

Tutorial 1. Training RU-Net

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This tutorial demonstrates how to train a RU-Net (Regression-U-Net) for predicting plankton properties. It covers information on:

- Defining Simulation Parameters
- Defining RU-Net using tensorflow.keras
- Training RU-Net model
- Testing the model on an experimental images



NOTE:

- If you're running this notebook on your local machine, please comment the code in the cell below

```
In [4]: !git clone https://github.com/softmatterlab/Quantitative-Microplankton-Tracker.git
!cd Quantitative-Microplankton-Tracker/training-tutorials/
```

```
In [5]: %matplotlib inline
import os
import sys
sys.path.insert(0, ".")
```

1. Setup

Imports the dependencies needed to run this tutorial.

```
In [6]: import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
from tqdm.notebook import tqdm
import deeptack as dt

# Load experimental data
experimental_image = np.load("../data/data_figure/flgl_data.npy")
```

2. Defining training dataset

2.1. Defining simulation parameters

We generate simulated holographic images of size 128 x 128 pixels to train the RU-Net. Each image contains plankton holograms of different properties as defined below.

```
In [7]: variables = {
    "pix_size": 3.6, # pixel size of the camera in microns - can be modified as per the camera size
    "radius_range": (1.5e-6, 10e-6), # range of the radius of the planktons in microns
    "r1_range": (1.35, 1.35), # range of the Refractive Index of the planktons
    "r2_range": (2300, 3000), # z-distance of the plankton in microns (distance from the camera sensor)
    "apod_val": 0.07, #Gaussian apodization value (to account for the coherence of the source beam)
    "z_pixel": 20, # in microns (Ideally this should be the same as the pixel size) Used to reduce the
    memory usage
}
```

2.2. Defining scatterer properties

Each plankton is a scatterer. We use the `Sphere` feature of DeepTrack to generate spherical scatterers. Since we are using lensless-holographic setup, planktons can be approximated as spherical objects. All the other properties are automatically filled from the variables defined above in the cell above.

```
In [8]: sphere_main = dt.Sphere(
    position=lambda: np.random.rand(2) * 128,
    position_unit="pixel",
    cam_pix_size=variables["pix_size"],
    radius=lambda: variables["radius_range"][0]
    + np.random.rand()
    * (variables["radius_range"][1] - variables["radius_range"][0]),
    refractive_index=lambda: variables["r1_range"][0]
    + np.random.rand() * (variables["r1_range"][1] - variables["r1_range"][0]),
    z=lambda: variables["z_range"][0] / variables["z_pixel"]
    + np.random.rand()
    * (variables["z_range"][1] - variables["z_range"][0])
    / variables["z_pixel"],
)
```

2.3. Defining the optical device

The scatterers are imaged with an optical device. We use the `Brightfield` feature of DeepTrack to define a microscope operating at wavelength of 633 nm.

```
In [9]: optics = dt.Brightfield(
    wavelength=633e-9,
    NA=1,
    resolution=variables["pix_size"] * 1e-6,
    resolution=variables["pix_size"] * 1e-6, variables["pix_size"] * 1e-6, variables["z_pixel"] * 1e-6
),
    magnification=1,
    refractive_index_medium=1.33,
    apod_val=variables["apod_val"],
    aberration=1,
    aberration=lambda: dt.GaussianApodization(apod_val + np.random.uniform(-1,1)*0.01),
    output_region=(0, 0, 128, 128),
)
```

2.4. Defining noises

We add gaussian noise to the generated images with a blur factor.

```
In [10]: from deeptack.noise import Noise
from skimage.filters import gaussian
import numpy as np
class BlurredGaussian(Noise):
    """Adds IID Gaussian noise to an image

    Parameters
    -----
    mu : float
        The mean of the distribution.
    sigma : float
        The root of the variance of the distribution.
    """
    def __init__(self, mu=0, sigma=1, blur=2, **kwargs):
        super().__init__(mu=mu, sigma=sigma, blur=blur, **kwargs)

    def get(self, image, mu, sigma, blur, **kwargs):
        noisy_image = mu + np.random.randn(image.shape) * sigma
        noisy_image = gaussian(noisy_image, sigma=blur)
        noisy_image = image + noisy_image
        return noisy_image

noise = BlurredGaussian(mu=0, sigma= lambda: .025, blur=0.9+np.random.uniform(0,1)*0.1)
```

2.5. Defining number of planktons in 128 x 128 px image

Each image contains 5 to 8 number of planktons with randomly sampled properties.

```
In [11]: sphere_main.no = lambda: np.random.randint(5, 8)
sample_normal = sphere_main * sphere_main.no
```

2.6. Combining all the properties defined above

Passing all the features to the optical device to generate sample images.

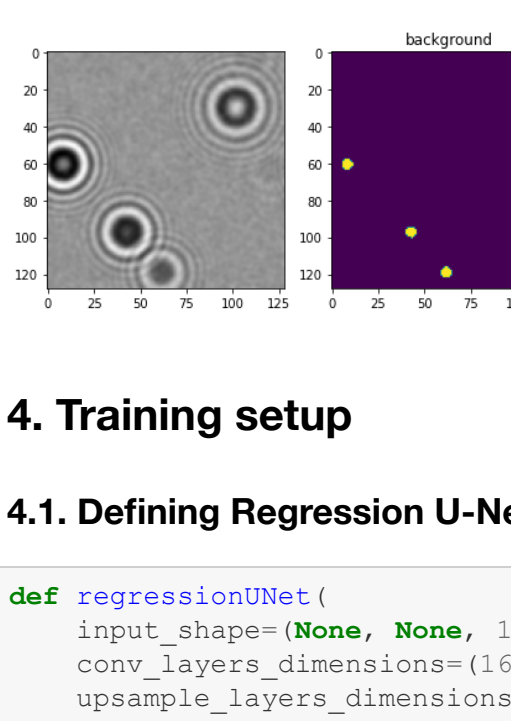
```
In [12]: image_formed = optics(sample_normal)

image_of_particles = dt.ConditionalSetFeature(
    on_true=image_formed + noise,
    on_false=dt.FlipUD(dt.FlipLR(dt.FlipDiagonal(image_formed))) + noise,
    condition="skip_aug",
    skip_aug=False,
)
```

2.7. Visualising an example image

```
In [13]: simulated_image = image_of_particles.update(skip_aug=True).resolve()
plt.imshow(simulated_image[:,0,0], cmap="gray")
```

```
Out[13]: <matplotlib.image.AxesImage at 0x7f3b7bf1af10>
```



3. Creating target images

3.1. Dry mass values

Function to check the range of possible dry mass values for parameters defined above.

```
In [14]: def dm_range(r1_range, r1_range):
    m = lambda r1: r1 * ((4 * np.pi) / 3) * ((rad * 1e6) ** 3) * (r1 - 1.33)
    return m(r1_range[0], r1_range[1])

dm_vals = dm_range(variables["radius_range"], variables["r1_range"])
dm_vals
```

```
Out[14]: (0.2827433388230816, 209.4395102393188)
```

3.2. Normalising target images

Function to generate the output channels for an input simulated image.

```
In [15]: def get_target_image(image_of_particles):
    label = np.zeros(image_of_particles.shape[:2], 5)

    X, Y = np.meshgrid(
        np.arange(0, image_of_particles.shape[0]),
        np.arange(0, image_of_particles.shape[1]),
    )

    for property in image_of_particles.properties:
        if "position" in property:
            distance_map = (X - position[1]) ** 2 + (Y - position[0]) ** 2

            # 2D positions
            label[distance_map < 9, 0] = 1

            # 3D positions
            z = property["z"]

            label[distance_map < 9, 1] = (
                z - variables["z_range"][0] / variables["z_pixel"]
            ) / (
                variables["z_range"][1] / variables["z_pixel"]
                - variables["z_range"][0] / variables["z_pixel"]
            )

            # Dry mass
            rad = property["radius"]
            r1 = property["refractive_index"]
            dm = ((4 * np.pi) / 3) * ((rad * 1e6) ** 3) * (r1 - 1.33)
            label[distance_map < 9, 2] = (dm - dm_vals[0]) / (
                dm_vals[1] - dm_vals[0]
            )

            label[distance_map < 9, 3] = (
                X[distance_map < 9] - position[1]
            ) / 3

            label[distance_map < 9, 4] = (
                Y[distance_map < 9] - position[0]
            ) / 3

    return label
```

3.3. Visualising sample input and target images

```
In [16]: for i in range(3):
    image_of_particles.update(skip_aug=True)
    images = image_of_particles.resolve()
    label_of_particles = get_target_image(images)

    fig = plt.figure(figsize=(12*2, 9*2))

    print(np.shape(images))

    plt.subplot(1, 6, 1)
    plt.imshow(images[0,0,0], cmap="gray")

    plt.subplot(1, 6, 2)
    plt.title("background")
    plt.imshow(label_of_particles[0,0,0])

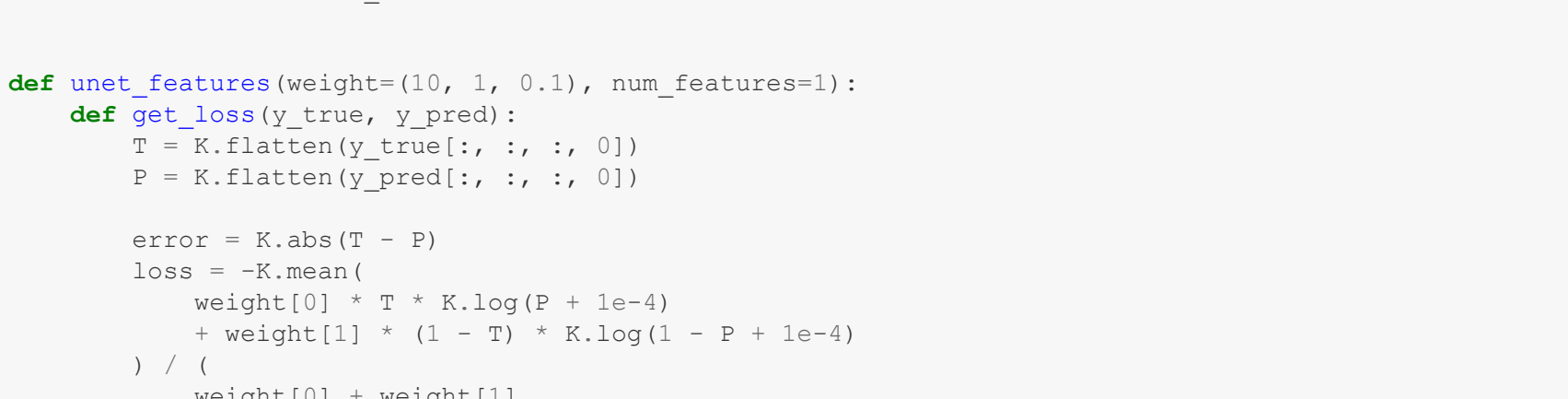
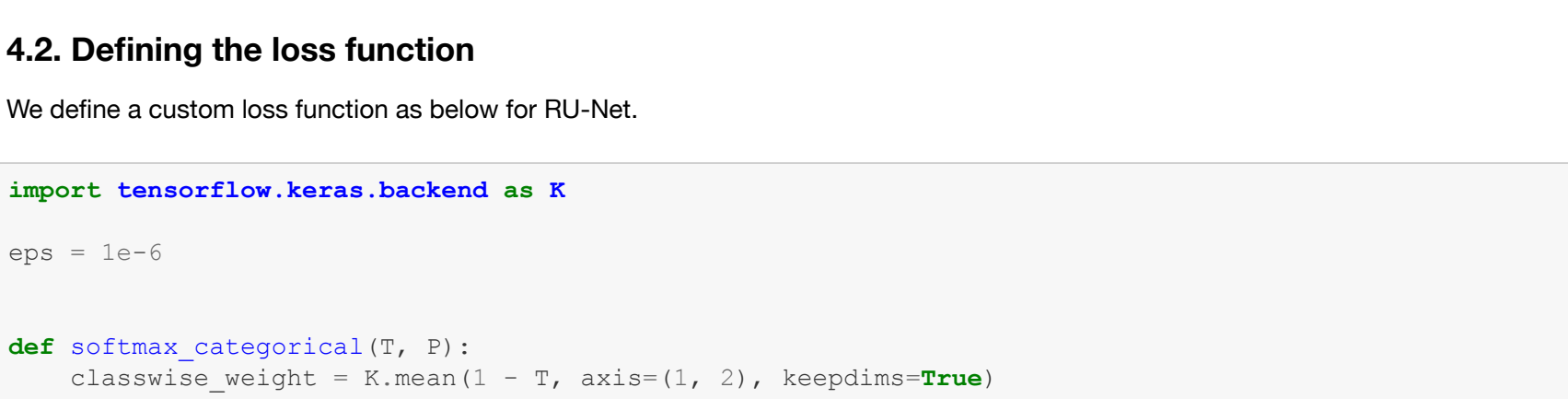
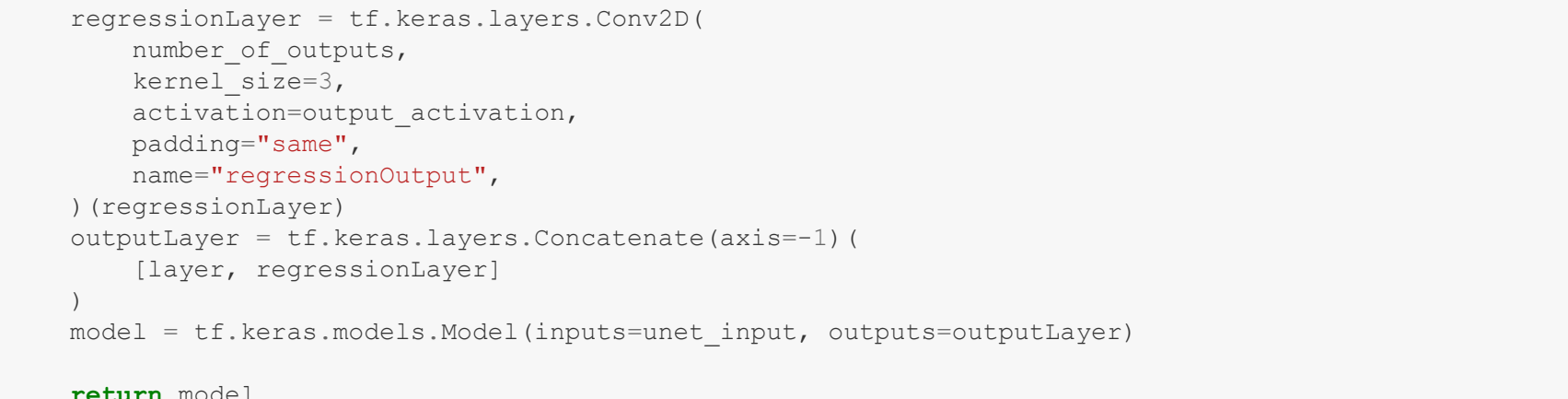
    plt.subplot(1, 6, 3)
    plt.title("x distance map")
    plt.imshow(label_of_particles[0,1,0])

    plt.subplot(1, 6, 4)
    plt.title("y distance map")
    plt.imshow(label_of_particles[0,4,0])

    plt.subplot(1, 6, 5)
    plt.title("x distance map")
    plt.imshow(label_of_particles[0,1,0])

    plt.subplot(1, 6, 6)
    plt.title("y distance map")
    plt.imshow(label_of_particles[0,4,0])

    plt.show()
```



4. Training setup

4.1. Defining Regression U-Net using keras with tensorflow backend.

```
In [17]: def regressionUnet(
    input_shape=(None, None, 1),
    conv_layers_dimensions=(16, 32, 64, 128),
    upsample_layers_dimensions=(16, 32, 64, 128),
    base_conv_layers_dimensions=(128, 128),
    output_conv_layers_dimensions=(16, 16),
    dropout=(),
    poolsize=2,
    steps_per_pooling=1,
    number_of_outputs=1,
    output_activation=None,
    loss="mse",
    layer_function=None,
    BatchNormalization=False,
    **kwargs
):
    """Creates a Regression U-Net (RU-Net).

    Parameters
    -----
    input_shape : tuple of ints
        Size of the images to be analyzed.
    conv_layers_dimensions : tuple of ints
        Number of convolutions in each convolutional layer during down-
        and upsampling.
    base_conv_layers_dimensions : tuple of ints
        Number of convolutions in each convolutional layer at the base
        of the unet, where the image is the most downsampled.
    output_conv_layers_dimensions : tuple of ints
        Number of convolutions in each convolutional layer after the
        upsampling.
    steps_per_pooling : int
        Number of convolutional layers between each pooling and upsampling
        step.
    number_of_outputs : int
        Number of convolutions in output layer.
    output_activation : str or keras activation
        The activation function of the output.
    loss : str or keras loss function
        The loss function of the network.
    layer_function : Callable[func] -> keras layer
        Function that returns a convolutional layer with convolutions
        determined by the input argument. Can be use to further customize the network.

    Returns
    -----
    keras.models.Model
    """
    def conv_step(layer, dimensions):
        layer = tf.keras.layers.Conv2D(
            dimensions, kernel_size=1, activation="relu", padding="same"
        )(layer)
        layer = tf.keras.layers.Conv2D(
            dimensions, kernel_size=3, activation="relu", padding="same"
        )(layer)
        layer = tf.keras.layers.Conv2D(
            dimensions, kernel_size=3, activation="relu", padding="same"
        )(layer)
        return layer

    if layer_function is None:
        layer_function = lambda dimensions: tf.keras.layers.Conv2D(
            conv_layer_dimension,
            kernel_size=3,
            activation="relu",
            padding="same",
        )

    unet_input = tf.keras.layers.Input(input_shape)
    concat_layers = []

    layer = unet_input

    # Downsampling step
    for conv_layer_dimension in conv_layers_dimensions:
        for _ in range(steps_per_pooling):
            layer = layer_function(conv_layer_dimension)(layer)
            concat_layers.append(layer)
            if BatchNormalization:
                layer = tf.keras.layers.BatchNormalization()(layer)
            if dropout:
                layer = tf.keras.layers.SpatialDropout2D(dropout[0])(layer)
                dropout = dropout[1:]
            layer = tf.keras.layers.MaxPooling2D(poolsize)(layer)

    # Base steps
    for conv_layer_dimension in base_conv_layers_dimensions:
        layer = layer_function(conv_layer_dimension)(layer)

    # Upsampling step
    regression_layer = layer
    for conv_layer_dimension, concat_layer in zip(
        reversed(upsample_layers_dimensions), reversed(concat_layers)
    ):
        layer = tf.keras.layers.Conv2DTranspose(
            conv_layer_dimension, kernel_size=poolsize, strides=poolsize
        )(layer)
        regression_layer = tf.keras.layers.Conv2DTranspose(
            conv_layer_dimension, kernel_size=poolsize, strides=poolsize
        )(regression_layer)
        layer = tf.keras.layers.Concatenate(axis=-1)(layer, concat_layer)
        regression_layer = tf.keras.layers.Concatenate(axis=-1)(
            regression_layer, concat_layer
        )
        for _ in range(steps_per_pooling):
            layer = layer_function(conv_layer_dimension)(layer)
            regression_layer = layer_function(conv_layer_dimension)(
                regression_layer
            )

    # Output step
    for conv_layer_dimension in output_conv_layers_dimensions:
        layer = layer_function(conv_layer_dimension)(layer)
        regression_layer = layer_function(conv_layer_dimension)(regression_layer)
        layer = tf.keras.layers.Conv2D(
            1,
            kernel_size=3,
            activation="sigmoid",
            padding="same",
            name="segmentationOutput",
        )(layer)
        regression_layer = tf.keras.layers.Concatenate(axis=-1)(
            regression_layer, layer
        )
        regression_layer = tf.keras.layers.Conv2D(
            number_of_outputs,
            kernel_size=3,
            activation=output_activation,
            padding="same",
            name="regressionOutput",
        )(regression_layer)
        output_layer = tf.keras.layers.Concatenate(axis=-1)(
            layer, regression_layer
        )
        model = tf.keras.models.Model(inputs=unet_input, outputs=output_layer)
    return model
```

4.2. Defining the loss function

We define a custom loss function as below for RU-Net.

```
In [18]: import tensorflow.keras.backend as K

eps = 1e-6

def softmax_categorical(T, P):
    classwise_weight = K.mean(1 - T, axis=(1, 2), keepdims=True)
    true_error = K.mean(T * K.log(P + eps) + classwise_weight, axis=-1)
    return -K.mean(true_error)

def unet_loss(weight=(1.0, 1, 0.1), num_features=1):
    def get_loss(y_true, y_pred):
        P1 = K.flatten(y_true[:, :, :, 1])
        P = K.flatten(y_pred[:, :, :, 0])
        error = K.abs(T - P)
        loss = -K.mean(
            weight[0] * T * K.log(P + 1e-4)
            + weight[1] * (1 - T) * K.log(1 - P + 1e-4)
        ) / (
            weight[0] + weight[1]
        )
        for i in range(num_features):
            T1 = K.flatten(y_true[:, :, :, i + 1])
            P1 = K.flatten(y_pred[:, :, :, i + 1])
            error = K.abs(T1 - P1)
            f_loss = K.sum(T * error) / (K.sum(T) + 1e-6) + K.sum(
                error * (1 - T)
            ) / (K.sum(1 - T) + 1e-6)
            loss += weight[2] * f_loss
        return loss
    return get_loss
```

4.3. Defining the model parameters

```
In [19]: model = regressionUnet(
    (None, None, 1),
    conv_layers_dimensions=[8, 16, 32, 64],
    base_conv_layers_dimensions=[32, 32],
    number_of_outputs=4,
    output_conv_layers_dimensions=[32, 32],
    loss=unet_loss(num_features=4, weight=(1, 1, 1)),
    output_activation=None,
)

model.summary()

Model: "functional_1"

Layer (type) Output Shape Param # Connected to
-----
input_1 (InputLayer) [(None, None, None, 0)
conv2d (Conv2D) (None, None, None, 8 0 input_1[0][0]
max_pooling2d (MaxPooling2D) (None, None, None, 8 0 conv2d[0][0]
conv2d_1 (Conv2D) (None, None, None, 1 1168 max_pooling2d[0][0]
max_pooling2d_1 (MaxPooling2D) (None, None, None, 1 0 conv2d_1[0][0]
conv2d_2 (Conv2D) (None, None, None, 3 4640 max_pooling2d_1[0][0]
max_pooling2d_2 (MaxPooling2D) (None, None, None, 3 0 conv2d_2[0][0]
conv2d_3 (Conv2D) (None, None, None, 6 18496 max_pooling2d_2[0][0]
conv2d_4 (Conv2D) (None, None, None, 3 18464 max_pooling2d_3[0][0]
conv2d_5 (Conv2D) (None, None, None, 3 9248 conv2d_4[0][0]
conv2d_transpose (Conv2DTranspose) (None, None, None, 1 9248 conv2d_5[0][0]
conv2d_transpose_1 (Conv2DTranspose) (None, None, None, 1 0 conv2d_transpose[0][0]
conv2d_transpose_2 (Conv2DTranspose) (None, None, None, 1 0 conv2d_transpose_1[0][0]
conv2d_transpose_3 (Conv2DTranspose) (None, None, None, 1 16512 conv2d_transpose_2[0][0]
conv2d_transpose_4 (Conv2DTranspose) (None, None, None, 1 221312 conv2d_transpose_3[0][0]
conv2d_transpose_5 (Conv2DTranspose) (None, None, None, 1 0 conv2d_transpose_4[0][0]
conv2d_transpose_6 (Conv2DTranspose) (None, None, None, 1 0 conv2d_transpose_5[0][0]
conv2d_transpose_7 (Conv2DTranspose) (None, None, None, 1 2064 conv2d_transpose_6[0][0]
conv2d_transpose_8 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_7[0][0]
conv2d_transpose_9 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_8[0][0]
conv2d_transpose_10 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_9[0][0]
conv2d_transpose_11 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_10[0][0]
conv2d_transpose_12 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_11[0][0]
conv2d_transpose_13 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_12[0][0]
conv2d_transpose_14 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_13[0][0]
conv2d_transpose_15 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_14[0][0]
conv2d_transpose_16 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_15[0][0]
conv2d_transpose_17 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_16[0][0]
conv2d_transpose_18 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_17[0][0]
conv2d_transpose_19 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_18[0][0]
conv2d_transpose_20 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_19[0][0]
conv2d_transpose_21 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_20[0][0]
conv2d_transpose_22 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_21[0][0]
conv2d_transpose_23 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_22[0][0]
conv2d_transpose_24 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_23[0][0]
conv2d_transpose_25 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_24[0][0]
conv2d_transpose_26 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_25[0][0]
conv2d_transpose_27 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_26[0][0]
conv2d_transpose_28 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_27[0][0]
conv2d_transpose_29 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_28[0][0]
conv2d_transpose_30 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_29[0][0]
conv2d_transpose_31 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_30[0][0]
conv2d_transpose_32 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_31[0][0]
conv2d_transpose_33 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_32[0][0]
conv2d_transpose_34 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_33[0][0]
conv2d_transpose_35 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_34[0][0]
conv2d_transpose_36 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_35[0][0]
conv2d_transpose_37 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_36[0][0]
conv2d_transpose_38 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_37[0][0]
conv2d_transpose_39 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_38[0][0]
conv2d_transpose_40 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_39[0][0]
conv2d_transpose_41 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_40[0][0]
conv2d_transpose_42 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_41[0][0]
conv2d_transpose_43 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_42[0][0]
conv2d_transpose_44 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_43[0][0]
conv2d_transpose_45 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_44[0][0]
conv2d_transpose_46 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_45[0][0]
conv2d_transpose_47 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_46[0][0]
conv2d_transpose_48 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_47[0][0]
conv2d_transpose_49 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_48[0][0]
conv2d_transpose_50 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_49[0][0]
conv2d_transpose_51 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_50[0][0]
conv2d_transpose_52 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_51[0][0]
conv2d_transpose_53 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_52[0][0]
conv2d_transpose_54 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_53[0][0]
conv2d_transpose_55 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_54[0][0]
conv2d_transpose_56 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_55[0][0]
conv2d_transpose_57 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_56[0][0]
conv2d_transpose_58 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_57[0][0]
conv2d_transpose_59 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_58[0][0]
conv2d_transpose_60 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_59[0][0]
conv2d_transpose_61 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_60[0][0]
conv2d_transpose_62 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_61[0][0]
conv2d_transpose_63 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_62[0][0]
conv2d_transpose_64 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_63[0][0]
conv2d_transpose_65 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_64[0][0]
conv2d_transpose_66 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_65[0][0]
conv2d_transpose_67 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_66[0][0]
conv2d_transpose_68 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_67[0][0]
conv2d_transpose_69 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_68[0][0]
conv2d_transpose_70 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_69[0][0]
conv2d_transpose_71 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_70[0][0]
conv2d_transpose_72 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_71[0][0]
conv2d_transpose_73 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_72[0][0]
conv2d_transpose_74 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_73[0][0]
conv2d_transpose_75 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_74[0][0]
conv2d_transpose_76 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_75[0][0]
conv2d_transpose_77 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_76[0][0]
conv2d_transpose_78 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_77[0][0]
conv2d_transpose_79 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_78[0][0]
conv2d_transpose_80 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_79[0][0]
conv2d_transpose_81 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_80[0][0]
conv2d_transpose_82 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_81[0][0]
conv2d_transpose_83 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_82[0][0]
conv2d_transpose_84 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_83[0][0]
conv2d_transpose_85 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_84[0][0]
conv2d_transpose_86 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_85[0][0]
conv2d_transpose_87 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_86[0][0]
conv2d_transpose_88 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_87[0][0]
conv2d_transpose_89 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_88[0][0]
conv2d_transpose_90 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_89[0][0]
conv2d_transpose_91 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_90[0][0]
conv2d_transpose_92 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_91[0][0]
conv2d_transpose_93 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_92[0][0]
conv2d_transpose_94 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_93[0][0]
conv2d_transpose_95 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_94[0][0]
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conv2d_transpose_100 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_99[0][0]
conv2d_transpose_101 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_100[0][0]
conv2d_transpose_102 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_101[0][0]
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conv2d_transpose_104 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_103[0][0]
conv2d_transpose_105 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_104[0][0]
conv2d_transpose_106 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_105[0][0]
conv2d_transpose_107 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_106[0][0]
conv2d_transpose_108 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_107[0][0]
conv2d_transpose_109 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_108[0][0]
conv2d_transpose_110 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_109[0][0]
conv2d_transpose_111 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_110[0][0]
conv2d_transpose_112 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_111[0][0]
conv2d_transpose_113 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_112[0][0]
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conv2d_transpose_115 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_114[0][0]
conv2d_transpose_116 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_115[0][0]
conv2d_transpose_117 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_116[0][0]
conv2d_transpose_118 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_117[0][0]
conv2d_transpose_119 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_118[0][0]
conv2d_transpose_120 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_119[0][0]
conv2d_transpose_121 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_120[0][0]
conv2d_transpose_122 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_121[0][0]
conv2d_transpose_123 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_122[0][0]
conv2d_transpose_124 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_123[0][0]
conv2d_transpose_125 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_124[0][0]
conv2d_transpose_126 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_125[0][0]
conv2d_transpose_127 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_126[0][0]
conv2d_transpose_128 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_127[0][0]
conv2d_transpose_129 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_128[0][0]
conv2d_transpose_130 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_129[0][0]
conv2d_transpose_131 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_130[0][0]
conv2d_transpose_132 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_131[0][0]
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conv2d_transpose_134 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_133[0][0]
conv2d_transpose_135 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_134[0][0]
conv2d_transpose_136 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_135[0][0]
conv2d_transpose_137 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_136[0][0]
conv2d_transpose_138 (Conv2DTranspose) (None, None, None, 1 3472 conv2d_transpose_137[0][0]
conv2d_transpose_139 (Conv2
```



```
[27]: #predictions
fig=plt.figure(figsize=(50,50))

[a,b,c,d]=[680,880,375,575]

plt.subplot(6,1,1)
plt.imshow((experimental_image/np.median(experimental_image))[a:b, c:d] , cmap="grey")
plt.title("Original")
plt.colorbar()

plt.subplot(6,1,2)
plt.imshow(np.squeeze(predicted_image[:, :, 0]) [a:b, c:d])
plt.title("Predicted, background")
plt.colorbar()

plt.subplot(6,1,3)
plt.imshow(np.squeeze(predicted_image[:, :, 1]) [a:b, c:d])
plt.title("Predicted, axial distance")
plt.colorbar()

plt.subplot(6,1,4)
plt.imshow(np.squeeze(predicted_image[:, :, 2]) [a:b, c:d])
plt.title("Predicted, dry mass")
plt.colorbar()

plt.subplot(6,1,5)
plt.imshow(np.squeeze(predicted_image[:, :, 3]) [a:b, c:d])
plt.title("Predicted, delta x")
plt.colorbar()

plt.subplot(6,1,6)
plt.imshow(np.squeeze(predicted_image[:, :, 4]) [a:b, c:d])
plt.title("Predicted, delta y")
plt.colorbar()

plt.show()
```

