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COMMENTS

Contrast Effects or Loss Aversion? Comment on Usher and McClelland (2004)

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M. Usher and J. L. McClelland (2004) recently proposed a new connectionist type of model to explain context effects on preferential choice including the similarity, attraction, and compromise effects. They compared their model with an earlier connectionist type model for these same effects proposed by R. Roe, J. R. Busemeyer, and J. T. Townsend (2001) and raised several new issues. The authors address these issues and point out the main theoretical differences between the 2 explanations for context effects.

Research on preferential choice has uncovered three paradoxical findings that have long resisted a coherent explanation: the similarity, attraction, and compromise effects (see Roe, Busemeyer, & Townsend, 2001, for a review). Referring to Figure 1, the similarity effect refers to the reduced preference for option *A* relative to *B* when option *S* is introduced; the attraction effect refers to the enhanced preference for option *A* relative to *B* when option *D* is introduced; and the compromise effect refers to the enhanced preference for option *C* relative to *B* when option *A* is introduced. Recently, several connectionist type models have been put forward to explain all three of these context effects on choice (Guo & Holyoak, 2002; Roe et al., 2001; Usher & McClelland, 2004). All three models build on earlier work by Tversky (1972) to explain the similarity effect; however, the models differ in terms of their explanations for the attraction and compromise effects. Two of these models (Guo & Holyoak, 2002; Roe et al., 2001) rely on the neural network concept of distant dependent–lateral inhibition to produce the attraction and compromise effects.[1] Using this mechanism, these context effects are an emergent property of the dynamic network interactions. Alternatively, the third model (Usher & McClelland, 2004) relies on the concept of loss aversion (Tversky & Simonson, 1993) to explain the attraction and compromise effects.[2]

Usher and McClelland (2004) put forth several arguments for the loss-aversion explanation as compared with the lateral inhibitory explanation. Their concerns with the latter were mainly targeted at Roe et al.'s (2001) model, and the purpose of this comment is to provide reactions to their arguments. Hereafter we refer to Roe et al.'s model as DFT (decision field theory) and Usher and McClelland's model as the LCA (leaky, competing accumulator) model.

Does Loss Aversion Pose a Problem for DFT?

As Usher and McClelland (2004) noted, DFT attempts to provide microlevel mechanisms to explain some of the macrolevel loss-aversion phenomena (see Busemeyer & Johnson, 2004). Usher and McClelland questioned whether DFT can explain all of these complex phenomena, and this remains to be seen. However, there is no logical inconsistency between DFT and the loss-aversion concept—one could code the inputs to the DFT system as positive or negative with respect to some reference point and apply a loss-aversion type of transformation to these inputs (Barkan & Busemeyer, 2003). Thus, loss-aversion phenomena are not inconsistent with DFT. In fact, the distinction between approach–avoidance factors has been a central feature of DFT since its inception (see Busemeyer & Townsend, 1993; Diederich, 2003; Townsend & Busemeyer, 1989).

Loss-aversion phenomena were used by Usher and McClelland (2004) to justify their model rather than to rule out DFT. It is an interesting question to ask, "why does the LCA model need this assumption?" Like DFT, the LCA model has lateral inhibitory connections; but unlike DFT, these connections are not distance dependent. Of course, it would be simple to modify the LCA model in this manner, but even if this were done, the model still

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[1] Lateral inhibition refers to feedback occurring between nodes in a network. In this case, the nodes contain information about the preferences for the choice options, and information about the preference for one option feeds back to influence the node representing another option. The lateral inhibition is distance dependent when the strength of the feedback influence decreases with dissimilarity between options.

[2] Loss aversion refers to the idea that a given change in value has a larger effect when it is interpreted as a loss as compared with when it is interpreted as a gain.

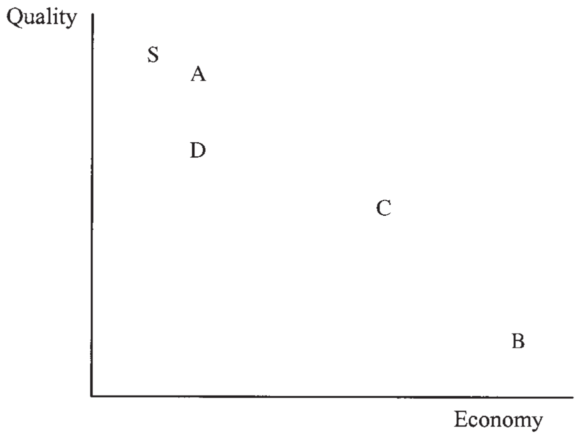

Figure 1. A schematic representation of the similarity, attraction, and compromise effects. Five choice options are represented spatially according to their utilities on two dimensions. For example, option *A* is a consumer product that is high in quality but low in economy, whereas option *B* is a consumer product that is low in quality but high in economy.

would not produce the contrast enhancement needed to explain the attraction effect. Why is this true? This is a consequence of the fact that the LCA model is restricted to positive activations: When a positive activation passes through a negative inhibitory connection, it must produce an inhibitory effect, rather than contrast enhancement. In DFT, the preference states are permitted to assume positive (approach) or negative (avoidance) levels: When a negative state passes through a lateral inhibitory connection, it produces a disinhibitory effect, which results in contrast enhancement (referring to Figure 1, option *A* appears more desirable when contrasted with option *D*). As Usher and McClelland pointed out, many (but not all) neural network models restrict activations to be positive, and by conforming to this restriction, the LCA model needs to adopt the loss-aversion hypothesis to explain the attraction effect.

Does the Restriction of Positive Activations and Nonlinear Dynamics Pose a Problem for DFT?

Usher and McClelland (2004) pointed out that the states are restricted to be positive to simulate neural firing rates, and nonlinear dynamics are required to satisfy this restriction (activations below zero are truncated to zero). DFT allows positive (approach) or negative (avoidance) preference states, and we use simple linear dynamics to describe the evolution of these states. We first explain the use of negative states and then turn to the reason why DFT uses linear dynamics.

How can one justify negative states? One way is to view negative states as activation that is suppressed below the baseline firing rate of a neural unit. It is well known that the basal ganglia–prefrontal cortex neural system is a complex network involving both excitatory as well as inhibitory interconnections (see Houk, Adams, & Barto, 1995). At rest, many neural units are actively suppressed below baseline firing rate by inhibitory inputs; but if the inhibiting units are suppressed by other outside activation, then the previously inhibited neural units are released from inhibition, which is the neural phenomenon of disinhibition (see Anderson, 1997, chap. 4).[3]

Now let us turn to the question regarding linear and nonlinear dynamics. As pointed out by Usher and McClelland (2004), neural network models usually use nonlinear dynamics for detailed models of the basal ganglia–prefrontal cortex interactions (see, e.g., Brown, Bullock, & Grossberg, 1999). What justifies our use of linear dynamics? Our goal is to build a mathematical representation that captures disinhibition in as simple a manner as possible. This is useful for deriving mathematical solutions to the equations rather than relying on computer simulation. Linearity is a useful approximation to nonlinear relations within a short extension (this is why Newtonian mechanics work within limits). So far we have been successful using linear dynamics, but we recognize that at some point we will reach the limits of this approximation, and we will need to turn to nonlinear dynamics. In summary, a negative state has a neural interpretation as a below baseline level of activation, and linear dynamics are retained until the variance predicted by introducing nonlinearities becomes large enough to justify a more complex model.

Are the Model Parameters Reasonable?

Usher and McClelland (2004) questioned the reasonableness of our selection of inhibitory parameters for explaining the similarity and compromise effects. They noted that the distance between the similar option and its target is smaller than the distance between the compromise option and its targets. Assuming distant dependent lateral inhibition, they claimed that we should have used a larger strength lateral inhibitory connection for the similarity application as compared with the compromise application. But they noted that we kept the parameter constant across applications, and they questioned whether we could in fact reproduce the correct pattern of results if we adjusted the parameters appropriately according to each situation.

Why did we keep the parameters constant across applications? Our purpose was to make it perfectly clear that we could reproduce all three findings with exactly the same parameters (this was shown in Figure 14 of Roe et al., 2001). If we are free to adjust the

[3] Restricting DFT to positive activation states does not imply that DFT can no longer account for attraction effects. Consider the following possible nonlinear version of DFT, restricted to positive activation states (cf. Grossberg, 1988, Equations 34 and 51):

$$dP_j(t + h) = s_{ii} \cdot P_j(t) + V_j - \sum_{i \neq j} s_{ij} \cdot [P_i(t) - b]; \qquad (1a)$$

$$P_j(t + h) = F[P_j(t) + dP_j(t + h)], \text{ and } F(x) = 0 \text{ if } x < 0,$$

$$F(x) = x \text{ if } x \geq 0. \qquad (1b)$$

DFT is an affine approximation, evaluated at the baseline level, of this nonlinear difference equation. This nonlinear positive activation version of DFT can still produce the attraction effect. Consider options *A*, *B*, and *D* shown in Figure 1. Note that option *D* is the asymmetrically dominated decoy that is located near option *A*, and option *B* is far from both *A* and *D*. If, for example, we set the parameters equal to $s_{ii} = .05$, $s_{AD} = s_{DA} = .05$, $s_{AB} = s_{BA} = s_{BD} = s_{DB} = 0$, $V_A = .60 = V_B$, and $V_D = .50$ and the baseline activation is set to $b = 50$, then this lateral inhibitory network model reproduces the attraction effect, but this time using only positive activation states as well as positive inputs. We would not wish to argue that it has achieved the status of a highly accurate neural account. This would require an even more detailed specification (e.g., Grossberg & Gutowski, 1987) that goes beyond the behavioral phenomena that we are trying to explain here.

parameters in an appropriate manner for each application, then it becomes even easier for DFT to produce the desired results. For example, Tversky's (1972) experiments on the similarity effect used simple stimuli (e.g., two outcome gambles) that were carefully controlled, whereas Simonson's (1989) experiments on the compromise effect used realistic stimuli (e.g., detailed descriptions of cameras), which were less well controlled. Accordingly, the lateral inhibitory parameter should be larger for the similarity application as compared with the compromise application because of the distance factor. However, the noise parameter should be smaller for the similarity application as compared with the compromise application because of the stimulus complexity factor. For example, consider the similarity effect represented with options *S*, *A*, and *B* in Figure 1. If we compute the predictions for this from DFT (as described in Roe et al., 2001) using a large lateral inhibition parameter (equal to .04) and a small noise standard deviation (equal to .1), then we predict a similarity effect equal to $Pr(A|\{A, B, S\}) - Pr(B|\{A, B, S\}) = -.16$, which is in the correct direction. Now, consider the compromise effect represented with options *A*, *B*, and *C* in Figure 1. If we compute the predictions for this from DFT using a smaller lateral inhibition parameter (equal to .035) and a larger noise standard deviation (equal to 1.0) for the compromise application, we predict a compromise effect equal to $Pr(C|\{A, B, C\}) - Pr(A|\{A, B, C\}) = .10$, which is again in the correct direction. The size of both of these effects can be changed by adjusting the model parameters. In summary, we held the parameters constant across applications simply to show that the model could reproduce all three context effects using the same exact parameters. But we can easily recover the correct pattern of predictions by adjusting the parameters in the appropriate direction for each application.[4]

The LCA model is not free of problems when it comes to interpreting parameters. A critical parameter that must be included in the LCA model is the parameter labeled I_0, which is required to prevent the inputs to the network from becoming negative. This parameter is problematic because it depends on the total loss-aversion contribution (i.e., loss aversion summed across all the alternatives). If the contributions from loss aversion increase (perhaps because of the magnitude of the disadvantages or because new options are added to the choice set), then this parameter needs to be increased to overcome the total loss-aversion contribution. Usher and McClelland (2004) set $I_0 = .75$ for all of their applications, but this selection can only work for a restricted set of choice problems. Consequently, there is no way to guarantee that this parameter can remain fixed across a wide variety of choice sets.

Conclusion

At this point we believe that both DFT and the LCA model provide competing explanations for similarity, attraction, and compromise context effects on preferential choice. As Usher and McClelland (2004) pointed out, these two theories share a common mechanism for explaining the similarity effect, but they primarily differ in terms of their explanation for the attraction and compromise effects. DFT explains these last two effects by a contrast enhancement mechanism, whereas the LCA model uses the concept of loss aversion. The selection of one theory over another should be based on new empirical tests of these two fundamentally different explanations. Usher and McClelland seem to agree with this position as they have suggested some interesting experimental tests for distinguishing the two hypotheses. We welcome the competition and look forward to the answer that nature provides.

[4] Recently we fit DFT to a large study of context effects (including attraction, compromise, and similarity manipulations) conducted by Douglas Wedell (2003), and the DFT model accounted for 98% of the data from 80 conditions using 7 parameters.

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