1. **D)** Both A and B
2. **A)** Linear regression is sensitive to outliers.
3. **B)** Negative
4. **B)** Correlation
5. **C)** Low bias and high variance
6. **B)** Predictive model
7. **D)** Regularization
8. **D)** SMOTE
9. **A)** TPR (True Positive Rate) and FPR (False Positive Rate)
10. **B)** False
11. **A)** Construction bag of words from a email
12. **A)** We don't have to choose the learning rate.
    B) It becomes slow when the number of features is very large.
13. **Regularization** is what we do when we want to establish a balance between fitting the training data well and avoiding excessive complexity in the model. When a model learns the training data too well and as a result, does not behave well to the new data, we say the model has entered an overfitting mode. So, in order to prevent overfitting, we deploy the technique of regularization.

    Regularization helps to prevent overfitting by adding a penalty to the loss function that is proportional to the complexity of the model. This penalty encourages the model to be simpler and to make fewer assumptions about the data.

    There are different types of regularization techniques, such as L1 regularization (Lasso), L2 regularization (Ridge), and Elastic Net regularization. These techniques introduce a regularization term that is added to the loss function during model training.

    Regularization helps in shrinking the magnitude of the model coefficients or selecting a subset of important features by imposing constraints on them. This prevents the model from relying too heavily on any single feature or exhibiting high sensitivity to individual data points.

    Regularization is an important technique for preventing overfitting. It can help to ensure that a model generalizes well to new data.

    Here are some of the benefits of regularization:

    - It can help to prevent overfitting.
    - It can improve the accuracy of a model.
    - It can make a model more robust to noise in the data.
    - It can make a model more interpretable.

    Here are some of the drawbacks of regularization:

    - It can reduce the accuracy of a model on the training data.
    - It can make a model more complex and difficult to train.
    - It can make a model less interpretable.

Overall, regularization is a powerful technique that can be used to improve the performance of machine learning models. However, it is important to be aware of the potential drawbacks of regularization before using it.

14. There are many different algorithms that can be used for regularization. Some of the most common algorithms include:
    a. **Ridge regression**: A type of linear regression that adds a penalty to the loss function that is proportional to the square of the coefficients. This encourages the coefficients to be small, but not necessarily zero.
    b. **Lasso regression**: A type of linear regression that adds a penalty to the loss function that is proportional to the absolute value of the coefficients. This encourages the coefficients to be small or zero.
    c. **Elastic net regression**: A combination of ridge regression and lasso regression. It adds a penalty to the loss function that is proportional to the sum of the square of the coefficients and the absolute value of the coefficients. This encourages the coefficients to be small, but not necessarily zero.
    d. **Principal component analysis (PCA)**: A dimensionality reduction technique that can be used to reduce the number of features in a dataset. This can help to prevent overfitting by reducing the complexity of the model.
    e. **Feature selection:** A technique that can be used to select a subset of features from a dataset. This can help to prevent overfitting by reducing the number of features that the model has to learn.
    f. **Support Vector Machines (SVM):** SVMs can incorporate regularization through the use of different kernel functions and hyperparameters that control the trade-off between the margin and the training error. This helps in finding the optimal decision boundary and avoiding overfitting.
    g. **Neural Networks**: Regularization techniques like L1 and L2 regularization, dropout, and early stopping can be applied to neural networks to prevent overfitting and improve generalization performance.

    The choice of which algorithm to use depends on the specific problem. Ridge regression is often used when there are a large number of features, or when it is not clear which features are important. Lasso regression is often used when there are a small number of features that are important. Elastic net regression is often used when a combination of both ridge regression and lasso regression is desired. PCA and feature selection can be used in conjunction with any of these algorithms to further reduce the complexity of the model and prevent overfitting.

15. The term "**error**" in a linear regression equation refers to the difference between the actual value of the dependent variable and the predicted value of the dependent variable. It represents the unexplained or residual variation in the data that is not captured by the linear relationship between the independent variables and the dependent variable.

    The error term accounts for the part of the dependent variable that cannot be predicted by the linear relationship with the independent variables. It captures the influence of other factors, measurement errors, or random variation that is not accounted for by the model. The goal of linear regression is to minimize the sum of squared errors (SSE) or the residuals, which represents the discrepancy between the predicted values and the actual values.

By estimating the regression coefficients, the linear regression model aims to minimize the overall error and find the best-fitting line or hyperplane that represents the relationship between the independent variables and the dependent variable.