hw8_prelim_analyses

December 3, 2024

[2]:
```
%matplotlib inline

# scientific computing and plotting
import numpy as np
import pandas as pd
import xarray as xr
import matplotlib.pyplot as plt
import seaborn as sns

# HDDM related packages
import pymc as pm
import hddm
import kabuki
import arviz as az
from kabuki.analyze import check_geweke
from kabuki.analyze import gelman_rubin

# miscellaneous
from IPython.display import clear_output
```

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1 Research Question

Do healthy individuals, individuals with remitted depression, and individuals with current depression and suicidal ideation differ in the speed of evidence accumulation (i.e., drift rate) in a task that assesses cognitive control (i.e., the flanker task)?

2 Variables

- `rt`: response time (in seconds)
- `response`: response made (left or right)
- `trial_type`: whether the trial consisted of congruent or incongruent targets
- `group`: whether the individual was healthy (HC), had remitted depression (rMDD), or had current depression and suicidal ideation (SI)

- α: boundary separation parameter in a drift diffusion model (DDM), which measures how much evidence needs to accumulated for a response to be executed.
- v: drift rate parameter in a DDM, which measures the speed of evidence accumulation.
- t: non-decision time parameter in a DDM, which measures the time taken to perform non-decision behaviors (e.g., perception, movement initiation and execution).
- z: bias parameter in a DDM, which measures the prepotent bias towards a certain stimulus.

2.1 Data Import

[25]:
```
data = hddm.load_csv("../all_cleaned/flanker_all.csv")
# exclude rows according to the exclusion flags
data_clean = data.loc[(data.exclude_trial == 0) & (data.exclude_part == 0), :]
# rename columns according to the HDDM model convention
data_clean = data_clean.rename(columns={"resp_rt": "rt", "resp_value":␣
 ↪"response",
                                        "trial_congruent_fac": "trial_type",
                                        "subject_id": "subj_idx"})
```

[26]:
```
data_clean.head()
```

[26]:

	subj_idx	trial_type	resp_corr	rt	response	mean_rt	sd_rt	\
0	1903	congruent	1	0.841311	left	0.945541	0.158969	\
1	1903	incongruent	1	1.105856	right	1.020937	0.151395	
2	1903	incongruent	1	1.151826	left	1.020937	0.151395	
3	1903	congruent	1	0.710728	right	0.945541	0.158969	
4	1903	incongruent	1	0.956795	left	1.020937	0.151395	

	exclude_thresh	exclude_trial	exclude_part	school	group
0	2.4	0	0	UIC	rMDD
1	2.4	0	0	UIC	rMDD
2	2.4	0	0	UIC	rMDD
3	2.4	0	0	UIC	rMDD
4	2.4	0	0	UIC	rMDD

2.2 Variable Summary

The following table shows the summary statistics of response times by group and trial type.

[34]:
```
data_clean[["rt", "group", "trial_type"]].groupby(["group", "trial_type"]).
 ↪describe()
```

[34]:

		rt						
		count	mean	std	min	25%	50%	
group	trial_type							
HC	congruent	1216.0	0.569351	0.117414	0.349459	0.486819	0.548058	\
	incongruent	1213.0	0.647026	0.140774	0.323711	0.559814	0.621350	
SI	congruent	688.0	0.609570	0.170033	0.000000	0.495791	0.576894	

```
      incongruent   690.0  0.701379  0.184837  0.325547  0.581031  0.659431
rMDD  congruent    1213.0  0.608990  0.209955  0.330845  0.488824  0.565600
      incongruent  1211.0  0.708031  0.258034  0.326785  0.570508  0.647860
```

```
                          75%       max
group trial_type
HC    congruent     0.628956  1.297988
      incongruent   0.713315  1.529910
SI    congruent     0.671899  1.722197
      incongruent   0.789454  1.535628
rMDD  congruent     0.654650  2.362939
      incongruent   0.753425  3.149707
```

[35]:
```
data_clean[["response", "group", "trial_type"]].groupby(["group",␣
↪"trial_type"]).describe()
```

[35]:
```
                    response
                       count unique    top freq
group trial_type
HC    congruent       1216      2   left  610
      incongruent     1213      2  right  609
SI    congruent        688      3   left  346
      incongruent      690      2   left  347
rMDD  congruent       1213      2  right  609
      incongruent     1211      2   left  619
```

3 Model

Let $Y = [\texttt{rt}, \texttt{response}]$

$Y_{ij} \sim F(a_i, z_i, v_i, t_i, sv, st, sz)$

Where F represents the DDM likelihood function as formulated by Daniel et al. (2009).

$\mu_\alpha \sim \Gamma(1.5, 0.75)$
$\mu_v \sim N(2, 3)$
$\mu_z \sim N(0.5, 0.5)$
$\mu_t \sim \Gamma(0.4, 0.2)$

$\sigma_\alpha \sim HN(0.1)$
$\sigma_v \sim HN(2)$
$\sigma_z \sim HN(0.05)$
$\sigma_t \sim HN(1)$

$\alpha_j \sim \Gamma(\mu_\alpha, \sigma_\alpha^2)$
$z_j \sim invlogit(N(\mu_z, \sigma_z^2))$
$v_j \sim N(\mu_v, \sigma_t^2)$

$t_j \sim N(\mu_t, \sigma_t^2)$

$sv \sim HN(2)$
$st \sim HN(0.3)$
$sz \sim B(1, 3)$

Where N represents a normal distribution parameterized by mean μ and standard deviation σ, HN represents a half-normal distribution bounded at 0 and parameterized by standard deviation σ, Γ represents a Gamma distribution parameterized by shape α and rate β, and B represents a Beta distribution parameterized by α and β.

3.1 Analysis

Here I only present a model that estimates all 4 parameters and regresses `v` on an interaction between `group` and `trial_type`.
I used 4 chains, each with 10000 iterations (first 5000 as warm-ups). Only every 5th sample was saved, resulting in 1000 samples per chain.

[ ]:
```
model_name = "m_reg_group*cond"
m_reg = hddm.models.HDDMRegressor(df, 'v ~ C(group):C(trial_type)',␣
 ↪include=['a', 'v', 'z', 't'])
m_reg.sample(10000, burn=5000, chains=4, return_infdata=True, save_name="../
 ↪models/" + model_name,
                              progress_bar=True, thin=5)
```

4 Results

[9]:
```
m_reg = hddm.load("../models/m_reg_group*cond.hddm")
```

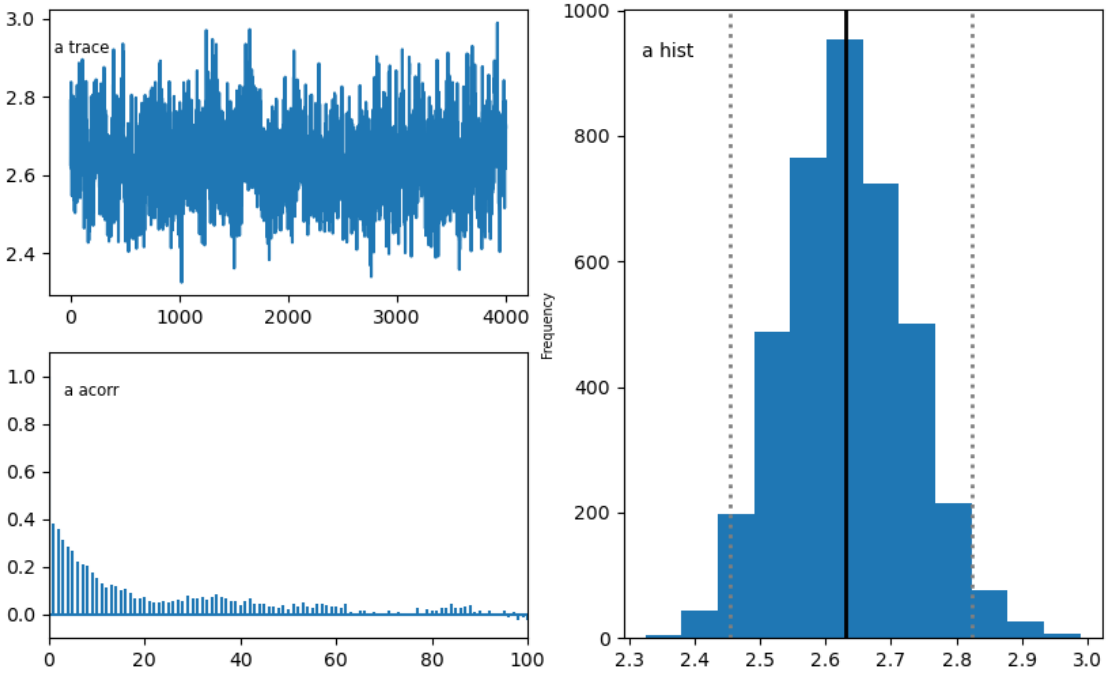
4.1 Convergence Diagnostics

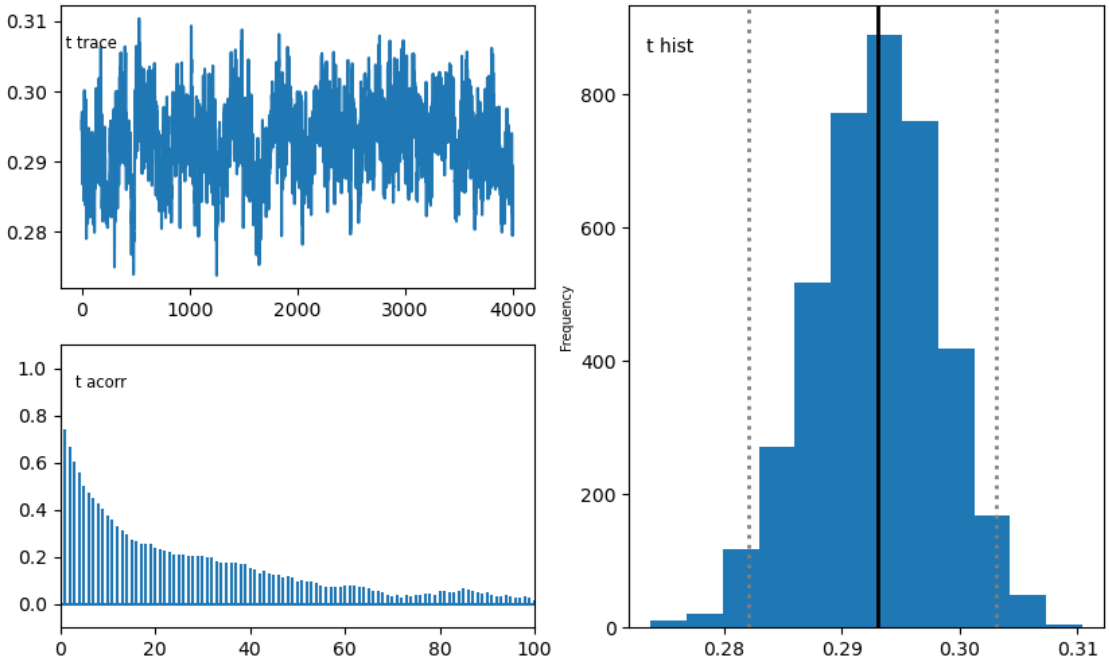
[21]:
```
params = ['a', 't', 'z',
          'v_Intercept',
          'v_C(trial_type)[T.incongruent]',
          'v_C(group)[T.SI]:C(trial_type)[congruent]',
          'v_C(group)[T.rMDD]:C(trial_type)[congruent]',
          'v_C(group)[T.SI]:C(trial_type)[incongruent]',
          'v_C(group)[T.rMDD]:C(trial_type)[incongruent]']
```

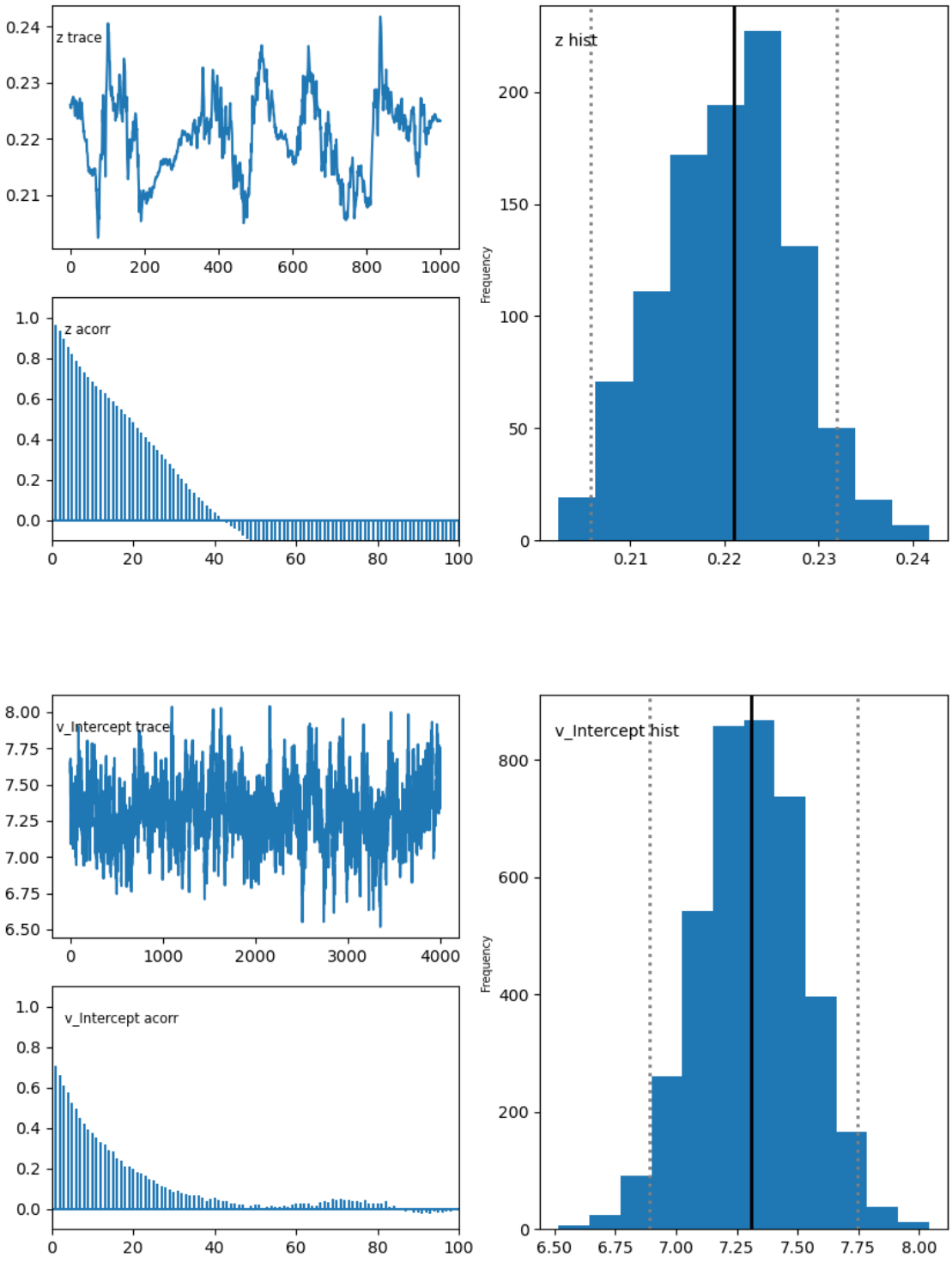
[22]:
```
# Trace plots
m_reg.plot_posteriors(params)
```

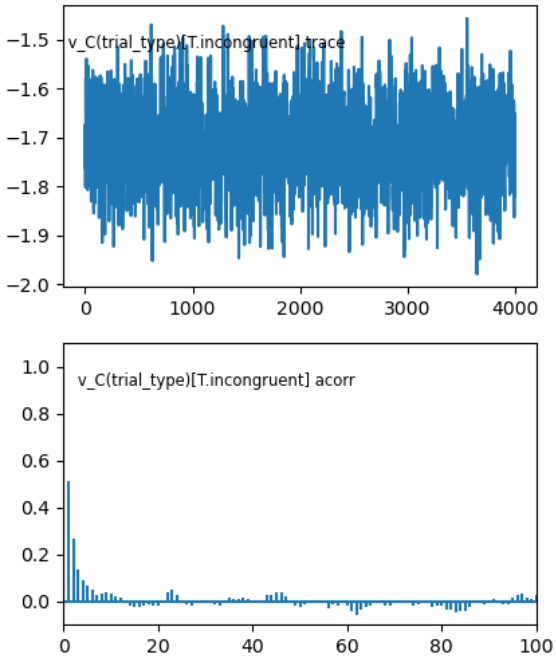
```
Plotting a
Plotting t
Plotting z
Plotting v_Intercept
Plotting v_C(trial_type)[T.incongruent]
```

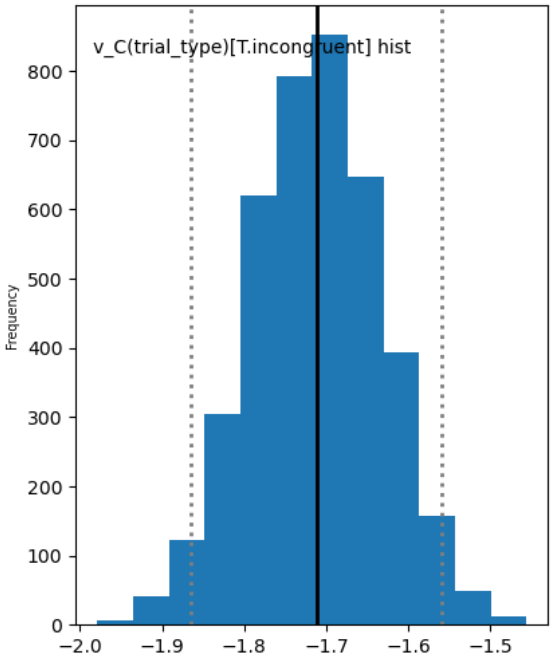
```
Plotting v_C(group)[T.SI]:C(trial_type)[congruent]
Plotting v_C(group)[T.rMDD]:C(trial_type)[congruent]
Plotting v_C(group)[T.SI]:C(trial_type)[incongruent]
Plotting v_C(group)[T.rMDD]:C(trial_type)[incongruent]
```

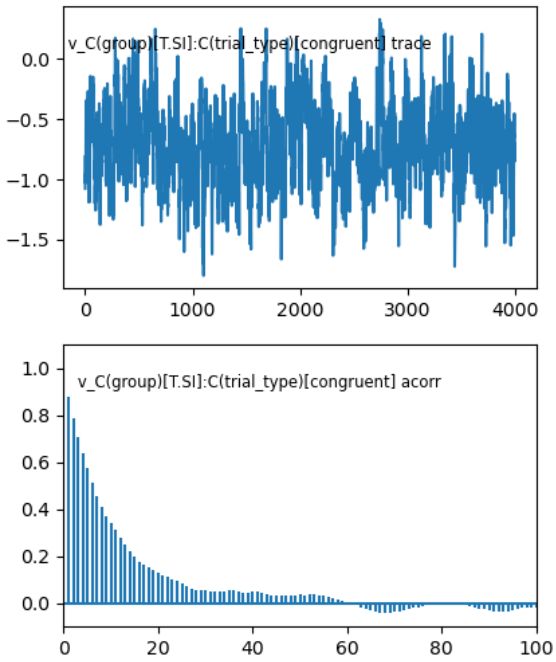


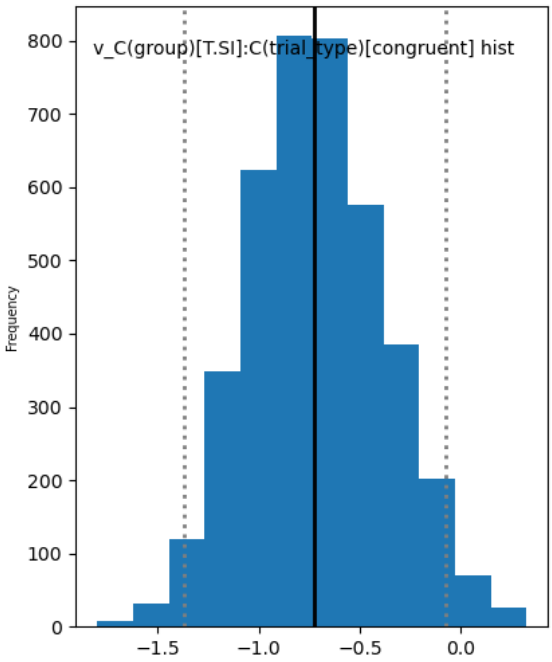


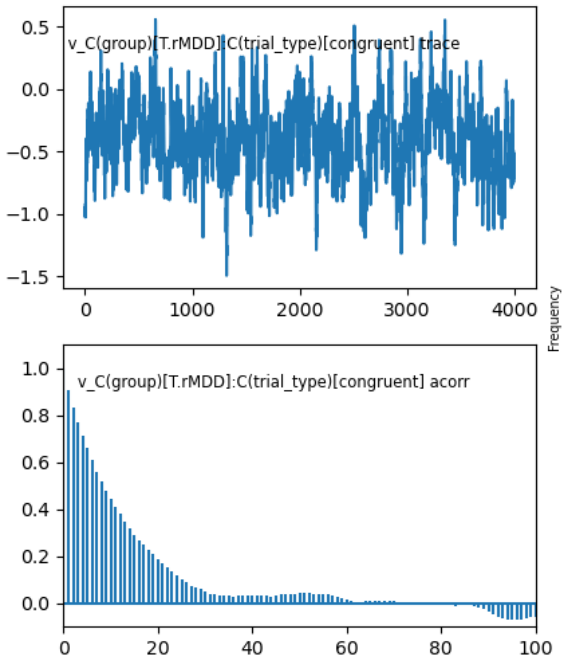

z trace
z acorr
z hist
Frequency
v_Intercept trace
v_Intercept acorr
v_Intercept hist
Frequency

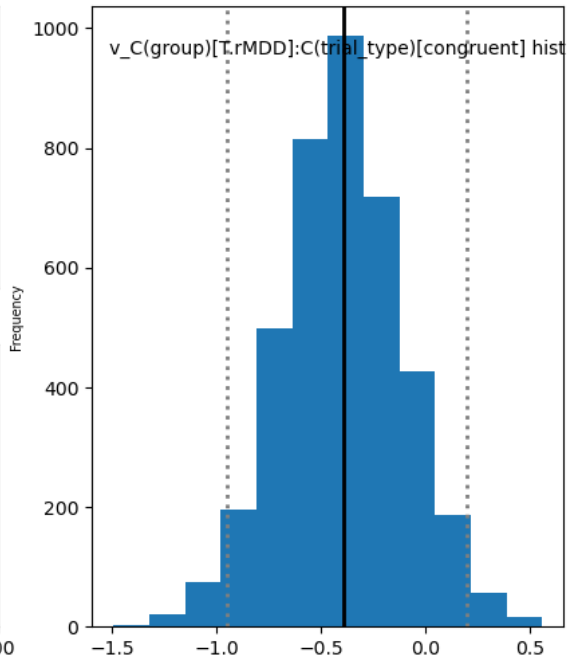

v_C(trial_type)[T.incongruent] trace
−1.5
−1.6
−1.7
−1.8
−1.9
−2.0
0
1000
2000
3000
4000
v_C(trial_type)[T.incongruent] acorr
1.0
0.8
0.6
0.4
0.2
0.0
0
20
40
60
80
100

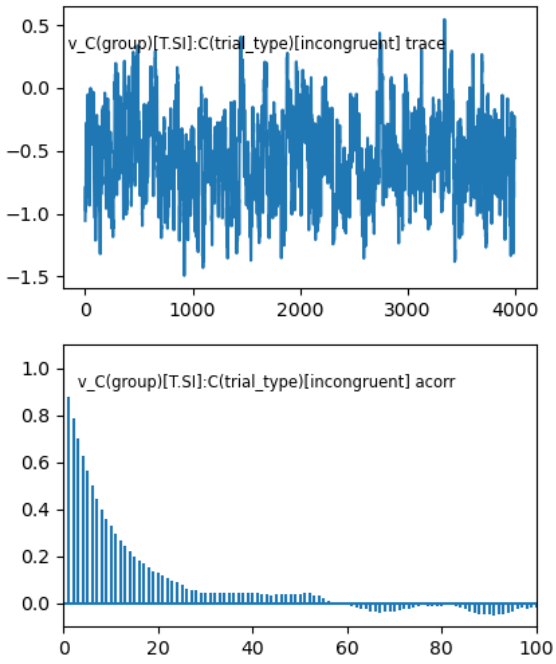

v_C(trial_type)[T.incongruent] hist
Frequency
800
700
600
500
400
300
200
100
0
−2.0
−1.9
−1.8
−1.7
−1.6
−1.5

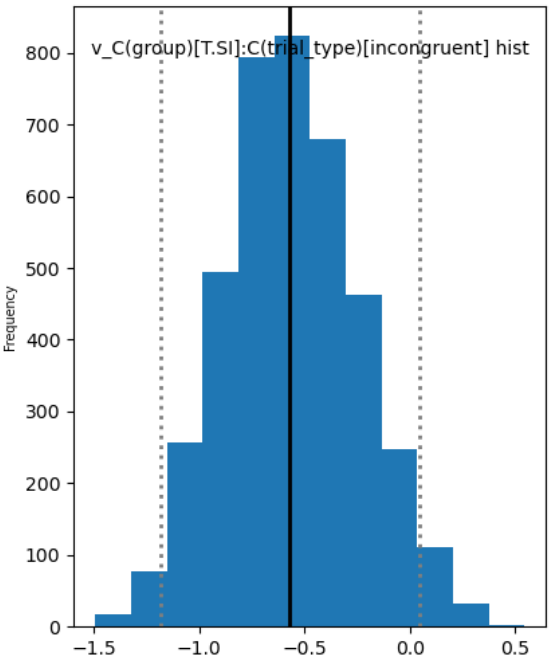

v_C(group)[T.SI]:C(trial_type)[congruent] trace
0.0
−0.5
−1.0
−1.5
0
1000
2000
3000
4000
v_C(group)[T.SI]:C(trial_type)[congruent] acorr
1.0
0.8
0.6
0.4
0.2
0.0
0
20
40
60
80
100

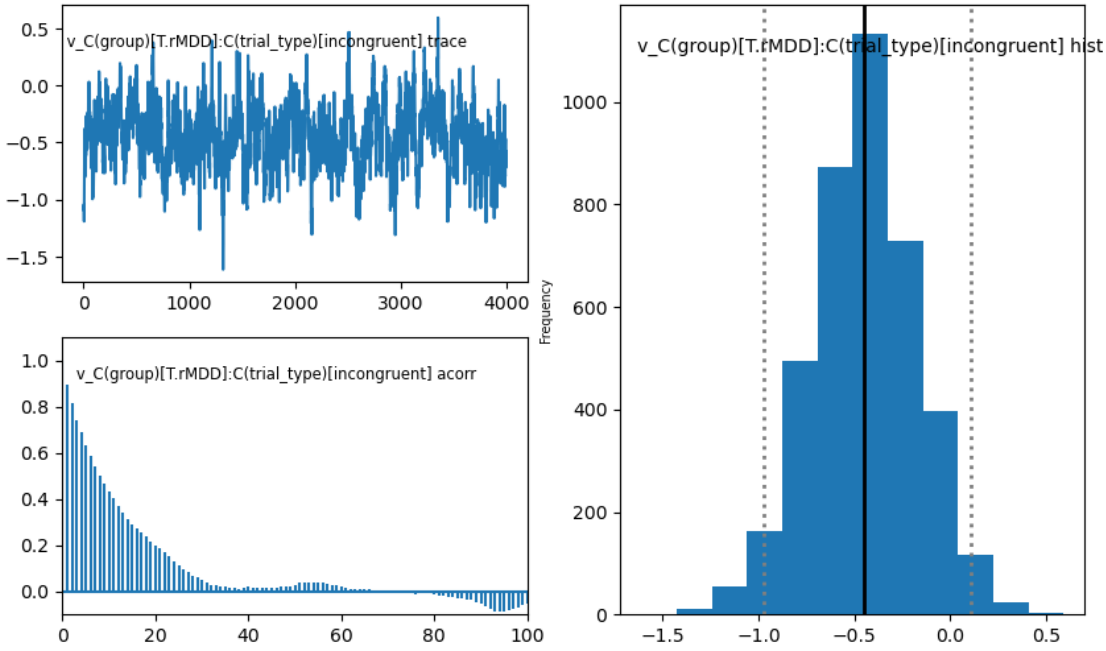

v_C(group)[T.SI]:C(trial_type)[congruent] hist
Frequency
800
700
600
500
400
300
200
100
0
−1.5
−1.0
−0.5
0.0


v_C(group)[T.rMDD]:C(trial_type)[congruent] trace
v_C(group)[T.rMDD]:C(trial_type)[congruent] acorr


v_C(group)[T.rMDD]:C(trial_type)[congruent] hist
Frequency


v_C(group)[T.SI]:C(trial_type)[incongruent] trace
v_C(group)[T.SI]:C(trial_type)[incongruent] acorr


v_C(group)[T.SI]:C(trial_type)[incongruent] hist
Frequency



4.2 Posterior Distributions

[23]:
```
stats = m_reg.gen_stats()
stats[stats.index.isin(params)]
```

[23]:

	mean	std	2.5q	
a	2.634257	0.095483	2.457069	\
t	0.2929	0.005365	0.282113	
z	0.22038	0.006889	0.207212	
v_Intercept	7.309539	0.218687	6.878841	
v_C(trial_type)[T.incongruent]	-1.712452	0.07877	-1.867891	
v_C(group)[T.SI]:C(trial_type)[congruent]	-0.712297	0.33551	-1.333878	
v_C(group)[T.rMDD]:C(trial_type)[congruent]	-0.397916	0.288671	-0.97463	
v_C(group)[T.SI]:C(trial_type)[incongruent]	-0.557444	0.317975	-1.146528	
v_C(group)[T.rMDD]:C(trial_type)[incongruent]	-0.447095	0.274718	-1.00644	

	25q	50q	75q	
a	2.568394	2.631004	2.698773	\
t	0.289346	0.29309	0.296626	
z	0.215288	0.220972	0.224888	
v_Intercept	7.163118	7.308666	7.45948	
v_C(trial_type)[T.incongruent]	-1.766828	-1.711131	-1.659821	
v_C(group)[T.SI]:C(trial_type)[congruent]	-0.947996	-0.726245	-0.48059	
v_C(group)[T.rMDD]:C(trial_type)[congruent]	-0.587161	-0.394161	-0.211399	
v_C(group)[T.SI]:C(trial_type)[incongruent]	-0.779555	-0.573029	-0.337942	

```
v_C(group)[T.rMDD]:C(trial_type)[incongruent] -0.624277 -0.450853 -0.264316

                                                    97.5q    mc err
a                                                2.829102  0.004049
t                                                0.303088  0.000332
z                                                0.233855  0.000649
v_Intercept                                      7.739039  0.013434
v_C(trial_type)[T.incongruent]                    -1.5625  0.002282
v_C(group)[T.SI]:C(trial_type)[congruent]       -0.030301  0.020345
v_C(group)[T.rMDD]:C(trial_type)[congruent]      0.181765  0.018439
v_C(group)[T.SI]:C(trial_type)[incongruent]      0.091049  0.019297
v_C(group)[T.rMDD]:C(trial_type)[incongruent]     0.07829  0.017429
```

[78]:
```
v_hc_con = m_reg.nodes_db.node['v_Intercept'].trace()
v_hc_con_mean = v_hc_con.mean()
v_hc_con_sd = v_hc_con.std()
v_hc_con_025 = np.percentile(v_hc_con, .025)
v_hc_con_975 = np.percentile(v_hc_con, .975)

v_hc_incon = m_reg.nodes_db.node['v_Intercept'].trace() +\
m_reg.nodes_db.node['v_C(trial_type)[T.incongruent]'].trace()
v_hc_incon_mean = v_hc_incon.mean()
v_hc_incon_sd = v_hc_incon.std()
v_hc_incon_025 = np.percentile(v_hc_incon, .025)
v_hc_incon_975 = np.percentile(v_hc_incon, .975)

v_rmdd_con = m_reg.nodes_db.node['v_Intercept'].trace() +\
                    m_reg.nodes_db.node['v_C(group)[T.rMDD]:
 ↪C(trial_type)[congruent]'].trace()
v_rmdd_con_mean = v_rmdd_con.mean()
v_rmdd_con_sd = v_rmdd_con.std()
v_rmdd_con_025 = np.percentile(v_rmdd_con, .025)
v_rmdd_con_975 = np.percentile(v_rmdd_con, .975)

v_rmdd_incon = m_reg.nodes_db.node['v_Intercept'].trace() +\
                     m_reg.nodes_db.node['v_C(group)[T.rMDD]:
 ↪C(trial_type)[congruent]'].trace() +\
                     m_reg.nodes_db.node['v_C(group)[T.rMDD]:
 ↪C(trial_type)[incongruent]'].trace()
v_rmdd_incon_mean = v_rmdd_incon.mean()
v_rmdd_incon_sd = v_rmdd_incon.std()
v_rmdd_incon_025 = np.percentile(v_rmdd_incon, .025)
v_rmdd_incon_975 = np.percentile(v_rmdd_incon, .975)

v_si_con = m_reg.nodes_db.node['v_Intercept'].trace() +\
                   m_reg.nodes_db.node['v_C(group)[T.SI]:
 ↪C(trial_type)[congruent]'].trace()
```

```
v_si_con_mean = v_si_con.mean()
v_si_con_sd = v_si_con.std()
v_si_con_025 = np.percentile(v_si_con, .025)
v_si_con_975 = np.percentile(v_si_con, .975)

v_si_incon = m_reg.nodes_db.node['v_Intercept'].trace() +\
                  m_reg.nodes_db.node['v_C(group)[T.SI]:
 ↪C(trial_type)[congruent]'].trace() +\
                  m_reg.nodes_db.node['v_C(group)[T.SI]:
 ↪C(trial_type)[incongruent]'].trace()
v_si_incon_mean = v_si_incon.mean()
v_si_incon_sd = v_si_incon.std()
v_si_incon_025 = np.percentile(v_si_incon, .025)
v_si_incon_975 = np.percentile(v_si_incon, .975)
```

[79]:
```
pd.DataFrame({'mean': [v_hc_con_mean, v_hc_incon_mean,
                       v_rmdd_con_mean, v_rmdd_incon_mean,
                       v_si_con_mean, v_si_incon_mean],
              'sd': [v_hc_con_sd, v_hc_incon_sd,
                       v_rmdd_con_sd, v_rmdd_incon_sd,
                       v_si_con_sd, v_si_incon_sd],
              '2.5q': [v_hc_con_025, v_hc_incon_025,
                       v_rmdd_con_025, v_rmdd_incon_025,
                       v_si_con_025, v_si_incon_025],
              '97.5q': [v_hc_con_975, v_hc_incon_975,
                       v_rmdd_con_975, v_rmdd_incon_975,
                       v_si_con_975, v_si_incon_975]},
             index=['HC congruent', 'HC incongruent',
                    'rMDD congruent', 'rMDD incongruent',
                    'SI congruent', 'SI incongrent'])
```

[79]:

	mean	sd	2.5q	97.5q
HC congruent	7.309539	0.218687	6.549412	6.799149
HC incongruent	5.597087	0.211446	4.845594	5.113322
rMDD congruent	6.911623	0.213450	6.142141	6.406015
rMDD incongruent	6.464528	0.438856	4.843601	5.366224
SI congruent	6.597242	0.269167	5.831092	5.990754
SI incongrent	6.039798	0.542169	4.484290	4.849278

For HCs, their average drift rate was 7.31 on congruent trials, and switching to incongruent trials significantly slowed down their drift rates (v_C(trial_type)[T.incongruent] = -1.71, 95%CI = [-1.87, -1.56]). Drift rate of individuals with rMDD did not differ significantly from that of HCs during congruent trials (v_C(group)[T.rMDD]:C(trial_type)[congruent] = -0.40, 95%CI = [-0.97, 0.18]). Drift rate of individuals with current SI was significantly lower than that of HCs during congruent trials (v_C(group)[T.SI]:C(trial_type)[congruent] = -0.71, 95%CI = [-1.33, -0.03]). The average drift rate of individuals with rMDD during incongruent trials was 6.46, and that of individuals with current SI during incongruent trials was 6.04.