In [13]: In [8]:	<pre>####################################</pre>
In [33]:	
In [9]:	h12 = -400 * x h21 = -400 * x h22 = 200 return np.array([[h11,h12],[h21,h22]]) def Rosenbrock(X): x, y = X return (1 - x)**2 + 100*(y - x**2)**2 def Grad_Rosenbrock(X):
	<pre>def Grad_Roselifock(x): x, y = X return np.array([</pre>
In [45]:	<pre>y = np.arange(-5, 5, 0.025) X, Y = np.meshgrid(x, y) Z = np.zeros(X.shape) mesh_size = range(len(X)) for i, j in product(mesh_size, mesh_size): x_coor = X[i][j] y_coor = Y[i][j] Z[i][j] = Rosenbrock(np.array([x_coor, y_coor])) fig = plt.figure(figsize=(6,6)) ax = fig.gca(projection='3d')</pre>
	<pre>ax = fig.gca(projection='3d') ax.set_title('Rosenbruck Function') ax.set_xlabel('\$x_1\$') ax.set_ylabel('\$x_2\$') ax.set_zlabel('\$f(x_1, x_2)\$') ax.plot_surface(X, Y, Z, cmap='viridis') plt.tight_layout() plt.show()</pre> <pre> Rosenbruck Function</pre>
	80000 60000 40000 20000
In [46]:	
	Parameters
	Value of `alpha` at the start of the optimization. rho: float, optional Value of alpha shrinkage factor. c1: float, optional Value to control stopping criterion. Returns
In [55]:	<pre>derphi0 = np.dot(gfk, pk) phi_a0 = f(xk + alpha0*pk) while not phi_a0 <= phi0 + c1*alpha0*derphi0: alpha0 = alpha0 * rho phi_a0 = f(xk + alpha0*pk) return alpha0, phi_a0 def GradientDescent(f, f_grad, init, alpha=1, tol=1e-3, max_iter=100000): """Gradient descent method for unconstraint optimization problem. given a starting point x ∈ Rⁿ,</pre>
	<pre>repeat 1. Define direction. p := -Vf(x). 2. Line search. Choose step length α using Armijo Line Search. 3. Update. x := x + αp. until stopping criterion is satisfied. Parameters</pre>
	<pre>init : array initial value of x. alpha : scalar, optional the initial value of steplength. tol : float, optional tolerance for the norm of f_grad. max_iter : integer, optional maximum number of steps. Returns</pre>
	<pre>ys : array f(x) in the learning path """ # initialize x, f(x), and f'(x) xk = init fk = f(xk) gfk = f_grad(xk) gfk_norm = np.linalg.norm(gfk) # initialize number of steps, save x and f(x) num_iter = 0 curve_x = [xk] curve_y = [fk] print('Initial condition: y = {:.4f}, x = {} \n'.format(fk, xk))</pre>
	<pre># take steps while gfk_norm > tol and num_iter < max_iter: # determine direction pk = -gfk #pk = np.linalg.inv(Hessian_Rosenbrock_f(x,y)) @ Grad_Rosenbrock_f(x,y) # calculate new x, f(x), and f'(x) alpha, fk = ArmijoLineSearch(f, xk, pk, gfk, fk, alpha0=alpha) xk = xk + alpha * pk gfk = f_grad(xk) gfk_norm = np.linalg.norm(gfk) # increase number of steps by 1, save new x and f(x) num_iter += 1 curve_x.append(xk)</pre>
In [56]:	<pre>curve_y.append(fk) print('Iteration: {} \t y = {:.4f}, x = {}, gradient = {:.4f}'.</pre>
	<pre>plt.suptitle('Gradient Descent Method') ax1.plot(xs[:,0], xs[:,1], linestyle='', marker='o', color='orange') ax1.plot(xs[-1,0], xs[-1,1], 'ro') ax1.set(title='Path During Optimization Process', xlabel='x1', ylabel='x2') CS = ax1.contour(X, Y, Z) ax1.clabel(CS, fontsize='smaller', fmt='%1.2f') ax1.axis('square')</pre>
	<pre>ax2.plot(ys, linestyle='', marker='o', color='orange') ax2.plot(len(ys)-1, ys[-1], 'ro') ax2.xaxis.set_major_locator(MaxNLocator(integer=True)) ax2.set(title='Objective Function Value During Optimization Process', xlabel='Iterations', ylabel='Objective Function Value') ax2.legend(['Armijo line search algorithm']) plt.tight_layout() plt.show()</pre>
In [57]:	<pre>x0 = np.array([-1.2, 1]) xs, ys = GradientDescent(Rosenbrock, Grad_Rosenbrock, init=x0) plot(xs, ys)</pre>































