

# Homework 7: Convex Programming

## 1. Enclosing circle.

Variables: The coordinate of the circle's center; the radius of this circle;

Objective:  $\min_R (\pi R^2)$

where R is the radius of the circle;

Constraints:  $(X_i - C)^2 < R^2$

where C is the center's coordinate of the circle,  $X_i$  is the coordinate of the  $i_{th}$  point.

In [1]:

```
1  ## generate the data points
2  using PyPlot, JuMP, Gurobi;
3
4  num = 50;
5  X = randn(2,num) .* 4;
6
7  m1 = Model(Gurobi.Optimizer);
8  set_silent(m1);
9
10 C = @variable(m1, [1:2,1:1]); ## circle center
11 @variable(m1,R2); ## radius's square
12
13
14 for i = 1:num
15     @constraint(m1, sum((X[:,i] - C).^2) <= R2);
16 end
17
18 @objective(m1, Min, pi * R2);
19 optimize!(m1);
20
```

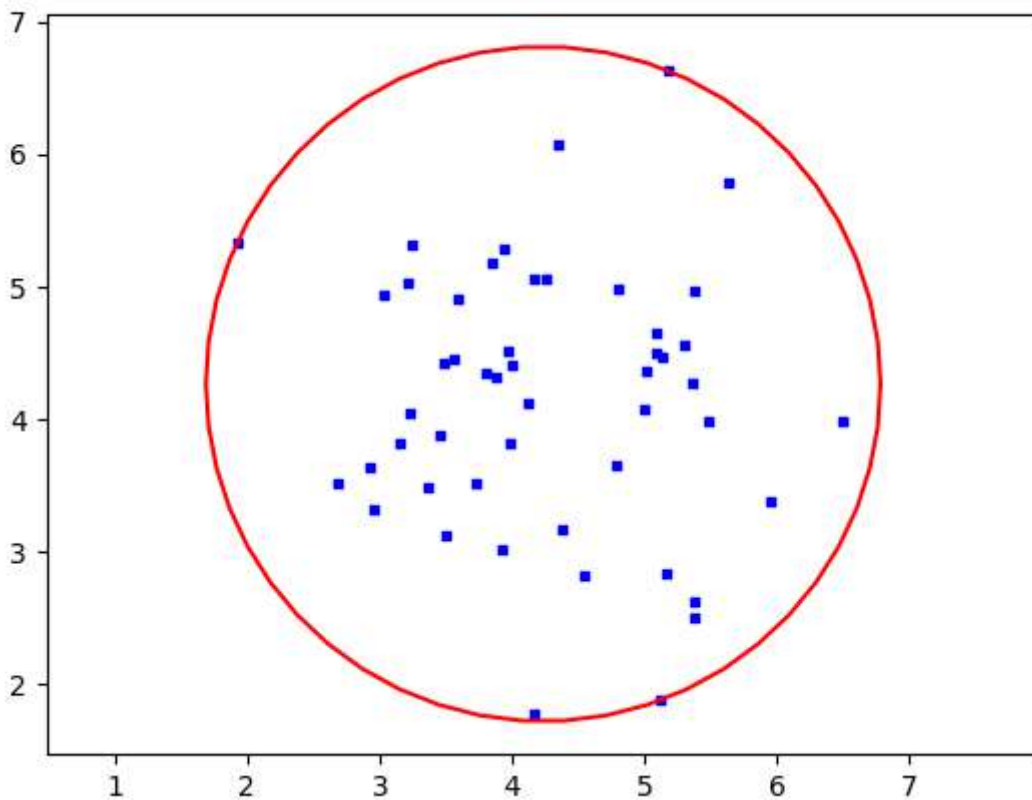
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In [2]:

```
1 center = value.(C);
2 radius = (value.(R2))^0.5;
3
4 edge = 50;
5
6 figure();
7 scatter(X[1,:],X[2:], s = 5, marker = "s", c = "blue");
8 t = (0:1:edge)./edge.*2*pi;
9 x = center[1] .+ cos.(t) .* radius;
10 y = center[2] .+ sin.(t) .* radius;
11 plot(x,y, c = "r");
12 title( "The center is $(round.(center,digits = 4))\nThe radius is $(radius).")
13 axis("equal");
```

The center is [4.2376; 4.2661]  
The radius is 2.5476439880508552.



## 2. The Huber loss.

a).

variables: slope, a, and intercept, b

objective: minimize  $\sum_i (y_i - ax_i - b_i)^2$

In [3]:

```
1 x = 1:15;
2 y = [6.31 3.78 5.12 1.71 2.99 4.53 2.11 3.88 4.67 26 2.06 23 1.58 2.17 0.02];
3
4 X1 = [x';y];
5 X2 = zeros(2,13);
6
7 ## generate the data without outliers
8 i1 = 1;
9 i2 = 1;
10 while i1 <= 15
11     if (i1 != 10) && (i1 != 12)
12         X2[:,i2] = X1[:,i1];
13         i2 += 1;
14     end
15     i1 += 1;
16 end
```

In [4]:

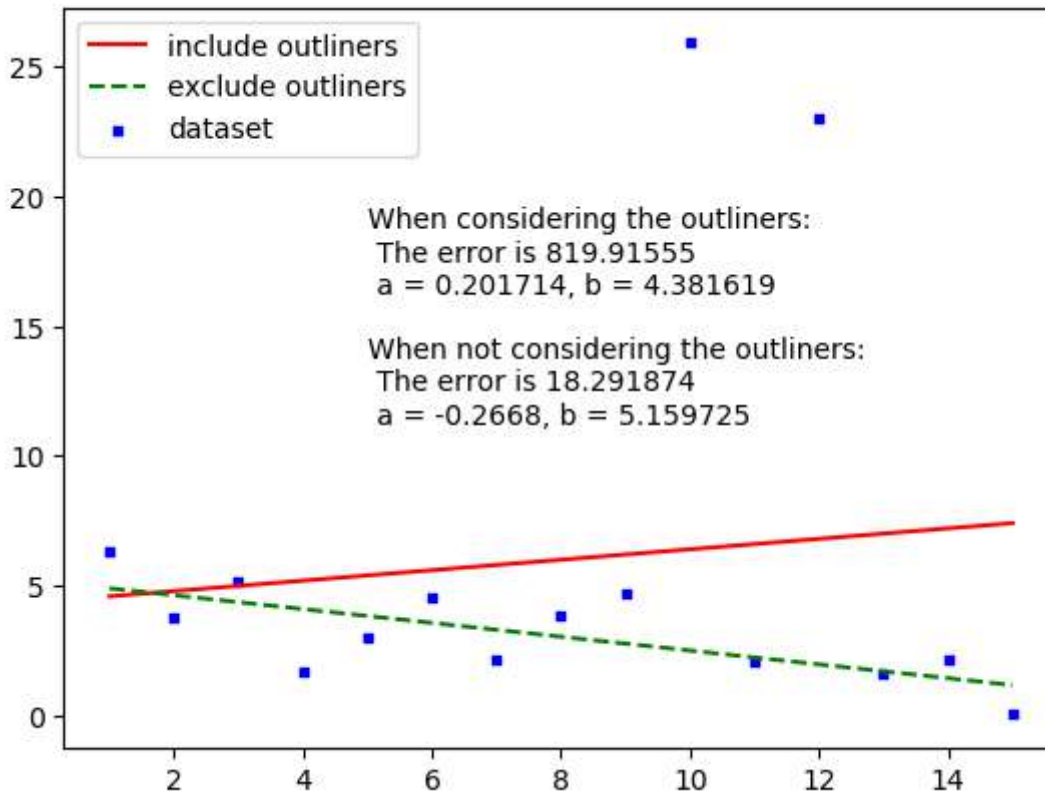
```
1 using PyPlot, JuMP, Gurobi;
2
3 m2a = Model(Gurobi.Optimizer);
4 set_silent(m2a);
5 #p1 = zeros(2,1); ## linear fit parameters (a and b)
6 #p2 = zeros(2,1);
7
8 ab = @variable(m2a, [1:2,1:1]);
9
10 @objective(m2a, Min, sum((X1[2,:] .- X1[1,:].*ab[1] .- ab[2]).^2));
11 optimize!(m2a);
12 p1 = value.(ab);
13 error1 = JuMP.objective_value(m2a);
14 @objective(m2a, Min, sum((X2[2,:] .- X2[1,:].*ab[1] .- ab[2]).^2));
15 optimize!(m2a);
16 p2 = value.(ab);
17 error2 = JuMP.objective_value(m2a);
```

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In [5]:

```
1 figure();
2 scatter(X1[1,:], X1[2,:], s = 5, c = "blue", marker = "s", label = "dataset");
3 plot(X1[1,:], p1[1].*X1[1,:].+p1[2], label = "include outliers", c = "r");
4 plot(X2[1,:], p2[1].*X2[1,:].+p2[2], label = "exclude outliers", c = "g", linestyle = "--");
5 text(5,15, "When considering the outliers:\n The error is $(round.(error1, digits = 6))\n a = $(round.(a, digits = 6))\n b = $(round.(b, digits = 6))");
6 text(5,10, "When not considering the outliers:\n The error is $(round.(error2, digits = 6))\n a = $(round.(a, digits = 6))\n b = $(round.(b, digits = 6))");
7 legend();
```



Let's say fit\_1 includes the outliers, while fit\_2 doesn't. From the plots we can see fit\_1 has a positive slope, but fit\_2's slope is negative; in the other words, the a in fit\_1 is positiv,but in fit\_2 is negative; The reason for this difference may be that the outliers are very far away from the expected locations. In  $l_2$  fit, we minimize the difference in Euclid distance; but the outliers are far away, so their contribution to the objective is much greater than other points when squared. Thus we get a positive a value, even though the other data shows a decreasing trend.

**b).**

variables: slope, a, and intercept, b

objective: minimize  $\sum_i |y_i - ax_i - b_i|$

In [6]:

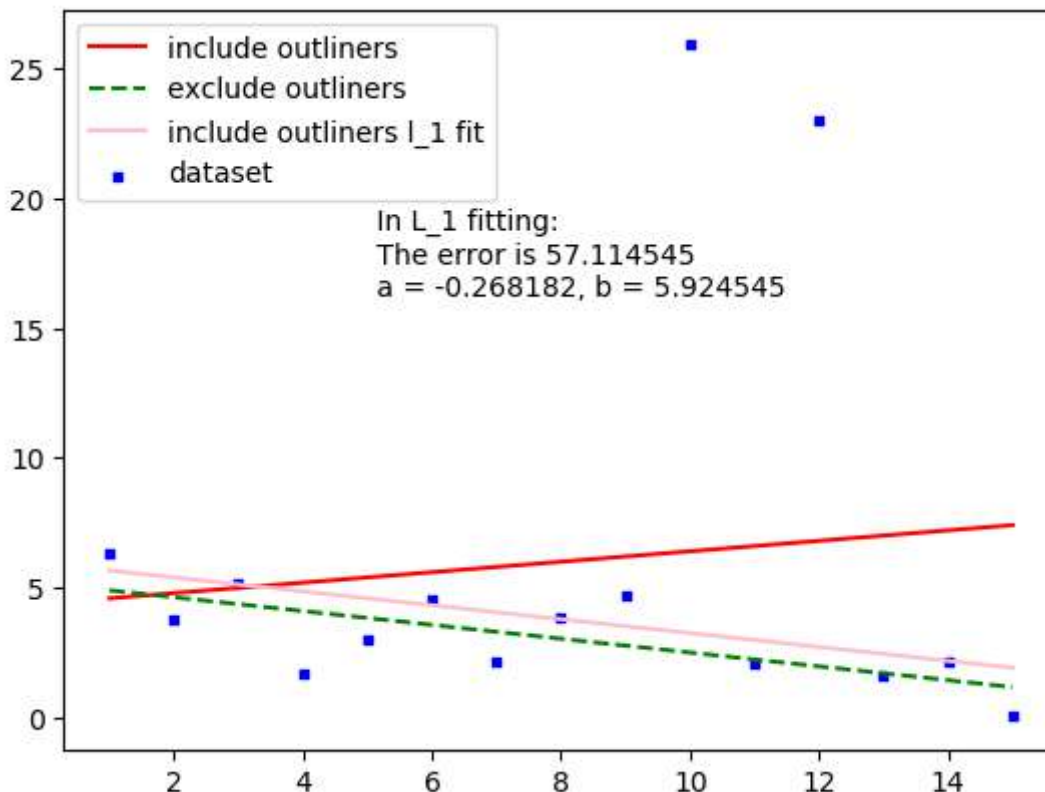
```
1 m2b = Model(Gurobi.Optimizer);
2 set_silent(m2b);
3
4 ## p3 as l1 fit
5
6 ab = @variable(m2b, [1:2,1:1]);
7 t = @variable(m2b, [1:length(X1[1,:])]);
8 @constraint(m2b, t .>= (X1[2,:] .- X1[1,:].*ab[1] .- ab[2] ));
9 @constraint(m2b, t .>= -(X1[2,:] .- X1[1,:].*ab[1] .- ab[2] ));
10 @objective(m2b, Min, sum(t));
11 optimize!(m2b);
12 p3 = value.(ab);
13 error3 = JuMP.objective_value(m2b);
14
```

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In [7]:

```
1 figure();
2 scatter(X1[1,:], X1[2,:], s = 5, c = "blue", marker = "s", label = "dataset");
3 plot(X1[1,:], p1[1].*X1[1,:] .+ p1[2], label = "include outliers", c = "r");
4 plot(X2[1,:], p2[1].*X2[1,:] .+ p2[2], label = "exclude outliers", c = "g", linestyle = "--");
5 plot(X1[1,:], p3[1].*X1[1,:] .+ p3[2], label = "include outliers l_1 fit", c = "pink");
6 text(5,15, " In L_1 fitting:\n The error is $(round.(error3, digits = 6))\n a = $(round.(p3[1], d:
7
8 legend();
```



From this figure we can see  $l_1$  fit is better than  $l_2$  fit when including the outliers, as the slope is almost the same as the  $l_2$  fitting without outliers, and the only difference is the intercept, but not significant.

The reason may be that, in  $l_1$  fit, the contribution from the outliers are still large, but not as significant as in  $l_2$  fit, where their contributions are squared. So a few outliers will not affect the linear fitting greatly in  $l_1$  approach.

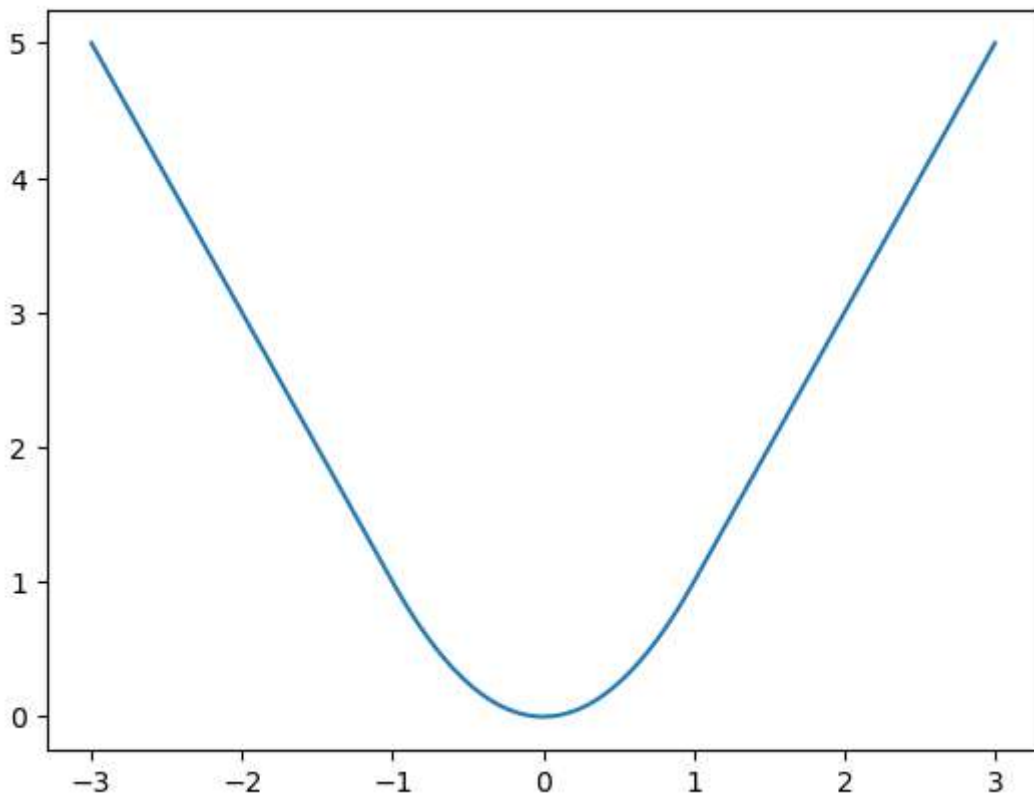
**c).**

variables: slope,  $a$ , and intercept,  $b$

objective: minimize  $\sum_i \phi(y_i - ax_i - b)$

In [8]:

```
1 using PyPlot, JuMP, Gurobi;
2
3 function Huber_loss(M, x)
4     m_Huber = Model(Gurobi.Optimizer);
5     set_silent(m_Huber);
6     @variable(m_Huber, w <= M);
7     @variable(m_Huber, v >= 0);
8     @constraint(m_Huber, w + v >= x);
9     @constraint(m_Huber, w + v >= -x);
10    @objective(m_Huber, Min, w^2 + 2*M*v);
11    optimize!(m_Huber);
12    return JuMP.objective_value(m_Huber);
13 end
14
15 function Huber_loss_array(M, x)
16     m_Huber = Model(Gurobi.Optimizer);
17     set_silent(m_Huber);
18     w = @variable(m_Huber, [1:length(x)]);
19     v = @variable(m_Huber, [1:length(x)]);
20     t = @variable(m_Huber, [1:length(x)]);
21     @constraint(m_Huber, w .<= M);
22     @constraint(m_Huber, v .>= 0);
23     @constraint(m_Huber, w + v .>= x);
24     @constraint(m_Huber, w + v .>= -x);
25     @constraint(m_Huber, t .>= w.^2 .+ 2 .*M.*v);
26     @objective(m_Huber, Min, sum(t));
27     optimize!(m_Huber);
28     return value.(t);
29 end
30
31 M = 1;
32
33 X_verify_m = 50;
34 X_verify = ((-X_verify_m:1:X_verify_m))./X_verify_m;
35 X_verify = X_verify .*3;
36
37 Y_verify = Huber_loss_array(M, X_verify);
38
39 #=
40 Y_verify = zeros(length(X_verify), 1);
41 for i = 1:length(Y_verify)
42     Y_verify[i] = Huber_loss(M, X_verify[i]);
43 end
44 =#
45 figure();
46 plot(X_verify, Y_verify);
```



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Ans:

So we can see this  $\phi(x)$  corresponds to the analytical expression in this question. We can see these two plots are exactly the same.

variables:  $w, v, a, b$

constraints:  $w_i \leq M, v_i \geq 0, w_i + v_i \geq |y_i - ax_i - b|$

objective: Minimize  $\sum_i w_i^2 + 2Mv_i$



In [9]:

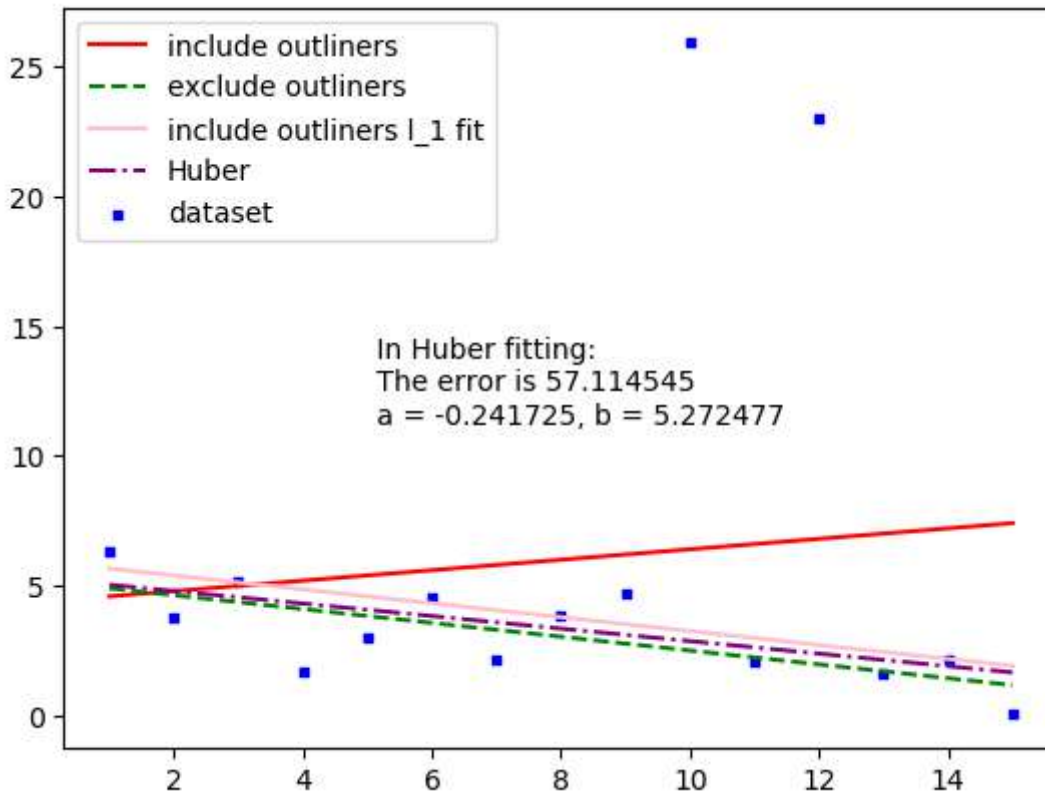
```
1
2 m2c = Model(Gurobi.Optimizer);
3 set_silent(m2c);
4 ab = @variable(m2c, [1:2,1:1]);
5 cost = @variable(m2c, [1:length(X1[1,:])]);
6 w = @variable(m2c, [1:length(X1[1,:])]);
7 v = @variable(m2c, [1:length(X1[1,:])]);
8
9 @constraint(m2c, (w .+ v) .>= (X1[2,:] .- X1[1,:].*ab[1] .- ab[2]));
10 @constraint(m2c, (w .+ v) .>= -(X1[2,:] .- X1[1,:].*ab[1] .- ab[2]));
11 @constraint(m2c, v .>= 0);
12 @constraint(m2c, w .<= M);
13 @constraint(m2c, cost .>= w.^2 + (2 * M) .* v);
14
15 @objective(m2c, Min, sum(cost));
16 optimize!(m2c);
17 p4 = value.(ab);
18 error4 = JuMP.objective_value(m2b);
```

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In [10]:

```
1 figure();
2 scatter(X1[1,:], X1[2,:], s = 5, c = "blue", marker = "s", label = "dataset");
3 plot(X1[1,:], p1[1].*X1[1,:] .+ p1[2], label = "include outliers", c = "r");
4 plot(X2[1,:], p2[1].*X2[1,:] .+ p2[2], label = "exclude outliers", c = "g", linestyle = "--");
5 plot(X1[1,:], p3[1].*X1[1,:] .+ p3[2], label = "include outliers l_1 fit", c = "pink");
6 plot(X1[1,:], p4[1].*X1[1,:] .+ p4[2], label = "Huber", c = "purple", linestyle = "-.");
7 text(5,10, " In Huber fitting:\n The error is $(round.(error4, digits = 6))\n a = $(round.(p4[1]
8
9 legend();
```



### 3.Heat pipe design.

a).

The velocity of the heat flow is  $v = \alpha_4 T r^2$ , so the amout of heat transferring in this tube is  $\pi r^2 v = \pi \alpha_4 T r^4$   
Convert this question into a geometric form, we thus have:

$$\begin{aligned} \max \quad & \pi \alpha_4 T r^4 \\ s.t \quad & T_{min} \leq T \leq T_{max} \\ & r_{min} \leq r \leq r_{max} \\ & w_{min} \leq w \leq w_{max} \\ & w \leq 0.1r \\ & \alpha_1 \frac{Tr}{w} + \alpha_2 r + \alpha_3 r w \leq C_{max} \end{aligned}$$

Then we can convert it to a generic form;

$$\begin{aligned} -\min \quad & (-\pi \alpha_4 T r^4) \quad s.t \quad \frac{T_{min}}{T} \leq 1 \quad \frac{T}{T_{max}} \leq 1 \\ & \frac{r_{min}}{r} \leq 1 \quad \frac{r}{r_{max}} \leq 1 \end{aligned}$$

$$\begin{aligned}\frac{w_{min}}{w} &\leq 1 & \frac{w}{w_{max}} &\leq 1 \\ \frac{10w}{r} &\leq 1 \\ \frac{\alpha_1 \frac{Tr}{w} + \alpha_2 r + \alpha_3 rw}{C_{max}} &\leq 1\end{aligned}$$

When apply logarithm on all the constraints, we have a convex optimization:

$$\begin{aligned}min \quad & -\log \pi \alpha_4 - \log T - 4 \log r \\ s.t \quad & \log T_{min} - \log T \leq 0 \quad \log T - \log T_{max} \leq 0 \\ & \log r_{min} - \log r \leq 0 \quad \log r - \log r_{max} \leq 0 \\ & \log w_{min} - \log w \leq 0 \quad \log w - \log w_{max} \leq 0 \\ & \log 10 + \log w - \log r \leq 0 \\ & \log \frac{\alpha_1 e^{\log T + \log r - \log w} + \alpha_2 e^{\log r} + \alpha_3 e^{\log r + \log w}}{C_{max}} \leq 0\end{aligned}$$

**b).**

Assume we have  $x = \log T$ ,  $y = \log r$ ,  $z = \log w$

$$\alpha_i = 1 \quad \forall i \in \{1, 2, 3, 4\}$$

$$C_{max} = 500$$

Hence we have:

$$\begin{aligned}min \quad & -\log \pi - x - 4y \\ s.t \quad & \log 10 + z - y \leq 0 \\ & \log \frac{e^{x+y-z} + e^y + e^{y+z}}{500} \leq 0\end{aligned}$$

In [11]:

```
1 using JuMP, Ipopt, PyPlot;
2 m3 = Model(Ipopt.Optimizer);
3 set_silent(m3);
4 @variable(m3, x);
5 @variable(m3, y);
6 @variable(m3, z);
7
8 @constraint(m3, log(10) + z - y <= 0);
9 @NLconstraint(m3, log((exp(x+y-z) + exp(y) + exp(y+z))/500) <= 0);
10 @objective(m3, Min, -log(pi) - x - 4*y);
11 optimize!(m3);
```

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The inequality constraints contain an invalid number  
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11 -2.5671926e+03 6.71e+02 1.11e+04 -1.0 6.78e+08 - 1.27e-07 6.63e-07f 21  
The inequality constraints contain an invalid number  
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The inequality constraints contain an invalid number  
Warning: Cutting back alpha due to evaluation error

In [12]:

```
1 T = exp(value.(x));
2 r = exp(value.(y));
3 w = exp(value.(z));
4 Heat_max = pi * T * r^4;
5 print("The maximum heat flow in this pip is $(Heat_max), \nwhere T = $(T), r = $(r), w = $(w).\n");
6 print("The cost is $(T*r/w + r + r*w).")
```

The maximum heat flow in this pip is 3.0679616908019958e9,  
where T = 0.24999999951949164, r = 250.00000024635135, w = 0.4999999993593595.  
The cost is 500.00000046867728.

In [ ]:

1