Data Mining

Lecture 10 - Deep Learning

The Deep Learning Revolution

EVERY INDUSTRY WANTS DEEP LEARNING

Cloud Service Provider

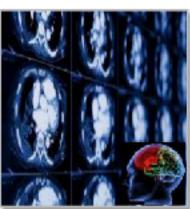
Medicine

Media & Entertainment

Security & Defense

Autonomous Machines











- > Image/Video classification
- Speech recognition
- Natural language processing
- Cancer cell detection
- Diabetic grading
- > Drug discovery

- Video captioning
- Content based search
- Real time translation
- > Face recognition
- > Video surveillance
- > Cyber security

- » Pedestrian detection.
- > Lane tracking
- > Recognize traffic sign



Video: https://www.youtube.com/watch?v=Dy0hJWltsyE

Why now?

KEY DRIVERS FOR DEEP LEARNING

Big Data

Better Algorithms

GPU Acceleration

facebook.

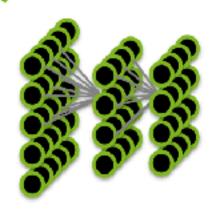
350 millions images uploaded per day



2.5 Petabytes of customer data hourly



300 hours of video uploaded every minute

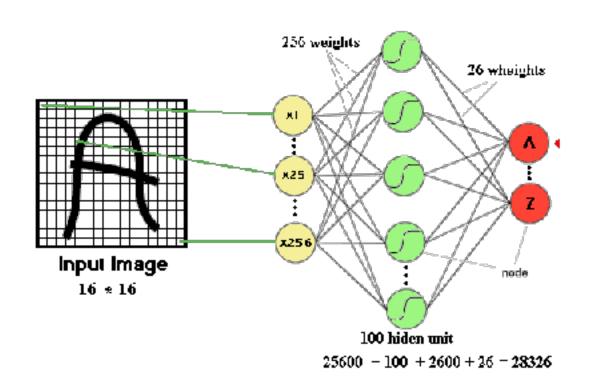




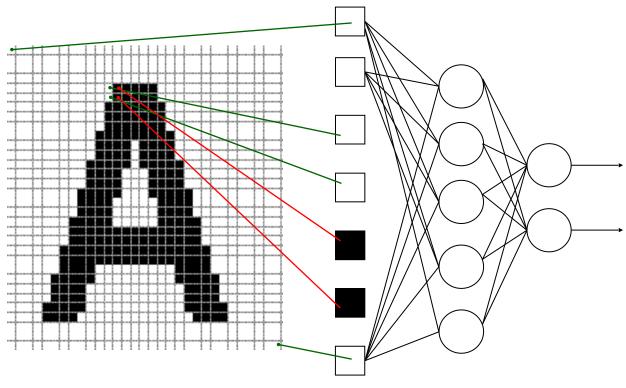
"The Three Breakthroughs that have Finally Unleashed A.I. on the World"



The number of trainable parameters becomes extremely large

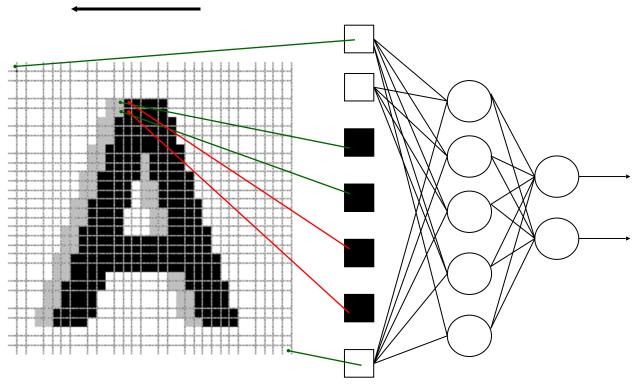


Little or no invariance to shifting, scaling, and other forms of distortion



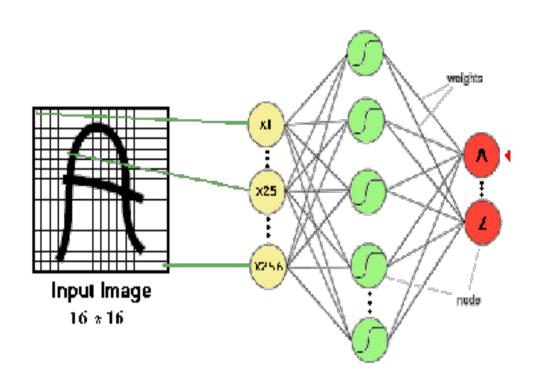
Little or no invariance to shifting, scaling, and other forms of distortion

Shift left





The topology of the input data is completely ignored



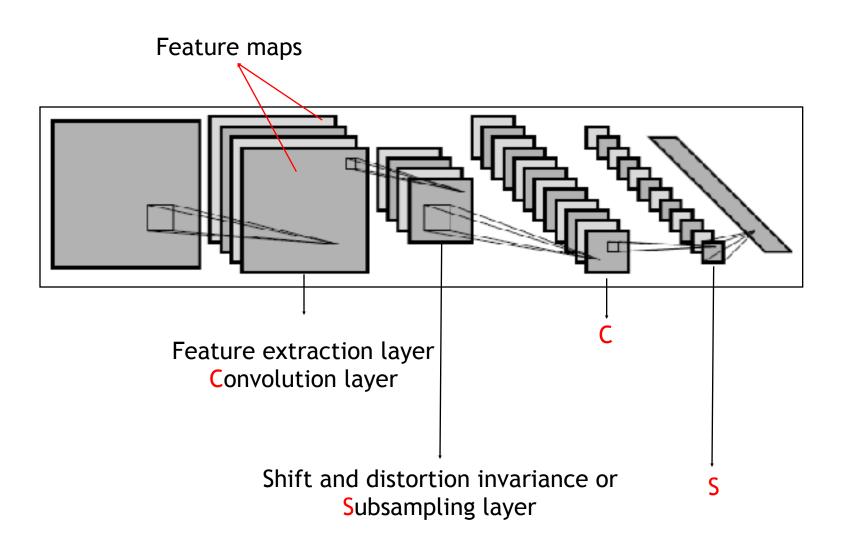
Convolutional neural networks (CNNs)

About CNN's

- CNN's were neurobiologically motivated by the findings of locally sensitive and orientation-selective nerve cells in the visual cortex.

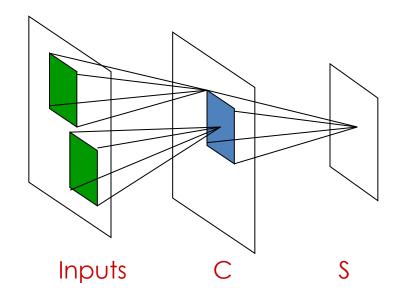
- They designed a network structure that implicitly extracts relevant features.
- Convolutional Neural Networks are a special kind of multi-layer neural networks.

CNN's Topology

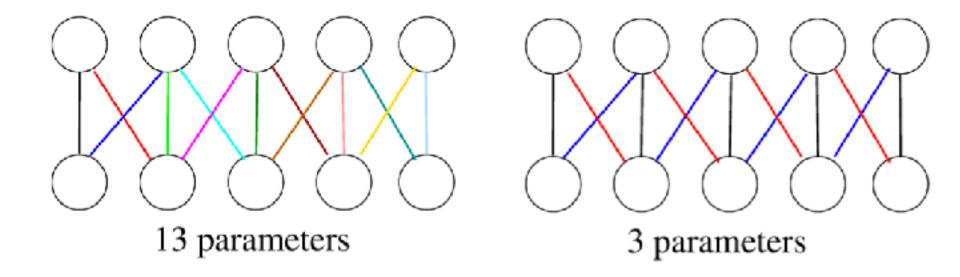


Feature extraction

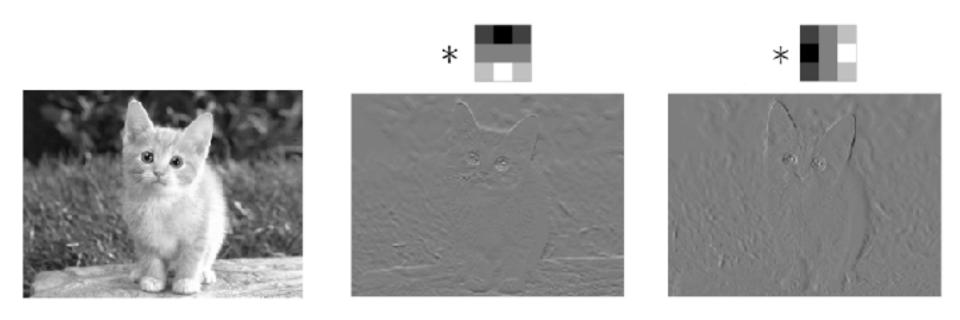
- Shared weights: all neurons in a feature share the same weights
- In this way all neurons detect the same feature at different positions in the input image.
- Reduce the number of free parameters.



Local connectivity



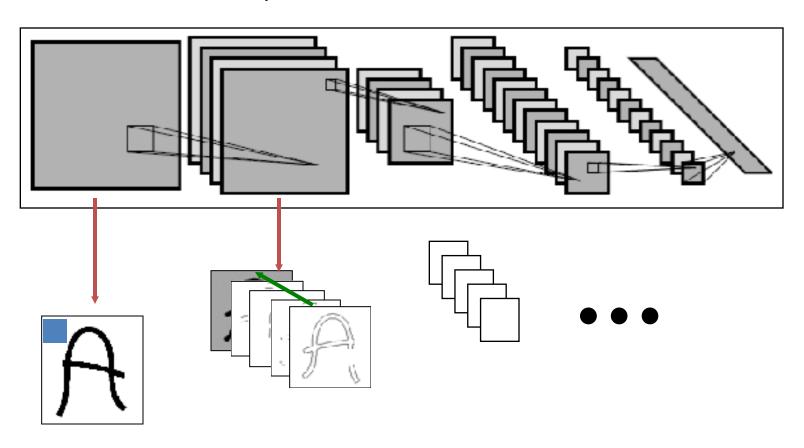
Convolution Details



Video at: http://cs231n.github.io/convolutional-networks/

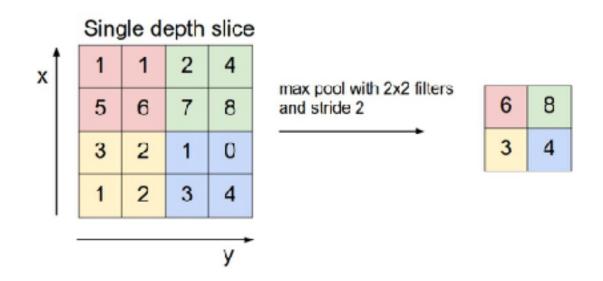
Feature extraction

If a neuron in the feature map fires, this corresponds to a match with the template.

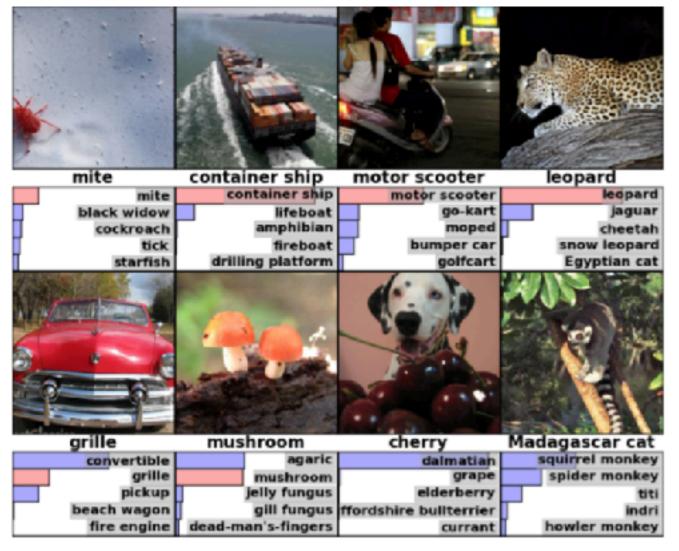


Subsampling layer

- The subsampling layers reduce the spatial resolution of each feature map (also called pooling)
- By reducing the spatial resolution of the feature map, a certain degree of shift and distortion invariance is achieved.



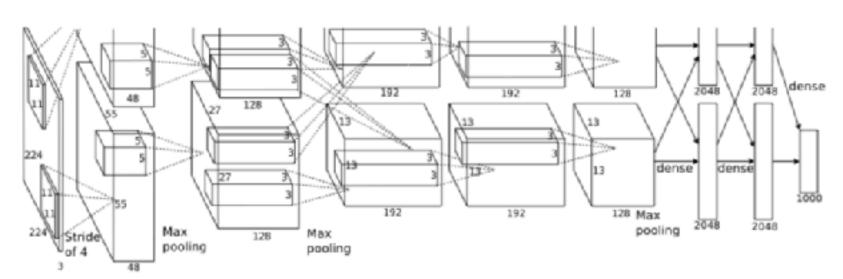
ImageNet - image classification



- 1.000 different classes
- 1.000.000 training images

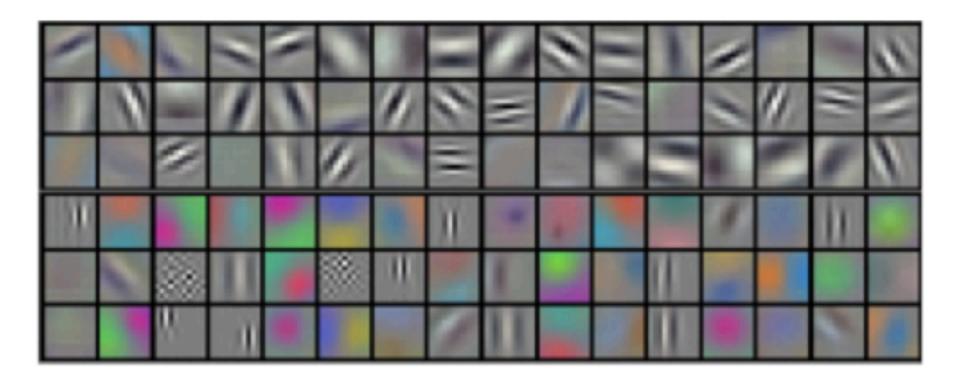
ImageNet Classification with Deep Convolutional Neural Networks

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www.cs.toronto.edu/~fritz/absps/imagenet.pdf

Learned features of first layer

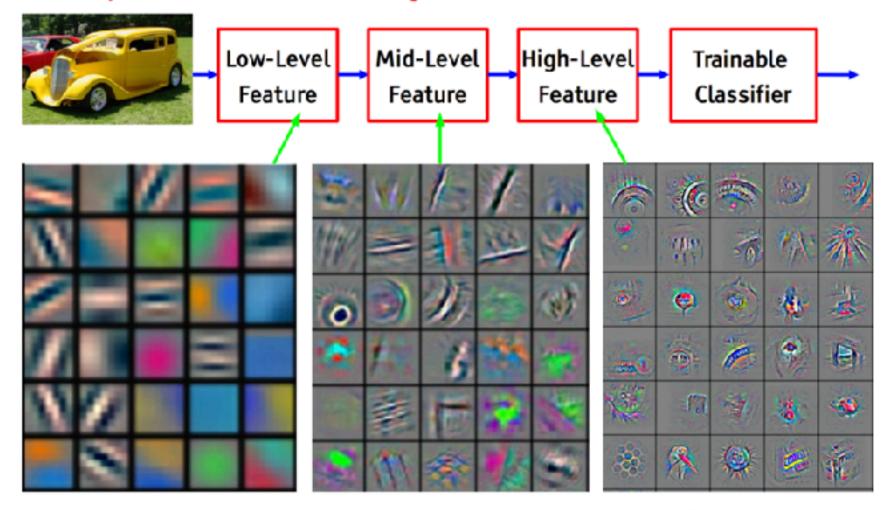


Deepvis: https://www.youtube.com/watch?v=AgkflQ4lGaM&feature=youtu.be

Deep Learning = Learning Hierarchical Representations

Y LeCun

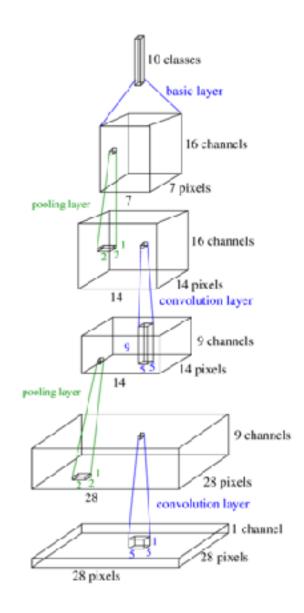
It's deep if it has more than one stage of non-linear feature transformation



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

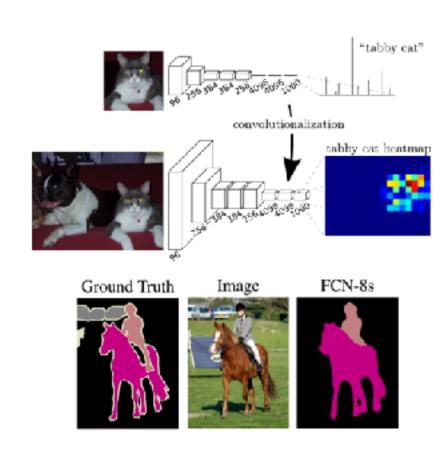
Network Example

- Often resolution is decreased and channels increased going up
- Important: Each unit looks at all channels of the previous layer
- Recent trends go towards small filters (3 × 3), sometimes even without pooling



Can also be used for Semantic Segmentation

 Basic idea: Slide a CNN to classify each location of the image

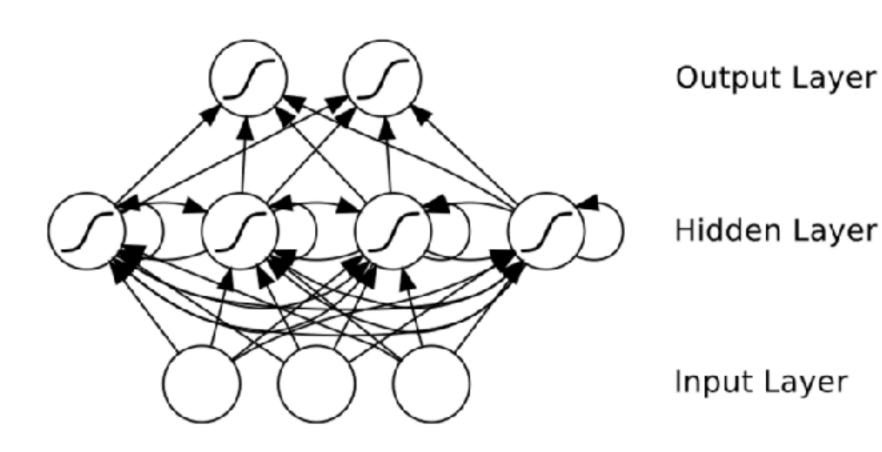


Long et al., 2015

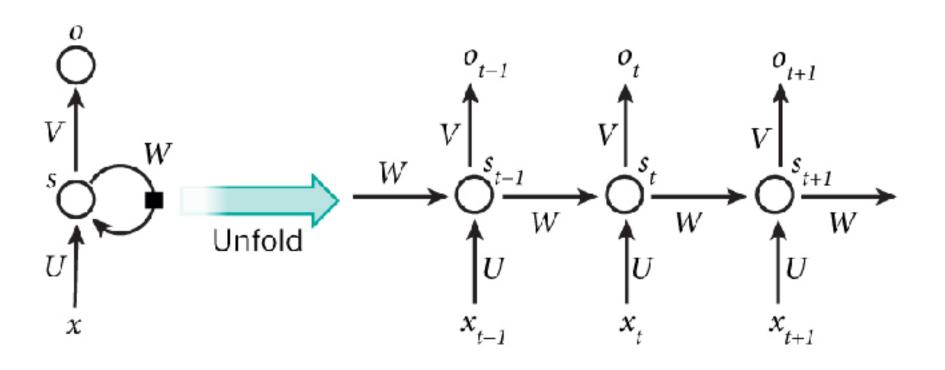
(Tensorflow+Keras)

```
47
     model = Sequential()
48
     model.add(Conv2D(32, kernel_size=(3, 3),
                      activation='relu'.
49
50
                      input shape=input shape))
51
     model.add(Conv2D(64, (3, 3), activation='relu'))
     model.add(MaxPooling2D(pool_size=(2, 2)))
52
53
     model.add(Dropout(0.25))
54
     model.add(Flatten())
     model.add(Dense(128, activation='relu'))
55
56
     model.add(Dropout(0.5))
57
     model.add(Dense(num_classes, activation='softmax'))
58
     model.compile(loss=keras.losses.categorical crossentropy,
59
60
                   optimizer=keras.optimizers.Adadelta(),
61
                   metrics=['accuracy'])
62
63
     model.fit(x train, y train,
               batch size=batch size,
64
65
               epochs=epochs,
66
               verbose=1,
               validation_data=(x_test, y_test))
67
     score = model.evaluate(x_test, y_test, verbose=0)
68
69
     print('Test loss:', score[0])
     print('Test accuracy:', score[1])
70
```

Recurrent Networks can learn sequential tasks



Recurrent Network Unrolled

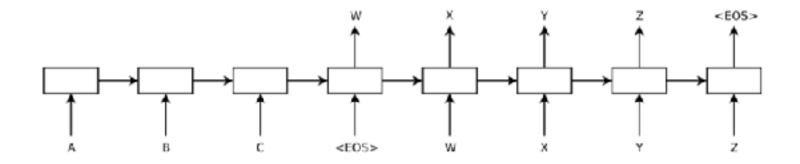


Sequence to Sequence Learning with Neural Networks

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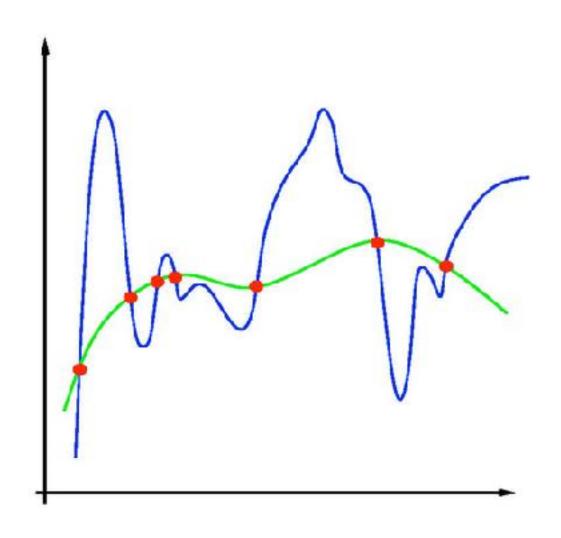


Neural network attention mechanisms



A woman is throwing a <u>frisbee</u> in a park.

The more parameters, the higher the chances of overfitting

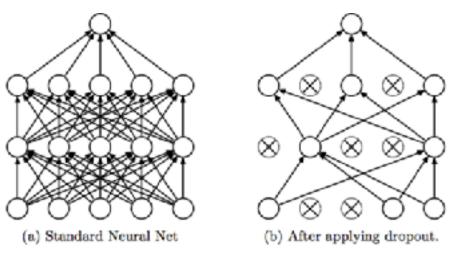


Tricks of the Trade: Early stopping

- Divide data into three sets:
 - Training
 - Testing
 - Validation
- Train model on training set
- Stop when error on validation set increases
- Evaluate accuracy on test set

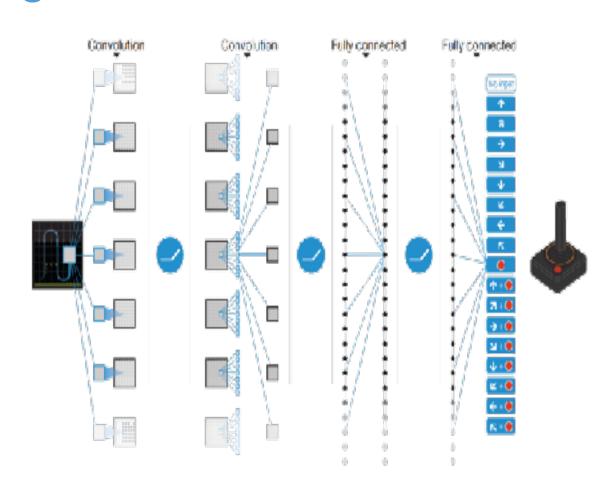
Tricks of the Trade cont.

- Careful initialisation
- Dropout
- Regularization (L1, L2)
- And many more



Srivastava et al., 2014

Deep Q-Learning: Mnih et al. "Humanlevel control through deep reinforcement learning"



Also works for Doom!



Videos: https://www.youtube.com/playlist?list=PLduGZax9wmiHg-XPFSgqGg8PEAV51q1FT

Paners https://projectors/pdf/1400.0FE21v1.pd

AlphaGo

 Combining Deep Neural Networks with Tree Search



