

# Predicting Multiple Sequence Alignment Uncertainty via Machine Learning

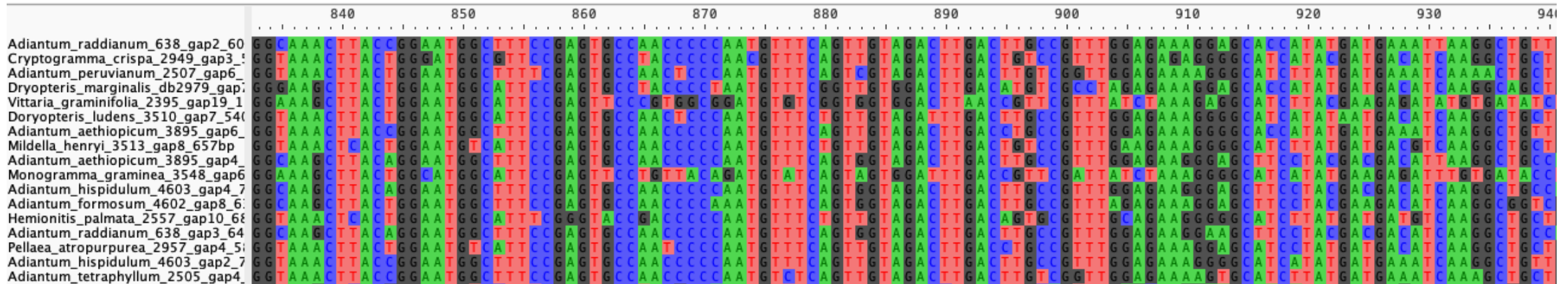
Mattis Bodynek, **Lucía Martín-Fernández**, Julia Haag,  
Ben Bettisworth, Alexandros Stamatakis

LEGEND 2025. Machine Learning for Evolutionary Genomics Data  
8<sup>th</sup>-12<sup>th</sup> December

# Multiple Sequence Alignment

## Definition

Process to identify regions of similarity across three or more biological sequences



## How?

Heuristic and probabilistic algorithms.

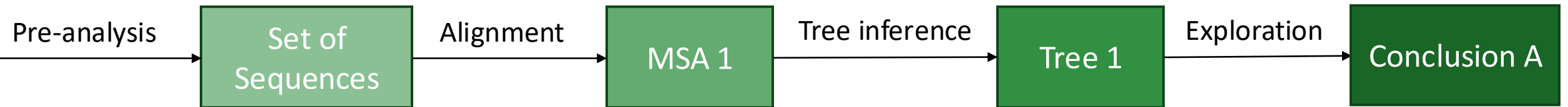
Each tool relies on different model assumptions.

## Problem

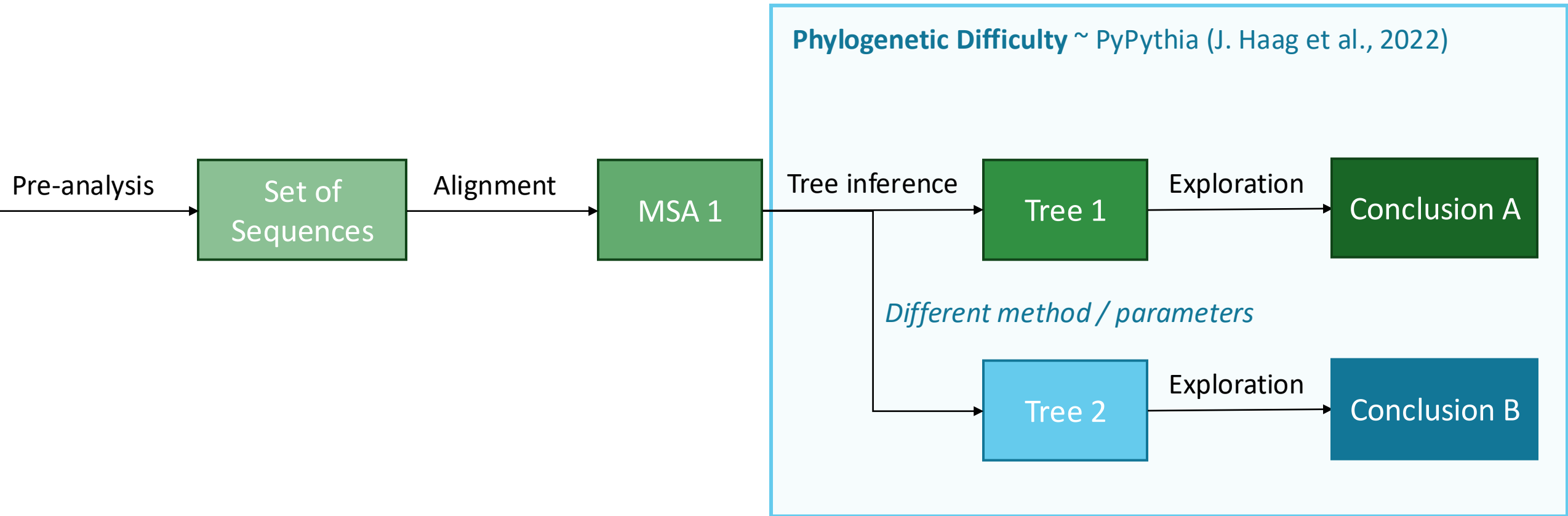
NP-Hard.

We can only approximate the optimal solution.

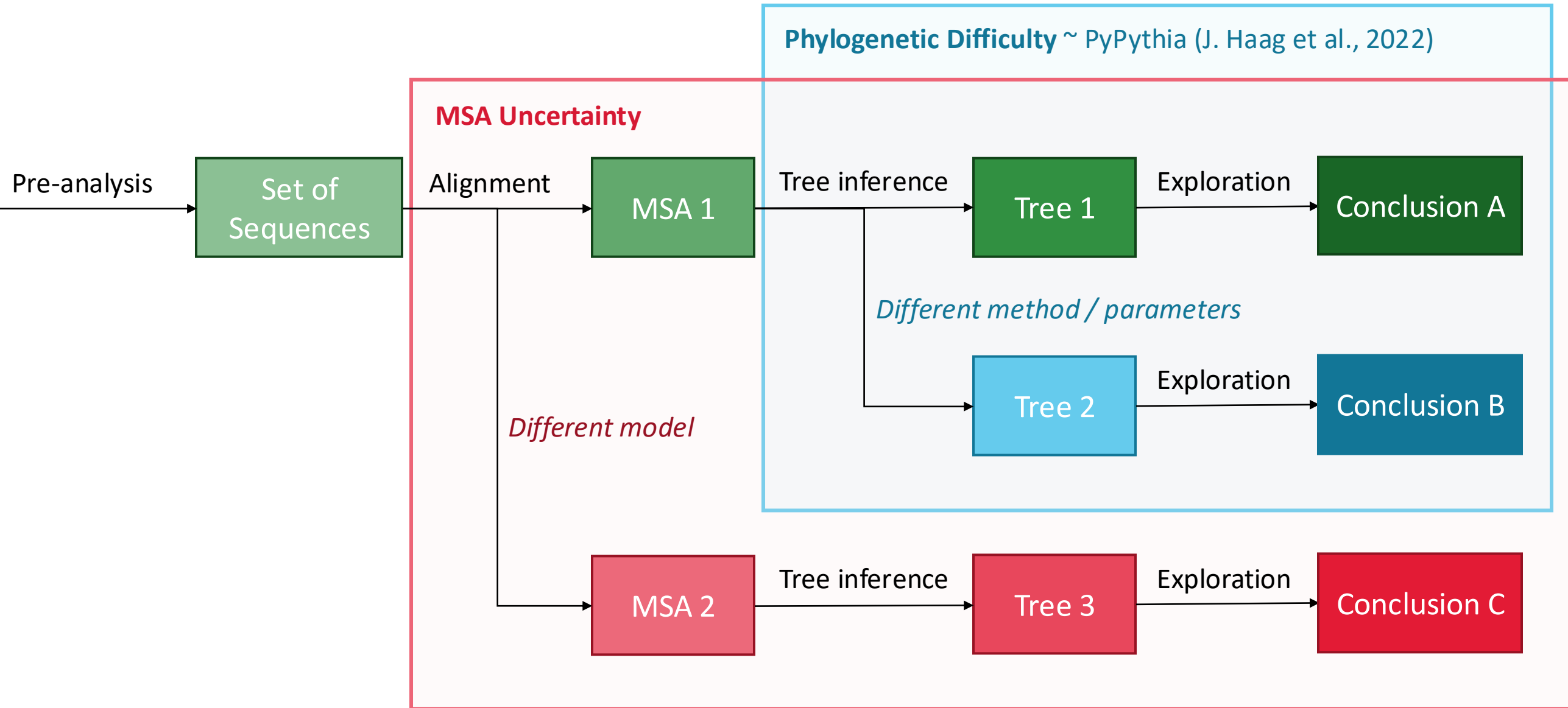
# MSA Uncertainty



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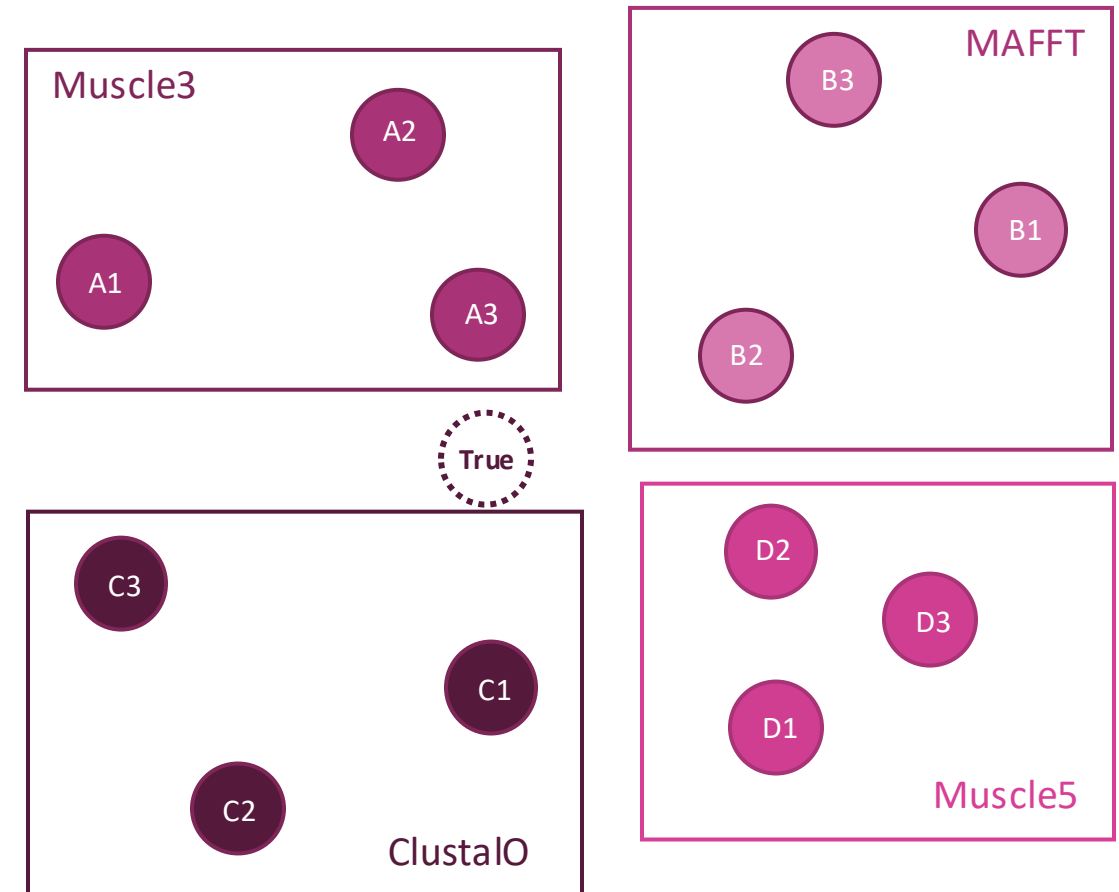
# MSA Uncertainty

So far, we know that...

- Multiple Sequence Alignment is an NP-Hard problem
- Different alignment tools with different parameters may generate different solutions

## MSA Uncertainty ~ MSA Difficulty

- How difficult is to generate a stable MSA?
- How much uncertainty exists in how accurately the MSA captures true homology?

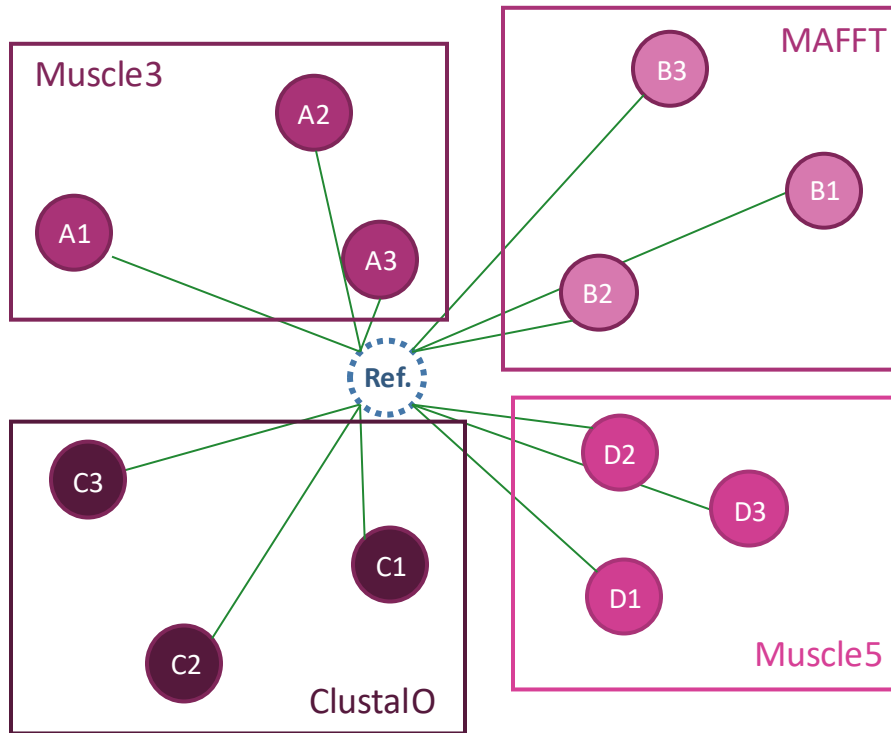


## ENSEMBLE

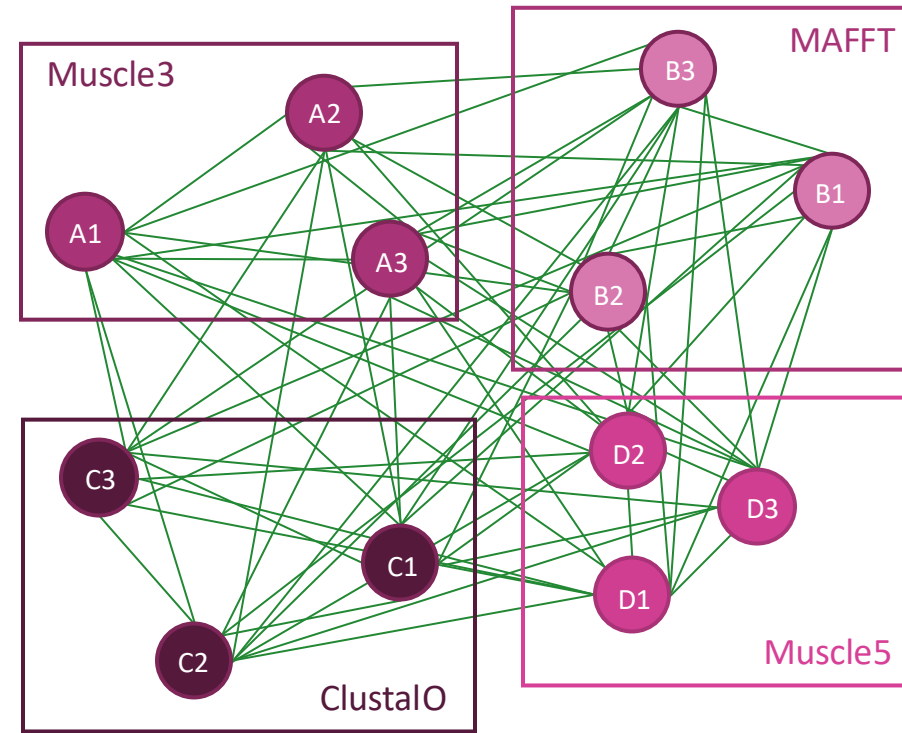
Different MSAs generated from one set of sequences using various algorithms and parameters

# MSA Uncertainty

## MSA Uncertainty score



Reference-Based score



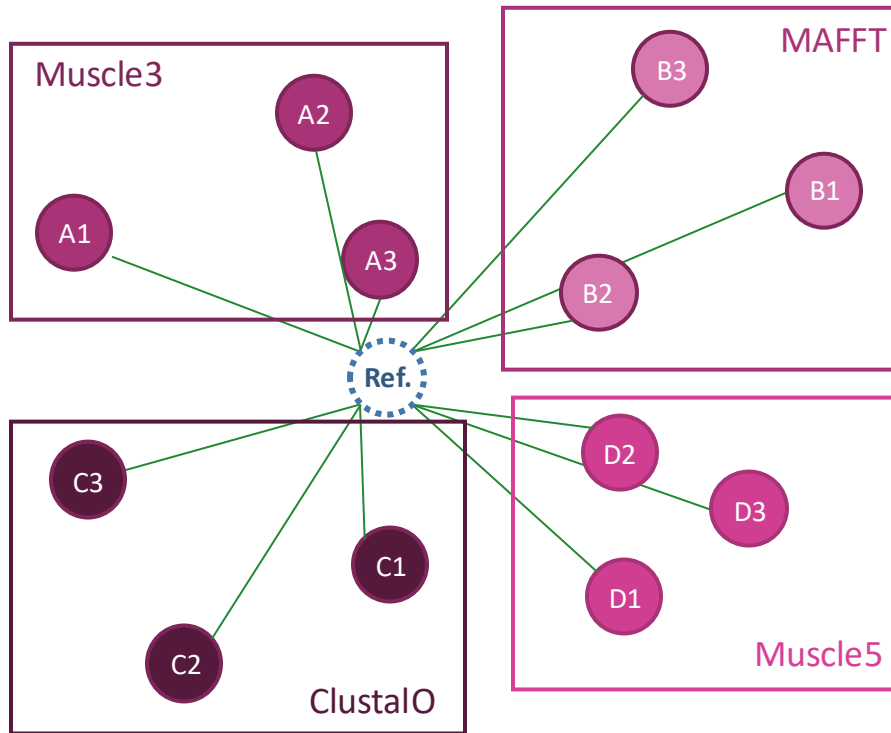
Reference-free score

**BALiBASE:** structural benchmark database

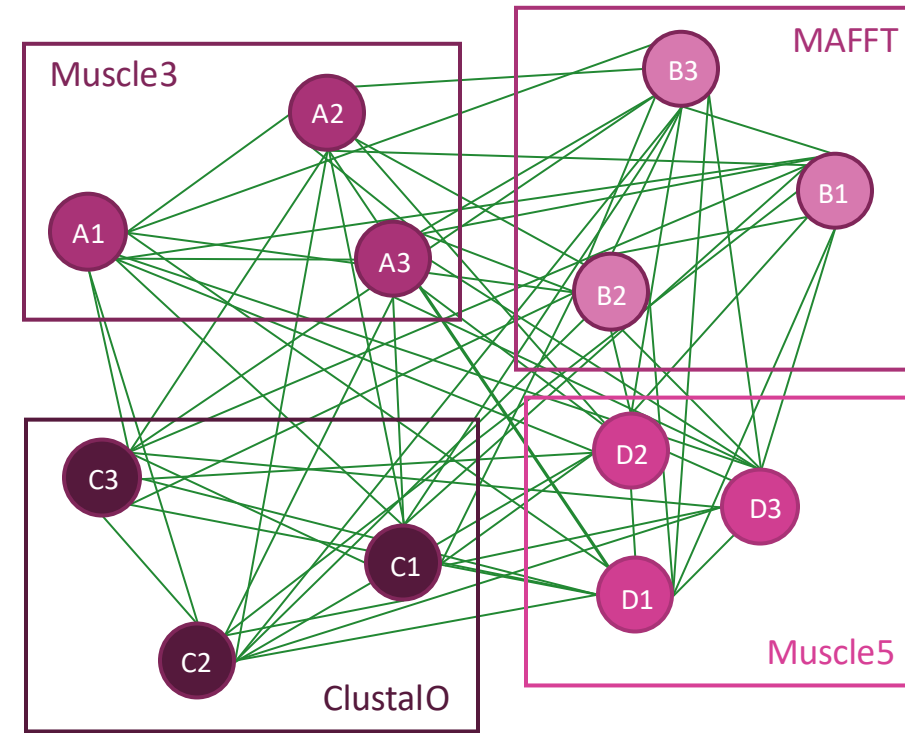
# MSA Uncertainty

## MSA Uncertainty score

We compared different **distance metrics** using **BALiBASE** (structural benchmark database) as reference.



Reference-Based score



Reference-free score

$d_{pos}$

- Uses positional homology sets of the alignments
- Incorporates positional information about gaps



# MSA Uncertainty

## MSA Uncertainty score

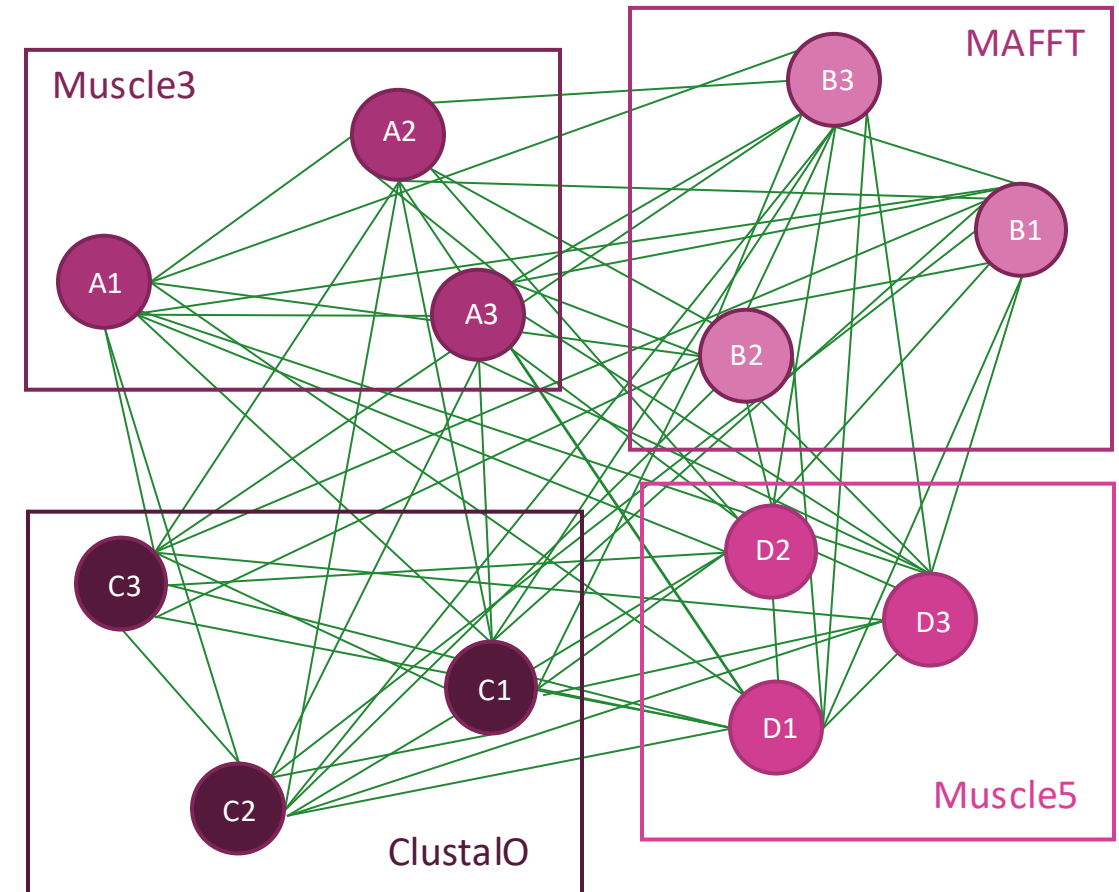
We measure how difficult it is to align a set of sequences:



Quantifies how much alignments differ within an **ensemble**  
~ average norm. **pairwise distance** ( $d_{pos}$ ) between all MSAs.

### MSA Uncertainty ~ MSA Difficulty

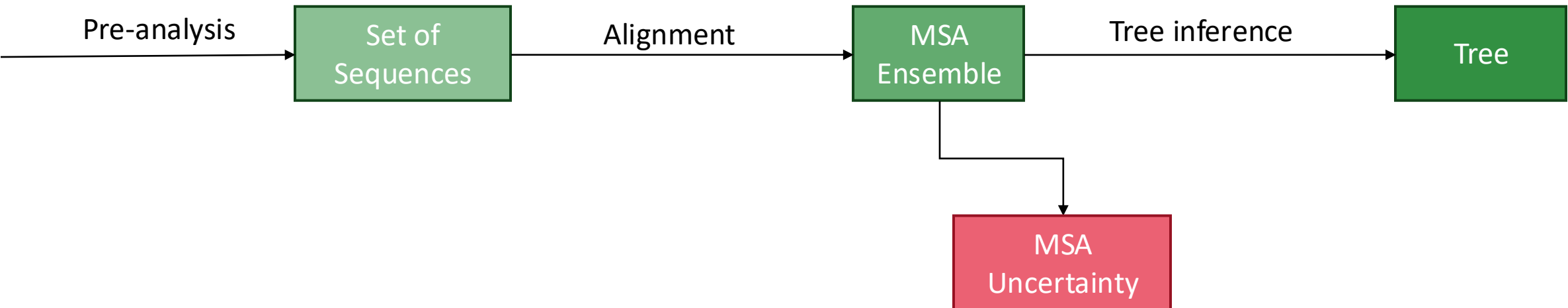
- How difficult is to generate a stable MSA?
- How much uncertainty exists in how accurately the MSA captures true homology?



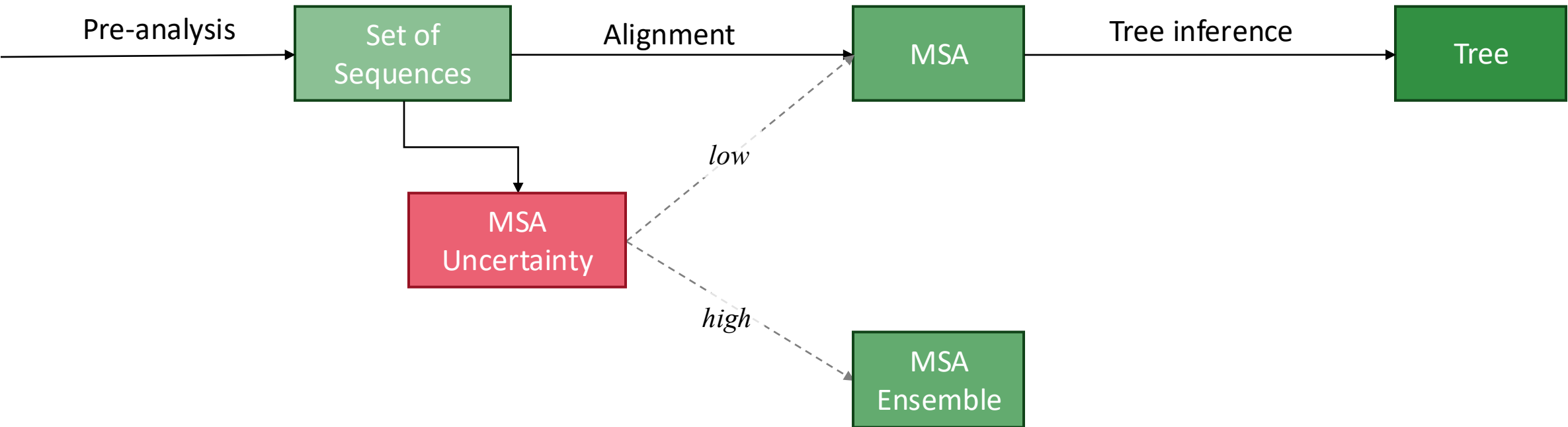
### ENSEMBLE

Different MSAs generated from one set of sequences using various algorithms and parameters

# MSA Uncertainty



# MSA Uncertainty



# Predicting MSA uncertainty

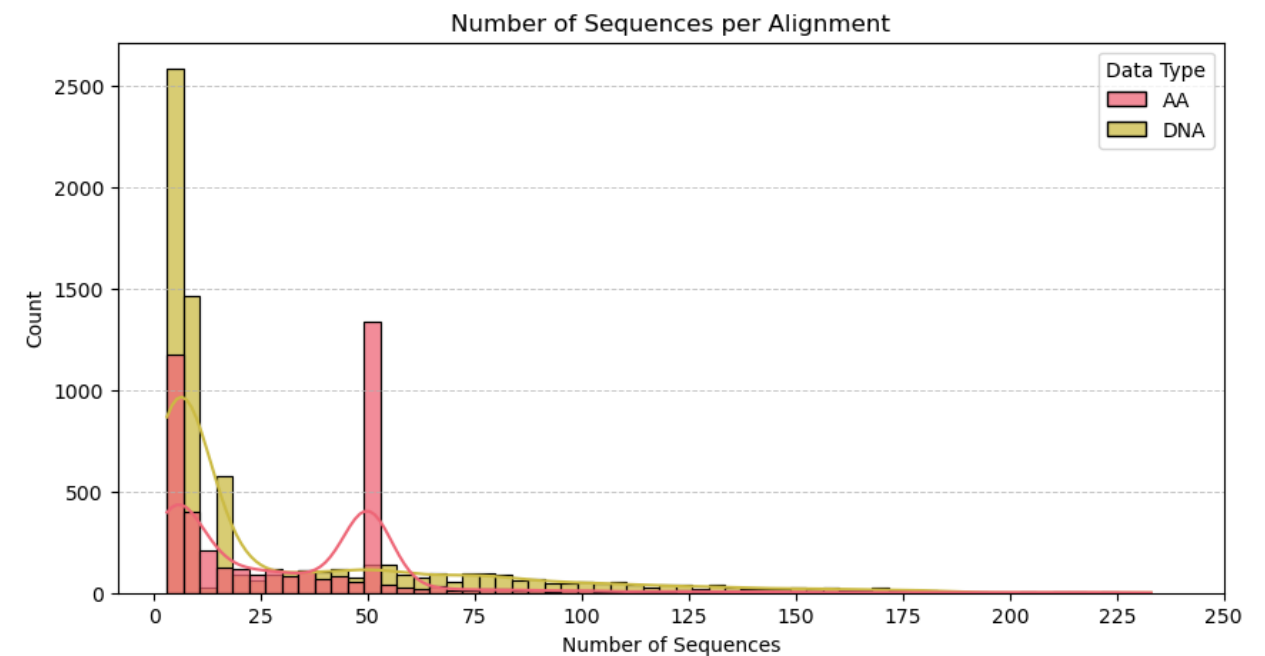
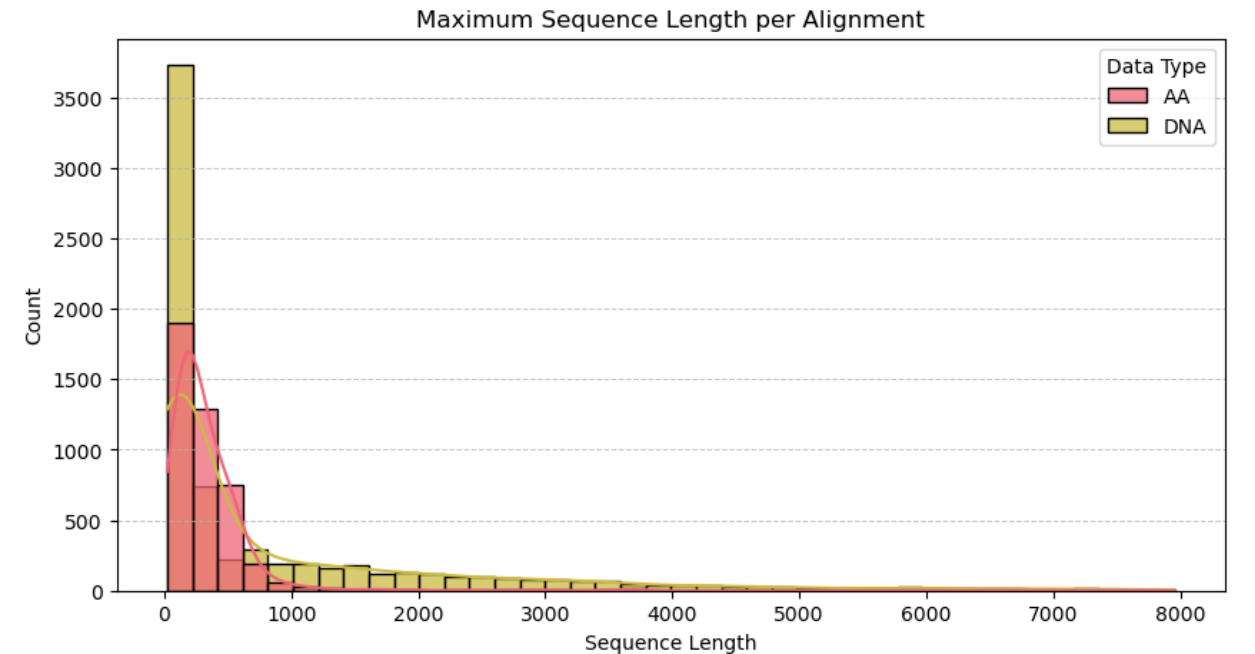
- 1. Data collection**
- 2. Label Generation**
- 3. Feature Generation**
- 4. Training the model**
- 5. Results**

# Predicting MSA uncertainty

## 1. Data collection

HOMSTRAD SABmark BALiBASE v3 PREFAB v2 OXBENCH ArthropodsP450	AA
TreeBASE	AA / DNA
BRAliBASE BALiBASE v2	RNA → DNA AA → DNA

11.432 sequence sets



# Predicting MSA uncertainty

## **1. Data collection**

11.432 sequence sets

## **2. Label Generation**

## **3. Feature Generation**

## **4. Training the Model**

## **5. Results**

# Predicting MSA uncertainty

## 1. Data collection

11.432 sequence sets

## 2. Label Generation

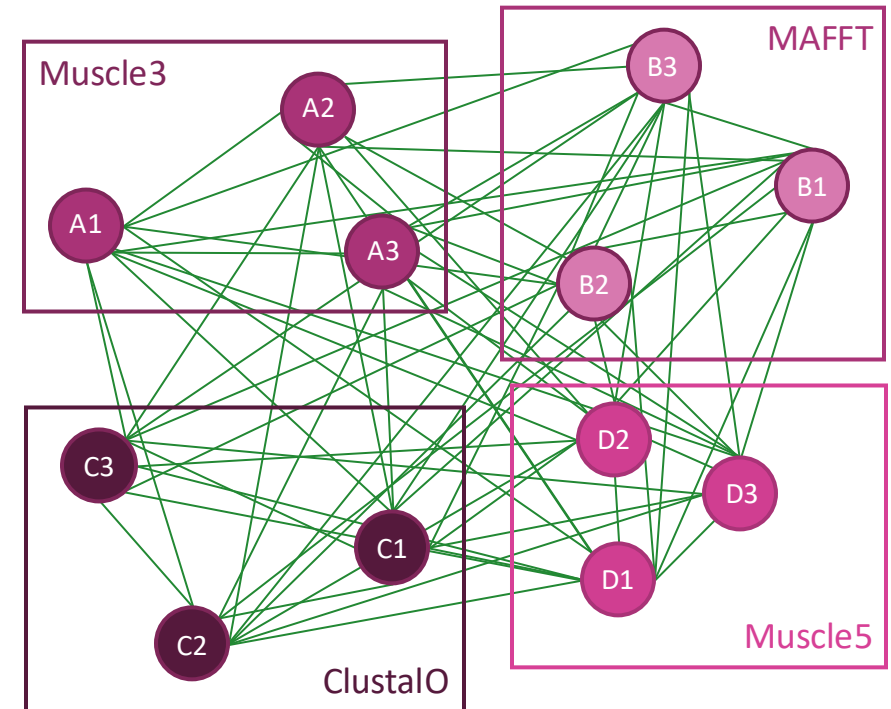
We calculated the MSA uncertainty score heuristically for the collected data.

We generate ensembles of 48 alignments per sequence set.

## 3. Feature Generation

## 4. Training the Model

## 5. Results



# Predicting MSA uncertainty

## 1. Data collection

11.432 sequence sets

## 2. Label Generation

We calculated the MSA uncertainty score heuristically for the collected data.

We generate ensembles of 48 alignments per sequence set.

## 3. Feature Generation

We define inexpensive to compute features on the unaligned sequences.

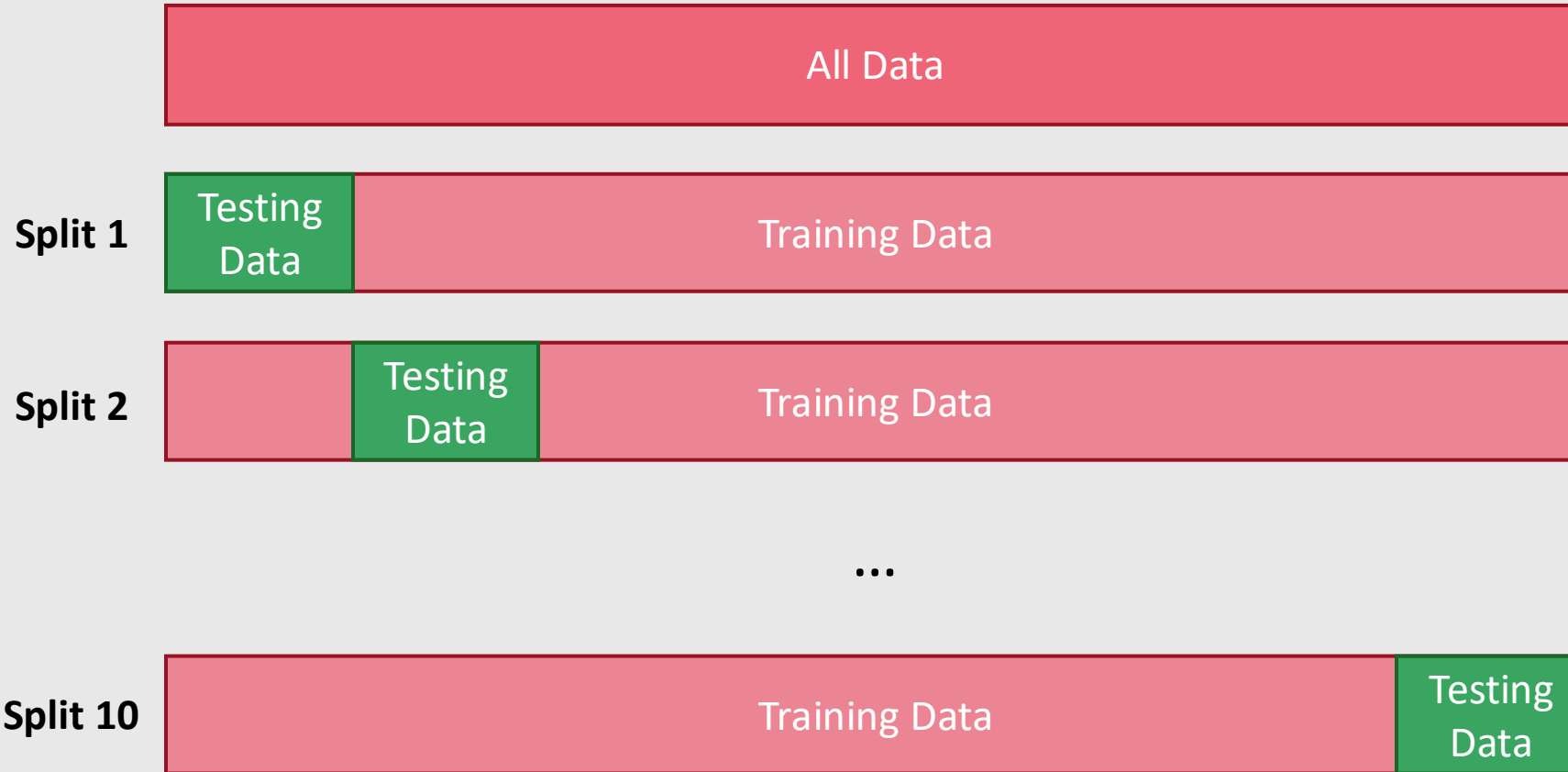
The majority of our features are stochastic because they subsample sequences.

## 4. Training the Model

## 5. Results



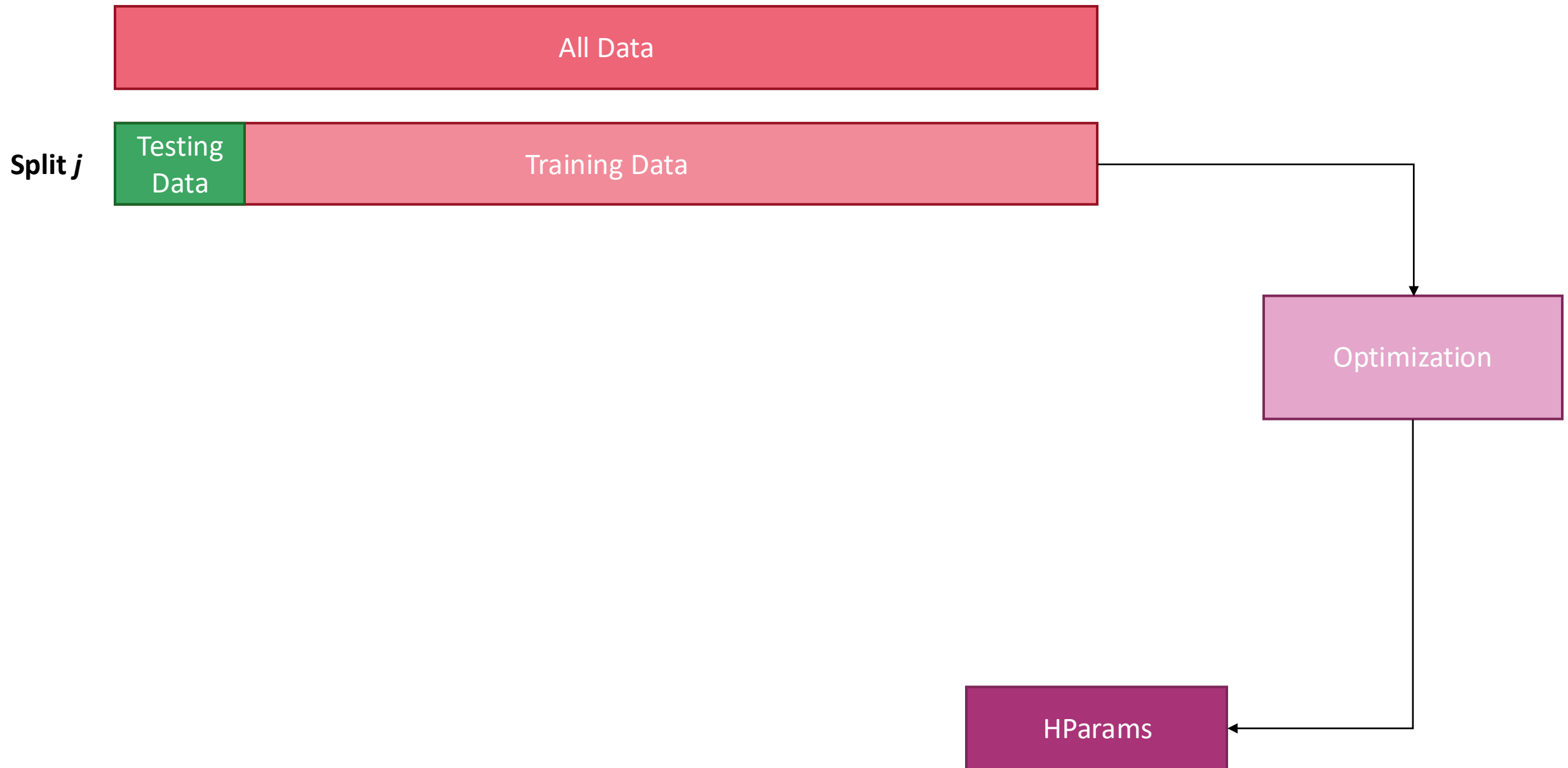
# Training the Model



X10 sampling seeds for stochastic Feature Generation

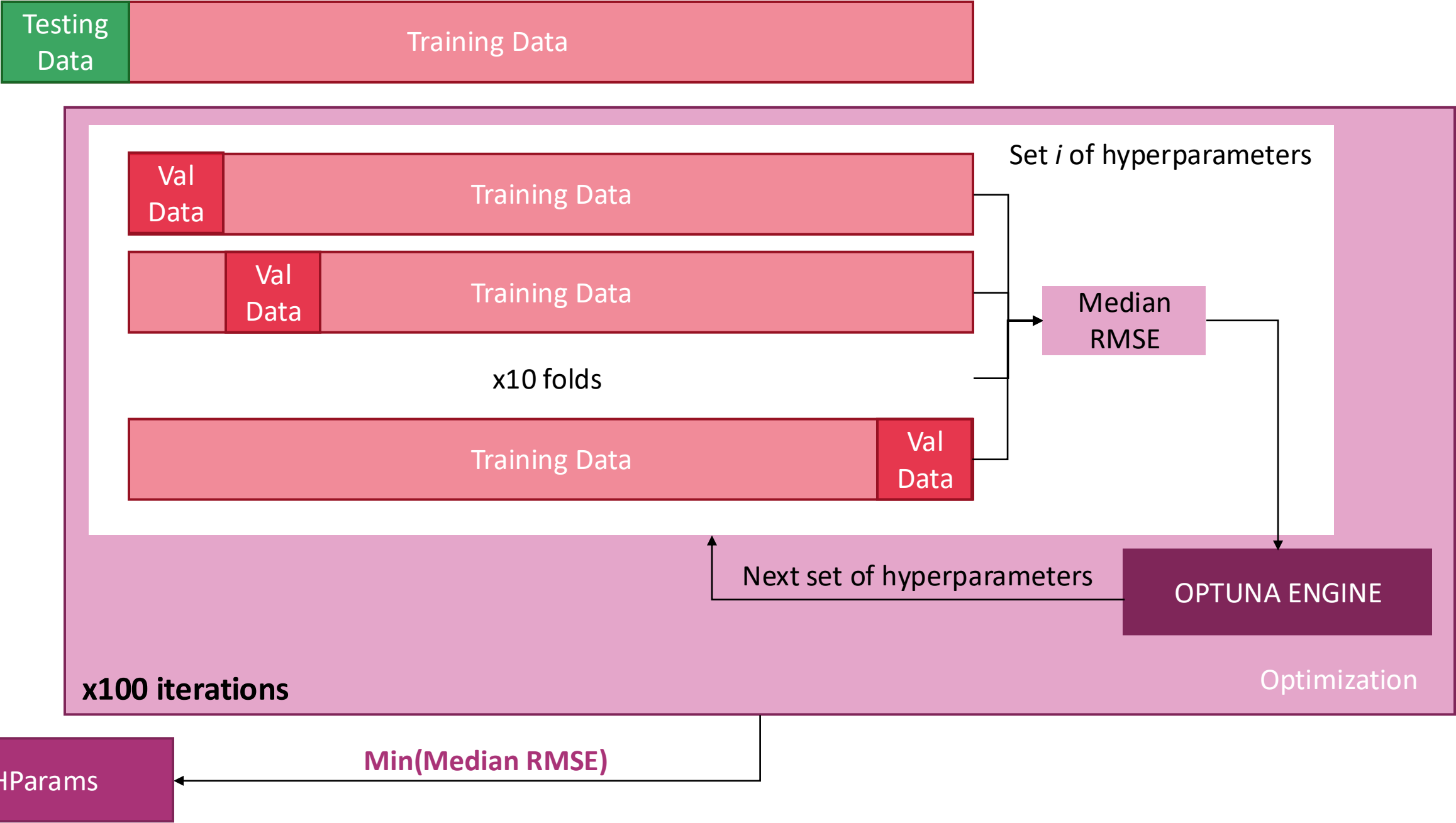
**10 splits x 10 sampling seeds = 100 Folds**

# Training the Model

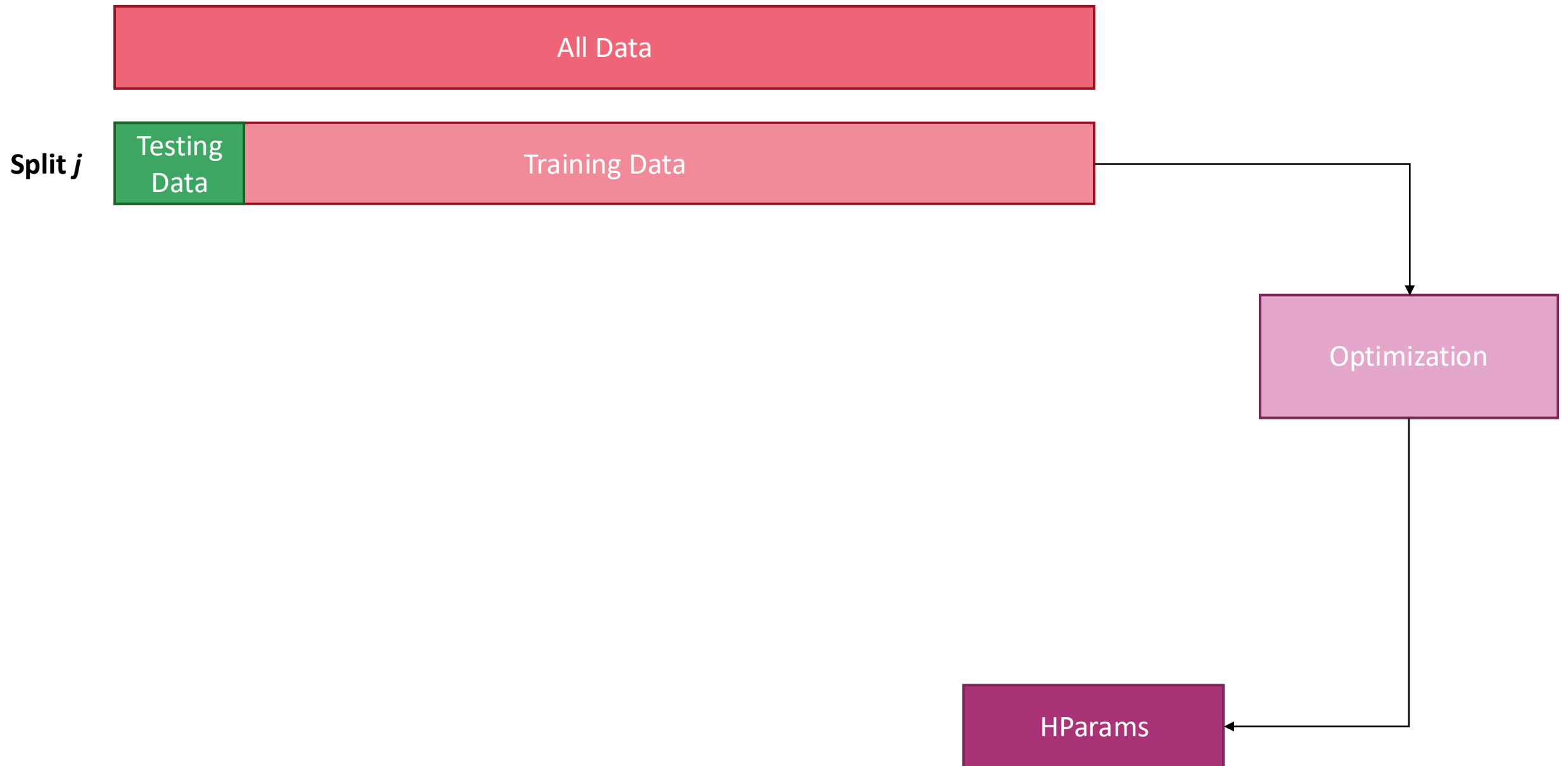


# Training the Model

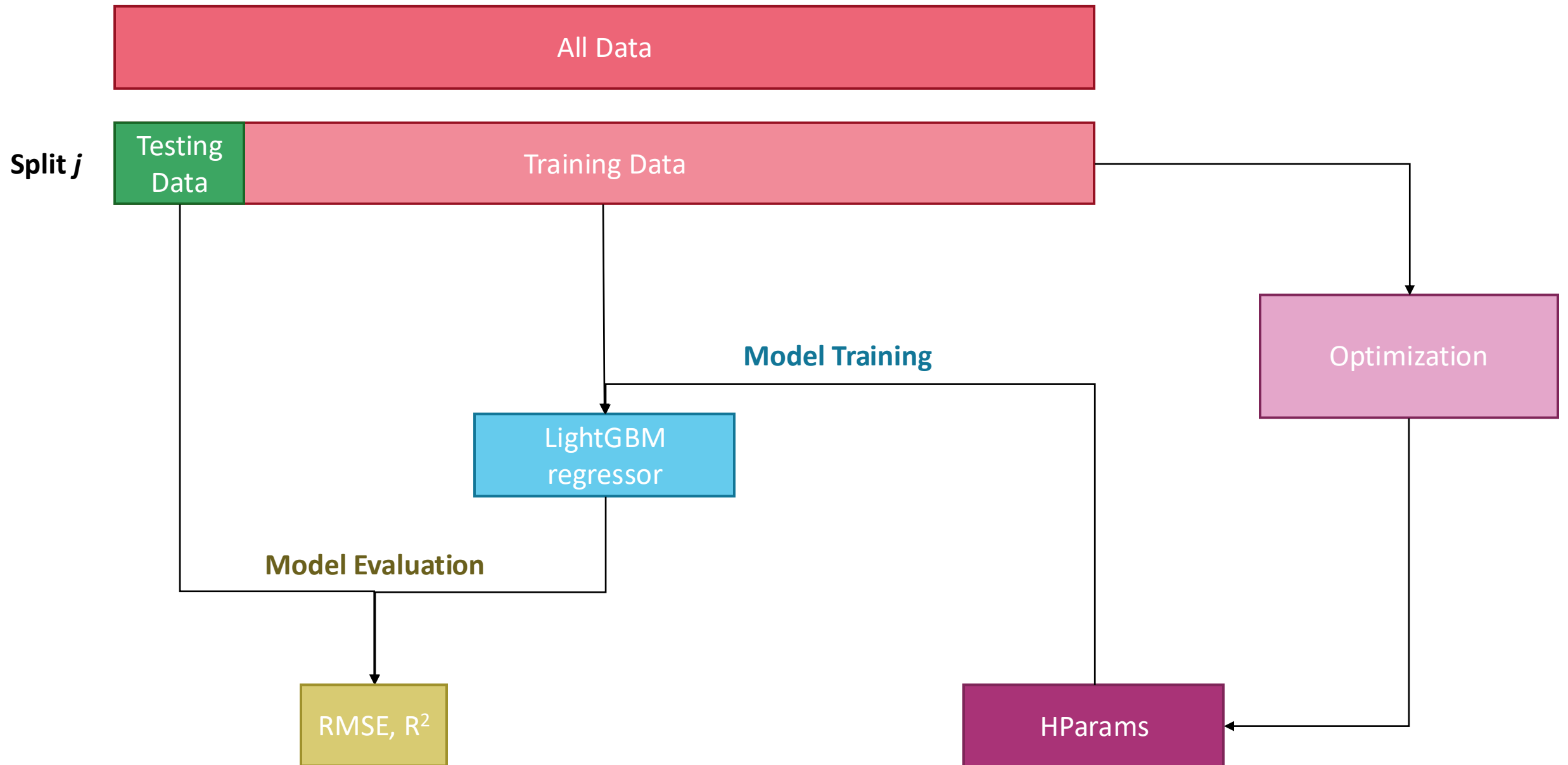
Split  $j$



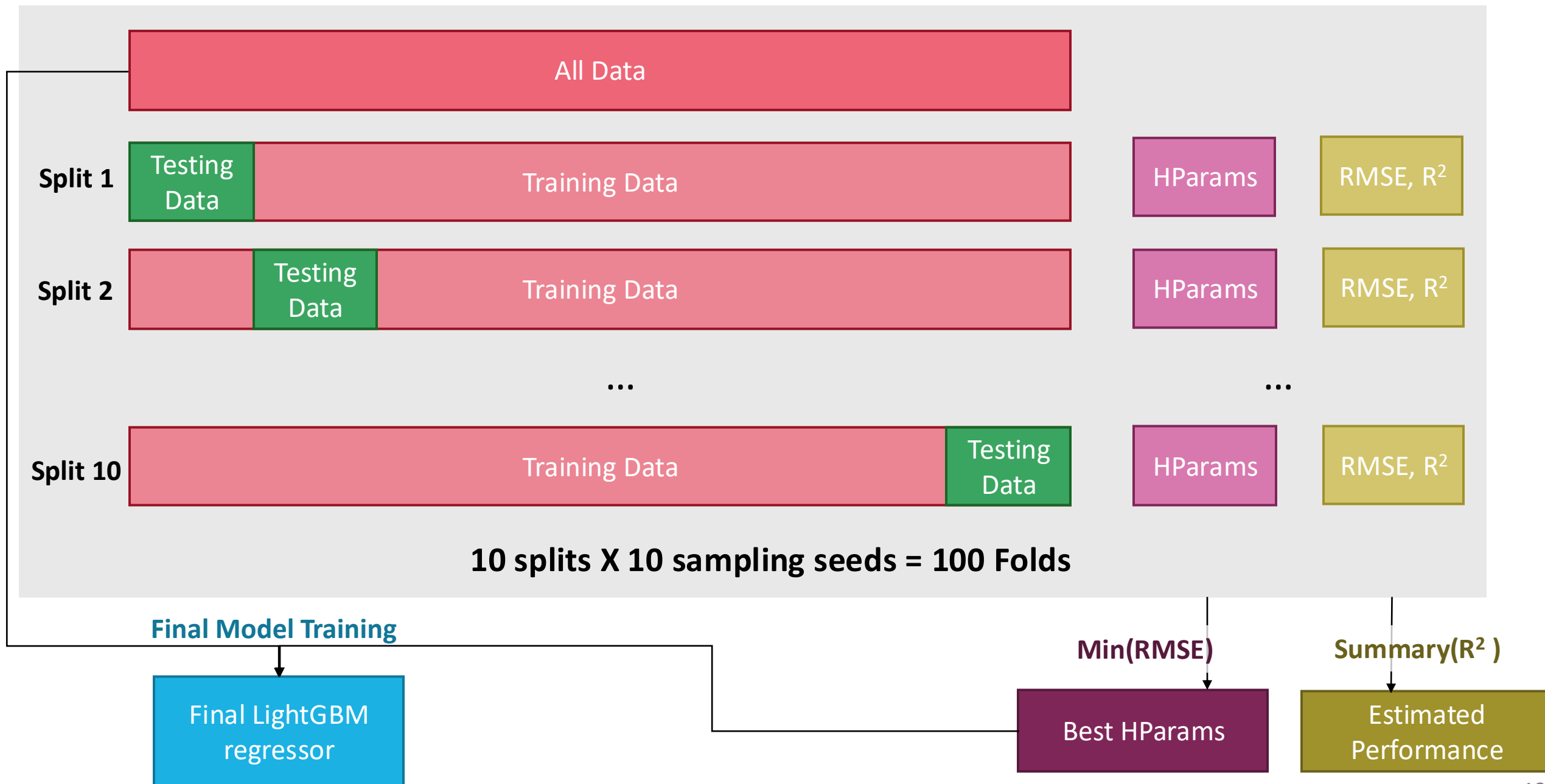
# Training the Model



# Training the Model



# Training the Model



# Final Model

Best HParams

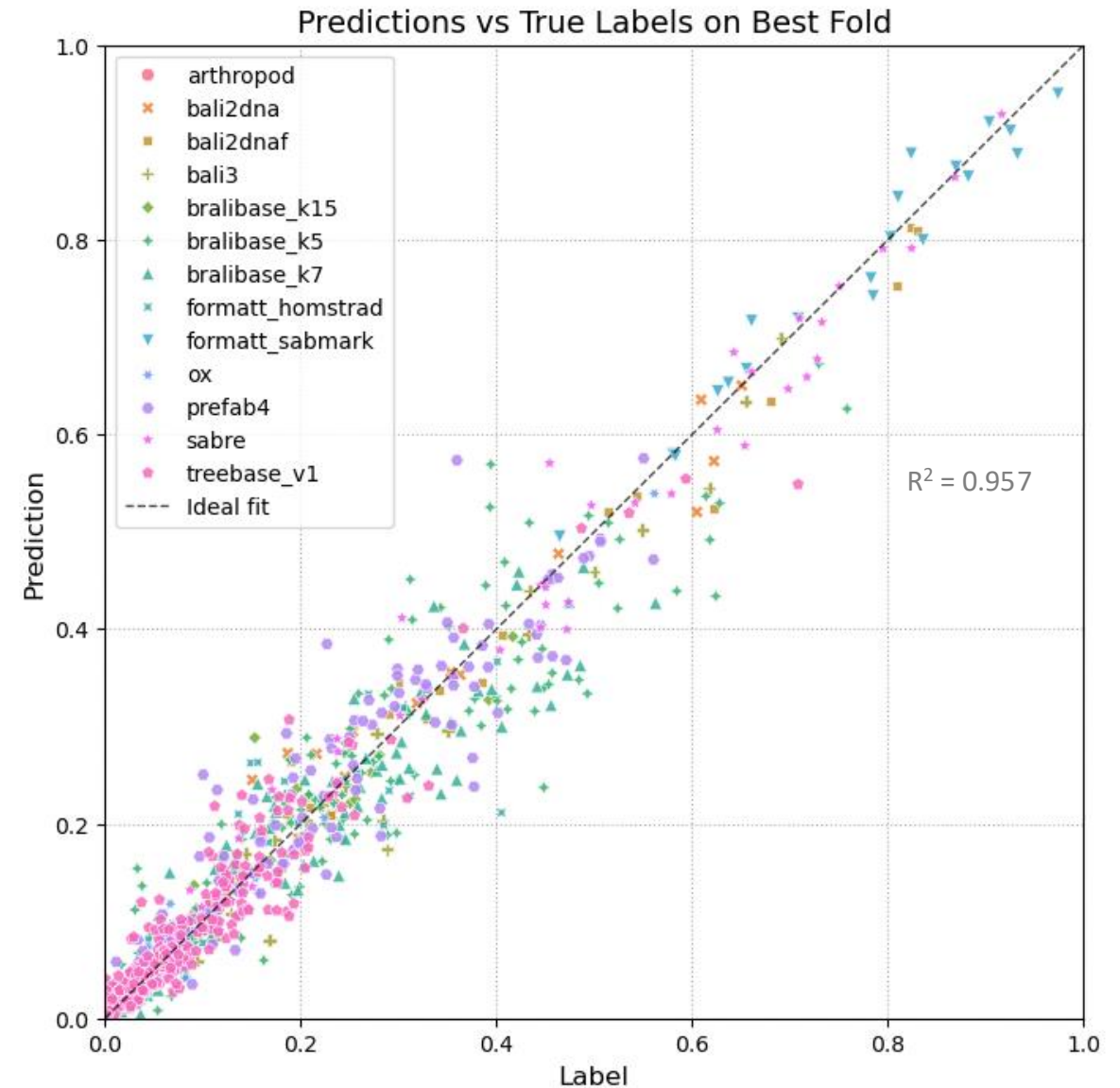
The set of optimized hyperparameters across all 100 folds with the lowest RMSE

Estimated Performance

**$R^2 = 0.945$  [0.939–0.951]**  
 $R^2$  median and its 10% and 90% percentiles across all 100 folds.

Final LightGBM regressor

Trained using all available data and the best hyperparameter set



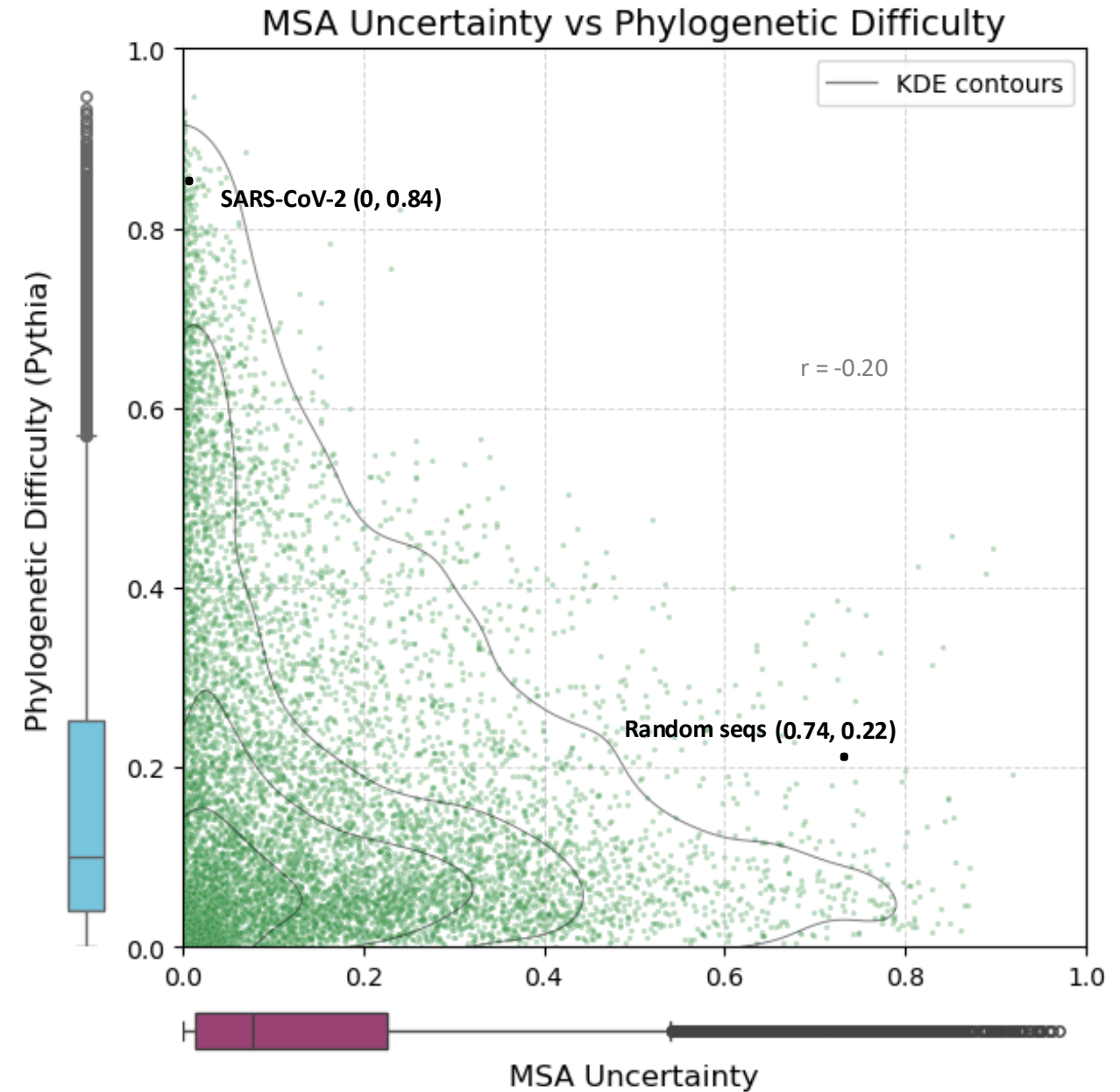
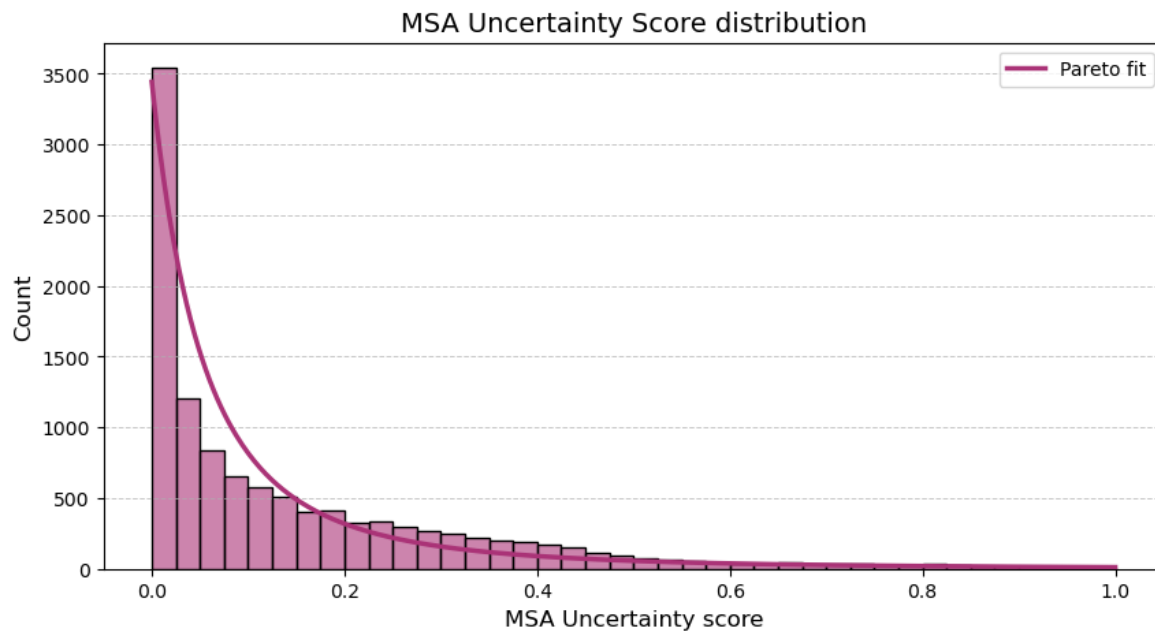
# MSA Uncertainty vs Phylogenetic Difficulty

## SARS-CoV-2. 4869 sequences

- MSA Uncertainty = 0
- Phylogenetic Difficulty = 0.84

## 20 Random DNA seqs (500 - 525bp)

- MSA Uncertainty = 0.74
- Phylogenetic Difficulty = 0.22

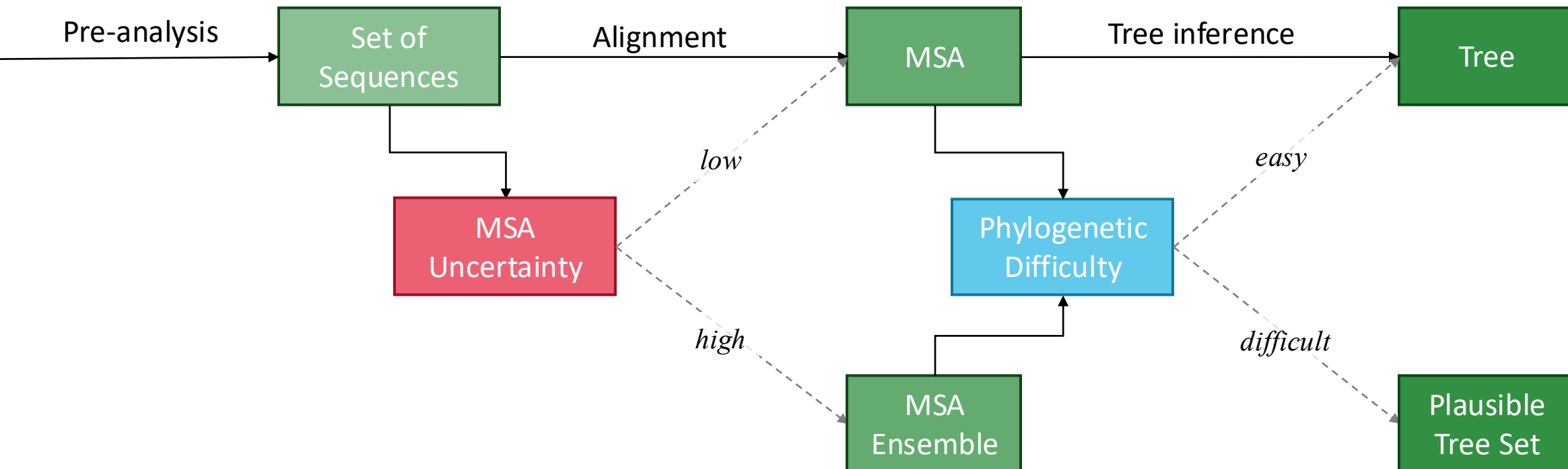




# Summary

## Conclusion

- Heuristic method to calculate MSA Uncertainty  
~ average norm. pairwise distance ( $d_{pos}$ ) between all 48 MSAs in an ensemble
- **LightGBM Regressor** to predict MSA Uncertainty given a set of sequences ( $R^2=0.945$ )
- **Inverse correlation** between Phylogenetic Difficulty and MSA uncertainty.



## Paper Loading . . .



<https://github.com/MaBody/aldiscore>

📖 README 📄 GPL-3.0 license



### AIDiScore - Alignment Difficulty Score

AIDiScore provides two approaches for quantifying multiple sequence alignment (MSA) difficulty:

1. **Heuristic Scoring:** Compute dispersion within an ensemble of alternative alignments
2. **Predictive Scoring:** Predict alignment difficulty from unaligned sequences using ML

### Features

- Command-line interface for heuristics and prediction
- Multiple scoring methods for ensemble analysis
- Pre-trained models for difficulty prediction
- Supports DNA and amino acid sequences





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