## ▲ Try again once you are ready

Grade received 62.50% To pass 80% or higher

Try again

## **Feature Selection**

Tota	noi	nts	ź

<ol> <li>Consider a binary classification problem in a 2D feature space. What is the shape of the boundary separating the 2 classes in an ideal setting?</li> </ol>	1 / 1 point
<ul><li>Linear</li></ul>	
O Parabola	
Sigmoid	
O Perceptron	
© Correct Exactly! This is the simplest functional form of a boundary.	
2. Feature selection is characterized by: (check all that apply).	1 / 1 point
Remove features that don't influence the outcome.	
○ Correct     Right on track! Feature selection deals with removing nuisance variables.	
Accounting for data changes over time (drift, seasonality, etc).	
Ensuring numerical features follow the same numerical range	
Ensuring that the serving dataset is representative of future inference requests.	
Identify features that best represent the relationship between two or more variables.	
⊙ Correct     Good Job! Feature selection identifies features with predictive power.	
3. What is the definition of backward elimination?	0 / 1 point
3. What is the definition of backward elimination? • We start by selecting all features in the feature set and calculating their feature importances. We then prune features from the current feature set to select a subset of the features based on the feature importances, We recursively prune features on the new subset until no model performance improvement is observed.	0 / 1 point
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