

# Topological Data Analysis

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**Keywords**

clustering, persistent homology, dimension reduction, manifold estimation, density trees

**Abstract**

Topological data analysis (TDA) can broadly be described as a collection of data analysis methods that find structure in data. These methods include clustering, manifold estimation, nonlinear dimension reduction, mode estimation, ridge estimation and persistent homology. This paper reviews some of these methods.

## 1. INTRODUCTION

Topological data analysis (TDA) refers to statistical methods that find structure in data. As the name suggests, these methods make use of topological ideas. Often, the term TDA is used narrowly to describe a particular method called persistent homology (discussed in Section 4). In this review, I take a broader perspective: I use the term TDA to refer to a large class of data analysis methods that use notions of shape and connectivity. The advantage of taking this broader definition of TDA is that it provides more context for recently developed methods. The disadvantage is that my review must necessarily be incomplete. In particular, I omit any reference to classical notions of shape, such as shape manifolds (Kendall 1984, Patrangenaru & Ellingson 2015) and related ideas, because they are a bit far afield from topics in this article.

Clustering is the simplest example of TDA. Clustering is a huge topic, and I only discuss density clustering, since this connects clustering to other methods in TDA. I also selectively review aspects of manifold estimation (also called manifold learning), nonlinear dimension reduction, mode and ridge estimation, and persistent homology.

In my view, the main purpose of TDA is to help the data analyst summarize and visualize complex datasets. Whether or not TDA can be used to make scientific discoveries is still unclear. There is another field that deals with the topological and geometric structure of data: computational geometry. The main difference is that in TDA we treat the data as random points, whereas in computational geometry the data are usually seen as fixed.

Throughout this article, we assume that we observe a sample

$$X_1, \dots, X_n \sim P, \tag{1}$$

where the distribution  $P$  is supported on some set  $\mathcal{X} \subset \mathbb{R}^d$ . Some of the technical results cited require either that  $P$  have sufficiently thin tails or that  $\mathcal{X}$  be compact.

Many of the methods in this article are implemented in the R package TDA, available at <https://cran.r-project.org/web/packages/TDA/index.html>. A tutorial on the package can be found in Fasy et al. (2014a).

## 2. DENSITY CLUSTERS

Clustering is perhaps the oldest and simplest version of TDA. The connection between clustering and topology is clearest if we focus on density-based methods for clustering.

### 2.1. Level Set Clusters

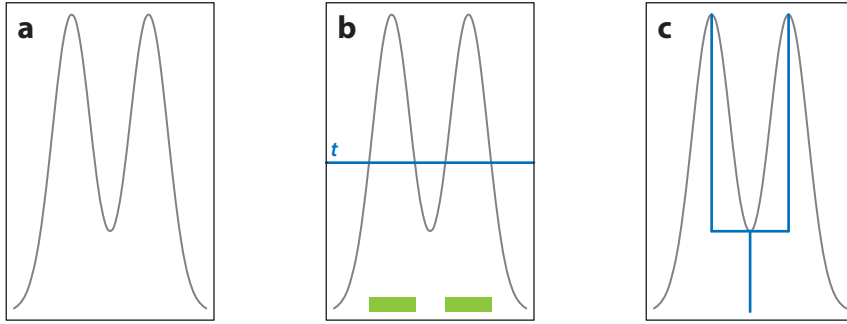
Let  $X_1, \dots, X_n$  be a random sample from a distribution  $P$  with density  $p$ , where  $X_i \in \mathcal{X} \subset \mathbb{R}^d$ . Density clusters are sets with high density. Hartigan (1975, 1981) formalized this as follows. For any  $t \geq 0$ , define the upper level set

$$L_t = \{x : p(x) > t\}. \tag{2}$$

The density clusters at level  $t$ , denoted by  $\mathcal{C}_t$ , are the connected components of  $L_t$ . The set of all density clusters is

$$\mathcal{C} = \bigcup_{t \geq 0} \mathcal{C}_t. \tag{3}$$

**Figure 1a** shows a density function, and **Figure 1b** shows the level set clusters corresponding to one particular value of  $t$ .



**Figure 1**

(a) A density function  $p$ . (b) Density clusters corresponding to  $L_t = \{x : p(x) > t\}$ . (c) The density tree corresponding to  $p$  is shown under the density. The leaves of the tree correspond to modes. The branches correspond to connected components of the level sets.

The estimated upper level set is

$$\widehat{L}_t = \{x : \widehat{p}(x) > t\}, \quad 4.$$

where  $\widehat{p}$  is any density estimator. A common choice is the kernel density estimator

$$\widehat{p}_b(x) = \frac{1}{n} \sum_{i=1}^n \frac{1}{b^d} K\left(\frac{\|x - X_i\|}{b}\right), \quad 5.$$

where  $b > 0$  is the bandwidth and  $K$  is the kernel. The theoretical properties of the estimator  $\widehat{L}_t$  are discussed, for example, by Cadre (2006) and Rinaldo & Wasserman (2010). In particular, Cadre (2006) shows, under regularity conditions and appropriate  $b$ , that  $\mu(\widehat{L}_t \Delta L_t) = O_P(1/\sqrt{nb^d})$ , where  $\mu$  is Lebesgue measure and  $A \Delta B$  is the set difference between two sets  $A$  and  $B$ .

To find the clusters, we need to get the connected components of  $\widehat{L}_t$ . Let  $I_t = \{i : \widehat{p}_b(X_i) > t\}$ . Create a graph whose nodes correspond to  $(X_i : i \in I_t)$ . Put an edge between two nodes  $X_i$  and  $X_j$  if  $\|X_i - X_j\| \leq \epsilon$ , where  $\epsilon > 0$  is a tuning parameter. (In practice  $\epsilon = 2b$  often seems to work well.) The connected components  $\widehat{C}_1, \widehat{C}_2, \dots$  of the graph estimate the clusters at level  $t$ . The number of connected components is denoted by  $\beta_0$ , which is the zeroth-order Betti number. This is discussed in more detail in Section 4.1.

Related to level sets is the concept of excess mass. Given a class of sets  $\mathcal{C}$ , the excess mass functional is defined to be

$$E(t) = \sup\{P(C) - t\mu(C) : C \in \mathcal{C}\}, \quad 6.$$

and any set  $C \in \mathcal{C}$  such that  $P(C) - t\mu(C) = E(t)$  is called a generalized  $t$ -cluster. If  $\mathcal{C}$  is taken to be all measurable sets and the density is bounded and continuous, then the upper level set  $L_t$  is the unique  $t$ -cluster. The excess mass functional is studied in Polonik (1995) and Müller & Sawitzki (1991).

One question that arises in the use of level set clustering is, How do we choose  $t$ ? One possibility is to choose  $t$  to cover some prescribed fraction  $1 - \beta$  of the total mass; thus we choose  $t$  to satisfy  $\int_{\widehat{L}_t} \widehat{p}(s) ds = 1 - \beta$ . Another idea is to look at clusters at all levels  $t$ . This leads us to the idea of density trees.

## 2.2. Density Trees

The set of all density clusters  $\mathcal{C}$  has a tree structure: If  $A, B \in \mathcal{C}$ , then either  $A \subset B$  or  $B \subset A$  or  $A \cap B = \emptyset$ . For this reason, we can visually represent a density and its clusters as a tree, which we denote by  $T_p$  or  $T(p)$ . Note that  $T_p$  is technically a collection of level sets, but it can be represented as a two-dimensional tree as in the **Figure 1c**. The tree, shown under the density function, shows the number of level sets and shows when level sets merge. For example, if we cut across at some level  $t$ , then the number of branches of the tree corresponds to the number of connected components of the level set. The leaves of the tree correspond to the modes of the density.

The tree is called a density tree or cluster tree. This tree provides a convenient, two-dimensional visualization of a density regardless of the dimension  $d$  of the space in which the data lie.

Two density trees have the same shape if their tree structure is the same. Chen et al. (2016) make this precise as follows. For a given tree  $T_p$ , define a distance on the tree between two points  $x$  and  $y$  by

$$d_{T_p}(x, y) = |p(x) + p(y) - 2m_p(x, y)|,$$

where

$$m_p(x, y) = \sup\{t : \text{there exists } C \in \mathcal{C}_t \text{ such that } x, y \in C\}$$

is called the merge height (Eldridge et al. 2015). For any two clusters  $C_1, C_2 \in T_p$ , we first define  $\lambda_1 = \sup\{t : C_1 \in \mathcal{C}_t\}$ , and  $\lambda_2$  analogously. We then define the tree distance function on  $T_p$  by

$$d_{T_p}(C_1, C_2) = \lambda_1 + \lambda_2 - 2m_p(C_1, C_2), \tag{7}$$

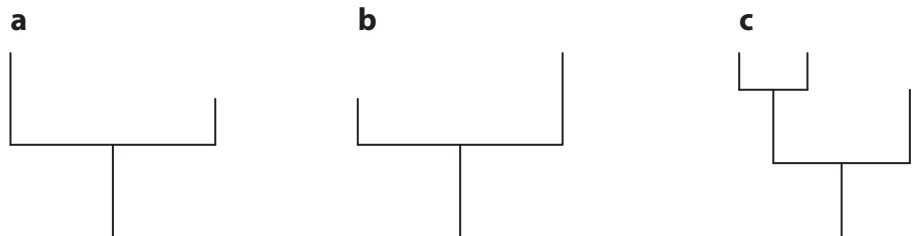
where

$$m_p(C_1, C_2) = \sup\{\lambda \in \mathbb{R} : \text{there exists } C \in T_p \text{ such that } C_1, C_2 \subset C\}.$$

This extends the earlier definition  $d_{T_p}$  so that it defines a distance between sets. Now  $d_{T_p}$  defines a distance on the tree, and it induces a topology on  $T_p$ . Given two densities  $p$  and  $q$ , we say  $T_p$  is homeomorphic to  $T_q$ , written  $T_p \cong T_q$ , if there exists a bicontinuous map from  $T_p$  to  $T_q$ . This means that  $T_p$  and  $T_q$  have the same shape—in other words, they have the same tree structure. An example is shown in **Figure 2**.

The density tree can be estimated by plugging in any density estimator. The estimated tree is denoted by  $\hat{T}$ —usually based on a kernel density estimator  $\hat{p}_b$ , which provides a nice visualization of the cluster structure of the data. Another choice of estimator is the  $k$ -nearest neighbor estimator, as in Chaudhuri & Dasgupta (2010).

To estimate the shape of the density tree, it is not necessary to let the bandwidth  $b$  go to 0 as  $n$  increases. Let  $p_b(x) = \mathbb{E}[\hat{p}_b(x)]$  be the mean of the estimator. It can be shown that, under



**Figure 2**

(*a, b*) Density trees in panels *a* and *b* are homeomorphic; there exists a bicontinuous map from one tree to the other. (*c*) The third tree is not homeomorphic to the other two. Thus, the first two trees represent densities with the same shape.

weak conditions, there exists  $b_0 > 0$  such that, for all  $0 < b < b_0$ ,  $T(p_b) \cong T(p)$ . This means that it suffices to estimate  $T_{p_b}$  for any small  $b > 0$ . This has important practical implications since  $T_{p_b}$  can be estimated at the rate  $O_p(n^{-1/2})$  independent of the dimensions  $d$ . Compare this to estimating  $p$  in the  $L_2$  loss; the best rate under standard smoothness conditions is  $O_p(n^{-2/(4+d)})$ , which is slow for large dimensions  $d$ . The key point is that estimating the cluster structure is easier than estimating the density itself. In other words, you can estimate  $p$  poorly but still get the shape of the tree correct. The reader is directed to Chen et al. (2016) for more details.

The bootstrap can be used to get confidence sets for the density tree (Chen et al. 2016). Let  $P_n$  be the empirical measure that puts mass  $1/n$  at each data point. Draw an independent and identically distributed sample  $X_1^*, \dots, X_n^* \sim P_n$  and compute the density estimator  $\hat{p}_b^*$ . Repeat this process  $B$  times to get density estimates  $\hat{p}_b^{(1)}, \dots, \hat{p}_b^{(B)}$  and define

$$\hat{F}_n(t) = \frac{1}{B} \sum_{j=1}^B I(\sqrt{n} \|\hat{p}_b^{(j)} - \hat{p}_b\|_\infty > t),$$

where  $I$  is the indicator function. For large  $B$ ,  $\hat{F}_n$  approximates

$$F_n(t) = P(\sqrt{n} \|\hat{p}_b - p_b\|_\infty > t).$$

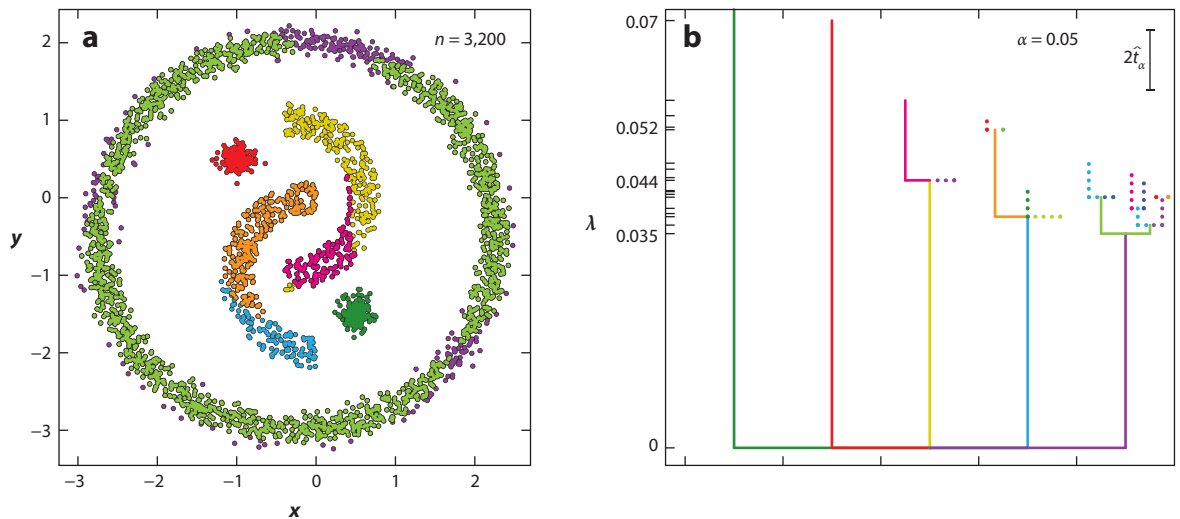
Let  $\hat{t}_\alpha = \hat{F}_n^{-1}(1 - \alpha)$ , which approximates  $t_\alpha = F_n^{-1}(1 - \alpha)$ . Then

$$\lim_{n \rightarrow \infty} P(T(p_b) \in \mathcal{T}) = 1 - \alpha,$$

where

$$\mathcal{T} = \left\{ T(p) : \|p - \hat{p}_b\|_\infty \leq \frac{\hat{t}_\alpha}{\sqrt{n}} \right\}.$$

Thus,  $\mathcal{T}$  is an asymptotic confidence set for the tree. The critical value  $\hat{t}_\alpha$  can be used to prune nonsignificant leaves and branches from  $\hat{T}$  (see **Figure 3**).



**Figure 3**

Example of density tree using the bootstrap from Chen et al. (2016), showing (a) the data and (b) the tree. The solid lines are the pruned trees; the dashed lines are leaves and branches that have been pruned away because they are smaller than the bootstrap significance level  $2\hat{t}_\alpha$  (indicated in the top right corner of panel b). The colors on the left correspond to clusters in the tree on the right.

A density tree is Hartigan consistent if, with probability tending to 1, the correct cluster structure is recovered. Generally, density trees based on consistent density estimators will be Hartigan consistent. For more on Hartigan consistency, see Chaudhuri & Dasgupta (2010), Eldridge et al. (2015), and Balakrishnan et al. (2013).

### 2.3. Mode Clustering and Morse Theory

Another density clustering method is mode clustering (Arias-Castro et al. 2015; Chacón 2012, 2015; Chacón & Duong 2013; Cheng 1995; Comaniciu & Meer 2002; Li et al. 2007). The idea is to find modes of the density and then define clusters as the basins of attraction of the modes. A point  $m$  is a (local) mode if there exists an open neighborhood  $N$  of  $x$  such that  $p(x) > p(y)$  for every  $y \in N$  such that  $y \neq x$ . Suppose that  $p$  has  $k$  local modes  $\mathcal{M} = \{m_1, \dots, m_k\}$ . Assume that  $p$  has gradient  $g$  and Hessian  $H$ .

A point  $x$  is a critical point if  $g(x) = (0, \dots, 0)^T$ . The function  $p$  is a Morse function if the Hessian is nondegenerate at each critical point (Milnor 2016). We will assume that  $p$  is Morse. In this case,  $m$  is a local mode if and only if  $g(m) = (0, \dots, 0)^T$  and  $\lambda_1(H(m)) < 0$ , where  $\lambda_1(A)$  denotes the largest eigenvalue of the matrix  $A$ .

Now let  $x$  be an arbitrary point. If we follow the steepest ascent path starting at  $x$ , we will eventually end up at one of the modes.<sup>1</sup> Thus, each point  $x$  in the sample space is assigned to a mode  $m_j$ . We say that  $m_j$  is the destination of  $x$ , which is written

$$\text{dest}(x) = m_j.$$

The path  $\pi_x : \mathbb{R} \rightarrow \mathbb{R}^d$  that leads from  $x$  to a mode is defined by the differential equation

$$\pi_x'(t) = \nabla p(\pi_x(t)), \quad \pi_x(0) = x.$$

The set of points assigned to mode  $m_j$  is called the basin of attraction of  $m_j$  and is denoted by  $C_j$ . The sets  $C_1, \dots, C_k$  are the population clusters. **Figure 4a** shows a bivariate density with four modes, and **Figure 4b** shows the partition induced by the modes.

To estimate the clusters, we find the modes  $\widehat{\mathcal{M}} = \{\widehat{m}_1, \dots, \widehat{m}_r\}$  of the density estimate. A simple algorithm called the mean shift algorithm (Cheng 1995, Comaniciu & Meer 2002) can be used to find the modes and to find the destination of any point  $x$ . For any given  $x$ , we define the iteration

$$x^{(j+1)} = \frac{\sum_i X_i K\left(\frac{\|x^{(j)} - X_i\|}{b}\right)}{\sum_i K\left(\frac{\|x^{(j)} - X_i\|}{b}\right)}$$

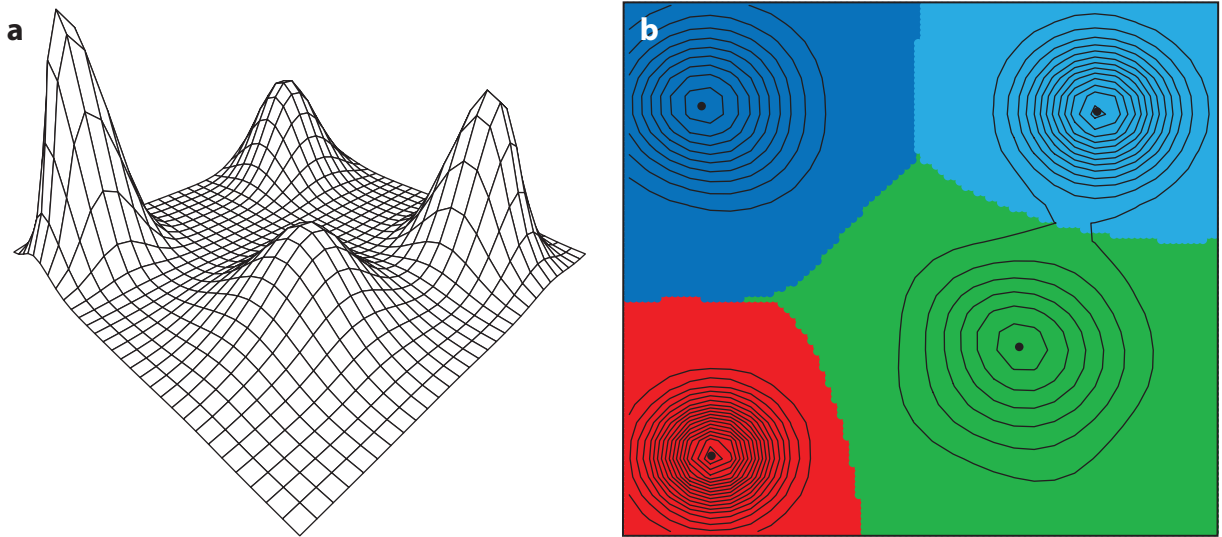
(see **Figure 5**). The convergence of this algorithm is studied in Arias-Castro et al. (2015).

It can be shown under suitable regularity conditions that the modes of the kernel density estimate are consistent estimates modes of the true density (see Genovese et al. 2016). Once again, however, it is not necessary to estimate the density well to estimate the mode clusters well. Specifically, define

$$c(x, y) = \begin{cases} 1 & \text{if } \text{dest}(x) = \text{dest}(y) \\ 0 & \text{if } \text{dest}(x) \neq \text{dest}(y). \end{cases}$$

Thus,  $c(x, y) = 1$  if  $x$  and  $y$  are in the same cluster. Similarly, the estimated clusters define a function  $\widehat{c}$ . Let  $C_1, \dots, C_k$  be the model clusters. Let  $t_1, \dots, t_k$  be constants and let  $C_j(t_j) = \{x \in C_j : p(x) > t_j\}$ . The sets  $C_1(t_1), \dots, C_k(t_k)$  are called cluster cores, and these are the high density

<sup>1</sup>This is true for all  $x$  except on a set of Lebesgue measure 0.



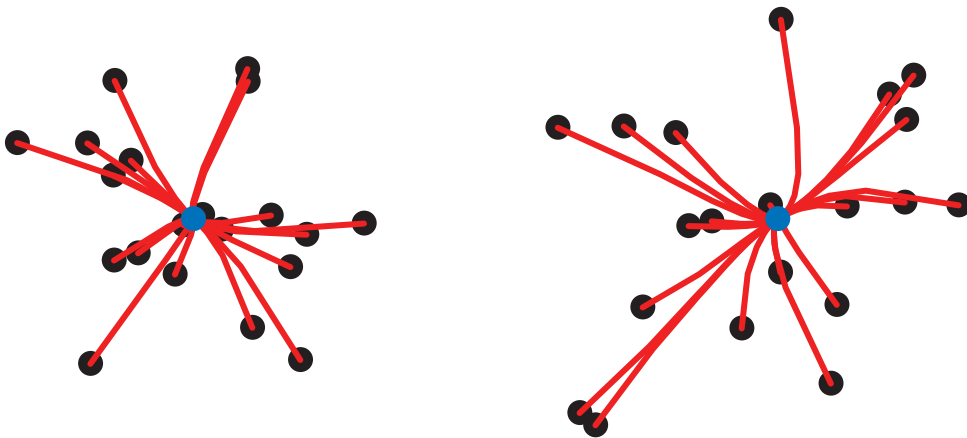
**Figure 4**

(a) A density with four modes. (b) The partition (basins of attraction) of the space induced by the modes. These are the population clusters.

points within the clusters. Let  $\text{Core} = \{X_i : X_i \in \bigcup_j C_j(t_j)\}$  be the data points in the cluster cores. Azizyan et al. (2015) show that, if  $t_1, \dots, t_k$  are sufficiently large, then

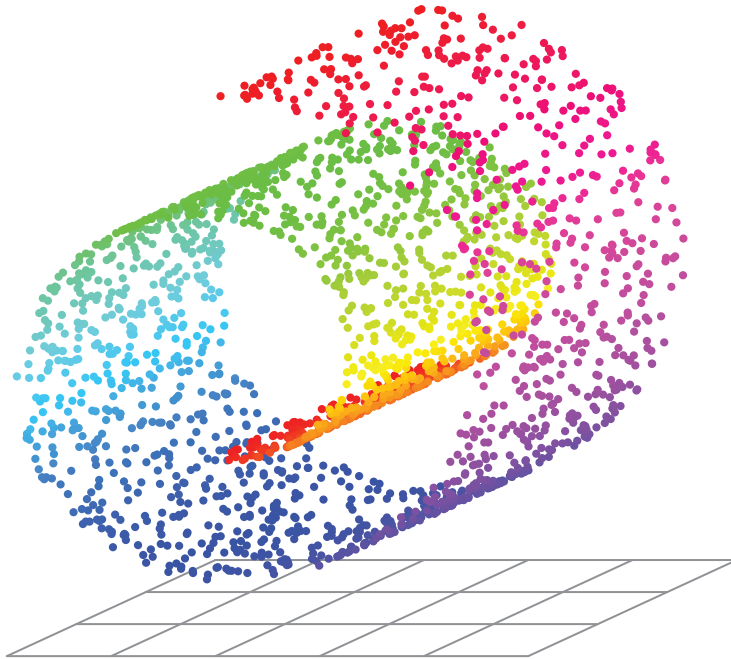
$$\mathbb{P}(\widehat{c}(X_j, X_k) \neq c(X_j, X_k) \text{ for any } X_j, X_k \in \text{Core}) \leq e^{-nb}$$

for some  $b > 0$ , independent of the dimension. This means that high density points can be accurately clustered using mode clustering.



**Figure 5**

The mean shift algorithm. The data are represented by the black dots. The two modes of the density estimate are the two blue dots. The red curves show the mean shift paths; each data point moves along its path toward a mode as we iterate the algorithm.



**Figure 6**

The Swiss-roll dataset. The ambient dimension is  $d = 3$ , but the data are supported on a set  $S$  of dimension  $r = 2$ .

### 3. LOW DIMENSIONAL SUBSETS

Sometimes the distribution  $P$  is supported on a set  $S$  of dimension  $r$  with  $r < d$ . (Recall that  $X_i$  has dimension  $d$ .) The set  $S$  might be of scientific interest, and it is also useful for dimension reduction. Sometimes the support of  $P$  is  $d$ -dimensional, but we are interested in finding a set  $S$  of dimension  $r < d$  that has a high concentration of mass.

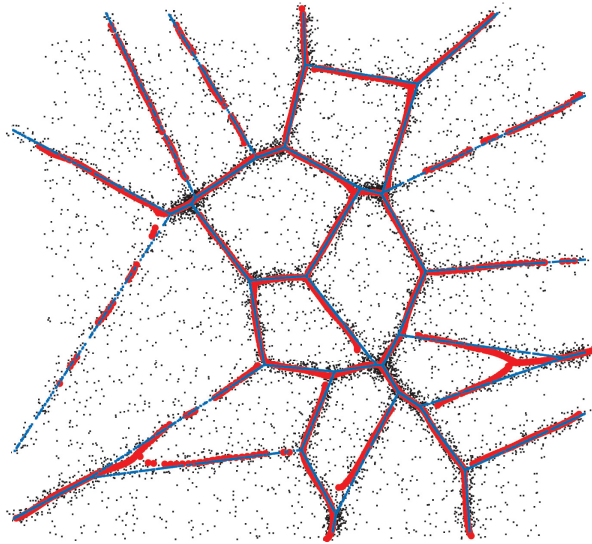
**Figure 6** shows an example known as the Swiss-roll dataset. Here, the ambient dimension is  $d = 3$ , but the support of the distribution  $S$  is a manifold of intrinsic dimension  $r = 2$ . **Figure 7** shows a more complex example. Here,  $d = 2$ , but clearly there is an  $r = 1$  intrinsic dimensional subset  $S$  with a high concentration of data. (This dataset mimics what we often see in some datasets from astrophysics.) The set  $S$  is quite complex and is not a smooth manifold. The red lines show an estimate of  $S$  based on the techniques described in Section 3.3.

#### 3.1. Manifolds

In the simplest case, the set  $S$  is a smooth, compact submanifold of dimension  $r$ . The term manifold learning can refer either to methods for estimating the set  $S$  or to dimension reduction methods that assume that the data are on (or near) a manifold. Principal component analysis can be thought of as a special case of manifold learning in which the data are assumed to lie near an affine subspace.

As a motivating example, consider images of a person's face as the person moves his or her head. Each image can be regarded as a high-dimensional vector. For example, a 16 by 16 image is a vector in  $\mathbb{R}^d$  where  $d = 16 \times 16 = 256$ . However, the set of images will not fill up  $\mathbb{R}^{256}$ . As the person moves his or her head, these vectors are likely to trace out a surface of dimension  $r = 3$ , corresponding to the three degrees of freedom corresponding to the motion of the head.





**Figure 7**

These data are two dimensional, but there is a set  $S$  of dimension  $r = 1$  with a high concentration of data. The red lines show an estimate of  $S$  using the methods in Section 3.3.

**3.1.1. Estimating  $S$ .** An estimator of  $S$  is  $\widehat{S} = \bigcup_{i=1}^n B(X_i, \epsilon_n)$ , which was suggested (in a different context) by Devroye & Wise (1980). The estimator  $\widehat{S}$  is  $d$ -dimensional, but it does converge to  $S$  in the following sense (Chazal et al. 2014b, Cuevas 2009, Cuevas et al. 2001, Fasy et al. 2014b, Niyogi et al. 2008). The Hausdorff distance  $H(A, B)$  between two sets  $A$  and  $B$  is

$$H(A, B) = \inf\{\epsilon : A \subset B \oplus \epsilon \text{ and } B \subset A \oplus \epsilon\}, \quad 8.$$

where

$$A \oplus \epsilon = \bigcup_{x \in A} B(x, \epsilon)$$

and  $B(x, \epsilon)$  denotes a ball of radius  $\epsilon$  centered at  $x$ . Suppose there exists  $c > 0$  such that, for every  $x \in S$  and every small  $\epsilon$ ,  $P(B(x, \epsilon)) \geq c\epsilon^r$ . Further, assume that the number of balls of size  $\epsilon$  required to cover  $S$  is  $C(1/\epsilon)^r$ . These assumptions mean that  $S$  is  $r$ -dimensional (and not too curved) and that  $P$  spreads its mass over all of  $S$ . Then

$$P(H(\widehat{S}, S) > \epsilon) \leq Cr^{-d} e^{-nc\epsilon^d}.$$

Hence, if we choose  $\epsilon_n \asymp (\log n/n)^{1/r}$ , then

$$H(\widehat{S}, S) = O_p\left(\frac{\log n}{n}\right)^{1/r},$$

where  $H$  is the Hausdorff distance defined in Equation 8. However, better rates are possible under some conditions. The difficulty of estimating  $S$  as defined by minimax theory is given under various sets of assumptions by Genovese et al. (2012a,b).

It is unlikely that a sample will fall precisely on a submanifold  $S$ . A more realistic model is that we observe  $Y_1, \dots, Y_n$ , where  $Y_i = X_i + \epsilon_i$ , where  $X_1, \dots, X_n \sim G$  is a sample from a distribution  $G$  supported on  $S$  and  $\epsilon_1, \dots, \epsilon_n$  are a sample from a noise distribution such as a Gaussian. In this case,

Genovese et al. (2012a) showed that estimating  $S$  is hopeless; the minimax rate of convergence is logarithmic. However, it is possible to estimate an  $r$ -dimensional, high density region  $R$  that is close to  $S$ . The set  $R$  corresponds to a ridge in the density of  $Y$  (see Section 3.3).

**3.1.2. Estimating the topology of a manifold.** Another problem is to find an estimate  $\widehat{S}$  of  $S$  that is topologically similar to  $S$ . If, for example,  $S$  is a three-dimensional image (see Section 7.2), then requiring  $\widehat{S}$  to be topologically similar ensures that  $\widehat{S}$  “looks like”  $S$  in some sense. But what does “topologically similar” mean?

Two sets  $S$  and  $T$  (equipped with topologies) are homeomorphic if there exists a bicontinuous map from  $S$  to  $T$ . Markov (1958) proved that, in general, the question of whether two spaces are homeomorphic is undecidable for dimension greater than four.

Fortunately, it is possible to determine if two spaces are homologically equivalent. Homology is a way of defining topological features algebraically using group theory. The zeroth order homology of a set corresponds to its connected components. The first order homology corresponds to one-dimensional holes (like a donut), the second order homology corresponds to two-dimensional holes (like a soccer ball), and so on. If two sets are homeomorphic then they are homologically equivalent. However, the reverse is not true. Thus, homological equivalence is weaker than topological equivalence.

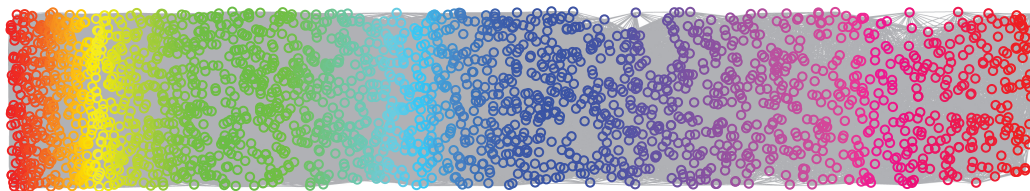
We discuss homology in more detail in Section 4.1. But here, we mention one of the first results about topology and statistics due to Niyogi et al. (2008). They showed that

$$\widehat{S} = \bigcup_{i=1}^n B(X_i, \epsilon)$$

has the same homology as  $S$  with high probability, as long as  $S$  has positive reach and  $\epsilon$  is small relative to the reach. The reach of  $S$  is the largest real number  $r$  such that any point  $x$  that is a distance less than  $r$  from  $S$  has a unique projection on  $S$ . The result assumes the data are sampled from a distribution supported on the submanifold  $S$ . Extensions that allow for noise are given by Niyogi et al. (2011). An unsolved problem is to find a data-driven method for choosing the tuning parameter  $\epsilon$ . The assumption that  $S$  has positive reach can be weakened: Chazal et al. (2009) define a quantity called  $\mu$ -reach that is weaker than reach, and they show that topological reconstructions are possible using this weaker regularity assumption.

**3.1.3. Dimension reduction.** There are many methods that leverage the fact that the data are supported on a low dimensional set  $S$  without explicitly producing an estimate  $\widehat{S}$  that is close to  $S$  in Hausdorff distance. Examples include Isomap (Tenenbaum et al. 2000, De’ath 1999), local linear embedding (Roweis & Saul 2000), diffusion maps (Coifman & Lafon 2006), Laplacian eigenmaps (Belkin & Niyogi 2001) and many others (Lee & Verleysen 2007). Here, I give a very brief description of Isomap.

The first step in Isomap is to form a graph from the data. For example, we connect two points  $X_i$  and  $X_j$  if  $\|X_i - X_j\| \leq \epsilon$ , where  $\epsilon$  is a tuning parameter and  $\|\cdot\|$  is Euclidean distance. Next we define the distance between two points as the shortest path between the two points among all paths in the graph that connect them. We now have a distance matrix  $D$ , where  $D_{ij}$  is the shortest path between  $X_i$  and  $X_j$ . The hope is that  $D_{ij}$  approximates the geodesic distance between  $X_i$  and  $X_j$  on the manifold. Finally, we use a standard dimension reduction method, such as multidimensional scaling (MDS), to embed the data in  $\mathbb{R}^r$  while trying to preserve the distances  $D_{ij}$  as closely as possible. For example, we find a map  $\phi$  to minimize the distortion  $\sum_{i < j} [D_{i,j}^2 - \|\phi(X_i) - \phi(X_j)\|^2]$ . The transformed data  $Z_i = \phi(X_i)$  now live in a lower dimensional space. Thus we have used the fact that the data live on a manifold, to perform a dimension reduction.



**Figure 8**

After applying Isomap to the Swiss-roll dataset with  $\epsilon = 5$ , we recover the underlying two-dimensional structure.

**Figure 8** shows the result of applying Isomap to the Swiss-roll data using  $\epsilon = 5$ . In this case, we perfectly recover the underlying structure. However, Isomap is a fragile procedure. It is very sensitive to outliers and the choice of tuning parameters. Other methods, such as diffusion maps and ridge estimation, are more robust.

### 3.2. Estimating Intrinsic Dimension

Many manifold estimation methods assume that the intrinsic dimension  $r$  of the manifold is known. In practice, we need to estimate the dimension. There is a large literature on this problem. Some examples include Costa & Hero (2004), Hein & Audibert (2005), Kégl (2002), Levina & Bickel (2004), Little et al. (2011), and Lombardi et al. (2011). Minimax theory for dimension estimation is provided by Koltchinskii (2000) and Kim et al. (2016). Estimating the intrinsic dimension when the data are only approximately supported on a lower dimensional set is much harder than the case where their support is precisely a lower dimensional set.

### 3.3. Ridges

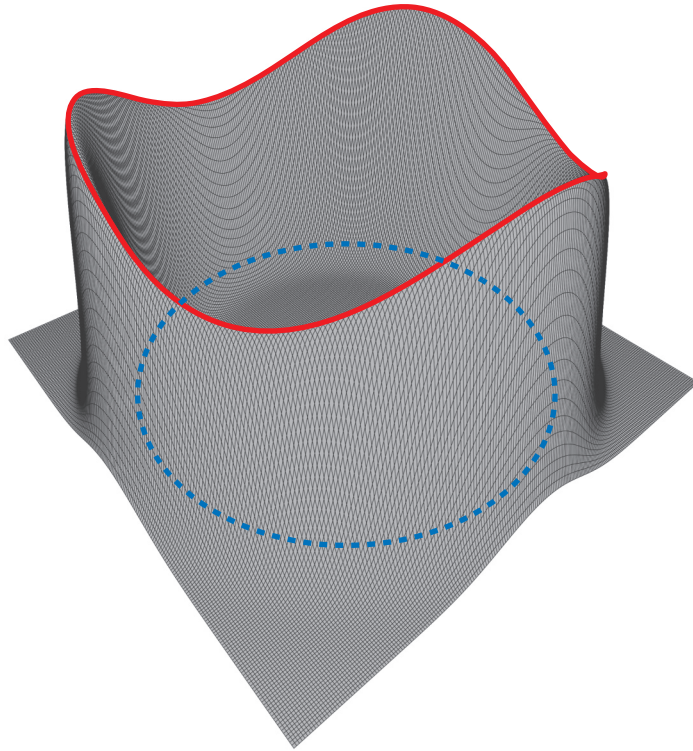
Most manifold learning methods assume that the distribution  $P$  is supported on some manifold  $S$ . This is a very strong and unrealistic assumption. A weaker assumption is that there may exist some low dimensional sets where the density  $p$  has a relatively high local concentration. One way to make this more precise is through the idea of density ridges.

A density ridge is a low dimensional set with large density. But the distribution  $P$  may not even have a density. To deal with this issue, we define the smoothed distribution  $P_b$  obtained by convolving  $P$  with a Gaussian. Specifically,  $P_b$  is the distribution with density

$$p_b(x) = \int K_b(x - u) dP(u),$$

where  $K_b(x) = b^{-d} (2\pi)^{-d/2} e^{-\|x\|^2 / (2b^2)}$ . Note that  $p_b$  is the mean of the kernel density estimator with bandwidth  $b$ . The smoothed distribution  $P_b$  always has a density, even if  $P$  does not. In topological inference, we imagine using a small but positive  $b$ . It is not necessary to let  $b$  tend to 0 as we usual do in density estimation. The salient topological features of  $P$  will be preserved by  $P_b$ .

Let  $g_b$  be the gradient of  $p_b$  and let  $H_b$  be the Hessian. Recall that a mode of  $p_b$  is a point  $x$  with  $g_b(x) = (0, \dots, 0)^T$  and  $\lambda_1(H_b(x)) < 0$ . A mode is a zero-dimensional ridge. More generally, an  $r$ -dimensional ridge is a set with sharp density in some directions, much like the ridge of a mountain (see **Figure 9**). In fact, there are many ways to define a ridge (see Eberly 1996). We use the following definition. At a point  $x$ , we will define a local tangent space of dimension  $r$  and local normal space of dimension  $d - r$ . Then  $x$  is a ridge point if it is a local mode in the direction of the normal. More precisely, let  $\lambda_1(x) \geq \dots \geq \lambda_d(x)$  be the eigenvalues of the Hessian  $H(x)$  and let



**Figure 9**

This is a plot of a two-dimensional density function with a clearly defined one-dimensional ridge (*blue circle*). The density above the ridge is in red.

$v_1(x), \dots, v_d(x)$  be the corresponding eigenvectors. Let  $V_r(x) = [v_{r+1}(x) \cdots v_d(x)]$  and define the projected gradient of  $p$  by

$$G_r(x) = V_r(x)V_r(x)^T g(x).$$

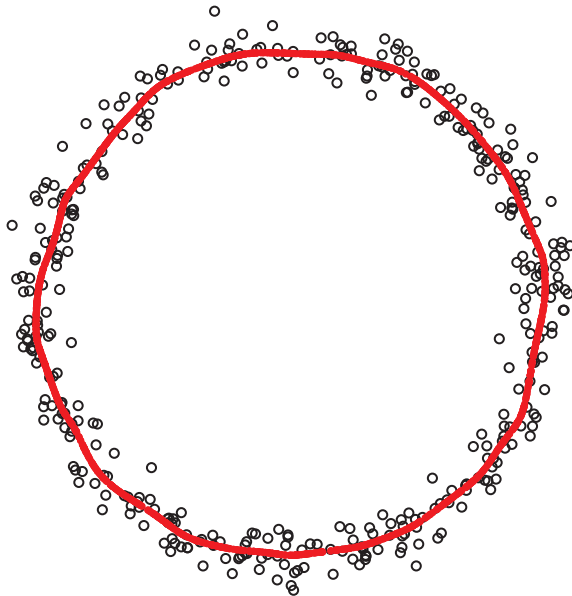
The  $r$ -ridge is

$$R_r(p) = \{x : G_r(x) = 0, \lambda_{r+1}(x) < 0\}.$$

Under suitable regularity conditions, this is indeed an  $r$ -dimensional set.

The ridge can be estimated by the ridge of a kernel density estimate. Specifically, we take  $\widehat{R} = R_r(\widehat{p}_b)$  to be the ridge of the kernel estimator. The properties of this estimator were studied by Genovese et al. (2014) and Chen et al. (2015a). An algorithm for finding the ridge set of  $\widehat{p}_b$  was given by Ozertem & Erdogmus (2011) and is called the subspace constrained mean shift (SCMS) algorithm. Examples are shown in **Figures 7** and **10**, and a further example is in Section 7.

Ridges can be related to manifolds as follows (Genovese et al. 2014). Suppose we observe  $Y_1, \dots, Y_n$  where  $Y_i = X_i + \sigma \epsilon_i$ ,  $X_1, \dots, X_n \sim G$  is a sample from a distribution  $G$  supported on a manifold  $S$ , and  $\epsilon_1, \dots, \epsilon_n$  are a sample from a noise distribution such as a Gaussian. As mentioned earlier,  $S$  can only be estimated at a logarithmic rate. However, if  $\sigma$  is small enough and  $S$  has positive reach, then the density  $p$  of  $Y$  will have a well-defined ridge  $R$  such that  $H(R, S) = O(\sigma)$ . Furthermore,  $R$  is topologically similar to  $S$  in a certain sense described by Genovese et al. (2014). In fact,  $p_b$  will have a ridge  $R_b$  such that  $H(R_b, S) = O(\sigma + b)$ , and  $R_b$  can be estimated at rate  $O_P(\sqrt{\log n/n})$  independently of the dimension.



**Figure 10**

The data for this figure are generated as  $Y_i = X_i + \epsilon_i$ , where the  $X_i$  are sampled from a circle and  $\epsilon_i$  are bivariate Gaussian. The ridge  $\hat{R}$  of the kernel density estimator is found using the subspace constrained mean shift (SCMS) algorithm and is shown in red.

An example is shown in **Figure 10**. The data are generated as follows. We sample  $X_1, \dots, X_n$  from a circle. Then we set  $Y_i = X_i + \epsilon_i$ , where  $\epsilon_1, \dots, \epsilon_n$  are draws from a bivariate Normal with mean  $(0, 0)$ . Next we find the kernel density estimator based on  $Y_1, \dots, Y_n$  and we find the ridge  $\hat{R}$  of the kernel estimator using the SCMS algorithm. The data are the black points in the plot, and the estimated ridge is shown in red. Notice that the data are full dimensional but the estimated ridge is one dimensional.

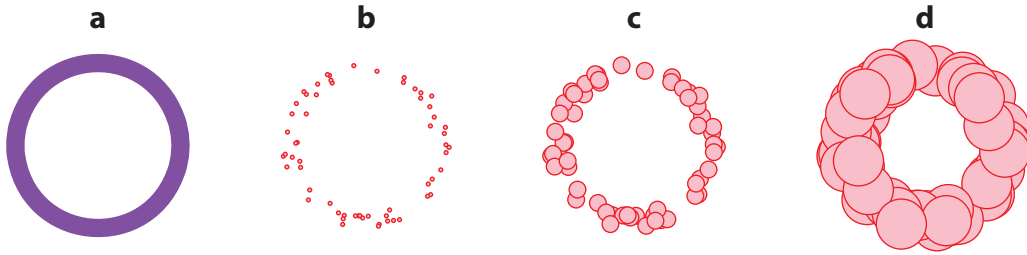
### 3.4. Stratified Spaces

Another generalization of manifold learning is to assume that the support of  $P$  is a stratified space, which means that the space can be decomposed into several intersecting submanifolds. Estimation of stratified spaces is much less developed than manifold estimation. Some examples include those presented by Bendich et al. (2007), Skraba & Wang (2014), and Bendich et al. (2007). Ridge based methods as discussed in Section 3.3 seem to work well in this case, but so far, this has not been established theoretically. A promising new approach due to Arias-Castro et al. (2011) is based on a version of local principal component analysis.

## 4. PERSISTENT HOMOLOGY

Persistent homology is a multiscale approach to quantifying topological features in data (Edelsbrunner & Harer 2008, 2010; Edelsbrunner et al. 2002). This is the branch of TDA that gets the most attention, and some researchers view TDA and persistent homology as synonymous.

A quick, intuitive idea of persistent homology is given in **Figures 11** and **12**. Here, we see some data, and we also see the set  $\bigcup_{i=1}^n B(X_i, \epsilon)$  for various values of  $\epsilon$ . The key observation is

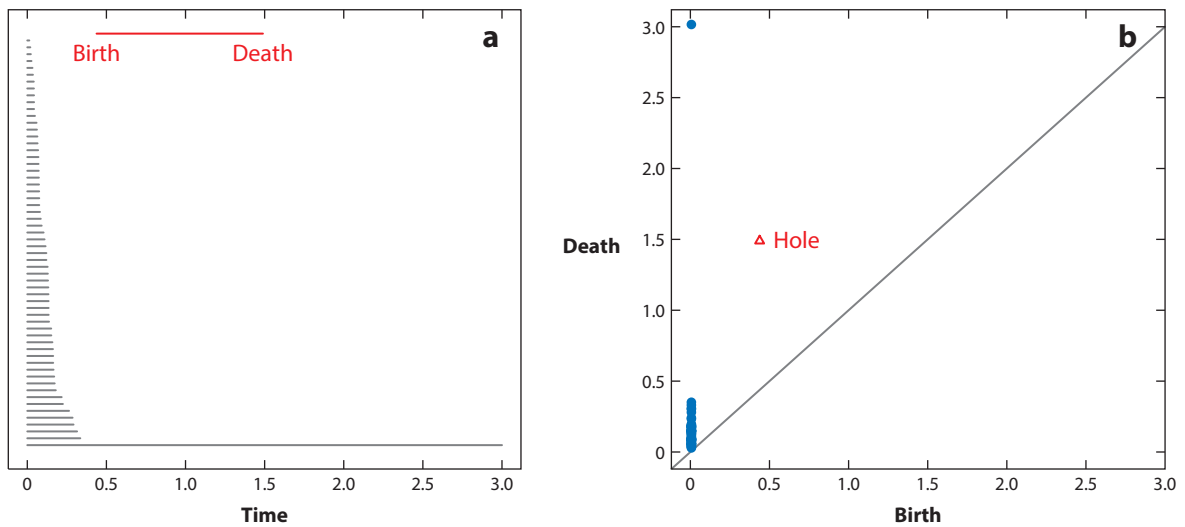


**Figure 11**

(a) The support  $S$  of the distribution. (b–d) Union of balls  $\bigcup_{i=1}^n B(X_i, \epsilon)$ , approximately 60 data points drawn from a uniform on  $S$ , with  $\epsilon = 0.03, 0.10, 0.30$ .

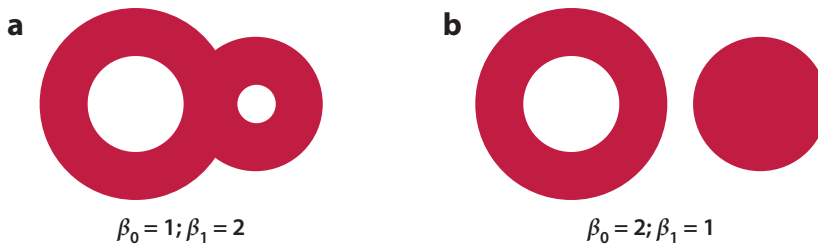
that the topological features appear and disappear as  $\epsilon$  increases. For example, when  $\epsilon = 0$ , there are  $n$  connected components (that is,  $n$  disconnected balls). As  $\epsilon$  increases, some of the connected components die (that is, they merge) until only one connected component remains. (A connected components consists of overlapping balls.) Similarly, at a certain value of  $\epsilon$ , a hole is born. The hole dies at a larger value of  $\epsilon$ .

Thus, each feature has a birth time and a death time. The left plot in **Figure 12** is a barcode plot, which represents the birth time and death time of each feature as a bar. The right plot is a persistence diagram, where each feature is a point on the diagram and the coordinates of the points are the birth time and death time. Features with a long lifetime correspond to points far from the diagonal. With this simple example in mind, we delve into more detail.



**Figure 12**

(a) The barcode plot corresponding to the data from **Figure 11**. The gray lines show the birth and death of each connected component as  $\epsilon$  increases. The red line shows the birth and death of the hole as  $\epsilon$  increases. (b) The persistence diagram. In this case, the birth and death time of each feature is represented by a point on the diagram. The blue points correspond to connected components. The red triangle corresponds to the hole. Points close to the diagonal have a short lifetime.



**Figure 13**

(a) This set has one connected component and two holes, and hence  $\beta_0 = 1$  and  $\beta_1 = 2$ . (b) This set has two connected components and one hole, and hence  $\beta_0 = 2$  and  $\beta_1 = 1$ .

#### 4.1. Homology

It is not possible to give a thorough review of homology given the present space constraints, but we can give a short, intuitive description that will suffice for what follows. More details are provided in Fasy et al. (2014b). Good introductions can be found in Hatcher (2000) and Edelsbrunner & Harer (2010).

Homology characterizes sets based on connected components and holes. Consider the set in **Figure 13a**. The set has one connected component and two holes. We write  $\beta_0 = 1$  and  $\beta_1 = 2$ . The numbers  $\beta_0, \beta_1, \dots$  are called Betti numbers. Intuitively,  $\beta_0$  is the number of connected components,  $\beta_1$  is the number of one-dimensional holes,  $\beta_2$  is the number of two-dimensional holes, and so on. (More formally,  $\beta_j$  is the rank of the  $j^{\text{th}}$  homology group.) The set in **Figure 13b** has two connected components and one hole, thus,  $\beta_0 = 2$  and  $\beta_1 = 1$ . These holes are one-dimensional: They can be surrounded by a loop (like a piece of string). The inside of a soccer ball is a two dimensional hole. To surround it, we need a surface. For a soccer ball,  $\beta_0 = 1, \beta_1 = 0, \beta_2 = 1$ . For a torus (a hollowed out donut),  $\beta_0 = 1, \beta_1 = 2, \beta_2 = 1$ .

The formal definition of homology uses the language of group theory. (The equivalence class of loops surrounding a hole have a group structure.) The details are not needed to understand the rest of this article. Persistent homology examines these homological features from a multiscale perspective.

#### 4.2. Distance Functions and Persistent Homology

A good starting point for explaining persistent homology is the distance function. Given a set  $S$ , the distance function is defined to be

$$d_S(x) = \inf_{y \in S} \|x - y\|,$$

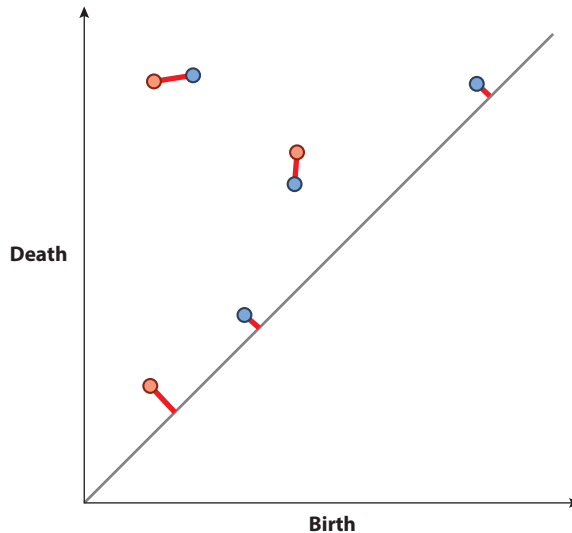
where  $\|\cdot\|$  is Euclidean distance. The lower level sets of the distance function are

$$L_\epsilon = \{x : d_S(x) \leq \epsilon\}.$$

We also have that

$$L_\epsilon = \bigcup_{x \in S} B(x, \epsilon).$$

So  $L_\epsilon$  can be thought of either as a union of balls, or as the lower level set of the distance function. As  $\epsilon$  increases, the sets  $L_\epsilon$  evolve. Topological features—connected components and holes—will



**Figure 14**

The bottleneck distance between two persistence diagrams is computed by finding the best matching between the two diagrams. This plot shows two diagrams that have been overlaid, with the points from the two diagrams represented by two colors. The matching is indicated by the lines joining the points from the two diagrams. Note that some points—those with short lifetimes—are matched to the diagonal.

appear and disappear. Consider the circle

$$S = \{(x, y) : x^2 + y^2 = 1\}.$$

The set  $L_\epsilon$  is an annulus of radius  $\epsilon$ . For all values of  $\epsilon$ ,  $L_\epsilon$  has one connected component. For  $0 \leq \epsilon < 1$ , the set  $L_\epsilon$  has one hole. The hole dies at  $\epsilon = 1$ . Thus, the hole has birth time  $\epsilon = 0$  and death time  $\epsilon = 1$ . In general, these features can be represented as a persistence diagram  $D$ , as in **Figure 12**. The diagram  $D$  represents the persistent homology of  $S$ .

Technically, the persistence diagram  $D$  is a multiset consisting of all pairs of points on the plot as well as all points on the diagonal. Given two diagrams  $D_1$  and  $D_2$ , the bottleneck distance defined by

$$\delta_\infty(D_1, D_2) = \inf_{\gamma} \sup_{z \in D_1} \|z - \gamma(z)\|_\infty, \quad 9.$$

where  $\gamma$  ranges over all bijections between  $D_1$  and  $D_2$ . Intuitively, this is like overlaying the two diagrams and asking how much we have to shift the points on the diagrams to make them the same (see **Figure 14**).

Now suppose we observe a sample  $X_1, \dots, X_n$  drawn from a distribution  $P$  supported on  $S$ . The empirical distance function is

$$\hat{d}(x) = \min_{1 \leq i \leq n} \|x - X_i\|.$$

Note that the lower level sets of  $\hat{d}$  are precisely the union of balls described in the last section:

$$\hat{L}_\epsilon = \{x : \hat{d}(x) \leq \epsilon\} = \bigcup_{i=1}^n B(X_i, \epsilon).$$

The persistence diagram  $\hat{D}$  defined by these lower level sets is an estimate of the underlying diagram  $D$ .



The empirical distance function is the most commonly used method for defining the persistence diagram of a dataset in the field of computational topology. But from a statistical point of view, this is a very poor choice. It is clear that  $\widehat{d}$  is highly nonrobust. Even a few outliers will play havoc with the estimator.

Fortunately, more robust and statistically sound methods are available. The first, and perhaps most natural for statisticians, is to replace the lower level sets of the empirical distance function with the upper level sets of a density estimator. This approach has been suggested by Phillips et al. (2015), Chazal et al. (2014a), Bobrowski et al. (2014), Chung et al. (2009), and Bubenik (2015). The idea is to consider the upper level sets  $\widehat{L}_t = \{x : \widehat{p}_b(x) > t\}$ . As  $t$  varies from  $\sup_x \widehat{p}_b(x)$  down to 0, the sets  $\widehat{L}_t$  evolve and the birth and death times of features are again recorded on a persistence diagram. In this case, the birth times are actually after the death times. This is just an artifact from using upper level sets instead of lower level sets.

An alternative is to redefine the distance function to be intrinsically more robust. Specifically, Chazal et al. (2011) defined the distance to a measure (DTM) as follows. Let  $0 \leq m \leq 1$  be a scale parameter and define

$$d_m^2(x) = \frac{1}{m} \int_0^m \delta_a^2(x) da,$$

where

$$\delta_a(x) = \inf\{r > 0 : P(B(x, r)) > a\}.$$

We can think of  $d_m$  as a function  $T(P)$  of the distribution  $P$ . The plug-in estimate of  $d_m$  obtained by inserting the empirical distribution in place of  $P$  is

$$\widehat{d}_m^2(x) = \frac{1}{k} \sum_{i=1}^k \|x - X_i(x)\|^2,$$

where  $k = \lfloor mm \rfloor$  and  $X_j(x)$  denote the data after reordering them, so that  $\|X_1(x) - x\| \geq \|X_2(x) - x\| \geq \dots$ . In other words,  $\widehat{d}_m^2(x)$  is just the average squared distance to the  $k$ -nearest neighbors.

The definition of  $d_m$  is not arbitrary. The function  $d_m$  preserves certain crucial properties that the distance function has, but it changes gracefully as we allow more and more noise. It is essentially a smooth, probabilistic version of the distance function. The properties of the DTM are discussed by Chazal et al. (2011, 2014a, 2015).

Whether we use the kernel density estimator or the DTM, we would like to have a way to decide when topological features are statistically significant. Chazal et al. (2014a) and Fasy et al. (2014b) suggest the following method. Let

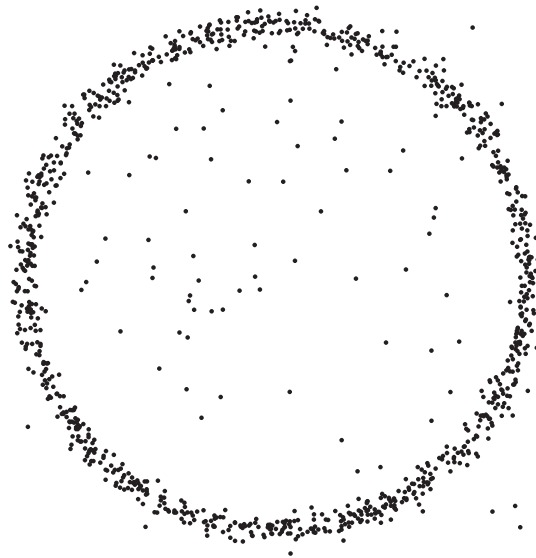
$$F(t) = P(\sqrt{n} \delta_\infty(\widehat{D}, D) \leq t),$$

where  $D$  is the true diagram and  $\widehat{D}$  is the estimated diagram. Any point on the diagram that is farther than  $t_\alpha = F^{-1}(1 - \alpha)$  from the diagonal is considered significant at level  $\alpha$ . Of course,  $F$  is not known but can be estimated by the bootstrap:

$$\widehat{F}(t) = \frac{1}{B} \sum_{j=1}^B I(\sqrt{n} \delta_\infty(\widehat{D}_j^*, \widehat{D}) \leq t),$$

where  $\widehat{D}_1^*, \dots, \widehat{D}_B^*$  are the diagrams based on  $B$  bootstrap samples. Then  $\widehat{t}_\alpha = \widehat{F}^{-1}(1 - \alpha)$  is an estimate of  $t_\alpha$ .

**Example.** We sampled 1,000 observations from a circle in  $\mathbb{R}^2$ . Gaussian noise was then added to each observation. Then we added 100 outliers sampled uniformly from the



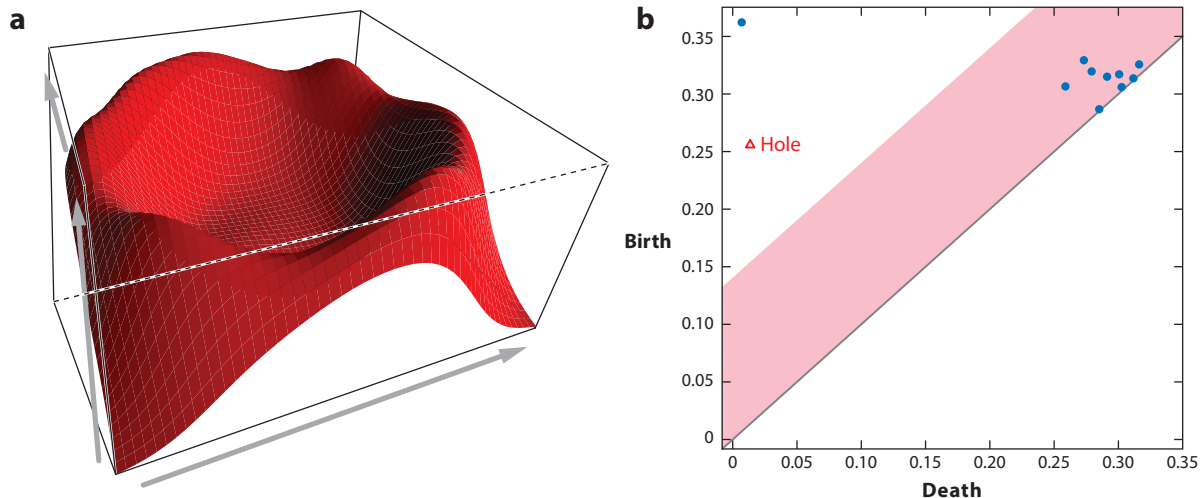
**Figure 15**

Data sampled from a circle, with Gaussian noise added. There are also 100 outliers sampled uniformly from the square.

square. The data are shown in **Figure 15**. **Figure 16** shows the kernel density estimator ( $b = 0.02$ ) and the persistence diagram based on the upper level sets of the estimator. The points in the pink band are not significant at level  $\alpha = 0.1$  (based on the bootstrap). The two points that are significant correspond to one connected component (*blue dot*) and one hole (*red triangle*). **Figure 17** shows a similar analysis of the same data using the DTM with  $m = 0.1$ . Generally, we find that the significant features are more prominent using the DTM rather than the kernel density estimator. Also, the DTM is less sensitive to the choice of tuning parameter, although it is not known why this is true.

### 4.3. Simplicial Complexes

The persistence diagram is not computed directly from  $\widehat{L}_\epsilon$ . Instead, one forms an object called a Čech complex. The Čech complex  $C_\epsilon$  is defined as follows. All singletons are included in  $C_\epsilon$ ; these are zero-dimensional simplices. All pairs of points  $X_i, X_j$  such that  $\|X_i - X_j\| \leq \epsilon$  are included in  $C_\epsilon$ ; these are one-dimensional simplices. Each triple  $X_i, X_j, X_k$  such that  $B(X_i, \epsilon/2) \cap B(X_j, \epsilon/2) \cap B(X_k, \epsilon/2)$  is nonempty, is included in  $C_\epsilon$ ; these are two-dimensional simplices—and so on. The Čech complex is an example of a simplicial complex. A collection of simplices is a simplicial complex if it satisfies the following condition: If  $F$  is a simplex in  $C_\epsilon$  and  $E$  is a face of  $F$ , then  $E$  is also on  $C_\epsilon$ . It can be shown that the homology of  $\widehat{L}_\epsilon$  is the same as the homology of  $C_\epsilon$ . But the homology of  $C_\epsilon$  can be computed using basic matrix operations. This is how homology is computed in practice (Edelsbrunner & Harer 2010). Persistent homology relates the complexes as  $\epsilon$  varies. Again, all the relevant computations can be reduced to linear algebra. Working directly with the Čech complex is computationally prohibitive. In practice, one often uses the Vietoris-Rips complex  $V_\epsilon$ , which is defined as follows. A simplex is included in  $V_\epsilon$  if each pair of vertices is no more than  $\epsilon$  apart. It can be shown that the persistent homology defined by  $V_\epsilon$  approximates the persistent homology defined by  $C_\epsilon$ .

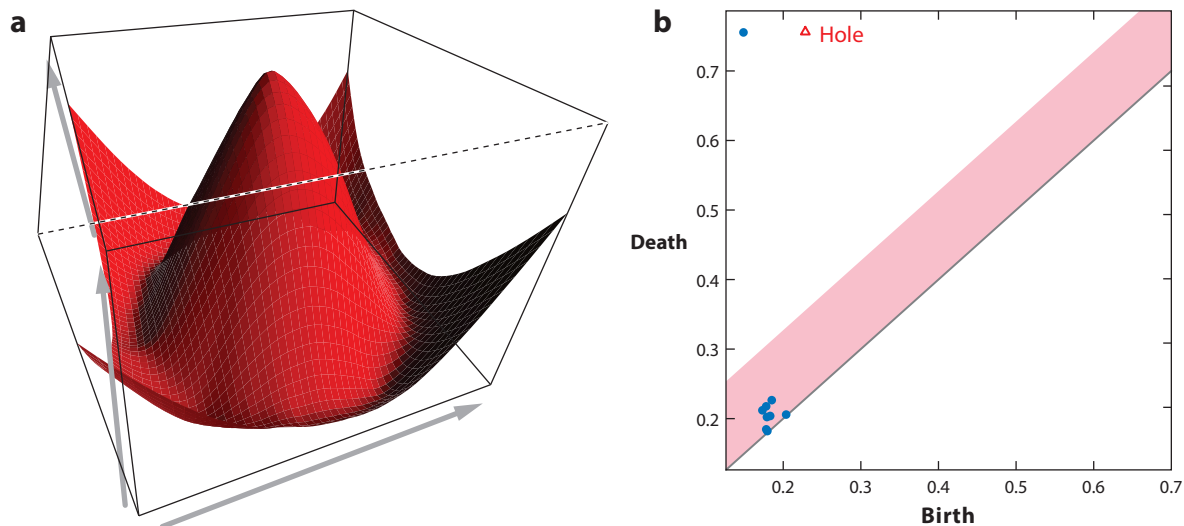


**Figure 16**

(a) The kernel density estimator. (b) The persistence diagram corresponding to the upper level sets of the estimator. The points above the pink band are significant compared to the bootstrap critical value. Note that one connected component (*blue dot*) and one hole (*red triangle*) are significant.

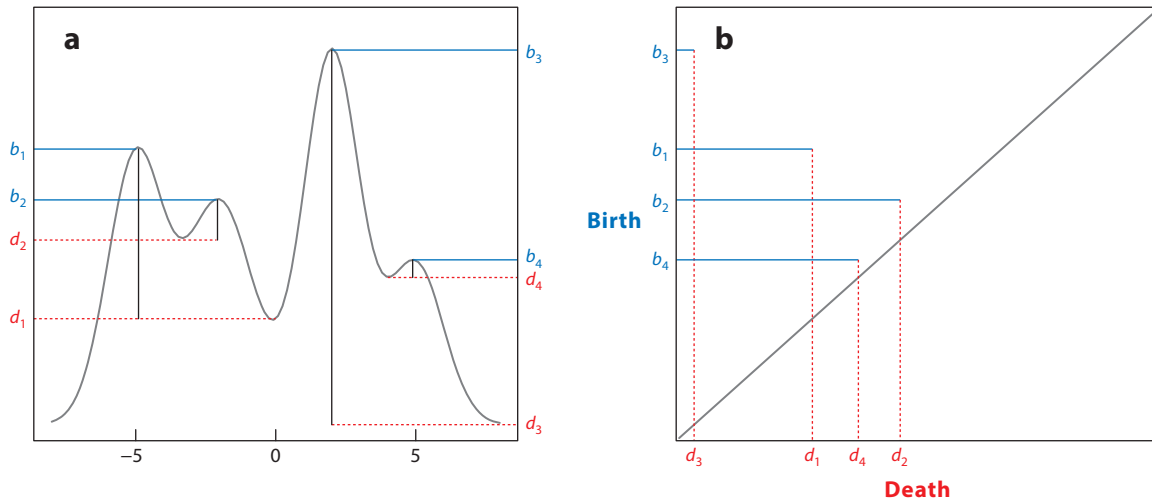
#### 4.4. Back to Density Clustering

Chazal et al. (2013) have shown that persistent homology can be used as a tool for density clustering. This idea was further examined by Genovese et al. (2016). Thus, we have come full circle and returned to the topic of Section 2.



**Figure 17**

(a) The distance to a measure (DTM). (b) The persistence diagram corresponding to the lower level sets of the DTM. The points above the pink band are significant compared with the bootstrap critical value. Note that one connected component (*blue dot*) and one hole (*red triangle*) are significant.



**Figure 18**

(a) Starting at the top of the density and moving down, each mode has a birth time  $b$  and a death time  $d$ . (b) The persistence diagram plots the points  $(d_1, b_1), \dots, (d_4, b_4)$ . Modes with a long lifetime are far from the diagonal.

Recall the mode clustering method described in Section 2.3. We estimate the density and find the modes  $\hat{m}_1, \dots, \hat{m}_k$  and the basins of attraction  $C_1, \dots, C_k$  corresponding to the modes.

But we can use more information. In the language of persistent homology, each mode has a lifetime (see **Figure 18**). Suppose we start with  $t = \sup_x p(x)$ . We find the upper level set  $L_t = \{x : p(x) \geq t\}$ . Now we let  $t$  decrease. (We can think of  $t$  as time, but in this case, time runs backwards, since it starts at a large number and tends to zero.) Every time we get to a new mode, a new connected component of  $L_t$  is born. However, as  $t$  decreases, the connected components can merge. When they merge, the most recently created component is considered to be dead while the other component is still alive. This is called the elder rule. Proceeding this way, small modes correspond to level sets with short lifetimes, and strong modes correspond to level sets with long lifetimes. We can plot the information as a persistence diagram, as in **Figure 18b**.

We can use this representation of the modes to decide which modes of a density estimator are significant (Chazal et al. 2013, 2014a). Define  $\hat{\tau}_\alpha$  by

$$\mathbb{P}\left(\sqrt{n}\|\hat{p}_b^* - \hat{p}_b\| > \hat{\tau}_\alpha \mid X_1, \dots, X_n\right) = \alpha,$$

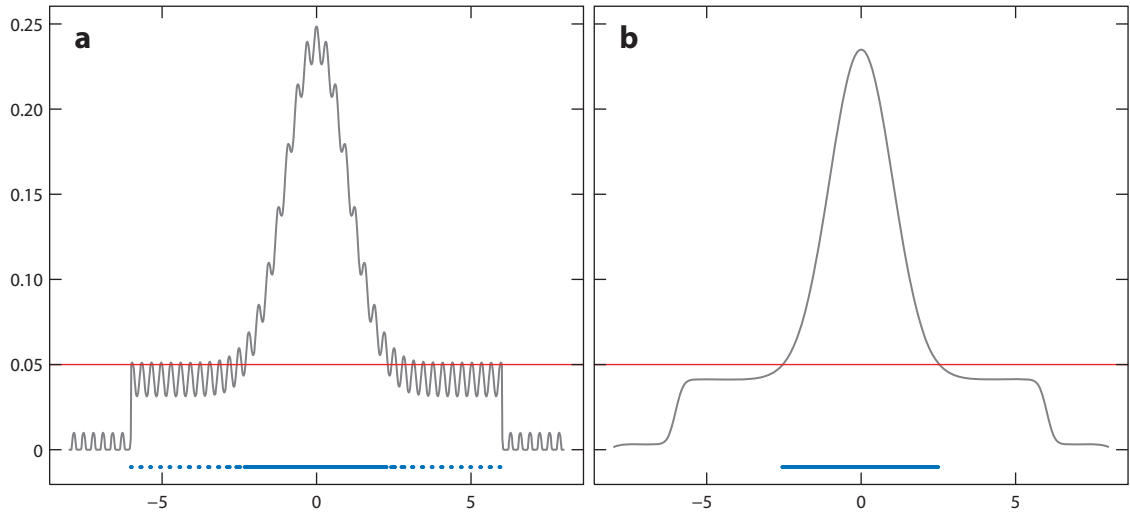
where  $\hat{p}_b^*$  is based on a bootstrap sample  $X_1^*, \dots, X_n^*$  drawn from the empirical distribution  $P_n$ . The above probability can be estimated by

$$\frac{1}{B} \sum_{j=1}^B I(\sqrt{n}\|\hat{p}_b^{*j} - \hat{p}_b\| > t).$$

Any mode whose corresponding point on the persistence diagram is farther than  $\hat{\tau}_\alpha$  from the diagonal is considered a significant mode.

## 5. TUNING PARAMETERS AND LOSS FUNCTIONS

Virtually every method we have discussed in this article requires the choice of a tuning parameter. For example, many of the methods involve a kernel density estimator which requires a bandwidth  $b$ .



**Figure 19**

(a) A density  $p$  and a level set  $\{p > t\}$ . (b) The smoothed density  $p_b$  and the level set  $\{p_b > t\}$ . The latter is biased but captures the shape of the true level set. The red line is  $t$ , which defines the level set. The blue data show the corresponding level set.

But the usual methods for choosing tuning parameters may not be appropriate for TDA. In fact, the problem of choosing tuning parameters is one of the biggest open challenges in TDA.

Let us consider the problem of estimating a density  $p$  with the kernel estimator  $\hat{p}_b$ . The usual  $L_2$  risk is  $\mathbb{E}[\int (\hat{p}_b(x) - p(x))^2 dx]$ . Under standard smoothness assumptions, the optimal bandwidth  $b \asymp n^{-1/(4+d)}$  yielding a risk of order  $n^{-4/(4+d)}$ .

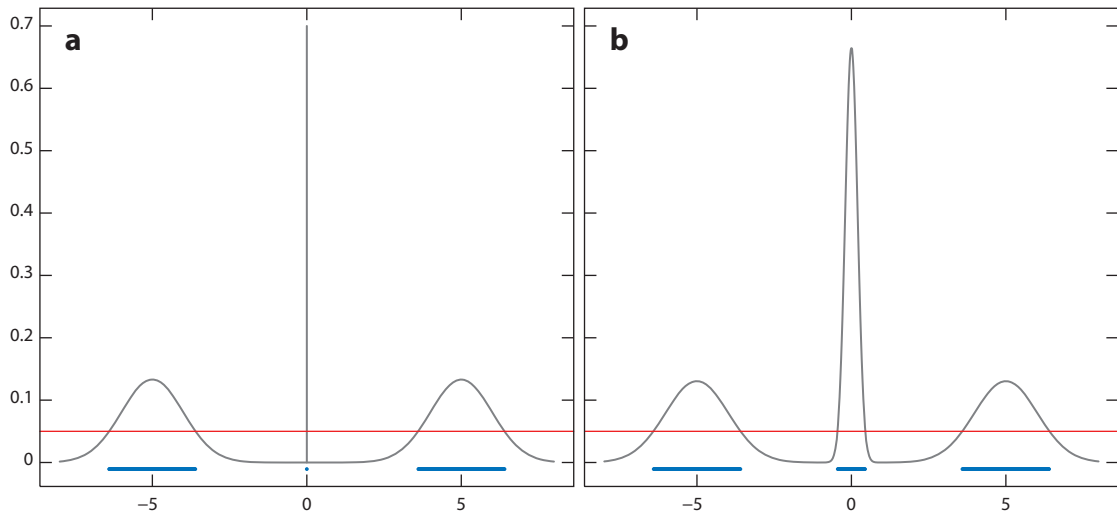
In TDA, we are interested in shape, not  $L_2$  loss (or  $L_p$  loss for any  $p$ ). And, as I have mentioned earlier, it may not even be necessary to let  $b$  tend to zero to capture the relevant shape information. In Section 2.2 we saw that, in some cases, the density tree  $T(p_b)$  has the same shape as the true tree  $T(p)$ , even for fixed  $b > 0$ . Here,  $p_b(x) = \mathbb{E}[\hat{p}_b(x)]$ .

Similarly, consider estimating a ridge  $R$  of a density  $p$ . In general, the ridge can only be estimated at rate  $O_p(n^{-2/(8+d)})$  (Genovese et al. 2014). Now suppose we use a small but fixed (nondecreasing) bandwidth  $b$ . Usually, the ridge  $R_b$  of  $p_b$  is a reasonably good but slightly biased approximation to  $R$ . But  $R$  can be estimated at rate  $O_p(\sqrt{\log n/n})$ . We are often better off living with the bias and estimating  $R_b$  instead of  $R$ .

In fact, one could argue that any shape information that can only be recovered with small bandwidths is very subtle and cannot be reliably estimated. The salient structure can be recovered with a fixed bandwidth. To explain this in more detail, we consider two examples from Chen et al. (2015b).

**Figure 19a** shows a density  $p$ . The blue points at the bottom show the level set  $L = \{x : p > 0.05\}$ . The right plot shows  $p_b$  for  $b = 0.2$ , and the blue points at the bottom show the level set  $L_b = \{x : p_b > 0.05\}$ . The smoothed-out density  $p_b$  is biased, and the level set  $L_b$  loses the small details of  $L$ . But  $L_b$  contains the main part of  $L$ , and it may be more honest to say that  $\hat{L}_b$  is an estimate of  $L_b$ .

As a second example, let  $P = (1/3)\phi(x; -5, 1) + (1/3)\delta_0 + (1/3)\phi(x; 5, 1)$ , where  $\phi$  is a Normal density and  $\delta_0$  is a point mass at zero. Of course, this distribution does not even have a density. **Figure 20a** shows the density of the absolutely continuous part of  $P$ , with a vertical line to show the point mass. The right plot shows  $p_b$ , which is a smooth, well-defined density. Again, the blue



**Figure 20**

(a) A distribution with a continuous component and a point mass at 0. (b) The smoothed density  $p_b$ . The level set  $L_b$  is biased but is estimable, and it approximates the main features of  $L$ . The blue data show the corresponding level set.

points show the level sets. As before,  $p_b$  is biased (as is  $L_b$ ). But  $p_b$  is well-defined, as is  $L_b$ , and  $\hat{p}_b$  and  $\hat{L}_b$  are accurate estimators of  $p_b$  and  $L_b$ . Moreover,  $L_b$  contains the most important qualitative information about  $L$ , namely, that there are three connected components, one of which is small.

The idea of viewing  $p_b$  as the estimand is not new. The “scale space” approach to smoothing explicitly argues that we should view  $\hat{p}_b$  as an estimate of  $p_b$ , and  $p_b$  is then regarded as a view of  $p$  at a particular resolution. This idea is discussed in detail by Chaudhuri & Marron (1999, 2000) and Godtliebsen et al. (2002).

If we do decide to base TDA on tuning parameters that do not go to zero as  $n$  increases, then we need new methods for choosing tuning parameters. One possibility, suggested by Chazal et al. (2014a) and Guibas et al. (2013), is to choose the tuning parameter that maximizes the number of significant topological features. In particular, Chazal et al. (2014a) use the bootstrap to assess the significance of topological features, and then they choose the smoothing parameter to maximize the number of such features. This maximal significance approach is promising, but so far there is no theory to support the idea.

The problem of choosing tuning parameters thus remains one of the greatest challenges in TDA. In fact, the same problem permeates the clustering literature. To date, there is no agreement on how to choose  $k$  in  $k$ -means clustering, for example.

## 6. DATA VISUALIZATION AND EMBEDDINGS

Topological ideas play a role in data visualization, either explicitly or implicitly. In fact, many TDA methods may be regarded as visualization methods. For example, density trees, persistence diagrams, and manifold learning all provide low dimensional representations of the data that are easy to visualize.

Some data visualization methods work by embedding the data in  $\mathbb{R}^2$  and then simply plotting the data. Consider a point cloud  $X_1, \dots, X_n$ , where  $X_i \in \mathbb{R}^d$ . Let  $\psi : \mathbb{R}^d \rightarrow \mathbb{R}^2$  and let  $Z_i = \psi(X_i)$ . Because the points  $Z_1, \dots, Z_n$  are in  $\mathbb{R}^2$ , we can easily plot the  $Z_i$ s. Perhaps the most familiar

version is MDS, where  $\psi$  is chosen to be a linear function minimizing some measure of distance between the original pairwise distances  $\|X_i - X_j\|^2$  and the embedded distances  $\|Z_i - Z_j\|^2$ . In particular, if we minimize  $\sum_{i \neq j} (\|X_i - X_j\|^2 - \|Z_i - Z_j\|^2)$ , then the solution is to project the data onto the first two principal components.

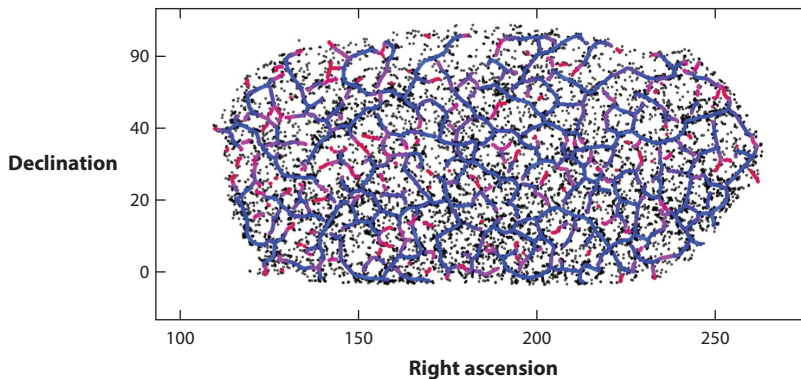
But traditional MDS does a poor job of preserving local structure such as clusters. Local, nonlinear versions of MDS do a better job of preserving local structure. An example is Laplacian eigenmaps, which was proposed by Belkin & Niyogi (2003). Here, we choose  $\psi$  to minimize  $\sum_{i,j} W_{ij} \|Z_i - Z_j\|^2$  (subject to some constraints), where the  $W_{ij}$  are localization weights such as  $W_{ij} = e^{-\|X_i - X_j\|^2 / (2b^2)}$ . The resulting embedding does a good job of preserving local structure. However, Maaten & Hinton (2008) noted that local methods of this type can cause the data to be too crowded together. They proposed a new method called t-distributed stochastic neighbor embedding (t-SNE) which seems to work better, but they provided no justification for the method. Carreira-Perpiñán (2010) provided an explanation of why t-SNE works. He showed that t-SNE optimizes a criterion that essentially contains two terms, one promoting localization and the other causing points to repel each other. Based on this insight, he proposed a new method called elastic embedding that explicitly has a term encouraging clusters to stay together and a term that repels points from each other. What is notable about t-SNE and elastic embedding is that they preserve clusters and loops. The loops are apparently preserved due to the repelling term. It appears, in other words, that these methods preserve topological features of the data.

This leads to the following question: Is it possible to derive low dimensional embedding methods that explicitly preserve topological features of the data? This is an interesting open question.

## 7. APPLICATIONS

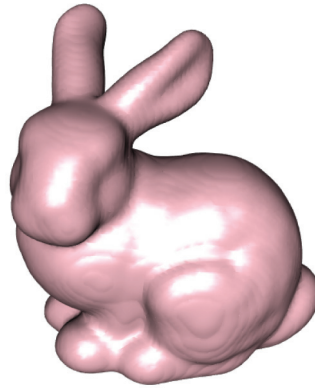
### 7.1. The Cosmic Web

The matter in the Universe is distributed in a complex, spider-web-like pattern known as the cosmic web. Understanding and quantifying this structure is one of the challenges of modern cosmology. **Figure 21** shows a two-dimensional slice of data consisting of some galaxies from the Sloan Digital Sky Survey ([www.sdss.org](http://www.sdss.org)), as analyzed by Chen et al. (2015c). The blue



**Figure 21**

A filament map from Chen et al. (2015c). The data are galaxies from the Sloan Digital Sky Survey. The blue lines are detected filaments. The red dots are clusters. Right ascension and declination measure position in the sky using, essentially, longitude and latitude. Adapted with permission from Chen et al. (2015c).



**Figure 22**

A three-dimensional image. Classifying such images requires features that are invariant to small deformations of the image. Topological data analysis can potentially provide such features.

lines are filaments that were found using the ridge methods discussed in Section 3.3. Also shown are clusters (*red dots*) that were found by previous researchers. Filament maps like this permit researchers to investigate questions about how structure formed in our Universe. For example, Chen et al. (2015d) investigated how the properties of galaxies differ depending on the distance from filaments.

Several papers, such as those of Van de Weygaert et al. (2010, 2011a,b), have used homology and persistent homology to study the structure of the cosmic web. These papers use TDA to quantify the clusters, holes, and voids in astronomical data. Sousbie et al. (2011) and Sousbie (2011) use Morse theory to model the filamentary structures of the cosmic web.

## 7.2. Images

Many researchers have used some form of TDA for image analysis. Consider **Figure 22**, which shows a three-dimensional image of a rabbit. Given a large collection of such images, possibly corrupted by noise, we would like to define features that can be used for classifying such images. It is critical that the features be invariant to shifts, rotations, and small deformations. Topological methods are thus a promising source of relevant features. A number of papers have used TDA to define such features, for example, Bonis et al. (2016), Li et al. (2014), and Carrière et al. (2015).

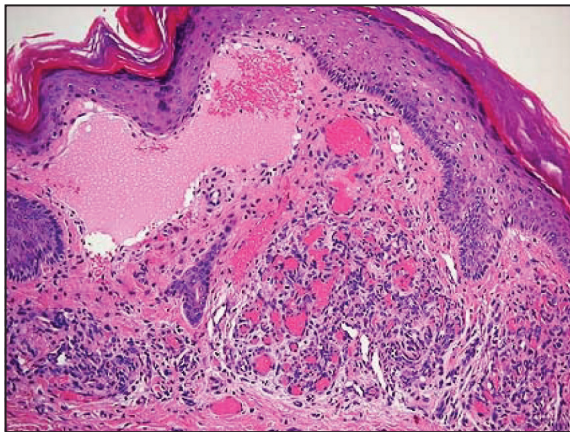
TDA has also been used in the classification of two-dimensional images. For example, Singh et al. (2014) considered breast cancer histology images. These images show the arrangement of cells of tissue samples. An example of a histology image is given in **Figure 23**.

A typical image has many clumps and voids, so TDA may be an appropriate method for summarizing the images. Singh et al. (2014) used the Betti numbers as a function of scale as features for a classifier. The goal was to discriminate different subtypes of cancer. They achieved a classification accuracy of 69.86 percent, which was better than competing methods.

## 7.3. Proteins

Kovacev-Nikolic et al. (2016) used TDA to study the maltose binding protein, which is a protein found in *Escherichia coli*. An example of such a protein is given in **Figure 24**. The protein is





**Figure 23**

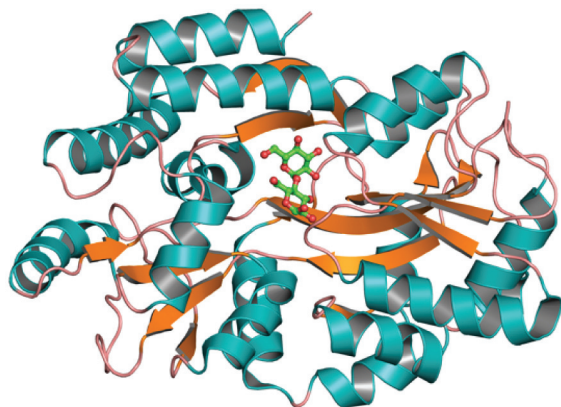
An example of a histology image from <http://medicalpicturesinfo.com/histology/>.

a dynamic structure and the changes in structure are of biological relevance. Quoting Kovacev-Nikolic et al. (2016, p. 21),

A major conformational change in the protein occurs when a smaller molecule called a ligand attaches to the protein molecule...Ligand-induced conformational changes are important because the biological function of the protein occurs through a transition from a ligand-free (apo) to a ligand-bound (holo) structure

The protein can be in an open or closed conformation, and the closed conformation is due to having a captured ligand. The goal of the authors is to classify the state of the protein.

Each protein is represented by 370 points (corresponding to amino acids) in three-dimensional space. The authors construct a dynamic model of the protein structure (since the structure changes over time) from which they define dynamical distances between the 370 points. Thus, a protein is represented by a 370 by 370 distance matrix. From the distance matrix, they construct a



**Figure 24**

A maltose binding protein. The image of the protein is from <http://lilith.nec.aps.anl.gov/Structures/Publications.htm>.

persistence diagram. Next, they convert the persistence diagrams into a set of functions called landscapes, as defined by Bubenik (2015). Turning the diagram into a set of one-dimensional functions makes it easier to use standard statistical tools. In particular, they do a two-sample permutation test using the integrated distances between the landscape functions as a test statistic. The  $p$ -value is  $5.83 \times 10^{-4}$ , suggesting a difference between the open and closed conformations. This suggests that landscapes can be used to classify proteins as open or closed. They also show that certain sites on the protein, known as active sites, are associated with loops in the protein.

## 7.4. Other Applications

Here I briefly mention a few other examples of TDA.

The Euler characteristic is a topological quantity that I did not describe in this article owing to space limitations. However, it has played an important role in various aspects of probability as well as to applications in astrophysics and neuroscience (Adler & Taylor 2009; Taylor & Worsley 2007; Worsley 1994, 1995, 1996). The Euler characteristic has also been used for classification of shapes (Richardson & Werman 2014; see also Turner et al. 2014). Bendich et al. (2010) used topological methods to study the interactions between root systems of plants.

Carstens & Horadam (2013) used persistent homology to describe the structure of collaboration networks. Xia et al. (2015) used TDA in the analysis of biomolecules. Adcock et al. (2014) used TDA to classify images of lesions of the liver. Chung et al. (2009) used persistence diagrams constructed from data on cortical thickness to distinguish control subjects and autistic subjects.

Offroy & Duponchel (2016) reviewed the role of TDA in chemometrics. Bendich et al. (2016) used persistent homology to study the structure of brain arteries. There is now a substantial literature on TDA in neuroscience, including Arai et al. (2014), Babichev & Dabaghian (2016), Basso et al. (2016), Bendich et al. (2016), Brown & Gedeon (2012), Cassidy et al. (2015), Chen et al. (2014), Choi et al. (2014), Chung et al. (2009), Curto (2016), Curto & Itskov (2008), Curto et al. (2013, 2015), Curto & Youngs (2015), Dabaghian et al. (2011, 2012, 2014), Dabaghian (2015), Dlotko et al. (2016), Ellis & Klein (2014), Giusti & Itskov (2013), Giusti et al. (2015, 2016), Hoffman et al. (2016), Jeffs et al. (2015), Kanari et al. (2016), Khalid et al. (2014), Kim et al. (2014), Lee et al. (2011), Lienkaemper et al. (2015), Manin (2015), Masulli & Villa (2015), Petri et al. (2014), Pirino et al. (2014), Singh et al. (2008), Sizemore et al. (2016a,b), Spreemann et al. (2015), Stolz (2014), Yoo et al. (2016), and Zeeman (1965). The website <http://www.chadgiusti.com/bib.html> maintains a bibliography of references in this area.

## 8. CONCLUSION: THE FUTURE OF TDA

TDA is an exciting area and is full of interesting ideas. But so far, it has had little impact on data analysis. Is this because the techniques are new? Is it because the techniques are too complicated? Or is it because the methods are simply not that useful in practice?

Right now, it is hard to know the answer. My personal opinion is that TDA is a very specialized tool that is useful in a small set of problems. For example, it seems to be an excellent tool for summarizing data relating to the cosmic web, but I doubt that TDA will ever become a general-purpose tool like regression. The exception is clustering, which of course is used routinely, although some might argue that it is a stretch to consider clustering part of TDA. I have seen a number of examples in which complicated TDA methods were used to analyze data but no effort was made to compare these methods to simpler, more traditional statistical methods. It is my hope that, in the next few years, researchers will do thorough comparisons of standard

statistical methods with TDA in a number of scientific areas so that we can truly assess the value of these new methods.

## DISCLOSURE STATEMENT

The author is not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

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## Errata

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