Explaining the Results of an Optimization-Based Decision Support System – A Machine Learning Approach

APMOD 2016
Brno University of Technology, Brno
June 9th, 2016

Irène Abi-Zeid
M. Léger, M. Morin
Laval University

F. Grondin, M. Pleau
Tetra Tech Quebec

Quebec, Canada

R. Thomopoulos
IATE, Montpellier, France

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Presentation Plan

- Background
- Problem statement
- Literature review
- Methodology
- Results
- Conclusion
- Future Work

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Background

- Combined sewer overflows is a major problem for many municipalities
- Major source of river pollution during and following some rainfall events
- Possible solution : Predictive Real Time Control of sewer systems to optimize wastewater management

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Background - CSOFT

- Decision Support System (DSS) for the flow management of a combined and sanitary wastewater system
  - commercial software
  - real-time decision support
  - deployed in many major cities and is used on a daily basis (US, France, Canada)

- Includes a simulator and an optimizer

- Designed to model water behavior within a sewer network and to recommend the best way to efficiently operate sewer systems

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Background - CSOFT

- Based on weather forecasts over a given time period, the simulator simulates the flow in the network

- The optimizer establishes, based on water flows (actual and predicted) a set of instructions to regulate flows using sluice gates and pumps
  - Optimal flow set point configurations (decision variables)

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Background - CSOFT

- Minimize a cost function (objective function)
  - minimize overflow volumes, storage facility dewatering time
  - ensure a balanced hydraulic load distribution throughout the network
- Constraints describe the behavior of the network
- Control policy every 5 minutes, two hour control horizon
  - Output: flow set points

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Background
Project

- Collaboration between Laval University and Tetra Tech Quebec

- Funded by a Canadian National Science Engineering Research Council - Engage grant
  - "project must generate new knowledge or apply existing knowledge in an innovative manner in order to solve a company-specific problem"
  - University - Industry partnership

- Over the years, our industrial partner has identified the need for **explanations** of the optimization results to the **users**

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Problem statement

- User does not agree with optimal solution provided by a DSS!
  - Sometimes the user wishes to apply another control strategy

- Our main goal is to help a user to understand why a proposed solution is good and why other solutions are worse
  - explain the optimization results

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Problem statement

Our goal

- Given an optimal solution to a mathematical program, we wish to enable an end-user to understand which characteristics of a solution render it more or less satisfactory

- Explanations should allow the user to understand which decision variables can be modified and their impact

Literature review

- Since the 90s, several studies have pointed out that end users have a low acceptance level of the solutions computed by DSSs
  - importance of feedback about a decision made
- However, studies about the effects of providing explanations on DSS advice acceptance were still extremely rare
- Explanations of DSS recommendations have only recently begun to emerge as an important consideration (*Du et al.*, 2014)

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Methodology

- Learn what makes a feasible solution a good solution
  - Attributes of a good solution
  - Rules to obtain a good solution

- Machine Learning approach
  - The art of learning by examples

- A supervised learning algorithm is provided with a training set S of examples

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Methodology

- Each example in set S is a pair (X;y) where X is an input and y is an output.
  - The input X is a vector of attributes values
  - The output can be a class, a real number, or it can have a structure
- X : set of decision variables (flow set points)
  - Maximum flow that a given sluice gate or a pump can send in the network at timestpe t
- y: True (good in terms of objective function) or False

Methodology

- A solution to the binary classification problem is a function h, called a classifier, that takes an input a vector X and that outputs True or False

- Result is a decision tree that provides rules to classify satisfactory and unsatisfactory solutions
  - reduced attributes set
  - high impact decision variables

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Methodology
Data set generation

- Start from an optimal solution
- Define a satisfactory solution as one which objective value is not « too far » from the optimal solution
  - In this case, does not exceed by more than 5% the optimal solution

- Repeat N number of times to obtain a set of N feasible solutions
  - Perturb the optimal values of the decision variables
  - Evaluate the associated objective function
  - Identify as satisfactory (T) or unsatisfactory (F)

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Methodology

- Partition S, the set of feasible solution into a Training set and an Evaluation set
- Use the training set to learn decision trees
- Evaluate the accuracy of the decision tree using the evaluation set
- Scikit-learn to construct decision trees
  - a machine learning library for the Python programming language

Results

Example of a Decision Tree

If

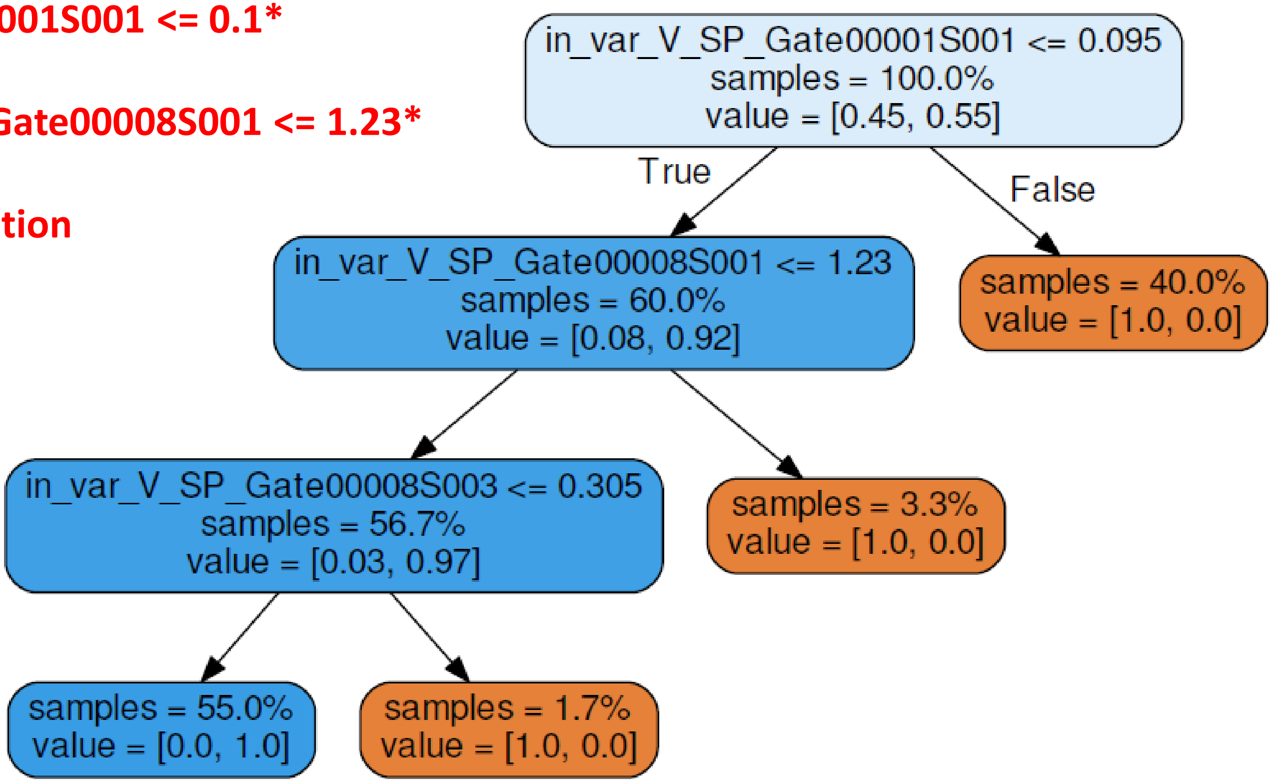
in_var_V_SP_Gate00001S001 <= 0.1*

AND

0.69< in_var_V_SP_Gate00008S001 <= 1.23*

then we have a satisfactory solution

Flow units: volume/time



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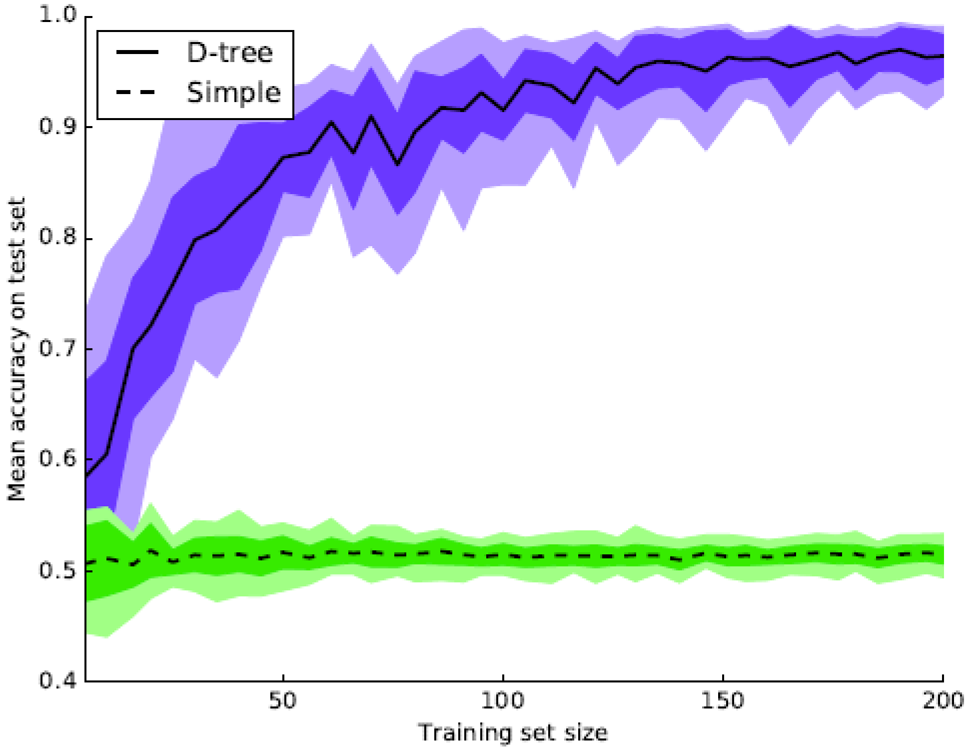
Results
Predictive accuracy of classifier

- We varied the size of the subset of S used for training
  - from 5 training examples to 200 training examples for a total of 40 subset sizes
  - we learned 10 different trees and aggregated the results
  - each tree is tested against the 9,800 remaining examples in the test set

Results

Classification accuracy vs training size



Conclusion

- We have proposed an approach using decision trees to explain the optimization results of a commercial software used for real-time decision support system

- Our solution allows analysts to identify the main variables that influence the objective function
  - Can help users in understanding the rationale behind a DSS's recommendations

- Proof of concept

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Future work

- Other performance criteria to qualify a solution
  - Not only departure from minimum objective function
  - We have identified some more important components of the objective function
- Identify the “optimal” size of the training set, allowing both a good quality of learning and a reasonable computing time
- Experiment our approach on other types of learning algorithms
  - Rough sets

References

- 1. Bakir, G., Hofmann, T., Schoölkopf, B., Smola, A.J., Taskar, B., Vishwanathan, S.V.N.(eds.): Predicting Structured Data. MIT press (2007)
- 2. Bishop, C.M.: Pattern Recognition and Machine Learning. Springer, New York (2006)
- 3. Breiman, L., Friedman, J., Olshen, R.A., Stone, C.J.: Classification and Regression Trees. Chapman and Hall, Belmont, CA (1984)
- 4. Davis, F.D., Kottemann, J.E.: Determinants of decision rule use in a production planning task. Organizational Behavior and Human Decision Processes 63(2), 145 – 157 (1995)
- 5. Du, G., Richter, M., Ruhe, G.: An explanation oriented dialogue approach and its application to wicked planning problems. Journal of Computing and Informatics 25, 223–249 (2006)
- 6. Du, G., Ruhe, G.: Two machine-learning techniques for mining solutions of the releaseplanner ™ decision support system. Information Sciences 259, 474–489 (2014)
- 7. Gönül, M.S., Önkal, D., Lawrence, M.: The effects of structural characteristics of explanations on use of a DSS. Decision Support Systems 42(3), 1481–1493 (2006)
- 8. Kleinmuntz, B.: Why we still use our heads instead of formulas: toward an integrative approach. Psychological Bulletin 107(3), 296–310 (1990)
- 9. Lawrence, M., Davies, L., O'Connor, M., Goodwin, P.: Improving forecast utilization by providing explanations. In: Proc. of 21st International Symposium on Forecasting, Atlanta - USA (2001)
- 10. Lehtola, L., Kujala, S.: Requirements prioritization challenges in practice. In: Proc. of 5th IntÂt'l Conf. on Product Focused Software Process Improvement (PROFES), Kansai Science City. pp. 497–508 (2004)
- 11. Lim, J.S., O'Connor, M.: Judgmental forecasting with time series and causal information. International Journal of Forecasting 12(1), 139–153 (1996)
- 12. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P.,Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher,
- M., Perrot, M., Duchesnay, E.: Scikit-learn: Machine learning in python. The Journal of Machine Learning Research 12, 2825–2830 (2011)
- 13. Pleau, M., Colas, H., Lavallée, P., Pelletier, G., Bonin, R.: Global optimal real-time control of the quebec urban drainage system. Environmental Modelling & Software 20(4), 401–413 (2005)

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