Learning Distributed Document Representations for Multi-Label Document Categorization

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B.Tech - M.Tech Dual Degree

Thesis Defense

Electrical Engineering

IIT Kanpur

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Outline

Intoduction to Multi-Label Document Categorization

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  - Learned classifier $\mathcal{H}$ is used to assign categories to new test documents

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Example :

Documents	Sports	Music	Arts	Technology	Literature	Politics
d_1	0	0	1	0	1	0
d_2	0	1	1	0	0	1
d_3	1	0	0	1	0	1
d_4	×	×	×	×	×	×
d_5	×	×	×	×	×	×

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Using $\mathcal{T}$, D and C the learning algorithm learns a multi-label classifier $\mathcal{H}$ to estimate category label vectors, l_{d_j} ($j > n$) for the test documents.

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2. *Learning Algorithm* : Algorithm to learn the multi-label classifier $\mathcal{H}$

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- Ignores word order

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Techniques to deal with sparsity and high-dimensionality in BOW

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$$G(t) = -\sum_{i=1}^{|C|} P(c_i)\log P(c_i) + P(t)\sum_{i=1}^{|C|} P(c_i|t)\log P(c_i|t) + P(\sim t)\sum_{i=1}^{|C|} P(c_i|\sim t)\log P(c_i|\sim t) \quad (1)$$

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- Latent Semantic Indexing (LSI)

$$X = TSD^T \quad (3)$$

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  - Cannot capture semantic similarity between words

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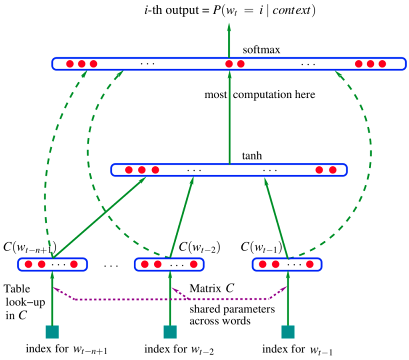

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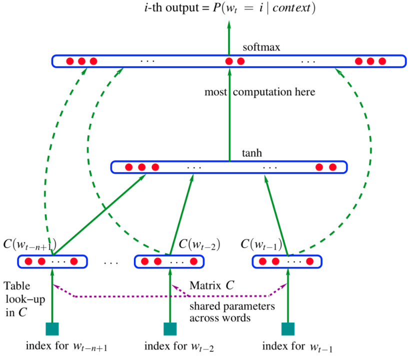

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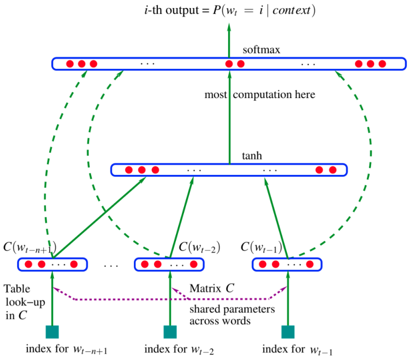

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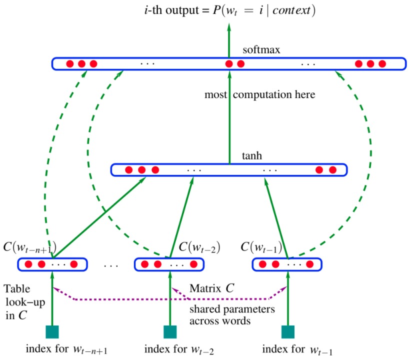

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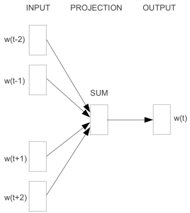

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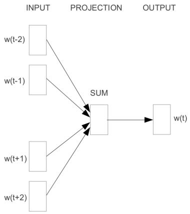

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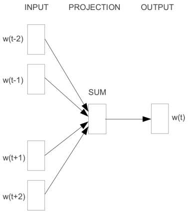

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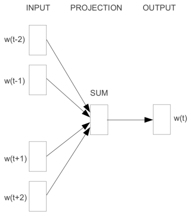

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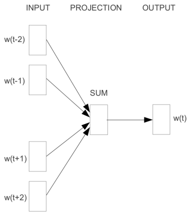

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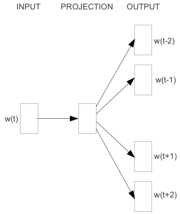

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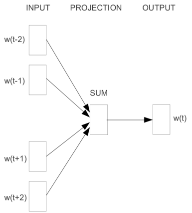

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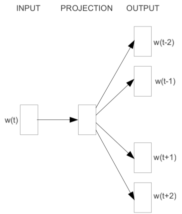

$$P(w_{t+j} | w_t) = \frac{e^{(v_{w_t} \cdot v_{w_{t+j}})}}{\sum_i e^{(v_{w_t} \cdot v_{w_i})}} \quad (10)$$

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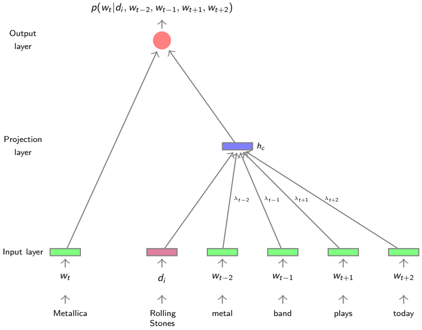

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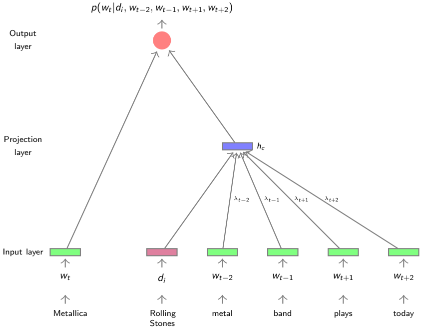
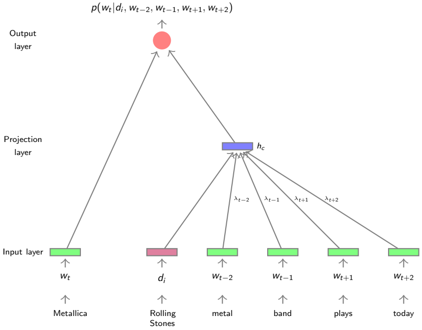


Context Representation :

$$h_c = \mathrm{v}^D_{d_i} + \lambda_{t-c}\mathrm{v}^W_{w_{t-c}} + \ldots + \lambda_{t-1}\mathrm{v}^W_{w_{t-1}} + \lambda_{t+1}\mathrm{v}^W_{w_{t+1}} + \ldots + \lambda_{t+c}\mathrm{v}^W_{w_{t+c}} \quad (11)$$



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Probability Estimation :

$$s_{w_i} = \sigma(\mathrm{v}^W_{w_i} \cdot h_c), \quad \sigma(x) = \frac{1}{1+e^{-x}} \tag{12}$$

$$p(w_t|d_i, w_{t-c}, \ldots, w_{t-1}, w_{t+1}, \ldots, w_{t+c}) = \frac{e^{s_{w_t}}}{\sum_{i \in V} e^{s_{w_i}}} \tag{13}$$

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$$\hat{\Theta} = \arg\max_{\Theta} \; l(\mathcal{T}, \Theta) \tag{14}$$

$$l(\mathcal{T}, \Theta) = \frac{1}{M} \sum_{m=1}^{M} \log \left[p(w_t^{(m)} | d_i^{(m)}, w_{t-c}^{(m)}, \ldots, w_{t-1}^{(m)}, w_{t+1}^{(m)}, \ldots, w_{t+c}^{(m)}) \right] \tag{15}$$

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4. Use Stochastic Gradient Descent (SGD) to update parameters

$$\theta_i^{(x)} = \theta_i^{(x-1)} + \gamma \frac{\partial l(\mathcal{T}, \Theta)}{\partial \theta_i} \tag{16}$$

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