Basic Terminology

**REVIEW from Data Structures!**

\[ G = (V, E); \] 
\( V \) is set of \( n \) nodes, \( E \) is set of \( m \) edges

- **Node or Vertex**: a point in a graph
- **Edge**: connection between nodes
- **Weight**: numerical cost or length of an edge
- **Direction**: arrow on an edge
- **Path**: sequence \((u_0, u_1, \ldots, u_k)\) with every \((u_{i-1}, u_i) \in E\)
- **Cycle**: path that starts and ends at the same node

Examples

- Roads and intersections
- People and relationships
- Computers in a network
- Web pages and hyperlinks
- Makefile dependencies
- Scheduling tasks and constraints
- (many more!)

Graph Representations

- **Adjacency Matrix**: \( n \times n \) matrix of weights.
  \( A[i][j] \) has the weight of edge \((u_i, u_j)\).
  Weights of non-existent edges usually 0 or \( \infty \).
  Size:

- **Adjacency Lists**: Array of \( n \) lists;
  each list has node-weight pairs for the *outgoing edges* of that node.
  Size:

- **Implicit**: Adjacency lists computed on-demand.
  Can be used for infinite graphs!

**Unweighted graphs** have all weights either 0 or 1.
**Undirected graphs** have every edge in both directions.
Simple Example

Adjacency Matrix:

<table>
<thead>
<tr>
<th></th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
</tr>
</thead>
<tbody>
<tr>
<td>a</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>b</td>
<td></td>
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<tr>
<td>e</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Adjacency List:

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Search Template

```python
def genericSearch(G, start, end):
    colors = {}
    for u in G.V:
        colors[u] = "white"
    # initialize fringe with node-weight pairs
    while len(fringe) > 0:
        (u, w1) = fringe.top()
        if colors[u] == "white":
            colors[u] = "gray"
            for (v, w2) in G.edgesFrom(u):
                if colors[v] == "white":
                    fringe.insert((v, w1+w2))
                elif colors[u] == "gray":
                    colors[u] = "black"
                else:
                    fringe.remove((u, w1))
```

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Basic Searches

To find a path from \( u \) to \( v \), initialize fringe with \((u, 0)\), and exit when we color \( v \) to "gray".

Two choices:

- **Depth-First Search**
  
  fringe is a stack. Updates are pushes.

- **Breadth-First Search**
  
  fringe is a queue. Updates are enqueues.

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Applications of Search

DAGs
Some graphs are acyclic by nature.
An acyclic undirected graph is a...
DAGs (Directed Acyclic Graphs) are more interesting:
  - Can have more than \( n - 1 \) edges
  - Always at least one "source" and at least one "sink"
  - Examples:

Linearization

Problem
Input: A DAG \( G = (V, E) \)
Output: Ordering of the \( n \) vertices in \( V \) as \((u_1, u_2, ..., u_n)\) such that only "forward edges" exist, i.e., for all \((u_i, u_j) \in E\), \( i < j \).
(Also called "topological sort").
Applications:

def linearize(G):
    order = []; colors = {}; fringe = []
    for u in G.V:
        colors[u] = "white"
        fringe.append(u)
    while len(fringe) > 0:
        u = fringe[-1]
        if colors[u] == "white":
            colors[u] = "gray"
            for (v,w2) in G.edgesFrom(u):
                if colors[v] == "white":
                    fringe.append(v)
            elif colors[u] == "gray":
                colors[u] = "black"
                order.insert(0, u)
        else :
            fringe.pop()
    return order
Linearization Example

Properties of DFS

- Every vertex in the stack is a child of the first gray vertex below it.

- Every descendant of \( u \) is a child of \( u \) or a descendant of a child of \( u \).

- In a DAG, when a node is colored gray its children are all white or black.

- In a DAG, every descendant of a black node is black.
Dijkstra's Algorithm

Dijkstra's is a modification of BFS to find shortest paths.
Solves the single source shortest paths problem.
Used millions of times every day (!) for packet routing

**Main idea:** Use a minimum priority queue for the fringe

**Requires all edge weights to be non-negative**

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Differences from the search template

- fringe is a priority queue
- No gray nodes! (No post-processing necessary.)

Useful variants:
- Keep track of the actual paths as well as path lengths
- Stop when a destination vertex is found

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Dijkstra example

![Dijkstra Graph Example](image)
def dijkstraHeap(G, start):
    shortest = {}
    colors = {}
    for u in G.V:
        colors[u] = "white"
    fringe = [(0, start)] # weight goes first for ordering.
    while len(fringe) > 0:
        (w1, u) = heappop(fringe)
        if colors[u] == "white":
            colors[u] = "black"
            shortest[u] = w1
        for (v, w2) in G.edgesFrom(u):
            heappush(fringe, (w1+w2, v))
    return shortest

def dijkstraArray(G, start):
    shortest = {}
    fringe = {}
    for u in G.V:
        fringe[u] = infinity
        fringe[start] = 0
    while len(fringe) > 0:
        w1 = min(fringe.values())
        for u in fringe:
            if fringe[u] == w1:
                break
        del fringe[u]
        shortest[u] = w1
        for (v, w2) in G.edgesFrom(u):
            if v in fringe:
                fringe[v] = min(fringe[v], w1+w2)
    return shortest

Applications of Search
Dijkstra Implementation Options
Heap Unsorted Array
Adj. Matrix
Adj. List
All-Pairs Shortest Paths

Let’s look at a new problem:

Problem: All-Pairs Shortest Paths

**Input:** A graph $G = (V, E)$, weighted, and possibly directed.

**Output:** Shortest path between every pair of vertices in $V$

Many applications in the precomputation/query model:

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Repeated Dijkstra’s

**First idea:** Run Dijkstra’s algorithm from every vertex.

**Cost:**
- Sparse graphs:
- Dense graphs:

---

Storing Paths

- Naïve cost to store all paths:
- Memory wall
- Better way:
**Recursive Approach**

Idea for a simple recursive algorithm:
- **New parameter** $k$: The highest-index vertex visited in any shortest path.
- **Basic idea**: Path either contains $k$, or it doesn’t.

**Three things needed:**
- **Base case**: $k = -1$. Shortest paths are just single edges.
- **Recursive step**: Use basic idea above. Compare shortest path containing $k$ to shortest path without $k$.
- **Termination**: When $k = n$, we’re done.

**Recursive Shortest Paths**

Shortest path from $i$ to $j$ using only vertices 0 up to $k$.

```python
def recShortest(AM, i, j, k):
    if k == -1:
        return AM[i][j]
    else:
        option1 = recShortest(AM, i, j, k-1)
        option2 = recShortest(AM, i, k, k-1) + recShortest(AM, k, j, k-1)
        return min(option1, option2)
```

**Analysis:**
Dynamic Programming Solution

**Key idea:** Keep overwriting shortest paths, using the same memory

This returns a matrix of ALL shortest path lengths at once!

```python
def FloydWarshall(AM):
    L = copy(AM)
    n = len(AM)
    for k in range(0, n):
        for i in range(0, n):
            for j in range(0, n):
                L[i][j] = min(L[i][j], L[i][k] + L[k][j])
    return L
```

### Analysis of Floyd-Warshall

- **Time:**
- **Space:**
- **Advantages:**
Another Dynamic Solution

What if \( k \) is the greatest number of edges in each shortest path?
Let \( L_k \) be the matrix of shortest-path lengths with at most \( k \) edges.

- **Base case**: \( k = 1 \), then \( L_1 = A \), the adjacency matrix itself!
- **Recursive step**: Shortest \((k + 1)\)-edge path is the minimum of \( k \)-edge paths, plus a single extra edge.
- **Termination**: Every path has length at most \( n - 1 \).
  So \( L_{n-1} \) is the final answer.

Min-Plus Arithmetic

Update step: \( L_{k+1}[i, j] = \min_{0 \leq \ell < n} (L_k[i, \ell] + A[\ell, j]) \)

Min-Plus Algebra

- The \(+\) operation becomes “\( \min \)”
- The \(\cdot\) operation becomes “\( \text{plus} \)”

Update step becomes:

APSP with Min-Plus Matrix Multiplication

We want to compute \( A^{n-1} \).

- Initial idea: Multiply \( n - 1 \) times.
- Improvement:
- Further improvement?
Transitive Closure

Examples of reachability questions:
  - Is there any way out of a maze?
  - Is there a flight plan from one airport another?
  - Can you tell me a is greater than b without a direct comparison?

Precomputation/query formulation: Same graph, many reachability questions.

Transitive Closure Problem

**Input:** A graph $G = (V, E)$, unweighted, possibly directed

**Output:** Whether $u$ is reachable from $v$, for every $u, v \in V$

TC with APSP

One vertex is reachable from another if the shortest path isn’t infinite.

Therefore transitive closure can be solved with repeated Dijkstra’s or Floyd-Warshall. Cost will be $\Theta(n^3)$.

Why might we be able to beat this?

Back to Algebra

Define $T_k$ as the reachability matrix **using at most k edges in a path**.

What is $T_0$?
What is $T_1$?

Formula to compute $T_{k+1}$:

Therefore transitive closure is just:
Greedy Optimization Problems

An optimization problem is one where there are many solutions, and we have to find the “best” one.

Examples we have seen:

Optimal solution can often be made as a series of “moves”
(Moves can be parts of the answer, or general decisions)

Greedy Design Paradigm

A greedy algorithm solves an optimization problem by a sequence of “greedy moves”.

Greedy moves:
- Are based on “local” information
- Don’t require “looking ahead”
- Should be fast to compute!
- Might not lead to optimal solutions

Example: Counting change
Appointment Scheduling

Problem
Given \( n \) requests for EI appointments, each with start and end time, how to schedule the maximum number of appointments?

For example:

<table>
<thead>
<tr>
<th>Name</th>
<th>Start</th>
<th>End</th>
</tr>
</thead>
<tbody>
<tr>
<td>Billy</td>
<td>8:30</td>
<td>9:00</td>
</tr>
<tr>
<td>Susan</td>
<td>9:00</td>
<td>10:00</td>
</tr>
<tr>
<td>Brenda</td>
<td>8:00</td>
<td>8:20</td>
</tr>
<tr>
<td>Aaron</td>
<td>8:55</td>
<td>9:05</td>
</tr>
<tr>
<td>Paul</td>
<td>8:15</td>
<td>8:45</td>
</tr>
<tr>
<td>Brad</td>
<td>7:55</td>
<td>9:45</td>
</tr>
<tr>
<td>Pam</td>
<td>9:00</td>
<td>9:30</td>
</tr>
</tbody>
</table>

Greedy Scheduling Options

How should the greedy choice be made?

1. First come, first served
2. Shortest time first
3. Earliest finish first

Which one will lead to optimal solutions?

Proving Greedy Strategy is Optimal

Two things to prove:

1. Greedy choice is always part of an optimal solution
2. Rest of optimal solution can be found recursively
**Greedy Matchings**

Pairing up people or resources is a common task. We can model this task with graphs:

**Maximum Matching Problem**

Given an undirected, unweighted graph $G = (V, E)$, find a subset of edges $M \subseteq E$ such that:

- Every vertex touches at most one edge in $M$
- The size of $M$ is as large as possible

**Greedy Algorithm**: Repeatedly choose any edge that goes between two unpaired vertices and add it to $M$. 

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**Greedy matching example**

[Diagram of a graph with edges and vertices labeled, showing a greedy matching example.]

**Maximum matching example**

[Diagram of a graph with edges and vertices labeled, showing a maximum matching example.]
How good is the greedy solution?

**Theorem:** The optimal solution is at most ___ times the size of one produced by the greedy algorithm.

**Proof:**

---

**Spanning Trees**

A *spanning tree* in a graph is a connected subset of edges that touches every vertex.

Dijkstra's algorithm creates a kind of spanning tree. This tree is created by *greedily* choosing the “closest” vertex at each step.

We are often interested in a minimal spanning tree instead.

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**MST Algorithms**

There are two *greedy* algorithms for finding MSTs:

- **Prim’s.** Start with a single vertex, and grow the tree by choosing the least-weight fringe edge. Identical to Dijkstra’s with different weights in the “update” step.

- **Kruskal’s.** Start with every vertex (a *forest* of trees) and combine trees by using the lease-weight edge between them.
**MST Examples**

- **Prim's:**
  - Graph with vertices and edges:
    - (a, b) with weight 6
    - (b, d) with weight 2
    - (c, d) with weight 4
    - (c, e) with weight 1
    - (a, c) with weight 5
    - (b, e) with weight 4

- **Kruskal's:**
  - Graph with vertices and edges:
    - (a, b) with weight 6
    - (b, d) with weight 2
    - (c, d) with weight 4
    - (c, e) with weight 1
    - (a, c) with weight 5
    - (b, e) with weight 4

**Vertex Cover**

**Problem:** Find the smallest set of vertices that touches every edge.

- Graph with vertices and edges:
  - (a, b, c, d, e, f, g, h, i, j, k, l, m)

**Approximating VC**

- Approximation algorithm for minimal vertex cover:
  - Find a greedy maximal matching
  - Take both vertices in every edge in the matching

Why is this always a vertex cover?

How good is the approximation?