ALGORITHMS:

MODEL EVALUATION:

We worked on two separate models: the first using a Deep Q Learning model with a Reinforcement learning policy and the second using a simple Machine Learning Markov model.

**Brief Evaluation of Markov model:**

The learning rate for the Markov model was pretty good, it takes about 15 tries for a brand-new model to start achieving a score of over 100 on an average. The highest score which our re-enforcement learning model achieved with the Markov model was about 800 which is relatively way better than most humans can perform in this game. The model worked very well when it came to spaced out obstacles, but it had a huge issue in certain situations when the obstacles were close by and performed worst in those scenarios.

Due to technical difficulties, we were unable properly include crouching into our model, which would have gone a long way to enhance the performance of our model. The result though was that our model performed very badly when it came to situations where it couldn’t jump over the birds. Lucky for us, those situations are very rare in the dino game itself, so our model was able to perform well even with that limitation.

**Brief Evaluation of Deep Q Learning model:**

The learning rate for the Deep Q Learning model was a lot slower, taking more than 2 million steps in order to get any kind of intelligent action from our dino. Even in our best model, the dino often hits the first obstacle, but can manage to jump over several obstacles consecutively on occasion, making it to a score of around 350 as a maximum. This version of the game allows us to crouch, which is more preferrable for our use.

**Justification of model choice:**

The Q Learning model uses a neural network, so it is more flexible and applicable in more situations, and with more practice, it has the potential to play the game better. Also, the Q Learning model is more interesting to us. For that reason, we will emphasize this model going forward.