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 $\in -active\ algorithm$ 1? ($e.g. the\ functional\ purpose\ of\ this\ algorithm$)

To improve the results of any active learning algorithm, the author proposes to overlap any existing algorithm by ε-acitve algorithm, which considers a random exploration ε at each iteration. Moreover, in ε-acitve algorithm, Activelearning can be any existing active learning algorithm.

Algorithm 1 ϵ-active

Input: X, ϵ

Output: x_t, r_t

$$x_t = \begin{cases} Activelearning(X) & if(q < \epsilon) \\ Random(X) & if(q \geq \epsilon) \end{cases}$$

if x was not queried in the past **then** Query O for label y of x

Observe reward r_t

ε-acitve algorithm

b) The equation (2) the reward formula {$\cos^{-1}$(d(h1|h2) should be $\cos^{-1}$(d(h1, h2) and d(h, h') $\in [1,1]$ $should\ be$ 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?

According to the variation between the hypotheses learned by the mode, If the variation is huge, then the reward will be high, otherwise, the reward will be low. This is because we want the exploration to be effective in random exploration. If the variation is low, there may be overlapping in the exploration. To avoid this situation, the reward will be low. On the other hand, if the variation is high, it means the model has explored different areas, which will increase the model's efficiency.

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]

Add another step at last: $\mathrm{p_k} \ <= \ \mathrm{p_k} / \sum_{\mathrm{i}=1}^{T} \mathrm{p_i}$
By doing this, the new $\mathrm{p_k}$ will be in the range of 0 and 1, which can be considered as probability and a suitable normalized update for weights.