**Math Psych Conference 2022**

**Monday, July 11th**

**Room**: Virtual ICCM I

**Q&A Time:** 1pm (login beginning at 12:30pm)

1. [**A comparison of quantum and multinomial processing tree models of the interference effect**](https://mathpsych.org/presentation/726)

 Dr. Christopher Fisher, Dr. Lorraine Borghetti, Prof. Joe Houpt, Dr. Leslie Blaha, Christopher Adam Stevens

We compare the qualitative predictions of an existing quantum model and a novel multinomial processing tree (MPT) model of the interference effect using parameter space partitioning (PSP). An interference effect occurs when categorizing a stimulus changes the marginal probability of a subsequent decision, leading to a violation of the law of total probability. The PSP analysis revealed that our MPT model can produce the same qualitative patterns as the quantum model. Further analysis, however, revealed that the models differ in several important ways. First, a larger volume of the MPT model's parameter space produces a smaller number of interference effects compared to the quantum model. Second, the distribution of volume across patterns is more diffuse for the MPT model, indicating it is more flexible than the quantum model. We discuss limitations and future directions.

<https://www.youtube.com/watch?v=gSu-AcbyKZY>

**Notes:**

-Interference effect: a judgment changes the marginal probability of a subsequent decision; violates the law of total probability  
-Two theoretical accounts: classical probability theory (CPT) and Quantum probability theory; CPT struggles to account for interference effect but quant allows for sequential events (so better able to measure interference effect)  
-Goal: develop CPT model that can produce interference effect similar to quantum  
-Experiment: participants presented with ‘good’ and ‘bad’ faces and must decide whether to attack or withdrawal  
-Conditions: XD (face and true category given), CD (face given and must decide category), and d (just face given)  
-Belief-Action Entanglement (BAE) Model has 4 vectors (attack/good, withdrawal/good, attack/bad, withdrawal/bad) and has utility and entanglement parameters   
-Judgment Revision Model (JRM) is a multinomial process tree model with three processes (category judgment, category revision process, decision process) and there are 12 trees for the different conditions and face/category type   
-Models compared with Parameter Space Partitioning (PSP) to show the relative space for the different model comparisons (y1>1y2; y1=y2; and y1</=y2) and volumes of region can be measured  
-3^4 = 81 patterns of interference effect (3 effects- positive, negative, and absent- and 4 face type/ conditions combination -face good vs bad; and d vs xd, d vs cd)  
-had constrained and unconstrained versions of each model; Constrained (JRM: ck=c; BAE: mu(tg,b)= -mu(tg,g)) and unconstrained (JRM: ck,c; and BAE: mu(tg,b),mu(tg,g))  
-used gini coefficient to account for n patterns/ dispersion of pattern distributions  
-JRM successfully illustrated interference effect and was more flexible than BAE

**Questions:**

***Questions for Dr. Houpt****:*

*How is interference measured?*

*How does PSP compare to Bayesian model comparison? Are they both different types of the same tool, or are they completely different approaches?*

**Citation:** Fisher, C. R., Borghetti, L., Houpt, J., Blaha, L., & Stevens, C. (2022, July). A comparison of quantum and multinomial processing tree models of the interference effect. Paper presented at Virtual MathPsych/ICCM 2022. Via [mathpsych.org/presentation/726](https://mathpsych.org/presentation/726).

**Room**: Memory and learning

**Q&A Time:** 2pm (login beginning at 1:30pm)

1. [**Mutual interference in working memory updating: A hierarchical Bayesian model**](https://mathpsych.org/presentation/752)

 Yiyang Chen, Mario Peruggia, Trisha Van Zandt

We built a hierarchical Bayesian model for the working memory updating task. This model jointly accounts for both responses and reaction times in the memory updating paradigm, which is a commonly used paradigm to measure working memory capacity. To model responses, we adopted a mutual interference framework from Oberauer & Kliegl (2006) that characterized activation levels of working memory items, and extended this framework into a Markov chain structure to characterize a wider range of responses. To model reaction times, we adopted a Wald diffusion framework where the Wald parameters were associated with activation levels of working memory items. This model allows us to investigate the mechanism underlying participant performance in the memory updating task under a joint theoretical framework. We applied this model to an empirical data set investigating the effects of working memory training. Modeling results revealed that training might not improve overall working memory capacity, but may lead to a general improvement in the speed of processing.

<https://www.youtube.com/watch?v=PgT3llgxeYo>

**Notes:**-used data from Salthouse et al. (1991) data set that looked at switching attentional focus and removing outdated info from working memory  
-ex of experiment: start with 3 #s to memorize; next step is a cue to change item 3 (for example +2); next step could be a cue to change item 1 (ex: -6); at the end the participants must recall all numbers after the updates are done  
-in another data set, they looked at transfer effects in working memory with a pre- and post-test, where three groups received different training between tests (memory updating task, binding task, and visual search)  
-question: does binding task training improve memory updating task performance?  
-looked at the different decision processes through response times  
-plotted RTs with a Wald diffusion model  
-looked at accumulation rates for updating and recall; assumed that more activated information leads to faster accumulation speed  
-plotted the mutual interference between each pair of items and is directly linked to the working memory capacity limitation  
-if training can improve the level of mutual interference, the updating group should have a larger decrease than the control group, which was seen in results  
-if a transfer effect is occurring, would expect the binding group to have a large decreases than control group, but results were opposite; no evidence of transfer effect > training doesn’t transfer between different working memory tasks  
-updating group had a largest accumulation rate in the recall period, but the binding group was also increased above the control group, which may indicate that training in the binding task might be able to improve the overall processing time in working memory and may transfer in memory updating task

**Questions:**

*Did not attend*

**Room**: Dimension reduction

**Q&A Time:** 3pm (login beginning at 2:30pm)

1. [**Principal-component exploration of individual differences in the general-speed component of response times.**](https://mathpsych.org/presentation/854)

 Adriana Felisa Chávez De la Peña, Dr. Jeffrey Rouder, Joachim Vandekerckhove

A common method to localize cognitive processes is Donders' subtractive method. For example, to localize inhibition in the Stroop task, performance in a congruent condition is subtracted from that in an incongruent condition. Many cognitive tasks purport to measure inhibition this way. A critical question is whether individual difference scores correlate across these tasks. We find that they do not. Inhibition response time difference scores correlate weakly at best, often below .1 in value. We revisit three large-scale data sets and find that overall task response times do correlate at over .5 in value. This result implies that participants are consistently fast or slow to respond across these tasks. The main source of individual variation is not inhibition, but rather overall or general speed. We explore the dimensionality and structure of general speed across individuals and tasks in extended data sets. With several tasks per set, it is possible to ask whether there is a unified general speed versus several varieties of general speed. A principal component analysis (PCA) revealed a strong first factor in all sets, consistent with a unidimensional, unified construct of general speed. One way of contextualizing these results is to compare them to human anthropometrics. While human bodies are similar in many ways, they seemingly vary on a “size” factor. We analyze a publicly available set of 93 body measurements collected across 6,068 US military personnel. Indeed, a strong first factor of size emerges, but so does a second factor that captures how heavy people are for their height. Perhaps surprisingly, the first-factor solution for general speed is comparable to or even stronger than it is for anthropometrics. Moreover, we were unable to identify a coherent second factor for general speed. We conclude that general speed is likely unidimensional.

<https://www.youtube.com/watch?v=1FBg9AXaBdk>

**Notes:**

-difference scores used to study cognitive control show weak correlations across tasks and poor test-retest reliability  
-they show that across many data sets, the general-speed component of response times in cognitive control tasks has an unifactorial solution  
-this unifactorial solution is even stronger than that found in anthropometric data  
 *anthropometric data= data on human body size and shape*  
-Donders’ subtraction method may inadvertently wash out the variance of interest in the data (area of possible future research: general speed component over differences in scores)  
-example of cognitive control task: stroop task (color task where name and visual color are different) with congruent and incongruent trials  
-traditionally, we would subtract differences between trials, ignoring the accuracy rates  
-looked at pre-existing data, and found very little correlation in differences across different cognitive control tasks was very low  
-the variance seems to be almost evenly allocated across all of the factors identified in each data set  
-when looking at the general-speed component, generated data to look at correlations between task 1 and task 2 for both true effect and observed effect  
-much higher correlations for general-speed component when applied to the battery of cognitive control tasks in the previous data sets  
-similar results when applied to other data sets  
-general-speed component may be a possible route for future research

**Questions:**

***Questions for Dr. Houpt:***

1. [**Specificity of the jumping-to-conclusion bias in social anxiety: An account using the Bayesian computational modeling approach**](https://mathpsych.org/presentation/793)

 Ms. Nicole Yuen Tan, Dr. Yiyun Shou, Dr. Junwen Chen, Bruce Christensen

To date, little is known about the role of social anxiety in the assignment of evidence weights which could contribute to the jumping-to-conclusion bias. The present study used a Bayesian computational method to understand the mechanism of jumping-to-conclusion bias in social anxiety, specifically through the assignment of weights to information sampled. The present study also investigated the specificity of the jumping-to-conclusion bias in social anxiety using three variations of beads tasks that consisted of neutral and socially threatening situations. A sample of 210 participants was recruited from online communities to complete the beads tasks and a set of questionnaires measuring the trait variables including social anxiety and the fears of positive and negative evaluation. The Bayesian model estimations indicated that social anxiety and fears of evaluation significantly biased the assignment of evidence weights to information received in certain conditions of the beads tasks. Our results indicated that social anxiety and fear of evaluation could influence belief updating depending on situations. However, the influences from these trait variables seemed to be insufficient in contributing to the jumping-to-conclusion bias.

<https://www.youtube.com/watch?v=Vn0JYqC4Xrs&feature=emb_imp_woyt>

**Notes:**

**Questions:**

**Tuesday, July 12th**

**Room**: Virtual ICCM II

**Q&A Time:** 1pm (login beginning at 12:30pm)

1. [**Towards a method for evaluating convergence across modeling frameworks**](https://mathpsych.org/presentation/729)

 Dr. Lorraine Borghetti, Dr. Christopher Fisher, Prof. Joe Houpt, Dr. Leslie Blaha, Dr. Glenn Gunzelmann, Christopher Adam Stevens

Model convergence is an alternative approach for evaluating computational models of cognition. Convergence occurs when multiple models provide similar explanations for a phenomenon. In contrast to competitive comparisons which focus on model differences, identifying areas of convergence can provide evidence for overarching theoretical ideas. We proposed criteria for convergence which require models to be high in predictive and cognitive similarity. We then used a cross fitting method to explore the extent to which models from distinct computational frameworks---quantum cognition and the cognitive architecture ACT-R---converge on explanations of the interference effect. Our analysis revealed the models to be moderately high in predictive similarity but mixed for cognitive similarity. Though convergence was limited, the analysis suggests that interference effects emerge from interactions between uncertainty and the degree to which an individual relies on typical cases to make decisions. This result demonstrates the utility of convergence analysis as a method for integrating insights from multiple models.

<https://www.youtube.com/watch?v=dWFyTdznZTk>

**Notes:**

-introduces model convergence as a relatively new model comparison method  
-evaluate model convergence between 2 distinct models of interference effects (existing quantum cognition model and novel model in ACT-R, a cognitive architecture)   
-traditional model comparison approaches are competitive, focusing on goodness of fit  
-model convergence emphasizes similarity, providing clarity on the underlying process represented computationally in a model  
-mod. Con. evaluates similarity along 2 orthogonal dimensions: predictive similarity (predictions follow same pattern) and cognitive similarity (similarity between processes, like how info is organized and how info is transformed, manipulated, and combined)  
-high similarity= models converge  
-low pred/ low cog= critical tests distinguish b/n competing representations  
-high pred/ low cog= mental representations not distinguishable   
-high pred/ high cog= model convergence  
-low pred/ high cog= contradictory evidence  
-interference effects reveal that cognition is sensitive to differences in context; they emerge when uncertainty about an event changes the marginal probability of a subsequent decision, resulting in a violation of the law of total probability (LOTP)  
-same good guy/bad guy attack/ withdrawal scenario from yesterday (the categorization-decision paradigm)   
-used the Belief-Action Entanglement (BAE) Model again  
-BAE has 3 sequential processes: initial state > categorization > action decision; the initial state is same across the conditions, but condition d is different than cd and xd in the categorization stage and condition xd is different than d and cd in the action decision stage  
-the ACT-R Model of interference Effects emphasizes mechanisms of the declarative memory (names, facts, dates, etc.) system   
-ACT-R has knowledge represented by slot-value pairs for a feature, category, and action; decisions are implemented by retrieval requests representing information known to the participant; ex: when a retrieval request is submitted to declarative memory, the relevant chunks compete for selection where the one with the highest activation value wins; that activation value for a given chunk is scaled by the beta parameters; a partial matching parameter allows for chunks not exactly matching the request to retrieve the delta parameter, which, at lower values, can be viewed as approximating uncertainty in the decision process  
-Act-R sequential processes: declarative memory, retrieval request, and retrieval process  
-if these two models converge, the processes should be relatable   
-Utility parameter= predictive similarity: two models had some discrepancies, but concluded overall that there was high similarity; cognitive similarity: only some variables were analogous, so similarity was moderate at best  
-Categorization parameter *j*= pred sim: high similarity; cog sim: low similarity  
-Entanglement parameter gamma= pred sim: moderately high sim for uncertain category knowledge but low for certain categorization; cog sim: high similarity   
-overall model convergence had mixed results  
-some divergence can be attributed to ACT-R’s partial matching mechanisms which is constrained to implementing penalties for mismatches in slot value pairs but not in the retrieval request  
-other dissimilarities also emerge from the ratios shown in the activation equations for ACT-R which can result in non-systematic retrieval processes, at least when interpreting parameter functions literally  
-that said, the BAE’s entanglement parameter and ACT-R’s partial matching mechanism offer very similar accounts for moderating the influence of bias on a decision

**Questions**So, I have a question from Dr. Borghetti’s presentation, but I’m not sure if it’s a dumb question/ completely left field/ too elementary/ phrased weird. Would it be okay if I run it by you first?

Is there a conceptual alteration to our understanding of interference/ the underlying mental representations involved due to the high predictive similarity?

##### Cite this as:

Borghetti, L., Fisher, C. R., Houpt, J., Blaha, L., Gunzelmann, G., & Stevens, C. (2022, July). Towards a method for evaluating convergence across modeling frameworks. Paper presented at Virtual MathPsych/ICCM 2022. Via [mathpsych.org/presentation/729](https://mathpsych.org/presentation/729).

**Room**: Evidence accumulation

**Q&A Time:** 2pm (login beginning at 1:30pm)

1. [**Linear ballistic accumulator models of confidence and response time.**](https://mathpsych.org/presentation/734)

 Ms. Haomin Chen, Andrew Heathcote, Dr. Jim Sauer, Dr. Adam Osth, Matt Palmer

Accurate decisions tend to be both confident and fast. Nonetheless, there are relatively few models that can simultaneously address this three-way relationship, especially for single stage decisions where participants indicate both their choice and their confidence. Extending on a common decision architecture of the linear ballistic accumulator framework, two models have been proposed – 1) a Multiple Threshold Race model which instantiates the Balance-of-Evidence hypothesis where confidence is determined through the difference between accumulated evidence for competing options (e.g., Reynolds, Osth, Kvam, & Heathcote, in revision), and 2) a newly developed Confidence Accumulator model which assumes that confidence itself is accumulated independently for each confidence option. To test these two confidence architectures, we ran two experiments manipulating the length of the confidence rating scale across 2-, 4-, or 6-options in a recognition memory task along with a perceptual task. Different models were compared that made different allowance for how the length of the confidence scale affected model parameters. While both model classes found that thresholds were affected by the length of the scale, drift rates were only minimally affected. Implications for models of confidence and response time will be discussed.

<https://www.youtube.com/watch?v=1Ksm__X7aO0>

**Notes:**

-recent work has focused on capturing the 3-way relationship between confidence, response latency, and choice accuracy, but more focus has been on confidence but not latency   
-confidence cab be measured directly or indirectly  
-to compare models fairly, we need to know that differences are due to different confidence computations, not other aspects such as noise, thus they chose the linear ballistic accumulator model (LBA)  
-confidence of each model is determined by losing accumulator model: if losing model does not pass threshold= high confidence; of it does pass threshold= low confidence

**Questions:**

The difference b/n drift diffusion & accumulator models:  
drift diff builds evidence for or against a boundary  
accumulator models build support for opposing models as a race, more as independent processes

Is there a time limit for diffusion models, going beyond a minute or so?  
Ans 1: Most times a drift diffusion would be applied to short decision models (few seconds); it should be possible in principle, but uncertain if it has good psychological approach  
Ans 2: has done a range of experiments in 2+ min models, and it still worked well, models fit well  
Dr. Houpt ans: relies on many more trials, which can be difficult to obtain, but math should be fine/ give good insight

**Room**: Neurocognitive modeling

**Q&A Time:** 3pm (login beginning at 2:30pm)

1. [**A neural index of resource availability: Unifying subsequent memory effect, primacy serial position effect, and word frequency effect**](https://mathpsych.org/presentation/812)

 Si Ma, Dr. Ven Popov, Qiong Zhang

Humans have a limited amount of cognitive resources to process various cognitive operations at a given moment. Based on the Source of Activation Confusion (SAC) model of episodic memory, resources are consumed during each processing and once depleted they need time to recover gradually. This has been supported by a series of behavioral findings in the past. However, the neural substrate of the resources is not known. In the present study, over an EEG dataset of a free recall task, we identified a neural index reflecting the amount of cognitive resources available for forming new memory traces. We showed that consistent with the model predictions, the index was able to capture the sequential effect of word frequency and the primacy serial position effect. In addition, greater available resources at encoding, as characterized by the neural index, are associated with better memory at recall. This provides an alternative explanation for the subsequent memory effect (SMEs, i.e. differential neural encoding patterns between subsequently recalled versus subsequently non-recalled items), which has been previously associated with attention, fatigue and properties of the stimuli.

<https://www.youtube.com/watch?v=cwGWkflTWKc>

**Notes:**

**Questions:**

**Room**: Poster and Fast Talk

**Q&A Time:** 4pm (login beginning at 3:30pm)

1. [**How to know what you should know: Implications of the choice of prior distribution on the behavior of adaptive design optimization**](https://mathpsych.org/presentation/848)

 Sabina J. Sloman, Daniel Cavagnaro, Stephen Broomell, Daniel Oppenheimer

Adaptive design optimization (ADO) is a state-of-the-art technique for designing experiments for cognitive modeling (Cavagnaro, Myung, Pitt, and Kujala, 2010). ADO dynamically identifies stimuli that, in expectation, yield the most information about the hypothetical construct of interest (e.g., parameters of a cognitive model). To calculate this expectation, ADO leverages the modeler’s existing knowledge, specified in the form of a prior distribution. “Informative” priors, constructed on the basis of domain knowledge or previous data, have the potential to align the prior with the empirical distribution in the participant population, thereby making ADO maximally efficient. However, if the informative prior is inaccurate, i.e., “misinformative,” then ADO may be led astray, leading to wasted trials and lower efficiency. To play it safe, many researchers turn to “uninformative” priors. Yet, priors chosen on the basis of their predictive agnosticism rather than insight are also unlikely to align with the population distribution, possibly making them equally inefficient. In on-going work, we investigate the consequences of informative, misinformative and uninformative prior distributions on the efficiency of experiments using ADO.

<https://www.youtube.com/watch?v=8sfapnzKMTU>

**Notes:**

**Questions:**

**Wednesday, July 13th**

**Room**: Women of Mathematical Psychology

**Q&A Time:** 11am (login beginning at 10:30am)

**Notes:**-Betsy Fox: worked with Dr. Houpt at Wright State as one of his first grad students  
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**Questions:**

**Room**: Virtual ICCM III

**Q&A Time:** 1pm (login beginning at 12:30pm)

1. [**Leveraging cognitive models for the wisdom of crowds in sequential decision tasks**](https://mathpsych.org/presentation/751)

 Erin Bugbee, Chase McDonald, Prof. Cleotilde (Coty) Gonzalez

Many decisions we face in life are sequential, where alternatives appear over time. We often must decide whether to take the opportunity and stop searching or to continue evaluating potentially better future alternatives. Research suggests that humans are notoriously poor at stopping optimally in sequential decision-making tasks. These sequential decisions are difficult because they involve the consideration of how past, present, and future decisions affect the outcome. Recent research suggests that the wisdom of the crowd (WoC) --- that is, aggregated decisions of many people that outperform most individuals --- can be applied to sequential decision tasks and potentially help improve stopping decisions. However, current models rely on a process of fitting human data, making it difficult to understand how those individuals would behave in new problems. Furthermore, these models do not account for the learning process that humans experience while making these decisions. In this work, we demonstrate how simulated agents using a cognitive model derived from Instance-Based Learning Theory (IBLT) can produce WoC that is similar to WoC from human participants in two sequential decision tasks. We demonstrate that the WoC performance from simulated groups of agents is better than the performance of most agents and that the Instance-Based Learning (IBL) crowd behavior is similar to the human crowd behavior. Thus, cognitive models that account for learning and experience can be used to inductively predict the behavior of human crowds in sequential decision tasks.

<https://www.youtube.com/watch?v=L74ebUhX0q0>

**Notes:**

-people are suboptimal when deciding to stop searching  
-wisdom of crowds: aggregating individual decisions to make crowd decision that should be wiser than any one individual at all  
-Exp 1: Balloon Analog Risk Task (BART): participants presented with balloons that start at $1; can pump (increased the $ of the balloon) or bank balloon as is, but pumping could cause the balloon to pop  
-Exp 2: Optimal Stopping Task: participants presented with sequence of cats, with the goal of selecting the heaviest cat; they were given the option to pass or select on each cat, but could not return to a previous cat; if they got to the end of the sequence without selecting a cat to be the heaviest, the last cat was automatically selected; once a selection is made, no more cats are shown; the participants only received the reward if they correctly selected the heaviest cat  
-same 56 participants did each exp with 40 problems in each condition  
-Wisdom of crowds: for each decision the crowd behavior was selected based on the behavior of the majority of the participants  
-Instance-Based Learning (IBL) Theory: incorporates some of the cognitive and memory mechanisms of the well-known ACT-R cognitive architecture. Generally, learning occurs by interacting with the environment and receiving feedback, and then instances are accumulated and stored in memory to be retrieved for future decisions. Instances are memory units that consist of three elements: situation (the contextual features) the decision being made, and the utility or feedback received from the decision.   
-IBL theory proposes that the decision making process consists of three main components. The *(#1) activation of instances* (each instance in memory has an activation value which dependent on the recency, frequency, and similarity to the current situation). The activation of an instance determines the *(#2) probability of retrieving* it, according to the softmax equation and a blended value is then calculated for each action through a mechanism called *(#3) blending*. This is calculated as the sum of the probability of retrieval multiplied by the outcome for each instance. Then ultimately the agent selects the action with the highest blended value greedily.

**Questions:**

**Room**: Reasoning and metacognition

**Q&A Time:** 2pm (login beginning at 1:30pm)

1. [**Measuring coherence in reasoning**](https://mathpsych.org/presentation/817)

 Nicole Cruz

Consider the inference sequence “The glass had orange juice, therefore it had orange juice or tequila, therefore if it did not have orange juice then it had tequila”. How convincing is it? To draw inferences like this, people may consider the meanings of the statements involved (how is “or” and “if” to be interpreted?), their degree of belief that each statement is true (do we know for certain that the glass had orange juice?), and any logical relations between the statements (e.g. does one statement entail or preclude another?). In reasoning research, these three pieces of information have often been treated as independent and potentially conflicting – with the logical information considered rational, and the content and beliefs considered biases. But theoretically such a conflict is not necessary, and empirically it does not seem plausible. In the Bayesian approach to reasoning described here, the three pieces of information are integrated and jointly necessary to draw good inferences. This approach is based on the concept of coherence. Degrees of belief in statements are coherent iff they follow the principles of probability theory (e.g. the glass cannot be less than empty or more than full; and if it contains orange juice and we add tequila, then the volumes of the two liquids will add up). But measuring the coherence of people’s uncertain reasoning is not straightforward, especially in situations in which the information available is uncertain, incomplete and changeable. To make such measurements, we must account for how logical constraints between probabilities shift when new information becomes available; define and adjust for the probability of making a coherent response just by chance; and ascertain which patterns of statement probabilities would allow us to make plausibly falsifiable, and thus informative, assessments of sensitivity to coherence. I describe some of these challenges, and discuss how we might be able to tackle them in the quest to increase our understanding of reasoning under uncertainty.

<https://www.youtube.com/watch?v=-BtVtWnUchI&feature=emb_imp_woyt>

**Notes:**

**Questions:**

**Room**: Attention and Perception

**Q&A Time:** 3pm (login beginning at 2:30pm)

1. [**Holistic processing for Chinese characters and English words**](https://mathpsych.org/presentation/866)

 Hanshu Zhang, Prof. Joe Houpt, Prof. Cheng-Ta Yang

Previous research reported conflicting evidence regarding whether Chinese characters are holistically processed. In past work, we applied Systems Factorial Technology to examine the processing efficiency for Chinese characters and English words. Our results indicated that native Chinese speakers exhibited limited capacity processing both characters and words. To identify the source of that limitation, our current research further investigated the mental architecture of processing Chinese characters and English words. Specifically, we hypothesized that observers’ performance would be indicative of a coactive processing architecture, where all information is pooled together to reach a single decision process. This architecture is often considered a benchmark of holistic perception. In Experiment 1, participants were asked to make a same/different judgment on the sequentially presented characters/words which either both or neither of the left and right components differed. The results indicated that participants adopted a parallel self-terminating strategy (i.e., same or both-different structure). Experiment 2 complemented the findings of experiment by examining performance with added conditions that either the left or right component could now be different (i.e., same, left-different, right-different, both-different). With the decisional uncertainty, the results indicated that most participants processed the stimuli with a parallel exhaustive architecture and a few participants exhibited the coactive architecture. To conclude, our current work provided evidence for weak holistic processing (parallel processing) for Chinese characters and English words, with the stopping-rule (self-terminating/exhaustive) dependent on the task and presentation context.

<https://www.youtube.com/watch?v=VvpNYnlFL8U&feature=emb_imp_woyt>

**Notes:**

**Questions:**

**Thursday, July 14th**

**Room**: Virtual ICCM IV

**Q&A Time:** 1pm (login beginning at 12:30pm)

1. [**Combining machine learning and cognitive models for adaptive phishing training**](https://mathpsych.org/presentation/830)

 Dr. Edward Cranford, Dr. Shahin Jabbari, Dr. Han-Ching Ou, Dr. Milind Tambe, Prof. Cleotilde (Coty) Gonzalez, Christian Lebiere

Organizations typically use simulation campaigns to train employees to detect phishing emails but are non-personalized and fail to account for human experiential learning and adaptivity. We propose a method to improve the effectiveness of training by combining cognitive modeling with machine learning methods. We frame the problem as one of scheduling and use the restless multi-armed bandit (RMAB) framework to select which users to target for intervention at each trial, while using a cognitive model of phishing susceptibility to inform the parameters of the RMAB. We compare the effectiveness of the RMAB solution to two purely cognitive approaches in a series of simulation studies using the cognitive model as simulated participants. Both approaches show improvement compared to random selection and we highlight the pros and cons of each approach. We discuss the implications of these findings and future research that aims to combine the benefits of both methods for a more effective solution.

<https://www.youtube.com/watch?v=69e8JR-nJRM&feature=emb_imp_woyt>

**Notes:**

**Questions:**

**Room**: Formal Analysis

**Q&A Time:** 2pm (login beginning at 1:30pm)

1. [**Constructing an unobservable critical path network from observable slacks**](https://mathpsych.org/presentation/707)

 Richard Schweickert

Critical Path Networks are models of the Psychological Refractory Period and of some cognitive tasks, such as visual search. A Critical Path Network is a directed acyclic network in which each arc represents a process that must be completed to perform a task, The processes on a path must be executed in order on the path. Processes not on a path together are unordered, and can be executed simultaneously. Each process has a duration. The time to complete the task, the response time, is the sum of the durations of the processes on the longest path through the network. If a process X precedes a process Y, the slack from X to Y is the longest amount of time by which X can be prolonged without making Y start late. Suppose processes in a task are executed in a Critical Path Network, but the network is unknown. By observing effects on response time of selectively influencing processes, one can learn for each pair of processes whether the pair is ordered or unordered. If they are ordered, one can learn the value of the slack from one to the other. From the order information a directed acyclic network can be constructed with the Transitive Orientation Algorithm. From the slacks a duration can be determined for each process. Several directed acyclic networks may be possible and the durations are not unique. If the slack values are valid for one of the possible directed acyclic networks, they are valid for all.

<https://www.youtube.com/watch?v=A7rbuSZjpJk&feature=emb_imp_woyt>

**Notes:**

-video a good walkthrough of critical path networks

**Questions:**

**Room**: Decision Making

**Q&A Time:** 3pm (login beginning at 2:30pm)

1. [**Discriminating between models of processing in multi-attribute choice**](https://mathpsych.org/presentation/777)

 Mr. Gavin Cooper, Guy Hawkins

Throughout the day, many of our choices integrate information from multiple attributes about an item we are considering. How do people process information about multiple attributes and choose whether to select a presented option? In the simplest scenario, for one option and two attributes, the decision to either accept or reject the option is based on combinations of the two attributes. Our model represents the evidence from each attribute towards accepting or rejecting the option as an accumulation process. We can model how the participant could combine this information into the final choice as combinations of these racing accumulators. For example, people may reject an option based on a single poor attribute but only accept the option if both attributes are highly valued. We constructed five different processing architectures and integrated them into a latent mixture modelling process to select between them. We use a hierarchical Bayesian approach to estimate individual participant processing architectures and overall group trends. I will show an initial assessment of our modelling framework using data simulated from the five processing architectures. I will also discuss an experimental task where participants viewed a series of hotel options that differ on two attributes - price and hotel rating. In this task, participants received instructions on how to combine the attribute information for their decisions. The modelling framework recovered the expected processing architectures for the different instruction manipulations, demonstrating good selective influence. Understanding consumer attribute processing helps us present information in such a way as to keep consumers as informed as possible about the consequences of their choices.

<https://www.youtube.com/watch?v=cjOnsvjFO44&feature=emb_imp_woyt>

**Notes:**

**Questions:**

**Friday, July 15th**

**9AM: Meeting with Dr. Houpt – CHANGE TO 11AM**

**Room**: ICCM V

**Q&A Time:** 1pm (login beginning at 12:30pm)

1. [**Evolving understandable cognitive models**](https://mathpsych.org/presentation/747)

 Dr. Peter Lane, Dr. Laura Bartlett, Dr. Noman Javed, Dr. Angelo Pirrone, Dr. Fernand Gobet

Cognitive models for explaining and predicting human performance in experimental settings are often challenging to develop and verify. We describe a process to automatically generate the programs for cognitive models from a user-supplied specification, using genetic programming (GP). We first construct a suitable fitness function, taking into account observed error and reaction times. Then we introduce post-processing techniques to transform the large number of candidate models produced by GP into a smaller set of models, whose diversity can be depicted graphically and can be individually studied through pseudo-code. These techniques are demonstrated on a typical neuro-scientific task, the Delayed Match to Sample Task, with the final set of symbolic models separated into two types, each employing a different attentional strategy.

<https://www.youtube.com/watch?v=yTDhlAvypwc>

**Notes:**

**Questions:**

**Room**: VMP 2022 Afterparty ?

**Time:** 2pm (login beginning at 1:30pm)

**Research-Related Questions and Notes**

From 7/11 1pm:

Could there be an interference effect occurring with chemo brain? How might we go about measuring it?

After 7/11 2pm:

Could working memory capacity decrease in individuals with chemo brain?

*General questions:*

*How do I get better at conferences? I follow pretty well when I can read or watch a YouTube video, but I feel like I end up getting lost at live events. I will be listening along, get caught on a term I don’t know, try and figure out that term (even just playing it back in my head), and then I’ve missed a whole chunk of information. Is there any way to get better at that?*

*I feel like a need a user guide on all the different models/ what they’re used for/ what makes them different, etc. How do I get better at that, or is that something I shouldn’t be focusing on at the moment?*

***SFT***

*What causes the switch from a negative to a positive SIC in serial exhaustive models?*

*I feel like I am way behind on the calculus side of things. What point in understanding should I be at, and how should I go about getting there?*

*So the point I’m at for a lot of these concepts is trying to go from definition to in-depth understanding. For me to really get something, I have to internalize it, which usually means coming up with metaphors or mini-stories to visualize it.*

*I get that the definition of nonparametric means that we don’t assume a specific underlying distribution, but I struggle with what that means in actual application. I’ve been trying to come up with a metaphor to help wrap my mind around it/ why we would need to use a nonparametric approach. The closest I can come up with is that if we land on another planet and are looking for aliens, we don’t want to assume that they will look like humans, or we might pass up who we want to talk to because we think “oh that’s a plant, not a person.”*

NOTES FROM MEETING

<https://www.amazon.com/Physical-Universe-Oxford-Cognitive-Architectures/dp/0195398955>

ACT-R book

<https://www.amazon.com/Quantum-Models-Cognition-Decision-Busemeyer/dp/1107419883>

quantum models

<https://www.amazon.com/First-Course-Probability-10th/dp/0134753119>

intro to probability theory