

<b>Code</b>	<b>SUPPORT_VECTOR_MACHINE.PY</b>
<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 linear support vector machine (SVM) to separate two groups of data, both from scratch and using sklearn, and also fits quadratic and cubic SVMs (using sklearn)
<b>Methods/ Process</b>	<p><a href="#">Support vector machine</a></p> <ul style="list-style-type: none"> <li>- Supervised learning method for generating boundary between groups of data</li> <li>- Classification threshold (hyperplane) can be linear or non-linear</li> <li>- <i>Support vectors</i> are the <i>margin</i> boundaries, and have the same functional form and slope as and are equidistant about the boundary vector</li> <li>- Optimization: <ul style="list-style-type: none"> <li>- <i>Hard margin</i>: no points permitted in region between support vectors (“demilitarized zone,” so to speak), and margin width maximized</li> <li>- <i>Soft margin</i>: number of points inside margin and/or their distance inside is minimized (for overlapping groups)</li> </ul> </li> </ul> <p>Steps (from scratch)</p> <ol style="list-style-type: none"> <li>1. Randomly select point from each group in the training data</li> <li>2. Take negative inverse of slope of line connecting those points – this new vector is orthogonal to line connecting the points, and is therefore an efficient initial guess for the SVM slope<sup>1</sup></li> <li>3. Fit line with this slope through each point in training data</li> <li>4. Identify support vectors, using group-level extremities of y-intercepts (from previous step), and considering the relative orientation of the groups</li> <li>5. Compute the margin (distance) between the two support vectors</li> <li>6. Optimize slope value (from step #2) to find local maximum margin width, using parametric variation (fixed number of iterations)</li> <li>7. Repeat this entire process for many different sets of randomly selected points</li> <li>8. Choose the SVM parameter set that yields the best separation (global maximum margin)</li> </ol>
<b>Training Data</b>	Synthetic data (randomly generated) consisting of two linearly separable groups
<b>Results</b>	Two methods align well (from scratch and using sklearn)

---

<sup>1</sup> This is because, rather than *connecting* the data, as linear fits do, SVMs best *separate* the groups.