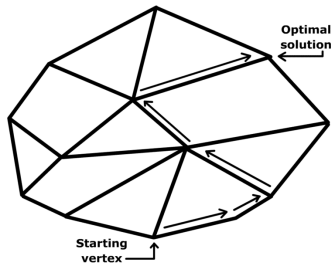


Lesson 28: Solving Linear Programs



linear programming, simplex methods, iterative search

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Recap

- Linear programs are problems that can be formulated as follows

$$\min_x c \cdot x$$

subject to

$$A^{\leq} x \leq b^{\leq}, \quad A^{\geq} x \geq b^{\geq}, \quad A^{\dagger} x = b^{\dagger}, \quad x \geq 0$$

- Where $x = (x_1, x_2, \dots, x_n)$
- A^* are matrices and we interpret the inequalities to mean

$$\forall k \quad \sum_{j=1}^n A_{kj}^{\leq} x_j \leq b_k^{\leq}$$

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Transforming Linear Programs

- We can always transform an inequality constraint into an equality constraint by adding slack variables

- E.g.

$$\begin{aligned} a_1 \cdot x \geq 0 &\Rightarrow a_1 \cdot x - z_1 = 0 \quad z_1 \geq 0 \\ a_2 \cdot x \leq 0 &\Rightarrow a_2 \cdot x + z_2 = 0 \quad z_2 \geq 0 \end{aligned}$$

z_1 (the excess) and z_2 (the deficit) are known as slack variables

- A linear program with just equality constraints and non-negativity constraints is said to be in normal form

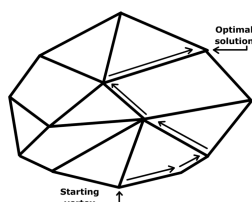
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5

Outline

- Recap
- Basic Feasible Solutions
- Simplex Method
- Classic LP Problems

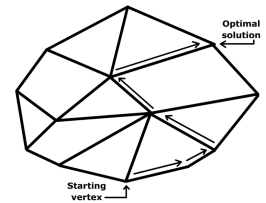


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- Recap
- Basic Feasible Solutions
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- Classic LP Problems



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Optima and Vertices

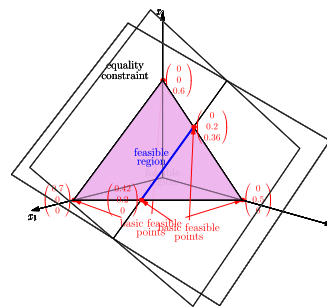
- Because the objective function is linear ($c \cdot x$) there is a direction where the objective is always improving
- Thus, the optima cannot lie in the interior of the search space
- When we meet a constraint that limits the direction we can move, but we can still move along the constraint
- We then meet another constraint which restricts the direction we can move by two degrees of freedom
- Eventually, we will reach n constraints which defines a vertex of the feasible region and is optimal

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Solving Linear Programming



- The basic feasible points for LP problems with n variables and m constraints have at least $n - m$ zero variables
- Typical number of basic feasible solutions is $\binom{n}{m} \geq \left(\frac{n}{m}\right)^m$
- Simplex algorithm organises iterative search for global solutions

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Basic Feasible Solution

- A basic feasible solution or basic feasible point is a solution that lies at a vertex of the feasible space
- To solve a linear program we will start at a basic feasible point and move to the neighbour which best improves the objective function
- When we cannot find a better solution we are at the optimal solution
- This is an example of an iterative improvement algorithm which gives an optimal solution

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Constraints

- There are two types of constraints
 - n non-negativity constraints $x_i \geq 0$
 - m additional constraints, which we can take to be equalities $Ax = b$
- Note that some of the variables might be slack variables
- We consider the case when there are more variables than additional constraints, i.e. $n > m$
- This is usually the case, but...
- If this isn't true it turns out you can consider an equivalent problem (dual problem) where you have a variable for each constraint and a constraint for each variable

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Initial Basic Feasible Solution

- One of the tricky bits of tackling a linear program is to find an initial feasible solution
- We do this in **phase one** of the simplex program
- To do this for each additional constraint we add a new **auxiliary variable** ξ_k , e.g.

$$\forall k \in \{1, 2, \dots, m\} \quad \xi_k + \sum_i A_{ki}x_i = b_k \geq 0$$

- We then can find a basic feasible solution by setting $x_i = 0$ so

$$\xi_k = b_k \quad \forall k \in \{1, 2, \dots, m\}$$

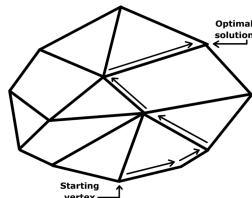
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Outline

- Recap
- Basic Feasible Solutions
- Simplex Method**
- Classic LP Problems



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Restricted Normal Form

- To perform the moves between vertices it helps to represent the problem in a **restricted normal form**
- Starting from a basic feasible point we have a constraint for each basic (non-zero) variable
- We write the constraints as an equality between basic and non-basic (zero valued) variables
- Similarly we write the objective function in terms of non-basic variables
- This is always possible as we can use the constraints to eliminate the basic variables

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Basic Variable

- In total we have n equality and m non-negativity constraints
- n constraints must be satisfied to be at a vertex of feasible region
- So at least $n - m$ of the non-negativity constraints are satisfied (i.e. $x_i = 0$)
- The $n - m$ variables that are zero are said to be **non-basic variables**
- The other m variables are said to be **basic variables**

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Eliminating Auxiliary Variables

- In phase one we run a simplex algorithm with an auxiliary cost function

$$\min f_{aux}(x, \xi) = \sum_{k=1}^m \xi_k$$

- This should find a solution where all the $\xi_k = 0$
- If no solution exists it means there is no feasible solution and we're finished
- If there is a solution then we can eliminate the auxiliary variables and we have a feasible solution

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Phase Two

- In phase two we now have an initial basic feasible solution (with $n - m$ zero variables)
- We then run the simplex algorithm on the original objective function $f(x) = c \cdot x$
- That is we move to a neighbouring vertex which gives the best increase in the objective function
- To help organise this search we write the objective function and constraints in a **restricted normal form** and then build a **tableau** showing the **basic variables** and the **non-basic variables**

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Tableau

$\max f(x) = 3.8x_1 + 5.4x_2 + 7.1x_3 + 8.2x_4 + 10.5x_5 + 12.6x_6 + 14.7x_7 + 16.8x_8 + 18.9x_9$
 where $x_8 = 3.2 - 6.4x_1 - 4.3x_2 - 5.5x_3 - 8.2x_4 - 5.9x_5 - 11x_6 - 0.089x_7 - 0.089x_8 \geq 0$
 $x_2 = 8.4 - 0.09x_1 - 0.09x_2 - 0.09x_3 - 0.09x_4 - 0.09x_5 - 0.09x_6 - 0.09x_7 - 0.09x_8 - 0.09x_9 \geq 0$
 $x_3 = 0.105 - 0.029x_1 - 0.029x_2 - 0.029x_3 - 0.029x_4 - 0.029x_5 - 0.029x_6 - 0.029x_7 - 0.029x_8 - 0.029x_9 \geq 0$
 $x_4 = 0.558 - 0.19x_1 - 0.19x_2 - 0.19x_3 - 0.19x_4 - 0.19x_5 - 0.19x_6 - 0.19x_7 - 0.19x_8 - 0.19x_9 \geq 0$
 $x_5 = 0.558 - 0.19x_1 - 0.19x_2 - 0.19x_3 - 0.19x_4 - 0.19x_5 - 0.19x_6 - 0.19x_7 - 0.19x_8 - 0.19x_9 \geq 0$
 $x_6 = 0.558 - 0.19x_1 - 0.19x_2 - 0.19x_3 - 0.19x_4 - 0.19x_5 - 0.19x_6 - 0.19x_7 - 0.19x_8 - 0.19x_9 \geq 0$
 $x_7 = 0.558 - 0.19x_1 - 0.19x_2 - 0.19x_3 - 0.19x_4 - 0.19x_5 - 0.19x_6 - 0.19x_7 - 0.19x_8 - 0.19x_9 \geq 0$
 $x_8 = 0.558 - 0.19x_1 - 0.19x_2 - 0.19x_3 - 0.19x_4 - 0.19x_5 - 0.19x_6 - 0.19x_7 - 0.19x_8 - 0.19x_9 \geq 0$
 $x_9 = 0.558 - 0.19x_1 - 0.19x_2 - 0.19x_3 - 0.19x_4 - 0.19x_5 - 0.19x_6 - 0.19x_7 - 0.19x_8 - 0.19x_9 \geq 0$

$f(x)$	3.8	5.4	7.1	8.2	10.5	12.6	14.7	16.8	18.9
x_1	0.1	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09
x_2	0.1	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09
x_3	0.1	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09
x_4	0.1	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09

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16

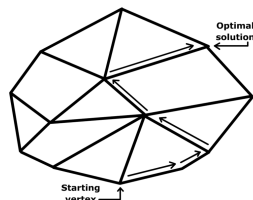
- If there are any column with all entries positive then this variable can be increase forever—this is a signal that the linear programming problem is unbounded
- You can also find that a basic variable becomes zero—this is known as a degenerate feasible vector
- It can be removed by exchanging variables on the left of the inequality with variables on the right
- This makes the algorithm a bit more complex to implement

Time Complexity of Simplex

- The time complexity of the updates is $O(n^2)$
- The critical question is how many updates are necessary
- It turns out that typically this is $O(n)$ making the simplex algorithm $O(n^3)$
- However, it is possible to cook up problems where there is a “long path” from the initial solution to the optimum which is exponentially big
- Thus the worst case time is exponential, although this almost never happens in practice

Outline

1. Recap
2. Basic Feasible Solutions
3. Simplex Method
4. **Classic LP Problems**



Maximum Flow

- In maximum flow we consider a directed graph representing a network of pipes
- We choose one vertex as the source and a second vertex as a sink
- Each edge has a flow capacity that cannot be exceeded
- The problem is to maximise the flow between source of sink
- This can be used to model the flow of a fluid, parts in an assembly line, current in an electrical circuit or packets through a communication network

- Although the tableau method is the “classic solver” it doesn’t cut the mustard for large scale problems
- The simplex update can also be viewed as solving a linear set of equations which is facilitated by performing an LU-decomposition
- However, the constraints are often very sparse so good solvers try to take advantage of the sparsity
- Top end simplex algorithms are rather complex
- There is a second approach known as the interior point method which is competitive on large problems

Interior Point Method

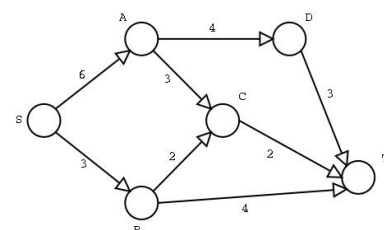
- An alternative to the simplex method is the interior point method which always remains in the feasible region, away from the constraints
- These method iterate towards the constraints and are provably polynomial
- For small linear programming problems they are out-performed in practice by the simplex method
- On large and very large problems they seem to perform as well if not better than the simplex method
- The high-end solvers will have a variety of interior point methods tailored to the particular problem

LP Problems

- Any problem that can be set up as a linear program can be solved in polynomial time
- One way is just to feed it to a LP-solver
- Sometimes the problems are important enough and have such a distinctive formulation that faster specialised algorithms have been developed
- We consider a couple of classic problems: *maximum flow* and *linear assignment*

Example

- Consider a firm that has to ship haggis from Edinburgh to Southampton
- The shipping firm transports this in crates which it sends through intermediate cities
- The number of crates is limited by the size of the lorries it uses



Flow

- We are given a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ where each edge has a capacity $c(i, j)$
- We define the flow from i to j as $f(i, j)$ with $0 \leq f(i, j) \leq c(i, j)$
- For all vertices except the source (s) and sink (t) we assume

$$\forall i \in \mathcal{V} \setminus \{s, t\} \quad \sum_{j \in \mathcal{V} \setminus \{i, j\} \in \mathcal{E}} f(i, j) = \sum_{j \in \mathcal{V} \setminus \{i, j\} \in \mathcal{E}} f(j, i)$$
 (i.e. no flow is lost from source to sink)
- We want to maximise the flow from the source

$$\sum_{i \in \mathcal{V} \setminus \{s, i\} \in \mathcal{E}} f(s, i)$$

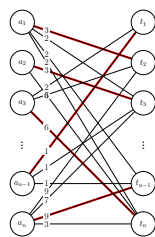
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Linear Assignment

- We are given a set of n agents, \mathcal{A} , and n tasks, \mathcal{T}
- Each agent has a cost associated with performing a task $c(a, t)$
- We want to assign an agent to one task so as to minimise the total cost
- Consider a taxi firm with taxi's at 5 different locations and 5 requests to fulfil. The cost is the distance to the clients. Which taxi should go to which client?



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Hungarian Algorithm

- Linear assignment is another classic problem that is commonly encountered
- Although it can be solved using a generic LP-solver this is not the most efficient algorithm
- The most efficient algorithm is the Hungarian algorithms
- This is rather complex (having once implemented it I can tell you from bitter experience it ain't easy)
- Its worst case time is $O(n^3)$ although it frequently takes $\Theta(n^2)$

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Lessons

- Linear programming is a classic problem
- We know a huge number of problems are solvable in polynomial time because they can be formulated as linear programs
- Linear programs occur sufficiently often that they are hugely important
- They aren't easy to solve, although standard simplex is not massively complex
- For particular LP problems with distinctive structure there are sometimes better algorithms than generic LP-solvers

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Solving Maximum Flow

- As set up we have a linear objective function with linear constraints
- We can therefore solve this problem with a LP-solver
- (Note the solution will typically involve a fraction flow)
- However, this is such a classic problem with a distinctive structure that we can solve it more quickly with other algorithms
- The classic algorithm is the Ford-Fulkerson method with run time $O(|\mathcal{E}| \times f_{\max})$ where f_{\max} is the maximum flow, although we won't cover this in the course

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LA as LP

- The linear assignment problem can be set as a linear programming problem

$$\begin{aligned} \min_{\mathbf{x}} \quad & \sum_{a \in \mathcal{A}, t \in \mathcal{T}} c(a, t) x_{a, t} \\ \text{subject to} \quad & \\ \forall a \in \mathcal{A} \quad & \sum_{t \in \mathcal{T}} x_{a, t} = 1 \\ \forall t \in \mathcal{T} \quad & \sum_{a \in \mathcal{A}} x_{a, t} = 1 \\ \forall (a, t) \in (\mathcal{A}, \mathcal{T}) \quad & x_{a, t} \geq 0 \end{aligned}$$

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Quadratic Programming

- If we have linear constraints and a quadratic objective function then we have a quadratic programming problem
- Again this can be solved in polynomial time
- Many of the ideas used are the same as for linear programming
- This also has important applications in science and engineering

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