Exploring High Dimensional Data Through Locally Optimized Viewpoint Selection

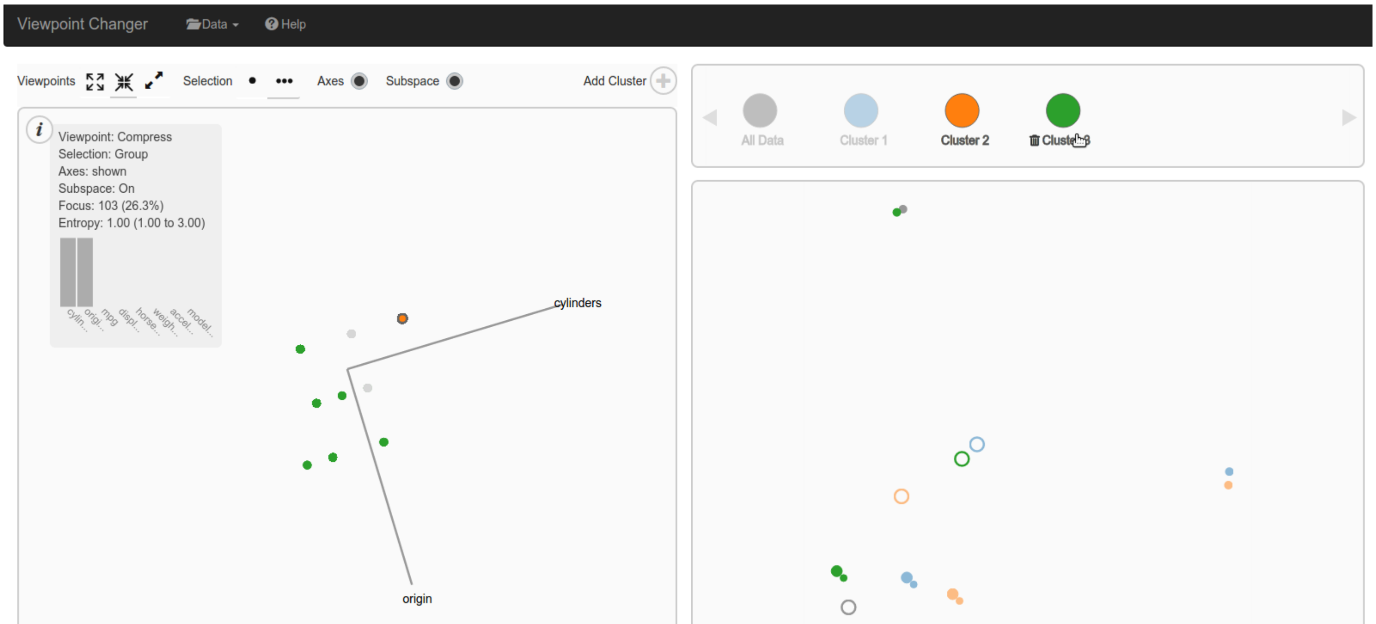

Fig. 1. Teaser here.

Abstract—Dimension reduced projection is usually obtained via a global optimization. It gives a good overview of the data, but cannot satisfy different users with different focuses. That's because any local data could be distorted and misleading due to projection errors. To address this problem, we propose an interactive visualization method, to customize projections for better local analysis. First, we allow users to define their point of interest (POI) data. Then we generate local projections to minimize distortions regarding the POI. Multipe optimizations are provided for different analyses. We also reveal relationships among different POIs, by comparing their local projections. At last, our method is proved effective via case studies with a real-world dataset.

Index Terms—Dimension-reduced projection, local analysis, high-dimensional data

1 Introduction

2 Related Work

2.1 Dimension-Reduced Projection

2.2 Projection Manipulation

[6]

2.3 High-dimensional Local Data Analysis

[9] [5] [10] [7] [4] [2] [3] [8] [9] [1]

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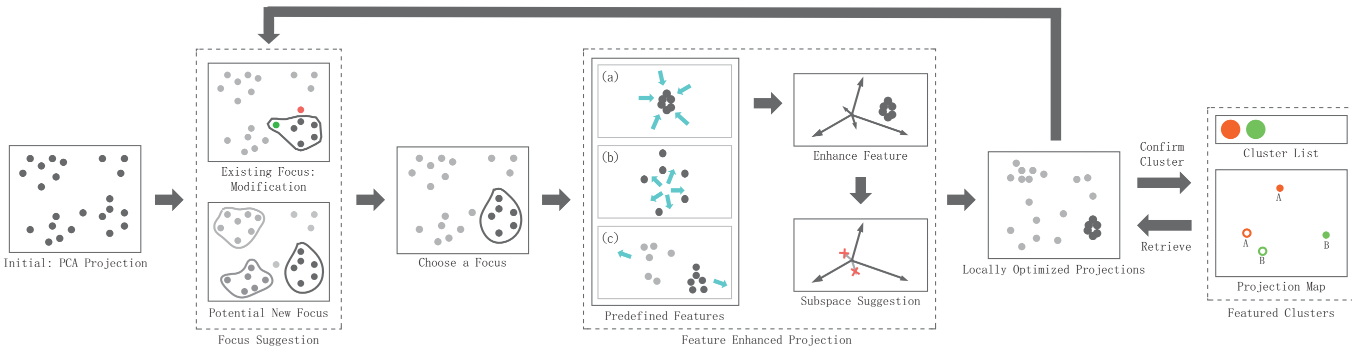

Fig. 2. The overview of delivery system.

3 Overview

4 High-dimensional Exploration via Locally Optimized Viewpoints

4.1 Find a Focus

4.1.1 Focus in Different Granularities

4.1.2 Distortion Hints

4.1.3 Focus Suggestion

4.2 Featured Viewpoints for the Focus

4.2.1 Desirable Local Features

4.2.2 Feature Enhanced Projections

4.2.3 Subspace Suggestion

4.3 From Focus to Cluster

4.3.1 Focus Improvement

4.3.2 Cluster Comparison via Viewpoint Map

5 Case Study

6 Discussion

7 Conclusion

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