

Mathematical Programming for All

Pano Santos, PhD



The World's Fastest Solver

Dedication

These video classes are dedicated to the memory of Saul I. Gass (1926-2013), a mentor and friend.



Goals

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- These video classes are designed for an audience with limited or no background in mathematical programming, and includes: Data Scientists, Computer Scientists, Systems/IT Engineers, and Business Analysts.
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 - **Data Scientists,**
 - **Computer Scientists,**
 - **Systems/IT Engineers,**
 - **Business Analysts.**

Goals

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- The students taking this class will learn the foundations of Linear Programming (LP) and Mixed Integer Linear Programming (MIP).
 - **The students taking this class will learn the foundations of:**
 - **Linear Programming (LP)**
 - **Mixed Integer Linear Programming (MIP).**

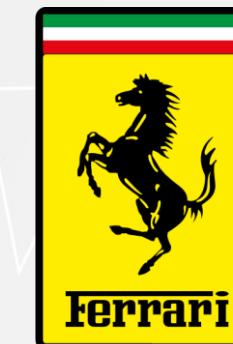
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- The students taking this class will learn the foundations of Linear Programming (LP) and Mixed Integer Linear Programming (MIP).
- You will learn how to formulate practical problems as Mixed Integer Linear Problems for: industrial, government, and military applications.
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Over 2,100 companies from approx. 50 industries use Gurobi for their mathematical programming applications
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Bank of America



Microsoft

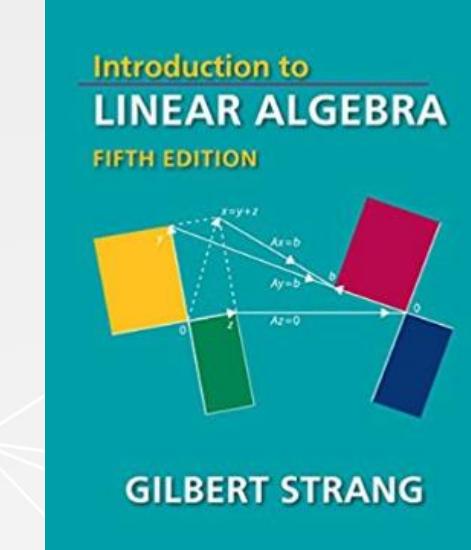
Walmart
Save money. Live better.



Prerequisites

Prerequisites

- Linear algebra and calculus
- Both at the college level
- Familiarity with mathematical notation.
 $e = mc^2$
- Basic knowledge of Python



Remarks



These mathematical optimization models shall capture the key features of an optimization problem (**effective**), and they should be solvable in a reasonable amount of time (**efficient**).

- In spite of the pragmatic nature of these videos, it is important to cover theoretical aspects of Linear Programming and Integer Programming problems in order to build and tune up efficient mathematical optimization models.

- These series of introduction to mathematical programming videos will have three main chapters.
 - Linear programming overview.
 - Mixed integer linear programming overview.
 - Mathematical programming model building overview.



- The duration of each video will be in the range of 10 min to 15 min.

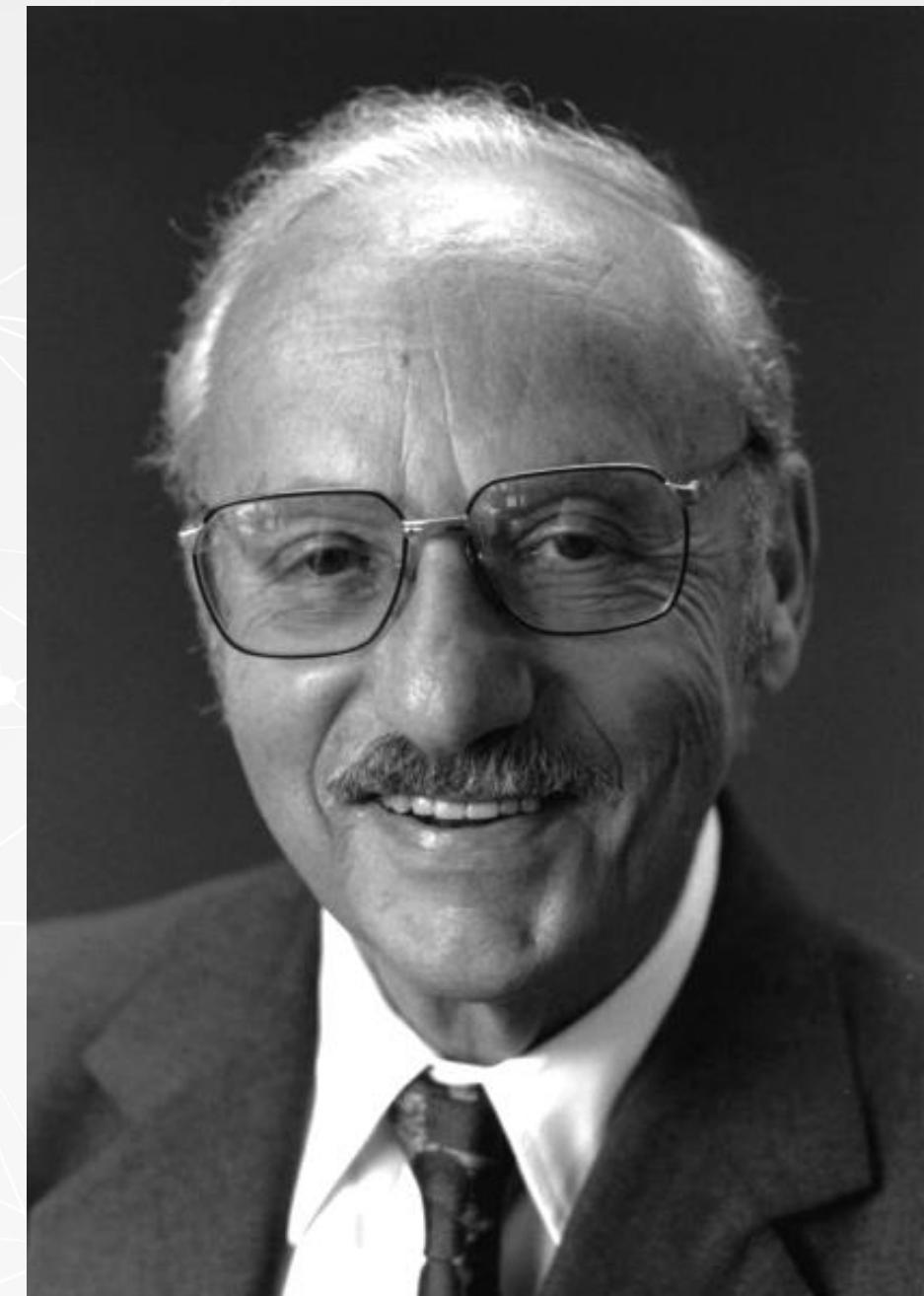
Mathematical Programming

Background and relevance

Origin of Mathematical Programming

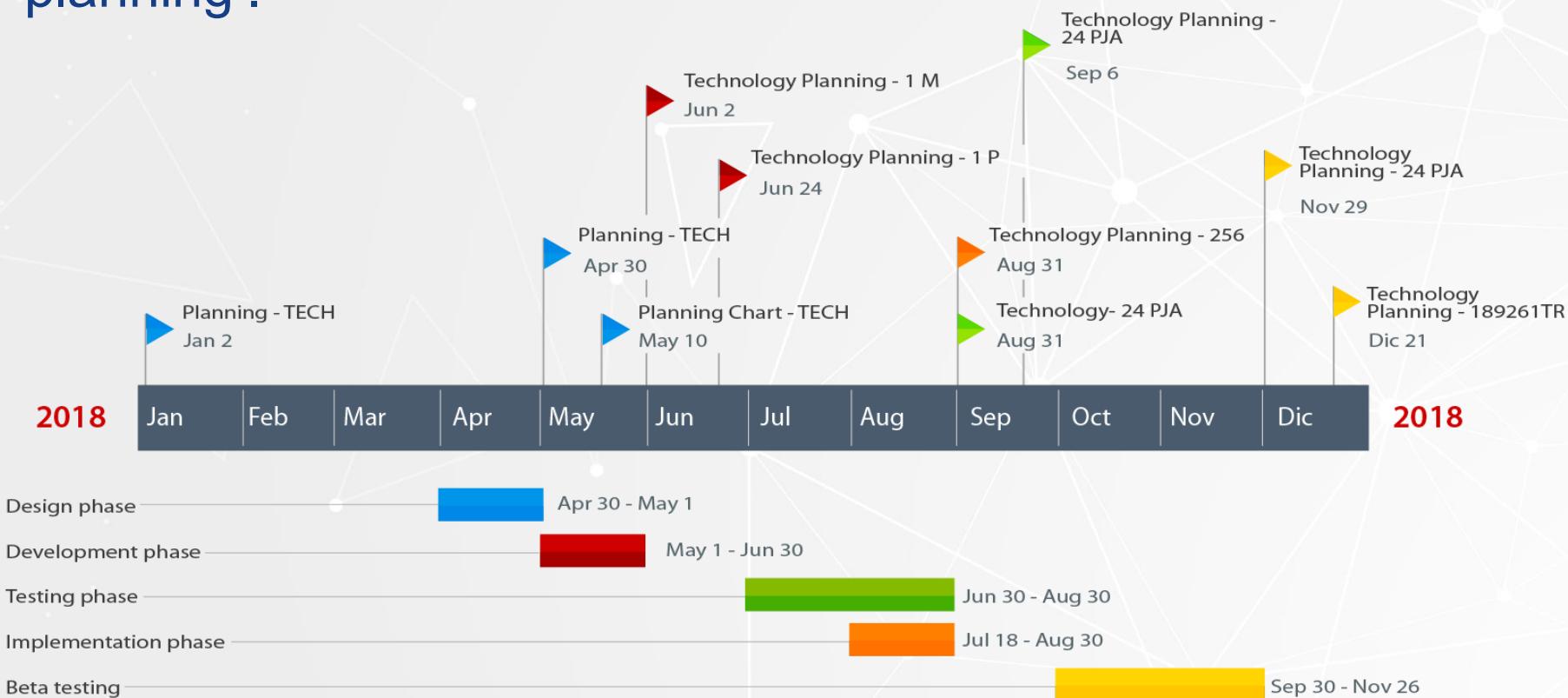
Origin of Mathematical Programming

- The origin of mathematical programming is the invention of linear programming in 1947, shortly after World War II.
- “Mathematical programming enables stating general goals and to lay out a path of detailed decisions to make in order to “best” achieve these goals when faced with a practical situation of great complexity”. –George Dantzig
- Mathematical programming entails
 - the formulation of real-world problems in detailed mathematical terms (models).
 - the development of techniques for solving those models (algorithms).
 - and the use of SW and HW to develop applications.



Mathematical Programming Remarks

- It should be pointed out that mathematical programming is different from computer programming.
 - Mathematical programming is ‘programming’ in the sense of ‘planning’.



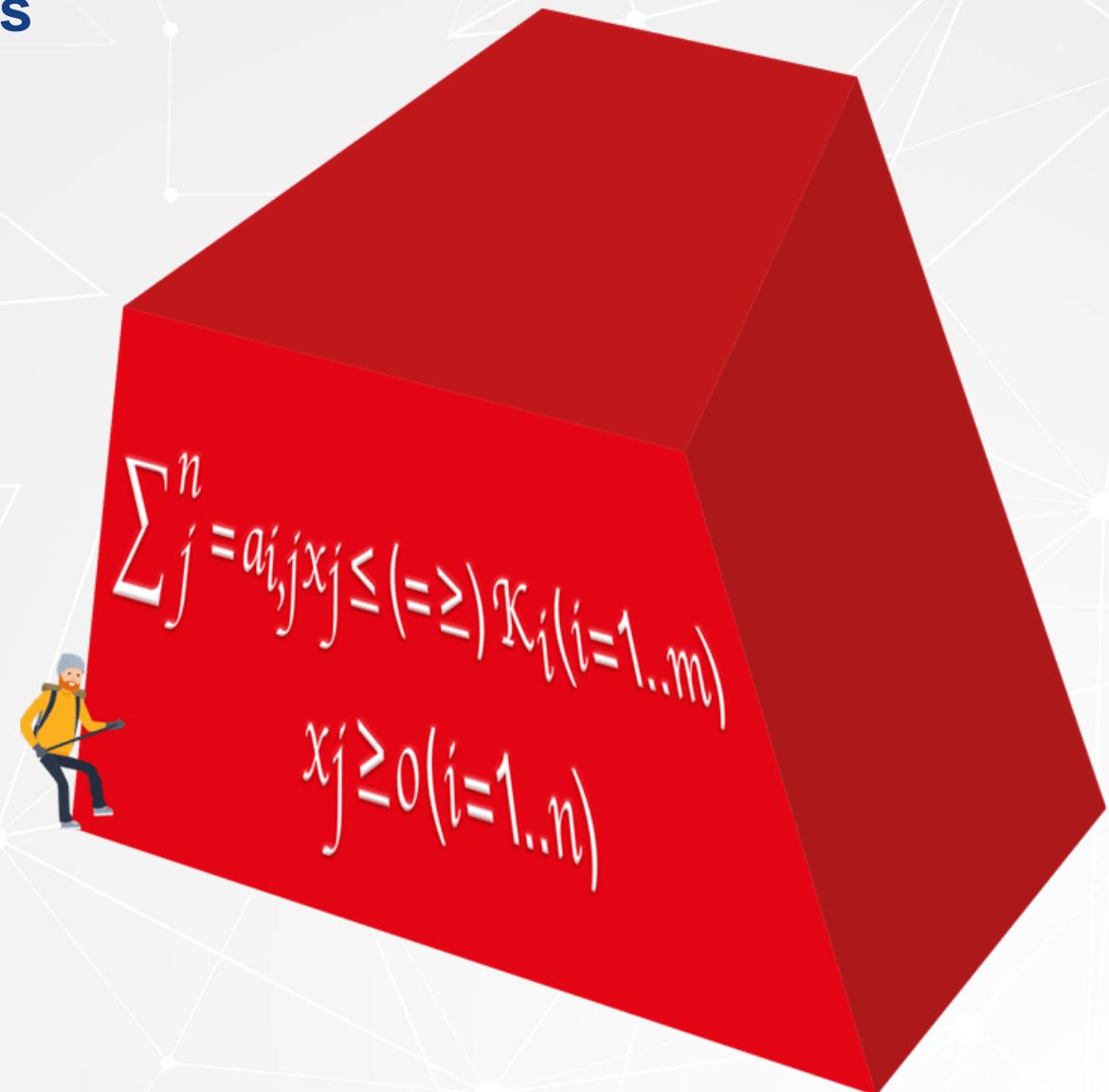
Mathematical Programming Remarks

- **The common feature that mathematical programming models have is that they all involve optimization.**
 - This is why mathematical programming is often called mathematical optimization.



Mathematical Programming Remarks

- In these video classes, we focus on two special types of mathematical programming models.
 - Linear Programming (LP) models.
 - Mixed Integer linear Programming (MIP) models.



Mathematical Programming Remarks

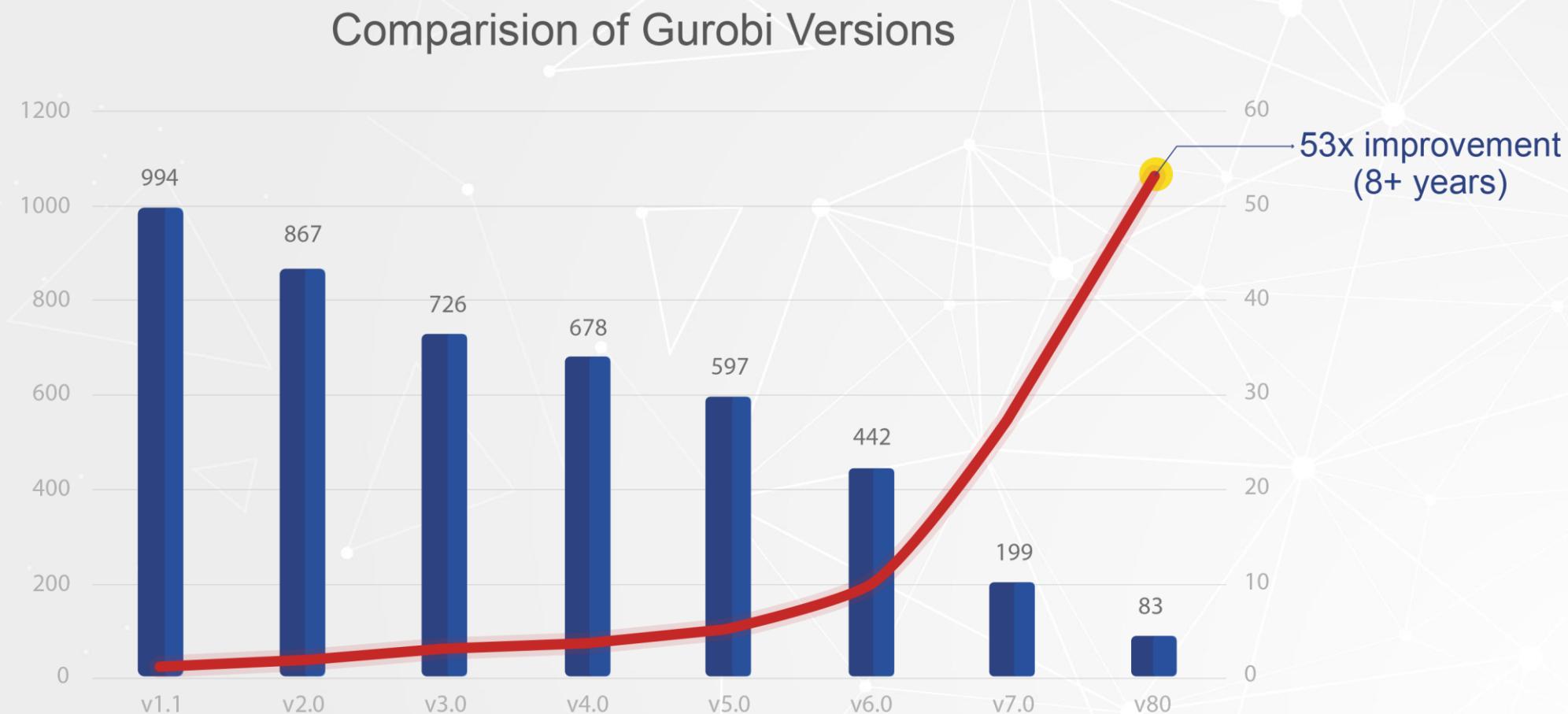
- Mathematical programming is a declarative approach where the modeler formulates a mathematical optimization problem that captures the key features of a complex decision problem.
- Mathematical optimization formulations can then be solved by standard LP algorithms and MIP algorithms.

Mathematical Programming Remarks

- Gurobi users formulate mathematical optimization problems that are solved by the Gurobi callable library.
- The mathematics and computer science behind Gurobi technology are leading edge.
- Gurobi has the best performance in the market.

Mathematical Programming Remarks

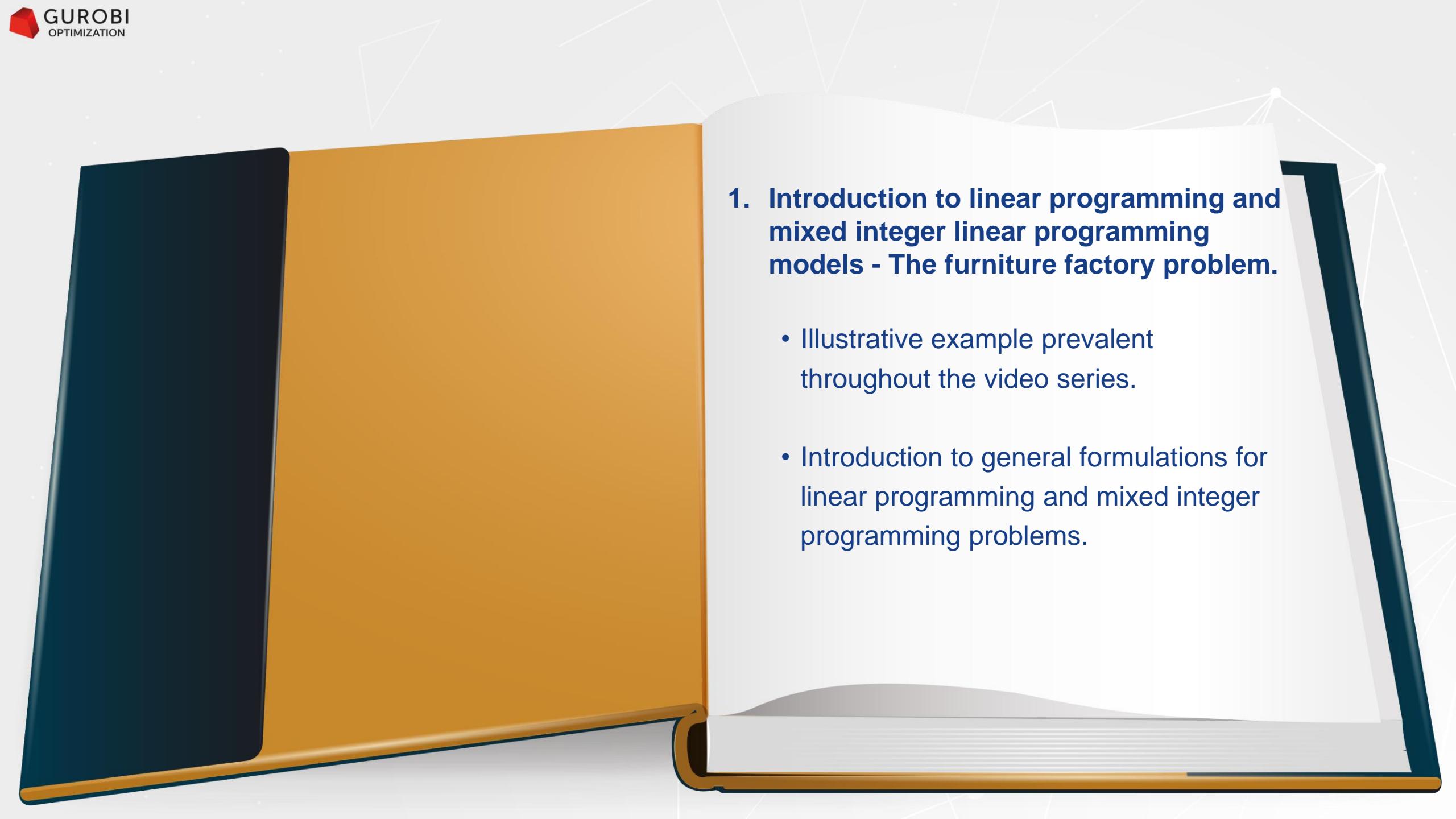
- Gurobi users formulate mathematical optimization problems that are solved by the Gurobi callable library.
- The mathematics and computer science behind Gurobi technology are leading edge, that is why Gurobi solver has the best performance in the market.



Mathematical Programming Remarks

- The particular implementation of the mathematics and computer science in the Gurobi Optimizer is quite complex.
- The user does not need to worry about how to solve the optimization problem at hand, this is done automatically by Gurobi behind the scenes.
- The user only needs to have an efficient LP or MIP model that captures the main characteristics of the optimization problem and the required data for the model.





1. Introduction to linear programming and mixed integer linear programming models - The furniture factory problem.

- Illustrative example prevalent throughout the video series.
- Introduction to general formulations for linear programming and mixed integer programming problems.

2. Furniture factory problem - Graphical Solution

- How to graphically solve the furniture problem when formulated as a linear programming model.
- Introduction to important concepts related to the theory of linear programming.

3. Overview - Simplex method to solve linear programming problems.

- How the simplex method works.
- Key concepts of the theory of linear programming.

4. Modeling and solving the furniture factory problem with the Gurobi python API.

- How to use the Gurobi Python API to formulate the furniture problem as a linear programming problem and solve it using the Gurobi callable library

5. Sensitivity analysis of LP problems with the Gurobi python API.

- How linear programming models have an economic interpretation and the impact on the objective function value derived from marginal changes on a resource capacity value.

6. Multiple optimal solutions, modeling opportunity with the Gurobi python API.

- How a linear programming problem can have multiple solutions.
- How having multiple solutions presents an opportunity to improve the linear programming problem formulation.

7. Unbounded solutions, modeling opportunity with the Gurobi python API.

- How a linear programming problem can be unbounded which means that the objective function value can be arbitrarily large.
- How an unbounded linear programming problem presents an opportunity to improve the linear programming problem formulation.

8. Infeasible solutions, modeling opportunity with the Gurobi python API.

- How a linear programming problem can be infeasible, lacking a solution that can satisfy all the constraints of the problem.
- How an infeasible linear programming problem presents an opportunity to improve the linear programming problem formulation.

9. Maximize or minimize objective function.

- How to tackle maximization and minimization linear programming problems.

10. Unconstrained decision variables.

- How Gurobi automatically handles unconstrained decision variables.

11. Initial basic solution.

- How to determine an initial solution of a linear programming problem in order to start the simplex method. This is done automatically by Gurobi.

12. Presolve.

- An example of how Presolve reduces the size of a linear programming problem. Gurobi by default calls Presolve to significantly reduce the size of an LP problem.

13. Matrix sparsity.

- An important characteristic of linear programming problems that is related to the number of non-zero coefficients associated with the variables in the problem formulation.

14. Duality in linear programming.

- One of the most important concepts in linear programming that allows the efficient characterization of optimal solutions of a linear programming problem.

15. Optimality conditions in linear programming.

- Discussion of duality and establish sufficient and necessary conditions of optimal solutions of a linear programming problem.

16. Dual simplex method.

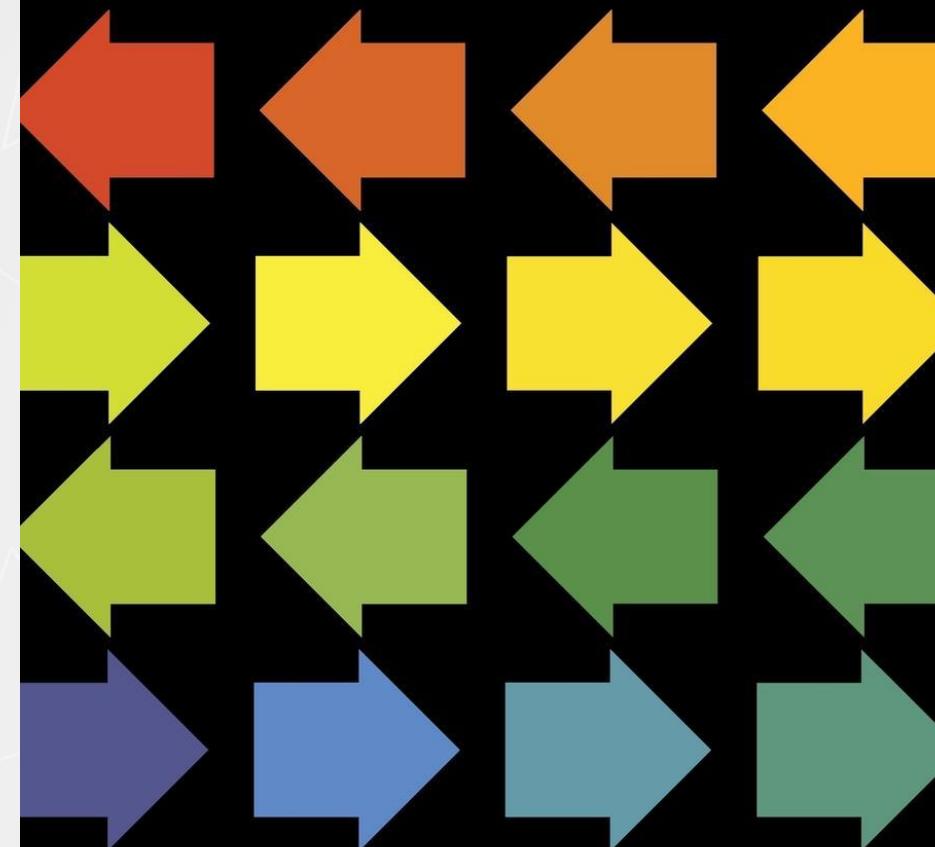
- A variation of the simplex method that is frequently used to solve mixed integer linear programming problems.

$$\begin{aligned}\sum_j^n a_{ij}x_j &\leq (\geq) K_i \quad (i=1..m) \\ x_j &\geq 0 \quad (i=1..n)\end{aligned}$$

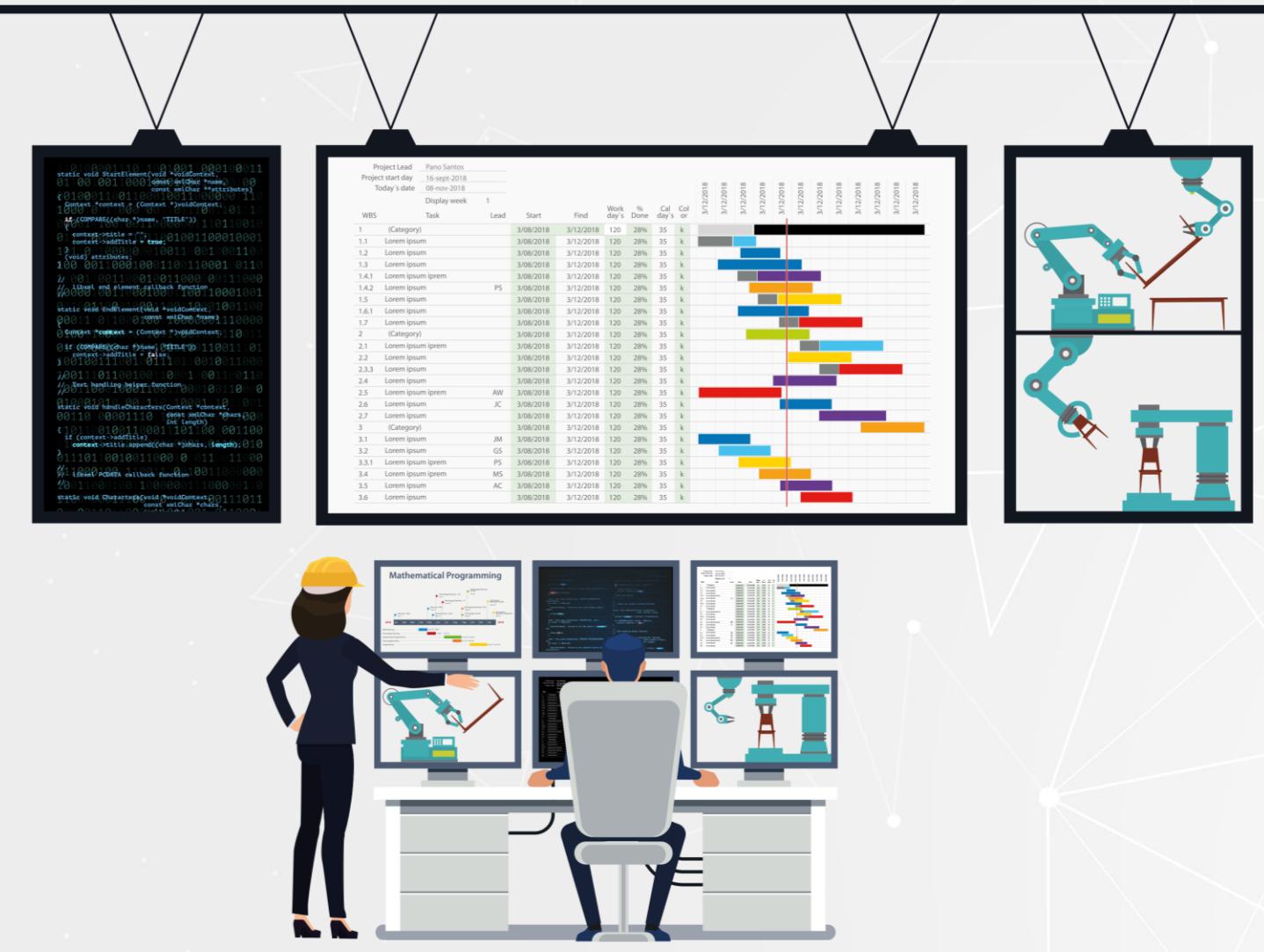
Introduction to linear programming

The Furniture Factory problem

An Illustrated Guide to Linear Programming



Saul I. Gass



The Furniture Factory Problem

A data scientist is in charge of developing the Weekly Production Plan of two key products that the furniture factory makes: chairs and tables.

The data scientist using machine learning techniques predicts that the selling price of a chair is \$45 and the selling price of a table is \$80 dollars.



The Furniture Factory Problem

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The data scientist using machine learning techniques predicts that the selling price of a chair is \$45 and the selling price of a table is \$80 dollars.

- **There are two critical resources in the production of chairs and tables:**
 - Mahogany (measured in board square-feet) and labor (measured in work hours).
 - There are 400 units of mahogany available at the beginning of each week.
 - There are 450 units of labor available during each week.



= 5



= 20



15 hrs.



The Furniture Factory Problem

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 - Mahogany (measured in board square-feet) and labor (measured in work hours).
 - There are 400 units of mahogany available at the beginning of each week.
 - There are 450 units of labor available during each week.
- **The data scientist estimates that**
 - One chair requires 5 units of mahogany and 10 units of labor.
 - One table requires 20 units of mahogany and 15 units of labor.
- **The marketing department has told the data scientist that ALL the production of chairs and tables can be sold.**

Problem statement:

What is the Production Plan that maximizes total revenue?



The Furniture Factory Problem

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The Furniture Factory Problem... 2

DATA	CHAIR	TABLE	CAPACITY
5 units	20 units	400 units	
10 hours	15 hours	450 hours	
	\$45	\$80	

Note: for the moment, we will assume we can produce and sell fractional quantities of a chair or table. In chapter 2 of these videos series we show how to tackle mathematical programming problems where you require that the decision variables must be integer numbers.

The data of the furniture problem can be summarized in the following table:

- To determine a **Production Plan**, we need to decide how many chairs and tables to make in order to maximize total revenue, while satisfying resources constraints.
- This problem has two decision variables:
 - x_1 : number of chairs to produce.
 - x_2 : number of tables to produce.
 - The number of chairs and tables to produce should be a non-negative number. That is, $x_1, x_2 \geq 0$.

- If we would know the value of the amount of chairs to produce (x_1), then since each chair generates \$45, the total revenue generated by the production of chairs can be determined by the term $45x_1$ ($45*x_1$).
- Similarly, the total revenue generated by the production of tables can be determined by the term $80x_2$ ($80*x_2$).
- Consequently, the total revenue generated by the production plan can be determined by the following equation.

$$\bullet \text{Revenue} = 45x_1 + 80x_2$$

The Furniture Factory Problem... 2

The data of the furniture problem can be summarized in the following table:

DATA	CHAIR	TABLE	CAPACITY
	5 units	20 units	400 units
	10 hours	15 hours	450 hours
	\$45	\$80	

- The Production Plan is constrained by the amount of resources available.
- How do we ensure that the production plan does not consume more mahogany than the amount of mahogany available?
- If we decide to produce x_1 number of chairs, then the total amount of mahogany consumed by the production of chairs is $5x_1$ ($5 \times x_1$).
- Similarly, if we decide to produce x_2 number of tables, then the total amount of mahogany consumed by the production of tables is $20x_2$ ($20 \times x_2$).
- Hence, the total consumption of mahogany by the production plan determined by the values of x_1 and x_2 is $(5x_1 + 20x_2)$. However, the consumption of mahogany by the production plan cannot exceed the amount of mahogany available. We can express these ideas in the following constraint:

$$5x_1 + 20x_2 \leq 400$$

The Furniture Factory Problem... 2

The data of the furniture problem can be summarized in the following table:

DATA	CHAIR	TABLE	CAPACITY
	5 units	20 units	400 units
	10 hours	15 hours	450 hours
	\$45	\$80	

- The production plan is constrained by the amount of resources available.
- In similar fashion, we can formulate the constraint for labor resources.
- The total amount of labor resources consumed by the production of chairs is 10 labor units multiplied by the number of chairs produced, that is $10x_1$ ($10*x_1$).
- The total amount of labor resources consumed by the production of tables is 15 labor units multiplied by the number of tables produced, that is $15x_2$ ($15*x_2$).
- Therefore, the total consumption of labor resources by the production plan determined by the values of x_1 and x_2 is $(10x_1 + 15x_2)$. This labor consumption cannot exceed the labor capacity available. Hence, this constraint can be expressed as follows:

$$10x_1 + 15x_2 \leq 450.$$

The Furniture Factory Problem... 2

The data of the furniture problem can be summarized in the following table:

DATA	CHAIR	TABLE	CAPACITY
	5 units	20 units	400 units
	10 hours	15 hours	450 hours
	\$45	\$80	

- The furniture problem formulation as a linear programming (LP) problem is

$$(1.0). \text{ Max revenue} = 45x_1 + 80x_2$$

$$(2.0) \quad 5x_1 + 20x_2 \leq 400 \quad \text{Units of mahogany capacity}$$

$$(3.0). \quad 10x_1 + 15x_2 \leq 450 \quad \text{Labor hours capacity}$$

$$x_1, x_2 \geq 0 \quad \text{Non - negativity}$$

The Furniture Factory Problem... 2

The data of the furniture problem is

DATA	CHAIR	TABLE	CAPACITY
5 units	20 units	400 units	400 units
	10 hours	15 hours	450 hours
	\$45	\$80	

Introduction linear programming and mixed integer linear programming problems

Key components of mathematical programming models

x_1 is the decision variable representing the number of chairs to produce. The index 1 refers to the product chair.

x_2 is the decision variable representing the number of tables to produce. The index 2 refers to the product table.

We can create a set of products mapping each product with the index associated with each decision variable. Then, the set products = {1: chair, 2: table} maps each index with its corresponding product.

Similarly, we can create a set for resources as follows: resources = {1: mahogany, 2: labor} where the index 1 maps to the resource mahogany, and the index 2 maps to the resource labor.

Key components of linear programming model

$$(1.0). \text{ Max revenue} = 45x_1 + 80x_2$$

$$(2.0) \quad 5x_1 + 20x_2 \leq 400 \quad \text{Units of mahogany capacity}$$

$$(3.0). \quad 10x_1 + 15x_2 \leq 450 \quad \text{Labor hours capacity}$$

$$x_1, x_2 \geq 0 \quad \text{Non-negativity}$$

This LP model has several types of parameters representing known quantities (data) that characterize the problem.

- Prices can be defined over the set of products, e.g. $b_1 = 45$ means that the price of a chair is \$45, and $b_2 = 80$ means that the price of a table is \$80.
- Resources capacity can be defined over the set of resources, e.g. $K_1 = 400$, means that the availability of mahogany is 400 units/week, and $K_2 = 450$ means that the availability of labor is 450 units/week.
- Technology coefficients describe the consumption of resources when building a product. For example,

$a_{1,1} = 5$ means that five units of mahogany are consumed when building one chair,

$a_{1,2} = 20$ means that twenty units of mahogany are consumed when building one table,

$a_{2,1} = 10$ means that ten units of labor are consumed when building one chair,

$a_{2,2} = 15$ means that fifteen units of labor are consumed when building one table.

Key components of linear programming model... 2

- (1.0). Max revenue = $45x_1 + 80x_2$
- (2.0) $5x_1 + 20x_2 \leq 400$ Units of mahogany capacity
- (3.0). $10x_1 + 15x_2 \leq 450$ Labor hours capacity

$$x_1, x_2 \geq 0 \text{ Non-negativity}$$

- Matrix of technology coefficients

 DATA	 CHAIR	 TABLE
 Mahogany	$a_{11} = 5$	$a_{12} = 20$
 Labor	$a_{21} = 10$	$a_{22} = 15$

Key components of linear programming model... 3

(1.0). Max revenue = $45x_1 + 80x_2$

(2.0) $5x_1 + 20x_2 \leq 400$ Units of mahogany capacity

(3.0). $10x_1 + 15x_2 \leq 450$ Labor hours capacity

$x_1, x_2 \geq 0$ Non – negativity

This LP model has two types of **constraints** limiting the number of chairs and tables that can be produced.

These constraints are defined over the set of resources, and represent that the consumption of each resource by a Production Plan cannot exceed the amount available of the resource.

The **objective function** is to maximize total revenue generated by the optimal Production Plan.

Linear Programming model components

Summary

**SET OF
INDICES**

- Set of resources = {1: mahogany, 2: labor}
- Set of products = {1: chairs, 2: tables}

Abstraction and generalization of furniture problem

Original LP problem formulation

$$\begin{aligned} (1.0). \quad & \text{Max revenue} = 45x_1 + 80x_2 \\ (1.0). \quad & \text{Max } (b_1 = 45)x_1 + (b_2 = 80)x_2 \\ (2.0). \quad & 5x_1 + 20x_2 \leq 400 \quad \text{Units of mahogany capacity} \\ (2.0). \quad & (a_{11} = 5)x_1 + (a_{12} = 20)x_2 \leq K_1 = 400 \\ (3.0). \quad & 10x_1 + 15x_2 \leq 450 \quad \text{Labor hours capacity} \\ (3.0). \quad & (a_{21} = 10)x_1 + (a_{22} = 15)x_2 \leq K_2 = 450 \\ & x_1, x_2 \geq 0, \text{Non-negativity} \\ & x_1, x_2 \geq 0 \end{aligned}$$

Parametrization of input data

Parametrization of input data of an LP problem allows one to separate the data from the model. That is, one can change the values of the data without changing the model.

Linear Programming model components

Summary

SET OF INDICES

- Set of resources = {1: mahogany, 2: labor}
- Set of products = {1: chairs, 2: tables}

PARAMETERS

- Product prices.
- Resources capacity.
- Technology coefficients.

DECISION VARIABLES

- x_1 : number of chairs to make,
- x_2 : number of tables to make

CONSTRAINTS

- Amount of mahogany available per week.
- Amount of labor available per week.

OBJECTIVE FUNCTION

- Maximize total weekly revenue.

Abstraction and generalization of furniture problem... 2

Parametrized LP problem formulation

$$(1.0) \quad \text{Max} \quad b_1x_1 + b_2x_2$$

$$(2.0) \quad a_{1,1}x_1 + a_{1,2}x_2 \leq K_1$$

$$(3.0) \quad a_{2,1}x_1 + a_{2,2}x_2 \leq K_2$$

Technology
coefficients

$$x_1, x_2 \geq 0$$

Prices

Resources
capacity

$$b_1x_1 + b_2x_2 = \sum_{j=1}^2 b_jx_j$$

$$\sum_{j=1}^2 a_{i,j}x_j \leq K_i \quad (i = 1,2)$$

$$x_j \geq 0, (j = 1,2)$$

Abstraction and generalization of furniture problem... 2

General LP problem formulation

The diagram illustrates the components of a linear programming problem:

- Objective Function:** $\text{Max } \sum_{j=1}^n b_j x_j$
- Constraints:** $\sum_{j=1}^n a_{i,j} x_j \leq K_i \quad (i = 1..m)$
- Technology coefficients:** $x_j \geq 0 \quad (j = 1..n)$
- Objective function coefficients:** b_j
- Decision Variables:** x_j
- RHS: right hand side:** K_i
- Set of indices for Constraints:** $i = 1..m$
- Set of indices for Variables:** $j = 1..n$

$n = 2$ number of decision variables (products)
 $m = 2$ number of constraints (resources)

Parametrized LP problem formulation

$$\begin{aligned}
 (1.0) \quad & \text{Max } b_1 x_1 + b_2 x_2 \\
 (2.0) \quad & a_{1,1} x_1 + a_{1,2} x_2 \leq K_1 \\
 (3.0) \quad & a_{2,1} x_1 + a_{2,2} x_2 \leq K_2 \\
 & x_1, x_2 \geq 0
 \end{aligned}$$

$$\begin{aligned}
 b_1 x_1 + b_2 x_2 &= \sum_{j=1}^2 b_j x_j \\
 \sum_{j=1}^2 a_{i,j} x_j &\leq K_i \quad (i = 1,2) \\
 x_j &\geq 0, \quad (j = 1,2)
 \end{aligned}$$

Linear, integer, binary, mixed programming models

Linear programming problems

Objective function examples:

- maximize total revenue
- minimize total cost.

Constraint examples:

- \leq constraints are typically considered for capacity constraints where you don't want to exceed capacity available.
- \geq constraints are used to model demand requirements where you want to ensure that at least certain level of demand is satisfied.
- $=$ constraints are used when you want to match exactly certain activities with a given requirement. For example, a job position can only be filled with one resource, and you have a set of possible qualified resources to assign to the job.

$$\text{Max (Min)} \sum_{j=1}^n b_j x_j$$

$$\sum_{j=1}^n a_{i,j} x_j \leq (=, \geq) K_i \quad (i = 1..m)$$

$$x_j \geq 0 \quad (j = 1..n)$$

Linear, integer, binary, mixed programming models

Integer programming problems

Objective function examples:

- maximize total revenue
- minimize total cost.

Constraint examples:

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$$\text{Max (Min)} \sum_{j=1}^n b_j x_j$$

$$\sum_{j=1}^n a_{i,j} x_j \leq (=, \geq) K_i \quad (i = 1..m)$$

$$x_j \geq 0 \text{ and integer } (j = 1..n)$$

Linear, integer, binary, mixed programming models

Binary programming problems

Objective function examples:

- maximize total revenue
- minimize total cost.

Constraint examples:

- \leq constraints are typically considered for capacity constraints where you don't want to exceed capacity available.
- \geq constraints are used to model demand requirements where you want to ensure that at least certain level of demand is satisfied.
- $=$ constraints are used when you want to match exactly certain activities with a given requirement. For example, a job position can only be filled with one resource, and you have a set of possible qualified resources to assign to the job.

$$\text{Max (Min)} \sum_{j=1}^n b_j x_j$$

$$\sum_{j=1}^n a_{i,j} x_j \leq (=, \geq) K_i \quad (i = 1..m)$$

$$x_j \text{ in } \{0,1\} \quad (j = 1..n)$$

Linear, integer, binary, mixed programming models

Blended integer linear programming problems

Objective function examples:

- maximize total revenue
- minimize total cost.

Constraint examples:

- \leq constraints are typically considered for capacity constraints where you don't want to exceed capacity available.
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$$\text{Max (Min)} \sum_{j=1}^n b_j x_j$$

$$\sum_{j=1}^n a_{i,j} x_j \leq (=, \geq) K_i \quad (i = 1..m)$$

$$x_j \geq 0 \quad (j = 1..n)$$

$x_j \geq 0$ and integer for some j

x_j in $\{0,1\}$ for some j

Solving MIP Problems

In Mixed Integer linear Programming it is possible to have equivalent formulations of a problem

- But the performance of a MIP solver can be drastically different.
- This is why when formulating a MIP model, its very important to understand how the MIP algorithms behind the MIP solver behave.
- Hence, we will present a limited discussion of the solution process associated with Linear Programming and Mixed Integer Linear Programming.
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Furniture Factory Problem

Graphical interpretation and solution of an LP problem

LP formulation of furniture problem

(1.0). Max revenue = $45x_1 + 80x_2$



(2.0) $5x_1 + 20x_2 \leq 400$ Units of mahogany capacity



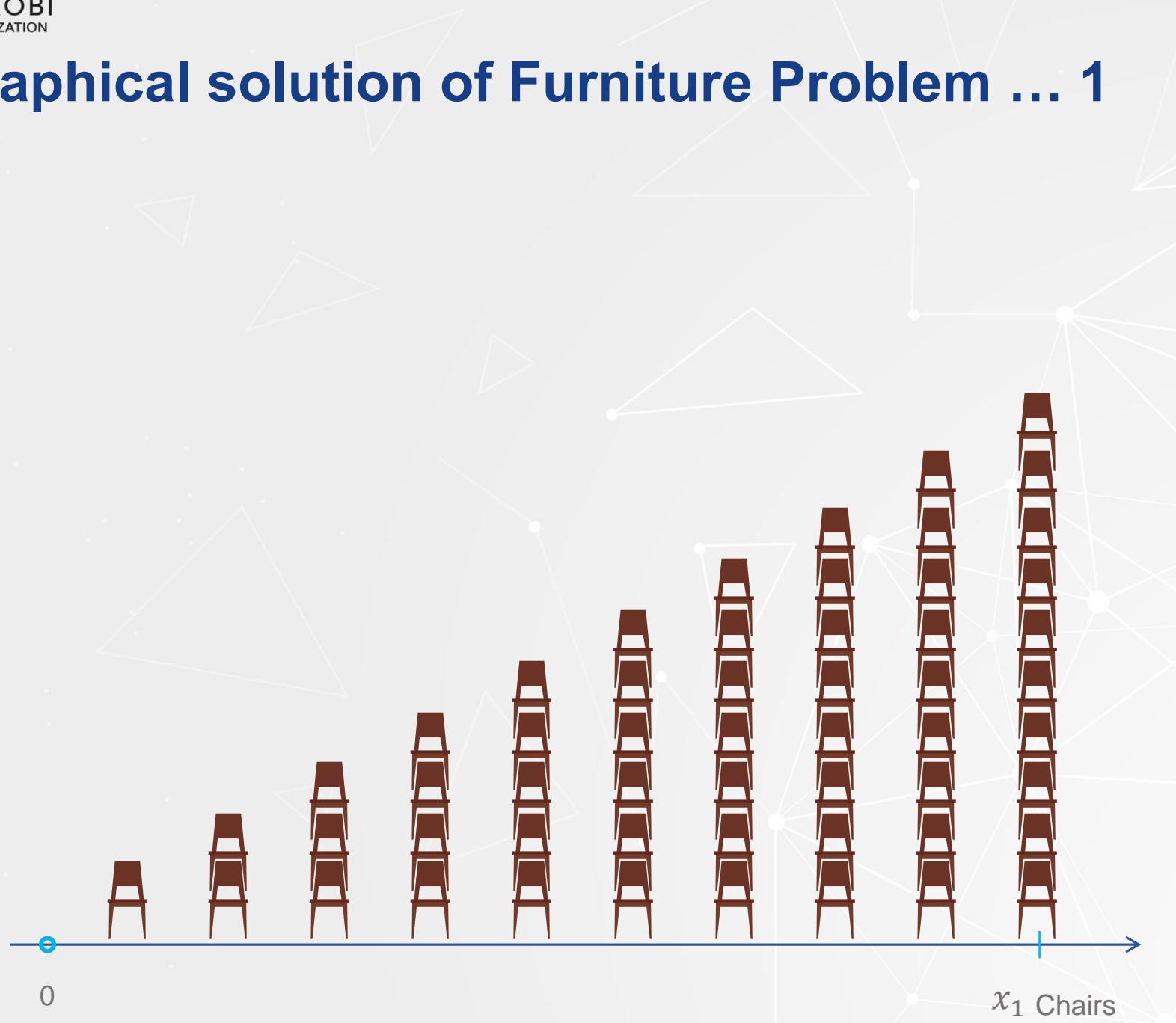
(3.0). $10x_1 + 15x_2 \leq 450$ Labor hours capacity



$x_1, x_2 \geq 0$

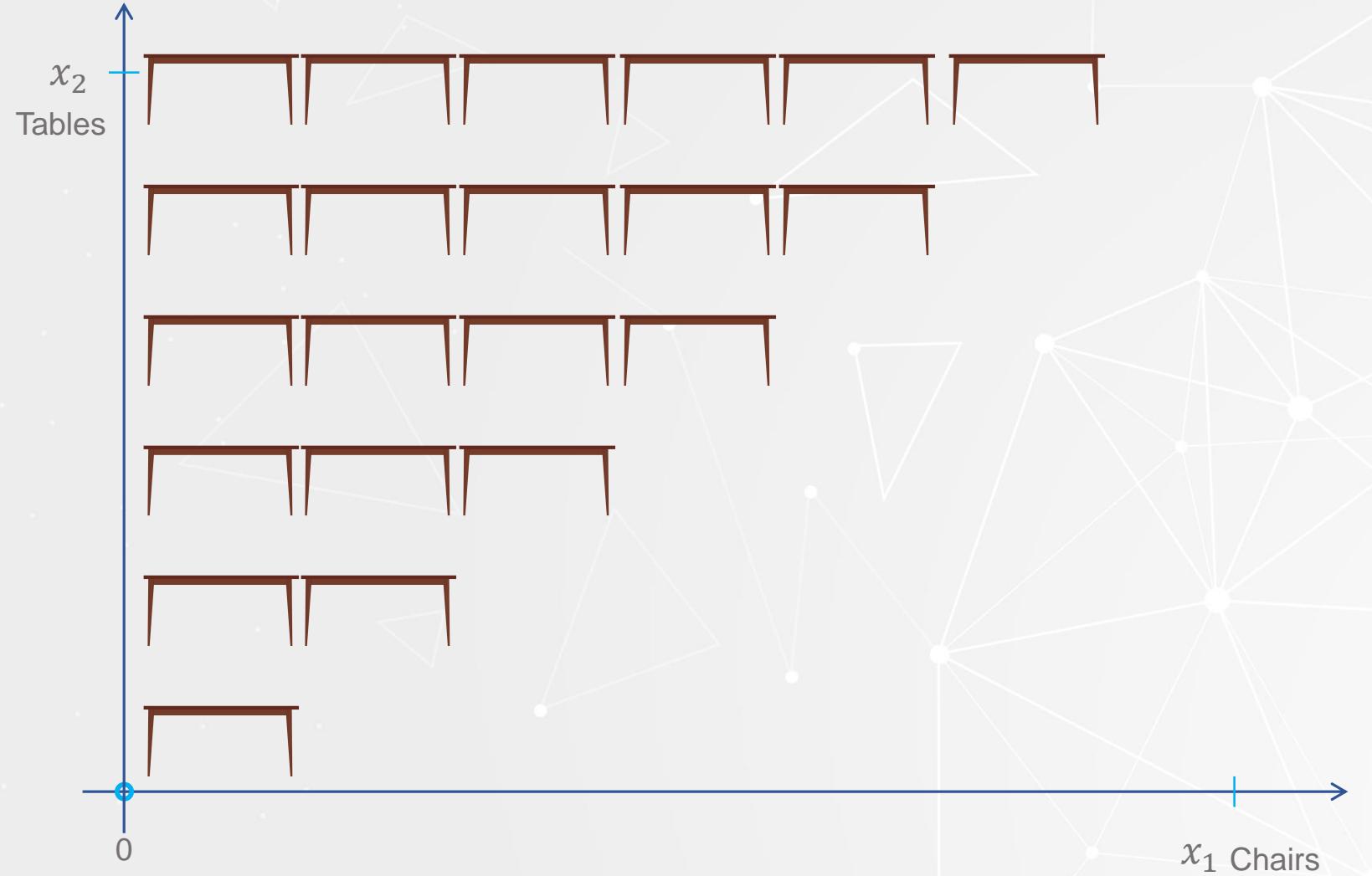
Non – negativity

Graphical solution of Furniture Problem ... 1



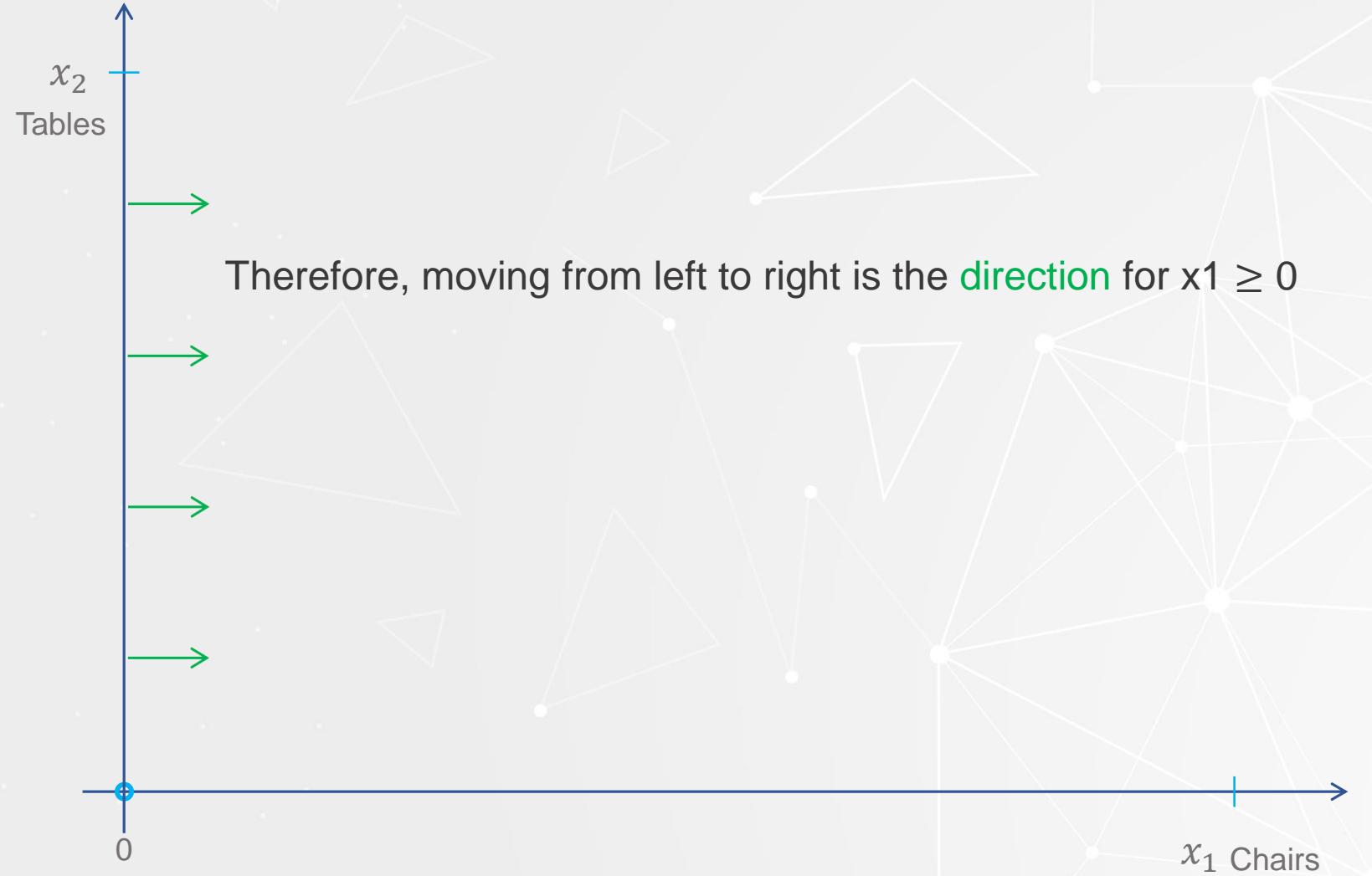
- (1.0). Max revenue = $45x_1 + 80x_2$
(2.0) $5x_1 + 20x_2 \leq 400$ Units of mahogany capacity
(3.0). $10x_1 + 15x_2 \leq 450$ Labor hours capacity
 $x_1, x_2 \geq 0$ Non-negativity

Graphical solution of Furniture Problem ... 2



- (1.0). Max revenue = $45x_1 + 80x_2$
(2.0) $5x_1 + 20x_2 \leq 400$ Units of mahogany capacity
(3.0). $10x_1 + 15x_2 \leq 450$ Labor hours capacity
- $x_1, x_2 \geq 0$ Non - negativity

Graphical solution of Furniture Problem ... 3



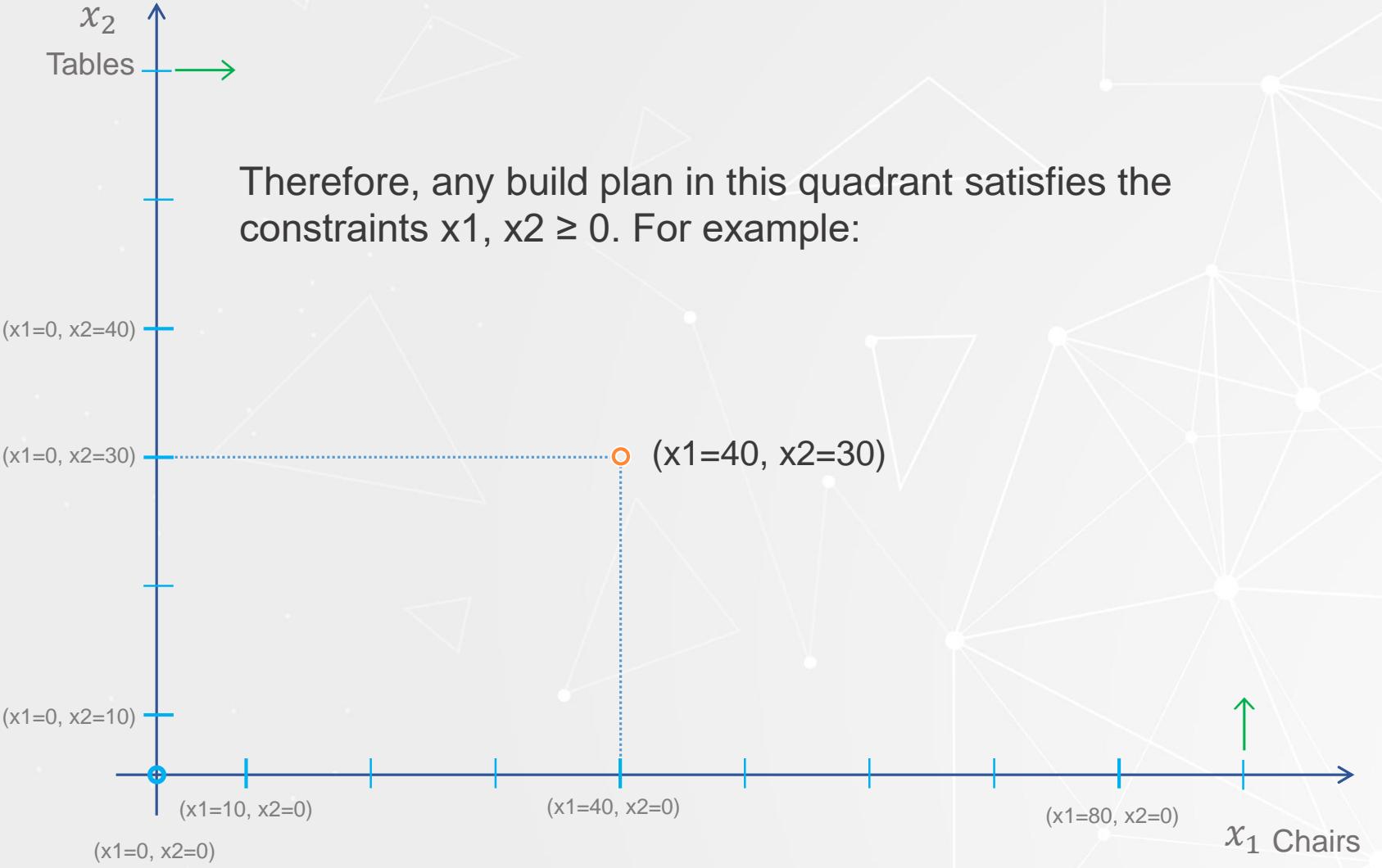
- (1.0). Max revenue = $45x_1 + 80x_2$
(2.0) $5x_1 + 20x_2 \leq 400$ Units of mahogany capacity
(3.0). $10x_1 + 15x_2 \leq 450$ Labor hours capacity
- $x_1, x_2 \geq 0$ Non-negativity

Graphical solution of Furniture Problem ... 4



- (1.0). Max revenue = $45x_1 + 80x_2$
(2.0) $5x_1 + 20x_2 \leq 400$ Units of mahogany capacity
(3.0). $10x_1 + 15x_2 \leq 450$ Labor hours capacity
 $x_1, x_2 \geq 0$ Non-negativity

Graphical solution of Furniture Problem ... 5



- (1.0). Max revenue = $45x_1 + 80x_2$
- (2.0) $5x_1 + 20x_2 \leq 400$ Units of mahogany capacity
- (3.0). $10x_1 + 15x_2 \leq 450$ Labor hours capacity
- $x_1, x_2 \geq 0$ Non-negativity

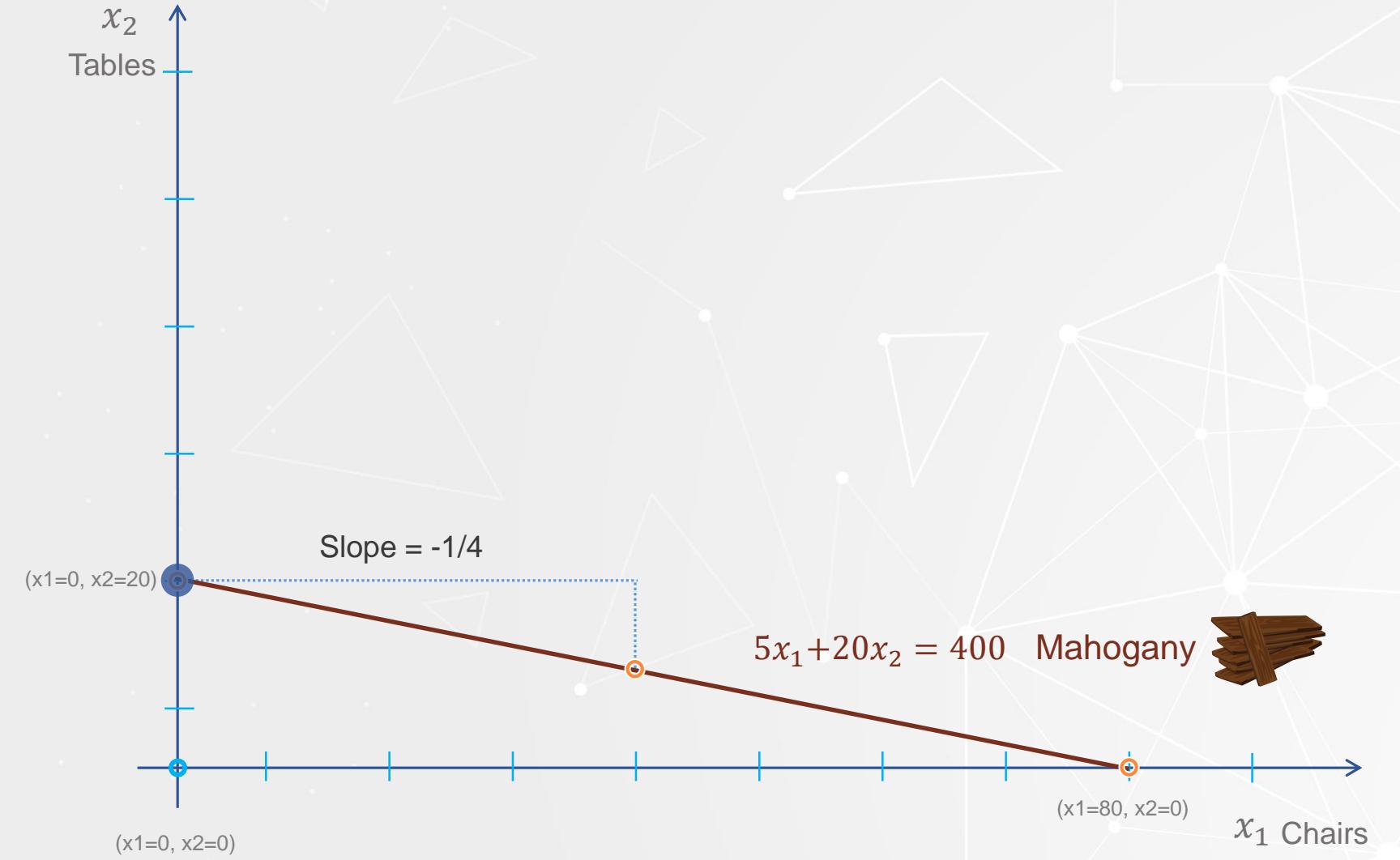
Graphical solution of Furniture Problem ... 6

- $5x_1 + 20x_2 \leq 400$ (mahogany constraint)
- $5x_1 + 20x_2 = 400$ (mahogany equation)
- Expressing x_2 in terms of x_1
 - $20x_2 = 400 - 5x_1$
 - $x_2 = 400/20 - (5/20)x_1$
 - Hence, $x_2 = 20 - (1/4)x_1$
- If $(x_1 = 0)$ then $(x_2 = 20)$
- If $(x_1 = 1)$ chairs, then $x_2 = 20 - (1/4)(x_1 = 1) = 19.75$ tables
- Mahogany tradeoff tables for chairs is $(1/4 = 0.25)$

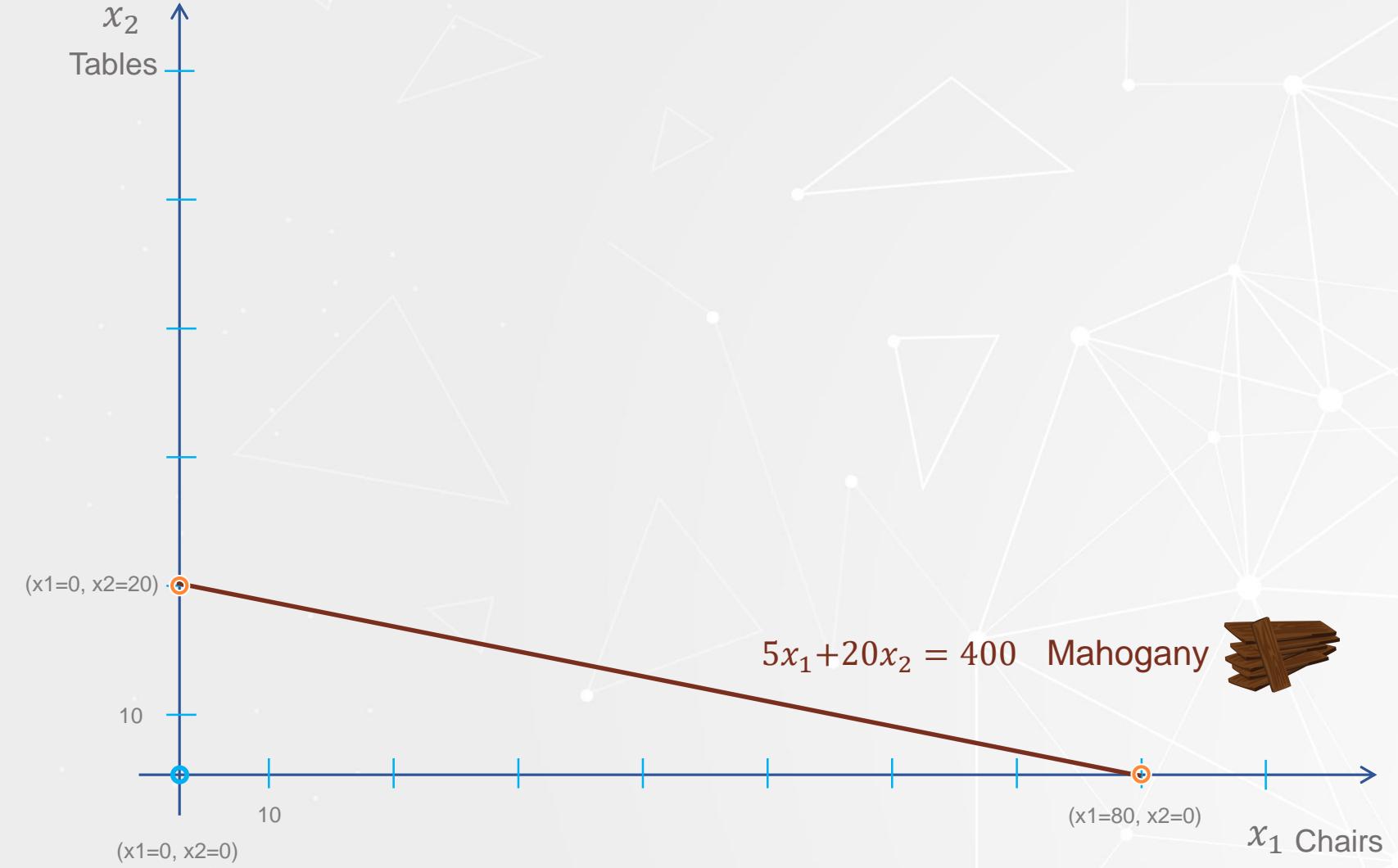


Graphical solution of Furniture Problem ... 7

- Let's graph the equation $x_2 = 20 - (1/4)x_1$

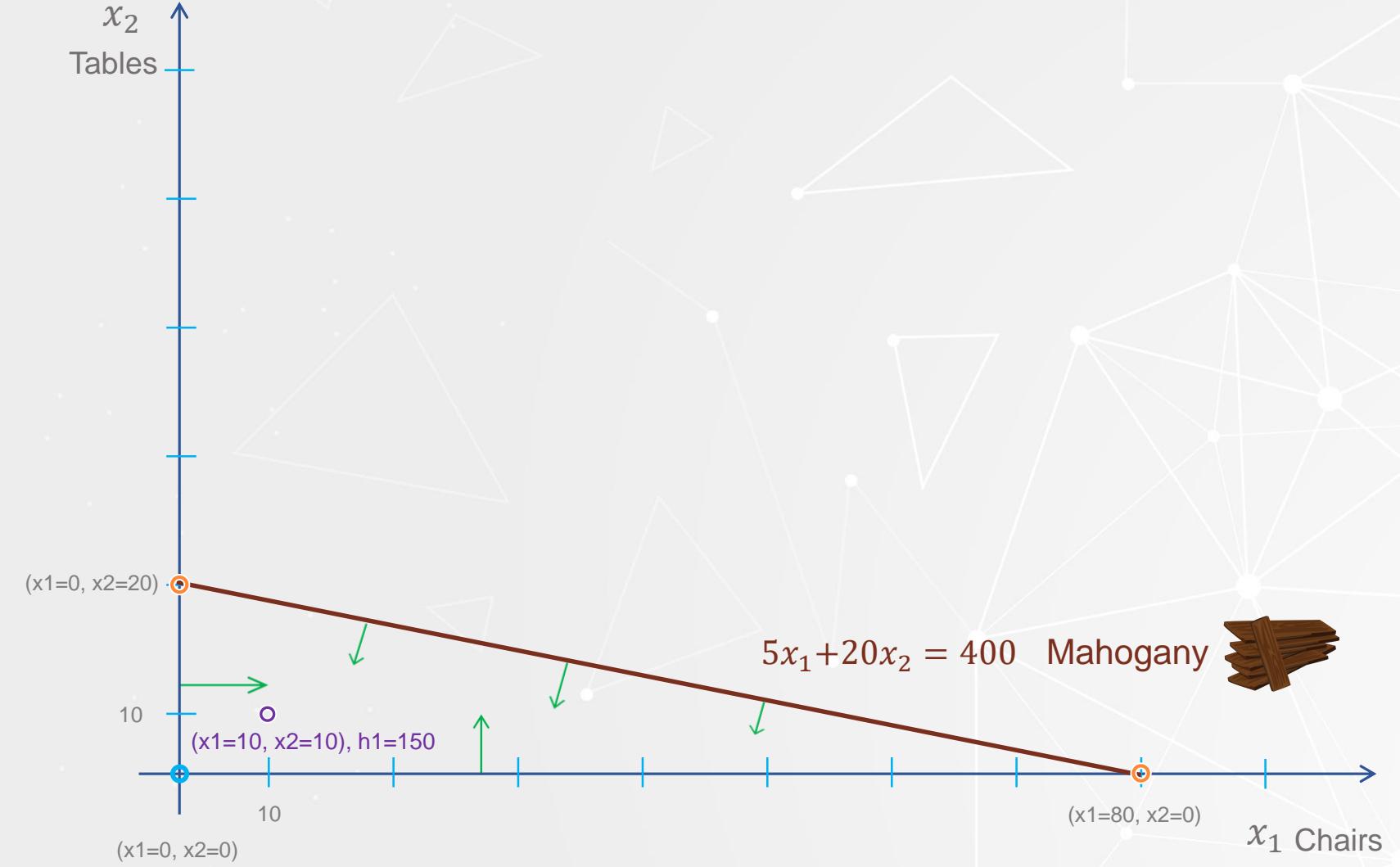


Graphical solution of Furniture Problem ... 8



- Mahogany constraint:
 $5x_1 + 20x_2 \leq 400$.
- (slack variable) $h_1 \geq 0$: amount of unused mahogany for Production Plan (x_1, x_2)
- Equation representing mahogany constraint
 $5x_1 + 20x_2 + h_1 = 400$

Graphical solution of Furniture Problem ... 8



- Consider Production Plan $(x_1=10, x_2=10)$
- Value of slack variable $h_1 = 400 - 5(x_1=10) - 20(x_2=10) = 150$

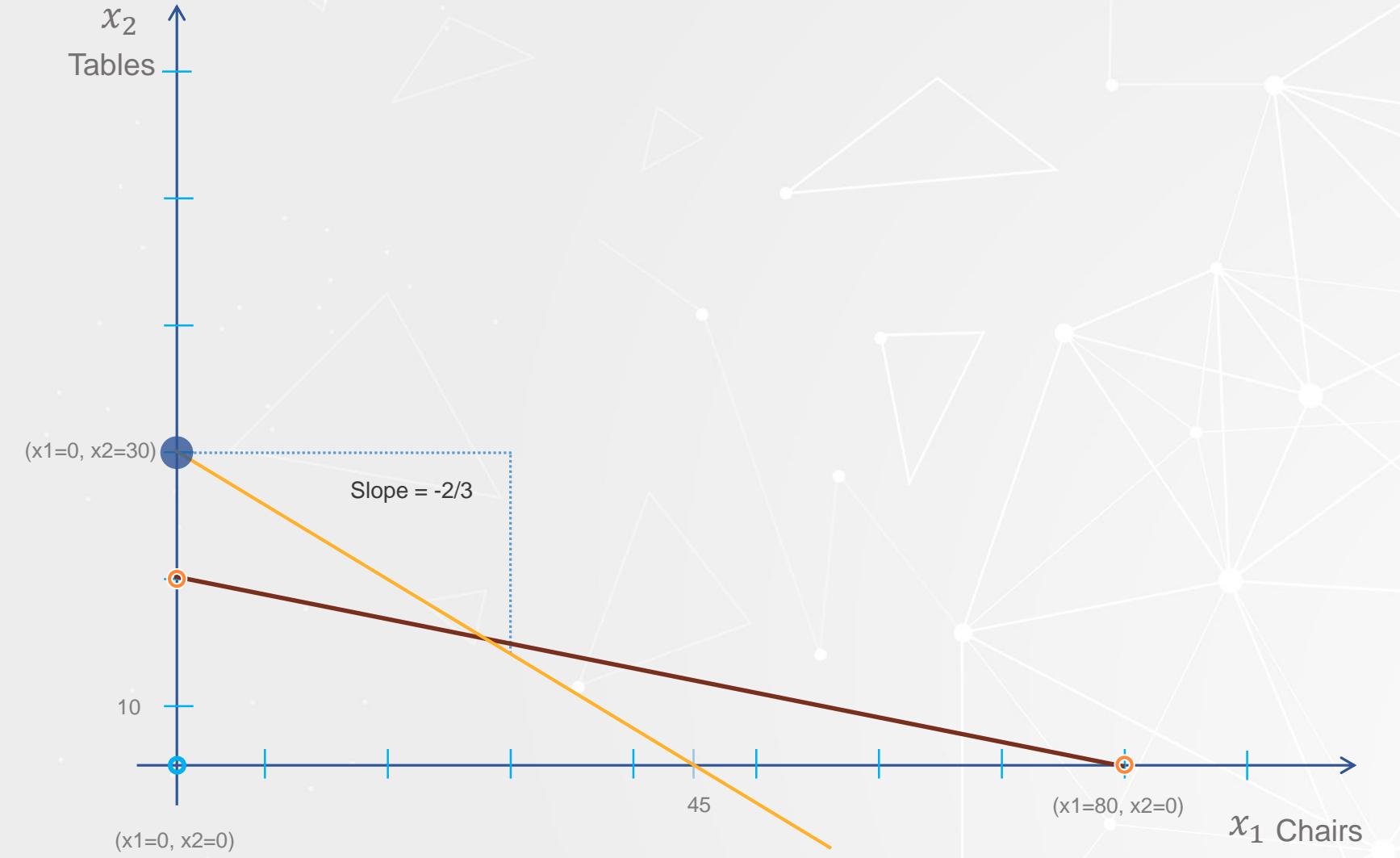
Graphical solution of Furniture Problem ... 9

- $10x_1 + 15x_2 \leq 450$ (labor constraint)
- $10x_1 + 15x_2 = 450$ (labor equation)
- Expressing x_2 in terms of x_1
 - $x_2 = 30 - (2/3)x_1$
- If $(x_1 = 0)$ then $(x_2 = 30)$
- If $(x_1 = 1)$ chair, then $x_2 = 30 - (2/3)(x_1 = 1) = 29.333$ tables
- Labor tradeoff tables for chairs is $(2/3 = 0.667)$

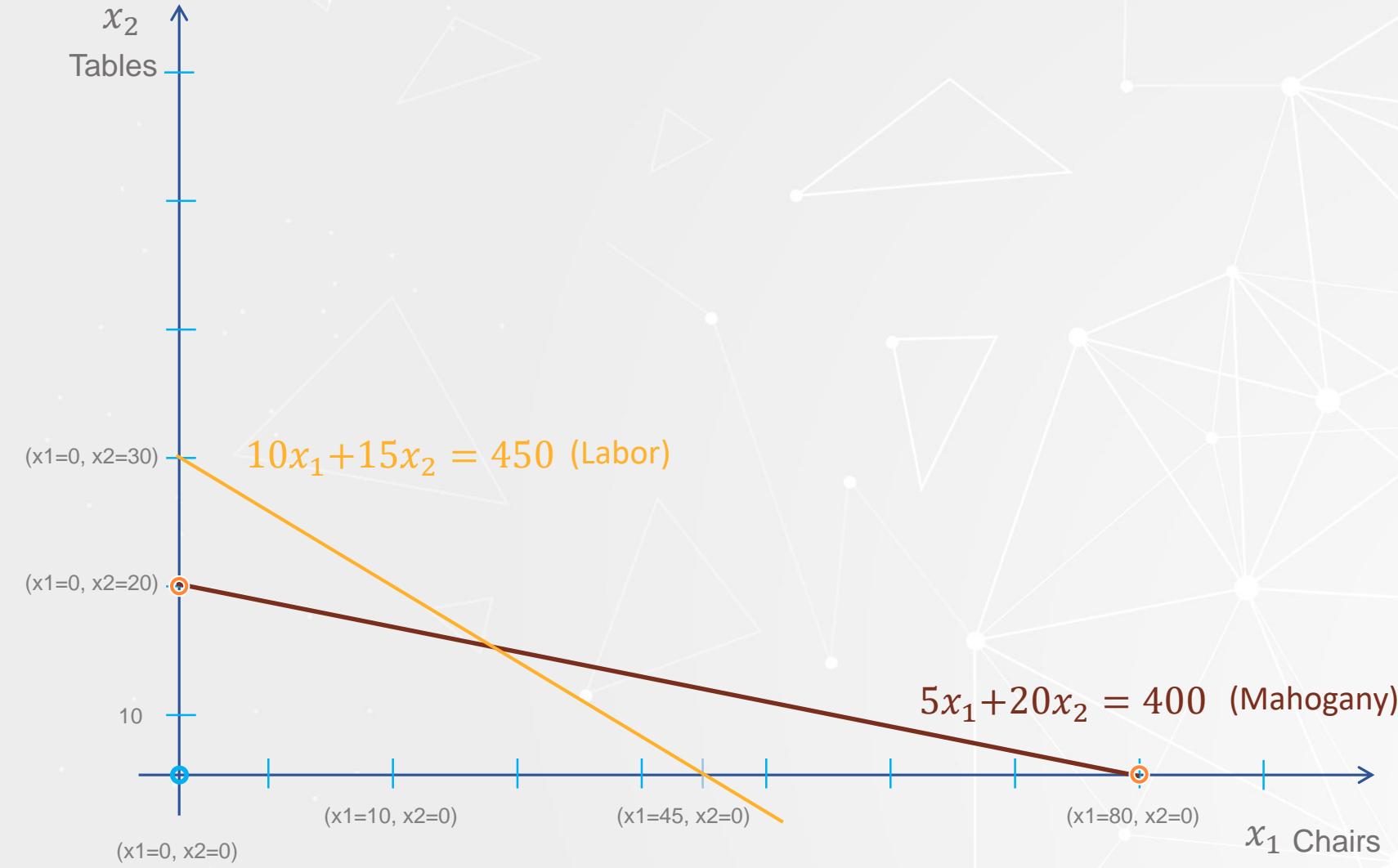


Graphical solution of Furniture Problem ... 10

- Let's graph the equation $x_2 = 30 - (2/3)x_1$

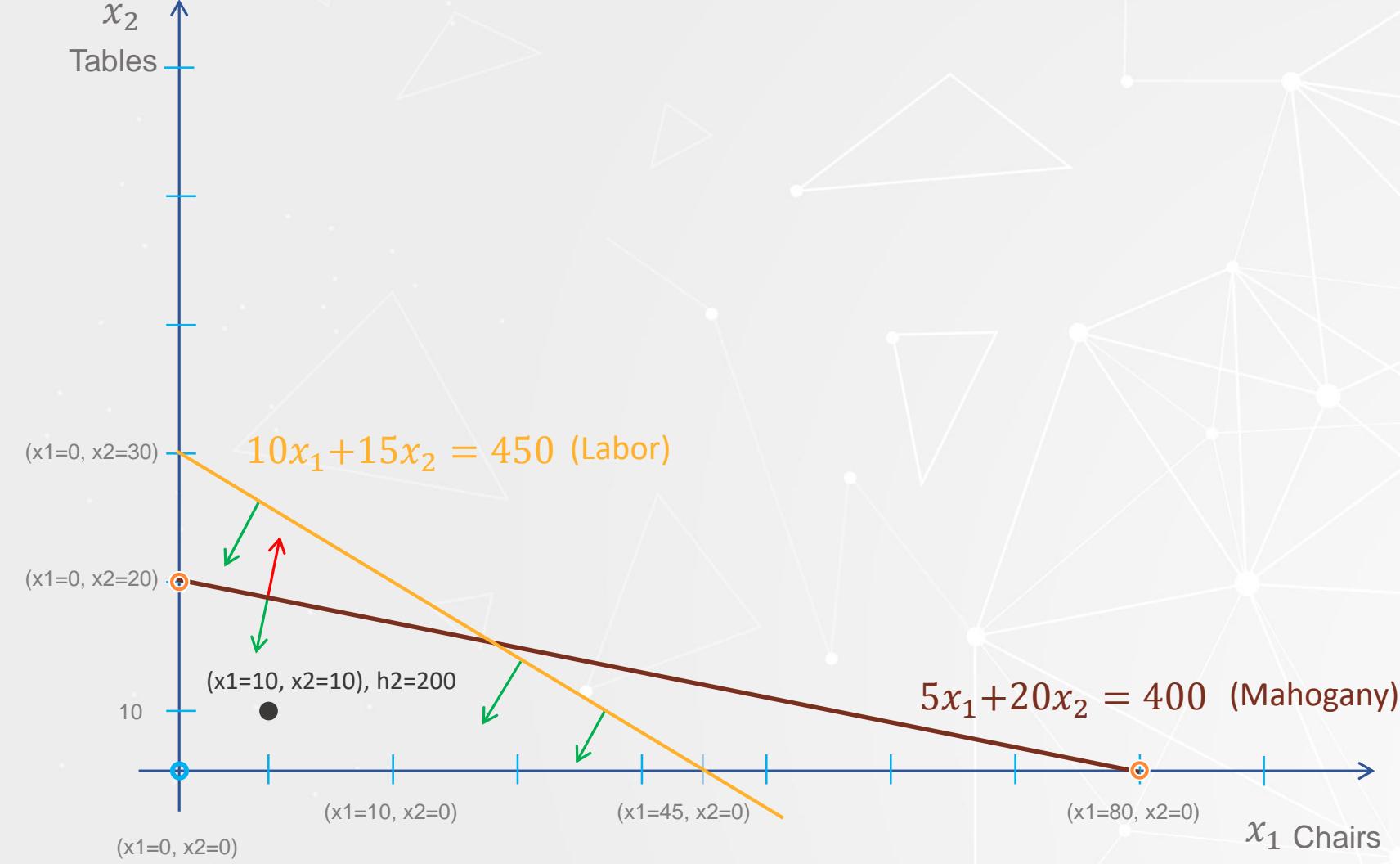


Graphical solution of Furniture Problem ... 11



- Labor constraint
 $10x_1 + 15x_2 \leq 450$
- (slack variable) $h_2 \geq 0$: amount of unused labor for production plan (x_1, x_2)
- Equation representing labor constraint
 $10x_1 + 15x_2 + h_2 = 450$

Graphical solution of Furniture Problem ... 11



- Production Plan ($x_1=10, x_2=10$)
- Slack variable value $h_2 = 450 - 10(x_1=10) - 15(x_2=10) = 200$

Graphical solution of Furniture Problem ... 12

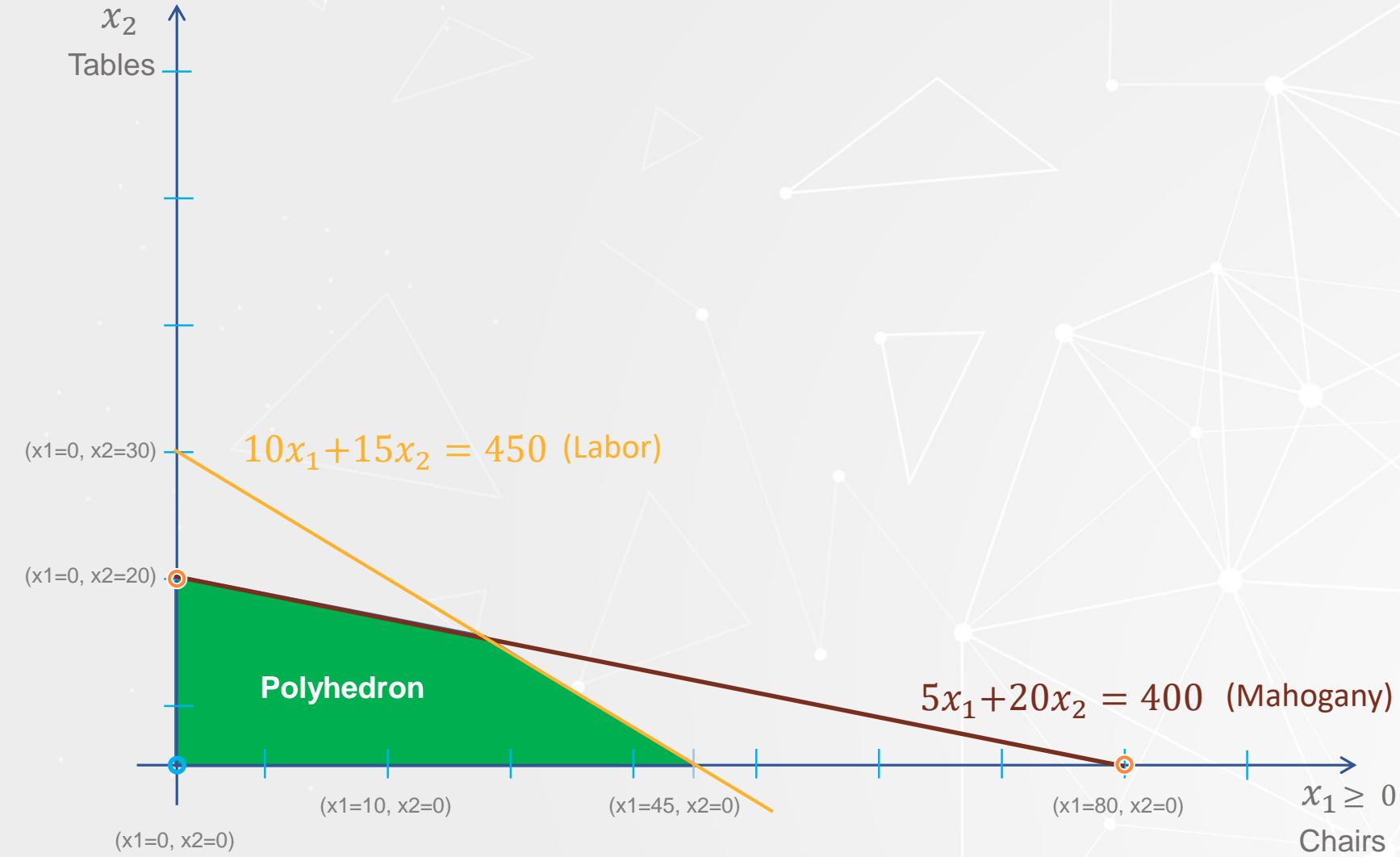


(2.0) $5x_1 + 20x_2 \leq 400$ Units of mahogany capacity

(3.0). $10x_1 + 15x_2 \leq 450$ Labor hours capacity

$x_1, x_2 \geq 0$ Non-negativity

Graphical solution of Furniture Problem ... 13



$$(2.0) \quad 5x_1 + 20x_2 \leq 400 \quad \text{Units of mahogany capacity}$$

$$(3.0). \quad 10x_1 + 15x_2 \leq 450 \quad \text{Labor hours capacity}$$

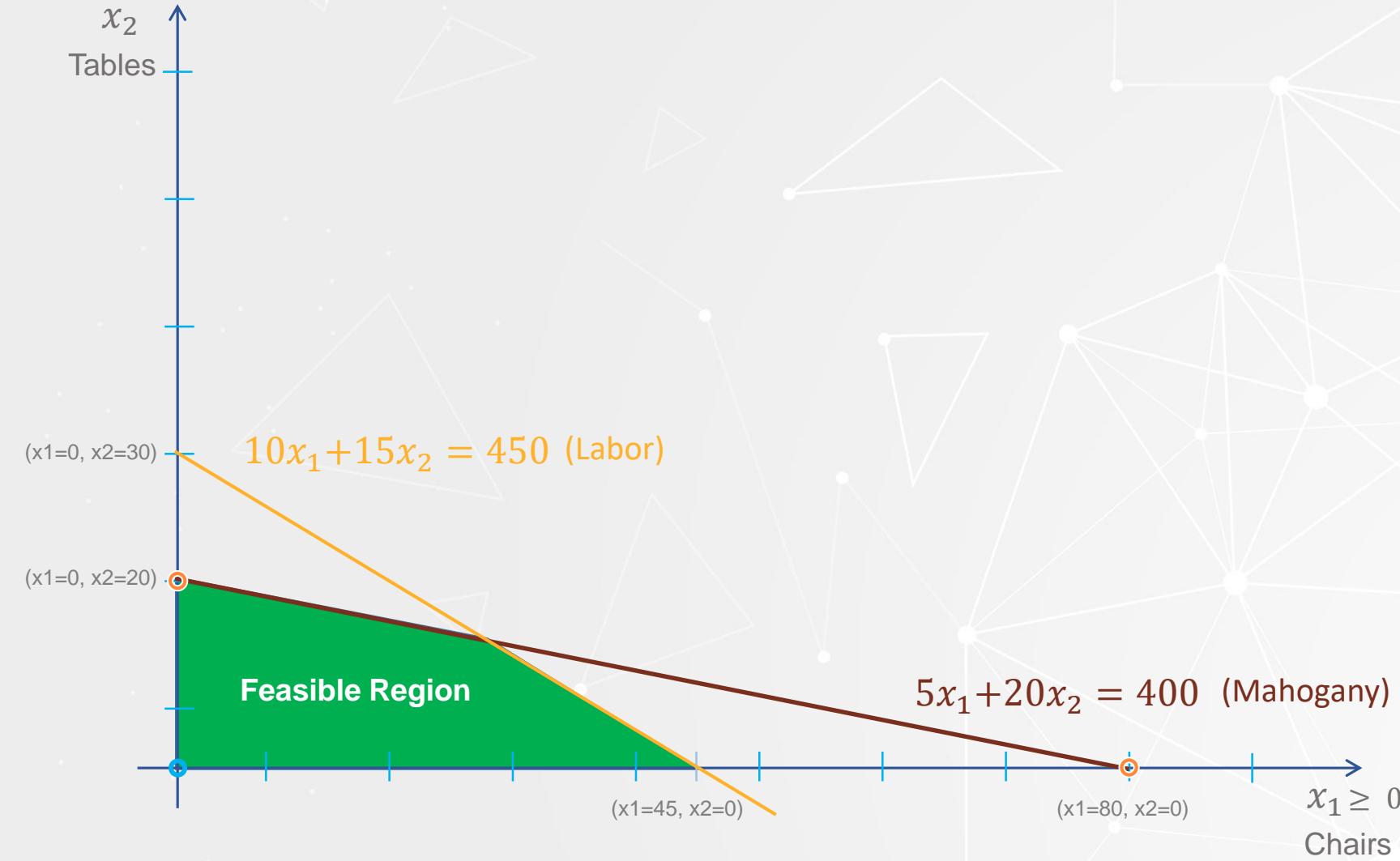
$$x_1, x_2 \geq 0 \quad \text{Non-negativity}$$

- In the theory of linear programming the feasible region is called a **Polyhedron**.

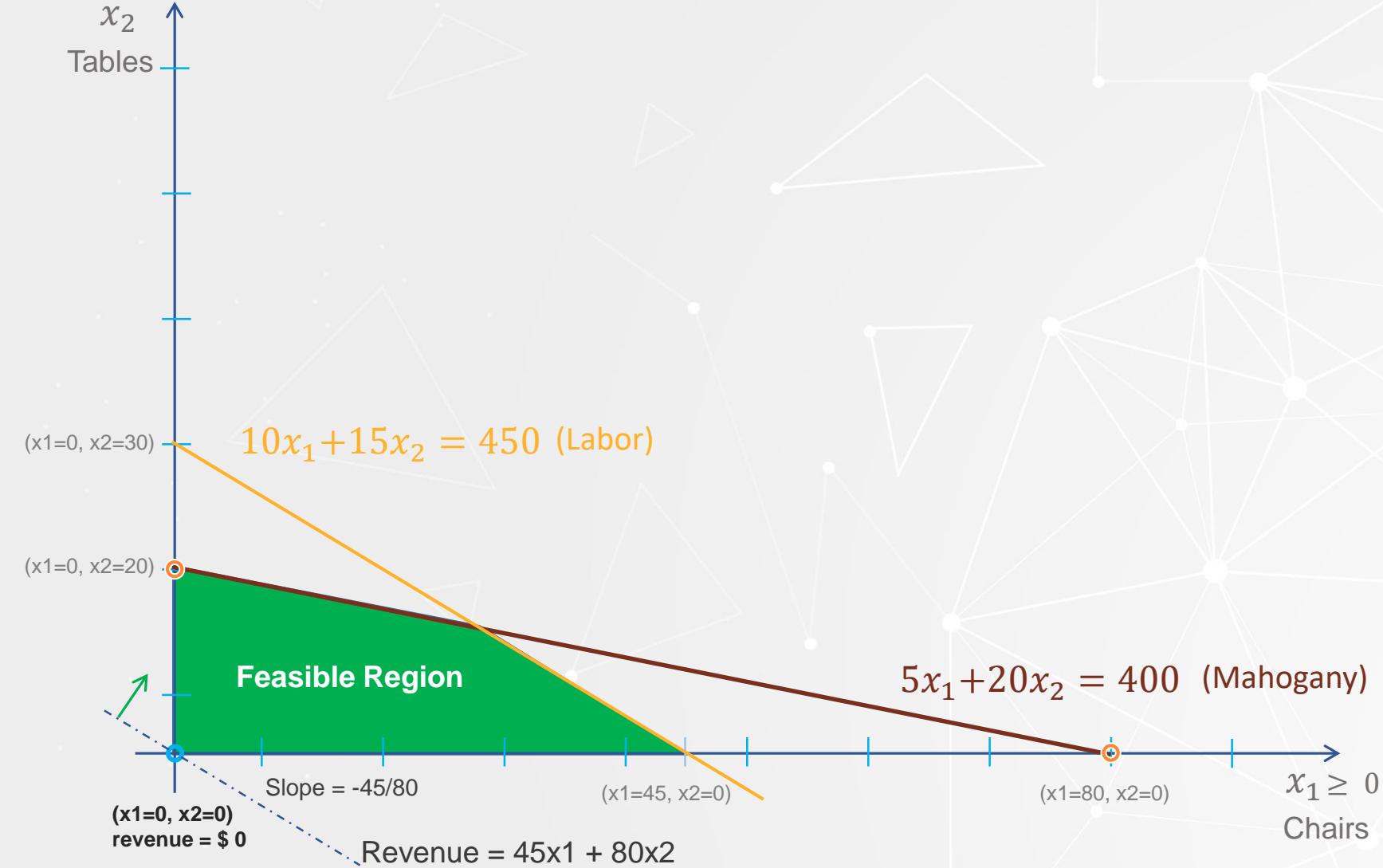
Graphical solution of Furniture Problem ... 14

- The objective function:
 $\text{revenue} = 45x_1 + 80x_2$

$$x_2 = \text{revenue}/80 - (45/80)x_1$$



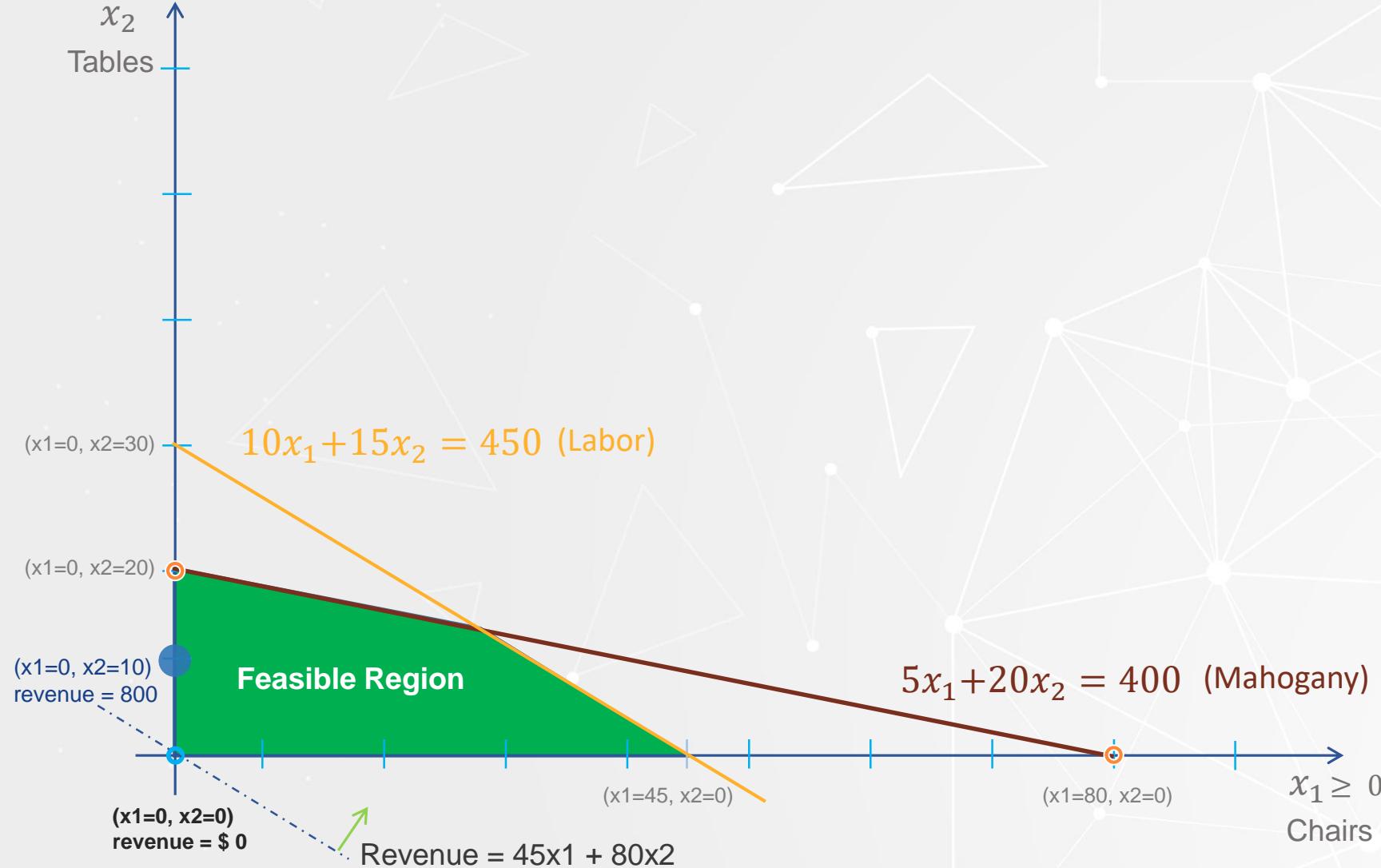
Graphical solution of Furniture Problem ... 14



$$x_2 = \frac{\text{revenue}}{80} - \left(\frac{45}{80}\right)x_1$$

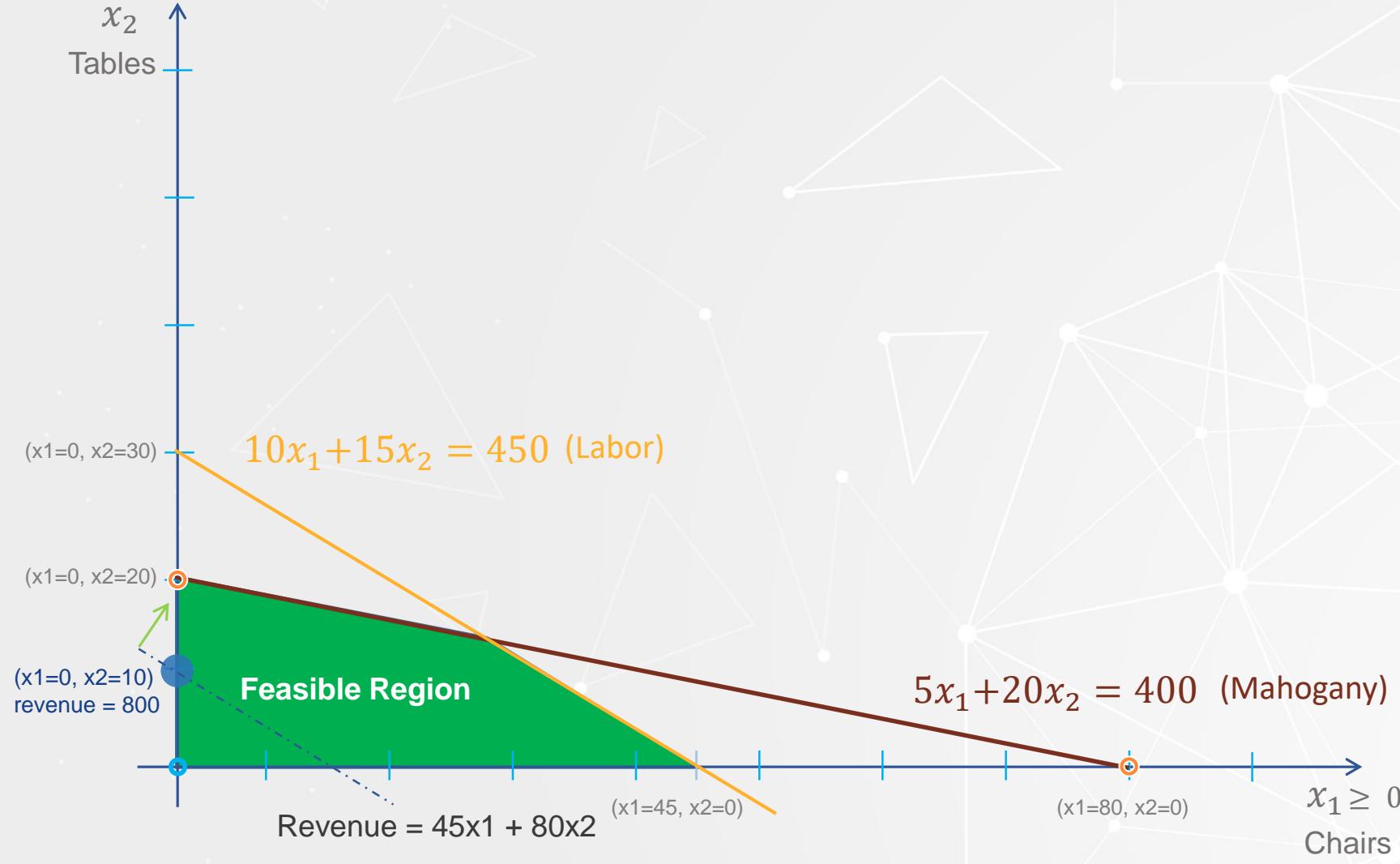
- If $(x_1=0, x_2=0)$, then revenue is \$0.00.

Graphical solution of Furniture Problem ... 15



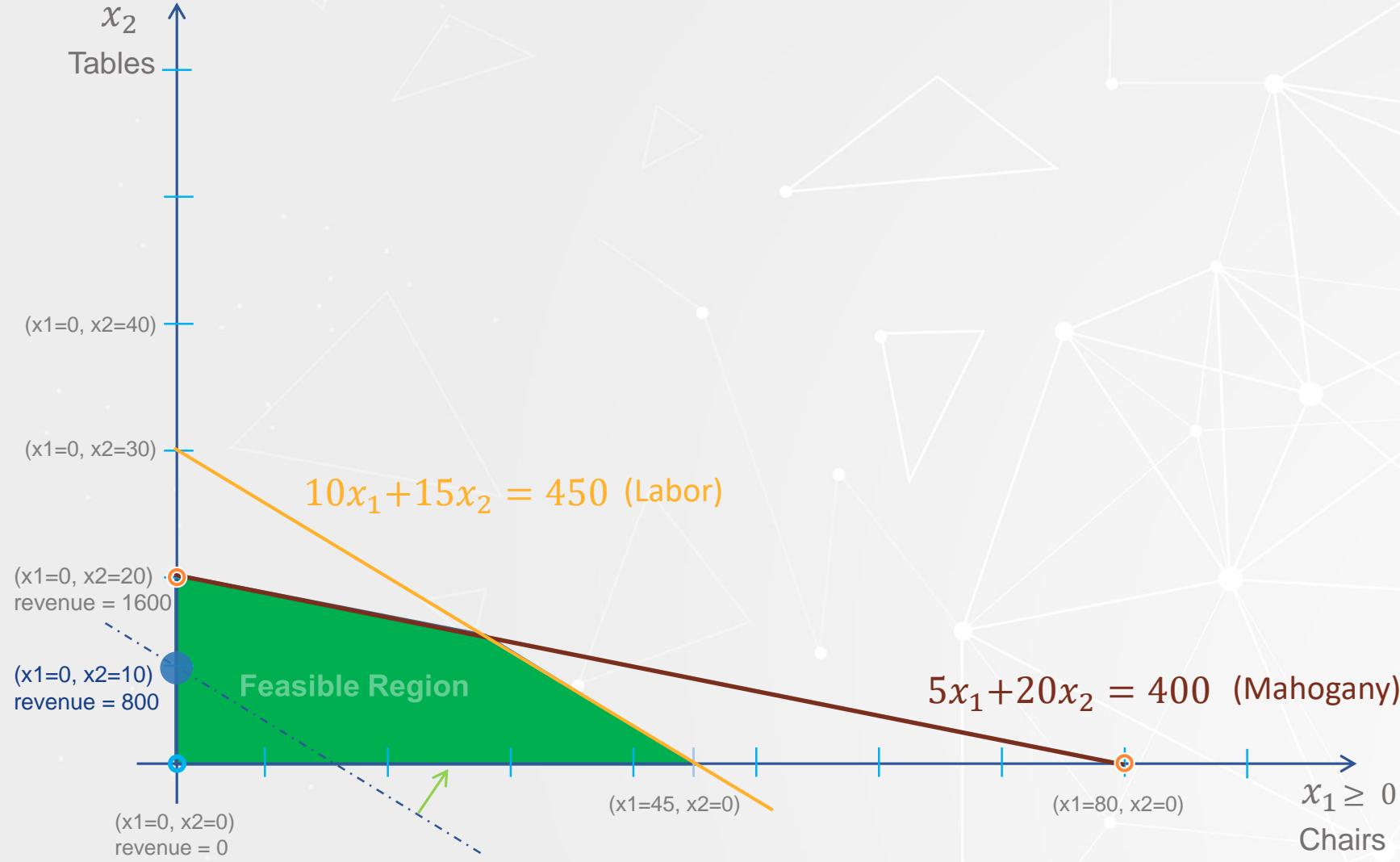
- Production Plan
 $(x_1 = 0, x_2 = 10)$
- Generates a revenue
 $= 45(x_1=0) + 80(x_2=10)$
 $= \$800$

Graphical solution of Furniture Problem ... 15



- Mahogany slack variable:
 $h_1 = 400 - 5(x_1=0) - 20(x_2=10) = 200$
- Labor slack variable:
 $h_2 = 450 - 10(x_1=0) - 15(x_2=10) = 150$
- 200 units of unused mahogany capacity
- 150 units of unused labor capacity

Graphical solution of Furniture Problem ... 16

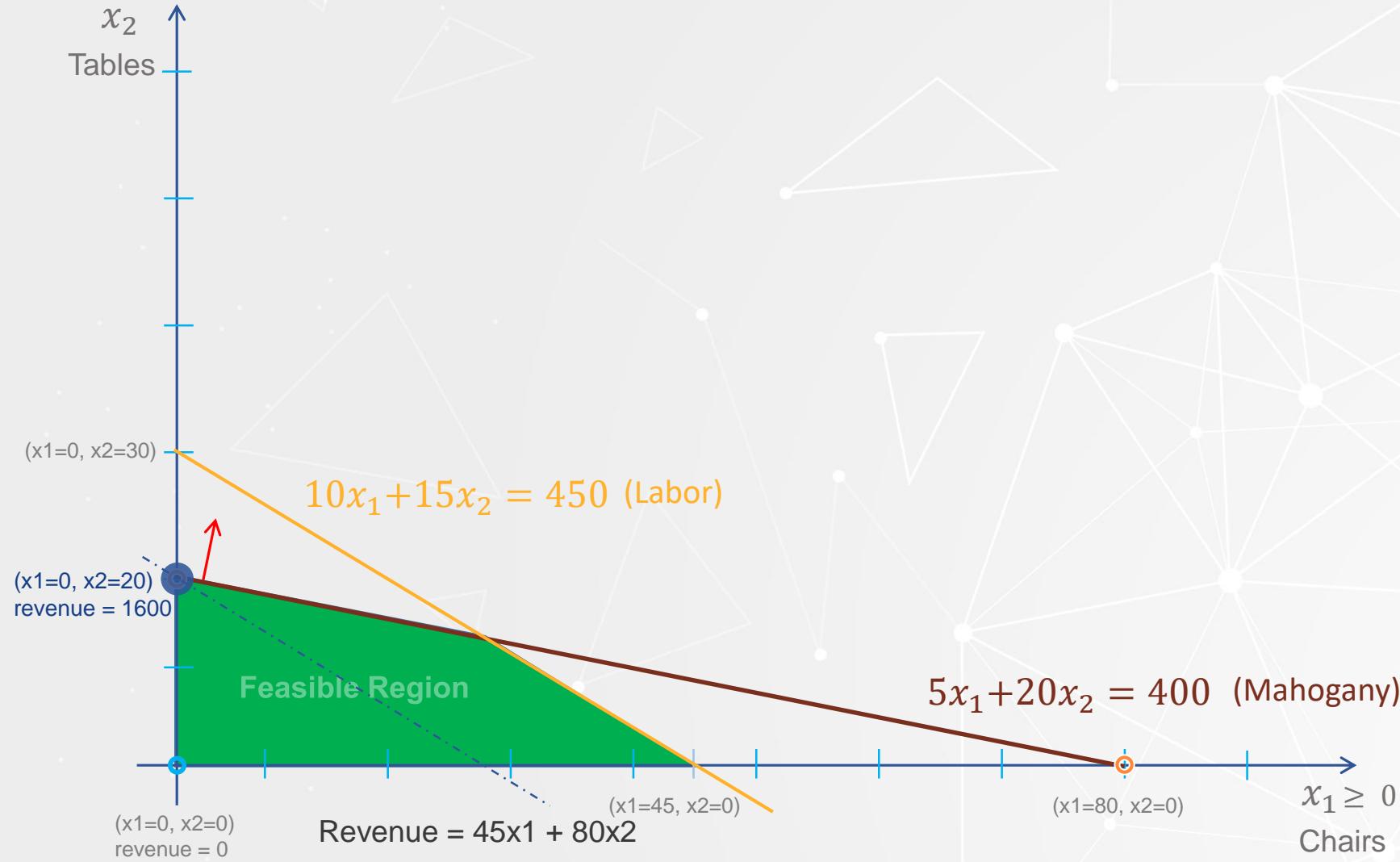


- How far can we increase the production of tables?

- Production Plan ($x_1=0, x_2=20$)

Revenue =
 $45(x_1 = 0) + 80(x_2=20) =$
\$1,600

Graphical solution of Furniture Problem ... 16

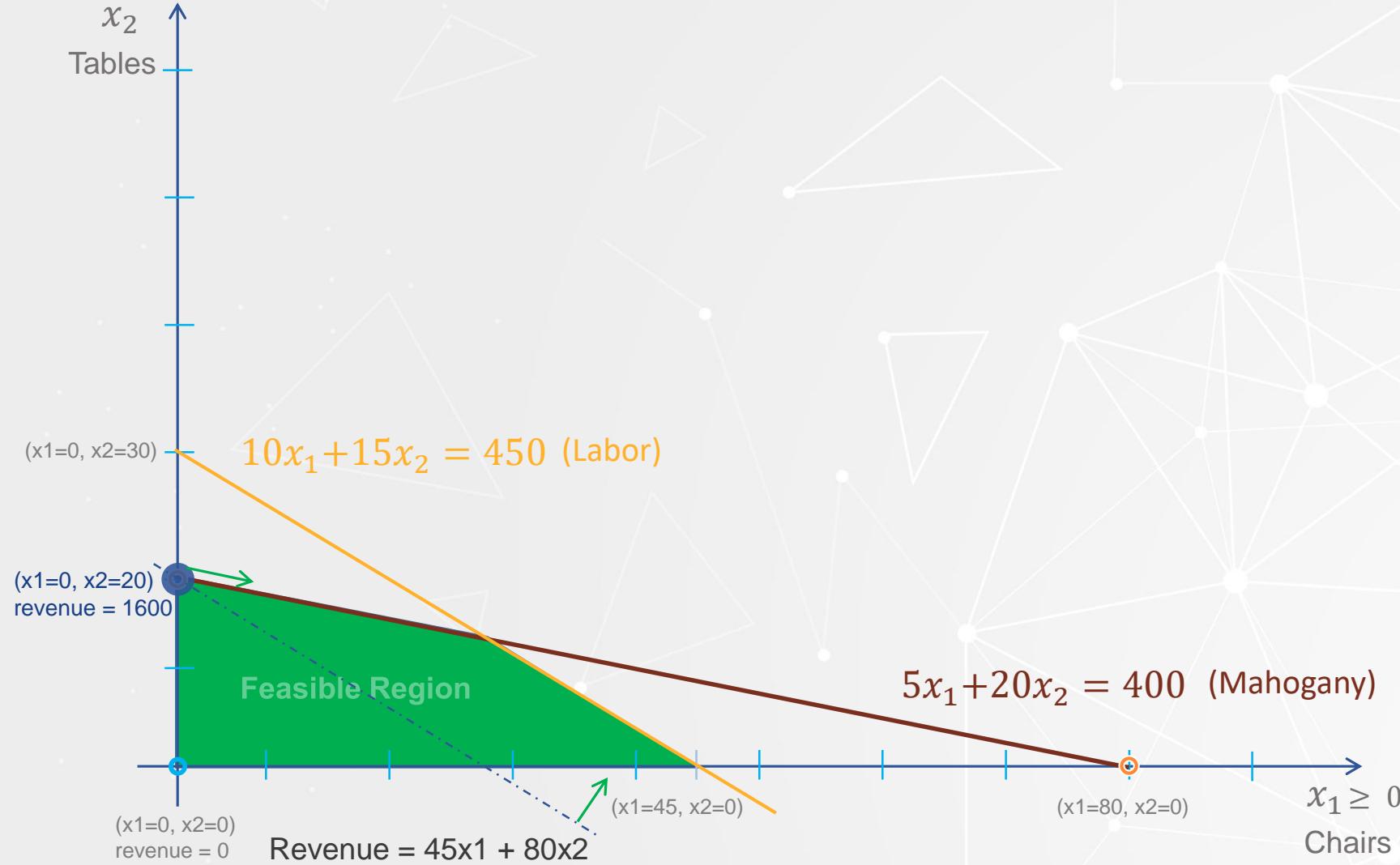


- Can we continue increasing the production tables?
- Production plan ($x_1=0, x_2=21$)

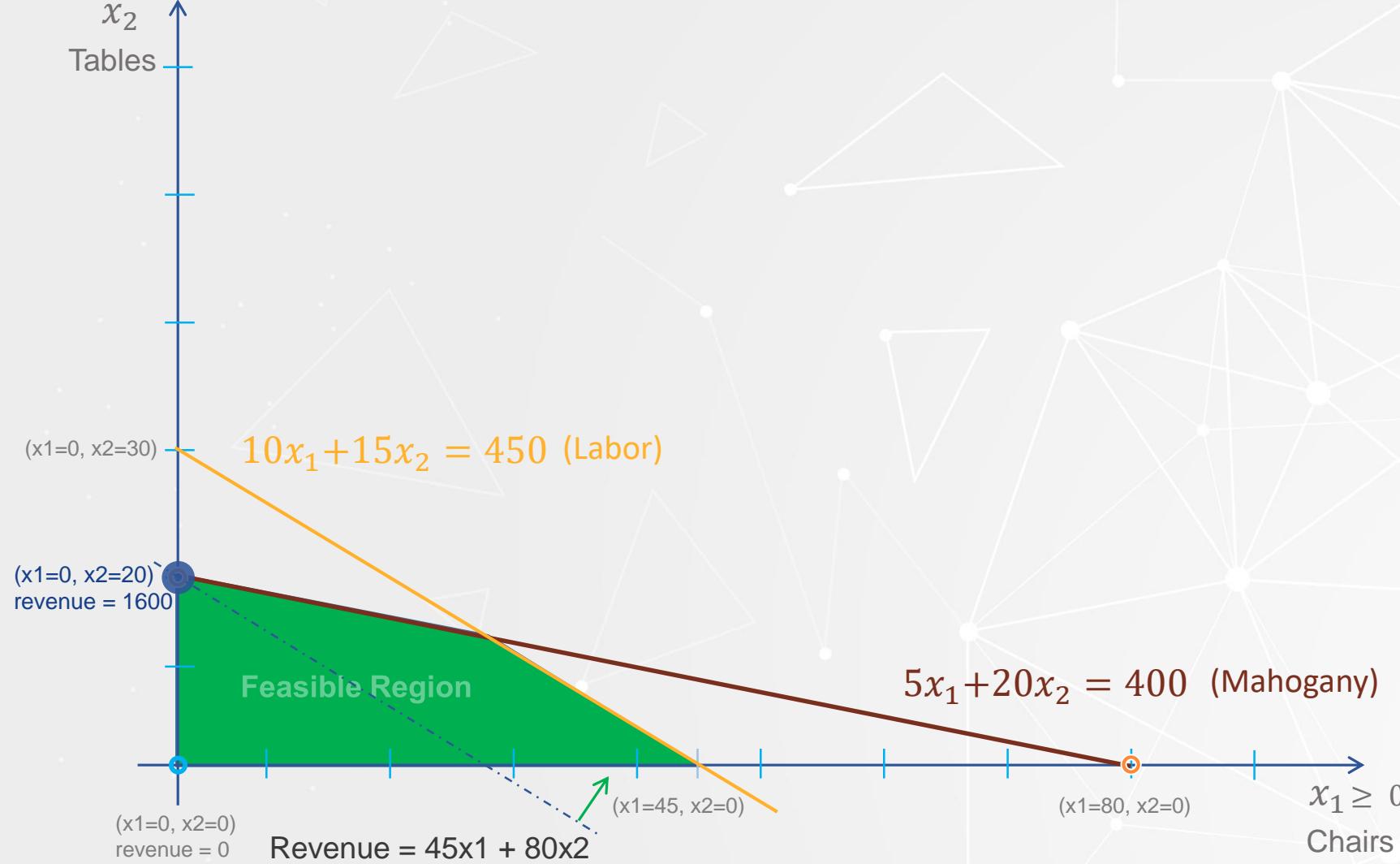
Revenue =
 $45(x_1 = 0) + 80(x_2=21) =$
\$1,680
- Mahogany slack variable
 $h_1 = 400 - 5(x_1=0) - 20(x_2=21) = -20$!!!
Infeasible

Graphical solution of Furniture Problem ... 17

- What else we can do?

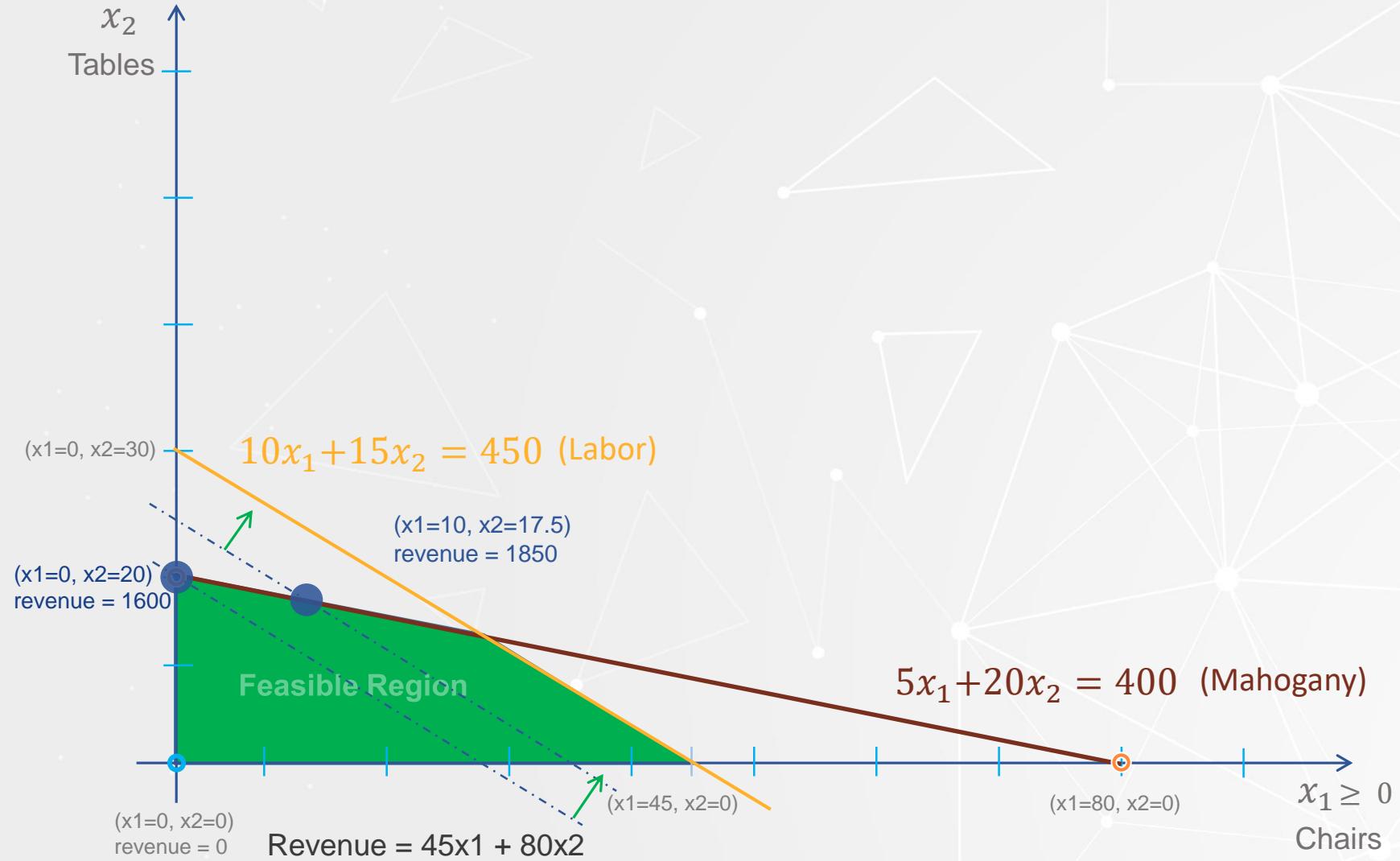


Graphical solution of Furniture Problem ... 17



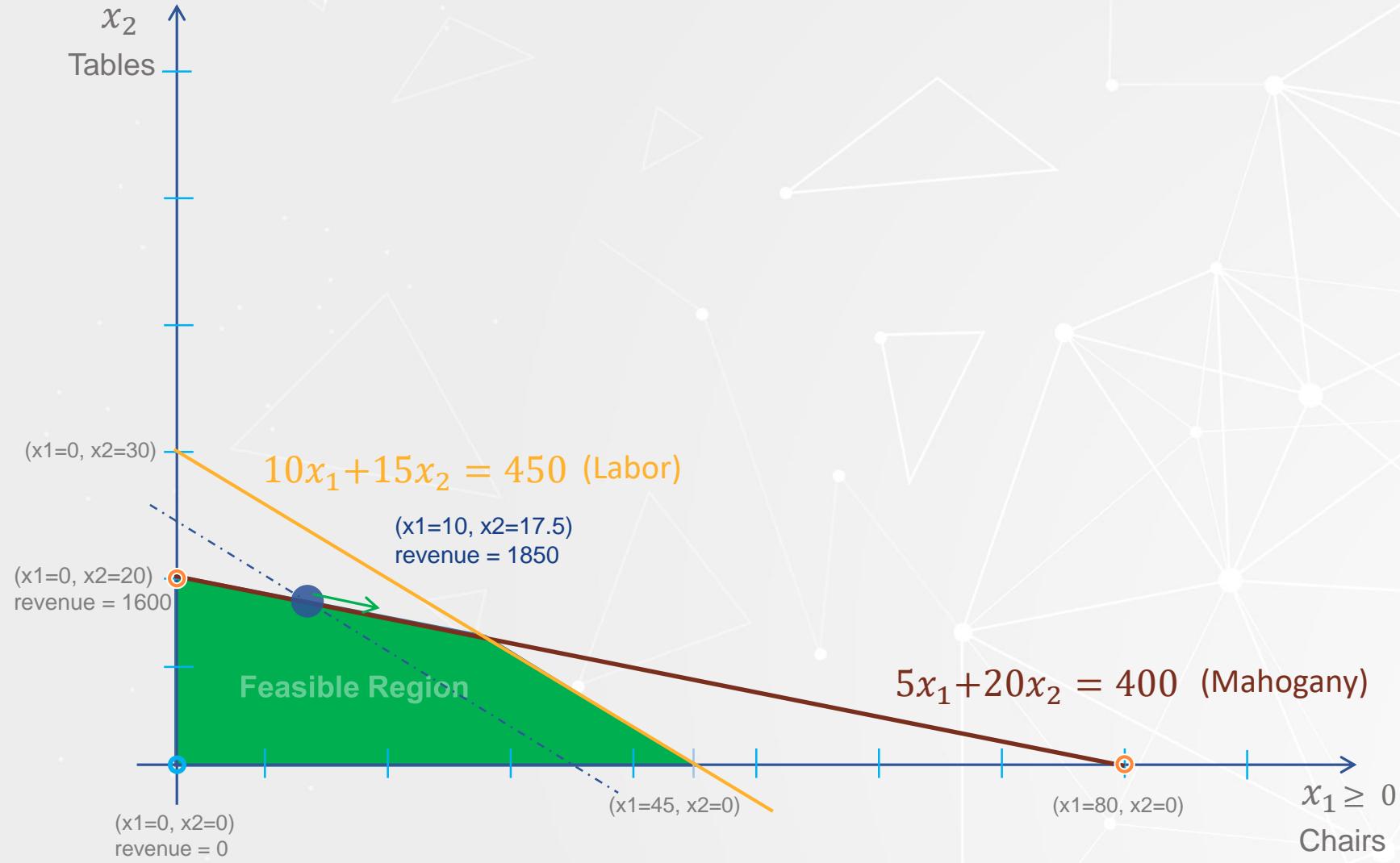
- Mahogany equation
 $x_2 = 20 - (1/4)x_1$

Graphical solution of Furniture Problem ... 18



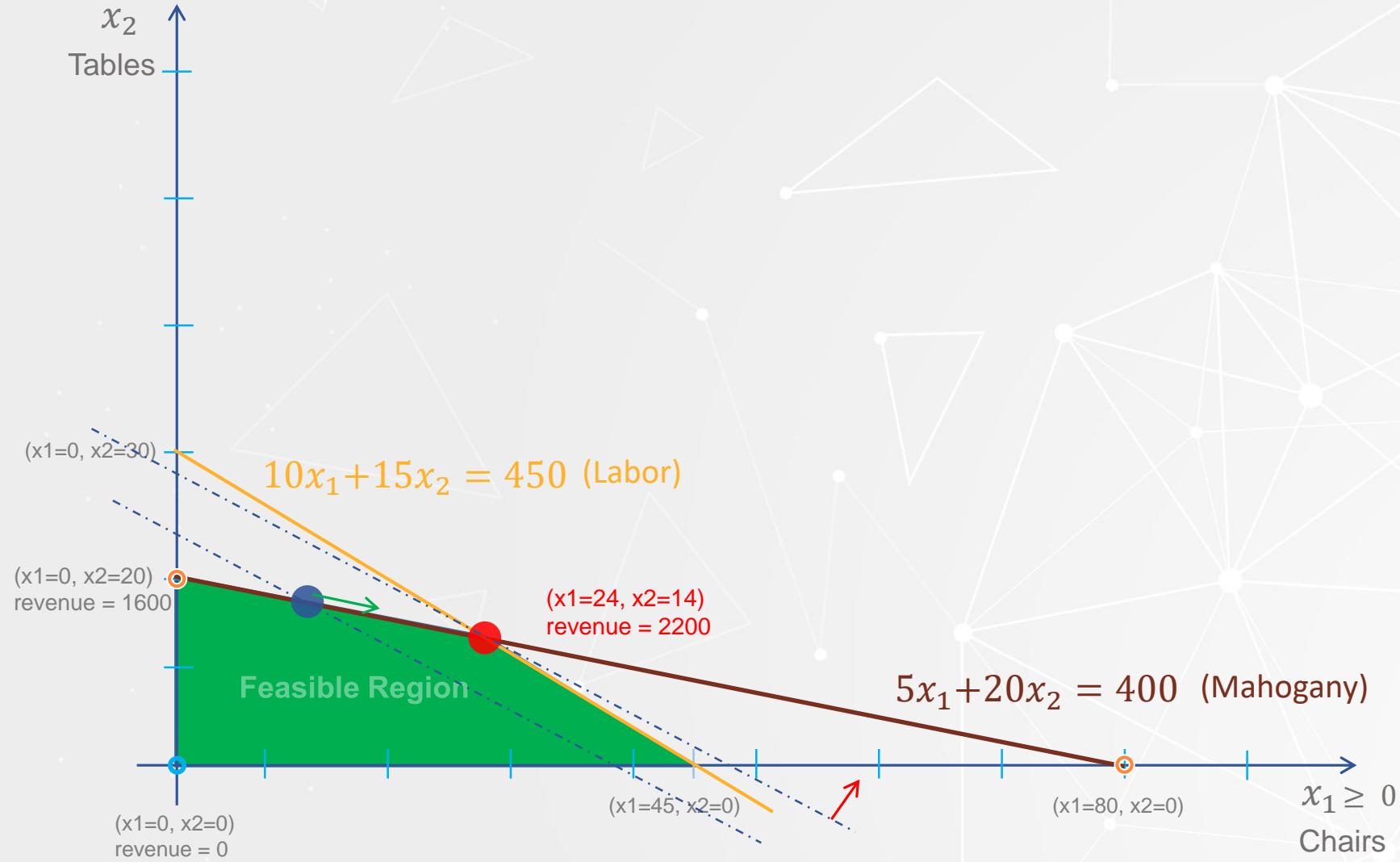
- How much can we keep increasing the production of chairs while keeping the production of tables as high as we can?
 - If we build 10 chairs, then:
 $x_2 =$
 $20 - (1/4)(x_1=10)$
 $= 17.5$ tables.
 - Mahogany slack variable
 $h_1 =$
 $400 - 5(x_1=10) -$
 $20(x_2=17.5) = 0$

Graphical solution of Furniture Problem ... 18



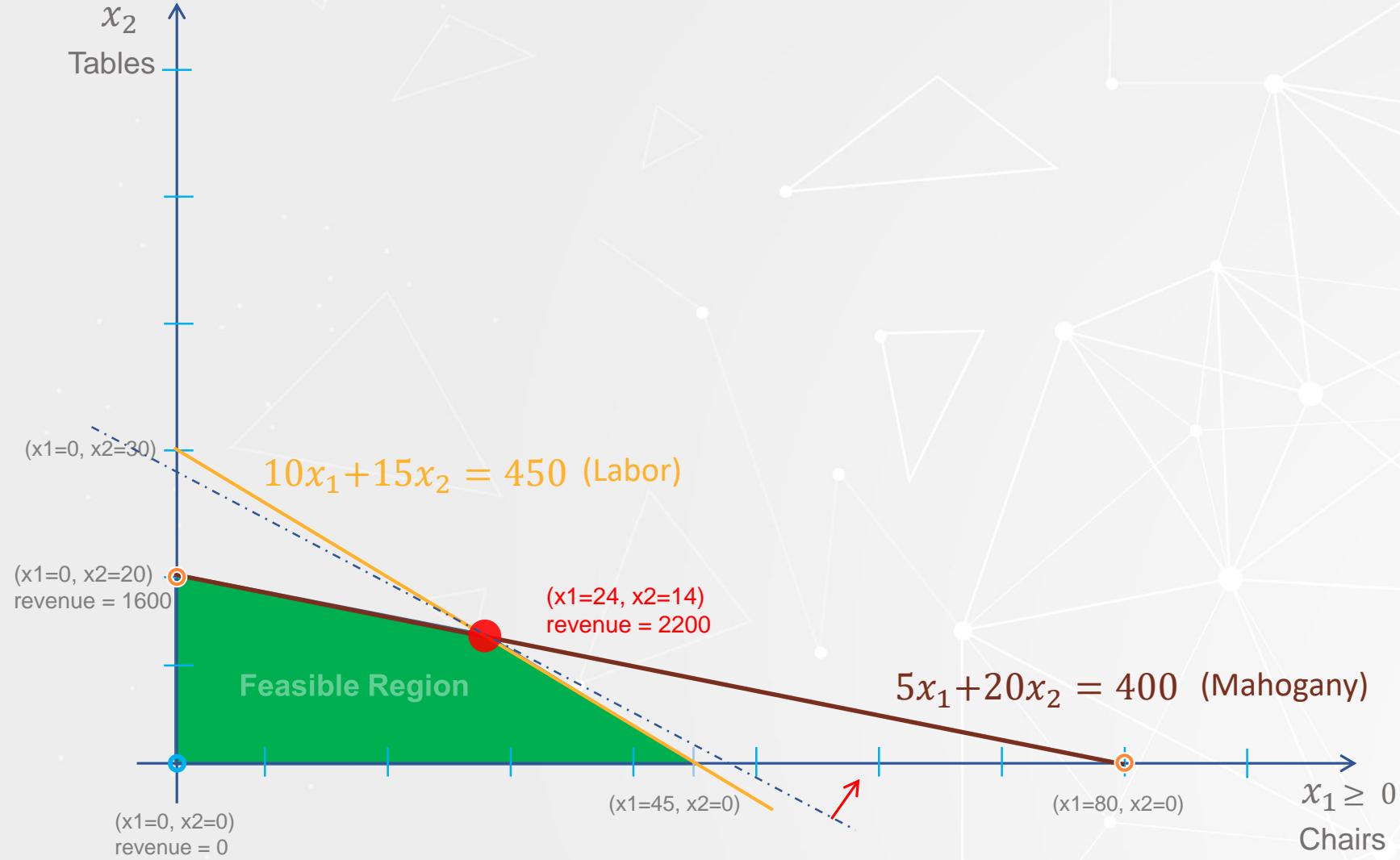
- Production plan ($x_1=10, x_2=17.5$)
- Revenue =
 $45(x_1=10) + 80(x_2=17.5)$
= \$1,850
- Labor slack variable
 $h_2 =$
 $450 - 10(x_1=10) -$
 $15(x_2=17.5) = 87.5$

Graphical solution of Furniture Problem ... 19



- Observe that when the production plan moving along the mahogany equation hits the labor equation, we cannot move any further.
- This happens when the equation that defines the mahogany constraint intersects with the equation that defines the labor constraint. The associated production plan is found by solving these system of equations.
- **STOP**, labor constraint limits production plan.

Graphical solution of Furniture Problem ... 19



Mahogany

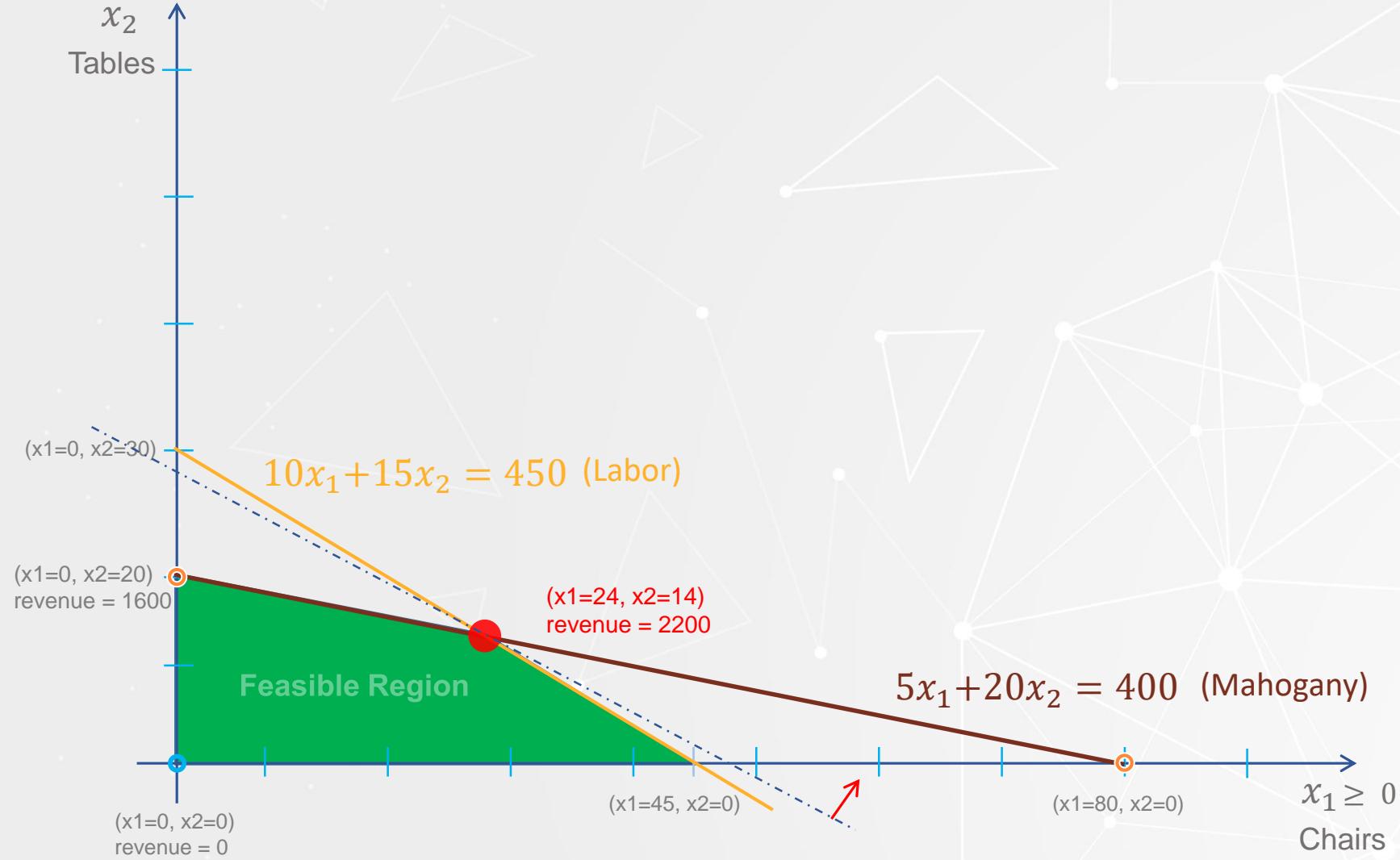
$$5x_1 + 20x_2 = 400$$

Labor

$$10x_1 + 15x_2 = 450$$

- Production Plan:
 - 24 chairs
 - 14 tables.
- Revenue =
 $45(x_1=24) + 80(x_2=14) = \$2,200$

Graphical solution of Furniture Problem ... 19



Production Plan
($x_1 = 24, x_2 = 14$) is
optimal

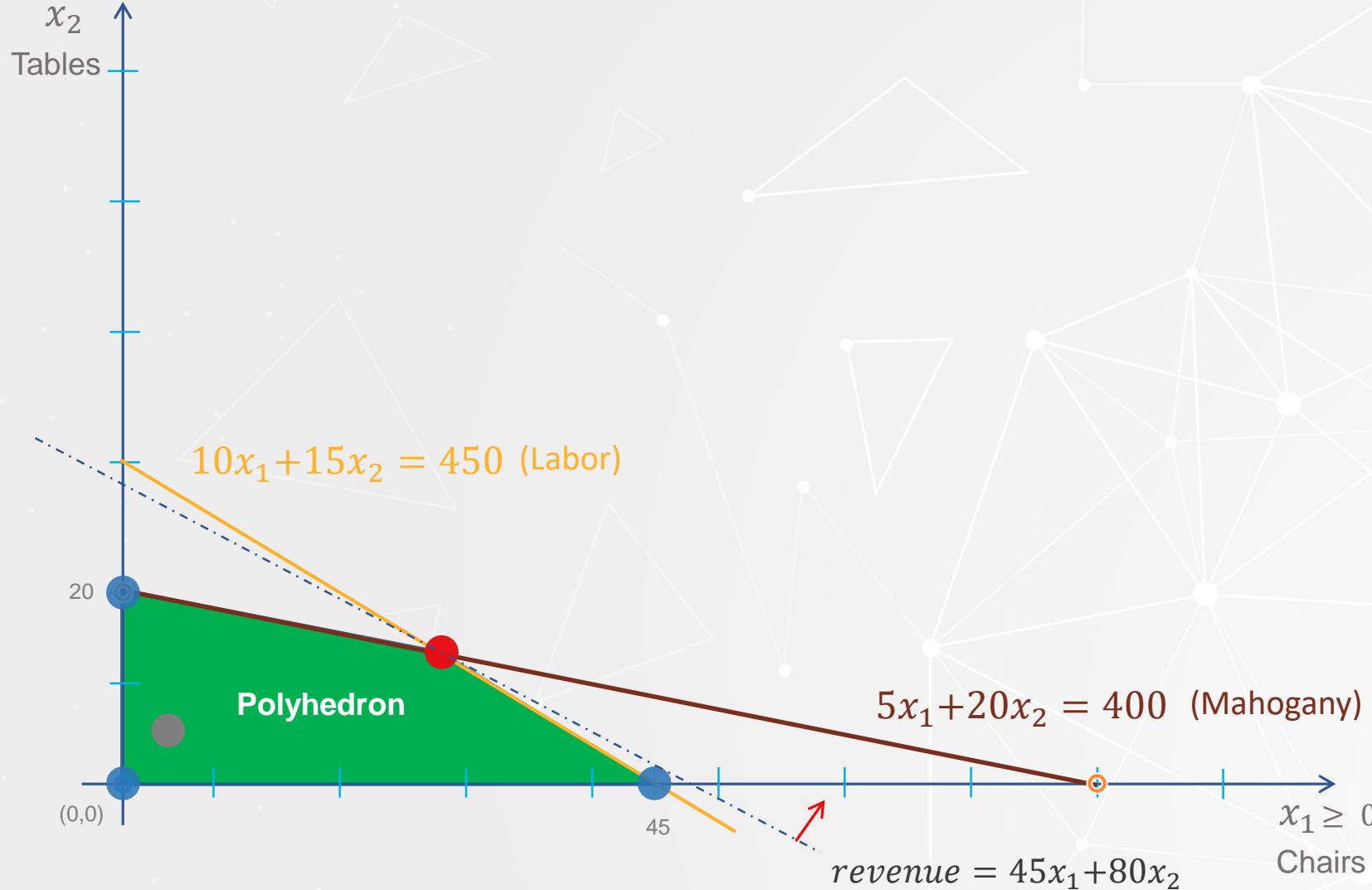
Efficient Production Plan

Mahogany slack variable
 $h_1 = 400 - 5(x_1=24) - 20(x_2=14) = 0$

Labor slack variable
 $h_2 = 450 - 10(x_1=24) - 15(x_2=14) = 0$

Break

Fundamental theorem of linear programming ..



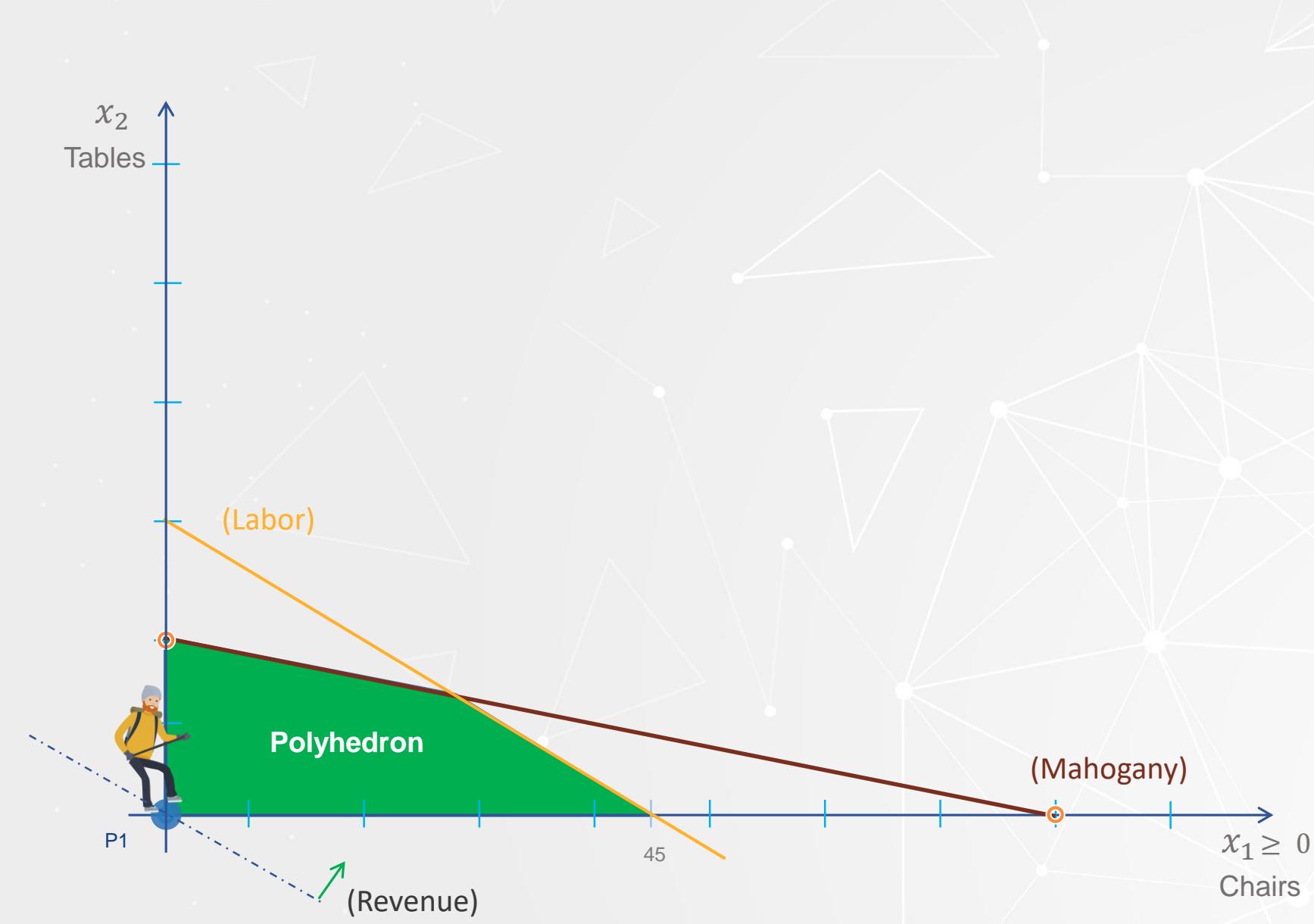
- **Definitions:**

- A **solution** of an LP problem is a set of values of the decision variables that satisfies all the constraints of the problem defined by the polyhedron.
- A **corner point solution** is a vertex of the polyhedron defining the feasible region of the LP problem.
- An **optimal solution** is a solution of the LP problem that cannot be improved.

- **Theorem:**

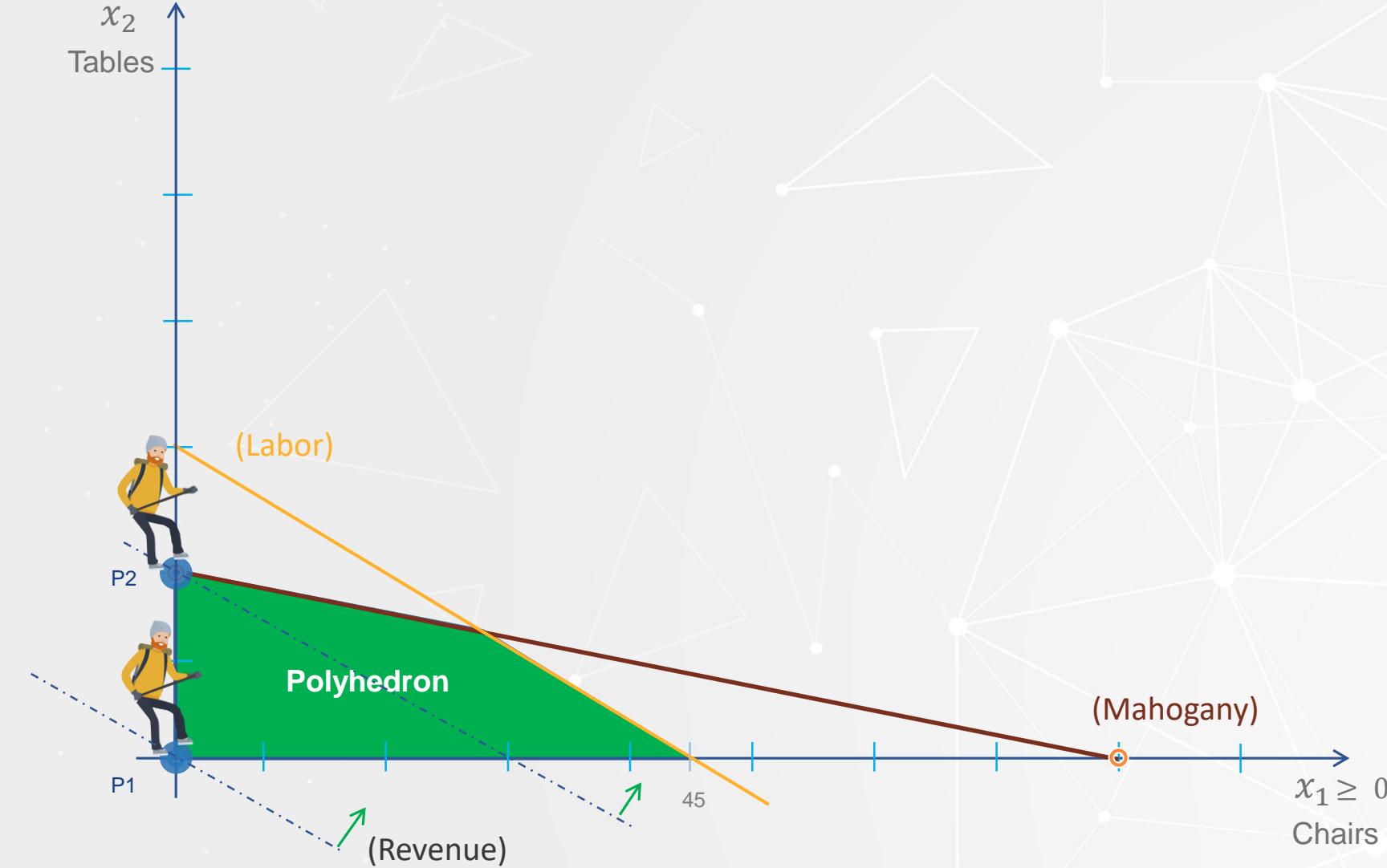
- If a linear programming problem has an optimal solution, there is at least one optimal solution that is a corner point solution.

Fundamental theorem of linear programming .. 2



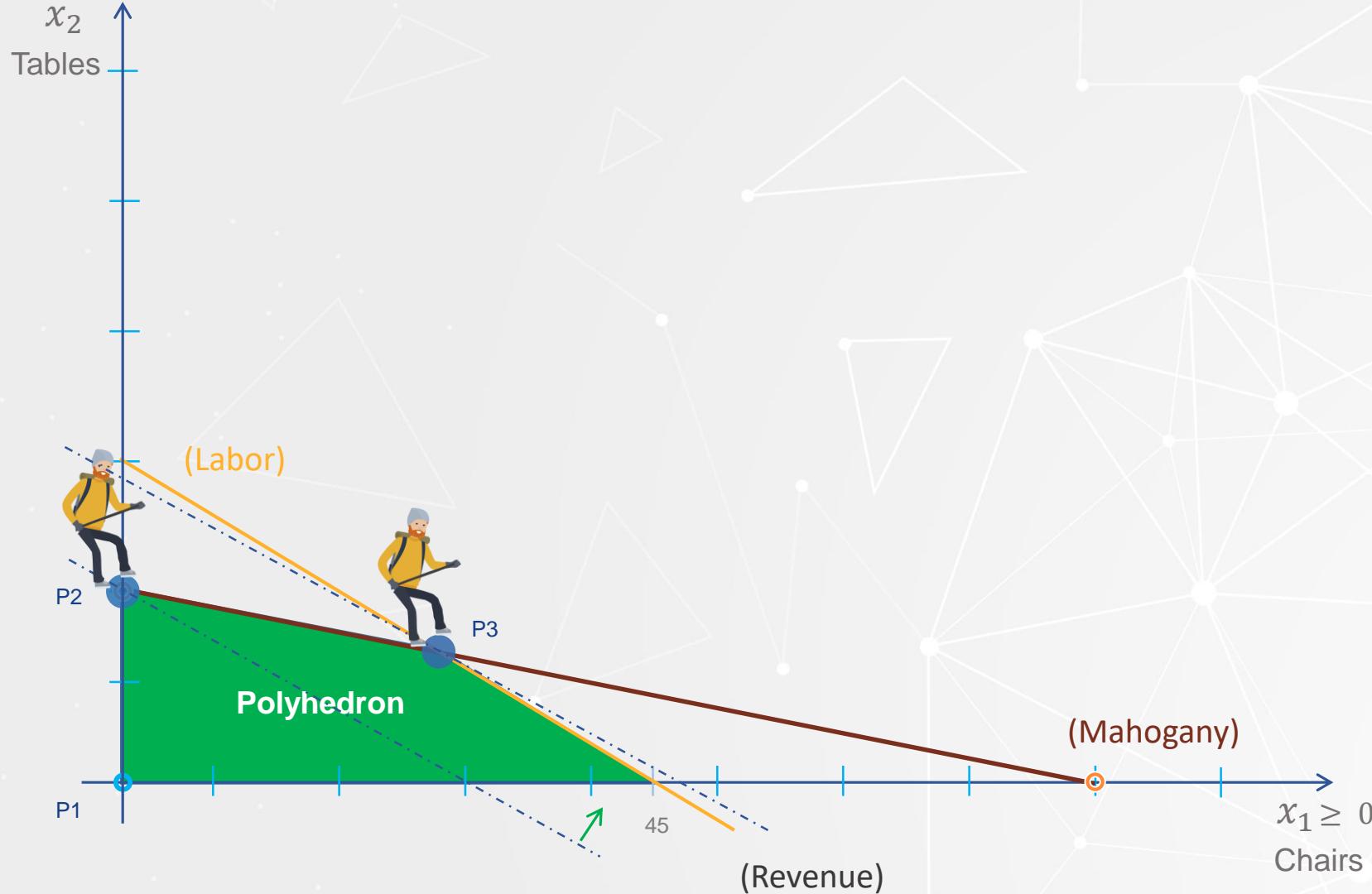
- **Theorem:**
 - If a linear programming problem has an optimal solution, there is at least one optimal solution that is a corner point solution.
 - Initial corner point solution
 $P_1 = (0 \text{ chairs}, 0 \text{ tables})$

Fundamental theorem of linear programming .. 2



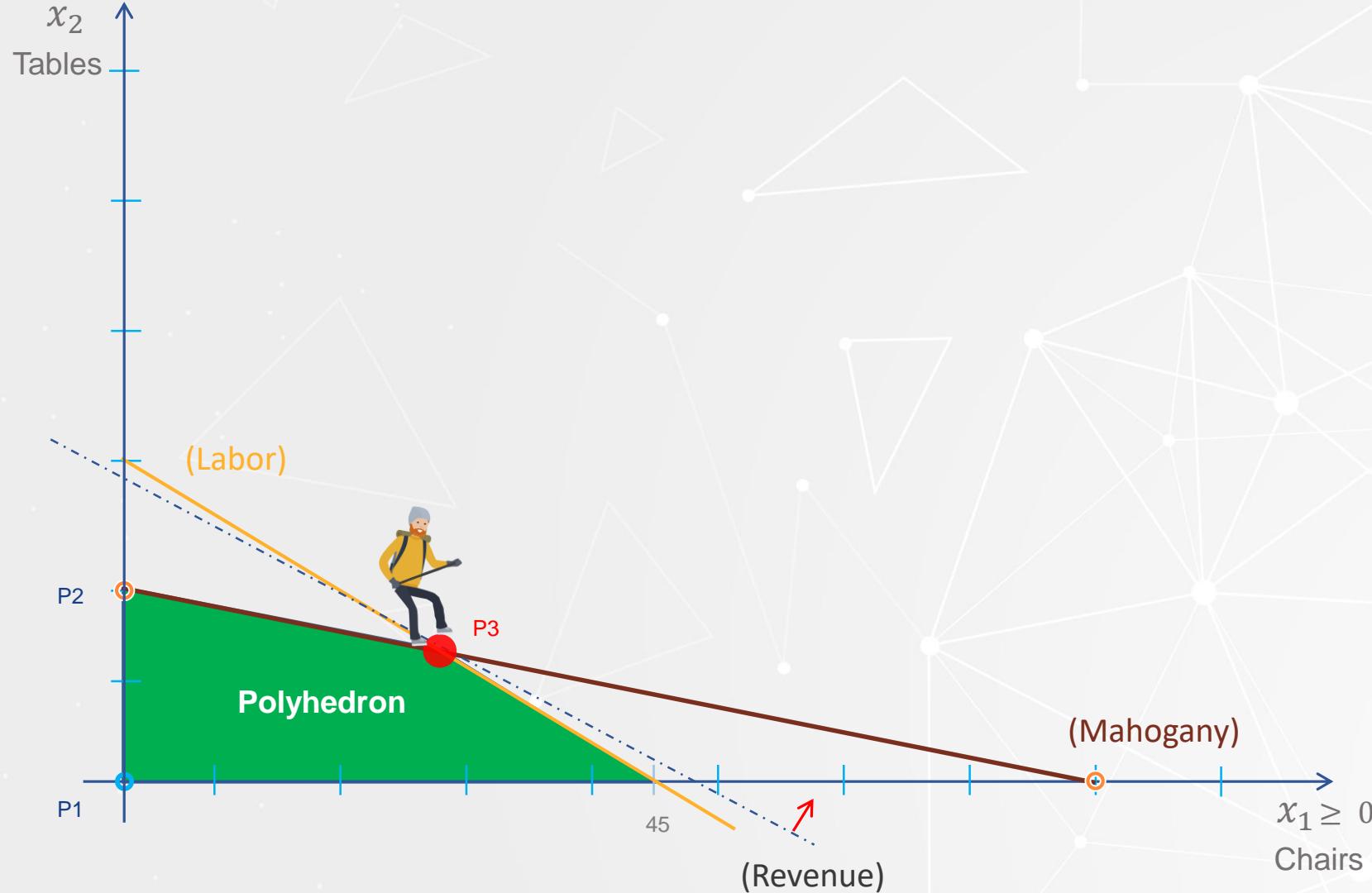
- **Theorem:**
 - If a linear programming problem has an optimal solution, there is at least one optimal solution that is a corner point solution.
 - Initial corner point solution
 $P_1 = (0 \text{ chairs}, 0 \text{ tables})$
 - Adjacent corner point solution
 $P_2 = (0 \text{ chairs}, 20 \text{ tables})$

Fundamental theorem of linear programming .. 2



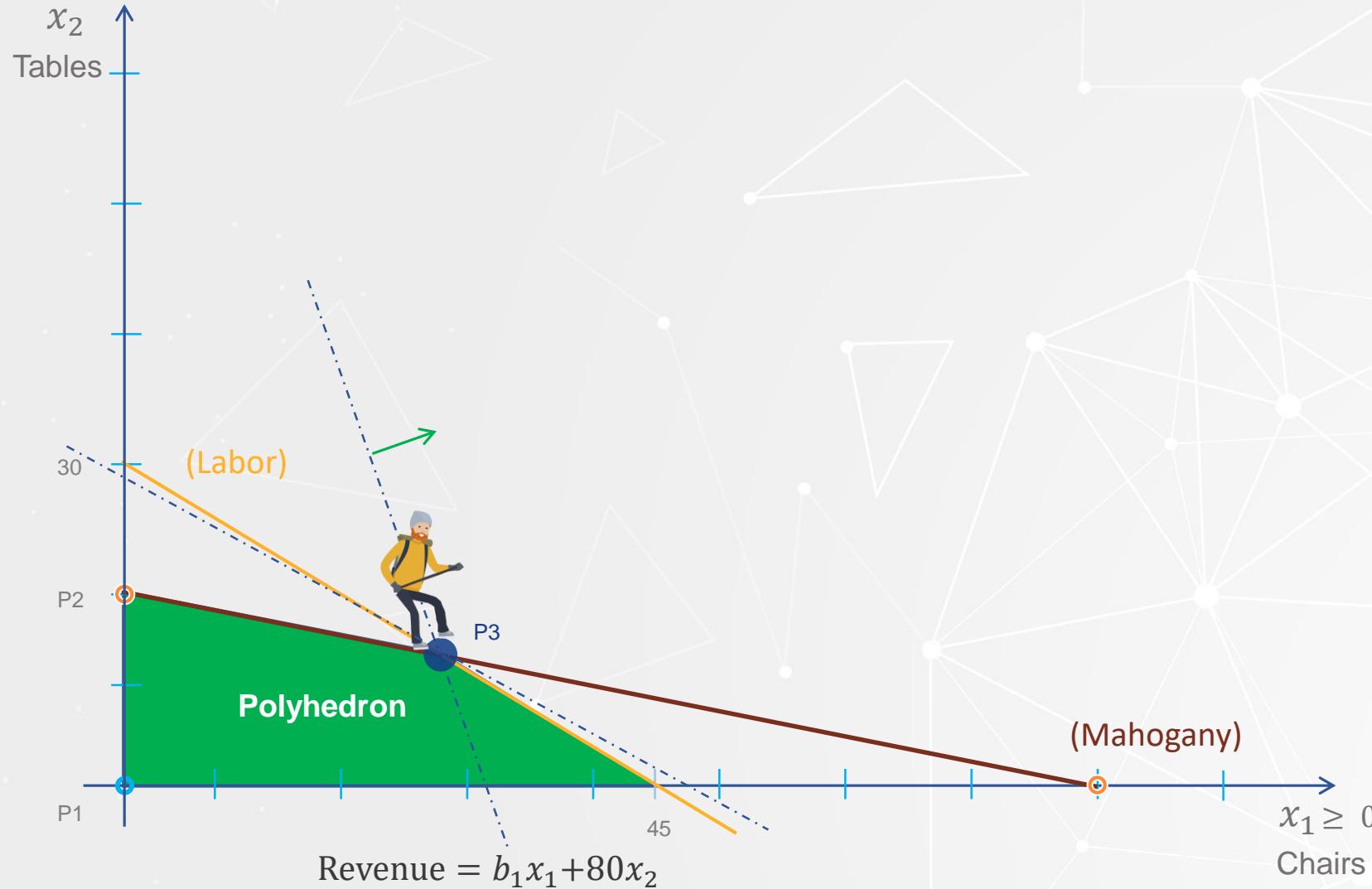
- **Theorem:**
 - If a linear programming problem has an optimal solution, there is at least one optimal solution that is a corner point solution.
 - Initial corner point solution
 $P1 = (0 \text{ chairs}, 0 \text{ tables})$
 - Adjacent corner point solution
 $P2 = (0 \text{ chairs}, 20 \text{ tables})$
 - Adjacent corner point solution
 $P3 = (24 \text{ chairs}, 14 \text{ tables})$

Fundamental theorem of linear programming .. 2



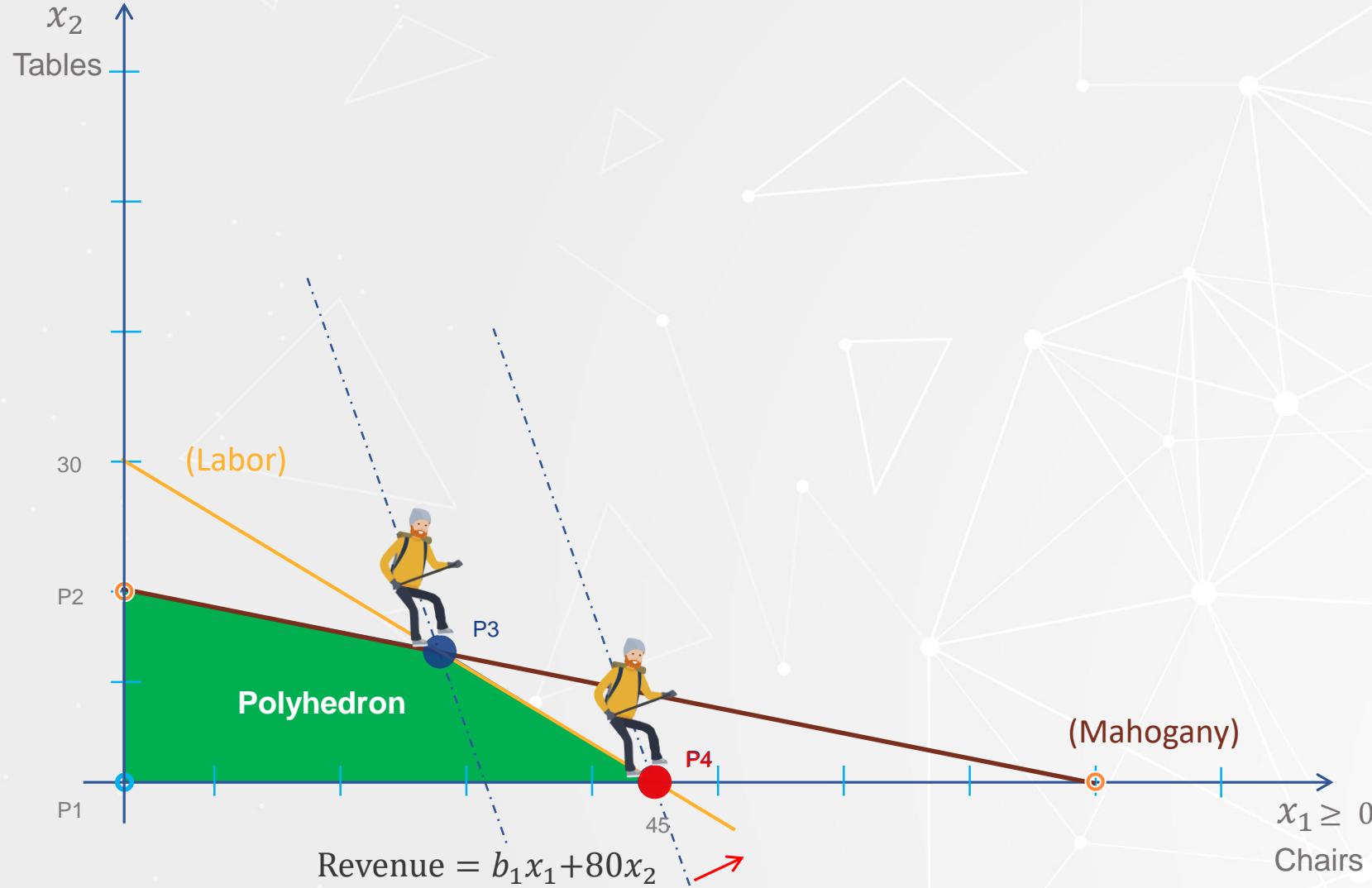
- **Theorem:**
 - If a linear programming problem has an optimal solution, there is at least one optimal solution that is a corner point solution.
 - Initial corner point solution
 $P1 = (0 \text{ chairs}, 0 \text{ tables})$
 - Adjacent corner point solution
 $P2 = (0 \text{ chairs}, 20 \text{ tables})$
 - Adjacent corner point solution
 $P3 = (24 \text{ chairs}, 14 \text{ tables})$

Fundamental theorem of linear programming .. 3



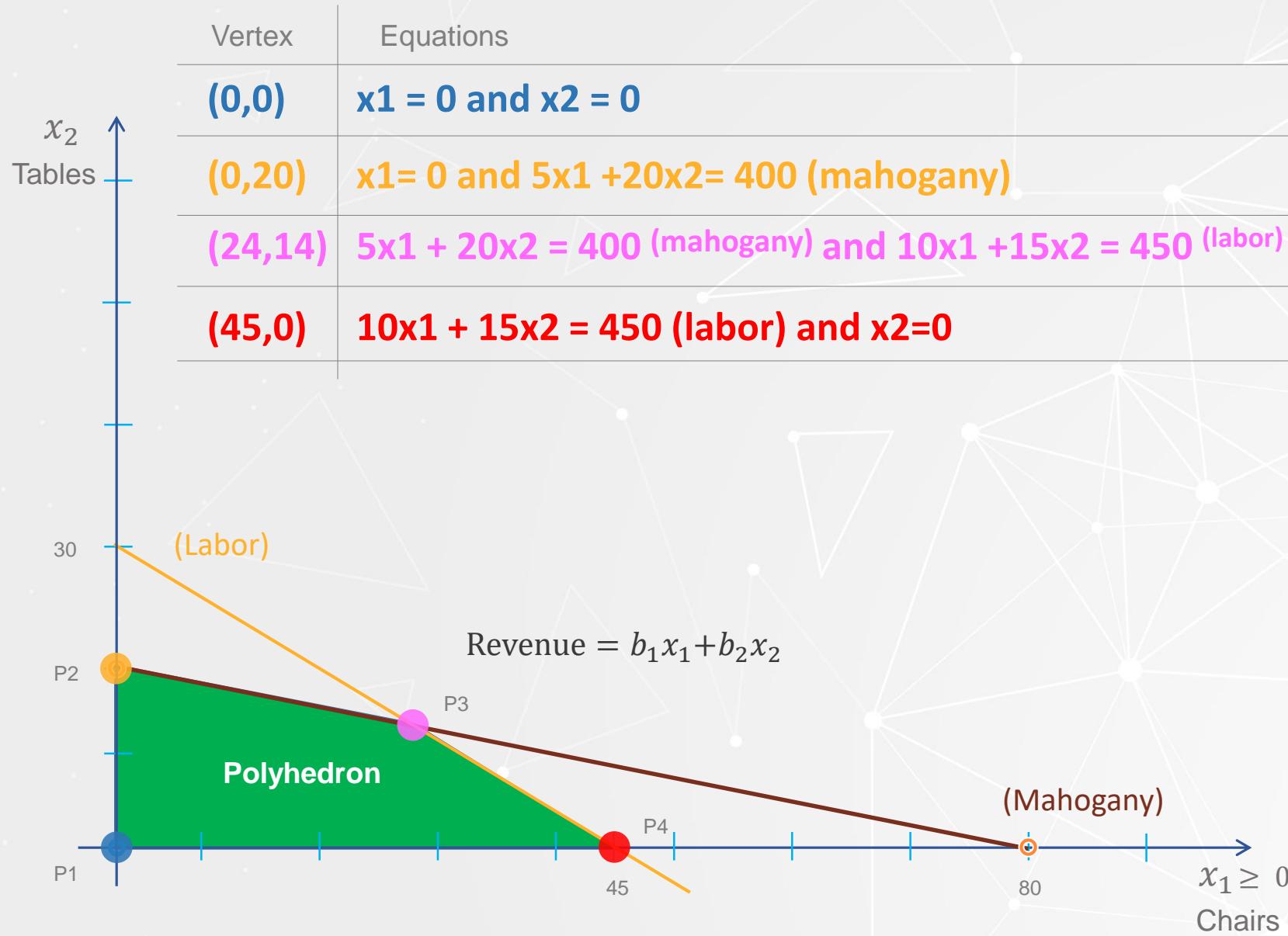
- Significant increase in the price (b_1) of chairs.
- New opportunity to increase revenue

Fundamental theorem of linear programming .. 3



- The new Production Plan $P4 = (45 \text{ chairs}, 0 \text{ tables})$ is optimal

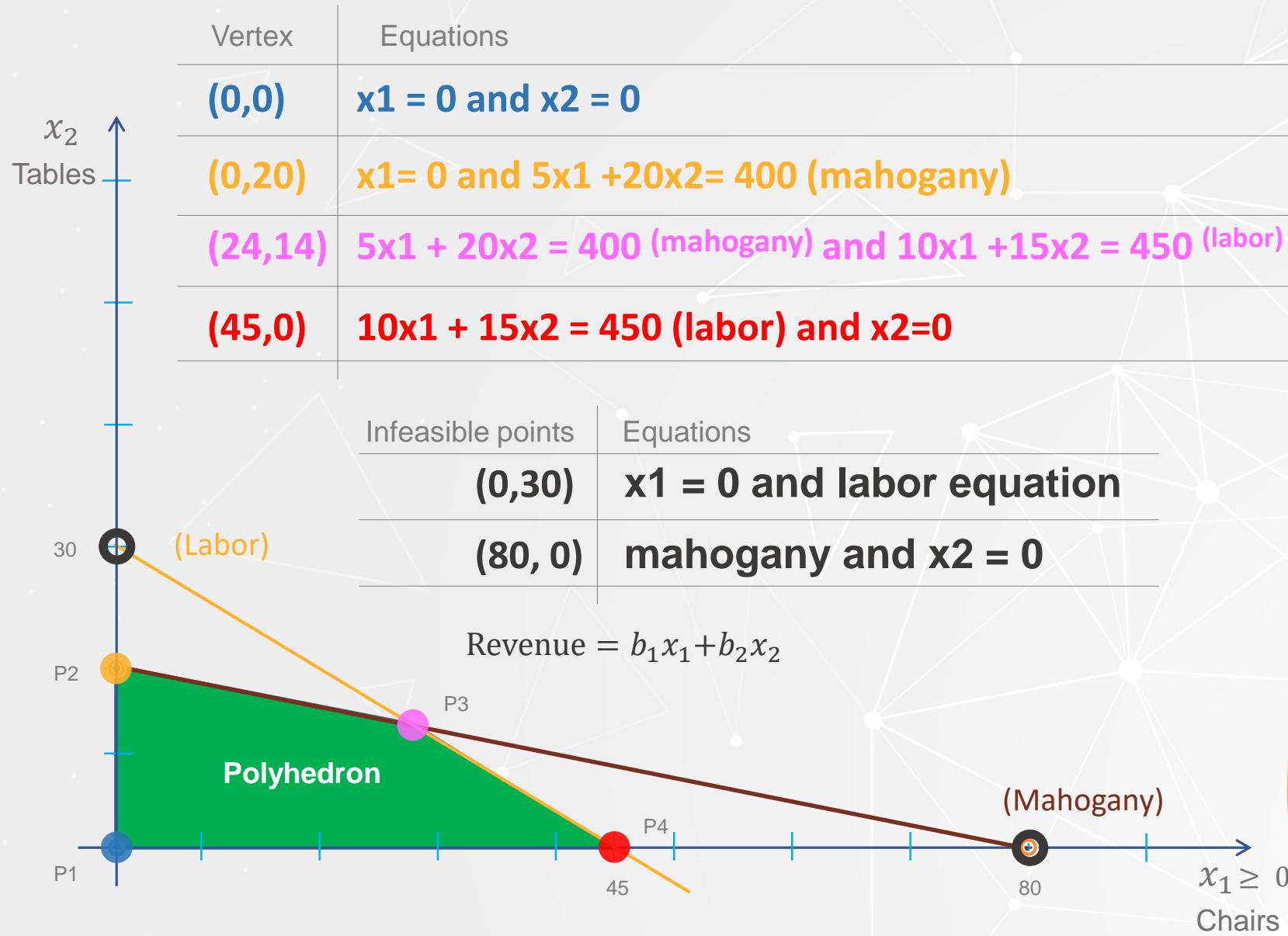
Fundamental theorem of linear programming .. 4



- **Theorem:**
 - If a linear programming problem has an optimal solution, there is at least one optimal solution that is a corner point solution.

Note that the vertices (corner points) of the polyhedron are the solution of a system of equations.

Fundamental theorem of linear programming .. 5



- **Theorem:**
 - If a linear programming problem has an optimal solution, there is at least one optimal solution that is a corner point solution.

Note that the vertices (corner points) of the polyhedron are the solution of a system of equations.

Also, observe that there are other points that are the solutions of a system of equations, although these points are infeasible because they are not vertices of the polyhedron.

Enumeration approach

Enumeration of solutions of the system of equations for the furniture problem

Points of interest	Vertex of the polyhedron	Objective function value. Revenue = $45x_1 + 80x_2$
(0,0)	Yes (feasible)	$0 = 45*0 + 80*0$
(0,20)	Yes (feasible)	$1600 = 45*0 + 80*20$
(24,14)	Yes (feasible)	$2200 = 45*24 + 80*14$ Optimal!!
(45,0)	Yes (feasible)	$2025 = 45*45 + 80*0$
(0,30)	No (infeasible)	$2400 = 45*30 + 80*30$
(80,0)	No (infeasible)	$3600 = 45*80 + 80*0$



$\sim 10^{88}$

**This number is larger
than the number of atoms
($\sim 10^{80}$) in the known
universe !!**

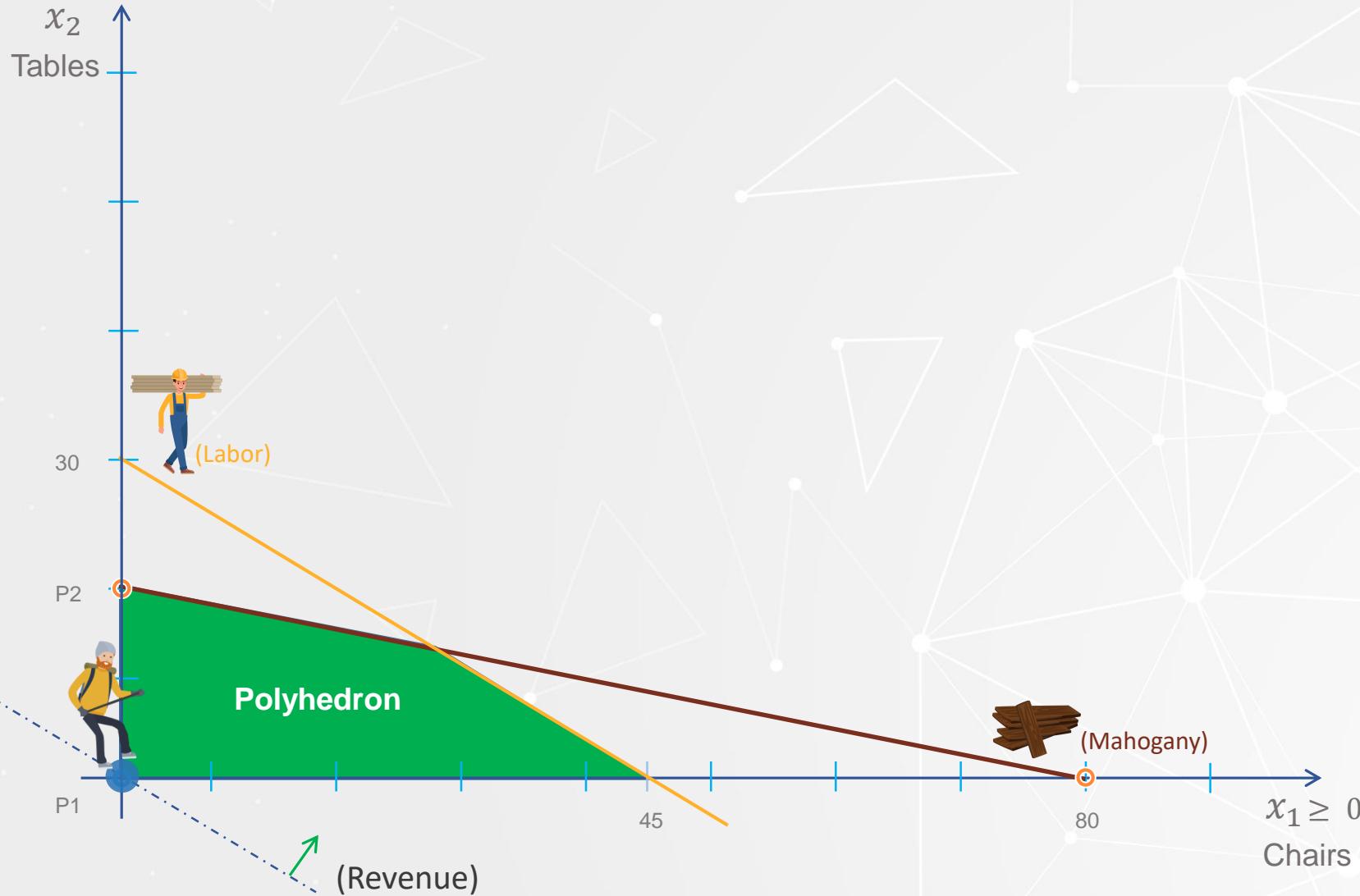
Is there a way that we can traverse vertices in the polyhedron in a more efficient way?



Simplex method

Overview

Linear Programming



Furniture problem LP problem formulation

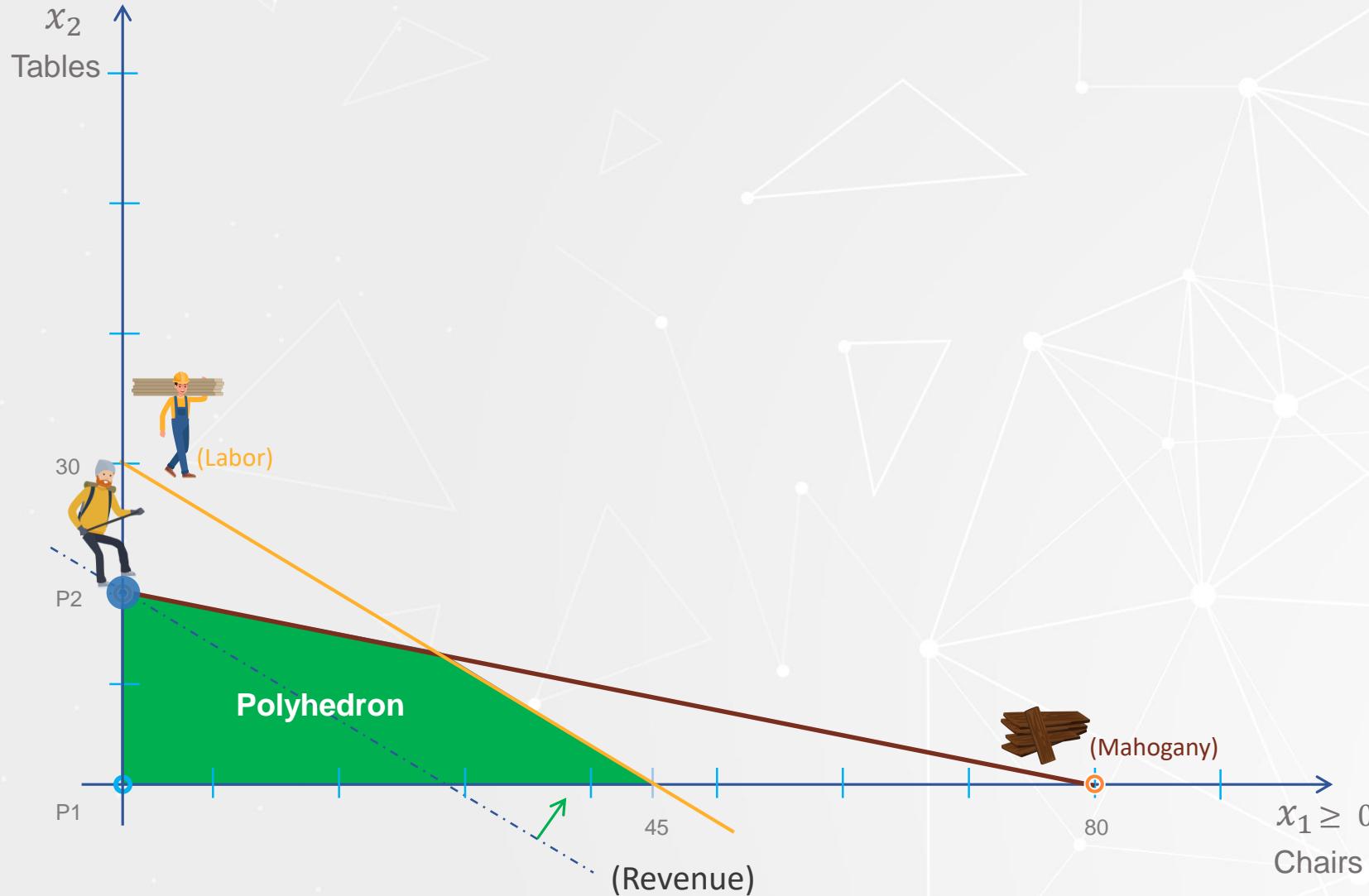
(1.0). Max revenue = $45x_1 + 80x_2$

(2.0) $5x_1 + 20x_2 \leq 400$ Mahogany

(3.0). $10x_1 + 15x_2 \leq 450$ Labor

$x_1, x_2 \geq 0$ Non-negativity

Linear Programming



Furniture problem LP problem formulation

(1.0). $\text{Max revenue} = 45x_1 + 80x_2$

(2.0) $5x_1 + 20x_2 \leq 400$ Mahogany

(3.0). $10x_1 + 15x_2 \leq 450$ Labor

$x_1, x_2 \geq 0$ Non-negativity

Linear Programming



Furniture problem LP problem formulation

(1.0). Max revenue = $45x_1 + 80x_2$

(2.0) $5x_1 + 20x_2 \leq 400$ Mahogany

(3.0). $10x_1 + 15x_2 \leq 450$ Labor

$x_1, x_2 \geq 0$ Non-negativity

Linear Programming/Simplex Method

We call the formulation of an LP problem the **original LP problem**

$$(1.0). \text{ Max revenue} = 45x_1 + 80x_2$$

$$(2.0) \quad 5x_1 + 20x_2 \leq 400 \quad \text{Mahogany}$$

$$(3.0). \quad 10x_1 + 15x_2 \leq 450 \quad \text{Labor}$$

$$x_1, x_2 \geq 0 \quad \text{Non - negativity}$$

Linear Programming/Simplex Method

The original LP problem in a **standard form** is:

$$(1.0). \text{ Max revenue} = 45x_1 + 80x_2$$

$$(2.0) \quad 5x_1 + 20x_2 + h_1 = 400 \quad \text{mahogany}$$

$$(3.0). \quad 10x_1 + 15x_2 + h_2 = 450 \quad \text{labor}$$

$$x_1, x_2, h_1, h_2 \geq 0 \quad \text{Non - negativity}$$

Original LP problem.

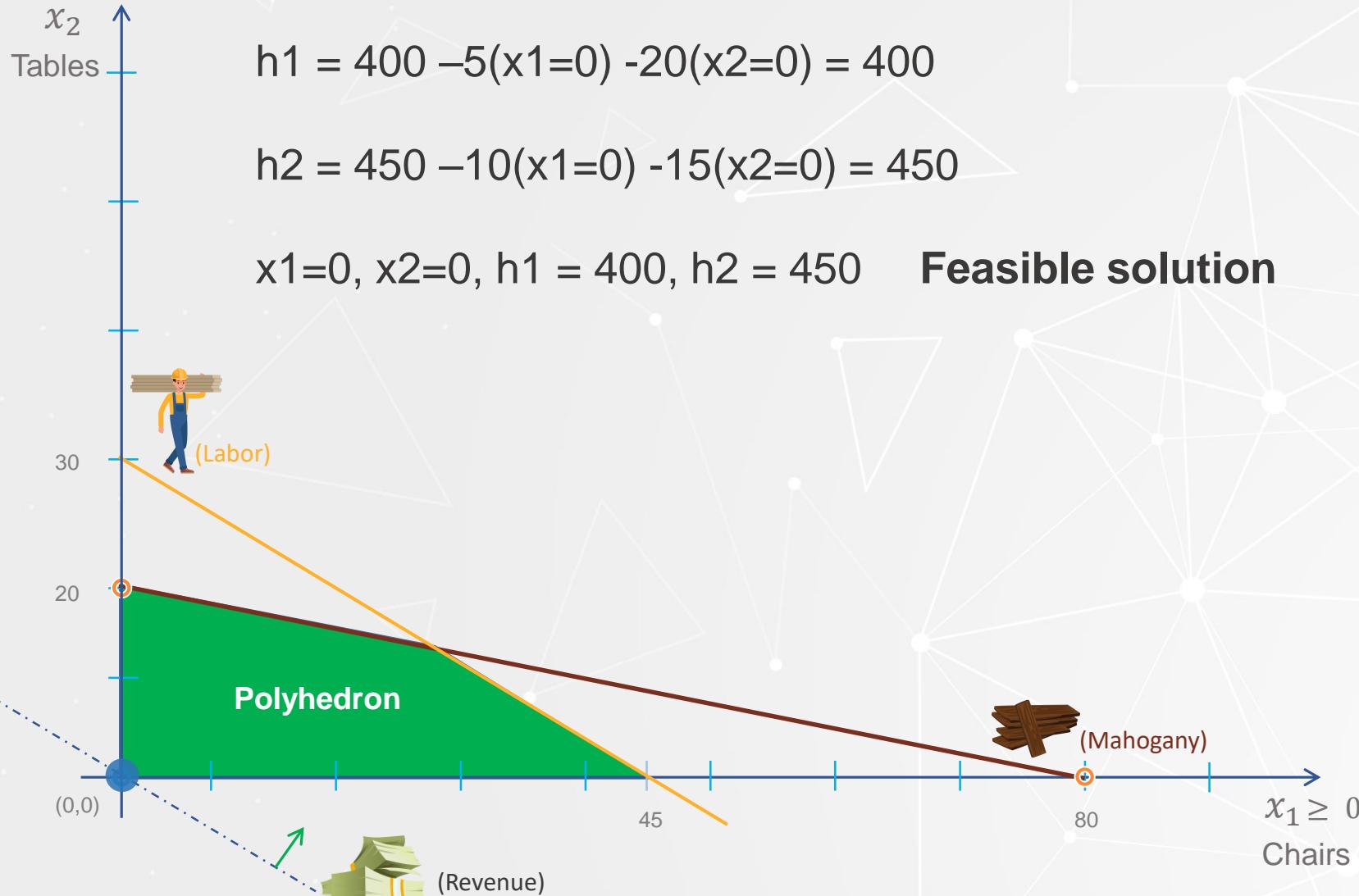
$$(1.0). \text{ Max revenue} = 45x_1 + 80x_2$$

$$(2.0) \quad 5x_1 + 20x_2 \leq 400 \quad \text{mahogany}$$

$$(3.0). \quad 10x_1 + 15x_2 \leq 450 \quad \text{labor}$$

$$x_1, x_2 \geq 0 \quad \text{Non - negativity}$$

Linear Programming/Simplex Method .. 2



Furniture problem standard form

(1.0). Max revenue = $45x_1 + 80x_2$

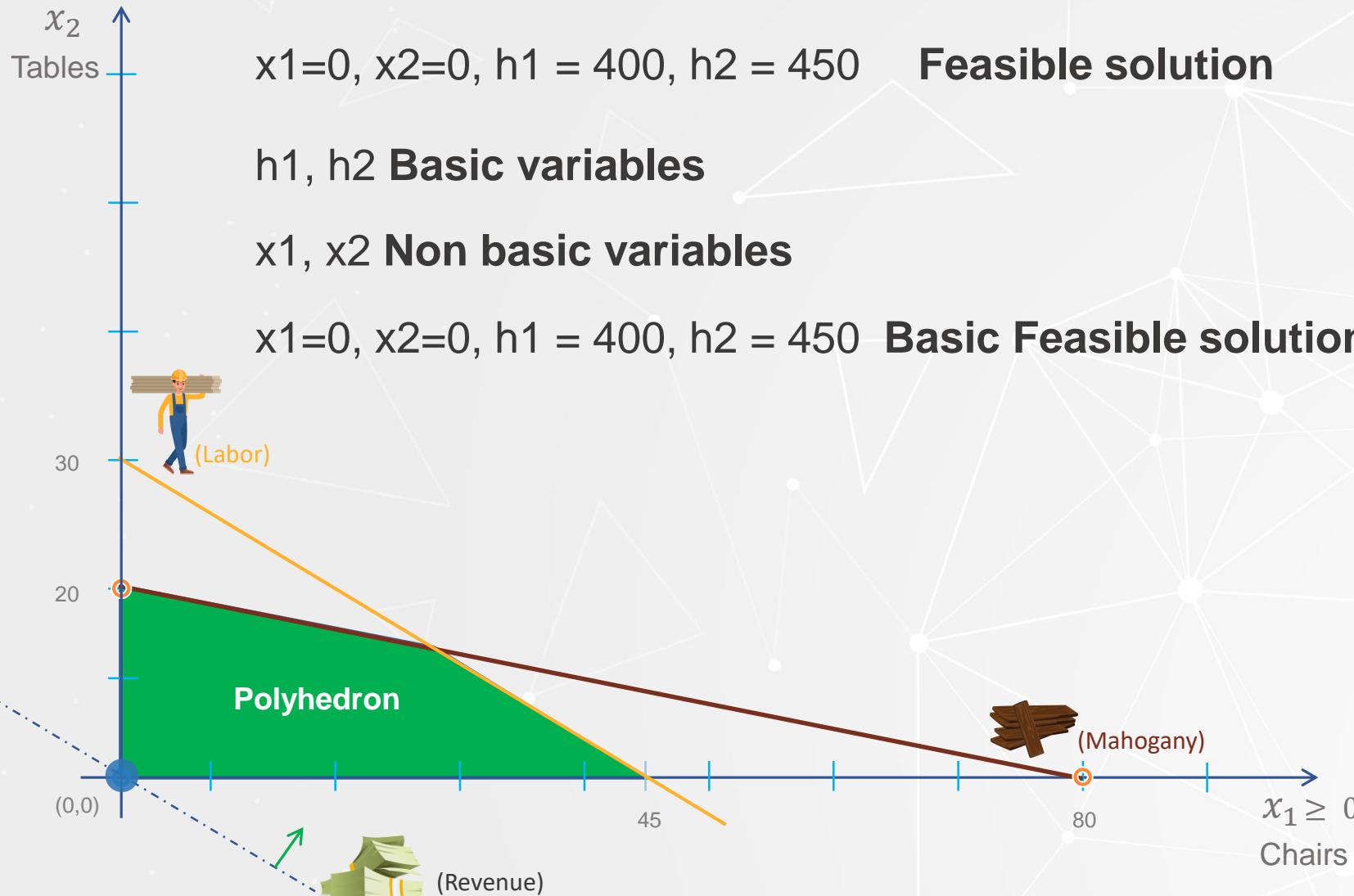
(2.0) $5x_1 + 20x_2 + h_1 = 400$ Mahogany

(3.0). $10x_1 + 15x_2 + h_2 = 450$ Labor

$x_1, x_2, h_1, h_2 \geq 0$ Non-negativity

$(x_1=0, x_2=0)$ initial solution
Revenue = 0

Linear Programming/Simplex Method .. 2

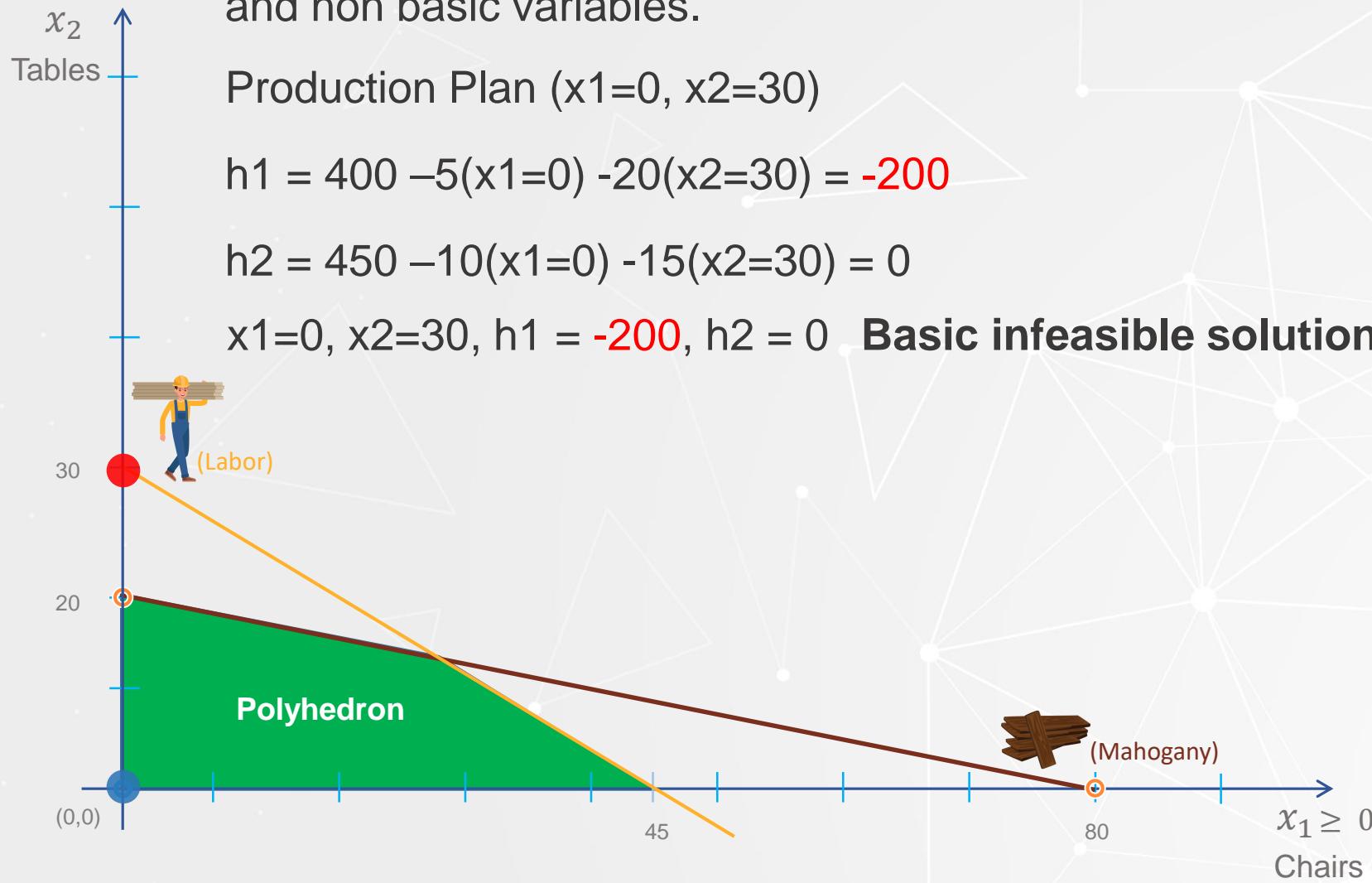


Furniture problem standard form

(1.0). Max revenue = $45x_1 + 80x_2$
(2.0) $5x_1 + 20x_2 + h_1 = 400$ Mahogany
(3.0). $10x_1 + 15x_2 + h_2 = 450$ Labor
 $x_1, x_2, h_1, h_2 \geq 0$ Non-negativity

Linear Programming/Simplex Method .. 3

A basic solution is defined by the values of the basic and non basic variables.



Furniture problem standard form

$$(1.0). \text{ Max revenue} = 45x_1 + 80x_2$$

$$(2.0) \quad 5x_1 + 20x_2 + h_1 = 400 \quad \text{Mahogany}$$

$$(3.0). \quad 10x_1 + 15x_2 + h_2 = 450 \quad \text{Labor}$$

$$x_1, x_2, h_1, h_2 \geq 0 \quad \text{Non-negativity}$$

Linear Programming/Simplex Method .. 4

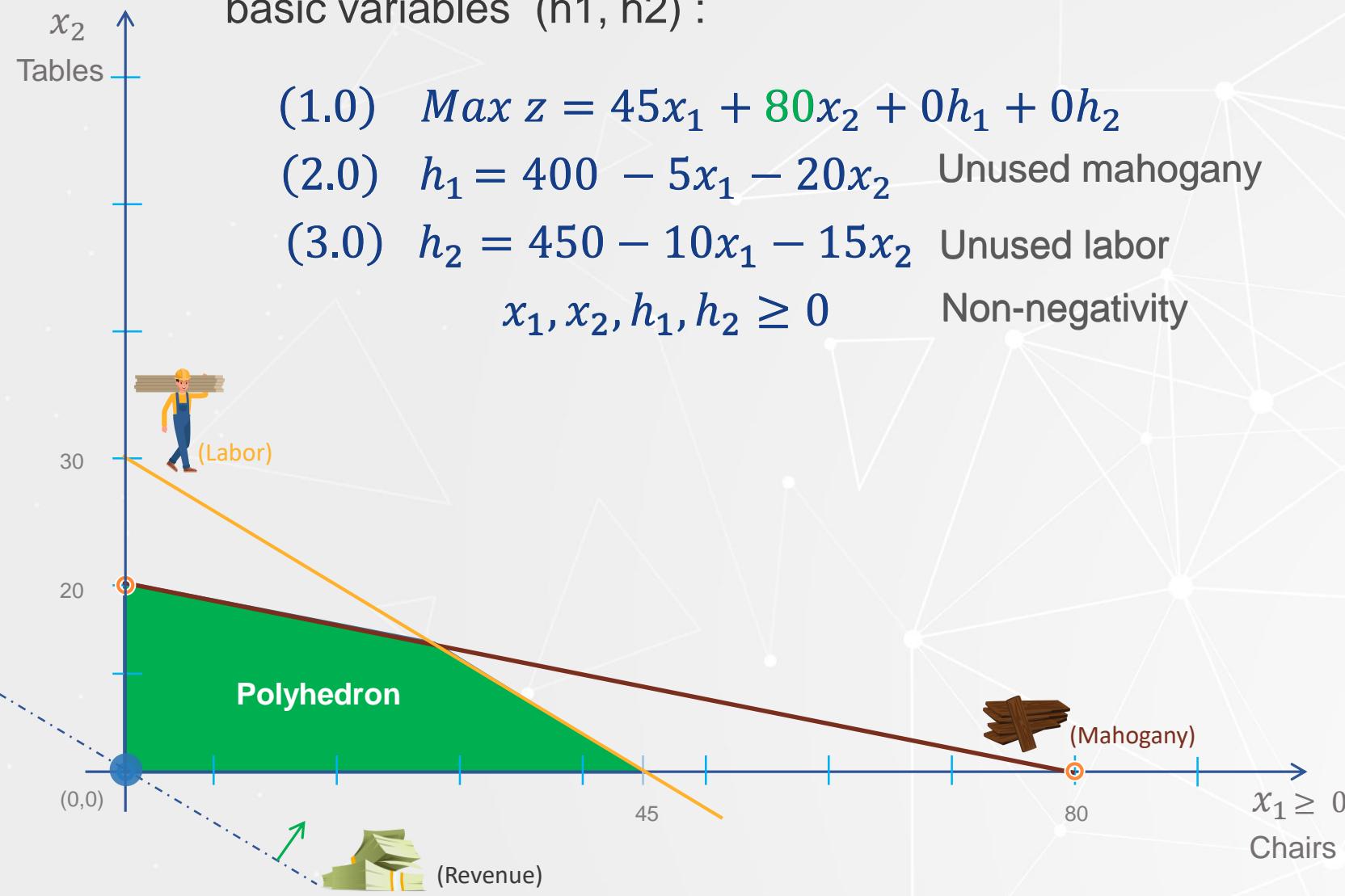
LP problem in a **canonical form** with respect to the basic variables (h_1, h_2) :

$$(1.0) \quad \text{Max } z = 45x_1 + 80x_2 + 0h_1 + 0h_2$$

$$(2.0) \quad h_1 = 400 - 5x_1 - 20x_2 \quad \text{Unused mahogany}$$

$$(3.0) \quad h_2 = 450 - 10x_1 - 15x_2 \quad \text{Unused labor}$$

$$x_1, x_2, h_1, h_2 \geq 0 \quad \text{Non-negativity}$$



Furniture problem standard form

$$(1.0). \quad \text{Max revenue} = 45x_1 + 80x_2$$

$$(2.0) \quad 5x_1 + 20x_2 + h_1 = 400 \quad \text{Mahogany}$$

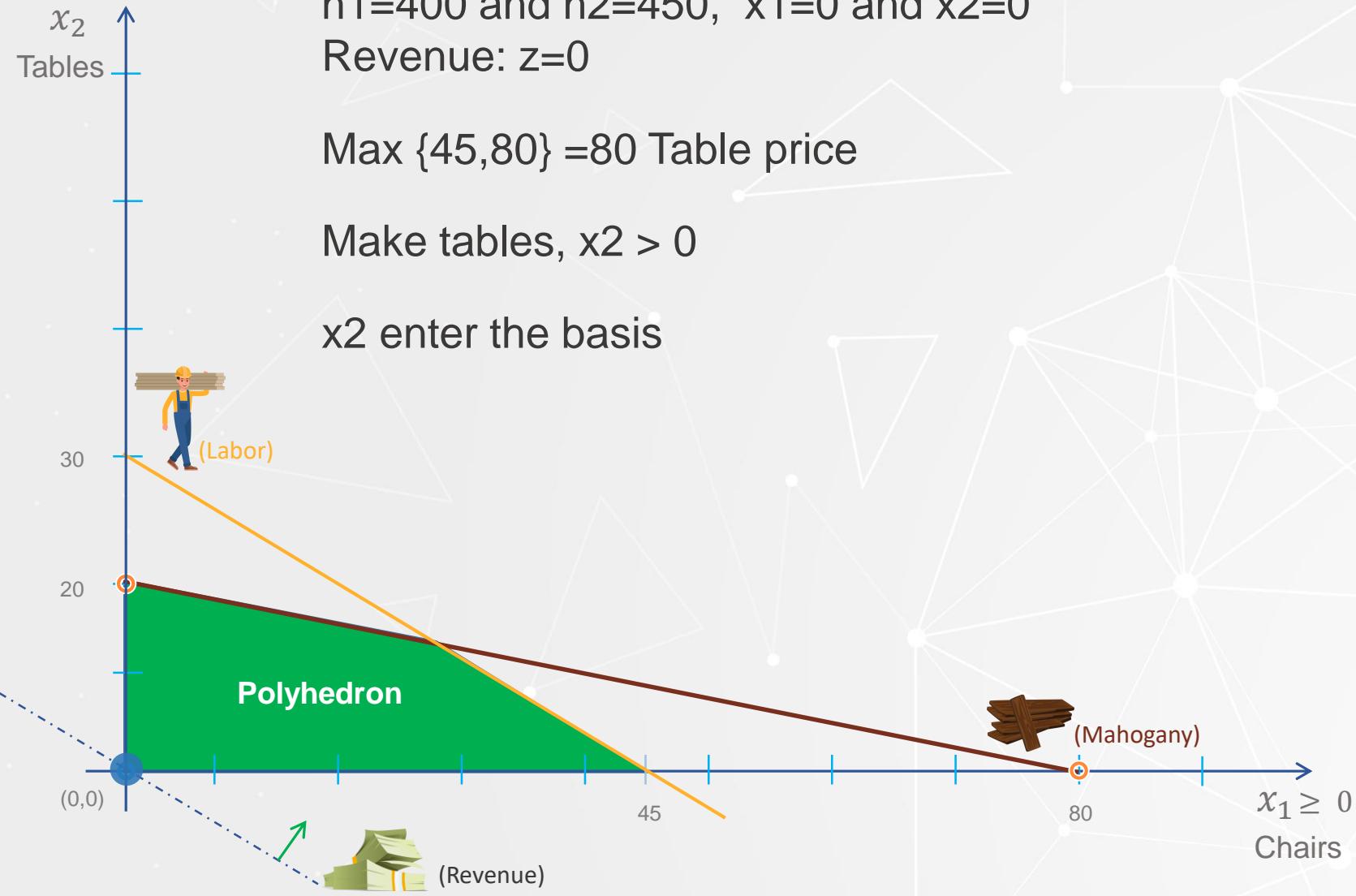
$$(3.0). \quad 10x_1 + 15x_2 + h_2 = 450 \quad \text{Labor}$$

$$x_1, x_2, h_1, h_2 \geq 0 \quad \text{Non-negativity}$$

Reduced costs:

Objective function coefficients of non basic variables (x_1, x_2)

Linear Programming/Simplex Method .. 5



Furniture problem **canonical form**

- (1.0) $\text{Max } z = 45x_1 + 80x_2 + 0h_1 + 0h_2$
 - (2.0) $h_1 = 400 - 5x_1 - 20x_2$ Mahogany
 - (3.0) $h_2 = 450 - 10x_1 - 15x_2$ Labor
- $x_1, x_2, h_1, h_2 \geq 0$ Non-negativity

Linear Programming/Simplex Method .. 5

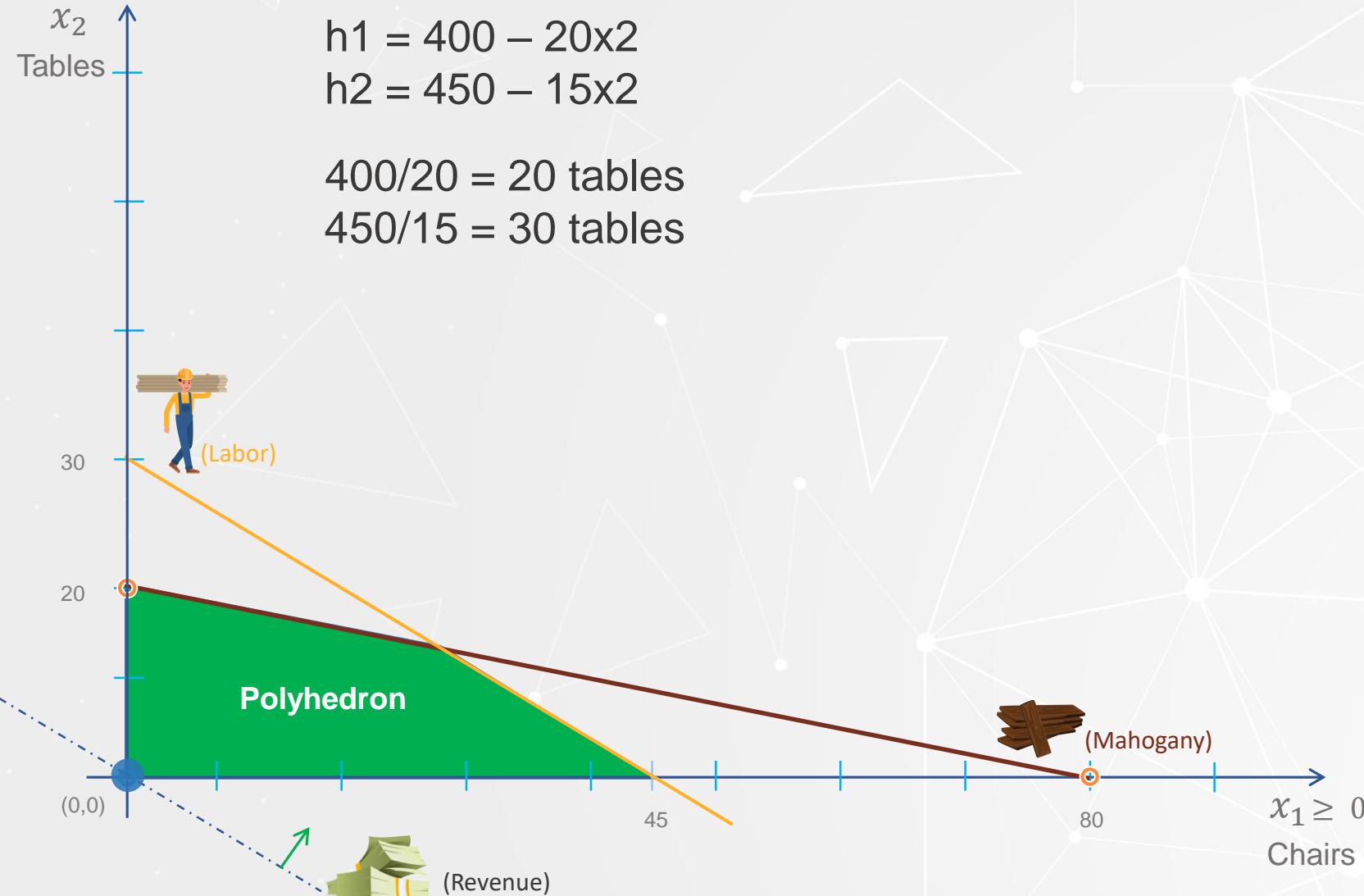
How many tables (x_2) can we make?

$$h_1 = 400 - 20x_2$$

$$h_2 = 450 - 15x_2$$

$$400/20 = 20 \text{ tables}$$

$$450/15 = 30 \text{ tables}$$



Furniture problem **canonical form**

(1.0) $\text{Max } z = 45x_1 + 80x_2 + 0h_1 + 0h_2$

(2.0) $h_1 = 400 - 5x_1 - 20x_2$ Mahogany

(3.0) $h_2 = 450 - 10x_1 - 15x_2$ Labor

$x_1, x_2, h_1, h_2 \geq 0$ Non-negativity

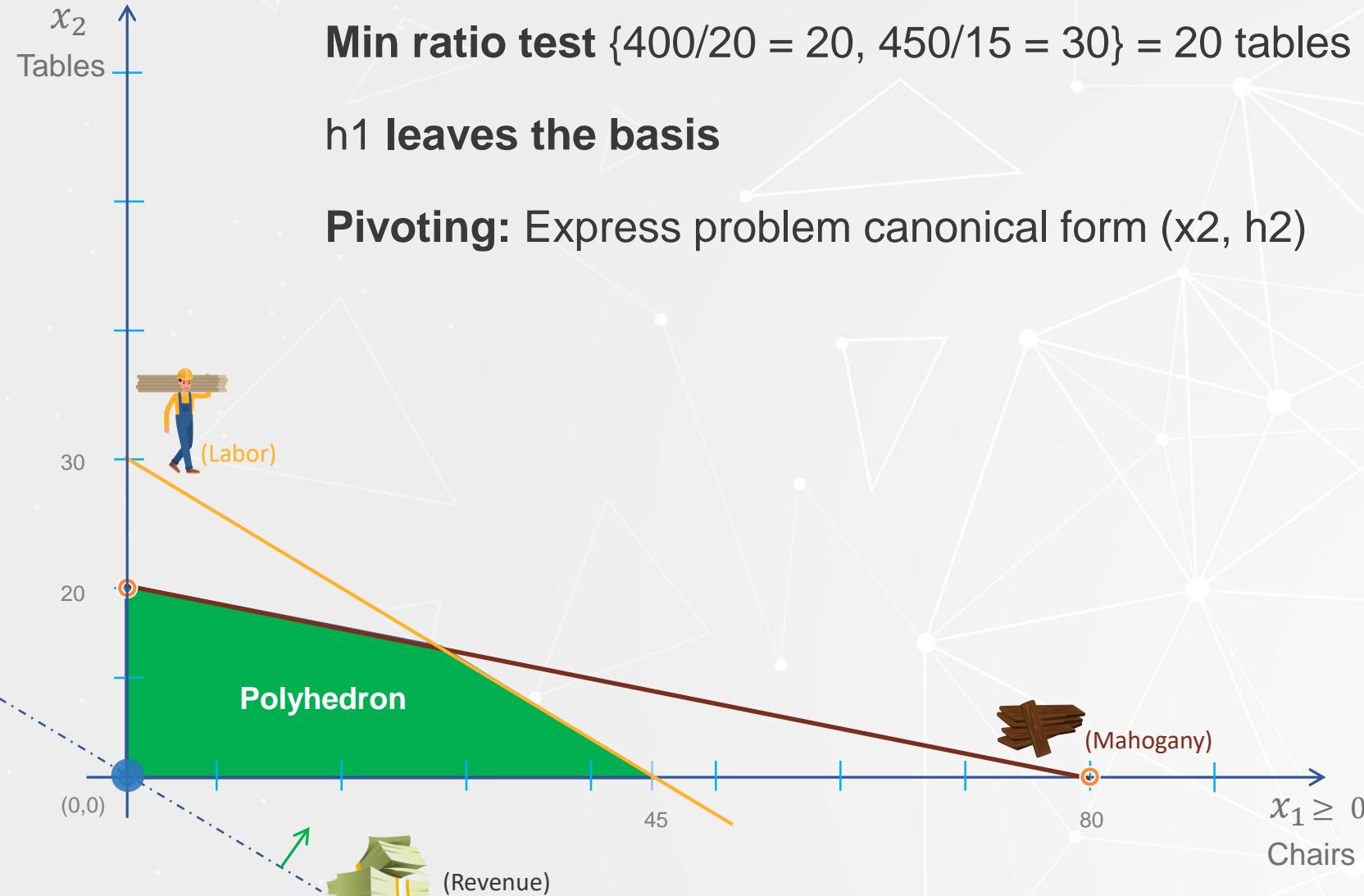
Linear Programming/Simplex Method .. 5

If $x_2 = 30$, $h_1 = 400 - 20(x_2=30) = \text{-200!!!!}$

Min ratio test { $400/20 = 20$, $450/15 = 30$ } = 20 tables

h1 leaves the basis

Pivoting: Express problem canonical form (x_2 , h_2)



Furniture problem **canonical form**

(1.0) $\text{Max } z = 45x_1 + 80x_2 + 0h_1 + 0h_2$

(2.0) $h_1 = 400 - 5x_1 - 20x_2$ Mahogany

(3.0) $h_2 = 450 - 10x_1 - 15x_2$ Labor
 $x_1, x_2, h_1, h_2 \geq 0$ Non-negativity

Linear Programming/Simplex Method (Pivoting) .. 6

$$(1.0) \quad \text{Max } z = 45x_1 + 80x_2 + 0h_1 + 0h_2$$

$$(2.0) \quad h_1 = 400 - 5x_1 - 20x_2$$

$$(3.0) \quad h_2 = 450 - 10x_1 - 15x_2$$

$$x_1, x_2, h_1, h_2 \geq 0$$

In equation 2.0, express x_2 in terms of x_1 and h_1

$$(2.0) \quad x_2 = 20 - (1/4)x_1 - (1/20)h_1$$

Linear Programming/Simplex Method (Pivoting) .. 6

In equation 2.0, express x_2 in terms of x_1 and h_1

$$(2.0) \quad x_2 = 20 - (1/4)x_1 - (1/20)h_1$$

We substitute the value of x_2 in equation (3.0)

$$\begin{aligned} (3.0) \quad h_2 &= 450 - 10x_1 - 15(x_2 = 20 - (1/4)x_1 - (1/20)h_1) \\ &= 150 - (25/4)x_1 + (3/4)h_1 \end{aligned}$$

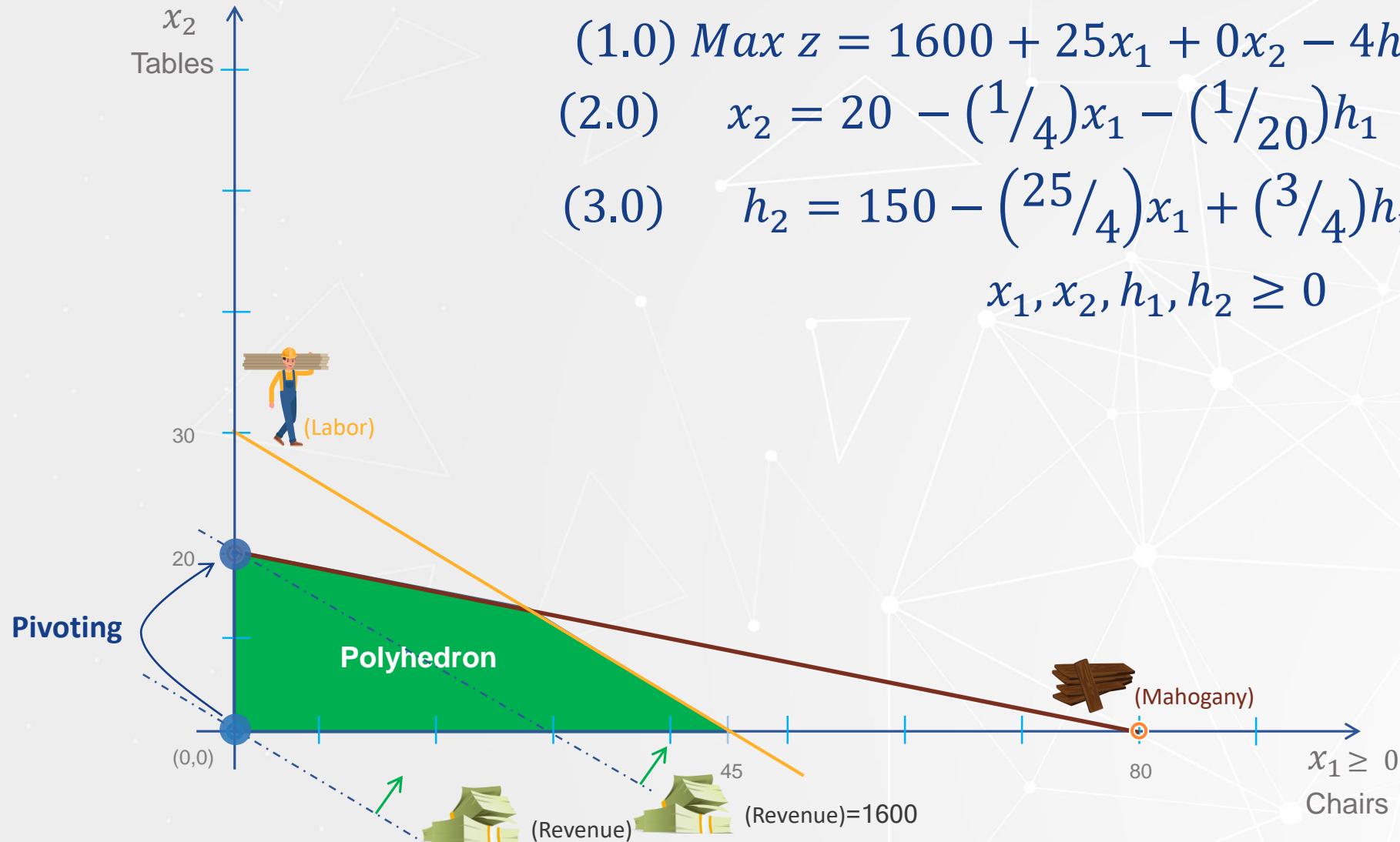
Substitute the value of x_2 in (1.0), the objective function

$$\begin{aligned} (1.0) \quad z &= 45x_1 + 80(20 - (1/4)x_1 - (1/20)h_1) + 0h_1 + 0h_2 \\ &= 1600 + 25x_1 + 0x_2 - 4h_1 + 0h_2 \end{aligned}$$

$$\begin{aligned} (1.0) \quad &\text{Max } z = 45x_1 + 80x_2 + 0h_1 + 0h_2 \\ (2.0) \quad &h_1 = 400 - 5x_1 - 20x_2 \\ (3.0) \quad &h_2 = 450 - 10x_1 - 15x_2 \\ &x_1, x_2, h_1, h_2 \geq 0 \end{aligned}$$

Linear Programming/Simplex Method .. 7

Furniture LP problem in a canonical form with respect to the basic variables (x_2 , h_2).



Linear Programming/Simplex Method (Pivoting) .. 8

$$(1.0) \text{ Max } z = 1600 + 25x_1 + 0x_2 - 4h_1 + 0h_2$$

$$(2.0) \quad x_2 = 20 - \left(\frac{1}{4}\right)x_1 - \left(\frac{1}{20}\right)h_1 \quad \text{Production of tables}$$

$$(3.0) \quad h_2 = 150 - \left(\frac{25}{4}\right)x_1 + \left(\frac{3}{4}\right)h_1 \quad \text{Unused labor capacity}$$

$$x_1, x_2, h_1, h_2 \geq 0 \quad \text{Non-negativity}$$

Simplex method: **iteration 2**

Step1: x_1 enters the basis.

Step2: minimum ratio test, $\min\{20/(1/4)=80, 150/(25/4)=24\}=24$. h_2 leaves the basis

Step3: Pivoting express problem in canonical form with respect to (x_2, x_1)

Linear Programming/Simplex Method (Pivoting) .. 9

In equation 3.0, express x_1 in terms of h_1 and h_2

$$(3.0) \quad x_1 = 24 + (3/25)h_1 - (4/25)h_2$$

We substitute the value of x_1 in equation (2.0)

$$(2.0) \quad x_2 = 14 - (2/25)h_1 + (1/25)h_2$$

Substitute the value of x_1 in (1.0), the objective function

$$z = 2200 + 0x_1 + 0x_2 - 1h_1 - 4h_2$$

$$(1.0) \quad \text{Max } z = 1600 + 25x_1 + 0x_2 - 4h_1 + 0h_2$$

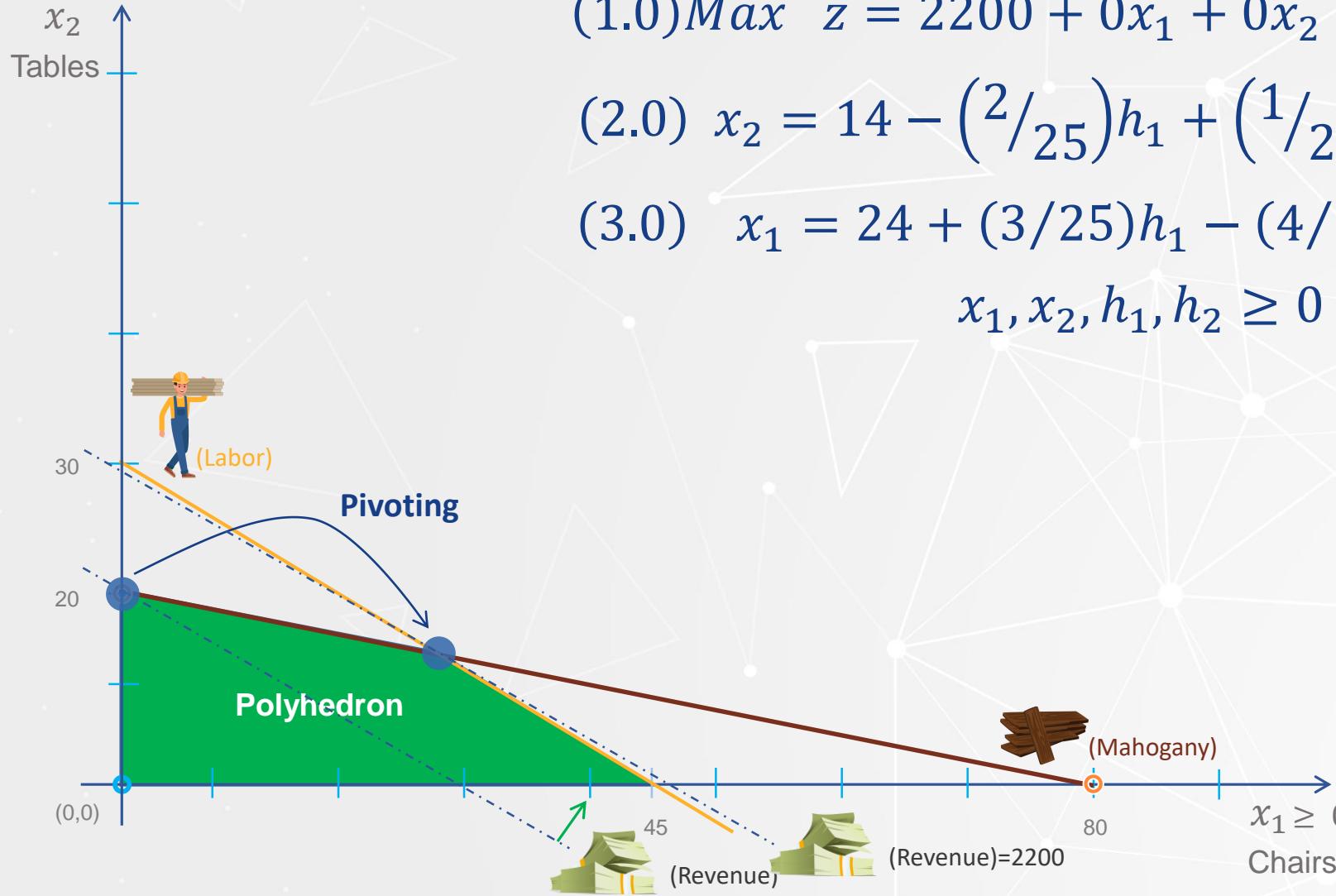
$$(2.0) \quad x_2 = 20 - (1/4)x_1 - (1/20)h_1$$

$$(3.0) \quad h_2 = 150 - (25/4)x_1 + (3/4)h_1$$

$$x_1, x_2, h_1, h_2 \geq 0$$

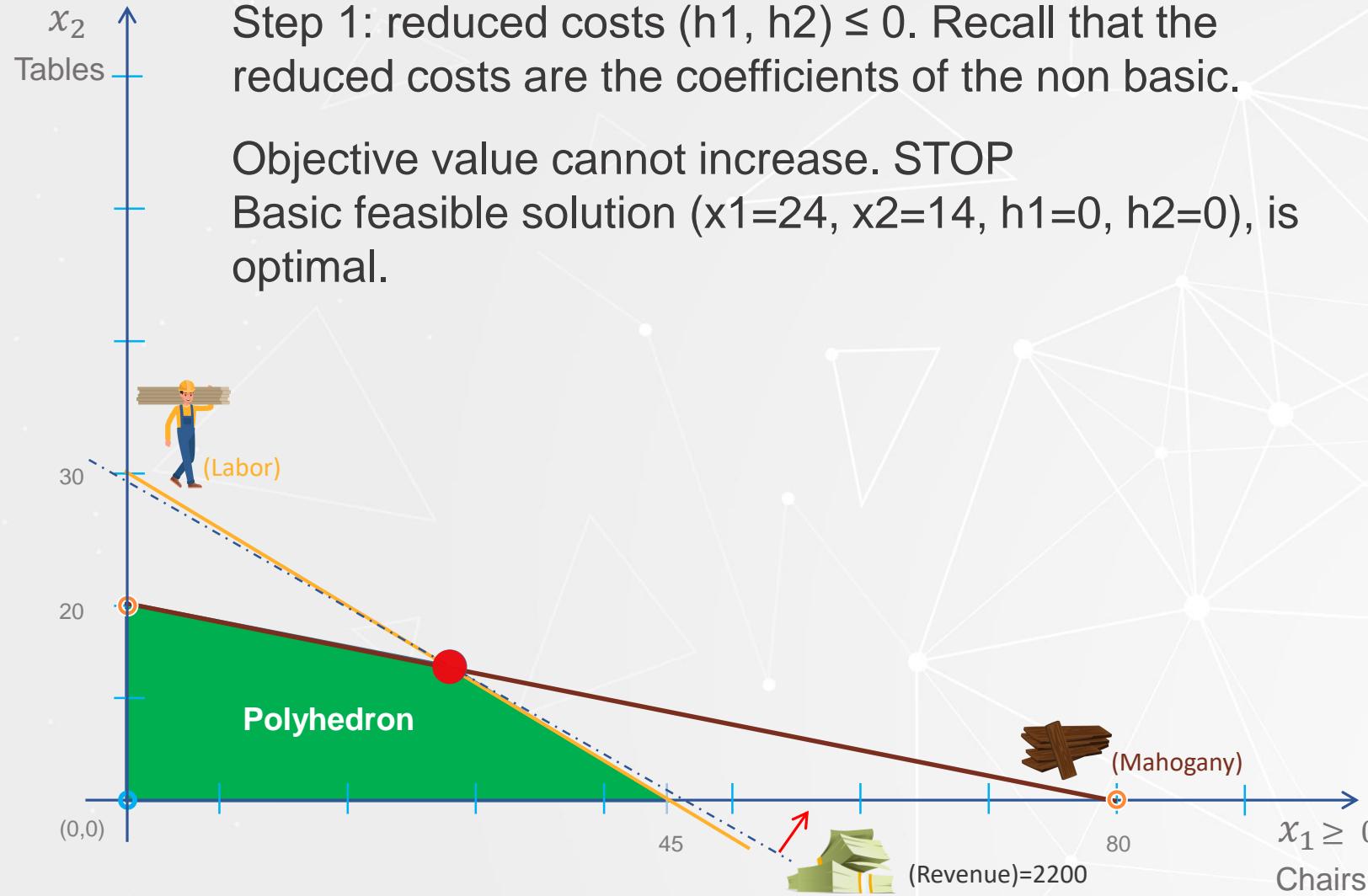
Linear Programming/Simplex Method (Pivoting) .. 10

Furniture LP problem in a canonical form with respect to the basic variables (x_2, x_1).



Linear Programming/Simplex Method.. 11

Simplex method: iteration 3.



$$(1.0) \text{Max } z = 2200 + 0x_1 + 0x_2 - 1h_1 - 4h_2$$

$$(2.0) x_2 = 14 - \left(\frac{2}{25}\right)h_1 + \left(\frac{1}{25}\right)h_2$$

$$(3.0) x_1 = 24 + \left(\frac{3}{25}\right)h_1 - \left(\frac{4}{25}\right)h_2$$
$$x_1, x_2, h_1, h_2 \geq 0$$

Summary of simplex method for the maximization case

1. Transform the original LP problem into the standard form. Consider an initial basic feasible solution.
2. Express the LP problem in a canonical form with respect to the current basic feasible solution.
3. If the reduced costs of all the non basic variables are ≤ 0 , **STOP** –the current basic feasible solution is optimal. Else, choose a non basic variable with the largest positive reduced cost to enter the basis.
4. Consider the column vector of the non basic variable entering the basis. If all the coefficients of this column vector are positive, the entering non basic variable can be arbitrarily large, hence the LP problem is unbounded.
 - i. Assume that the column vector has at least one negative component.
 - ii. Apply the minimum ratio test over the equations where the entering non basic variable has negative coefficients to determine the basic variable that will leave the basis.
 - iii.(Pivoting) Go to 2.) to determine the new basic solution.

Modeling and solving LP problems

Gurobi Python API

Furniture Problem: solved with Gurobi ... 1

Manufacturing Problem: Furniture factory

$$\text{Max Revenue} = 45x_1 + 80x_2$$

Subject to :

$$\text{Mahogany : } 5x_1 + 20x_2 \leq 400$$

$$\text{Labor : } 10x_1 + 15x_2 \leq 450$$

$$\text{Non - negativity : } x_1, x_2 \geq 0$$

```
# import gurobi Library
from gurobipy import *

# Create Furniture new model
f = Model("Furniture")

# Create variables
x1 = f.addVar(name="chairs")
x2 = f.addVar(name="tables")

# Define objective function
f.setObjective(45*x1 + 80*x2, GRB.MAXIMIZE)

# Add mahogany constraint
f.addConstr(5*x1 + 20*x2 <= 400, "mahogany")
# add Labor constraint
f.addConstr(10*x1 + 15*x2 <= 450, "labor")
```

This command imports the Gurobi functions and classes.

The Model() constructor creates a model object **f**. The name of this new model is 'Furniture'. This new model **f** initially contains no decision variables, constraints, or objective function.

This method adds a decision variable to the model object **f**, one by one; i.e. x_1 and then x_2 . The argument of the method gives the name of added decision variable. The default values are applied here; i.e. the decision variables are of type continuous and non-negative, with no upper bound.

This method adds the objective function to the model object **f**. The first argument is a linear expression (LinExpr) and the second argument defines the sense of the optimization.

A linear expression object (LinExpr) consists of a constant term, plus a sum of coefficient-variables pairs that capture the linear terms. This method adds a constraint to the model object **f** and considers a linear expression (LinExpr) as the left-hand-side of the constraints, the sense of the constraint, and its capacity value. The last argument gives the name of the constraint.

Furniture Problem: solved with Gurobi ... 2

```
# Run optimization engine  
f.optimize()
```

```
Optimize a model with 2 rows, 2 columns and 4 nonzeros  
Coefficient statistics:
```

```
Matrix range [5e+00, 2e+01]  
Objective range [5e+01, 8e+01]  
Bounds range [0e+00, 0e+00]  
RHS range [4e+02, 5e+02]
```

```
Presolve time: 0.01s
```

```
Presolved: 2 rows, 2 columns, 4 nonzeros
```

Iteration	Objective	Primal Inf.	Dual Inf.	Time
0	6.500000e+31	2.968750e+30	6.500000e+01	0s
2	2.200000e+03	0.000000e+00	0.000000e+00	0s

```
Solved in 2 iterations and 0.02 seconds  
Optimal objective 2.200000000e+03
```

```
# Display optimal production plan  
for v in f.getVars():  
    print(v.varName, v.x)  
  
print('Optimal total revenue:', f.objVal)
```

```
('chairs', 24.0)  
('tables', 14.0)  
('Optimal total revenue:', 2200.0)
```

This method runs the optimization engine to solve the LP problem in the model object f

Minimum and maximum absolute value of the matrix of technology coefficients.
Minimum and maximum absolute value of the objective function coefficients.
Minimum and maximum absolute value of the upper and lower bound values.
Minimum and maximum absolute value of the RHS values.

Simplex method iteration information.

An optimal solution was found.

This method retrieves a list of all variables in the model object f

The print function displays the decision variable names and solution value

The print function displays the objective function value of the model object f

Optimal Production Plan

*What if our LP problem has
hundreds of thousands variables
and constraints?*

- The Gurobi python code just presented is too manual and would take too long to build a large scale LP problem.*

- We should use appropriate data structures and Gurobi python functions and objects to abstract the problem, and have the Gurobi python code build the LP problem of any size.**

Furniture Problem (abstracted): solved with Gurobi .. 1

General Furniture model formulation

Let $price_p$ be the price of product $p \in products = \{chairs, tables\}$, and let $capacity_r$ be the capacity available of resource $r \in resource = \{mahogany, labor\}$.

Let $bom_{r,j}$ be the amount of resource r required by product p . Then the general formulation of the Furniture problem is:

Parametrized furniture LP
problem formulation

$$\begin{aligned} & \text{Max } \sum_{p \in products} price_p make_p \\ & \text{Subject to :} \\ & \sum_{p \in products} bom_{r,p} make_p \leq capacity_r \quad \forall r \in resources \\ & make_p \geq 0 \quad \forall p \in products \end{aligned}$$

Furniture Problem: Parametrized solved with Gurobi .. 2

```
# import gurobi library
from gurobipy import *
```

```
# resources data
resources, capacity = multidict({
    'mahogany': 400,
    'labor': 450 })
```

```
# products data,
products, price = multidict({
    'chair': 45,
    'table': 80 })
```

```
# Bill of materials: resources required by each product
bom = {
    ('mahogany', 'chair'): 5,
    ('mahogany', 'table'): 20,
    ('labor', 'chair'): 10,
    ('labor', 'table'): 15 }
```

The multidict function returns a list which maps each resource (key) to its capacity value.

This multidict function returns a list which maps each product (key) to its price value.

This dictionary has a 2-tuple as a key, mapping the resource required by a product with its quantity per.

Furniture Problem: Parametrized solved with Gurobi .. 3

```
# Declare and initialize model  
f = Model('Furniture')
```

The `Model()` constructor creates a model object `f`.

```
# Create decision variables for the products to make  
make = f.addVars(products, name="make")
```

This method adds decision variables to the model object `f`, and returns a Gurobi tupledict object (`make`) that contains the variables recently created.

The first argument (`products`) provides the indices that will be used as keys to access the variables in the returned tupledict. The last argument gives the name '`make`' to the decision variables. The decision variables are of type continuous and non-negative, with no upper bound.

Furniture Problem: Parametrized solved with Gurobi .. 4

This method adds constraints to the model object f.

$$\sum_{p \in \text{products}} bom_{r,p} make_p \leq capacity_r \quad \forall r \in \text{resources}$$

```
res = f.addConstrs(((sum(bom[r,p]*make[p] for p in products) <= capacity[r]) for r in resources), name='R')
```

Furniture Problem: Parametrized solved with Gurobi .. 5

```
# The objective is to maximize total profit  
f.setObjective(make.prod(revenue), GRB.MAXIMIZE)
```

$$\text{Max} \sum_{p \in \text{products}} \text{price}_p \text{make}_p$$

This method adds the objective function to the model object f. The first argument is a linear expression which is generated by the (prod) method. The (prod) method is the product of the object (revenue) with the object (make) for each product p in the set (products). The second argument defines the sense of the optimization.

Furniture Problem: Parametrized solved with Gurobi .. 6

```
# save model for inspection
f.write('furniture.lp')
```

```
\ Model Furniture
\ LP format - for model browsing. Use MPS format to capture full model detail.
Maximize
  80 make[table] + 45 make[chair]
Subject To
  R[mahogany]: 20 make[table] + 5 make[chair] <= 400
  R[labor]: 15 make[table] + 10 make[chair] <= 450
Bounds
End
```

Furniture Problem: Parametrized solved with Gurobi .. 7

```
# run optimization engine
f.optimize()
```

Optimize a model with 2 rows, 2 columns and 4 nonzeros

Coefficient statistics:

Matrix range	[5e+00, 2e+01]
Objective range	[5e+01, 8e+01]
Bounds range	[0e+00, 0e+00]
RHS range	[4e+02, 5e+02]

Presolve time: 0.02s

Presolved: 2 rows, 2 columns, 4 nonzeros

Iteration	Objective	Primal Inf.	Dual Inf.	Time
0	6.5000000e+31	2.968750e+30	6.500000e+01	0s
2	2.2000000e+03	0.000000e+00	0.000000e+00	0s

Solved in 2 iterations and 0.02 seconds

Optimal objective 2.200000000e+03

```
# display optimal values of decision variables
for v in f.getVars():
    if (abs(v.x) > 1e-6):
        print(v.varName, v.x)
```

```
# display optimal total profit value
print('total revenue', f.objVal)
```

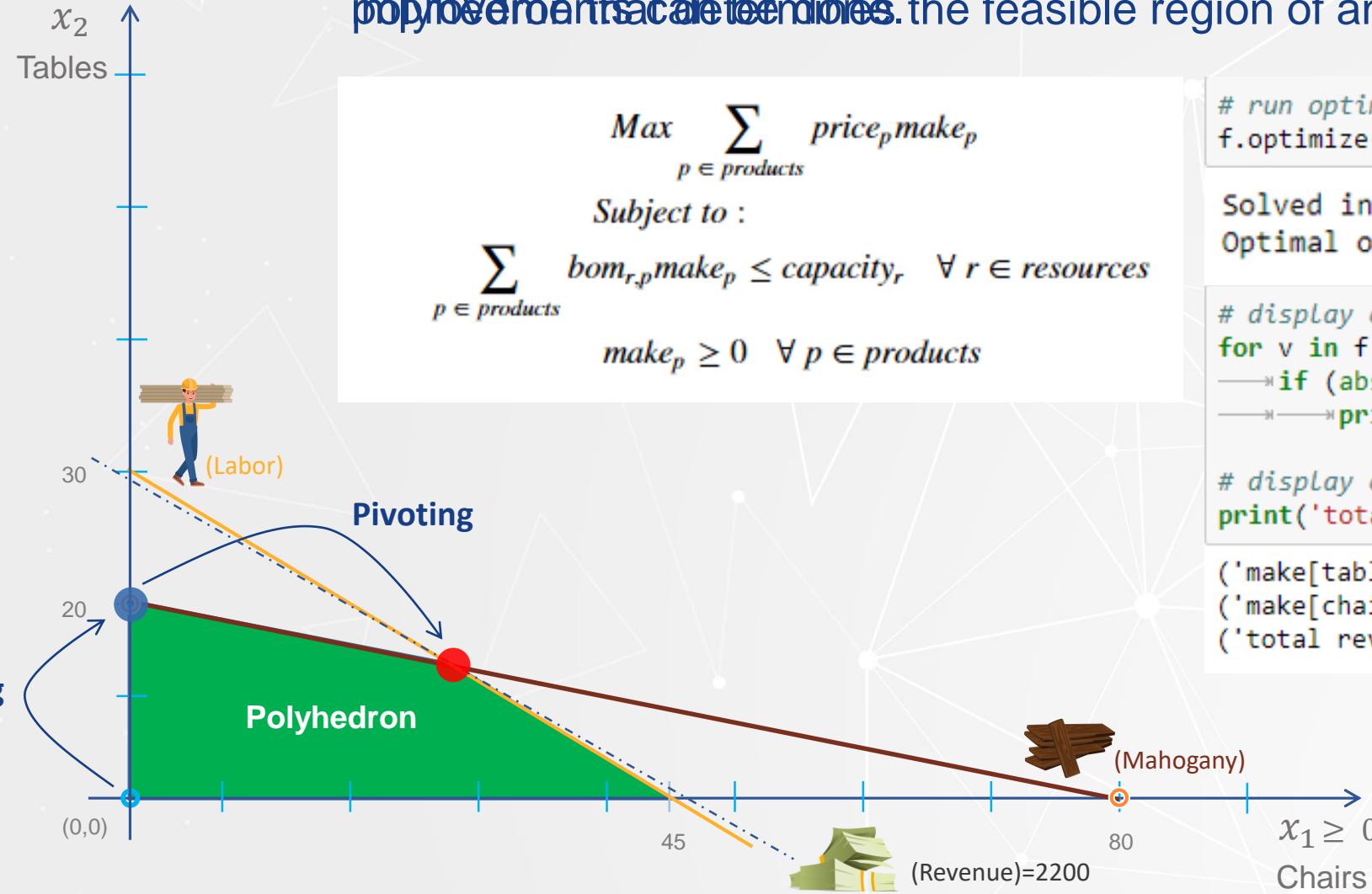
```
('make[table]', 14.0)
('make[chair]', 24.0)
('total revenue', 2200.0)
```

This method runs the optimization engine to solve the LP problem in the model object f

Optimal Production Plan

Final Remarks

- The simplex method iterates from basic feasible solutions to other, adjacent vertices in the direction of the steepest increase of the objective function value, until it reaches the vertex of the polyhedron that satisfies all constraints.



```
# run optimization engine
f.optimize()

Solved in 2 iterations and 0.02 seconds
Optimal objective 2.20000000e+03

# display optimal values of decision variables
for v in f.getVars():
    if (abs(v.x) > 1e-6):
        print(v.varName, v.x)

# display optimal total profit value
print('total revenue', f.objVal)

('make[table]', 14.0)
('make[chair]', 24.0)
('total revenue', 2200.0)
```

Sensitivity analysis of LP problems

Gurobi Python API

Furniture Problem: economic interpretation

Economic interpretation in Linear Programming models

- Solving LP problems provides more information than only the values of the decision variables and the value of the objective function.
- Associated with an LP optimal solution there are ***shadow prices*** (a.k.a. ***dual variables***, or ***marginal values***) for the constraints.
- The shadow price of a constraint associated with the optimal solution, represents the change in the value of the objective function per unit of increase in the right-hand side value of that constraint.
- There are shadow prices associated with the non-negativity constraints. These shadow prices are called the ***reduced costs***.

Furniture Problem: economic interpretation .. 2

- For example, suppose the labor capacity is increased from 450 hours to 451 hours. What is the increase in the objective function value from such increase?
- Since the constraints on mahogany capacity (2.0) and labor capacity (3.0) define the optimal solution, we can solve the following system of equations

$$5x_1 + 20x_2 = 400 \quad \text{Mahogany capacity}$$

$$10x_1 + 15x_2 = 451 \quad \text{Labor capacity}$$

- The new values of the decision variables are: chairs (x_1) = 24.16, tables (x_2) = 13.96
- The new value of the objective function (revenue) is = \$2,204
- The shadow price associated with the labor capacity is \$2,204 - \$2,200 = \$4. That is, we can get \$4 of increased revenue per hour of increase in labor capacity.
- **Remark:** The shadow price value of \$4 remains constant over a range of value changes of the mahogany capacity. The calculation of this range is beyond the scope of this course.

Furniture Problem: economic interpretation .. 3

- Similarly, we can compute the shadow price of the mahogany constraint by solving the following system of equations

$$\begin{aligned} 5x_1 + 20x_2 &= 401 && \text{Mahogany capacity} \\ 10x_1 + 15x_2 &= 450 && \text{Labor capacity} \end{aligned}$$

- The new values of the decision variables are: chairs (x_1) = 14.08, tables (x_2) = 23.88
- The new value of the objective function (revenue) is = \$2,201
- The shadow price associated with the mahogany capacity is \$2,201 - \$2,200 = \$1. That is, we can get \$1 of increased revenue per unit of increase in mahogany capacity.
- Remark:** The shadow price value of \$1 remains constant over a range of value changes of the labor capacity.

Furniture Problem: simplex method revisited

The LP problem in a canonical form with respect to the optimal basic variables (x_1, x_2) is

$$\text{Max } z = 2200 + 0x_1 + 0x_2 - 1h_1 - 4h_2$$

$$(2.0) \quad x_2 = 14 - \left(\frac{2}{25}\right)h_1 + \left(\frac{4}{25}\right)h_2$$

$$(3.0) \quad x_1 = 24 + \left(\frac{3}{25}\right)h_1 - \left(\frac{4}{25}\right)h_2$$

$$x_1, x_2, h_1, h_2 \geq 0$$

- **Remarks:** Recall that if we add 2 more the slack variables associated with the mahogany capacity constraint will be capacity by \$4. The value of h_2 (unused capacity of labor) by one the total revenue will be reduced by \$4.
- The interpretation of the slack variables is the amount of resource capacity not consumed by the production of chairs and tables.
- The shadow price of mahogany is \$1 and the one of labor is \$4 !!!
- The optimal solution is
- Revenue = \$2,200, chairs (x_1) = 24, tables (x_2) = 14
- **Conclusion:** The simplex method automatically give us the shadow prices of the resources.
 - Slack variable (h_1) of mahogany constraint = 0, and
 - Slack variable (h_2) of labor constraint = 0

Furniture Problem: solved with Gurobi

This method adds constraints to the model object f. We store the constraints generated in an object called (res).

```
res = f.addConstrs(((sum(bom[r,p]*make[p] for p in products) <= capacity[r]) for r in resources), name='R')
```

For each resource constraint in the dictionary (res), check if its associated shadow price is greater than zero. Then print the resource constraint name and the resource constraint shadow price.

Recall that the object (res) stores all the information related to the constraints of the model f.

```
# display shadow prices of resources constraints
for r in res:
    if (abs(res[r].Pi) > 1e-6):
        print(res[r].ConstrName, res[r].Pi)
```

```
('R[mahogany]', 1.0)
('R[labor]', 4.0)
```

Furniture Problem: economic interpretation .. 4

- Is it profitable to make a third product, like desks?
 - Assume that the price of the desk is \$110,
 - and the desk consumes 15 units of mahogany and 25 units of labor
- The previous python code has parametrized the Furniture LP model, i.e. the model formulation does not depend on the data of the problem. Therefore, we just generate a new set of data that includes the new product information

```
# products data,  
products, price = multidict({  
    'chair': 45,  
    'table': 80,  
    'desk': 110 })  
  
# Bill of materials: resources required by each product  
bom = {  
    ('mahogany', 'chair'): 5,  
    ('mahogany', 'table'): 20,  
    ('mahogany', 'desk'): 15,  
    ('labor', 'chair'): 10,  
    ('labor', 'table'): 15,  
    ('labor', 'desk'): 25 }
```

Furniture Problem: economic interpretation .. 5

- The new LP model is

```
# save model for inspection
f.write('furniture.lp')
```

```
\ Model Furniture
\ LP format - for model browsing. Use MPS format to capture full model detail.
Maximize
    80 make[table] + 45 make[chair] + 110 make[desk]
Subject To
    mahogany: 20 make[table] + 5 make[chair] + 15 make[desk] <= 400
    labor: 15 make[table] + 10 make[chair] + 25 make[desk] <= 450
Bounds
End
```

Furniture Problem: economic interpretation .. 6

```
# run optimization engine
f.optimize()

# display optimal values of decision variables
for v in f.getVars():
    if (abs(v.x) > 1e-6):
        print(v.varName, v.x)

# display optimal total profit value
print('total profits', f.objVal)

('make[table]', 14.0)
('make[chair]', 24.0)
('total profits', 2200.0)

# display shadow prices of resources constraints
for r in res:
    if (abs(res[r].Pi) > 1e-6):
        print(res[r].ConstrName, res[r].Pi)

('R[mahogany]', 1.0)
('R[labor]', 4.0)
```

It is not profitable to produce desks. The optimal solution remains the same.

The shadow prices of the resources remain the same.

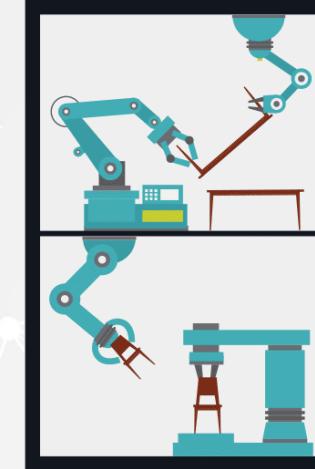
Furniture Problem: economic interpretation .. 7

- Notice that we can use the shadow price information of the resources to check if it is worth it to make desks.
 - The shadow price of the mahogany capacity constraint is \$1
 - The shadow price of the labor capacity constraint is \$4
 - Let's compute the opportunity cost of making one desk and compare it with the price of a desk. If this opportunity cost is greater than the price, then it is not worth it to make desks.
 - The opportunity cost can be computed by multiplying the units of mahogany capacity that one desk built consumes by the shadow price of mahogany capacity, and multiplying the hours of labor capacity that one desk built consumes by the shadow price of labor capacity:
 - That is, $(\$1)*15 \text{ (units of mahogany)} + (\$4)*25 \text{ (hours of labor)} = \$115 > \$110$
- Therefore, investing resources to produce desks, otherwise used to produce chairs and tables, is not profitable.

Multiple optimal solutions

Gurobi Python API

Furniture Problem

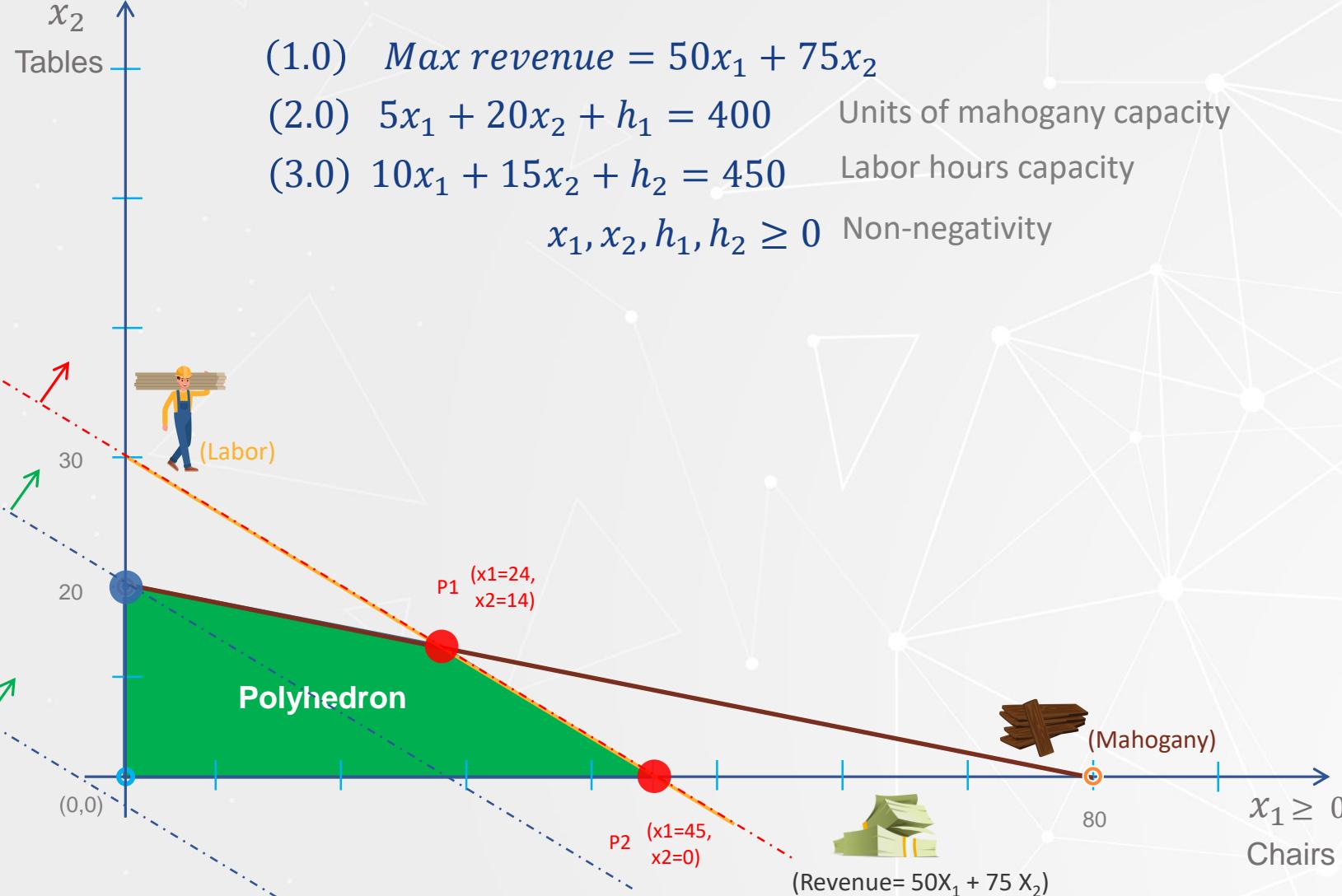


New business conditions

- The data scientist in charge of production planning for the furniture factory uses machine learning to predict that the market price of a chair is now \$50 and the market price of a table is \$75.
- The equation of the objective function under these new business conditions is:
$$\text{revenue} = 50x_1 + 75x_2.$$

Furniture Problem

Furniture problem standard form



New business conditions

- In this case, the production plan **P1** of building 24 chairs and 14 tables and the plan **P2** of building 45 chairs and 0 tables are both optimal.
- The production plan **P1** is defined by the mahogany and labor constraints. The associated optimal basic feasible solution is $x_1=24$, $x_2=14$, $h_1=0$, $h_2=0$.
- The production plan **P2** is defined by the labor and a non-negativity constraint ($x_2 = 0$), i.e. no tables are built. The associated optimal basic feasible solution is $x_1=45$, $x_2=0$, $h_1=175$, $h_2=0$.

Modified Furniture Problem: solved with Gurobi ... 1

General Furniture model formulation -alternative optimal solutions

Let $price_p$ be the price of product $p \in products = \{chairs, tables\}$, and let $capacity_r$ be the capacity available of resource $r \in resources = \{mahogany, labor\}$.

Let $bom_{r,j}$ be the amount of resource r required by product p . Then the general formulation of the Furniture problem is:

$$\text{Max} \sum_{p \in products} price_p make_p$$

Subject to :

$$\sum_{p \in products} bom_{r,p} make_p \leq capacity_r \quad \forall r \in resources$$

$$make_p \geq 0 \quad \forall p \in products$$

Parametrized furniture LP problem formulation

We modify the objective function as follows:

New	Price
Chairs	\$50
Tables	\$75

```
# products data.  
products, price = multidict({  
    'chair': 50,  
    'table': 75 })
```

New data, same model formulation

Modified Furniture Problem: solved with Gurobi ... 2

```
# run optimization engine
f.optimize()

# display optimal values of decision variables
for v in f.getVars():
    print(v.varName, v.x)

# display optimal total profit value
print('total revenue', f.objVal)

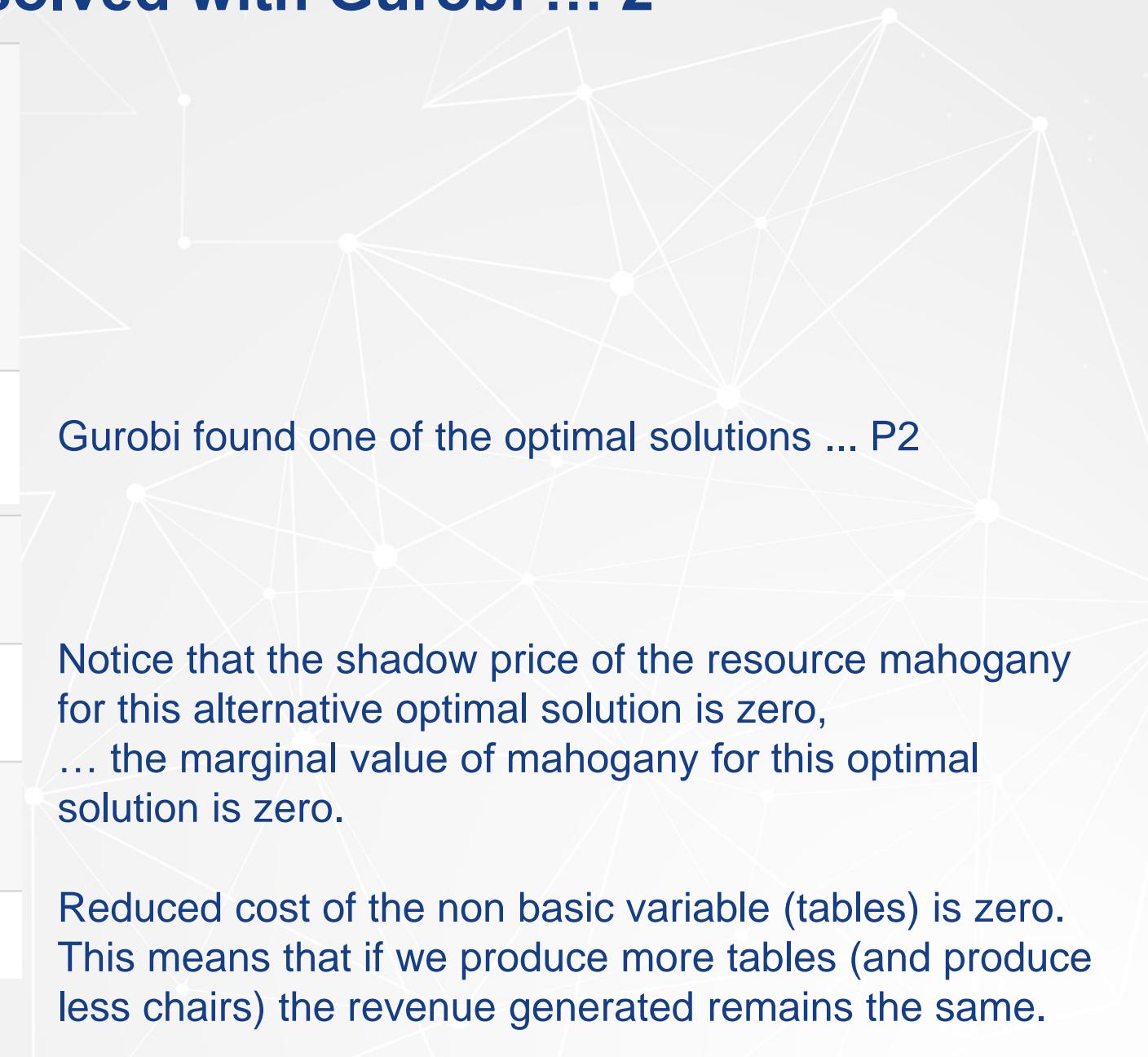
('make[table]', 0.0)
('make[chair]', 45.0)
('total revenue', 2250.0)

# display shadow prices of resources constraints
for r in res:
    print(res[r].ConstrName, res[r].Pi)

('R[mahogany]', 0.0)
('R[labor]', 5.0)

# display reduced costs of decision variables
for v in f.getVars():
    print(v.varName, abs(v.rc))

('make[table]', 0.0)
('make[chair]', 0.0)
```



Furniture Problem: simplex method revisited .. 1

New (original) LP problem

$$\begin{aligned} \text{Max } z &= 50x_1 + 75x_2 \\ \text{s.t. } &5x_1 + 20x_2 \leq 400 \\ &10x_1 + 15x_2 \leq 450 \\ &x_1, x_2 \geq 0 \end{aligned}$$

The LP problem in a standard form is

$$\begin{aligned} \text{Max } z &= 50x_1 + 75x_2 + 0h_1 + 0h_2 \\ \text{s.t. } &5x_1 + 20x_2 + h_1 = 400 \\ &10x_1 + 15x_2 + h_2 = 450 \\ &x_1, x_2, h_1, h_2 \geq 0 \end{aligned}$$

LP problem in canonical form with respect to the optimal basic variables (x_1, h_1) found by Gurobi:

$$\begin{aligned} \text{Max } z &= 2,250 + (0x_1 + 0h_1) + (0x_2 - 5h_2) \\ &\quad \text{Non basic variables} \end{aligned}$$

$$h_1 = 175 - \left(\frac{25}{2}\right)x_2 + \left(\frac{1}{2}\right)h_2 \quad (2.0)$$

$$x_1 = 45 - \left(\frac{3}{2}\right)x_2 - \left(\frac{1}{10}\right)h_2 \quad (3.0)$$

$$x_1, x_2, h_1, h_2 \geq 0$$

The reduced cost of non basic variable x_2 is zero, hence if we increase its value, the optimal objective function value does not change. Let's decide which basic variable should become non basic (value of zero) by computing the minimum ratio test:

$\min\{175/(25/2) = 14, 45/(3/2) = 30\} = 14$;
therefore h_1 will become non basic variable. Hence, we pivot on constraint (2.0) and the column of variable x_2 .

Furniture Problem: simplex method revisited .. 2

LP problem in canonical form with respect to the basic variables (x_1, x_2):

$$\text{Max } z = 2,250 + 0h_1 - 5h_2$$

$$x_2 = 14 - \left(\frac{2}{25}\right)h_1 + \left(\frac{1}{25}\right)h_2 \quad (2.0)$$

$$x_1 = 24 - \left(\frac{3}{25}\right)h_1 - \left(\frac{4}{25}\right)h_2 \quad (3.0)$$

$$x_1, x_2, h_1, h_2 \geq 0$$

Modeling Opportunity

From the mathematical model point of view, we have two alternative optimal solutions $S1 = (x_1 = 24, x_2 = 14, h_1=0, h_2= 0)$ and $S2 = (x_1 = 45, x_2 = 0, h_1= 175, h_2 = 0)$, both with a maximum total revenue of \$2,250.

The data scientist points out that from the business perspective, the “optimal” solution $S1$ is preferred to the “optimal” solution $S2$, because the latter solution wastes 175 units of mahogany.

The data scientist decides to modify the LP model by now interpreting the slack variables as the amount of wasted resources, and defines the new decision variables:

x_3 is the amount of unused mahogany and x_4 is the amount of unused labor.

The data scientists uses machine learning to predict that the per unit inventory carrying cost of mahogany is \$1 , and the unused per hour labor cost is \$2. Then, the new LP model formulation is:

Furniture Problem: simplex method revisited .. 2

Modeling Opportunity

From the mathematical model point of view, we have two alternative optimal solutions $S1 = (x_1 = 24, x_2 = 14, x_3 = x_4 = 0)$ and $S2 = (x_1 = 45, x_2 = 0, x_3 = 175, x_4 = 0)$, both with a maximum total revenue of \$2,250.

The data scientist notice that from the business perspective, the “optimal” solution $S1$ is preferred to “optimal” solution $S2$, because with the latter solution is wasting 175 units of mahogany.

The data scientist decides to modify the LP model by now interpreting the slack variables as the amount of wasted resources, and defines the new decision variables: x_3 is the amount of unused mahogany and x_4 is the amount of unused labor.

The data scientists using machine learning estimates that the per unit inventory carrying cost of mahogany is \$1, and the unused per hour labor cost is \$2. Then, the new LP model formulation is:

$$\text{Max } z = 50x_1 + 75x_2 - 1x_3 - 2x_4$$

$$\text{s.t. } 5x_1 + 20x_2 + x_3 = 400$$

$$10x_1 + 15x_2 + x_4 = 450$$

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

New Furniture Problem: solved with Gurobi ... 1

General Furniture model formulation -Penalize wasting resources

Let $price_p$ be the price of product $p \in products = \{chairs, tables\}$, and let $capacity_r$ be the capacity available of resource $r \in resources = \{mahogany, labor\}$.

Let $waste_r$ be a new decision variable that measures the amount of unused resource $r \in resources = \{mahogany, labor\}$. Let $cost_r$ be the per unit cost of unused resource capacity.

Let $bom_{r,p}$ be the amount of resource r required by product p . Then the new formulation of the Furniture problem is:

$$\begin{aligned} & \text{Max } \sum_{p \in products} price_p make_p - \sum_{r \in resources} cost_r waste_r \\ & \text{Subject to :} \\ & \sum_{p \in products} bom_{r,p} make_p + waste_r = capacity_r \quad \forall r \in resources \\ & make_p \geq 0 \quad \forall p \in products \\ & waste_r \geq 0 \quad \forall r \in resources \end{aligned}$$

Price

	Per unit	Price
Chairs	\$50	
Tables	\$75	

Resources cost table:

	Per unit	Cost
Mahogany	\$1	
Labor	\$2	

New Furniture Problem: solved with Gurobi ... 2

```
# import gurobi Library
from gurobipy import *

# resources data
resources, capacity, cost = multidict({
    'mahogany': [400, 1],
    'labor': [450, 2] })

# products data,
products, price = multidict({
    'chair': 50,
    'table': 75 })

# Bill of materials: resources required by each product
bom = {
    ('mahogany', 'chair'): 5,
    ('mahogany', 'table'): 20,
    ('labor', 'chair'): 10,
    ('labor', 'table'): 15 }
```

We add a cost parameter to the resources multidict to penalize the waste of resources.

New Furniture Problem: solved with Gurobi ... 3

```
# Declare and initialize model  
f = Model('Furniture')
```

```
# Create decision variables for the products to make  
make = f.addVars(products, name="make")
```

```
# Create decision variables for the wasted resources  
waste = f.addVars(resources, name="waste")
```

```
# Capacity resource constraints:  
# The amount consumed by the products made + the waste = capacity
```

```
res = f.addConstrs(((sum(bom[r,p]*make[p] for p in products) + waste[r] == capacity[r]) for r in resources), name='R')
```

```
# The objective is to maximize total profit  
f.setObjective(make.prod(price) - waste.prod(cost) , GRB.MAXIMIZE)
```

We add a new type of decision variable to measure the unused resource capacity.

$$\sum_{p \in \text{products}} bom_{r,p} make_p + waste_r = capacity_r \quad \forall r \in \text{resources}$$

$$\text{Max} \sum_{p \in \text{products}} price_p make_p - \sum_{r \in \text{resources}} cost_r waste_r$$

New Furniture Problem: solved with Gurobi ... 4

```
# run optimization engine
f.optimize()
```

```
# display optimal values of decision variables
for v in f.getVars():
    print(v.varName, v.x)

# display optimal total profit value
print('total profits', f.objVal)
```

```
('make[table]', 14.0)
('make[chair]', 24.0)
('waste[mahogany]', 0.0)
('waste[labor]', 0.0)
('total profits', 2250.0)
```

The optimal solution is now making 14 tables and 24 chairs with a total objective function value of \$2,250.

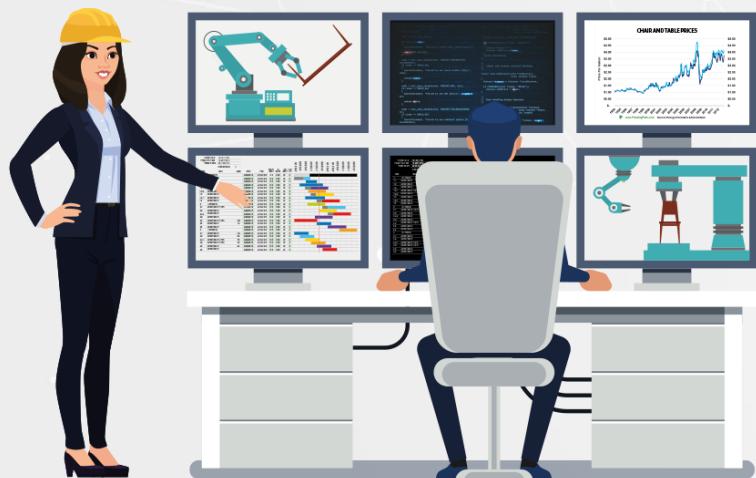
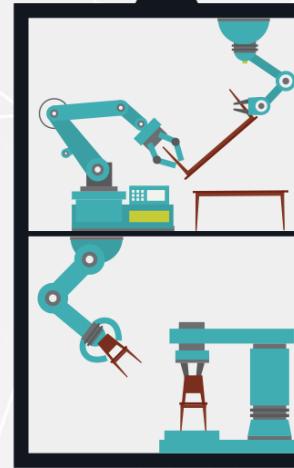
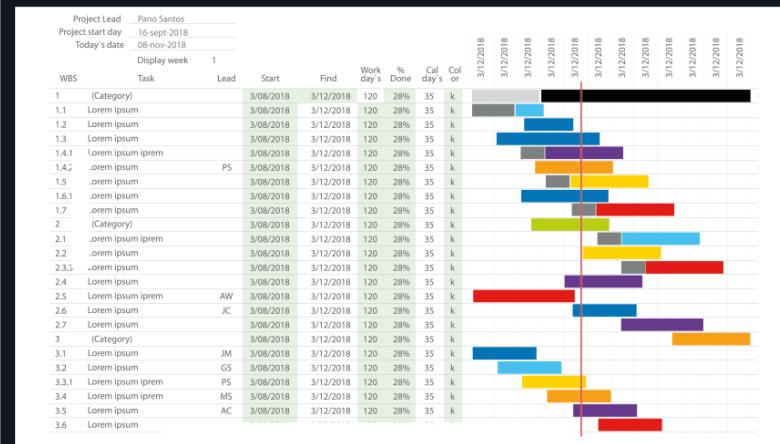
Notice that the solution of making 0 tables and 45 chairs is no longer optimal since the objective function value is $(\$50 \cdot 45 = \$2,250) - (\$1 \cdot 175 = \$175) = \$2,075$. That is, the alternative solution (chairs = 45, tables = 0) is no longer optimal.

Unbounded LP problem

Gurobi Python API

Furniture Problem

```
static void StartElement(void *voidContext, const char *name, const char *attributes) {  
    if (strcmp(name, "table") == 0) {  
        int rows = 10;  
        int cols = 5;  
        for (int i = 0; i < rows; i++) {  
            for (int j = 0; j < cols; j++) {  
                cout << "Cell " << i << "," << j << endl;  
            }  
        }  
    }  
}
```



New business conditions

- The operations manager of the furniture factory tells the data scientist that she is negotiating with the supplier of mahogany to obtain an unlimited amount of mahogany as long as the factory procures at least 400 units of mahogany per week.
- In addition, the operations manager is negotiating with the union to obtain extra workforce as long as the factory hires at least 450 hours of labor per week.

Furniture Problem

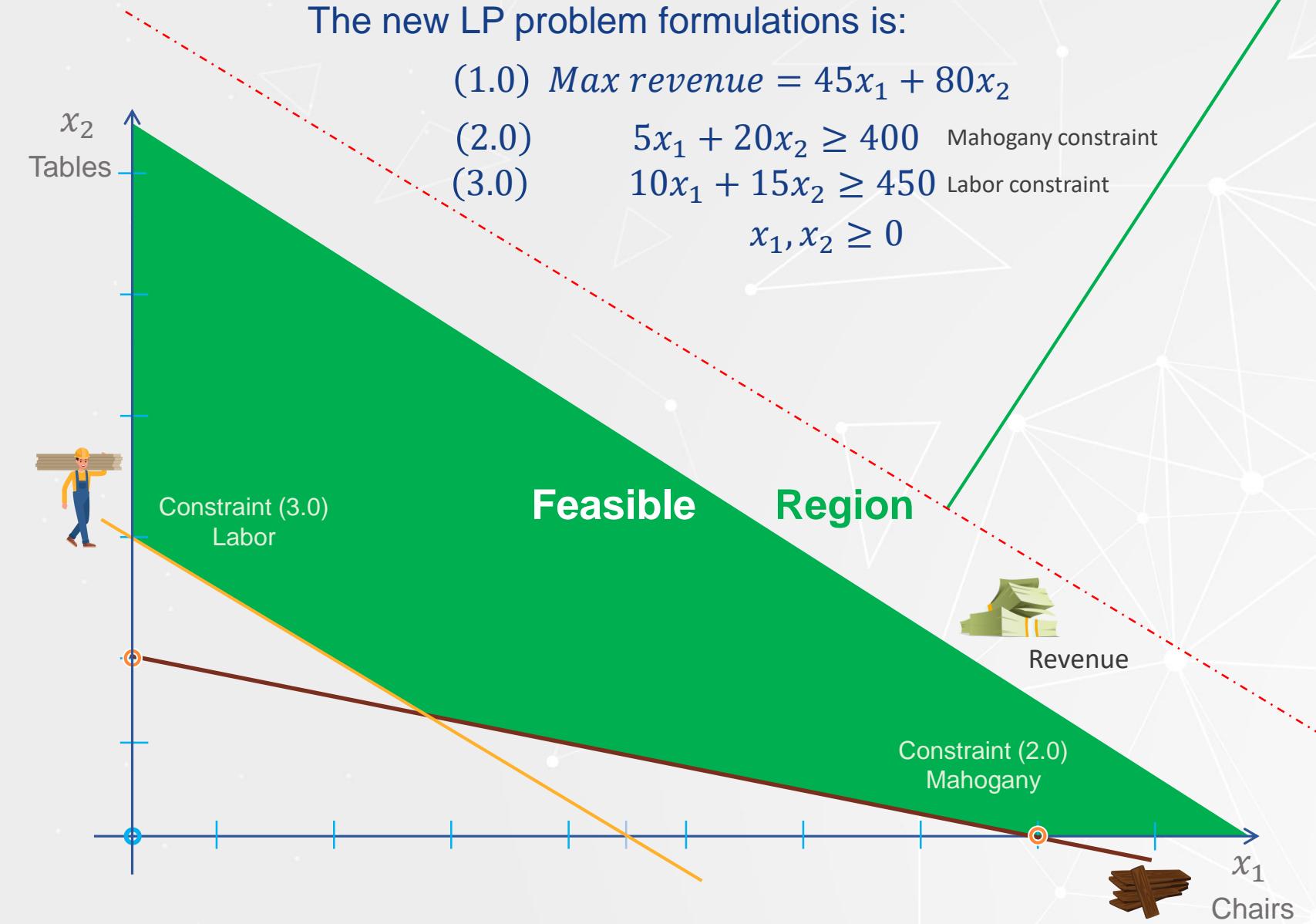
The new LP problem formulations is:

$$(1.0) \text{ Max revenue} = 45x_1 + 80x_2$$

$$(2.0) \quad 5x_1 + 20x_2 \geq 400 \quad \text{Mahogany constraint}$$

$$(3.0) \quad 10x_1 + 15x_2 \geq 450 \quad \text{Labor constraint}$$

$$x_1, x_2 \geq 0$$



New business conditions

- Notice that the polyhedron defined by the feasible region is unbounded.
- Clearly, the maximum of the objective function is unbounded, since the revenue that we can make can be arbitrarily large by increasing the number of chairs (x_1) and/or the number of tables (x_2) as much as we want. Recall, that we had assumed that we sell everything that we produce.
- Conclusion: With unlimited mahogany and labor, revenue is unlimited.

Unbounded Furniture Problem: solved with Gurobi .. 1

```
# Create an object of type list to store  
#the constraints for each resource
```

```
res = f.addConstrs(((sum(bom[r,p]*make[p] for p in products) >= capacity[r]) for r in resources), name='R')
```

$$\sum_{p \in \text{products}} bom_{r,p} make_p \geq capacity_r \quad \forall r \in \text{resources}$$

```
# run optimization engine  
f.optimize()
```

```
Optimize a model with 2 rows, 2 columns and 4 nonzeros
```

```
Coefficient statistics:
```

```
Matrix range [5e+00, 2e+01]  
Objective range [5e+01, 8e+01]  
Bounds range [0e+00, 0e+00]  
RHS range [4e+02, 5e+02]
```

```
Presolve time: 0.03s
```

```
Solved in 0 iterations and 0.03 seconds  
Infeasible or unbounded model
```

The Gurobi solver could not find an optimal solution and declares the problem either infeasible or unbounded.

Unbounded Furniture Problem: solved with Gurobi .. 2

```
print('total profits', f.objVal)
for v in f.getVars():
    print(v.varName, v.x)
```

Since an optimal solution does not exist, the objective function value and the value of the decision variables is void. In this case, we get an error when trying to print these values.

```
AttributeError                                     Traceback (most recent call last)
<ipython-input-11-a1b5e7b87473> in <module>()
----> 1 print('total profits', f.objVal)
      2 for v in f.getVars():
      3     print(v.varName, v.x)

model.pkl in gurobipy.Model.__getattr__ (<.../src/python/gurobipy.c:50100>)

model.pkl in gurobipy.Model.getAttribute (<.../src/python/gurobipy.c:65080>)

model.pkl in gurobipy.Model.__getattribute__ (<.../src/python/gurobipy.c:99204>)

AttributeError: Unable to retrieve attribute 'objVal'
```

```
# display optimal values of decision variables
if f.status == GRB.Status.OPTIMAL:
    print('Optimal solution found')
    print('total profits', f.objVal)
    for v in f.getVars():
        print(v.varName, v.x)
```

To avoid the error, we need to check the status of the LP model, and only print the solution values if an optimal solution was found.

Unbounded Furniture Problem: solved with Gurobi .. 3

```
f.setObjective(make.prod(profit), GRB.MINIMIZE)
f.optimize()
```

Optimize a model with 2 rows, 2 columns and 4 nonzeros

Coefficient statistics:

```
Matrix range [5e+00, 2e+01]
Objective range [5e+01, 8e+01]
Bounds range [0e+00, 0e+00]
RHS range [4e+02, 5e+02]
```

Presolve time: 0.01s

Presolved: 2 rows, 2 columns, 4 nonzeros

Iteration	Objective	Primal Inf.	Dual Inf.	Time
0	0.0000000e+00	1.062500e+02	0.000000e+00	0s
2	2.2000000e+03	0.000000e+00	0.000000e+00	0s

Solved in 2 iterations and 0.02 seconds

Optimal objective 2.200000000e+03

```
# display optimal values of decision variables
if f.status == GRB.Status.OPTIMAL:
    print('Optimal solution found')
    print('total profits', f.objVal)
    for v in f.getVars():
        print(v.varName, v.x)
```

```
Optimal solution found
('total profits', 2200.0)
('make[table]', 14.0)
('make[chair]', 24.0)
```

We changed the sense of the optimization to check if the model has a feasible solution.



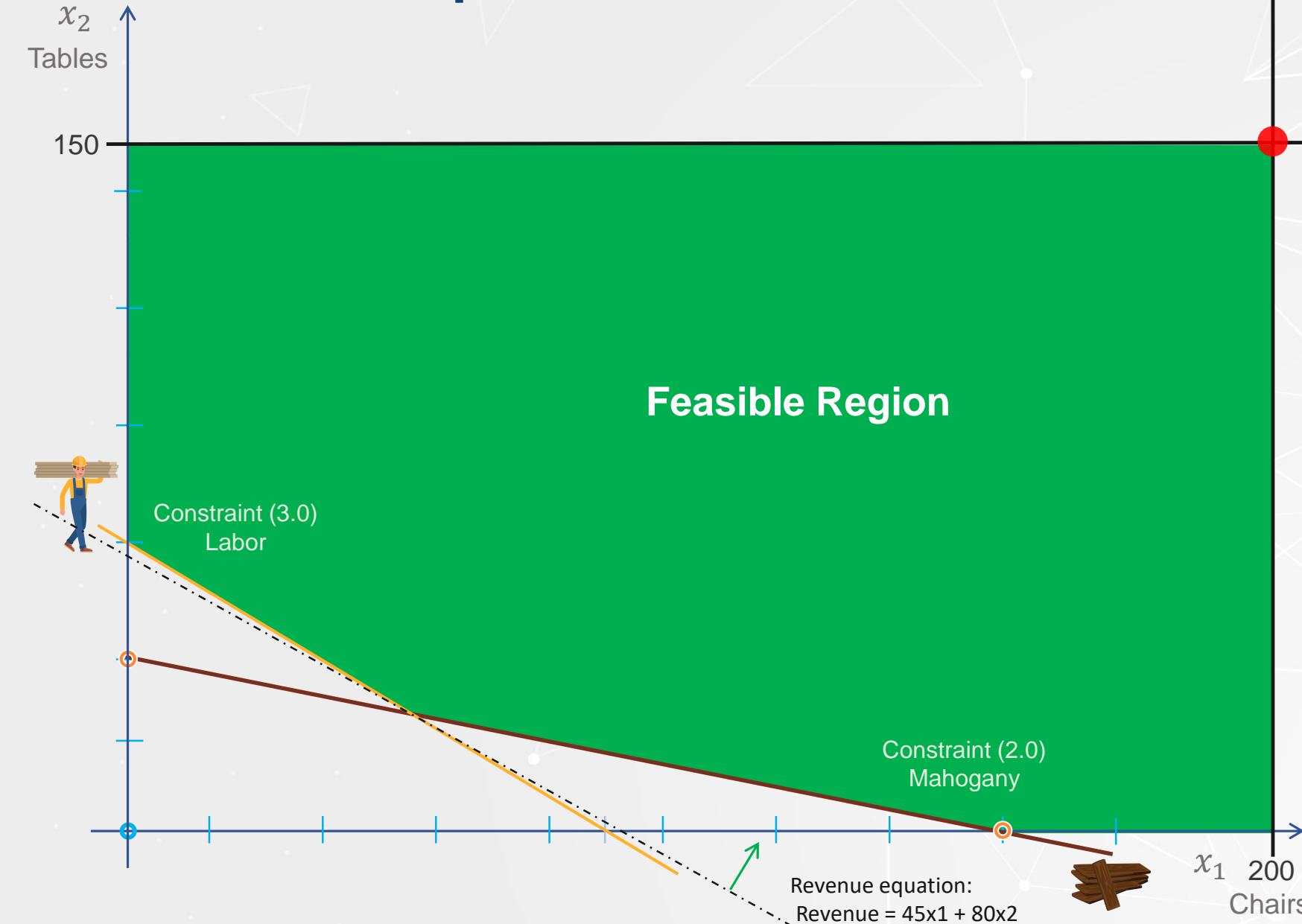
The Gurobi solver now finds a minimum optimal solution. Hence, the LP problem is feasible and for the revenue maximization problem, it is unbounded.



New business conditions

- The data scientist recognized that it is unrealistic to assume that an infinite amount of chairs and tables can be sold.
- The data scientist using predictive analytics techniques has determined that at most 200 chairs and 150 tables can be sold.

New furniture problem



New business conditions

- (1.0) $\text{Max revenue} = 45x_1 + 80x_2$
- (2.0) $5x_1 + 20x_2 \geq 400$ Mahogany constraint
- (3.0) $10x_1 + 15x_2 \geq 450$ Labor constraint
- $0 \leq x_1 \leq 200 \quad 0 \leq x_2 \leq 150$

Unbounded Furniture Problem: solved with Gurobi ..4

Let $price_p$ be the price of product $p \in products = \{chairs, tables\}$, and let $capacity_r$ be the capacity available of resource $r \in resources = \{mahogany, labor\}$.

Let's assume that we have an unlimited availability of resources. The only constraint is that the suppliers of mahogany and labor requires to consume at least 400 units of mahogany and 450 units of labor per planning period.

However, the marketing department has established that at most 200 chairs and 150 tables can be sold.

Let's define the upper bound on chairs and tables be the vector $upBound_p$

Let $bom_{r,p}$ be the amount of resource r required by product p . Then the general formulation of the Furniture problem is:

$$\text{Max} \sum_{p \in products} price_p make_p$$

Subject to :

$$\sum_{p \in products} bom_{r,p} make_p \geq capacity_r \quad \forall r \in resources$$

$$0 \leq make_p \leq upBound_p \quad \forall p \in products$$

```
# products data,  
products, price, upBound = multidict({  
    'chair': [45, 200],  
    'table': [80, 150] })
```

Adding the upper bounds to the multidict for products

Unbounded Furniture Problem: solved with Gurobi .. 5

```
# Declare and initialize model  
f = Model('Furniture')
```

```
# Create decision variables for the products to make  
make = f.addVars(products, ub=upBound, name="make")
```

Adding the upper bounds to the multidict for products

```
# Create an object of type list to store  
#the constraints for each resource
```

```
res = f.addConstrs(((sum(bom[r,p]*make[p] for p in products) >= capacity[r]) for r in resources), name='R')
```

```
# The objective is to maximize total profit  
f.setObjective(make.prod(profit), GRB.MAXIMIZE)
```

Unbounded Furniture Problem: solved with Gurobi .. 6

```
# save LP model for inspection
f.write('Furniture0065.lp')
```

```
\ Model Furniture
\ LP format - for model browsing. Use MPS format to capture full model detail.
Maximize
  80 make[table] + 45 make[chair]
Subject To
R[mahogany]: 20 make[table] + 5 make[chair] >= 400
R[labor]: 15 make[table] + 10 make[chair] >= 450
Bounds
  make[table] <= 150
  make[chair] <= 200
End
```

Unbounded Furniture Problem: solved with Gurobi .. 7

```
# run optimization engine
f.optimize()
```

Optimize a model with 2 rows, 2 columns and 4 nonzeros

Coefficient statistics:

```
Matrix range      [5e+00, 2e+01]
Objective range   [5e+01, 8e+01]
Bounds range      [2e+02, 2e+02]
RHS range         [4e+02, 5e+02]
```

Presolve removed 2 rows and 2 columns

Presolve time: 0.04s

Presolve: All rows and columns removed

Iteration	Objective	Primal Inf.	Dual Inf.	Time
0	2.1000000e+04	0.000000e+00	0.000000e+00	0s

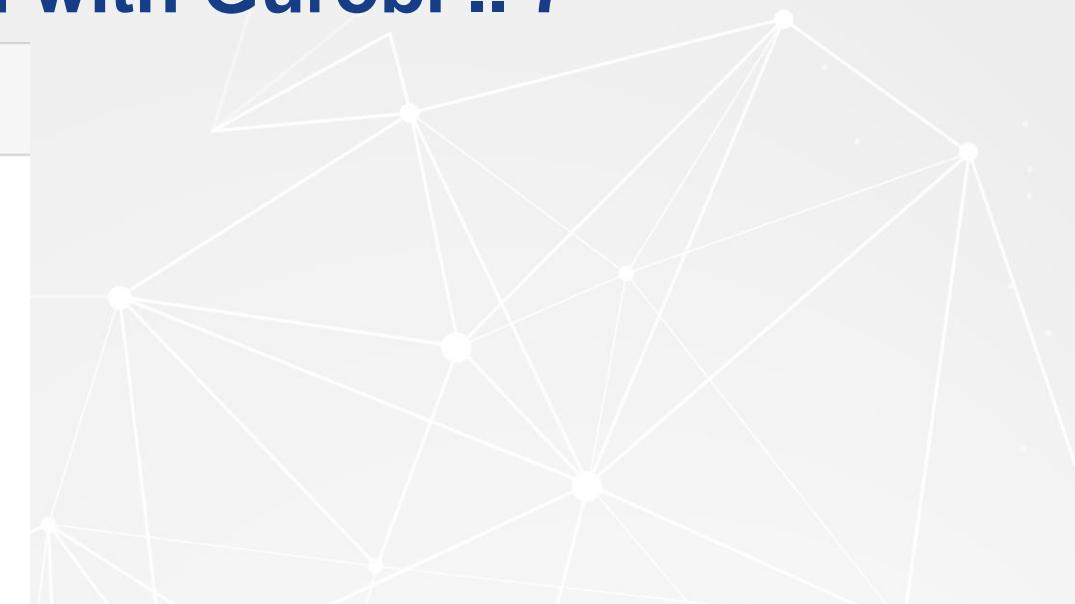
Solved in 0 iterations and 0.15 seconds

Optimal objective 2.10000000e+04

```
# display optimal values of decision variables
```

```
if f.status == GRB.Status.OPTIMAL:
    print('Optimal solution found')
    print('total revenue', f.objVal)
    for v in f.getVars():
        print(v.varName, v.x)
```

```
Optimal solution found
('total revenue', 21000.0)
('make[table]', 150.0)
('make[chair]', 200.0)
```



As expected, Gurobi solver now finds an optimal solution.

The optimal number of chairs to make is equal to the chairs upper bound and the optimal number of tables to make is equal to the tables upper bound.

The optimal objective function value is a total revenue of \$21,000

Infeasible LP problem

Gurobi Python API

Minimum Optimal Solution



New business conditions

- The data scientist receives a memo from the CEO of the furniture company saying that the new board of directors of the company requires a total revenue of at least \$4,500 per week.

Furniture Problem

The new LP problem formulations is:

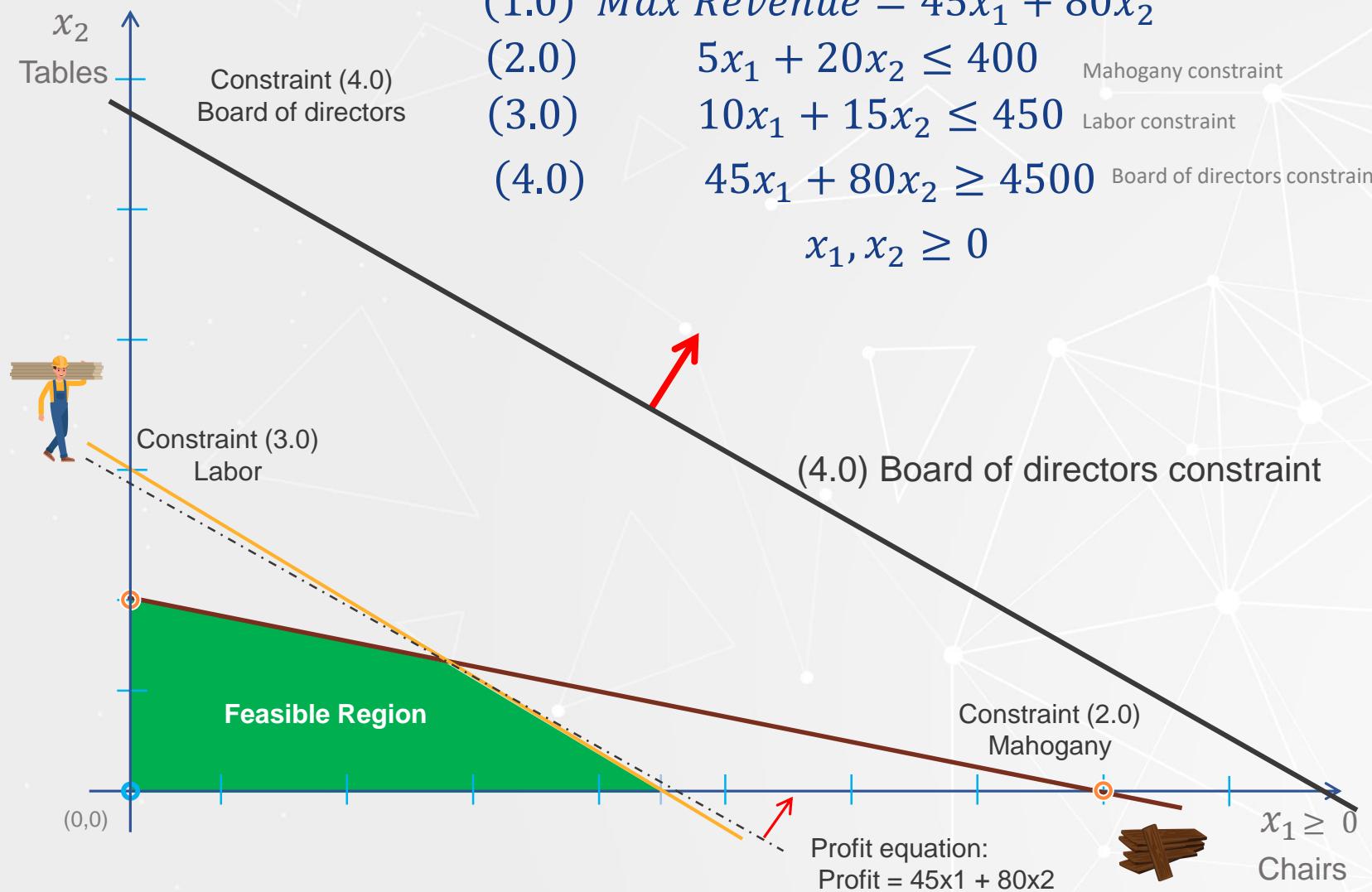
$$(1.0) \text{ Max Revenue} = 45x_1 + 80x_2$$

$$(2.0) \quad 5x_1 + 20x_2 \leq 400$$

$$(3.0) \quad 10x_1 + 15x_2 \leq 450$$

$$(4.0) \quad 45x_1 + 80x_2 \geq 4500 \quad \text{Board of directors constraint}$$

$$x_1, x_2 \geq 0$$



New business conditions

- Evidently, there are no points that satisfy all the constraints simultaneously. Hence this LP problem is infeasible.

Infeasible Furniture Problem: using with Gurobi .. 1

Let $price_p$ be the price of product $p \in products = \{chairs, tables\}$, and let $capacity_r$ be the capacity available of resource $r \in resources = \{mahogany, labor\}$.

The board of directors has imposed a constraint of a minimum revenue, $minRev = \$4,500$, per week.

Let $bom_{r,p}$ be the amount of resource r required by product p . Then the general formulation of the Furniture problem is:

$$\text{Max} \sum_{p \in products} price_p make_p$$

Subject to :

$$\sum_{p \in products} bom_{r,p} make_p \leq capacity_r \quad \forall r \in resources$$

$$\sum_{p \in products} price_p make_p \geq minRev$$

$$make_p \geq 0 \quad \forall p \in products$$

$minRev = 4500$

Defining a new parameter to capture the minimum revenue value that the board of directors may impose.

Board constraint of minimum revenue

```
minProfitConstr = f.addConstr((sum(price[p]*make[p] for p in products) >= minRev), name='B')
```

Adding a new constraint to the f model to ensure that the minimum revenue impose by the Board is satisfied.

Infeasible Furniture Problem: solved with Gurobi .. 2

```
# save model for inspection
f.write('furnitureB.lp')
```

```
\ Model Furniture
\ LP format - for model browsing. Use MPS format to capture full model detail.
Maximize
  80 make[table] + 45 make[chair]
Subject To
  R[mahogany]: 20 make[table] + 5 make[chair] <= 400
  R[labor]: 15 make[table] + 10 make[chair] <= 450
  B: 80 make[table] + 45 make[chair] >= 4500
Bounds
End
```

Infeasible Furniture Problem: solved with Gurobi .. 3

```
# run optimization engine
f.optimize()
```

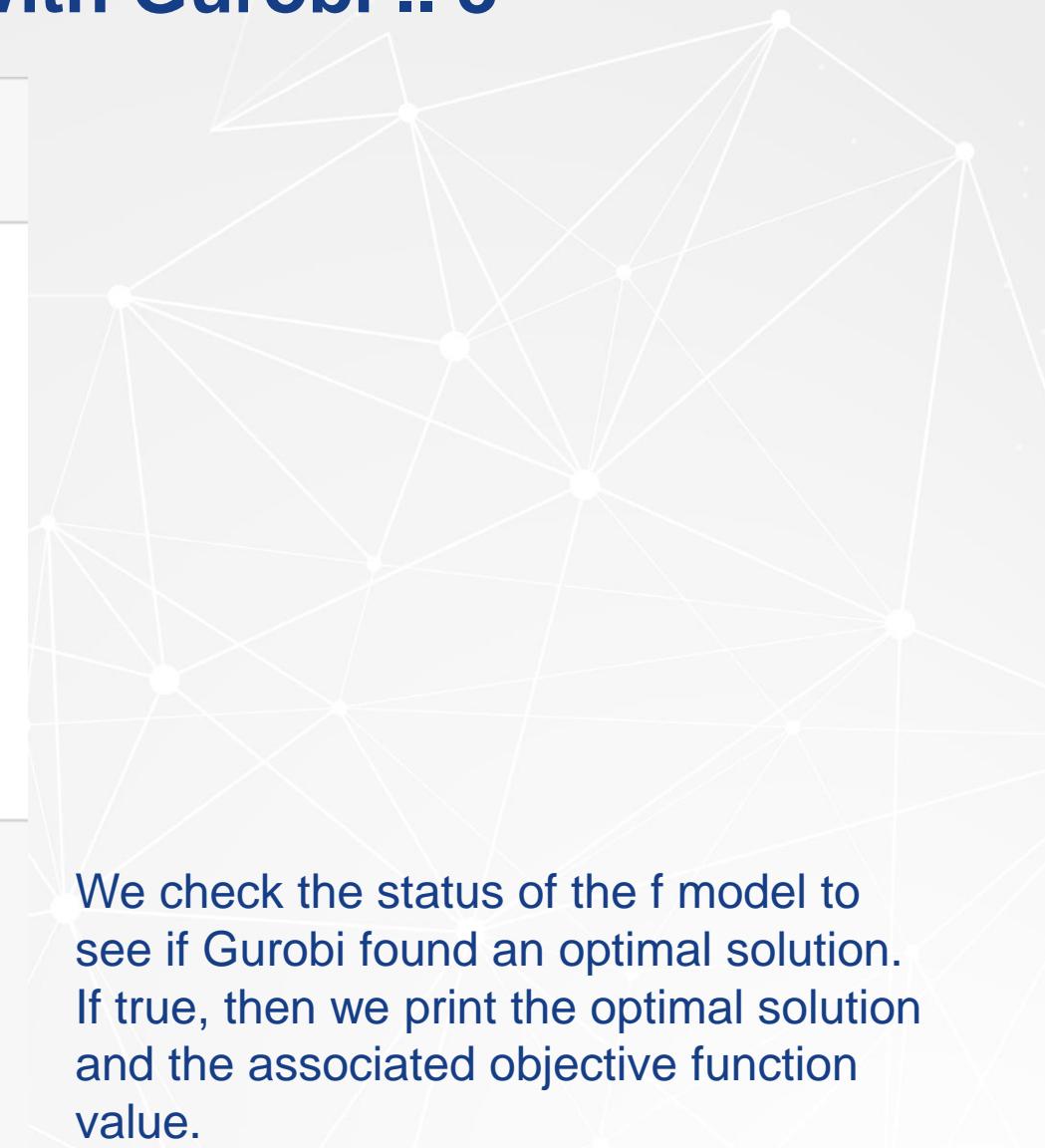
Optimize a model with 3 rows, 2 columns and 6 nonzeros
Coefficient statistics:

Matrix range [5e+00, 8e+01]
Objective range [5e+01, 8e+01]
Bounds range [0e+00, 0e+00]
RHS range [4e+02, 5e+03]

Presolve time: 0.03s

Solved in 0 iterations and 0.03 seconds
Infeasible or unbounded model

```
# display optimal values of decision variables
if f.status == GRB.Status.OPTIMAL:
    print('Optimal solution found')
    print('total revenue', f.objVal)
    for v in f.getVars():
        print(v.varName, v.x)
```



We check the status of the `f` model to see if Gurobi found an optimal solution. If true, then we print the optimal solution and the associated objective function value.

Infeasible Furniture Problem: solved with Gurobi .. 3

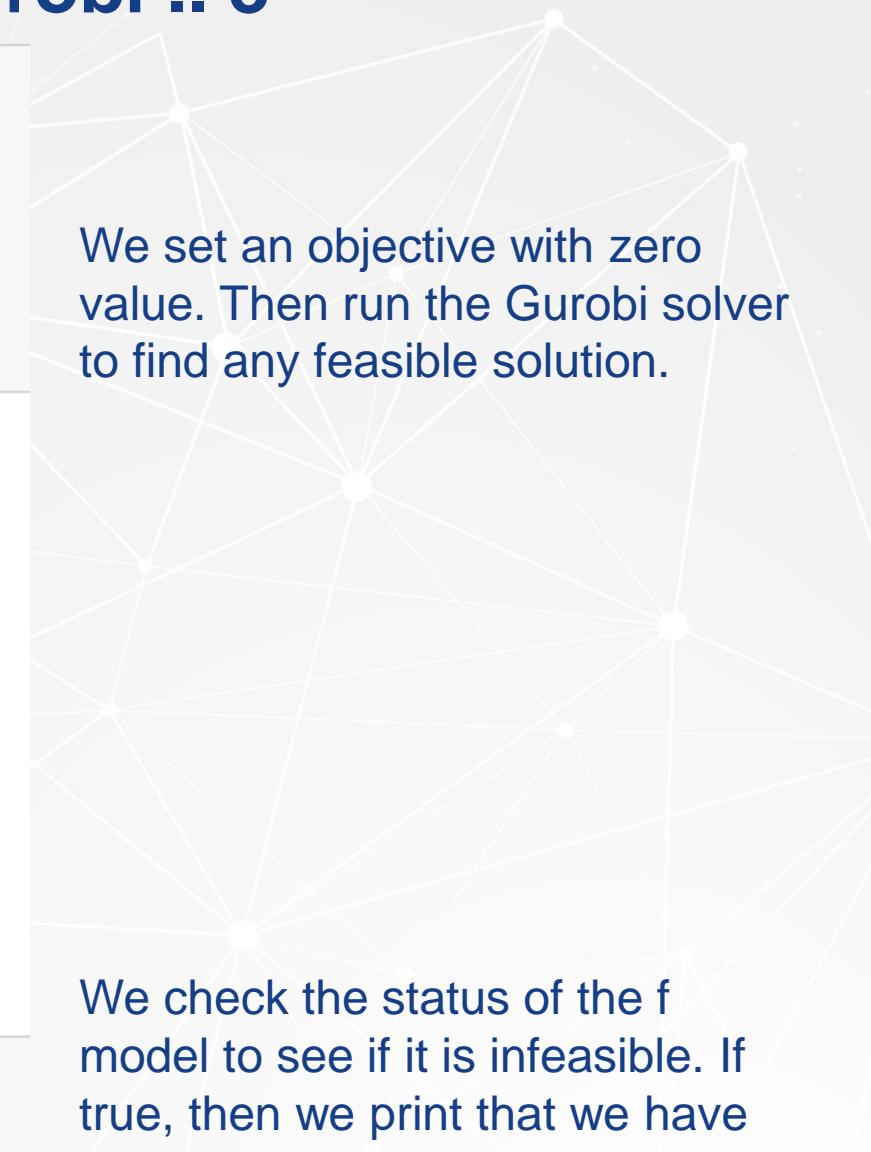
```
#Check if model infeasible or unbounded
if f.status == GRB.Status.INF_OR_UNBD :
    print('LP problem is either infeasible or unbounded')
    print('Checking if LP problem is feasible')
    print('set objective function to zero value and re-run engine' )
    f.setObjective( 0, GRB.MAXIMIZE)
    f.optimize()
```

```
LP problem is either infeasible or unbounded
Checking if LP problem is feasible
set objective function to zero value and re-run engine
Optimize a model with 3 rows, 2 columns and 6 nonzeros
Coefficient statistics:
  Matrix range      [5e+00, 8e+01]
  Objective range   [0e+00, 0e+00]
  Bounds range      [0e+00, 0e+00]
  RHS range         [4e+02, 5e+03]
Presolve time: 0.01s
```

```
Solved in 0 iterations and 0.01 seconds
Infeasible model
```

```
#Check if model with zero objective is infeasible
if f.status == GRB.Status.INFEASIBLE :
    print('LP problem is proven to be infeasible')
```

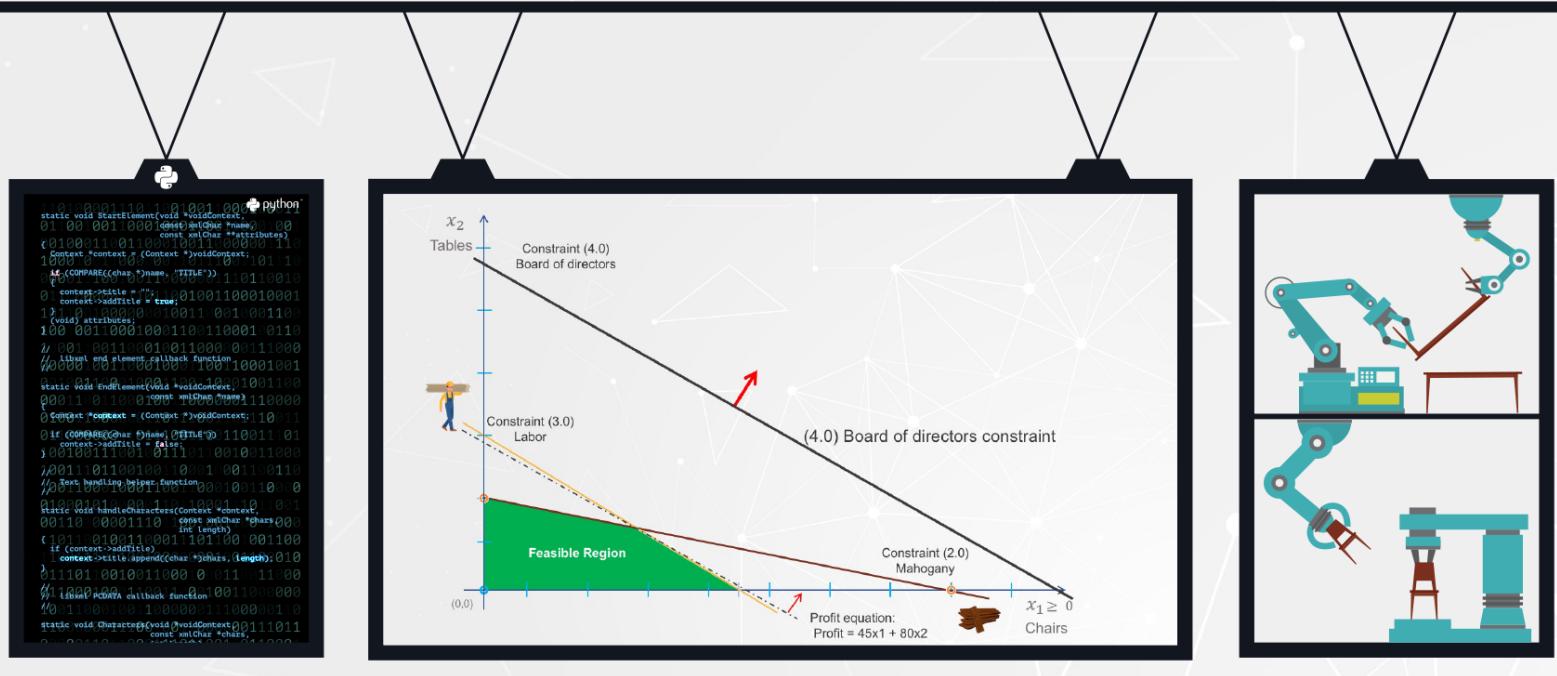
```
LP problem is proven to be infeasible
```



We set an objective with zero value. Then run the Gurobi solver to find any feasible solution.

We check the status of the model to see if it is infeasible. If true, then we print that we have proven that the model is infeasible.

Infeasible Furniture Problem



Addressing infeasibility

- There is a Board of Director meeting and the data scientist cannot tell the Board that their requirement of having a total revenue of at least \$4,500 per week is Infeasible !!!
- The data scientist knows that the cause of infeasibility is the limited capacity available of resources that does not allow the production of chairs and tables to reach the minimum level of total revenue.
- The data scientist calls the supplier of mahogany and talks with the labor union and they agree to increase the supply at a cost. An extra unit of mahogany will cost \$20 and one hour of overtime of labor will cost \$30.

Furniture Problem: addressing infeasibility .. 2

Furniture model formulation: buying extra supply

Let $price_p$ be the price of product $p \in products = \{chairs, tables\}$, and let $capacity_r$ be the capacity available of resource $r \in resources = \{mahogany, labor\}$.

The board of directors has imposed a constraint of a minimum revenue, $minRev = \$4,500$, per week.

To satisfy Board of Directors demands, the supplier of mahogany can get extra mahogany at a rate of \$20 per unit; and the labor union can provide overtime of labor at a rate of \$30 per unit.

Let's define a new decision variable, $extra_r$, that measures the extra capacity of resource $r \in resources = \{mahogany, labor\}$ which are required to meet the Board of Directors demands. Let the cost of extra capacity be defined by the parameter $extraCost_r$ for each resource $r \in resources = \{mahogany, labor\}$.

Let $bom_{r,p}$ be the amount of resource r required by product p . Then the general formulation of the Furniture problem is:

$$\text{Max} \sum_{p \in products} price_p make_p - \sum_{r \in resources} extraCost_r extra_r$$

Subject to :

$$\sum_{p \in products} bom_{r,p} make_p - extra_r \leq capacity_r \quad \forall r \in resources$$

$$\sum_{p \in products} price_p make_p \geq minRev$$

$$make_p \geq 0 \quad \forall p \in products$$

$$extra_r \geq 0 \quad \forall r \in resources$$

Furniture Problem: addressing infeasibility .. 2

$$\begin{aligned}
 & \text{Max} \sum_{p \in \text{products}} \text{price}_p \text{make}_p - \sum_{r \in \text{resources}} \text{extraCost}_r \text{extra}_r \\
 & \text{Subject to :} \\
 & \sum_{p \in \text{products}} \text{bom}_{r,p} \text{make}_p - \text{extra}_r \leq \text{capacity}_r \quad \forall r \in \text{resources} \\
 & \sum_{p \in \text{products}} \text{price}_p \text{make}_p \geq \text{minRev} \\
 & \text{make}_p \geq 0 \quad \forall p \in \text{products} \\
 & \text{extra}_r \geq 0 \quad \forall r \in \text{resources}
 \end{aligned}$$

```
# resources data
resources, capacity, extraCost = multidict({
    'mahogany': [400, 20],
    'labor': [450, 30]
})
```

```
# Create decision variables for extra capacity of resources
extra = f.addVars(resources, name="extra")
```

```
# Create an object of type list to store
#the constraints for each resource
```

$$\sum_{p \in \text{products}} \text{bom}_{r,p} \text{make}_p - \text{extra}_r \leq \text{capacity}_r \quad \forall r \in \text{resources}$$

```
res = f.addConstrs(((sum(bom[r,p]*make[p] for p in products) - extra[r]) <= capacity[r]) for r in resources), name='R')
```

We add a decision variable (extra) to the RHS of each resource constraint to add the extra capacity to satisfy the Board constraint.

```
# The objective is to maximize total revenue
f.setObjective(make.prod(price) - extra.prod(extraCost), GRB.MAXIMIZE)
```

We subtract the cost of the extra capacity to meet the Board constraint .

$$\text{Max} \sum_{p \in \text{products}} \text{price}_p \text{make}_p - \sum_{r \in \text{resources}} \text{extraCost}_r \text{extra}_r$$

We include in the resources multidict the extra cost of adding resource capacity.

Create a new decision variable to measure the extra resource capacity to meet the Board constraint.

Furniture Problem: addressing infeasibility .. 3

```
# save model for inspection  
f.write('furnitureB.lp')
```

```
\ Model Furniture  
\ LP format - for model browsing. Use MPS format to capture full model detail.  
Maximize  
  80 make[table] + 45 make[chair] - 20 extra[mahogany] - 30 extra[labor]  
Subject To  
R[mahogany]: 20 make[table] + 5 make[chair] - extra[mahogany] <= 400  
R[labor]: 15 make[table] + 10 make[chair] - extra[labor] <= 450  
B: 80 make[table] + 45 make[chair] >= 4500  
Bounds  
End
```

Furniture Problem: addressing infeasibility .. 3

```
# run optimization engine
f.optimize()
```

Optimize a model with 3 rows, 4 columns and 8 nonzeros

Coefficient statistics:

Matrix range	[1e+00, 8e+01]
Objective range	[2e+01, 8e+01]
Bounds range	[0e+00, 0e+00]
RHS range	[4e+02, 5e+03]

Presolve time: 0.10s

Presolved: 3 rows, 4 columns, 8 nonzeros

Iteration	Objective	Primal Inf.	Dual Inf.	Time
0	1.0625000e+31	1.015625e+30	1.062500e+01	0s
4	-1.4000000e+04	0.000000e+00	0.000000e+00	0s

Solved in 4 iterations and 0.16 seconds

Optimal objective -1.400000000e+04

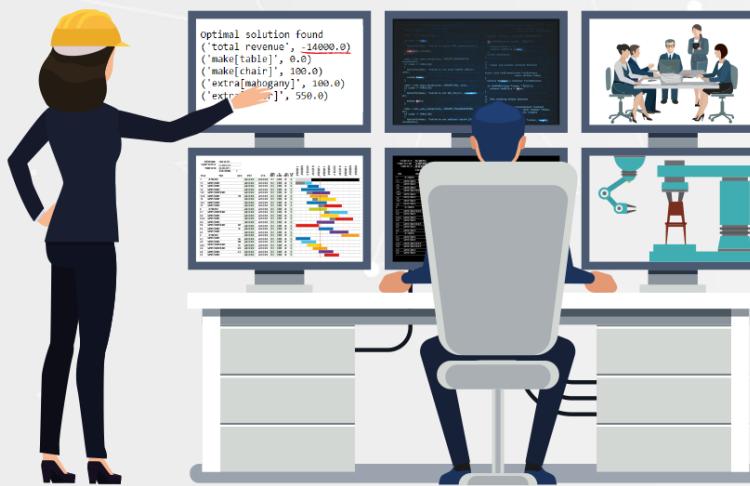
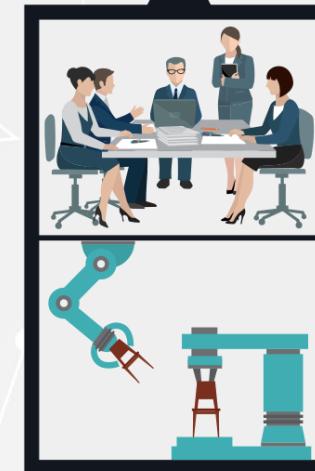
```
# display optimal values of decision variables
if f.status == GRB.Status.OPTIMAL:
    print('Optimal solution found')
    print('total revenue', f.objVal)
    for v in f.getVars():
        print(v.varName, v.x)
```

Gurobi solver found an optimal solution.

Furniture Problem: addressing infeasibility

```
static void StartElement(void *voidContext, const intChar *name, ...)
```

Optimal solution found
('total revenue', -14000.0)
('make[table]', 0.0)
('make[chair]', 100.0)
('extra[mahogany]', 100.0)
('extra[labor]', 550.0)

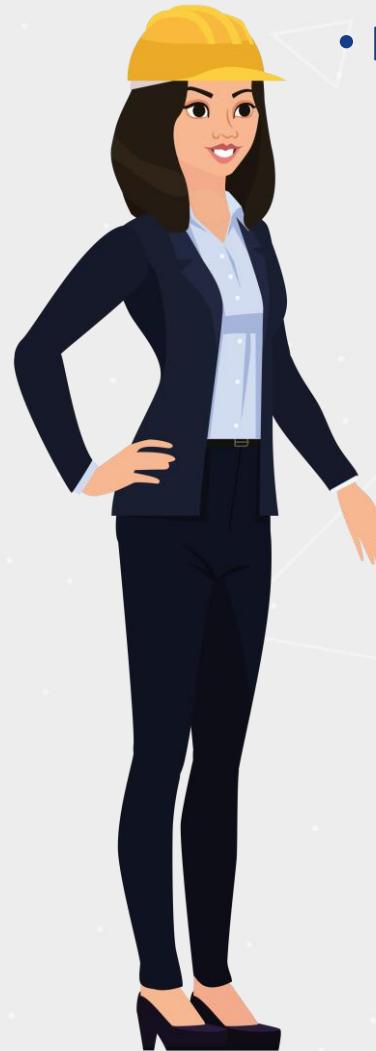


To meet the Board request requires 100 extra units of mahogany and 550 extra units of overtime.
The optimal production plan is to produce only 100 chairs.

The company will lose \$14,000 per week !!!

The Board request was proven not to be a good idea.

Final Remarks about model status



- It is a good modeling practice that the LP problem is well characterized.
 - This means that when the data of the LP problem satisfy the specified modeling assumptions, the LP problem has an optimal solution.
 - That is, the LP problem is never infeasible, unbounded, and there are no alternate optimal solutions.
 - To avoid infeasibility add “artificial” variables to the constraints that may be infeasible. These artificial variables will have a “high” penalty in the objective function in such a way that they become positive only to make the problem feasible. Ideally, these artificial variables have a business meaning that the user of the decision support application can properly interpret.
 - To avoid that the LP problem is unbounded, define realistic upper bounds for all the decision variables of the LP problem.
 - If the LP problem has alternate optimal solutions, if possible add another objective functions that eliminates the alternate optimal solutions.

Linear Programming Overview

Further considerations:

- Maximize or minimize objective function
- Unconstrained decision variables
- Initial basic solution
- Presolve
- Matrix sparsity

What if we need to minimize an objective function?

We have assumed that we are maximizing an LP problem. Notice that the rules for a non-basic variables to become basic variables can be changed to address the minimization problem.

Alternatively, since $\text{Min } \sum_{j=1}^n b_j x_j = -\text{Max } -\sum_{j=1}^n b_j x_j$, then we solve

$\text{Max } \sum_{j=1}^n (-b_j) x_j$.

Example: $\text{Min } \{1, 2\} = -\text{Max } \{-1, -2\} = 1$

```
# The objective is to maximize total revenue
f.setObjective(make.prod(price) - extra.prod(extraCost), GRB.MAXIMIZE)
```

Note: The default sense in Gurobi is to minimize the objective function of the LP problem we want to solve. If we want to maximize the objective we need to use the Gurobi argument (GRB.MAXIMIZE) when defining the objective function.

What if a decision variable can be positive or negative?

If the decision variable is unconstrained in sign, the Gurobi Optimizer will take care of this automatically.

An example of a decision variable that is unconstrained is profit. Negative profit is interpreted as a loss.

How to determine an initial basic feasible solution?

- Gurobi behind the scenes may use a technique called Phase 1 of Linear Programming:
 - This technique entails adding non-negative artificial variables to the equations (=) and greater-or-equal (\geq) inequalities.
 - Then replace the original objective function by a new objective, minimize the summation of the artificial variables.
 - If the minimum value of the summation of artificial variables is positive, the LP problem is infeasible.
 - If the minimum value of the summation of artificial variables is zero, then the basic feasible variables of the optimal solution are an initial basic feasible solution of the original LP model (*).

(*) There are some subtleties about this statement beyond the scope of this class.

How to determine an initial basic feasible solution? .. 2

- Consider the following LP problem with the Furniture factory board request.

$$\text{Max } \sum_{p \in \text{products}} \text{price}_p \text{make}_p - \sum_{r \in \text{resources}} \text{extraCost}_r \text{extra}_r$$

Subject to :

$$\sum_{p \in \text{products}} \text{bom}_{r,p} \text{make}_p - \text{extra}_r \leq \text{capacity}_r \quad \forall r \in \text{resources}$$

$$\sum_{p \in \text{products}} \text{price}_p \text{make}_p \geq \text{minRev}$$

$$\text{make}_p \geq 0 \quad \forall p \in \text{products}$$

$$\text{extra}_r \geq 0 \quad \forall r \in \text{resources}$$

- An instance of the parametrized formulation is

$$\text{Max } z = 45x_1 + 80x_2 - 20x_3 - 30x_4$$

$$5x_1 + 20x_2 - x_3 \leq 400$$

$$10x_1 + 15x_2 - x_4 \leq 450$$

$$45x_1 + 80x_2 \geq 4500$$

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

How to determine an initial basic feasible solution? .. 2

- Original LP problem.

$$\begin{aligned} \text{Max } z &= 45x_1 + 80x_2 - 20x_3 - 30x_4 \\ 5x_1 + 20x_2 - x_3 &\leq 400 \\ 10x_1 + 15x_2 - x_4 &\leq 450 \\ 45x_1 + 80x_2 &\geq 4500 \\ x_1, x_2, x_3, x_4 &\geq 0 \end{aligned}$$

- We add an artificial variable alpha to the \geq constraint. At Phase 1 of linear programming, we minimize the value of alpha, i.e. alpha should be equal to zero and non-basic variable, to identify an initial basic feasible solution.

Original LP Problem

$$\begin{aligned} \text{Min } w &= \alpha \\ 5x_1 + 20x_2 - x_3 &\leq 400 \\ 10x_1 + 15x_2 - x_4 &\leq 450 \\ 45x_1 + 80x_2 + \alpha &\geq 4500 \\ x_1, x_2, x_3, x_4, \alpha &\geq 0 \end{aligned}$$

LP Problem Standard Form

$$\begin{aligned} \text{Max } w &= -\alpha \\ 5x_1 + 20x_2 - x_3 + h_1 &= 400 \\ 10x_1 + 15x_2 - x_4 + h_2 &= 450 \\ 45x_1 + 80x_2 + \alpha - s_1 &= 4500 \\ x_1, x_2, x_3, x_4, \alpha, h_1, h_2, s_1 &\geq 0 \end{aligned}$$

LP Problem Canonical Form

$$\begin{aligned} \text{Max } w &= -4500 + 45x_1 + 80x_2 - s_1 \\ h_1 &= 400 - 5x_1 - 20x_2 + x_3 \\ h_2 &= 450 - 10x_1 - 15x_2 + x_4 \\ \alpha &= 4500 - 45x_1 - 80x_2 + s_1 \\ x_1, x_2, x_3, x_4, \alpha, h_1, h_2, s_1 &\geq 0 \end{aligned}$$

How to determine an initial basic feasible solution? .. 3

We apply the simplex method to the Phase 1 LP problem in canonical form with respect to the basis (h_1, h_2, α) . The following table shows the basic feasible solution at each iteration of the simplex method, the non basic variable entering the basis and the basic variable leaving the basis.

Iteration	Basic feasible solution Phase 1	Non basic variable entering the basis	Basic variable leaving the basis
1	$h_1 = 400, h_2 = 450, \alpha = 4500$	x_2	h_1
2	$x_2 = 20, h_2 = 150, \alpha = 2900$	x_3	h_2
3	$x_2 = 30, x_3 = 200, \alpha = 2100$	x_4	α
4	$x_2 = 56.25, x_3 = 725, x_4 = 393.75$	x_1	x_2
5	$x_1 = 100, x_3 = 100, x_4 = 550$	This solution is optimal.	

Notice that α is non basic and = 0. This solution is an initial basic feasible solution of the original LP problem.

Iteration 4 continues with Phase 2 of the simplex method, where we find the optimal feasible basic solution.

Optimal solution found using Gurobi

```
# run optimization engine
f.optimize()
```

Optimize a model with 3 rows, 4 columns and 8 nonzeros

Coefficient statistics:

Matrix range	[1e+00, 8e+01]
Objective range	[2e+01, 8e+01]
Bounds range	[0e+00, 0e+00]
RHS range	[4e+02, 5e+03]

Presolve time: 0.10s

Presolved: 3 rows, 4 columns, 8 nonzeros

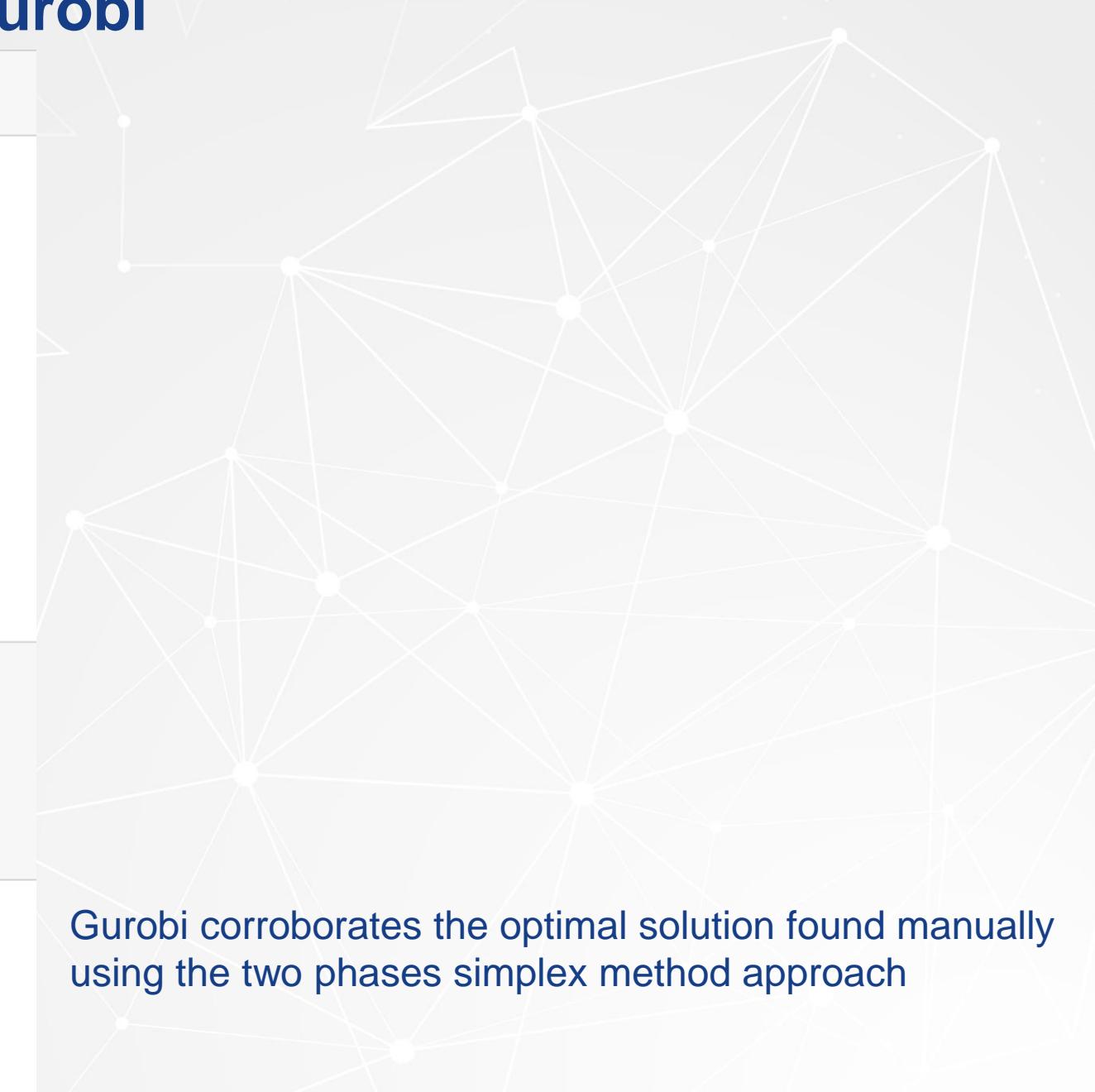
Iteration	Objective	Primal Inf.	Dual Inf.	Time
0	1.0625000e+31	1.015625e+30	1.062500e+01	0s
4	-1.4000000e+04	0.000000e+00	0.000000e+00	0s

Solved in 4 iterations and 0.16 seconds

Optimal objective -1.400000000e+04

```
# display optimal values of decision variables
if f.status == GRB.Status.OPTIMAL:
    print('Optimal solution found')
    print('total revenue', f.objVal)
    for v in f.getVars():
        print(v.varName, v.x)
```

```
Optimal solution found
('total revenue', -14000.0)
('make[table]', 0.0)
('make[chair]', 100.0) →      x1 = 100
('extra[mahogany]', 100.0) →  x3 = 100
('extra[labor]', 550.0) →     x4 = 550
```



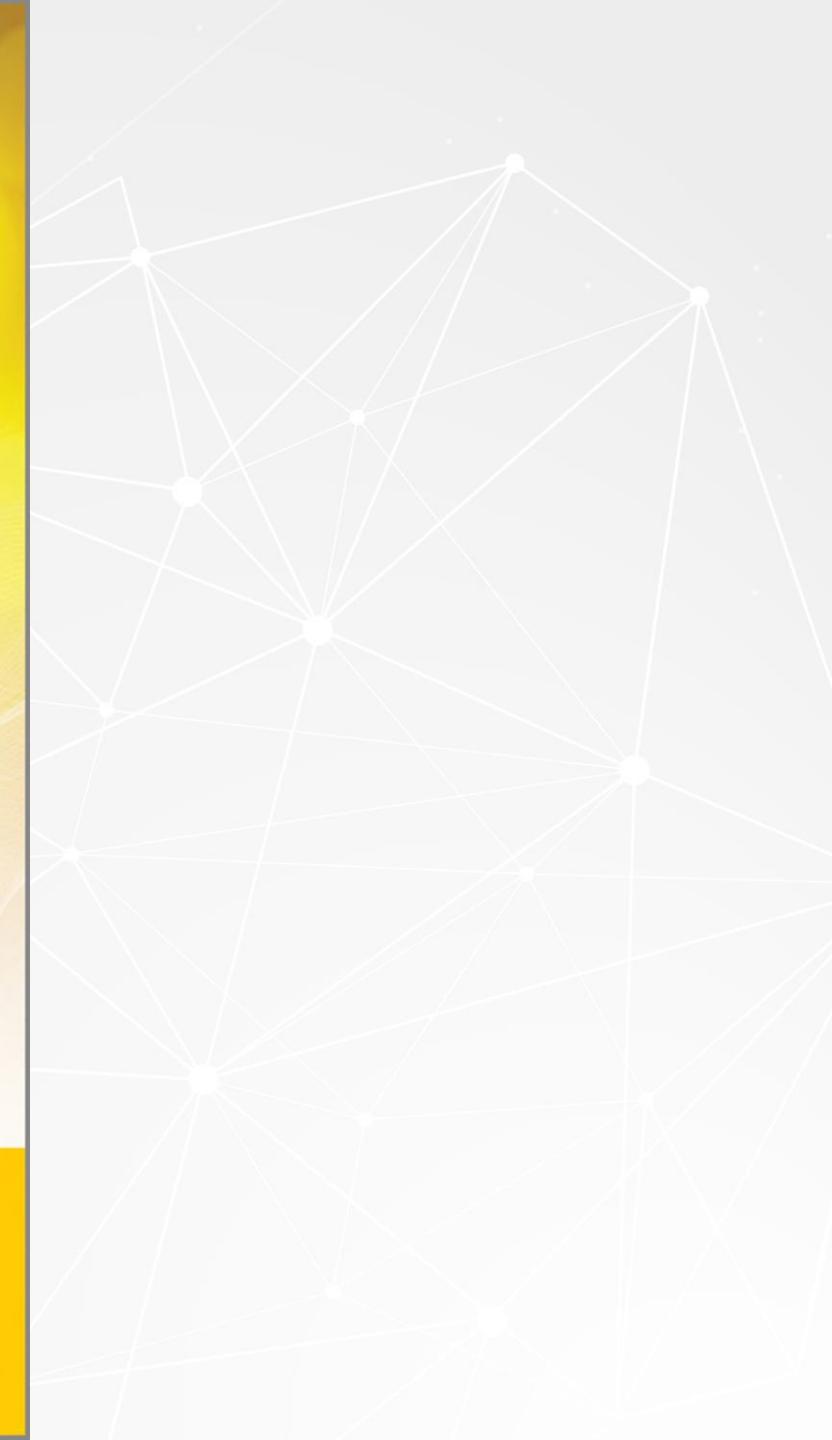
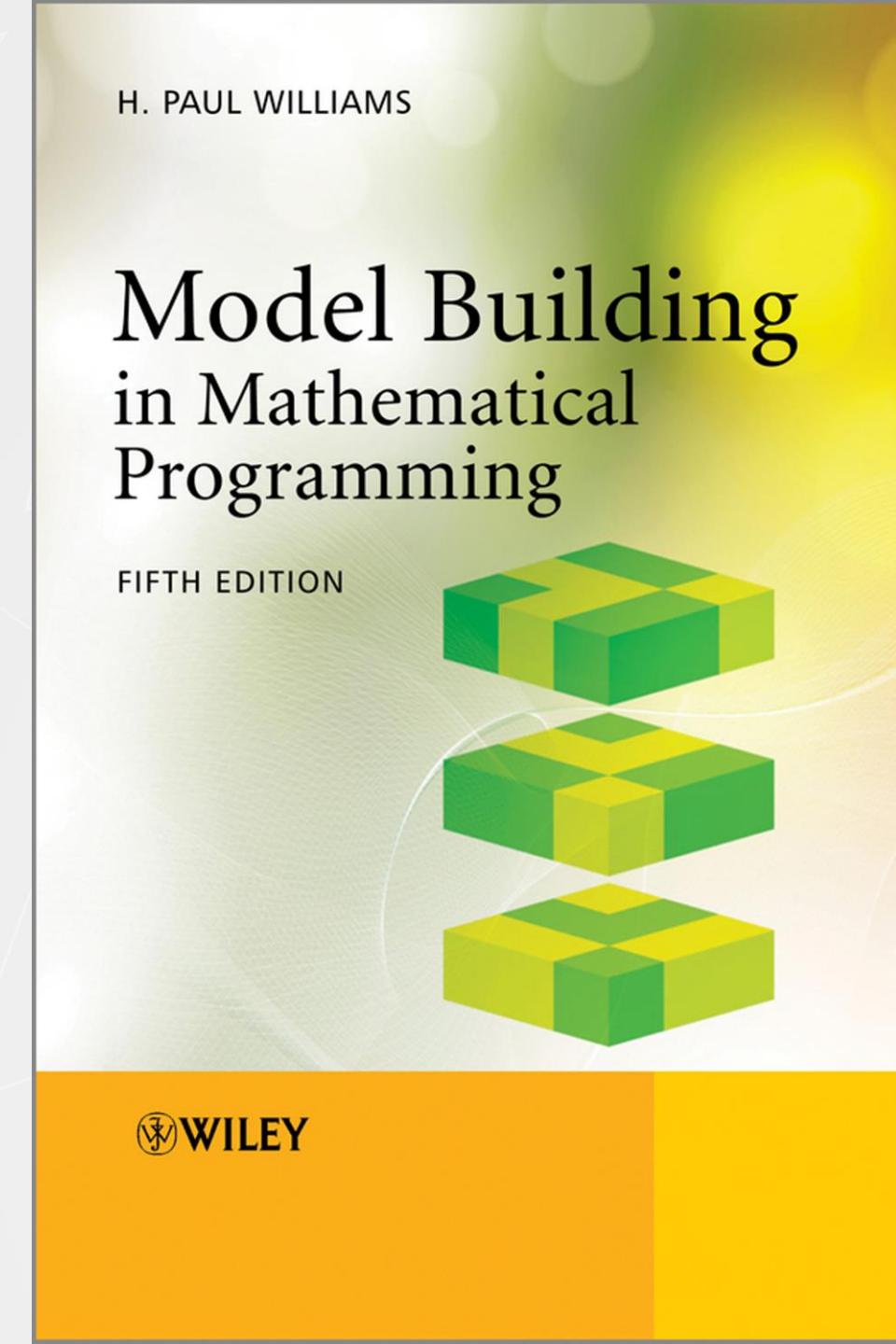
Gurobi corroborates the optimal solution found manually using the two phases simplex method approach

How to determine an initial basic feasible solution? .. 4

Remarks

- Gurobi user does not need to provide an initial basic feasible solution, or solve the phase 1 minimization of the sum of artificial variables problem to generate an initial basic solution.
- Gurobi only needs the original LP formulation. It automatically finds an initial feasible basic solution to start the simplex method.

Presolve



Presolve

- LP problems can use a large amount of computer time, consequently it is advisable to have LP models that can be solved as quickly as possible.
- The Presolve engine of Gurobi can dramatically reduce the size of an LP problem. The reduced problem can then be solved faster than the original one. The solution of the reduced problem is then used to generate a solution of the original problem.
- To briefly illustrate the core ideas behind a Presolve approach consider the following example.

- Max $2x_1 + 3x_2 - x_3 - x_4 \dots (0)$
- Subject to: $x_1 + x_2 + x_3 - 2x_4 \leq 4 \dots (1)$
- $-x_1 - x_2 + x_3 - x_4 \leq 1 \dots (2)$
- $x_1 + x_4 \leq 1 \dots (3)$
- $x_1, x_2, x_3, x_4 \geq 0 \dots (4)$

- Notice that x_3 has a negative objective coefficient. We have a maximization problem, then we want to make x_3 as small as possible.
- Observe that x_3 has positive coefficient in constraints (1) and (2),
- and these constraints are of the ' \leq ', then we want to make x_3 as small as possible.
- Therefore, x_3 can be reduced to its lower bound of zero and eliminated as a redundant variable.

Presolve ..2

- $\text{Max } 2x_1 + 3x_2 - x_4 \dots (0)$
- Subject to: $x_1 + x_2 - 2x_4 \leq 4 \dots (1)$
- $-x_1 - x_2 - x_4 \leq 1 \dots (2)$
- $x_1 + x_4 \leq 1 \dots (3)$
- $x_1, x_2, x_3, x_4 \geq 0 \dots (4)$

- After removing x_3 , let's analyze constraint (2) $-x_1 - x_2 - x_4 \leq 1$. Notice that all coefficients of the variables in this constraint are negative. For any positive value of variables x_1 , x_2 , and x_3 constraint (2) is satisfied, consequently this constraint is redundant and can be eliminated. The reduced problem is then:

This simple Presolve approach eliminated one variable and one constraint.

- $\text{Max } 2x_1 + 3x_2 - x_4 \dots (0)$
- Subject to: $x_1 + x_2 - 2x_4 \leq 4 \dots (1)$
- $x_1 + x_4 \leq 1 \dots (3)$
- $x_1, x_2, x_4 \geq 0 \text{ and } x_3=0 \dots (4)$

With large models, a Presolve approach could lead to significant reductions in the amount of computation needed to solve the model. I have seen Gurobi Presolve reduce a large scale problem to less than 10% of its original size.

Example of the power of Gurobi Presolve

Gurobi Case Study:

Project Portfolio Optimization at the former Hewlett Packard Global IT



- Solution approach:
- Problem statement: how to optimize the selection and scheduling of a portfolio of IT projects such that the trade-offs among various objectives are optimized while automating the number of ongoing processes, selecting the best projects jointly within satisfying resource constraints (e.g. labor availability and budgets) and other business constraints (e.g. project precedence constraints).
- Gurobi solver was used to solve this complex MIP problem.

Example of the power of Gurobi Presolve .. 3

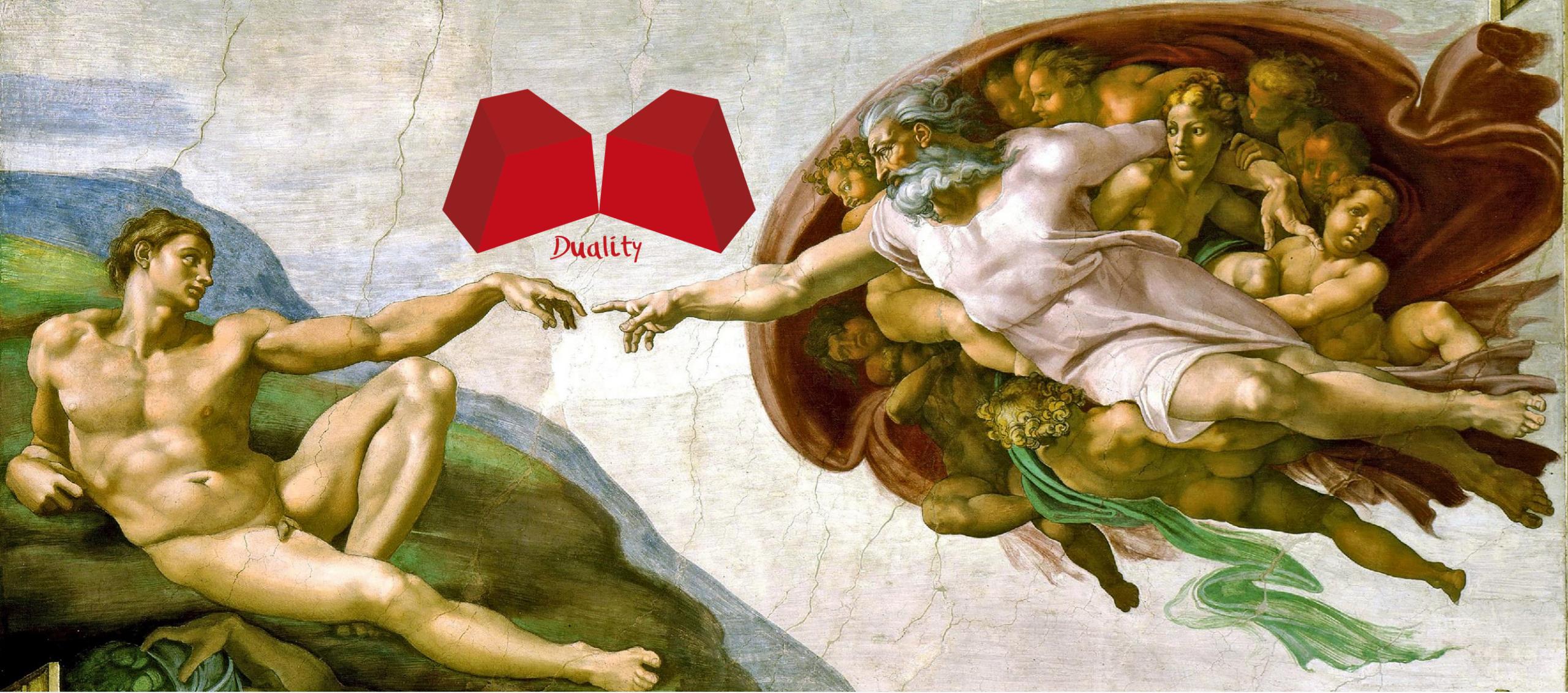
Size	PPO model	PPO model after Presolve	Reduction %
Total # of variables	9307	3170	66 %
Total # of constraints	6461	337	94 %
Gurobi solving time	—	8.53 s	—
Gurobi solving time no presolve	156.1 s	—	—

**Gurobi with
Presolve runs
17X faster**

Matrix sparsity of LP problems

- An important feature of practical LP models is that the matrix of technology coefficients is significantly **sparse**. This significantly reduces the size of the problem.
- This means that a small number of coefficients in the matrix of technology coefficients is effectively exploited in a very efficient computer implementation of the simplex method called the **revised simplex method**.

$$\begin{aligned} \text{Objective Function} & \rightarrow \text{Max } \sum_{j=1}^n b_j x_j && \text{Objective function coefficients} \\ \text{Constraints} & \rightarrow \sum_{j=1}^n a_{i,j} x_j \leq K_i \quad (i = 1 \dots m) && \text{Decision Variables} \\ \text{Technology coefficients} & && \text{RHS: right hand side} \\ & && \text{Set of indices for Constraints} \\ & && \text{Set of indices for Variables} \end{aligned}$$



Duality in Linear Programming

Linear Programming Duality

In the section of sensitivity analysis of Linear Programming, we asked the following question:

- For the furniture problem, is it profitable to make a third product, like desks?
 - Assume that the price of the desk is \$110,
 - and the desk consumes 15 units of mahogany and 25 units of labor.
- Shadow prices determine the marginal worth of an additional unit of a resource:
 - The shadow price of the mahogany capacity constraint is \$1.
 - The shadow price of the labor capacity constraint is \$4.
- Let's compute the opportunity cost of making one desk and compare it with the price of a desk. If this opportunity cost is greater than the desk price, then it is not worth it to make desks.
 - The opportunity cost can be computed by multiplying the units of mahogany capacity that one desk built consumes by the shadow price of mahogany capacity, and multiplying the units of labor capacity that one desk built consumes by the shadow price of labor capacity:
 - That is, $(\$1)*15$ (units of mahogany) + $(\$4)*25$ (hours of labor) = $\$115 > \110 .
- Therefore, investing resources to produce desks, otherwise used to produce chairs and tables, is not profitable.

Linear Programming Duality .. 2

Duality in Linear Programming is an unifying theory that established the relation between an LP problem – called **Primal Problem**, and another related LP problem –called **Dual Problem**, where its decision variables (**dual variables**) are the shadow prices of the resource constraints.

Furniture Problem: Primal and Dual problems

The primal and dual of the Furniture problem are:

Primal

$$(1.0) \text{ Max revenue} = 45x_1 + 80x_2$$

$$(2.0) \quad 5x_1 + 20x_2 \leq 400$$

$$(3.0) \quad 10x_1 + 15x_2 \leq 450$$

$$x_1, x_2 \geq 0$$

Chairs Tables

Mahogany
Labor

Dual

$$(4.0) \text{ Min Cost} = 400w_1 + 450w_2$$

$$(5.0) \quad 5w_1 + 10w_2 \geq 45 \quad \text{Chairs}$$

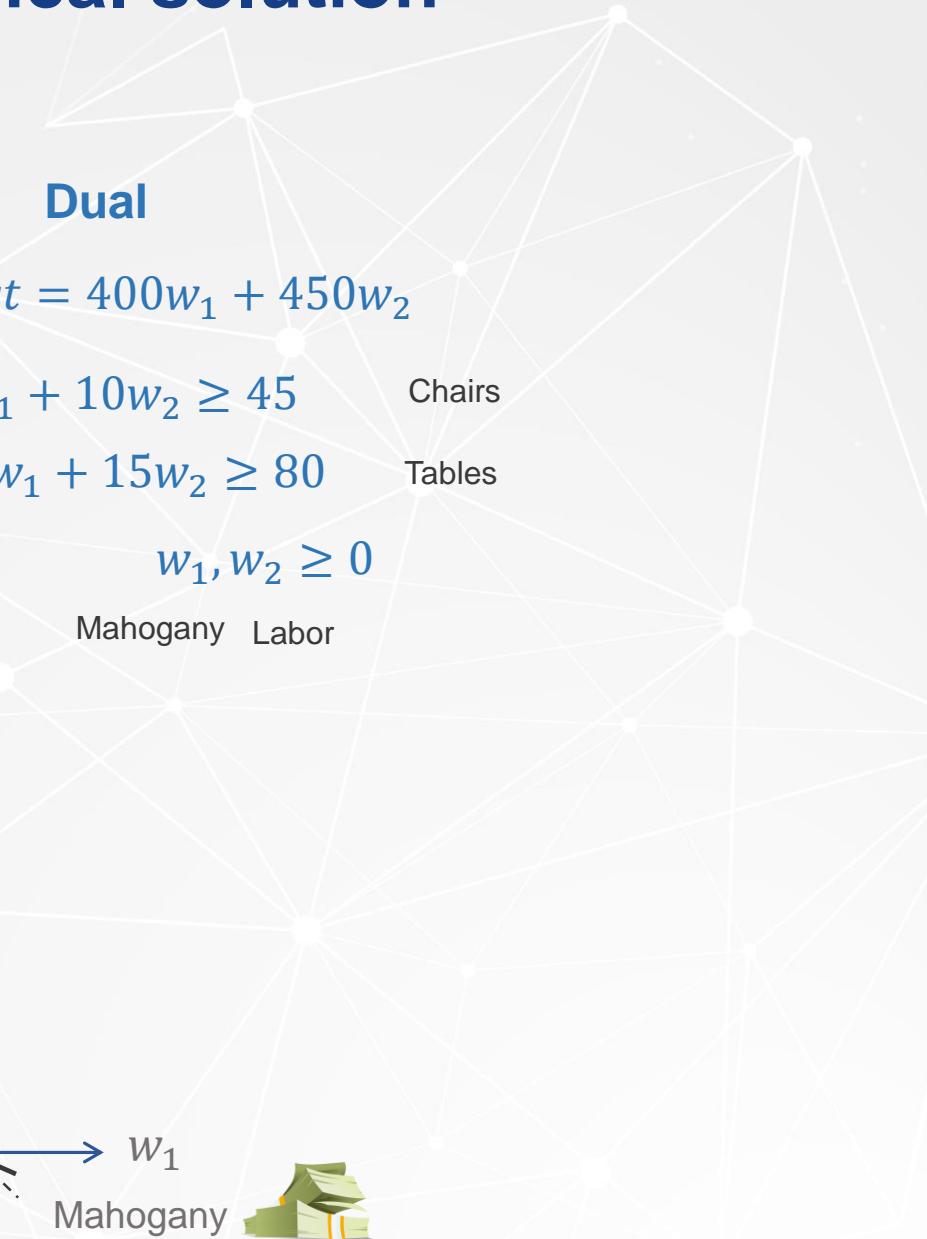
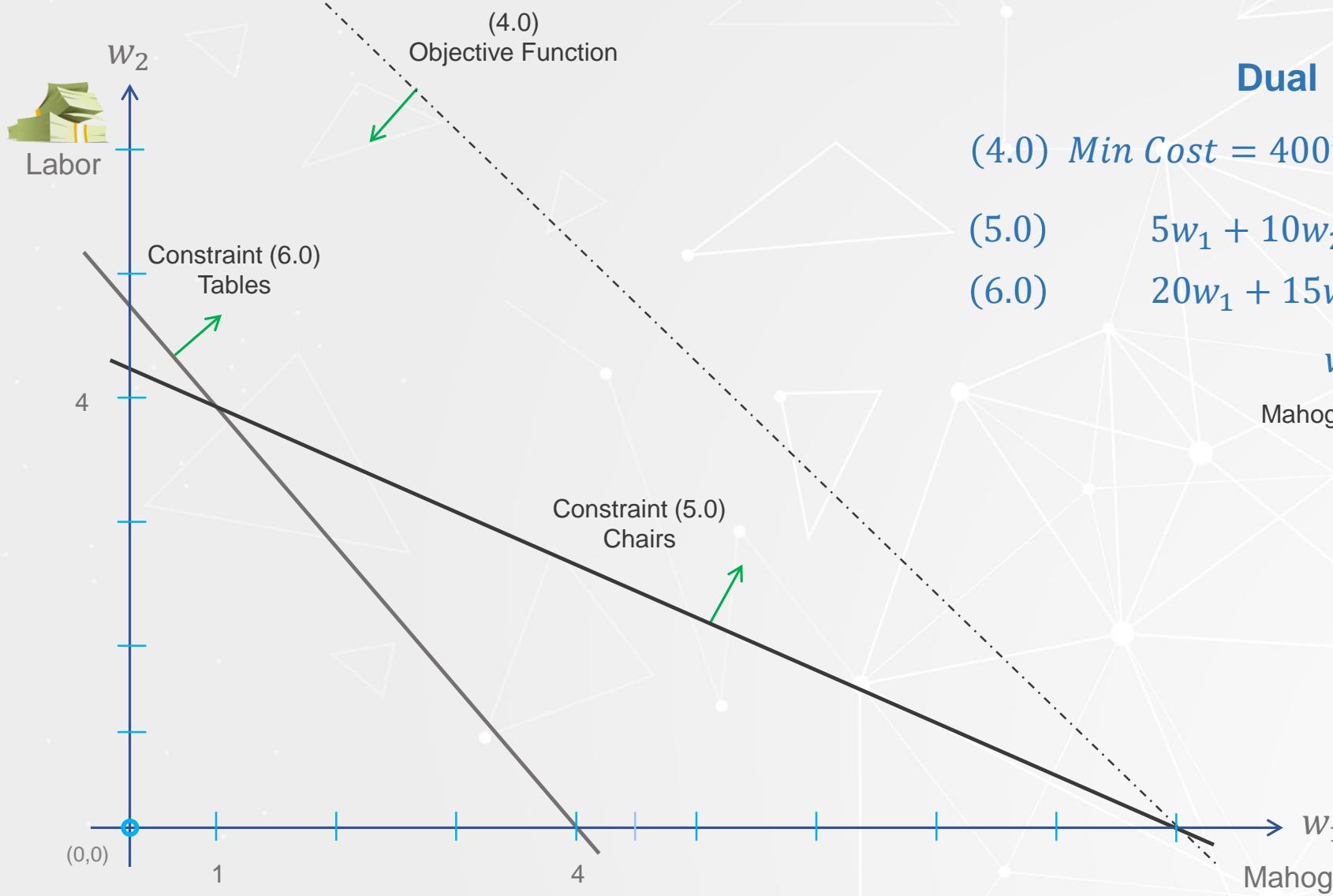
$$(6.0) \quad 20w_1 + 15w_2 \geq 80 \quad \text{Tables}$$

$$w_1, w_2 \geq 0$$

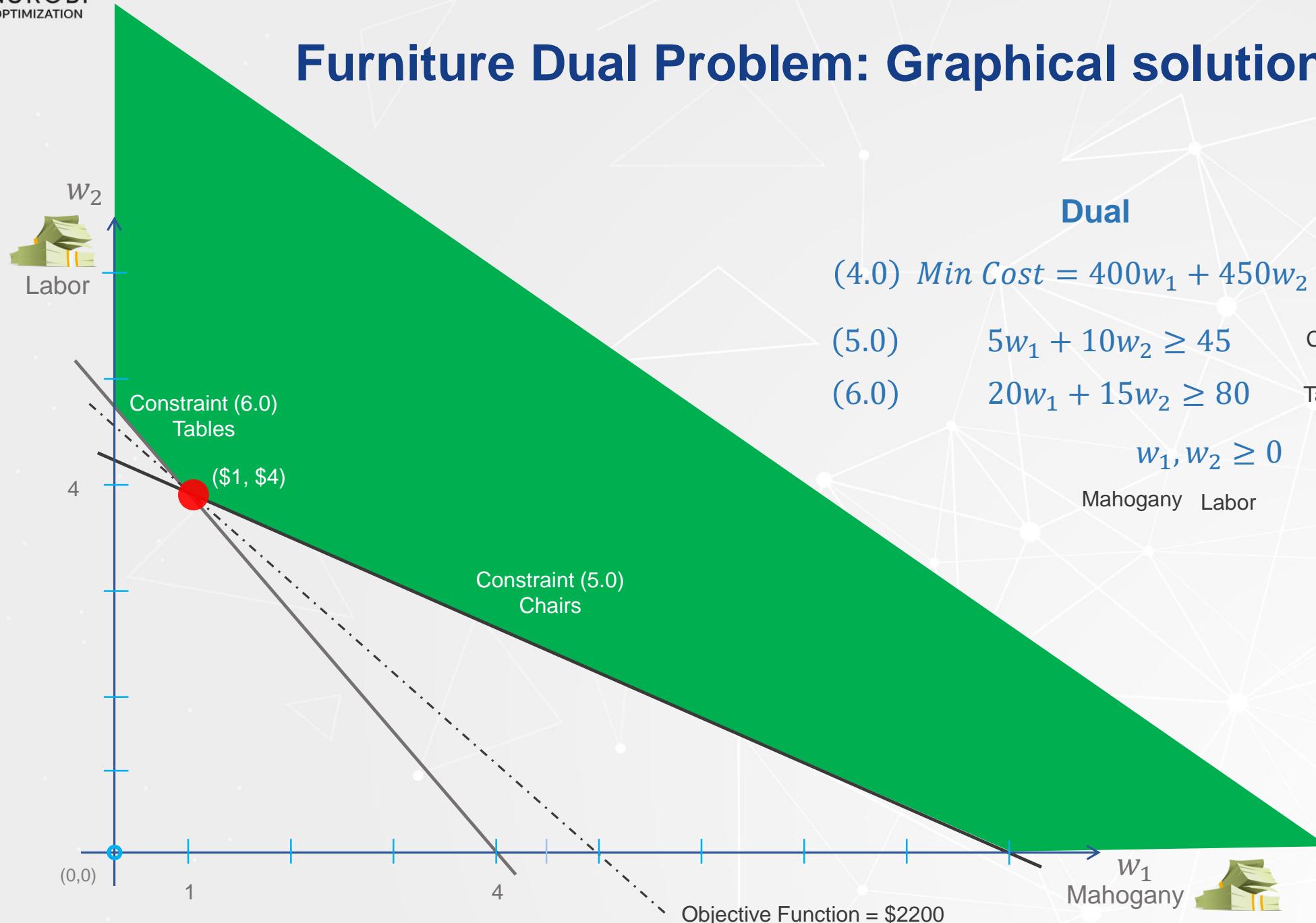
Mahogany Labor

- In this dual problem, the decision variable w_1 represents the opportunity cost of the mahogany resource, and w_2 is the opportunity cost of the labor resource. These decision variables are the shadow prices of mahogany and labor capacity.
- Notice the switch between the objective function coefficients and the right hand sides of the primal and dual problems.
- Also, notice that the rows of the primal problem are the columns of the dual problem. This means that inequalities (5.0) and (6.0) ensures that the opportunity costs of consumption of resources per unit of production of chairs and tables, respectively, should be at least the value of their price. The objective is to minimize the resource opportunity costs.

Furniture Dual Problem: Graphical solution



Furniture Dual Problem: Graphical solution



Furniture Dual Problem: Parametrized

Furniture dual problem

Let $price_p$ be the price of product $p \in products = \{chairs, tables\}$, and let $capacity_r$ be the capacity available of resource $r \in resources = \{mahogany, labor\}$. Let $bom_{r,j}$ be the amount of resource r required by product p .

Let $shadowPrice_r$ be the shadow price, or opportunity cost, of resource $r \in resources = \{mahogany, labor\}$

$$\text{Min} \sum_{r \in resources} capacity_r shadowPrice_r$$

Subject to :

$$\sum_{r \in resources} bom_{r,p} shadowPrice_r \geq price_p \quad \forall p \in products$$

$$shadowPrice_r \geq 0 \quad \forall r \in resources$$

Furniture Dual Problem: Solved with Gurobi ..1

The data of the Furniture Dual problem **is identical** to the original Furniture problem –called Primal Problem.

```
# resources data
resources, capacity = multidict({
    'mahogany': 400,
    'labor': 450 })
```

```
# products data,
products, price = multidict({
    'chair': 45,
    'table': 80 })
```

```
# Bill of materials: resources required by each product
bom = {
    ('mahogany', 'chair'): 5,
    ('mahogany', 'table'): 20,
    ('labor', 'chair'): 10,
    ('labor', 'table'): 15 }
```

Furniture Dual Problem: Solved with Gurobi ..2

The right hand side of the constraints are the price of each product. The left hand side is the opportunity cost of consuming each resource when making the products. The sense of the inequalities is greater than equal to have an evaluation of the resource at least equal to the price.

```
# Declare and initialize model
f = Model('Furniture')
```

```
# Create decision variables for the resources capacity
shadowPrice = f.addVars(resources, name="price")
```

$$\sum_{r \in \text{resource}} bom_{r,p} shadowPrice_r \geq price_p \quad \forall p \in \text{products}$$

```
# Create an object of type list to store the constraints for each product
```

```
pro = f.addConstrs(((sum(bom[r,p]*shadowPrice[r] for r in resources) >= price[p]) for p in products), name='V')
```

```
f.setObjective(shadowPrice.prod(capacity))
```

GRB.MINIMIZE is the default

Coefficients in the objective function are the resource capacities

Furniture Dual Problem: Solved with Gurobi ..3

```
# save model for inspection
f.write('furnitureDual.lp')
```

```
\ Model Furniture
\ LP format - for model browsing. Use MPS format to capture full model detail.
Minimize
    400 price[mahogany] + 450 price[labor]
Subject To
    V[table]: 20 price[mahogany] + 15 price[labor] >= 80
    V[chair]: 5 price[mahogany] + 10 price[labor] >= 45
Bounds
End
```

Furniture Dual Problem: Solved with Gurobi ..4

```
# run optimization engine
```

```
f.optimize()
```

```
Optimize a model with 2 rows, 2 columns and 4 nonzeros
```

```
Coefficient statistics:
```

```
Matrix range      [5e+00, 2e+01]
Objective range   [4e+02, 5e+02]
Bounds range      [0e+00, 0e+00]
RHS range         [5e+01, 8e+01]
```

```
Presolve time: 0.13s
```

```
Presolved: 2 rows, 2 columns, 4 nonzeros
```

Iteration	Objective	Primal Inf.	Dual Inf.	Time
0	0.0000000e+00	1.562500e+01	0.000000e+00	0s
2	2.2000000e+03	0.000000e+00	0.000000e+00	0s

```
Solved in 2 iterations and 0.16 seconds
```

```
Optimal objective 2.200000000e+03
```

```
# display optimal values of decision variables
```

```
for v in f.getVars():
    if (abs(v.x) > 1e-6):
        print(v.varName, v.x)
```

```
# display optimal total revenue value
```

```
print('total revenue', f.objVal)
```

```
('price[mahogany]', 0.999999999999996) →
```

```
('price[labor]', 4.00000000000001) →
```

```
('total revenue', 2200.000000000005) →
```

\$1.00 The optimal value of the shadow price for mahogany is \$1.00
\$4.00 The optimal value of the shadow price for labor is \$4.00
\$2,200 The optimal objective function value is \$2,200



Furniture Dual Problem: Solved with Gurobi .. 5

```
# display shadow prices of product constraints
for p in pro:
    if (abs(pro[p].Pi) > 1e-6):
        print(pro[p].ConstrName, pro[p].Pi)

('v[table]', 14.0)
('v[chair]', 24.00000000000004)
```

- The “shadow prices” of the products’ constraints are 14 tables and 24 chairs. These are the optimal (make) values of the Furniture primal problem. Notice that in both problems, primal and dual, the optimal objective function value is \$2,200. This is not a coincidence!!!

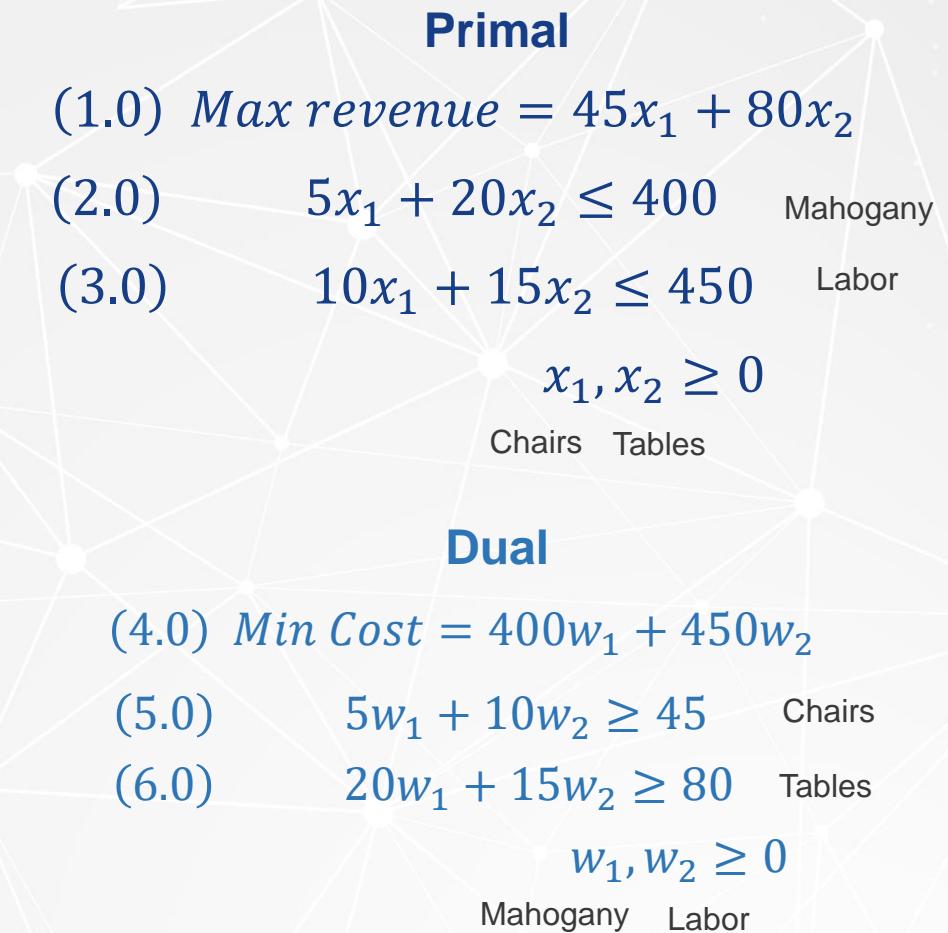
Duality in Linear Programming

Remarks:

- In general, it can be shown that the dual of a dual problem is the primal problem, and that when either problem has an optimal solution, the other problem also has an optimal solution, and the optimal objective function value of both problems is the same.
- Another important feature of duality in linear programming is that the optimal solution of the dual problem is contained in the information provided by the simplex method while solving and finding an optimal solution to the primal problem.
- Duality in linear programming provides a good characterization of optimality conditions that can be exploited computationally to solve LP problems efficiently.

Relationship between primal and dual problems

	Primal (maximize)	Dual (minimize)
1)	i'th constraint \leq	i'th variable ≥ 0
2)	i'th constraint \geq	i'th variable ≤ 0
3)	i'th constraint $=$	i'th variable unrestricted
4)	j'th variable ≥ 0	j'th constraint \geq
5)	j'th variable ≤ 0	j'th constraint \leq
6)	j'th variable unrestricted	j'th constraint $=$



Remark:

Notice that the relationship between the Furniture primal and dual problems is captured by rows 1) and 4)

Optimality conditions

Linear Programming

Optimality conditions in linear programming .. 1

Consider the Furniture primal and dual problems:

Primal

$$(1.0) \text{ Max revenue} = 45x_1 + 80x_2$$

$$(2.0) \quad 5x_1 + 20x_2 \leq 400 \quad \begin{matrix} \text{Mahogany} \\ \text{Labor} \end{matrix}$$

$$(3.0) \quad 10x_1 + 15x_2 \leq 450 \quad \begin{matrix} \text{Mahogany} \\ \text{Labor} \end{matrix}$$

$$x_1, x_2 \geq 0$$

Chairs Tables

Dual

$$(4.0) \text{ Min Cost} = 400w_1 + 450w_2$$

$$(5.0) \quad 5w_1 + 10w_2 \geq 45 \quad \begin{matrix} \text{Chairs} \\ \text{Tables} \end{matrix}$$

$$(6.0) \quad 20w_1 + 15w_2 \geq 80 \quad \begin{matrix} \text{Chairs} \\ \text{Tables} \end{matrix}$$

$$w_1, w_2 \geq 0$$

Mahogany Labor

Furniture primal and dual problems in standard form

$$(1.0) \text{ Max revenue} = 45x_1 + 80x_2$$

$$(2.0) \quad 5x_1 + 20x_2 + h_1 = 400 \quad \begin{matrix} \text{Mahogany} \\ \text{Labor} \end{matrix}$$

$$(3.0) \quad 10x_1 + 15x_2 + h_2 = 450 \quad \begin{matrix} \text{Mahogany} \\ \text{Labor} \end{matrix}$$

$$x_1, x_2, h_1, h_2 \geq 0$$

Chairs Tables

$$(4.0) \text{ Min Cost} = 400w_1 + 450w_2$$

$$(5.0) \quad 5w_1 + 10w_2 - s_1 = 45 \quad \begin{matrix} \text{Chairs} \\ \text{Labor} \end{matrix}$$

$$(6.0) \quad 20w_1 + 15w_2 - s_2 = 80 \quad \begin{matrix} \text{Chairs} \\ \text{Tables} \end{matrix}$$

$$w_1, w_2, s_1, s_2 \geq 0$$

Mahogany Labor

h_1 is the slack variable of the mahogany constraint

h_2 is the slack variable of the labor constraint

s_1 is the surplus variable of the chairs constraint

s_2 is the surplus variable of the tables constraint

Optimality conditions in linear programming .. 2

Consider the optimal solution of both problems, primal and dual

Primal optimal solution:

$$x_1 = 24, x_2 = 14, h_1 = 0, h_2 = 0$$

$$(1.0) \text{ Max revenue} = 45(x_1 = 24) + 80(x_2 = 14) = 2200$$

Mahogany

$$(2.0) 5(x_1 = 24) + 20(x_2 = 14) + (h_1 = 0) = 400 \quad \text{binding}$$

Labor

$$(3.0) 10(x_1 = 24) + 15(x_2 = 14) + (h_2 = 0) = 450 \quad \text{binding}$$

$$x_1, x_2, h_1, h_2 \geq 0$$

Chairs Tables

Remarks

- Note that the mahogany and labor constraints are binding, i.e. the slack variables ($h_1 = h_2 = 0$).
- Note that the shadow price of the mahogany and labor constraints are positive, i.e. ($w_1 = 1, w_2 = 4$).
- Note that the chairs and tables constraints are binding, i.e. the surplus variables ($s_1 = s_2 = 0$).
- Note that the “shadow price” of the chairs and tables constraints are positive, i.e. ($x_1 = 24, x_2 = 14$).

Dual optimal solution:

$$w_1 = 1, w_2 = 4, s_1 = 0, s_2 = 0$$

$$(4.0) \text{ Min Cost} = 400(w_1 = 1) + 450(w_2 = 4) = 2200$$

Chairs

$$(5.0) 5(w_1 = 1) + 10(w_2 = 4) - (s_1 = 0) = 45$$

Tables

$$(6.0) 20(w_1 = 1) + 15(w_2 = 4) - (s_2 = 0) = 80$$

$$w_1, w_2, s_1, s_2 \geq 0$$

Mahogany Labor

Optimality conditions in linear programming .. 3

In summary

Primal optimal solution	Dual optimal solution
Chair variable $x_1 = 24$	Chair constraint (is binding) surplus variable $s_1 = 0$
Table variable $x_2 = 14$	Table constraint (is binding) surplus variable $s_2 = 0$
Mahogany constraint (is binding) slack variable $h_1 = 0$	Mahogany shadow price $w_1 = 1$
Labor constraint (is binding) slack variable $h_2 = 0$	Labor shadow price $w_2 = 4$

Complementary (a.k.a. orthogonality) conditions in linear programming optimal solutions

- $x^*s = 0$. At optimality, the product of the decision variables in the primal problem and the associate surplus (slack) variables in the dual problem is always zero.
- $h^*w = 0$. At optimality, the product of the slack (surplus) variables in the primal problem and the associate shadow prices in the dual problem is always zero.

Summary of optimality conditions for linear programming

- A solution ($x_1=24$, $x_2=14$) to the primal problem and a solution ($w_1=1$, $w_2=4$) of the dual problem are optimal, if and only if:
 - Primal feasibility: we have found a solution of the primal problem that satisfy all its constraints.
 - The production plan satisfies the mahogany and labor constraints.

$$(2.0) \quad 5(x_1 = 24) + 20(x_2 = 14) = 400 \quad \text{Mahogany capacity}$$

$$(3.0) \quad 10(x_1 = 24) + 15(x_2 = 14) = 450 \quad \text{Labor capacity}$$

- Dual feasibility: we have found a solution of the dual problem that satisfy all its constraints.
 - The shadow prices associated to the mahogany and labor resources satisfy the price constraints for the chairs and the tables.

$$(5.0) \quad 5(w_1 = 1) + 10(w_2 = 4) = 45 \quad \text{Chair price}$$

$$(6.0) \quad 20(w_1 = 1) + 15(w_2 = 4) = 80 \quad \text{Table price}$$

Summary of optimality conditions for linear programming

- Complementary (orthogonality) conditions:
- The product of the decision variables in the primal problem and the associate surplus variables in the dual problem is always zero. (**Cost efficient**).
 - Since we are building 24 chairs, the surplus variable of the constraint of the price of chairs is 0. That is, $x_1^*s_1=0$. This means that the opportunity costs of building chairs is equal to the price of the chair:

$$(5.0) \quad 5(w_1 = 1) + 10(w_2 = 4) - (s_1 = 0) = 45$$

- Since we are building 14 tables, the surplus variable of the constraint of the price of tables is 0. That is, $x_2^*s_2=0$. This means that the opportunity costs of building tables is equal to the price of the table:

$$(6.0) \quad 20(w_1 = 1) + 15(w_2 = 4) - (s_2 = 0) = 80$$

Summary of optimality conditions for linear programming

- The product of the decision variables in the dual problem and the associate slack variables in the primal problem is always zero. **(Resource efficient).**
- Since the shadow price (opportunity cost) of mahogany is \$1, the slack variable of the mahogany constraint is 0. This means we are using the mahogany resource efficiently and there is no waste.

$$(2.0) \quad 5(x_1 = 24) + 20(x_2 = 14) + (h_1 = 0) = 400$$

- Since the shadow price (opportunity cost) of labor is \$4, the slack variable of the labor constraint is 0. This means we are using the labor resource efficiently and there is no waste.

$$(3.0) \quad 10(x_1 = 24) + 15(x_2 = 14) + (h_2 = 0) = 450$$

Summary of optimality conditions for linear programming

- The optimal objective function value of the primal problem = the optimal objective function of the dual problem. This mathematical theorem is known as **strong duality**.

$$(1.0) \text{ Max revenue} = 45(x_1 = 24) + 80(x_2 = 14) = 2200$$

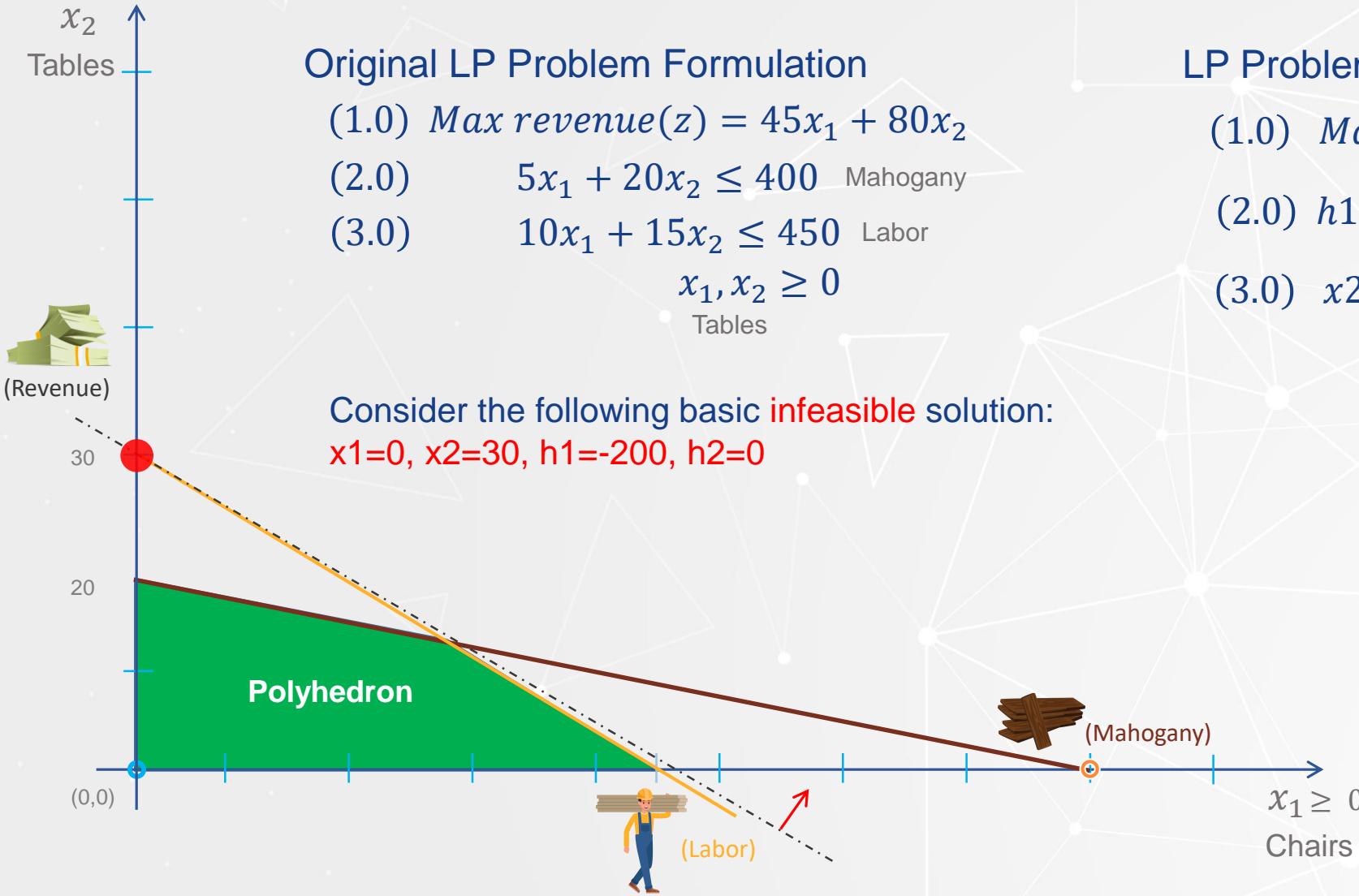
$$(4.0) \text{ Min Cost} = 400(w_1 = 1) + 450(w_2 = 4) = 2200$$

Dual Simplex method

Variation of Simplex method

The Dual simplex method

The key idea of the dual simplex method is to apply the simplex method to the dual problem, but using the canonical form of the primal problem.



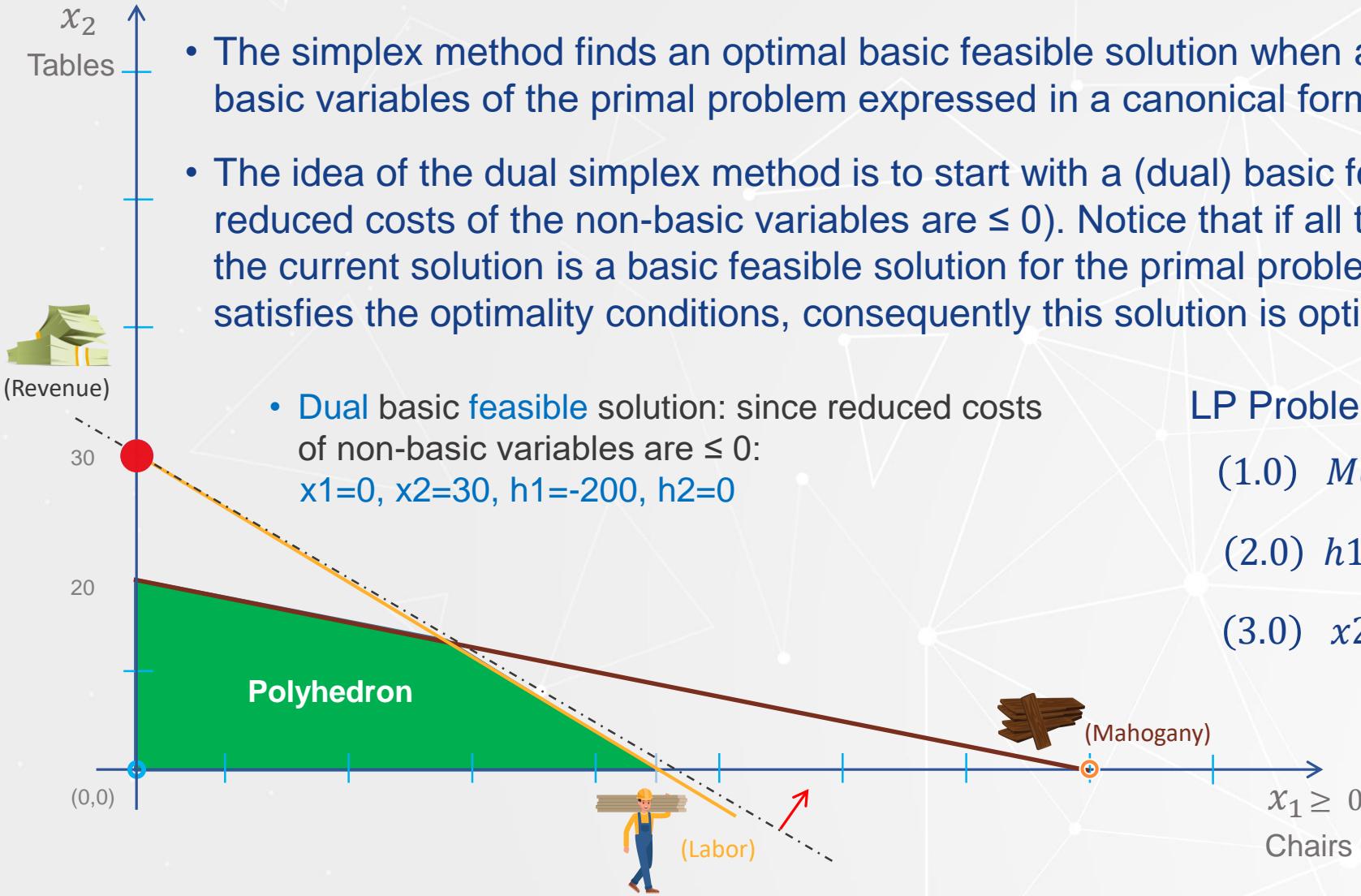
LP Problem Formulation in Canonical Form

- (1.0) $\text{Max } z = 2400 - \frac{25}{3}x_1 - \frac{80}{15}h_2$
- (2.0) $h_1 = -200 + \frac{25}{3}x_1 + \frac{4}{3}h_2$
- (3.0) $x_2 = 30 - \frac{2}{3}x_1 - \frac{1}{15}h_2$

$x_1, x_2, h_1, h_2 \geq 0$

The Dual simplex method ..2

- Recall that the simplex method iterates from one basic feasible solution to another, always trying to improve the value of the objective function.
- The simplex method finds an optimal basic feasible solution when all the reduced costs of the non-basic variables of the primal problem expressed in a canonical form are ≤ 0 . (Maximization problem).
- The idea of the dual simplex method is to start with a (dual) basic feasible solution (i.e. all the reduced costs of the non-basic variables are ≤ 0). Notice that if all the basic variables are ≥ 0 , then the current solution is a basic feasible solution for the primal problem in a canonical form that satisfies the optimality conditions, consequently this solution is optimal.



- Dual basic feasible solution: since reduced costs of non-basic variables are ≤ 0 :
 $x_1=0, x_2=30, h_1=-200, h_2=0$

LP Problem Formulation in Canonical Form

$$(1.0) \quad \text{Max } z = 2400 - \frac{25}{3}x_1 - \frac{80}{15}h_2$$

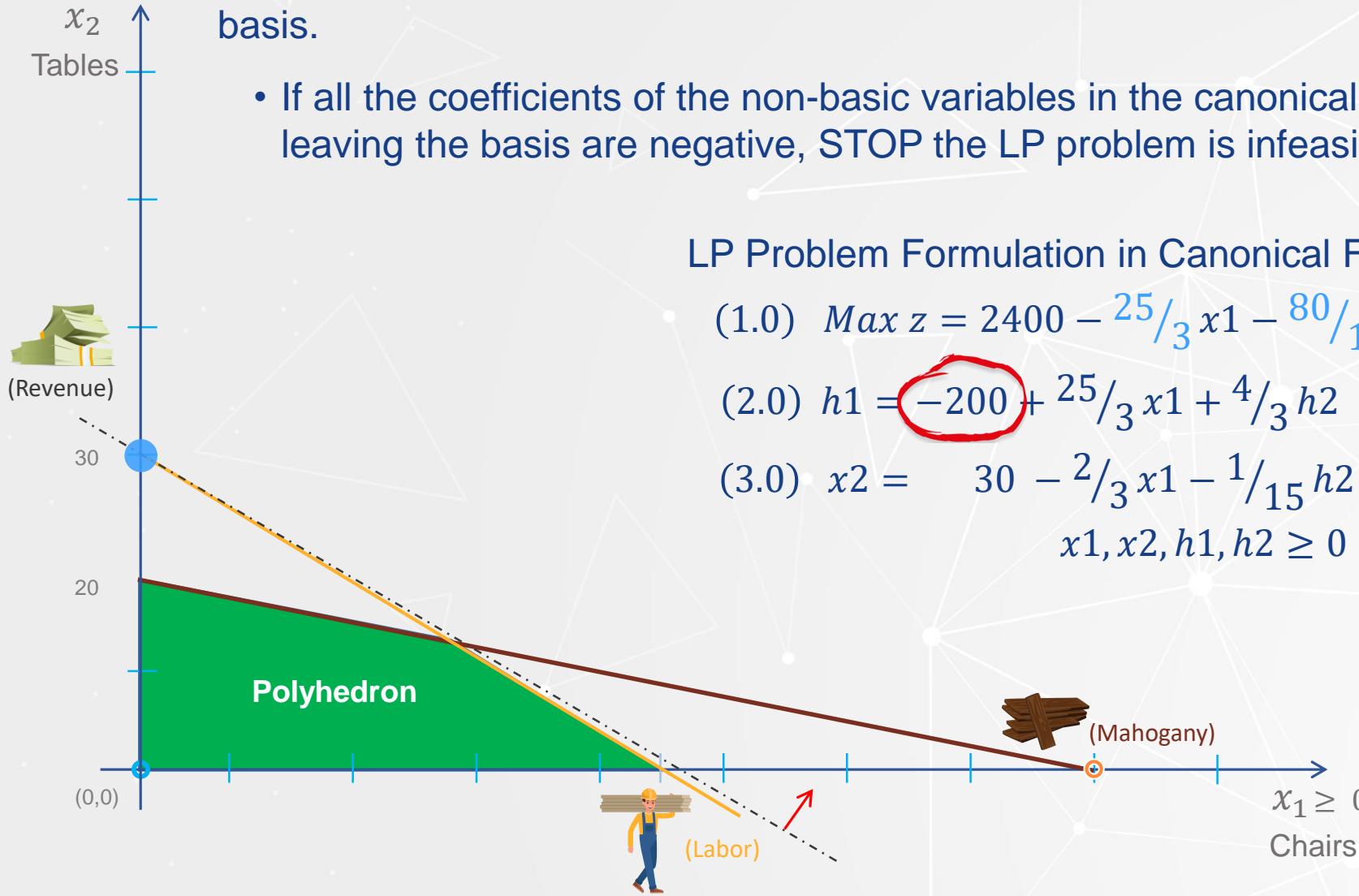
$$(2.0) \quad h_1 = -200 + \frac{25}{3}x_1 + \frac{4}{3}h_2$$

$$(3.0) \quad x_2 = 30 - \frac{2}{3}x_1 - \frac{1}{15}h_2$$

$$x_1, x_2, h_1, h_2 \geq 0$$

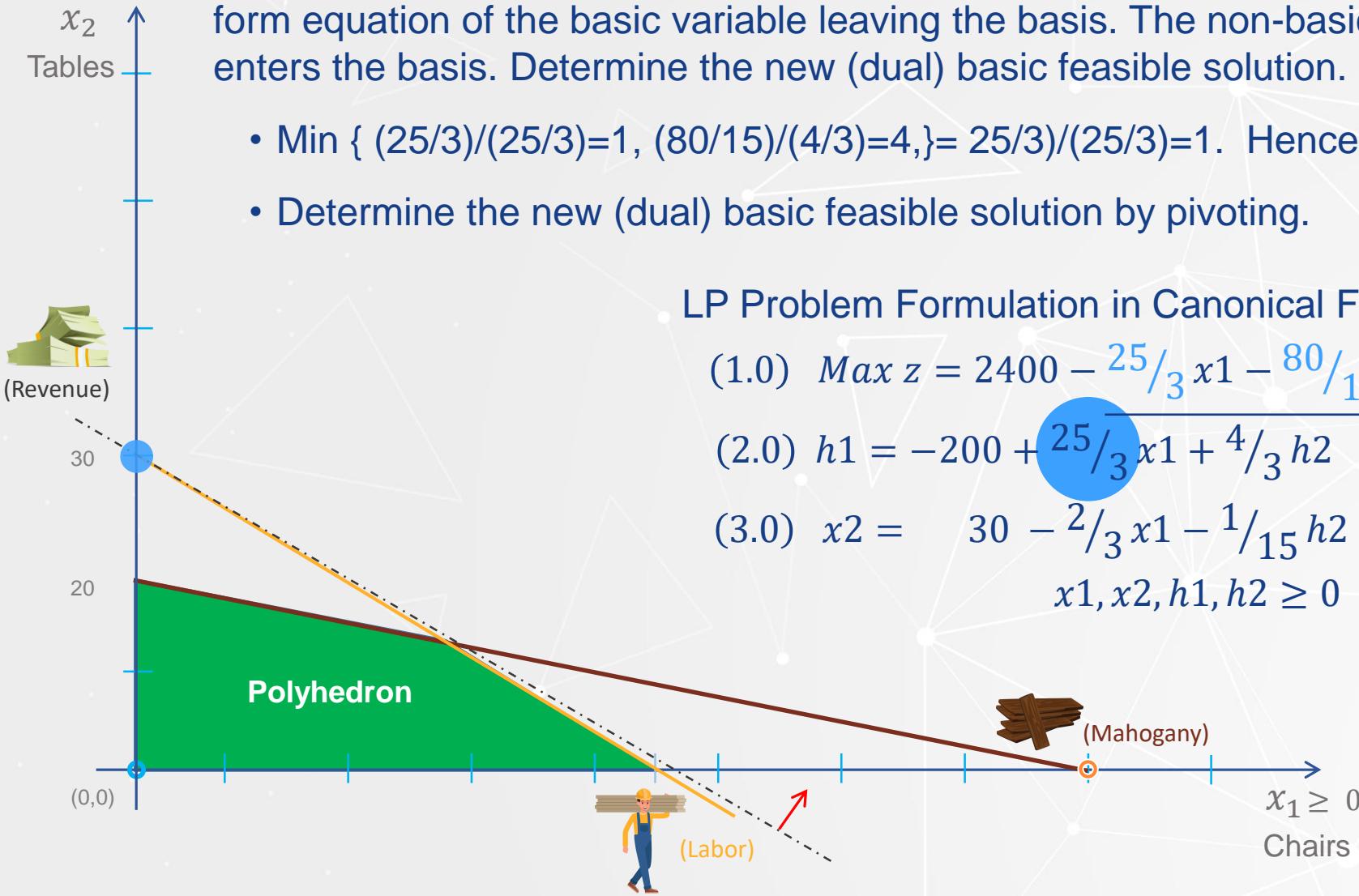
The Dual simplex method ..3

- Suppose that at least there is one basic variable that is negative. Choose the basic variable with the most negative value as the variable to leave the basis. In this example, the variable h_1 will leave the basis.
 - If all the coefficients of the non-basic variables in the canonical form equation of the basic variable leaving the basis are negative, STOP the LP problem is infeasible.



The Dual simplex method ..4

- Else, there is at least one non-basic variable with a positive coefficient, consider the minimum ratio test of the absolute of the reduce costs and the positive coefficient of non-basic variables in the canonical form equation of the basic variable leaving the basis. The non-basic variable with the minimum ratio enters the basis. Determine the new (dual) basic feasible solution. Minimum ratio test:
 - Min { $(25/3)/(25/3)=1$, $(80/15)/(4/3)=4$, } = $25/3)/(25/3)=1$. Hence, the variable x_1 enters the basis.
 - Determine the new (dual) basic feasible solution by pivoting.



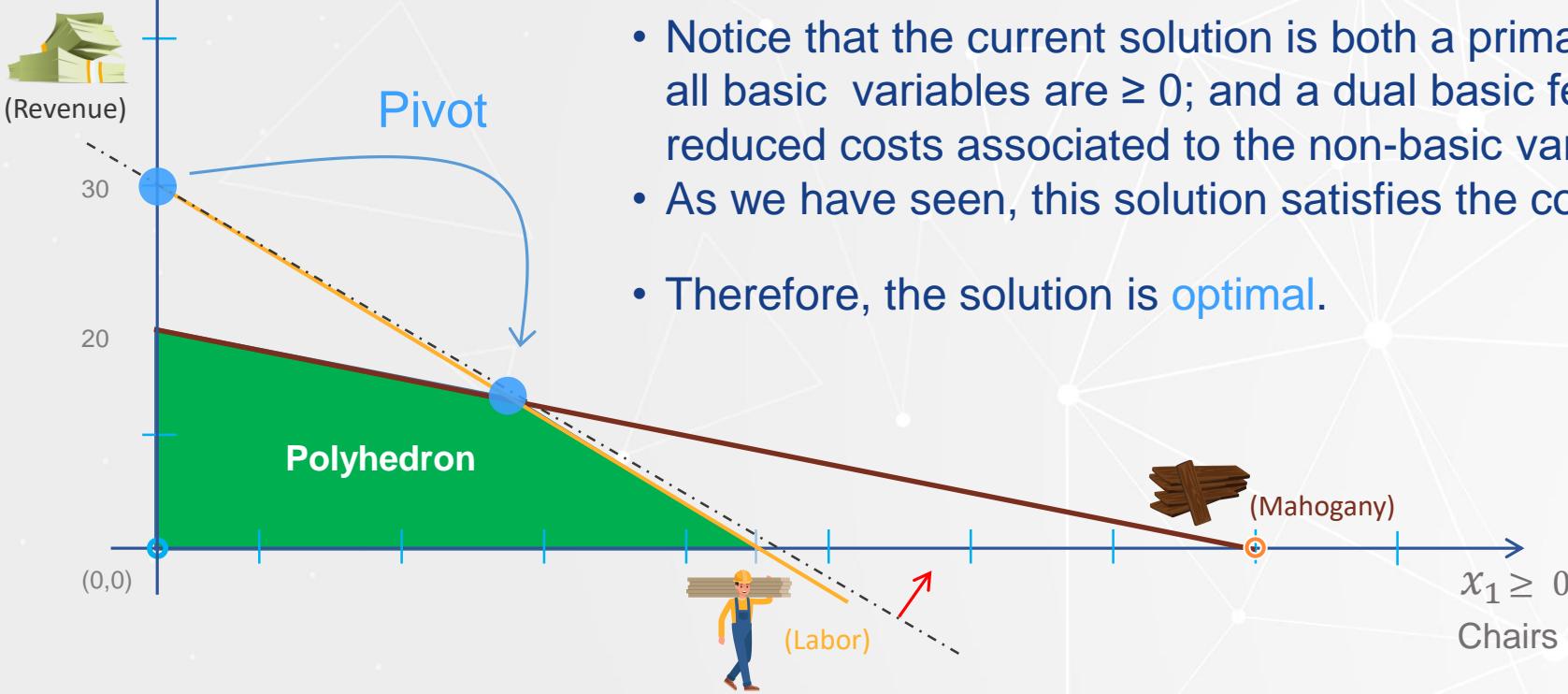
The Dual simplex method ..5

- Pivoting). In equation (2.0), express basic variable x_1 in terms of non-basic variables h_1 and h_2 :

$$(2.0) \quad x_1 = 24 + \frac{3}{25}h_1 - \frac{4}{25}h_2$$

- In equation (3.0), replace the value of x_1 : (3.0) $x_2 = 14 - \frac{2}{25}h_1 - \frac{1}{25}h_2 \quad x_1, x_2, h_1, h_2 \geq 0$

- In the objective function (1.0), replace the value of x_1 : (1.0) $\text{Max } z = 2200 - 1h_1 - 4h_2$



- Notice that the current solution is both a primal basic feasible solution, since all basic variables are ≥ 0 ; and a dual basic feasible solution, since all the reduced costs associated to the non-basic variables are ≤ 0 .
- As we have seen, this solution satisfies the complementary conditions:
- Therefore, the solution is optimal.

The Dual simplex method ..5

- The dual simplex method is recommended for LP problems in which a dual basic feasible solution is available.
- The dual simplex method is particularly useful for reoptimizing an LP problem after a constraint has been added, since we don't need to start the solution approach from scratch.
- The cutting planes method to solve MIP problems relies heavily on the dual simplex. The core idea of the cutting planes method is to add a constraint to the LP problem continuous relaxation whenever an integer variable has a fractional value in the optimal solution. The added constraint will make this fractional value of the integer variable infeasible.

END