News Article Classification

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

Lauren Contard, Archit Datar, Bobby Lumpkin, Haihang Wu

The Ohio State University

STAT 6500

Overview

1. Introduction and Problem Statement
2. KNN Based Approaches
   - Binary Relevance
   - ML-KNN Algorithm
   - Results
3. Neural Network Based Approaches
   - Architectures: Feed Forward & Recurrent Networks
   - Loss Functions: Cross Entropy vs BPMLL
   - Results
4. Discussion and Conclusions

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.

ML-KNN Algorithm: Overall Approach

Overall Approach: This ML-KNN algorithm takes a parametric, Bayesian approach towards estimating the Bayes Optimal Classifier. As with the single-label algorithm, it does this using the K nearest neighbors of an instance. Namely...

ML-KNN Algorithm: Overall Approach

Overall Approach: This ML-KNN algorithm takes a parametric, Bayesian approach towards estimating the Bayes Optimal Classifier. As with the single-label algorithm, it does this using the K nearest neighbors of an instance. Namely...

- Given a test instance, t, $\vec{Y}_t$ is determined using the MAP estimate:

ML-KNN Algorithm: Overall Approach

Overall Approach: This ML-KNN algorithm takes a parametric, Bayesian approach towards estimating the Bayes Optimal Classifier. As with the single-label algorithm, it does this using the K nearest neighbors of an instance. Namely...

- Given a test instance, t, $\vec{Y}_t$ is determined using the MAP estimate:

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

ML-KNN Algorithm: Overall Approach

Overall Approach: This ML-KNN algorithm takes a parametric, Bayesian approach towards estimating the Bayes Optimal Classifier. As with the single-label algorithm, it does this using the K nearest neighbors of an instance. Namely...

- Given a test instance, t, $\vec{Y}_t$ is determined using the MAP estimate:

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

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

Notation:

ML-KNN Algorithm: More Notation

Notation:

- Let $N(x)$ denote the set of K nearest neighbors of x, identified in the training set.

ML-KNN Algorithm: More Notation

Notation:

- Let $N(x)$ denote the set of K nearest neighbors of x, identified in the training set.
- Let $\vec{C}_x(\ell) = \sum_{a \in N(x)} \vec{y}_a(\ell)$ $(\ell \in \mathcal{Y})$ define a membership counting vector.

Notation:

- Let $N(x)$ denote the set of K nearest neighbors of x, identified in the training set.
- Let $\vec{C}_x(\ell) = \sum_{a \in N(x)} \vec{y}_a(\ell)$ $(\ell \in \mathcal{Y})$ define a membership counting vector.
- Let H_0^ℓ denote the event that test instance t does not have a label ℓ and let H_1^ℓ denote the event that it does have label ℓ.

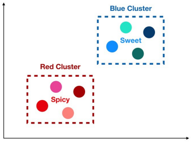
ML-KNN Algorithm: More Notation

Notation:

- Let $N(x)$ denote the set of K nearest neighbors of x, identified in the training set.
- Let $\vec{C}_x(\ell) = \sum_{a \in N(x)} \vec{y}_a(\ell)$ $(\ell \in \mathcal{Y})$ define a membership counting vector.
- Let H_0^ℓ denote the event that test instance t does not have a label ℓ and let H_1^ℓ denote the event that it does have label ℓ.
- 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

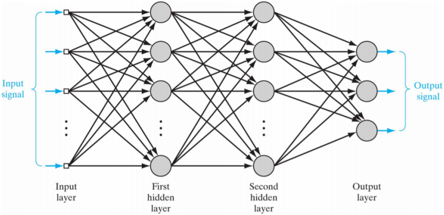
Having a high dimensional feature space causes Euclidian distances between points to be fairly similar as the distance vector components are partitioned across many dimensions.

Neural Network Based Approaches

Network Architectures (Feed Forward vs Recurrent)

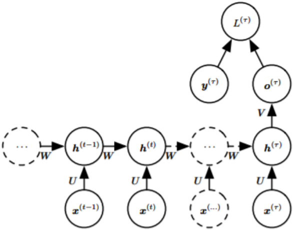
Feed Forward Networks

- 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.



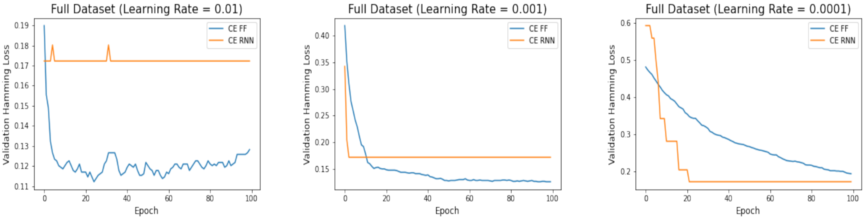
Recurrent Neural Networks (RNNs)

- 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)

Artificial Neural Network Results: Full Dataset

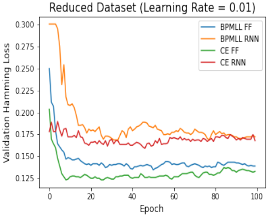


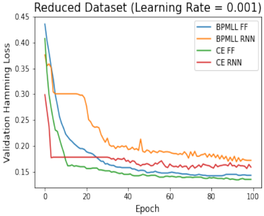
Learning Rate	CE FF	CE RNN
0.01	0.3020833333	0.2379807692
0.001	0.17868589740	0.1730769231
0.0001	0.2115384615	0.1770833333

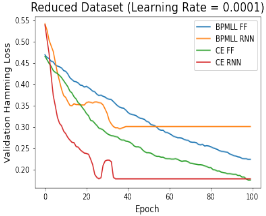
Table 1: Hamming Loss with Threshold Function Learning

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.