

# 1 TSFX: A Python package for time series feature 2 extraction

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## Software

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## 5 Summary

6 TSFX is a Python ([Van Rossum & Drake, 2009](#)) library for extracting features from time series data. It is inspired by the tsfresh ([Christ et al., 2018](#)) Python package with a special focus on performance on large time series datasets. To this end, it utilizes Polars ([Vink et al., 2023](#)) which is a fast DataFrame library written in Rust ([The Rust Programming Language, 2015](#)) with Python bindings facilitated through PyO3 ([Project & Contributors, 2023](#)). The feature extraction functions are implemented in Rust for even faster execution. To benchmark, the “1 billion row challenge” ([Morling, 2024](#)) was used. In this benchmark, TSFX took approx. 200 seconds (using 64 CPU cores) to extract features vs tsfresh which took 2000 seconds (using 80 CPU cores). This means that compared to tsfresh, TSFX offers approximately 10 times higher performance, using the same set of time series features.

TSFX can be installed using pip:

```
pip install tsfx
```

TSFX can also be configured using a TOML ([TOML, 2021](#)) configuration file (default name .tsfx-config.toml).

Below is a simple example of extracting features from a time series dataset:

```
import polars as pl
from tsfx import (
    ExtractionSettings,
    FeatureSetting,
    extract_features,
)

df = pl.DataFrame(
    {
        "id": ["a", "a", "a", "b", "b", "b", "c", "c", "c"],
        "val": [1.0, 2.0, 3.0, 1.0, 2.0, 3.0, 1.0, 2.0, 3.0],
        "value": [4.0, 5.0, 6.0, 6.0, 5.0, 4.0, 4.0, 5.0, 6.0],
    },
).lazy()
settings = ExtractionSettings(
    grouping_cols=["id"],
    feature_setting=FeatureSetting.Efficient,
    value_cols=["val", "value"],
)
gdf = extract_features(df, settings)
gdf = gdf.sort(by="id")
```

```
with pl.Config(set_tbl_width_chars=80):
    print(gdf)
```

<sup>20</sup> Running the code above generates a new DataFrame with the extracted features:

shape: (3, 314)

id	length	val_su_m_value	val_me	...	value_n_	value_n_	value_n_	value_n_
str	u32	s	f64	...	number_peaks_n_3	number_peaks_n_5	number_peaks_n_10	number_peaks_n_50
a	3	6.0	2.0	...	0.0	0.0	0.0	0.0
b	3	6.0	2.0	...	0.0	0.0	0.0	0.0
c	3	6.0	2.0	...	0.0	0.0	0.0	0.0

<sup>21</sup> If the DataFrame has a time column, it is also possible to extract over a time window by passing DynamicGroupBySettings into the feature extraction settings, like so:  
<sup>22</sup> ExtractionSettings(..., dynamic\_settings=DynamicGroupBySettings(...)).

## <sup>24</sup> Statement of need

<sup>25</sup> Time series is a ubiquitous data modality, present in many domains such as finance, industry,  
<sup>26</sup> meteorology, and medicine, to mention a few. As hardware to collect and store time series  
<sup>27</sup> data is becoming increasingly affordable, the amount of available time series data is increasing  
<sup>28</sup> in many domains. A common preprocessing step when dealing with time series is feature  
<sup>29</sup> extraction. This involves calculating representative features such as mean, variance, skewness,  
<sup>30</sup> etc. from the time series to be used in downstream tasks such as classification, regression  
<sup>31</sup> or clustering. For large time series datasets, performance is important for enabling timely  
<sup>32</sup> data preprocessing. TSFX is made for this purpose: extracting features from large time series  
<sup>33</sup> datasets.

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## <sup>39</sup> References

- <sup>40</sup> Christ, M., Braun, N., Neuffer, J., & Kempa-Liehr, A. W. (2018). Time series FeatuRe extraction on basis of scalable hypothesis tests (tsfresh – a python package). *Neurocomputing*, 307, 72–77. <https://doi.org/10.1016/j.neucom.2018.03.067>
- <sup>43</sup> Morling, G. (2024). *The one billion row challenge*. <https://www.morling.dev/blog/one-billion-row-challenge/>
- <sup>45</sup> Project, P., & Contributors. (2023). PyO3. GitHub. <https://github.com/PyO3>
- <sup>46</sup> The rust programming language. (2015). <https://rust-lang.org/>.
- <sup>47</sup> TOML: Tom's obvious minimal language. (2021). <https://toml.io/en/>

- 48 Van Rossum, G., & Drake, F. L. (2009). *Python 3 reference manual*. CreateSpace.  
49 ISBN: 1441412697
- 50 Vink, R., Gooijer, S. de, Beedie, A., Zundert, J. van, Hulselmans, G., Grinstead, C., Gorelli, M.  
51 E., Santamaria, M., Heres, D., ibENPC, Leitao, J., Heerden, M. van, Jermain, C., Russell,  
52 R., Pryer, C., Castellanos, A. G., Goh, J., Wilksch, M., illumination-k, ... Keller, J. (2023).  
53 *Pola-rs/polars: Python polars 0.16.11* (py-0.16.11). Zenodo. <https://doi.org/10.5281/zenodo.7699984>
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