

Science teachers often complain that their students either easily forget or can't apply the general concepts they have "learned" in class. Unlike the teachers, students have not established a network of learning paths that would help them remember and apply those general concepts.

Students must force themselves to learn. The amount of force depends on how steep the learning path is. The amount of energy required is a function of the force and the distance.

Students may waste a lot more energy following a learning path than is needed. They may travel in circles or they may encounter friction. We'll define a high friction path as one filled with distractions and small meaningless exercises. Movement on a high friction learning path generates heat, which we can define as frustration, dissatisfaction or anger. As in the real world, there is always some friction along learning paths. This friction decreases significantly each time a student repeats a learning path.

A closer examination of learning space provides insight into the value of inductive learning versus deductive learning. Inductive learning is where the learner does not know what or where the desired knowledge is. The teacher provides them with numerous facts along the base of the hill and hopes they can induce their way to the top of the hill. The learner does not know what concept is at the top of the hill. Deductive learning involves showing the learner one or more paths to the peak. The learner is then asked to follow the same paths down the hill with homework problems. Ultimately the learner may be asked to solve a problem that requires them to blaze their own path up or down the hill. As the student learns, the paths become smoother with less friction and the student requires less energy to follow them.

Other physics parameters can be used to define a student's abilities to travel in learning space. For example, students bring a certain amount of **potential energy** to a class. A high **power** student can concentrate and focus on a subject well.

Mass is inversely related to a person's motivation to learn. It is a person's personal philosophy about learning. A closed mind, a person who does not believe there is anything more to learn or that learning has no value, is a very massive object. Students with deep-rooted misconceptions are high-mass objects. A huge amount of **force** is required to force the student along a learning path. The desire to learn, the inverse of mass, may come from various sources. It may be instinctive or it may be an altruistic desire or it may be seen as just a means to get a better grade or job.

Extending this analogy can help science teachers label, define and analyze what good experienced teachers already know about teaching and learning: Teachers should attempt to guide students along numerous learning paths. Teachers should utilize the energy a student brings to class. Encourage

students to bring more energy to class. Don't allow students to waste their energy. Observe and maintain learning momentum. Students naturally follow the paths of lowest energy. The teacher must ensure those paths do involve learning the material. Each student has a certain amount of learning power, a measure of the student's ability to focus and concentrate. Each student has a unique desire to learn. Teachers should encourage this desire.

Quantifying Terms and Optimizing Student Learning

Specific mathematical relationships also arise from the physics analogy. These common sense relationships can be used to create a mathematical model of a classroom. If we can quantify certain parameters as a student's concentration power, a student's "mass" and the time a student spends on a learning path we may be able to calculate the energy required to follow the learning path from $E = \int P \cdot dt$. If we can quantify a student's desire to learn then we could map out the topography of learning space, i.e., the material in a course, from $E = mgh$. The following table summarizes terms and relationships that may be useful.

Physics Term	Equivalent Educational Term	Symbol, Relationship
Path	Learning Path	r
Space	Knowledge = $f(x,y)$, Learning Space	x,y , or more dimensions
Height	Knowledge Complexity	h
Force	Learning effort	$F = dE / ds$
Work	Work	$W = \int F \cdot ds$
Power	Ability to concentrate, focus	$P = dE / dt$
Energy	Energy	$E = \int P \cdot dt$
Potential Well	$E(r)$	$F = dE(r) / ds$
Velocity	Learning rate	v
Mass	Inverse of desire to learn.	m
Momentum	Learning momentum	$p = m v$
Friction	Distractions, roughness in learning path	k
Heat	Frustrations, Dissatisfaction, Anger	Q
Gravity	Desire to not work	g
Potential Energy	Available amount of energy	$P.E. = mgh$
Kinetic Energy	Current energy being used	$K.E. = p^2 / 2m$

By examining data from a large group of students, we can generate a topographical map of learning space for a given topic or course. We can evaluate paths quantitatively and thus select the best paths for each individual.

Quantifying Terms

Quantifying a student's potential energy, concentration power and mass may be accomplished with a pre-class self-evaluation form as shown below. Another approach would be to let a student proceed with an endless exercise until they exhaust themselves. The time they spend on the exercise and the progress they make is related to their energy and concentration power.

Example Questionnaire

Estimate the amount of energy you bring to this class as compared to other classes you've taken on a scale of 1-5. 5 is the highest energy.

Estimate the amount of energy you bring to this class as compared to other students in this class.

Estimate the total amount of time in hours per week you expect to spend on this including class time.

Estimate how highly motivated you are to learn this material.

You have no calculator. Calculate the square root of 2 to as many places as possible until you want to leave. Write down your answer and the amount of time you spent on that answer. Make sure your answer is correct.

We now have a means to evaluate the learning paths we create for students. Are the learning paths too steep? Are the steps in the learning path too broad? Has the student followed enough progressively steeper paths to a general concept to effectively follow new deduction paths on their own? A series of exercises can be generated to test how much the student has learned:

1. Exact repetition of learning path followed in class.
2. Replacement of numerical values in this learning path.
3. Redefine one or more variables in the learning path.
4. Unique application of general concept.

Collecting this data, mapping out learning space and tracking student energy levels and momentum is greatly simplified with a networked computer system. Students can perform computerized exercises that are designed to collect and track this information. The network can time students. Fortunately such a network already exists and is being used to teach over 1000 students per year general chemistry.

Addendum: Learning Space and Networks

If we think of a person's knowledge and skills as somehow imprinted on a vast network of neurons in the brain, then we can realize that this network has certain features. The most general knowledge and skills

or general concepts must have more connections. For example, Newton's second law, $F=ma$, might have a pyramidal or mountain like shape of network connections.

The mountain continues down with network connections to the person's more basic background experiences.

The complexity of a concept depends on the number of network connections it has or the height of the mountain. These connections give rise to a unique topography for a given concept.

When we talk of teaching and learning, we are talking about the transfer of the teacher's (or textbook author's) network of knowledge to the student's network of knowledge. We can think of the teacher's knowledge as the learning space the student must traverse in a course. We can think of learning as a change of network states, from the student's current state to the desired learning space state.

Implanting a network of knowledge, a change of states, in the student requires energy. It also depends on the student's background of knowledge.

State changes also depend on the student's ability to efficiently think of new states and test them to see if they match with the desired state in learning space. This ability depends on student energy, momentum, concentration and mass. These are quantifiable parameters.

Momentum: How fast a student creates new states and compares them to the desired learning space state.

Energy: This is a function of the student's momentum and the time the student can work.

Concentration: How many network connections the student can work with at a given moment.