

# **BIOCOMPOUNDML** A GENERAL SCREENING TOOL FOR BIOLOGICAL COMPOUND PROPERTY PREDICTION USING MACHINE LEARNING

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# EVALUATING CHEMICAL PROPERTIES

Technique	Strengths	Weaknesses
Experimental Validation	High Accuracy and Precision Gold Standard for property prediction	Expensive Time Consuming May require impossible to attain chemical quantities
Direct Computational Simulation (e.g., Quantum Mechanical Methods, Density Functional Theory)	Huge quantities of chemical information High Precision Trusted estimation quality	Huge computational requirements Long periods of simulation Potentially catastrophic accuracy failure
Machine Learning and Big Data Analytics	Measurable Accuracy and Precision Very Fast Leverages Chemical Property Correlations	Unclear underlying model (Black Box) Approximate measurement (unspecific) Extrapolation failure

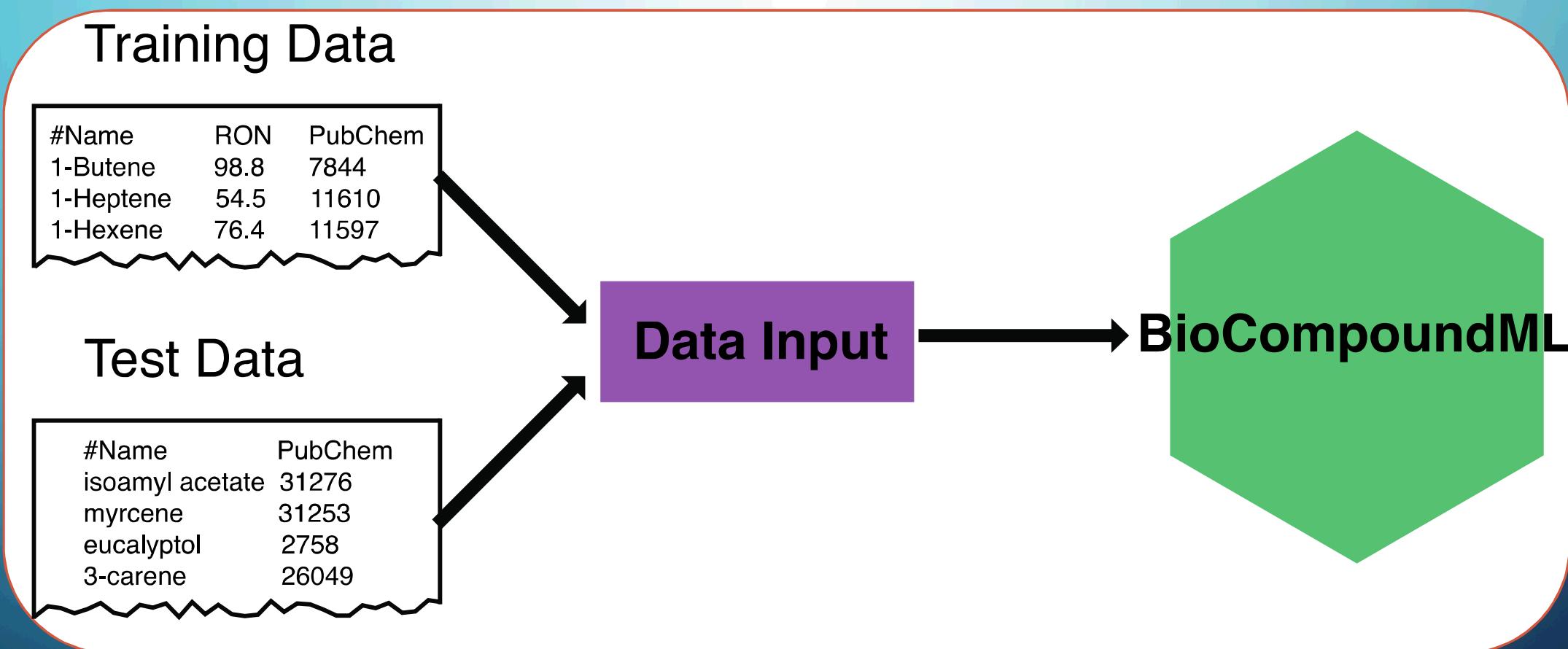
# SOFTWARE PURPOSE

- **BioCompoundML was developed to rapidly screen a very large number of biologically-producible compounds for chemical properties that are important in research and industrial settings**
- Any chemical to be seriously considered in manufacture will require experimental measurement
- But, if time-consuming and expensive measurements and estimations are the first stage, a large chunk of the chemical universe will not be considered
- Frequently, we've found that synthetic chemists and biologists have rather direct and binary criteria for evaluating chemical performance (**at least in the early stages**)

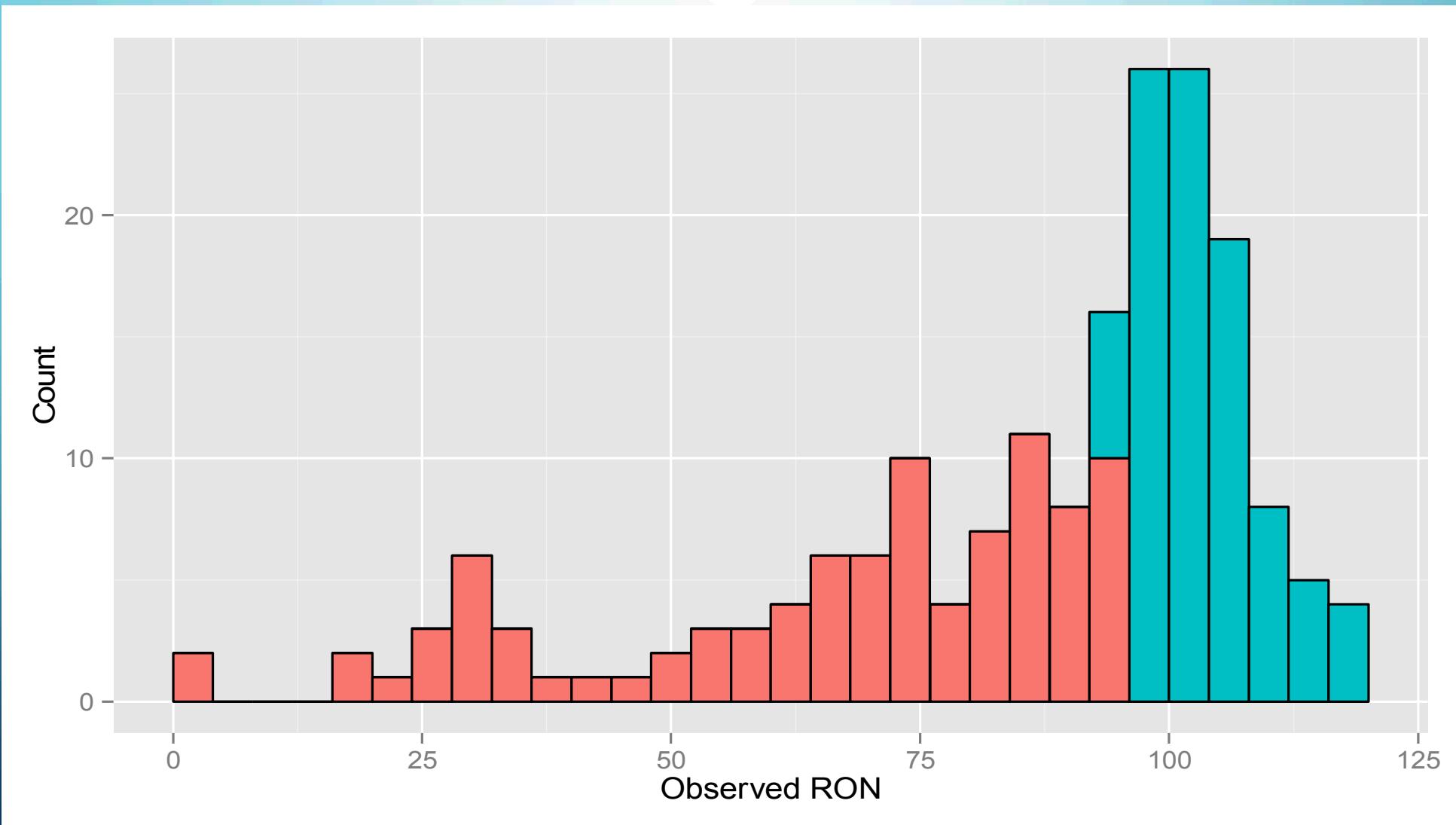
## AN EXAMPLE: RESEARCH OCTANE NUMBER (RON)

- RON is a fundamental fuel property
- Measures the resistance of a spark ignition (SI) fuel to autoignition under compression
- Co-OPTIMA (a multilab DOE-funded project) is interested in evaluating a large number of potential Low-Greenhouse Gas produced chemicals for offsetting petroleum fuel in blendstocks (petroleum + chemical mix)
- One of the key components for any SI-added chemical is high RON

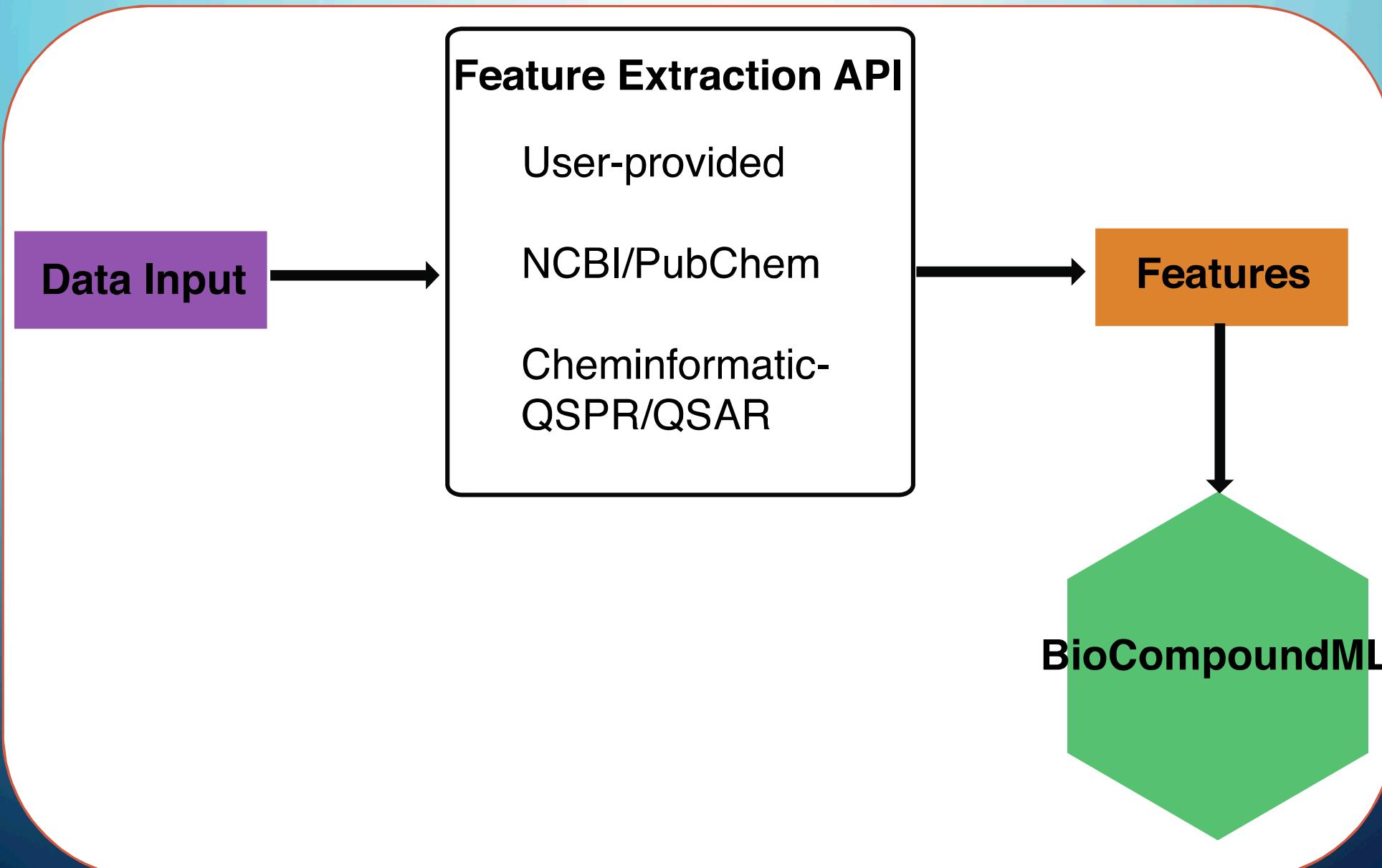
# Input Requirements



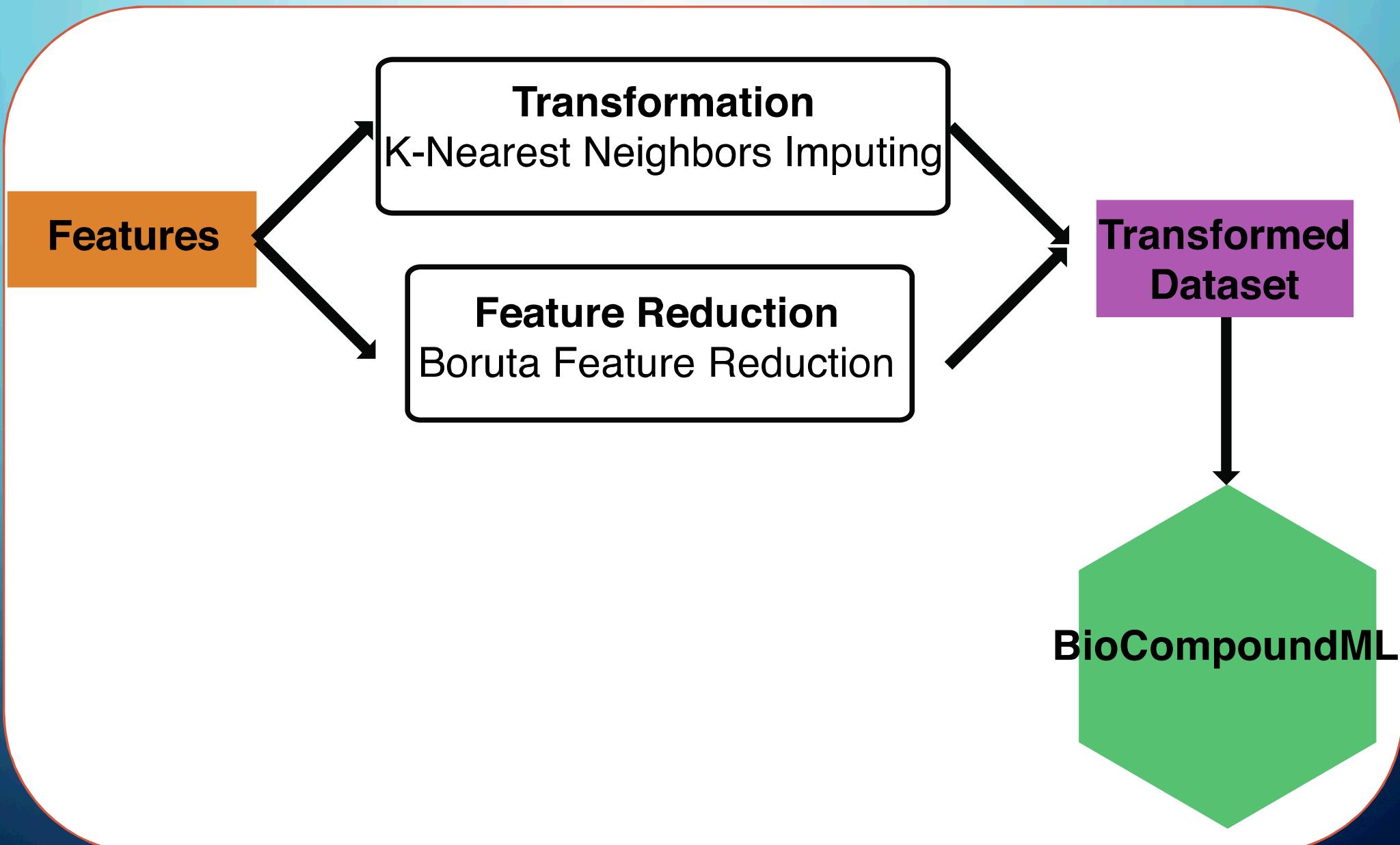
# RON TRAINING DATA



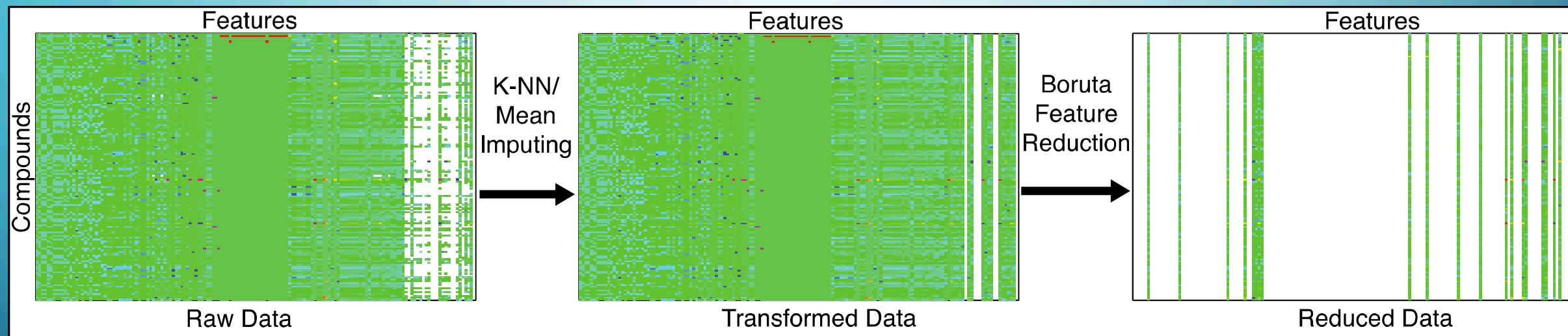
# Feature Collection



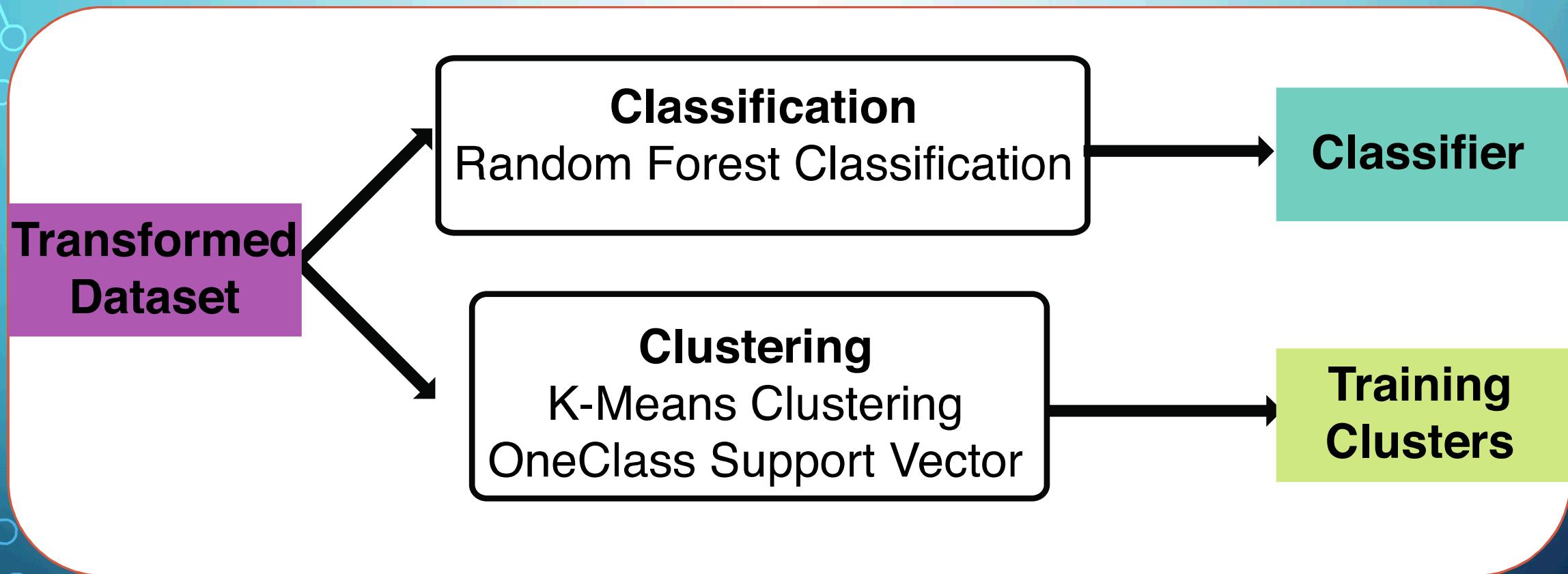
# Data Reduction and Correction



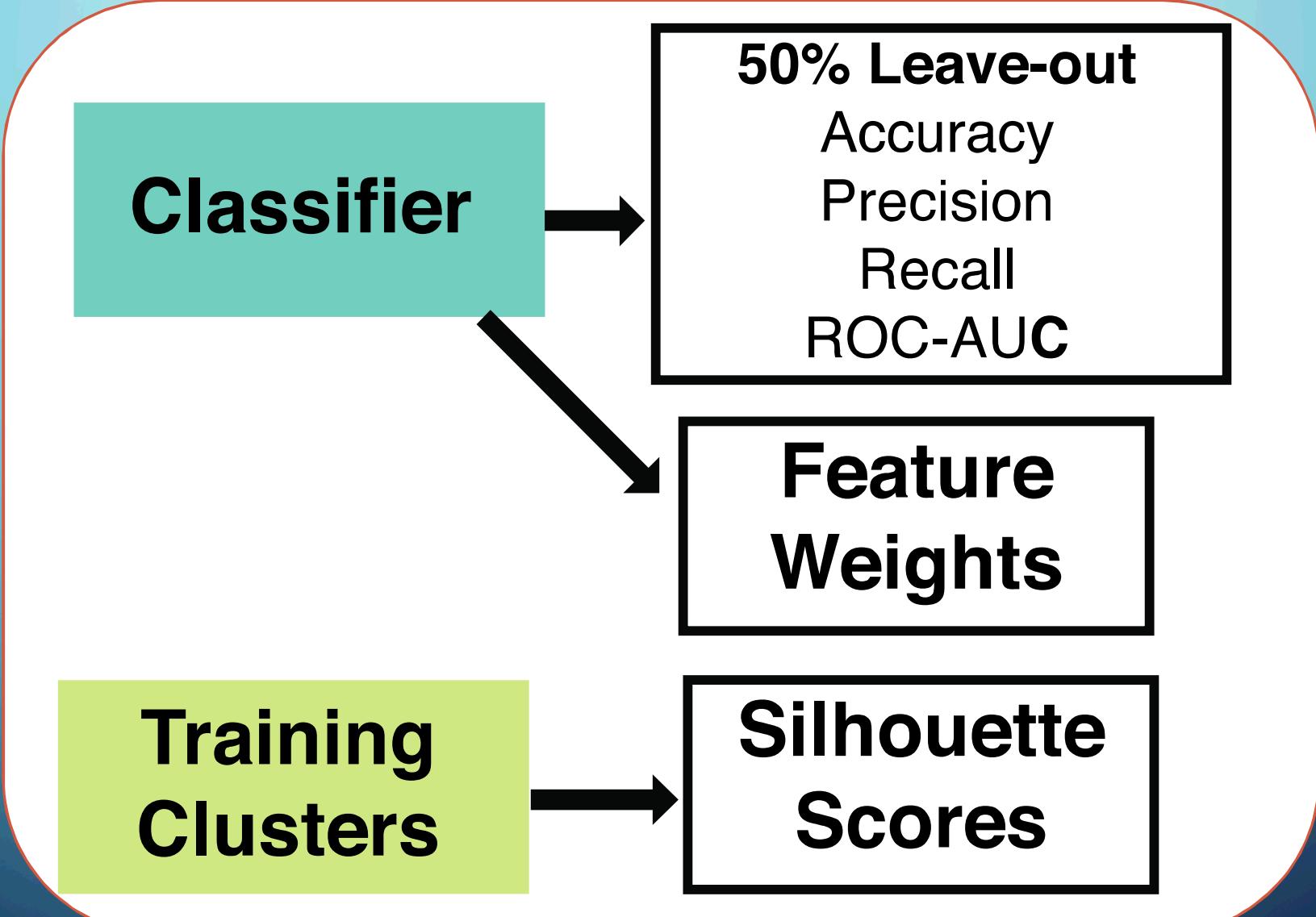
# SCALE OF DATA REDUCTION – INITIAL VS. FINAL FEATURE SET



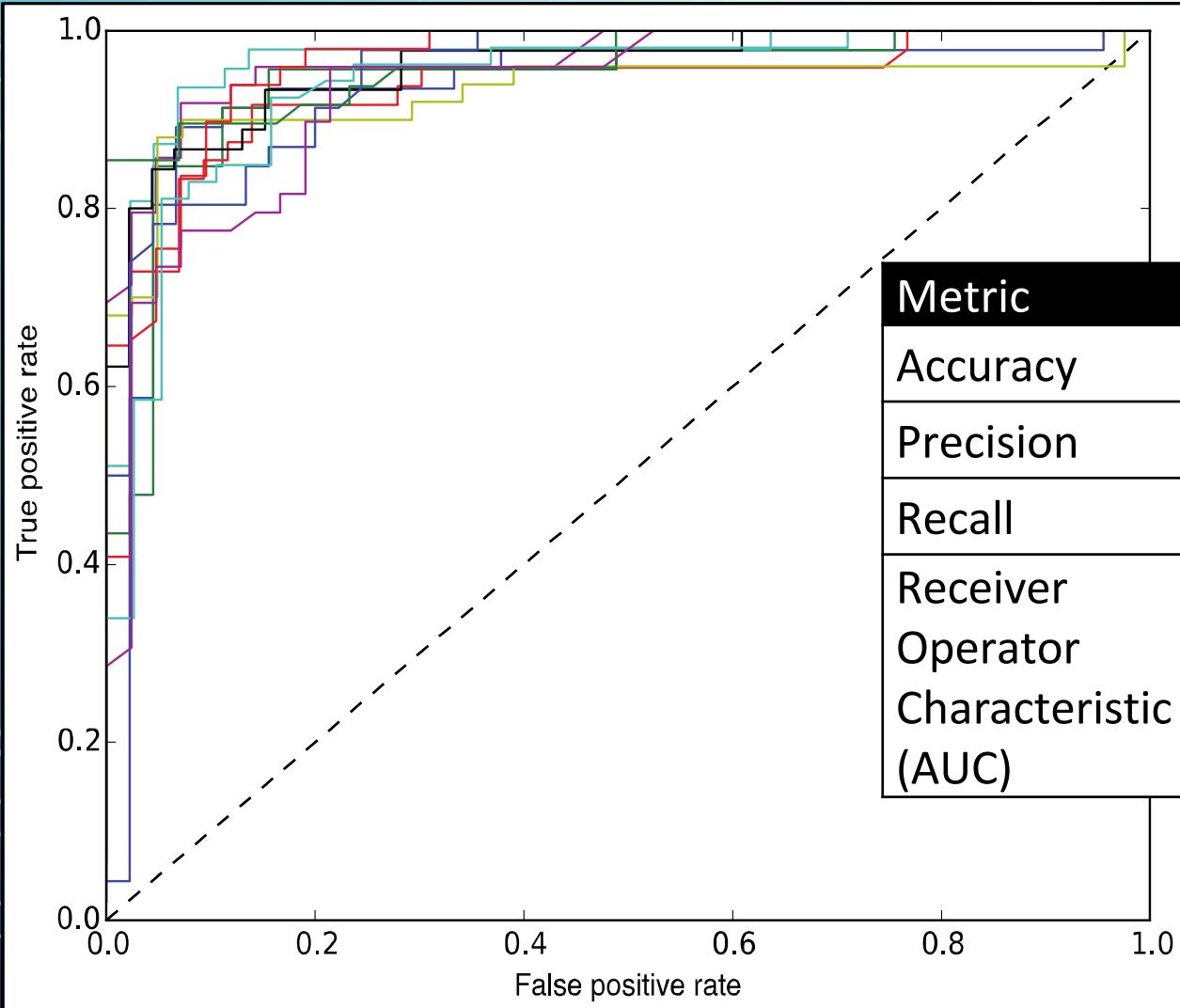
# Classification and Clustering



# Assessment



# RON MODEL ASSESSMENT



# TESTING RON MODEL – EXPERIMENTAL VALIDATION

CAS-No	Compound	Measured RON	Prediction	Probability in High RON Class	Accurate
106-21-8	3,7-Dimethyl-1-Octanol	64.9	Not High RON	0.707	Yes
13466-78-9	3-Carene	68.9	Not High RON	0.754	Yes
13877-91-3	Ocimene	72.9	Not High RON	0.463	Yes
78-69-3	3,7-Dimethyl-3-octanol	76.3	Not High RON	0.76	Yes
123-35-3	Myrcene	82.5	Not High RON	0.799	Yes
80-56-8	$\alpha$ -Pinene	83.3	Not High RON	0.63	Yes
5989-27-5	(R)-(+)-Limonene	87.6	Not High RON	0.695	Yes
78-70-6	Linalool	96.7	Unclear	0.869	Marginal
470-82-6	Eucalyptol	99.2	High RON	0.916	Yes
142-62-1	Butyl Acetate	100.7	High RON	0.99	Yes
123-92-2	Isoamyl Acetate	101	High RON	0.967	Yes
93-58-3	Methyl-Benzoate	101.1	High RON	0.998	Yes
115-18-4	2-methyl-3-buten-2-ol	103.5	High RON	0.967	Yes
110-19-0	Isobutyl Acetate	108.7	High RON	0.977	Yes
67-64-1	Acetone	111.3	High RON	0.908	Yes
209-117-3	Isopropyl Acetate	>120	High RON	0.971	Yes

# TOP 20 METACYC COMPOUNDS

Compound	Probability High RON	CAS	PubChem	Formula
butyl acetate	0.99	123-86-4	31272	C6H12O2
1,4-benzoquinone	0.98	106-51-4	4650	C6H4O2
fumarate	0.98	110-17-8	5460307	C4H2O4
ethanol	0.97	64-17-5	702	C2H6O
diacetyl	0.97	431-03-8	650	C4H6O2
1-O-methylsalicylate	0.97	119-36-8	4133	C8H8O3
2-methylbutanol	0.97	137-32-6	8723	C5H12O
anisole	0.97	100-66-3	7519	C7H8O
ethyl acetate	0.97	141-78-6	8857	C4H8O2
2-methylbut-3-en-2-ol	0.97	115-18-4	8257	C5H10O
methylglyoxal	0.97	78-98-8	880	C3H4O2
patulin	0.96	149-29-1	4696	C7H6O4
3-methylbutanol	0.96	123-51-3	31260	C5H12O
cyclopentanone	0.96	120-92-3	8452	C5H8O
acetoin	0.96	513-86-0	179	C4H8O2
1,3-propanediol	0.96	504-63-2	10442	C3H8O2
(-)-camphor	0.96	464-48-2	444294	C10H16O
(R)-mevalonate	0.96	150-97-0	5288798	C6H11O4
2-butyne-1,4-diol	0.96	110-65-6	8066	C4H6O2
2-methylphenol	0.96	95-48-7	335	C7H8O

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BioCompoundML is a software tool for rapidly screening chemicals by chemical properties, using machine learning. — [Edit](#)

6 commits 2 branches 0 releases 1 contributor

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 [coreymhudson](#) Fixed README Latest commit [8d7bf62](#) 2 days ago

 [bcml](#) Fixed build directory issue 2 days ago

 [.travis.yml](#) Cleaning test suite 2 days ago

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 [README.md](#) Fixed README 2 days ago

 [requirements.txt](#) Cleaning test suite 2 days ago

 [setup.py](#) Cleaning test suite 2 days ago

 [README.md](#)

[build](#) passing

## BioCompoundML

Rapidly screen a large number of compounds for fuel and chemical properties using machine learning. It's quick -- build in minutes, screen in seconds. It's clean -- cluster, predict, report and validate in a single interface. And it directly connects to the PubChem API and a variety of Quantitative Structure (Property and Activity) Relationship predictors (QSPR/QSAR).

## Documentation

See documentation at <http://sandialabs.github.io/BioCompoundML/>

## Build

The most difficult part of the build is getting scikit-learn up and running and beautiful-soup. It is best that you use an existing tool, like conda or canopy or another scientific python distribution. If not, it may take some effort to get BioCompoundML running on your machine. Ultimately, you will need numpy, scipy, scikit-learn, matplotlib and beautiful-soup. If you have those the rest of the setup should be fairly painless.

```
git clone https://github.com/sandialabs/BioCompoundML.git
pip install -r requirements.txt
```



# LIMITATIONS IN REACHING USERS

- Difficulty of use
  - Command line driven
  - Requires modern understanding of Python and its dependencies
  - Huge parameter set
  - Difficult install
- Collection and curation of training data
  - No central repository for measured training data
- Exposure
  - Reach the actual audience of interest
- Underlying machine learning paradigm not explained through visuals

# HOW THE GRASSROOTS SOFTWARE TOOL COMPETITION COULD HELP

- Movement of the software from research to production quality
- Provide web-based presentation of visuals (both results and machine learning tutorials)
- Associate the tool with an existing suite tools for synthetic biologists
- Expose JBEI and National Laboratory researchers to tool

# ACKNOWLEDGEMENTS

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