Branch & Bound and Knapsack Lab

Objectives

- Preform the branch and bound algorithm
- Apply branch and bound to the knapsack problem
- Understand the geometry of the branch and bound algorithm

Brief description: In this lab, we will try solving an example of a knapsack problem with the branch-and-bound algorithm. We will also see how adding a cutting plane helps in reducing the computation time and effort of the algorithm. Lastly, we will explore the geometry of the branch and bound algorithm.

In [1]:
```
# imports -- don't forget to run this cell
import pandas as pd
import gilp
from gilp.visualize import feasible_integer_pts
from ortools.linear_solver import pywraplp as OR
```

Part 1: Branch and Bound Algorithm

Recall that the branch and bound algorithm (in addition to the simplex method) allows us to solve integer programs. Before applying the branch and bound algorithm to the knapsack problem, we will begin by reviewing some core ideas. Furthermore, we will identify a helpful property that will make branch and bound terminate quicker later in the lab!

Q1: What are the different ways a node can be fathomed during the branch and bound algorithm? Describe each.

A: A node can be fathomed when its value is a decimal such that its decimal value is greater than another nodes integer value. For example, if one node has a value of 24.2 and another has a value of 24, the 24.2 node can be fathomed as it will only produce a value 25 or greater on the next iteration. This works the same way when maximizing, where if one node is 24 and another is 23.5, the 23.5 node can be fathomed as it will produce a value 23 or less.

Q2: Suppose you have a maximization integer program and you solve its linear program relaxation. What does the LP-relaxation optimal value tell you about the IP optimal value? What if it is a minimization problem?

A: The LP-relaxation optimal value will give an upper bound for the IP optimal value in maximization. In minimizing, the LP-relaxation optimal will be a lower bound for the IP optimal value.

Q3: Assume you have a maximization integer program with all integral coefficents in the objective function. Now, suppose you are running the branch and bound algorithm and come across a node with an optimal value of 44.5. The current incumbent is 44. Can you fathom this node? Why or why not?

A: We can fathom the node because 44.5 will be an upper bound for the next branch-and-bound iteration, meaning the highest IP value it will produce is 44. Since we have a node with 44, we do not need the 44.5 node.

Q4: If the optimal solution to the LP relaxation of the original program is integer, then you have found an optimal solution to your integer program. Explain why this is true.

A: The LP-relaxation problem always provides an upper or lower bound to the IP problem. So, the LP value, if it were integer, would be the optimal value for the IP.

Q5: If the LP is infeasible, then the IP is infeasible. Explain why this is true.

A: The LP and IP have the same feasible solution region, but the LP have more feasible values. The IP has more constraints, so if the LP solution is infeasible, it will also be infeasible in the IP. All IP feasible solutions and feasible LP solutions.

The next questions ask about the following branch and bound tree. If the solution was not integral, the fractional x_i that was used to branch is given. If the solution was integral, it is denoted *INT*. In the current iteration of branch and bound, you are looking at the node with the *.

Q6: Can you determine if the integer program this branch and bound tree is for is a minimization or maximixation problem? If so, which is it?

A: 15.4 represents the LP solution, which provides a boundary for the IP. This would be a minimization problem because the LP solution is providing a lower bound and the with each iteration, the IP feasible value is greater than the LP feasible.

Hint: For **Q7-8**, you can assume integral coefficents in the objective function.

Q7: Is the current node (marked z^*) fathomed? Why or why not? If not, what additional constraints should be imposed for each of the next two nodes?

A: No it is not fathomed. Since we are minimizing, this 16.3 represents a lower bound to that branch of nodes. So the lowest that branch can be is 17, as opposed to the opposite branch's maximum value of 18. The additional constraints would be that one node is greater than or equal to 17 and the other would be less than or equal to 16.

Q8: Consider the nodes under the current node (where z = 16.3). What do you know about the optimal value of these nodes? Why?

A: The optimal value must be an integer greater than or equal to 17. This is because in the minimization problem, the 16.3 represents a lower bound to that branch of nodes.

Part 2: The Knapsack Problem

In this lab, you will solve an integer program by branch and bound. The integer program to be solved will be a knapsack problem.

Knapsack Problem: We are given a collection of n items, where each item i = 1, ..., n has a

weight w_i and a value v_i. In addition, there is a given capacity W, and the aim is to select a maximum value subset of items that has a total weight at most W. Note that each item can be brought at most once.

max
Consider the following data which we import from a CSV file:

In [2]:
```
data = pd.read_csv('knapsack_data_1.csv', index_col=0)
data
```

Out[2]:

item	value	weight
1	50	10
2	30	12
3	24	10
4	14	7
5	12	6
6	10	7
7	40	30

and W = 18.

Q9: Are there any items we can remove from our input to simplify this problem? Why? If so, replace `index` with the item number that can be removed in the code below. Hint: how many of each item could we possibly take?

A: We can remove item 7 because our maximum summed weight must be less than or equal to 18. Since this has a weight of 30, this automatically breaks our constraint and is infeasible.

In [3]:
```
# TODO: replace index
data = data.drop(7)
```

Q10: If we remove item 7 from the knapsack, it does not change the optimal solution to the integer program. Explain why.

A: Item 7 would never have been included in the optimal solution for the IP because its weight alone discounts it from any feasible solution.

Q11: Consider removing items i such that w_i > W from a knapsack input. How does the LP relaxation's optimal value change?

A: The LP relaxation's optimal value will not change.

In **Q10-11**, you should have found that removing these items removes feasible solutions from the linear program but does not change the integer program. This is desirable as the gap between the optimal IP and LP values can become smaller. By adding this step, branch and bound may terminate sooner.

Recall that a branch and bound node can be fathomed if its bound is no better than the value of

the best feasible integer solution found thus far. Hence, it helps to have a good feasible integer solution as quickly as possible (so that we stop needless work). To do this, we can first try to construct a good feasible integer solution by a reasonable heuristic algorithm before starting to run the branch and bound procedure.

In designing a heuristic for the knapsack problem, it is helpful to think about the value per unit weight for each item. We compute this value in the table below.

In [4]:
```
data['value per unit weight'] = (data['value'] / data['weight']).round(2)
data
```

Out[4]:

item	value	weight	value per unit weight
1	50	10	5.00
2	30	12	2.50
3	24	10	2.40
4	14	7	2.00
5	12	6	2.00
6	10	7	1.43

Q12: Design a reasonable heuristic for the knapsack problem. Note a heuristic aims to find a decent solution to the problem (but is not necessarily optimal).

A: Take as much as you can of the highest value per unit weight and pick and choose until you get close or at 18.

Q13: Run your heuristic on the data above to compute a good feasible integer solution. Your heuristic should generate a feasible solution with a value of 64 or better. If it does not, try a different heuristic (or talk to your TA!)

A: A good feasible solution would include items 1 and 4, giving a feasible solution of 17 and a value of 64.

We will now use the branch and bound algorithm to solve this knapsack problem! First, let us define a mathematical model for the linear relaxation of the knapsack problem.

Q14: Complete the model below.

In [5]:
```
def Knapsack(table, capacity, integer = False):
    """Model for solving the Knapsack problem.

    Args:
        table (pd.DataFrame): A table indexd by items with a column for value an
        capcity (int): An integer-capacity for the knapsack
        integer (bool): True if the variables should be integer. False otherwise
    """
    ITEMS = list(table.index)          # set of items
    v = table.to_dict()['value']       # value for each item
    w = table.to_dict()['weight']      # weight for each item
    = capacity                         # capacity of the knapsack
```

```
    # define model
    m = OR.Solver('knapsack', OR.Solver.CBC_MIXED_INTEGER_PROGRAMMING)

    # decision variables
    x = {}
    for i in ITEMS:
        if integer:
            x[i] = m.IntVar(0, 1, 'x_%d' % (i))
        else:
            x[i] = m.NumVar(0, 1, 'x_%d' % (i))

    # define objective function here
    m.Maximize(sum(v[i]*x[i] for i in ITEMS))

    # TODO: Add a constraint that enforces that weight must not exceed capacity
    m.Add(sum(w[i]*x[i] for i in ITEMS) <= W)
    # recall that we add constraints to the model using m.Add()

    return (m, x)  # return the model and the decision variables
```

In [6]:
```
# You do not need to do anything with this cell but make sure you run it!
def solve(m):
    """Used to solve a model m."""
    m.Solve()

    print('Objective =', m.Objective().Value())
    print('iterations :', m.iterations())
    print('branch-and-bound nodes :',m.nodes())

    return ({var.name() : var.solution_value() for var in m.variables()})
```

We can now create a linear relaxation of our knapsack problem. Now, `m` represents our model and `x` represents our decision variables.

In [7]:
```
m, x = Knapsack(data, 18)
```

We can use the next line to solve the model and output the solution

In [8]:
```
solve(m)
```

```
Objective = 70.0
iterations : 0
branch-and-bound nodes : 0
```

Out[8]:
```
{'x_1': 1.0,
 'x_2': 0.6666666666666667,
 'x_3': 0.0,
 'x_4': 0.0,
 'x_5': 0.0,
 'x_6': 0.0}
```

Q15: How does this optimal value compare to the value you found using the heuristic integer solution?

A: It is better than what I found.

Q16: Should this node be fathomed? If not, what variable should be branched on and what additional constraints should be imposed for each of the next two nodes?

A: This node should not be fathomed because its decimal value is less than the integer value found in the other node. It's value can increase to be 1, improving the solution. The x2 node should be branched out into the constraints x2 <= 0 and x2 >= 1.

After constructing the linear relaxation model using `Knapsack(data1, 18)` we can add additional constraints. For example, we can add the constraint x_2 \leq 0 and solve it as follows:

In [9]:
```
m, x = Knapsack(data, 18)
m.Add(x[2] <= 0)
solve(m)
```

```
Objective = 69.2
iterations : 0
branch-and-bound nodes : 0
```

Out[9]:
```
{'x_1': 1.0, 'x_2': 0.0, 'x_3': 0.8, 'x_4': 0.0, 'x_5': 0.0, 'x_6': 0.0}
```

NOTE: The line `m, x = Knapsack(data1, 18)` resets the model `m` to the LP relaxation. All constraints from branching have to be added each time.

Q17: Use the following cell to compute the optimal value for the other node you found in **Q16**.

In [10]:
```
m, x = Knapsack(data, 18)
m.Add(x[2] >= 1)
solve(m)
```

```
Objective = 60.0
iterations : 0
branch-and-bound nodes : 0
```

Out[10]:
```
{'x_1': 0.6000000000000001,
 'x_2': 1.0,
 'x_3': 0.0,
 'x_4': 0.0,
 'x_5': 0.0,
 'x_6': 0.0}
```

Q18: What was the optimal value? Can this node be fathomed? Why? (Hint: In **Q13**, you found a feasible integer solution with value 64.)

A: The optimal value to this branch is 60, which can be fathomed because we found a feasible solution with an objective value greater than 60.

If we continue running the branch and bound algorithm, we will eventually reach the branch and bound tree below where the z^* indictes the current node we are looking at.

Q19: The node with z = 64.857 was fathomed. Why are we allowed to fathom this node? (Hint: think back to **Q3**)

A: For the z=64.857 node would provide an upper bound of 64 since this is a maximization problem. Therefore, this branch will be 64 or less but we found a branch and node that already has 64 so this node can be fathomed.

Q20: Finish running branch and bound to find the optimal integer solution. Use a separate cell for each node you solve and indicate if the node was fathomed with a comment. (Hint: Don't include the constraints further up in the branch and bound tree.)

In [11]:
```
# Template
m, x = Knapsack(data, 18)
# Add constraints here
m.Add(x[2]<=0)
m.Add(x[3]<=0)
m.Add(x[4]>=1)
m.Add(x[5]<=0)
m.Add(x[6]>=1)

solve(m)
# fathomed?
```

```
Objective = 44.0
iterations : 0
branch-and-bound nodes : 0
```

Out[11]:
```
{'x_1': 0.4, 'x_2': 0.0, 'x_3': 0.0, 'x_4': 1.0, 'x_5': 0.0, 'x_6': 1.0}
```

In [12]:
```
m, x = Knapsack(data, 18)
# Add constraints here
m.Add(x[2]<=0)
m.Add(x[3]<=0)
m.Add(x[4]>=1)
m.Add(x[5]<=0)
m.Add(x[6]<=0)

solve(m)
```

```
Objective = 64.0
iterations : 0
branch-and-bound nodes : 0
```

Out[12]:
```
{'x_1': 1.0, 'x_2': 0.0, 'x_3': 0.0, 'x_4': 1.0, 'x_5': 0.0, 'x_6': 0.0}
```

In [13]:
```
# Template
m, x = Knapsack(data, 18)
# Add constraints here
m.Add(x[2]<=0)
m.Add(x[3]<=0)
m.Add(x[4]>=1)
m.Add(x[5]<=0)
m.Add(x[1]<=0)

solve(m)
# fathomed?
```

```
Objective = 24.0
iterations : 0
branch-and-bound nodes : 0
```

Out[13]:
```
{'x_1': 0.0, 'x_2': 0.0, 'x_3': 0.0, 'x_4': 1.0, 'x_5': 0.0, 'x_6': 1.0}
```

A: The items used would be x1 and x4.

Q21: How many nodes did you have to explore while running the branch and bound algorithm?

A: I explored 11 nodes running the algorithm.

In the next section, we will think about additional constraints we can add to make running branch and bound quicker.

Part 3: Cutting Planes

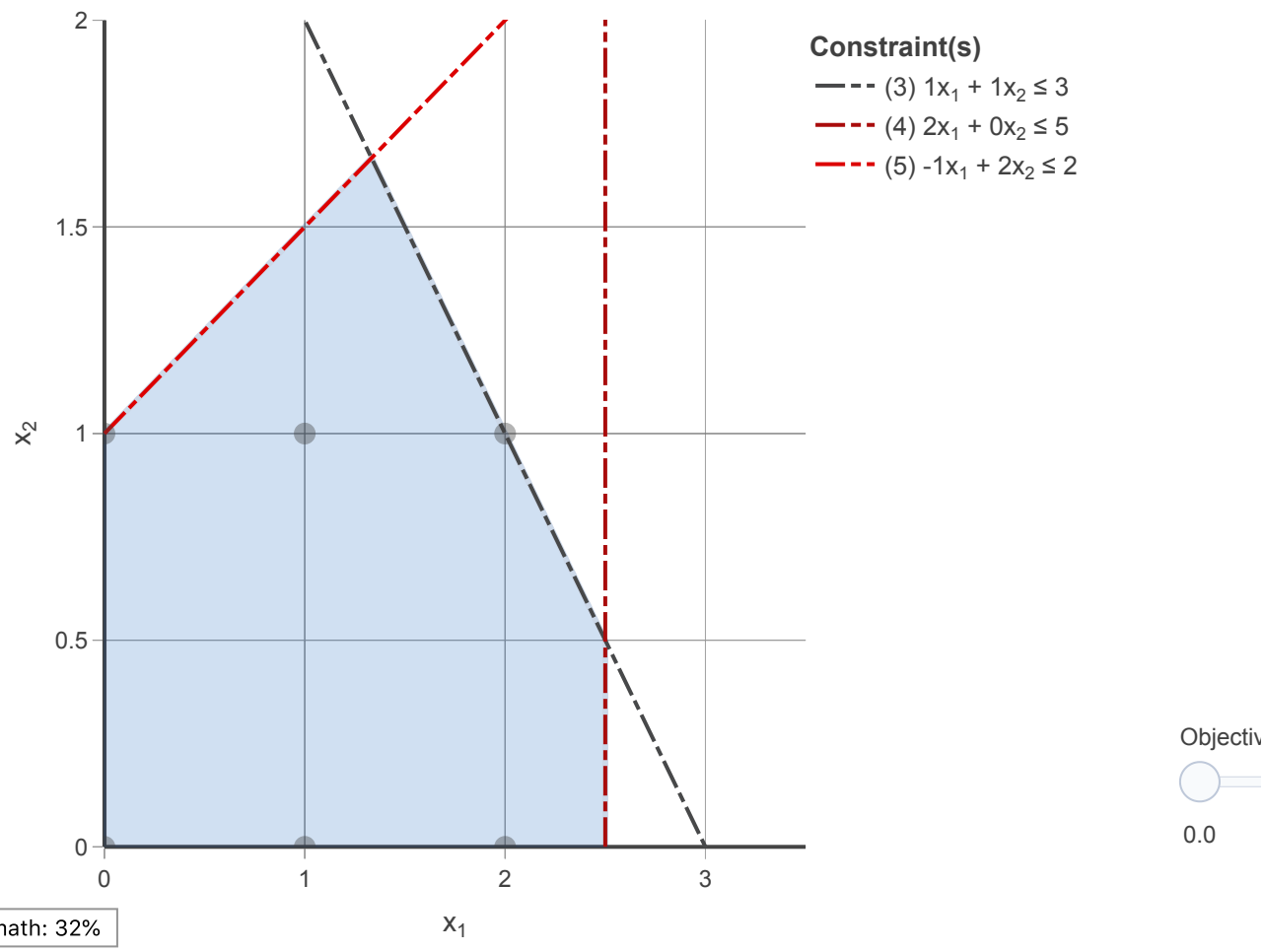
In general, a cutting plane is an additional constraint we can add to an integer program's linear relaxation that removes feasible linear solutions but does not remove any integer feasible solutions. This is very useful when solving integer programs! Recall many of the problems we have learned in class have something we call the "integrality property". This is useful because it allows us to ignore the integrality constraint since we are garunteed to reach an integral solution. By cleverly adding cutting planes, we strive to remove feasible linear solutions (without removing any integer feasible solutions) such that the optimal solution to the linear relaxation is integral!

Conisder an integer program whose linear program releaxation is

$$\begin{align*} \max \quad & 2x_1+x_2\\ \text{s.t.} \quad & x_1 + x_2 \leq 3 \\ & 2x_1 \leq 5 \\ & -x_1 + 2x_2 \leq 2 \\ & x_1, x_2 \geq 0 \end{align*}$$

We can define this linear program and then visualize its feasible region. The integer points have been highlighted.

In [14]:
```
lp = gilp.LP([[1,1],[2,0],[-1,2]],
             [3,5,2],
             [2,1])
fig = gilp.lp_visual(lp)
fig.set_axis_limits([3.5,2])
fig.add_trace(feasible_integer_pts(lp, fig))
fig
```



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Q22: List every feasible solution to the integer program.

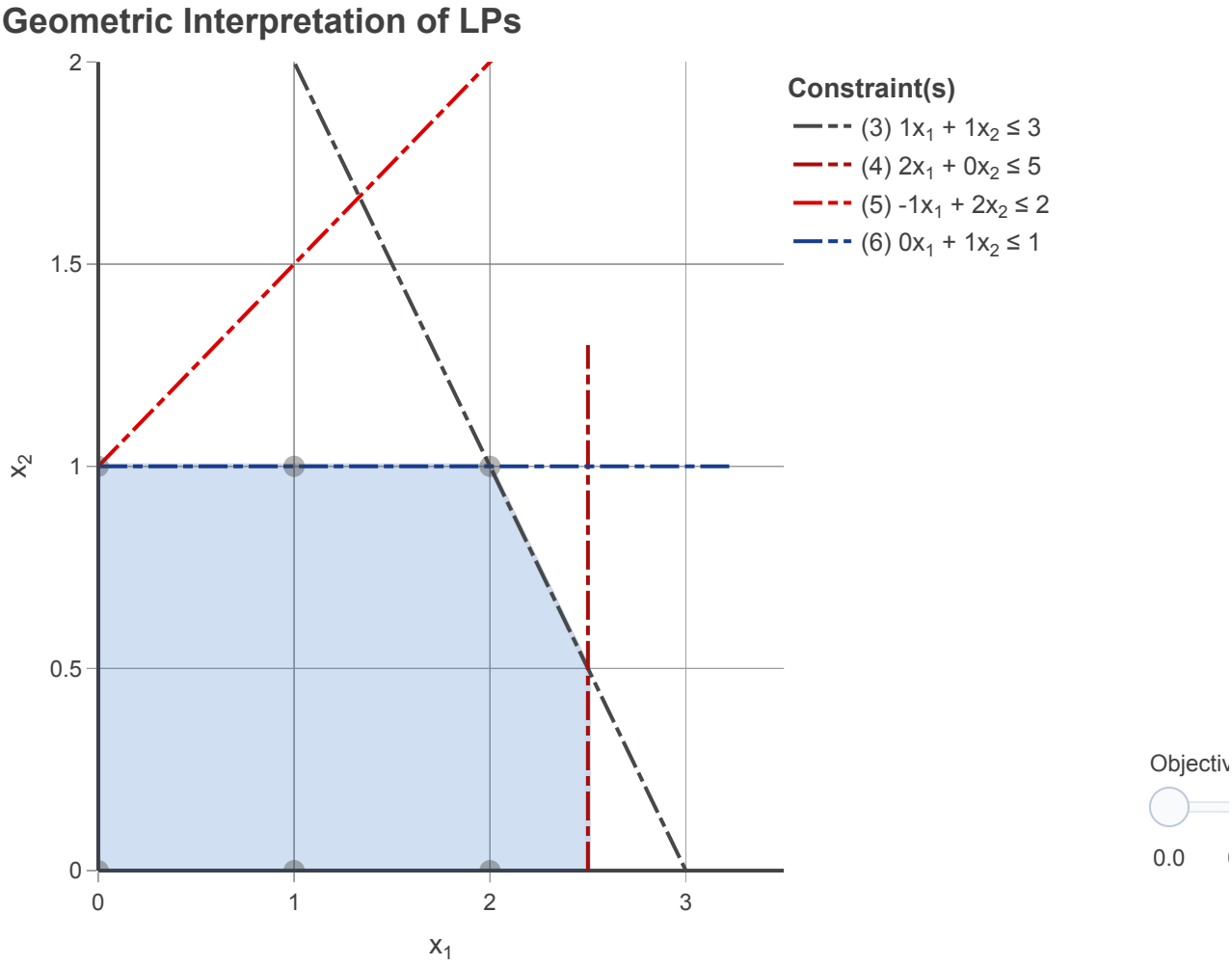
A: (0,0),(1,0),(2,0),(0,1),(0,2),(1,1),(2,1)

Q23: Is the constraint x_2 \leq 1 a cutting plane? Why? (Hint: Would any feasible integer points become infeasible? What about feasible linear points?)

A: Yes because it removes some feasible LP solution points but none of the IP feasible solution points.

Let's add this cutting plane to the LP relaxation!

In [15]:
```
lp = gilp.LP([[1,1],[2,0],[-1,2],[0,1]],
             [3,5,2,1],
             [2,1])
fig = gilp.lp_visual(lp)
fig.set_axis_limits([3.5,2])
fig.add_trace(feasible_integer_pts(lp, fig))
fig
```



Q24: Is the constraint x_1 \leq 3 a cutting plane? Why?

A: No it is not a cutting because it does not further restrict the feasible solution range.

Q25: Can you provide another cutting plane? If so, what is it?

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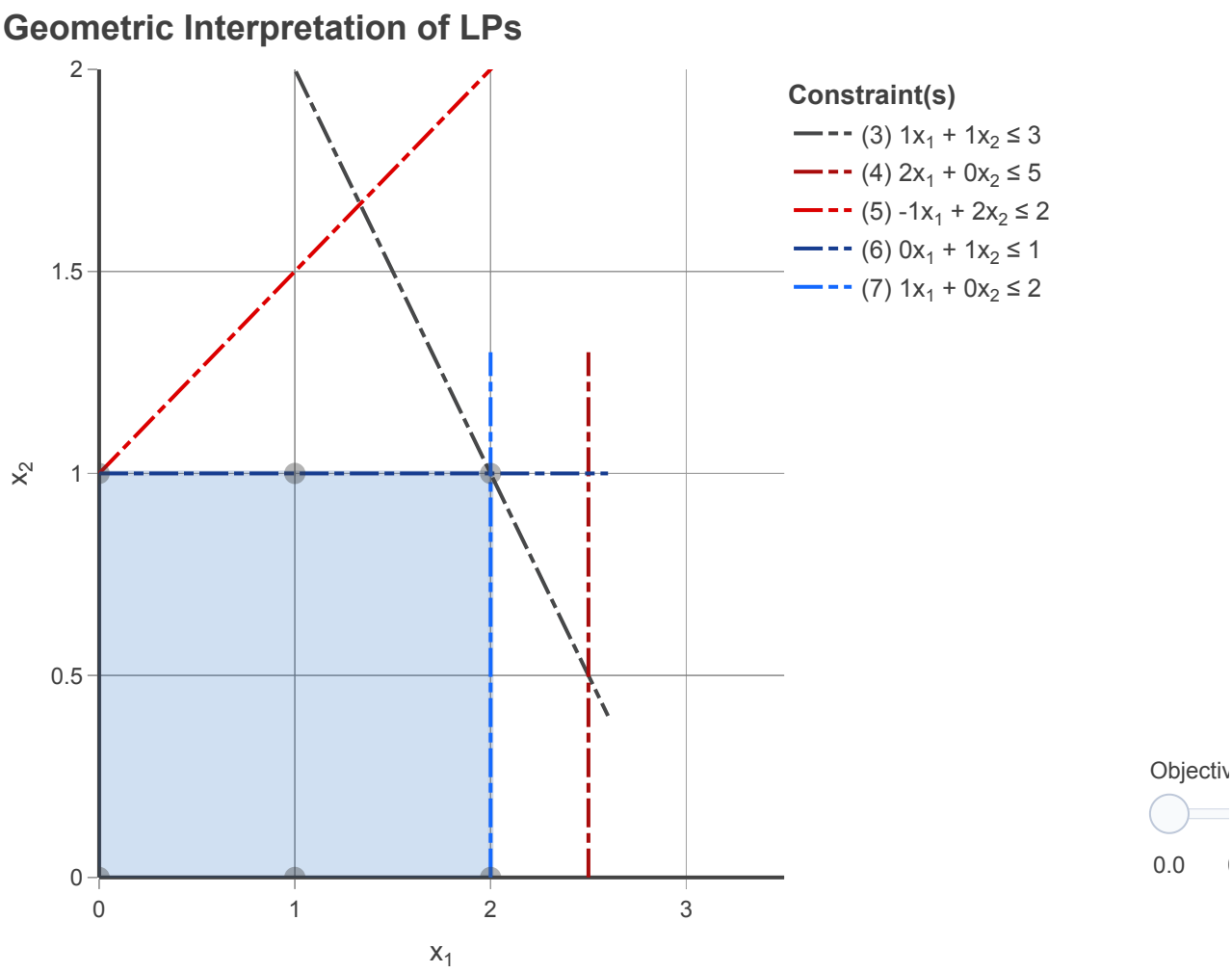
Let's look at the feasible region after adding the cutting plane from **Q23** and one of the possible answers from **Q25**. Notice the optimal solution to the LP relaxation is now integral!

In [16]:
```
lp = gilp.LP([[1,1],[2,0],[-1,2],[0,1],[1,0]],
             [3,5,2,1,2],
             [2,1])
fig = gilp.lp_visual(lp)
fig.set_axis_limits([3.5,2])
fig.add_trace(feasible_integer_pts(lp, fig))
fig
```



Let's try applying what we know about cutting planes to the knapsack problem! Again, recall our input was W = 18 and:

In [17]:
```
data
```

Out[17]:

item	value	weight	value per unit weight
1	50	10	5.00
2	30	12	2.50
3	24	10	2.40
4	14	7	2.00
5	12	6	2.00

item	value	weight	value per unit weight
6	10	7	1.43

Q26: Look at items 1, 2, and 3. How many of these items can we take simultaneously? Can you write a new constraint to capture this? If so, please provide it.

A: We can only take at most 1 item from those listed items. (x1+x2+x3)<=1

Q27: Is the constraint you found in **Q26** a cutting plane? If so, provide a feasible solution to the linear program relaxation that is no longer feasible (i.e. a point the constraint *cuts off*).

A: It is a cutting plane. (1,.66666667,0,0,0,0) is a feasible solution that is no longer feasible.

Q28: Provide another cutting plane involving items 4,5 and 6 for this integer program. Explain how you derived it.

A: (x4+x5+x6)<=2. Taking two of each of those items brings our weight less than 18 but taking another would put us over.

Q29: Add the cutting planes from **Q26** and **Q28** to the model and solve it. You should get a solution in which we take items 1 and 4 and \frac{1}{6} of item 5 with an objective value of 66.

In [18]:
```
m, x = Knapsack(data, 18)
# TODO: Add cutting planes here
m.Add((x[1]+x[2]+x[3])<=1)
m.Add((x[4]+x[5]+x[6])<=2)

solve(m)
```

```
Objective = 66.0
iterations : 0
branch-and-bound nodes : 0
```

Out[18]:
```
{'x_1': 1.0,
 'x_2': 0.0,
 'x_3': 0.0,
 'x_4': 1.0,
 'x_5': 0.16666666666666696,
 'x_6': 0.0}
```

Let's take a moment to pause and reflect on what we are doing. Recall from **Q9-11** that we dropped item 7 becuase its weight was greater than the capcity of the knapsack. Essentially we added the constraint x_7 \leq 0. This constraint was a cutting plane! It eliminated some linear feasible solutions but no integer ones. By adding these two new cutting planes, we can get branch and bound to terminate earlier yet again! So far, we have generated cutting planes by inspection. However, there are more algorithmic ways to identify them (which we will ignore for now).

If we continue running the branch and bound algorithm, we will eventually reach the branch and bound tree below where the z^* indictes the current node we are looking at.

Processing math: 32% o not forget about the feasible integer solution our heuristic gave us with value 64.

Q30 Finish running branch and bound to find the optimal integer solution. Use a separate cell for each node you solve and indicate if the node was fathomed with a comment. Hint: Don't forget the cutting plane constraints should be included in every node of the branch and bound tree.

In [19]:
```
# Template
m, x = Knapsack(data, 18)
# Add constraints here
m.Add((x[1]+x[2]+x[3])<=1)
m.Add((x[4]+x[5]+x[6])<=2)
m.Add(x[5]>=1)
m.Add(x[4]<=0)

solve(m)
# fathomed?
```

```
Objective = 64.85714285714286
iterations : 0
branch-and-bound nodes : 0
```

Out[19]:
```
{'x_1': 1.0,
 'x_2': 0.0,
 'x_3': 0.0,
 'x_4': 0.0,
 'x_5': 1.0,
 'x_6': 0.28571428571428586}
```

In [20]:
```
m, x = Knapsack(data, 18)
# Add constraints here
m.Add((x[1]+x[2]+x[3])<=1)
m.Add((x[4]+x[5]+x[6])<=2)
m.Add(x[5]>=1)
m.Add(x[4]>=1)

solve(m)
```

```
Objective = 51.0
iterations : 0
branch-and-bound nodes : 0
```

Out[20]:
```
{'x_1': 0.5, 'x_2': 0.0, 'x_3': 0.0, 'x_4': 1.0, 'x_5': 1.0, 'x_6': 0.0}
```

In [21]:
```
m, x = Knapsack(data, 18)
# Add constraints here
m, x = Knapsack(data, 18)
# Add constraints here
m.Add((x[1]+x[2]+x[3])<=1)
m.Add((x[4]+x[5]+x[6])<=2)
m.Add(x[5]>=1)
m.Add(x[4]<=0)
m.Add(x[6]<=0)

solve(m)
```

```
Objective = 62.0
iterations : 0
branch-and-bound nodes : 0
```

Out[21]:
```
{'x_1': 1.0, 'x_2': 0.0, 'x_3': 0.0, 'x_4': 0.0, 'x_5': 1.0, 'x_6': 0.0}
```

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```
Knapsack(data, 18)
# Add constraints here
```

```
m, x = Knapsack(data, 18)
# Add constraints here
m.Add((x[1]+x[2]+x[3])<=1)
m.Add((x[4]+x[5]+x[6])<=2)
m.Add(x[5]>=1)
m.Add(x[4]<=0)
m.Add(x[6]>=1)

solve(m)
```

```
Objective = 47.0
iterations : 0
branch-and-bound nodes : 0
```

Out[22]:
```
{'x_1': 0.5, 'x_2': 0.0, 'x_3': 0.0, 'x_4': 0.0, 'x_5': 1.0, 'x_6': 1.0}
```

A: The optimal value is 64 using items 1 and 4.

Q31: Did you find the same optimal solution? How many nodes did you explore? How did this compare to the number you explored previously?

A: I found the same optimal solution. We explored 9 nodes which is less than what we found before.

Part 4: Geometry of Branch and Bound

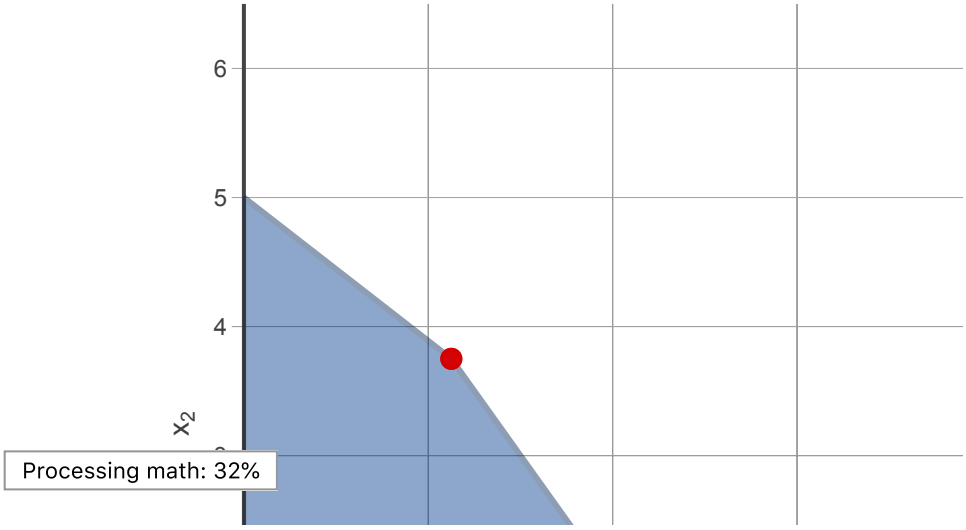
Previously, we used the `gilp` package to viusualize the simplex algorithm but it also has the functionality to visualize branch and bound. We will give a quick overview of the tool. Similar to `lp_visual` and `simplex_visual`, the function `bnb_visual` takes an `LP` and returns a visualization. It is assumed that every decision variable is constrained to be integer. Unlike previous visualizations, `bnb_visual` returns a series of figures for each node of the branch and bound tree. Let's look at a small 2D example:

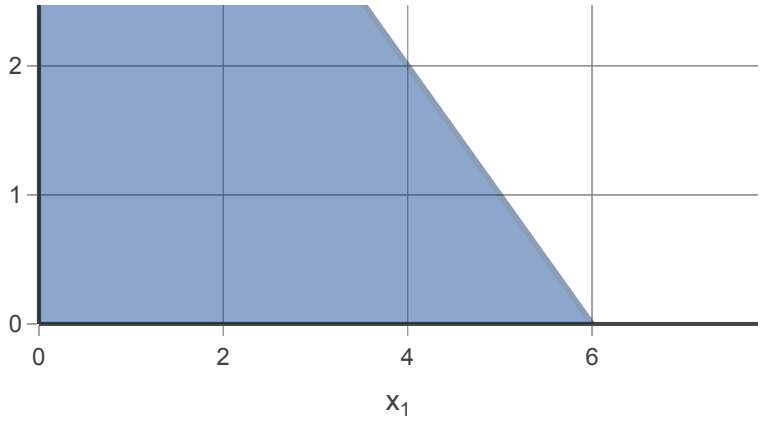
$$\begin{align*} \max \quad & 5x_1+ 8x_2\\ \text{s.t.} \quad & x_1 + x_2 \leq 6 \\ & 5x_1 + 9x_2 \leq 45 \\ & x_1, x_2 \geq 0, \quad \text{integral} \end{align*}$$

In [23]:
```
nodes = gilp.bnb_visual(gilp.examples.STANDARD_2D_IP)
```

In [24]:
```
nodes[0].show()
```

Geometric Interpretation of LPs





Run the cells above to generate a figure for each node and view the first node. At first, you will see the LP relaxation on the left and the root of the branch and bound tree on the right. The simplex path and isoprofit slider are also present.

Q32: Recall the root of a branch and bound tree is the unaltered LP relaxation. What is the optimal solution? (Hint: Use the objective slider and hover over extreme points).

A: The optimal value is 41.25 where (2.25,3.75).

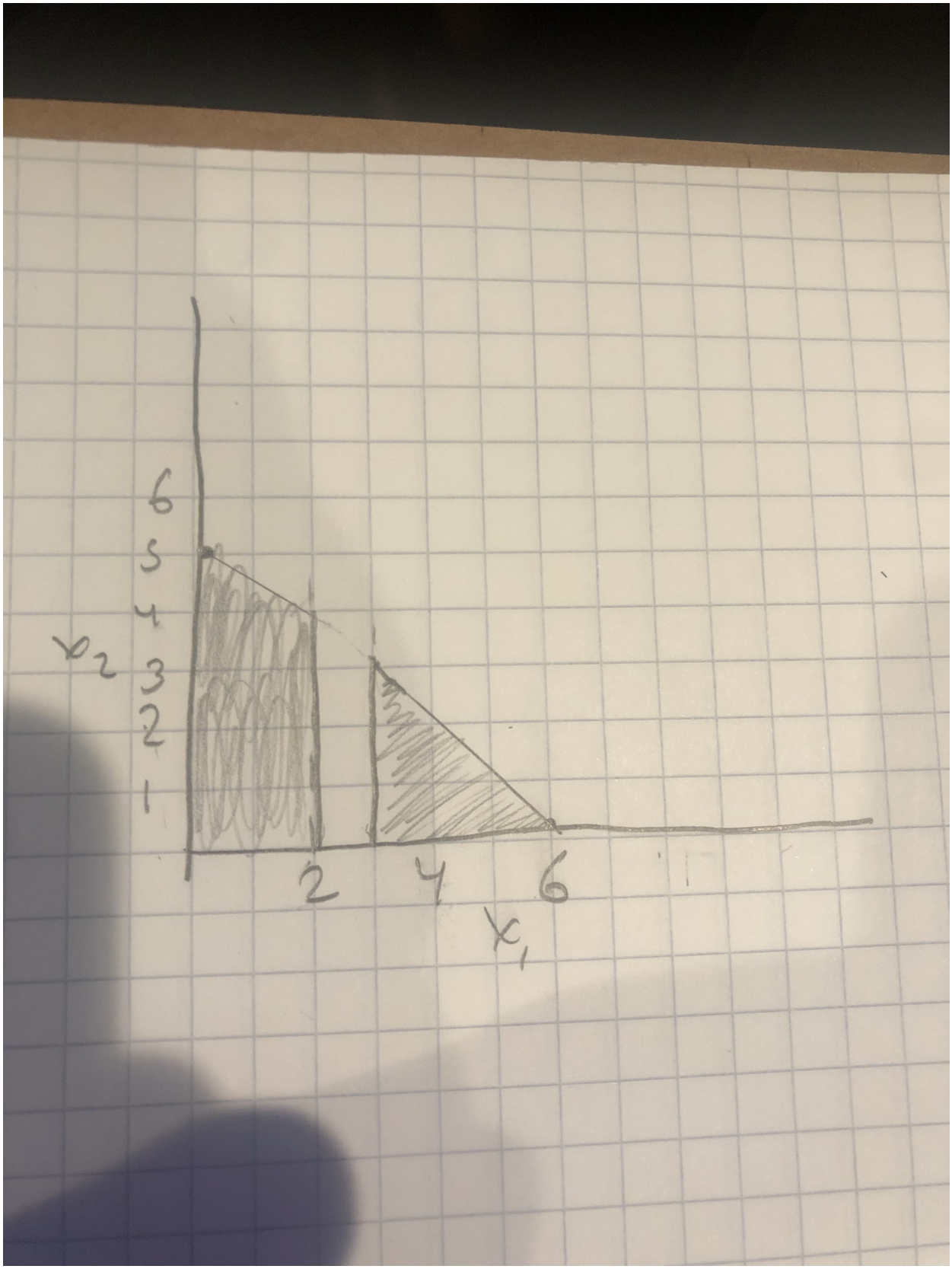
Q33: Assume that we always choose the variable with the minimum index to branch on if there are multiple options. Write down (in full) each of the LPs we get after branching off the root node.

A: max 5x1+8x2, x1+x2<=6, 5x1+9x2<=45, x1<=2, x1,x2 >= 0 integral

max 5x1+8x2, x1+x2<=6, 5x1+9x2<=45, x1>=3, x1,x2 >= 0 integral

Q34: Draw the feasible region to each of the LPs from **Q33** on the same picture.

A:



Run the following cell to see if the picture you drew in **Q34** was correct.

In [25]:
```
nodes[1].show()
```

Geometric Interpretation of LPs

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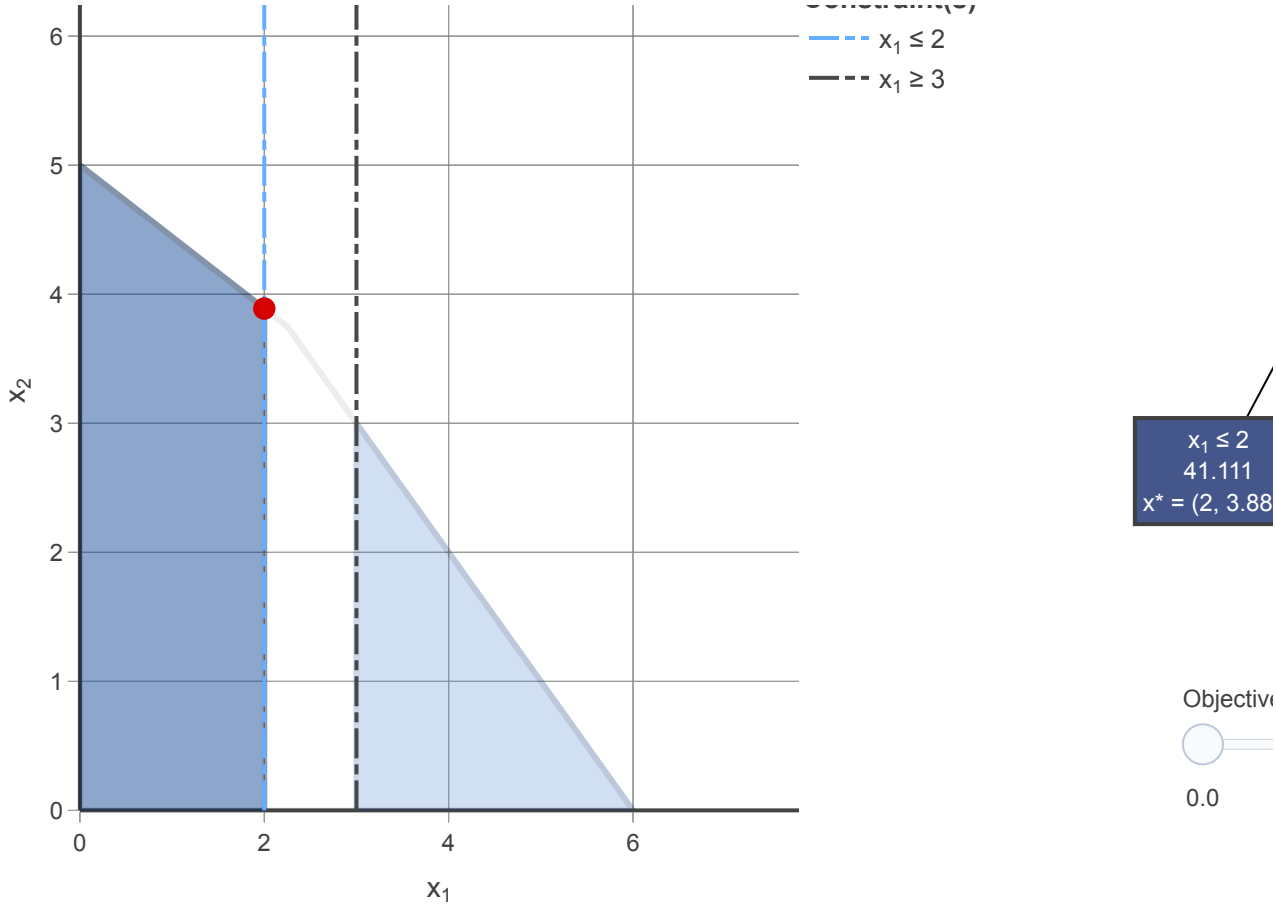
Constraint(s)



The outline of the original LP relaxation is still shown on the left. Now that we have eliminated some of the fractional feasible solutions, we now have 2 feasible regions to consider. The darker one is the feasible region associated with the current node which is also shaded darker in the branch and bound tree. The unexplored nodes in the branch and bound tree are not shaded in.

Q35: Which feasible solutions to the LP relaxation are removed by this branch?

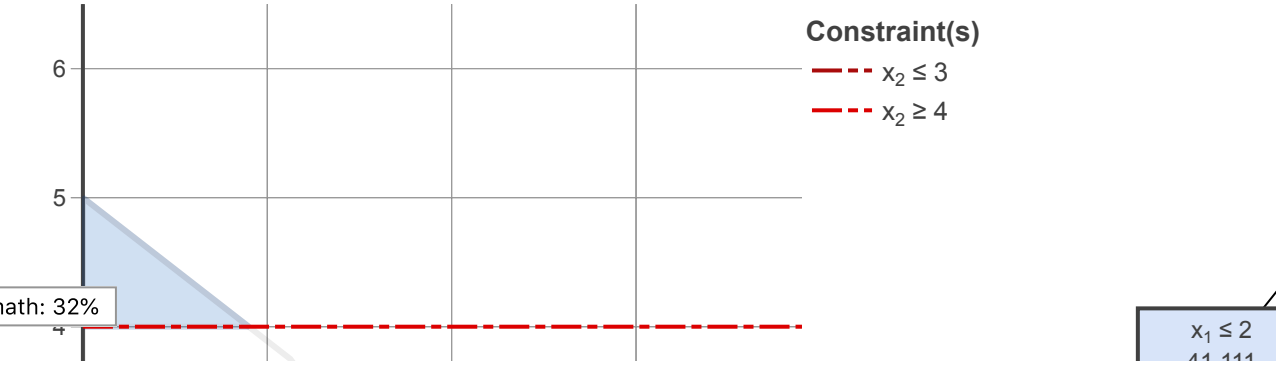
A: The feasible solutions removed are all solutions where x1 was between 2 and 3.

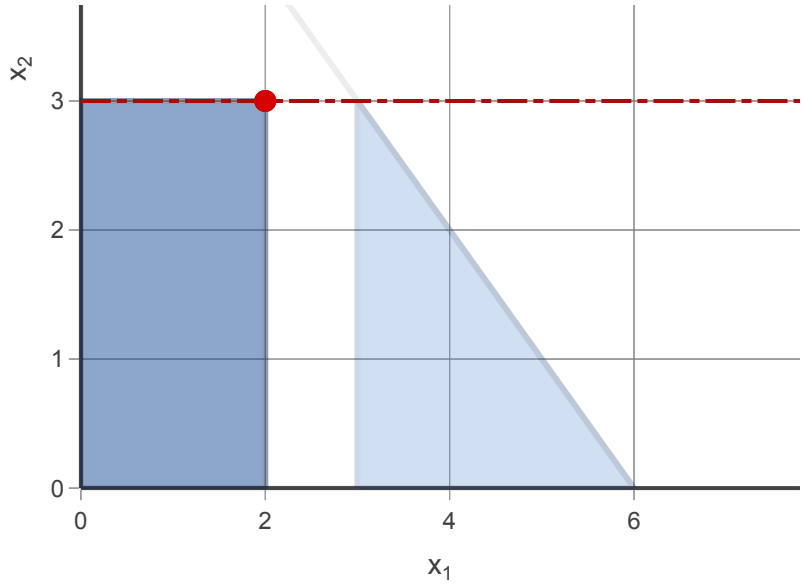
Q36: At the current (dark) node, what constraints will we add? How many feasible regions will the original LP relaxation be broken into?

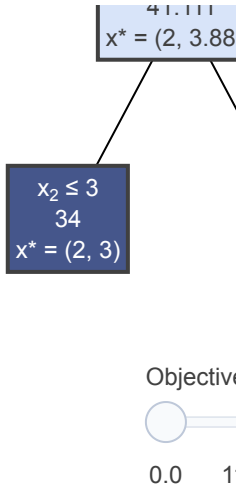
A: The constraints added would be x2<=3 and x2>= 4. There will be a total of 3 feasible regions.

In [26]:
```
nodes[2].show()
```

Geometric Interpretation of LPs







Q37: What is the optimal solution at the current (dark) node? Do we have to further explore this branch? Explain.

A: The optimal solution value is 34 and the solution is (2,3). We do not have to explore this branch further because we have reached a feasible integer value so going further would produce a less optimal solution.

Q38: Recall shaded nodes have been explored and the node shaded darker (and feasible region shaded darker) correspond to the current node and its feasible region. Nodes not shaded have not been explored. How many nodes have not yet been explored?

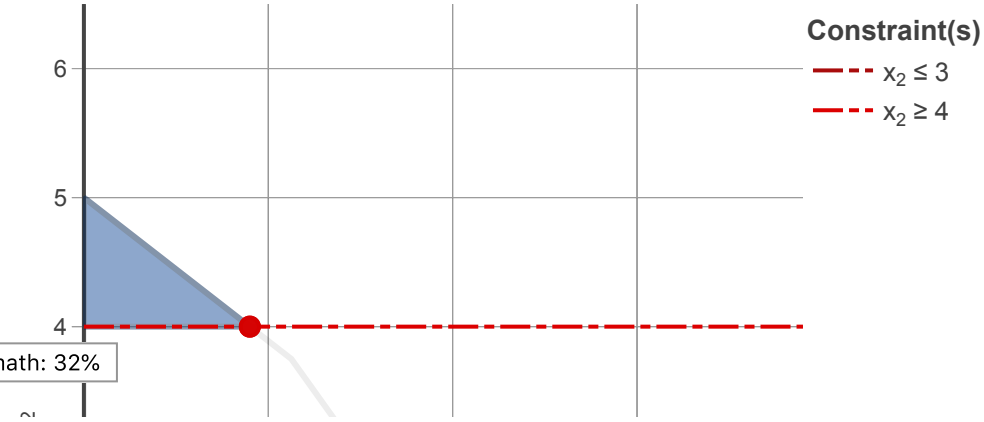
A: 2 nodes have yet to be explored.

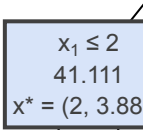
Q39: How many nodes have a degree of one in the branch and bound tree? (That is, they are only connected to one edge). These nodes are called leaf nodes. What is the relationship between the leaf nodes and the remaining feasible region?

A: Currently there are 3 leaf nodes in the iteration because the bottom most nodes all have 0 branches.

In [27]:
```
# Show the next two iterations of the branch and bound algorithm
nodes[3].show()
nodes[4].show()
```

Geometric Interpretation of LPs





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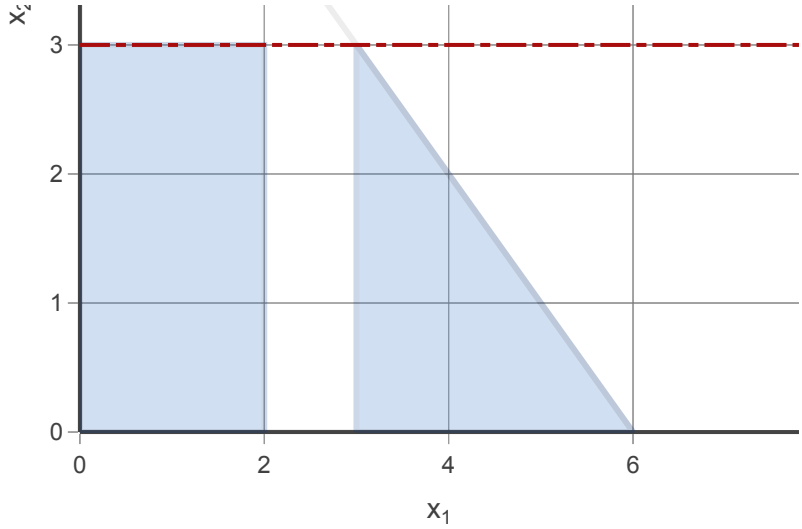
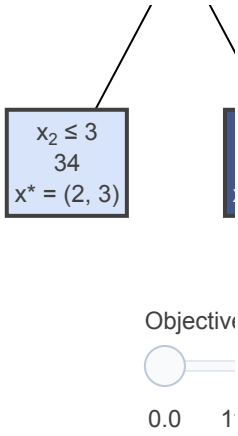
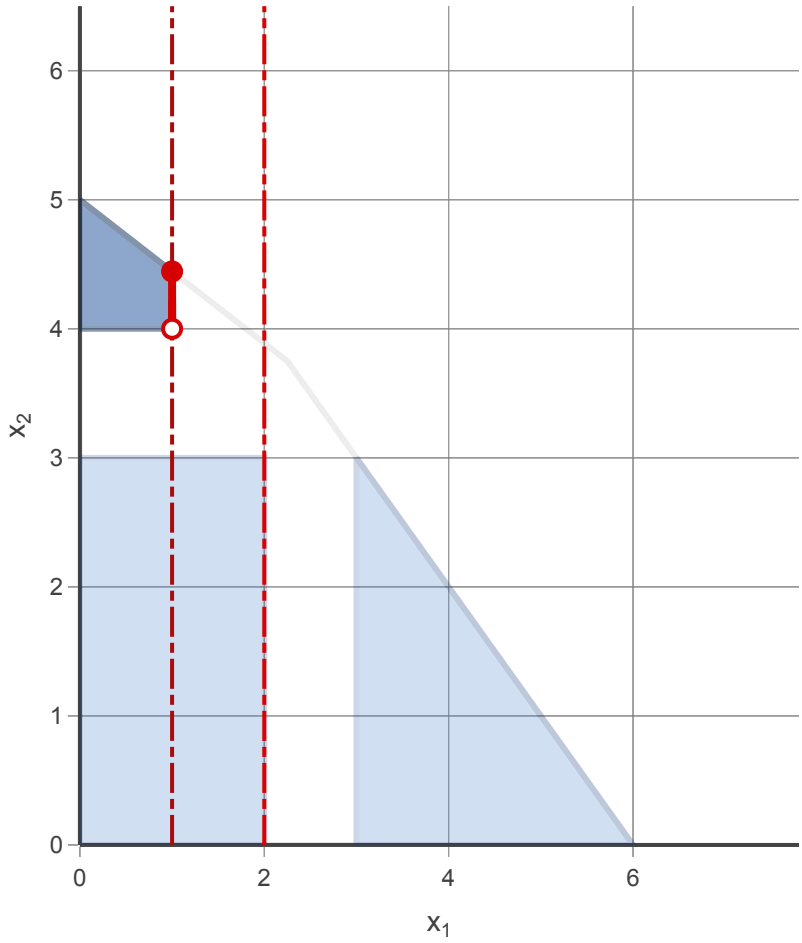
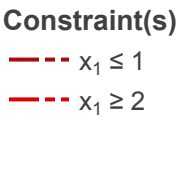
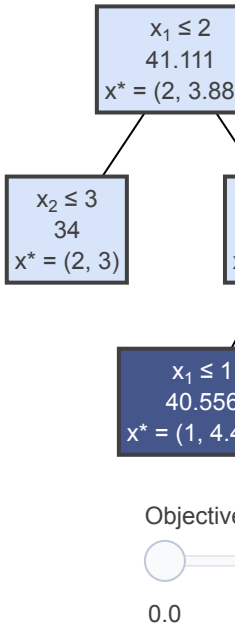




Geometric Interpretation of LPs







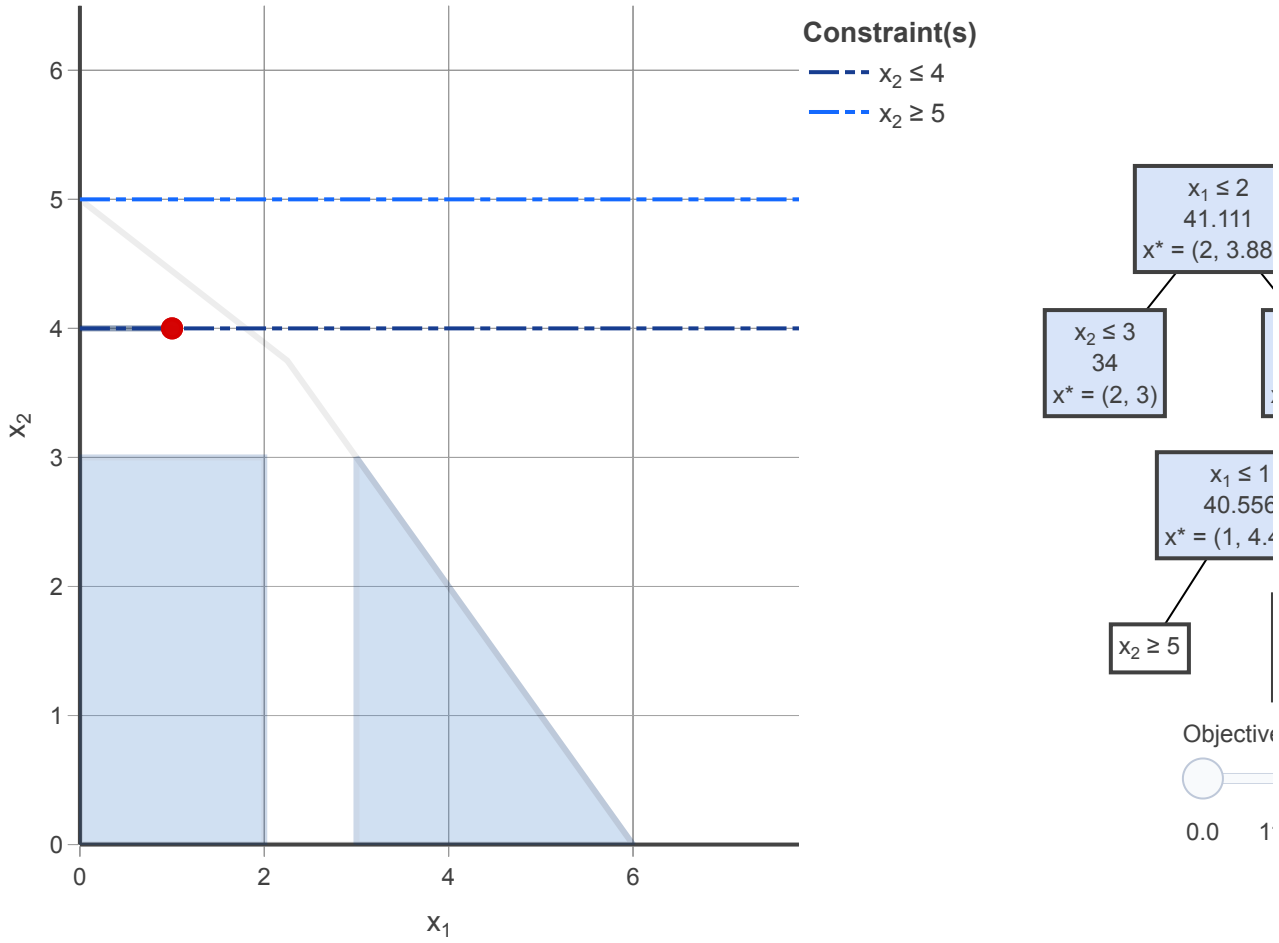
Q40: At the current (dark) node, we added the constraint x_1 \leq 1. Why were the fractional solutions 1 < x_1 < 2 not eliminated for x_2 <= 3?

A: They were not eliminated because the x2<=3 constraint reached a feasible solution and therefore was fathomed, which did not further limit the graph. Also, limiting the graph by x2<=3 would not remove the solutions from x1 to x2.

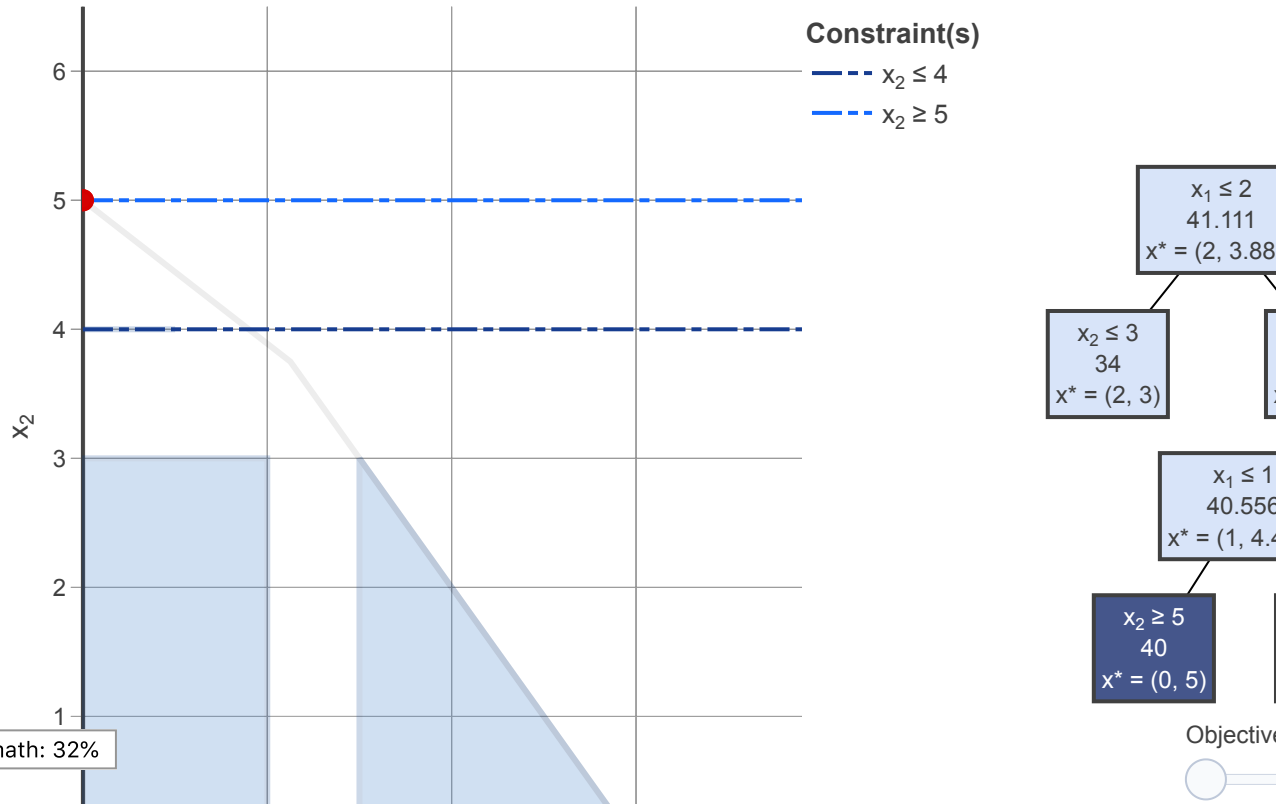
In [28]:
```
# Show the next three iterations of the branch and bound algorithm
5].show()
```

```
nodes[6].show()
nodes[7].show()
```

Geometric Interpretation of LPs



Geometric Interpretation of LPs



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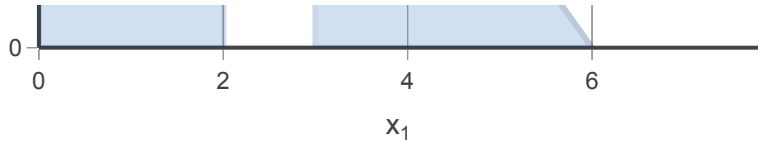
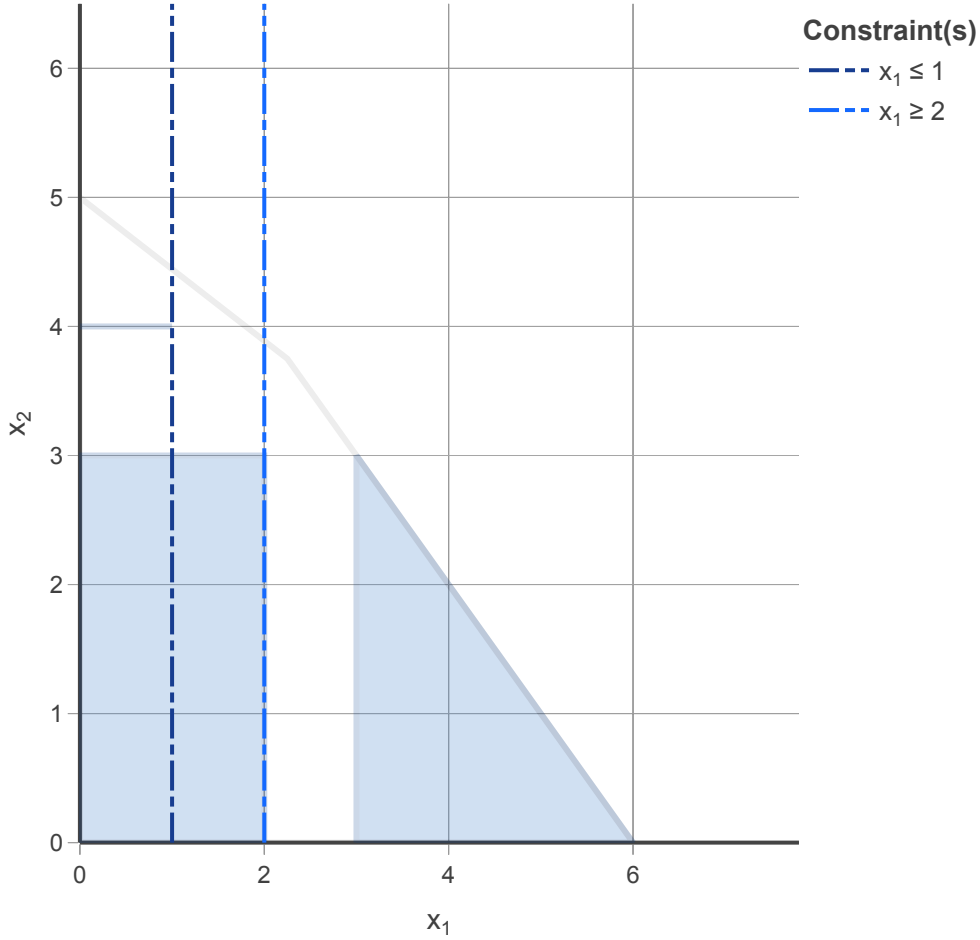
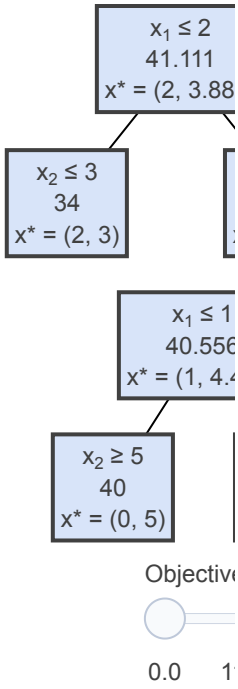


0.0 1

Geometric Interpretation of LPs



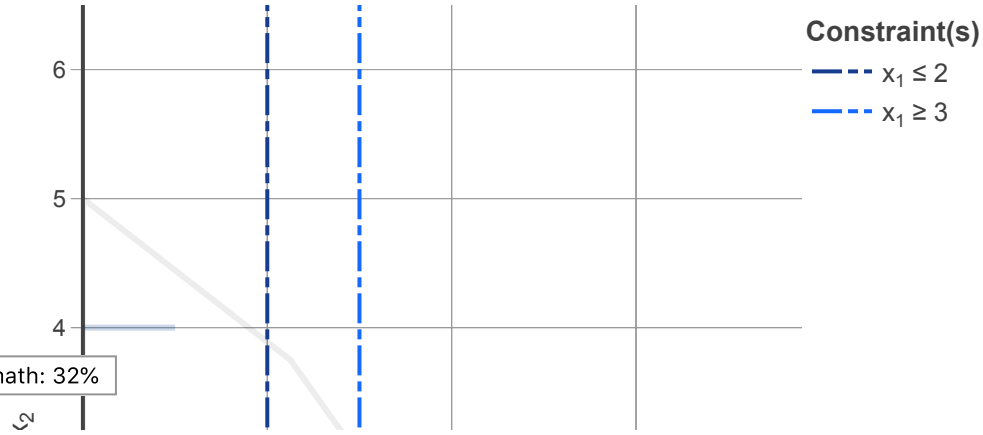


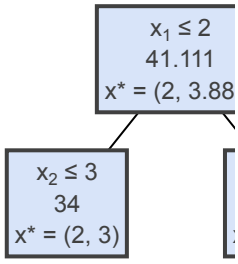
Q41: What constraints are enforced at the current (dark) node? Why are there no feasible solutions at this node?

A: The constraint x1<=2, x2>=4, x1>=2. This implies that x1 must be equal to 2. At x1 = 2, the max x2 value is less than 4 so it cannot be >=4 making this infeasible.

In [29]:
```
nodes[8].show()
```

Geometric Interpretation of LPs





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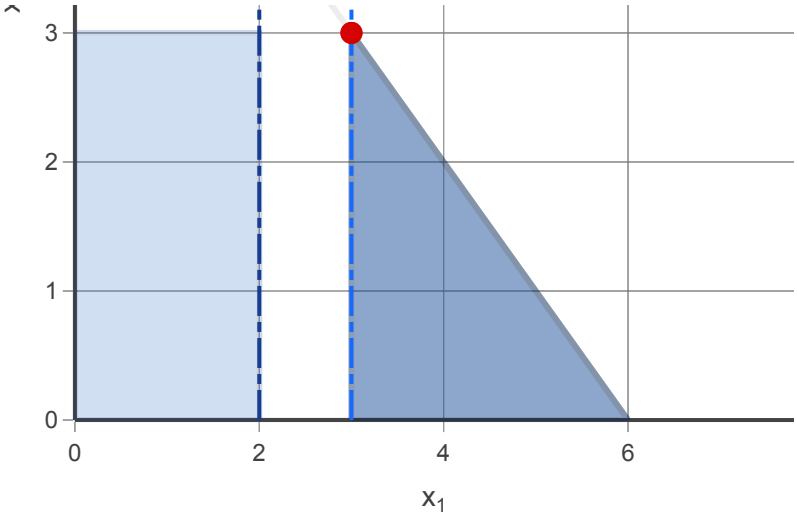
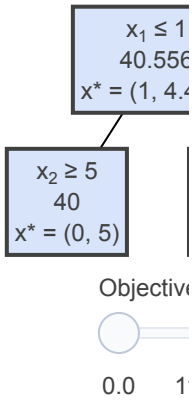




Q42: Are we done? If so, what nodes are fathomed and what is the optimal solution? Explain.

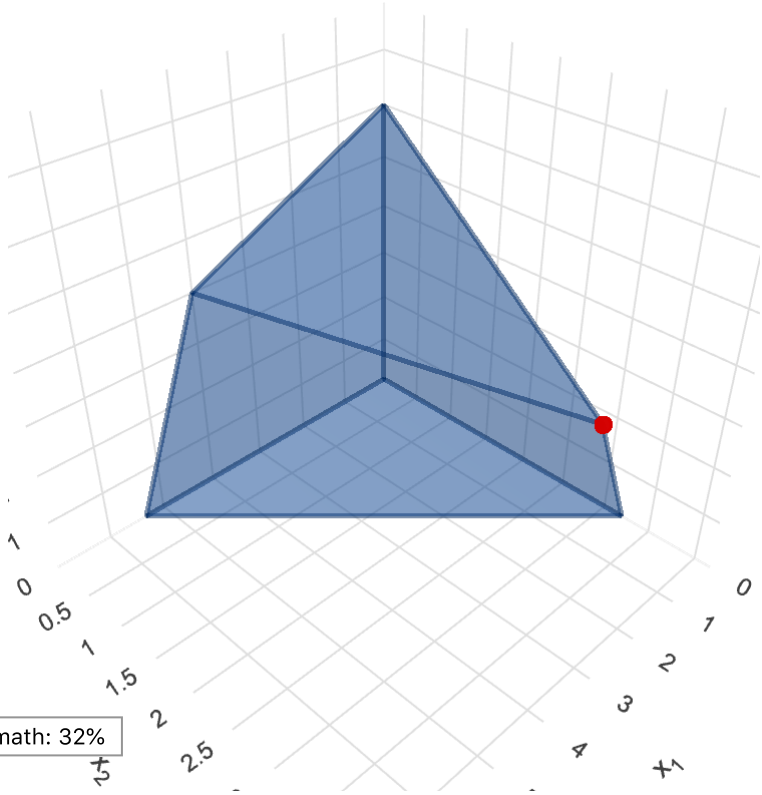
A: Yes. The fathomed nodes are all the leaf nodes that aren't part of the feasible solution (the infeasible node for example). The optimal solution is 40 at (0,5).

Let's look at branch and bound visualization for an integer program with 3 decision variables!

In [30]:
```
nodes = gilp.bnb_visual(gilp.examples.VARIED_BRANCHING_3D_IP)
```

In [31]:
```
# Look at the first 3 iterations
nodes[0].show()
nodes[1].show()
nodes[2].show()
```

Geometric Interpretation of LPs



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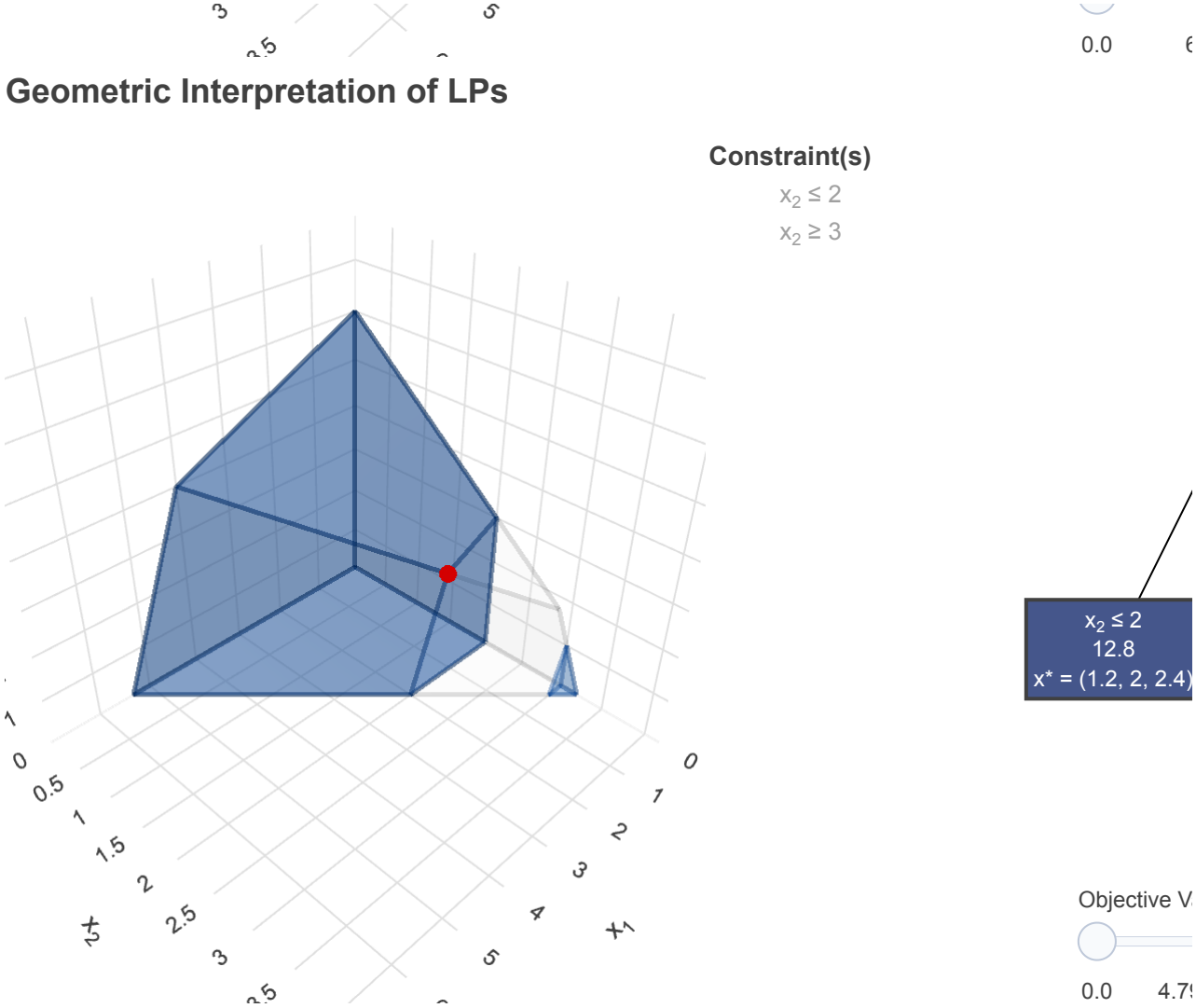
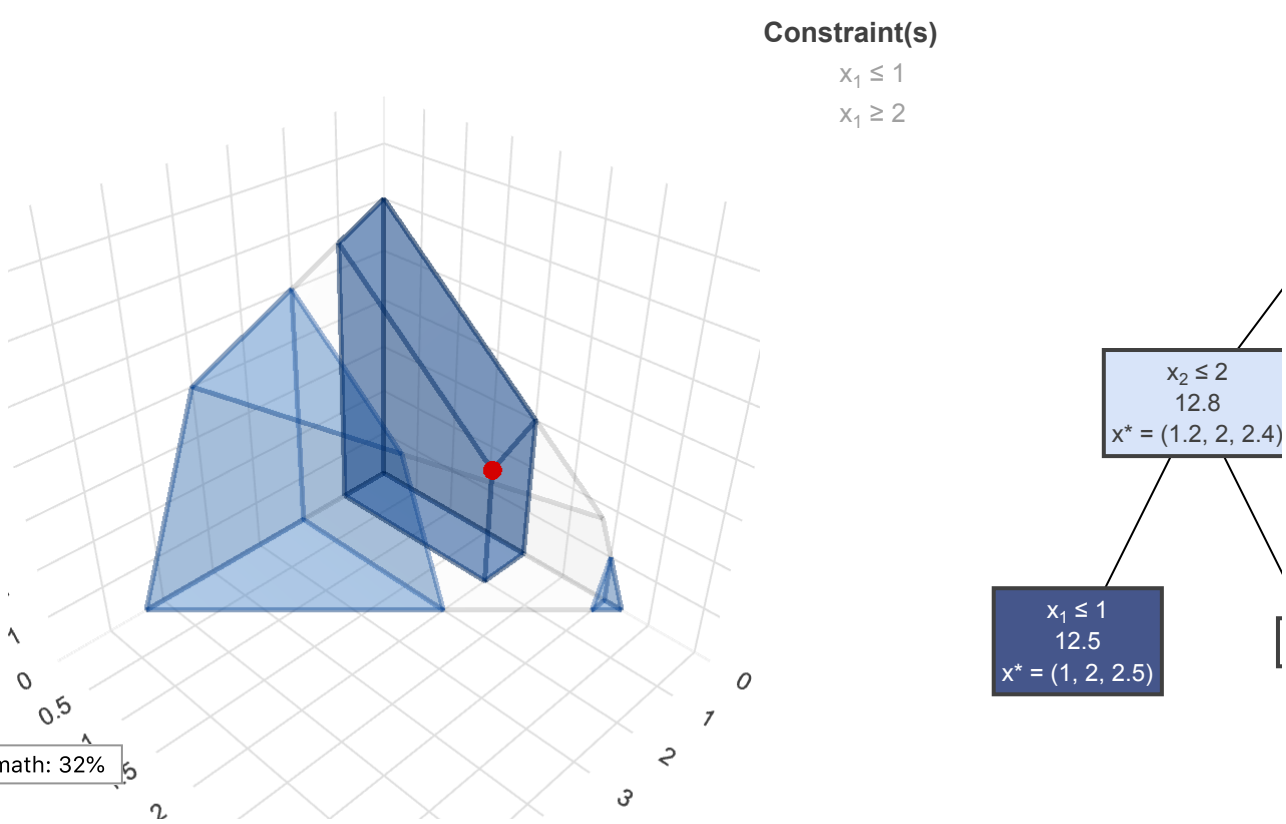


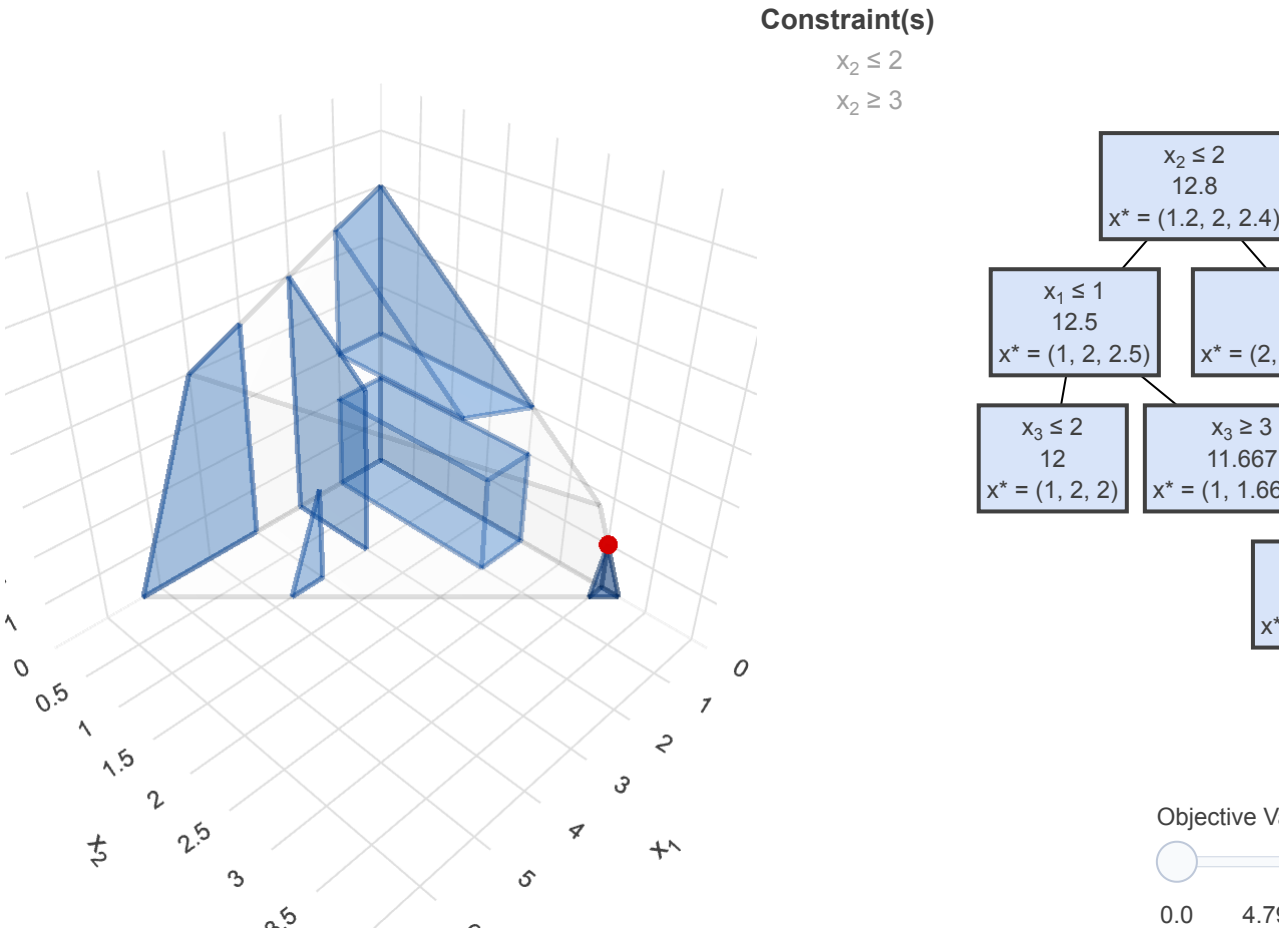


Processing math: 32%

Let's fast-forward to the final iteration of the branch and bound algorithm.

In [32]:
```
nodes[-1].show()
```

Geometric Interpretation of LPs



Q43: Consider the feasible region that looks like a rectangular box with one corner point at the origin. What node does it correspond to in the tree? What is the optimal solution at that node?

A: It corresponds to the node (1,2,2) which has an optimal solution of 12.

Q44: How many branch and bound nodes did we explore? What was the optimal solution? How many branch and bound nodes would we have explored if we knew the value of the optimal solution before starting branch and bound?

A: We've explored 13 nodes and the optimal solution is 13 at (0,3,1). We could have just explored 1 if we knew before hand.

Bonus: Branch and Bound for Knapsack

Consider the following example:

item	value	weight
1	2	1
2	9	3
3	6	2

The linear program formulation will be:

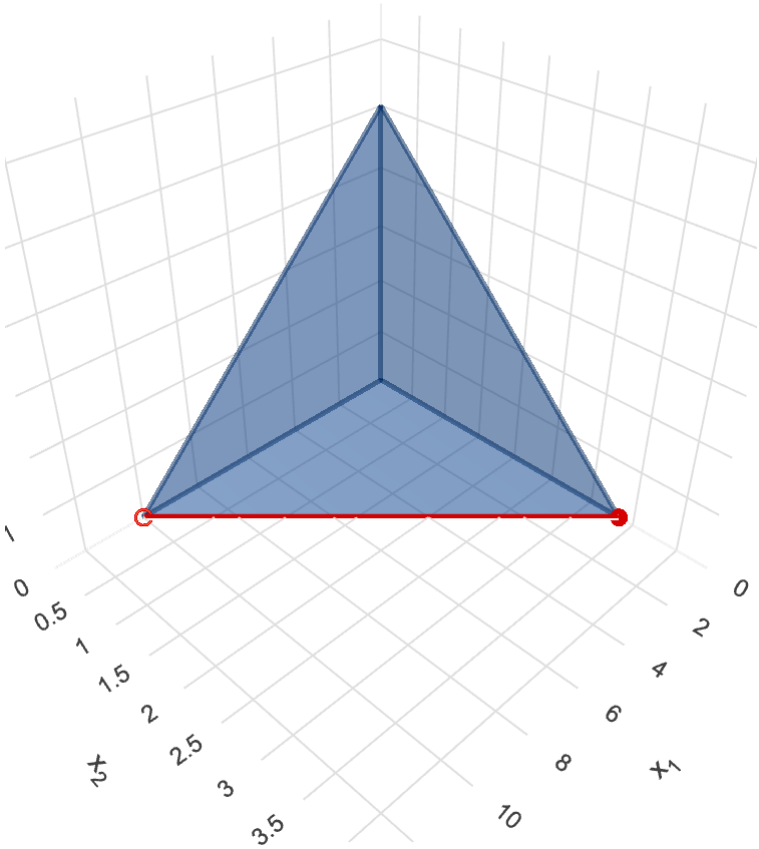
$$\begin{aligned} \max \quad & 2x_1+9x_2+6x_3 \\ \text{s.t.} \quad & 1x_1+3x_2+2x_3 \leq 10 \\ & x_1, x_2, x_3 \geq 0, \quad \text{integer} \end{aligned}$$

In gilp, we can define this lp as follows:

In [34]:
```
lp = gilp.LP([[1,3,2]],
             [10],
             [2,9,6])

for fig in gilp.bnb_visual(lp):
    fig.show()
```

Geometric Interpretation of LPs



Objective V
0.0 13.

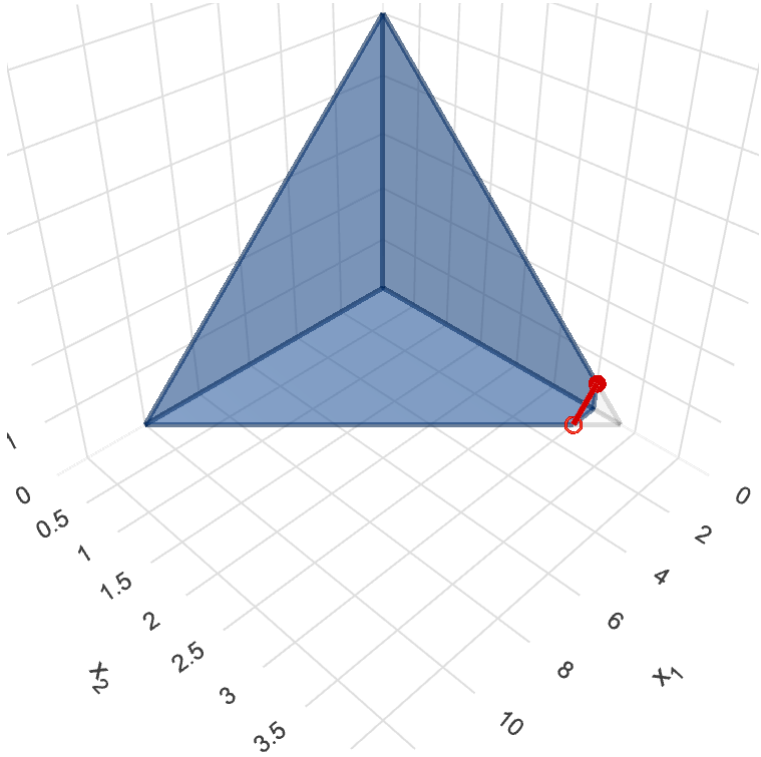
Geometric Interpretation of LPs

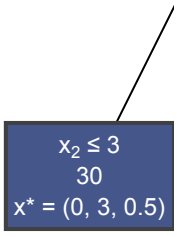
Constraint(s)

$x_2 \leq 3$

$x_2 \geq 4$

Processing math: 32%





Objective V

0.0 13.

Processing math: 32%

In [ ]: