Efficient Algorithms for Generating Provably Near-Optimal Cluster Descriptors for Explainability

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Background

Artificial Intelligence (AI)/ Machine Learning (ML)

- Artificial intelligence is the simulation of human intelligence processes by machines, especially computer systems
- Machine learning is an application of AI that enables systems to learn and improve from experience without being explicitly programmed

Clustering

- An ML application that divides a set of data points into groups such that the data points in any given group are more like other data points in the same group than those in other groups.

Clustering Methods (Examples)

- Centroid-based Clustering
- Density-based Clustering
- Distribution-based Clustering

Goals of Explainable Artificial Intelligence (XAI)

- To produce more explainable models, while maintaining a high level of learning performance (prediction accuracy)
- Enable human users to understand, appropriately trust, and effectively manage the emerging generation of artificially intelligent partners

Linear Programming (LP)

- A method to achieve an optimal outcome (such as maximum profit or lowest cost) in a mathematical model whose requirements are represented by linear constraints and objectives
- Solutions obtained using the Gurobi solver

Integer Linear Programming (ILP)

- Same as linear programming
- Variables are constrained to have values from suitable subsets of integers (e.g., {0, 1})

Notation and Definitions

- $S = \{s_1, \ldots, s_n\}$ are items in the dataset
- $\pi = \{C_1, \ldots, C_K\}$ is a partition of S into $k \geq 2$ clusters
- $T = \{t_1, \ldots, t_N\}$ are tags that the items can have (that describe them)
- Each $s_i \in S$ is associated with a subset $T_i \subseteq T$ of tags
- A solution X is represented as a collection $X = \{X_1, \ldots, X_K\}$ where $X_k \subseteq T$ is the descriptor for cluster C_k
- In some formulations, X_k are pairwise disjoint

Project Description

Motivation

- Obtaining an optimal explanation is computationally intractable (NP-hard) in general.
- Instead, we use ILP, LP, and rounding algorithms to achieve near-optimal explanations (i.e., descriptors).

Task

- A more specific goal of this project is to extend the current findings of [Davidson et al., NeurIPS 2018] and the more recent [Sambaturu et al., 2020]
- To further show that not only can a set of clusters be explained, but that the process can be further optimized

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Current Work

Python Code

- Optimizations and alterations were made to the original code, allowing for the usage of their algorithms on more than two clusters and the option to easily swap between maximizing coverage and minimizing costs
- Also allows for easier result generation, as the range of coverages/costs can be used as inputs to generate many forms of results
- Generated synthetic datasets to mimic the clustering algorithms while also assigning tags to each item
- Organic dataset pre-processing such that those datasets will be properly processed when given to the algorithms for generating descriptors

Experimentation

Integer Linear Programming

- Synthetic datasets were used to test the scalability of the algorithm when cost is the independent variable
- Organic datasets were used to test the algorithm when %coverage is the independent variable
- Runtime is measured to show the combinatorial aspect of the problem at hand

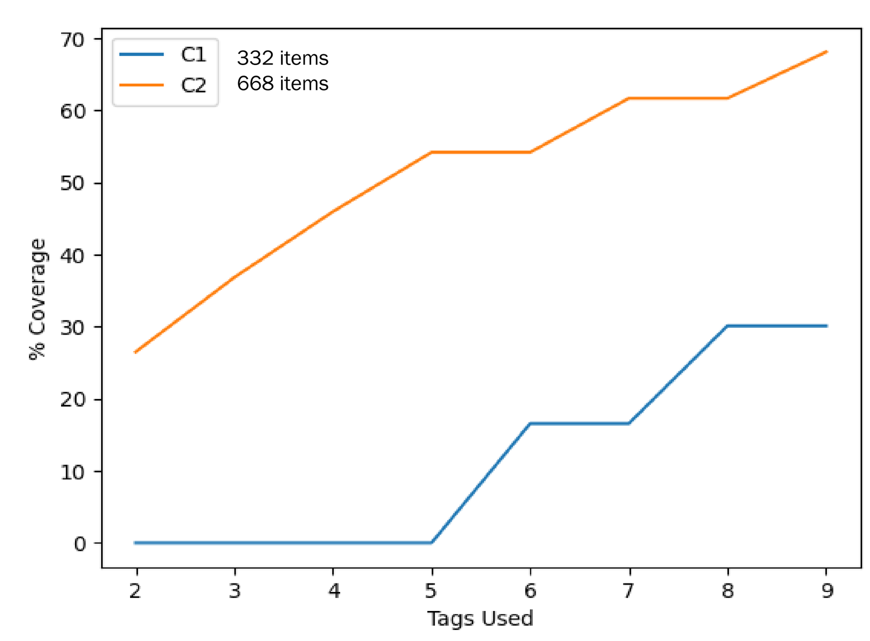

Figure 1: Total tags used (x-axis) and coverage percent in each cluster (y-axis) for Synthetic Dataset 1

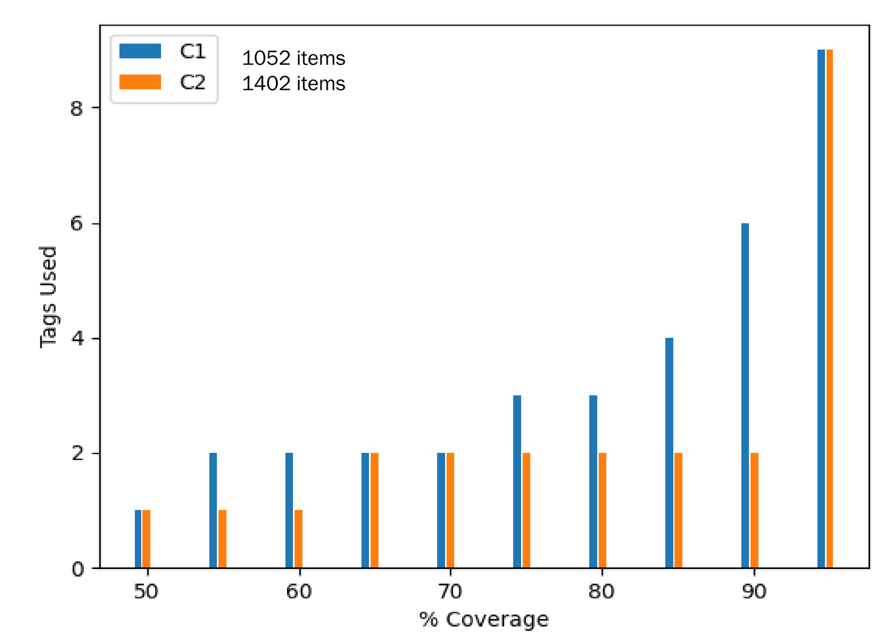

Figure 2: Coverage percent in each cluster (x-axis) and the total tags used (y-axis) for the Flickr Dataset

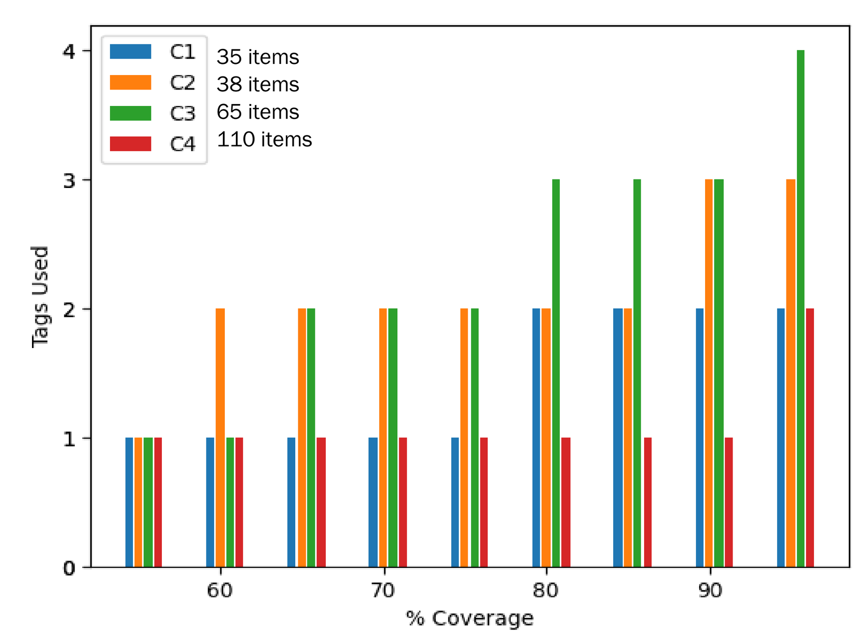

Figure 3: Coverage percent in each cluster (x-axis) and the total tags used (y-axis) for the Threat Dataset

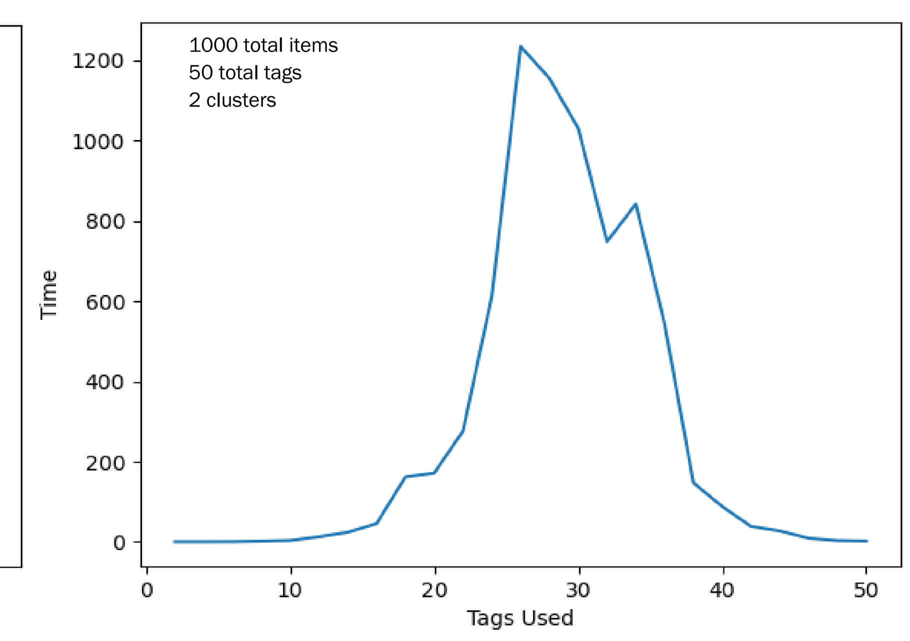

Figure 4: Solution cost/tags used (x-axis) and runtime in seconds (y-axis) for Synthetic Dataset 2

Future Work

- **Experiments:** Run more tests on the LP + Rounding Algorithm
- **Documentation:** Create meaningful and clear explanations of the code at hand
- **Journal Paper:** Assist Professor Ravi in writing the paper for the AI Journal

Primary References

(1) Sambaturu, P., Gupta, A., Davidson, I., Ravi, S. S., Vullikanti, A., & Warren, A. 2020. Efficient Algorithms for Generating Provably Near-Optimal Cluster Descriptors for Explainability. In Proc. AAAI 2020, 1636-1643.

(2) Davidson, I.; Gourru, A.; and Ravi, S. S. 2018. The cluster description problem – Complexity results, formulations and approximations. In Proc. NeurIPS, 6193–6203.