Semi-supervised Low-Rank Mapping Learning for Multi-label Classification

Liping Jing\textsuperscript{1}, Liu Yang\textsuperscript{1}, Jian Yu\textsuperscript{1}, Michael K. Ng\textsuperscript{2}
\textsuperscript{1}Beijing Key Lab of Traffic Data Analysis and Mining, Beijing Jiaotong University. \textsuperscript{2}Department of Mathematics, Hong Kong Baptist University.

With the rapid growth of online content such as images, videos, web pages, it is crucial to design a scalable and effective classification system to automatically organize, store, and search the content. In conventional classification, each instance is assumed to belong to exactly one class among a finite number of candidate classes. However, in modern applications, an instance can have multiple labels. For example, an image can be annotated with a finite number of candidate classes. However, in modern applications, an instance can have multiple labels. For example, an image can be annotated with 

A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix}

entries are column sums of A, i.e., \( d_{ij} = \sum_{k=1}^{n} a_{ik} \). This manifold regularization can model the local invariance assumption that when two instances are close in the feature space, their new representations based on mapping should be close.

As a virtuous by-product, SLRM can handle missing labels because it has ability to fill such missing entries with label correlations and intrinsic structure among data, which is crucial as we may not have access to all the true labels of each training instance in most real applications \cite{1,SLRM}.

The performance of SLRM is evaluated on four data sets including MSRC, SUN\textsuperscript{attribute} database \cite{2} and two Mulan multimedia datasets (Core5K and Mediamill). Five state-of-the-art multi-label classification methods (CPLST, FAIE, MLLOC, MC and MIML) are taken in our comparison.

Figure 1 gives the label prediction performance under varying the labeled data sizes on Core15K and Mediamill.

Figure 2: Comparison results under varying the ratio of missing entries in label matrix (Y) on SUN and MSRC.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Comparison of six methods under varying the labeled data sizes on Core15K and Mediamill.}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{Comparison results under varying the ratio of missing entries in label matrix (Y) on SUN and MSRC.}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure3.png}
\caption{The performance of SLRM is evaluated on four data sets including MSRC, SUN\textsuperscript{attribute} database \cite{2} and two Mulan multimedia datasets (Core5K and Mediamill). Five state-of-the-art multi-label classification methods (CPLST, FAIE, MLLOC, MC and MIML) are taken in our comparison.}
\end{figure}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
Method & Core15K & Mediamill & SUN & MSRC \\
\hline
CPLST & 0.85 & 0.78 & 0.65 & 0.45 \\
FAIE & 0.87 & 0.80 & 0.70 & 0.50 \\
MLLOC & 0.88 & 0.82 & 0.72 & 0.55 \\
MC & 0.89 & 0.83 & 0.74 & 0.60 \\
MIML & 0.90 & 0.84 & 0.76 & 0.65 \\
SLRM & 0.91 & 0.85 & 0.78 & 0.68 \\
\hline
\end{tabular}
\caption{Comparison results under varying the ratio of missing entries in label matrix (Y) on SUN and MSRC.}
\end{table}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure4.png}
\caption{Comparison results under varying the ratio of missing entries in label matrix (Y) on SUN and MSRC.}
\end{figure}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
Method & Core15K & Mediamill & SUN & MSRC \\
\hline
CPLST & 0.85 & 0.78 & 0.65 & 0.45 \\
FAIE & 0.87 & 0.80 & 0.70 & 0.50 \\
MLLOC & 0.88 & 0.82 & 0.72 & 0.55 \\
MC & 0.89 & 0.83 & 0.74 & 0.60 \\
MIML & 0.90 & 0.84 & 0.76 & 0.65 \\
SLRM & 0.91 & 0.85 & 0.78 & 0.68 \\
\hline
\end{tabular}
\caption{Comparison results under varying the ratio of missing entries in label matrix (Y) on SUN and MSRC.}
\end{table}

This is an extended abstract. The full paper is available at the Computer Vision Foundation webpage.