Context-Aware Event Recommendation in Event-Based Social Networks (RecSys 2015)

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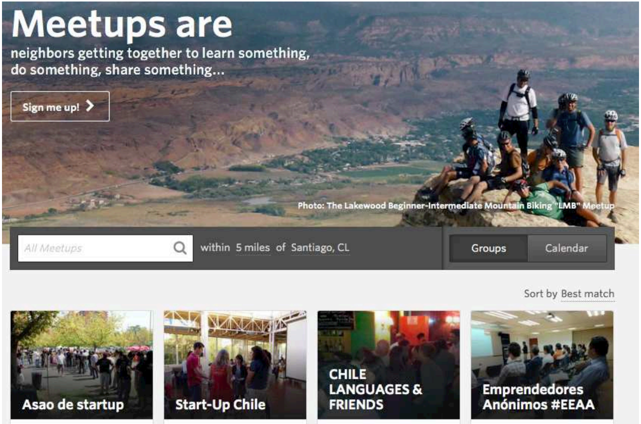
Event-Based Social Networks (EBSNs)

People can create events of any kind and share it with other users.



Which events best match the user's preferences?

Outline

- Problem Setting and Motivation
- Contextual Models (Social, Content, Location, Time)
- Experimental and Evaluation
- Conclusions

Problem

Event Recommendation is Intrinsically **Cold-Start**

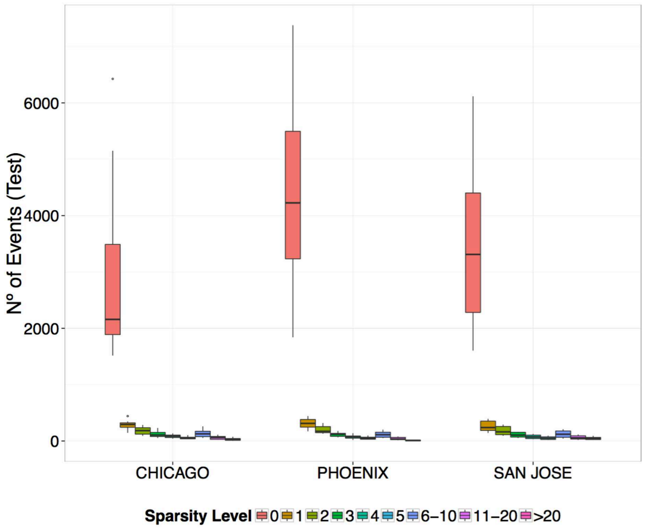
Events are always in the future.

Idea 1: Use RSVP as a Proxy for Event Attendance

RSVP: ”please respond”. After the creation of a public event, any user can RSVP to it with ”yes” or ”no”.

However, RSVP data is very sparse!

Sparsity Level per User



Idea 2: Use Contextual Data

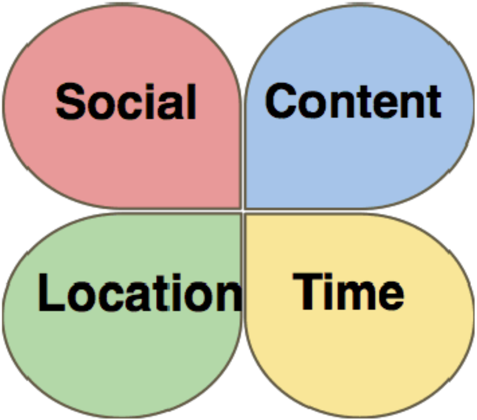
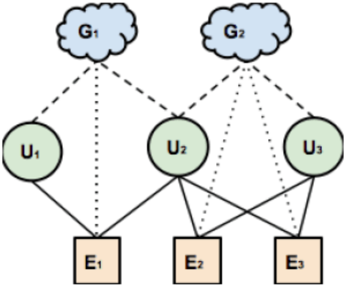


Figure: Multi-Contextual Learning to Rank Events (MCLRE)

Social-Aware: Group Frequency

The more events a user attends in a group, the higher the probability he will attend a new event of this group. Formally:

$$\hat{s}(u, e) := \frac{|E_{u,g_e}|}{E_u}$$



Multi-Relational Matrix Factorization [Drumond, 2012]

$$argmin_{\Theta} \underbrace{\alpha L(R_{UE}, UE^T) + \beta L(R_{UG}, UG^T) + \gamma L(R_{GE}, GE^T)}_{\text{sum of weighted losses}} \underbrace{+\lambda_U \parallel U \parallel + \lambda_E \parallel E \parallel + \lambda_G \parallel G \parallel}_{\text{regularization term}} \quad (1)$$

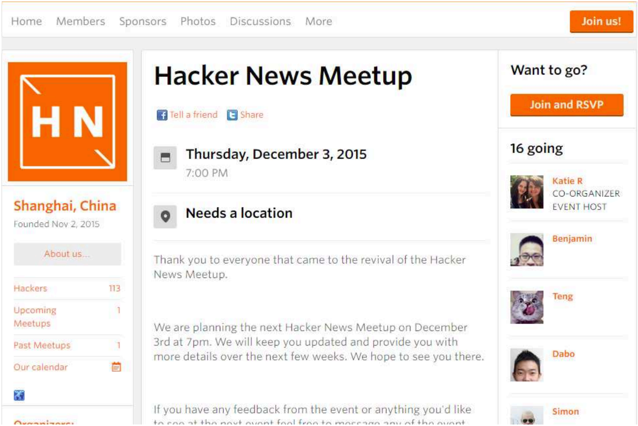
- $R_{XY} \ldots$ Relation between X and Y.
- $\Theta := \{U, E, G\} \ldots$ latent matrices of U, E, G resp.
- $L \ldots$ BPR loss function.

The recommendation score is given by:

$$\hat{s}(u, e) = \sum_{f=1}^{k} \vec{u_f} \vec{e_f}$$

Content-Aware

Content may help to capture similar and recurrent events.



TF-IDF with time decay

User profile is the aggregation of all her events' TF-IDFs weighted:

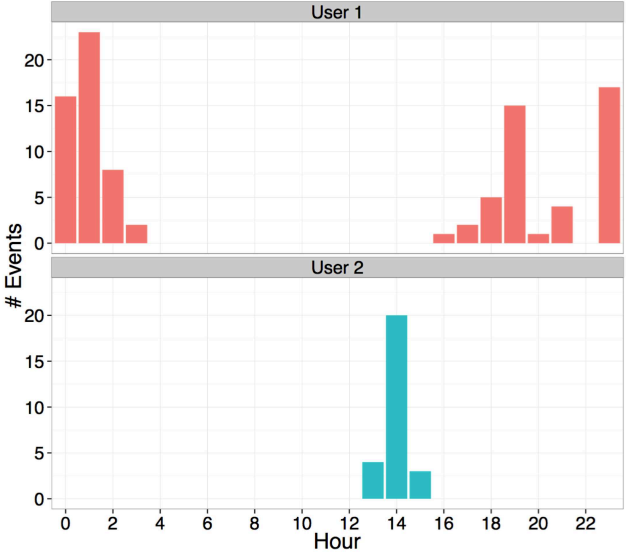
$$\vec{u} := \sum_{e \in E_u} \frac{1}{(1+\alpha)^{\tau}} \times \vec{e}.$$

- $\vec{e}$ ...TF-IDF of event e.
- α ...time decay factor.
- $\tau(e)$ ...days from the RSVP to e until the recommendation moment.

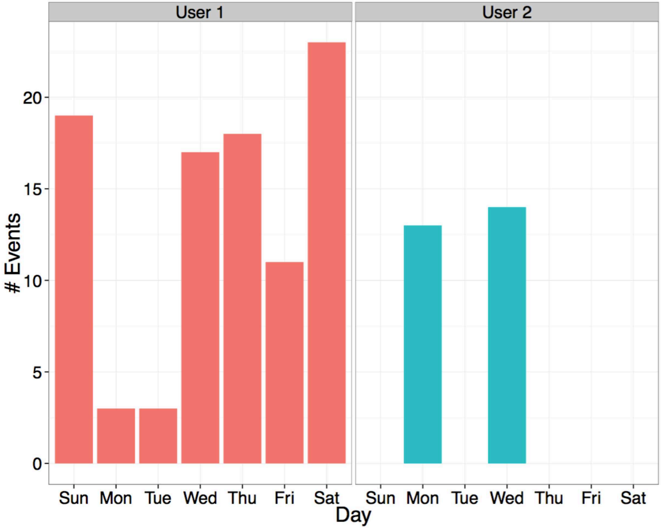
The recommendation score is given by:

$$\hat{s}(u,e) = cos(\vec{u}, \vec{e}).$$

Which time do users go to events?



Which day do users go to events?



Time-Aware

Each user is the centroid of the events she attended in the past:

$$\vec{u} := \frac{1}{E_u} \sum_{e \in E_u} \vec{e}.$$

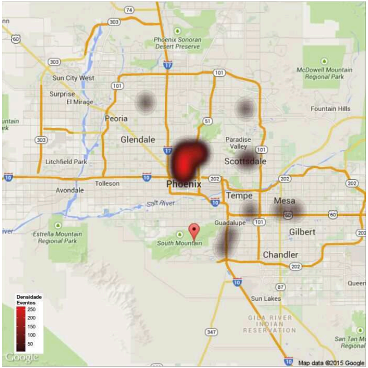
where $\vec{e}$ is a 24×7-dimensional vector in the space of all possible days of the week and hours of the day.

The recommendation score is now:

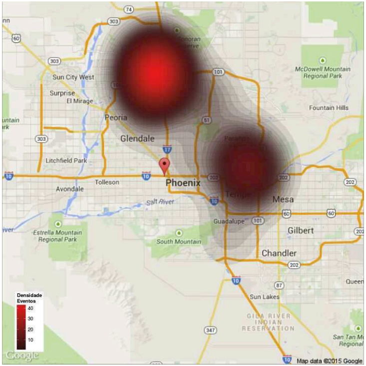
$$\hat{s}(u, e) := cos(\vec{u}, \vec{e})$$

Location-Aware

Assumption: Users tend to attend events close to the events they attended in the past.



(a) User 1



(b) User 2

Kernel Density Estimation

The recommendation score is given by

$$\hat{s}(u, e) = \frac{1}{|L_u|} \sum_{l' \in L_u} K_H(l_e - l').$$

where l_e is the lat-long coordinate of event e and K_H is the Gaussian kernel.

Learning to Rank

Let $\mathcal{D} := \{(x_1, y1), \ldots, (x_n, y_n)\}$ be the training set where $x_i := (\hat{s_1}(u, e), \ldots, \hat{s_m}(u, e), |U_e|)$ is a feature vector containing the scores for each recommender and $y_i = \{0, 1\}$ denote whether user u attended event e or not.

The goal is to learn a function $h(x)$ s.t. for any pair (x_i, y_i) and (x_j, y_j) the following holds:

$$h(x_i) > h(x_j) \Leftrightarrow y_i > y_j.$$

We have used **Coordinate Ascent** [Metzler, 2007], a state-of-the-art listwise learning to rank approach.

Research Questions

*Q*1. How **effective** is MCLRE for event recommendation?

*Q*2. How **robust** is MCLRE to **sparsity** in the RSVP data?

*Q*3. Which contextual **features** are **effective** recommenders?

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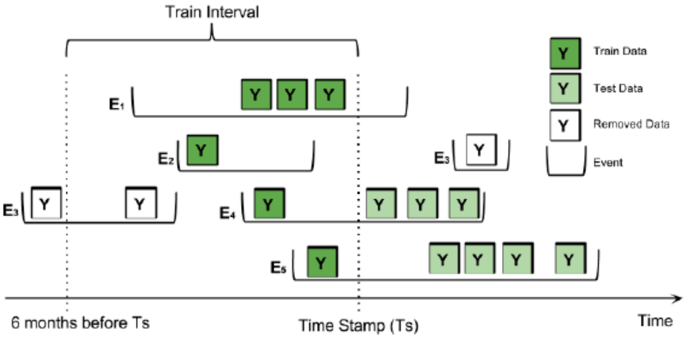
Evaluation Protocol

- Meetup.com data from January, 2010 to April, 2014
- Cities Collected: Phoenix, Chicago and San Jose

City	$\|G\|$	$\|U\|$	$\|E\|$	**RSVPs**	**Sparsity**
Chicago	2,321	207,649	190,927	1,375,154	99.99%
Phoenix	1,661	117,458	222,632	1,209,324	99.95%
San Jose	2,589	242,143	206,682	1,607,985	99.99%

Evaluation Protocol

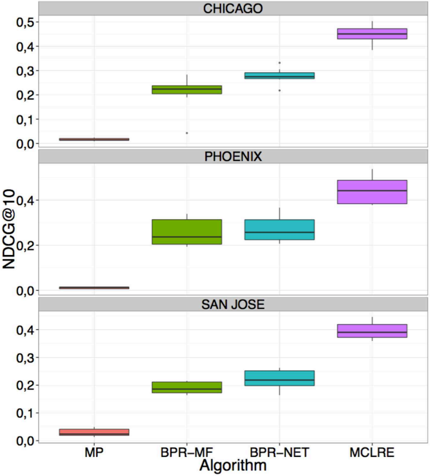
- 12 time stamps equally spaced in time over 52 months.
- Sliding training window.
- For each city, the four initial partitions are used as validation sets and the remaining partitions for evaluation.



Compared Algorithm

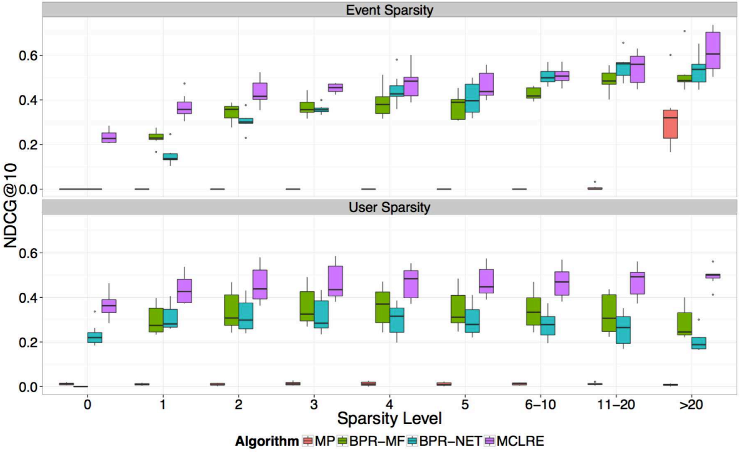
- Most Popular
- BPR-MF [Rendle, 2009]
- BPR-NET [Qiao, 2014]
- **MCLRE**
- Evaluation Metric: NDCG@10

Recommendation Effectiveness



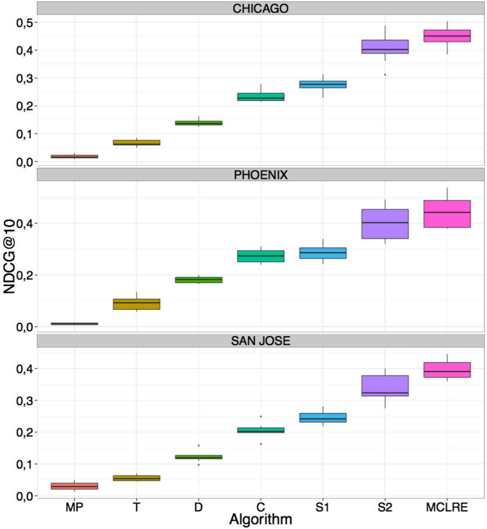
Improvement of up to 79%!

Robustness to Data Sparsity



Only method able to recommend in full cold-start!

Contextual Feature Analysis



Conclusions

- The use of multiple contexts can both lead to highly accurate recommendations and mitigate the cold-start problem.
- Events created by groups of which a user is a member are far more relevant than the content of the events or collaborative RSVP data.