

Loss function

- ▶ Hemming loss:

$$\frac{1}{L} \sum_{i \in [1, 2, \dots, L]} (\hat{y}_i \text{ xor } y_i)$$

- ▶ exact loss

0 if $\hat{y} = y$ else 1

- ▶ trade off

$$\sum_{i \in \hat{Y}} [1 - a - y_i]$$

Algorithm

We can consider each "superarm" of the label powerset as a separate class and then from there we can apply multiclass method. Let k be the cardinality of the labelset

for $i = 1, 2, \dots, T$:

1) input x

2) calculate $\hat{y} = \operatorname{argmax}(W^T x)$

3) calculate $p_r = (1 - \gamma)|r = \hat{y}| + \frac{\gamma}{k}$

4) predict \tilde{y} according to the distribution p and receive $\tilde{y} \cap Y$

5) update w according to $w = w - \nabla L$ where L is the loss

Random k dataset for multilabel classification

Let L be the set of labels of size M , training set be D and labelset size be k . Define $m = \lceil M/k \rceil$.

Randomly Partition L into m disjoint labelsets (R_j) of size k . Next make training sets $D_j, j \in 1, 2, \dots, m$ such that for every example x_i in D , their annotation will be $Y_i \cap R_j$.

After this we train m different classifiers on D_j s. When we predict for the examples in test set we output the union of the predictions of m different classifiers

Idea to incorporate RAKEI for our bandit algorithm

Same as for the previous case we will be making m different classifiers. When an example x is input, we will take the union of the different classifiers and then predict that. When we get the feedback $\tilde{y} \cap Y$, we will consider $\tilde{y} \cap Y \cap R_j$ for updating the weights for each classifier.