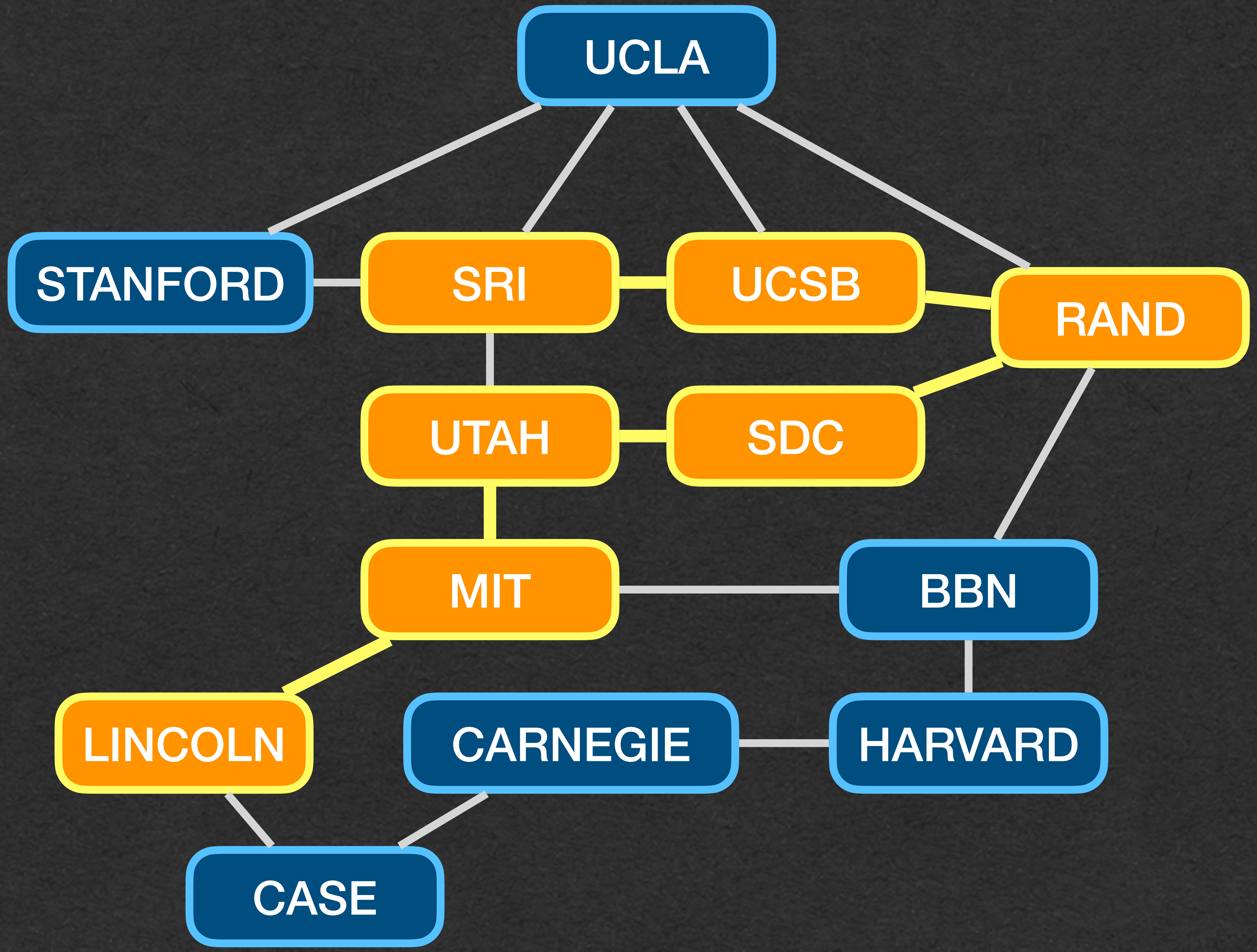
Pathfinding with BFS

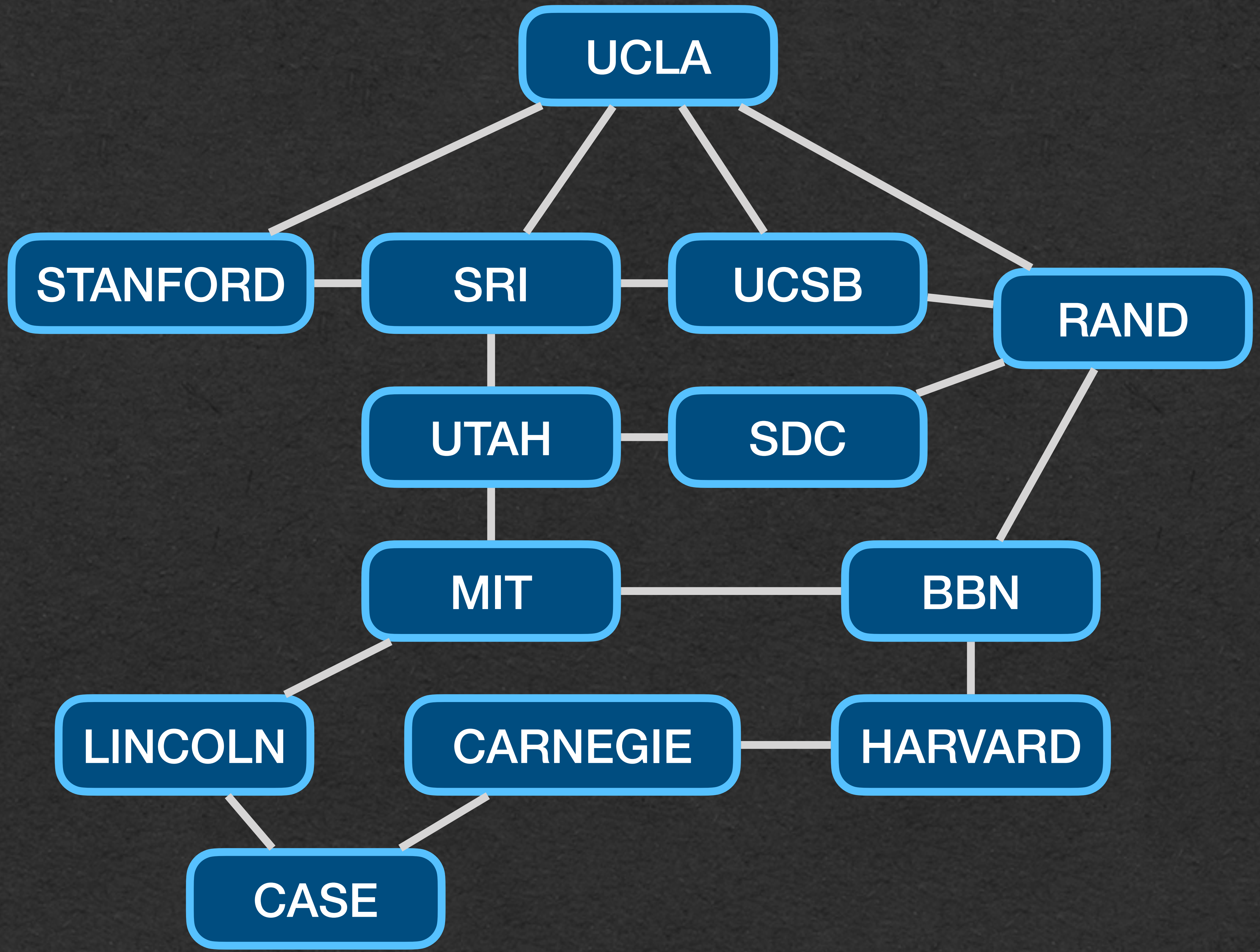
Paths

- Path: A sequence of nodes with each adjacent pair of nodes connected by an edge
- The length of a path is the number of edges it contains (number of nodes - 1)
- [LINCOLN, MIT, UTAH, SDC, RAND, UCSB, SRI] <-- Path of length 6



Distance

- Distance between two nodes: The length of the shortest path between the nodes
- Distance between LINCOLN and SRI == 3
- Distance between RAND and BBN == 1

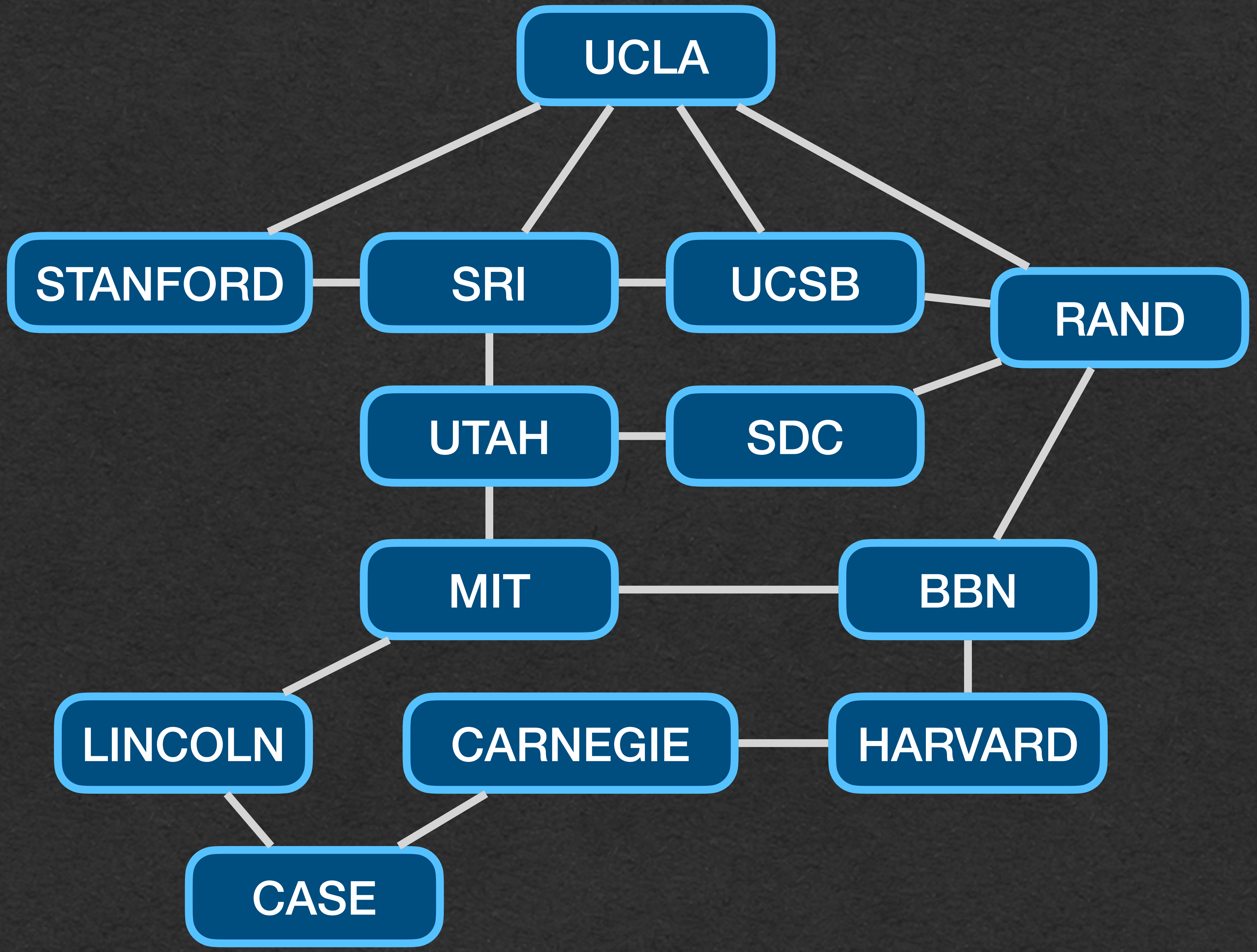


Use BFS to find the distance between nodes

Track the shortest path for pathfinding

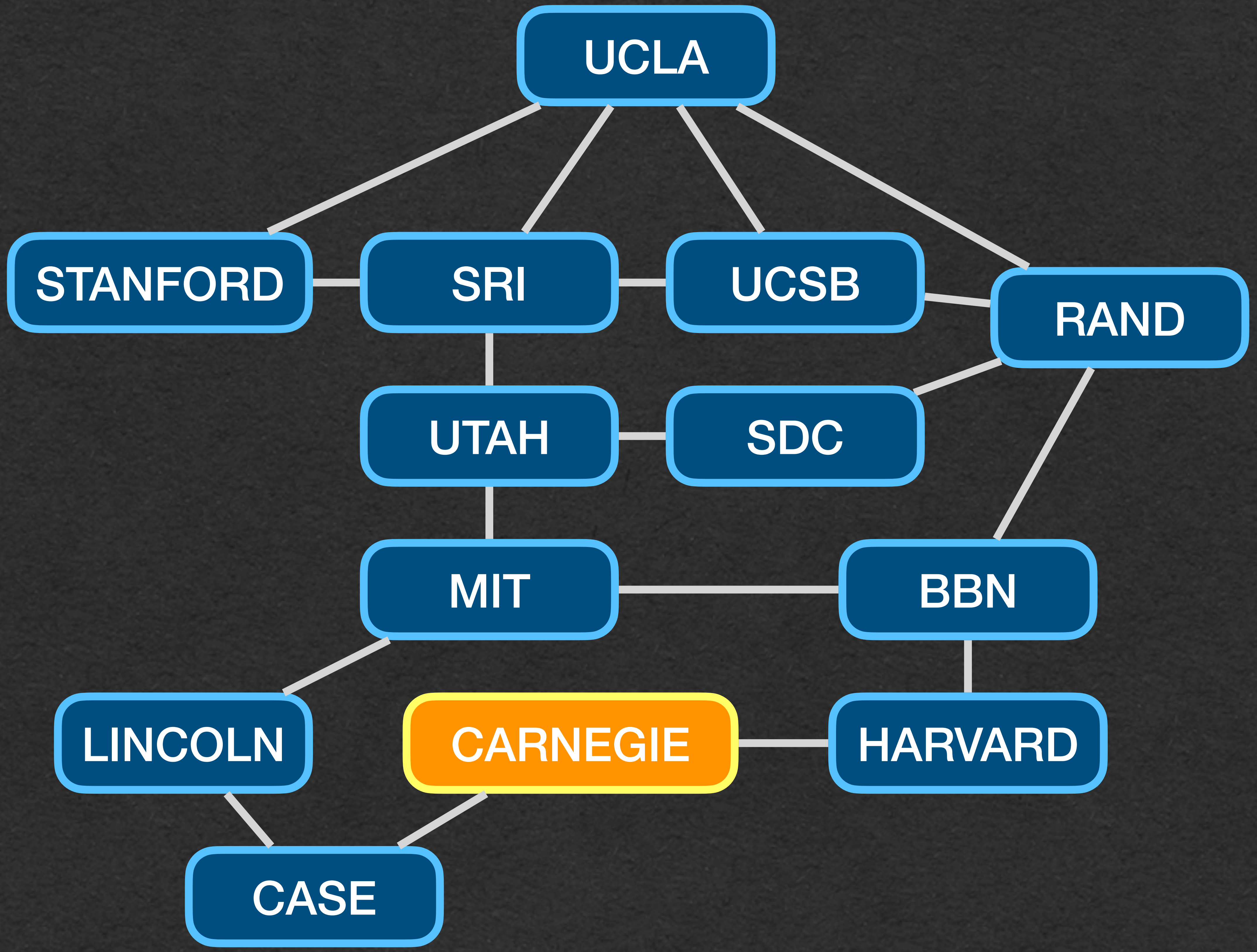
There's Levels to This

- Let's run through BFS again
    - Instead of just finding the connected component, let's track the paths taken to explore each node



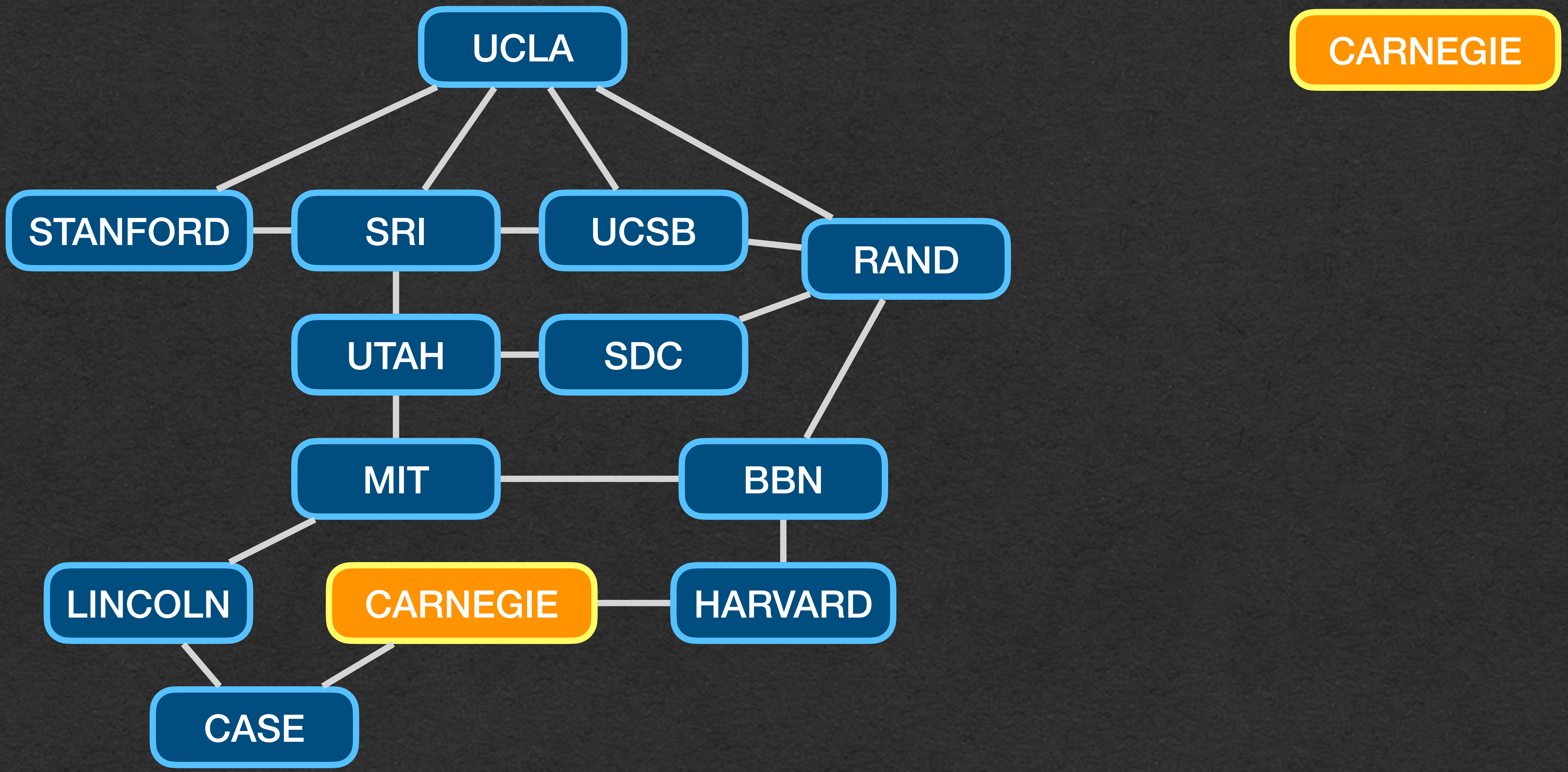
There's Levels to This

- Let's start at CARNEGIE this time



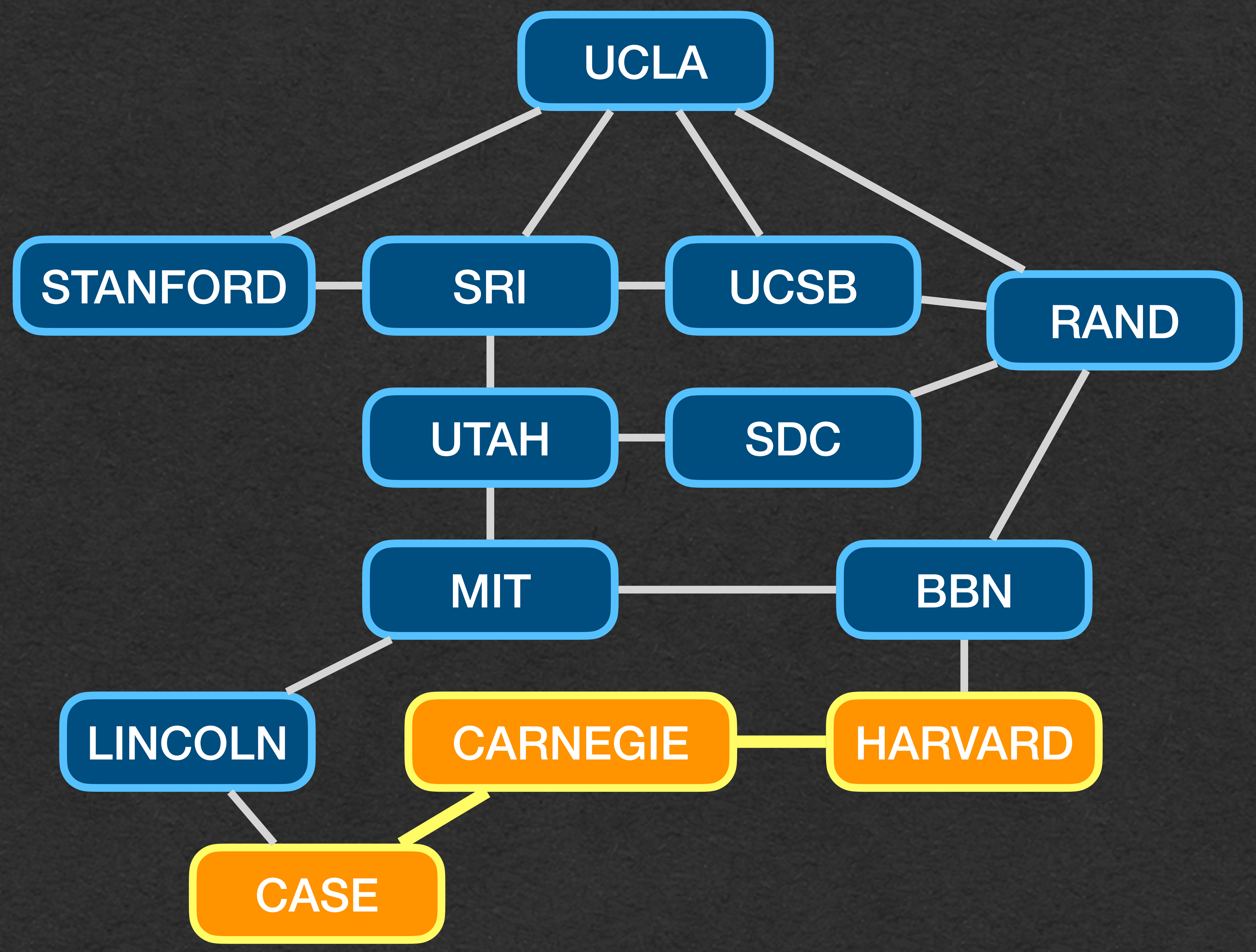
There's Levels to This

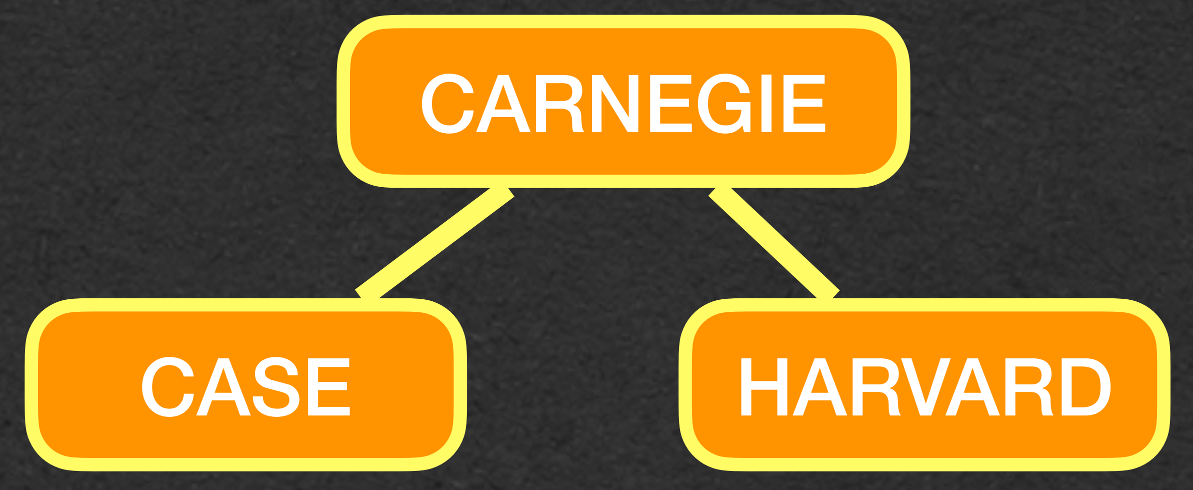
- Keep track of all edges used to explore new nodes
- Redraw the graph with only these edges



There's Levels to This

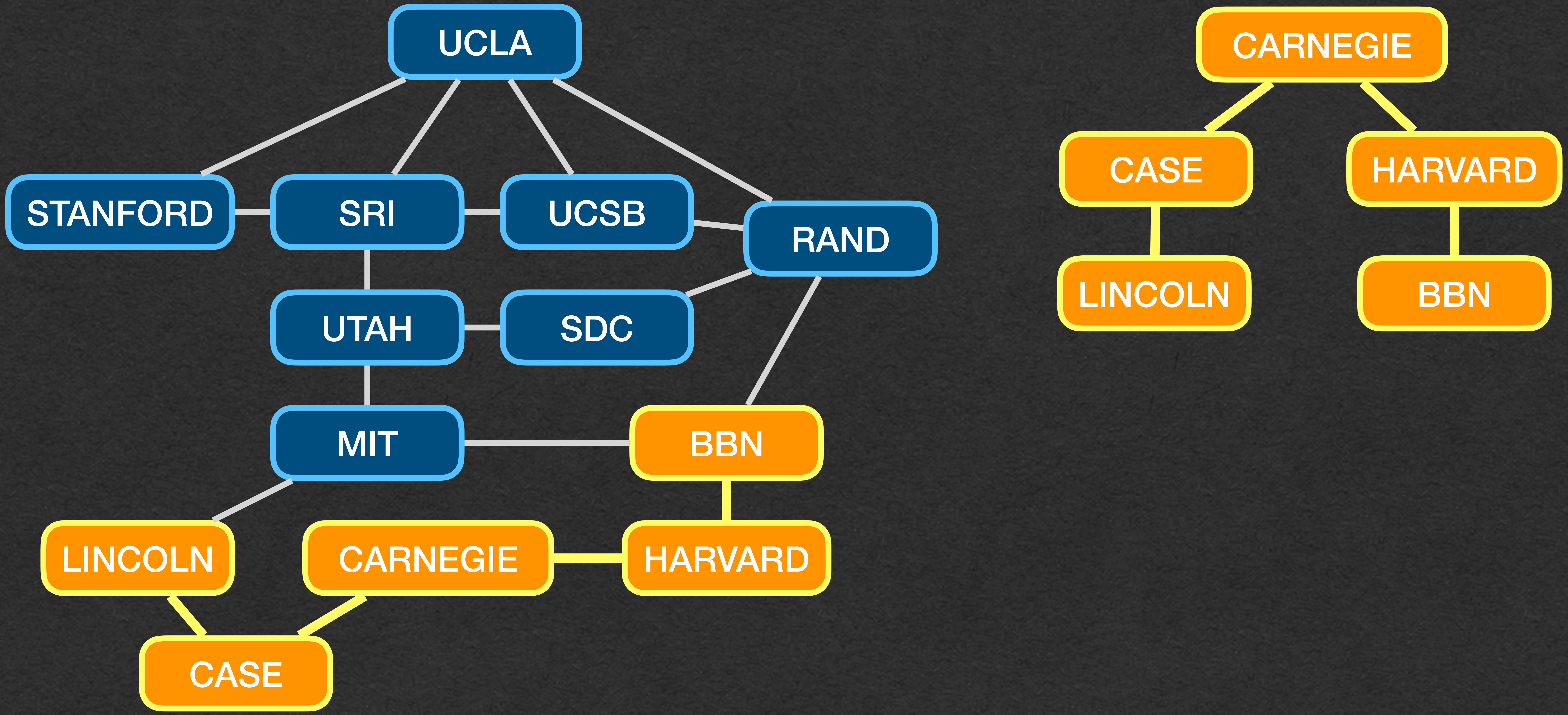
- Explore all neighbors of the starting node





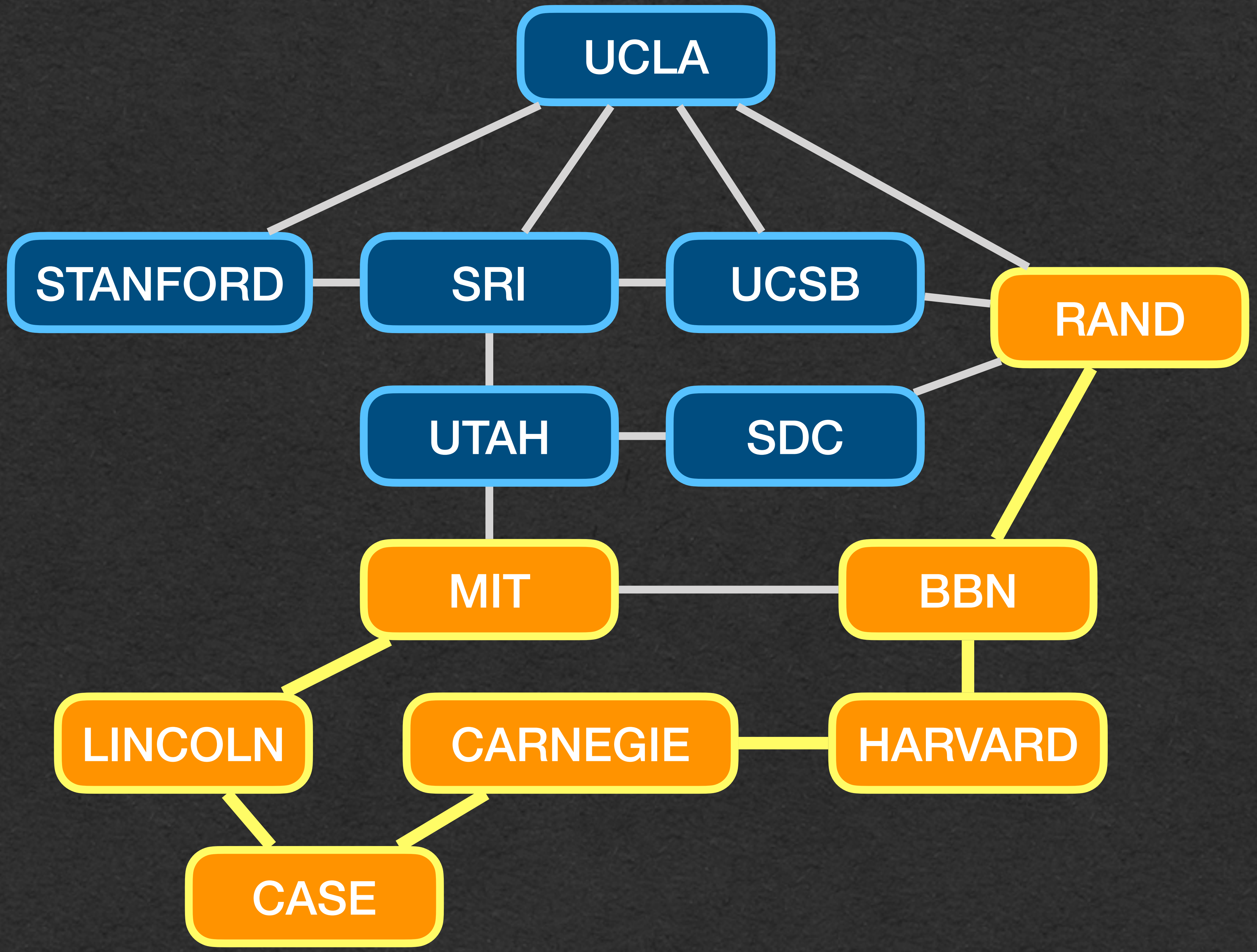
There's Levels to This

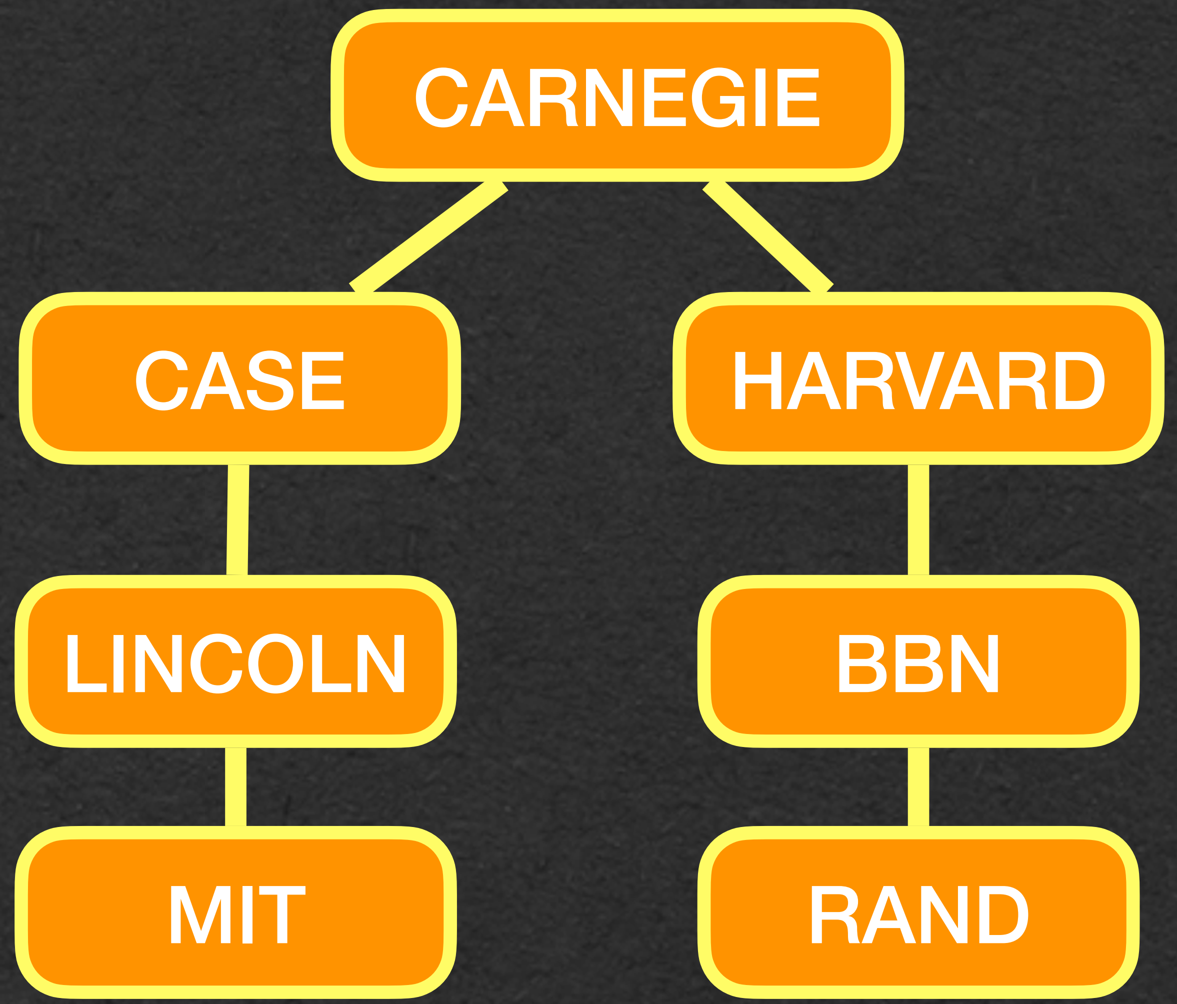
- Explore all neighbors of the nodes explored in the last step



There's Levels to This

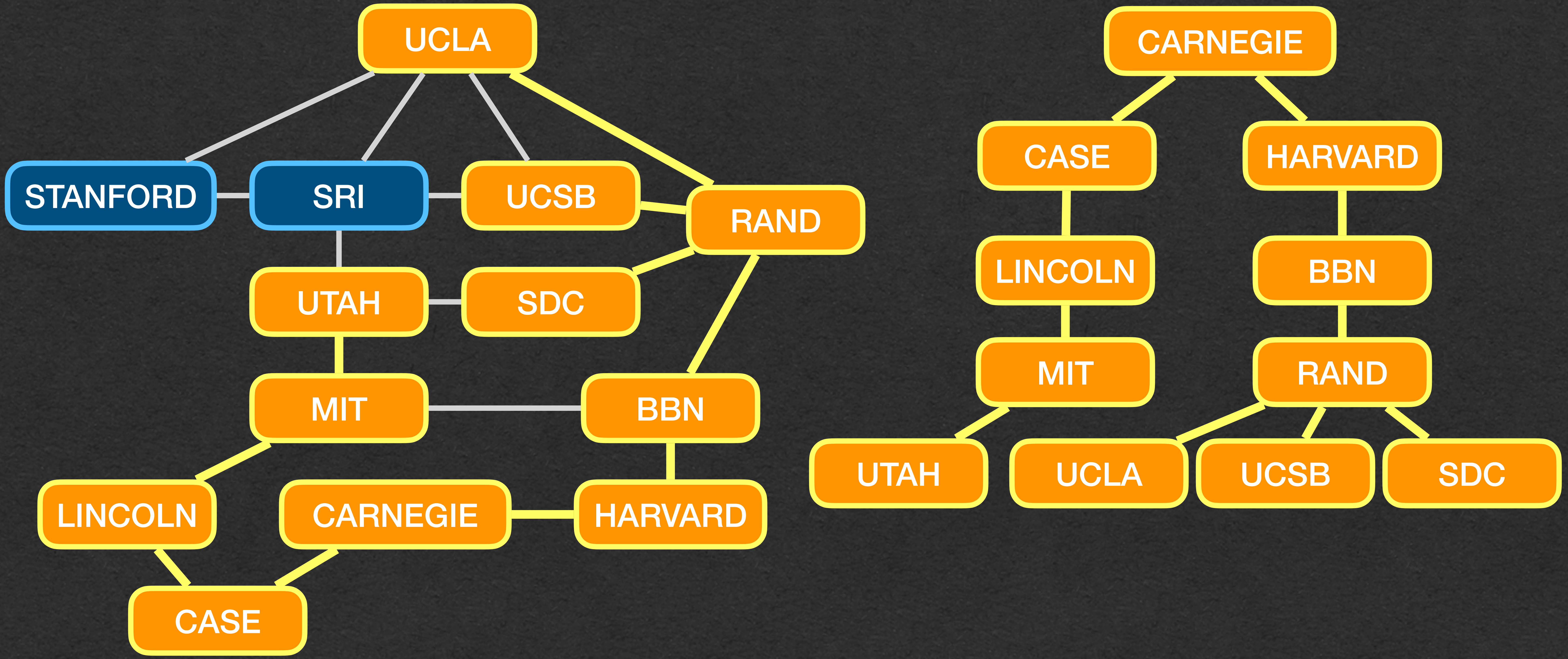
- Repeat
- Choose edge to use for MIT arbitrarily





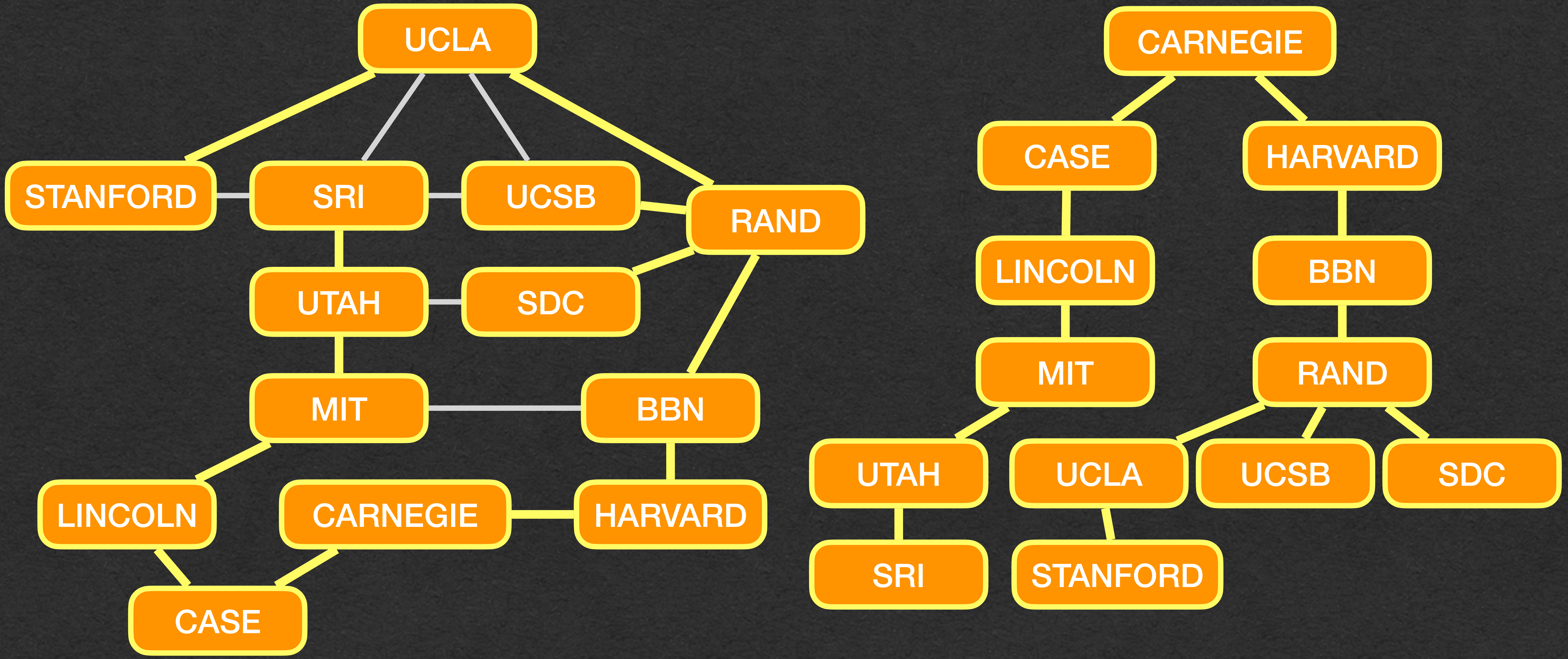
There's Levels to This

- Each step we explore all nodes that can be reached from the nodes added in the previous step



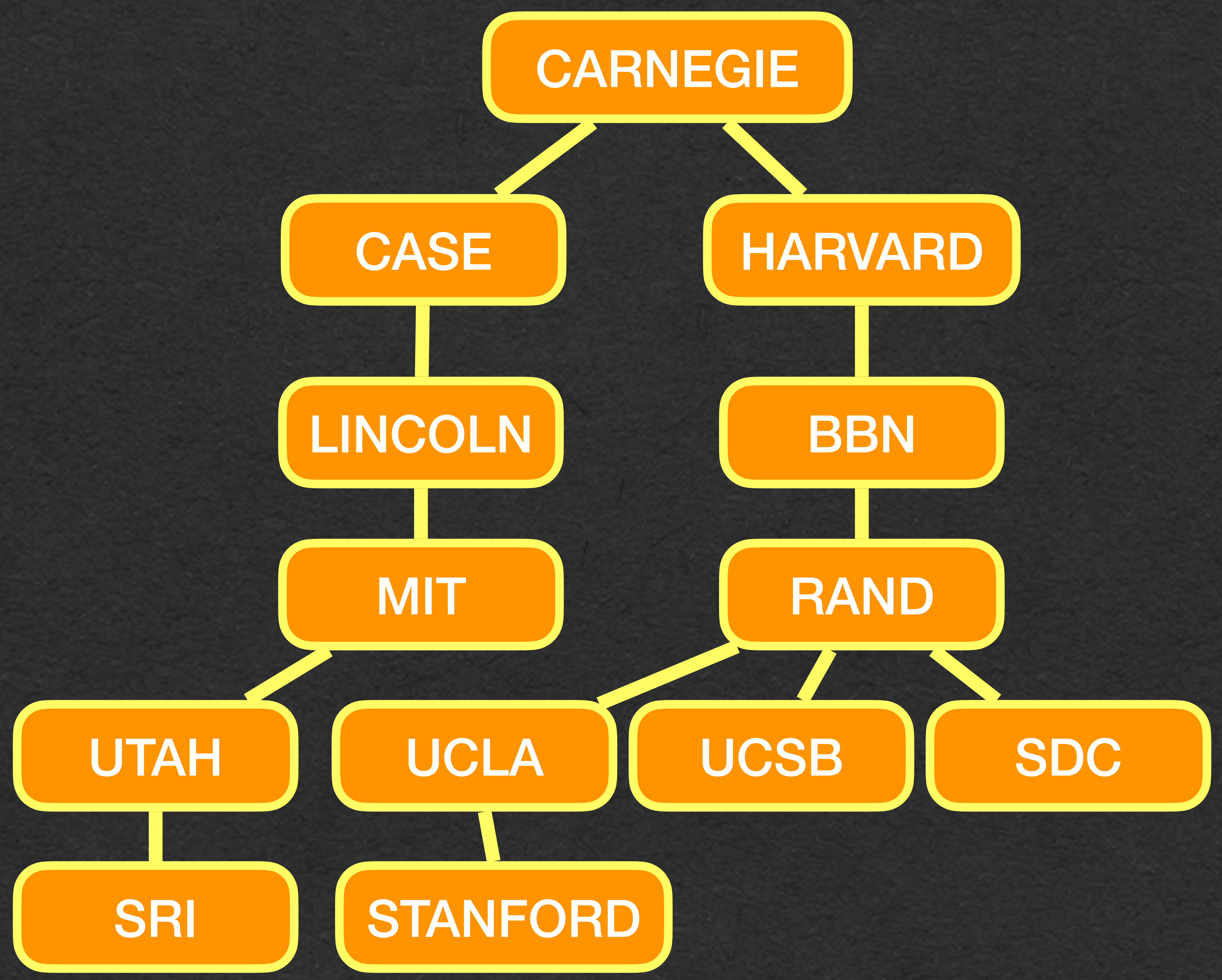
There's Levels to This

- Each step we explore all nodes that can be reached from the nodes added in the previous step



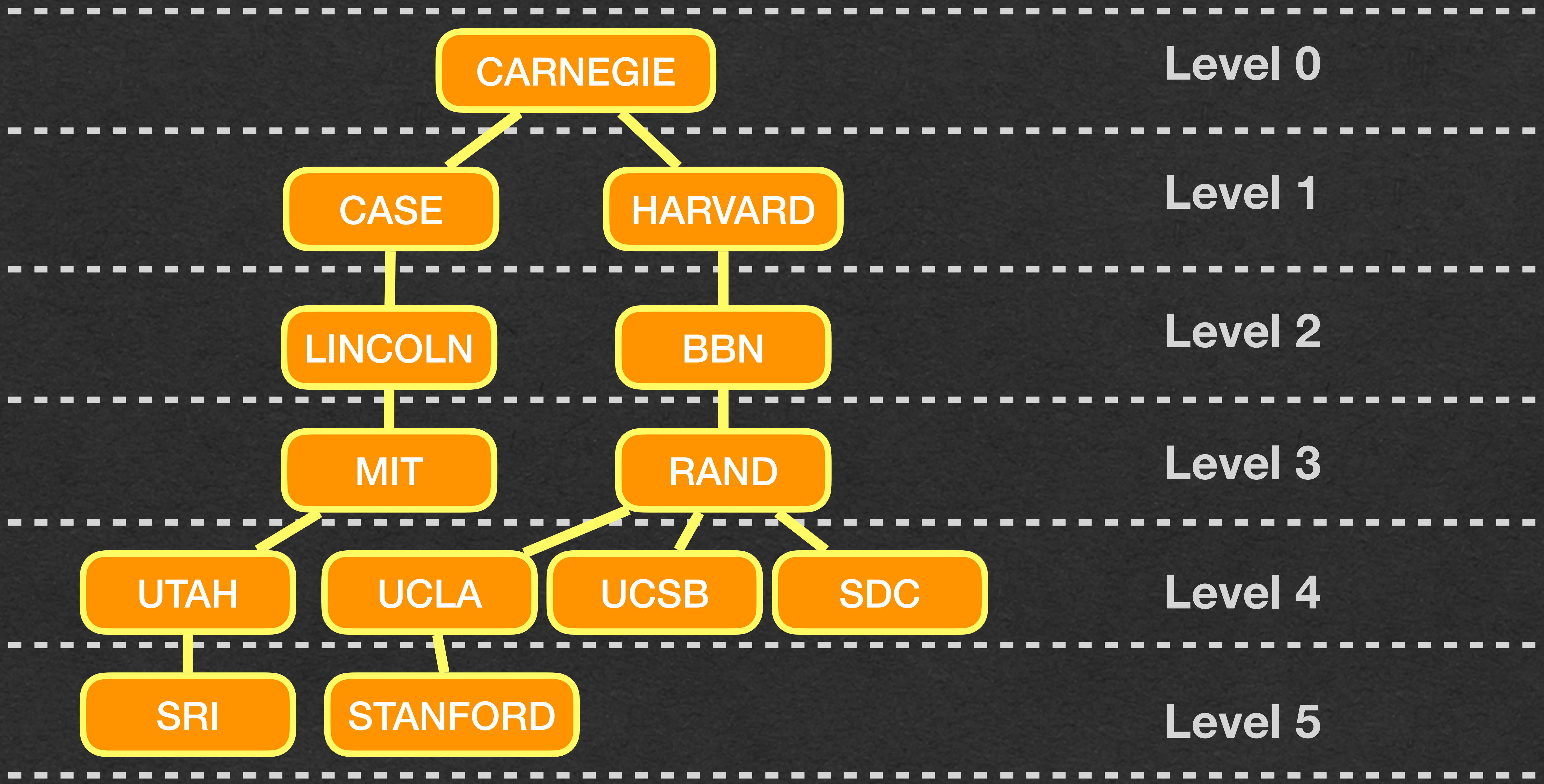
There's Levels to This

- We have a new graph with a few edges removed
- This graph is a tree (no cycles)



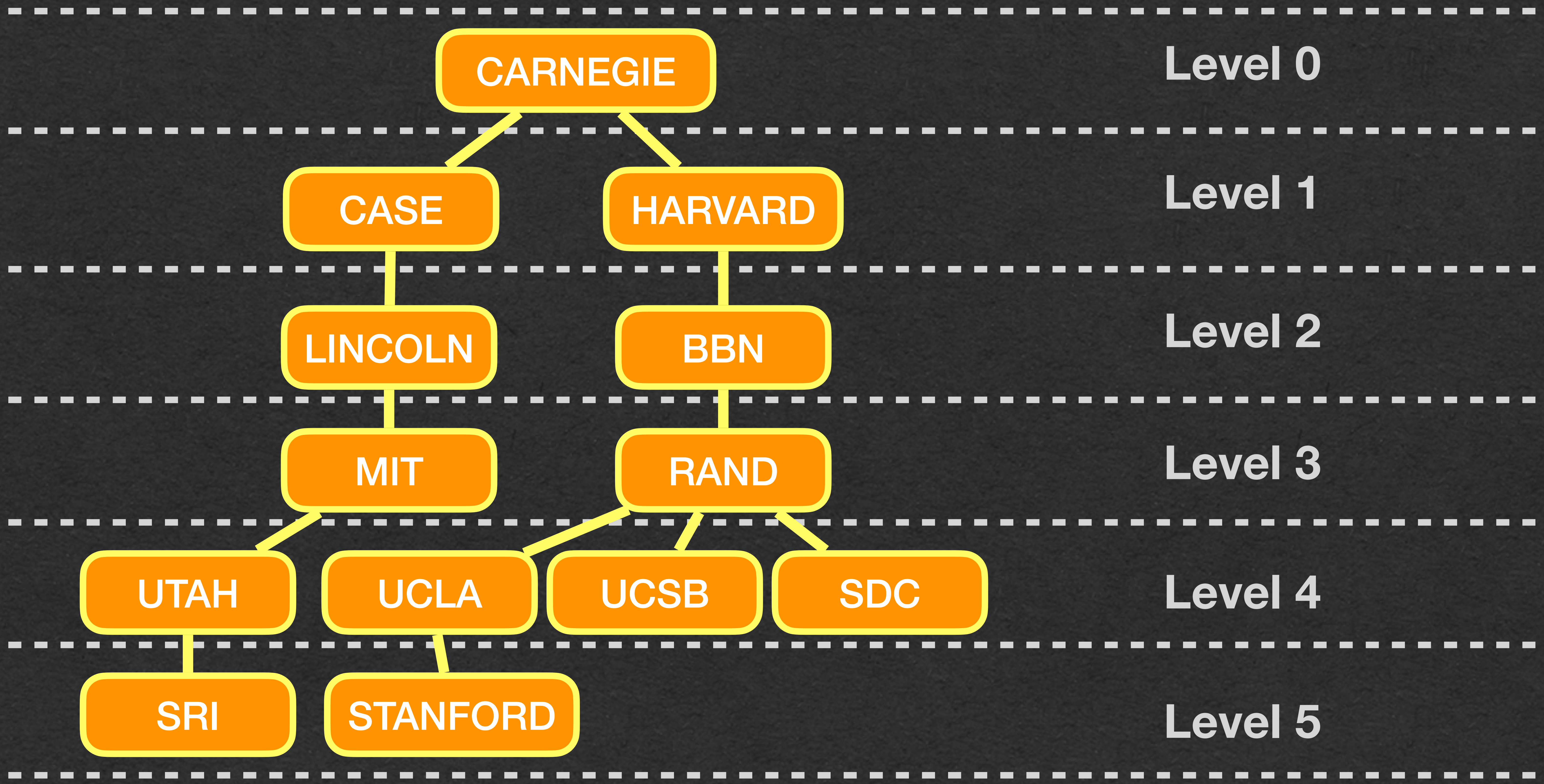
There's Levels to This

- And it has levels!



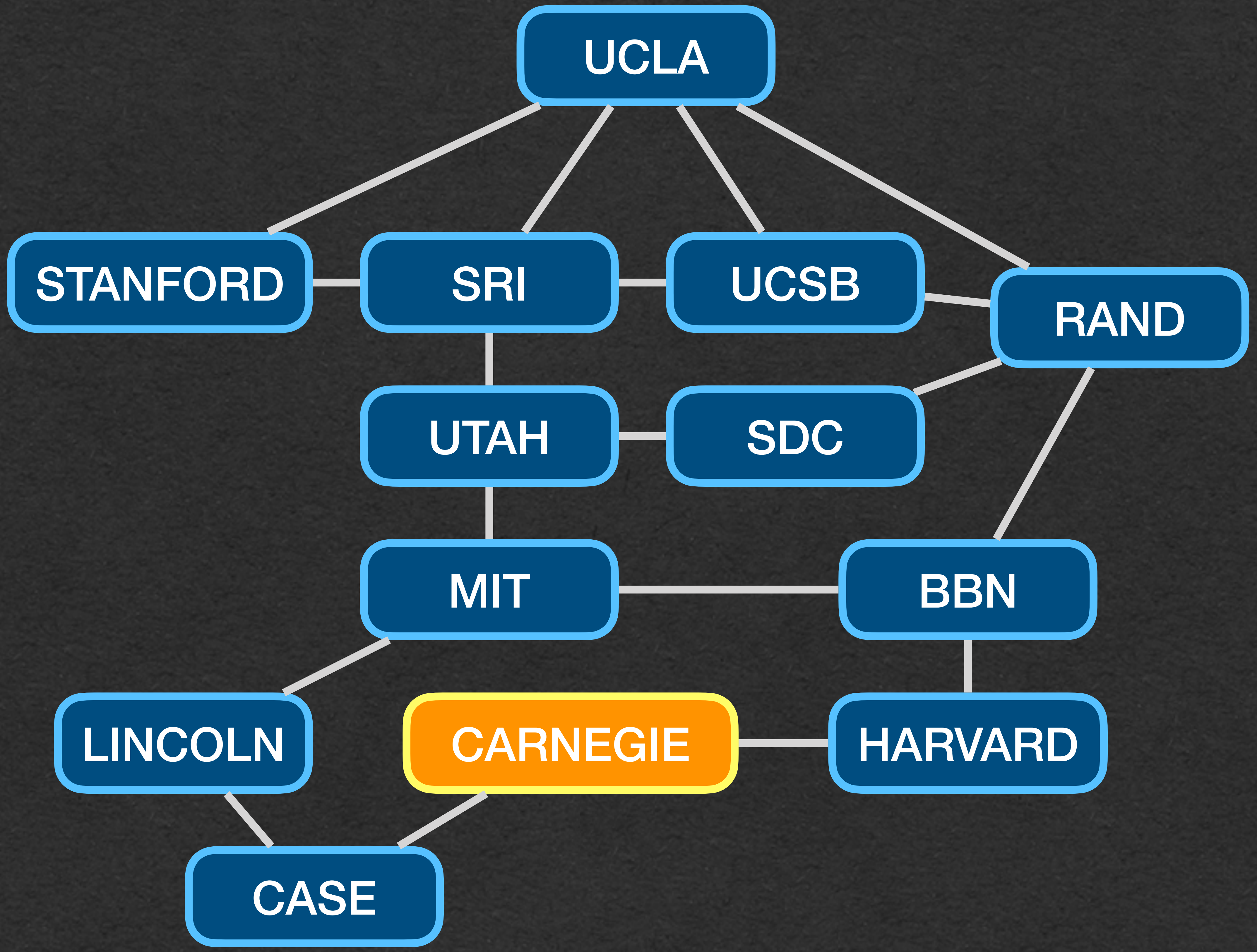
There's Levels to This

- Number the levels starting with 0
- The level number == the distance from the starting node to any node in that level



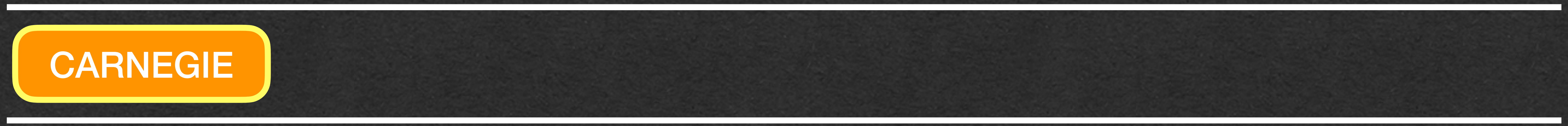
BFS and Distance

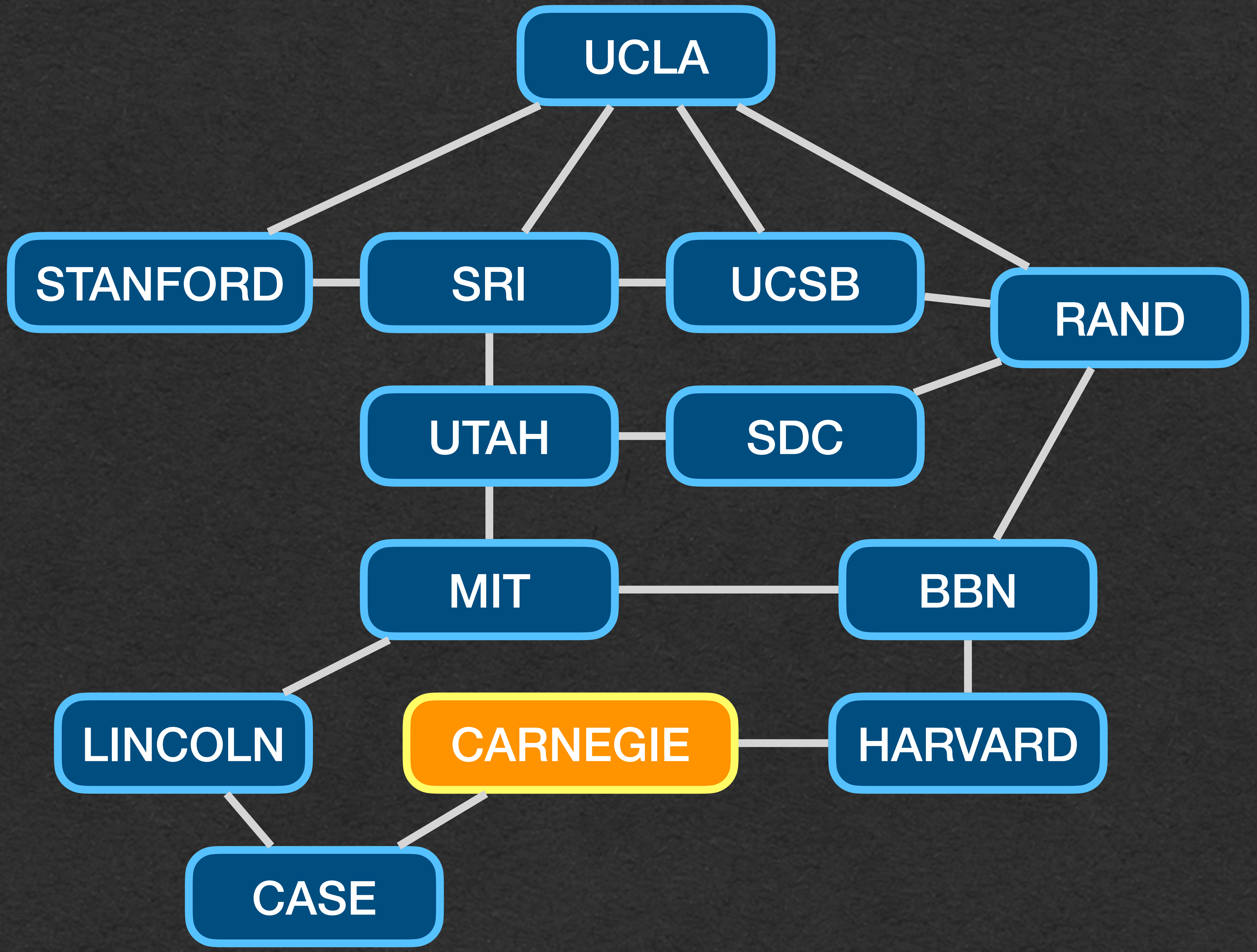
- But how do we track the levels?
- Track levels in a data structure



UCLA	∞
STANFORD	∞
SRI	∞
UCSB	∞
RAND	∞
UTAH	∞
SDC	∞
MIT	∞
BBN	∞
LINCOLN	∞
CARNEGIE	0
HARVARD	∞
CASE	∞

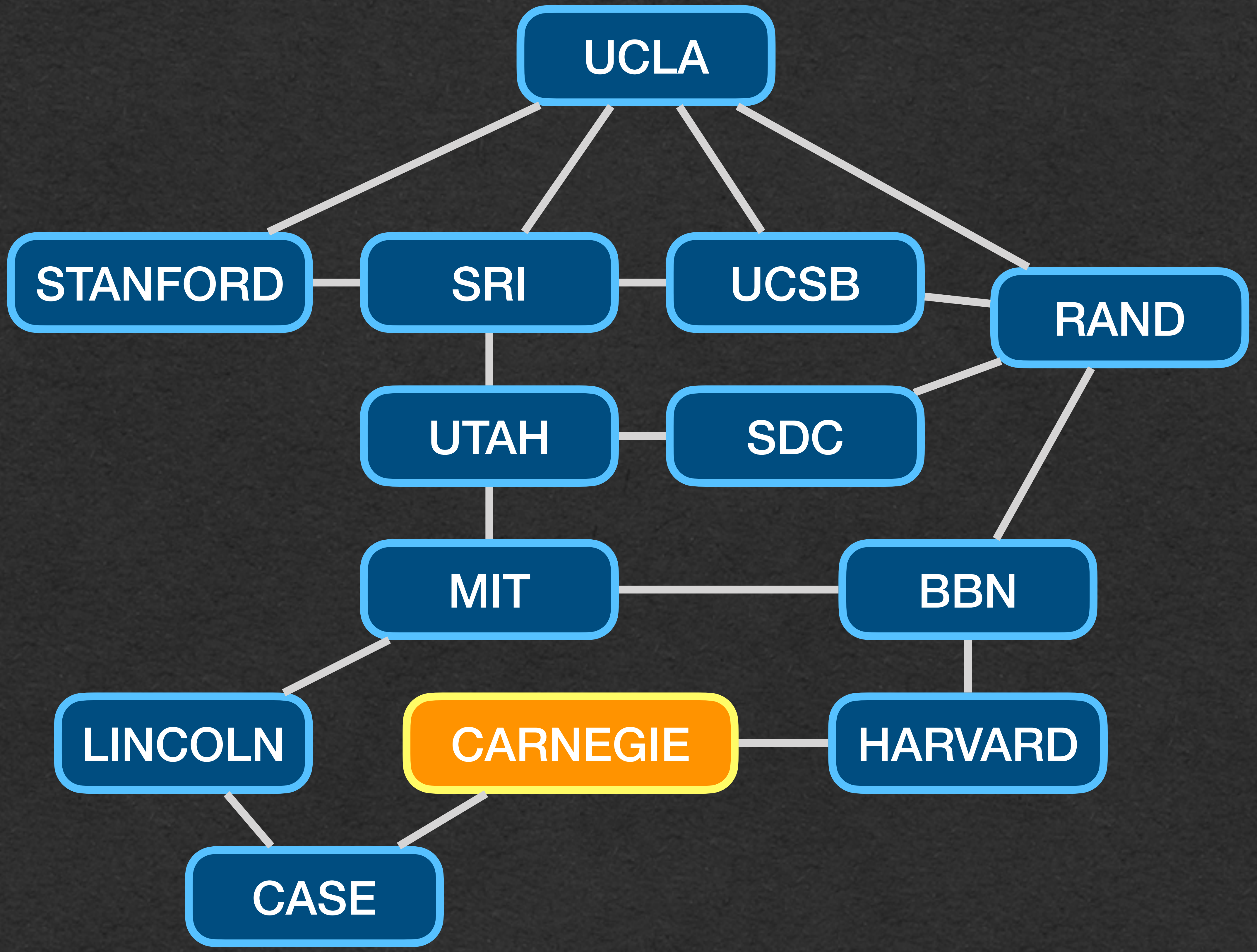
- To find distance in your code
  - You can use 3 data structures





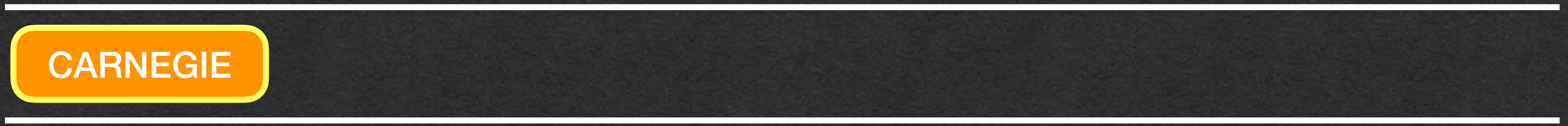
UCLA	∞
STANFORD	∞
SRI	∞
UCSB	∞
RAND	∞
UTAH	∞
SDC	∞
MIT	∞
BBN	∞
LINCOLN	∞
CARNEGIE	0
HARVARD	∞
CASE	∞

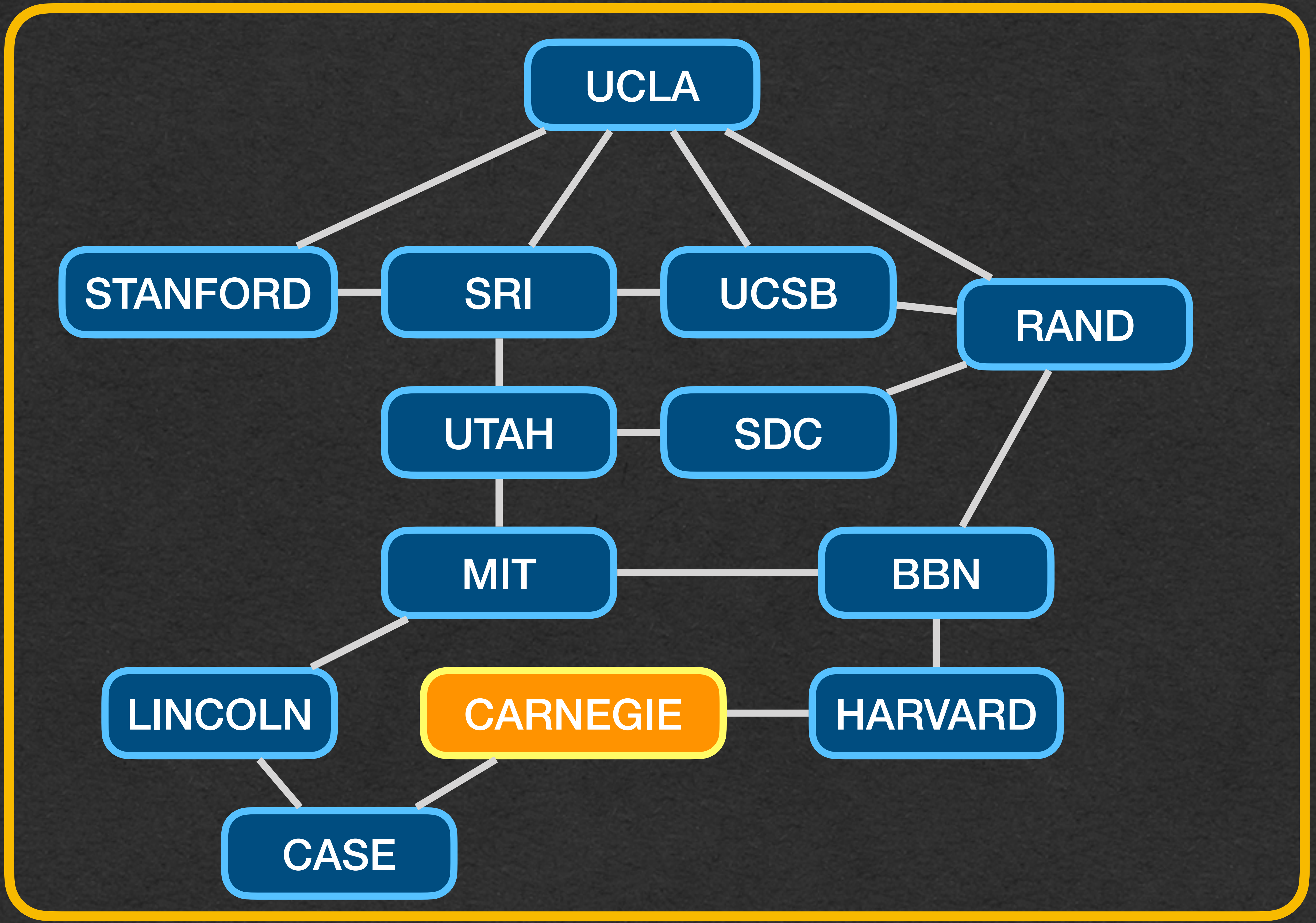
- A Queue
  - Track the nodes that need to be visited



UCLA	∞
STANFORD	∞
SRI	∞
UCSB	∞
RAND	∞
UTAH	∞
SDC	∞
MIT	∞
BBN	∞
LINCOLN	∞
CARNEGIE	0
HARVARD	∞
CASE	∞

- A List/Array/Set/Tree
  - Track the nodes have already been explored

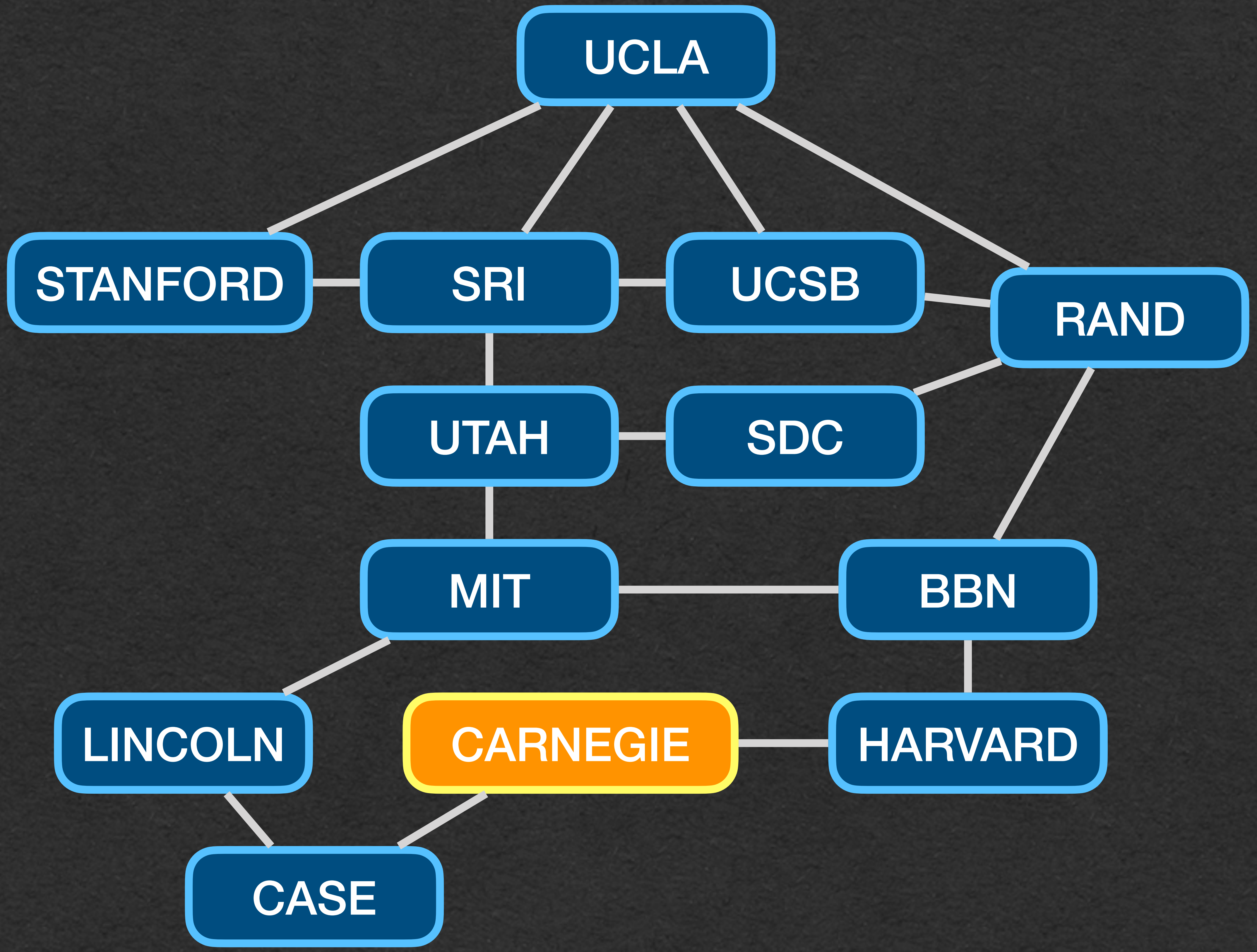




UCLA	∞
STANFORD	∞
SRI	∞
UCSB	∞
RAND	∞
UTAH	∞
SDC	∞
MIT	∞
BBN	∞
LINCOLN	∞
CARNEGIE	0
HARVARD	∞
CASE	∞

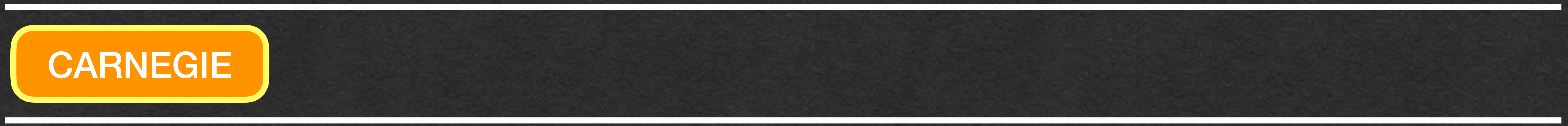
- A Map
  - Store the distances/levels for every node

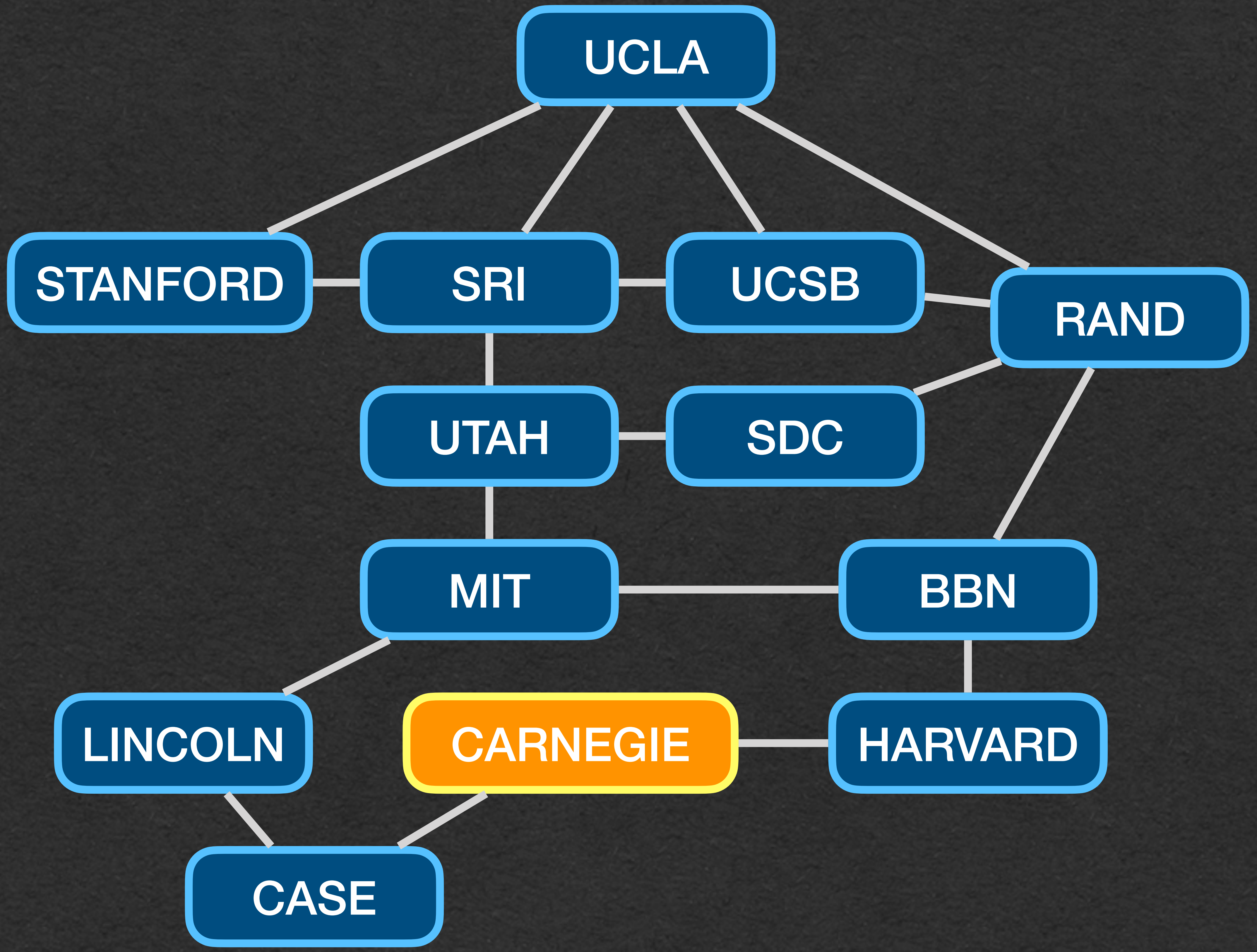
CARNEGIE



UCLA	∞
STANFORD	∞
SRI	∞
UCSB	∞
RAND	∞
UTAH	∞
SDC	∞
MIT	∞
BBN	∞
LINCOLN	∞
CARNEGIE	0
HARVARD	∞
CASE	∞

- To write your code
  - Create and update these data structures as you explore the graph

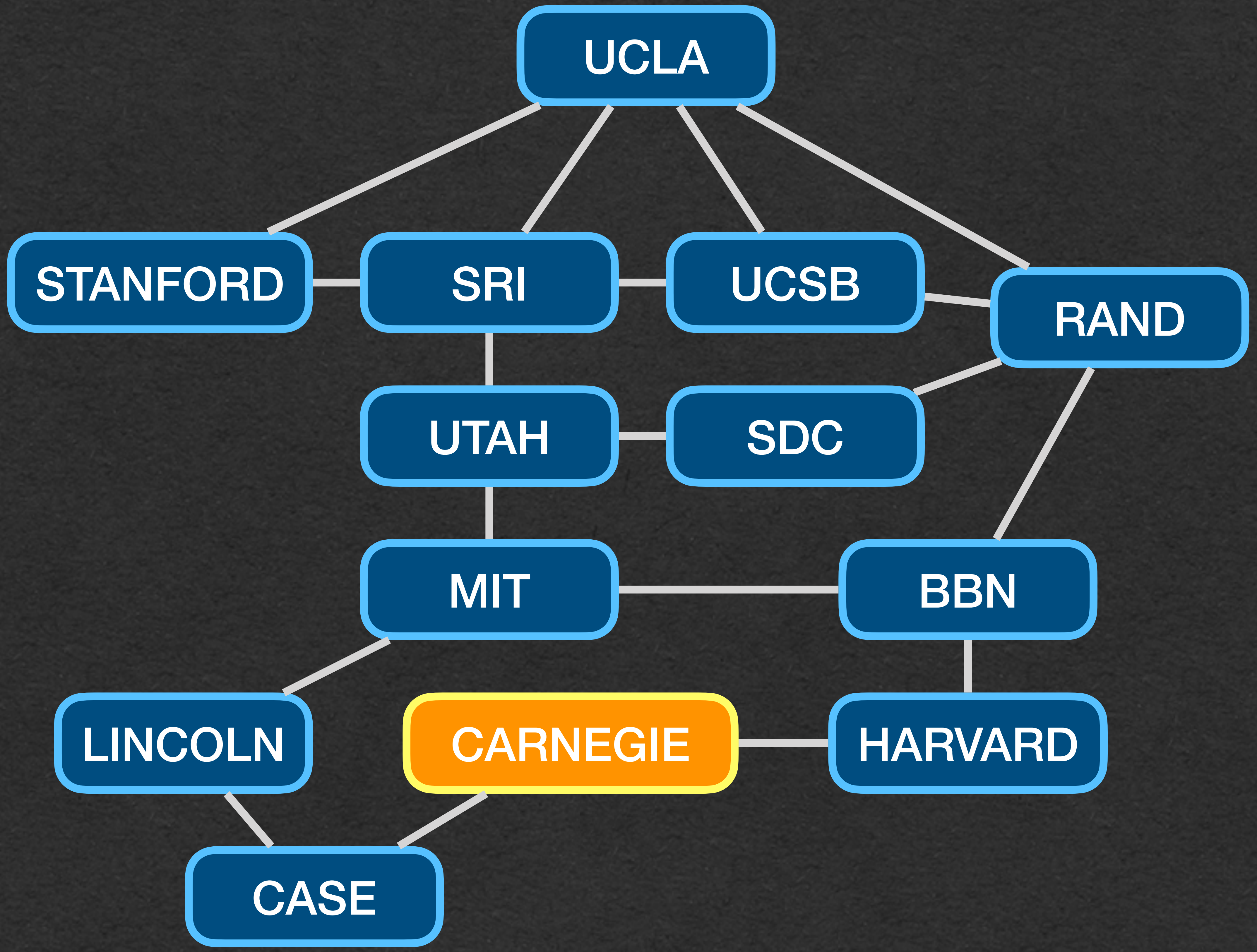




UCLA	∞
STANFORD	∞
SRI	∞
UCSB	∞
RAND	∞
UTAH	∞
SDC	∞
MIT	∞
BBN	∞
LINCOLN	∞
CARNEGIE	0
HARVARD	∞
CASE	∞

BFS and Distance

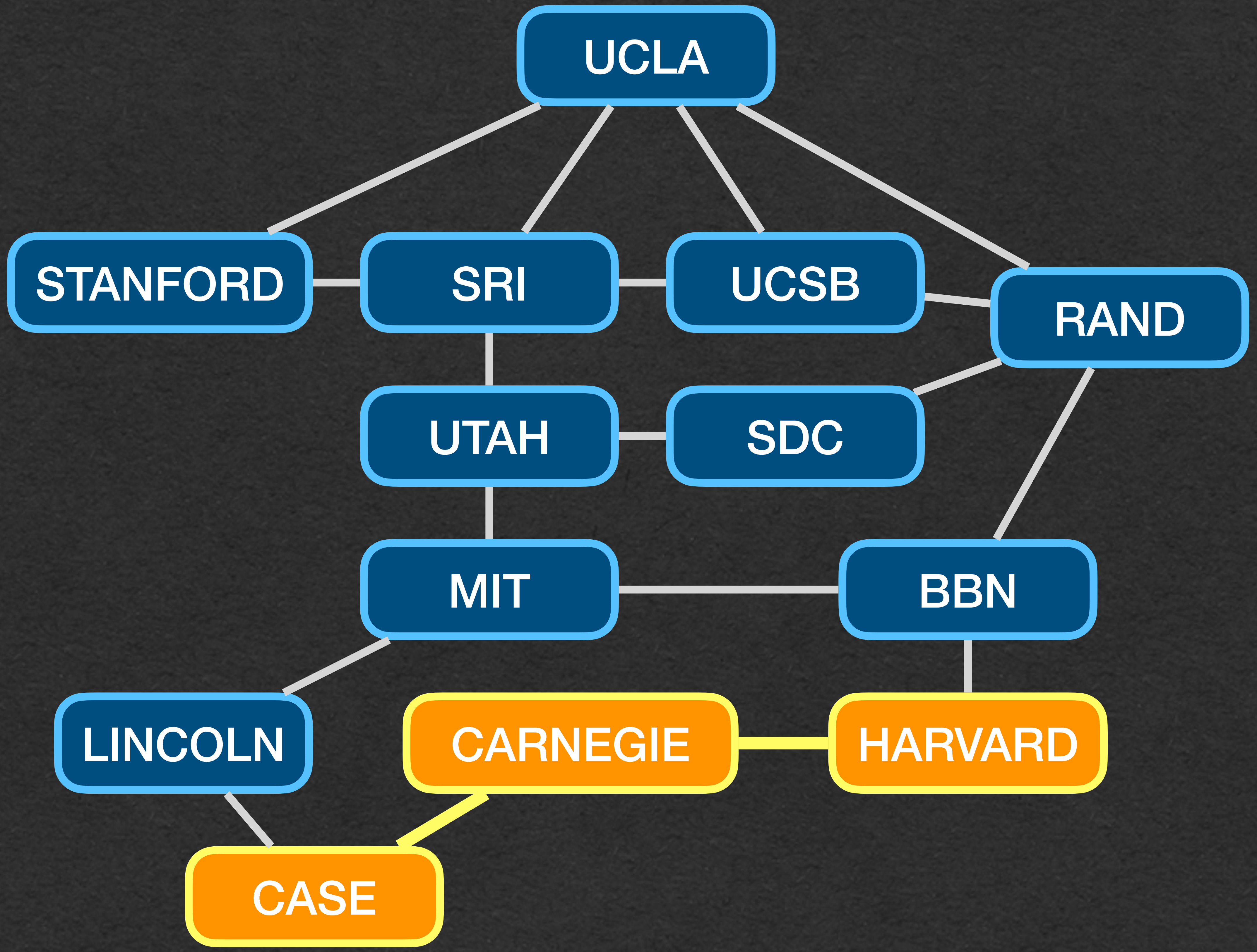
CARNEGIE



UCLA	∞
STANFORD	∞
SRI	∞
UCSB	∞
RAND	∞
UTAH	∞
SDC	∞
MIT	∞
BBN	∞
LINCOLN	∞
CARNEGIE	0
HARVARD	∞
CASE	∞

BFS and Distance

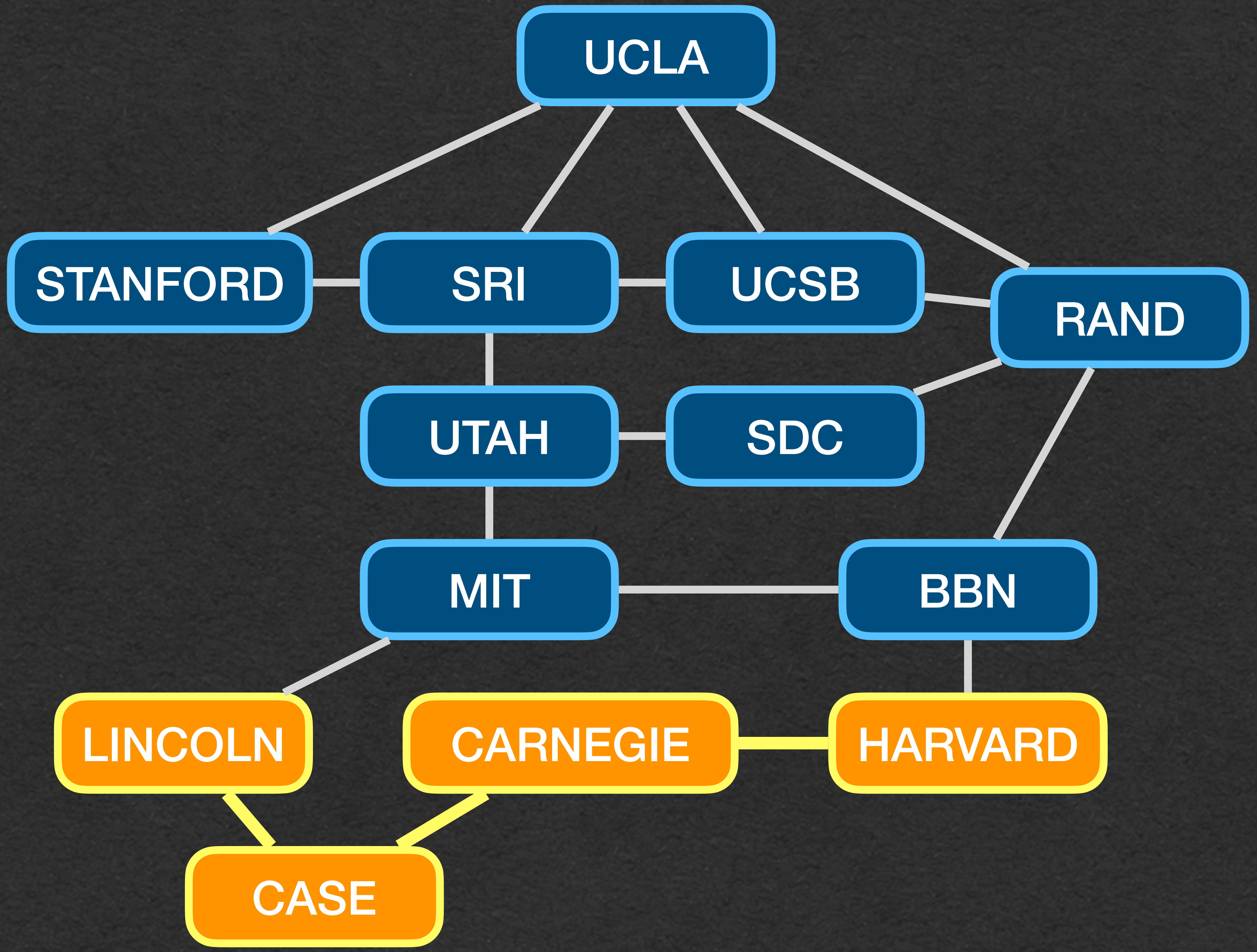
CASE HARVARD



UCLA	∞
STANFORD	∞
SRI	∞
UCSB	∞
RAND	∞
UTAH	∞
SDC	∞
MIT	∞
BBN	∞
LINCOLN	∞
CARNEGIE	0
HARVARD	1
CASE	1

BFS and Distance

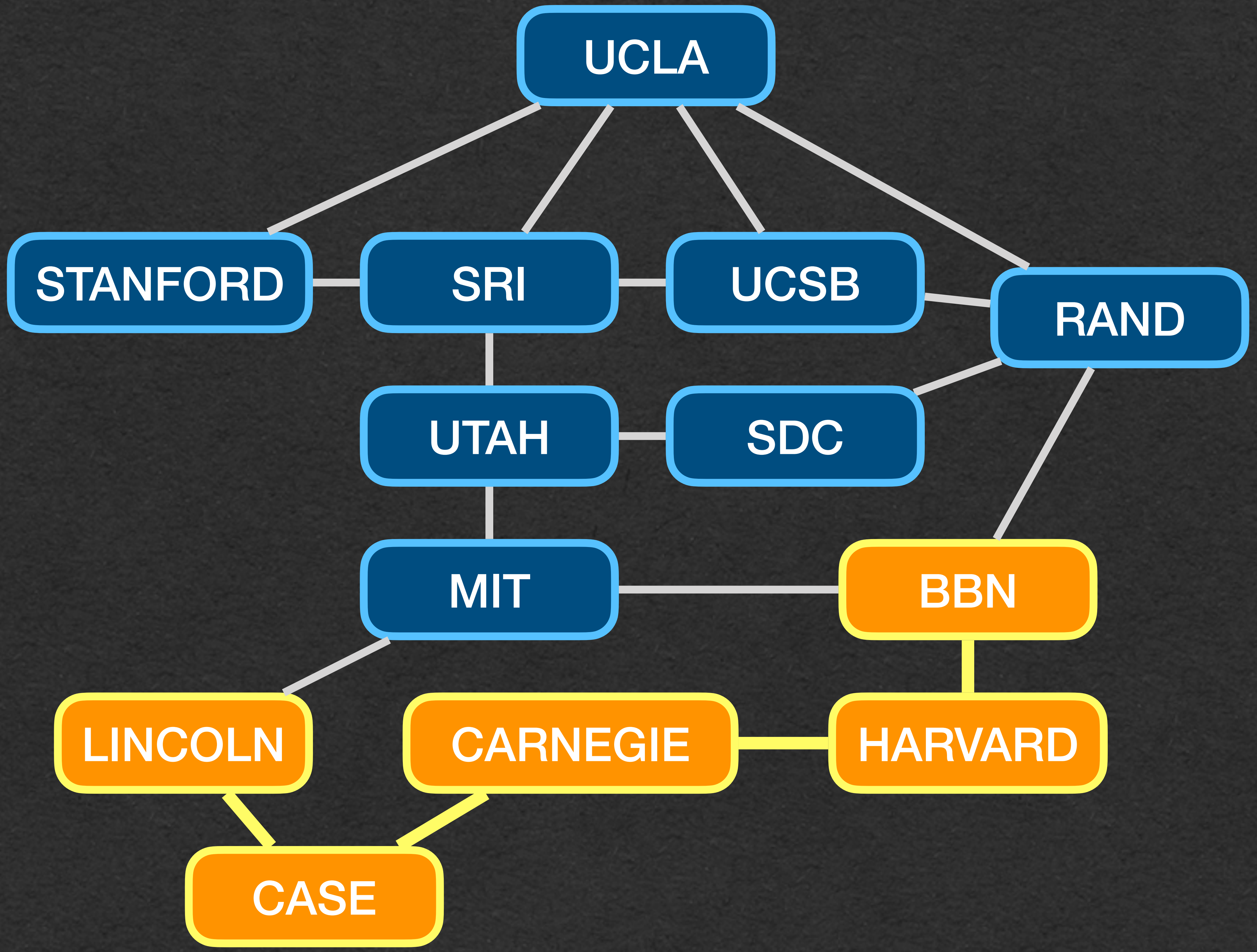
HARVARD LINCOLN



UCLA	∞
STANFORD	∞
SRI	∞
UCSB	∞
RAND	∞
UTAH	∞
SDC	∞
MIT	∞
BBN	∞
LINCOLN	2
CARNEGIE	0
HARVARD	1
CASE	1

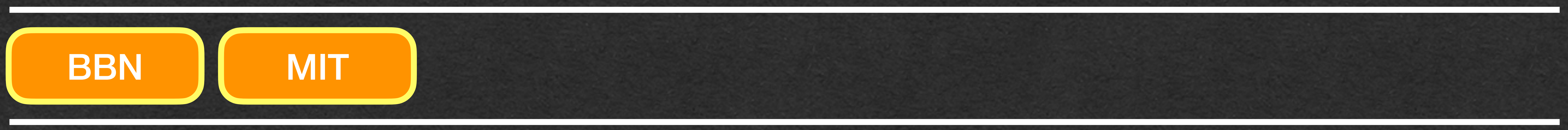
BFS and Distance

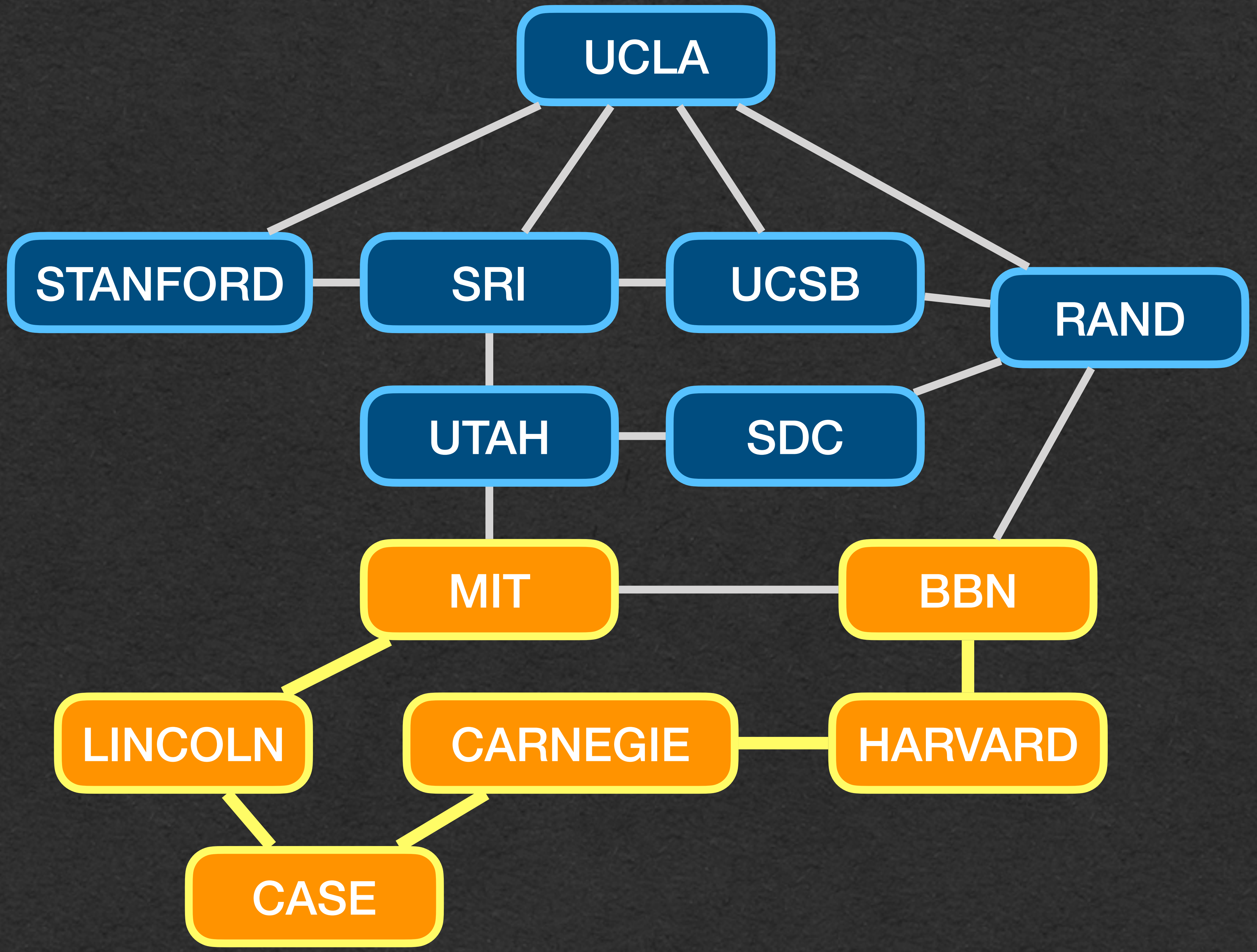
LINCOLN	BBN



UCLA	∞
STANFORD	∞
SRI	∞
UCSB	∞
RAND	∞
UTAH	∞
SDC	∞
MIT	∞
BBN	2
LINCOLN	2
CARNEGIE	0
HARVARD	1
CASE	1

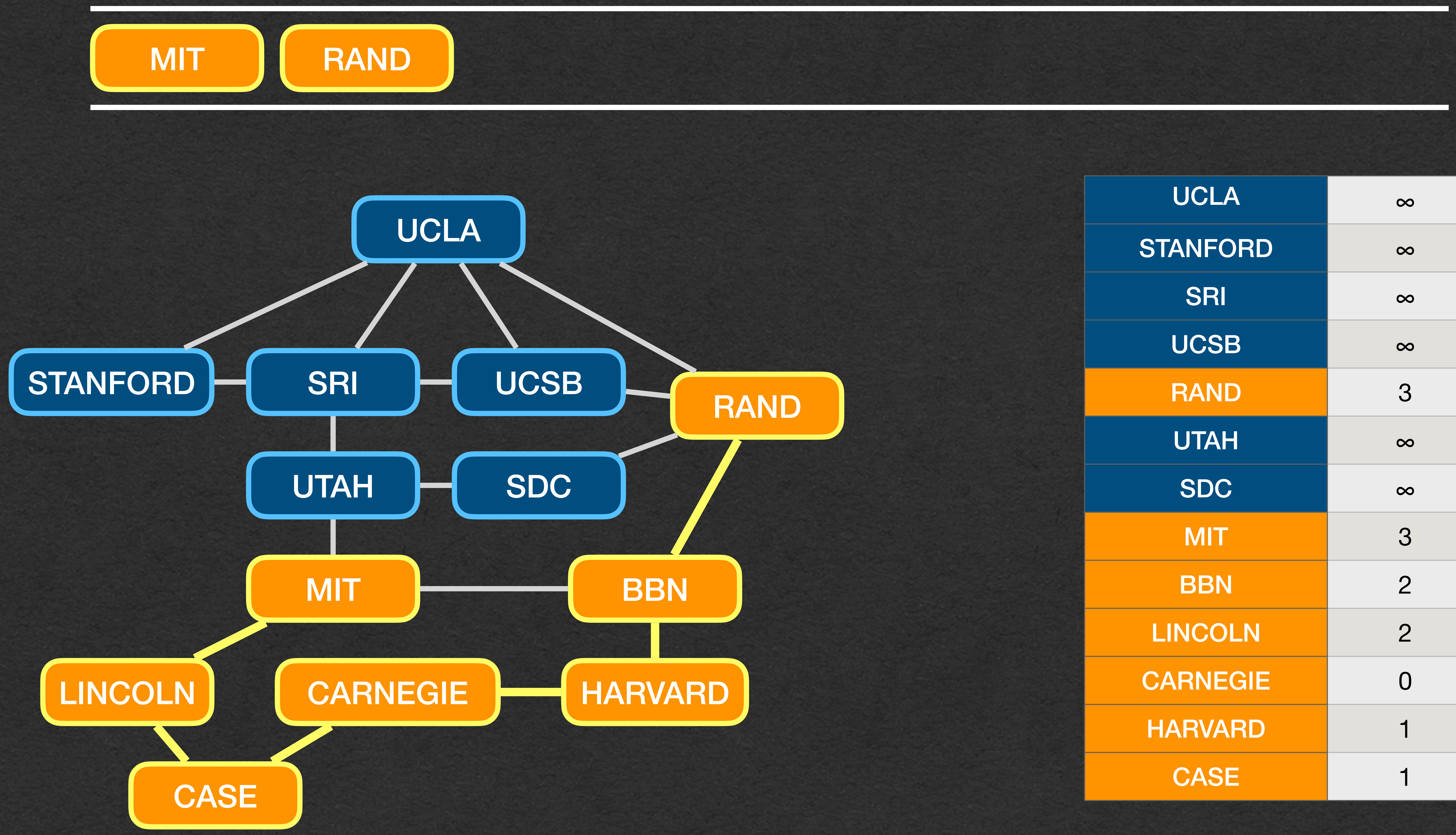
BFS and Distance





UCLA	∞
STANFORD	∞
SRI	∞
UCSB	∞
RAND	∞
UTAH	∞
SDC	∞
MIT	3
BBN	2
LINCOLN	2
CARNEGIE	0
HARVARD	1
CASE	1

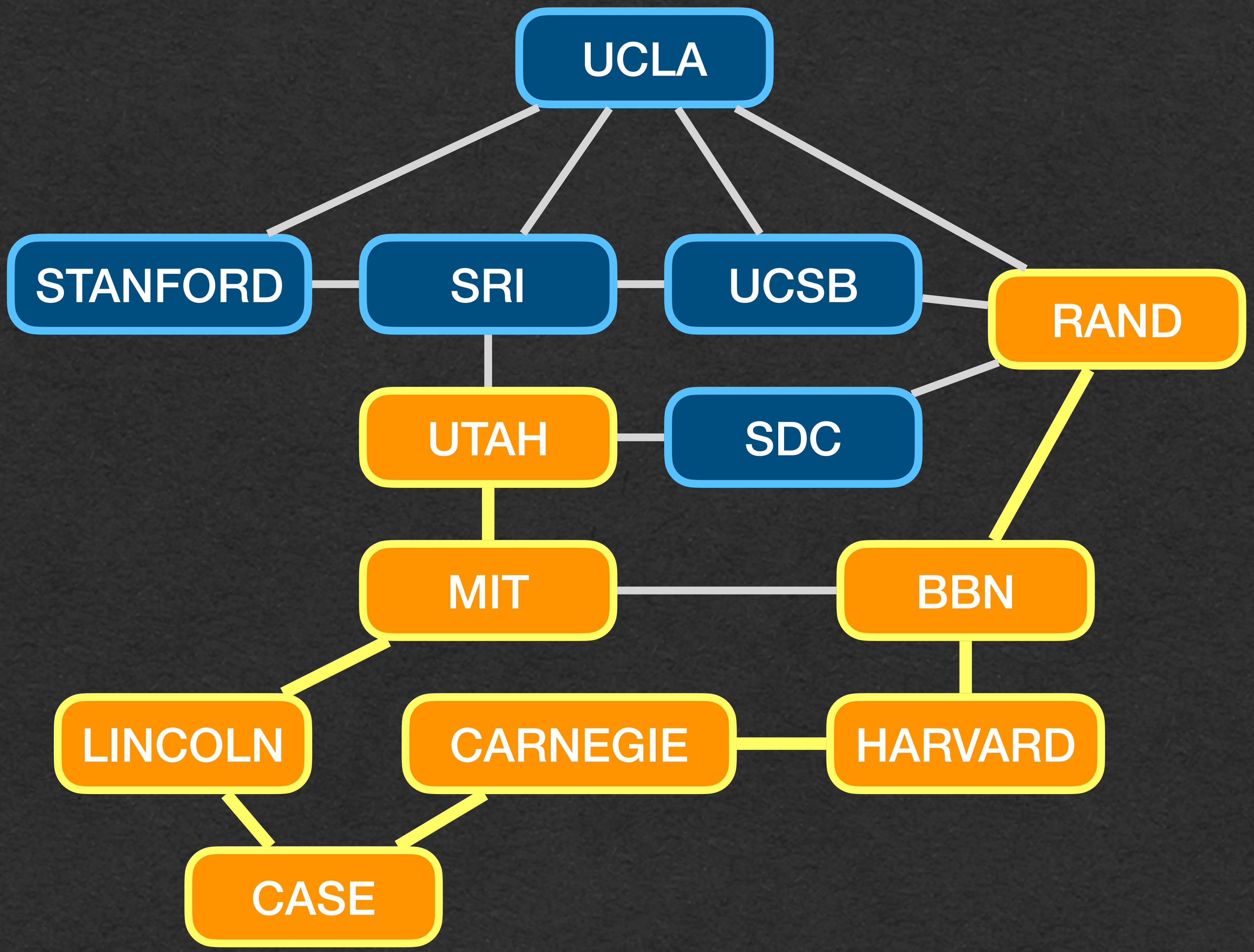
BFS and Distance



UCLA	∞
STANFORD	∞
SRI	∞
UCSB	∞
RAND	3
UTAH	∞
SDC	∞
MIT	3
BBN	2
LINCOLN	2
CARNEGIE	0
HARVARD	1
CASE	1

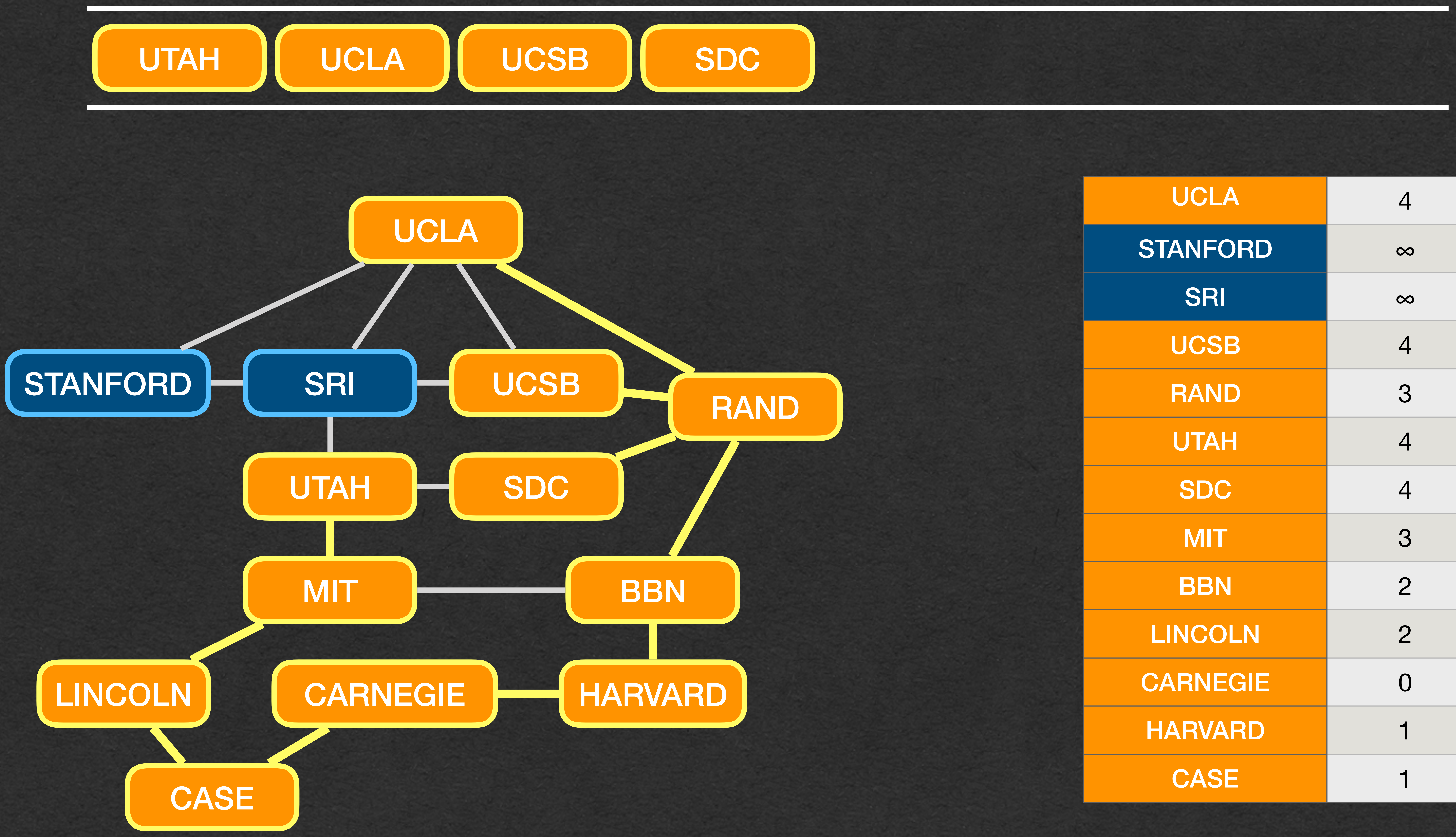
BFS and Distance

RAND	UTAH



UCLA	∞
STANFORD	∞
SRI	∞
UCSB	∞
RAND	3
UTAH	4
SDC	∞
MIT	3
BBN	2
LINCOLN	2
CARNEGIE	0
HARVARD	1
CASE	1

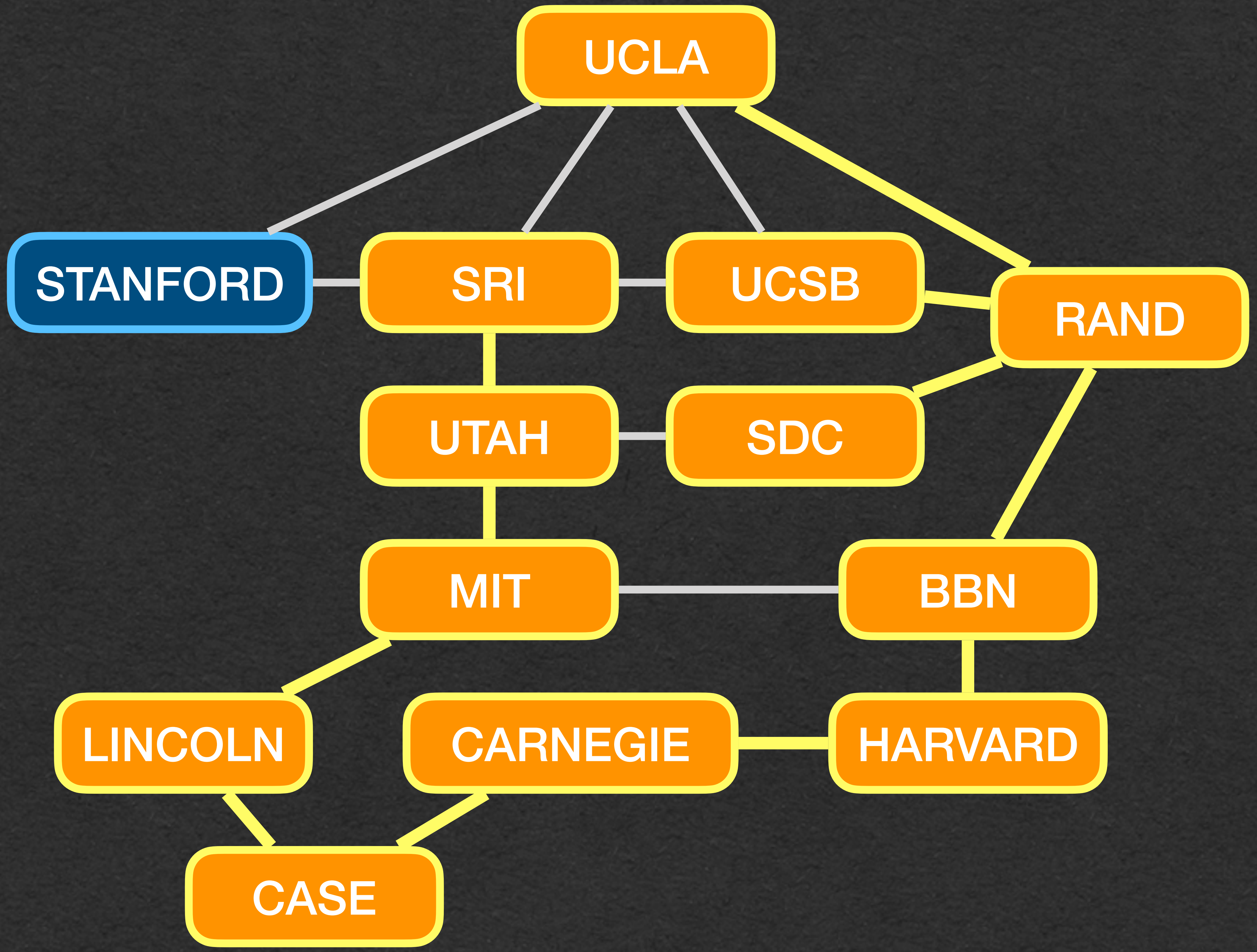
BFS and Distance



UCLA	4
STANFORD	∞
SRI	∞
UCSB	4
RAND	3
UTAH	4
SDC	4
MIT	3
BBN	2
LINCOLN	2
CARNEGIE	0
HARVARD	1
CASE	1

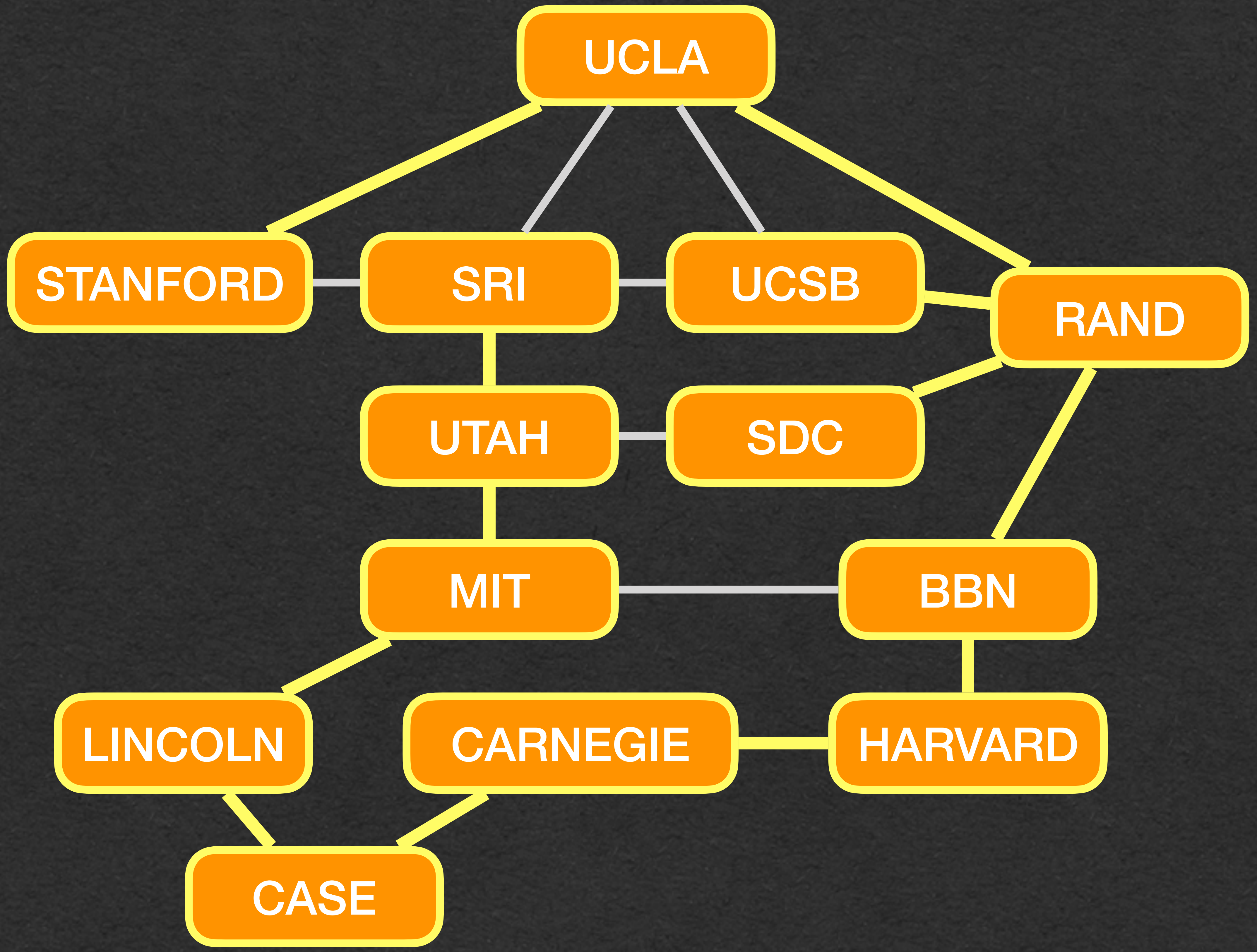
BFS and Distance

UCLA	UCSB	SDC	SRI



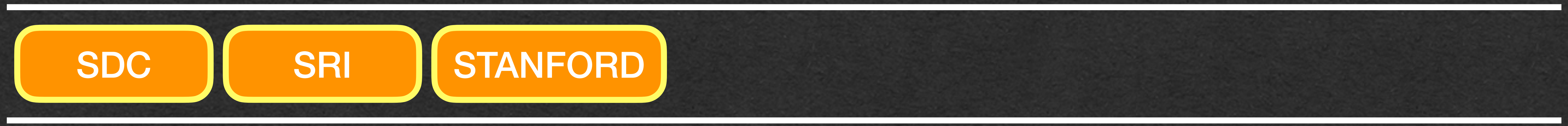
UCLA	4
STANFORD	∞
SRI	5
UCSB	4
RAND	3
UTAH	4
SDC	4
MIT	3
BBN	2
LINCOLN	2
CARNEGIE	0
HARVARD	1
CASE	1

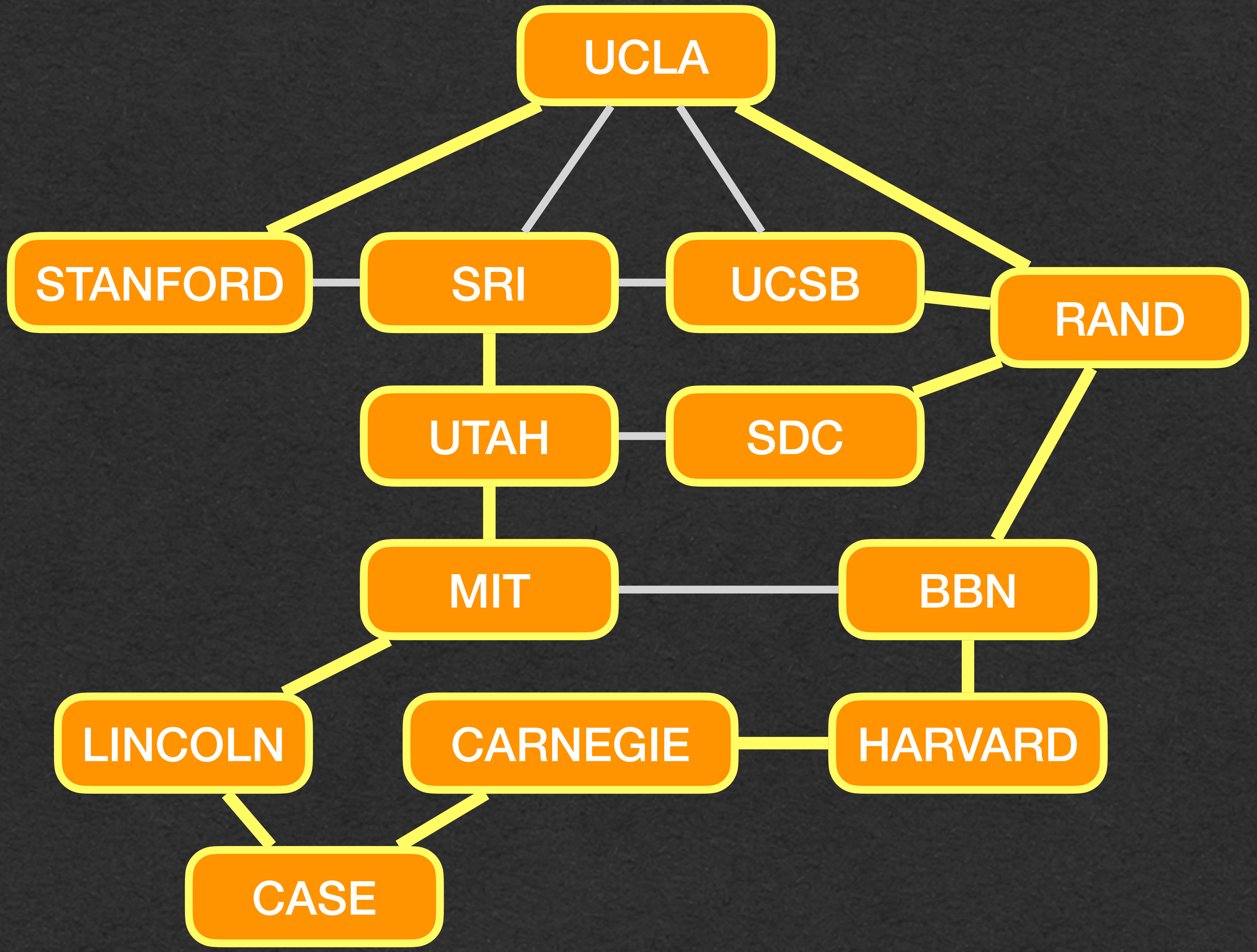
BFS and Distance



UCLA	4
STANFORD	5
SRI	5
UCSB	4
RAND	3
UTAH	4
SDC	4
MIT	3
BBN	2
LINCOLN	2
CARNEGIE	0
HARVARD	1
CASE	1

BFS and Distance

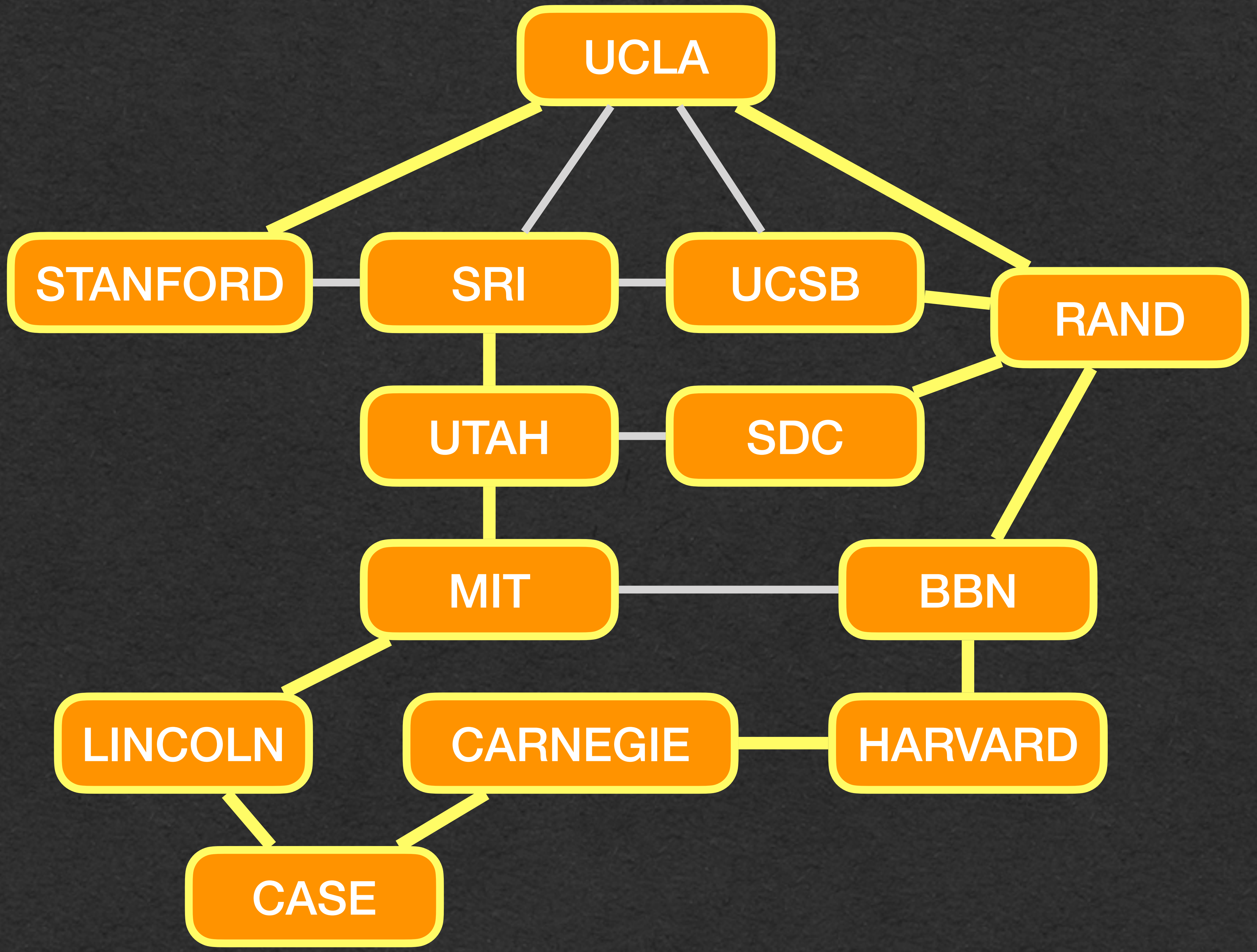




UCLA	4
STANFORD	5
SRI	5
UCSB	4
RAND	3
UTAH	4
SDC	4
MIT	3
BBN	2
LINCOLN	2
CARNEGIE	0
HARVARD	1
CASE	1

BFS and Distance

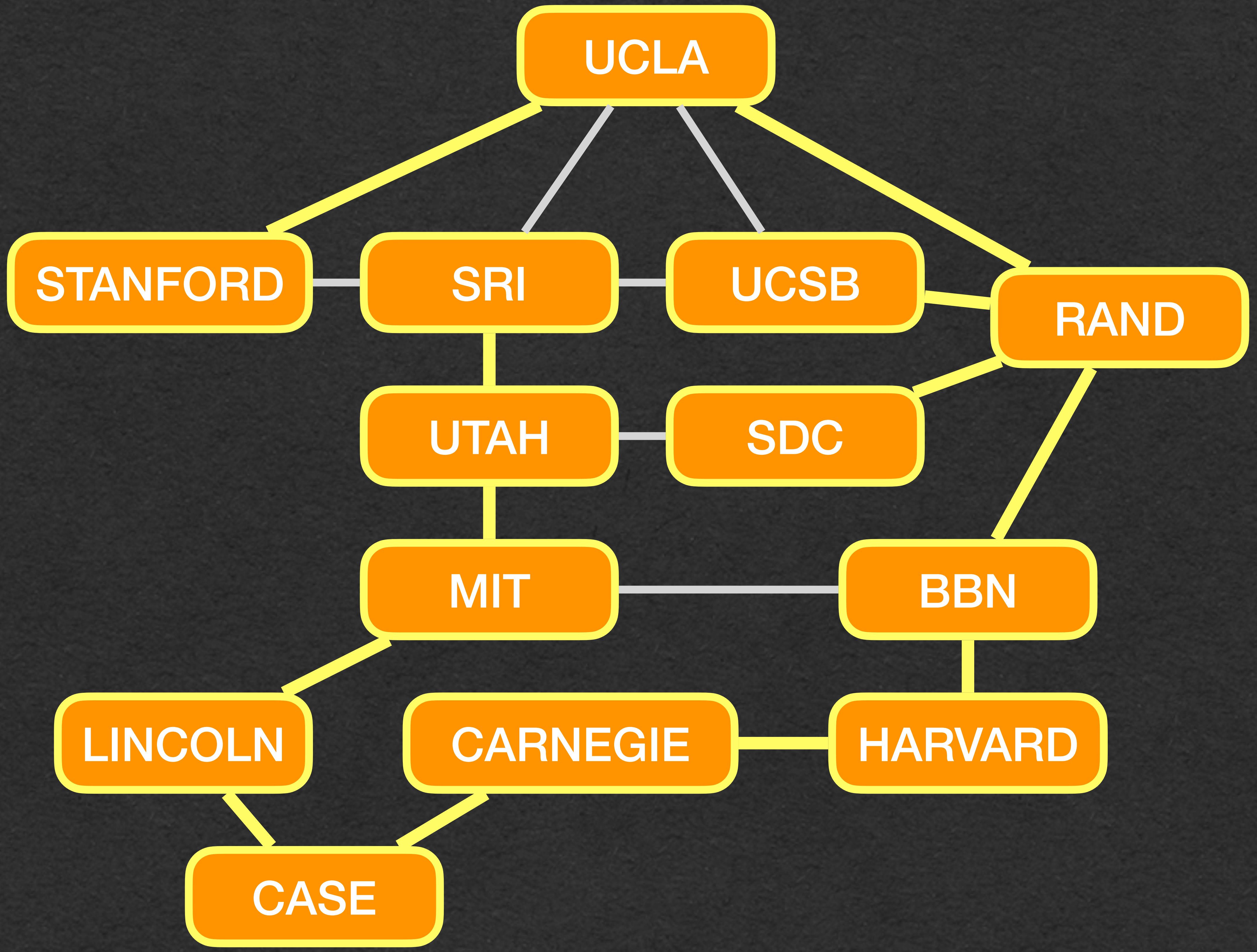
SRI | STANFORD



UCLA	4
STANFORD	5
SRI	5
UCSB	4
RAND	3
UTAH	4
SDC	4
MIT	3
BBN	2
LINCOLN	2
CARNEGIE	0
HARVARD	1
CASE	1

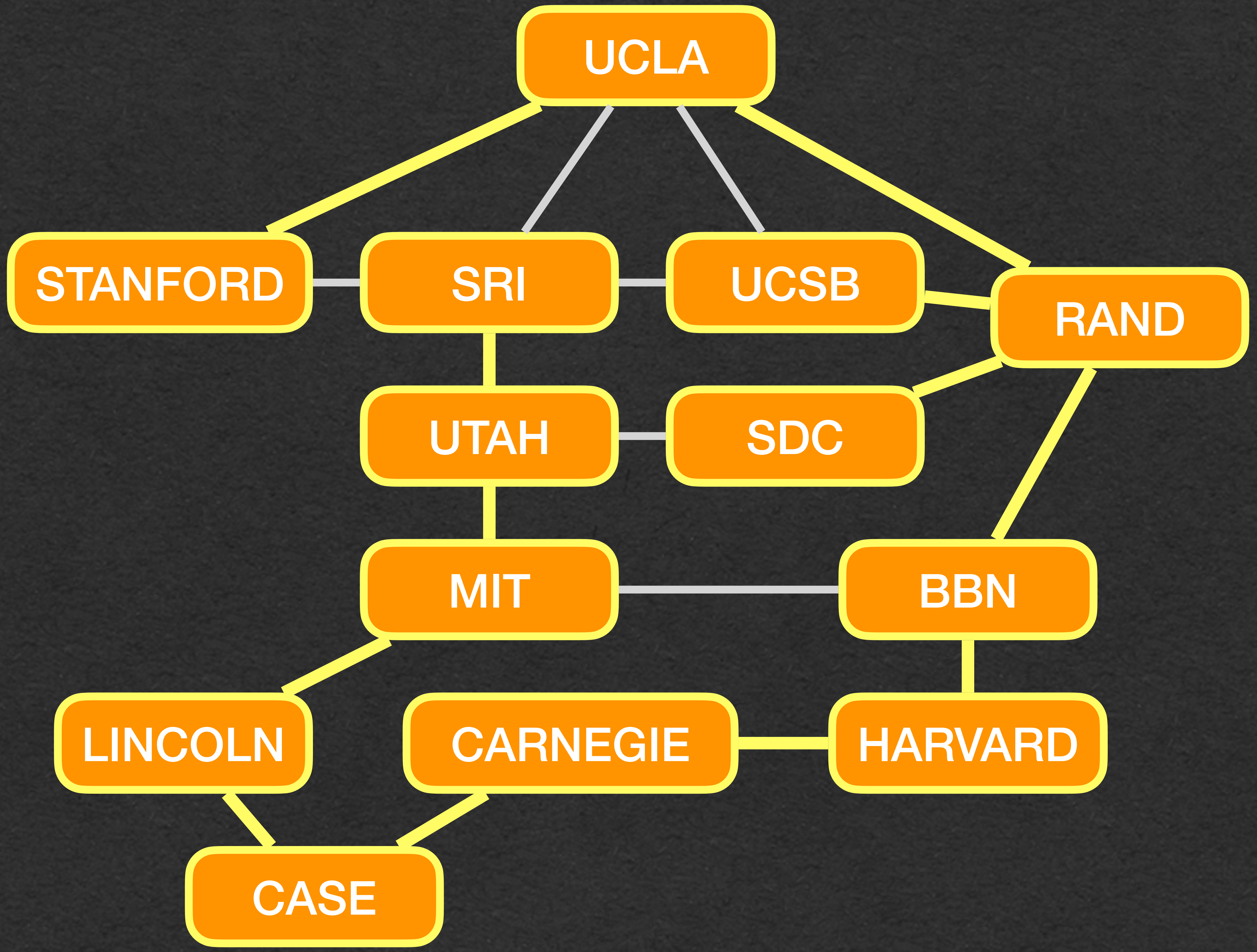
BFS and Distance

STANFORD



UCLA	4
STANFORD	5
SRI	5
UCSB	4
RAND	3
UTAH	4
SDC	4
MIT	3
BBN	2
LINCOLN	2
CARNEGIE	0
HARVARD	1
CASE	1

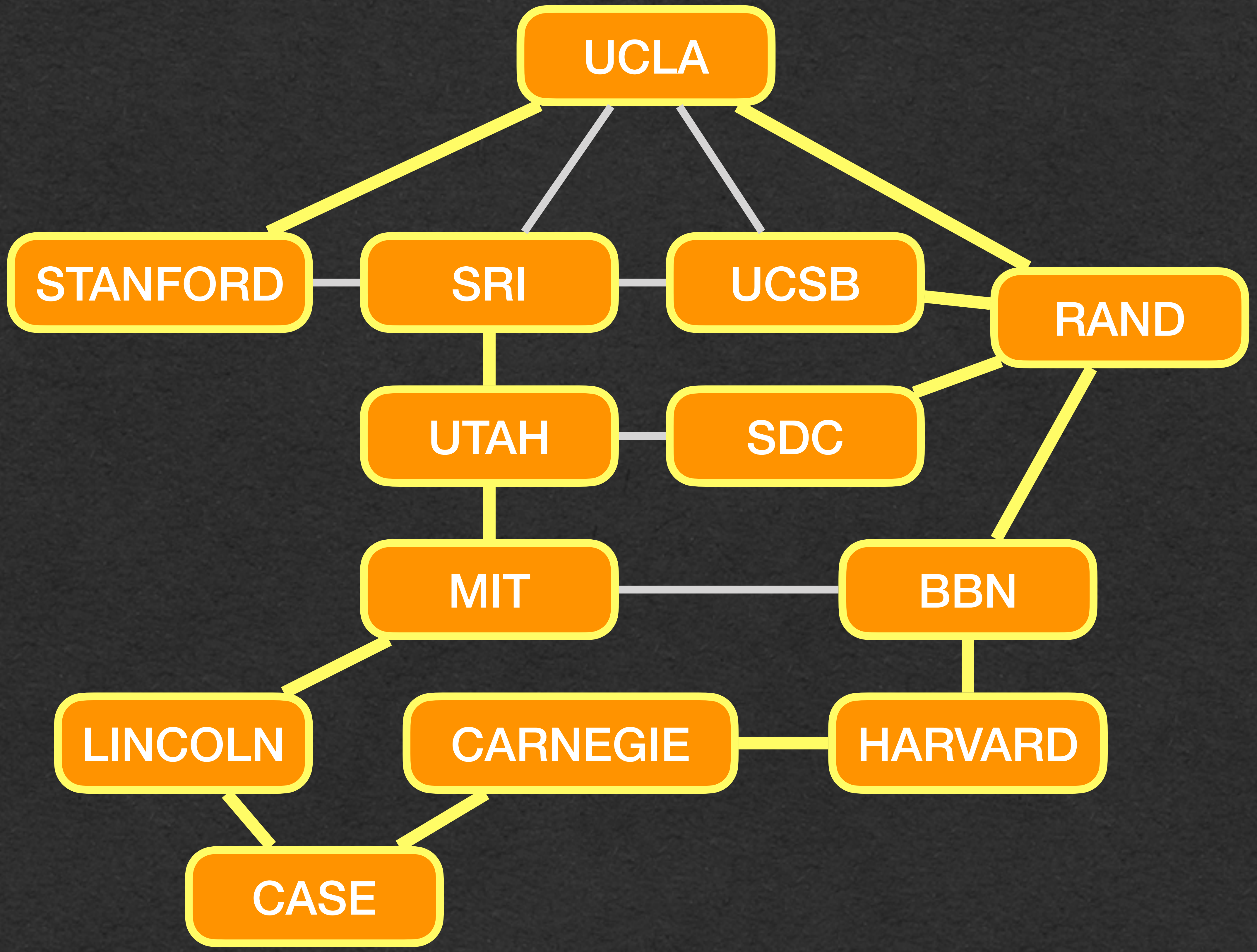
BFS and Distance



UCLA	4
STANFORD	5
SRI	5
UCSB	4
RAND	3
UTAH	4
SDC	4
MIT	3
BBN	2
LINCOLN	2
CARNEGIE	0
HARVARD	1
CASE	1

BFS and Distance

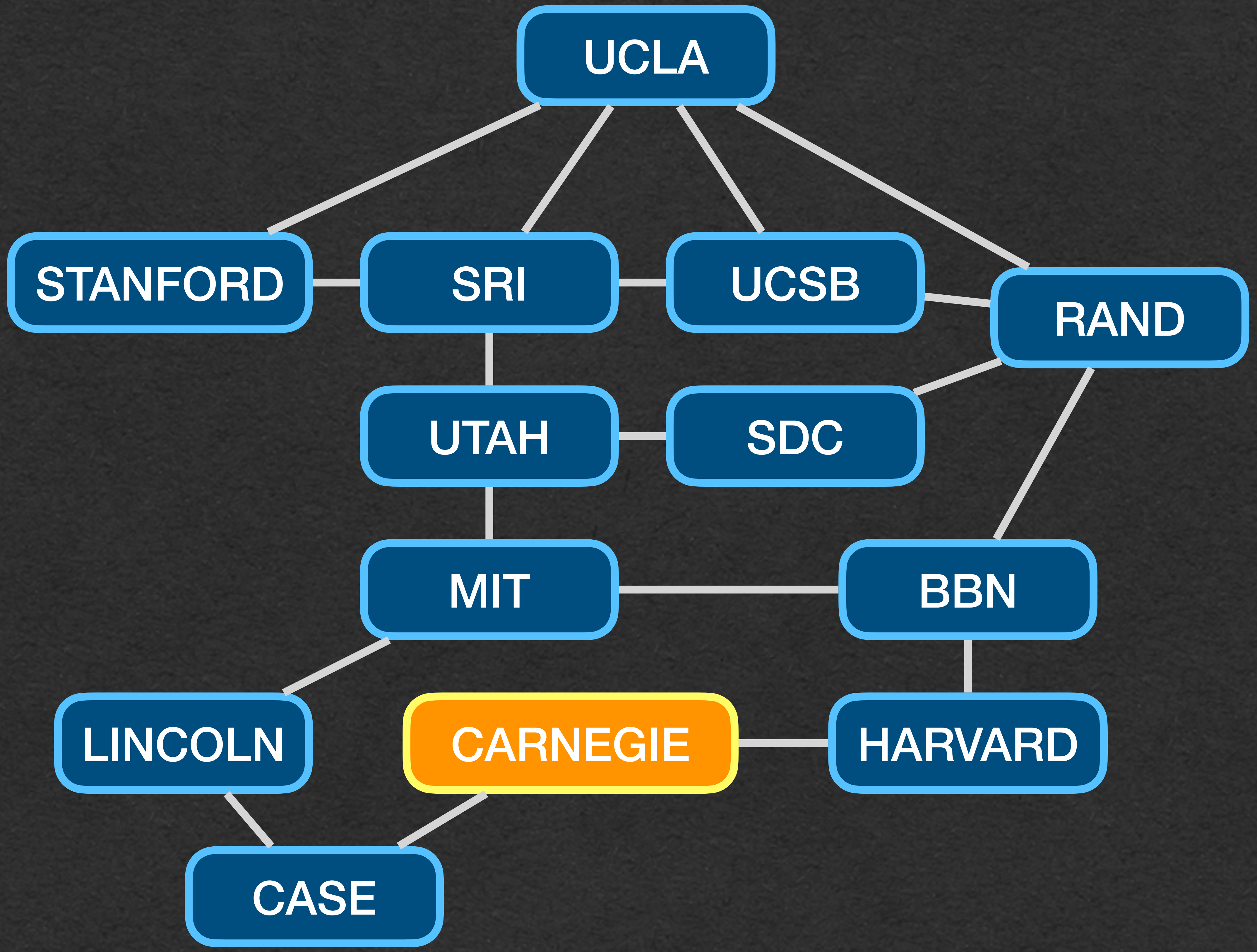
- And we have the distance from the start node to all other nodes in the graph



UCLA	4
STANFORD	5
SRI	5
UCSB	4
RAND	3
UTAH	4
SDC	4
MIT	3
BBN	2
LINCOLN	2
CARNEGIE	0
HARVARD	1
CASE	1

BFS and Pathfinding

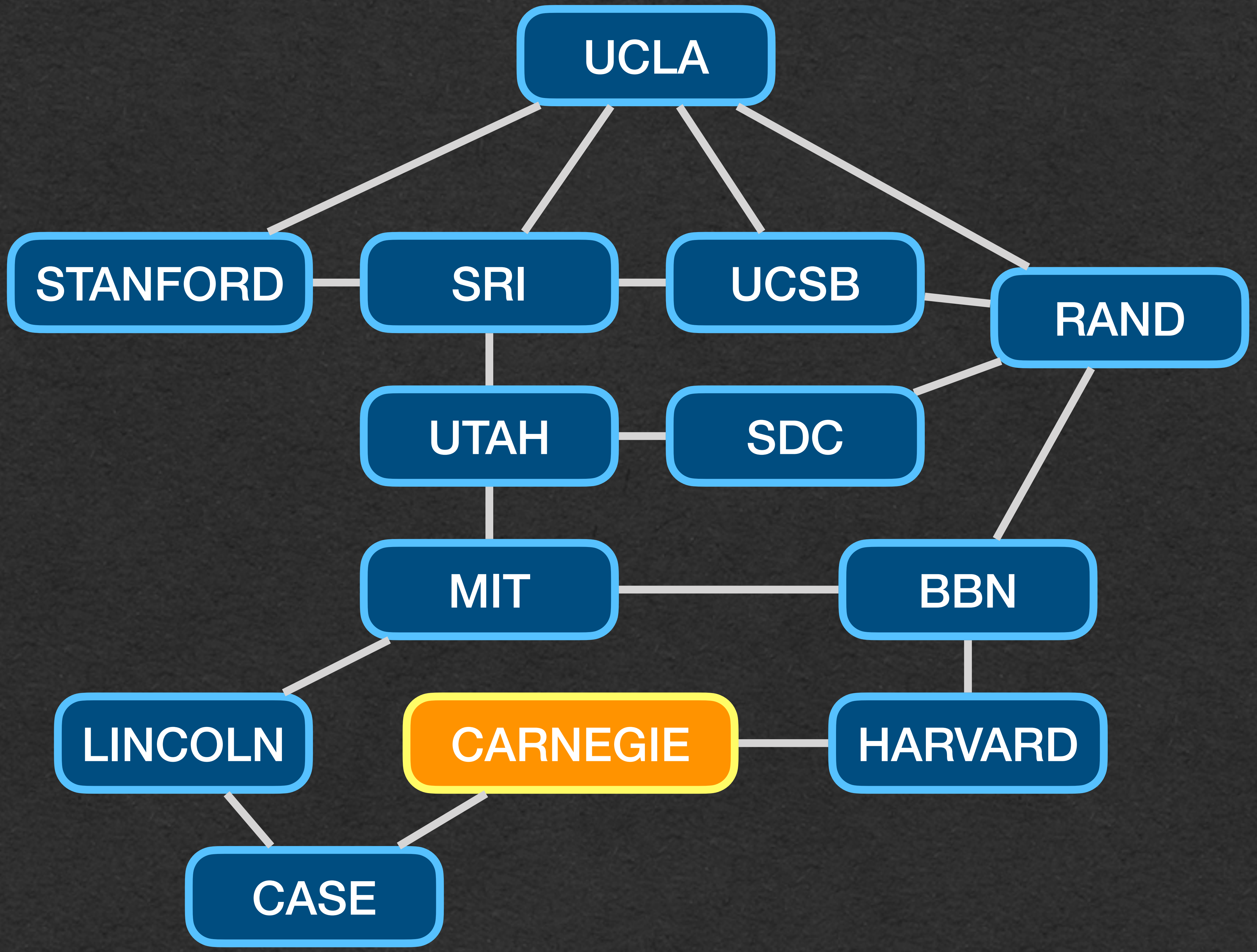
- This gives you the distance of each node
- How do we find a path to each node



UCLA	∞
STANFORD	∞
SRI	∞
UCSB	∞
RAND	∞
UTAH	∞
SDC	∞
MIT	∞
BBN	∞
LINCOLN	∞
CARNEGIE	0
HARVARD	∞
CASE	∞

BFS and Pathfinding

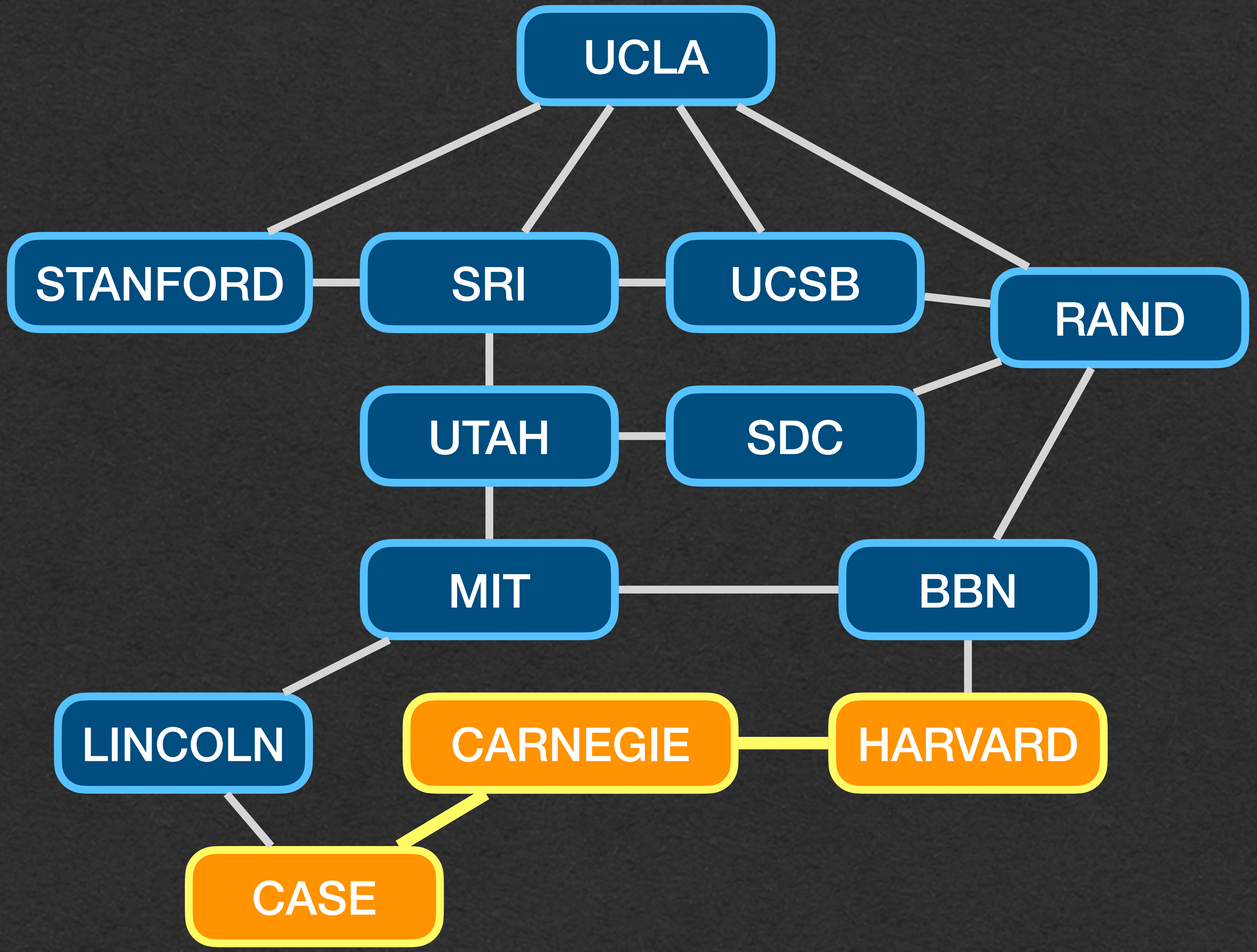
- Instead of tracking the distance, track the node that discovered each node



UCLA	unexplored
STANFORD	unexplored
SRI	unexplored
UCSB	unexplored
RAND	unexplored
UTAH	unexplored
SDC	unexplored
MIT	unexplored
BBN	unexplored
LINCOLN	unexplored
CARNEGIE	<START>
HARVARD	unexplored
CASE	unexplored

BFS and Pathfinding

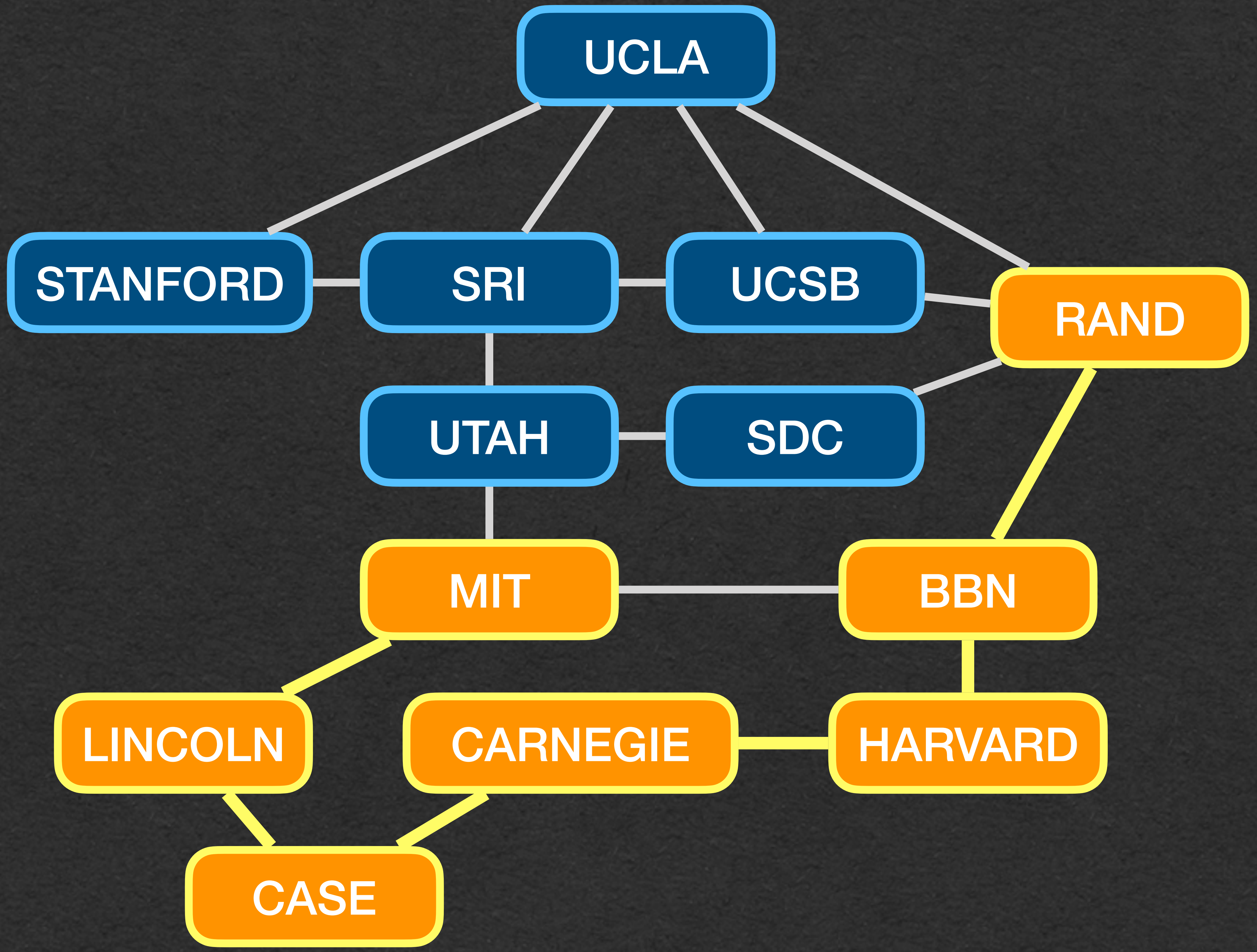
- Now each node remembers how it was reached



UCLA	unexplored
STANFORD	unexplored
SRI	unexplored
UCSB	unexplored
RAND	unexplored
UTAH	unexplored
SDC	unexplored
MIT	unexplored
BBN	unexplored
LINCOLN	unexplored
CARNEGIE	<START>
HARVARD	CARNEGIE
CASE	CARNEGIE

BFS and Pathfinding

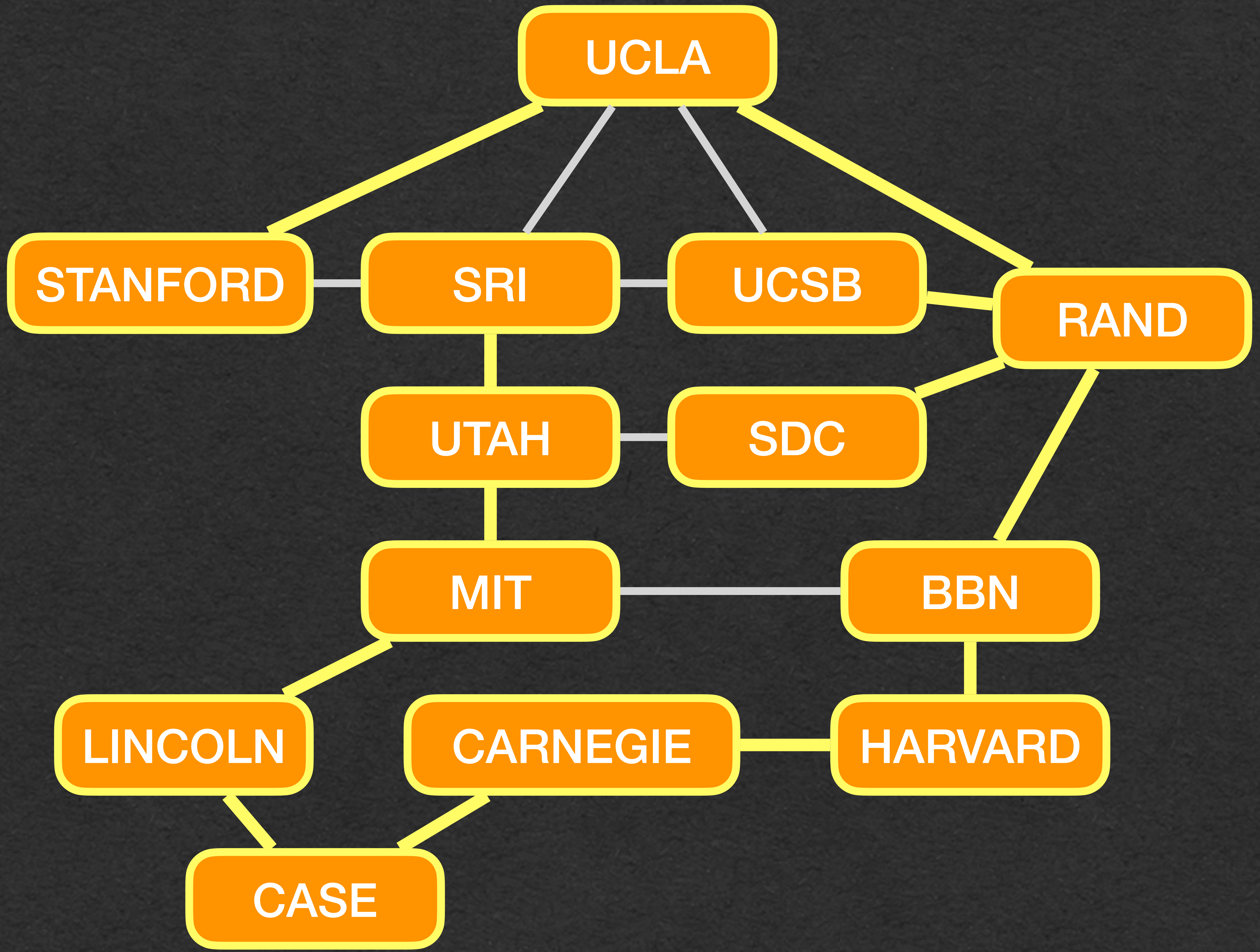
- Repeat at each step



UCLA	unexplored
STANFORD	unexplored
SRI	unexplored
UCSB	unexplored
RAND	BBN
UTAH	unexplored
SDC	unexplored
MIT	LINCOLN
BBN	HARVARD
LINCOLN	CASE
CARNEGIE	<START>
HARVARD	CARNEGIE
CASE	CARNEGIE

BFS and Pathfinding

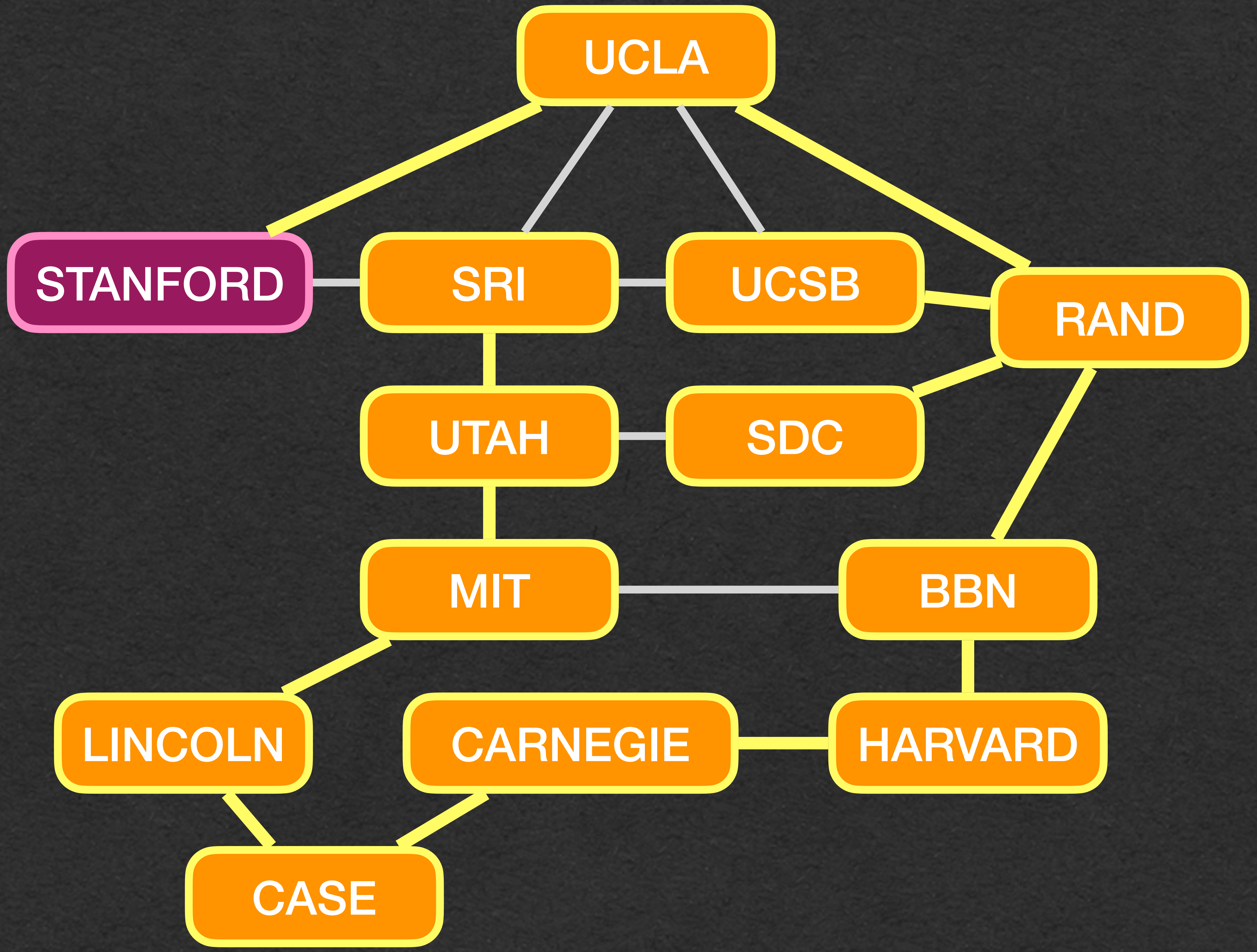
- At the end of the algorithm you'll know how each node was discovered



UCLA	RAND
STANFORD	UCLA
SRI	UTAH
UCSB	RAND
RAND	BBN
UTAH	MIT
SDC	RAND
MIT	LINCOLN
BBN	HARVARD
LINCOLN	CASE
CARNEGIE	<START>
HARVARD	CARNEGIE
CASE	CARNEGIE

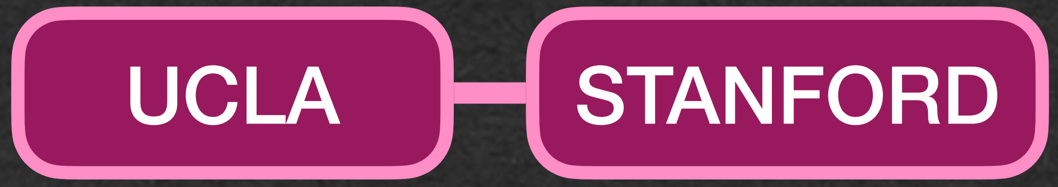
BFS and Pathfinding

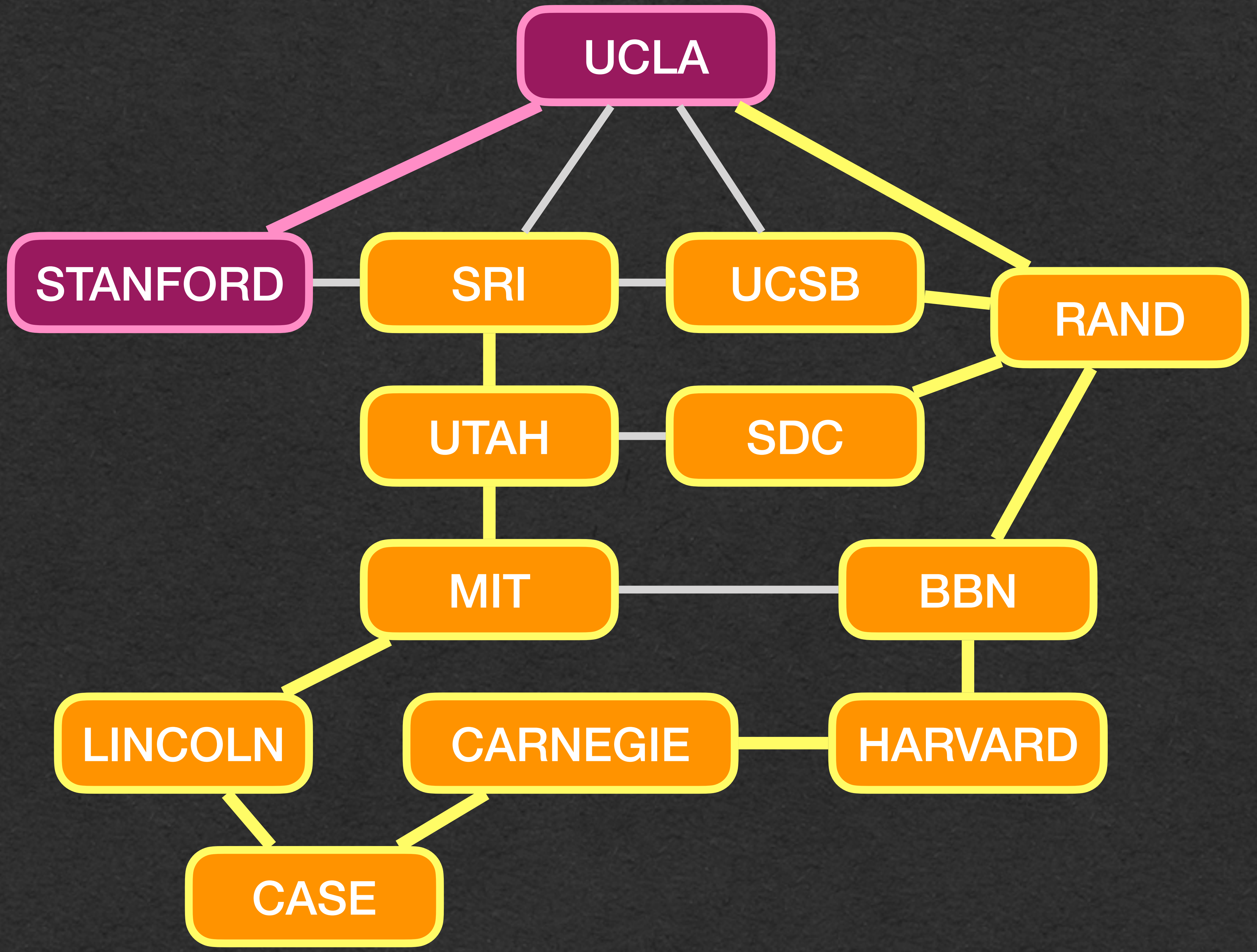
- Work backwards to build the shortest path
- Find path from CARNEGIE to STANFORD



UCLA	RAND
STANFORD	UCLA
SRI	UTAH
UCSB	RAND
RAND	BBN
UTAH	MIT
SDC	RAND
MIT	LINCOLN
BBN	HARVARD
LINCOLN	CASE
CARNEGIE	<START>
HARVARD	CARNEGIE
CASE	CARNEGIE

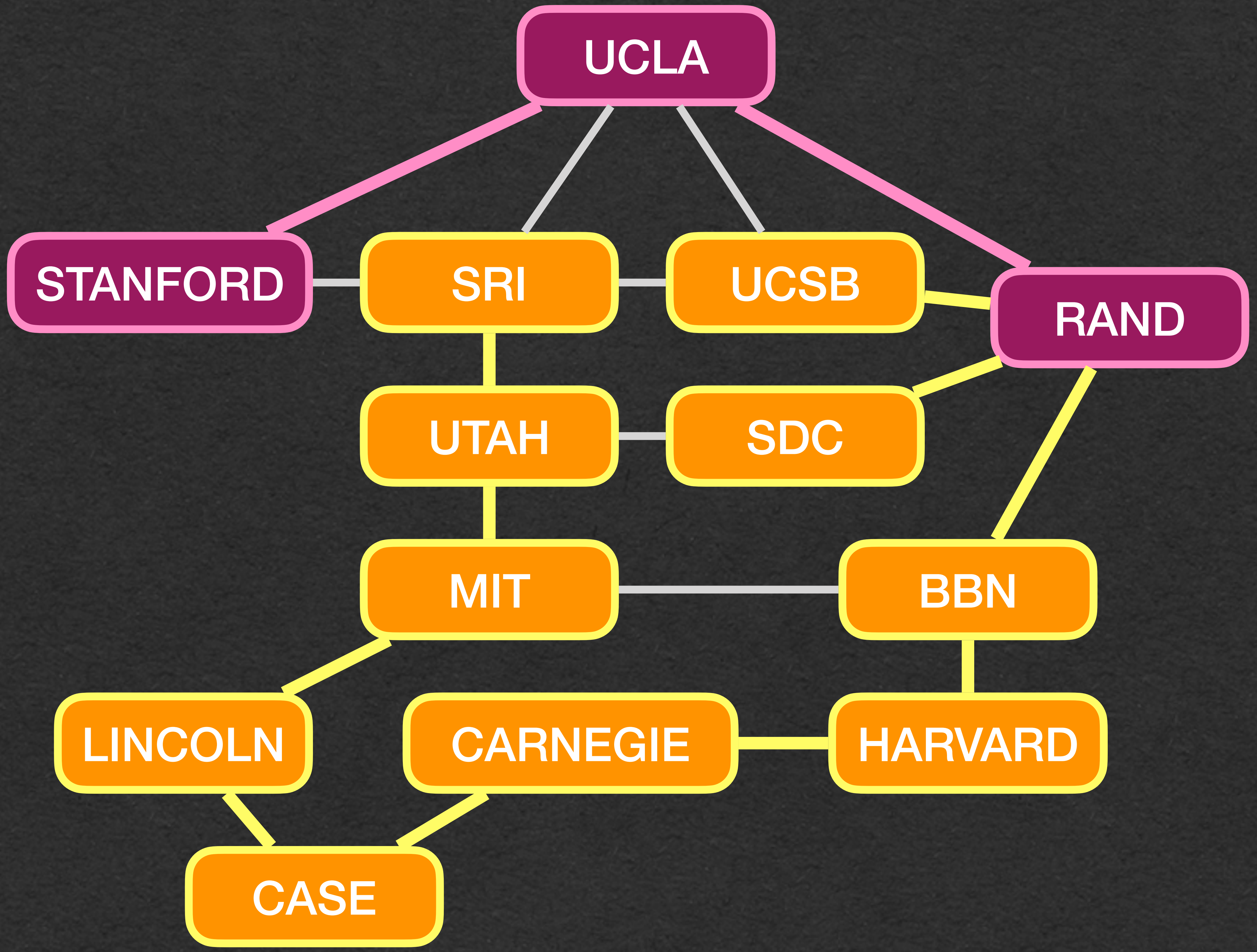
BFS and Pathfinding





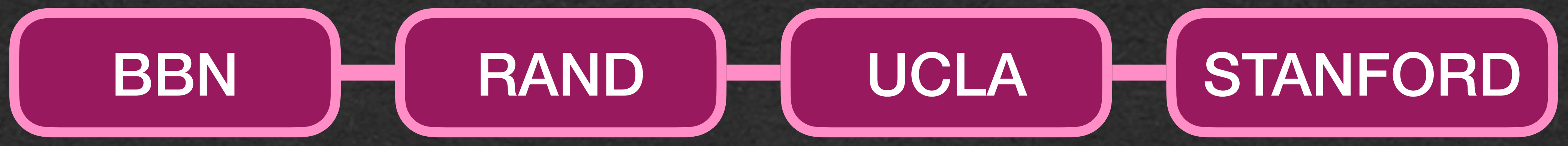
UCLA	RAND
STANFORD	UCLA
SRI	UTAH
UCSB	RAND
RAND	BBN
UTAH	MIT
SDC	RAND
MIT	LINCOLN
BBN	HARVARD
LINCOLN	CASE
CARNEGIE	<START>
HARVARD	CARNEGIE
CASE	CARNEGIE

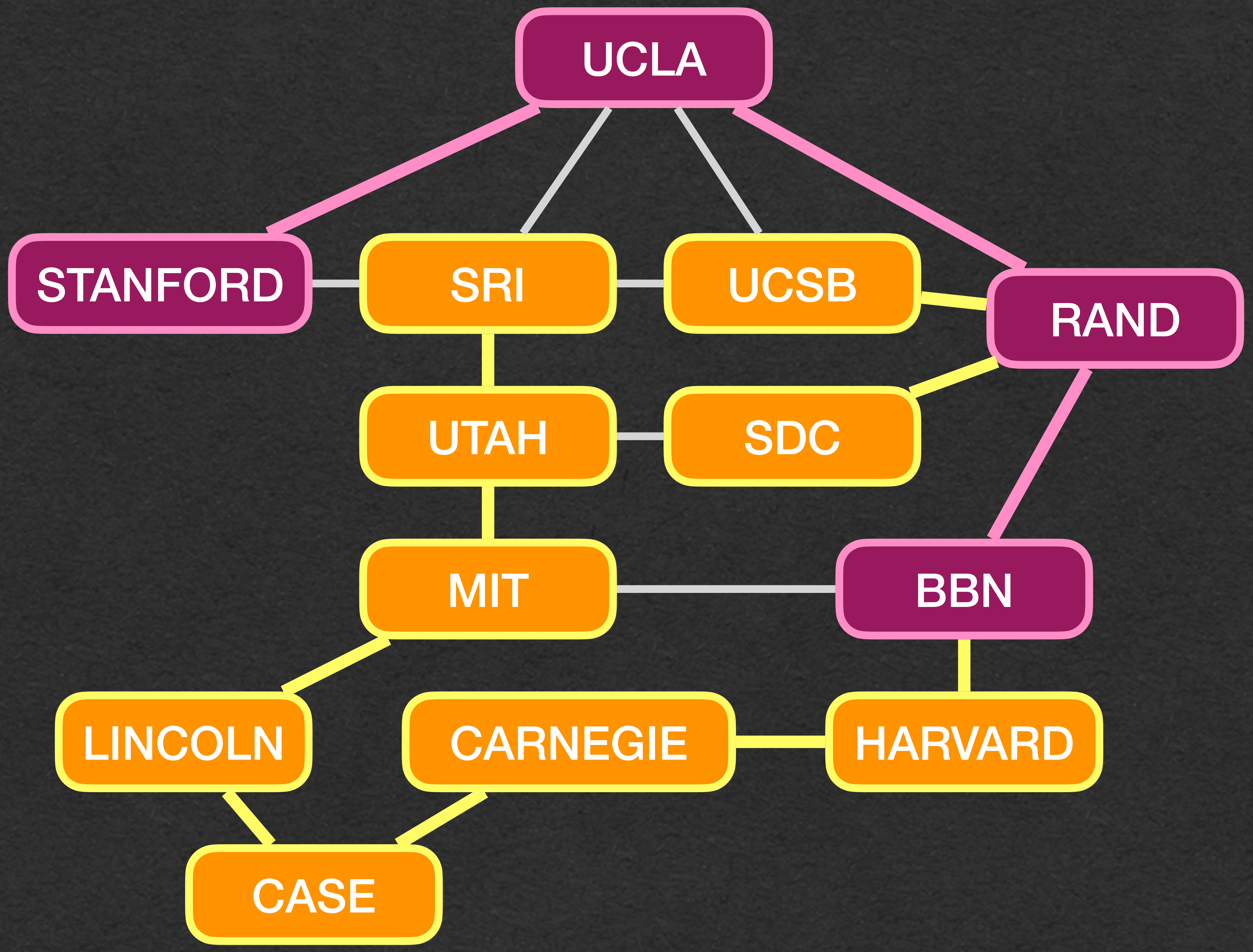
BFS and Pathfinding



UCLA	RAND
STANFORD	UCLA
SRI	UTAH
UCSB	RAND
RAND	BBN
UTAH	MIT
SDC	RAND
MIT	LINCOLN
BBN	HARVARD
LINCOLN	CASE
CARNEGIE	<START>
HARVARD	CARNEGIE
CASE	CARNEGIE

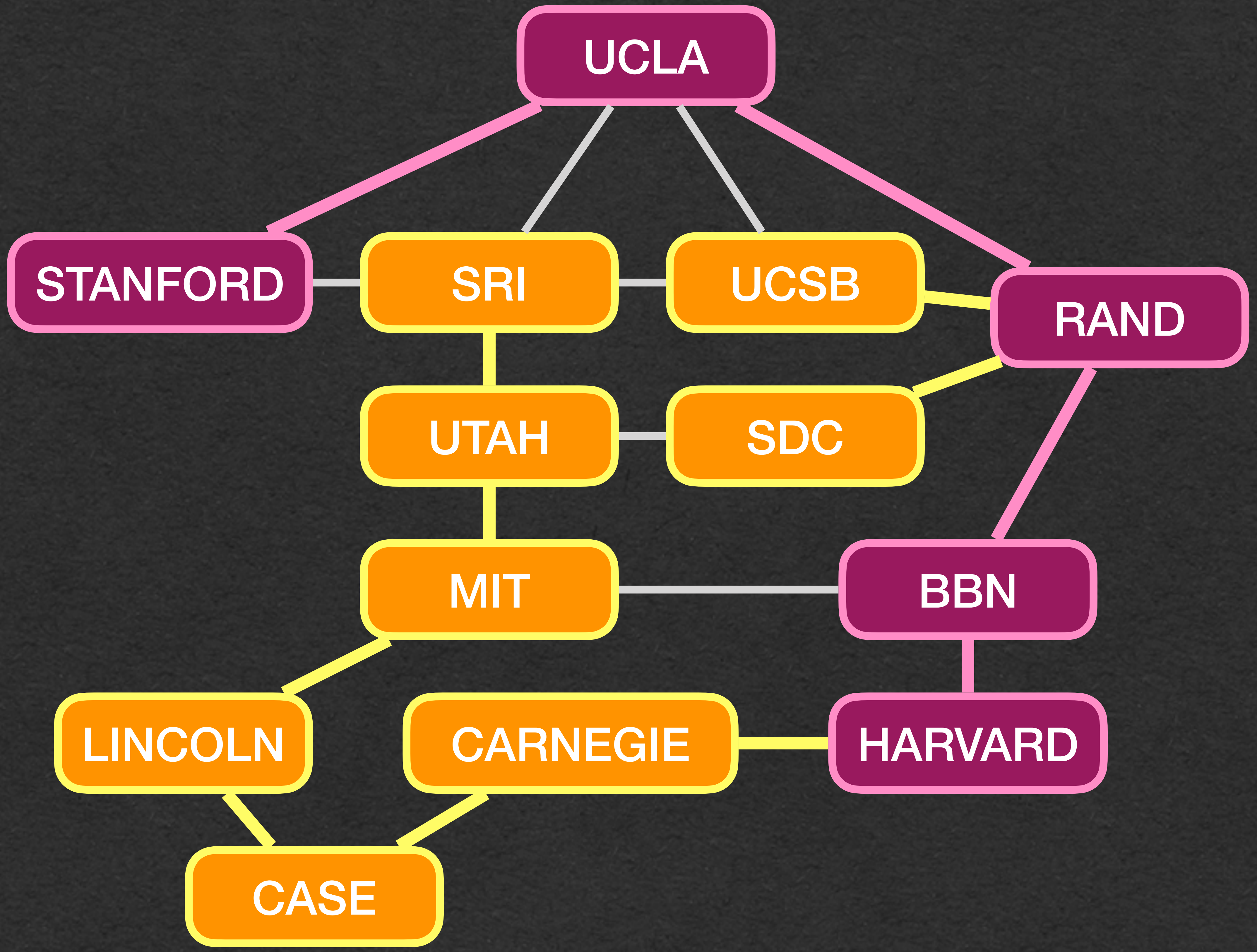
BFS and Pathfinding





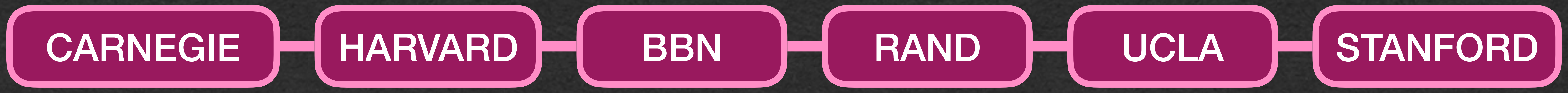
UCLA	RAND
STANFORD	UCLA
SRI	UTAH
UCSB	RAND
RAND	BBN
UTAH	MIT
SDC	RAND
MIT	LINCOLN
BBN	HARVARD
LINCOLN	CASE
CARNEGIE	<START>
HARVARD	CARNEGIE
CASE	CARNEGIE

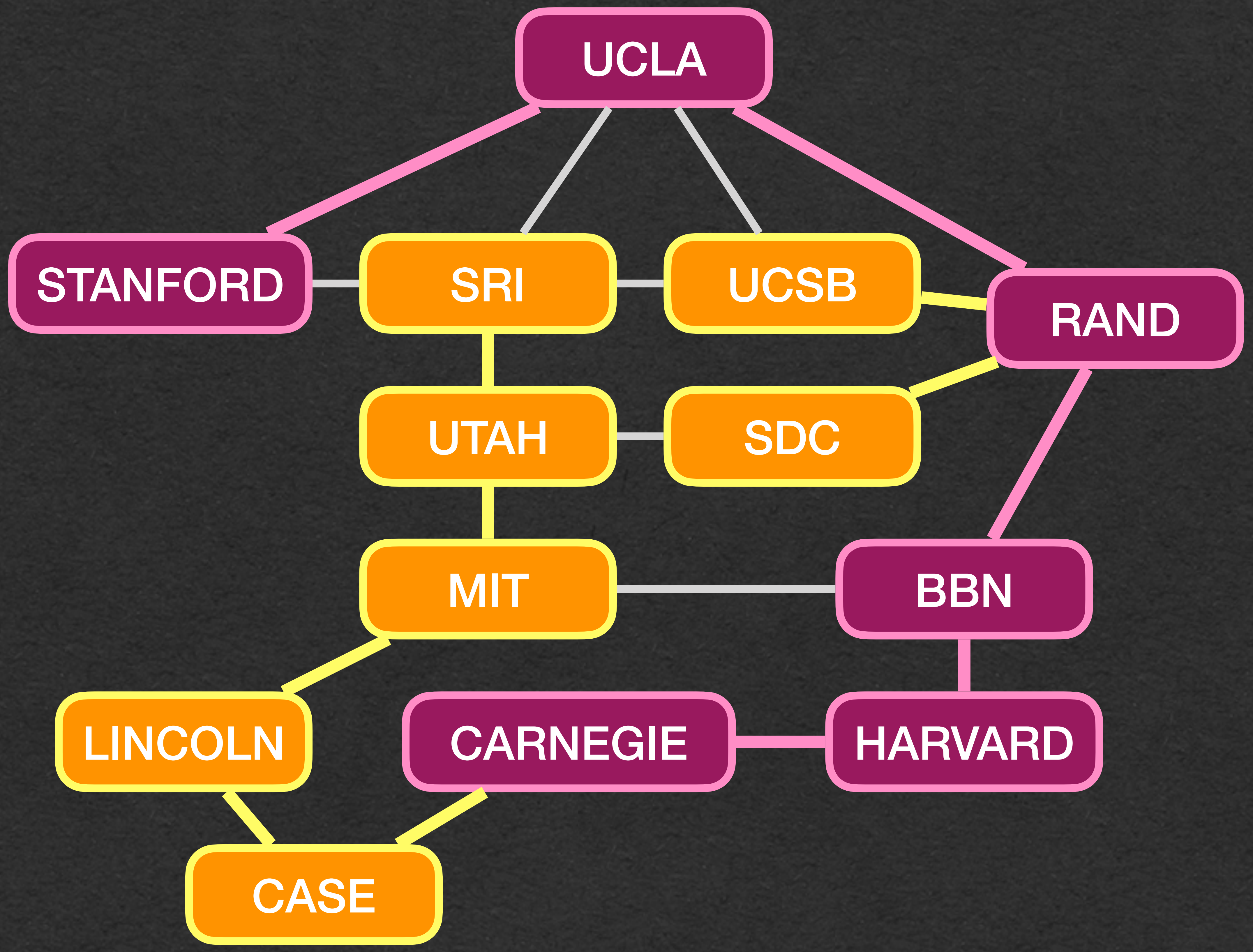
BFS and Pathfinding



UCLA	RAND
STANFORD	UCLA
SRI	UTAH
UCSB	RAND
RAND	BBN
UTAH	MIT
SDC	RAND
MIT	LINCOLN
BBN	HARVARD
LINCOLN	CASE
CARNEGIE	<START>
HARVARD	CARNEGIE
CASE	CARNEGIE

BFS and Pathfinding

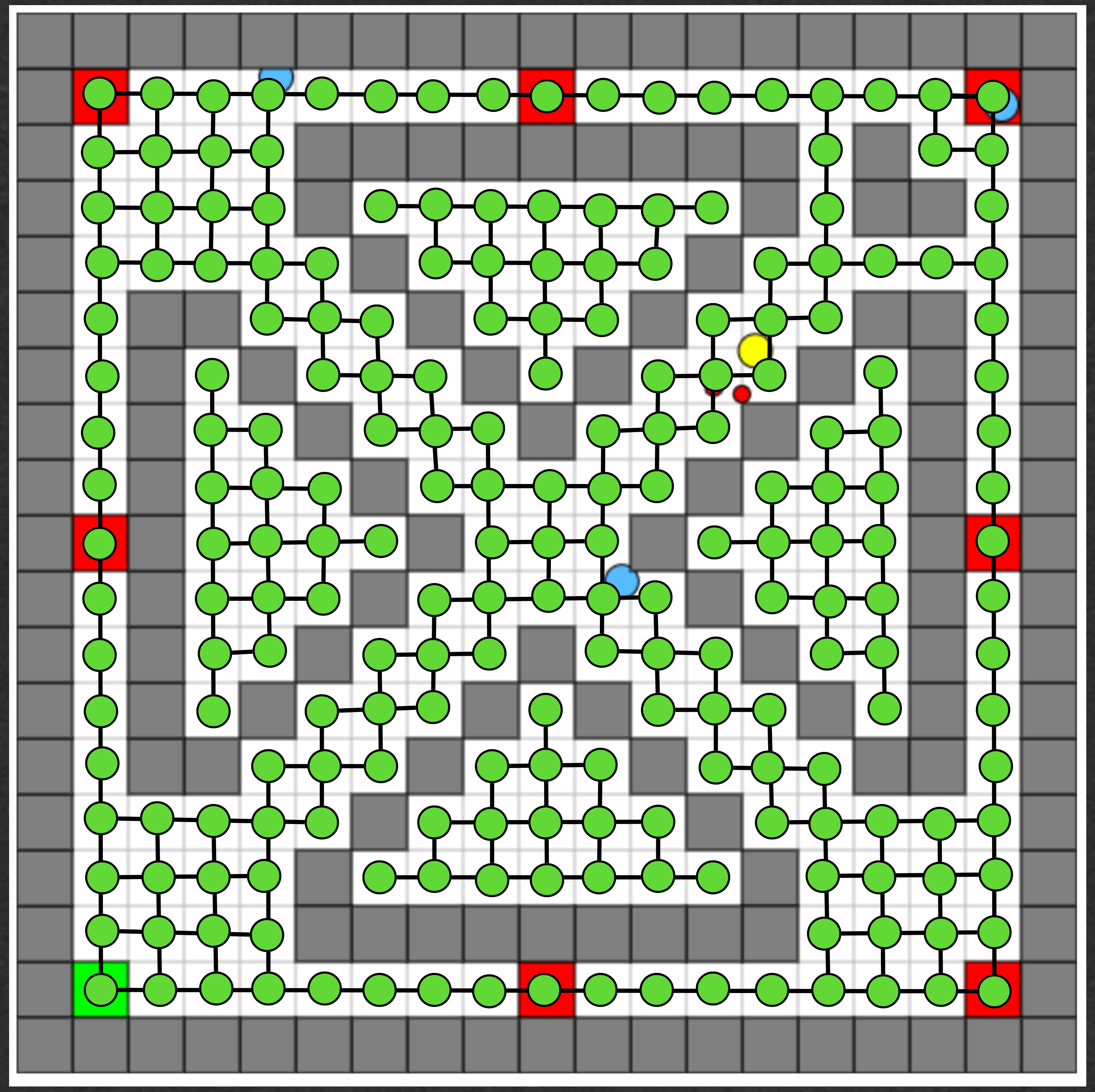




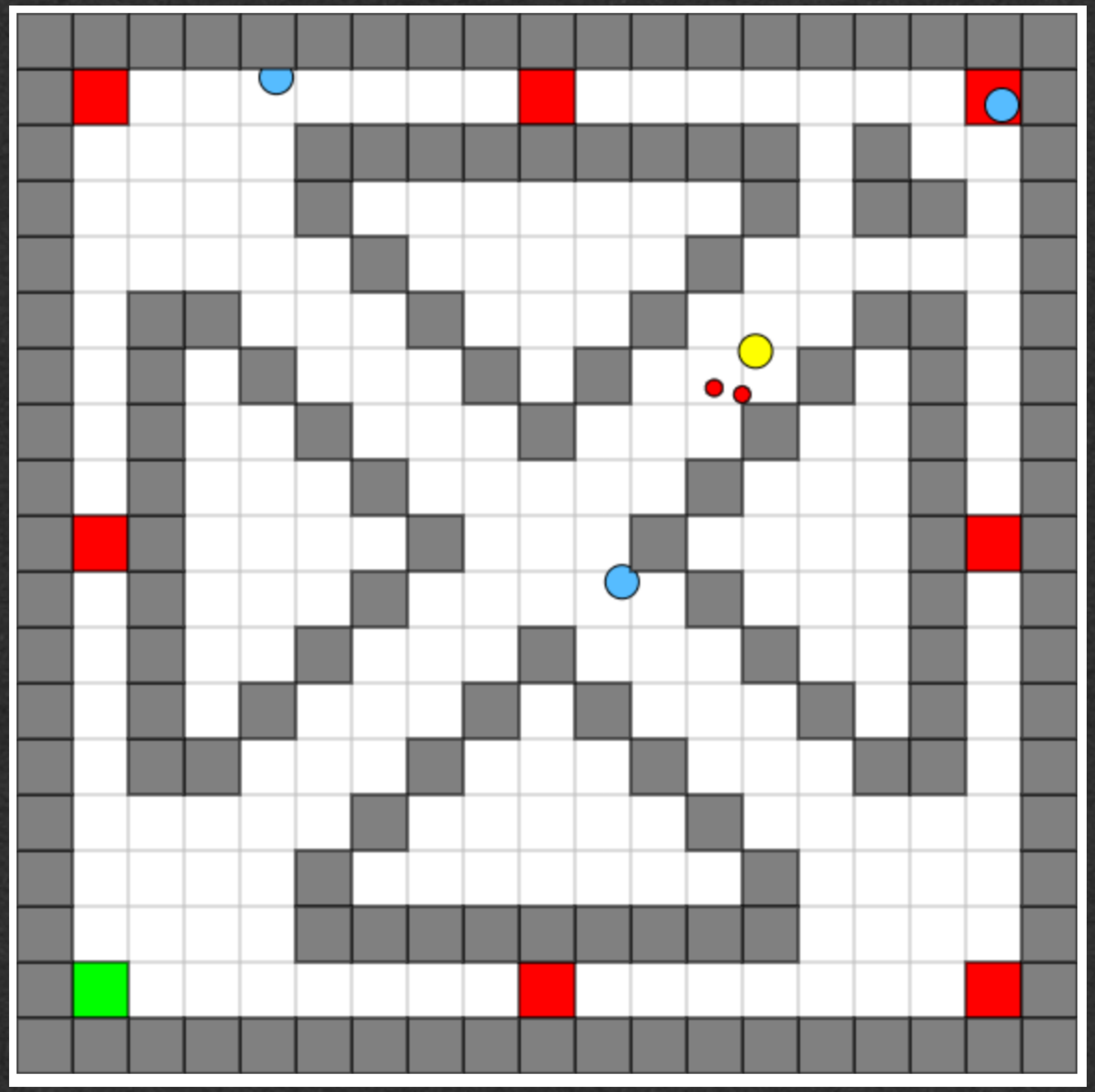
UCLA	RAND
STANFORD	UCLA
SRI	UTAH
UCSB	RAND
RAND	BBN
UTAH	MIT
SDC	RAND
MIT	LINCOLN
BBN	HARVARD
LINCOLN	CASE
CARNEGIE	<START>
HARVARD	CARNEGIE
CASE	CARNEGIE

Pathfinding on a Grid

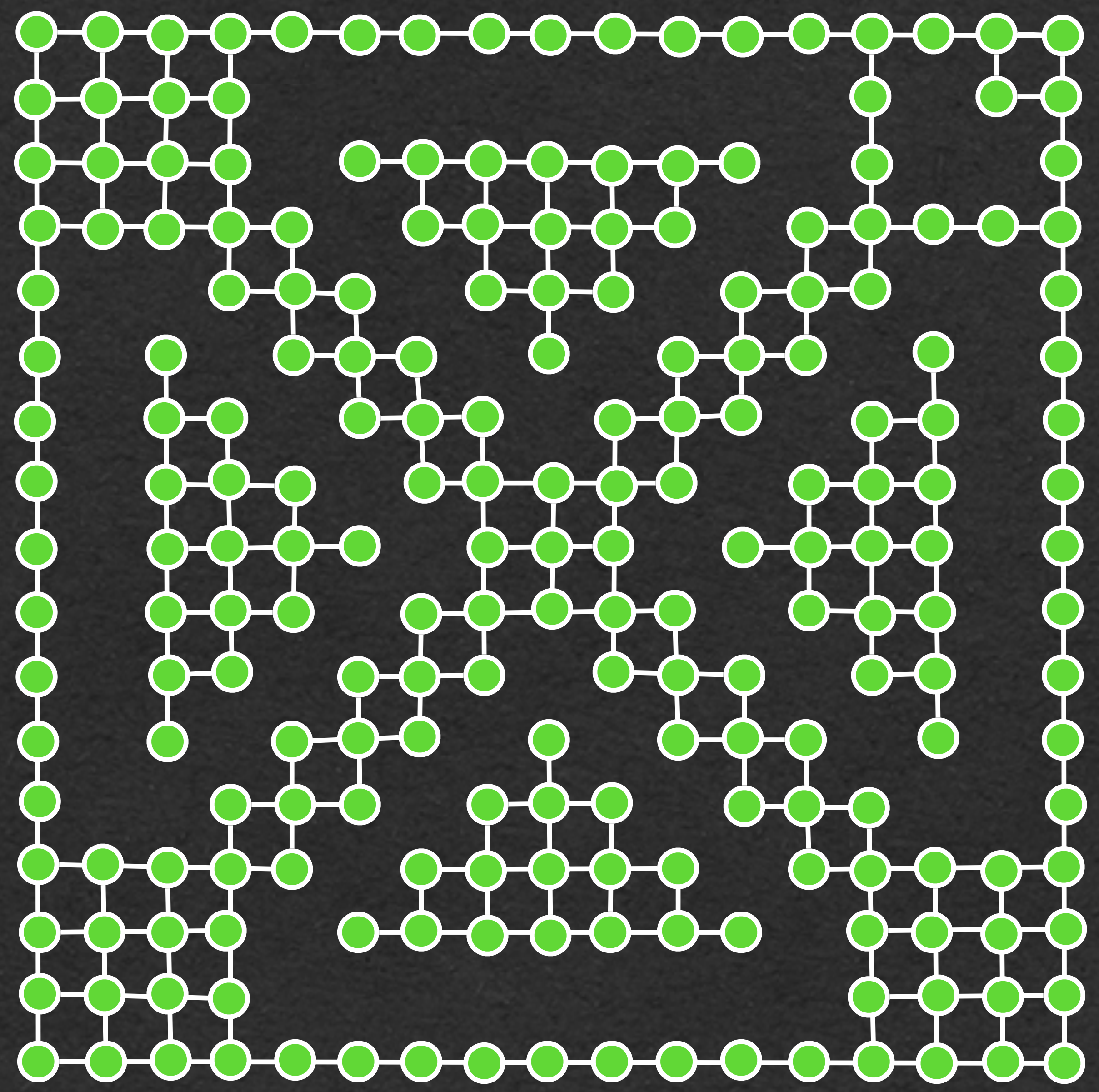
- Convert the level to a graph
- Run BFS from the starting tile
- Backtrack from the end tile to build the path



We see this:



AI sees this:



Distance

- Ok, but how does this apply to degrees of separation between actors?

```
The Hunger Games,Jennifer Lawrence,Josh Hutcherson,Elizabeth Banks
The Lego Movie,Chris Pratt,Will Ferrell,Elizabeth Banks
Guardians of the Galaxy,Chris Pratt,Zoe Saldana
```

Distance

- Build a graph
- Run BFS

```
The Hunger Games,Jennifer Lawrence,Josh Hutcherson,Elizabeth Banks
The Lego Movie,Chris Pratt,Will Ferrell,Elizabeth Banks
Guardians of the Galaxy,Chris Pratt,Zoe Saldana
```

Distance

- If two people starred in a movie together, they have distance one
  - Sounds like an edge

```
The Hunger Games,Jennifer Lawrence,Josh Hutcherson,Elizabeth Banks
The Lego Movie,Chris Pratt,Will Ferrell,Elizabeth Banks
Guardians of the Galaxy,Chris Pratt,Zoe Saldana
```

Distance

- Run BFS to find the length of a shortest path between two people
  - This is their degrees of separation

```
The Hunger Games,Jennifer Lawrence,Josh Hutcherson,Elizabeth Banks
The Lego Movie,Chris Pratt,Will Ferrell,Elizabeth Banks
Guardians of the Galaxy,Chris Pratt,Zoe Saldana
```