Q1. R-squared (Coefficient of Determination)

- **Concept:** R-squared measures how much of the **variation in the dependent variable (Y)** is explained by the independent variable(s) in the regression model.

- **Formula:**

$$R^2 = 1 - \frac{\text{SS}_{\text{res}}}{\text{SS}_{\text{tot}}}$$

Where:

- $\text{SS}_{\text{res}} = \sum_i (y_i - \hat{y}_i)^2$ → Residual sum of squares

- $\text{SS}_{\text{tot}} = \sum_i (y_i - \bar{y})^2$ → Total sum of squares

- **Interpretation:**
  - $R^2 = 0$ → Model explains 0% of the variance
  - $R^2 = 1$ → Model explains 100% of the variance
  - Example: If $R^2 = 0.8$, 80% of the variation in Y is explained by the model.

Q2. Adjusted R-squared

- **Concept:** Adjusted R-squared accounts for the **number of predictors** in the model, penalizing unnecessary variables.

- **Formula:**

$$\text{Adjusted } R^2 = 1 - \frac{(1-R^2)(n-1)}{n-p-1}$$

Where:

- nnn = number of observations
- ppp = number of predictors
- **Difference from R-squared:**
  - R-squared always increases when more variables are added.
  - Adjusted R-squared increases **only if the added variable improves the model beyond chance**.

Q3. When to use Adjusted R-squared

- **Use it when comparing models with different numbers of predictors.**
- Helps **avoid overfitting** by penalizing unnecessary variables.
- Example: Model A has 3 features, Model B has 8 features. Even if Model B has higher R^2, adjusted R^2 may be lower if extra features don't add predictive power.

Q4. RMSE, MSE, and MAE

Metric	Formula	Interpretation

MSE (Mean Squared Error)	$\frac{1}{n} \sum (y_i - \hat{y}_i)^2$	Average squared error; penalizes large errors mo

		re
RMSE (Root Mean Squared Error)	MSE\sqrt{\text{MSE}}MSE	Same units as Y; sensitive to large errors
MAE (M	(\frac{1}{n} \sum	y_i - \

eanAbsoluteError)

hat{y}_i

- **Use in regression:** These metrics evaluate model performance; **lower values = better fit**.

Q5. Advantages & Disadvantages

- **MSE:**
    - ■ Penalizes large errors strongly
  - – Sensitive to outliers
- **RMSE:**
    - ■ Same unit as Y (easy to interpret)
  - – Sensitive to outliers
- **MAE:**
    - ■ Robust to outliers

- – Doesn’t penalize large errors strongly

Q6. Lasso vs Ridge Regularization

Aspect	Ridge (L2)	Lasso (L1)
Penalty	λ∑βj2\lambda \sum \beta_j^2λ∑βj2	(\lambda \sum
Effect	Shrinks coefficients but **keeps all variables**	Shrinks coefficients and **can set some to 0** (feature selection)
Use Case	When all features are potentially important	When you want to **select key features**

- **Key difference:** Lasso can perform **automatic feature selection**, Ridge cannot.

Q7. Regularized Linear Models Prevent Overfitting

- **How:** Regularization **adds a penalty for large coefficients**, discouraging the model from fitting noise in the training data.
- **Example:** Predicting house prices with many correlated features:
  - Without regularization: model overfits
  - With Ridge or Lasso: reduces overfitting and improves generalization

---

Q8. Limitations of Regularized Models

- May **underfit** if penalty λ is too high

- Lasso can randomly select one feature from a group of correlated features, ignoring others
- Not always the best for **non-linear relationships** (then use polynomial regression or tree-based models)

Q9. Comparing Model Performance (RMSE vs MAE)

- Model A: RMSE = 10
- Model B: MAE = 8

Interpretation:

- Direct comparison is tricky because RMSE and MAE scale differently.
- If errors are expected to be normally distributed, RMSE is more appropriate.
- If robustness to outliers is desired, MAE is better.
- **Limitation:** One metric alone cannot fully capture performance; better to compare both metrics.

Q10. Ridge vs Lasso Comparison

- Model A: Ridge (λ=0.1)
- Model B: Lasso (λ=0.5)

Interpretation:

- Lasso might select fewer features due to higher penalty → simpler model
- Ridge keeps all features → better if all variables matter

- **Trade-off:** Lasso = interpretability and sparsity, Ridge = stability and less variance

Decision: Depends on whether you want **feature selection** (Lasso) or **all coefficients** (Ridge) to remain.
