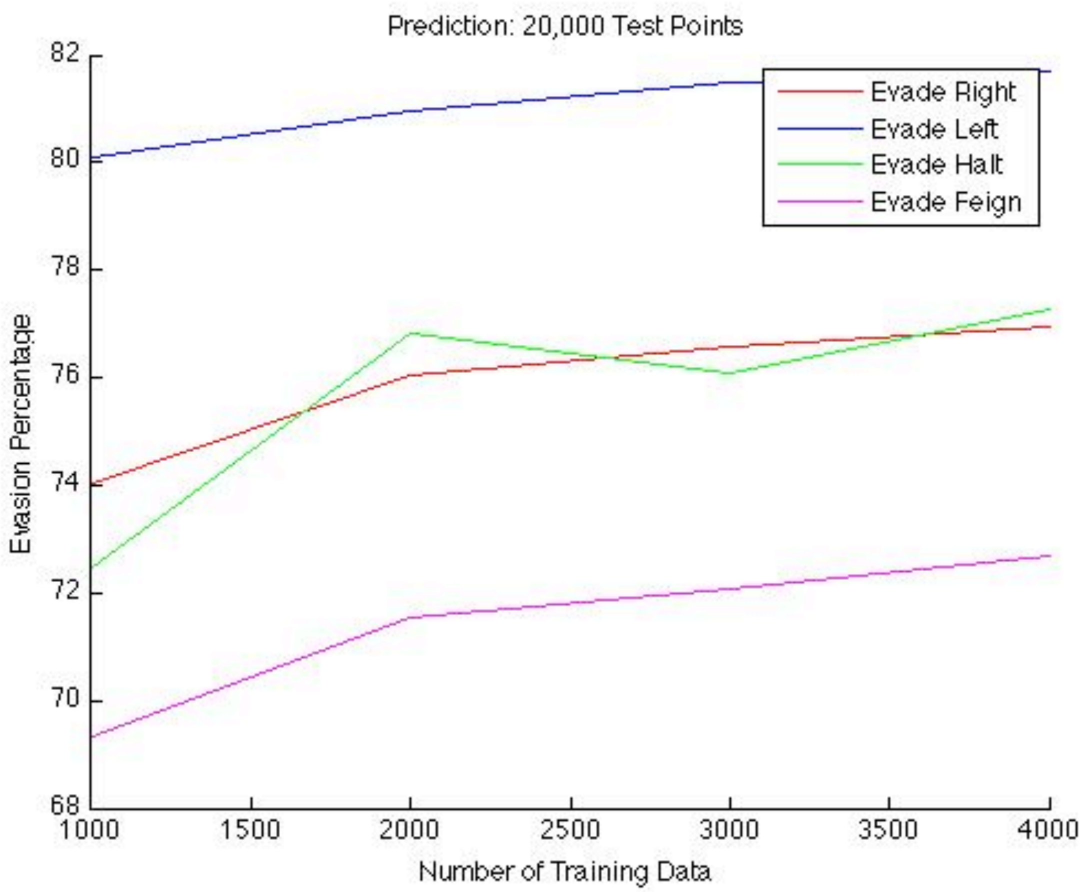
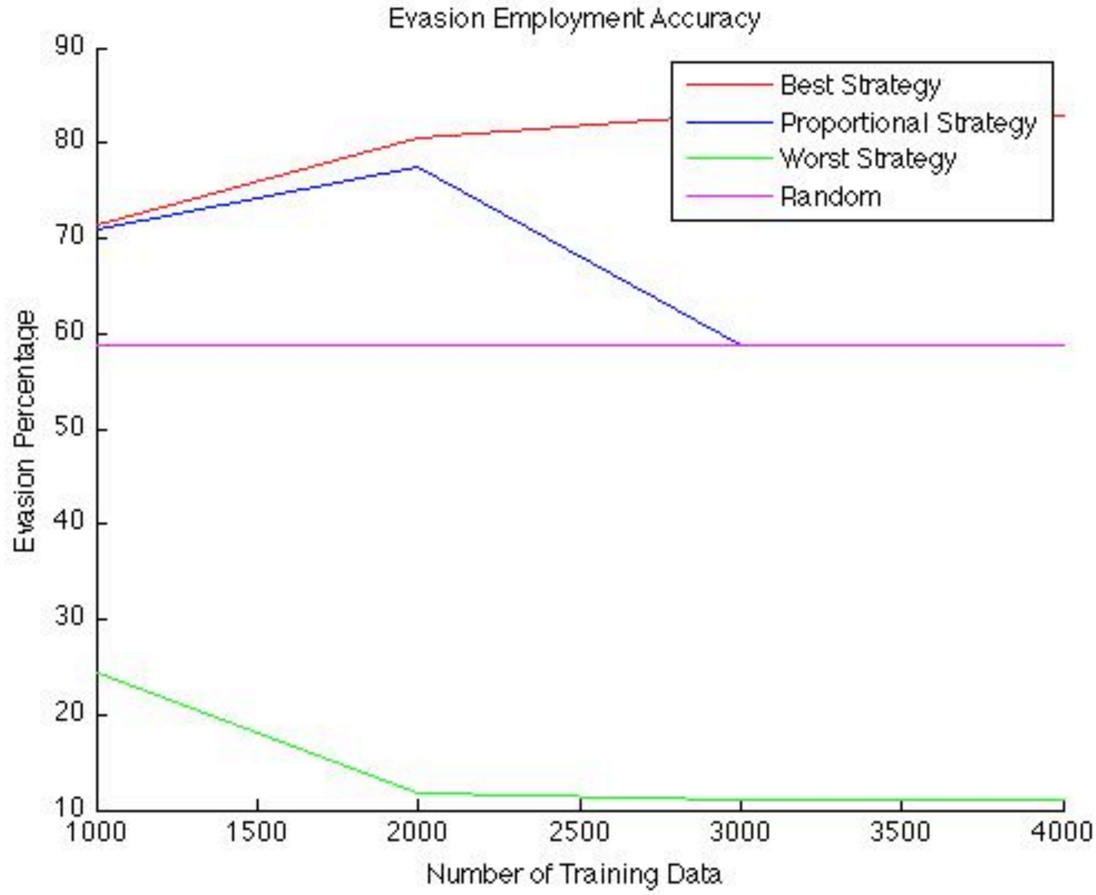
Evasion Strategy Results Explained

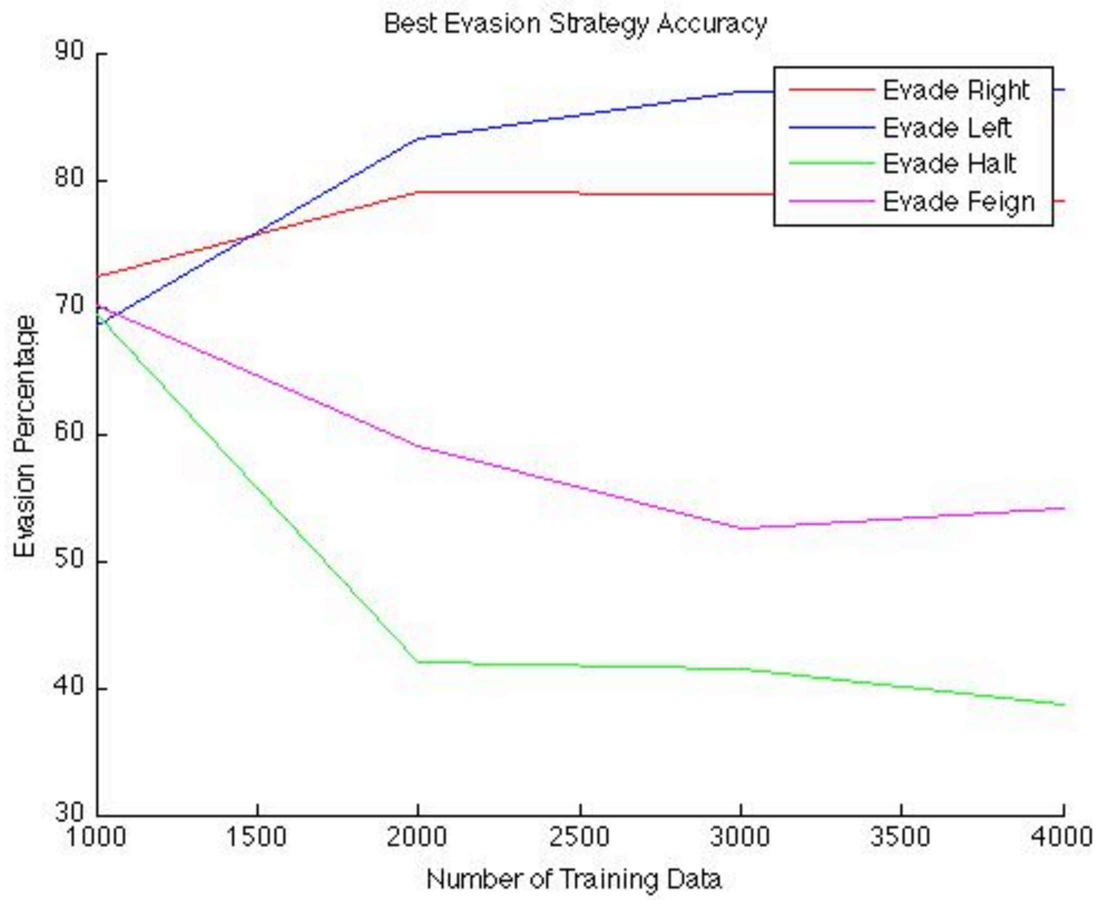
Using the four evasion strategies (evade left, right, halt, and feign), SVM models were trained using an RBF kernel with a 5-fold cross validation grid search to optimize the hyper-parameters (slack penalty and kernel bandwidth). Four different training datasets varying in size (1,000, 2,000, 3,000, and 4,000 training points per each evasion strategy) were collected and used to train the models, leading to a total of 16 SVMs. Training data was collected using 10 different enemy agents. A test data set, comprised of 20,000 data points per each evasion strategy, was used to test the SVMs for accuracy:



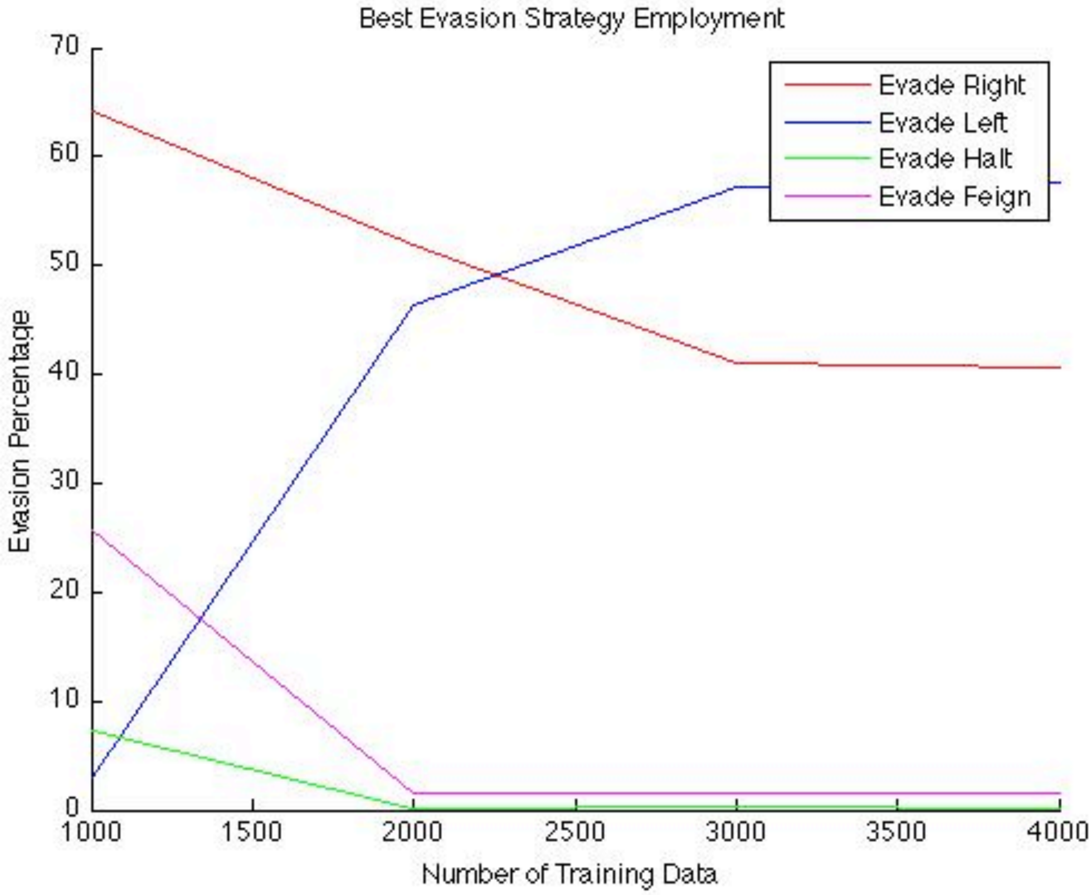
As the chart indicates, as the number of training data points increases, so does the accuracy of the individual SVMs. However, this increase tends to increase less gradually as the number of training data points increases. However, what we are truly interested in is the accuracy based on the employment of the predictions during battles. Using probability SVM models, three different employment agents were designed: one to employ the best evasion strategy, one to employ a proportionally randomly drawn evasion, and one to employ the worst evasion strategy, all according to the probability estimates provided by the SVMs. Each of these agents were then tested against the different opponents for 10,000 battles:



In the chart above, the ‘Random’ strategy is simply choosing a random strategy to employ each time the agent is fired upon, and the evasion percentage serves as a baseline from which the other employment agents can be compared. As expected, choosing the best evasion strategy according to the SVM probability estimates leads to the greatest evasion percentage, whereas choosing the worst evasion strategy leads to the worst evasion percentage. Furthermore, choosing the evasion strategy proportionally to the probability estimates leads to worse behavior as the number of training examples increase. For all strategies, as the number of training examples increase, the performance begins to approach an asymptotic evasion percentage, suggesting that employment performance does not change as training examples increase after a given point. This is to be expected due to the nature that each enemy agent will ultimately target their opponent in a different manner, thus leading to models not being capable of capturing every form of targeting. However, as the chart shows, employing the best strategy according to SVM probability estimates outperforms randomly choosing a strategy, and thus it is clear that general targeting learning has occurred. To understand exactly what has been learned by our SVMs, we will look closer into the employment of each individual evasion strategy based on the number of training examples when using the best strategy at each instance:



Using the best evasion strategy, we find that as the number of training data increase, evading via halting or feigning seems to decrease in evasion accuracy, while evading via movement to the left or right seems to increase. This is somewhat concerning, as we saw earlier that employing the best strategy leads to an asymptotically increasing evasion accuracy that lead to a 20% evasion percentage increase compared to randomly employing the strategies. However, if we turn our attention to the percentages of employment with respect to each strategy, we find that as the training examples increase, evading left and right are used a majority of the time. Thus, we see that the SVMs are learning that there are more situations in which evading by movement to the left / right is likely to be successful compared to evading by halting or feigning:



By visual inspection, we have found that evading left / right is typically employed in a manner as to avoid pushing the agent towards a wall. If there is a wall directly towards the evade left direction, the agent will typically choose to evade to the right, and vice versa. Similarly, feign is typically employed when the agent gets caught in a corner, which is a position which occurs infrequently (thus the low employment percentage of the strategy) and often yields to being his by the bullet (thus the low evasion accuracy when feign is employed). Lastly, we typically only see halt employed when the agent is far away and a lot of movement in occurring between both agents. Typical this strategy fails, and luckily is not used often. However, when other agents attempt to fire where they estimate we will be given our current heading, speed, and distance away from them, this strategy is effective.