Discovering routine behaviour from time series data

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Knowledge-Based Systems
Volume 113, 1 December 2016, Pages 61-74

An incremental algorithm for discovering routine behaviours from smart meter data

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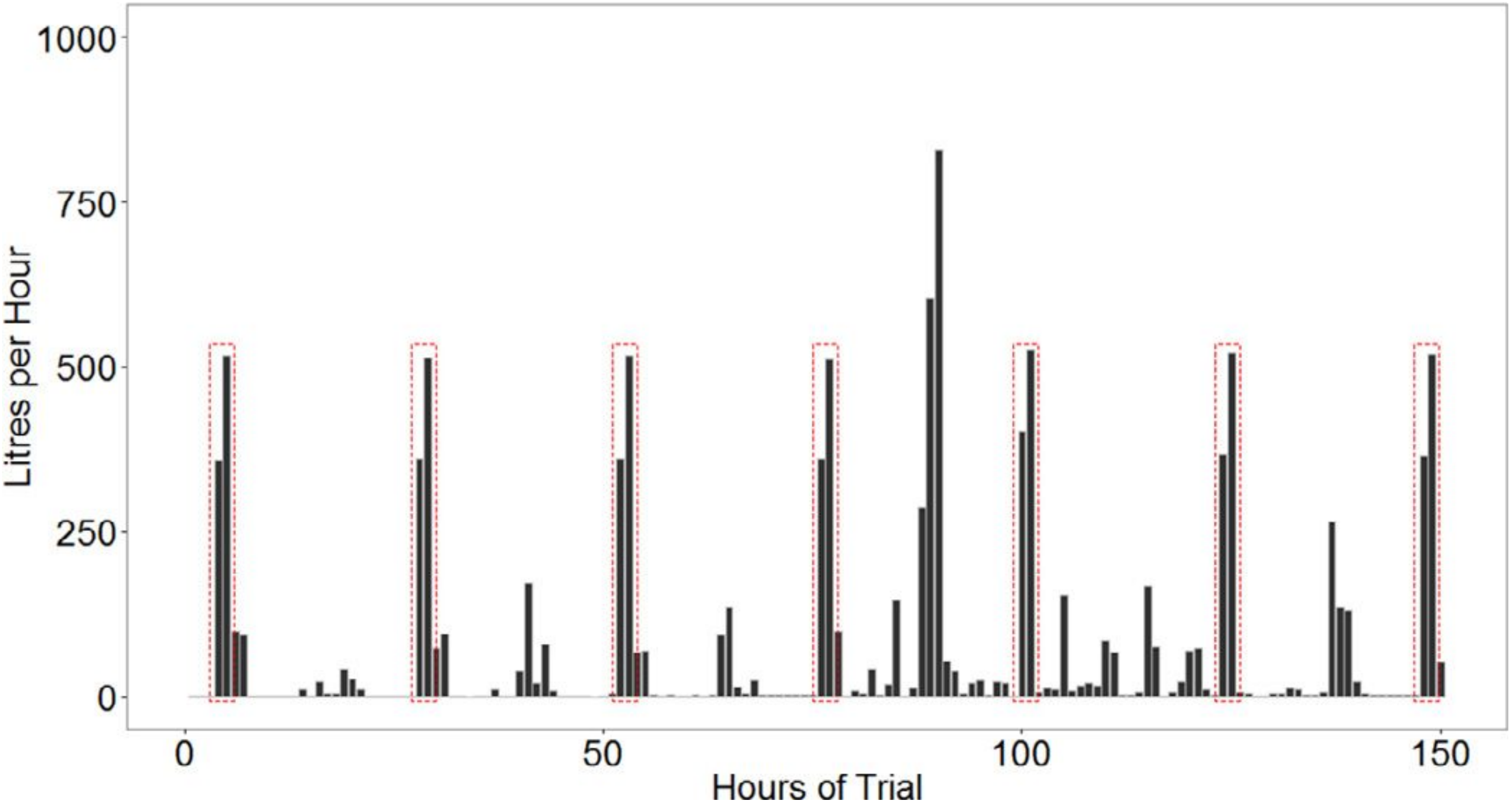
A research paper **excellent** written and presented



Litres per Hour
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750
500
250
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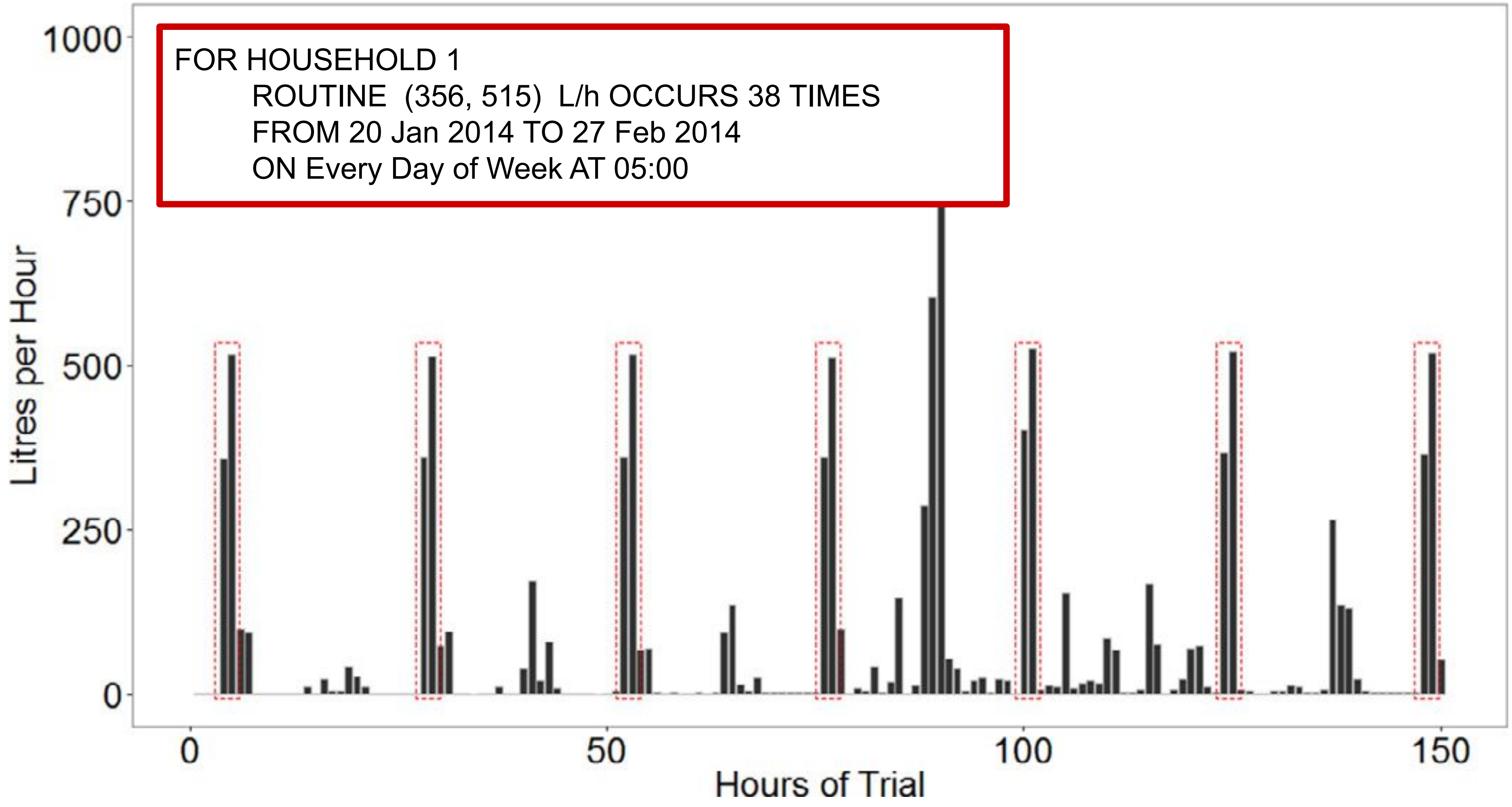
50
100
150
Hours of Trial


FOR HOUSEHOLD 1
ROUTINE (356, 515) L/h OCCURS 38 TIMES
FROM 20 Jan 2014 TO 27 Feb 2014
ON Every Day of Week AT 05:00
Litres per Hour
1000
750
500
250
0
0
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100
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Hours of Trial

The Problem

The problem of discovering routines is **to find all frequently occurring subsequences of variable lengths** in a smart meter time series.

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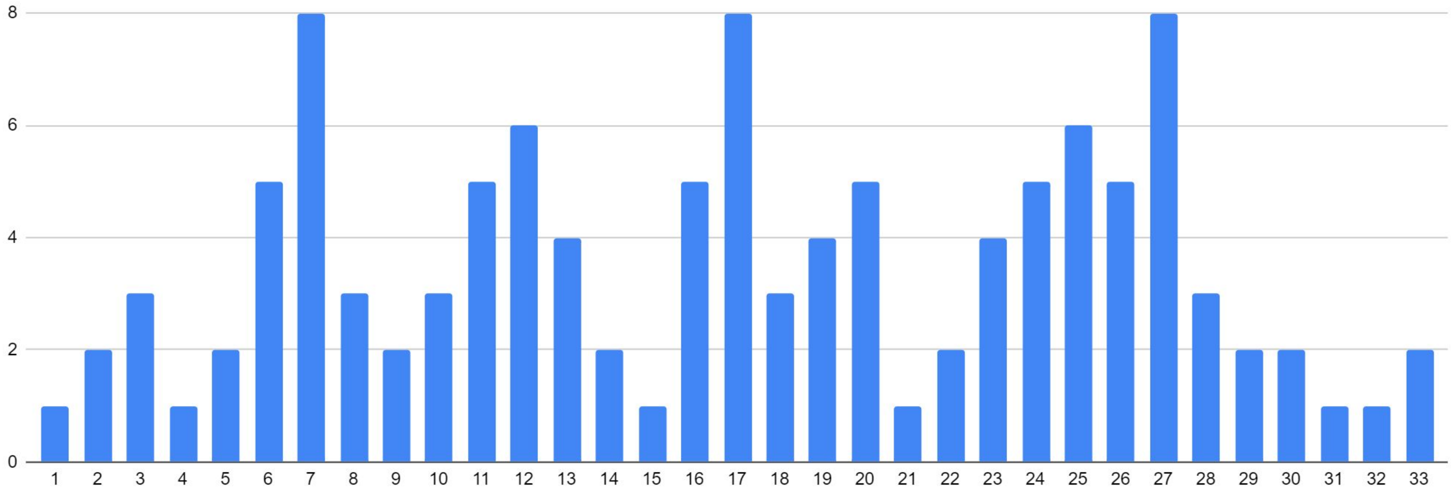
Challenges

1. We are interested in the **shape** and in the **values** of subsequences.
2. There is no prior knowledge about the **length** of the subsequences.
3. The subsequences usually consist of only a **few** elements.

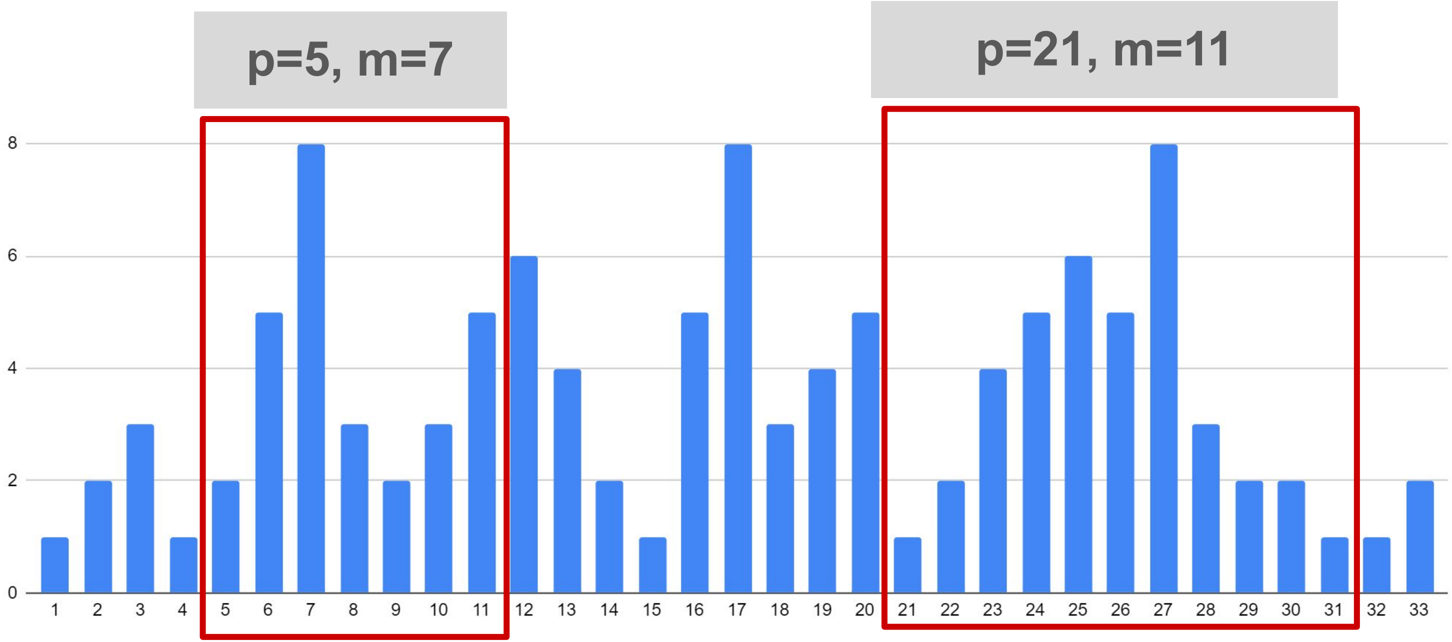
The paper presents

1. **Brute force** algorithm to detect routines
2. **Novel** algorithm to efficiently discover all routines of variable length

Definition 1. *Smart Meter Time Series*: A time series $X = (x_1, x_2, \ldots, x_n)$ is a sequence of n real valued numbers ordered in time.

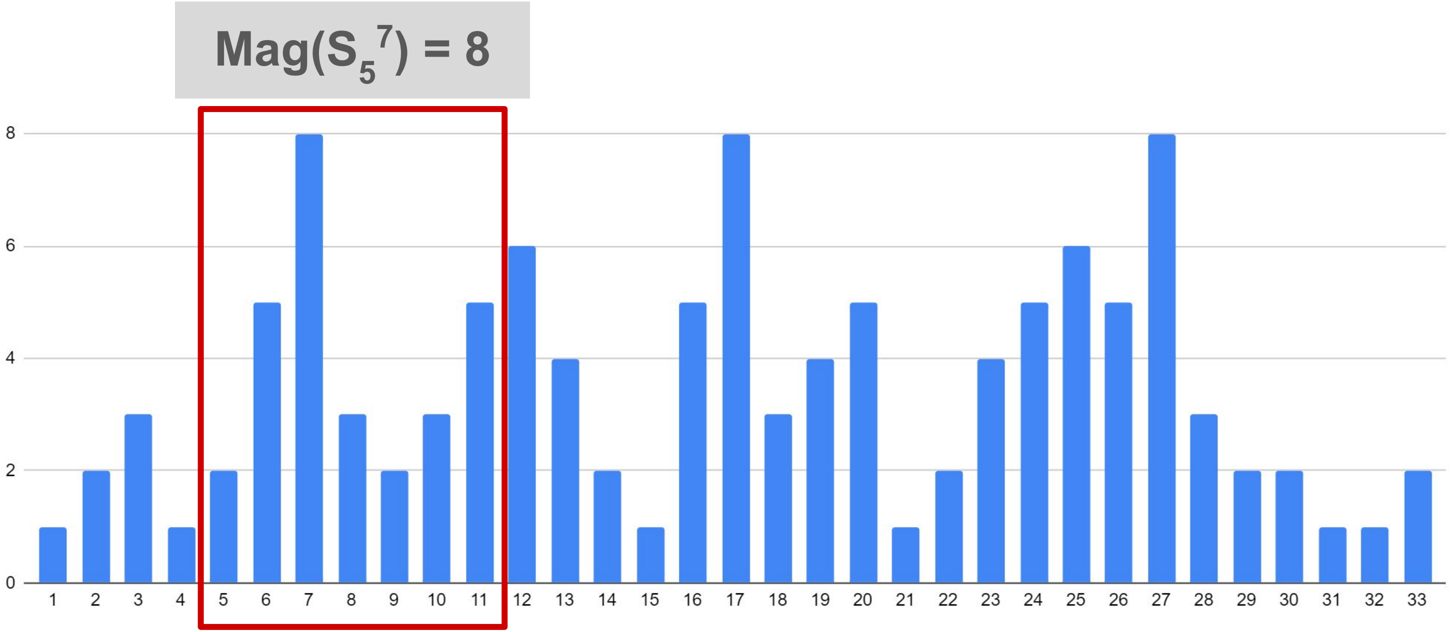


Definition 2. *Subsequence*: Given a time series X of length n, a subsequence S is a subset of m consecutive observations from X, i.e., $S_p^m = (x_p, \ldots, x_{p+m-1})$, where $1 \leq p \leq n - m + 1$, and $m < n$.



Definition 3. *Magnitude*: Given a subsequence S_p^m of length m, the magnitude of S_p^m is the maximum of all the elements in the subsequence, i.e.,

$$Mag(S_p^m) = \max_{1 \le t \le m} (x_t),$$



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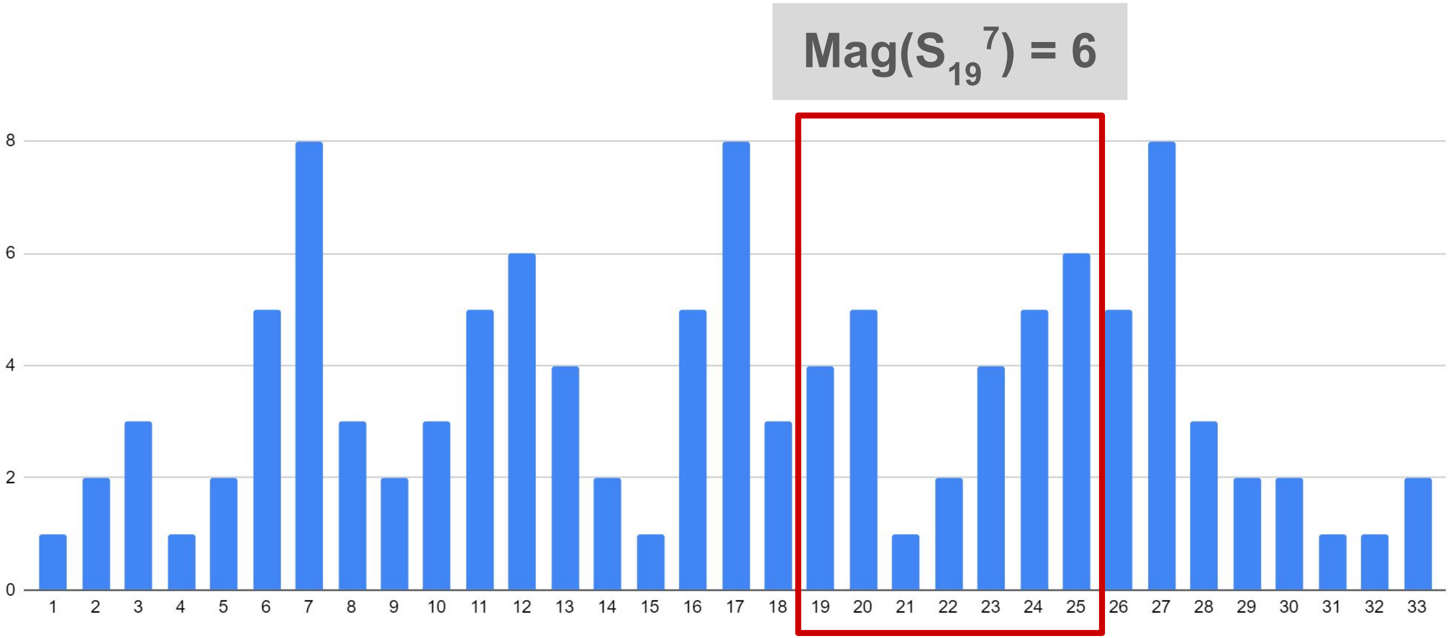
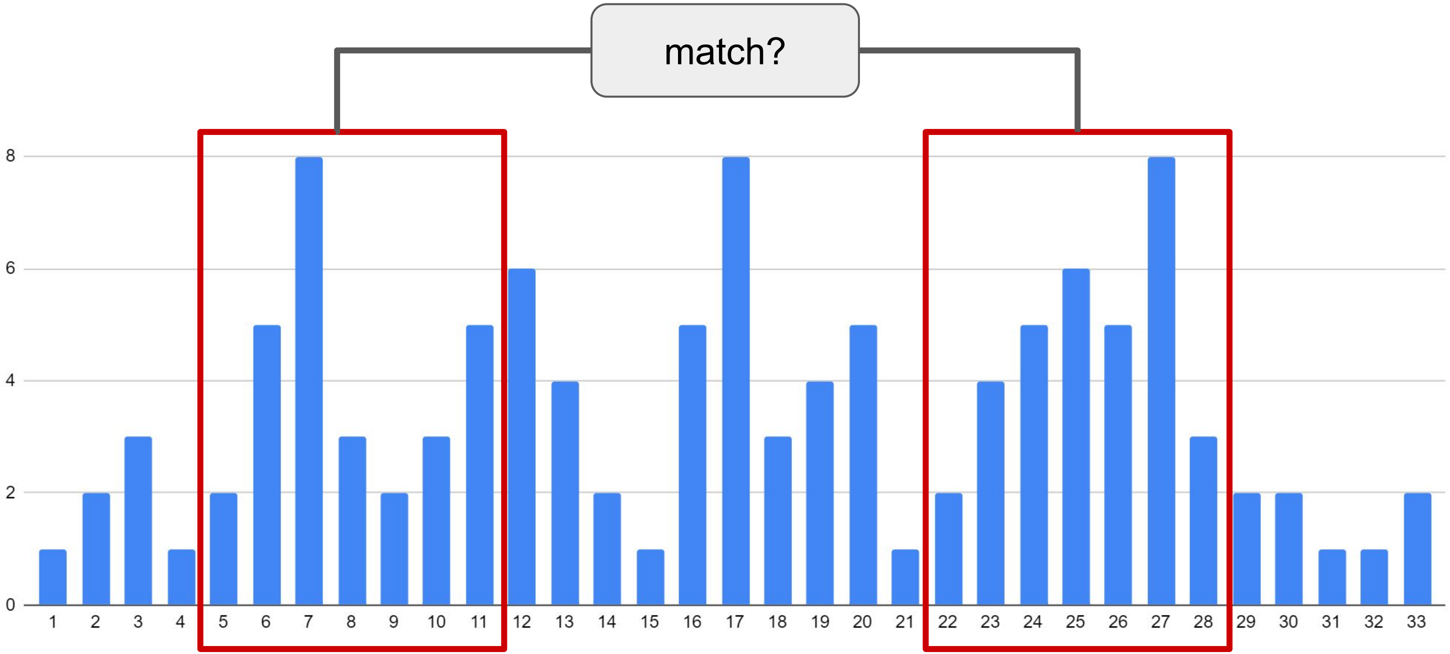
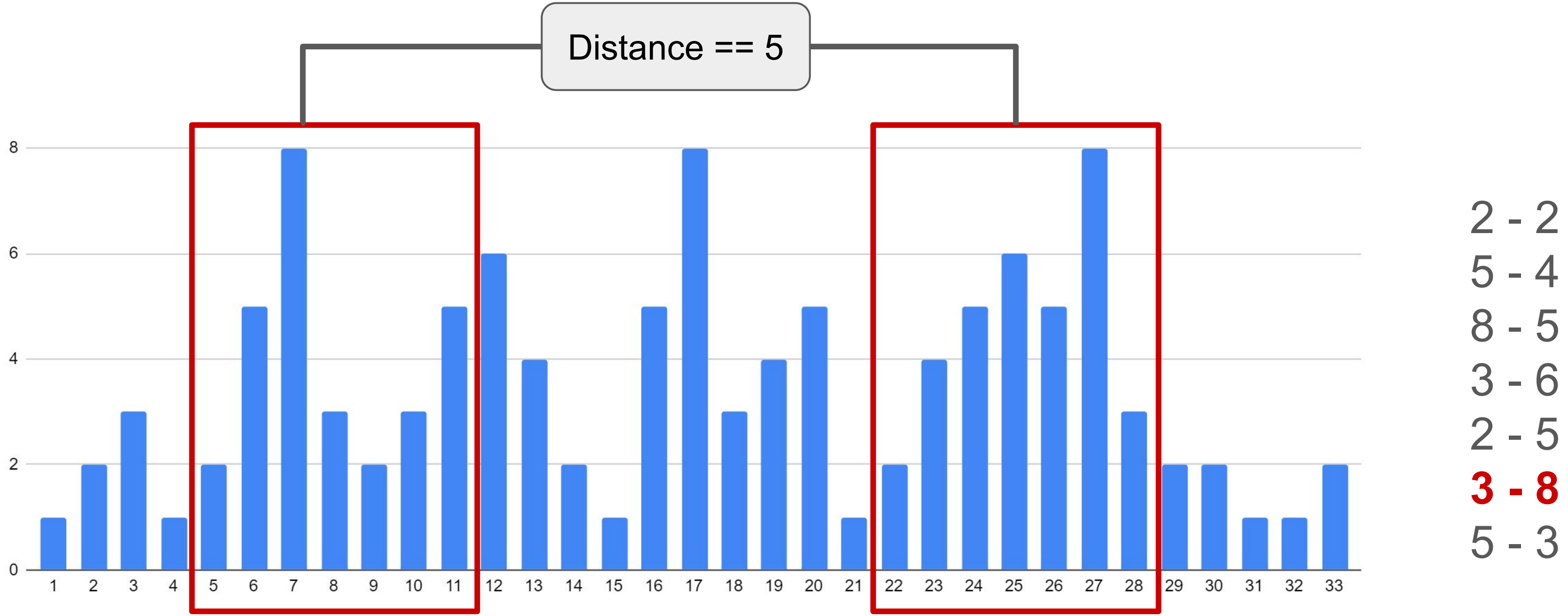


Definition 4. *Match*: Given two subsequences, S_i^m and S_j^m, with the same length of m from X, if the distance between the two subsequences is no greater than a threshold R, i.e., $Dist(S_i^m, S_j^m) \le R$, then the two subsequences are *matched*.



Definition 6. *Distance*: Given two subsequences, S_i^m and S_j^m, of the same length m, the distance between S_i^m and S_j^m is the maximum element-wise difference between S_i^m and S_j^m, i.e.,

$$Dist(S_i^m, S_j^m) = \max_{0 \le t \le m-1} (|x_{i+t} - x_{j+t}|)$$



Definition 7. *Motif*: Given a time series X, a subsequence length m, and a distance threshold R, the most significant motif is the subsequence of length m that has most number of matched occurrences under the distance threshold, i.e., $\forall i, j : Dist(S_i^m, S_j^m) \leq R$.

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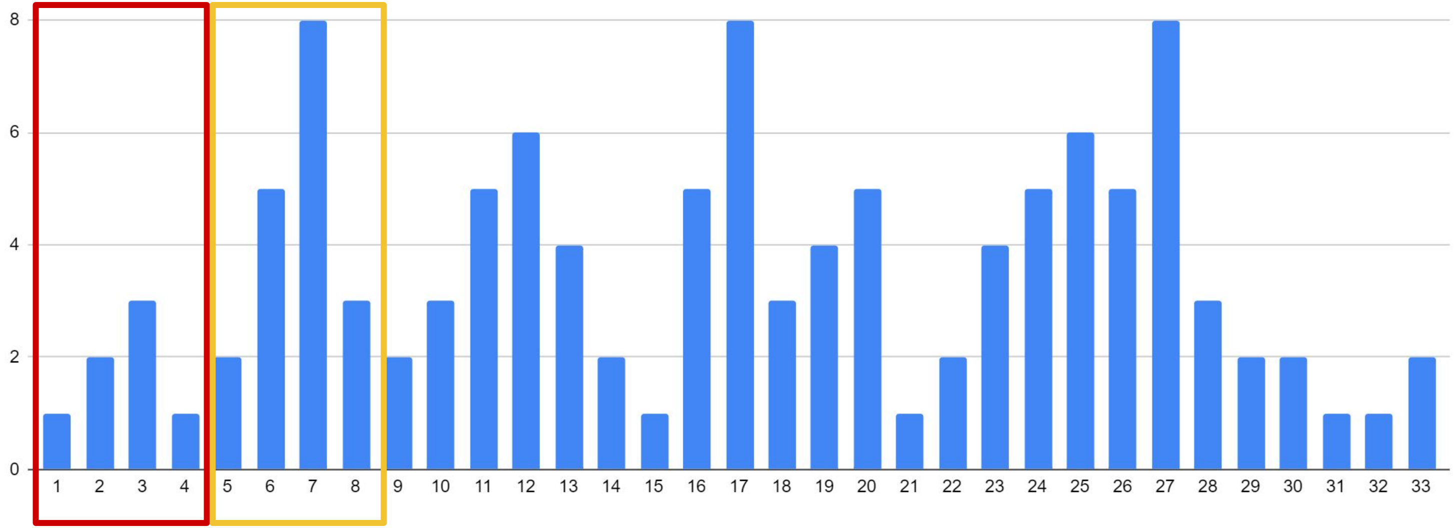
m=4, R=3

d == 5



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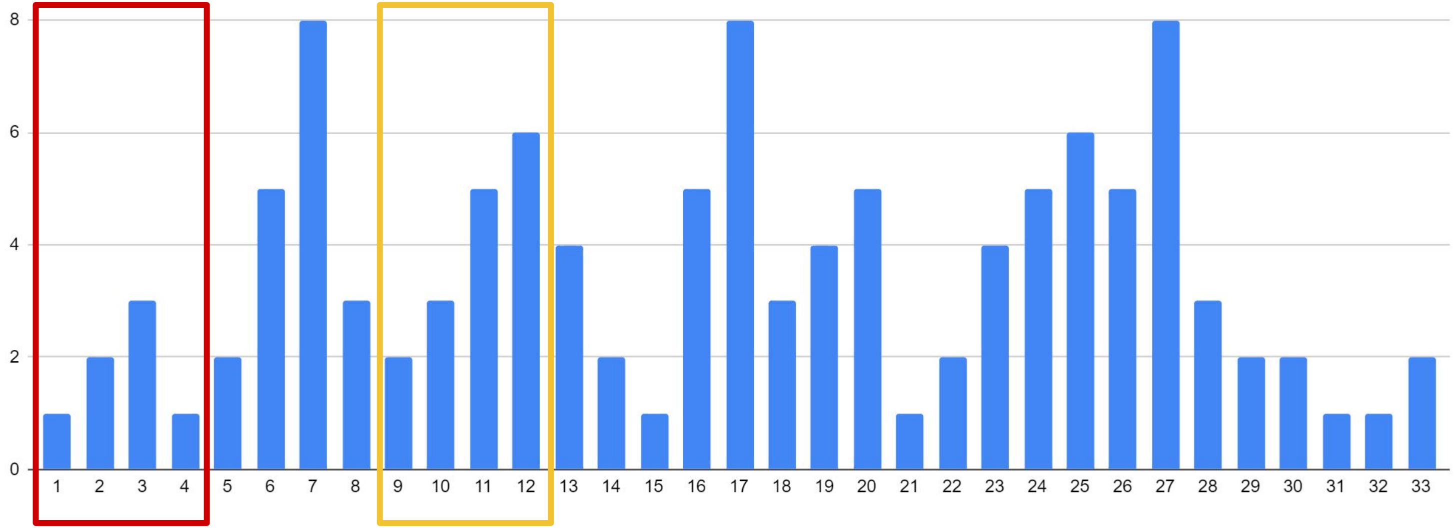

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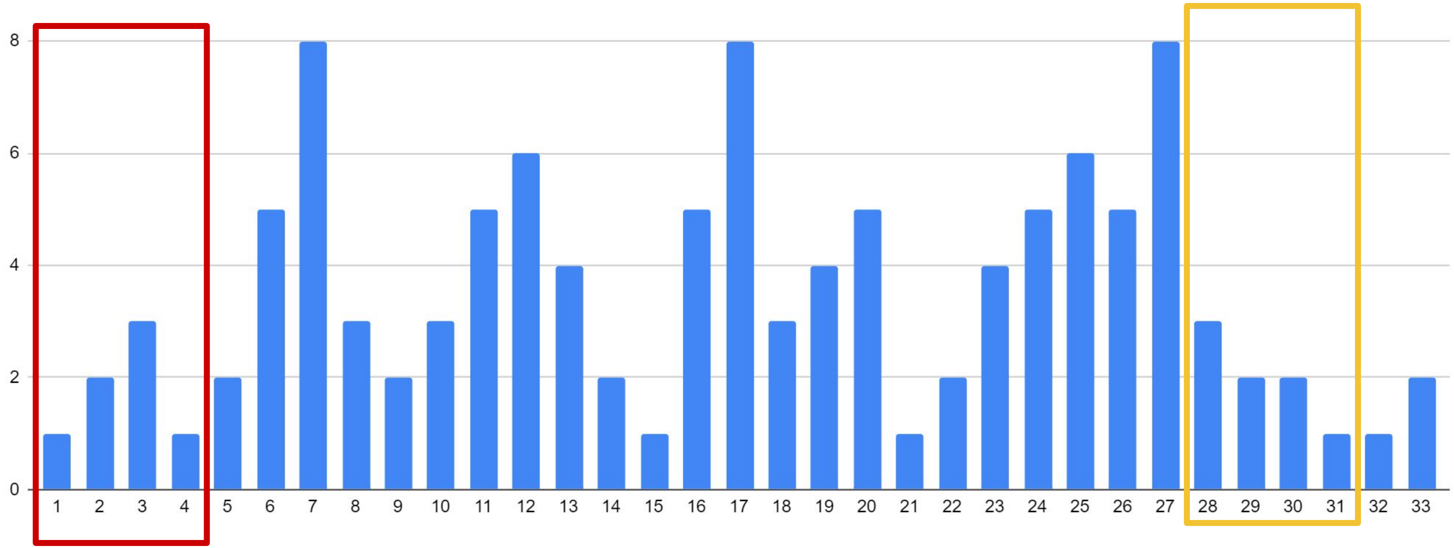
m=4, R=3

d == 2



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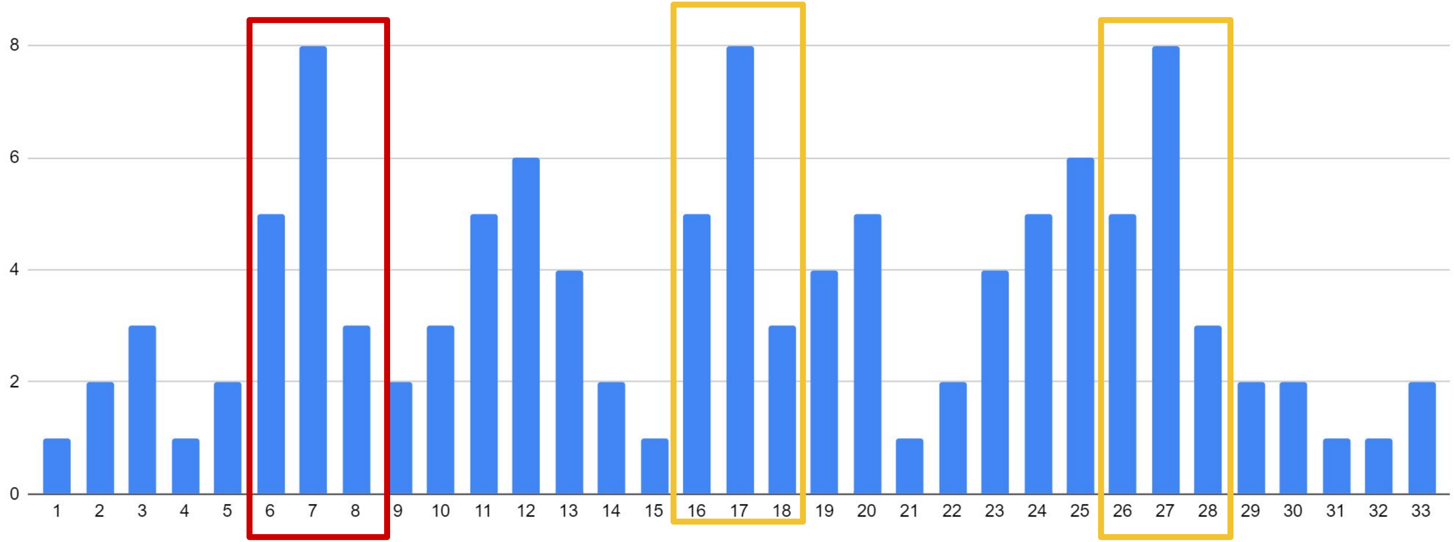
m=3, R=1



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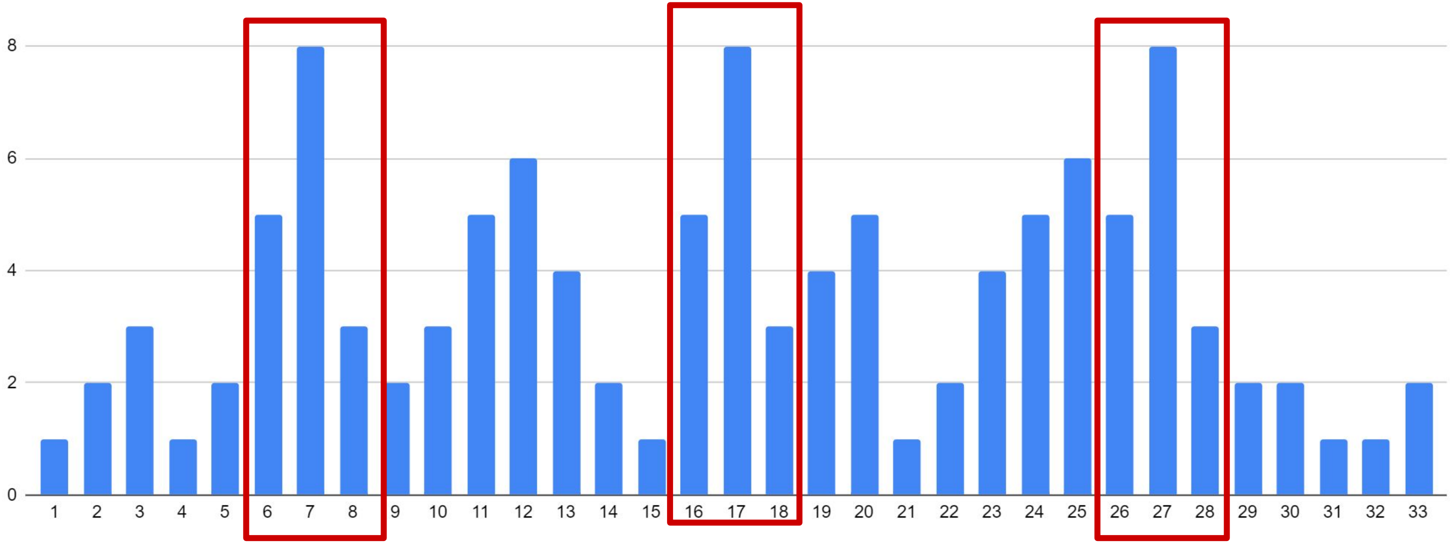
It is a routine with C = 3 and G = 7



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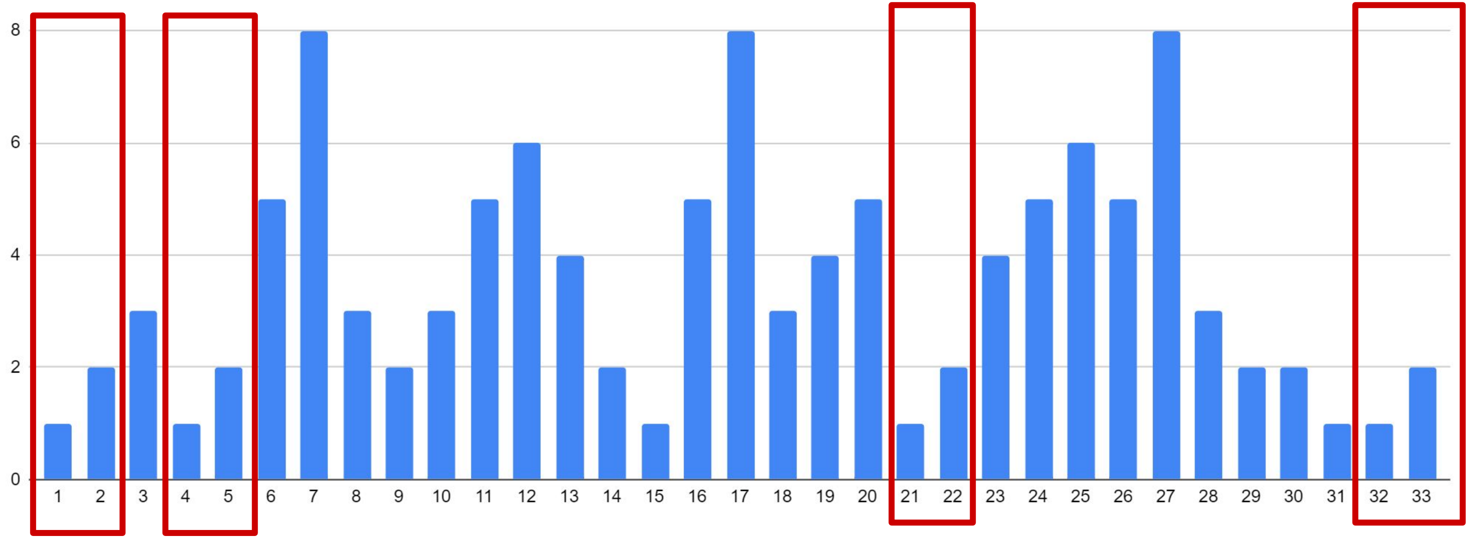

The routine discovery problem is to find all routines with lengths 1 to m that occur in a smart meter time series X given a magnitude threshold G and frequency threshold C.

m	G	C	R

DRVL

for m in [m_{min}, m_{max}]

DRFL(m)

Algorithm 1: Discovering Routine of Fixed Length (DRFL).

Input : a time series of length n
Parameters: routine length m, distance threshold R; frequency threshold C, magnitude threshold G, overlap parameter ϵ
Output : m-length routines B^m

for $i = 1$ **to** $n - m - 1$ **do**
  extract subsequence S_i^m;
$B^m \leftarrow$ `SubGroup(`S^m, R, C, G`)` ; // See Algorithm 2
for $i = 1$ **to** $|B^m| - 1$ **do**
  for $j = i$ **to** $|B^m|$ **do**
    // See Algorithm 3
    $K_i, K_j \leftarrow$ `OLTest(Inst(`B_i^m`), Inst(`B_j^m`),` ϵ`)` ;
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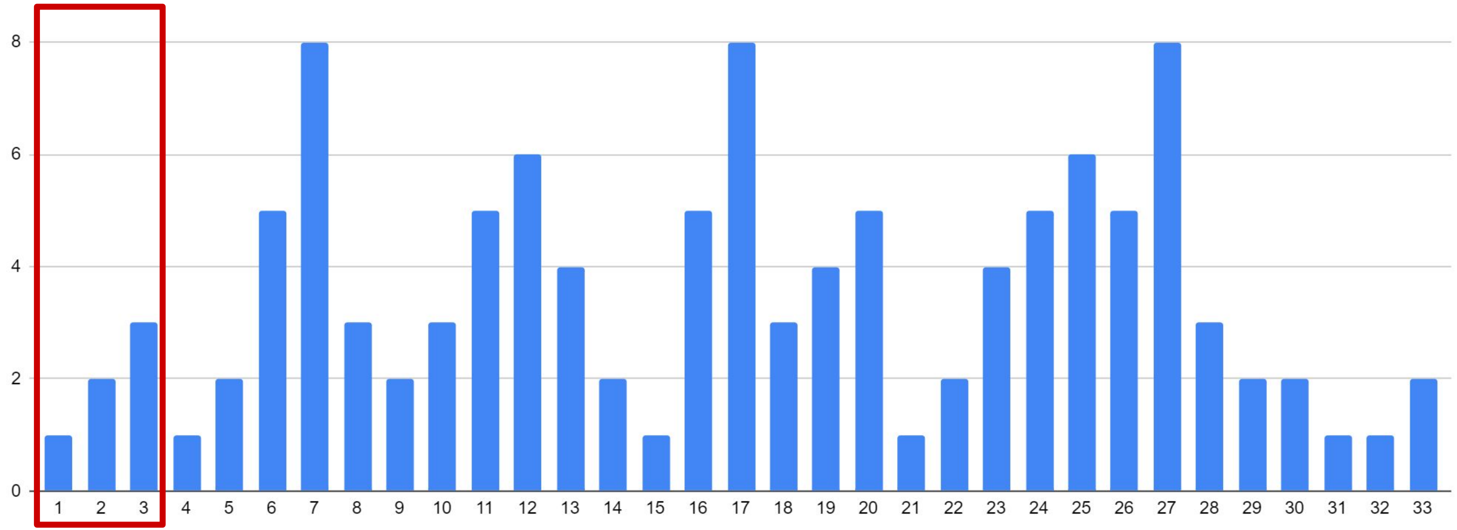

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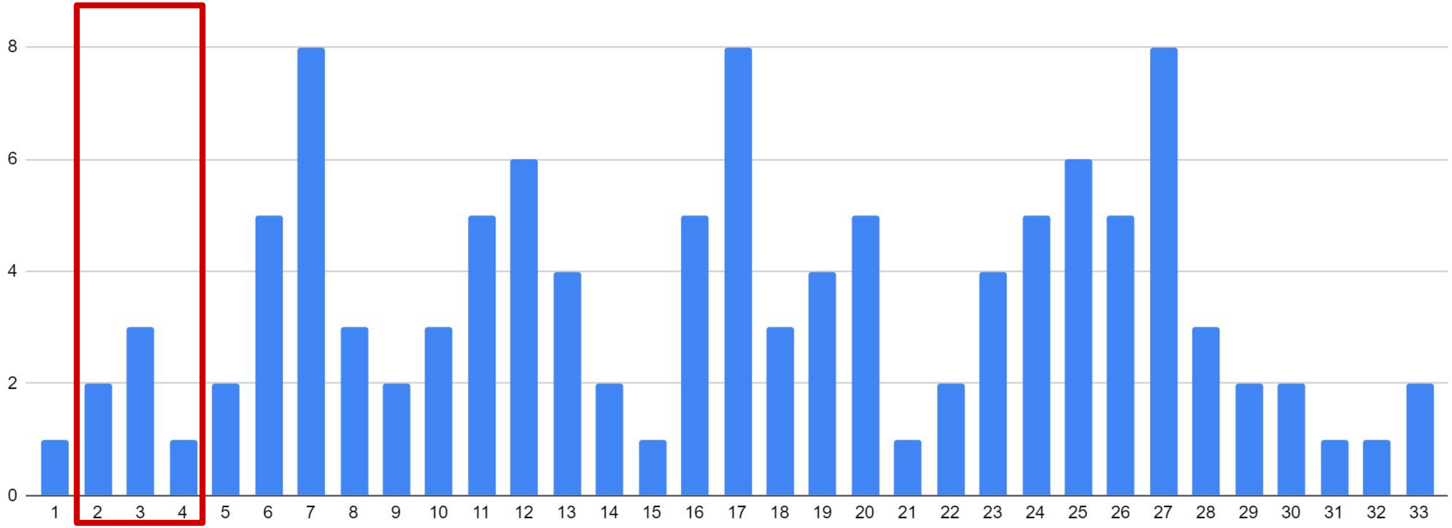

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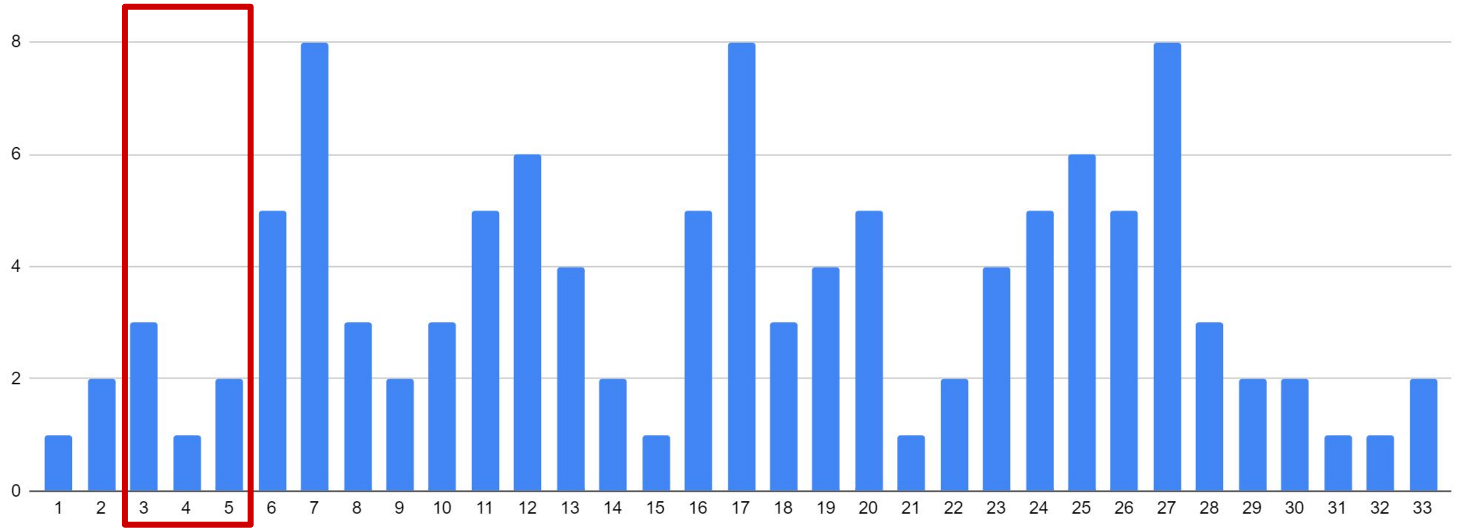

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clustering

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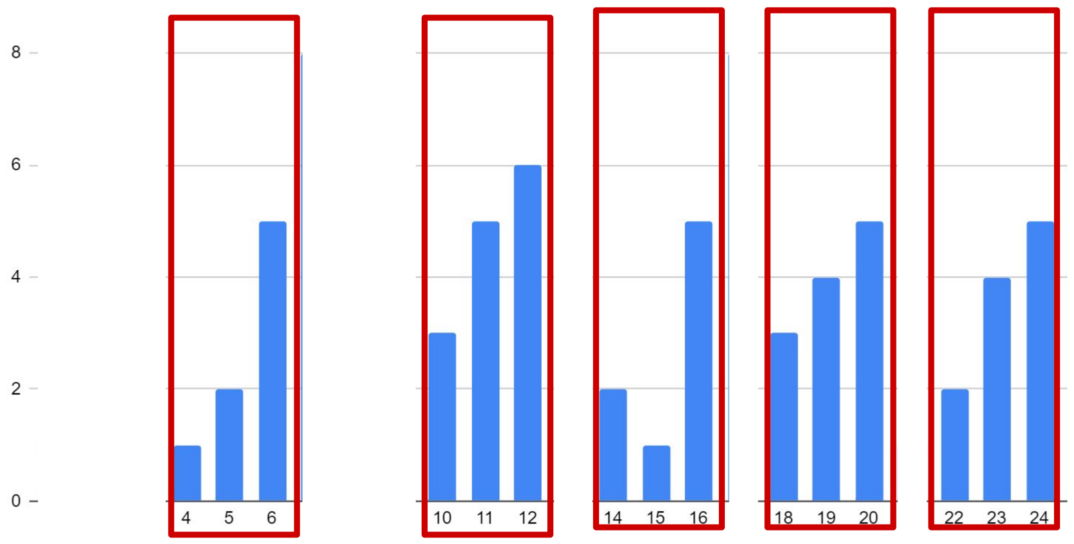
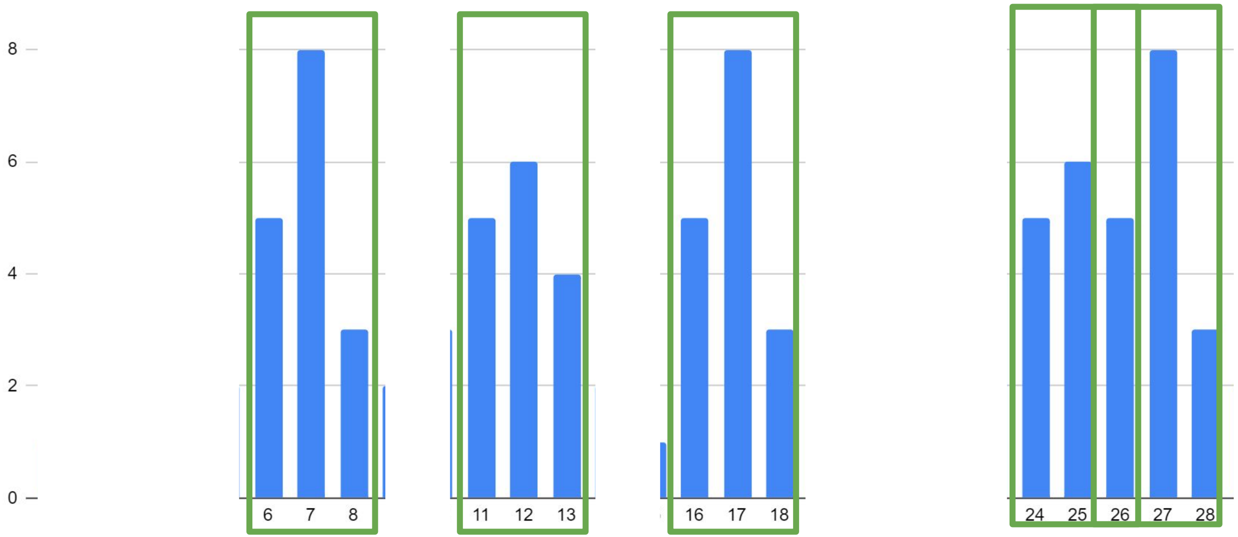
Overlapping clusters

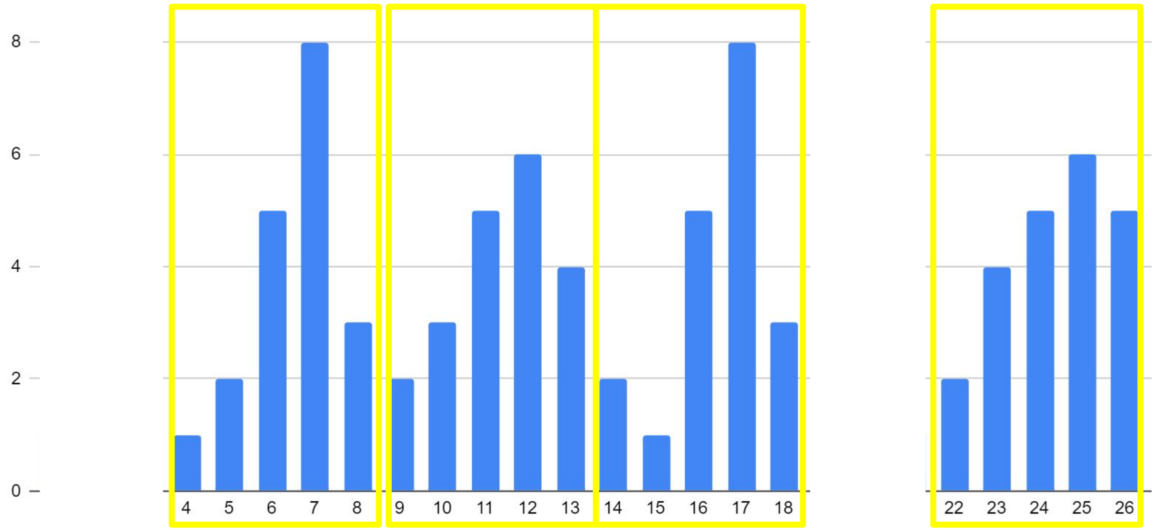
m = 3, R = 2, G = 5, C = 4

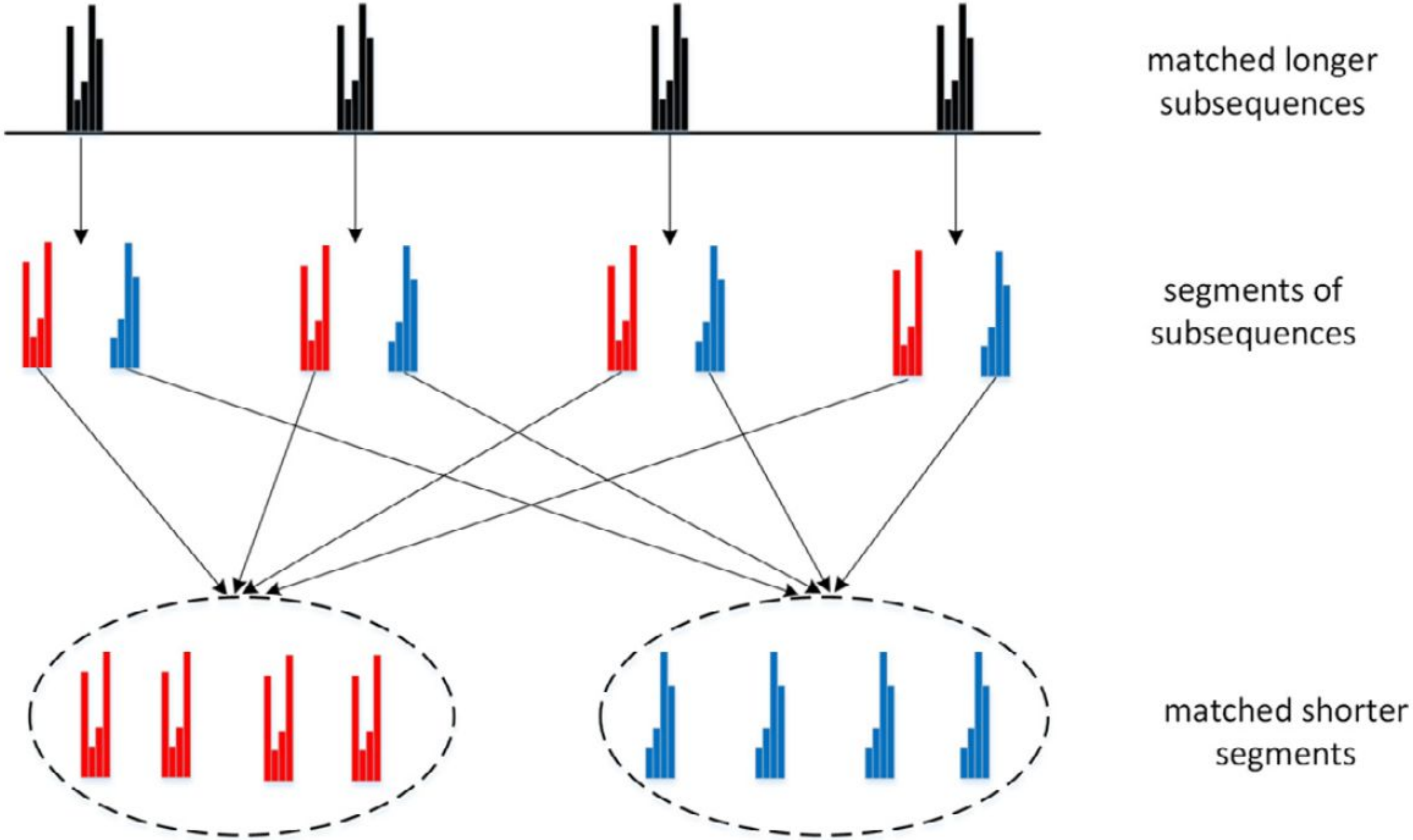


m = 3, R = 2, G = 5, C = 4

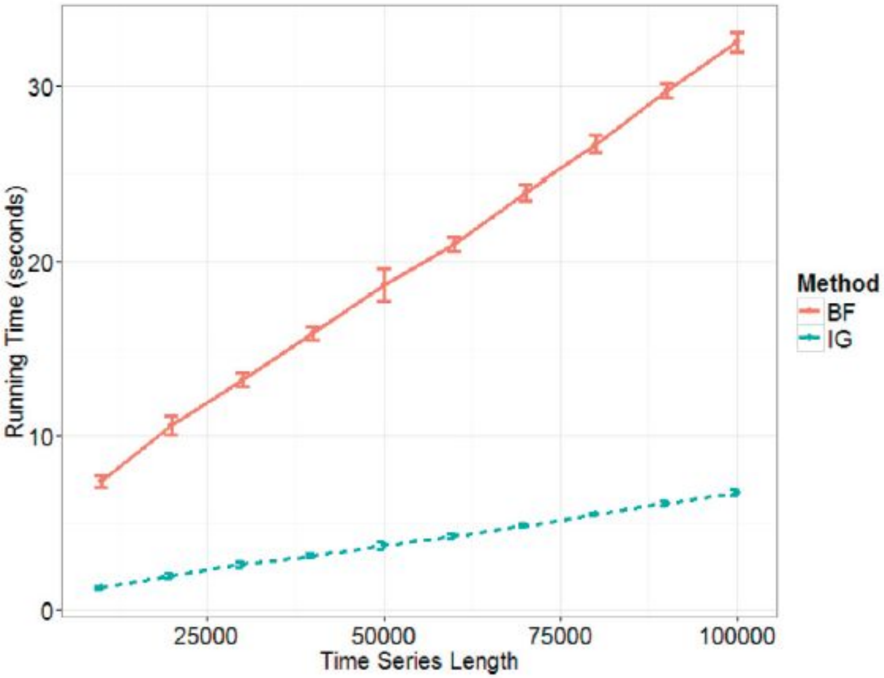


m = 5, R = 2, G = 5, C = 3

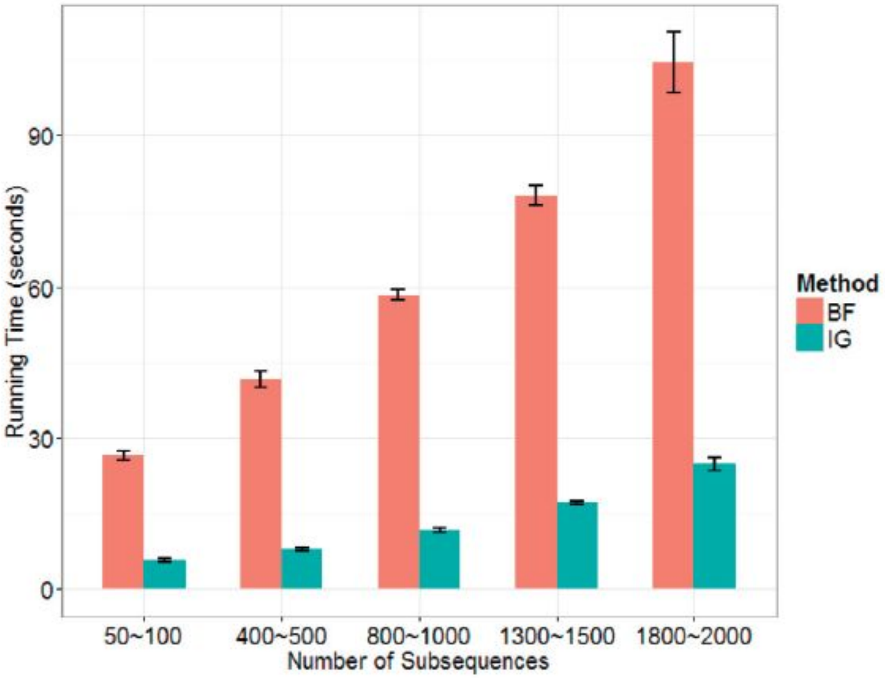



matched longer subsequences
segments of subsequences
matched shorter segments

Experiments on synthetic database



(a) Different sequence lengths.

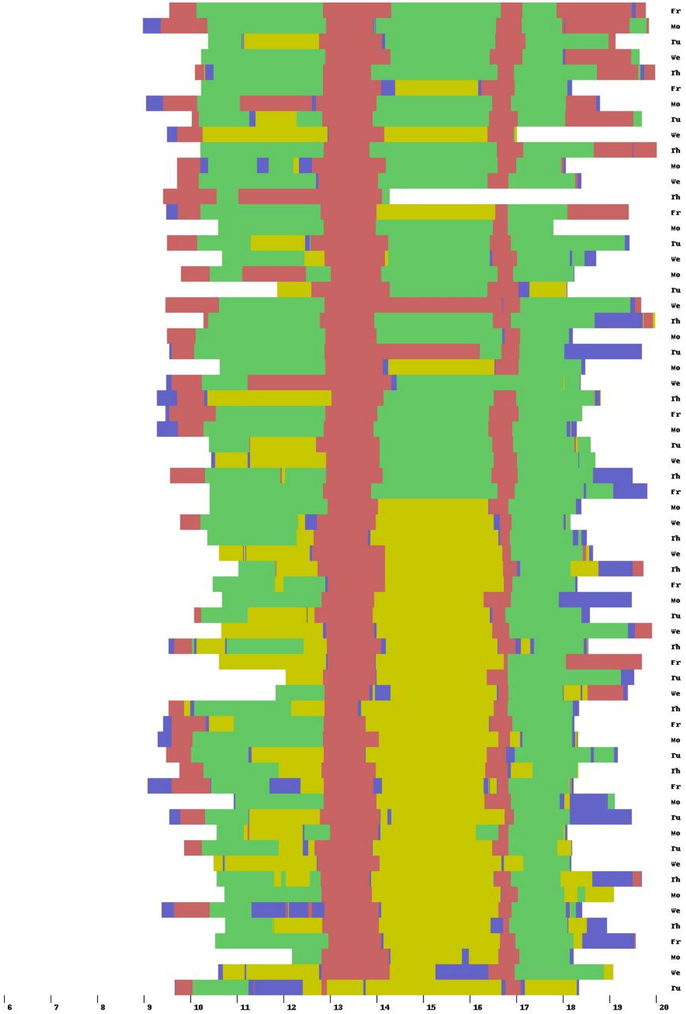


(b) Different numbers of subsequence instances

Experiments on real datasets

1. More than one dataset
2. A state of the art method is used to comparisons

This paper is interesting for **us** because...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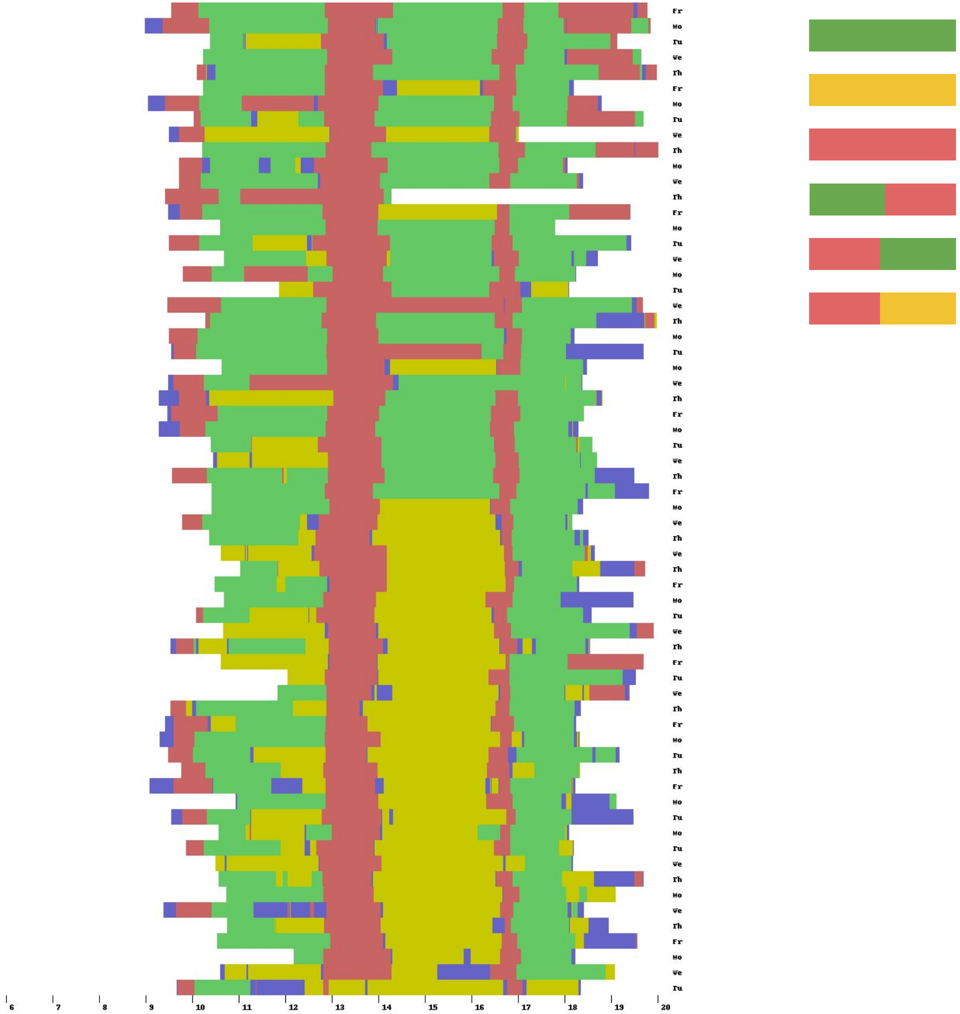
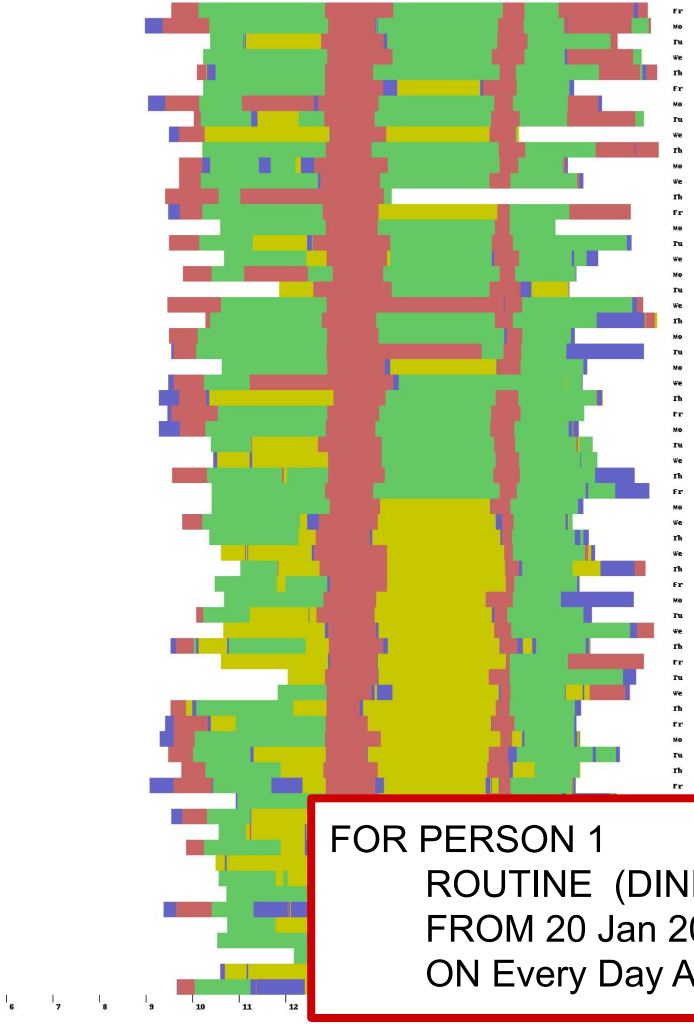

6 7 8 9 10 11 12 13 14 15 16 17 18 19 20



FOR PERSON 1

ROUTINE (DINING ROOM, TV ROOM) OCCURS 23 TIMES

FROM 20 Jan 2014 TO 27 Feb 2014

ON Every Day AT 15:00