ASSIGNMENT 7 REPORT
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Part 3:

In case of L2 regularization,

- If λ = 0, the solution is same as in regular
least-squares
linear regression
- If$\lambda \rightarrow \infty$,thesolution w$\rightarrow$0
- Positive λ will cause the magnitude of the weights to be
smaller than in the usual linear regression.

In case of L1 regularization,
λ might help in reducing some of the unnecessary weights to 0, instead of a finite value, which is not the case in L2 regularization. L2 regularization does not lead to weights becoming 0, unless $\lambda \rightarrow \infty$.

Part 4:

In the case of ML, both ridge regression and Lasso find their respective advantages. Ridge regression does not completely eliminate (bring to zero) the coefficients in the model whereas lasso does this along with automatic variable selection for the model. This is where it gains the upper hand. While this is preferable, it should be noted that the assumptions considered in linear regression might differ sometimes.

Both these techniques tackle overfitting, which is generally present in a realistic statistical model. It all depends on the computing power and data available to perform these techniques on a statistical software. Ridge regression is faster compared to lasso but then again lasso has the advantage of completely reducing unnecessary parameters in the model.

The Lasso Regularization works with the absolute values of the magnitudes of the weights, whereas the Ridge Regularization works with the squares of the magnitudes of the weights.