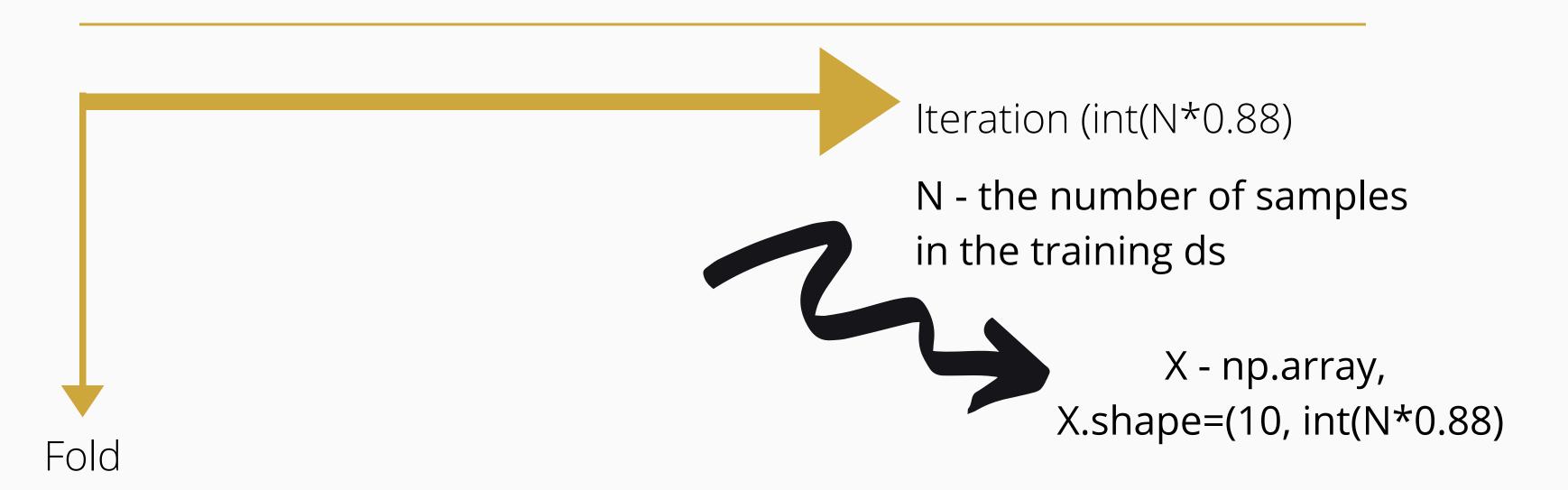
SCAMs Project Update

Goals

- Add error plot ("average the different repetitions and visualize mean value + standard deviation")
- Run pipeline with different parameters
 (experiment with models, sampling, splitting and datasets, etc.)

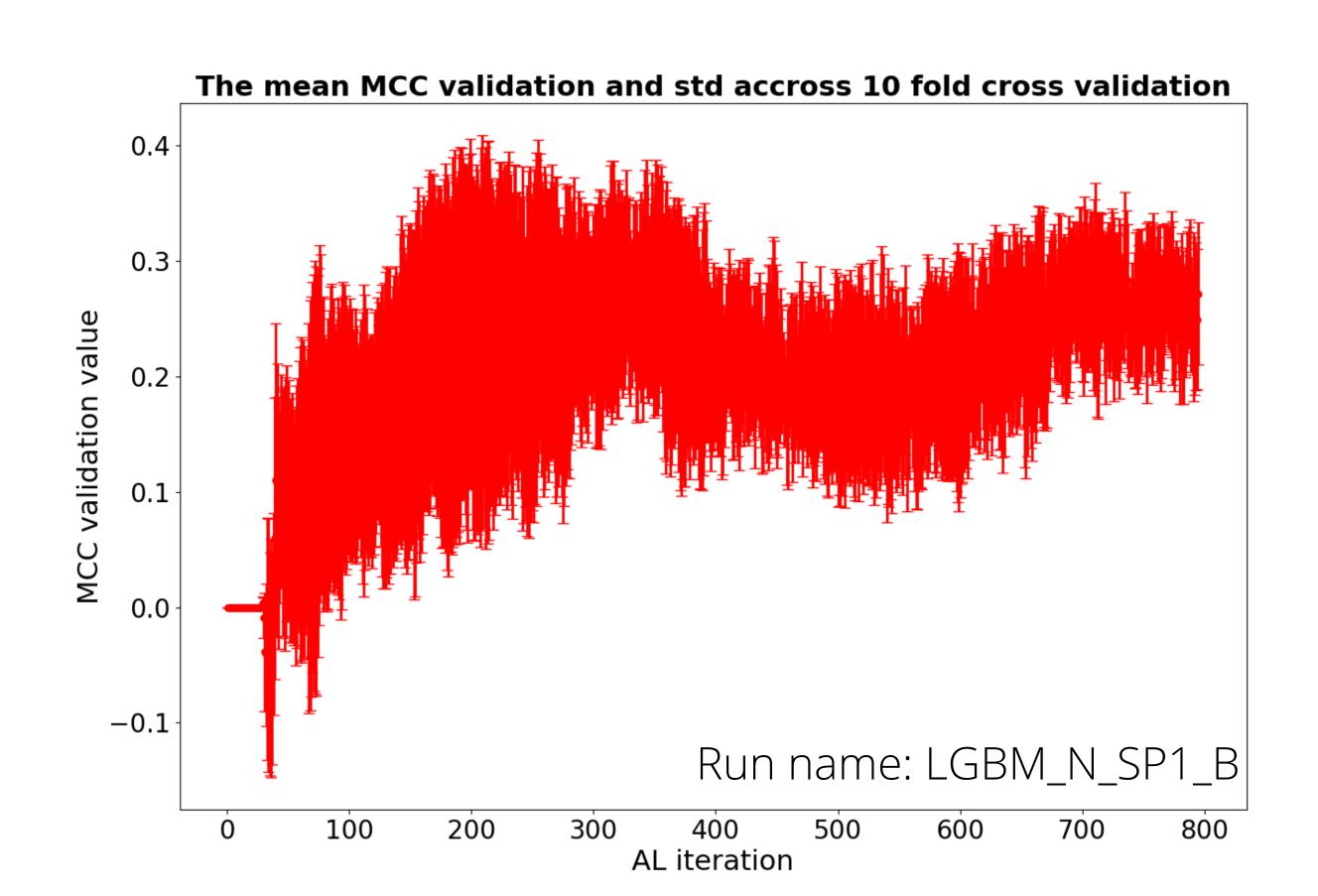
Error Plot



For the arrays (X) with calculated metrics (accuracy, F1, MCC, AUC LB, AUC, AUC UB) on test and validation datasets, I calculated mean - X.mean(axis=0) and std - X.std(axis=0) and visualized using matplotlib error plot

[IV]

Error plot, example



Covered Runs



I only managed to experiment with LightGBM, but from previous runs (please, see the folder early_runs), RF yielded lower performance. For example, I calculated the mean AL validation MCC value for RF (0.279) and LGBM (0.405). Do I need to further run the pipeline using RF?



SF

Classical (without sampling and TTS) - 1 run
Only with up/down sampling - 4 runs
Only with splitting (butina or scaffold_splitter) - 2
With sampling and splitting - 8 runs



SP1

Classical (without sampling and TTS) - 1 run
Only with splitting (butina or scaffold_splitter) - 2

We do not run sampling with the balanced dataset



SP2

Classical (without sampling and TTS) - 1 run
Only with up/down sampling - 4
runs
Only with splitting (butina or scaffold_splitter) - 2
With sampling and splitting - 8
runs

15 runs

15 runs

3 runs

Results



It could be too time-consuming to check every folder, therefore I decided to make a table with a summary.

I use run names as the table index and metrics as a column and the following notations:

- 1) AL_T the mean AL value is higher and the difference is statistically significant
- 2) AL_F the mean AL value is higher and the difference is not statistically significant
- 3) N_AL_T the mean non-AL value is higher and the difference is statistically significant
- 4) N_AL_F the mean AL value is higher and the difference is not statistically significant
- 5) E the mean AL and non-AL values are equal

Please, see the full table on GitLab. Also, I a generated table with value_counts(), so it could be easier to drawn conclusions from

| | AUC_LB_test | AUC_test | AUC_UB_test | Accuracy_test | F1_test | MCC_test | AUC_LB_validation | AUC_validation | ${\sf AUC_UB_validation}$ | Accuracy_validation | F1_validation | MCC_validation |
|------|-----------------|----------|-------------|---------------|---------|----------|-------------------|----------------|-----------------------------|---------------------|---------------|----------------|
| AL. | _ F 16.0 | 15.0 | 15.0 | 4.0 | 13.0 | 5.0 | 6.0 | 6.0 | 6.0 | 2 | 2 | 3.0 |
| AL. | _ T 17.0 | 18.0 | 18.0 | 29.0 | 20.0 | 27.0 | 27.0 | 27.0 | 27.0 | 28 | 25 | 29.0 |
| N_AL | _ F 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 2 | 4 | 0.0 |
| N_AL | _ T 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | 1 | 2 | 1.0 |

We can observe that **AL outperforms non-AL strategy** with high probability (385/12*33=**97%**) for runs with LGBM



Futher plans

Make code more elegant
 and UML diagram

Add Bayesian AL module

Add Tropsha's and DeepSCMAs models

I think it could be interesting to add the following modules and make a UML diagram after, but looking forward to receiving feedback from you.