

Your Mind, Quantified

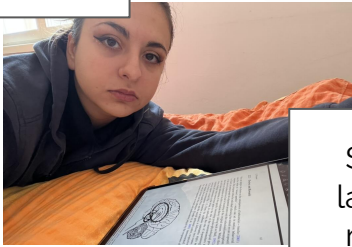
“You are not the person I used to know”

“You are not the person I used to know”



Major Depressive Episode in 2021

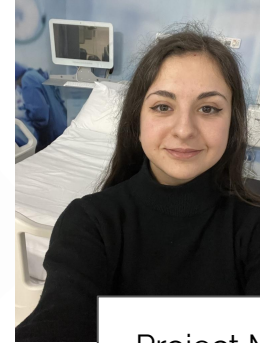
Researching and
developing the
concept



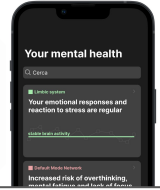
Failed first round of
investment



Studying how to
launch innovative
medical devices



Project Manager in
SaMD company



Launch of free
version of Nearine

2021

2022

2023

2024

2025

What's Nearine?



See how your **stress levels** evolve based on your **Heart Rate Variability** and activities, using your Apple Watch

Explore **intuitive charts** that track your stress, mood, and habits over time **to reveal hidden partners** and psycho-social triggers

Write notes when you notice patterns or shifts. Your insights are just as important as the numbers

Access bite-sized, easy-to-understand **neuroscience content to help you interpret your data** and better understand your mind

Starting from self-awareness to build fulfilling lives

Technology as our ally for self-awareness

“The **quantified self movement** empowers individuals to track biological, physical, behavioral, and environmental data with the goal of gaining personal insights and driving change.”

But with such a constant flow of information,
how do we transform raw data into meaningful
health insights?

Data exploration
and cleaning



Definition of questions
and features engineering



Correlations



Takeaways for future
predictions

Data exploration
and cleaning



Definition of questions
and features engineering

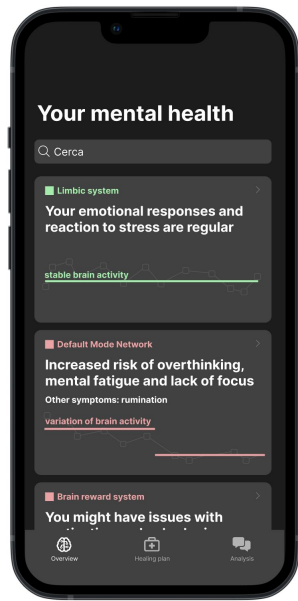


Correlations



Takeaways for future
predictions





```
jupyter Untitled Last Checkpoint: 26 days ago
File Edit View Run Kernel Settings Help
JupyterLab Python (venv)

Exploring data

[4]: import pandas as pd
import matplotlib.pyplot as plt

# Load data
folder_data = "data/"
stress_df = pd.read_csv(folder_data+"stress.txt", header=None, names=["timestamp", "value"])
emotion_df = pd.read_csv(folder_data+"emotion.txt", header=None, names=["timestamp", "value"])
activity_df = pd.read_csv(folder_data+"activity_normalized.txt", header=None, names=["timestamp", "value"])
menstrual_cycle_df = pd.read_csv(folder_data+"menstrual_cycle.txt", header=None, names=["timestamp", "value"])
stai_tests_df = pd.read_csv(folder_data+"stai_tests.txt", header=None, names=["timestamp", "value"])
bdi_tests_df = pd.read_csv(folder_data+"bdi_tests.txt", header=None, names=["timestamp", "value"])

# Convert timestamps
stress_df["time"] = pd.to_datetime(stress_df["timestamp"], unit="ms")
emotion_df["time"] = pd.to_datetime(emotion_df["timestamp"], unit="ms")
activity_df["time"] = pd.to_datetime(activity_df["timestamp"], unit="ms")
menstrual_cycle_df["time"] = pd.to_datetime(menstrual_cycle_df["timestamp"], unit="s")
stai_tests_df["time"] = pd.to_datetime(stai_tests_df["timestamp"], unit="ms")
bdi_tests_df["time"] = pd.to_datetime(bdi_tests_df["timestamp"], unit="ms")

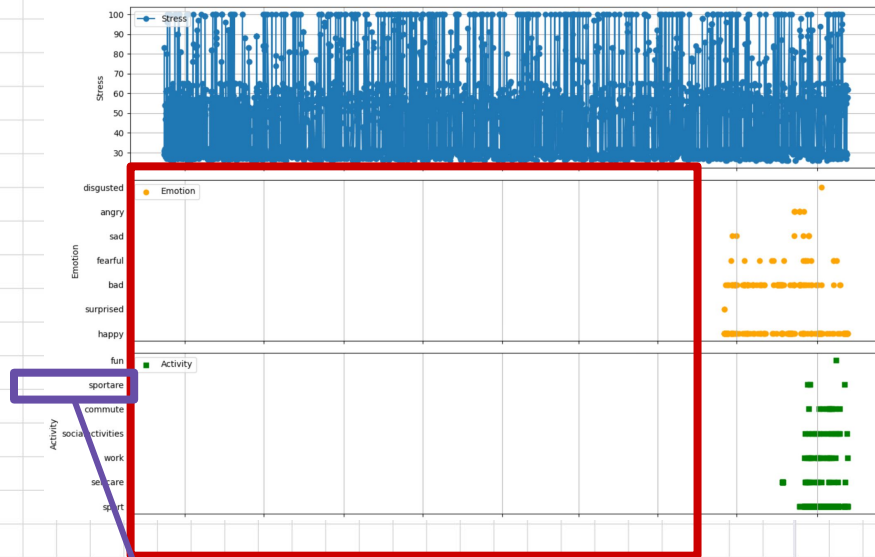
# Create subplots (6 rows, share x-axis)
fig, (ax1, ax2, ax3, ax4, ax5, ax6) = plt.subplots(
    6, 1, figsize=(14,18), sharex=True
)

# Stress
ax1.plot(stress_df["time"], stress_df["value"], marker="o", label="Stress")
ax1.set_ylabel("Stress")
ax1.legend()
ax1.grid(True)

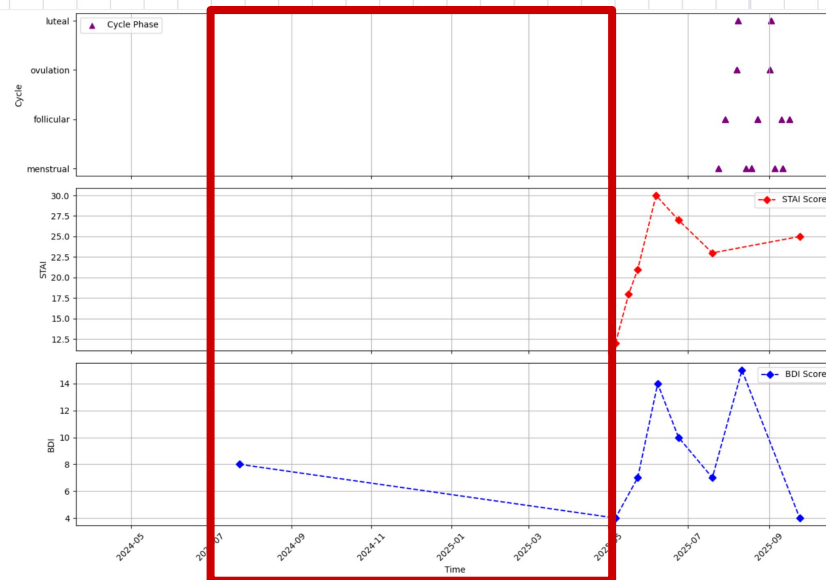
# Emotions
ax2.scatter(emotion_df["time"], emotion_df["value"], marker="o", color="orange", label="Emotion")
ax2.set_ylabel("Emotion")
ax2.legend()
ax2.grid(True, axis="x")

# Activities
```

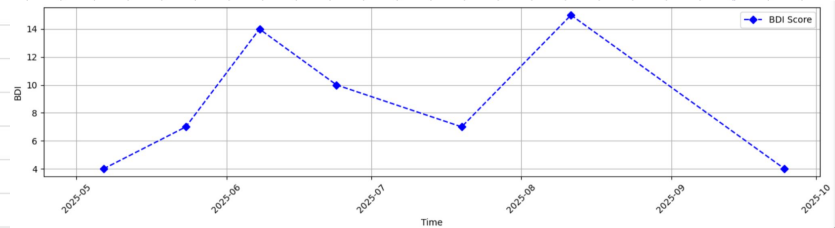
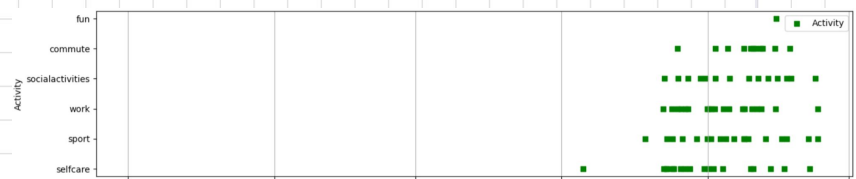
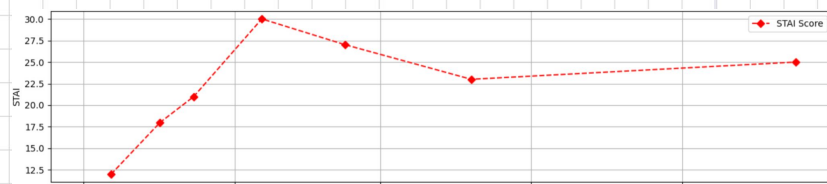
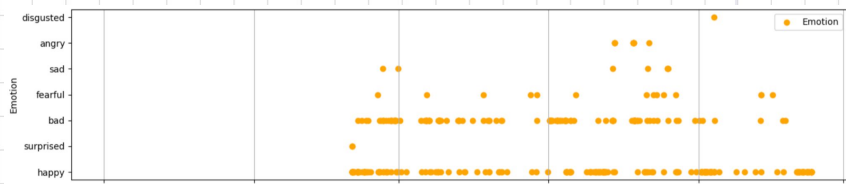
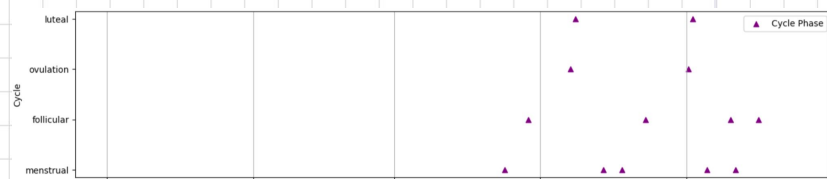
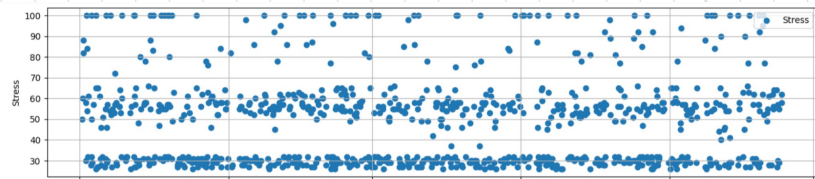
Import of Nearine
data in Python



Bug in Nearine:
"sportare" label



Lack of user inputs
before July 2025



Data exploration
and cleaning



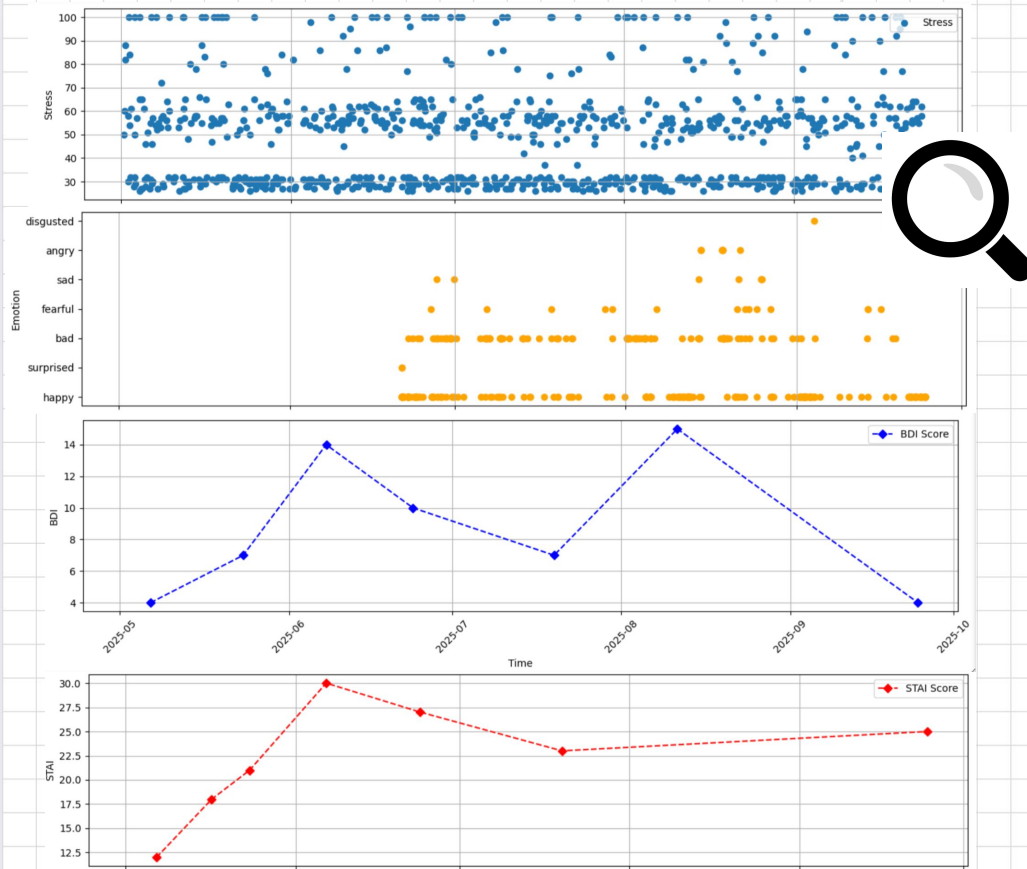
Definition of questions
and features engineering



Correlations

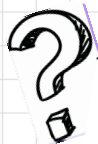


Takeaways for future
predictions

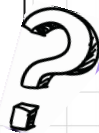


Some “visual” observations

- In mid-august: spike in the depression score + cluster of “angry” emotion + cluster “fearful”
- End of September: decrease in depression score + decrease in the frequency of “bad” emotion
- For the anxiety score it is unknown, as user input is missing
- The frequency of 100% stress level spikes seem to follow a repetitive pattern (low second-half july, high first half august, low second half august, high first half september)

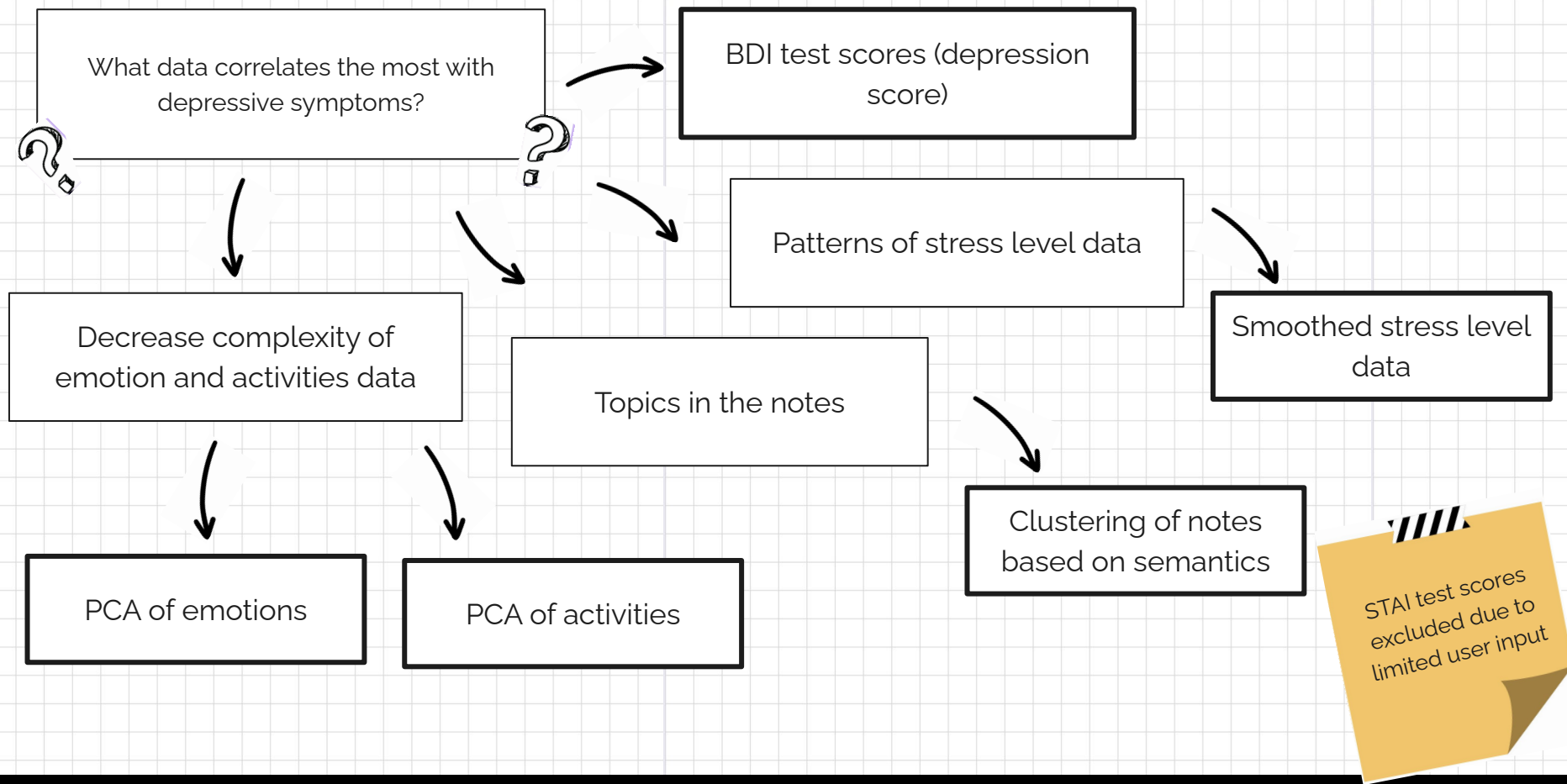


What data could I potentially use to predict an increase in depressive symptoms?



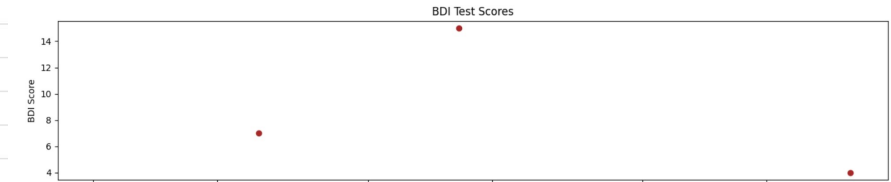
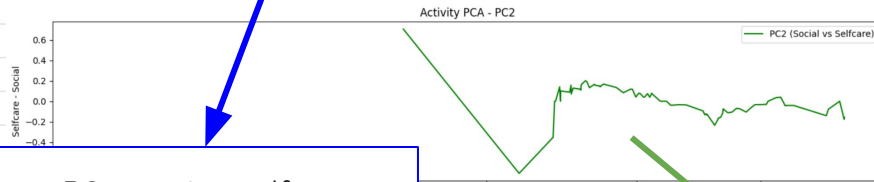
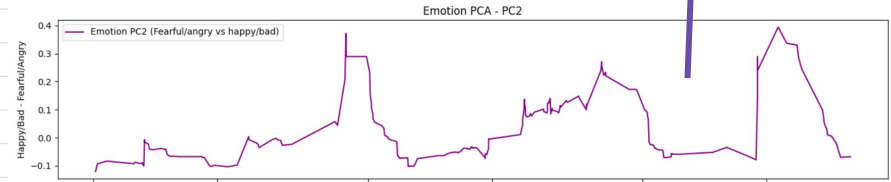
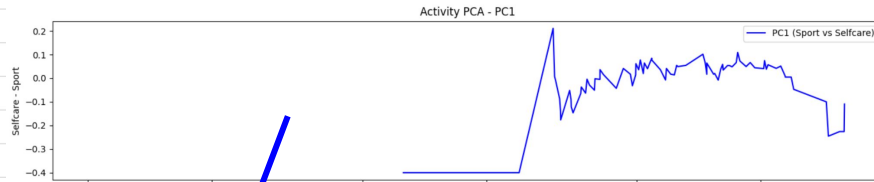
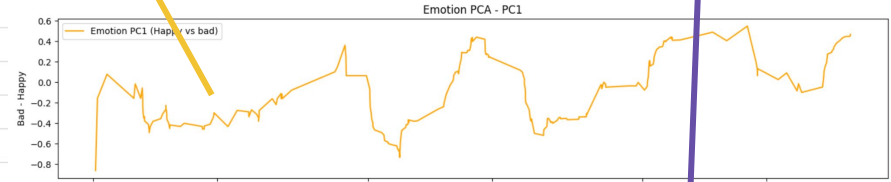
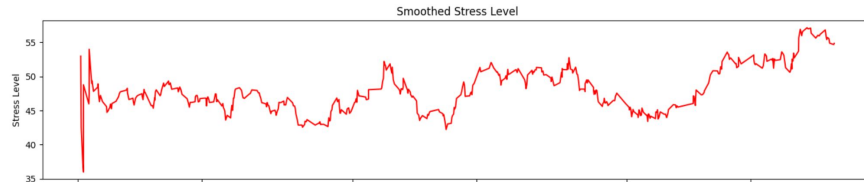
What data correlates the most with depressive symptoms?





PC1: happy vs bad (valence)

PC2: fearful/angry
vs happy/bad (arousal)



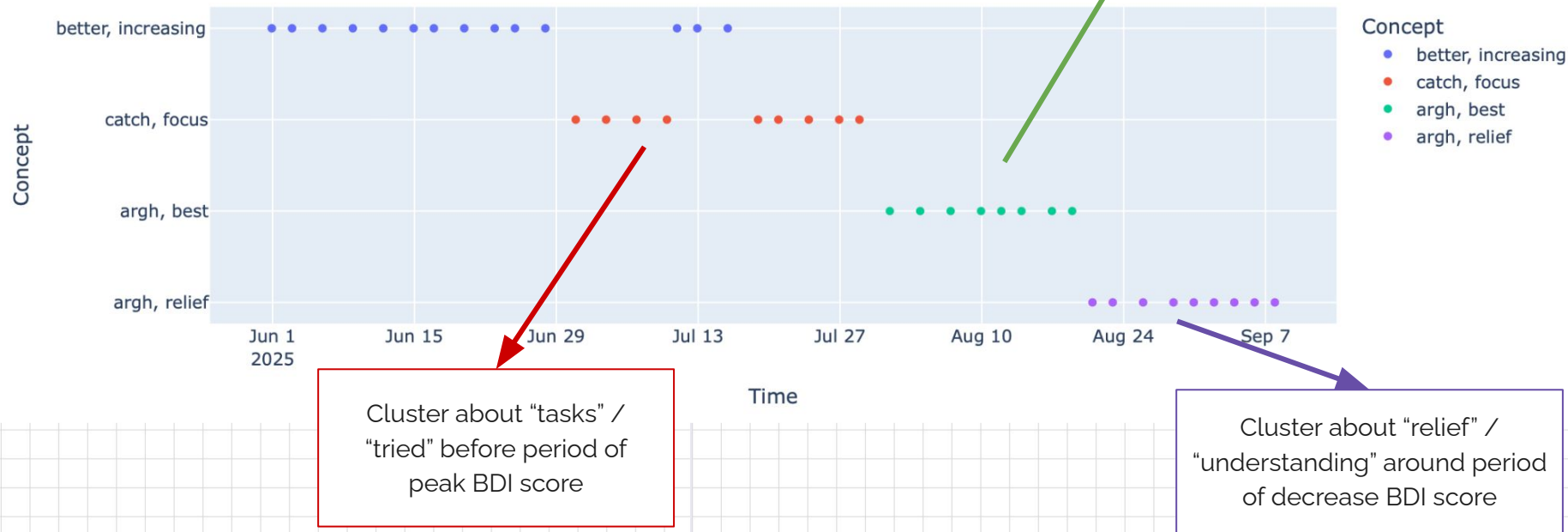
PC1: sport vs selfcare

PC2: social activities
vs selfcare

	cluster	cluster_label	cluster_label_short
0	2	better, increasing, stress, today, work	better, increasing
11	0	catch, focus, tasks, today, tried	catch, focus
23	1	argh, best, feeling, overwhelmed, panic	argh, best
31	3	argh, relief, today, tried, understanding	argh, relief

Cluster about
"overwhelmed" / "panic"
around period of peak BDI
score

Semantic Evolution of Notes



Data exploration
and cleaning



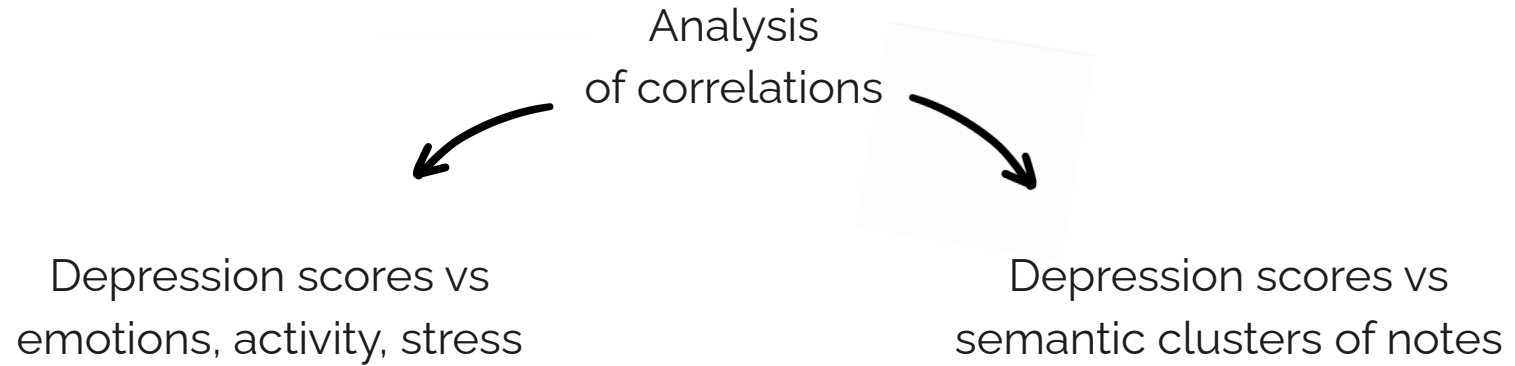
Definition of questions
and features engineering

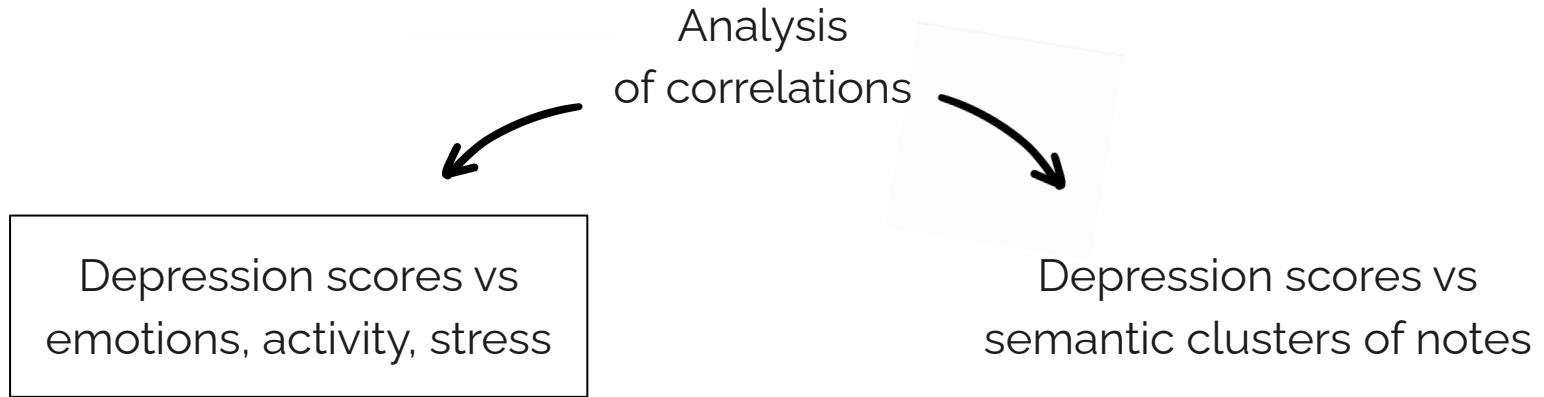


Correlations



Takeaways for future
predictions





Correlation with BDI:

stress_mean	-0.747643
stress_std	0.550531
stress_integral	-0.596691
stress_slope	-0.178195

activity_PC1_mean	-1.000000
activity_PC1_std	NaN
activity_PC1_integral	-1.000000
activity_PC1_slope	NaN
activity_PC2_mean	1.000000
activity_PC2_std	NaN
activity_PC2_integral	1.000000
activity_PC2_slope	NaN

emotion_PC1_mean	-0.693095
emotion_PC1_std	0.763308
emotion_PC1_integral	-0.777341
emotion_PC1_slope	0.053591
emotion_PC2_mean	-0.204946
emotion_PC2_std	0.019092
emotion_PC2_integral	-0.198089
emotion_PC2_slope	-0.313062

Name: value, dtype: float64

Perfect correlation between
activities and BDI score,
probably due to low quantity of
data

Discard result and check it
again in the next months

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emotion_PC2_integral	-0.198089
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The higher the depression score the **higher the variability of emotional valence**

The higher the depression score, the **more negative** their emotional valence over time.

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Name: value, dtype: float64

Inverse correlation between
depression and **stress level**
(mean and cumulative)

The higher stress variability the
higher the depression

Perfect correlation between
activities and BDI score,
probably due to low quantity of
data

The higher the depression
score the **higher the variability**
of emotional valence

The higher the depression
score, the **more negative** their
emotional valence over time.

Temporal offset or
compensatory behavior?

Correlation of shifted stress features with BDI (7d shift):

timestamp	-0.435960
mean_stress_prev_days	-0.604671
std_stress_prev_days	0.570673
integral_stress_prev_days	-0.952349

Name: value, dtype: float64

Correlation of shifted stress features with BDI (14d shift):

timestamp	-0.435960
mean_stress_prev_days	-0.743999
std_stress_prev_days	0.543824
integral_stress_prev_days	-0.644848

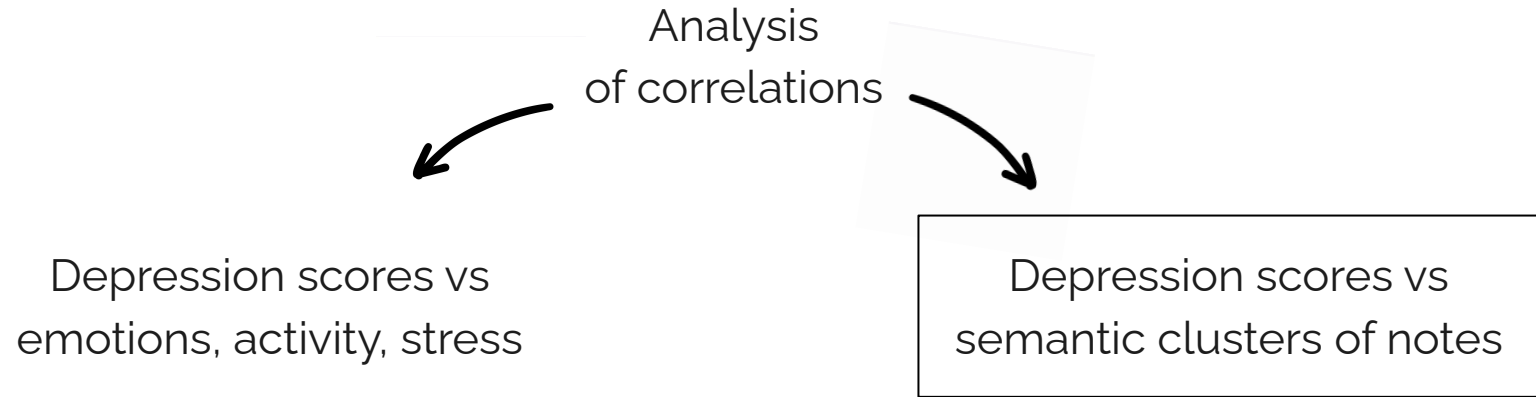
Name: value, dtype: float64

Correlation of shifted stress features with BDI (21d shift):

timestamp	-0.435960
mean_stress_prev_days	-0.807721
std_stress_prev_days	-0.637605
integral_stress_prev_days	0.999117

Name: value, dtype: float64

The higher the cumulative stress in the previous 21 days, the higher the BDI score



cluster_id	top keywords	num notes	median_BDI	mean_BDI
1	argh, best, feeling, overwhelmed, panic	8	15.0	15.000000
3	argh, relief, today, trying, understanding	5	15.0	10.600000
2	better, increasing, stress, today, work	13	10.0	11.384615
0	argh, catch, motivated, tasks, tried	4	8.5	8.500000
4	focused, noticed, overwhelmed, today, tried	10	7.0	9.100000

Notes about "overwhelm" and "panic" associated with the period with highest BDI score



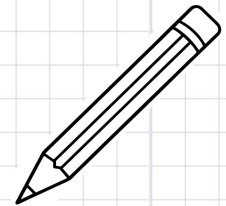
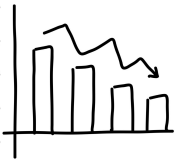
The higher stress variability the
higher the depression

The higher the cumulative
stress in the previous 21 days,
the higher the BDI score

The more depressed the
person feels (higher BDI), the
**higher the variability of
emotional valence**

The more depressed the
person feels (higher BDI), the
more negative their emotional
valence over time.

Notes about “overwhelm” and
“panic” associated with the
period with highest BDI score



Data exploration
and cleaning



Definition of questions
and features engineering



Correlations



Takeaways for future
predictions

Individualized analysis
of data

Iterative process based
on this first learnings

Reflections

Potentially use it
for predictions

Technology doesn't make us less human.
It can make us more aware of who we truly are

Thank you

Chiara Masci

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Website

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m.nearine.com (mobile)