We study the power of the Laplace Beltrami Operator (LBO) in processing and analyzing geometric information. The decomposition of the LBO at one end, and the heat operator at the other end provide us with efficient tools for dealing with images and shapes. Denoising, segmenting, filtering, exaggerating are just few of the problems for which the LBO provides an efficient solution. We review the optimality of a truncated basis provided by the LBO, and a selection of relevant metrics by which such optimal bases are constructed. Specific example is the scale invariant metric for surfaces that we argue to be a natural selection for the study of articulated shapes and forms. In contrast to geometry understanding there is a new emerging field of deep learning. Learning systems are rapidly dominating the areas of audio, textual, and visual analysis. Recent efforts to convert these successes over to geometry processing indicate that encoding geometric intuition into modeling, training, and testing is a non-trivial task. It appears as if approaches based on geometric understanding are orthogonal to those of data-heavy computational learning. We propose to unify these two methodologies by computationally learning geometric representations and invariants and thereby take a small step towards a new perspective on geometry processing. I will present examples of shape matching, facial surface reconstruction from a single image, reading facial expressions, shape representation, and finally definition and computation of invariant operators and signatures.