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Center for Visual & Decision Informatics

Project# 10a.002.TAU_WP4 - Computationally Efficient Graph-Embedded Subspace-Learning Methods

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Project # 10a.002.TAU_WP4 Computationally Efficient Graph-Embedded Subspace-Learning Methods

Contents

Personnel

- Prof Moncef Gabbouj (PI)
- Fahad Sohrab (Researcher)
- Pauli Ervi (Mentor, IAB member, DeadSetBit)

Executive Summary/Abstract

In this project, we propose a novel subspace learning framework for obtaining a mapping along with data description in low-dimensional feature space. The proposed framework presents the problem in the form of graph embedding. It includes the previously proposed subspace one-class techniques as its special cases and provides further insight into what these techniques optimize. The framework allows for incorporating other meaningful optimization goals via the graph preserving criterion. It reveals a spectral solution and a spectral regression-based solution as alternatives to the previously used gradient-based technique.

We combine the subspace learning framework iteratively with Support Vector Data Description (SVDD) applied in the subspace to formulate Graph-Embedded Subspace Support Vector Data Description (GESSVDD). We experimentally analyzed the performance of newly proposed different variants. We demonstrate improved performance against the baselines and the recently proposed subspace learning methods for one-class classification.

In this project, we also present a novel dataset that captures facial expressions and the associated physiological signals, such as heart rate (HR), electrodermal activity (EDA), and skin temperature (TEMP), under different stress levels. The data was collected from 20 participants at different sessions for 26 hours. The data includes seven different signal types, including both computer vision and physiological features that can be used to detect stress. This part of the project is carried out in collaboration with the University of Louisiana at Lafayette.

Goals and Objectives

The project aims at developing novel method(s) for obtaining a mapping along with data description in low-dimensional feature space. The learning algorithm will employ different intrinsic and penalty graphs in the optimization process of data description for better predictive modeling of data in an optimized low-dimensional feature space. The advanced graph-embedding techniques will be helpful in a multisensory environment for enhancing the decision-making process in an emphatic building environment.

Differences from Current State of Art

In this paper, we formulated subspace learning for one-class classification in the graph embedding framework and discussed the novel insights obtained from this formulation. In particular, we showed that subspace learning for SVDD applies a weighted Principal Component Analysis (PCA) over the support vectors and outliers to define the projection matrix. We discussed how this information could be combined with other data relationships in the optimization process via an adaptable graph. We also formulated a novel GESSVDD with gradient-based, spectral, and spectral regression-based solutions and different adaptable graphs.

This work also presents a multimodal stress-emotion dataset containing stress data from wearable devices and emotion data extracted from facial expressions through a video feed. We analyze human expressions and biometric signals under different stress levels. The dataset presented is the first effort toward identifying stress from non-wearable devices in general and facial expressions in particular. The current study is inspired by our initial effort to use facial expressions to study satisfaction [1]. The dataset is the first of its kind, where facial features and physiological features are combined for stress measurement.

Methods and Datasets

We propose the subspace learning for SVDD in the general graph embedding framework for subspace learning. Different graphs create different variants and can be selected to encode geometric data relationships in the subspace accordingly. While earlier subspace SVDD variants [2], [3], [4] have only used gradient-based solution, we now have three alternatives: 1) gradient-based, 2) spectral, and 3) spectral regression-based updates.

To evaluate the proposed method's performance, we used nine different datasets. The datasets used in the experiments are Seeds, Qualitative bankruptcy, Somerville happiness, Liver, Iris, Ionosphere, Sonar, Heart (from UCI [1]machine learning repository), and MNIST [5] with original dimensionality

We manually created a corrupted version of the heart dataset to report the impact of noise. We added the noise in the manner described in [6]. The corrupted data were created by adding pseudo-random values drawn from the standard normal distribution to the features. We bound the range of added noise for the corresponding attribute to the maximum and minimum value of each feature of the target class in the training set.

We also present EmpathicSchool, a novel dataset that captures facial expressions and the associated physiological signals, such as heart rate, electrodermal activity, and skin temperature,

[1] http://archive.ics.uci.edu/ml

under different stress levels. The data was collected from 20 participants at different sessions for 26 hours. The data includes seven different signal types, including both computer vision and physiological features that can be used to detect stress. In addition, various experiments were conducted to validate the signal quality.

Results

In this project, we evaluated the proposed framework over nine different datasets by considering each class of a dataset as a target class at a time. The results showed that the proposed framework with the kNN graph as the adaptable graph had the best overall performance, while the gradient-based solution was more stable than the spectral and spectral regression-based solutions.

To summarize, the results of the new framework, it places subspace learning for SVDD in the general graph embedding framework with a fixed data-dependent SVDD graph , which resembles PCA on the support vectors and outliers, and an additional constraint graph , which allows to incorporate other meaningful data relationships to the subspace learning step. In the earlier works, the overall objective function has been minimized via gradient-descent. However, the new framework hints that it can also make sense to reverse the objective and maximize instead of minimizing. Also this approach has been previously followed in the literature in [7], where kernel PCA was successfully applied for novelty detection. The main idea of PCA and SVDD along with graphs are illustrated in Fig. 1.

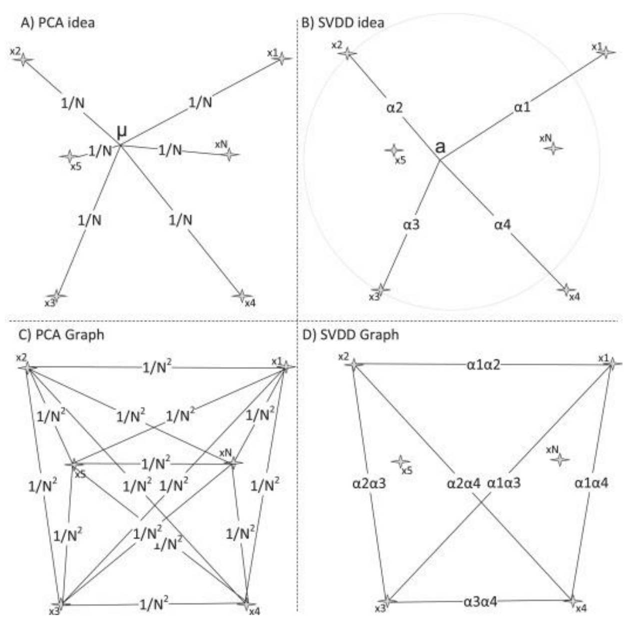

Figure 1. A) PCA considers the (unweighted) variance of all the points from the center . B) SVDD considers weighted variance of support vectors and outliers from the SVDD center . C) PCA graph is fully-connected with equal weights. D) SVDD graph is sparse

We analyzed the physiological signals obtained from the Empatica E4 watch and the predicted facial expressions from the video data for different tasks mentioned in Table 1.

Task	Action performed	Duration (min)	Expected Stress Level
T1	Reading a magazine	9	Normal
T2	Preparing a presentation	9	Stressed
T3	Delivering the presentation	5-9	Stressed
T4	Rest and recovery	9	Normal
T5	IQ test / Stroop Color-Word Test	9	Stressed
T6	Listening to calm music	9	Normal
T7	Watching amusing video(s)	9	Amused
T8	Controlled breathing exercise	9	Normal
T9	Recovery	9	Normal

Table 1: List of tasks performed by participants, the total duration of the data included in the release, and the expected stress level for each task.

Figure 2 shows the happiness curves and physiological signals of subjects A-F performing different tasks (T1-T9). The happiness curve is observed to fluctuate more in T5 and T7 for subjects A-F as compared to other tasks. For a given task, the temperature is observed to stay steady within the task; however, some difference has been observed in the temperature values between the tasks. EDA curve is observed to stay steady during T1 and T2, while slight variation is observed in T3. We also observed a peak heart rate value for subjects B, C, and D for T3. These observations gave a brief insight into the data and validated the assumption that different tasks have different natural influences on the expressions and biometric signals; nevertheless, they alone cannot explain the reasons for changes or any correlation in the curves. Similar plots can be generated for comparing other emotions (Angry, Disgust, Fear, Sad, Surprise) to the physiological signals provided in the dataset.

Figure 2 Analysis of Subjects A-F biometrics and facial expressions for tasks 1-9.

Functionality of Innovation(s)

We aim to enhance the predictive modeling of multimodal data in cases where the available data from one of the categories is scarce. The proposed methods will improve the users' experience in an emphatic building environment by enhancing self-monitoring (wellbeing) and identifying the cues causing different stressful events. The predictive model receives input from physiological data sensors, outputs the stress level, and determines the possible changes in data collected by a single sensor, causing an increase in stress levels. This information is used for analyzing the influence of different sensor data on physiological data in an emphatic building platform.

Conclusions and Recommendations

The dataset presented is the first effort toward identifying stress from non-wearable devices in general and facial expressions in particular. The dataset is the first of its kind, where facial features and physiological features are combined for stress measurement. While the proposed subspace learning framework showed promising results over different datasets and can be applied to different domain applications, there are some limitations that can be considered in the future. The methods exploit only a single Laplacian to enforce local/global data relations relevant to the task. This can be enhanced by exploiting multiple graphs by combining the geometric data relationships using a weight parameter. In the future, we plan to extend the proposed methods in the framework by investigating other kernel types in the non-linear case.

Impact and Uses/Benefits

The developed methods will be useful for stress-detection, anomaly detection, abnormal behavior/event detection, self-monitoring (wellbeing). Companies actively developing empathic building technologies can exploit this research's output to optimize the different models distributed throughout the empathic building.

Publications

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