

Geometry of Simplex Lab

Objectives

- Understand the geometry of a linear program's feasible region.
- Use isoprofit lines and planes to solve 2D and 3D LPs graphically.
- Identify the most limiting constraint in an iteration of simplex both algebraically and geometrically.
- Identify the geometric features corresponding to dictionaries.
- Describe the geometrical decision made at each iteration of simplex.

Review

Recall, linear programs (LPs) have three main components: decision variables, objective function. The goal of linear programming is to find a **feasible solution** (satisfying every constraint) with the highest objective value. The set of feasible solutions is called the **feasible region**. In lecture, we learned about isoprofit lines. For every objective function, we can define an isoprofit line. Isoprofit lines have the property that two solutions on the same isoprofit line have the same objective value and all isoprofit lines are parallel.

In the first part of the lab, we will use a Python package called GILP to solve LPs graphically. We introduce the package now.

GILP

If you are running this file in a Google Colab Notebook, uncomment the following lines. Otherwise, you can ignore it.

```
In [51]: #pip install gilp
```

This lab uses default LPs built in to GILP. We import them below.

```
In [1]: from gilp import examples as ex
```

We access the LP examples using `ex.NAME` where `NAME` is the name of the example, consider:

$$\begin{aligned}
 \max \quad & 5x_1 + 3x_2 \\
 \text{s.t.} \quad & 2x_1 + 1x_2 \leq 20 \\
 & 1x_1 + 1x_2 \leq 16 \\
 & 1x_1 + 0x_2 \leq 7 \\
 & x_1, x_2 \geq 0
 \end{aligned}$$

This example LP is called `ALL_INTEGER_2D_LP`. We assign this LP to the variable `lp`.

```
In [2]: lp = ex.ALL_INTEGER_2D_LP
```

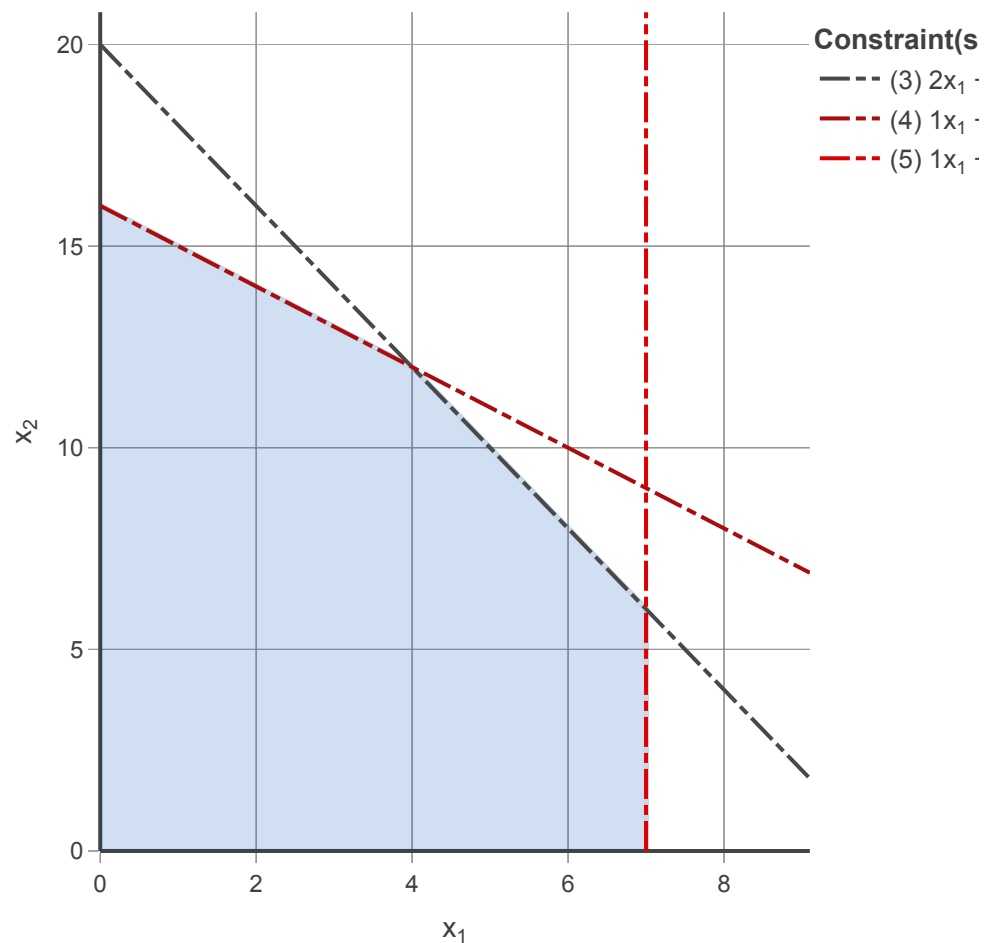
We can visualize this LP using a function called `lp_visual()`. First, we must import the function.

```
In [3]: from gilp.visualize import lp_visual
```

The function `lp_visual()` takes an LP and returns a visualization. We then call the function to display the visualization.

```
In [4]: lp_visual(lp).show()
```

Geometric Interpretation of LPs



On the left, you can see a coordinate plane where the x -axis corresponds to the value of x_1 and the y -axis corresponds to the value of x_2 . The region shaded blue is the feasible region. The perimeter of the feasible region, you can see points where two edges come together. These are called **corner points**. You can hover over these corner points to see information about them. Only some of the information in the hover box will be relevant for Part I. The first two values of **BFS** represent the coordinates of the corner point, and **Obj** is the objective value. For example, the upper left corner point has coordinates $x_1 = 0$ and $x_2 = 16$ with objective value 48. The dashed lines represent the constraints.

click on the constraints in the legend to mute and un-mute them. Note this does just changes visibility. Lastly, the objective slider allows you to see the isoprofit objective values.

Part I: Solving Linear Programs Graphically

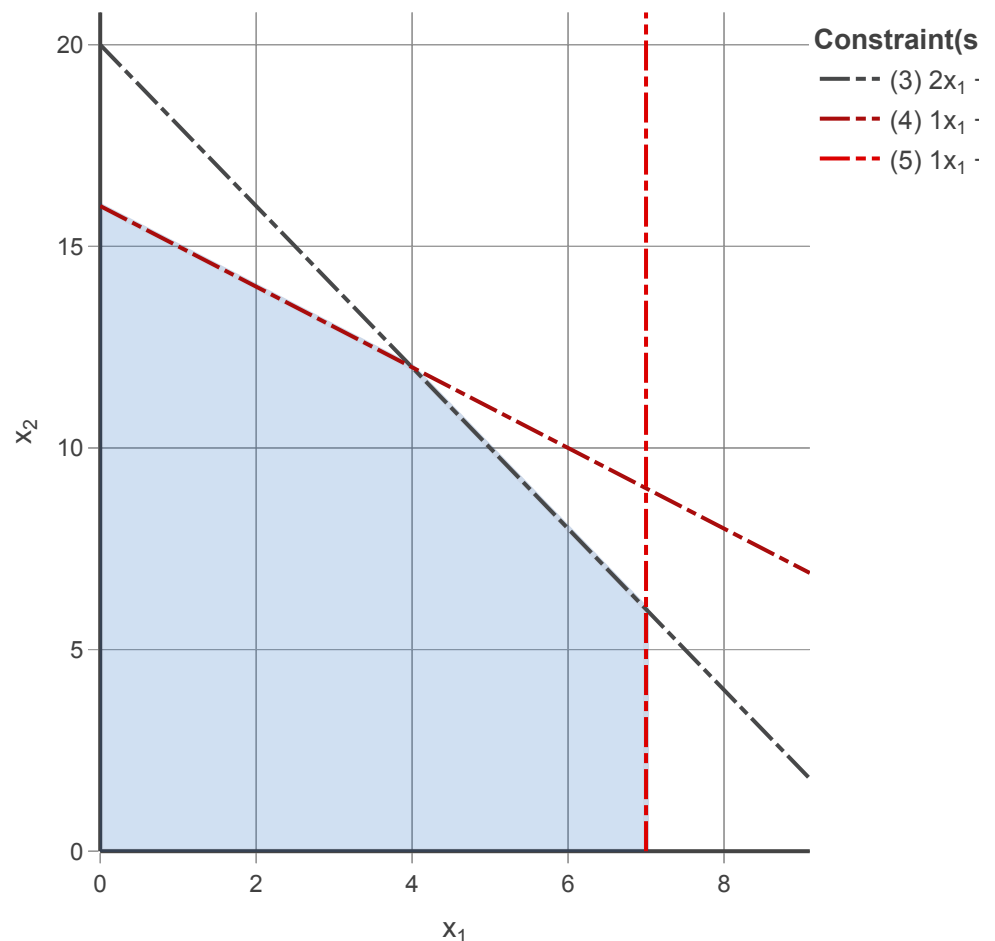
Let's use GILP to solve the following LP graphically:

$$\begin{aligned} \max \quad & 5(4) + 3(12) \\ \text{s.t.} \quad & 2(4) + 1(12) \leq 20 \\ & 1(4) + 1(12) \leq 16 \\ & 1(4) + 0(12) \leq 7 \\ & 1(4), (12) \geq 0 \end{aligned}$$

Recall, this LP is called `ALL_INTEGER_2D_LP`.

```
In [5]: lp = ex.ALL_INTEGER_2D_LP # get LP example
lp_visual(lp).show() # visualize it
```

Geometric Interpretation of LPs



Q1: How can you use isoprofit lines to solve LPs graphically?

A: The optimal objective value would be the isoprofit line that is furthest from 1 still in the domain.

Q2: Use the objective slider to solve this LP graphically. Give an optimal solution value. Argue why it is optimal. (Hint: The objective slider shows the isoprofit line objective value.)

A: Our objective value is 56 and the optimal solution is where $x_1 = 4$ and $x_2 =$ because the line is on the boundary of the domain.

Q3: Plug your solution from **Q2** back into the LP and verify that each constraint (forget non-negativity constraints!) and the objective value is as expected. Show

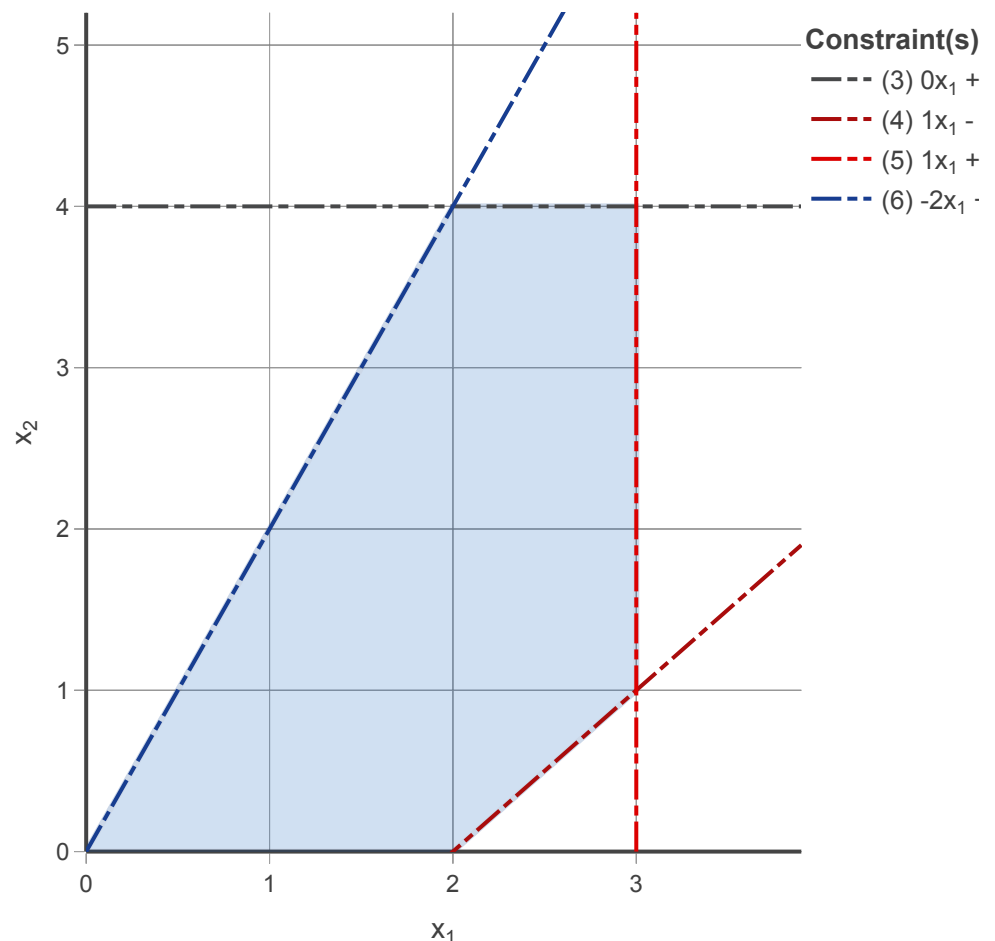
A: Each constraint is satisfied. We put the values into solving LP graphically.

Let's try another! This LP is called `DEGENERATE_FIN_2D_LP`.

$$\begin{array}{ll} \max & 1x_1 + 2x_2 \\ \text{s.t.} & 0x_1 + 1x_2 \leq 4 \\ & 1x_1 - 1x_2 \leq 2 \\ & 1x_1 + 0x_2 \leq 3 \\ & -2x_1 + 1x_2 \leq 0 \\ & x_1, x_2 \geq 0 \end{array}$$

```
In [6]: lp = ex.DEGENERATE_FIN_2D_LP # get LP example
lp_visual(lp).show() # visualize it
```

Geometric Interpretation of LPs



Q4: Use the objective slider to solve the `DEGENERATE_FIN_2D_LP` LP graph optimal solution and objective value. (Hint: The objective slider shows the isoprofit line for some objective value.)

A: Our objective value is 11 and the optimal solution is 3 for x_1 and 4 for x_2 .

You should now be comfortable solving linear programs with two decision variables. In this case, each constraint is a line representing an inequality. These inequalities define a region in the coordinate plane which is our feasible region. Lastly, to find an optimal solution, we just increase the objective value while the corresponding isoprofit line still intersects the 2D feasible region.

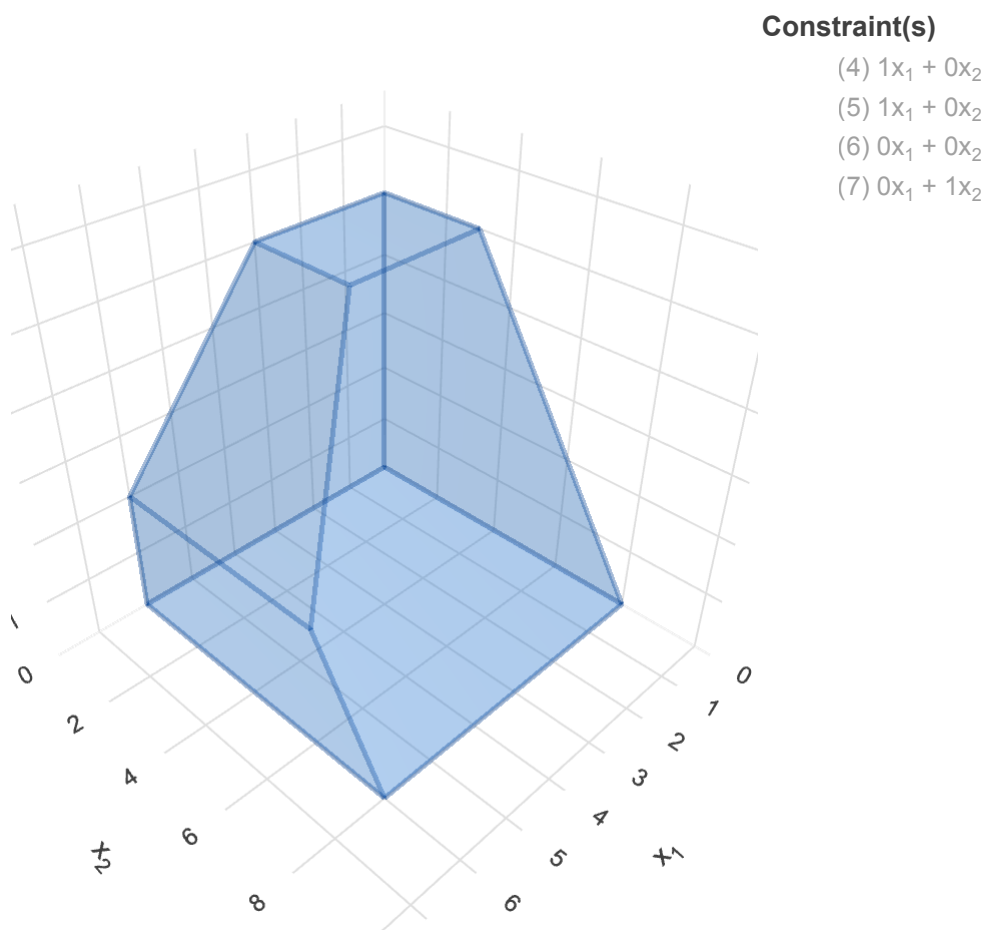
Now, we will try to wrap our head around an LP with three decision variables! We can plot solutions to a 3D LP on a plot with 3 axes. Here, the x -axis corresponds to the value of x_1 as before, and the y -axis corresponds to the value of x_2 as before. Furthermore, the z -axis corresponds to the value of x_3 . Now, constraints are *planes* representing an inequality. These planes define a 3D shaded region which is our feasible region. The isoprofit planes are isoprofit planes. To find an optimal solution, we just increase the objective value while the isoprofit plane still intersects the 3D feasible region. Let us look at an example

This LP is called ALL_INTEGER_3D_LP :

$$\begin{aligned}
 \max \quad & 1x_1 + 2x_2 + 4x_3 \\
 \text{s.t.} \quad & 1x_1 + 0x_2 + 0x_3 \leq 6 \\
 & 1x_1 + 0x_2 + 1x_3 \leq 8 \\
 & 0x_1 + 0x_2 + 1x_3 \leq 5 \\
 & 0x_1 + 1x_2 + 1x_3 \leq 8 \\
 & x_1, x_2 \geq 0
 \end{aligned}$$

```
In [7]: lp = ex.ALL_INTEGER_3D_LP # get LP example
lp_visual(lp).show() # visualize it
```

Geometric Interpretation of LPs



The 3D feasible region is shown on the left. Hold and drag the mouse to examine angles. Next, click on a constraint to un-mute it. Each constraint is a gray plane. Mute the constraints one by one to see how they define the 3D feasible region. Use the objective slider to see the isoprofit planes. The isoprofit plane is light gray and the intersection of the isoprofit plane with the feasible region is shown in red. Like the 2D visualization, you can hover over a point to get information about that point.

Q5: Use the objective slider to solve this LP graphically. Give an optimal solution value. (Hint: The objective slider shows the isoprofit plane for some objective value. The intersection of the isoprofit plane with the feasible region is shown in red.)

A: Our objective value is 29 and our optimal solution is $x_1 = 5$ and $x_2 = 6$.

When it comes to LPs with 4 or more decision variables, our graphical approach find a different way to solve linear programs of this size.

Part II: The Simplex Algorithm for Solving

Dictionary Form LP

First, let's answer some guiding questions that will help to motivate the simplex

Q6: Does there exist a unique way to write any given inequality constraint? If so, the constraint can only be written one way. Otherwise, give 2 ways of writing the same constraint.

A: Yes, there is a unique way to write any given inequality constraint. We can multiply by the same number or divide them.

Q7: Consider the following two constraints: $2x_1 + 1x_2 \leq 20$ and $2x_1 + 1x_2 \leq 20$. x_1 and x_2 are nonnegative. Are these the same constraint? Why? (This question is tricky)

A: Yes, they are the same constraint. When we subtract x_3 on both sides, $20 - x_3$

Q8: Based on your answers to **Q6** and **Q7**, do you think there exists a unique way to write a given LP?

A: While there are unique ways to write the constraint, there aren't any unique way to write an LP.

You should have found that there are many ways to write some LP. This begs the question: are some ways of writing an LP harder or easier to solve than others? Consider the following LP:

$$\begin{aligned} \max \quad & 56 - 2x_3 - 1x_4 \\ \text{s.t.} \quad & x_1 = 4 - 1x_3 + 1x_4 \\ & x_2 = 12 + 1x_3 - 2x_4 \\ & x_5 = 3 + 1x_3 - 1x_4 \\ & x_1, x_2, x_3, x_4, x_5 \geq 0 \end{aligned}$$

Q9: Just by looking at this LP, can you give an optimal solution and its objective value? What property of the LP allows you to do this. (Hint: Look at the objective function)

A: The objective value is 56 and the optimal solution is (4,12,0,0,3). And the property that allows you to do this would be having non-negative coefficients.

The LP above is the same as `ALL_INTEGER_2D_LP` just rewritten in a different form.

form (which we found is easier to solve) was found using the simplex algorithm. The simplex algorithm strategically rewrites an LP until it is in a form that is "easy"

The simplex algorithm relies on an LP being in **dictionary form**. Recall the form of an LP in dictionary form:

- All constraints are equality constraints
- All variables are constrained to be nonnegative
- Each variable only appears on the left-hand side (LHS) or the right-hand side of constraints (not both)
- Each constraint has a unique variable on the LHS
- The objective function is in terms of the variables that appear on the RHS only.
- All constants on the RHS of the constraints are nonnegative

Q10: Rewrite the example LP `ALL_INTEGER_2D_LP` in dictionary form. Show your work.

$$\begin{aligned} \max \quad & 5x_1 + 3x_2 \\ \text{s.t.} \quad & 2x_1 + 1x_2 \leq 20 \\ & 1x_1 + 1x_2 \leq 16 \\ & 1x_1 + 0x_2 \leq 7 \\ & x_1, x_2 \geq 0 \end{aligned}$$

$$\mathbf{A:} \quad x_3 = 20 - 2x_1 - 1x_2 \quad x_4 = 16 - 1x_1 - 1x_2 \quad x_5 = 7 - 1x_1 - 0x_2$$

$$x_1, x_2, x_3, x_4, x_5 \geq 0$$

Most Limiting Constraint

Once our LP is in dictionary form, we can run the simplex algorithm! In every iteration of the simplex algorithm, we will take an LP in dictionary form and strategically rewrite it to be in dictionary form. Note: it is important to realize that rewriting the LP **does not** change the feasible region. Let us examine an iteration of simplex on a new LP.

$$\begin{aligned} \max \quad & 5x_1 + 3x_2 \\ \text{s.t.} \quad & 1x_1 + 0x_2 \leq 4 \\ & 0x_1 + 1x_2 \leq 6 \\ & 2x_1 + 1x_2 \leq 9 \\ & 3x_1 + 2x_2 \leq 15 \\ & x_1, x_2 \geq 0 \end{aligned}$$

Q11: Is this LP in dictionary form? If not, rewrite this LP in dictionary form.

A: This is not in dictionary form because we say an LP is in dictionary form if all constraints are equality constraints, and all variables are constrained to be nonnegative.

$$\max z = 5x_1 + 3x_2$$

$$x_3 = 4 - 1x_1 - 0x_2 \quad x_4 = 6 - 0x_1 - 1x_2 \quad x_5 = 9 - 2x_1 - 1x_2 \quad x_6 = 15 - 3x_1 - 2x_2$$

$$x_1, x_2, x_3, x_4, x_5, x_6 \geq 0$$

Q12: Recall from **Q9** how you found a feasible solution (which we argued to be looking at the LP. Using this same strategy, look at the LP above and give a feasible objective value for this LP. Describe how you found this feasible solution. Is it optimal?

A: (0, 0, 4, 6, 9, 15). This is not an optimal solution because x_3 through x_6 is not zero. The objective value will be 0.

From **Q12** we see that every dictionary form LP has a corresponding feasible solution if there are positive coefficients in the objective function. Hence, we can increase the objective value by increasing the corresponding variable. In our example, both x_1 and x_2 have positive coefficients in the objective function. Let us choose to increase x_1 .

Q13: What do we have to be careful about when increasing x_1 ?

A: We have to make sure that x_1 follows all of the constraints in the dictionary form LP.

Q14: After choosing a variable to increase, we must determine the most limiting constraint. Look at the first constraint $x_3 = 4 - 1x_1 - 0x_2$. How much can x_1 increase? (What do the dictionary form LP require about the constant on the RHS of constraints?)

A: We can increase x_1 by 4.

Q15: Like in **Q14**, determine how much each constraint limits the increase in x_1 . What is the most limiting constraint?

A:

$x_3 =$ by 4, $x_4 =$ no limit, $x_5 =$ by 4.5, $x_6 =$ by 5,

The most limiting constraint would be the first constraint.

If we increase x_1 to 4, note that x_3 will become zero. Earlier, we identified that (0, 0, 4, 6, 9, 15) has a corresponding feasible solution achieved by setting variables on the RHS of the objective function to zero. Hence, since x_3 will become zero, we want to rewrite the constraint so that x_3 appears on the RHS. Furthermore, since x_1 is no longer zero, it should now appear on the LHS.

Q16: Rewrite the most limiting constraint $x_3 = 4 - 1x_1 - 0x_2$ such that x_1 and x_2 appear on the left and x_3 appears on the right.

A: $x_1 = 4 - x_3$

Q17: Using substitution, rewrite the LP such that x_3 appears on the RHS and x_1 appears on the LHS. (Hint: Don't forget the rule about which variables can appear in the objective function.)

A:

$$\max z = 20 - 5x_3 + 3x_2$$

$$x_1 = 4 - 1x_3 \quad x_4 = 6 - 1x_2 \quad x_5 = 1 + 2x_3 - 1x_2 \quad x_6 = 3 + 3x_3 - 2x_2$$

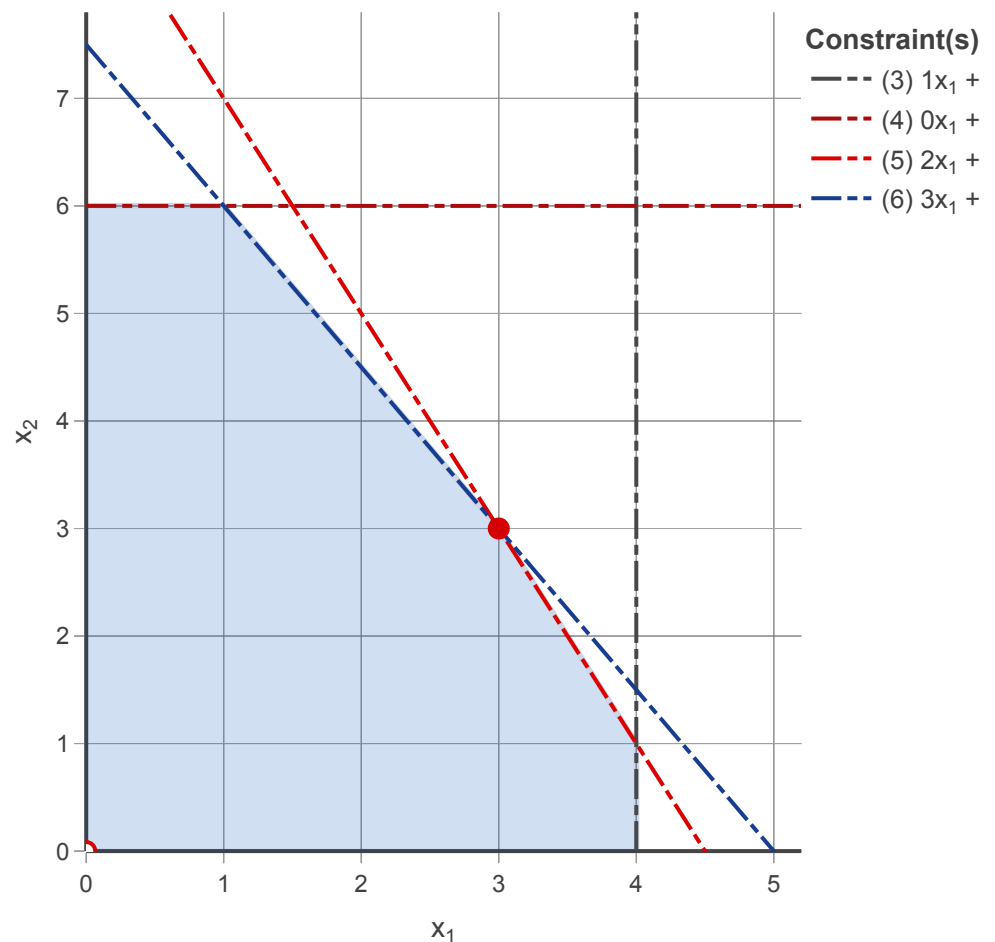
Q18: We have now completed an iteration of simplex! What is the corresponding of the new LP?

A: (4, 0, 0, 6, 1, 3) objective function = 20

Now that we have seen an iteration of simplex algebraically, let's use GILP to . example we have been using is called `LIMITING_CONSTRAINT_2D_LP` . To must import a function called `simplex_visual()` .

```
In [8]: from gilp.visualize import simplex_visual # import the fun
import numpy as np
lp = ex.LIMITING_CONSTRAINT_2D_LP # get the LP example
simplex_visual(lp, initial_solution=np.array([[0],[0]])).s
```

Geometric Interpretation of LPs



This visualization is much the same as the previous one but we now have an allows you to toggle through iterations of simplex. Furthermore, the correspond every iteration of simplex is shown in the top right. If you toggle between two i see the dictionary form for both the previous and next LP at the same time.

Q19: Starting from point (0,0), by how much can you increase x_1 before the problem becomes infeasible? Which constraint do you *hit* first? Does this match what you found algebraically?

A: We can increase x_1 by 4, and we hit constraint (3) first. And yes this matches algebraically.

Q20: Which variable will be the next increasing variable and why? (Hint: Look at the dictionary form LP at iteration 1)

A: We have to increase x_2 because in our graph that is the only remaining variable that can increase. And also looking back at our calculations, x_2 has a positive coefficient.

Q21: Visually, which constraint do you think is the most limiting constraint? How much can you increase? Give the corresponding feasible solution and its objective value of the dictionary form LP. (Hint: hover over the feasible points to see information about them.)

A: We can increase x_2 by 1. Corresponding feasible solution = (4, 1, 0, 5, 0, 1). Objective value = 1.

Q22: Move the slider to see the next iteration of simplex. Was your guess from Q21 correct? Describe how your guess was wrong.

A: Our guess was correct.

Q23: Look at the dictionary form LP after the second iteration of simplex. Which variable is the most limiting constraint? Identify the most limiting constraint graphically and algebraically. Show the next feasible solution and its objective value. Verify they are the same constraint. In addition, give the next feasible solution value.

A: We are trying to maximize x_3 because it has a positive coefficient. The most limiting constraint is the last one. $3x_1 + 2x_2 \leq 15$, $x_6 = 15 - 3x_1 - 2x_2$. We are going to substitute x_6 for the original input (with x_1 and x_2). The next feasible solution is (3, 3, 1, 3, 0, 0). The objective value is 3.

x_6 is the most limiting constraint. $x_6 = 1 - x_3 + 2x_5$ (iteration 2)

substitute values for x_3 and x_5 .

Q24: Is the new feasible solution you found in Q23 optimal? (Hint: Look at the dictionary form LP)

A: The solution is optimal because the coefficients in the objective function are all non-positive.

Q25: In Q21 and Q23, how did you determine the most limiting constraint graphically?

A: We travel along the constraints and along the boundaries of the constraint region.

(BONUS): In 2D, we can increase a variable until we hit a 2D line representing a constraint. What would be the analogous situation in 3D?

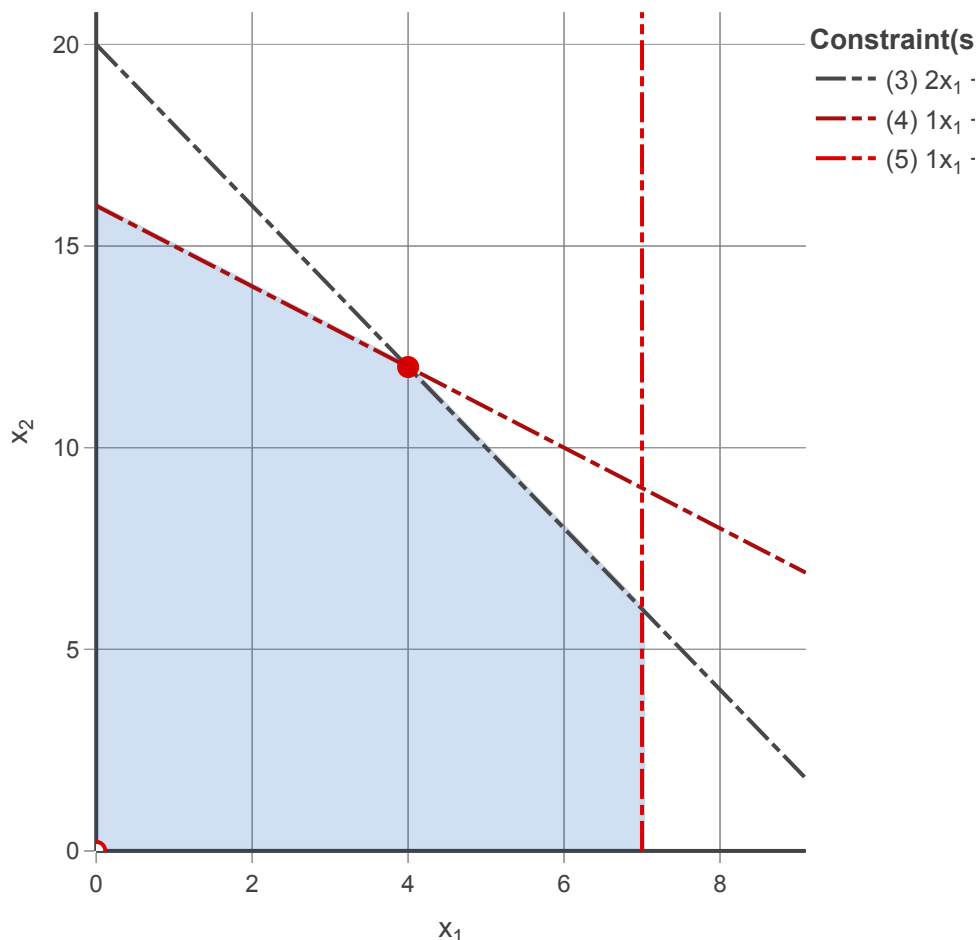
A:

Part III: Geometrical Interpretation of the Dictionary

We have seen how the simplex algorithm transforms an LP from one dictionary to another. Each dictionary form has a corresponding dictionary defined by the variables and constraints. Furthermore, each dictionary form has a corresponding feasible region. In this section, we will explore the geometric interpretation of a dictionary.

```
In [9]: lp = ex.ALL_INTEGER_2D_LP # get LP example
simplex_visual(lp, initial_solution=np.array([[0],[0]])).s
```

Geometric Interpretation of LPs



Recall, we can hover over the corner points of the feasible region. **BFS** indicates the basic feasible solution corresponding to that point. For example, (7,0,6,9,0) means $x_1 = 7$, $x_2 = 0$, $x_3 = 6$, $x_4 = 9$, and $x_5 = 0$. **B** gives the indices of the variables in the dictionary. For example, (1,3,4) means that x_1 , x_3 , and x_4 are in the dictionary. Lastly, the objective function value at that point is given.

Q26: Hover over the point (7,6) where $x_1 = 7$ and $x_2 = 6$. What is the feasible point?

A: The feasible solution at this point would be (7,6,0,3,0).

We have a notion of *slack* for an inequality constraint. Consider the constraint solution where $x_1 = 7$ has a slack of 7 in this constraint. Consider the constraint The feasible solution with $x_1 = 7$ and $x_2 = 6$ has a slack of 0 in this constraint.

Q27: What is the slack in constraint $1x_1 + 1x_2 \leq 16$ when $x_1 = 7$ and $x_2 =$

A: The slack is 3 for this constraint.

Q28: Look at the constraint $2x_1 + 1x_2 \leq 20$. After rewriting in dictionary form $x_3 = 20 - 2x_1 - 1x_2$. What does x_3 represent?

A: x_3 is the slack of the inequality constraint.

Q29: What do you notice about the feasible solution at point (7,6) and the slack

A: The slack in each constraint is the solution for each of the x variables in the

It turns out that each decision variable is really a measure of slack in some constraint!

Q30: If the slack between a constraint and a feasible solution is 0, what does it relationship between the feasible solution and constraint geometrically?

A: It has reached the maximum capacity of the constraint.

Q31: For (7,6), which variables are **not** in the dictionary? For which constraints the slack? (Hint: The **B** in the hover box gives the indices of the variables in the

A: x_3 and x_5 are not in the dictionary. The slack is equal to 0.

Q32: For (7,6), what are the values of the non-dictionary variables? Using what **Q30**, what does their value tell you about the feasible solution at (7,6)?

A: 0. The fact that the values of the non-dictionary variables are 0 tell us that c

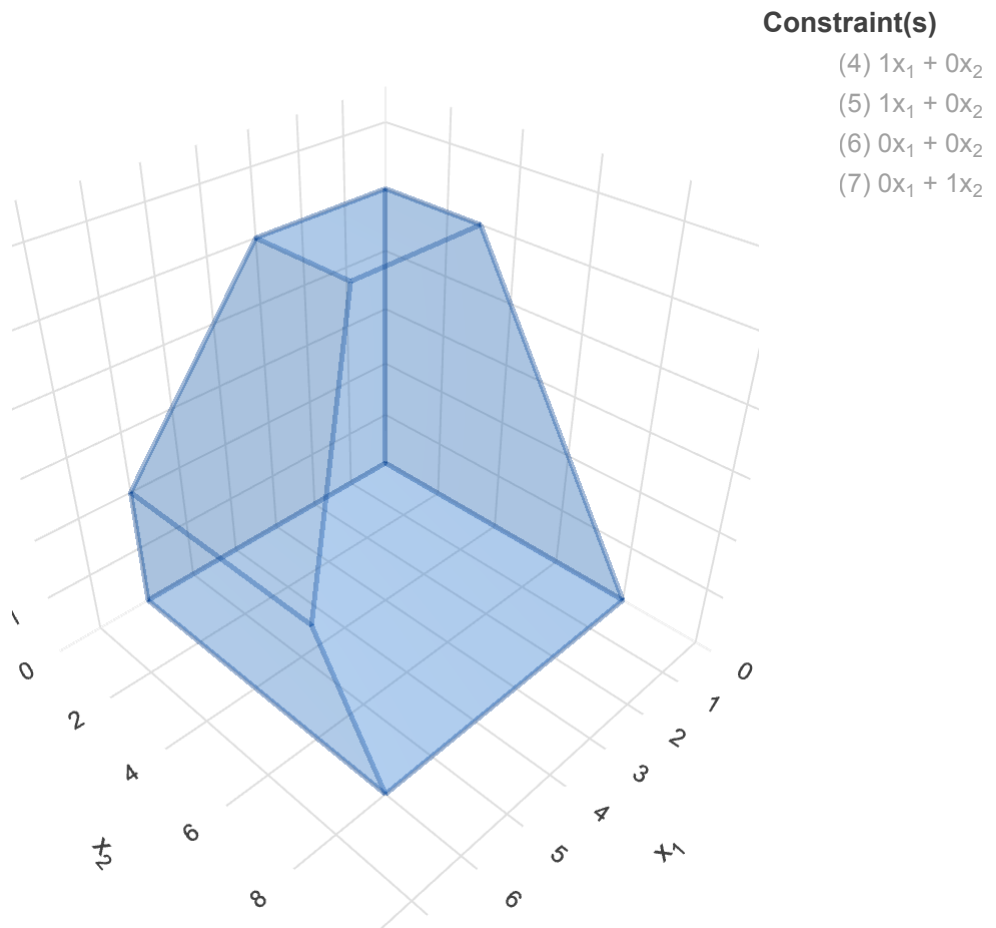
Q33: Look at some other corner points with this in mind. What do you find?

A: I find that there are more feasible solutions but the one the top right has the value, leading us to make the conclusion that that is our optimal solution.

Now, let's look at a 3 dimensional LP!

```
In [10]: lp = ex.ALL_INTEGER_3D_LP # get LP example
lp_visual(lp).show() # visualize it
```

Geometric Interpretation of LPs



Q34: Hover over the point (6,6,2) where $x_1 = 6$, $x_2 = 6$, and $x_3 = 2$. Note what is in the dictionary. Toggle the corresponding constraints on. What do you notice?

A: The variables x_4 , x_5 , and x_7 are not in the dictionary. We can see that this point is on the borders of the feasible region. The constraints have been optimized.

Q35: Look at some other corner points and do as you did in Q34. Do you see a pattern? Combining what you learned in Q33, what can you say about the relationship between a corner point not in the dictionary at some corner point, and the corresponding constraints?

A: We can say that the variables not in the dictionary put constraints for the vertices of the feasible region so as to optimize the constraint (intersection between the planes).

Q36: What geometric feature do feasible solutions for a dictionary correspond to?

A: The point of intersection between the planes that the constraints create.

Part IV: Pivot Rules

The first step in an iteration of simplex is to choose an increasing variable. So multiple options since multiple variables have a positive coefficient in the objective function. We will explore what this decision translates to geometrically.

In this section, we will use a special LP commonly referred to as the Klee-Mint

Furthermore, we will use an optional parameter called `rule` for the `simplex` function. This rule tells simplex which variable to choose as an increasing variable among multiple options.

```
In [ ]: simplex_visual(ex.KLEE_MINTY_3D_LP, rule='dantzig', initial=0)
```

```
In [ ]:
```

Q37: Use the iteration slider to examine the path of simplex on this LP. What does it look like?

A: We notice that the path starts increases in the order of x_1 , x_2 , x_4 , x_3 , x_5 , x_4 .

Above, we used a pivot rule proposed by Dantzig. In this rule, the variable with the largest coefficient in the objective function enters the dictionary. Go through the iterations and see how this rule works.

Let us consider another pivot rule proposed by Bland, a professor here at Cornell. In this rule, among variables with positive coefficients in the objective function, the one with the smallest index enters the dictionary. Let us examine the path of simplex using this pivot rule! Again, look at the dictionary and see how it changes every iteration.

```
In [ ]: simplex_visual(ex.KLEE_MINTY_3D_LP, rule='manual_select', initial=0)
```

Q38: What is the difference between the path of simplex using Dantzig's rule and Bland's rule?

A: Bland's rule goes from x_1 , x_2 , x_3 , x_5 , x_4 . Less iterations.

Can you do any better? By setting `rule='manual_select'`, you can choose the entering variable explicitly at each simplex iteration.

Q39: Can you do better than 5 iterations? How many paths can you find? (By changing the initial value.)

A: Yes, we can do better than 5 iterations. We can straight up maximize x_3 and x_5 in 1 iteration.

```
In [ ]: simplex_visual(ex.KLEE_MINTY_3D_LP, rule='manual_select', initial=0)
```

Q40: What does the choice of increasing variable correspond to geometrically?

A: It means that we are moving onto the next constraint's plane from the previous one.

Q41: Are there any paths you could visualize taking to the optimal solution that are not shown?

rule='manual_select' prevented you from taking? If yes, give an example that is not a valid path for simplex to take. (Hint: Look at the objective value after each iteration.)

▲ The path 2 → 1 → 3 → 5 → 4 would not work because it would unoptimize the constraints.

Part V: Creating LPs in GLP (Optional)

We can also create our own LPs! First, we must import the `LP` class.

```
In [ ]: from gilp.simplex import LP
```

Let us create the following LP.

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

We will create this LP by specifying 3 arrays of coefficients. We define the `A`, `b`, and `c` and then pass them to the `LP` class to create the LP.

```
In [ ]: A = np.array([[2,1], # LHS constraint coefficients
                     [0,1]])
        b = np.array([6,2]) # RHS constraint coefficients
        c = np.array([3,2]) # objective function coefficients
        lp = LP(A,b,c)
```

Let's visualize it!

```
In [ ]: lp_visual(lp).show()
```

... and solve it!

```
In [ ]: simplex_visual(lp, initial_solution=np.array([[0],[0]])).s
```

```
In [ ]:
```

```
In [ ]:
```

```
In [ ]:
```