News Article Classification

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

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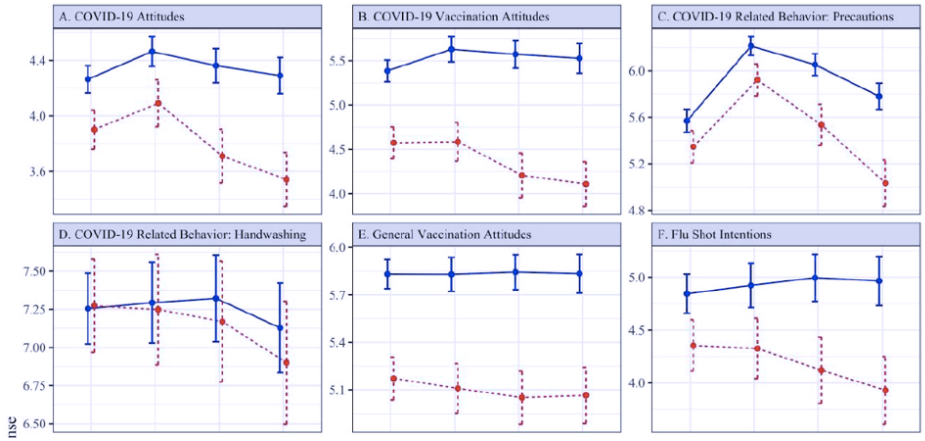
STAT 6500

Overview

Introduction and Problem Statement

Introduction

- People in the U.S. have shown polarized attitudes and behaviors in response to COVID-19.
- What could be some of the drivers? We aim to explore whether and how mainstream news media in the U.S. play a role in the polarization of the public's attitudes and behaviors.



Description of Datasets

- We analyzed news content about elite communication from 10 news media, including newspapers (e.g., New York Times) and cable network news (e.g., ABC news).
- We got the list of news articles from the GDELT database and used the Python package "Scrapy" to get the full text.
- We have 8588 news articles in total and randomly selected 290 paragraphs of them to label.
- We manually labeled our paragraphs into 15 categories. One paragraph usually has multiple labels.

Two Examples from the Dataset

"Meanwhile, Bottoms has repeatedly urged residents to stay home. On Friday, she tweeted coronavirus fatality statistics for the state: 'The numbers speak for themselves. PLEASE STAY HOME.'" (From USAtoday, 04/25/2020)

- Threats/impacts
- Responses/actions
- Severity
- Self-efficacy
- Public Health
- Negative

"You know, I wonder, I think there's been a lot of self-congratulations every day that we see in those briefings, frankly, about the testing in the United States, and we're doing so well, we're doing now more than South Korea did." (From abcnews, 03/29/2020)

- Responses/actions
- External-efficacy
- Public health
- Political evaluation
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Problem Statement

- We have a multi-label classification problem. We adapted two learning algorithms: k-NN and Neural Networks to handle multi-label data directly.

  RQ1: Which learning algorithm performs better in the multi-label classification problem?

- Our data has high dimensions.

  RQ2: Which one of the dimension reduction methods performs better in the multi-label classification problem: linear or non-linear?

- The sequence of features need to be considered in the classification.

  RQ3: Which type of the features perform better in the multi-label classification problem: with or without considering the order of words?

KNN Based Approaches

Binary Relevance (A Naive Approach)

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

EX#	l_1
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4	false

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EX#	l_3
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$\rightarrow$ We implement a KNN based binary relevance model and compare with a more novel adaptation: the ML-KNN model.

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- 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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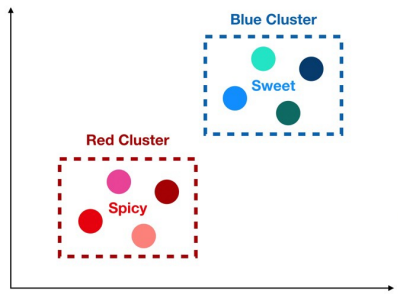
- Let H_0^ℓ denote the event that test instance t does not have a label ℓ and let H_1^ℓ denote the event that it does have label ℓ.
- Let E_j^ℓ $(j \in \{1, ..., K\})$ denote the event that, among the K nearest neighbors of t, there are exactly j instances which have label ℓ.

ML-KNN Algorithm: Reasons for dimension reduction



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.

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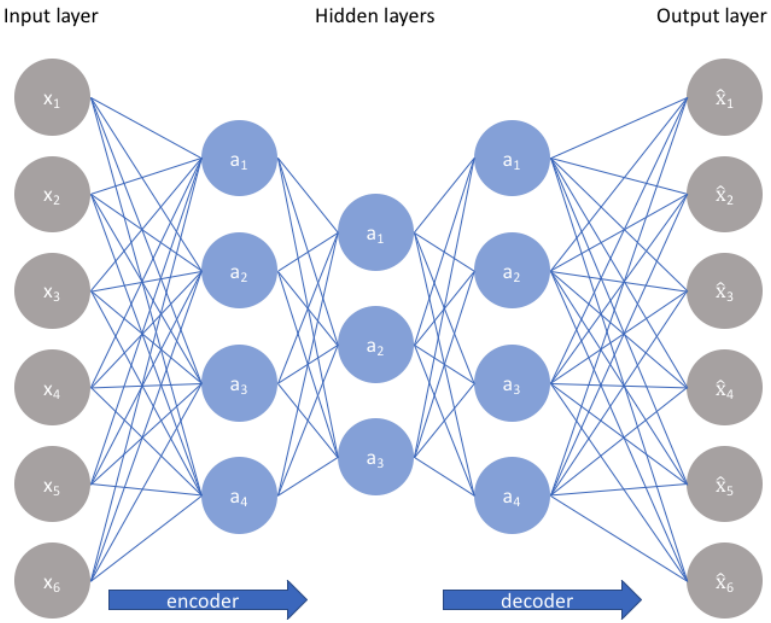

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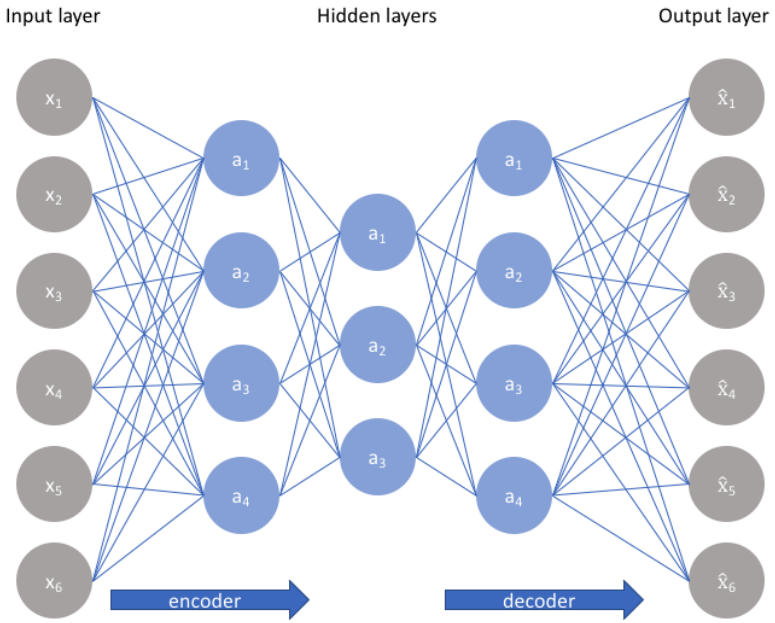
→ Use bottleneck layer values as encodings of the data.



Neural Network Based Approaches

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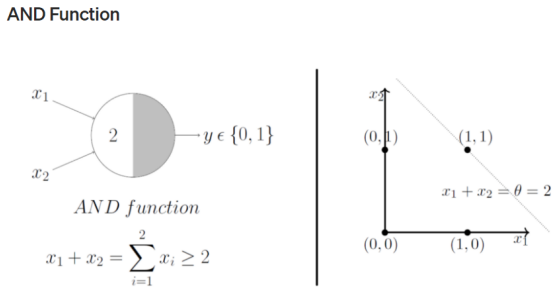

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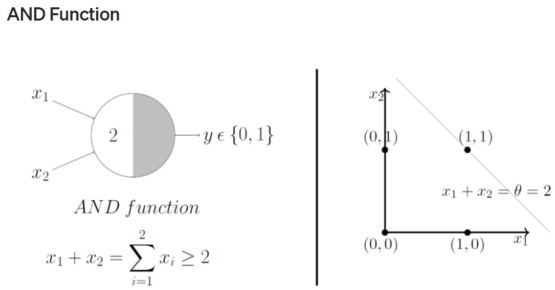

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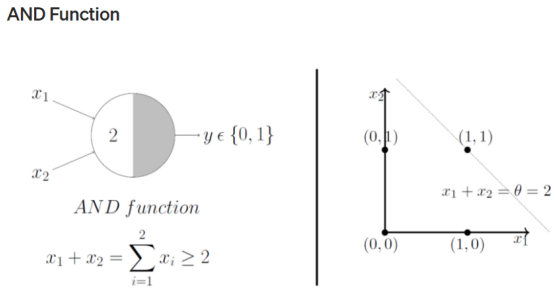

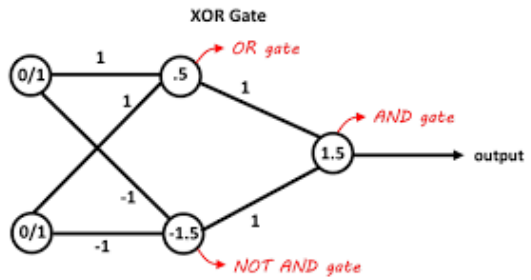

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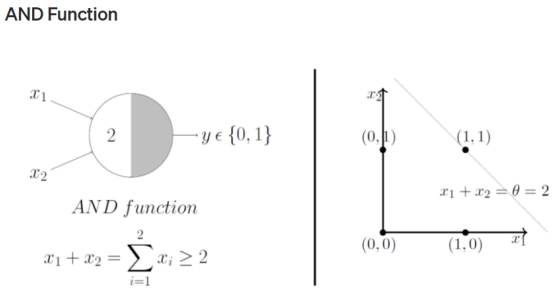
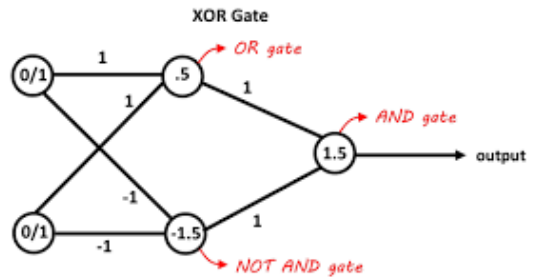
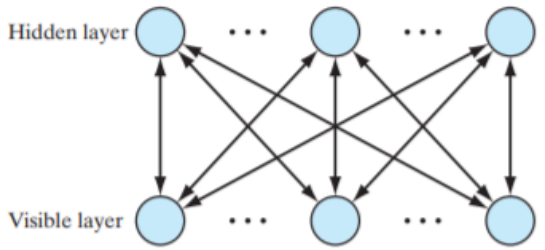
- In the early 1980s, research on neural networks resurged largely due to successful learning algorithms for multi-layer neural networks and are used today for various tasks such as computer vision, associative memory, representation learning, NLP, etc..



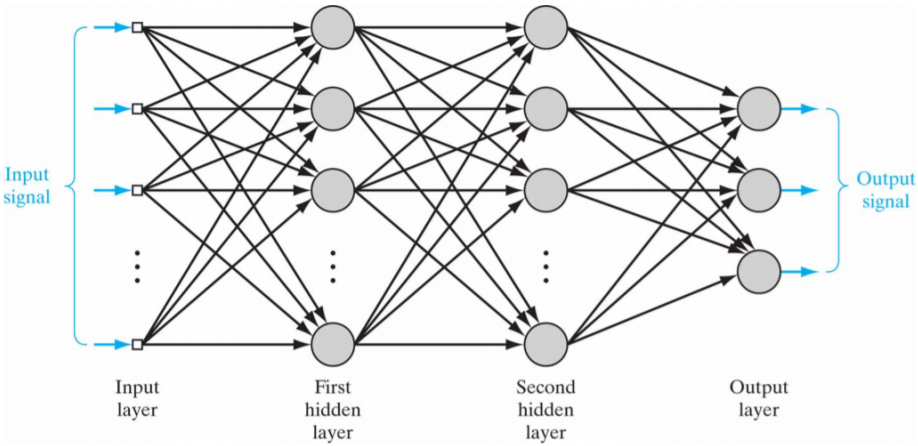




Network Architectures (Feed Forward vs Recurrent)

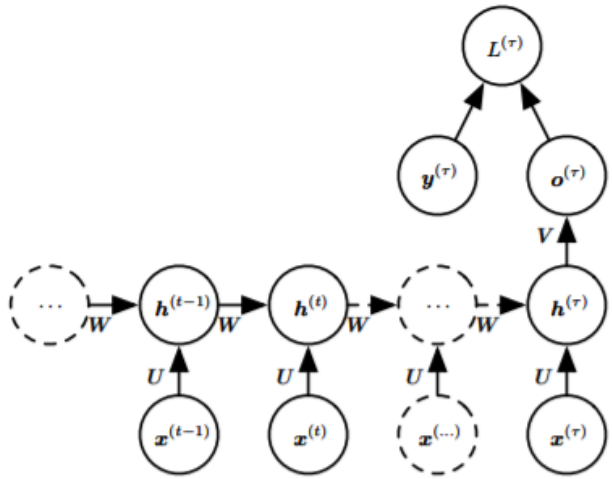
Feed Forward Networks

- 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).



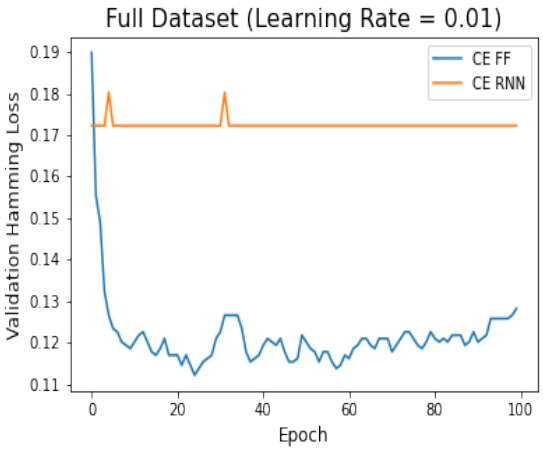
Naive vs Novel Approaches (Cross Entropy vs BPMLL)

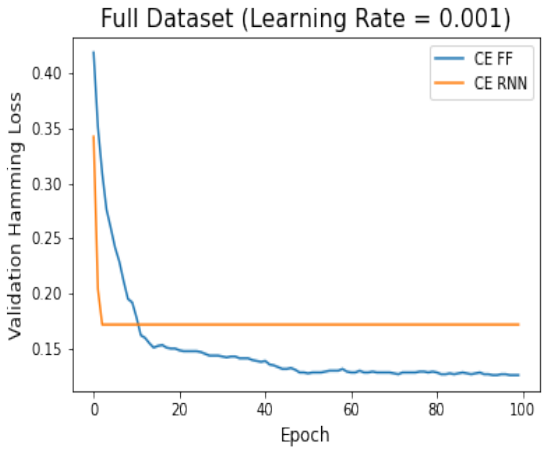
- By "naive" we refer to multilabel networks that utilize a cross entropy loss for training.
- By comparison, Zhang and Zhou bpmll proposed a novel loss, that emphasizes pairwise ranking accuracy.

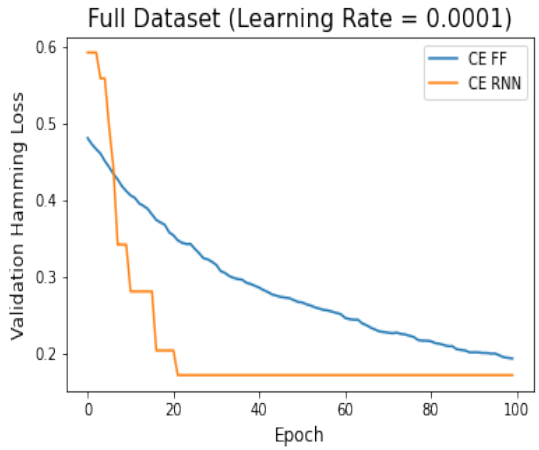
$$E = \sum_{i=1}^{m} E_i = \sum_{i=1}^{m} \frac{1}{|Y_i||\overline{Y}_i|} \sum_{(k,l)\in Y_i \times \overline{Y}_i} \exp(-(c_k^i - c_l^i))$$

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





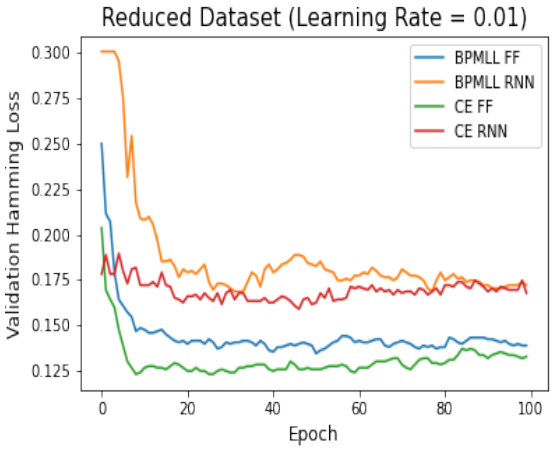


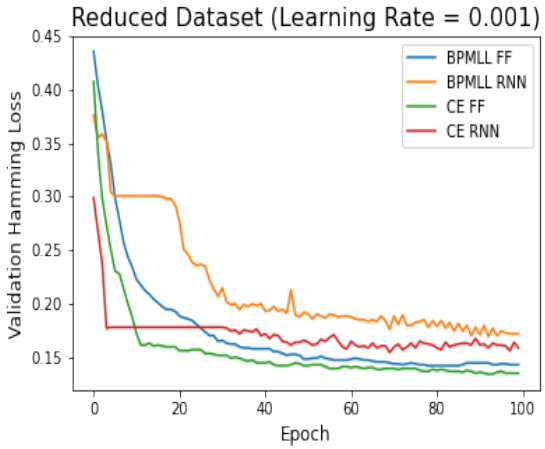
Learning Rate	CE FF	CE RNN
0.01	0.3020833333	0.2379807692
0.001	0.17868589740	0.1730769231
0.0001	0.2115384615	0.1770833333

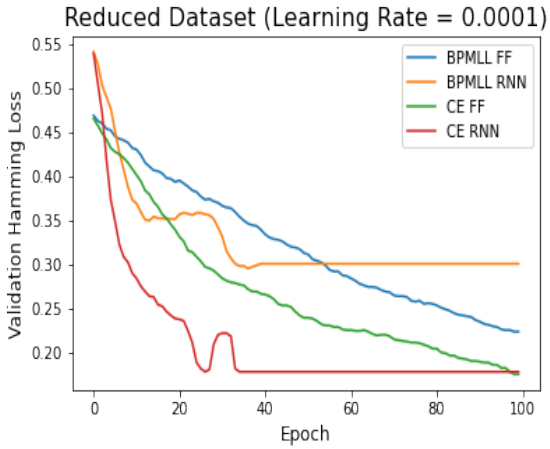
Table 1: Hamming Loss with Threshold Function Learning

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

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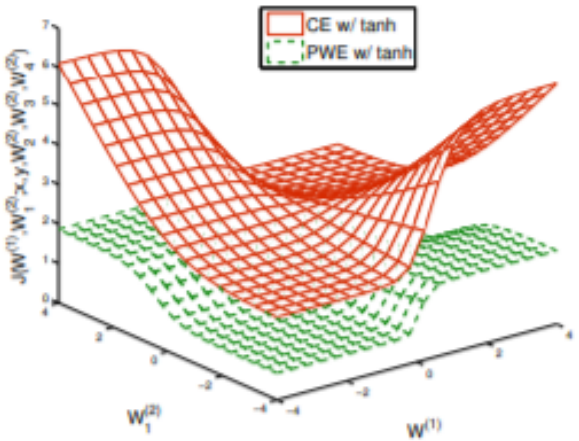

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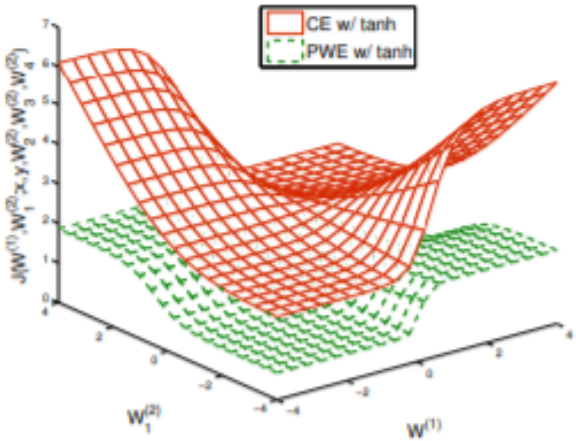
2. The cross entropy networks tend to outperform the BPMLL networks.
   - → The surface for the BPMLL loss with tanh activations has plateaus in which gradient descent can be very slow in comparison with the cross-entropy (Nam et al. [2014]). The case may be similar for ReLU activations.



   - → While BPMLL is supposed to leverage correlations between labels, Nam et al. [2014] conjecture that these correlations also may cause overfitting.

Discussion and Conclusions: ANN Approaches (continued)

3. Models saw no improvement from using a learned threshold function.

Discussion and Conclusions: ANN Approaches (continued)

3. Models saw no improvement from using a learned threshold function.
   $\rightarrow$ Models could sufficiently separate predicted logits about 0.5.

Discussion and Conclusions: ANN Approaches (continued)

3. Models saw no improvement from using a learned threshold function.
   - → Models could sufficiently separate predicted logits about 0.5.
   - → This approach may be more useful for models that require extensive resources for sufficient training (improved less extensively trained models).

References

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