

# Ontologies – Future Perspectives

Semantic Web

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## 1 Exercise 1: FolkRank

Given are the following tag assignments:

(u1, t1, r1)

(u1, t2, r1)

(u1, t2, r2)

(u2, t2, r2)

1. Compute the FolkRank for the folksonomy induced by the given tag assignments (only perform the first Iteration,  $d = 0.5$ ). The Vector  $\vec{w}$  should be initialized as follows:

$$\vec{p} = \begin{pmatrix} \text{ranking score of } u_1 \\ \text{ranking score of } u_2 \\ \text{ranking score of } t_1 \\ \text{ranking score of } t_2 \\ \text{ranking score of } r_1 \\ \text{ranking score of } r_2 \end{pmatrix} = \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \end{pmatrix}$$

The preference vector is given as follows:

$$\vec{p} = \begin{pmatrix} \text{preference in } u_1 \\ \text{preference in } u_2 \\ \text{preference in } t_1 \\ \text{preference in } t_2 \\ \text{preference in } r_1 \\ \text{preference in } r_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 21 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

Note that  $\vec{p}$  has to fulfill the condition  $\|\vec{w}\|_1 = \|\vec{p}\|_1$ .

### 1.1 Solution

From the given tag assignments we construct a graph, which is then modeled within the adjacency matrix  $A$ . Therefore, we construct  $A$  by going through the given tag assignments step by step.

#### Construction of Adjacency Matrix $A$ :

The dimensions of  $A$  have to correspond to the dimensions of the preference

vector  $\vec{p}$  and the vector  $\vec{w}$ , i.e.:

|       | $u_1$ | $u_2$ | $t_1$ | $t_2$ | $r_1$ | $r_2$ |
|-------|-------|-------|-------|-------|-------|-------|
| $u_1$ |       |       |       |       |       |       |
| $u_2$ |       |       |       |       |       |       |
| $t_1$ |       |       |       |       |       |       |
| $t_2$ |       |       |       |       |       |       |
| $r_1$ |       |       |       |       |       |       |
| $r_2$ |       |       |       |       |       |       |

Step 1  $((u_1, t_1, r_1))$ :

|       | $u_1$ | $u_2$ | $t_1$ | $t_2$ | $r_1$ | $r_2$ |
|-------|-------|-------|-------|-------|-------|-------|
| $u_1$ |       |       | 1     |       | 1     |       |
| $u_2$ |       |       |       |       |       |       |
| $t_1$ | 1     |       |       |       | 1     |       |
| $t_2$ |       |       |       |       |       |       |
| $r_1$ | 1     |       | 1     |       |       |       |
| $r_2$ |       |       |       |       |       |       |

Step 2  $((u_1, t_2, r_1))$ :

|       | $u_1$ | $u_2$ | $t_1$ | $t_2$ | $r_1$ | $r_2$ |
|-------|-------|-------|-------|-------|-------|-------|
| $u_1$ |       |       | 1     | 1     | 2     |       |
| $u_2$ |       |       |       |       |       |       |
| $t_1$ | 1     |       |       |       | 1     |       |
| $t_2$ | 1     |       |       |       | 1     |       |
| $r_1$ | 2     |       | 1     | 1     |       |       |
| $r_2$ |       |       |       |       |       |       |

Step 3  $((u_1, t_2, r_2))$ :

|       | $u_1$ | $u_2$ | $t_1$ | $t_2$ | $r_1$ | $r_2$ |
|-------|-------|-------|-------|-------|-------|-------|
| $u_1$ |       |       | 1     | 2     | 2     | 1     |
| $u_2$ |       |       |       |       |       |       |
| $t_1$ | 1     |       |       |       | 1     |       |
| $t_2$ | 2     |       |       |       | 1     | 1     |
| $r_1$ | 2     |       | 1     | 1     |       |       |
| $r_2$ | 1     |       |       | 1     |       |       |

Step 4  $((u_2, t_2, r_2))$ :

|       | $u_1$ | $u_2$ | $t_1$ | $t_2$ | $r_1$ | $r_2$ |
|-------|-------|-------|-------|-------|-------|-------|
| $u_1$ |       |       | 1     | 2     | 2     | 1     |
| $u_2$ |       |       |       | 1     |       | 1     |
| $t_1$ | 1     |       |       |       | 1     |       |
| $t_2$ | 2     | 1     |       |       | 1     | 2     |
| $r_1$ | 2     |       | 1     | 1     |       |       |
| $r_2$ | 1     | 1     |       | 2     |       |       |

Step 5 – Build the 1-norm for each row:

|       | $u_1$         | $u_2$         | $t_1$         | $t_2$         | $r_1$         | $r_2$         |
|-------|---------------|---------------|---------------|---------------|---------------|---------------|
| $u_1$ |               |               | $\frac{1}{6}$ | $\frac{2}{6}$ | $\frac{2}{6}$ | $\frac{1}{6}$ |
| $u_2$ |               |               |               | 0.5           |               | 0.5           |
| $t_1$ | 0.5           |               |               |               | 0.5           |               |
| $t_2$ | $\frac{2}{6}$ | $\frac{1}{6}$ |               |               | $\frac{1}{6}$ | $\frac{2}{6}$ |
| $r_1$ | 0.5           |               | 0.25          | 0.25          |               |               |
| $r_2$ | 0.25          | 0.25          |               | 0.5           |               |               |

**Compute  $\vec{w}_0$** 

For the computation of  $\vec{w}_0$  we have to set  $d = 1$  so that there is no influence of the preference vector ( $\vec{w}_0 \leftarrow A \cdot \vec{w}_0$ ).

Iteration 1:

$$\vec{w}_{0,1} = A \cdot \vec{w}_{0,0} = \begin{pmatrix} 0 & 0 & \frac{1}{6} & \frac{2}{6} & \frac{2}{6} & \frac{1}{6} \\ 0 & 0 & 0 & 0.5 & 0 & 0.5 \\ 0.5 & 0 & 0 & 0 & 0.5 & 0 \\ \frac{2}{6} & \frac{1}{6} & 0 & 0 & \frac{1}{6} & \frac{2}{6} \\ 0.5 & 0 & 0.25 & 0.25 & 0 & 0 \\ 0.25 & 0.25 & 0 & 0.5 & 0 & 0 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \end{pmatrix} = \begin{pmatrix} 4.5 \\ 5 \\ 3 \\ 3.5 \\ 2.25 \\ 2.75 \end{pmatrix}$$

**Compute  $\vec{w}_1$** 

For the computation of  $\vec{w}_1$  we work with the given value  $d = 0.5$  and the given preference vector ( $\vec{w}_1 \leftarrow dA \cdot \vec{w}_1 + (1-d)\vec{p}$ ).

Iteration 1:

$$\vec{w}_{1,1} = dA \cdot \vec{w}_{1,0} + (1-d)\vec{p} = 0.5 \cdot \begin{pmatrix} 0 & 0 & \frac{1}{6} & \frac{2}{6} & \frac{2}{6} & \frac{1}{6} \\ 0 & 0 & 0 & 0.5 & 0 & 0.5 \\ 0.5 & 0 & 0 & 0 & 0.5 & 0 \\ \frac{2}{6} & \frac{1}{6} & 0 & 0 & \frac{1}{6} & \frac{2}{6} \\ 0.5 & 0 & 0.25 & 0.25 & 0 & 0 \\ 0.25 & 0.25 & 0 & 0.5 & 0 & 0 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \end{pmatrix} + 0.5 \cdot \begin{pmatrix} 0 \\ 0 \\ 21 \\ 0 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 2.25 \\ 2.5 \\ 12 \\ 1.75 \\ 1.125 \\ 1.375 \end{pmatrix}$$

**Compute  $\vec{w}$** 

$$\vec{w} = \vec{w}_1 - \vec{w}_0 = \begin{pmatrix} 2.25 \\ 2.5 \\ 12 \\ 1.75 \\ 1.125 \\ 1.375 \end{pmatrix} - \begin{pmatrix} 4.5 \\ 5 \\ 3 \\ 3.5 \\ 2.25 \\ 2.75 \end{pmatrix} = \begin{pmatrix} -2.25 \\ -2.5 \\ 9 \\ -1.75 \\ -1.125 \\ -1.375 \end{pmatrix}$$

## 2 Exercise 2: Personomy, Association Rules

Given are the following tag assignments:

(u1, jazz, r1)  
(u1, trumpet, r1)  
(u2, music, r1)  
(u2, jazz, r2)  
(u3, chet-baker, r2)  
(u3, music, r2)  
(u1, classic, r3)  
(u2, music, r3)

1. Write down the *Personomies* for each user.
2. Detect two “good” association rules.

### 2.1 Solution – Personomies

Personomy of user  $u_1$ :  $P_{u_1} := (T_{u_1}, R_{u_1}, Y_{u_1})$ , where:

- $T_{u_1} = \{\text{jazz, trumpet, classic}\}$
- $R_{u_1} = \{r_1, r_3\}$
- $Y_{u_1} = \{(\text{jazz}, r_1), (\text{trumpet}, r_1), (\text{classic}, r_3)\}$

Personomy of user  $u_2$ :  $P_{u_2} := (T_{u_2}, R_{u_2}, Y_{u_2})$ , where:

- $T_{u_2} = \{\text{music, jazz}\}$
- $R_{u_2} = \{r_1, r_2, r_3\}$
- $Y_{u_2} = \{(\text{music}, r_1), (\text{jazz}, r_2), (\text{music}, r_3)\}$

Personomy of user  $u_3$ :  $P_{u_3} := (T_{u_3}, R_{u_3}, Y_{u_3})$ , where:

- $T_{u_3} = \{\text{chet-baker, music}\}$
- $R_{u_3} = \{r_2\}$
- $Y_{u_3} = \{(\text{chet-baker}, r_2), (\text{music}, r_2)\}$

### 2.2 Solution – Association Rules

The set of items is equal to the set of tags:  $I = T = \{\text{jazz, trumpet, music, chet-baker, classic}\}$

Transactions:  $D = \{D_{r_1}, D_{r_2}, D_{r_3}\}$ , where  $D_{r_1} = \{\text{jazz, trumpet, music}\}$ ,  $D_{r_2} = \{\text{jazz, chet-baker, music}\}$ , and  $D_{r_3} = \{\text{classic, music}\}$ .

Examples for association rules:

#### 1. music $\implies$ jazz

$$\text{support}(\text{music} \implies \text{jazz}) = \frac{2}{3}, \text{confidence}(\text{music} \implies \text{jazz}) = \frac{2}{3}$$

**2. jazz  $\implies$  music**

$$\text{support}(\text{jazz} \implies \text{music}) = \frac{2}{3}, \text{confidence}(\text{jazz} \implies \text{music}) = \frac{2}{2} = 1$$

**3. trumpet  $\implies$  classic**

$$\text{support}(\text{trumpet} \implies \text{classic}) = \frac{0}{3} = 0, \text{confidence}(\text{trumpet} \implies \text{classic}) = \frac{0}{1} = 0$$

**4. classic  $\implies$  music**

$$\text{support}(\text{classic} \implies \text{music}) = \frac{1}{3}, \text{confidence}(\text{classic} \implies \text{music}) = \frac{1}{1}$$

**Discussion:**

If we compare rule 1 and 2 then we can clearly say that “*jazz  $\implies$  music*” (rule 2) is a better rule than “*music  $\implies$  jazz*” (rule 1). Both rules have the same support level. However, the confidence of rule 2 is higher than the one of rule 1. In particular, “*confidence(jazz  $\implies$  music) = 1*” means that whenever “jazz” occurs then “music” occurs as well.

The hypothesis of the ontology learning approach, which is based on association rules, is the following: An association rule “*tag<sub>x</sub>  $\implies$  tag<sub>y</sub>*” learned from a folksonomy can be interpreted as “*tag<sub>x</sub> is a sub-concept of tag<sub>y</sub>*”. For our example, we could thus say that “*jazz is a sub-concept of music*”, which makes sense.

Assumption of the ontology learning approach, which is based on association rules: More general tags occur more often than specialized tags. Hence, the probability that “*confidence(super-tag  $\implies$  sub-tag)  $\leq$  confidence(sub-tag  $\implies$  super-tag)*” is higher than “*confidence(sub-tag  $\implies$  super-tag)  $\leq$  confidence(super-tag  $\implies$  sub-tag)*”.