Cognitive Modeling - Assignment 3

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Libraries

In [ ]:
```
import math
import random

from model import Model
from dmchunk import Chunk

import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns

import statsmodels.api as sm
import statsmodels.formula.api as smf
```

Pulses

These are functions found on brightspace from week 2.

In [ ]:
```
t_0 = 0.011
a = 1.1
b = 0.015
add_noise = True

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

def time_to_pulses(time, t_0 = t_0, a = a, b = b, add_noise = add_noise):
    pulses = 0
    pulse_duration = t_0

    while time >= pulse_duration:
        time = time - pulse_duration
```

```
        pulses = pulses + 1
        pulse_duration = a * pulse_duration + add_noise * noise(b * a * pulse_duration)

    return pulses

def pulses_to_time(pulses, t_0 = t_0, a = a, b = b, add_noise = add_noise):
    time = 0
    pulse_duration = t_0

    while pulses > 0:
        time = time + pulse_duration
        pulses = pulses - 1
        pulse_duration = a * pulse_duration + add_noise * noise(b * a * pulse_duration)

    return time
```

Motivation

This is an extract of the models found on brightspace in week 5 named Boksem.ipynb.

In [ ]:

```
class ModelWithMotivation(Model):
    da = 0.5  # distraction activation
    discount = 0.1 # discount due to motivation drop

    def discount_goal_activation(self):
        self.ga -= self.discount

    def __str__(self):
        return "\n=== Model ===\n" \
        "Time: " + str(self.time) + " s \n" \
        "Goal:" + str(self.goal) + "\n" \
        "DM:" + "\n".join([str(c) for c in self.dm]) + "\n" \
        "ga: " + str(self.ga) + "\n"

    def distraction(self):
        return self.da + self.noise(self.s) > self.ga + self.noise(self.s)

# Experiment timing:
distraction_mean_time = 0.2 # average distraction time
distraction_variation = 0.1 # variation in distraction (uniform)
focus_loss_probability = 0.2 # probability to lose focus once prepared
focus_latency = 0.2 # if we decide to stay focussed, we focus for this amount of time
```

```
def distraction_time():
    return random.uniform(distraction_mean_time - distraction_variation, distraction_mean_time + distraction_variation)
```

Full Experiment

In [ ]:
```
def experiment(participants):

    reward_visibility = [
        [0, 0],
        [1, 0],
        [1, 1],
        [0, 1]]
    foreperiod_location = [
        [0.3, 0],
        [0.3, 1],
        [0.6, 0],
        [0.6, 1],
        [0.9, 0],
        [0.9, 1]]

    # visibility 0 = poor
    # location 0 = left

    recording = False
    count = 0
    for participant in range(participants):

        # prep the model, add a single instance to avoid an error with NoneType
        model = ModelWithMotivation()
        pulses = time_to_pulses(0.6)
        chunk = Chunk(name = "time" + "train", slots = {"type": "time", "value": pulses})
        model.add_encounter(chunk)
        model.time += 0.1

        # shuffle the lists
        random.shuffle(reward_visibility)
        random.shuffle(foreperiod_location)

        index_block = 0
        index_trial = 0

        for block in range(16):

            if(index_block == 4):
                random.shuffle(reward_visibility)
                index_block = 0
```

```
        reward = reward_visibility[index_block][0]
        visibility = reward_visibility[index_block][1]

        if(reward == 1):
            model.ga = 1.0

        for trial in range(30):

            if(index_trial == 6):
                random.shuffle(foreperiod_location)
                index_trial = 0

            foreperiod = foreperiod_location[index_trial][0]
            location = foreperiod_location[index_trial][1]
            intertrial_interval = random.uniform(0.5, 0.8)
            cue_stimulus_interval = foreperiod + intertrial_interval

            # pre stimulus
            start = model.time
            blend_pattern = Chunk(name = "foreperiod", slots = {"type": "time"})
            chunk, latency = model.retrieve_blended_trace(blend_pattern, "value")
            model.time += latency

            # assessing the motivation
            running = True
            prepared = False
            while(running):
                if(model.time - start < cue_stimulus_interval and not model.distraction()):
                    prepared = True
                    model.time += focus_latency + 0.05
                elif(model.time - start < cue_stimulus_interval):
                    model.time += distraction_time() + 0.1
                elif(prepared):
                    model.time += 0.05
                    running = False
                else:
                    model.time += 0.1
                    running = False

            # stimulus, 0.75 weight for anticipation of the stimulus.
            difference = foreperiod - pulses_to_time(chunk * 0.75)

            # estimation of stimulus arrival.
            # introduces a small bias for when visibility is high
            if (difference >= 0.075):
                model.time += 0.075 - (0.01 * visibility)
            elif(difference <= 0):
```

```
                model.time += 0.1
            else:
                model.time += 0.075 + difference - (0.01 * visibility)

            reaction_time = model.time - start - (0.025 * visibility) - cue_stimulus_interval

            if(not recording):
                results = np.array([[participant, block, trial, reward, visibility, foreperiod, location, reaction_time]])
                recording = True
            else:
                results = np.append(results, [[participant, block, trial, reward, visibility, foreperiod, location, reaction_time]], axis=0)

            # post stimulus
            pulses = time_to_pulses(foreperiod)
            chunk = Chunk(name = "time" + str(count), slots = {"type": "time", "value": pulses})
            model.add_encounter(chunk)
            model.time += intertrial_interval + 0.1

            model.discount_goal_activation()

            # simple printout to see progress.
            print("Participant: {}/{}".format(participant + 1, participants), end="\r")
            count += 1

            index_trial += 1
        index_block += 1

    return results
```

Run the Experiment

In [ ]:
```
data = experiment(200)
```

```
Participant: 200/200
```

Data Analysis

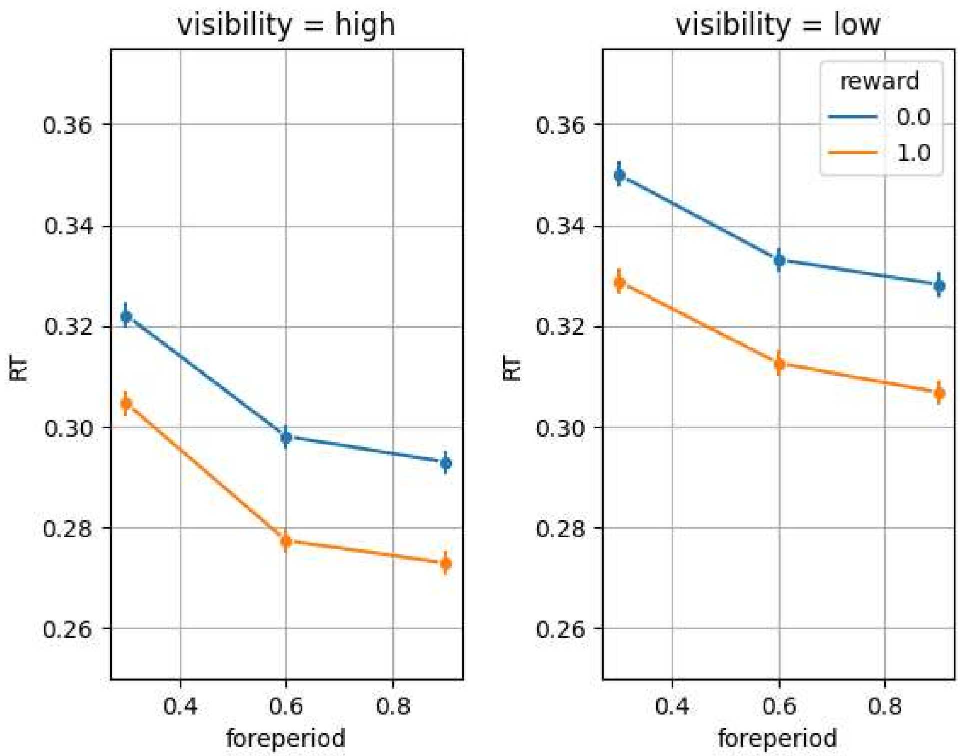
Graphing

In [ ]:
```
dataFrame = pd.DataFrame(data)
dataFrame.columns = ["participant", "block", "trial", "reward", "visibility", "foreperiod", "location", "RT"]

# mean and std
data_mean_std = dataFrame
```

```
data_mean_std.drop('participant', inplace=True, axis=1)
data_mean_std.drop('block', inplace=True, axis=1)
data_mean_std.drop('trial', inplace=True, axis=1)
data_mean_std.drop('location', inplace=True, axis=1)

print(data_mean_std.groupby(["reward", "visibility", "foreperiod"]).mean())
print(data_mean_std.groupby(["reward", "visibility", "foreperiod"]).std())

# Graph
df1 = dataFrame[dataFrame["visibility"] == 1]
df2 = dataFrame[dataFrame["visibility"] == 0]

fig, ax = plt.subplots(1,2)
ax1 = sns.lineplot(data=df1, x="foreperiod", y="RT", hue = "reward", ax=ax[0], marker="o", err_style="bars", errorbar=('ci', 95), legend=False)
ax2 = sns.lineplot(data=df2, x="foreperiod", y="RT", hue = "reward", ax=ax[1], marker="o", err_style="bars", errorbar=('ci', 95))

ax1.set_ylim(0.25, 0.375)
ax2.set_ylim(0.25, 0.375)

ax1.set(title="visibility = high")
ax2.set(title="visibility = low")

ax1.grid()
ax2.grid()

fig.subplots_adjust(wspace=0.4)
```

reward	visibility	foreperiod	RT
0.0	0.0	0.3	0.350049
		0.6	0.333158
		0.9	0.328185
	1.0	0.3	0.322107
		0.6	0.298047
		0.9	0.292936
1.0	0.0	0.3	0.328830
		0.6	0.312597
		0.9	0.306796
	1.0	0.3	0.304641
		0.6	0.277374
		0.9	0.272863

reward	visibility	foreperiod	RT
0.0	0.0	0.3	0.098031
		0.6	0.097948
		0.9	0.096114
	1.0	0.3	0.098124
		0.6	0.096965
		0.9	0.097117
1.0	0.0	0.3	0.096704
		0.6	0.097681
		0.9	0.097107
	1.0	0.3	0.098488
		0.6	0.098082
		0.9	0.098019



Linear Mixed Effect Regression Model

In [ ]:

```
mixed = smf.mixedlm("RT ~ foreperiod*reward*visibility", dataFrame, groups=dataFrame["participant"], re_formula="~foreperiod")
mixed_fit = mixed.fit(method=["lbfgs"])
print(mixed_fit.summary())
```

```
                 Mixed Linear Model Regression Results
========================================================================
Model:                   MixedLM      Dependent Variable:      RT
No. Observations:        96000        Method:                  REML
No. Groups:              200          Scale:                   0.0095
Min. group size:         480          Log-Likelihood:          87109.0975
Max. group size:         480          Converged:               Yes
Mean group size:         480.0
------------------------------------------------------------------------
                              Coef.  Std.Err.    z    P>|z| [0.025 0.975]
------------------------------------------------------------------------
Intercept                      0.359    0.002 213.432 0.000  0.356  0.362
foreperiod                    -0.036    0.003 -13.933 0.000 -0.042 -0.031
reward                        -0.021    0.002  -8.861 0.000 -0.026 -0.016
foreperiod:reward             -0.000    0.004  -0.078 0.938 -0.007  0.007
visibility                    -0.025    0.002 -10.802 0.000 -0.030 -0.021
foreperiod:visibility         -0.012    0.004  -3.348 0.001 -0.019 -0.005
reward:visibility              0.004    0.003   1.227 0.220 -0.002  0.011
foreperiod:reward:visibility -0.004    0.005  -0.790 0.430 -0.014  0.006
Group Var                      0.000    0.000
Group x foreperiod Cov        -0.000    0.000
foreperiod Var                 0.000    0.000
========================================================================
```

```
c:\GitHub\CM-3\.venv\lib\site-packages\statsmodels\regression\mixed_linear_model.py:2237: ConvergenceWarning: The MLE may be on the boundary of the par
ameter space.
  warnings.warn(msg, ConvergenceWarning)
```