KU LEUVEN

Complete decision tree induction functionality in scikit-learn

Ir. Sven Van Hove

Thesis submitted for the degree of Master of Science in Artificial Intelligence, option Engineering and Computer Science

Thesis supervisors:
Prof. dr. Jesse Davis
Prof. dr. ir. Hendrik Blockeel

Assessor:
Dr. ir. Marc Claesen

Mentor:
Elia Van Wolputte

Academic year 2017 – 2018

Preface

I would like to thank everybody who kept me busy the last year, especially my promoter and my assistants. I would also like to thank the jury for reading the text. My sincere gratitude also goes to my wive and the rest of my family.

Ir. Sven Van Hove

Contents

Abstract

The `abstract` environment contains a more extensive overview of the work. But it should be limited to one page. [EHWP16]

Chapter 1

Introduction

Decision tree induction is one of the most well-known tools in the machine learning community. Most of the theoretical groundwork was laid in the last three decades of the previous century. Researchers Leo Breiman and Ross Quinlan have been particularly influential in this space. Contemporary AI researchers focus most of their attentions on neural networks and in particular deep learning — the recent hype around DeepMind's AlphaGo [SSS+17] victories comes to mind — but decision tree research is not dead. Researchers still continue to propose new or improved algorithms and analyses.

Theory is one thing, but the algorithms need to be implemented as computer programs to actually be useful. Sci-kit learn [PVG+11] is a very popular machine learning library written in Python. As such, it also contains implementations of various decision tree induction algorithms. Before sci-kit learn became popular, a Java-based library called Weka [EHWP16] (or "Waikato Environment for Knowledge Analysis" in full) was often used instead. Even today, the implementations of decision tree algorithms in Weka are still in many respects superior to those in scikit-learn. Other libraries that implement similar algorithms exist (e.g., Apache Spark [ZXW+16]), but those are beyond the scope of this text.

The goal of this thesis is to alleviate the discrepancies between sci-kit learn and Weka concerning decision tree induction. Mind that decision tree induction tools can never be truly "complete" as stated in the title because the field is immensely broad and still continues to grow. Nevertheless, an effort can be made to improve feature parity between these two popular tools.

1.1 Thesis structure

The structure of the remainder of this text is as follows. First, an overview of the literature study concerning decision tree induction will be presented. In particular the link between an implementation and its underlying algorithm will be clarified, including the effects of that choice on the capabilities of the tool.

Chapter 2

Literature review

The relevant literature for this thesis mostly consists of papers concerning decision tree induction. These go back many decades, but fortunately there are some review and survey papers that provide a convenient overview [Mur98, RM05, KZP07]. On top of the classic literature, the source code and accompanying documentation of scikit-learn and Weka has also been a rich source of information.

2.1 Prerequisites

The reader ought to be familiar with basic machine learning concepts such as supervised learning, classification, regression, bias-variance trade-off, model validation and ensemble learning. Furthermore, basic knowledge of decision tree induction is expected. The most important basic concepts will be discussed briefly. Topics that are particularly important for the next chapters will be elaborated on.

2.2 Scope

A wide variety of decision tree induction algorithms exists. Here, only the *top down induction of decision trees (TDIDT)* family is considered because it is the most common approach and it is particularly relevant to the software tools under scrutiny.

Furthermore, only classification trees are considered. With little effort, most TDIDT classification algorithms can be converted to regression algorithms. Yet, these are far less popular and better alternatives such as Xgboost [CG16] exist.

Ensemble methods are also out of scope. Recent decision tree algorithms rarely work with a single tree, but rather with an ensemble of trees. Random forests [Bre01] is a very popular example of bootstrap aggregating or *bagging*. Regardless, the scope of this thesis concerns the fundamentals of decision trees, and not their derivatives. Implementation improvements suggested in this thesis could still potentially benefit related ensemble methods.

The algorithms in scope are all offline learning methods invented before the big data era. This implies that computation is done locally and that all data has to fit

in memory. As such, online learning methods or distributed algorithms are out of scope.

Finally, only univariate tests are in scope. The test performed in each internal node must only evaluate one attribute of the observation. For categorical attributes, this typically implies checking whether or not the input is equal to a fixed category. For numeric attributes, the input value is compared against a fixed threshold using $\leq$ or $>$. Consequently, the input space is partitioned recursively using axis-aligned hyperplanes. This scope limitation precludes well-known but seldom used extensions such as oblique trees.

2.3 Terminology

Throughout the relevant literature, there is a lack of ubiquitous vocabulary shared by all researchers. To avoid confusion, some basic terms are reviewed. A *decision tree* consists of *(internal) nodes* which are connected to other nodes via a one-to-many *parent-child* relation on one hand, and *leaves* which have no children on the other hand. The *root node* is the only node without parent. In a *binary tree*, the number of children per node is either zero or two.

Induction algorithms typically receive a *training set* as input data to construct a decision tree while a *test set* is used afterwards for model validation. These sets are tables of data where each row represents an *observation*. All observation are fully described by a common set of *attributes*. Some attributes are *categorical*, others may be *numeric*. Because decision tree induction is a part of supervised learning, one or more *class labels* are also associated with each observation. If the output domain only consists of two classes, the task is called *binary classification*. Otherwise it is called *multiclass classification*.

The *purity* of a node is defined as the percentage of observations in that node that belong to the majority class. A *pure node* is a node with 100% purity.

2.4 Advantages and disadvantages

The popularity of decision trees can be attributes to a couple of factors [PVG+11, Mur98, KZP07]:

1. Comprehensible: makes intuitive sense even for the uninitiated.
2. Transparent, as opposed to for example artificial neural networks
3. Easy to visualize tree (if number of nodes remains small)
4. Non-parametric, makes very few assumptions about data
5. No data normalization required
6. Handles both categorical and numeric data
7. Handles missing data elegantly

8. Fast training
9. Fast inference
10. Can process multi-output problems

Of course decision tree induction algorithms are not perfect:

1. Unstable: small modifications in training data can result in a completely different tree
2. Learning optimal trees is an NP-Complete problem [HR76], so heuristics are used to find approximations
3. Prone to overfitting if not actively countered by adding early stopping criteria or an extra pruning step
4. Prone to bias when one class appears more much frequently in the training set than others.

2.5 Comparison to other ML algos

2.6 A generic TDIDT algorithm

A typical TDIDT algorithm for classification consists of two phases: a grow phase and an optional prune phase. The grow phase requires three functions with fixed signatures: a test generation function, a splitting function and a stopping function. Historically, researchers presented their TDIDT algorithms with fixed functions. Because of the common interface it is now common to choose these functions *à la carte*. One could try to evaluate the performance of each function separately, but choosing the best of each function does not guarantee a global optimum. Holistic tests must be performed to ensure the best configuration is chosen.

2.6.1 Test generation

2.6.2 Splitting

Classic TDIDT algorithms work by recursively splitting nodes based on some optimal test $\tau \in \mathcal{T}$, the set of all possible tests. A heuristic called the splitting criterion is required to determine this τ. A few such criteria have stood the test of time.

Purity

The perfect test τ^* creates a partition $\mathcal{S}_{\tau^*} = \{S_1, \ldots, S_k\}$ wherein each subset is pure, so optimizing for weighted average partition purity $p(\mathcal{S}_\tau)$ is a sensible first criterion.

$$p(\mathcal{S}_\tau) = \sum_{S_i \in \mathcal{S}_\tau} \frac{|S_i|}{|S|} p(S_i) \tag{2.1}$$

Here, $S = S_1 \cup \ldots \cup S_k$ and $p(S)$ is the set purity as described above.

Entropy and information gain

In practice purity does not appear to work very well. That is why researchers came up with an alternative based on Shannon's information theory [Sha48]. Quinlan used such metrics in many of his prominent algorithms such as ID3 and C4.5 [Qui86, Qui93], but it was already invented earlier for the Concept Learning System (CLS) [HMS66]. Define entropy (or missing information) of a variable V with possible values v_i and associated probabilities p_i as follows:

$$s(V) = -\sum_i p_i \log_2(p_i) \tag{2.2}$$

The same concept can be applied to the class variable. Define the class entropy $s_C(S)$:

$$s_C(S) = -\sum_c p(c) \log_2(p(c)) \tag{2.3}$$

where $p(c)$ is the probability that a random observation in S belongs to class c. This value can be defined for any node, before splitting begins.

Once we consider a specific partition, a similar definition can be given for each subset S_i:

$$s_C(S_i) = -\sum_c p_i(c) \log_2(p_i(c)) \tag{2.4}$$

For the entropy of a partition $\mathcal{S}_\tau$, again use the weighted average entropy of its subsets:

$$s_C(\mathcal{S}_\tau) = \sum_i \frac{|S_i|}{|S|} s_C(S_i) \tag{2.5}$$

Finally, calculate the information gain $IG(\tau, S)$ of the split that resulted from test τ:

$$IG(\tau, S) = s_C(S) - s_C(\mathcal{S}_\tau) \tag{2.6}$$

where $\mathcal{S}_\tau$ is the partition resulting from test τ.

Gain ratio

The information gain criterion is biased towards tests with many possible outcomes. This could be a problem in non-binary trees. The gain ratio alleviates this problem. First define split information $SI(\tau, S)$ — the maximum possible information gain — as follows:

$$SI(\tau, S) = -\sum_i \frac{|S_i|}{|S|} \log_2 \frac{|S_i|}{|S|} \tag{2.7}$$

Finally, define the gain ratio:

$$GR(\tau, S) = \frac{IG(\tau, S)}{SI(\tau, S)} \tag{2.8}$$

In binary trees, this heuristic typically causes a less balanced tree compared to the information gain criterion [Qui93].

Gini

Distance metrics such as the Gini impurity index can be used instead of heuristics based on information theory [BFSO84]. The definitions follow the same pattern as those of the information gain:

$$g(S) = \sum_c p(c)(1 - p(c)) \tag{2.9}$$

$$g(S_i) = \sum_c p_i(c)(1 - p_i(c)) \tag{2.10}$$

$$g(\mathcal{S}_\tau) = \sum_i \frac{|S_i|}{|S|} g(S_i) \tag{2.11}$$

$$Q(\tau, S) = g(S) - g(\mathcal{S}_\tau) \tag{2.12}$$

2.6.3 Stopping

Breiman argues in his CART book [BFSO84] that choosing good stopping criteria is far more important than choosing good splitting criteria. If early stopping was not applied or no pruning (see below) was performed afterwards, trees would grow excessively large on real world data sets. This is a classic case of overfitting. It negatively impacts many factors that make decision trees attractive in the first place, such as their comprehensibility and their fast training and inference. It is also detrimental to the performance of the model on unseen data since the model fails to generalize properly.

Some simple stopping criteria are based on the depth of the tree, the purity of a node or the number of observations belonging to a node.

More complex stopping criteria are based on the Minimum Discription Length (MDL) of a tree [Ris78] or on statistical techniques such as a Ξ^2-test. Quilan proposed to use the latter in his ID3 algorithm but decided not to include it in the successor (C4.5) [Qui86, Qui93].

2.6.4 Pruning

[Qui87] [EK01a] [MRA+95] [KC01] [Man97] [BA97] [Elo99] [Min89] [EK01b] [EMSK97]

2.7 Extensions

2.8 Conclusion

Chapter 3

Software for decision tree induction

Intro

3.1 Capabilities

3.2 Conclusion

Chapter 4

Methodology

Intro

4.1 Conclusion

Chapter 5

Results and discussion

Intro

5.1 Pruning

5.2 Categorical attributes

5.3 Conclusion

Chapter 6

Conclusion

Intro

6.1 Contributions

6.2 Retrospective

6.3 Future work

Appendices

Appendix A

The First Appendix

Appendices hold useful data which is not essential to understand the work done in the master's thesis. An example is a (program) source. An appendix can also have sections as well as figures and references.

Bibliography

[BA97] Leonard A Breslow and David W Aha. Simplifying decision trees: A survey. *The Knowledge Engineering Review*, 12(1):1–40, 1997.

[BFSO84] Leo Breiman, Jerome Friedman, Charles J Stone, and Richard A Olshen. *Classification and regression trees*. CRC press, 1984.

[Bre01] Leo Breiman. Random forests. *Machine learning*, 45(1):5–32, 2001.

[CG16] Tianqi Chen and Carlos Guestrin. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, pages 785–794. ACM, 2016.

[EHWP16] F Eibe, MA Hall, IH Witten, and JC Pal. The weka workbench. *Online appendix for "data mining: practical machine learning tools and techniques.": Fourth Morgan Kaufmann*, 2016.

[EK01a] Tapio Elomaa and Matti Kääriäinen. An analysis of reduced error pruning. *Journal of Artificial Intelligence Research*, 15:163–187, 2001.

[EK01b] Tapio Elomaa and Matti Kaariainen. An analysis of reduced error pruning. *Journal of Artificial Intelligence Research*, 15:163–187, 2001.

[Elo99] Tapio Elomaa. The biases of decision tree pruning strategies. In *International Symposium on Intelligent Data Analysis*, pages 63–74. Springer, 1999.

[EMSK97] Floriana Esposito, Donato Malerba, Giovanni Semeraro, and J Kay. A comparative analysis of methods for pruning decision trees. *IEEE transactions on pattern analysis and machine intelligence*, 19(5):476–491, 1997.

[HMS66] Earl B Hunt, Janet Marin, and Philip J Stone. Experiments in induction. 1966.

[HR76] Laurent Hyafil and Ronald L Rivest. Constructing optimal binary decision trees is np-complete. *Information processing letters*, 5(1):15–17, 1976.

[KC01] Boonserm Kijsirikul and Kongsak Chongkasemwongse. Decision tree pruning using backpropagation neural networks. In *Neural Networks, 2001. Proceedings. IJCNN'01. International Joint Conference on*, volume 3, pages 1876–1880. IEEE, 2001.

[KZP07] Sotiris B Kotsiantis, I Zaharakis, and P Pintelas. Supervised machine learning: A review of classification techniques. *Emerging artificial intelligence applications in computer engineering*, 160:3–24, 2007.

[Man97] Yishay Mansour. Pessimistic decision tree pruning based on tree size. In *MACHINE LEARNING-INTERNATIONAL WORKSHOP THEN CONFERENCE-*, pages 195–201. Citeseer, 1997.

[Min89] John Mingers. An empirical comparison of pruning methods for decision tree induction. *Machine learning*, 4(2):227–243, 1989.

[MRA+95] Manish Mehta, Jorma Rissanen, Rakesh Agrawal, et al. Mdl-based decision tree pruning. In *KDD*, volume 95, pages 216–221, 1995.

[Mur98] Sreerama K Murthy. Automatic construction of decision trees from data: A multi-disciplinary survey. *Data mining and knowledge discovery*, 2(4):345–389, 1998.

[PVG+11] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

[Qui86] J. Ross Quinlan. Induction of decision trees. *Machine learning*, 1(1):81–106, 1986.

[Qui87] J. Ross Quinlan. Simplifying decision trees. *International journal of man-machine studies*, 27(3):221–234, 1987.

[Qui93] J Ross Quinlan. *C4.5: Programs for Machine Learning*. Morgan Kaufmann, 1993.

[Ris78] Jorma Rissanen. Modeling by shortest data description. *Automatica*, 14(5):465–471, 1978.

[RM05] Lior Rokach and Oded Maimon. Top-down induction of decision trees classifiers-a survey. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 35(4):476–487, 2005.

[Sha48] Claude E Shannon. A mathematical theory of communication (parts i and ii). *Bell System Tech. J.*, 27:379–423, 1948.

[SSS+17] David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, et al. Mastering the game of go without human knowledge. *Nature*, 550(7676):354, 2017.

[ZXW+16] Matei Zaharia, Reynold S. Xin, Patrick Wendell, Tathagata Das, Michael Armbrust, Ankur Dave, Xiangrui Meng, Josh Rosen, Shivaram Venkataraman, Michael J. Franklin, Ali Ghodsi, Joseph Gonzalez, Scott Shenker, and Ion Stoica. Apache spark: A unified engine for big data processing. *Commun. ACM*, 59(11):56–65, October 2016.

Master's thesis filing card

Student: Ir. Sven Van Hove

Title: Complete decision tree induction functionality in scikit-learn

Dutch title: Complete beslissingsboom inductie functionaliteit in scikit-learn

UDC: 681.3*I20

Abstract:
500 word abstract

Thesis submitted for the degree of Master of Science in Artificial Intelligence, option Engineering and Computer Science

Thesis supervisors: Prof. dr. Jesse Davis
Prof. dr. ir. Hendrik Blockeel

Assessor: Dr. ir. Marc Claesen

Mentor: Elia Van Wolputte