Autonomous Learning

Exercise 10 - Assignment 3

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June 29, 2020

University of Kiel, Summer Term 2020

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Convolutional Neural Network

What We See

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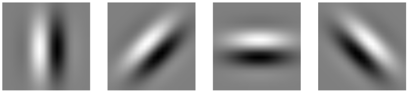
What Computers See

- input: $32 \times 32 \times 3$ (x-axis $\times$ y-axis $\times$ RGB)
- values from 0 to 255
- output: 80% dog and 20% cat

FEATURES

1. fur
2. ears
3. four paws

1. corners
2. edges
3. curves



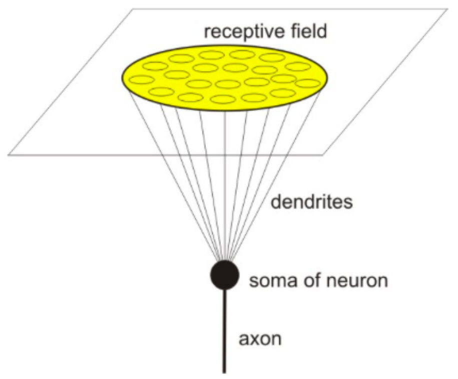
INSPIRATON FROM BIOLOGY

- research by *Hubel and Wiesel* on the brain of mammals
- *simple cells (S cells)*:

  basic shapes within certain within a certain range and angle
- *complex cells (C cells)*:

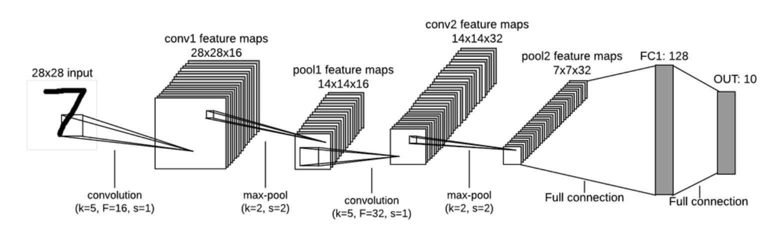
  larger receptive fields $\rightarrow$ no limitation to a specific position

RECEPTIVE FIELD



- region of the retina
- influences triggering of the associated neuron
- Every sensor neuron has the same receptive field.
- Receptive fields can overlap.

ARCHITECTURE



Two components:

1. Hidden layers / feature extraction:

   Multiple convolutions and pooling operations → features are recognised

2. Classification:

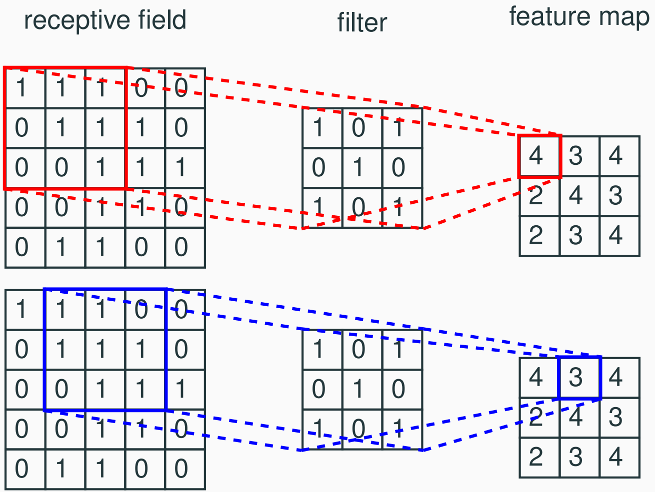
   fully connected layers → classifier working on the extracted features

Convolution

... is the mathematical combination of two functions to create a third one: Two information sets are combined.

- convolution on input data using kernel/filter $\rightarrow$ feature map
- The filter moves across the input and performs a matrix multiplication in every step.

CONVOLUTION



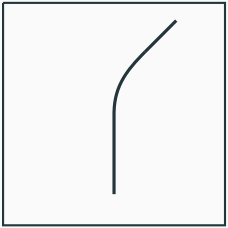
Filter

- array of numbers
- parameters or weights (numbers)
- element-wise multiplication
- slides/convolves across the input
- The depth of the filter must match the input.

High Level Perspective

- feature identifier
- edges, basic colours, and curves

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0



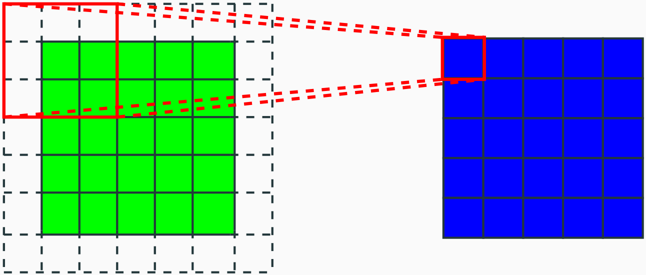
Stride

... is the step size of the filter moving across the input, normally 1 (pixel per step). Higher stride leads to less overlapping.

Padding

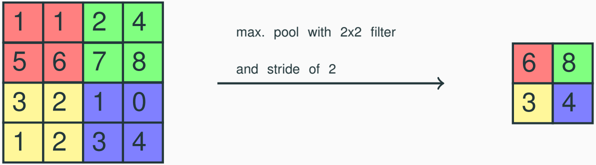
... is wrapping the input with a layer of zeros so the feature map is guaranteed to be no smaller than the input. This also ensures that filter and stride fit within the input.

Padding



POOLING

- between convolution layers
- reduces dimensionality → less parameters
- reduces training time
- counteracts overfitting

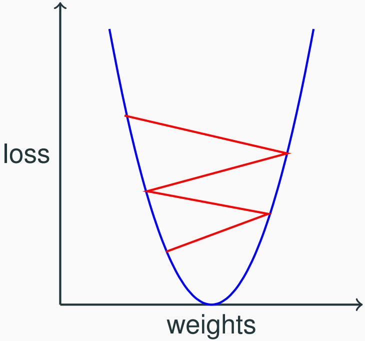


- The convolution is followed by *fully connected layers*.
- Convolution generates 3-dimensional data (several layers).
- Fully connected layers accept only 1-dimensional data.

$\Rightarrow$ Flatten

Learning Rate

- determines the step size while updating the weights
- higher learning rate $\rightarrow$ model converges faster
- learning too high $\rightarrow$ overshooting the optimal point



KERAS


```python
from keras.layers import Dense, Conv2D, Flatten
from keras.models import Sequnetial
from keras.optimizers import RMSprop

model = Sequential()

# 1st Convolutional Layer
model.add(Conv2D(16, 5, strides=1, activation='relu', input_shape=(32, 32, 2),
      kernel_initializer='he_normal', padding='same'))
# 2nd Convolutional Layer
model.add(Conv2D(32, 1, strides=1, activation='relu', kernel_initializer='he_normal',padding
      ='same'))

# Flatten Function
model.add(Flatten())

# Fully Connected Layer
model.add(Dense(128, activation='relu', kernel_initializer='he_normal'))
model.add(Dense(8, activation='linear', kernel_initializer='he_normal'))

model.compile(loss='mse',optimizer=RMSprop(lr=0,00025))
```

Improvements for DQN

Double Learning

- Agent tends to over-approximate the Q values.

$$Q(s, a) \to r + \gamma \max_{a} Q(s', a)$$

- Example:
  - All agents have the same true Q-value for s.
  - The estimation is inherently noisy $\to$ different from Q_{true}
  - $\max \to$ The action with the highest positive error is chosen
  - Error is propagated to future states.
    $\Rightarrow$ positive bias / value overestimation

Double Learning

- Solution: Double Learning
- Standard Q-Learning:
  - Two Q-functions Q_1 and Q_2 are learned independently.
  - One chooses the action which is to maximised.
  - The other determines the value of the chosen action.
  - One of the functions is randomly chosen to be updated:

$$Q_1(s,a) \to r + \gamma Q_2(s', \operatorname*{argmax}_a Q_1(s',a))$$

or

$$Q_2(s,a) \to r + \gamma Q_1(s', \operatorname*{argmax}_a Q_2(s',a))$$

Double Deep Q-Learning

- already two different Q-functions
- $Q(s, a; \theta)$
- $Q(s, a; \theta^-)$

$$Q(s, a; \theta) \rightarrow r + \gamma Q(s', \underset{a}{\operatorname{argmax}}\, Q(s', a; \theta); \theta^-)$$

- increased stability $\rightarrow$ more complex problems

- So far: All experience is treated equally
- But: From some you can learn more than from others.
- Idea: Prefer those transitions that *fit* the current estimation of the Q-function *the least*.

  $\rightarrow$ greates potential

Prioritised Replay Memory

- The error of sample $S = (s, a, r, s')$ is the distance between $Q(s, a)$ and its target $T(S)$.

$$error = |Q(S, a) - T(S)|$$

- The error is saved together with S and updated during each learning step.

  $\rightarrow$ Greedy Prioritisation

- Samples with a small TD-error during their first occurrence have a very small probability of being sampled ever again.

Stochastic Prioritisation

- Priority:

$$p_i = \frac{1}{rank(i)}$$

- *rank*: position in the buffer (sorted by TD-error)
- Priority is converted to a probability:

$$P(i) = \frac{p_i^\alpha}{\sum_k p_k^\alpha}$$

- α determines how much prioritisation is used $\alpha = 0 \rightarrow$ standard case ($0 \leq \alpha \leq 1$)

Proportional Prioritisation

- error $\rightarrow$ priority:

$$p_i = (error_i + \epsilon)^{\alpha}$$

- ϵ: small positive constant $\rightarrow$ no priority of 0
- α determines how much prioritisation is used $\alpha = 0 \rightarrow$ standard case ($0 \leq \alpha \leq 1$)
- Priority is converted to a probability:

$$P(i) = \frac{p_i}{\sum_k p_k}$$

Annealing Bias

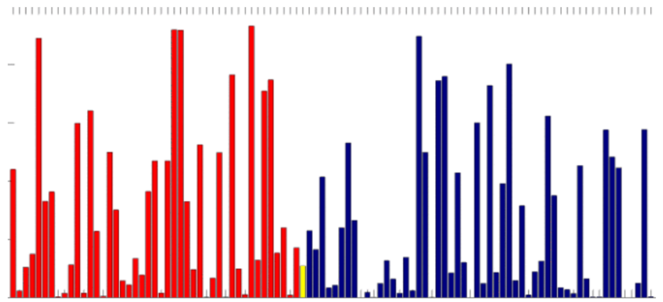
- uncontrolled distribution change $\rightarrow$ induced bias
- Solution: Weighted Importance Sampling

$$w_i = \left(\frac{1}{N} * \frac{1}{P(i)}\right)^{\beta}$$

- β: linearly towards 1
- When $\beta = 1$ the weights completely compensate the uneven distribution $P(i)$.

Sampling

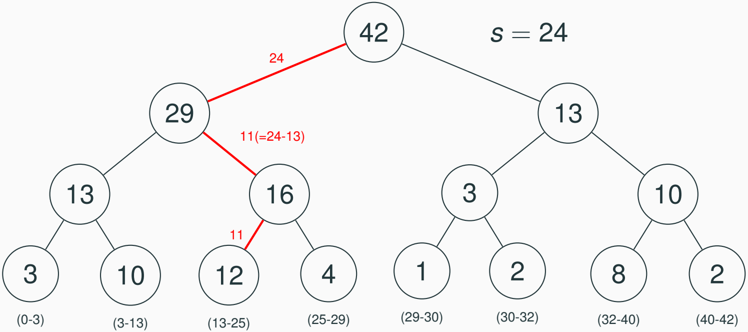
- draw a random number s with $0 \leq s \leq \sum_k p_k$
- traverse the memory from left to right
- sum up the priorities
- stop when s is reached



runtime: $O(n)$

Sum Tree

- Unsorted Sum Tree $\rightarrow$ a binary tree
- value of the parent $=$ the sum of its children
- samples in the leaves



runtime: $O(\log n)$

Advantage

- Q-value: quality of action a in state s

$$Q(s, a) = V(s) + A(s, a)$$

- $V(s)$: How good is it to be in state s?
- $A(s, a)$: How much better is it to chose action a over all others?
  $\rightarrow$ Advantage

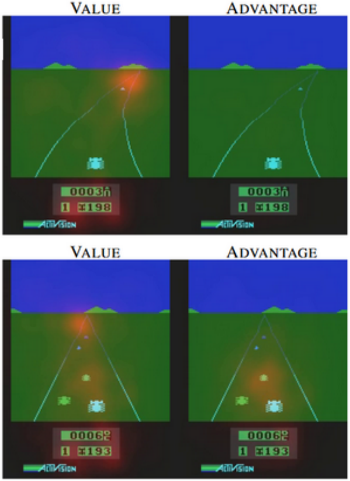
Duelling DQN

- The Network calculates $V(s)$ and $A(s, a)$ seperately and combines them to $Q(s, a)$.
- The agent is not necessarily interessted in both values.
- Why calculating the values for all actions, if they all lead to death?

  $\Rightarrow$ more robust estimation of $V(s)$

EXAMPLE

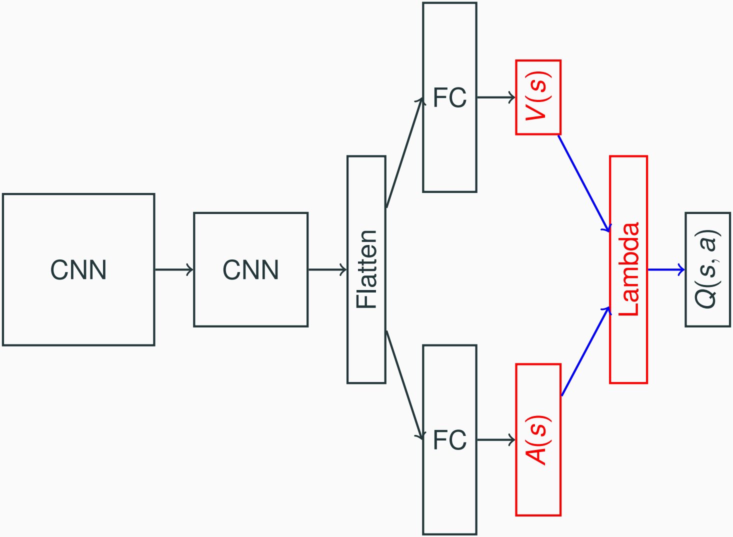
<u>Focus on 2 things:</u>
- The horizon where new cars appear
- On the score



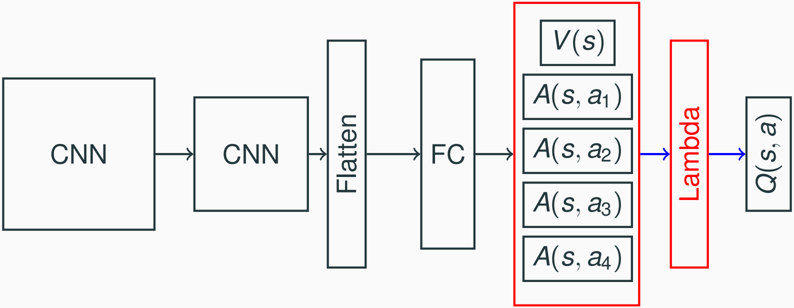
No car in front, **does not pay much attention because action choice making is not relevant**

Pays attention to the front car, in this case **choice making is crucial to survive**

ARCHITECTURE



Architecture



Naïve approach:

$$Q(s, a; \theta, \alpha, \beta) = V(s; \theta, \beta) + A(s, a; \theta, \alpha)$$

BUT: problem of identifiability

$\Rightarrow$ Given $Q(s, a)$ it is not possible to determine $A(s, a)$ and $V(s)$.

$\Rightarrow$ Problem for Backpropagation

AGGREGATION

Solution: Forcing the advantage function to 0 for the chosen action through subtraction of the mean advantage of all actions:

$$Q(s, a; \alpha, \beta) = V(s, \theta, \beta) + \left(A(s, a; \theta, \alpha) - \frac{1}{A}\sum_{a'} A(s, a'; \theta, \alpha)\right)$$

- α: parameter of the advantage stream
- β: parameter of the value stream

Lamba-Layer

- Keras layer
- To define custom layers
- Example:

```python
from keras.layers import Lambda
from keras.models import Sequential
from keras import backend as K

model = Sequential()

model.add(Dense(16, activation='relu', input_dim=2))

# Calculates the square
model.add(Lambda(lambda x: x ** 2))

# Determines the mean
model.add(Lambda(lambda sq: K.mean(sq))

model.add(Dense(8)
```

Bibliography

Pictures

- https://adeshpande3.github.io/adeshpande3.github.io/A-Beginner's-Guide-To-Understanding-Convolutional-Neural-Networks/
- https://view.stern.de/de/rubriken/tiere/hund-hunde-ohren-basset-hound-dumbo-basset-original-2012281.html
- https://www.quora.com/What-do-channels-refer-to-in-a-convolutional-neural-network
- https://medium.freecodecamp.org/an-intuitive-guide-to-convolutional-neural-networks-260c2de0a050
- https://jaromiru.com/2016/11/07/lets-make-a-dqn-double-learning-and-prioritized-experience-replay/
- https://medium.freecodecamp.org/improvements-in-deep-q-learning-dueling-double-dqn-prioritized-experience-replay-and-fixed-58b130cc5682