Zürich, Switzerland | 12-14 June, 2017

UMR 5205 CNRS

Recommendation of Short-Term Activity Sequences During Distributed Events

Laboratoire d'InfoRmatique en Image et Systèmes d'information

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INSTITUT NATIONAL DES SCIENCES APPLIQUÉES LYON

LIRIS DRIM Distribution, Recherche d'Information et Mobilité

STeamer - LIG Spatial and Temporal Information Systems

La Région Auvergne-Rhône-Alpes

Agenda

- Scenario
- Research Questions
- Uncertainty

General Context

Problem Statement & State-of-the-Art

- Problem Statement
- State-of-the-Art

- General Overview
- Personalised Scores of Activity
- Behavioural Pattern Mining
- Itinerary Construction

Our Approach: ANASTASIA

Evaluation & Conclusion

- Dataset
- Evaluation Protocol
- Results
- Conclusion

General Context

Scenario

FÊTE DES LUMIÈRES

pinkpop

COACHELLA
COACHELLA VALLEY MUSIC AND ARTS FESTIVAL

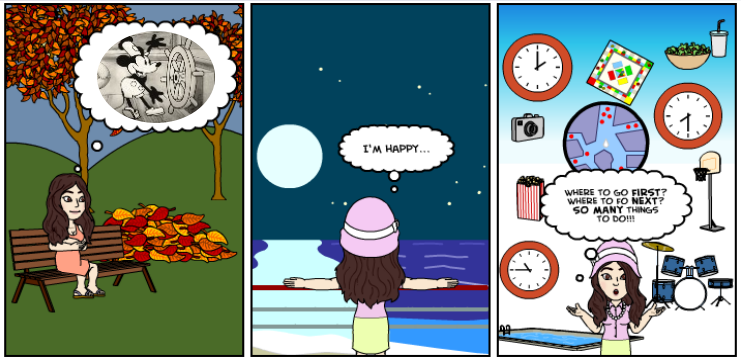
SAN DIEGO COMIC CON INTERNATIONAL

Royal Caribbean INTERNATIONAL

Disney CRUISE LINE

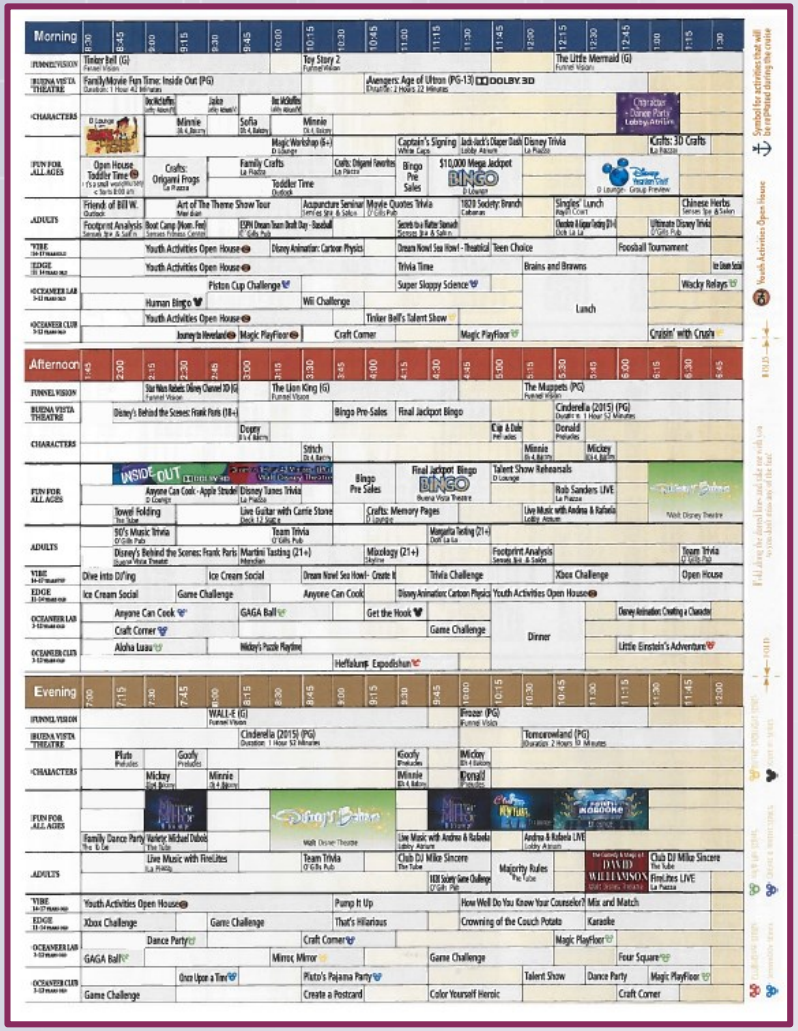
WWW 2017

40th SIGIR 2017 TOKYO • JAPAN

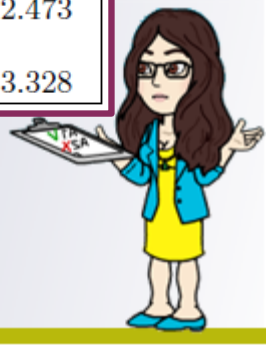


LIRIS

Scenario



Time Slots	Activity	Travel Time, min
14:00 - 14:30	*Towel Folding*	3.999
14:15 - 15:00	Anyone Can Cook - Apple Strudel	3.193
15:45 - 16:15	Bingo Pre-Sales. Final Jackpot	1.701
16:15 - 17:00	Bingo: Final Jackpot	0.000
17:00 - 18:00	*Professional Portraits*	2.556
17:00 - 18:00	Talent Show Rehearsals	2.141
18:15 - 19:00	*Disney's Believe*	2.473
19:15 - 20:30	*Professional Portraits*	3.328
19:30 - 20:00	Mirror Mirror	2.141
21:30 - 22:30	*Professional Portraits*	2.141
21:45 - 22:15	Mirror Mirror	2.141
22:15 - 22:45	*Club New Year's Eve*	0.000
23:00 - 23:30	*The Comedy & Magic of David Williamson*	2.473
23:30 - 00:00	FireLites LIVE	3.328



Research Questions

*How can we **predict** and **maximise users' satisfaction** with undertaken sequence of activities, given their past experience?*

How can we **tackle the uncertain users' preferences** and **evaluate the users' interest for an activity** happening **in future,** given **little information** about it?

How can we **retrieve users' behavioural patterns** from historical data?

How can we **organise activities into a sequence** that **maximizes users' satisfaction** while taking into account **spatio-temporal constraints** and **sequential nature** of activities?

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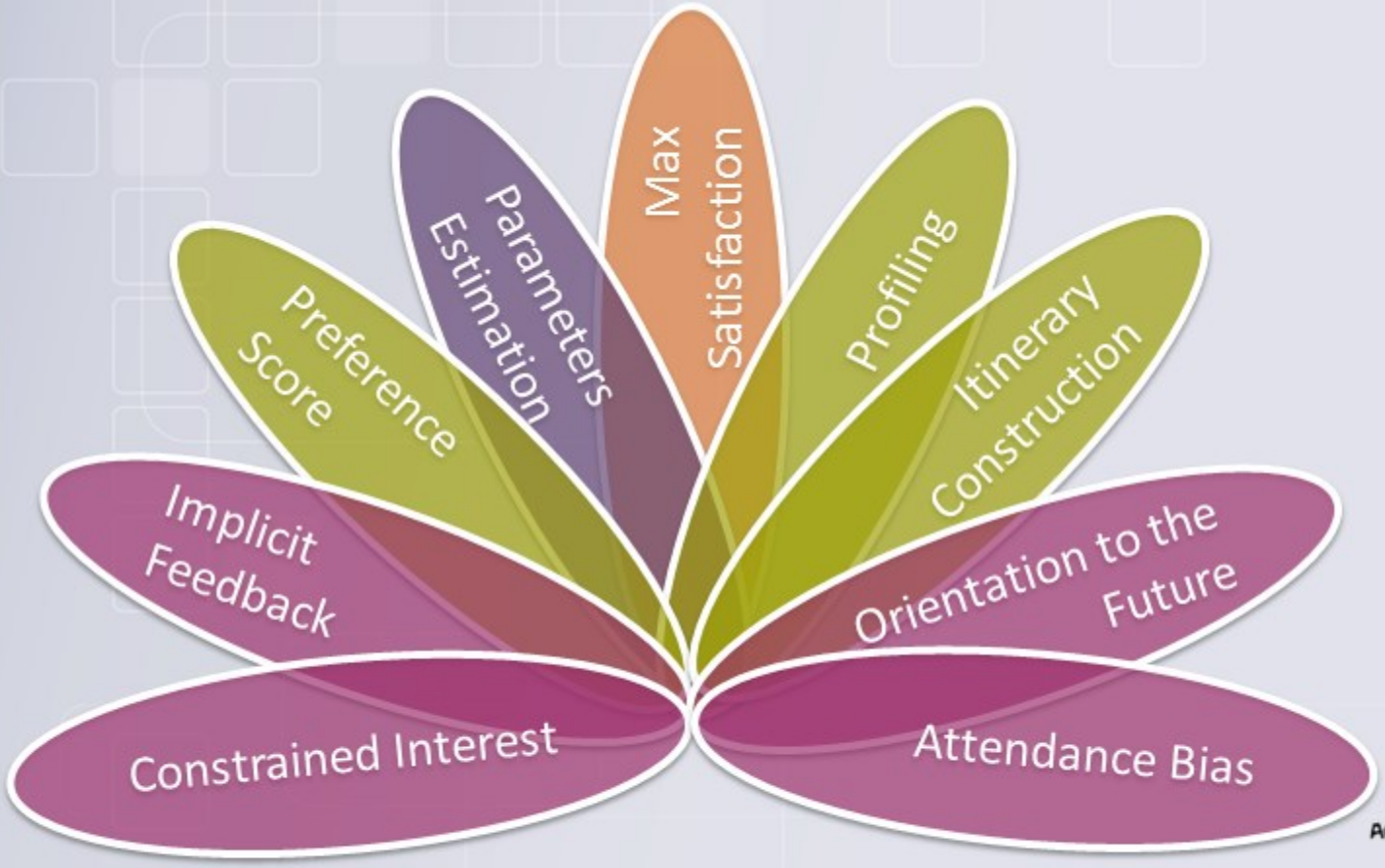
Uncertainty



Data

Model

Parameters

Assumption

Problem Statement & State-of-the-Art

Problem Statement: STAS

What We Have

- **Set of Activities, $\mathcal{A} = \{a_i\}_{i=\overline{1,N}}$:**

$$a = \langle l, t, \delta, c, d \rangle$$

$l = (x, y, z)$ – location

$t = (t_s, t_e)$ – time window (start & end)

$\delta \leq (t_e - t_s)$ – duration

$c = (c_1, c_2, \dots, c_k)$ – vector of categories

d – textual description

- **Set of Users, $\mathrm{U} = \{u_j\}_{j=\overline{1,M}}$**

- **Users' History, $\mathcal{M}$:**

$$\mathcal{M}_{i,j} = \begin{cases} 1, j^{th} \text{ user joined } i^{th} \text{ activity} \\ 0, \text{otherwise} \end{cases}$$

What We Want

- **Activity Sequence (itinerary),**

$$\xi(u) = \left(a_{(1)} \to \cdots \to a_{(s)} \to \cdots \to a_{(s+k)}\right),$$
$$1 \leq s \leq s + k \leq N$$

  - Activity availability constraint:

$$t_s(a_{(i)}) \leq start(a_{(i)}) \leq t_e(a_{(i)})$$

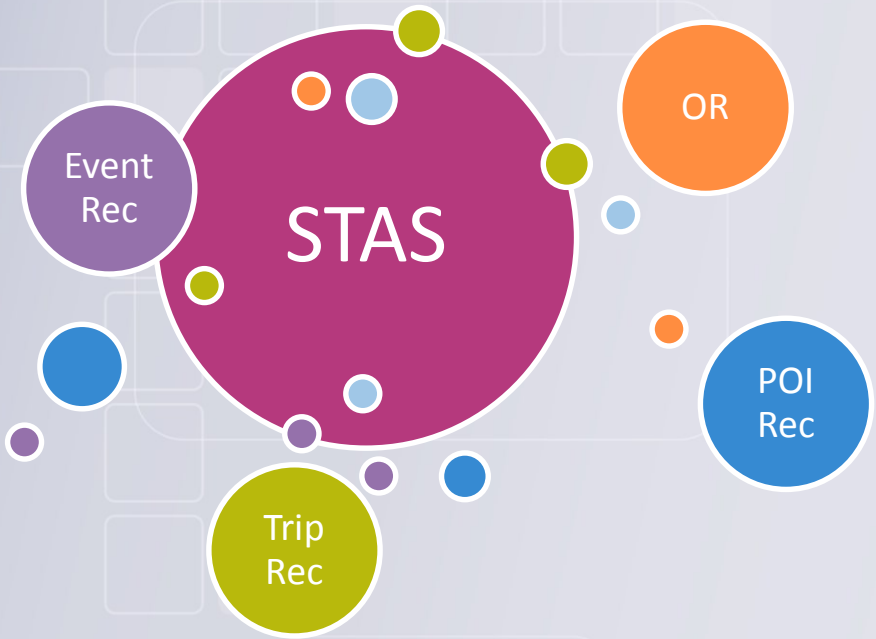
$$start(a_{(i)}) = \max\{start(a_{(i-1)}) + \delta(a_{(i-1)}) + time(a_{(i-1)}, a_{(i)}),\ t_s(a_{(i)})\}$$

  - Time budget constraint:

$$\sum_{a_{(i)} \in \xi(u)} time(a_{(i-1)}, a_{(i)}) + \delta(a_{(i)}) \leq T_{max}$$

- **User's Satisfaction :**
  - w.r.t. activity $r(a, u)$, $r: \mathcal{A} \to \mathbb{R}^+$
  - w.r.t. itinerary $\rho(\xi, u)$, $\rho: \Xi \to \mathbb{R}^+$
- **Find: $\forall u \in U$, $\xi(u)$: $\max \rho(\xi, u)$**

State of the Art



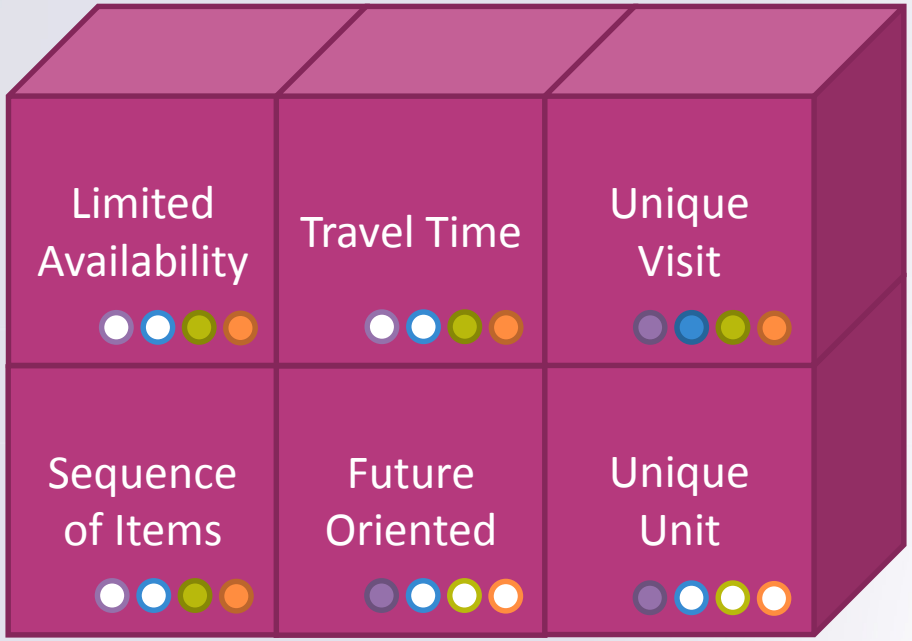
STAS – recommendation of **S**patio-**T**emporal **A**ctivity **S**equences

Event Rec – Event Recommendation

POI Rec – Point-of-Interest Recommendation

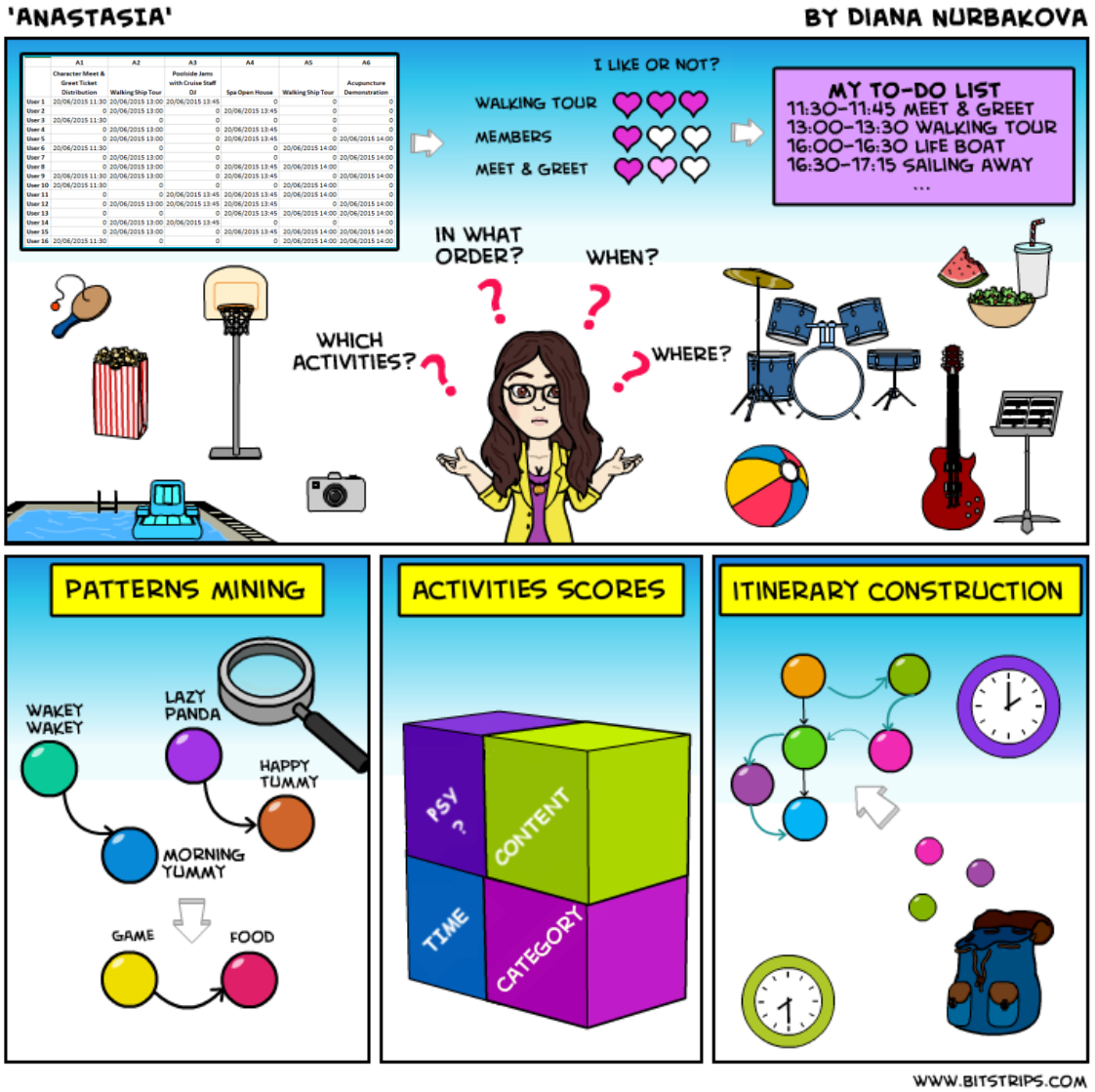
Trip Rec – Trip Recommendation

OR – Scheduling in Operational Research



ANASTASIA: A Novel Approach for Spatio-Temporal Activity Sequence and Itinerary recommendAtion

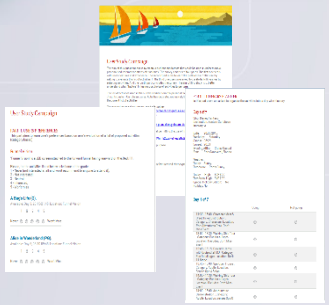
ANASTASIA: General Overview



	A1	A2	A3	A4	A5	A6
	Character Meet & Greet Ticket Distribution	Walking Ship Tour	Poolside Jams with Cruise Staff DJ	Spa Open House	Walking Ship Tour	Acupuncture Demonstration
User 1	20/06/2015 11:30	20/06/2015 13:00	20/06/2015 13:45	0	0	0
User 2	0	20/06/2015 13:00	0	20/06/2015 13:45	0	0
User 3	20/06/2015 11:30	0	0	0	0	0
User 4	0	20/06/2015 13:00	0	20/06/2015 13:45	0	0
User 5	0	20/06/2015 13:00	0	20/06/2015 13:45	0	20/06/2015 14:00
User 6	20/06/2015 11:30	0	0	0	20/06/2015 14:00	0
User 7	0	20/06/2015 13:00	0	0	0	20/06/2015 14:00
User 8	0	20/06/2015 13:00	0	20/06/2015 13:45	20/06/2015 14:00	0
User 9	20/06/2015 11:30	20/06/2015 13:00	0	20/06/2015 13:45	0	20/06/2015 14:00
User 10	20/06/2015 11:30	0	0	0	20/06/2015 14:00	0
User 11	0	0	20/06/2015 13:45	20/06/2015 13:45	20/06/2015 14:00	0
User 12	0	20/06/2015 13:00	20/06/2015 13:45	20/06/2015 13:45	0	20/06/2015 14:00
User 13	0	0	0	20/06/2015 13:45	20/06/2015 14:00	20/06/2015 14:00
User 14	0	20/06/2015 13:00	20/06/2015 13:45	0	0	0
User 15	0	20/06/2015 13:00	0	20/06/2015 13:45	20/06/2015 14:00	20/06/2015 14:00
User 16	20/06/2015 11:30	0	0	0	20/06/2015 14:00	20/06/2015 14:00

ANASTASIA: Overview

Statistics	
Number of Users	23
Number of Activities	595
Number of Days	7
Number of DCL Categories	10
Number of No DCL Categories	42
Number of Locations	47



Spatio-Temporal Activities

- Category-based Score
- Content-based Score
- Temporal Score
  ** Adaptation of [2]*
- 2 Calculation Strategies
  - All-at-Once
  - Day-after-Day

Personalised Scores of Activities

ANASTASIA: Overview

- Sequence Mining
- Activity-Activity Transition Modelling
- Category-Category Transition Modelling
- Estimation of Transition Probabilities

  ** Adaptation of [4]*

Behavioural Pattern Mining

- Category-based Score
- Content-based Score
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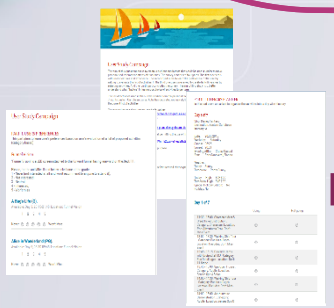

Spatio-Temporal Activities

ANASTASIA: Overview

- Modelling as an instance of OPTW (Orienteering Problem with Time Windows)
- Iterated Algorithm

  ** Adaptation of Iterated Local Search (ILS) algorithm [3]*

Itinerary Construction

- Sequence Mining
- Activity-Activity Transition Modelling
- Category-Category Transition Modelling
- Estimation of Transition Probabilities

  ** Adaptation of [4]*

Behavioural Pattern Mining

- Category-based Score
- Content-based Score
- Temporal Score

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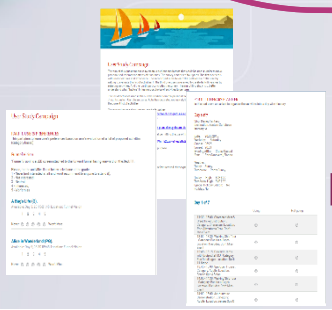

Spatio-Temporal Activities

ANASTASIA: Personalised Score of Activity

similarity w.r.t. categories of user's past activities :

$$\hat{r}_{cat}(a_i, u) = \sum_{c_j \in \mathcal{C}_a} \frac{\left|A_{u,c_j}\right| \cdot w_a}{|A_u|}$$

- $\left|A_{u,c_j}\right|$ - the number of activities performed by user u that belong to category c_j : $A_{u,c_j} = \{a_l\}: a_l \in c_j$
- A_u - the set of activities performed by user u
- $w_a = {}^{1}/_{|\mathcal{C}_a|}$ - weight coefficient

Category-based Score

ANASTASIA: Personalised Score of Activity

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Category-based Score

textual similarity w.r.t. descriptions of past activities :

$$\hat{r}_{text}(a_i, u) = \alpha_u \cdot \cos(U_{pos}, \vec{e}) - \beta_u \cdot \cos(U_{neg}, \vec{e})$$

- U_{pos} - user's positive profile composed of TF-IDF vectors of performed past activities
- U_{neg} - user's negative profile composed of TF-IDF vectors of not performed past activities
- $\vec{e}$ - TF-IDF vector of activity a_i
- $\cos(\cdot,\cdot)$ – cosinus similarity

Content-based Score

ANASTASIA: Personalised Score of Activity

similarity w.r.t. categories of user's past activities :

$$\hat{r}_{cat}(a_i, u) = \sum_{c_j \in \mathcal{C}_a} \frac{\left|A_{u,c_j}\right| \cdot w_a}{|A_u|}$$

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Category-based Score

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- U_{neg} - user's negative profile composed of TF-IDF vectors of not performed past activities
- $\vec{e}$ - TF-IDF vector of activity a_i
- $\cos(\cdot,\cdot)$ – cosinus similarity

Content-based Score

temporal similarity w.r.t. time slots of user's past activities :

$$\hat{r}_{time}(a_i, u) = \begin{cases} 1, & \text{if } t_a \cap t_u \\ 0.5, & \text{if } t_a \cap \{t_u - 1 \cup t_u + 1\} \\ 0.1, & otherwise \end{cases}$$

- t_a - 1×96-dimensional binary vector corresponding to time slots of activity a
- t_u - 1×96-dimensional binary vector corresponding to time slots of user's past activities
- $t_u \pm 1$ – preceding or next time slot

Temporal Score

ANASTASIA: Personalised Score of Activity

similarity w.r.t. categories of user's past activities :

$$\hat{r}_{cat}(a_i, u) = \sum_{c_j \in \mathcal{C}_a} \frac{\left|A_{u,c_j}\right| \cdot w_a}{|A_u|}$$

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Content-based Score

Option 1:

$$r_{hyb}(a_i, u) = \left(\gamma_u \cdot \hat{r}_{cat}(a_i, u) + \delta_u \cdot \hat{r}_{text}(a_i, u)\right) \cdot \hat{r}_{time}(a_i, u)$$

Option 2:

$$r_{log}(a_i, u) = \frac{1}{1 + e^{-(\eta_0 + \eta_1 \mathbf{x})}}$$

- $\hat{r}_{cat}$ - category-based score
- $\hat{r}_{text}$ - content-based score
- $\hat{r}_{time}$ - temporal score
- $\mathbf{x} = (\hat{r}_{cat}, \hat{r}_{text}, \hat{r}_{time})$

Hybrid Score

temporal similarity w.r.t. time slots of user's past activities :

$$\hat{r}_{time}(a_i, u) = \begin{cases} 1, & \text{if } t_a \cap t_u \\ 0.5, & \text{if } t_a \cap \{t_u - 1 \cup t_u + 1\} \\ 0.1, & otherwise \end{cases}$$

- t_a - 1×96-dimensional binary vector corresponding to time slots of activity a
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- $t_u \pm 1$ – preceding or next time slot

Temporal Score

ANASTASIA: Personalised Score of Activity

- **Strategy 1: All-at-Once**
- Iterated calculation of scores

Input: User's Attendance Matrix $\mathcal{M}$, New activities $NewEvent$;
Output: Activities scores $\mathcal{R}$;

Calculate $\mathcal{R}(NewEvent, \mathcal{M})$

- **Strategy 2: Day-after-Day**
- Iterated enrichment of history data with estimations from the previous step

Input: User's Attendance Matrix $\mathcal{M}$, New activities $NewEvent$, Number of past days $PastDays$, Total number of days $DayNum$;
Output: Activities scores $\mathcal{R}$;

Initialisation $\mathcal{M}^{(0)} \leftarrow \mathcal{M}$;

for $i \leftarrow PastDays$ to $DayNum$ do
  Calculate $\mathcal{R}^{(i)}(NewEvent^{(i)}, \mathcal{M}^{(i)})$;
  $\mathcal{M}^{(i)} \leftarrow \mathcal{M}^{(i)} \cup \mathcal{R}^{(i)}$;
  $i \leftarrow i + 1$
end

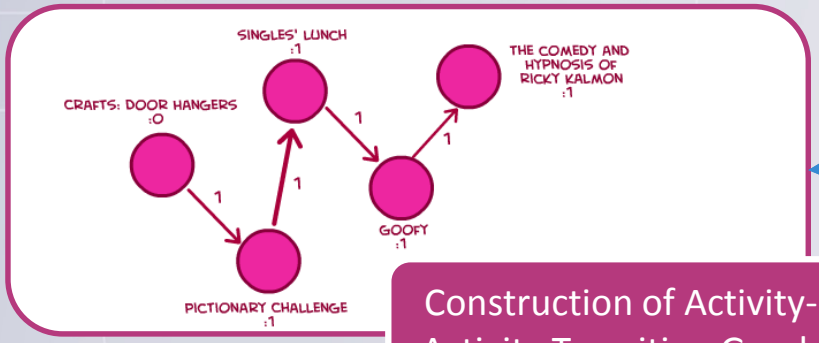
ANASTASIA: Behavioural Pattern Mining

Crafts: Door Hangers → Pictionary Challenge → Singles' Lunch → Goofy → The Comedy and Hypnosis of Ricky Kalmon

Sequence Extraction

ANASTASIA: Behavioural Pattern Mining

*Adaptation of L2TG (LORE [4])



Construction of Activity-Activity Transition Graph

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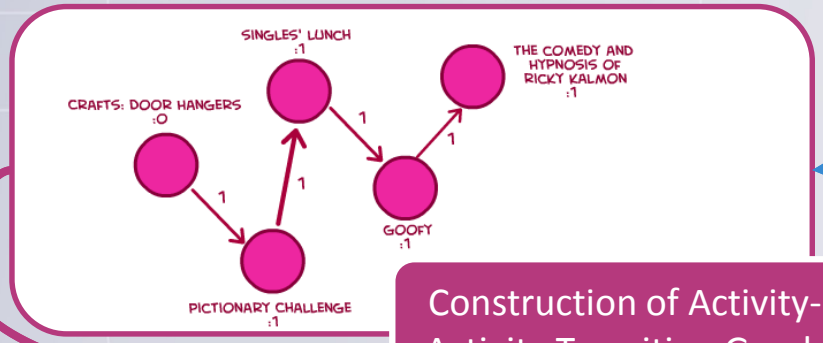

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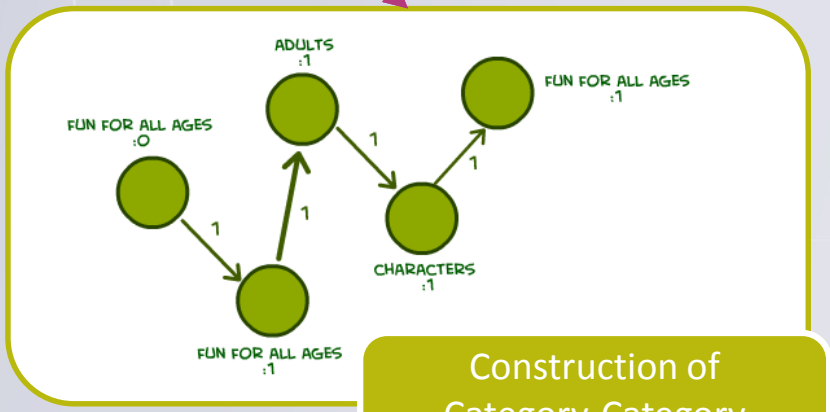

Construction of Category-Category Transition Graph

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Sequence Extraction

Activities sub-sequence	Categories sub-sequence
$\{Crafts: Door\ Hangers \rightarrow Pictionary\ Challenge \rightarrow Singles'Lunch \rightarrow Goofy \rightarrow The\ Comedy\ and\ Hypnosis\ of\ Ricky\ Kalmon\}$	$\{Fun\ for\ All\ Ages \rightarrow Fun\ for\ All\ Ages \rightarrow Adults \rightarrow Characters \rightarrow Fun\ for\ All\ Ages\}$

ANASTASIA: Behavioural Pattern Mining

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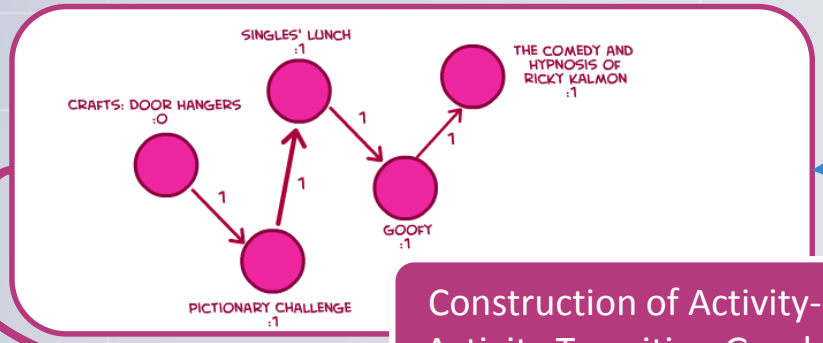

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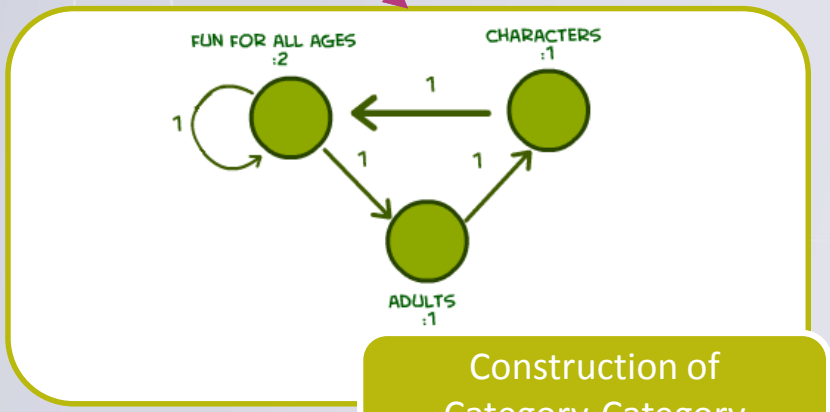

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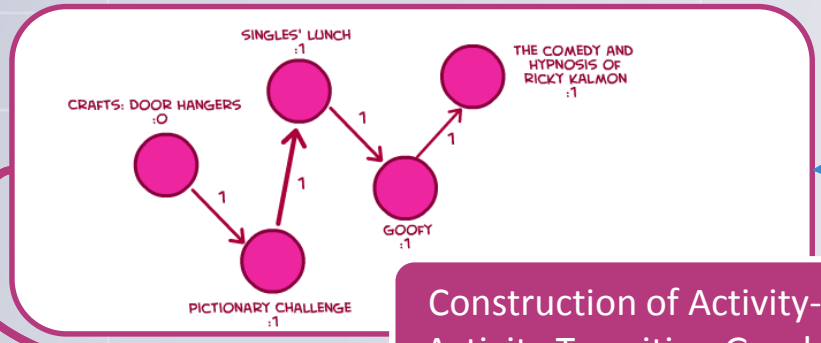

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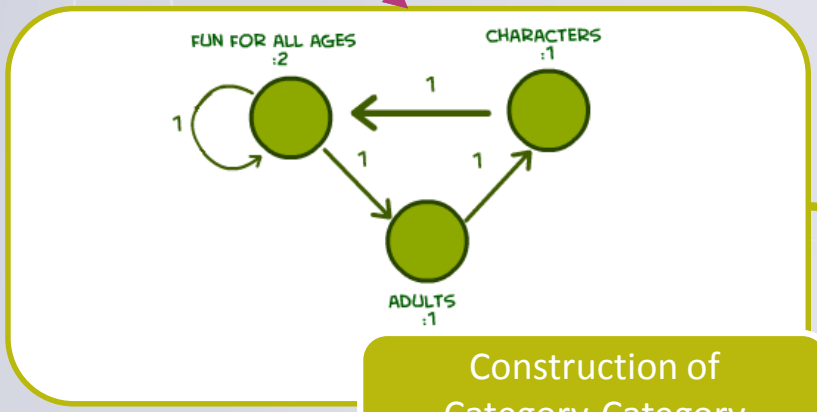

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Estimation of Transition Probability

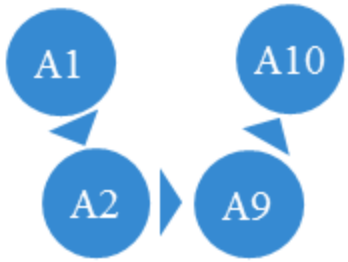
$$P_T(Fun\ for\ All\ Ages \rightarrow Fun\ for\ All\ Ages) = \frac{1}{2}$$

$$P_T(Fun\ for\ All\ Ages \rightarrow Adults) = \frac{1}{1} = 1$$

$$P_T(Adults \rightarrow Characters) = \frac{1}{1} = 1$$

$$P_T(Characters \rightarrow Fun\ for\ All\ Ages) = 1/2$$

ANASTASIA: Itinerary Construction



Id : Activity : Location : Start – End : Duration : Score : Wait : MaxShift

A1 : Character Meet & Greet Ticket Distribution : Port Adventures Desk : 11h30 – 15h00 : 10 min : 5 : 0 : 1h20
A2 : Walking Ship Tour : Preludes : 13h00 – 13h30 : 30 min : 5 : 1h20 : 0
A9 : Mandatory Life Boat Drill : Assembly Station : 16h00 – 16h30 : 30 min : 5 : 2h30 : 0
A10 : Sailing Away : Deck Stage : 16h30 – 17h15 : 45 min : 5 : 0 : 0

Current Sequence

Id : Activity : Shift : Ratio : $Ratio_{NEW} = \frac{(S*P_T)^2}{Shift}$

A3 : Poolside Jams with Cruise Staff DJ : 0h45 : 0,089 : = $\frac{\left(2*\frac{2}{3}\right)^2}{45} = 1,027$ **max!**

A4 : Spa Open House : 1h30 : 0,044 : = $\frac{(2*0)^2}{90} = 0$

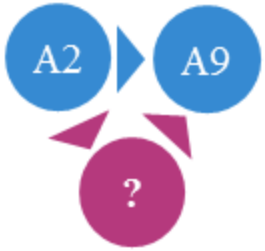
A6 : Acupuncture Demonstration : 2h00 : 0,033 : = $\frac{(2*0)^2}{120} = 0$

A7 : Disney Vacation Club: Members Celebration :1h45 : 0,01 : = $\frac{\left(1*\frac{2}{3}\right)^2}{105} = 0,004$

A8 : Spa Raffle : 2h00 : 0,033 : = $\frac{(2*0)^2}{120} = 0$

Calculation of Ratio and Insertion of a Vertex

Id : Activity : Location : Start – End : Duration : Score



A3 : Poolside Jams with Cruise Staff DJ : Deck 11 Stage : 13h45 – 15h15 : 30 min : 2
A4 : Spa Open House : Senses Spa & Salon : 13h45 – 15h00 : 75 min : 2
A6 : Acupuncture Demonstration : Senses Spa & Salon : 14h00 – 15h00 : 60 min : 2
A7 : Disney Vacation Club: Members Celebration : D Lounge : 14h30 – 15h15 : 45 min : 1
A8 : Spa Raffle : Senses Spa & Salon : 15h00 – 15h30 : 30 min : 2

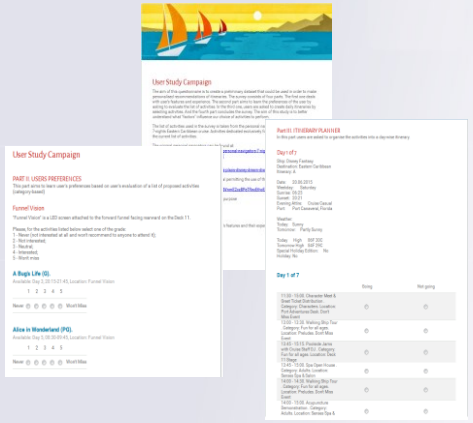
Search for the best vertex to insert

** Modification of ILS [3]*

Evaluation

Evaluation: Dataset

Dataset Statistics	
Number of users	23
Number of activities in overall program	595
Number of days	7
Number of DCL categories	10
Number of No DCL categories	42
Number of locations	47



Evaluation: Protocol

Dataset

- Created dataset based on Disney's 7 nights cruise
- Split: users history, test set

2 stepped Evaluation

- Rating accuracy of estimated scores
- Evaluation of generated sequences

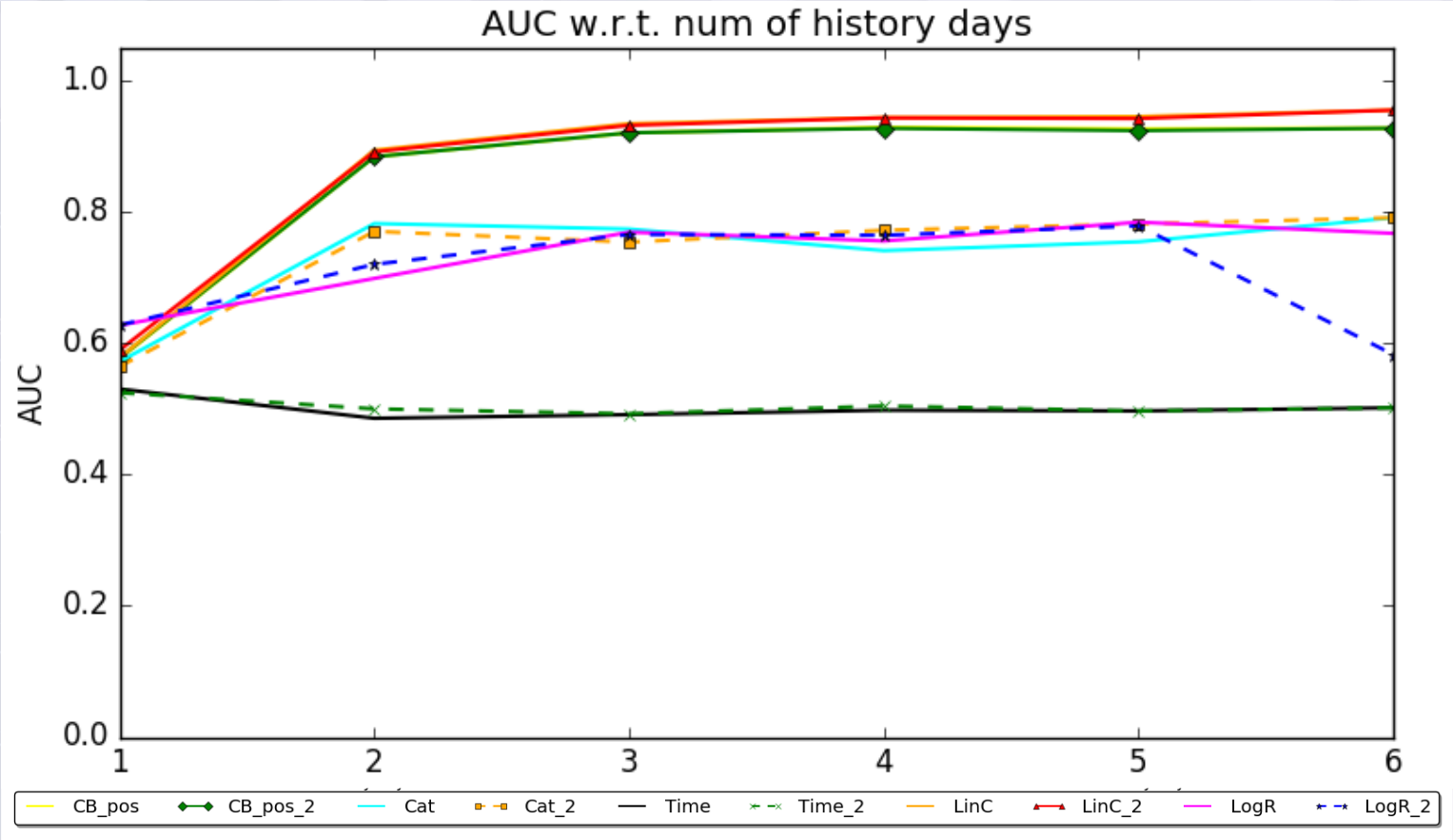
Rating Accuracy

- Mean Absolute Error, $MAE = \sqrt{\frac{1}{|\mathcal{T}|}\sum_{(u,i)\in\mathcal{T}}|\hat{r}_{ui} - r_{ui}|}$
- Root Mean Squared Error, $RMSE = \sqrt{\frac{1}{|\mathcal{T}|}\sum_{(u,i)\in\mathcal{T}}(\hat{r}_{ui} - r_{ui})^2}$
- Precision at rank k, $P@k$
- Area under the Curve, AUC

Sequence Evaluation

- Comparison of Recommended Sequence with Ground Truth (proportion of matches)
- Ground Truth – sequence of activities tagged by users with "Going"

Evaluation: Results



Evaluation: Results

Improvement of ILS_TP over ILS in term of similarity to Ground Truth, %
Hybrid scores of activities are considered

	1	2	3	4	5	6	Average
Strategy 1	6.1	3.4	6.5	6.2	9.9	11.3	**7.4**
Strategy 2	25.0	10.3	4.4	13.5	14.3	11.3	**13.5**

Conclusion

- Formulation of STAS problem
- ANASTASIA, an integrated framework to solve STAS:
  - textual influence
  - categorical influence
  - temporal influence
  - sequential influence
- User study and the Dataset of spatio-temporal activities

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Future work:

- New types of influence to explore (demographics, psychology, group of users)
- New types of constraints to take into account (e.g. multiple time windows, multiple locations of the same activity)
- Crowdsourced dataset
- Crowdsourced evaluation


The End
A
WARNER BROS.-FIRST NATIONAL
PICTURE

References

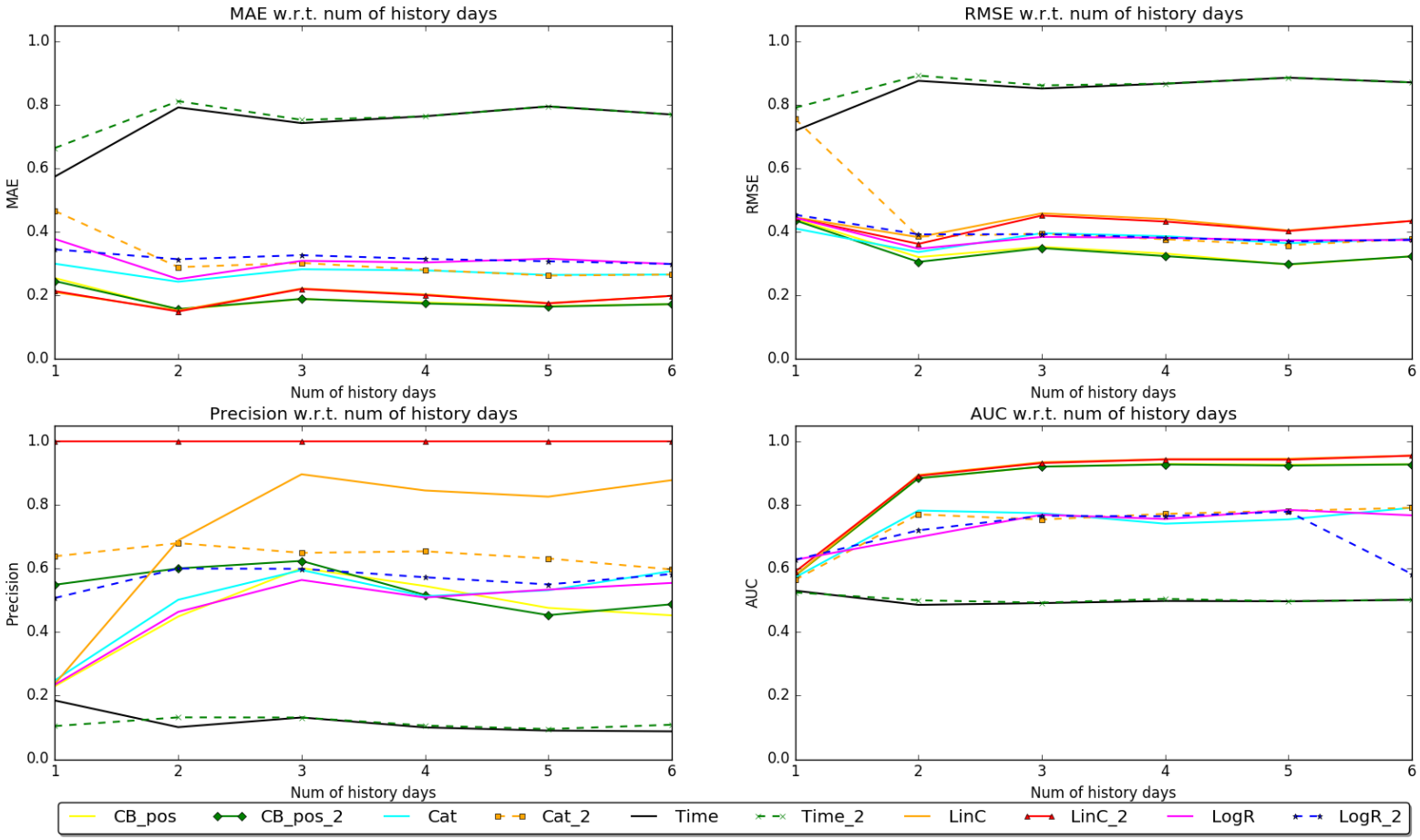
[1] **Florida-Caribbean Cruise Association**. Cruise Industry Overview – 2017. State of the Cruise Industry. Available at: http://www.f-cca.com/downloads/2017-Cruise-Industry-Overview-Cruise-Line-Statistics.pdf

[2] **Sang, J., Mei, T., & Xu, C**. (2015). Activity Sensor: Check-In Usage Mining for Local Recommendation. *ACM Trans. Intel. Syst.. 6*, pp. 41:1--41:24. ACM.

[3] **Vansteenwegen, P., Souffriau, W., Vanden Berghe, G., & Van Oudheusden, D.** (2009). Iterated local search for the team orienteering problem with time windows. *Comput. Oper. Res., 36*(12), pp. 3281-3290.

[4] **Zhang, J.-D., & Chow, C.-Y.** (2015). Spatiotemporal Sequential Influence Modeling for Location Recommendations: A Gravity-based Approach . *ACM Trans. Intel. Syst.* 7 (1), pp. 11:1--11:25. ACM.

Evaluation: Results



Evaluation: Dataset

! Need for Dataset

Type	Characteristic	MC-TOP-MTW	Other OP-based with TW	Other OP-based	TREC CS 2013	TREC CS 2014	TREC CS 2015	TripBuilder Dataset	Yelp	Foursquare_1	Foursquare_2	Flickr	Twitter	Meetup
Point	*Time windows*	✓	✓						✓					
	Coordinates	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Service Time	✓	✓	✓										
	Categories	✓						✓						✓
	Price	✓						✓		✓				
	Point Additional Attributes								✓			✓		✓
	Description											✓	✓	
Tour	Time budget	✓	✓	✓										
	Starting/Ending Point	✓	✓	✓										
	Tour Additional Attributes						✓							
User	User's personal data						✓							✓
User-Point	*Historical Data*				✓	✓	✓	✓		✓	✓	✓	✓	✓
	Score	✓	✓	✓	✓	✓	✓			✓	✓			
User-User	Social links								✓	✓	✓			✓