FEATURE ENGINEERING 2
Solutions: -

Q1.
The Filter method in feature selection involves evaluating the relevance of each feature independently of the predictive model. It typically entails statistical measures or tests to score the features based on certain criteria, such as correlation with the target variable or their information gain. Features are then ranked or selected based on these scores, and only the top-ranked features are retained for further modeling.

Q2.
The Wrapper method, unlike the Filter method, involves evaluating the performance of a predictive model trained with different subsets of features. It uses a specific machine learning algorithm to train models iteratively with different feature combinations, assessing their performance through cross-validation or another evaluation metric. This method considers the interaction between features and the model's performance, potentially leading to better feature selection but requiring more computational resources compared to the Filter method.

Q3.
Embedded feature selection methods incorporate feature selection within the process of model training. Common techniques include LASSO (Least Absolute Shrinkage and Selection Operator), which adds a penalty term to the model's cost function to enforce feature sparsity, and decision tree-based algorithms like Random Forest and Gradient Boosting, which inherently perform feature selection by selecting the most informative features for splitting nodes during tree construction.

Q4.
Drawbacks of using the Filter method for feature selection include its inability to consider feature interactions and its reliance on predefined criteria, which might not be optimal for the predictive model. Additionally, it may discard potentially relevant features if they don't meet the specified criteria, leading to information loss.

Q5.

The Filter method is preferable over the Wrapper method when computational resources are limited, and a quick feature selection process is desired. It's also suitable when feature independence is assumed or when there's a large number of features compared to the dataset size, making wrapper methods computationally expensive.

Q6.
To use the Filter Method for selecting attributes in the telecom company's churn prediction project, you'd start by calculating statistics like correlation coefficients or mutual information scores between each feature and the churn outcome. Features with high scores indicating strong relationships with churn would be selected for the model, while those with low scores could be discarded.

Q7.
In the soccer match outcome prediction project, you could employ an Embedded method like Random Forest or Gradient Boosting. These algorithms inherently perform feature selection during model training by selecting the most informative features for splitting nodes in the decision trees. By analyzing the importance scores assigned to each feature by the model, you can identify the most relevant features for predicting match outcomes.

Q8.
For the house price prediction project, you could use the Wrapper method, such as recursive feature elimination with cross-validation (RFECV). RFECV recursively removes features, fitting the model each time, and evaluates performance through cross-validation to determine the optimal subset of features that maximizes predictive accuracy. This approach ensures that the final set of features selected is the most important for predicting house prices while considering interactions between features