Exploiting Micro-Clusters to Close The Loop in Data-Mining Robots for Human Monitoring

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Abstract

This paper describes our approach to integrating representation, reasoning, learning, and execution in our data-mining robots by exploiting micro-clusters to close the loop of the KDD process model. Based on our several kinds of autonomous mobile robots that monitor humans with Kinect and discover patterns, we are working on designing data-mining robots, each of which makes trials and errors in its data observation, data processing, pattern extraction, and mobile explorations. In other words, the robots continuously refine their goals at the micro-cluster level. We briefly discuss our four research directions, i.e., the balance between the exploitation and the exploration, the use of weak labels, the anytime algorithm, and the countermeasure to the concept drift, and describe potential, promising approaches for some of them.

Data-Mining Robots for Human Monitoring

We have constructed several kinds of autonomous mobile robots that monitor humans with Kinect and discover patterns. For instance, one to three robots, either a TurtleBot 2 or a hand-crafted robot each with Kobuki, jointly monitor a walking human, typically with elderly-experience equipment, to discover fall risks by clustering his/her skeletons (Deguchi et al. 2017; Takayama et al. 2014). Another example is a TurtleBot 2 with Kobuki that clusters facial expressions to discover smiling, yawning, and reading clusters of a desk worker (Kondo, Deguchi, and Suzuki 2014). This robot was later used to detect his/her hidden fatigue by clustering classifiers of neutral faces and smiling faces, which were observed every 30 minutes with their weak class labels input through a wireless mouse (Deguchi and Suzuki 2015). Figure 1 shows snapshots of these robots in the respective series of experiments.

All these robots represent the monitored person with micro clusters, which are learnt based on procedures similar to BIRCH, a hierarchical clustering algorithm (Zhang, Ramakrishnan, and Livny 1997; Han, Kamber, and Pei 2012). A micro cluster, which represents a group of similar examples each described with a set of numerical features, in its original form is a triplet $(n, \mathbf{v}, \mathrm{s})$, where n, $\mathbf{v}$, and s respectively represent the number of examples in the micro cluster, the add-sum of the examples in the micro cluster, and the add-sum of the squared L2-norm of the examples in the micro cluster (Zhang, Ramakrishnan, and Livny 1997). This triplet is called a Clustering Feature (CF) vector and has virtues of enabling an exact, incremental update and a reproduction of various cluster-wise distances without using the original examples. We initially adopted this approach to cluster colors of subimages observed by an autonomous mobile robot (Suzuki, Matsumoto, and Kouno 2012), and then extended the idea to cluster skeletons (Deguchi et al. 2017; Takayama et al. 2014), facial expressions (Kondo, Deguchi, and Suzuki 2014), and linear classifiers (Deguchi and Suzuki 2015). In these applications, an example is represented by a point in an Euclidean space spanned by the vectors of features, e.g., instability features described with skeleton joints inferred by Kinect (Deguchi et al. 2017; Takayama et al. 2014), action units inferred by Kinect to code emotional facial expressions (Kondo, Deguchi, and Suzuki 2014), coefficients of a logistic repression classifier to discriminate between neutral faces and smiling faces (Deguchi and Suzuki 2015).

Currently, we are working on extending our robots to data-mining robots, each of which makes trials and errors in its data observation, data processing, pattern extraction, and mobile explorations. The idea comes from the Knowledge Discovery in Databases (KDD) process model (Fayyad, Piatetsky-Shapiro, and Smyth 1996) shown in Figure 2. The Knowledge Discovery in Databases (KDD) process model states that a data mining process can be modeled as a series of several kinds of pre-/post-processing and pattern extraction. Our application domain is on a TurtleBot with Kobuki equipped with Kinect ver. 2 that continuously navigates inside a 90-m^2 room, observes desk workers, report discovered patterns to them, and receives their comments as rewards through its mouse. We believe that our data-mining robots are still goal-oriented, though their goals are unclear at the pattern level during their operations due to the nature of the KDD process model.

Exploiting Micro-Clusters to Close The Loop

Our previous robots either neglect the discovered patterns and micro-clusters or use them through static proce-

Figure 1: Snapshots of our autonomous mobile robots that monitor humans with Kinect and discover patterns. (Top left) TurtleBot 2 with Kobuki clusters facial expressions to discover smiling, yawning, and reading clusters of a desk worker (Kondo, Deguchi, and Suzuki 2014). (Right) Two TurtleBots 2 with Kobuki jointly monitor a walking human with elderly-experience equipment to discover fall risks by clustering his/her skeletons (Deguchi et al. 2017; Takayama et al. 2014). (Bottom left) TurtleBot 2 with Kobuki detects hidden fatigue of a desk worker by clustering classifiers of neutral faces and smiling faces, which were observed every 30 minutes with their weak class labels input through a wireless mouse (Deguchi and Suzuki 2015).

dures (Deguchi et al. 2017; Takayama et al. 2014; Kondo, Deguchi, and Suzuki 2014; Deguchi and Suzuki 2015). On the other hand, our intended data-mining robots closes "The Loop", i.e., realizes the trials and errors of the KDD process model especially by exploiting their results of the pattern discovery in their data observation and mobile explorations. In other words, the robots continuously refine their goals at the micro-cluster level. We have adopted four research directions: the balance between the exploitation and the exploration, the use of weak labels, the anytime algorithm, and the countermeasure to the concept drift.

Realizing the balance between the exploitation and the exploration requires care in our application due to the difficulty in estimating the interestingness of a discovered pattern in data mining. Though we have already built naive methods, e.g., moving to observe from a different angle when the set of micro clusters reaches a pre-defined degree of stability, the reward given by humans is not necessarily related to such diversity and how to estimate the correct, new angle for observation is unclear. Note that we are mostly faced with signal data, as the symbol grounding problem is far from being resolved. Modeling the diversity related to the interestingness would be the next step, though the exploration for new data would remain hard-wired.

We define a weak label as a piece of information related with supervisory signal, or the desired output value. It could be a class label of a bag of examples in the multiple instance learning, a class label in relevant learning tasks in multi-task or transfer learning, a (probabilistic) constraint on the target class labels in classification. See for instance (Mann and McCallum 2010). In our problem, the reward by a desk workers is rarely given, even if our robot reports an interesting pattern. We have recently developed a one-class selective transfer machine for personalized anomalous facial expression detection (Fujita, Matsukawa, and Suzuki 2018), which would be useful in both designing how to exploit weak labels and using the detected anomalous facial expressions as weak labels.

Naturally, our robot has to adopt an anytime algorithm, e.g., (Ueno et al. 2006), which can return the so-far best output anytime by using the available resources, especially the computation time. In BIRCH (Zhang, Ramakrishnan, and Livny 1997; Han, Kamber, and Pei 2012) and our discovery robots (Deguchi et al. 2017; Takayama et al. 2014; Kondo, Deguchi, and Suzuki 2014; Deguchi and Suzuki 2015), the micro-clusters are managed by a Clustering Feature (CF) tree, which may be viewed as a result of hierarchical clustering (Han, Kamber, and Pei 2012). Handling and reporting the micro-clusters in an intermediate level of the CF tree is a naive but natural solution. The closing the loop problem dictates that this research direction is deeply related with the first one: the balance between the exploitation and the exploration. Combined with the other two problems, designing an adequate anytime algorithm for our robots raises numerous challenges, even if partial solutions exist in the literature, e.g., (Ivanov, Blumberg, and Pentland: 2001).

Last but not least, our robot has to take a countermeasure to the concept drift, which is inherent in data stream

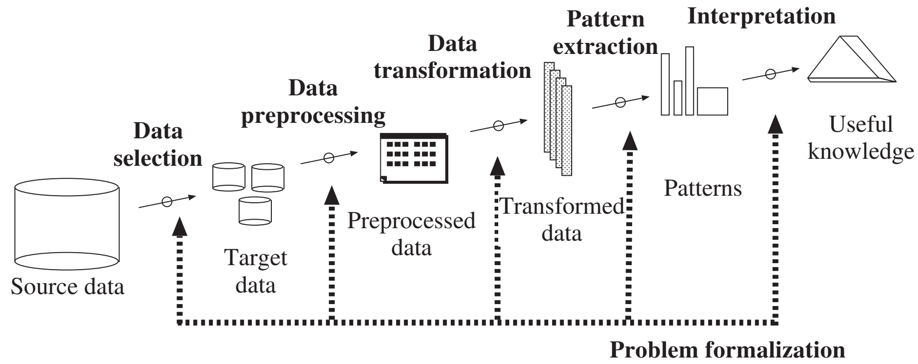

Figure 2: KDD process model (adopted and modified from (Fayyad, Piatetsky-Shapiro, and Smyth 1996)).

mining (Krempl et al. 2014). The statuses of desk workers change gradually or abruptly, though our robot platform including its batteries and sensors is reliable and can be regarded as static. Comparing CF trees (Boubou, Hafez, and Suzuki 2015) is in fact a nontrivial procedure and thus we are rather seeking for another approach of managing a set of micro-clusters.

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