Q1. **Lasso Regression**:

- Lasso Regression, short for Least Absolute Shrinkage and Selection Operator, is a linear regression technique that adds a penalty term to the ordinary least squares (OLS) cost function.
- Unlike traditional linear regression, Lasso Regression penalizes the absolute values of the coefficients, encouraging sparsity in the model.
- It differs from Ridge Regression by using an L1 penalty instead of an L2 penalty.

Q2. **Advantage of using Lasso Regression in feature selection**:

- The main advantage of Lasso Regression in feature selection is its ability to automatically select a subset of relevant features while setting the coefficients of irrelevant features to zero.
- This feature selection property of Lasso Regression can help improve model interpretability and reduce overfitting by removing redundant or uninformative features from the model.

Q3. **Interpretation of coefficients in Lasso Regression**:

- In Lasso Regression, the coefficients represent the change in the dependent variable for a one-unit change in the corresponding independent variable, similar to other regression techniques.
- However, since Lasso Regression encourages sparsity, some coefficients may be exactly zero, indicating that the corresponding features have been excluded from the model.

Q4. **Tuning parameters in Lasso Regression**:

- The main tuning parameter in Lasso Regression is the regularization parameter, often denoted as lambda or alpha.
- The regularization parameter controls the strength of the penalty applied to the absolute values of the coefficients.
- Increasing the regularization parameter leads to greater shrinkage of coefficients and a sparser model.

Q5. **Use of Lasso Regression for non-linear regression problems**:

- Lasso Regression is inherently a linear regression technique and is best suited for linear relationships between the independent and dependent variables.
- However, Lasso Regression can be combined with techniques like polynomial features or basis function expansion to model non-linear relationships between variables.

Q6. **Difference between Ridge Regression and Lasso Regression**:

- The main difference between Ridge Regression and Lasso Regression lies in the penalty term used to regularize the coefficients.

- Ridge Regression uses an L2 penalty, which penalizes the squared values of the coefficients, while Lasso Regression uses an L1 penalty, which penalizes the absolute values of the coefficients.
- As a result, Ridge Regression tends to shrink coefficients towards zero, while Lasso Regression can set some coefficients exactly to zero, effectively performing feature selection.

Q7. **Handling multicollinearity in Lasso Regression**:

- Lasso Regression can handle multicollinearity to some extent by automatically selecting a subset of relevant features while setting the coefficients of correlated features to zero.
- However, if multicollinearity is severe, Lasso Regression may still struggle to select the most relevant features and may benefit from preprocessing techniques like principal component analysis (PCA) or feature engineering.

Q8. **Choosing the optimal value of the regularization parameter in Lasso Regression**:

- The optimal value of the regularization parameter in Lasso Regression can be chosen using techniques like cross-validation.
- Cross-validation involves splitting the dataset into training and validation sets, fitting the Lasso Regression model with different values of the regularization parameter on the training set, and selecting the parameter that yields the best performance on the validation set.