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

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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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  - Cannot capture semantic similarity between words

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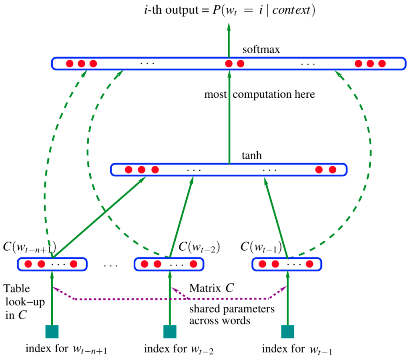

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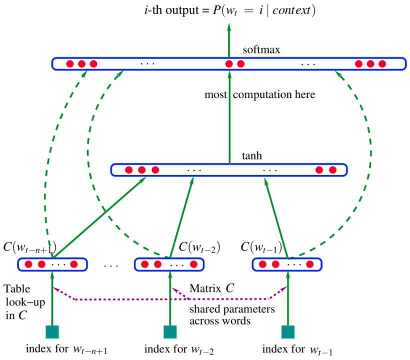

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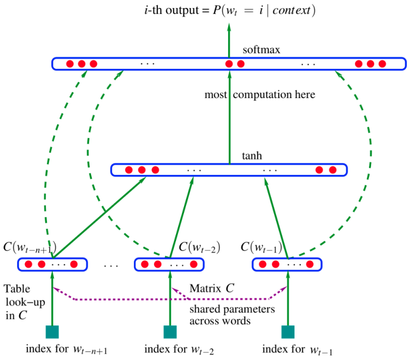

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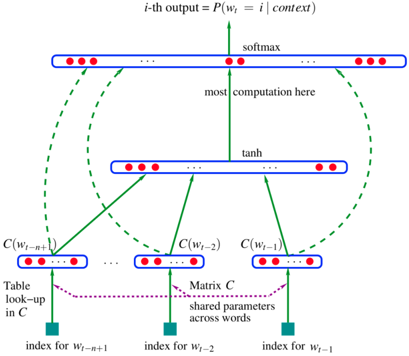

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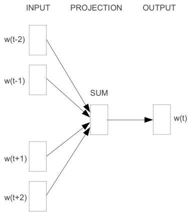

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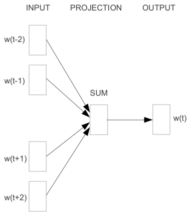

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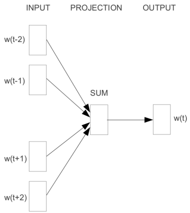

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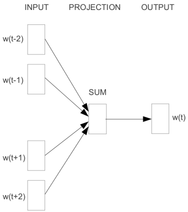

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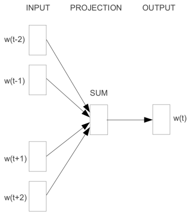

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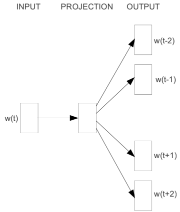

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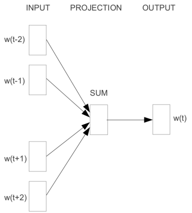

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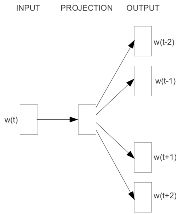

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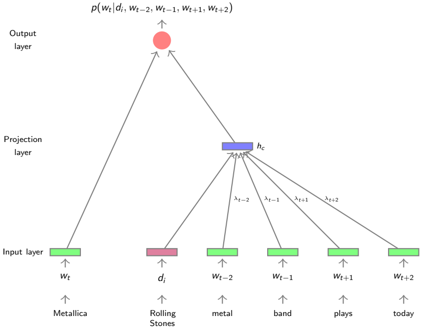

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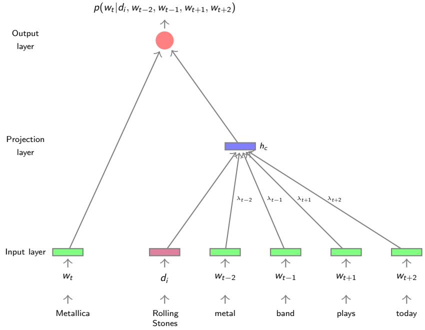

Context Representation :

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

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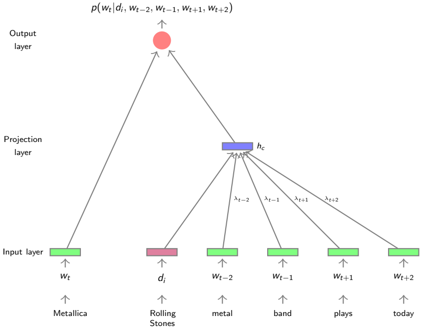

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Probability Estimation :

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

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

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

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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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The logarithm of the probability estimate is given by,

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

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Parameter Estimation

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

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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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Algorithm for learning Document Representations

1: **Input:** D, k, c, n, β, γ, $epochs$
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    $epochs \leftarrow epochs - 1$
return D, W

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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

$P_{\mathrm{D,C}}(y_m = y^{(m)})$ is a shorthand notation for $P(y_m = y^{(m)} | d_i, c_j, \mathrm{D}, \mathrm{C})$
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$$l(\mathcal{T}, \Theta) = \sum_{m=1}^{T} \log P_{\mathrm{D,C}}(y_m = y^{(m)}) \tag{37}$$

Similar to learning document embeddings, category embeddings updates are given by,

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

$P_{\mathrm{D,C}}(y_m = y^{(m)})$ is a shorthand notation for $P(y_m = y^{(m)} | d_i, c_j, \mathrm{D}, \mathrm{C})$

y_m is the predicted label

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

	$\lvert D \rvert$	$\lvert C \rvert$	$\lvert V \rvert$	**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

Experimental Setup

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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

Baselines

1. **Bag-of-Words** : Most widely used representation with *tf-idf* weighing

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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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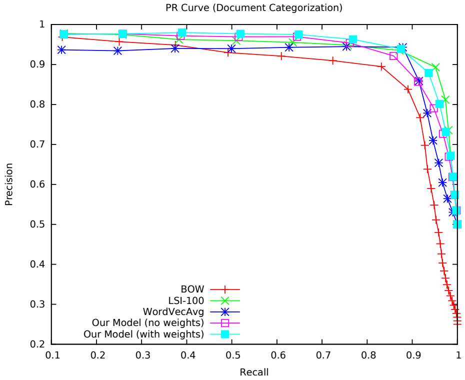

Document Categorization Performance Evaluation Physics - Wikipedia

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**

Precision/Recall/F1 for Document Categorization on Physics dataset

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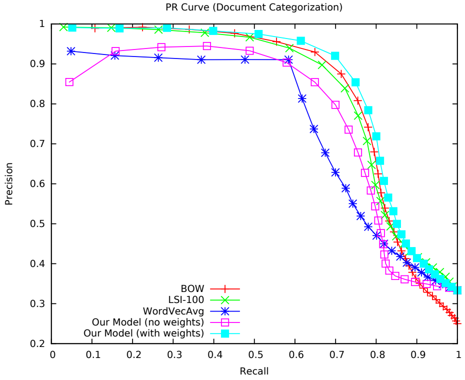

Document Categorization Performance Evaluation Biology - Wikipedia

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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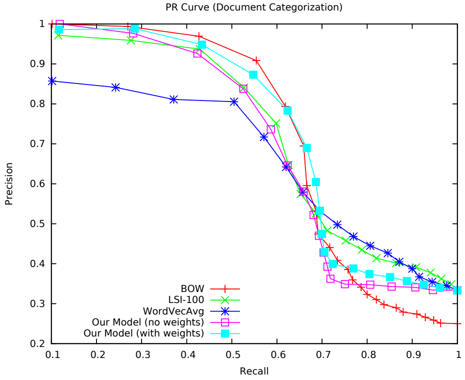

Document Categorization Performance Evaluation Mathematics - Wikipedia

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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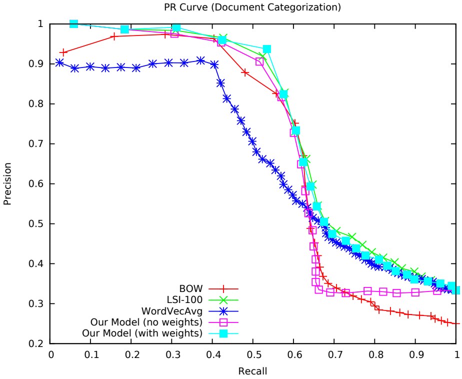

Document Categorization Performance Evaluation
Sports - Wikipedia

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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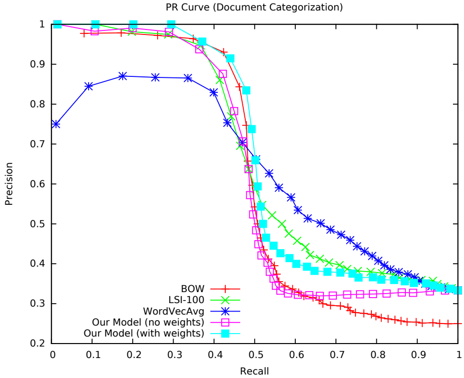

Imputing Missing Categories in Wikipedia

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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6. Learned distributed representations allow semantic similarity estimation

Future Work

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