A M A L T H E A R E U 2 0 1 6

SHAPE RETRIEVAL ON THE WAVELET DENSITY HYPERSPHERE

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ABSTRACT

A novel solution for shape retrieval is presented. Shapes are represented as probability densities; specifically, we expand the square-root of the density in a multiresolution wavelet basis. Under this model, each density (of a corresponding shape) is mapped to a unit hypersphere. The ensuing geometry is used to create hierarchical representations of shape categories and perform shape warping---increasing retrieval speed and accuracy.

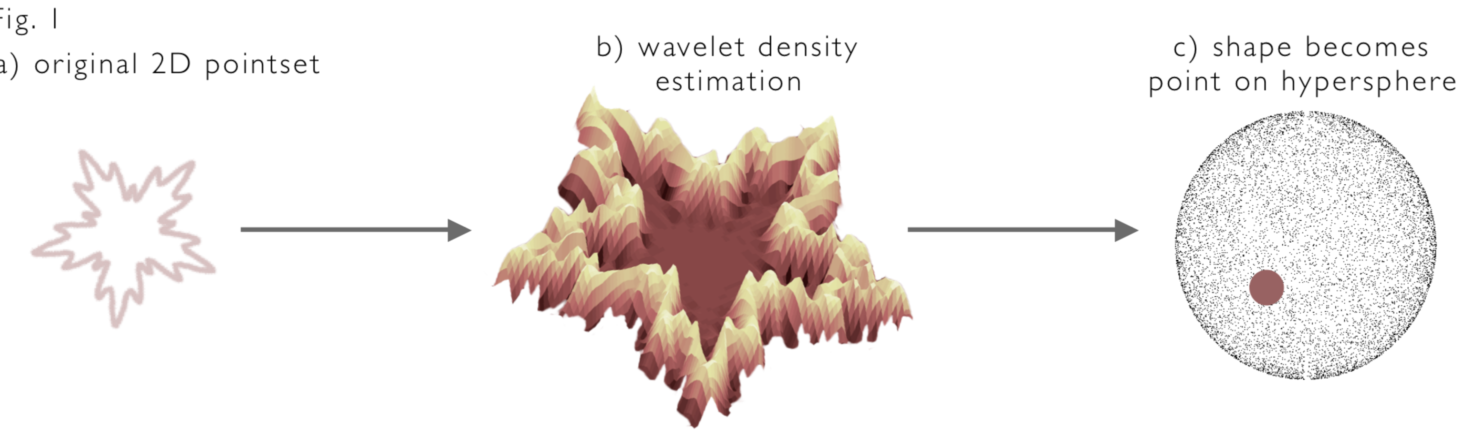
CONTRIBUTIONS

- Optimized performance of 2D multiresolution wavelet density estimator
- Improved shape similarity metric using linear assignment and multiresolution wavelets
- Implemented hierarchical clustering algorithm on high-dimensional unit hypersphere and analyzed algorithmic complexity

APPROACH

WAVELET DENSITY ESTIMATION

Fig. 1



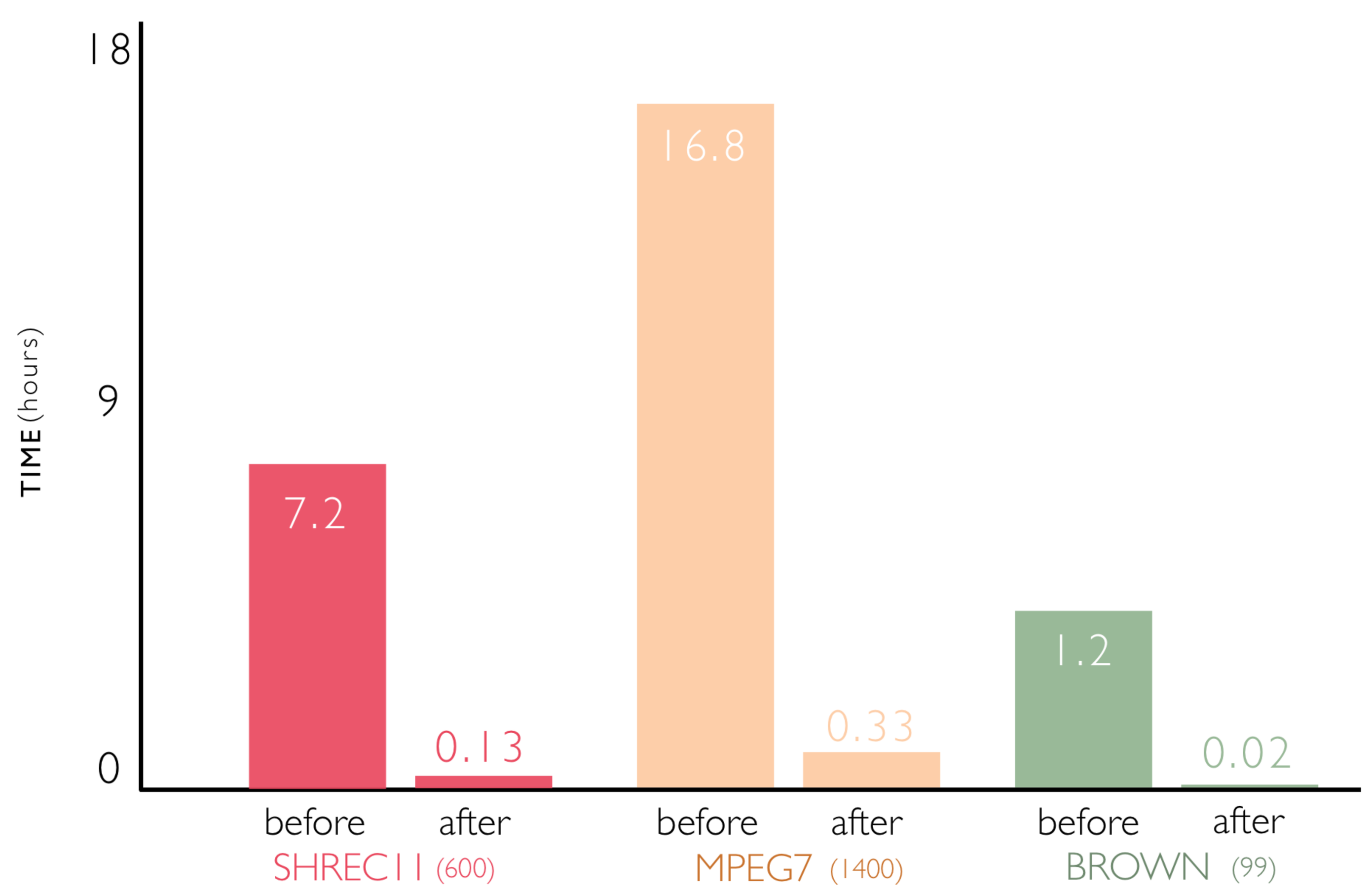
Wavelets are crucial mathematical functions that form an orthonormal basis for probability density functions. Given a point-set representation of a shape, we use a constrained maximum likelihood approach to estimate the coefficients of the wavelet density basis expansion in eq. (1).

$$\sqrt{p(\mathbf{x})} = \sum_{j_0,\mathbf{k}} \alpha_{j_0,\mathbf{k}} \phi_{j_0,\mathbf{k}}(\mathbf{x}) + \sum_{j \geq j_0,\mathbf{k}}^{j_1} \sum_{w=1}^{3} \beta_{j,\mathbf{k}}^{w} \psi_{j,\mathbf{k}}^{w}(\mathbf{x}) \quad (1)$$

APPROACH & RESULTS

WDE OPTIMIZATION

Fig. 2 OPTIMIZATION TIMING RESULTS



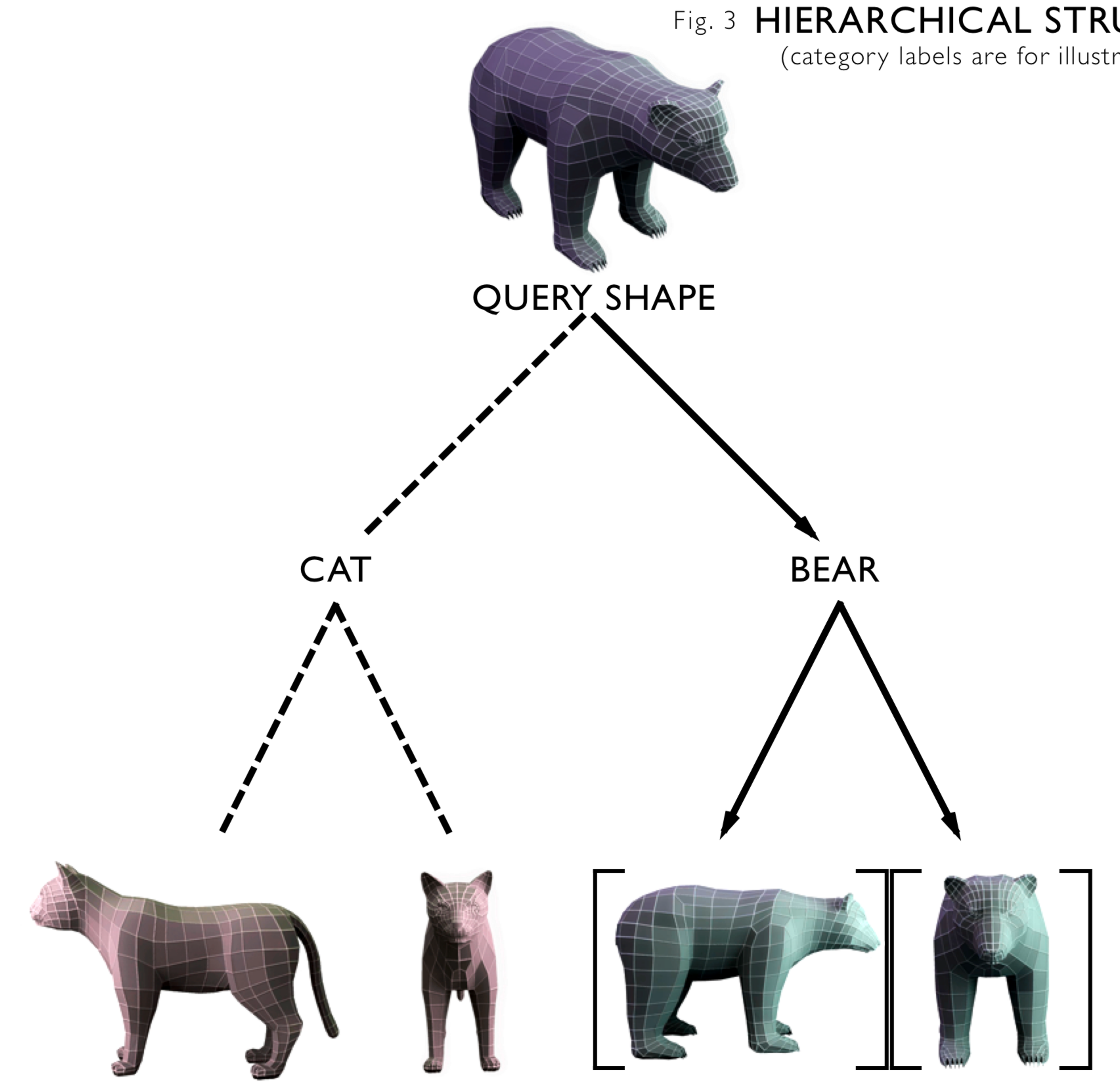
Wavelet density estimation (WDE) involves estimating the wavelet coefficients (α and β in eq.1) which is a computationally expensive task. Through parallelization we were able to significantly improve the algorithm's run time.

100× FASTER

APPROACH & RESULTS

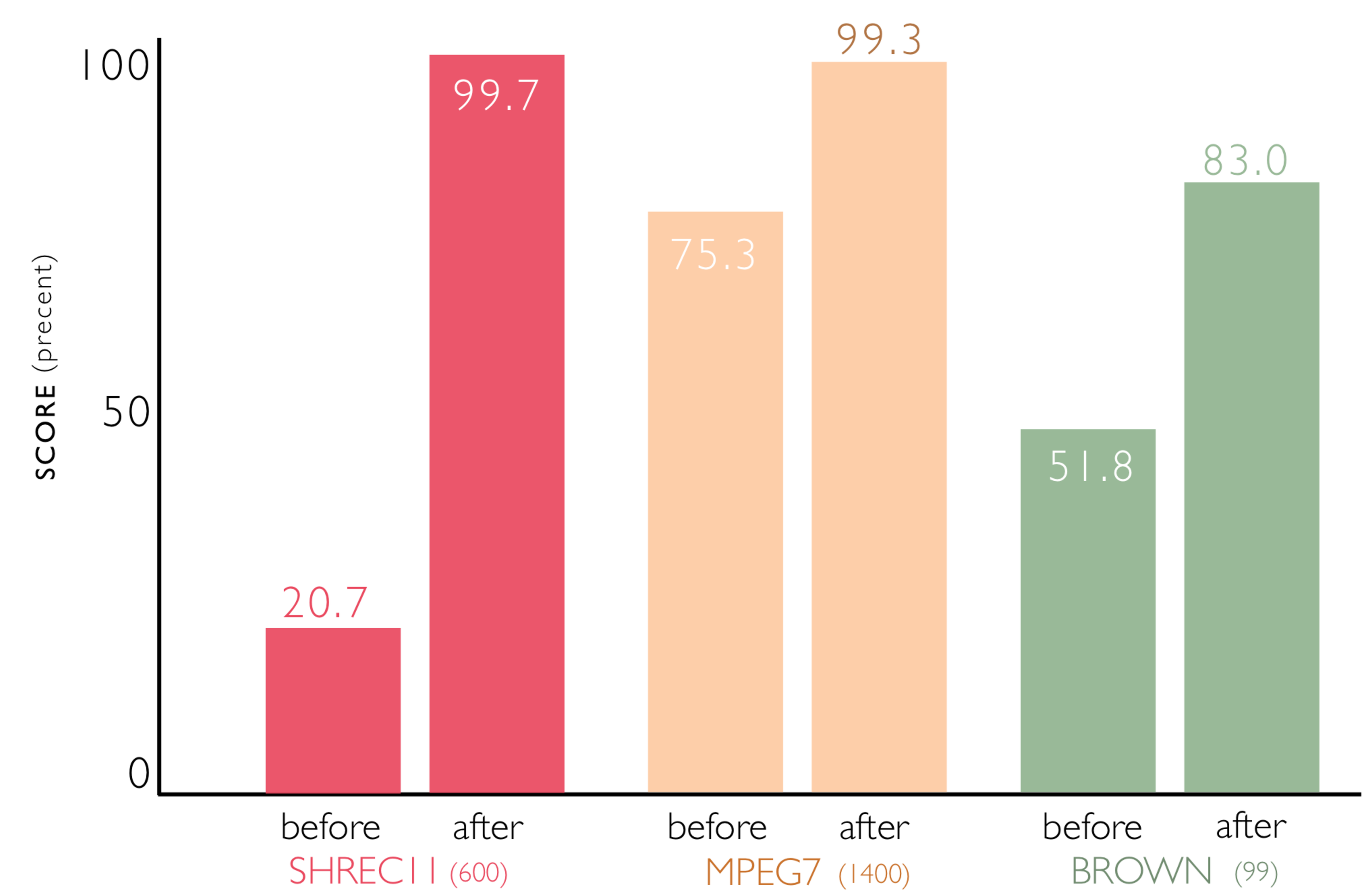
HIERARCHICAL SHAPE RETRIEVAL

Fig. 3 HIERARCHICAL STRUCTURE
(category labels are for illustration only)



Hierarchical clustering uses different levels of abstraction to group similar shapes together. Using spherical k-means, a recursive tree structure on the cluster centers is formed on the hypersphere---the means of one level form the children of the higher level--increasing retrieval speed and accuracy.

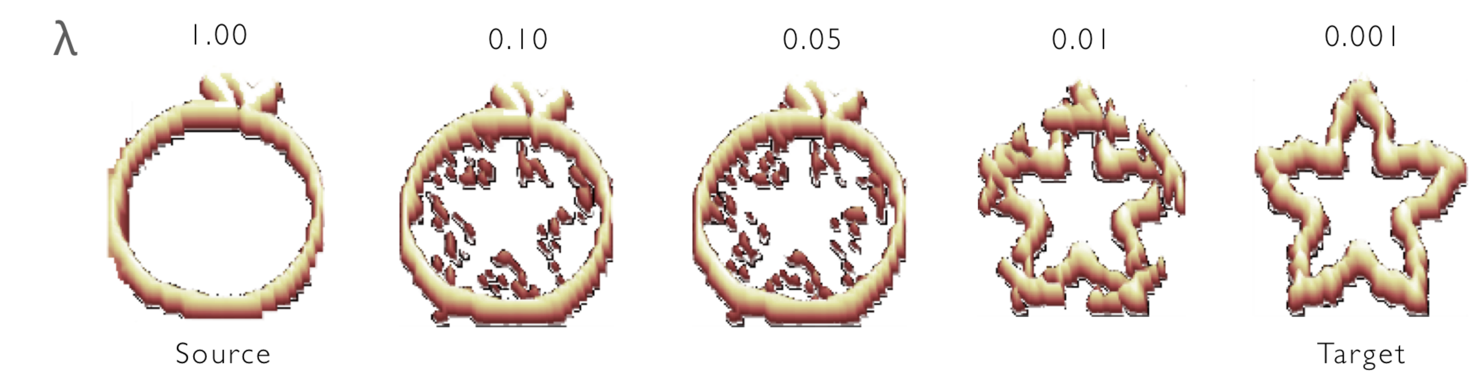
Fig. 4 ACCURACY
HIERARCHICAL v. NONHIERARCHICAL



APPROACH & RESULTS

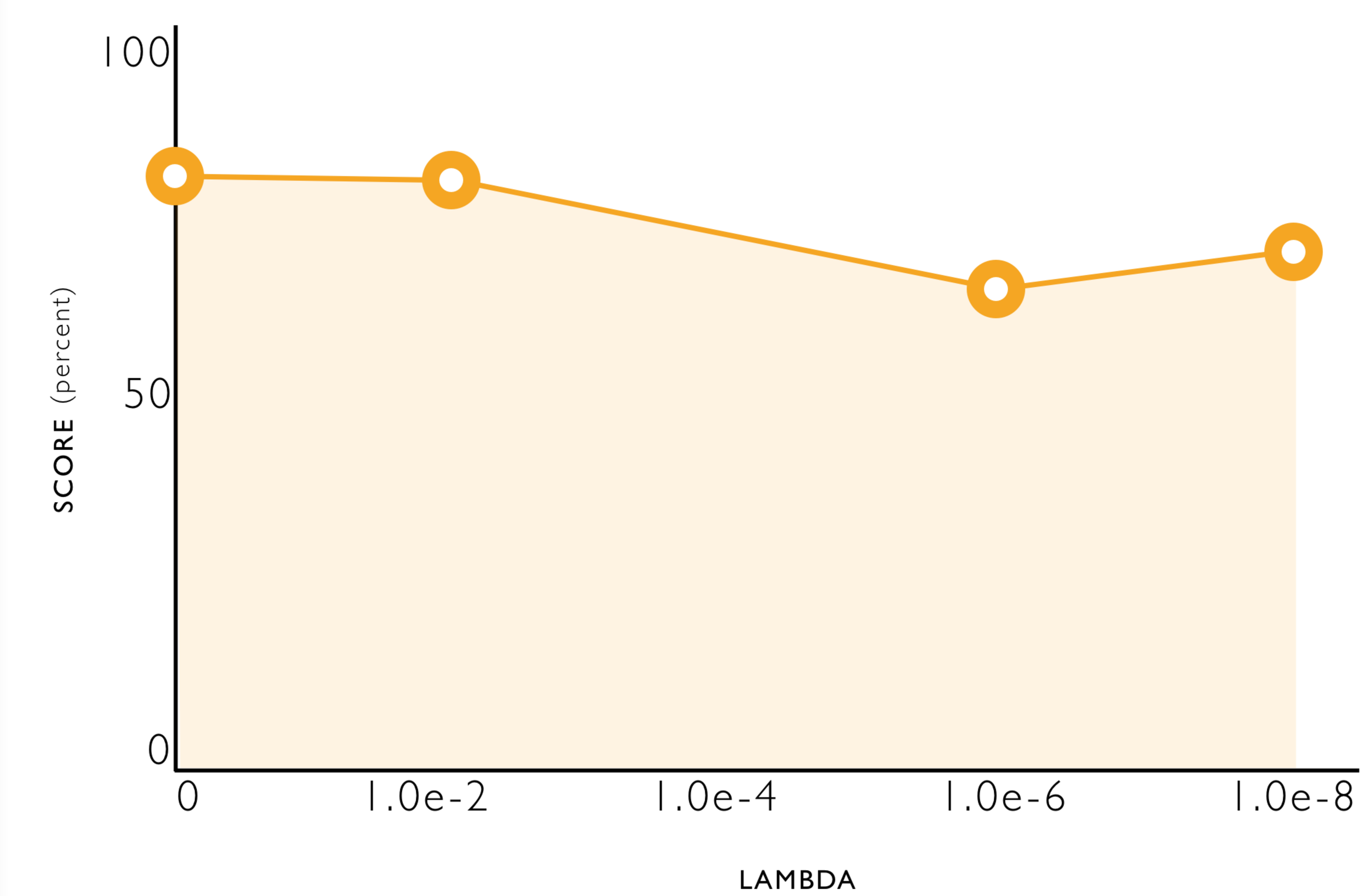
LINEAR ASSIGNMENT

Fig. 5 WARPING FROM SOURCE TO TARGET



By warping two shapes together, the distance between similar shapes decreases and dissimilar shapes increases, respectively. To perform this warping, we use a constrained linear assignment objective function, where lambda regularizes the amount of warping. As lambda decreases, the amount of warping increases.

Fig. 6 ACCURACY WITH VARYING LAMBDA



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