

Transferring Heterogeneous Links across Location-Based Social Networks



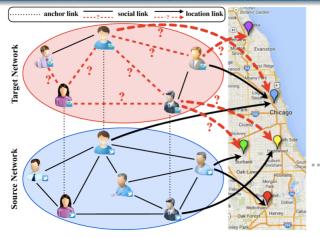
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1. Multiple Aligned LBSNs & Link Prediction Problem



- 1. Location-based social networks (LBSNs) are one kind of online social networks offering geographic services.
- 2. Multiple Aligned Networks: users are usually involved in multiple networks simultaneously.
- 3. Link Prediction: predict links to be formed in the future based on a snapshot of online social networks.

Figure 1: Example of collective link transferring across two aligned location-based social networks.4. Social Links & Location Links

Problem Studied:

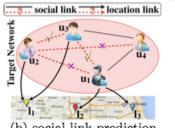
Predict Social Links and Location Links for a New

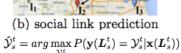
Location-based social network.

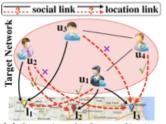
Challenges:

- Collective Link Prediction: Multiple link prediction tasks in one network can be correlated.
- 2. **New Network Problem**: Information in new networks is very sparse.

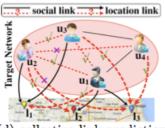
2. Solve Challenge 1: Collective Link Prediction







(c) location link prediction $\hat{\mathcal{Y}}_{l}^{t} = \arg \max P(\mathbf{y}(\mathbf{L}_{l}^{t}) = \mathcal{Y}_{l}^{t} | \mathbf{x}(\mathbf{L}_{l}^{t}))$



(d) collective link prediction $\hat{\mathcal{Y}}_{s}^{t}, \hat{\mathcal{Y}}_{t}^{t} = \arg\max_{\mathcal{V}^{t}, \mathcal{V}_{s}^{t}} P(\mathbf{y}(\mathbf{L}_{s}^{t}) = \mathcal{Y}_{s}^{t} | \mathbf{y}(\mathbf{L}_{t}^{t}) = \mathcal{Y}_{t}^{t}, \mathbf{x}(\mathbf{L}_{s}^{t}))$

 $\mathbf{x}(L)$: feature vectors of links in L; $\mathbf{y}(L)$: labels of links in L, Ls: social links, L: location links.

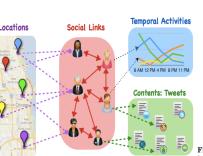




Figure 2: Example of information accumulation for locations from online posts.

Extracted Features

 Table 2: Features extracted from vector x and y

 Features
 Descriptions

 Extended Degree Count (EDC)
 $\|x\|_1, \|y\|_1$

 Extended Degree Ratio (EDR)
 $\|x\|_1/\|y\|_1$

 Extended Common Neighbour (ECN)
 $x \cdot y$

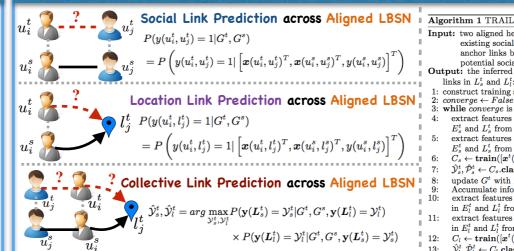
 Extended Jaccard's Coefficient (EJC)
 $\frac{x \cdot y}{\|x\|_1 \cdot \|y\|_1}$

 Extended Preferential Attachment (EPA)
 $\|x\|_1 \cdot \|y\|_1$

 Euclidean Distance (ED)
 $(\sum_k (x_k - y_k)^2)^{1/2}$

 Cosine Similarity (CS)

3. Solve Challenge 2: New Network Problem



Alternatively Update to get the optimal labels

$$\hat{\mathcal{Y}}_{s}^{t(\tau)} = \arg \max_{\mathcal{Y}_{s}^{t}} P(\mathbf{y}(\mathbf{L}_{s}^{t}) = \mathcal{Y}_{s}^{t} | G^{t}, G^{s}, \mathbf{y}(\mathbf{L}_{s}^{t}) = \hat{\mathcal{Y}}_{s}^{t(\tau-1)}, \quad \hat{\mathcal{Y}}_{l}^{t(\tau)} = \arg \max_{\mathcal{Y}_{l}^{t}} P(\mathbf{y}(\mathbf{L}_{l}^{t}) = \mathcal{Y}_{s}^{t} | G^{t}, G^{s}, \mathbf{y}(\mathbf{L}_{s}^{t}) = \hat{\mathcal{Y}}_{s}^{t(\tau)}, \quad \parallel 18: \text{ end if } \mathbf{y}(\mathbf{L}_{s}^{t}) = \mathbf{y}(\mathbf{L}_{s}^{t}) = \hat{\mathcal{Y}}_{s}^{t(\tau-1)}$$

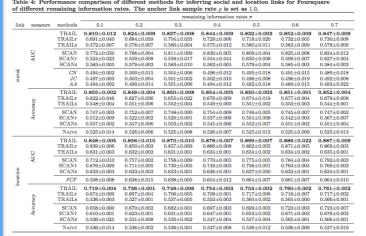
$$\mathbf{y}(\mathbf{L}_{l}^{t}) = \hat{\mathcal{Y}}_{l}^{t(\tau-1)}) \quad \mathbf{y}(\mathbf{L}_{l}^{t}) = \hat{\mathcal{Y}}_{l}^{t(\tau-1)}$$

$$\parallel \mathbf{y}(\mathbf{L}_{s}^{t}) = \hat{\mathcal{Y}}_{s}^{t(\tau-1)}$$

Algorithm 1 TRAIL Input: two aligned heterogeneous LBSNs, G^s , G^t . existing social links and location links: E^t_s , E^t_t anchor links between G^t and G^s : $A^{t,s}$, $A^{s,t}$ potential social links and location links: L^t_s , L^t_t Output: the inferred labels and existence probabilities of links in L^t_s and L^t_t : $\dot{\mathcal{Y}}^t_s$, $\dot{\mathcal{P}}^t_s$, $\dot{\mathcal{Y}}^t_t$, $\dot{\mathcal{P}}^t_t$ 1: construct training sets, test sets with E^t_s , E^t_t , L^t_s and L^t_t . 2: converge \leftarrow False

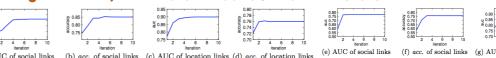
- 3: while converge is False do
 4: extract features $\boldsymbol{x}^t(E_s^t)$ and $\boldsymbol{x}^t(L_s^t)$ for social links in E_s^t and L_s^t from G^t .
 5: extract features $\boldsymbol{x}^s(E_s^t)$ and $\boldsymbol{x}^s(L_s^t)$ for social links in
- $E_s^t \text{ and } L_s^t \text{ from } G^s \text{ by utilizing anchor links in } A^{t,s}$ $\vdots \quad C_s \leftarrow \mathbf{train}([\boldsymbol{x}^t(E_s^t)^T, \boldsymbol{x}^s(E_s^t)^T, \boldsymbol{y}^s(E_s^t)]^T, \boldsymbol{y}^t(E_s^t))$ $7: \quad \mathcal{Y}_s^t, \hat{\mathcal{P}}_s^t \leftarrow C_s.\mathbf{classify}([\boldsymbol{x}^t(L_s^t)^T, \boldsymbol{x}^s(L_s^t)^T, \boldsymbol{y}^s(L_s^t)]^T)$ $3: \quad \text{update } G^t \text{ with } \hat{\mathcal{Y}}_s^t, \hat{\mathcal{P}}_s^t$
- 9: Accumulate information for locations
 10: extract features x^t(E^t_l) and x^t(L^t_l) for location links in E^t_l and L^t_l from G^t.
- extract features x^s(E_t^t) and x^s(L_t^t) for location links in E_t^t and L_t^t from G^s by utilizing anchor links in A^{t,s}.
 C_l ← train([x^t(E_t^t)^T, x^s(E_t^t)^T, y^s(E_t^t)]^T, y^t(E_t^t))
 ŷ_t^t, ŷ_t^t ← C_t classify([x^t(L_t^t)^T, x^s(L_t^t)^T, y^s(L_t^t)]^T)
- 14: update G^t with $\hat{\mathcal{Y}}_t^t, \hat{\mathcal{P}}_t^t$ 15: if $\hat{\mathcal{Y}}_s^t, \hat{\mathcal{P}}_t^t, \hat{\mathcal{Y}}_t^t, \hat{\mathcal{P}}_t^t$ all converge then $converge \leftarrow True$
- 16: converge $\leftarrow True$ 17: end if
 18: end while
 19: Return $\hat{\mathcal{Y}}_i^t, \hat{\mathcal{P}}_i^t, \hat{\mathcal{Y}}_i^t, \hat{\mathcal{P}}_i^t$

Experiments



| Part |

Convergence Analysis: (a)-(d) are the results when $\sigma=0.5$ and $\rho=1.0$; (e)-(h) are the same results when $\sigma=1.0$ and $\rho=0.5$



5. Acknowledgements

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