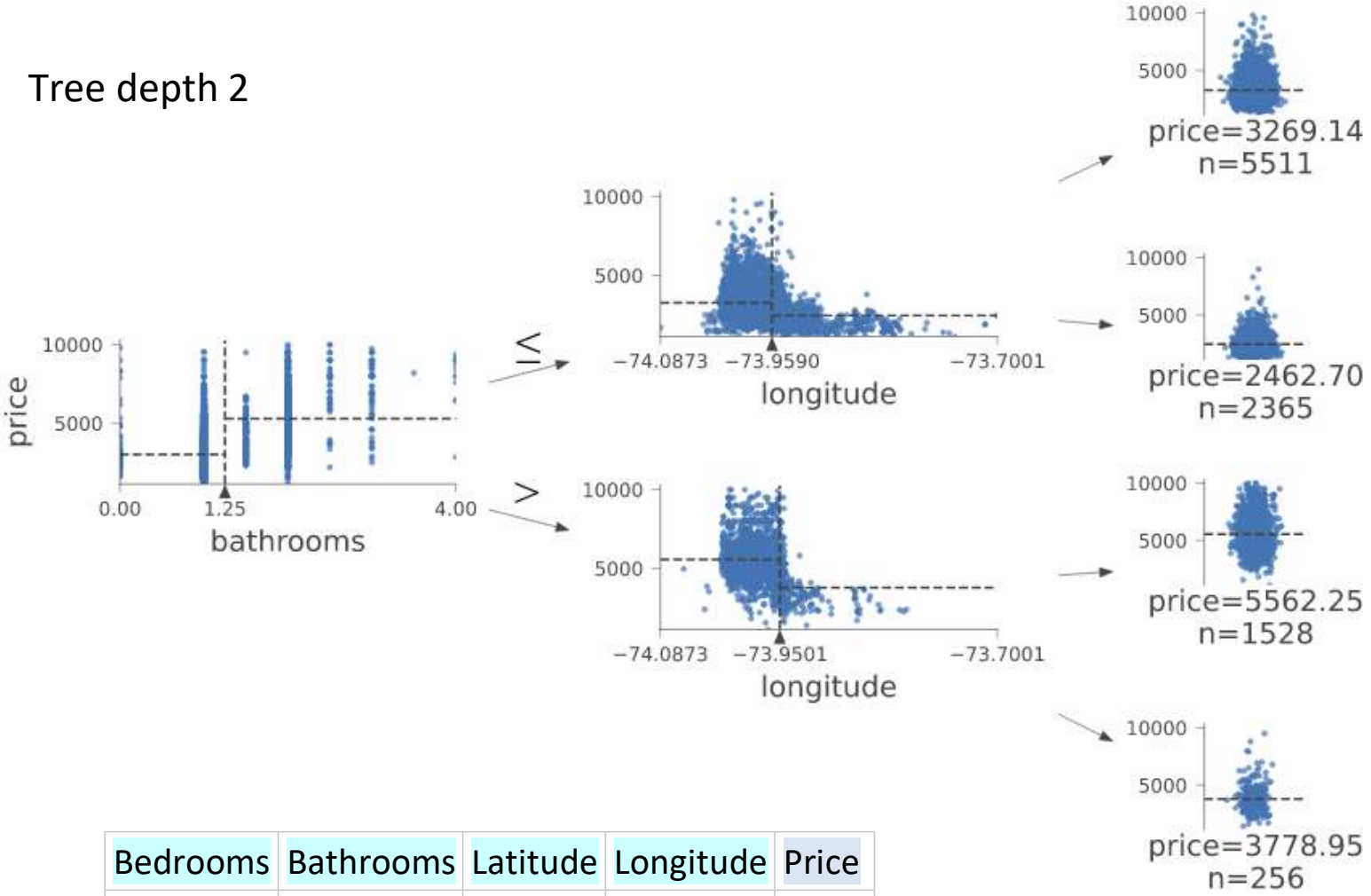
Regression - Rent prices of Appartments 1

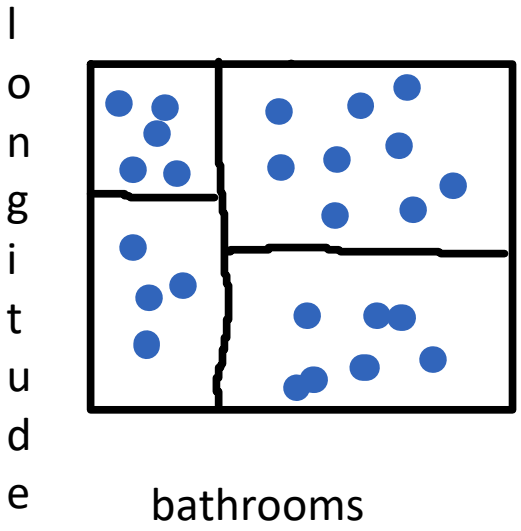
Prof. Dr. Ingo Claßen

Donnerstag, 1. Juli 2021 13:58

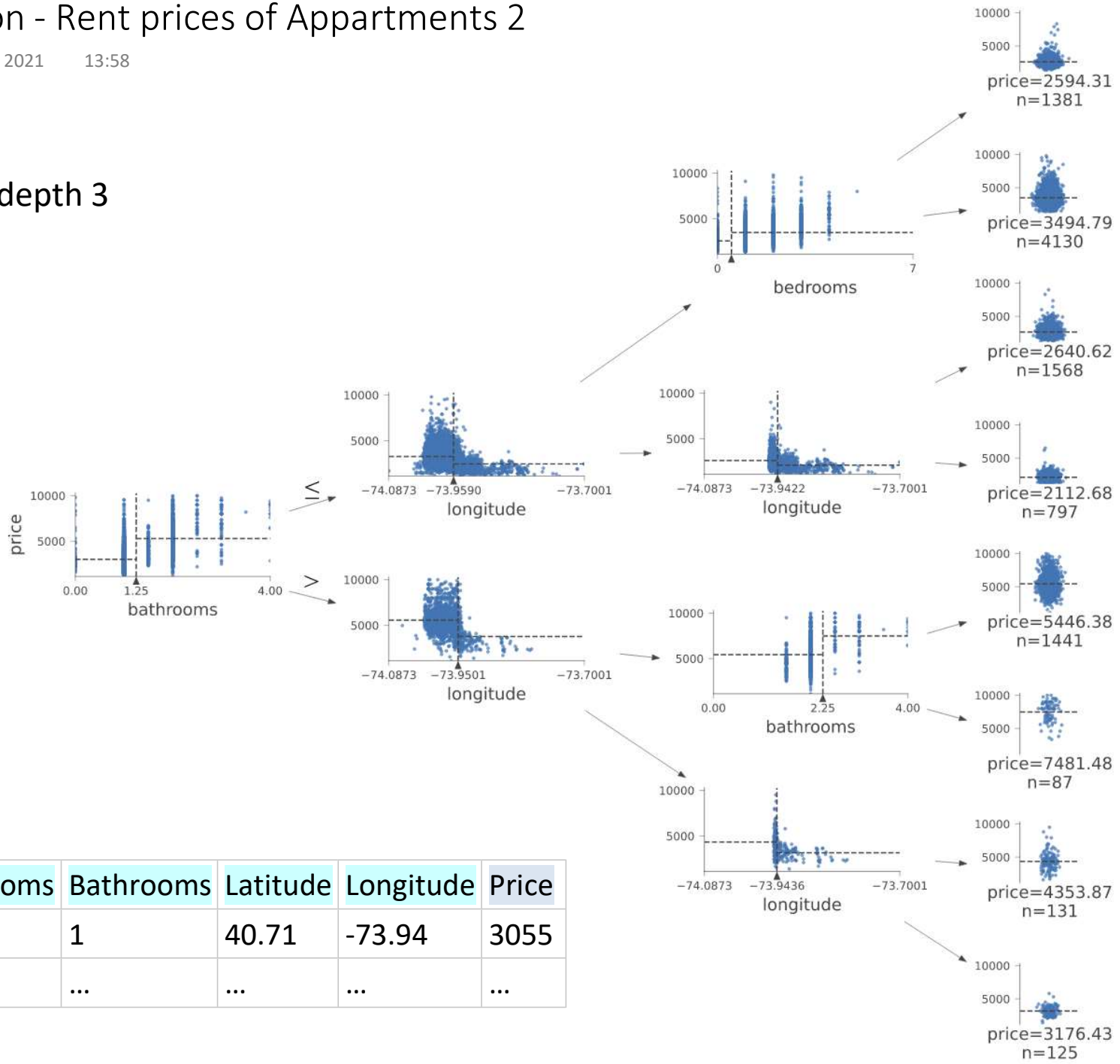
Tree depth 2



Bedrooms	Bathrooms	Latitude	Longitude	Price
1	1	40.71	-73.94	3055
…	…	…	…	…



Tree depth 3



Bedrooms	Bathrooms	Latitude	Longitude	Price
1	1	40.71	-73.94	3055
…	…	…	…	…

Decomposition of Feature Space

Prof. Dr. Ingo Claßen

Mittwoch, 30. Juni 2021 11:50

Feature space:

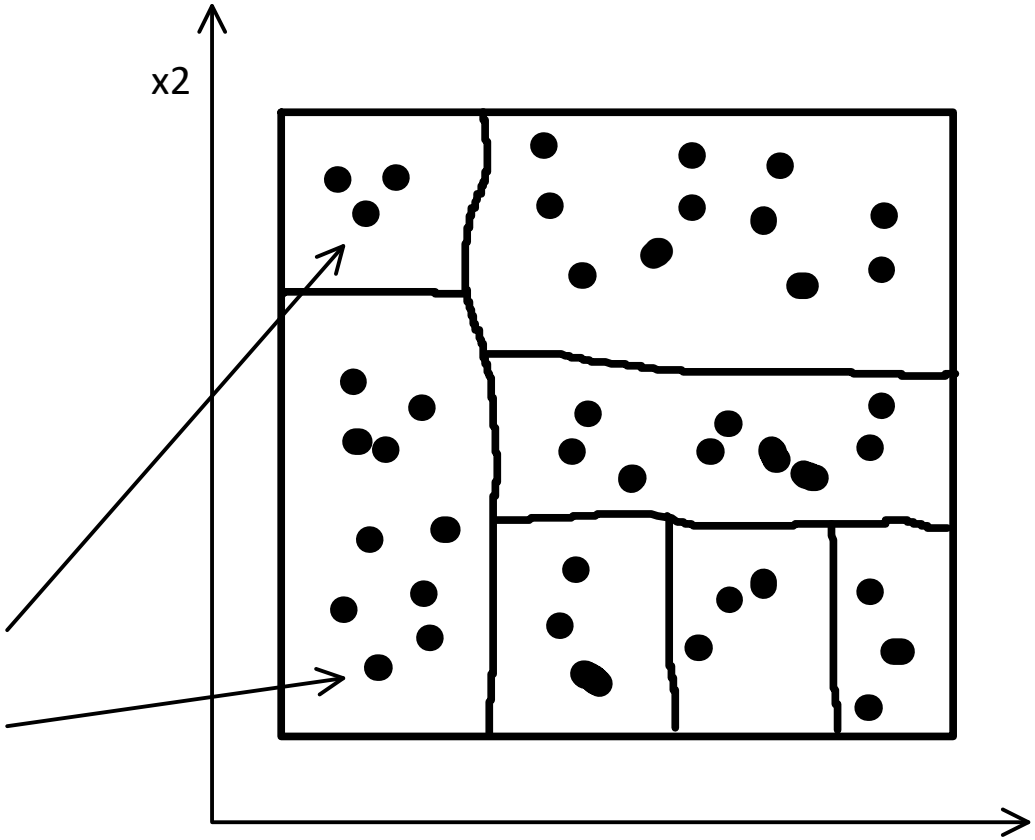
- 2 features: x1, x2: plane
- 3 features: x1, x2, x3: cube
- n features: x1, …, xn: n-dimensional cube

Simplifcation for presentation purposes

- Only two features: x1, x2
- Regions are rectangles

Find rectangular non-overlapping decomposition of space

- Leads to n-dimensional sub-cubes (regions)
- Each region should be as "uniform" as possible
- Average value of all records in region (regression)
- Majority vote in region (classification)



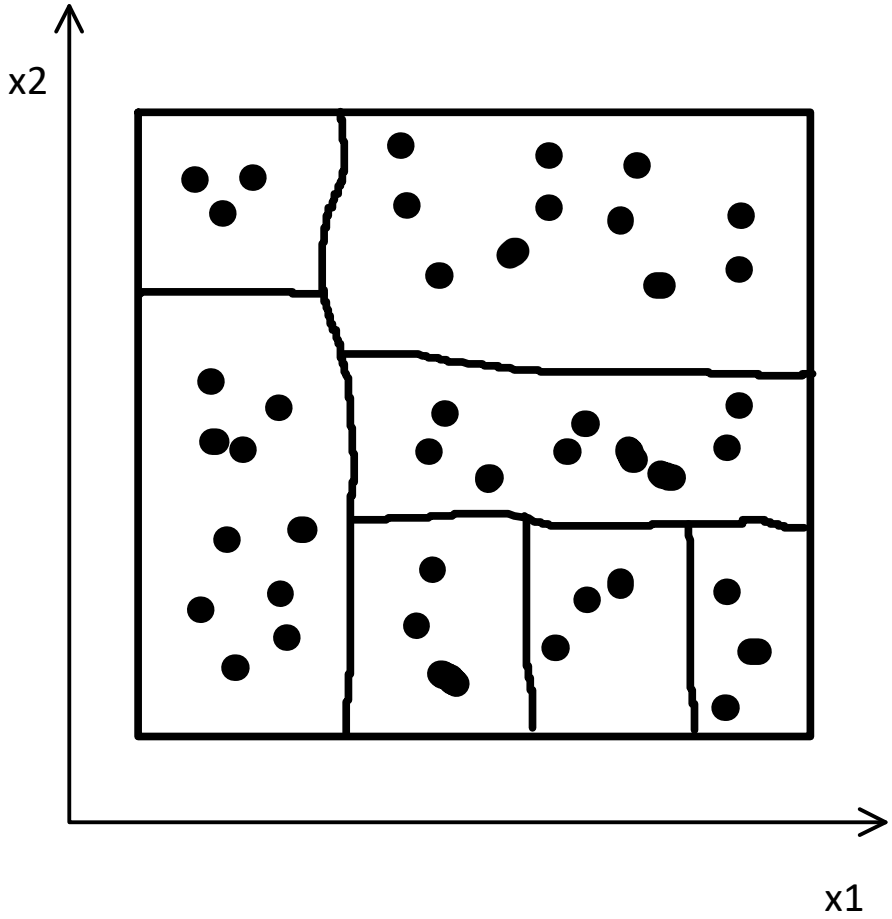
Finding an optimal decomposition automatically is infeasable (combinatorical explosion)

General idea of decision trees:

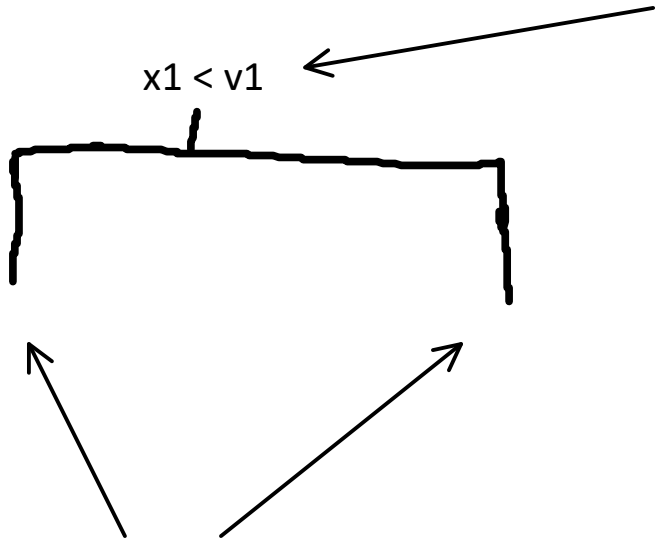
- Gready decomposition of feature space by recursive binary splitting
- Stop splitting according to criterion, e.g.
  - minimal numbers of instances in region
  - max depth of tree
  - minimal performance gain

Finding splits

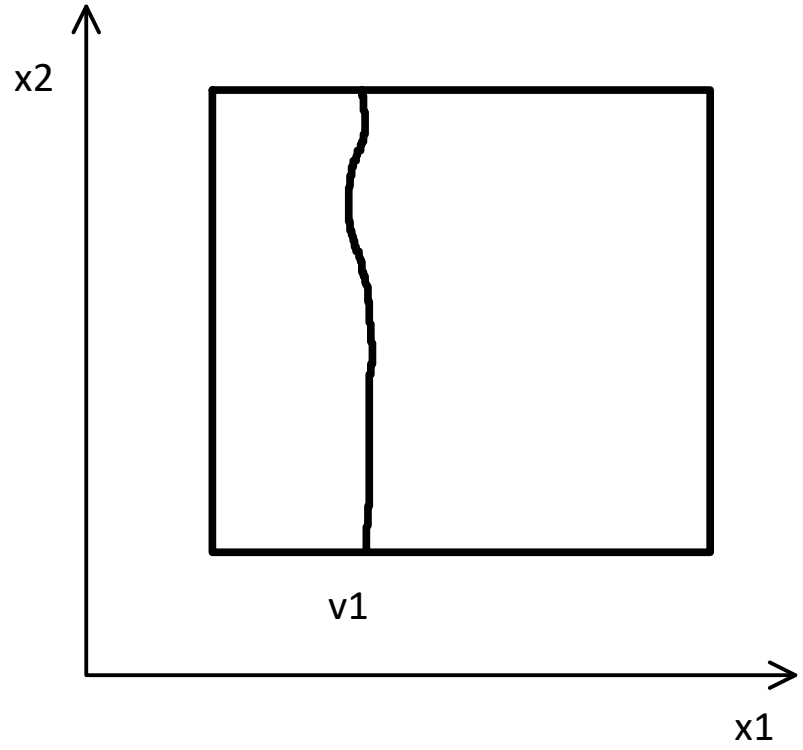
- Search through all features
- For each feature: consider all split values
- Take "best" (feature, splitval) combination

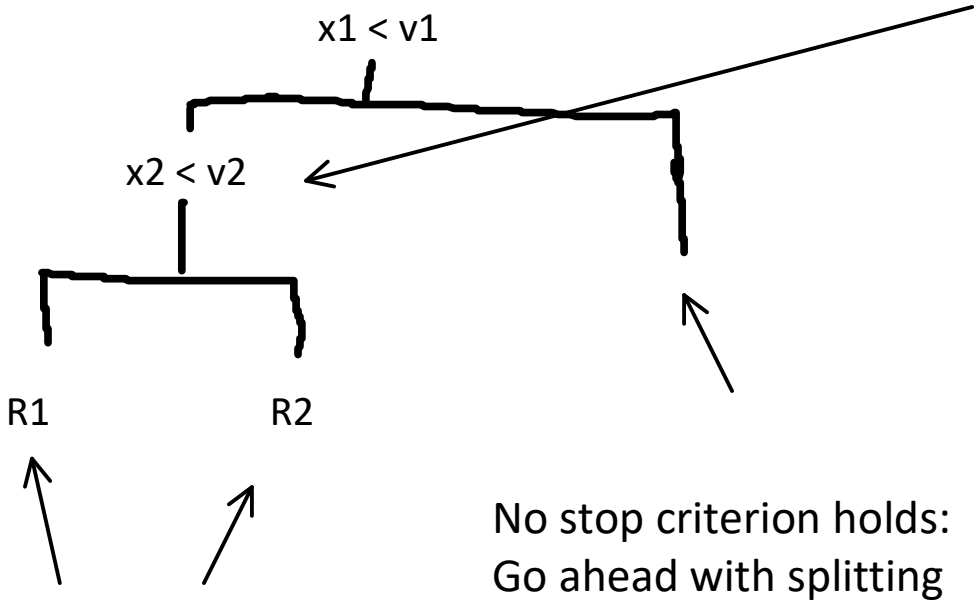


split feature	split value
x1	v1



No stop criterion holds:
Go ahead with splitting

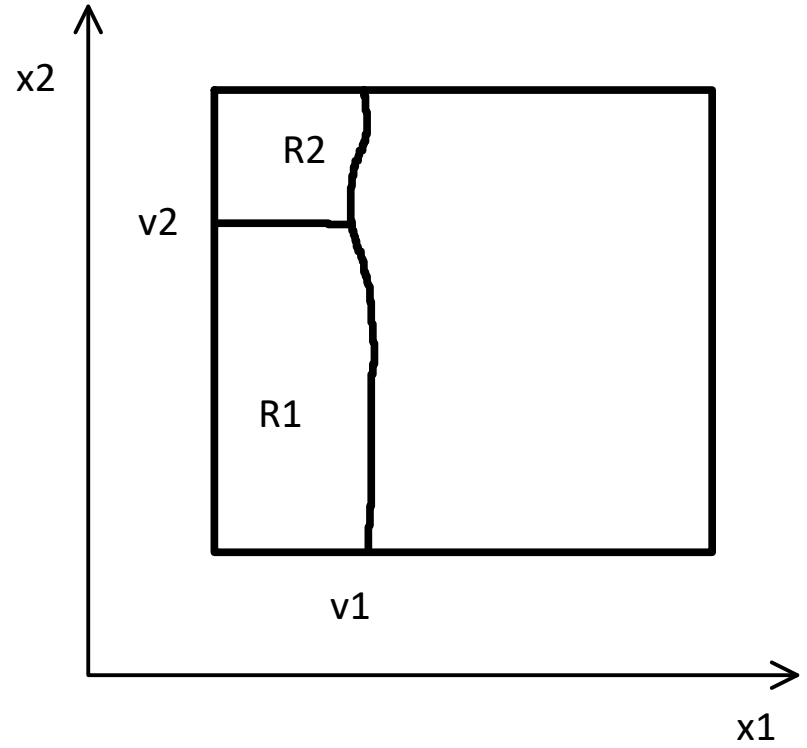




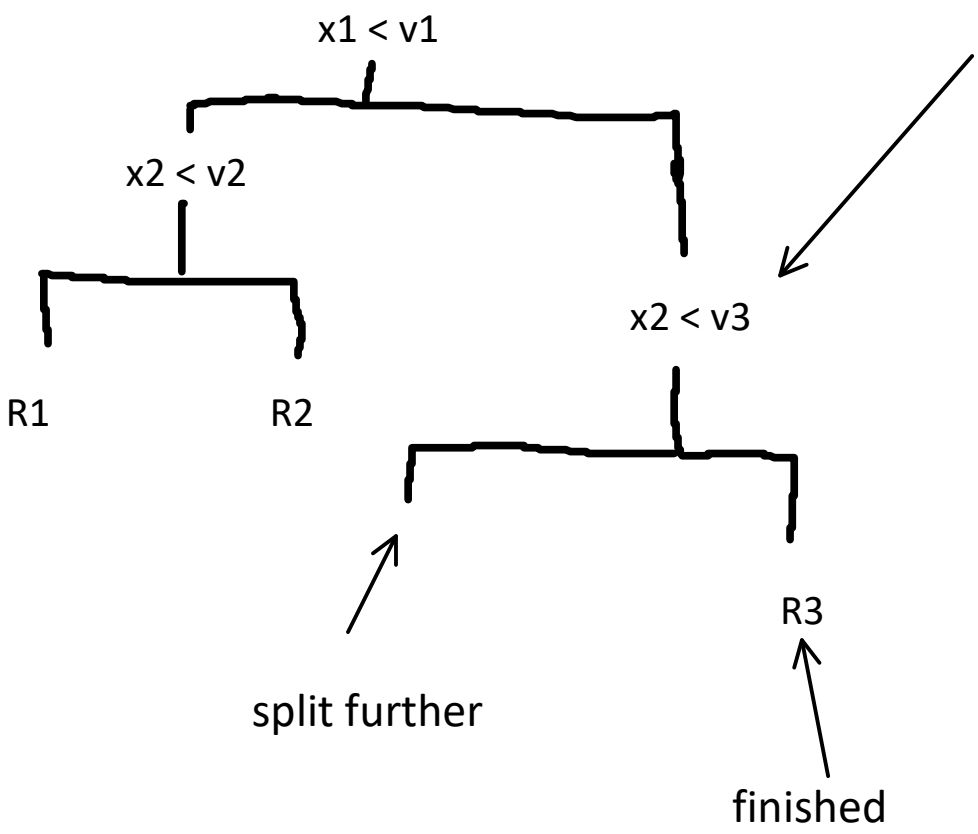
No stop criterion holds:
Go ahead with splitting

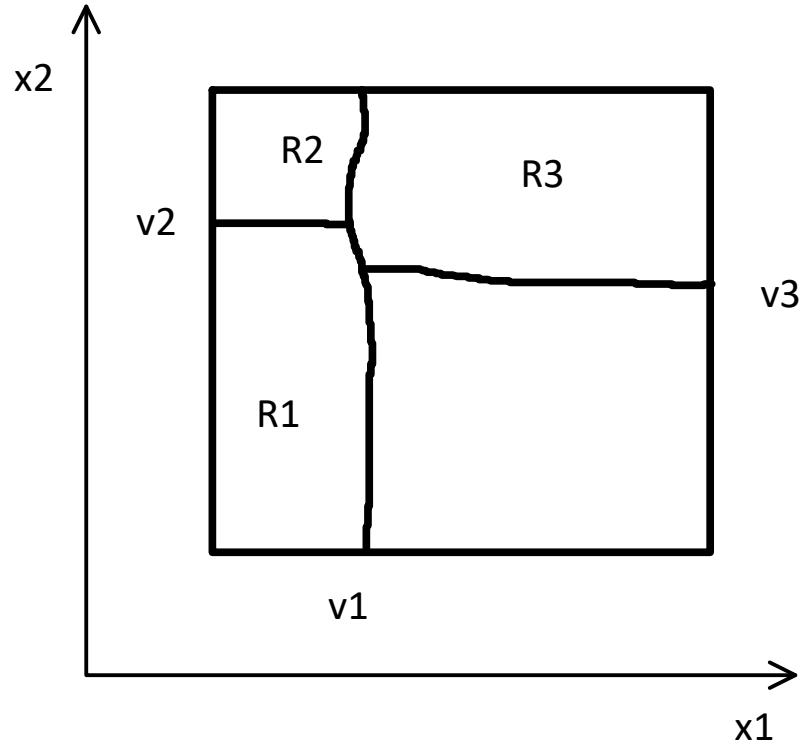
Stop criterion holds:
do not further split

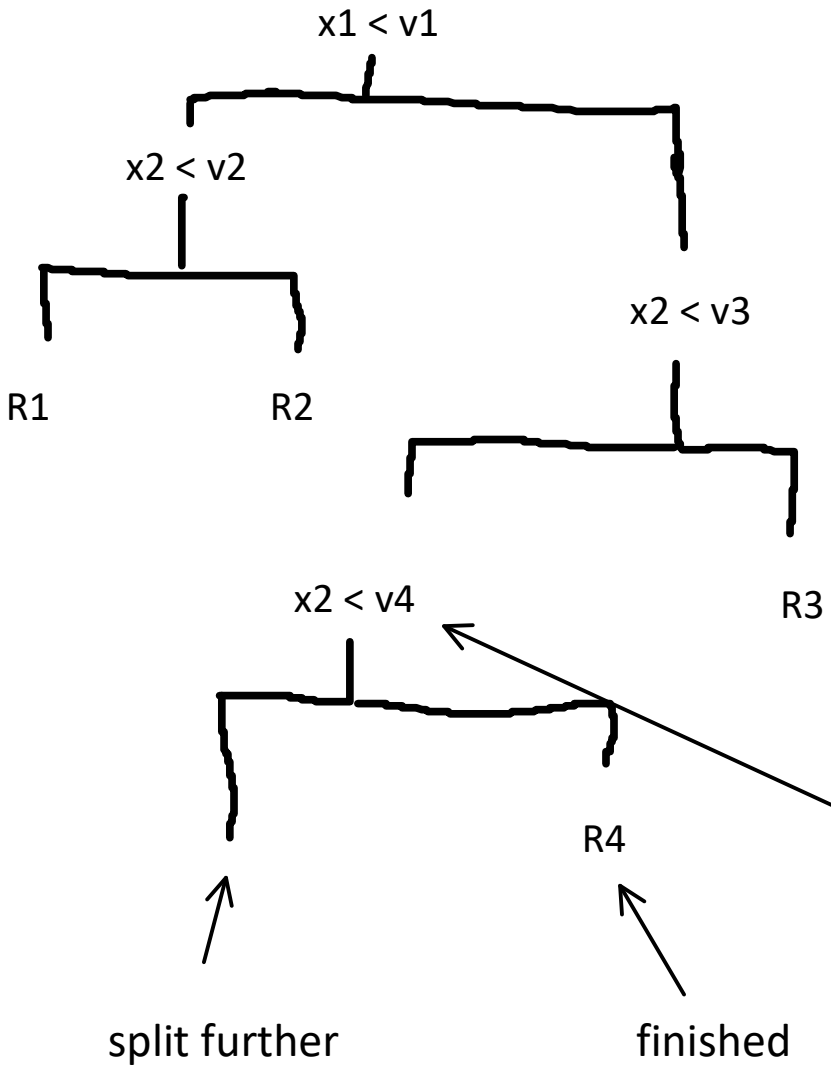
split feature	split value
x2	v2

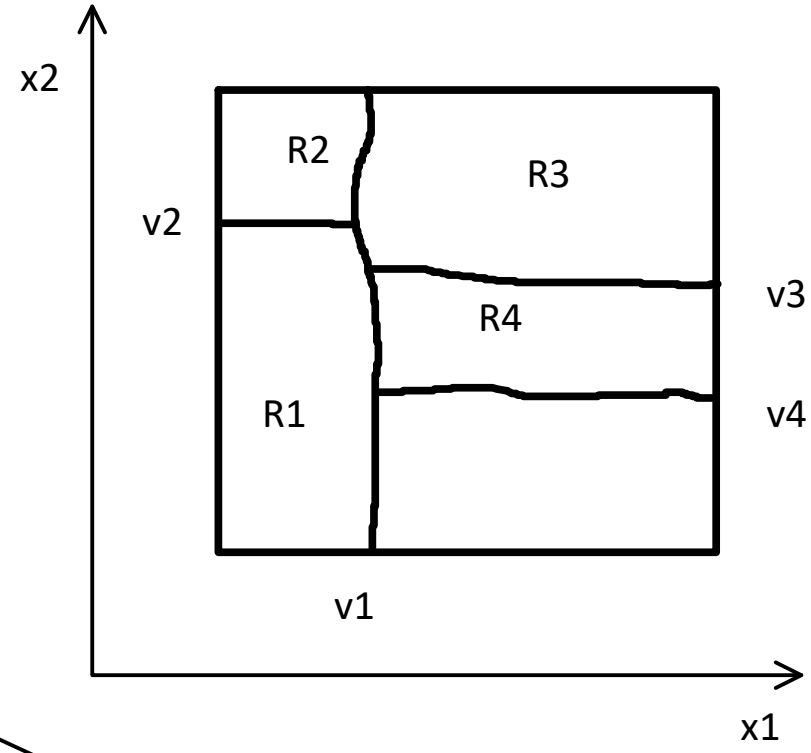


split feature	split value
x2	v3

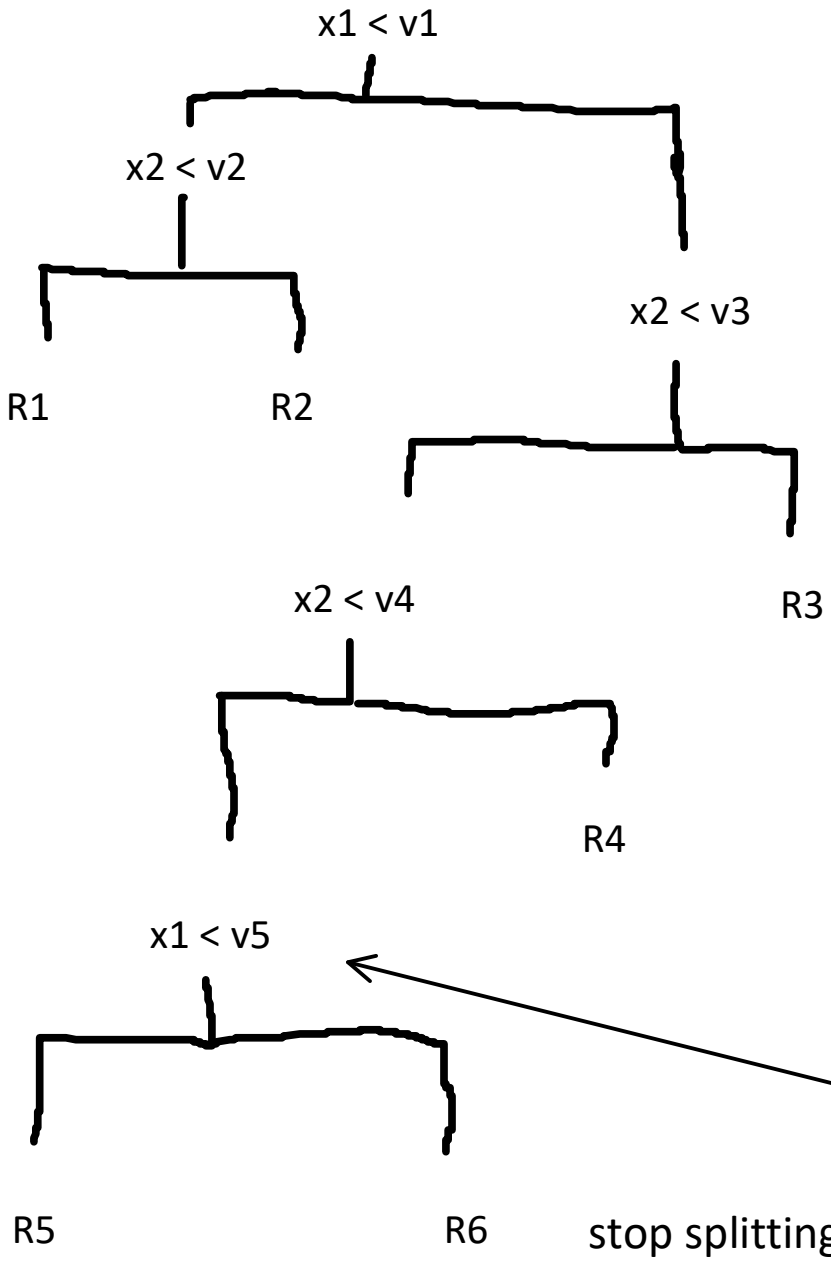


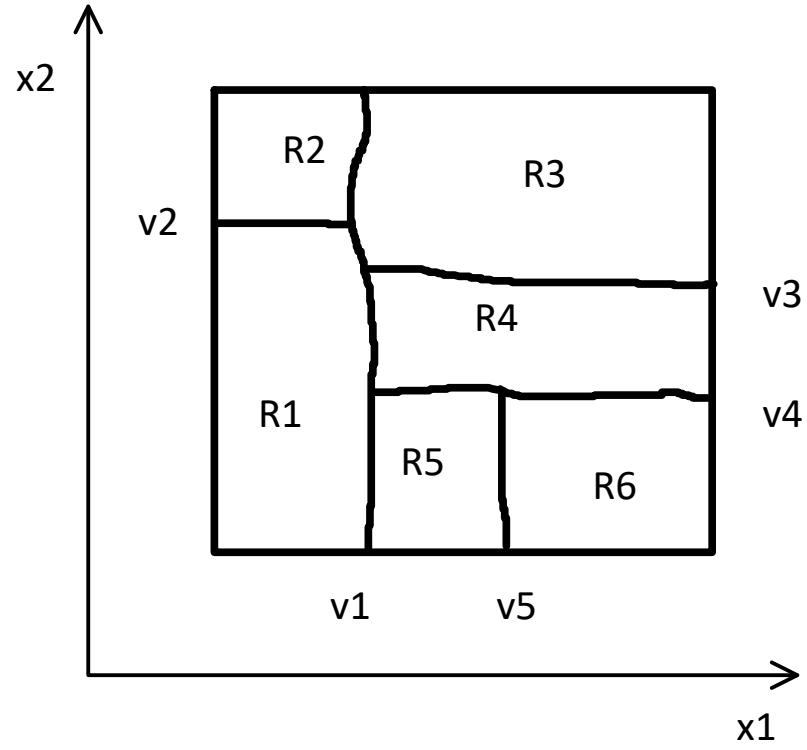






split feature	split value
x2	v4



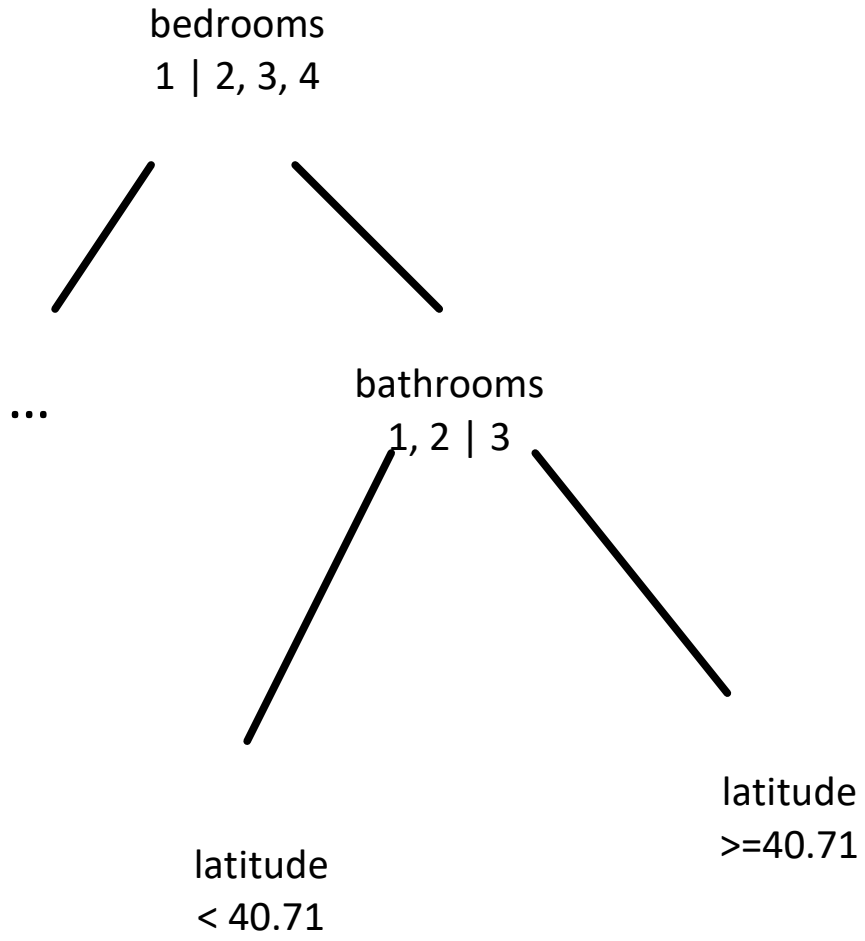


split feature	split value
x1	v5

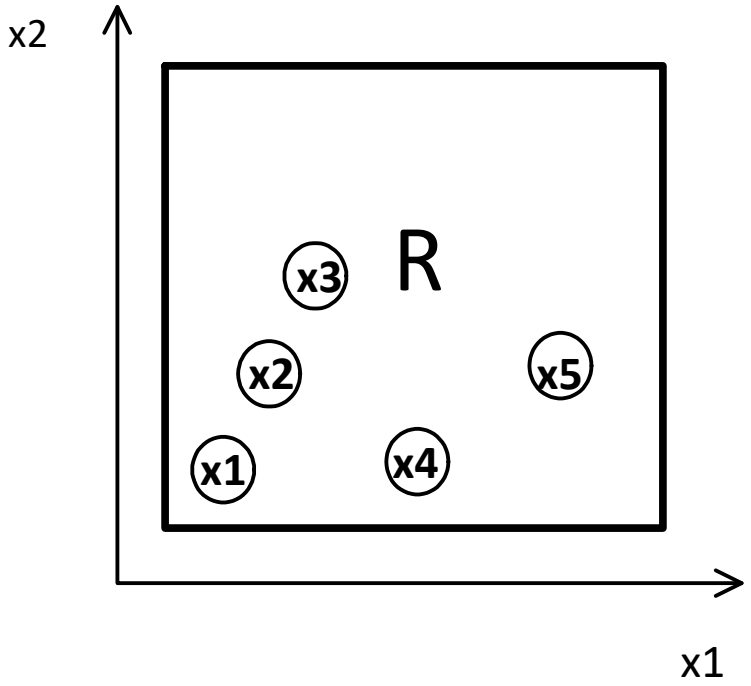
Example for appartment rents

Freitag, 18. Juni 2021 10:32

Split on best combination of feature and split point



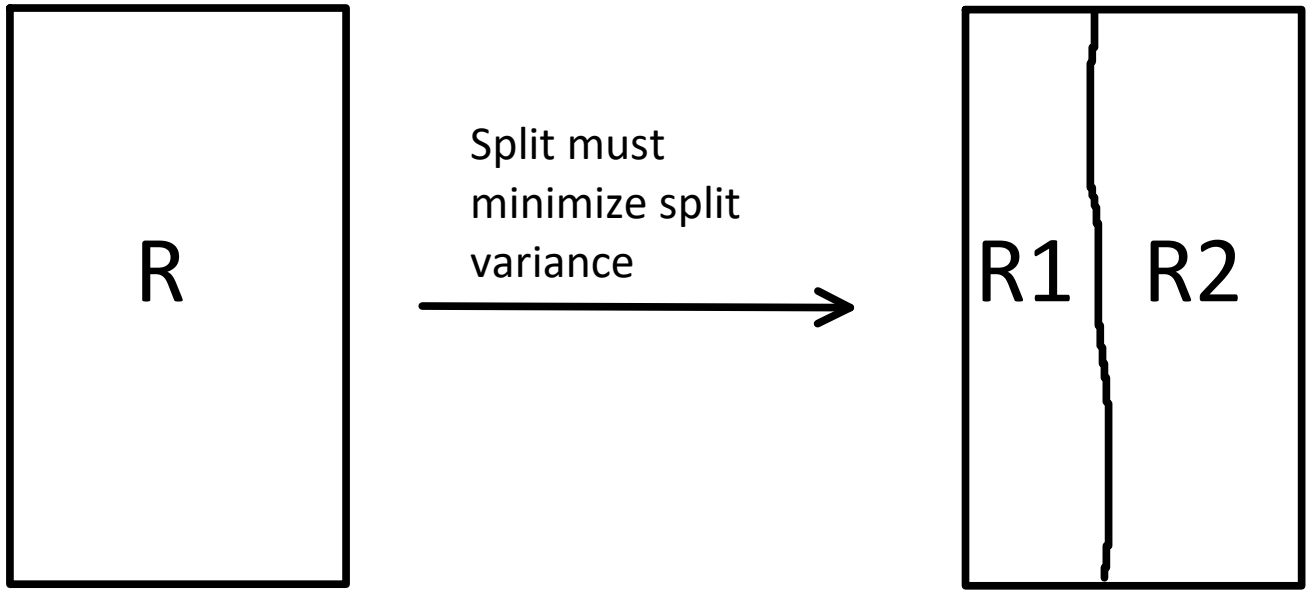
$$\mathrm{MSE}(R) = \frac{1}{\mathrm{count}(y_i)} \sum_{\mathbf{x}_i \in R} (y_i - \mathrm{avg}(y_i))^2$$



	x1	x2	y
x1	1	1	20
x2	1	2	30
x3	2	3	20
x4	3	1	10
x5	4	2	20

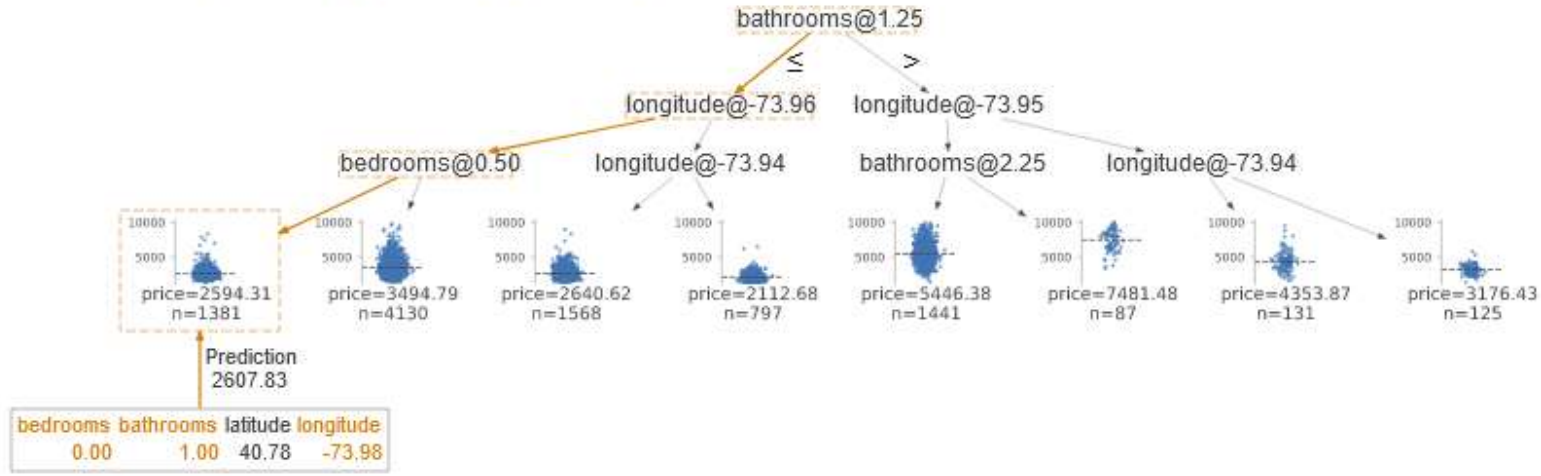
$$\mathrm{avg}(y_i) = 20$$

$$\begin{aligned}
\mathrm{MSE}(R) &= \frac{1}{5}\left((20-20)^2 + (30-20)^2 + (20-20)^2 + (10-20)^2 + (20-20)^2\right) \\
&= \frac{1}{5}\left(0 + 100 + 0 + 100 + 0\right) \\
&= \frac{1}{5} * 200 \\
&= 40
\end{aligned}$$



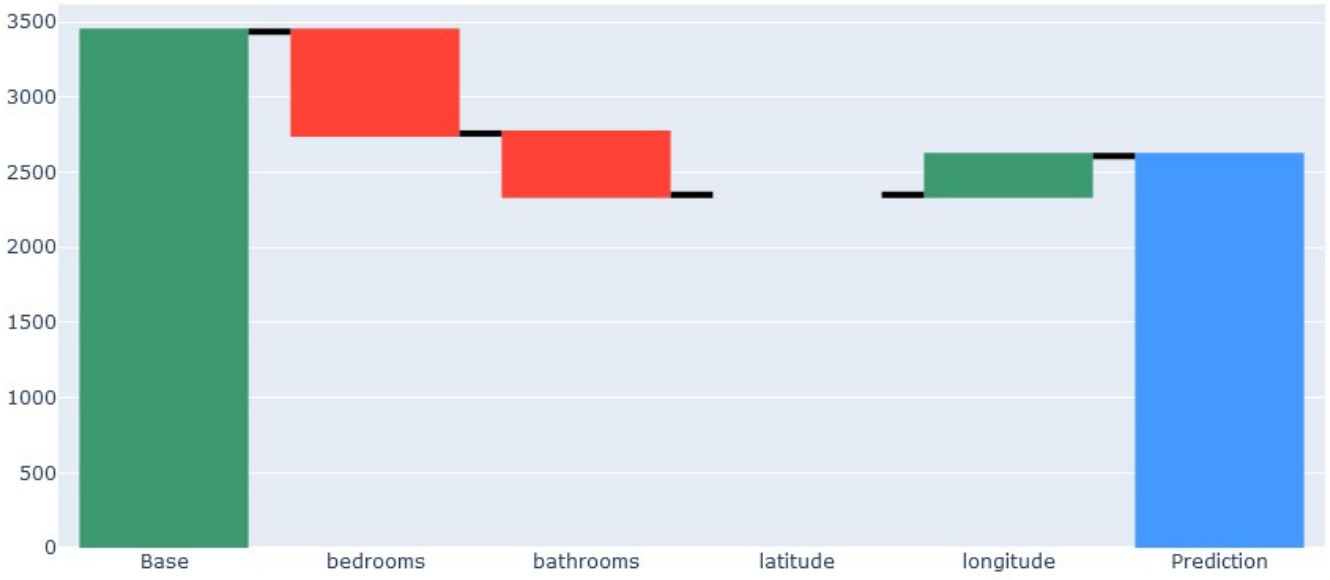
$$\text{SplitVariance} = \frac{1}{\text{count}(R_1)}\text{MSE}(R_1) + \frac{1}{\text{count}(R_2)}\text{MSE}(R_2)$$

	bedrooms	bathrooms	latitude	longitude	price
19791	0	1.0	40.7757	-73.981	2190

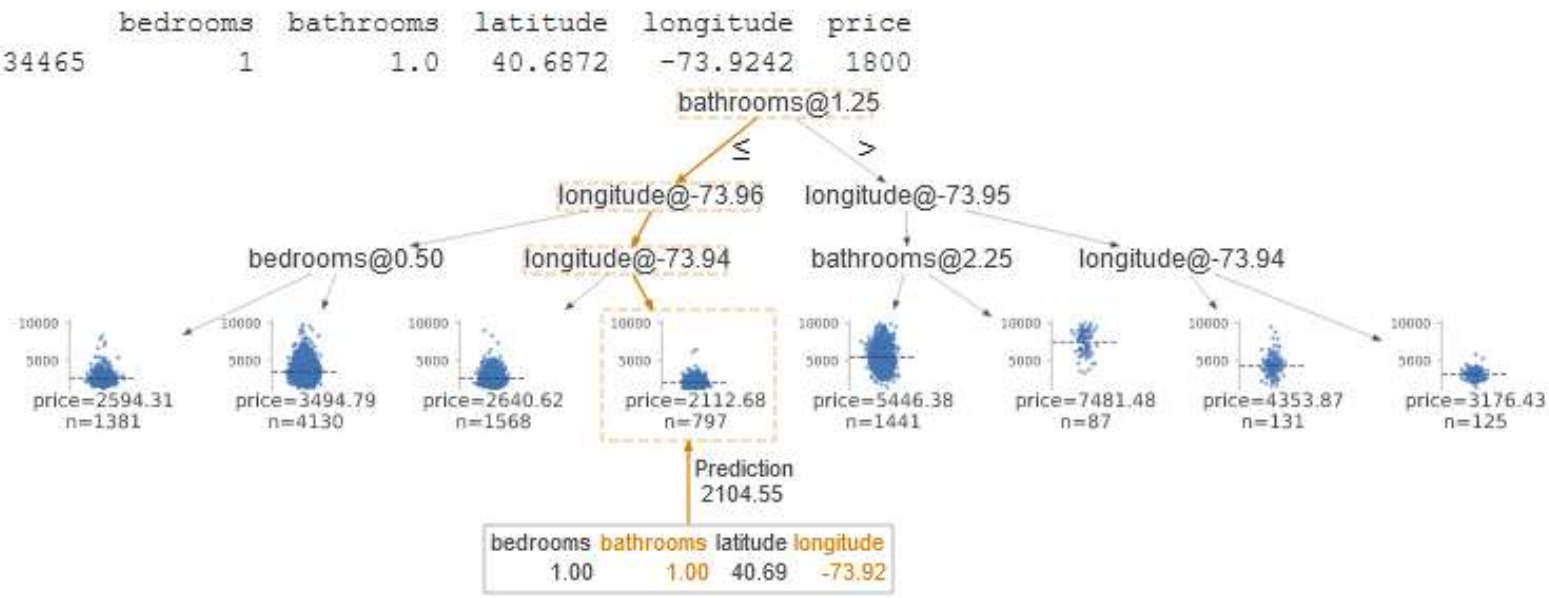


	Contributions
Base	3435.888690
bedrooms	-677.945519
bathrooms	-407.762466
latitude	0.000000
longitude	257.648895
Prediction	2607.829600

Prediction : 2607.8296004300305

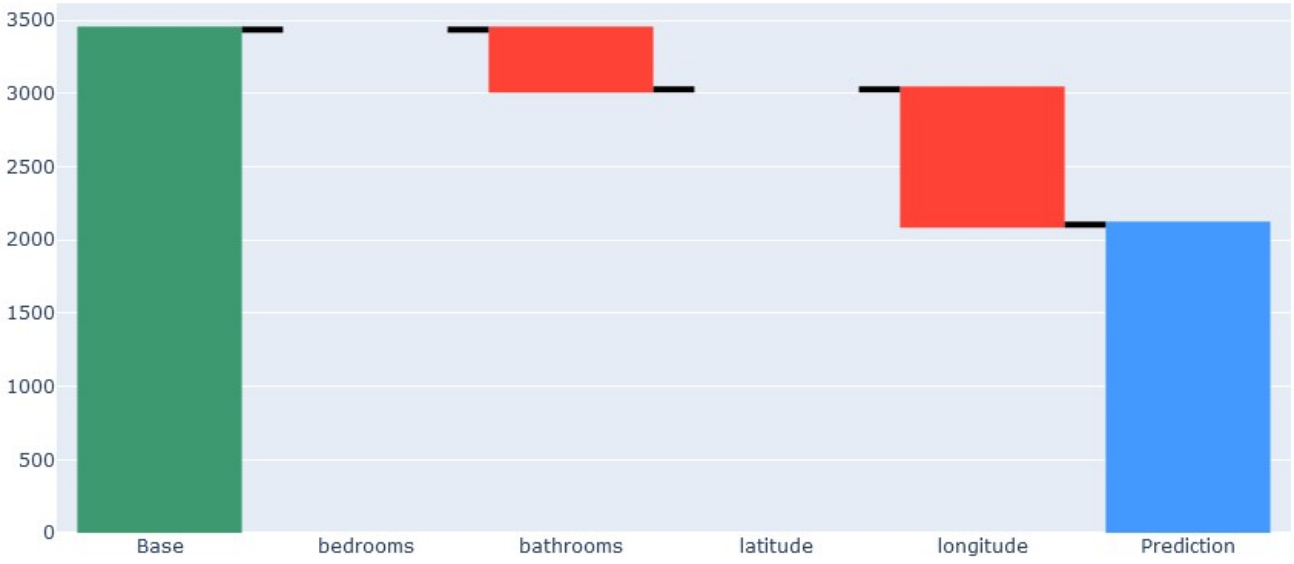


	bedrooms	bathrooms	latitude	longitude	price
34465	1	1.0	40.6872	-73.9242	1800

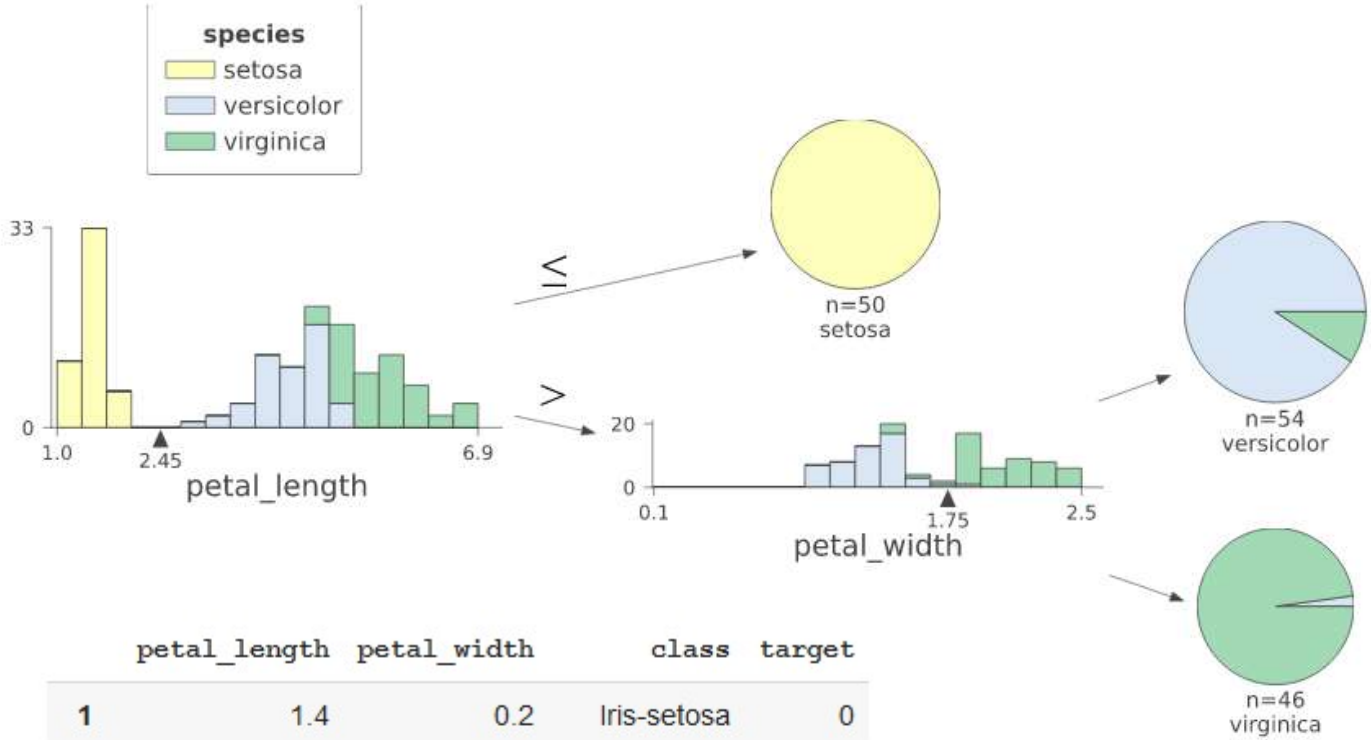


	Contributions
Base	3435.888690
bedrooms	0.000000
bathrooms	-407.762466
latitude	0.000000
longitude	-923.580824
Prediction	2104.545400

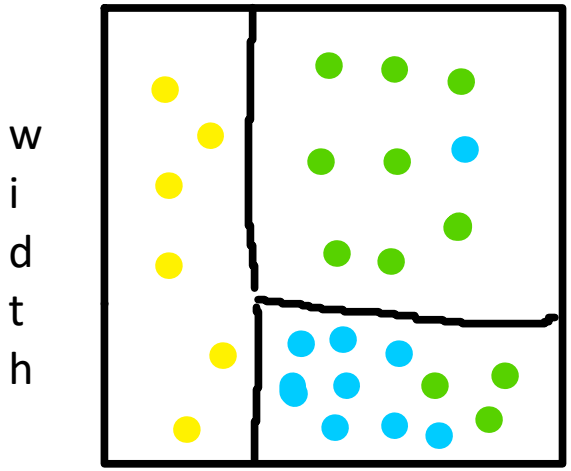
Prediction : 2104.545399698341



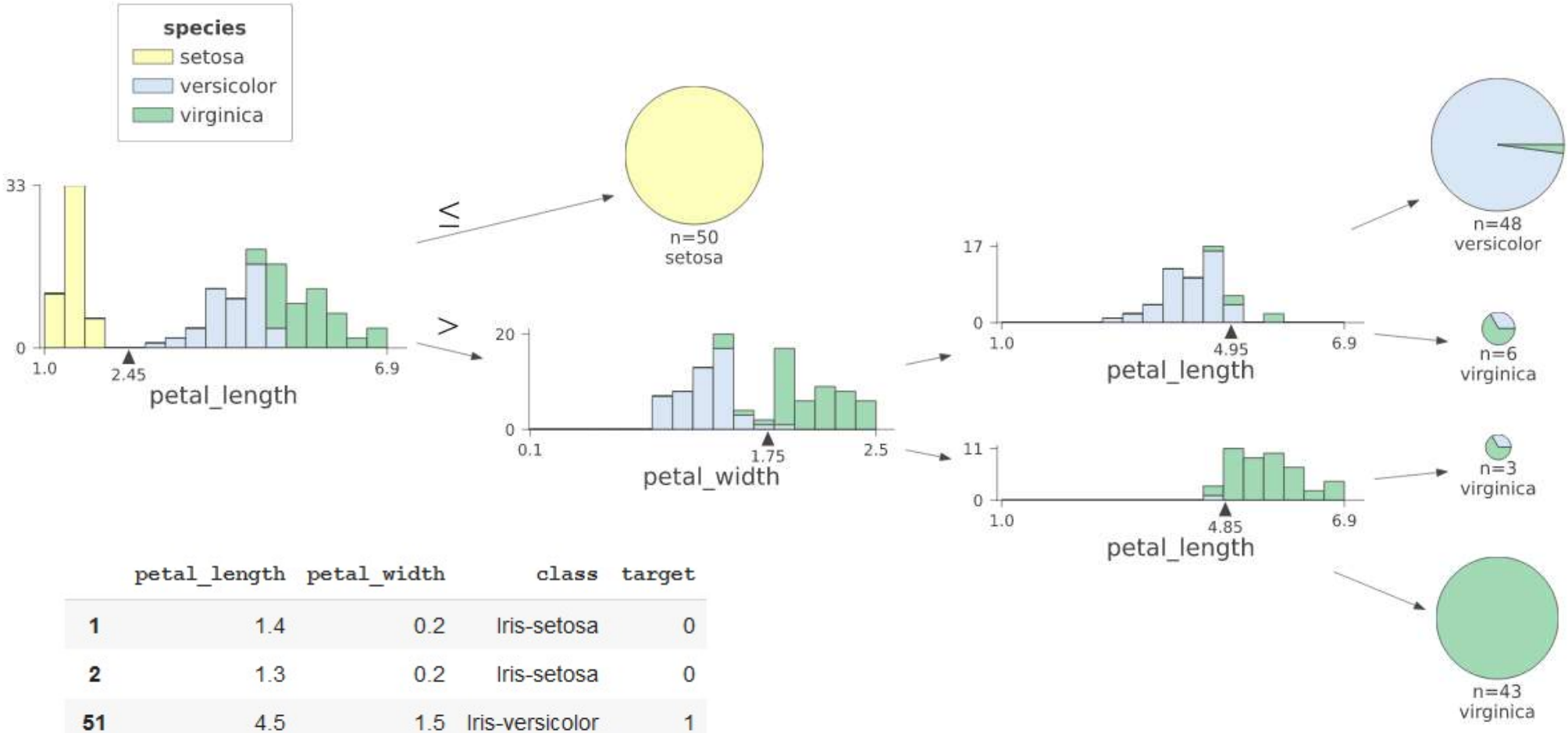
Tree depth 2



	petal_length	petal_width	class	target
1	1.4	0.2	Iris-setosa	0
2	1.3	0.2	Iris-setosa	0
51	4.5	1.5	Iris-versicolor	1
52	4.9	1.5	Iris-versicolor	1
101	5.1	1.9	Iris-virginica	2
102	5.9	2.1	Iris-virginica	2



Tree depth 3



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101	5.1	1.9	Iris-virginica	2
102	5.9	2.1	Iris-virginica	2

Gini Value of Region

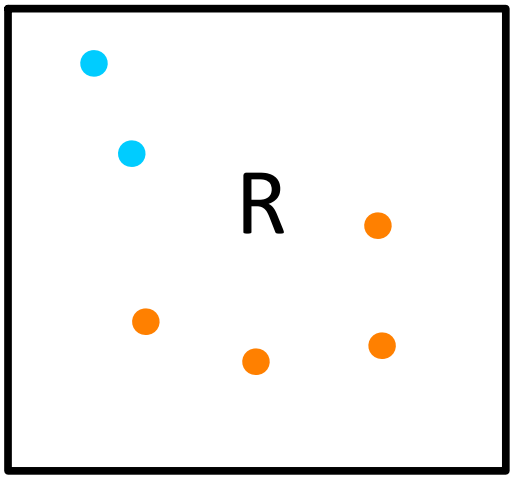
Mittwoch, 30. Juni 2021 15:17

$$\text{Gini}(R) = 1 - \sum_{c \in C} \text{Prob}(c, R)^2$$

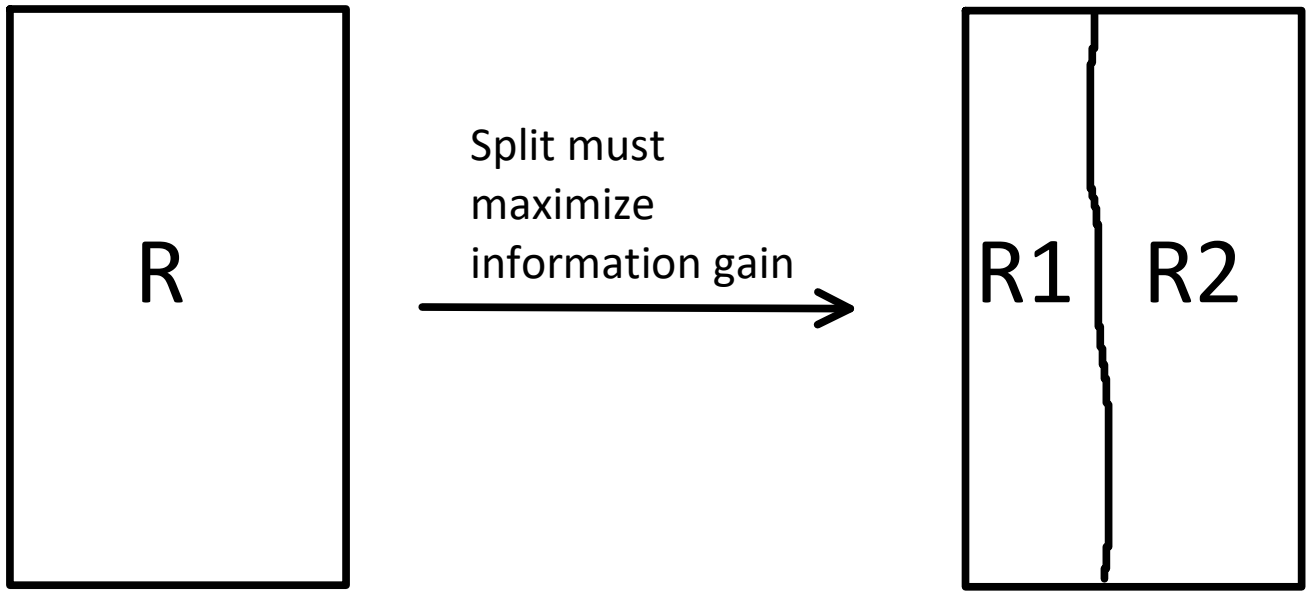
R	Region
Prob	Probability
Gini	Gini Value
C	Set of all classes
c	Single class

Class tags:

- Class1: orange
- Class2: blue



$$\begin{aligned}
\text{Gini}(R) &= 1 - \left(\left(\frac{2}{6}\right)^2 + \left(\frac{4}{6}\right)^2 \right) \\
&= 1 - \left(\left(\frac{1}{3}\right)^2 + \left(\frac{2}{3}\right)^2 \right) \\
&= 1 - \left(\frac{1}{9} + \frac{4}{9} \right) \\
&= 1 - \frac{5}{9} \\
&= \frac{4}{9}
\end{aligned}$$



$$\text{InformationGain} = \text{Gini}(R) - \left(\frac{1}{\text{count}(R_1)} \text{Gini}(R_1) + \frac{1}{\text{count}(R_2)} \text{Gini}(R_2) \right)$$

See:
https://towardsdatascience.com/decision-tree-an-algorithm-that-works-like-the-human-brain-8bc0652f1fc6

Problems of trees

- Too specific
- Overfit on trainings data

Assume leafs only contain one record

- Trainings error would get zero

Train many tree models

- Randomly select subset of training data (with replacement, bootstrapping)
- Randomly select subset of features

Prediction - Regression

- Ask all trees for prediction
- Average results
- Two levels of averaging
  - Leaf level of each singular tree
  - Average of all trees

Prediction - Classification

- Ask all trees for prediction
- Majority vote
- Two levels of voting
  - Leaf level of each singular tree
  - Combining votes of all trees

Selected Trees from the Forest

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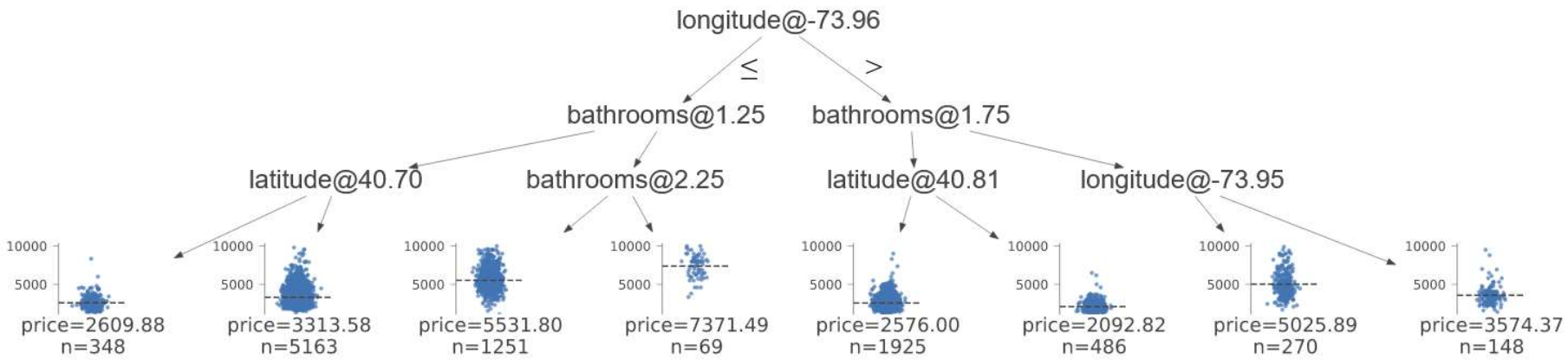
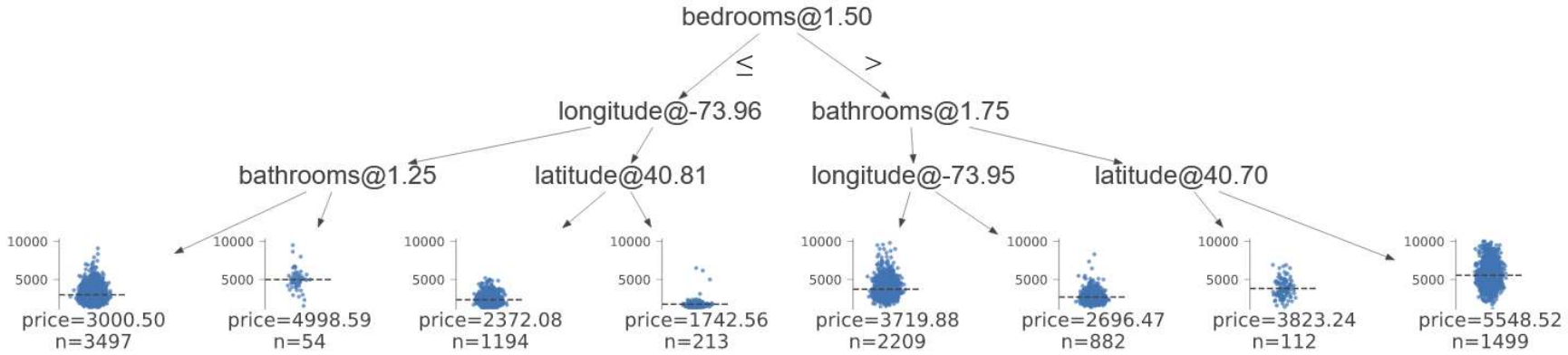
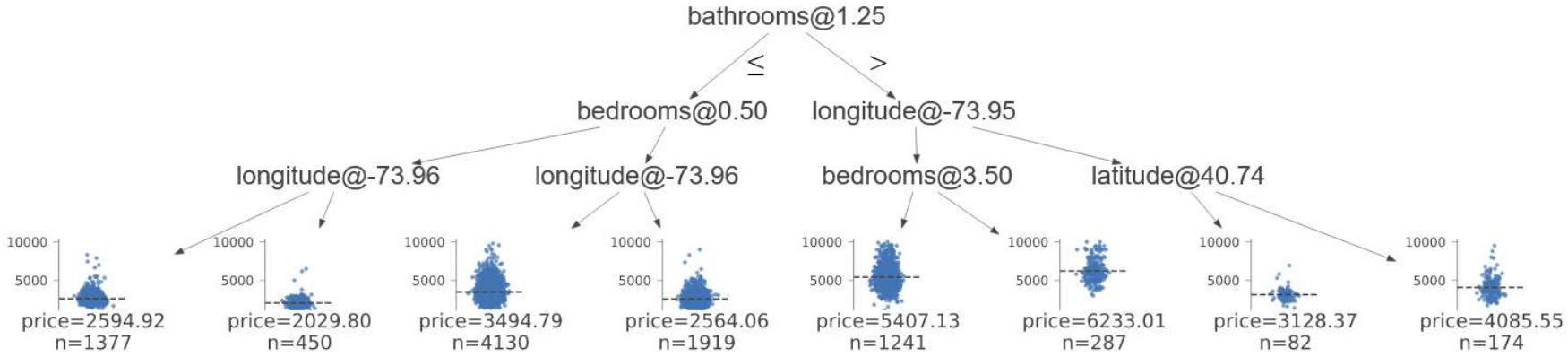
Donnerstag, 1. Juli 2021 15:31







Permutation Importance