



Meta-path based Multi-Network Collective Link Prediction

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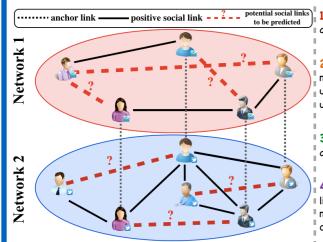
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1. Multi-Network Collective Link Prediction Problem



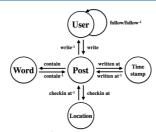
- 1. Problem Studied: Collective social link prediction across multiple aligned heterogeneous social networks.
- 2. Anchor User & Non-anchor Users: Users who join multiple social networks simultaneously are called anchor users. The remaining unshared users are called non-anchor
- 3. Aligned Social Networks: networks sharing common anchor users are called aligned social networks.
- 4. Collective Social Link Prediction: Predicting social links to be formed in the future based on a snapshot of multiple aligned online social network simultaneously is called collective social link prediction problem.

Challenge 1: What kind of features can be extracted from the network?

Challenge 2: How to formulate the social link prediction problem?

Challenge 3: How to predict social links in multiple aligned networks simultaneously?

2. Feature extraction based on intra & inter-network meta paths



Definition 10 (Intra-Network Social Meta Path): For a given meta path $\Phi = T_1 \xrightarrow{R_1} T_2 \xrightarrow{R_2} \cdots \xrightarrow{R_{k-1}} T_k$ defined based on S_G , if T_1 and T_k are both the "User" node type, then P is defined as a *social meta path*. Depending on whether T_1, \dots, T_k and R_1, \dots, R_{k-1} are the same or not, P can be divided into two categories: homogeneous intranetwork social meta path and heterogeneous intra-network

Definition 11 (Intra-Network Social Meta Path based Features): For a given link (u, v), the feature extracted for it pased on meta path $\Phi = T_1 \xrightarrow{R_1} T_2 \xrightarrow{R_2} \cdots \xrightarrow{R_{k-1}} T_k$ from the network is defined to be the expected number of formed path instances between u and v in the network:

$$x(u,v) = I(u,T_1)I(v,T_k)$$

$$\sum_{n_1 \in \{u\}, n_2 \in T_2, \dots, n_k \in \{v\}} \prod_{i=1}^{k-1} p(n_i, n_{i+1}) I((n_i, n_{i+1}), R_i)$$

wise, $p(n_i, n_{i+1})$ denotes the formation probability of link path from G^i to G^j is $\Upsilon(U^i, U^j)$ and the length of $\Upsilon(U^i, U^j)$ (n_i, n_{i+1}) to be introduced in Subsection 3.2.

intra-network meta paths

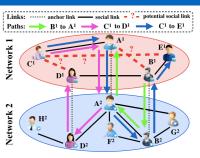
Homogeneous Intra-Network Social Meta Path

- ID 0. Follow: User \xrightarrow{follow} User, whose notation is
- ID 1. Follower of Follower: User \xrightarrow{follow} User \xrightarrow{follow} User, whose notation is " $U \to U \to U$ " or $\Phi_1(U, U)$.
- ID 2. Common Out Neighbor: User \xrightarrow{follow} User \xrightarrow{follow} User, whose notation is " $U \to U \leftarrow U$ " or $\Phi_2(U, U)$.
- ID 3. Common In Neighbor: User $\xrightarrow{follow^{-1}}$ User \xrightarrow{follow} User, whose notation is " $U \leftarrow U \rightarrow U$ " or $\Phi_3(U,U)$.

Heterogeneous Intra-Network Social Meta Path

- ID 4. Common Words: User \xrightarrow{write} Post $\xrightarrow{contain}$ whose notation is $\Psi_1(U^i, U^i)$;
- ID 5. Common Timestamps: User ^{write} Post ^{co}
- ID 6. Common Location Checkins: User \xrightarrow{write} Post

 \blacksquare **Definition 12** (Anchor Meta Path): Let $U^i,\ U^j$ be the $\prod p(n_i, n_{i+1})I((n_i, n_{i+1}), R_i)$, we user nodes of G^i and G^j respectively and $A^{i,j}$ be the anchor \blacksquare anchor meta path between network G^i and G^j iff $T_1 = U^i$ where $p(n_i, n_{i+1}) = 1.0$ if $(n_i, n_{i+1}) \in E_{u,u}$ and other- \mathbb{I} and $T_2 = U^j$ and $R_1 = A^{i,j}$. The notation of anchor meta



inter-network meta paths

■ Category 1: $\Upsilon(U^i, U^j) \circ (\Phi(U^j, U^j) \cup \Phi_0(U^j, U^j)) \circ \Upsilon(U^j, U^i)$, $\begin{array}{c} \text{Word} \xrightarrow{contain^{-1}} \text{Post} \xrightarrow{write^{-1}} \text{User, whose notation} \\ \text{is } "U \to P \to W \leftarrow P \leftarrow U" \text{ or } \Phi_4(U,U). \end{array} \\ \begin{array}{c} \text{\textbf{Category 2:}} (\Phi(U^i,U^i)) \circ \Phi(U^i,U^j)) \circ \Phi(U^i,U^j) \circ \Phi(U^j,U^j) \circ \Phi(U^j,$

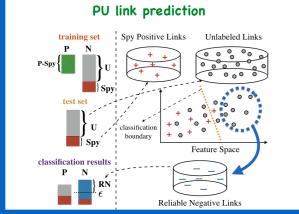
 $(\Phi(U^i, U^i) \cup \Phi_0(U^i, U^i))$, whose notation is $\Psi_3(U^i, U^i)$ Category 4.: $(\Phi(U^i, U^i)) \cup \Phi_0(U^i, U^i)) \circ \Upsilon(U^i, U^j) \circ (\Phi(U^j, U^j)) \cup \Phi_0(U^i, U^i) \circ \Upsilon(U^i, U^j) \circ (\Phi(U^j, U^j)) \circ \Upsilon(U^i, U^j) \circ (\Phi(U^i, U^j)) \circ \Upsilon(U^i, U^j) \circ (\Phi(U^i, U^j)) \circ \Upsilon(U^i, U^j) \circ (\Phi(U^i, U^j)) \circ \Upsilon(U^i, U^j) \circ \Upsilon(U^i, U^i) \circ \Upsilon(U^$ Time $\xrightarrow{contain^{-1}} \operatorname{Post} \xrightarrow{write^{-1}} \operatorname{User}$, whose notation is $\blacksquare \Phi_0(U^j, U^j) \circ \Upsilon(U^j, U^i) \circ (\Phi(U^i, U^i)) \oplus \Phi_0(U^i, U^i)$, whose notation is $\Psi_0(U^j, U^j) \circ \Upsilon(U^j, U^i) \circ (\Phi(U^i, U^i)) \oplus \Phi_0(U^i, U^i)$.

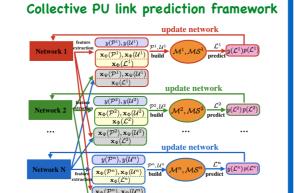
where $\Phi(U^i, U^i) \cup \Phi_0(U^i, U^i) = \{\Phi_0(U^i, U^i), \cdots, \Phi_6(U^i, U^i)\}$ \blacksquare denote the 7 intra-network social meta paths of network G^i

Let variable $X_i \in [\mathbf{x}_{\Phi}^T, \mathbf{x}_{\Psi}^T]^T$ be a feature extracted based on a meta path in $\{\Phi, \Psi\}$ and variable Y be the label. P(Y = y) denotes the prior probability that links in the training set having label y and $P(X_i = x)$ represents the frequency that I links between G^i and G^j . Meta path $\Upsilon = T_1 \stackrel{R_1}{\longleftrightarrow} T_2$ is an feature X_i has value x. Information theory related measure mutual information (mi) is used as the ranking criteria:

$$mi(X_i) = \sum_{x} \sum_{y} P(X_i = x, Y = y) \log \frac{P(X_i = x, Y = y)}{P(X_i = x)P(Y = y)}$$

3. Positive-Unlabeled (PU) Link Prediction Framework





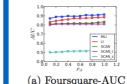
4. Experiment Results & Parameter Analysis & Convergence Analysis

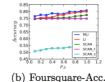
		Remaining information rates $ ho_T$ of Twitter					T of Twitter						Remaining info	rmation rates ρ_F	of Foursquare.
network	measure	methods	0.1	0.2	0.3	0.4	0.5	network	measure	methods	0.1	0.2	0.3	0.4	0.5
Foursquare	AUG	Mu Li	0.862±0.003 0.831±0.005	0.867 ± 0.004 0.834 ± 0.004	0.87 ± 0.003 0.846 ± 0.004	0.873±0.005 0.853±0.005	0.885±0.003 0.855±0.005	Foursquare	AUG	MLI LI	0.677 ± 0.023 0.573 ± 0.019	$\substack{\textbf{0.776} \pm \textbf{0.011} \\ 0.68 \pm 0.023}$	$0.844 {\pm} 0.008$ $0.806 {\pm} 0.01$	$0.887 {\pm} 0.005 \\ 0.853 {\pm} 0.004$	0.906 ± 0.003 0.866 ± 0.003
		SCAN SCANT SCANS	$0.81\pm0.007 \\ 0.81\pm0.007 \\ 0.504\pm0.007$	0.81 ± 0.008 0.81 ± 0.007 0.51 ± 0.003	$0.812 \pm 0.005 \\ 0.81 \pm 0.007 \\ 0.511 \pm 0.005$	0.817 ± 0.007 0.81 ± 0.007 0.516 ± 0.005	0.816 ± 0.01 0.809 ± 0.007 0.522 ± 0.004			SCAN SCANT SCANS	$0.549\pm0.009 \\ 0.5\pm0.083 \\ 0.524\pm0.013$	0.56 ± 0.009 0.503 ± 0.007 0.524 ± 0.017	0.662 ± 0.03 0.613 ± 0.012 0.524 ± 0.012	0.745 ± 0.009 0.739 ± 0.008 0.524 ± 0.005	$\substack{0.786 \pm 0.014 \\ 0.764 \pm 0.013 \\ 0.524 \pm 0.002}$
	Accuracy	MLI LI	0.78±0.003 0.745±0.011	0.786 ± 0.005 0.762 ± 0.005	0.789±0.004 0.768±0.007	0.794±0.005 0.772±0.007	0.793±0.004 0.777±0.008		Accuracy	Mu Li	0.632 ± 0.01 0.568 ± 0.013	0.692 ± 0.007 0.624 ± 0.053	0.755±0.005 0.699±0.004	0.769 ± 0.004 0.722 ± 0.006	0.779 ± 0.002 0.761 ± 0.01
		SCAN SCANT SCANS	$0.749\pm0.007 \\ 0.748\pm0.003 \\ 0.692\pm0.011$	0.754 ± 0.006 0.748 ± 0.003 0.717 ± 0.008	$0.754\pm0.007 \\ 0.747\pm0.003 \\ 0.725\pm0.008$	0.757 ± 0.006 0.748 ± 0.003 0.746 ± 0.008	0.758±0.007 0.748±0.003 0.741±0.006			SCAN SCANT SCANS	0.558 ± 0.007 0.491 ± 0.019 0.548 ± 0.011	0.6 ± 0.006 0.568 ± 0.004 0.548 ± 0.055	0.683 ± 0.071 0.65 ± 0.008 0.548 ± 0.007	0.714 ± 0.009 0.685 ± 0.007 0.548 ± 0.008	0.721 ± 0.007 0.714 ± 0.007 0.548 ± 0.007
	F1	MLI LI	0.768±0.004 0.721±0.02	0.774±0.005 0.734±0.01	0.778±0.006 0.734±0.012	0.784±0.006 0.736±0.012	0.785±0.005 0.744±0.012		F1	Mu Li	0.644±0.01 0.63±0.017	0.695±0.022 0.635±0.015	0.722±0.013 0.66±0.007	0.742±0.005 0.684±0.01	0.761±0.005 0.715±0.016
		SCAN SCANT SCANS	0.717 ± 0.01 0.713 ± 0.01 0.509 ± 0.02	0.718 ± 0.007 0.712 ± 0.01 0.514 ± 0.014	$0.714 \pm 0.009 \\ 0.712 \pm 0.01 \\ 0.524 \pm 0.014$	$0.715\pm0.009 \\ 0.713\pm0.01 \\ 0.529\pm0.013$	0.718±0.011 0.713±0.01 0.54±0.009			SCAN SCANT SCANS	0.6 ± 0.02 0.534 ± 0.196 0.56 ± 0.016	$0.609\pm0.006 \\ 0.559\pm0.004 \\ 0.56\pm0.041$	0.614 ± 0.031 0.565 ± 0.016 0.56 ± 0.015	0.632 ± 0.018 0.584 ± 0.011 0.56 ± 0.015	0.645 ± 0.018 0.645 ± 0.011 0.56 ± 0.013
	AUC	Mu Li	0.837±0.004 0.772±0.009	0.858±0.004 0.829±0.008	0.905±0.005 0.871±0.009	0.926±0.003 0.887±0.002	0.924±0.002 0.887±0.002	- - 10	AUC	Mu Li	0.884±0.004 0.841±0.003	0.891 ± 0.003 0.847 ± 0.002	0.915 ± 0.003 0.852 ± 0.003	0.917 ± 0.003 0.862 ± 0.002	0.923 ± 0.002 0.873 ± 0.002
_		SCAN SCANT SCANS	0.706 ± 0.008 0.555 ± 0.133 0.687 ± 0.008	0.771 ± 0.012 0.678 ± 0.006 0.687 ± 0.002	0.799 ± 0.009 0.753 ± 0.044 0.687 ± 0.005	0.817 ± 0.002 0.754 ± 0.019 0.687 ± 0.002	0.819±0.002 0.764±0.014 0.687±0.002			SCAN SCANT SCANS	0.801 ± 0.003 0.802 ± 0.002 0.508 ± 0.002	0.814 ± 0.002 0.802 ± 0.002 0.543 ± 0.002	0.819 ± 0.003 0.802 ± 0.002 0.584 ± 0.003	0.817 ± 0.002 0.802 ± 0.002 0.631 ± 0.001	$\substack{0.819 \pm 0.002 \\ 0.802 \pm 0.002 \\ 0.653 \pm 0.002}$
witter	Accuracy	MLI LI	0.821 ± 0.005 0.706 ± 0.002	0.864 ± 0.001 0.834 ± 0.011	0.892 ± 0.008 0.877 ± 0.003	0.914 ± 0.004 0.898 ± 0.005	0.925±0.002 0.912±0.001		Accuracy	MLI LI	0.92 ± 0.003 0.899 ± 0.004	0.927 ± 0.002 0.904 ± 0.004	0.927 ± 0.003 0.908 ± 0.004	0.929 ± 0.004 0.913 ± 0.002	0.93 ± 0.003 0.916 ± 0.003
F		SCAN SCANT SCANS	0.594 ± 0.006 0.547 ± 0.062 0.59 ± 0.009	$0.716\pm0.009 \atop 0.645\pm0.038 \atop 0.59\pm0.007$	0.781 ± 0.005 0.723 ± 0.048 0.59 ± 0.004	0.801 ± 0.003 0.786 ± 0.004 0.59 ± 0.004	0.823 ± 0.002 0.8 ± 0.002 0.59 ± 0.002			SCAN SCANT SCANS	0.831 ± 0.005 0.827 ± 0.003 0.568 ± 0.004	0.835 ± 0.003 0.827 ± 0.003 0.577 ± 0.003	0.837 ± 0.006 0.827 ± 0.003 0.585 ± 0.002	$\substack{0.842 \pm 0.001 \\ 0.827 \pm 0.003 \\ 0.587 \pm 0.002}$	$\substack{0.844 \pm 0.002 \\ 0.827 \pm 0.003 \\ 0.591 \pm 0.003}$
	F1	MLI LI	0.713±0.009 0.651±0.006	0.762±0.005 0.671±0.023	0.791±0.006 0.749±0.014	0.81±0.004 0.779±0.007	0.81±0.002 0.801±0.003		F1	MLI LI	$0.804 {\pm} 0.002$ $0.776 {\pm} 0.005$	$\substack{0.808 \pm 0.002 \\ 0.785 \pm 0.005}$	0.809 ± 0.003 0.792 ± 0.005	0.811 ± 0.003 0.8 ± 0.003	0.812 ± 0.003 0.804 ± 0.003
		SCAN SCANT SCANS	0.6 ± 0.017 0.552 ± 0.113 0.575 ± 0.025	0.633 ± 0.023 0.574 ± 0.016 0.575 ± 0.016	0.657 ± 0.013 0.604 ± 0.031 0.575 ± 0.005	0.684±0.004 0.618±0.003 0.575±0.006	0.703±0.004 0.63±0.001 0.575±0.004			SCAN SCANT SCANS	0.682±0.006 0.683±0.003 0.53±0.006	$0.686\pm0.004 \\ 0.683\pm0.003 \\ 0.546\pm0.006$	0.69 ± 0.006 0.683 ± 0.003 0.559 ± 0.004	0.699 ± 0.001 0.683 ± 0.003 0.564 ± 0.004	$0.703\pm0.003 \\ 0.683\pm0.003 \\ 0.571\pm0.004$

5. Acknowledgement

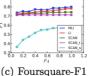
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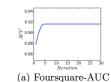
Parameter Analysis











Convergence Analysis

