generateData—a 2D data generator

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ABSTRACT

generateData is a MATLAB/Octave function for generating 2D data clusters. Data is created along straight lines, which can be more or less parallel depending on the selected input parameters. The function also allows to fine-tune the generated data with respect to number of clusters, total data points, average cluster separation and several other distributional properties.

Code metadata

| Current code version | v2.0.0 |
|----------------------|--------|
| Permanent link to code/repository used for this code version | https://github.com/SoftwareImpacts/SIMPAC-D-20-00014 |
| Legal Code License | MIT License |
| Code versioning system used | Git |
| Software code languages, tools, and services used | MATLAB/GNU Octave |
| Compilation requirements, operating environments & dependencies | MATLAB ≥ R2011a or GNU Octave ≥ 4.0.0 |
| If available Link to developer documentation/manual | https://github.com/fakenmc/generateData/blob/v2.0.0/README.md nuno.fachada@ulusofona.pt |
| Support email for questions | nuno.fachada@ulusofona.pt |

1. Introduction

Massive amounts of data are being produced everyday, raising a number of challenges on its storing and processing [1–3]. However, there are still many instances where, for the intended purposes, data is insufficient and/or expensive — thus making synthetic data generation an appealing alternative [4–7]. One such instance is data generation for evaluating clustering algorithms [8,9].

In this paper we discuss the impact of generateData, a MATLAB [10] and GNU Octave [11] function for generating 2D data primarily aimed at testing clustering algorithms. Section 2 offers an overview of how the data generation algorithm works as well as some output examples. The impact of generateData is presented in Section 3. The limitations of this work, as well as potential improvements are discussed in Section 4.

2. Description

generateData is a MATLAB/Octave function for generating 2D data clusters. The function allows to fine-tune several characteristics of the generated data through a number of required and optional parameters, summarized in Tables 1 and 2, respectively. In any case, data is created along straight lines. The exact angle of these lines with respect to the x axis is drawn from the normal distribution. The mean and standard deviation of this distribution correspond to parameters angleMean and angleStd in Table 1. The latter influences how parallel are the lines supporting the data. A standard deviation of zero yields completely parallel lines, while higher values increasingly randomize line orientation. In turn, line length is drawn from the folded normal distribution, with mean and standard deviation given as parameters lengthMean and lengthStd, respectively.

The method for placing points around lines is as follows. First, a projection of each point on the line is obtained from the distribution specified in optional parameter pointDist. The default is the uniform distribution, i.e., point projections are placed evenly along the line. Using the normal distribution, the line center is used as the mean, with the line length corresponding to 3 standard deviations — thus, there is a small chance projections are placed outside the line. After the point projections are determined, points are either placed around their projections using the bivariate normal distribution (a 2D placement, the
default), or on a second line, perpendicular to the original one, using a normal distribution (a 1D placement). In either case, the projection is used as the mean value, while the standard deviation is given by the lateralStd parameter. The type of placement, 1D or 2D, is defined by the optional pointOffset parameter.

Fig. 1 shows four datasets created with generateData using the parameters given in Table 3.

3. Impact

The generateData script was originally created to test the AMVIDC clustering algorithm [12]. The algorithm performs agglomerative hierarchical clustering using minimum volume increase and minimum direction change clustering criteria, and was inspired by the typical layout of spectrometric data after being processed with principal component analysis (PCA). More specifically, the PCA score plots of spectrometric data were found to exhibit distinct groups scattered along a preferential direction, forming low volume clusters. The AMVIDC algorithm [12] was inspired by the iterative hierarchical clustering using minimum volume increase and minimum direction change clustering criteria, and was inspired by the typical layout of spectrometric data after being processed with principal component analysis (PCA). More specifically, the PCA score plots of spectrometric data were found to exhibit distinct groups scattered along a preferential direction, forming low volume clusters. The AMVIDC algorithm.

In reference [19], Hao et al. presented a video summarization approach consisting of generating a short video summary while maintaining the overall meaning of the original video. The approach worked by applying sparse subspace clustering with automatically estimated number of clusters to deep features of objects in key-frames. generateData was used to produce synthetic data for testing the accuracy of the method for estimating the number of clusters.

Olukanmi et al. [20,21] used generateData to assemble scenarios with one million data points with the purpose of assessing the proposed k-means-lite and k-means-lite++ clustering algorithms — highly scalable versions of their non-lite counterparts.

4. Limitations and potential improvements

With the goal of evaluating D3CAS, a dynamical and big data-oriented clustering algorithm for processing data streams, Molina & Hasperü [14,15] used generateData to create datasets with up to 100,000 points, an adequate size for their testing requirements.

Alabdulatif et al. [16–18] made use of generateData for a series of investigations on cloud and edge computing privacy-related data analytics. Datasets were generated with the purpose of evaluating distributed and privacy-preserving versions of several clustering algorithms in a number of different scenarios.

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### Table 1
Required parameters.

| Parameter | Description |
|-----------|-------------|
| angleMean | Mean angle in radians of the lines on which clusters are based. Angles are drawn from the normal distribution. |
| angleStd | Standard deviation of line angles. |
| numClusts | Number of clusters (and therefore of lines) to generate. |
| xClustAvgSep | Average separation of line centers along the X axis. |
| yClustAvgSep | Average separation of line centers along the Y axis. |
| lengthMean | Mean length of the lines on which clusters are based. Line lengths are drawn from the folded normal distribution. |
| lengthStd | Standard deviation of line lengths. |
| lateralStd | Cluster “fatness”, i.e., the standard deviation of the distance from each point to its projection on the line. The way this distance is obtained is controlled by the optional pointOffset parameter. |
| totalPoints | Total points in generated data. These will be randomly divided between clusters using the half-normal distribution with unit standard deviation. |

### Table 2
Optional named parameters.

| Name | Default | Description |
|------|---------|-------------|
| allowEmpty | false | Allow empty clusters? |
| pointDist | ‘unif’ | Specifies the distribution of points along lines, with two possible values: (1) ‘unif’ distributes points uniformly along lines; or, (2) ‘norm’ distributes points along lines using a normal distribution (line center is the mean and line length is equal to 3 standard deviations). |
| pointOffset | ‘2D’ | Controls how points are created from their projections on the lines, with two possible values: (1) ‘1D’ places points on a second line perpendicular to the cluster line using a normal distribution centered at their intersection; or, (2) ‘2D’ places points using a bivariate normal distribution centered at the point projection. |
Fig. 1. Examples of datasets created with generateData in MATLAB using various parameters. Parameters for each figure are shown in Table 3. The allowEmpty parameter was always set to false.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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