1. **Problem**

**Predicted**

**Yes No**

**Actual Yes TP FN**

**No FP TN**

**In this confusion matrix:**

**True Positives (TP) are the cases where the model correctly predicted that the customer would churn (Yes).**

**True Negatives (TN) are the cases where the model correctly predicted that the customer would not churn (No).**

**False Positives (FP) are the cases where the model incorrectly predicted that the customer would not churn (No), but they actually did churn (Yes).**

**False Negatives (FN) are the cases where the model incorrectly predicted that the customer would churn (Yes), but they actually did not churn (No).**

**The most relevant elements in this case would be the true negatives (TN) and the false negatives (FN). The true negatives represent the customers that the model correctly predicted would not churn, while the false negatives represent the customers that the model incorrectly predicted would not churn but actually did churn. It would be ideal for the model to have a high number of true negatives and a low number of false negatives, as this would indicate that the model is accurately predicting which customers are likely to churn and which are not.**

**----------------------------------------------------------**

Here the objective is to determine customers that will not churn and retain them. In the dataset, churn customers are annotated with 'Yes' has churned and 'No' they still with the company. The relevant elements in this case would be the non-churned customers, as the objective is to retain them. The churned customers would be considered negative examples, but the focus should be on identifying and retaining the non-churned customers.

* True positives (TP): These are instances where the model correctly predicts that a customer will not churn (i.e., they are a non-churned customer).
* True negatives (TN): These are instances where the model correctly predicts that a customer will churn (i.e., they are a churned customer).
* False positives (FP): These are instances where the model incorrectly predicts that a customer will not churn (i.e., they are actually a churned customer).
* False negatives (FN): These are instances where the model incorrectly predicts that a customer will churn (i.e., they are actually a non-churned customer).

In this classification problem, the relevant elements are the non-churned customers, so the true positives and false negatives would be the most important to consider. The false positives and true negatives would still be important to consider, as they can give insight into how well the model is performing overall, but the primary focus should be on accurately predicting the non-churned customers.

1. **Fff**
2. **fff**

The appropriate learning metrics for an imbalanced dataset with a churn class that is less prevalent would be precision, recall, and the F1 score. These metrics take into account both the number of true positives (correctly predicted churn clients) and the number of false negatives (incorrectly predicted non-churn clients). In an imbalanced dataset, it is important to consider these metrics rather than just overall accuracy, as the classifier may achieve high accuracy by simply predicting the majority class (in this case, non-churn clients) for all instances, which would not be useful for detecting churn clients.

It is generally recommended to use a metric that takes into account the imbalanced nature of the target class, such as balanced accuracy or F1 score. Using scoring="balanced\_accuracy" as a parameter in cross validation **can be a good option** in this case. However, it is important to also consider other metrics, such as precision, recall, and specificity, to get a more complete understanding of the model's performance. Additionally, it may be useful to consider using techniques such as **oversampling or undersampling** to balance the target class before building the model.