Learning Distributed Document Representations for Multi-Label Document Categorization

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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 Representations
5. Document Categorization Algorithm
6. Results
7. Conclusion and Future Work

Introduction to Multi-Label Document Categorization

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Why need Multi-Label Document Categorization?

- Text Documents usually belong to more than one conceptual class.
  For E.g. an article on Music Piracy
- Wide range real-world applications :
  - Web-page tagging
  - Medical Patient Record Management
  - Wikipedia Article Management
  - Document Recommendation etc.

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Multi-label classification belongs to a general class of *supervised learning* algorithms where, given,

- A set of documents $D = \{d_1, \ldots, d_{|D|}\}$
- A set of categories $C = \{c_1, \ldots, c_{|C|}\}$
- Training data for n ($n < |D|$) documents, $\mathcal{T} = \{l_{d_1}, \ldots, l_{d_n}\}$

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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   - Each document $d_i \in D$ is represented using a vector $v_{d_i} \in \mathbb{R}^k$
   - Embedding documents in a k-dimensional space is called the *Vector Space Model*
   - The set D can be represented by a matrix $\mathrm{D} \in \mathbb{R}^{k \times |D|}$
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2. *Learning Algorithm*
   - Algorithm to learn the multi-label classifier $\mathcal{H}$

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   - k-Nearest Neighbor (k-NN)
   - Linear Least Square Fit
   - Decision Trees
   - Generative Probabilistic Models

Background on Text Representation

Bag of Words Model

- Document d_i represented by $v_{d_i} \in \mathbb{R}^{|V|}$
- Each element in v_{d_i} denotes presence/absence of each word
- Weighing techniques employed to give importance to important terms
  - Term Frequency (*tf*)
  - Inverse Document Frequency (*idf*)
  - Term Frequency - Inverse Document Frequency (*tf-idf*) : $tf \times idf$

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Drawbacks of the Bag-of-Words model

- High-dimensionality
- Sparsity
- Inability to encode word contexts
- Ignores word order
- Lack of similarity measures

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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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$$I(t,c) = \log \frac{P(t \wedge c)}{P(t) \times P(c)}, \qquad I_{avg}(t) = \sum_{i=1}^{|C|} P(c_i) I(t, c_i) \quad (2)$$

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- Latent Semantic Indexing (LSI)

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

X is the Term-Document Matrix

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Need for Distributed Word Representations

- Curse of Dimensionality
  - One-hot representations grow with the size of vocabulary
  - Parameters in language modeling grow exponentially with the size of vocabulary
- No Word Similarity Measure
  - One-hot representations are orthogonal representations
  - Cannot capture semantic similarity between words

Neural Probabilistic Language Model

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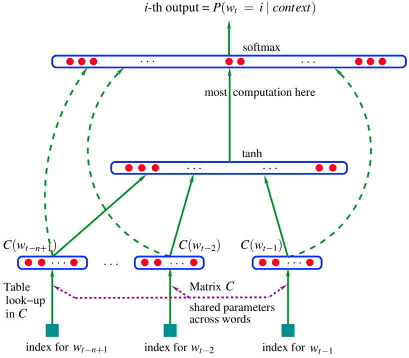

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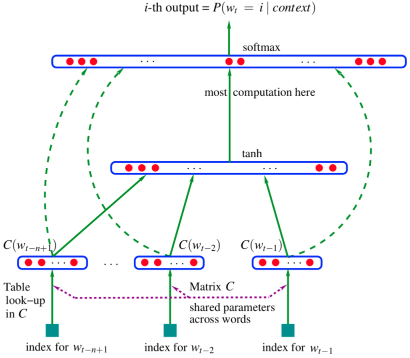

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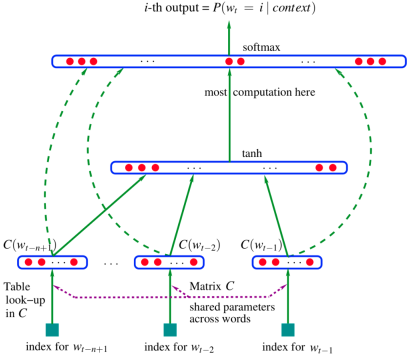

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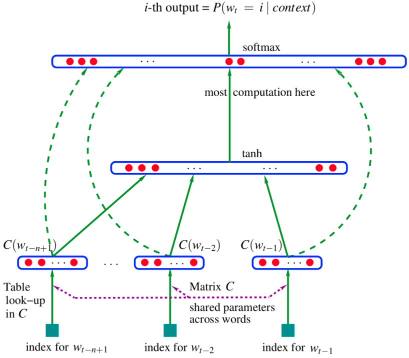

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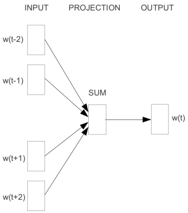

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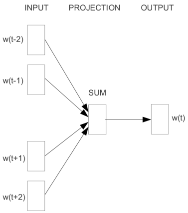

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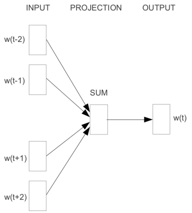

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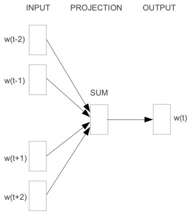

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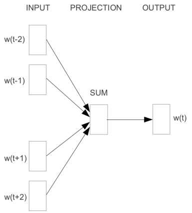

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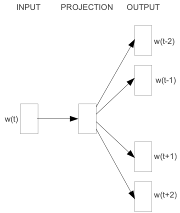

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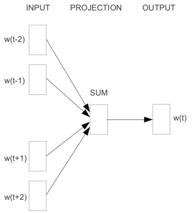

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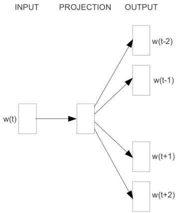

$$P(w_{t+j}|w_t) = \frac{e^{(v_{w_t} \cdot v_{w_{t+j}})}}{\sum_i e^{(v_{w_t} \cdot v_{w_i})}} \quad (10)$$

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3. Compositionality of word vectors beyond weighted average [12, 18, 17, 6, 11]
4. Recursive Tensor Neural Network (RTNN) [16] for learning sentence representations using the syntactic dependency has issues
    - Parsing, a computationally expensive step required for each sentence
    - Composing sentence vectors to represent documents is not straight-forward

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1. Learns distributed representations for document (and words) that encode the different semantic content in the documents
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4. Maximizes probability of predicting the middle word correctly to learn vectors

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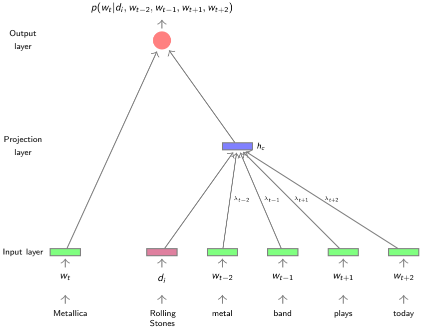

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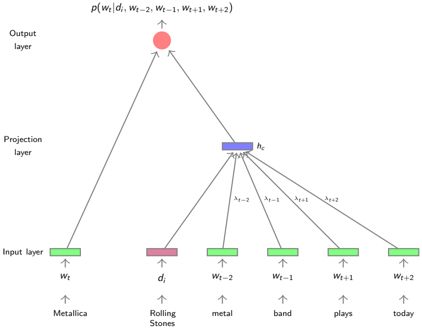

Context Representation :

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

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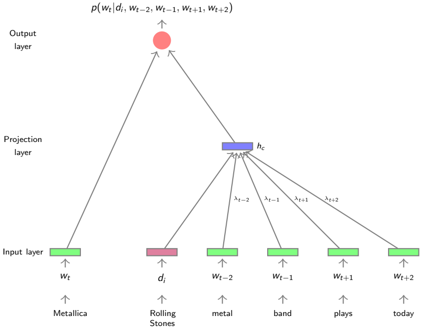

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Probability Estimation :

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

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

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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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2. Speed-ups using **Hierarchical soft-max** [15] and **Importance sampling** to approximate the likelihood gradient [3, 1]
    - Finding well-performing trees in Hierarchical soft-max is not trivial
    - Importance sampling suffers from stability issues

Noise Contrastive Estimation

1. Soft-max computation is expensive, $\mathcal{O}(V)$
2. Speed-ups using **Hierarchical soft-max** [15] and **Importance sampling** to approximate the likelihood gradient [3, 1]
   - Finding well-performing trees in Hierarchical soft-max is not trivial
   - Importance sampling suffers from stability issues
3. **Noise Contrastive Estimation** (NCE) [8] fits unnormalized probabilities
   - Reduces the problem of *probability density estimation* to *probabilistic binary classification*
   - Adaptation to NPLM [14] and learning word embeddings [13] show significant training time speed-ups

Noise Contrastive Estimation (contd.)

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1. New labeled training data : $\mathcal{T} = \{d_i^{(m)}, w_{t-c}^{(m)}, \ldots, w_{t+c}^{(m)}, Y^{(m)} = 1\}_{m=1}^{m=M}$

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   - The observed middle word w_t is replaced by a corrupt word w_x drawn from a noise distribution $P_n(w)$
   - E.g. $\{d_i, w_{t-c}, \ldots, w_{t-1}, w_x, w_{t+1}, \ldots, w_{t+c}, Y = 0\}$

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3. Complete training data : $\mathcal{T} = \{d_i^{(m)}, w_{t-c}^{(m)}, \dots, w_{t+c}^{(m)}, Y^{(m)}\}_{m=1}^{m=M+nM}$

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$$P(Y = 1 | d_i, w_{t-c}, \dots, w_{t+c}, \Theta) = \sigma(\mathrm{v}_{w_t}^{W} \cdot h_c) \tag{17}$$

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$$P(Y | d_i, w_{t-c}, \ldots, w_{t+c}, \Theta) = [\sigma(\mathrm{v}_{w_t}^{W} \cdot h_c)]^{Y} [1 - \sigma(\mathrm{v}_{w_t}^{W} \cdot h_c)]^{1-Y} \tag{19}$$

Learning Objective with NCE

Given the training data $\mathcal{T} = \{d_i^{(m)}, w_{t-c}^{(m)}, \ldots, w_{t+c}^{(m)}, Y^{(m)}\}_{m=1}^{m=M+nM}$, we maximize the log-likelihood of observing it

$P_\Theta(Y_m)$ is a shorthand notation for $P(Y_m | d_i^{(m)}, w_{t-c}^{(m)}, \ldots, w_{t+c}^{(m)}, \Theta)$
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$$\hat{\Theta} = \arg\max_{\Theta} \; l(\mathcal{T}, \Theta) \tag{20}$$

$$l(\mathcal{T}, \Theta) = \sum_{m=1}^{M+nM} \log P_{\Theta}(Y_m = Y^{(m)}) \tag{21}$$

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The logarithm of the probability estimate is given by,

$$\log P_{\Theta}(Y_m = Y^{(m)}) = Y^{(m)} \log \sigma(\mathrm{v}_{w_t^{(m)}}^{W} \cdot h_c^{(m)}) + (1 - Y^{(m)}) \log(1 - \sigma(\mathrm{v}_{w_t^{(m)}}^{W} \cdot h_c^{(m)})) \tag{22}$$

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Parameter Estimation

We use SGD to learn parameters i.e. document and word vectors and the neural network weights

$$\theta_i^{(x)} = \theta_i^{(x-1)} + \gamma \frac{\partial l(\mathcal{T}, \Theta)}{\partial \theta_i} \tag{23}$$

$d = \mathrm{v}_{w_t}^{W} \cdot h_c$, is the pre-sigmoid activation

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Update rule for Parameters

1. Document Vector :

$$(\mathrm{v}^{D}_{d_i^{(m)}})^{(i+1)} = (\mathrm{v}^{D}_{d_i^{(m)}})^{(i)} + \gamma \left[(Y^{(m)} - \sigma(\mathrm{v}^{W}_{w_t^{(m)}} \cdot h_c^{(m)}))\mathrm{v}^{W}_{w_t^{(m)}} - \beta \mathrm{v}^{D}_{d_i^{(m)}} \right] \tag{28}$$

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$$(\mathrm{v}^{W}_{w_{t+j}^{(m)}})^{(i+1)} = (\mathrm{v}^{W}_{w_{t+j}^{(m)}})^{(i)} + \gamma \left[(Y^{(m)} - \sigma(\mathrm{v}^{W}_{w_t^{(m)}} \cdot h_c^{(m)}))\lambda_{t+j}\mathrm{v}^{W}_{w_t^{(m)}} - \beta \mathrm{v}^{W}_{w_{t+j}^{(m)}} \right] \tag{30}$$

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4. Neural Network Weights :

$$\lambda_{t+j}^{(i+1)} = \lambda_{t+j}^{(i)} + \gamma \left[(Y^{(m)} - \sigma(\mathrm{v}^W_{w_t^{(m)}} \cdot h_c^{(m)}))(\mathrm{v}^W_{w_t^{(m)}} \cdot \mathrm{v}^W_{w_{t+j}^{(m)}}) - \beta \lambda_{t+j} \right] \tag{31}$$

Algorithm for learning Document Representations

1: **Input:** D, k, c, n, β, γ, $epochs$
2: **Output:** Document Vectors D, Word Vectors W

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Input: D, k, c, n, β, γ, *epochs*

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$V \leftarrow Extractfrom(D)$

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$\mathrm{W} \leftarrow random(\mathbb{R}^{k \times |V|})$

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while *epochs* ≥ 1 **do**
    for all $\{d_i, w_{t-c}, \ldots, w_{t+c}, Y\} \in \mathcal{T}$ **do**
        $h_c \leftarrow \mathrm{v}^D_{d_i} + \lambda_{t-c}\mathrm{v}^W_{w_{t-c}} + \ldots + \lambda_{t+c}\mathrm{v}^W_{w_{t+c}}$

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while $epochs \geq 1$ **do**

  for all $\{d_i, w_{t-c}, \ldots, w_{t+c}, Y\} \in \mathcal{T}$ **do**

    $h_c \leftarrow \mathrm{v}^D_{d_i} + \lambda_{t-c}\mathrm{v}^W_{w_{t-c}} + \ldots + \lambda_{t+c}\mathrm{v}^W_{w_{t+c}}$

    $\mathrm{v}^D_{d_i} \leftarrow \mathrm{v}^D_{d_i} + \gamma \left[(Y - \sigma(\mathrm{v}^W_{w_t} \cdot h_c))\mathrm{v}^W_{w_t} - \beta \mathrm{v}^D_{d_i} \right]$

    $\mathrm{v}^W_{w_t} \leftarrow \mathrm{v}^W_{w_t} + \gamma \left[(Y - \sigma(\mathrm{v}^W_{w_t} \cdot h_c))h_c - \beta \mathrm{v}^W_{w_t} \right]$

    for all $j \in \{t-c, \ldots, t-1, t+1, \ldots, t+c\}$ **do**

      $\mathrm{v}^W_{w_{t+j}} \leftarrow \mathrm{v}^W_{w_{t+j}} + \gamma \left[(Y - \sigma(\mathrm{v}^W_{w_t} \cdot h_c))\lambda_{t+j}\mathrm{v}^W_{w_t} - \beta \mathrm{v}^W_{w_{t+j}} \right]$

      $\lambda_{t+j} \leftarrow \lambda_{t+j} + \gamma \left[(Y - \sigma(\mathrm{v}^W_{w_t} \cdot h_c))(\mathrm{v}^W_{w_t} \cdot \mathrm{v}^W_{w_{t+j}}) - \beta \lambda_{t+j} \right]$

    $epochs \leftarrow epochs - 1$

return D, W

Hyper-parameters of the Model

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3. Number of Negative Samples (n)
4. Number of Epochs (*epochs*)
5. Learning Rate (γ)
6. Regularization Constant (β)

Document Categorization using Logistic Regression

Given,

1. Set of documents, $D = \{d_1, \ldots, d_{|D|}\}$

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3. Learn a probabilistic logistic classifier to assign categories

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$$\log P(y | d_i, c_j, \mathrm{D}, \mathrm{C}) = y \log \sigma(\mathrm{v}_{d_i}^{D} \cdot \mathrm{v}_{c_j}^{C}) + (1 - y) \log(1 - \sigma(\mathrm{v}_{d_i}^{D} \cdot \mathrm{v}_{c_j}^{C})) \tag{35}$$

Learning Category Embeddings

Given the training data $\mathcal{T} = \{d_i^{(m)}, c_j^{(m)}, y^{(m)}\}_{m=1}^{m=T}$, learn category embeddings $(\Theta = C)$ by maximizing log-likelihood of training data

$P_{\mathrm{D},\mathrm{C}}(y_m = y^{(m)})$ is a shorthand notation for $P(y_m = y^{(m)} | d_i, c_j, \mathrm{D}, \mathrm{C})$
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Similar to learning document embeddings, category embeddings updates are given by,

$$(\mathrm{v}^C_{c_j^{(m)}})^{(i+1)} = (\mathrm{v}^C_{c_j^{(m)}})^{(i)} + \gamma \left[(y^{(m)} - \sigma(\mathrm{v}^D_{d_i^{(m)}} \cdot \mathrm{v}^C_{c_j^{(m)}}))\mathrm{v}^D_{d_i^{(m)}} - \beta \mathrm{v}^C_{c_j^{(m)}} \right] \tag{38}$$

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Algorithm for learning Document Representations

Algorithm 1 Learning Category Vector Representations

Input: D, C, $\mathcal{T}$, k, β, γ

Output: Category Vectors C

$\mathrm{C} \leftarrow random(\mathbb{R}^{k\times|C|})$

while not converged **do**

  for all $\{d_i, c_j, y\} \in \mathcal{T}$ **do**

    $\mathrm{v}^C_{c_j} \leftarrow \mathrm{v}^C_{c_j} + \gamma \left[(y - \sigma(\mathrm{v}^D_{d_i} \cdot \mathrm{v}^C_{c_j}))\mathrm{v}^D_{d_i} - \beta \mathrm{v}^C_{c_j} \right]$

return C

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5. Usage of SGD makes algorithm completely online

Performance Evaluation : Datasets

1. **Reuters-21578** : Standard dataset for categorization evaluation

	$\|D\|$	$\|C\|$	$\|V\|$	**Data Points**	**Sparsity**
Train Set	7,767	90	39,853	9,585	0.0137
Test Set	3,019	90	39,853	3,745	0.0138

2. **Wikipedia Datasets** : Extracted for 4 top categories

	$\|D\|$	$\|C\|$	$\|V\|$	**Data Points**	**Sparsity**
Physics	4,229	2,999	81,614	14,070	0.0010
Biology	1,604	2,051	63,767	5,908	0.0018
Sports	1,529	2,829	59,058	3,745	0.0008
Mathematics	1,193	1,519	43,398	3,916	0.0013

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For document categorization evaluation, 80% *of the documents are used for training and the rest are equally divided for test and validation purposes*

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Document Categorization Performance Evaluation Reuters-21578

Reuters-21578	P	R	**F1**
BOW	77.8	91.5	84.1
LSI-100	84.8	96.7	90.4
WordVecAvg	94.1	88.1	91.0
SVM (poly) [9]	-	-	86.0
SVM (rbf) [9]	-	-	86.4
CMLF (CRF) [5]	-	-	87.0
Binary-MFoM [4]	-	-	88.4
MC-MFoM [4]	-	-	88.8
Our Model (no weight)	92.1	86.1	89.0
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Precision/Recall/F1 for Document Categorization on Reuters-21578

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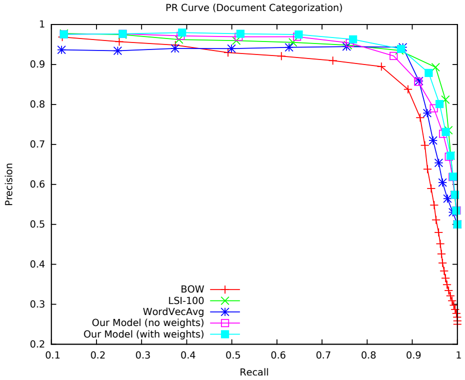

Document Categorization Performance Evaluation Physics - Wikipedia

Physics (Wikipedia)	P	R	**F1**
BOW	87.8	70.1	77.9
LSI-100	83.4	69.5	75.8
WordVecAvg	91.0	59.1	71.7
Our Model (no weights)	86.1	64.6	73.8
Our Model (with weights)	88.6	72.4	**79.7**

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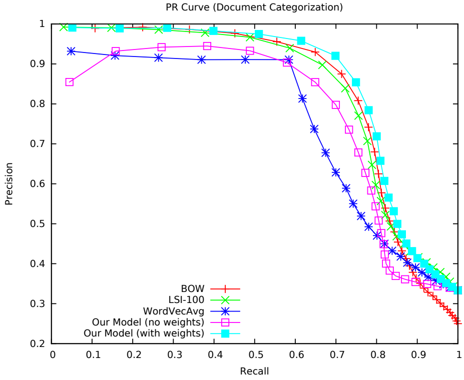

Document Categorization Performance Evaluation Biology - Wikipedia

Biology (Wikipedia)	P	R	**F1**
BOW	90.3	59.5	**69.0**
LSI-100	82.1	51.6	63.4
WordVecAvg	79.4	50.4	61.6
Our Model (no weights)	80.3	53.8	64.4
Our Model (with weights)	79.7	59.0	67.8

Precision/Recall/F1 for Document Categorization on Biology dataset

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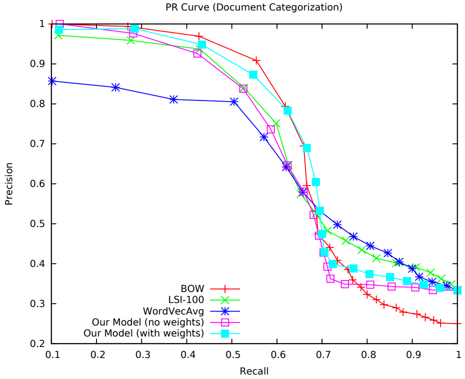

Document Categorization Performance Evaluation Mathematics - Wikipedia

Mathematics (Wikipedia)	P	R	**F1**
BOW	65.6	65.1	65.3
LSI-100	89.7	50.3	64.4
WordVecAvg	90.5	40.3	55.7
Our Model (no weights)	78.4	57.4	66.3
Our Model (with weights)	85.3	56.8	**68.2**

Precision/Recall/F1 for Document Categorization on Mathematics dataset

Document Categorization Performance Evaluation Mathematics - Wikipedia

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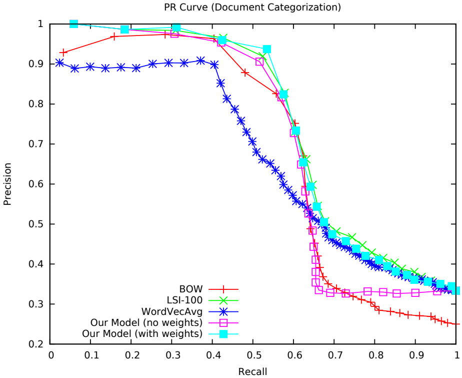

Document Categorization Performance Evaluation
Sports - Wikipedia

Sports (Wikipedia)	P	R	F1
BOW	91.7	41.3	56.9
LSI-100	91.2	40.1	55.7
WordVecAvg	81.8	37.5	51.4
Our Model (no weights)	80.5	40.1	53.6
Our Model (with weights)	82.1	44.0	**57.3**

Precision/Recall/F1 for Document Categorization on Sports dataset

Document Categorization Performance Evaluation Sports - Wikipedia

Sports (Wikipedia)	P	R	**F1**
BOW	91.7	41.3	56.9
LSI-100	91.2	40.1	55.7
WordVecAvg	81.8	37.5	51.4
Our Model (no weights)	80.5	40.1	53.6
Our Model (with weights)	82.1	44.0	**57.3**

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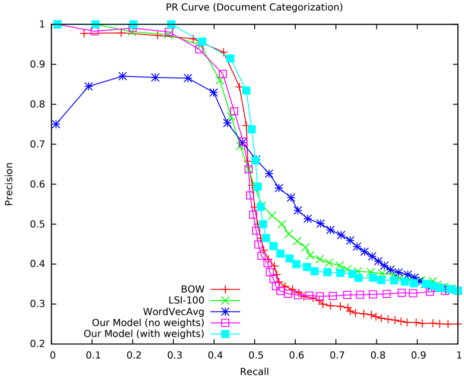

Imputing Missing Categories in Wikipedia

1. Real-life databases contain missing information
2. Wikipedia is a large-scale database with non-expert annotators

We evaluate our model on imputing missing categories in the Wikipedia datasets

	Physics			Biology			Mathematics			Sports			**Combined**		
	P	R	**F1**	P	R	**F1**	P	R	**F1**	P	R	**F1**	P	R	**F1**
PMF	73.0	64.3	68.4	72.1	47.5	57.3	41.6	58.2	48.5	51.3	35.6	42.0	63.0	54.8	58.6
LSI-100	59.5	82.3	69.0	49.9	71.6	58.8	47.1	73.0	57.3	43.1	68.2	52.8	52.5	76.3	62.2
BOW	76.1	79.4	77.7	69.7	67.7	68.7	70.9	63.5	67.0	64.8	49.3	56.0	72.5	69.4	70.9
WordVecAvg	88.0	63.5	73.8	80.7	50.3	61.9	71.8	46.7	56.6	87.2	35.4	50.3	84.2	53.4	65.4
Our Model (without weights)	88.6	69.1	77.7	80.5	55.3	65.6	74.3	53.1	61.9	84.7	40.2	54.5	85.4	58.5	69.2
Our Model (with weights)	89.9	74.5	**81.5**	84.9	63.8	**72.9**	79.9	60.7	**69.0**	81.1	45.6	**58.4**	86.3	65.2	**74.3**

Estimating Similarity between Categories and Words

1. We embed words, document and categories in the same k-dimensional space
2. This allows us to estimate similarity between entities non directly related

Category	Nearest Neighbors
Evolutionary Biology	gene, phylogenetics, speciation, ancestor, Darwin, lineage, evolutionary, interbreeding
Statistical Mechanics	ergodicity, Eigenstate, Universality, DMFT, Markovian, Parisi, Combinatorics
Thermodynamics	Convection, ecosystem, Enthalpy, Joule, calorimetric, compressible, Thermodynamic
Trade	import, Pledges, Tariff, Trade, competitiveness, toll, billion, basket, Ditch, Worldwide
Money-FX	Borrowing, franc, banker, Currency, banks, nervous, sideways, Markets, FORWARD
Virology	nucleoside, ribozyme, adenoviruses, Virology, retroviruses, poliovirus, Viroid
Neurobiology	purinergic, cyclase, vertebral, Ehrlich, nexus, steroid, lean, gendered, reticular
Physical Exercise	Fitness, aerobics, metabolic, workout, Exercise, Stretching, pelvic, Physiology, fibers
Algebra	subalgebra, Algebras, nilpotent, adjoints, octonions, bicommutant, diagonalizable
Theoretical Physicists	Dipankar, DSc, Hubert, Aneesur, Uri, Ignaz, Chia, Stig, Diderot, Dannie
Mathematical Physics	covectors, pseudotensor, spacelike, dyadic, Curl, torque, contractions, wavefunctions
Sports Venues	stadion, decoration, tracks, seating, buildings, parcourse, architectural, arenas, circular
Indian Mathematics	utkrama, ecliptic, Siddhanta, Hellenistic, Brahmi, sexagesimal, scribe, Islamic, Sanskrit

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Future Work

1. Improving compositionality of Word Vectors

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Thank You!
Questions?

Snacks outside