Recommendation of Short-Term Activity Sequences During Distributed Events

Laboratoire d'InfoRmatique en Image et Systèmes d'information

Diana Nurbakova, Léa Laporte, Sylvie Calabretto, Jérôme Gensel
Agenda

- Scenario
- Research Questions
- Uncertainty

Problem Statement & State-of-the-Art
- General Overview
- Personalised Scores of Activity
- Behavioural Pattern Mining
- Itinerary Construction

Our Approach: ANASTASIA
- Dataset
- Evaluation Protocol
- Results
- Conclusion

General Context
- Problem Statement
- State-of-the-Art

Evaluation & Conclusion
General Context
Scenario
Scenario
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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How can we organise activities into a sequence that maximizes users’ satisfaction while taking into account spatio-temporal constraints and sequential nature of activities?
Uncertainty

Data
Model
Parameters
Assumption

LIRiS
Problem Statement & State-of-the-Art
Problem Statement: STAS

What We Have

- Set of Activities, $\mathcal{A} = \{a_i\}_{i=1}^{N}$:
  $a = \langle l, t, \delta, c, d \rangle$
  $l = (x, y, z)$ – location
  $t = (t_s, t_e)$ – time window (start & end)
  $\delta = (t_e - t_s)$ – duration
  $c = (c_1, c_2, ..., c_k)$ – vector of categories
  $d$ – textual description

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

- 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), $\xi(u) = (a(1) \rightarrow \cdots \rightarrow a(s) \rightarrow \cdots \rightarrow a(s+k))$, $1 \leq s \leq s + k \leq N$

- Activity availability constraint:
  $t_s(a(i)) \leq \text{start}(a(i)) \leq t_e(a(i))$
  $\text{start}(a(i)) = \max\{\text{start}(a(i-1)) + \delta(a(i-1)) + \text{time}(a(i-1), a(i)), t_s(a(i))\}$

- Time budget constraint:
  $\sum_{a(i) \in \xi(u)} \text{time}(a(i-1), a(i)) + \delta(a(i)) \leq T_{max}$

- User’s Satisfaction:
  - w.r.t. activity $r(a, u)$, $r: \mathcal{A} \rightarrow \mathbb{R}^+$
  - w.r.t. itinerary $\rho(\xi, u)$, $\rho: \Xi \rightarrow \mathbb{R}^+$

- Find: $\forall u \in U$, $\xi(u)$: max $\rho(\xi, u)$
State of the Art

**STAS** – recommendation of **Spatio-Temporal Activity Sequences**
**Event Rec** – Event Recommendation

**POI Rec** – Point-of-Interest Recommendation
**Trip Rec** – Trip Recommendation
**OR** – Scheduling in Operational Research

- **Limited Availability**
- **Travel Time**
- **Unique Visit**
- **Sequence of Items**
- **Future Oriented**
- **Unique Unit**
ANASTASIA: A Novel Approach for Spatio-Temporal Activity Sequence and Itinerary recommendation
ANASTASIA: Overview

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

Statistics

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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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Personalised Scores of Activities

Spatio-Temporal Activities

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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

- Category-based Score
- Content-based Score
- Temporal Score
  * Adaptation of [2]
- 2 Calculation Strategies
  - All-at-Once
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Personalised Scores of Activities

Behavioural Pattern Mining

- Sequence Mining
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Spatio-Temporal Activities

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ANASTASIA: Personalised Score of Activity

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

\[
\hat{r}_{cat}(a_i, u) = \sum_{c_j \in C_a} \frac{|A_{u,c_j}| \cdot w_a}{|A_u|}
\]

- \(|A_{u,c_j}|\) - 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 \(u\)
- \(w_a = \frac{1}{|c_a|}\) - weight coefficient

Category-based Score
ANASTASIA: Personalised Score of Activity

**Simularity w.r.t. categories of user’s past activities:**

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

- \( |A_{u,c_j}| \) - the number of activities performed by user \( u \) that belong to category \( c_j \): \( A_{u,c_j} = \{a_l\}: a_l \in c_j \)
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- \( w_a = \frac{1}{|c_a|} \) - weight coefficient

**Textual simularity w.r.t. descriptions of past activities:**

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

- \( U_{\text{pos}} \) - user’s positive profile composed of TF-IDF vectors of performed past activities
- \( U_{\text{neg}} \) - user’s negative profile composed of TF-IDF vectors of not performed past activities
- \( \tilde{e} \) - TF-IDF vector of activity \( a_i \)
- \( \cos(\cdot, \cdot) \) – cosinus similarity
ANASTASIA: Personalised Score of Activity

**Category-based Score**

\[
\hat{r}_{cat}(a_i, u) = \frac{\sum_{c_j \in C_a} |A_{u,c_j}| \cdot w_a}{|A_u|}
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**Content-based Score**

\[
\hat{r}_{text}(a_i, u) = \alpha_u \cdot \cos(U_{pos}, \vec{e}) - \beta_u \cdot \cos(U_{neg}, \vec{e})
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- \(U_{pos}\) - user’s positive profile composed of TF-IDF vectors of performed past activities
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- \(\vec{e}\) - TF-IDF vector of activity \(a_i\)
- \(\cos(\cdot, \cdot)\) – cosinus similarity

**Temporal Score**

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

- \(t_a\) - \(1 \times 96\)-dimensional binary vector corresponding to time slots of activity \(a\)
- \(t_u\) - \(1 \times 96\)-dimensional binary vector corresponding to time slots of user’s past activities
- \(t_u \pm 1\) – preceding or next time slot
ANASTASIA: Personalised Score of Activity

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

\[ \hat{r}_{\text{cat}}(a_i, u) = \sum_{c_j \in C_u} \frac{|A_{u,c_j}| \cdot w_a}{|A_u|} \]

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Option 1:

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

Option 2:

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

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

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

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

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

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ANASTASIA: Personalised Score of Activity

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

**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 $NewEvent$;

**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])

Sequence Extraction

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

Construction of Activity-Activity Transition Graph
ANASTASIA: Behavioural Pattern Mining

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Construction of Activity-Activity Transition Graph

Construction of Category-Category Transition Graph

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

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**ANASTASIA: Behavioural Pattern Mining**

- **Construction of Activity-Activity Transition Graph**
- **Construction of Category-Category Transition Graph**

*Adaptation of L2TG (LORE [4])*

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Construction of Activity-Activity Transition Graph

Construction of Category-Category Transition Graph

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

Sequence Extraction

Estimation of Transition Probability

\[
P_T(\text{Fun for All Ages} \rightarrow \text{Fun for All Ages}) = \frac{1}{2}
\]

\[
P_T(\text{Fun for All Ages} \rightarrow \text{Adults}) = 1
\]

\[
P_T(\text{Adults} \rightarrow \text{Characters}) = 1
\]

\[
P_T(\text{Characters} \rightarrow \text{Fun for All Ages}) = \frac{1}{2}
\]

Activities sub-sequence | Categories sub-sequence
--- | ---
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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

**Id : Activity : Shift : Ratio** : 

\[ \text{Ratio}_{\text{NEW}} = \frac{(S+P_T)^2}{\text{Shift}} \]

- **A3** : Poolside Jams with Cruise Staff DJ : 0h45 : 0,089 : \(\frac{(2+3)^2}{45} = 1,027\) 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 = \(\frac{(1+3)^2}{105} = 0,004\)
- **A8** : Spa Raffle : 2h00 : 0,033 : \(\frac{(2+0)^2}{120} = 0\)

**Search for the best vertex to insert**

*Modification of ILS [3]*
Evaluation
Evaluation: Dataset

<table>
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<th>Dataset Statistics</th>
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<tr>
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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, $MAE = \sqrt{\frac{1}{|T|} \sum_{(u,i) \in T} |\hat{r}_{ui} - r_{ui}|}$
- Root Mean Squared Error, $RMSE = \sqrt{\frac{1}{|T|} \sum_{(u,i) \in T} (\hat{r}_{ui} - r_{ui})^2}$
- 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

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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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- Formulation of STAS problem
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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
References


Evaluation: Results

- MAE w.r.t. num of history days
- RMSE w.r.t. num of history days
- Precision w.r.t. num of history days
- AUC w.r.t. num of history days

Legend:
- CB_pos
- CB_pos_2
- Cat
- Cat_2
- Time
- Time_2
- LinC
- LinC_2
- LogR
- LogR_2
## Need for Dataset

### Evaluation: Dataset

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