# Reinforcement Learning for Evolutionary Distance Metric Learning Systems Improvement

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## ABSTRACT

This paper introduces a hybrid system called R-EDML, combining the sequential decision making of Reinforcement Learning (RL) with the evolutionary feature prioritizing process of Evolutionary Distance Metric Learning (EDML) in clustering aiming to optimize the input space by reducing the number of selected features while maintaining the clustering performance. In the proposed method, features represented by the elements of EDML distance transformation matrices are prioritized. Then a selection control strategy using Reinforcement Learning is learned . R-EDML was compared to normal EDML and conventional feature selection. Results show a decrease in the number of features, while maintaining a similar accuracy level.

## CCS CONCEPTS

• **Computing methodologies** → *Machine learning*;

## KEYWORDS

Distance Metric Learning, Evolutionary Algorithm, Reinforcement Learning

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## 1 INTRODUCTION

Today's data processing approaches and advances in computer science may not be enough against the ever growing amount of data, so a technique that can direct attention to specific portions of data can be useful. Furthermore, data collection sometimes can be time consuming and even in some cases expensive.

Evolutionary Distance Metric Learning (EDML) [1] is a distance metric learning algorithm where a data space transformation matrix is used to learn a distance function over objects and the diagonal elements represent scaling factors to corresponding features. In addition to that, EDML needs to optimize simultaneously the values and important elements in the metric. This optimization is done by utilizing a self-adaptive differential evolution (jDE) [2] algorithm. In order to include explicit sequential feature selection to the EDML process, Reinforcement learning is introduced.

Reinforcement Learning (RL) based feature selection can learn different subsets of features according to the input and can explicitly select and learn the elements importance. R-EDML [3] can take advantage of the evolutionary feature weighting process in EDML along with RL sequential decision making. This combination of EDML and RL-based metric filtering achieved promising results, where the feature space was dramatically reduced while maintaining the clustering performance. In addition to a previous R-EDML paper results [3], in this paper R-EDML had outperformed EDML and 2 conventional feature selection methods with respect to the number of selected features. Also, R-EDML showed adequate results in detecting fake features in synthetic data sets.

## 2 PROPOSED METHOD

The general idea is to merge the RL sequential decision process inside the EDML evolutionary generation process. This will take place through inserting the elements in a sequential manner in the matrices and learning the correct number of elements for any given EDML generation.The reason is that EDML Evolutionary Algorithm mutates and changes the elements values after each generation, so a new RL policy tailored for each generation is believed to give better results.

### 2.1 R-EDML Model as an MDP

R-EDML is based on Markov Decision Processes (MDP) which consists of four elements:

1.$\boldsymbol{S}$: a set of states. 2.$\boldsymbol{A}$: a set of actions. 3.$Ts,a,s'$ : a transition function. 4.$Rs,a$: expected reward of performing action $a$ in state $s$.

The state is the EDML matrices after selecting a certain element. The action is selecting an element; an already selected element cannot be selected again. There is no stochastic behavior in the environment.

### 2.2 R-EDML Process

The overall process of R-EDML can be described as follows:

1- First EDML creates a generation; this generation population is a set of $\boldsymbol{M}$ distance matrices responsible for the data set transformation.

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2- The diagonal elements of $\boldsymbol{M}$ correspond to the features in the data set. The diagonal elements for each $\boldsymbol{M}$ will be stored for future reference.

3- Then all the diagonal elements in all the matrices for this generation will be reset to a value close to zero.

4- After that, RL will insert the original elements in a sequential manner and evaluate with each insertion the clustering accuracy which is the F-measure using K-means.

5- According to this evaluation, RL will either stop inserting new elements or continue. The stopping condition for each episode will either be the threshold that is satisfied after evaluation or all the elements were inserted in the matrices.

6- After all the episodes finish, RL will suggest which elements should be used that will give the best performance in this generation.

7- The selected number of features will either be saved for later comparisons or will be used to change the EDML generation.

8- After that, EDML Evolutionary Algorithm will create a new generation and RL will start learning again with a newly developed policy for the new generation and the whole process continues until a fixed number of generations are created.

9- The output is the selection of the best $\boldsymbol{M}$ with the closest accuracy to EDML and least number of elements / features possible.

# 3 EXPERIMENTS AND RESULTS

## 3.1 Scenarios

A variety of scenarios were tested, some wait for EDML to converge first then change it, others change EDML before it converges, others explore not changing EDML and run RL independently in parallel with it and others merge all these ways together.The scenarios were filtered and 3 were chosen for their best results [3].

## 3.2 Database Used

The tests are performed on the UCI machine learning database[1]. The data sets used are Glass, Wine and Vehicle. Also some tests were performed on a synthetic Cube data set to test R-EDML ability to detect fake features. It contained 210 normalized data points, 13 features (3 important features and 10 fake features) and 3 classes.

## 3.3 Tests

The experiments performed on all UCI data sets show that R-EDML selected fewer features compared to EDML important features and 2 conventional feature selection methods [4] while maintaining a similar accuracy level as shown in Tables 1, 2, and 3 . Also R-EDML showed adequate results in detecting fake features in the synthetic data test as the average number of the selected features was close to the number of important features as shown in Table 4.

# 4 CONCLUSION

The constant growth in data has presented a challenge in the data processing world on how to manage this data. In this paper, a hybrid system R-EDML is introduced that takes advantage of the sequential decision making in RL and the evolutionary process in EDML. Results show that R-EDML reduced the required features needed by EDML while maintaining the clustering performance which shows promising potential in using this new method.

[1] http://www.ics.uci.edu/mlearn/mlrepository.html

**Table 1: Glass data set results**

| Glass (9 Features) | | |
|---|---|---|
| **Type** | **F-measure** | **#Features** |
| EDML | **0.5416** | <u>3.3</u> |
| R-EDML | <u>0.5386</u> | **1** |
| Feature Subset selection | 0.5377 | 4.5 |
| Feature Scoring | 0.5348 | 3.5 |

**Table 2: Wine data set results**

| Wine (13 Features) | | |
|---|---|---|
| **Type** | **F-measure** | **#Features** |
| EDML | **0.9497** | 6.3 |
| R-EDML | 0.8990 | **2.9** |
| Feature Subset selection | 0.8652 | <u>5.5</u> |
| Feature Scoring | <u>0.9311</u> | 7 |

**Table 3: Vehicle data set results**

| Vehicle (18 Features) | | |
|---|---|---|
| **Type** | **F-measure** | **#Features** |
| EDML | 0.4285 | 3.6 |
| R-EDML | **0.4453** | **2.2** |
| Feature Subset selection | 0.4187 | <u>3.5</u> |
| Feature Scoring | <u>0.4363</u> | 6.5 |

**Table 4: Synthetic data set results**

| Cube (3 important and 10 fake Features) | | |
|---|---|---|
| **Scenario** | **F-measure** | **#Features** |
| Scenario 1 | **1** | 2.4 |
| Scenario 2 | <u>0.9820</u> | <u>2</u> |
| Scenario 3 | 0.9210 | **1.6** |

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