# Research Statement

My research interests broadly fall into the areas of computer vision, machine learning and pattern recognition. All these related fields have seen many achievements to date and many successful algorithms have been developed to solve a wide variety of problems. Most of these studies assume that objects live in feature spaces, i.e. each object is represented based on a set of specific features intrinsic to the object itself [7]. The problem with this dominant view is that for many real-world applications such a vectorial representation might be hard to obtain or simply computationally impractical. In example, expressing relational information essentially requires structural representations such as graphs and trees and cannot be captured effectively by a conventional feature-based representation. On the other hand, the available tools for learning with structured data is not so diverse as compared to those for feature-based statistical learning.

The approach to filling in this gap centers on a fresh view which tackles the issue by exploiting similarity information per se [8, 1]. This so-called similarity-based approach suggests directly working on similarities (or dissimilarities) between data objects. In this regard, it is closely related to highly popular kernel-based learning [14], which has become quite a popular technique in recent years. The main difference between the two is that the similarity-based approach does not suffer from common technical difficulties associated with kernel-based methods such as the metric requirements of kernel functions. In practice, (dis)similarities can be asymmetric as well as negative.

The foundation for my intellectual curiosity about the above paradigm stems from my Ph.D. research at Middle East Technical University, which explores the role of similarity information in shape recognition and shape classification tasks. In particular, during my doctoral study, I investigated the use of a coarse skeleton-based shape representation [3] for the aforementioned visual recognition tasks.

In a collaborative work with a M.Sc. student, we developed a contextual distance measure for shape matching [4], which is very much in line with Tversky's seminal contrast model [16] and allows for different roles in similarity comparisons. The query shape is considered to be compared with an individual shape belonging to a known class. This extra category knowledge provides a context in determining the distinctive properties of the database shape, improving the retrieval performance and leading to an asymmetric measure.

I also studied skeleton-based shape classification from a similarity-based perspective. Although there is a vast amount of literature devoted to skeleton-based shape matching, so far little attempt has been made to address shape classification when one employs a skeleton-based structural representation of shapes. I demonstrated that a given shape can be classified solely based on its similarities to a set of prototypical shape skeletons, each of which representing a certain class [11].

After my Ph.D. study, I spent nearly one and a half years as a post-doctoral researcher at the University of Venice (UNIVE), in Italy, during which I was funded by the SIMBAD project [1]. The sole objective of this EU FP7 project was to explore the theoretical and computational foundations of similarity-based methods. This position gave me the opportunity to deepen my knowledge and understanding of the subject area. I was also exposed to evolutionary game theory [17] as a powerful mathematical machinery to model several pattern recognition and machine learning problems, such as clustering and matching.

During my time at UNIVE, I first investigated the problem of unsupervised learning of shape categories which was beyond the scope of my Ph.D. research and therefore was left as future work. Specifically, I tackle the “chicken and egg” dilemma inherent to the clustering task but ignored by traditional bottom-up or pairwise clustering techniques. On one hand, similarities must be known in order to reveal underlying class structure in an unsupervised way. On the other hand, class knowledge strongly influences similarity computations. To address this problem, I proposed an EM-like algorithm which alternates between these two interrelated processes: estimating shape classes and updating similarities in the presence of category structure [12]. It makes use of both the game-theoretic clustering approach in [15] which can cope with asymmetric similarities and the contextual distance measure proposed in [4].

As part of my post-doctoral research, I also studied the problem of learning with partially labeled data, generally referred to as semi-supervised learning (SSL), which differs from the traditional supervised learning by additionally exploiting the information of the unlabeled data [20, 5]. In my research, I considered the transductive setting that assumes the test points are available at the time of learning, and formulated transductive learning as a multi-player game played on graphs [10]. Compared to existing methods, my approach can handle not just symmetric but also asymmetric and negative similarities. Although some work has been done on extending available methods to work with asymmetric [18] and negative similarities [13], to my knowledge, this method is the only one that can cope with all the three types of similarity relations.

One of my current research concerns extending the aforementioned work with ordinary graphs to hypergraphs with edges of size larger than two. The vast number of graph-based SSL methods just consider pairwise relationship between data points, although in many real-world situations this imposes a serious limitation. Ordinary graphs are simply not capable enough to capture more complex relationships, and naively rendering a complex relationship with a set of pairwise ones leads to loss of information. In the literature, there is only a limited number of studies which investigate higher order similarity relations in transductive learning [19, 2]. I believe that game theory will again provide a well-established ground to model this challenging problem.

Secondly, together with a colleague of mine, I am investigating multiple-instance learning (MIL) [6], which gained much attention lately as a new paradigm for learning with ambiguously labeled data. In MIL setting, training data are given in the form of bags of instances and label information is available for the bags but not necessarily for the instances. In a preliminary work [9], we propose an effective MIL scheme, which offers a new solution to select a set of instance prototypes, for transforming a given MIL problem into a standard supervised (single instance) learning problem. Our algorithm exhibits very promising results when applied to standard benchmark data sets and image classification.

To summarize, my research so far has mainly focused on exploiting similarity information to develop novel and alternative solutions to pattern recognition and machine learning problems, and I would like to pursue this direction further. Moreover, I would also like to explore game theory as a design tool to facilitate the development of effective and theoretically-sound methods for challenging learning problems.

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