

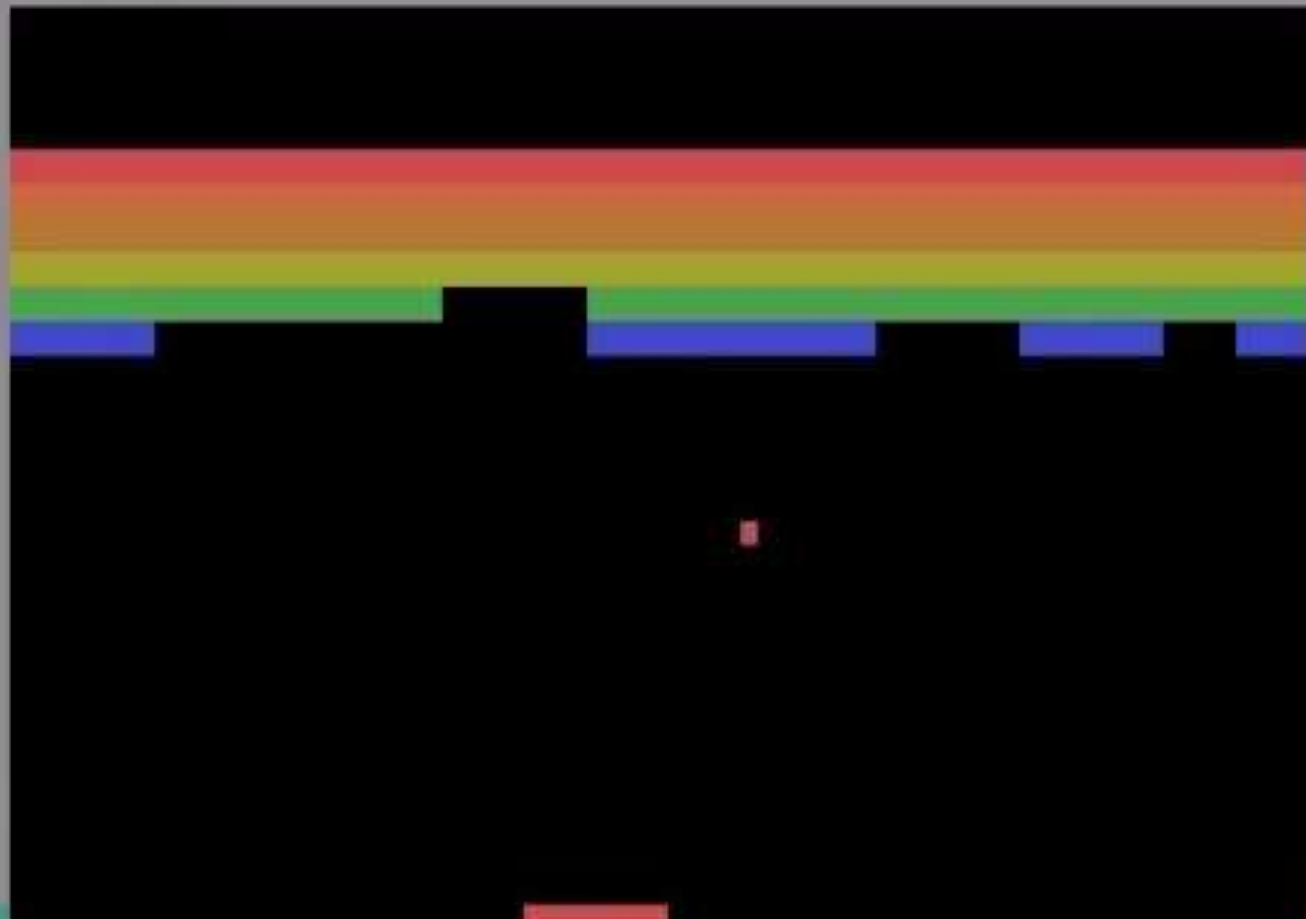
# Neocognitron

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Making a Neural Network that plays  
Breakout





# Motivations

- Many students now studying CS have an appreciation of video games.
- Having a neural net play a video game is a task more concrete than analysis of data.
- Reinforcement learning can be used for video game playing as shown by Google DeepMind. [Mnih et al.]

Gen 34 species 14 genome 14 (37%)  
Fitness: 724 Max Fitness: 4322 40

□ &  
□ B  
□ X  
□ Y  
□ Up  
□ Down  
□ Left  
□ Right

Marl/O - Machine Learning for Video Games

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SethBling  
Published on Jun 13, 2015

Marl/O is a program made of neural networks and genetic algorithms that kicks butt at Super Mario World.  
Source Code: <http://pastebin.com/ZZmSNaHX>  
Game Super Mario World - 1990 (YouTube Gaming)

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# Influences

- SethBling taught a neural net called Marl/O to play Super Mario World and a net called MariFlow to play Mario Kart.  
[\[https://www.polygon.com/2017/11/5/16610012/mario-kart-mariflow-neural-network-video\]](https://www.polygon.com/2017/11/5/16610012/mario-kart-mariflow-neural-network-video)
- Google DeepMind taught a neural net to play 49 Atari games using the same reinforcement DQN topology for each network. [Mnih et al.]
- DeepMind also created a reinforcement net to play Go at a superhuman level. [Silver et al.]
- Two students at Carnegie Mellon University taught a reinforcement net to play Doom deathmatch. [Lample and Chaplot]

# Aims

- Teach a neural net to play Breakout using pixel data;
  - Would need to
    - Interpret and store visual data
      - [memory=1,000,000, height=84, width=84, frames=4 or 5] uint8, float32
    - Determine appropriate actions
      - [no-op, fire, move left, move right] -> [no-op, move left, move right]
- Observe the learning process of the neural net;

# Code

- We used an approach similar to that of Mnih et al.'s Atari networks.
  - Preprocessing
    - Cut input resolution
      - When training: normalize frame batches, float32
      - When storing: downsample, grayscale, uint8
    - Input only every fourth frame and repeat chosen action for the next three frames
      - Deterministic/NoFrameSkip
  - State-action (Q) Function based reinforcement learning
  - 3 Convolutional layers to process input
  - Epsilon greedy exploration approach
    - Linear annealing for the first 1 million frames

## Code pt. 2

- We used an approach similar to that of Mnih et al.'s Atari networks.
  - Reward Schedule
    - Clipping the reward to  $(-1, 1)$ 
      - Reward is never negative
      - Reward is reset every death
  - No-op max
    - Up to 30 frames of no-ops to diversify initial frame states
  - Loss Function
    - Huber (less resistant to outlier data), logcosh, mean squared error
  - Lots of hyperparameters:

# Hyperparameters!

## Breakout Main Loop:

```
'GAME' : 'BreakoutDeterministic-v4', # Name of the game
# v1-4 Deterministic

'DISCRETE_FRAMING' : True, # 2 discrete set of actions

'LOAD_WEIGHTS' : '', # Loads weights from a file
# leave '' if starting from scratch

'RENDER_ENV' : False, # shows the screen
# massively slows down training
# default: False

'HEIGHT' : 84, # height in pixels
'WIDTH' : 84, # and width in pixels
# defaults: 84, 84

'FRAME_SKIP_SIZE' : 4, # how many frames to skip
# choose an action every 4 frames
# default: 4

'MAX_EPISODES' : 12000, # defined as how many episodes
# winning a round
# default: 12,000

'MAX_FRAMES' : 5000000, # max number of frames
# default: 50,000,000

'SAVE_MODEL' : 500, # how many episodes
# default: when the model has improved

'TARGET_UPDATE' : 10000, # on what model should we update
# default: 10000
```

## DQNAgent:

```
'WATCH_Q' : False, # watch the Q function and see what decision it picks
```

## Replay and Remember Memory:

```
'LEARNING_RATE' :
```

```
'INIT_EXPLORATION' :
'EXPLORATION' :
'MIN_EXPLORATION' :
```

```
'OPTIMIZER' :
```

```
'MIN_SQUARED_GRADIENT' :
```

```
'GRADIENT_MOMENTUM' :
```

```
'LOSS' : 'huber'
```

```
'NO_OP_MAX' : 1000
```

```
'SHOW_FIT' : 0,
```

```
# shows the fit of the model and it's work, turn to 0 for off
# default: 0 for off
```

```
'REPLAY_START' : 50000,
```

```
# when to start using replay to update the model
# default: 50000 frames
```

```
'MEMORY_SIZE' : 1000000,
```

```
# size of the memory bank
# default: 1,000,000
```

```
'GAMMA' : 0.99,
```

```
# integration of rewards, discount factor,
# preference for present rewards as opposed to future rewards
# default: 0.99
```

```
# 4 * 8 = 32 batch
```

```
'REPLAY_ITERATIONS' : 4,
```

```
# how many iterations of replay
# default: 4
```

```
'BATCH_SIZE' : 8
```

```
# batch size used to learn
# default: 8
```



# Results

- The first successful results came from training over 1 million frames using an NVIDIA 1080 GPU. This yielded an average reward/score of around 40. This training took a little over 10 hours to complete.
- Training takes a while! We are still training to achieve a higher average reward. An instance is training right now that is working to train over 20 million frames rather than the previous 1 million. This training is expected to be complete in two or three more days. The current average reward is around 70.
- Even though it has not completely cleared the game yet, it has achieved a high score of 215 and on average, exceeds the playing abilities of many human players.

# Building the Demo

- We are using the weights from the training to play a game of breakout.
- Acknowledgement: Dr. Phillips contributed some of the code for the demo.

# Administrative Team



To The Demo!

