DISCRIMINATIVE PROBABILISTIC FRAMEWORK FOR GENERALIZED MULTI-INSTANCE LEARNING

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①. Compute α . Recall that $\alpha_i(k) \triangleq p(n_{bi} = k | \mathbf{X}_b, \mathbf{w}')$. Consequently, $\alpha_{i+1}(k)$ can be computed by marginalizing $p(n_{b(i+1)} = k, n_{bi} = l, y_{b(i+1)} = c | \mathbf{X}_b, \mathbf{w}')$ over $y_{b(i+1)}$ and n_{bi} as follows

$$\alpha_{i+1}(k) = p(n_{b(i+1)} = k | \mathbf{X}_b, \mathbf{w}')$$

$$= \sum_{l=0}^{n_b} \sum_{s=0}^{1} p(n_{b(i+1)} = k, n_{bi} = l, y_{b(i+1)} = c | \mathbf{X}_b, \mathbf{w}')$$

Using conditional rule and the independent assumption among instance labels we obtain

$$\alpha_{i+1}(k) = \sum_{l=0}^{n_b} \sum_{c=0}^{1} p(n_{b(i+1)} = k | n_{bi} = l, y_{b(i+1)} = c)$$
$$p(n_{bi} = l | \mathbf{X}_b, \mathbf{w}') p(y_{b(i+1)} = c | \mathbf{x}_{b(i+1)}, \mathbf{w}')$$

Replace $p(n_{b(i+1)} = k | n_{bi} = l, y_{b(i+1)} = c) = \mathbb{I}[k = l+c]$ we obtain the result for $\alpha_{i+1}(k)$ as follows

$$\alpha_{i+1}(k) = p(y_{b(i+1)} = 1 | \mathbf{x}_{b(i+1)}, \mathbf{w}') \alpha_i(k-1) + p(y_{b(i+1)} = 0 | \mathbf{x}_{b(i+1)}, \mathbf{w}') \alpha_i(k).$$
(1)

The intuition behind above equation is that: there are two cases that there are k positive instances in the first (i+1) instances. First, the (i+1)th instance is positive and there are k-1 positive instances in the first i instances. Second, the (i+1)th instance is negative and there are k positive instances in the first i instances.

(2). Compute β . Recall that $\beta_i(k) \triangleq p(Y_b|n_{bi} = k, \mathbf{X}_b, \mathbf{w}')$. Consequently, $\beta_i(k)$ can be computed by marginalizing $p(Y_b|n_{bi} = k, \mathbf{X}_b, \mathbf{w}')$ over $y_{b(i+1)}$ and $n_{b(i+1)}$ as follows

$$\beta_i(k) = p(Y_b|n_{bi} = k, \mathbf{X}_b, \mathbf{w}')$$

$$= \sum_{l=0}^{n_b} \sum_{c=0}^{1} p(Y_b, n_{b(i+1)} = l, y_{b(i+1)} = c|n_{bi} = k, \mathbf{X}_b, \mathbf{w}')$$

Using conditional rule and the independent assumption among instance labels we obtain

$$\beta_i(k) = \sum_{l=0}^{n_b} \sum_{c=0}^{1} p(Y_b | n_{b(i+1)} = l, \mathbf{X}_b, \mathbf{w}')$$

$$p(n_{b(i+1)} = l | y_{b(i+1)} = c, n_{bi} = k) p(y_{b(i+1)} = c | \mathbf{x}_{b(i+1)}, \mathbf{w}')$$

Replace $p(n_{b(i+1)} = l | y_{b(i+1)} = c, n_{bi} = k) = 1$ if l = k + c we obtain the result for $\beta_i(k)$ as follows

$$\beta_{i}(k) = p(y_{b(i+1)} = 1 | \mathbf{x}_{b(i+1)}, \mathbf{w}') \beta_{i+1}(k+1)$$

$$+ p(y_{b(i+1)} = 0 | \mathbf{x}_{b(i+1)}, \mathbf{w}') \beta_{i+1}(k).$$
 (2)

③. Compute $p(y_{bi} = 1|Y_b, \mathbf{X}_b, \mathbf{w}', \mathbf{v}')$. Using conditional probability we obtain

$$p(y_{bi} = 1|Y_b, \mathbf{X}_b, \mathbf{w}', \mathbf{v}')$$

$$= \frac{p(y_{bi} = 1, Y_b|\mathbf{X}_b, \mathbf{w}', \mathbf{v}')}{p(y_{bi} = 0, Y_b|\mathbf{X}_b, \mathbf{w}', \mathbf{v}') + p(y_{bi} = 1, Y_b|\mathbf{X}_b, \mathbf{w}', \mathbf{v}')}.$$
(3)

First, we obtain $p(y_{bi}=1,Y_b|\mathbf{X}_b,\mathbf{w}',\mathbf{v}')$ by marginalizing over n_{bi} and $n_{b(i-1)}$ as follows

$$p(y_{bi} = 1, Y_b | \mathbf{X}_b, \mathbf{w}', \mathbf{v}') = \sum_{l=0}^{n_b} \sum_{k=0}^{n_b} p(y_{bi} = 1, Y_b, n_{bi} = l, n_{b(i-1)} = k | \mathbf{X}_b, \mathbf{w}', \mathbf{v}').$$

Using the conditional rule and the independent assumption among instance labels we obtain

$$p(y_{bi} = 1, Y_b | \mathbf{X}_b, \mathbf{w}', \mathbf{v}') = \sum_{l=0}^{n_b} \sum_{k=0}^{n_b} p(Y_b | n_{bi} = l, \mathbf{X}_b, \mathbf{w}') p(n_{bi} = l | n_{b(i-1)} = k, y_{bi} = 1)$$

$$p(n_{b(i-1)} = k | \mathbf{X}_b, \mathbf{w}') p(y_{bi} = 1 | \mathbf{x}_{bi}, \mathbf{w}').$$

Using the fact that $p(n_{bi} = l | n_{b(i-1)} = k, y_{bi} = 1) = \mathbb{I}[l = k+1]$, we obtain

$$p(y_{bi} = 1, Y_b | \mathbf{X}_b, \mathbf{w}', \mathbf{v}') =$$

$$\sum_{k=0}^{n_b} p(Y_b | n_{bi} = k + 1, \mathbf{X}_b, \mathbf{w}') \times$$

$$p(n_{b(i-1)} = k | \mathbf{X}_b, \mathbf{w}') p(y_{bi} = 1 | \mathbf{x}_{bi}, \mathbf{w}').$$

Using the definition of α and β we obtain

$$p(y_{bi} = 1, Y_b | \mathbf{X}_b, \mathbf{w}', \mathbf{v}') = \sum_{k=0}^{n_b} \beta_i(k+1)\alpha_{i-1}(k)p(y_{bi} = 1 | \mathbf{x}_{bi}, \mathbf{w}').$$
(4)

Using similar proof technique, we obtain

$$p(y_{bi} = 0, Y_b | \mathbf{X}_b, \mathbf{w}', \mathbf{v}') =$$

$$\sum_{k=0}^{n_b} \beta_i(k) \alpha_{i-1}(k) p(y_{bi} = 0 | \mathbf{x}_{bi}, \mathbf{w}').$$
(5)

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Then, we obtain the instance membership probability $p(y_{bi} = 1|Y_b, \mathbf{X}_b, \mathbf{w}', \mathbf{v}')$ as follows

$$p(y_{bi} = 1|Y_b, \mathbf{X}_b, \mathbf{w}', \mathbf{v}') = \frac{\pi_1}{\pi_1 + \pi_0}$$
 (6)

where

$$\pi_{1} = \sum_{k=0}^{n_{b}} \alpha_{i-1}(k)\beta_{i}(k+1)p(y_{bi} = 1|\mathbf{x}_{bi}, \mathbf{w}'),$$

$$\pi_{0} = \sum_{k=0}^{n_{b}} \alpha_{i-1}(k)\beta_{i}(k)p(y_{bi} = 0|\mathbf{x}_{bi}, \mathbf{w}').$$

4. Compute $p(n_{bi} = n|Y_b, \mathbf{X}_b, \mathbf{w}', \mathbf{v}')$. Using conditional probability we obtain

$$p(n_{bi} = n|Y_b, \mathbf{X}_b, \mathbf{w}', \mathbf{v}') = \frac{p(n_{bi} = n, Y_b|\mathbf{X}_b, \mathbf{w}', \mathbf{v}')}{\sum_{k=0}^{n_b} p(n_{bi} = k, Y_b|\mathbf{X}_b, \mathbf{w}', \mathbf{v}')},$$

where $p(n_{bi} = k, Y_b | \mathbf{X}_b, \mathbf{w}', \mathbf{v}')$ is computed by using the conditional rule

$$p(n_{bi} = k, Y_b | \mathbf{X}_b, \mathbf{w}', \mathbf{v}') = p(Y_b | n_{bi} = k, \mathbf{v}')$$
$$\times p(n_{bi} = k | \mathbf{X}_b, \mathbf{w}').$$

Using the definition of α and β we obtain the probability of the number of positive instances $p(n_{bi} = n|Y_b, \mathbf{X}_b, \mathbf{w}', \mathbf{v}')$ as follows

$$p(n_{bi} = n | Y_b, \mathbf{X}_b, \mathbf{w}', \mathbf{v}') = \frac{\alpha_i(n)\beta_i(n)}{\sum_{k=0}^{n_b} \alpha_i(k)\beta_i(k)}.$$
 (7)