Time Series Analysis
Using Transprecision Computing

Ivan Fernandez Vega
OPRECOMP Summer of Code
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About me

- 2nd-year **PhD Student at University of Malaga** (Spain)
- Advisors: Oscar Plata and Eladio Gutierrez
- Research topic: **Acceleration of time series analysis**
- Currently at **ETH Zürich** as an academic guest in SAFARI group, supervised by Prof. Onur Mutlu

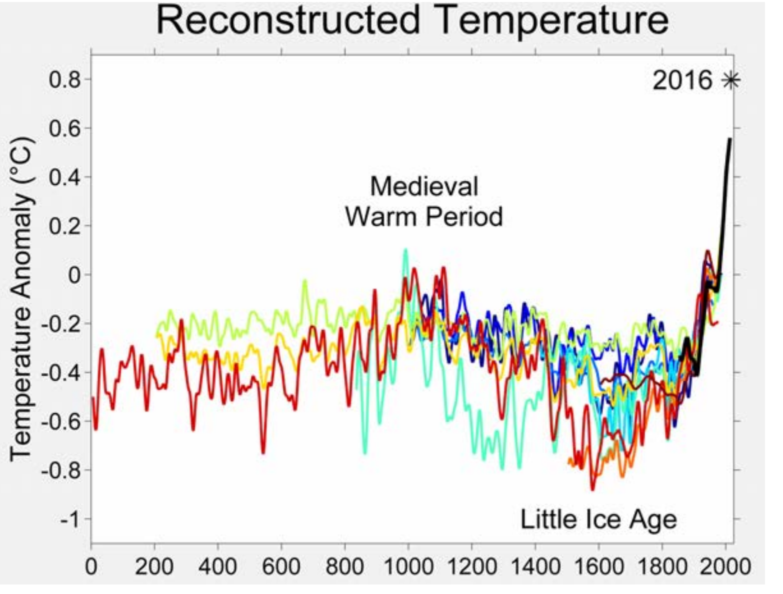
Outline

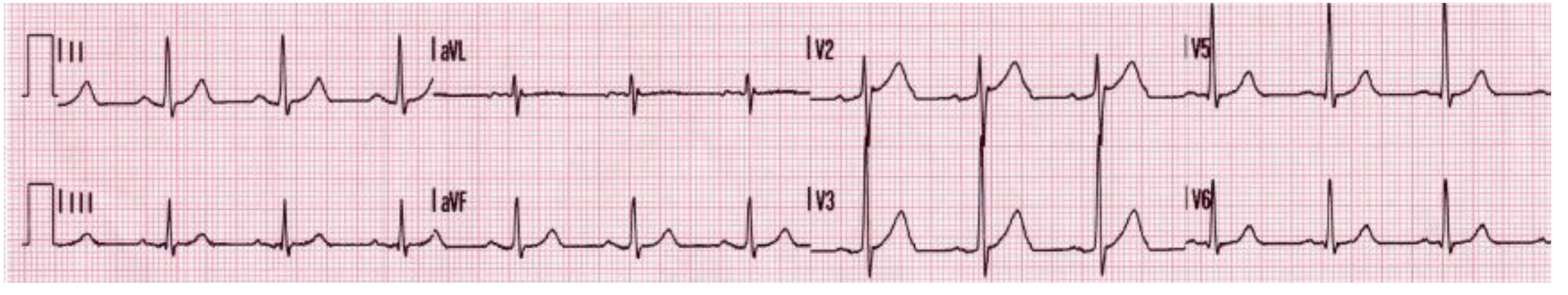
- **Introduction**
- **Background**
- **Implementation**
- **Results**
- **Conclusions and Future Work**

Introduction

Introduction

- **Time series analysis** has a huge interest in many fields
  - Climate
  - Seismology
  - Entomology
  - Bioinformatics
  - Traffic Prediction
  - Voice Recognition
  - Energy Conservation

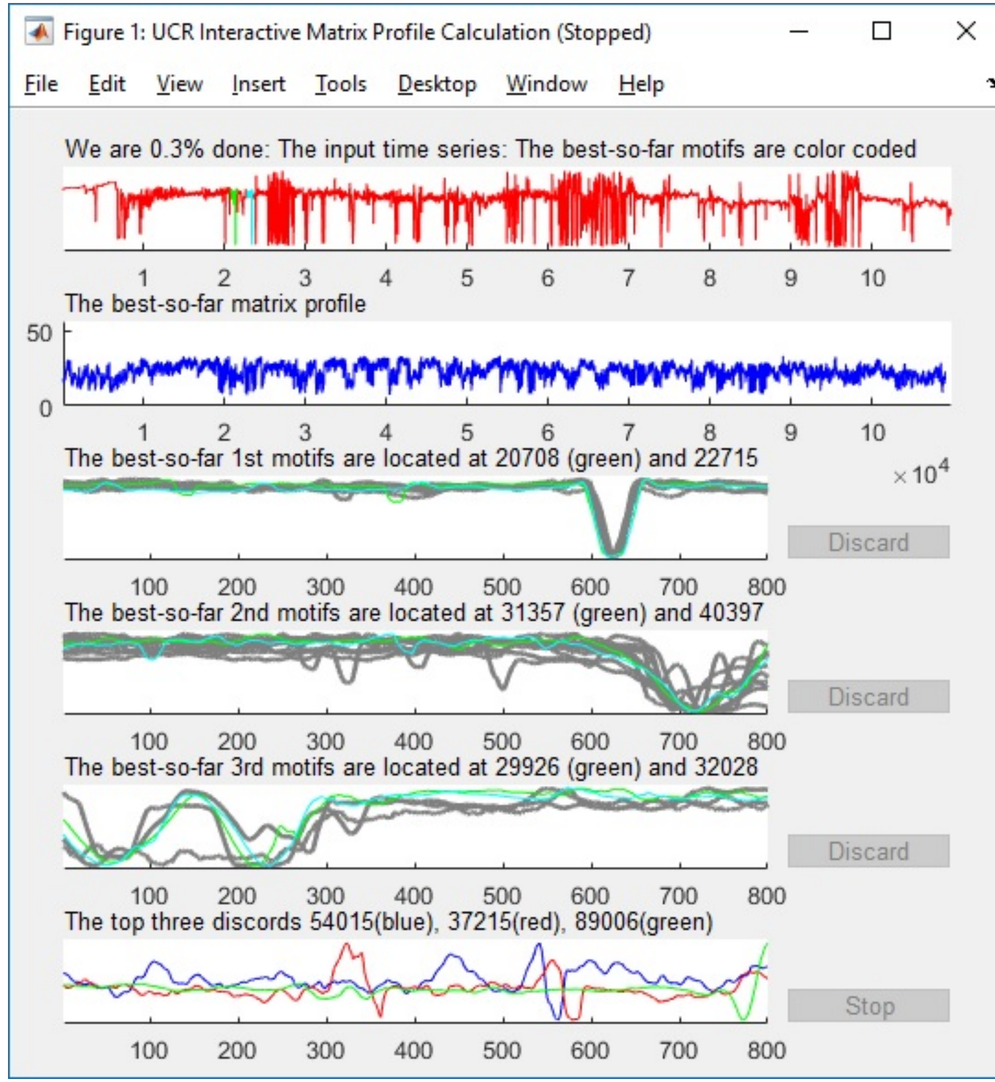




Introduction

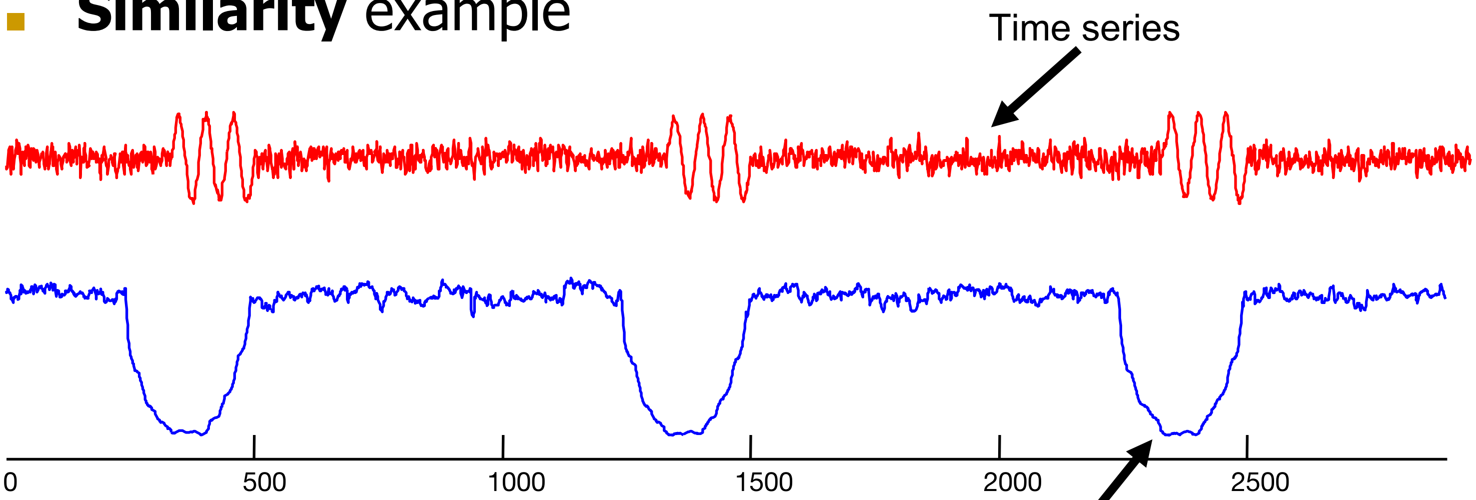
- **Matrix Profile (from UCR Riverside)**
  - Open source tool for **motif discovery** (anomalies, similarities, …)
  - Implemented in several languages: C++, Python, CUDA, R, MATLAB

Matrix Profile website



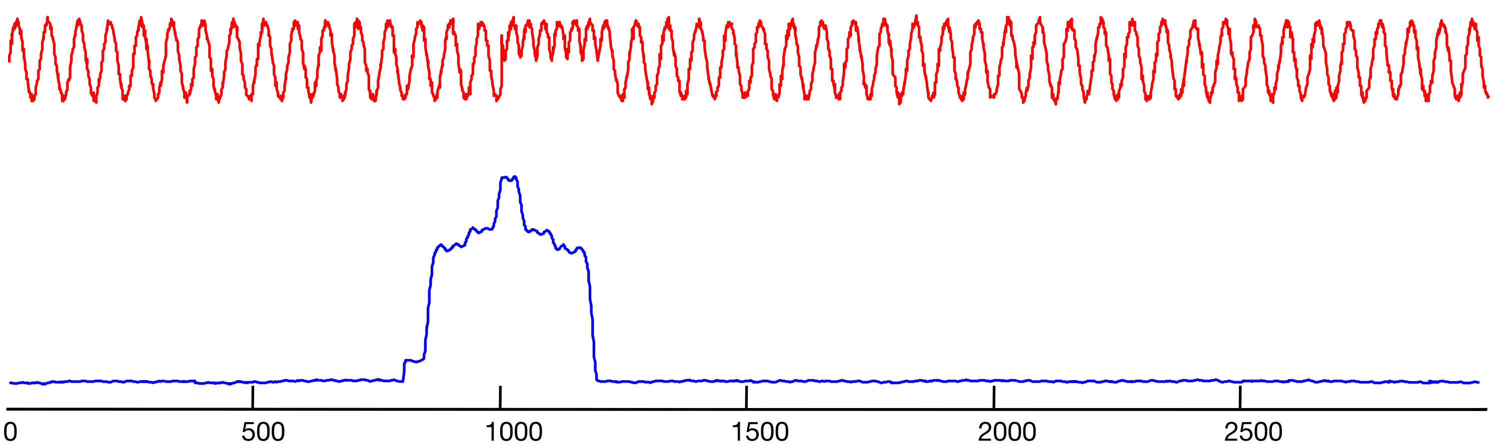
Introduction

- **Similarity** example



> **Observation**
> Similarities appear as lower values of Matrix Profile

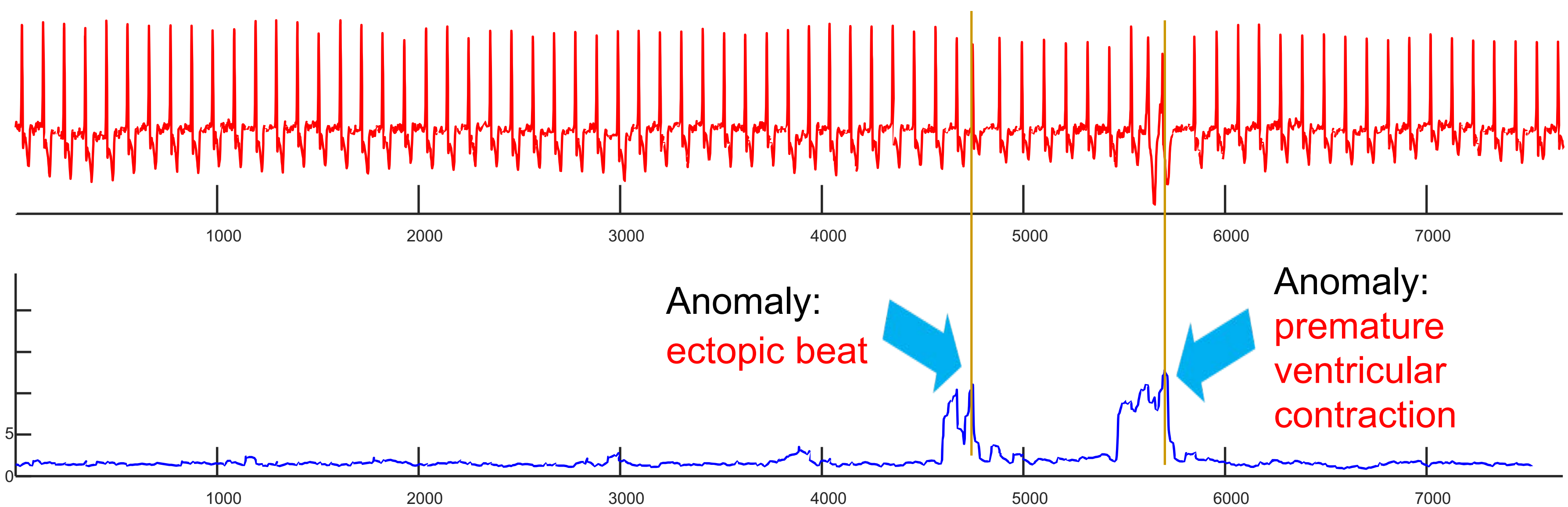
- **Anomaly** example



> **Observation**
> Anomalies appear as higher values of Matrix Profile

Motivation

- Real data example: **electrocardiogram**
- In this case there are **two anomalies** annotated by MIT cardiologists
- Here the subsequence length was set to 150, but we still find these anomalies if we half or double that length



Motivation

- Typical data type used for the computation is **double** precision, while the algorithm allows for **single** or mixed **precision**

- **No previous study using** lower precision or **flex float approach**

- Analysing a time series of **131,072** elements using a window size of **1,024** elements requires:

	2.4 Billion subtractions (-)
	2.7 Billion multiplications (*)
	2.9 Billion divisions (/)
	2.8 Billion multiply-accumulations (FMA)
+	2.8 Billion comparisons (<)

13.6 Billion operations !!!

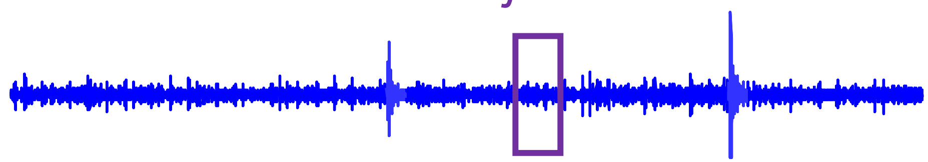
Observation

The number of operations increases exponentially with the time series length

Background

Distance Matrix

j th



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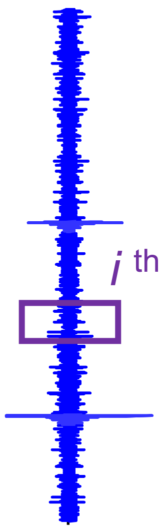


$d_{1,1}$	$d_{1,2}$	…	…	…	$d_{1,n-m+1}$	D_1
$d_{2,1}$	$d_{2,2}$	…	…	…	$d_{2,n-m+1}$	D_2
…	…	…	…	…	…	
$d_{i,1}$	$d_{i,2}$	…	$\boldsymbol{d_{i,j}}$	…	$d_{i,n-m+1}$	D_i
…	…	…	…	…	…	
$d_{n-m+1,1}$	$d_{n-m+1,2}$	…	…	…	$d_{n-m+1,n-m+1}$	D_{n-m+1}

$\mathit{Min}(D_1)$ $\mathit{Min}(D_2)$ $\mathit{Min}(D_i)$ $\mathit{Min}(D_{n-m+1})$

P_1	P_2	…	…	…	P_{n-m+1}

- Symmetric matrix
- Main diagonal = 0
- Cells close to diagonal very small

$d_{i,j}$ is the distance between the i^{th} window and the j^{th} window of the time series

Matrix Profile: a vector of distance between each subsequence and its most similar one

Distance metric

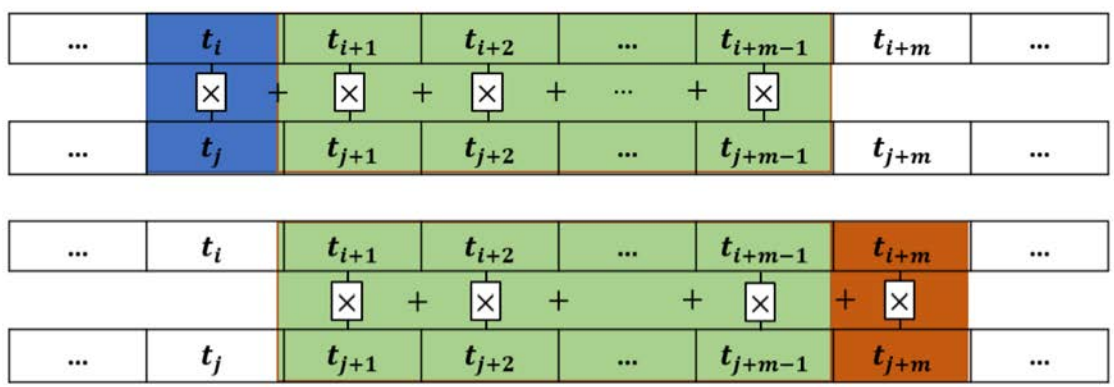
- The similarity $d_{i,j}$ is based on Euclidean distances:

$$d_{i,j} = \sqrt{2m\left(1 - \frac{Q_{i,j} - \mu_i \mu_j}{m \sigma_i \sigma_j}\right)}$$

- The dot product ($Q_{i,j}$) can be calculated as follows:

$$T_i T_j = \sum_{k=0}^{m-1} t_{i+k} t_{j+k}$$

$$T_{i+1} T_{j+1} =$$



$$T_{i+1} T_{j+1} = T_i T_j - t_i t_j + t_{i+m} t_{j+m}$$

$O(1)$ time complexity

Implementation

Goal

- The goal is to provide a benchmark to explore how the **accuracy** of the results of SCRIMP are affected by **changing the precision** of the floating-point operations

- This tool would be **useful for architects when designing a custom accelerator** for time series analysis

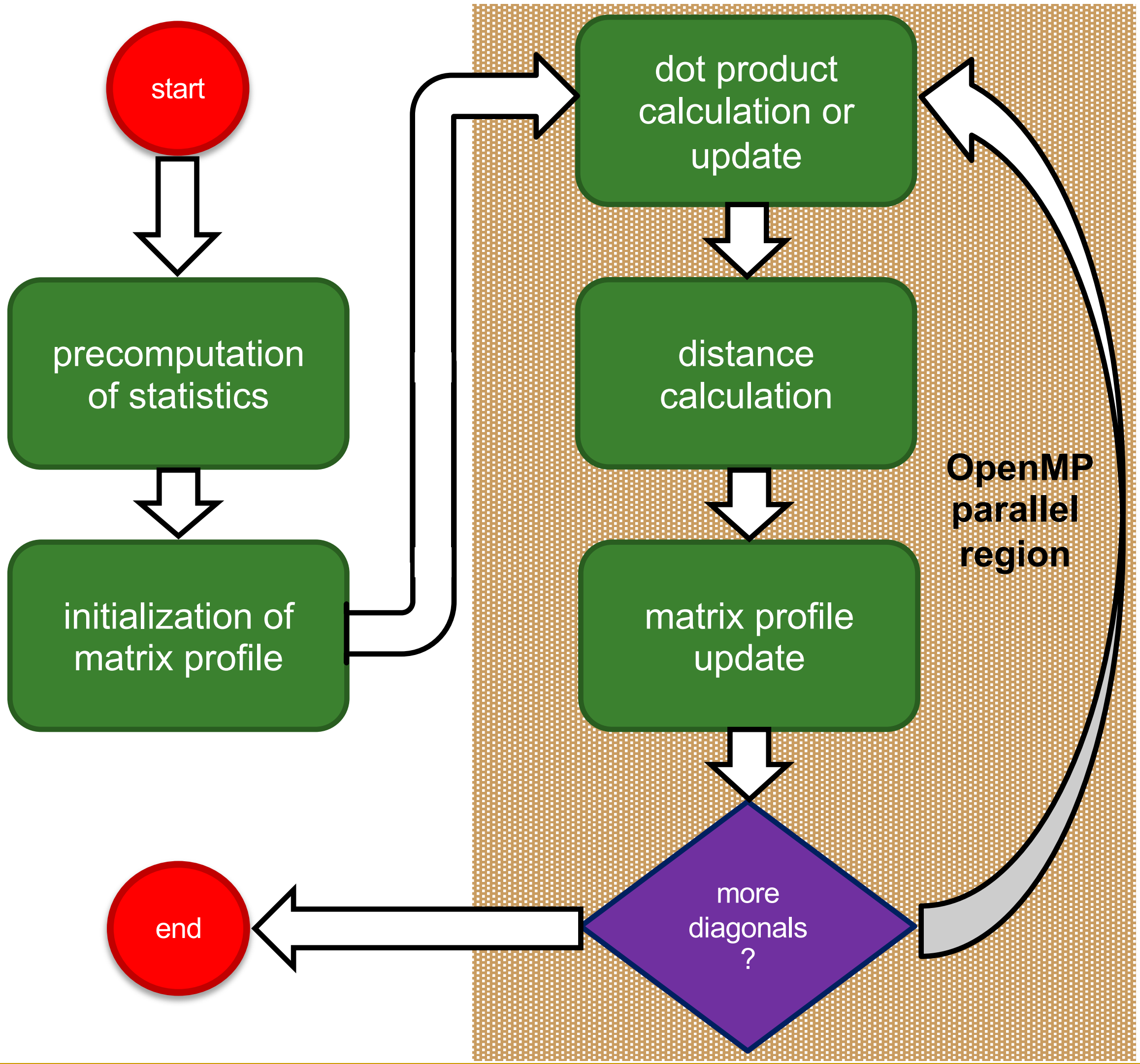
- The implementation is **open source** and based on **FlexFloat**

```
SCRIMP
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
| F l e x F l o a t     B e n c h m a r k |
+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+-+
```

FlexFloat @ Github

SCRIMP FF

- SCRIMP FF computation scheme and configuration parameters



The user can configure individually the precision for each block via a config file

Configurable precisions
Statistics (μ and σ)
Dot product
Distance
Matrix profile

User Interface

- SCRIMP FF example **input**:

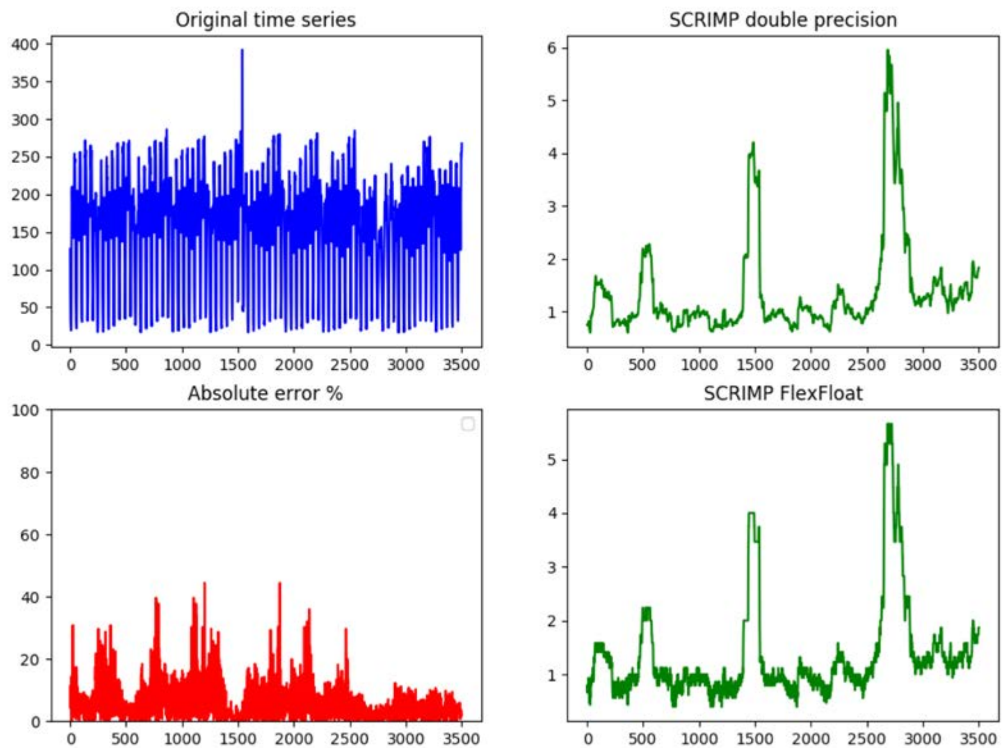
```
./scrimp_ff    power_demand.txt    200    72    0.1
```

`./scrimp_ff` — binary; `power_demand.txt` — time series file; `200` — window size; `72` — # threads; `0.1` — scale factor

- SCRIMP FF example **output**:

original time series →

absolute error % →



← result using original implementation (64 bits)

← result using FlexFloat implementation

FF parameters [exp, man] => distance=[7, 16]; dotprod=[7, 16]; stats=[6, 12]; profile=[5, 2]

Results

Experiments

- The benchmark has been tested using a server equipped with two Intel Xeon Gold 6154 (**72 threads**) and 384 GB of DDR4 memory

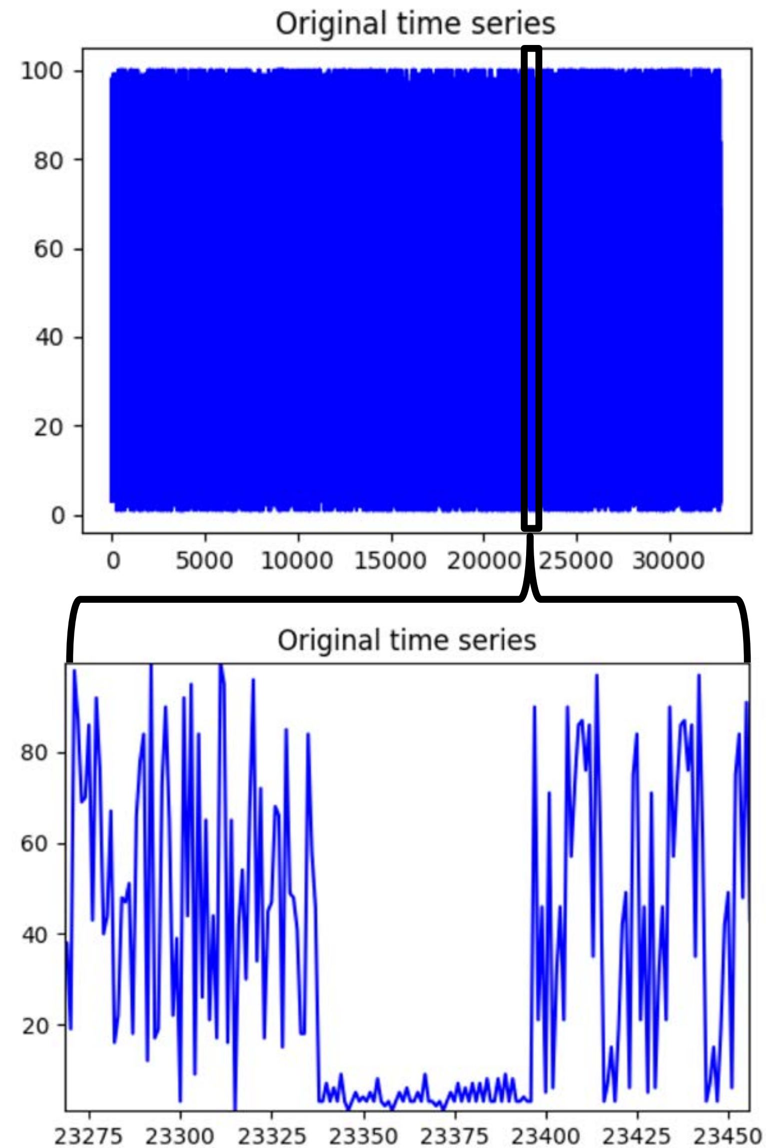
- Each FlexFloat execution is compared with the original code

- In this presentation I cover four didactical examples:
  - (1) Synthetic **random time series** with one anomaly
  - (2) Synthetic **random time series** with two (very) similar subsequences
  - (3) **Real data** time series with four anomalies
  - (4) **Real data** time series with twelve anomalies

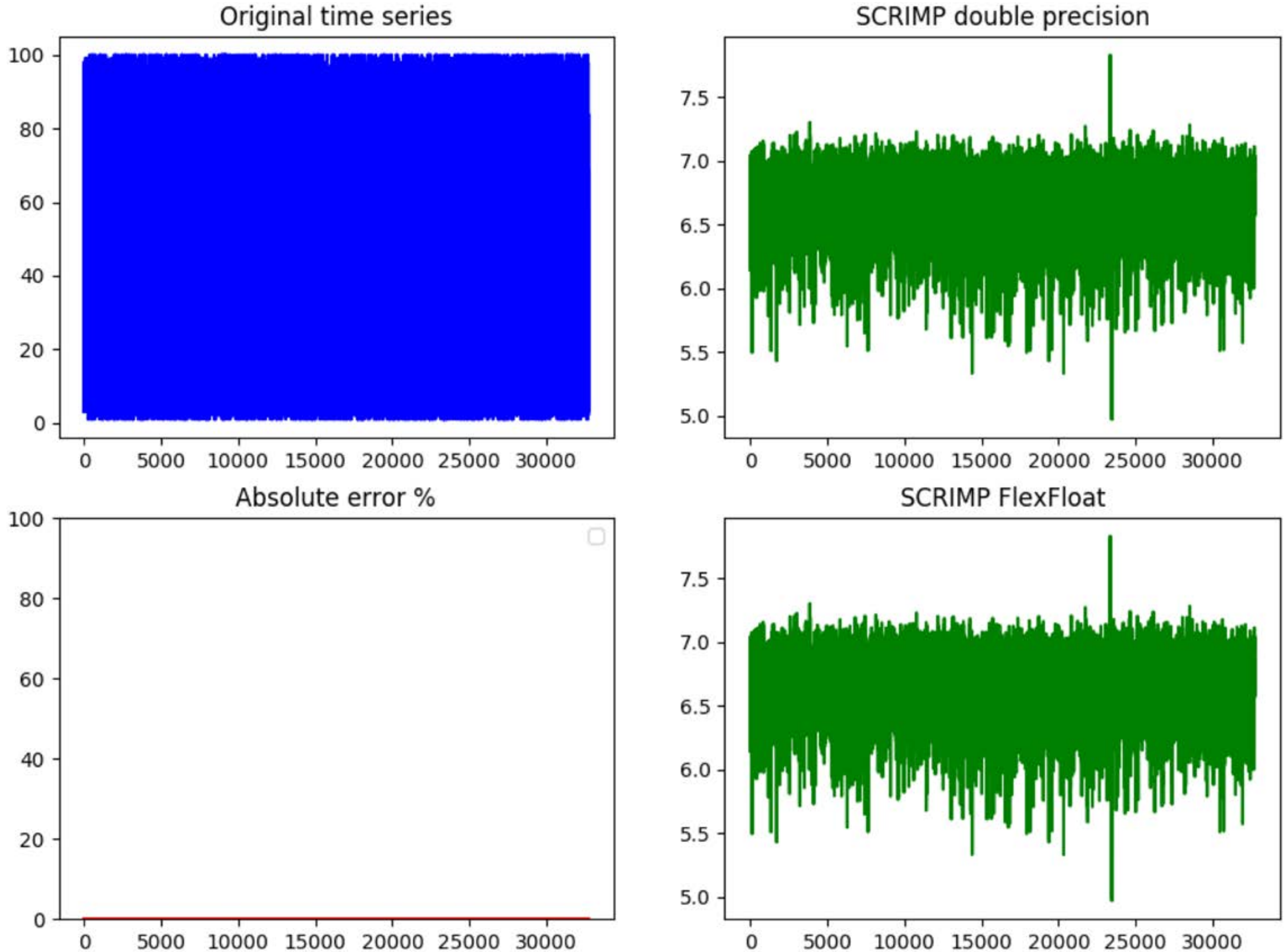
> Computing a 32,768 elements time series takes approx. 4 minutes in this sever

Random Serie Anomaly

- **Case study #1**
  - Random time series
  - Values from 0 to 100
  - 32,768 elements
  - 50 window size length
  - One anomaly



Random Serie Anomaly - 64 Bits

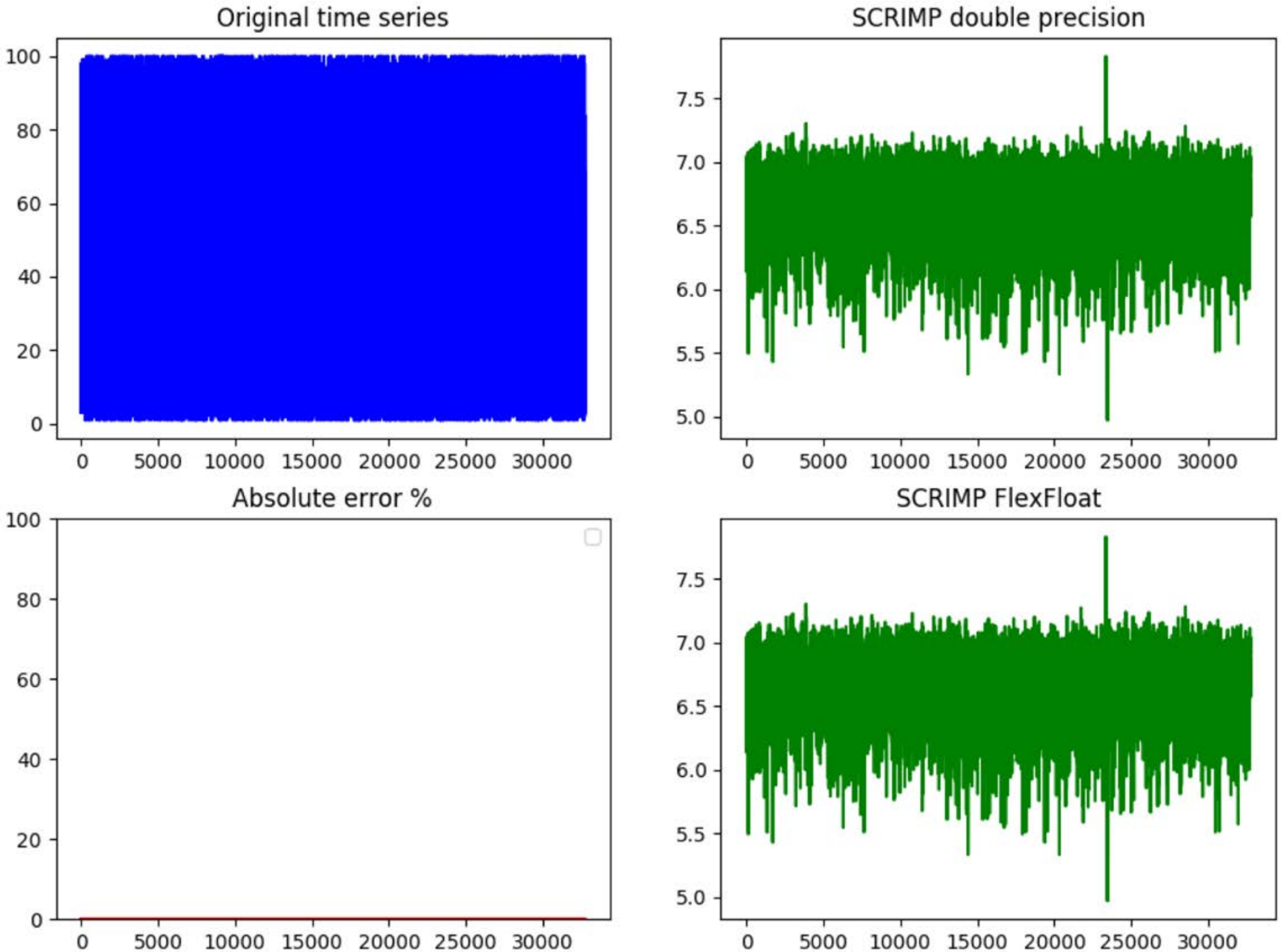


FF parameters [exp, man] => distance=[11, 52]; dotprod=[11, 52]; stats=[11, 52]; profile=[11, 52]

Observation

Using 64-bit precision and Flex Float we obtain no error, as expected

Random Serie Anomaly - 32 Bits

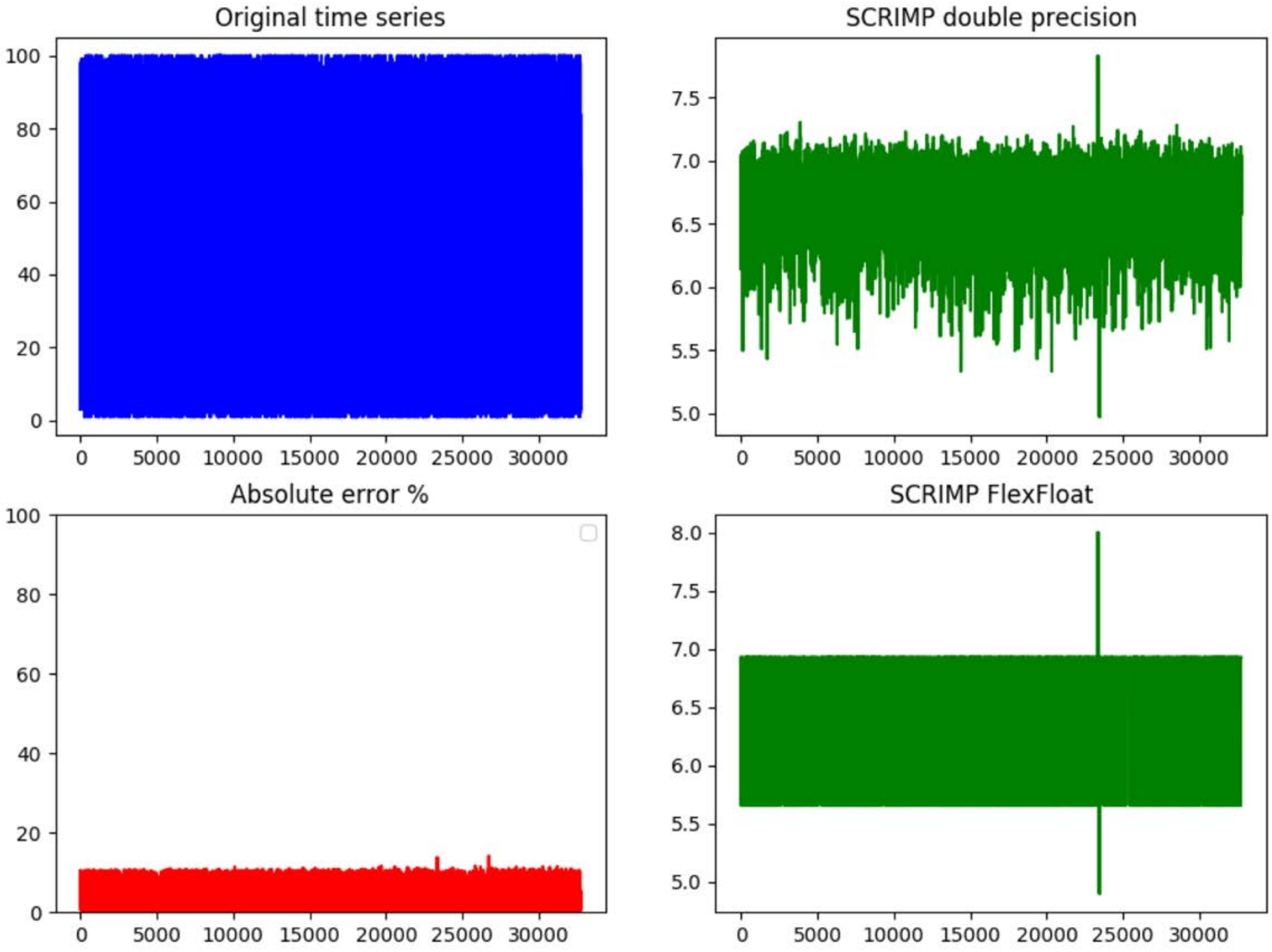


FF parameters [exp, man] => distance=[8, 23]; dotprod=[8, 23]; stats=[8, 23]; profile=[8, 23]

Observation

Using 32-bit precision and Flex Float we still obtain no error!!

Random Serie Anomaly - Reduced

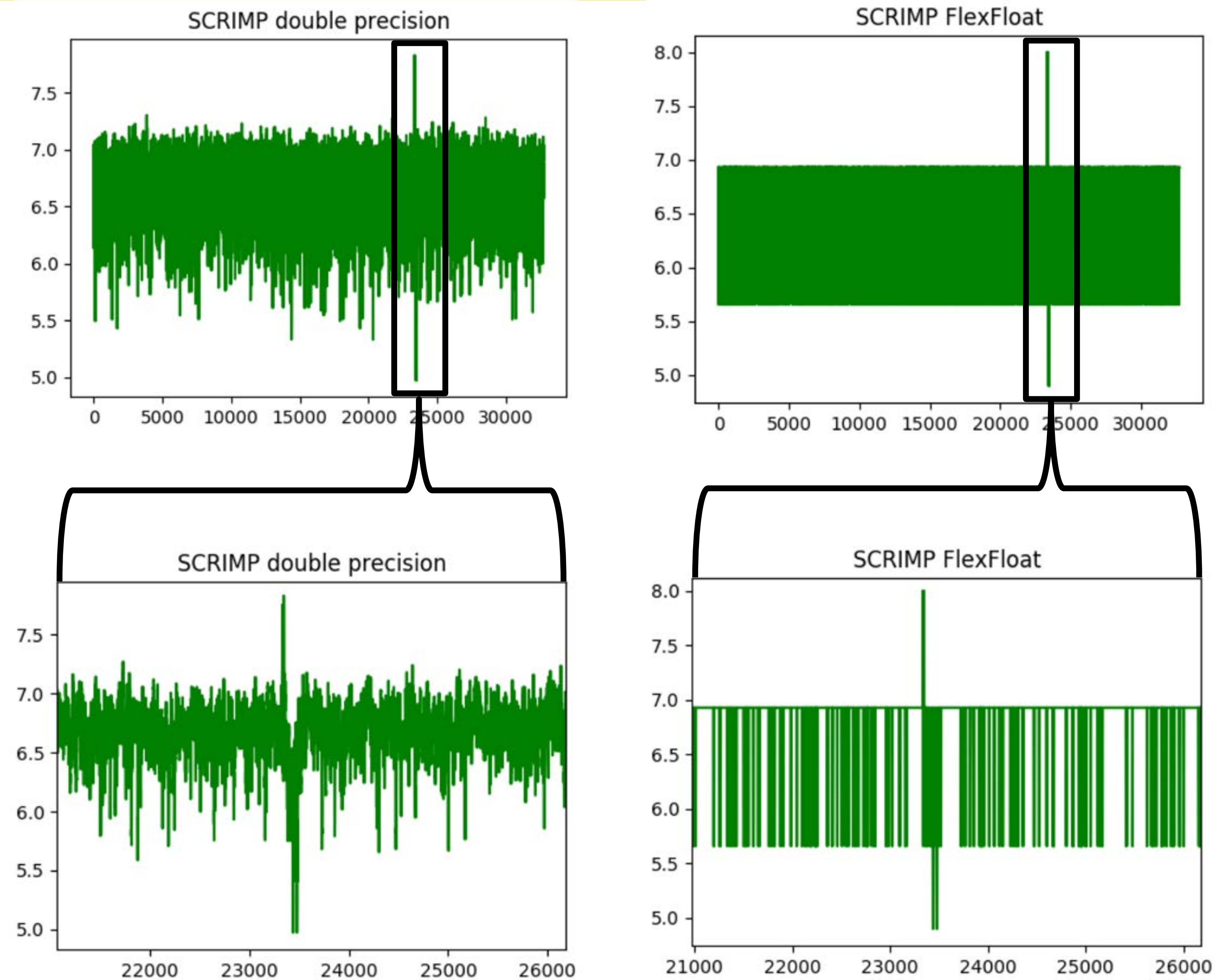


FF parameters [exp, man] => distance=[6, 15]; dotprod=[6, 10]; stats=[6, 12]; profile=[6, 1]

Observation

When we reduce significantly the precision we get just ~10% error

Random Serie Anomaly - Profile Zoom

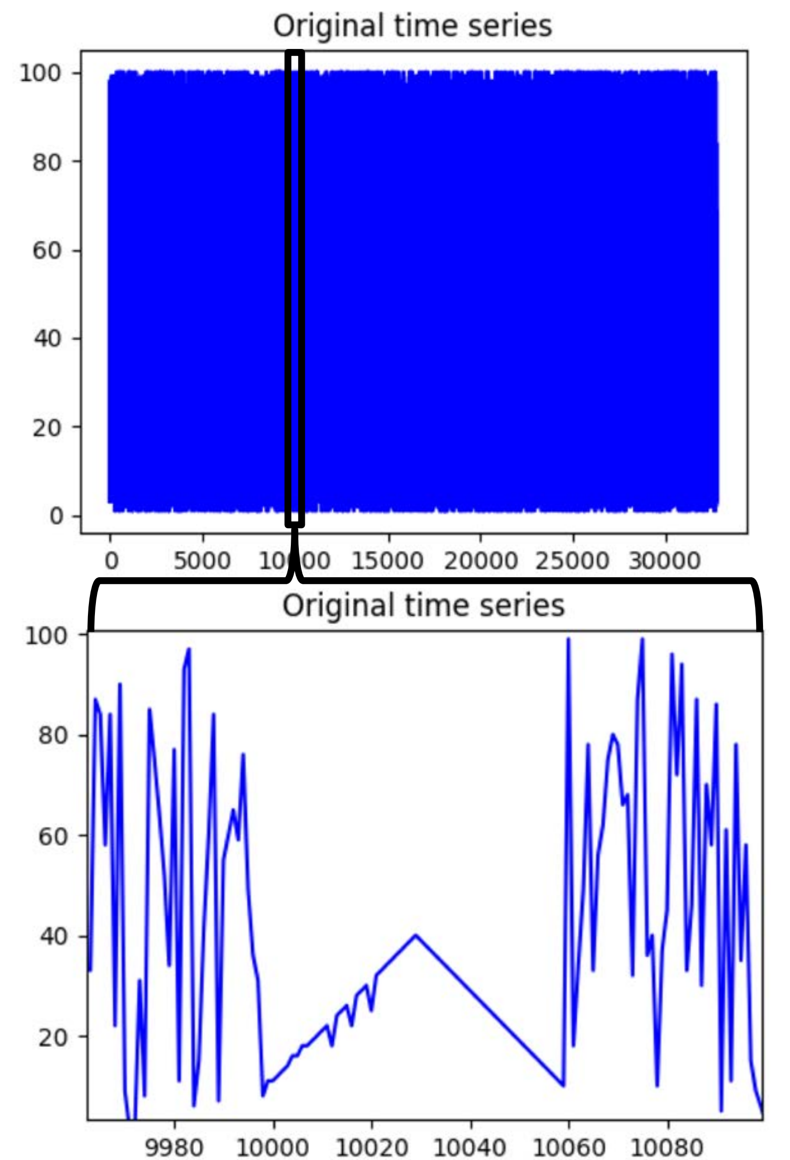


Observation

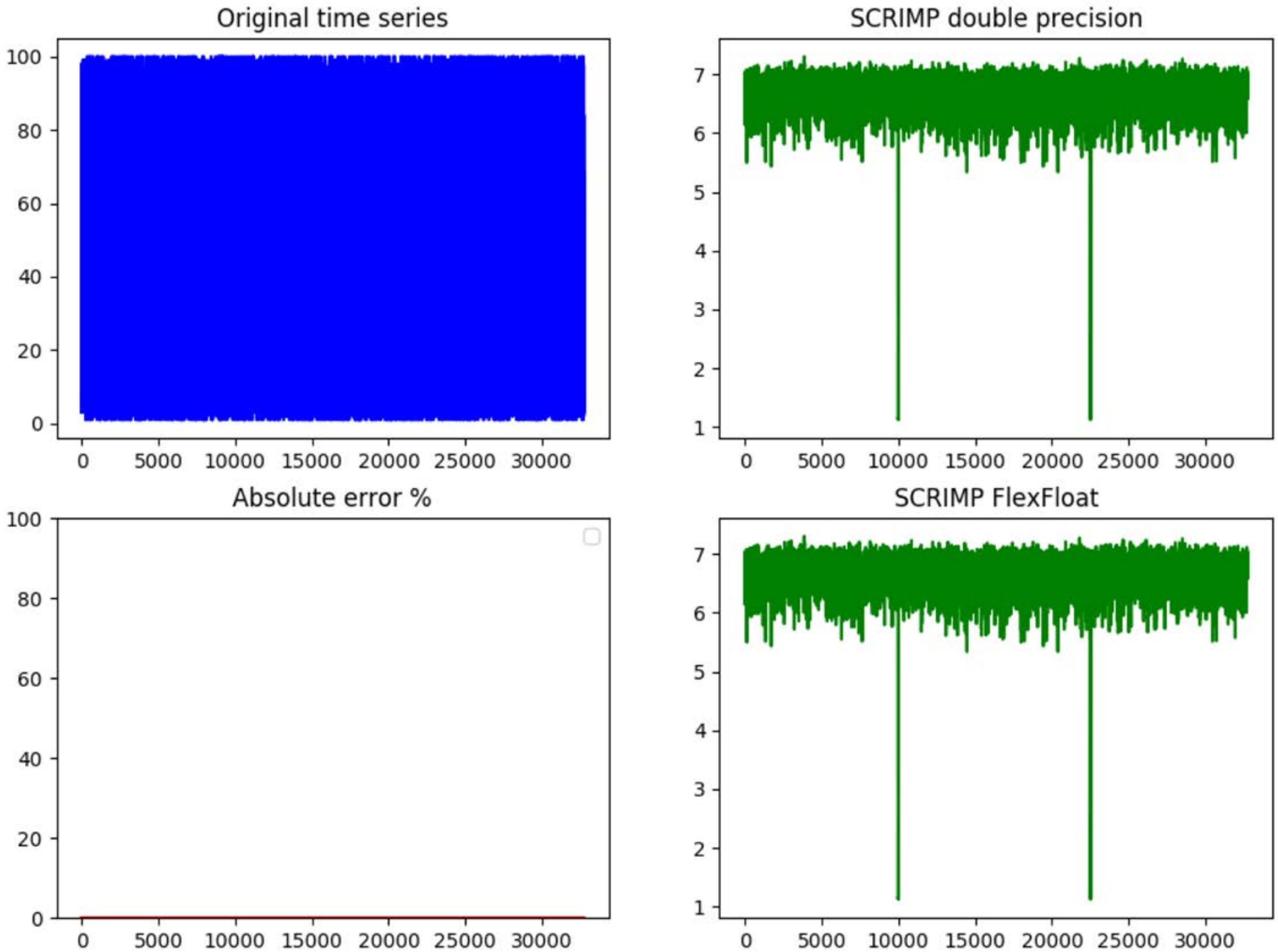
The anomaly is very easily detectable using the Flex Float approach

Random Serie Similarity

- **Case study #2**
  - Random time series
  - Values from 0 to 100
  - 32,768 elements
  - 50 window size length
  - Two (very) similar subsequences



Random Serie Similarity - 64 bits

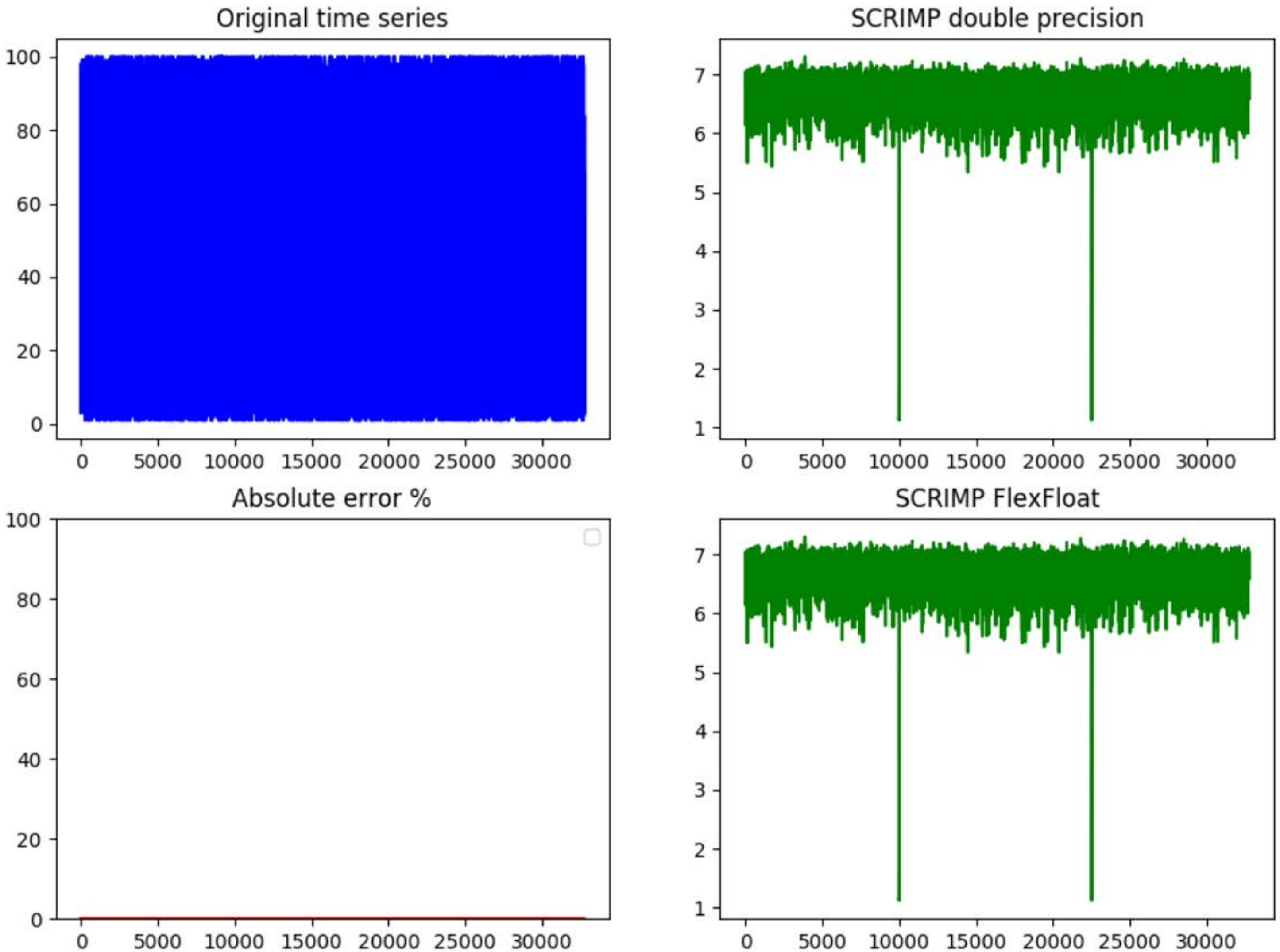


FF parameters [exp, man] => distance=[11, 52]; dotprod=[11, 52]; stats=[11, 52]; profile=[11, 52]

Observation

Using 64-bit precision and Flex Float we obtain no error, as expected

Random Serie Similarity - 32 Bits

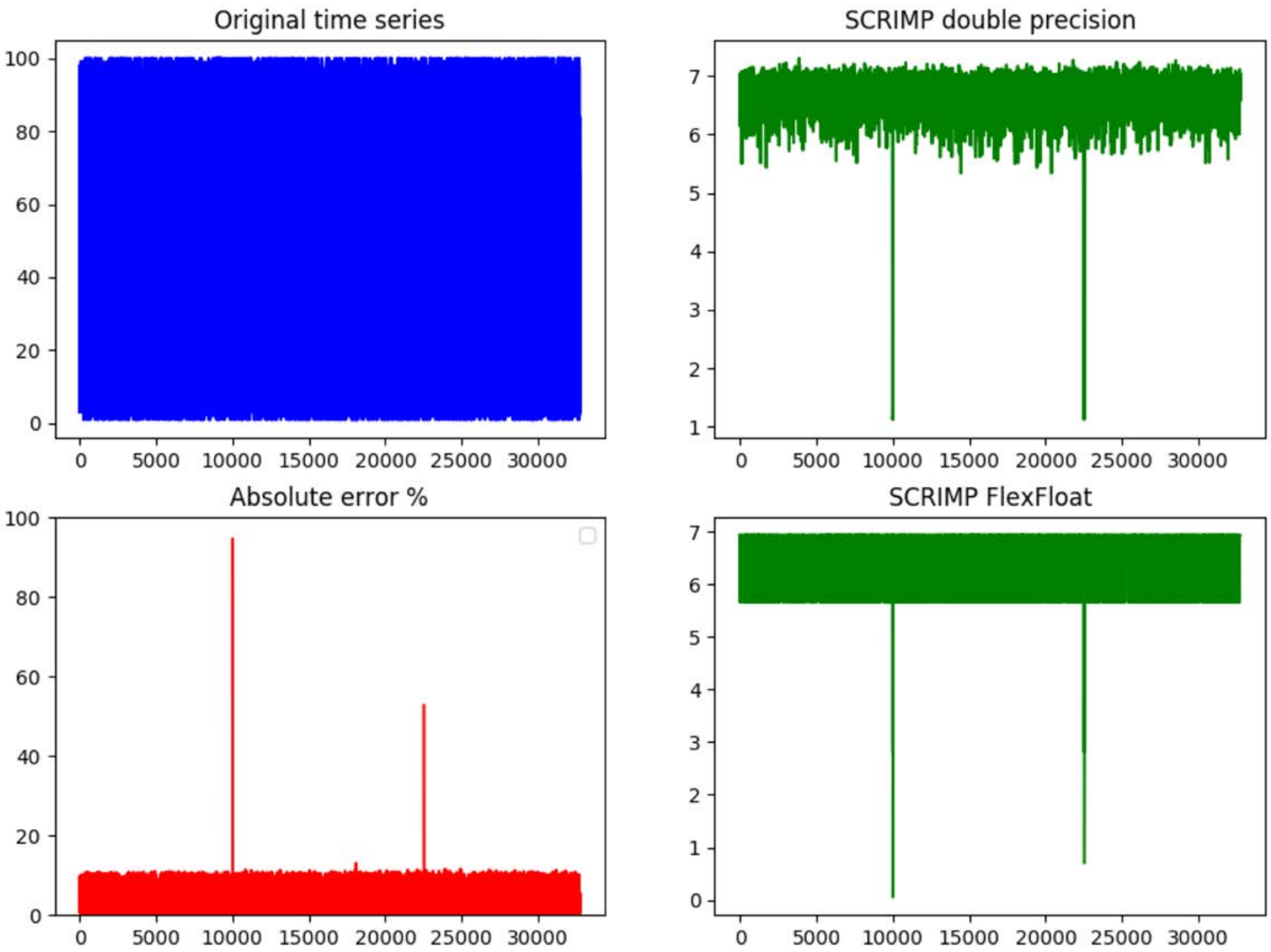


FF parameters [exp, man] => distance=[8, 23]; dotprod=[8, 23]; stats=[8, 23]; profile=[8, 23]

Observation

Using 32-bit precision and Flex Float we still obtain no error!!

Random Serie Similarity - Reduced

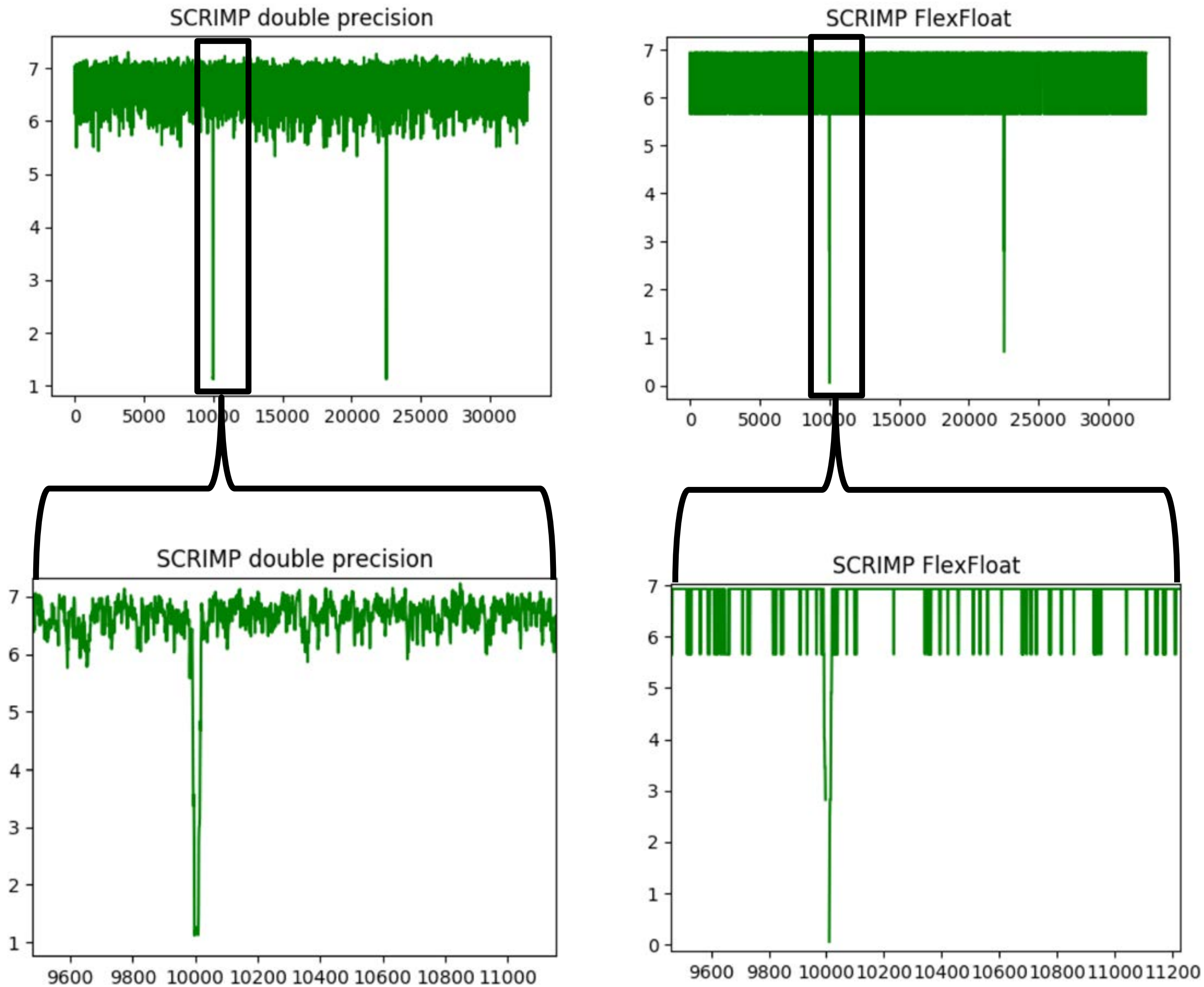


FF parameters [exp, man] => distance=[6, 17]; dotprod=[6, 15]; stats=[6, 10]; profile=[5, 1]

Observation

We obtain error in the lower values, however they are still detectable

Random Serie Similarity - Profile Zoom

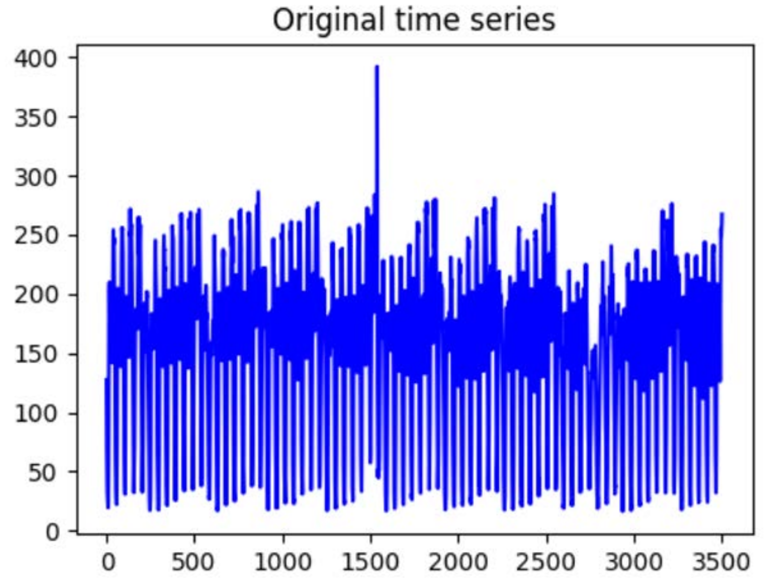


Observation

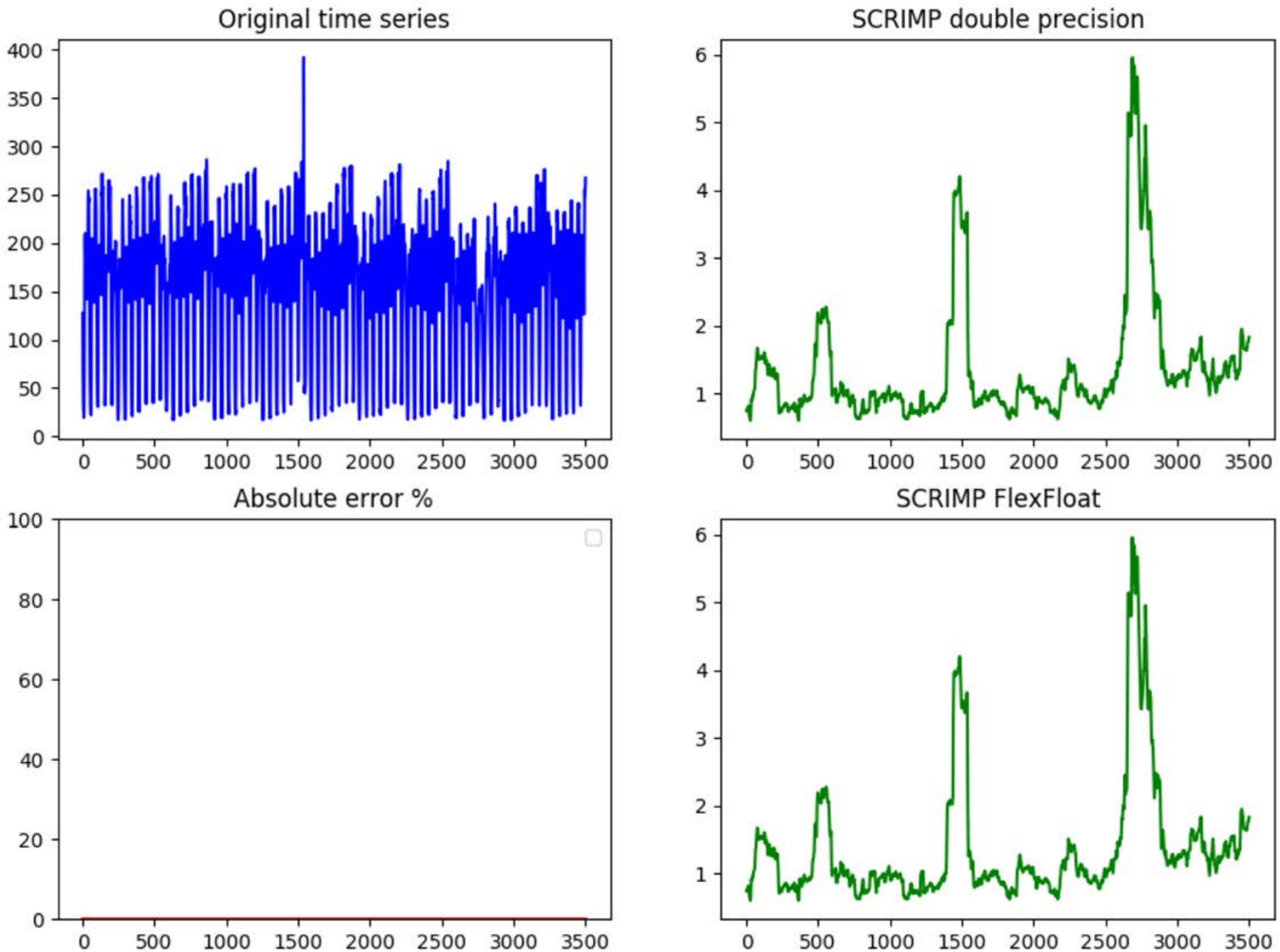
The similarities are still detectable using Flex Float

Taxi Demand Data

- **Case study #3**
  - Taxi demand data
  - 3,600 elements
  - 50 window size length
  - Four anomalies



Taxi Demand Data - 64 Bits

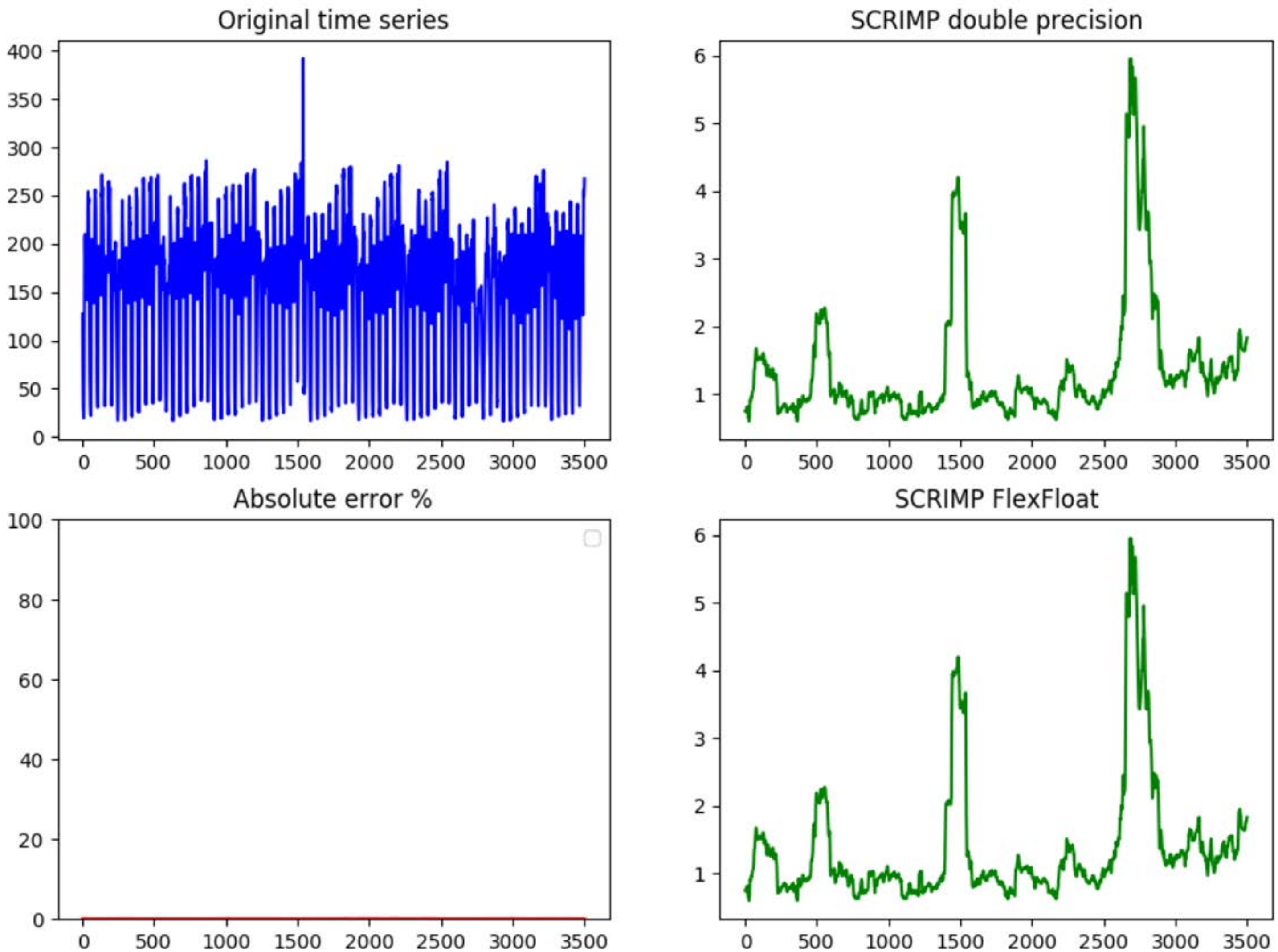


FF parameters [exp, man] => distance=[11, 52]; dotprod=[11, 52]; stats=[11, 52]; profile=[11, 52]

Observation

Using 64-bit precision and Flex Float we obtain no error, as expected

Taxi Demand Data - 32 Bits

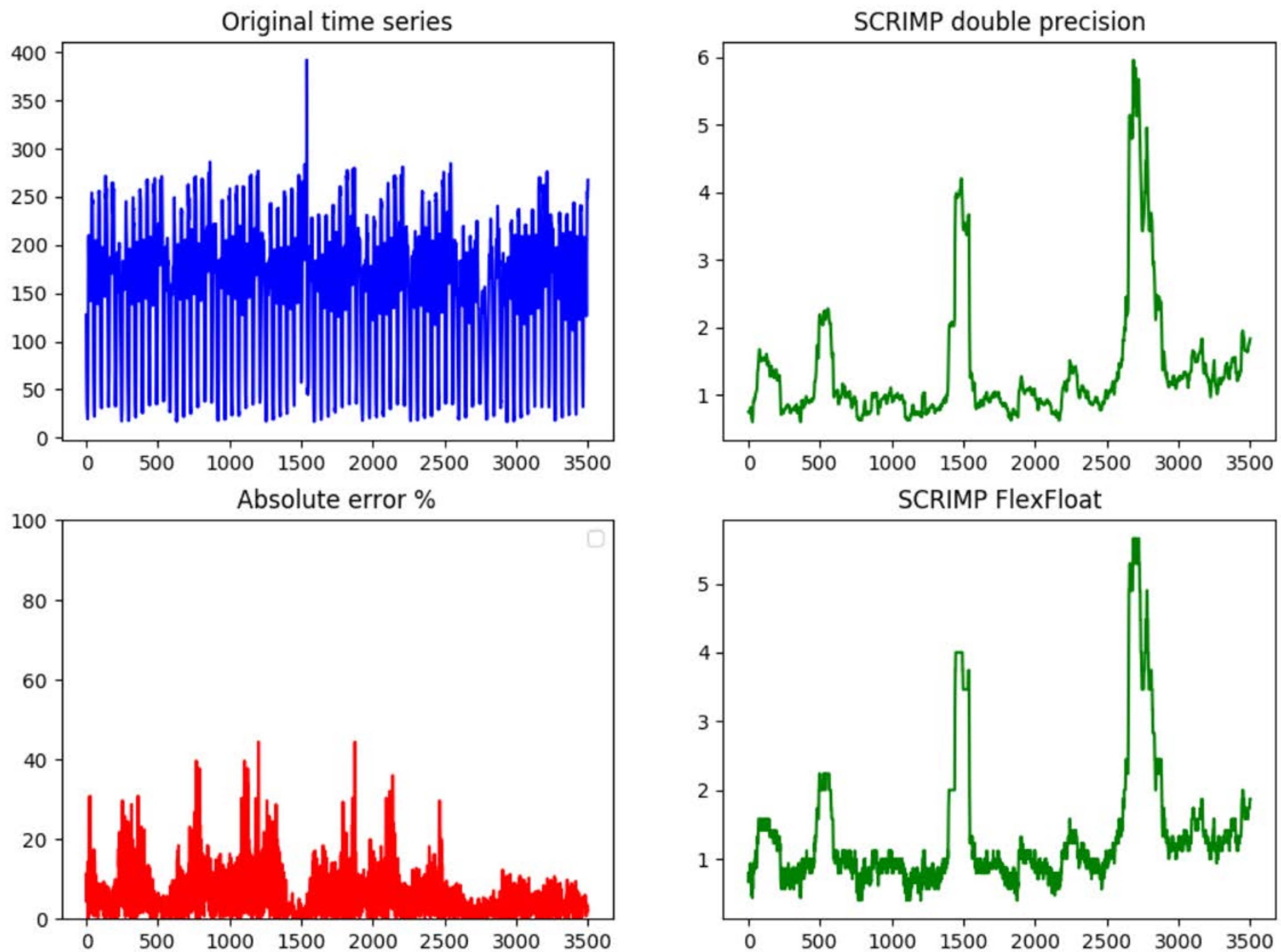


FF parameters [exp, man] => distance=[8, 23]; dotprod=[8, 23]; stats=[8, 23]; profile=[8, 23]

Observation

Using 32-bit precision and Flex Float we still obtain no error!!

Taxi Demand Data - Reduced

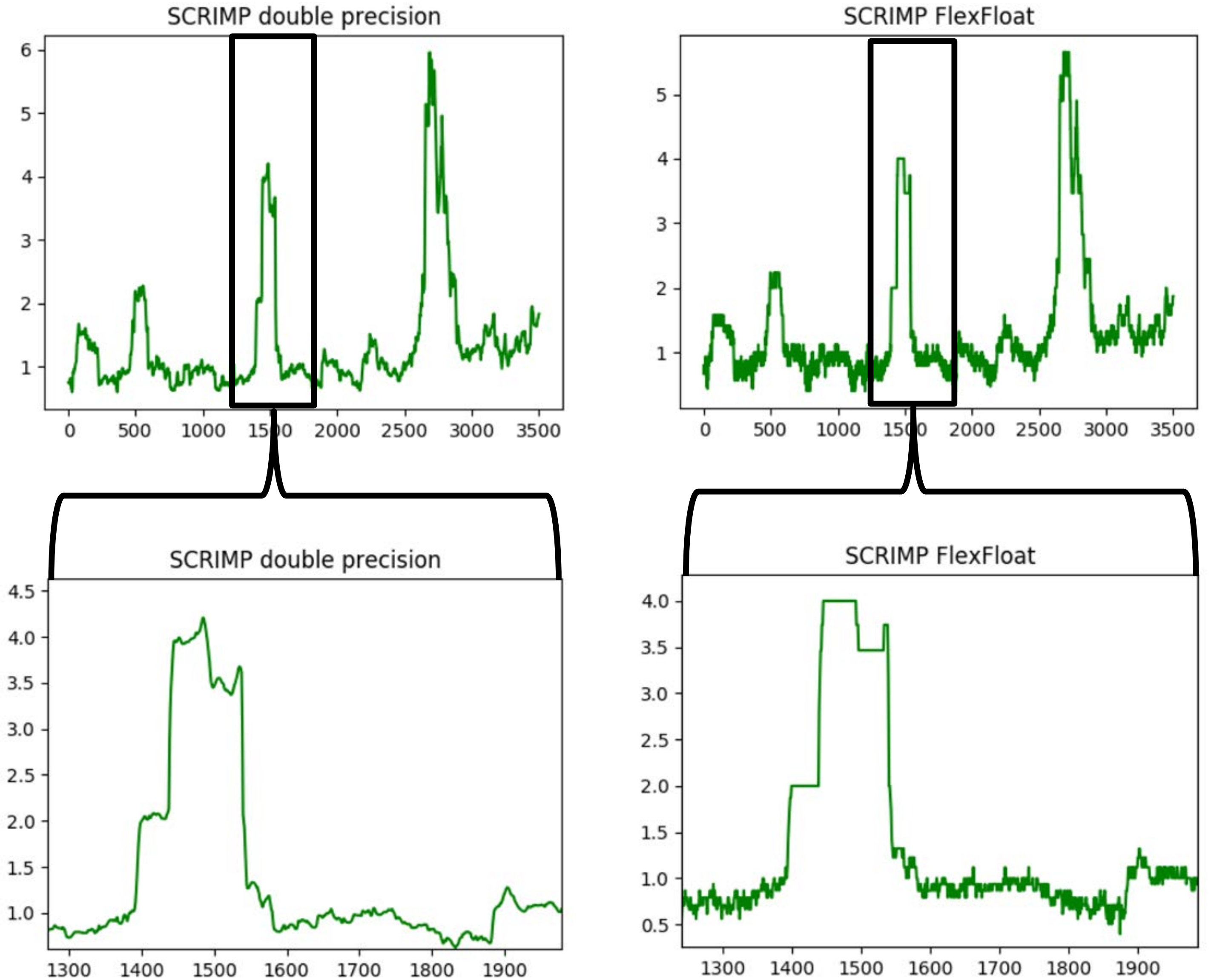


FF parameters [exp, man] => distance=[7, 16]; dotprod=[7, 16]; stats=[6, 12]; profile=[5, 2]

Observation

We obtain error in lower values, but anomalies are still detectable

Taxi Demand Data - Profile Zoom

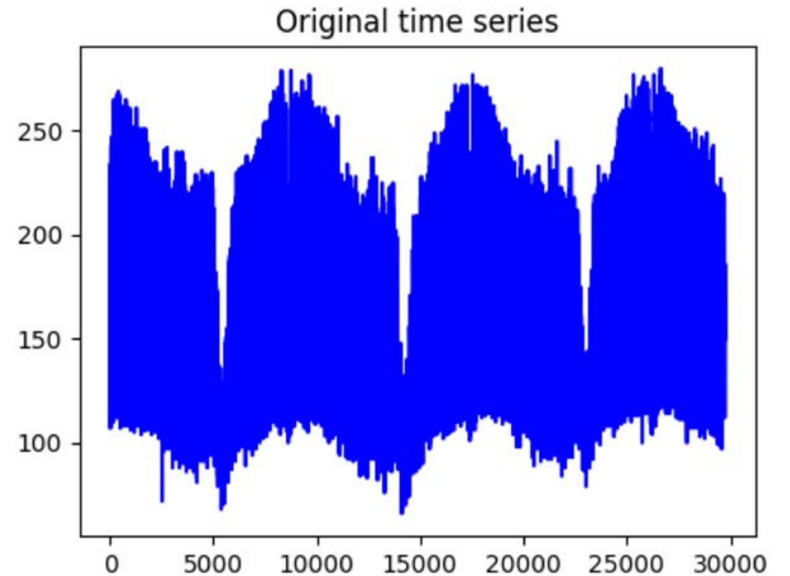


Observation

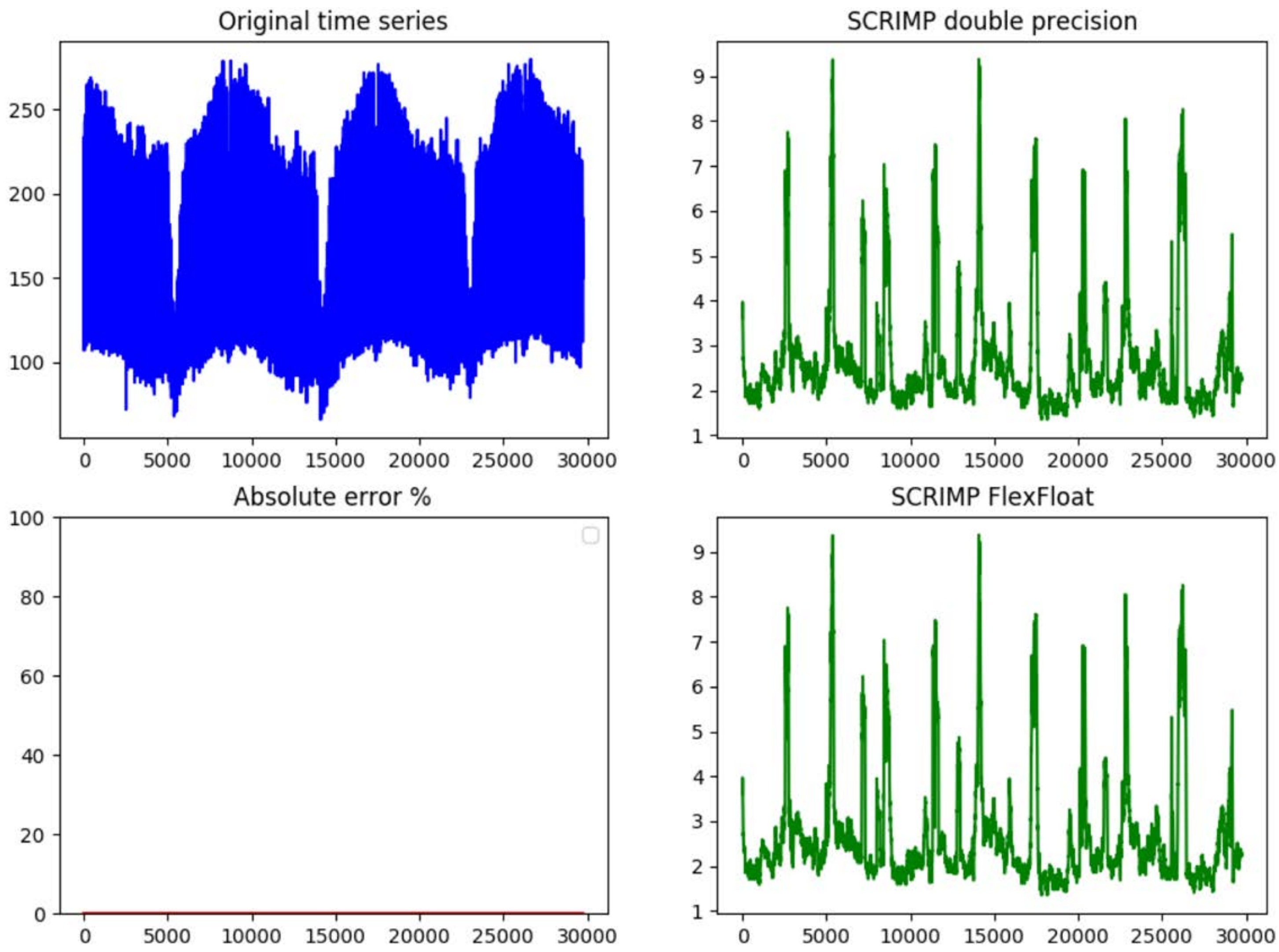
The anomalies are still detectable using Flex Float

Power Demand Data

- **Case study #4**
  - Electric power demand data
  - 30,000 elements
  - 50 window size length
  - Twelve anomalies



Power Demand Data - 64 Bits

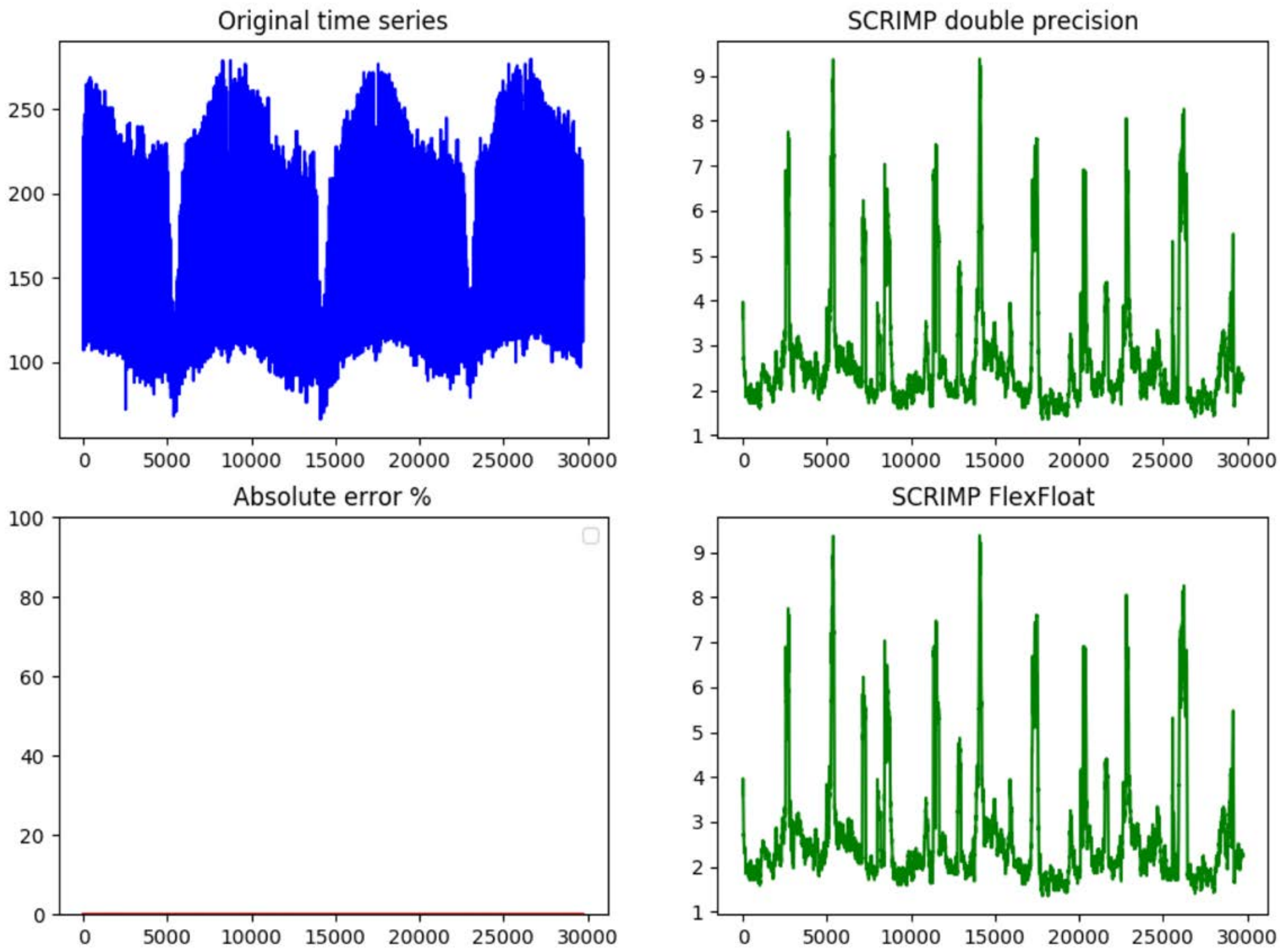


FF parameters [exp, man] => distance=[11, 52]; dotprod=[11, 52]; stats=[11, 52]; profile=[11, 52]

Observation

Using 64-bit precision and Flex Float we obtain no error, as expected

Power Demand Data - 32 Bits

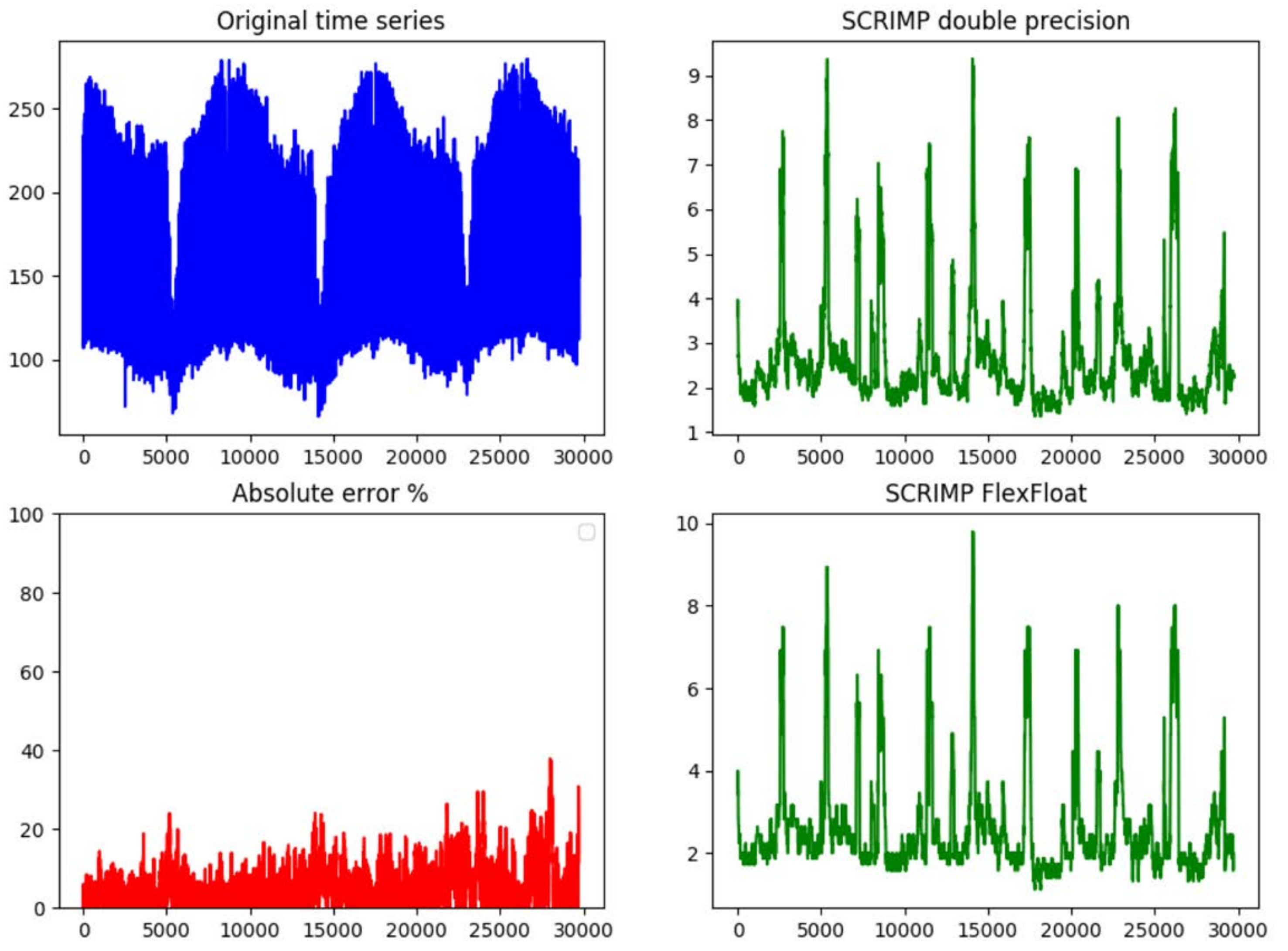


FF parameters [exp, man] => distance=[8, 23]; dotprod=[8, 23]; stats=[8, 23]; profile=[8, 23]

Observation

Using 32-bit precision and Flex Float we still obtain no error!!

Power Demand Data - Reduced

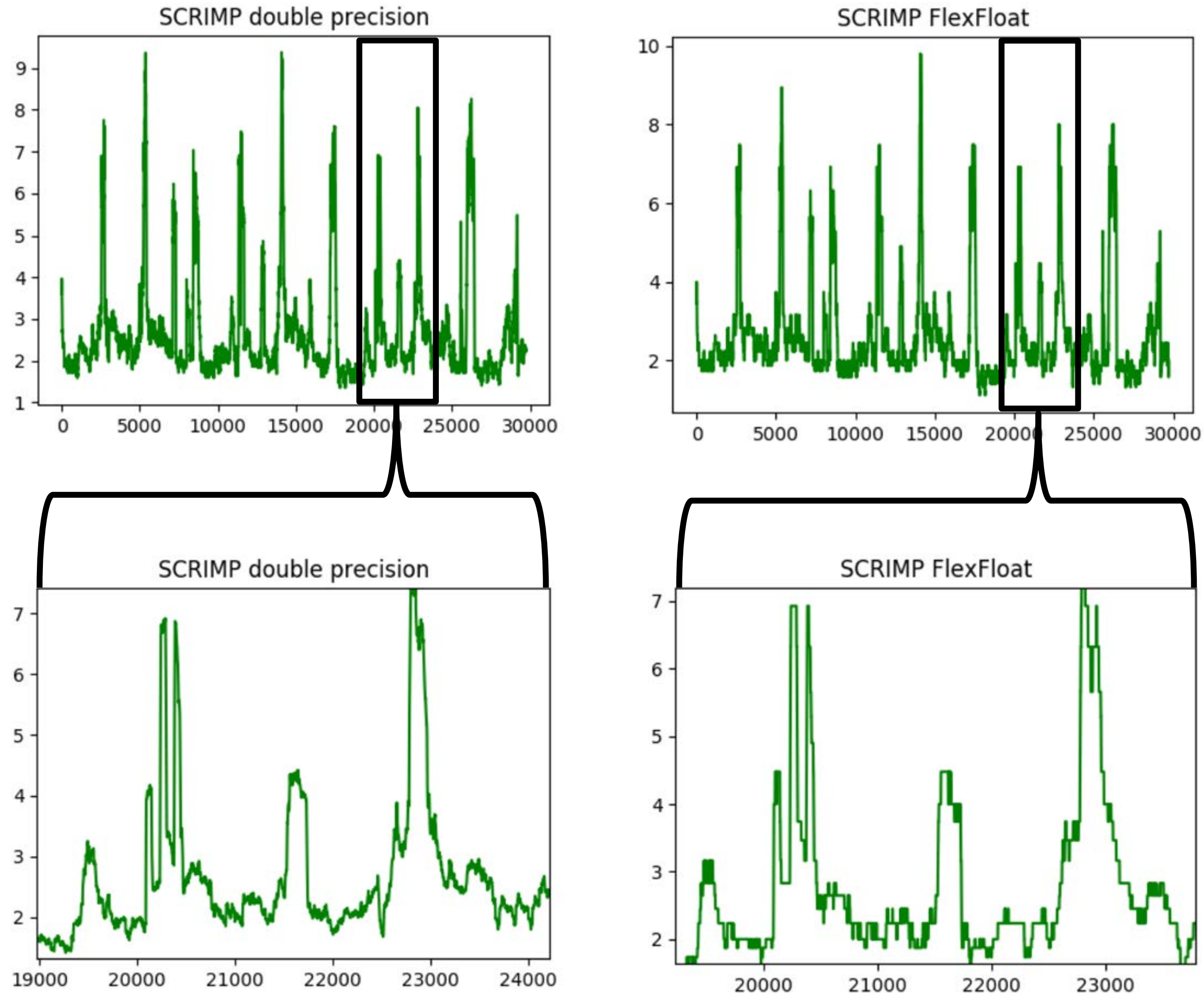


FF parameters [exp, man] => distance=[6, 17]; dotprod=[6, 17]; stats=[6, 17]; profile=[5, 2]

Observation

We obtain error in lower values, but anomalies are still detectable

Power Demand Data - Profile Zoom



Observation

The anomalies are still detectable using Flex Float

Conclusions and Future Work

Conclusions and Future Work

- Matrix profile can be useful for **many** time series motif discovery **applications**
- SCRIMP FlexFloat benchmark allows the **exploration of reduced precision** computation of Matrix Profile
- Architects could design accelerators using the exact amount of precision needed for each application, **maximizing performance** and **minimizing energy consumption**
- **Future work** comprises evaluating time series analysis using a non emulated transprecision computing environment as pulp-platform

References

- Some of the examples are taken from the **Matrix Profile tutorial** available at https://www.cs.ucr.edu/~eamonn/MatrixProfile.html

- **SCRIMP**:
  - Zhu, Y., Yeh, C. C. M., Zimmerman, Z., Kamgar, K., & Keogh, E. (2018, November). Matrix profile XI: SCRIMP++: time series motif discovery at interactive speeds. In *2018 IEEE International Conference on Data Mining (ICDM)* (pp. 837-846). IEEE.
  - https://sites.google.com/site/scrimpplusplus/

- **FlexFloat**:
  - G. Tagliavini, A. Marongiu and L. Benini, "FlexFloat: A Software Library for Transprecision Computing," in *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*.
  - https://github.com/oprecomp/flexfloat

Time Series Analysis
Using Transprecision Computing

Ivan Fernandez Vega

OPRECOMP Summer of Code

4 September 2019