Resnet Mode

```
In [ ]: import tensorflow as tf
        from tensorflow.keras.layers import Input, Add, Dense, Layer
        from tensorflow.keras.models import Model
        from tensorflow.keras.optimizers import Adam
        class H1Layer(Layer):
            def __init__(self, **kwargs):
                 super(H1Layer, self).__init__(**kwargs)
            def build(self, input_shape):
                 self.b = self.add_weight(shape=(input_shape[-1],),
                                          initializer='random normal',
                                          trainable=True)
                 super(H1Layer, self).build(input_shape)
            def call(self, x):
                 return self.b * (2 * x)
                #return (2 * x)
        class H2Layer(Layer):
            def __init__(self, h1, **kwargs):
                 super(H2Layer, self).__init__(**kwargs)
                 self.h1 = h1
            def call(self, x):
                 return (2*x*(self.h1(x)))-2
        class H3Layer(Layer):
            def __init__(self, h2, **kwargs):
                 super(H3Layer, self).__init__(**kwargs)
                 self.h2 = h2
            def call(self, x):
                 return (2*x*(self.h2(x)))-(4*self.h2(x))
        class H4Layer(Layer):
            def __init__(self, h3, **kwargs):
                super(H4Layer, self).__init__(**kwargs)
                 self.h3 = h3
            def call(self, x):
                 return (2*x*(self.h3(x)))-(6*self.h3(x))
        class TensorDecompositionLayer(Layer):
            def init (self, rank, **kwargs):
                 self.rank = rank
                 super(TensorDecompositionLayer, self).__init__(**kwargs)
            def build(self, input_shape):
```

```
self.factors_a = self.add_weight(shape=(input_shape[-1], self.rank),
                                         initializer='random_normal',
                                         trainable=True)
        self.factors_b = self.add_weight(shape=(self.rank, input_shape[-1]),
                                         initializer='random_normal',
                                         trainable=True)
        super(TensorDecompositionLayer, self).build(input_shape)
   def call(self, x):
        return tf.matmul(tf.matmul(x, self.factors_a), self.factors_b)
def polynomial_activation(x, degree=1):
   if degree == 1:
        return x
   elif degree == 2:
        return x * x
   elif degree == 3:
        return x**3
   elif degree ==4:
        return x**4
   else:
        raise ValueError("Invalid degree specified, only 1st, 2nd and 3rd degree po
def resnet_block(x, filters, activation_1, activation_2, rank=None):
   h1 = H1Layer()
   h2 = H2Layer(h1)
   x = Dense(filters)(x)
   x = h2(x)
   x = Dense(filters)(x)
   return x
def build_model(input_shape, num_blocks, filters, activation_1, activation_2, rank=
   input layer = Input(shape=input shape)
   x = input_layer
   for in range(num blocks):
        x = resnet_block(x, filters, activation_1, activation_2, rank)
   output_layer = Dense(1)(x)
   model = Model(inputs=input_layer, outputs=output_layer)
   return model
input\_shape = (1,)
num_blocks = 3
filters = 16
# activation_1 = tf.keras.activations.relu
activation_1 = lambda x: polynomial_activation(x, degree=1)
#activation 2 = tf.keras.activations.linear
activation_2 = lambda x: polynomial_activation(x, degree=1)
rank = 2
model = build_model(input_shape, num_blocks, filters, activation_1, activation_2, r
```

```
optimizer = Adam(learning_rate=0.00001) # Reduce Learning rate
model.compile(optimizer='adam', loss='mse')
```

- Just uses up to n= 2
- When applied Higher values explode and predictions become NAN
- Just trained for 300 epochs, good results appear before 100

```
In [ ]: import numpy as np
        np.random.seed(42)
        n_samples = 10000
        lower_bound = -2 * np.pi
        upper_bound = 2 * np.pi
        \#lower\_bound = -10
        #upper_bound = 10
        X = np.random.uniform(lower_bound, upper_bound, size=(n_samples, 1))
        y = np.cos(X)
        from sklearn.model_selection import train_test_split
        X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state
        batch_size = 64
        epochs = 300
        history = model.fit(X_train, y_train,
                             batch_size=batch_size,
                             epochs=epochs,
                             verbose=1,
                             validation_data=(X_val, y_val))
```

```
Epoch 1/300
9989e-04
Epoch 2/300
ss: 2.5815e-04
Epoch 3/300
ss: 1.9536e-04
Epoch 4/300
ss: 2.2846e-04
Epoch 5/300
ss: 2.2109e-04
Epoch 6/300
ss: 1.9032e-04
Epoch 7/300
ss: 2.9657e-04
Epoch 8/300
ss: 2.3761e-04
Epoch 9/300
ss: 7.3954e-04
Epoch 10/300
9.9799e-04
Epoch 11/300
ss: 3.2174e-04
Epoch 12/300
ss: 2.9682e-04
Epoch 13/300
ss: 2.7721e-04
Epoch 14/300
ss: 1.9927e-04
Epoch 15/300
ss: 2.2289e-04
Epoch 16/300
ss: 2.4305e-04
Epoch 17/300
ss: 4.3881e-04
Epoch 18/300
ss: 2.9173e-04
Epoch 19/300
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ss: 0.0011
Epoch 20/300
ss: 3.1900e-04
Epoch 21/300
ss: 3.0187e-04
Epoch 22/300
ss: 2.3844e-04
Epoch 23/300
ss: 4.3095e-04
Epoch 24/300
ss: 3.0362e-04
Epoch 25/300
ss: 3.2856e-04
Epoch 26/300
ss: 4.5812e-04
Epoch 27/300
ss: 4.1298e-04
Epoch 28/300
ss: 7.0030e-04
Epoch 29/300
ss: 3.1821e-04
Epoch 30/300
ss: 2.7011e-04
Epoch 31/300
ss: 2.4967e-04
Epoch 32/300
ss: 1.7664e-04
Epoch 33/300
ss: 2.5729e-04
Epoch 34/300
ss: 3.9529e-04
Epoch 35/300
ss: 8.7878e-04
Epoch 36/300
ss: 2.3609e-04
Epoch 37/300
ss: 2.2606e-04
Epoch 38/300
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ss: 2.9346e-04
Epoch 39/300
2.6308e-04
Epoch 40/300
ss: 2.0870e-04
Epoch 41/300
125/125 [===========] - 0s 935us/step - loss: 3.6899e-04 - val lo
ss: 2.3082e-04
Epoch 42/300
ss: 1.9689e-04
Epoch 43/300
ss: 3.3106e-04
Epoch 44/300
ss: 2.6976e-04
Epoch 45/300
ss: 6.8533e-04
Epoch 46/300
ss: 2.3376e-04
Epoch 47/300
ss: 3.1570e-04
Epoch 48/300
5.9289e-04
Epoch 49/300
ss: 3.0997e-04
Epoch 50/300
ss: 3.2725e-04
Epoch 51/300
ss: 5.5215e-04
Epoch 52/300
ss: 3.0774e-04
Epoch 53/300
ss: 2.3617e-04
Epoch 54/300
ss: 2.5875e-04
Epoch 55/300
ss: 0.0011
Epoch 56/300
ss: 0.0040
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Epoch 57/300
ss: 2.0359e-04
Epoch 58/300
ss: 0.0024
Epoch 59/300
ss: 6.5778e-04
Epoch 60/300
ss: 2.3066e-04
Epoch 61/300
ss: 5.1548e-04
Epoch 62/300
ss: 2.1132e-04
Epoch 63/300
ss: 0.0028
Epoch 64/300
4.3768e-04
Epoch 65/300
ss: 2.9563e-04
Epoch 66/300
ss: 2.1807e-04
Epoch 67/300
ss: 3.4431e-04
Epoch 68/300
ss: 2.0743e-04
Epoch 69/300
ss: 3.8378e-04
Epoch 70/300
ss: 1.8178e-04
Epoch 71/300
ss: 0.0045
Epoch 72/300
ss: 3.3002e-04
Epoch 73/300
ss: 2.7567e-04
Epoch 74/300
ss: 3.2205e-04
Epoch 75/300
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ss: 2.2033e-04
Epoch 76/300
ss: 2.4852e-04
Epoch 77/300
ss: 4.6560e-04
Epoch 78/300
ss: 4.2760e-04
Epoch 79/300
ss: 9.3792e-04
Epoch 80/300
ss: 4.3491e-04
Epoch 81/300
ss: 2.0003e-04
Epoch 82/300
ss: 2.3197e-04
Epoch 83/300
ss: 3.5214e-04
Epoch 84/300
ss: 3.3936e-04
Epoch 85/300
ss: 4.9366e-04
Epoch 86/300
ss: 4.2338e-04
Epoch 87/300
ss: 2.2118e-04
Epoch 88/300
ss: 4.0625e-04
Epoch 89/300
ss: 4.0907e-04
Epoch 90/300
ss: 6.2270e-04
Epoch 91/300
ss: 3.1046e-04
Epoch 92/300
ss: 2.7099e-04
Epoch 93/300
ss: 3.8175e-04
Epoch 94/300
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ss: 7.9996e-04
Epoch 95/300
ss: 2.8357e-04
Epoch 96/300
ss: 2.6260e-04
Epoch 97/300
125/125 [===========] - 0s 937us/step - loss: 5.2480e-04 - val lo
ss: 6.7679e-04
Epoch 98/300
ss: 5.2756e-04
Epoch 99/300
ss: 4.0544e-04
Epoch 100/300
ss: 2.3085e-04
Epoch 101/300
ss: 5.7679e-04
Epoch 102/300
ss: 3.5505e-04
Epoch 103/300
ss: 2.3477e-04
Epoch 104/300
ss: 6.5139e-04
Epoch 105/300
ss: 4.3056e-04
Epoch 106/300
ss: 5.8766e-04
Epoch 107/300
ss: 1.9171e-04
Epoch 108/300
ss: 2.5778e-04
Epoch 109/300
ss: 5.2843e-04
Epoch 110/300
ss: 3.5004e-04
Epoch 111/300
ss: 0.0010
Epoch 112/300
ss: 2.6675e-04
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Epoch 113/300
ss: 0.0012
Epoch 114/300
ss: 5.3969e-04
Epoch 115/300
ss: 3.0325e-04
Epoch 116/300
ss: 7.3187e-04
Epoch 117/300
ss: 2.1476e-04
Epoch 118/300
ss: 6.8005e-04
Epoch 119/300
ss: 4.6937e-04
Epoch 120/300
ss: 3.2968e-04
Epoch 121/300
ss: 0.0011
Epoch 122/300
ss: 2.5285e-04
Epoch 123/300
ss: 2.3238e-04
Epoch 124/300
ss: 7.5039e-04
Epoch 125/300
ss: 7.2906e-04
Epoch 126/300
ss: 1.8414e-04
Epoch 127/300
ss: 3.7566e-04
Epoch 128/300
ss: 4.8864e-04
Epoch 129/300
ss: 2.5620e-04
Epoch 130/300
ss: 2.1311e-04
Epoch 131/300
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ss: 4.2913e-04
Epoch 132/300
ss: 2.5499e-04
Epoch 133/300
ss: 3.7360e-04
Epoch 134/300
ss: 0.0034
Epoch 135/300
ss: 8.5245e-04
Epoch 136/300
ss: 7.4251e-04
Epoch 137/300
ss: 2.9799e-04
Epoch 138/300
ss: 2.6942e-04
Epoch 139/300
ss: 2.9634e-04
Epoch 140/300
ss: 2.1828e-04
Epoch 141/300
ss: 4.2096e-04
Epoch 142/300
ss: 3.8806e-04
Epoch 143/300
ss: 2.5108e-04
Epoch 144/300
ss: 5.5803e-04
Epoch 145/300
ss: 1.9914e-04
Epoch 146/300
ss: 2.5264e-04
Epoch 147/300
ss: 4.4443e-04
Epoch 148/300
ss: 3.8862e-04
Epoch 149/300
ss: 3.2726e-04
Epoch 150/300
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ss: 4.4276e-04
Epoch 151/300
ss: 4.0987e-04
Epoch 152/300
ss: 3.3218e-04
Epoch 153/300
ss: 5.9893e-04
Epoch 154/300
ss: 3.6592e-04
Epoch 155/300
ss: 2.5401e-04
Epoch 156/300
ss: 4.0790e-04
Epoch 157/300
ss: 4.6107e-04
Epoch 158/300
ss: 2.7759e-04
Epoch 159/300
ss: 4.1654e-04
Epoch 160/300
3.2780e-04
Epoch 161/300
ss: 2.8061e-04
Epoch 162/300
ss: 2.0388e-04
Epoch 163/300
ss: 3.4503e-04
Epoch 164/300
ss: 2.0606e-04
Epoch 165/300
ss: 3.6965e-04
Epoch 166/300
ss: 4.2515e-04
Epoch 167/300
ss: 2.0713e-04
Epoch 168/300
ss: 3.1398e-04
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Epoch 169/300
ss: 3.8013e-04
Epoch 170/300
ss: 2.0581e-04
Epoch 171/300
ss: 3.4173e-04
Epoch 172/300
ss: 4.7830e-04
Epoch 173/300
ss: 2.1215e-04
Epoch 174/300
ss: 3.4084e-04
Epoch 175/300
ss: 2.1494e-04
Epoch 176/300
ss: 2.3164e-04
Epoch 177/300
ss: 3.6401e-04
Epoch 178/300
ss: 4.3501e-04
Epoch 179/300
ss: 4.9910e-04
Epoch 180/300
ss: 2.7546e-04
Epoch 181/300
ss: 4.5182e-04
Epoch 182/300
ss: 2.4665e-04
Epoch 183/300
ss: 2.8320e-04
Epoch 184/300
ss: 2.9964e-04
Epoch 185/300
ss: 2.5144e-04
Epoch 186/300
ss: 5.7161e-04
Epoch 187/300
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ss: 2.8942e-04
Epoch 188/300
ss: 3.6266e-04
Epoch 189/300
ss: 2.7974e-04
Epoch 190/300
ss: 2.7604e-04
Epoch 191/300
ss: 4.1050e-04
Epoch 192/300
ss: 4.8691e-04
Epoch 193/300
ss: 7.6109e-04
Epoch 194/300
ss: 2.6623e-04
Epoch 195/300
ss: 3.0914e-04
Epoch 196/300
ss: 3.5438e-04
Epoch 197/300
ss: 2.1850e-04
Epoch 198/300
ss: 5.8242e-04
Epoch 199/300
ss: 2.7462e-04
Epoch 200/300
ss: 3.2626e-04
Epoch 201/300
s: 4.9040e-04
Epoch 202/300
ss: 3.9322e-04
Epoch 203/300
ss: 2.4644e-04
Epoch 204/300
ss: 2.2411e-04
Epoch 205/300
ss: 4.8670e-04
Epoch 206/300
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ss: 2.8518e-04
Epoch 207/300
ss: 4.0946e-04
Epoch 208/300
ss: 2.8293e-04
Epoch 209/300
125/125 [===========] - 0s 931us/step - loss: 3.6469e-04 - val lo
ss: 4.2455e-04
Epoch 210/300
125/125 [============] - 0s 936us/step - loss: 3.5546e-04 - val_lo
ss: 2.2053e-04
Epoch 211/300
ss: 7.4603e-04
Epoch 212/300
ss: 7.4813e-04
Epoch 213/300
ss: 2.4832e-04
Epoch 214/300
ss: 4.3882e-04
Epoch 215/300
ss: 2.7622e-04
Epoch 216/300
ss: 2.5697e-04
Epoch 217/300
ss: 3.4096e-04
Epoch 218/300
ss: 2.4670e-04
Epoch 219/300
ss: 6.7591e-04
Epoch 220/300
ss: 2.5022e-04
Epoch 221/300
ss: 3.8926e-04
Epoch 222/300
ss: 4.3060e-04
Epoch 223/300
ss: 1.8779e-04
Epoch 224/300
ss: 4.8510e-04
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Epoch 225/300
ss: 8.2755e-04
Epoch 226/300
ss: 2.0946e-04
Epoch 227/300
ss: 2.5861e-04
Epoch 228/300
ss: 2.9617e-04
Epoch 229/300
ss: 1.9993e-04
Epoch 230/300
ss: 2.8516e-04
Epoch 231/300
ss: 0.0013
Epoch 232/300
ss: 2.9388e-04
Epoch 233/300
ss: 2.5039e-04
Epoch 234/300
ss: 2.4219e-04
Epoch 235/300
ss: 1.8264e-04
Epoch 236/300
ss: 2.6753e-04
Epoch 237/300
ss: 4.5329e-04
Epoch 238/300
ss: 3.9686e-04
Epoch 239/300
ss: 6.1341e-04
Epoch 240/300
ss: 2.6280e-04
Epoch 241/300
ss: 3.5609e-04
Epoch 242/300
ss: 3.3690e-04
Epoch 243/300
```

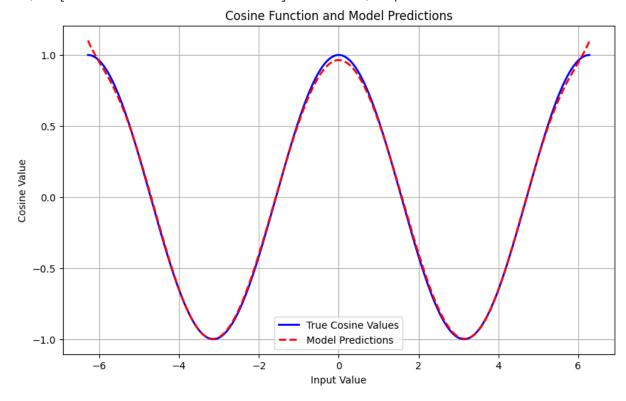
```
ss: 3.5740e-04
Epoch 244/300
ss: 1.8718e-04
Epoch 245/300
ss: 2.4812e-04
Epoch 246/300
ss: 2.4280e-04
Epoch 247/300
ss: 2.2795e-04
Epoch 248/300
ss: 5.2819e-04
Epoch 249/300
ss: 3.3930e-04
Epoch 250/300
ss: 2.2815e-04
Epoch 251/300
ss: 2.9354e-04
Epoch 252/300
ss: 2.5125e-04
Epoch 253/300
ss: 4.9274e-04
Epoch 254/300
ss: 1.9689e-04
Epoch 255/300
ss: 4.7815e-04
Epoch 256/300
ss: 2.1606e-04
Epoch 257/300
ss: 3.6534e-04
Epoch 258/300
ss: 2.3017e-04
Epoch 259/300
s: 3.3468e-04
Epoch 260/300
ss: 2.9721e-04
Epoch 261/300
ss: 2.2484e-04
Epoch 262/300
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ss: 5.3690e-04
Epoch 263/300
ss: 6.0077e-04
Epoch 264/300
ss: 0.0023
Epoch 265/300
125/125 [============] - 0s 940us/step - loss: 3.8045e-04 - val lo
ss: 4.2577e-04
Epoch 266/300
ss: 2.4248e-04
Epoch 267/300
ss: 3.0695e-04
Epoch 268/300
ss: 3.2753e-04
Epoch 269/300
ss: 3.6922e-04
Epoch 270/300
ss: 2.4000e-04
Epoch 271/300
ss: 2.9462e-04
Epoch 272/300
ss: 2.3128e-04
Epoch 273/300
ss: 2.0473e-04
Epoch 274/300
ss: 2.4051e-04
Epoch 275/300
ss: 5.8070e-04
Epoch 276/300
ss: 3.7938e-04
Epoch 277/300
ss: 3.1214e-04
Epoch 278/300
ss: 5.9967e-04
Epoch 279/300
ss: 1.9951e-04
Epoch 280/300
ss: 2.9964e-04
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Epoch 281/300
ss: 5.4941e-04
Epoch 282/300
ss: 5.3297e-04
Epoch 283/300
ss: 3.3563e-04
Epoch 284/300
ss: 2.9016e-04
Epoch 285/300
ss: 1.8703e-04
Epoch 286/300
ss: 2.4718e-04
Epoch 287/300
ss: 2.1201e-04
Epoch 288/300
ss: 2.5036e-04
Epoch 289/300
ss: 7.0423e-04
Epoch 290/300
ss: 3.8124e-04
Epoch 291/300
ss: 3.3972e-04
Epoch 292/300
ss: 4.3617e-04
Epoch 293/300
ss: 2.0218e-04
Epoch 294/300
ss: 6.0164e-04
Epoch 295/300
ss: 6.9189e-04
Epoch 296/300
ss: 3.6729e-04
Epoch 297/300
ss: 2.5479e-04
Epoch 298/300
ss: 8.6920e-04
Epoch 299/300
```

```
In [ ]: val_loss = model.evaluate(X_val, y_val, verbose=0)
        print(f"Validation loss: {val loss}")
        import matplotlib.pyplot as plt
        num test samples = 1000
        X_test = np.linspace(lower_bound, upper_bound, num=num_test_samples).reshape(-1, 1)
        y true = np.cos(X test)
        y_pred = model.predict(X_test)
        plt.figure(figsize=(10, 6))
        plt.plot(X_test, y_true, label='True Cosine Values', color='b', linewidth=2)
        plt.plot(X_test, y_pred, label='Model Predictions', color='r', linestyle='--', line
        plt.xlabel('Input Value')
        plt.ylabel('Cosine Value')
        plt.title('Cosine Function and Model Predictions')
        plt.legend()
        plt.grid()
        plt.show()
```

Validation loss: 0.00038418357144109905 32/32 [=======] - 0s 515us/step



Validation loss: 0.00038

LAYER MODE

```
In [ ]: import tensorflow as tf
        from tensorflow.keras.layers import Input, Add, Dense, Layer
        from tensorflow.keras.models import Model
        from tensorflow.keras.optimizers import Adam
        class H1Layer(Layer):
            def __init__(self, **kwargs):
                super(H1Layer, self).__init__(**kwargs)
            def build(self, input shape):
                self.b = self.add_weight(shape=(input_shape[-1],),
                                          initializer='random_normal',
                                          trainable=True)
                super(H1Layer, self).build(input_shape)
            def call(self, x):
                return self.b * (2 * x)
                #return (2 * x)
        class H2Layer(Layer):
            def __init__(self, h1, **kwargs):
                super(H2Layer, self). init (**kwargs)
                self.h1 = h1
            def call(self, x):
                return (2*x*(self.h1(x)))-2
        class H3Layer(Layer):
            def __init__(self, h2, **kwargs):
                super(H3Layer, self).__init__(**kwargs)
                self.h2 = h2
            def call(self, x):
                return (2*x*(self.h2(x)))-(4*self.h2(x))
        class H4Layer(Layer):
            def __init__(self, h3, **kwargs):
                super(H4Layer, self).__init__(**kwargs)
                self.h3 = h3
            def call(self, x):
                return (2*x*(self.h3(x)))-(6*self.h3(x))
        def build_model(input_shape, filters):
            input_layer = Input(shape=input_shape)
            x = input_layer
            h1 = H1Layer()
            h2 = H2Layer(h1)
            h3 = H3Layer(h2)
```

```
h4 = H4Layer(h3)
    x = Dense(filters)(x)
    x = h2(x)
   x = Dense(filters)(x)
    x = h3(x)
   x = Dense(filters)(x)
    x = h4(x)
    x = Dense(filters)(x)
    output_layer = Dense(1)(x)
    model = Model(inputs=input_layer, outputs=output_layer)
    return model
input_shape = (1,)
filters = 16
model = build_model(input_shape, filters)
optimizer = Adam(learning_rate=0.00001) # Reduce Learning rate
model.compile(optimizer='adam', loss='mse')
```

- n = 4
- Values does not explode since it is just one layer of each, On resnet it repeats the number of blocks
- Has to be trained arround 600 epochs to get proper results

```
In [ ]: import numpy as np
        np.random.seed(42)
        n \text{ samples} = 10000
        lower_bound = -2 * np.pi
        upper bound = 2 * np.pi
        \#Lower\_bound = -10
        #upper_bound = 10
        X = np.random.uniform(lower bound, upper bound, size=(n samples, 1))
        y = np.cos(X)
        from sklearn.model_selection import train_test_split
        X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state
        batch_size = 64
        epochs = 600
        history = model.fit(X_train, y_train,
                             batch_size=batch_size,
                             epochs=epochs,
                             verbose=1,
                             validation_data=(X_val, y_val))
```

```
Epoch 1/600
loss: 1276851.8750
Epoch 2/600
loss: 1019170.6875
Epoch 3/600
oss: 817324.3750
Epoch 4/600
s: 647281.8125
Epoch 5/600
oss: 518242.2500
Epoch 6/600
oss: 422671.1250
Epoch 7/600
oss: 361106.1250
Epoch 8/600
oss: 319342.0938
Epoch 9/600
oss: 292208.1562
Epoch 10/600
oss: 273723.7812
Epoch 11/600
oss: 257008.8125
Epoch 12/600
oss: 245400.6406
Epoch 13/600
oss: 233437.2031
Epoch 14/600
oss: 223296.2500
Epoch 15/600
oss: 213733.6250
Epoch 16/600
oss: 205211.1406
Epoch 17/600
oss: 196651.4062
Epoch 18/600
oss: 188842.0781
Epoch 19/600
```

```
oss: 182335.1406
Epoch 20/600
oss: 173950.9844
Epoch 21/600
oss: 166765.8906
Epoch 22/600
oss: 160311.4844
Epoch 23/600
oss: 153316.2031
Epoch 24/600
oss: 148960.6719
Epoch 25/600
oss: 140235.5938
Epoch 26/600
oss: 133998.7812
Epoch 27/600
oss: 129615.2031
Epoch 28/600
oss: 120997.3984
Epoch 29/600
oss: 115027.4062
Epoch 30/600
oss: 109245.3984
Epoch 31/600
oss: 102967.5312
Epoch 32/600
ss: 96522.3438
Epoch 33/600
ss: 90743.1250
Epoch 34/600
ss: 84302.1094
Epoch 35/600
ss: 80464.9062
Epoch 36/600
ss: 74693.6484
Epoch 37/600
ss: 63487.3164
Epoch 38/600
```

```
ss: 56038.9805
Epoch 39/600
ss: 49487.6641
Epoch 40/600
ss: 40003.6094
Epoch 41/600
125/125 [===========] - 0s 957us/step - loss: 34846.6133 - val lo
ss: 31368.6914
Epoch 42/600
ss: 24278.6602
Epoch 43/600
ss: 17738.2285
Epoch 44/600
ss: 12378.9316
Epoch 45/600
ss: 8257.5117
Epoch 46/600
s: 5710.0649
Epoch 47/600
s: 4122.0020
Epoch 48/600
s: 2332.8792
Epoch 49/600
s: 1673.3623
Epoch 50/600
s: 1547.1133
Epoch 51/600
s: 1971.7130
Epoch 52/600
s: 1111.4652
Epoch 53/600
s: 915.5558
Epoch 54/600
125/125 [=============== ] - 0s 932us/step - loss: 1206.2803 - val_los
s: 1160.9067
Epoch 55/600
s: 811.4371
Epoch 56/600
s: 1505.0990
```

```
Epoch 57/600
s: 761.6125
Epoch 58/600
s: 831.0743
Epoch 59/600
s: 736.5197
Epoch 60/600
s: 722.0576
Epoch 61/600
s: 629.0802
Epoch 62/600
s: 748.1063
Epoch 63/600
s: 1000.4028
Epoch 64/600
s: 561.8860
Epoch 65/600
s: 800.6354
Epoch 66/600
s: 1174.6930
Epoch 67/600
s: 1074.1169
Epoch 68/600
s: 488.2314
Epoch 69/600
s: 571.8184
Epoch 70/600
s: 521.0869
Epoch 71/600
s: 437.9417
Epoch 72/600
s: 597.3618
Epoch 73/600
s: 480.8543
Epoch 74/600
s: 379.6210
Epoch 75/600
```

```
s: 395.6931
Epoch 76/600
s: 426.1862
Epoch 77/600
s: 349.2906
Epoch 78/600
s: 475.1355
Epoch 79/600
s: 2026.3497
Epoch 80/600
s: 2395.2734
Epoch 81/600
s: 322.9944
Epoch 82/600
s: 986.7665
Epoch 83/600
s: 3599.5144
Epoch 84/600
s: 2447.6194
Epoch 85/600
s: 8488.3027
Epoch 86/600
s: 11528.7715
Epoch 87/600
ss: 806.7758
Epoch 88/600
ss: 5868.4810
Epoch 89/600
125/125 [================ ] - 0s 948us/step - loss: 2884.1819 - val_los
s: 860.2871
Epoch 90/600
ss: 17130.9941
Epoch 91/600
s: 5551.3765
Epoch 92/600
ss: 26195.2715
Epoch 93/600
ss: 20059.5215
Epoch 94/600
```

```
ss: 34115.3984
Epoch 95/600
s: 345.6289
Epoch 96/600
s: 44919.0781
Epoch 97/600
ss: 4623.0293
Epoch 98/600
ss: 228.4012
Epoch 99/600
s: 375.6993
Epoch 100/600
s: 239.8168
Epoch 101/600
s: 264.9565
Epoch 102/600
s: 61437.9961
Epoch 103/600
ss: 490.2524
Epoch 104/600
s: 821.6905
Epoch 105/600
ss: 7129.7378
Epoch 106/600
ss: 4332.3291
Epoch 107/600
ss: 20617.1777
Epoch 108/600
ss: 2083.4531
Epoch 109/600
ss: 14426.4902
Epoch 110/600
ss: 657.2724
Epoch 111/600
s: 272.7592
Epoch 112/600
s: 32402.0312
```

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Epoch 113/600
ss: 974.9263
Epoch 114/600
ss: 17058.0020
Epoch 115/600
ss: 355.6284
Epoch 116/600
s: 1555.3185
Epoch 117/600
s: 420.8553
Epoch 118/600
125/125 [=============== ] - 0s 939us/step - loss: 6402.0405 - val_los
s: 9219.7285
Epoch 119/600
s: 121997.4375
Epoch 120/600
ss: 284.3832
Epoch 121/600
s: 683.6874
Epoch 122/600
s: 2902.4553
Epoch 123/600
s: 2016.7931
Epoch 124/600
s: 21388.3945
Epoch 125/600
s: 8079.4907
Epoch 126/600
s: 122.4553
Epoch 127/600
s: 465.5215
Epoch 128/600
s: 1117.4768
Epoch 129/600
s: 495.6732
Epoch 130/600
s: 5761.0688
Epoch 131/600
```

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s: 248.2971
Epoch 132/600
s: 6316.7939
Epoch 133/600
s: 1230.3436
Epoch 134/600
s: 472.9588
Epoch 135/600
s: 703.8463
Epoch 136/600
s: 632.0864
Epoch 137/600
s: 130.5993
Epoch 138/600
s: 388.2206
Epoch 139/600
s: 52.8147
Epoch 140/600
s: 749.9799
Epoch 141/600
s: 894.8829
Epoch 142/600
125/125 [=============== ] - 0s 942us/step - loss: 4246.6118 - val_los
s: 114.9303
Epoch 143/600
s: 487.0881
Epoch 144/600
s: 1176.8020
Epoch 145/600
s: 109.6760
Epoch 146/600
125/125 [================= ] - 0s 948us/step - loss: 2545.0037 - val_los
s: 420.0151
Epoch 147/600
s: 5209.7407
Epoch 148/600
s: 98.4271
Epoch 149/600
s: 33311.1328
Epoch 150/600
```

```
125/125 [============] - 0s 943us/step - loss: 5308.6587 - val_los
s: 31.0927
Epoch 151/600
53.3165
Epoch 152/600
125/125 [================= ] - 0s 947us/step - loss: 51.7583 - val_loss:
124.7220
Epoch 153/600
125/125 [================= ] - 0s 938us/step - loss: 76.7934 - val_loss:
62.5165
Epoch 154/600
125/125 [============== ] - 0s 937us/step - loss: 74.2726 - val_loss:
97.3857
Epoch 155/600
s: 169.6882
Epoch 156/600
s: 47.3723
Epoch 157/600
s: 52.3664
Epoch 158/600
s: 56.6394
Epoch 159/600
s: 2558.4807
Epoch 160/600
s: 57.9927
Epoch 161/600
s: 243.7272
Epoch 162/600
s: 34.9272
Epoch 163/600
s: 30.6647
Epoch 164/600
s: 25.3110
Epoch 165/600
125/125 [================= ] - 0s 932us/step - loss: 93.5037 - val_loss:
114.7529
Epoch 166/600
s: 78.8786
Epoch 167/600
s: 509.1085
Epoch 168/600
s: 16.0887
```

```
Epoch 169/600
125/125 [=============== ] - 0s 944us/step - loss: 63.9946 - val_loss:
35.9673
Epoch 170/600
125/125 [================ ] - 0s 951us/step - loss: 67.5534 - val_loss:
18.2196
Epoch 171/600
s: 456.1453
Epoch 172/600
s: 94.6872
Epoch 173/600
s: 77.2884
Epoch 174/600
19.3656
Epoch 175/600
s: 677.3408
Epoch 176/600
s: 23.0918
Epoch 177/600
12.3676
Epoch 178/600
s: 381.3550
Epoch 179/600
s: 7.7418
Epoch 180/600
125/125 [=============] - 0s 952us/step - loss: 14.0000 - val_loss:
7.5871
Epoch 181/600
11.1510
Epoch 182/600
125/125 [================= ] - 0s 944us/step - loss: 63.5266 - val_loss:
548.1908
Epoch 183/600
s: 56.1533
Epoch 184/600
s: 10.7425
Epoch 185/600
53.5913
Epoch 186/600
125/125 [=============== ] - 0s 950us/step - loss: 45.6273 - val_loss:
73.8190
Epoch 187/600
```

```
s: 656.6247
Epoch 188/600
s: 6.1328
Epoch 189/600
Epoch 190/600
35.2476
Epoch 191/600
s: 7.6579
Epoch 192/600
2.6782
Epoch 193/600
43.6082
Epoch 194/600
125/125 [=============== ] - 0s 960us/step - loss: 96.7617 - val_loss:
10.6598
Epoch 195/600
57.7062
Epoch 196/600
3.3224
Epoch 197/600
96.2533
Epoch 198/600
125/125 [============== ] - 0s 941us/step - loss: 37.7227 - val_loss:
3.3527
Epoch 199/600
s: 15.2633
Epoch 200/600
0.5754
Epoch 201/600
1.5928
Epoch 202/600
0.4158
Epoch 203/600
4.4234
Epoch 204/600
4.6812
Epoch 205/600
6.8483
Epoch 206/600
```

```
125/125 [============] - 0s 946us/step - loss: 23.4335 - val_loss:
66.8272
Epoch 207/600
s: 1.4675
Epoch 208/600
1.3318
Epoch 209/600
0.2657
Epoch 210/600
Epoch 211/600
Epoch 212/600
1.6327
Epoch 213/600
0.3322
Epoch 214/600
237.3506
Epoch 215/600
2.7715
Epoch 216/600
0.3518
Epoch 217/600
0.2619
Epoch 218/600
0.2060
Epoch 219/600
0.3872
Epoch 220/600
1.2513
Epoch 221/600
0.5911
Epoch 222/600
125/125 [=============== ] - 0s 936us/step - loss: 15.1355 - val_loss:
Epoch 223/600
4.6271
Epoch 224/600
84.0281
```

```
Epoch 225/600
125/125 [=============== ] - 0s 937us/step - loss: 15.1741 - val_loss:
0.8519
Epoch 226/600
0.9064
Epoch 227/600
Epoch 228/600
Epoch 229/600
0.2135
Epoch 230/600
0.8041
Epoch 231/600
39.2556
Epoch 232/600
125/125 [================== ] - 0s 941us/step - loss: 19.8258 - val_loss:
0.4622
Epoch 233/600
0.7796
Epoch 234/600
0.2190
Epoch 235/600
0.7014
Epoch 236/600
1.1734
Epoch 237/600
0.1675
Epoch 238/600
1.4891
Epoch 239/600
3.0948
Epoch 240/600
0.1813
Epoch 241/600
8.4712
Epoch 242/600
0.0977
Epoch 243/600
```

```
0.0611
Epoch 244/600
Epoch 245/600
Epoch 246/600
0.5755
Epoch 247/600
0.1210
Epoch 248/600
0.1121
Epoch 249/600
0.0354
Epoch 250/600
0.0571
Epoch 251/600
0.0346
Epoch 252/600
0.0237
Epoch 253/600
0.0218
Epoch 254/600
0.0255
Epoch 255/600
0.0217
Epoch 256/600
0.0280
Epoch 257/600
0.0457
Epoch 258/600
0.0372
Epoch 259/600
0.0456
Epoch 260/600
0.0189
Epoch 261/600
0.0144
Epoch 262/600
```

```
0.2323
Epoch 263/600
0.2133
Epoch 264/600
0.0167
Epoch 265/600
0.1366
Epoch 266/600
Epoch 267/600
Epoch 268/600
0.0230
Epoch 269/600
0.7544
Epoch 270/600
0.0110
Epoch 271/600
0.0593
Epoch 272/600
25.9112
Epoch 273/600
0.0126
Epoch 274/600
0.0089
Epoch 275/600
0.0079
Epoch 276/600
0.0063
Epoch 277/600
0.0059
Epoch 278/600
0.0442
Epoch 279/600
0.0461
Epoch 280/600
13.3144
```

```
Epoch 281/600
0.1353
Epoch 282/600
0.0887
Epoch 283/600
Epoch 284/600
Epoch 285/600
0.0076
Epoch 286/600
0.0752
Epoch 287/600
0.0300
Epoch 288/600
5.9786
Epoch 289/600
0.3831
Epoch 290/600
0.0685
Epoch 291/600
0.2285
Epoch 292/600
0.1164
Epoch 293/600
0.2961
Epoch 294/600
0.0090
Epoch 295/600
0.0133
Epoch 296/600
4.7658
Epoch 297/600
0.0023
Epoch 298/600
8.4000e-04
Epoch 299/600
```

```
0.0016
Epoch 300/600
Epoch 301/600
Epoch 302/600
7.4690e-04
Epoch 303/600
0.2419
Epoch 304/600
0.0115
Epoch 305/600
5.7291e-04
Epoch 306/600
2.6593e-04
Epoch 307/600
0.0605
Epoch 308/600
0.1236
Epoch 309/600
0.0020
Epoch 310/600
0.0231
Epoch 311/600
0.0938
Epoch 312/600
0.0063
Epoch 313/600
4.6858e-04
Epoch 314/600
9.5985e-04
Epoch 315/600
0.0023
Epoch 316/600
0.0359
Epoch 317/600
0.2756
Epoch 318/600
```

```
0.0010
Epoch 319/600
ss: 1.1497e-04
Epoch 320/600
ss: 0.0032
Epoch 321/600
15.5338
Epoch 322/600
Epoch 323/600
0.0010
Epoch 324/600
ss: 1.9076e-04
Epoch 325/600
ss: 1.7681e-04
Epoch 326/600
ss: 2.1057e-04
Epoch 327/600
ss: 4.9664e-05
Epoch 328/600
ss: 4.3848e-05
Epoch 329/600
ss: 1.3562e-04
Epoch 330/600
ss: 6.5467e-05
Epoch 331/600
ss: 5.3193e-05
Epoch 332/600
ss: 9.9064e-05
Epoch 333/600
ss: 2.8471e-04
Epoch 334/600
ss: 5.2122e-05
Epoch 335/600
0.0035
Epoch 336/600
0.1603
```

```
Epoch 337/600
1.3132e-04
Epoch 338/600
0.0661
Epoch 339/600
Epoch 340/600
Epoch 341/600
0.0320
Epoch 342/600
0.0037
Epoch 343/600
0.0172
Epoch 344/600
4.4520
Epoch 345/600
4.9724e-04
Epoch 346/600
ss: 3.1672e-04
Epoch 347/600
ss: 3.7769e-04
Epoch 348/600
8.4644e-04
Epoch 349/600
0.0011
Epoch 350/600
s: 0.7576
Epoch 351/600
0.3575
Epoch 352/600
0.3444
Epoch 353/600
0.2941
Epoch 354/600
0.2559
Epoch 355/600
```

```
0.3569
Epoch 356/600
0.2108
Epoch 357/600
Epoch 358/600
0.1792
Epoch 359/600
0.1533
Epoch 360/600
0.1554
Epoch 361/600
0.1327
Epoch 362/600
0.1148
Epoch 363/600
0.1347
Epoch 364/600
0.0919
Epoch 365/600
0.0848
Epoch 366/600
0.0718
Epoch 367/600
0.0618
Epoch 368/600
0.0584
Epoch 369/600
0.0540
Epoch 370/600
0.0578
Epoch 371/600
0.0421
Epoch 372/600
0.0388
Epoch 373/600
0.0431
Epoch 374/600
```

```
0.0231
Epoch 375/600
0.0373
Epoch 376/600
0.0220
Epoch 377/600
0.0163
Epoch 378/600
Epoch 379/600
0.0155
Epoch 380/600
0.0195
Epoch 381/600
0.0136
Epoch 382/600
0.0103
Epoch 383/600
0.0074
Epoch 384/600
0.0075
Epoch 385/600
0.1248
Epoch 386/600
0.1165
Epoch 387/600
0.1322
Epoch 388/600
0.0284
Epoch 389/600
0.0074
Epoch 390/600
0.0723
Epoch 391/600
0.0236
Epoch 392/600
0.0703
```

```
Epoch 393/600
0.0599
Epoch 394/600
0.1749
Epoch 395/600
Epoch 396/600
Epoch 397/600
0.0422
Epoch 398/600
0.0246
Epoch 399/600
0.0396
Epoch 400/600
0.0278
Epoch 401/600
0.0215
Epoch 402/600
0.0484
Epoch 403/600
0.3874
Epoch 404/600
0.0559
Epoch 405/600
0.0144
Epoch 406/600
0.0715
Epoch 407/600
0.0682
Epoch 408/600
0.0053
Epoch 409/600
0.5150
Epoch 410/600
0.0234
Epoch 411/600
```

```
0.0114
Epoch 412/600
0.0080
Epoch 413/600
Epoch 414/600
0.0305
Epoch 415/600
0.0222
Epoch 416/600
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Epoch 417/600
0.0061
Epoch 418/600
0.0302
Epoch 419/600
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Epoch 420/600
0.0252
Epoch 421/600
0.0300
Epoch 422/600
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Epoch 423/600
0.0067
Epoch 424/600
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Epoch 425/600
Epoch 426/600
0.0067
Epoch 427/600
0.0014
Epoch 428/600
0.0034
Epoch 429/600
0.0016
Epoch 430/600
```

```
0.0029
Epoch 431/600
0.0327
Epoch 432/600
0.0053
Epoch 433/600
0.0159
Epoch 434/600
Epoch 435/600
0.0634
Epoch 436/600
0.0042
Epoch 437/600
0.0071
Epoch 438/600
0.0011
Epoch 439/600
0.0039
Epoch 440/600
0.0048
Epoch 441/600
0.0582
Epoch 442/600
0.0062
Epoch 443/600
9.8442e-04
Epoch 444/600
0.1113
Epoch 445/600
0.0024
Epoch 446/600
Epoch 447/600
0.0036
Epoch 448/600
0.0337
```

```
Epoch 449/600
7.8102e-04
Epoch 450/600
0.0693
Epoch 451/600
Epoch 452/600
Epoch 453/600
0.0025
Epoch 454/600
0.0020
Epoch 455/600
2.4725e-04
Epoch 456/600
0.0029
Epoch 457/600
0.0020
Epoch 458/600
0.0192
Epoch 459/600
0.0073
Epoch 460/600
0.0014
Epoch 461/600
0.0054
Epoch 462/600
0.0147
Epoch 463/600
0.0015
Epoch 464/600
0.0131
Epoch 465/600
0.0464
Epoch 466/600
3.5544e-04
Epoch 467/600
```

```
ss: 3.4677e-04
Epoch 468/600
0.0018
Epoch 469/600
Epoch 470/600
0.0312
Epoch 471/600
1.5964e-04
Epoch 472/600
ss: 2.6574e-04
Epoch 473/600
ss: 6.8929e-04
Epoch 474/600
0.0023
Epoch 475/600
ss: 1.4895e-04
Epoch 476/600
0.0035
Epoch 477/600
0.0561
Epoch 478/600
0.0018
Epoch 479/600
ss: 2.6009e-04
Epoch 480/600
ss: 6.4464e-04
Epoch 481/600
0.3680
Epoch 482/600
0.0046
Epoch 483/600
0.0053
Epoch 484/600
2.2083e-04
Epoch 485/600
0.0308
Epoch 486/600
```

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0.0305
Epoch 487/600
0.0042
Epoch 488/600
0.0304
Epoch 489/600
6.0824e-04
Epoch 490/600
Epoch 491/600
1.6909e-04
Epoch 492/600
5.9077e-04
Epoch 493/600
0.0026
Epoch 494/600
3.3672e-04
Epoch 495/600
ss: 0.0011
Epoch 496/600
2.1595e-04
Epoch 497/600
ss: 2.1600e-04
Epoch 498/600
0.0039
Epoch 499/600
0.0284
Epoch 500/600
0.0047
Epoch 501/600
6.4339e-04
Epoch 502/600
0.0021
Epoch 503/600
5.1906e-04
Epoch 504/600
8.6983e-04
```

```
Epoch 505/600
2.7660e-04
Epoch 506/600
0.0019
Epoch 507/600
Epoch 508/600
Epoch 509/600
1.0423e-04
Epoch 510/600
ss: 2.5346e-04
Epoch 511/600
ss: 2.4650e-04
Epoch 512/600
ss: 8.5352e-05
Epoch 513/600
ss: 2.7494e-04
Epoch 514/600
ss: 1.7937e-04
Epoch 515/600
0.0532
Epoch 516/600
5.1995e-05
Epoch 517/600
ss: 6.0552e-05
Epoch 518/600
ss: 3.4690e-05
Epoch 519/600
ss: 4.1109e-05
Epoch 520/600
ss: 4.6548e-05
Epoch 521/600
ss: 1.0690e-04
Epoch 522/600
ss: 4.2453e-05
Epoch 523/600
```

```
ss: 3.2718e-05
Epoch 524/600
ss: 4.4730e-05
Epoch 525/600
ss: 1.5068e-04
Epoch 526/600
ss: 5.1879e-05
Epoch 527/600
ss: 1.7254e-04
Epoch 528/600
ss: 1.2623e-04
Epoch 529/600
ss: 0.0022
Epoch 530/600
2.5610e-05
Epoch 531/600
ss: 1.6421e-05
Epoch 532/600
ss: 1.3686e-04
Epoch 533/600
ss: 3.2327e-05
Epoch 534/600
ss: 0.0043
Epoch 535/600
0.0016
Epoch 536/600
ss: 6.3579e-05
Epoch 537/600
ss: 7.3695e-06
Epoch 538/600
ss: 7.2372e-05
Epoch 539/600
ss: 3.8247e-04
Epoch 540/600
33.6107
Epoch 541/600
0.0538
Epoch 542/600
```

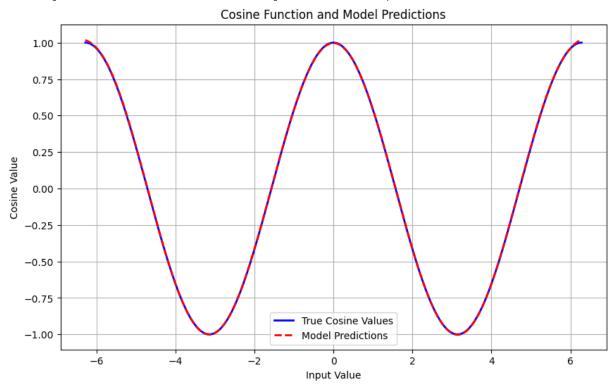
```
0.0374
Epoch 543/600
0.0306
Epoch 544/600
0.0222
Epoch 545/600
0.0150
Epoch 546/600
Epoch 547/600
0.0057
Epoch 548/600
0.0045
Epoch 549/600
0.0036
Epoch 550/600
0.0027
Epoch 551/600
0.0026
Epoch 552/600
0.0022
Epoch 553/600
0.0022
Epoch 554/600
0.0021
Epoch 555/600
0.0020
Epoch 556/600
0.0021
Epoch 557/600
0.0018
Epoch 558/600
0.0017
Epoch 559/600
0.0016
Epoch 560/600
0.0016
```

```
Epoch 561/600
0.0018
Epoch 562/600
0.0017
Epoch 563/600
Epoch 564/600
Epoch 565/600
0.0014
Epoch 566/600
0.0012
Epoch 567/600
0.0026
Epoch 568/600
0.0013
Epoch 569/600
0.0020
Epoch 570/600
0.0013
Epoch 571/600
0.0044
Epoch 572/600
0.0010
Epoch 573/600
8.0223e-04
Epoch 574/600
0.0013
Epoch 575/600
0.0012
Epoch 576/600
6.7772e-04
Epoch 577/600
ss: 7.8066e-04
Epoch 578/600
5.0716e-04
Epoch 579/600
```

```
0.0027
Epoch 580/600
ss: 0.0034
Epoch 581/600
Epoch 582/600
7.4119e-04
Epoch 583/600
0.0099
Epoch 584/600
0.0012
Epoch 585/600
6.5049e-04
Epoch 586/600
ss: 0.0020
Epoch 587/600
0.0012
Epoch 588/600
125/125 [============== ] - 0s 944us/step - loss: 9.1598e-04 - val_lo
ss: 8.0035e-04
Epoch 589/600
ss: 6.8720e-04
Epoch 590/600
ss: 1.6684e-04
Epoch 591/600
2.0361e-04
Epoch 592/600
1.8657e-04
Epoch 593/600
ss: 1.4808e-04
Epoch 594/600
ss: 0.0034
Epoch 595/600
0.0037
Epoch 596/600
ss: 2.3268e-04
Epoch 597/600
0.0017
Epoch 598/600
```

```
In [ ]: val_loss = model.evaluate(X_val, y_val, verbose=0)
        print(f"Validation loss: {val_loss}")
        import matplotlib.pyplot as plt
        num_test_samples = 1000
        X_test = np.linspace(lower_bound, upper_bound, num=num_test_samples).reshape(-1, 1)
        y_true = np.cos(X_test)
        y_pred = model.predict(X_test)
        plt.figure(figsize=(10, 6))
        plt.plot(X_test, y_true, label='True Cosine Values', color='b', linewidth=2)
        plt.plot(X_test, y_pred, label='Model Predictions', color='r', linestyle='--', line
        plt.xlabel('Input Value')
        plt.ylabel('Cosine Value')
        plt.title('Cosine Function and Model Predictions')
        plt.legend()
        plt.grid()
        plt.show()
```

Validation loss: 1.1370399079169147e-05 32/32 [=======] - 0s 527us/step



Validation loss: 0.000011