A Statement Report on the Use of Multiple Embeddings for Visual Analytics of Multivariate Networks

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Abstract: The visualization of large multivariate networks (MVN) continues to be a great challenge and will probably remain so for a foreseeable future. The field of Multivariate Network Embedding seeks to meet this challenge by providing MVN-specific embedding technologies that targets different properties such as network topology or attribute values for nodes or links. Although many steps forward have been taken, the goal of efficiently embedding all aspects of a MVN remains distant. This position paper contrasts the current trend of finding new ways of jointly embedding several properties with the alternative strategy of instead using, and combining, already existing state-of-the-art single scope embedding technologies. From this comparison, we argue that the latter strategy provides a more generic and flexible approach with several advantages. Hence, we hope to convince the visual analytics community to invest more work in resolving some of the key issues that would make this methodology possible.

1 INTRODUCTION

A large amount of research effort has been put into the problem of visualization and visual analytics (VA) regarding large multivariate networks (MVNs). This is a complex and challenging problem both from a pure visualization perspective as well as from a computational perspective. While the field of MVN visualization is well-studied—and there exist several approaches for displaying and interacting with MVNs (Kerren et al., 2014; Martins et al., 2017; Nobre et al., 2019)—the size of many MVNs (for example social networks such as Twitter and Facebook) exceed the limits of what can be efficiently handled by such methods directly. This means that in many cases, effective pre-processing and extensive computations are vital steps before visualization even becomes feasible. Furthermore, there is a constant need for more efficient analysis algorithms from a computational perspective. Hence, methods for effective representations and efficient calculations for MVNs would be beneficial from both a visualization perspective and a VA perspective. It is our conviction that combined forces from these two areas are needed to achieve the progress needed.

Embeddings are relatively low-dimensional vector representations of the embedded items and embedding algorithms exist for different types of data. (E.g., the nodes of a network or the words of a text corpus). The main goal of the emdedding algorithm is usually to produce embeddings in a way so that items that are similar (from some chosen aspect) in the original data set are embedded in vectors that lie close to each other in the embedding space (with regard to some chosen distance metric). Therefore embeddings can, for instance, be used for efficient similarity computations over a data set. From a technical viewpoint there are several arguments to suggest that embedding technology is probably a suitable candidate for meeting the challenge of MVN visualization and MVN visual analytics. The main argument for this is that it has already proven to be an efficient and successful strategy within other problem areas (Goyal and Ferrara, 2017; Toshevska et al., 2020) In recent years, several embedding techniques specific to MVNs have been introduced (Cui et al., 2019) allowing for new and ingenious progress (see Figure 1). Therefore, it is not surprising that a lot of effort is currently being put into exploring ways to create new and better MVN embeddings. In this scenario, a common approach is to try to simultaneously embed several prop-

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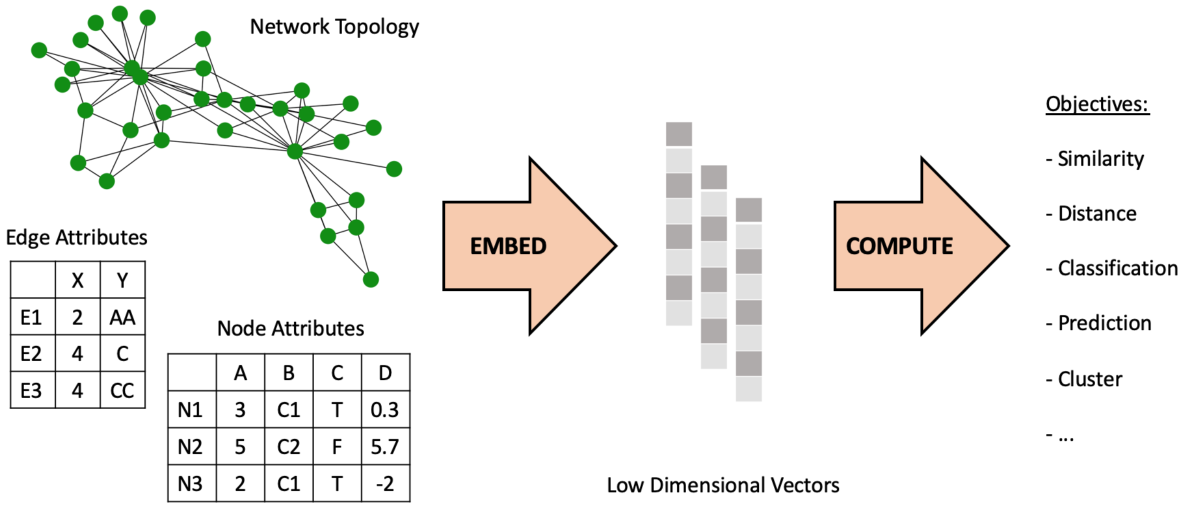

	X	Y
E1	2	AA
E2	4	C
E3	4	CC

	A	B	C	D
N1	3	C1	T	0.3
N2	5	C2	F	5.7
N3	2	C1	T	-2

Figure 1: Embeddings have become important tools for MVN analysis and made the way for substantial progress. Technologies for embedding properties such as network topology and attributes on nodes or edges have enabled more computationally-efficient ways to support common objectives and tasks.

erties (by this we mean different characteristics of the MVN such as network topology, attributes on nodes or edges etc.) using so-called content-enhanced representation learning or similar techniques (Hamilton et al., 2018; Sun et al., 2016; Lerique et al., 2020). While this has proven successful for some applications, we would like to point out that the typical multi-property MVN embedding technology is quite narrow in its scope regarding the amount of properties it can capture (typically only two). Hence, the quest for the—highly desirable—algorithm capable of capturing *all* properties of the MVN at once still remains an open challenge, at least for the foreseeable future.

In this paper, we therefore argue for an alternative approach, and take the position that there seems to be a currently unexploited way that could hopefully lead towards the goal of comprehensive and efficient MVN embeddings. The alternative strategy that we propose is to seek novel ways to combine and leverage the plethora of already-existing state-of-the-art embedding technologies, also from other fields that do not necessarily target MVNs. Furthermore, we argue that this should be done in a way that will allow for exploitation of:

1. *the benefits of single focus*,
2. *the flexibility of separation*, and
3. *the power of combination*.

These three concepts are outlined in the following sections and provide the overall structure of this paper. To make our reasoning more concrete, and hopefully easier to follow, we will assume that the embeddings we discuss are used for similarity calculations (which is a common case), but our arguments are not dependent on this.

2 THE BENEFITS OF SINGLE FOCUS

Embedding algorithms are typically quite complex in their structure (Cui et al., 2019) (for example, it is not uncommon that they are based on model training and loss function minimization.) Therefore, calculating good embeddings for even a single property is usually a non-trivial task in itself, with many challenges. The case of simultaneously embedding two or more properties (see Figure 2) can, in general, be viewed as a joint optimization problem, so that more complexity is added on top of the already existing one. Furthermore, joint optimization problems usually contain some amount of trade-off between objectives since it may be hard, or impossible, to find a common optima (Ngatchou et al., 2005). It is therefore reasonable to argue that an embedding algorithm that targets a single property will have the potential for higher-quality similarity calculations (for that specific property) than an algorithm that tries to bundle it together with others. There is, of course, no strict guarantee that that will be the case for all situations and for all data sets.

Thus, we claim that it is likely that the highest quality for similarity calculations, as measured on a per-property basis, will be obtained by algorithms that target only a single property. Furthermore, we note that this line of reasoning deliberately opens the possibility to use algorithms that do not specifically tar-

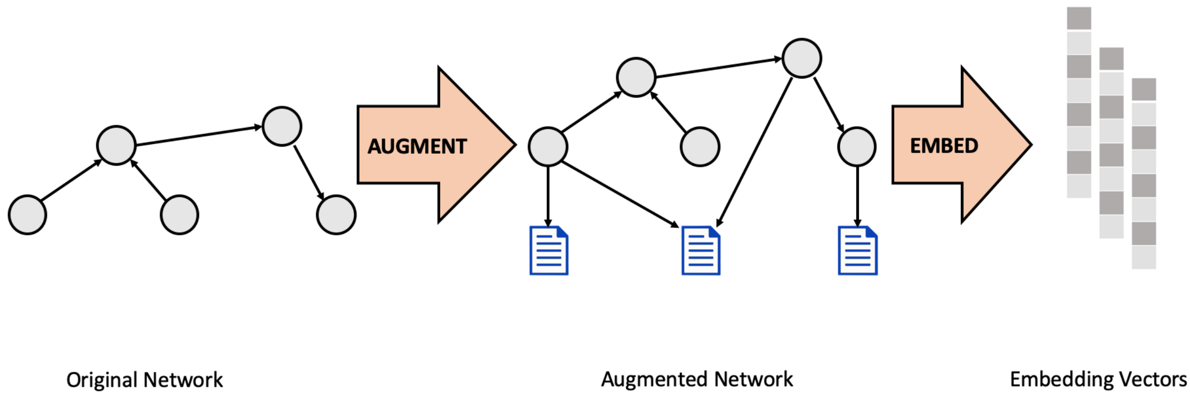

Figure 2: In the CENE framework (Sun et al., 2016), the original MVN is extended by adding new nodes. For each text attribute on an existing node, a new child node (of a different type) is added with links to its parent node(s). The resulting augmented (multimodal) network, now containing two different types of nodes and two different types of links, is then used in the embedding algorithm for joint optimization of network structure and textual content.

get MVNs. This is highly desirable and precisely our goal, since a state-of-the-art algorithm from the field of word/text embedding, for example, might also work perfectly well for embedding any text attributes of an underlying MVN. In other words, the main idea here would be to apply property-by-property embedding using single-focus embedding methods (as they would, in theory, produce the best results), and to find a clever way to combine them, as discussed in Section 4.

3 THE FLEXIBILITY OF SEPARATION

Even for algorithms that do not encounter the problem of simultaneous minimization of loss functions, mentioned above, there is still a disadvantage in the fact that the resulting similarities can only be evaluated in combination, and not in separation. While this may be a desirable in some cases, it is also a drawback since, as with (Sun et al., 2016), a combined embedding of network topology and text attributes provides for detection of nodes that lie "near" each other and have similar text content, but it does not provide for comparison of nodes that have similar text content but lie far apart in the network (cf. Figure 2). However, if the embeddings had been separated into one for each property, it would have provided for any combination of the separate similarities, including inverted similarity. This would allow users to pose interesting questions such as "*Show me all the items that are similar with regard to property A and* <u>*dissimilar*</u> *with regard to property B*". Thus, we claim that a combined set of single focus embeddings will always provide for a wider, and more flexible, range of similarity calculations than a joint embedding of the same set. In fact, the range of possible similarity calculations of a joint property embedding will always be a subset of the range of possibilities of the set of the same properties embedded one by one. When considering the use of VA techniques and user domain expertise, this approach becomes even more powerful compared to the joint embedding, as it would allow for a more flexible and complex exploration of the underlying data.

4 THE POWER OF COMBINATION

For many of the properties that could be of interest for MVN embedding (e.g., network topology, textual content, or categorical attributes of nodes) there actually already exist several state-of-the-art embedding methods, each with their own strengths and weaknesses. Therefore, instead of trying to make a choice for the best one (which can be subjective and may vary from case to case), a feasible strategy would be to try to leverage them all in an ensemble combination. This is a well-known strategy in many other areas (Dong et al., 2020), relying for example on the fact that a well-chosen combination of different classifiers often has the potential to outperform any of the individual contributing classifiers.

Another argument to support this claim is the fact that a combination may hold a larger exploitable potential, since what has been missed by one classifier may be compensated for by another. This effect is especially strong for situations when the classifiers have a low level of inter-dependency, and hence it is desirable to combine different technologies. Furthermore, it is not unusual to obtain synergy effects for ensem-

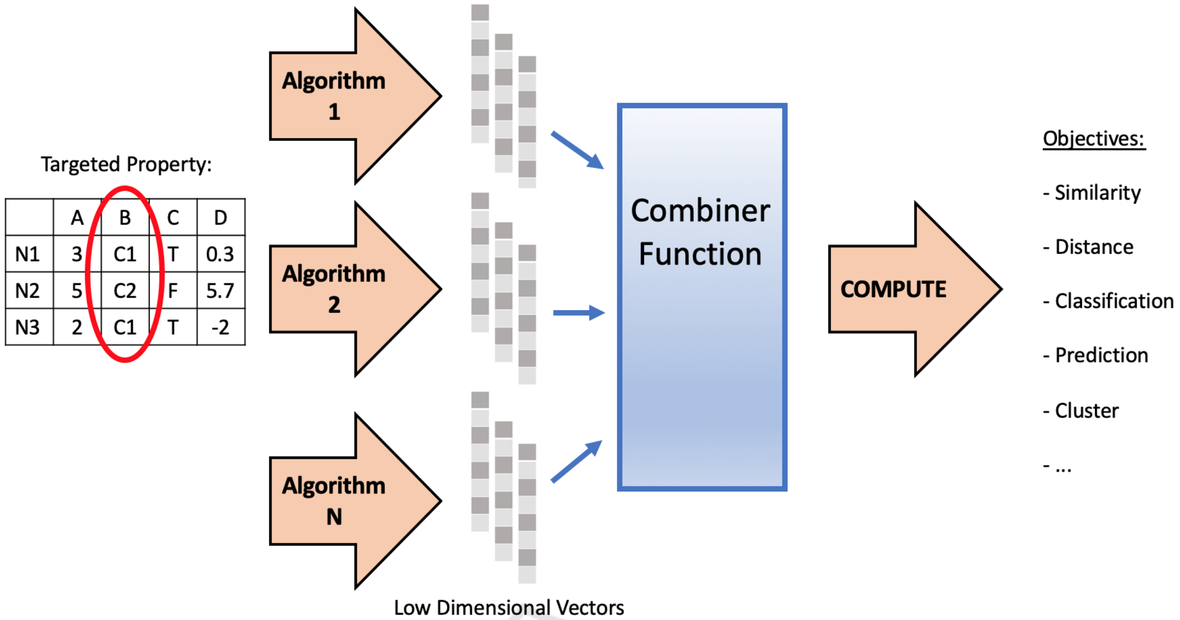

Figure 3: Applying the general idea of ensemble analysis to embeddings. A selected property is embedded by several different algorithms (or the same algorithm with different settings) and the results are combined to hopefully achieve a higher quality.

ble combinations such that the quality of the combined result is significantly higher than for any of the contributing parts taken by itself (Opitz and Maclin, 1999). By applying the same line of reasoning, with some modifications, to embeddings we believe that it is possible to use the general idea of ensemble analysis as a valid strategy also for this case (see Figure 3 for details).

5 CONCLUSIONS AND EARLY RESULTS

In line with the reasoning above, we conclude that trying to find ways to simultaneously embed several different properties of an MVN is a challenging task with some inevitable disadvantages. Therefore, a feasible strategy, that will likely provide for the highest quality and the maximal flexibility, is to instead embed properties one-by-one using state-of-the-art algorithms that target the data type of the specific property. Furthermore, if several state-of-the-art algorithms exist for a specific property, their respective yields could probably be combined for even higher quality by using ensemble calculations. From our perspective, the main pros of this approach are listed in the following:

- It gives a straight-forward method to obtain and combine embeddings of many important aspects of MVNs.
- Using an "all-embedding" approach allows for building homogeneous and effective pipelines for back-end calculations and processing.
- Advances from other areas can be readily reused within the field of MVN visualization and VA.

In contrast, the major cons of our approach might be:

- Tailor-made multi-feature embeddings may still be a better choice for specific applications.
- An "all-embedding" strategy is not necessarily the best for MVN analysis.
- Ensemble analysis is not a trivial task, and it will have to be adapted to the specific circumstances of each situation.

Taking all aspects into account, our overall conclusion is that the pros out-weight the cons, and with this paper we hope to convince the VA community to invest more work and time to develop

- novel approaches for combining existing embedding technologies in a MVN context,
- generic approaches for analyzing the quality and yield from embeddings of different data types, and
- generic approaches for assessing the performance of different ensemble strategies when facing several state-of-the-art algorithms.

To give further credibility to our claims we conclude by giving some early results from our work showing that the general ideas from ensemble analysis can indeed be applied to embeddings. In our test setup we have used some 3000 article abstracts from the IEEE conferences and embedded them in five different ways using paragraph-sized text embedding technologies. Performing all-to-all similarity calculations and verifying the results with regards to a small, manually labeled, ground-truth set indicates that an ensemble approach yields better quality than any of the single embeddings taken by themselves (Witschard et al., 2020). However, much work remains to be done to fully understand the general rules behind this process. Nevertheless, these promising first results, together with the generalizability of the approach to any embedding type, encourage us to use this as a foundation for attempting a general framework for MVN embedding.

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