

Master Thesis Seminar Talk Progress Update

Fabrice Beaumont

Department of Information Systems and Artificial Intelligence - Dr. Pascal Welke

10. August 2022

Recap progress



- Cleaning the datasets
- Preparing comparison
- Re-thinking the WLLT structure
- ► Tree-Wasserstein distances

 [2019, Tam Le, Tree-Sliced Variants of Wasserstein Distances]
- "Naive" feedback loop

Naive feedback loop



- ► Initialize all edge weights as 1.0.
- Compute the Tree Wasserstein Distance¹ between two graphs
- Pics the n highest differences in the weighted difference vector.²
- \blacktriangleright Push and pull graphs by changing the weights py percentage (0.1):

$$w' = egin{cases} w*(1+p_{\mathsf{push}}) \ w*(1-p_{\mathsf{pull}}) \end{cases}$$

¹Normalized weighted distance between their wl-label histograms.

²Most expensive earth that had to be moved.

Naive feedback loop



- ► Initialize all edge weights as 1.0.
- Compute the Tree Wasserstein Distance³ between two graphs
- Pics the n highest differences in the weighted difference vector.⁴
- ightharpoonup Push and pull graphs by changing the weights py percentage (0.1):

$$w' = egin{cases} w*(1+p_{\mathsf{push}}) \ w*(1-p_{\mathsf{pull}}) \end{cases}$$

- ! Ensure that the sum of the edge weights is the same
- ! Ensure that the impact on the weights is proportional to the number of graphs in the sample

³Normalized weighted distance between their wl-label histograms.

⁴Most expensive earth that had to be moved.



Evaluation process

Implemented:

- Silhouette score
- Mean weight per WLLT layer

Outlook for august



- 1. Play with the settings, document different results
- 2. Fix and extend the evaluation process:
 - ▶ Mean intra distance in and inter distance between clusters
 - Percentage of changed weights
 - Classification accuracy compared to other methods

Further outlook



Further outlook:

- Implement different edge weight training:
 - ▶ Batch learning, Weight update after each distance computation
 - Treat weights in WLLT layers differently (e.g. update only leaves)
 - Update all weights in the WLLT path
 - ▶ ...
- Initialize edge weights via FRM method

Thank you all for listening.

I will be happy to answer any questions and hear your comments.



Preparation of the performance comparison

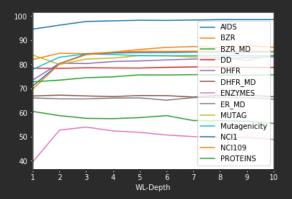


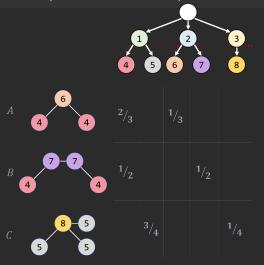
Figure: Classification accuracies on databases using Weisfeiler-Lehman.

grakel.kernels.WeisfeilerLehman(n_iter=[1-10], base=grakel.kernels.VertexHistogram, normalize=True)

10. August 2022

UNIVERSITÄT BONN Lab

Example of the whole procedure



Tree metric:

Wasserstein Dist.:

$$W_t(A, B) = \frac{4}{3}$$

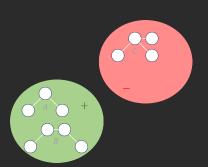
 $W_t(A, C) = 3$
 $W_t(B, C) = 3$

$$d_{WLLT}(B, C) = 2 * \frac{2}{4} + 4 * \frac{1}{4} + 4 * \frac{1}{4} = \frac{12}{4} = 3$$

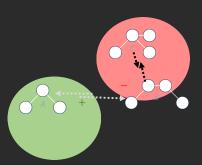
Example of the whole procedure



Current clustering:



Target clustering:

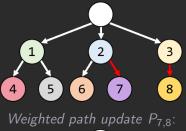


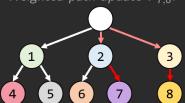
Idea: Reduce distance between B and C, by updating the edge weights.

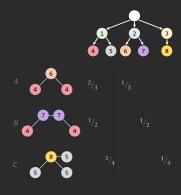


Example of the whole procedure

Local update P_{7,8}:







Implementation road-map 1/2



- WLLT Construction:
 - ▶ Write to file and read from file. Construct WL-iteration based.
 - ► All weights *equal*.
 - (Random initial weights.)
 - ► (Use *a priori* knowledge.)
- Wasserstein-Distance feedback:
 - "Biggest pile of dirt". ("Smallest", to increase the distance.)
 - Distribution proportional to the pile size.
 - Distribution proportional to the cost of moving the pile size.

Implementation road-map 2/2



- Update rule:
 - Value:
 - ightharpoonup Constant λ .
 - Gradient descent.
 - ▶ Location:
 - Local: Only update the first and last edge weights of the connecting path.
 - Weighted path: Update all edge weights on the path, with less magnitude for edges closer to the root.
 - Path: Update all edges on the path.
 - ► Global: Update all edges, related to all occurring labels.