

A New Projection Pursuit Index for Big Data

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May 2021

Abstract. Visualization of extremely large datasets in static or dynamic form is a huge challenge because most traditional methods cannot deal with big-data problems. A new visualization method for big-data is proposed based on Projection Pursuit, Guided Tour and Data Nuggets methods, that will help display interesting hidden structures such as clusters, outliers and other nonlinear structures in big-data. The Guided Tour is a dynamic graphical tool for high-dimensional data combining Projection Pursuit and Grand Tour methods. It displays a dynamic sequence of low-dimensional projections obtained by using Projection Pursuit (PP) index functions to navigate the data space. Different PP indices have been developed to detect interesting structures of multivariate data but there are computational problems for big-data using the original guided tour with these indices. A new PP index is developed to be computable for big-data, with the help of a data compression method called “Data Nuggets” that reduces large datasets while maintaining the original data structure. Simulation studies are conducted and a real large dataset is used to illustrate the proposed methodology. Static and dynamic graphical tools for big-data can be developed based on the proposed PP index to detect nonlinear structures.

Keywords: Big Data; Projection Pursuit; Guided Tour; Data Nuggets.

1. Introduction

In today’s world, huge amounts of data are continuously stored in almost all fields. This creates many computational and methodological issues when analyzing big data with standard methods and tools. For example, data visualization plays an important role in displaying the essential information and structures of data, that maybe useful in business decision making, scientific finding, etc. But it’s a huge challenge to visualize extremely large data sets in static or dynamic form because most traditional data visualization methods can’t deal with big-data problems. The aim of our research is to develop new visualization methods for big-data, based on a combination of Projection Pursuit, Guided Tour and Data Nuggets

methods, that will help display interesting hidden structures such as clusters, outliers and other nonlinear structures.

A common visualization technique to explore multivariate data is Projection Pursuit. It is an effective method for finding static low-dimensional projections that uncover interesting structures, via the optimization of Projection Pursuit (PP) indices. A PP index function numerically measures features of low-dimensional projections for which higher values correspond to more "interesting" structures, such as point mass, holes, clusters, outliers and other linear and nonlinear structures. There are two kinds of PP indices. One is for finding specific structures such as Holes Index, Central Mass Index and Linear Discriminant Analysis Index, etc.. The other we are focusing on is for finding general non-linear structures, including the Legendre Index (Friedman, 1987), the Hermite Index (Hall, 1989) and the Natural Hermite Index (Cook, 1993). These three indices were all developed to detect departures from normality because unusual projections look non-normal.

Grand Tour is a technique of data visualization providing a dynamic sequence of interpolated random low dimensional projections, to visually extrapolate from low-dimensional shapes to multidimensional structures. Projection Pursuit and Grand Tour are combined into a dynamic graphical tool for exploring high-dimensional data, called a Projection Pursuit Guided Tour (Cook, 1995). It uses a PP index function to navigate the data space, so the next projection plane during the tour is selected by optimizing a PP index. The PP guided tour is available in the R package, *tourr* (Wickham et al. 2011), which provides optimization routines and a data visualization tool.

However, the original guided tour is computationally expensive for visualizing big-data and most data visualization tools including *tourr* ran into computational problems with big-data. In this paper, for the purpose of visualizing big-data in a more efficient way, we propose a new Projection Pursuit index that can be computable for big-data, with the help of a data compression method called "data-nuggets" that reduces a large dataset into a smaller collection of data nuggets that maintain the overall data structure. In section 2, the methodology of the new PP index for big-data is proposed. Section 3 shows the performance of the new index on simulated data and optimization of the index is implemented in section

4. A real data set is used to illustrate the proposed methodology in section 5 and future work is discussed in section 6. The new PP index can be used to develop new data visualization tools including a guided tour to generate interactive, dynamic and efficient visualization for big-data.

2. A new Projection Pursuit index for big data

Assume that $\mathbf{X} \in \mathbb{R}^{n \times p}$ be a big data matrix representing a p -dimensional dataset, and assume that \mathbf{X} has been spherized by a linear transformation. Let $A \in \mathbb{R}^{p \times d}$ be a random orthogonal projection matrix that projects \mathbf{X} into a d -dimensional space ($d < p$). Let $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_n]^T \triangleq \mathbf{X}\mathbf{A} \in \mathbb{R}^{n \times d}$ be the projected data in the d -dimensional space. Consider density $f(\mathbf{y})$ of the projected data \mathbf{Y} and standard multivariate Gaussian density $\phi(\mathbf{y})$. An index, I , can be constructed by measuring the distance of $f(\mathbf{y})$ from the standard normal. The Legendre index, I^L , proposed by Friedman (1987) is defined by

$$I^L = \int_{\mathbb{R}^d} \{f(\mathbf{y}) - \phi(\mathbf{y})\}^2 \frac{1}{2\phi(\mathbf{y})} d\mathbf{y}$$

Observing upweighted tails in the Legendre index, Hall (1989) proposed the Hermite index that measures the L^2 -distance between $f(\mathbf{y})$ and the standard normal density with respect to Lebesgue measure:

$$I^H = \int_{\mathbb{R}^d} \{f(\mathbf{y}) - \phi(\mathbf{y})\}^2 d\mathbf{y}$$

Based on the Hermite Index, Cook (1993) proposed the Natural Hermite Index:

$$I^N = \int_{\mathbb{R}^d} \{f(\mathbf{y}) - \phi(\mathbf{y})\}^2 \phi(\mathbf{y}) d\mathbf{y}$$

It can be regarded as a weighted version of the Hermite Index and it's simple and more radical in its treatment of tail weight. Therefore, here we consider using the same idea of the Nature Hermite Index to deal with big data.

When dealing with extremely large data sets, it's computationally expensive for those PP indices because of the density estimation and calculation of the integral. Moreover, guided tour is hard to implement for big data because the index need to be optimized at each

step during the tour, which will take much longer time with large data sets. Therefore, we propose a new PP index based on the data nugget method that was developed by Beavers (2019) for reducing large datasets while maintaining the data structure.

The data Nugget method reduces a large dataset into a small collection of nuggets of data while maintaining the overall data structure and each nugget corresponds to a subset of the data represented by its center, weight, and scale parameters. The center and weight of a nugget is the mean and the number of observations inside the nugget respectively. The scale $s_i = \sqrt{\text{Max}\{\text{diag}(\text{Cov}(\mathbf{X}_i))\}}$ where \mathbf{X}_i is the observations belonging to data nugget i . And when the weight of data nugget is 1, the scale $s_i = 0$. To provide each data nugget with a more common level of within-nugget variability, data nuggets can be refined by splitting those nuggets with large scale parameters. After refining a set of data nuggets, they would be more spherical than the original set.

The new PP index for big data is constructed based on the obtained refined data nuggets using the idea of the Natural Hermite Index. The constructing process and its definition are described below.

Definition 1 The Projection Pursuit index for Big Data is constructed as follows:

Step 1. Construct and refine data nuggets for the big data set to obtain m data nuggets with centers, weights and scales.

Step 2. Sphere the obtained data nugget centers with weights, i.e., weighted mean is zero and weighted covariance is identity matrix.

Step 3. Let $\mathbf{X} \in \mathbb{R}^{m \times p}$ denote the nugget centers spherized with weights \mathbf{w} where $\mathbf{w} \in \mathbb{R}^m$ is the weight vector of the data nuggets. Let $\mathbf{Y} \triangleq \mathbf{XA} \in \mathbb{R}^{m \times d}$ be the projected nugget centers and let $\mathbf{s} \in \mathbb{R}^m$ be the scale vector. A new PP index based on the data nuggets that represent the whole data is defined by

$$I^B = \int_{\mathbb{R}^d} \{\hat{f}_B(\mathbf{y}) - \phi(\mathbf{y})\}^2 \phi(\mathbf{y}) d\mathbf{y} \quad (2.1)$$

where $\mathbf{y} \in \mathbb{R}^d$, $\phi(\cdot)$ is the standard multivariate Normal density, and the estimated density function is calculated based on the nuggets:

$$\hat{f}_B(\mathbf{y}) = \sum_{i=1}^m w_i |\mathbf{S}_i|^{-1/2} \phi(\mathbf{S}_i^{-1/2} \mathbf{y}) \quad (2.2)$$

where $\mathbf{S}_i = \max\{s_i^2, \delta^2\}\mathbf{I}_d$ with a pre-determined minimal scale level δ . Alternatively, $\mathbf{S}_i = \text{median}\{\mathbf{s}^2\}\mathbf{I}_d$ for all $i = 1, 2, \dots, m$ if \mathbf{s} has a wide variety.

This new PP index will be computationally much cheaper than using the original indices for the whole data set, because calculations are based on the obtained small collection of data nuggets rather than the whole big data set. Also, since data nuggets maintain the overall data structure, this new PP index will help find hidden structures in the original big data set.

3. Performance of the new index on simulated data

In order to check the performance of the proposed PP index for big data, we conducted simulations with simple data sets that we generated. To generate the data we first constructed the data nugget centers equally spaced on the grid and provide them with random weights and scales. After obtaining all the nuggets, we generate raw data from a uniform distribution inside a sphere of radius $2s$ around each data nugget center, where s is the scale parameter. Then the original Natural Hermite Index I^N for the raw data and the new PP index I^B based on the data nuggets are calculated and compared. We conducted the simulations for both $p = 4$ and $p = 6$ and considered the 2-dimensional projection. Moreover, in order to make the raw data with a hidden structure, the first variables of nugget centers were adjusted to make two obvious clusters in the simulated data.

Firstly, for $p = 4$, we constructed 256 data nuggets with centers equally spaced on $[-2, 2]^4$ and 9106 observations of raw data are generated. Figure 1 shows the histograms of the first variables of the raw data and nugget centers, from which two obvious clusters are shown. Figure 2 shows two examples of 2-dimensional random projections. The left ones are the projected raw data and right ones are the projected data nuggets. The color of each data nugget corresponds to its weight. Lighter green means a lower weight while darker green means a larger weight. For Figure 2(a), there's no obvious structure and the original Natural Hermite Index I^N for the raw data is **0.000128** while the new PP index I^B equals **0.000216**. For Figure 2(b), there are two clear clusters and I^N for the raw data is **0.008222** while the

new PP index I^B based on the data nuggets equals **0.007861**. Therefore, the values of the new PP index based on data nuggets are very similar with the original index for the whole raw data.

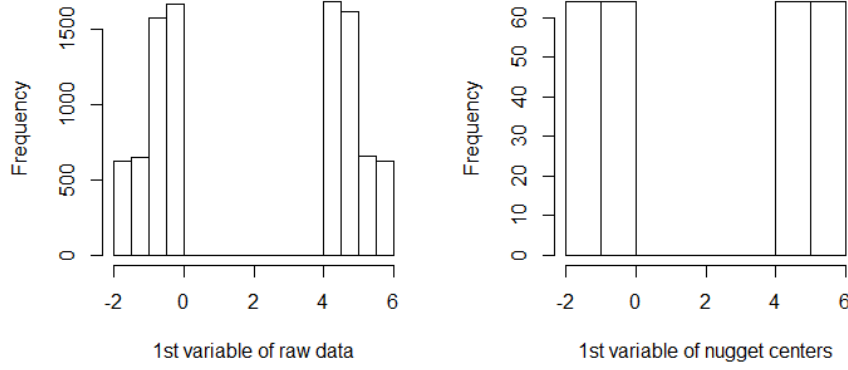


Figure 1: Histograms of the first variables of the raw data and data nuggets for 4-dimensional simulated data

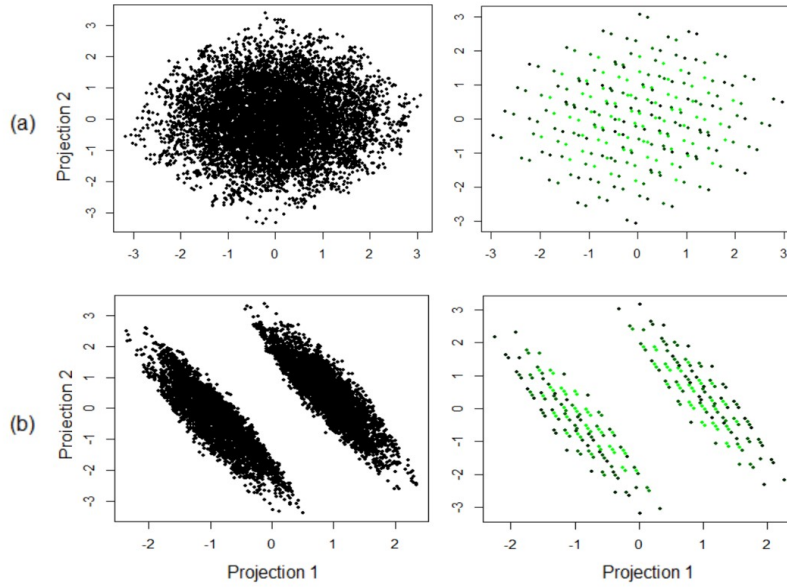


Figure 2: 2-dimensional random projected raw data and data nuggets of the 4-dimensional simulated data

In order to check the performance of the new PP index for finding interesting projec-

tions, we formed a sequence of projections by iterating a small random rotation R_δ over the projection in Figure 2(b). We completed the path projections in the opposite direction by iterating R_δ^{-1} . In this way we constructed a path of projections that follows a geodesic on the manifold of projections and is centered around the projection in Figure 2(b). Figure 3 shows the path of rotations plus the two curves of the indices, the top one for the new PP index I^B based on data nuggets and the bottom one for the original Natural Hermite Index I^N for the raw data. The plots shown between the two curves are the projected raw data and nuggets for each rotated projections. The highlighted middle plot of the sequence shows the same projection as Figure 2(b) clearly indicating two clusters. We can find that the projected structure is getting blurry on both directions. Therefore, in this local region, by rotating the projection plane a little bit, we can find the local optimal projections found by the new PP index and the original Natural Hermite Index are the same. Also, the values and trends of the two indices are similar to each other.

We also conducted similar simulations for $p = 6$. There are 88218 raw data with 4096 data nuggets. Figure 4 displays two 2-dimensional projections showing a random view of the data and a view of the underlying structure, respectively. Figure 4(a) shows no obvious structure and I^N for the raw data is **0.000098** while the new PP index I^B equals **0.000107**. For Figure 4(b) showing two clear clusters, the new PP index I^B based on the nuggets equals **0.003067** while I^N for the raw data is **0.003661**.

Similarly, based on the projection in Figure 4(b), we iterated a small rotation on both directions and obtained the path of projections in Figure 5. Figure 5 displays two curves of the Natural Hermite indices for the projections of the original data and the data nuggets respectively. The graph shows a high similarity of the two curves in both the trends and the local optimum.

The calculation of the original Natural Hermite index for the projected whole data involves n evaluations of each of n densities centered at each point so it is of order n^2 . For the projected data nuggets the evaluation of the new PP index is of the order m^2 . The projection calculation is of linear order so the computation of the two indices is of order n^2 and m^2 respectively. In the examples of Figure 2, since $m = 256$ and $n = 9106$, the savings

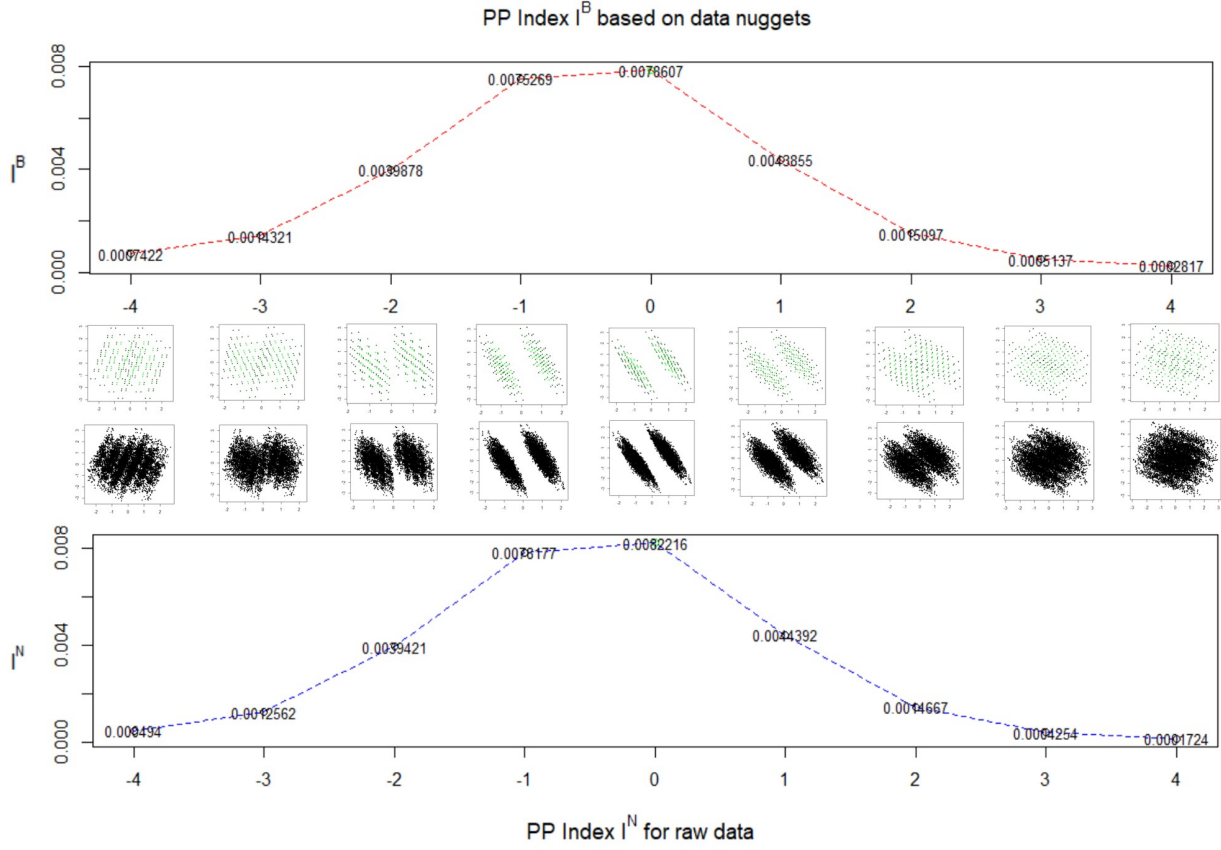


Figure 3: The path of rotations and two curves of I^B , I^N for the 4-dimensional simulated data. The x axis represents different projections.

by using data nuggets is of the order $n^2/m^2 \sim 10^3$. For the example in Figure 4 the savings is a factor of 10^2 . The results above show that the performance of the new PP index with the data nuggets on simulated data is comparable to the original index on the full data but the computation is of an order of magnitude less.

4. Optimization of the new index

Apart from the performance of the new PP index itself, we implemented the optimization algorithm for it to find the most interesting static projection which has the largest PP index value. Here we used the modified simulated annealing method that Lee et al. (2005) used, with a neighborhood temperature parameter and the other (cooling parameter) for the probability that guards against getting trapped in a local maximum. The neighborhood

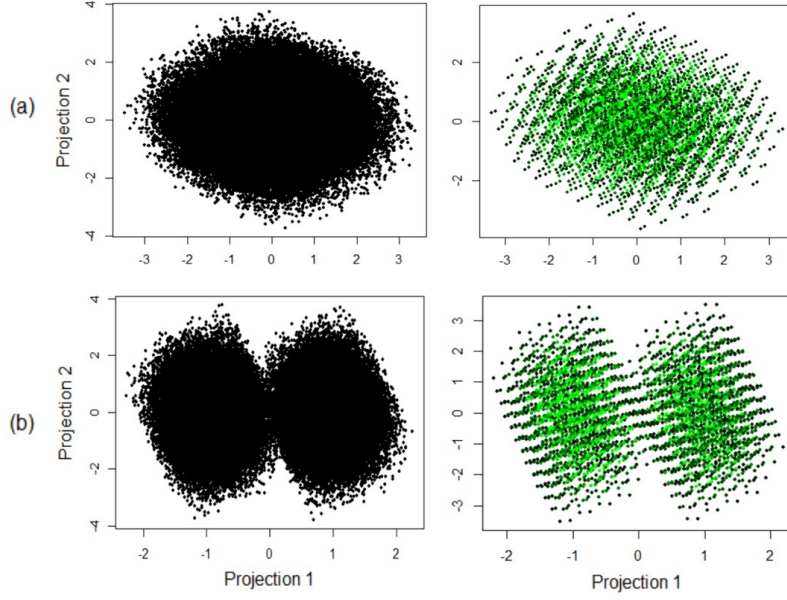


Figure 4: 2-dimensional random projected raw data and data nuggets of the 6-dimensional simulated data

temperature is rescaled by the other cooling parameter enabling escape from the local maximum to look for other maxima. For the purpose of illustration, we used the optimization algorithm with two parameters both equaling 0.9, for the new PP index I^B and the Natural Hermite index I^N . We applied it on the two simulated data sets we analyzed in Section 3 and compared the projections found by optimizing the indices.

For the data nuggets, we implemented the algorithm for the new PP index I^B , and for the raw data we optimized the original Natural Hermite index I^N . For the 4-dimensional simulated data set of which two random projections are shown in Figure 2, the optimal new PP index we found for the nuggets equals **0.016647** while the optimal I^N for the whole raw data is **0.013007**. The left plot of Figure 6(a) shows the optimal projection of data nuggets in which many nuggets are overlapped with each other. The middle plot of Figure 6(a) shows the projected raw data using the optimal projection matrix found by the new PP index I^B for the nuggets, for which the estimated Natural Hermite index I^N equals **0.012709**. The right plot of Figure 6(a) displays the optimal projection of the whole raw data found by the Natural Hermite index I^N with a 2-dimensional small-angle rotation.

Similar results are shown in Figure 6(b) for the 6-dimensional simulated data set for

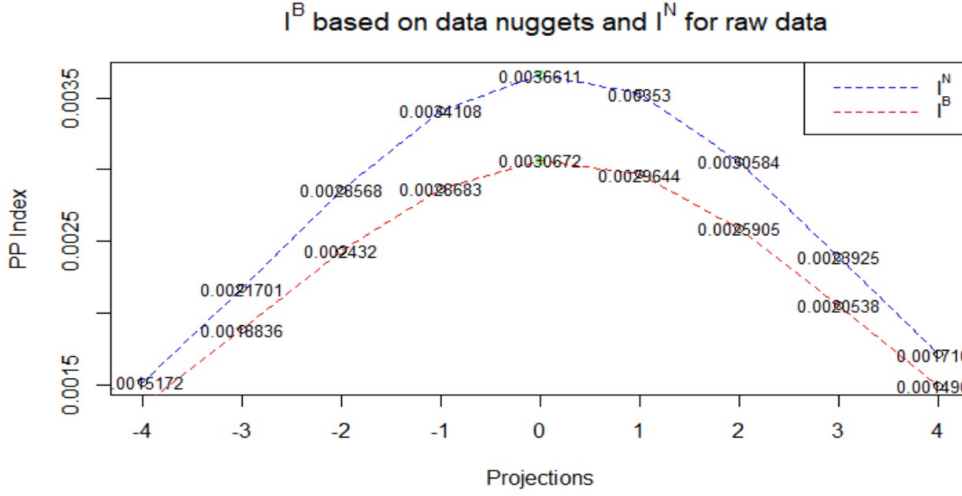


Figure 5: *PP indices along the path of rotations for the 6-dimensional simulated data*

which Figure 4 shows two random projections. The optimal projection of the data nuggets found by maximizing I^B is shown in the left plot of Figure 6(b) and the right plot is the slightly rotated optimal projection of the whole raw data by optimizing I^N . The optimal new PP index I^B for the nuggets equals **0.012011** and the value of the optimal I^N for the entire data set equals **0.019609**. For the projection shown in the middle plot of Figure 6(b), which is the projected raw data with the optimal projection matrix found by I^B , its estimated Natural Hermite index I^N equals **0.019447**. For both simulated data sets, the optimal projections found by the new PP index for the data nuggets show clearly the underlying two clusters and they are approximately same with those found by the original Natural Hermite index for the entire data set but with much less computational cost.

5. A real data application

Flow cytometry experiments are common in immunological research and they use fluorochrome-conjugated antibodies to differentiate cell populations based on surface and internal expression of delineating proteins. Data sets generated by a standard flow cytometry experiment routinely include the measurement of the abundance of 12 or more proteins at each cell. Beavers, Cabrera, et al. (2019) analyzed a flow cytometry dataset of an experiment involv-

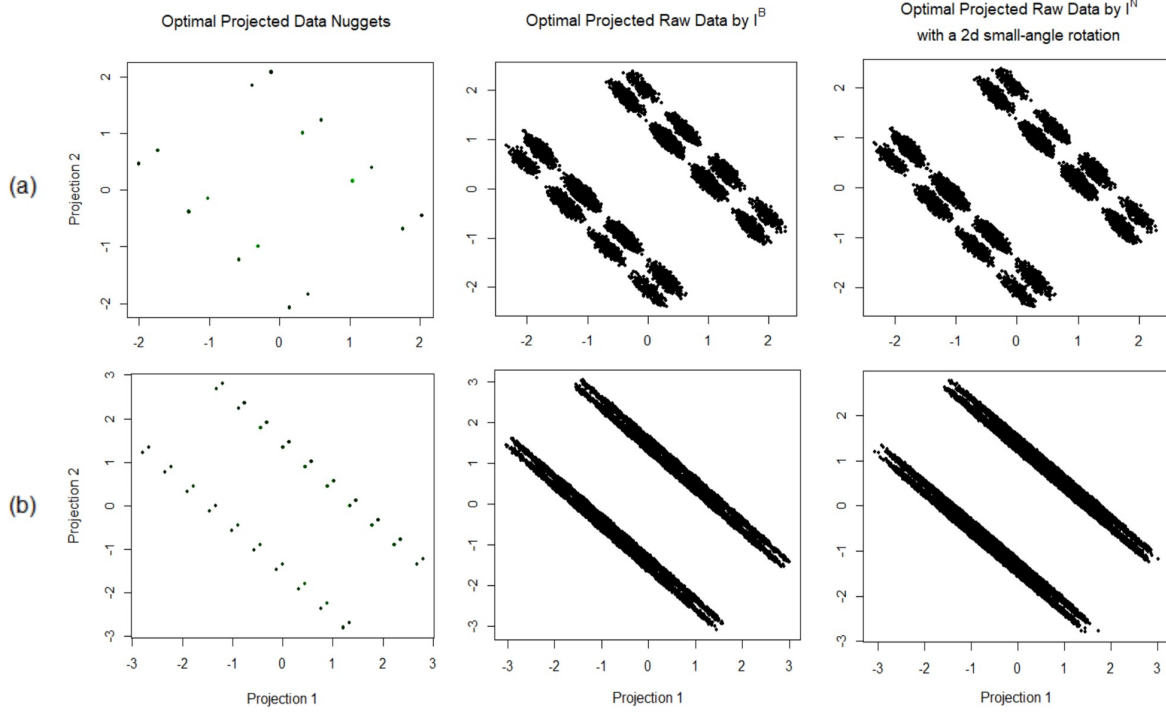


Figure 6: The optimal projections found for the (a) 4-dim simulated data and (b) 6-dim simulated data.

ing 9 proteins measurements of 1 million B-cells. The objective of the experiment was to detect clusters of B-cells with a protein profile suggesting high activity mode and to estimate the proportion of B cells with high activity mode in the sample. Projection Pursuit is a good way to find hidden structures in it but calculating the original PP indices based on this whole large data set is computationally expensive and it's also hard to perform the guided tour for the raw data. Here we apply the proposed methodology to this big data set to explore interesting structures inside it.

After obtaining about three thousand refined data nuggets, we used weighted PCA to get the principal components of them. Figure 7(a) shows the projection of the 1st and 2nd principal components and the projection in Figure 7(b) is obtained by the 2nd and 3rd principal components. The left plots in Figure 7 are the projected data nuggets while the right plots are the corresponding projected raw data with the same projection matrices. The middle plots show the estimated densities with contours which are calculated by (2.2) with the weights and scales of data nuggets. And by (2.1), we obtain the new PP index values for

these two principal components projections, which equal 0.029763 and 0.069515 for Figure 7(a) and (b) respectively. There's no obvious structure in Figure 7(a) with its small index value and Figure 7 (b) shows a vague L-shape with a little higher index.

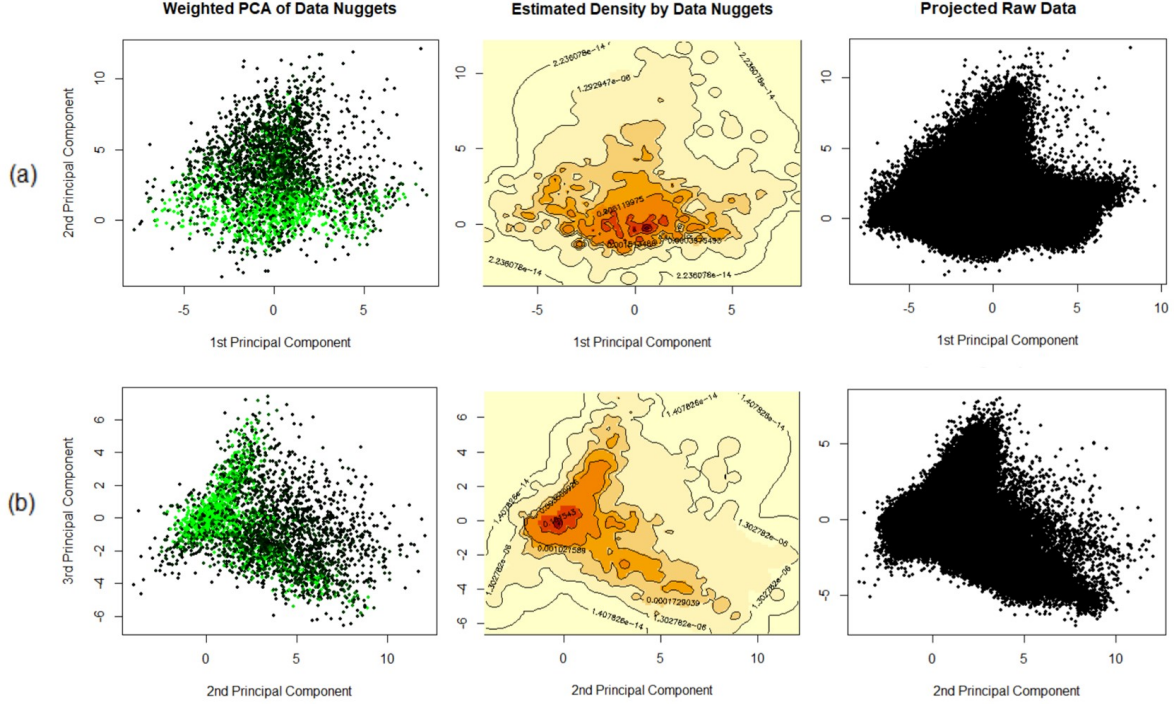


Figure 7: *Weighted PCA for the data nuggets, estimated densities and the corresponding projected raw data. (a): The 1st PC vs the 2nd PC. (b): The 2nd PC vs the 3rd PC.*

By checking 2-dimensional random projections, we found two interesting projections shown in Figure 8(a) and (b). Figure 8(a) shows an approximately diamond shape with four clusters at the vertices and the most populated one is at the left vertex. For Figure 8(b), there is a vague clustering structure with a large cluster at the left side and the other small one on the right. Figure 8(c) and (d) are the projections with larger index values, and indeed (d) is the optimal 2-dimensional projection we found by the optimization algorithm implemented in section 4 for the new PP Index I^B based on data nuggets. The estimated new PP index values, I^B , for those four projections in Figure 8 are: (a) 0.032799, (b) 0.042806, (c) 0.141540 and (d) 0.161497.

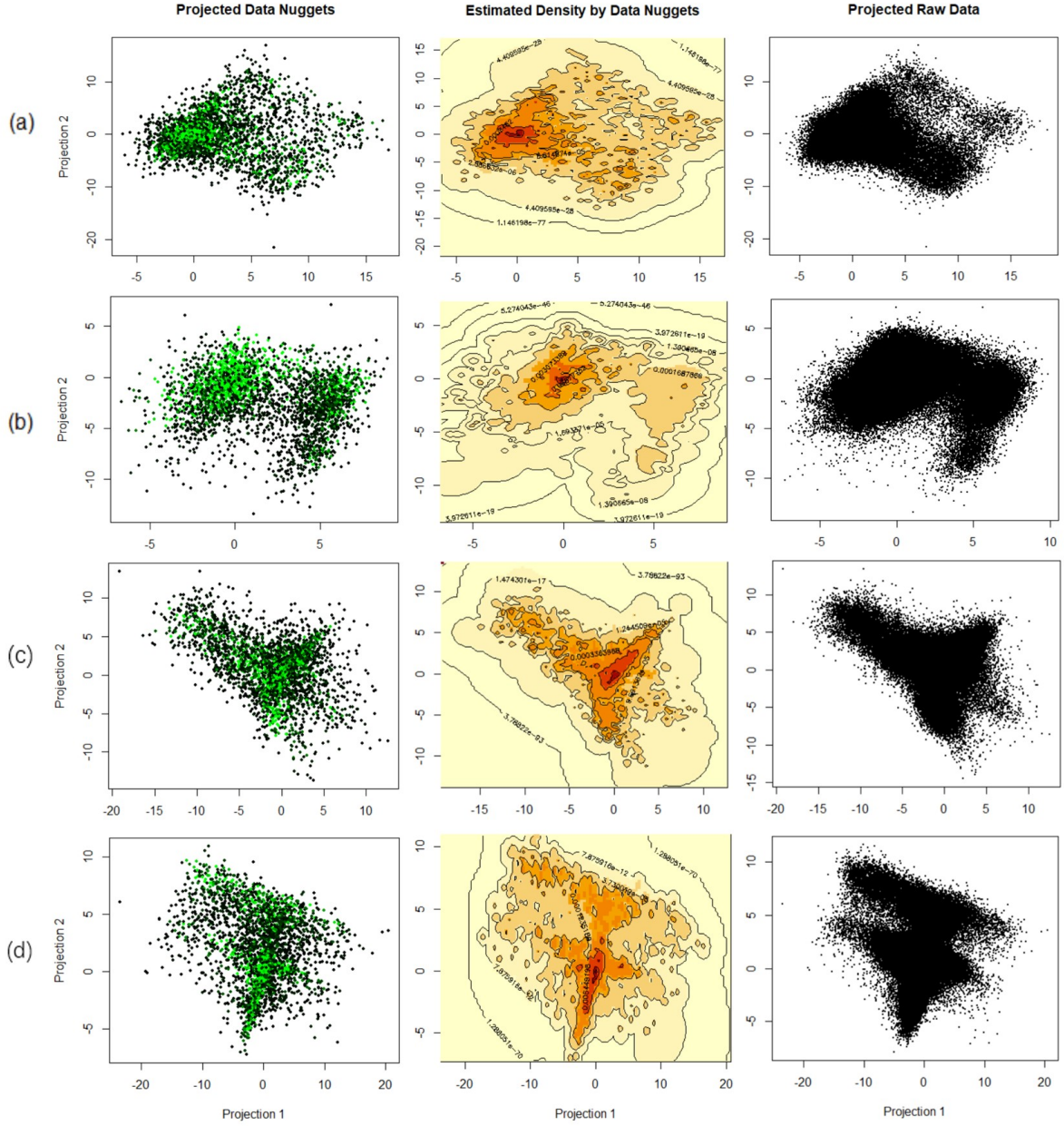


Figure 8: (a) and (b): two interesting projections with small index values. (c): a projection with a large index value. (d): the optimal projection found with the largest index value.

For Figure 8(c), it displays a Y-shape and looks like a spaceship, and the shape of the optimal projection in Figure 8(d) is like two letters F back-to-back together. Compared with the projections in Figure 7, Figure 8(a) and (b), the projections with much higher new PP indices in Figure 8(c) and (d) display significantly more clear unusual shapes, indicating

potential data structures inside the large data set. Therefore, the proposed new PP index based on the data nuggets will help find more interesting projections and hidden structures in the whole large data set with considerably less computational cost than the original PP indices. And by Figure 8(a) and (b), it seems that a new PP index specifically for the clustering structure based on data nuggets can be developed with great prospects.

6. Future work

In the future, we plan to develop several new methods based on the proposed methodology. Firstly, we will design a much more efficient optimization algorithm for the proposed new PP index to find the most interesting static projection for a large data set. Secondly, the guided tour for big data will be developed based on the new index with the optimization method, to provide a dynamic graphical tool for detecting non-linear structures. Thirdly, other PP indices based on the data nuggets will be proposed with visualization tools, including the indices for specific structures such as clusters, holes, and so on. Moreover, there are other potential applications of the new PP index including regarding it as a dissimilarity measure for clustering functional data.

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