

Deep Dive Into AI4K12's Five Big Ideas in AI

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RockCS — June 5, 2021.



RockCS
ROCKY MOUNTAIN COMPUTER SCIENCE
CONFERENCE FOR P-12 EDUCATORS



The AI4K12 Initiative, a joint project of:

AAAI (Association for the Advancement of Artificial Intelligence)



CSTA (Computer Science Teachers Association)



With funding from National Science
Foundation ITEST Program
(DRL-1846073)

Carnegie Mellon University
School of Computer Science



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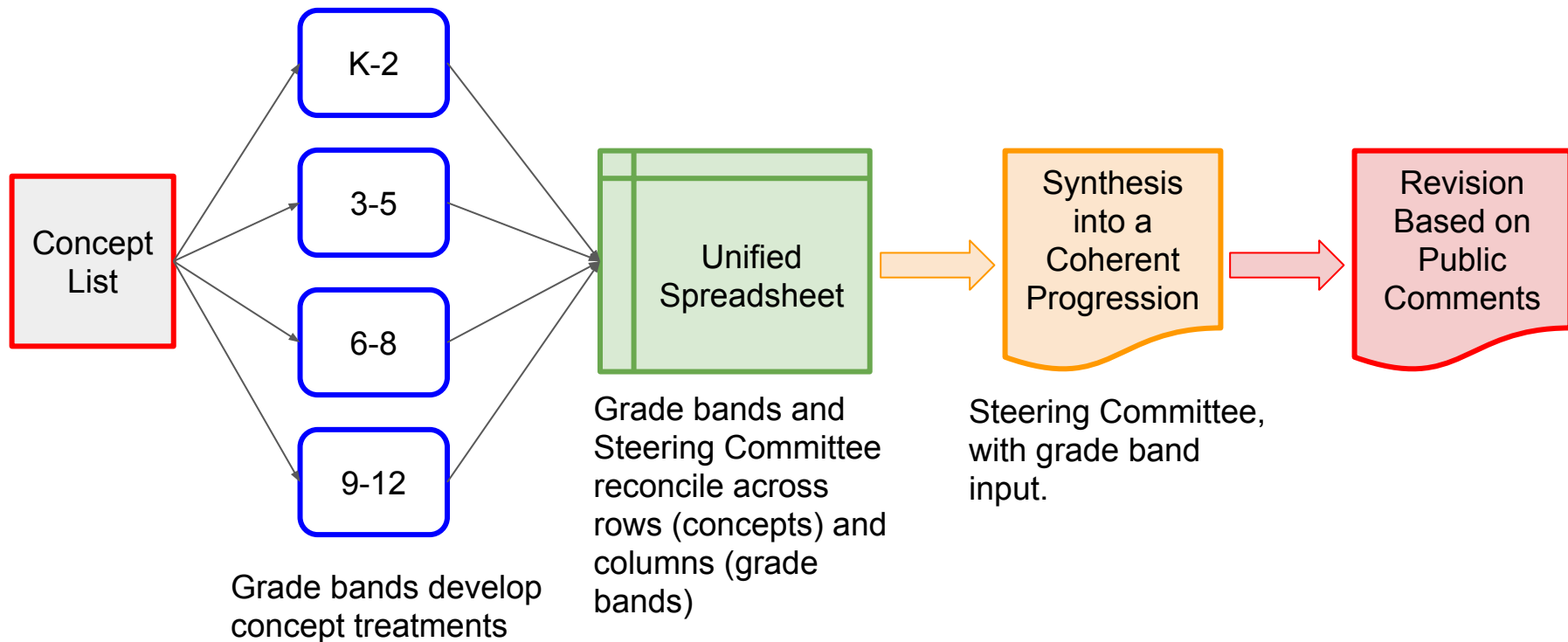
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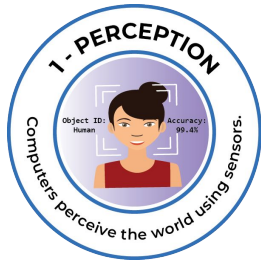
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Drafting the Guidelines for One Big Idea



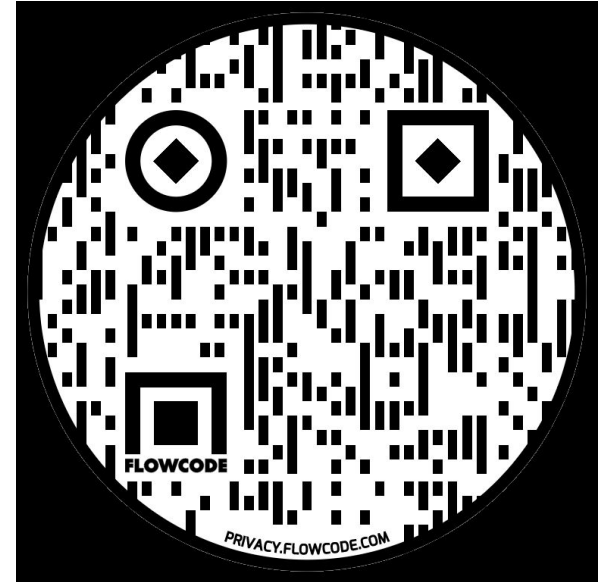
What Do The Guidelines Look Like?



Big Idea #1: Perception - Progression Chart

FEEDBACK WELCOMED!!!

Big Idea #1: Perception		Computers perceive the world using sensors.		Perception is the extraction of meaning from sensory information using knowledge.		The transformation from signal to meaning takes place in stages, with increasingly abstract features and higher level knowledge applied at each stage.		LO = Learning Objective: what students should be able to do. EU = Enduring Understanding: what students should know.	
Concept		K-2		3-5		6-8		9-12	
Sensing (Living Things) 1.A.i		LO: Identify human senses and sensory organs. EU: People experience the world through sight, hearing, touch, taste, and smell.		LO: Compare human and animal perception. EU: Some animals experience the world differently than people do. Unpacked: Bats and dolphins use sonar. Bees can see ultraviolet. Rats are blind to red; dogs are red-green colorblind. Dogs and rats can hear higher frequencies than humans.		LO: Give examples of how humans combine information from multiple modalities. EU: People can exploit correlations between senses, such as sight and sound, to make sense of ambiguous signals. Unpacked: In a noisy environment, speech is more understandable when the speaker's mouth is visible. People learn the sounds associated with various actions (such as dropping an object) and can recognize when the sound doesn't match their expectation.		N/A -- for AI purposes, this topic has already been adequately addressed in the lower grade bands. Other courses, such as biology or an elective on sensory psychology, could go into more detail about topics such as taste, smell, proprioception, and vestibular organs. Possible enrichment material: look at optical illusions (Müller-Lyer illusion, Kanizsa triangle) and ask which ones are computer vision systems also subject to.	
		LO: Locate and identify sensors (cameras, microphone) on computers, phones, robots, and other devices. EU: Computers "see" through video cameras and "hear" through microphones.		LO: Illustrate how computer sensing differs from human sensing. EU: Most computers have no sense of taste, smell, or touch, but they can sense some things that humans can't, such as infrared emissions, extremely low or high frequency sounds, or magnetism.		LO: Give examples of how intelligent agents combine information from multiple sensors. EU: Self-driving cars combine computer vision with radar or lidar imaging, GPS measurement, and accelerometer data to form a detailed representation of the environment and their motion through it.		LO: Describe the limitations and advantages of various types of computer sensors. EU: Sensors are devices that measure physical phenomena such as light, sound, temperature, or pressure. Unpacked: Cameras have limited resolution, dynamic range, and spectral sensitivity. Microphones have limited sensitivity and frequency response. Signals may be degraded by noise, such as a microphone in a noisy environment. Some sensors can detect things that people cannot, such as infrared or ultraviolet imagery, or ultrasonic sounds.	
Sensing (Digital Encoding) 1.A.ii		N/A		LO: Explain how images are represented digitally in a computer. EU: Images are encoded as 2D arrays of pixels, where each pixel is a number indicating the brightness of that piece of the image, or an RGB value indicating the brightness of the red, green, and blue components of that piece.		LO: Explain how sounds are represented digitally in a computer. EU: Sounds are digitally encoded by sampling the waveform at discrete points (typically several thousand samples per second), yielding a series of numbers.		LO: Explain how radar, lidar, GPS, and accelerometer data are represented. EU: Radar and lidar do depth imaging: each pixel is a depth value. GPS triangulates position using satellite signals and gives a location as longitude and latitude. Accelerometers measure acceleration in 3 orthogonal dimensions. Unpacked: Radar and lidar measure distance as the time for a reflected signal to return to the transceiver. GPS determines position by triangulating precisely timed signals from three or more satellites. Accelerometers use orthogonally oriented strain gauges to measure acceleration in three dimensions.	



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Big Idea #1: Perception

Computers perceive the world using sensors.

Perception is the extraction of meaning from sensory information using knowledge.

The transformation from signal to meaning takes place in stages, with increasingly abstract features and higher level knowledge applied at each stage.

AIHK12

Big Idea #1: Perception

Progression Chart

www.AIHK12.org

Concept	K-2	3-5	6-8	9-12
Perception	<p>Students understand that perception is the process of extracting meaning from sensory information.</p> <p>Students understand that perception is the process of extracting meaning from sensory information.</p>	<p>Students understand that perception is the process of extracting meaning from sensory information.</p> <p>Students understand that perception is the process of extracting meaning from sensory information.</p>	<p>Students understand that perception is the process of extracting meaning from sensory information.</p> <p>Students understand that perception is the process of extracting meaning from sensory information.</p>	<p>Students understand that perception is the process of extracting meaning from sensory information.</p> <p>Students understand that perception is the process of extracting meaning from sensory information.</p>

V.0.1 - Released May 18, 2020

Subject to change based on public feedback

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Big Idea #1 Concept List

1-A: Sensing

- 1-A-i: Living Things
- 1-A-ii: Computer Sensors
- 1-A-iii: Digital Encoding

Big Idea 1: Perception	Concepts	K-2	3-5	6-8	9-12
Sensing	1-A-i: Living Things	1-A-i: Living Things	1-A-i: Living Things	1-A-i: Living Things	1-A-i: Living Things
	1-A-ii: Computer Sensors	1-A-ii: Computer Sensors	1-A-ii: Computer Sensors	1-A-ii: Computer Sensors	1-A-ii: Computer Sensors
Processing	1-B-i: Sensing vs. Perception	1-B-i: Sensing vs. Perception	1-B-i: Sensing vs. Perception	1-B-i: Sensing vs. Perception	1-B-i: Sensing vs. Perception
	1-B-ii: Feature Extraction	1-B-ii: Feature Extraction	1-B-ii: Feature Extraction	1-B-ii: Feature Extraction	1-B-ii: Feature Extraction
Domain Knowledge	1-C-i: Types of Domain Knowledge	1-C-i: Types of Domain Knowledge	1-C-i: Types of Domain Knowledge	1-C-i: Types of Domain Knowledge	1-C-i: Types of Domain Knowledge
	1-C-ii: Inclusivity	1-C-ii: Inclusivity	1-C-ii: Inclusivity	1-C-ii: Inclusivity	1-C-ii: Inclusivity

1-B: Processing

- 1-B-i: Sensing vs. Perception
- 1-B-ii: Feature Extraction
- 1-B-iii: Abstraction Pipeline: Language
- 1-B-iv: Abstraction Pipeline: Vision

1-C: Domain Knowledge

- 1-C-i: Types of Domain Knowledge
- 1-C-ii: Inclusivity

1-A-i: Sensing in Living Things

K-2

LO: Identify human senses and sensory organs.

EU: People experience the world through sight, hearing, touch, taste, and smell.

3-5

LO: Compare human and animal perception.

EU: Some animals experience the world differently than people do.

Unpacked: Bats and dolphins use sonar. Bees can see ultraviolet. Rats have no color vision...

LO (Learning Objective): What students should be able to do.

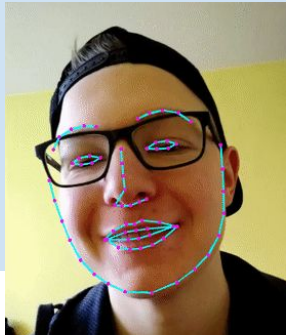
EU (Enduring Understanding): What students should know.

1-B-ii: Feature Extraction

3-5

LO: Illustrate how face detection works by extracting facial features.

EU: Face detectors use special algorithms to look for eyes, noses, mouths, and jawlines.



6-8

LO: Illustrate the concept of feature extraction from images by simulating an edge detector.

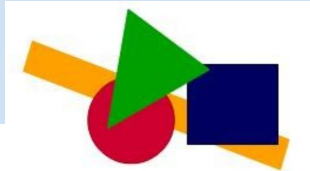
EU: Locations and orientations of edges in an image are features that can be extracted by looking for specific arrangements of light and dark pixels in a small (local) area.

1-B-iv: Abstraction Pipeline: Vision

3-5

LO: Illustrate how outlines of partially occluded (blocked) objects differ from the real shapes of the objects.

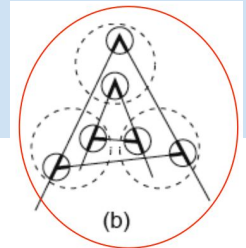
EU: Understanding complex scenes requires taking into account the effects of occlusion when recognizing objects.



6-8

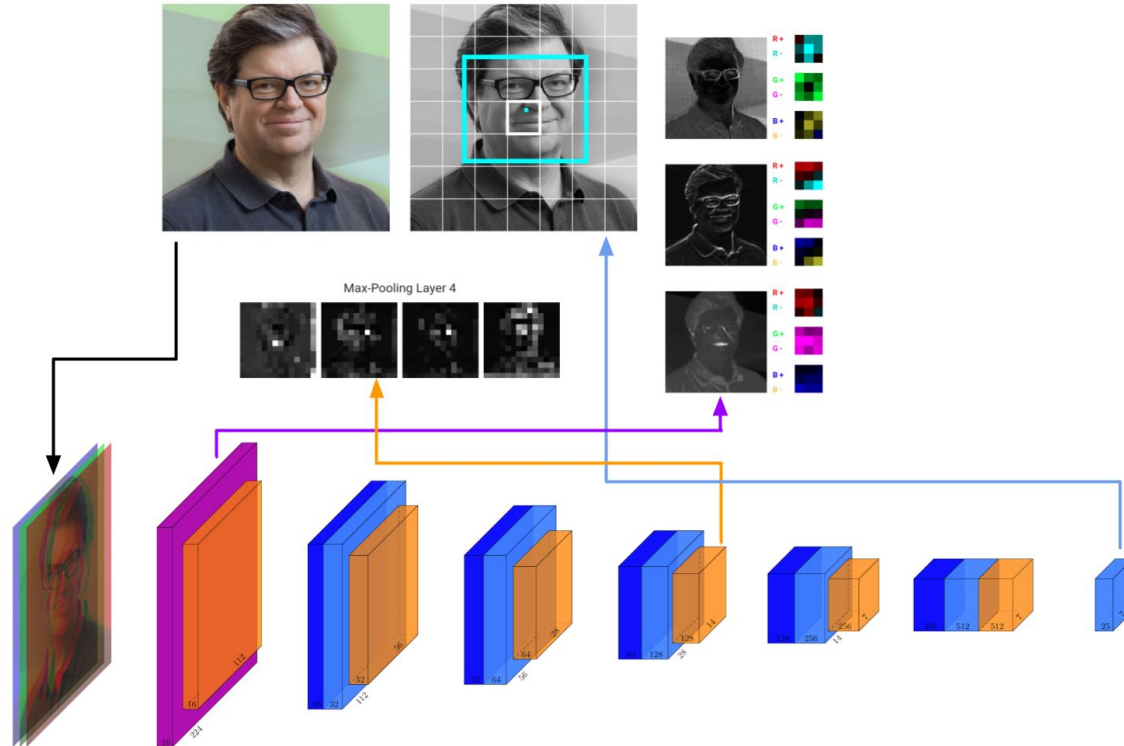
LO: Describe how edge detectors can be composed to form more complex feature detectors for letters or shapes.

EU: The progression from image to meaning takes place in stages, with increasingly complex features extracted at each stage.



Abstraction Pipeline In A Deep Neural Network

<https://www.cs.cmu.edu/~dst/FaceDemo>



1-C-i: Types of Domain Knowledge

3-5

LO: Demonstrate how a text to speech system can resolve ambiguity based on context, and how its error rate goes up when given ungrammatical or meaningless inputs.

EU: Speech recognition systems are trained on millions of utterances ... which helps them select the most likely interpretation of the signal.

9-12

LO: Analyze one or more online image datasets and describe the information they provide and how this can be used to extract domain knowledge for a vision system.

EU: Domain knowledge in AI systems is often derived from statistics collected from millions of utterances or images.

Unpacked: Can use ImageNet, Coco...

1-C-ii: Inclusivity

K-2

LO: Discuss why intelligent agents need to understand languages other than English.

EU: Speech recognition systems need to accommodate different languages because many different types of people will use them.



9-12

LO: Describe some of the technical difficulties in making computer perception systems function for diverse groups.

EU: Dark or low contrast facial features are harder to recognize than high contrast features. Children's speech is in a higher register and less clearly articulated than adult speech.

Big Idea 2: Representation and Reasoning

(not publicly released yet)

Temporary URL:
https://www.cs.cmu.edu/~dst/Big_Idea_2_Draft.pdf

Big Idea #2: Representation and Reasoning

Computers maintain representations of the world and use them for reasoning.

Representations are data structures; reasoning methods are algorithms.

Representations support reasoning; reasoning methods operate on representations.

"Knowing" something means the ability to both represent it and reason with it.

Agents are considered intelligent if they employ a non-trivial sense-deliberate-act cycle to make progress toward achieving their goals.

Big Idea #2 Concept List

2-A: Representation

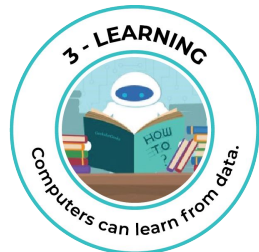
- 2-A-i: Abstraction
- 2-A-ii: Symbolic Representations
- 2-A-iii: Data Structures
- 2-A-iv: Feature Vectors

2-B: Search

- 2-B-i: State Spaces and Operators
- 2-B-ii: Combinatorial Search

2-C: Reasoning

- 2-C-i: Types of Reasoning problems
- 2-C-ii: Reasoning Algorithms



Big Idea #3: Learning - Progression Chart

Draft Big Idea 3 - Progression Chart

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FEEDBACK
WELCOMED!!!

Big Idea #3: Learning Concept	Computers can learn from data.	LO = Learning Objective: What students should be able to do.	EU = Enduring Understanding: What students should know.	Unpacked descriptions are included when necessary to illustrate the LO or EU
	K-2	3-5	6-8	9-12
Nature of Learning (Humans vs. machines)	LO: Describe and provide examples of how people learn and how computers learn. EU: Computers learn differently than people. Unpacked: People learn by observation, by being told, by asking questions, by experimentation, by practice, and by making connections to past experience. Computers learn by finding patterns in data, or by trial and error. Activities: Describe a time when you learned something by being told, by watching another person, or by asking questions. A demo such as Teachable Machine can be used to illustrate a computer learning something from positive and negative examples.	LO: Differentiate between how people learn and how computers learn. EU: Both people and computers can learn by finding patterns in data, or by trial and error. But people are flexible learners who can adapt to unfamiliar situations and learn in other ways, such as by observing others, by asking questions, or by making connections to prior learning. Unpacked: People are natural learners, while computers have to be programmed to learn. Presently there are two ways that computers can be programmed to learn: they can learn by finding patterns in human-supplied examples, or they can learn by trial and error.	LO: Contrast the unique characteristics of human learning with the ways machine learning systems operate. EU: People learn by observation, by being told, by asking questions, by experimentation, by practice, and by making connections to past experience. Computers learn by applying specialized algorithms to large amounts of training data, or by thousands or even millions of trial and error experiences, to solve narrowly defined problems. Unpacked: People are flexible learners who employ multiple strategies. Computers use specialized algorithms that require large amounts of data or many trials, and only solve narrowly defined problems. While humans can construct reasons by explicitly programming them, for complex problems it is often more convenient to let the machine learning algorithm do the work.	LO: Define supervised, unsupervised, and reinforcement learning algorithms, and give examples of human learning that are similar to each algorithm. EU: Both supervised and unsupervised learning algorithms find patterns in data. Supervised learning uses features to predict the class label supplied by a teacher; unsupervised learning groups similar instances together, creating its own classes. Reinforcement learning uses trial and error to find a policy for choosing actions that maximizes the reinforcement signal. Unpacked: Supervised learning is like being corrected by a coach. Unsupervised learning is like noticing that your store has three kinds of customers based on their distinctive purchasing patterns. Reinforcement learning is like trying different moves in a video game and seeing which yields the most points (greatest reward).
Nature of Learning (Finding patterns in data)	LO: Identify patterns in labeled data and determine the features that predict labels. EU: Classes can be defined in terms of feature values. The relevant features can be inferred by examining labeled examples. Unpacked: To give students a feel for the problem of learning to classify we must ask them to learn a class that's not intuitively obvious, e.g., learn "poisonous fish" by examining cartoon fish images labeled "poisonous" or "not poisonous". They can then be asked to describe which features indicate a fish is poisonous, e.g., red fish with square heads. Using images as input simplifies the task because the features are intuitive, even though the classification rule should not be.	LO: Model how supervised learning identifies patterns in labeled data. EU: When learning to classify labeled data, the patterns (or rules) that are discovered can be expressed as weights in a neural network or nodes in a decision tree. Unpacked: This extends the K-2 version by having students draw a decision tree instead of merely verbalizing their proposed rule. In addition, the task can be made richer in 3-5 by increasing the number of classes or by making the class definitions more complex. For example, a fish could be poisonous if it is either red with a square head or blue with a round head or purple with pointy spines and any shape head. Each node of the decision tree can test one feature value, e.g., color, so complex features require deeper trees.	LO: Model how unsupervised learning finds patterns in unlabeled data. EU: Unsupervised learning is useful when we don't know in advance what classes exist. It discovers patterns (or classes) in data by grouping nearby points into clusters. Once a set of clusters has been found, new points can be classified based on distance from the cluster boundaries. Unpacked: This can be done graphically using points in the plane and visually constructing cluster boundaries by outlining (e.g., drawing an ellipse around) each cluster.	LO: Model how machine learning constructs a reasoner for classification or prediction by adjusting the reasoner's parameters (its internal representations). EU: Supervised learning adjusts the parameters of a mathematical model (selected in advance by a human) to generate correct classifications or predictions. This model could be a simple linear equation, a high-degree polynomial, or an even more complex nonlinear equation such as a deep neural network. The internal representations that encode the relationship between inputs and outputs express the "patterns" found in the data. Unpacked: In regression, we pick a mathematical model such as a linear equation $y=mx+b$ and then adjust its parameters to fit a set of data points as best we can. The model can then be used to predict a y value for any x value. Linear regression can be done with a ruler by eyeballing the distance between the line and the points. Students can model polynomial or logistic regression by giving them a graphical display with sliders to control the parameter values. They can manually adjust the sliders to reach what they perceive as a best fit to the data. More advanced students can be shown how quality of fit can be measured mathematically using mean squared error. For classification problems the Y value is either 1 for "in class" or 0 for "not in class" and the decision boundary is the line or surface $y=0.5$.



bit.ly/3oT0xE9

Big Idea #3: Learning

Computers can learn from data.

Machine learning allows a computer to acquire behaviors without people explicitly programming those behaviors.

Learning of new behaviors is brought about by changes in the internal representations of a reasoning model, such as a neural network or decision tree.

Large amounts of training data are required to narrow down the learning algorithm's choices when the reasoning model is capable of a great variety of behaviors.

The reasoning model constructed by the machine learning algorithm can be applied to new data to solve problems or make decisions.

Big Idea #3 Concept List

3-A: Nature of Learning

- 3-A-i: Humans vs. Machines
- 3-A-ii: Finding Patterns in Data
- 3-A-iii: Training a Model
- 3-A-iv: Constructing a Reasoner
- 3-A-v: Adjusting Parameters
- 3-A-vi: Learning from Experience

3-B: Neural Networks

- 3-B-i: Structure of a Neural Network
- 3-B-ii: Weight Adjustment

3-C: Datasets

- 3-C-i: Feature Sets
- 3-C-ii: Large Datasets
- 3-C-iii: Bias

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**Thank
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