566 A Proofs

567 Proof of Theorem 2:

Proof. $g(\{\emptyset, c_1, c_2\}) = c_1 \ge 1 \land c_2 \ge 1$ is the target function. Using \emptyset_p to represent the background poison signal and \emptyset_B to represent the indiscriminate background noise, The training distribution contains negative samples (y = -1) of the form $\{\emptyset_p = 1, \emptyset_B \ge 1, c_1 = 1\}$ and $\{\emptyset_p = 1, \emptyset_B \ge 1, c_2 = 1\}$, and positive samples (y = 1) of the form $\{\emptyset_B \ge 1, c_1 = 1, c_2 = 1\}$.

By exhaustive enumeration, only two possible logic rules can distinguish the positive and negative bags. Either the (MIL) rule $c_1 \ge 1 \land c_2 \ge 1$, and the non-MIL rule $\emptyset_p = 0$. However, a MIL model cannot legally learn to use \emptyset_p because it occurs only in negative bags.

By changing the test distribution to evaluate the sample $\emptyset_B = 1, c_1 = 1, c_2 = 1$ and observing the model produce the negative label y = -1, the only possible conclusion is it has learned the non-MIL hypothesis.

578 Proof of Theorem 3:

Proof. $g(\{\emptyset, c_1, c_2\}) = c_1 \ge 1 \land c_2 \ge 1$ is the target function. Using \emptyset_B to represent the indiscriminate background noise, The training distribution contains negative samples (y = -1) of the form $\{\emptyset_B \in [1, 10], c_1 \in [1, 2]\}$ and $\{\emptyset_B \in [1, 10], c_2 \in [1, 2]\}$, and positive samples (y = 1) of the form $\{\emptyset_B \in [1, 10], c_1 \in [1, 2], c_2 \in [1, 2]\}$.

By exhaustive enumeration, only two possible logic rules can distinguish the positive and negative bags: $c_1 \ge 1 \land c_2 \ge 1$. However, there is a naive MIL rule that can obtain non-random, but not perfect accuracy, $c_1 + c_2 \ge 3$.

By changing the test distribution to evaluate the samples $\emptyset_B = 1, c_1 \ge 35$ and $\emptyset_B = 1, c_2 \ge 35$ and observing the model produce the positive label y = 1, the only possible conclusion is it has learned the non-threshold MIL hypothesis.

589