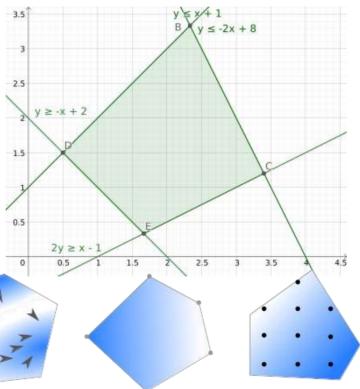
# **Linear Programming 2**

#### COMP4691 / 8691



## LP Topic Outline

- LP Introduction
- Modelling and solving
- Feasible region and convexity
  - Feasibility
  - Feasible region
  - Convex sets
  - Optimality of LP
  - Network flow example
- Simplex algorithm
- Relaxations and approximations
- The dual of a linear program

# Feasibility

 $\min_{x \in \mathbb{R}^n} c^{\mathsf{T}} x$ 

s.t.  $Ax \leq b$ 

A feasible point or feasible solution is a point  $x^* \in \mathbb{R}^n$  that satisfies all constraints

If no such point exists then the **problem** is infeasible

**Feasible region / solution space** = the set of all feasible points

A feasible solution might be **optimal** or **suboptimal** for a given objective

LP feasibility is somewhat analogous to the possible outcomes of solving a *system of linear equations*.

$$Ax = b$$

m linearly independent equations with n variables:

```
\mathbf{m} < \mathbf{n} \Rightarrow \text{Underdetermined, infinite solutions} \quad \mathbf{x} + \mathbf{y} = \mathbf{5} \ (\mathbf{m} < \mathbf{n})
```

$$\mathbf{m} = \mathbf{n} \Rightarrow \text{Single unique solution}$$
  $x - y = 5 (m = n)$ 

$$\mathbf{m} > \mathbf{n} \Rightarrow \text{Overdetermined, no solution}$$
  $3x + y = 0 \text{ (m>n)}$ 

Inequalities further complicate things.

An inequality defines a **half-space.** A half-space is a hyperplane partitioning space into two regions

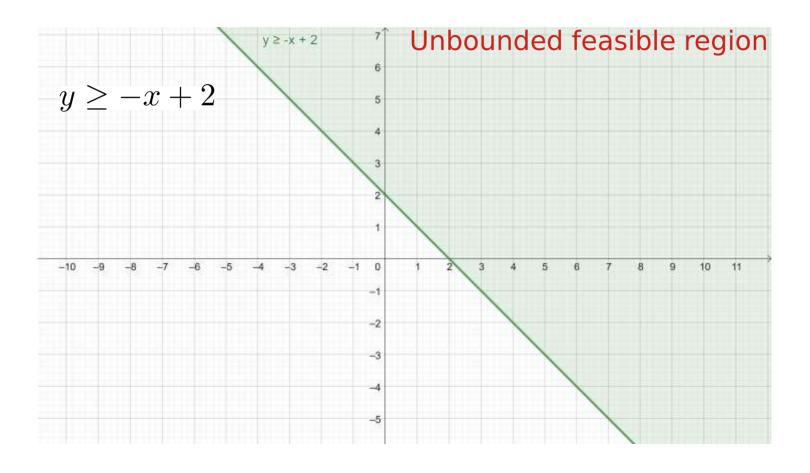
$$Ax \leq b$$

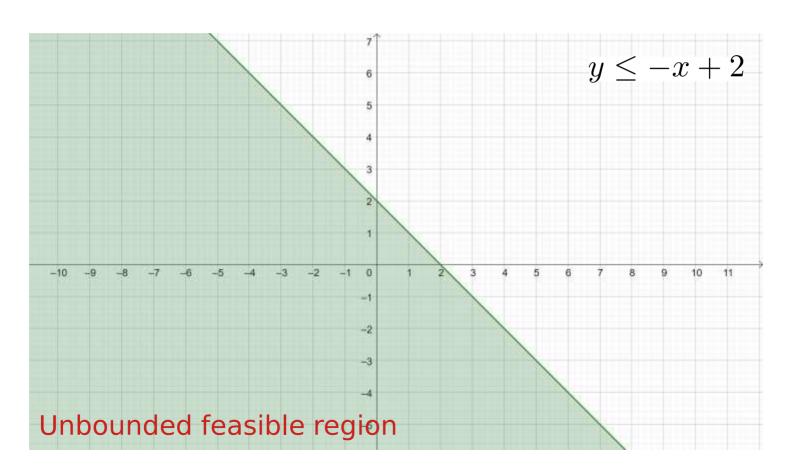
A single inequality defines an unbounded feasible region.

Multiple inequalities can define:

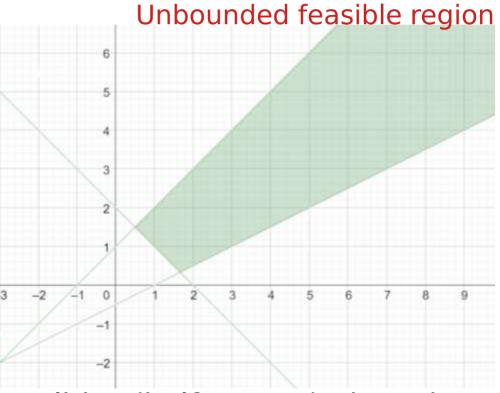
- bounded feasible regions
- unbounded feasible regions
- an empty region, i.e. an infeasible problem

Let's plot some examples of feasible regions.





$$y \ge -x + 2$$
$$2y \ge x - 1$$
$$y \le x + 1$$



The intersection of the inequalities (half-spaces) gives the feasible region

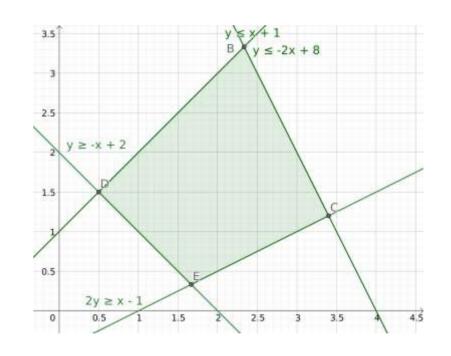
$$y \ge -x + 2$$

$$2y \ge x-1$$

$$y \le x + 1$$

$$y \le -2x + 8$$

Bounded feasible region



Iterative example here:

https://www.geogebra.org/graphing/bhrfuq27

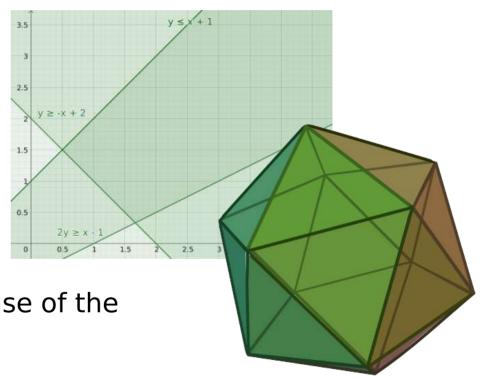
# Feasible Region

The intersection of half-spaces gives us a **convex**, possibly unbounded, **polyhedron\***.

#### When bounded:

- 2-D Convex Polygon
- 3-D Convex Polyhedron
- *n*-D Convex Polytope

Linear programming is a special case of the more general convex optimisation



<sup>\*</sup> In the mathematical optimisation community polyhedron is commonly used for the arbitrary dimension possibly unbounded object, with polytope reserved for the bounded case.

#### Convex Sets

A convex set or region in a vector space over the real numbers is a subset:

$$\mathcal{R} \subseteq \mathbb{R}^n$$

which must satisfy the following condition:

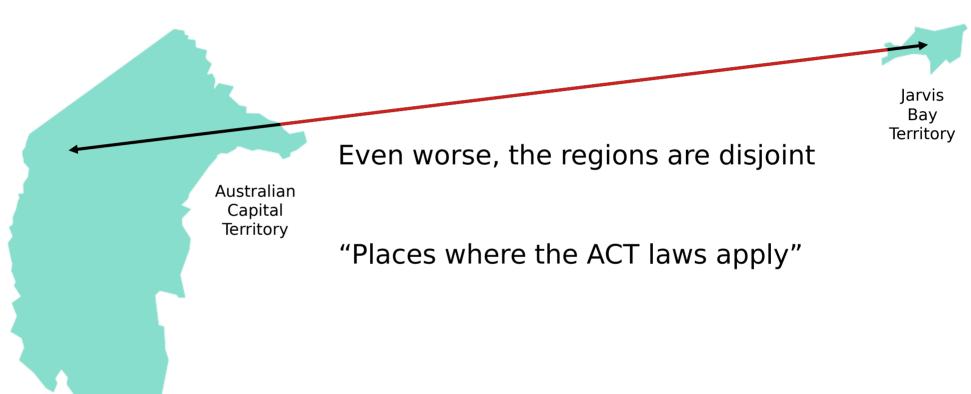
A line segment between any two points in the region must also lie within the region:

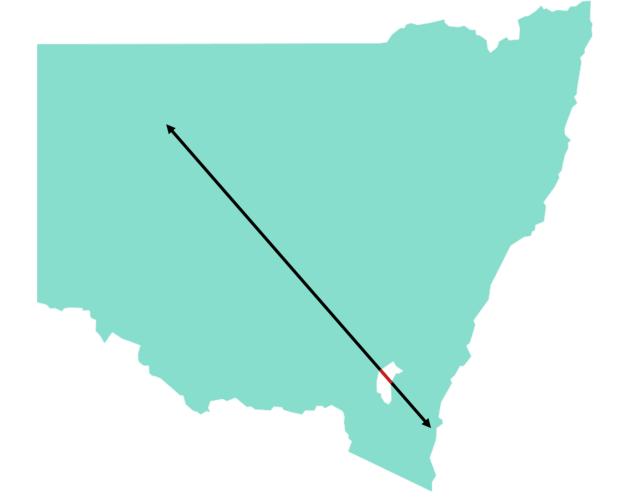
$$\forall x, y \in \mathcal{R} : \{x + \alpha(y - x) | \alpha \in [0, 1]\} \subseteq \mathcal{R}$$

i.e., direct line of sight to every other point in region!

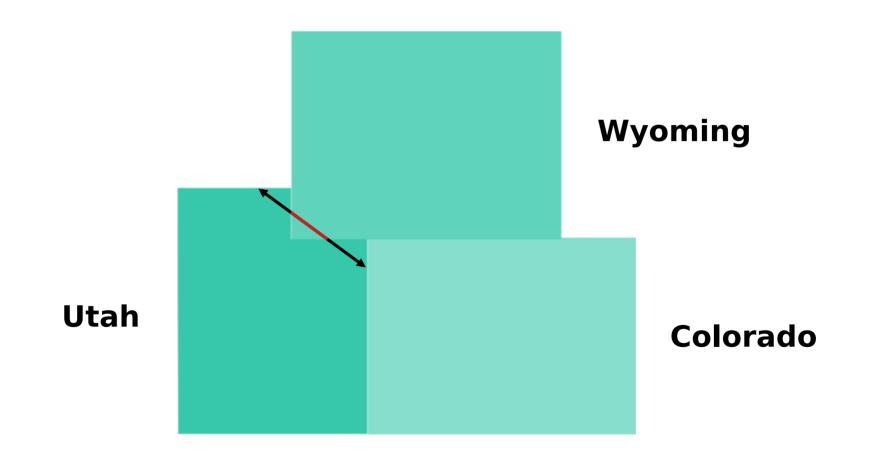
Why might this be a useful property in optimisation?











#### Convex Sets

An important property:

The intersection of convex sets is a convex set

Using this:

- · Linear inequality constraints define half-spaces, and
- half-spaces define convex regions, therefore
- their intersection (combination of all constraints) is a convex region.

Ta-dah!

(Note that the empty set is convex)

### Intersection of Convex Sets

Pretty intuitive, and the proof is also straight-forward.

Given two convex sets in A and B in  $\mathbb{R}^n$ 

The definition of convexity:

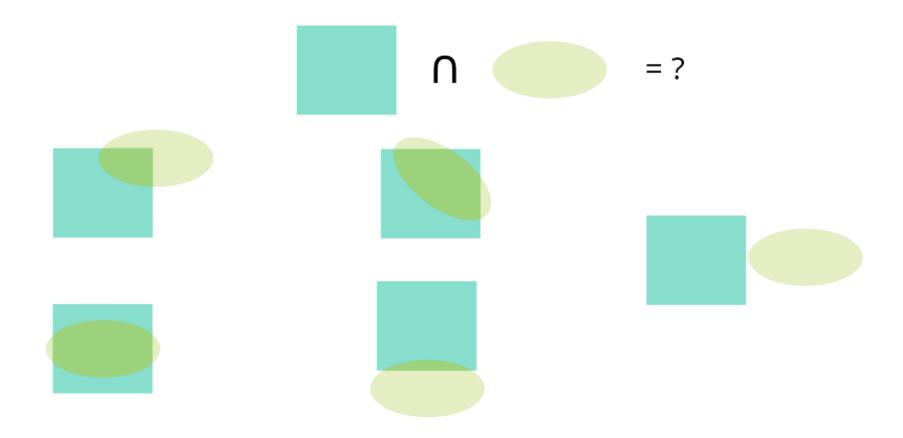
$$\forall x, y \in A: \{x + \alpha(y - x) | \alpha \in [0, 1]\} \subseteq A$$

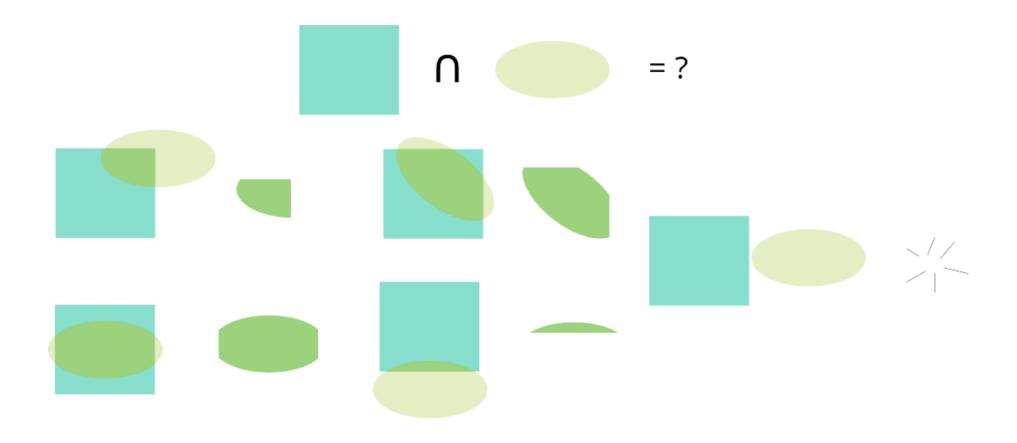
$$\forall x, y \in B: \{x + \alpha(y - x) | \alpha \in [0, 1]\} \subseteq B$$

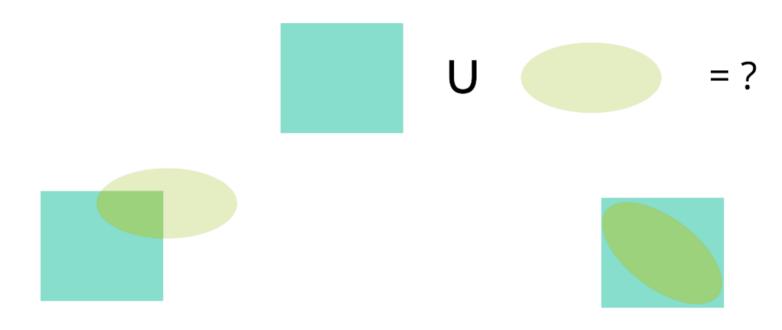
Any points in both A and B will also have their line segment in A and B, and so it will also be in the intersection of A and B:

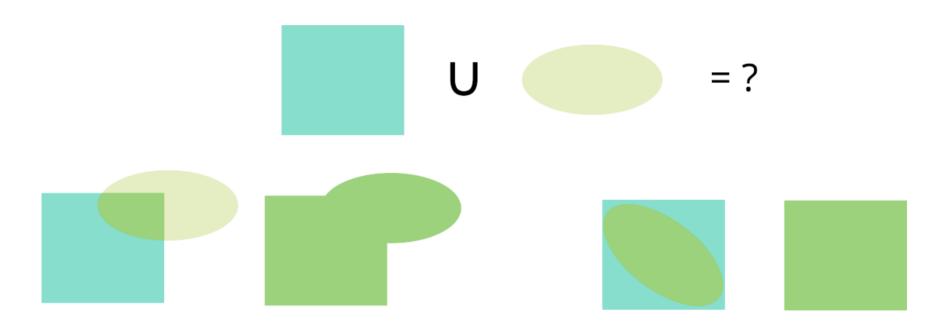
$$\forall x, y \in A \cap B : \{x + \alpha(y - x) | \alpha \in [0, 1]\} \subseteq A \cap B$$

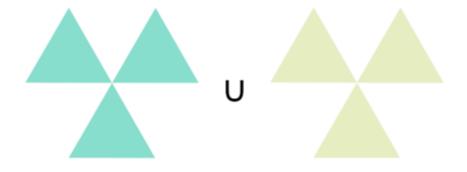


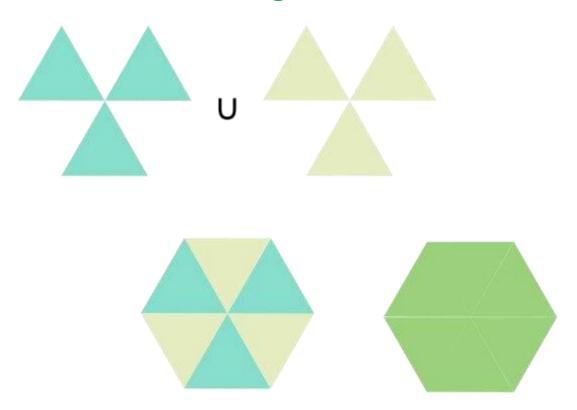












## Convexity

**Strict convexity**: all open line segments (excluding end points) are in the interior of the region.

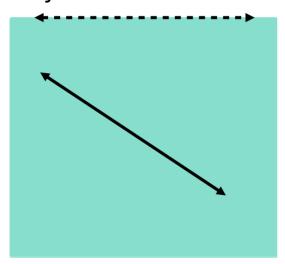
The **convex hull** of a set S is the smallest possible convex set that contains S.

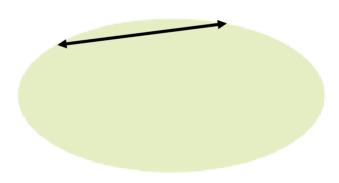
An **extreme point** of a convex set S does not belong to an open line segment for **any** two points in S.

We will come back to convexity in the convex optimisation part of the course. In particular with defining what we mean by *convex functions* and some of their useful properties. But for now (well after a few more examples), that is enough convexity!

# **Strict Convexity**

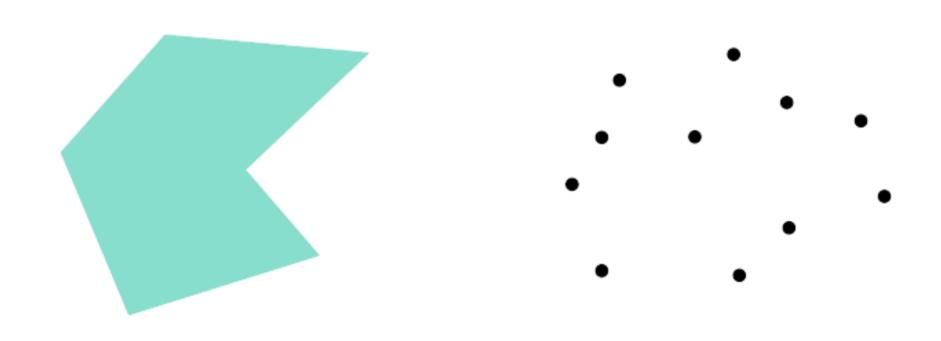
This line segment has values (other than endpoints) that are on the boundary: therefore the region is not strictly convex



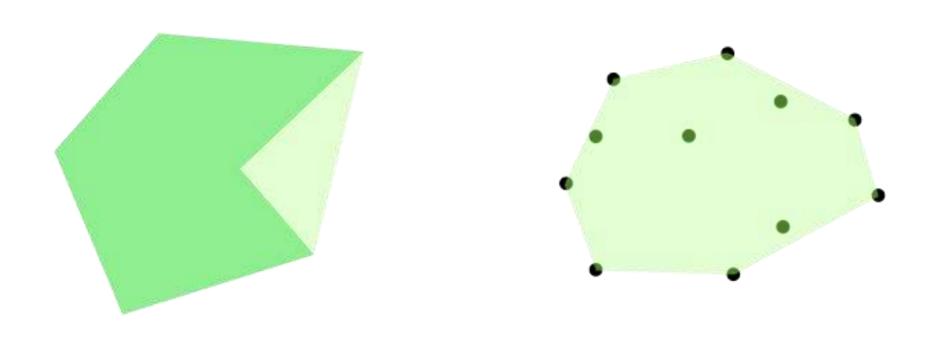


A strictly convex region.

## Convex Hull



## Convex Hull



## Convex Hull



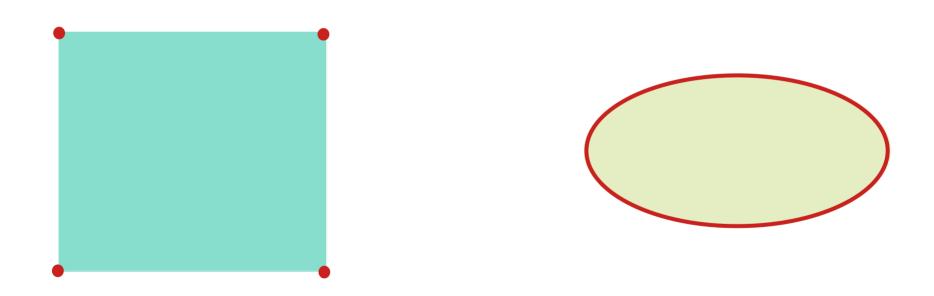








#### **Extreme Points**



For a convex polyhedron, extreme points are vertices and vice versa.

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## Optimisation

**Decision problems** in computer science look for the presence of a solution that satisfies some conditions (any value in the feasible region), **optimisation problems** search for the "best" solution among these according to some objective.

When we combine the notions of feasibility and optimality we get the following possible outcomes for an LP.

# Optimality of an LP

**Unbounded** - feasible region must be unbounded

 The problem is probably modelled incorrectly, rarely in the real world can we generate an infinite amount of value from something, we normally hit some limit at some point

A single optimal solution – feasible region may be unbounded, bounded or a single point

Solution lies at a vertex

**An infinite number of optimal solutions** – feasible region may be unbounded or bounded

• Optimal solutions lie along an edge / ... / facet of the feasible region polyhedron (or the entire regions itself), including the relevant vertices

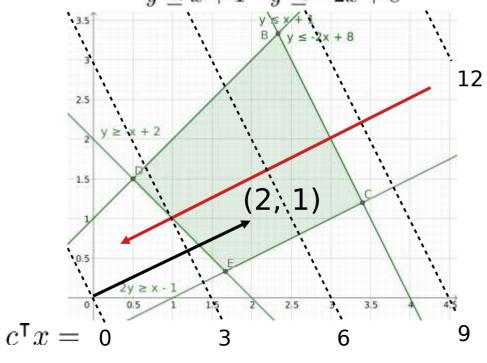
Infeasible - feasible region must be empty

 It might not be possible to do what the problem states, or an error in the modelling

## Objective Visualisation

$$\underline{\min_{x,y}} 2x + y$$

s.t. 
$$y \ge -x + 2$$
  $2y \ge x - 1$   
 $y \le x + 1$   $y \le -2x + 8$ 



Let's visualise the objective, by plotting the vector "c".

$$\min_{x \in \mathbb{R}^n} c^{\mathsf{T}} x$$
s.t.  $Ax \le b$ 

Which direction gives better solutions?

For min, want to move in opposite direction to c.

Does the magnitude of c matter?

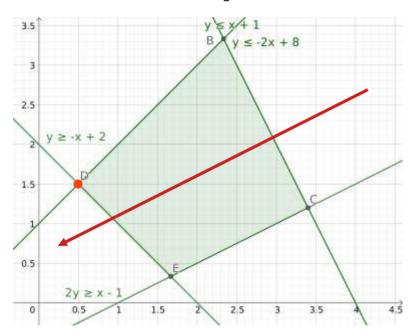
Can multiply the objective by a scalar k > 0 and will get same solution.

What is the optimal solution?

At vertex "D".

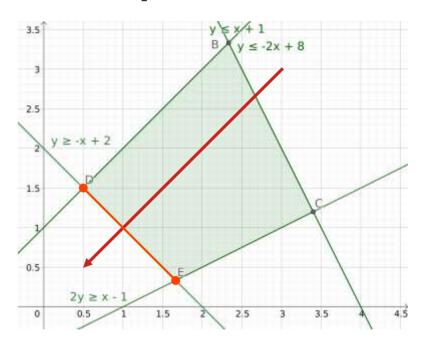
----- **Level set** of objective / contours of equal objective value

## **Optimality Examples**



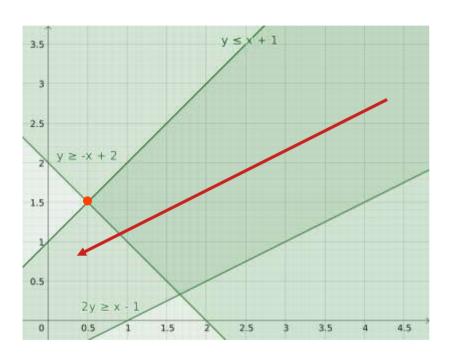
How many optimal solutions?

Single unique optimum



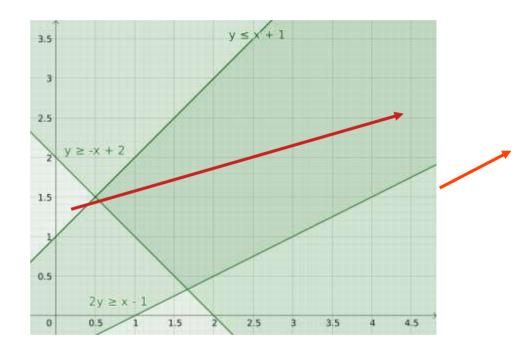
How many optimal solutions? Infinite number of optimal solutions

### **Optimality Examples**



#### Can we find an optimal solution?

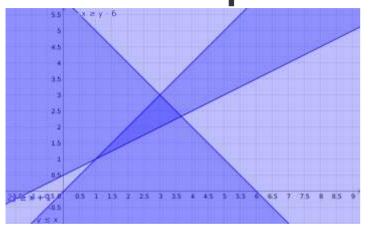
- Unbounded feasible region
- Single unique solution



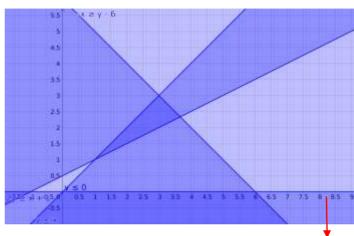
#### Can we find an optimal solution?

- Unbounded feasible region
- No solution

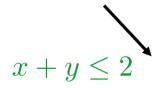
## **Optimality Examples**

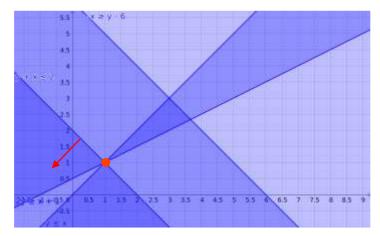






Infeasible problem

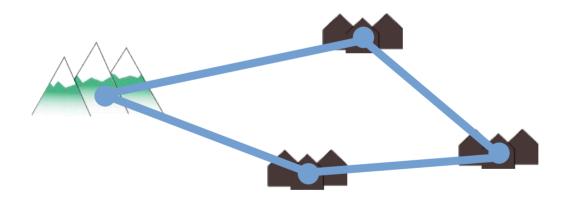




Single feasible point and optimal solution

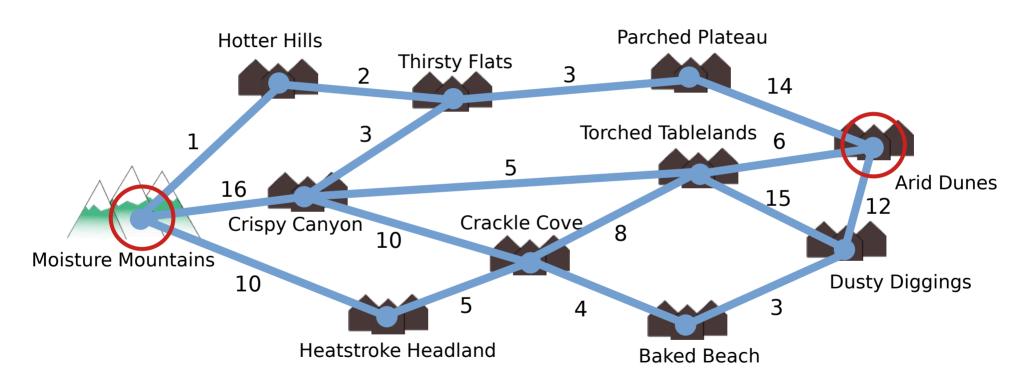
### Water Supply Examples

To demonstrate these points on the optimality of LPs, we will look the task of **distributing water** in a network of pipes.



These are examples of "network flow" type problems.

### Maximum Flow



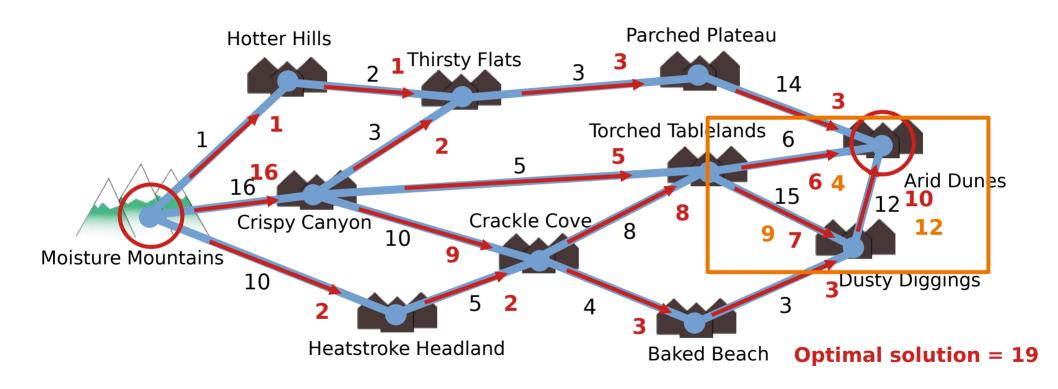
Maximum flow between a source and sink where edges have limited capacities. What would be the problem formulation?

#### Maximum Flow

Directed graph: G:=(V,E) Maximum flow between two vertices: (s,n)

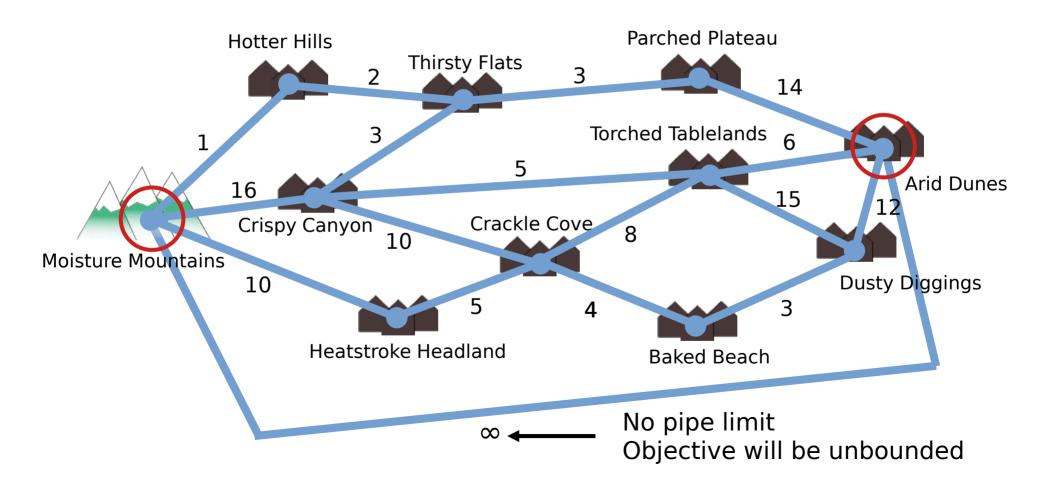
$$\max_{x} \sum_{(j,n) \in E} x_{j,n} - \sum_{(n,i) \in E} x_{n,i}$$
 Source Sink s.t. 
$$\sum_{(i,k) \in E} x_{i,k} - \sum_{(k,j) \in E} x_{k,j} = 0 \quad \forall k \in V \setminus \{s,n\}$$
 Graph is directed, but we allow flow in both directions. 
$$x_{3,1}$$
 3 
$$x_{1,4}$$
 4 
$$x_{1,5}$$
 5 See water max flow.py

### Maximum Flow

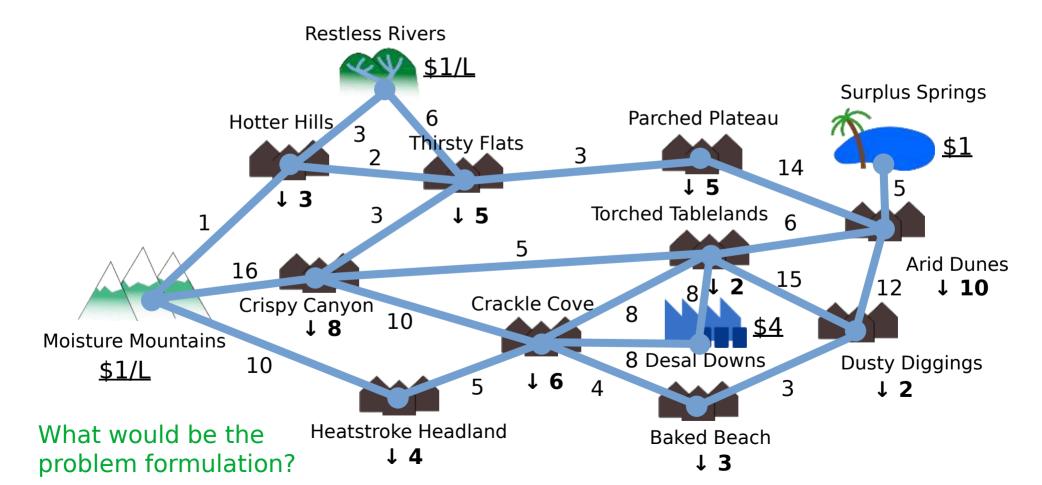


Multiple optimal solutions

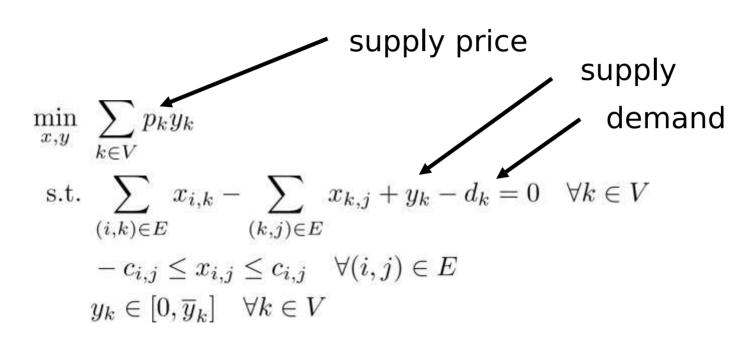
#### Unbounded Problem



# Minimum Cost Supply

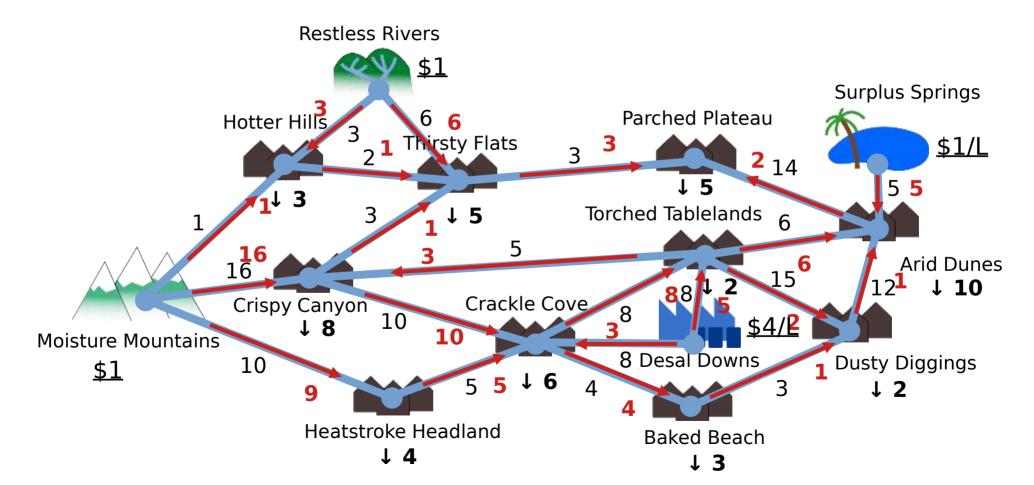


# Minimum Cost Supply

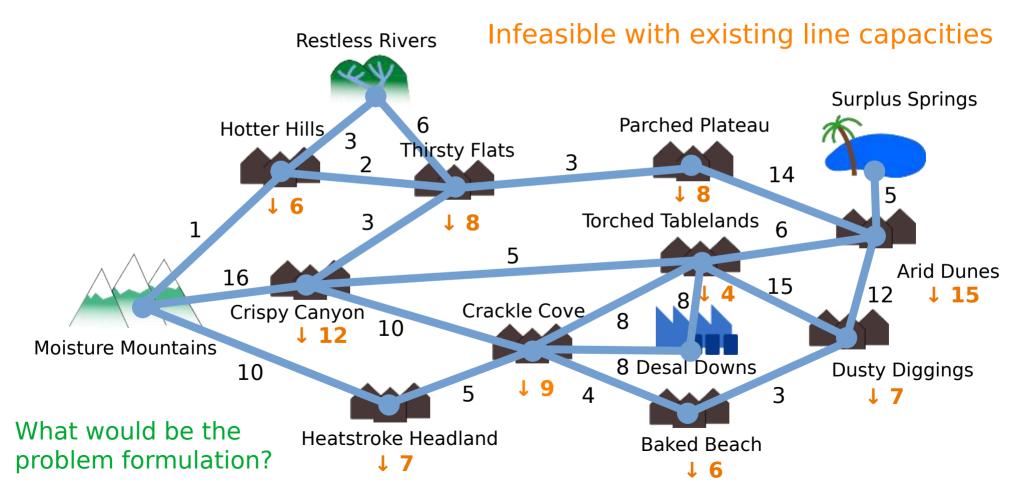


See water\_supply.py

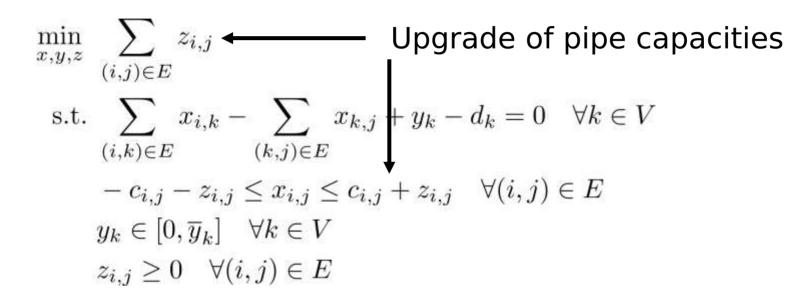
# Minimum Cost Supply



# Minimum Pipe Upgrades

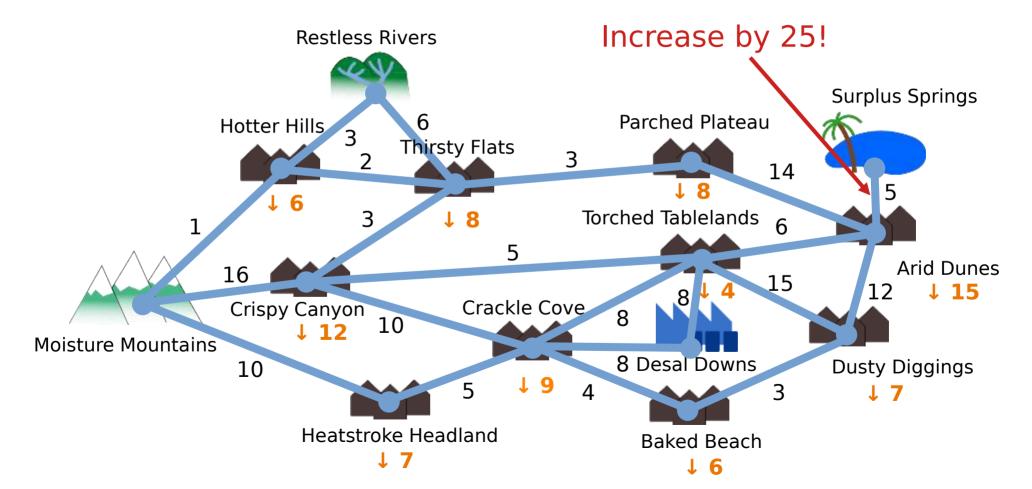


# Minimum Pipe Upgrades



One of the lab implementation problems

# Minimum Pipe Upgrades



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