Supervised learning of sparse context reconstruction coefficients for data representation and classification

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Abstract Context of data points, which is usually defined as the other data points in a data set, has been found to play important roles in data representation and classification. In this paper, we study the problem of using context of a data point for its classification problem. Our work is inspired by the observation that actually only very few data points are critical in the context of a data point for its representation and classification. We propose to represent a data point as the sparse linear combination of its context and learn the sparse context in a supervised way to increase its discriminative ability. To this end, we propose a novel formulation for context learning, by modeling the learning of context parameter and classifier in a unified objective, and optimizing it with an alternative strategy in an iterative algorithm. Experiments on three benchmark data set show its advantage over state-of-the-art context-based data representation and classification methods.

Keywords Pattern classification · Data representation · Context · Nearest neighbors · Sparse regularization

1 Introduction

Pattern classification is a major problem in machine learning research [13, 14, 30, 43, 44, 49]. This problem is defined as a problem of predicting a binary class label of a given data point. There are many examples of this problem in real-world applications. For example, in computer vision area, given an image of face, we may want to predict whose face it is [7, 22, 24, 40, 45, 48, 50]. In natural language processing applications, given a text, we also want to predict which topic it is about [1, 10, 19, 21, 26, 28]. Moreover, in applications of wireless sensor network, it is important to detect whether one node is normal or at fault. To solve this problem, we usually first represent the data point as a feature vector and then learn a classifier function to predict the class label from its feature vector. The two most important topics of pattern classification are data representation and classifier learning. Most data representation and classification methods are based on single data point. When one data point is considered for representation and classification, all other data points are ignored. For example, in the most popular data representation method, feature selection scheme, when we have a feature vector, one data point, we simply reduce the abandoned features and re-organize the remaining feature to a new feature vector to obtain the representation of the data point [5, 17].
In this procedure, no other data points are considered beside the data point to represent. Another example is the most classification method, support vector machine (SVM). When we have a test, a linear function is applied to its feature vector to predict its class label [18, 20]. In this procedure, no other data points are considered. However, the other data points other than the data point under consideration may play important roles in its representation and classification. These data points are called “context” of the considered data point. A data point may have different true nature in different context. Thus, it is necessary to explore the contexts of data points when they are represented and/or classified. To this end, some methods have been proposed to use the context of a data point for its representation and classification. In this paper, we investigate the problem of learning effective representation of a data point from its context guided by its class label and proposed a novel supervised context learning method using sparse regularization and linear classifier learning formulation.

1.1 Related works

This paper is to explore the context information for data representation and classification, and thus, we give some brief review of existing context-based data representation and classification methods.

- The most popular context-based data classification is \( k \) nearest neighbor classification (KNN). Given a test data point and a training set, we first search the training set to find the \( k \) nearest neighbors of the test data point to present its context, and then, we determine its class label by a majority vote of the labels of the context [2, 3]. All the data points of the context contribute equally to the final classification result, and no representation procedure is needed.

- Wright et al. [47] proposed sparse representation-based classification (SRBC), to use the data points of one class as a context of a test data point and reconstruct it by its context. The reconstruction coefficients are imposed to be sparse. Moreover, the class with the minimum reconstruction error is assigned to the test data point. This method does not require to learn an explicate classifier to predict the class label. Thus, it cannot take advantages of the classifier learning technologies.

- Melacci and Belkin [25] proposed Laplacian support vector machine (LSVM), to use the \( k \) nearest neighbors of a training data point to present its context and learn a linear classifier to respect the context. Specifically, the classification result of a training data point is imposed to be similar to its contextual data points. However, after the classifier is trained and used to classify a test data point, the context of the test data point is ignored.

- Gao et al. [9] proposed Laplacian sparse coding (LSC) to represent the context of a data point by using its \( k \) nearest neighbors and represent the data points with regard to the contexts. Each data point is reconstructed as a linear combination of the codewords of a dictionary, and the combination coefficients are imposed to be sparse. Moreover, the combination coefficients of a data point are imposed to be similar to those of its contextual data points. This method is unsupervised simply a data representation method, and the class label information is ignored.

1.2 Contributions

We propose a novel method to explore the context of a data point and use it to represent it. Moreover, a linear classifier function is learned to predict its class label from its representation based on its context. We use its \( k \) nearest neighbors as its context and try to reconstruct it by the data points in its context. The reconstruction errors are imposed to be spares, and we measure the sparsity by a \( \ell_1 \) norm regularization, similar to sparse coding [23, 29, 37–39]. Moreover, the reconstruction result is used as the new representation of this data point. We apply a linear function to predict its class label. To learn the reconstruction coefficient vectors of the data points and the classifier parameter vector, we build a unified objective function. In this function, the reconstruction error is measured by a squared \( \ell_2 \) norm distance, and the classification error is measured by the hinge loss. Moreover, the \( \ell_1 \) norm regularization is applied to the reconstruction coefficient vectors to encourage their sparsity, and the squared \( \ell_2 \) norm regularization is applied to the classifier parameter vector to reduce the complexity of the classifier. By optimizing the objective function with regard to both the reconstruction coefficient vectors and the classifier parameter vector, the context-based representation and classifier are learned simultaneously. In this way, the context and the classifier can regularize the learning of each other. To minimize the proposed objective function, we use the Lagrange multiplier and an alternate optimization method and develop an iterative algorithm based on the optimization results. The contributions of this paper are of twofolds:

1. We propose a novel context representation formulation. A data point is represented by its sparse reconstruction of its context. The motivation of this contribution is that for each data point, only a few data points in its context are of the same class as itself. However, it is critical to find which data points play the most important roles in its context for the classification of the data point itself. To find the critical contextual data points, we proposed to learn
the classifier together with the sparse context. The classifier can be used to regularize the learning of the reconstruction coefficient vector and thus find the critical data points in the context. We mode this problem as a minimization problem. In this problem, the context reconstruction error, reconstruction sparsity, classification error, and classifier complexity are minimized simultaneously.

2. We also propose a novel iterative algorithm to solve this minimization problem. We first reformulate it as its Lagrange formula and use an alternative optimization method to solve it. In each iteration, we first fix the classifier parameter vector to update the reconstruction vectors and then fix the reconstruction vectors to update the classifier parameter vector.

1.3 Paper organization

This paper is organized as follows. In Sect. 2, we introduce the proposed method. In Sect. 3, we evaluate the proposed method experimentally. In Sect. 4, this paper is concluded with future works.

2 Proposed method

In this section, we introduce the proposed classification method which explores the context information. The learning problem is firstly formulated by modeling an objective function, and then, it is optimized in an iterative algorithm.

2.1 Problem formulation

We consider a binary classification problem, and a training set of $n$ data points are given as \( \{ \mathbf{x}_i \}_{i=1}^n \), where \( \mathbf{x}_i \in \mathbb{R}^d \) is a $d$-dimensional feature vector of the $i$th data point. The binary class labels of the training points are given as \( \{ y_i \}_{i=1}^n \) and \( y_i \in \{ +1, -1 \} \) is the class label of the $i$th point. To learn from the context of the $i$th data point, we find its $k$ nearest neighbors and denote them as \( \{ \mathbf{x}_{ij} \}_{j=1}^k \), where \( \mathbf{x}_{ij} \) is the $j$th nearest neighbor of the $i$th point. They are further organized as a $d \times k$ matrix \( \mathbf{X}_i = [\mathbf{x}_{i1}, \ldots, \mathbf{x}_{ik}] \in \mathbb{R}^{d \times k} \), where the $j$th column is \( \mathbf{x}_{ij} \). The $k$ nearest neighbors of the $i$th point is used to represent its context information. We represent \( \mathbf{x}_i \) by linearly reconstructing it from its contextual points as

\[
\mathbf{x}_i \approx \tilde{\mathbf{x}}_i = \sum_{j=1}^k \mathbf{x}_{ij}v_{ij} = \mathbf{X}_i\mathbf{v}_i
\]

where \( \tilde{\mathbf{x}}_i \) is its reconstruction, and \( \mathbf{v}_{ij} \) is the reconstruction coefficient of the $j$th nearest neighbor. \( \mathbf{v}_i = [v_{i1}, \ldots, v_{ik}]^T \in \mathbb{R}^k \) is the reconstruction coefficient vector of the $i$th data point. The reconstruction coefficient vectors of all the training points are organized in reconstruction coefficient matrix \( \mathbf{V} = [\mathbf{v}_1, \ldots, \mathbf{v}_n] \in \mathbb{R}^{k \times n} \), with its $i$th column as \( \mathbf{v}_i \). The key idea of this method is an assumption for both the reconstruction and classification of \( \mathbf{x}_i \); only a few of its nearest neighbors play important role, while the remaining neighbors could be discarded, resulting a sparse context. To encourage the sparsity of the context, we impose a $\ell_1$ norm penalty to the contextual reconstruction coefficient vector \( \mathbf{v}_i \). Moreover, to learn contextual reconstruction coefficient vectors, we also propose to minimize the reconstruction error measured by a squared $\ell_2$ norm penalty between \( \mathbf{x}_i \) and \( \mathbf{X}_i\mathbf{v}_i \), and the following optimization problem is obtained,

\[
\min_{\mathbf{V}} \beta \sum_{i=1}^n \| \mathbf{x}_i - \mathbf{X}_i\mathbf{v}_i \|^2_2 + \gamma \sum_{i=1}^n \| \mathbf{v}_i \|_1
\]  

(2)

where $\beta$ and $\gamma$ are trade-off parameters.

To classify \( \mathbf{x}_i \), instead of applying a classifier to \( \mathbf{x}_i \) itself, we apply a linear classifier to its contextual reconstruction \( \tilde{\mathbf{x}}_i \). The classifier is defined as

\[
f(\tilde{\mathbf{x}}_i) = \mathbf{w}^T\tilde{\mathbf{x}}_i = \mathbf{w}^T\mathbf{X}_i\mathbf{v}_i
\]

(3)

where \( \mathbf{w} \in \mathbb{R}^d \) is the classifier parameter vector. To learn the classifier, we consider the hinge loss function and the squared $\ell_2$ norm regularization simultaneously. The following optimization problem is obtained with regard to the classifier learning,

\[
\min_{\mathbf{w},\mathbf{V}} \frac{1}{2} \| \mathbf{w} \|^2 + \alpha \sum_{i=1}^n \xi_i
\]  

(4)

s.t. \( 1 - y_i(\mathbf{w}^T\mathbf{X}_i\mathbf{v}) \leq \xi_i, \quad \xi_i \geq 0, \quad i = 1, \ldots, n, \)

where $\frac{1}{2} \| \mathbf{w} \|^2$ is the squared $\ell_2$ norm regularization term to reduce the complexity of the classifier, $\xi_i$ is the slack variable for the hinge loss of the $i$th training point, $\xi = [\xi_1, \ldots, \xi_n]^T$ and $\alpha$ is a tradeoff parameter.

The overall optimization problem is obtained by combining the problems in both (2) and (4) as

\[
\min_{\mathbf{w},\mathbf{V}} \left\{ \frac{1}{2} \| \mathbf{w} \|^2 + \alpha \sum_{i=1}^n \xi_i + \beta \sum_{i=1}^n \| \mathbf{x}_i - \mathbf{X}_i\mathbf{v}_i \|^2_2 + \gamma \sum_{i=1}^n \| \mathbf{v}_i \|_1 \right\}
\]  

s.t. \( 1 - y_i(\mathbf{w}^T\mathbf{X}_i\mathbf{v}) \leq \xi_i, \quad \xi_i \geq 0, \quad i = 1, \ldots, n. \)

(5)

From the above problem, we can see that by encouraging the sparsity of $\mathbf{v}_i$, we learn a sparse context for both the reconstruction and classification of $\mathbf{x}_i$.
2.2 Optimization

To optimize the constrained problem in (5), we write the Lagrange function of this problem as
\[
\mathcal{L}(w, V, \xi, \delta) = \frac{1}{2}||w||_2^2 + \eta \sum_{i=1}^{n} \xi_i + \beta \sum_{i=1}^{n} ||x_i - X_i v_i||_2^2 + \gamma \sum_{i=1}^{n} ||v_i||_1
\]
where \( \delta_i \) is the Lagrange multiplier for the constrain of \( 1 - y_i (w^T x_i) \leq \xi_i \), and \( \epsilon_i \) is the Lagrange multiplier for the constrain of \( \xi_i \geq 0 \). According to the dual theory of optimization, the following dual optimization problem is obtained,
\[
\max_{\delta, \epsilon} \quad \mathcal{L}(w, V, \xi, \delta) = \frac{1}{2}||w||_2^2 + \eta \sum_{i=1}^{n} \xi_i + \beta \sum_{i=1}^{n} ||x_i - X_i v_i||_2^2 + \gamma \sum_{i=1}^{n} ||v_i||_1
\]
\[
\text{s.t. } \delta \geq 0, \quad \epsilon \geq 0,
\]
where \( \delta = [\delta_1, \ldots, \delta_n]^T \), and \( \epsilon = [\epsilon_1, \ldots, \epsilon_n]^T \). By setting the partial derivative of \( \mathcal{L} \) with regard to \( w \) to zero, we have
\[
\frac{\partial \mathcal{L}}{\partial w} = 0 \Rightarrow w = \sum_{i=1}^{n} \delta_i y_i X_i v_i.
\]
By setting the partial derivative of \( \mathcal{L} \) with regard to \( \xi_i \) to zero, we have
\[
\frac{\partial \mathcal{L}}{\partial \xi_i} = 0 \Rightarrow \alpha - \delta_i - \epsilon_i = 0
\]
\[
\Rightarrow \alpha = \delta_i = \epsilon_i
\]
\[
\epsilon_i \geq 0 \Rightarrow \alpha \geq \delta_i.
\]
Substituting (8) and (9) to (7), we eliminate \( w \) and \( \delta \)
\[
\max_{\delta} \min_{V} \left\{ -\frac{1}{2} \sum_{i=1}^{n} \delta_i y_i y_i^T X_i^T X_i v_i + \beta \sum_{i=1}^{n} ||x_i - X_i v_i||_2^2 + \gamma \sum_{i=1}^{n} ||v_i||_1 \right\}
\]
\[
\text{s.t. } \alpha \geq \delta \geq 0.
\]
max \( \delta \)
\[
\min_{V} \left\{ -\frac{1}{2} \sum_{i=1}^{n} \delta_i y_i y_i^T X_i^T X_i v_i + \beta \sum_{i=1}^{n} ||x_i - X_i v_i||_2^2 + \gamma \sum_{i=1}^{n} ||v_i||_1 \right\}
\]
\[
\text{s.t. } \alpha \geq \delta \geq 0.
\]

2.2.1 Solving \( V \) while fixing \( \delta \)

When \( \delta \) is fixed and only \( V \) is considered, the problem in (10) is reduced to
\[
\min_{v_i} \left\{ -\frac{1}{2} \sum_{j=1}^{n} \delta_j y_i y_j^T X_j^T X_i v_i + \beta \sum_{i=1}^{n} ||x_i - X_i v_i||_2^2 + \gamma \sum_{i=1}^{n} ||v_i||_1 \right\}
\]
\[
\text{s.t. } v_i \geq 0.
\]

Instead of solving \( V \) at one time, we solve \( v_i \) one by one. When the contextual reconstruction vector of the \( i \)th point \( v_i \) is considered, we fix \( v_i \) as in (13).

This problem could be solved efficiently by the modified feature-sign search algorithm proposed by Gao et al. [8].

2.2.2 Solving \( \delta \) while fixing \( V \)

When \( V \) is fixed and only \( \delta \) is considered, the problem in (10) is reduced to
\[
\max_{\delta} \quad \min_{V} \left\{ -\frac{1}{2} \sum_{i=1}^{n} \delta_i y_i y_i^T X_i^T X_i v_i + \beta \sum_{i=1}^{n} ||x_i - X_i v_i||_2^2 + \gamma \sum_{i=1}^{n} ||v_i||_1 \right\}
\]
\[
\text{s.t. } \alpha \geq \delta \geq 0.
\]

This problem is a typical constrained quadratic programming (QP) problem, and it can be solved efficiently by the active set algorithm.

2.3 Iterative algorithm

The iterative algorithm to learn both the classifier parameter \( w \) and the contextual reconstruction coefficient vectors in \( V \) is given in Algorithm 1. As we can see from the algorithm, the iterations are repeated \( T \) times and then the updated \( V \) and \( \delta \) are outputs. Please note that the variables of this algorithm are initialized randomly.

Algorithm 1: Iterative Learning algorithm.

Input Training point set \( \{x_i\}_{i=1}^{n} \) and label set \( \{y_i\}_{i=1}^{n} \);
Input Nearest neighbor size parameter \( k \);
Input Tradeoff parameters \( \alpha, \beta \) and \( \gamma \);
Input Maximum iteration number \( T \);
Initialization Find nearest neighbors \( \{x_{ij}\}_{j=1}^{k} \) for each data point \( x_i, i = 1, \ldots, n \);
Initialization Initialize \( \delta^0 \) randomly;
For \( t = 1, \ldots, T \)
1. Fix \( \delta^{t-1} \) and update the contextual reconstruction coefficient vectors \( v_{i}^{n} \) one by one by solving the problem in (12);
2. Fix \( v_{i}^{n} \) and update the classifier parameter vector \( w' \) by solving \( \delta' \) as in (13).
Endfor
Output classifier parameter vector \( w = \sum_i^n \delta_i^T y_i X_i v_i^T \).

2.4 Classifying a test point

When a new test point \( x \in \mathbb{R}^d \) comes, to represent its context, we also find its \( k \) nearest neighbors from the training set and put them in a \( d \times k \) matrix \( X \). Given a classifier parameter vector \( w \), and a candidate class label \( y \in \{+1, -1\} \), we seek its class conditional context reconstruction coefficient vector, by solving the following minimization problem,

\[
\mathbf{v}^y = \arg \min_{\mathbf{v}} \left\{ -y \mathbf{w}^T (X \mathbf{v}) + \beta \|x - X \mathbf{v}\|_2^2 + \gamma \|\mathbf{v}\|_1 \right\}. \tag{14}
\]

This problem can also be solved by the modified feature-sign search algorithm proposed by Gao et al. [8]. The final class label \( y^* \) of the test data point is obtained as the candidate label minimizing the following objective,

\[
y^* = \min_{y \in \{+1, -1\}} \{-y \mathbf{w}^T (X \mathbf{v})\}. \tag{15}
\]

3 Experiments

In this section, we evaluate the proposed supervised sparse context learning (SSCL) algorithm on several benchmark data sets.

3.1 Data sets

In the experiments, we used three date sets, which are introduced as follows:

- **MANET loss data set**: The packet losses of the receiver in mobile ad hoc networks (MANET) can be classified into three types, which are wireless random errors caused losses, the route change losses induced by node mobility, and network congestion. It is very important to recognize which class a packet loss belongs in research and application of mobile ad hoc networks. The first data set used in our experiments is a MANET loss data set. To construct this data set, we simulate a MANET scenario by using a network simulator NS-2 [12, 27]. We put 30 nodes in a 400 m \( \times \) 800 m area and select a TFRC flow as the observation stream and a TCP flow as the background traffic between two randomly selected nodes. The random error rate is confined from 1 to 10 %.

- **Twitter data set**: The second data set is a Twitter data set. The target of this data set is to predict the gender of the twitter user, male or female, given one of his/her Twitter message. To construct this data set, we downloaded Twitter massages of 50 male users and 50 female users of 100 days. We collected 53,971 twitter massages in total, and among them there are 28,012 messages sent by male users and 25,959 messages sent by female users.

- **Arrhythmia data set**: The third data set is publicly available at [http://archive.ics.uci.edu/ml/datasets/Arrhythmia](http://archive.ics.uci.edu/ml/datasets/Arrhythmia). In this data set, there are 452 data points, and they belong to 16 different classes.

3.2 Experiment setup

To conduct the experiments, we used the tenfold cross validation. A entire data set is split into tenfolds, and each of them was used as a test set in turn. The remaining ninefolds are combined and used as a training set. The learning algorithm was applied to the training set to learn the classifier parameter. The algorithm is adjusted by using a ninefold cross validation on the training set. The learned classifier was then applied to the test set to predict the class labels of the testing data points. The prediction performance is evaluated by the prediction accuracy, which is defined as,

\[
\text{Prediction accuracy} = \frac{\text{Number of correctly predicted testing data points}}{\text{Total number of testing data points}}. \tag{16}
\]

3.3 Results

In the experiments, we first compare the proposed context-based data representation and classification algorithm, SSCL, to several context-based data representation and/or classification methods. Then, we study the sensitivity of the proposed algorithm to its parameters experimentally. Finally, we study the convergency of the proposed iterative algorithm.
3.3.1 Comparison to context-based representation and classification methods

Since the proposed algorithm is a context-based classification and sparse representation method, we compared the proposed algorithm to three popular context-based classifiers and one context-based sparse representation method. The three context-based classifiers are traditional KNN, Wright et al.’s SRBC [47], and Melacci and Belkin’s LSVM [25]. The context-based sparse representation method is Gao et al.’s LSC [9]. The boxplots of the tenfold cross validation of the compared algorithms are given in Fig. 1. From the figures, we can see that the proposed method SSCL outperforms all the other methods on all three data sets. Among median values of the boxplots of prediction accuracies over three data sets, SSCL is always the highest one. In most cases, the 25th percentiles of SSCL is even higher than the median values of other algorithms. The second best method is SRBC, which also uses sparse context to represent the data point. However, compared to SSCL, it does not learn any explicit classifier for the classification problem. Thus, it cannot take advantage of the classifier design tricks. This is the main reason that SRBC is inferior to SSCL. KNN also uses context to classify a data point without using an explicit classifier. However, unlike SRBC whose context is class conditional, KNN uses a general context and treats all contextual data points equally, and obtains the worst classification results. This is a strong evidence that learning a supervised sparse context is critical for classification problem. LSVM also uses context information to regularize the learning of classifier. However, once the classifier is learned, the context is ignored in the classification procedure, and thus, its performance is inferior to SSCL. LSC is an unsupervised learning algorithm, and it is not surprising that its performance is not good.

3.3.2 Sensitivity to parameters

In the proposed formulation, there are three tradeoff parameters, $\alpha, \beta$, and $\gamma$. Moreover, we have one more parameter, which is the size of the neighborhood, $k$. It is interesting to investigate how these parameters affect the performance of the proposed algorithm. We plot the curve

![Boxplots of prediction accuracy of different context-based algorithms.](a) MANET loss data set. (b) Twitter data set. (c) Arrhythmia data set.
of mean prediction accuracies against different values of parameters and show them in Fig. 2. From Fig. 2a, b, we can see the accuracy is stable to the parameter $\alpha$ and $\beta$. More specifically, in Fig. 2a, it seems that the performances are little better with a median value of $\alpha$. $\alpha$ is the weight of the hinge loss function, and when it makes sense, the classifier has a better performance with a median value, since a too large value leads to over-fitting, while a too small value leads to training error over the training set. It is also interesting to note that $\beta$ also achieves the best performance with a median value, 10. $\beta$ is the weight of the reconstruction error term. A small weight of this term makes the representation of a data point irrelevant to itself, while a large weight does not guarantee its discriminative ability. From Fig. 2c, d, we can see a larger $\gamma$ or $k$ leads to better classification performances. $\gamma$ is the weight of the sparsity term, a larger $\gamma$ achieves a higher prediction accuracy means prediction result benefits from a sparsity representation. This is because that in the context of a data point, only a few data points play important roles. Sparsity of the context forces the model to select those important contextual data points. $k$ is the size of the context, and a larger $k$ provides more candidate contextual data points and helps the model to find the critical contextual data points.

3.3.3 Algorithm convergency

We are also interested in the convergency of the proposed iterative algorithm SSCL. We plot the objective function of the formulation in (5) in different iterations and show the convergency curve in Fig. 3. From this figure, it is clear that the algorithm converges after the 50th iteration.

3.3.4 Running time analysis

We also provide an analysis of the running time of the compared algorithms over the MANET loss data set. The running time of the algorithms is given in Fig. 4. The unit of the running time is second. From the figure, we can see that the least time-consuming algorithm is KNN; however,
its classification performance is poor. Our algorithm, SSCL, is the second least time-consuming algorithm. It takes no more than 250 s, while all other algorithms take more than that. Moreover, SSCL achieves the best classification results. It leads to the conclusion that the proposed algorithm can achieve the best classification performance with a reasonable running time.

4 Conclusion and future works

In this paper, we study the problem of using context to represent and classify data points. Our motivation is that although data points in context of a data point play important roles in its classification, only a few of them is critical. Thus, it is necessary to learn a sparse context. To this end, we propose to use a sparse linear combination of the data points in the context of a data point to represent itself. Moreover, to increase the discriminative ability of the new representation, we develop an supervised method to learn the sparse context by learning it and a classifier together in an unified optimization framework. Experiments on three benchmark data sets show its advantage over state-of-the-art context-based data representation and classification methods.

Although the proposed method works well for small data sets, it cannot scale up to large data set. The reason is that in each iteration, it solves a QP problem with regard to the number of data points in (13). This procedure works with small number of data points; however, when it is large, it is too consuming to solve such a QP problem with so many variables. In the future, we will investigate to release this QP problem to a linear problem, by using the expectation-maximization (EM) framework to release the hinge loss to a linear function. Moreover, we also plan to extend the proposed algorithm to different applications, e.g., bioinformatics [34, 35, 42, 46], computer vision [6, 31, 32, 36], and information retrieval [11, 16, 33, 41].

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