A Bagging method for Cost-sensitive Imprecise Classification

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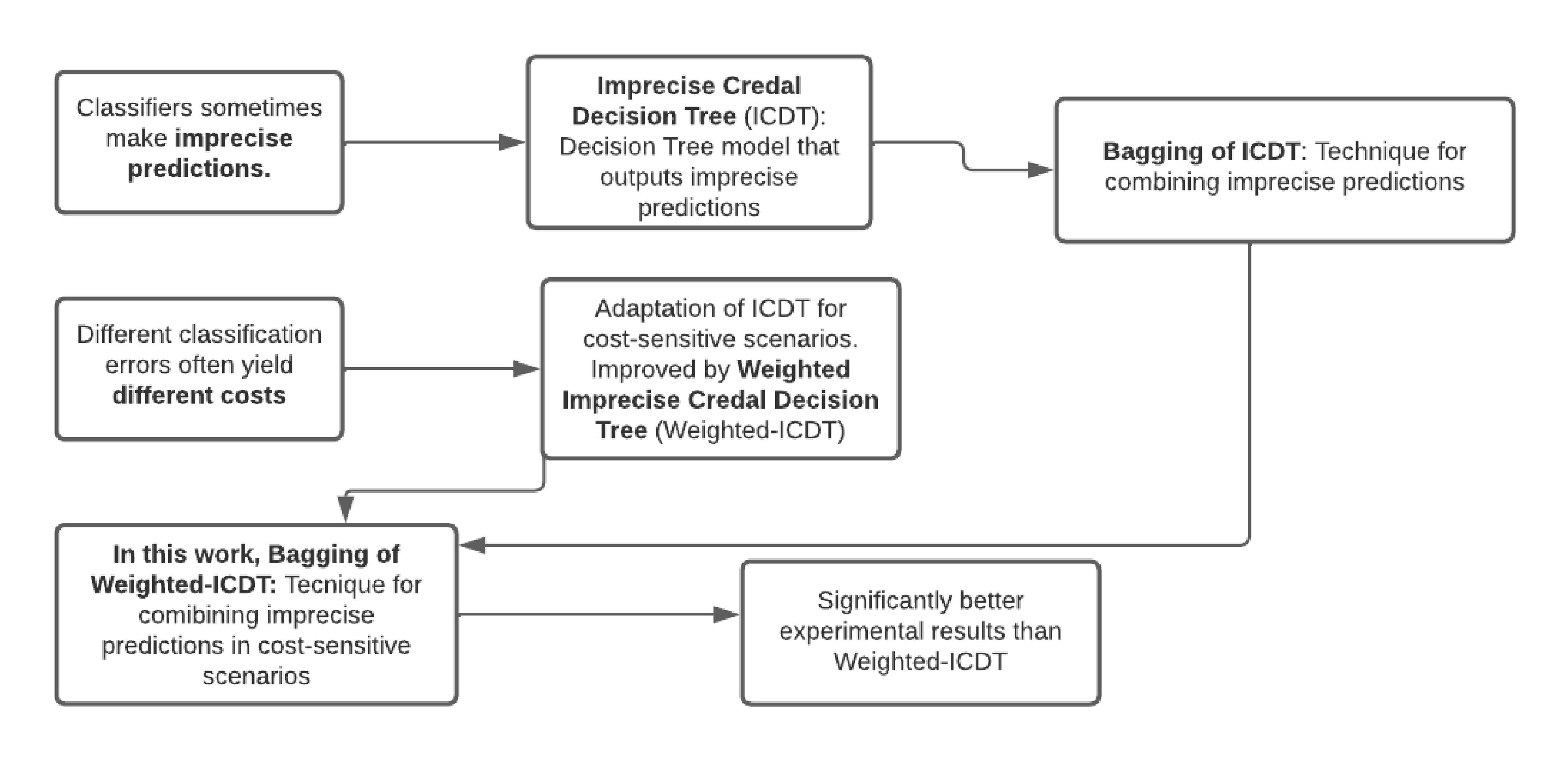
Introduction



Bagging of Imprecise Credal Decision Tree

- n_t = number of classifiers considered.
- For each $i = 1, 2, \ldots, n_t$:

1. Select a bootstrapped sample of the original training set with replacement.
2. Build a classifier using ICDT and the selected sample as the training set.

- **Predicted set of class values** for an instance: Those predicted as dominated by the minimum number of classifiers.

Weighted Imprecise Credal Decision Tree

- Weights for the instances depending on the error costs and the Approximate Non-Parametric Predictive Inference Model (A-NPI-M).
- **Split criterion** in a node:
  - Probability distribution for the class variable: weighted proportion of instances in the arrangement of maximum entropy with the A-NPI-M.

    Information gain based on that probability distribution.
- **Leaf node**:
  - Probability intervals using the A-NPI-M and instance weights.
  - Dominance criterion on such intervals to obtain the predicted set of class values.

Bagging of Weighted Imprecise Credal Decision Tree

- n_t = number of classifiers considered.
- For each $i = 1, 2, \ldots, n_t$:

1. Select a bootstrapped sample of the original training set with replacement.
2. Build a classifier using Weighted-ICDT and the selected sample as the training set.

- **Predicted set of class values** for an instance: Those close to the minimum dominance level (established threshold).
- **Key issues**:
  - Each base classifier takes the misclassification costs into account.
  - **Informativeness**: class values not close to the minimum level of dominance predicted as dominated.
  - **Error costs** of the ensemble: not only the class values with minimum dominance.

Experimental analysis

- **Evaluation measure for Imprecise Classifiers** (MIC): Costs of misclassifications and number of predicted class values.

Obtained results:

Dataset	Weighted-ICDT	Bagging-Weighted-ICDT
autos	0.9456	**1.3085**
balance-scale	**0.6066**	0.5701
car	1.1336	**1.1793**
cmc	**0.0968**	0.0854
dermatology	1.6533	**1.7224**
iris	**0.9592**	0.9530
vehicle	0.6155	**0.6871**
vowel	1.1891	**1.5918**
wine	0.9308	**0.9780**
zoo	1.5987	1.6822

Concluding remarks

- First ensemble for cost-sensitive Imprecise Classification. Combine predictions: class values close to minimum dominance $\Rightarrow$ ensemble informative but also considering error costs.
- Significantly better performance than a single Weighted-ICDT.
- Therefore, our proposed technique suitable for an ensemble for cost-sensitive Imprecise Classification.

Future work

- **Other ensemble schemes** adapted for cost-sensitive Imprecise Classification.
- **Other techniques** of combining multiple imprecise predictions for cost-sensitive scenarios.

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