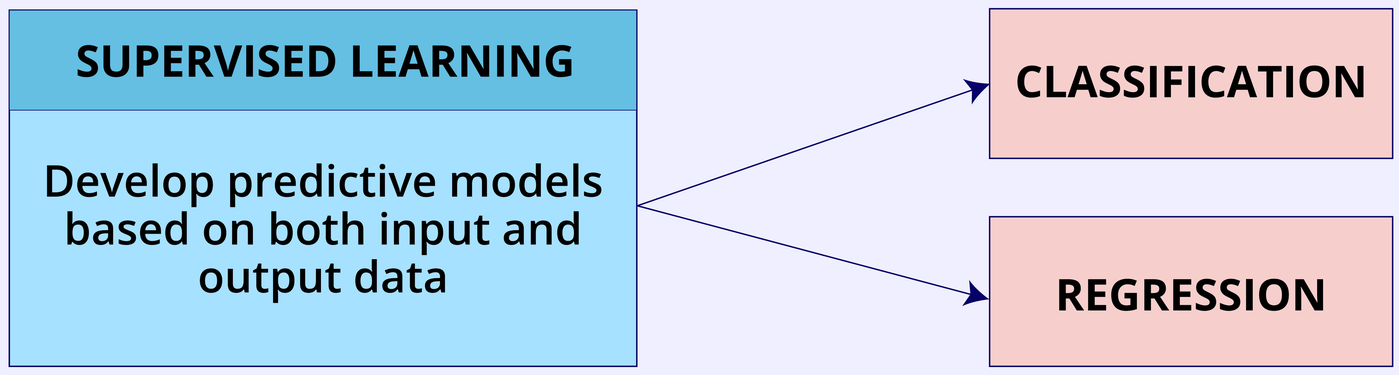
Classification vs. Regression

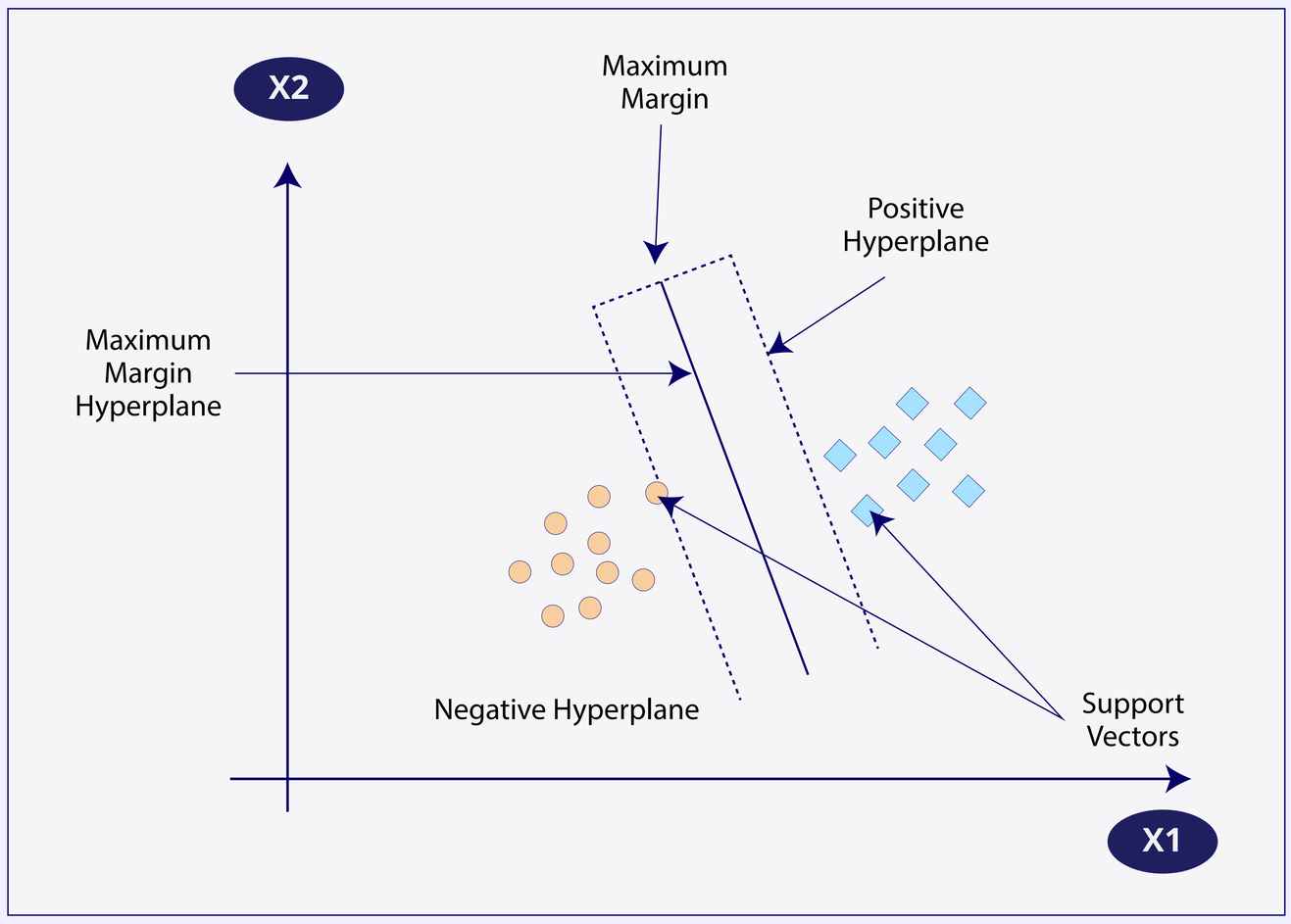
Classification	Regression
Classification predicts categorical labels based on known labels.	**Regression** predicts continuous values based on known values.
Advantages: • Easy to interpret results, providing a clear classification for each input • Useful for categorical output scenarios, such as spam detection or image recognition	**Advantages:** • A wide variety of relationships between variables, not limited to linear relationships • Suitable for predicting continuous values
Disadvantages: • Data may be linearly separable, which might not always be true • A risk of overfitting, especially with complex models, leading to poor generalization	**Disadvantages:** • A chance of outliers significantly affecting the regression line and predictions • Linearity in the data



Combined Models

1: Support Vector Machines (SVMs)

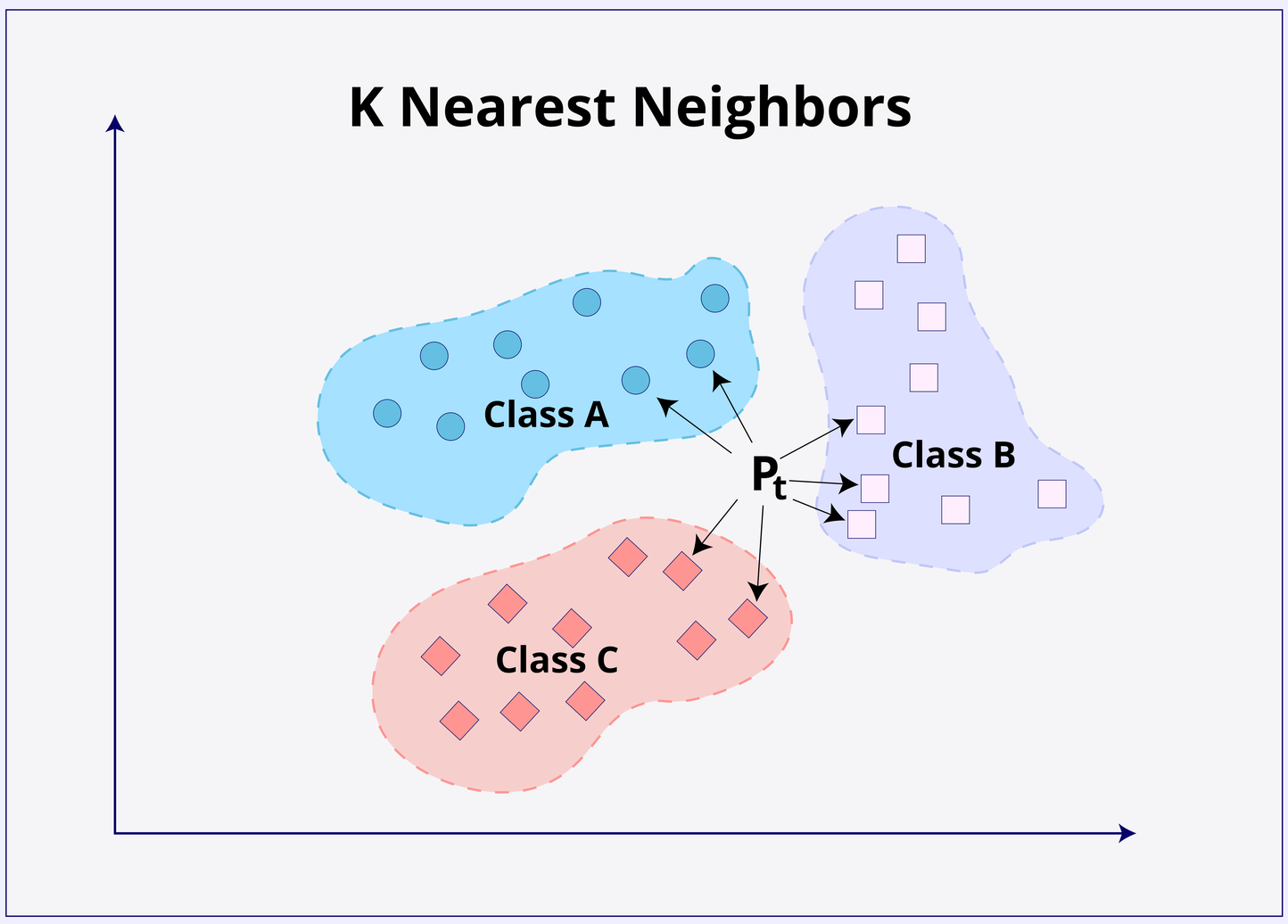
Classification	Regression
SVMs work by finding the hyperplane that best separates different classes in classification tasks, maximizing the margin between classes.	SVMs find the hyperplane that best fits the data, aiming to minimize the error between predicted and actual values.



• Data may be linearly separable, which might not always be true • A risk of overfitting, especially with complex models, leading to poor generalization	• A chance of outliers significantly affecting the regression line and predictions • Linearity in the data

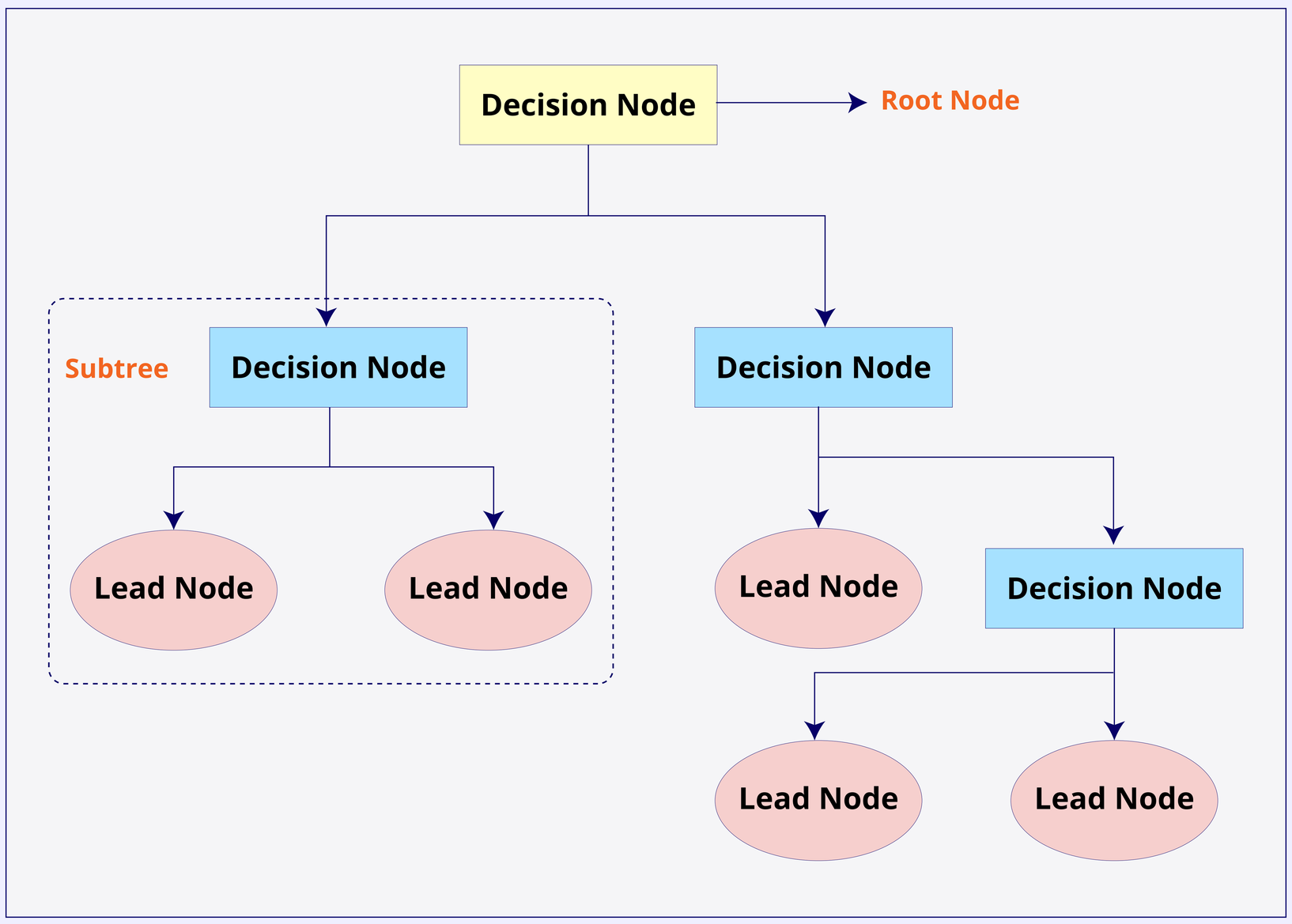
2: K-Nearest Neighbors (KNN)

Classification	Regression
SVMs work by finding the hyperplane that best separates different classes in classification tasks, maximizing the margin between classes.	KNN calculates the average of the numerical values of its k nearest neighbors to predict the value for a new data point.



3: Decision Tree

Classification	Regression
A decision tree divides the input space into regions, each corresponding to a different class. It recursively splits the data based on the features to create distinct groups.	A decision tree predicts the output value of a new data point by averaging the target values of the training samples in the leaf node to which the data point belongs.



Classification vs. Regression

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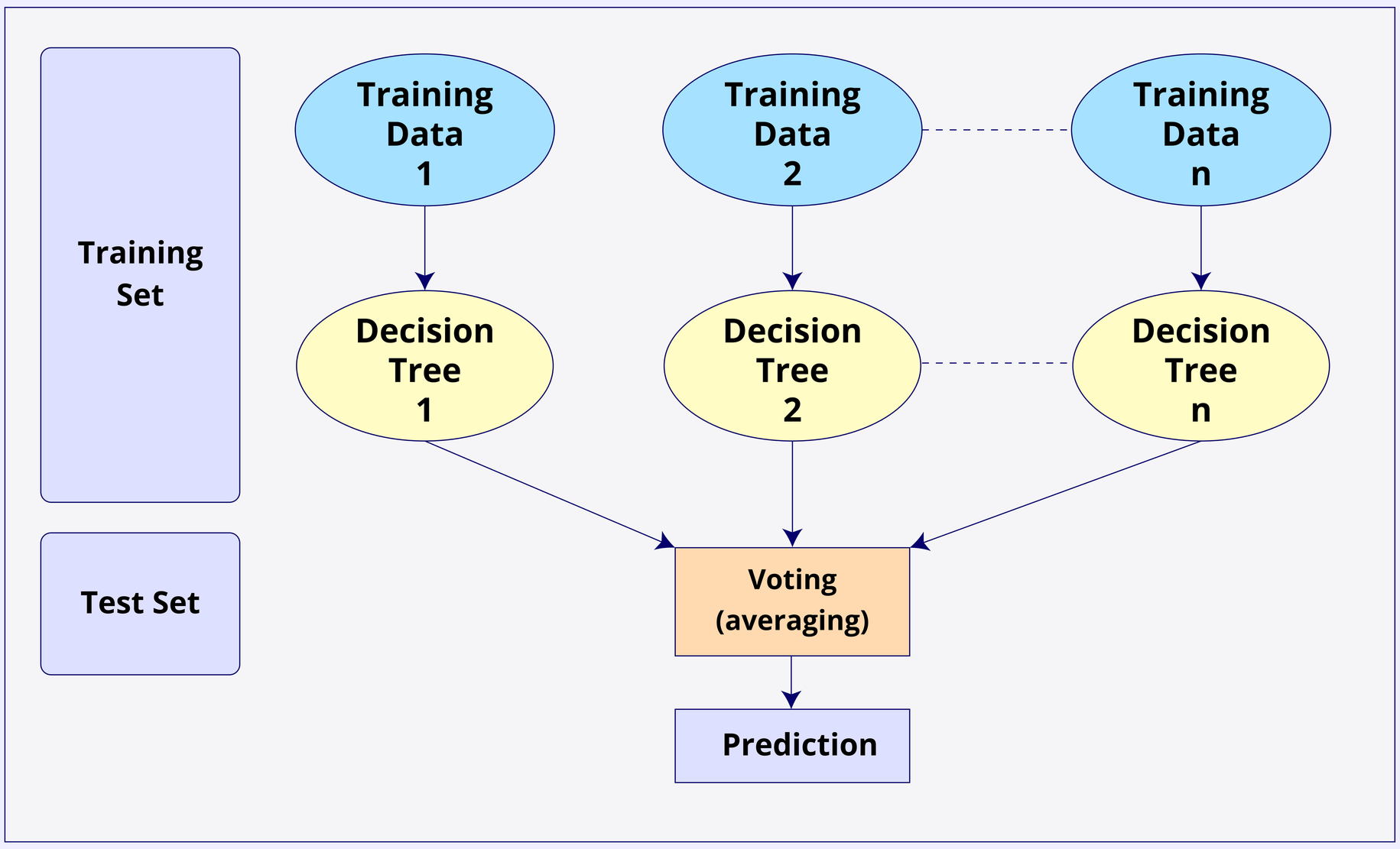
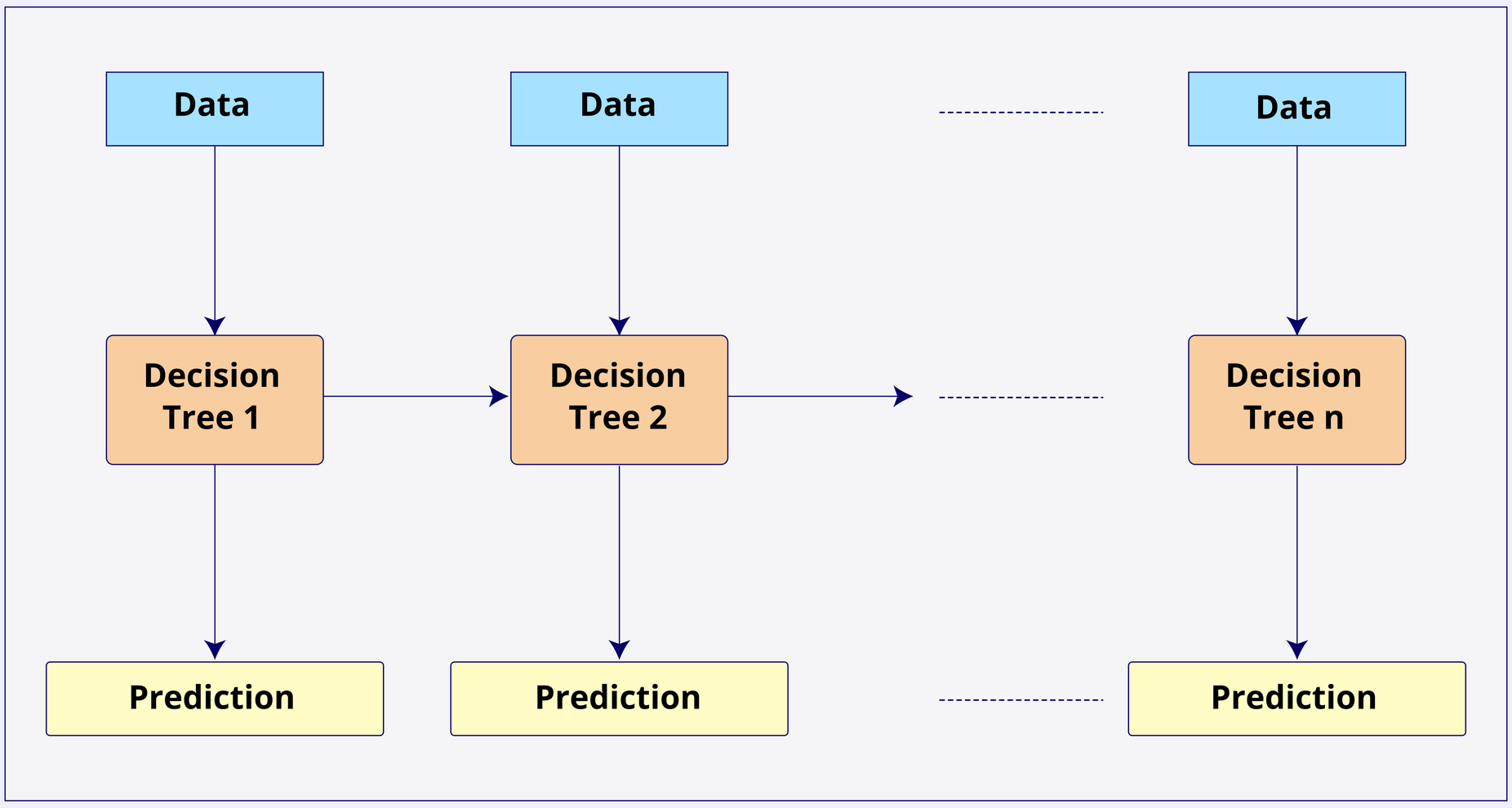
4: Random Forest

Classification	Regression
A random forest is an ensemble of decision trees for classification, where each tree is trained on a random subset of the data. Each tree “votes” for the class, and the class with the most votes is the final prediction.	Each tree predicts a continuous value. The final prediction is the average of all tree predictions.



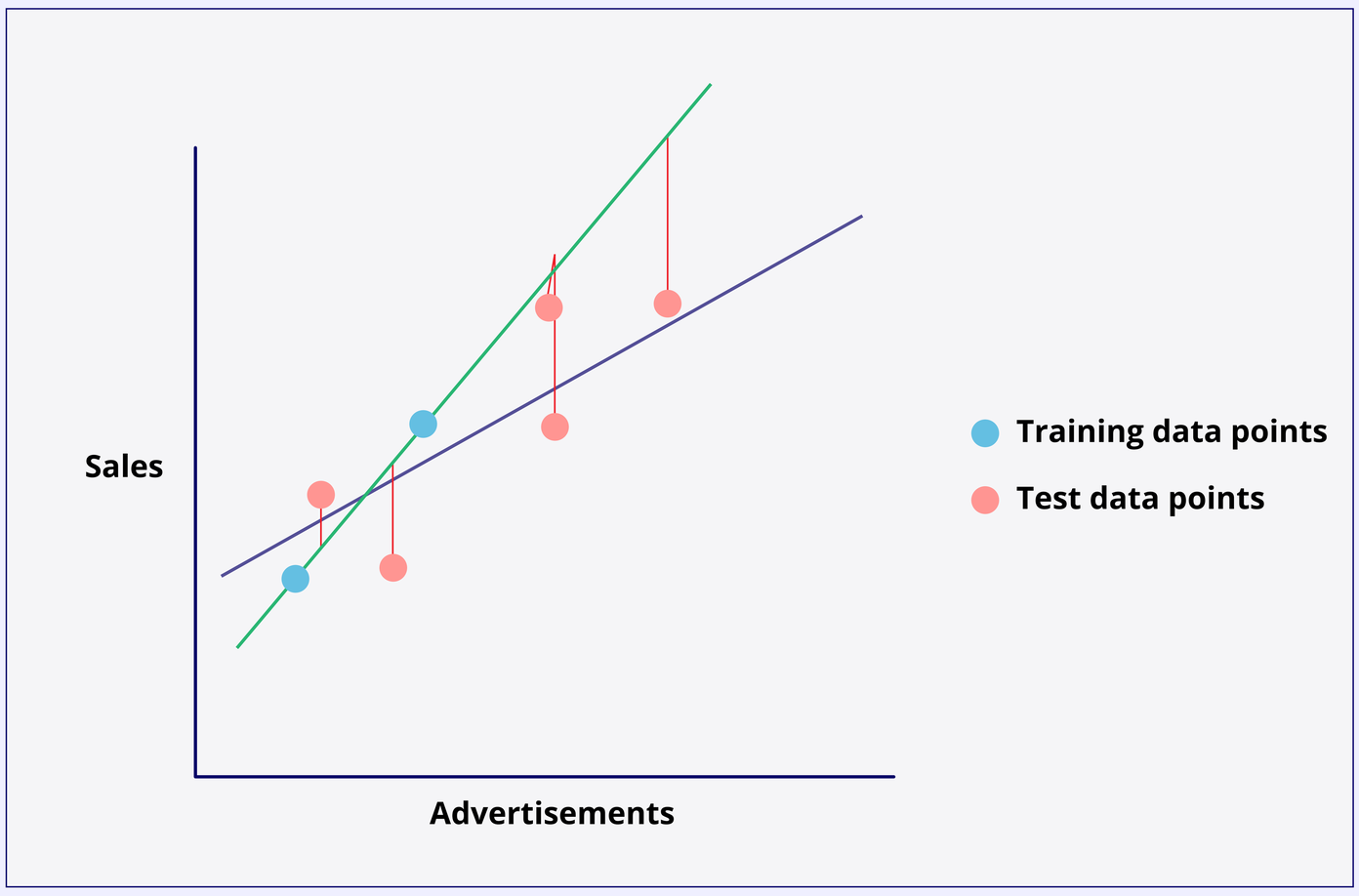
5: Gradient Boosting

Classification	Regression
Gradient boosting works by sequentially combining multiple weak classifiers (often decision trees), where each new classifier corrects the errors of its predecessor. A weighted sum makes the final predictions from all the classifiers.	Gradient boosting in regression is similar to how it works in classification but predicts a continuous value. It sequentially fits new models to the residual errors made by the previous models, refining the prediction with each iteration until a satisfactory model is achieved.



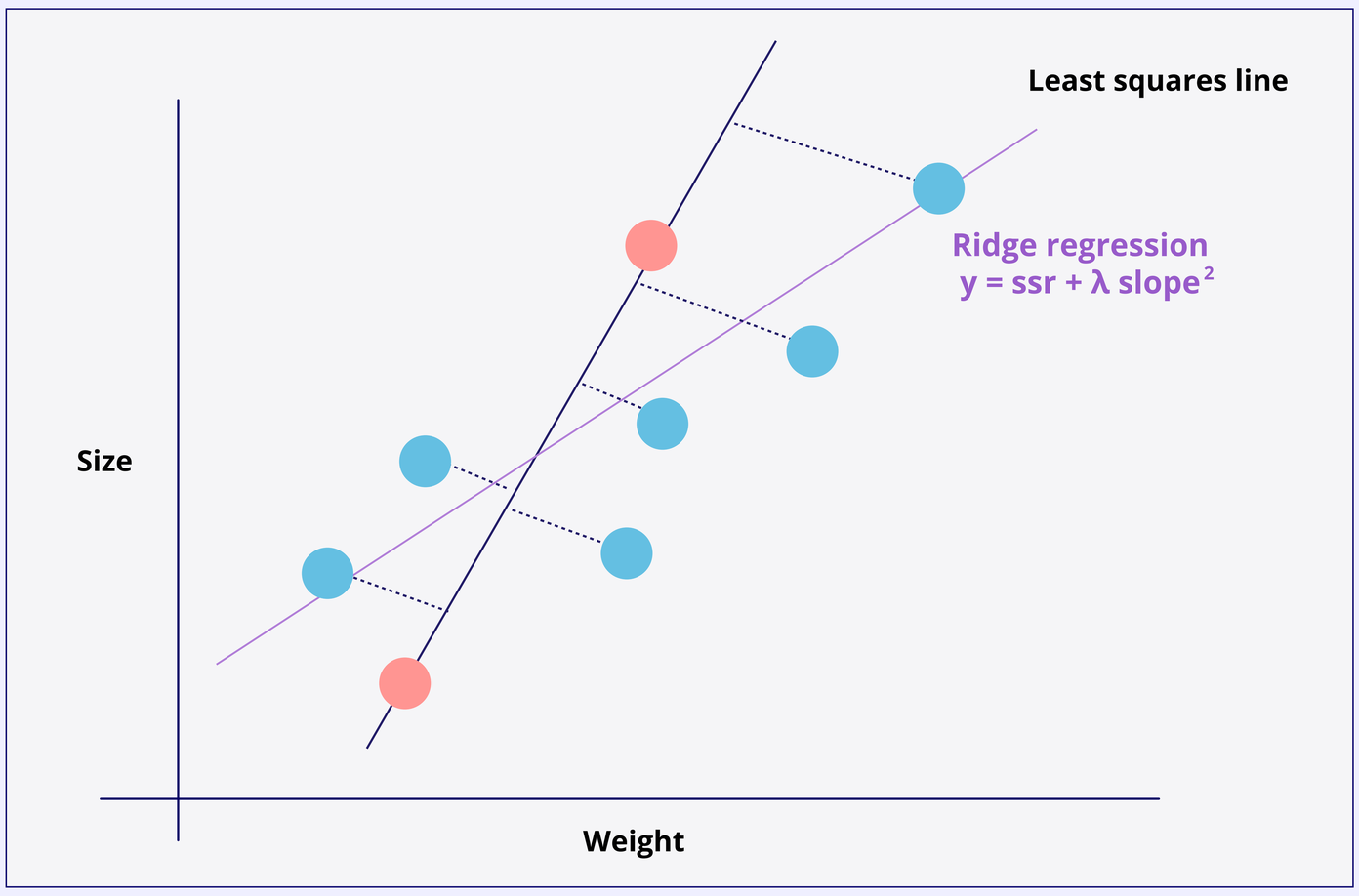
6: Lasso Regression

Classification	Regression
Lasso regression penalizes the absolute size of coefficients, shrinking some to zero. It helps in feature selection by excluding irrelevant features, simplifying the model, and improving classification accuracy.	Lasso regression minimizes the sum of the squared differences between the observed and predicted values, with an additional penalty for the absolute size of coefficients. This encourages a simpler model by shrinking less influential features to zero, aiding in feature selection and reducing overfitting.



7: Ridge Regression

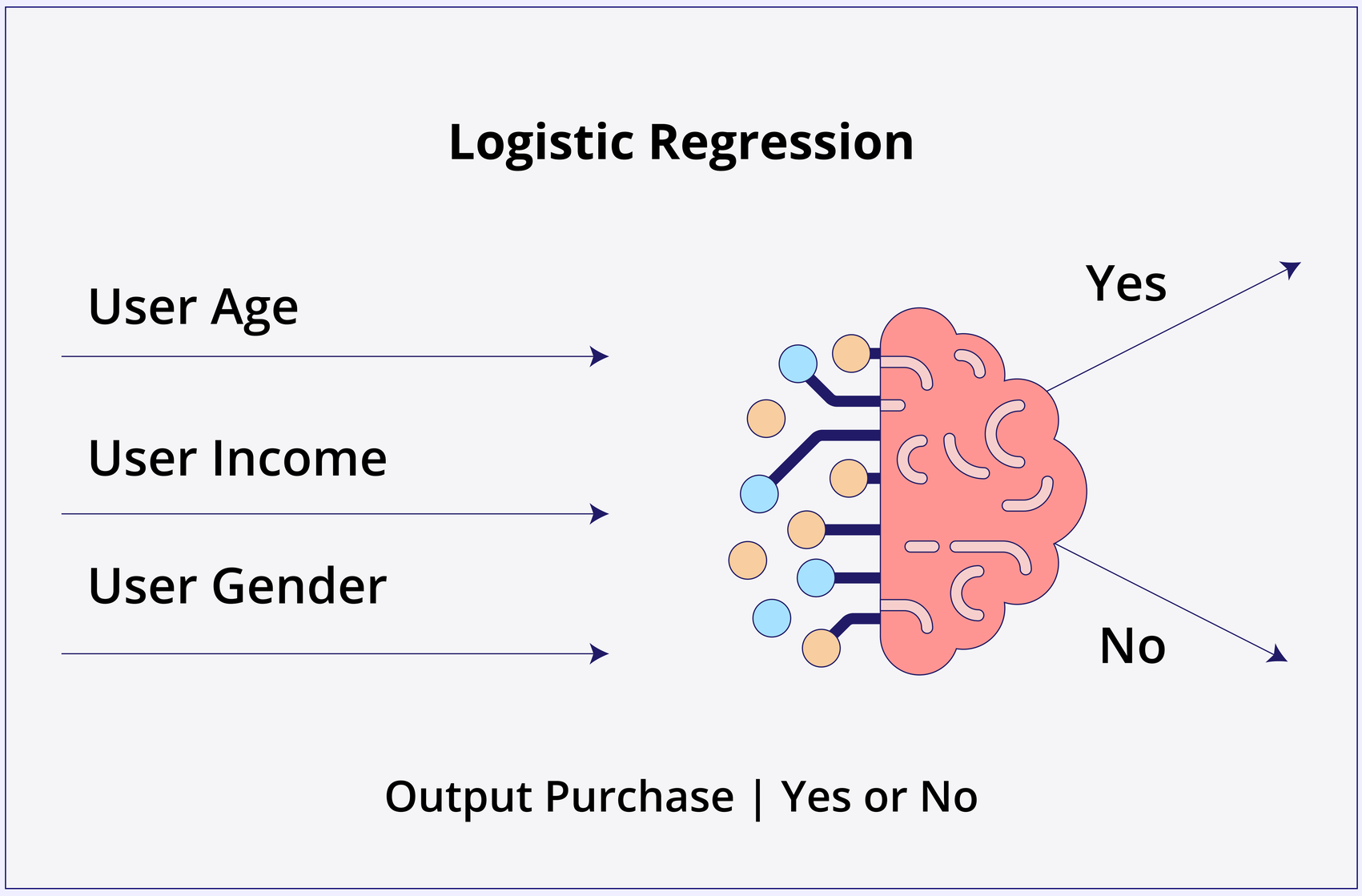
Classification	Regression
Ridge regression penalizes the square of coefficients, pushing them toward zero. This helps reduce model complexity and mitigate overfitting, leading to better generalization.	Ridge regression minimizes the sum of the squared differences between the observed and predicted values, with an additional penalty for the square of coefficients. This helps reduce the impact of less important features, making the model more robust and less sensitive to noise in the data.



Classification Models

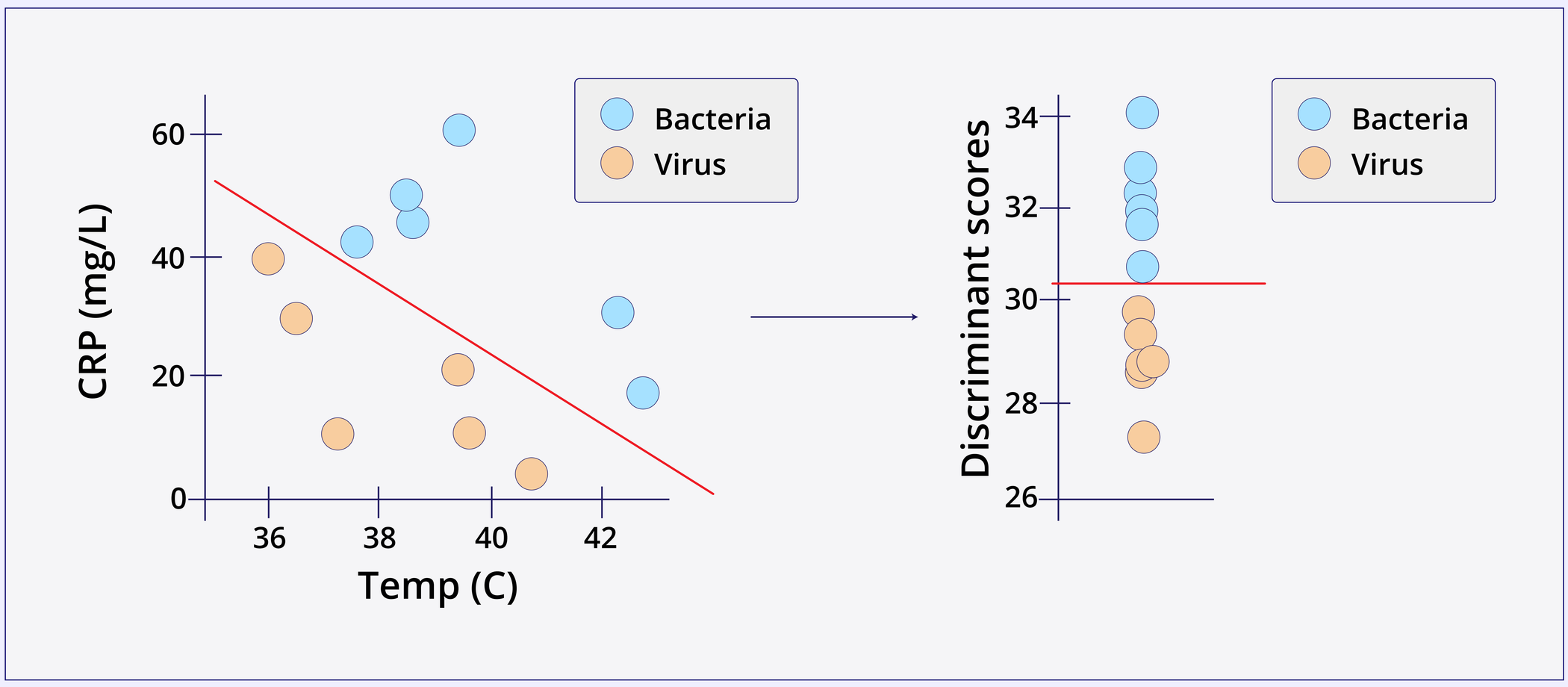
1: Logistic Regression

Logistic regression models the probability of a binary outcome based on input variables.



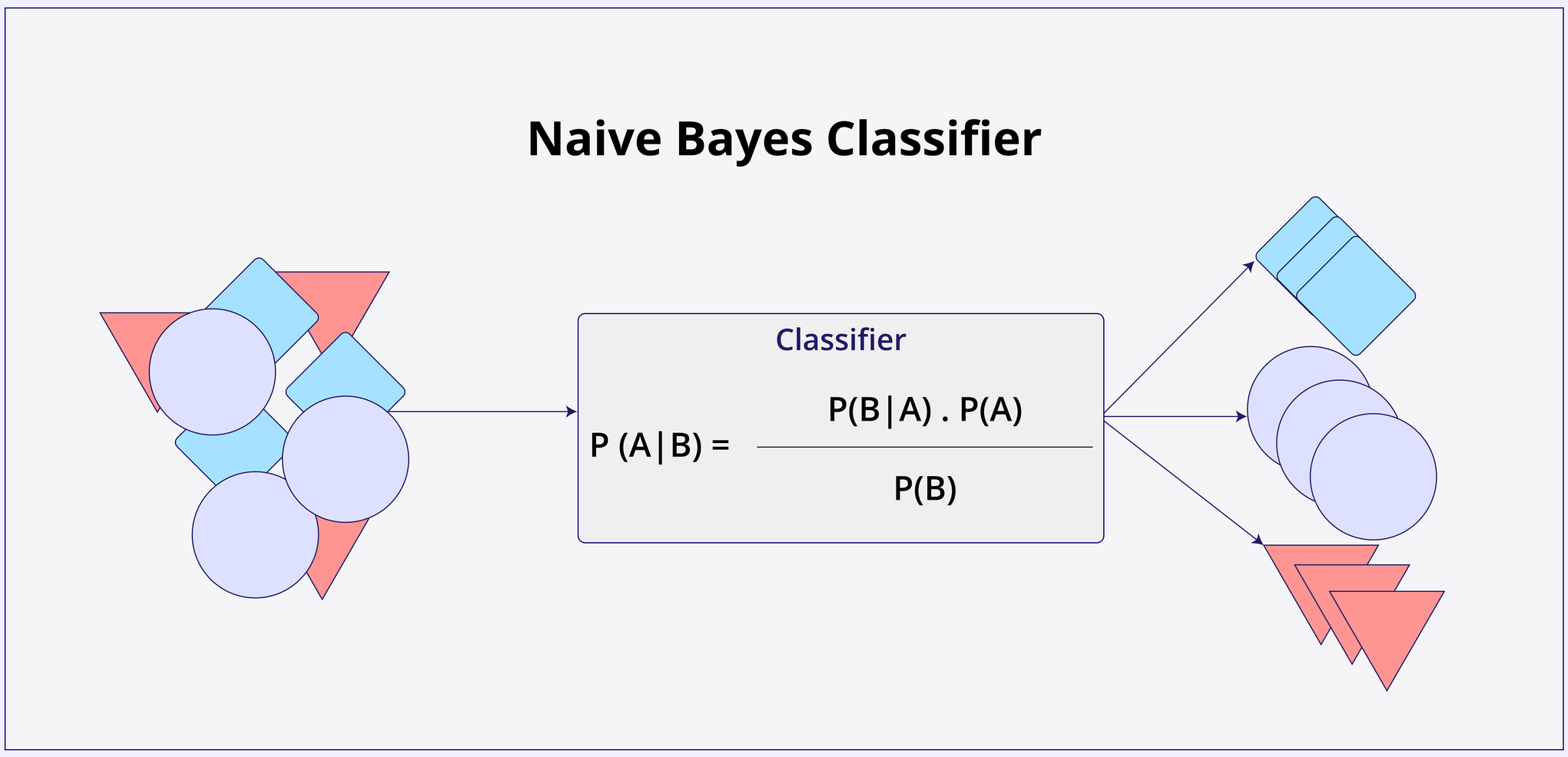
2: Linear Discriminant Analysis

Linear discriminant analysis is a method used for dimensionality reduction and classification. It works by finding the linear combination of features that best separates multiple classes.



3: Naive Bayes Classifier

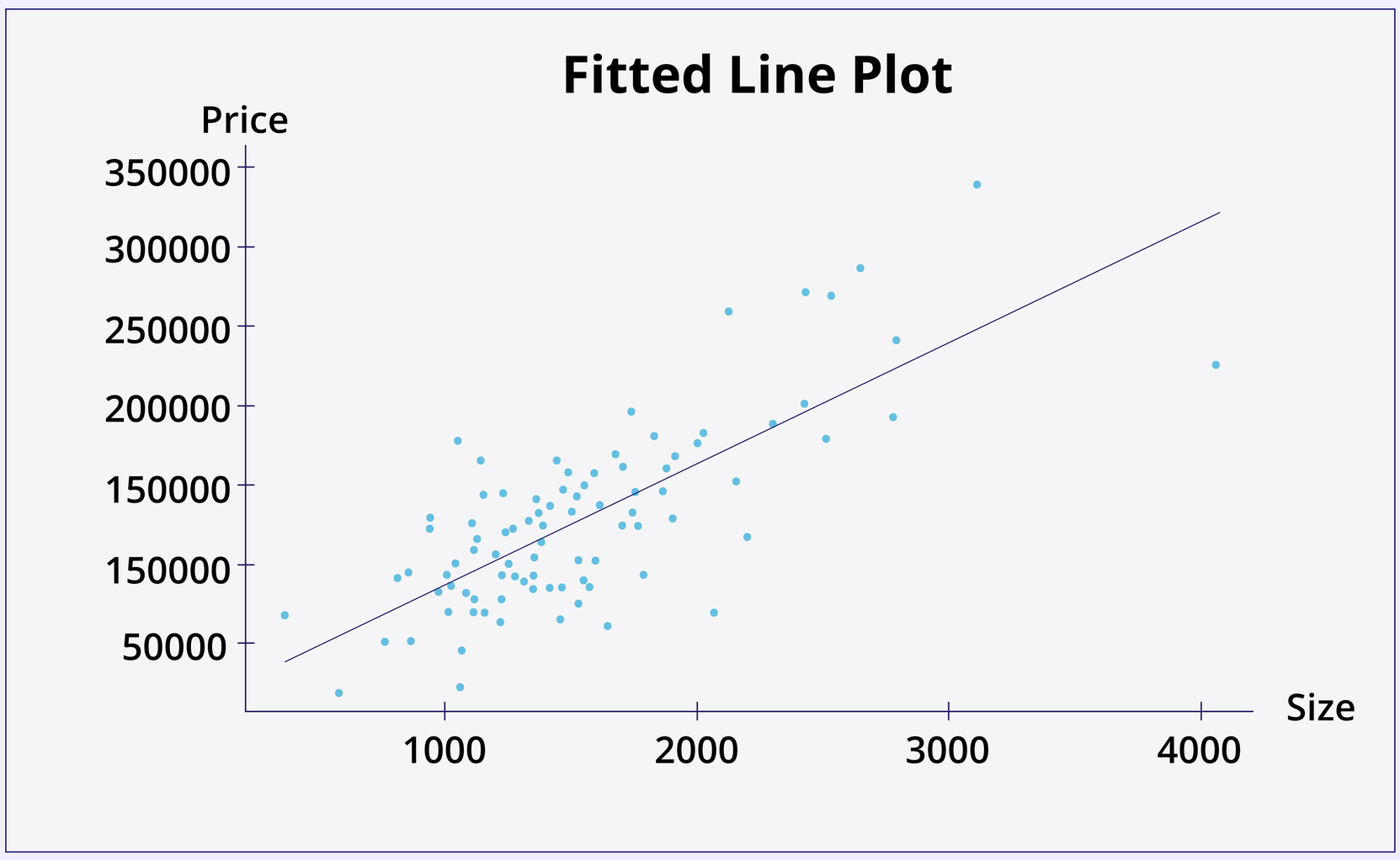
The Naive Bayes classifier calculates probabilities for each class and selects the one with the highest probability.



Regression Models

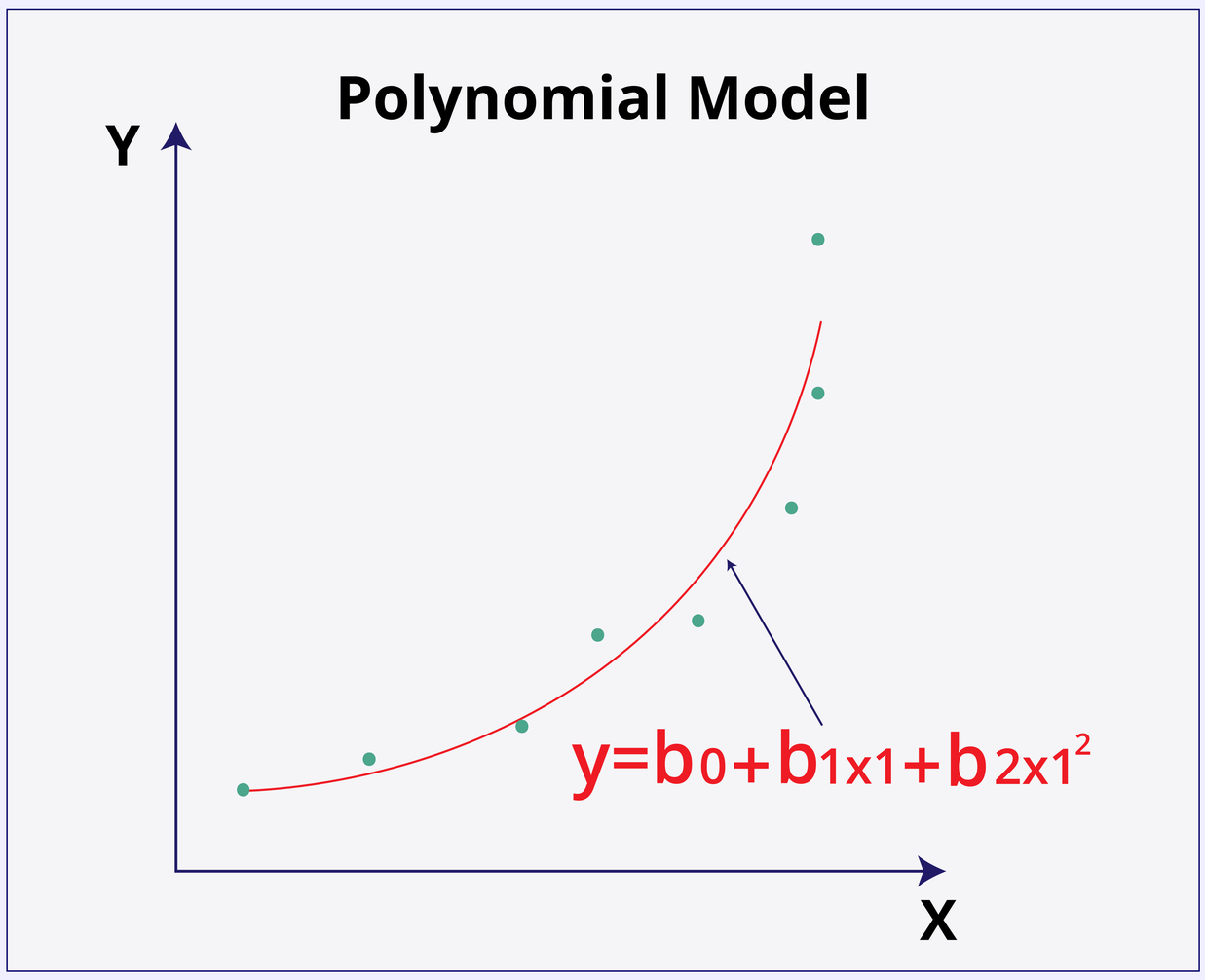
1: Linear Regression

Linear regression works by finding the best-fitting straight line through a set of data points to predict the relationship between the independent and dependent variables.



2: Polynomial Regression

Polynomial regression works by fitting a polynomial equation to the data points to capture the non-linear relationship between the independent and dependent variables.



3: Gaussian Process Regression (GPR)

GPR uses probability to predict the values. This helps make predictions for our data and new data points, along with a measure of uncertainty for each prediction.