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Connectivism

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Abstract: Connectivism is the thesis that knowledge is constituted of the sets of connections between entities, such that a change in one entity may result in a change in the other entity, and that learning is the growth, development, modification or strengthening of those connections. This paper presents an overview of connectivism, offering a connectivist account of learning and a detailed analysis of how learning occurs in networks. It then offers readers an interpretation of connectivism, that is, a set of mechanisms for talking about and implementing connectivism in learning networks, and finally, pedagogy.

Keywords: connectivism, education, learning, networks, pedagogy

Highlights

What is already known about this topic:

- Connectivism attributed to be a learning theory for a digital age
- Connectivism argues that learning occurs throughout human and non-human networks

What this paper contributes:

- This paper provides an overview and an interpretation of the Connectivism
- This paper contributes to our understanding on how learning occurs on networks.

Implications for theory, practice and/or policy:

- Connectivism focuses on learners'' capacity to live, work, and thrive within a wider interconnected community.
- Knowledge is the network that is grown and developed from interactions with other entities in the network and in the world generally. Hence the objective of teaching is to stimulate such interactions, which is achieved by modeling and demonstrating the relevant sort of activity.

Introduction

Connectivism is sometimes depicted, as it was by George Siemens (2004) as "a learning theory for a digital age". And though the rise of digital technology was influential in the formation of connectivism, the theory is not a response to digitization, but rather, a way to use the insights derived from digitization to address long-standing issues in the fields of learning and development.

In this field, students and practitioners are typically presented with a set of 'learning theories' including, variously, theories based on behaviour, methods of instruction, transactional distance and interaction, construction of knowledge and meaning, activity theory, motivational theory, and more. Often these theories are presented as tools or 'lenses' through which the phenomena being studied may be interpreted.

But throughout there's no concurrence on what constitutes knowledge and learning beyond a few superficial taxonomies or characterizations, much less a common account of what constitutes

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'successful' learning. Meanwhile, there is widespread dissatisfaction with teaching programs, testing programs, and education in general. Despite this, people learn; they learn a lot, and this phenomenon remains fundamentally unexplained.

The digital age has revealed the artificiality of traditional theories of instruction. As Watters (2021) documents, despite pretensions of personalized learning and meaningful education, the best even the most advanced educational technology can produce is little better than a mechanized, impersonal, standardized process: teaching machines based on Skinner boxes and behaviourism. Connectivism is offered as a response, not to digitalization, but to the paucity of contemporary theory in education, and offers, not black boxes and metaphors, but an account of knowledge and learning based on the most current understanding of natural and artificial intelligence possible.

In this regard, connectivism does not offer itself as an alternative 'learning theory' or 'lens' with which to interpret phenomena in the process of doing the same sort of instructional activities teachers and researchers have always done. It instead offers an empirical basis for an understanding of teaching and learning, redefining how we think of knowledge, how learning occurs, what we are trying to do when we learn, and how learning is delivered and assessed.

What is connectivism?

What is learning?

What is connectivism? Connectivism has to do with learning. And we ask, to begin, what is learning? And there have been numerous choices or options or theories presented over the years.

Gagne (1977), for example, says learning is a change and human disposition or capability. This is a theory that reflects a behaviorist approach as characterized by, say, Gilbert Ryle (1949). From a more cognitive perspective, Mayer (1982) talks about learning being a change in a person's knowledge. At the cornerstone of Bingham and Conner's (2010) argument is that learning is a transformative process of taking in information. And we also have the sense of learning as acquisition or acquiring knowledge and skills from both Smith (1982) and McDaniel et.al. (2014). I don't think learning is any of that and I think these theories are incorrect in some important ways.

They are what I call "black box theories". And what I mean by a black box theory is that they don't tell us exactly what is happening when somebody says, say, "learning is a change in disposition." What that means is that they behave differently after learning than they did before learning. But how does that happen? What makes that happen? We don't know. If somebody says, "somebody acquires information", again, there is something that's happening inside a black box. Did they put information in their head? I don't really think that's the case.

For me, connectivism is the thesis that knowledge is distributed across a network of connections, and therefore that learning consists of the ability to construct and traverse those networks. I've talked about and used that definition many times and today I'll talk quite a bit about what I mean by that.

A connectivist account of learning

So, what does it mean then for a connectivist to talk about learning when I say that learning is in the formation of connections in a network? I mean this quite literally. This is not a metaphor. There are a lot of theories of learning which are based on metaphors (we'll talk a bit about that) but this is not a metaphor. When a person learns, or when something learns, a connection is physically created between two nodes or two entities in a network.

And what do I mean by a connection? Again, this is an actual description of a physical event, not a metaphor, not a black box. I say a connection exists between two entities when a change of state in one entity can cause or result in a change of state in the second entity. Learning is a thing that networks do, it's a thing that all networks do, and arguably a thing that only networks do, and it consists of the following:

- the addition or subtraction of nodes in the network (that is, the entities that are connected to the rest of the network),
- or the addition or subtraction or strengthening or weakening of the connections between those nodes.
- And then we can also talk about changes in the properties of the nodes or the connections.

The first two are known collectively as “plasticity” and sometimes you'll hear people talk about “neuroplasticity”, and what they mean is that in the brain we sometimes lose neurons and gain neurons, and the connections form and break between neurons as well.

In the case of the third, this may mean that the strength of a connection can vary. For example, it might take more or less energy for a change of state in one node to result in a change of state in another node. And it may mean that there can be changes in activation functions inside neurons, such that different patterns of energy input may result in different sequences of signals being sent.

Self-Organization

How does ‘connection’, as described in the above section, become something we would recognize as learning? It takes place through a process of self-organization. Connected entities that change states in each other can through that fact alone become synchronized or organized in some way.

There is an experiment you can do for yourself to see how this phenomenon may occur. Arrange a set of metronomes on a piece of wood and place the piece of wood on two cans. Start the metronomes randomly, so they are not ticking at the same time. And then, as you watch, they slowly become synchronized, and now if you look at them, they're all ticking at the same time. (Bahraminasab, 2007)

Figure 1. The Metronome Effect (UCLA, 2013)

And the question is, what's happening here? Each one of these metronomes is connected to the others, and the way they're connected is through that piece of wood sitting on those two pop cans so that each time a metronome goes back and forth it pushes a little bit on the piece of wood, moving it back and forth, influencing the other metronomes, speeding them up or slowing them down until they all tick together.

This is an example of what is called ‘self-organization’, and the idea is that independent things, like metronomes in this case, that are connected can by virtue of that connection alone become organized or synchronized themselves without needing any other intervention. It doesn't need direction, you don't need to organize the synchronization, there isn't a ‘head metronome’, nothing like that. And that's the sort of thing that I have in mind.

The Siemens Model of Connectivism

The term ‘connectivism’ is attributed to George Siemens, who made an important contribution with his paper ‘Connectivism, A learning theory for the digital age’ (Siemens, 2004).

Let's look at George's principles for a bit. George Siemens wrote his paper on connectivism in 2004 and came up with these eight principles:

- Learning and knowledge rest in a diversity of opinions. And that of course is to state that learning and knowledge exist in networks, not just in one place.
- Learning is a process of connecting specialized nodes or information sources.
- Learning may reside in non-human appliances. That's the idea that personal learning and social learning are all one part of one large learning network.
- [The] capacity to know more is more critical than what is currently known. That's an important point. I won't talk a whole lot about it, but we both agree that learning isn't just the acquisition of content. Learning is about developing a way of seeing and interacting with the world.
- Nurturing and maintaining connections is needed to facilitate continual learning.
- [The] ability to see connections between fields, ideas, and concepts is a core skill. Now, I ask, what does that mean? Because I always ask what does that mean? And we'll talk about that later.
- Currency (accurate, up-to-date knowledge) is the intent of all connectivist learning activities.
- Decision-making is a learning process. And I'll talk a bit more later on in this presentation about that.

There are different things that can learn because there are different kinds of networks, for example, neural networks (Kasabov, 2014) and social networks (Oddone, 2018). Connectivism is about learning both in neural networks and in social networks.

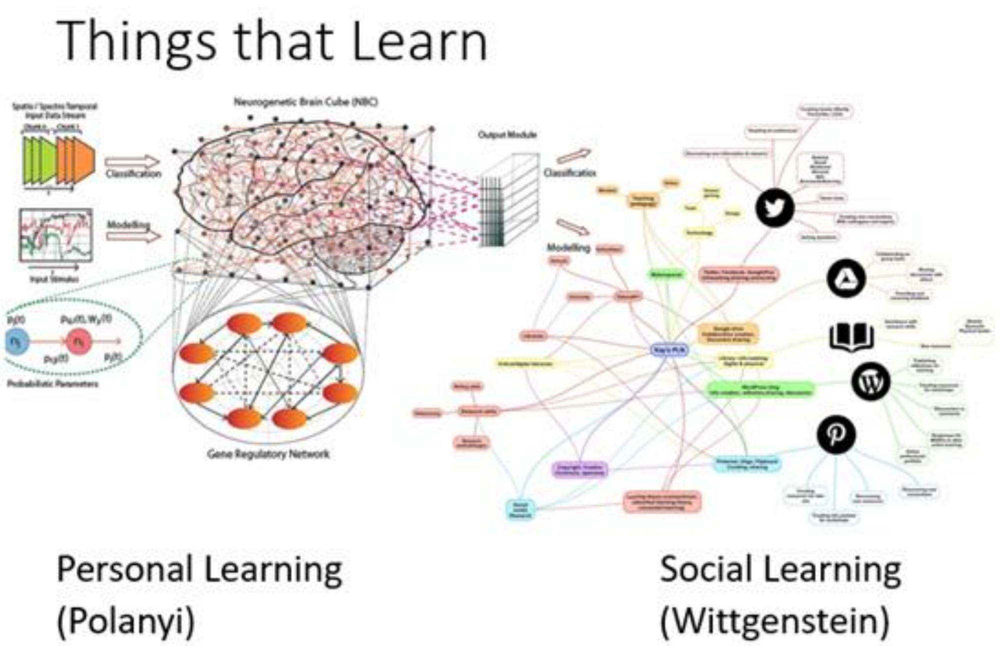

Figure 2. Personal Learning and Social Learning

One of the big differences between George Siemens and myself is the way we interpret learning. The way George would say it is that neural networks and social networks form one big network, that our knowledge consists of all the connections inside our mind and the way this is connected to everything else that's in the world, and the way it's connected with itself. So, our knowledge is partially in ourselves and partially in Twitter or WordPress or Pinterest or our network of friends, etc.

By contrast, I keep these two networks separate. I think personal learning (neural network) is one network and social learning (social network) is another network, and they're two separate networks, but that they interact with each other through the process of perception. To me, perception is the way a neural network interacts with the social network, and communication or conversation is the way the social network is able to interact with the neural network. To describe this interface, we'll talk a little bit later about the processes of emergence and recognition.

Connectivism As Distinguished from Other Learning Theories

Connectivism can be distinguished from other learning theories in a few important ways:

As non-instructivist: One way is to distinguish it from theories that are based on content, for example, instructivism or transactional distance theory and distance education. Connectivism says that the brain is not a book or a library. It's not an accumulation of facts and sentences and propositions that we bring in and organize and we store like a whole bunch of stuff. The brain does not get full of too much information. There's nothing resembling the pages of a book or the books of the library. There's nothing resembling the text and the sentences inside the brain. If you cut open a brain or if you analyze a brain, you will not see any of that. All you will see is a network and signals that go back and forth between the different entities in the network.

As non-cognitivist: What I mean by that is that therefore connectivism is 'non-cognitivist'. You've probably seen a lot about knowledge and learning that is based on cognitivist theories of mind or cognitivist theories of learning where they talk about sensory memory and working memory and long-term memory, they talk about encoding and constructing schemas and cognitive load.

All of this is from a metaphor of the computer. According to the metaphor, the brain is like an information processing system, very much like a computer. However, the brain is not like that. There are ways that we could interpret some cognitive phenomena using the metaphors of working memory, for example, or cognitive load, but these are not descriptions of processes, these are not descriptions of actual learning that occurs.

Also, we have theories that tell us that learning is about constructing knowledge or representing reality. A lot of constructivist theories tell us this. But what does that mean? Again, we run into this black box problem.

As non-representational: For the brain to be like this, it must be some kind of representational system, like a language or a logical system, or even a graphical image system, or some other symbol set, some other system of signs where the signs represent objects out there in the world. And there would have to be rules or mechanisms for creating entities and manipulating entities in that representational system.

And there's nothing like that if we look at actual cognition. There's nothing like that it's happening. And it's interesting because people are using this computer metaphor to talk about human learning when even artificial intelligence doesn't use this model anymore. This model characterizes what we used to call expert systems or symbol-based systems or rule-based systems of artificial intelligence. But in fact, almost all artificial intelligence has moved away from this model, and they use the model of neural networks.

Connectivism to me is a non-representational theory. That makes it quite different from other theories. What I mean by that is there's no real concept of transferring knowledge, making knowledge, or building knowledge. Rather learning and knowing are descriptions of physical processes that happen in our brains.

As based on growth: When we learn, when we know, what we're doing is more like growing and developing ourselves the way we might build a muscle. And you don't tell a muscle, “Okay muscle, now you will get bigger.” You don't ‘acquire’ new physical strength. That's not how it works.

And I don't know why people, when they're talking about learning, would think that it's different. We're working with a physical system, the human body, composed of physical properties, and in particular, a neural net that grows and develops based on the experiences it has, in the activities, and results of those activities it undertakes.

How Does Learning Occur?

Overview

How does learning occur? There have been numerous theories over the years, and in fact, there's a whole domain of learning theories about processes, there’s Kolb, for example, there's Dewey's model of experiential learning. They're doing something similar: describing processes that include elements such as concrete experience, observation, theory, and deductive inferences. See Kolb (1984), for some examples.

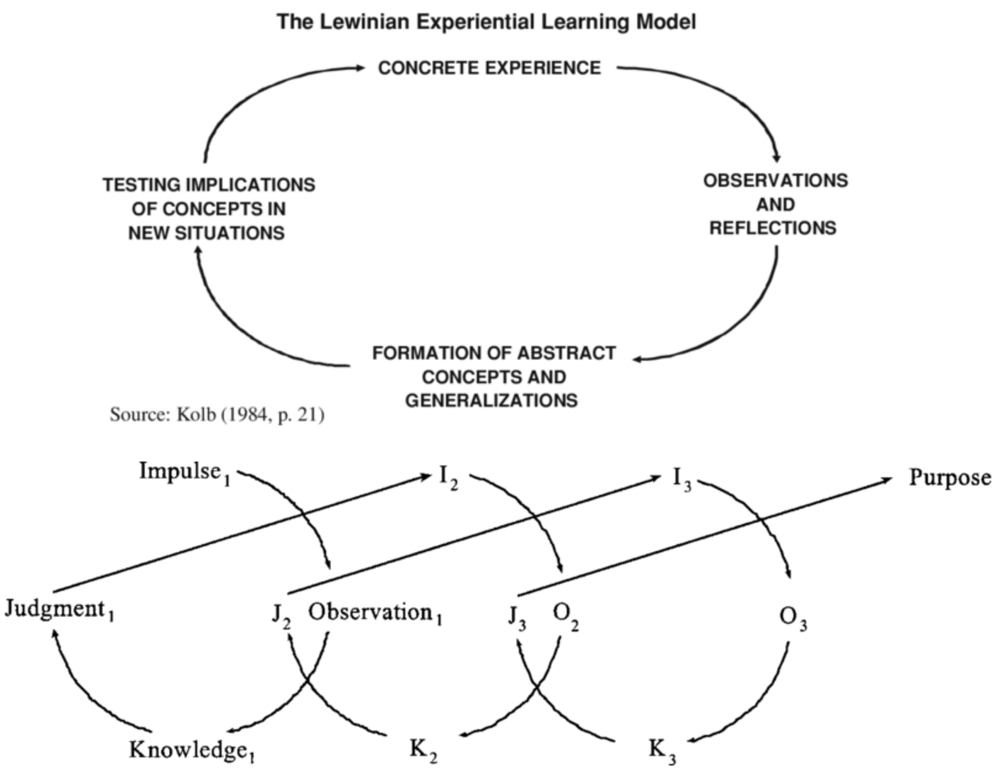

Figure 3. Experiential Learning (Kolb, 1984)

What these theories have in common is that they’re about the processes that create learning, and in fact, we could go on forever talking about the processes that create learning and talk about whether this process is better than that process, but what we're doing is we're describing the conditions around the person rather than the person themselves. And we're talking about the sorts of activities, like Gagne's nine events of instruction (Gagne, 1977), talking about the activities that are set up and organized by an instructor or a teacher rather than what learning is like from the perspective of the individual.

Here's what learning is like from the perspective of the individual (Lucy Reading-Ikkanda in Wolchover, 2017):

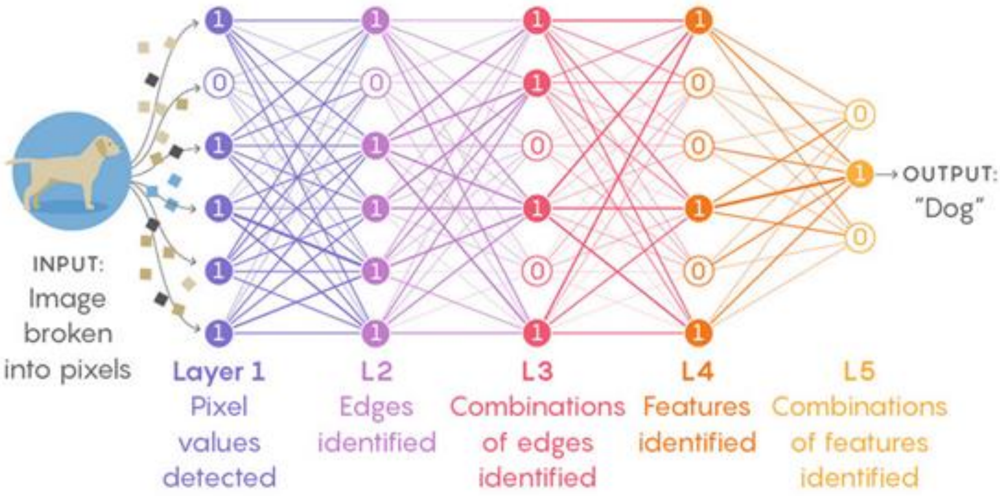

Figure 4. Learning Using Neurons

Now, this is just one of many kinds of the neural networks, we'll talk about that, but this kind of gives you an idea. Looking at the way this network works, we have what we might call an input layer of neurons that are connected to a second layer which identifies edges. These are connected to a third layer that combines edges. These are connected to a fourth layer that identifies features.

Now, this is the sort of processing, if we can call it processing, that happens in the visual cortex that's located back here (pointing to the back of my head). It comes in through your eyes and sits back here and the visual cortex takes all the input impacting your eyes and detects what Marr (1982) described as the two and a half dimensional sketch, edge detection and all of that.

These are our interpretations of what these neurons are doing. These neurons aren't actually saying, "Oh I'm looking for an edge." That's not what's happening. These neurons are simply receiving input and then sending output. That's all they're doing. They're not 'intended to' or 'created to' detect edges. That's the interpretation that we put on. That's what we say that they are doing from our perspective.

Signals, Interaction, Structures

Siemens discusses network characteristics in several places, but the terminology he uses should be more precise. So, for example, when he talks about networks having 'content', it is better to talk about networks having 'signals', because not all network interactions are meaningful in the way that 'content' suggests meaningfulness.

Additionally, Siemens discusses the 'data' or the 'information' in the brain or in our mind. These are very technical terms. A datum represents a fact. Information, strictly speaking, if we follow Dretske (1981), is 'the reduction of possible states of affairs in the world from the point of view of the receiver.' These terms again say more than we should be saying, and so again it is better to use the word 'signals'.

As Siemens says, there are 'interactions'. That is, connections form and signals are sent through these connections. That's how we get interactivity. One entity sends a signal to another entity, and that signal has the potential of changing the state of that entity. This should be distinguished from the term 'interactivity' as it is used in a broader educational context, which is used widely to refer to informational exchanges such as conversations or discussions.

Siemens also refers to static and dynamic knowledge structures. These terms are vague as well, as they may be thought of as referring to cognitive or representational structures, such as models or frameworks, or they may refer to physical structures such as social networks or neural networks. In connectivism as precisely understood, by 'knowledge' we are not alluding to cognitive or representational structures, but rather, specifically and only to patterns of connectivity between entities in such physical structures.

Similarly, when we talk about dynamic structures, we are thinking of the way the neural network receives new signals. Siemens talks about 'new information' and 'new data', but it is more accurate to say 'new (or incoming) sensory perceptions.' According to Siemens, the connections within a network are strengthened by emotion, motivation, exposure, patterning, logic, and experience and are influenced by socialization and technology (Melrose et al., 2013) and even by 'self-updating nodes', (and again, more precision is necessary, as these may refer to internal sensations as Dickens [1843, p. 24] famously said, a dream might be "an undigested bit of beef, a blot of mustard, a crumb of cheese, a fragment of underdone potato"), vertigo, sickness, nutrition, or even nodes in recurrent networks that send signals in a loop to themselves.

It is easier to talk in terms of thoughts, beliefs, intentions, and mental contents as though they exist as stand-alone cognitive entities and are not reducible to physical causes – as Dennett (1987) would say, to take an 'intentional stance'. And there is nothing wrong with the use of such terminology, provided that a connotation of a term is not imported into the explanation of phenomena the term is used to describe. Just as we don't really say a computer 'thinks' when we say, "the computer thinks it is out of memory", we don't really say we have acquired new facts, or even that they have received new information when they receive and respond to perceptual signals.

Learning Theories

There are ways to talk about learning without taking an intentional stance. For example, we can describe the factors that govern the formation and strength of connections between neurons; these, more properly than descriptions of pedagogical practices, may be understood as 'learning theories.' We can, for example, talk about four major types of connectivity:

- Hebbian connectivity, which is basically the principle that "what fires together wires together" (Hebb, 1949). If you have this neuron and this neuron and they both fire and they both stay silent, and they both fired and they both stay silent at the same time, they will eventually grow a connection between each other. That's the simplest form of network formation.
- Contiguity, which describes cases where entities that are in some way located together. One example might be the 'pool' of nodes in an Interactive Activation and Competition network (IAC) which compete against each other and are interconnected with negative weights (McClelland, 1981), or, for example, the different cells in the eye are arranged beside each other, which informs how they're connected to the different layers of the visual cortex.
- Back propagation, in which feedback propagates back through a network and adjusts connection weights. It's not clear that back propagation works in human neural networks, although we do say people learn from feedback. Certainly, back propagation is used in artificial neural networks. It was developed by Rumelhart and colleagues in the 1980s (Rumelhart et.al., 1995) and for a long time was the most promising form of neural network learning.

- Boltzmann connectivity, in which a network tries to achieve the most thermodynamically stable state by adjusting connection weights (Hinton, 2007). Boltzmann processes are stimulated by a process similar to annealing metal by heating it up and cooling it down. A useful metaphor is when a rock is thrown into a pond; atoms of water slosh and jostle but eventually they all settle into a stable flat surface.

These are rough generalizations and today's artificial neural networks are not classified by these learning theories in particular. A range of factors define the different types of neural networks extant today, including topography, activation functions, and features detected.

These core ideas, nonetheless, can be found in both major categories of artificial intelligence using neural networks: machine learning, and deep learning. Machine learning involves some human intervention to identify or classify the data. Deep learning uses layers of neurons to identify and classify data on their own.

Properties of Networks

A key question is, what makes these artificial neural networks work? In the field of artificial intelligence, the answer is arguably trial and error. Researchers develop models to solve specific problems and compete against each other at international conferences. These models allow researchers to vary network parameters so that they can adjust to meet the sort of output that's desired and are then trained using predefined training sets.

So here, for example, is what might happen in one single neuron (Gavrilova, 2020):

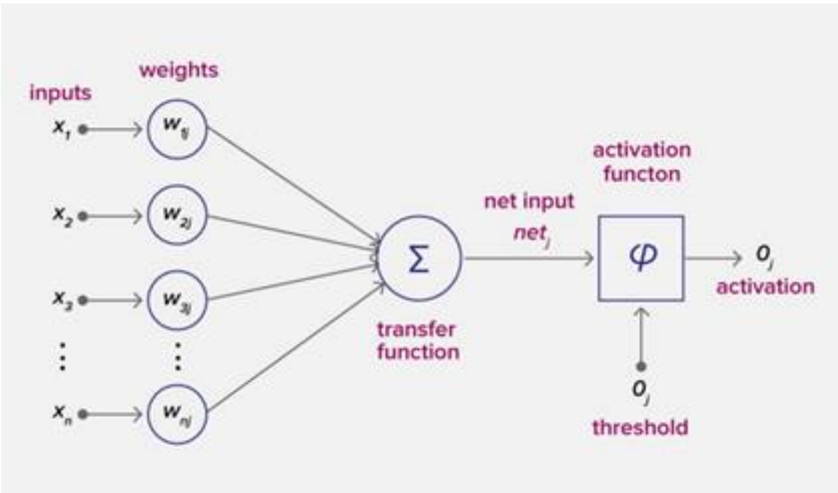

Figure 5. Parts of a Neuron

It accepts as input signals from other neurons through network connections. Each input has a weight, which may be a function of connection strength, which is considered by a transfer function. There are many ways to define this function: maybe it simply adds the input values, or maybe it takes the highest value input, or the strongest two, or takes the middle to and drops the strongest in the weakest.

Whatever the outcome of the transfer function, it is then considered by the activation function, which will determine whether the neuron responds to the inputs by sending a signal of its own based on whether these inputs meet a threshold value. In human neurons, activation functions are built from electrical potentials; these can be described at the molecular level (Lumen Learning, 2021). There are again many ways to define this function. In artificial neural networks, the Boltzmann mechanism described above works by lowering and then gradually raising threshold values over successive iterations of neural interactions.

It is worth noting that while artificial neural networks are designed using only working a few different types of neurons, in a human brain there are thousands of different types of neurons (Masland, 2004) which continue to be collected and categorized to this day (Hippocampome, 2021). Neuronal diversity occurs by function, by region of the brain, and in response to the environment. While diversity in human brains is undoubtedly important, we're a long way from understanding how that plays into this, how different types of neurons interact together.

Neural network topologies also vary (Pai, 2020). One such is the Hebbian network referenced above, which may here be redescribed as a 'feed-forward neural network' or 'perceptron'. This was one of the earliest types of neuron artificial neural networks. The input signal is sent through layers of neurons and in each individual neuron, as the signals come in, the activation function decides whether to fire or not, and then it fires. These are simple networks; they can only be used for what we call 'linear regression', that is, identifying straight line or curved line linear relationships between things. They are useful for organizing tabular data, image data, or text data, but they can't learn about complex relationships.

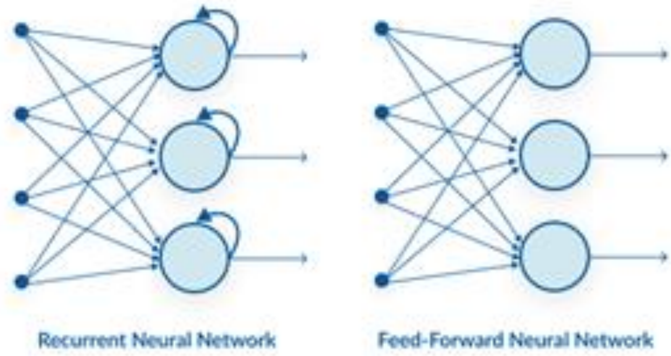

Figure 6. Two Types of Network

A different model called a recurrent neural network will feed signals from a neuron back into the same neuron. In this way, it preserves data that comes as a series, for example, the words in a sentence or a sequence of events. This type of network, called a 'recurrent neural network', is used to solve problems related to time series data and text data, like language translation audio data such as automated transcription. Complex recurrent neural networks are in use today in applications such Google's sound recorder, which transcribes the audio signals into text as the words are being spoken.

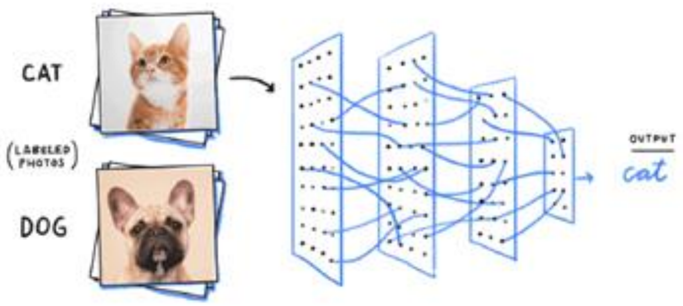

Figure 7. Convolutional Neural Network

A third type of network, called a 'convolutional neural network', can be used to captures the spatial features of an image. It looks at the arrangements of pixels as presented and can be used to distinguish, say, an image of a cat from an image of a dog. We can think of this as similar to the learning by 'contiguity', as discussed above. There are many more configurations; a full discussion is beyond the scope of this paper. What is important here is to understand that there are many types of networks formed from many types of neurons.

How Networks Learn

Artificial neural networks of thousands, or in some cases millions, of connections are still small compared to the human brain. The typical brain has a hundred billion neurons in the brain and many more connections. And what we learn from the description is that neural networks have a huge capacity to receive and transmit and reorganize and grow, to produce interesting and relevant phenomena, to see something and respond.

How does this relate to learning? We might say that networks ‘process information’, but that’s not really what’s happening; the network doesn’t look at the ‘content’ of the signals. We might say (with Gilbert Ryle (1949)) that learning is a change in disposition, but a change of disposition is explainable as a change in the neural network. When we talk about how networks learn, what we want to talk about is how networks acquire the properties they do: how neurons grow and develop, how they connect to each other, and how network topologies take shape.

Obviously, there is a role played by genetics and heredity, but these establish only the physical platform in which learning will occur. Similarly, there are environmental constraints, such as nutrition and physical trauma, that can shape this platform. But what we more properly think of as ‘learning’ in neural networks is how perception and experience shape and develop the connectivity of the neural network, how we ‘grow’, in other words, our knowledge. In humans, this shaping and development of the neural network is known as bioneural plasticity, that is, “the ability of the nervous system to change its activity in response to intrinsic or extrinsic stimuli by reorganizing its structure, functions, or connections” (Mateos-Aparicio & Rodríguez-Moreno, 2019).), while in artificial neural networks it occurs as a result of ‘training’.

The term ‘training’ has a poor connotation in the world of education because it signifies rote and repetition, as in vocational training, without reference to deeper understanding or cognition. But that isn’t exactly the meaning in use here. ‘Training’ in this context is just the process that a person goes through, or even more accurately, the process that a network goes through, during repeated iterations of experience, to acquire the configuration (the set of connections, and the set of weights of connections) appropriate to whatever it’s experiencing.

As signals are sent through networks, the properties of neurons, the nature and strength of the connections between them, and ultimately the overall network topology are shaped through processes described by one or more of the learning theories described above. In the training of artificial neural networks waves of these signals are repeatedly sent in ‘epochs’ and ‘iterations’ – there’s a whole language describing that – but essentially the method is to “feed it new sensory signals, propagate the signal through the network, and adapt to that process.”

Interpreting Connectivism

Talking About Learning

We are unlikely to ever be able to say ‘this specific change’ in the network produces ‘this specific type of learning’ because, although we are all human and though we all start off with a similar set of neurons, our experiences of change are different for each one of us from the moment of our birth. So, one person’s neural net and another person’s neural net, although similar in some respects, are nonetheless going to be different, and the sort of input that would lead one person to say something and would lead another to say the same thing are quite different.

A good example of that is language. One person may have the word ‘flower’ that they use to refer to or represent something that that they see, while another person will have a different word ‘fleur’ to refer to or represent something they see. Neither of those words is ‘right’, they’re both based on the different backgrounds and the different experiences that we’ve had in our lives. Even more importantly, the terms ‘flower’ and ‘fleur’ are not coextensive; even if they (somehow) refer to all and only the same objects in the world, they have different senses, different connotations, for each speaker in each language, based on the individually unique experiences each person has had with respect to that word (see, eg. Quine, 1970).

Thus, it is difficult, if not impossible, to talk about learning using language descriptive of words and concepts. When we talk about data and information and knowledge and meaning, we are not talking about any internal state of a person; for any given word, each person’s internal state is unique. So, such talk of learning refers not to an individual’s mental state but rather to their behaviour with respect to public artifacts such as languages, theories, and ontologies.

Rather than postulating internal states composed of words and concepts like ‘flower’ and ‘fleur’ we need a way to interpret a network theory of cognition so that we can use it in theories of knowledge, learning and cognition.

Overview: Networks in the World

‘Interpretations’ of a theory are different ways of taking the theory and applying it to the world. It’s the explanation we offer about why the world behaves in the way described by the theory. An interpretation does not merely describe what we mean when we use sentences in the theory, the interpretation also tells us what grounds the theory, what makes these propositions true (or relevant, or informative, as the case may be).

By analogy, we can consider different interpretations of probability theory. Here are three possibilities:

- Probability is really ‘the frequency of events that happen’, as argued by Reichenbach (1949);
- Probability is ‘the number of total possible states of affairs’, as described by Carnap (1950);
- Probability is ‘how much we would bet on a certain outcome’, as Ramsey (1931) would say.

These interpretations of probability not only define different ways of thinking about probability, but they also take the basic calculus and apply it to different domains of thought, to different disciplines. Frequency theory leads to statistical inference and regression. State theory leads to ontology, taxonomy, and classification science. And of course, a discussion of betting leads us to game theory, chance, and sociology.

Like probability, network theory can be found in the world in many ways. In mathematics, we encounter graph theory. In computer science, we find connectionism, artificial neural networks, and artificial intelligence. In biology, there are theories of ecology and ecosystems. In sociology, we have social network analysis and actor network theory. In physiology, there are accounts of perception and neuroscience.

Additionally, just as we might demonstrate probability theory in the world by rolling some dice, we can perform simple demonstrations to illustrate network theory. We have cited the Metronome Effect above and will use the Murmuration effect example in this section (and there are many more, described by people such as Alfred Lazlo Barabási (2002) and Duncan J. Watts (2003).

Figure 8. Murmuration. Mike Hewitt/Getty Images, Donovan (2021)

In a murmuration a flock of starlings will exhibit network behaviour as it flies in a shape-shifting flock, demonstrating cohesiveness without any form of leadership or direction. “These murmurations are actually self-organized, meaning that it's the individual's little behavioral rules that make it scale up to the large group. In order to understand this behavior, we have to go from the local scale — what is the individual doing, what are the rules that the individual is following? — to the global scale; what is the outcome?” (Donovan, 2021)

In this case and others like it, “Coordination among social animals requires rapid and efficient transfer of information among individuals, which may depend crucially on the underlying structure of the communication network.” (Rosenthal et al., 2015) Similar properties are found in networks everywhere, such as in social organizations (corporate networks, political networks), in infrastructure (the electrical grid or the internet, a worldwide information network) and in social networks, some of them better designed, like the network of websites, some of them badly designed to like Facebook and Twitter.

These phenomena (and others like them) are observable as physical phenomena and formally described by the mathematics of graph theory (Euler, 1995) and artificial neural networks. Connectivism describes phenomena related to teaching and learning in these same terms, appealing to the same underlying principles and abstractions. Thus, one of the advantages of a network way of looking at the world is parsimony, that is, being able to apply the same theory in multiple domains, thus creating broader explanations for related phenomena. A second is transference. If the same logic underlies different domains, then a discovery in one domain can lead to insights in another domain. Thus, if we learn something about how networks behave by studying computer networks, this may lead us to insights about human neural networks.

A Theory for the Digital Age

Understanding connectivism as postulated in Siemens's original paper as “a theory for a digital age” should be thought of as understanding connectivism as an answer to the question of “what is knowledge?” It is no coincidence that Siemens, in his follow-up book, writes that “knowledge has changed from categorization and hierarchies to networks and ecologies. This changes everything and emphasizes the need to change the spaces and structures of our organizations.” (Siemens, 2005a, p. v)

We said at the beginning of this article “knowledge is the organization of connections in a network.” But what does that mean on a day-to-day basis? If we say, “Fred knows something,” we are saying Fred is organized in a certain way. Fred has a certain neural network, he's grown his neural network in a certain way, and therefore he knows something, say, mathematics.

What does that mean? Does it mean that the person has memorized the multiplication table or the Pythagorean theorem? No. Knowledge is more than memory. Knowledge isn't really like memory at all, at least. Memory is like a parlor game where you're able to recite back what you were told. It's like the spelling bees that they have in the United States where children memorize how to spell obscure words without ever using them in a sentence. They have no idea what the words mean or why the word would be useful (Melby-Lervåg & Hulme, 2013). Knowledge is something more than that.

It could be said that knowledge is a way of understanding the world. There are two familiar types of knowledge: qualitative knowledgebased on properties such as the shape of something, the color of something, or the size of something; and quantitative knowledge, which may be based on the mass or weight of something, the volume or size of something, or the quantity or number of things. These are the types of knowledge you're familiar with and people talk a lot about qualitative and quantitative research (Creswell, 2020). Connectivism argues that there is a third kind of knowledge, which is connective knowledge, which is based on organization and structure. (Downes, 2008)

Connective knowledge is what enables us to comprehend phenomena like the murmuration. A murmuration is not a network like a brain or a computer network, but it's still a network. The starlings are interacting with each other and forming shapes in the sky. But there's no 'head starling', no starling in charge. The starling at one end of this murmuration cannot even see the starling on the other. Each bird is responding only to a few of the birds around it. But they collectively produce behaviour that seems to be the flock moving as a whole. Observers can see the waves that happen when one bird moves and causes the next to move, then the next to the move, and so on, until the entire flock moves. It's an advantageous response for the flock as a whole; if a predator arrives at the edge of the flock, all it takes one starling to act, and the entire flock reacts.

This is the key difference between connective knowledge and either qualitative or quantitative knowledge. What we can say of the flock does not apply to any individual. Knowledge of, or about, or derived from, the flock is over and above the knowledge of any individual starling.

Figure 9. Emergence

Similarly, consider the image of a woman (Figure 9). The image is just a series of circles. And yet, when people look at this image, they see a woman wearing a hat. This common phenomenon makes it possible to watch a sporting event on a dot matrix screen on television. But the woman is not actually in the picture, nor is the sporting event in the dot matrix screen. It is only because of the way they're organized that they are perceived as they are.

This is known as 'emergence', and this phenomenon is central to connectivism. Saying that 'to know' is 'to be organized in a certain way' could be thought of as a type of emergence. From the interaction of the entities, in a network, a pattern over and above the entities in network 'emerges'. So, when we say somebody ‘knows’ something, what I'm saying is that they are organized in such a way as to be able to, first, recognize phenomena in the world just in the same way you recognize a picture of a woman in that image or a murmuration of starlings, and second, be recognized as possessing knowledge of the woman or the murmuration.

That's what a person who ‘knows’ does. To know something is to be organized in a certain way, to learn is to acquire patterns, to learn is to have experienced something frequently enough to form a characteristic response to that thing. Knowledge, in other words, is recognition.

This is quite different from traditional theories of knowledge, though it is common and familiar to everyone. A traditional theory of knowledge might say you understand the parts of something, or you understand the rules, or you remember the specific configuration. But a person meeting their mother at a bus station in a crowd of people doesn’t analyze the crowd nor make a rules-based assessment; they look at the crowd until they see a pattern that they recognize as their mother. It's an instant awareness and instant matching of what's out there in the world with the configuration of your network as it exists. And it's very individual, it’s very context specific.

Not only is the process different, but in connectivist knowledge, the requirements are also different. For example, the dot matrix image could have been someone more specific than the generic woman; it could have been a dot matrix picture of Arnold Schwarzenegger, who is a well-known cultural figure. But not everybody will recognize the image as Arnold Schwarzenegger. The same picture shown to our grandparents before Arnold Schwarzenegger was even born would not be recognized as Schwarzenegger. Recognition depends on what you have already experienced.

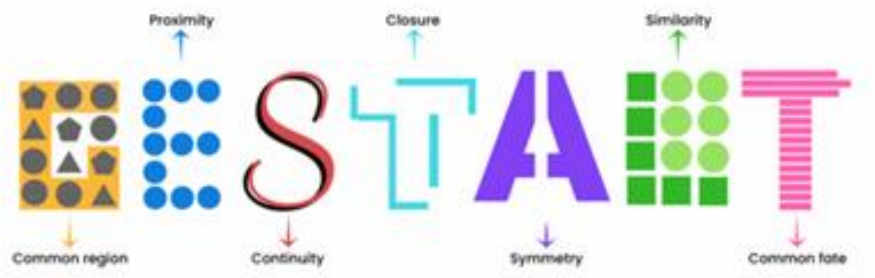

Figure 10. Gestalt principles of design, from Bufe (2021)

In the past, we have attempted to explain connective knowledge appealing to the ‘unconscious mind’ using, for example, Gestalt psychology (Guberman, 2017), and to implement it using Gestalt principles of design (Bufe, 2021). With digital technology, both in the form of connectionist artificial neural networks, and in the form of a worldwide communications network, it has become possible to design and built large scale networks and observe how they function directly, and to suggest mechanisms based, not on a theory of the unconscious, but on common network design principles.

Network design principles

What would make a good network? This is a question that can be asked of networks generally, and not merely neural networks or computer networks. Perhaps we want a network that's able to learn, but what do we mean by that? We want it to be able to grow and form connections such that it responds appropriately to the stimuli, the perceptions, that it encounters. But what would constitute responding ‘appropriately’?

In this section, we suggest that appropriately structured networks yield appropriate responses. In the case of artificial networks, we can speak of this in terms of network design, while for natural systems we can speak of the evolution of the entities that interact to form networks. This suggestion is based on the observation that networks in nature, such as (say) the immune system, tend toward a ‘sweet spot’ of connectivity. More formally, for example, it can be said that “critical systems are said to operate at the edge of chaos, that is to say, at an optimal ‘sweet-spot’ between order and disorder, which paradoxically affords flexibility and stability. Practically speaking, the brain exhibits both stability when generating consistent behavior, and variability when learning new patterns. By navigating critical boundaries, complex systems fundamentally avoid being dominated by one of two extreme poles.” (Ros et.al., 2014).

There is an intuitive appeal to this phenomenon. Entities in a network must be connected somehow, otherwise, no communication happens. But by the same token, not everything can be connected to everything. What, then, would constitute good design principles leading to this outcome? The following are offered as hypotheses, not rules, but can be said to constitute the core structure of connectivist learning systems design.

Decentralization

This principle describes a preference in network topology. In a centralized network, entities are linked to ‘central’ entities creating a set of characteristic ‘star’ formations within a network. A small number of entities have many connections, while most entities have few connections. Decentralized networks reduce the dependence on central entities and create a more equitable distribution of connections. One type of decentralized network is the ‘mesh’ network, where each entity has a few connections to neighbouring entities. Another way to achieve decentralization is to arrange entities in layers, creating characteristic ‘deep’ learning networks.

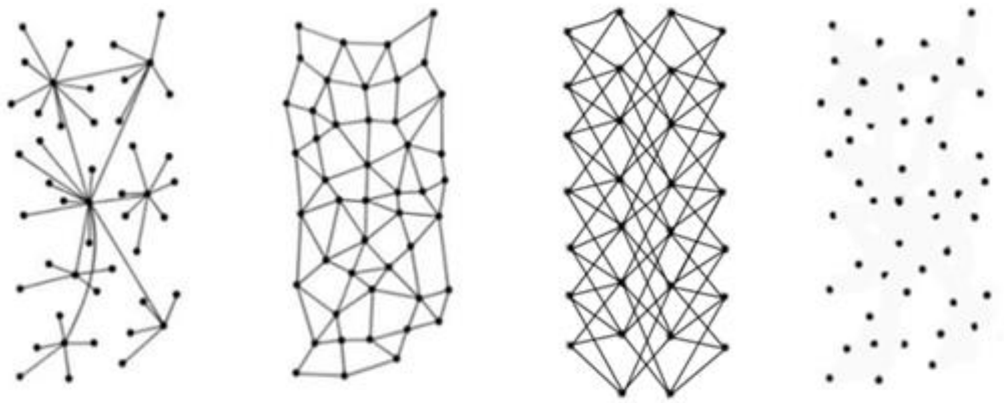

Figure 11. Centralized (or star), decentralized (or mesh), layered, and disconnected (or swarm)

In the figure above, different network topologies are illustrated. One has a characteristic ‘star’ formation, as contrasted to a mesh network, as contrasted to a swarm, which has no connections whatsoever. The fourth obviously has too few connections; there are no connections. The first also arguably has too few connections. It puts too much emphasis and too much reliance on a few neurons, a few entities, which creates a single point of failure. The mesh and layered networks (second and third respectively) distribute the number of connections equitable and are decentralized form of networks.

Distribution

Even in the brain, neurons are not all located together in the same part of the brain. The brain has different lobes: the hippocampus and the cerebellum, etc. Similarly, in a society, we don't want to put an entire communications network inside a single building. That would be a bad idea, because if the building fails the entire network fails. On the internet, this reliability is achieved in distributed networks such as peer-to-peer networks like email or Gnutella or content syndication networks like RSS. Those often are more reliable than centralized networks like Facebook or Twitter. When one of these fails, it fails for the entire network. If we really wanted a good teams application, it would not depend on the single central source in a single central application.

Distribution also offers an alternative to representational systems of cognition. In a representational system, each concept is located in a single, discrete space, as though in the head there's a specific place where we have an idea, as though we could point to your head and say, “your idea of a cat is here, your idea of a dog is here” (this is known as the ‘physical symbol system hypothesis’ (Newell & Simon, 1976). But there is an alternative.

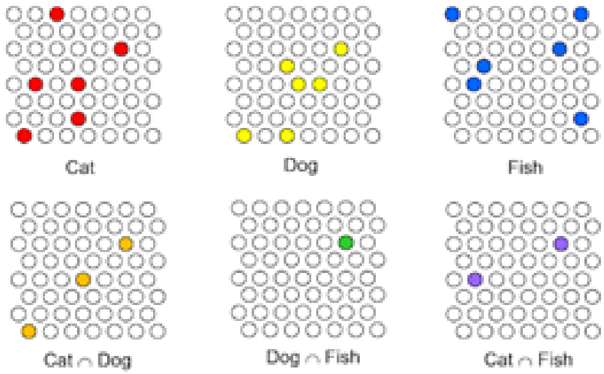

Figure 12. Distributed Representation

Instead (and this is an obvious oversimplification) our concept of a ‘cat’ is the set of neurons that are activated over time when we see a cat, and our concept of a dog the neurons over time that are activated when we see a dog. Similarly, there are neurons that are activated when we see a fish. Now, what's important is they're all using the same network of neurons. And that means the cat and dog can overlap, the dog and fish can overlap, the cat and fish can overlap. Thus, what we know about cats influences what we know about dogs. What we know about fish influences what we know about cats and vice versa. That's a really important concept and I wish I had several hours to talk about just this concept.

But what's important here is this is not the word ‘cat’ in our brain. There isn't a formal logical structure or classification of cats, dogs and fish. They just happen to overlap. Our perceptions overlap in the neural network the way our neurons are organized, that's it. This is what might be called sub-symbolic cognition. It does not use symbols, it does not use words, it does not use rules of grammar or anything like that. It's all just patterns of activations of neurons and the connections of neurons.

Disintermediation

Disintermediation is the idea of removing the barriers between the source and the receiver so that signals flow unimpeded from one entity to the next. In a neural network, a number of structures work to ensure signals propagate unimpeded; for example, the myelin sheath allows electrical impulses to transmit quickly and efficiently along with the nerve cells (Morell et al., 1999). Various brain disorders occur when this fails, and these signals break down. In social networks, disintermediation can refer to removing editors and publishers, etc., that stands between somebody saying something and somebody listening to something.

Disintermediation does not entail the complete elimination of all barriers between source and receiver. Moderation and flow control are still required in networks. Without some form of mediation, we would be overwhelmed by too much information; the difference is between slowing all communications, which is disabling, as opposed to selecting or filtering communication, which creates mechanisms for interpretation and perspective. There are types of mental diseases where that kind of filter just doesn't work and the person is overwhelmed, and the subject has sensory overload all the time.

Disaggregation

Disaggregation resembles distributed representation. It is the idea that we should design things as one single unified indivisible whole. Applied to physical objects, such as computer systems or power networks, this is the idea that functionality is distributed across many interconnected devices or entities. Applied to content, this is the idea that content should not be bundled into a single package, like a course or a book. This is the motivation behind concepts such as learning objects or open educational resources, where the organization or structure or the whole is created by the receiver, not the developer. Disaggregation allows for multiple interpretations of the same components, and more easily enables the integration of new elements with the old.

Disaggregation also applied to concepts and conceptual organization. For example, take the concept of a dog. It is hard not to conceive of a dog as a single entity. In one sense, we can: we can think of a nose and ears and other dog parts. But on the other hand, it's hard not to think a dog really presents itself as an object in the world. However, it is important to recognize that we bring this sort of organization to the world. W.V.O. Quine (1960, 1970), for example, asks, what does the word ‘dog’ mean? Does it also include a puppy? Does it also include a three-legged dog? Does it mean the overall state of the universe in the current form of a dog? There are many ways we can interpret that concept in that perception, and none of them is necessarily right. So, we should not assume that the world comes presented to us a nice human-shaped objects or human-sized objects. It probably doesn't. And (yet) these are interpretations that we are imposing onto the world.

Disintegration

By ‘disintegration’, we mean that entities in a network are not components of each other. They are independent. The structure of an entity sending a signal is logically distinct from the entity receiving that signal. This principle signifies an important distinction between systems theory and connectivism. A system is “an organized or complex whole; an assemblage or combination of things or parts forming a complex or unitary whole” (Johnson et al., 1964). In systems theory, the different parts are all part of a whole in the sense that the whole is trying to move towards some objective or some purpose. In connectivism, there is no sense of goal or purpose unifying the whole.

Disintegration is important from the perspective of interpreting theories. For example, sometimes people interpret say Darwin's theory of evolution that way, saying that we are all evolving and that there are higher and lower forms of life. But evolution doesn't have a purpose. Birds don't grow wings in order to fly. Rather, it’s the other way around. Birds are able to fly because through this process of random selection they have grown wings, and this gave them an advantage. That's why it is important to ‘disintegrate’ the entities. It is a mistake to think of a part, like wings, as essential to an entity, like birds. But they’re not. In a different world, in different circumstances, birds would never have developed wings.

Democratization

The principle of democratization is derived from the need for the entities to be autonomous and the need for them to be diverse. We can see how democratization is in this sense a structural principle, in that autonomy and diversity are essential conditions for a network to function, where we can define ‘function’ strictly as ‘a change of state in one entity being capable of resulting in a change of state in another entity'. If entities are not autonomous, and if diversity is not possible, then all entities are in the same state, and hence (for all practical purposes) no change of state is possible. Democratization might also be thought of more broadly as defining a capacity for entities that change each other's states, which may create a need for additional parameters such as equity and inclusion.

This principle also brings with it additional considerations that are discussed under the heading of the 'semantic condition'. This is the condition that for better or worse ensures that the network will stay coherent and that the network has the capacity to respond to changing circumstances in the environment. This condition is discussed in a separate section below.

Dynamization

This principle is related to the previous. A network needs to be thought of as fluid, as changing, as growing. It's only through the process of change that a network can learn. It's only through the process of change that the possibility of growth exists. Hence, efforts to lock a network into a static state cause the network to ease to function.

Desegregation

Although it is tempting to take entities and classify them into groups and say, "this is one group and this is another group and this is another group," even though we can see patterns and shapes and clusters in a network, these are nonetheless interpretations of the network, and not inherent to the network itself. Clustering entities into groups based on, say, common sets of properties, location, or other qualitative features may lead us to ascribe function and utility based on these commonalities, rather than on the actual interactions between entities, which may lead to misunderstandings about the networks being studied.

For example, consider the map of science.

Figure 13. Map of Science (Bollen et al., 2009)

This diagram was created from the references in paper to each other and then grouped them according to those references. We can see some clusters – the red designating 'nursing', above it 'social work' and then 'dermatology', and so on. There is a temptation to think of these as entirely separate fields, and indeed, they are taught that way and represented that way. But the sciences are all on the same graph because they're all related to each other the people who work in these different domains all interact and communicate with each other.

At the same time, no one person talks to everybody. There is not the analogous case of context collapse (Marwick & boyd, 2011) in the map of science that we find in Facebook or Twitter. But they're connected just enough so that a concept in pharmaceutical research, like say the discovery of mRNA as a cure for a virus, could connect through the different parts of the network to have an impact, say, on social work. We may want to categorize them into different groups, but each person and each paper is a part of a much more complex network. And seeing the world that way and representing in structuring the world that way is more likely to be successful than keeping it all segregated into different classes and categories and attempting to draw generalizations based on those classes or categories.

The Semantic Principle

The semantic principle may be represented with the following diagram:

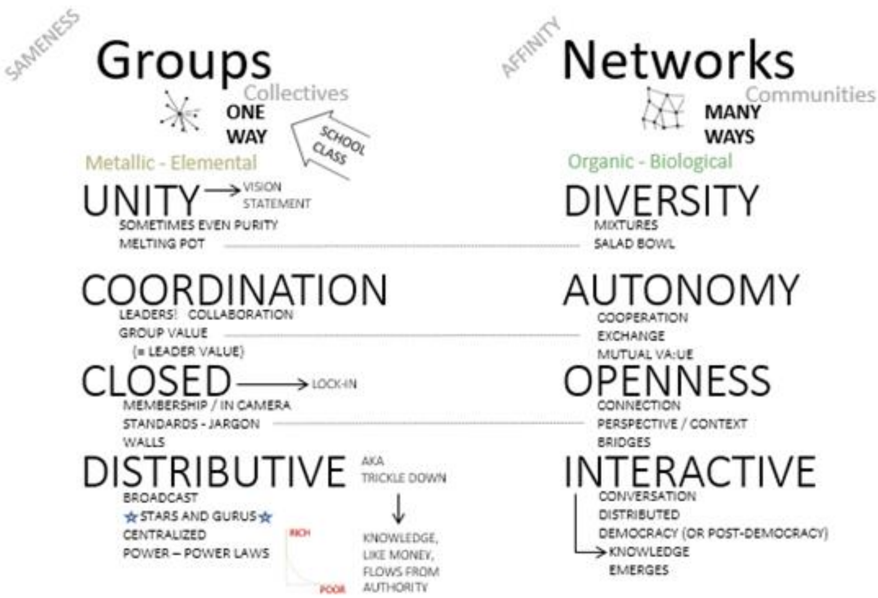

Figure 14. The Semantic Principle.

In the diagram networks are characterized as being ‘groups’ and ‘networks’. In the discussion of decentralization, above, networks were characterized using a diagram with a star, mesh and layer configuration. In this diagram, the group is the star, and the network is the mesh or layer. The semantic principle asserts, essentially, that star networks (aka ‘groups’) are less successful networks, while mesh and layer networks (aka ‘networks’) are more successful networks.

The four principles (diversity, autonomy, openness, and interactivity) are principles that describe networks that can adapt to changing circumstances. This is what makes such networks successful. Their opposites by contrast represent a type of brittleness or fragility on the part of the network, which makes it more difficult for the network to adapt and makes it more difficult for it to learn and to grow.

Diversity

If ‘unity’, as opposed to ‘diversity’, is valued, then everything is the same in a network. So, there would be no point in sending signals, and no way for these signals to have an impact. There's nothing for the members of the network to talk about. You can't see any change because everything's the same.

Of course, nothing is ever completely the same, but the distinction here is in proposing sameness as a value. For example, people often push for more sameness in a society rather than less sameness. Arguably, this makes the society less resilient and less capable of responding to change. By analogy, we can consider the case of a monoculture in agriculture, where entire crops are less resistant to disease (Ekroth et al., 2019). In a human, sameness in neurons would be a disaster; we would not be capable of thought. And, in a society, sameness makes it more difficult for the society to recognize different points of view that might otherwise enable it to recognize large-scale changes such as, say, global warming.

Autonomy

In a successful network, although individuals are connected to each other and influencing each other, they are nonetheless each of them 'deciding' (in the sense that each of them sends signals according only to the input that they receive and on their internal state (see Raghavachary, 2021). Such a network is more responsive than a network that requires coordination.

In a human neural network, it almost makes no sense to talk about coordination. There is no individual neuron that is 'in charge' and coordinating the actions of other neurons (some cognitive theories reference an 'executive function', but this is a black box, as discussed above, or at best, a metaphor, and not a description of actual human cognition). In a society, the more coordination required, the longer it takes to adapt to change. So, within constraints required to continue functioning as a network, the more autonomy individuals have, the faster a society will be able to respond to changing circumstances and new conditions.

Openness

There are different ways of thinking of openness. Openness of membership, such that a network is able to add entities, makes growth a possibility for networks. Being open to new experiences or concepts enables the network to recognize new possible states of affairs in the world. By contrast, a closed network is unable to adapt to new ways of experiencing and recognizing outside its own direct previous experience.

Openness is not simply an attitude or approach to life. It is a physical property of networks. Conversely, networks can be created such that they default to a 'closed' state. For example, the Apple ecosystem has developed a reputation for being closed and "not being able to work well with others" (Worstall, 2012). This creates an advantage for the company at the expense of Apple users, because they are 'locked in' to the Apple computer and ecosystem. Your capacity to create and deploy capacity not defined by Apple is limited.

Interactivity

By 'interactivity' we mean here that the knowledge of a network is created by means of the interaction between entities, and not distributed from one entity to the next, where knowledge is created at the center and then sent out. This is an important principle because if knowledge is distributive, the best possible state is to have copies of whatever there was at the source transmitted in each of the different entities. So, the knowledge of the network can never exceed the capacity of any given individual member of the network. However, when knowledge is created through an interactive process of all the individual entities working and interacting together then the knowledge of the whole can be greater than the knowledge of any individual. And that's a very important principle.

In a human brain, this principle is essential, because an individual neuron is not very smart. An individual neuron cannot do anything except receive signals and send signals. But a human brain, a hundred billion neurons all connected, is incomparably smarter. The same is true in a society. Compared to a whole society, an individual person is not very smart. Even the smartest person in the world is not as smart as a whole society (Surowiecki, 2004).

Sometimes we act as though individuals are smarter than society. But arguably that's because we've organized our society very badly. In such cases we're just comparing one smart person with another smart person. But there are numerous ways to show that the knowledge of a society is much greater than that possessed by any individual. No individual person knows and understands all of science. No individual person comprehends the entirety of the economy. No individual person can recall the placement of every room in every building in a city. In fact, the danger is felt when the individual substitutes his or her own perspective over and above the society as a whole. Such a society is fragile, brittle, and often quickly collapses.

Connectivism as Pedagogy

The Connectivist Principle of Pedagogy

If it had to be summarized in a single sentence, the connectivist principle of pedagogy would read: “to teach is to model and demonstrate; to learn is to practice and reflect”. In this regard, connectivism is very similar to other empirical theories of pedagogy, for example, John Dewey’s progressive idea that “schools and classrooms should be representative of reallife situations, allowing children to participate in learning activities interchangeably and flexibly in a variety of social settings” (Williams, 2017).

As such, however, connectivism represents a break from more traditional theories of distance and online education based on information theory and the transmission of content. One such theory is Moore’s theory of transactional distance, where the focus is on “the extent and quality of dialogue between instructors and learners” (Moore, 1997). In such an approach, the objective is to ensure information integrity, that is, “the representational faithfulness of information to the true state of the subject that the information represents” (University of Waterloo, 2021). This creates requirements for peer review to ensure high-quality content, and for testing and examinations, to ensure students can faithfully replicate it.

By contrast, in connectivism, knowledge is not understood as the content that is transferred from person to person, but rather, knowledge is the network that is grown and developed from interactions with other entities in the network and in the world generally. Hence the objective of teaching is to stimulate such interactions, which is achieved by modeling and demonstrating the relevant sort of activity. The actual growth of the network is achieved entirely by the individual through practice and a mechanism that enables a refinement of that network because of that practice. The outcome of a connectivist learning activity is a type of knowledge as recognition of relevant phenomena, where recognition may include relevant responses to those phenomena (See, e.g., Boesch, 2021; Simpson, 2013).

Disintegrating Content

By 'disintegrating' here we mean 'dis-integrating', that is, to unbundle, or to not present as a single integrated unit. In contemporary pedagogy, there is a great emphasis on managing and ordering the presentation of content and learning activities, as evidenced by the IMS Global Learning Design and Simple Sequencing specifications. Such emphasis is also manifest in a focus on foundational knowledge, prerequisites, coverage of course material, and course completion, as seen for example in evaluations of the success, or non-success, of MOOCs (Jordan, 2015). Numerous pedagogical theories, for example, direct instruction and worked examples (e.g., Kirschner et al., 2006), demonstrate this emphasis on content and sequence (a 'worked example' is a case where a problem is presented, and then the steps taken by an expert to achieve the solution are presented).

To understand the connectivist response to this it is useful to consider the distinction between learning using stories and learning using maps. Suppose I'm discovering in a new city. Somebody in the city might tell me how to get to Franklin Square by saying “you take this road to the end of the park, then you take this street, and then turn right here, and then turn right again, and then go up 17th, and you're at Franklin Square.” This presents something very complicated, very complex, as though it were a single thing, and this knowledge is fragile. It is difficult to remember and limited by cognitive load, lacks cohesion, and is easily disrupted (for example, by a road closure).

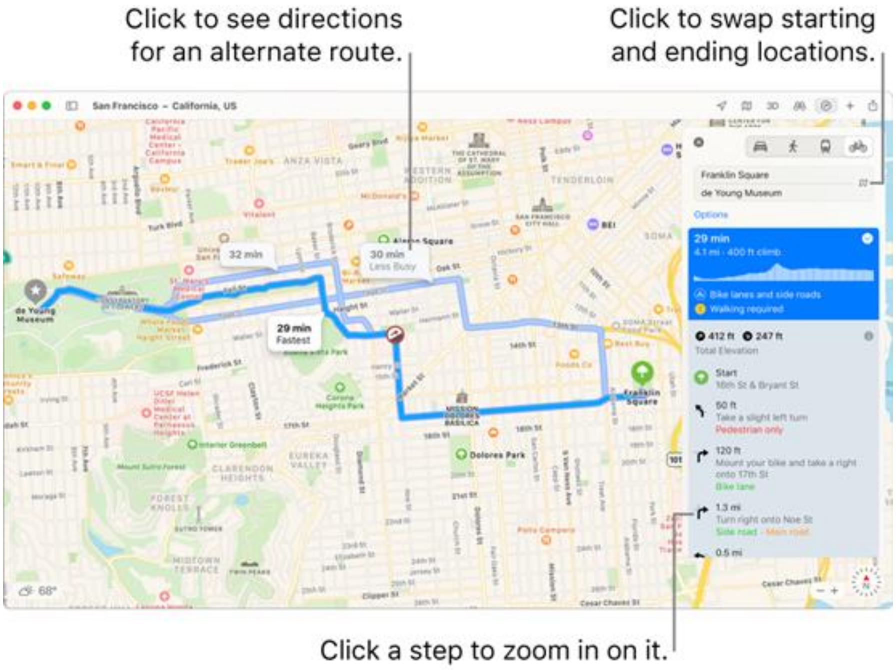

Figure 15. Maps versus Stories.

But there are, as can be seen in the diagram, alternative routes. Or the traveler could choose to go to different places. But even more to the point: if a person’s knowledge of the city is represented as only the line from one place to the next, then if this line breaks in any point, then they have no understanding at all. But if I see the city as a set of distinct entities related to each other with multiple routes between them, then my understanding of a city is much better. A connectivist understanding of a city is more robust than a cognitivist understanding based on sequences and stories.

And a connectivist understanding is different. There’s no real sense to be made of the concept of ‘completing’ a map. And while we expect a map to be faithful to the city being represented, there is no one map that is most faithful; the integrity of the map has much more to do with what you want to do than the accuracy of its presentation (Kukla, 2021). And most importantly, the knowledge isn’t the map. The knowledge consists of whatever neural network structures are developed by using the map and exploring the city, or perhaps conducting activities in the city. ‘Knowing’, in this sense, isn’t remembering the map; it is successful navigation through the city.

The AARRFF Method

Traditionally in pedagogy, we find things like instructional theory, such as the elements that Bruner (1966) describes: things like the learning predisposition, the design of concepts, how to present an instructional design, the successful and proper progression of ideas beginning from foundations, for example, and then, of course, the administration of rewards and punishments. As may be imagined, these and similar approaches have very little to do with connectivism. But one may ask, what does one do if engaging in a connectivist form of learning?

In response, connectivist pedagogy may be described in terms of ARRFF method, where ARRFF stands for aggregating, remixing, repurpose, and feed-forward. This pattern is not unique to connectivism and can be found in many other sources. It combines the idea of gathering things together, remixing them, adopting them to your own purpose, translating to your own language, and then sharing.

What makes ARRFF unique in connectivism is that it was developed from the perspective of, “what does a neuron do?” It asks, if you were a single entity in a network, what are you doing? And from what we’ve seen thus far, the answer is that we receive the signal, we process the signal in some way, and then via an activation function, we fire fourth a signal of our own. The method can be summarized in the slogan, “Be the node.” “Be the entity in the network.”

As an instructional theory, connectivism is based on the core skill of seeing connections between information sources and making decisions, even in rapidly changing environments, based on the capacity to recognize things, to be able to continually update and change our knowledge based on new phenomena that are presented. So it's not simply, “can you repeat something back?” but “Can you work in a rapidly changing and dynamic environment?”

The MOOC

Learning activity in connectivism is based on putting people into a kind of environment, not in a formal course, but in an overall sort of environment like that. That's what we tried to create, George Siemens and myself, when we created the first massive open online course (MOOC). The figure below depicts the physical construction of that network

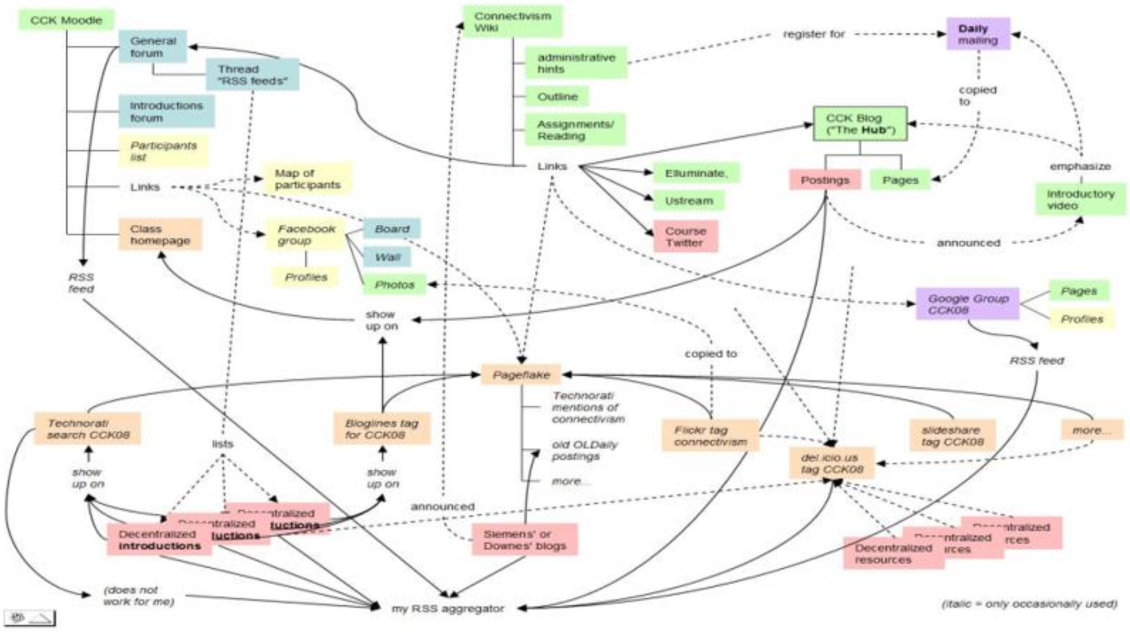

Figure 16. Connectivism and Connective Knowledge MOOC, 2008. Image by Matthias Melcher.

The original idea was to enable to scale the presentation more efficiently than in a previous conference presentation, but ultimately what we wanted to do is give an example of connectivism by putting people in an actual functioning learning network, going into that network ourselves, showing how we learned in that network and giving them the chance to practice learning for themselves in the network. This is what was accomplished in the first MOOC.

We did not care what they learned. There was no content we wanted them to learn (in the sense of acquiring knowledge and re-presenting it accurately) and we even said to them, “You determine what counts as success for you; we don't have a body of content here. What's important to us is that you can function in a network and learn things from the network, and that's connectivism."

A Connectivist Model of Literacy

From a connectivist perspective, what we think of as 'literacy' isn't about language, it isn't about rules and grammars, it's about patterns. It's about recognizing common patterns and phenomena. This enables a practical application of connectivism, a connectivist model of literacy.

To present this model briefly, we begin by observing that there are many types of literacy already extant: textual (or traditional) literacy, mathematical literacy (also known as numeracy), information literacy, cultural literacy, emotional literacy, digital literacy, and more. Such literacies are discussed at length in the literature, and the discussions typically depict these literacies as a collection of knowledge (of facts, of rules, of meanings) and skills (which define a sort of fluency). It is arguable that knowledge of any domain or discipline may be represented in this way; to 'know' a discipline or science or field isn't simply to remember a set of facts related to that field, but rather, to be fluent in the field such that, through social interactions with other experts in the field, these other experts would recognize you as an expert in the field.

There are probably many ways to depict the sorts of pattern recognition that constitute knowledge and expertise in a field. Here we offer six major types of patterns that constitute the sort of social interactions that we would think of as literacy, and hence, constituitive of expertise. There might be more, there might be fewer, there might be better ways of describing these patterns. It doesn't matter; this discussion is a preliminary sketch.

The six patterns are: syntax, semantics, pragmatics, cognition, context and change. Learning theorists have read and written about and read about all six of these concepts at length. But the idea here is to think of them not as basic concepts, but as patterns in the environment that you are recognizing because your neural network is shaped a certain way.

Syntax

'Syntax' refers to any sort of pattern based on form or structure. Syntax encompasses more than just rules and grammar, Chomsky (1957) notwithstanding. Indeed, grammar might be thought of as repeated patterns in language, and not based on rules at all; there's a series of grammar called the Cobuild (Collins UK, 2017) series that represents grammar that way. Syntax may also comprehend forms and archetypes and envisioned (say) by Plato and Jung respectively. Plato is known for his theory of forms, and Jung for the theory of archetypes. Both are idealized shapes or images (eg., a triangle, a mandela). The idea here is that these shapes are patterns that we recognize in our perceptions of the world. Similarities are a form of syntax. So are operations, procedures, or motor skills.

Semantics

Semantics includes theories of truth, meaning, purpose, goals. Again, though, on this model, these are not 'theories' properly so-called, but are kinds of patterns. Semantics includes sense and reference, interpretations, forms of association. In the world we find semantics expressed in decision-making, voting, finding consensus, ethical attributions and findings of value.

Pragmatics

Pragmatics encompasses patterns of use, action and impact. Writers such as J.L. Austin and John Searle describe pragmatics as speech acts and the way we do things with words, for example, the way we direct people or express things or make statements, but also the way we harm people, harass people, or bully people. Hate speech, for example, falls under this category. Pragmatics includes also interrogation and presupposition.

Cognition

While we may say that we need cognition to know and to learn, connectivism turns this around and suggests that cognition itself is a very involved form of pattern recognition. Cognition can be divided into four major categories of inference: description, definition, argument, and explanation. Each of these can be recognized via characteristic forms and enable distinctive responses that help us advance and evaluate forms of reasoning.

Context

Context is the environment, locale or external circumstances surrounding an activity or event. Recognizing context is essential to recognizing patterns in general. Bas van Fraassen (1980), for example, says an explanation is an answer to a 'why' question, and you can only answer a 'why' question in terms of what else was possible. Quine, as referenced above, argues that meaning is context sensitive. Context appears as core in writers as varied as Jacques Derrida talking about vocabulary and George Lakeoff talking about frames and worldviews.

Change

A classic way of talking about patterns is to talk about patterns of change. The I Ching describes the change, but so did Marshall McLuhan, so did Hagel, all talking about different ways to see and understand the change in the world. Talk of change also includes talk of game theory, progression, logic, branching tree scenarios, scheduling, and timetables.

Assessment

As suggested above, any discipline may be represented as a type of literacy along the lines just proposed. For example, consider 'performance', in the sense of acting in movies or theater, and consider the syntax of performance: what are the forms, rules, operations, patterns or similarities? Based on this, we could analyze the concept of performance. There may be basic elements, like the ability to remember one's lines. Or there may be detailed and complex accounts, such as Stanislavski's system of method acting. Performance may include rituals, as in funerals and weddings. All of these are ways of seeing, all of these are ways of recognizing different aspects of performance.

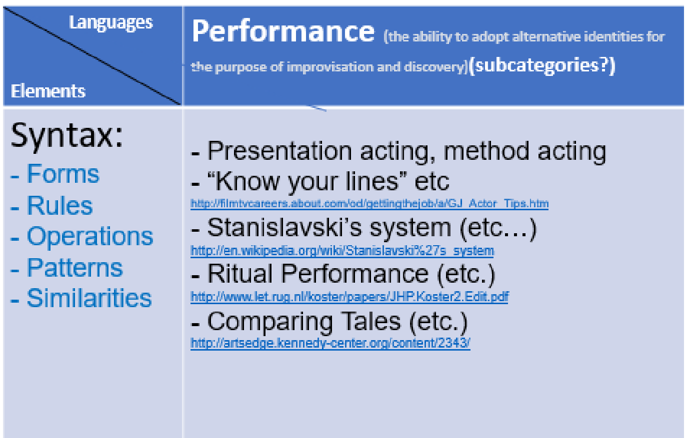

Figure 17. Elements of assessment of performance.

But though these constitute the contents of a successful performance, they do not constitute the process of assessing performance. Such an analysis may be useful as a guide or a checklist, but actual evaluation proceeds quite differently.

When we have people who are working in high skill high stakes environments - for example, people like surgeons or doctors in a hospital, airline pilots, maybe military commanders, etc., lawyers, even - we don't simply give them a test, and we don't simply ask them to state knowledge back. What we do, and you can see this for yourself, is that we put them in a real environment and see how they perform. We put interns in a hospital, we have lawyers article with law firms, we put pilots into flight simulation systems or on an actual airplane. And then somebody who is already an expert in the domain watches their performance. There might be a checklist, but their assessment is not based on any set of rules or principles or even knowledge that a person has. What the evaluator is doing is looking at the person overall and asking themselves, “Do I recognize this person as a doctor as a pilot as a lawyer? Do I recognize them?”

And what this means is, “Do they function in their environment as though they recognize the things around them? Are they responding appropriately, using the words in the right way, are they asking the right questions, are they treating the right things as data and information, are they performing skills in the right way?” It’s the combination of things. It’s not possible to list them all; it’s not possible to create a list and make sure they’re doing each individual thing. Expertise in a discipline is composed of minutia and nuance, it consists of novel responses to novel circumstances or behaviours that bear resemblances to, but are not identical with, previous practice. Our expert looks at a person’s work overall and asks, “Do I recognize this as performance in this environment?”

Concluding remarks

Connectivism is focused on a wider understanding of learning and an understanding of learning that's based not just on facts and information, but rather on a person's capacity to live, work, and thrive within a wider interconnected community. I've said before, you look for the success of learning, not in task scores and grades or even graduations, you look for success in learning in social indices, like lower crime rates, better health, greater happiness among the people. These are, to me, the proper measurements, the proper indicators of learning, and the proper ways to evaluate a learning theory.

This paper should not be understood as an argument for connectivism. It is not offering connectivism as a theory which requires belief or acceptance. Indeed, every statement in this paper should be subjected to empirical scrutiny and testing. It is understood that the language and descriptions in this paper may be subject to refinement or even refutation by further research and study. The terms, descriptions and mechanisms offered to provide a framework for understanding learning and development, but this framework should not be used as a tool so much as it should be understood as a set of propositions offered to allow the field, as a whole, to begin to develop a genuine science of education.

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