BenchmarkDR

A modular and expandable benchmarking pipeline for machine learning based antimicrobial resistance prediction

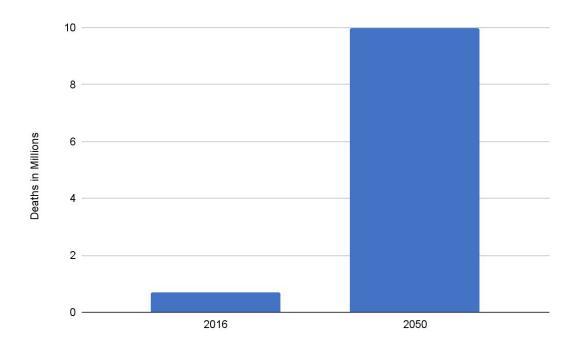
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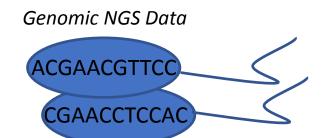
Multi-drug-resistant pathogenic bacteria are an increasing global threat

Deaths linked to multi-drug-resistant (MDR) microbials (J. O'Neill, 2016)





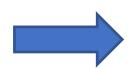
Machine Learning (ML) is a useful tool to fight pathogenic drug resistant bacteria



Drug Susceptibility Test Data

Bacterial Isolate		Antibiotic 1		
1		Resistant		
2	Bacterial Isolate		Antibiotic 1	
	1		MIC X	
	2		MIC Y	

ML Methods for Classification and Regression



All Models

Clinical Diagnostics

Interpretable Models

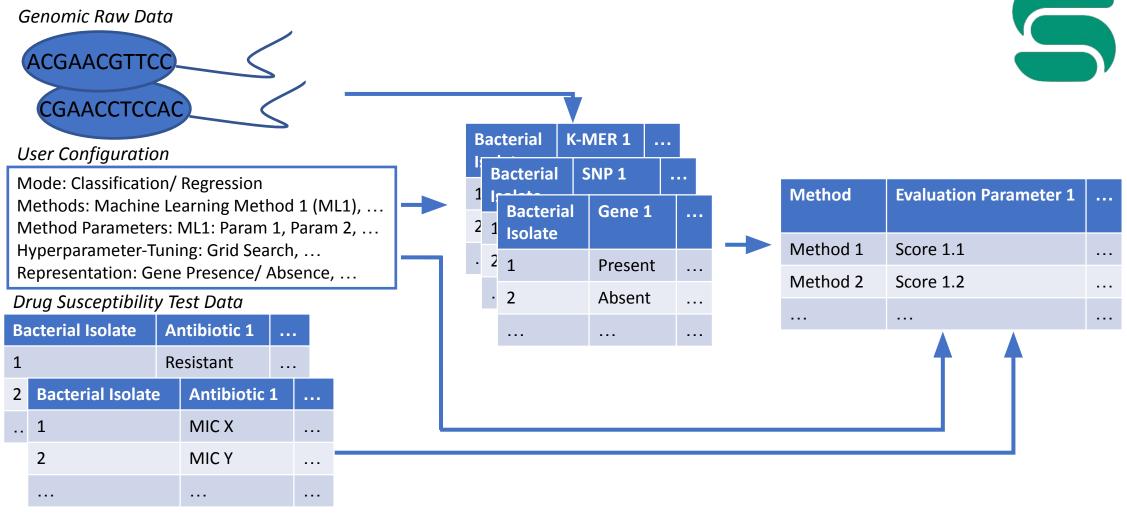
Identification of Biomarkers Research of resistance causing mechanisms

Different features of the genome as well as different ML methods have been used by researchers

ML Methods Representations Genes Logistic Regression ...ATCAAATCCGTTTCAAGGTCCCTTGCCAACCGGTTGGAACG **Linear Regression** Single Nucleotide Polymorphisms (SNPs) ...ATCAAAT@CGTTTCAAGGTCCTTTGCCAACCGGTTGGAACG Random Forests G **Support Vector Machines** K-MERs ...ATCAAATCCGTTTCAAGGTCCCTTGCCAACCGGTTGGAACG **ATCA TCAA New Ones**

How to compare methods performance on different representations of different data?

We built an end-to-end pipeline to allow users to compare representations and methods



Input Representation Evaluation

What does the pipeline have under the hood?

Representations

- Tools based on benchmark papers, popularity and ease of use

ML Methods

- 17 for Classification (Scikit-Learn (Pedregosa, F. et al., 2011) & INGOT-DR (Zabeti, H. et al., 2021))
- 9 for Regression

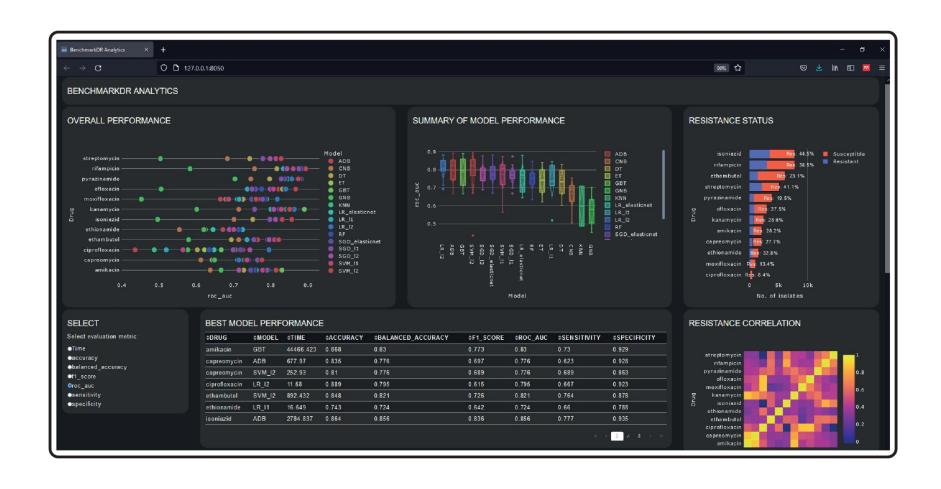
- Evaluation

- Time and Prediction Performance

Configuration can be adapted at different levels of detail

```
sklearn_ADBC:
127
          module: sklearn.ensemble
128
          model: AdaBoostClassifier
129
130
          params:
            n estimators: 50
131
            learning rate: 0.0001
132
133
134
            n_estimators: [50, 100, 500, 1000]
            learning rate: [0.0001, 0.001, 0.01, 0.1, 1.0]
135
136
137
        sklearn GBTC:
          module: sklearn.ensemble
138
          model: GradientBoostingClassifier
139
140
          params:
            max_features: 'auto'
141
            n iter no change: 20
142
143
          cv:
            learning rate: [0.001, 0.01, 0.1, 1]
144
            n estimators: [100, 300, 500, 1000]
145
            min_samples_split: [2, 5, 10, 15]
146
            max_depth: [5, 10, 15, 30]
147
```

A dashboard prototype provides an convenient overview of results and further details



Conclusions & Future Outlook

- Easily useable and extensible end-to-end pipeline to benchmark 26 different ML methods on genomic data represented in 3 ways
- → Applicable for other microbial phenotype predictions

Future Work

- Further Extensions (Methods, Representations)
- Provision of comprehensive gold standard datasets
- Adding explainability approaches, e.g. SHAP
- Include long-read sequencing data
- Grow the tool with the community

Acknowledgements

Repository: https://github.com/WGS-TB/BenchmarkDR

- Fernando Guntoro
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- Dr. John Lees (Supervision)
- Dr. Hooman Zabeti (Supervision)









Key References

Guntoro, F. (2021), Benchmarking antimicrobial resistance prediction with an automated pipeline for machine learning models using BenchmarkDR [Master's Thesis, Imperial College London].

J. O'Neill (2016). Review on Antimicrobial Resistance. *Tackling Drugresistant Infections Globally: Final Report and Recommendations*. Review on Antimicrobial Resistance, 2016.

Pedregosa, F. et al. (2011), Scikit-learn: Machine Learning in Python, Journal of Machine Learning Research, 12.

Stotzem, N. (2021), An End-to-end Machine Learning Pipeline for Drug Resistance Prediction in Bacteria [Master's Thesis, Imperial College London].

Zabeti, H., Dexter, N., Safari, A. H., Sedaghat, N., Libbrecht, M., & Chindelevitch, L. (2021). *INGOT-DR: an interpretable classifier for predicting drug resistance in M. tuberculosis*. Algorithms for Molecular Biology, 16(1), 17.

Images

https://theconversation.com/antibiotic-resistance-new-discovery-could-change-the-future-of-treatment-131262 https://github.com/snakemake

Backup

We selected the tools used to create the representations based on published benchmarks, popularity and ease of use

Representation	Tools
Gene Presence/ Absence	SPAdes v3.15.2 (Assembly), Prokka v1.13.4 (Annotation)
Single Nucleotide Polymorphisms (Requires Reference Genome)	BWA v0.1.17 (Alignment), Samtools v1.12 (Sorting), Picard v2.25.6 (Duplicate Removal), VarScan v2.4.4 (SNP calling)
K-mers	KMC v3.1.2.rc1

The pipeline includes - so far - a variety of standard ML methods and INGOT-DR

Binary Classification (Resistant/ Susceptible)	Regression (MIC)
Logistic Regression* Support Vector Machine Classification* Decision Trees Random Forests Extremely Randomized Trees AdaBoost Decision Tree Classifier Gradient Boosted Decision Trees Stochastic Gradient Descent Classifier* K-Nearest Neighbours Gaussian/ Complement Naive Bayes INterpretable GrOup Testing for Drug Resistance (INGOT-DR) (Zabeti, H. et al., 2021)	Linear Regression* Support Vector Machine Regression Decision Tree Regressor Random Forest Regressor Gradient Boosted Trees Regressor AdaBoost Decision Tree Regressor

^{*} incl. variations with I1 and I2 regularization

Several evaluation metrics are provided

Classification	Regression
Accuracy, Balanced Accuracy, F1-Score, AUC, Sensitivity, Specificity	Mean Squared Error, Mean Squared Log Error, Coefficient of Determination