1. In constructing the Support Vector Machine (SVM) model, we control the strength of regularization through the parameter C. By adjusting the value of C, we can manage the complexity of the model. A low C value results in smoother decision boundaries, which places a greater emphasis on avoiding overfitting. However, this can lead to the model failing to adequately capture the underlying statistical characteristics of the training data, resulting in poor performance on both the training and testing datasets. Conversely, a high C value may produce more complex boundaries, which can lead to overfitting and poor performance on new data, as the model learns the noise present in the training data. Through regularization mechanisms, the SVM model can adapt to the complexity of the data while maintaining good generalization capability.
2. In the logistic regression model, we employed L1 regularization techniques. By applying an L1 penalty within the model, some weight coefficients are driven to zero, thus achieving feature selection. By adding a regularization term to the loss function, the weights are controlled to remain within a smaller range during the training process, preventing certain features from exerting too much influence on the decision in the linear combination. Additionally, an appropriate regularization strength (controlled by adjusting parameter C) can help establish a balance between the training and testing data, thereby enhancing generalization capabilities.
3. During the construction of the XGBoost model, regularization techniques are implemented by controlling the L1 (*reg\_alpha*) and L2 (*reg\_lambda*) parameters. L1 regularization penalizes weights with large absolute values, reducing the weights of unimportant features to zero, which aids in feature selection and enhances the model's interpretability. L2 regularization, on the other hand, penalizes the square values of the weights, encouraging the model to learn smaller weight values, thereby reducing model complexity and the risk of overfitting.
4. When building the model with CatBoost, we effectively incorporated regularization techniques to control model complexity and enhance generalization capabilities by adjusting parameters such as *L2\_leaf\_reg*, *random\_strength*, and *subsample*.
5. AdaBoost typically uses decision trees as weak learners. In decision trees, regularization is primarily reflected in several aspects: controlling tree growth further through parameters like *min\_samples\_split* and *min\_samples\_leaf*. These parameters help prevent the model from becoming overly complex on the training set, thus increasing the model's regularization.
6. The Random Forest model does not employ traditional regularization techniques; rather, its design and hyperparameter settings (such as *min\_samples\_leaf* and *min\_samples\_split*) inherently provide mechanisms for controlling model complexity and enhancing generalization capabilities. Through appropriate parameter tuning, the performance of the model can be effectively improved, combating overfitting and making the model more reliable in practical applications.
7. The regularization process in LightGBM is similar to that in XGBoost, controlling model complexity through parameter settings.

(8) In the MLP model, L2 regularization is introduced as well by setting the *alpha* parameter.