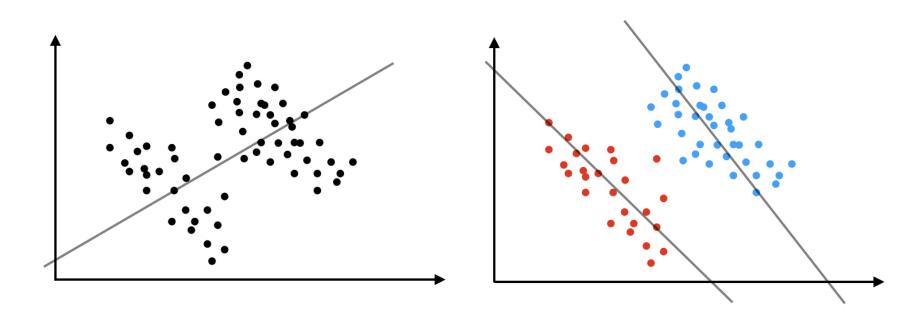




Problem Statement

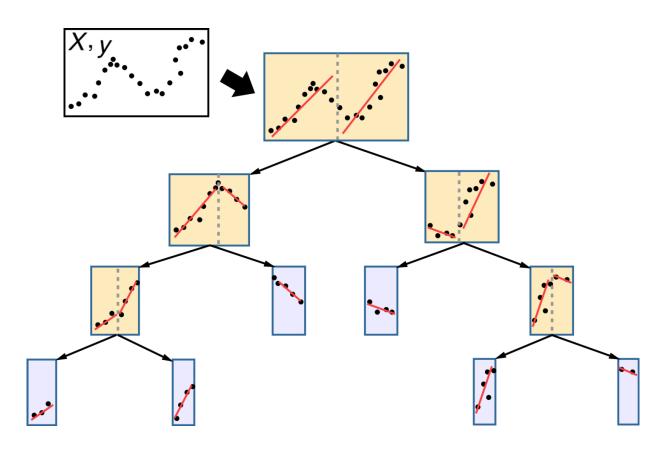
Simpson's paradox



A result that is present when data is put into groups that reverses or disappears when the data is combined



HRT - General Concepts



How does it work, advantages

Fits local linear regression in the leaves with alternative impurity measure*

- + Explainability
- + Non-linearity
- + Requires small tree depth
- + Can be run in parallel
- Is trained longer than LR, GBT
- Ensemble Hybrid is not explainable
- Poorly covers feature interaction

^{*}Linear Regression in Regression Tree Leaves. A.Karalik (1992)



Deep Dive in Theory

Hybrid Regression Tree

- Class value is estimated as linear function of attributes;
- Impurity measure of an example set E:

$$I(E) = \frac{1}{W(E)} \sum_{e_i \in E} (y_i - g(\vec{x}_i))^2$$

Function ξg epresents the regression plane through the example set.

 Expected utility of the split - defined in similar way as for CART.

Basic CART

- Class value is estimated as **constant value**;
- Impurity measure of an example set E estimate of variance of the class values:

$$\sigma^{2}(E) = \frac{1}{W(E)} \sum_{e_{i} \in E} w_{i}(y_{i} - \mu(E))^{2}$$

Here w_i is the weight of example. , i W(E) sum of example weights, $\mu(E)$ mean class value.

• Expected utility of the split:

$$I_{exp} = p_l I_l + p_r I_r$$

Here p_l, p_r probabilities of transitions into left/right son of the node, I_l, I_r corresponding impurities.



Datasets

PIK



Goal: Predict flats sales

Metric: RMSE

Shape: (8726, 47)

Data:

- Flats characteristics
- Macroeconomic data
- Geo data

StarSkill



Goal: Predict unique units

made per timestamp

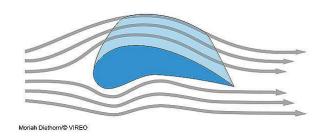
Metric: RMSE

Shape: (3395, 20)

<u>Data</u>:

- Game attributes
- Players actions

Airfoil



Goal: Sound pressure level

prediction

Metric: RMSE

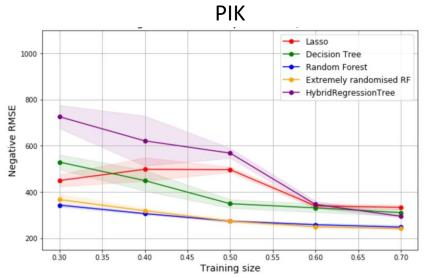
Shape: (1503, 6)

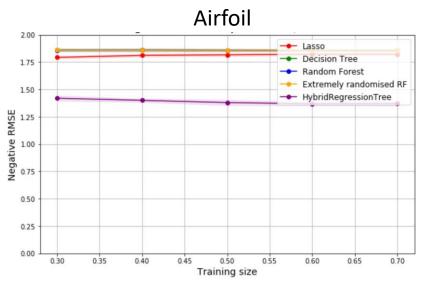
Data:

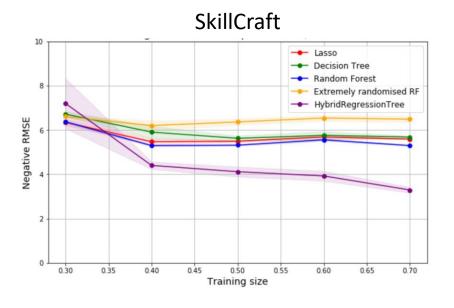
 NASA data, aerodynamics and acoustic tests of airfoil blade sections



Comparison – Forecasting Quality



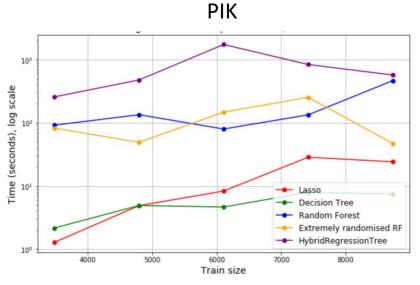


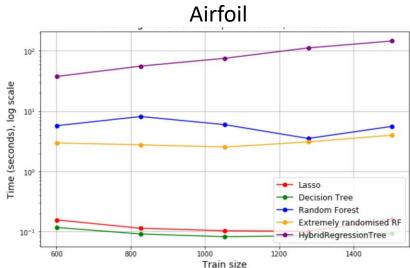


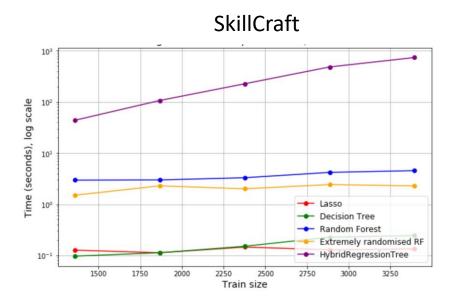
- HRT outperforms other methods for 2/3 datasets
- The better Lasso is, the better HRT is
- HRT is dependent on the number of data it is trained on



Comparison – Training Time







- HRT is trained longer than all other methods (as expected)
- Its train time scale worse in train size than other methods
- For larger datasets it could perform better than RF, ERRF



Conclusion & Further steps

Conclusion

- For some cases HRT outperforms RF,
 Extremely Randomized RF and Lasso
- In general, HRT **improves Lasso** results
- HRT captures **non-linear** data structure
- HRT is sensitive to the number of data
 it is trained on
- HRT is computationally expensive
- HRT is suitable for middle size datasets

Further steps

- Compare HRT to GBT
- Consider other algorithm in leafs except linear regression
- Implement HRT with parallelization
- Apply HRT to big data sets



Our Team

Input of each team member was focused on, but not restricted to:



Gazdieva Milena:

- HRT theory
- HRT code
- Data cleansing



Maksimov Ivan:

- HRT ensembles
- Pipeline
- Benchmarks



Belikova Kristina:

- HRT code
- Benchmarks
- Results analysis



Nikita Alexeichyk:

- HRT debugging
- Pipeline
- Visualization



Mikhail Kuzin:

- HRT debugging
- Feature engineering
- Visualization