

Today

- Ensemble methods
 - Bagging
 - Random forest
 - Boosting

Boosted regression tree

Algorithm

load y, x, x_{new}

set parameters: $d, \text{ntrees}, \lambda$

set $\hat{f}(x_{\text{new}}) = 0$

set $r \leftarrow y$ (residuals equal to the data)

for b in 1 to ntrees

 train d split tree model on r and x

 predict residuals, $\hat{r}_b(x)$, from trained tree

 update residuals: $r \leftarrow r - \lambda \hat{r}_b(x)$

 predict y increment, $\hat{f}_b(x_{\text{new}})$, from trained tree

 update prediction: $\hat{f}(x_{\text{new}}) \leftarrow \hat{f}(x_{\text{new}}) + \lambda \hat{f}_b(x_{\text{new}})$

return $\hat{f}(x_{\text{new}})$

Boosted regression tree

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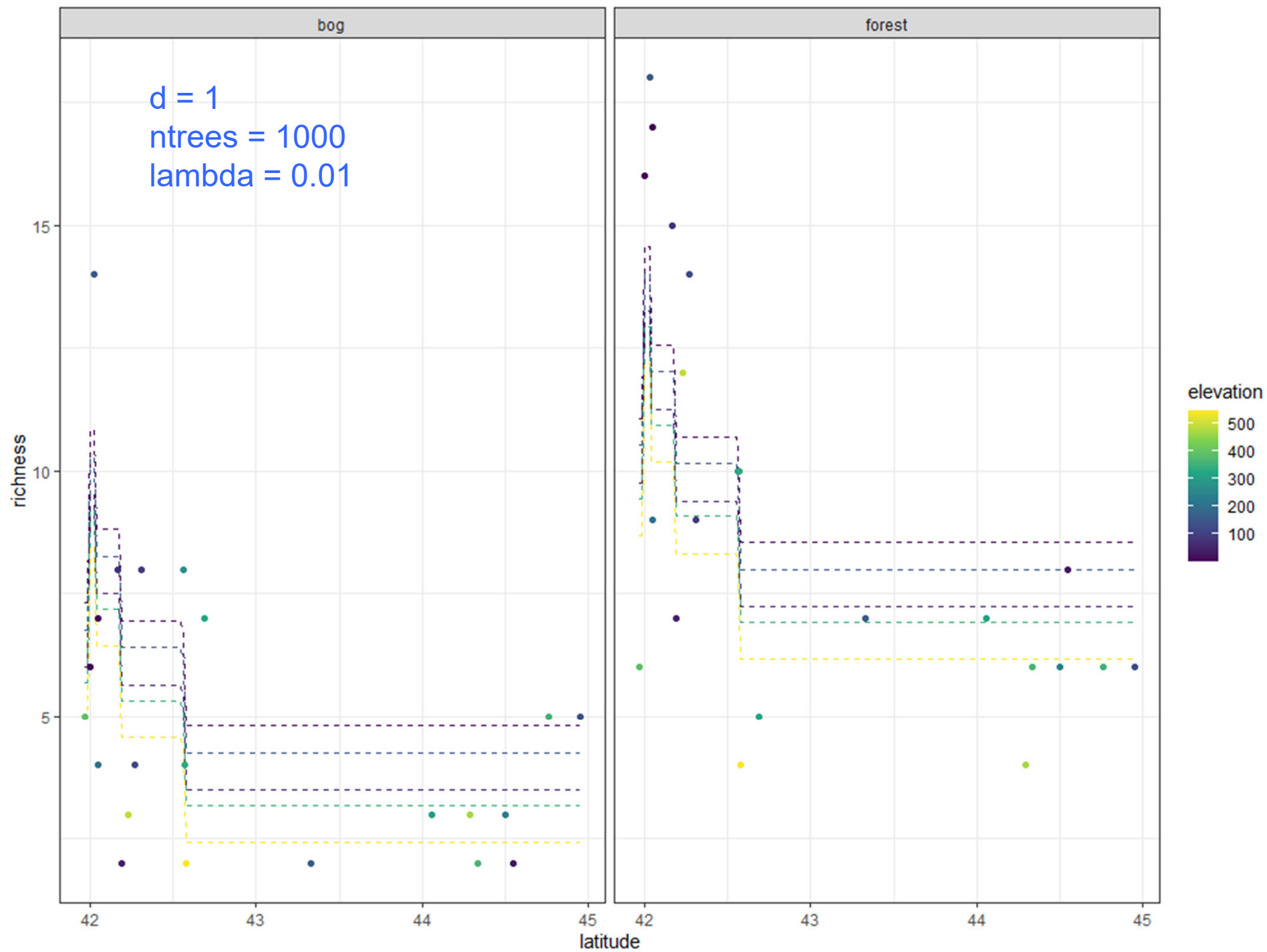
predict y increment, $\hat{f}_b(x_{\text{new}})$, from trained tree

update prediction: $\hat{f}(x_{\text{new}}) \leftarrow \hat{f}(x_{\text{new}}) + \lambda \hat{f}_b(x_{\text{new}})$

return $\hat{f}(x_{\text{new}})$

Can be any
model





Boosted regression tree

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Gradient
descent



Gradient descent

predict residuals, $\hat{r}_b(x)$, from trained tree

update residuals: $r \leftarrow r - \lambda \hat{r}_b(x)$

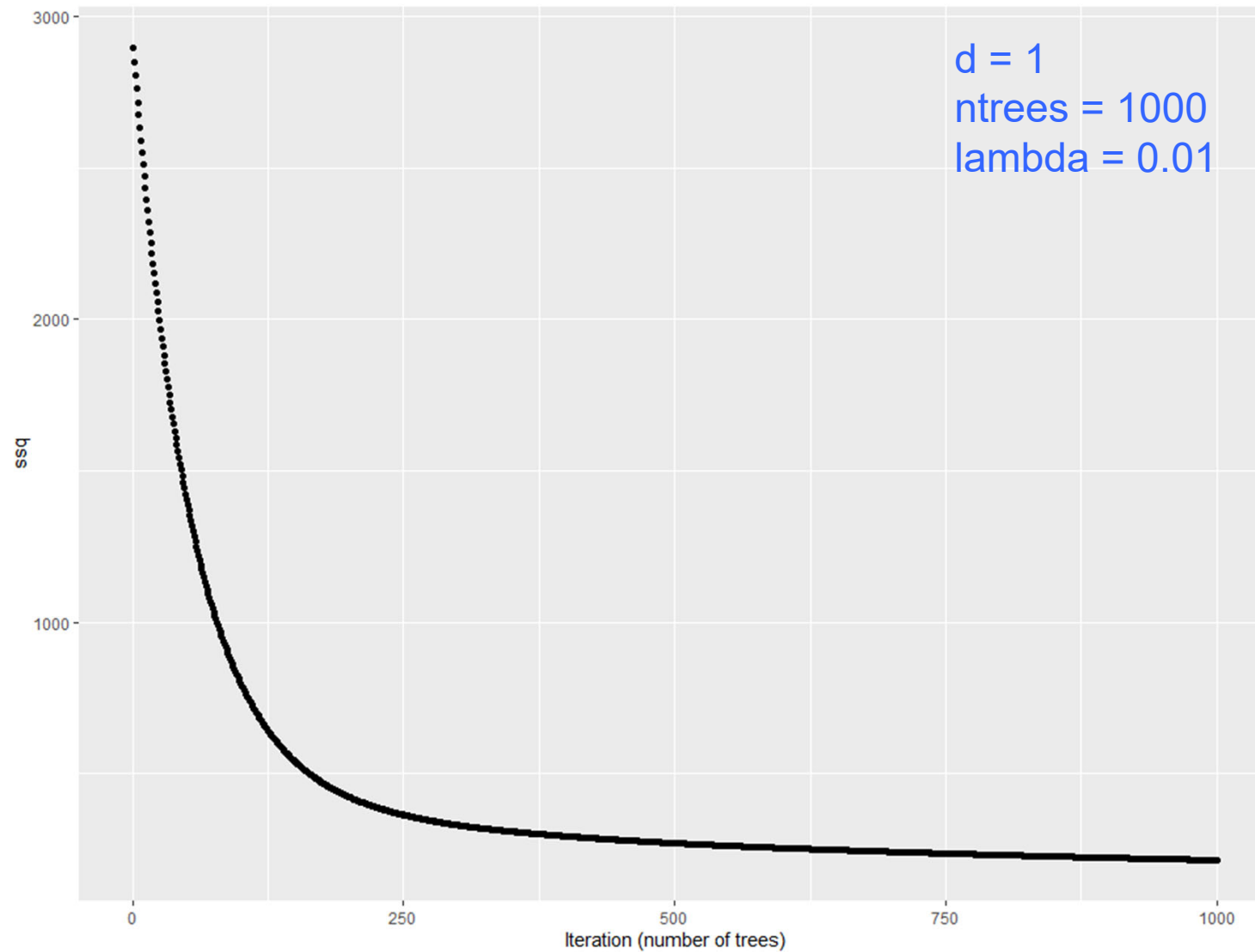
Loss function is SSQ and we are descending it's surface

Estimated gradient at x is the predicted residual $\hat{r}_b(x)$

λ is the **increment** taken down the gradient

r gets closer to 0 at each step, so SSQ goes down

Gradient descent



Stochastic gradient descent

Algorithm

for b in 1 to ntrees

randomly sample rows from (r, x) \leftarrow new step

train d split tree model on the random sample

predict residuals, $\hat{r}_b(x)$, from trained tree

update residuals: $r \leftarrow r - \lambda \hat{r}_b(x)$

predict y increment, $\hat{f}_b(x_{\text{new}})$, from trained tree

update prediction: $\hat{f}(x_{\text{new}}) \leftarrow \hat{f}(x_{\text{new}}) + \lambda \hat{f}_b(x_{\text{new}})$

return $\hat{f}(x_{\text{new}})$