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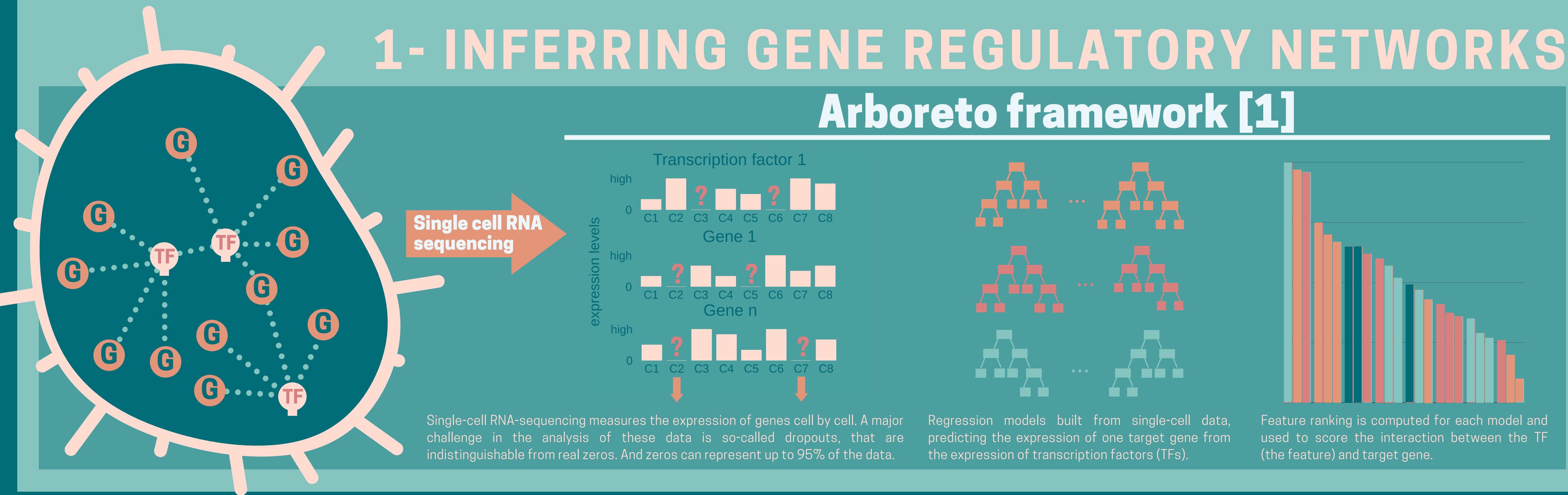
Semi-supervised learning for tree-based regressors to improve the prediction of the interactions between genes

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1- INFERRING GENE REGULATORY NETWORKS

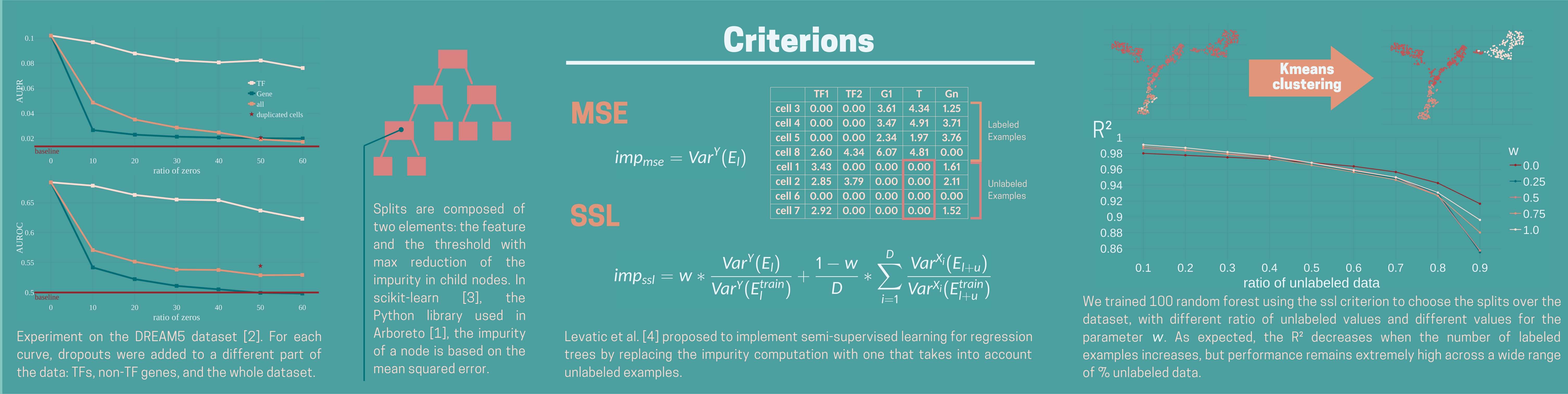
Arboreto framework [1]



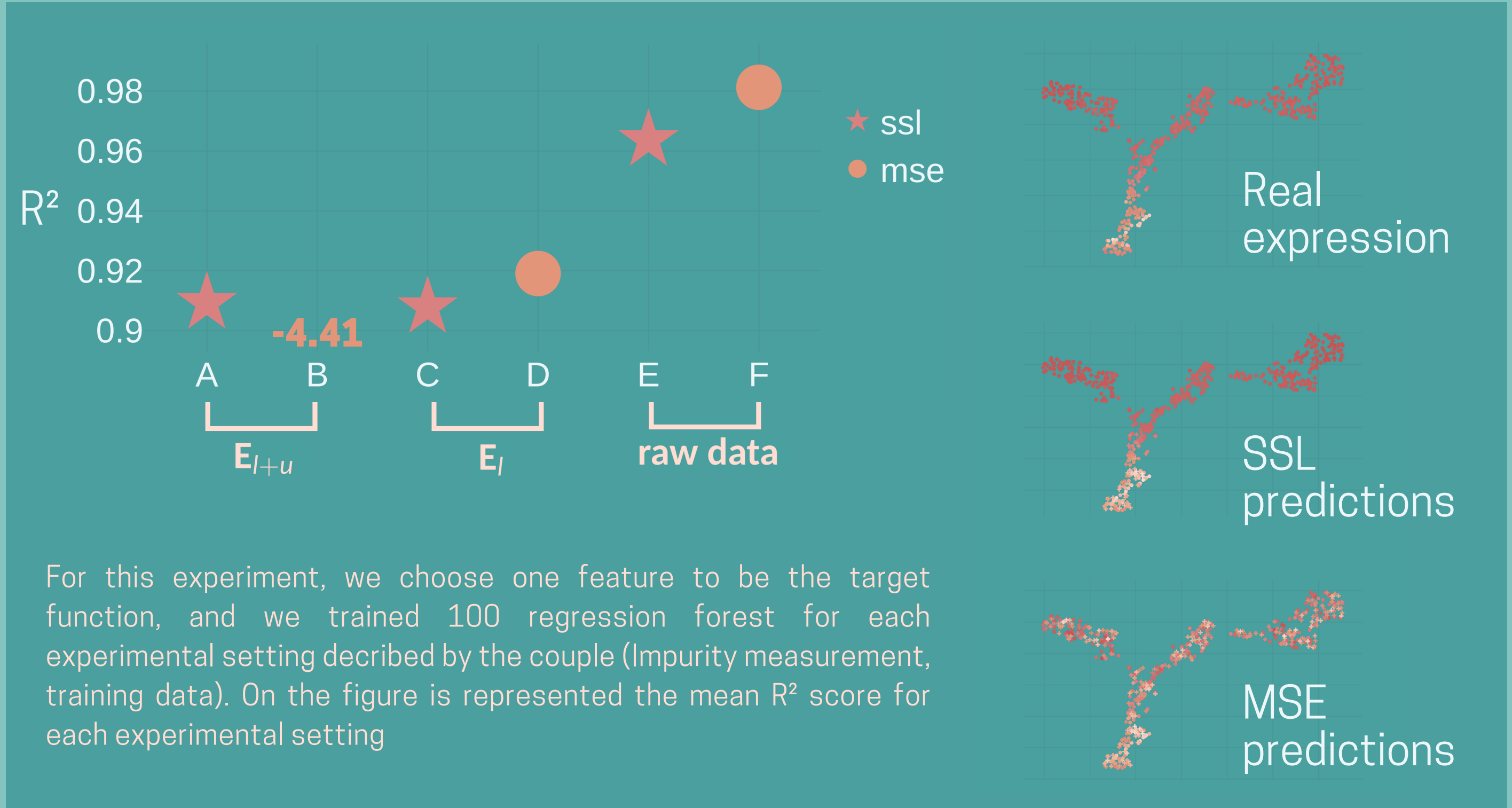
QUESTIONS

- How to build tree-based models that integrate measured values and handle the uncertain origins of zeros?
- How to efficiently build the tree regression models in order to use the algorithm in the Arboreto pipeline?
- Can we find a unique optimal value of the parameter for all single-cell datasets?

2- SEMI-SUPERVISED LEARNING FOR TREES



3- RESULTS



4- LIMITS

COMPUTATION TIME

- Scikit-learn implements a so-called impurity proxy that has the same monotony as the real impurity. This reduces the time needed to find the optimal split at each node. For now, our implementation in scikit-learn [3] does not come with such a proxy, but finding and implementing one could reduce the computational power needed.
- Reducing the number of features on which to compute the second term is also a possibility by using a random subset of features.

NEW PARAMETER

In this impurity definition, a new parameter is introduced: w . Tuning this parameter might be an issue, but according to the original paper [4] and the early results we have, it is possible that the value of the parameter will not have such a big influence in our experimental setting. This is still an open question.

REAL SETTING

The implementation of this impurity measure still needs to be tested in a realistic situation, to reproduce the experiment presented in Section 2. This is time-consuming but necessary to answer the initial questions.

[1] T. Moerman, S. Aibar Santos, C. Bravo González-Blas, et al., "GRNBoost2 and Arboreto: Efficient and scalable inference of gene regulatory networks", Bioinformatics, Jun. 2019, issn: 1367-4803,1460-2059, doi:10.1093/bioinformatics/bty916.

[2] D. Marbach, J. C. Costello, R. Küffner, et al., "Wisdom of crowds for robust gene network inference", Nature methods, Jul. 2012, issn:1548-7091, doi:10.1038/nmeth.2016.

[3] F. Pedregosa, G. Varoquaux, A. Gramfort, et al., "Scikit-learn: Machine learning in Python", Journal of Machine Learning Research, 2011.

[4] J. Levatic, M. Ceci, T. Stepišnik, et al., "Semi-supervised regression trees with application to QSAR modelling", Expert Systems with Applications, Nov. 2020, doi: 10.1016/j.eswa.2020.113569.