Quiz 4 - Supervised Learning Algorithms

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Tree based Models

Algorithm Decision Tree Learning Algorithm

Require: Training data $\{(F_i, y_i)\}_{i=1}^n$, stopping criteria

Ensure: Decision tree T

- 1: Initialize tree with single root node containing all data
- 2: while nodes can be split and stopping criteria not met do
- 3: **for** each leaf node with region \mathcal{R} **do**
- 4: Find (j^*, τ^*) that maximizes:

5:
$$IG(j,\tau) = I(\mathcal{R}) - \frac{|\mathcal{R}_L|}{|\mathcal{R}|}I(\mathcal{R}_L) - \frac{|\mathcal{R}_R|}{|\mathcal{R}|}I(\mathcal{R}_R)$$

6: Where
$$\mathcal{R}_L = \{F \in \mathcal{R} : F_j \leq \tau\}$$
 and $\mathcal{R}_R = \{F \in \mathcal{R} : F_j > \tau\}$

- 7: Split node using rule $F_{j^*} > \tau^*$
- 8: end for
- 9: end while
- 10: Assign prediction to each leaf node (majority class)
- 11: return T

- Minimize Mean Squared Error
- Maximize Information Gain
- Minimize Sum of Squared Errors
- Gradient Descent

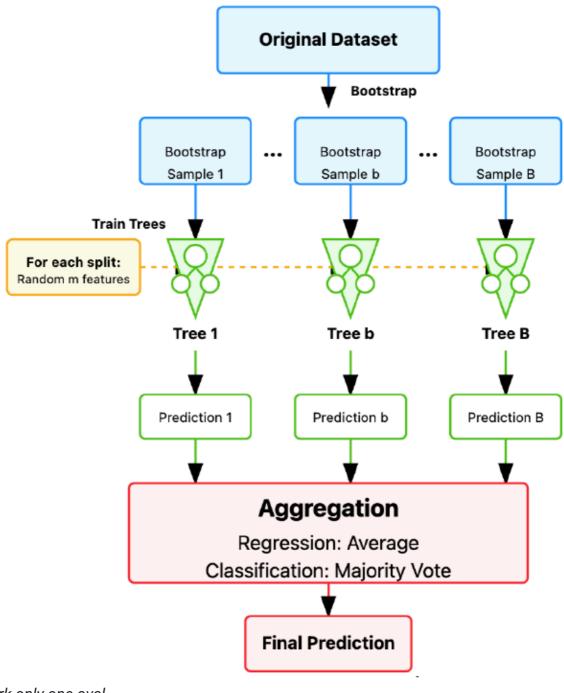
Algorithm Regression Tree Learning Algorithm

Require: Training data $\{(F_i, y_i)\}_{i=1}^n$, stopping criteria

Ensure: Regression tree T

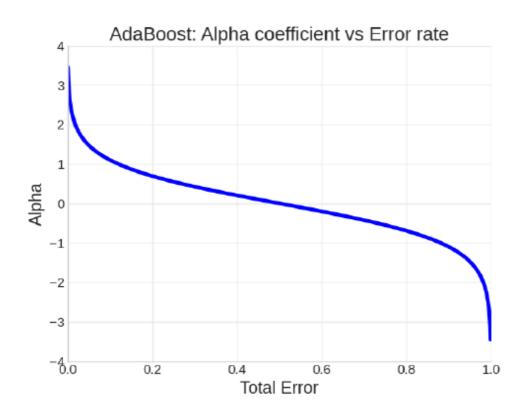
- 1: Initialize tree with single root node containing all data
- 2: while nodes can be split and stopping criteria not met do
- **for** each leaf node with region \mathcal{R} **do** 3:
- Find (j^*, τ^*) that minimizes:
- $SSE(j,\tau) = \sum_{i:F_i \in \mathcal{R}_L} (y_i \bar{y}_{\mathcal{R}_L})^2 + \sum_{i:F_i \in \mathcal{R}_R} (y_i \bar{y}_{\mathcal{R}_R})^2$ Where $\mathcal{R}_L = \{F \in \mathcal{R} : F_j \leq \tau\}$ and $\mathcal{R}_R = \{F \in \mathcal{R} : F_j \leq \tau\}$ 5:
- $F_i > \tau$
- Split node using rule $F_{i^*} > \tau^*$ 7:
- end for 8:
- 9: end while
- 10: Assign prediction \bar{y}_{R_m} to each leaf node (average of y_i in the region)
- 11: return T

- Maximize Information Gain
- Minimize Sum of Squared Errors in resulting regions
- Maximize the number of samples in each region
- Minimize the entropy in each region



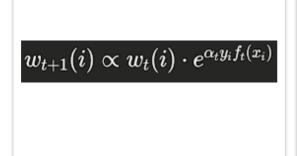
Rando	m F	orest	uses	subsets	of	featu	res	s at e	each	split	
		_		_							

- Random Forest only uses a single decision tree with random initialization
- Random Forest only applies to regression problems
- Random Forest eliminates bootstrapping entirely



True

False



 $w_{t+1}(i) \propto w_t(i) \cdot e^{-lpha_t y_i f_t(x_i)}$

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В

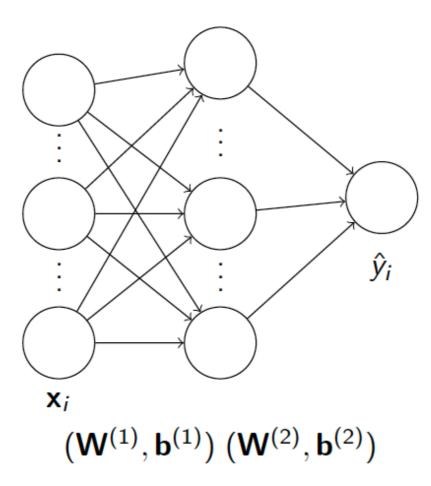
$$w_{t+1}(i) \propto w_t(i) \cdot e^{lpha_t(1-2\cdot \mathbb{I}\{y_i=f_t(x_i)\})}$$

 $w_{t+1}(i) \propto w_t(i) \cdot e^{-lpha_t(1-2\cdot \mathbb{I}\{y_i=f_t(x_i)\})}$

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Neural Networks



- Only the weights connecting input to hidden layer
- Only the weights connecting hidden to output layer
- Weights connecting input to hidden layer and hidden to output layer
- Weights and biases for both hidden and output layers
- Which activation function has the range [0,1] and is commonly used as the 1 point output activation for binary classification problems?

- ReLU
- Tanh
- Sigmoid
- ELU

10.	For a multi-class classification problem with K classes, which loss function and final layer activation would typically be used?	1 point
	Mark only one oval.	
	Mean Squared Error with linear activation	
	Binary Cross-Entropy with sigmoid activation	
	Categorical Cross-Entropy with softmax activation	
	Mean Absolute Error with tanh activation	
11.	In a regression task with potential outliers in the data, which loss function would be most appropriate?	1 point
	Mark only one oval.	
	Mean Squared Error (MSE)	
	Mean Absolute Error (MAE) or Huber Loss	
	Binary Cross-Entropy	
	Categorical Cross-Entropy	

Algorithm Gradient Descent Algorithm

Require: Training data $\{(\mathbf{x}_i, y_i)\}_{i=1}^n$, loss function \mathcal{L} , learning rate α , iterations T

Ensure: Optimized parameters θ

- 1: Initialize parameters $\theta^{(0)}$ randomly
- 2: **for** t=1 to T **do** $\theta^{(t)} = \theta^{(t-1)} \alpha \cdot \nabla_{\theta} \mathcal{L}(\theta^{(t-1)})$
- 3: **if** Convergence criteria met **then**
- 4: break
- 5: end if
- 6: end for
- 7: **return** Final parameters $\theta^{(T)}$

Mark only one oval.

- Convergence will be very slow
- The algorithm may overshoot the minimum and potentially diverge
- The algorithm will always converge to the global minimum

Questions

13. Any comment ?

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