Chapter 7
Adaptive Resonances Across Scales

7.1 Social and Neural Networks

As Stephen Grossberg developed his famous equations of cooperative-competitive neural interactions, he briefly examined their applicability for characterizing economic systems. He showed that some of his models described equally well neurons competing locally while exhibiting globally coordinated behaviour, and production companies driven by Adam Smith's "invisible hand" in a class of stable competitive markets (Grossberg 1980a, b, 1988). Interestingly, at macroscopic level some systems seemed cooperative while in reality they were competitive. Whether the competing components could ultimately begin to cooperate to establish structures that are more complex remained an open question. At the time, that line of research was pursued no further, but in the age of virtual social networks and big data analysis it may gain renewed importance.

Considering that the invisible hand is a mix of market signals related to prices, perceived demand, customer opinions, company reputations etc., all of them enhanced by the speed of modern communications, one can view today's economy to a large extent as a virtual social network. The link between the fields of social networks and neural networks was perhaps best summarized by Bruno Apolloni'sremark that, "The social network is a fractal extension of our brain networks" (Apolloni 2013). This is a modern variation of the old idea about monadology by Leibniz (1714), who suggested that each living creature, plant or animal, contains in itself a multitude of its own micro replicas.

This book ends with a discussion about an analogy between the operations in the adaptive resonance theory (ART) neural network (See Box 7.1) and some of the essential procedures in leader-electing social organizations. The possible foundations for such a common mechanism are examined, as well as the implications for the social sciences of a knowledge transfer from mathematical and computational neuroscience.

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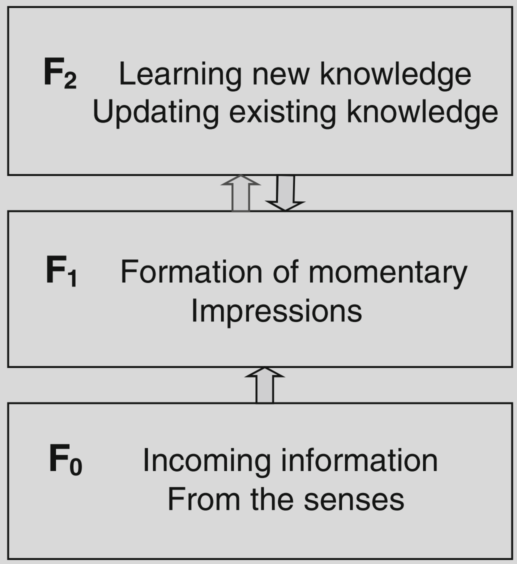
Box 7.1. Adaptive Resonance Theory

Scholars in ancient times discovered that people distort reality when perceiving it. In the 1st century C.E., the Greek philosopher Epictetus noticed that humans are affected not by events happening around them, but by their own attitudes to those events. Indian gurus made a similar observation by saying that, "You cannot see more than what you are". As society developed, that idea began to receive scientific garments. Johannes Mueller, a 19th century physiologist and mentor of Herman von Helmholtz, proclaimed in 1826 that we do not comprehend what we see directly, but only absorb our own neural responses to external stimuli. Helmholtz (1866, 1896) combined theoretical and experimental methods to develop his theory of unconscious inference. It stated that people learn new knowledge only after their senses modify all incoming information under the guiding influence of previous knowledge. In other words, we perceive and learn what we expect to perceive, based on previous experience and education.

Scholars from the humanities and social sciences have often come across the same insight. It is present in the works of prominent figures such as art historians Gombrich (1972, 1989) and Bell (2007) and science historian Kuhn (1962) . It is also popular in the folklore of various professions. Earlier in the book, I quoted human resource managers who claimed that, "Reality is not the facts, it is the interpretation of facts". Financier George Soros observed a similar phenomenon in the capital markets: the agents' beliefs affect the fundamentals behind share prices, whereby reality is driven away from those beliefs. The latter gradually become inadequate and need updating (Soros 1988, 1995).

This mindset is summarized scientifically by adaptive resonance theory (ART), initially introduced by Grossberg (1976a, b, 1980a, b, 1982), and further developed in cooperation with Gail Carpenter (Carpenter and Grossberg 1987a, b, 1990) and others (Carpenter et al. 1991a, b, 1992, 1998, etc.). It is built from the same three differential equations or their algebraic approximations. According to this theory, all knowledge is stored in connections among neurons in the brain whereby, to a first approximation, three neural layers are instrumental. They exchange signals in two directions: a "bottom-up" stream comes in from the senses and provokes a "top-down" response of associations, based on previous knowledge. Both streams are compared and matched to produce "impressions", which, if found adequate in a certain mathematical sense, are eventually memorized. These interactions are shown in the Figure.



Grossberg introduced a model clarifying how one manages to learn new knowledge without destroying the existing. It posits that the brain is "plastic" as it is able to accommodate change, and at the same time "stable" as it retains what has been learned before. This is the solution to the famous "stability-plasticity dilemma". It is the object of adaptive resonance theory (ART) and its central element—the ART neural network. The term "adaptive resonance" denotes information processing and is analogous to the physical resonance in mechanical and electrical systems. It is *information* that "resonates", as multidimensional signals are exchanged between layers F_1 and F_2 in the Figure. Responding to an incoming image, the neural network instantly scans its memories to find a sufficiently close match. If one exists, all related neurons are activated to exchange signals with the impressions layer. This process is called adaptive resonance. Until it lasts, knowledge update takes place. The interaction is local as it affectsa limited number of synaptic connections. If the old memories fail to offer an adequate match, a new set of neurons assimilates the incoming signals and patterns, whereby the network enters again a resonant state.

7.2 A Fractal-Type Analogy

Now that enough was said about the neuroscientific part of the alliance, let us discuss briefly its self-similarity component. The fractal school of thought flourished in the last decades of the 20th century due to Mandelbrot and others, and gave fruits in the shape of research methodologies for the natural sciences and life sciences (Mandelbrot 1983). Often, the fractality idea was not straightforwardly utilized, either because of a lack of scientific rigour, or due to the huge distance between the subset and superset domains, but assumed the form of analogy between phenomena across scales, and exerted only indirect intellectual influence. For example, an important analogy by Ernest Rutherford suggested that the electrons in the atom circle around a small but heavy nucleus, just like the planets move around the sun in the solar system. Newton's law of gravity inspired the development of international economics' gravity models, positing that trade between two countries is more intense when they are geographically closer and have bigger economies. Similarly, the Navier–Stokes heat and mass transfer equations were adapted to model capital flows in finance.

The analogy across scales, suggested here, is in line with the insights of Grossberg and Apolloni, but is more concrete. The main idea is summarized in Fig. 7.1, showing typical parliamentary procedures in a democratic establishment that resemble the operations in an ART neural network. There are many similar details between the two sequences of events.

The left column in Fig. 7.1 describes political events characterizing parliamentary democracies. The civilized manner in which these governments, their leaders, and members, replace each other tends to disguise the intense and often fierce power struggle behind the scene. The example here is modelled after the typical contemporary European country, yet it could be easily reshaped in line with the procedures in North America or in the ancient democracies of the Greek cities and Rome. With some adaptation, the chart would comfortably fit the cardinals' conclave electing a new Pope. Similar in principle are the ways in which corporations and all kinds of institutions, large and small, replace their chief executive officers, presidents, commanders-in-chief, deans, editors-in-chief etc. Moreover, all totalitarian dictatorships also have their own mechanisms for power transfer that could be accommodated by variations of the left column in Fig. 7.1. Hardly different, though simpler, is the power handover in the animal world, where each species has developed its own rituals—generally brutal—to determine the next leader of the herd.

The right column in Fig. 7.1 describes the operations in the adaptive resonance theory (ART) neural network as they happen in time. Today we know that adaptive resonances are widespread in the brain (Grossberg 2013) and take part in many cognitive processes. Recalling Stephen Jay Gould's vision that the human brain was not build for a restricted purpose, but as it evolved for hunting, social cohesion and other functions, it transcended the adaptive boundaries of its original purpose (Gould 1981), it seems plausible that the mechanism of adaptive resonance could have extended to interpersonal relations. That is how and why individuals in a

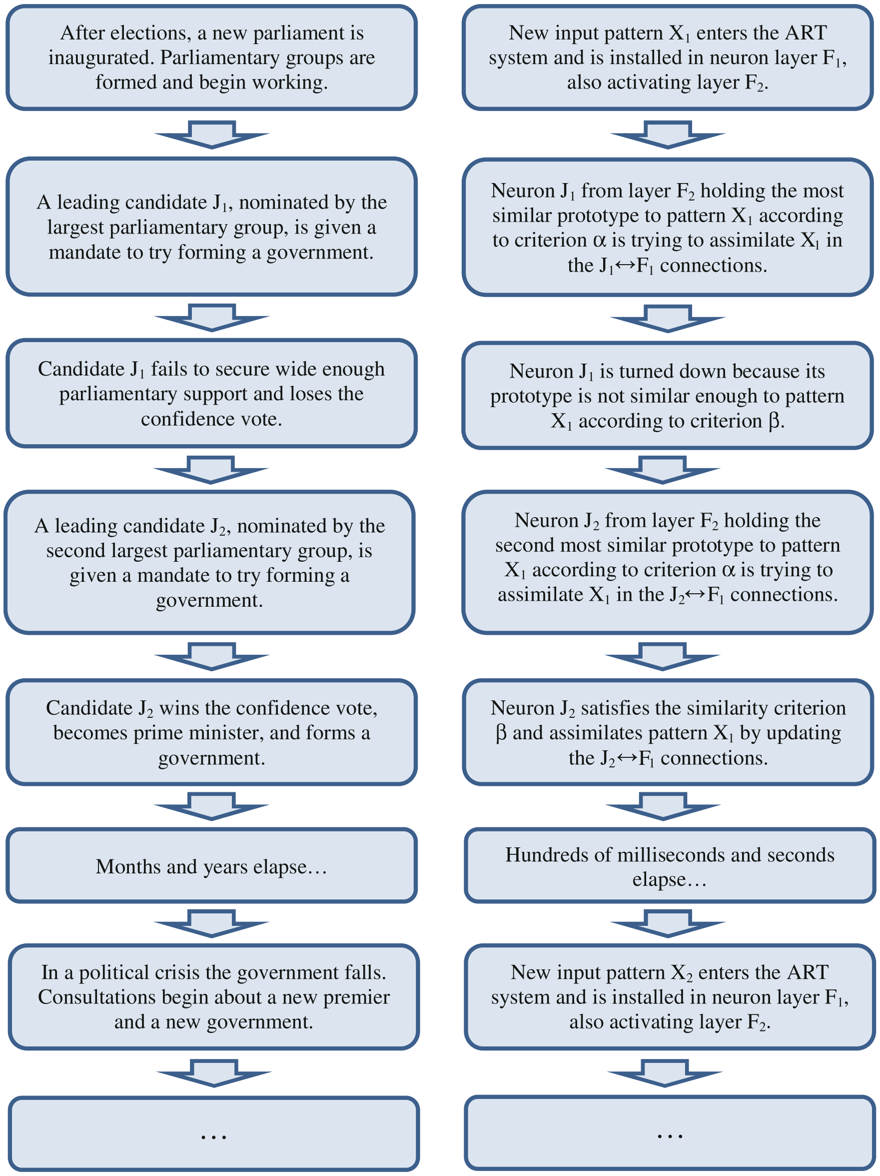


Fig. 7.1 An analogy between parliamentary procedures and neural network interactions. The way in which political leaders are elected resembles the way neurons in the F_2 layer of an ART neural network get activated to accommodate new knowledge

social network, such as the political system or any other socioeconomic system with a hierarchy, may resemble neurons in an ART neural network.

The right column in Fig. 7.1 is drawn to represent the activity in a single ART module, but could be adapted for an ARTMAP system (e.g., Carpenter et al. 1991a, b, 1992, 1998; Carpenter 2003) where the ART_a module would be analogous to a country's political establishment with its parliament, parties, leaders etc., while ART_b, the senior module, would embody either the "sovereign"—the people in their more important collective actions, or abstract entities and concepts like the laws of history, the imperatives of social development, or something of this kind.

7.3 Socioeconomic Fractality

Taking seriously the analogy between the ART neural network and any leader-electing social system may help to open new directions for research in the social sciences. Indeed, contemporary mathematical neuroscience has already developed a multitude of suitable models—the analogy in Fig. 7.1 in no way exhausts the pool of potential applications. It should be considered only as a starting point and an illustrative example. The recurrent gated dipole looks like a straightforward candidate for analyzing social processes in which emotion is involved. The dynamics of various markets, the sentiments in virtual social networks, any socially or politically motivated mass protests are all suitable examples. Moreover, neural models that are more complex may tackle successfully the relations among entities such as a country's political establishment, industry, labour force, trade unions, third sector, professional and other communities. Even today, there exist models of the brain's ability to decompose information into streams dealing separately with the various important aspects of an attended phenomenon while processing them in parallel (Grossberg 2009, 2013; Grossberg and Vladushich 2010). Each stream loses information about everything except its own highly specialized function, thus avoiding combinatorial explosion of data. Then all streams accomplish fusion at a higher cognitive level.

In time, science will mature and explain with rigour the projection from brain to socioeconomic processes—a research field that might be called *social fractality*. Because economic aspects often tend to be important, their influence may make more relevant some other term, for example *socioeconomic* fractality.

Thus, a promising application domain for existing neuroscience models are some of the traditional social sciences—sociology, social psychology, organizational psychology, management science, and economics. Of course, these fields have their own methods and models, yet they could benefit from a transfer from such a powerful body of theoretical knowledge. For example, the kind of models coming from the Grossberg School could be used to forecast the evolution of important trends and events in socioeconomic systems, previously unpredictable. And if prediction may seem too ambitious, another important goal is to generate new philosophical explanations of poorly understood social phenomena from the past or the present. For instance, in the 1990s, the peoples in Eastern Europe embraced democracy with its key attributes such as free elections—now taking place frequently—and parliamentary procedures exactly as in Fig. 7.1's left column. However, they were soon disappointed by the hardships of economic reforms leading to pain and suffering. Putting that social development side by side with neural network operations shows it in a new perspective: It now looks like those societies had undertaken a learning process on a grand scale and were taking only the first steps in a journey of historic proportions.

A different but related new field for applying the models of mathematical and computational neuroscience may become the study of virtual social networks. Research in that area has gained momentum not least due to the invasion of Facebook, Twitter, LinkedIn and other internet platforms that have already become household names. In response, over the years many scientific journals devoted special issues to the subject, while leading international publishers even launched new dedicated journals. However, their content has remained mostly empirically oriented, a fact suggesting that a deep theoretical grasp is hard to achieve.

The future may bring about new alliances between neuromodelling and web data analyses. In fact, such examples already exist. A study by Sakata and Yamamori (2007) revealed a topological similarity between the brain and some social networks. It was based on positive and negative influences among the participating units—i.e., neurons and people respectively. That effort quantified some of the realistic boundaries of the analogy between the two domains.

There are essential pragmatic aspects of the suggested knowledge transfer. It is generally believed that the collective mind is less sophisticated than the single mind, not least because the brain has orders of magnitude more elements (neurons) and connections than any social network. Therefore, the advocated foray into socioeconomic systems should begin with some of the simpler neural models such as gated dipoles, ART and ARTMAP networks. A major difficulty would be to identify prospective concepts and variables from the social sciences that could be mapped onto suitable components of the neuroscience models. This nontrivial task may take quite long. Yet, as was discussed already in the previous chapters, some small steps have already been taken by a number of researchers.

A hypothetical neuroscience-inspired social science model could look like the creation of some branches of contemporary theoretical physics: a mathematical structure nicely fitting key elements from the general picture, yet containing quantities about which little or nothing is known. However, phenomenological and semi-empirical models are the natural early companions of each pioneering effort. All the same, if the hypothesized link between neural systems operating in the millisecond-to-second range and socioeconomic systems evolving over months and years becomes the object of intense research, it may open immense opportunities for a new kind of social science.

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