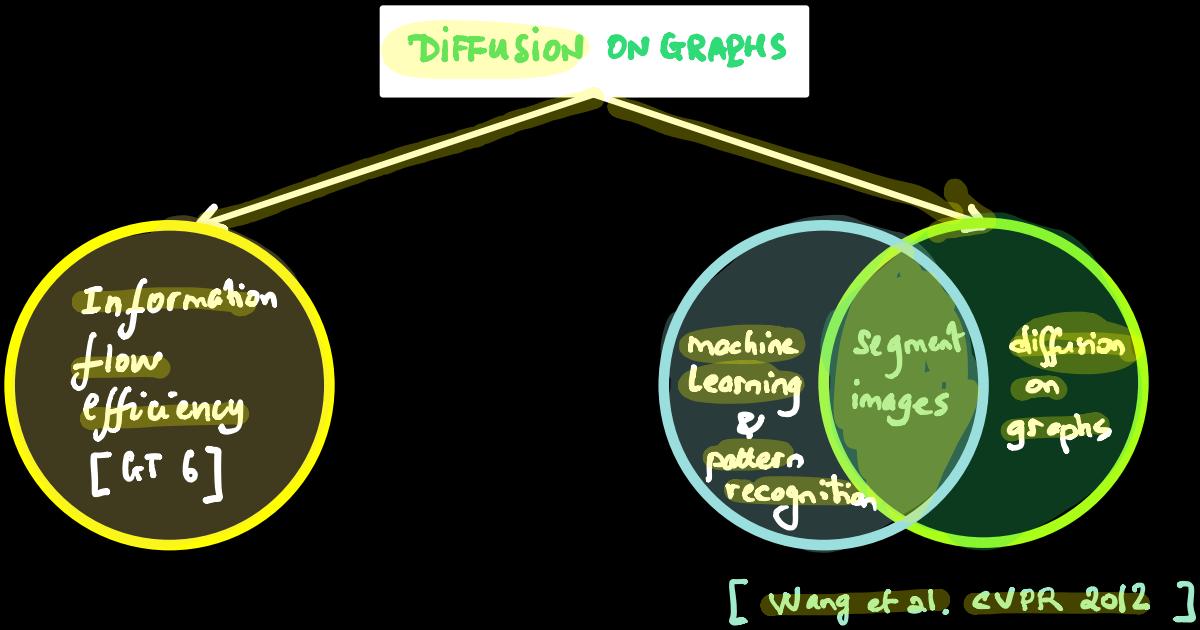


Graph \mathcal{T}



▼ Bo Wang CVPR 2012.pdf

Affinity Learning via Self-diffusion for Image Segmentation and Clustering

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Abstract. Computing a faithful affinity map is essential to the clustering and segmentation tasks. In this paper, we propose a graph-based affinity (matrix) learning method and its corresponding self-diffusion process for image segmentation. Our method, self-diffusion SLD, performs a diffusion process on the manifold of data points. Theoretical analysis is given on the SLD algorithm and we provide a way of deriving the critical parameters. The proposed method is able to learn a better feature representation and leads to significantly improved affinity maps, which are used for image segmentation. Experiments show, in addition, we show that much improved image segmentation results can be obtained by combining SLD with e.g. the non-local means denoising operator. The proposed method is able to deliver robust affinity maps for a range of problems.

1. Introduction

Graph-based methods for segmentation [26] and meaningful pair-wise distances/measures on top of meaningful pair-wise distances/measures which can equivalently represent the data as a graph have been widely used. They are further generalized into complex graphs [23, 30]. Therefore, constructing a faithful metric becomes crucial as a visual representation for clustering and segmentation.

A large body of literature on manifold learning [10, 24, 25, 27, 28] has shown that the concept of a particular learned distance notion. A recent line of work in machine learning introduces the idea of distance propagation which is able to propagate the information along the low-dimensional data manifold; moreover, they do not need to know the explicit graph structure. This propagation is typically a computation demanding task. This situation is more tempting when the output by a particular algorithm is a sparse graph. In this case, the propagation is a hard task. Data Manifold (RDM) [38]. In particular, RDM uses a similarity-induced diffusion kernel to improve the ranking of the neighbors [38].

methods have been shown to be effective in the classification/segmentation tasks, they lack the notion of a global similarity metric, which is crucial in many applications.

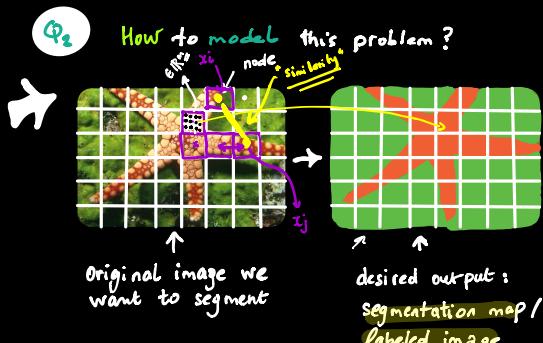
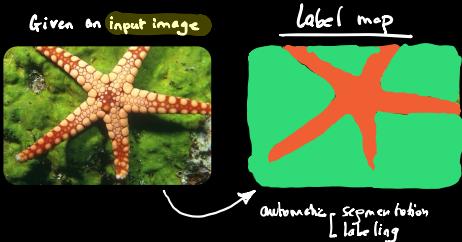
Another type of diffusion-based learning, diffusion maps (DM) [15] defines diffusion distances between data points on a non-linear manifold, it is computed through a diffusion process. There is no explicit notion of a global distance metric in DM and the diffusion map provides a local measure of the distance. Recently, a self-smoothing operator (SSO) is introduced in [18] to smooth the diffusion map. It is a fast learning approach and related to diffusion maps [15]. However, instead of using the notion of diffusion distances between data points, it uses the notion of diffusion distances between data points and their neighbors. The main idea is to compute map directly using a self-induced smoothing kernel. Both DM and SSO are able to learn a global similarity metric, it is lacking in the current DM and SSO.

Once a global similarity metric is learned, various graph Laplacian-based applications can be performed, such as image clustering (semi-supervised), image segmentation (unsupervised), and interactive image segmentation (semi-supervised), which are all challenging problems. The problem of image segmentation has been a long-standing problem and typical approaches include region growing [1, 2, 3], active contour [4, 5, 6], and fast graph-based approach [11]. Dynamic-based methods (e.g. RDM, SSO) are difficult to be applied in segmentation tasks due to the following reasons: 1) they require a large computation cost which hinders them dealing with large images; 2) they are slow due to the large iteration number, it is lacked by most dynamic-based methods; 3) they ignore the effect of iteration steps, and our method provides a principled way of determining the iteration of the best solution steps.

In this paper, we focus on developing an effective algorithm to deliver enhanced affinity maps for clustering and image segmentation. We propose a diffusion-based learning method, diffusion learning (DL), which is a generalization of the graph diffusion methods such as DM [15] and SSO [18].

Q1

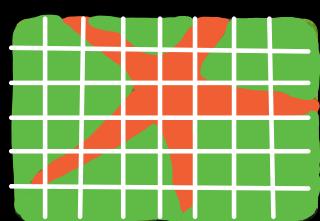
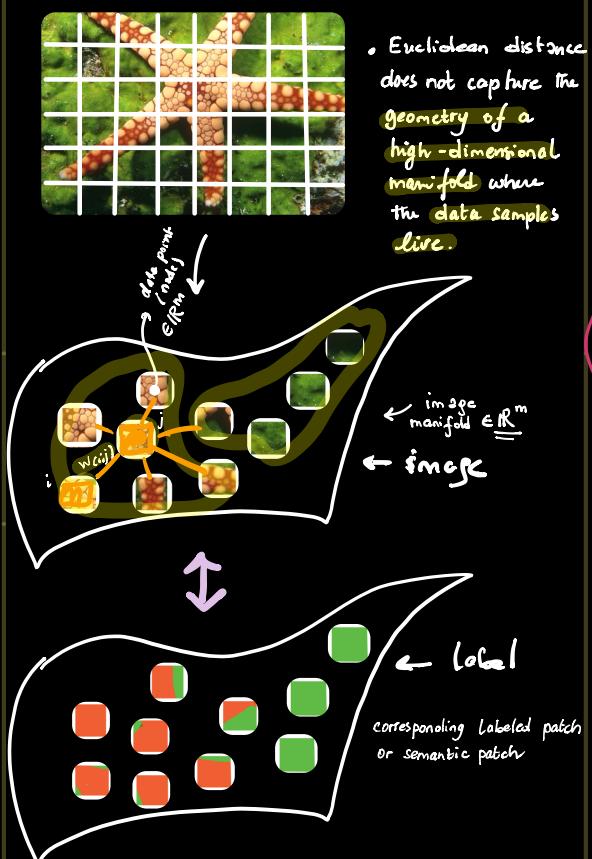
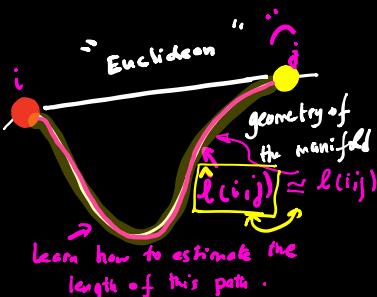
What is the problem to solve?



Q3 How to leverage graphs to solve this problem?

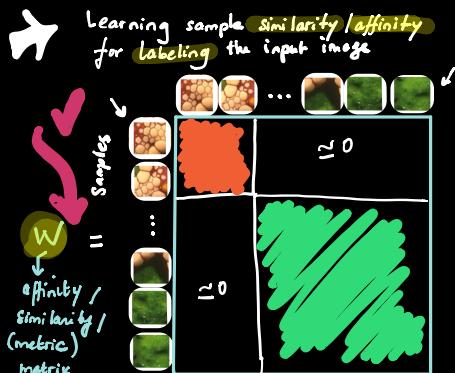
(Solution): learn the similarity (i.e., edge weights) between pairs of patches (i.e., nodes) in the input image (i.e., graph).

↳ why not use Euclidean distance between two "samples" (e.g. patches or pixels)?

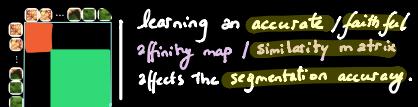


Q3

How to solve this problem?



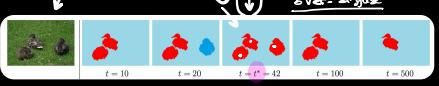
Proposed solution → Wang et al. propose a graph-based affinity (metric) learning method based on diffusion.



Once W is properly learned one can use a conventional segmentation method to partition the image into semantically homogeneous regions.

Q4 How to estimate W ?

- Use graph self-diffusions (SD) ↗ local ↘ global
- it works directly on the input affinity map and uses regularization in each diffusion iteration.
- assumption long-range similarities can be approximated by an accumulation of local similarities



- Given a graph $G = (\Omega, W)$ where $\Omega = \{x_i\}_{i=1}^n$ is a collection of data samples.
- W is the similarity matrix in $\mathbb{R}^{n \times n}$.
- $W(i, j) \in [0, 1]$, where $W(i, j) = 1 \Leftrightarrow x_i = x_j$.

- $W(i, j) = \exp(-d^2(i, j)/c^2)$ (Gaussian Kernel)
- $D(i, i) = \sum_{k=1}^n W(i, k)$ (diagonal node strength matrix)

- $P = D^{-1}W$ (transition kernel)

- $P_{ij} = \frac{W_{ij}}{S_i}$
- $W = \begin{bmatrix} w_{11} & w_{12} & \dots \\ w_{21} & w_{22} & \dots \\ \vdots & \vdots & \ddots \\ w_{n1} & w_{n2} & \dots \end{bmatrix}$

- $W_t = W_{t-1}P + I$ → iterative self-diffusion of W

- $W^* = W_t D^{-1}$ (closed form solution)

Q₃

Why it works? [theoretical proof]

☺ Intuitive explanation is good but theoretical proof is best!

↳ There is a closed form for estimating an appropriate t^* at which the effect of SD is the best.

1. Computing the smoothing kernel:

$$P = D^{-1}W$$

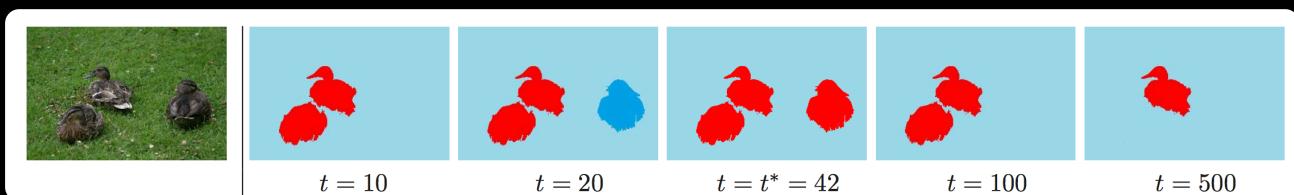
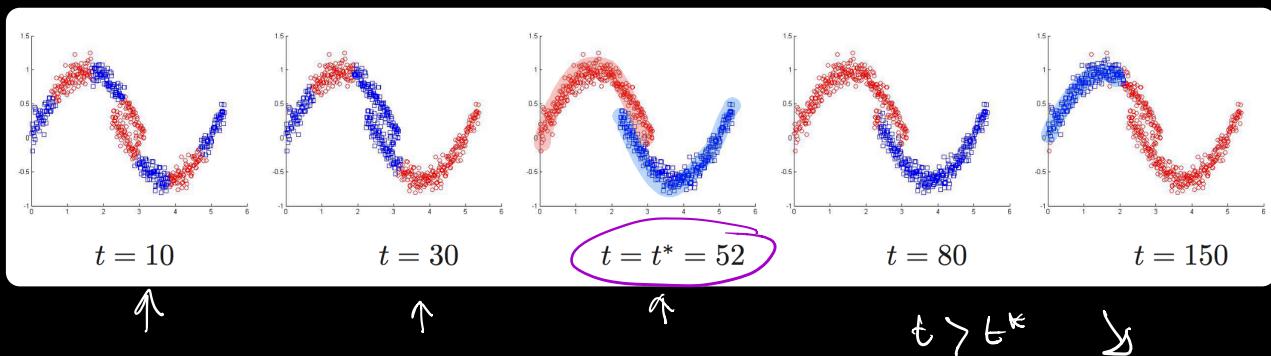
where D is a diagonal matrix with $D(i, i) = \sum_{k=1}^n W(i, k)$.

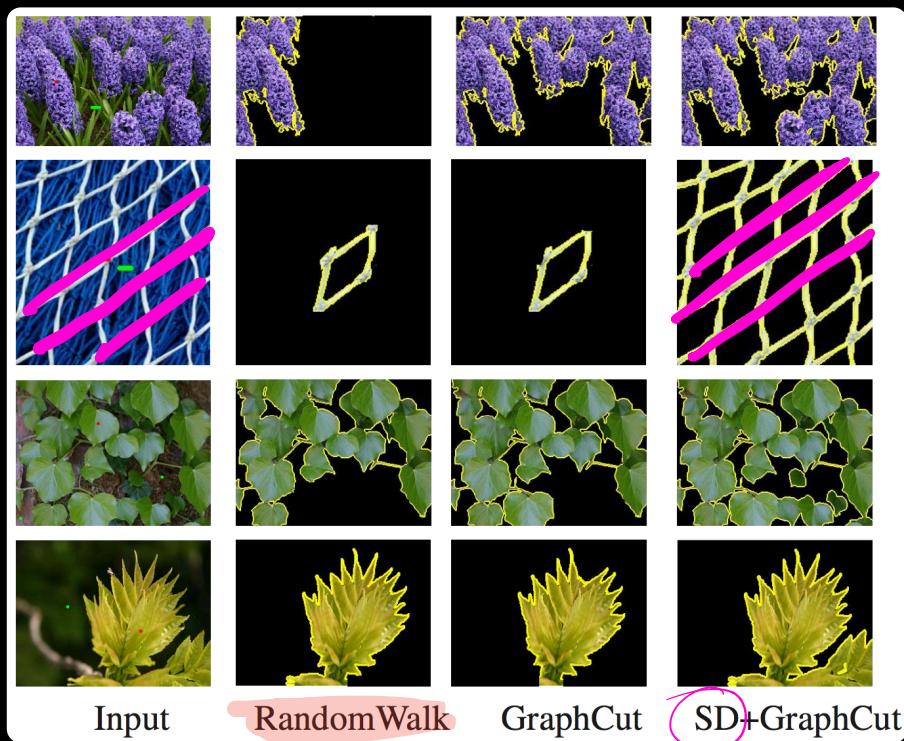
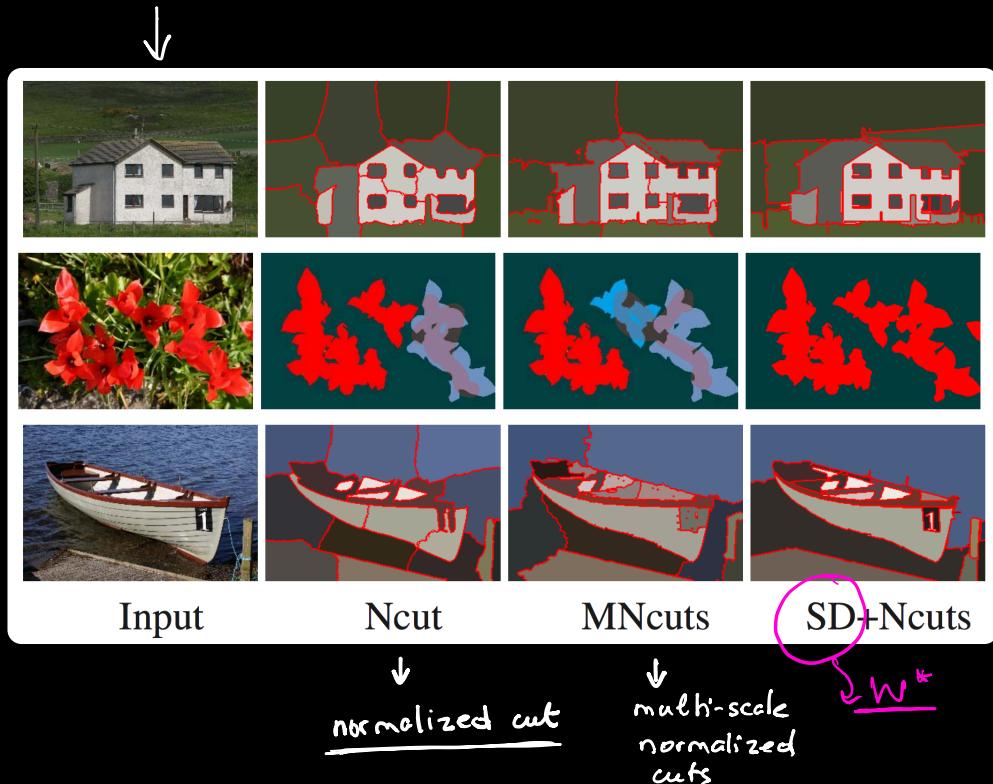
wrong or at 2x2

2. Performing smoothing for t^* steps:

$$W_t = W_{t-1}P + I.$$

3. Self-normalization: $W^* = W_t * D^{-1}$





$$\begin{cases} P = D^{-1} W \\ W_t = W P^t \end{cases}$$

running random walk t times

Affinity Learning via Self-diffusion for Image Segmentation and Clustering

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Abstract. Computing a faithful affinity map is essential to the clustering and segmentation tasks. In this paper, we propose a graph-based affinity (metric) learning method and show its application in image clustering and segmentation. Our method, self-diffusion (SD), performs a diffusion process by iteratively updating the similarity matrix along the geometric manifold of data points. Theoretical analysis is given to the SD algorithm and we provide a way of deriving the critical time stamp t . Our method therefore has nearly no parameter tuning and leads to significantly improved affinity maps, which help to greatly enhance the quality of clustering. In addition, we show that much improved image segmentation results can be obtained by combining SD with e.g. the normalized cuts algorithm. The proposed method can be used to deliver robust affinity maps for a range of problems.

1. Introduction

Graph-based approaches for segmentation [26] and manifold learning [24, 30] build their success on top of meaningful pair-wise distances/metrics which can equivalently be represented as affinity maps/similarity measures; they are further generalized into Laplacian graphs [2, 38]. Therefore, constructing a faithful metric becomes crucial in a variety of Laplacian graph-based applications [26, 10, 37].

A large body of literature on manifold learning [30, 24, 5] explicitly construct new embedding spaces with an enhanced distance notion. A recent line of work in machine learning introduces the idea of distance propagation/diffusion [37, 5], allowing the derived distances to follow the intrinsic data manifolds; moreover, they do not need to explicitly construct the geometry of the manifolds, which is typically a computation demanding task. This situation is more common when the output by a particular algorithm [3] only indicates pairwise similarity measures with no explicit linkage feature. Other examples include Markov random walks on manifolds [29] and Ranking on Data Manifolds (RDM) [36]. In particular, RDM uses a similarity-induced diffusion kernel to improve the ranking result with respect to a single query. Although the above

methods have been shown to be effective in the classification/ranking tasks, they lack the notion of a global similarity metric, which is crucial in many applications.

Along the line of diffusion-based metric learning, diffusion maps (DM) [5] defines diffusion distances between data samples. An input similarity matrix is then improved through a diffusion process. There is also an equivalent notion of global distance metric in DM. The diffusion step t provides a way of doing multi-scale data analysis. More recently, a self-smoothing operator (SSO) is introduced in [16] which is a diffusion-based unsupervised metric learning approach and related to diffusion maps [5]. However, instead of using the notion of diffusion distances between data samples, SSO works on the similarity matrix/affinity map directly using a self-induced smoothing kernel. Both DM and SSO have the tuning parameter t to specify; in general, it is critical to have a principled way of deciding t , which is lacking in the current DM and SSO.

Once a faithful affinity map/similarity matrix is learned, various graph Laplacian-based applications can be performed. Here, we focus on the task of clustering (unsupervised), image segmentation (unsupervised), and interactive image segmentation (semi-supervised), which are all dependent on accurate affinity maps. Image segmentation has been a long-standing problem and typical approaches include Normalized Cuts [26], DDMCMC [32], Mean-shift [6], and fast graph-based approach [11]. Dynamic-based methods (e.g. DM, SSO) are difficult to be applied in segmentation due to two reasons: (1) Dynamic-based methods require a large computation cost which hinder them dealing with large scale segmentation; (2) Derivation of a proper iteration step is checked by most dynamic-based methods. Fig. (1) illustrates the effect of iteration steps, and our method provides a closer-form reasonable approximation of the best iteration steps.

In this paper, we focus on developing an effective algorithm to deliver enhanced affinity maps for clustering and image segmentation. Our method is related to distance propagation/diffusion methods such as DM [5] and SSO

input image



Normalized
cut

Normalized
cut +
SD

scikit-image

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Normalized Cut

This example shows to download the full example code. [Normalized Cut](#)

DOI: J. Matij, J. "Normalized cuts and image segmentation", Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 22, no. 8, pp. 888-905, August 2000.

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