Geostatistics and Machine Learning
Advanced Worflows

Lecture outline . . .

- Advanced Workflows
- Artificial Neural Networks (ANN)
- Convolutional Neural Networks (CNN)
- Long Short-Term Memory Networks (LSTM)

Instructor: Michael Pyrcz, the University of Texas at Austin

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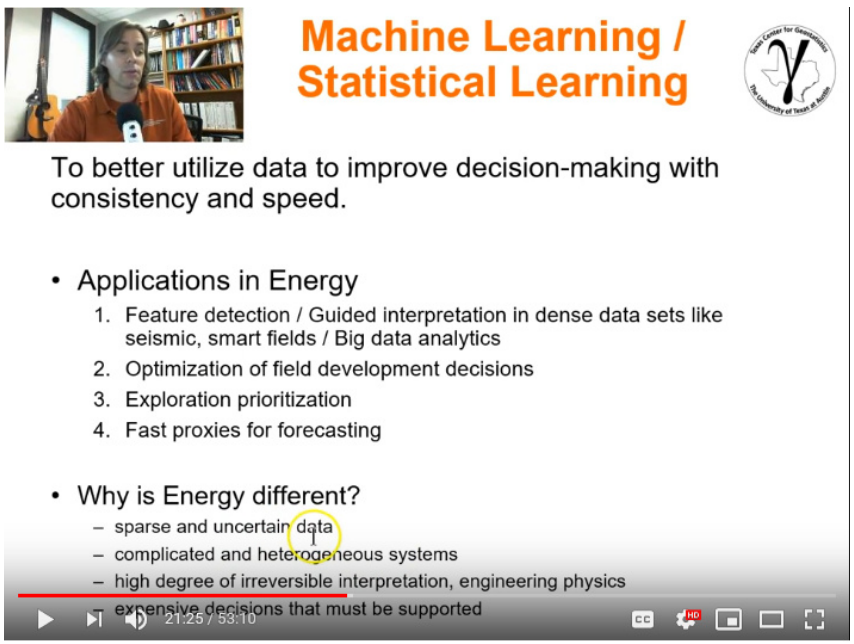
Other Resources:

- **Statistical Learning, Dimensional Reduction and Decision Tree**



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Goals of This Lecture

- Build awareness.
- Show opportunities in subsurface modeling with machine learning.

Geostatistics and Machine Learning
Advanced Worflows

Lecture outline . . .

- Advanced Workflows

Introduction

Data Analytics

Inferential Methods

Predictive Methods

Advanced Methods

Conclusions

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Machine Learning for Subsurface Modeling

- A set of powerful machine learning methods to support subsurface modeling with initial workflows.
- We are actively working in this area.
- Concepts are represented in a simplified manner.
- We have workflows available.

Methods Covered:

- Artificial Neural Networks (ANN)
- Convolutional Neural Networks (CNN)
- Deep Convolutional Generative Adversarial Networks (DCGANs)

Geostatistics and Machine Learning
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- Advanced Workflows
- Artificial Neural Networks (ANN)

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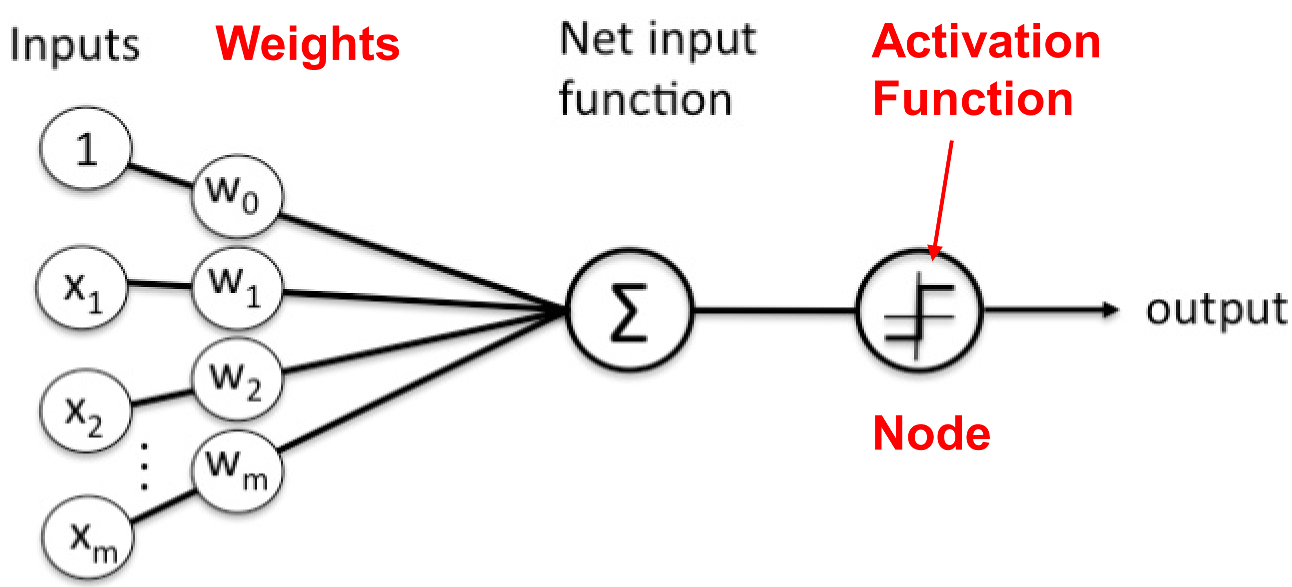
Neural Nets

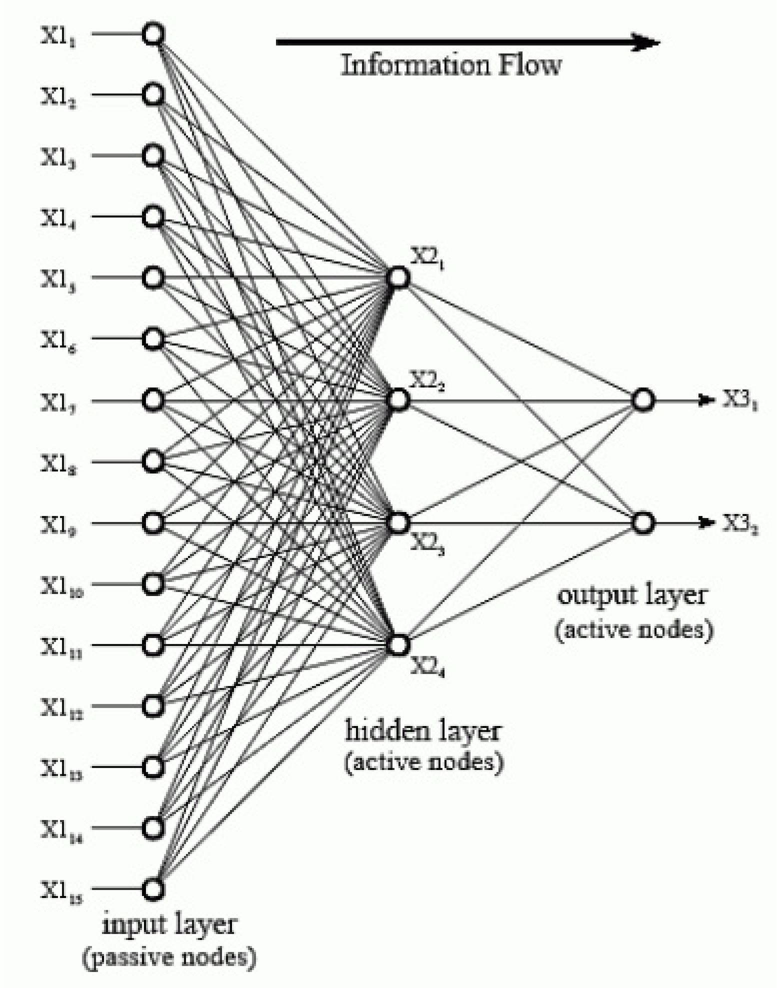
- Mimic the human brain for pattern recognition
- A set of interconnected **nodes**, organized into layers
- Nodes fire when their input exceeds a threshold, **activation function**
- Each data-to-node or node-to-node path has **weights**
- Weights and activation functions are **trained** to improve accuracy



Single Node Neural Net Image from https://skymind.ai/wiki/neural-network

Neural Nets

- As the number of nodes increases along with the number of node layers and interconnections, more complicated predictions are possible.
- Complicated activation functions and signals are also possible.
- These are very parameter rich, complicated models with low model bias but high model variance.
- Require more training data.
- Deep learning simply means more than one hidden layer!



Fully connected neural net diagram from https://www.dspguide.com/ch26/2.htm

Neural Nets

- Demonstrate neural nets with MPS training images and simulated models
- Train a neural net to determine the TI that resulted in the current simulated model

Workflow developed by Honggeun Jo, PhD student at The University of Texas at Austin.

Neural Nets

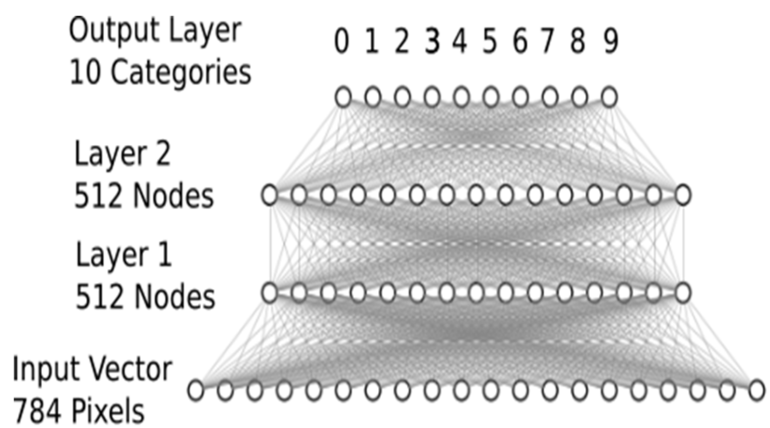
- Generate TIs with 9 different setting
  (4 channels, 4 lobate shapes, and 1 circular sand body)
- Realize 1,000 models each from different Tis
- Label their realization with the related Ti
- Construct Neural Networks (ANN)
  - Input: reservoir (facies) model
  - output: probability to be realized from each TI (different geo. set)

Workflow developed by Honggeun Jo, PhD student at The University of Texas at Austin.

Neural Nets

- Modified National Institute of Standards and Technology database
- 60,000 training and 10,000 testing images of digits with labels

- Optical digit recognition is an artificial neural net



Number from 0 - 9

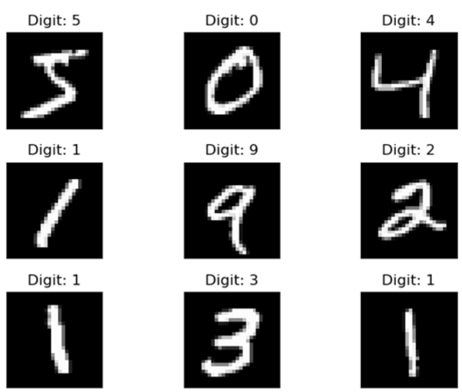
Value in each pixel.

MNIST image from https://upload.wikimedia.org/wikipedia/commons/2/27/MnistExamples.png

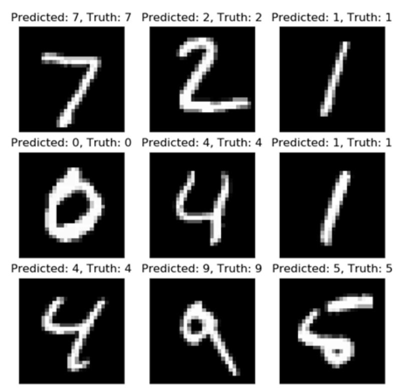
Neural Nets

- Modified National Institute of Standards and Technology database
- 60,000 training and 10,000 testing images of digits with labels

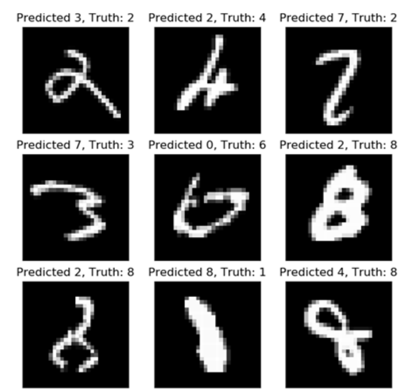
Training



Correct Classification

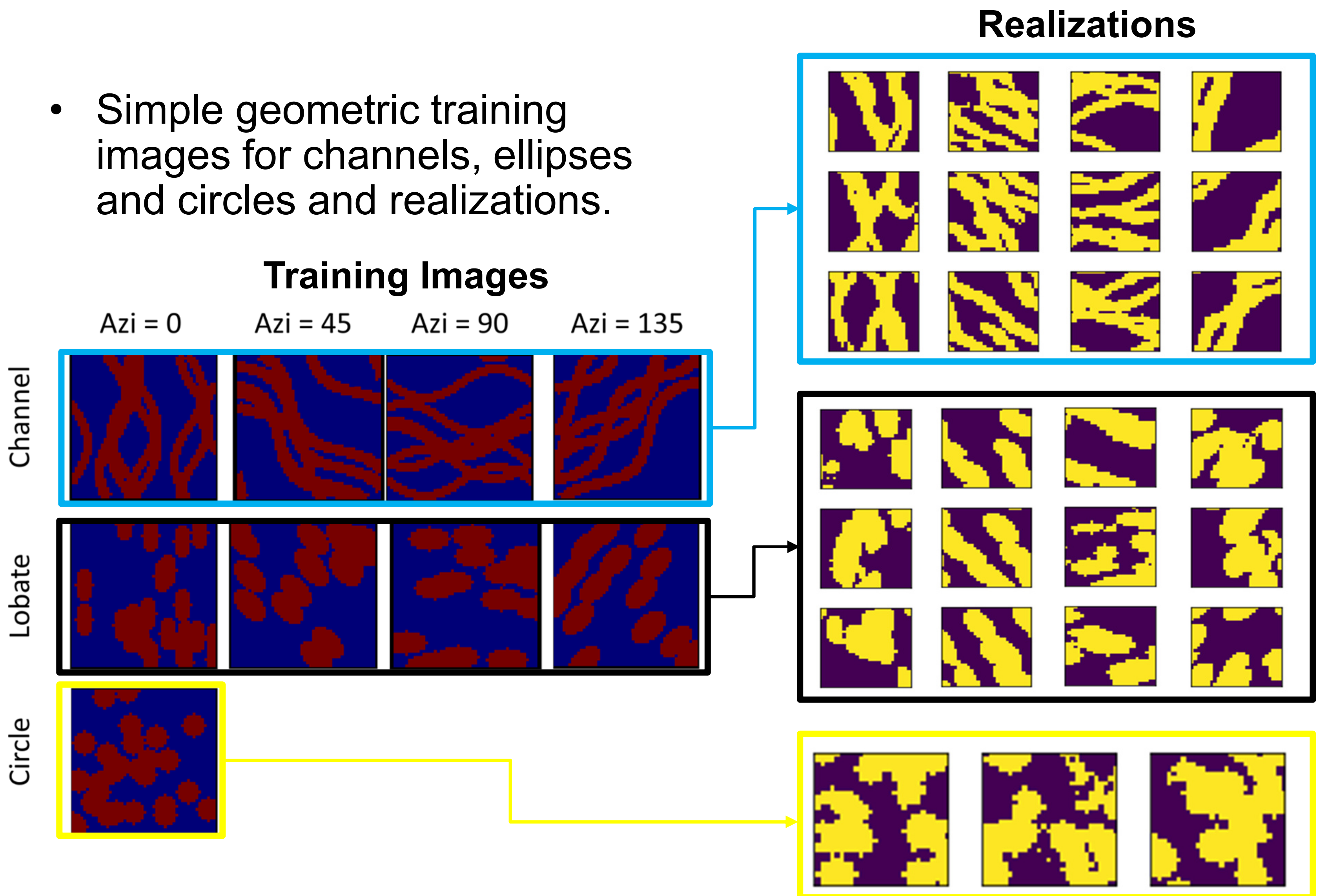


Incorrect Classification



Neural Nets

- Simple geometric training images for channels, ellipses and circles and realizations.



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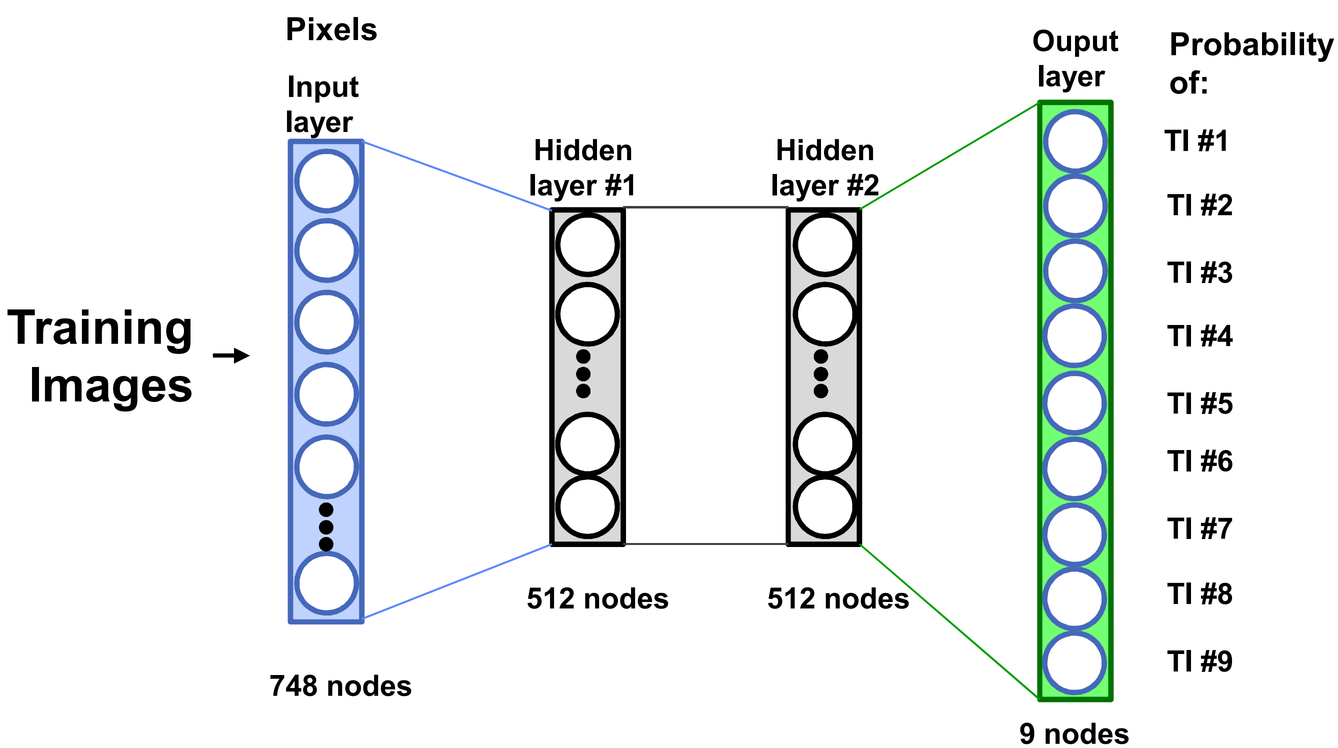
Neural Nets

- Structure of the artificial neural network.
- Note, the image is ‘flattened’ to a list of pixel values.



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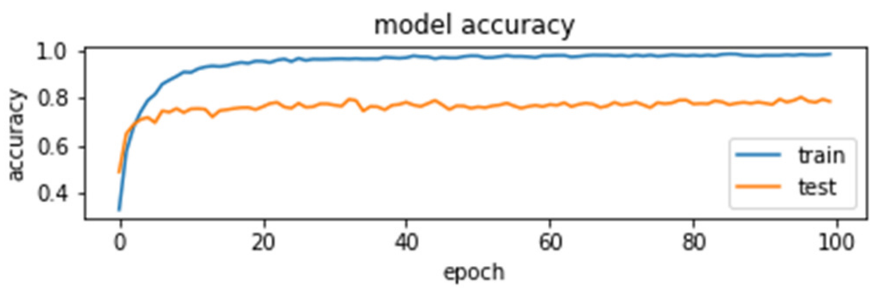
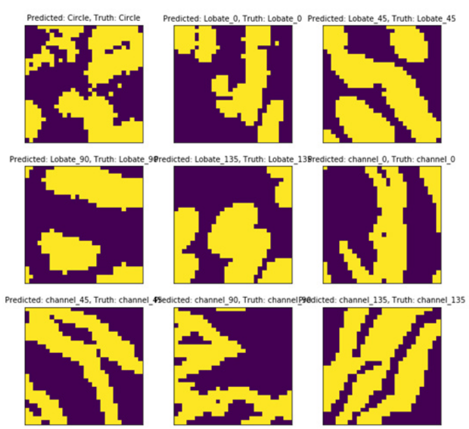
Neural Nets

- The training and testing accuracy vs. number of training cycles, **Epoch**
- Levels off at about 78% accuracy



Correct Identification



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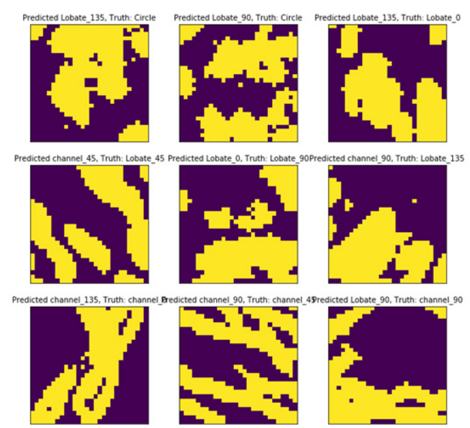

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Geostatistics and Machine Learning
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Lecture outline . . .

- Convolutional Neural Networks (CNN)

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Convolutional Neural Nets

- A type of deep neural net used for image data, **2D information**
- Hierarchical approach segmenting image into smaller simpler patterns
- Inspired by visual cortex of animals
- **Convolution** step identifies features with trained filters
- **Subsampling** extracts features to a lower dimensional summary

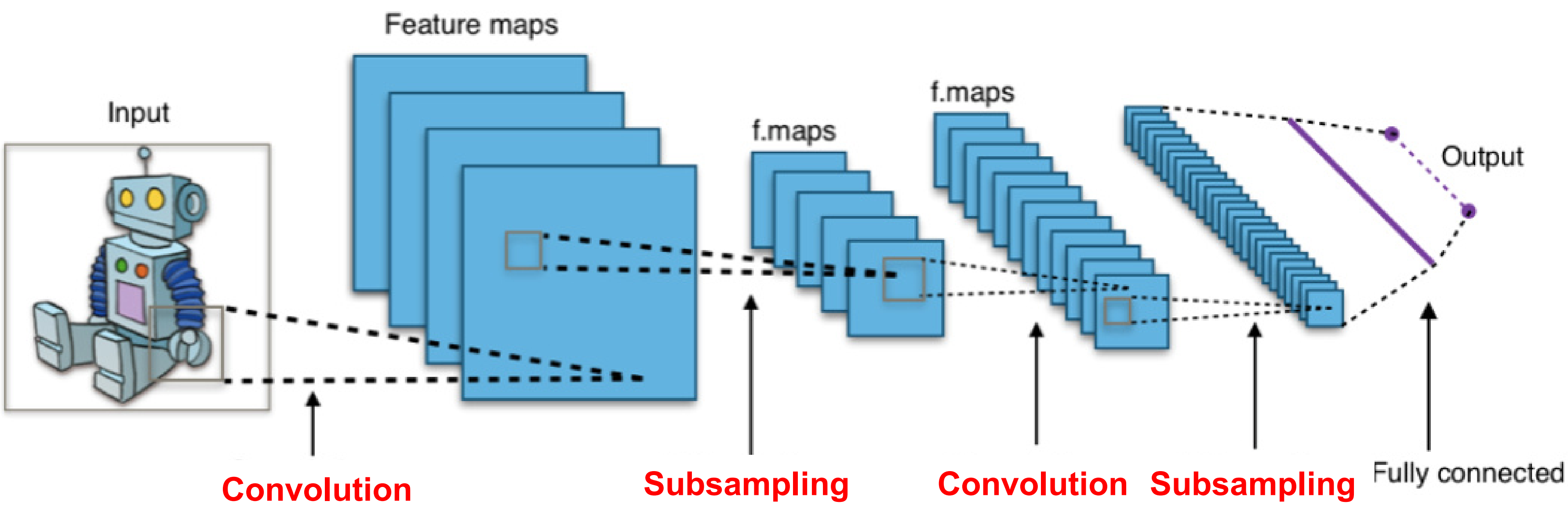
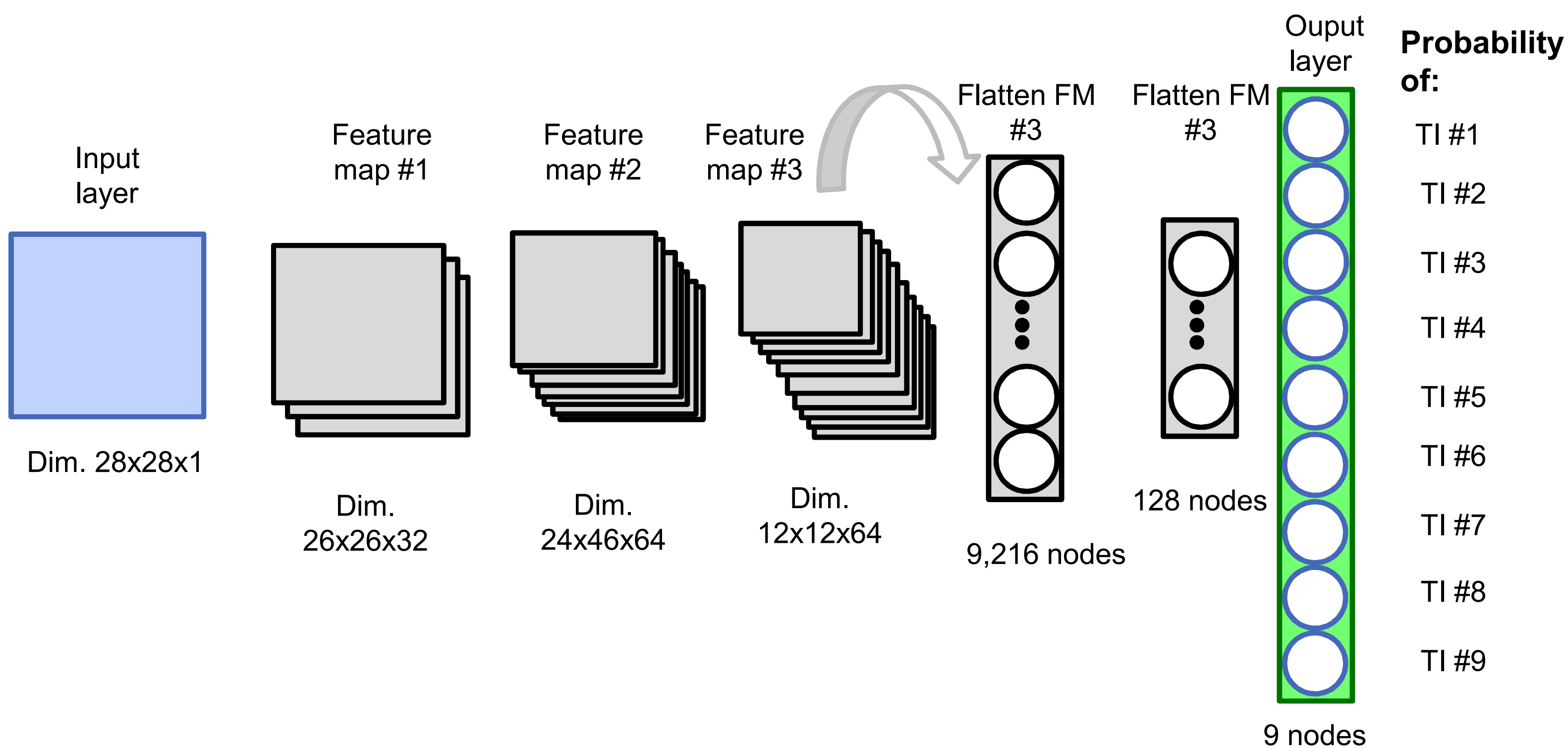


Image from https://en.wikipedia.org/wiki/Convolutional_neural_network#/media/File:Typical_cnn.png

Convolutional Neural Nets

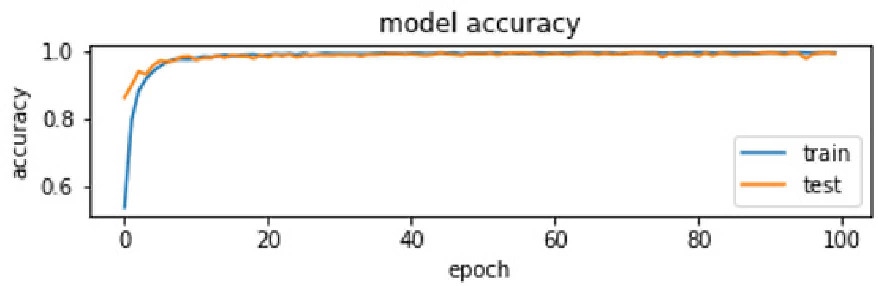
- Could we improve the previous result by moving to convolutional neural nets.
- Here's the design of a CNN to determine the probability of training image 1-9.



Workflow developed by Honggeun Jo, PhD student at The University of Texas at Austin.

Convolutional Neural Nets

- The training and testing accuracy vs. number of training cycles, **Epoch**
- Achieved close to 100% accuracy



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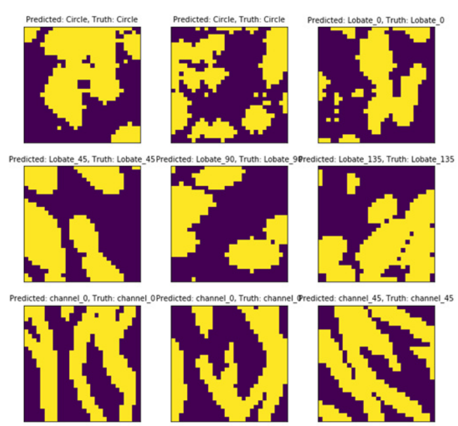

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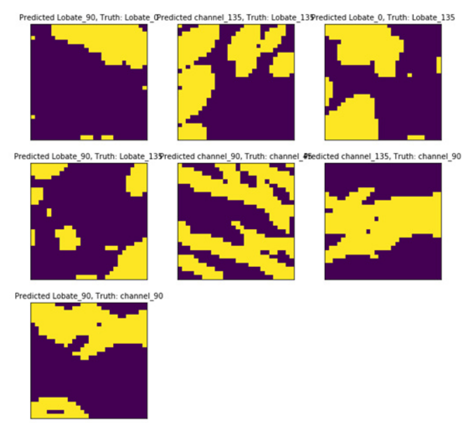
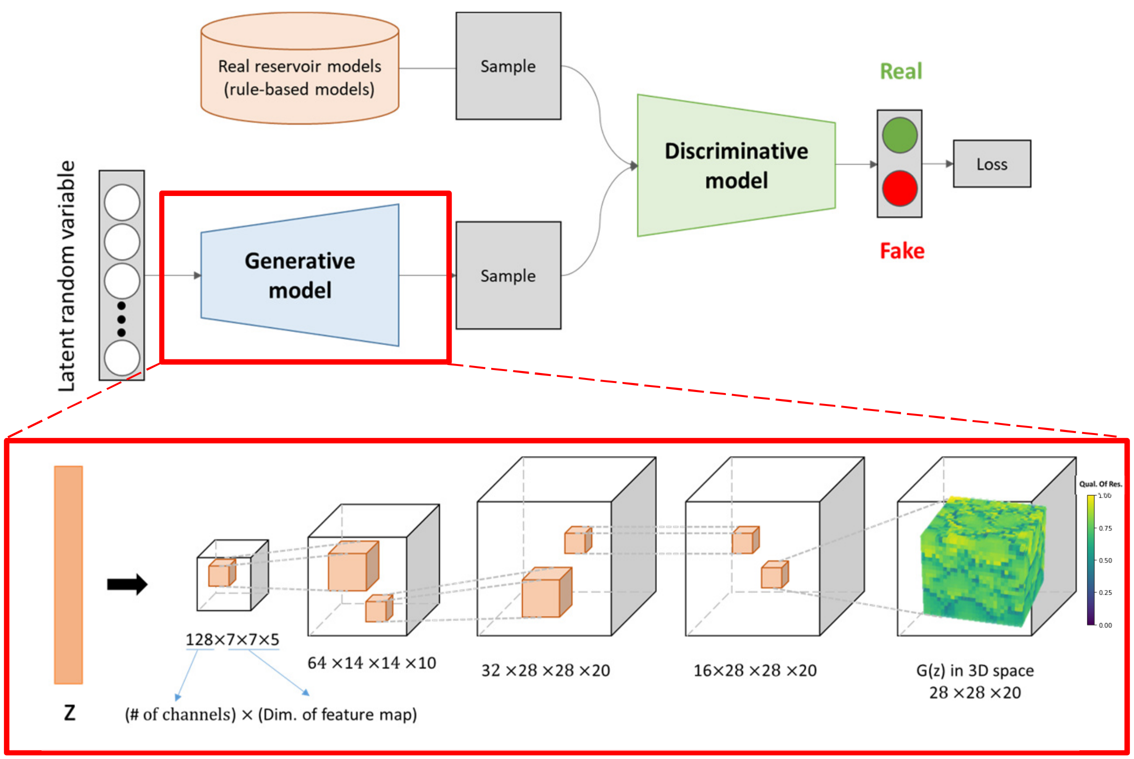


Workflow developed by Honggeun Jo, PhD student at The University of Texas at Austin.

Convolutional Neural Nets

- Can we build reservoir models with convolutional neural nets?
  - We built a Deep Convolutional Generative Adversarial Network (DCGAN)
  - Generative model works to fool the discriminative model with fake models.



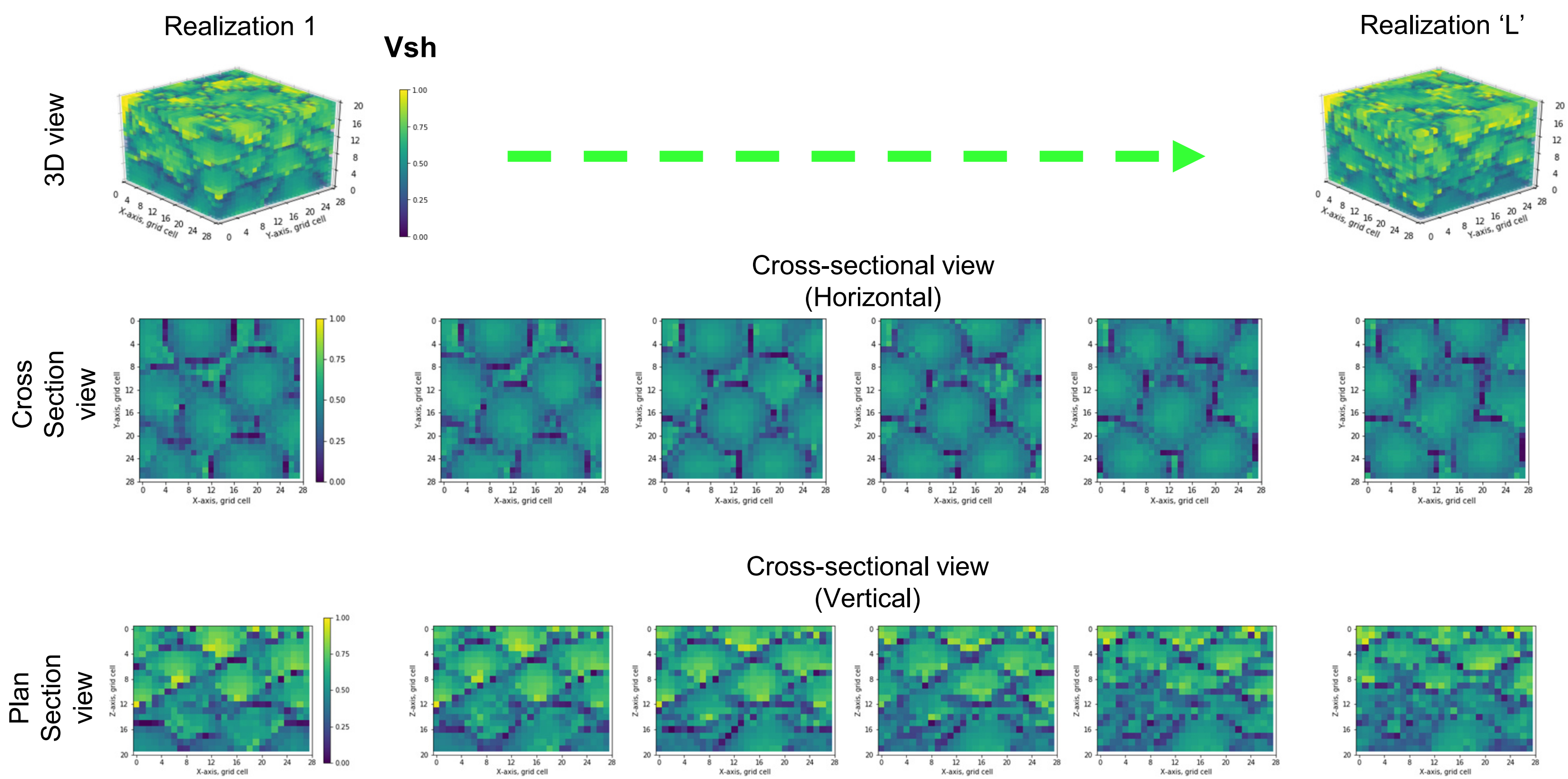
DCGAN workflow by Radford et al., 2015.

Workflow developed by Honggeun Jo, PhD student at The University of Texas at Austin.

Convolutional Neural Nets

Can explore the space of uncertainty along a continuous manifold.

- A latent reservoir manifold based on a single paramter



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Convolutional Neural Nets

Filling In Missing Spatial Information

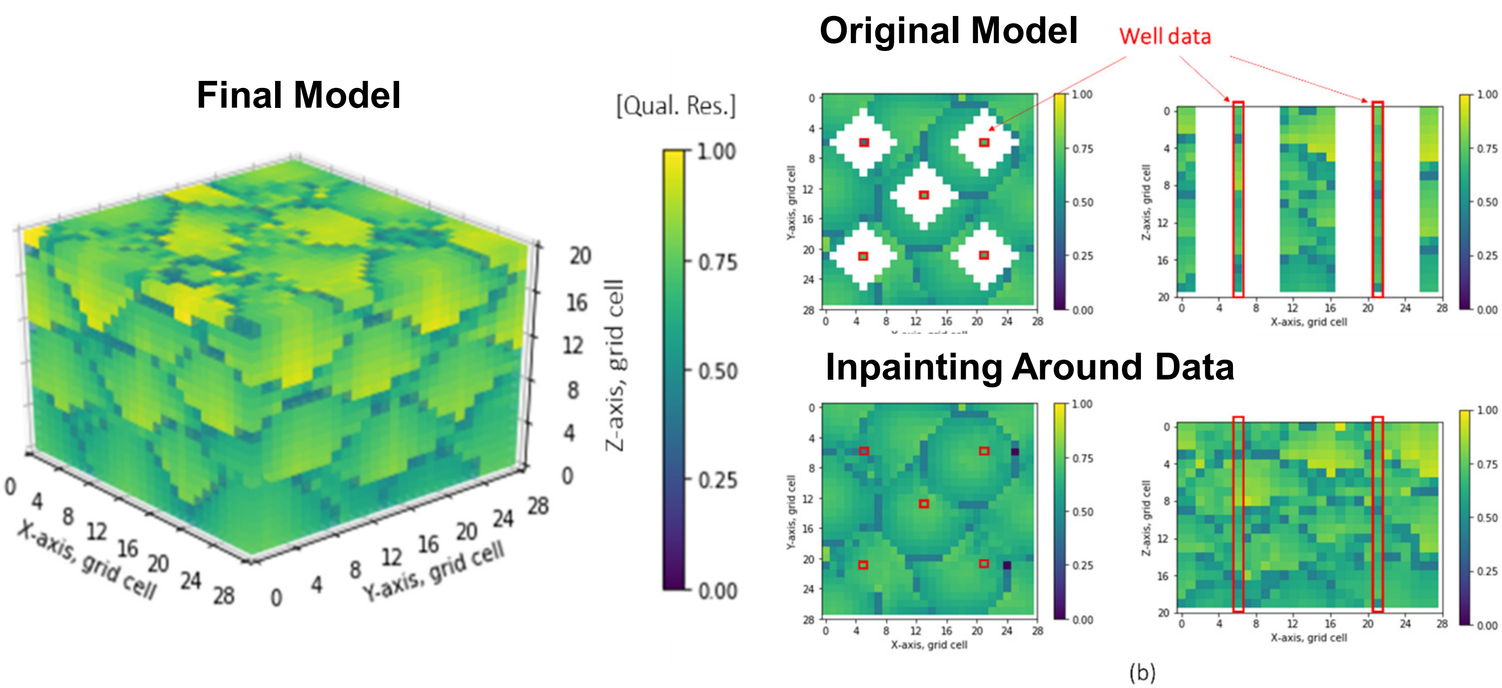
- Semantic inpainting algorithm (Yeh et al., 2015).
- Using conceptual and perceptual information

Examples of semantic image inpainting with DCGAN (Yeh et al., 2016)

Convolutional Neural Nets

Conditioning to Well Data?

- Remove model around data
- Use conceptual (model around mask) and perceptual (model elsewhere to fill in missing model consistent with data



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- Long Short-Term Memory Networks

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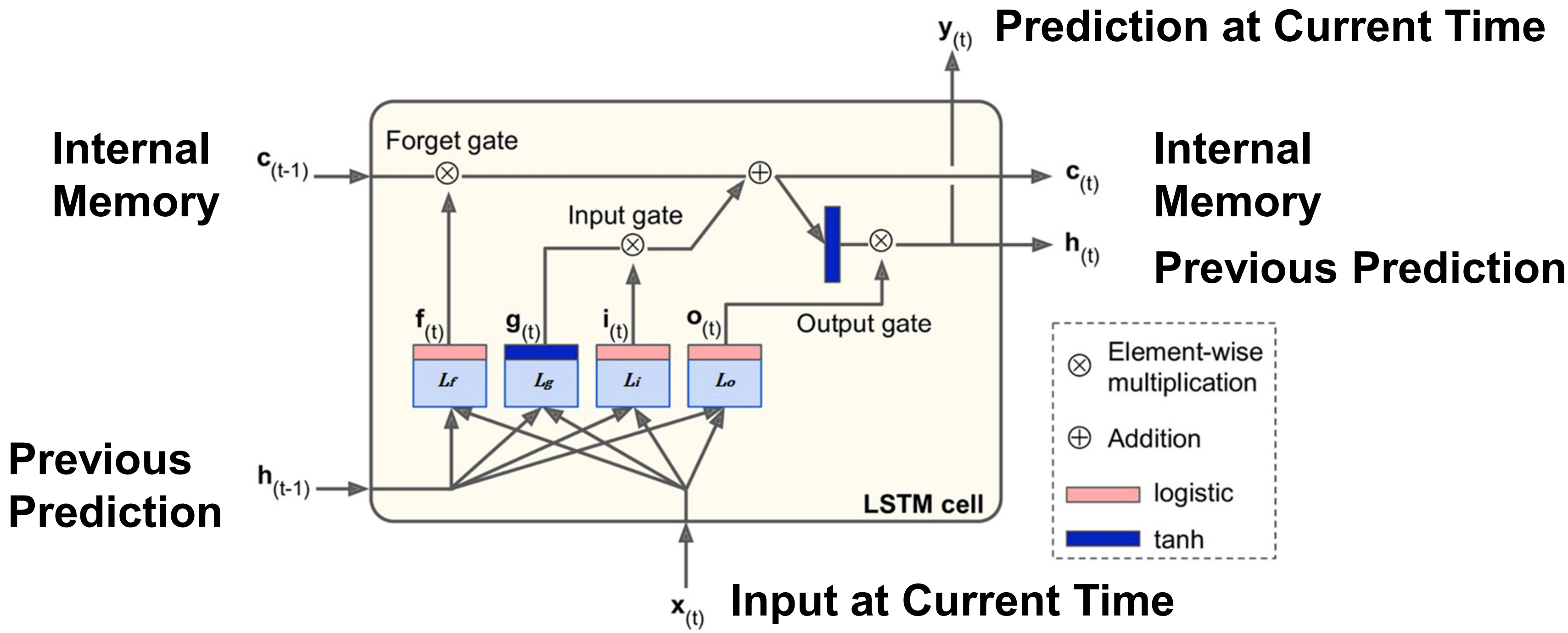
Long Short-Term Memory Networks

Neural networks often don't perform well with time series data as they do not hold memory.

- The Long Short-Term Memory (LSTM) Networks approach combine previous long and short term experience.



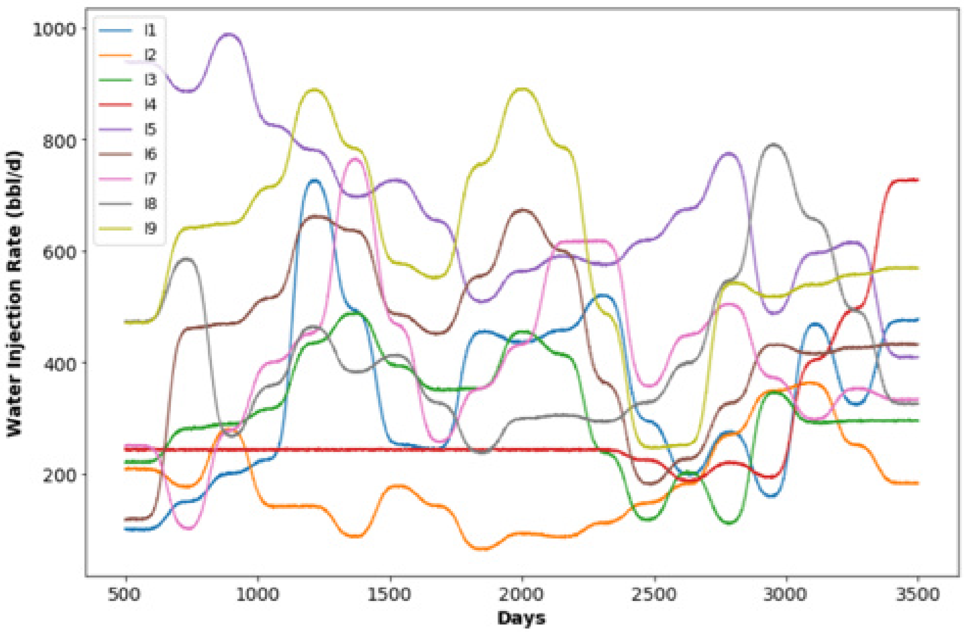
Workflow developed by Azor Nwachukwu, PhD student at The University of Texas at Austin, image from Géron, 2017 .

Long Short-Term Memory Networks

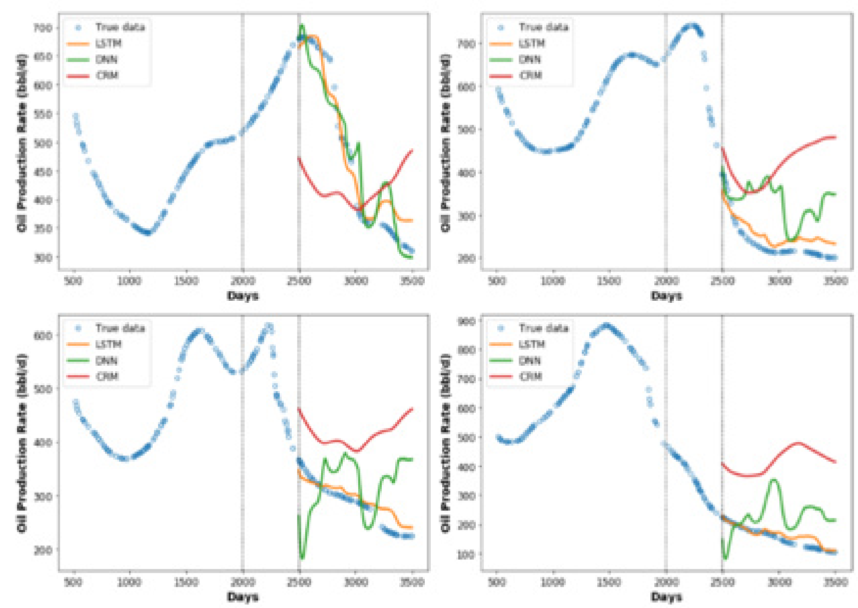
Prediction of producer flow rates based on complicated interactions of injectors.

- Train with 2500 days and predict future 100 days.

Injection Rates Over Train and Test Intervals



Production Over Train and Modeled Over Test



Workflow developed by Azor Nwachukwu, PhD student at The University of Texas at Austin.

Advanced Machine Learning Applications

Topic	Application to Subsurface Modeling
Support Vector Machines	Powerful method for developing segmentation decision rules. *Use to maximize differentiation in space, given labeled training data.*
Artificial Neural Nets	Flexible prediction models. *Use to formulate complicated decision rules, but loses spatial context, and very parameter rich.*
Convolutional Neural Nets	Flexible prediction models accounting for 2D hierarchical arrangements and features. *Use to explore, test and build models.*
Long Short-Term Memory Networks	Flexible prediction models accounting for 1D arrangements and features while accounting for memory. *Use to explore, test and build models predicting time series.*

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