Combined PINN Training and Estimating Paramters (Inverse Problem)

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import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
# -- Forward problem: known parameters (real values)
lamb real = 2.0
mu_real = 1.0
0 = 4.0
# Neural Network definition
class SimplePINN(tf.keras.Model):
         def __init__(self, layer_sizes):
                  super(SimplePINN, self).__init__()
                  self.hidden_layers = [tf.keras.layers.Dense(size, activation='tanh') for size in layer_sizes[:-1]]
                  self.output_layer = tf.keras.layers.Dense(layer_sizes[-1])
         def call(self, x):
                  for layer in self.hidden_layers:
                          x = laver(x)
                   return self.output_layer(x)
def stiffness_matrix(lamb, mu, case="plane_strain"):
         lamb = tf.convert_to_tensor(lamb, dtype=tf.float32)
         mu = tf.convert_to_tensor(mu, dtype=tf.float32)
         if case == "plane_stress":
                 raise ValueError("Invalid case: Choose 'plane stress' or 'plane strain'")
         elif case == "plane_strain":
                 C11 = lamb + 2*mu
                 C12 = lamb
                 C66 = mu
                  raise ValueError("Invalid case: Choose 'plane_stress' or 'plane_strain'")
                 [C11, C12, 0],
                  [C12, C11, 0],
                  [0, 0, C66]
         1)
         return C
def body_force_fn(points, lamb, mu, Q):
         x = points[:,0:1]
         y = points[:,1:2]
         f0 = lamb * (4 * np.pi ** 2 * tf.cos(2 * np.pi * x) * tf.sin(np.pi * y) - np.pi * tf.cos(np.pi * x) * Q * y**3) + \
                   mu * (9 * np.pi ** 2 * tf.cos(2 * np.pi * x) * tf.sin(np.pi * y) - np.pi * tf.cos(np.pi * x) * Q * y**3)
          \texttt{f1} = \texttt{lamb} * (-3 * \texttt{tf.sin}(\texttt{np.pi} * \texttt{x}) * \texttt{Q} * \texttt{y**2} + \texttt{2} * (\texttt{np.pi**2}) * \texttt{tf.sin}(\texttt{2} * \texttt{np.pi} * \texttt{x}) * \texttt{tf.cos}(\texttt{np.pi} * \texttt{y})) + \texttt{Note of the property of th
                     \\ \text{mu * (-6 * tf.sin(np.pi * x) * Q * y**2 + 2 * (np.pi**2) * tf.sin(2 * np.pi * x) * tf.cos(np.pi * y) + ((np.pi**2) * tf.sin(np.pi * x) * tf.cos(np.pi * y) + ((np.pi**2) * tf.sin(np.pi * x) * tf.cos(np.pi * y) + ((np.pi**2) * tf.sin(np.pi * x) * tf.cos(np.pi * y) + ((np.pi**2) * tf.sin(np.pi * x) * tf.cos(np.pi * y) + ((np.pi**2) * tf.sin(np.pi * x) * tf.cos(np.pi * y) + ((np.pi**2) * tf.sin(np.pi * x) * tf.cos(np.pi * y) + ((np.pi**2) * tf.sin(np.pi * x) * tf.cos(np.pi * y) + ((np.pi**2) * tf.sin(np.pi * x) * tf.cos(np.pi * y) + ((np.pi**2) * tf.sin(np.pi * x) * tf.cos(np.pi * y) + ((np.pi**2) * tf.sin(np.pi * x) * tf.cos(np.pi * y) + ((np.pi**2) * tf.sin(np.pi * x) * tf.cos(np.pi * y) + ((np.pi**2) * tf.sin(np.pi * x) * tf.cos(np.pi * y) + ((np.pi**2) * tf.sin(np.pi * x) * tf.cos(np.pi * y) + ((np.pi**2) * tf.sin(np.pi * x) * tf.cos(np.pi * x) * 
         return tf.stack([tf.reshape(f0, [-1]), tf.reshape(f1, [-1])], axis=1))
def compute_pde_residual(model, points, StiffMat, lamb, mu, Q, body_force_fn):
         with tf.GradientTape(persistent=True) as outer tape:
                  outer_tape.watch(points)
                  with tf.GradientTape(persistent=True) as inner tape:
                          inner_tape.watch(points)
                           predicted_uv = model(points)
                           predicted_u = predicted_uv[:, 0:1]
                           predicted_v = predicted_uv[:, 1:2]
                  grad_u = inner_tape.gradient(predicted_u, points)
                  grad_v = inner_tape.gradient(predicted_v, points)
                  Sxx = StiffMat[0, 0] * grad_u[:, 0:1] + StiffMat[0, 1] * grad_v[:, 1:2]
                  Syy = StiffMat[1, 0] * grad_u[:, 0:1] + StiffMat[1, 1] * grad_v[:, 1:2]
                  Sxy = StiffMat[2, 2] * (grad_u[:, 1:2] + grad_v[:, 0:1])
         Sxx_x = outer_tape.gradient(Sxx, points)[:, 0]
         Syy_y = outer_tape.gradient(Syy, points)[:, 1]
         grad_Sxy = outer_tape.gradient(Sxy, points)
         Sxy_x = grad_Sxy[:, 0]
         Sxy_y = grad_Sxy[:, 1]
         del inner_tape, outer_tape
         body_force = body_force_fn(points, lamb, mu, Q)
         \label{eq:residue} residue = tf.stack([Sxx_x + Sxy_y + body\_force[:, 0], Sxy_x + Syy_y + body\_force[:, 1]], \ axis=1)
         return residue
def compute_total_loss(model, points, left, right, bottom, top, StiffMat, lamb, mu, Q, body_force_fn, data_points=None, data_u=None, data_
         # PDE residual loss
         residue = compute_pde_residual(model, points, StiffMat, lamb, mu, Q, body_force_fn)
         pde_loss = tf.reduce_mean(tf.square(residue[:, 0])) + tf.reduce_mean(tf.square(residue[:, 1]))
         # Boundary losses (same as forward)
         with tf.GradientTape(persistent=True) as inner tape:
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inner_tape.watch(left)
                predicted_uv = model(left)
                predicted_u = predicted_uv[:, 0:1]
                predicted_v = predicted_uv[:, 1:2]
        grad_u = inner_tape.gradient(predicted_u, left)
        grad_v = inner_tape.gradient(predicted_v, left)
        del inner_tape
        \label{eq:sxx}  \mbox{Sxx} = \mbox{StiffMat[0, 0] * grad\_u[:, 0:1] + StiffMat[0, 1] * grad\_v[:, 1:2]} 
        left_boundary_loss = tf.reduce_mean(tf.square(predicted_v)) + tf.reduce_mean(tf.square(Sxx))
        with tf.GradientTape(persistent=True) as inner_tape:
                inner tape.watch(right)
                predicted_uv = model(right)
                predicted_u = predicted_uv[:, 0:1]
                predicted_v = predicted_uv[:, 1:2]
        grad_u = inner_tape.gradient(predicted_u, right)
        grad_v = inner_tape.gradient(predicted_v, right)
        del inner tape
        Sxx = StiffMat[0, 0] * grad_u[:, 0:1] + StiffMat[0, 1] * grad_v[:, 1:2]
        right_boundary_loss = tf.reduce_mean(tf.square(predicted_v)) + tf.reduce_mean(tf.square(Sxx))
        bottom\_boundary\_loss = tf.reduce\_mean(tf.square(model(bottom)[:, 0:1])) + tf.reduce\_mean(tf.square(model(bottom)[:, 1:2])) + tf.reduce\_mean(tf.square(model(b
        with tf.GradientTape(persistent=True) as inner tape:
                inner_tape.watch(top)
                predicted_uv = model(top)
                predicted_u = predicted_uv[:, 0:1]
                predicted_v = predicted_uv[:, 1:2]
        grad_u = inner_tape.gradient(predicted_u, top)
        grad_v = inner_tape.gradient(predicted_v, top)
        del inner tape
        Syy = StiffMat[1, 0] * grad_u[:, 0:1] + StiffMat[1, 1] * grad_v[:, 1:2]
        top_boundary_loss = tf.reduce_mean(tf.square(predicted_u)) + tf.reduce_mean(tf.square(Syy - (lamb + 2*mu) * Q * tf.sin(np.pi * top[:,
        \verb|total_loss| = \verb|pde_loss| + \verb|left_boundary_loss| + \verb|right_boundary_loss| + \verb|bottom_boundary_loss| + \verb|top_boundary_loss| + top_boundary_loss| + top_bound
        # If data is provided, add data mismatch loss
        if data_points is not None and data_u is not None and data_v is not None:
                pred_data = model(data_points)
                data_loss = tf.reduce_mean(tf.square(pred_data[:, 0:1] - data_u)) + tf.reduce_mean(tf.square(pred_data[:, 1:2] - data_v))
                total_loss += data_loss
        return total_loss
# Setup domain points and boundaries
num_collocation_points = 50
x_points, y_points = tf.meshgrid(tf.linspace(0.0, 1.0, num_collocation_points), tf.linspace(0.0, 1.0, num_collocation_points), indexing="
points = tf.stack([tf.reshape(x_points, [-1]), tf.reshape(y_points, [-1])], axis=1)
x_{\text{left}}, y_{\text{left}} = tf.meshgrid(tf.linspace(0.0, 0.0, 1), tf.linspace(0.0, 1.0, num_collocation_points), indexing="ij")
left = tf.stack([tf.reshape(x_left, [-1]), tf.reshape(y_left, [-1])], axis=1)
x_right, y_right = tf.meshgrid(tf.linspace(1.0, 1.0, 1), tf.linspace(0.0, 1.0, num_collocation_points), indexing="ij")
right = tf.stack([tf.reshape(x_right, [-1]), tf.reshape(y_right, [-1])], axis=1)
x_top, y_top = tf.meshgrid(tf.linspace(0.0, 1.0, num_collocation_points), tf.linspace(1.0, 1.0, 1), indexing="ij")
top = tf.stack([tf.reshape(x_top, [-1]), tf.reshape(y_top, [-1])], axis=1)
 x\_bottom, \ y\_bottom = tf.meshgrid(tf.linspace(0.0, 1.0, num\_collocation\_points), \ tf.linspace(0.0, 0.0, 1), \ indexing="ij") 
bottom = tf.stack([tf.reshape(x\_bottom, [-1]), tf.reshape(y\_bottom, [-1])], \ axis=1)
case2D = "plane_strain"
# ----- FORWARD PROBLEM TRAINING -----
print("Starting forward problem training with real lambda and mu")
model_forward = SimplePINN([50, 50, 50, 50, 50, 2])
optimizer_forward = tf.keras.optimizers.Adam(learning_rate=0.001)
num epochs forward = 1500
tolerance = 1e-6
previous_loss = float('inf')
for epoch in range(num_epochs_forward):
        with tf.GradientTape() as tape:
                StiffMat = stiffness_matrix(lamb_real, mu_real, case2D)
                loss = compute_total_loss(model_forward, points, left, right, bottom, top, StiffMat, lamb_real, mu_real, Q, body_force_fn)
        gradients = tape.gradient(loss, model_forward.trainable_variables)
        optimizer_forward.apply_gradients(zip(gradients, model_forward.trainable_variables))
        if epoch % 100 == 0:
                print(f"Forward Epoch {epoch}, Loss: {loss.numpy():.6f}")
                 if abs(previous loss - loss.numpv()) < tolerance:
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print(f"Forward problem converged at epoch {epoch}")
            break
        previous_loss = loss.numpy()
# Generate synthetic data from forward-trained model (simulate measurements)
num_data_points = 100
x_data, y_data = tf.meshgrid(tf.linspace(0.0, 1.0, int(np.sqrt(num_data_points))), tf.linspace(0.0, 1.0, int(np.sqrt(num_data_points))),
data_points = tf.stack([tf.reshape(x_data, [-1]), tf.reshape(y_data, [-1])], axis=1)
pred_uv_data = model_forward(data_points)
data u = pred uv data[:, 0:1]
data_v = pred_uv_data[:, 1:2]
# ------ INVERSE PROBLEM: Estimate lambda and mu ------
print("\nStarting inverse problem to estimate lambda and mu")
# Initial guess for lambda and mu (different from real)
lamb_inv = tf.Variable(1.0, dtype=tf.float32, trainable=True)
mu_inv = tf.Variable(0.5, dtype=tf.float32, trainable=True)
model_inverse = SimplePINN([50, 50, 50, 50, 50, 2])
optimizer inverse = tf.keras.optimizers.Adam(learning rate=0.001)
num_epochs_inverse = 1500
previous_loss = float('inf')
for epoch in range(num_epochs_inverse):
    with tf.GradientTape() as tape:
       StiffMat = stiffness matrix(lamb inv, mu inv, case2D)
       loss = compute_total_loss(model_inverse, points, left, right, bottom, top, StiffMat, lamb_inv, mu_inv, Q, body_force_fn, data_poi
    gradients = tape.gradient(loss, model_inverse.trainable_variables + [lamb_inv, mu_inv])
   optimizer\_inverse.apply\_gradients(zip(gradients, model\_inverse.trainable\_variables + [lamb\_inv, mu\_inv]))
    if epoch % 100 == 0:
        print(f"Inverse\ Epoch\ \{epoch\},\ Loss:\ \{loss.numpy():.6f\},\ lamb:\ \{lamb\_inv.numpy():.4f\},\ mu:\ \{mu\_inv.numpy():.4f\}")
        if abs(previous_loss - loss.numpy()) < tolerance:</pre>
           print(f"Inverse problem converged at epoch {epoch}")
            break
        previous_loss = loss.numpy()
print(f"\nEstimated lambda: {lamb_inv.numpy():.6f}, Estimated mu: {mu_inv.numpy():.6f}")
# Plot predicted displacement fields from inverse problem
num_plot_points = 100
x_plot, y_plot = tf.meshgrid(tf.linspace(0.0, 1.0, num_plot_points), tf.linspace(0.0, 1.0, num_plot_points), indexing="ij")
plot_points = tf.stack([tf.reshape(x_plot, [-1]), tf.reshape(y_plot, [-1])], axis=1)
pred_uv_inv = model_inverse(plot_points)
pred_u_inv = tf.reshape(pred_uv_inv[:, 0], (num_plot_points, num_plot_points))
pred_v_inv = tf.reshape(pred_uv_inv[:, 1], (num_plot_points, num_plot_points))
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.contourf(x_plot, y_plot, pred_u_inv, levels=50, cmap='jet')
plt.colorbar()
plt.title('Inverse Problem: Predicted displacement u')
plt.subplot(1, 2, 2)
plt.contourf(x_plot, y_plot, pred_v_inv, levels=50, cmap='jet')
plt.colorbar()
plt.title('Inverse Problem: Predicted displacement v')
plt.show()
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Forward Epoch 0, Loss: 8315.508789
Forward Epoch 100, Loss: 427.472137
Forward Epoch 200, Loss: 32.589241
Forward Epoch 300, Loss: 14.044405
Forward Epoch 400, Loss: 8.402592
Forward Epoch 500, Loss: 5.635145
Forward Epoch 600, Loss: 3.891035
Forward Epoch 700, Loss: 2.850995
Forward Epoch 800, Loss: 2.160311
Forward Epoch 900, Loss: 1.738838
Forward Epoch 1000, Loss: 1.444879
Forward Epoch 1100, Loss: 1.259560
Forward Epoch 1200, Loss: 1.112703
Forward Epoch 1300, Loss: 9.071963

Forward Epoch 1400, Loss: 0.912297

Starting inverse problem to estimate lambda and mu
Inverse Epoch 0, Loss: 2079.945801, lamb: 0.9990, mu: 0.4990
Inverse Epoch 100, Loss: 232.326721, lamb: 0.9314, mu: 0.4333
Inverse Epoch 200, Loss: 8.863537, lamb: 0.9245, mu: 0.4248
Inverse Epoch 300, Loss: 3.048697, lamb: 0.9246, mu: 0.4237
Inverse Epoch 400, Loss: 1.884100, lamb: 0.9238, mu: 0.4230
Inverse Epoch 500, Loss: 1.137267, lamb: 0.9237, mu: 0.4226
Inverse Epoch 600, Loss: 0.837011, lamb: 0.9235, mu: 0.4222
Inverse Epoch 700, Loss: 0.662789, lamb: 0.9235, mu: 0.4219
Inverse Epoch 800, Loss: 0.547804, lamb: 0.9232, mu: 0.4215
Inverse Epoch 900, Loss: 0.459769, lamb: 0.9232, mu: 0.4213
Inverse Epoch 1000, Loss: 0.397038, lamb: 0.9223, mu: 0.4208
Inverse Epoch 1100, Loss: 0.343207, lamb: 0.9225, mu: 0.4207
Inverse Epoch 1200, Loss: 0.885965, lamb: 0.9225, mu: 0.4202
Inverse Epoch 1300, Loss: 0.269509, lamb: 0.9224, mu: 0.4200

Inverse Epoch 1400, Loss: 0.241715, lamb: 0.9223, mu: 0.4198

Estimated lambda: 0.921852, Estimated mu: 0.419261



