Life Is On | Schneider Electric

DRIVENDATA

# Rinse over Run


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Private Score: 0.2658 (2nd Place)

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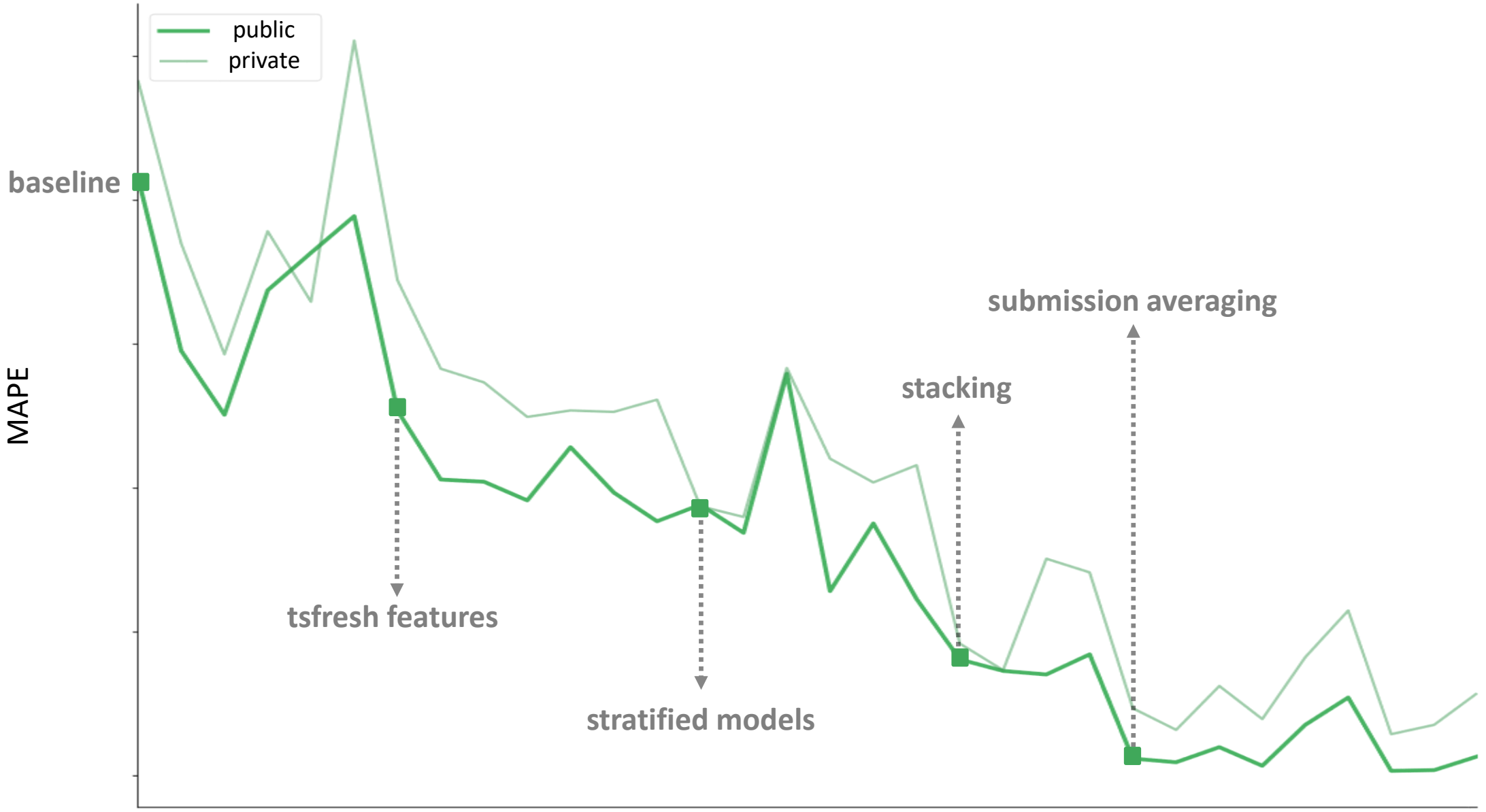
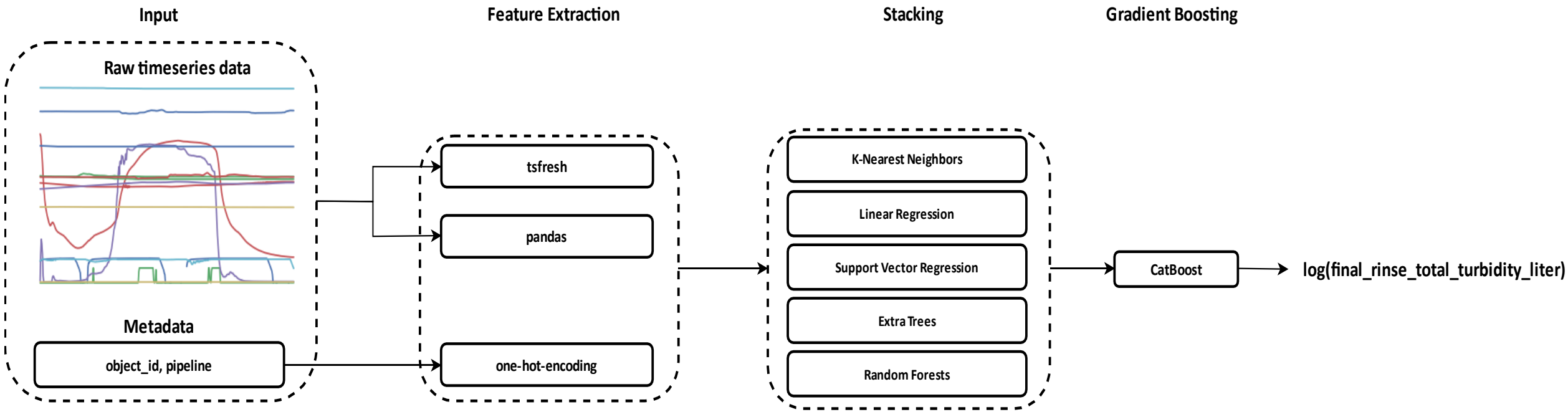
# Starting with a simple baseline, using useful features and smart stratification, and ending up with a complex high performant ensemble, secured us the second spot



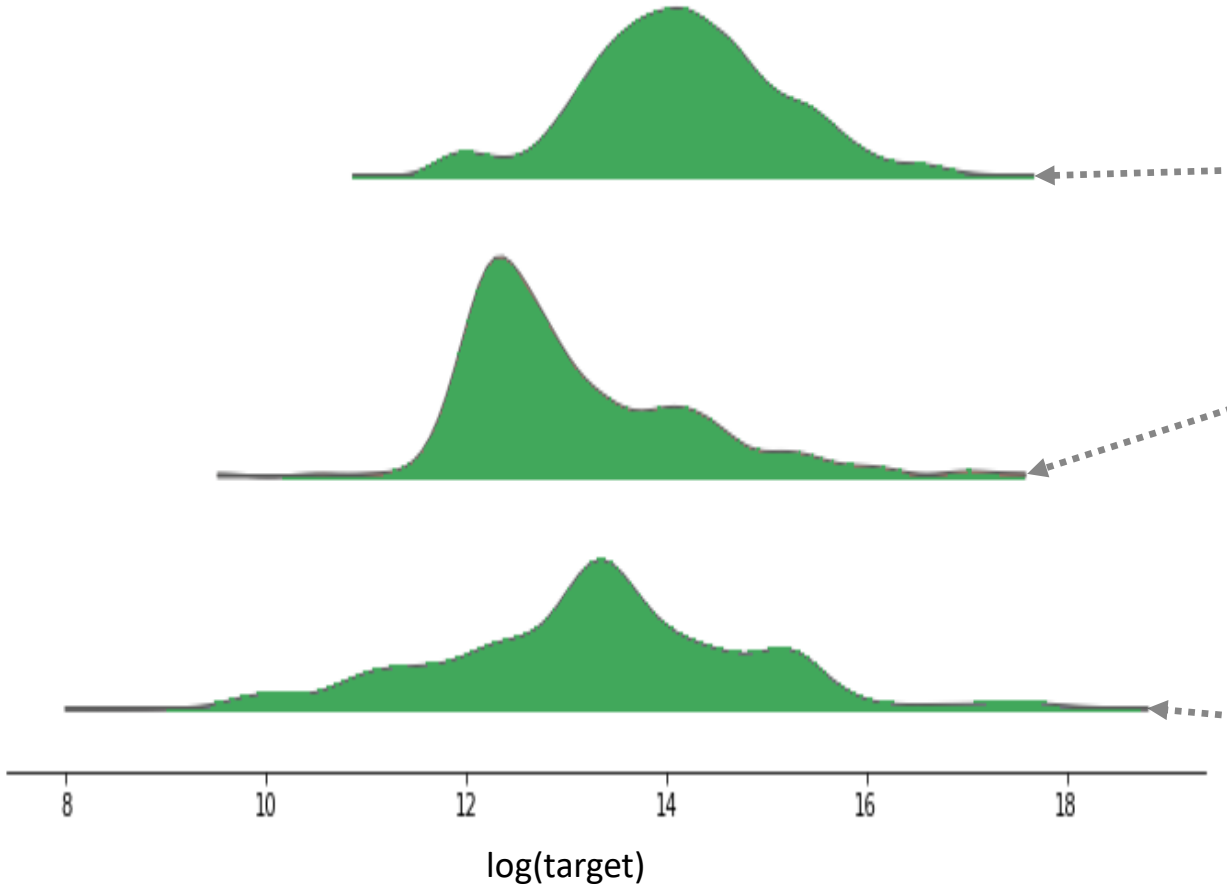
# An overview of our final pipeline

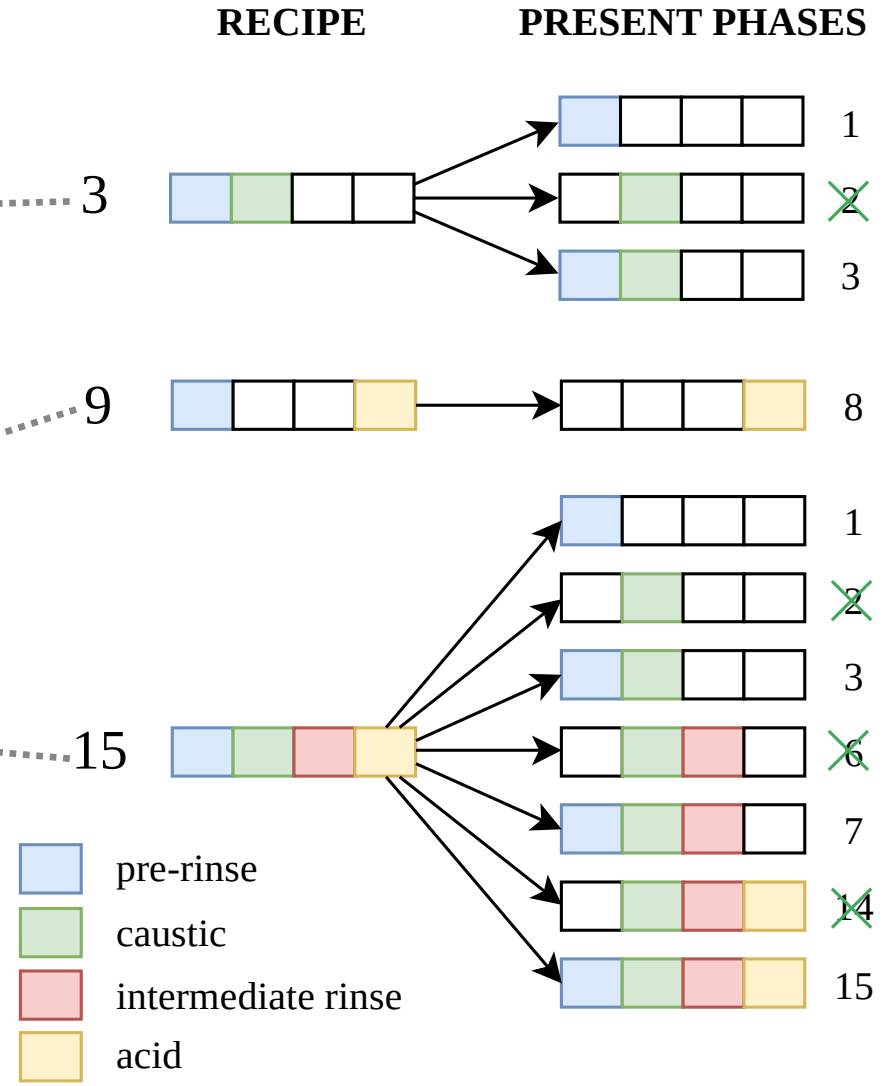



CatBoost (https://github.com/catboost/catboost)

tsfresh (https://github.com/blue-yonder/tsfresh)

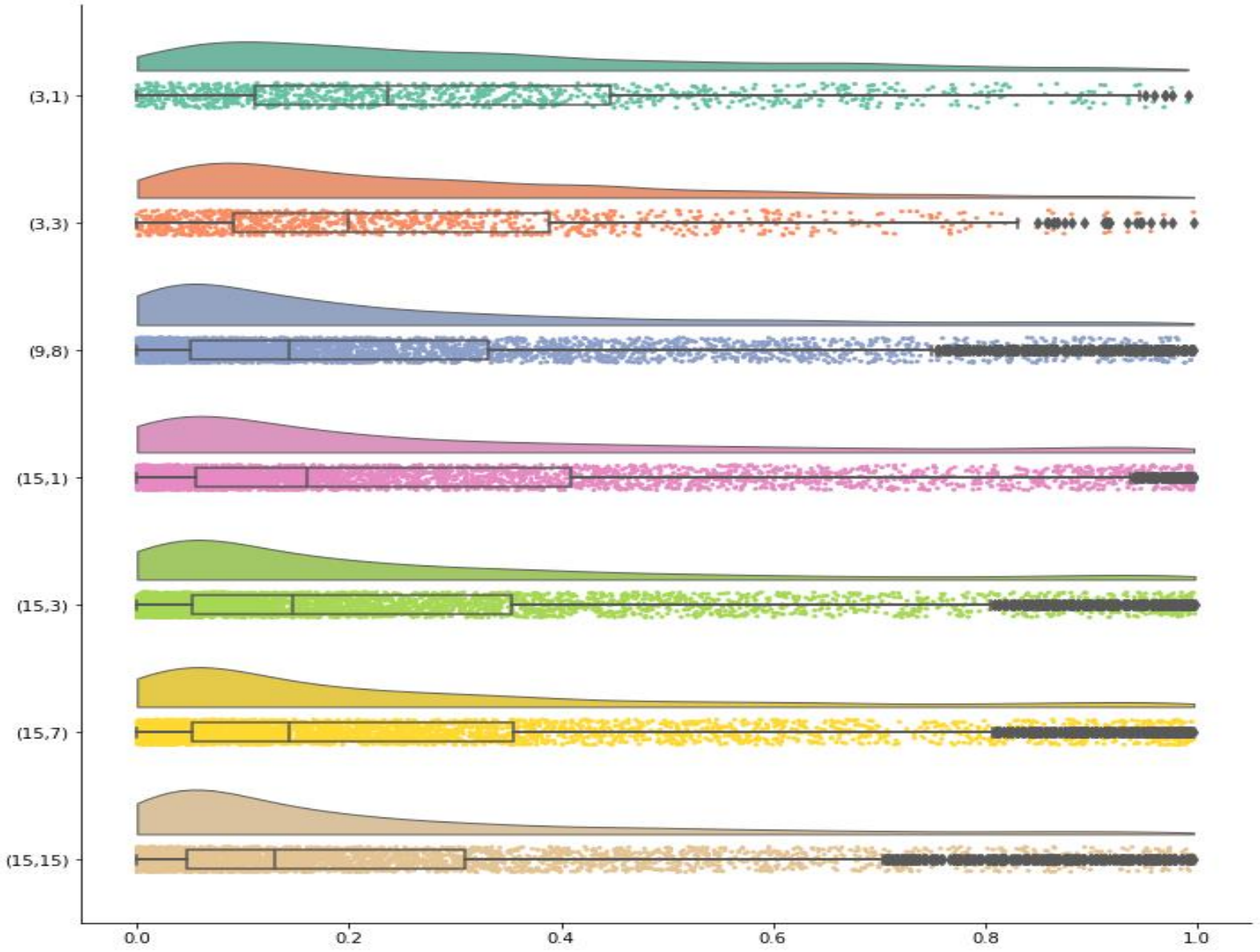
# Stratifying models allow to predict after every cleaning phase and explains differences in variance in the outcome of the three cleaning recipes



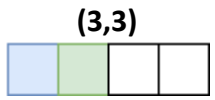
## A higher number of processes and using more phases per processes decreases the five-fold cross-validation error, and reveals very high variance, hence, the choice for ensemble techniques

(*) the fraction of test processes (**) model without stacking



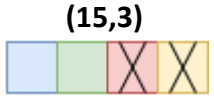

| Group | MAPE $(\mu \pm \sigma)$ | Weight* |
|---|---|---|
| (3,1) | $0.35 \pm 0.36$ | 0.022 |
| (3,3) | $0.29 \pm 0.32$ | 0.17 |
| (9,8) | $0.38 \pm 0.33$ | 0.04 |
| (15,1) | $0.30 \pm 0.37$ | 0.07 |
| (15,3) | $0.28 \pm 0.36$ | 0.23 |
| (15,7) | $0.27 \pm 0.34$ | 0.22 |
| (15,15) | $0.25 \pm 0.37$ | 0.22 |
| **Total:** ** | **$0.29 \pm 0.36$** | |

# By using logistic regression, together with a p-value correction by means of the Benjamini-Hochberg correction (FDR, $\alpha = 0.05$), we identified positive and negative significant features which explain high targets



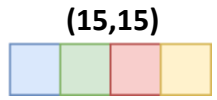
(3,3)

difference between recipes

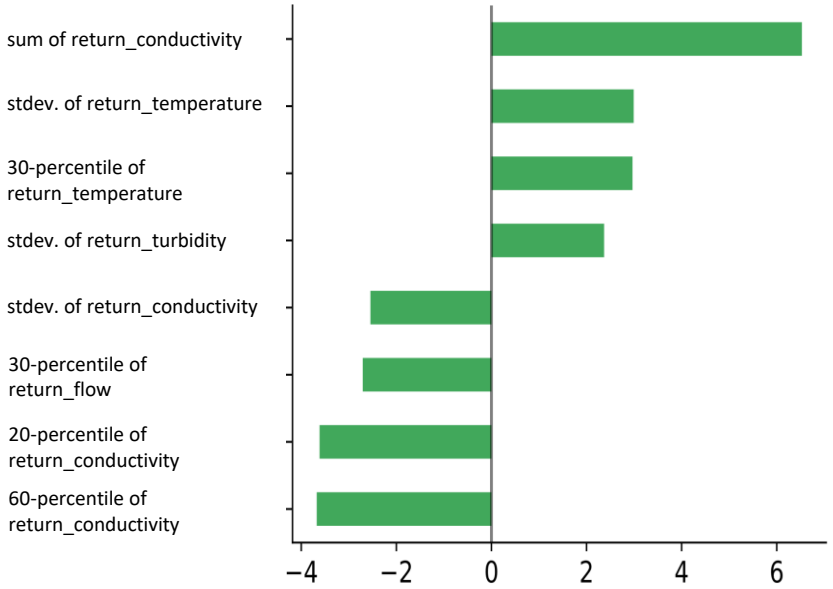


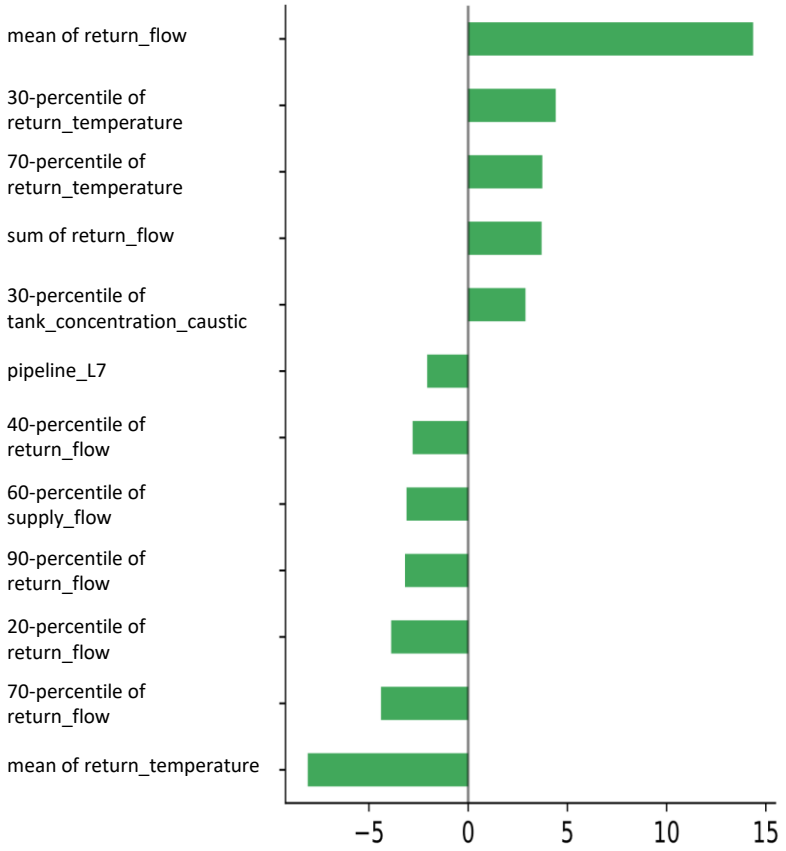
(15,3)

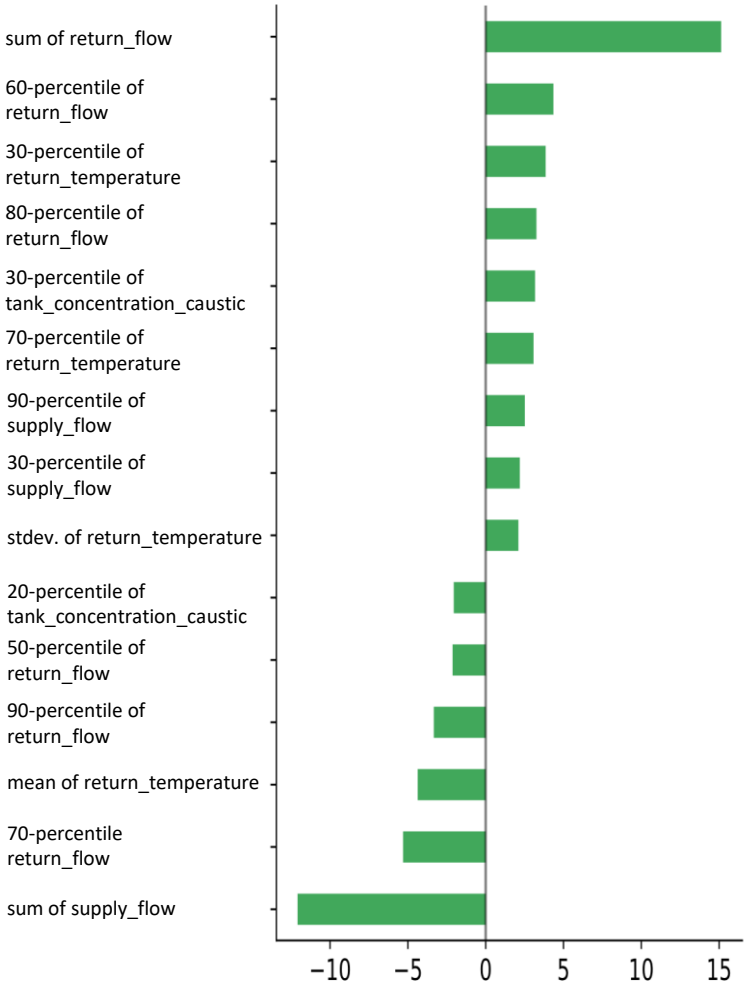
difference over time



(15,15)



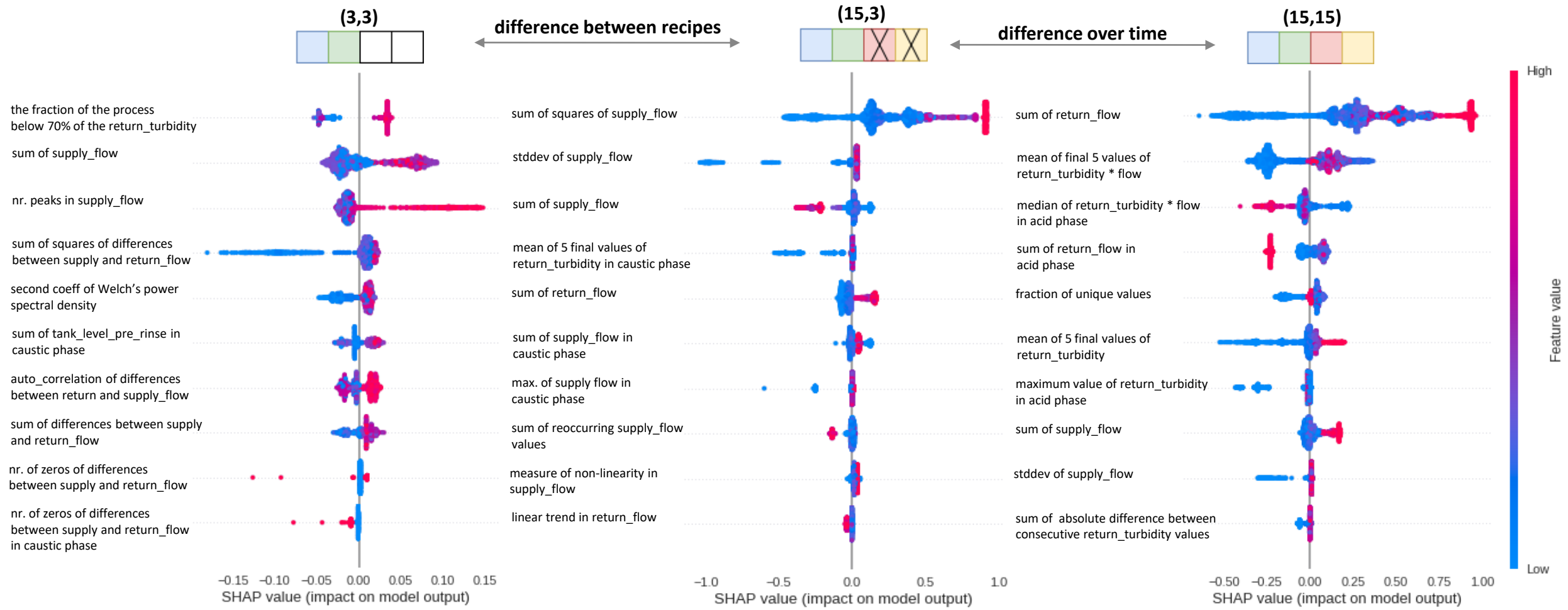



# Shapley values allow to highlight most impactful features for the final rinse outcome

**INTERPRETATION:**

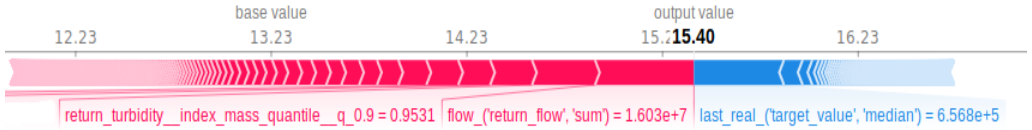
- dots along the x-axis are the different impacts on the model (left = large negative impact; right = large positive impact)
- color of dot impact feature magnitude (blue = lowest value, red = highest value)
→ e.g. for (3, 3), a higher number of peaks in supply_flow increases the prediction



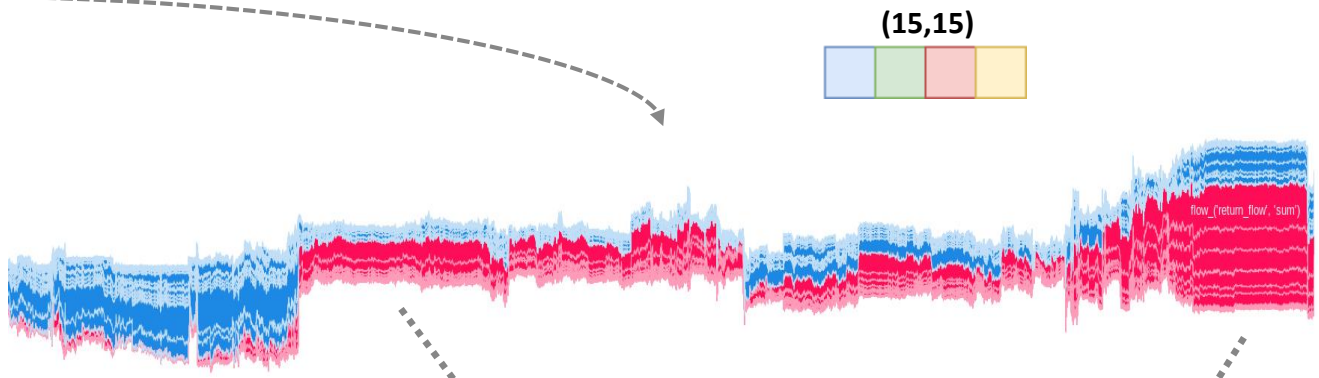

shap (https://github.com/slundberg/shap)

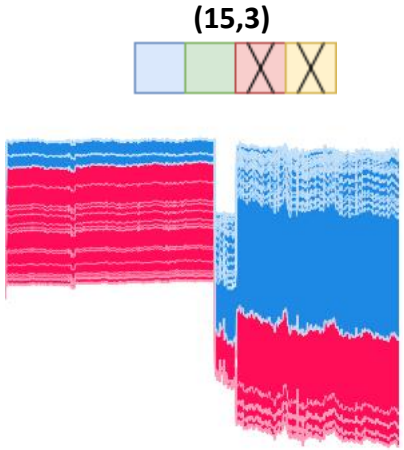
# Shapley values can be generated for each individual prediction and can be grouped together to find clusters of similar predictions and model behavior

individual Shapley plot

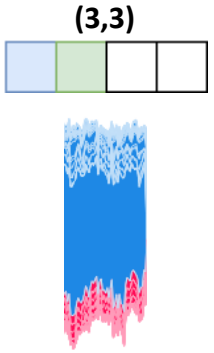



rotate & cluster



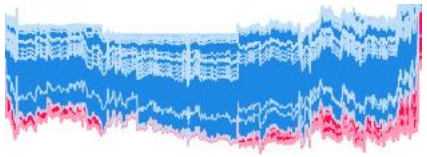




~ 300 predictions around 2.25 million liters due to high non-linearity in supply_flow



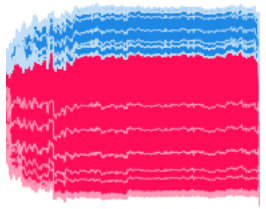

~ 50 predictions around 750,000 liters due to objects 205-209

~ 300 predictions around 1.25 million liters due to low non-linearity and high variance in supply_flow



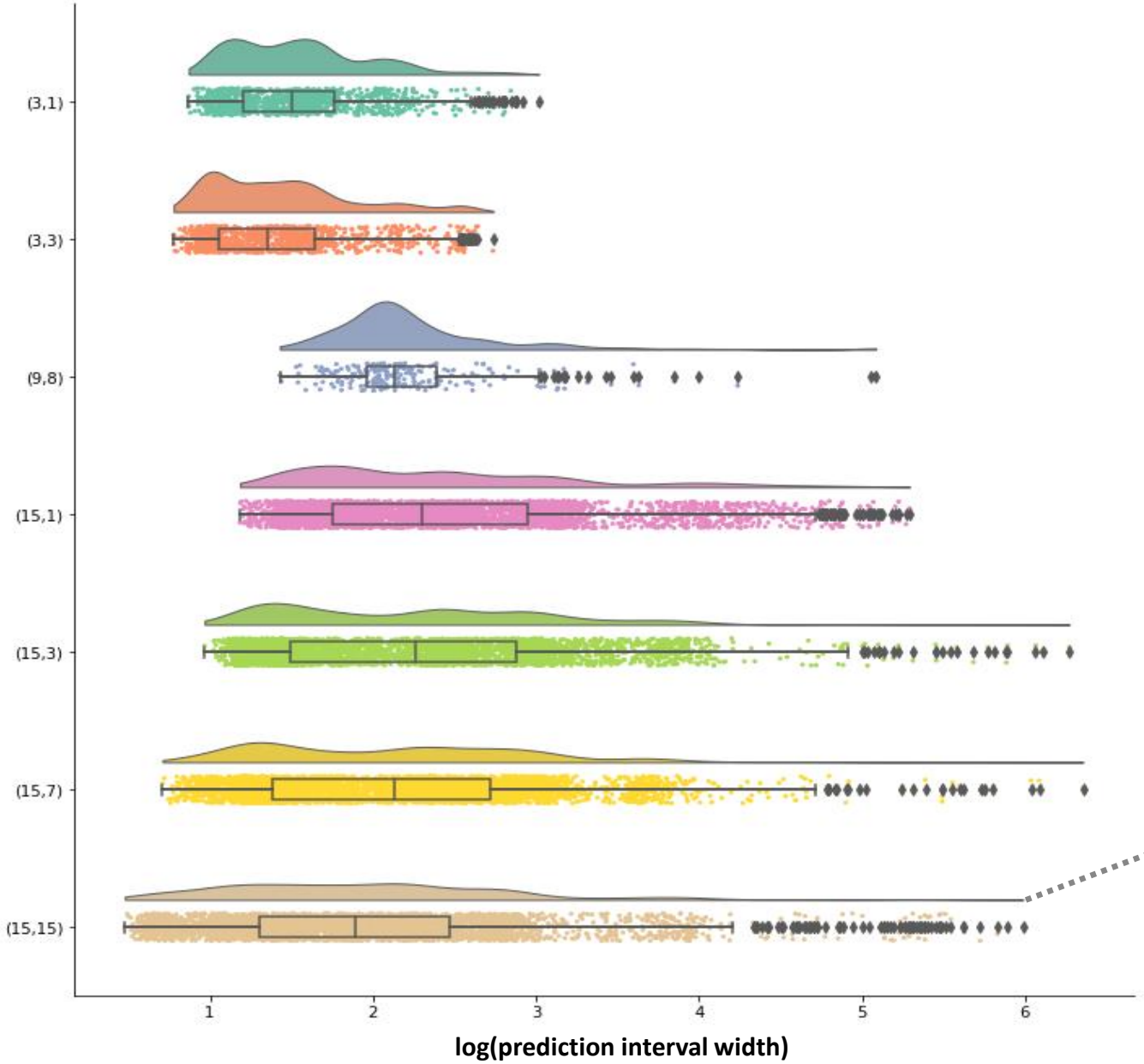
~ 400 predictions around 150,000 liters due to low sum of return_flow and high variance in supply_flow

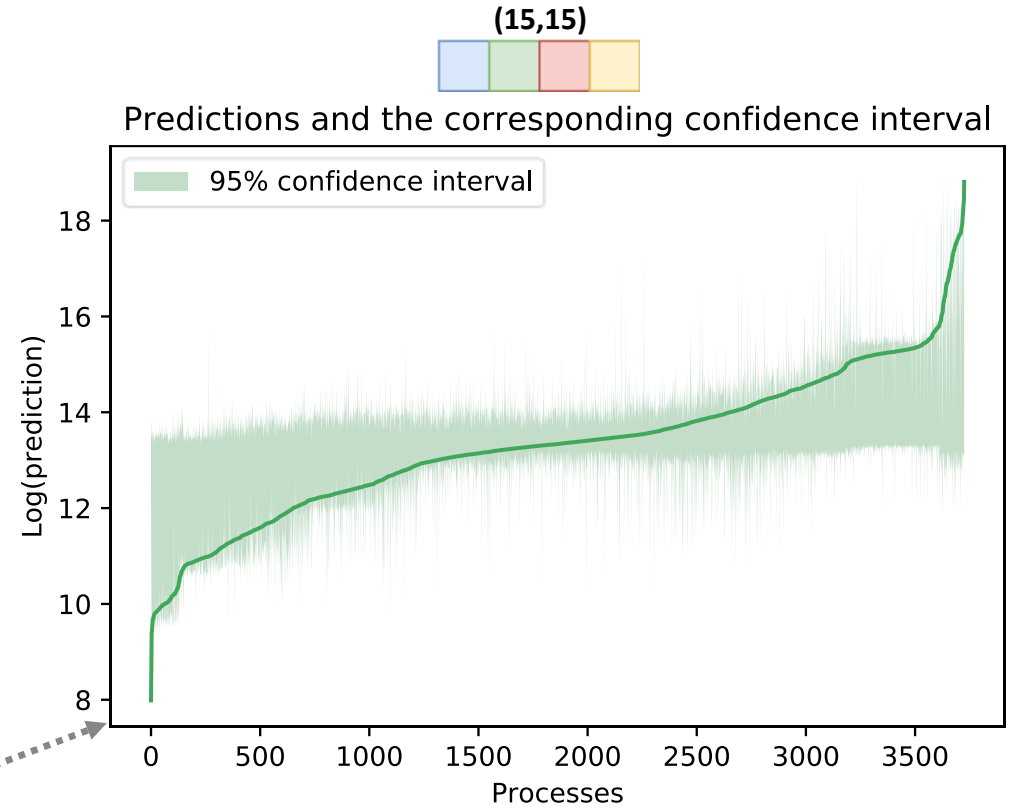
~ 600 predictions around 800,000 liters due to relatively large sum of return_flow



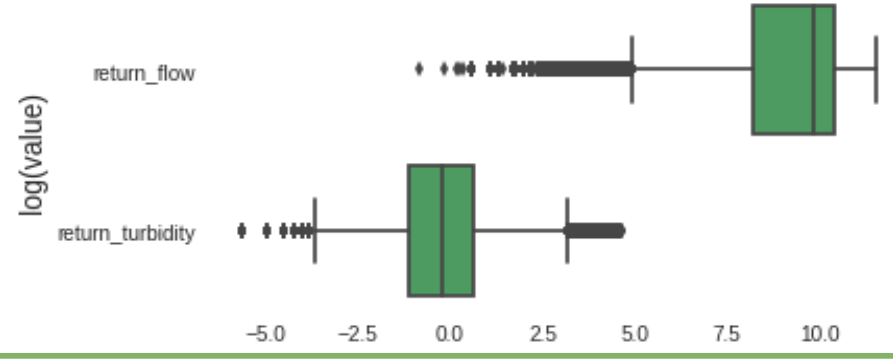
~ 350 predictions around 2 million liters due to much higher return_flow and supply_flow sums

# Training two gradient boosters with quantile loss (1 - $\frac{\alpha}{2}$ and $\frac{\alpha}{2}$) allows to construct (1 - $\alpha$)-prediction intervals with $\alpha = 0.05$



# An aggregated target causes the less controllable return turbidity to be masked by return flow, which is of a larger order of magnitude while less informative




correlation

causation

return_turbidity

return_flow

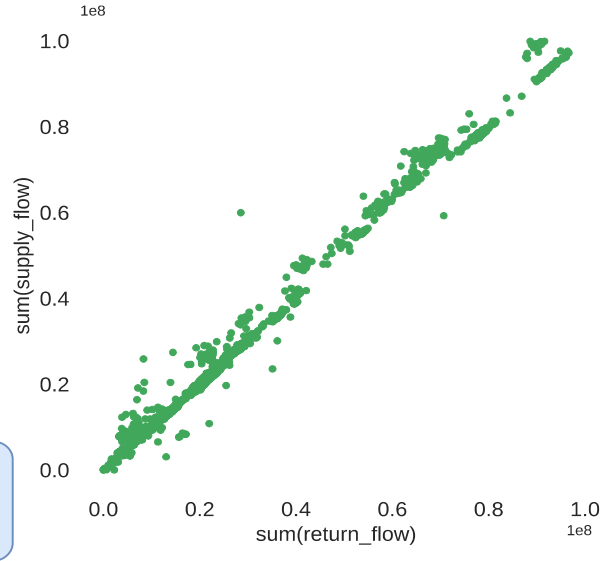
final_rinse_total_turbidity_liter

return_temperature

supply/return_caustic

object_id

supply_flow




target_time_period

NOR

return_caustic

return_acid

# Predicting the turbidity outcome of the final rinse seems a harder task than predicting the flow outcome, however, interesting interactions appear

**return_turbidity**

| Group | MAPE $(\mu \pm \sigma)$ |
|---|---|
| (3,3) | $0.33 \pm 0.40$ |
| (9,8) | $0.54 \pm 0.49$ |
| (15,15) | $0.33 \pm 0.46$ |
| **Total:** | **0.34 ± 0.45** |

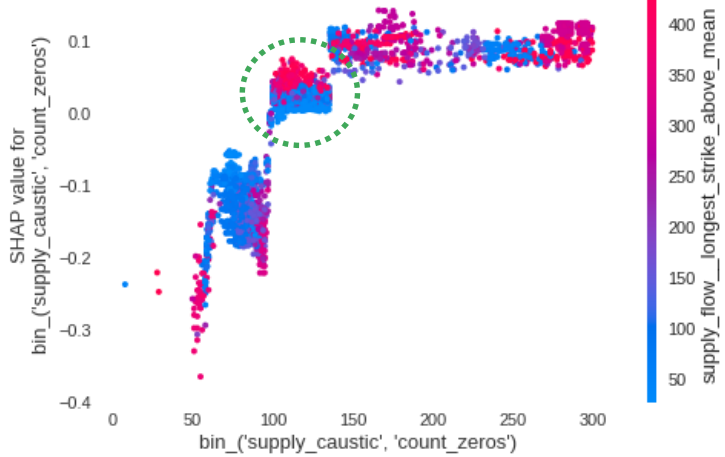
**return_flow**

| Group | MAPE $(\mu \pm \sigma)$ |
|---|---|
| (3,3) | $0.11 \pm 0.15$ |
| (9,8) | $0.16 \pm 0.17$ |
| (15,15) | $0.10 \pm 0.15$ |
| **Total:** | **0.10 ± 0.15** |

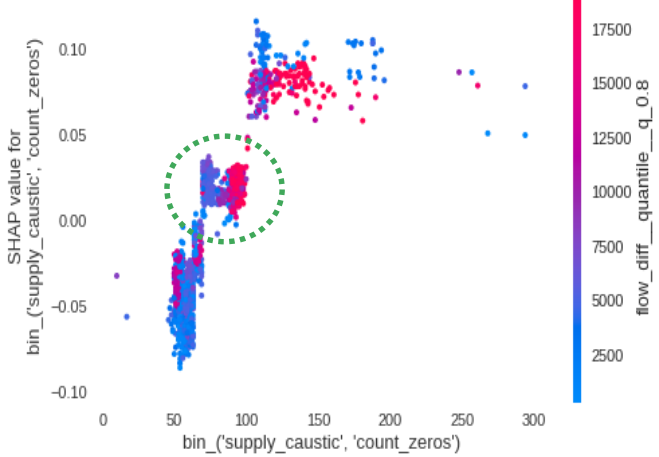
| Group | MAPE $(\mu \pm \sigma)$ |
|---|---|
| (3,3) | $0.10 \pm 0.16$ |
| (9,8) | $0.19 \pm 0.21$ |
| (15,15) | $0.11 \pm 0.17$ |
| **Total:** | **0.11 ± 0.17** |

use only 22 flow features

**(15,3)**

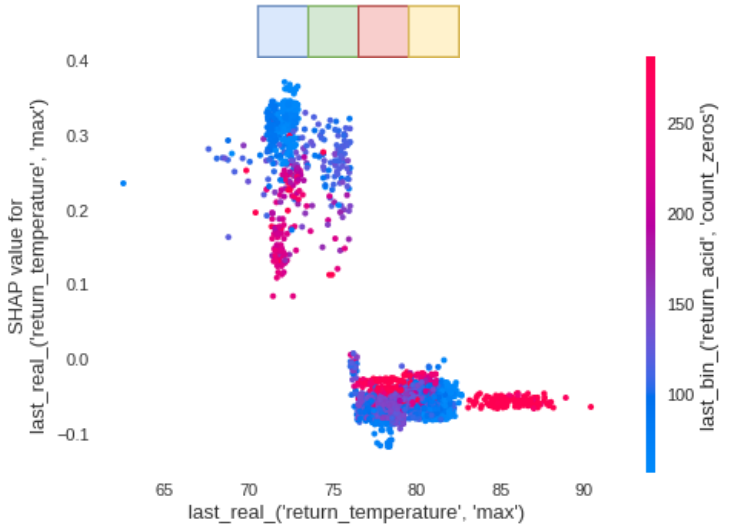



**(3,3)**




three clusters can be identified, for both recipes, after the caustic phase, based on nr. zeros in supply_caustic, whereas within the highlighted clusters another partition can be made

**(15,15)**




when the maximum return_temperature exceeds 76 °C the return_turbidity from the final rinse will be lower, moreover within low-temperature processes, a new partition can be made depending on the inactivity duration of the acid valve