Who will Attend This Event Together? Event Attendance Prediction via Deep LSTM Networks

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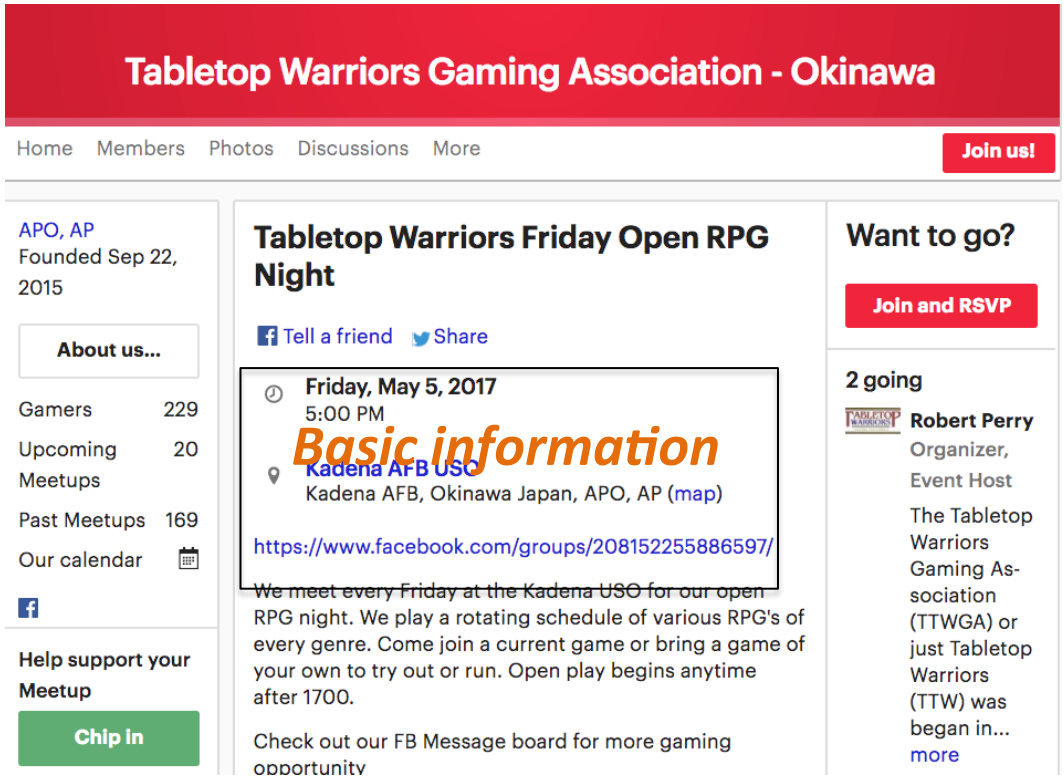
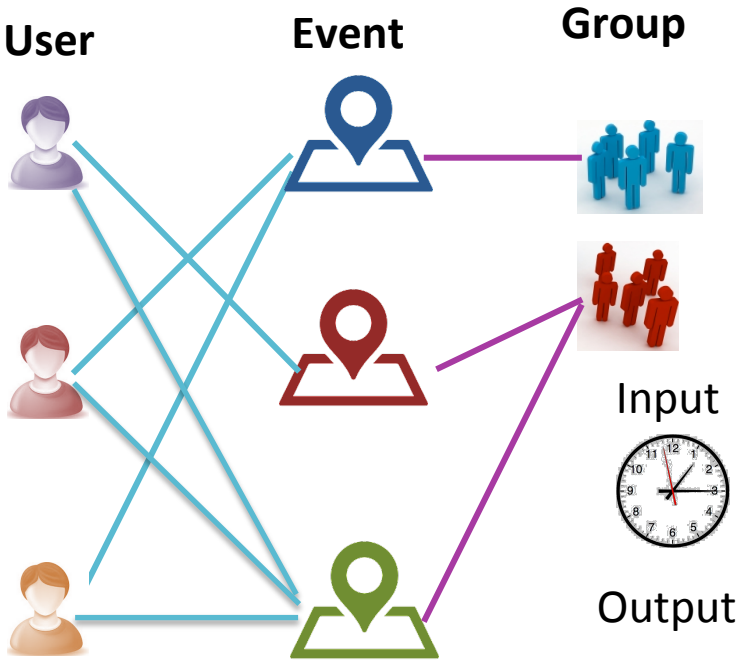
Event based Social network

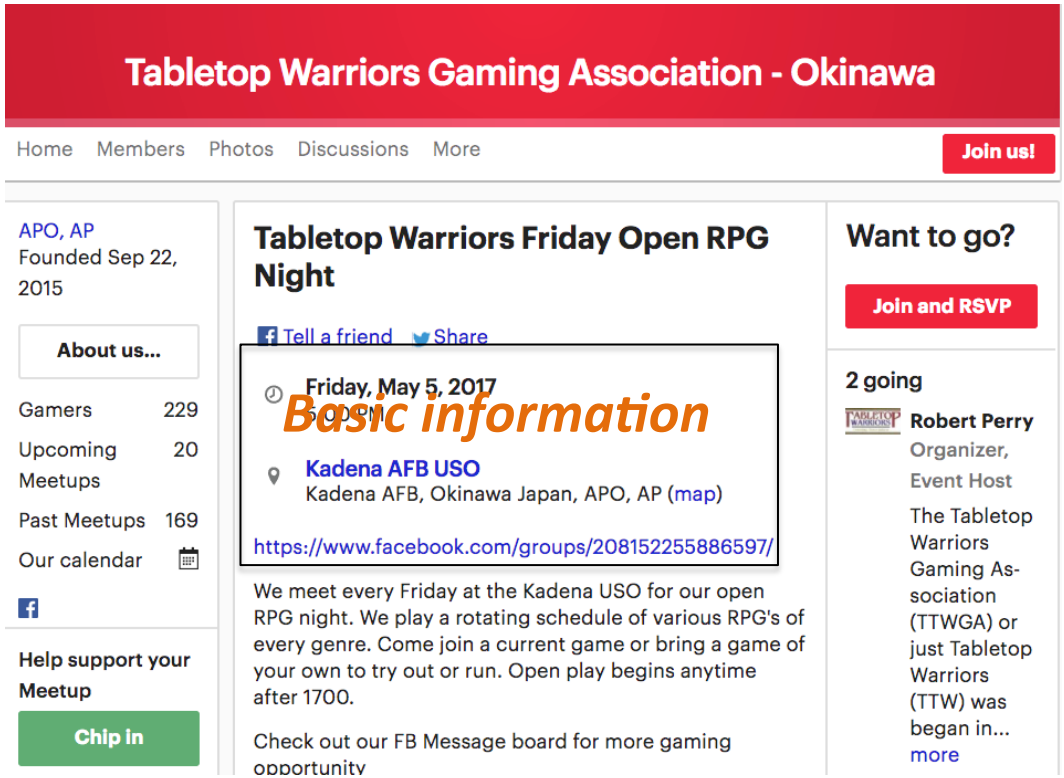




A snapshot of a event homepage in Meetup.com

Event Attendance Prediction

Given an incoming event, who will attend this event?



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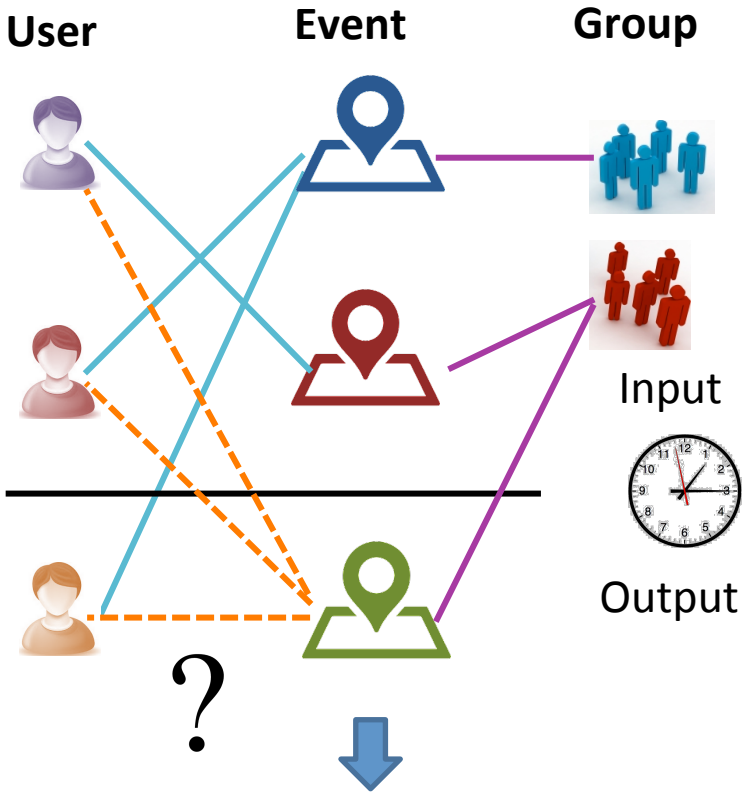


Learning a predictive model

Event Attendance Prediction

Previous work: **static** scenario— the assumption of users' static preference

Real-word: **dynamic** scenario — users' event preferences evolve over time

Event Attendance Prediction

Challenges:

1. Events in EBSNs are typically short-lived

2. The underlying factors may change over time

3. Users' event attendance behaviors are closely related to the contextual information of events

4. The connections between event attendance can be arbitrary since any pair of events could potentially be related for various reasons.

Challenges

Event cold start challenge:

Events in EBSNs are typically *short-lived* and are always in *future*.

It is challenging to explore the trace of events' historical attendance, in order to infer their future attendance.

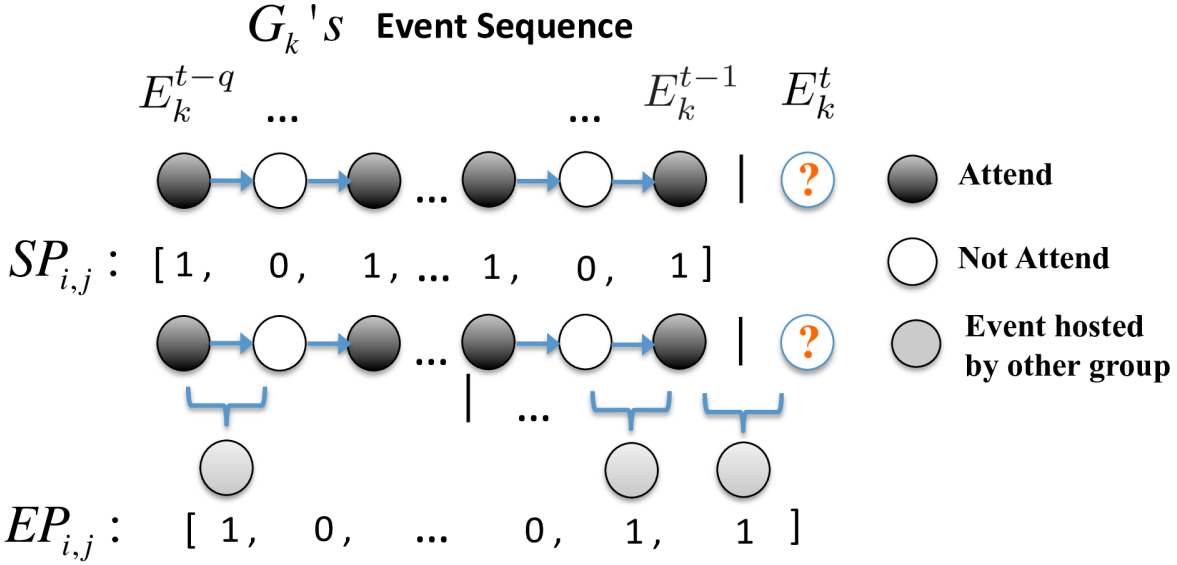
Users' evolving preference challenge:

the factors influence an individual's attendance may change over time

It is difficult to model the dynamic nature of individuals' behavior.

Model

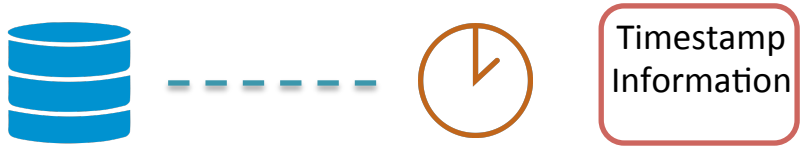
1. Sequential & Exclusive Preferences



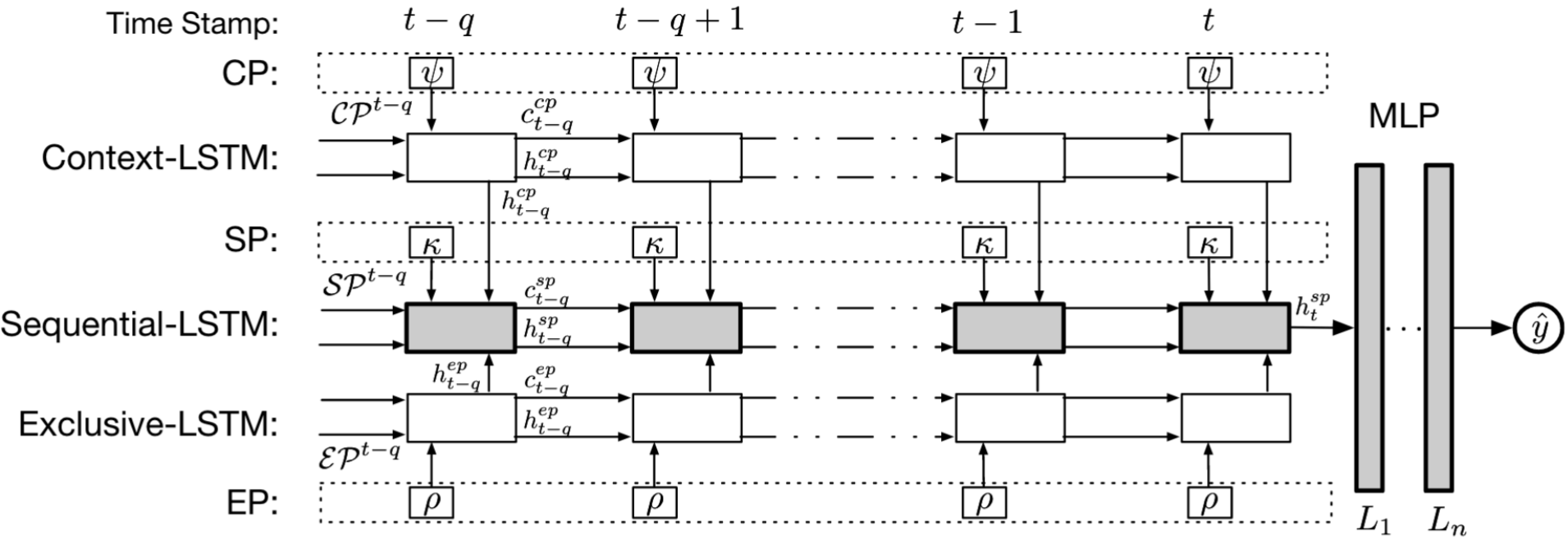
2. Contextual Preferences

Spatial Dimension

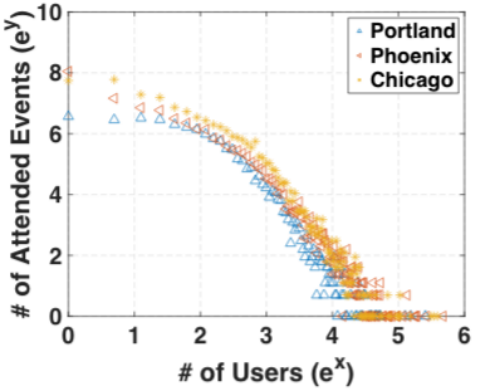
Temporal Dimension



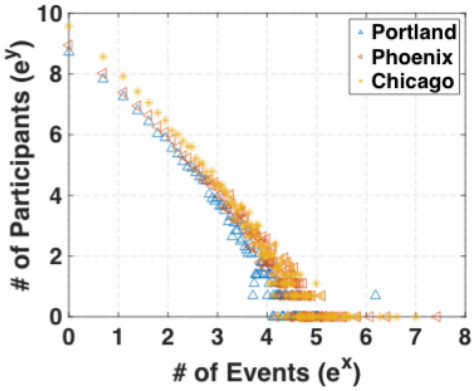
The DEAP Framework



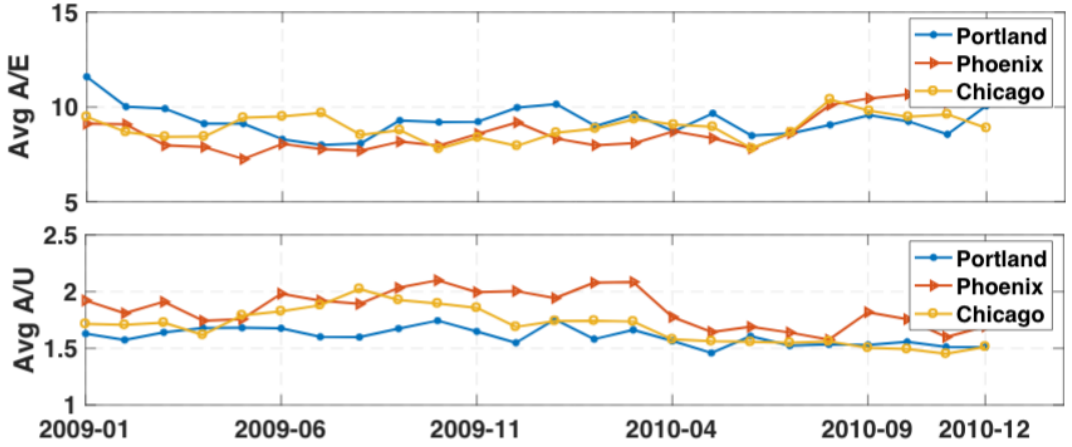
Evaluation



(a) Distribution of Users' Attended Events



(b) Distribution of Events' Participants



(c) Event Attendance Distributions over Time (Avg A/E: Average Number of Participants for each event; Avg A/U: Average Number of Attended Events for each user.)

Evaluation Results (Accuracy-1/5)

Table 4: Performance of all compared methods on Portland

Month	Jan-Feb		Mar-Apr		May-Jun		Jul-Aug		Sep-Oct	
Algorithm	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1
TF	0.222	0.255	0.211	0.249	0.212	0.256	0.194	0.227	0.206	0.250
NMF	0.178	0.236	0.177	0.192	0.204	0.259	0.193	0.171	0.115	0.184
DNN	0.207	0.269	0.163	0.242	0.093	0.169	0.162	0.273	0.106	0.200
LSTM	0.218	0.252	0.155	0.213	0.192	0.234	0.199	0.229	0.236	0.276
MCLRE	0.220	0.289	0.211	0.264	0.161	0.248	0.239	0.304	0.196	0.288
ST-RNN	0.313	0.337	0.323	0.356	0.306	0.346	0.290	0.320	0.284	0.327
DEAP	**0.346**	**0.367**	**0.339**	**0.375**	**0.357**	**0.377**	**0.332**	**0.336**	**0.338**	**0.367**

Table 5: Performance of all compared methods on Phoenix

Month	Jan-Feb		Mar-Apr		May-Jun		Jul-Aug		Sep-Oct	
Algorithm	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1
TF	0.218	0.387	0.210	0.329	0.226	0.373	0.187	0.272	0.187	0.274
NMF	0.176	0.218	0.151	0.159	0.190	0.236	0.165	0.199	0.116	0.192
DNN	0.088	0.190	0.163	0.273	0.212	0.342	0.114	0.227	0.127	0.226
LSTM	0.217	0.386	0.182	0.235	0.244	0.334	0.156	0.194	0.193	0.255
MCLRE	0.248	0.462	0.12	0.289	0.169	0.323	0.201	0.392	0.195	0.318
ST-RNN	0.295	0.484	0.300	0.425	0.329	0.457	0.299	0.448	0.252	0.354
DEAP	**0.342**	**0.508**	**0.322**	**0.439**	**0.360**	**0.467**	**0.323**	**0.460**	**0.281**	**0.374**

Evaluation Results (Accuracy-2/5)

Prediction Results on Dec with High-Level Region in NYC

Table 6: Performance of all compared methods on Chicago

Month	Jan-Feb		Mar-Apr		May-Jun		Jul-Aug		Sep-Oct	
Algorithm	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1	Macro-F1	Micro-F1
TF	0.246	0.335	0.224	0.276	0.212	0.287	0.223	0.278	0.227	0.312
NMF	0.201	0.293	0.135	0.200	0.204	0.259	0.193	0.171	0.206	0.240
DNN	0.235	0.344	0.199	0.289	0.140	0.249	0.125	0.212	0.209	0.226
LSTM	0.246	0.340	0.226	0.263	0.208	0.254	0.224	0.305	0.182	0.296
MCLRE	0.283	0.398	0.186	0.271	0.148	0.235	0.227	0.319	0.250	0.368
ST-RNN	0.332	0.437	0.321	0.366	0.331	0.410	0.329	0.380	0.353	0.440
DEAP	**0.370**	**0.461**	**0.347**	**0.383**	**0.362**	**0.425**	**0.349**	**0.399**	**0.373**	**0.447**

Conclusion

---- We propose to predict event attendance of each user in a dynamic scenario, where user preferences evolve over time. To address this task, we develop a DEAP framework which explicitly models evolving preferences of users from multi-dimensions.

---- We evaluate our new solution on three real-world Meetup datasets. The experimental results demonstrate the effectiveness of our model and show that DEAP outperforms other state-of-the-art baselines in terms of prediction accuracy.

Thank You!

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