In the paper, Exponentiated Gradient Exploration for Active Learning by Djaner Bouneffouf 2015 as attached, an exponential gradient (EG)-active random exploration strategy that can improve the active learning performance is proposed. Read the paper, and answer the questions in no more than 100 words each.

a) What is the role of ∈ -active algorithm 1?
(e. g. the functional purpose of this algorithm)

To achieve random exploration, in algorithm 1 the author uses random() instead of active learning() when q exceeds \in for a given \in , and use this to calculate reward, thus enhancing exploration.

b) The equation (2) the reward formula $\{\cos^{-1}(d(h1|h2) \text{ should be } \cos^{-1}(d(h1,h2) \text{ and } d(h,h') \in [1,1] \text{ should be } d(h,h') \in [-1,1] \}$. Explain the role of the reward used in random exploration of selecting unlabeled samples. If cosine similarity score between two hypotheses is high, then the reward is low, otherwise the reward is high. Why?

The reward indicates the preference to select a sample, and what we want is to select sample of which hypotheses are very different. Therefore, if the cosine similarity is higher, it means that the two hypotheses is more similar, which makes us less likely to select this sample.

c) In algorithm 2 EG-active the last step formula updating the sampling probability p_k , there is some confusion, it cannot guarantee the value is between 0 and 1, Please revise it as you wish to make it a probability and also suitable normalize update for weights.

[Note the k in (1-k) should not be the same as the k in k/T because otherwise it will be negative value when k>1]

I think we can change it to

$$p_k = \left(\frac{1}{k+1}\right) \left(\frac{w_k}{\sum_{j=1}^T w_j} + \frac{k}{T}\right) \qquad k = 1, \dots, T$$

Since $0 < \frac{w_k}{\sum_{j=1}^T w_j} < 1$, $0 < \frac{k}{T} \le 1$ and $0 < \frac{1}{k+1} \le \frac{1}{2}$, the modified p_k is guaranteed between 0 and 1.