

Branch & Bound and Knap

Objectives

- Perform 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 integer programming problem using a branch-and-bound algorithm. We will also see how to compute the computation time and effort of the algorithm. Lastly, we will see how to visualize the branch and bound algorithm.

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

Part 1: Branch and Bound Algo

Recall that the branch and bound algorithm (in addition to solving integer programs). Before applying the branch and bound algorithm, we will begin by reviewing some core ideas. Furthermore, we will make branch and bound terminate quicker later in the lab.

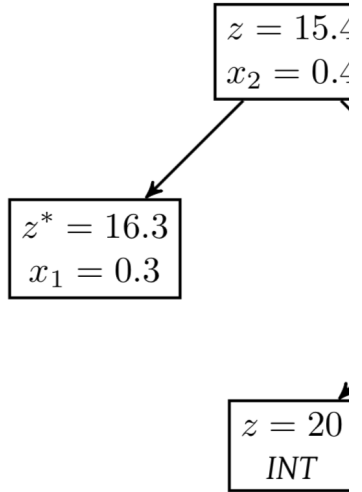
Q1: What are the different ways a node can be fathomed in the branch and bound algorithm? Describe each.

A: A node can be fathomed if there is no better integer program solution

Q2: Suppose you have a maximization integer programming problem. What does the LP-relaxation optimal value tell you if it is a minimization problem?

A: It is an upper bound in a maximization problem and a lower bound in a minimization problem

Q3: Assume you have a maximization integer programming problem with a linear objective function. Now, suppose you are running the branch and bound algorithm. What happens if the LP-relaxation optimal value is not an integer?

	<p>across a node with an optimal value of 44.5. The current node? Why or why not?</p> <p>A: Yes because there is no other integer solution possible.</p>
	<p>Q4: If the optimal solution to the LP relaxation of the problem found an optimal solution to your integer program. Explain.</p> <p>A: This is because the bound is an integer, thus the LP solution is integer.</p>
	<p>Q5: If the LP is infeasible, then the IP is infeasible. Explain.</p> <p>A: Because the IP is a feasible solution to the LP.</p>
	<p>The next questions ask about the following branch and bound tree. In the current iteration of branch and bound, the fractional x_i that was used to branch is denoted INT. In the current iteration of branch and bound, the fractional x_i that was used to branch is denoted INT. *****.</p>
	
	<p>Q6: Can you determine if the integer program this branch and bound tree represents is a minimization or maximization problem? If so, which is it?</p> <p>A: Yes, minimization</p>
	<p>Hint: For Q7-8, you can assume integral coefficients in the objective function and constraints.</p>
	<p>Q7: Is the current node (marked z^*) fathomed? Why or why not? What constraints should be imposed for each of the next two nodes?</p> <p>A: It is fathomed</p>

	<p>Q8: Consider the nodes under the current node (when optimal value of these nodes? Why?</p> <p>A: They are lower bounds for the IP</p>
	<h2>Part 2: The Knapsack Problem</h2> <p>In this lab, you will solve an integer program by branch and bound. The problem solved will be a knapsack problem.</p>
	<p>Knapsack Problem: We are given a collection of n items, each with a weight w_i and a value v_i. In addition, there is a given maximum weight W. The goal is to find a subset of items that has a total weight at most W and a maximum value.</p> $\begin{aligned} \max \quad & \sum_{i=1}^n v_i x_i \\ \text{s.t.} \quad & \sum_{i=1}^n w_i x_i \leq W \\ & 0 \leq x_i \leq 1, \text{ integer} \end{aligned}$
	<p>Consider the following data which we import from a file:</p>

```
In [4]: data = pd.read_csv('knapsack_data_1.csv', index_col=0)
data
```

	value	weight
item		
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? Replace `index` with the item number that can be removed. For each item could we possibly take?

A: 7 can be dropped because it alone is more than W

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

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

A: It is bigger than W on its own so it cannot be carried

Q11: Consider removing items i such that $w_i > W$. How does the linear relaxation's optimal value change?

A: It does not

In **Q10-11**, you should have found that removing the item 7 from the knapsack does not change the integer program's optimal value. However, the optimal IP and LP values can become smaller. By how much? Can you terminate sooner?

Recall that a branch and bound node can be fathomed if:

the best feasible integer solution found thus far. Hence, we need a solution as quickly as possible (so that we stop need to construct a good feasible integer solution by a reasonable heuristic). We run the branch and bound procedure.

In designing a heuristic for the knapsack problem, it is useful to compute the value per unit weight for each item. We compute this value in the following code:

```
In [ ]: data['value per unit weight'] = (data['value'] / data['weight'])
```

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

A: Pick the biggest value per weight and then pick the items until the knapsack is full.

Q13: Run your heuristic on the data above to compute the value of the solution. What is the value? How good is this solution? (Your heuristic should generate a feasible solution with a value of 64. Try to improve it with a different heuristic (or talk to your TA!))

A: Got 64

We will now use the branch and bound algorithm to solve the knapsack problem. We will define a mathematical model for the linear relaxation of the problem.

Q14: Complete the model below.

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

        Args:
            table (pd.DataFrame): A table indexed by items
            capacity (int): An integer-capacity for the knapsack
            integer (bool): True if the variables should be integers

        Returns:
            The optimal value of the knapsack problem.

        """
        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
        W = 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))

# recall that we add constraints to the model using
m.Add(W >= sum(w[i] for i in ITEMS))

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

```

```

In [ ]: # You do not need to do anything with this cell but make sure it runs
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.getVarMap().values()})

```

We can now create a linear relaxation of our knapsack problem. x represents our decision variables.

```

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

```

We can use the next line to solve the model and output the results.

```

In [ ]: solve(m)

```

****Q15:**** How does this optimal value compare to the integer solution?

****A:**** It is larger

Q16: Should this node be fathomed? If not, what var

A: It should not be fathomed. x_3 should be branche

After constructing the linear relaxation model using 1

constraints. For example, we can add the constraint

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

NOTE: The line `m, x = Knapsack(data1, 18)` resets th
constraints from branching have to be added each ti

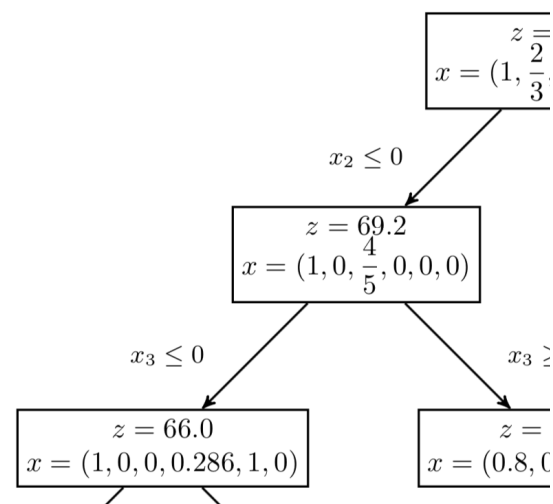
Q17: Use the following cell to compute the optimal v

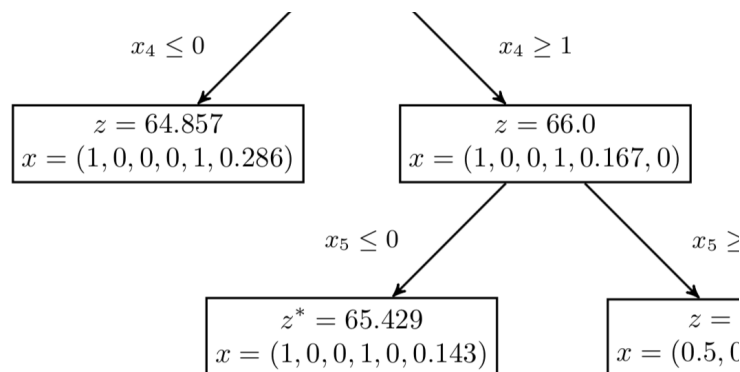
```
In [ ]: m, x = Knapsack(data, 18)
m.Add(x[2] <= 0)
m.Add(x[2] >= 1)
solve(m)
```

Q18: What was the optimal value? Can this node be
feasible integer solution with value 64.)

A: It was 60 and it can be fathomed because $60 < 6$.

If we continue running the branch and bound algorithm
bound tree below where the z^* indicates the current r





Q19: The node with $z = 64.857$ was fathomed. Why think back to **Q3**)

A: There's no integer between it and 64.

Q20: Finish running branch and bound to find the optimal solution. For each node you solve and indicate if the node was fathomed to include the constraints further up in the branch and bound tree.

```
In [ ]: # Template
m, x = Knapsack(data, 18)
m.Add(x[2] <= 0)
m.Add(x[2] >= 1)
m.Add(x[3] >= 1)
m.Add(x[3] <= 0)
solve(m)
# fathomed: x_3 <= 0
```

```
In [ ]: # Template
m, x = Knapsack(data, 18)
m.Add(x[2] <= 0)
m.Add(x[2] >= 1)
m.Add(x[3] >= 1)
m.Add(x[3] <= 0)
m.Add(x[4] >= 1)
m.Add(x[4] <= 0)
solve(m)
# fathomed: x_3 <= 0, x_4 <= 0
```

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



```

m.Add(x[2] <= 0)
m.Add(x[2] >= 1)

m.Add(x[3] >= 1)
m.Add(x[3] <= 0)
m.Add(x[4] >= 1)
m.Add(x[4] <= 0)
m.Add(x[5] >= 1)
m.Add(x[5] <= 0)
solve(m)
# fathomed: x 3 <= 0, x 4 <= 0

```

```

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

```

A: 64

Q21: How many nodes did you have to explore while
A: 10

In the next section, we will think about additional cor
and bound quicker.

Part 3: Cutting Planes

In general, a cutting plane is an additional constraint
relaxation that removes feasible linear solutions but
solutions. This is very useful when solving integer pr

have learned in class have something we call the "in
allows us to ignore the integrality constraint since we
By cleverly adding cutting planes, we strive to remove

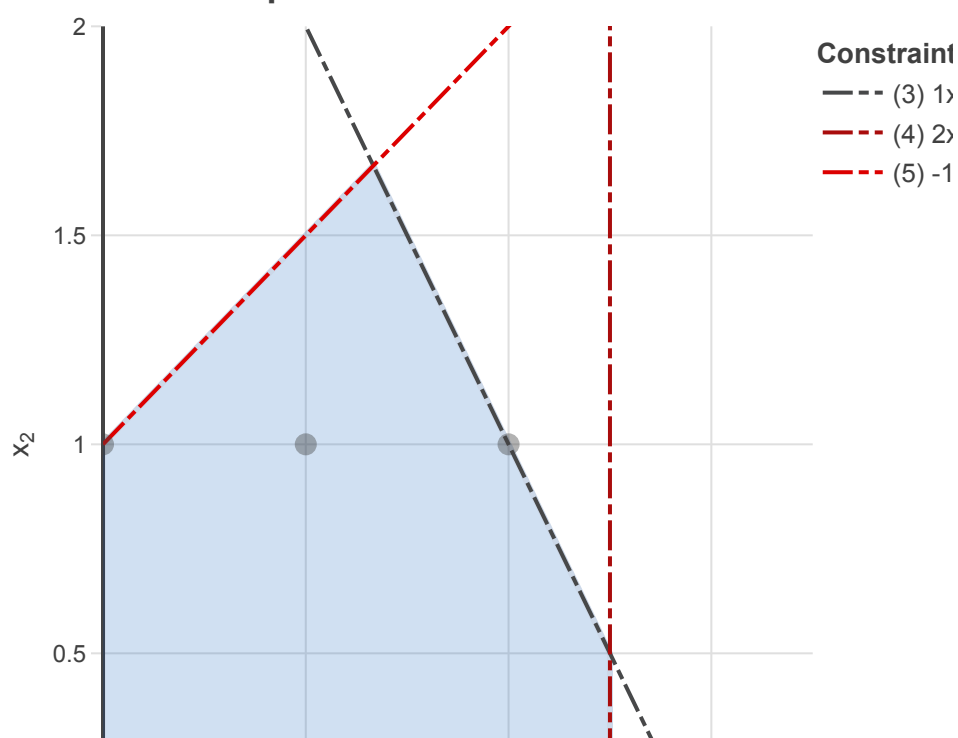
Consider an integer program whose linear program r

$$\begin{aligned} \max \quad & 2x_1 + x_2 \\ \text{s.t.} \quad & x_1 + x_2 \leq 2 \\ & 2x_1 \leq 5 \\ & -x_1 + x_2 \leq 1 \\ & x_1, x_2 \geq 0 \end{aligned}$$

We can define this linear program and then visualize
been highlighted.

```
In [2]: 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
```

Geometric Interpretation of LPs



Q22: List every feasible solution to the integer program

A: 0,1,2,3,4

Q23: Is the constraint $x_2 \leq 1$ a cutting plane? Why? become infeasible? What about feasible linear points

A: It is a cutting plane. It removes feasible solutions

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

```
In [ ]: 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 removes no feasible solutions

Q25: Can you provide another cutting plane? If so

A: $x_1 \leq 4$

Let's look at the feasible region after adding the cutting plane answers from **Q25**. Notice the optimal solution to the

```
In [ ]: 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:
input was $W = 18$ and:

```
In [5]: data
```

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

Q26: Look at items 1, 2, and 3. How many of these items can you fit in a knapsack with capacity 18? If so, please provide the items.

A: $x_1 + x_2 \leq 18$, $x_2 + x_3 \leq 18$, $x_3 + x_1 \leq 18$

Q27: Is the constraint you found in **Q26** a cutting plane for the linear program relaxation that is no longer feasible (i.e., it cuts off some feasible points)?

A: yes it cuts off fractional values of each item

Q28: Provide another cutting plane involving items 1, 2, and 3. How did you derive it?

A:

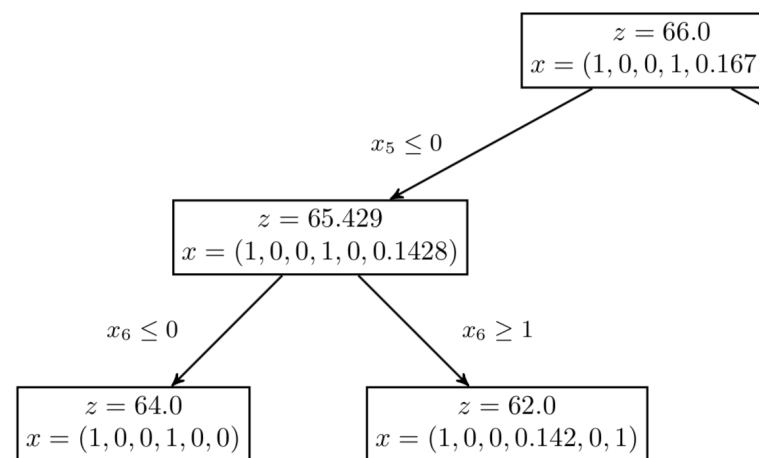
Q29: Add the cutting planes from **Q26** and **Q28** to the knapsack problem. What is the optimal solution in which we take items 1 and 4 and $\frac{1}{6}$ of item 5?

```
In [ ]: m, x = Knapsack(data, 18)
        # TODO: Add cutting planes here

        solve(m)
```

Let's take a moment to pause and reflect on what we dropped item 7 because its weight was greater than added the constraint $x_7 \leq 0$. This constraint was a c feasible solutions but no integer ones. By adding the branch and bound to terminate earlier yet again! So inspection. However, there are more algorithmic way now).

If we continue running the branch and bound algorithm bound tree below where the z^* indicates the current r



NOTE: Do not forget about the feasible integer solution

Q30 Finish running branch and bound to find the optimal solution. For each node you solve and indicate if the node was fathomed. If the cutting plane constraints should be included in the node.

```

In [ ]: # Template
        m, x = Knapsack(data, 18)
        # Add constraints here

        solve(m)
        # fathomed?
  
```

```

In [ ]:
  
```

```

In [ ]:
  
```

A:

Q31: Did you find the same optimal solution? How much does it compare to the number you explored previously?

A:

Part 4: Geometry of Branch and Bound

Previously, we used the `gilp` package to visualize the branch and bound functionality to visualize branch and bound. We will use `gilp_visual` and `simplex_visual`, the function `bnb_visual` is assumed that every decision variable is constrained to be non-negative. In visualizations, `bnb_visual` returns a series of figures. Let's look at a small 2D example:

$$\begin{aligned} \max \quad & 5x_1 + 8x_2 \\ \text{s.t.} \quad & x_1 + x_2 \leq 10 \\ & 5x_1 + 9x_2 \leq 45 \\ & x_1, x_2 \geq 0. \end{aligned}$$

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

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

Run the cells above to generate a figure for each node. 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 optimal solution? (Hint: Use the objective slider and the isoprofit line.)

A:

Q33: Assume that we always choose the variable with the largest reduced cost. Are there multiple options. Write down (in full) each of the options.

A:

Q34: Draw the feasible region to each of the LPs from the branch and bound tree.

A:

Run the following cell to see if the picture you drew is correct.

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

The outline of the original LP relaxation is still shown. Some of the fractional feasible solutions, we now have one is the feasible region associated with the current branch and bound tree. The unexplored nodes in the

Q35: Which feasible solutions to the LP relaxation are
A:

Q36: At the current (dark) node, what constraints of the original LP relaxation are broken into?
A:

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

Q37: What is the optimal solution at the current (dark) node? Explain.
A:

Q38: Recall shaded nodes have been explored and the darker shaded (darker) correspond to the current node and if it has been explored. How many nodes have not yet been explored?
A:

Q39: How many nodes have a degree of one in the tree (i.e., only connected to one edge). These nodes are called the leaf nodes and the remaining feasible region?
A:

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

Q40: At the current (dark) node, we added the constraint $x_1 < 2$ to eliminate the fractional solutions. How many nodes are eliminated?
A:

```
In [ ]: # Show the next three iterations of the branch and bound
nodes[5].show()
nodes[6].show()
nodes[7].show()
```

Q41: What constraints are enforced at the current (current) solutions at this node?

A:

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

Q42: Are we done? If so, what nodes are fathomed and why?

A:

Let's look at branch and bound visualization for an instance.

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

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

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

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

Q43: Consider the feasible region that looks like a rectangle in the origin. What node does it correspond to in the tree? \

A:

Q44: How many branch and bound nodes did we explore? How many branch and bound nodes would we have explored if we had a solution before starting branch and bound?

A:

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:

$$\max \quad 2x_1 + 9x_2 +$$

$$\text{s.t.} \quad 1x_1 + 3x_2 +$$

$$x_1, x_2, x_3 \geq$$

In gilp, we can define this lp as follows:

```
In [ ]: lp = gilp.LP([[1,3,2]],  
                    [10],  
                    [2,9,6])  
  
for fig in gilp.bnb_visual(lp):  
    fig.show()
```