#### Homework 3 - Answer

For more details see the docs

The first part of the notebook, just checks that the requisite packages are installed.

We then move onto defining the model

```
class MyModel(nn.Module):
    def __init__(self):
        super(MyModel, self).__init__()
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=2, kernel_size=5, stride=2)
        self.conv2 = nn.Conv2d(in_channels=2, out_channels=3, kernel_size=5, stride=2)
        self.relu = nn.ReLU()
        self.d1 = nn.Linear(48, 48)
        self.d2 = nn.Linear(48, 10)
    def forward(self, x):
        # 32x1x28x28 => 32x32x26x26
        x = self.conv1(x)
        x = self.relu(x)
        x = self.conv2(x)
        x = self.relu(x)
        # flatten => 32 x (32*26*26)
        x = x.flatten(start_dim = 1)
        # 32 x (32*26*26) => 32x128
        x = self.d1(x)
        x = self.relu(x)
        # logits => 32x10
        logits = self.d2(x)
        return logits
circuit = MyModel()
```

Thanks to Pedro: @pedrocoelho22 who pointed out that the comments are incorrect and should be

```
conv1: 32x1x28x28 => 32x2x12x12,
conv2: 32x2x12x12 => 32x3x4x4,
flatten: 32x3x4x4 => 32 x (3x4x4=48),
d1: 32x48 => 32x48,
d2: 32x48 => 32x10 (edited)
```

```
shape = [1, 28, 28]
# After training, export to onnx (network.onnx) and create a data file (input.json)
x = 0.1*torch.rand(1,*shape, requires_grad=True)
# Flips the neural net into inference mode
circuit.eval()
    # Export the model
torch.onnx.export(circuit,
                                        # model being run
                                         # model input (or a tuple for multiple inputs)
                      model_path,
                                           # where to save the model (can be a file or file-like object)
                     export_params=True,
                                               # store the trained parameter weights inside the model file
                      opset_version=10,
                                                # the ONNX version to export the model to
                     do_constant_folding=True, # whether to execute constant folding for optimization
                      input_names = ['input'],  # the model's input names
                      output_names = ['output'], # the model's output names
                      dynamic_axes={'input' : {0 : 'batch_size'},
                                                                    # variable length axes
                                    'output' : {0 : 'batch_size'}})
data_array = ((x).detach().numpy()).reshape([-1]).tolist()
data = dict(input_data = [data_array])
    # Serialize data into file:
json.dump( data, open(data_path, 'w' ))
```

### We serialise the inputs for later

```
[ ] cal_path = os.path.join("calibration.json")

data_array = (torch.rand(20, *shape, requires_grad=True).detach().numpy()).reshape([-1]).tolist()

data = dict(input_data = [data_array])

# Serialize data into file:
    json.dump(data, open(cal_path, 'w'))

ezkl.calibrate_settings(cal_path, model_path, settings_path, "resources")
```

We can now create the circuit and do the rest of gthe setup

```
[ ] res = ezkl.compile_circuit(model_path, compiled_model_path, settings_path)
    assert res == True

[ ] # srs path
    res = ezkl.get_srs( settings_path)

[ ] # now generate the witness file

    res = ezkl.gen_witness(data_path, compiled_model_path, witness_path)
    assert os.path.isfile(witness_path)
```

# ezkl.setup will give us the proving and verification keys

We can now create the proof

```
[] # GENERATE A PROOF

proof_path = os.path.join('test.pf')

res = ezkl.prove(
    witness_path,
    compiled_model_path,
    pk_path,
    proof_path,

    "single",
)

print(res)
assert os.path.isfile(proof_path)
```

### and verify it

## Terminology

<u>stride</u>