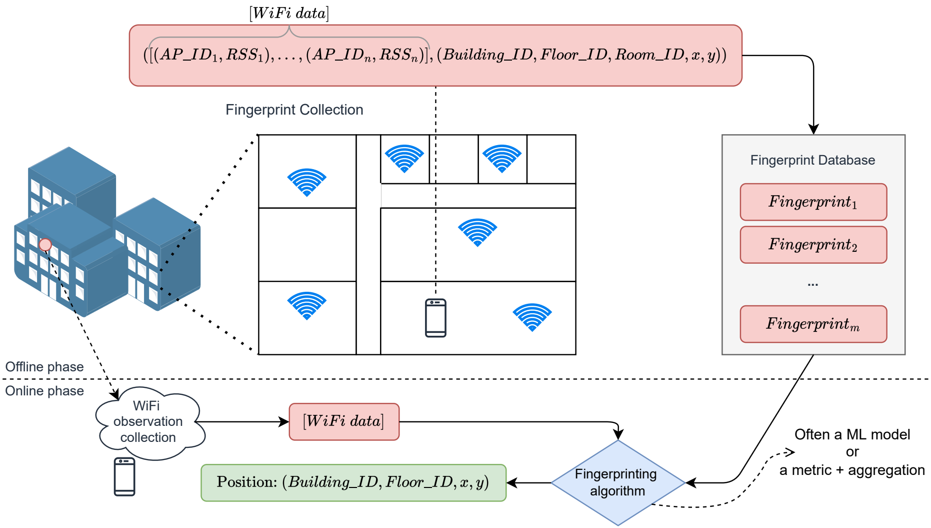
Fourth UK Mobile, Wearable and Ubiquitous Systems Research Symposium

Improving the Estimation of Fingerprint Spatial Relationships via Deep Metric Learning on Continuous Similarities

Nicola Saccomanno*, Andrea Brunello, Angelo Montanari
University of Udine, Italy
*currently visiting PhD student at UCL
nicola.saccomanno@uniud.it

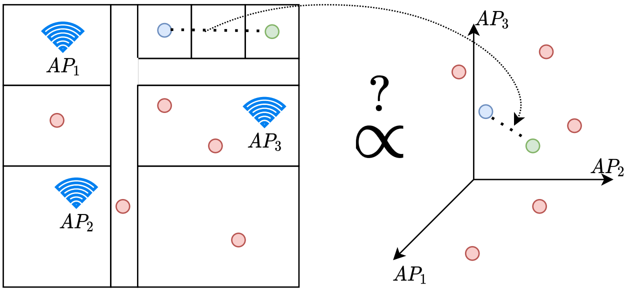
4th-5th July 2022, UCL

Indoor WiFi Fingerprint-based Localisation

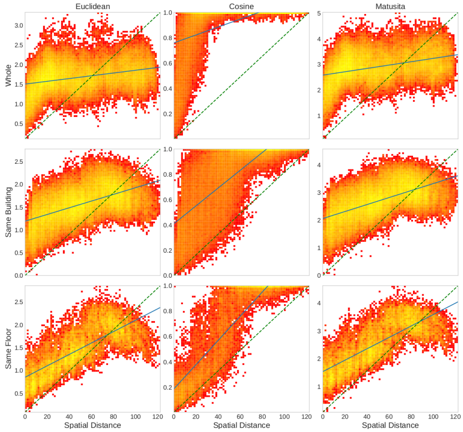


Main research question

Given a collection of (fingerprint, location) pairs $\mathcal{P} = \{(\mathbf{x}, \mathbf{y})_i \mid \mathbf{x} \in \mathbb{R}^m, \mathbf{y} \in \mathbb{R}^p\}_{i=1}^N$, where m is the number of available APs and p is the number of dimensions used to represent the locations, is it possible to determine the *spatial relationships* between fingerprints' locations by reasoning directly in the fingerprint space $\mathbb{R}^m$?



Fingerprints and Spatial Relationships - Classical Metrics

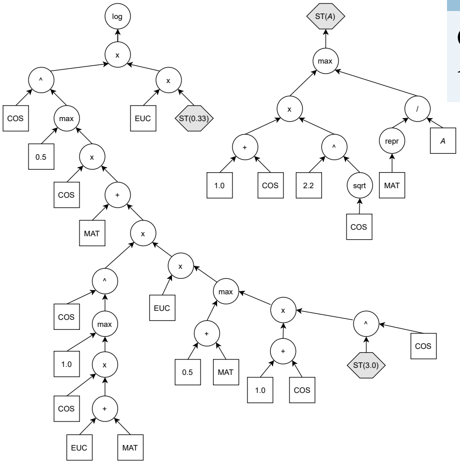


Research question

Can *classical* metrics characterise the spatial relationship between fingerprints' positions?

- Large systematic study on multiple metrics, datasets and granularities
- Metrics have rather heterogeneous behaviour, with some outperforming the others (e.g., cosine similarity)
- Variability across different scenarios
- Performance far from the optimal case: **classical metrics fail at characterising the spatial relationship between fingerprints' positions**

Fingerprints and Spatial Relationships - a Meta-metric



Research question

Could we get better performance by exploiting the heterogeneity of the individual metrics?

- Genetic programming to solve a symbolic regression task → *Learned Meta-metric*
- Good generalisation capabilities on unseen datasets
- Better results, but still not optimal: **likely to be limited from the considered data representation**
- *Bonus*: Correlation maximisation is a good proxy task for positioning: the meta-metric achieves top performance

Deep Metric Learning in a Nutshell

Deep Metric Learning (DML) aims to learn similarity metrics in an end-to-end fashion with deep neural networks. It consists of learning an embedding function $\phi_\theta : \mathcal{X} \rightarrow \mathcal{Z}$ from the feature space ($\mathcal{X}$) to a new latent one ($\mathcal{Z}$) in such a way that elements deemed similar according to a given similarity function (often evaluated over $\mathcal{X}$'s labels $\mathcal{Y}$) are mapped closer in $\mathcal{Z}$ than those considered to be dissimilar.

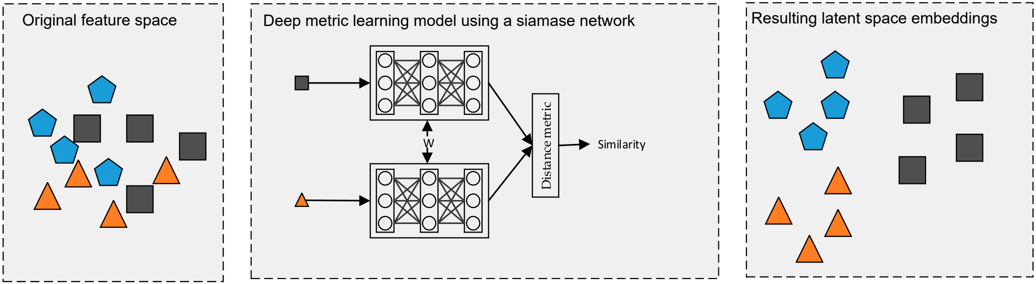


Figure adapted from Kaya M, Bilge HŞ. Deep Metric Learning: A Survey. *Symmetry*. 2019.

- Mainly developed by the computer vision community for tasks like face recognition, person re-identification, zero-shot and self-supervised learning
- Performance largely depends on the loss function and the sampling strategies
  - How to learn comprehensive relationships and leverage all the batch elements?
  - How to implicitly or explicitly mine informative tuples only?

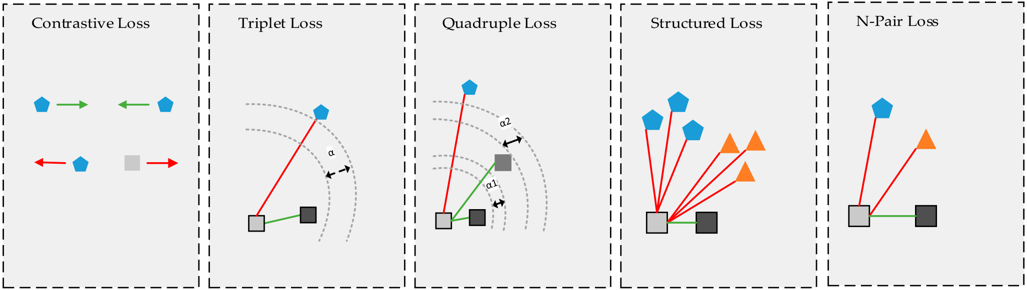


Figure from Kaya M, Bilge HŞ. Deep Metric Learning: A Survey. *Symmetry*. 2019.

DML for Fingerprinting

Research question

Can we leverage Deep Metric Learning to obtain an effective similarity function that captures the spatial relationship in the fingerprint space?

Dealing with fingerprints and spatial quantities requires *continuous similarity* assessments

Problem! DML has been defined almost only for binary similarities:

- **Continuous case is more complex** - ranking and proportionality
- Notions of negative and positive elements for tuples construction are not viable anymore
- Defining thresholds for binarization is domain and application dependent and rather ineffective

DML for Fingerprinting - a Possible Approach

A possible solution to achieve DML preserving the desired properties is to rely on distance ratios, requiring that:

$$\frac{s(\mathbf{y}_i, \mathbf{y}_j)}{s(\mathbf{y}_k, \mathbf{y}_h)} = c \cdot \frac{\| \phi_\theta(\mathbf{x}_i) - \phi_\theta(\mathbf{x}_j) \|_2^2}{\| \phi_\theta(\mathbf{x}_k) - \phi_\theta(\mathbf{x}_h) \|_2^2} ,$$

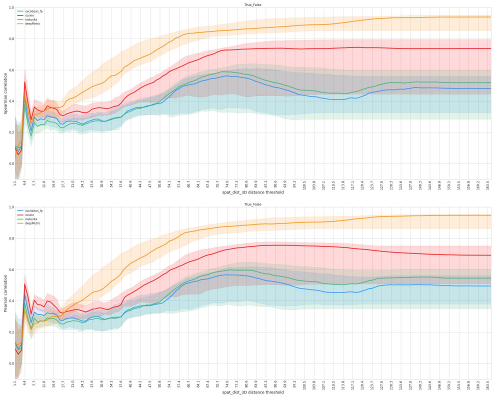
where $s : \mathbb{R}^p \times \mathbb{R}^p \to \mathbb{R}$ is a similarity function over the label space (e.g., in fingerprinting, the Euclidean distance), c is a scaling factor, and $i, j, k, h \in 1, \ldots, N$.

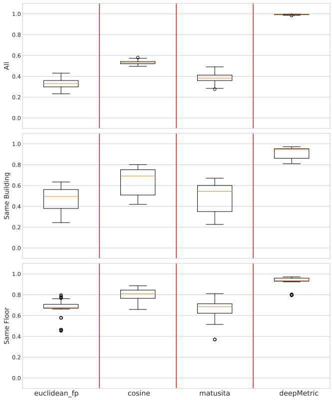
Note that ratios have some interesting properties in this context:

- The learning task becomes independent from s, and the scale of the labels
- The choice of the metric used over $\mathcal{Z}$ becomes (almost) irrelevant
- Preserving proportions grants ranking

Preliminary results are very encouraging but:

- Problems that are solved in binary-supervised DML here might be open
- Specific continuous-related issues, e.g., imbalance in the distances distribution





DML for Fingerprinting - Why Does it Matter?

- Ease the radio-map creation and maintenance:
  - Having a more reliable metric should allow for a more sparse fingerprint collection
- Promoting the development of semi-supervised localisation solutions:
  - DML is a supervised task, yet it requires knowing only the spatial distances between two fingerprints...
  - ... but such information can be acquired using auxiliary sensors
  - crowdsourcing + a few points labelled with the precise location
- Possible improvement in other downstream tasks
- The approach is rather general and thus may be interesting per se for the ML community, beyond the specific application domain

Questions?

nicola.saccomanno@uniud.it

Some references:

- Saccomanno, N., Brunello, A., & Montanari, A. (2021). What you sense is not where you are: On the relationships between fingerprints and spatial knowledge in indoor positioning. IEEE Sensors Journal
- Brunello, A., Montanari, A., & Saccomanno, N. (2022). A Genetic Programming Approach to WiFi Fingerprint Meta-distance Learning. Under Review
- Kim, S., Seo, M., Laptev, I., Cho, M., & Kwak, S. (2019). Deep metric learning beyond binary supervision. IEEE/CVF CVPR