Learning Distributed Document Representations for Multi-Label Document Categorization

Nitish Gupta

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IIT Kanpur

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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
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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 $\mathcal{H}$

Background on Learning Algorithms

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   - Generative Probabilistic Models

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- Ignoring word wordering

References

[1] G. Salton and C.-S. Yang. On the specification of term values in automatic indexing. *Journal of documentation*, 29(4):351–372, 1973.