HW4_JonasSchweisthal_s4535561

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1 Homework #4

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[1]:
```
from model import Model
from dmchunk import Chunk
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import random
import math
```

[2]:
```
def noise(s):
    rand = random.uniform(0.001,0.999)
    return s * math.log((1 - rand)/rand)
```

[3]:
```
def time_to_pulses(time, t_0 = 0.011, a = 1.1, b = 0.015):
    pulses = 0
    pulse_duration = t_0
    while time >= pulse_duration:
        time = time - pulse_duration
        pulses += 1
        pulse_duration = a * pulse_duration + noise(b * a * pulse_duration)
    return pulses
```

[4]:
```
def pulses_to_time(pulses, t_0 = 0.011, a = 1.1, b = 0.015):
    time = 0
    pulse_duration = t_0
    while pulses > 0:
        time = time + pulse_duration
        pulses = pulses - 1
        pulse_duration = a * pulse_duration + noise(b * a * pulse_duration)
    return time
```

[5]:
```
def ready_set_go(n_participants, n_trials = 1500):
    subjects = range(1,n_participants+1)
    conditions = [1, 2, 3]
```

```python
    trials = range(1,n_trials+1)
    df_js = pd.read_csv("dataJS.csv")
    # selecting intervals from JS data
    intervals = df_js.groupby("Cond")["Ts"].unique()/1000
    df = pd.DataFrame(columns = ["Subj", "Cond", "line", "Trial", "Ts", "Tp", "Main"])
    main = False
    line = 0
    for subj in subjects:
        # shuffling order of conditions randomly per subject
        np.random.shuffle(conditions)
        for cond in conditions:
            # create a new model for each subject and condition as there's much time between testing the
            # different conditions per subject
            m = Model()
            # g = Chunk(name = "goal", slots = {"isa": "retrieve-time-goal","current-pulses": np.nan})
            # m.goal = g
            for trial in trials:
                line += 1
                # Checking if trial is training trial
                if trial > 500:
                    main = True
                else:
                    main = False
                # 1 second preparing time
                m.time += 1
                # no exact infos for truncated exponential distribution of random delay in paper:
                # -> simplifed with continuos random uniform
                delay = np.random.uniform(0.25, 0.85)
                m.time += delay
                # draw out of 11 discrete values of discrete uniform distribution per condition
                ts = np.random.choice(intervals[cond])
                m.time += ts

                # time to pulses
                pulses = time_to_pulses(ts)
                fact = Chunk(name = "pf" + str(pulses), slots ={"isa": "pulses-fact", "pulses": pulses})
                # adding encounter of the perceived interval as pulses at the end time point of the presented interval
                m.add_encounter(fact)
                # adding time for storing encounter in memory
```

```
                m.time += .05
                # retrieving blended trace
                request = Chunk(name = "retrieve", slots = {"isa":␣
↪"pulses-fact"})
                pulses_retrieved, latency = m.retrieve_blended_trace(request,␣
↪"pulses")
                # m.time += latency is NOT added as discussed in supervision␣
↪session
                # converting blended trace of retrieved pulses to seconds
                tp = pulses_to_time(pulses_retrieved)
                # adding production time
                m.time += tp
                # store times in milliseconds in dataframe
                df.loc[line-1] = [subj, cond, line, trial, ts*1000, tp*1000,␣
↪main]

    return df, m
```

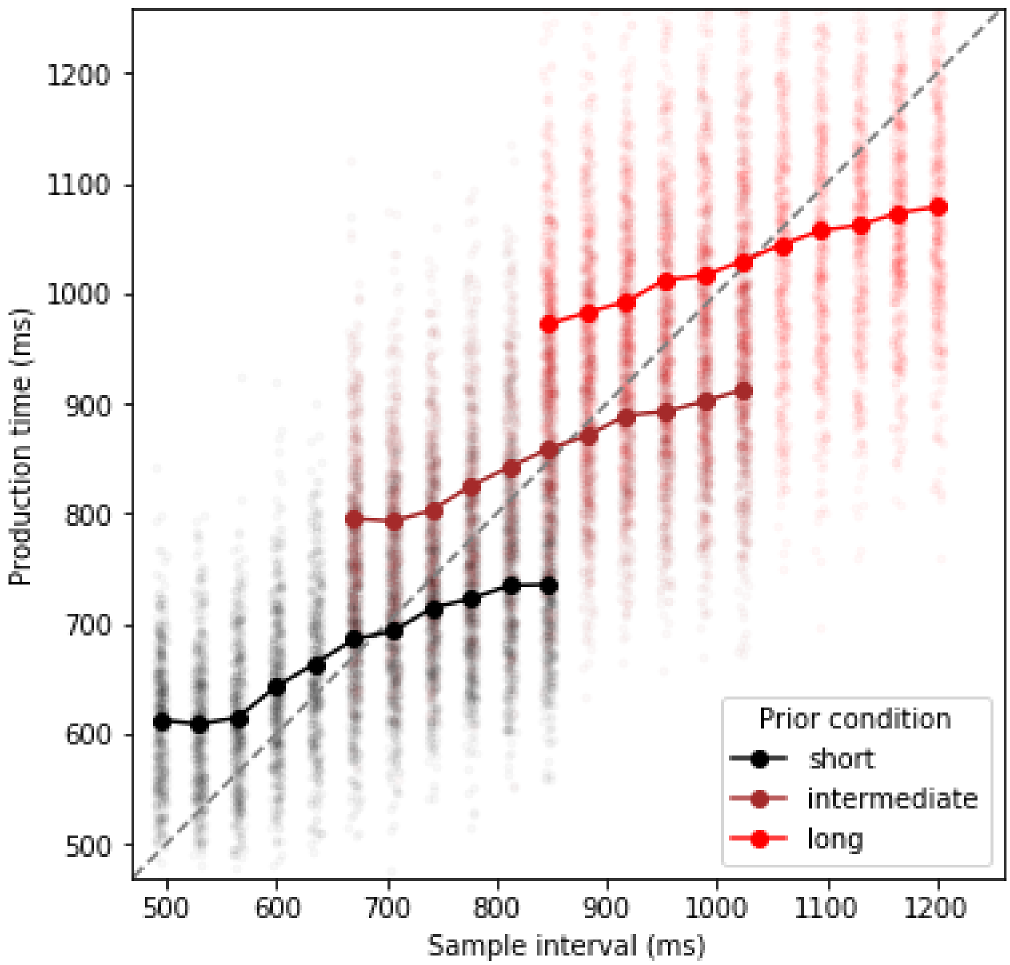
[6]:
```
df, m = ready_set_go(5, n_trials = 1500)
```

[7]:
```
# Remove training trials
dat = df[df['Main'] == True]

# Calculate mean Tp by condition
mean_tp = dat.groupby(['Cond', 'Ts'])['Tp'].mean().reset_index()


yrange = np.multiply((min(mean_tp['Ts']), max(mean_tp['Ts'])), [0.95, 1.05])

# Subset data for plotting

cond1 = mean_tp.loc[mean_tp['Cond'] == 1]
cond2 = mean_tp.loc[mean_tp['Cond'] == 2]
cond3 = mean_tp.loc[mean_tp['Cond'] == 3]

# Add jitter noise
jitter = dat.copy()
jitter['Ts'] = jitter['Ts'] + np.random.uniform(-5, 5, len(dat))
cond1_jitter = jitter.loc[jitter['Cond'] == 1]
cond2_jitter = jitter.loc[jitter['Cond'] == 2]
cond3_jitter = jitter.loc[jitter['Cond'] == 3]

# Make plot
f, ax = plt.subplots(figsize = (6,6))

ax.set(xlim = yrange, ylim = yrange)
f.gca().set_aspect('equal', adjustable = 'box')
```

```
ax.set_xlabel('Sample interval (ms)')
ax.set_ylabel('Production time (ms)')

ax.plot(yrange, yrange, linestyle = '--', color ='gray')

ax.scatter(cond1_jitter['Ts'], cond1_jitter['Tp'], marker = '.', color =␣
 ↪'black', alpha = 0.025, label = None)
ax.scatter(cond2_jitter['Ts'], cond2_jitter['Tp'], marker = '.', color =␣
 ↪'brown', alpha = 0.025, label = None)
ax.scatter(cond3_jitter['Ts'], cond3_jitter['Tp'], marker = '.', color = 'red',␣
 ↪alpha = 0.025, label = None)

ax.plot(cond1['Ts'], cond1['Tp'], color = 'black', marker = 'o', label =␣
 ↪"short")
ax.plot(cond2['Ts'], cond2['Tp'], color = 'brown', marker = 'o', label =␣
 ↪"intermediate")
ax.plot(cond3['Ts'], cond3['Tp'], color = 'red', marker = 'o', label = "long")

ax.legend(title = 'Prior condition', loc = 4)
```

```
C:\Users\jonas\AppData\Roaming\Python\Python37\site-
packages\matplotlib\cbook\__init__.py:1402: FutureWarning: Support for multi-
dimensional indexing (e.g. `obj[:, None]`) is deprecated and will be removed in
a future version.  Convert to a numpy array before indexing instead.
  x[:, None]
C:\Users\jonas\AppData\Roaming\Python\Python37\site-
packages\matplotlib\axes\_base.py:276: FutureWarning: Support for multi-
dimensional indexing (e.g. `obj[:, None]`) is deprecated and will be removed in
a future version.  Convert to a numpy array before indexing instead.
  x = x[:, np.newaxis]
C:\Users\jonas\AppData\Roaming\Python\Python37\site-
packages\matplotlib\axes\_base.py:278: FutureWarning: Support for multi-
dimensional indexing (e.g. `obj[:, None]`) is deprecated and will be removed in
a future version.  Convert to a numpy array before indexing instead.
  y = y[:, np.newaxis]
```

```
[7]: <matplotlib.legend.Legend at 0x1a202a7aa88>
```



In homework 3, within the conditions the condition specific mean value for almost every sample interval could be considered as production time, but there were big differences between the conditions. This is probably due to the fact that for each new condition a new model was initialized for each subject and that after the 500 training trials the activation of each pulse chunk in memory was so high that especially the noise of the activations had a great influence on the choice of the retrieved chunk, which made it nearly random choice within the conditions. Additionally, higher deviations within the higher conditions were visible, due to logistic noise in time_to_pulses and pulses_to_time fuctions.

In this homework a mix form between the randomness within the conditions and using the recently seen intervals was used by using a blended trace. Thus, the higher weighting of the more recent observations results in a plot with a visible individual effect of the seen interval and a trend to the mean value of the conditions, which is similar to the plot in the paper, but the mean value effect is not so strong in the paper. The calculated probability for the last seen interval is probably underestimated in our blended trace. The stronger trend to the mean value for the longer conditions from the paper is also slightly visible here and is generated by the larger noise for larger intervals (coming from the logistic noise). The logistic noise also causes flattening tails at the ends of the conditions, due to less frequent occurrence of perceived pulses in the outer areas of the conditions.