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Abstract

People often perceive their in-groups as more heterogeneous than their out-groups. We propose an information sampling explanation for this in-group heterogeneity effect. We analyze a model in which an agent forms beliefs and attitudes about social groups from her experience. Consistent with robust evidence from the social sciences, we assume that people are more likely to interact again with in-group members than with out-group members. This implies that people obtain larger samples of information about in-groups than about out-groups. Because estimators of variability tend to be right-skewed, but less so when sample size is large, sampled in-group variability will tend to be higher than sampled out-group variability. This implies that even agents that process information correctly – even if they are naive intuitive statisticians – will be subject to the in-group heterogeneity effect. Our sampling mechanism complements existing explanations that rely on how information about in-group and out-group members is processed.

Keywords: Information Sampling, Judgment Bias, Perception of Variability.

Introduction

A large amount of research has shown that people frequently perceive their groups as more heterogeneous than groups to which they do not belong (Boldry, Gaertner, & Quinn, 2007; Rubin & Badea, 2012; Ostrom & Sedikides, 1992). For example, Park and Judd (1990) found that students majoring in one subject judged students with other major as less variable on such characteristics as extroversion, impulsiveness, and how analytical and reserved they are. This "in-group heterogeneity effect" has received several classes of explanations. One class of existing explanations rely on differences in how information about in-groups and out-groups is processed (Ostrom & Sedikides, 1992; Ostrom, Carpenter, Sedikides, & Li, 1993; Park & Rothbart, 1982) or encoded (Linville, Fischer, & Salovey, 1989; Linville & Fischer, 1998; Judd & Park, 1988; Park & Judd, 1990). Another explanation takes as a premise that heterogeneity is seen as a positive feature of social groups and that people want to have a positive view of their in-groups (this is the much studied "in-group out-group bias", see Hewstone, Rubin, and Willis (2002)). People would thus be motivated to see in-groups as more heterogeneous than out-groups (Ostrom & Sedikides, 1992; Rubin & Badea, 2012).

Here, we propose a distinct, sampling-based, explanation for the in-group heterogeneity effect. We note that people tend to obtain larger samples of information about in-groups than about out-groups. For example, people can avoid interacting again with an out-group if they had a bad experience with members of this group. By contrast, people have to keep interacting frequently with members of the in-group even if they had negative experiences with those. Avoidance of the in-group is thus less likely (there is a large literature on this differential 'adaptive sampling' behavior, see Denrell, 2005; Fazio, Eiser, & Shook, 2004; Fiedler & Juslin, 2006).

The second premise of our explanation is that the variability of samples of information tends to increase with the size of the sample. Consider for example the variance of a sample of k independent standard normal variables (with mean $\mu = 0$ and variance $\sigma = 1$ both unknown). This is a random variable that can be written $\hat{\sigma}_k = Q/(k-1)$ where Q is a distributed according to a chi-squared distribution with $k-1$ degrees of freedom χ^2_{k-1}. The mean of Q is $k-1$. Two features of chi-squared distribution are noteworthy: Q is right-skewed (the probability that the sample variance is lower than the mean is higher than 50%) and the skewness is decreasing in k (the skewness is equal to $\sqrt{8/(k-1)}$). Overall this means that the sample variance tends to underestimate the true variance ($\sigma = 1$) and that the extent of the underestimation decreases as the sample size increases.

These two premises jointly imply that the experienced variability of in-groups will tend to be higher than the experienced variability of out-groups. Under the assumption that people's subjective perception of group variability is closely related to the variance of the sample of information they obtained about this group (Kareev, Arnon, & Horwitz-Zeliger, 2002; Weber, Shafir, & Blais, 2004; see Boldry et al., 2007 for a review), this implies that people will tend to perceive in-groups as more variable than out-groups.

This explanation for the in-group heterogeneity effect operates at a different level than existing explanations. Whereas existing explanations focus on how the mind processes information, our explanation focuses on the properties of the samples of information to which the mind has access. We emphasize how the structure of the environment can lead to systematic sampling asymmetries, which in turn imply systematic judgment asymmetries. As such, our explanation fits in the 'sampling approach' to human judgment (Denrell, 2005; Fazio et al., 2004; Fiedler & Juslin, 2006; Le Mens & Denrell, 2011).

Model

Consider a setting where one agent forms attitudes and beliefs about two groups ($g = in, out$). The agent belongs to one of the two groups – the in-group. In this simple model, we assume that the agent observes two dimensions of the groups: an attitudinal dimension, A and another dimension X. Here we assume that the dimension X is not stereotypical in the sense that it does not serve as the basis for categorization. In each period, the agent samples the group or not. When the agent samples a group she observes both dimensions A and X of one of its members.

Belief Updating Let $A_{t,g}$ denote attitude of the agent toward group g at the end of period t. If she samples the group in period t, two things happen.

- She updates are attitude toward the group. Her new attitude is a weighted average of her previous attitude and the new observation $a_{t,g}$:

$$A_{t,g} = (1-b)A_{t-1,g} + ba_{t,g}, \tag{1}$$

  where $b \in [0,1]$. We assume that $a_{t,g}$ is normally distributed (with mean 0 and variance 1). This attitude updating rule has been found to provide good fit to experimental data on sequential choice under uncertainty (see Denrell, 2005 for a review).

- She obtains an observation $x_{t,g}$ of the non-attitudinal dimension. We assume that $x_{t,g}$ is normally distributed (with mean 0 and variance 1)

If the agent does not sample the group, her attitude does not change ($A_{t,g} = A_{t-1,g}$) and she does not obtain any additional observation of the X dimension.

Perception of Variability Consistent with the sampling approach tradition, we assume that the agent processes sampled information correctly. Let $V_{t,g}$ denote the perceived variability on dimension X at the end of period t. Here, we assume that this is given by the standard unbiased sample variance estimator. (In the next section, we consider other estimators of variability.)

$$V_{t,g} = \frac{1}{n_{t,g}-1}\sum_{k=1}^{t}(x_{k,g} - \bar{x}_{t,g})^2 I_{k,g}, \tag{2}$$

where $I_{k,g}$ is an indicator variable equal 1 if group g is sampled in period k (and equal to 0 otherwise), $n_{t,g}$ is the number of samples ($n_{t,g} = \sum_k I_{k,g}$), $\bar{x}_{t,g}$ is the mean of the sampled observations on the X dimension at the end of period t, and $x_{k,g}$ is the observation in period k.

Sampling Rule To ensure that variability estimates exist for both groups, we assume that the agent has sampled 2 observations from each group before the first period. In the subsequent periods, the sampling rule follows that used in Denrell (2005). In each period the agent samples the in-group or the out-group based on the current attitude towards that group. Note that sampling rule does not depend on observations on dimension X. The probability that the agent samples the in-group is given by the exponential version of the Luce choice rule (Denrell, 2005):

$$P_{t+1,in} = r + (1-r)\frac{e^{sA_{t,in}}}{e^{sA_{t,in}} + e^{sA_{t,out}}}, \tag{3}$$

Here s is a parameter that regulates the sensitivity of the sampling probability to the current attitude, and $r \in [0,1]$ is a parameter that corresponds to the sampling 'bias' in favor of the in-group. The higher r is, the higher is the baseline probability that the agent will sample the in-group. When r is high, the agent is likely to frequently sample the in-group even if she has a negative attitude toward it ($A_{t,in}$ is low). This sampling 'bias' in favor of the in-group implies that the agent will gather larger samples of information about the in-group than about the out-group.

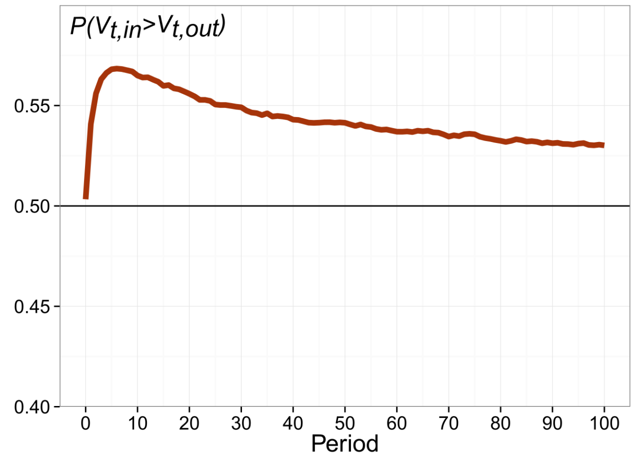

Figure 1: Model with unbiased variance estimator: Likelihood that the estimate of in-group variability is higher than the estimate of out-group variability ($P(V_{t,in} > V_{t,out})$) as a function of time. Each point is based on 10^5 simulations with $b = 0.5, r = 0.5, s = 3$.

Analysis

We ran computer simulations of the above model. The parameter values that were used in all simulations are $b = 0.5, r = 0.5, s = 3$. These values are similar to estimated parameter values in sequential choice experiments (Denrell, 2005).

Figure 1 displays the likelihood that the estimate of the in-group variability is higher than the estimate of the out-group variability, $P(V_{t,in} > V_{t,out})$, as a function of the number of periods. It is higher than 0.5 for all periods after period 1. In other words, the in-group tends to be perceived as more variable than the out-group. The likelihood that the in-group is perceived as more variable than the out-group first increases quickly and then decreases very slowly with the number of periods. It is equal to 0.54 after 50 periods and 0.53 after 100 periods. This suggests that this asymmetry persists even after many periods.

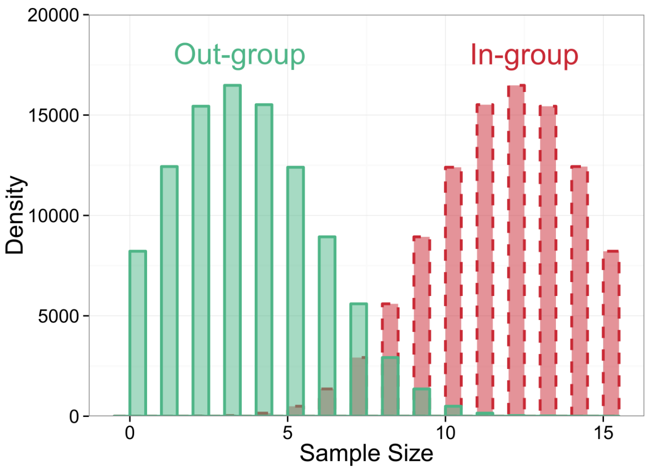

Figure 2: Model with unbiased variance estimator. Distribution of the sample sizes of the two groups after 15 periods. Based on 10^5 simulations with $b = 0.5, r = 0.5, s = 3$.

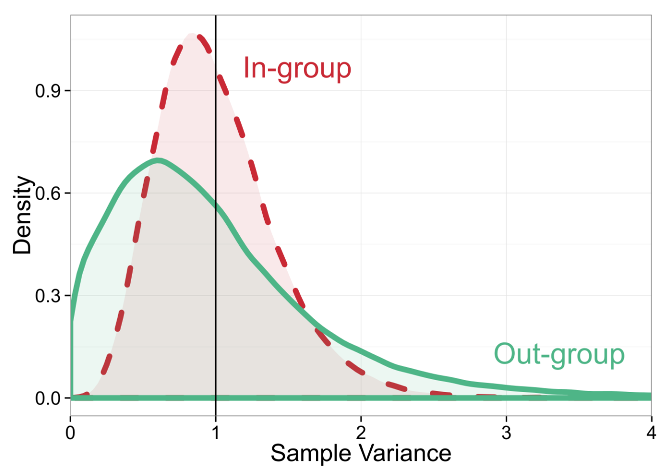

Figure 3: Model with unbiased variance estimator. Distributions of the variability estimates (according to eq. 2) $V_{15,in}$ and $V_{15,out}$ after 15 periods. Black vertical line denotes the true variance on the X dimension ($\sigma = 1$). Based on 10^5 simulations with $b = 0.5, r = 0.5, s = 3$.

To develop an intuition for this result, we focus on the end of period 15. First note that the in-group is sampled more times than the out-group (Figure 2). This is because of the assumed sampling advantage of the in-group (eq. 3). Second, note that the distributions of sampled variabilities for the two groups are right skewed but to a *different extent* (see Figure 3). The distribution of the sampled variability for the in-group $V_{15,in}$ is less skewed than the distribution of the sampled variability for the out-group, $V_{15,out}$. By contrast, the mean sample variabilities are the same:[1] $E(V_{15,in}) = E(V_{15,out}) = \sigma^2 = 1$. Overall, this implies that $V_{15,in}$ tends to be larger than $V_{15,out}$.

More generally, the distribution of variability estimates for a group is skewed, but the skewness decreases with sample size. If $V_{t,g}$ is based on n observations, it is a random variable with a χ^2 distribution with $n-1$ degrees of freedom (the mean is assumed to be unknown to the agent). The χ^2 distribution is skewed to the right, therefore the probability that the variance estimate is lower than the true variance ($\sigma^2 = 1$) is higher than 0.5. Consider the probability mass below 1 for sample sizes 5, 10, 15, 20 and 50. The probability masses are 0.59, 0.56, 0.55, 0.54, and 0.53, respectively. In all cases, it is higher than 50%, but it goes down as sample size increases and converges to 0.50 as the sample size becomes large. Because our assumptions about the sampling process imply that the sample collected about the in-group tends to be larger than the sample collected about the out-group, the distribution of $V_{t,in}$ is likely less skewed than the distribution of $V_{t,out}$. This implies that $V_{t,in}$ is likely larger than $V_{t,out}$. In other words, an in-group heterogeneity effect emerges.

[1]This is because the variance estimator we used is statistically unbiased, see eq. 2.

Other Estimators of Variability

A Bayesian Estimator of Variability An alternative implementation of our assumption that information is processed 'correctly' is to assume that the agent is a Bayesian processor of information, with correct priors about the true variance. For simplicity, we assume that the mean on the X dimension is *known* and equal to 0.[2] The true variance is drawn from an inverse gamma distribution with parameters α and β. The inverse gamma distribution is a conjugate distribution: the posterior also follows an inverse gamma distribution.

$$f(\hat{\sigma}^2_{t,g}) \sim IG\left(\alpha + \frac{\sum_{k=1}^{t} I_{k,g}}{2}, \beta + \frac{\sum_{k=1}^{t} (x_{k,g} - \bar{x}_{t,g})^2 I_{k,g}}{2}\right) \quad (4)$$

We simulated the model by assuming the same attitude updating rule and sampling rule as before, but with the Bayesian estimator of variability in equation 4. We assumed $\alpha = 15/2$ and $\beta = \alpha$.[3]

Figure 4 displays the evolution of $P(V_{t,in} > V_{t,out})$. In this Bayesian setting as well, the in-group tends to be perceived as more variable than the out-group. This result is important, because it demonstrates that even a rational processor of information will tend to perceive the in-group as more variable than the out-group in settings where the in-group is more likely to be sampled again (i.e. $r > 0$). A similar pattern would emerge if the agent were also updating her attitudes ($A_{t,g}$) using Bayes' rule, provided that the sampling rule implies that larger samples are obtained about the in-group than about the out-group.

[2]Similar results hold if the mean is unknown, but the formulas are much more complicated.

[3]The prior hyperparameters were chosen to match the setup of the example discussed above ($N(0,1)$ payoff distribution and $t =$

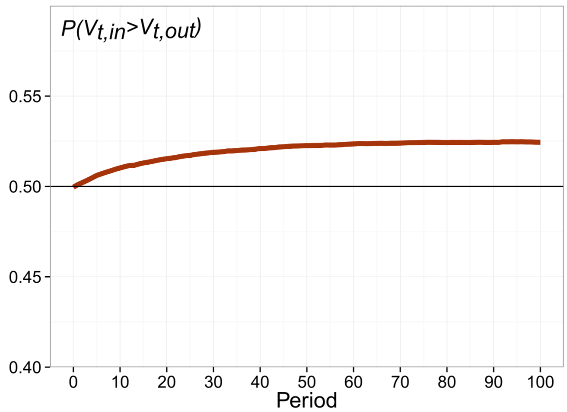

Figure 4: Model with Bayesian estimator of variability. Likelihood that the posterior estimate of in-group variability is higher than the posterior estimate of out-group variability ($P(V_{t,in} > V_{t,out})$) as a function of time. Based on 10^5 simulations with $b = 0.5, r = 0.5, s = 3, \alpha = 15/2, \beta = \alpha$.

Sample Variance In the main analysis, we assumed that the agent estimated the group variabilities using a statistically unbiased estimator (eq. 2). We did so because we wanted to demonstrate that an asymmetry in the perception of variability could emerge even in this case. Several papers have assumed that people use the standard sample variance estimator (e.g. Juslin, Winman, & Hansson, 2007; Kareev et al., 2002):

$$V_{t,g} = \frac{1}{n_{t,g}} \sum_{k=1}^{t} (x_{k,g} - \bar{x}_{t,g})^2 I_{k,g}, \tag{5}$$

This estimator is biased for small samples, and the size of the bias is stronger for smaller samples. Unsurprisingly, simulations based on this estimator lead to a stronger asymmetry than in the above analyses. For example, after 15 periods, the likelihood that the estimate of in-group variability is higher than the estimate of out-group variability is $P(V_{15,in} > V_{15,out}) = 0.62$. This number was 0.56 when the unbiased variance estimator was used.

We did not find empirical evidence that suggests that people's intuitive variability estimates are closer to the unbiased or the biased estimators. Qualitatively, this is not an issue for our argument, because the asymmetry in perception of group-variability emerges in both cases. Further work should investigate this issue. This would allow for quantitative predictions about the size of the in-group heterogeneity effect.

Relation to Existing Literature on In-group Heterogeneity

Most prior explanations of the in-group heterogeneity effect have invoked differences in how information about in-group and out-group is processed. Here we discuss how our explanation differs from this prior work (we use a taxonomy similar to Ostrom and Sedikides (1992)).

Several explanations rely on motivated cognition (Kunda, 1990). The first mechanism invokes people's desires for positive identities. Those who want a positive social identity are motivated to view their in-groups more positively than other groups (Tajfel, 1982). At the same time, heterogeneity is frequently perceived as a positive feature of social groups (Ostrom & Sedikides, 1992). Therefore, people are motivated to perceive the in-group as more heterogeneous than out-groups. A related mechanism invokes people's desire for distinct identities. A more heterogeneous in-group allows people to see themselves as unique within the in-group. Thus, people are motivated to see their in-groups as heterogeneous (Pickett & Brewer, 2001). Yet another explanation based on motivated cognition notes that it is easier to dehumanize more homogeneous groups (Haslam, 2006; Brewer, 1999). Therefore, if the out-group is perceived as less variable than the in-group, it is easier to justify negative attitudes and even cruel actions towards out-group members.

Another explanation notes that people tend to have prior beliefs that the out-group is more homogeneous. Park and Hastie (1987) showed that if participants first observed exemplars from a group followed by a description of its general characteristics, they perceived this group as more variable compared to when they observed that information in reversed order. This suggests that the prior about homogeneity affects how information is encoded. This finding implies an in-group heterogeneity effect under a (reasonable) assumption that people often learn descriptions of out-groups before interacting with some of their members (e.g. through stereotypes communicated by others in their environment) whereas they learn about natural in-groups by direct observations.

A third class of explanations notes that the self is part of the in-group (Park & Judd, 1990). Since the self is often perceived as particularly differentiated and unique, this would contribute to an impression that the in-group is more heterogenous than the out-group.

A fourth class of explanations suggests that information about different groups is encoded and retrieved in different fashions. For example, Ostrom et al. (1993) found that information about in-group members is stored in categories related to individual information whereas the information about the out-group members is stored in categories related to stereotypical attributes. Therefore, when the information is recalled, the in-group tends to be associated with more individuating information compared to stereotype based homogeneous information about the out-group. In terms of recall, Park and Judd (1990) suggested that participants recall more extreme exemplars about in-groups than about out-groups. This suggests that memory search processes might differ across in-group and out-group.

These four classes of explanations emphasize features of information processing. By contrast, our explanation focuses properties of the sample of information on which the mind

15). The interpretation of the parameters is that the prior is based on a sample of size $2\alpha = 15$ with variance $\beta/\alpha = 1$.

operates. Because our explanation focuses on a different level than explanations that focus on information processing, it does not contradict these. Rather, it complements them. Our analyses and the experimental findings discussed above suggest that both types of mechanisms likely play a role in explaining why people see their in-groups as more heterogeneous than their out-groups.

The most closely related paper to ours is a paper by Linville et al. (1989). It analyzes an exemplar model that describes how information about groups is encoded, stored and recalled. The authors argue that higher familiarity with the in-group than with the out-group is the cause of the bias. Familiarity in this case is the number of exemplars of each group a person has encountered. They model the encoding, storage and recall of the information using a set of parameters and show that the strength of the bias depends on the information processing. They also consider the case of perfect memory (perfect encoding, no forgetting, and perfect recall). They find an asymmetry in expected variability estimates ($E(V_{in}) > E(V_{out})$). Their argument is similar to the logic of our model, but their analysis focuses on the asymmetry produced by reliance on the biased variance estimator we discussed above (see eq. 5). Our results differ, because they demonstrate that a systematic tendency to perceive the in-group as more heterogeneous can emerge even when people use an *unbiased* estimator of variability. In some sense, our result is stronger because the asymmetry in expected variability implied by the biased variance estimator goes down very quickly with sample size. The asymmetry based on the skewness of the distribution of estimators of variability persists even as sample size becomes somewhat large (although it disappears for very large samples). Another difference is that our model focuses on sampling from the environment whereas this prior paper focused on sampling within the mind.

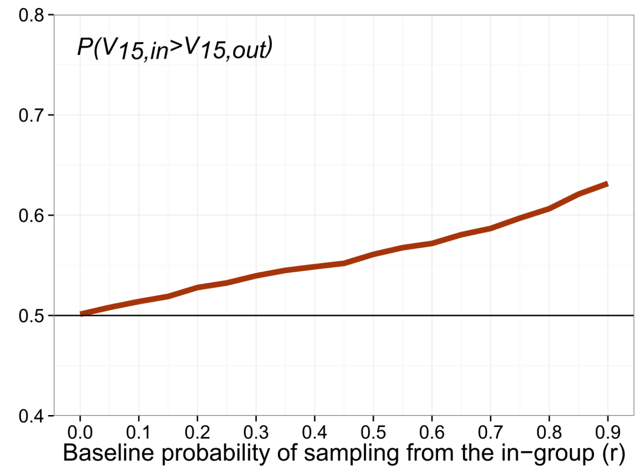

Figure 5: Model with unbiased variance estimator: Likelihood that the estimate of in-group variability is higher than the estimate of out-group variability ($P(V_{t,in} > V_{t,out})$) after 15 periods, as a function of the baseline probability of sampling the in-group (r). Based on 10^5 simulations with $b = 0.5, s = 3$.

Discussion

Sensitivity Analysis

The magnitude of the in-group heterogeneity effect produced by our model depends on the model parameters.

The baseline probability of sampling the in-group (r in eq. 3) has a large effect on the magnitude of the bias. For r values close to zero, the likelihood that the in-group is perceived as more variable becomes close to 0.5 (e.g., 0.51 for $r = 0.05$), but when the advantage of the in-group is high ($r = 0.9$), the likelihood that the in-group is perceived as more variable can be as high as 0.64 (see Figure 5). The baseline probability of sampling from the in-group reflects the difficulty of obtaining information about the members of the out-group. Its value depends on the empirical setting. For example, depending on the social group and socioeconomic structure of a country, the probability can range from small values (for fairly international and integrates societies) to very high values (in isolated homogeneous societies).

The other parameters, b (the weight of the new attitude, see eq. 1) and s (the slope parameter in the sampling rule, see eq. 3) have a positive effect on the strength of the in-group heterogeneity effect, but the effect is not strong.

A different but related model to ours would not assume an inherent sampling advantage for the in-group (take $r = 0$). In this case, our model does not predict any in-group heterogeneity effect if the groups are equally attractive (i.e., $a_{t,in}$ and $a_{t,out}$ are drawn from the same distribution). But suppose that the in-group is more attractive. It is possible to model this by assuming that the mean of the distribution of $a_{t,in}$ is higher than the mean of the distribution of $a_{t,out}$ (for simplicity, we assume the variances are equal). In this case, the agent will obtain larger samples about the in-group than about the out-group and an in-group heterogeneity effect will emerge if s and b are high enough.

In-Group Homogeneity

Several papers have documented instances of an in-group *homogeneity* effect that seems to contradict the dominant finding of an in-group *heterogeneity* effect (Simon & Pettigrew, 1990; Rubin & Badea, 2007). Our sampling mechanism can acomodate some of these findings.

An in-group homogeneity effect has been found when the feature under consideration is used as a basis for categorization. That is, the value of that feature defines whether the person is categorized into the in- or out-group (Rubin & Badea, 2007). In this case, the true variability of the in-group might be smaller than the variability of the out-group on the focal feature. Our model can be adapted to this setting by relaxing the assumption that the true variances are the same for the two groups. We can assume instead $\sigma^2_{in} < \sigma^2_{out}$. Our model implies that the variabilities of both groups will tend to be underestimated, but that the in-group variability will be underestimated to a lower extent than the out-group variability. If the difference in the extent of underestimation is smaller than the difference in true variabilities, our model implies the emergence of an in-group *homogeneity* effect, in line with the true difference in variabilities. But if the difference in true variabilities is small, our model can lead to the emergence of an in-group *heterogeneity* effect.

Although most prior research conceptualized the 'in-group' and the 'out-group' as specific groups, some papers have conceptualized the out-group as 'everyone but the in-group' (e.g. Alves, Koch, & Unkelbach, 2016). In this case, the true variability of the out-group is likely much larger than the true variability of the in-group. This setting is a special case of the setting discussed in the previous paragraph.

Finally, there is some evidence that when the in-group is a minority it tends to be judged as more homogeneous than the out-group (Simon & Pettigrew, 1990). Our model can be adapted to this setting as well. Consider a situation where the in-group is smaller than the out-group and, furthermore, the number of in-group members is smaller than the number of periods. The agent will sample all the in-group members but the sample size will remain small (bounded by the number of members). To illustrate this, let us return to our example where the number of periods is $t = 15$ and let us also assume that the sizes of the in-group and out-group are 5 and at least 10, respectively. Then the sample size for the in-group will not exceed 5 whereas the size of the out-group members sample will be at least 10. This sample size asymmetry in favor of the out-group implies an in-group *homogeneity* effect.

Conclusion

People frequently obtain larger samples of information about in-groups than about out-groups. Because estimators of variability tend to be more strongly right-skewed when samples are smaller, this implies that people will be likely to perceive in-groups as more variable than out-groups. In this paper, we showed that this in-group heterogeneity effect emerges even when people process information correctly – even if they are naive intuitive statisticians. Our theory complements existing explanations that proposed that information about in-group and out-group members was processed in different fashions.

Acknowledgments

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