

1 **Supplementary Information:**

2 **Human mate-choice copying is domain-general social learning**

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29 **1. Experimental design**

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31 **1.1 Memorability of initial ratings**

32

33 Our experimental design involved participants providing initial ratings and viewing social
34 information for a block of images, before re-rating the images ('final ratings') following
35 completion of the block (Methods). Participants completed the experiment in either in 3
36 blocks of 10 trials (for 4 of 6 experimental groups, N=33 participants) or 6 blocks of 5 trials
37 (for 2 of 6 experimental groups, N=16 participants). Consequently, there was a time delay
38 between providing initial ratings and providing final ratings, of ~10 minutes where longer
39 blocks were used, or ~5 minutes where shorter blocks were used. Shorter blocks were used
40 in addition to longer blocks, in case the greater time delay caused by longer blocks
41 undermined the ability of participants to remember their initial ratings and social information
42 when re-rating images.

43

44 In the post experiment questionnaire (SI 1.3), participants were asked to record, using a
45 sliding scale, the extent to which they could remember their initial ratings when providing
46 their final ratings, on a scale from 0 to 100. Participants reported mostly being able to
47 remember their own ratings (mean 72.18, ± 20.35). Further, self-reported memorability of
48 initial ratings did not differ between participants who completed the study in 6 blocks of 5
49 trials (N=16) or 3 blocks of 10 trials (N=33, two sample T-test: $T=-0.07$, $p=0.94$). Therefore,
50 we pooled data across the two blocking conditions for all analyses.

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56 **1.2 Participant instructions**

57

58 *Read aloud to participants:*

59

60 “In this study you will see images of human faces, human hands and works of art. Your task
61 will be to rate these images for attractiveness. You will receive a £5 Amazon voucher for
62 taking part. The study consists of 30 questions arranged into [3 blocks of 10/6 blocks of 5].
63 Within each block, first you will rate all the images and be told what some of the other
64 participants thought. You will be shown the average rating of some or all of the other
65 participants, but you will not know whose ratings you are seeing. After rating all the images
66 within the block, you will then re-rate all the images, although the order will be different. After
67 you have completed all the blocks the study will end.”

68

69 “During the experiment, please interact only with the white window open on your screen now
70 and please do not talk to other participants until you have been handed a debriefing sheet.
71 You are free to withdraw at any time should you wish. One of us will be sitting in the
72 adjacent room throughout the entire experiment should you have any problems.”

73

74 *Ask if they all understand or have questions*

75

76 “Please click the arrow on your screen to continue.”

77

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83 1.3 Post-experiment questionnaire

84

85 After completion of the study, participants were asked to complete a short questionnaire.

86 Participants were reminded that their responses were voluntary, and all questions included a

87 'prefer not to say' option. Participants had to be aged 18 or over to take part in the study, but

88 we did not request participants' ages in the post-experiment questionnaire. Participants were

89 asked to report their sexual orientation using a 7-point scale (where 0 indicated exclusively

90 heterosexual and 6 exclusively homosexual). 42/49 participants reported their sexual

91 orientation as 0 or 1, while 7/49 reported their sexual orientation as 2-6. Participants were

92 asked to self-describe their ethnicity using a free response box. Participants were asked

93 whether they did or did not know any other participants in the group. 15/49 reported that they

94 did know one or more of the other participants in the group, 32/49 reported that they did not,

95 and 2/49 reported 'prefer not to say'. Participants were asked to report, using a sliding scale,

96 to what extent they could remember their initial ratings when providing their final ratings,

97 where 100=maximum and 0=minimum, reporting a mean and standard deviation of 72.18,

98 ± 20.35 .

99

100 Participants were asked to describe, using a free response box, how they decided to follow

101 or ignore the social information they were shown. Of the 48/49 participants who responded

102 to this question, 23 could be classified as reporting using a mixture of both their own

103 judgement and the social information, while 24 reported using mostly their own judgement,

104 and 1 gave an unclear answer. 15 of these 48 participants felt that they used the social

105 information differently between the image types, and of 10 reporting being influenced most

106 strongly by one image type in particular, 6 reported being most influenced for images of art,

107 4 for hands, and 2 for faces. Finally, participants were asked to describe, using a free

108 response box, what they thought the intention of the experiment was. Of the 48/49

109 participants that responded to this question, all but one understood that the point of the

110 experiment was to study social learning, but only 3 showed awareness that the intention was

111 to compare copying between different types of image. No participant responded in a way
112 suggesting that they misunderstood the experimental task, or did not believe that the social
113 information was genuine. Therefore, we were confident that participants understood the
114 experimental task and treated the social information as genuine.

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117 **2. Supplementary results**

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119 **2.1 Supplementary analysis including non-heterosexual participants**

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121 In our main analysis, we include only those participants (N=42) self-identifying as exclusively
122 or near-exclusively heterosexual (0 or 1 on a 7-point scale where 0 indicates exclusively
123 heterosexual, and 6 exclusively homosexual). When running our analysis on all (N=49)
124 participants, we find highly similar results.

125

126 *Model performance*

127

128 As in our main analysis, there was a correlation of 0.92 between predicted and observed
129 final ratings (pseudo-R² 0.84, N=1470), confirming that the model was appropriate for the
130 data.

131

132 *Chain performance*

133

134 Similarly to our main analysis, chain convergence was confirmed by large effective sample
135 sizes (range 3472 to 16538), and Gelman-Rubin statistics (all point estimates = 1, all upper
136 C.I.s = 1.01) across all estimated parameters.

137

138 *Effect of condition on social influence*

139

140 Similarly to our main analysis, when all participants were included, social information
141 affected participants' final ratings of images of faces (social influence median estimate =
142 0.14, [95% CI: 0.06, 0.22]), hands (social influence = 0.12, [0.04, 0.19]) and abstract art
143 (social influence = 0.15, [0.08, 0.22]). Again, medians and 95% CI for contrasts in social
144 influence between conditions suggested that differences were very close to zero (faces –
145 hands = 0.03 [-0.02, 0.07], faces – art = -0.01 [-0.05, 0.04], art – hands = 0.03, [-0.02, 0.08]).

146

147 *Individual participant effects*

148

149 As in our main analysis, the median variance of the random participant effect was 0.06 [0.04,
150 0.09], suggesting that relatively little of the variance in social influence was explained by
151 consistent differences in social influence between participants.

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172 **2.2 Supplementary analysis allowing participant effects to differ between conditions**

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174 As in our main analysis, here we include only those participants (N=42) self-identifying as
175 exclusively or near-exclusively heterosexual.

176

177 *Model performance*

178

179 Very similarly to our main analysis, there was a correlation of 0.92 between predicted and
180 observed final ratings (pseudo- R^2 0.85, N=1260), confirming that the model was appropriate
181 for the data.

182

183 *Chain performance*

184

185 The model included three parallel chains, each of 50,000 iterations thinned by 10 to reduce
186 autocorrelation. At completion, the effective sample size for the different variables ranged
187 from 4,813 to 16,068. Chain convergence was checked using the Gelman-Rubin
188 convergence diagnostic (all point estimates = 1, all upper C.I. = 1, except in one case where
189 the upper C.I. was 1.01).

190

191 *Effect of condition on social influence*

192

193 Very similarly to our main analysis, when allowing participant effects to vary with condition,
194 social information affected participants' final ratings of images of faces (social influence
195 median estimate = 0.13, [95% CI: 0.04, 0.22]), hands (social influence = 0.15, [0.05, 0.25])
196 and abstract art (social influence = 0.13, [0.04, 0.22]). Again, 95% CI for contrasts in social
197 influence between conditions suggested that differences were close to, if not precisely, 0
198 (faces – hands = -0.02 [-0.15, 0.12], faces – art = <0.01 [-0.13, 0.13], art – hands = -0.02, [-
199 0.15, 0.11]).

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Effect of condition on participant effects

We find that the variance between participants in social influence is very similar for images of artwork (0.08 [0.05, 0.12]), faces (0.08 [0.05, 0.12]) and hands (0.08, [0.05, 0.14]). All contrasts between conditions in the between-participant variance were very close to zero (faces – hands = -0.01 [-0.06, 0.05], faces – art = >-0.01 [-0.05, 0.05], art – hands = -0.01 [-0.07, 0.05]).

224 **2.3 Supplementary analysis with flatter prior distributions**

225

226 The careful choice of priors is an essential part of a Bayesian analysis. In the main paper,
227 we present the results of an analysis that used “weakly regularizing priors” as suggested by
228 an anonymous reviewer. These are priors that minimally constrain the output of the analysis
229 by encouraging the model to focus on biologically plausible values. For instance, the social
230 influence parameters for each condition were given, as a prior, a normal distribution with a
231 mean of 0 and a variance of 1. This encourages the model to favour estimates of these
232 parameters with a magnitude close to 0 and gives a very high chance that the magnitude is
233 less than 3. Given that a value of 0 is no social information use, and a value of 1 is total
234 conformity, this seems reasonable. Nonetheless it is important to check that the results are
235 not unduly influenced by the choice of priors, so here we present the results of another
236 analysis in which the priors were extremely flat. In this case the priors for the condition
237 effects are normal distributions with a mean of 0 and a variance of 100. The prior for the
238 variation between participants, which was an exponential distribution with a parameter value
239 of 1 in the main paper, is instead gamma distributed with a shape and rate of 0.001.

240

241 Weakly regularizing priors are typically considered a better option than these extremely flat
242 priors, as our anonymous reviewer pointed out. For instance, the extremely broad priors for
243 the condition effects imply that the conditions are likely to be extremely different from each
244 other and characterized by extreme values of social influence. While biologically plausible
245 values will mainly fall between 0 and 1, values such as -200 are treated as perfectly
246 plausible by the model with flat priors. Nonetheless, with enough data the priors can be
247 overwhelmed and results should not be unduly affected. We therefore present these
248 additional results to verify the robustness of our findings.

249

250

251 *Model performance*

252

253 As with our main analysis, we found a correlation of 0.92 between predicted and observed
254 final ratings (pseudo- R^2 0.84, $N=1260$), confirming that the model was appropriate for the
255 data.

256

257 *Chain performance*

258

259 Chain convergence was confirmed by large effective sample sizes (range 5334 to 7068) and
260 Gelman-Rubin statistics (all point estimates = 1, all upper C.I.s = 1.01).

261

262 *Effect of condition on social influence*

263

264 Replicating the results of our main analysis, social influence was highly similar for images of
265 faces (median estimate = 0.13, 95% CI: [0.08, 0.17]), hands (0.13, [0.08, 0.18]) and abstract
266 artwork (0.14, [0.10, 0.19]). As before, contrasts in social influence were effectively zero
267 (faces – hands = <-0.01 [-0.05, 0.05], faces – art = -0.02 [-0.06, 0.03], art - hands = 0.01, [-
268 0.04, 0.06])

269

270 *Individual participant effects*

271

272 Similarly to our main analysis, we found a low random participant effect (median estimate =
273 0.01 [<0.01 , 0.02]), suggesting little evidence of consistent individual differences in social
274 influence.

275

276 **3. Dataset details and analysis code**

277

278 **3.1 Details of dataset**

279 **‘Street_et_al_image_preference_data_2017.csv’ contains the following columns:**

280

281 **playerID** numerical player identifier (1-49)

282

283 **trialID** numerical trial identifier (1-1470)

284

285 **groupID** numerical group identifier (1-6)

286

287 **nplayers** number of players in group (5-10)

288

289 **condition** type of image viewed and rated in the trial (art, faces or hands)

290

291 **questions.per.block** number of questions in block (5 or 10)

292

293 **initial.rating** initial attractiveness rating (minimum 0, maximum 100)

294

295 **initial.decision.time** time taken to provide initial attractiveness rating (milliseconds)

296

297 **social.rating** attractiveness rating of some or all other players (minimum 0,
298 maximum 100)

299

300 **social.decision.time** time taken to view social information (milliseconds)

301

302 **final.rating** final attractiveness rating (minimum 0, maximum 100)

303

304	final.decision.time	time taken to provide final attractiveness rating (milliseconds)
305		
306	orientation	participant sexual orientation (minimum 0=exclusively heterosexual,
307		maximum 6=exclusively homosexual)
308		
309	know.anyone	whether participant knew any others in the group (yes, no,
310		prefer_not_to_answer)
311		
312	remember.initial.ratings	to what extent participant reported being able to remember initial
313		ratings when providing final ratings (minimum 0, maximum 100)
314		
315	use.social.info	coded from free responses to question of how participant chose to use
316		or ignore social information (mostly_individual = participant
317		reported using only or primarily individual preferences,
318		both_social_and_individual = participant reported using both social
319		information and individual preferences, not_clear = participant did
320		not provide a clear answer, no_answer = participant provided no
321		answer).
322		
323	experiment.intent	coded from free responses to question of what participant thought
324		was the intention of the experiment (social_influence = participant
325		perceived the intention of the study to be related to social influence,
326		non_social_influence = participant perceived the intention of the
327		study to be unrelated to social influence,
328		social_influence_image_types = participant perceived the intention
329		of the experiment as comparing social influence between image
330		types, no_answer = participant provided no answer).

331 **3.2 R code for main analysis**

```
332
333 # load packages
334 library(rjags)
335 library(coda)
336
337 # load data
338 data<-read.csv("Street_et_al_image_preference_data_2017.csv",
339 header=T)
340 str(data) # data file contains 1470 observations from total 49
341 players
342
343 # for the main analysis, include only participants who are
344 exclusively or near-exclusively heterosexual (0 or 1 on the response
345 scale)
346 data2<-subset(data, orientation<2)
347 str(data2) # data file contains 1260 observations from total 42
348 players
349
350 # re-assign player ID numbers (must be numbered 1:42 for model to
351 run)
352 data2$playerIDnew<-as.numeric(as.factor(data2$playerID))
353
354 # select the variables for analysis
355 initial<-data2$initial.rating # participants' initial rating
356 social<-data2$social.rating # social information
357 final<-data2$final.rating # participants' final rating
358 player<-data2$playerIDnew # player identity
359 condition<-as.numeric(data2$condition) # content type (art=1,
360 faces=2, hands=3)
361
362 # extract the sample sizes
363 N<-length(final) # total number of trials
364 N_players<-length(unique(data2$playerID)) # total number of
365 participants
366
367 # transform all ratings to fall between 0 and 1
368 p.final<-(final/100)*0.999+0.0005
369 p.initial<-(initial/100)*0.999+0.0005
370 p.social<-(social/100)*0.999+0.0005
371
372 # load the model, setup to run for 3 chains, with a burn-in period
373 of 5000 iterations
374 model<-jags.model("Street_et_al_2017_main_model_JAGS_code.bug.txt",
375 data=list('p.initial'=p.initial, 'p.social'=p.social,
376 'p.final'=p.final, 'player'=player, 'N_players'=N_players,
377 'condition'=condition, 'N'=N), n.chains=3, n.adapt=5000, quiet=F)
378
379 # run the model (takes around 25 minutes, runs 50000 iterations,
380 sampling every 10 generations for each chain)
```

```

381
382 # RUN ONLY ONE OF THE FOLLOWING TWO OPTIONS:
383
384 # OPTION 1: this line monitors the predicted final ratings, the
385 social influence parameter, the effect of image condition, the
386 random participant effect and the variance of the random participant
387 effect
388 results<-coda.samples(model, c('final_pred', 'social_influence',
389 'condition_influence_baseline', 'random_player_influence_effect',
390 'tau_players_social'), n.iter=50000, thin=10)
391 save(results, file="model_samples_full.txt")
392
393 # OPTION 2: this line is the same as the above but does not monitor
394 predicted final ratings, social_influence, or random player effects
395 (although these are still in the model). It will take up less space
396 on your hdd.
397 results<-coda.samples(model, c('condition_influence_baseline',
398 'tau_players_social'), n.iter=50000, thin=10)
399 save(results, file="model_samples_lite.txt")
400
401 # check the minimum effective sample sizes for all parameters
402 sample_size <- effectiveSize(results)
403 range(sample_size)
404
405 # check the Gelman convergence diagnostic for all parameters
406 # note this may break if using model_samples_full, suggest using
407 model_samples_lite instead
408 rhats <- gelman.diag(results)
409 rhats
410
411 # combine all three chains into a single data frame
412 combined_results <- rbind(as.data.frame(results[[1]]),
413 as.data.frame(results[[2]]), as.data.frame(results[[3]]))
414
415 # medians & 95% CI for condition effects on social learning #
416 quantile(combined_results$('condition_influence_baseline[1]',
417 c(0.025, 0.5, 0.975)) # art
418 quantile(combined_results$('condition_influence_baseline[2]',
419 c(0.025, 0.5, 0.975)) # faces
420 quantile(combined_results$('condition_influence_baseline[3]',
421 c(0.025, 0.5, 0.975)) # hands
422
423 # plot showing effect of condition (as used in Figure 2)
424 par(mfrow=c(3,1))
425 par(mar=c(7.5,6,2,2))
426 hist(combined_results$('condition_influence_baseline[1]',
427 col=rgb(1,0,0,0.75), xlab="", main="", cex.axis=2.5, xlim=c(-0.05,
428 0.30), ylim=c(0, 1500), breaks=50, ylab="", las=1, xaxt="n") # art
429 axis(1, at=c(-0.05, 0, 0.05, 0.10, 0.15, 0.20, 0.25, 0.30),
430 labels=F)
431 abline(h=0)

```

```

432 abline(v=median(combined_results$'condition_influence_baseline[1]'),
433 lty=2, lwd=3)
434 abline(v=quantile(combined_results$'condition_influence_baseline[1]'
435 , 0.025), lty=2)
436 abline(v=quantile(combined_results$'condition_influence_baseline[1]'
437 , 0.975), lty=2)
438 hist(combined_results$'condition_influence_baseline[2]',
439 col=rgb(0,0,1,0.75), breaks=50, main="", cex.axis=2.5, xlim=c(-0.05,
440 0.30), ylim=c(0, 1500), ylab="", las=1, xlab="", xaxt="n") # faces
441 axis(1, at=c(-0.05, 0, 0.05, 0.10, 0.15, 0.20, 0.25, 0.30),
442 labels=F)
443 abline(h=0)
444 abline(v=median(combined_results$'condition_influence_baseline[2]'),
445 lty=2, lwd=3)
446 abline(v=quantile(combined_results$'condition_influence_baseline[2]'
447 , 0.025), lty=2)
448 abline(v=quantile(combined_results$'condition_influence_baseline[2]'
449 , 0.975), lty=2)
450 hist(combined_results$'condition_influence_baseline[3]',
451 col=rgb(1,1,0,0.75), breaks=50, main="", xlim=c(-0.05, 0.30),
452 ylim=c(0, 1500), xlab="", ylab="", las=1, xaxt="n", cex.axis=2.5) #
453 hands
454 axis(1, at=c(-0.05, 0, 0.05, 0.10, 0.15, 0.20, 0.25, 0.30),
455 labels=T, cex.axis=2.5, padj=1)
456 abline(h=0)
457 abline(v=median(combined_results$'condition_influence_baseline[3]'),
458 lty=2, lwd=3)
459 abline(v=quantile(combined_results$'condition_influence_baseline[3]'
460 , 0.025), lty=2)
461 abline(v=quantile(combined_results$'condition_influence_baseline[3]'
462 , 0.975), lty=2)
463 mtext("Social influence by condition", side=1, line=5, cex=1.75)
464
465 # contrasts in effects of condition on social learning
466 Faces_v_Hands<-(combined_results$'condition_influence_baseline[2]'-
467 combined_results$'condition_influence_baseline[3]') # faces vs.
468 hands
469 quantile(Faces_v_Hands, c(0.025, 0.5, 0.975))
470
471 Faces_v_Art<-(combined_results$'condition_influence_baseline[2]'-
472 combined_results$'condition_influence_baseline[1]') # faces vs. art
473 quantile(Faces_v_Art, c(0.025, 0.5, 0.975))
474
475 Art_v_Hands<-(combined_results$'condition_influence_baseline[1]'-
476 combined_results$'condition_influence_baseline[3]') # art vs. hands
477 quantile(Art_v_Hands, c(0.025, 0.5, 0.975))
478
479 # individual participant effect
480 par(mfrow=c(1,1))
481 par(mar=c(5.1, 4.1, 4.1, 2.1))
482 hist(1/combined_results$tau_players_social)

```



```

483 1/median(combined_results$tau_players_social)
484 1/quantile(combined_results$tau_players_social, c(0.025, 0.975))
485 1/quantile(combined_results$tau_players_social, c(0.025, 0.5,
486 0.975))
487
488 # IF OPTION 1 WAS SELECTED, CHECK CORRESPONDENCE OF PREDICTED AND
489 OBSERVED FINAL RATINGS
490
491 # extract predicted final ratings from all chains
492 results_means<-colMeans(combined_results) # take the column means,
493 to get the mean predicted final rating for each trial across the
494 posterior distribution
495 results_predicted_final<-results_means[grep("final_pred",
496 names(results_means))] # extract only the columns with predicted
497 final ratings
498
499 # Pseudo R^2 - Pearson's correlation of predicted vs. observed final
500 ratings
501 cor.test(results_predicted_final, p.final, method="pearson") #
502 Pearson's corr
503 cor.test(results_predicted_final, p.final,
504 method="pearson")$estimate^2 # pseudo R squared
505
506 # distribution of modelled final ratings compared to observed final
507 ratings (as used in Figure 3)
508 par(mfrow=c(2,1))
509 par(mar=c(7.5,6,4,2))
510 hist(p.final, cex.lab=2, col=rgb(0.3,0.6,0.3,0.25), main="",
511 cex.axis=2, ylim=c(0, 60), breaks=50, ylab="", las=1, xlab="Observed
512 final ratings")
513 hist(results_predicted_final, col=rgb(0.3,0.6,0.3,0.75), ylim=c(0,
514 60), breaks=50, xlab="Predicted final ratings", cex.axis=2,
515 cex.lab=2, main="", las=1, ylab="")
516
517
518
519

```

520 3.3 JAGS code for main analysis

521

```
522 ### Model
523
524 model{
525
526   for (i in 1:N) {
527
528     p.final[i] ~ dbeta(a_final[i], b_final[i]) # final ratings are
529     modelled as a beta distribution
530
531     a_final[i] <- final_pred[i] * phi_final # alpha shape parameter
532     for the beta distribution
533
534     b_final[i] <- (1 - final_pred[i]) * phi_final # beta shape
535     parameter for the beta distribution
536
537     logit(final_pred[i]) <- final_lp[i] # logit link function
538
539     final_lp[i] <- logit(p.initial[i]) + social_influence[i] *
540     social_deviation[i] # final ratings are predicted by the amount of
541     social influence, relative to the amount that initial ratings and
542     social information differ
543
544     social_deviation[i] <- logit(p.social[i]) - logit(p.initial[i])
545     + 0.00001 # social deviation is the difference between the social
546     information and the initial ratings, with a tiny constant added to
547     avoid zero values
548
549     social_influence[i] <-
550     condition_influence_baseline[condition[i]] +
551     random_player_influence_effect[player[i]] # social influence can
552     vary by image condition (faces, hands or art), and by a random
553     effect of participant identity
554
555   }
556
557 ### Priors
558
559   phi_final ~ dexp(1) # exponential prior for the shape parameters
560   for the beta distribution of modelled final ratings
561
562   for (i in 1:3) {
563     condition_influence_baseline[i] ~ dnorm(0,1) # normal prior for
564     the effect of image condition
565   }
566
567   for (i in 1:N_players) {
```

```
568     random_player_influence_effect[i] ~ dnorm(0, tau_players_social)
569 # normal prior for the random participant effect
570 }
571
572     tau_players_social ~ dexp(1) # exponential prior for the variance
573 of the random participant effect
574
575 }
576
577
```

578 3.4 R code for supplementary analysis

```
579 # load packages
580 library(rjags)
581 library(coda)
582
583 # load data
584 data<-read.csv("Street_et_al_image_preference_data_2017.csv",
585 header=T)
586 str(data) # data file contains 1470 observations from total 49
587 players
588
589 ### supplementary analysis: does participant self-reported ability
590 to remember initial ratings differ between blocking conditions (3 x
591 10 vs. 6 x 5 blocks)?
592
593 ppt_data<-aggregate(data[,c("playerID", "questions.per.block",
594 "remember.initial.ratings")], by=list(data$playerID), FUN="mean") #
595 collapse data to participant level. For convenience we aggregate by
596 the function 'mean'.
597
598 mean(ppt_data$remember.initial.ratings) # overall mean and SD for
599 self-reported memorability of initial ratings
600 sd(ppt_data$remember.initial.ratings)
601
602 t.test(ppt_data$remember.initial.ratings~as.factor(ppt_data$question
603 s.per.block), var.equal=T) # t-test assuming equal variances
604
605 library("car") # check if the assumption of equal variances is
606 violated using function in the 'car' package
607 leveneTest(remember.initial.ratings~as.factor(questions.per.block),
608 data=ppt_data) # assumption of equal variances not violated
609
610 #### supplementary analysis: replicating main analysis without
611 excluding any participants based on sexual identity
612
613 # select the variables for analysis
614 initial<-data$initial.rating # participants' initial rating
615 social<-data$social.rating # social information
616 final<-data$final.rating # participants' final rating
617 player<-data$playerID # player identity
618 condition<-as.numeric(data$condition) # content type (art=1,
619 faces=2, hands=3)
620
621 # extract the sample sizes
622 N<-length(final) # total number of trials
623 N_players<-length(unique(data$playerID)) # total number of
624 participants
625
626 # transform all ratings to fall between 0 and 1
627 p.final<-(final/100)*0.999+0.0005
```

```

628 p.initial<-(initial/100)*0.999+0.0005
629 p.social<-(social/100)*0.999+0.0005
630
631 # load the model, setup to run for 3 chains, with a burn-in period
632 of 5000 iterations
633 model<-jags.model("Street_et_al_2017_main_model_JAGS_code.bug.txt",
634 data=list('p.initial'=p.initial, 'p.social'=p.social,
635 'p.final'=p.final, 'player'=player, 'N_players'=N_players,
636 'condition'=condition, 'N'=N), n.chains=3, n.adapt=5000, quiet=F)
637
638 # run the model (takes around 25 minutes, runs 50000 iterations,
639 sampling every 10 generations for each chain)
640
641 # RUN ONLY ONE OF THE FOLLOWING TWO OPTIONS:
642
643 # OPTION 1: this line monitors the predicted final ratings, the
644 social influence parameter, the effect of image condition, the
645 random participant effect and the variance of the random participant
646 effect
647 results<-coda.samples(model, c('final_pred', 'social_influence',
648 'condition_influence_baseline', 'random_player_influence_effect',
649 'tau_players_social'), n.iter=50000, thin=10)
650 save(results, file="model_samples_full_all_ppts.txt")
651
652 # OPTION 2: this line is the same as the above but does not monitor
653 predicted final ratings, social_influence, or random player effects
654 (although these are still in the model). It will take up less space
655 on your hdd.
656 results<-coda.samples(model, c('condition_influence_baseline',
657 'tau_players_social'), n.iter=50000, thin=10)
658 save(results, file="model_samples_lite_all_ppts.txt")
659
660 # check the minimum effective sample sizes for all parameters
661 sample_size <- effectiveSize(results)
662 range(sample_size)
663
664 # check the Gelman convergence diagnostic for all parameters
665 # note this may break if using model_samples_full, suggest using
666 model_samples_lite instead
667 rhats <- gelman.diag(results)
668 rhats
669
670 # combine all three chains into a single data frame
671 combined_results <- rbind(as.data.frame(results[[1]]),
672 as.data.frame(results[[2]]), as.data.frame(results[[3]]))
673
674 # medians & 95% CI for condition effects on social learning #
675 quantile(combined_results$('condition_influence_baseline[1]',
676 c(0.025, 0.5, 0.975)) # art
677 quantile(combined_results$('condition_influence_baseline[2]',
678 c(0.025, 0.5, 0.975)) # faces

```

```

679 quantile(combined_results$'condition_influence_baseline[3]',
680 c(0.025, 0.5, 0.975)) # hands
681
682 # contrasts in effects of condition on social learning
683 Faces_v_Hands<-(combined_results$'condition_influence_baseline[2]'-
684 combined_results$'condition_influence_baseline[3]') # faces vs.
685 hands
686 quantile(Faces_v_Hands, c(0.025, 0.5, 0.975))
687
688 Faces_v_Art<-(combined_results$'condition_influence_baseline[2]'-
689 combined_results$'condition_influence_baseline[1]') # faces vs. art
690 quantile(Faces_v_Art, c(0.025, 0.5, 0.975))
691
692 Art_v_Hands<-(combined_results$'condition_influence_baseline[1]'-
693 combined_results$'condition_influence_baseline[3]') # art vs. hands
694 quantile(Art_v_Hands, c(0.025, 0.5, 0.975))
695
696 # individual participant effect
697 1/quantile(combined_results$tau_players_social, c(0.025, 0.5,
698 0.975))
699
700 # IF OPTION 1 WAS SELECTED, CHECK CORRESPONDENCE OF PREDICTED AND
701 OBSERVED FINAL RATINGS
702
703 # extract predicted final ratings from all chains
704 results_means<-colMeans(combined_results) # take the column means,
705 to get the mean predicted final rating for each trial across the
706 posterior distribution
707 results_predicted_final<-results_means[grep("final_pred",
708 names(results_means))] # extract only the columns with predicted
709 final ratings
710
711 # Pseudo R^2 - Pearson's correlation of predicted vs. observed final
712 ratings
713 cor.test(results_predicted_final, p.final, method="pearson") #
714 Pearson's corr
715 cor.test(results_predicted_final, p.final,
716 method="pearson")$estimate^2 # pseudo R squared
717
718

```

719 3.5 JAGS code for supplementary analysis

```
720
721 ### Model
722
723 model{
724
725   for (i in 1:N) {
726
727     p.final[i] ~ dbeta(a_final[i], b_final[i]) # final ratings are
728 modelled as a beta distribution
729
730     a_final[i] <- final_pred[i] * phi_final # alpha shape parameter
731 for the beta distribution
732
733     b_final[i] <- (1 - final_pred[i]) * phi_final # beta shape
734 parameter for the beta distribution
735
736     logit(final_pred[i]) <- final_lp[i] # logit link function
737
738     final_lp[i] <- logit(p.initial[i]) + social_influence[i] *
739 social_deviation[i] # final ratings are predicted by the amount of
740 social influence, relative to the amount that initial ratings and
741 social information differ
742
743     social_deviation[i] <- logit(p.social[i]) - logit(p.initial[i])
744 + 0.00001 # social deviation is the differences between the social
745 information and the initial ratings, with a tiny constant added to
746 avoid zero values
747
748     social_influence[i] <-
749 condition_influence_baseline[condition[i]] +
750 random_player_influence_effect[condition[i], player[i]] # social
751 influence can vary by image condition (faces, hands or artwork), and
752 by a random effect of participant identity. Additionally, the random
753 participant identity effect can differ by condition.
754
755   }
756
757 ### Priors
758
759   phi_final ~ dexp(1) # exponential prior for the shape parameters
760 for the beta distribution of modelled final ratings
761
762   for (i in 1:3) {
763     condition_influence_baseline[i] ~ dnorm(0,1) # normal prior for
764 the effect of image condition
765   }
766
767   for (i in 1:3) {
```

```
768     tau_players_social[i] ~ dexp(1) # exponential prior for the
769 variance of the random participant effect
770     for (j in 1:N_players) {
771         random_player_influence_effect[i, j] ~ dnorm(0,
772 tau_players_social[i]) # normal prior for the random participant
773 effect dependent on image condition (faces, hands or art).
774     }
775 }
776 }
777
778
779
780
```


781 **4. Additional code**

782 **4.1 STAN code supplied by an anonymous reviewer**

783 The reviewer who suggested we use weakly regularizing priors also kindly provided code to
784 run our analysis in STAN, another piece of Bayesian analysis software. STAN runs the same
785 kinds of analyses as JAGS, but uses different sampling algorithms which can greatly
786 increase the efficiency with which models run. If readers are familiar with both JAGS and
787 STAN and wish to reproduce our analyses they will likely find that STAN is the faster way to
788 do this.

789

```
790 # Stan model
791 library(rstan)
792
793 stan_model_code <- "
794 data{
795   int<lower=1> N;
796   int<lower=1> N_condition;
797   int<lower=1> N_player;
798   real final[N];
799   real initial[N];
800   real social[N];
801   int condition[N];
802   int player[N];
803 }
804 parameters{
805   vector[N_condition] b_condition;
806   vector[N_player] b_player;
807   real<lower=0> sigma;
808   real a;
```

```

809  real<lower=0> phi;
810  }
811  model{
812  vector[N] b;
813  vector[N] p;
814  phi ~ exponential( 1 );
815  a ~ normal( 0 , 1 );
816  sigma ~ exponential( 1 );
817  b_player ~ normal( 0 , sigma );
818  b_condition ~ normal( 0 , 1 );
819  for ( i in 1:N ) {
820  b = a + b_condition[condition] + b_player[player];
821  p = ( 1 - b ) * logit(initial) + b * logit(social);
822  p = inv_logit(p);
823  }
824  final ~ beta( p*phi , (1-p)*phi );
825  }
826  generated quantities{
827  vector[3] social_influence_condition;
828  for ( i in 1:3 ) social_influence_condition = a + b_condition;
829  }
830  "
831
832  data_list <- list(
833  N=N,
834  N_condition=3,
835  N_player=N_players,
836  final=p.final,

```

```
837  initial=p.initial,
838  social=p.social,
839  condition=condition,
840  player=player
841  )
842
843  stan_fit <- stan( model_code=stan_model_code , data=data_list , chains=3 , cores=3 )
844
845  # diagnostics and such
846  print(stan_fit,probs=c(0.025,0.975))
847
848  # extract permuted samples
849  post <- extract(stan_fit)
```