

On the Social Influence in Human Behavior

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Outline

- > Social Influence and Human Behavior Prediction
- > Case of Study
 - EBSN
- > Communities as sources of influence
- > Social Influence (Deep) Learning
- > Conclusion and Future Works

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- > ***Social influence***: change in individual's thoughts, feelings, attitudes, or behaviors that results from interaction with another individual or a group.



- > **Application:**
 - > Human Behavior Prediction (actions, decisions, mobility)
 - > Recommendation (LBSN, EBSN, products)
 - > Viral Marketing
 - > Targeted Advertising



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Event Based Social Network (EBSN)

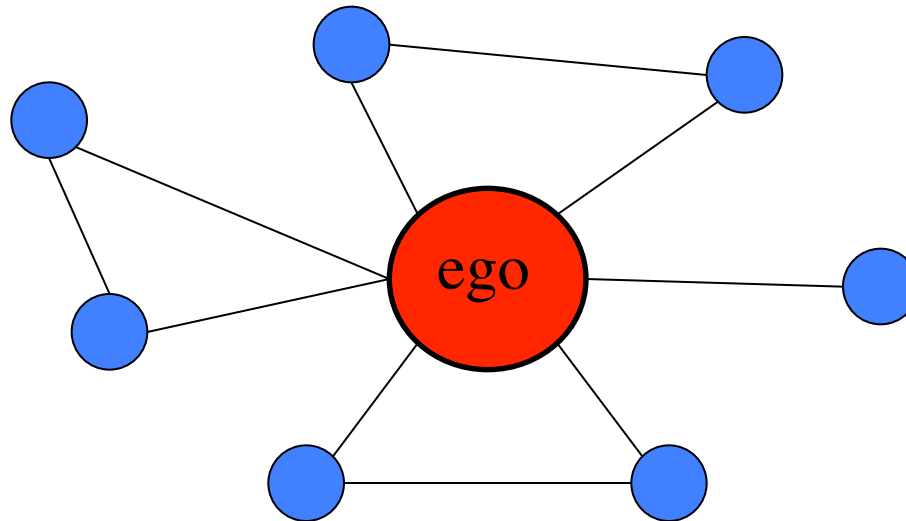
- > “Plancast is a service for sharing your upcoming plans with friends”.
 - > Events attended by the users
 - > Location of the events
 - > User subscriptions (following/follower)

- > Dataset:
 - > 93041 users
 - > 401634 events
 - > 1702058 user subscriptions
 - > 869200 user-event participations

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- > The ***ego network*** is typically utilized to represent subject's community and to analyze social influence.



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 - > Physical Community,
 - > Homophily Community,
 - > Social Community,
 - > and the ego network.

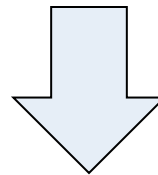
On the Social Influence in Human Behavior: Physical, Homophily, and Social Communities
Luca Luceri, Alberto Vancheri, Torsten Braun, Silvia Giordano

Event Based Social Network (EBSN)

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- > Physical, Homophily, and Social Community
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Groups
{*ego*, *SC*, *PC*, *HC*}



Features Creation

- > For each user u , group g , and event e we evaluate the feature:

$$p_e^g = \frac{|\{i \in g | e \in A_i\}|}{|g|}$$

where

- A_i are the events attended by user i
- $g = \{ego, SC, PC, HC\}$

Features Creation

u_1	ego	SC	PC	HC
e_1	0.3	0.2	0.7	0.8
e_2	0.6	0.7	0.1	0.3
e_3	...			
...		...		
...			...	
e_N				...

Participation Prediction

Performances

TABLE I: Prediction performances comparison.

	DT	SVM	DNN
Accuracy	77%	81%	81%
Precision	74%	84%	85%
Recall	72%	76%	75%

Participation Prediction

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TABLE II: Prediction performances utilizing one feature among {*ego*, *SC*, *PC*, *HC*}.

	<i>ego</i>	<i>SC</i>	<i>PC</i>	<i>HC</i>
Accuracy	77%	77%	77%	76%
Precision	81%	81%	82%	82%
Recall	72%	71%	69%	67%

Participation Prediction

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TABLE III: Prediction performances comparison: all features vs. fixed feature vs. feature selection.

	all features	fixed feature	feature selection
Accuracy	81%	77%	80%
Precision	84%	82%	84%
Recall	76%	70%	76%

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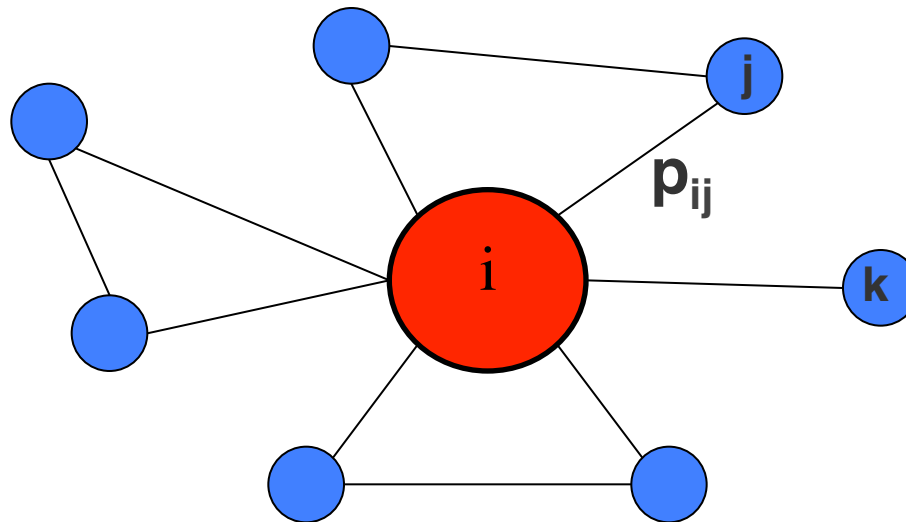
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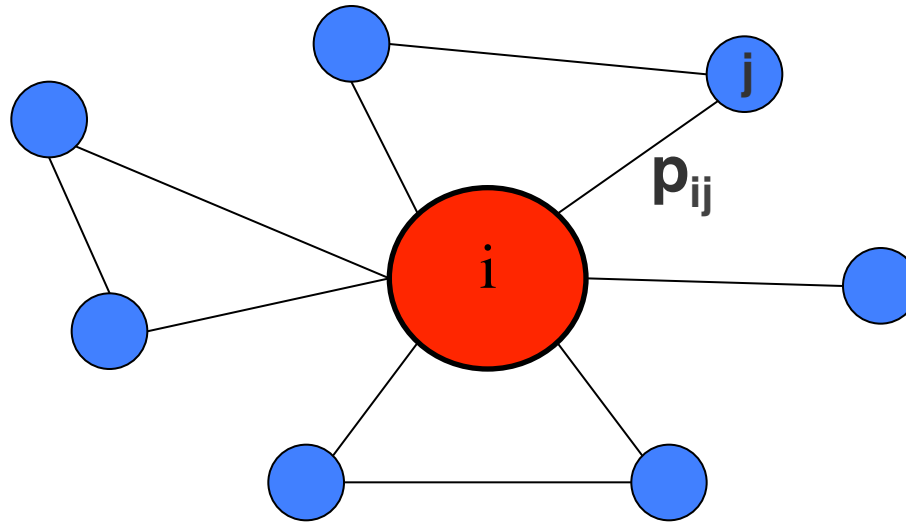
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> Social Influence Learning: *State of the Art*



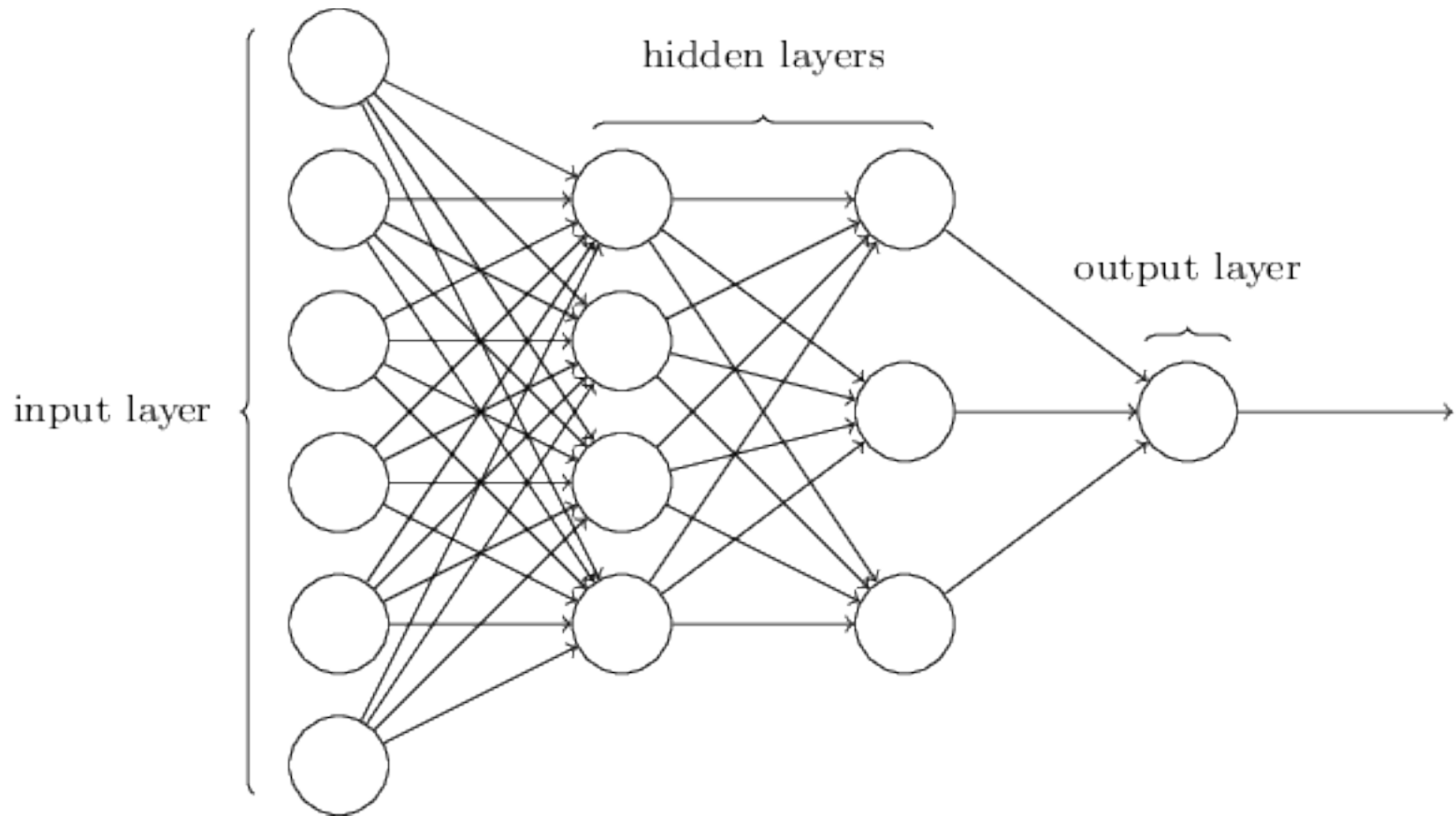
$$P_i(e) = 1 - \prod_{j \in pf(i)} (1 - p_{ij})$$

> Social Influence Learning: *State of the Art*

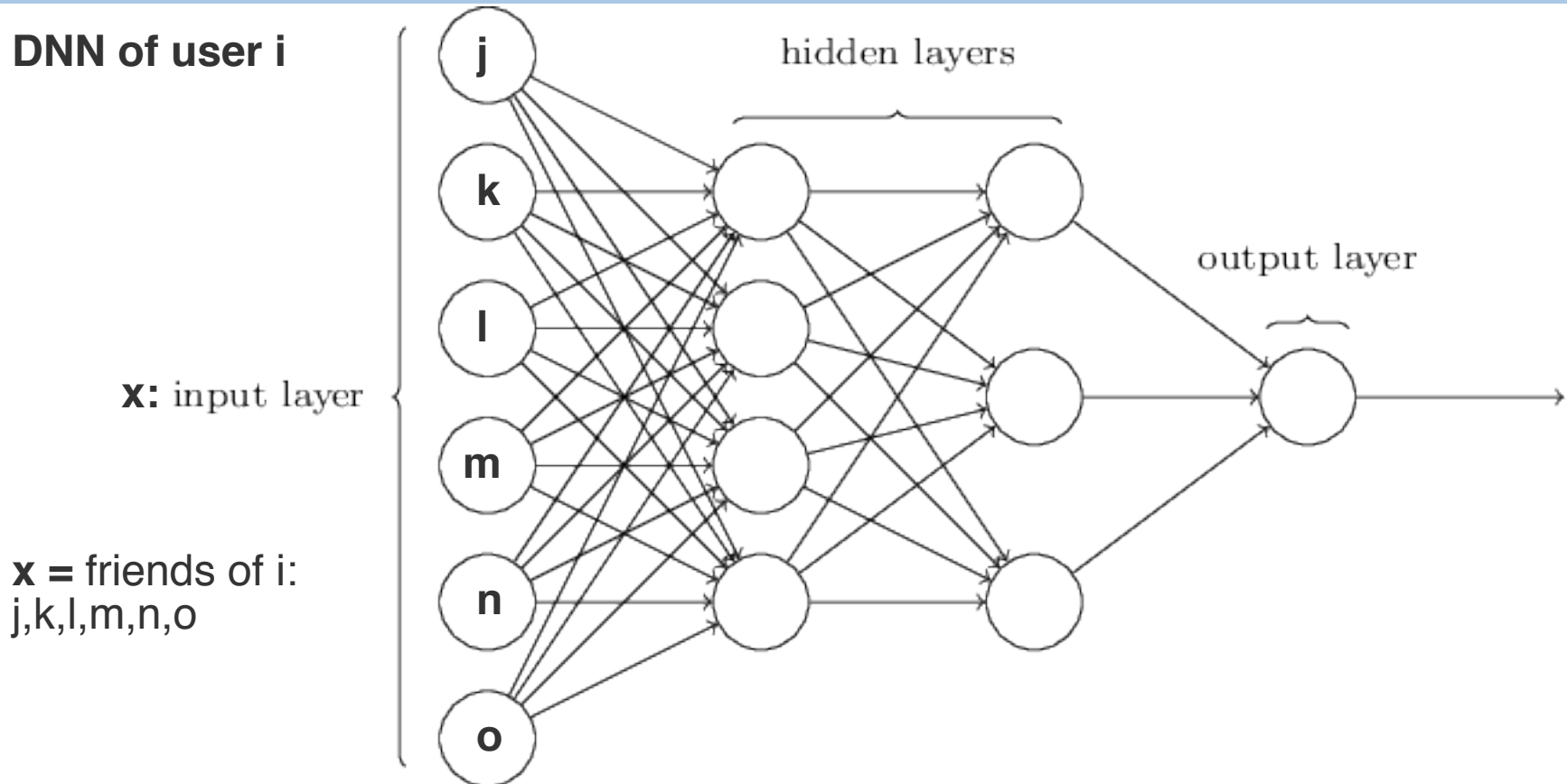


$$P_i(e) = 1 - \prod_{j \in pf(i)} (1 - p_{ij}) \implies P_i(e) = \begin{cases} 1 & \text{if } P_i(e) > \theta \\ 0 & \text{otherwise} \end{cases}$$

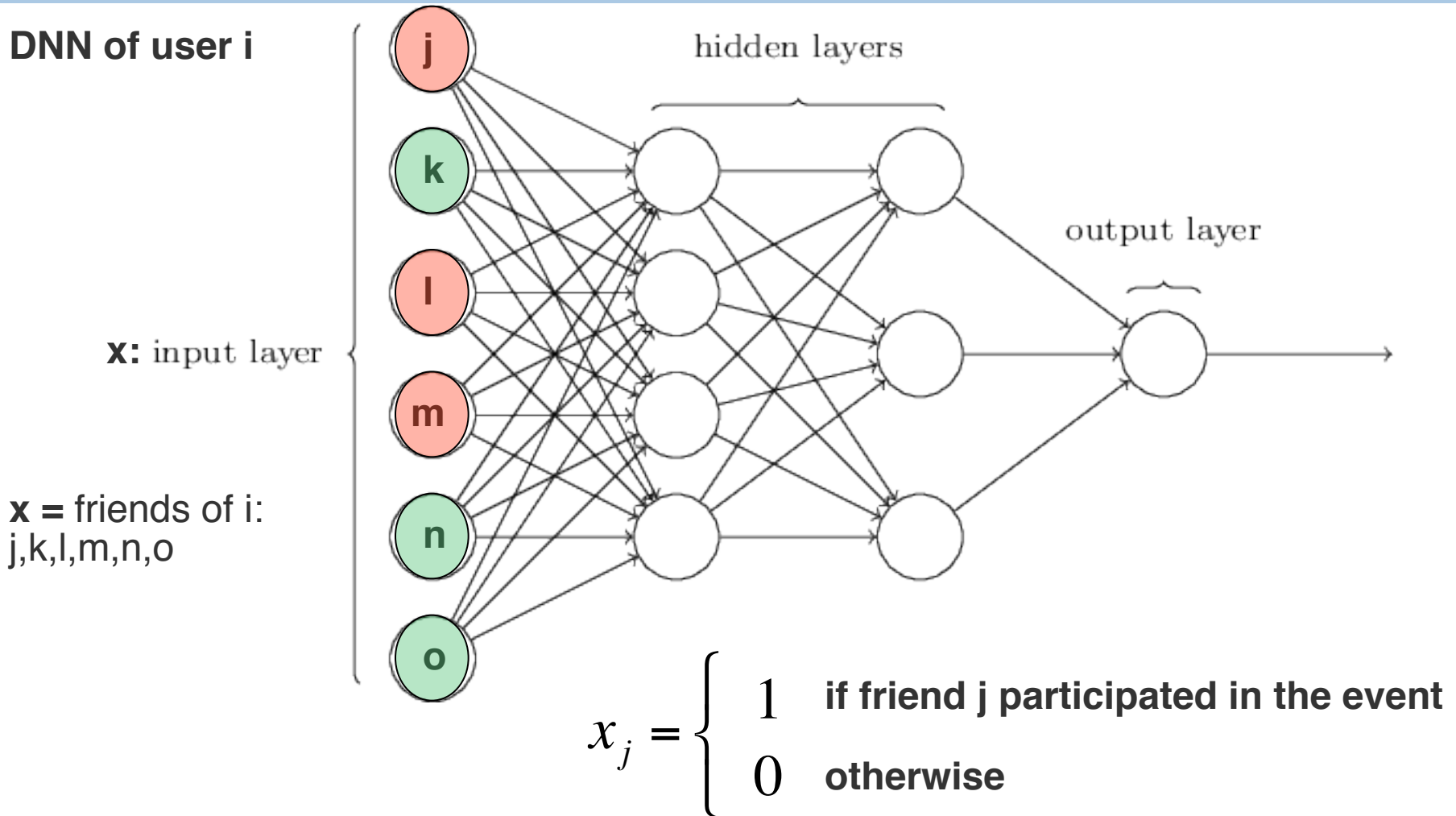
> *Our Approach: Deep Neural Network (DNN)*



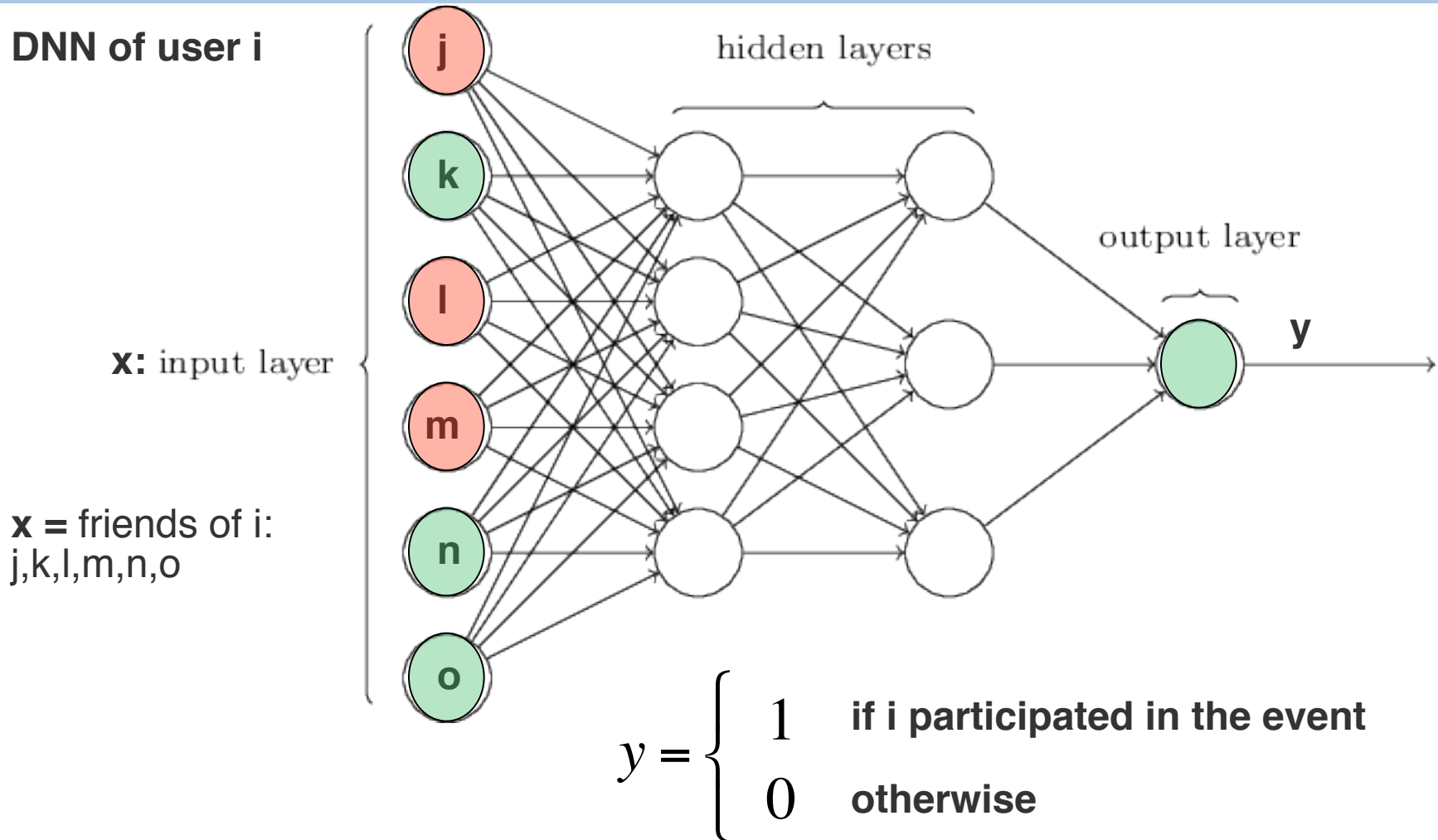
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Our Approach: Deep Neural Network (DNN)



Results

	DNN	GT ⁽¹⁾	IC ⁽²⁾
Accuracy	85%	78%	75%
TPR	75%	74%	54%
FPR	5%	14%	4%

- > (1) Goyal, Amit, Francesco Bonchi, and Laks VS Lakshmanan. "Learning influence probabilities in social networks." Proceedings of the third ACM international conference on Web search and data mining.
- > (2) Saito, Kazumi, Ryohei Nakano, and Masahiro Kimura. "Prediction of information diffusion probabilities for independent cascade model." Knowledge-based intelligent information and engineering systems.

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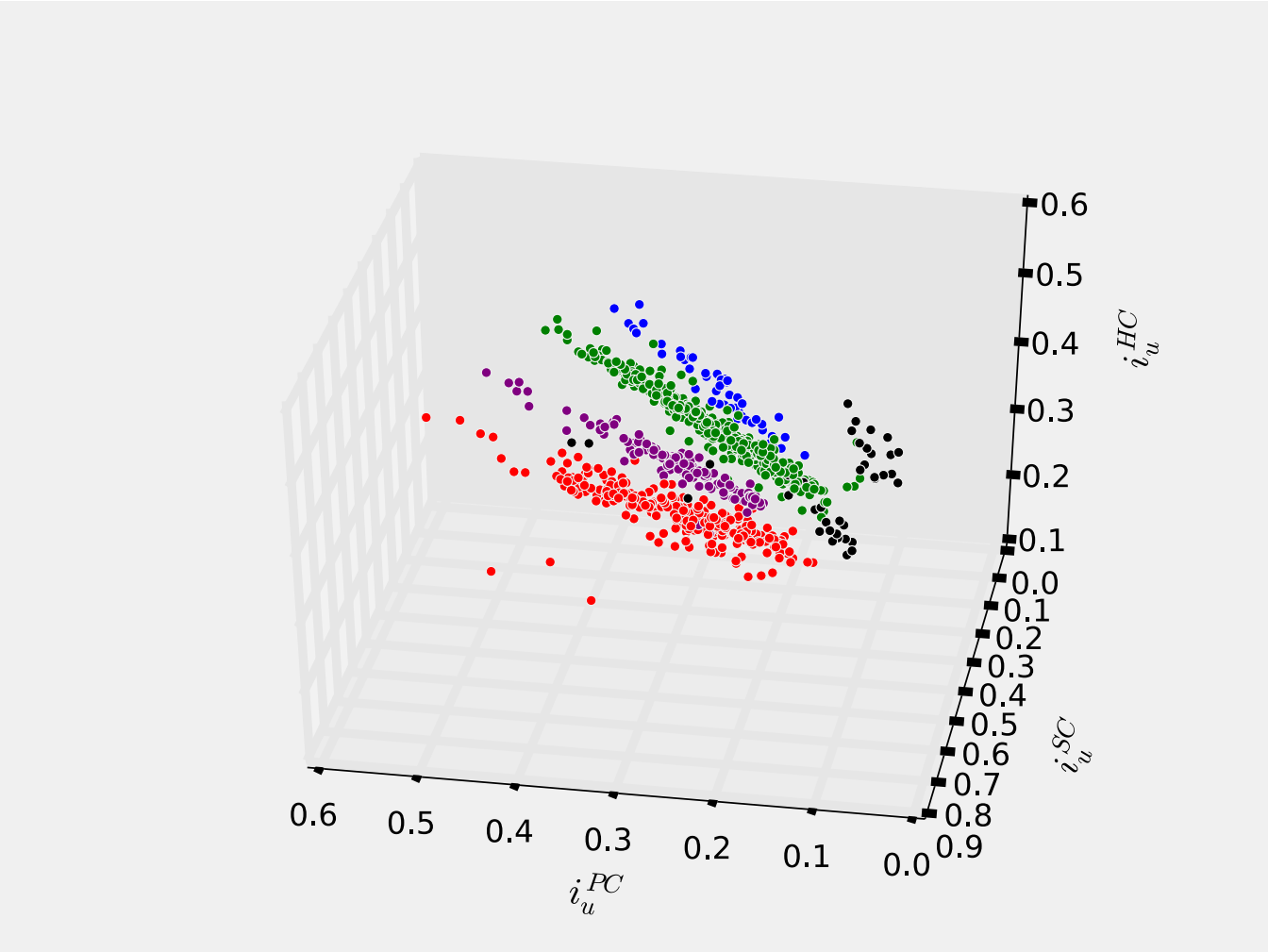
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- > We introduced a novel interpretation of physical, homophily, and social community, as sources of social influence
- > We proved that the ego network alone is not sufficient to model social influence
- > We proposed a new method to learn social influence and predict human behavior

- > Merge the two works in a unique Social Influence framework: include SC, HC, PC in the DNN
- > Validate it with different datasets
- > Include Social Influence framework in an application scenario, e.g. recommendation:
 - > LBSN
 - > EBSN



Results



Community-Features Correlation

- > For each user u , group g , and event e we evaluate the feature:

$$p_e^g = \frac{|\{i \in g | e \in A_i\}|}{|g|}$$

where A_i are the events attended by user i .

- > We utilize the four features related to the groups to:
 - > infer users participation to the events;
 - > evaluate the relation among the communities and classify users accordingly.

User Classification

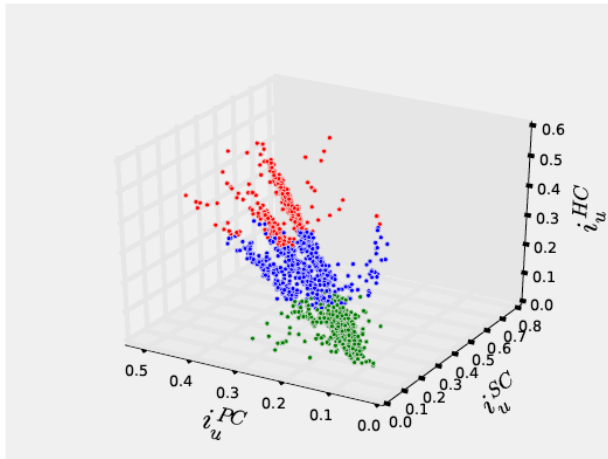
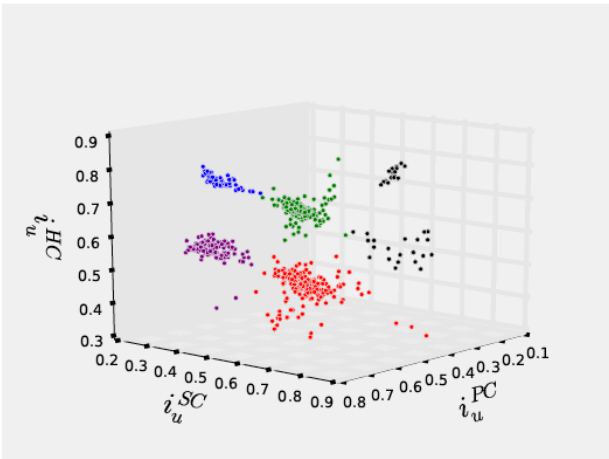
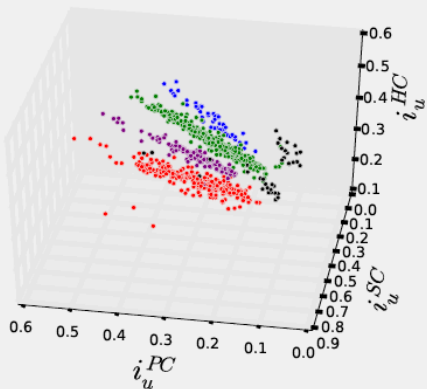


TABLE V: Performance of the prediction based on both fingers and classes of influence.

	average	low	medium	high
Accuracy	82%	74%	83%	89%
Precision	84%	75%	86%	92%
Recall	79%	73%	78%	85%

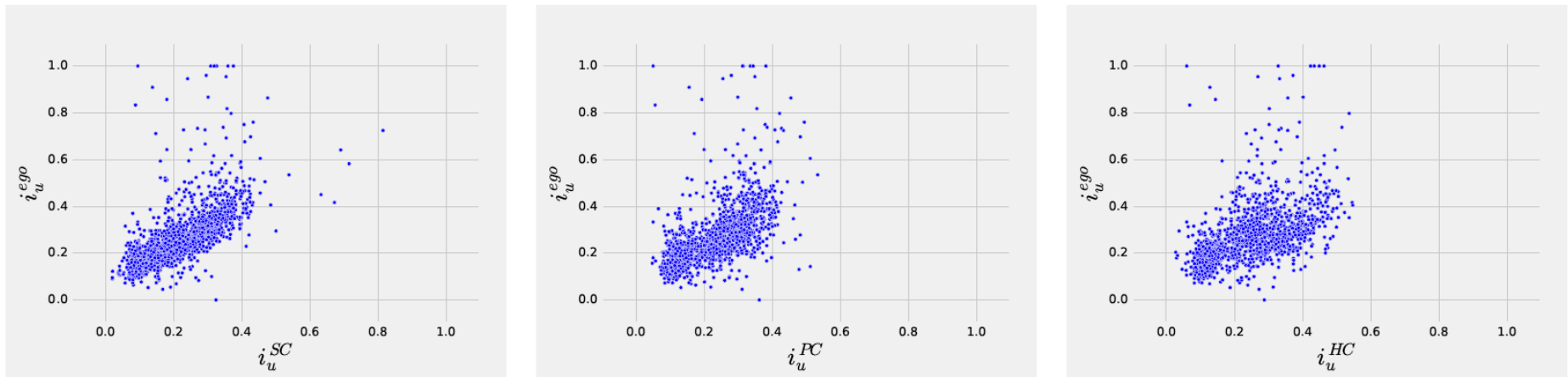


Fig. 1: Scatter plots of i_u^{ego} vs. i_u^{SC} , i_u^{PC} , and i_u^{HC} . Each point represents a user.