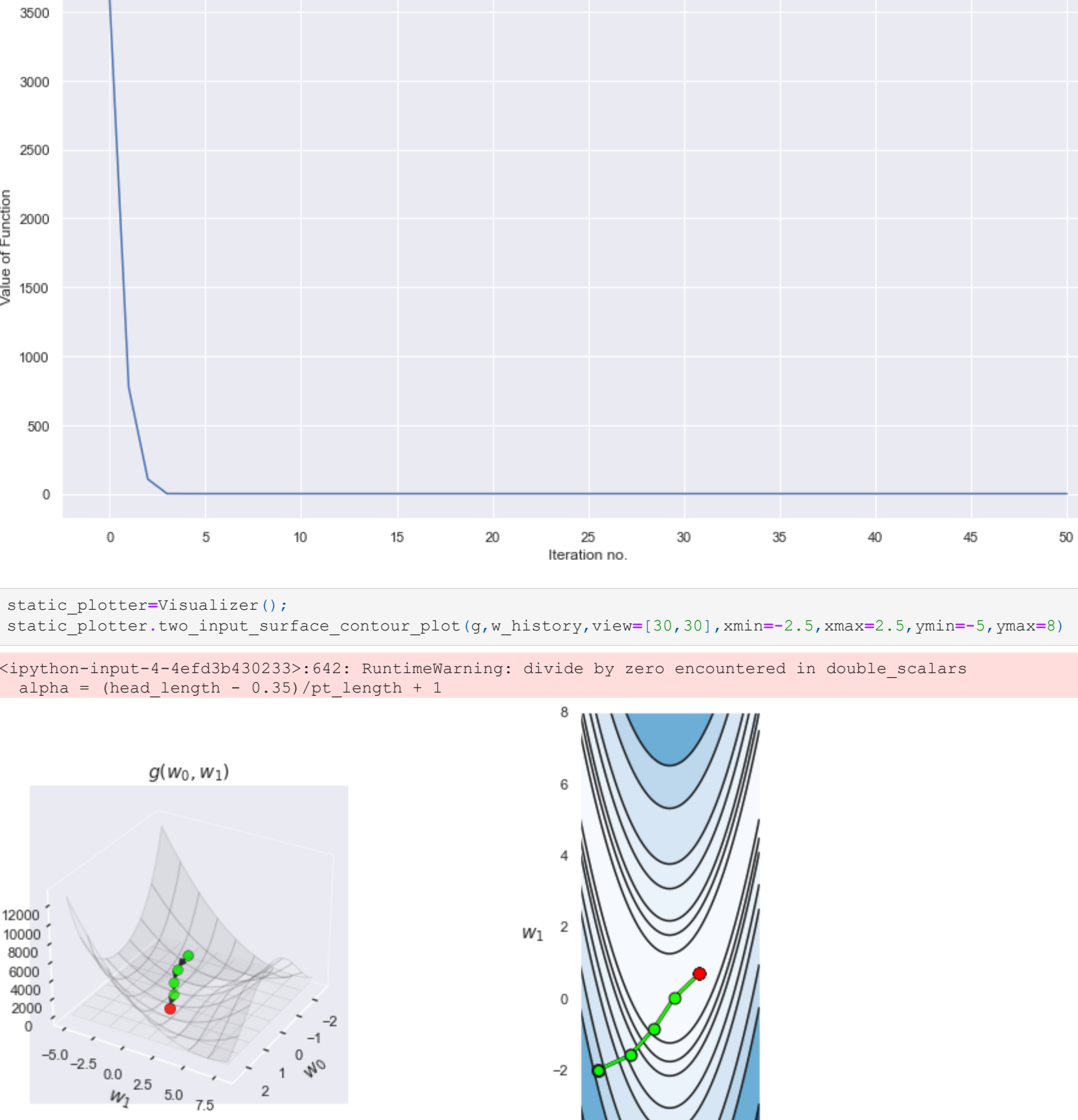




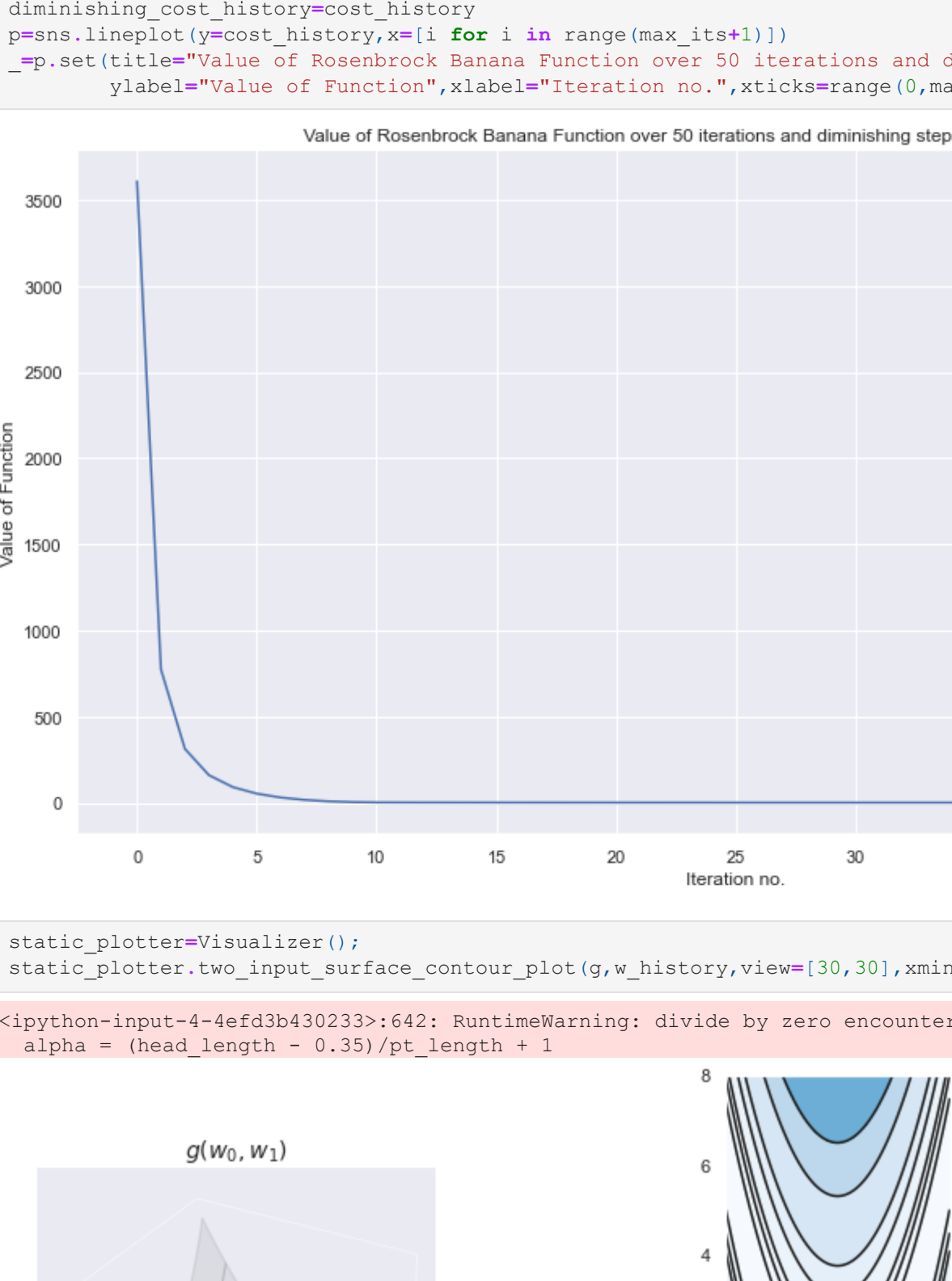


Value of Rosenbrock Banana Function over 50 iterations and stepsize of 1 using random search

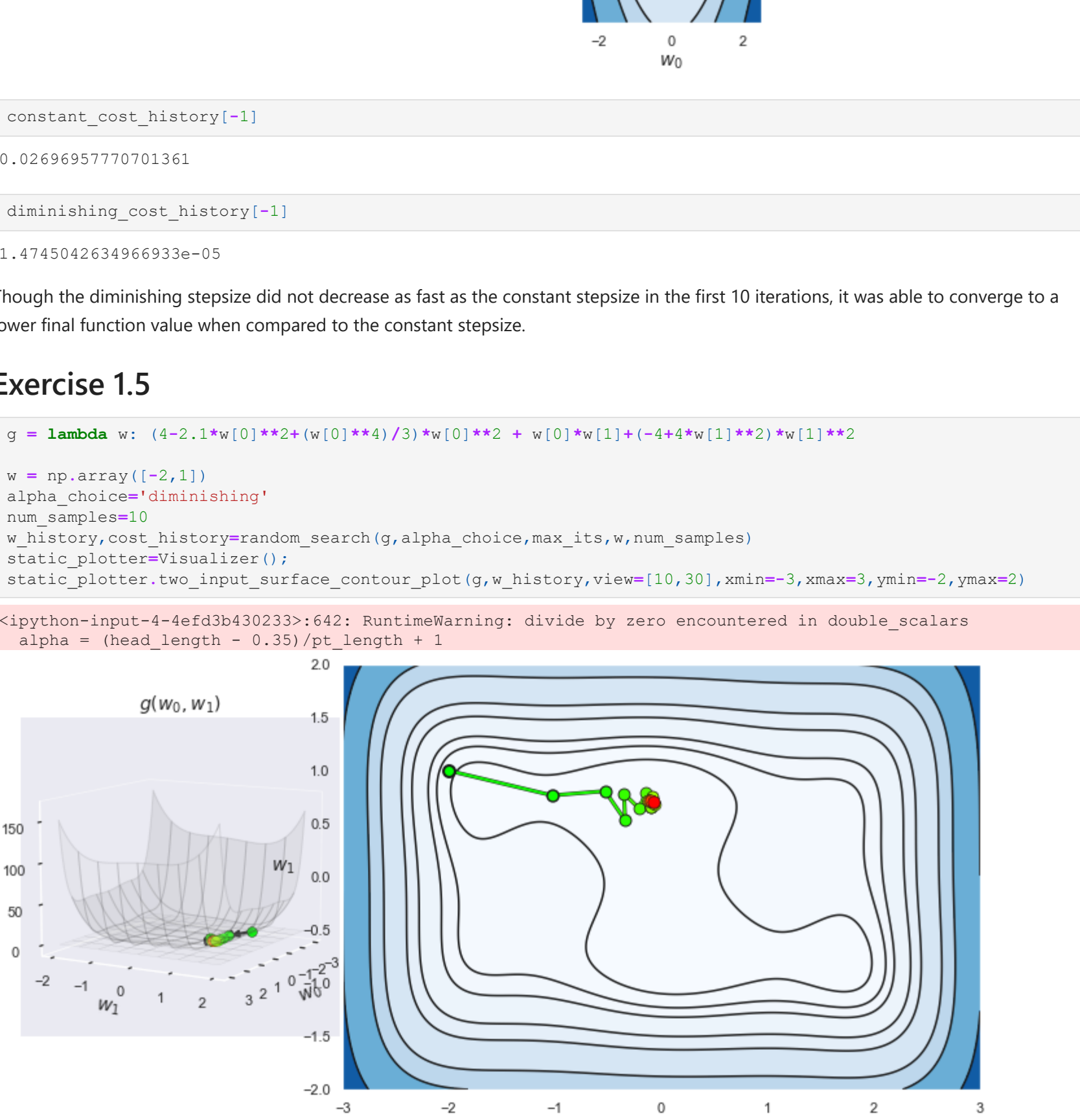


```
In [45]: static_plotter=Visualizer();
static_plotter.two_input_surface_contour_plot(g,w_history,view=[30,30],xmin=-2.5,xmax=2.5,ymin=-5,ymax=8)

<ipython-input-4-4efdb3430233>:642: RuntimeWarning: divide by zero encountered in double_scalars
  alpha = (head_length - 0.35)/pt_length + 1
```



```
In [46]: alpha_choice='diminishing';
w_history,cost_history=random_search(g,alpha_choice,max_its,w,num_samples)
diminishing_cost_history=cost_history
sns.lineplot(y=cost_history,x=[i for i in range(max_its+1)])
static_plotter=Visualizer();
_p.set(title='Value of Rosenbrock Banana Function over 50 iterations and diminishing stepsize using random search',
       ylabel='Value of Function',xlabel='Iteration no.',xticks=range(0,max_its+1,5))
```



```
In [47]: static_plotter=Visualizer();
static_plotter.two_input_surface_contour_plot(g,w_history,view=[30,30],xmin=-2.5,xmax=2.5,ymin=-5,ymax=8)

<ipython-input-4-4efdb3430233>:642: RuntimeWarning: divide by zero encountered in double_scalars
  alpha = (head_length - 0.35)/pt_length + 1
```



```
In [48]: constant_cost_history=[1]

Out[48]: 0.0269695777071361

In [49]: diminishing_cost_history=[1]

Out[49]: 1.4745042634966933e-05
```

Though the diminishing stepsize did not decrease as fast as the constant stepsize in the first 10 iterations, it was able to converge to a lower final function value when compared to the constant stepsize.

### Exercise 1.5

```
In [138]: g = lambda w: (4-2.1*w[0]**2 + w[1]**2)*(w[0]**4/3) + w[0]**2 + w[0]*w[1]*(-4+4*w[1]**2) + w[1]**2

w = np.array([-2,1])
alpha_choice='diminishing'
num_samples=10
w_history,cost_history=random_search(g,alpha_choice,max_its,w,num_samples)
diminishing_cost_history=cost_history
static_plotter=Visualizer();
static_plotter.two_input_surface_contour_plot(g,w_history,view=[10,30],xmin=-3,xmax=3,ymin=-2,ymax=2)

<ipython-input-4-4efdb3430233>:642: RuntimeWarning: divide by zero encountered in double_scalars
  alpha = (head_length - 0.35)/pt_length + 1
```



```
In [139]: w_history=[1]

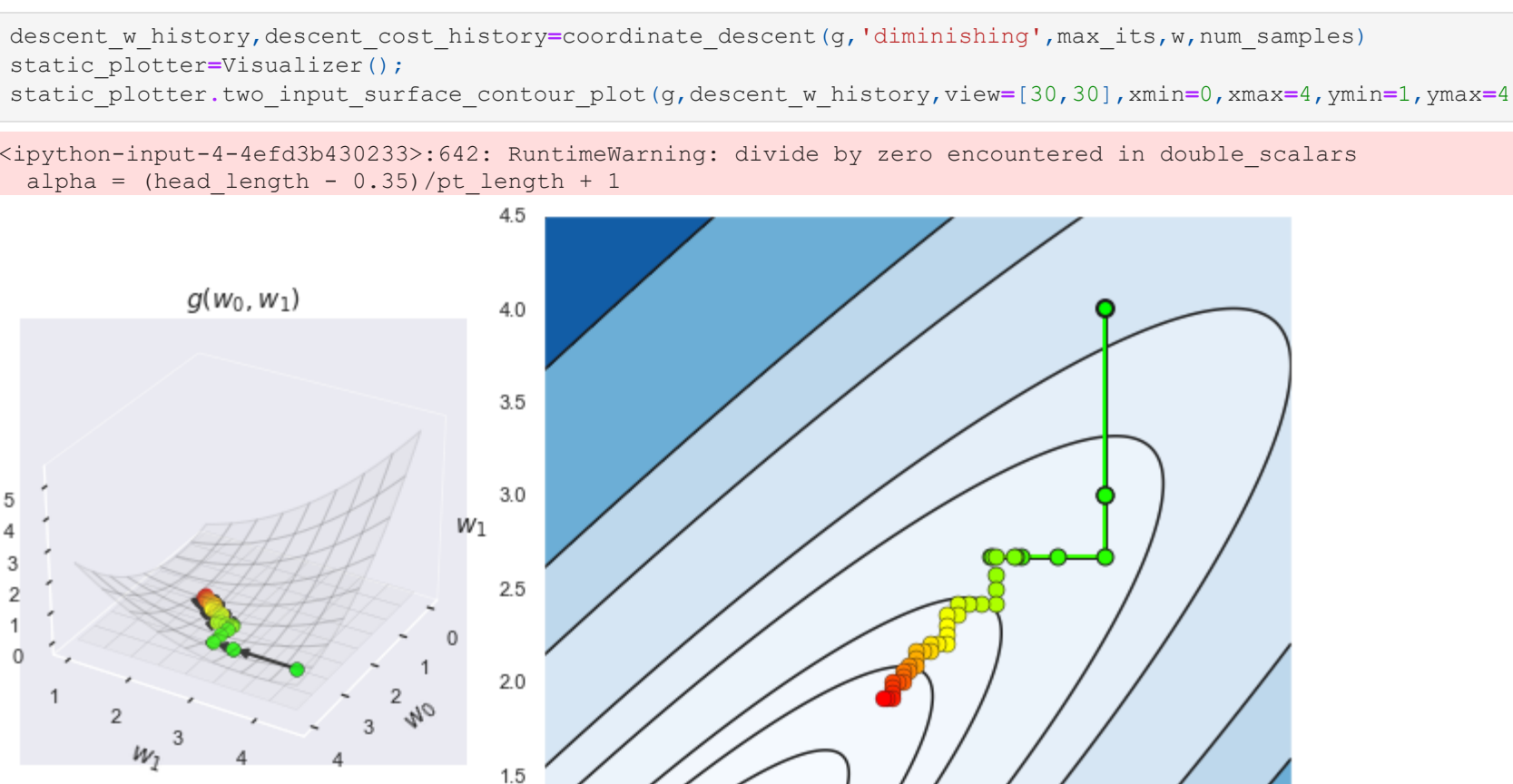
Out[139]: array([-0.07767658, 0.70911791])
```

The function converges to the point  $(-0.0777, 0.7091)$ , and is able to converge relatively close to the global minima of  $(-0.0898, 0.7126)$ . However this could change depending on whether I use a different alpha or max number of iterations.

### Exercise 2

```
In [57]: ##Exercise 2
g = lambda w: np.dot(w,T,w) + 2
# random search function
def random_search(g,P,N):
    # run random search
    w = np.zeros(N)
    directions = np.random.randn(P,N) #Generate P different directions
    directions_shuffled = np.random.permutation(directions) #Randomly shuffle possible vectors
    num_descending=np.sum(np.array([g(i) for i in w_candidates])<g(w))
    return num_descending
Ns=[10,100,1000,10000]
P=[1,2,12,12]
fig,ax=plt.subplots(2,2,sharex='col',sharey='row')
for i,f in enumerate(Ns):
    num_descending=[]
    for N in Ns:
        num_descending.append(num_of_descending(g,P,N)/P)
    ax[i//2,i%2].plot(Ns,num_descending)
    ax[i//2,i%2].set_title('P = '+str(P))
    fig.text(0.5, 0.04, 'No. of dimensions', ha='center')
fig.text(0.04, 0.5, 'Proportion of possible directions selected that are descending', va='center', fontsize=10)
```

```
Out[57]: Text(0.04, 0.5, 'Proportion of possible directions selected that are descending')
```



For all sample sizes, as the number of possible dimensions of our vector increases, the probability of selecting a direction that is descending decreases towards 0. As we increase the number of dimensions, random searching for a function minimum becomes increasingly inefficient as the probability of selecting a descending vector decreases. Although increasing the sample size might give us more descending vectors, it also increases the overall runtime of the algorithm. Because of this, random sampling is an inefficient method of optimization for high dimensional functions.

### Exercise 3

#### 3.1

```
In [139]: # random search function
def coordinate_descent(g,alpha_choice,max_its,w,num_samples):
    # run random search
    w_history = [] # container for w history
    cost_history = [] # container for corresponding cost function history
    alpha = 0
    vector_dim=w.shape[0] #Number of dimensions for function
    best_w= #initialize the best point in space as the current point
    w_history.append(best_w)
    cost_history.append(g(best_w))
    for k in range(1,max_its+1):
        # check if diminishing steplength rule used
        if alpha_choice == 'diminishing':
            alpha = 1/float(k)
        else:
            alpha = alpha_choice

        directions = np.identity(vector_dim) #Calculate all possible directions (both positive and negative)
        directions_shuffled = np.random.permutation(directions) #Randomly shuffle possible vectors
        for i in directions_shuffled: #loop through shuffled directions and if function is lower, replace set
            if g(best_w+alpha*i)<g(best_w):
                best_w=best_w+alpha*i
                break
            elif g(best_w-alpha*i)<g(best_w):
                best_w=best_w-alpha*i
                break

        w_history.append(best_w)
        cost_history.append(g(best_w))
    return w_history,cost_history

# random search function
def coordinate_search(g,alpha_choice,max_its,w,num_samples):
    # run random search
    w_history = [] # container for w history
    cost_history = [] # container for corresponding cost function history
    alpha = 0
    vector_dim=w.shape[0] #Number of dimensions for function
    best_w= #initialize the best point in space as the current point
    w_history.append(best_w)
    cost_history.append(g(best_w))
    for k in range(1,max_its+1):
        # check if diminishing steplength rule used
        if alpha_choice == 'diminishing':
            alpha = 1/float(k)
        else:
            alpha = alpha_choice

        #Generate all possible directions and select for the one with the lowest cost functions
        directions = np.concatenate([np.zeros(vector_dim).reshape(1,-1),np.identity(vector_dim)],np.identity(vector_dim))
        new_vectors = alpha*directions+best_w
        best_w = new_vectors[np.argmin([g(k) for k in new_vectors])]

        w_history.append(best_w)
        cost_history.append(g(best_w))
    return w_history,cost_history
```

#### 3.2

```
In [138]: g = lambda w: 0.26*(w[0]**2 + w[1]**2)-0.48*w[0]*w[1]

w = np.array([3,4])
num_samples=40;
max_its=40;
search_w_history,search_cost_history=coordinate_search(g,'diminishing',max_its,w,num_samples)
static_plotter=Visualizer();
static_plotter.two_input_surface_contour_plot(g,search_w_history,view=[30,30],xmin=0,xmax=4,ymin=1,ymax=4.5)

<ipython-input-4-4efdb3430233>:642: RuntimeWarning: divide by zero encountered in double_scalars
  alpha = (head_length - 0.35)/pt_length + 1
```



```
In [139]: descent_w_history,descent_cost_history=coordinate_descent(g,'diminishing',max_its,w,num_samples)
static_plotter=Visualizer();
static_plotter.two_input_surface_contour_plot(g,descent_w_history,view=[30,30],xmin=0,xmax=4,ymin=1,ymax=4.5)

<ipython-input-4-4efdb3430233>:642: RuntimeWarning: divide by zero encountered in double_scalars
  alpha = (head_length - 0.35)/pt_length + 1
```



```
In [143]: sns.lineplot(y=search_cost_history,x=[i for i in range(max_its+1)])
_p.set(title='Value of cost function over 40 iterations and diminishing stepsize using coordinate search',
       ylabel='Value of Function',xlabel='Iteration no.',xticks=range(0,max_its+1,5))
```



```
In [144]: sns.lineplot(y=descent_cost_history,x=[i for i in range(max_its+1)])
_p.set(title='Value of Function over 40 iterations and diminishing stepsize using coordinate descent',
       ylabel='Value of Function',xlabel='Iteration no.',xticks=range(0,max_its+1,5))
```



While the descent function might computationally be more efficient, it does not reach as low as a final value as the search function despite undergoing the same number of iterations. However, at higher dimensions, the decreased runtime afforded by a coordinate descent makes it more desirable to use than a coordinate search.