Learning Distributed Document Representations for Multi-Label Document Categorization

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B.Tech - M.Tech Dual Degree

Thesis Defense

Electrical Engineering

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Outline

1. Multi-Label Document Categorization
2. Related Work
   - Text Representations
   - Learning Algorithms
3. Distributed Word Representations
4. Learning Distributed Document Represenations
5. Document Cateogorization Algorithm
6. Results
7. Conclusion and Future Work

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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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- Information Gain

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

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- Latent Semantic Indexing (LSI)

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

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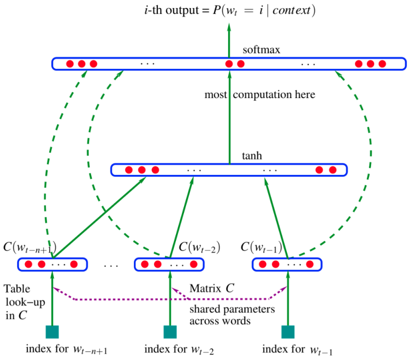

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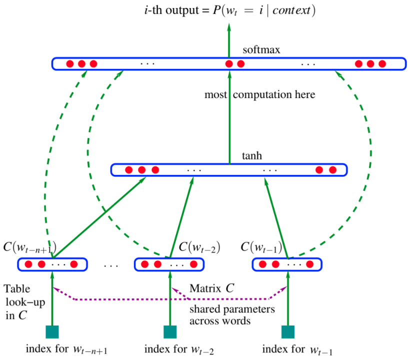

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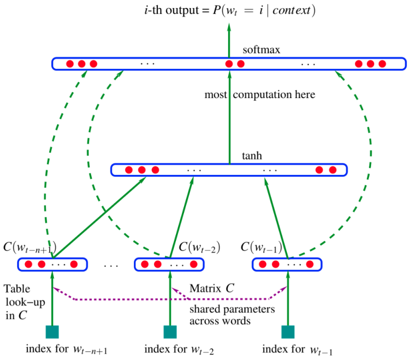

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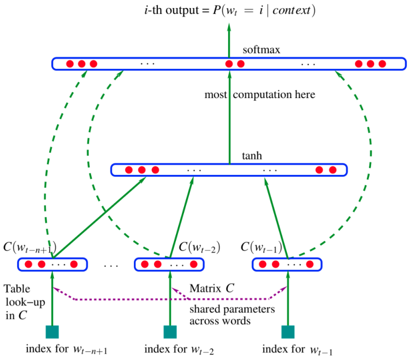

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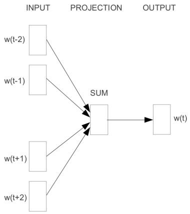

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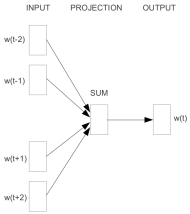

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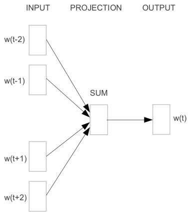

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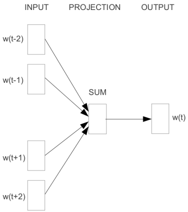

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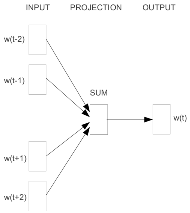

$$h = w_{t-k} + \ldots + w_{t-1} + w_{t+1} + \cdots + w_{t+k} \quad (7)$$

$$y = b + Uh, \quad y \in \mathbb{R}^{|V|} \quad (8)$$

$$P(w_t | w_{t-k}, \ldots, w_{t+k}) = \frac{e^{y_{w_t}}}{\sum_i e^{y_i}} \quad (9)$$

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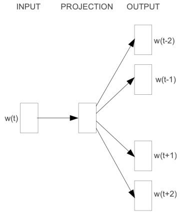

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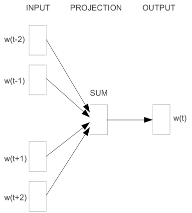

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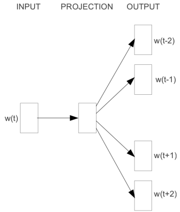

$$P(w_{t+j} | w_t) = \frac{e^{(v_{w_t} \cdot v_{w_{t+j}})}}{\sum_i e^{(v_{w_t} \cdot v_{w_i})}} \tag{10}$$

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2. Embeds document and words in the same k-dimensional space such that semantically similar entities have similar vector representations

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