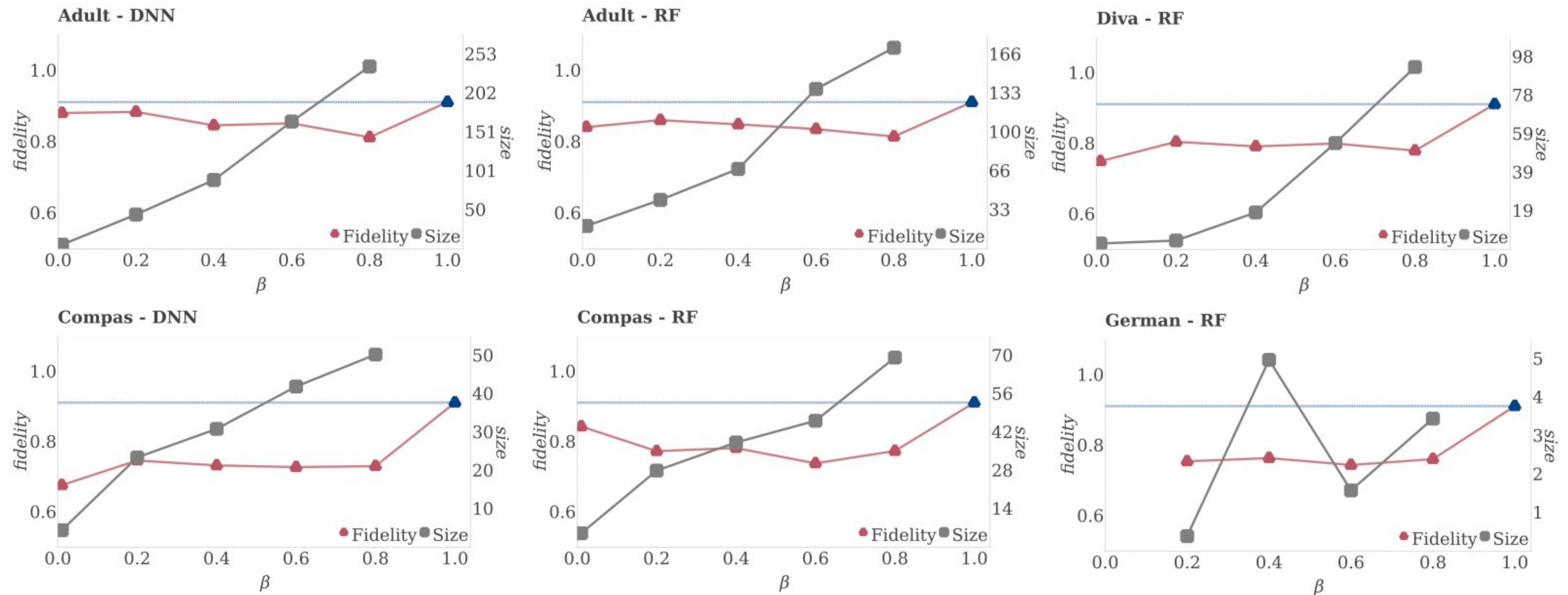
reserved to GLocalX



blind

Input size: how many rules do we need?

Acquiring local explanation can be costly, can we get away with using fewer local explanations?



How simple can we make our explanations?

The higher the filter, the less rules we output.

<i>α-percentile</i>	Fidelity	Size	Length
75	83.0 ± 3.6	31.0 ± 19.4	5.36 ± 2.41
90	84.7 ± 5.14	11.5 ± 6.4	5.43 ± 2.46
95	84.5 ± 5.48	6.625 ± 2.9	5.17 ± 2.59
99	84.0 ± 5.0	3.625 ± 2.6	5.97 ± 3.04

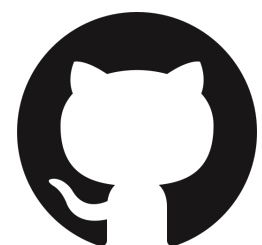
GLocalX VS natively global models

	Fidelity	Size	Length
<i>GLocalX</i>	85.1	8.5	4.28 ± 1.42
<i>GLocalX*</i>	83.5	9.5	4.79 ± 1.67
<i>CPAR</i>	86.6	91.6	3.06 ± 1.66
<i>Decision Tree</i>	87.5	1036.5	6.60 ± 1.86
<i>Pruned Decision Tree</i>	85.5	29.1	2.64 ± 0.73
<i>Union</i>	76.8	2660.2	4.14 ± 1.63

GLocalX

From Local to Global Explanations of Black Box AI Models

- Explaining globally by explaining locally
- Explanation cost: how many explanations do we really need?
- Local to Global vs Global explanation paradigm



github.com/msetzu/glocalx



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