

Multiple Choice Question Review

Stat 151A: Linear Models

Multiple choice questions

Below, you will find the multiple choice questions from the quizzes, but not the candidate responses.

I encourage you to try to think of correct (and incorrect) answers for yourself as a way of preparing for the final exam!

Questions

Quiz 0

1. If a square, symmetric matrix A is invertible, then...
2. Let X denote a full-rank $N \times P$ matrix with $N > P$. Then...
3. Suppose that u and v are orthogonal N -vectors with $N \geq 2$. Then...
4. Let X denote an $N \times P$ matrix, with $P < N$, β a nonzero P -vector, and Y an N -vector. Which of these matrix expressions is **not** well-defined?
5. Suppose that x_n are IID Gaussian with mean $\mathbb{E}[x_n] = 2$ and $\text{Var}(x_n) = 9$. Which of the following expressions diverges (goes to positive or negative infinity) as $N \rightarrow \infty$?

Quiz 1

1. Suppose that $x_n = Az_n$ for all n , where A is invertible but not symmetric. For the regressions $y \sim \beta^\top x$ and $y \sim \gamma^\top z$, it is necessarily true that...
2. Which of the following is *never* a well justified reason to choose $\hat{\beta}$ by minimizing the mean of squared errors $\frac{1}{N} \sum_{n=1}^N (y_n - x_n^\top \beta)^2$?
3. Let $P_X = X(X^\top X)^{-1}X^\top$ denote the projection matrix onto the columns of X , where X is full rank. Which of the following expressions is false?

4. Suppose that x_{n1} and x_{n2} are mean zero and very highly (but not perfectly) positively correlated, and we regress $y_n \sim \beta_1 x_{n1} + \beta_2 x_{n2}$. Then...
5. Let S_1, \dots, S_K denote a partition of the space of regressors, so that for each n , $x_n \in S_k$ for exactly one k . Let $z_{nk} = \mathbb{1}(x_n \in S_k)$, and consider regressing $y \sim \beta_1 z_{n1} + \dots + \beta_K z_{nK}$, without a constant. Assume that each S_k has at least one observation in it. Then, conditionally on the regressors...

Quiz 2

For the multiple choice questions, recall our four classes of assumptions:

- (A) The normal assumption: $y_n|x_n \sim \mathcal{N}(\beta^{*\top} x_n, \sigma^2)$.
- (B) The homoskedastic assumption: $\varepsilon_n = y_n - \beta^{*\top} x_n$, with $\mathbb{E}[\varepsilon_n|x_n] = 0$, and $\text{Var}(\varepsilon_n|x_n) = \sigma^2$.
- (C) The heteroskedastic assumption: Like (B), but $\text{Var}(\varepsilon_n|x_n) = \sigma_n^2$, where σ_n is some function of x_n that is different for different x_n .
- (D) The machine learning assumption: (x_n, y_n) are IID.

In each assumption assume that the pairs (x_n, y_n) are IID and that X is full-rank, and that all necessary conditions hold for the application of the CLT and LLN as in the lecture notes.

Recall that $\hat{\sigma}^2 = \frac{1}{N-P} \sum_{n=1}^N (y_n - \hat{\beta}^\top x_n)^2$.

1. Under the normal assumption (A), under the null, the standard t-statistic based on $\hat{\sigma}$...
2. Under the homoskedastic assumption (B), under the null, the standard t-statistic based on $\hat{\sigma}$...
3. Under the heteroskedastic assumption (C), under the null, the standard t-statistic based on the sandwich covariance...
4. Under the heteroskedastic assumption (C), inference that is incorrectly based on the homoskedastic assumption (B) will, in general...
5. Let $\beta^* := \mathbb{E}[x x^\top]^{-1} \mathbb{E}[x y]$. Under the machine learning assumption (D),

Quiz 3

1. In a machine learning problem with ridge regression, it is typically best practice to select the ridge parameter using...
2. When running ridge regression, as you *decrease* the ridge penalty parameter...
3. For machine learning, a good reason to use a highly expressive spline basis is...
4. For machine learning, you don't want your spine basis to be too expressive because...
5. In Bayesian analysis, the ridge parameter corresponds to...