

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm
import plots # Custom functions for plotting
```

Tricking your cerebellum

Exercise 4 – Motor Noise (Group A)

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*equal contribution

Task 1: Implementation of motor noise

Implement motor noise as additional perturbation

We define these global variables to control the noise strength throughout the blocks and each individual trial:

```
{python}
noise_mean = 0
noise_std = 0
noise_active = False
noise_instance = 0
```

The noise is sampled from a random distribution:

```
{python}
def sample_random_noise():
    global noise_mean, noise_std
    return np.random.normal(noise_mean, noise_std)
```

Noise is applied as soon as the pint leaves the control zone:

```
{python}
def apply_noise():
    global pint_velocity, noise_instance
    pint_velocity[0] += noise_instance

# PINT_MOVEMENTS
def handle_mouse_input():
    ...
    else:
        ...
        apply_noise()
        ...
    ...
```

Design your own experiment to test effect of motor noise

```
{python}
small_noise_mean = 0
small_noise_std = 1

medium_noise_mean = 1.5
medium_noise_std = 2

large_noise_mean = 2.5
large_noise_std = 3

sudden_force = 2
n_trials_no_perturbation = 10
n_trials_perturbation = 30
feedback_setting = "endpos"

block_structure = [
    # 1
    {
        "feedback": feedback_setting, "num_trials": n_trials_no_perturbation,
        "perturbation": False,
        "drink_beer": False,
        "noise_active": False,
    },
    {
        "feedback": feedback_setting, "num_trials": n_trials_perturbation,
        "perturbation": True, "gradual": False, "sudden_force": sudden_force,
        "drink_beer": False,
        "noise_active": False
    },
    {
        "feedback": feedback_setting, "num_trials": n_trials_no_perturbation,
        "perturbation": False,
        "drink_beer": False,
        "noise_active": False
    },
    # 2
    {
        "feedback": feedback_setting, "num_trials": n_trials_no_perturbation,
        "perturbation": False,
        "drink_beer": True,
        "noise_active": True, "noise_mean": small_noise_mean, "noise_std":
small_noise_std
    },
    {
        "feedback": feedback_setting, "num_trials": n_trials_perturbation,
        "perturbation": True, "gradual": False, "sudden_force": sudden_force,
        "drink_beer": False,
        "noise_active": True, "noise_mean": small_noise_mean, "noise_std":
small_noise_std
    },
    {
        "feedback": feedback_setting, "num_trials": n_trials_no_perturbation,
        "perturbation": False,
        "drink_beer": False,
        "noise_active": True, "noise_mean": small_noise_mean, "noise_std":
small_noise_std
    },
    # 3
    {
        "feedback": feedback_setting, "num_trials": n_trials_no_perturbation,
        "perturbation": False,
        "drink_beer": True,
        "noise_active": True, "noise_mean": medium_noise_mean, "noise_std":
medium_noise_std
    },
    {
        "feedback": feedback_setting, "num_trials": n_trials_perturbation,
        "perturbation": True, "gradual": False, "sudden_force": sudden_force,
        "drink_beer": False,
        "noise_active": True, "noise_mean": medium_noise_mean, "noise_std":
medium_noise_std
    },
    {
        "feedback": feedback_setting, "num_trials": n_trials_no_perturbation,
        "perturbation": False,
        "drink_beer": False,
        "noise_active": True, "noise_mean": medium_noise_mean, "noise_std":
medium_noise_std
    },
    # 4
    {
        "feedback": feedback_setting, "num_trials": n_trials_no_perturbation,
        "perturbation": False,
        "drink_beer": True,
        "noise_active": True, "noise_mean": large_noise_mean, "noise_std":
large_noise_std
    },
    {
        "feedback": feedback_setting, "num_trials": n_trials_perturbation,
        "perturbation": True, "gradual": False, "sudden_force": sudden_force,
        "drink_beer": False,
        "noise_active": True, "noise_mean": large_noise_mean, "noise_std":
large_noise_std
    },
    {
        "feedback": feedback_setting, "num_trials": n_trials_no_perturbation,
        "perturbation": False,
        "drink_beer": False,
        "noise_active": True, "noise_mean": large_noise_mean, "noise_std":
large_noise_std
    }
]
```

Task 2: Analysis of motor noise on unbiased subjects

By the end of the trials, the unbiased subject got a bit annoyed with the task and tended to perform shorter throws in order to get the experiment over with quicker.

```
In [2]: # Read subject data
experiment, full_experiment = plots.define_experiment()

subject1 = pd.read_csv("Subject_1.csv")
subject1 = pd.merge(subject1, full_experiment, on = "Trial")
```

```
In [3]: small_noise_mean = 0
small_noise_std = 1

medium_noise_mean = 1.5
medium_noise_std = 2

large_noise_mean = 2.5
large_noise_std = 3

x = np.linspace(-10, 12, 1000)
y_small = norm.pdf(x, small_noise_mean, small_noise_std)
y_medium = norm.pdf(x, medium_noise_mean, medium_noise_std)
y_large = norm.pdf(x, large_noise_mean, large_noise_std)
```

```
In [4]: fig, axs = plt.subplots(nrows = 1, ncols = 2, figsize = (12, 4))

axs[0].plot(x, y_small, label = rf"Small noise: $\mu$ = {small_noise_mean}, \sigma = {small_noise_std}")
axs[0].plot(x, y_medium, label = rf"Medium noise: $\mu$ = {medium_noise_mean}, \sigma = {medium_noise_std}")
axs[0].plot(x, y_large, label = rf"Large noise: $\mu$ = {large_noise_mean}, \sigma = {large_noise_std}")
axs[0].set_xlabel("Motor noise")
axs[0].set_ylabel("Probability density")
axs[0].set_title("Distribution of small, medium, and large motor noise")
axs[0].legend(loc = "center left", bbox_to_anchor = (1, 0.5))

colors, unique_periods = plots.get_experiment_colors(experiment)
```

```
# Show the different experimental periods
for i, change in experiment.iterrows():
    label = change.Type
    if change.Type in unique_periods:
        unique_periods[change.Type] = change.Type

    start = change.Trial
    end = change.TrialEnd

    axs[1].axvspan(
        start, end,
        alpha = 0.2,
        label = label,
        color = colors.get(change.Type)
    )

axs[1].scatter(
    subject1.Trial,
    subject1.NoiseInstance,
    s = 5,
    label = "Noise"
)

axs[1].legend(loc = "center left", bbox_to_anchor = (1, 0.5))
axs[1].set_title("Noise in each attempt")
axs[1].set_xlabel("Motor noise")
axs[1].set_ylabel("Attempt")

fig.tight_layout()
plt.show()
```

Figure 1. (Left) Distributions of the motor noise used throughout the experiment. (Right) Individual noise instances during each attempt.

```
In [5]: fig, axs = plt.subplots(nrows = 1, ncols = 2, figsize = (12, 4))
plots.plot_running_score(experiment, subjects = [subject1], ax = axs[0], show_legend = False)
plots.plot_trial_score(experiment, subjects = [subject1], ax = axs[1])
fig.tight_layout()
```

Figure 2. (Left) The running score across the experiment and (right) the score for each trial, with vertical lines representing the mean score for each block, for subject 1. The different experimental blocks are visually highlighted. The subject shows a significant decline in performance during the final block.

```
In [6]: plots.plot_throw_positions(subject1)
```

Figure 3.1. Final pint positions for subject 1. (Right) The mean final position, marked by a cross, and its error, marked by the confidence ellipse. (Left) Final pint position for all trials. The experimental blocks are marked by different colors. The variability of the final position tends to increase with increasing motor noise.

```
In [7]: plots.plot_throw_perturbation(subject1)
```

Figure 3.2. Final pint positions, their mean and confidence ellipse during no perturbation and perturbation periods of each experimental block, for subject 1. For all blocks, perturbed attempts are shifted in the direction of perturbation. For small motor noise and large motor noise there is a visible after-effect, and the mean of the final position is shifted in the direction opposite to perturbation.

Task 3: Discussion

Is feedback still helpful even if motor noise is present? How large can the motor noise be until learning no longer takes place?

We notice that the subject's performance declines with increasing motor noise, and their attempts appear more random. It is difficult to attribute this to the induced noise alone; during the experiment, the subject was getting increasingly annoyed when they could not control the pint, and started performing random throws out of frustration by the end of the experiment.

However, in the case of the small motor noise, the subject has clearly learned to adapt to the induced perturbation. This is visible in the after effect - the unperturbed trials after the perturbation are shifted in the opposite direction to the perturbation, stronger than before the perturbation was induced. For the medium motor noise, the effect is not as pronounced. In the case of the large motor noise, no comment can be made - it is unclear whether the subject learned something or the observed after-effect appears by chance.

Overall, the feedback is helpful when the noise is not too strong and the subject can still link their actions to the results they produce (and thus successfully update the internal model). Even though this process is supposed to be subconscious, the large noise was quite strong and the subject noticed that the system does not behave as they expect, thus getting frustrated and performing poorly. So, the second question is more difficult to answer with this specific experiment (or at least the data we have).

Task 4

Defining correct experimental settings as well as being consistent is as important as the experiment itself. Due to this we noticed a couple of things:

- First being consistent with respect to the experimental material is quite important. In the classroom we set the friction parameters such that it was challenging to hit the green wedge but also not impossible to run over. Those settings were determined on a MacBook. On the other hand while performing the experiments on another computer (ThinkPad), we noticed it was now way harder to reach the target. We suppose both laptops had different settings with respect to the maximal cursor speed. Therefore, we started multiple runs with the subjects to find nice friction parameters on the ThinkPad. This leads us directly to the next point.
- Frustration is a very important thing if you would like to have the subject motivated while finding new friction parameters (Run 1 - 3). The subject aborted the runs multiple times, either because it could not reach the target (Run 1) or just overshoots almost all the time (run 2 - 3) and needed persuasion (real beer afterwards) to start the final run (run 4). The next source of frustration came along when we started to perturb the experiment. The subject became not willing to learn anything but just rather complete the task. So we conclude: wisely chosen parameters also in perturbation (maybe truncate perturbation next time) are crucial.

```
In [8]: subject2 = pd.read_csv("logs_1.csv")
subject2 = pd.merge(subject2, full_experiment, on = "Trial")
subject3 = pd.read_csv("logs_2.csv")
subject3 = pd.merge(subject3, full_experiment, on = "Trial")
subject4 = pd.read_csv("logs_3.csv")
subject4 = pd.merge(subject4, full_experiment, on = "Trial")
fig, axs = plt.subplots(nrows = 1, ncols = 2, figsize = (12, 4), sharex=True)
plots.plot_running_score(experiment, subjects = [subject2, subject3, subject4, subject1], ax = axs[0])
plots.plot_experiment_layout(experiment, ax=axs[1])
plt.plot(1- subject2["Friction"], label="Run 1")
plt.plot(1- subject3["Friction"], label="Run 2")
plt.plot(1- subject1["Friction"], label="Run 3")
plt.plot(1- subject1["Friction"], label="Run 4")
axs[1].set_title("Friction Coefficient")
axs[1].legend(loc = "center left", bbox_to_anchor = (1, 0.5))
# plots.plot_trial_score(experiment, subjects = [subject1], ax = axs[1])
fig.tight_layout()
```

