SUPPLEMENT TO
CHAPTER 3, V1[1]:
CORE NETWORK PRINCIPLES:
THE EXPLANATORY NUCLEUS

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PRINCIPLE 1: UNCONSCIOUS PROCESSING VIA NETWORK CASCADE

Neural Architecture

Psychology is interested in explaining individual differences. Learning is a major source of these differences. Chapter 4 in Tryon (2014) emphasized the role of synaptic change as a learning mechanism. Here I report on a study showing that individual differences in neural network architecture, how the brain is wired, provides additional information regarding individual differences in memory. McGaugh and LePort (2014) identified people with Highly Superior Autobiographical memory (HSAM). Their HSAM test consisted of three parts. First, participants had to score at least 50% correct on a public events quiz. Second, they had to be able to identify the day of the week that corresponds to ten dates chosen at random from the past several decades. Third, they had to excel at a test linking names to faces. Brain scan (fMRI) revealed the following two neural network architectural differences between people with HSAM and normal controls. a) Their **uncinate fascicle** is better connected to their temporal and frontal cortices. b) Their **parahippocampal gyrus** is better connected to other brain areas.

The Human Connectome Project[2] aims to provide a wiring diagram of the major brain circuits; i.e., how the many neural networks that constitute the human brain are interconnected. This map will hopefully serve as a standard reference against which individual variations can be assessed.

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[1] V1 stands for Version 1 which implies that subsequent chapter updates will become available.
[2] See http://www.humanconnectomeproject.org/

More Empirical Evidence of Unconscious Processing

The material presented in this section extends the discussion by Tryon (2014, p. 142) in Chapter 3. Pessiglione et al. (2008) have shown that operant and respondent conditioning can occur without awareness when stimuli are rendered invisible via masking. Raio, Carmel, Carrasco, and Phelps (2012) and Seitz, Kim, and Watanabe (2009) have shown that conditioning can occur unconsciously when stimuli are rendered invisible due to binocular rivalry. See Shanks (2010), Shanks and St. John (1994), and Lovibond and Shanks (2002) for an alternative view. Extensive empirical work on implicit learning by Reber (1967) using artificial grammars and by Nissen and Bullemer (1987) using sequence-learning tasks have also demonstrated unconscious learning. Atas, Faivre, Timmermans, Cleeremans, and Kouider (2014) demonstrated nonconscious learning using a perceptual task.

Systems 1 and 2

Kahneman (2011a, b) labeled modes of operating as Systems 1 and 2. I prefer to describe Kahneman's System 1 as the **Default Conscious Mode (DCM)** to better reflect its essential character. I prefer to describe Kahneman's System 2 as the **Effortful Conscious Mode (ECM)** to better reflect its essential character. Referring to modes of consciousness as default and effortful reflects varying degrees of involvement by various neural networks instead of implying discrete systems. I fully expect that the ECM entails additional activation of already active neural networks over that present during the DCM in that neural networks are not completely inactive even under mild anesthesia.

PRINCIPLE 2: LEARNING AND MEMORY

Cultural Neuroscience

This section extends the brief mention of culture made by Tryon (2014, p. 209). I did not know that the field of cultural neuroscience existed when my book went to press.

Han et al. (2013) reported that the term cultural neuroscience was initially introduced by Chiao and Ambady (2007) as "a theoretical and empirical approach to investigate and characterize the mechanisms by which [the] hypothesized bidirectional, mutual constitution of culture, brain, and genes occurs" (p. 238). According to Chiao (2009) "Cultural neuroscience is an emerging, interdisciplinary field that examines the bidirectional influence of culture and genes to brain and behavior across multiple timescales" (p. 287). According to Han et al. (2014) "Cultural neuroscience (CN) is an interdisciplinary field that investigates the relationship between culture (e.g., value and belief systems and practices shared by groups) and human brain functions" (p. 335). Chaio (2009) claims that the following two research questions predominate this field: a) how do cultural values, beliefs, and practices shape neurobiology and b) how do neurobiological mechanisms facilitate the emergence and transmission of cultural values and traits. Han et al. (2014) describe the origin and aims of cultural neuroscience. They define central concepts and discuss relevant methodology. They concluded their review with an overview of empirical findings. Han et al. (2014) concluded that "Taken together, these brain-imaging findings indicate that the same neural substrates are tuned to a particular task in opposite patterns in different cultures" (p. 347). No mechanism information was provided to explain these results.

Chiao (2011) proposed a neurovariation theory to explain differences in neural activation across cultural groups. While notably ambitious, cultural neuroscience has not yet produced mechanism information that meets the criteria set forth by Tryon (2014). For instance, Chiao and Blizinsky (2010, 2013) have only provided mediation models. Tryon (2014, Chapter 13) clearly distinguished between mediation and mechanism information. Mechanisms explain how effects are instantiated; mediators do not.

PRINCIPLE 3: TRANSFORMATION

Tryon's (2014) discussion of the transformation principle has several problems that this supplement seeks to address. They primarily include various limitations of factor analysis.

Data Before Computation?

All methods of factor analysis require that data collection is completed before analysis begins. Living creatures do not operate this way. It is not possible to acquire a life-time of experience, data, before computing the first latent construct. Living organisms continually process data in real time. The results, latent constructs, gradually change over time. Qualitative differences emerge across developmental epochs.

Summation as Mechanism

Brains appear to extract latent constructs via summations as discussed by Tryon (2014) in Chapter 3 because that is the major mathematical operation that neurons perform. That people form psychological states, constructs, and do so with their brain is definitive evidence in my view that summation is sufficient to extract latent constructs. The summation-based factor extraction method discussed in Chapter 3 provides possible mechanism information.

Realism?

Borsboom, Mellenbergh, and Van Heerden (2003) questioned the theoretical status of latent variables in psychological theory. They asked:

> Should we assume that the latent variable signifies a real entity or conceive of it as a useful fiction, constructed by the human mind? Should we say that we measure a latent variable in the sense that it underlies and determines our observations, or is it more appropriately considered to be constructed out of the observed scores? What exactly constitutes the relation between latent variables and observed scores? Is this relation of a causal nature? (p. 204).

Moreover, they asserted that:

> In the course of discussing these questions, we will see that latent variable theory is not philosophically neutral; specifically, we will argue that, without a realist interpretation of latent variables, the use of latent variables analysis is hard to justify. At the same time, however, the relation between latent variables and individual processes proves to be too weak to defend causal interpretations of latent variables at the level of the individual." (p. 204)

The Bio↔Psychology Network theory endorses realism because it assumes, is based on, physical causality[3]. Hence, Tryon (2014) endeavors to think about psychology and behavior in physical

[3] The following evidence is provided for this realistic position. I get up in class, stand behind a student, place my hands on their shoulders, and gently shake them. I then ask them the following

rather than mental terms. We seek causal mechanism information in physical terms. Borsboom et al. (2003) appear to reject realism. They concluded that "The realist interpretation of latent variable theory seems to lead to conclusions that we are not willing to draw" (p. 217). Consequently, they are unwilling to grant causal status to latent constructs.

Local Independence

Borsboom et al. (2003) attacked latent constructs on psychometric grounds by emphasizing a crucial rule for the principle of local independence as follows:

> The basic statistical idea of latent variables analysis is simple. If a latent variable underlies a number of observed variables, then conditionalizing on that latent variable will render the observed variables statistically independent. This is known as the *principle of local independence*. The problem of latent variables analysis is to find a set of latent variables that satisfies this condition for a given set of observed variables" (p. 203, italics in the original).

Notice the **If-Then** construction of their argument. **If** a latent variable underlies a number of observed variables, **then** (meaning only then) local independence must occur. Put otherwise, they imply that the absence of local independence deprives it of meaning and consequently precludes causal interpretations based on it. That this view is not true can be seen by restating the principle of local independence into correlational terms that may be more familiar to most readers[4]. If factors could be independently measured[5] and were partialed out from every correlation coefficient in the matrix of intercorrelations among observed variables, indicators, then all entries in that matrix will be exactly zero when local independence exists. It should be obvious that this

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two questions. a) Did you feel that; was it real to you? b) How likely is it that you spontaneously imagined my shaking you? Then I ask the following two questions to all other students in the class. A) Did you see that; was what I did real to you? b) How likely is it that all of you simultaneously and spontaneously imagined what I just did? The positive answers to the first questions and the improbability of a positive answer to the second questions is evidence that realism exists at least to a point where consensus that psychology can be a natural science is concerned.

[4] What follows is based on personal communication with Professor Charles Lewis on 2/5/14.

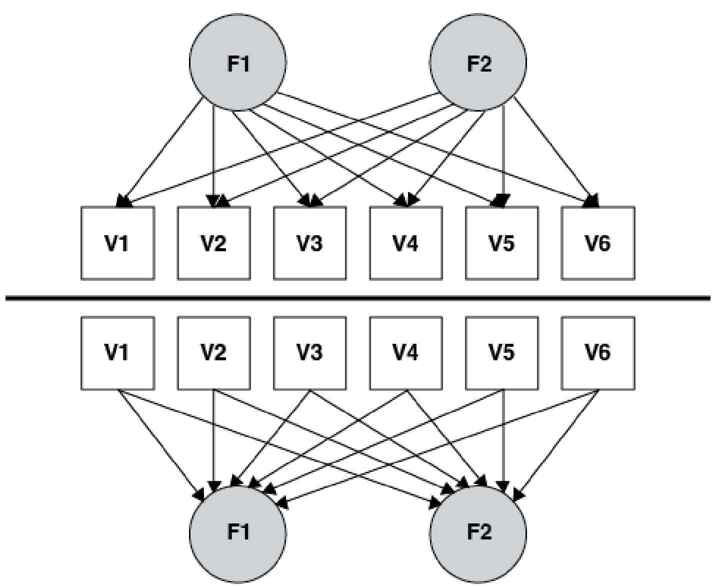
[5] I know that factors cannot be independently measured. This example concerns a conceptual experiment in which factors can be conceptually measured.

is an extreme condition that only occurs when all of the extracted factors jointly explain 100% of the variation in the observed variables. This virtually never happens. The probability of any one partial correlation coefficient being zero to 99 decimal places is astronomically small. The probability of obtaining an entire matrix of zero partial correlations is even more remote.

Further proof that local indepdence is not a requirement of legitimate factors is that if this were true then factor analytic routines implemented in commercial statistics packages would almost never run. Factor analytic routines may sometimes not run because of too few observations for the number of variables involved or because matrix inversion is not possible but never because local independence does not occur. Local independence is not a requirement that legitimate latent constructs must meet in order to carry explanatory value. We can therefore confidently proceed with a factor analytic mechanism for how neural networks, including real brain networks, compute latent constructs.

Reflective and Formative Models

The following figure should replace Figure 3.12 in order to distinguish between reflective and formative latent models. The top panel of the new figure illustrates a generic **reflective**

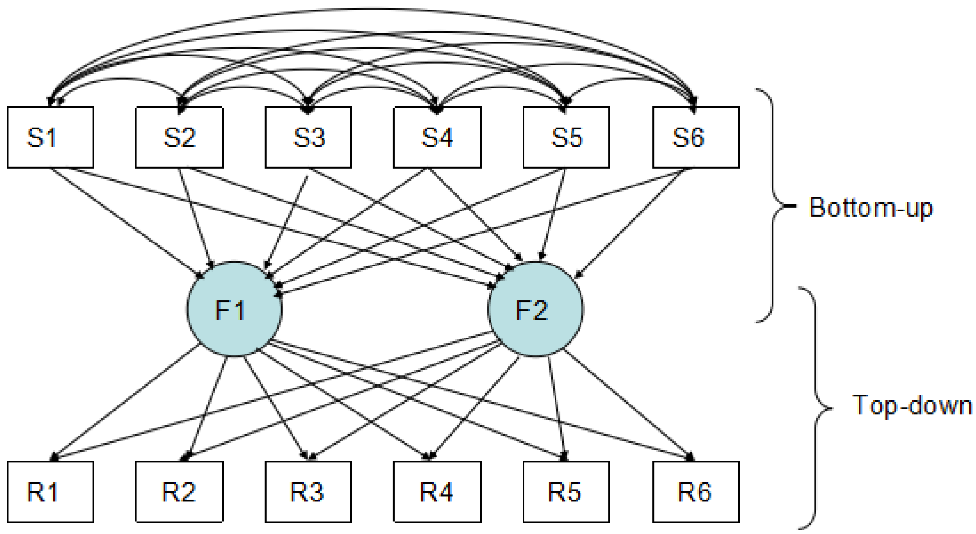


Supplemental Figure 3.1. Distinguishing reflective from formative models.

model where the intercorrelations among observed variables V1 – V6 are explained by the latent psychological constructs F1 and F2. Hence, causal arrows eminate from the latent factors down to the observed variables. This is a model of what we will call **Top-Down** processing when we discuss Principle 10 in Chapter 4 and again in Chapter 11.

The bottom panel of the new figure illustrates a generic **formative model** where latent constructs F1 and F2 are formed on the basis of indicators represented by variables V1 – V6. This is a model of what we will call **Bottom-Up** processing when we discuss Principle 10 in Chapter 4 and again in Chapter 11. Three observations are crucial here. **First**, latent constructs are taken to be real psychological constructs on the basis that the Bio↔Psychology Network theory is a realistic theory and on the psychometric basis that local independence is not required for the extraction of valid factors. **Second**, the computer identifies each factor by computing factor loadings that quantify the extent to which each indicator defines the positive and/or negative poles of the identified concept. In factor analytic terminology we would say that wings, feathers, and beaks load positively and antlers load negatively on the latent construct "bird". Factor loadings range from -1.0 through 0 to +1.0. The connectionist weights computed by neural networks also range from -1.0 through 0 to +1.0. **Third**, humans only provide labels for the factors that the computer creates after reviewing the factor loadings that the computer calculated. These labels are not needed by neural networks to make use of the identified constructs. Psychologists have willingly and comfortably labeled such computer calculated constructs as intelligence, extraversion, and neuroticism, to name but a few core psychological concepts that have been widely and confidently used to explain behavior for over a century. Hence, psychologists should be just as willing to accept latent constructs created by both artificial and real neural networks as genuine.

Figure 3.2 below is a substantive improvement over Figure 3.12 in Tryon (2014).



Supplemental Figure 3.2. An improvement on the model presented in Figure 3.12 that is psychometrically identified and distinguishes bottom-up and top-down processing.

P-Technique Factor Analysis

Raymond Cattell (1957)[6] distinguished among the six techniques of factor analysis presented in the Supplemental Table 3.1 presented below.

Table 3.1

Technique	**Factor**	**Across**	**Constant**
R	Variables	Respondents	Occasions
Q	Respondents	Variables	Occasions
P	**Variables**	**Occasions**	**Respondents**
O	Occasions	Variables	Respondents
S	Respondents	Occasions	Variables
T	Occasions	Respondents	Variables

Supplemental Table 3.1. Six techniques of factor analysis identified by Cattell (1957)

The R-technique is what Chapter 3 implied was used. A major problem for our Principle 3: Transformation is that the covariance matrix that is factor analyzed consists of correlations

[6] See http://en.wikipedia.org/wiki/Raymond_Cattell

among variables across different people. Hence, the factors pertain to the group of people participating in the study rather than to any one person as our transformation principle implies.

The P-technique was introduced by Cattell, Cattell, and Rhymer (1947). It is preferable for present purposes in that it factors a matrix consisting of correlations among variables over time for a single person. This method has been used by Browne and Nesselroade (2005), Jones and Nesselroade (1990), Lebo and Nesselroade (1978), Lebo and Nesselroade (1978), Molenaar (2007), Nesselroade (2002, 2006), Nesselroade and Ford (1985) and Zevon and Tellegen (1982) to study individual differences within a person over time.

A remaining problem is how the repeated measurements might be buffered in order to have sufficient repeated measurements to compute correlations. One solution to this problem is to recognize that three observations are sufficient to compute correlations with one degree of freedom. These correlations will be unstable from sample to sample. Factors extracted from such a matrix will be highly unstable but aggregation over time is likely to stabilize them.

A second solution is to recognize that repeated measurements may be made at EEG frequencies that can range from the low end of Delta waves (0.1 Hz) up through Gamma waves (40 Hz)[7]. Taking the midrange of Delta waves (0.1 – 3 Hz) as 1 Hz means that 60 measurements are taken per minute. At 40 Hz, 240 measurements might be taken per minute. These sampling rates would produce sample sizes that would yield more stable factors. Extracting factors every minute would yield 960 extractions in 16 hours which leaves 8 hours for sleep during each circadian cycle.

Semantic Cognition

Rogers and McClelland (2008) published a précis to a book by Rogers and McClelland (2004) entitled *Semantic Cognition: A Parallel Distributed Processing Approach* in which they endeavor to explain how connectionist neural networks form psychological constructs. They do not claim to have a complete explanation of semantic cognition but believe that they, along with others, are pursuing a productive line of inquiry. I have yet to study this approach in detail but believe that it may well avoid the problems associated with a factor analytic explanation.

[7] See http://www.brainmaster.com/generalinfo/eegbands/eegbands.html

Conclusion

That brains are able to generate latent constructs using massive networks of simple highly interconnected neurons whose main computation is summation and a nonlinear activation function indicates that the parallel distributed processing connectionist neural network approach to how people transform stimulus microfeatures into psychological constructs is on the right track. Any and all criticisms regarding the details of proposed mechanisms cannot negate this fact.

PRINCIPLE 4: ACTIVATION AND REACTIVATION

Reactivation differs from ordinary processing in that external stimuli need not be involved. But does reactivation warrant its own separate principle? I made activation/reactivation its own principle to emphasize the distinction between processing new incoming stimuli and all forms of "memory". Every form of memory entails reconstruction and these reconstructions require reactivating neural networks. When someone asks you your opinion about a topic your reply entails reactivation in that you are generating a response based on prior experience and thought. Activation is involved in that you must process what the person's speech in order to understand what was asked of you but your response requires reactivation of other neural networks. I believe that this distinction is sufficiently important to warrant giving reactivation its own principle.

INTERESTING LINK

I found the following link to epigenetics regarding diet be of interest. It is a Radiolab podcast http://www.radiolab.org/story/251885-you-are-what-your-grandpa-eats/

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[8] References not included in this list are in the reference section of the Tryon (2014).

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