## Solution to Midterm paper

1. Proof. It's a trivial fact that $x$ is an extreme point of $Q$ implies $x$ is an extreme point of $\partial Q$.
Now assume $x$ is an extreme point of $\partial Q$, we need to show that $x$ cannot be written as $\lambda x_{1}+(1-\lambda) x_{2}$ with $\lambda \in(0,1)$. One can argue by contradiction. Suppose $x_{1}, x_{2} \in \partial Q$, then by assumption such a $\lambda \in(0,1)$ does not exist. Thus at least one $x_{i}$ belongs to $Q^{i n}$, where $Q^{i n}$ denotes the interior of $Q$. Without loss of generality, we may assume that $x_{1} \in Q^{i n}$. We claim that this implies $x \in Q^{i n}$. In fact, if $x_{2} \in Q^{i n}$, then by the convexity of $Q^{i n}, x \in Q^{i n}$. So we may assume that $x_{2} \in \partial Q$. At this stage we appeal to the expression $x=\lambda x_{1}+(1-\lambda) x_{2}$, which implies that $x_{1}$ can be written as a linear combination of $x$ and $x_{2}$. If $x \in \partial Q$, this implies that $x_{1}$ must lie on the line determined by $x$ and $x_{2}$. Since $Q$ is assumed to be a convex polytope, this is impossible. (Note that this is the only place where we use the assumption that $Q$ is a polytope)
Now we have proved the existence of a $\lambda \in(0,1)$ such that $x=\lambda x_{1}+(1-\lambda) x_{2}$ implies that $x \in Q^{i n}$, but this contradicts with the assumption that $x$ is an extreme point of $\partial Q$ (so in particular $x \in \partial Q$ ). This completes the proof.
2. (a) To convert the LPP to its standard form, we introduce the slack variables $x_{4}$ and $x_{5}$, use $x_{2}-9$ to replace the original $x_{2}$, and use $-z$ to replace the original $z$. The answer is as follows.
Maximize $z=-3 x_{1}-8 x_{2}-4 x_{3}$ subject to

$$
\begin{cases}x_{1}+x_{2}-x_{4} & =-1 \\ -2 x_{1}+3 x_{2}-x_{5} & =27 \\ x_{1}, x_{2}, x_{3}, x_{4}, x_{5} & \geq 0\end{cases}
$$

(b) We simply need to use $x_{2}-9$ to replace the original $x_{2}$.

Minimize $z=3 x_{1}+8 x_{2}+4 x_{3}$ subject to

$$
\left\{\begin{aligned}
-x_{1}-x_{2} & \leq 1 \\
2 x_{1}-3 x_{2} & \leq-27 \\
x_{1}, x_{2}, x_{3} & \geq 0
\end{aligned}\right.
$$

3. We construct the LPP following the hint. The two rays $\ell_{1}, \ell_{2}$ are simply taken to be $y=2 x$ and $y=\frac{1}{2} x$ with $x \geq 0$. The feasible region $F$ is bounded by $\ell_{1}$ and $\ell_{2}$ and taken to be

$$
F=\left\{(x, y) \in \mathbb{R}^{2} \left\lvert\, \frac{1}{2} x \leq y \leq 2 x\right., x \geq 0\right\}
$$

This determines the constraints of our LPP:

$$
\begin{cases}2 x-y & \geq 0 \\ 2 y-x & \geq 0 \\ x & \geq 0 \\ y & \geq 0\end{cases}
$$

It's easy to see the optimizer can be taken to be $z=x+y$, because the vector $\mathbf{v}=(1,1)$ is a direction of the unbounded convex set $F$. So we end up with the following LPP, which does not admit an optimal solution.
Maximize $z=x+y$ subject to

$$
\begin{cases}2 x-y & \geq 0 \\ 2 y-x & \geq 0 \\ x & \geq 0 \\ y & \geq 0\end{cases}
$$

4. Let $\mathbf{a}_{1}, \mathbf{a}_{2}, \mathbf{a}_{3}$ denote the colums of the matrix $\left[\begin{array}{lll}2 & 1 & 4 \\ 3 & 1 & 5\end{array}\right]$, then we see that

$$
\mathbf{a}_{1}+2 \mathbf{a}_{2}-\mathbf{a}_{3}=0
$$

i.e. $\alpha_{1}=1, \alpha_{2}=2, \alpha_{3}=-1$. We compute

$$
\frac{x_{1}}{\alpha_{1}}=1, \frac{x_{2}}{\alpha_{2}}=\frac{1}{2}
$$

from which we deduce $r=2$. It then follows that

$$
\begin{gathered}
\widehat{x}_{1}=x_{1}-x_{2} \frac{\alpha_{1}}{\alpha_{2}}=1-1 \cdot \frac{1}{2}=\frac{1}{2} . \\
\widehat{x}_{2}=0, \\
\widehat{x}_{3}=x_{3}-x_{2} \frac{\alpha_{3}}{\alpha_{2}}=2+1 \cdot \frac{1}{2}=\frac{5}{2} .
\end{gathered}
$$

So $\widehat{\mathbf{x}}=\left(\frac{1}{2}, 0, \frac{5}{2}\right)^{T}$.
5. First we convert it to a standard LPP by adding the slack variables $x_{4}, x_{5}, x_{6}$. The resulting LPP is:
maximize $z=8 x_{1}+9 x_{2}+5 x_{3}$ subject to

$$
\begin{cases}x_{1}+x_{2}+2 x_{3}+x_{4} & =2 \\ 2 x_{1}+3 x_{2}+4 x_{3}+x_{5} & =3 \\ 6 x_{1}+6 x_{2}+2 x_{3}+x_{6} & =8 \\ x_{1}, x_{2}, x_{3}, x_{4}, x_{5}, x_{6} & \geq 0\end{cases}
$$

The initial table is

|  | $x_{1}$ | $x_{2}$ | $x_{3}$ | $x_{4}$ | $x_{5}$ | $x_{6}$ |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $x_{4}$ | 1 | 1 | 2 | 1 | 0 | 0 | 2 |
| $x_{5}$ | 2 | 3 | 4 | 0 | 1 | 0 | 3 |
| $x_{6}$ | 6 | 6 | 2 | 0 | 0 | 1 | 8 |
|  | -8 | -9 | -5 | 0 | 0 | 0 | 0 |
|  |  |  |  |  |  |  |  |

It's clear from the table that the entering variable is $x_{2}$, and after computing the $\theta$-ratios we see that the departing variable is $x_{5}$. Applying Gaussian elimination we get:


At this stage we should choose $x_{1}$ as the entering variable. Again by computing $\theta$-ratios we see that the corresponding departing variable is $x_{6}$. Using Gaussian elimination we get the following table.

|  | $x_{1}$ | $x_{2}$ | $x_{3}$ | $x_{4}$ | $x_{5}$ | $x_{6}$ |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $x_{4}$ | 0 | 0 | $\frac{5}{3}$ | 1 | 0 | $-\frac{1}{6}$ | $\frac{2}{3}$ |
| $x_{2}$ | 0 | 1 | $\frac{10}{3}$ | 0 | 1 | $-\frac{1}{3}$ | $\frac{1}{3}$ |
| $x_{1}$ | 1 | 0 | -3 | 0 | -1 | $\frac{1}{2}$ | 1 |
|  | 0 | 0 | 1 | 0 | 1 | 1 | 11 |
|  |  |  |  |  |  |  |  |

It's clear that this is the final table, so $z_{\max }=11$ and the optimal solution is

$$
\left(x_{1}, x_{2}, x_{3}, x_{4}, x_{5}, x_{6}\right)=\left(1, \frac{1}{3}, 0, \frac{2}{3}, 0,0\right)
$$

6. (i) We have

$$
a_{i_{j}}=B y_{i_{j}}=\sum_{k=1}^{n} y_{k, i_{j}} a_{i_{k}} .
$$

Since $a_{i_{1}}, \cdots, a_{i_{m}}$ are linearly independent, we have

$$
y_{j, i_{j}}=1 \text { and } y_{k, i_{j}}=0 \text { whenever } j \neq k,
$$

which implies that $\left(y_{1, i_{j}}, \cdots, y_{m, i_{j}}\right)^{T}$ are columns of $I$.
(ii) We argue by induction. Denote by $B^{\prime}$ and $Y^{\prime}$ the matrices corresponding to $B$ and $Y$ at the $i+1$-th step, then we have

$$
y_{r k}^{\prime}=\frac{y_{r k}}{y_{r j}}, \forall k=1, \cdots, n .
$$

And for each $i \neq r$,

$$
y_{i k}^{\prime}=y_{i k}-y_{i j} \cdot \frac{y_{r k}}{y_{r j}}, k=1, \cdots, n .
$$

Using the above one can compute

$$
B^{\prime} Y^{\prime}=\mathbf{y}_{k},
$$

which is the $k$-th column of $B Y$. Since the initial step of the induction is trivial, we are done.
(iii) This can again by argued by induction. With the same notation conventions as above, we have

$$
x_{i r}^{\prime}=\frac{x_{i r}}{y_{r j}},
$$

and for any $k \neq r$,

$$
x_{i k}^{\prime}=x_{i k}-y_{k j} \cdot \frac{x_{i r}}{y_{r j}}
$$

Use this we have

$$
\begin{aligned}
A \mathbf{x}_{i}^{\prime} & =\mathbf{x}_{i r}^{\prime} \cdot \mathbf{a}_{r}+\sum_{k \neq r} \mathbf{x}_{i k}^{\prime} \cdot \mathbf{a}_{k} \\
& =\mathbf{b}
\end{aligned}
$$

Since for the initial table, we trivially have $A \mathbf{x}_{i}=\mathbf{b}$, the proof is complete.
(iv) Since

$$
\begin{aligned}
d_{j} & =c_{j}-z_{j} \\
& =c_{j}-\mathbf{c}_{B}^{T} \cdot \mathbf{y}_{j}
\end{aligned}
$$

for $1 \leq j \leq m$ we have

$$
\begin{aligned}
d_{i_{j}} & =c_{j_{j}}-\mathbf{c}_{B}^{T} \cdot \mathbf{y}_{i_{j}} \\
& =c_{i_{j}}-c_{i_{j}} \\
& =0 .
\end{aligned}
$$

