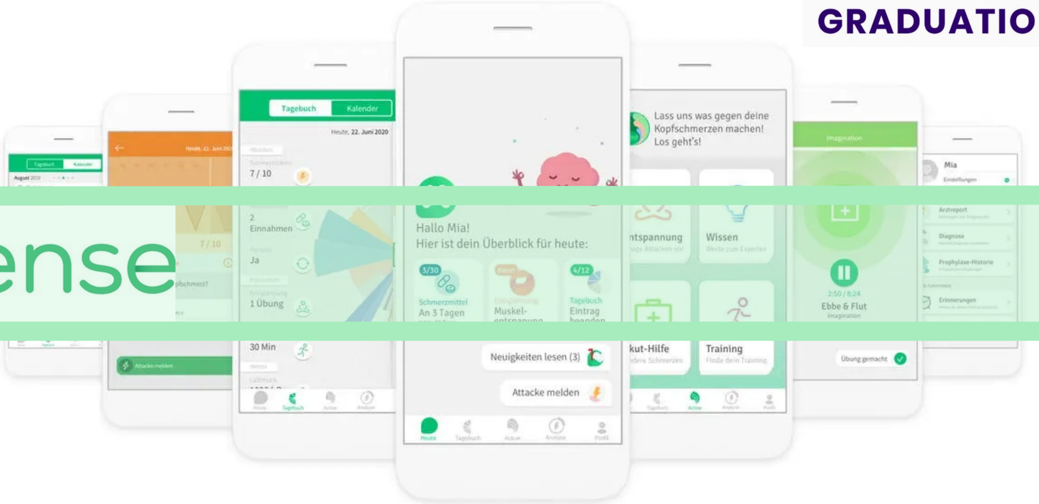
SPICED

Migraine Data Analysis

Garlic Boosting
GRADUATION

M-sense



scikit learn

PostgreSQL

pandas

SQLAlchemy

matplotlib

seaborn

Felix M. Schneider 24.11.2022

Project Idea

- M-sense:
  - Headache Diary App
  - running for 6 years (2016-2022)
  - Data from 80000 users
- Backend: Postgres Database (running on aws and using Metabase)

Questions:

- Periodicity in the occurrence of headache days?
- What are potential headache triggers?
- Make use out of it for prediction?

M-sense

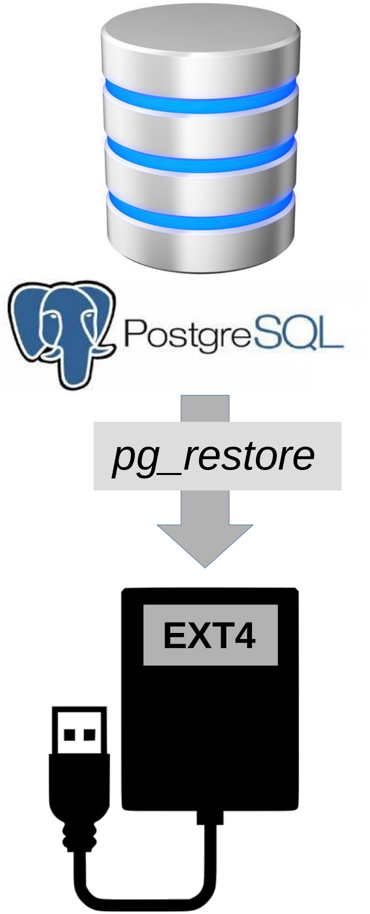
External Partner:
Markus Dahlem
(CEO Founder)

I. Data Extraction

- Data were delivered as a binary Postgres dump
  Size: **26.2 GB**
- First try: run it locally not possible due to HD restrictions
- Solutions:

  Set up database on external hard disk

  - format external hard disk as EXT4
  - mount hard disk as if it was an internal HD
  - change postgres data path from /var/… to mount point
- Size of extracted data set: **137GB** Data of about 80.000 users

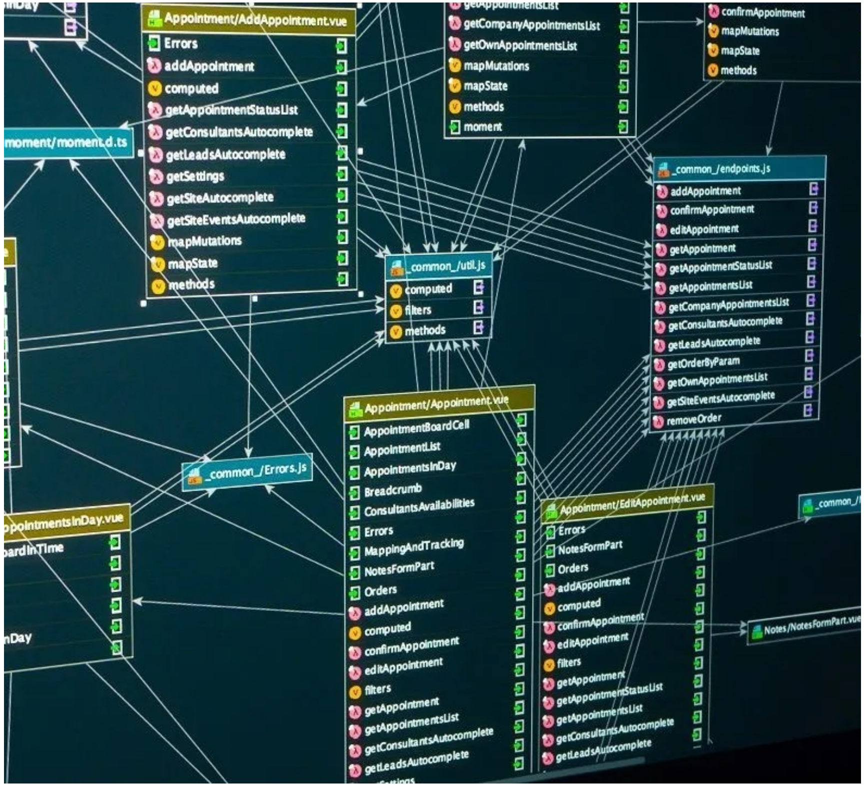


II. Working with “Big Data”

Access the data:

- Database shape complicated
- advanced SQL-Queries are needed to retrieve headache time series data

- Solution:
  python *Class* NslUser.py
  - comfortable access data using SQLAlchemy
  - apply operations



```
-- SQL-QUERY TO RETRIEVE HEADACHE TIME SERIES FOR USER 11 --

WITH CTE1 AS (
SELECT event_time_range, value FROM
      quantity q JOIN factor f
                   ON    q.user_id          =  f.user_id
                  AND    q.server_factor_id =  f.server_factor_id
                WHERE    q.user_id          =  11
                  AND    global_id          IN ('headacheType')
                  AND    q.deleted_at       IS null
             ORDER BY    LOWER(event_time_range)),

CTE2 AS (
SELECT GENERATE_SERIES(LOWER(event_time_range)::DATE,
                       UPPER(event_time_range)::DATE, '1 day') AS hd, value
FROM CTE1),

CTE_MIN_MAX AS (
SELECT MIN(hd) AS min_hd, MAX(hd) AS max_hd FROM CTE2),

CTE_TIMELINE AS (
SELECT GENERATE_SERIES(min_hd::DATE, max_hd::DATE, '1 day') AS timel FROM
CTE_MIN_MAX)

SELECT timel, CASE WHEN value IS null THEN 0 ELSE value END AS value_ FROM
      CTE_TIMELINE cte_t LEFT JOIN CTE2 c2
                               ON cte_t.timel = c2.hd
                         ORDER BY cte_t.timel;
```

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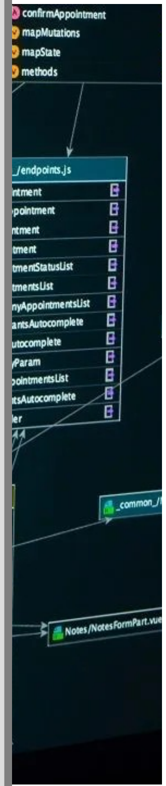

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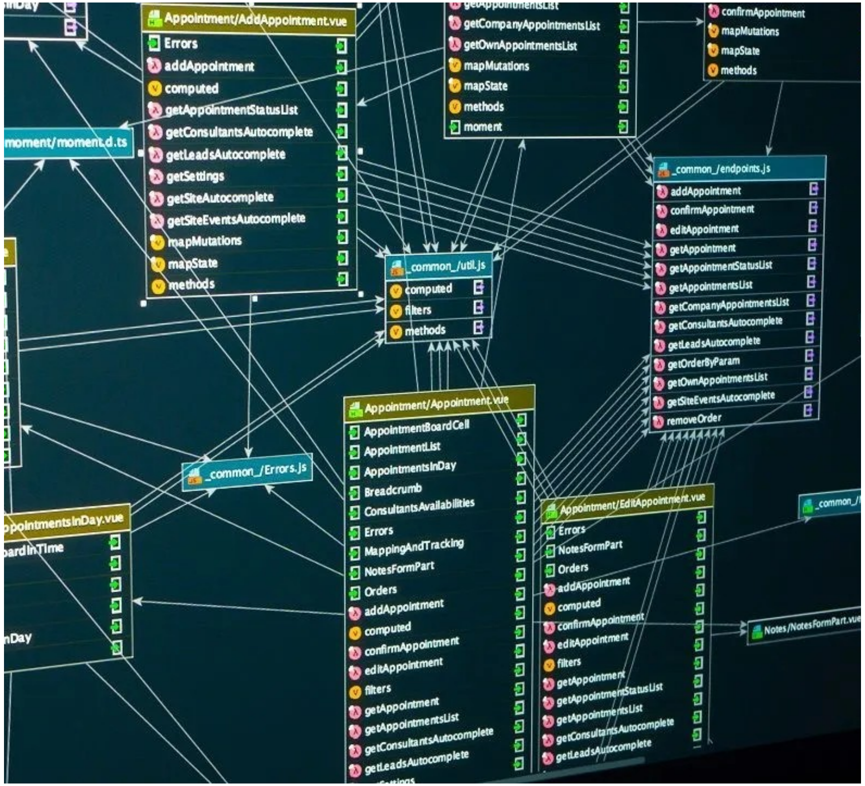

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```
from nsl_user import NslUser

NslUser(11)
```

Initialization

```
HOST = localhost
PORT = 5432
USERNAME = postgres
DB = nsl_timeline
engine = Engine(postgresql://postgres

userId      = 11
```

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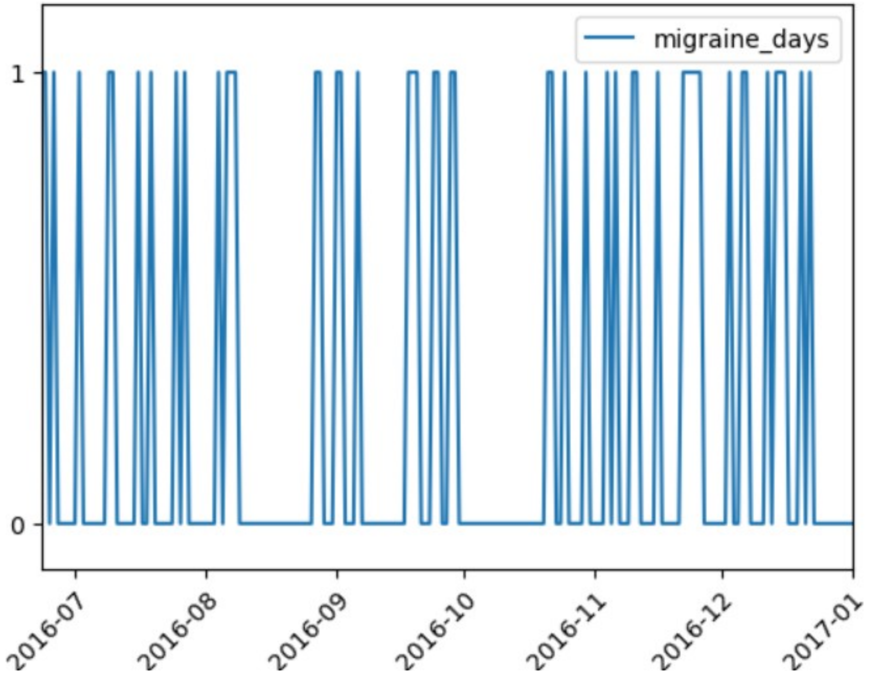
```
user_11.plot_feature("migraine_days")
```



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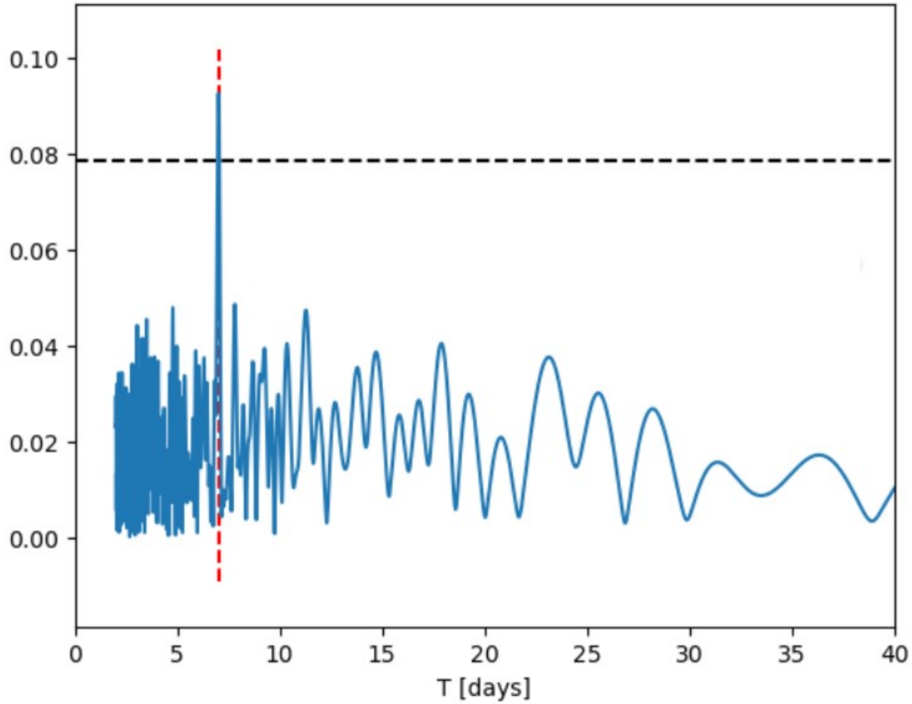
```
user_11.plotspec()
```



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Spectral Analysis

Each Time-Series can be approximated by sum of *cos* functions with different amplitudes, frequencies ω and phase φ

$$\Sigma A_k * \cos(\omega_k t + \varphi_k)$$

Fourier-Transformation (numpy.fft.fft):

- Unfolding spectral components:
  - *Amplitude* and *Phase* Spectrum:
    A(ω) *cos*(ωt + ***φ(ω)***)
- Analyze whole dataset:
  Spectra of 40000 user

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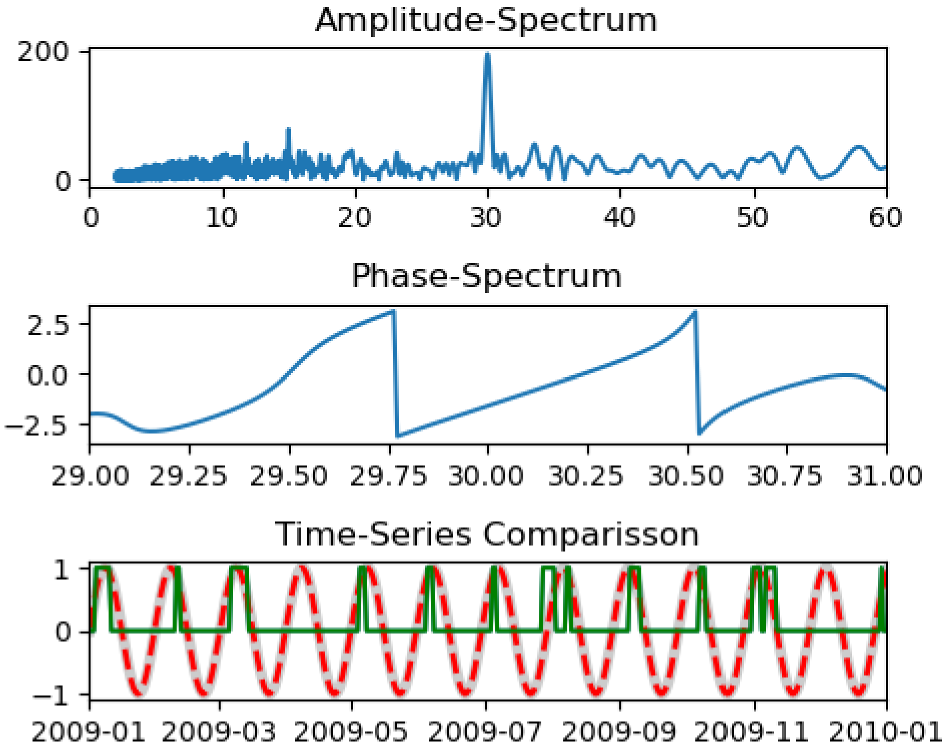
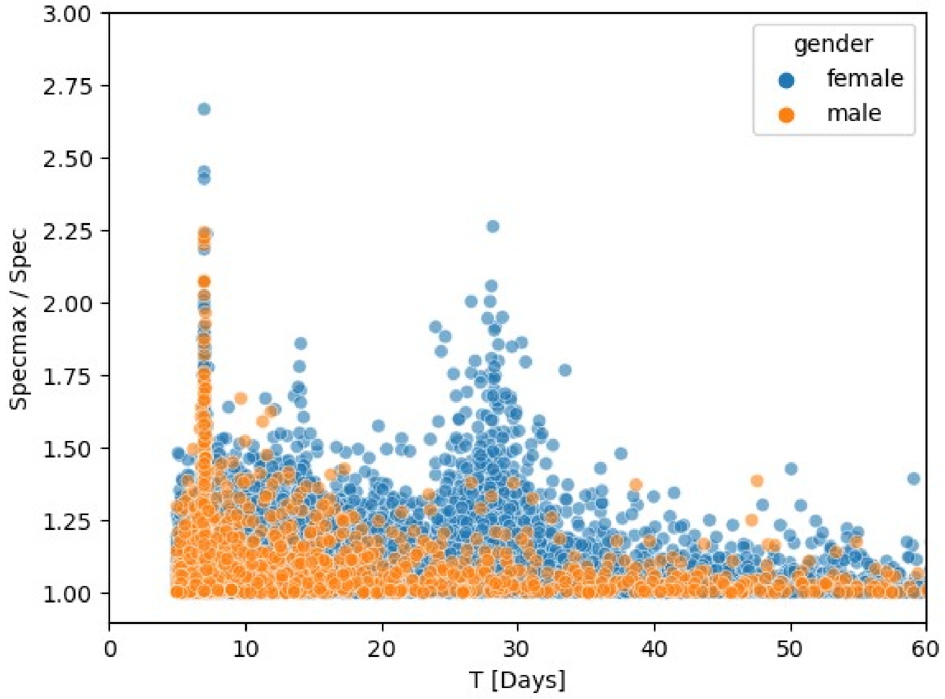
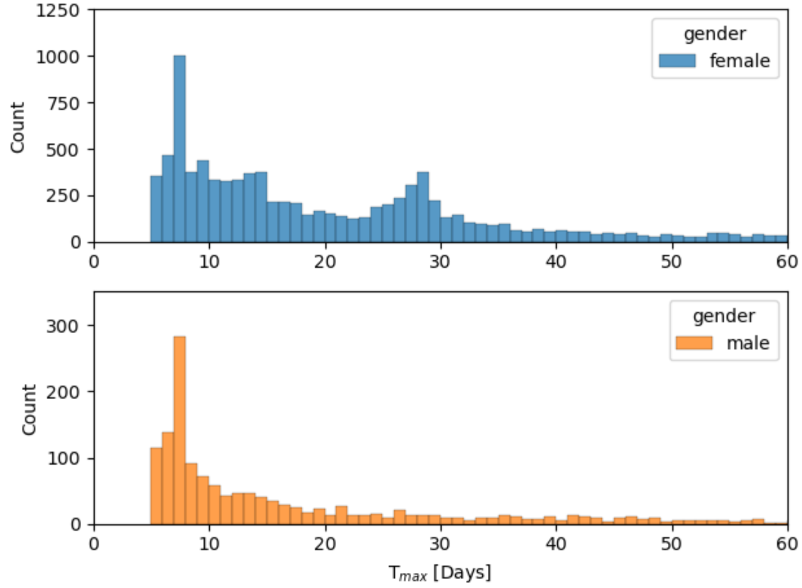


Dominant Period



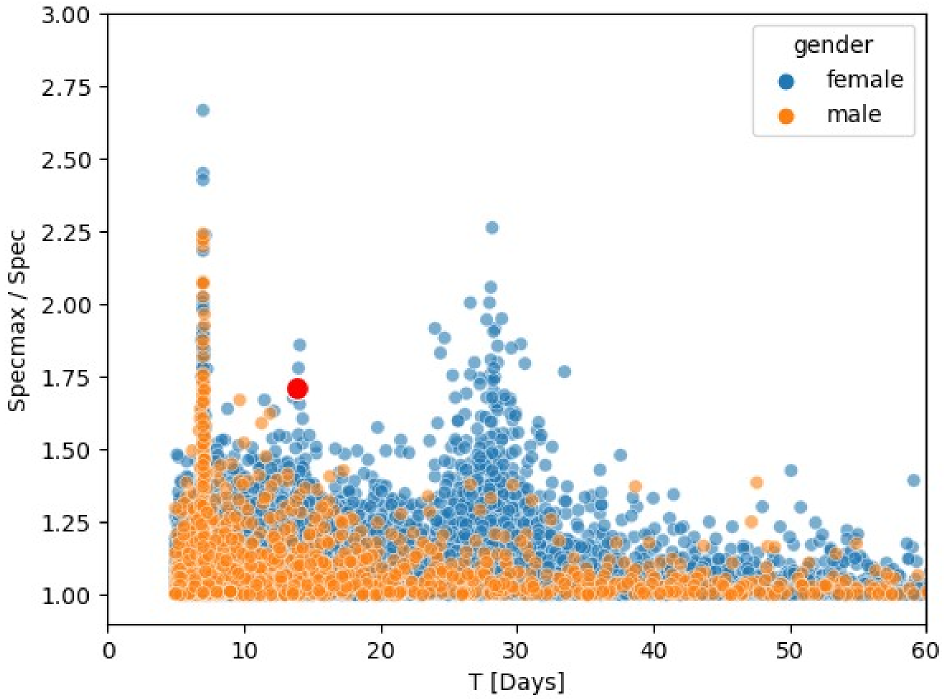
Overall about 35000

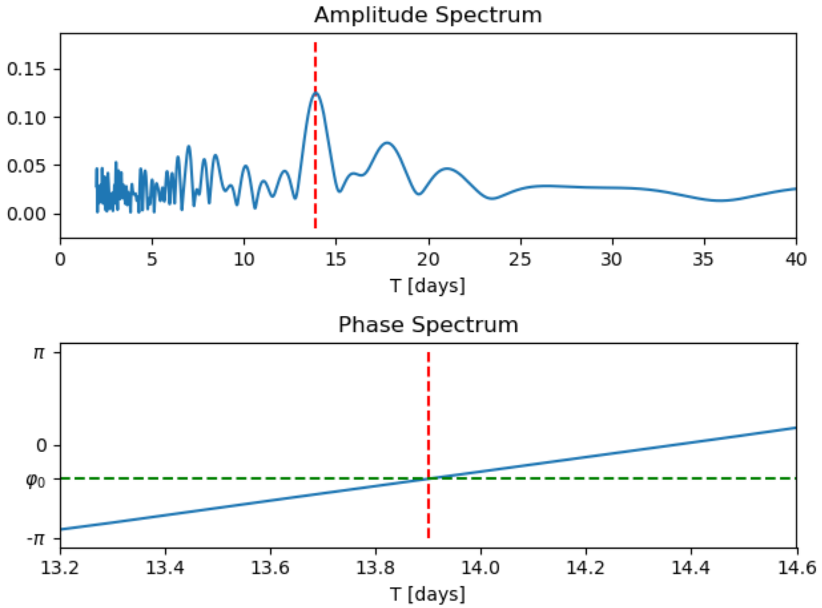
Count Plot of dominant Period:



male + female: dominant peek only at 7 days
female : 2nd peak at menstruation cycle

Dominant Period





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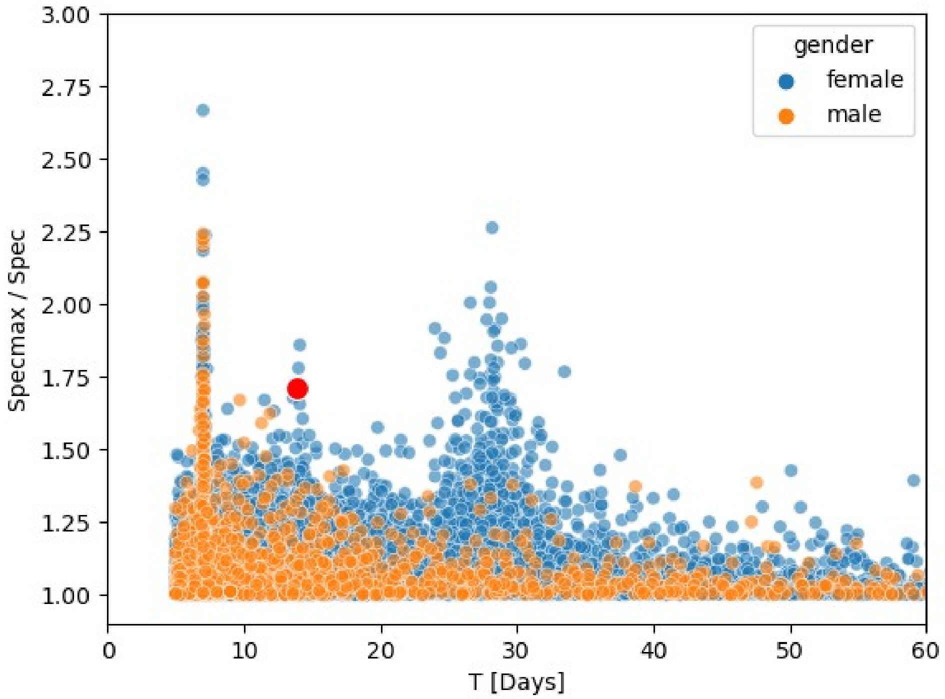

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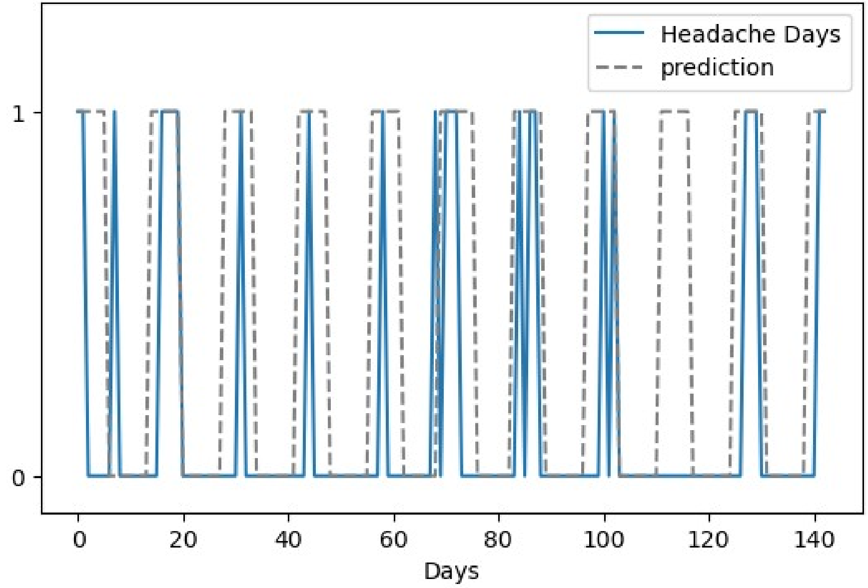
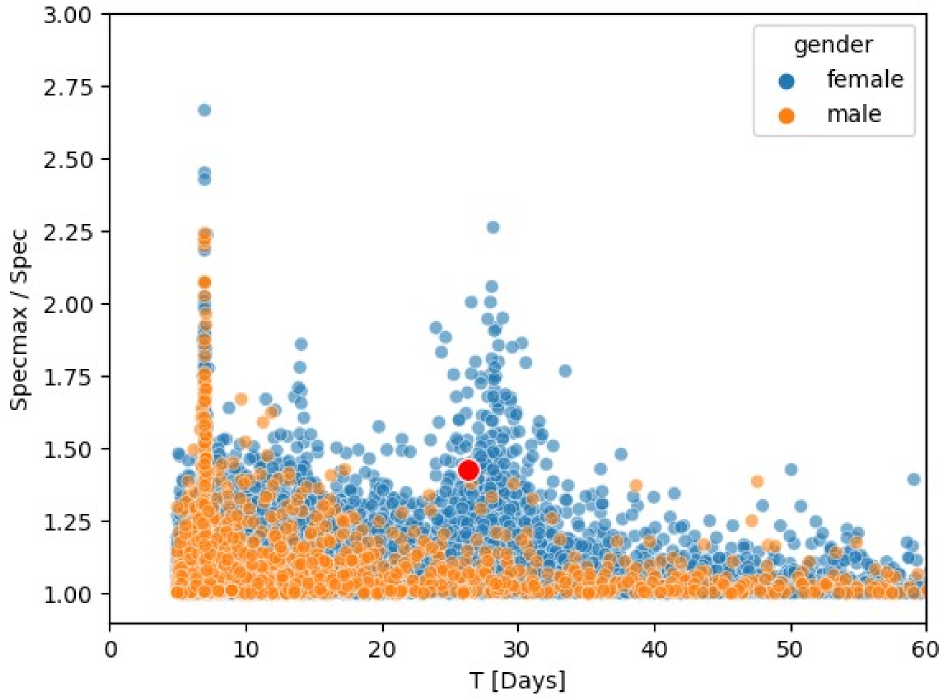
Periodicity based Prediction:



accuracy and recall relatively high

Dominant Period



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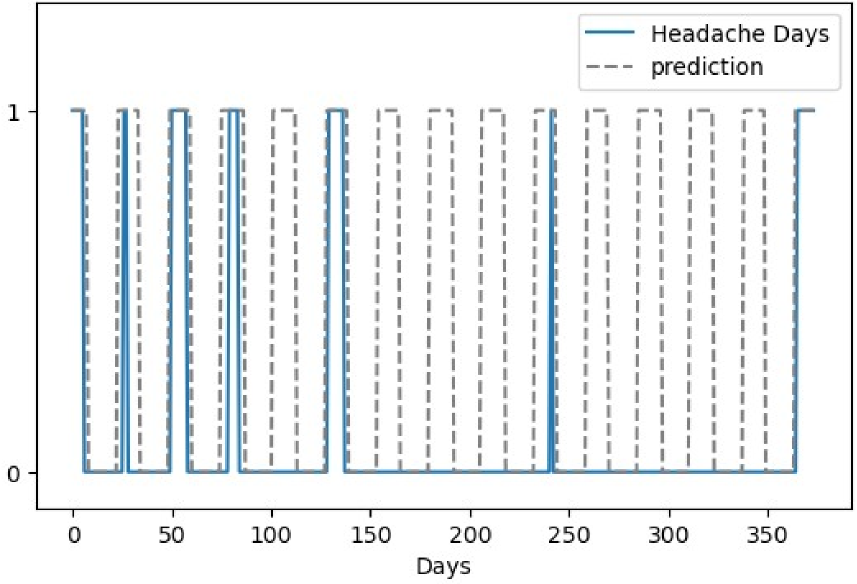

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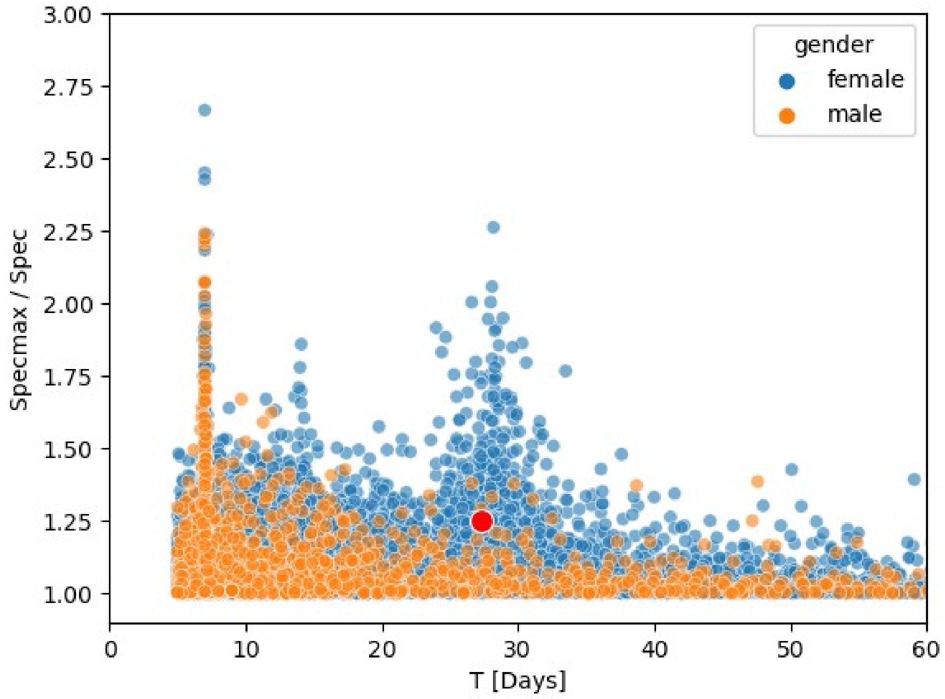

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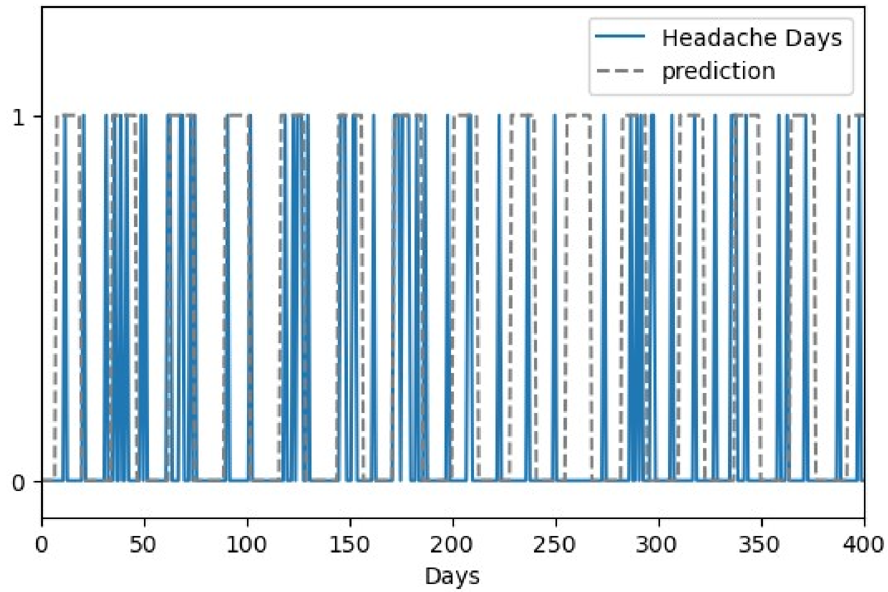


accuracy and lower recall
(many false negative)

Thank You!

- Markus Dahlem -sense
- Garlic Boosting - Cohort

Especially:

- Liljana: conceptual discussion
- Florian: SQL-support
- ALL GARLICS for a very good time

SPICED -Team / Teachers

- **Dina**
- Jens
- Rakib
- Carmine
- Marija
- Sara
- Thomas
- ...

Bundesagentur für Arbeit (Funding)

- My familiy: Anja, Paul, Hannah and Luise

Next Steps

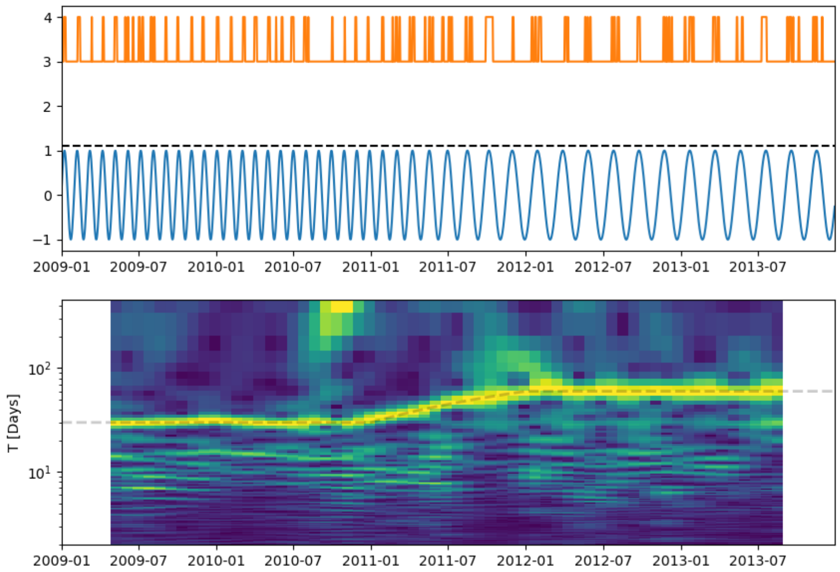
- Evaluate for which users periodicity based prediction is possible
- Define/choose metric for prediction evaluation
    - accuracy, recall, precision, ...
- Investigate statistic for “non-periodic” events

Implement Frequency Adaptation:

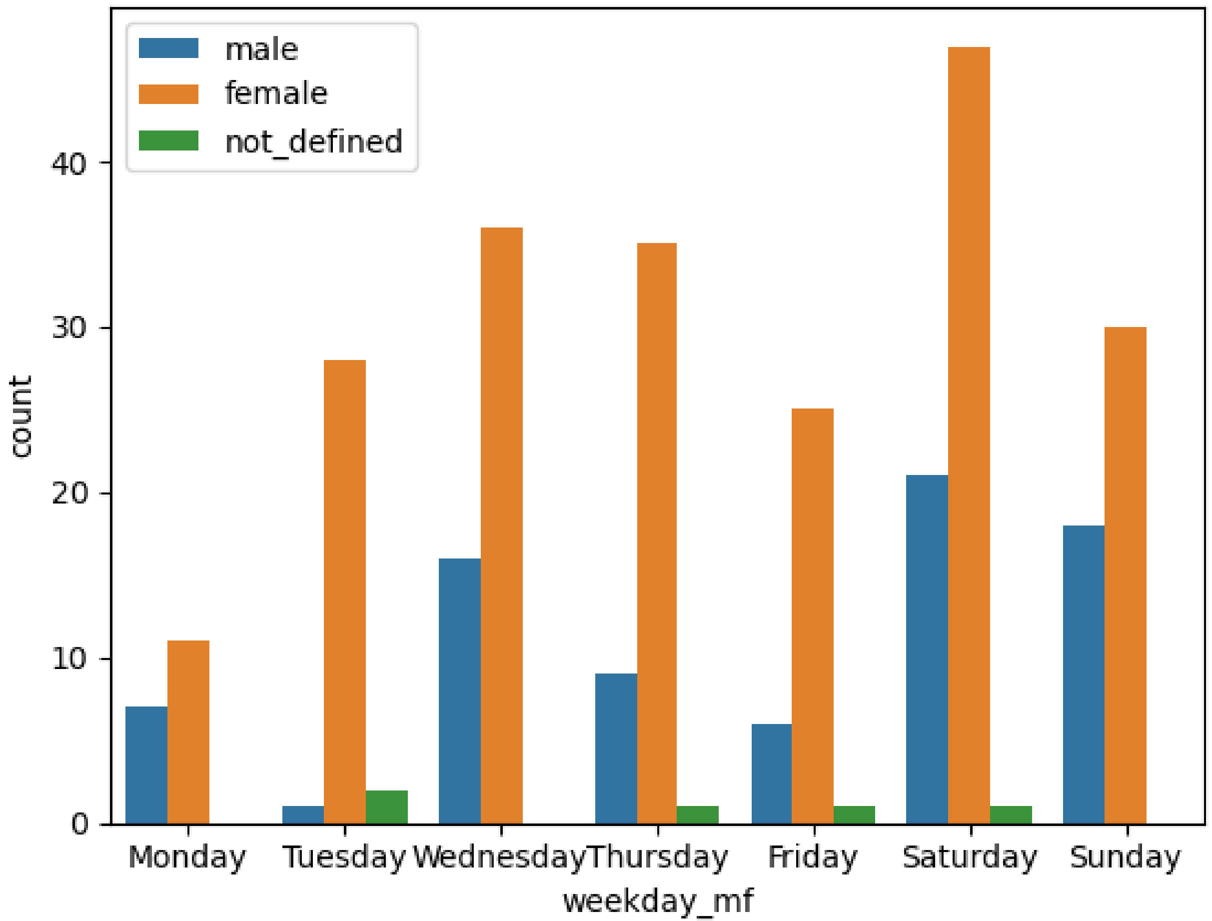
Allow Period changes:
Update frequency with incoming data in order to account for periodicity changes

- Windowed Fourier Analysis
- Kalman Filter

Spectrogram



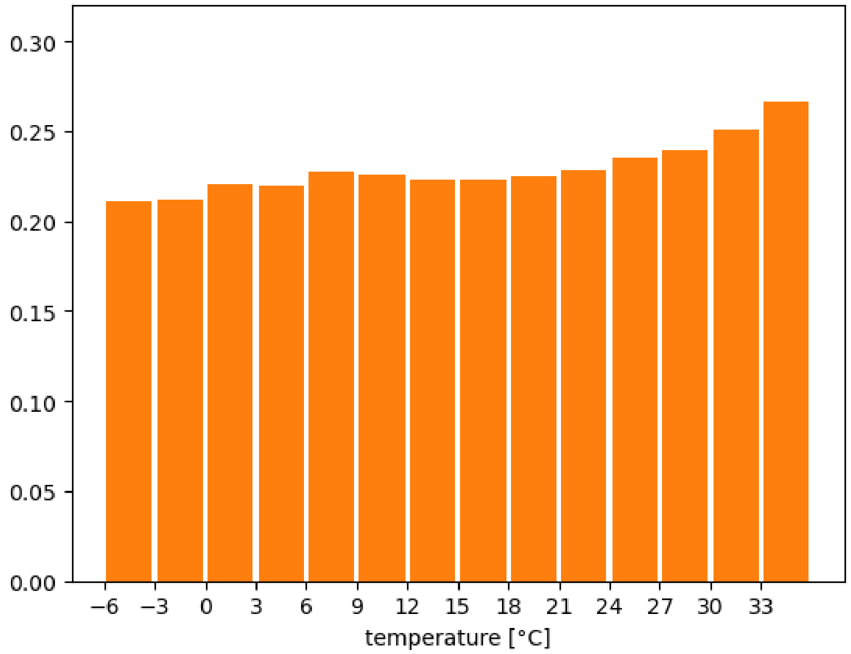
Most frequent day of week for T=7.0 users



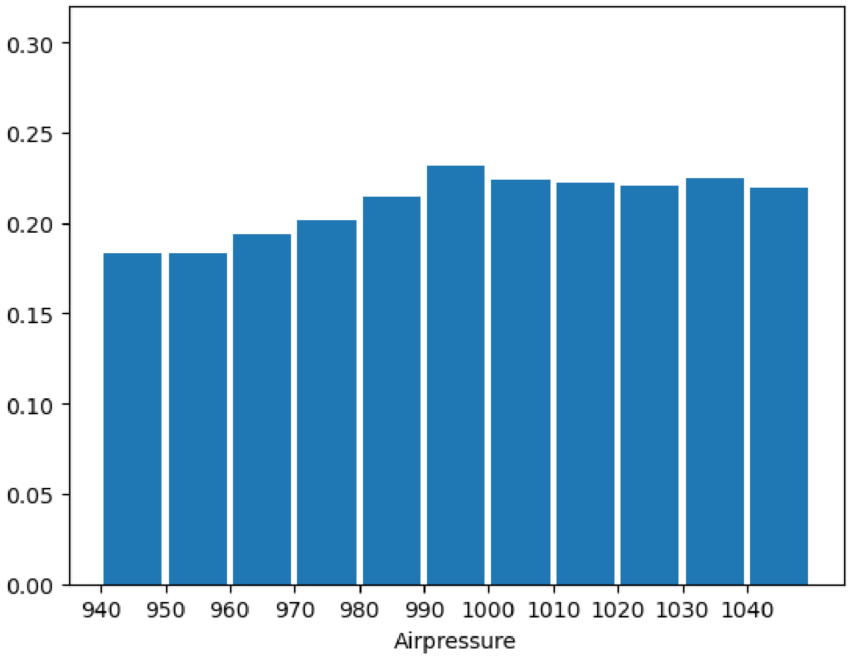
Dependency on Weather Data

Normalized Distributions: Fraction of data with headachday = 1

Temperature



Airpressure



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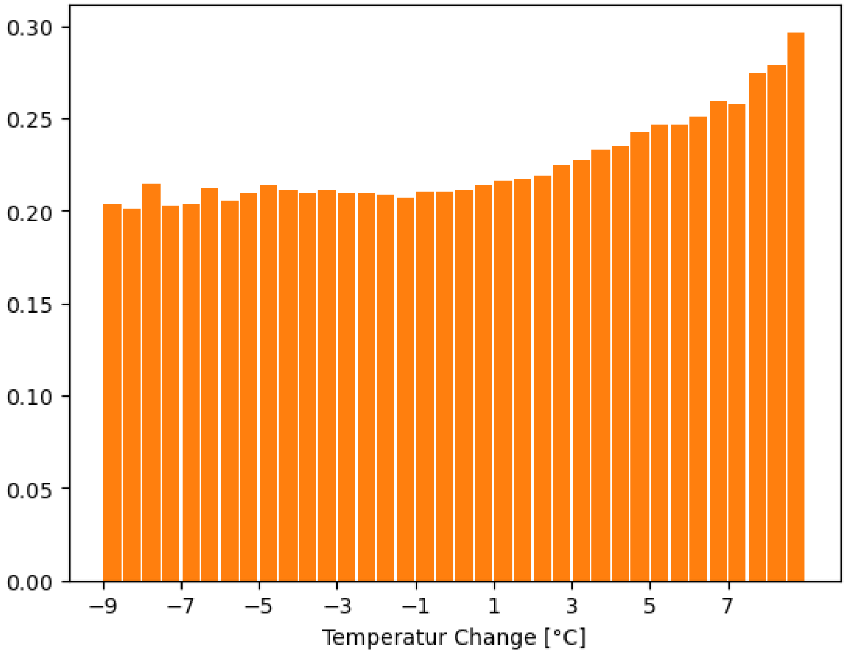
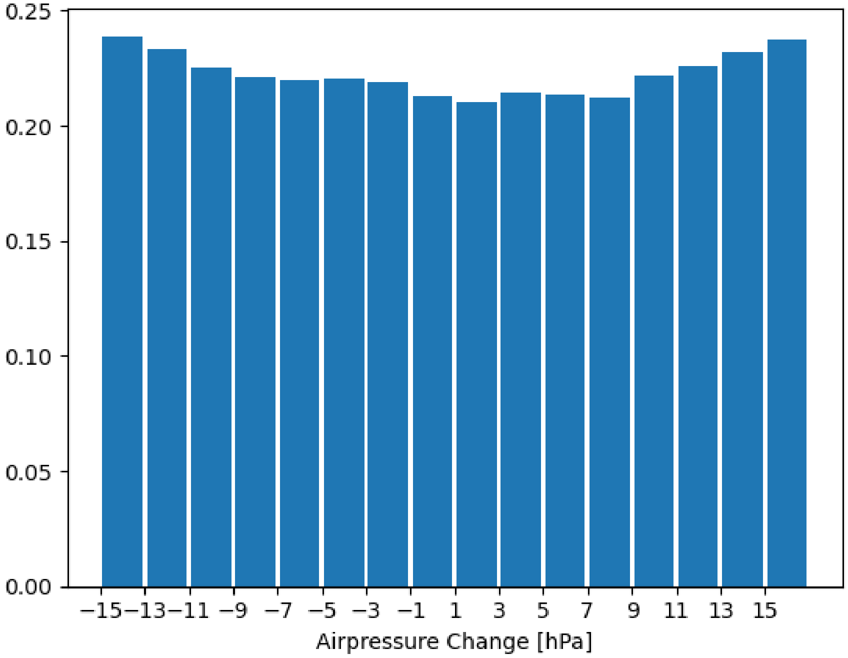
Temperature Change



Airpressure Change



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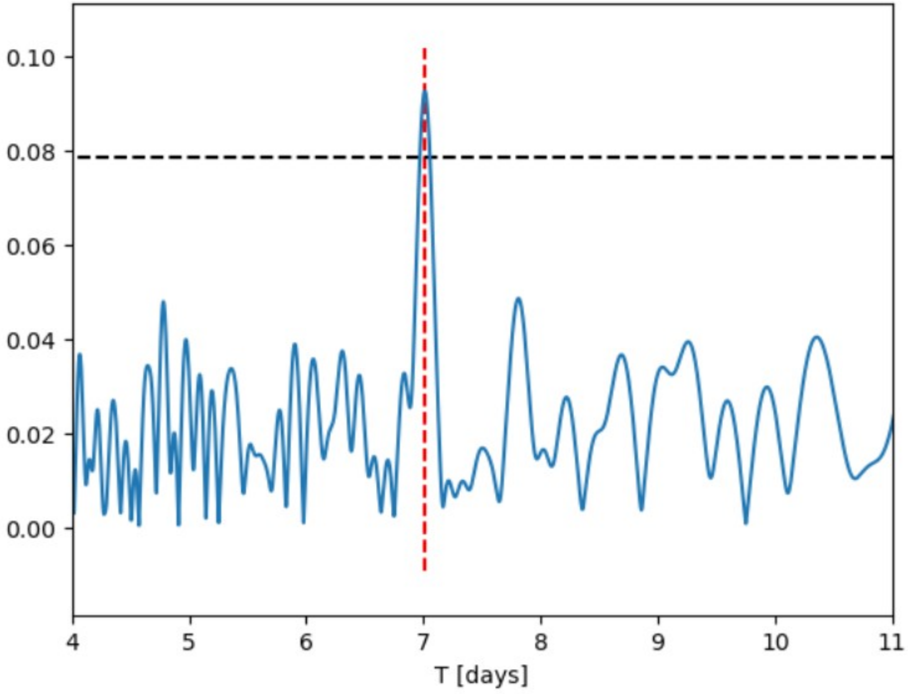
```
user_11.plotspec(T1=4, T2=11)
```



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