

Sensitivity Analysis and Revised Simplex

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1 - Mathematical Formulation

Given the data, the factory-planning problem model will look like this:

$$\begin{aligned} \max \quad & 19x_1 + 13x_2 + 12x_3 + 17x_4 \\ \text{s.t.} \quad & 3x_1 + 2x_2 + x_3 + 2x_4 \leq 225 \\ & x_1 + x_2 + x_3 + x_4 \leq 117 \\ & 4x_1 + 3x_2 + 3x_3 + 4x_4 \leq 420 \\ & x_1, x_2, x_3, x_4 \geq 0 \end{aligned}$$

We can implement it in python and bring to the equational standard form to get the initial tableau:

```
import numpy as np
from fractions import Fraction
from util import tableau

n = 4
m = 3

# model in standard form
A = np.array([
    [3, 2, 1, 2],
    [1, 1, 1, 1],
    [4, 3, 3, 4]
])
b = np.array([225, 117, 420])
c = np.array([19, 13, 12, 17])

# equational standard form
```

```

A = np.hstack([A, np.identity(m)])
c = np.hstack([c, np.zeros(m)])

# initial tableau
T = np.column_stack([
    np.vstack([A, c]),
    np.append(np.zeros(m), [1]), # -z
    np.append(b, [0]) # b
])

# make it pretty
T = np.array(T, dtype = object)
for j in range(m + 1):
    for i in range(n + m + 2):
        T[j][i] = Fraction(T[j][i])

tableau(T)

```

x1	x2	x3	x4	x5	x6	x7	-z	b
3	2	1	2	1	0	0	0	225
1	1	1	1	0	1	0	0	117
4	3	3	4	0	0	1	0	420
19	13	12	17	0	0	0	1	0

2 - Optimal Tableau

Using Original Simplex

Choose variable to bring to the basis

```
def ratio_test():
    enter = np.argmax(T[-1][:n + m]) # index of biggest reduced cost
    if T[-1][enter] <= 0:
        return [None, None] # no positive rc - optimal

    ratios = [
        T[j][-1] / T[j][enter] # b term / entering column term
        if T[j][enter] > 0
        else float('inf')
        for j in range(m)
    ]

    leave = np.argmin(ratios) # index of smallest ratio
    if ratios[leave] == float('inf'):
        return [None, None] # all ratio terms are <= 0 - unbounded

    return [enter, leave] # indices in T

enter, leave = ratio_test()
print(f"pivot: ({enter}, {leave})")
```

pivot: (0, 0)

So according to the ratio_test x_1 should enter and x_5 should leave

```
def update_tableau(enter, leave):
    T[leave] /= T[leave][enter] # normalize row to get 1 in entering col
    for j in range(m + 1):
        if j != leave:
            T[j] -= T[j][enter] * T[leave][enter] # all other rows set to 0 in entering col

update_tableau(enter, leave)
tableau(T)
```

x1	x2	x3	x4	x5	x6	x7	-z	b
1	2/3	1/3	2/3	1/3	0	0	0	75
0	1/3	2/3	1/3	-1/3	1	0	0	42
0	1/3	5/3	4/3	-4/3	0	1	0	120
0	1/3	17/3	13/3	-19/3	0	0	1	-1425

And we repeat:

```
def pivot():
    enter, leave = ratio_test()
    update_tableau(enter, leave)
    tableau(T)
```

```
pivot()
```

x1	x2	x3	x4	x5	x6	x7	-z	b
1	1/2	0	1/2	1/2	-1/2	0	0	54
0	1/2	1	1/2	-1/2	3/2	0	0	63
0	-1/2	0	1/2	-1/2	-5/2	1	0	15
0	-5/2	0	3/2	-7/2	-17/2	0	1	-1782

```
pivot()
```

x1	x2	x3	x4	x5	x6	x7	-z	b
1	1	0	0	1	2	-1	0	39
0	1	1	0	0	4	-1	0	48
0	-1	0	1	-1	-5	2	0	30
0	-1	0	0	-2	-1	-3	1	-1827

And we've reached optimality as there are no more positive reduced costs. The solution agrees with the statement in the exercise that in the optimal solution x_1 , x_3 and x_4 will be in basis.

Using Revised Simplex

```

B = [0, 2, 3] # final basis
N = [1, 4, 5, 6]

A_Binv = np.linalg.inv(A[:, B])

# A and c - basic
T[:,m, B] = np.identity(m)
T[-1, B] = np.zeros(m)

# A and c - nonbasic
T[:,m, N] = A_Binv @ A[:, N]
T[-1, N] = c[N] - c[B] @ T[:,m, N]

# b and d
T[:,m, -1] = A_Binv @ b
T[-1, -1] = - c[B] @ T[:,m, -1]

# make it pretty again
T = np.array(T, dtype = object)
for j in range(m + 1):
    for i in range(n + m + 2):
        T[j][i] = Fraction(round(T[j][i]))

tableau(T)

```

	x1	x2	x3	x4	x5	x6	x7	-z	b
	1	1	0	0	1	2	-1	0	39
	0	1	1	0	0	4	-1	0	48
	0	-1	0	1	-1	-5	2	0	30
	0	-1	0	0	-2	-1	-3	1	-1827

We achieved the exact same tableau with non-positive reduced cost therefore we found the optimal solution - again.

3 - Reduced Cost

What's the increase in price that would make x_2 worth being produced?
We remember that:

$$\bar{c}_2 = c_2 - \sum_i y_i a_{i2}$$

where \bar{c}_2 is the reduced cost of x_2 after last iteration.

To make x_2 worth producing the reduced cost should be positive, and from the above formula we see that the increase in price will correspond to the same increase in the reduced cost. As the reduced cost of x_2 is equal to -1 after the last iteration, the increase in price that would make x_2 worth being produced is any amount > 1 .

4 - Shadow Price

Shadow prices can be read directly from the last tableau:

2 — for an hour of work

1 — for a unit of metal

3 — for a unit of wood

5 - Complementary Slackness Theorem

Are all the constraints binding?

The Complementary Slackness Theorem implies for x^* and y^* - optimal solutions of the Primal and Dual problems respectively:

$$\forall_j (b_j - \sum_i a_{ji} x_i^*) y_j^* = 0$$

Which means that for each constraint it's either binding, or it's shadow price is 0. Seeing that all of the shadow prices are non-zero (previous subtask) we can conclude that all constraint of the Primal problem are binding (active).

On a side note: We can also observe that none of the slack variables are in basis in the optimal solution, which means there is no slack capacity, which is yet another way of concluding the above.

6 - Economical Interpretation

The imputed (reduced) cost of x_2 is:

$$\bar{c}_2 = c_2 - \sum_i y_i a_{i2} = -1 < 0$$

Which means that the cost of resources needed to produce a unit of product x_2 is significantly higher than the price of the product itself, making it not a viable option to produce. In other words: there is slack in the 2nd constraint of the Dual.

7 - Increased Net Profit

As mentioned previously - the increase in the reduced cost is equal to the increase in the original net profit. So change in desk net profit from 13 to 15 would cause the increase in the reduced cost of x_2 of 2, which is more than 1, so we will be able to do one more iteration of the simplex and bring x_2 in the basis.

```
T[-1][1] += 2 # increase x2 reduced cost
tableau(T)
```

x1	x2	x3	x4	x5	x6	x7	-z	b
1	1	0	0	1	2	-1	0	39
0	1	1	0	0	4	-1	0	48
0	-1	0	1	-1	-5	2	0	30
0	1	0	0	-2	-1	-3	1	-1827

```
pivot()
```

x1	x2	x3	x4	x5	x6	x7	-z	b
1	1	0	0	1	2	-1	0	39
-1	0	1	0	-1	2	0	0	9
1	0	0	1	0	-3	1	0	69
-1	0	0	0	-3	-3	-2	1	-1866

We reach a new optimal solution with an even higher objective function.

8 - Increased Material Availability

We need to recalculate the final b - column of the tableau.

```
# b and d
T[:m, -1] = A_Binv @ (b + [0, 125 - 117, 0]) # new b
T[-1, -1] = - c[B] @ T[:m, -1]

# make pretty again
for j in range(m + 1):
    T[j][-1] = Fraction(round(T[j][-1]))

tableau(T)
```

	-----+	-----+	-----+	-----+	-----+	-----+	-----+	-----+	-----+	
	x1	x2	x3	x4	x5	x6	x7	-z	b	
	-----+	-----+	-----+	-----+	-----+	-----+	-----+	-----+	-----+	
	1	1	0	0	1	2	-1	0	55	
	0	1	1	0	0	4	-1	0	80	
	0	-1	0	1	-1	-5	2	0	-10	
	-----+	-----+	-----+	-----+	-----+	-----+	-----+	-----+	-----+	
	0	-1	0	0	-2	-1	-3	1	-1835	
	-----+	-----+	-----+	-----+	-----+	-----+	-----+	-----+	-----+	

We get an infeasible solution. We would need to apply the dual simplex in order to retrieve feasibility.

TODO: apply the dual here?

9 - New Product

We need to insert a new column into our tableau, calculate it for the current iteration and check whether we should bring the new variable into the basis or not.

```
T = np.column_stack([
    T[:, :n + m],
    np.zeros(m + 1), # insert new column after the slacks as x8
    T[:, n + m:]
])

n += 1

# new column updated
T[:, 7] = A_Binv @ [3, 1, 2]
T[-1, 7] = 14 - c[B] @ T[:, 7]

# make pretty again
for j in range(m + 1):
    T[j][7] = Fraction(round(T[j][7]))

tableau(T)
```

x1	x2	x3	x4	x5	x6	x7	x8	-z	b
1	1	0	0	1	2	-1	3	0	39
0	1	1	0	0	4	-1	2	0	48
0	-1	0	1	-1	-5	2	-4	0	30
0	-1	0	0	-2	-1	-3	1	1	-1827

We observe that new variable's reduced cost is positive.

```
pivot()
```

x1	x2	x3	x4	x5	x6	x7	x8	-z	b
1/3	1/3	0	0	1/3	2/3	-1/3	1	0	13
-2/3	1/3	1	0	-2/3	8/3	-1/3	0	0	22
4/3	1/3	0	1	1/3	-7/3	2/3	0	0	82
-1/3	-4/3	0	0	-7/3	-5/3	-8/3	0	1	-1840

Turns out coffee tables are worth producing.

10 - New Constraint

We need to introduce a new row, but also a new slack column. The new constraint is:

$$x_3 \leq 5x_2 \implies 0x_1 - 5x_2 + x_3 + 0x_4 \leq 0$$

Since each Simplex iteration is just elementary row operations, we can simply add the new constraint to the final tableau without having to recalculate anything.

```
T = np.column_stack([
    T[:, :n + m],
    np.zeros(m + 1), # new slack
    T[:, n + m:]
])

T = np.vstack([
    T[:m, :],
    [0, -5, 1, 0, 0, 0, 0, 1, 0, 0], # new constraint
    T[-1, :]
])

m += 1

# make pretty again
for j in range(m + 1):
    T[j][7] = Fraction(T[j][7])
for i in range(n + m + 2):
    T[3][i] = Fraction(T[3][i])

tableau(T)
```

	x1	x2	x3	x4	x5	x6	x7	x8	-z	b
	1	1	0	0	1	2	-1	0	0	39
	0	1	1	0	0	4	-1	0	0	48
	0	-1	0	1	-1	-5	2	0	0	30
	0	-5	1	0	0	0	0	1	0	0
	0	-1	0	0	-2	-1	-3	0	1	-1827

Now we just need to bring the tableau into the canonical form. We can already make some assumptions about what will happen after we do that. In current solution we aren't producing any desks, because they're less valuable than chairs. So after we introduce the new constraint

on chair production their production will have to go down - or the desk production will have to go up instead of something more valuable. Either way we expect a loss in our income, which means the solution that we have right now will become infeasible.

```
update_tableau(2, 1) # pivot of the column that breaks the canonical form
tableau(T)
```

	x1	x2	x3	x4	x5	x6	x7	x8	-z	b
	1	1	0	0	1	2	-1	0	0	39
	0	1	1	0	0	4	-1	0	0	48
	0	-1	0	1	-1	-5	2	0	0	30
	0	-6	0	0	0	-4	1	1	0	-48
	0	-1	0	0	-2	-1	-3	0	1	-1827

As expected - we reached the canonical form and our solution became infeasible. Similarly as with increasing material availability - we would have to apply the dual simplex.