RASP: Robust Mining of Frequent Temporal Sequential Patterns under Temporal Variations - Supplementary Document

A ADDITIONAL EXPERIMENTAL RESULTS

Appendix A is attached to the main paper.

B EXTENSION OF RASP TO ALLOW DUPLICATE EVENTS

We only allowed distinct events to maintain clarity and readability in our descriptions. Allowing duplicate events could complicate the already complex explanations of our concepts and algorithms. Fortunately, it is technically feasible to extend our methodology to accommodate duplicate events. Below, we provide a detailed description of this extension, emphasizing the modifications required in the concepts and algorithms to incorporate duplicate events.

B.1 Preliminary Concepts (Sect. 3.1)

Temporal Sequential Patterns. A *temporal sequential pattern* (TSP) $\alpha = (\langle E_1, E_2, \cdots, E_l \rangle, \langle \Delta t_1, \Delta t_2, \cdots, \Delta t_{l-1} \rangle)$ of size l is defined as a pair of ordered sets of (a) events and (b) non-negative *time gaps* between two consecutive events. That is, $E_i \in \mathcal{E}, 1 \leq \forall i \leq l$, $\cancel{E_i \neq E_j}$, $1 \leq \forall i \neq j \leq l$, and $\Delta t_i \in \mathbb{N}_0, 1 \leq \forall i \leq l-1$.

B.2 Relaxed TSPs and Duplicated Pattern Matching (Sect. 4.3)

Mining Frequent TSPs of Size 2 (Algorithm 5). Algorithm 5 depicts how RASP discovers frequent TSPs of size 2.

Mining Frequent TSPs of Size i (> 2) (Algorithm 6). Algorithm 6 depicts how RASP discovers frequent TSPs of a larger size.

C OTHER EVALUATION METRICS

As additional evaluation metrics, we measure NDCG@20 and RC@5 in each setting and report them in Fig. 14 (**S1. Variation-Free**), Fig. 15 (**S2. Variations**), Fig. 16 (**S3. Event Count**), and Fig. 17 (**S4. Mixed-Easy** and **S5. Mixed-Hard**), respectively. Our proposed method, RASP, demonstrates superior accuracy compared to its competitors across all evaluation metrics and settings.

D VARIOUS BIN SIZES

Regarding the effects of bin sizes on the performance of the considered methods, we present the results for a time span L of 50 seconds in Fig. 18. For the results when L is 100 seconds, refer to Appendix A.3. of the main paper.

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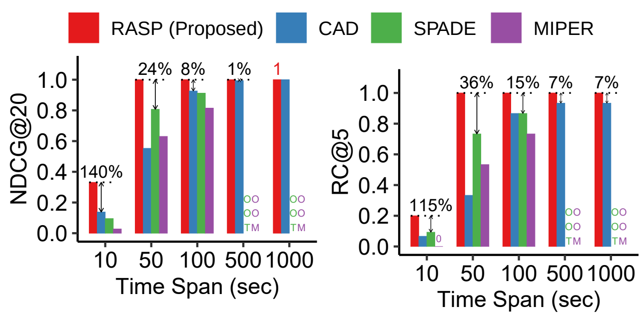
Algorithm 5: Mining Frequent TSP (Size 2)

Input: (1) W: mapping between (event, relative occurrence time) pairs and their WIDs,
(2) F_1: mapping between events and their WIDs,
(3) m_2: max number of TSPs of size 2,
(4) δ: max time gap between consecutive events,
(5) I: tolerance against temporal variations
Output: F_2: mapping between frequent TSPs of size 2 and (WIDs, frequency) pairs

```
Lines 1-2 of Algorithm 3 of the main paper
foreach E_1 ∈ F_1.keys() do
    foreach E_2 ∈ ℰ ~~\{E_1}~~ do
        for t ← 0 to ⌊δ/I⌋ do
            α ← (⟨E_1, E_2⟩, ⟨tI⟩)            // tI = ΔT̄_t (Sect. 4.3)
            if E_1 ≠ E_2 then
                W_α ←
                  F_1[E_1] ∩ (∪_{w=-I}^{I-1} W[(E_2, min(tI + w, δ))])
            else
                W_α ← ∅
                for w ← -I to I - 1 do
                    if min(tI + w, δ) ≠ 0 then
                        W_α ← W_α ∪ W[(E_2, min(tI + w, δ))]
                W_α ← F_1[E_1] ∩ W_α
            Lines 8-15 of Algorithm 3 of the main paper
    return F_2
```

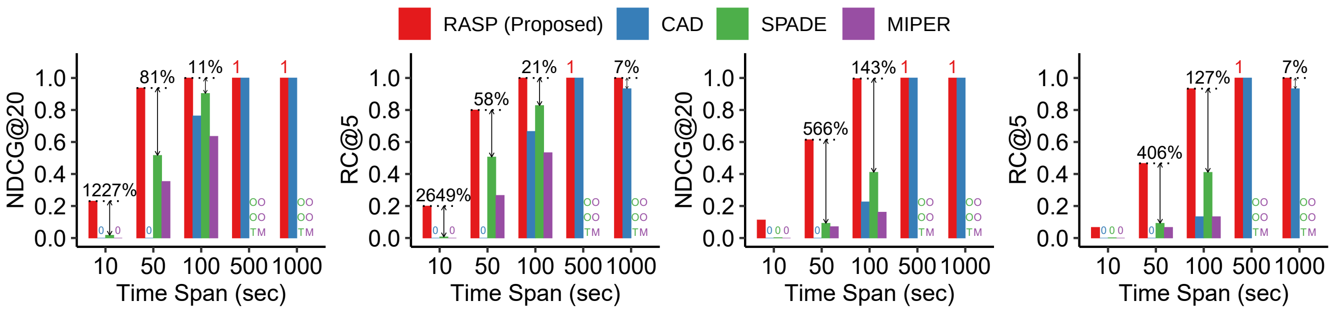


(a) NDCG@20 **(b) RC@5**

Figure 14: S1. Variation-Free. Our proposed method, RASP, exhibits superior accuracy compared to its competitors in the dataset settings without temporal variations or probabilistic participation.

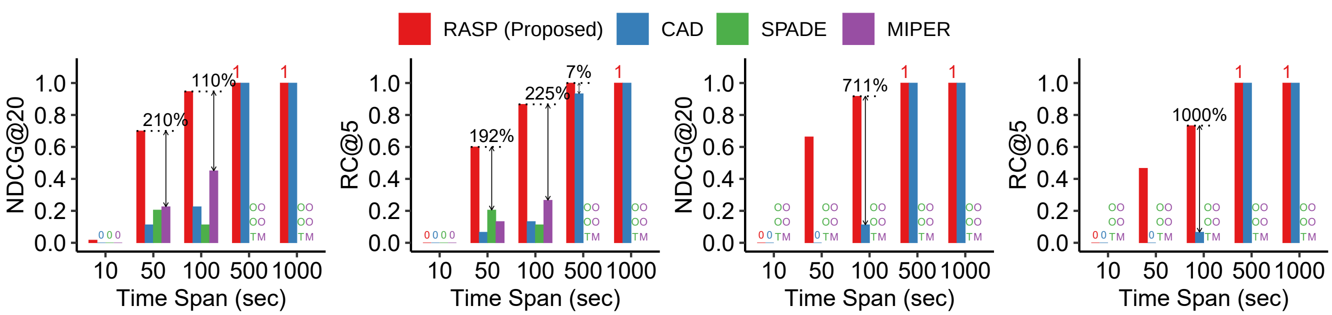
E EXAMPLES OF TSPS

We present the two most frequent TSPs identified by RASP for the precipitation dataset (Sect. 5.6.2). In Fig. 19, the AWS locations for the two most frequent TSPs in the precipitation dataset are situated closely near Hallasan on Jeju Island, South Korea.



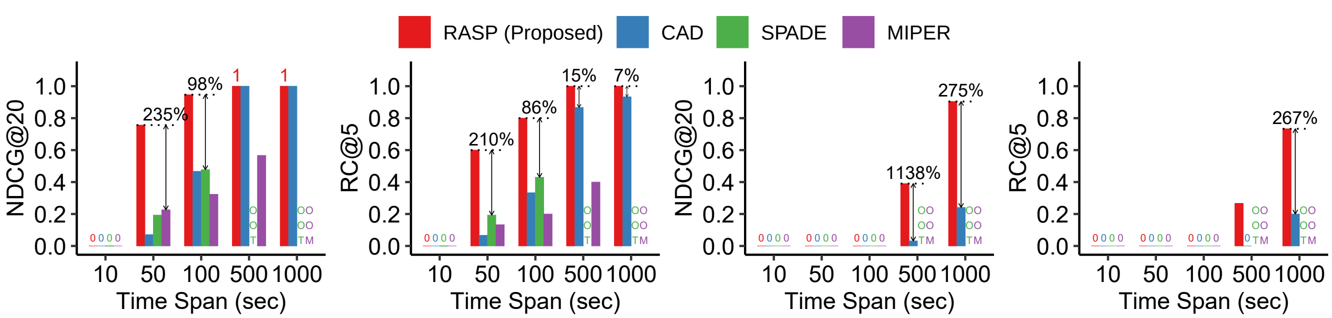
(a) 10 ms / NDCG@20
(b) 10 ms / RC@5
(c) 20 ms / NDCG@20
(d) 20 ms / RC@5

Figure 15: S2. Variations. Our proposed method, RASP, exhibits superior accuracy compared to its competitors in the dataset settings with temporal variations with a specified standard deviation.



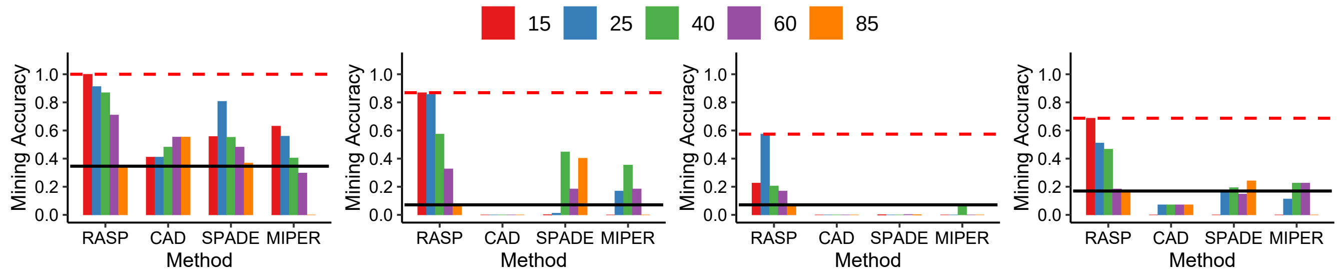
(a) 100 events / NDCG@20
(b) 100 events / RC@5
(c) 1,000 events / NDCG@20
(d) 1,000 events / RC@5

Figure 16: S3. Event Count. Our proposed method, RASP, exhibits superior accuracy compared to its competitors across dataset settings with varying numbers of events.



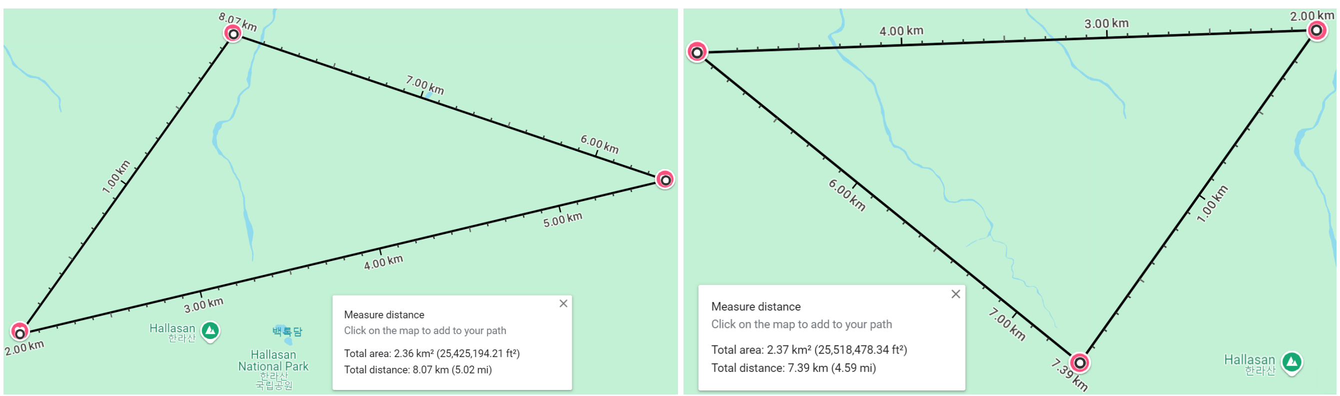
(a) Easy / NDCG@20
(b) Easy / RC@5
(c) Hard / NDCG@20
(d) Hard / RC@5

Figure 17: S4. Mixed-Easy and S5. Mixed-Hard. Our proposed method, RASP, exhibits superior accuracy compared to its competitors across two dataset settings: S4. Mixed-Easy and S5. Mixed-Hard.



(a) S1. Variation-Free **(b) S2. Variations (10 ms)** **(c) S2. Variations (20 ms)** **(d) S4. Mixed-Easy**

Figure 18: Results with various bin sizes in milliseconds, when the time span L is 50 seconds (see the main paper for the results with a time span L of 100 seconds). Red dotted lines and black solid line show the best and worst performances of RASP. Note that larger time bins tend to benefit CAD, but not necessarily the other methods for which the optimal bin size tends to increase with larger temporal variations. With a proper bin size, RASP performs best in all the settings.



(a) Most Frequent TSP **(b) 2nd Most Frequent TSP**

Figure 19: The AWS locations for the two most frequent TSPs identified by RASP from the precipitation dataset.

Algorithm 6: Mining Frequent TSP (size i)

Input: (1) W: mapping between (event, relative occurrence time) pairs and their WIDs,
(2) F_{i-1}: mapping between frequent TSPs of size $(i-1)$ and (WIDs, frequency) pairs,
(3) m_i: max number of TSPs of size i,
(4) δ: max time gap between consecutive events,
(5) L: max time span of a TSP,
(6) I: tolerance against temporal variations
Output: F_i: mapping between frequent TSPs of size i and (WIDs, frequency) pairs

Lines 1-2 of Algorithm 4 of the main paper
foreach $\alpha' \in F_{i-1}.keys()$ **do**
  $(\langle E_1, \cdots, E_{i-1}\rangle, \langle \Delta t_1, \cdots, \Delta t_{i-2}\rangle) \leftarrow \alpha'$
  $(W_{\alpha'}, freq_{\alpha'}) \leftarrow F_{i-1}[\alpha']$
  foreach $E_i \in \mathcal{E}$ $\cancel{\setminus\{E_1, \cdots, E_{i-1}\}}$ **do**
    for $t \leftarrow 0$ ***to*** $(\lfloor \min(\delta, L - \sum_{j=1}^{i-2} \Delta t_j)/I \rfloor)$ **do**
      $\Delta t_{i-1} = tI$; $t_i = \sum_{j=1}^{i-1} \Delta t_j$
      $\alpha'' \leftarrow (\langle E_2, \cdots, E_i\rangle, \langle \Delta t_2, \cdots, \Delta t_{i-1}\rangle)$
      if $\alpha'' \in F_{i-1}.keys()$ **then**
        $\alpha \leftarrow (\langle E_1, \cdots, E_i\rangle, \langle \Delta t_1, \cdots, \Delta t_{i-1}\rangle)$
        if $E_i \neq E_j, 1 \leq \forall j \leq i-1$ **then**
          $W_\alpha \leftarrow$
          $W_{\alpha'} \cap (\cup_{w=-I}^{I-1} W[(E_i, \min(t_i + w, \delta))])$
        else
          $W_\alpha \leftarrow \emptyset$
          for $w \leftarrow -I$ ***to*** $I - 1$ **do**
            if $\min(t_i + w, \delta) \neq 0$ **then**