**Categorization Revived: A Novel Connectionist Approach to Addressing Intransitivity and Event Dynamics**Cory Parker

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**Abstract**

This pathetic attempt at a research proposal descends upon the modern theories of concepts and event knowledge representation to see if the integration of some of their notions can address the limitations of the classical view, such as the *intransivity* issue of category membership. In this proposal, a *connectionist model* that learns distributed representations of event knowledge from natural data is the Joker, which juggles the semantic content and temporal structure of events. The model would be tested on its ability to exhibit graded category membership, generate appropriate inferences, and generalize to novel event sequences. If successful, there will likely be implications to theories of categorization, decision making, and event cognition, as I hope to explain… ( ͡ಥ ͜ʖ ͡ಥ)

**Introduction**:

The classical view of concepts often struggles with typicality effects and intransitivity. This view posits that categories are defined by necessary and sufficient conditions, which faces profound challenges in accounting for typicality effects and intransivity (Murphy, 2002). Alternative perspectives, such as Prototype and exemplar theories, offer robust frameworks for understanding how objects are categorized but the question remains whether we can represent the complex relational structures such as *events. Event knowledge* emphasizes the importance of paying attention to the *temporal* and *causal* structure of events (Elman & McRae, 2019). This departs from a simple feature-based representation, which is mainly context-independent, and instead narrows in on the dynamic interactions and sequences that influence understanding and memory.

**Limitations of the Classical View**

The classical view of concepts has been the dominant theory in understanding human categorization since Aristotle. Yet, as Murphy (2002) points out, this view is limited by its inability to account for graded structure of categories, typicality effects, and the intransivity of category membership. For example, you may consider a car seat chair. As a chair would be typically regarded furniture, people do not consider, on average, that a car seat is furniture. These limitations led researchers to consider alternative models, such as the prototype and exemplar theories, which seem to offer more flexible perspectives for the complications that arise in human categorization. This illustrates the issue of the classical view’s inability to include the context-dependent and dynamic nature of category boundaries.

This has forced researchers to consider different models (prototype and exemplar) for a more nuanced perspective of categorization. Departing from the classical view which assumes clear and definitive category memberships, these models handle the variability and the “fuzziness” of category boundaries, allowing them to be more flexible for categorization.

**Prototype Theory**

Prototype theory represents categories based on typical features, which are then weighted by their importance \***(Rosch & Mervis).\***. This approach alleviates the pains involved in a single category, like the different dog-fur lengths when identifying a particular dog. A hairless dog would be considered atypical and fuzzy in the classical view, whereas for the prototype model, each of the differences are associated with weights based on their prevalence and distinction within the given category (Murphy 2002).

**Exemplar Theory**

The exemplar theory extends the fluidity of categorization by suggesting humans categorize new stimuli by comparing them to individual instances previously encountered and stored in memory (Nosofsky, 1986). A detailed memory trace of each instance is possible in this theory, supporting a superior categorization approach for cases where different instances share few common aspects. This is a more useful categorization approach where the variability within a category is non-trivial. For instance, one uses exemplar theory by recalling certain memories of different robins they’ve encountered before, where each slightly varies in size, color, etc. Comparing a new bird to the stored memories of individual robins, the observer in question categorizes the new bird based on its similarity to these memory examples. This is an effective method when the birds don’t share a set of uniform features but recognized through a diverse set of individual characteristics remembered from past experiences (Nosofsky, 1986).

**Event Knowledge and Temporal Dynamics in Categorization**

Recent advancements in understanding event knowledge acknowledges the importance of temporal and causal structures in categorization (Elman & McRae, 2019). Dynamic models of event knowledge integrate the sequence and causal relationships between events. This offers a richer and fuller representation of categories as they unfold over time, unlike statics approaches (feature-based). Elman and McRae’s (2019) connectionist model of event knowledge demonstrates how a recurrent neural network can learn to predict the temporal structure of events from naturalistic data. Their model exhibits properties of human event cognition, most interestingly, predictive inferences and to generalize to novel activity sequences. The model can generate expectations about upcoming events based on its prior experience from learning distributed representations that isolate the temporal, causal relationships between event components.

Events are made up of activity sequences, where an *activity* is a collection of actions or other components, and an action is essentially a *verb* in a sentence. The internal structure of activities is comprised of agents, actions, patients, instruments, and contexts (like the environment). Reinforcement learning models like, Q-Learning, are used to learn the value of various decisions available based on experience (Sutton & Barto, 1998). The models update value estimates based on the difference or *gap* between predicted and actual outcomes. This allows for adaptive decision making, where the *value* is often combined with other factors like, uncertainty in decision making. An example would be the exploration-exploitation of tradeoff balances the need to get novel information (exploration) with the desire to maximize rewards based on current knowledge (exploitation) (Cohen, McClure, & Yu, 2007).

Uncertainty has a significant role in *choice mechanisms.* People tend to be risk-averse, preferring options with known probabilities over those with ambiguous ones (Ellsberg, 1961). Event knowledge can impact choice mechanisms by providing a framework for predicting outcomes and reducing uncertainty, like understanding the typical sequence of events in a restaurant scenario. This allows an individual to anticipate the consequences of ordering a certain dish, reducing their uncertainty in their decision making (Elman & McRae, 2019).

Thresholding and action selection of which the Basal Ganglia plays a crucial role, where the direct pathways of the basal ganglia facilitate the selection of actions needed to exceed a certain threshold, whereas the indirect pathway suppresses competing actions, known as *competitive inhibition.* Generalization could occur in the threshold processing through the transfer of learned thresholds across similar contexts to actions. The threshold for selecting a particular action in one context may generalize to similar events, allowing for rapid decision making in novel circumstances (Seger & Peterson, 2013).

**Shortcomings of These Models**

Existing models of generalization in categorization and decision making, such as the Generalized Context Model (Nosofsky, 1986) and the Rational Model of Categorization (Anderson, 1991), have made contributions to our understanding of these processes. Yet, these models struggle with to capture the rich temporal and causal structures of events, as well as the intransitivity of category membership. Research in the future will hopefully focus on integrating insights from event knowledge and the dynamic nature of categorization into these models to better account for our cognition’s flexibility and context-sensitivity.

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The classical theory’s *intransivity* issue is where a member of one category doesn’t necessarily translate well into membership in a related category. For example, typically people would regard clocks as furniture especially when considering the context most people living in developed countries experience. Yet, people believe Big Ben is a clock, but they don’t regard Big Ben as furniture. More explicitly, transitivity describes *relations* among sets, where A is a subset of B and B is a subset of C, where a relation is defined as, “*When two objects, qualities, classes, or attributes, viewed together by the mind, are seen under some connexion, that connexion is called a relation.*” (Augustus De Morgan). The transitivity part establishes that A must also be a subset of C. If A is represented as Big Ben, B is represented by clocks, and C represents furniture, it follows here that A is not a subset of C. Thus, the problem of intransitivity.

Attempting to address these conceptual challenges, this paper intends to explore the potential use of linear algebra axioms, specifically a theorem that states that if a vector space has two subspaces, then one subspace must contain the other. The hope is that such a mathematical model could bypass the intransitivity problem by developing a formal framework for understanding category membership and their relationships.

**Vector Space Model Proposal**

In linear algebra, if a vector space can be defined for the purposes of this paper, a theorem, among many others, could help in the endeavor of understanding dynamic event knowledge and enriching the categorization and generalization processes to better simulate the human brain’s cognitive processes that govern ideal decision making. One such theorem, for example, states that, given a vector space of a category along with its members, if two subspaces are both subspaces of the same vector space, then one of the subspaces must be contained in the other. Hopefully it’s clear that this would certainly bypass the difficulty in the classical view’s intransitivity. Though there is more work to be done with regards to the formalism, this would be major triumph over the limitations of current models.

In addressing the limitation of existing models, I’m proposing a representation of categories and their members in a high-dimensional vector space. In this type of framework, each category and its members would be represented as vectors, with the distance and direction between vectors reflecting the typicality and relationships between categories as this approach could potentially bypass the intransitivity problem, allowing for a more nuanced representation of category membership, where the relationships between categories are not strictly hierarchical but can exhibit much more complexity in its patterns in the vector space. Then, as I hope to be the case, we could develop useful algorithms to discover more about human cognition in terms of decision making through categorization and generalization, thus helping silly humans make better decisions, not only individually, but in aggregate.

**Conclusion**

Concluding this half-baked rant, this research proposal explores the idea of integrating the modern theories of concepts and event knowledge representation to tackle the limitations of the classical view, head on, particularly in the intransitivity issue in category membership. Proposing a connectionist model which learns distributed representations of event knowledge and conceptually initializing a vector space approach via linear algebra axioms, my hope is to develop a more comprehensive and dexterous framework for modeling categorization and decision making. This vector space model could have the potential to provide a nuanced representation of category membership, where the relationships between categories are not strictly hierarchical but can exhibit more complex patterns in high-dimensional space. This novel approach could lead to the development of algorithms that better capture our cognition in terms of decision making through categorization and generalization, in hopes to aid humans make better decisions, collectively. Future research, if this proposal serves useful, might refine these models, testing against human data, as well as exploring potential applications in artificial intelligence for sake of proper alignment.

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**Figures**

A diagram of a model

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*[Figure 1]*

A diagram of a model

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*[Figure 2]*

A diagram of a event

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*[Figure 3]*