CS 109a - Milestone #4

Alex Lin

Melissa Yu

November 28, 2016

## 1 Possible Strangeness Functions

Let Z be the set of points already examined and let  $z_n$  be a newly added point. Given a point  $z_i \in Z \cup \{z_n\}$ , we wish to calculate its strangeness  $\alpha_i$ . There are a wide variety of strangeness functions that we can consider, each with its own pros and cons. In particular, any classification method can be used in our strangeness calculations. We give a few examples here:

## 1.1 Nearest-Neighbors

This is the most widely used method, as it is found in two out of the three papers. Let  $z_i = (x_i, y_i)$  for all i, where  $x_i$  represents the features and  $y_i$  represents the class of point i. (Note that for us,  $y_i$  will be the stock symbol of the data). The Nearest Neighbors strangeness function is presented as

$$\alpha_i = \frac{\min_{j \neq i: y_j = y_i} d(x_i, x_j)}{\min_{j \neq i: y_j \neq y_i} d(x_i, x_j)}$$

It is a ratio of the distance to the closest in-class point over the distance to the closest out-of-class point. Thus, high strangeness values will involve a point  $x_i$  being farther from points in its own class relative to points in other classes.

## 1.2 Support Vector Machines

This method is found in the final of the three papers. Given a series of points  $(x_1, y_1) \dots (x_n, y_n)$ , we use SVM to draw a separating hyperplane between the class  $y_i$  of the point i in question and all other classes. Then, we define  $\alpha_i$  as simply the distance between  $x_i$  and the separating hyperplane. Again, high strangeness values will involve a point  $x_i$  being far from the hyperplane.

Other possibilities include logistic regression and decision trees. However, the methods by which we can compute strangeness values are not clear for these cases.