

<b>Code</b>	RIDGE_LASSO_REGRESSION.PY
<b>Author</b>	Nathaniel Heatwole, PhD ( <a href="mailto:heatwolen@gmail.com">heatwolen@gmail.com</a> ) ( <a href="#">GitHub</a> ) ( <a href="#">LinkedIn</a> )
<b>Summary</b>	Uses ridge, lasso, and elastic net regression to predict body mass index (BMI) <sup>1</sup> using weight, height, and age. <sup>2</sup> Selects hyperparameters using built-in cross-validation.
<b>Methods/ process</b>	<p><a href="#">Ridge</a> / <a href="#">lasso</a> / <a href="#">elastic net</a> regression:</p> <ul style="list-style-type: none"> <li>- Extends concepts of linear regression to the case where there are significant correlations among the predictor variables (<a href="#">multicollinearity</a>).</li> <li>- Avoids tendency of simple linear regression to overfit when multicollinearity exists, improving predictions for out-of-sample test cases.</li> <li>- Adds an additional term (penalty) to the typical least-squares regression: <ul style="list-style-type: none"> <li>- <i>Ridge</i>: sum of <i>squares</i> of the regression coefficients.</li> <li>- <i>Lasso</i>: sum of <i>absolute values</i> of the regression coefficients.</li> <li>- <i>Hyperparameter</i> (<math>\alpha</math>): multiplied onto the term in either case, controlling its influence in the optimization (<math>\alpha = 0</math> is simple linear regression).</li> </ul> </li> <li>- <i>Elastic net</i>: combines ridge and lasso, using a weighted average, introducing an additional hyperparameter, controlling the lasso weight (versus ridge).</li> <li>- Ridge shrinks all coefficients proportionally, whereas lasso does not. As such, lasso can perform variable selection (i.e., by zeroing out some coefficients).</li> <li>- Continuous features (both X and Y) must be transformed (e.g., <a href="#">z-scores</a>) to prevent some variables from have undue influence in the regression.</li> <li>- Intercept term generally unneeded, because of what these regressions optimize.</li> <li>- Model fit typically assessed the same as in ordinary linear regression.<sup>3</sup></li> </ul> <p>Steps:</p> <ol style="list-style-type: none"> <li>1. Import and clean training data (including z-scores).</li> <li>2. Apply all three regression types (ridge, lasso, elastic net).</li> </ol>
<b>Training data</b>	<a href="#">BMI data</a> – empirical health-related data for 741 persons (from Kaggle).
<b>Output</b>	<p>Plot</p> <ul style="list-style-type: none"> <li>- Training data scatter matrix (univariate distributions, 2D relationships)</li> </ul> <p>Summary</p> <ul style="list-style-type: none"> <li>- Training data stats</li> <li>- Regression coefficients</li> <li>- Regression summary</li> </ul>
<b>Result</b>	All regressions are highly accurate (adj. $R^2 = 0.97$ ). The coefficients signs for weight and height are as expected (i.e., BMI increasing in weight and decreasing in height). However, the hyperparameters for lasso and elastic net are minimal ( $\alpha = 0.01$ ).

<sup>1</sup> BMI is a height-normalized measure of weight. It is defined as: weight / height<sup>2</sup>.

<sup>2</sup> These predictors are expected to be correlated, and so ridge/lasso regression is appropriate.

<sup>3</sup> For example:  $R^2$ , adjusted  $R^2$ , AIC, BIC, log-likelihood, MSE.