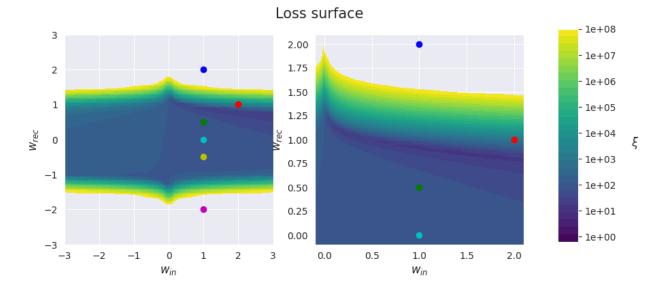
```
import numpy as np # Matrix and vector computation package
import matplotlib
import matplotlib.pyplot as plt # Plotting library
from matplotlib import cm # Colormaps
from matplotlib.colors import LogNorm
import seaborn as sns # Fancier plots
# Set seaborn plotting style
sns.set style('darkgrid')
# Set the seed for reproducability
np.random.seed(seed=1)
# Create dataset
num samples = 30
seq_length = 20
# Create the sequences
X = np.random.uniform(low=0, high=2, size=(num samples, seq length))
X = np.ceil(X * 2) / 2 \# Zaokrąglanie do 0.5 lub 1
X = np.where(X == 1.5, 0.5, X) # Zmiana 1.5 na 0.5
# Create the targets for each sequence
t = np.sum(X == 0.5, axis=1)
# Define the forward step functions
def update state(xk, sk, wx, wRec):
    Compute state k from the previous state (sk) and current
    input (xk), by use of the input weights (wx) and recursive
    weights (wRec).
    0.00
    return xk * wx + sk * wRec
def forward states(X, wx, wRec):
    Unfold the network and compute all state activations
    given the input X, input weights (wx), and recursive weights
    (wRec). Return the state activations in a matrix, the last
    column S[:,-1] contains the final activations.
    0.00
    # Initialise the matrix that holds all states for all
    # input sequences. The initial state s0 is set to 0.
    S = np.zeros((X.shape[0], X.shape[1]+1))
    # Use the recurrence relation defined by update state to update
    # the states trough time.
    for k in range(0, X.shape[1]):
        \# S[k] = S[k-1] * wRec + X[k] * wx
        S[:,k+1] = update state(X[:,k], S[:,k], wx, wRec)
```

```
return S
def loss(y, t):
    """MSE between the targets t and the outputs y."""
    return np.mean((t - y)**2)
def output_gradient(y, t):
    Gradient of the MSE loss function with respect to the output v.
    return 2. * (y - t)
def backward gradient(X, S, grad out, wRec):
    Backpropagate the gradient computed at the output (grad out)
    through the network. Accumulate the parameter gradients for
    wX and wRec by for each layer by addition. Return the parameter
    gradients as a tuple, and the gradients at the output of each
layer.
    # Initialise the array that stores the gradients of the loss with
    # respect to the states.
    grad over time = np.zeros((X.shape[0], X.shape[1]+1))
    grad over time[:,-1] = grad out
    # Set the gradient accumulations to 0
    wx grad = 0
    wRec grad = 0
    for k in range(X.shape[1], 0, -1):
        # Compute the parameter gradients and accumulate the results.
        wx grad += np.sum(
            np.mean(grad over time[:,k] * X[:,k-1], axis=0))
        wRec grad += np.sum(
            np.mean(grad over time[:,k] * S[:,k-1]), axis=0)
        # Compute the gradient at the output of the previous layer
        grad over time[:,k-1] = grad over time[:,k] * wRec
    return (wx grad, wRec grad), grad over time
# Perform gradient checking
# Set the weight parameters used during gradient checking
params = [1.2, 1.2] # [wx, wRec]
# Set the small change to compute the numerical gradient
eps = 1e-7
# Compute the backprop gradients
S = forward states(X, params[0], params[1])
grad out = output gradient(S[:,-1], t)
backprop grads, grad over time = backward gradient(
    X, S, grad out, params[1])
# Compute the numerical gradient for each parameter in the layer
```

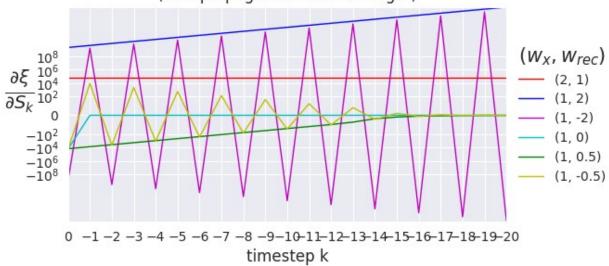
```
for p idx, in enumerate(params):
    grad backprop = backprop grads[p idx]
    # + eps
    params[p idx] += eps
    plus loss = loss(forward states(X, params[0], params[1])[:,-1], t)
    # - eps
    params[p idx] -= 2 * eps
    min loss = loss(forward states(X, params[0], params[1])[:,-1], t)
    # reset param value
    params[p idx] += eps
    # calculate numerical gradient
    grad num = (plus loss - min loss) / (2*eps)
    # Raise error if the numerical grade is not close to
    # the backprop gradient
    if not np.isclose(grad num, grad backprop):
        raise ValueError((
            f'Numerical gradient of {grad num:.6f} is not close to '
            f'the backpropagation gradient of {grad backprop:.6f}!'))
print('No gradient errors found')
No gradient errors found
# Define plotting functions
# Define points to annotate (wx, wRec, color)
points = [(2,1,'r'), (1,2,'b'), (1,-2,'m'), (1,0,'c'),
          (1,0.5, 'g'), (1,-0.5, 'y')]
def get loss surface(w1 low, w1 high, w2 low, w2 high,
                     nb of ws, loss func):
    """Plot the loss surface."""
    # Vector of weights for which we want to plot the loss.
    w1 = np.linspace(w1 low, w1 high, num=nb of ws) # Weight 1
    w2 = np.linspace(w2 low, w2 high, num=nb of ws) # Weight 2
    ws1, ws2 = np.meshgrid(w1, w2) # Generate grid
    loss ws = np.zeros((nb of ws, nb of ws)) # Initialize loss matrix
    # Fill the loss matrix for each combination of weights
    for i in range(nb of ws):
        for j in range(nb of ws):
            loss_ws[i,j] = loss_ws[i,j], ws2[i,j])
    return ws1, ws2, loss ws
def plot_surface(ax, ws1, ws2, loss_ws):
    """Plot the loss in function of the weights."""
    surf = ax.contourf(
        ws1, ws2, loss_ws, levels=np.logspace(-0.2, 8, 30),
        cmap=cm.viridis, norm=LogNorm())
```

```
ax.set xlabel('$w {in}$', fontsize=12)
    ax.set ylabel('$w {rec}$', fontsize=12)
    return surf
def plot points(ax, points):
    """Plot the annotation points on the given axis."""
    for wx, wRec, c in points:
        ax.plot(wx, wRec, c+'o', linewidth=2)
def get loss surface figure(loss func, points):
    """Plot the loss surfaces together with the annotated points."""
    # Plot figures
    fig = plt.figure(figsize=(10, 4))
    # Plot overview of loss function
    ax 1 = fig.add subplot(1,2,1)
    ws1_1, ws2_1, loss_ws_1 = get_loss_surface(
        -3, 3, -3, 3, 50, loss func)
    surf 1 = plot surface(ax 1, ws1 1, ws2 1, loss ws 1 + \frac{1}{1})
    plot points(ax 1, points)
    ax 1.set xlim(-3, 3)
    ax 1.set ylim(-3, 3)
    # Plot zoom of loss function
    ax 2 = fig.add subplot(1,2,2)
    ws1 2, ws2 2, loss ws 2 = get loss surface(
        -0.1, \(\frac{2}{2}\).1, \(-0.\bar{1}\), \(\frac{2}{2}\).1, \(\frac{50}{50}\), \(\bar{1}\) loss \(\frac{1}{2}\) func)
    surf 2 = plot surface(ax 2, ws1 2, ws2 2, loss ws 2 + \frac{1}{1})
    plot_points(ax_2, points)
    ax 2.set xlim(-0.1, 2.1)
    ax 2.set ylim(-0.1, 2.1)
    # Show the colorbar
    fiq.subplots adjust(right=0.8)
    cax = fig.add axes([0.85, 0.12, 0.03, 0.78])
    cbar = fig.colorbar(
        surf 1, ticks=np.logspace(0, 8, 9), cax=cax)
    cbar.ax.set ylabel(
         '$\\xi$', fontsize=12, rotation=0, labelpad=20)
    cbar.set ticklabels(
         ['\{:.0e\}'.format(i) for i in np.logspace(0, 8, 9)])
    fig.suptitle('Loss surface', fontsize=15)
    return fig
def plot gradient over time(points, get grad over time):
    """Plot the gradients of the annotated points and how
    they evolve over time."""
    fig = plt.figure(figsize=(7, 3))
    ax = plt.subplot(111)
    # Plot points
```

```
for wx, wRec, c in points:
        grad over time = get grad over time(wx, wRec)
        x = np.arange(-grad over time.shape[1]+1, 1, 1)
        plt.plot(
            x, np.sum(grad over time, axis=0), c+'-',
            label=f'({wx}, {wRec})', linewidth=1, markersize=8)
    plt.xlim(0, -grad over time.shape[1]+1)
    # Set up plot axis
    plt.xticks(x)
    plt.vscale('symlog')
    plt.yticks([10**8, 10**6, 10**4, 10**2, 0, -10**2, -10**4,
                -10**6, -10**81)
    plt.xlabel('timestep k', fontsize=12)
    plt.ylabel('$\\frac{\\partial \\xi}{\\partial S {k}}$',
               fontsize=20, rotation=0)
    plt.title(('Unstability of gradient in backward propagation.'
               '\n(backpropagate from left to right)'))
    # Set legend
    leg = plt.legend(
        loc='center left', bbox_to_anchor=(1, 0.5),
        frameon=False, numpoints=1)
    leg.set title('$(w x, w {rec})$', prop={'size':15})
    fig.subplots adjust(right=0.8)
def get grad over time(wx, wRec):
    """Helper func to only get the gradient over time
    from wx and wRec."""
    S = forward states(X, wx, wRec)
    grad out = output gradient(S[:,-1], t).sum()
    _, grad_over_time = backward_gradient(X, S, grad out, wRec)
    return grad over time
# Plot loss surface and gradients
# Get and plot the loss surface figure with markers
fig = get loss surface figure(
    lambda w1, w2: loss(forward states(X, w1, w2)[:,-\frac{1}{2}], t), points)
# Get the plots of the gradients changing by backpropagating.
plot gradient over time(points, get grad over time)
# Show figures
plt.show()
```



Unstability of gradient in backward propagation. (backpropagate from left to right)



```
# Define Rprop optimisation function
def update_rprop(X, t, W, W_prev_sign, W_delta, eta_p, eta_n):
    Update RProp values in one iteration.
Args:
        X: input data.
        t: targets.
        W: Current weight parameters.
        W_prev_sign: Previous sign of the W gradient.
        W_delta: RProp update values (Delta).
        eta_p, eta_n: RProp hyperparameters.
Returns:
        (W_delta, W_sign): Weight update and sign of last weight
```

```
gradient.
    # Perform forward and backward pass to get the gradients
    S = forward states(X, W[0], W[1])
    grad out = output gradient(S[:,-1], t)
    W_grads, _ = backward_gradient(X, S, grad_out, W[1])
    W sign = np.sign(W grads) # Sign of new gradient
    # Update the Delta (update value) for each weight
    # parameter seperately
    for i, in enumerate(W):
        if W_sign[i] == W_prev_sign[i]:
            W_delta[i] *= eta p
        else:
            W delta[i] *= eta n
    return W delta, W sign
# Perform Rprop optimisation
# Set hyperparameters
eta_p = 1.2
eta n = 0.5
# Set initial parameters
W = [-1.5, 2] \# [wx, wRec]
W_{delta} = [0.001, 0.001] # Update values (Delta) for W
W \text{ sign} = [0, 0] \# Previous sign of W
ls of ws = [(W[0], W[1])] # List of weights to plot
# Iterate over 500 iterations
for i in range(500):
    # Get the update values and sign of the last gradient
    W delta, W sign = update rprop(
        X, t, W, W sign, W delta, eta p, eta n)
    # Update each weight parameter seperately
    for i, _ in enumerate(W):
        W[i] -= W sign[i] * W delta[i]
    ls_of_ws.append((W[0], W[1])) # Add weights to list to plot
print(f'Final weights are: wx = \{W[0]:.4f\}, wRec = \{W[1]:.4f\}')
Final weights are: wx = 0.9549, wRec = 0.9223
# Plot the loss surface with the weights over the iterations.
# Define plot function
def plot optimisation(ls of ws, loss func):
    """Plot the optimisation iterations on the loss surface."""
    ws1, ws2 = zip(*ls of ws)
    # Plot figures
    fig = plt.figure(figsize=(10, 4))
```

```
# Plot overview of loss function
    ax 1 = fig.add subplot(1, 2, 1)
    ws1 1, ws2 1, loss ws 1 = get loss surface(
        -3, 3, -3, 3, 50, loss func)
    surf_1 = plot_surface(ax_1, wsl_1, wsl_1, wsl_1, loss ws 1 + 1)
    ax_1.plot(ws1, ws2, 'wo', markersize=3)
    ax = 1.scatter(ws1[-1], ws2[-1], color='w', marker='*', s=150,
edgecolors='k')
    ax 1.set xlim([-3, 3])
    ax 1.set ylim([-3, 3])
    # Plot zoom of loss function
    ax_2 = fig.add_subplot(1, 2, 2)
    ws1_2, ws2_2, loss_ws_2 = get_loss_surface(
        0, 2, 0, 2, 50, loss func)
    surf_2 = plot_surface(ax_2, ws1_2, ws2_2, loss_ws_2 + 1)
    ax 2.set xlim([0, 2])
    ax 2.set_ylim([0, 2])
    surf 2 = plot surface(ax 2, ws1 2, ws2 2, loss ws 2)
    ax 2.plot(ws1, ws2, 'wo',
               label='RProp iterations', markersize=3)
    ax 2.\text{scatter}(\text{ws1}[-1]), \text{ws2}[-1], \text{color}='\text{w}', \text{marker}='^*, \text{s}=150,
edgecolors='k')
    ax 2.legend()
    # Show the colorbar
    fig.subplots adjust(right=0.8)
    cax = fig.add axes([0.85, 0.12, 0.03, 0.78])
    cbar = fig.colorbar(
        surf 1, ticks=np.logspace(0, 8, 9), cax=cax)
    cbar.ax.set ylabel(
        '$\\xi$', fontsize=12, rotation=0, labelpad=20)
    cbar.set ticklabels(
        ['\{:.0e\}'.format(i) for i in np.logspace(0, 8, 9)])
    plt.suptitle('Loss surface', fontsize=12)
    plt.show()
# Plot the optimisation
plot optimisation(
    ls of ws, lambda w1, w2: loss(forward states(X, w1, w2)[:,-\frac{1}{1}],
plt.show()
```

