

# Master Thesis Seminar Talk Progress Upade

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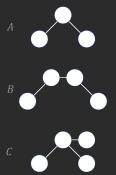
11. May 2022

## Progress overview

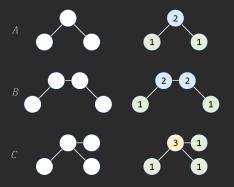


- Task formulation, registration of the thesis:
   "Learning graph similarity measures using the
   Weisfeiler-Lehman label hierarchy"
   Definition of several sub-goals a programming road-map.
- Implementation of a dynamic Dataset Loader (GarKel, OGB, from file).
  - Easily expandable for other frameworks.

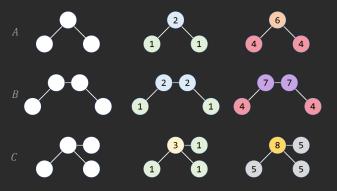




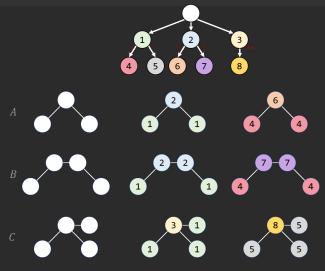
















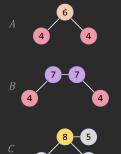








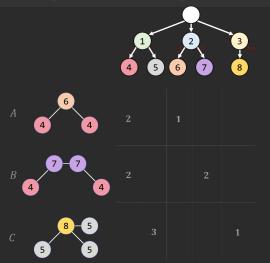




Tree metric between the WL-labels:

$$\begin{pmatrix}
4 & 5 & 6 & 7 & 8 \\
 & 2 & 4 & 4 & 4 \\
 & & & 4 & 4 & 4 \\
 & & & & \ddots & 2 & 4 \\
 & & & & & & \ddots & 4
\end{pmatrix}$$

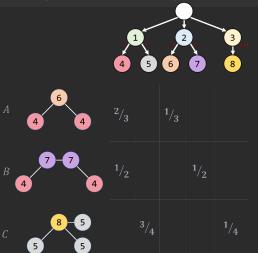




#### Tree metric:

$$\begin{pmatrix} 4 & 5 & 6 & 7 & 8 \\ \cdot & 2 & 4 & 4 & 4 \\ & \cdot & 4 & 4 & 4 \\ & & \cdot & 2 & 4 \\ & \uparrow \uparrow & & \cdot & 4 \end{pmatrix}$$

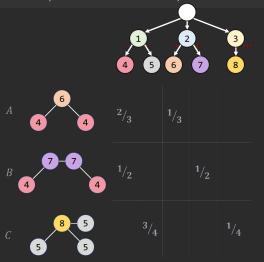




#### Tree metric:

$$\begin{pmatrix} 4 & 5 & 6 & 7 & 8 \\ \cdot & 2 & 4 & 4 & 4 \\ & \cdot & 4 & 4 & 4 \\ & & \cdot & 2 & 4 \\ & \uparrow \uparrow & & \cdot & 4 \end{pmatrix}$$



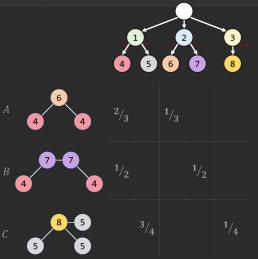


#### Tree metric:

#### Wasserstein Dist.:

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





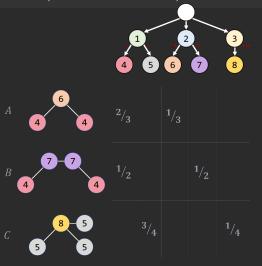
#### Tree metric:

#### Wasserstein Dist.:

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

$$d_{\text{WLLT}}(A, C) = 2 * \frac{8}{12} + 4 * \frac{1}{12} + 4 * \frac{4}{12} = \frac{18}{6} = 3$$





#### Tree metric:

#### Wasserstein Dist.:

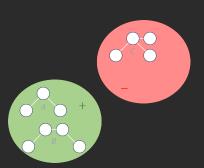
$$W_t(A, B) = \frac{4}{3}$$
  
 $W_t(A, C) = 3$   
 $W_t(B, C) = 3$ 

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

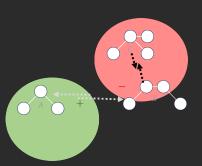
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## Example of the whole procedure

#### **Current clustering:**



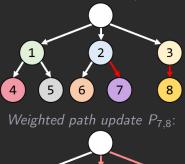
#### Target clustering:

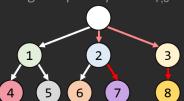


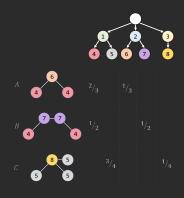
Idea: Reduce distance between B and C, by updating the edge weights.



#### Local update P<sub>7,8</sub>:

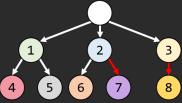




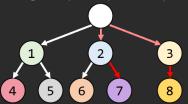




#### Local update P<sub>7,8</sub>:



#### Weighted path update P<sub>7.8</sub>:



#### Update rule:

#### Value:

- ightharpoonup Constant  $\lambda$ .
- ► 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: . . .
- ► Global: ...

### Next steps



- Implement the usage of the Wasserstein Distance.
- Implement a "naive" feedback loop to update the WLLT edge weights.
  - (And the more and more complex variations.)

## Thank you all for listening.

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

## 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  $\lambda$ .
    - 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.