News Article Classification

(Multi-Label Learning: ML-KNN & BP-MLL)

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STAT 6500

Overview

Introduction and Problem Statement

KNN Based Approaches

Binary Relevance (A Naive Approach)

- An intuitive approach to deal with the multilabel paradigm.
- Works by decomposing the multi-label learning task into a number of independent binary learning tasks (one per class label).

$L = \{l_1, l_2, l_3, l_4\}$

EX#	Label set
1	$\{l_1, l_2\}$
2	$\{l_2, l_4\}$
3	$\{l_1, l_3, l_4\}$
4	$\{l_4\}$

EX#	l_1
1	**true**
2	false
3	**true**
4	false

EX#	l_2
1	**true**
2	**true**
3	false
4	false

EX#	l_3
1	false
2	false
3	**true**
4	false

EX#	l_4
1	false
2	**true**
3	**true**
4	**true**

→ Often criticized in the literature because of its label independence assumption.

→ We implement a KNN based binary relevance model and compare with a more novel adaptation: the ML-KNN model.

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$$\begin{aligned}
\vec{y}_t(\ell) &= \operatorname*{argmax}_{b\in\{0,1\}} \mathbb{P}\left(\mathrm{H}_b^\ell | E^\ell_{\vec{C}_t(\ell)}\right), \quad \ell \in \mathcal{Y} \\
&= \operatorname*{argmax}_{b\in\{0,1\}} \frac{\mathbb{P}\left(\mathrm{H}_b^\ell\right) \cdot \mathbb{P}\left(E^\ell_{\vec{C}_{t(\ell)}} | \mathrm{H}_b^\ell\right)}{\mathbb{P}\left(E^\ell_{\vec{C}_t(\ell)}\right)} \\
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\end{aligned}$$

- Where we take a Bayesian approach towards estimating the prior probabilities, $\mathbb{P}\left(\mathrm{H}_b^\ell\right)$, and conditional probabilities, $\mathbb{P}\left(E^\ell_{\vec{C}_{t(\ell)}} | \mathrm{H}_b^\ell\right)$.

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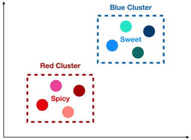
- Let E_j^ℓ $(j \in \{1, ..., K\})$ denote the event that, among the K nearest neighbors of t, there are exactly j instances which have label ℓ.

ML-KNN Algorithm: Reasons for dimension reduction

Data points



Low dimensional space

	Reddish	Bluish
	1	0
	1	0
	1	0
	1	0
	0	1
	0	1
	0	1
	0	1

High dimensional space

	Red	Maroon	Pink	Flamingo	Blue	Turquoise	Seaweed	Ocean
	1	0	0	0	0	0	0	0
	0	1	0	0	0	0	0	0
	0	0	1	0	0	0	0	0
	0	0	0	1	0	0	0	0
	0	0	0	0	1	0	0	0
	0	0	0	0	0	1	0	0
	0	0	0	0	0	0	1	0
	0	0	0	0	0	0	0	1

Having a high dimensional feature space causes Euclidian distances between points to be fairly similar as the distance vector components are partitioned across many dimensions.

Neural Network Based Approaches

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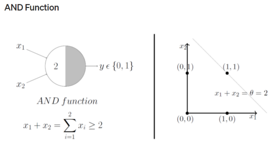

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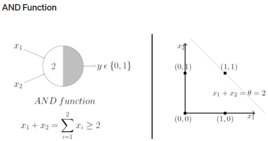

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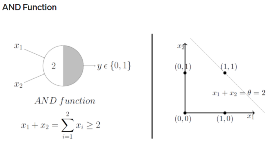

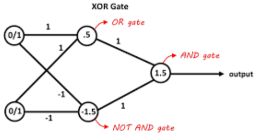

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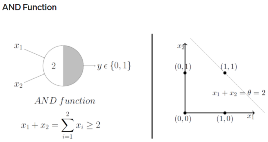
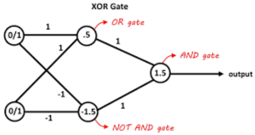
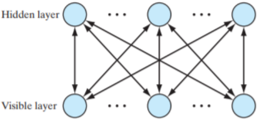
- In the early 1980s, research on neural networks resurged largely due to successful learning algorithms for multi-layer neural networks and are used today for various tasks such as computer vision, associative memory, representation learning, NLP, etc..



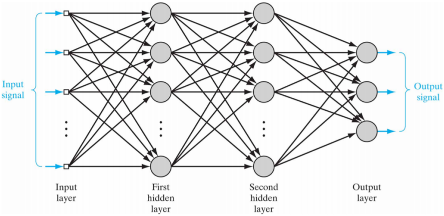




Network Architectures (Feed Forward vs Recurrent)

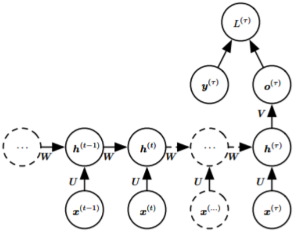
Feed Forward Networks

- Neurons in the first layer represent components of the input vectors.
- The output of the neuron in the next layer is determined by applying a non-linear "activation function" to a linear combination of the input components, plus a bias.



Recurrent Neural Networks (RNNs)

- RNNs are a popular adaptation for NLP problems.
- They utilize hidden unit connections with shared weights.
- Unfolding an RNN let's us visualize it like a feed forward network (see below).



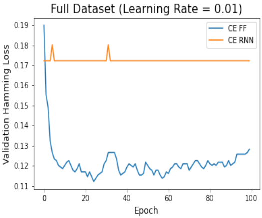
Naive vs Novel Approaches (Cross Entropy vs BPMLL)

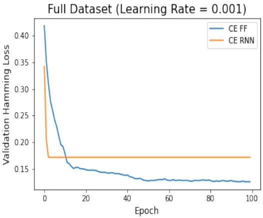
- By "naive" we refer to multilabel networks that utilize a cross entropy loss for training.
- By comparison, Zhang and Zhou bpmll proposed a novel loss, that emphasizes pairwise ranking accuracy.

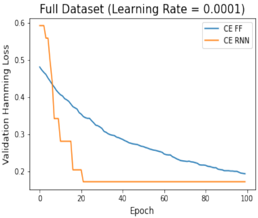
$$E = \sum_{i=1}^{m} E_i = \sum_{i=1}^{m} \frac{1}{|Y_i||\overline{Y}_i|} \sum_{(k,l)\in Y_i \times \overline{Y}_i} \exp(-(c_k^i - c_l^i))$$

so that the i^{th} error term is severely penalized if c_k^i is much smaller than c_l^i.

Artificial Neural Network Results: Full Dataset





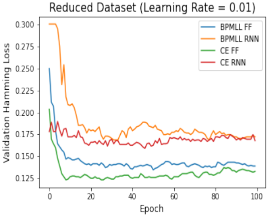


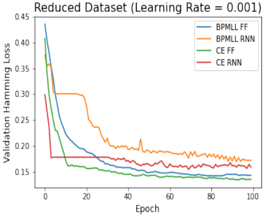
Learning Rate	CE FF	CE RNN
0.01	0.3020833333	0.2379807692
0.001	0.17868589740	0.1730769231
0.0001	0.2115384615	0.1770833333

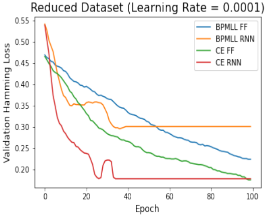
Table 1: Hamming Loss with Threshold Function Learning

CE FF outperform CE RNN in constant threshold but underperform in learned threshold; The effect of learning rate.

Artificial Neural Network Results: Reduced Dataset







Learning Rate	CE FF	BPMLL FF	CE RNN	BPMLL RNN
0.01	0.1520979021	0.145979021	0.2447552448	0.2194055944
0.001	0.1853146853	0.2578671329	0.1791958042	0.20454545
0.0001	0.2071678322	0.1844405594	0.1896853147	0.2132867133

Table 2: Hamming Loss with Threshold Function Learning

Same conclusion for RNN and FF; BPMLL shows NO better performance in hamming loss than cross entropy.

Discussion and Conclusions

References

Min-Ling Zhang and Zhi-Hua Zhou. Ml-knn: A lazy learning approach to multi-label learning. *Pattern Recognition*, 40(7):2038–2048, 2007. doi: 10.1016/j.patcog.2006.12.019.

Min-Ling Zhang and Zhi-Hua Zhou. Multilabel neural networks with applications to functional genomics and text categorization. *IEEE Transactions on Knowledge and Data Engineering*, 18(10):1338–1351, 2006. doi: doi:10.1109/TKDE.2006.162.