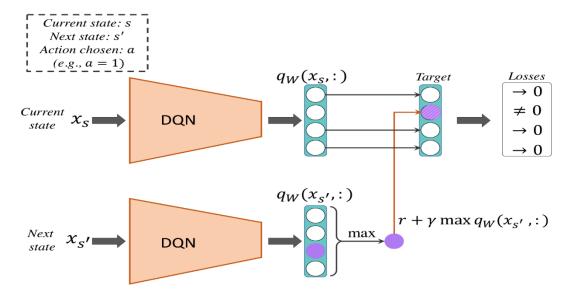
Calculating gradients of variables in Pytorch.

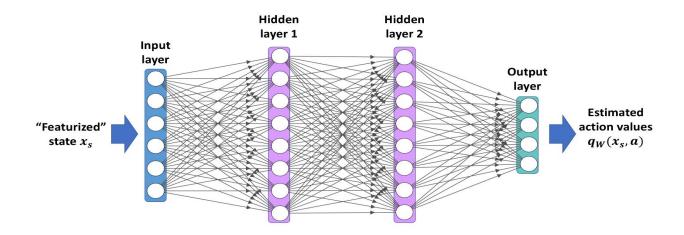
The output of the NN will be a matrix of size (batch_size, action_space)
Action space could be "up","down","left",etc..

The Task is framed as a regression problem using the MSE loss function. This means that the loss takes in single values, instead of tensors. The loss takes in 2 scaler values

- a. The output value given from the NN for the action that was taken
- b. The target value, which is constructed by the Bellman equation.

On back-propagation, the only node that should be used to back-propagate the error is the one representing the action that was taken, this is the only node with a non-zero loss, and thus a non-zero gradient. The only weights to be updated, between the hidden and output layer, will be the ones projecting onto that node.





Tensor_states (Batch_size,action_space)

4.0	2.5	2.9
1.2	1.5	1.9
5.0	5.5	5.9
4.8	2.5	2.9
4.0	2.8	3.9

Actions (Indices)

2
1
1
0
1

Result of gather()

Predicted_state_action_values

4.0	2.5	2.9
1.2	1.5	1.9
5.0	5.5	5.9
4.8	2.5	2.9
4.0	2.8	3.9

2.91.55.54.8
4.8
2.8

Loss = (predicted_state_action_values, target_state_action_values)

Gradients for each sample. Just an example, nothing was calculated.

0	0	1,3
0	0.63	0
0	2.01	0
3.03	0	0
0	2.02	0

Gather() operation on predicted_state_values()

predicted_state_action_values = main_net(tensor_states).gather(1, tens
or actions

The loss/gradients for the non-yellow elements will be 0. (This is done in the 2^{nd} code snippet)

```
Predictions = \begin{bmatrix} 5.0 & 5.5 & 5.9 & 5.0 \end{bmatrix}

Index = 1

Prediction = \begin{bmatrix} 5.5 & 5.5 & 5.9 & 5.0 \end{bmatrix}

Target = \begin{bmatrix} 2.9 & 5.5 & 5.9 & 5.0 \end{bmatrix}

Output = \begin{bmatrix} MSE(prediction, target) & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5.0 & 5
```

Output.backward() # Calculate the gradients for the elements that were fed into the loss function.

1st Code Snippet

```
Python 3.7.9 (default, Aug 31 2020, 17:10:11) [MSC v.1916 64 bit (AMD64)] :: Anaconda, Inc. on win32
```

>>> import torch

>>> import torch.nn as nn

>>> predictions = torch.tensor([0.235,1.200,1.321], requires_grad = True)

>>> predictions

tensor([0.2350, 1.2000, 1.3210], requires_grad=True)

>>> targets = torch.tensor([2.335,0.890,1.154])

>>> targets

tensor([2.3350, 0.8900, 1.1540])

>>> prediction = predictions[1]

>>> target = targets[1]

>>> prediction

tensor(1.2000, grad_fn=<SelectBackward>)

>>> target

```
tensor(0.8900)

>>> loss = nn.MSELoss()

>>> output = loss(prediction, target)

>>> output.backward()

>>> prediction.grad

>>> target.grad

>>> predictions.grad

tensor([0.0000, 0.6200, 0.0000])

>>> targets.grad

>>> 2 * (prediction - target) [The Derivative of the MSE w.r.t.

prediction works out to be 2(prediction-target)]

tensor(0.6200, grad_fn=<MulBackward0>)
```

2nd Code snippet

Computing the gradients with the gather() function.

Same approach, but using the gather() function. The gather function is used instead of simply indexing.

(base) C:\Users\billy>python

Python 3.7.9 (default, Aug 31 2020, 17:10:11) [MSC v.1916 64 bit (AMD64)] :: Anaconda, Inc. on win32

>>> import torch.nn as nn

>>> import torch

```
>>> predictions = torch.randn(3,requires grad = True)
>>> predictions
tensor([ 0.9243, -0.5061, -0.0116], requires grad=True)
>>> prediction = torch.gather(predictions,0,torch.tensor([0]))
>>> prediction
tensor([0.9243], grad fn=<GatherBackward>)
>>> target = torch.tensor([2.565])
>>> target
tensor([ 2.565])
>>> prediction.size()
torch.Size([1])
>>> target.size()
torch.Size([1])
>>> loss = nn.MSELoss()
>>> output = loss(prediction, target)
>>> output.backward() # Calculate gradients
>>> predictions.grad
tensor([-3.2815, 0.0000, 0.0000]) # The gradient is calculated and
stored in a specific index. The optimizer then uses these gradients to
update the values e.g. value += learning rate * value.grad
>>> target.grad (This is empty as the 'target' is never updated)
>>> 2*(prediction-target) [This again is the partial derivative w.r.t. the
MSELoss function.
```

requires_grad: This member, if true starts tracking all the operation history and forms a backward graph for gradient calculation.

grad: grad holds the value of gradient. If requires_grad is False it will hold a None value. Even if requires_grad is True, it will hold a None value unless <code>.backward()</code> function is called from some other node. For example, if you call <code>out.backward()</code> for some variable *out* that involved <code>x</code> in its calculations then <code>x.grad</code> will hold <code>\delta out/\delta x</code>.

Backward() simply calculates the gradients

The .backward() function is called on the error!

FULL EXAMPLE OF THE Q-LOSS FUNCTION CODE

This is the 'Naïve' version which loops every sample in a batch.

```
criterion = nn.MSELoss()
def naive_dqn_loss_V2(batch, main_net, target_net, gamma, batch_size = 32, device
 = "cuda", optimizer = 'opt'):
    tensor_states,tensor_next_non_final_states,tensor_actions,tensor_rewards,non_
final mask = batch
    # create predicted (NN output)
    predicted_state_action_values = main_net(tensor_states) # dims = batch_size,n
umber_of_actions
    next_state_values = torch.zeros((batch_size,predicted_state_action_values.siz
e()[1]), device=device)
    #print(next_state_values)
    with torch.no grad():
        next_state_values[non_final_mask] = target_net(tensor_next_non_final_stat
es) #
        next_state_values = next_state_values.detach()
    next state values = next state values * gamma
    batch loss = 0.0
    for prediction, reward, action, tensor in zip(predicted_state_action_values,
tensor_rewards,tensor_actions, next_state_values):
        target = tensor.max() + reward
        target = target.detach() # detach, no gradient flow to the ground Truth!!
        prediction = prediction[action]
        # scalar, NOT vector inputs to the loss function!
        sample_loss = criterion(prediction, target)
        batch loss += sample loss
    return batch loss / batch size
```

The batch version of the Loss, using the gather() function on the tensor states() matrix.

```
def simple_dqn_loss(batch, main_net, target_net, gamma, batch_size = 32, device="
cuda"):
    tensor_states,tensor_next_non_final_states,tensor_actions,tensor_rewards,non_
final mask = batch
    predicted_state_action_values = main_net(tensor_states).gather(1, tensor_acti
ons.unsqueeze(-1)).squeeze(-1)
    next_state_values = torch.zeros(batch_size, device=device)
    with torch.no_grad():
        #compute next state values using Target network
        next_state_values[non_final_mask] = target_net(tensor_next_non_final_stat
es).max(1)[0] #only take the values and not the indices
        #detach from pytorch computation graph
        next state values = next state values.detach()
    #target values using Bellman aproximation
    target state action values = tensor rewards + (gamma * next state values )
    return criterion(predicted_state_action_values,target_state_action_values)
```