EDiT: Interpreting Ensemble Models via Compact Soft Decision Trees

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ICDM 2019

Outline

- **Introduction**
- Proposed Method
- Experiments
- Conclusion

Black Box Models

- Most ML models are *black boxes*
  - Learned structures are random and complex
  - Their decisions are not explainable

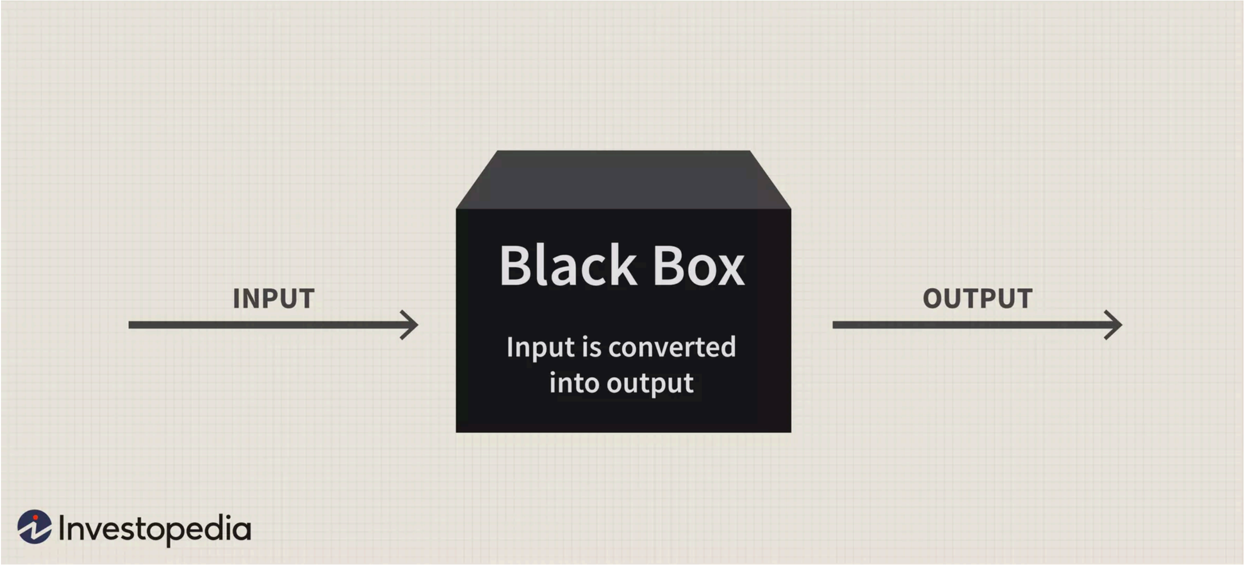

Image from https://www.investopedia.com/terms/b/blackbox.asp

Interpretable ML

- Research to interpret a model's decisions
  - Important when each decision is irreversible
- Two types of interpretable models:
  - *Linear models*
  - *Decision trees*
- However, their accuracy is not good

Ensemble Models

- *Ensemble models*
  - Combine the predictions of weak models
  - Produce robust and accurate predictions
- However, they have low interpretability
  - Decisions are made by hundreds of learners

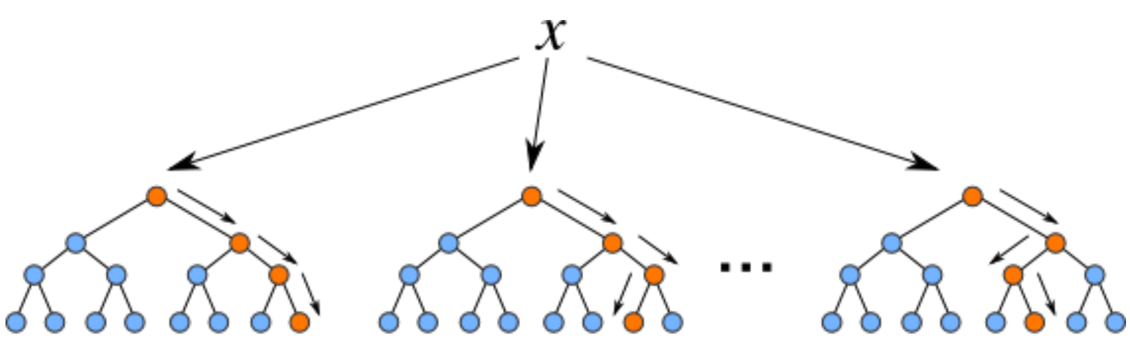

Image from https://dsc-spidal.github.io/harp/docs/examples/rf/

Problem Definition

- **Given** a trained ensemble model M
- **Train** an *interpretable* classifier S
- **Such that**
  - S achieves similar accuracy to M
  - S contains fewer parameters than M

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Proposed Method

- **Ensemble to Distilled Tree (EDiT)**
  - Given an ensemble model
  - Trains a *compact* soft decision tree
    - Interpretable & more efficient than SDTs
- EDiT is based on three main ideas
  - **Idea 1:** Knowledge distillation
  - **Idea 2:** Weight sparsification
  - **Idea 3:** Tree pruning

Preliminary: SDTs

- SDTs are interpretable tree-based models
  - Each internal node is a linear classifier
  - Each leaf node learns a probability distribution

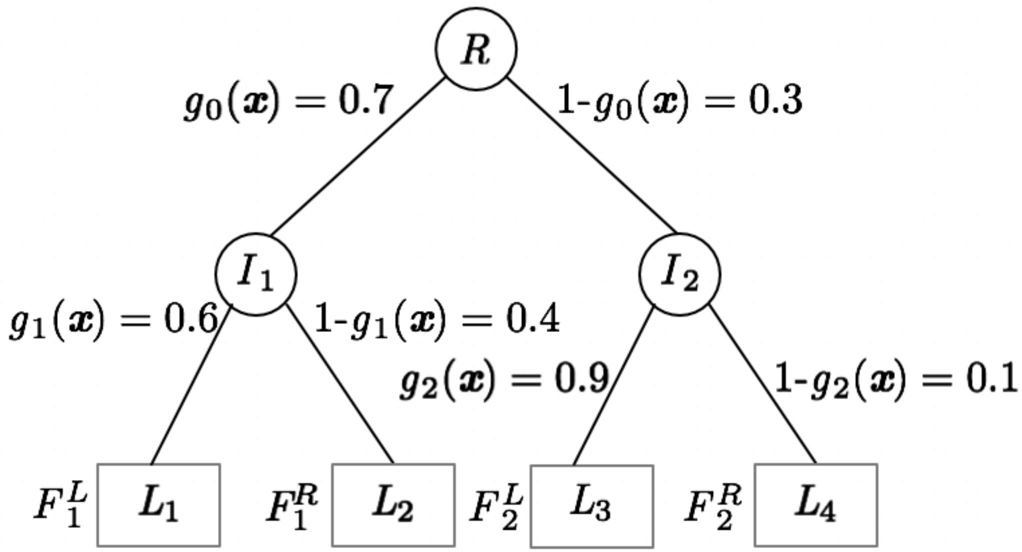


Image from "Rule-Extraction from Soft Decision Trees" (L. Huang, M. Hsieh, and M. Rajati, BDAI 2019)

Idea 1: Distillation

- *Knowledge distillation*
  - Transfers the knowledge of a teacher to a student
- Replace the labels $\mathbf{y}$ in training data $\mathcal{D}$ as

$$\mathbf{y}_i \leftarrow \frac{M(\mathbf{x}_i) + \mathbf{y}_i}{2} \text{ for each } (\mathbf{x}_i, \mathbf{y}_i) \text{ in } \mathcal{D}$$

  - $\mathbf{x}_i$ is a feature vector that corresponds to y_i

Idea 2: Sparse Weights (1)

- *Weight sparsification*
  - Improves the efficiency by sparse weights
- Propose three different approaches
  - **1)** L1 regularization
    - Adds an L1 regularizer to the loss function
  - **2)** Weight masking
    - Inactivates randomly some of the weights
  - **3)** Weight pruning
    - Prunes weights whose learned values are small

Idea 2: Sparse Weights (2)

- **Weight masking:** 2 steps

Random masking → Training

- **Weight pruning:** 3 steps

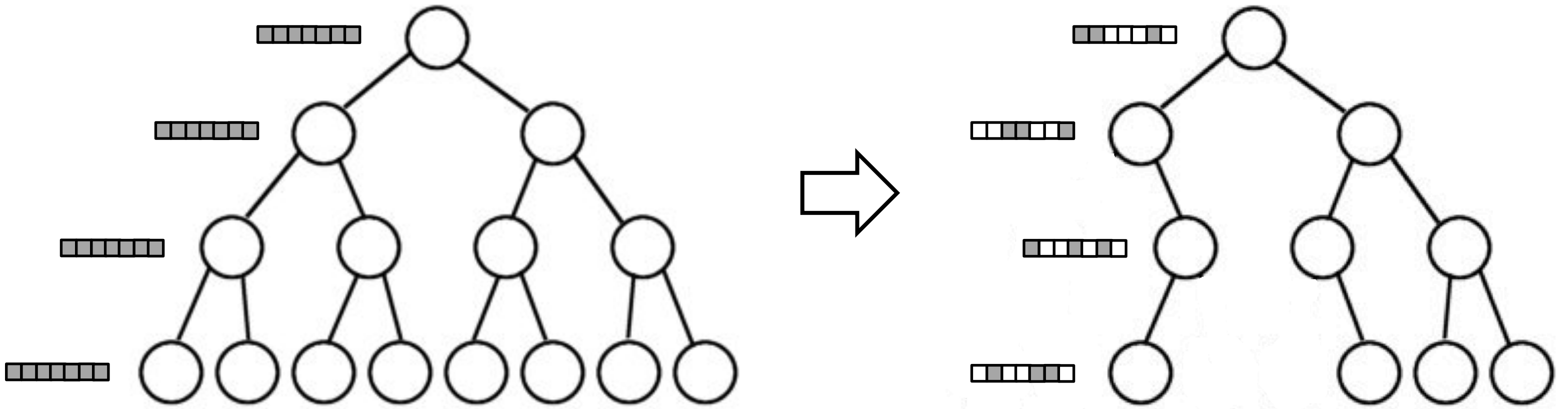
Pre-training → Pruning → Fine-tuning

Idea 3: Tree Pruning

- *Tree pruning*
  - Removes nodes of small arrival probabilities
  - Enables a large depth to be adopted
- Tree pruning vs. weight pruning
  - Weight pruning removes redundant weights
  - Tree pruning removes redundant tree nodes

Summary

- Result of applying our ideas to an SDT



  - Sparse weights from sparsification
  - Narrow tree structure from tree pruning

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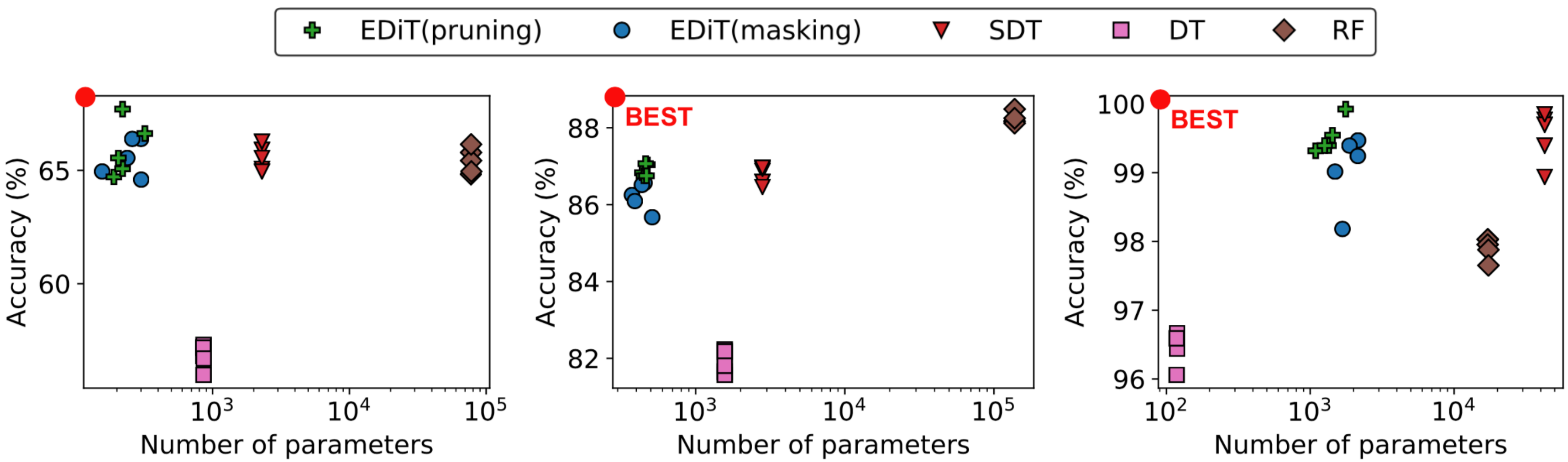
Accuracy & Complexity

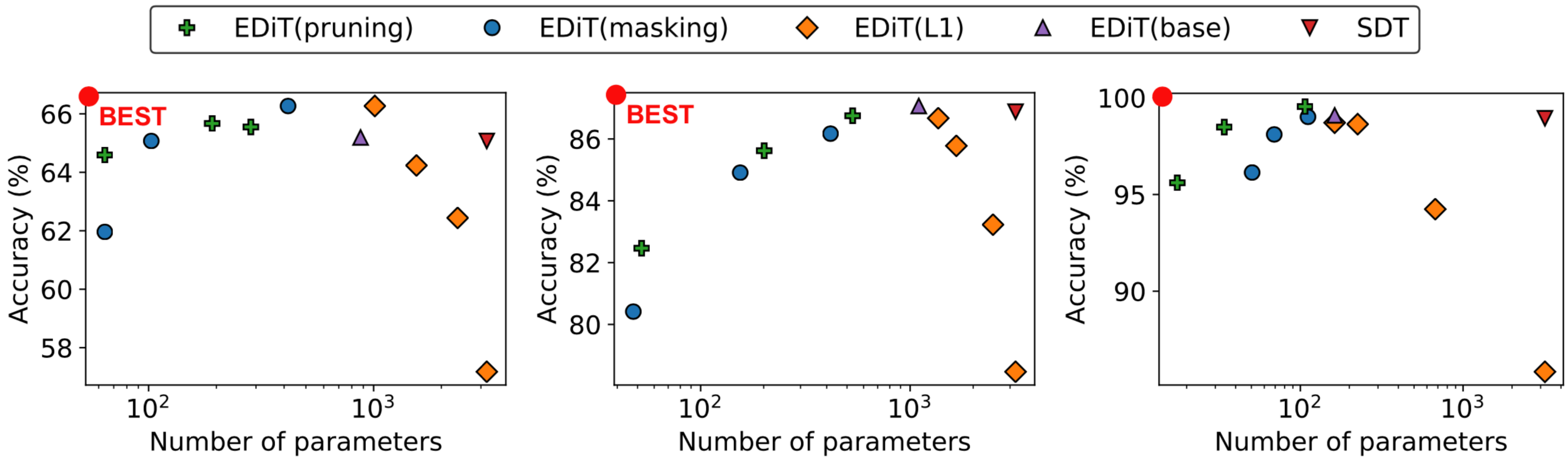
- **Does EDiT outperform the baselines?**
- EDiT shows the best balance in all cases
  - High accuracy with only a few parameters



(a) ABALONE (b) MAGIC (c) MUSK-2

Sparsification Methods

- **Which is the best sparsification method?**
- *Weight pruning* works generally the best
  - L1 regularization fails even with large λ



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Conclusion

- **Ensemble to Distilled Tree (EDiT)**
  - Our approach to interpret ensemble models
    - **Idea 1:** Knowledge distillation
    - **Idea 2:** Weight sparsification
    - **Idea 3:** Tree pruning
- EDiT gives the most efficient predictions
  - **Accuracy:** DT $\ll$ RF $\approx$ SDT $\approx$ **EDiT**
  - **Parameters:** DT $\approx$ **EDiT** $\ll$ SDT $<$ RF

Thank you !

GitHub: https://github.com/leesael/EDiT