One Size Fits Many: Column Bundle for Multi-X Learning

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Abstract

Much recent machine learning research has been directed towards leveraging shared statistics among labels, instances and data views, commonly referred to as multi-label, multi-instance and multi-view learning. The underlying premises are that there exist correlations among input parts and among output targets, and the predictive performance would increase when the correlations are incorporated. In this paper, we propose Column Bundle (CLB), a novel deep neural network for capturing the shared statistics in data. CLB is generic that the same architecture can be applied for various types of shared statistics by changing only input and output handling. CLB is capable of scaling to thousands of input parts and output labels by avoiding explicit modeling of pairwise relations. We evaluate CLB on different types of data: (a) multi-label, (b) multi-view, (c) multi-view/multi-label and (d) multi-instance. CLB demonstrates a comparable and competitive performance in all datasets against state-of-the-art methods designed specifically for each type.

1 Introduction

A canonical setting in machine learning is that each training instance is comprised of an input vector and an output label. However, there are many learning tasks in which, samples may consist of multiple input parts and outputs. For example, a video can have multiple types of input features such as audio, vision and text description; and in image annotation, an image can be tagged with multiple concepts such as horses, grass fields and trees. For the past decades, machine learning has leveraged shared statistics between labels, instances, tasks and data views. These have given rise to fruitful research directions for multi-output data such as multi-label [Elisseeff and Weston, 2001], multi-task [Caruana, 1997] and for multi-input data such as multi-view [Gönen and Alpaydln, 2011], multi-instance [Dieterich et al., 1997] and multi-source learning [Crammer et al., 2008]. Let us simplify the notion by calling these directions as multi-X learning.

Developed independently is deep learning – a scheme emphasizing learning multiple abstractions [LeCun et al., 2015] through multiple steps of computation. Central to the recent record-breaking successes in deep learning is architecture engineering, the art of designing neural nets that best address the structure of the problems at hand. There is limited work on neural architectures for leveraging shared statistics in training data. One example is Column Network (CLN) [Pham et al., 2017], which is a network of thin nets known as columns, designed for leveraging the relations between data points.

In this paper, we ask a bold question: Is this possible to build a generic neural architecture that simultaneously addresses many questions in multi-X learning? Inspired by Column Networks, we propose a deep architecture called Column Bundle (CLB), which is a set of columns connected in a specific way for shared statistics. Unlike Column Networks where the relations are pre-defined, Column Bundles integrate separate inputs (e.g., views, parts and instances) indirectly through a central column. Each input is represented as a mini-column, which is recurrently connected to the central column. The central column plays the role of an “executive function” in human brain. In the inference phase, it first serves as a buffer (working memory) for multiple parts to interact in a sequential manner. The central column then sends output signals to separate outputs (e.g., label, task) that are also represented as mini-columns connected to the central column recurrently. In the learning phase, training signals from (multiple) labels will propagate back to multiple mini-columns in the input parts. The mini-columns interact through the central column, therefore the correlations among inputs or among labels are established through the bundle. Overall, our system is a single neural architecture that solves many separately considered sub-problems in recent machine learning.

We evaluate the Column Bundle model on a comprehensive suite of tasks designed for each of the multi-X problems, as well as data designed for joint multi-instance/view multi-label learning. Compared with specific methods designed for each task, our generic architecture exhibits comparable and competitive results.

Our main contributions are:

• We suggest the rethinking of recent separate developments in machine learning, which include multi-X settings, where X is label, task, view, instance or part. After all, these developments are all based on the notion that related information should be shared to leverage the strength of statistics.
• We design a generic neural architecture called Column Bundle showing that the same architecture can be used for any multi-X problem by changing only input and output handling.
• A comprehensive evaluation, comparing against state-of-the-art algorithms designed for each setting.

The rest of the paper is organized as follows. Relevant work about shared statistical strength is discussed in Sec. 2. The CLB model is proposed in Sec. 3 followed by the experimental study (Sec. 4). Finally, we conclude our paper and discuss future work in Sec. 5.

2 Related work

Since this paper touches many fruitful developments of recent machine learning, we limit ourselves to the most relevant work that aims at leveraging the shared statistical strength among inputs and outputs in data.

Multi-label learning refers to annotating an instance by more than one label, usually of the same broad type (e.g., textual tags for an image) [Zhang and Zhou, 2014]. Much work attempted to adapt single-label algorithms to deal with the multi-label setting, such as ML-kNN [Zhang and Zhou, 2007] (k-nearest neighbor for multi-label data) and Rank-SVM [Elisseeff and Weston, 2001] (Kernel learning for multi-label data). Explicit correlations can also be modeled using conditional random fields as in [Ghamrawi and McCallum, 2005]. Alternatively, the multi-label learning problem can be transformed into a sequence of single-label classification problems, where later classifiers in the sequence take the predictions of previous labels as inputs [Cheng et al., 2010]. Multi-task learning is similar to multi-label learning, but more flexible on task definition (e.g., a task per an instance, not necessarily multiple tasks per an instance) [Caruana, 1997]. In contrast to having more than one label per data instance, we might just have one label per several instances, leading to multi-instance learning [Dietterich et al., 1997]. Alternatively, when there is redundancy in representing the same data, we have a multi-view setting [Gönen and Alpaydın, 2011]. This includes multimodality as in multimedia [Srivastava and Salakhutdinov, 2014]. One of the earliest set of algorithms for multi-view learning is co-training, in which two classifiers for two views learn to agree on the classification for unlabeled data [Kumar and Daumé, 2011]. Alternatively one can resort to multiple kernel learning in which kernels correspond to different views [Gönen and Alpaydın, 2011], and subspace learning to discover a latent subspace shared by multi-views [Salzmann et al., 2010]. Occasionally when both multiple outputs and input parts are available, we have a joint setting, for example, a mixture of multiple instances, views and labels [Feng and Zhou, 2017].

Neural networks have been demonstrated to be highly versatile to handle multiple tasks [Collobert et al., 2011]. Our Column Bundle bears some similarity to a recent architecture designed for set-to-set mapping [Vinyals et al., 2016], but we do not sequence unordered sets and aim at encoding shared information among set elements. Recently, a deep architecture for multi-instance/multi-label (DeepMIML) learning has been proposed [Feng and Zhou, 2017]. DeepMIML retains sub-concepts for each label, and learns a sub-concept layer, which is a 3D tensor to model the matching scores between instances and sub-concepts of labels. DeepMIML does not model the interactions among labels or instances. Instead, the sub-concept layer is pooled twice by the instance dimension and then by the sub-concept dimension to get a vector of predictions for all labels.

3 Method

In this section, we present our main contribution, the Column Bundle (CLB). Denote by $X = \{X^1, ..., X^N\}$ the input set of $N$ examples with the corresponding output set $Y = \{Y^1, ..., Y^N\}$. Each $X^i$ consists of $M_V$ ($M_V \geq 1$) input parts: $X^i = \{x^i_1, ..., x^i_{M_V}\} \in \mathbb{R}^{d_{M_V}}$ and each $Y^i$ consists of $M_L$ ($M_L \geq 1$) outputs: $Y^i = \{y^i_1, ..., y^i_{M_L}\}$, where $y^i_j$ can be either binary or multi-class. We call each input $x^i_j$ or each label $y^i_j$ as a part. For any unobserved-label example $X^{unk}$, a multi-X model predicts $Y^{unk}$ as the set of outputs for $X^{unk}$. In what follows, the superscripts indicating sample indices are removed for clarity.

When $M_V > 1$ and $M_L = 1$, the data contain multi-input parts and a single label, e.g., multi-instance and multi-view learning. When $M_V = 1$ and $M_L > 1$, the data contain only an input part and multi-outputs, the problem becomes multi-label or multi-task learning. When both $M_V > 1$ and $M_L > 1$, the setting is a combination of the two previous problems, e.g., multi-label/multi-view and multi-label/multi-instance learning.

3.1 Column design

![Figure 1: A Column Bundle with 2 mini-columns. (Left) Forward flow at the central column, (Right) Forward flow at the mini-columns.](image)

CLB is inspired by a recent architecture – Column Network [Pham et al., 2017], which is a neural network of thin feedforward nets known as mini-columns. These columns are inter-connected through pre-defined relations. We borrow this idea to handle the correlations among multiple input/output parts in data. However, when the number of parts grows, modeling the correlation between two parts by a link is impossible as the number of connections is quadratic in the number of parts. In a CLB, each part is processed by a mini-column and mini-columns link to a central column only (See Fig.[Left]). The central column processes inputs from itself and from the mini-columns, and then redistributes the output to the mini-columns (See Fig.[Right]). Through multiple layers, the
correlations among mini-columns are established. With the CLB model, the number of connections is only the number of parts in data, therefore saving memory and computational cost.

To be more precise, a column bundle consists of a central column and \( M \) mini-columns. Each column is a feedforward neural network of \( T \) hidden layers. Denote by \( \hat{h}_c^t \) the hidden activation at layer \( t \) of the central column and by \( h_i^{t-1} \) the hidden activation at layer \( t \) of the \( i^{th} \) mini-column. At the first layer in a bundle, each mini-column reads an input part of data and the central column can read inputs from multiple sources, depending on the data type (See Sec. 3.2 for details). At each layer \( t \) \( (1 < t \leq T) \), \( \hat{h}_c^t \) is a non-linear transformation of its previous hidden state \( \hat{h}_c^{t-1} \) and previous hidden states \( h_i^{t-1} \) \( (i = 1, \ldots, M) \) from all mini-columns. At each mini-column \( i \), \( h_i^t \) is a non-linear function of its previous hidden state \( h_i^{t-1} \) and the previous hidden state \( \hat{h}_c^{t-1} \) from the central column. The transformations are written as follows:

\[
\begin{align*}
\hat{h}_c^t &= g \left( W_c^t h_c^{t-1} + \frac{1}{M} \sum_{i=1}^M U_i^t h_i^{t-1} \right) \quad (1) \\
h_i^t &= g \left( W_i^t h_i^{t-1} + V_i^t h_c^{t-1} \right) \quad (2)
\end{align*}
\]

where \( W_c^t, U_i^t, W_i^t \) and \( V_i^t \) are weight matrices at layer \( t \). Here, biases are omitted for clarity. At the top layer, the hidden state \( h_c^T \) can be returned for further purposes.

**Highway Networks as columns**

Each column (mini- or central one) in a bundle can be any feedforward neural network. However, training traditional deep feedforward neural nets is difficult as non-linear functions prevent data signals and gradients from passing easily through the network. In our implementation, we opt for Highway Networks \cite{srivastava2015highway}, a solution addressing the problem by adding gates that let previous states propagate partly through layers:

\[
h_i^t = \alpha_i^1 \hat{h}_i^t + \alpha_i^2 h_i^{t-1}
\]

where \( \hat{h}_i^t \) is a non-linear candidate function of inputs at layer \( t \) and \( \alpha_i^1, \alpha_i^2 \in (0, 1) \) are learnable gates. This enables input signals and error gradients to propagate through very deep networks. We set the gate \( \alpha_i^1 \) as a sigmoid function and the gate \( \alpha_i^2 = 1 - \alpha_i^1 \) following \cite{srivastava2015highway}.

In a CLB, the candidate functions \( \hat{h}_c^t \) for the central column \( c \) and \( h_i^t \) for each mini-column \( i \) are computed using Eq. (1) and Eq. (2), respectively. The gates \( \alpha_i^1 \) at the central column and \( \alpha_{i1} \) at each mini-column are modeled as:

\[
\begin{align*}
\alpha_{c1}^t &= \sigma \left( W_c^t h_c^{t-1} + \frac{1}{M} \sum_{i=1}^M U_i^t h_i^{t-1} \right) \quad (3) \\
\alpha_{i1}^t &= \sigma \left( W_i^t h_i^{t-1} + V_i^t h_c^{t-1} \right) \quad (4)
\end{align*}
\]

**Parameter sharing among layers**

The number of parameters grows with the number of hidden layers in feedforward networks and with the number of labels in data. This may cause overfitting in very deep networks. To address this, work has been done using the idea of parameter sharing in Recurrent Neural Networks (RNNs) \cite{pham2016lstm, pham2017multi, liao2016multi}, that is hidden layers share the same set of parameters. This helps the depth of neural nets to grow whilst saving parameters. When parameters are shared among layers, the weights in Eq. (1, 2) become:

\[
\begin{align*}
W_c^t = \ldots = W^T = W, \quad U_i^t = \ldots = U^T = U, \quad W_i^t = \ldots = W^T = W_i \quad (i = 1, \ldots, M).
\end{align*}
\]

It is similar for the weight matrices of the gates in Eqs. (3, 4).

### 3.2 CLB for different multi-X settings

There are different types of multi-X data: multi-input (e.g., multi-instance, multi-view), multi-output (e.g., multi-task, multi-label) and a combination of both (e.g., multi-instance/multi-label, multi-view/multi-label). Our CLB model can work on all of these types without changing the structure. For each type of data, we only need to set up the inputs and the outputs for the CLB. In this subsection, we describe the ways that inputs and outputs are handled for each multi-X problem.

**Multi-outputs**

The CLB for multi-output problems (i.e., multi-task, multi-label learning) is shown in Fig. 2a. The central column processes and distributes the input signals to the mini-columns. The mini-columns process these signals and send the output signals back to the central column. The process repeats recurrently along the layers. At the top, each mini-column predicts its own output. Let \( M_L \) be the number of labels, \( y_i \) be the class of the label \( i^{th} \) and \( x \) be the feature vector for a sample. For simplicity, at the first layer, the central column and all the mini-columns read the feature vector:

\[
\begin{align*}
\hat{h}_c^1 &= g \left( W^1 x \right) \\
h_i^1 &= g \left( V_i^1 x \right)
\end{align*}
\]

for \( i = 1, \ldots, M_L \) and process the data signals as described in Sec. 3.1. The mini-column \( i^{th} \) predicts a class for the label \( i^{th} \)
\(i = 1 \ldots M_L\) as normal: \(P_i(y_i = 1) = \sigma(Zh_i^T)\) for binary classification and \(P_i(y_i = c) = \text{softmax}(Qh_i^T)\) for multi-class classification. The loss function for a sample is the sum of the negative-log likelihood of all labels

\[L = - \sum_{i=1}^{M_L} \log (P_i(y_i))\]  

(7)

### Multi-inputs

The model for multi-input data (e.g., multi-instance, multi-view) is illustrated in Fig. 2b. The central column recurrently feeds these vectors to the mini-columns as inputs. The model retains embedded vectors for label indices and then instead of learning an embedding matrix for classes, the CLB classes use to address the problem of multi-class learning with many labels. For multi-input problems, input parts are feature vectors in different dimensions. Before being passed to the mini-columns, input parts are projected into the same vector space.

\[h_c^1 = g \left( \frac{1}{M_V} \sum_{i=1}^{M} U_i^1 x_i \right)\]  

(8)

\[h_i^1 = g \left( W_i^1 x_i \right)\]  

(9)

for \(i = 1 \ldots M_V\). The hidden activation at the top layer of the central column \(h_c^T\) can be used for predicting the output.

### Multi-inputs/multi-outputs

This setting occurs when both multi-inputs and multi-outputs are available in data, for example, multi-instance/multi-label and multi-view/multi-label data. The model for multi-input/multi-output setting is simply a combination of the two settings described above (See Fig. 2c for illustration). The hidden activation at the top layer of the central column for multi-inputs is passed to the central column for multi-outputs.

### 3.3 Scaling up for thousands of parts

Each mini-column processes an input or output in data. These inputs/outputs may be of different types, thus normally each mini-column has its own parameters, except multi-instance learning where instances are of the same type. However, some datasets contain many input parts or labels, for example, MediaMill dataset (See Sec. 3.2) with 101 labels. The number of parameters for the mini-columns in these cases would be extremely huge. To tackle this issue, mini-columns can share parameters (it is different from parameter sharing among layers described in Sec. 3.1). That means the weight matrices in Eqs. (1, 2) become: \(U_1 = \ldots = U_M\), \(W_1 = \ldots = W_M\) and \(V_1 = \ldots = V_M\). It is similar for the weight matrices of the gates in Eq. (3, 4).

For multi-label problems, if the parameters of the mini-columns are shared, the mini-columns return the same output as they receive the same data signals from the central column and process the information by the same weights. To resolve the issue, we borrow the idea of label embedding, which is used to address the problem of multi-class learning with many classes [Amit et al., 2007] [Bengio et al., 2010]. In our work, instead of learning an embedding matrix for classes, the CLB model retains embedded vectors for label indices and then feeds these vectors to the mini-columns as inputs. The model learns an embedding matrix \(E \in \mathbb{R}^{d_e \times M_L}\), where \(M_L\) is the number of labels, \(d_e\) is the embedding dimension and the column \(E_i\) is the embedded vector of the label \(i^{th}\). Each mini-column \(i\) reads the vector \(E_i\) as the input signal for the label \(i^{th}\). The Eq. (5, 6) are now replaced by:

\[h_c^1 = g \left( W^1 x + \frac{1}{M_L} \sum_{i=1}^{M_L} U_i^1 E_i \right)\]  

(10)

\[h_i^1 = g \left( W_i^1 E_i + V_i^1 x \right)\]  

(11)

For multi-input problems, input parts are feature vectors in different dimensions. Before being passed to the mini-columns, input parts are projected into the same vector space.

### 4 Experiments

We demonstrate the effectiveness of CLB in handling various types of multi-X settings by experimenting on Multi-label, Multi-view, Multi-view/Multi-label and Multi-instance datasets.

#### 4.1 Implementation

For all experiments with CLB, dropout is applied before and after the recurrent layers of the model. To handle data imbalance, each class is weighted by the log of the multiplicative inverse of its frequency. This implies that the model attends more to samples from an under-represented class. Each dataset is divided into 3 separated sets: training, validation and test sets. The learning rate starts at 0.001. After 10 epochs, the learning rate is divided by 2 if the model cannot find a better result on the validation set. Learning is terminated after 4 times of halving the learning rate or after 500 epochs. For hyper-parameter tuning, we set the number of hidden layers by 10 and search for (i) hidden dimensions of the central column, (ii) hidden dimensions of the mini-columns (we set all the mini-columns in the same dimension), (iii) embedding dimension for label embedding and (iv) optimizers: Adam or RMSprop. The best setting is chosen by the validation set and the results of the test set are reported as the mean result of 5 runs. Code for CLB model can be found on Github[4].

#### 4.2 Multi-label

Datasets

Our first set of experiments test the CLB as a model for multi-label learning (See Sec. 3.2 and Fig. 2b). We use 3 datasets with different number of labels and density. The first dataset is Movielens Latest Dataset[3]. The task is to predict genres for each movie given plot summary. After removing all movies without plot summary, the dataset contains 18,352 movies. The other two datasets - tmc2007 and MediaMill - are downloaded from Mulan website[2]. The statistics of the three datasets are reported in Table[1].

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[1] link omitted for review
[2] https://grouplens.org/datasets/movielens/
[3] http://mulan.sourceforge.net/datasets-mlc.html
Dataset | n_samples | n_feats | n_labels | Density |
--- | --- | --- | --- | --- |
Movielens | 18,352 | 1000 | 9 | 0.212 |
tmc2007 | 28,596 | 500 | 22 | 0.098 |
MediaMill | 43,907 | 120 | 101 | 0.046 |

Table 1: Statistics of Multi-label datasets

Baselines and experiment settings
For comparison, we employed baseline methods specifically designed for (a) multi-label learning and (b) deep neural nets for training each label separately. For the former, we used 3 methods listed below:

- Probabilistic Classifier Chains (PCC) [Cheng et al., 2010]
- Learning label-specific features for multi-label classification (LLSF) [Huang et al., 2015]
- Back Propagation Neural Network for multi-label (BPNN) - a method in Meka toolkit [Read et al., 2016]

For deep neural nets, we implemented Highway Network with shared parameters among layers (HWN), trained each label separately with a neural network, and then combined the results of all the labels.

In the CLB model, the parameters of the mini-columns are not shared for datasets with small number of labels (Movielens dataset), and shared using label embedding (See Sec. 3.2 for datasets with large number of labels (tmc2007 and MediaMill datasets).

Results
Table 2 summarizes the Micro F1-scores and Hamming Loss obtained by all models on the three datasets. CLB is stable, comparable or better than other baselines in all three datasets. On Movielens, although PCC outperforms CLB on Micro F1-score and HWN outperforms CLB on Hamming Loss, the two baselines fail to compete with our method on the other metric. On tmc2007 dataset, CLB achieves a F1-score of 76.5%, followed by 76% and 73.2%, achieved by HWN and PCC. HWN performs quite well with small number of labels and high density but it fails to handle MedialMill dataset with low label density and 101 labels.

Fig. 3 (Left) shows the pairwise cosine similarity of label embedded vectors and (Right) The pairwise correlations of 101 labels for MediaMill dataset. The correlations are computed based on label co-occurrence. The two matrices are quite similar. It suggests that the learned label embedded vectors somehow capture the correlations among labels.

4.3 Multi-view and Multi-view/Multi-label

Dataset
For multi-view learning (See Sec. 3.2 and Fig. 2b), we evaluate our model on Youtube dataset [Madani et al., 2013]. The dataset consists of features and labels of 120,000 videos. The task is to classify each video into one of 31 classes where each class (except class 31) corresponds to a video game and class 31 corresponds to other games that do not belong to any of the 30 games. Each video sample is described by 13 views, from 3 feature families: textual, visual and auditory features. In our experiments, for fair comparison with other baselines, we use textual (3 views) and visual (5 views) features only. Text features are in bag-of-word representation. We preprocessed the data by removing all words with doc-frequency smaller than 0.01.

For multi-view/multi-label learning (See Sec. 3.2 and Fig. 2c), we use NUS-WIDE dataset [Chua et al., 2009]. The dataset contains 269,648 images associated with tags from Flickr and six types of low-level features (visual and textual) extracted from these images. Visual features include 64-D color histogram, 144-D color correlogram, 73-D edge direction histogram, 128-D wavelet texture and 225-D block-wise color moments extracted over 5x5 fixed grid partitions, and textual features are 500-D bag-of-word descriptions. We only use these low-level features for experiments. Each image can be labeled with some of 81 concepts (e.g., water, buildings, mountain, cars, etc.). The label density is only 0.023.

Baselines and experiment settings
We compare CLB against two baselines: (i) a highway net that reads the concatenation of all views as input (HWN) and (ii) deep Boltzmann Machines for Multimodal learning (BMM) [Srivastava and Salakhutdinov, 2014]. For the latter, we use the code provided by the authors in which all textual feature vectors are concatenated into a view and all visual feature vectors are concatenated into another view. BMM is used to extract a unified representation for the two views and this representation is then fed to a Highway Network as input features for classification. We set the dimension of extracted feature vectors to 1024 and tune the hidden layer size of the Highway Network.

For a fair comparison with BMM, we evaluate the performance of CLB in 2 settings of data: (i) 2-view setting where views in the same types are concatenated, same as in BMM method and (ii) all-view setting where each mini-column processes a view.

For NUS-WIDE dataset, we use the CLB model as in Fig. 2c. The two baselines train each label separately and then combine the results of all labels.

Results
The performance of CLB and the baselines on Youtube and NUS-WIDE datasets is reported in Table 3. Both settings of CLB beat all baselines. The CLB model performs on the all-view setting slightly better than it does on the 2-view setting.

In Youtube dataset, we randomly choose 2 samples in the same class and visualize their hidden states through 10 layers
of 8 mini-columns (See Fig. 4). It is interesting that each pair of mini-columns from the two samples are in the similar patterns.

| Method     | Youtube MicroF1 | Youtube HLoss | NUS-WIDE MicroF1 | NUS-WIDE HLoss |
|------------|-----------------|---------------|------------------|---------------|
| HWN        | 97.3            | 0.027         | 53.1             | 0.022         |
| 2views-BMM | 95.2            | 0.048         | 50.0             | 0.023         |
| 2views-CLB | 97.9            | 0.021         | 56.9             | 0.019         |
| CLB        | 98.0            | 0.020         | 57.7             | 0.019         |

Table 3: Results on Youtube and NUS-WIDE datasets, reported in Micro F1-score (%) and Hamming Loss (HLoss).

For comparison, 3 baselines for multi-instance learning are employed: the two first algorithms are miVLAD and miFV [Wei et al., 2014], and the third is MI-Net [Wang et al., 2016] using highway network. In a MI-Net, instances of each bag are passed to a highway network and hidden states of instances at the top layer are pooled (mean and max pooling) to a vector, which is then used for label prediction. Max pooling works badly on this dataset, therefore, only the results of MI-Net with mean pooling are reported. Table 4 summarizes the results.

| Method | IMDB MicroF1 | IMDB HLoss |
|--------|--------------|------------|
| miVLAD | 81.6         | 0.186      |
| miFV   | 83.9         | 0.162      |
| MI-Net | 84.7         | 0.158      |
| CLB    | 85.4         | 0.150      |

Table 4: Performance of CLB and the baseline on IMDB sentiment classification in multi-instance setting.

5 Conclusion

We have proposed Column Bundle (CLB), a deep neural network model for leveraging shared statistics in multi-X problems, where X stands for view, label and instance and any combination of these. This is the capability not seen in existing work. A CLB consists of a bundle of mini-columns connected to a central column. Each mini-column represents an input part or an output target, and the central column acts as a hub for the mini-columns to exchange information. The structure effectively captures the correlations among the mini-columns without explicitly defining pairwise links. With sharing parameters among the mini-columns, CLB is capable of modeling data with a huge number of inputs and labels, e.g., image tagging in vision with thousands of tags. CLB is efficient as it has only linear complexity in the number of inputs/outputs in both training and inference. Empirically, CLB demonstrates a competitive and comparable performance against rivals designed specifically for multi-label, multi-view, multi-instance learning and multi-view/multi-label learning.

CLB opens rooms for future work. For example, a database record of multiple fields can be represented naturally using a CLB, hence we can carry out common tasks such as retrieval, record linkage or database completion. One might also learn an attention mechanism so that the model can assign more weight to important parts. We can also exploit variable computation steps in mini-columns so that some easy and linear tasks (inputs) only need short decoding (encoding).
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