Landmark-based Spectral Clustering Methods for Large Image and Text Data

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1. Motivation and Background

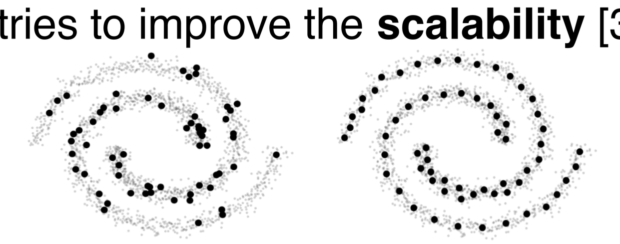
Verizon is interested in gaining insights from cell phone user data such as browsing history [1]. Clustering can be used with this data to perform customer segmentation. Clustering is an **unsupervised machine learning** task that involves grouping data.

Spectral clustering refers to a family of algorithms that use **spectral decomposition** on a **similarity matrix** to reduce the dimensionality for clustering, commonly via **k-means** [2].This can give good performance but requires multiple **computationally complex** operations, limiting its application to large datasets.

Our team is developing new **landmark-based spectral clustering (LSC)** methods by modifying existing techniques, which can solve this issue. It does so by constructing a **sparse affinity matrix** between the data points and landmark points.

2. Landmark-based Spectral Clustering

LSC is one existing method that tries to improve the **scalability** [3]. The main steps are as follows:



i) Landmark Selection:

By uniform sampling

- observations are sampled randomly
- very fast

By k-means

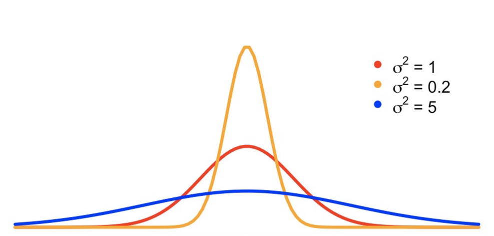
- p centroids
- very slow for larger datasets
- can be more representative

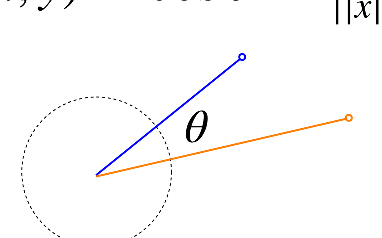
ii) Similarity Computation

- **Gaussian similarity** is computed as: $s(x, y) = e^{-\frac{||x-y||^2}{2\beta\sigma^2}}$

σ^2 is estimated with the distance between landmarks and β is a tuning parameter.

- **Cosine similarity** is computed as: $s(x, y) = \cos\theta = \frac{x \cdot y}{||x|| \cdot ||y||}$

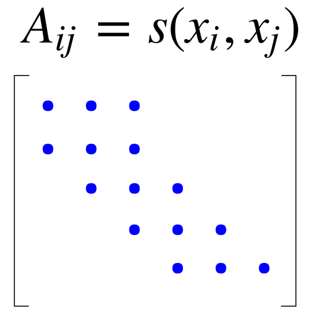




iii) Nearest Landmarks:

$A_{ij} = s(x_i, x_j)$

- The largest **r** entries in each row are kept. The rest are set to zero.
- Makes the affinity matrix **sparse**, speeding up computations
- Makes clustering more **robust** to noise

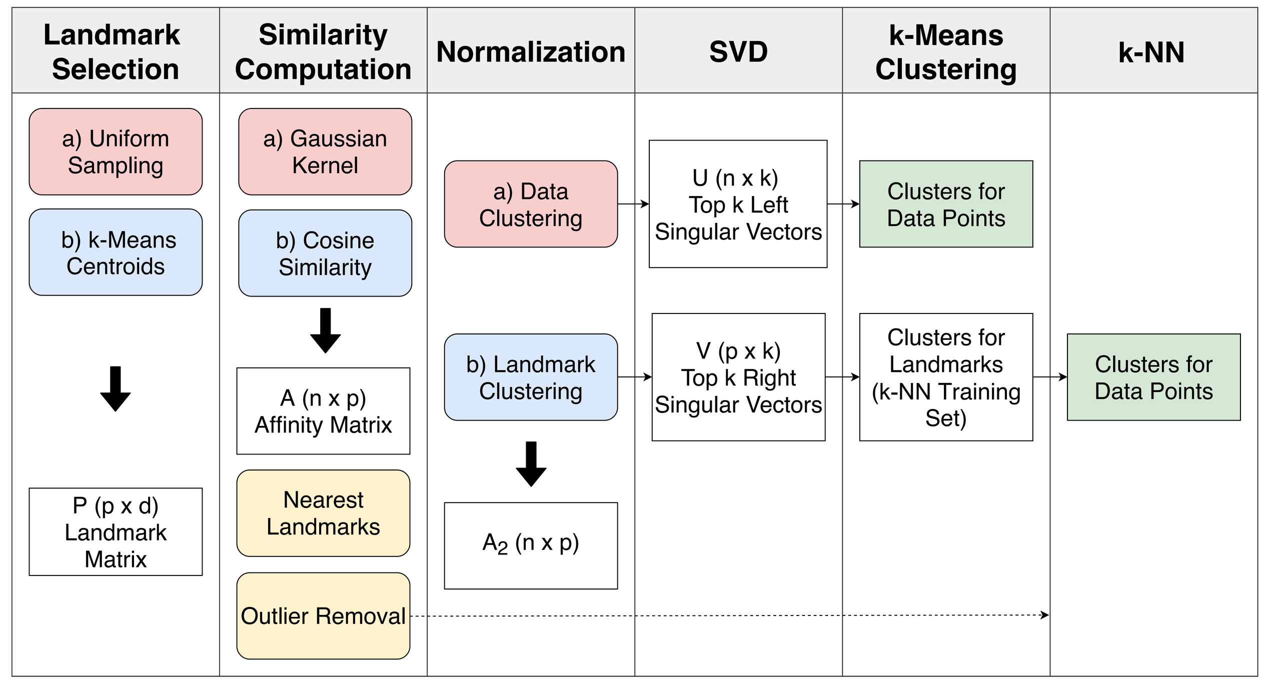


$n \times p$

iv) Data Clustering:

- L_1 row normalization, then $\sqrt{L_1}$ column normalization on A
- Find the top k left singular vectors of A_2
- L_2 row normalization on U
- k-means on U outputs cluster assignments on the data

3. New Algorithm Overview



Input:

- n data points
- **k**: # of desired clusters
- **p**: # of landmarks
- **r**: # of nearest landmarks
- landmark selection method
- similarity measure
- α_1: proportion of data to treat as outliers
- α_2: proportion of landmarks to be removed as outliers
- β: the σ^2 tuning parameter for Gaussian similarity
- knn: the number of neighbors considered for **k-nearest neighbor (k-NN)** classification

Output:

- k cluster assignments

4. New Methods

Outlier Removal on the Affinity Matrix

- **Landmark outliers** have low column sums (dissimilar from most data) and are removed.
- **Data outliers** have low row sums (dissimilar from most landmarks) and can be given the zero label or reclassified

Landmark Clustering

- L_1 column normalization, then $\sqrt{L_1}$ row normalization on A
- Find the top k right singular vectors of A_2
- L_2 row normalization on V
- k-means on V outputs cluster assignments on the landmarks
- k-NN outputs cluster assignments on the data

5. Experiments

For evaluating the algorithm and studying **parameter sensitivity**, we tested on three image (handwritten digits) datasets and three text datasets in **R**. These descriptions are recorded after our **preprocessing** steps.

Type	Dataset	# of Instances	# of Features	# of Classes
Text	20Newsgroups	18768	100	20
	Reuters	8067	18933	30
	TDT2	9394	36771	30
Image	USPS	9298	256	10
	Pendigits	10992	16	10
	MNIST	70000	784	10

Compared Algorithms

- **R-D:** LSC, random landmark selection, data clustering
- **R-LM:** LSC, random landmark selection, landmark clustering
- **KM-D:** LSC, k-means landmark selection, data clustering
- **KM-LM:** LSC, k-means landmark selection, landmark clustering
- **NJW:** spectral clustering algorithm developed by Ng, Jordan, and Weiss [4]

- **Evaluation metric:** overall classification accuracy
- CPU run-time on the SJSU Golub server is recorded
- All experiments are run for 20 seeds
- Unless specified, the algorithm is run for Cosine similarity, p = 500, r = 6, α_1 = 0, α_2 = 0, and knn = 1.

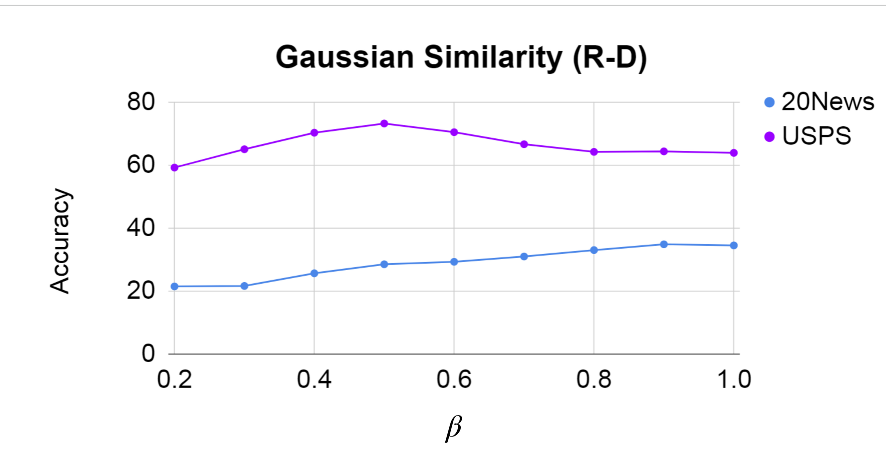
6. Results

Accuracy (%)

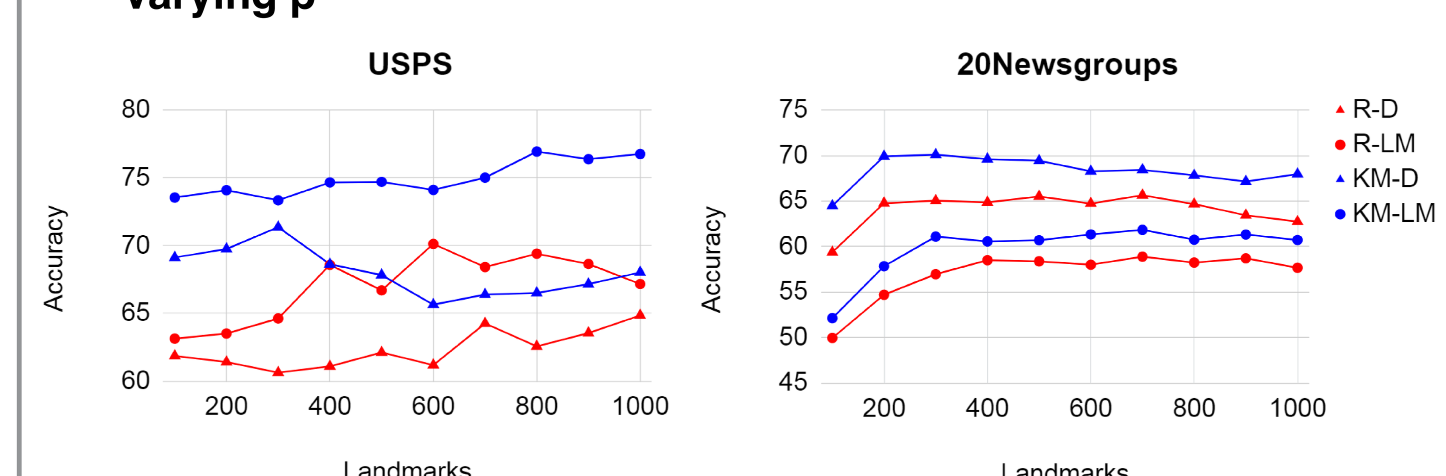
Dataset	k-means LM selection: Landmark Clustering	k-means LM selection: Data Clustering	Random LM Selection: Landmark Clustering	Random LM Selection: Data Clustering	NJW
20Newsgroups	60.69	**69.42**	58.37	65.51	63.36
Reuters	**31.21**	27.38	27.50	25.37	25.68
TDT2	**65.69**	59.45	64.34	59.85	44.38
USPS	**74.70**	67.83	66.70	62.12	67.74
Pendigits	**81.59**	77.94	78.76	78.81	73.75
MNIST	65.10	**69.43**	59.41	63.32	--

CPU Run-time (s)

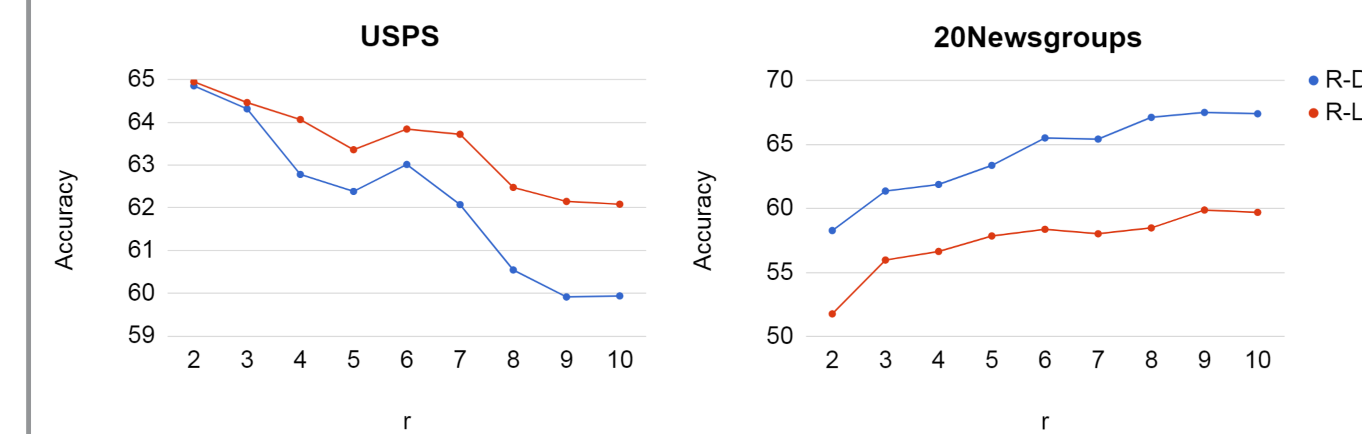
Dataset	k-means LM selection: Landmark Clustering	k-means LM selection: Data Clustering	Random LM Selection: Landmark Clustering	Random LM Selection: Data Clustering	NJW
20Newsgroups	10.82	12.75	**3.94**	5.95	150.96
Reuters	503.76	451.88	**6.11**	7.38	52.31
TDT2	2098.67	1912.68	**11.86**	12.12	49.46
USPS	11.34	11.65	**3.68**	3.93	55.46
Pendigits	3.51	3.76	**2.15**	2.70	95.13
MNIST	597.01	584.06	**27.97**	31.05	--



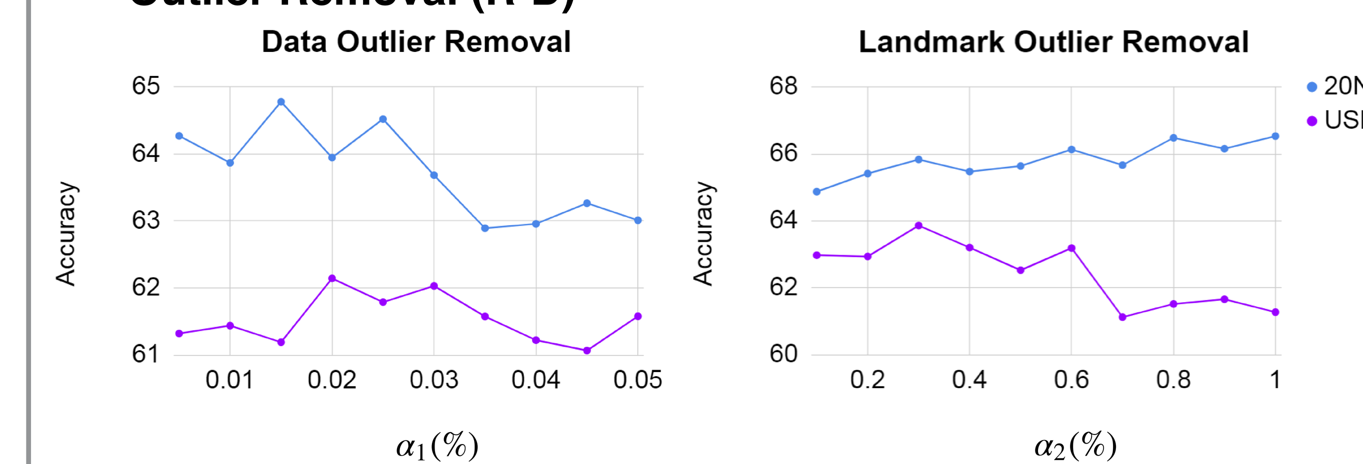
Varying p



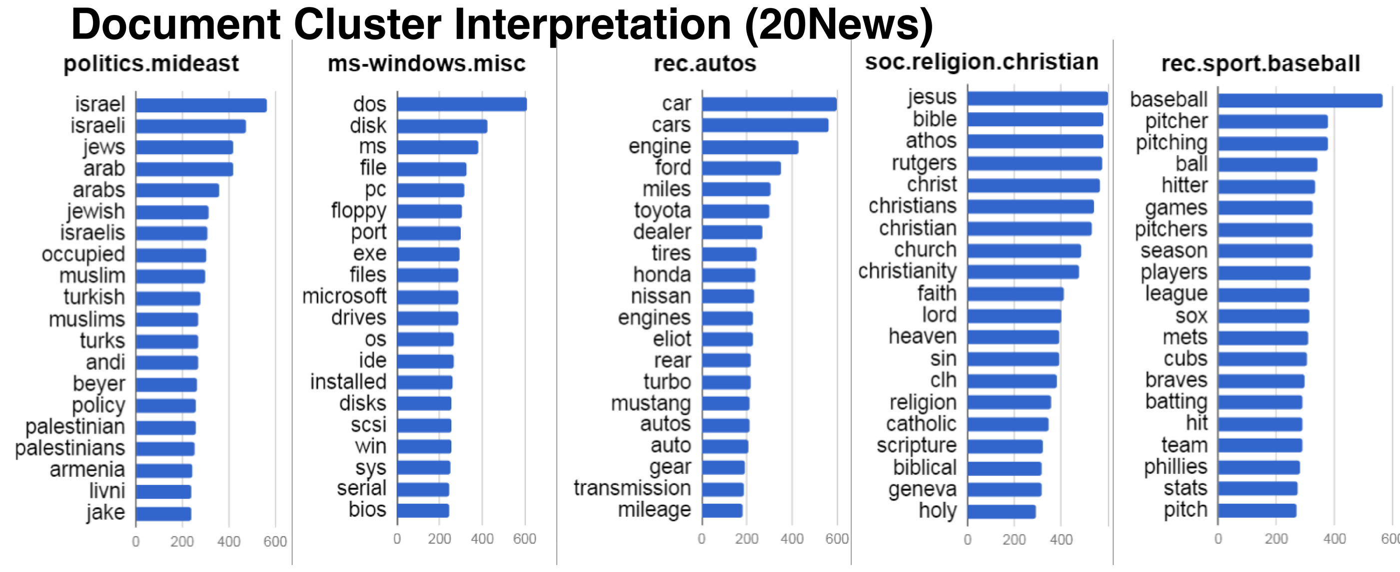
Varying r



Outlier Removal (R-D)



Document Cluster Interpretation (20News)



Sum of the tf-idf values per cluster [5]

7. Conclusions

- LSC often provides both speed and accuracy improvements compared to NJW
- Random landmark selection is very efficient compared to k-means, achieving reasonable accuracy in far less time
- Landmark clustering is a promising method, often providing speed and accuracy improvements compared to data clustering
- r and p can be sensitive depending on the dataset

Further Research

- Image segmentation with LSC techniques
- More evaluation metrics
- Further investigation on outlier removal

Acknowledgments

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References

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