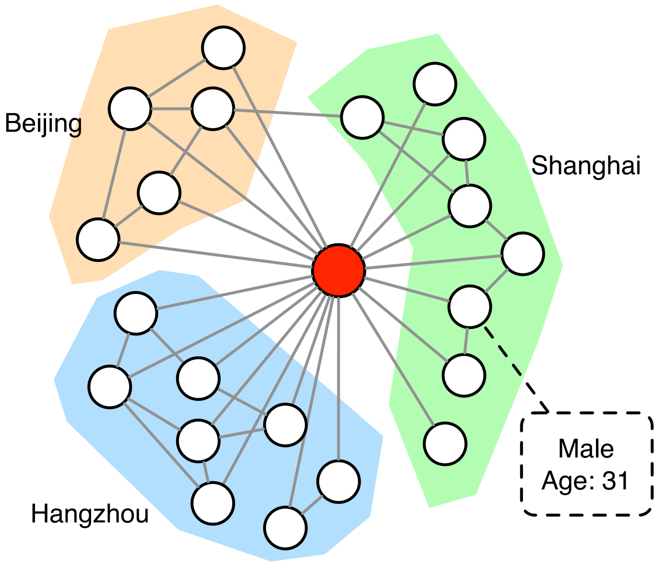
移居者的都市梦：城市移民群体行为研究

- 问题
  - 移民群体和本地人群在行为模式上存在怎样的差异？
  - 这些差异多大程度能帮助我们区分这两类群体？
  - 是否能衡量移民者的融入程度？

- Yang Yang, Chenhao Tan, **Zongtao Liu**, Fei Wu, and Yueting Zhuang. Urban Dreams of Migrant: A Case Study of Migrant Integration in Shanghai. **AAAI’18.**

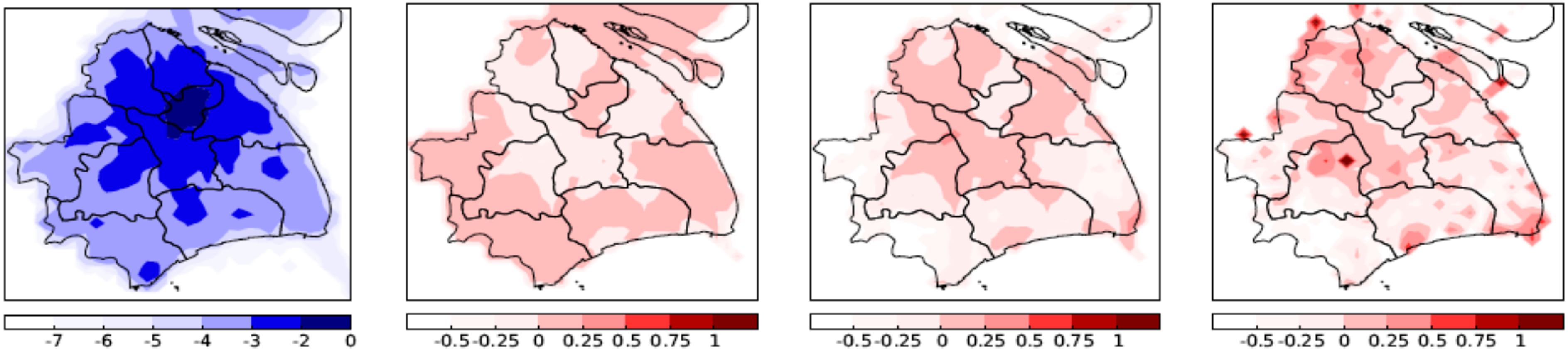
用户通话网络

- 数据来源：2016年9月上海电信全网通话元数据
  - 通话记录 + 基站GPS信息
  - 7亿条通话记录，5400万用户



不同群体的行为模式差异

- 本地人：出生在本地的上海人
- 老移民者：在上海已经生活了一段时间、安顿下来了的移民者
- 新移民者：刚来上海一周的移民者



(a) Log overall average probability.

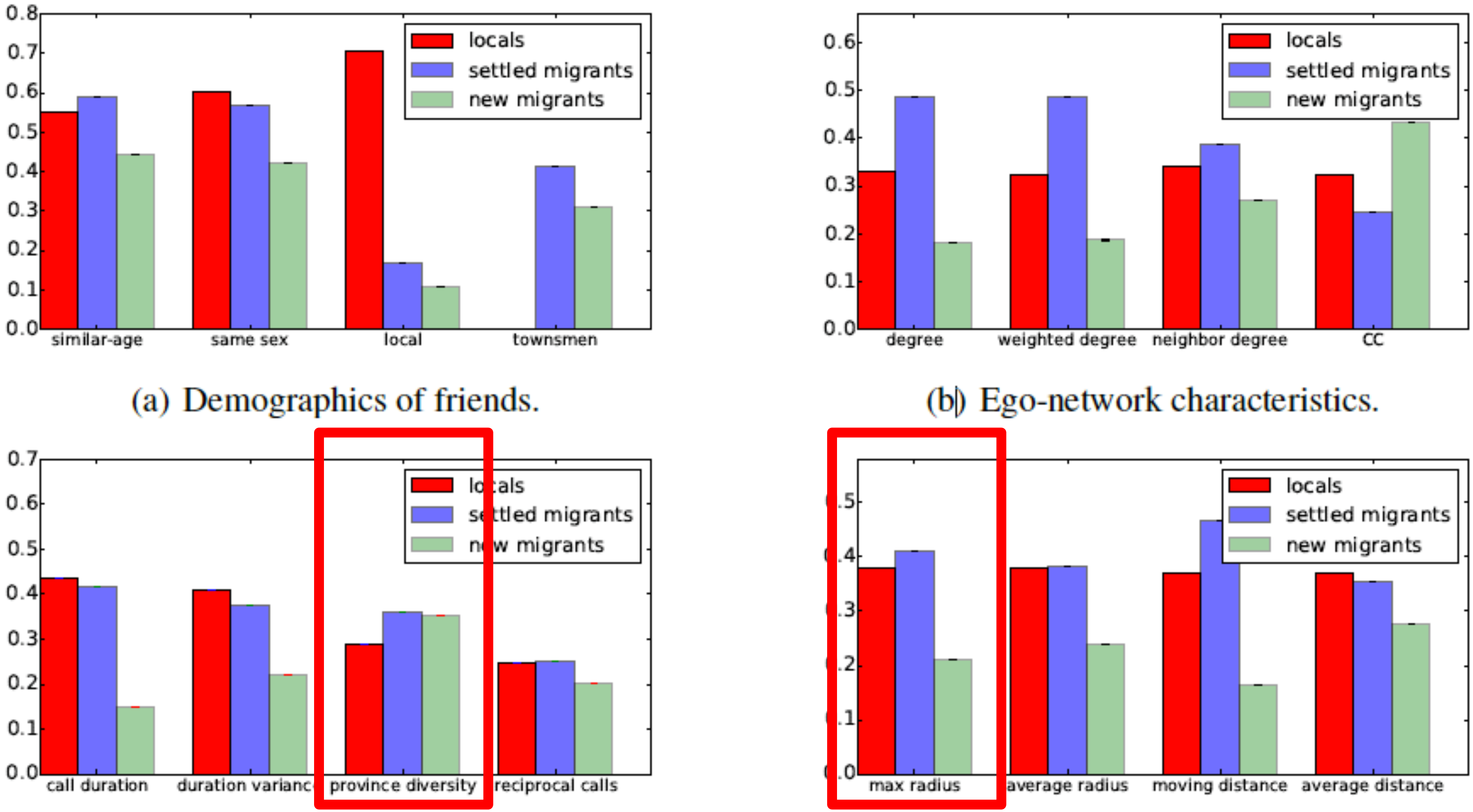
(b) Log odds ratio for locals.

(c) Log odds ratio for settled migrants.

(d) Log odds ratio for new migrants.

本地人：1.7M，老移民者：1.0M，新移民者：34K

移民者有更多元的人际关系，更大的活动区域



(a) Demographics of friends.

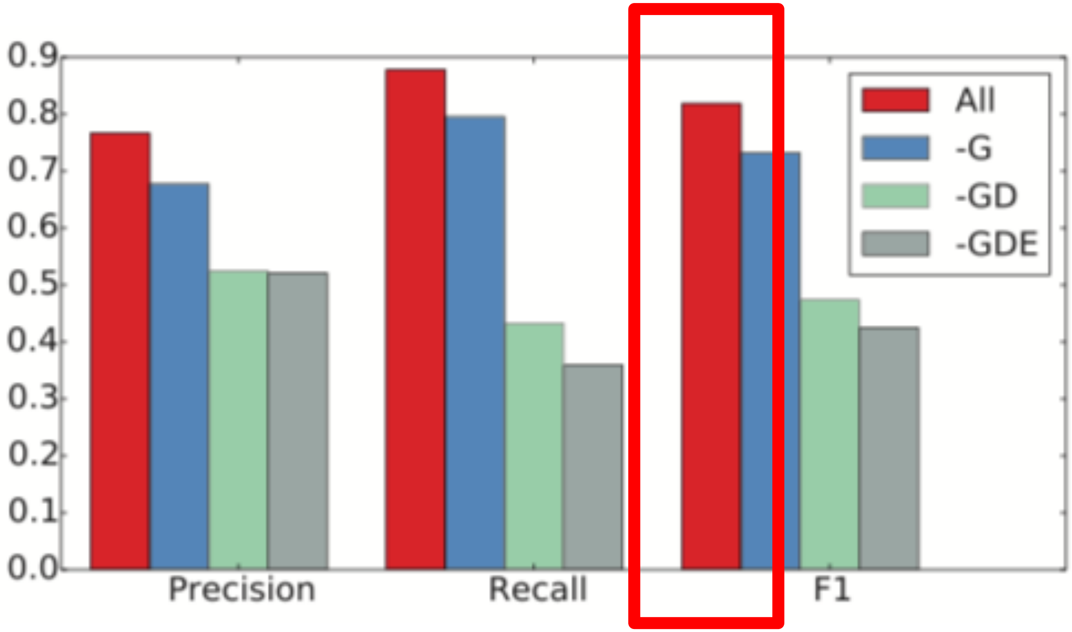
(b) Ego-network characteristics.

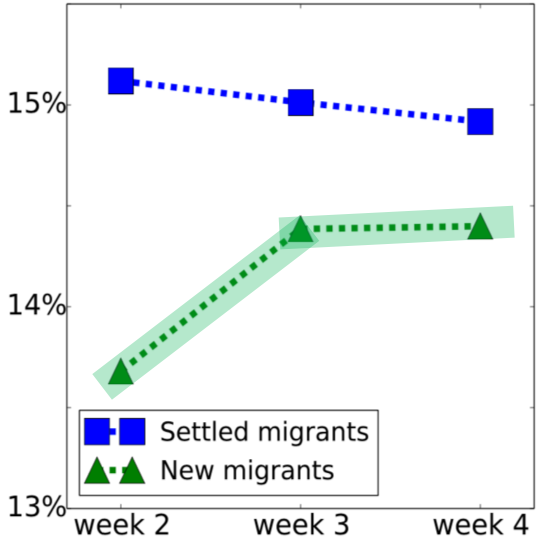
(c) Call behavior.

(d) Geographical features.

新移民逐渐向本地人趋近

- 二分类：根据首周用户通话记录，判断其为本地人, 老移民者

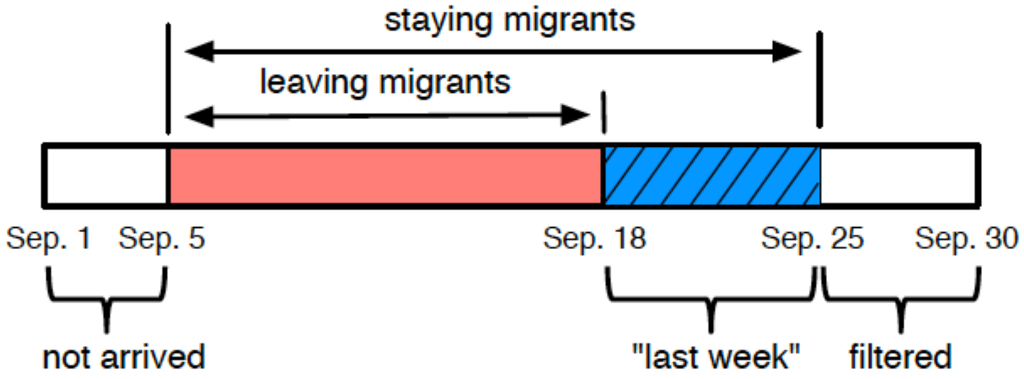




老移民者与新移民者中，被误判为本地人的比例

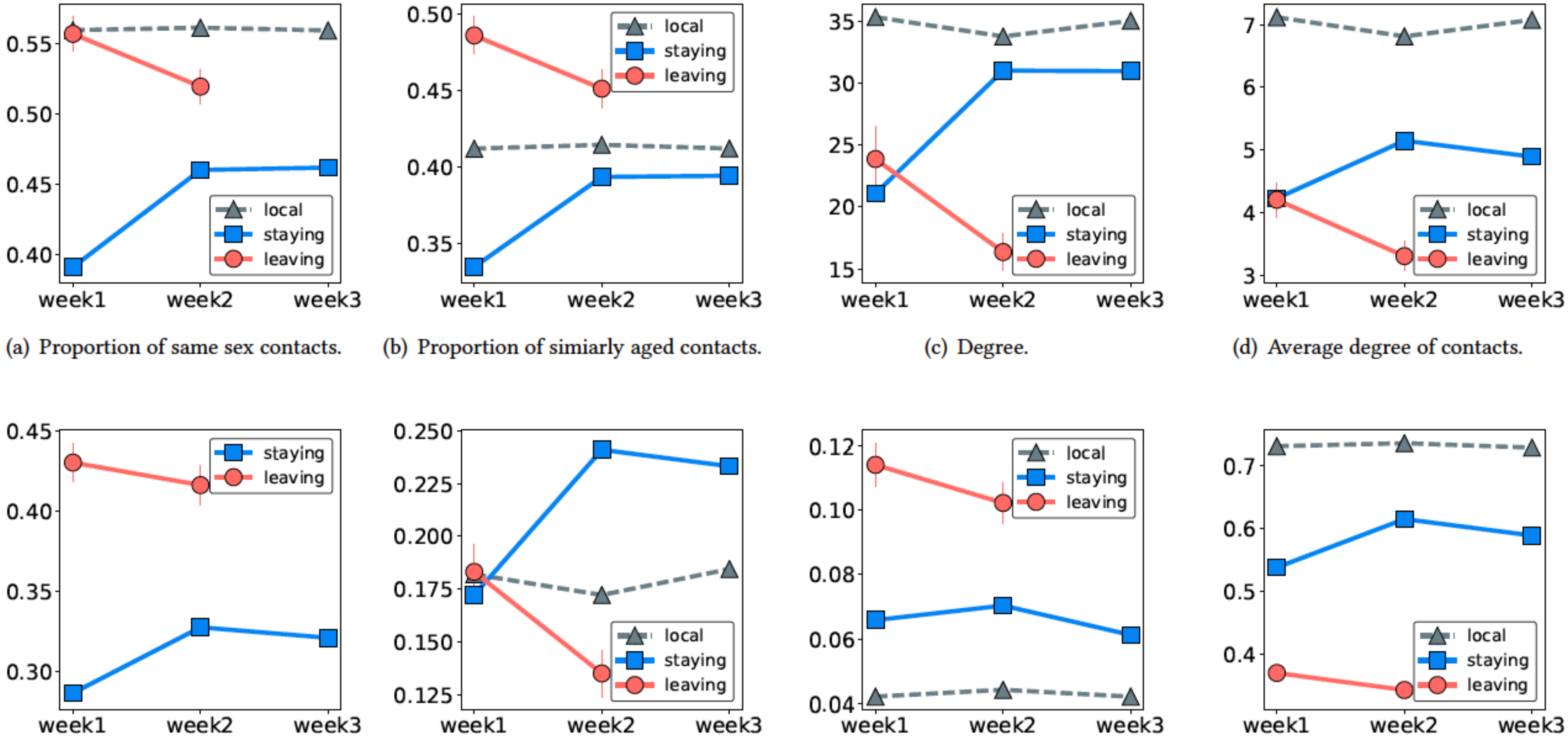
什么因素导致移民者离开都市?

- 抵达都市后的**前两周**很关键!
- 进一步将新移民者划分为流失移民者(1.5K)和暂存移民者(34K)
- 2016年9月下旬，**4%**的新移民者离开了上海



- Yang Yang, Zongtao Liu, Chenhao Tan, Fei Wu, and Yueting Zhuang. To Stay or to Leave: Exploring the Initial Period of Migrant Integration. **WWW’18.**

初步构建当地关系网络



(a) Proportion of same sex contacts.

(b) Proportion of simiarly aged contacts.

(c) Degree.

(d) Average degree of contacts.

(e) Proportion of townspeople.

(f) Province diversity.

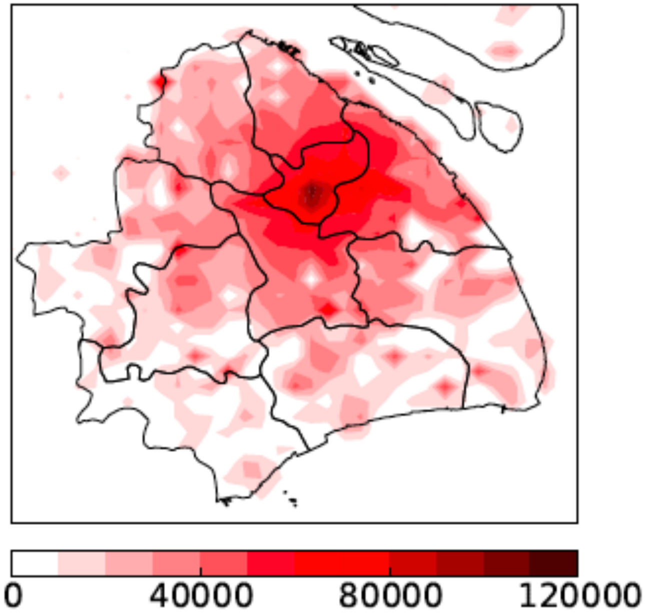
(g) Clustering coefficient.

(h) Communication diversity.

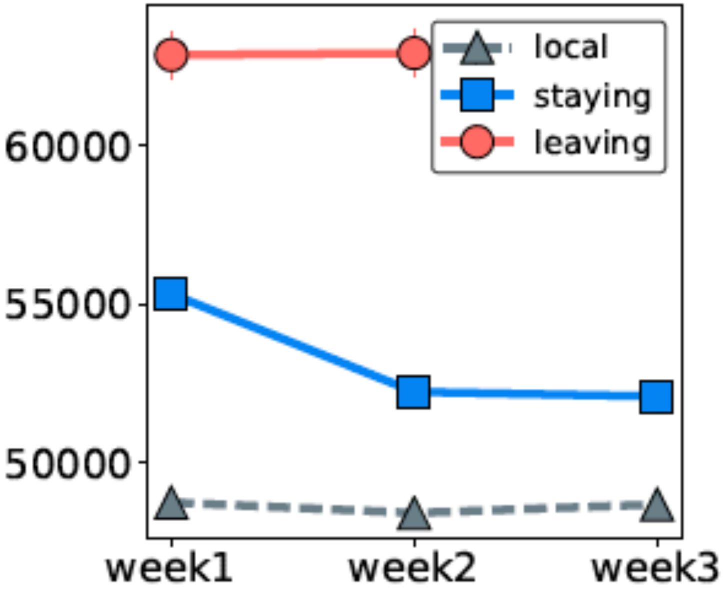
积极扩展人脉、发展**多样性**的关系与移民者能否留在都市的关联性很强

找到合适的居住地

- 根据用户的GPS数据，挖掘其居住地，结合上海市房地产数据，分析用户居住地的房价



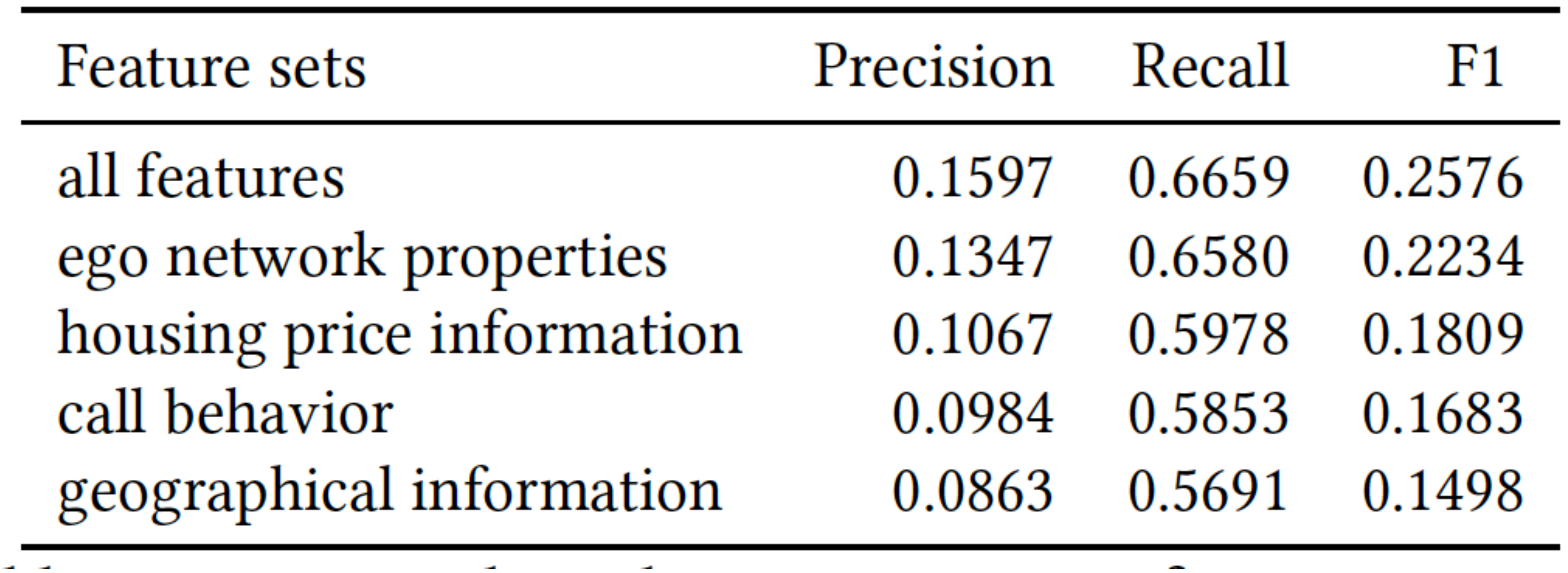
(a)上海市房价热点分布



(b)用户居住地的平均房价

流失移民 vs. 留存移民

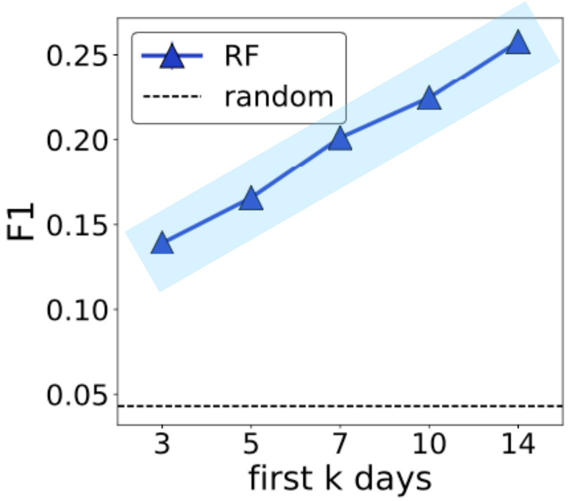
- 根据新移民者过去两周的通话数据，预测其两周后是否会离开上海



Feature sets	Precision	Recall	F1
all features	0.1597	0.6659	0.2576
ego network properties	0.1347	0.6580	0.2234
housing price information	0.1067	0.5978	0.1809
call behavior	0.0984	0.5853	0.1683
geographical information	0.0863	0.5691	0.1498

流失移民 vs. 留存移民

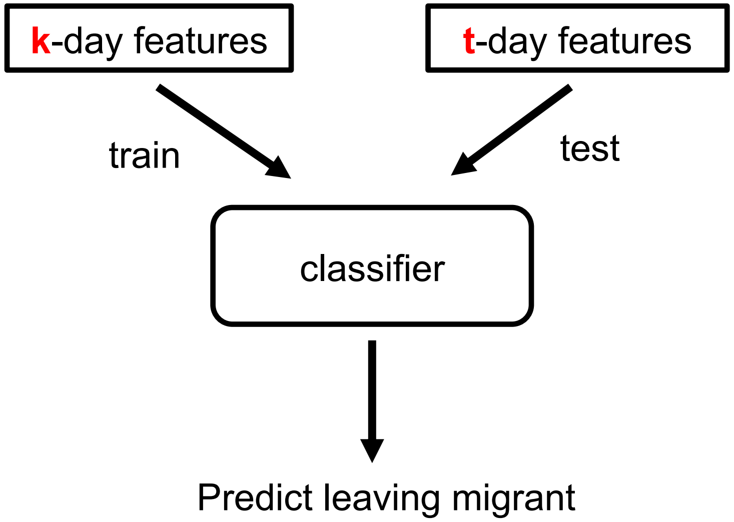
- 在移居早期识别移民的流失
  - 是否能在小于两周的时间识别流失的移民?
    - 如果可以，政府和公益团体也许能为这类移民提供帮助
  - 基于前k天数据提取特征进行训练和预测：



(c) F1.

流失移民 vs. 留存移民

- 探究预测效果提升的原因
  - 解耦可能导致效果提升的两个因素：模型和特征



k-day features

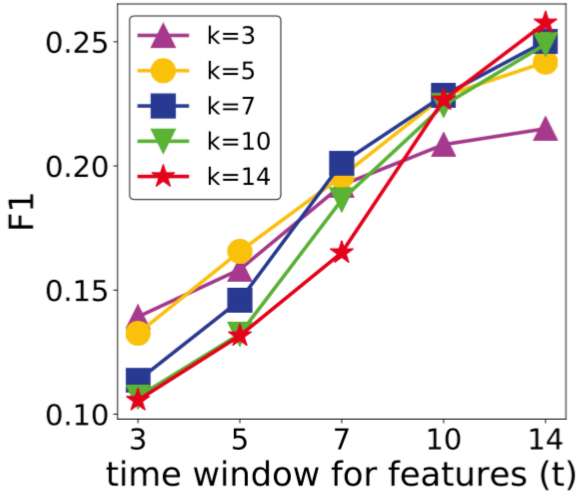
t-day features

train

test

classifier

Predict leaving migrant



(d) Disentangling performance improvement.

使用5天数据，分类器就能达到用14天数据的预测效果！

社交感知的时序补全算法

- 时序数据补全
  - 时序数据缺失会影响基于这类数据的分析和建模，研究合适的补全方法十分有必要
  - 时序补全的方法
    - 插值，平滑
    - 深度模型：GRU-D，LSTM-impute
- 社交网络中的时间序列
  - 在社交网络分析中，时序数据也起着重要作用
  - 基于同质性(Homophily)现象，联系人的行为模式可以帮助他的数据缺失
  - 目前缺乏结合社交上下文和深度模型来进行时间序列补全的工作

- **Zongtao Liu**, Yang Yang, Wei Huang, Zhongyi Tang, Ning Li and Fei Wu. How Do Your Neighbors Disclose Your Information: Social-Aware Time Series Imputation. **WWW'19.**

社交感知的时序补全算法

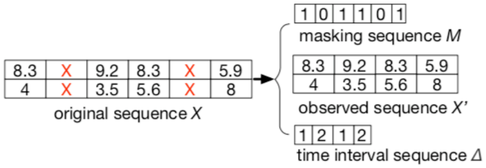
Definition

social network: $G =< V, E >$

behavior data : $X = \{x_1, x_2, ..., x_T\}$

observed data : $X' = \{x_{s_1}, x_{s_2}, ..., x_{s_L}\}$

time intervals : $\delta_l = \begin{cases} 1, & l = 1 \\ s_l - s_{l-1}, & l \neq 1 \end{cases}$



8.3	X	9.2	8.3	X	5.9
4	X	3.5	5.6	X	8

original sequence X

1	0	1	1	0	1

masking sequence M

8.3	9.2	8.3	5.9
4	3.5	5.6	8

observed sequence X'

1	2	1	2

time interval sequence Δ

Time gap-aware LSTM (T-LSTM)

In encoding step, we use a variant LSTM to handle irregular time gaps.

The original memory cell is replaced by:

$$c_t^s = tanh(W_d c_{t-1} + b_d)$$

$$\hat{c}_t^s = c_{t-1}^s \cdot \boxed{g(\delta)}$$

decaying function

$$c_{t-1}^l = c_{t-1} - c_{t-1}^s$$

$$c_{t-1}^* = c_{t-1}^l + \hat{c}_t^s$$

$$\tilde{c} = tanh(W_c x_t + U_c h_{t-1} + b_c)$$

$$c_t = f_t \cdot c_{t-1}^* + i_t \cdot \tilde{c}$$

General idea: how neighbors' behaviors patterns can relate to her current state.

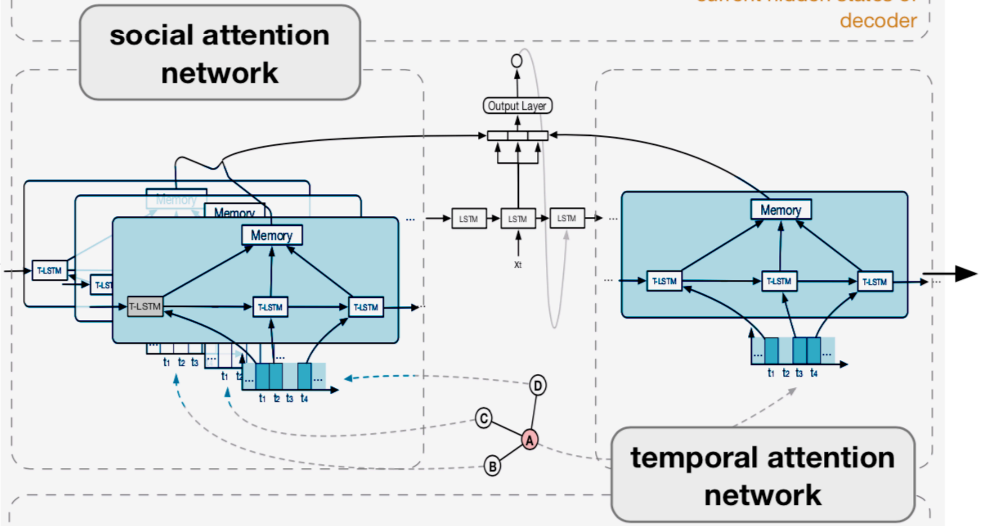
- **Encode neighbor's behavioral data:**

$$h_{s(p)}, c_{s(p)} = T - LSTM(x'_{s(p)}, \delta_{s(p)}, h_{s-1(p)}, c_{s-1(p)})$$

- **Extract social context $\hat{a}$ by a memory-based attention mechanism:**

$$C_k = \sum_{s=0}^{|S|} \alpha_{sk} h_s, \alpha_{sk} = softmax(W_\alpha h_s \cdot l_s) \ \ \hat{a} = \sum_{i=0}^{K} \hat{\beta}_i \tilde{C}_i, \hat{\beta} = softmax(W_{\hat{\beta}} \boxed{h^*})$$

current hidden states of decoder



General idea: how a user's historical and future behaviors can relate to her current state.

- **Encode a user's behavioral data:**

$$h_s, c_s = T - LSTM(x'_s, \delta_s, h_{s-1}, c_{s-1})$$

- **Compute the memory matrix and extract temporal context a:**

$$a = \sum_{i=0}^{K} \beta_i C_i, \beta = softmax(W_\beta h^*)$$

Learning and Imputation

Predict the targets:

$$x_t^* = \phi(h_t^*, \hat{a}_t, a_t)$$

Loss function:

$$\mathcal{L}(X^N, X^{*N}) = \sum_{n=1}^{N}[\sum_{t=1}^{T}\sum_{d=1}^{D} m_t^{(n)} \times (x_t^{d(n)} - x_t^{*d(n)})^2)]$$

Training:

1. Draw a mini-batch of sequences and their neighbors' data;
2. Compute social context and temporal context;
3. For each input in decoding step, sample $p \sim \mathcal{U}(1)$:

$$\textbf{if } p > \gamma \textbf{ then } x' = x_{t-1}^*$$
$$\textbf{else } x' = \boxed{x_{t-1}^*} \cdot (1 - m_{t-1}) + x_{t-1} \cdot m_{t-1}$$

predicted value

4.Compute loss and apply updates.

Imputation:

for each input in decoding step :

$$x' = x_{t-1}^* \cdot (1 - m_{t-1}) + x_{t-1} \cdot m_{t-1}$$

实验结果

Scenario

Given a user v, her neighbors are people whose living places are close to v.

Datasets

Electrical Consumption (EC) : Time series of daily electrical usage recorded by 80,000 watt-hour meters. Each series has 90 timestamps.

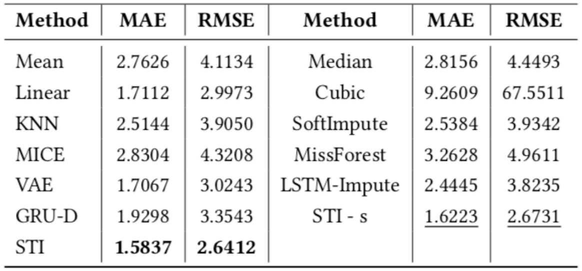
Real-Time Voltage (RV) : Electricity load series, each of which describes voltage values in three phases. Each series has 32 timestamps.

Tasks

Randomly Missing: Elements are randomly dropped with a missing rate.

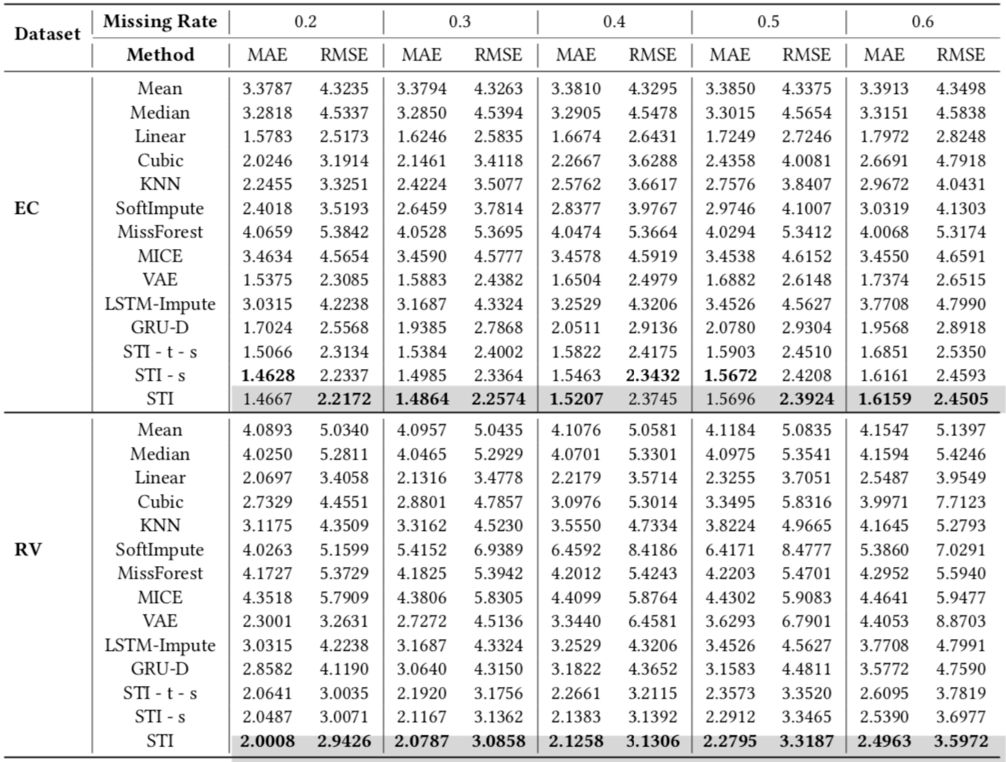
Simulated Missing: An element is dropped if there exists a missing elements after 90 days (only on EC dataset).

Results with Simulated Missing (EC):



Method	MAE	RMSE	Method	MAE	RMSE
Mean	2.7626	4.1134	Median	2.8156	4.4493
Linear	1.7112	2.9973	Cubic	9.2609	67.5511
KNN	2.5144	3.9050	SoftImpute	2.5384	3.9342
MICE	2.8304	4.3208	MissForest	3.2628	4.9611
VAE	1.7067	3.0243	LSTM-Impute	2.4445	3.8235
GRU-D	1.9298	3.3543	STI - s	1.6223	2.6731
STI	**1.5837**	**2.6412**			

Results with Randomly Missing



Dataset	Missing Rate	0.2		0.3		0.4		0.5		0.6	
	Method	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
EC	Mean	3.3787	4.3235	3.3794	4.3263	3.3810	4.3295	3.3850	4.3375	3.3913	4.3498
	Median	3.2818	4.5337	3.2850	4.5394	3.2905	4.5478	3.3015	4.5654	3.3151	4.5838
	Linear	1.5783	2.5173	1.6246	2.5835	1.6674	2.6431	1.7249	2.7246	1.7972	2.8248
	Cubic	2.0246	3.1914	2.1461	3.4118	2.2667	3.6288	2.4358	4.0081	2.6691	4.7918
	KNN	2.2455	3.3251	2.4224	3.5077	2.5762	3.6617	2.7576	3.8407	2.9672	4.0431
	SoftImpute	2.4018	3.5193	2.6459	3.7814	2.8377	3.9767	2.9746	4.1007	3.0319	4.1303
	MissForest	4.0659	5.3842	4.0528	5.3695	4.0474	5.3664	4.0294	5.3412	4.0068	5.3174
	MICE	3.4634	4.5654	3.4590	4.5777	3.4578	4.5919	3.4538	4.6152	3.4550	4.6591
	VAE	1.5375	2.3085	1.5883	2.4382	1.6504	2.4979	1.6882	2.6148	1.7374	2.6515
	LSTM-Impute	3.0315	4.2238	3.1687	4.3324	3.2529	4.3206	3.4526	4.5627	3.7708	4.7990
	GRU-D	1.7024	2.5568	1.9385	2.7868	2.0511	2.9136	2.0780	2.9304	1.9568	2.8918
	STI - t - s	1.5066	2.3134	1.5384	2.4002	1.5822	2.4175	1.5903	2.4510	1.6851	2.5350
	STI - s	**1.4628**	2.2337	1.4985	2.3364	1.5463	**2.3432**	**1.5672**	2.4208	1.6161	2.4593
	STI	1.4667	**2.2172**	**1.4864**	**2.2574**	**1.5207**	2.3745	1.5696	**2.3924**	**1.6159**	**2.4505**
RV	Mean	4.0893	5.0340	4.0957	5.0435	4.1076	5.0581	4.1184	5.0835	4.1547	5.1397
	Median	4.0250	5.2811	4.0465	5.2929	4.0701	5.3301	4.0975	5.3541	4.1594	5.4246
	Linear	2.0697	3.4058	2.1316	3.4778	2.2179	3.5714	2.3255	3.7051	2.5487	3.9549
	Cubic	2.7329	4.4551	2.8801	4.7857	3.0976	5.3014	3.3495	5.8316	3.9971	7.7123
	KNN	3.1175	4.3509	3.3162	4.5230	3.5550	4.7334	3.8224	4.9665	4.1645	5.2793
	SoftImpute	4.0263	5.1599	5.4152	6.9389	6.4592	8.4186	6.4171	8.4777	5.3860	7.0291
	MissForest	4.1727	5.3729	4.1825	5.3942	4.2012	5.4243	4.2203	5.4701	4.2952	5.5940
	MICE	4.3518	5.7909	4.3806	5.8305	4.4099	5.8764	4.4302	5.9083	4.4641	5.9477
	VAE	2.3001	3.2631	2.7272	4.5136	3.3440	6.4581	3.6293	6.7901	4.4053	8.8703
	LSTM-Impute	3.0315	4.2238	3.1687	4.3324	3.2529	4.3206	3.4526	4.5627	3.7708	4.7991
	GRU-D	2.8582	4.1190	3.0640	4.3150	3.1822	4.3652	3.1583	4.4811	3.5772	4.7590
	STI - t - s	2.0641	3.0035	2.1920	3.1756	2.2661	3.2115	2.3573	3.3520	2.6095	3.7819
	STI - s	2.0487	3.0071	2.1167	3.1362	2.1383	3.1392	2.2912	3.3465	2.5390	3.6977
	STI	**2.0008**	**2.9426**	**2.0787**	**3.0858**	**2.1258**	**3.1306**	**2.2795**	**3.3187**	**2.4963**	**3.5972**