

Rcpp Implementation of Entropy Based Feature Selection Algorithms with Sparse Matrix Support

by Zygmunt Zawadzki, Marcin Kosiński

Abstract Feature selection is a process of extracting valuable features that have significant influence on dependent variable. Time efficient feature selection algorithms are still an active field of research and are in the high demand in the machine learning area.

We introduce **FSelectorRcpp**, an R package (R Core Team, 2012) that includes entropy based feature selection algorithms. Methods presented in this package are not new, they were reimplemented in C++ and originally come from **FSelector** package (Romanski and Kotthoff, 2016), but we provide many technical improvements. Our reimplementation occurs to have shorter computation times, it does not require earlier Java nor Weka (Hall et al., 2009) installation and provides support for sparse matrix format of data, e.g. presented in **Matrix** package (Bates and Maechler, 2016). This approach facilitates software installation and improves work with bigger datasets, in comparison to the base R implementation in **FSelector**, which is even not optimal in the sense of R code.

Additionally, we present new, C++ implementation of continuous variables Multi-Interval Discretization (MDL) method (Fayyad and Irani, 1993), which is required in entropy calculations during the feature selection process in showed methods. By default, regular **FSelector** implementation uses **entropy** package (Hausser and Strimmer, 2014), for which we also attach the computation times comparison.

Finally, we announce the full list of available functions, which are divided to 2 groups: entropy based feature selection methods and stepwise attribute selection functions that might use any evaluator to choose proper features, e.g. presented entropy based algorithms.

Introduction and Motivation

In modern statistical learning the biggest bottlenecks are computation times of model training procedures and the overfitting. Both are caused by the same issue - the high dimension of explanatory variables space. Researchers have encountered problems with too big sets of features used in machine learning algorithms also in terms of model interpretation. This motivates applying feature selection algorithms before performing statistical modeling, so that on smaller set of attributes the training time will be shorter, the interpretation might be clearer and the noise from non important features can be avoided. More motivation can be found in John et al. (1994).

Many methods were developed to reduce the curse of dimensionality like Principal Component Analysis (F.R.S., 1901) or Singular Value Decomposition (Eckart and Young, 1936) which approximates the variables by smaller number of combinations of original variables, but this approach is hard to interpret in the final model.

Sophisticated methods of attribute selection as Boruta algorithm (Kursa and Rudnicki, 2010), genetic algorithms (Kuhn and Johnson, 2013; Aziz et al., 2013) or simulated annealing techniques (Khachaturyan et al., 1981) are known and broadly used but in some cases for those algorithms computations can take even days, not to mention that datasets are growing every day.

Few classification and regression models can reduce redundant variables during the training phase of statistical learning process, e.g. Decision Trees (Rokach and Maimon, 2008; Breiman et al., 1984), LASSO Regularized Generalized Linear Models (with cross-validation) (Friedman et al., 2010) or Regularized Support Vector Machine (Xu et al., 2009), but still computations starting with full set of explanatory variables are time consuming and the understanding of the feature selection procedure in this case is not simple and those methods are sometimes used without the understanding.

In business applications there appear a need to provide a fast feature selection that is extremely easy to understand. For such demands easy methods are preferred. This motivates using simple techniques like Entropy Based Feature Selection (Lageron et al., 2011), where every feature can be checked independently so that computations can be performed in a parallel to shorten the procedure's time. For this approach we provide an R interface to Rcpp reimplementation of methods included in **FSelector** package which we also extended with parallel background and sparse matrix support. This has significant impact on computations time and can be used on greater datasets than regular R implementation prepared by **FSelector** original author, Piotr Romański.

Discretization

Entropy Based Feature Selection Algorithms

In the information theory the term **entropy** (Shannon, 2001) is

Stepwise Attribute Selection Evaluators

FSelectorRcpp and FSelector Computation Times Comparison

Conclusion

Acknowledgment

Bibliography

- A. S. A. Aziz, A. T. Azar, M. A. Salama, A. E. Hassanien, and S. E. O. Hanfy. Genetic algorithms with different feature selection techniques for anomaly detectors generation. In M. P. M. Ganzha, L. Maciaszek, editor, *Proceedings of the 2013 Federated Conference on Computer Science and Information Systems*, pages 769–774. IEEE, 2013. [p1]
- D. Bates and M. Maechler. *Matrix: Sparse and Dense Matrix Classes and Methods*, 2016. URL <https://CRAN.R-project.org/package=Matrix>. R package version 1.2-7. [p1]
- L. Breiman, J. Friedman, R. Olshen, and C. Stone. *Classification and Regression Trees*. Wadsworth and Brooks, Monterey, CA, 1984. new edition ?? [p1]
- C. Eckart and G. Young. The approximation of one matrix by another of lower rank. *Psychometrika*, 1(3):211–218, 1936. doi: 10.1007/BF02288367. [p1]
- U. M. Fayyad and K. B. Irani. Multi-Interval Discretization of Continuous-Valued Attributes for Classification Learning. In *13th International Joint Conference on Uncertainty in Artificial Intelligence(IJCAI93)*, pages 1022–1029, 1993. [p1]
- J. Friedman, T. Hastie, and R. Tibshirani. Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software*, 33(1):1–22, 2010. URL <http://www.jstatsoft.org/v33/i01/>. [p1]
- K. P. F.R.S. Liii. on lines and planes of closest fit to systems of points in space. *Philosophical Magazine Series 6*, 2(11):559–572, 1901. [p1]
- M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten. The weka data mining software: An update. *SIGKDD Explor. Newsl.*, 11(1):10–18, Nov. 2009. ISSN 1931-0145. doi: 10.1145/1656274.1656278. URL <http://doi.acm.org/10.1145/1656274.1656278>. [p1]
- J. Hausser and K. Strimmer. *entropy: Estimation of Entropy, Mutual Information and Related Quantities*, 2014. URL <https://CRAN.R-project.org/package=entropy>. R package version 1.2.1. [p1]
- G. H. John, R. Kohavi, and K. Pfleger. Irrelevant features and the subset selection problem. In *MACHINE LEARNING: PROCEEDINGS OF THE ELEVENTH INTERNATIONAL*, pages 121–129. Morgan Kaufmann, 1994. [p1]
- A. Khachatryan, S. Semenovskaya, and B. Vainshtein. The thermodynamic approach to the structure analysis of crystals. *Acta Crystallographica Section A*, 37(5):742–754, Sep 1981. [p1]
- M. Kuhn and K. Johnson. *Applied predictive modeling*, 2013. URL <http://www.amazon.com/Applied-Predictive-Modeling-Max-Kuhn/dp/1461468485/>. [p1]
- M. B. Kursa and W. R. Rudnicki. Feature selection with the Boruta package. *Journal of Statistical Software*, 36(11):1–13, 2010. URL <http://www.jstatsoft.org/v36/i11/>. [p1]

- C. Largeron, C. Moulin, and M. Géry. Entropy based feature selection for text categorization. In *Proceedings of the 2011 ACM Symposium on Applied Computing, SAC '11*, pages 924–928, New York, NY, USA, 2011. ACM. ISBN 978-1-4503-0113-8. doi: 10.1145/1982185.1982389. URL <http://doi.acm.org/10.1145/1982185.1982389>. [p1]
- R Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2012. URL <http://www.R-project.org/>. ISBN 3-900051-07-0. [p1]
- L. Rokach and O. Maimon. *Data Mining with Decision Trees: Theory and Applications*. World Scientific Publishing Co., Inc., River Edge, NJ, USA, 2008. ISBN 9789812771711, 9812771719. [p1]
- P. Romanski and L. Kotthoff. *FSelector: Selecting Attributes*, 2016. URL <https://CRAN.R-project.org/package=FSelector>. R package version 0.21. [p1]
- C. E. Shannon. A mathematical theory of communication. *SIGMOBILE Mob. Comput. Commun. Rev.*, 5(1):3–55, Jan. 2001. ISSN 1559-1662. doi: 10.1145/584091.584093. URL <http://doi.acm.org/10.1145/584091.584093>. [p2]
- H. Xu, C. Caramanis, and S. Mannor. Robustness and regularization of support vector machines. *J. Mach. Learn. Res.*, 10:1485–1510, Dec. 2009. ISSN 1532-4435. URL <http://dl.acm.org/citation.cfm?id=1577069.1755834>. [p1]

Zygmunt Zawadzki

zygmunt@zstat.pl

Marcin Kosiński
Warsaw University of Technology
Faculty of Mathematics and Information Science
Koszykowa 75, Warsaw Poland
m.kosinski@mini.pw.edu.pl