

Complete decision tree induction functionality in scikit-learn

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Current status

- Reviewed literature
 - Result: overview of algorithm capabilities
- Implemented REP (classification) in scikit-learn
- Created automated test bench + plot generation
- Performed experimental comparison



Algorithm capabilities (1)

| Capability | ID3 | C4.5 | Weka J48 | CART | scikit DT | scikit RF | scikit GBT |
|--|-----|------|----------|------|-----------|-----------|------------|
| Categorical attributes | Υ | Υ | Υ | Υ | N | N | N |
| Numerical attributes | N | Υ | Υ | Υ | Υ | Υ | Υ |
| Binary classification (y in [-1,1]) | Υ | Υ | Υ | Υ | Υ | Υ | Υ |
| Multiclass classification (y in [0,, K-1]) | N | | Υ | | Υ | Υ | Υ |
| Multilabel classification | N | | | | Υ | Υ | N |
| Multioutput multiclass | N | | N | | Υ | Υ | N |
| Regression (y in R) | N | N | N | Υ | Υ | Υ | Υ |
| max_depth | N | | N | | Υ | Υ | Υ |
| min_samples_leaf | N | | Υ | | Υ | Υ | Υ |
| min_samples_split | N | | N | | Υ | Υ | Υ |
| max_leaf_nodes | N | | N | | Υ | Υ | Υ |
| max_features | N | | N | | Υ | Υ | Υ |
| predict_proba | N | | N | | Υ | Υ | Υ |
| Reduced-error pruning (REP) | N | N | Υ | | N | N | N |
| Error based pruning (EBP, classification only) | N | Υ | Υ | N | N | N | N |
| Minimal cost complexity tree pruning (CCP) | N | N | N | Υ | N | N | N |
| Pessimistic pruning | N | N | N | | N | N | N |
| Rule-based post-pruning | N | Υ | N | N | N | N | N |
| MDL-based pruning | N | N | N | N | N | N | N |

Algorithm capabilities (2)

| Capability | ID3 | C4.5 | Weka J48 | CART | scikit DT | scikit RF | scikit GBT |
|---|-----|------|----------|------|-----------|-----------|------------|
| Missing values | N | Υ | Υ | Υ | N | N | N |
| Generate rulesets | N | Υ | N | N | N | N | N |
| Binary splits on categorical values | N | | Υ | Υ | Υ | Υ | Υ |
| Non-binary splits on categorical values | Υ | Υ | Υ | N | N | N | N |
| Class weights | N | N | Υ | | Υ | Υ | N |
| Purity split (classification) | N | N | N | N | N | N | N |
| Entropy split (classification) | Υ | | Υ | | N | N | N |
| Info gain split (classification) | Υ | Υ | Υ | Υ | Υ | Υ | N |
| Gain ratio split (classification) | N | | Υ | | N | N | N |
| Gini split (classification) | N | | N | Y | Υ | Υ | N |
| MSE split (regression) | N | N | N | | Υ | Υ | Υ |
| Friedman_MSE split (regression) | N | N | N | | Υ | N | Υ |
| MAE split (regression) | N | N | N | | Υ | Υ | Υ |
| Chi-square stop criteria | Υ | N | N | N | N | N | N |
| Hierarchical attributes | N | N | N | N | N | N | N |
| Learn oblique trees | N | N | N | N | N | N | N |
| Clustering (unsupervised) | N | N | N | N | N | N | N |
| Generate model tree | N | N | N | N | N | N | N |
| Online learning | N | N | N | N | N | N | N |



Algorithm capabilities – key take-aways

- No nominal attribute support in scikit-learn
- No regression trees in weka
- No pruning in scikit-learn
 - Instead: pseudo-pruning
- EBP and REP in weka
- Only binary trees in CART, scikit-learn



Experimental setup

- Classifiers
 - PrunableDecisionTreeClassifier
 - J48
- Datasets
 - iris
 - wine
 - diabetes
 - ionosphere
 - wdbc
 - activity

- Pruning options
 - none
 - min_samples_leaf
 - REP [prune_percentage]
 - EBP [confidence_factor]
- Metrics
 - Number of nodes and leaves
 - Accuracy and F1 score
 - Fit and score duration
- 100 repeats, 10-fold cross-validation



J48 options

- Configured to behave similar to scikit-learn decision trees
 - Binary trees only
 - No tree collapsing
 - No subtree raising
 - No MDL correction
 - minNumObject=1 (default=2)
- TODO also test weka with default options (baseline)

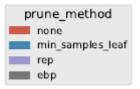


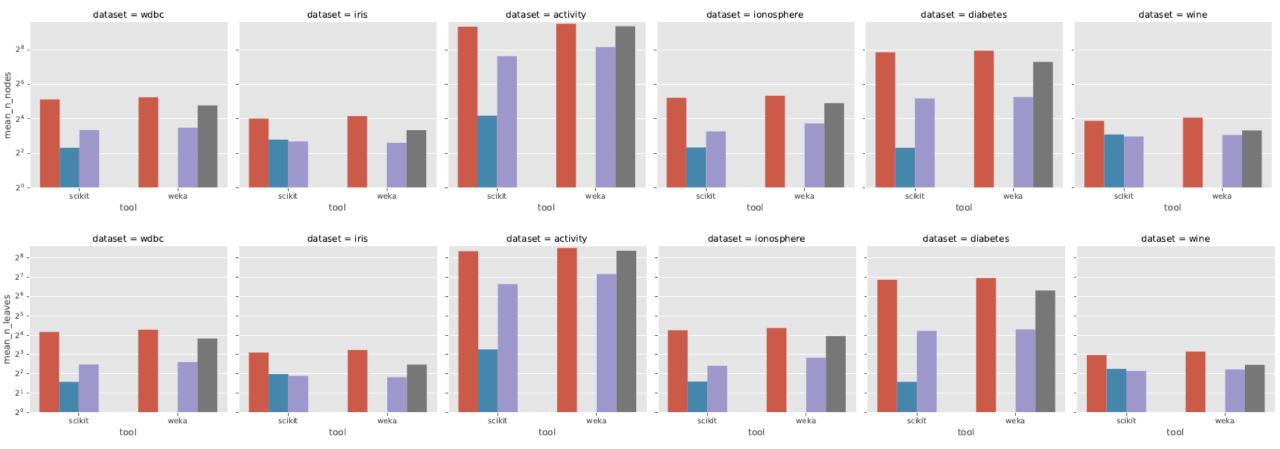
Hypotheses – number of nodes and leaves

- Number of nodes ~ number of leaves
- Pruned trees have fewer nodes and leaves
- Pseudo-pruning (i.e., min_samples_leaf): even fewer nodes
- REP vs. EBP?



Plots – number of nodes and leaves





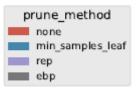


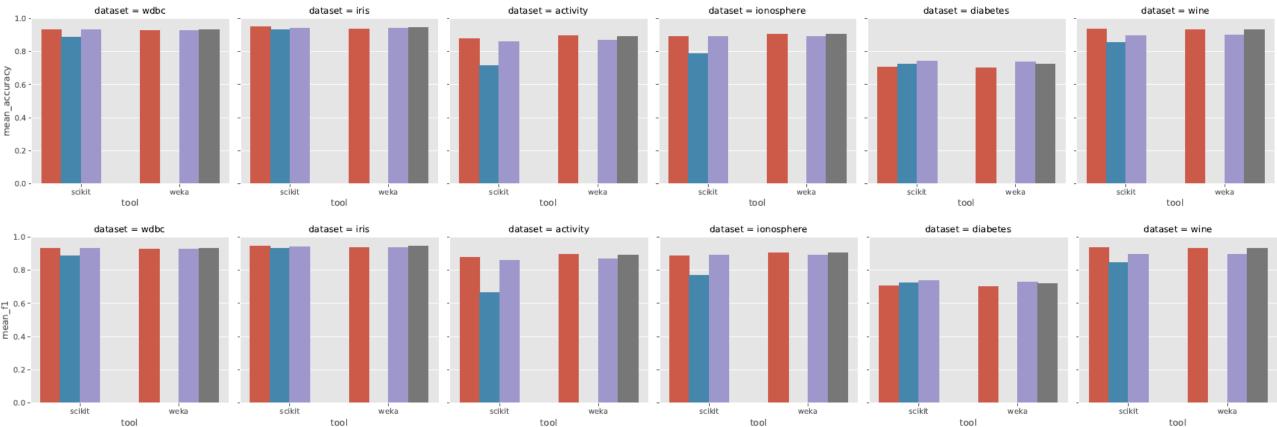
Hypotheses – Accuracy & F1 score

- Accuracy score ≈ F1 score (for balanced class distributions)
- Pruned trees have similar or better accuracy (less overfitting)
- Aggressive pruning (i.e., min_samples_leaf): lower accuracy
- Weka and scikit score similarly
 - Except for activity dataset?



Plots – Accuracy & F1 score



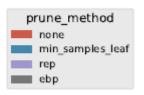


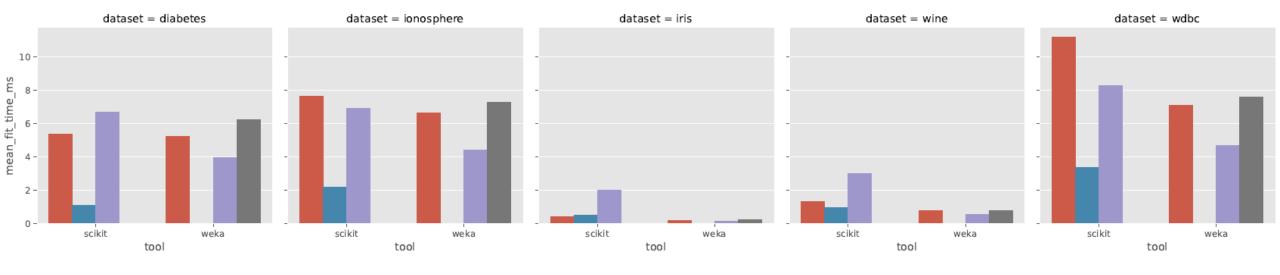
Hypotheses – fit and score duration

- Pruned trees fit more slowly
- Pseudo-pruned trees fit faster compared to unpruned trees
- Score time ~ tree size / max depth
 - Pruned trees score more quickly
- Notes
 - Weka (Java) and scikit (Python/Cython/C): apples and oranges
 - Using built-in timers of weka and scikit-learn
 - Measurement accuracy?



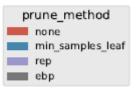
Plots – fit duration (without activity)

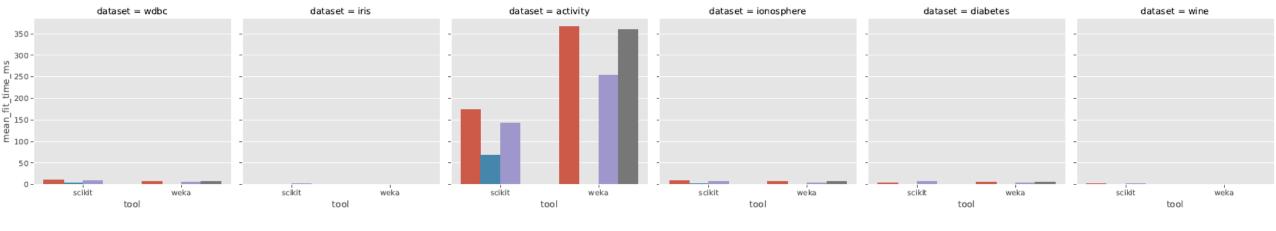


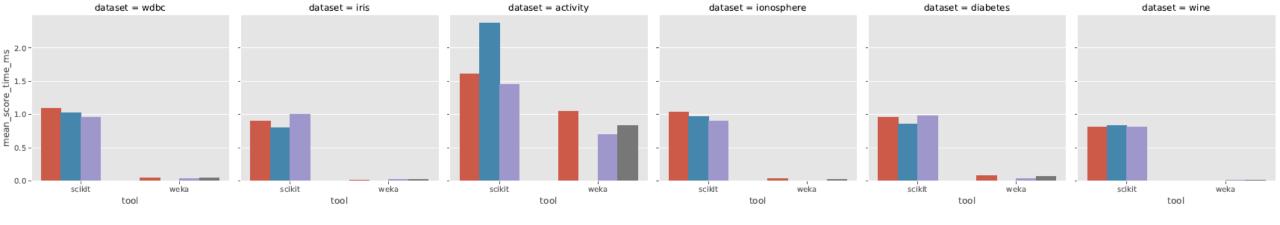




Plots – fit and score duration









Next steps (MoSCoW)

| Must have | Should have | Could/would have |
|------------------------------------|---------------------------|--------------------------|
| REP for regression | Code documentation | Python 2.x compatibility |
| Thesis text (*) | Study effect on ensembles | Contribution-ready code |
| Other pruning algorithm(s) | Multi-output support | Missing values |
| Analyze score duration discrepancy | Improve memory usage | Nominal values |
| Reproduce accuracy problem | Speed up (Cython?) | Online learning |

(*) Dutch thesis title?



Thank you

