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Chapter 45
Computational Modeling Entertainment Media Choice and Decision-Making in Communication Science

Abstract: Media researchers and industry practitioners aim to predict and explain what content people select on entertainment platforms. However, the high complexity of this stochastic media selection process and low explanatory power of current approaches present an obstacle for theory development. Emerging behavioral experimentation methods drawn from decision science, coupled with the increasing availability of logged media selection data from streaming entertainment platforms, present new opportunities to verify existing theories and develop new theories with greater explainability and predictability. To exploit this emerging opportunity, media researchers need to transition from verbal theory to formal computational models, with novel parameter estimation, data simulation, and model verification methods. Here, we will introduce the basic concepts and analytical knowledge for formal modeling methods, as well as a theoretical framework rooted in decision science for interpreting and forecasting humans' entertainment behaviors.

Keywords: computational modeling, value-based decision-making, formal theory, drift diffusion model, media selection

Media exposure for entertainment content is determined by people's subjective choices. Due to the rise of interactive and personalized media platforms as well as the rapidly expanding array of entertainment content made available by streaming services, people now have enormous freedom to choose entertainment content based on their subjective preferences. These changes in people's media usage habits are reshaping mass communication processes, producing "big" digital trace data for entertainment, and creating the so-called attention economy or screenomics (Reeves et al., 2020), where varieties of informational content compete with each other for audiences' limited attention resources. Within this media landscape, how do people decide *what* content to select and *when* to select it? Answering this question has both practical and theoretical utility. However, the majority of existing theoretical models addressing this question express verbal, rather than formal (or mathematical) relationships between relevant variables. This presents a challenge that potentially limits the maturation of this line of inquiry because verbal theories are often vague in their specificity, tolerant of disconfirming evidence, flexible for alternative explanations, and lead to diverging lines of research under distinct contexts (Muthukrishna & Henrich, 2019; Yarkoni & Westfall, 2017).

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By comparison, a computational modeling approach specifies a theory by formalizing complex relationships between variables using mathematical formulae and estimates the value of parameterized variables, rather than testing hypothesized directional relationships in a verbal model. Compared to verbal models, computational models have several advantages in that they (1) eliminate ambiguity common to verbal descriptions of relationships between variables; (2) enable estimation of pre-defined parameters; and (3) render comparability across multiple attributes by building a generalized framework (Fisher & Hamilton, 2021). In this chapter, we will show how computational modeling and its application to decision-making (Dayan & Daw, 2008; Ratcliff et al., 2016; Roberts & Hutcherson, 2019) provides entertainment researchers with a domain-general framework to investigate media selection. We will also show how this approach leads to more complete explanations of communication behavior (Huskey et al., 2020).

1 What Is a Computational Model? And How Is It Different from a Statistical Model?

Computational models specify a set of algorithmic processes that use mathematical equations to link observed independent variables to outcome variables[1] in the immediate future (Wilson & Collins, 2019). Through computational techniques, including data simulation, parameter estimation, model evaluation/comparison, and latent variable inference, computational models are able to make better sense of behavioral outcomes, explain and predict complex social or behavioral phenomena, and encourage integrative theoretical frameworks (Wilson & Collins, 2019; Fisher & Hamilton, 2021). These computational modeling approaches are not new to communication research (e.g., Chung & Fink, 2022; Fink, 1993; Wang et al., 2011). However, they have never quite taken hold, either. In cognate disciplines like psychology and cognitive neuroscience, computational modeling has experienced a resurgence of interest and enthusiasm (Guest & Martin, 2021; Muthukrishna & Henrich, 2019; Smaldino, 2017, 2020). Our argument is that computational models should be added to the communication scientist's toolkit.

We assume that, at least for most communication scientists trained in quantitative methods, statistical models feel like familiar and comfortable territory. By comparison, something called a "computational model" might feel unfamiliar. Possibly even uncomfortable. Yet, statistical and computational models share some commonalities, and are often used in conjunction with one another. Both computational and statistical models take numerical inputs and yield numerical outputs. However, the ambition of each model differs. A statistical model offers standardized and generic

1 Here we mainly discuss behavior as the outcome variable for entertainment research.

tools (e.g., the general linear model) to make inferences about hypothesized patterns and associations among variables against assumed null distributions of parameters. A computational model, by comparison, provides a tailored mathematical specification to investigate algorithmic data-generating mechanisms by model evaluation and data simulation. This distinction of ambitions leads to several practical differences.[2]

First, statistical models usually take a reductionist approach by breaking up patterns in data into several key variables or factors and hypothesizing simple relationships among variables (Shmueli, 2010). Linear models are one common reductionist approach. They specify outcome variables that can be explained by a linear combination of one or more independent variables. For example, imagine a taqueria owner who wants to know how much to charge for a burrito and hypothesizes that price is a function of burrito volume. The owner might engage in some market research and gather two pieces of data from multiple observations (n): burrito volume (x_i), and burrito price (y_i). A linear statistical model would test the price ~ volume hypothesis by constructing a simple statistical (regression) model (eq. 1).

$$y_i = b_0 + b_1 x_i + \varepsilon_i \tag{1}$$

By comparison, computational models are often designed to capture the complex relationships between variables, without necessarily reducing them to a smaller set of explanatory factors. Rather than attempting to simplify relationships (e.g., linear relationships), the aim is often to create a model that can capture complex nonlinear relationships between individual input variables with the goal of describing an observation rather than making an inference about the distribution of a population-level variable. Back to our taqueria example. To test their hypothesis, the owner needs to first measure burrito volume (x_i). But what determines a burrito's volume? One answer to that question requires some new assumptions (e.g., burritos are a perfect cylinder), measurements of the burrito's radius (r_i) and height (h_i), and a computational model that integrates the measurements with the assumptions (eq. 2).

$$x_i = \pi\, r_i^2 h_i \tag{2}$$

Second, statistical and computational models treat uncertainty associated with the data-generation process in different ways. Statistical models simplify the data-generation process and specify that uncertainty comes from a meaningless error term (ε_i), which can be approximated by a probabilistic distribution, usually, a normal distribution (eq. 3) with zero error mean and error variance (σ^2).

$$\varepsilon_i \sim N\left(0, \sigma^2\right) \tag{3}$$

2 Despite being distinct in many ways, there often is a relationship between computational and statistical models. In fact, many computational models are often subject to subsequent statistical inference. This is most certainly true of the models we will describe later in this chapter.

On the contrary, instead of approximating uncertainty, computational models explicitly specify that uncertainty comes from a set of meaningful random processes in a generative way. These random processes are combined with deterministic processes and connected as a sequence of algorithmic steps, by which computational methods can simulate the behavior of the system with varying input parameters. Returning again to our taqueria example. The owner might have a target volume of food they want to fill their burrito with but be uncertain about the shape of the burrito they should offer (e.g., long and slender, short and wide). By solving for a known value of burrito volume (x_i) at different values of r_i and h_i in an algebraic way, it would be possible for the owner to get a distribution of different burrito shapes from which they might choose. In short, statistical models regard uncertainty as errors or noise, but computational models consider uncertainty in data as a meaningful random process that can be described by methods such as simulation.

Lastly, as a generic tool, statistical models hold a set of strong assumptions. For instance, regression models assume independent and identically distributed errors, normality of errors, and linearity of relationships. With these assumptions, information in data can be condensed into a set of summary statistics, such as the arithmetic mean ($\bar{x}$), sample variance (S^2), or sample covariance ($S_{x,y}$). These statistics help researchers draw conclusions about the underlying population from which data is sampled. One challenge is that the specific parameters of a statistical model may not generalize well to new data (Yarkoni & Westfall, 2017), due to model variance or violation of assumptions. For instance, the specific parameters of a price ~ volume model estimated from data collected in Los Angeles, California may not readily generalize to observations gathered in Columbus, Ohio. This might be for a variety of reasons (e.g., food is often more expensive in Los Angeles relative to Columbus, regional preferences that influence burrito ingredient cost/quantity/volume).

Unlike a statistical model, computational models are highly dependent on the particular application or problem being studied, thus more tailored for generalizing to new data with fewer assumptions (Jolly & Chang, 2019). For instance, our volume calculation is appropriate for a variety of burritos—with more or less ingredients, with lower or higher quality ingredients, ones from Los Angeles or Columbus, and so on. Good computational models have domain generality, while statistical models are bound to what is presumed from its underlying verbal theory and its specific parameterization.

Our burrito example provides a simple intuition for how computational models work for entertainment research. If we want to understand and predict a burrito's price, we need a model that specifies: (1) observable input variables (e.g., x_i) and latent variables (e.g., r and h), (2) algorithmic steps as mathematical expressions that link input variables, latent variables, and outcome variables (e.g., eqs. 1 and 2), (3) in a way that variables and parameters can be numerically measured or estimated. In practice, understanding human behavior is complex, and often requires more complicated models than those necessary to calculate a burrito's volume or price. Developing and applying these models requires communication researchers to have certain computational skills. To ease this learning process, our chapter bridges this gap by introducing a computational modeling framework (i.e., value-based decision-making), applying it to a communication problem (entertainment media selection), and providing theoretical explanations and technical implementation illustrations.

2 A Value-Based Media Decision-Making Framework

The media decision-making framework we present considers people's choice of media as a value-based decision-making process. This means that media selection is determined by people's subjective valuations of different media options, which quantifies the level of individuals' preference for different media options (Williams et al., 2021) in a way that a higher subjective value indicates stronger preference. Value-based decision-making is a pervasive process in nature. It governs a range of selection processes, such as simple decisions like animal foraging, or complex decisions like human financial decisions or social decisions (Rangel et al., 2008). We adopt value-based decision-making's algorithmic framework from recent developments in neuroeconomics, which separate the process into five components: representation, valuation, action selection, outcome evaluation, and learning (Rangel et al., 2008).

First, during the representation stage, decision-makers need to identify the set of available feasible choices (Rangel et al., 2008), such as movies in a theater or videos on YouTube. Each option will be decomposed and represented by a set of media features, which will be used for evaluation in the next step. For instance, movie options might be represented by production characteristics (e.g., cast, director, producer), genres (e.g., comedy, crime, action), affective properties (e.g., valence, arousal), or cultural factors (e.g., religion, politics, language).

Second, in the evaluation stage, decision-makers need to evaluate the value of the choices based on the media's features and depending on individual differences and their current mental state (Rangel et al., 2008). Here, people use a *value function* to assign different types of value to media options. These *value functions* are governed by distinct valuation systems. In detail, people have three types of value systems: Pavlovian, habit, and goal-oriented (Rangel et al., 2008). The Pavlovian system evaluates media content in an unconscious and hard-wired (or inborn) way, the habit system assigns value to actions in a habitual stimulus-response association way, and the goal-oriented system assigns value to options depending on people's anticipated choice outcomes in a model-based way, where decisions are made based on the anticipated consequences of the corresponding choices.

Third, in the action selection stage, decision-makers compare the values of different options to make a decision (Rangel et al., 2008). Economic theories suggest that people use a *decision function* to map options to utilities, which will be used to compare different options. This idea is supported by evidence from neuroscience that our brain uses a common currency system to compute values or utilities of objects and actions to make a decision (Levy & Glimcher, 2012). When people are making a media decision, the valuations of different aspects of media content would be integrated into a singular subjective value, which will be compared between different options. For instance, when people are deciding which movie to watch, different attributes of the movie, such as arousal, valence, genre, reputation, cast, and directors, will be evaluated through the valuation system and then integrated into a single value. Then the values of different movie options will be compared, and the movie of the highest value will be chosen.

The final two stages are learning stages: outcome evaluation and reinforcement learning (Rangel et al., 2008). The learning process can be considered a type of media effect. People might learn and update the value of media through reinforcement learning mechanisms, in a way such that high-reward outcomes will result in repeated selection of the same or similar media choices and low-reward outcomes will cause avoidance of the same or similar media choices (Fisher & Hamilton, 2021). The learning process is important for media decision-making theories as the media decision is indeed a dynamic and interactive process, thus crucial to understanding people's media choices in the long-term. For instance, after listening to a favorable song, listeners might choose to listen to this song again or songs from the same artist and develop reinforced listening behaviors.

3 Formal Modeling of Media Choice Behaviors

Following the value-based decision-making framework presented above, it becomes possible to construct formal models to account for people's media choices about *what* is selected and *when* it is selected. To do so, our computational models would comprise two major components: *valuation function* and *decision function* (Fisher & Hamilton, 2021).

The valuation function maps the available media options to their associated subjective values. As illustrated above, during the representation and evaluation stage, options will be represented by a set of media features, then be transformed into a numerical value by a linear or nonlinear function. Formally, this process can be shown in eq. (4), where V represents the subjective value for media options, and f_{value} represents the valuation function.[3]

$$V(option) = f_{value}(media\,feature,\ individual\,difference,\ mental\ state) \tag{4}$$

3 For example, the Pavlovian system might assign a high subjective value to a song based on its tune, harmonics, or voice acoustics. The habit system might assign high subjective values to music that is familiar and more frequently listened to. The goal-oriented system might assign subjective value to

This valuation function can be expressed as an additive linear function of observable input variables. In addition, subjective value can also be a dynamic function, which recognizes that the subjective value of the options is time-varying and depends on temporal variables (Wang et al., 2011), or as a reinforcement learning function, which considers that subjective value is updated through individuals' previous media selection experiences (Fisher & Hamilton, 2021; Lindström et al., 2021).

The *decision function* maps the media options' subjective values to the observed choice outcomes of interest, as shown in eq. (5), where *O* denotes the observed outcome variables.

$$O(option) = f_{decision}\left(V_{opion1},\ V_{option2,}\ \ldots\right) \tag{5}$$

If specified appropriately, the *decision function* allows researchers to explain a large variety of media selection outcome variables, such as *what* is chosen and *when* it is chosen. To do so, researchers need to ask what the data-generation process is to produce the observed choices or reaction times. Conceptually, the decision function generating choice outcomes can be considered as a random process of tossing a biased coin or rolling a biased dice, where the possible outcomes are the available media choices and the biasness represents subjective value for each feasible media choice outcome. Thus, we can specify the probability of choosing an option as a nonlinear multinomial logistic function (a common modeling approach for tossing a coin or rolling a die) of the subjective values, as shown in eq. (6), where *P* denotes the probability of choosing a specific media option.

$$P(option^*) = \exp\left(V_{option*}\right)/1 + \sum_{i=1}^{n-1} \exp\left(V_{option_i}\right) \tag{6}$$

This two-step value-based decision-making model, as shown in eqs. (4) and (5), decomposes the complex media selection process into multiple algorithmic stages, which helps researchers to systematically and separately examine selection mechanisms with distinct focuses. Moreover, it provides an integrative framework for researchers to construct, estimate, and statistically test their hypothetical models with high flexibility. For instance, Busemeyer et al. (2006) proposed a television channel change model, which specifies that the choice of television channels is determined by a valuation function, where the subjective value of each channel is determined by channel attraction and channel boredom, and a decision function, where the probability of choosing a channel is determined by subjective values for each channel, and where the time of switching is determined by a Wald distribution governed by the subjective values. They discovered

music depending on the listening contexts, in a way such that a peaceful and inspiring classical music piece will have high value in a learning environment because it might help the listener to focus on their studying.

that the length of the television channel's narrative determines channel attraction, and channel viewing time, modeled with a Wald distribution, better fits the data compared to competing models with an exponential distribution.

Due to the flexibility of the value-based decision-making framework, it is possible for researchers to investigate the valuation function and the decision function simultaneously (Wang et al., 2011), or to scrutinize one function at a time in favor of model simplicity and robustness. In this way, researchers interested in decision mechanisms, such as media multitasking, can directly measure or manipulate people's subjective value of media options and only focus on evaluating distinct hypothesized decision functions for media choices of multitasking. Similarly, researchers interested in media preferences, such as studying people's preference for music of varying valence or arousal, can fix the decision mechanisms, and test different hypothesized value functions with manipulated media attributes. Focusing on one component of the media selection process can reduce the model complexity, ease the experimental procedures, and increase the model robustness.

4 An Example: The Drift Diffusion Model

One of the main research questions for media decision-making studies is to reveal people's valuation function for media content and to understand how different factors influence people's preferences for different aspects of media content. However, the value-based media decision-making framework requires specifying both the valuation function and the decision function, therefore redundantly complicating the study design when the research questions only focus on the valuation function. A simple solution is to fix the decision function. One incredibly well-validated approach for doing this is the *drift diffusion model* (DDM; Ratcliff & McKoon, 2007).

DDM assumes people's decision-making is an evidence accumulation process (Figure 1), where the decision maker starts from a *starting point* between *decision boundaries* representing options, takes a random walk with a constant *drift rate* favoring an option with higher subjective value, reaches one of the decision boundaries, and eventually executes the choice. All of this is reflected by the time cost during the drifting process. Previous studies have shown that the DDM is a good approximation of the algorithmic and neurological implementation of people's value-based decision-making (Brunton et al., 2013; Polanía et al., 2014). In addition, compared to the canonical choice model (such as the multinomial logistic function; eq. 6), DDM gives richer inference for the decision process and predictions (Clithero, 2018) for people's preferences (Gong & Huskey, 2023).

When researchers use the DDM to fix the decision function, it becomes possible to concentrate on research questions related to the media valuation process. More specifically, researchers can study different valuation functions. Practically, with the

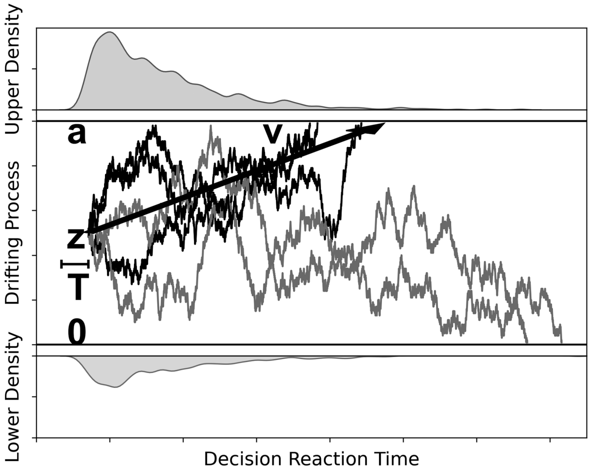

Figure 1: The decision function specified by the DDM. The upper distribution is the decision RT distribution for the higher value option (upper boundary), and the lower distribution is the decision RT distribution for the lower value option (lower boundary). The middle plot depicts the drift diffusion process that generates the choice and the RT data. After a non-decision time (T), the decision begins from a starting point with a bias (z) toward one of the two decision boundaries (0, a), and makes a random walk drifting toward one of the decision boundaries with drift rate (v). The dark black lines demonstrate simulated decision processes of choosing the option represented by the upper boundary, and the lighter gray lines demonstrate simulated decision processes of choosing the option represented by the lower boundary.

value-based decision-making framework, researchers would hypothesize the valuation function by theorizing media selection as a decision scenario in a grounded way or fitting a decision-theoretic model to existing media selection theories. For instance, researchers might consider people's subjective value as determined by factors (Adamowicz et al., 1998) such as media features (e.g., affect, novelty, or social factors), media types (e.g., movies, videos, or news articles), media presentation (e.g., posters, headlines, or trailers), individual differences of media users (e.g., age, gender). Understanding these questions will help researchers design a decision problem that is akin to decisions in real life and maximize the efficacy of expressing the decision problem to participants.

5 Collecting Empirical Choice Data

Different entertainment media selection scenarios have distinct characteristics in the selection process. Researchers need to adjust their computational models accordingly. After specification of the *value function* (e.g., eq. 4) and the *decision function* (e.g., DDM), researchers can start collecting empirical media choice data for model fitting.

Compared to statistical models which utilize aggregated simple statistics at subject-level (e.g., choice frequency) computational models analyze trial-by-trial choice data (Daw, 2011). This allows computational models to systematically and precisely reveal the valuation function. However, modeling trial-level choice data is difficult. This is for multiple reasons. First, people's subjective valuation of media options is a latent variable, thus it is unobservable and can only be inferred from behavioral data such as choice and reaction time, or neuroimaging data, such as functional magnetic resonance imaging (fMRI) or electroencephalography (EEG) data (Polanía et al., 2014).

Second, empirical choice data are highly stochastic, which violates the *weak axiom of revealed preference* assumption (WARP; Samuelson, 1938). Based on WARP, if we observe people choose A against B in one setting, we can not observe the same person choose B against A in the same setting. However, the WARP assumption is often violated due to inconsistent choices observed in empirical data. Said differently, people sometimes choose the lower-subjective-value option. Thus, in order to estimate people's valuation function, computational modeling methods need to account for the stochasticity in media choice behaviors by collecting repeatedly measured choice data from an individual or a group of individuals to form a choice distribution.

There are two common methods for collecting choice data to reveal valuation function, the *revealed preference* (RP) method and *stated preference* (SP) method. RP methods use realistic observational choice data, while SP methods collect people's choice data through lab-based research settings such as questionnaires or behavioral experiments (Louviere et al., 2000). RP methods are popular, particularly in entertainment media selection research, and are commonly operationalized using either direct observation or retrospective self-reports (Clay et al., 2013) in real media selection scenarios (e.g., Reeves et al., 2020). On the other hand, SP methods are less common in entertainment research.

We recommend that researchers augment their toolkit to include SP methods for several reasons. The first reason is that SP allows for experimentally controlling the levels of media features. With the SP method, researchers can conveniently design artificial media options and orthogonally manipulate media features of interest. Thus SP is suited to investigate how media features influence people's valuation function. Second, RP methods collect observational choice data in realistic media selection scenarios. One drawback of this approach is that people's behavior is vulnerable to uncontrollable systematic biases, such as presentation bias (Bar-Ilan et al., 2009), which are difficult to analytically account for and can easily bias the result of formal modeling analysis. Finally, compared with RP methods, SP methods can help media researchers reduce the un-trackable randomness and complexity in decision-making contexts while relying on other hallmarks of classic experimental design including high internal validity, control over unmeasured third variables, and causal intervention.

For the SP method, two types of methods have been widely utilized to collect choice data for estimating people's valuation of decision options (Johnston et al., 2017). The first type is the cardinal method, which assumes people's valuation can be expressed as a numerical value. A typical approach of the cardinal method is the *discrete choice valuation* (DCV), which asks decision-makers if they are willing to be paid a certain amount of money in exchange for a proposed change or product. For instance, by asking if people are willing or not to forego a social media app in exchange for receiving a certain amount of money, researchers can estimate the economic valuation of different media options. Research investigating people's digital media valuation using this approach showed that WhatsApp has a higher value (worth $619) than Facebook (worth $112; Brynjolfsson et al., 2019).

The second method is the ordinal method, which assumes that people's valuation can only be expressed in an ordinal manner. The typical approach of the ordinal method is the *discrete choice experiment* (DCE),[4] where subjects are asked to indicate their preference for two or more decision options with different attributes. For media selection research, DCE is advantageous to DCV because DCE uses an attribute-based method that aims to reveal people's valuation for attributes of options, while DCV is an object-based method that can only reveal valuation for the specific option (Adamowicz et al., 1998; Johnston et al., 2017). Said differently, in order to reveal people's preference for a media attribute, we recommend media researchers to use the DCE method compared to the DCV method.

Practically, DCE can be designed as either a two-option decision task or a multiple-option decision task. The two-option decision task is the most commonly used method to reveal people's valuation or preferences. In addition, two-choice tasks are substantially more tractable to design, especially when considering the complexity of naturalistic media stimuli, and less computationally costly to model. The DDM, described above, is a classic example of a two-choice DCE.

To conduct an empirical study collecting empirical choice data, researchers need to follow multiple steps in a pipeline (Gong & Huskey, 2023). First, researchers create the media option stimuli which systematically vary according to the media features as specified in the valuation function. Second, researchers randomly draw options from the option set to create the decision trials (see an example decision trail shown in Figure 2). Third, researchers design and implement the experiment, which delivers the decision trials to participants in an experimental setting, which enables collecting behavioral data or biological data such as psycho-physiological signals (Wang et al., 2011). The last step is to collect data with a sufficient sample size that guarantees sufficient power for parameter estimation.

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4 A formal definition of DCE is: "A discrete choice experiment (DCE) is a general preference elicitation approach that asks agents to make choice(s) between two or more discrete alternatives where at least one attribute of the alternative is systematically varied across respondents in such a way that information related to preference parameters of an indirect utility function can be inferred" (Carson & Louviere, 2011, p. 543).

Figure 2: An example of a two-option decision trial delivered in image format (i.e., movie poster). In this decision trial, participants will make a media choice regarding which movie they prefer to watch by pressing the Z button (choosing left option) or pressing the M button (choosing the right option).

6 Model Fitting and Model Evaluation

Similar to statistical models, multiple approaches are available for model estimation, such as the Maximum Likelihood Estimation (MLE) or the Bayesian approach. And there are plenty of useful tutorials and didactic examples from previous studies that researchers can follow (Gong & Huskey, 2023; Wilson & Collins, 2019; Daw, 2011). In general, researchers need to construct the likelihood function for each media choice observation, by combining the valuation function and the decision function together. Then MLE will find the estimated model parameters after optimizing the likelihood function, and the Bayesian approach will find the posterior probability of the estimated model utilizing the prior probability of the model and the likelihood function following the Bayes rule. As an example, to fit a DDM, we can adopt an MLE approach. Doing so requires constructing the likelihood function which takes the RT and choice data and DDM parameters (e.g., drift rate, decision boundaries, etc.) as inputs, and outputs the probability of observing the choice data given the model parameters.[5] Since the choice data is observed as fixed, MLE will optimize this likelihood function by varying model parameters, and eventually obtain point estimates of parameters that best fit the data. Model fitting can also be accomplished with a Bayesian approach. A modern Bayesian fitting method is the *Hierarchical Drift Diffusion Model* (HDDM; Wiecki et al., 2013), which can obtain the entire distribution of parameters, rather than point estimates as in the MLE method.

After model fitting, researchers can use the estimated parameters to make inferences and draw conclusions supporting or falsifying hypotheses via statistical analysis. If using a frequentist approach, researchers can test their hypotheses by either examining whether or not the estimated parameters significantly differ from the expected parameters under the null hypothesis, or by comparing the performance of the hypothetical model and a null model. Alternatively, researchers using a Bayesian approach can compare the posterior probability distribution to zero, or against other posterior probability distributions as specified in their hypotheses (Kruschke, 2013).

Alternatively, inferences can be made by evaluation and comparison of models constructed from competing hypotheses or theories. There are multiple methods for evaluating the performance of computational models of media selection. Researchers can either compare the prediction performance (Yarkoni & Westfall, 2017) of models by computing the prediction accuracy for out-of-sample data, which is calculated as the percentage of accurate prediction, or compare the explanation performance of models by computing model evaluation metrics of in-sample data, such as Akaike Information Criterion (AIC; Akaike, 1998).

Finally, the estimated formal model is a generative model, which allows researchers to forecast individuals' media behaviors. Practically, the valuation function estimates preference on simulated media content options, which can be carried out by transforming the randomly sampled media features into subjective values, and the decision function produces the estimated probability of choosing an option or spending time on deciding an option, which can be used to generate the simulated media behavioral data by random sampling media behaviors with the estimated probabilities. Forecasting media behaviors enables analysis of computational models with simulated data before empirical data collection, such as power analysis by calculating the sufficient sample size for hypothesis testing (Ratcliff & McKoon, 2007), and verification of formal models after empirical data collection by a comparison between the observed empirical data and the simulated data.

5 This likelihood function can be shown as the upper density RT distribution (choosing the upper boundary choice) and lower density RT distribution (choosing the lower boundary choice) in Figure 1.

7 Conclusion

In summary, we reviewed the theoretical background for media selection as a value-based decision-making process, as well as the economic and psychological theoretical foundations of decision experiments to understand media preferences. We also provided a conceptual overview of the methodological pipeline for specifying, estimating, and evaluating computational media selection models. Thus, this chapter paves the way for interested researchers to understand the formal modeling methods of media selection and bridges the knowledge gap for implementing the methods in their own research.

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