MACHINE LEARNING

In Q1 to Q11, only one option is correct, choose the correct option:

1. Which of the following methods do we use to find the best fit line for data in Linear Regression?
   A) Least Square Error B) Maximum Likelihood
   C) Logarithmic Loss D) Both A and B

   Answer:- A) Least Square Error

2. Which of the following statement is true about outliers in linear regression?
   A) Linear regression is sensitive to outliers B) linear regression is not sensitive to outliers
   C) Can't say D) none of these

   Answer:-A) Linear regression is sensitive to outliers

3. A line falls from left to right if a slope is_______?
   A) Positive B) Negative
   C) Zero D) Undefined

   Answer:-B) Negative

4. Which of the following will have symmetric relation between dependent variable and independent variable?
   A) Regression B) Correlation
   C) Both of them D) None of these

   Answer:-B) Correlation

5. Which of the following is the reason for over fitting condition?
   A) High bias and high variance B) Low bias and low variance
   C) Low bias and high variance D) none of these

   Answer:-C) Low bias and high variance

6. If output involves label then that model is called as:
   A) Descriptive model B) Predictive modal
   C) Reinforcement learning D) All of the above

   Answer:- B) Predictive Model

7. Lasso and Ridge regression techniques belong to__________?
   A) Cross validation B) Removing outliers
   C) SMOTE D) Regularization

   Answer:- D) Regularization

MACHINE LEARNING

8. To overcome with imbalance dataset which technique can be used?
   A) Cross validation B) Regularization
   C) Kernel D) SMOTE

   Answer:-D) SMOTE

9. The AUC Receiver Operator Characteristic (AUCROC) curve is an evaluation metric for binary classification problems. It uses______to make graph?
   A) TPR and FPR B) Sensitivity and precision
   C) Sensitivity and Specificity D) Recall and precision

   Answer:- C)TPR and FPR

10. In AUC Receiver Operator Characteristic (AUCROC) curve for the better model area under the curve should be less.
    A) True B) False

    Answer:-A)True

11. Pick the feature extraction from below:
    A) Construction bag of words from a email
    B) Apply PCA to project high dimensional data
    C) Removing stop words
    D) Forward selection

    Answer:- A) Construction bag of words from a email
    B) Apply PCA to project high dimensional data
    C) Removing stop words

In Q12, more than one options are correct, choose all the correct options:

12. Which of the following is true about Normal Equation used to compute the coefficient of the Linear Regression?
    A) We don't have to choose the learning rate.
    B) It becomes slow when number of features is very large.
    C) We need to iterate.
    D) It does not make use of dependent variable.

    Answer:- A) We don't have to choose the learning rate.
    B) It becomes slow when number of features is very large.
    C) We need to iterate

MACHINE LEARNING

Q13 and Q15 are subjective answer type questions, Answer them briefly.

13. Explain the term Regularization?

Answer:-

Regularization refers to techniques that are used to calibrate machine learning models in order to minimize the adjusted loss function and prevent overfitting or underfitting.

There are two main types of regularization techniques:

1. Lasso Regularization(L1 Regularization)

2. Ridge Regularization(L2 Regularization)

3. Elastic-Net regression

1. Lasso Regularization(L1 Regularization)

It modifies the over-fitted or under-fitted models by adding the penalty equivalent to the sum of the absolute values of coefficients.

Lasso regression also performs coefficient minimization, but instead of squaring the magnitudes of the coefficients, it takes the true values of coefficients. This means that the coefficient sum can also be 0, because of the presence of negative coefficients. Consider the cost function for Lasso regression :

Cost function = Loss + λ x $\sum\|w\|$

Here,

Loss = Sum of the squared residuals

λ = Penalty for the errors

w = slope of the curve/ line

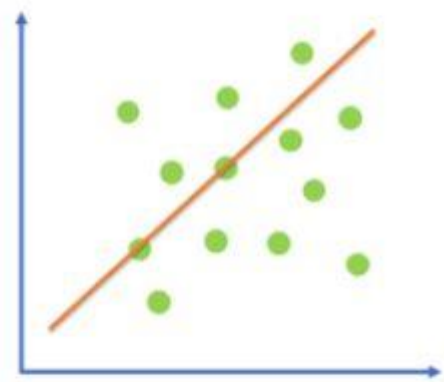
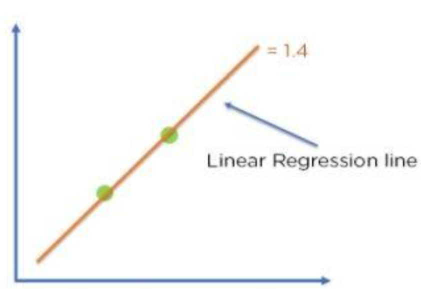


Figure:- Cost function for Lasso Regression

We can control the coefficient values by controlling the penalty terms, just like we did in Ridge Regression. Again consider a Linear Regression model :



MACHINE LEARNING

Figure: Linear Regression Line

Cost function = Loss + λ x ∑‖w‖
For Linear Regression line, let's assume,
Loss = 0 (considering the two points on the line)
λ = 1
w = 1.4
Then, Cost function = 0 + 1 x 1.4
= 1.4
For Ridge Regression, let's assume,
Loss = 0.32 + 0.12 = 0.1
λ = 1
w = 0.7
Then, Cost function = 0.1 + 1 x 0.7
Cost function = 0.8

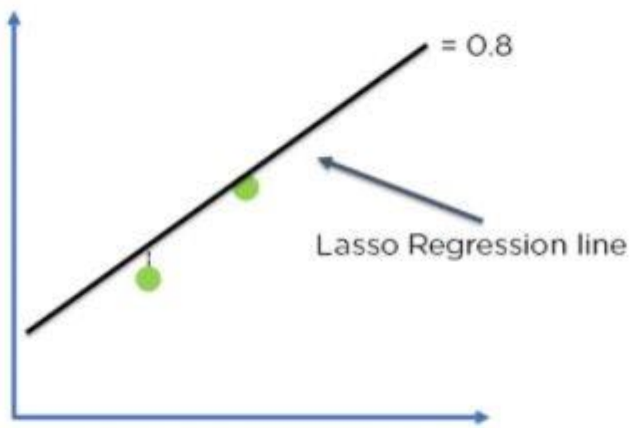


Figure: Lasso Regression

Comparing the two models, with all data points, we can see that the Lasso regression line fits the model more accurately than the linear regression line.

2. Ridge Regularization(L2 Regularization)

Also known as Ridge Regression, it modifies the over-fitted or under fitted models by adding the penalty equivalent to the sum of the squares of the magnitude of coefficients.

This means that the mathematical function representing our machine learning model is minimized and coefficients are calculated. The magnitude of coefficients is squared and added. Ridge Regression performs regularization by shrinking the coefficients present. The function depicted below shows the cost function of ridge regression :

MACHINE LEARNING

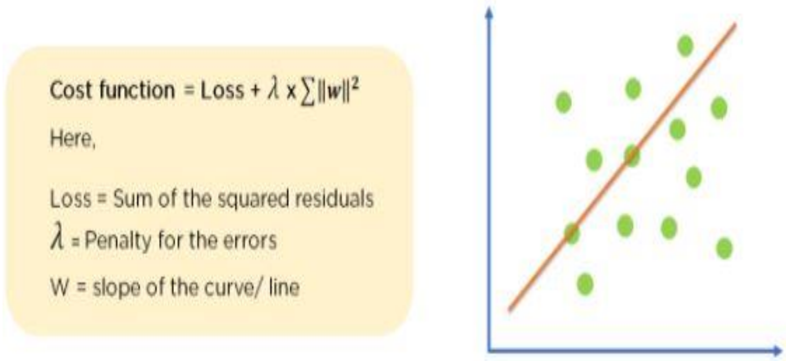


Figure: Cost Function of Ridge Regression

In the cost function, the penalty term is represented by Lambda λ. By changing the values of the penalty function, we are controlling the penalty term. The higher the penalty, it reduces the magnitude of coefficients. It shrinks the parameters. Therefore, it is used to prevent multicollinearity , and it reduces the model complexity by coefficient shrinkage.

Consider the graph illustrated below which represents Linear regression :

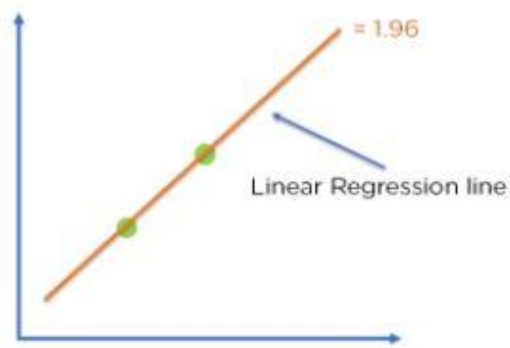


Figure: Linear regression model

Cost function = Loss + λ x∑||w||^2

For Linear Regression line, let’s consider two points that are on the line,

Loss = 0 (considering the two points on the line)

λ= 1

w = 1.4

Then, Cost function = 0 + 1 x 1.42

= 1.96

For Ridge Regression, let’s assume,

MACHINE LEARNING

Loss = 0.32 + 0.22 = 0.13

λ = 1

w = 0.7

Then, Cost function = 0.13 + 1 x 0.72

Cost function = 0.62

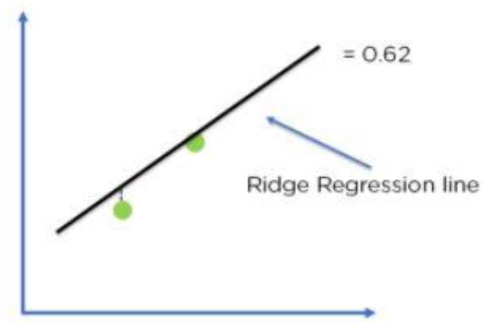


Figure: Ridge regression model

Comparing the two models, with all data points, we can see that the Ridge regression line fits the model more accurately than the linear regression line.

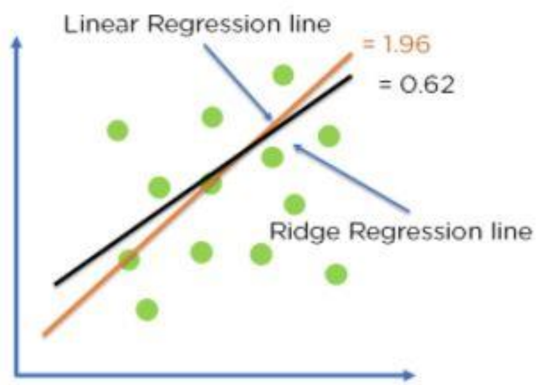


Figure: Optimization of model fit using Ridge Regression

3. Elastic-Net regression

Combination of both Lasso and Ridge Regularization

Let's look at how regularization can be implemented in Python:

1. Lasso Regularization(L1 Regularization)

   from sklearn.linear_model import Lasso

2. Ridge Regularization(L2 Regularization)

   from sklearn.linear_model import Ridge

MACHINE LEARNING

14. Which particular algorithms are used for regularization?

Answer:-

Understanding the use of Regularization algorithms ,such as

1. Ridge
2. Lasso
3. Dropout

Ridge and Lasso can be used for any algorithms involving weight parameters, including neural nets. Dropout is primarily used in any kind of neural networks e.g. ANN, DNN, CNN or RNN to moderate the learning. Let's take a closer look at each of the techniques.

1. Ridge Regression (L2 Regularization)

Ridge regression is also called L2 norm or regularization.

When using this technique, we add the sum of weight's square to a loss function and thus create a new loss function which is denoted thus:

$$\text{Loss} = \sum_{j=1}^{m}\left(Yi - Wo - \sum_{i=1}^{n} Wi\,Xji\right)^2 + \lambda\sum_{i=1}^{n} Wi^2$$

As seen above, the original loss function is modified by adding normalized weights. Here normalized weights are in the form of squares.

You may have noticed parameters λ along with normalized weights. λ is the parameter that needs to be tuned using a cross-validation dataset. When you use λ=0, it returns the residual sum of square as loss function which you chose initially. For a very high value of λ, loss will ignore core loss function and minimize weight's square and will end up taking the parameters' value as zero.

Now the parameters are learned using a modified loss function. To minimize the above function, parameters need to be as small as possible. Thus, L2 norm prevents weights from rising too high.

2. Lasso Regression (L1 Regularization)

Also called lasso regression and denoted as below:

$$\text{Loss} = \sum_{j=1}^{m}\left(Yi - Wo - \sum_{i=1}^{n} Wi\,Xji\right)^2 + \lambda \sum_{i=1}^{n} |Wi|$$

This technique is different from ridge regression as it uses absolute weight values for normalization. λ is again a tuning parameter and behaves in the same as it does when using ridge regression.

As loss function only considers absolute weights, optimization algorithms penalize higher weight values.

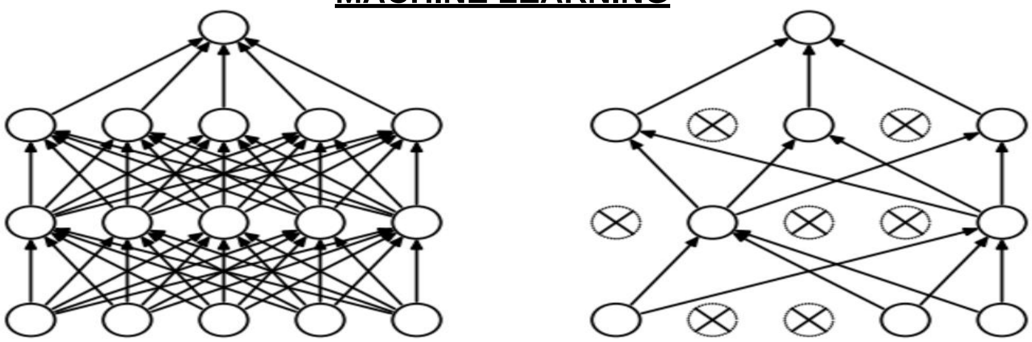
In ridge regression, loss function along with the optimization algorithm brings parameters near to zero but not actually zero, while lasso eliminates less important features and sets respective weight values to zero. Thus, lasso also performs feature selection along with regularization.

3. Dropout

Dropout is a regularization technique used in neural networks. It prevents complex co-adaptations from other neurons.

In neural nets, fully connected layers are more prone to overfit on training data. Using dropout, you can drop connections with *1-p* probability for each of the specified layers. Where *p* is called **keep probability parameter** and which needs to be tuned.

MACHINE LEARNING



(a) Standard Neural Net (b) After applying dropout.

With dropout, you are left with a reduced network as dropped out neurons are left out during that training iteration.

Dropout decreases overfitting by avoiding training all the neurons on the complete training data in one go. It also improves training speed and learns more robust internal functions that generalize better on unseen data. However, it is important to note that Dropout takes more epochs to train compared to training without Dropout (If you have 10000 observations in your training data, then using 10000 examples for training is considered as 1 epoch).

Along with Dropout, neural networks can be regularized also using L1 and L2 norms. Apart from that, if you are working on an image dataset, image augmentation can also be used as a regularization method.

For real-world applications, it is a must that a model performs well on unseen data. The techniques we discussed can help you make your model learn rather than just memorize.

15. Explain the term error present in linear regression equation?

Answer:-

Term error is the difference between the actual value and Predicted value and the goal is to reduce this difference.

MACHINE LEARNING

Let's understand this with the help of a diagram.

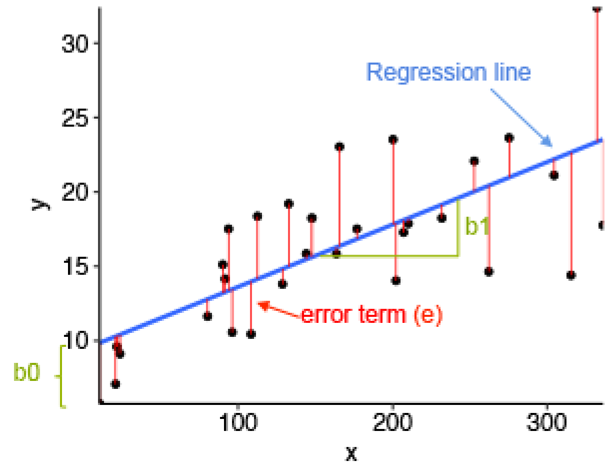


Figure: error term

In the above diagram,

- x is our dependent variable which is plotted on the x-axis and y is the dependent variable which is plotted on the y-axis.
- Black dots are the data points therefore the actual values.
- b_o is the intercept which is 10 and b_1 is the slope of the x variable.
- The blue line is the best fit line predicted by the model therefore the predicted values lie on the blue line.

The vertical distance between the data point and the regression line is known as **error** or **residual**. Each data point has one residual and the sum of all the differences is known as the **Sum of Residuals/Errors.**

Mathematical Approach:

Residual/Error = Actual values – Predicted Values

Sum of Residuals/Errors = Sum(Actual- Predicted Values)

Square of Sum of Residuals/Errors = (Sum(Actual- Predicted Values))^2