

We can THINK only with on-board knowledge: on-line does not cut it.



Learning Categories from a Neuroscience Perspective

THE LEARNING UNIVERSE

Connecting Learning Science to Neocortical Networks & Synapses

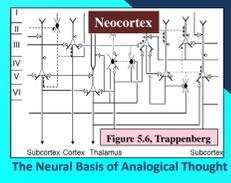


Figure 5.6. Trappenberg. The Neural Basis of Analogical Thought

Learning Categories: Any parsing of learning methods (aka teaching approaches) into categories is **intrinsically arbitrary**: red-line boundaries do not exist. But there are real differences because different categories engage neocortex/hippocampus in distinct, crucial ways. The 3 specific categories used here differ greatly in terms of style and baud (information transfer rate). **Synaptic Learning Theory** is a network-based formulation of Hebbian Learning provided in 2015 posters: www.zfhindbrain.com -scroll down DMR page

NODAL THEORY: The linking of ANY two items REQUIRES that those items become connected in **Neocortical Space**. Neuroscientists do not know how this happens but activation of **information nodes** (aka Auto-Associative Networks) via compact neural messages (packets, neural words) is central to both rote learning and the making of new, higher-level connections aka **Cognitive Advancement**. *Packet Routing and Nodal Theory* are discussed in Belloch-O'Malley, 2017 on DMR page at www.zfhindbrain.com (at bottom). For deeper dive see *Neural Words* essay, mid-page.

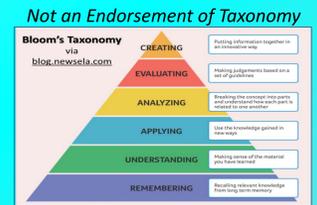
Knowledge Transfer Rate

Adaptive Learning
- highest throughput, e.g. Knewton
- automated tidbit-addition, personalized
- but brains are not "flash drives"

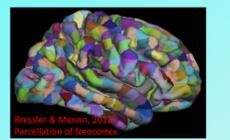
Modeled after **Adaptive Testing**, computer algorithms monitor progress and proffer new knowledge tidbits to add to our neocortical database. ≈ Equivalent to rote lecturing, but computer-personalized.

Reflective Learning
- medium throughput
- e.g. pair & share; muddiest point
- avoids "cramming tedium"
- often Metacognitive (e.g. Tanner, 2012)

Active Learning: e.g. Projects, Cases
- slowest throughput, but ≈ deepest learning
- acquire & apply knowledge, build on experience
- concept maps, peer review, collaborations
- *example*: build DNA model, figure out base-pairing



Not an Endorsement of Taxonomy
While **Adaptive Learning** typically entails Levels 1 and 2, **Reflective Learning** moves higher and **Active/Project Learning** can invoke the highest levels. But this is NOT EVEN CLOSE to being a hard and fast rule.



Neocortex has about 200 Parcels and each P. has about 100 million neurons or about **10,000 I-nodes** (2 million I-nodes total, each might store 1000's of patterns). But many I-nodes do other brain tasks, besides learning. Assumes 10k neurons / I-node, which equates to 50 I-nodes per fMRI voxel.

Neural Basis of Adaptive Learning
Basic neural mechanisms here are used in all 3 L-categories: "word" nodes are activated and linked, e.g. camels-humps, tigers-stripes. Utilizes neocortical **I-nodes** and "hippocampal context" plus neocortical broadcast systems. see **SNOPs** below

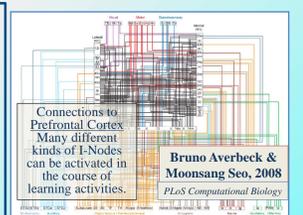
More Resources Used

Neural Basis of Reflective Learning
Re-activates I-Nodes (stored knowledge) & engages neocortical "sentence constructor" to write or explain. Much temporal lobe activity. And **Metacognition** engages frontal lobes. Plus more intense SCIP (see below).

Yet More** Resources Used

Neural Basis of Active Learning
Likely uses the greatest variety of neocortex resources / regions. Conversations, tactile inputs, motor acts and other elements all engage more I-nodes and lead to greater convergence onto new concept nodes: e.g. build double-helix with H-bonded base pairs → easier retrieval, "knowing".

Why Complementary Memory Systems?
- Hippocampus is FAST LEARNING system
- Neocortex slowly updates Knowledge Systems
- OR perhaps fast neocortical learning is key?
- DMRs likely stored in Neocortex (zfhindbrain.com)
- Linking of DMR items: fast & experience-based
- MMR = *McClellan et al. 1995, Psychological Review*



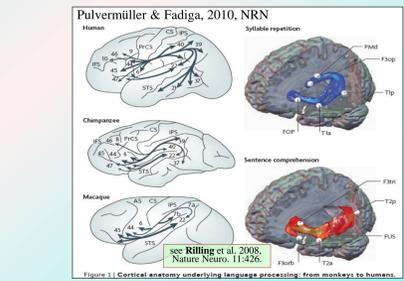
Every learning method operates within the constraints of neocortical network operations-- governed by biophysical laws. Disobedience is not an option!
Our DMR (Daily Memory Record) is the **FIRST** constraint

General Principles of NeuroLearning
- all learning is synaptic (neural plasticity)
- physical connections btw. I-nodes is key
- 10kCon enables amazing things*
- **Knowledge Pavements**** lead to expertise

*A neuron can be connected to 10,000 other neurons.
**Concepts must be precisely aggregated in the brain.

** While **Active / Project Learning** uses a greater variety of resources, **Adaptive Learning** uses specific resources much more intensively/repetitively, leading to fatigue, tedium and ↓ motivation: think MCAT prep!

Self-Regulated Learning: entails cognition, metacognition and motivation; including forethought, planning (Schunk, 2005; Schraw et al., 2006). **Metacognition:** "Do I understand this topic?" or "How do I best study this topic". SRL entails monitoring self-progress and figuring out how to improve studying. SRL is unequivocally "reflective" but can be part of active L. as well



Rilling showed enhanced trans-cortical STS connectivity in humans which might facilitate fully symbolic neuronal operations (SNOPs) aka Language. Requires SCIP = sub-conscious information processing

Universal Physics
Universal Grammar
Universal Physics
Neocortical Modules know myriad aspects of the world from visual cliffs to joining visual blips into objects. **This is the neural foundation** that supports all learning and ultimately language.

Innate Knowledge aka: Evolutionary Learning
Darwin's Contribution
Evolution organized the vertebrate brain to create maps, assess stimuli and make decisions. Much world knowledge is encoded in our genome, e.g. fear of snakes.

Analogical Reasoning
Flexible Dancers vs. The Cognitively Inflexible

Resonant Brain Modules
The modular nature of neocortical columns offers a natural means to form resonant structures in discrete Knowledge Domains. **Analogies can thus build new Knowledge Architectures by ≈ replicating the structure of existing AAN / I-node-clusters.** Abstract analogies are derived from real-world U.P. constructs (which also enable SNOPs)

Melissa B. McElligott & Donald M. O'Malley: How Reflective and Adaptive Learning Strategies relate to a Nodal Theory of Neocortical Computation, Northeastern University

Nodes and Pathways
- DTI and PFC maps highlight major thoroughfares
- 20 billion neurons means lots of Info. Nodes (I-nodes) aka auto-associative networks (all-to-all wiring is not possible)
- coherent packets must be routed between nodes
- How e.g. *Pink* can be associated w/ *Elephant* is unknown!

Learning in Neural Space: Nodes & Symbols

SCIP = Sub-Conscious Information Processing
All our thoughts and sentences emerge from SCIP and appear in Stream of Consciousness likely due to focal γ -band in neocortex. Then DMR "excerpts" are stored and are the basis of all long-term Declarative Memory (episodic + semantic) i.e. of all knowledge. **SCIP runs all of this w/ help of motivation.**

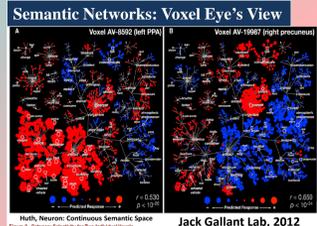


Linguistic SNOPS = vastly expressive symbol manipulation system, but rides upon SNOPS-nl [non-linguistic symbol system] which is derived from vast evolutionary learning/calculations which stored vast innate knowledge aka U.P.

Auto-Associative Networks Store Information
- The hippocampus & neocortex have many AANs
- during ENCODING new patterns are stored
- during RETRIEVAL partial input recalls full pattern
- AAN's can tolerate extensive loss of cells, synapses & might be used for long-term neocortical storage

SNOPs are Symbolic Neuronal Operations

Linguistic & Physical Items are Richly Entangled
- the Chimp brain represents pre-linguistic encoding
- massive neocortex expansion co-occurred w/ language
- both linguistic tags & real-world items are deeply connected
- but "new conversations" are largely symbolic, fragile
- sub-linguistic SNOPs might entail massive SCIP



www.MazeFire.com has many **Reflective Learning** games (click-n-play) in e.g. Bio1, Physiology, Neurobiology, Micro, Biochem and Pharmacology

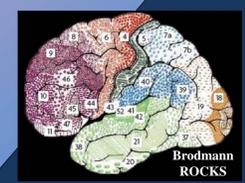


Fig. 8.2 -Trappenberg for Network Capacity Limits see Trappenberg's *Computational Neuroscience*