

Details for Deriving the Optimal Convergence Rates

Sandra S. Y. Tan

This document is intended to be supplementary material for the paper “A Unified Framework for the Convergence Analysis of Optimization Algorithms via Sum-of-Squares”. It provides full details for the proving the results given in that paper.

1 Full Details for PGM with Constant Step Size

The constraints characterizing the function class and algorithm are

$$\begin{aligned} g_1 : \quad & \mathbf{x}_{k+1} - \mathbf{x}_k + \gamma(\mathbf{g}_k + \mathbf{s}_{k+1}) = 0 \\ g_2 : \quad & \mathbf{g}_* + \mathbf{s}_* = 0 \\ h_1 : \quad & f_k - f_{k+1} - \mathbf{g}_{k+1}^T(\mathbf{x}_k - \mathbf{x}_{k+1}) - \alpha \left[\frac{1}{L} \|\mathbf{g}_k - \mathbf{g}_{k+1}\|^2 + \mu \|\mathbf{x}_k - \mathbf{x}_{k+1}\|^2 \right. \\ & \quad \left. - 2 \frac{\mu}{L} (\mathbf{g}_{k+1} - \mathbf{g}_k)^T (\mathbf{x}_{k+1} - \mathbf{x}_k) \right] \geq 0 \\ h_2 : \quad & f_k - f_* - \mathbf{g}_*^T(\mathbf{x}_k - \mathbf{x}_*) - \alpha \left[\frac{1}{L} \|\mathbf{g}_k - \mathbf{g}_*\|^2 + \mu \|\mathbf{x}_k - \mathbf{x}_*\|^2 \right. \\ & \quad \left. - 2 \frac{\mu}{L} (\mathbf{g}_* - \mathbf{g}_k)^T (\mathbf{x}_* - \mathbf{x}_k) \right] \geq 0 \\ h_3 : \quad & f_{k+1} - f_k - \mathbf{g}_k^T(\mathbf{x}_{k+1} - \mathbf{x}_k) - \alpha \left[\frac{1}{L} \|\mathbf{g}_{k+1} - \mathbf{g}_k\|^2 + \mu \|\mathbf{x}_{k+1} - \mathbf{x}_k\|^2 \right. \\ & \quad \left. - 2 \frac{\mu}{L} (\mathbf{g}_k - \mathbf{g}_{k+1})^T (\mathbf{x}_k - \mathbf{x}_{k+1}) \right] \geq 0 \\ h_4 : \quad & f_{k+1} - f_* - \mathbf{g}_*^T(\mathbf{x}_{k+1} - \mathbf{x}_*) - \alpha \left[\frac{1}{L} \|\mathbf{g}_{k+1} - \mathbf{g}_*\|^2 + \mu \|\mathbf{x}_{k+1} - \mathbf{x}_*\|^2 \right. \\ & \quad \left. - 2 \frac{\mu}{L} (\mathbf{g}_* - \mathbf{g}_{k+1})^T (\mathbf{x}_* - \mathbf{x}_{k+1}) \right] \geq 0 \\ h_5 : \quad & f_* - f_k - \mathbf{g}_k^T(\mathbf{x}_* - \mathbf{x}_k) - \alpha \left[\frac{1}{L} \|\mathbf{g}_* - \mathbf{g}_k\|^2 + \mu \|\mathbf{x}_* - \mathbf{x}_k\|^2 \right. \\ & \quad \left. - 2 \frac{\mu}{L} (\mathbf{g}_k - \mathbf{g}_*)^T (\mathbf{x}_k - \mathbf{x}_*) \right] \geq 0 \\ h_6 : \quad & f_* - f_{k+1} - \mathbf{g}_{k+1}^T(\mathbf{x}_* - \mathbf{x}_{k+1}) - \alpha \left[\frac{1}{L} \|\mathbf{g}_* - \mathbf{g}_{k+1}\|^2 + \mu \|\mathbf{x}_* - \mathbf{x}_{k+1}\|^2 \right. \\ & \quad \left. - 2 \frac{\mu}{L} (\mathbf{g}_{k+1} - \mathbf{g}_*)^T (\mathbf{x}_{k+1} - \mathbf{x}_*) \right] \geq 0 \\ h_7 : \quad & h_k - h_{k+1} - \mathbf{s}_{k+1}^T(\mathbf{x}_k - \mathbf{x}_{k+1}) \geq 0 \\ h_8 : \quad & h_k - h_* - \mathbf{s}_*^T(\mathbf{x}_k - \mathbf{x}_*) \geq 0 \\ h_9 : \quad & h_{k+1} - h_k - \mathbf{s}_k^T(\mathbf{x}_{k+1} - \mathbf{x}_k) \geq 0 \\ h_{10} : \quad & h_{k+1} - h_* - \mathbf{s}_*^T(\mathbf{x}_{k+1} - \mathbf{x}_*) \geq 0 \\ h_{11} : \quad & h_* - h_k - \mathbf{s}_k^T(\mathbf{x}_* - \mathbf{x}_k) \geq 0 \\ h_{12} : \quad & h_* - h_{k+1} - \mathbf{s}_{k+1}^T(\mathbf{x}_* - \mathbf{x}_{k+1}) \geq 0 \end{aligned}$$

where $\gamma = \frac{2}{L+\mu}$. Substituting g_1 and g_2 into the other constraints, we eliminate variables \mathbf{x}_{k+1} and \mathbf{s}_* . Taking $n = 1$, we match coefficients of the monomials in

$$\begin{aligned} p(\mathbf{z}) &:= t(f_k + h_k) + (1-t)(f_* + h_*) - (f_{k+1} + h_{k+1}) \\ &= \mathbf{z}_1^T Q \mathbf{z}_1 + \sum_{i=1}^{12} \lambda_i h_i(\mathbf{z}) \end{aligned}$$

to obtain the following set of linear equalities

$$\begin{aligned} 0 &= Q(1, 1) \\ f_* : \quad 1 - t &= 2Q(1, 2) - \lambda_2 - \lambda_4 + \lambda_5 + \lambda_6 \\ f_k : \quad t &= 2Q(1, 3) + \lambda_1 + \lambda_2 - \lambda_3 - \lambda_5 \\ f_{k+1} : \quad -1 &= 2Q(1, 4) - \lambda_1 + \lambda_3 + \lambda_4 - \lambda_6 \\ h_* : \quad 1 - t &= 2Q(1, 5) - \lambda_8 - \lambda_{10} + \lambda_{11} + \lambda_{12} \\ h_k : \quad t &= 2Q(1, 6) + \lambda_7 + \lambda_8 - \lambda_9 - \lambda_{11} \\ h_{k+1} : \quad -1 &= 2Q(1, 7) - \lambda_7 + \lambda_9 + \lambda_{10} - \lambda_{12} \\ 0 &= Q(1, i) \quad i = 8, \dots, 14 \\ 0 &= Q(i, j) = Q(j, i) \quad i = 2, \dots, 7, \quad j = i, \dots, 14 \\ x_*^2 : \quad 0 &= Q(8, 8) - \alpha\mu(\lambda_2 + \lambda_4 + \lambda_5 + \lambda_6) \\ x_* x_k : \quad 0 &= 2Q(8, 9) + 2\alpha\mu(\lambda_2 + \lambda_4 + \lambda_5 + \lambda_6) \\ x_* g_* : \quad 0 &= 2Q(8, 10) + \lambda_2 + \lambda_4 - \lambda_8 - \lambda_{10} + 2\alpha\frac{\mu}{L}(\lambda_2 + \lambda_4 + \lambda_5 + \lambda_6) \\ x_* g_k : \quad 0 &= 2Q(8, 11) - 2\alpha\mu \left[\frac{1}{L}(\lambda_2 + \lambda_5) + \gamma(\lambda_4 + \lambda_6) \right] - \lambda_5 \\ x_* g_{k+1} : \quad 0 &= 2Q(8, 12) - 2\alpha\frac{\mu}{L}(\lambda_4 + \lambda_6) - \lambda_6 \\ x_* s_k : \quad 0 &= 2Q(8, 13) - \lambda_{11} \\ x_* s_{k+1} : \quad 0 &= 2Q(8, 14) - 2\alpha\mu\gamma(\lambda_4 + \lambda_6) - \lambda_{12} \\ x_k^2 : \quad 0 &= Q(9, 9) - \alpha\mu(\lambda_2 + \lambda_4 + \lambda_5 + \lambda_6) \\ x_k g_* : \quad 0 &= 2Q(9, 10) - \lambda_2 - \lambda_4 + \lambda_8 + \lambda_{10} - 2\alpha\frac{\mu}{L}(\lambda_2 + \lambda_4 + \lambda_5 + \lambda_6) \\ x_k g_k : \quad 0 &= 2Q(9, 11) + 2\alpha\mu \left[\frac{1}{L}(\lambda_2 + \lambda_5) + \gamma(\lambda_4 + \lambda_6) \right] + \lambda_5 \\ x_k g_{k+1} : \quad 0 &= 2Q(9, 12) + 2\alpha\frac{\mu}{L}(\lambda_4 + \lambda_6) + \lambda_6 \\ x_k s_k : \quad 0 &= 2Q(9, 13) + \lambda_{11} \\ x_k s_{k+1} : \quad 0 &= 2Q(9, 14) + 2\alpha\mu\gamma(\lambda_4 + \lambda_6) + \lambda_{12} \\ g_*^2 : \quad 0 &= Q(10, 10) - \frac{\alpha}{L}(\lambda_2 + \lambda_4 + \lambda_5 + \lambda_6) \\ g_* g_k : \quad 0 &= 2Q(10, 11) + 2\frac{\alpha}{L}[\lambda_2 + \lambda_5 + \mu\gamma(\lambda_4 + \lambda_6)] + \gamma(\lambda_4 - \lambda_{10}) \\ g_* g_{k+1} : \quad 0 &= 2Q(10, 12) + 2\frac{\alpha}{L}(\lambda_4 + \lambda_6) \\ g_* s_k : \quad 0 &= Q(10, 13) \\ g_* s_{k+1} : \quad 0 &= 2Q(10, 14) + \gamma(\lambda_4 - \lambda_{10}) + 2\alpha\frac{\mu}{L}\gamma(\lambda_4 + \lambda_6) \\ g_k^2 : \quad 0 &= 2Q(11, 11) - \frac{\alpha}{L}(\lambda_1 + \lambda_2 + \lambda_3 + \lambda_5) \\ &\quad - \alpha\mu\gamma^2(\lambda_1 + \lambda_3 + \lambda_4 + \lambda_6) + 2\alpha\gamma\frac{\mu}{L}(\lambda_1 + \lambda_3) + \gamma\lambda_3 \end{aligned} \tag{1}$$

$$\begin{aligned}
g_k g_{k+1} : \quad & 0 = 2Q(11, 12) - \gamma(\lambda_1 + \lambda_6) + 2\frac{\alpha}{L} [\lambda_1 + \lambda_3 - \mu\gamma(\lambda_1 + \lambda_3 + \lambda_4 + \lambda_6)] \\
g_k s_k : \quad & 0 = 2Q(11, 13) + \gamma\lambda_9 \\
g_k s_{k+1} : \quad & 0 = 2Q(11, 14) + 2\alpha\gamma\frac{\mu}{L}(\lambda_1 + \lambda_3) + \gamma(\lambda_3 - \lambda_7 - \lambda_{12}) \\
& \quad - 2\alpha\mu\gamma^2(\lambda_1 + \lambda_3 + \lambda_4 + \lambda_6) \\
g_{k+1}^2 : \quad & 0 = Q(12, 12) - \frac{\alpha}{L}(\lambda_1 + \lambda_3 + \lambda_4 + \lambda_6) \\
g_{k+1} s_k : \quad & 0 = Q(12, 13) \\
g_{k+1} s_{k+1} : \quad & 0 = 2Q(12, 14) - \gamma(\lambda_1 + \lambda_6) - 2\alpha\gamma\frac{\mu}{L}(\lambda_1 + \lambda_3 + \lambda_4 + \lambda_6) \\
s_k^2 : \quad & 0 = Q(13, 13) \\
s_k s_{k+1} : \quad & 0 = 2Q(13, 14) + \gamma\lambda_9 \\
s_{k+1}^2 : \quad & 0 = Q(14, 14) - \alpha\mu\gamma^2(\lambda_1 + \lambda_3 + \lambda_4 + \lambda_6) - \gamma(\lambda_7 + \lambda_{12})
\end{aligned}$$

The SDP is thus minimizing t subject to these linear equalities as well as

$$\begin{aligned}
Q &\succeq 0 \\
\lambda_i &\geq 0 \quad i = 0, \dots, 12 \\
0 &\leq t \leq 1
\end{aligned}$$

For $\gamma = \frac{2}{L+\mu}$, the optimal values of t and λ 's correspond to

$$\begin{aligned}
t &= \left(\frac{L - \mu}{L + \mu} \right)^2 & \lambda_1 &= \frac{L - \mu}{L + \mu} & \lambda_5 &= 2\mu \frac{L - \mu}{(L + \mu)^2} \\
\lambda_6 &= \frac{2\mu}{L + \mu} & \lambda_7 &= \left(\frac{L - \mu}{L + \mu} \right)^2 & \lambda_{12} &= \frac{4L\mu}{(L + \mu)^2}
\end{aligned}$$

and $\lambda_i = 0$ for $i = 2, \dots, 4, 8, \dots, 11$. The optimal Q is a sparse symmetric matrix, with the non-zero entries in the upper triangular portion being:

$$\begin{aligned}
Q(8, 8) &= \frac{2L^2\mu^2}{(L + \mu)^2(L - \mu)} & Q(8, 9) &= -\frac{2L^2\mu^2}{(L + \mu)^2(L - \mu)} & Q(8, 10) &= -\frac{2L\mu^2}{(L + \mu)^2(L - \mu)} \\
Q(8, 11) &= \frac{L\mu}{(L + \mu)(L - \mu)} & Q(8, 12) &= \frac{L\mu}{(L + \mu)(L - \mu)} & Q(8, 14) &= \frac{2L^2\mu}{(L + \mu)^2(L - \mu)} \\
Q(9, 9) &= \frac{2L^2\mu^2}{(L + \mu)^2(L - \mu)} & Q(9, 10) &= \frac{2L\mu^2}{(L + \mu)^2(L - \mu)} & Q(9, 11) &= -\frac{L\mu}{(L + \mu)(L - \mu)} \\
Q(9, 12) &= -\frac{L\mu}{(L + \mu)(L - \mu)} & Q(9, 14) &= -\frac{2L^2\mu}{(L + \mu)^2(L - \mu)} & Q(10, 10) &= \frac{2L\mu}{(L + \mu)^2(L - \mu)} \\
Q(10, 11) &= -\frac{\mu}{(L + \mu)(L - \mu)} & Q(10, 12) &= -\frac{\mu}{(L + \mu)(L - \mu)} & Q(10, 14) &= -\frac{2\mu^2}{(L + \mu)^2(L - \mu)} \\
Q(11, 11) &= \frac{1}{2(L - \mu)} & Q(11, 12) &= \frac{1}{2(L - \mu)} & Q(11, 14) &= \frac{L}{(L + \mu)(L - \mu)} \\
Q(12, 12) &= \frac{1}{2(L - \mu)} & Q(12, 14) &= \frac{L}{(L + \mu)(L - \mu)} & Q(14, 14) &= 2\frac{L^2 + L\mu - \mu^2}{(L + \mu)^2(L - \mu)}
\end{aligned}$$

These fulfill the set of linear equalities in the SDP. Q is also PSD, as can be verified by hand or by symbolic computation. This completes the proof that

$$f_{k+1} - f_* \leq \left(\frac{L - \mu}{L + \mu} \right)^2 (f_k - f_*)$$

2 Full Details for PGM with Exact Line Search

The constraints characterizing the function class and algorithm are

$$\begin{aligned}
g_1 : & \quad \mathbf{g}_{k+1}^T \mathbf{g}_k + \mathbf{g}_{k+1}^T \mathbf{s}_{k+1} + \mathbf{s}_{k+1}^T \mathbf{g}_k + \|\mathbf{s}_{k+1}\|^2 = 0 \\
g_2 : & \quad \mathbf{g}_{k+1}^T \mathbf{x}_{k+1} - \mathbf{g}_{k+1}^T \mathbf{x}_k + \mathbf{s}_{k+1}^T \mathbf{x}_{k+1} - \mathbf{s}_{k+1}^T \mathbf{x}_k = 0 \\
g_3 : & \quad \mathbf{g}_* + \mathbf{s}_* = 0 \\
h_4 : & \quad f_k - f_{k+1} - \mathbf{g}_{k+1}^T (\mathbf{x}_k - \mathbf{x}_{k+1}) - \alpha \left[\frac{1}{L} \|\mathbf{g}_k - \mathbf{g}_{k+1}\|^2 + \mu \|\mathbf{x}_k - \mathbf{x}_{k+1}\|^2 \right. \\
& \quad \left. - 2 \frac{\mu}{L} (\mathbf{g}_{k+1} - \mathbf{g}_k)^T (\mathbf{x}_{k+1} - \mathbf{x}_k) \right] \geq 0 \\
h_5 : & \quad f_k - f_* - \mathbf{g}_*^T (\mathbf{x}_k - \mathbf{x}_*) - \alpha \left[\frac{1}{L} \|\mathbf{g}_k - \mathbf{g}_*\|^2 + \mu \|\mathbf{x}_k - \mathbf{x}_*\|^2 \right. \\
& \quad \left. - 2 \frac{\mu}{L} (\mathbf{g}_* - \mathbf{g}_k)^T (\mathbf{x}_* - \mathbf{x}_k) \right] \geq 0 \\
h_6 : & \quad f_{k+1} - f_k - \mathbf{g}_k^T (\mathbf{x}_{k+1} - \mathbf{x}_k) - \alpha \left[\frac{1}{L} \|\mathbf{g}_{k+1} - \mathbf{g}_k\|^2 + \mu \|\mathbf{x}_{k+1} - \mathbf{x}_k\|^2 \right. \\
& \quad \left. - 2 \frac{\mu}{L} (\mathbf{g}_k - \mathbf{g}_{k+1})^T (\mathbf{x}_k - \mathbf{x}_{k+1}) \right] \geq 0 \\
h_7 : & \quad f_{k+1} - f_* - \mathbf{g}_*^T (\mathbf{x}_{k+1} - \mathbf{x}_*) - \alpha \left[\frac{1}{L} \|\mathbf{g}_{k+1} - \mathbf{g}_*\|^2 + \mu \|\mathbf{x}_{k+1} - \mathbf{x}_*\|^2 \right. \\
& \quad \left. - 2 \frac{\mu}{L} (\mathbf{g}_* - \mathbf{g}_{k+1})^T (\mathbf{x}_* - \mathbf{x}_{k+1}) \right] \geq 0 \\
h_8 : & \quad f_* - f_k - \mathbf{g}_k^T (\mathbf{x}_* - \mathbf{x}_k) - \alpha \left[\frac{1}{L} \|\mathbf{g}_* - \mathbf{g}_k\|^2 + \mu \|\mathbf{x}_* - \mathbf{x}_k\|^2 \right. \\
& \quad \left. - 2 \frac{\mu}{L} (\mathbf{g}_k - \mathbf{g}_*)^T (\mathbf{x}_k - \mathbf{x}_*) \right] \geq 0 \\
h_9 : & \quad f_* - f_{k+1} - \mathbf{g}_{k+1}^T (\mathbf{x}_* - \mathbf{x}_{k+1}) - \alpha \left[\frac{1}{L} \|\mathbf{g}_* - \mathbf{g}_{k+1}\|^2 + \mu \|\mathbf{x}_* - \mathbf{x}_{k+1}\|^2 \right. \\
& \quad \left. - 2 \frac{\mu}{L} (\mathbf{g}_{k+1} - \mathbf{g}_*)^T (\mathbf{x}_{k+1} - \mathbf{x}_*) \right] \geq 0 \\
h_{10} : & \quad h_k - h_{k+1} - \mathbf{s}_{k+1}^T (\mathbf{x}_k - \mathbf{x}_{k+1}) \geq 0 \\
h_{11} : & \quad h_k - h_* - \mathbf{s}_*^T (\mathbf{x}_k - \mathbf{x}_*) \geq 0 \\
h_{12} : & \quad h_{k+1} - h_k - \mathbf{s}_k^T (\mathbf{x}_{k+1} - \mathbf{x}_k) \geq 0 \\
h_{13} : & \quad h_{k+1} - h_* - \mathbf{s}_*^T (\mathbf{x}_{k+1} - \mathbf{x}_*) \geq 0 \\
h_{14} : & \quad h_* - h_k - \mathbf{s}_k^T (\mathbf{x}_* - \mathbf{x}_k) \geq 0 \\
h_{15} : & \quad h_* - h_{k+1} - \mathbf{s}_{k+1}^T (\mathbf{x}_* - \mathbf{x}_{k+1}) \geq 0
\end{aligned}$$

Again, we take $n = 1$ and match coefficients of the monomials in

$$\begin{aligned}
p(\mathbf{z}) &:= t(f_k + h_k) + (1 - t)(f_* + h_*) - (f_{k+1} + h_{k+1}) \\
&= \mathbf{z}_1^T Q \mathbf{z}_1 + \sum_{j=1}^3 \lambda_j g_j(\mathbf{z}) + \sum_{i=4}^{15} \lambda_i h_i(\mathbf{z})
\end{aligned}$$

to obtain a set of linear equalities. The resulting SDP thus seeks to minimize t subject to

$$\begin{aligned}
0 &\leq t \leq 1 \\
\lambda_i &\geq 0 \quad i = 4, \dots, 16 \\
Q &\succeq 0 \\
0 &= Q(1, 1)
\end{aligned} \tag{2}$$

$$\begin{aligned}
f_* : & 1 - t = 2Q(1, 2) - \lambda_5 - \lambda_7 + \lambda_8 + \lambda_9 \\
f_k : & t = 2Q(1, 3) + \lambda_4 + \lambda_5 - \lambda_6 - \lambda_8 \\
f_{k+1} : & -1 = 2Q(1, 4) - \lambda_4 + \lambda_6 + \lambda_7 - \lambda_9 \\
h_* : & 1 - t = 2Q(1, 5) - \lambda_{11} - \lambda_{13} + \lambda_{14} + \lambda_{15} \\
h_k : & t = 2Q(1, 6) + \lambda_{10} + \lambda_{11} - \lambda_{12} - \lambda_{14} \\
h_{k+1} : & -1 = 2Q(1, 7) - \lambda_{10} + \lambda_{12} + \lambda_{13} - \lambda_{15} \\
& 0 = Q(1, i) \quad i = 8, 9, 10, 12, 13, 15, 16 \\
g_* : & 0 = 2Q(1, 11) + \lambda_3 \\
s_* : & 0 = 2Q(1, 14) + \lambda_3 \\
& 0 = Q(i, j) \quad i = 2, \dots, 7, \quad j = i, \dots, 16 \\
x_*^2 : & 0 = Q(8, 8) - \alpha\mu(\lambda_5 + \lambda_7 + \lambda_8 + \lambda_9) \\
x_*x_k : & 0 = 2Q(8, 9) + 2\alpha\mu(\lambda_5 + \lambda_8) \\
x_*x_{k+1} : & 0 = 2Q(8, 10) + 2\alpha\mu(\lambda_7 + \lambda_9) \\
x_*g_* : & 0 = 2Q(8, 11) + \lambda_5 + \lambda_7 + 2\alpha\frac{\mu}{L}(\lambda_5 + \lambda_7 + \lambda_8 + \lambda_9) \\
x_*g_k : & 0 = 2Q(8, 12) - 2\alpha\frac{\mu}{L}(\lambda_5 + \lambda_8) - \lambda_8 \\
x_*g_{k+1} : & 0 = 2Q(8, 13) - 2\alpha\frac{\mu}{L}(\lambda_7 + \lambda_9) - \lambda_9 \\
x_*s_* : & 0 = 2Q(8, 14) + \lambda_{11} + \lambda_{13} \\
x_*s_k : & 0 = 2Q(8, 15) - \lambda_{14} \\
x_*s_{k+1} : & 0 = 2Q(8, 16) - \lambda_{15} \\
x_k^2 : & 0 = Q(9, 9) - \alpha\mu(\lambda_4 + \lambda_5 + \lambda_6 + \lambda_8) \\
x_kx_{k+1} : & 0 = 2Q(9, 10) + 2\alpha\mu(\lambda_4 + \lambda_6) \\
x_kg_* : & 0 = 2Q(9, 11) - \lambda_5 - 2\alpha\frac{\mu}{L}(\lambda_5 - \lambda_8) \\
x_kg_k : & 0 = 2Q(9, 12) + 2\alpha\frac{\mu}{L}(\lambda_4 + \lambda_5 + \lambda_6 + \lambda_8) + \lambda_6 + \lambda_8 \\
x_kg_{k+1} : & 0 = 2Q(9, 13) - \lambda_2 - \lambda_4 - 2\alpha\frac{\mu}{L}(\lambda_4 + \lambda_6) \\
x_k s_* : & 0 = 2Q(9, 14) - \lambda_{11} \\
x_k s_k : & 0 = 2Q(9, 15) + \lambda_{12} + \lambda_{14} \\
x_k s_{k+1} : & 0 = 2Q(9, 16) - \lambda_2 - \lambda_{10} \\
x_{k+1}^2 : & 0 = Q(10, 10) - \alpha\mu(\lambda_4 + \lambda_6 + \lambda_7 + \lambda_9) \\
x_{k+1}g_* : & 0 = 2Q(10, 11) - \lambda_7 - 2\alpha\frac{\mu}{L}(\lambda_7 + \lambda_9) \\
x_{k+1}g_k : & 0 = 2Q(10, 12) - 2\alpha\frac{\mu}{L}(\lambda_4 + \lambda_6) - \lambda_6 \\
x_{k+1}g_{k+1} : & 0 = 2Q(10, 13) + \lambda_2 + \lambda_4 + \lambda_9 + 2\alpha\frac{\mu}{L}(\lambda_4 + \lambda_6 + \lambda_7 + \lambda_9) \\
x_{k+1}s_* : & 0 = 2Q(10, 14) - \lambda_{13} \\
x_{k+1}s_k : & 0 = 2Q(10, 15) - \lambda_{12} \\
x_{k+1}s_{k+1} : & 0 = 2Q(10, 16) + \lambda_2 + \lambda_{10} + \lambda_{15} \\
g_*^2 : & 0 = Q(11, 11) - \frac{\alpha}{L}(\lambda_5 + \lambda_7 + \lambda_8 + \lambda_9) \\
g_*g_k : & 0 = 2Q(11, 12) + 2\frac{\alpha}{L}(\lambda_5 + \lambda_8) \\
g_*g_{k+1} : & 0 = 2Q(11, 13) + 2\frac{\alpha}{L}(\lambda_7 + \lambda_9)
\end{aligned}$$

$$\begin{aligned}
& 0 = Q(11, i) \quad i = 14, \dots, 16 \\
g_k^2 : & 0 = Q(12, 12) - \frac{\alpha}{L}(\lambda_4 + \lambda_5 + \lambda_6 + \lambda_8) \\
g_k g_{k+1} : & 0 = 2Q(12, 13) + \lambda_1 + 2\frac{\alpha}{L}(\lambda_4 + \lambda_6) \\
& 0 = Q(12, i) \quad i = 14, 15 \\
g_k s_{k+1} : & 0 = 2Q(12, 16) + \lambda_1 \\
g_{k+1}^2 : & 0 = Q(13, 13) - \frac{\alpha}{L}(\lambda_4 + \lambda_6 + \lambda_7 + \lambda_9) \\
& 0 = Q(13, i) \quad i = 14, 15 \\
g_{k+1} s_{k+1} : & 0 = 2Q(13, 16) + \lambda_1 \\
& 0 = Q(i, j) \quad i = 14, 15, \quad j = i, \dots, 16 \\
s_{k+1}^2 : & 0 = Q(16, 16) + \lambda_1
\end{aligned}$$

The optimal values of t and λ 's correspond to

$$\begin{aligned}
t &= \left(\frac{L - \mu}{L + \mu} \right)^2 & \lambda_1 &= -\frac{2}{L + \mu} & \lambda_2 &= -1 & \lambda_4 &= \frac{L - \mu}{L + \mu} \\
\lambda_8 &= 2\mu \frac{L - \mu}{(L + \mu)^2} & \lambda_9 &= \frac{2\mu}{L + \mu} & \lambda_{10} &= \left(\frac{L - \mu}{L + \mu} \right)^2 & \lambda_{15} &= \frac{4L\mu}{(L + \mu)^2}
\end{aligned}$$

and $\lambda_i = 0$ for $i = 3, 5, \dots, 7, 11, \dots, 14, 16$. The optimal Q is a sparse symmetric matrix, with the non-zero entries in the upper triangular portion being:

$$\begin{aligned}
Q(8, 8) &= \frac{2L^2\mu^2}{(L + \mu)^2(L - \mu)} & Q(8, 9) &= -\frac{L\mu^2}{(L + \mu)^2} & Q(8, 10) &= -\frac{L\mu^2}{(L - \mu)(L + \mu)} \\
Q(8, 11) &= -\frac{2L\mu^2}{(L + \mu)^2(L - \mu)} & Q(8, 12) &= \frac{L\mu}{(L + \mu)^2} & Q(8, 13) &= \frac{L\mu}{(L - \mu)(L + \mu)} \\
Q(8, 16) &= \frac{2L\mu}{(L + \mu)^2} & Q(9, 9) &= \frac{L\mu(L + 3\mu)}{2(L + \mu)^2} & Q(9, 10) &= -\frac{L\mu}{2(L + \mu)} \\
Q(9, 11) &= \frac{\mu^2}{(L + \mu)^2} & Q(9, 12) &= -\frac{\mu(3L + \mu)}{2(L + \mu)^2} & Q(9, 13) &= -\frac{\mu}{2(L + \mu)} \\
Q(9, 16) &= -\frac{2L\mu}{(L + \mu)^2} & Q(10, 10) &= \frac{L\mu}{2(L - \mu)} & Q(10, 11) &= \frac{\mu^2}{(L - \mu)(L + \mu)} \\
Q(10, 12) &= \frac{\mu}{2(L + \mu)} & Q(10, 13) &= -\frac{\mu}{2(L - \mu)} & Q(11, 11) &= \frac{2L\mu}{(L + \mu)^2(L - \mu)} \\
Q(11, 12) &= -\frac{\mu}{(L + \mu)^2} & Q(11, 13) &= -\frac{\mu}{(L - \mu)(L + \mu)} & Q(12, 12) &= \frac{L + 3\mu}{2(L + \mu)^2} \\
Q(12, 13) &= \frac{1}{2(L + \mu)} & Q(12, 16) &= \frac{1}{L + \mu} & Q(13, 13) &= \frac{1}{2(L - \mu)} \\
Q(13, 16) &= \frac{1}{L + \mu} & Q(16, 16) &= \frac{2}{L + \mu}
\end{aligned}$$

These fulfill the set of linear equalities in the SDP. Q is also PSD, as can be verified by hand or by symbolic computation. This completes the proof that

$$f_{k+1} - f_* \leq \left(\frac{L - \mu}{L + \mu} \right)^2 (f_k - f_*)$$