

Response to reviewers

Manuscript ID **sensors-1909090**

I am very grateful to the reviewers for the insightful and constructive comments on my paper. All suggestions were considered, the detailed responses and relevant changes are given below.

A revised version of the manuscript is submitted, along with a version where the changes are highlighted.

In addition to the above comments, all spelling and grammatical errors have been corrected to my best knowledge. I am looking forward to hear from the reviewers regarding this submission and to respond to any further questions and comments they might have.

September 22, 2022

Gábor Kertész

Response to the Reviewer #1

I would like to thank the reviewer for the careful reading of this manuscript and for the thoughtful comments and constructive suggestions, which helped to improve the quality.

Response to comments

Reviewer Point 1.1 — Abstract: It's better to add the experimental analysis in this part. It's better to point out the main problem to be dealt with.

Reply: I thank the reviewer for this comment, and I agree: abstract has been extended.

Multiple studies have concluded that the selection of input samples is key for deep metric learning. For triplet networks, the selection of the anchor, positive and negative pairs is referred to as triplet mining. The selection of the negatives is considered the be the most complicated task, due to ~~the~~a large number of possibilities. The goal is to select a negative that results in a positive triplet loss, however, there are multiple approaches for this; semi-hard negative mining or hardest mining are well-known among random selection. Since its introduction, semi-hard mining proved to outperform other negative mining techniques, ~~however~~; however, in the last years selection of the so-called hardest negative has shown promising results in different experiments. This paper introduces a ~~technique of novel~~ negative sampling solution based on dynamic policy switching, referred to as Negative Sampling Probability Annealing, which aims to exploit the positives of all approaches. Results are validated on an experimental synthetic dataset using cluster analysis methods, finally, the discriminative ability of trained models are measured on real-life data.

Reviewer Point 1.2 — Introduction: The type of metric learning based on Riemannian manifold [1-3] can be added to enrich this part, and more basic knowledge about manifold can be referred to [3].

[1] R. Wang, X. -J. Wu and J. Kittler, "Graph Embedding Multi-Kernel Metric Learning for Image Set Classification With Grassmannian Manifold-Valued Features," in IEEE Transactions on Multimedia, vol. 23, pp. 228-242, 2021, doi: 10.1109/TMM.2020.2981189.

[2] M. Dai and H. Hang, "Manifold Matching via Deep Metric Learning for Generative Modeling," 2021 IEEE/CVF International Conference on Computer Vision (ICCV), 2021, pp. 6567-6577, doi: 10.1109/ICCV48922.2021.00652.

[3] X. Hua, Y. Ono, L. Peng and Y. Xu, "Unsupervised Learning Discriminative MIG Detectors in Nonhomogeneous Clutter," in IEEE Transactions on Communications, vol. 70, no. 6, pp. 4107-4120, June 2022, doi: 10.1109/TCOMM.2022.3170988.

Reply: Based on this valuable comment, the literature review is further extended with metric learning solutions on non-Euclidean spaces.

A different viewpoint of the problem concentrates on the fact that metric learning is done on Euclidean space, however loss is based on non-Euclidean distances [?]. Novel solutions are based on a special type of Riemannian manifold, e.g. the Grassmann manifold or the Stiefel manifold [?]. Multiple studies have concluded, that the application of metric learning in nonlinear structures are showing promising results in face recognition [?, ?, ?].

Reviewer Point 1.3 — It's better to add some references for the existing equations.

Reply: Thank you for this suggestion: in the revised manuscript existing equation (triplet loss, eq. (1)) has been cited. Other equations, formal representations of triplet learning partly appeared in classic literature of the topic, but during my research I haven't met a single publication such representation; therefore, I'm not able to give references.

Reviewer Point 1.4 — It's better to summary the main contribution in the introduction part.

Reply: Thank you for this suggestion: the end of the introduction section has been extended.

In this paper, a method of cluster analysis is introduced, based on the observations a novel negative sampling method is proposed and evaluated. Main contributions of the current study are:

1. Formal description and summarization of negative sampling methods;
2. Cluster analysis methods formally introduced and applied during different experiments on a synthetic dataset;
3. Introduction of the Negative Sampling Probability Annealing algorithm for negative selection, evaluation of results on synthetic dataset as well as actual data; it can bve concluded that while best performing models behave similarly, on general NSPA and random hard sampling seem to outperform other approaches.

Reviewer Point 1.5 — Conclusion: The authors missed the potential drawbacks of the proposed method.

Reply: Thank you for pointing this out: the relevant part of the conclusions section has been extended accordingly.

In this paper a novel negative sampling solution is presented. Results indicate that the approach is promising, however further research on hyperparameter tuning [?] could improve the applicability. It is worth mentioning, that some experiments with suboptimal parameter settings showed similar behavior as the worst performing setups.

Response to the Reviewer #2

First of all, I am very grateful to the reviewer for the detailed overview of the manuscript. I am very thankful for the encouraging comments. All suggestions were considered, the detailed responses are given below.

Response to comments

Reviewer Point 2.1 —

1. The findings are sufficiently novel to warrant publication.
2. The conclusions are adequately supported by the data presented.
3. The article is clearly and logically written so that it can be understood by one who is not an expert in the specific field.
4. The work provides an important contribution to its field, consistent with the scope of the journal, the problematics is clearly described. Methods are described and but not explained.

Reply: Thank you for recognizing these, I really appreciate it! Actually, the main goals when preparing the manuscript were to provide a proper formal description of the fundamentals and related literature, and to introduce and verify the NSPA method.

To support understanding and for open science purposes, all related materials are available online at <https://github.com/kerteszg/nspace> and <https://github.com/kerteszg/EmbeddingNet>.

Reviewer Point 2.2 — Rows 109 – 111: Please introduce the literature to the equations (1) – (11)

Reply: Thank you for this suggestion: in the revised manuscript existing equation (triplet loss, eq. (1)) has been cited. Other equations, formal representations of triplet learning partly appeared in classic literature of the topic, but during my research I haven't met a single publication such representation; therefore, I'm not able to give references.

Reviewer Point 2.3 — Row 112: Please introduce the literature about cluster analysis

Reply: Thank you for pointing this out. Relevant literature for cluster analysis has been cited, a classical book, and a recent paper.

To observe the effects of different sampling methods, cluster properties are observed on a synthetic dataset during triplet loss based metric learning. The following properties were defined and implemented, and measured during training, section ?? presents the findings.

For cluster analysis [?, ?], let's define the centroid c_y of class y as (...)

Reviewer Point 2.4 — Rows 116 -132: Please introduce the literature to the equations (12) – (20)

Reply: Thank you for the feedback. As these equations were defined by the author especially for this publication, no relevant references are available for each equation. However, for cluster analysis some work has been addressed, as described in the comment above.

Reviewer Point 2.5 — Row 174: Please introduce the applied software and shortly describe the minig method. All essential steps you have described only by the literature citation.

Reply: I am grateful for the reviewer for the thorough and detailed overview of my manuscript. The referred row is in subsection 3.1 *Synthetic Cluster Analysis*, where the actual implementation is briefly described. It was the intention of the author to keep the technical description short.

The software applied is the mentioned EmbeddingNet, and is implemented in Keras over TensorFlow. The prepared configurations are described element-by-element. EmbeddingNet and NSPA implementations are available online in public github repositories, mentioned above.

Training was implemented in Keras [?] and Tensorflow [?] using a slightly modified version of the EmbeddingNet framework [?, ?]. The embedding network used in the triplet earchitecture is a simple 32-to-16-to-2 fully-connected network with ReLU activations. Adam optimizer [?] was used with a learning rate set to $5 \cdot 10^{-4}$. No pretraining was applied. Mining was done by selecting 20-20 samples from each 5 classes in each training step. A training iteration (or epoch) consisted of 50 training steps. Training concluded when loss measured on the validation set stopped improving for at least 25 epochs.