

# AI/ML for prediction of biological properties of molecules

Module 3. Training an AI model for bioactivity prediction

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# Course overview

Day 1: M0 – Introduction to AI for DD

Day 2 – 3: M1 – Using AI models for DD

Day 4: M2 – Setting up your computational environment

Day 5: M3 – Building an AI model

- Steps to build an AI classifier (morning)
- Training your own AI model (afternoon)

Day 6: M4 – The Ersilia Model Hub

- Joint presentation with BTT students (morning)
- Model deployment & wrap up (afternoon)

# Classification tasks

# Classification tasks

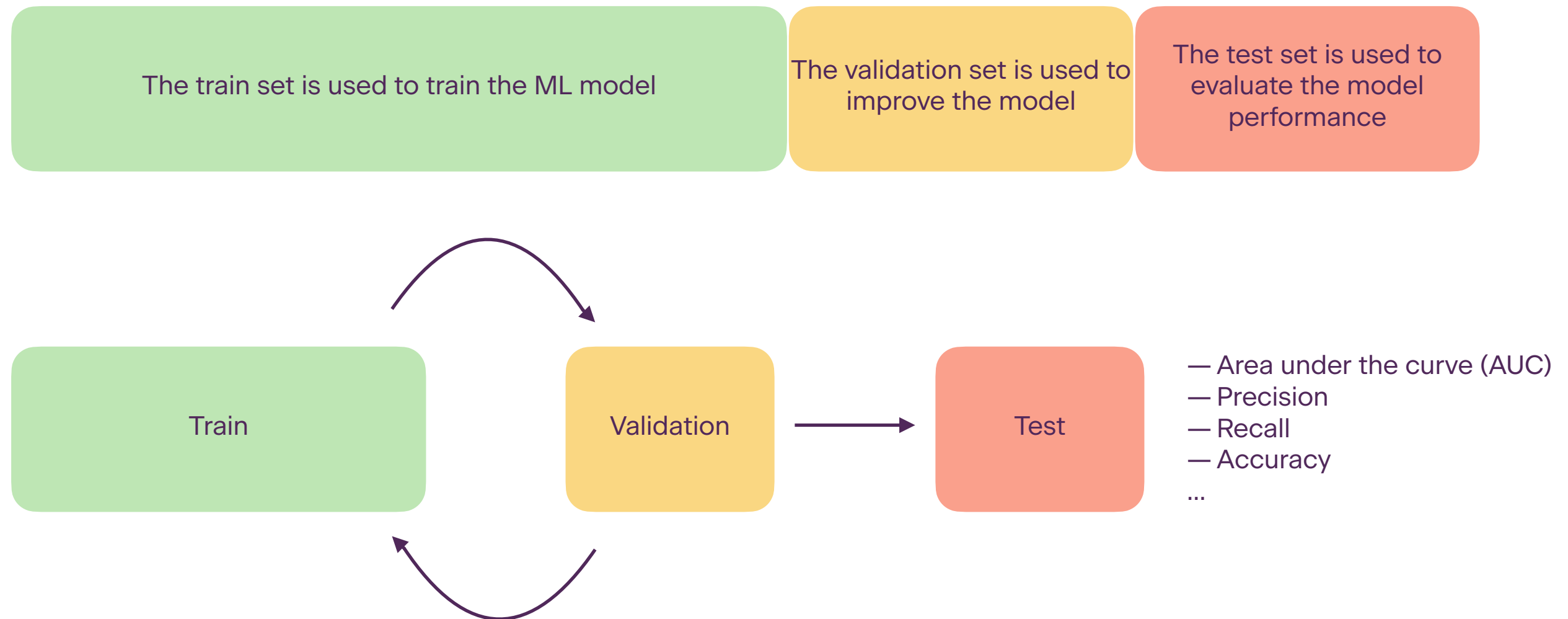
A classifier identifies the category of a new data point. In the case of bioactivity data, we usually find two categories (hence, a binary classifier):

- Active: 1
- Inactive: 0

To learn more about classifications, we will use a hands-on example with the Open Source Malaria data to create an AI model that predicts whether a drug will be active or not against the malaria parasite in vitro:

- Experiment: IC50
- Values: microMolar

# Train, test and validation sets



In our case-study, we will use an AutoML tool that internally performs the Train and Validation split, so we will only do a Train-Test split

# Main steps to train a classifier

1. Observe our data. If the outcome is continuous, we will need to define a cut-off to binarize it
2. Divide the data into train and test sets, ensuring we keep balance between classes (active, inactive)
3. Featurize the molecules (convert the SMILES to vectors or embeddings)
4. Train the ML model: fit
5. Predict the results for the test set and evaluate the performance of the model

# Main steps to train a classifier

1. Observe our data. If the outcome is continuous, we will need to define a cut-off to binarize it
2. Divide the data into train and test sets, ensuring we keep balance between classes (active, inactive)

👉 Go to the course repository <https://github.com/ersilia-os/ersilia-intro-workshop>

👉 Go to notebooks

👉 Open the m3-building-a-model.ipynb

👉 Click on “Open with Colab”

# Our Colab Notebook

m3\_building\_a\_model.ipynb ☆

File Edit View Insert Runtime Tools Help [All changes saved](#)

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..

sample\_data

model\_eosce.joblib

model\_morgan.joblib

osm\_all.csv

test\_set.csv

train\_set.csv

+ Code + Text

Train an AI model

This notebook contains the basic steps to train a classifier for bioactivity prediction.

It is prepared to run on Google Colaboratory, if you want to run it locally make sure to create a conda environment with Python 3.10 and install the packages indicated below.

*Remember that the ! sign indicates a bash command, to run it in the terminal simply copy the command without !*

Supervised Machine Learning

Uses previously **labeled** data to train an algorithm (i.e the output is known). The algorithm learns if it is doing right by comparing the predicted vs the real output.

Simplified steps:

1. Data collection and processing.
2. Division of training data in Train and Test sets.
3. Use the train set to train the model.
4. Predict an output for the test set and compare the predicted vs real results.
5. Improve the model until we are satisfied with the performance on the test set

Types of supervised ML models

Classification

Classification problems are characterized by having categorical output (i.e: active, inactive), so the model tries to predict to which class the

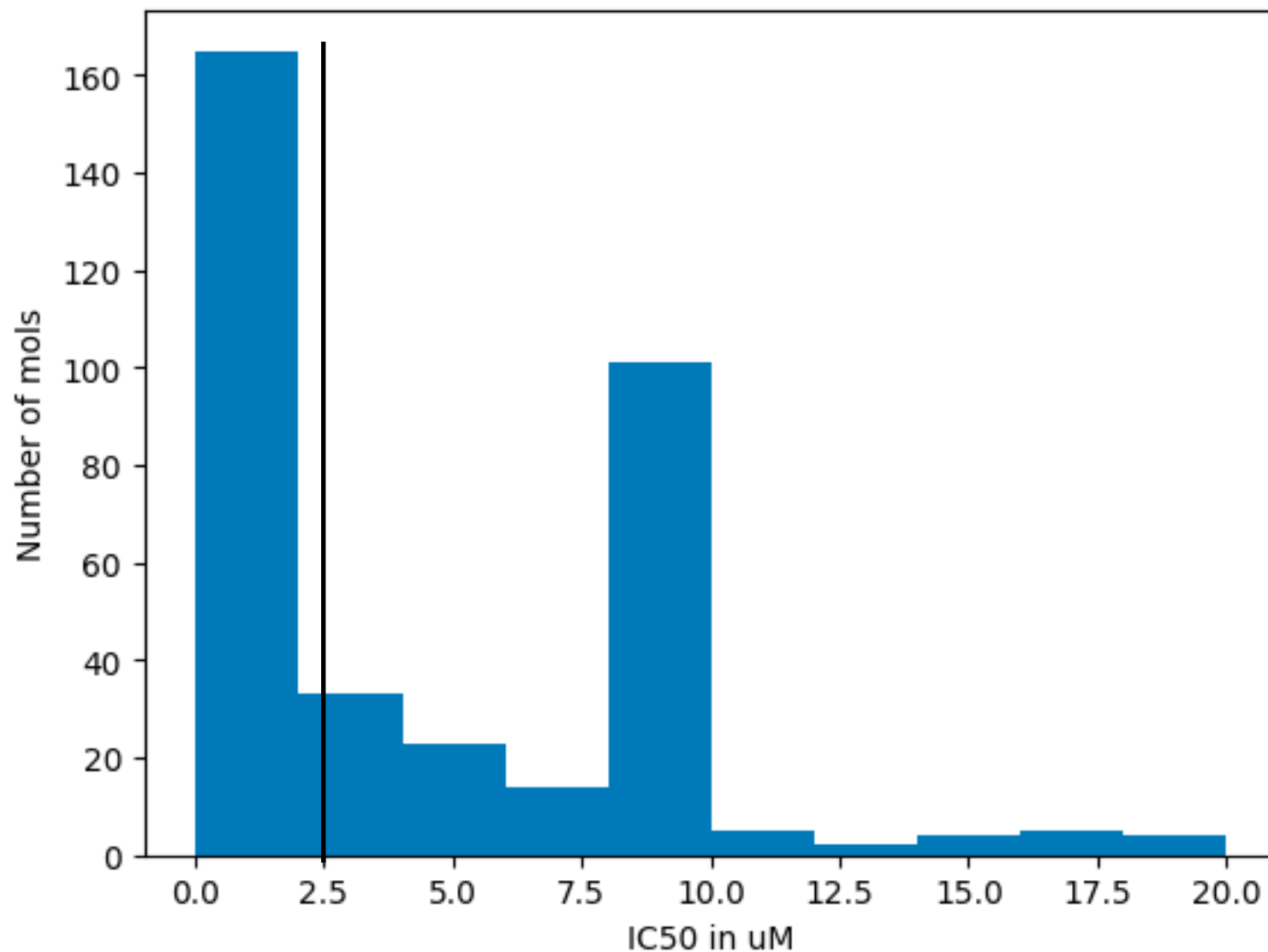
✓ RAM  Disk

81.15 GB available

✓ Connected to Python 3 Google Compute Engine backend



# Data processing



Total molecules: 415  
Active molecules: 177  
Inactive molecules: 238  
Frequency of Actives (%): 42.65

The direction of the assay is important.

👉 In which case we might want to select high values as active?

Train set: 332 molecules

Test set: 83 molecules

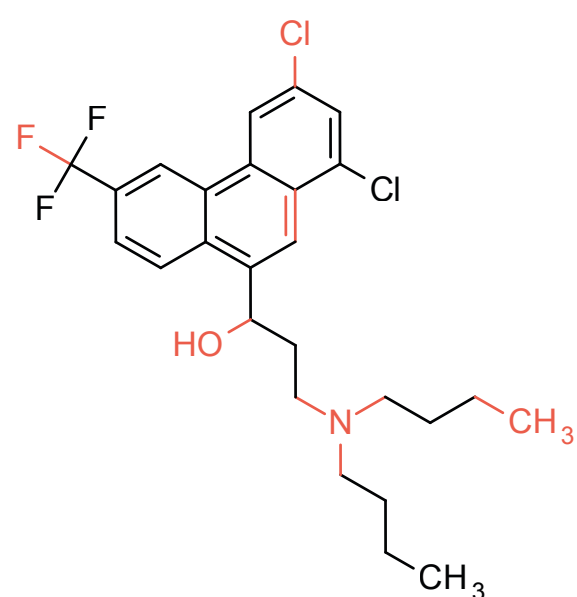
Random  
Keeping the class balance

# Main steps to train a classifier

3. Featurize the molecules (convert the SMILES to vectors or embeddings)
4. Train the ML model: fit

- 👉 Which are some featurizers we might use?
- 👉 What are good packages to train ML models?

# Molecular featurization



Calculated properties

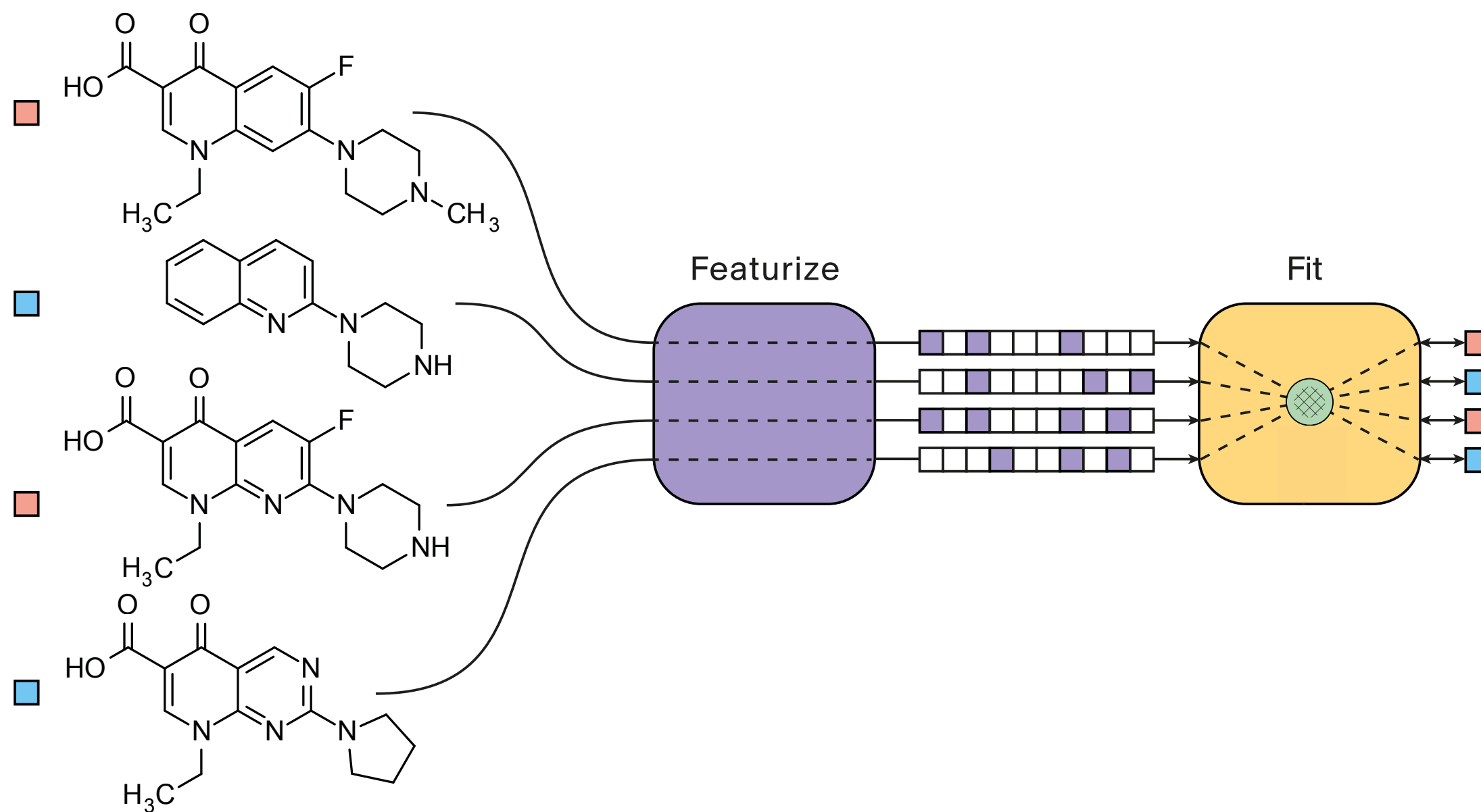
- Molecular weight
- LogP or LogD
- Hydrogen bonds
- pKa
- Topological surface area (TPSA)
- ...



Halofantrine belongs to the class of organic compounds known as **phenanthrenes** and derivatives. These are polycyclic compounds containing a phenanthrene moiety, which is a tricyclic aromatic compound with three non-linearly fused benzene. Halofantrine is a synthetic **antimalarial** which acts as a **blood schizonticide**. It is effective against multi drug resistant (including mefloquine resistant) *P. falciparum* malaria. The mechanism of action of Halofantrine may be similar to that of chloroquine, quinine, and mefloquine; by forming toxic **complexes with ferritoporphyrin IX** that damage the membrane of the parasite. It appears to inhibit polymerisation of heme molecules (by the parasite enzyme '**heme polymerase**'), resulting in the parasite being poisoned by its own waste. Halofantrine has been shown to preferentially block open and inactivated **HERG channels** leading to some degree of **cardiotoxicity**. Side effects include coughing noisy, rattling, troubled breathing, loss of appetite, aches and pain in joints, indigestion, and **skin itching** or rash, *et cetera*, *et cetera*.



# Building a AI model



SMILES

Morgan fingerprint

Binary  
activity

# Main steps to train a classifier

5. Predict the results for the test set
6. Evaluate the performance of the model

- 👉 What will be the output of our model?
- 👉 What evaluation metrics we can use for a classification task?

# Classification outputs

```
array([[0.4572469 , 0.5427531 ],
       [0.4572469 , 0.5427531 ],
       [0.4572469 , 0.5427531 ],
       [0.69371699, 0.30628301],
       [0.57326782, 0.42673218],
       [0.59258     , 0.40742     ],
       [0.59258     , 0.40742     ],
       [0.55096183, 0.44903817],
       [0.57326782, 0.42673218],
       [0.59680676, 0.40319324],
       [0.4572469 , 0.5427531 ],
       [0.55096183, 0.44903817],
       [0.4572469 , 0.5427531 ],
       [0.4572469 , 0.5427531 ],
       [0.57326782, 0.42673218],
       [0.59680676, 0.40319324],
       [0.4572469 , 0.5427531 ],
       [0.57326782, 0.42673218],
```

Once the model is fitted, we can predict the category of each molecule in the validation and test sets. A classifier outputs two numbers per each prediction:

- Probability of 0 (first column)
- Probability of 1 (second column)

# Classification outputs

In a classification, the output is a probability. We need to define a cut-off or threshold to transform the results into a binary output (0 or 1) again. The threshold is typically set at 0.5 by default

Proba 0	Proba 1	Cut-off: 0.5	Cut-off: 0.7	Cut-off: 0.3
0.39	0.61	1	0	1
0.3	0.7	1	1	1
0.69	0.31	0	0	1
0.21	0.79	1	1	1

# Classification outputs

Original datasets: train, test

- X datasets: X\_train, X\_test
- Y datasets: Y\_train, Y\_test

Predictions:

- y\_hat: output of the classifier, expressing the probability that a molecule is inactive (0) or active (1).
- y\_hat\_bin: binarized activity based on the predicted probability, the cut-off is set by the researcher.



# Model Evaluation: Confusion Matrix

Real	Inactives	True Negative	False Positive
	Actives	False Negative	True Positive
		Inactives	Actives
		Predicted	

Precision: how many positives are actually positive

$$TP / (TP + FP)$$

Recall: how many positives are we able to identify

$$TP / (TP + FN)$$

Precision

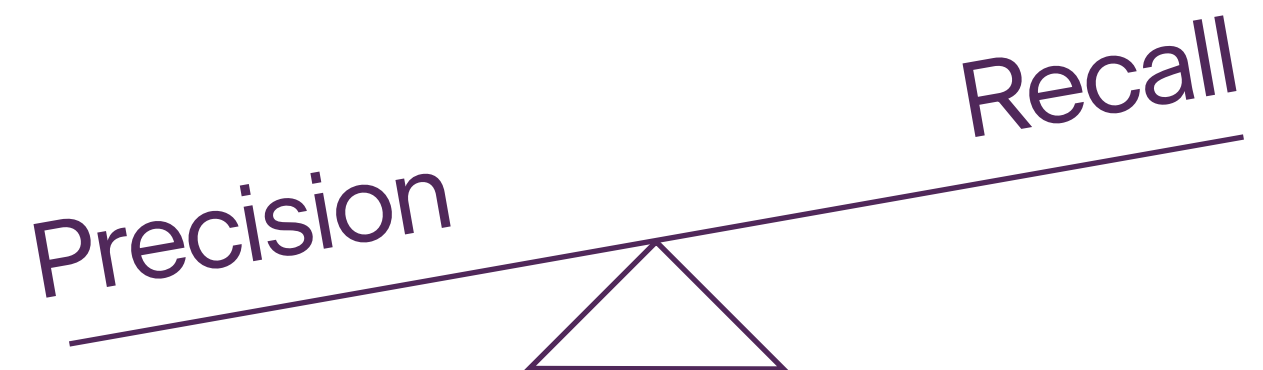
Recall



# Model Evaluation: Confusion Matrix

Real	Inactives	True Negative	False Positive
	Actives	False Negative	True Positive
		Inactives	Actives
		Predicted	

Higher, more restrictive  
threshold in proba1



Lower, less restrictive  
threshold in proba1



# Model Evaluation: Confusion Matrix

Real	Inactives	True Negative	False Positive
	Actives	False Negative	True Positive
		Inactives	Actives
		Predicted	

👉 In which scenarios we might want a high precision?

👉 In which scenarios we might want a high recall?

# Model Evaluation: ROC Curves

Real	Inactives	True Negative	False Positive
	Actives	False Negative	True Positive
		Inactives	Actives
		Predicted	

True Positive Rate (sensitivity or recall): proportion of correctly predicted positives of all positive observations

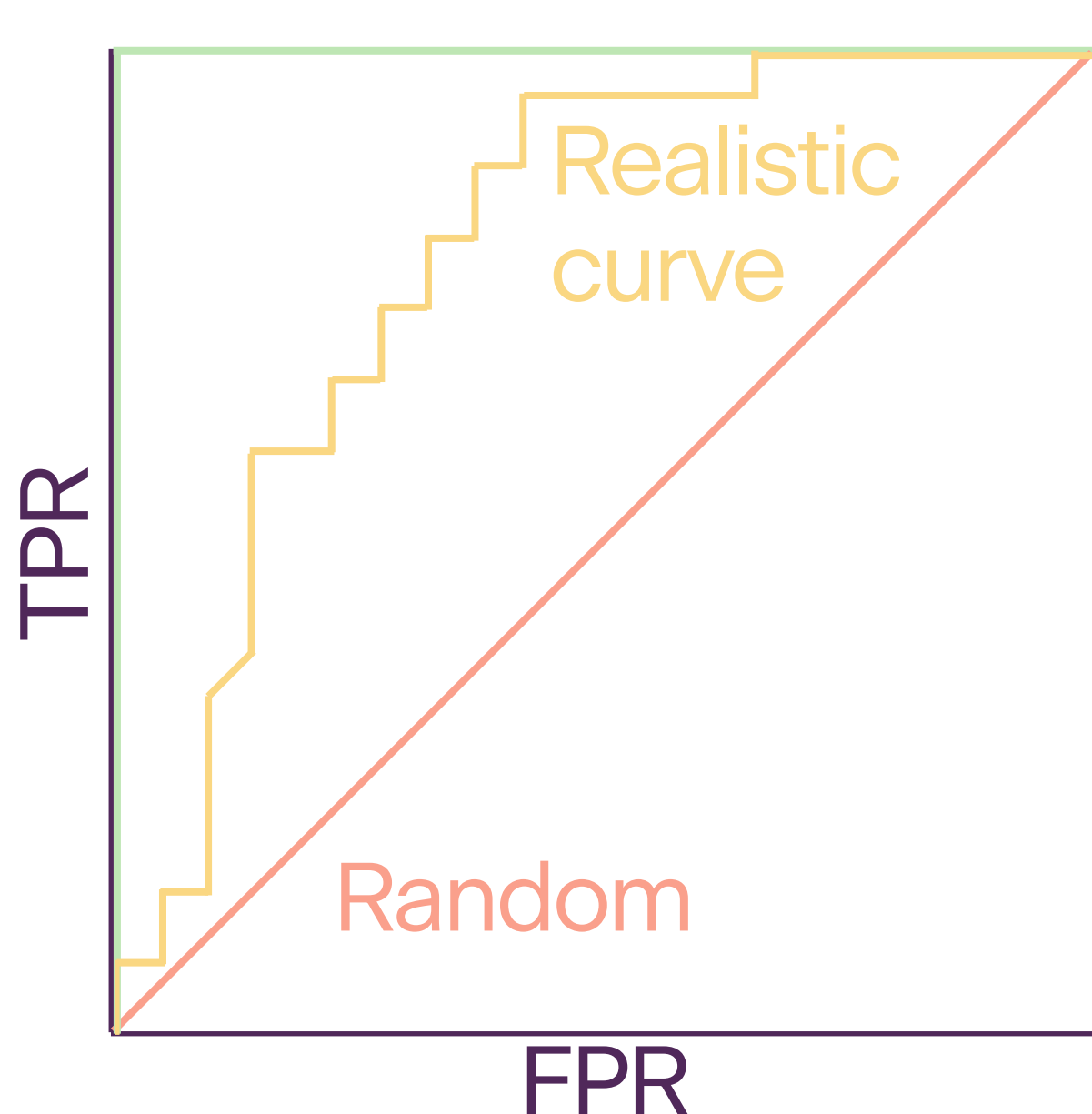
$$TP / (TP + FN)$$

False Positive Rate (100-sensitivity): proportion of incorrectly predicted positives of all negative observations

$$FP / (TN + FP)$$

# Model Evaluation: AUROC

ROC Curve: performance of the model at all classification thresholds (from 0 to 1)



Perfect  
model

Realistic  
curve

Random

Area Under the Curve  
(AUC): aggregate  
measures of model  
performance. It does not  
depend on the threshold

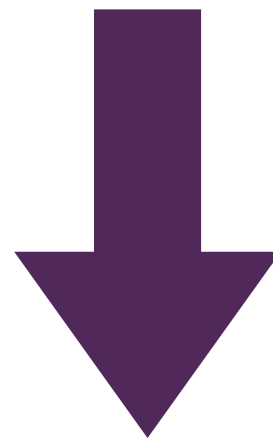
# At the end of the pipeline, we will...

The train set is used to train the ML model

The validation set is used to improve the model

The test set is used to evaluate the model performance

Use all our available data to train the final model



Save the model to run predictions on new data.  
We can use it locally or deploy it online, for example in the Ersilia Model Hub

menti.org  
4663 2789

<https://ersilia.io>  
[hello@ersilia.io](mailto:hello@ersilia.io)  
[@ersiliaio](#)