Multialternative Decision Field Theory: A Dynamic Connectionist Model of Decision Making

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Big Picture

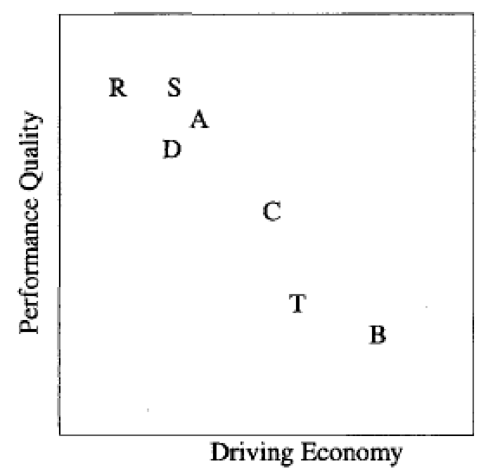
- The authors propose that the decision maker's preference for each option evolves during deliberation by integrating a stream of comparisons of evaluations among options on attributes over time.
- They represent this evolution using a neural network composed of two layers.
  - One layer is feed-forward.
  - The second layer is a competitive recursive network.

Overview

- Central Findings on Multialternative Preferential Choice
- Multialternative Decision Field Theory
- Applications of MDFT to Central Empirical Findings
- Comparisons with Other Models
- Conclusions

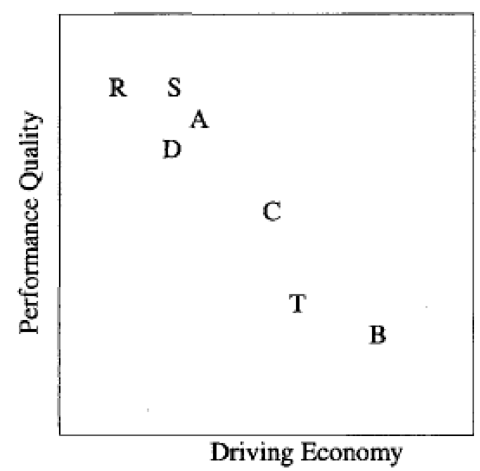
Central Findings on Multialternative Preferential Choice

- Similarity Effect
  - The introduction of a new competitive product to the choice set reduces the probability of choosing similar products more than dissimilar products.
  - Violates a preferential choice property called *independence from irrelevant alternatives*, also known as Chernoff's condition.
  - This rules out the entire class of simple scalable choice models.



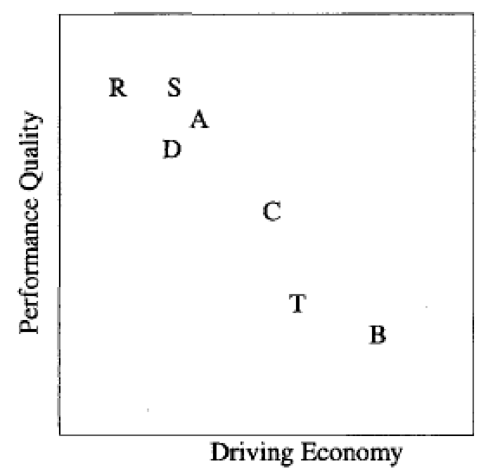
Central Findings on Multialternative Preferential Choice

- Attraction Effect
  - The introduction of a new dominated product to a choice set increases the probability of choosing the dominant product.
  - This is the opposite of the similarity effect.
  - This violates the *regularity principle*, which states that the addition of option D should only decrease the probability that option A would be chosen.



Central Findings on Multialternative Preferential Choice

- Compromise Effect
  - When all three options are available for choice, the compromise is chosen more frequently than either of the extremes.
  - This effect is even seen when the trinary choice set is presented before the three binary comparisons, so is not the result of new information.
- Until this paper, no single theoretical explanation has explained all three of these effects within one theory.



Multialternative Decision Field Theory

- Multialternative Dynamic Decision Process
  - Extends sequential sampling models to multialternative preferential choice situations.
  - Valences: $V_i(t)$ is the momentary advantage or disadvantage of option *i* when compared with other options or attributes. Determined by:
    - personal evaluation of each option on each attribute (value matrix M)
    - the attention weight allocated to each attribute in a moment in time (weight vector W(t))
    - the comparison process that contrasts the weighted evaluations of each option (contrast matrix C)

Multialternative Decision Field Theory

- $V(t) = CMW(t)$

- $V(r) = CMW(r) = CM_1W_1(t) + \mathcal{E}(t)$
  - personal evaluation of each option on each attribute (value matrix M)
  - the attention weight allocated to each attribute in a moment in time (weight vector W(t))
  - the comparison process that contrasts the weighted evaluations of each option (contrast matrix C)
  - Where $\mathcal{E}(t)$ is a residual term.

Multialternative Decision Field Theory

- Preferences: $P_i(t)$ represents the integration of all the valences considered for alternative *i* up to that point in time.
- $P(t+1)$ is formed from the previous preference state $P(t)$ and the new input valence vector, $V(t)$, in addition to the feedback matrix S

$$\mathbf{P}(t+1) = \mathbf{SP}(t) + \mathbf{V}(t+1). \qquad (2)$$

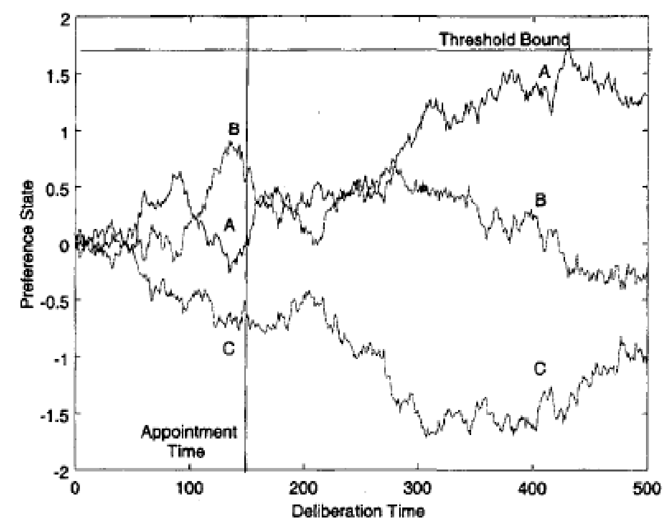
- The initial preference state is a residual bias from previous interactions, it can also be set to 0.
- If the self-feedback loop is set to 0, then there is no memory of previous state, a setting of 1 would be a perfect memory.

Multialternative Decision Field Theory

- Dynamic Thurstone model:
  - when all cross-feedback is set to 0, S is an identity matrix
  - MDFT is a dynamic generalization of the Thurstone preference model.
- Parameters:
  - W (mean weight) and M (value) are required for classic multiattribute utility models
  - the residual variance contributed by the irrelevant attributes and required by any Thurstone model
  - S is the symmetric feedback matrix which is required by any dynamic connectionist model

Multialternative Decision Field Theory

- Multialternative Choice Rules
  - Externally controlled stopping time: when the decision has to be made at an appointed time (ex: job offer acceptance date)
    - Used to study the dynamics of memory
  - Internally controlled stopping time: the decision maker is free to decide how long to deliberate before committing (ex: leaving the car dealership and then calling when ready)
    - Used to study decision making

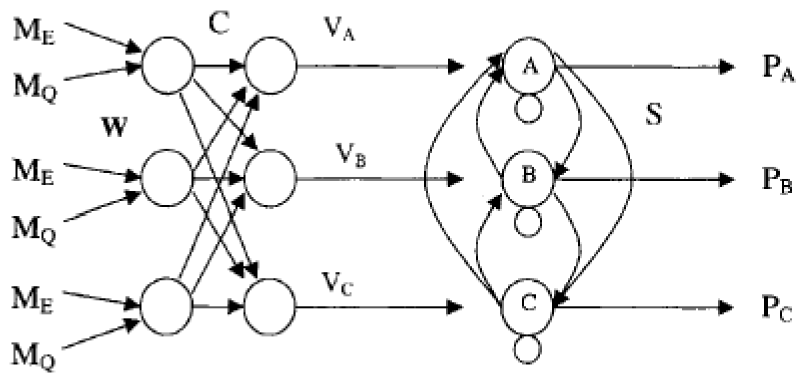


$$\Pr[\mathrm{A} \mid \{\mathrm{A}, \mathrm{B}, \mathrm{C}\} \text{ at time } t] =$$

$$\Pr[P_{\mathrm{A}}(t) > P_{\mathrm{B}}(t) \text{ and } P_{\mathrm{A}}(t) > P_{\mathrm{C}}(t)]. \quad (3)$$

Multialternative Decision Field Theory

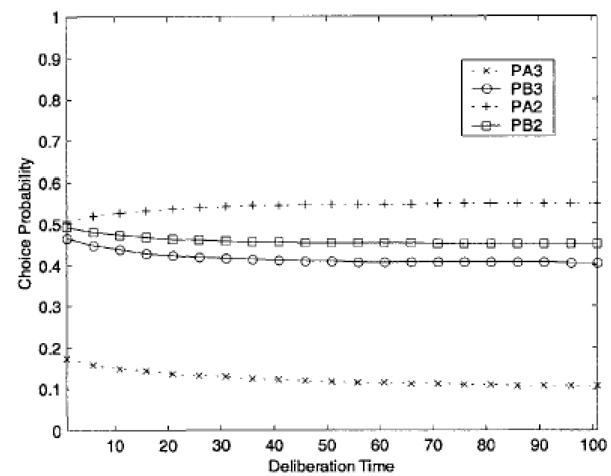
- Connectionist Interpretation



  - Layer 1 is the momentary attention weights
  - C is the group of contrast coefficients, which produce comparisons among the weighted evaluations.
  - V is the output valences of the first layer
  - Layer 2 is a competitive recursive network
  - The output represents the strength of preference at a particular point in time

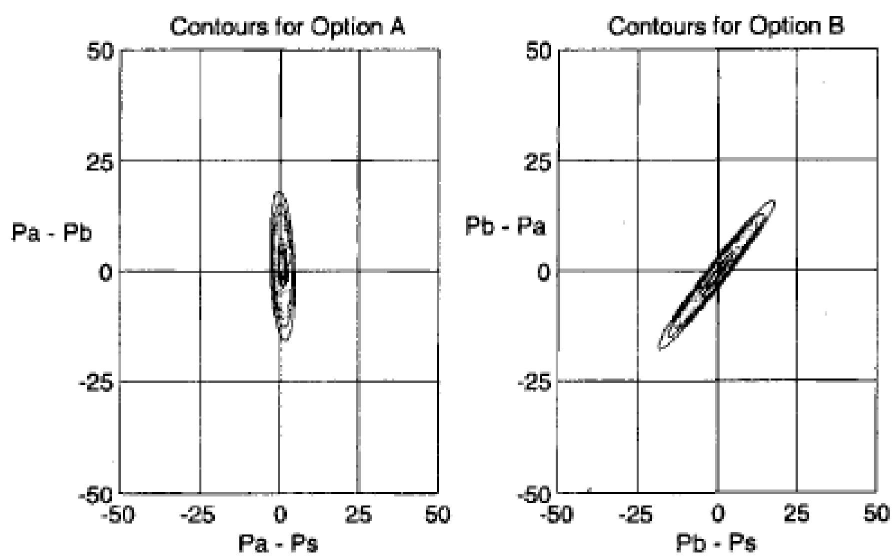
Applications of MDFT to Central Empirical Findings

- Predictions for the Similarity Effect
  - The valences of A and S are positively correlated with each other and negatively correlated with B.
  - The self-connections were set high (.94) to allow a long memory, the inhibitory connections between distant alternatives were low (-.001), and the inhibitory connections between similar alternatives were set to be greater (-.025).
  - This model correctly predicts that B is more likely than A for the trinary choice.



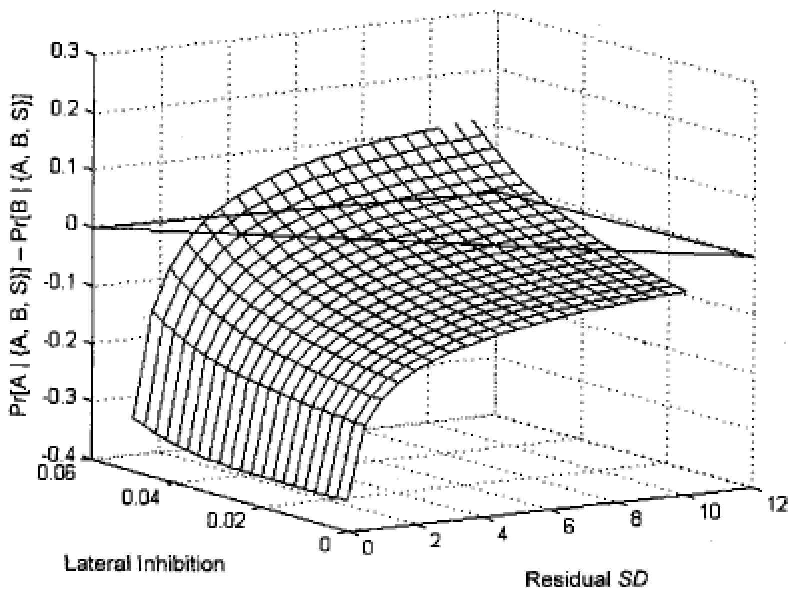
Applications of MDFT to Central Empirical Findings

- Choice probability is related to the area above and to the right of the zero preference state.
- If the correlations among primary attributes is diminished and the variance due to irrelevant attributes is amplified, the similarity effect disappears.



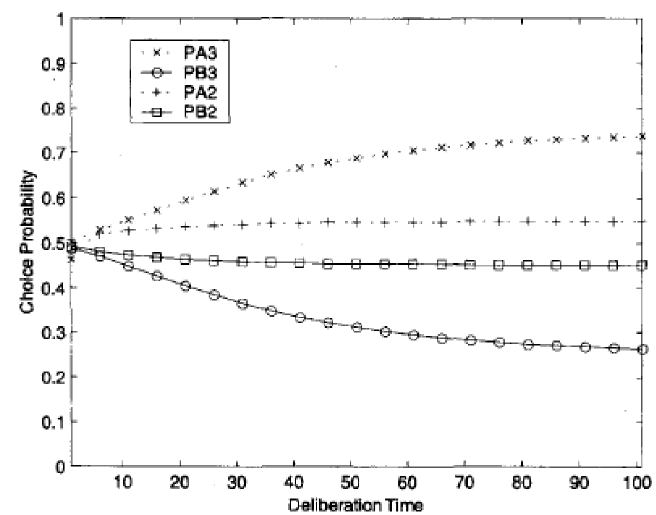
Applications of MDFT to Central Empirical Findings

- Similarity effect is strongest when the inhibitory connections are set to 0.
- The similarity effect occurs when the difference between Pr[A] – Pr[B] is negative in the trinary case.



Applications of MDFT to Central Empirical Findings

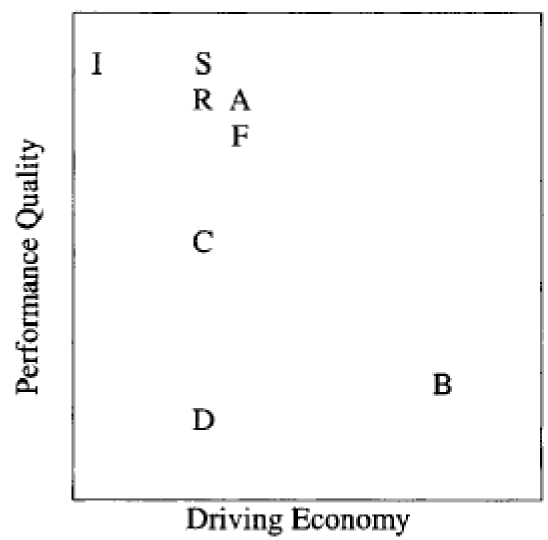
- Predictions for the Attraction Effect
  - Comparing the dominated decoy to the other two options produces a negative inhibitory link to the closest dominant option.
  - The decoy makes the dominant option “appear” stronger
  - Only the value matrix changes from the similarity tests.
  - The expected results were shown
  - If lateral inhibitory connections were set to 0, which makes S a diagonal matrix, the attraction effect disappears.



Applications of MDFT to Central Empirical Findings

- Similarity and Attraction Interactions
  - The attraction effect gradually disappears with distance after moving from R to C to D.
  - Range decoys (weaker on weak dimension) produce a stronger effect than frequency decoys (increases frequency of items below).
  - The inhibitory connection between F and B is stronger than between R and B.

Quality	A to decoy inhibition	Pr(A|A, B)	Pr[A|{A, B, C}]
3.00 (R)	−.025	.55	.65
1.50 (C)	−.008	.55	.63
.75 (C)	−.003	.55	.58
.50 (D)	−.001	.55	.55

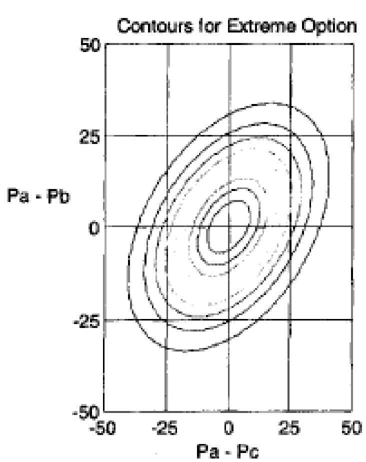


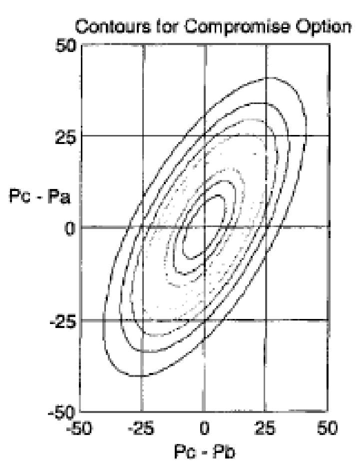
Applications of MDFT to Central Empirical Findings

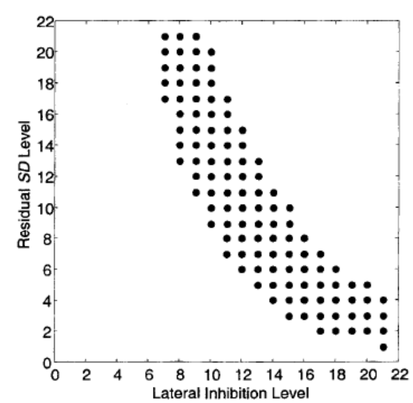
- Predictions for the Compromise Effect
  - Challenging because there are no special mechanisms built into the theory to produce this effect.
  - Required changes to the model parameters:
    - M was changed to represent the new locations
    - The inhibitory connections needed to be changed due to the equal distances between the compromise and extreme options.
      - These were the same as used for the attraction effect, but A and C are set to the same as between C and B.
    - Quality and Economy were set to have equal weights

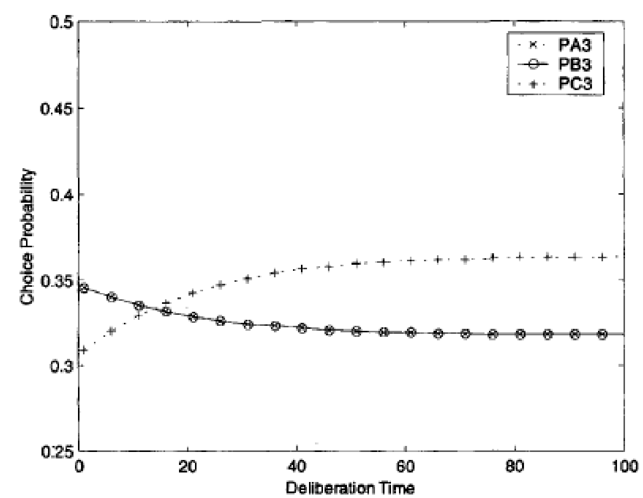
Applications of MDFT to Central Empirical Findings

- The model predicts that the probability of choosing the compromise is higher than the extremes, even though the binary probabilities are equal.
- Lateral inhibition is crucial for producing this effect
- All three effects are present for the solid dots.
- For the polarization effects, the compromise effect hurt one extreme more than the other. This can be accommodated by relaxing the assumption that the distances are exactly equal









Applications of MDFT to Central Empirical Findings

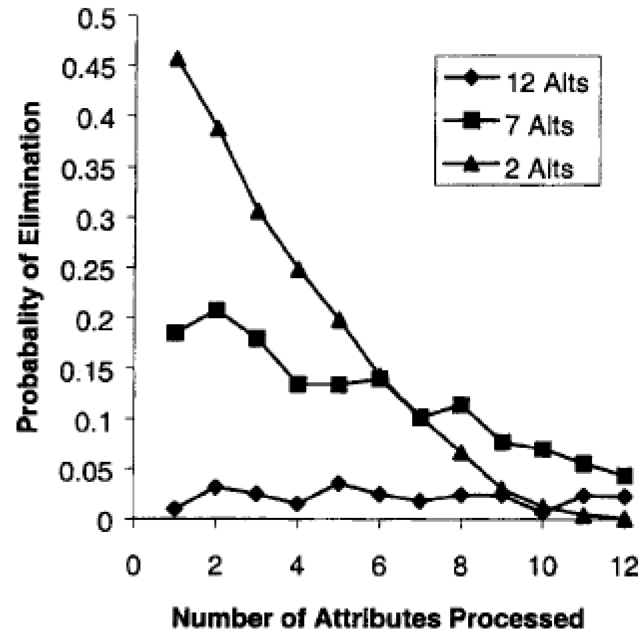
- 3 advantages of MDFT over Tversky and Simonson's model:
  - The context-dependent advantage model fails to account for the similarity effect.
  - Others have not addressed the interactions between similarity and attraction.
  - The context-dependent advantage model down not have a mechanism for describing predecisional search measures.

Applications of MDFT to Central Empirical Findings

- Predecisional Search
  - Dependent on number of alternatives in choice set
  - MDFT mimics this sort of strategy-switching by adding a lower elimination boundary
  - The complete version uses both an upper and lower boundary, which introduces two ways an option can be chosen: crossing the upper boundary or being the only option to survive.
  - Proven using a simulation with the data sets from an original predecisional study
    - Participants presented with 2, 7, or 12 alternatives described by 12 attributes with 1 of 3 evaluations assigned to them

Applications of MDFT to Central Empirical Findings

- For the 12-alternative set, most options are rejected quickly based on the first or second attributes
- The proportion of information searched decreased from a high of .89 for 2-alternative sets to .45 for the 7-alternative set to a low of .25 for the 12-alternative set.



Applications of MDFT to Central Empirical Findings

- Summary of Empirical Applications
  - The attraction and compromise effects should be attenuated by time pressure, but the similarity effect should not be.
  - MDFT can also be used to filter a large set of options to a smaller competitive set.

Comparisons with Other Models

- Decision Theories
  - First to explain all three effects.
  - Also accounts for differences between range and frequency decoys and the positions of inferior decoys on the attraction effect.
- Previous Artificial Neural Networks
  - Proposed to deal with consumer behaviors and EBA choice processes, but not the similarity effect or search results.
- Sequential Sampling Models
- Implications for Future Research

Comparisons with Other Models

- Sequential Sampling Models
  - Innovations include the valences and the incorporation of lateral inhibition to define S.
- Implications for Future Research
  - MDFT predicts that the compromise effect should gradually turn into a similarity effect as the compromise option is moved along the diagonal towards an extreme option.
  - The researchers expected to test this prediction and others.

Conclusions

- Authors extended their previous work to multialternatives and implemented as a neural network.
- MDFT is the only formal theory that has explained all three effects.

Applet

- http://mypage.iu.edu/~edimperi/MDFT/index.html
- Eric Dimperio's applet, as part of Dr. Busemeyer's lab.

- Thank you for your attention. Any questions, comments, or concerns are welcome.