```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib as mpl
from glob import glob
```

Tricking your cerebellum with a reaching task

Exercise 1 – Perturbation & after-effect

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Task 1: Implementation of perturbation

- Implement a sudden clockwise perturbation of 30°
- Implement a gradual counterclockwise perturbation of 3° (10 steps, 3 attempts each)

```python
# TASK1: CALCULATE perturbed_mouse_pos
# PRESS 'h' in game for a hint
if perturbation_mode:
    if perturbation_type == "sudden":
        # sudden clockwise perturbation of perturbation_angle
        # 30 degree
        perturbed_mouse_angle = perturbation_angle

    elif perturbation_type == "gradual":
        # gradual counterclockwise perturbation of perturbation_angle in 10 steps, with
perturbation_angle/10, each step lasts 3 attempts
        perturbed_mouse_angle = np.deg2rad(((gradual_attempts // 3) + 1) *
np.rad2deg(perturbation_angle) / 10)

    rot_mat = np.array([[np.cos(perturbed_mouse_angle), -np.sin(perturbed_mouse_angle)],
                        [np.sin(perturbed_mouse_angle), np.cos(perturbed_mouse_angle)]])
    perturbed_mouse_pos = rot_mat @ (np.array(mouse_pos) - START_POSITION) +
START_POSITION
    circle_pos = perturbed_mouse_pos.tolist()
else:
    circle_pos = pygame.mouse.get_pos()
```

Task 2: Analysis of experiment on unbiased subjects

- Calculate the signed error_angles between target and circle cursor, exclude slow attempts where "MOVE FASTER" appeared.
- Plot the error angles over all attempts and highlight the experiment segments.
- What is the motor variability (MV) in the unperturbed segments?
- Run the experiment a second time with `mask_mode = false`. What do you observe in subject's movements in the now unmasked part?

For this task only attempts until 200 are interesting. The rest can be ignored for now.

```python
experiment = pd.DataFrame({
    "Attempt": [1, 40, 80, 120, 160, 200, 240, 280, 320],
    "AttemptEnd": np.array([40, 80, 120, 160, 200, 240, 280, 320, 361]) - 1,
    "Perturbation": [
        "No perturbation", "Gradual",
        "No perturbation", "Sudden",
        "No perturbation", "Gradual reversed",
        "No perturbation", "Sudden reversed",
        "No perturbation"
    ]
})

n_attempts = 360

attempts = list(range(1, n_attempts + 1))

perturbations = []
for i in range(len(experiment)):
    start = experiment["Attempt"][i]
    end = experiment["Attempt"][i + 1] if i + 1 < len(experiment) else n_attempts + 1
    perturbations.extend([experiment["Perturbation"][i]] * (end - start))

full_experiment = pd.DataFrame({ "Attempt": attempts, "Perturbation": perturbations })
```

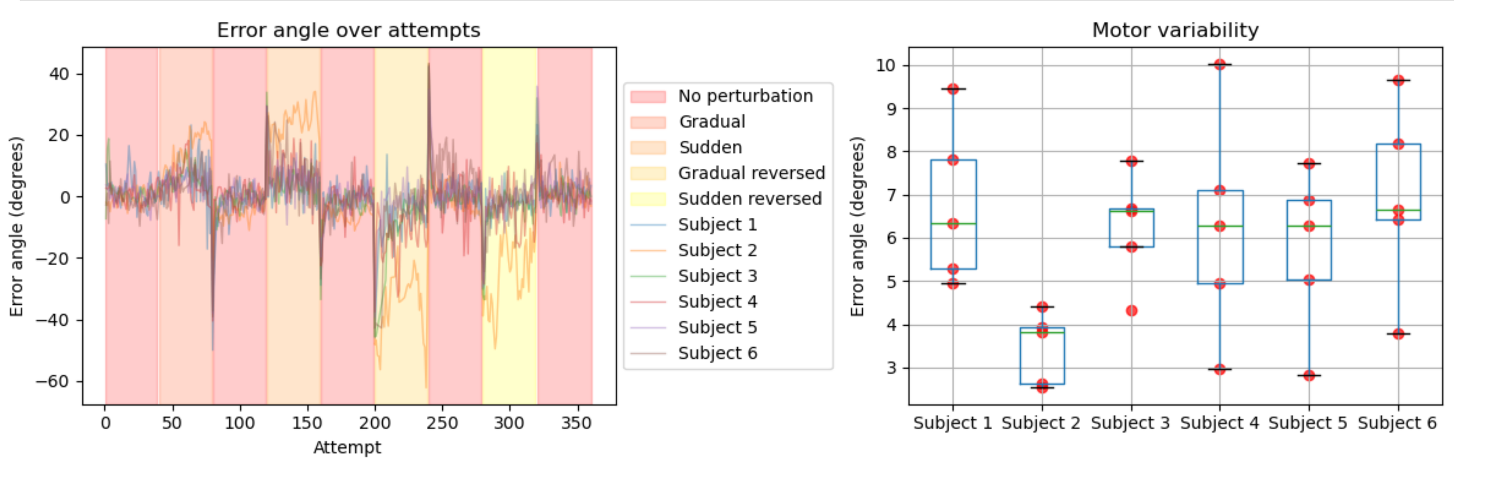
```python
def read_data(filename):
    res = np.load(filename, allow_pickle = True)
    return pd.DataFrame({
        "MoveFaster": res.item()["move_faster_logs"],
        "ErrorAngle": res.item()["error_angle_logs"],
        "Time": res.item()["time_logs"],
        "Attempt": np.arange(len(res.item()["move_faster_logs"])) + 1
    })


def preprocess(data, design):
    # Merge with experimental design describing perturbation conditions
    data = pd.merge(data, design)

    # Remove trials where move faster appeared
    data = data[data.MoveFaster == 0]
    data.reset_index(drop = True, inplace = True)

    return data


def evaluate_statistics(data):
    statistics = []

    for _, change in experiment.iterrows():
        selected_data = data[(data.Attempt >= change.Attempt) & (data.Attempt <= change.AttemptEnd)
        error_angle = selected_data.ErrorAngle.to_numpy()
        error_angle = error_angle[~selected_data.MoveFaster.to_numpy().astype(bool)]

        statistics.append(pd.DataFrame({
            "Perturbation": change.Perturbation,
            "ErrorAngleStd": [error_angle.std()],
            "ErrorAngleMean": [error_angle.mean()],
            "TimeStd": [selected_data.Time.std()],
            "TimeMean": [selected_data.Time.mean()]
        }))

    statistics = pd.concat(statistics, ignore_index = True)

    return statistics
```

```python
def plot_error_angle(subjects, experiment, stats):
    fig, axs = plt.subplots(nrows = 1, ncols = 2, figsize = (12, 4))

    color_map = mpl.colormaps["autumn"]
    n_colors = len(experiment.Perturbation.unique())
    colors = [color_map(idx / (n_colors - 1)) for idx in range(n_colors)]
    colors = dict(zip(experiment.Perturbation.unique(), colors))
    unique_periods = experiment.Perturbation.unique()

    # Show the different experimental periods
    for i, change in experiment.iterrows():
        label = change.Perturbation if change.Perturbation in unique_periods else ""
        unique_periods = unique_periods[unique_periods != change.Perturbation]

        start = change.Attempt
        end = change.AttemptEnd

        axs[0].axvspan(
            start, end,
            alpha = 0.2,
            label = label,
            color = colors.get(change.Perturbation)
        )

    for i, subject in enumerate(subjects):
        error_angle: np.ndarray = subject.ErrorAngle.to_numpy()
        error_angle[subject.MoveFaster.to_numpy().astype(bool)] = np.nan
        axs[0].plot(
            subject.Attempt,
            error_angle,
            linewidth = 1,
            label = f"Subject {i + 1}",
            alpha=0.4
        )

    axs[0].set_ylabel("Error angle (degrees)")
    axs[0].set_xlabel("Attempt")
    axs[0].legend(loc = "center left", bbox_to_anchor = (1, 0.5))
    axs[0].set_title("Error angle over attempts")

    # Plotting the statistics
    no_perturbation_stats = stats[stats.Perturbation == "No perturbation"]
    no_perturbation_stats.boxplot(ax = axs[1], column = "ErrorAngleStd", by = "Subject", showfliers

    subject_list = [f"Subject {idx + 1}" for idx in range(len(pd.unique(no_perturbation_stats["Subj
    for subject, group in no_perturbation_stats.groupby("Subject"):

        x = subject_list.index(subject) + 1
        y = group["ErrorAngleStd"]
        axs[1].scatter([x] * len(y), y, color = "red", alpha = 0.7)

    axs[1].set_ylabel("Error angle (degrees)")
    axs[1].set_title("Motor variability")
    axs[1].set_xlabel("")

    # Remove the suptitle from boxplot
    plt.suptitle("")

    fig.tight_layout()
```

Performing the experiment with *mask_mode = True*

```python
# List of all subjects
subjects = [preprocess(read_data(file), full_experiment) for file in glob("data/*mask_on.npy")]

# Evaluate subject statistics
stats = []
for i, subject in enumerate(subjects):
    subject_stats = evaluate_statistics(subject)
    subject_stats["Subject"] = f"Subject {i + 1}"
    stats.append(subject_stats)
stats = pd.concat(stats, ignore_index = True)
```

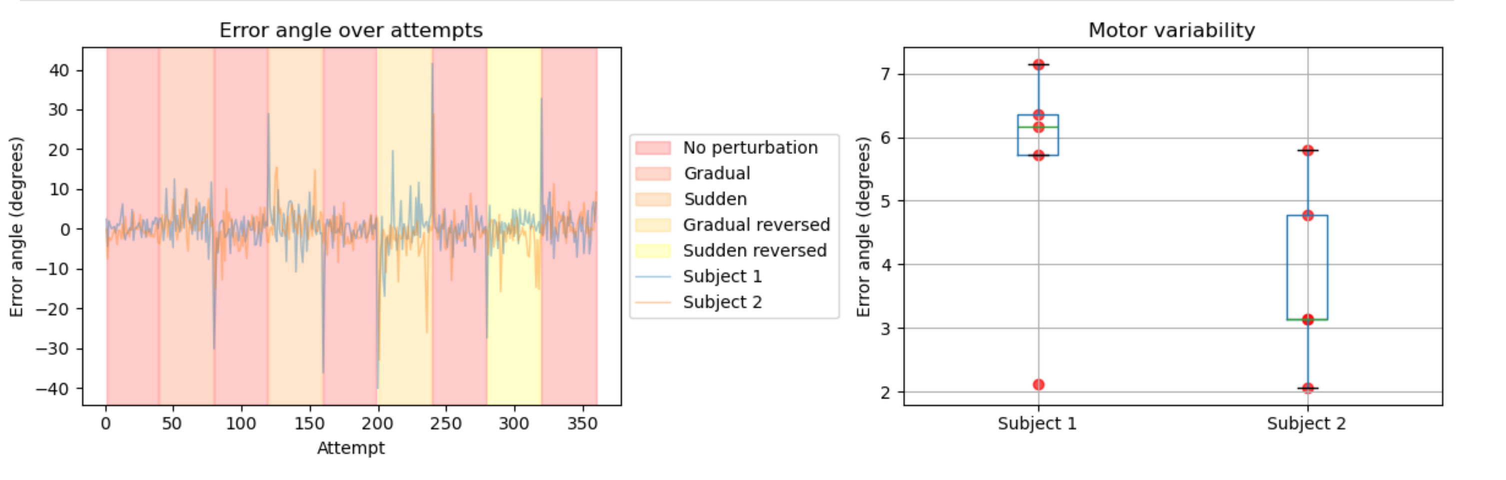
```python
plot_error_angle(subjects, experiment, stats)
```



Performing the experiment with *mask_mode = False*

```python
subjects = [preprocess(read_data(file), full_experiment) for file in glob("data/*mask_off.npy")]

# Evaluate subject statistics
stats = []
for i, subject in enumerate(subjects):
    subject_stats = evaluate_statistics(subject)
    subject_stats["Subject"] = f"Subject {i + 1}"
    stats.append(subject_stats)
stats = pd.concat(stats, ignore_index = True)
```

```python
plot_error_angle(subjects, experiment, stats)
```



Task 3: Discussion of your results

What do you see when perturbation is introduced? Is there an after-effect? What is the difference between gradual and sudden perturbation? Why is it important to mask the last part of the trajectory?

When perturbation is introduced to a movement, we typically observe an immediate deviation from the intended motion pattern. The motor system responds with compensatory adjustments to maintain task performance. These adjustments can manifest as increased variability in movement trajectories and changes in muscle activation patterns.

After-effects are indeed present following perturbation exposure. When the perturbation is removed, movements often show a temporary bias in the opposite direction of the original perturbation, indicating that the motor system adapted its internal model during the perturbation phase.

Gradual versus sudden perturbations reveal different adaptation mechanisms. Gradual perturbations often lead to smoother adaptation with smaller errors and more implicit learning, as the motor system can continuously adjust without triggering explicit awareness. Sudden perturbations typically cause larger initial errors and may engage more explicit strategic corrections.

Masking the last part of the trajectory is crucial because it prevents visual feedback during movement completion. This helps isolate feedforward control mechanisms and ensures that observed adaptations reflect genuine motor learning rather than online corrections based on visual feedback.

Task 4: Implementation of our own idea

Our own idea was to is basically just applying the lecture from the 15.01.2025 and reversing the perturbation. Therefore, we would like to have seen if the subject is able to recognize the same perturbation but applied now in the other direction. This results in the complete perturbation schedule:

1. No perturbation
2. Gradual
3. No perturbation
4. Sudden
5. No perturbation
6. Gradual reversed
7. No perturbation
8. Sudden reversed
9. No perturbation

So we add two steps of perturbation and arrive at:

```
if perturbation_mode:
    if perturbation_type == "sudden":
        # sudden clockwise perturbation of perturbation_angle
        # 30 degree
        perturbed_mouse_angle = perturbation_angle

    elif perturbation_type == "gradual":
        # gradual counterclockwise perturbation of perturbation_angle in 10 steps, with
perturbation_angle/10, each step lasts 3 attempts
        perturbed_mouse_angle = np.deg2rad(
            ((gradual_attempts // 3) + 1) * np.rad2deg(perturbation_angle) / 10
        )

    if perturbation_type == "sudden_reversed":
        # sudden clockwise perturbation of perturbation_angle
        # 30 degree
        perturbed_mouse_angle = -perturbation_angle

    elif perturbation_type == "gradual_reversed":
        # gradual counterclockwise perturbation of perturbation_angle in 10 steps, with
perturbation_angle/10, each step lasts 3 attempts
        perturbed_mouse_angle = -np.deg2rad(
            ((gradual_attempts // 3) + 1) * np.rad2deg(perturbation_angle) / 10
        )

    rot_mat = np.array(
        [
            [np.cos(perturbed_mouse_angle), -np.sin(perturbed_mouse_angle)],
            [np.sin(perturbed_mouse_angle), np.cos(perturbed_mouse_angle)],
        ]
    )
```

As we can see in the masked plot there are a couple of similarities like the overcorrection after going back into the unperturbed state but now the other way around and also the annealing error before going into the next kind of perturbation but again also from the other side but also with a comparable amplitude.

Differences are clearly in the gradual reversed perturbation. The perturbation for the normal gradual case is increasing slowly until the end of this step but for the gradual reversed step it is very high in the beginning but decreases until the end. Therefore, you could infer a learning effect about the gradual perturbation or it could also be easier to adjust to a perturbation which requires you to go to the left with your right hand because all subjects use the right hand to move the mouse.
Further we notice a similar curve form for the sudden reversed perturbation but with less standard deviation (besides the outlier of subject 3).

In [8]: