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.
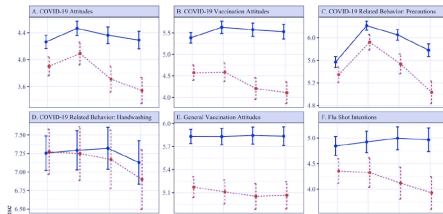
Description of Datasets

- 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: k-NN or neural networks??

- Our data has high dimensions.

  RQ2: How can we effectively implement linear and non-linear dimensions reduction in the multi-label classification problem?

- 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

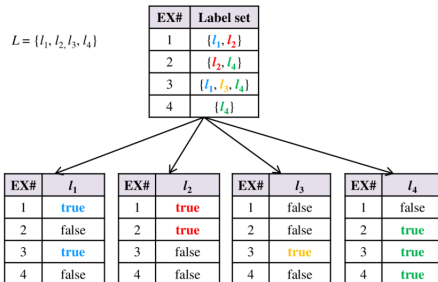# Binary Relevance (A Naive Approach)

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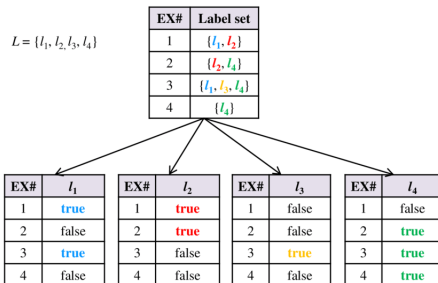
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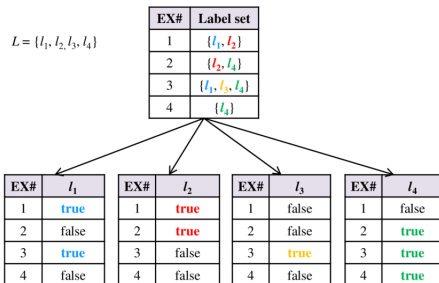# Binary Relevance (A Naive Approach)

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

ML-KNN Algorithm: Overall Approach

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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, $\mathbb{P}\left(E_{\vec{C}_{t(\ell)}}^\ell | \mathrm{H}_b^\ell\right)$.

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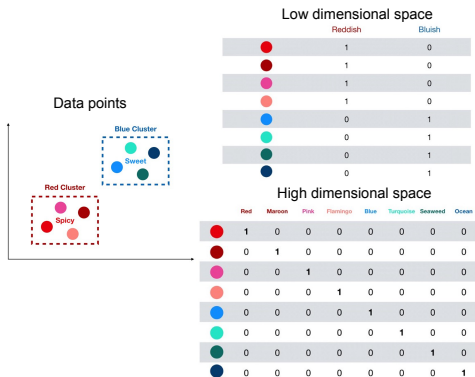
Having a high dimensional feature space causes Euclidian distances between points to be fairly similar as the distance vector components are partitioned across many dimensions.

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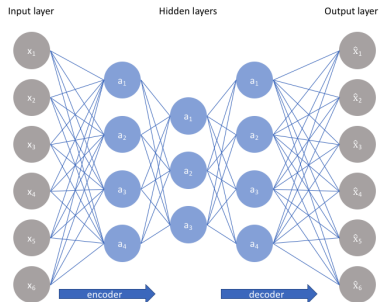
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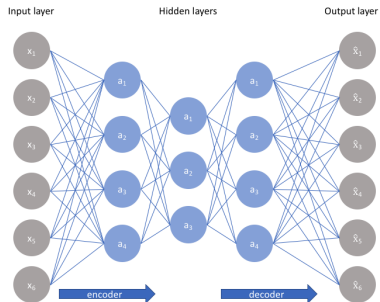
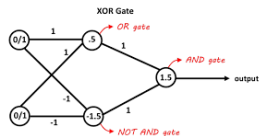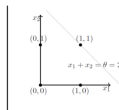# Neural Network Based Approaches

A Brief History

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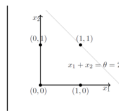
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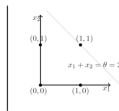
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- In the early 1980s, research on neural networks resurged largely due to successful learning algorithms for multi-layer neural networks and are used today for various tasks such as computer vision, associative memory, representation learning, NLP,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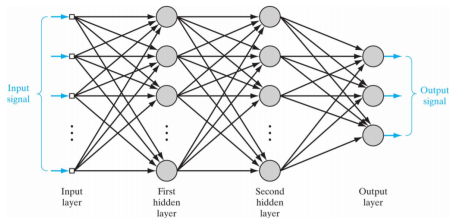

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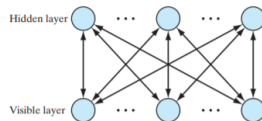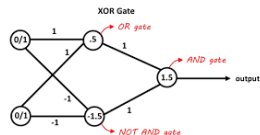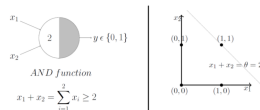
# Network Architectures (Feed Forward vs Recurrent)

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.
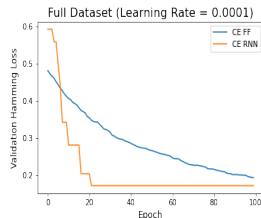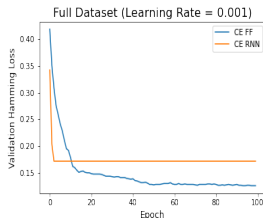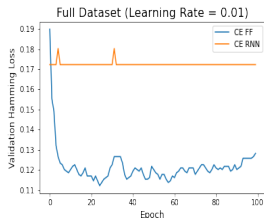- Unfolding an RNN let's us visualize it like a feed forward network (see below).
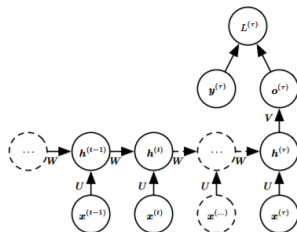
Naive vs Novel Approaches (Cross Entropy vs BPMLL)

- 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 ith error term is severely penalized if c_k^i is much smaller than c_l^i.

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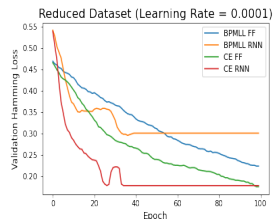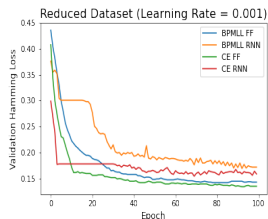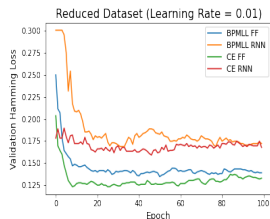
Learning Rate	CE FF	BPMLL FF	CE RNN	BPMLL RNN
0.01	0.1520979021	0.145979021	0.2447552448	0.2194055944
0.001	0.1853146853	0.2578671329	0.1791958042	0.20454545
0.0001	0.2071678322	0.1844405594	0.1896853147	0.2132867133

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

Discussion and Conclusions: ANN Approaches

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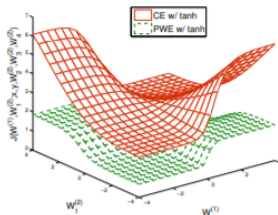
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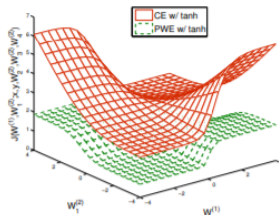
   - → While BPMLL is supposed to leverage correlations between labels, Nam et al. [2014] conjecture that these correlations also may cause overfitting.

Discussion and Conclusions: ANN Approaches (continued)

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    - $\rightarrow$ Models could sufficiently separate predicted logits about 0.5.
    - $\rightarrow$ This approach may be more useful for models that require extensive resources for sufficient training (improved less extensively trained models).

References

Jinseok Nam, Jungi Kim, Eneldo Loza Mencía, Iryna Gurevych, and Johannes Fürnkranz. Large-scale multi-label text classification — revisiting neural networks. In Toon Calders, Floriana Esposito, Eyke Hüllermeier, and Rosa Meo, editors, *Machine Learning and Knowledge Discovery in Databases*, pages 437–452, Berlin, Heidelberg, 2014. Springer Berlin Heidelberg.

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: $10.1016/\text{j.patcog.}2006.12.019$.

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: $\text{doi:}10.1109/\text{TKDE.}2006.162$.