Meta-modelling Execution Time of Data Minning Algorithms

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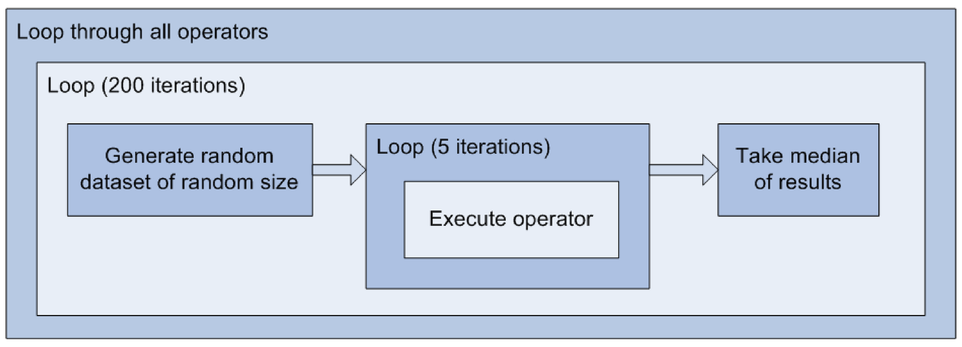
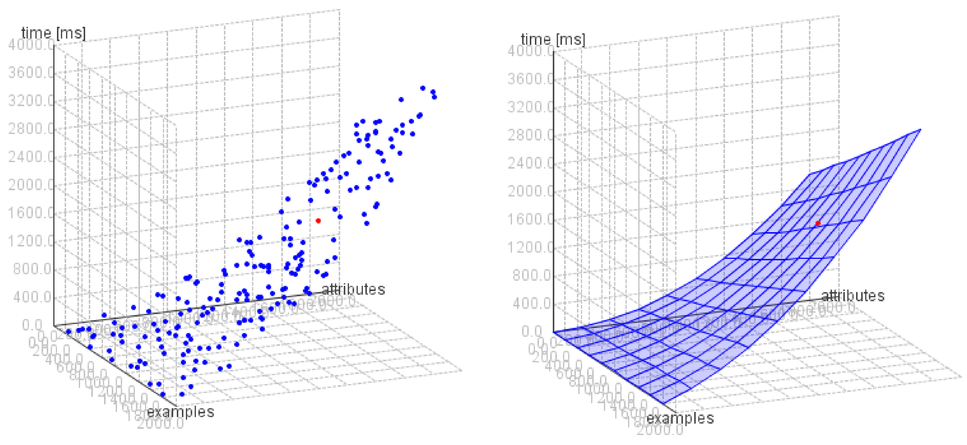
Abstract

Knowing the execution time of a computational model, especially when dealing with large data, is crucial in deciding whether the solution of the problem is attainable in acceptable time. In the case of data mining processes, typically both the modelling and the model application execution time are important. We developed a meta-mining framework for execution time estimation of data mining algorithms built in RapidMiner. Operator execution time estimation is treated as a machine learning problem for which we built prediction models using execution times obtained by running algorithms on a set of predetermined datasets. With the appropriate refitting, this experimental methodology is applicable to any data mining environment. We an present overall framework with modelling results for a subset of RapidMiner operators, and compare non-parametric distance measures based predictions with polynomial function fitting. Finally, we demonstrate the integration of these models in the form of a standalone RapidMiner extension and discuss issues related to reliability, scalability and applicability for the overall workflow execution time modelling.

Measuring execution time



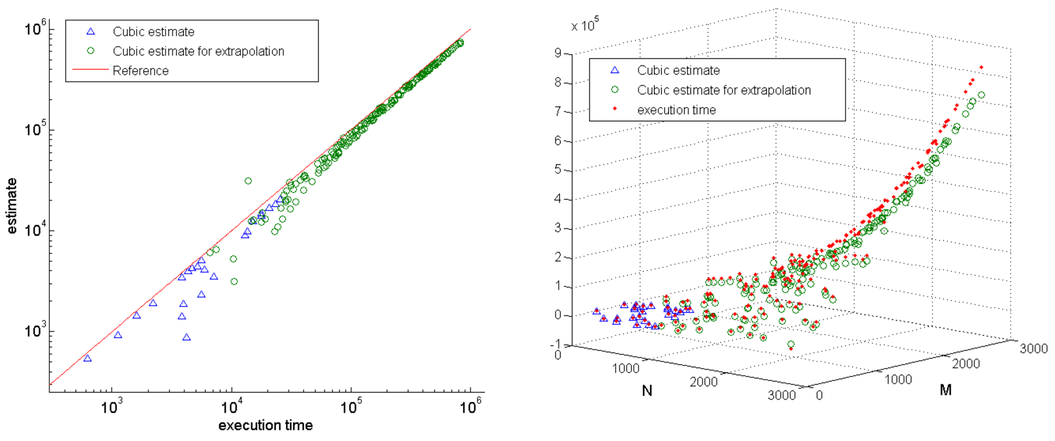
Estimation methodology



Pager: A kNN-based algorithm for regression [12], Pager is a parameterless algorithm, providing reliable and robust estimations without the need for providing the explicit regression equation. Our implementation is done in Java.

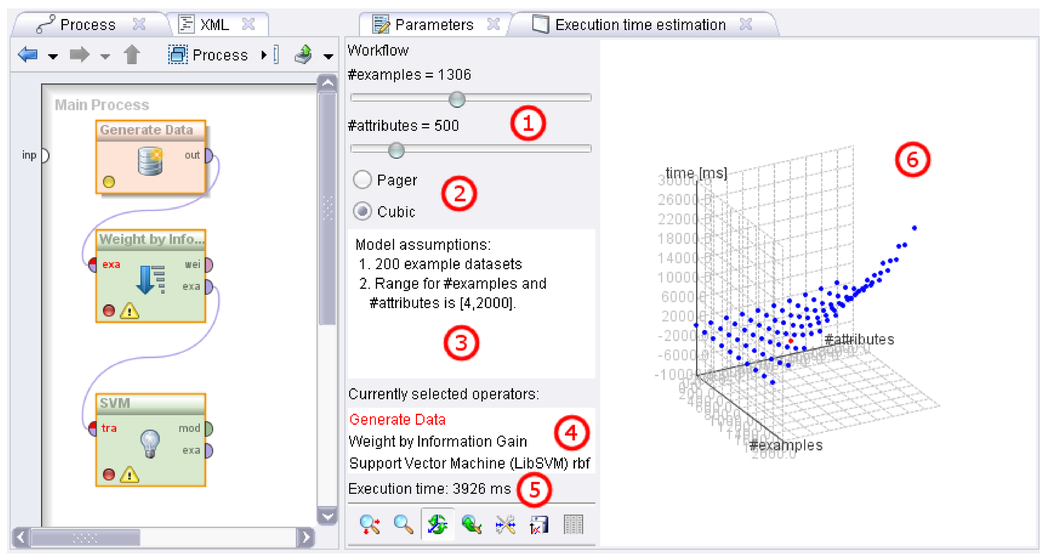
Polynomial: Cubic function fitting, suitable for a small number of meta-features. Our implementation is a simple gradient descent, optimised with the fminsearch function in Matlab.

Extrapolation of estimations



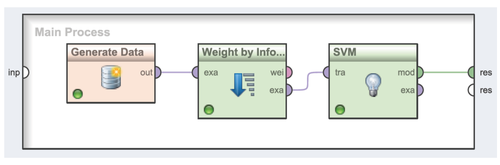
Extrapolation of estimated execution times to parameter ranges not used in experimentation for polynomial model. This example shows execution time estimates for a simple workflow consisting of "Weight by Information Gain" and "SVM" with rbf kernel operators where individual estimates for each operator are summed. Graphs show comparison between estimates and real values of execution times for test cases inside experimentation range (triangles) and outside experimentation range (circles). Red points on the right are real execution times while red line on the left is a reference representing ideal estimation.

Execution time extension for RapidMiner

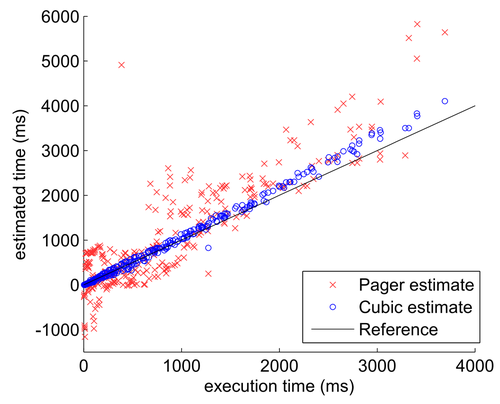


We implemented a RapidMiner extension that interactively displays execution time information for operators selected in the main process. Basic functionalities are: (1) sliders for choosing number of attributes and examples for the input dataset, (2) prediction model (Pager or polynomial), (3) info box about for the estimation model, (4) list of currently selected operators and (5) their execution time estimate, (6) interactive display showing execution time surface in relation to the number of examples and number of attributes.

Use case: a simple classification workflow



Simple use case consisting of feature weighting operator ("Weight by Information Gain") and classification operator ("SVM" with rbf kernel). On the right is the comparison of estimated and real execution times for estimation with Pager and polynomial model.



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