Beyond the shortest path : Unsupervised Domain Adaptation by Sampling Subspaces along the Spline Flow

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In the past few years there has been a growing interest on the study and development of techniques, (e.g. domain adaptation, transfer learning [4, 9]) that enable the adaptation of classifiers to handle mismatches between the underlying distribution of the training and testing data (also known as source and target domains respectively).

Applications in computer vision often involve the study of real world problems where this scenario arises very naturally e.g. [1, 2, 6, 7]. The training and testing data can be acquired using sensors with different characteristics (e.g. image resolution or quality), under diverse lighting conditions (e.g. indoor controlled illumination vs outdoor environments) or from different camera viewpoints (e.g. same object in different poses).

For example, recently several important applications using domain adaptation were presented: Hoffman [7] proposed a novel framework for large scale detection through adaptation (LSDA). They created a fast and effective large scale detection network by combining adaptation techniques with deep convolutional models. Fernando [1] showed that using domain adaptation techniques is possible to deal with the image variability induced by large time lags. They presented a framework to automatically associate ancient pictures to modern ones, e.g. location recognition and interactive location retrieval. Ho [6] demonstrated that using domain adaptation techniques is feasible to recognize faces in scenarios where images corresponding to the source and the target domain are acquired under varying degree of factors such as illumination, expression, blur and alignment. Finally, Gopalan [2] presented a top-down approach through adaptation for estimating geographic location from images. They obtain competitive results for this challenging task compared with some landarmark papers in the field, e.g. [5].

Recently, a particular paradigm [3] in the domain adaptation field has received considerable attention by introducing novel and important insights to the problem (SGF - Subspaces by Sampling Geodesic Flow). In this case, the source and target domains are represented in the form of subspaces, which are treated as points on the Grassmann manifold. The geodesic curve between them is sampled to obtain intermediate points. Then a classifier is learnt using the projections of the data onto these subspaces.

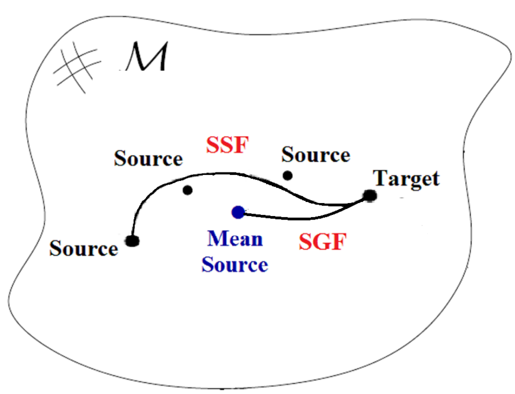

Figure 1: This image illustrates the SSF (Sampling Spline Flow) versus the SGF (Sampling Geodesic Flow) [3, 4]. The SGF deals with multiple sources by computing the respective mean and then a geodesic curve is defined between the mean-source and the target domain. The SSF uses smooth polynomial functions described by splines on the manifold to interpolate between all the sources and the target domain. The spline can be computed as an approximation (the curve passes close to the intermediate points) or exact spline [10]. The goal is to compute a curve able to extract more meaningful information from the sources.

Despite its relevance and popularity, this paradigm [3] contains some limitations. Firstly, in real-world applications, that simple curve (i.e. shortest path) does not provide the necessary flexibility to model the domain shift between the training and testing data sets. Secondly, by using the geodesic curve, we are restricted to only one source domain, which does not allow to take fully advantage of the multiple datasets that are available nowadays.

It is then, natural to ask whether this popular concept could be extended to deal with more complex curves and to integrate multi-sources domains. This is a hard problem considering the Riemannian structure of the space, but we propose a mathematically well-founded idea that enables us to solve it. As argued by Gopalan [3, 4]: humans adapt (better) between extreme domains if they gradually walk through the path between the domains. Grounding in the same biological principle, we extend the SGF [3, 4] using smooth polynomial functions described by splines on the Grassmann manifold (SSF - Subspaces by Sampling Spline Flow).

We exploit the geometric insight of rolling maps [8, 11] to compute a spline curve on the Grassmann manifold. An association of unwrapping methods via local diffeomorphisms, and rolling motions (the manifold is rolled, without slipping or twisting, as a rigid body) enables us to map the data from the manifold to its affine tangent space at a point, compute the curve on the latter and then the final curve on the manifold is obtained by wrapping back while unrolling. The problem in the tangent space is solved using the De Casteljau's algorithm [10], which is a geometric method to construct smooth curves.

Figure 2: Images examples from the four datasets (Amazon, Caltech-256, Webcam, DSLR) used (Monitor category).

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This is an extended abstract. The full paper is available at the Computer Vision Foundation webpage.