Distributional Semantics meets Multi Label Learning

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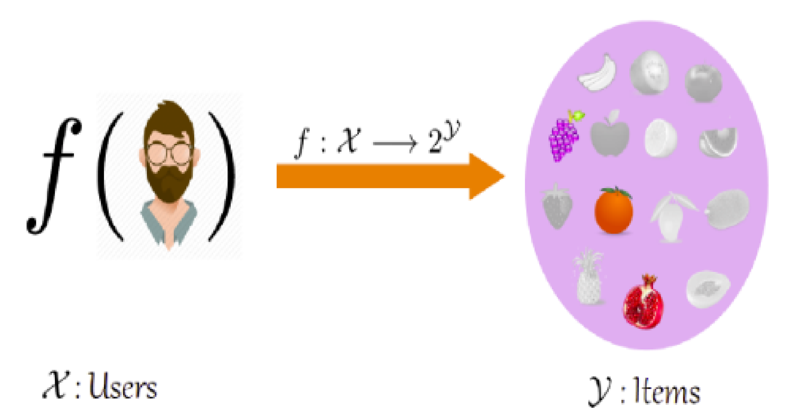
Extreme Multi-Label Learning

- Learning with millions of labels
- Learning with heavy tail distribution of labels
- Learning with missing labels
- Learning to promote diverse recommendations



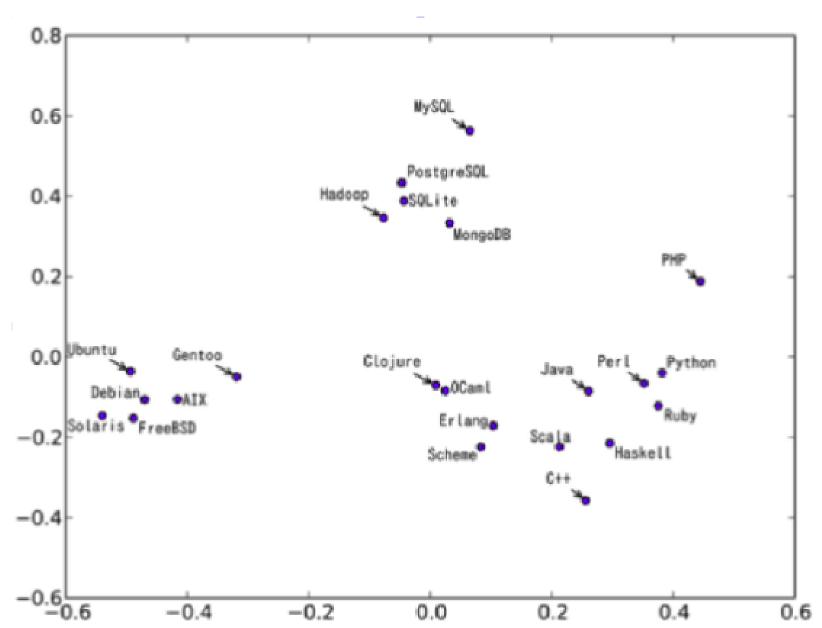
Methods for Extreme Learning

- Tree based : split examples by labels
- Embedding based : embed labels or examples
- One-vs-all: one classifier per label

Method	Accuracy	Scalable	Predict Cost	Model Size	Theory
1-vs-All	☺	☹	☹	☹	☺
Embedding	☺	☺	☺	☺	☺
Tree	☺	☺	☺	☹	☹

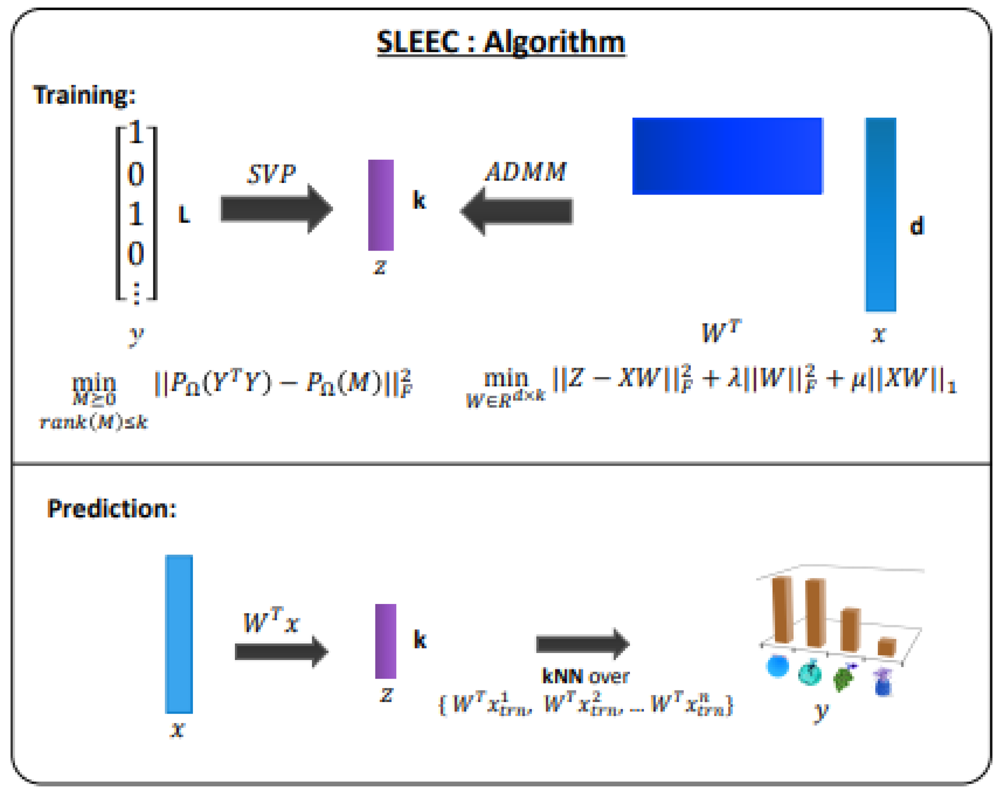
Distributional Semantics

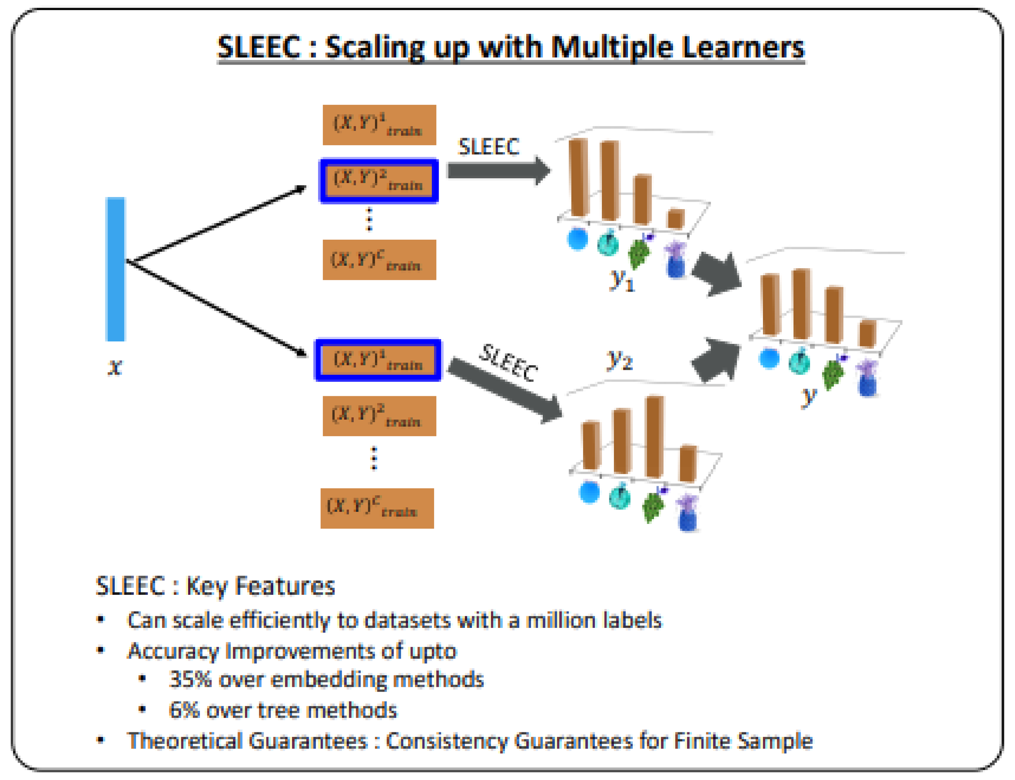
- Each word (w) or sentence (s) is represented using a vector $\vec{v} \in \mathrm{R}^d$
- Semantically similar words or sentences occur closer in the vector space



- Various methods word2vec (SGNS, CBOW) and Doc2vec (PV-DM, PV- DBOW) by Mikolov et al.

SLEEC: Embedding based Algorithm





SGNS meets Label Embedding

- $\mathbb{S}^i = \{j; j \in NN_i\}_{j=1}^K$, here NN_i denote nearest neighbour of y_i
- $K_{ij} = cos(z_i, z_j) = \frac{z_i . z_j}{\|z_i\|\|z_j\|}$, where z_i,z_j label embedding of y_i, y_j
- $z_i = Vx_i$, where $V \in \mathbb{R}^{l \times D}$

Optimization Objective

$$P_i(j \in S^i) = \sigma(\gamma K_{ij})$$

$$\mathbb{J}_i = \sum_{j \in S_i} \log(P_i(j \in S^i)) + \sum_{k \notin S_i}^{K} \log(P_i(k \notin S^i))$$

$$\mathbb{J}_i = \sum_{j \in S_i} \log(\sigma(\gamma K_{ij})) + \sum_{k \notin S_i}^{K} \log(\sigma(-\gamma K_{ik}))$$

Optimization by Matrix Factorization

Theorem (levy et. al. 2014) : SGNS objective is equivalent to weighted matrix factorization of SPPMI (shifted PMI) matrix

$$PMI_{ij}(M) = log\left(\frac{M_{ij} * |M|}{\sum_k M_{(i,k)} * \sum_k M_{(k,j)}}\right)$$

$$SPPMI_{ij}(M) = \max(PMI_{ij}(M) - log(k), 0)$$

Here, PMI(M) is point wise mutual information matrix, |M| represent sum of all element in matrix M

ExMLDS Algorithm

- Multi-iter SVP algorithm replaced with single step SVD on SPPMI
- Regression and Prediction algorithm are exactly same to the SLEEC
- ExMLDS is 10x faster than the SLEEC with similar performance

Incorporating Label Correlation

- Learn embedding of labels as well as instances jointly
- Overall Idea: think of labels as individual words, whereas instances as a sentence
- PV-DBoW maximize similarity between embedded sentence and words of the sentence.
- Can incorporate auxiliary label-label correlation information

Joint Learning of Embedding and Regressor

$$\nabla_V \mathbb{J}_i = \gamma \sum_{j \in S_i} \sigma(-\gamma K_{ij}) \nabla_V K_{ij} - \gamma \sum_{k \notin S_i} \sigma(\gamma K_{ik}) \nabla_V K_{ik}$$

$$\nabla_V K_{ij} = -ab^3 c z_i (x_i)^T - abc^3 z_j (x_j)^T + bc(z_i x_j^T + z_j x_i^T)$$

$$a = z_i^T z_j, b = \frac{1}{\|z_i\|}, c = \frac{1}{\|z_j\|}$$

Experiments

- We compared our method with several state of art extreme classification algorithms on several datasets
- We used the two most popular metrics Prec@k and nDCG@k for evaluation

Results: ExMLDS1 training time

Method	Bibtex	Delicious	Eurlex	Media mill	Delicious 200K
ExMLDS1	**23**	**259**	**580.9**	**1200**	**1937**
ExMLDS2	143.19	781.94	880.64	12000	13000
SLEEC	313	1351	4660	8912	10000

Results: Missing 80% Labels

Dataset	Prec@k	ExMLDS3	SLEEC	LEML	LEML-IMC
Bibtex	P@1	**48.51**	30.5	35.98	41.23
	P@3	**28.43**	14.9	21.02	25.25
	P@5	**20.7**	9.81	15.50	18.56
Eurlex	P@1	**60.28**	51.4	26.22	39.24
	P@3	**44.87**	37.64	22.94	32.66
	P@5	**35.31**	29.62	19.02	26.54
rcv1v2	P@1	**81.67**	41.8	64.83	73.68
	P@3	**52.82**	17.48	42.56	48.56
	P@5	**37.74**	10.63	31.68	34.82

Results: Joint Learning

Dataset	Prec@k	ExMLDS4	AnnexML	SLEEC
Delicious-200K	P@1	47.70	46.66	**47.85**
	P@3	41.22	40.79	**42.21**
	P@5	37.98	37.64	**39.43**
Wikipedia-500K	P@1	62.27	**63.86**	58.39
	P@3	41.43	**42.69**	37.88
	P@5	31.42	**32.37**	28.21
Amazon-670K	P@1	41.47	**42.08**	35.05
	P@3	36.35	**36.65**	31.25
	P@5	32.43	**32.76**	28.56

References

For dataset details refer to Extreme Classification Repository by Manik Varma (`https://goo.gl/3LvVa6`)