

Improving Decision Sparsity

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Sparsity is important for interpretability



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The Magical Number Seven, Plus or Minus Two

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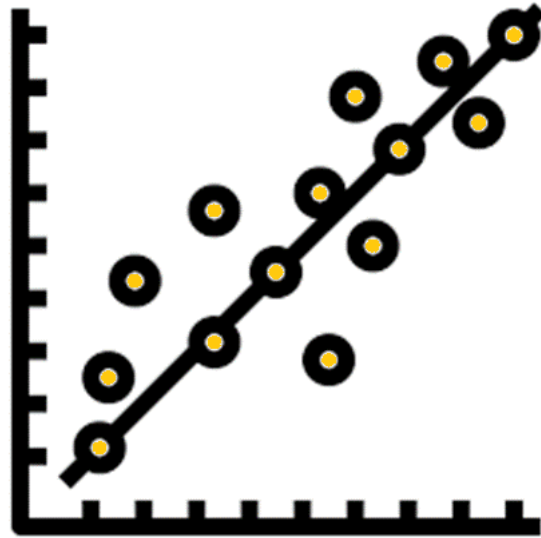
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"The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information"^[1] is one of the most highly cited papers in psychology.^{[2][3][4]} It was written by the [cognitive psychologist George A. Miller](#) of [Harvard University's Department of Psychology](#) and published in 1956 in *Psychological Review*. It is often interpreted to argue that the number of objects an average human can hold in [short-term memory](#) is 7 ± 2 . This has occasionally been referred to as *Miller's law*.^{[5][6][7]}

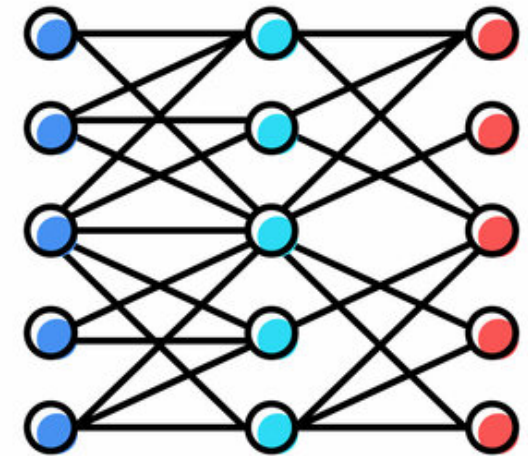
Common metrics for evaluating sparsity of the model



of terms
in linear regressions

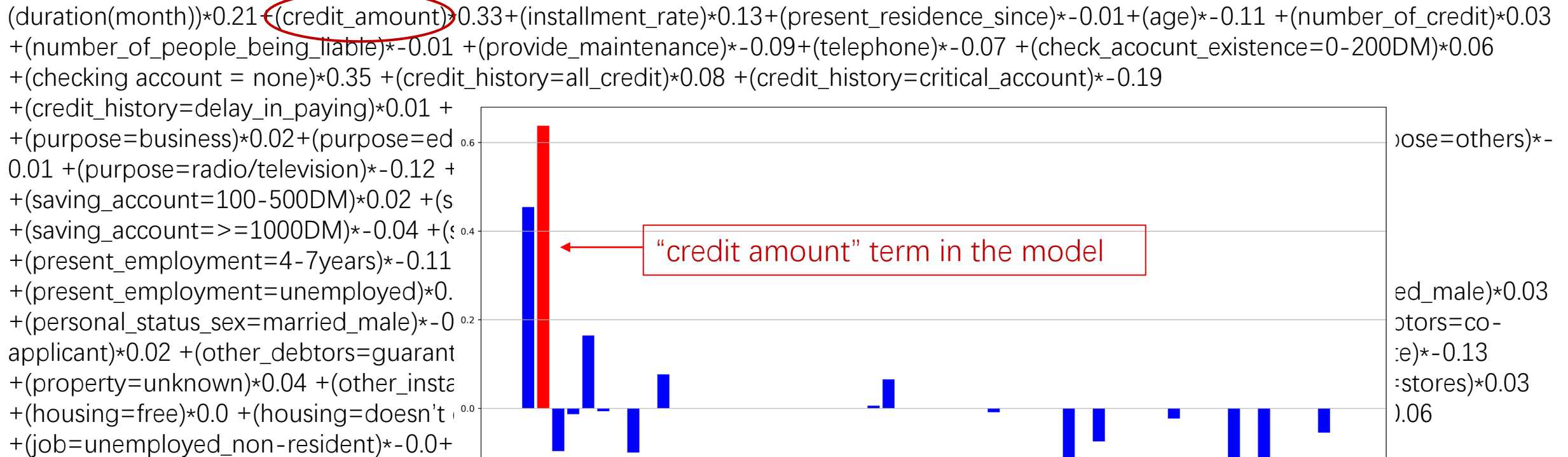


of leaf nodes
in decision trees



of parameters
in neural networks

This is not a sparse model.



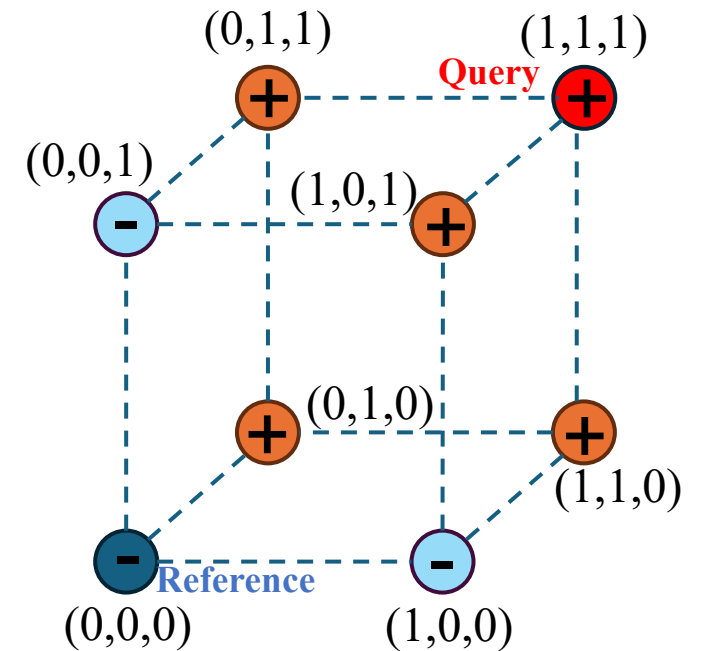
Why was Arun's loan application denied?

The prediction is determined by *one feature*!

He asked for over \$10K!

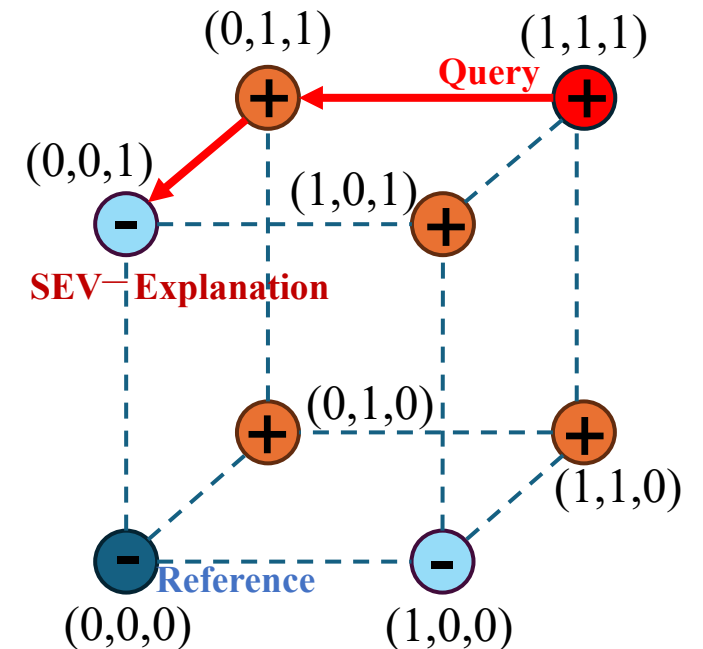
Recap of **Decision Sparsity**: SEV^-

- Step 1: Define **reference** (usually either **0** or average of negative class)
- Step 2: Define Boolean hypercube for **query x** :
 - coordinate $_j$ is 1 if feature j is x_j
 - coordinate $_j$ is 0 if feature j is at reference value r_j

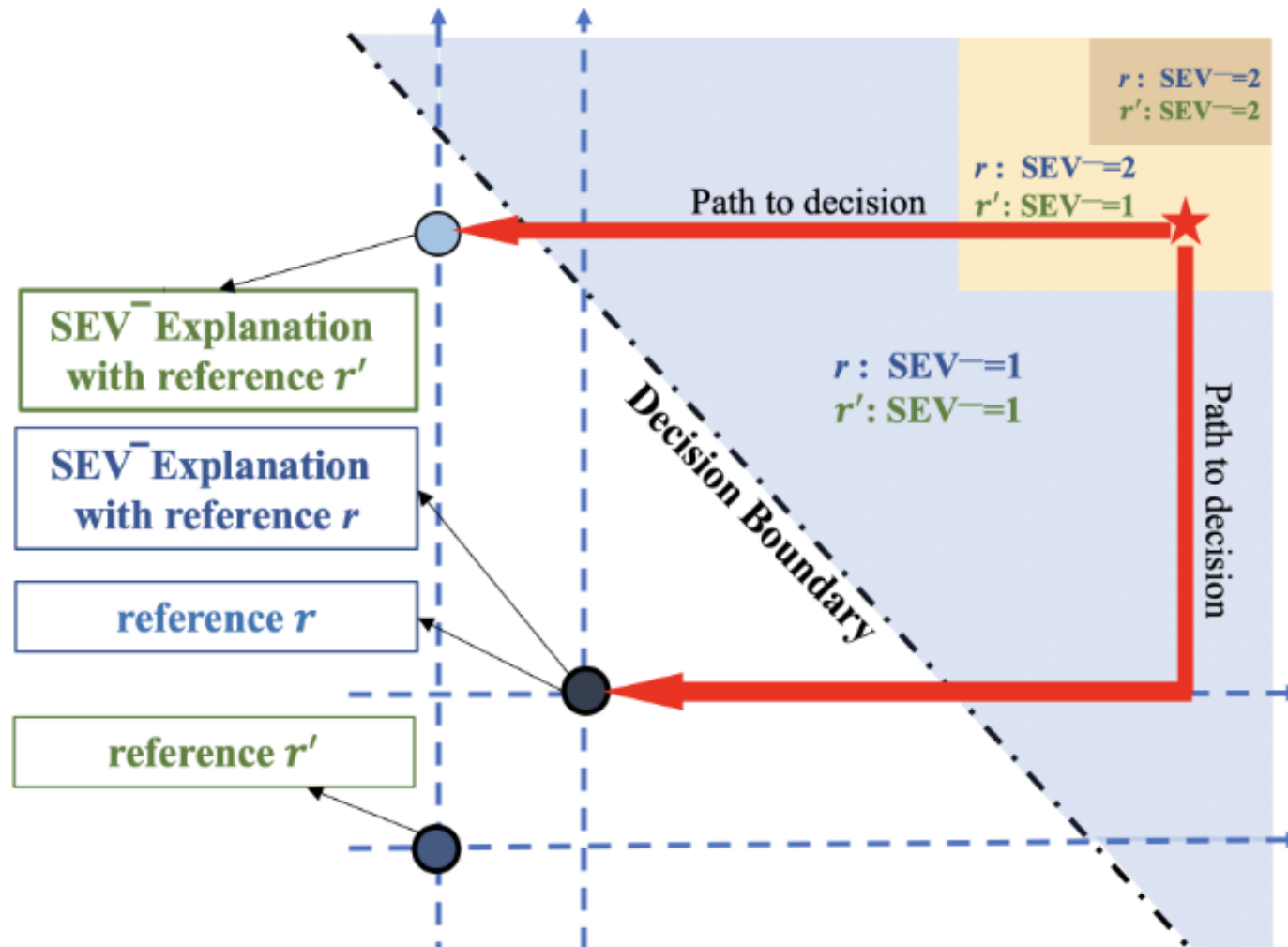


Recap of Explanation Sparsity: SEV^-

- Step 1: Define **reference** (usually either **0** or average of negative class)
- Step 2: Define Boolean hypercube for **query x** :
 - coordinate $_j$ is 1 if feature j is x_j
 - coordinate $_j$ is 0 if feature j is at reference value r_j
- Step 3: Define SEV^- for x . Moving from x towards **reference**, SEV^- is the minimum l_0 distance to a **negative** label.



SEV^- is sensitive to the reference selection



Selection criteria for references

Minimum number of features used for explaining decisions

Reference and Query are under the same subpopulations

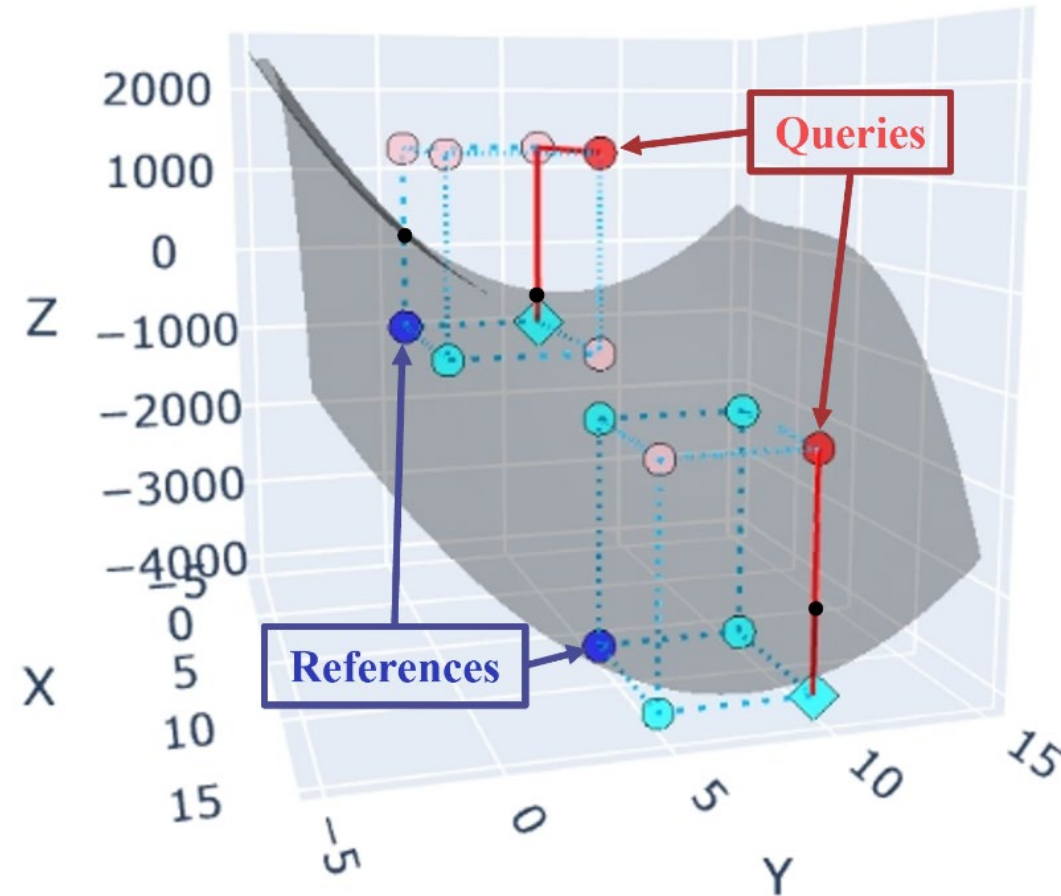
$$\|\mathbf{x}_i - \mathbf{r}_i\|, \mathbf{r}_i \in \mathcal{R} \quad (\text{Closeness})$$

$$\text{SEV}^-(f, \mathbf{x}_i, \mathbf{r}_i), \mathbf{r}_i \in \mathcal{R} \quad (\text{Sparsity})$$

$$-P(\mathbf{x}_i^{\text{expl}, \mathbf{r}_i} | X^-) \quad (\text{Negated Credibility})$$

Sparse explanations are under the original data distribution

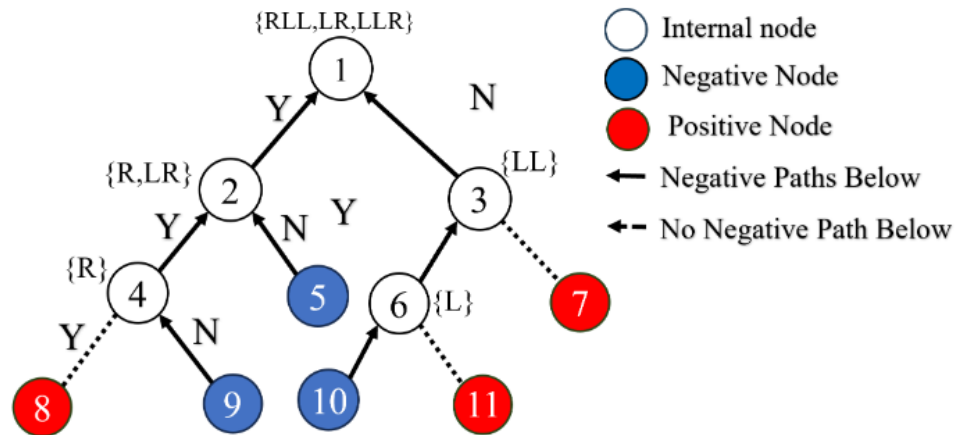
Improving Closeness: Cluster-based SEV (SEV-C)



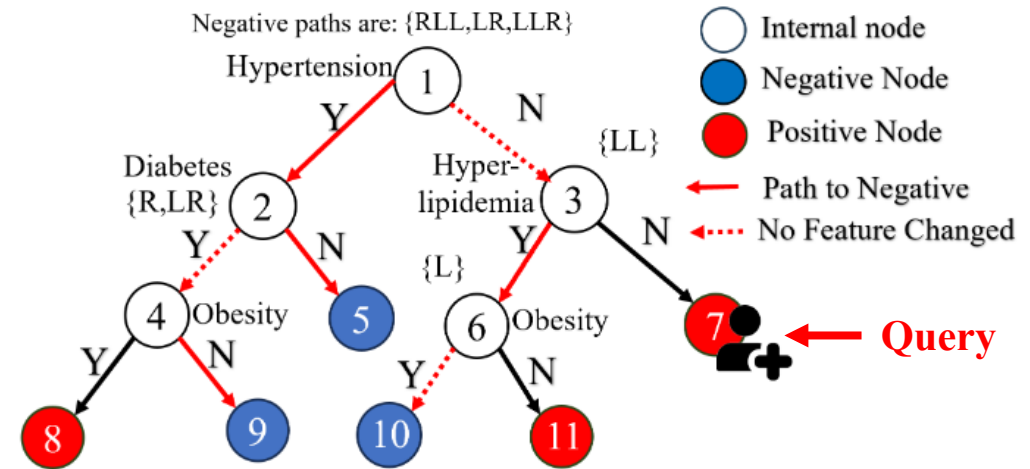
The process for calculating the SEV-C:

- **Step 1:** Selects the references by clustering the negative populations, and **regarding the cluster centroid points as the references.**
- **Step 2:** Assign each query their closest cluster centroid as their reference points.
- **Step 3:** Go over the original SEV Calculation

Special case for SEV-C: Tree-based SEV



Step 1: SEV-T Preprocessing: Collect negative leaf node information for each internal nodes



Step 2: Efficient SEV-T Calculation: Go over internal node of decision path, and check all negative paths

It have many useful properties and computational benefits!

Optimizing SEV Variants for Models

Gradient-based Optimization (AllOpt)

- Maximize the fraction of points with $SEV^- = 1$

Search-based Optimization (TOpt)

- Find a model with the lowest SEV with
in a set of classification models with
the best performance

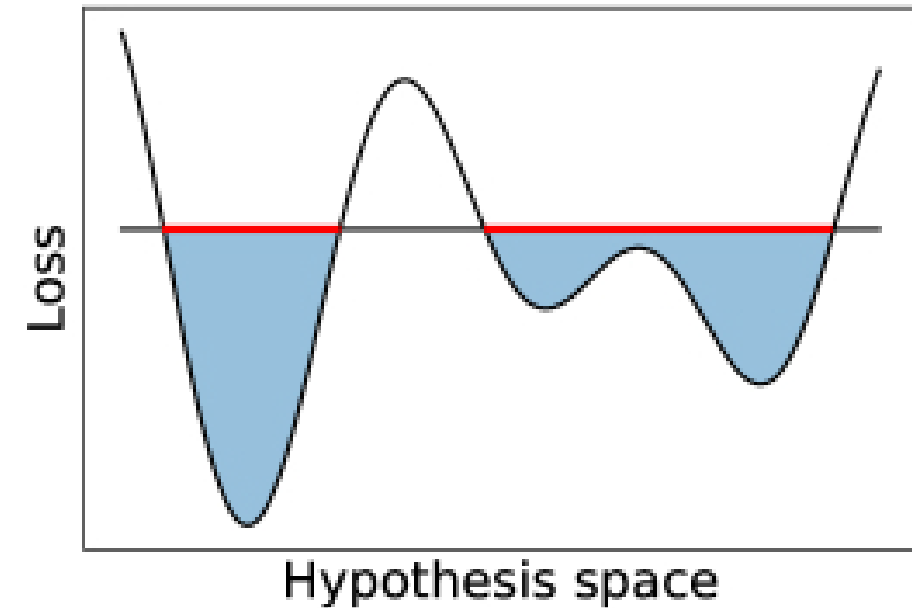
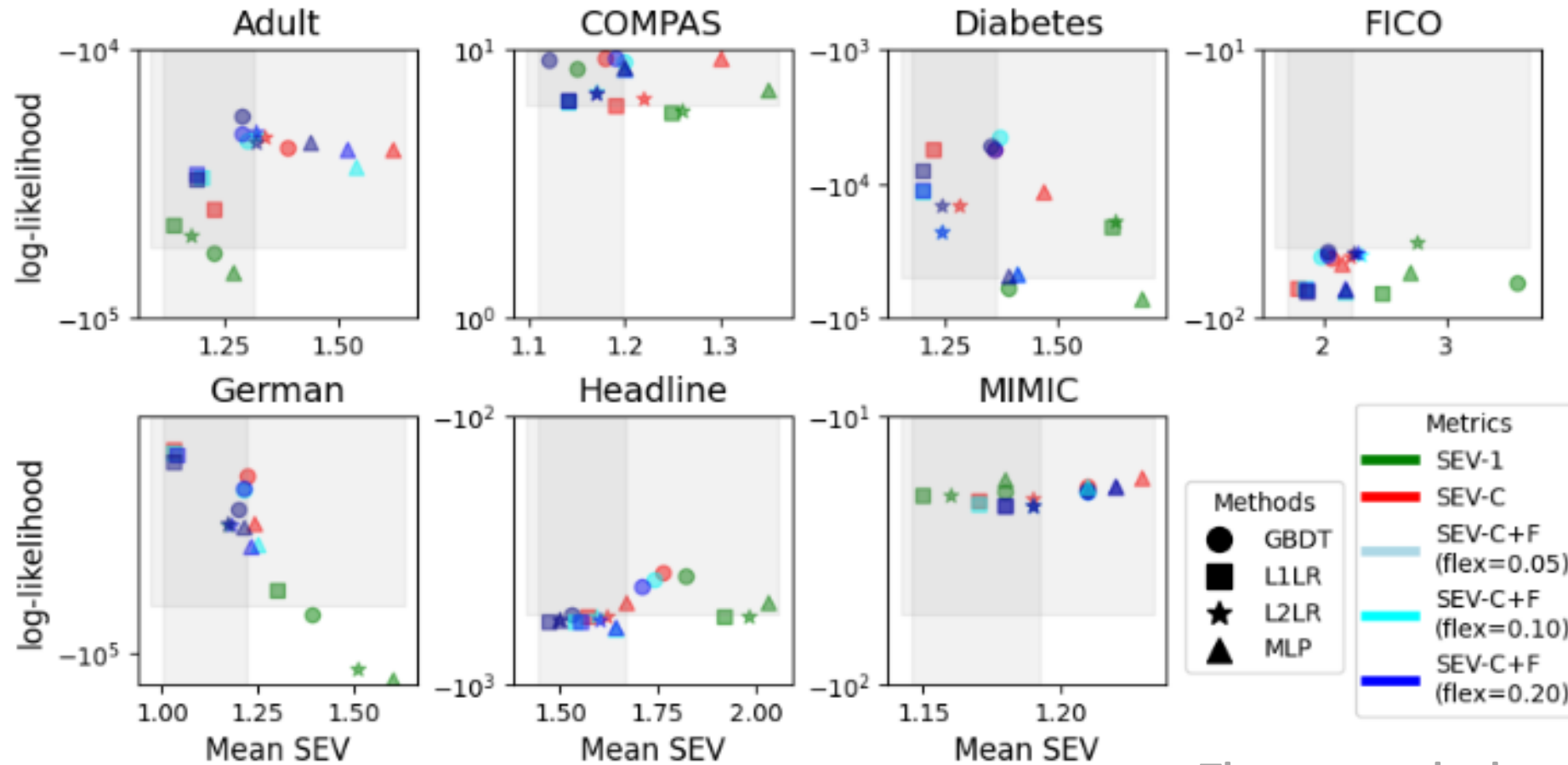


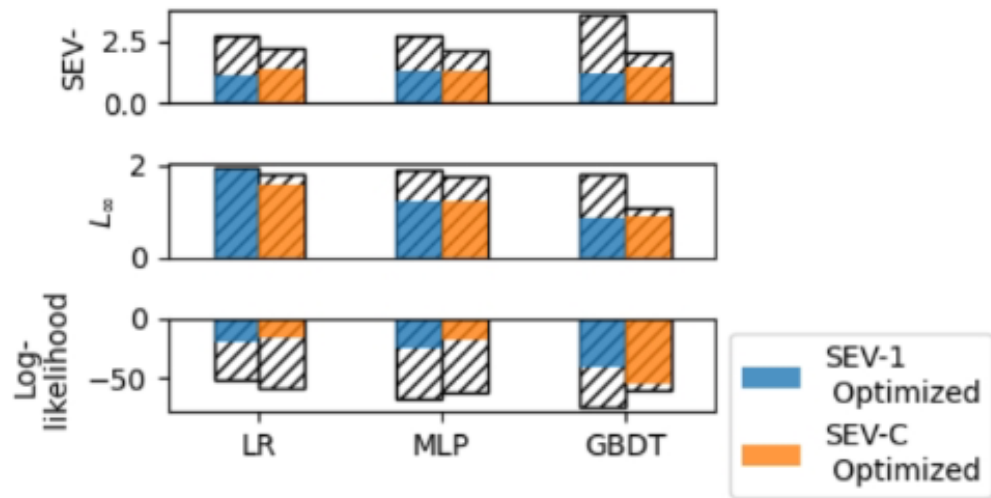
Figure 1: Rashomon Sets

SEV-C improves in credibility and closeness



The grayer, the better.

Optimization improves explanations while preserving model performance



(a) All-Opt⁻ Performance

	TRAIN ACC	TEST ACC	MEAN SEV ^T
CART	0.71 ± 0.01	0.71 ± 0.01	1.10 ± 0.03
C4.5	0.71 ± 0.01	0.71 ± 0.01	1.13 ± 0.05
GOSDT	0.70 ± 0.01	0.70 ± 0.01	1.08 ± 0.02
TOpt	0.70 ± 0.01	0.70 ± 0.01	1.00 ± 0.00

(b) SEV^T performance on different tree-based models

More in the paper

- SEV Variants for further improving the sparsity and credibility of the explanations.
- Sparsity and Credibility comparison with counterfactual explanation methods.
- Score-based soft K-Means for avoiding positive predicted references
- Detailed Algorithms for tree-based SEV
- Timing experiments
- ...

SEV Paper



NeurIPS Paper

