HW 9

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Research Question

> Is there a difference in how people imagine the future self when they are primed to think about the self as stable or changeable?

Variables

- `Vividness`: subjective rating of the vividness of the imagined future self (2 items on a 6 point scale averaged)
- `Connectedness`: subjective rating of the perceived connectedness of the imagined future self (2 items on a 6 point scale averaged)
- `Distance`: subjective rating of the temporal distance of the imagined future self (2 items on a 6 point scale averaged)
- `Relevance`: subjective rating of how relevant the imagined future self feels (2 items on a 6 point scale averaged)
- `Condition`: 1 = self-stability, 2 = self-change

Import Data

```
data <- read_sav("data.sav")
```

Variable Summary

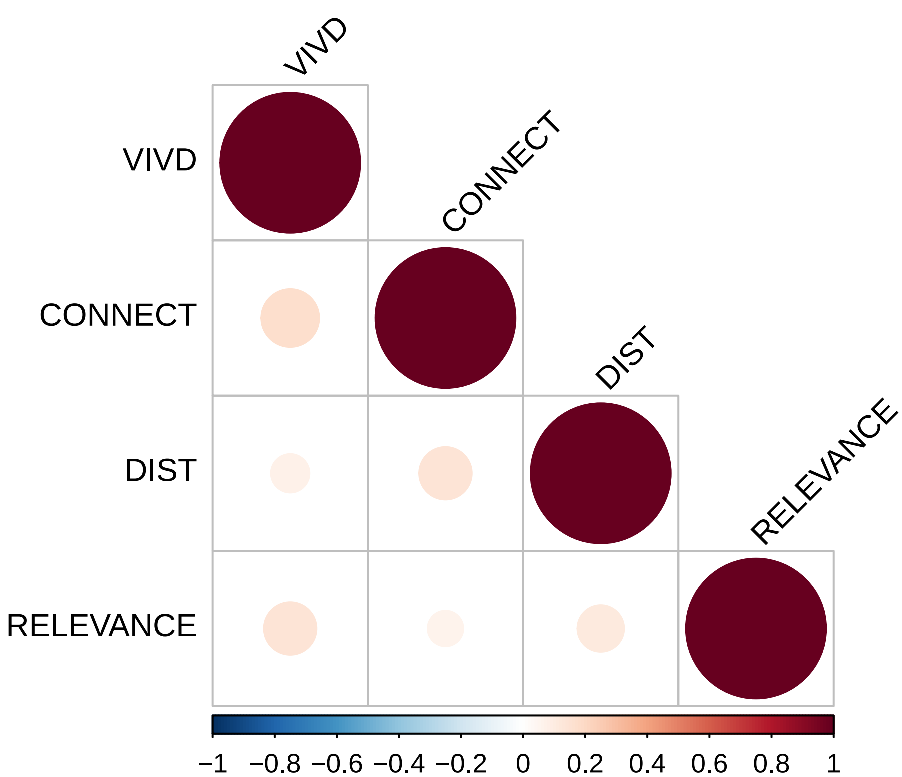
```
#Data
# describe(data)

##Summary Statistics for Variables of Interest
describeBy(data.frame(data$VIVD, data$CONNECT, data$DIST, data$RELEVANCE), data$COND)
```

```
##
##  Descriptive statistics by group
## group: 1
##                 vars   n mean   sd median trimmed  mad min max range skew
## data.VIVD          1 138 3.39 0.42    3.5    3.39 0.00 2.5 4.5   2.0 0.04
## data.CONNECT       2 138 3.85 0.55    4.0    3.84 0.74 2.0 5.0   3.0 0.11
```

```
## data.DIST          3 138 3.62 0.45    3.5    3.60 0.74 2.5 5.0    2.5 0.47
## data.RELEVANCE     4 138 3.66 0.57    3.5    3.61 0.74 1.5 6.0    4.5 0.72
##                kurtosis   se
## data.VIVD          0.42 0.04
## data.CONNECT       0.08 0.05
## data.DIST          0.76 0.04
## data.RELEVANCE     3.20 0.05
## ------------------------------------------------------------
## group: 2
##                vars   n mean   sd median trimmed  mad min max range  skew
## data.VIVD         1 142 3.39 0.51    3.5    3.39 0.74 2.0 5.0     3  0.13
## data.CONNECT      2 142 3.79 0.55    3.5    3.78 0.74 2.5 5.5     3  0.34
## data.DIST         3 142 3.54 0.52    3.5    3.57 0.74 2.0 5.0     3 -0.50
## data.RELEVANCE    4 142 3.56 0.52    3.5    3.55 0.00 1.0 5.0     4 -0.41
##                kurtosis   se
## data.VIVD          0.42 0.04
## data.CONNECT       0.10 0.05
## data.DIST          0.81 0.04
## data.RELEVANCE     3.91 0.04
```

```
##Correlation Matrix
source("http://www.sthda.com/upload/rquery_cormat.r")
#Combined
rquery.cormat(data[c("VIVD","CONNECT","DIST","RELEVANCE")], type="flatten")
```




```
## $r
```

```
##       row    column   cor      p
## 1    VIVD   CONNECT 0.170 0.0039
## 2    VIVD      DIST 0.075 0.2100
## 3 CONNECT      DIST 0.140 0.0230
## 4    VIVD RELEVANCE 0.140 0.0200
## 5 CONNECT RELEVANCE 0.064 0.2900
## 6    DIST RELEVANCE 0.110 0.0710
##
## $p
## NULL
##
## $sym
## NULL
```

```
#By Condition
data.short <- data[c("COND","VIVD","CONNECT","DIST","RELEVANCE")]


#Exploratory Factor Analysis
```

Model

Let Y = VIVIDNESS, CONNECTION, TEMPORAL DISTNACE, & RELEVANCE, G = CONDITION (CONTINUITY v CHANGE)

Model:

$$Y_{i,G=0} \sim N(\mu_1, \sigma_1)$$
$$Y_{i,G=1} \sim N(\mu_2, \sigma_2)$$

Prior:

$$\mu_1 \sim N(0,1)$$
$$\mu_2 \sim N(0,1)$$
$$\sigma_1 \sim N^+(0,1)$$
$$\sigma_2 \sim N^+(0,1)$$

Running Stan

We used 4 chains, each with 4,000 iterations (first 2,000 as warm-ups).

```
# 1. form the data list for Stan
vivid <- with(data,
    list(N1 = sum(COND == 1),
         N2 = sum(COND == 2),
         y1 = VIVD[which(COND == 1)],
         y2 = VIVD[which(COND == 2)])
)

conn <- with(data,
    list(N1 = sum(COND == 1),
         N2 = sum(COND == 2),
         y1 = CONNECT[which(COND == 1)],
```

```
        y2 = CONNECT[which(COND == 2)])
)

dist <- with(data,
    list(N1 = sum(COND == 1),
         N2 = sum(COND == 2),
         y1 = DIST[which(COND == 1)],
         y2 = DIST[which(COND == 2)])
)

rel <- with(data,
    list(N1 = sum(COND == 1),
         N2 = sum(COND == 2),
         y1 = RELEVANCE[which(COND == 1)],
         y2 = RELEVANCE[which(COND == 2)])
)

# 2. Run Stan
m.vivid <- stan(
    file = "stan.stan",
    data = vivid,
    seed = 1234,  # for reproducibility
    iter = 4000
)

m.conn <- stan(
    file = "stan.stan",
    data = conn,
    seed = 1234,  # for reproducibility
    iter = 4000
)

m.dist <- stan(
    file = "stan.stan",
    data = dist,
    seed = 1234,  # for reproducibility
    iter = 4000
)

m.rel <- stan(
    file = "stan.stan",
    data = rel,
    seed = 1234,  # for reproducibility
    iter = 4000
)
```

Results

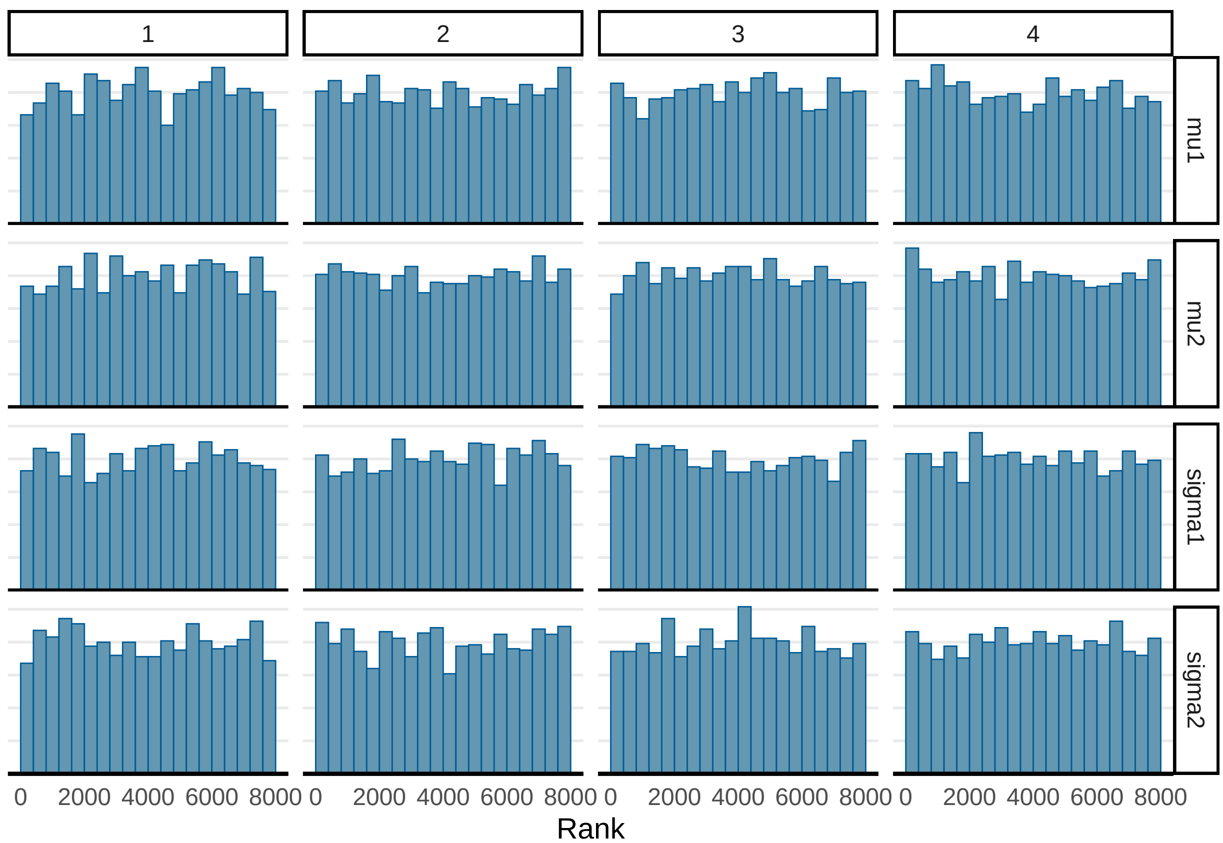
As shown in the graph below, the chains mixed well and the ESS is very high.

```r
# print(m.vivid, pars = c("mu1", "mu2", "sigma1", "sigma2"))

m.vivid %>%
    as_draws() %>%
    subset_draws(variable = c("mu1", "mu2", "sigma1", "sigma2")) %>%
    summarize_draws() %>%
    knitr::kable()
```

variable	mean	median	sd	mad	q5	q95	rhat	ess_bulk	ess_tail
mu1	3.3907349	3.3910878	0.0352901	0.0348142	3.3320337	3.4486169	1.000423	9188.010	6280.981
mu2	3.3842857	3.3841431	0.0429780	0.0419531	3.3132136	3.4546273	1.000507	9566.941	6243.262
sigma1	0.4241624	0.4230054	0.0262570	0.0260272	0.3831639	0.4697922	1.000106	9100.622	5994.965
sigma2	0.5163976	0.5146121	0.0316075	0.0316704	0.4678833	0.5705620	1.000568	9074.299	5858.812

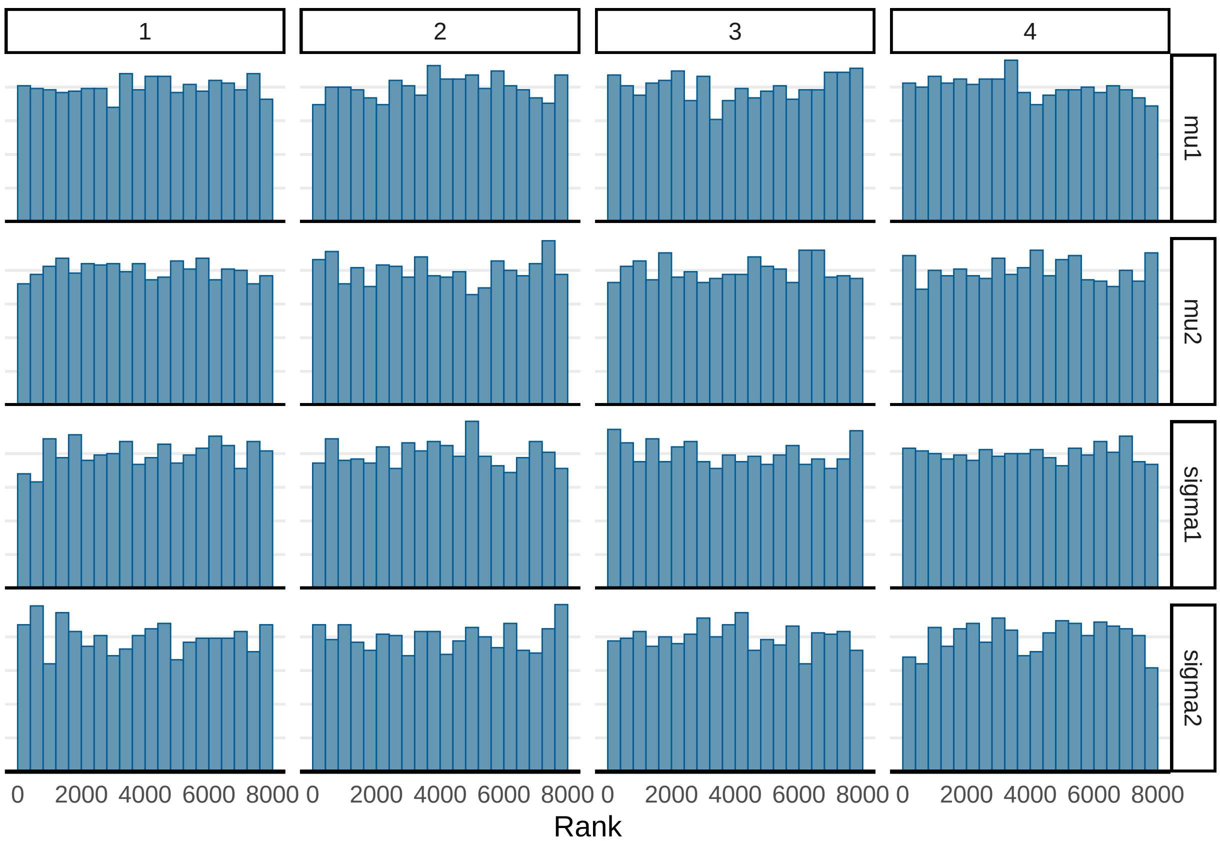
```r
mcmc_rank_hist(m.vivid, pars = c("mu1", "mu2", "sigma1", "sigma2"))
```




```r
m.conn %>%
    as_draws() %>%
    subset_draws(variable = c("mu1", "mu2", "sigma1", "sigma2")) %>%
    summarize_draws() %>%
    knitr::kable()
```

variable	mean	median	sd	mad	q5	q95	rhat	ess_bulk	ess_tail
mu1	3.8430574	3.8429508	0.0469256	0.0457713	3.7654191	3.9215139	1.000405	9979.452	6239.443
mu2	3.7802845	3.7798784	0.0464829	0.0462095	3.7046060	3.8573242	1.000036	9826.342	6514.629
sigma1	0.5557392	0.5544471	0.0326691	0.0320328	0.5048525	0.6116920	1.000070	9121.289	5569.636
sigma2	0.5506291	0.5489496	0.0330004	0.0322975	0.5003631	0.6073617	1.000624	10344.865	6463.065

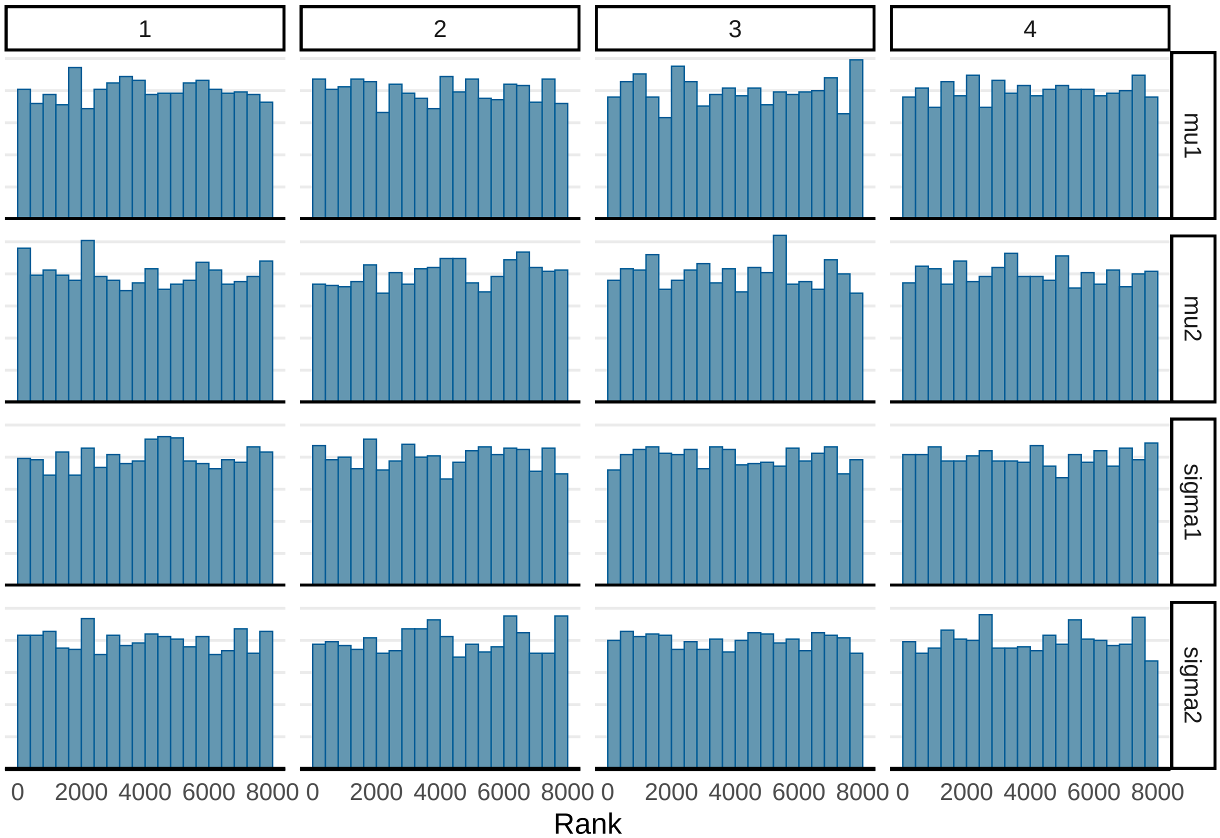
```
mcmc_rank_hist(m.conn, pars = c("mu1", "mu2", "sigma1", "sigma2"))
```




```
m.dist %>%
    as_draws() %>%
    subset_draws(variable = c("mu1", "mu2", "sigma1", "sigma2")) %>%
    summarize_draws() %>%
    knitr::kable()
```

variable	mean	median	sd	mad	q5	q95	rhat	ess_bulk	ess_tail
mu1	3.6101415	3.6101170	0.0390757	0.0392591	3.5470783	3.6750709	0.9999150	8917.722	6073.976
mu2	3.5320689	3.5317296	0.0447203	0.0449557	3.4594890	3.6051741	1.0006984	9339.992	6376.772
sigma1	0.4569586	0.4553705	0.0278949	0.0277808	0.4144171	0.5052760	0.9998198	9940.592	6114.560
sigma2	0.5204312	0.5188662	0.0310412	0.0306295	0.4728284	0.5737163	0.9998475	9206.605	6301.722

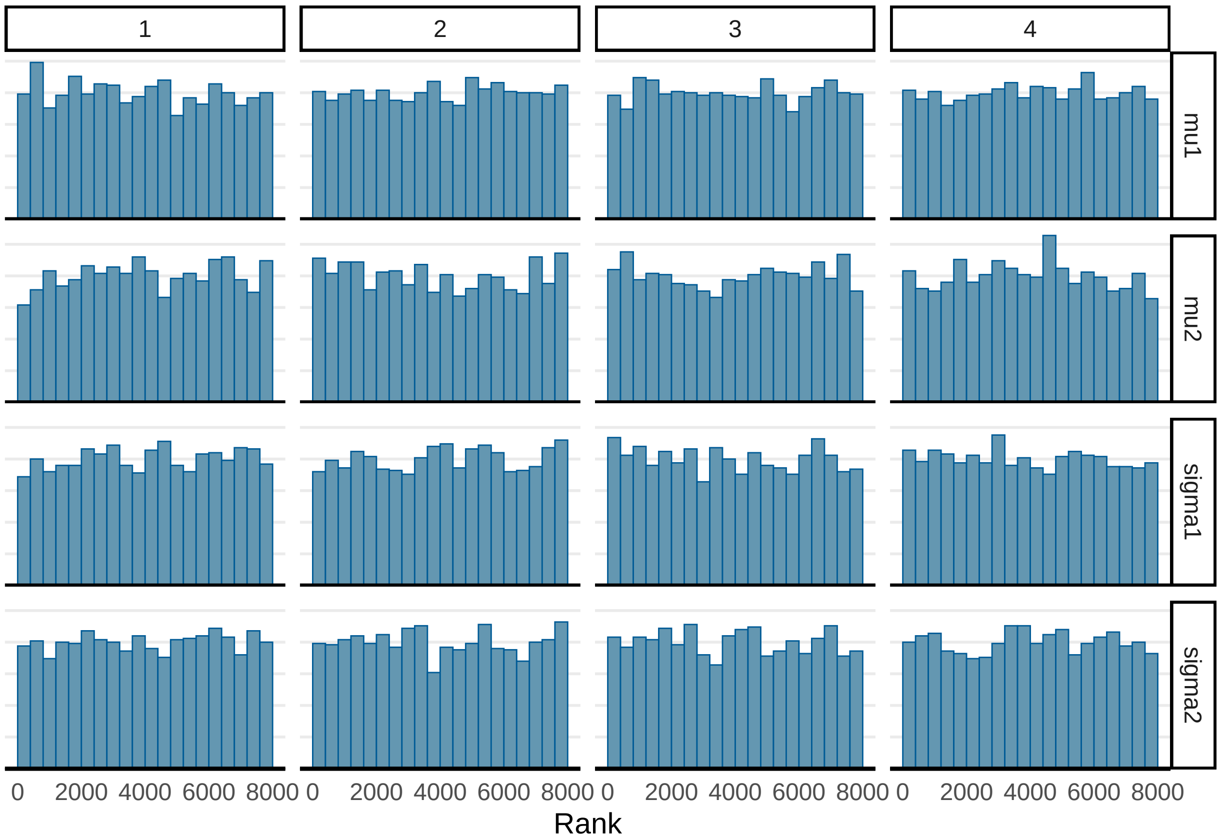
```r
mcmc_rank_hist(m.dist, pars = c("mu1", "mu2", "sigma1", "sigma2"))
```




```r
m.rel %>%
    as_draws() %>%
    subset_draws(variable = c("mu1", "mu2", "sigma1", "sigma2")) %>%
    summarize_draws() %>%
    knitr::kable()
```

variable	mean	median	sd	mad	q5	q95	rhat	ess_bulk	ess_tail
mu1	3.6472633	3.6472525	0.0485154	0.0478558	3.5675065	3.7275468	1.001161	8520.292	6423.841
mu2	3.5492926	3.5489831	0.0443474	0.0445801	3.4763958	3.6218185	1.000738	8790.563	5861.538
sigma1	0.5709442	0.5695976	0.0353045	0.0353547	0.5161341	0.6308926	1.000152	8267.167	5871.464
sigma2	0.5236025	0.5221812	0.0322051	0.0318594	0.4729996	0.5792244	1.000783	8575.671	6327.083

```r
mcmc_rank_hist(m.rel, pars = c("mu1", "mu2", "sigma1", "sigma2"))
```



The following table shows the posterior distributions of μ_1, μ_2, σ_1, σ_2, and $\mu_2 - \mu_1$.

```
summ_m.vivid <- as_draws_df(m.vivid) %>%
    subset_draws(variable = c("mu1", "mu2", "sigma1", "sigma2")) %>%
    mutate_variables(`mu2 - mu1` = mu2 - mu1) %>%
    summarise_draws()
knitr::kable(summ_m.vivid, digits = 2)
```

variable	mean	median	sd	mad	q5	q95	rhat	ess_bulk	ess_tail
mu1	3.39	3.39	0.04	0.03	3.33	3.45	1	9188.01	6280.98
mu2	3.38	3.38	0.04	0.04	3.31	3.45	1	9566.94	6243.26
sigma1	0.42	0.42	0.03	0.03	0.38	0.47	1	9100.62	5994.97
sigma2	0.52	0.51	0.03	0.03	0.47	0.57	1	9074.30	5858.81
mu2 - mu1	-0.01	-0.01	0.06	0.06	-0.10	0.09	1	9348.93	5756.37

```
summ_m.conn <- as_draws_df(m.conn) %>%
    subset_draws(variable = c("mu1", "mu2", "sigma1", "sigma2")) %>%
    mutate_variables(`mu2 - mu1` = mu2 - mu1) %>%
    summarise_draws()
knitr::kable(summ_m.conn, digits = 2)
```

variable	mean	median	sd	mad	q5	q95	rhat	ess_bulk	ess_tail
mu1	3.84	3.84	0.05	0.05	3.77	3.92	1	9979.45	6239.44
mu2	3.78	3.78	0.05	0.05	3.70	3.86	1	9826.34	6514.63
sigma1	0.56	0.55	0.03	0.03	0.50	0.61	1	9121.29	5569.64
sigma2	0.55	0.55	0.03	0.03	0.50	0.61	1	10344.87	6463.07
mu2 - mu1	-0.06	-0.06	0.07	0.07	-0.17	0.05	1	10142.12	5900.34

```r
summ_m.dist <- as_draws_df(m.dist) %>%
    subset_draws(variable = c("mu1", "mu2", "sigma1", "sigma2")) %>%
    mutate_variables(`mu2 - mu1` = mu2 - mu1) %>%
    summarise_draws()
knitr::kable(summ_m.dist, digits = 2)
```

variable	mean	median	sd	mad	q5	q95	rhat	ess_bulk	ess_tail
mu1	3.61	3.61	0.04	0.04	3.55	3.68	1	8917.72	6073.98
mu2	3.53	3.53	0.04	0.04	3.46	3.61	1	9339.99	6376.77
sigma1	0.46	0.46	0.03	0.03	0.41	0.51	1	9940.59	6114.56
sigma2	0.52	0.52	0.03	0.03	0.47	0.57	1	9206.61	6301.72
mu2 - mu1	-0.08	-0.08	0.06	0.06	-0.18	0.02	1	9320.43	5794.30

```r
summ_m.rel <- as_draws_df(m.rel) %>%
    subset_draws(variable = c("mu1", "mu2", "sigma1", "sigma2")) %>%
    mutate_variables(`mu2 - mu1` = mu2 - mu1) %>%
    summarise_draws()
knitr::kable(summ_m.rel, digits = 2)
```

variable	mean	median	sd	mad	q5	q95	rhat	ess_bulk	ess_tail
mu1	3.65	3.65	0.05	0.05	3.57	3.73	1	8520.29	6423.84
mu2	3.55	3.55	0.04	0.04	3.48	3.62	1	8790.56	5861.54
sigma1	0.57	0.57	0.04	0.04	0.52	0.63	1	8267.17	5871.46
sigma2	0.52	0.52	0.03	0.03	0.47	0.58	1	8575.67	6327.08
mu2 - mu1	-0.10	-0.10	0.06	0.06	-0.20	0.01	1	8700.72	6632.65

The analysis showed that on average, the two conditions did not differ significantly in how vividly they imagined the future self, with a posterior mean of -0.01. However, the stability condition did perceive the future self as more connected -0.06, temporally closer -0.08, and more relevant -0.1.