

EMPIRICAL COMPARISON OF TRAVELING SALESPERSON APPROXIMATION ALGORITHMS

Thesis Defense for Shayan Daijavad

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Ventura

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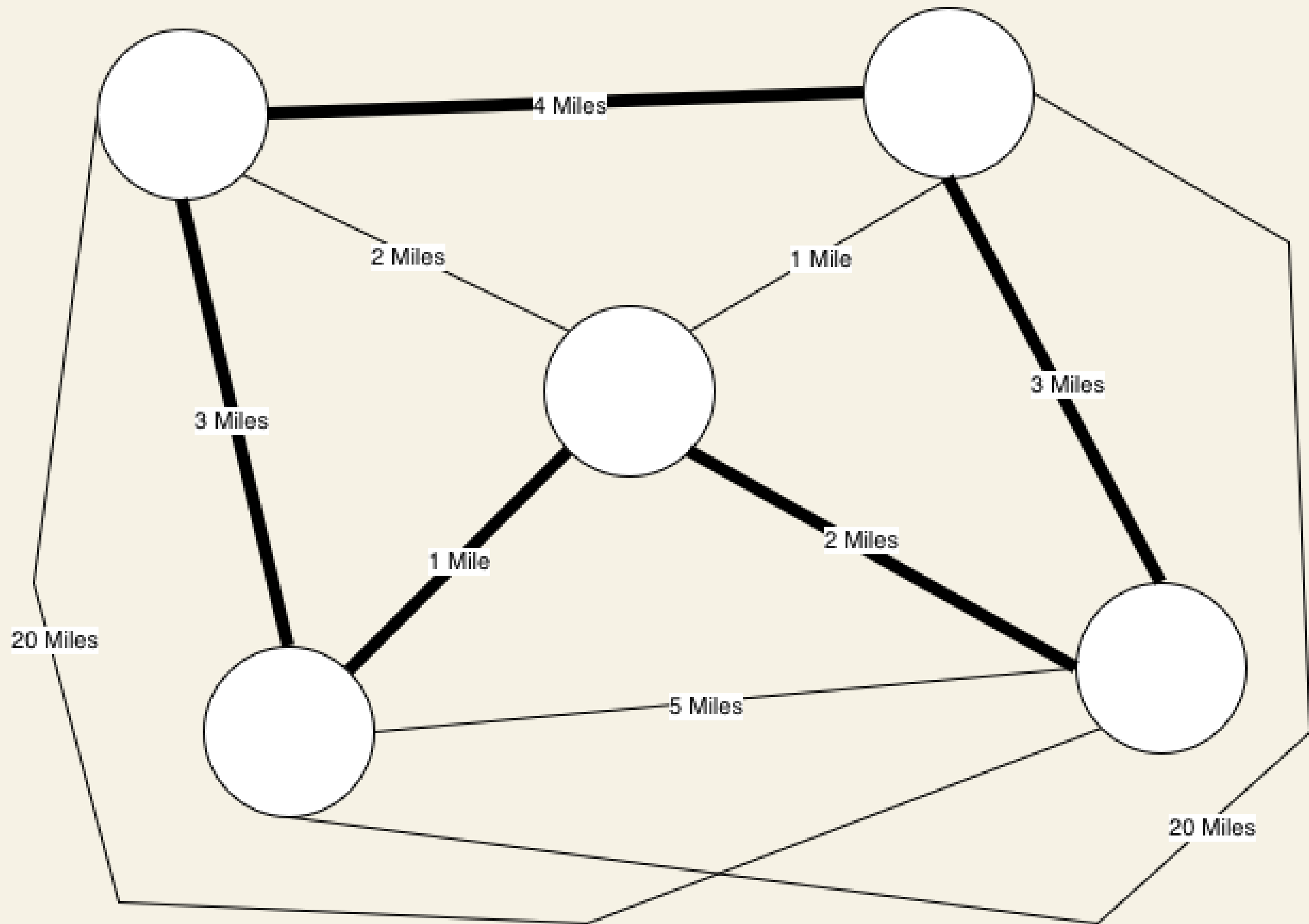
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 - TSPLIB
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INTRODUCTION

The Traveling Salesperson Problem

- **Definition:** Given a set of n points with pairwise distances between them, find the shortest tour that visits all n points exactly once and returns back to the starting point of the tour.

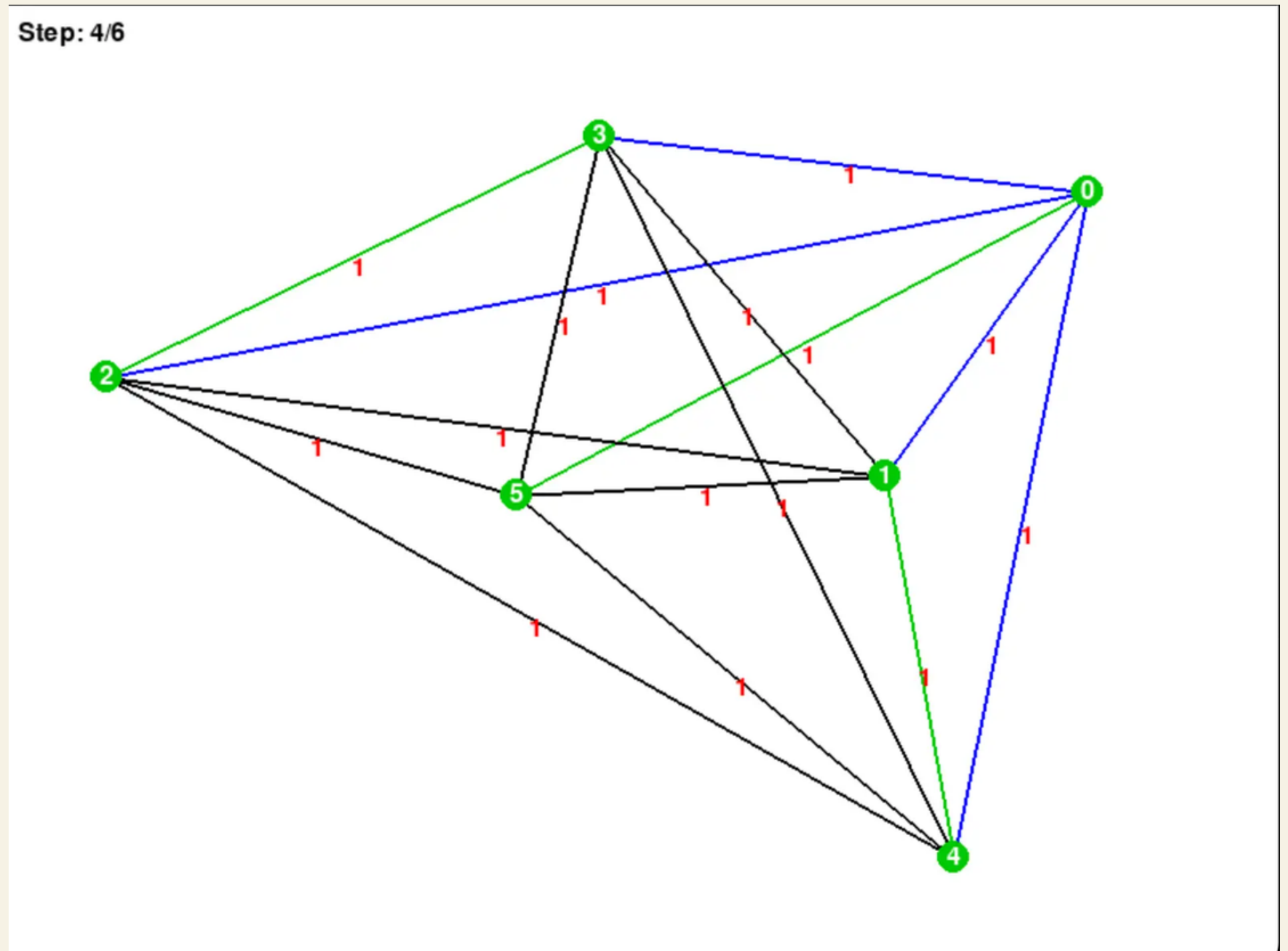


Origins + Applications

- Karl Menger
- Vehicle routing
- Circuit board drilling
- Computer wiring
- Molecular biology

My Interest in the Problem

- CSC 349 with Professor Migler
- CSC 549 with Professor Frishberg
- Mamano et al. paper



Two Algorithms

- Multifragment Heuristic with Nearest Neighbor Chain
 - $O(n \log n)$ runtime
 - $O(\log n)$ approximation
- 2-Approximation
 - $O(n^2)$ runtime
 - 2OPT approximation

Research Questions

- RQ1: In practice, what are the tradeoffs in approximation performance, runtime, and implementation simplicity between these algorithms?
- RQ2: In theory, NNC gives a speedup for the MFH. In practice, how much of a speedup is there?

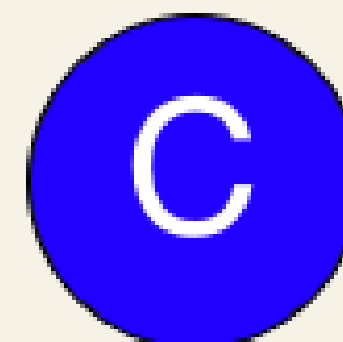
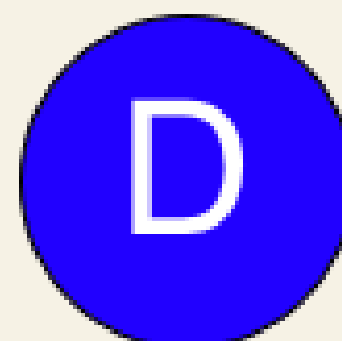
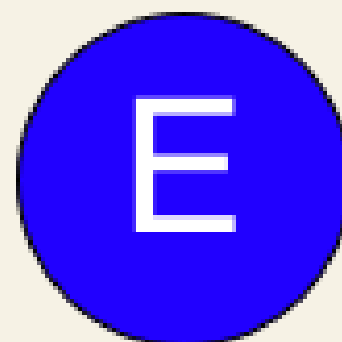
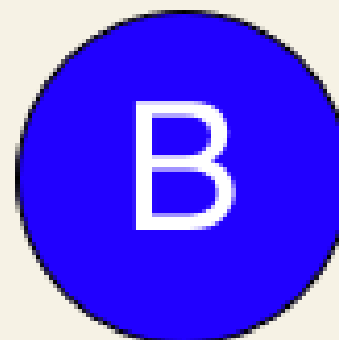
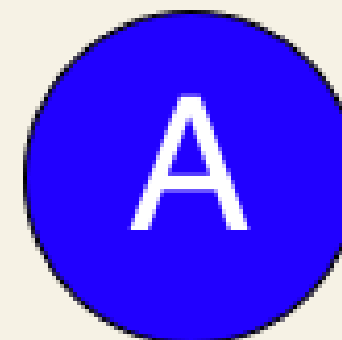
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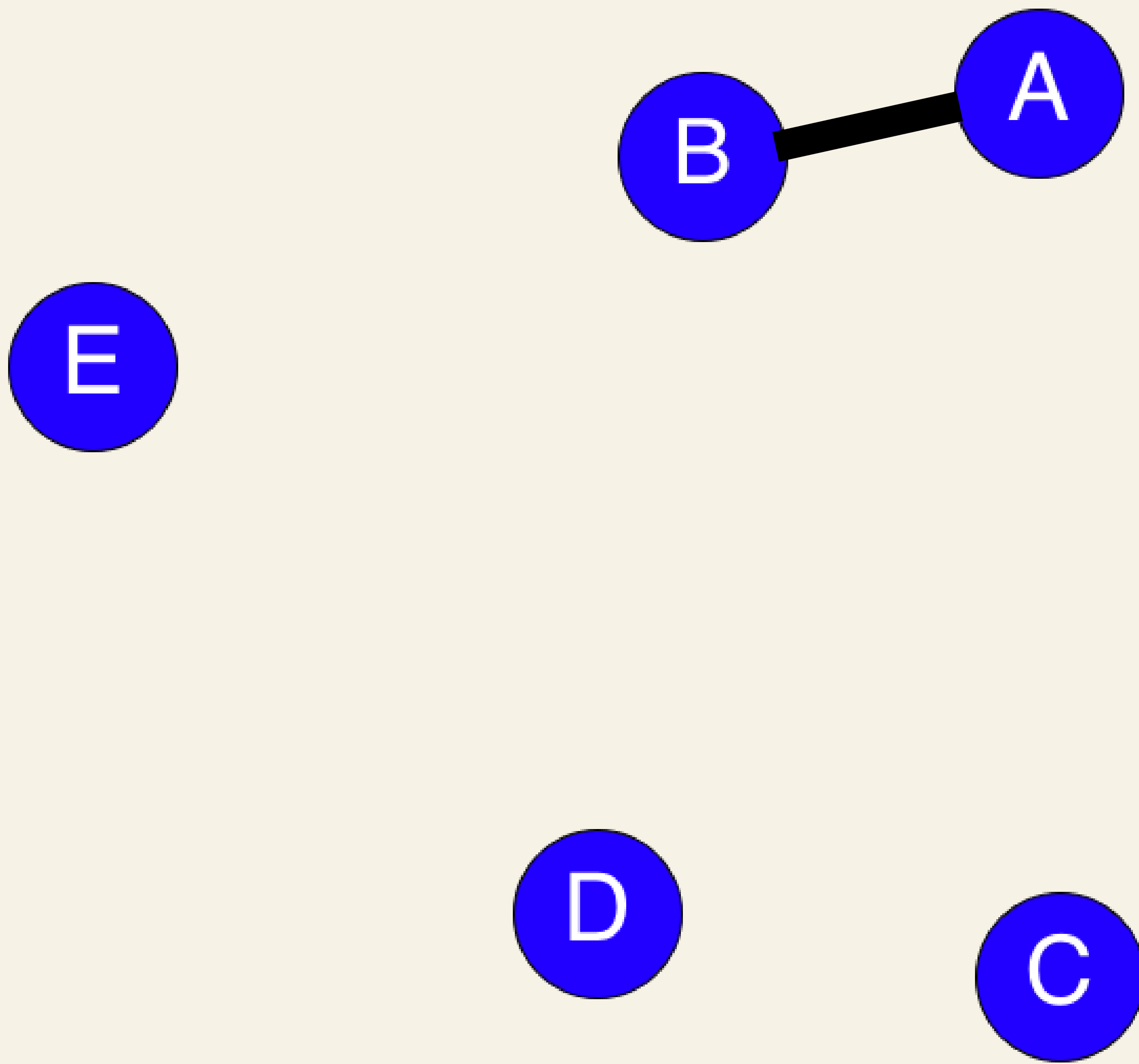
Background Details

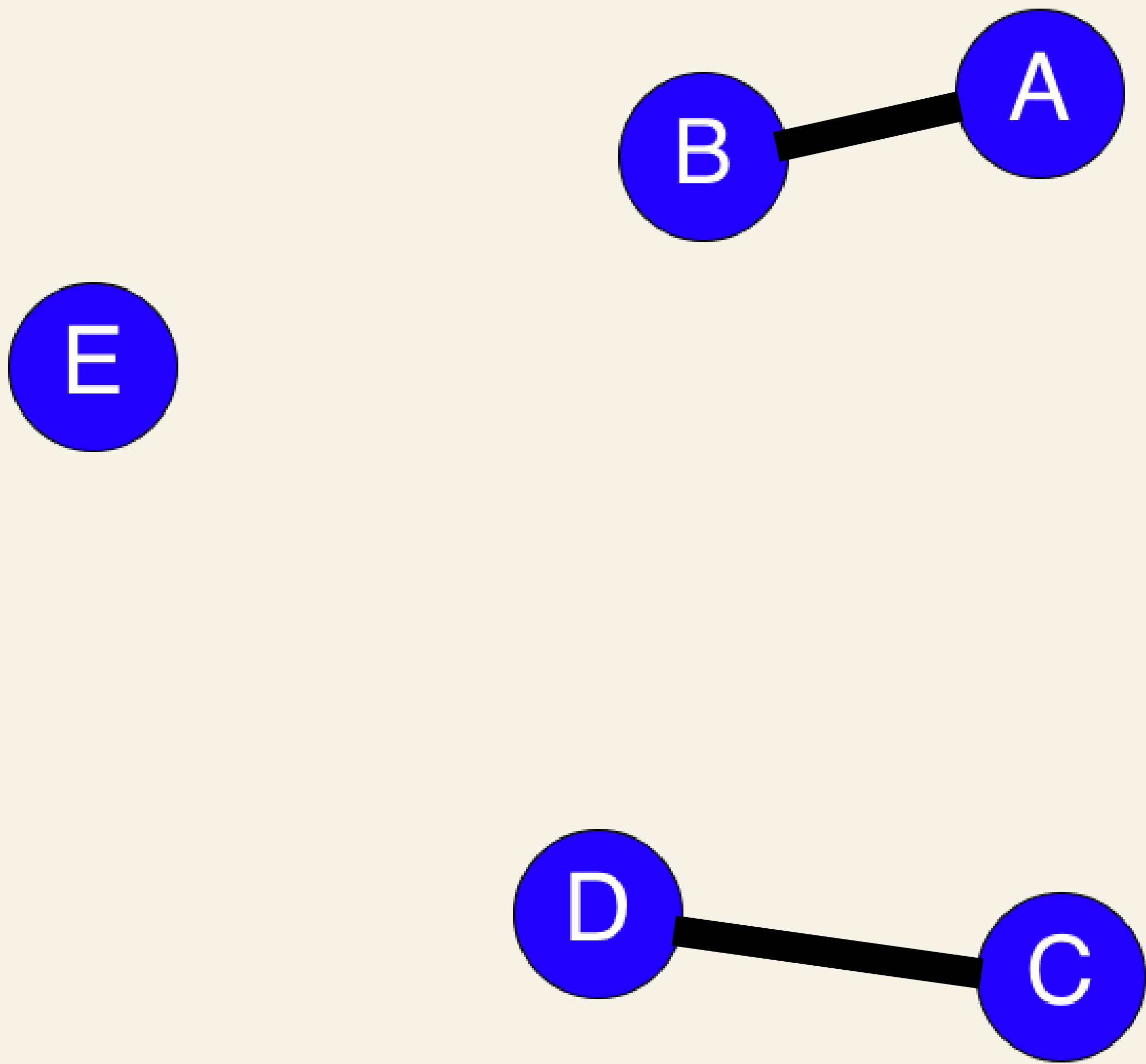
- C++ for speed
- Timeline:
 - Naive MFH Implementation
 - NNC MFH Implementation
 - Christofides
 - Pivot
 - 2-Approximation Implementation

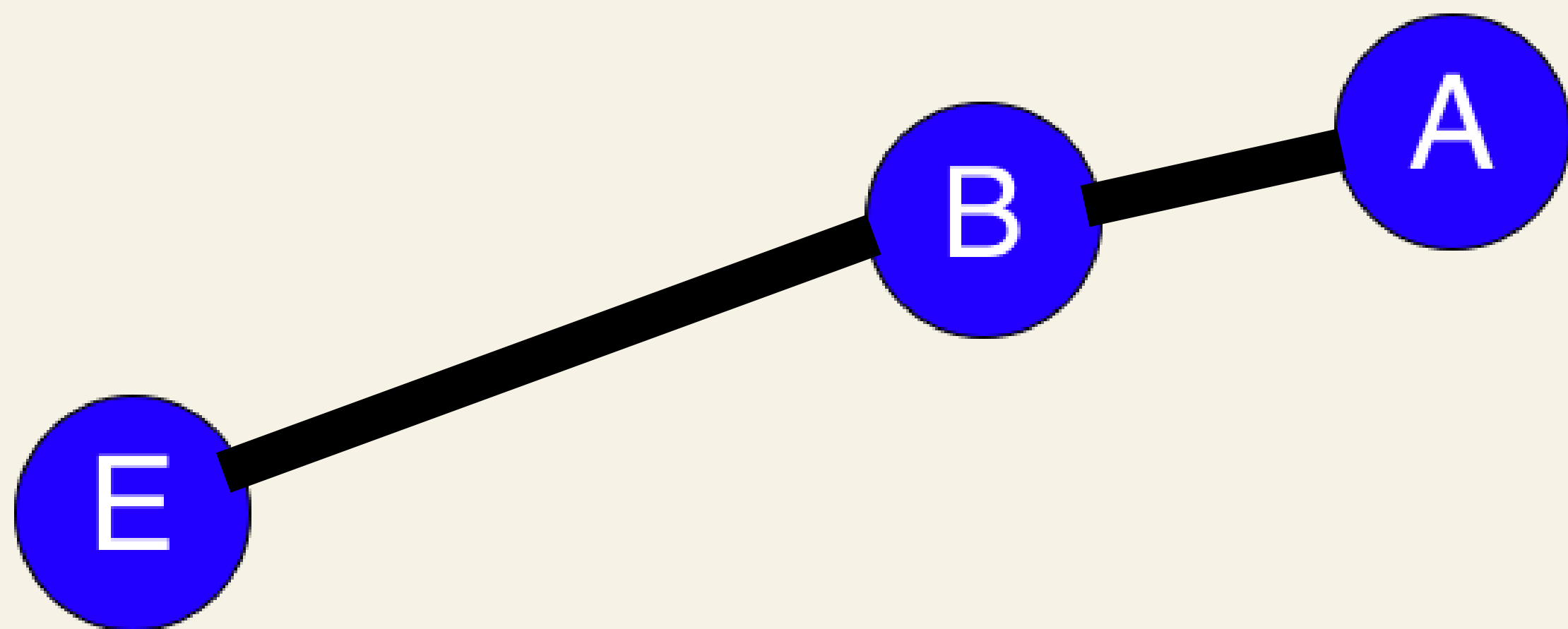
THE MULTIFRAGMENT HEURISTIC

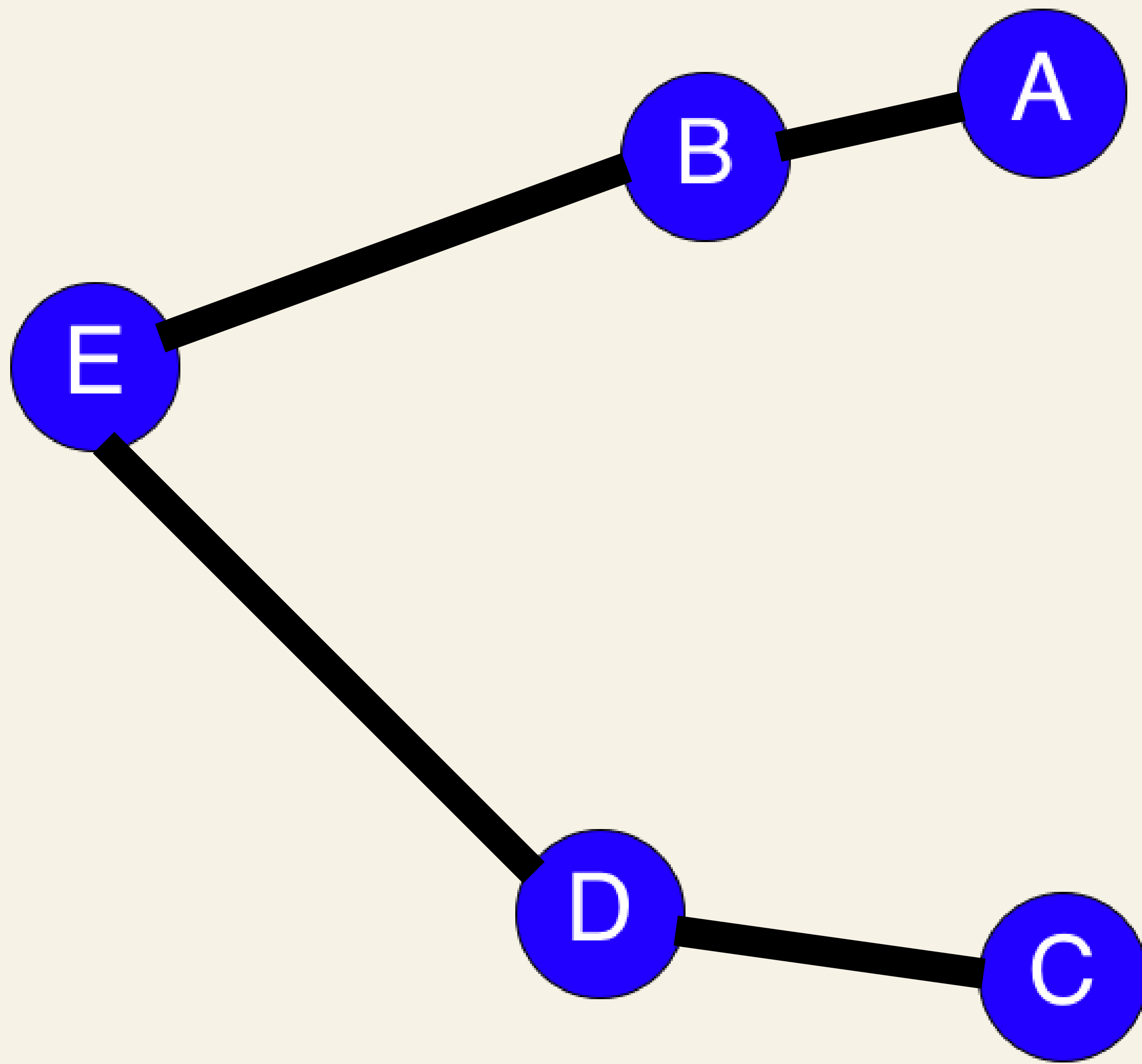
Intuition

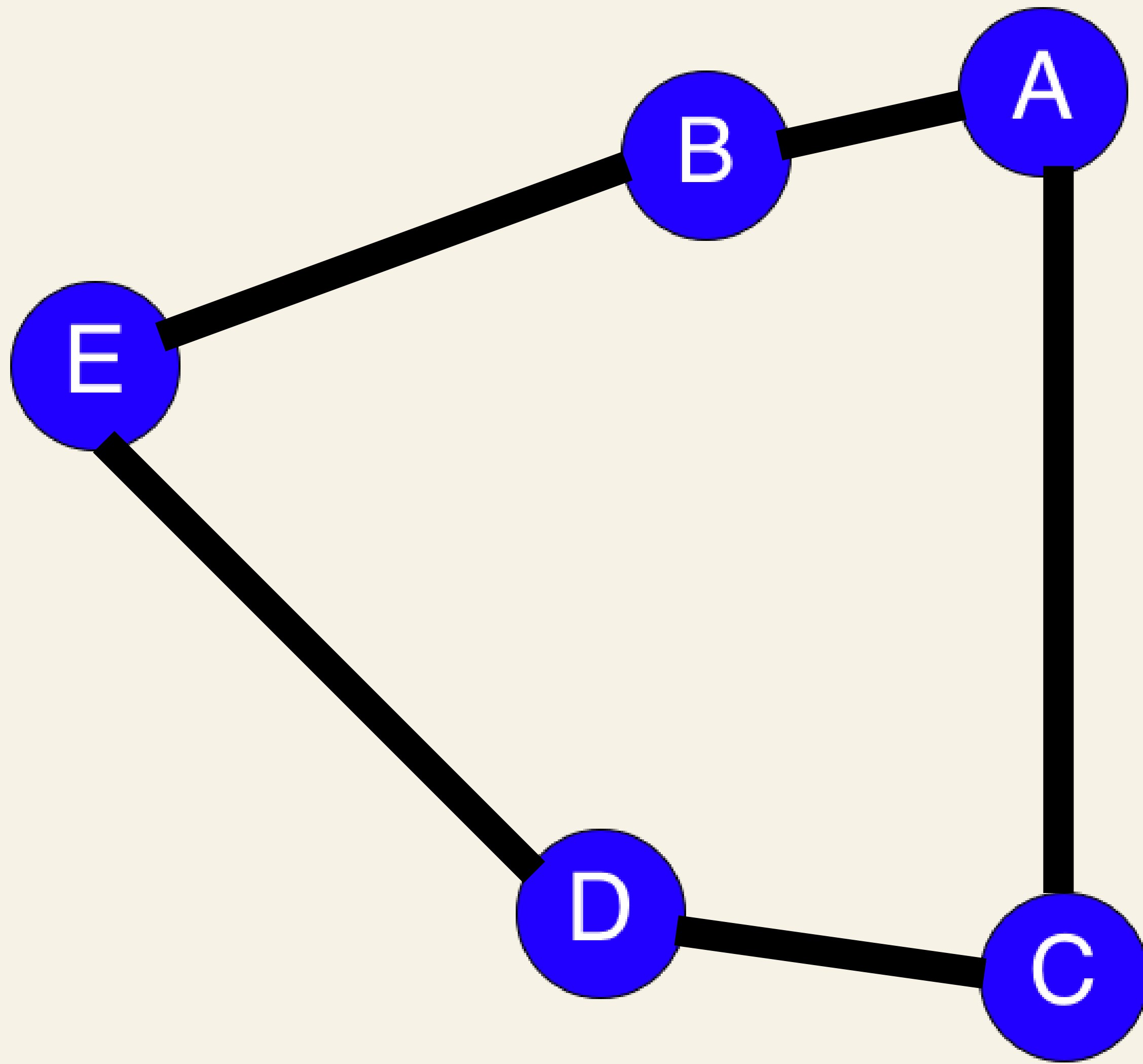


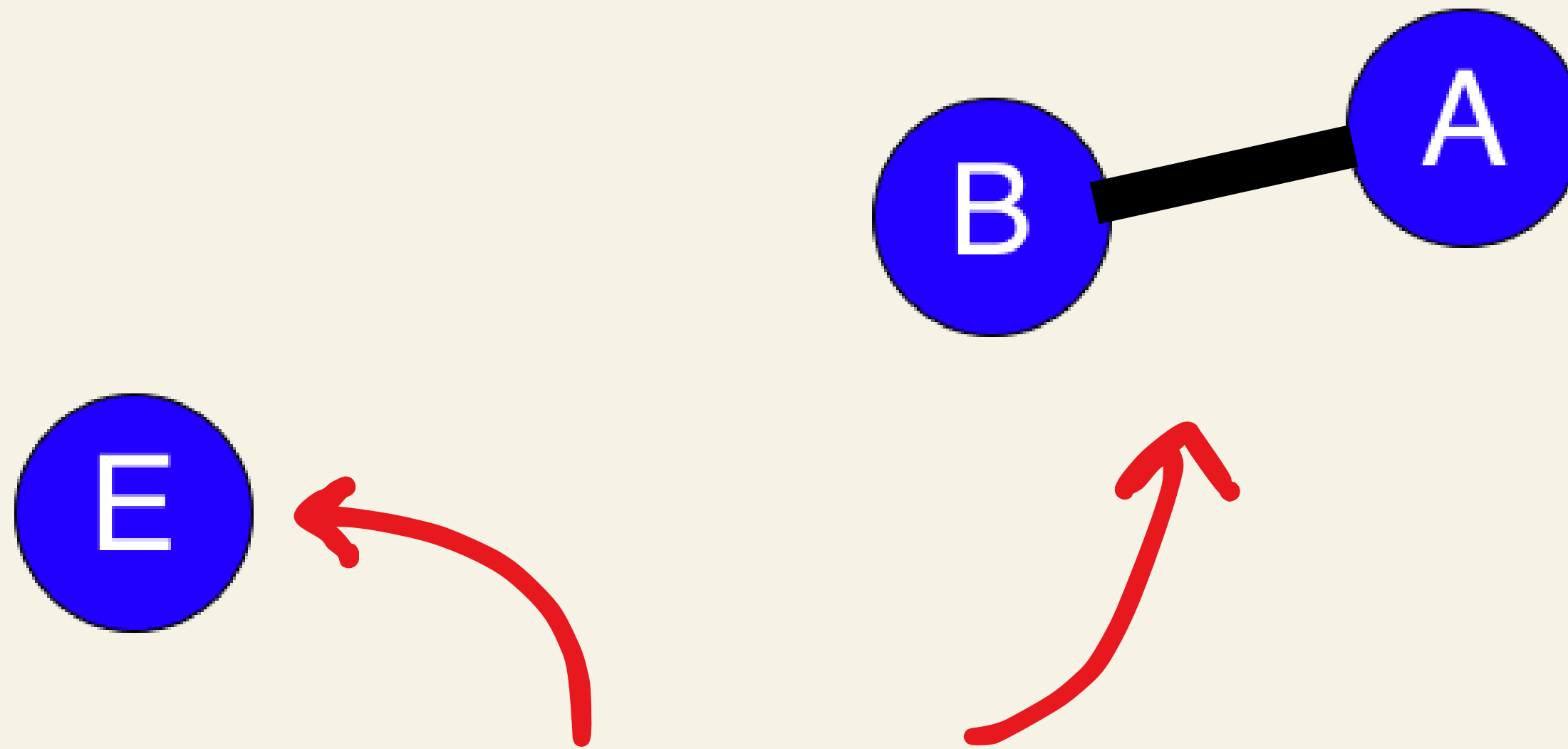




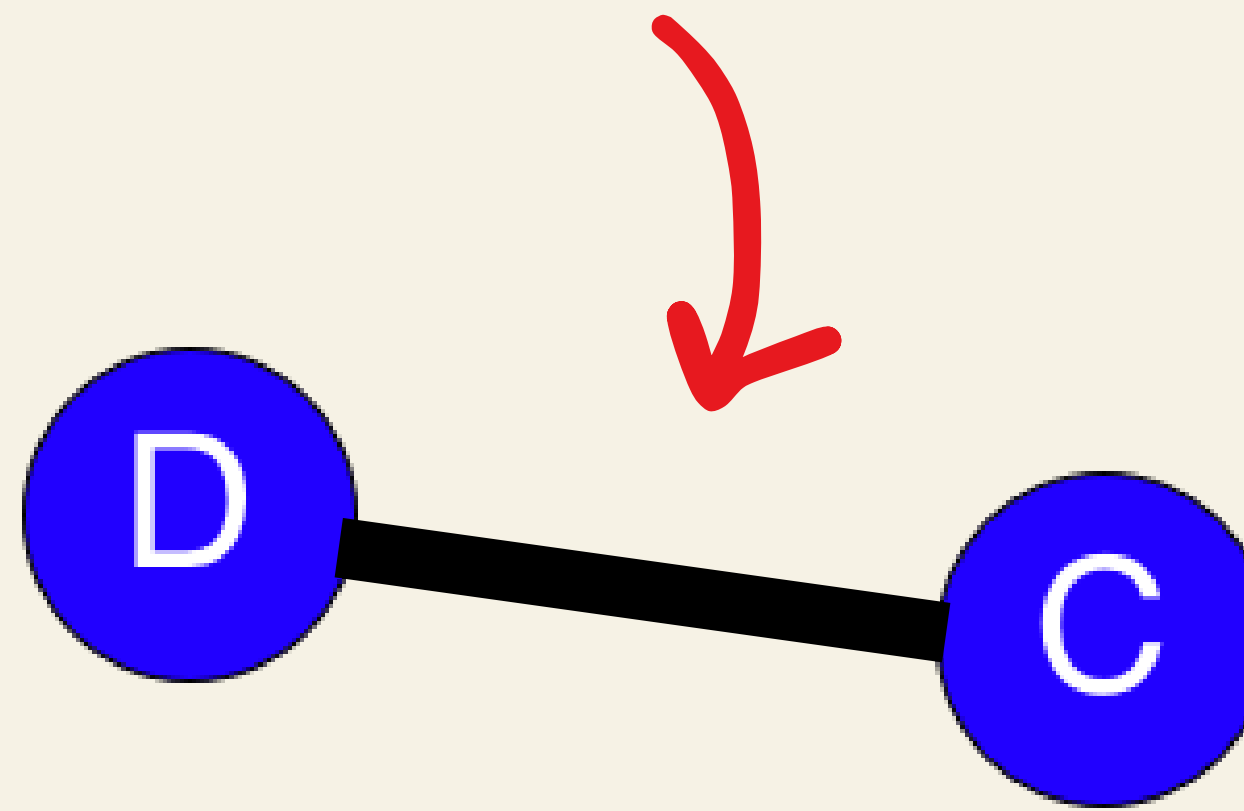


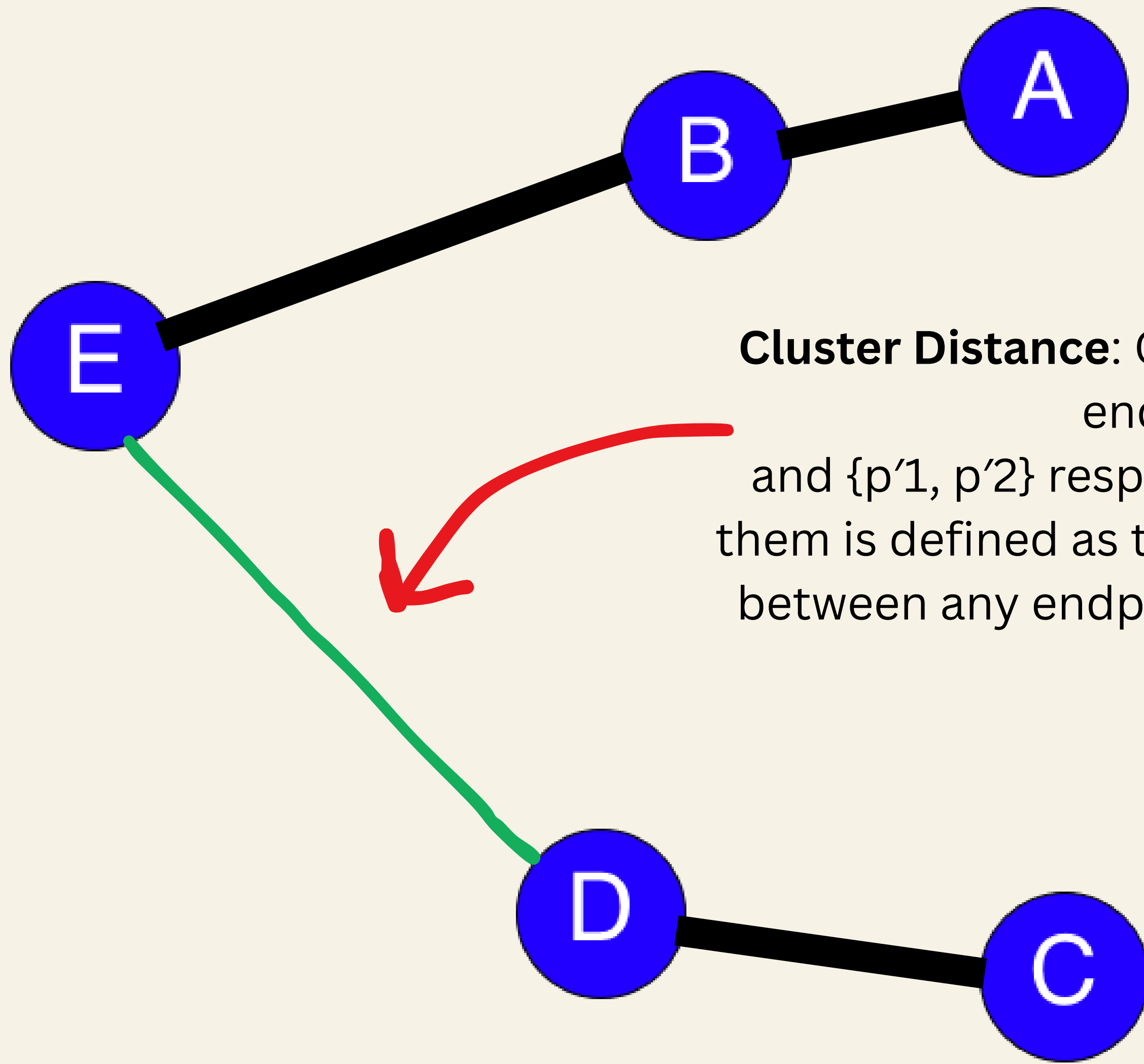




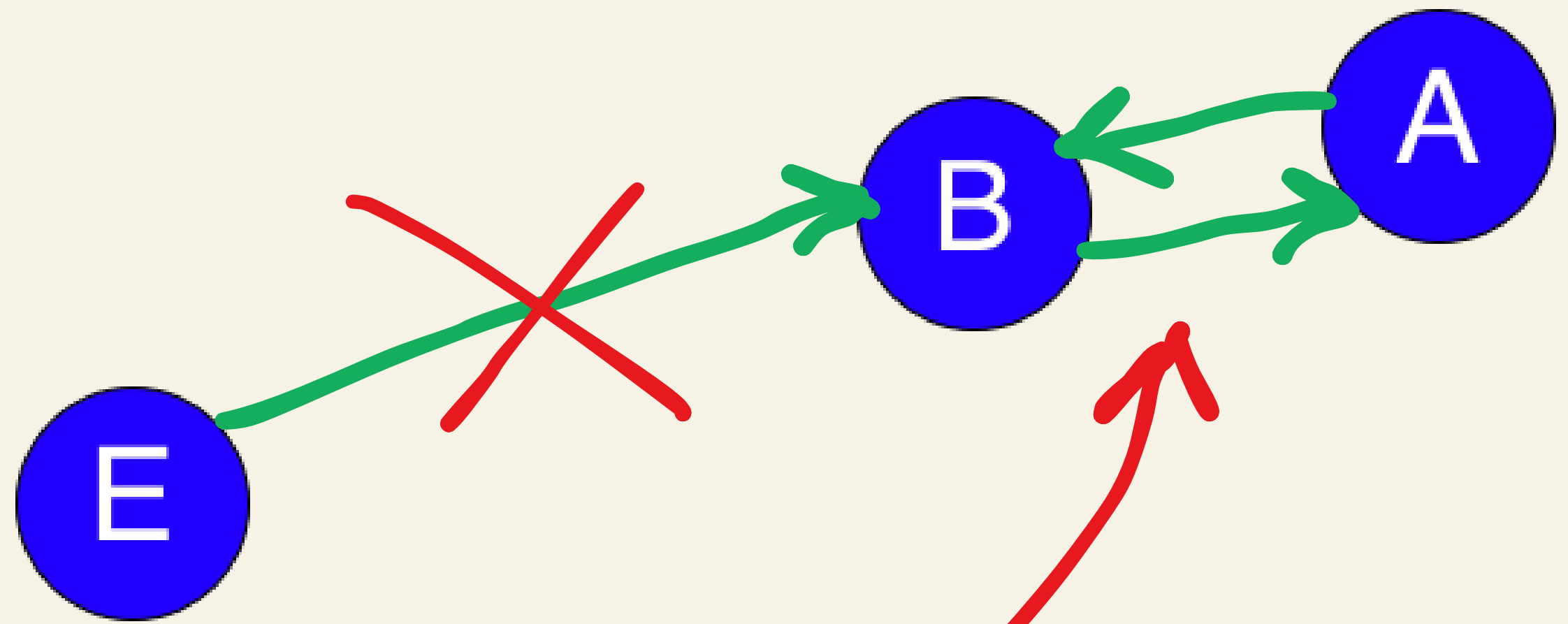


Cluster: A cluster (or path) is a sequence of points $(p_1, p_2, \dots, p_n)$ connected by edges, where p_1 and p_n are the endpoints of the cluster.

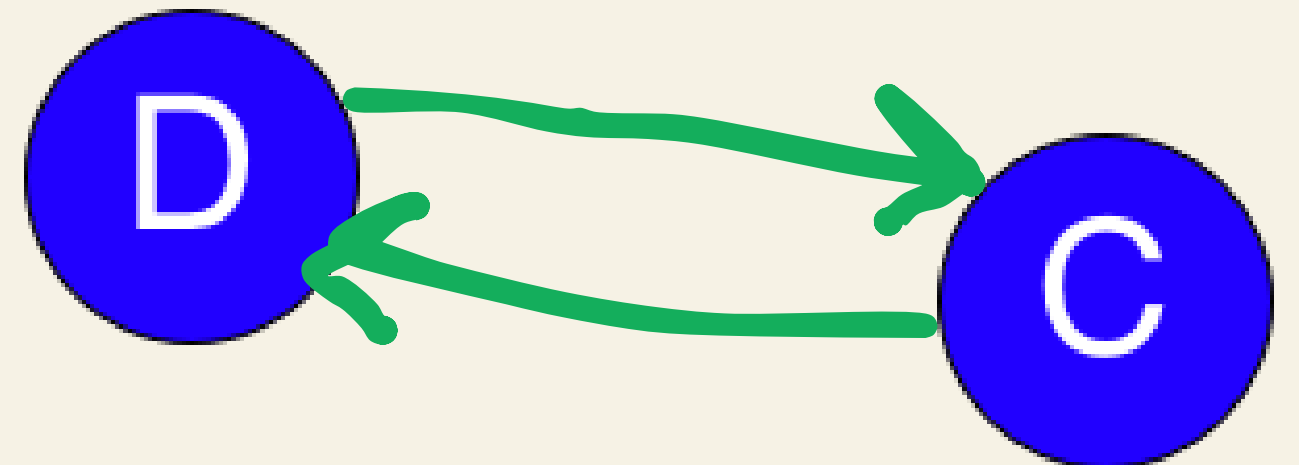
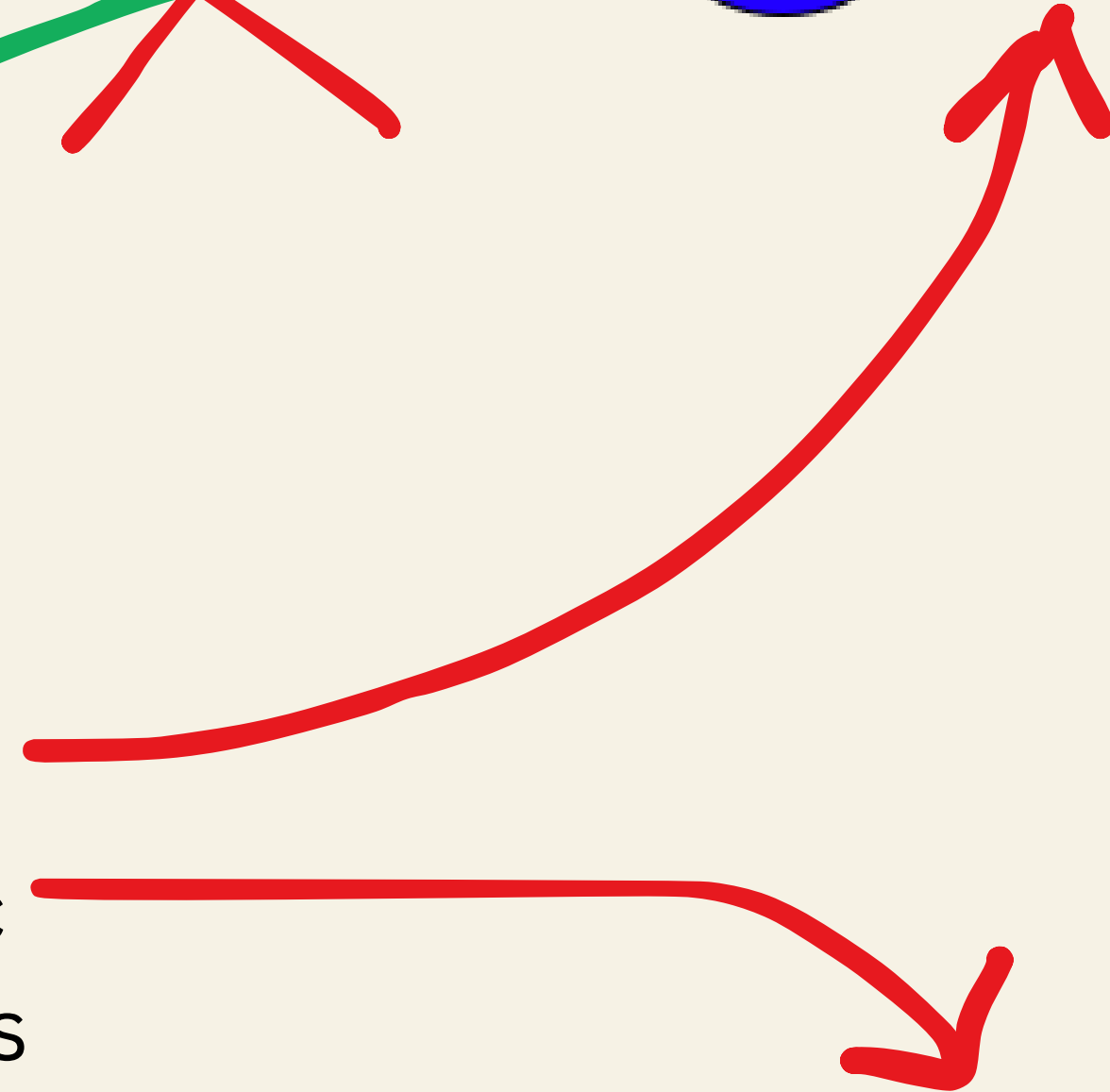


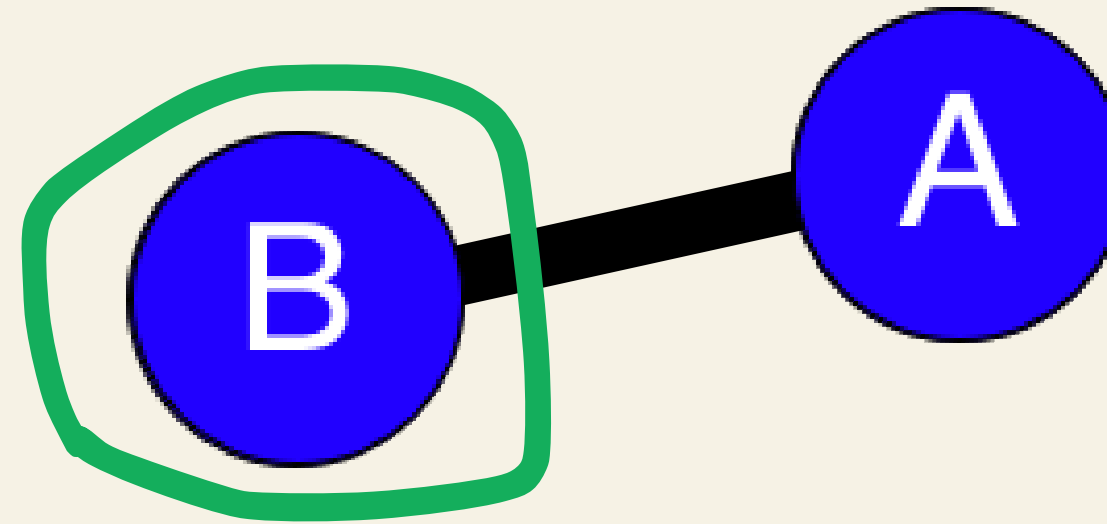
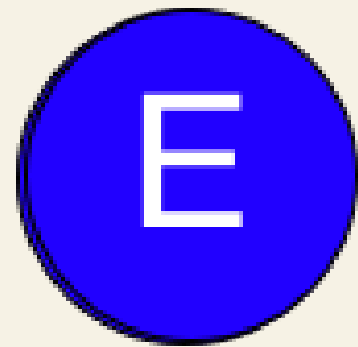


Cluster Distance: Given two clusters c and c' with endpoints $\{p_1, p_2\}$ and $\{p'_1, p'_2\}$ respectively, the distance between them is defined as the minimum Euclidean distance between any endpoint of c and any endpoint of c'

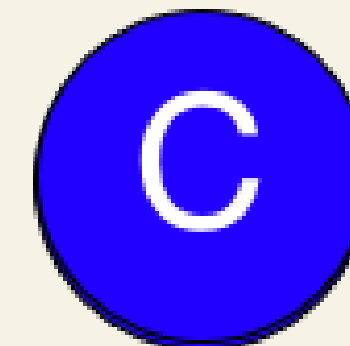
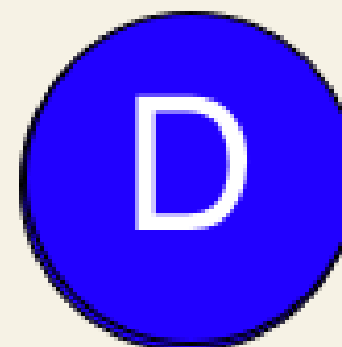
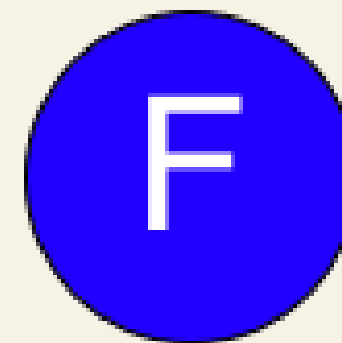


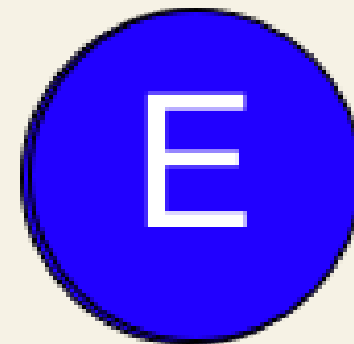
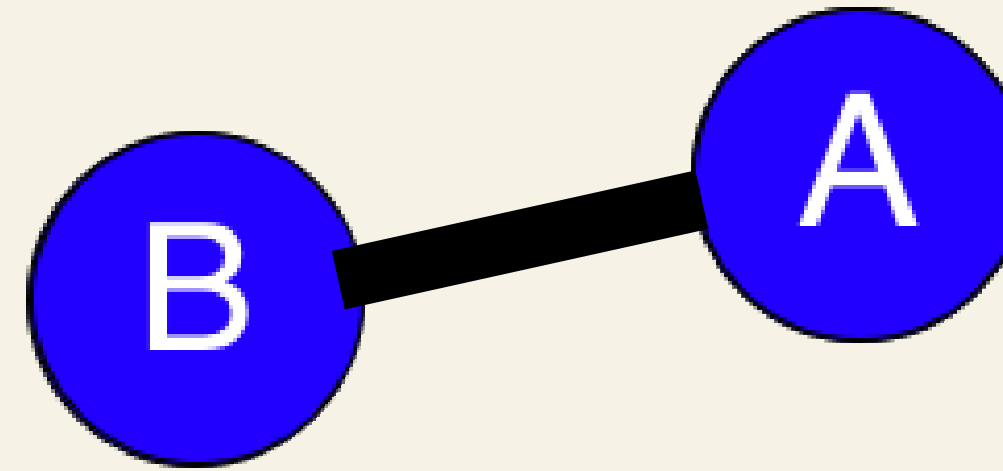
Mutually Nearest Neighbors: A nearest neighbor of a cluster is the cluster with minimum cluster distance to it. Clusters c and c' are mutually nearest neighbors if c 's nearest neighbor is c' and c 's nearest neighbor is c .



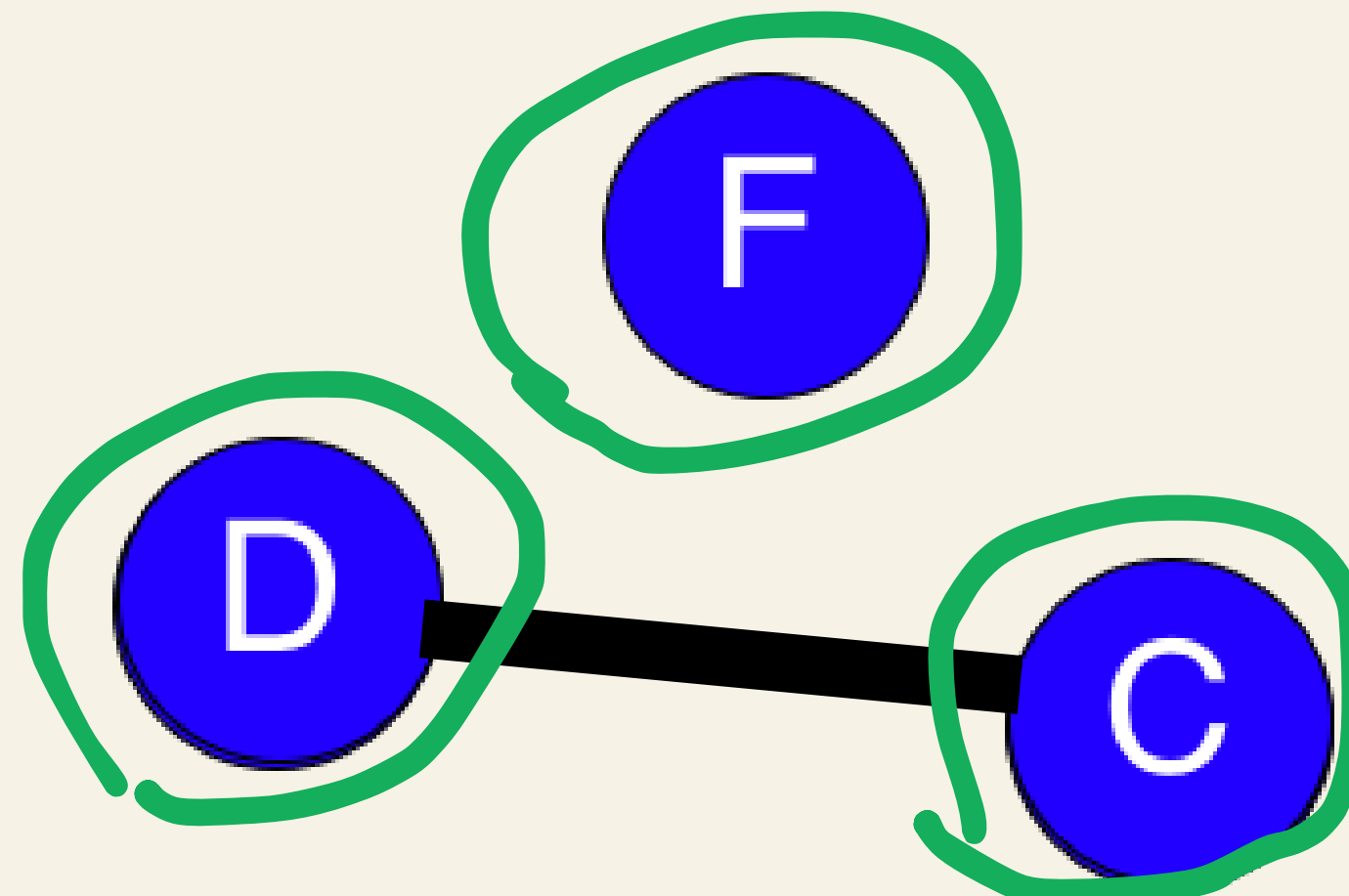


Hard answer: A single point that is the nearest neighbor of the input point.





Soft answer: Three points that are mutually closer to each other than the input point is to its nearest neighbor.



Algorithm Structure

- Multifragment
 - NextCluster
 - Naive Approach
 - Soft Answers (QueryCluster)
 - SNNQuery

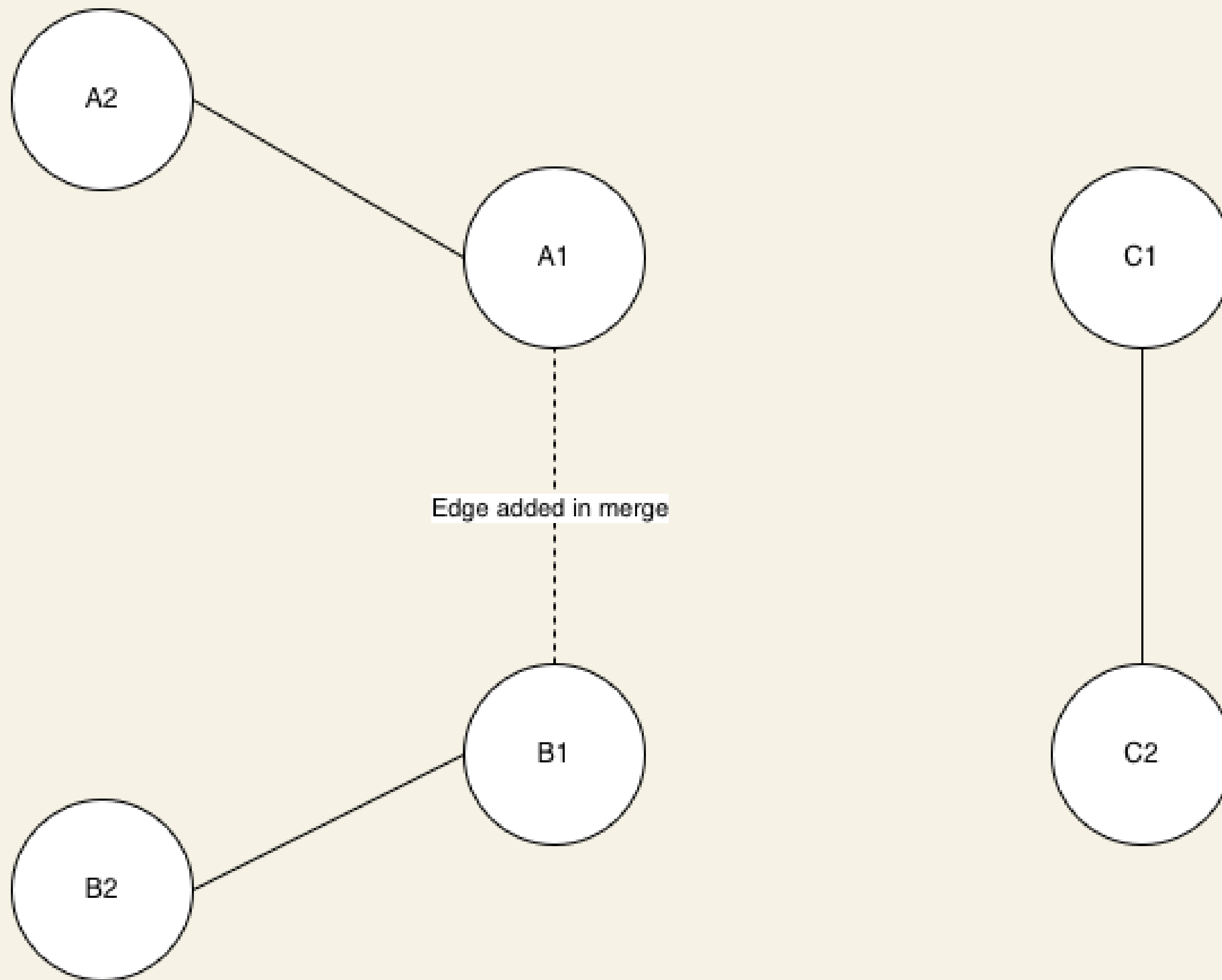
Global Local Equivalence

- Assuming that there are no ties in the pairwise distances between clusters, the two strategies for picking nearest neighbors produce the same tour.
- Requires **reducibility** and **monotonic decrease**

Reducibility

Lemma 6 (Reducibility) *Let A , B , and C be three distinct clusters, and let $A \cup B$ denote the cluster formed by merging A and B . Then*

$$d(A \cup B, C) \geq \min(d(A, C), d(B, C)).$$



Monotonic Decrease

Lemma 7 (Strict Monotonic Decrease along a Chain) *Let $c_1, c_2, \dots, c_k$ be a chain, where c_{i+1} is the nearest neighbor of c_i for every i . Under the no-ties assumption,*

$$d(c_1, c_2) > d(c_2, c_3) > \dots > d(c_{k-1}, c_k).$$

Chain Must End

$d(A, B) > d(B, C) > d(C, A) >$
 $d(A, B)$, which is a contradiction. $d(A, B)$
cannot be greater than $d(A, B)$.

Multifragment

Algorithm 2.1: MULTIFRAGMENT

Require: Point set P with $|P| = n$, neighbor count k , approximation factor ε

Ensure: Tour edge set E

```
1:  $\mathcal{C} \leftarrow \{ \{p\} : p \in P \}$ 
2:  $E \leftarrow \emptyset$ ;  $S \leftarrow$  empty stack
3: while  $|\mathcal{C}| > 1$  do
4:   if  $S$  is empty then
5:     push  $(c, \perp)$  onto  $S$  for an arbitrary  $c \in \mathcal{C}$ 
6:     continue
7:    $(u, v) \leftarrow \text{top}(S)$ 
8:    $(a, b) \leftarrow \text{NEXTCLUSTER}(u, v)$ 
9:   if  $v \neq \perp$  and  $\{a, b\} = \{u, v\}$  then
10:    pop  $S$ 
11:    if  $S$  nonempty and top of  $S$  contains  $u$  or  $v$  then
12:      pop  $S$ 
13:    merge  $u$  and  $v$  into a new cluster in  $\mathcal{C}$ , add the connecting edge to  $E$ 
14:   else
15:     push  $(a, b)$  onto  $S$ 
16: add the closing edge between the endpoints of the final path to  $E$ 
17: return  $E$ 
```

Multifragment

Table 2.1: Trace of the multifragment heuristic on Figure 2.1.

Step	Action	Stack
0	initialize	$[\]$
1	push $(A, \perp)$	$[(A, \perp)]$
2	$NN(A) = B$; push (A, B)	$[(A, \perp), (A, B)]$
3	$NN(B) = A$: merge AB ; add edge AB	$[\]$
4	push $(C, \perp)$	$[(C, \perp)]$
5	$NN(C) = D$; push (C, D)	$[(C, \perp), (C, D)]$
6	$NN(D) = C$: merge CD ; add edge CD	$[\]$
7	push $(E, \perp)$	$[(E, \perp)]$
8	$NN(E) = AB$; push (E, AB)	$[(E, \perp), (E, AB)]$
9	$NN(AB) = E$: merge ABE ; add edge BE	$[\]$
10	push $(ABE, \perp)$	$[(ABE, \perp)]$
11	$NN(ABE) = CD$; push (ABE, CD)	$[(ABE, \perp), (ABE, CD)]$
12	$NN(CD) = ABE$: merge; add edge ED	$[\]$
13	close: add edge AC	$[\]$

NextCluster

Algorithm 2.2: NEXTCLUSTER (*naive variant, hard answers only*)

Require: Cluster pair (u, v) , where v may be $\perp$

Ensure: Candidate cluster pair (a, b)

1: **if** $v = \perp$ **then**

2: $c \leftarrow u$

3: **else**

4: $c \leftarrow v$

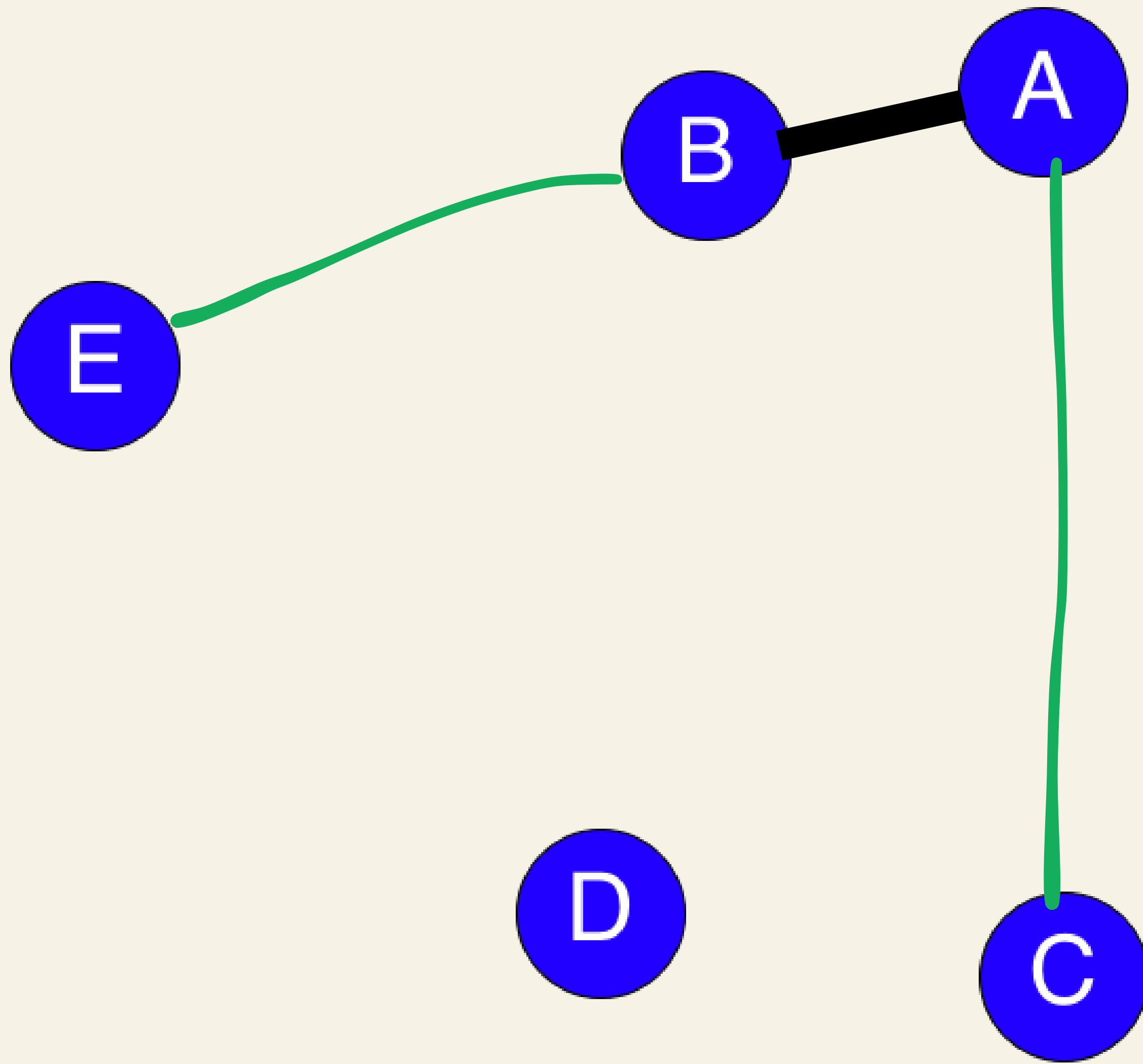
5: $(q_1, q_2) \leftarrow$ endpoints of c

6: $p_1 \leftarrow$ exact nearest neighbor of q_1 in (active points $\setminus \{q_1, q_2\}$)

7: $p_2 \leftarrow$ exact nearest neighbor of q_2 in (active points $\setminus \{q_1, q_2\}$)

8: $p^* \leftarrow$ whichever of p_1, p_2 is closer to its query point

9: **return** $(c, \text{cluster}(p^*))$



NextCluster

Algorithm 2.3: NEXTCLUSTER (soft variant)

Require: Cluster pair (u, v) , where v may be $\perp$

Ensure: Candidate cluster pair (a, b)

- 1: $M \leftarrow \{u\} \cup \text{QUERYCLUSTER}(u)$
 - 2: **if** $v \neq \perp$ **then**
 - 3: $M \leftarrow M \cup \{v\} \cup \text{QUERYCLUSTER}(v)$
 - 4: **return** $\arg \min_{\{x, y\} \subseteq M} d(x, y)$
-

QueryCluster

Algorithm 2.4: QUERYCLUSTER

Require: Cluster c with endpoints q_1, q_2 , active point set P , neighbor count k , approximation factor ε

Ensure: Set $\mathcal{S}$ of candidate cluster IDs

- 1: $A_1 \leftarrow \text{SNNQUERY}(q_1, P \setminus \{q_1, q_2\}, k, \varepsilon)$
 - 2: $A_2 \leftarrow \text{SNNQUERY}(q_2, P \setminus \{q_1, q_2\}, k, \varepsilon)$
 - 3: **return** $\{ \text{cluster}(p) : p \in A_1 \cup A_2, \text{cluster}(p) \neq c \}$
-

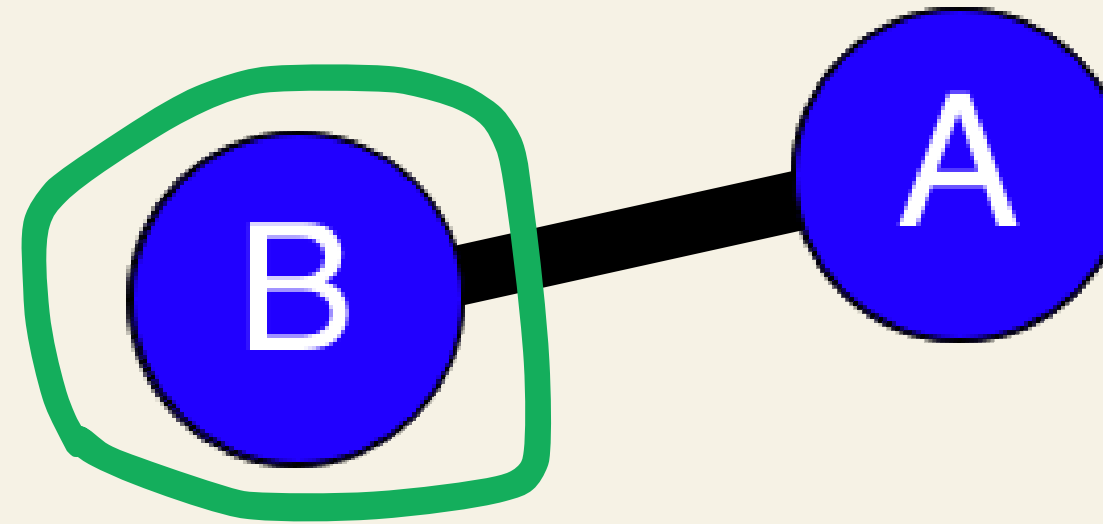
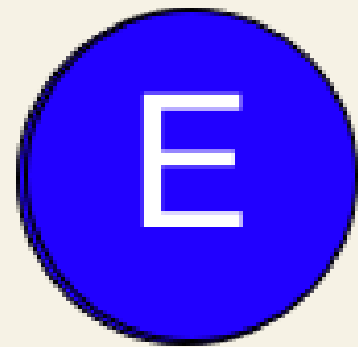
SNNQuery

Algorithm 2.5: SNNQUERY

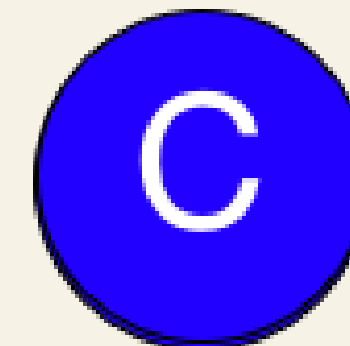
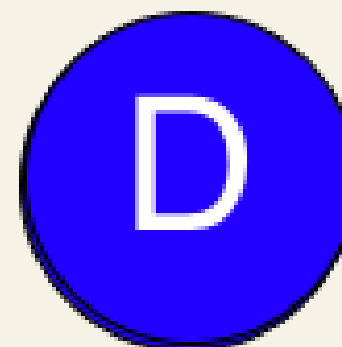
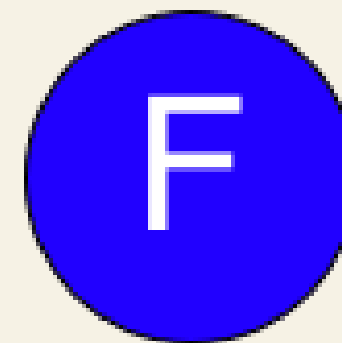
Require: Query point q , point set P , neighbor count k , approximation factor ε

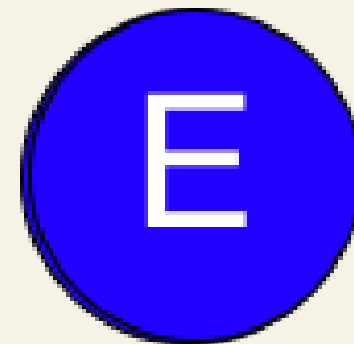
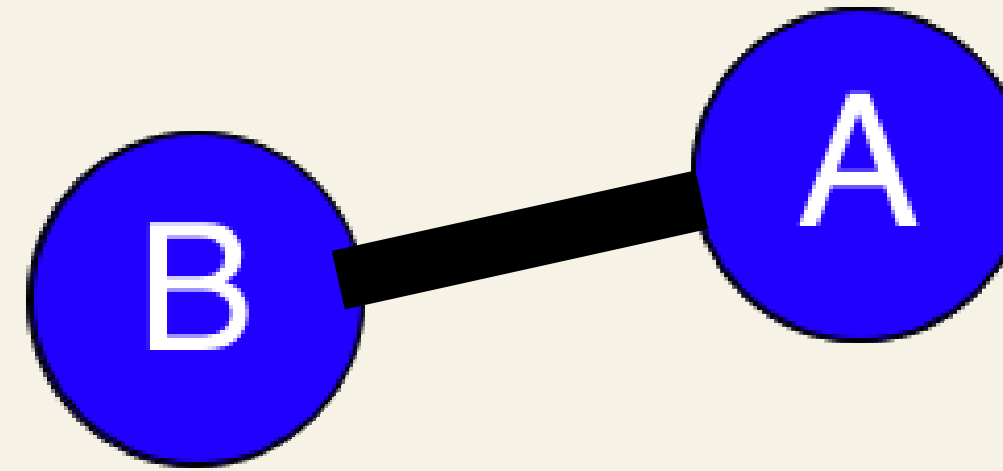
Ensure: A hard answer $p^* \in P$, or a soft answer $\{a, b, c\} \subseteq P$ with pairwise distances all less than $d(q, p^*)$

- 1: $N \leftarrow (1 + \varepsilon)$ -approximate k nearest neighbors of q in P
 - 2: $p^* \leftarrow \arg \min_{p \in N} d(q, p)$
 - 3: $d^* \leftarrow d(q, p^*)$
 - 4: **for all** triples $\{a, b, c\} \subseteq N$ **do**
 - 5: **if** $d(a, b) < d^*$ **and** $d(a, c) < d^*$ **and** $d(b, c) < d^*$ **then**
 - 6: **return** soft answer $\{a, b, c\}$
 - 7: **return** hard answer p^*
-

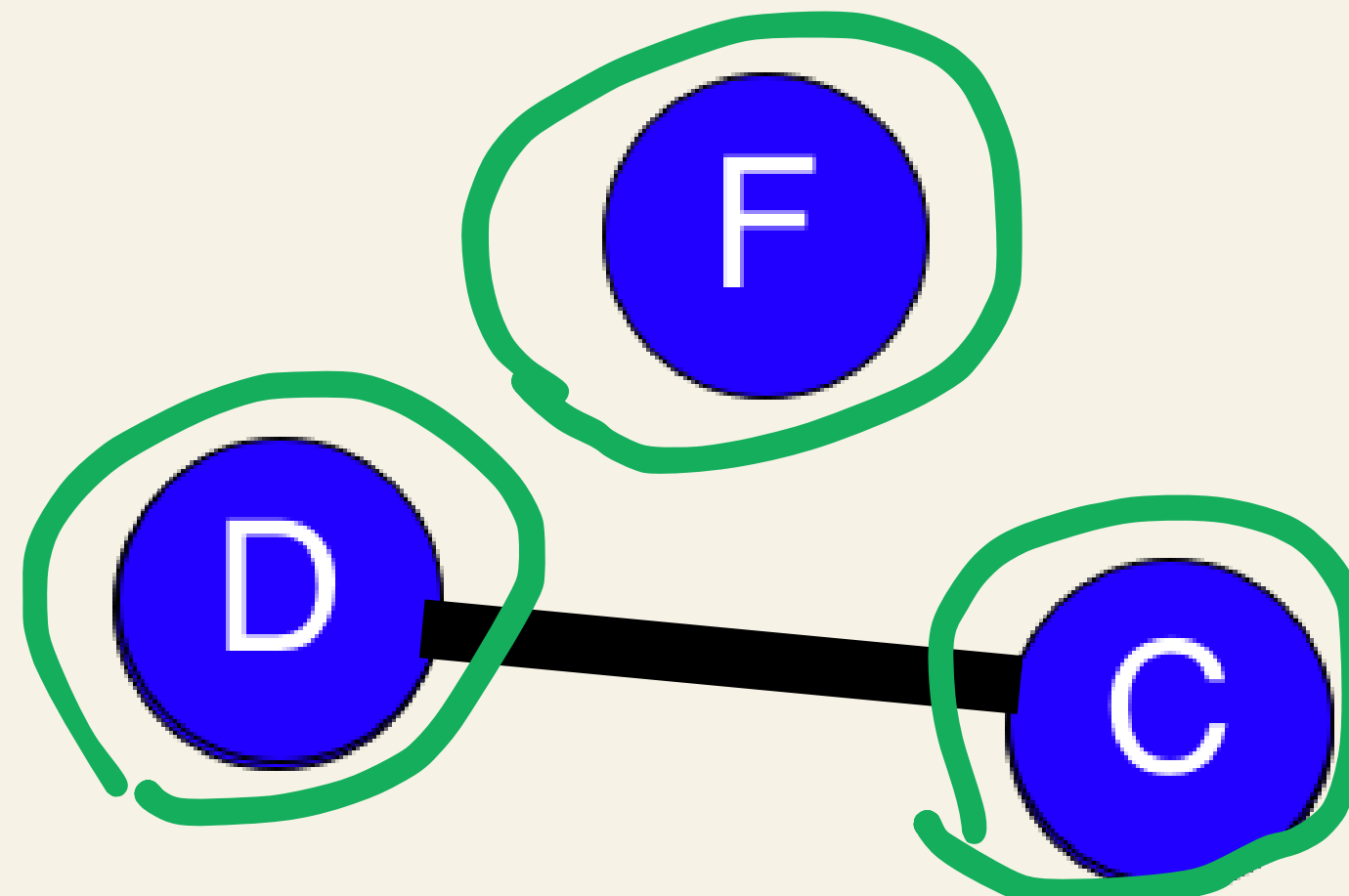


Hard answer: A single point that is the nearest neighbor of the input point.



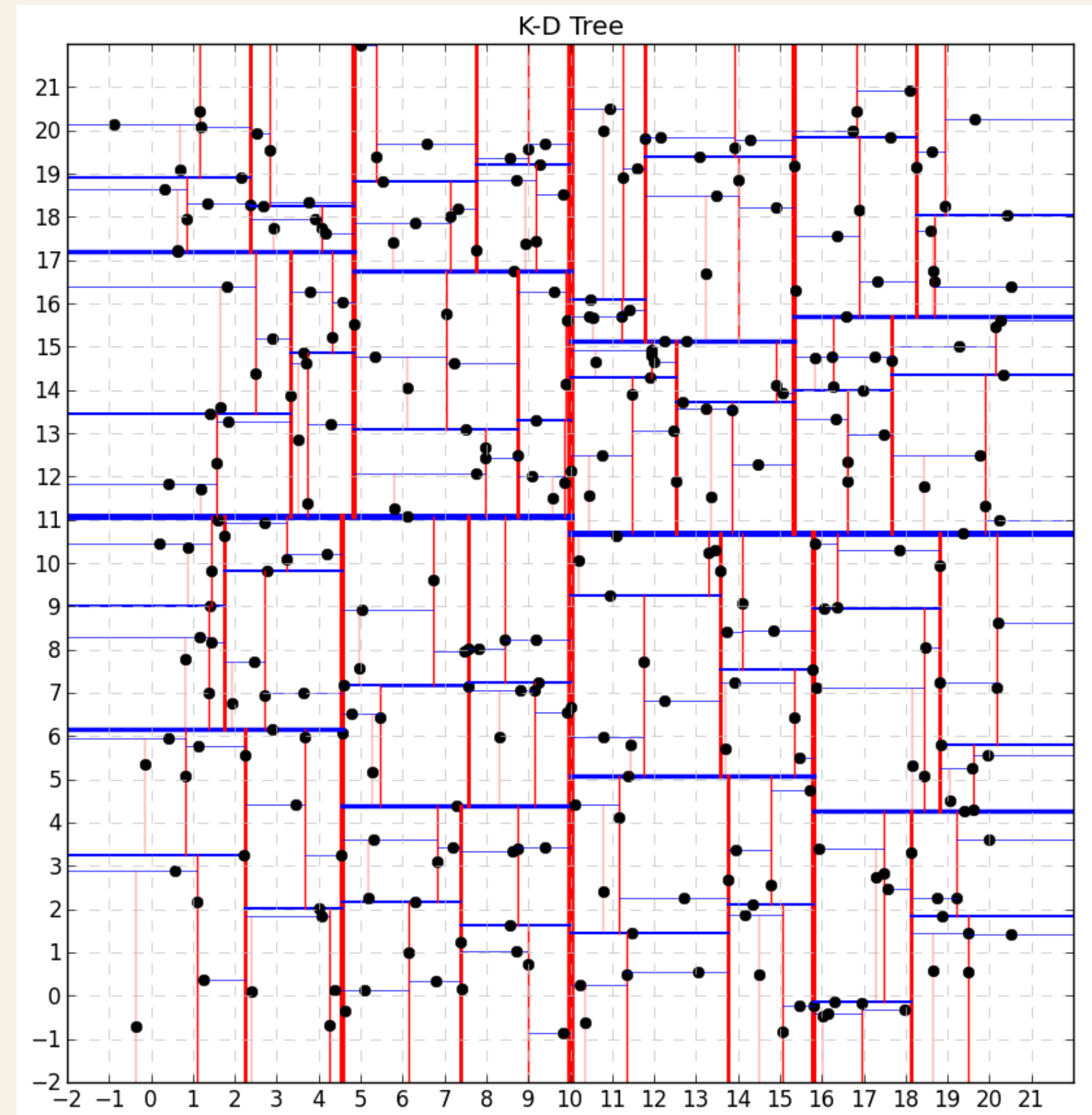


Soft answer: Three points that are mutually closer to each other than the input point is to its nearest neighbor.



ANN Data Structure

- KD Tree (split nodes)
- BD Tree (shrink nodes)
- k and ϵ



2-APPROXIMATION

4 Steps

- Minimum Spanning Tree (Prim's Algorithm)
- Double edges
- Eulerian Circuit (Hierholzer's Algorithm)
- Shortcut for Hamiltonian Tour

MINIMUM SPANNING TREE PRIM'S ALGORITHM

Minimum Spanning Tree

- A **minimum spanning tree** is a subset of edges in a graph that connects all vertices together without creating any cycles and with minimum total weight.

Distances

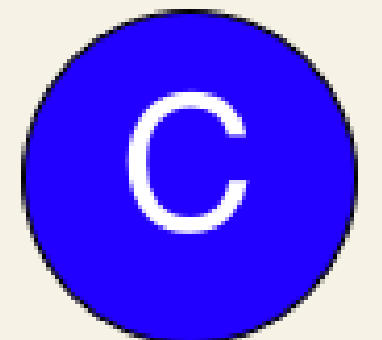
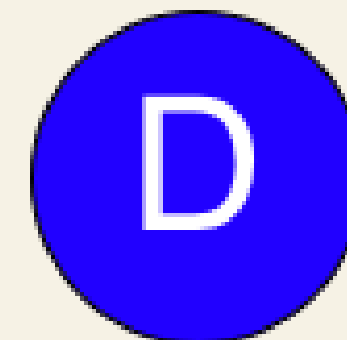
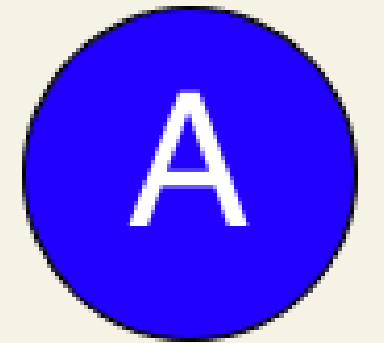
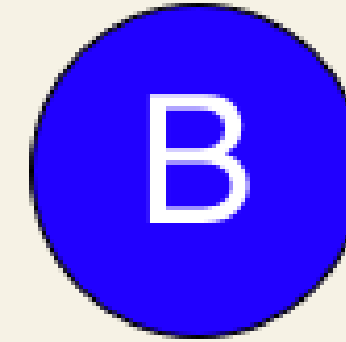
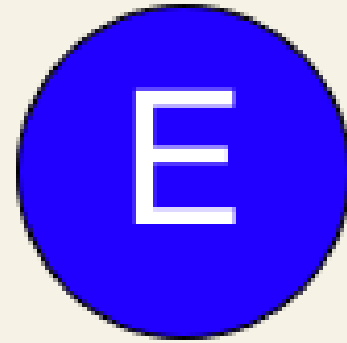
A: ∞

B: ∞

C: ∞

D: ∞

E: 0



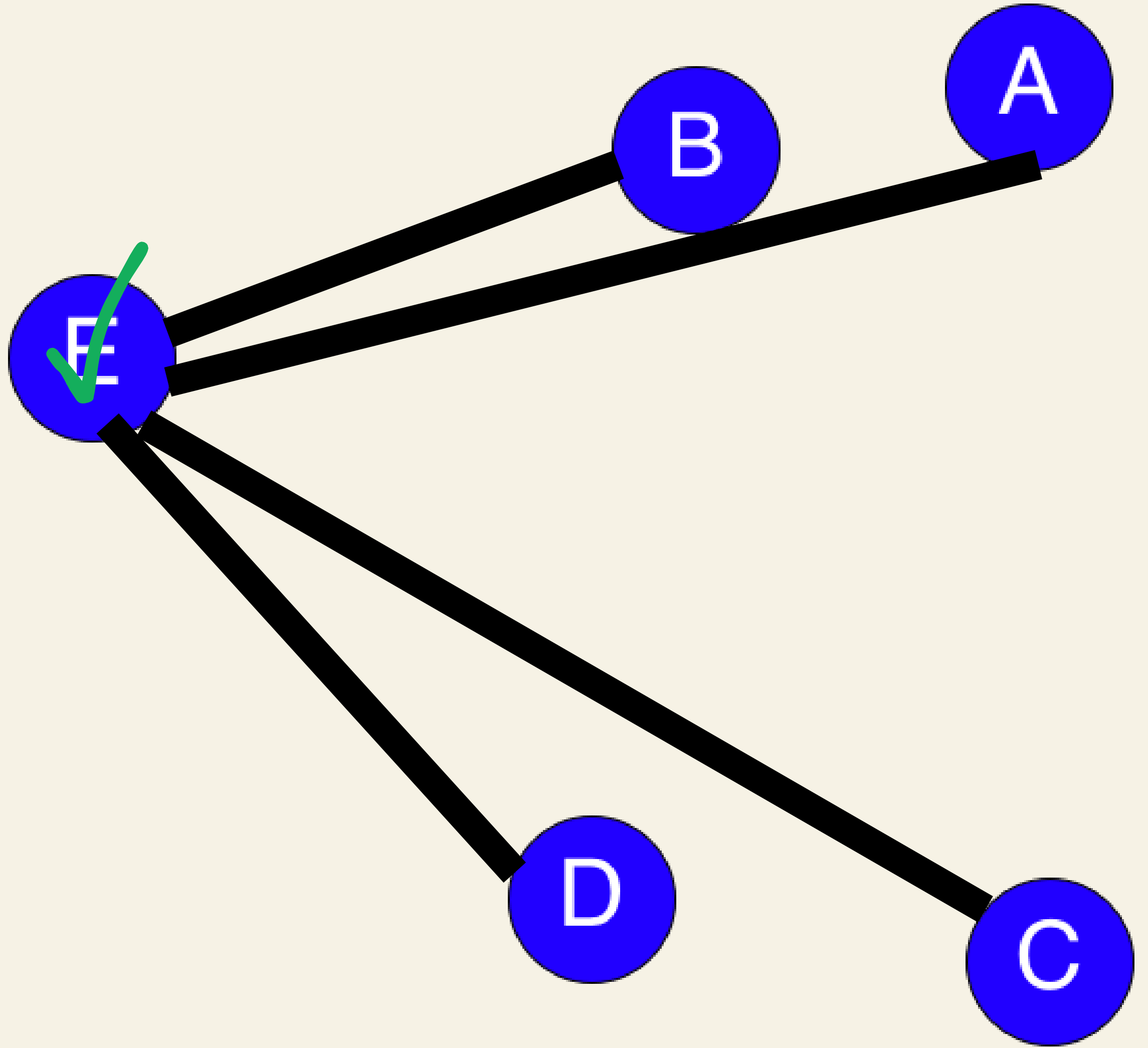
Distances

A: 6

B: 4

C: 7

D: 5



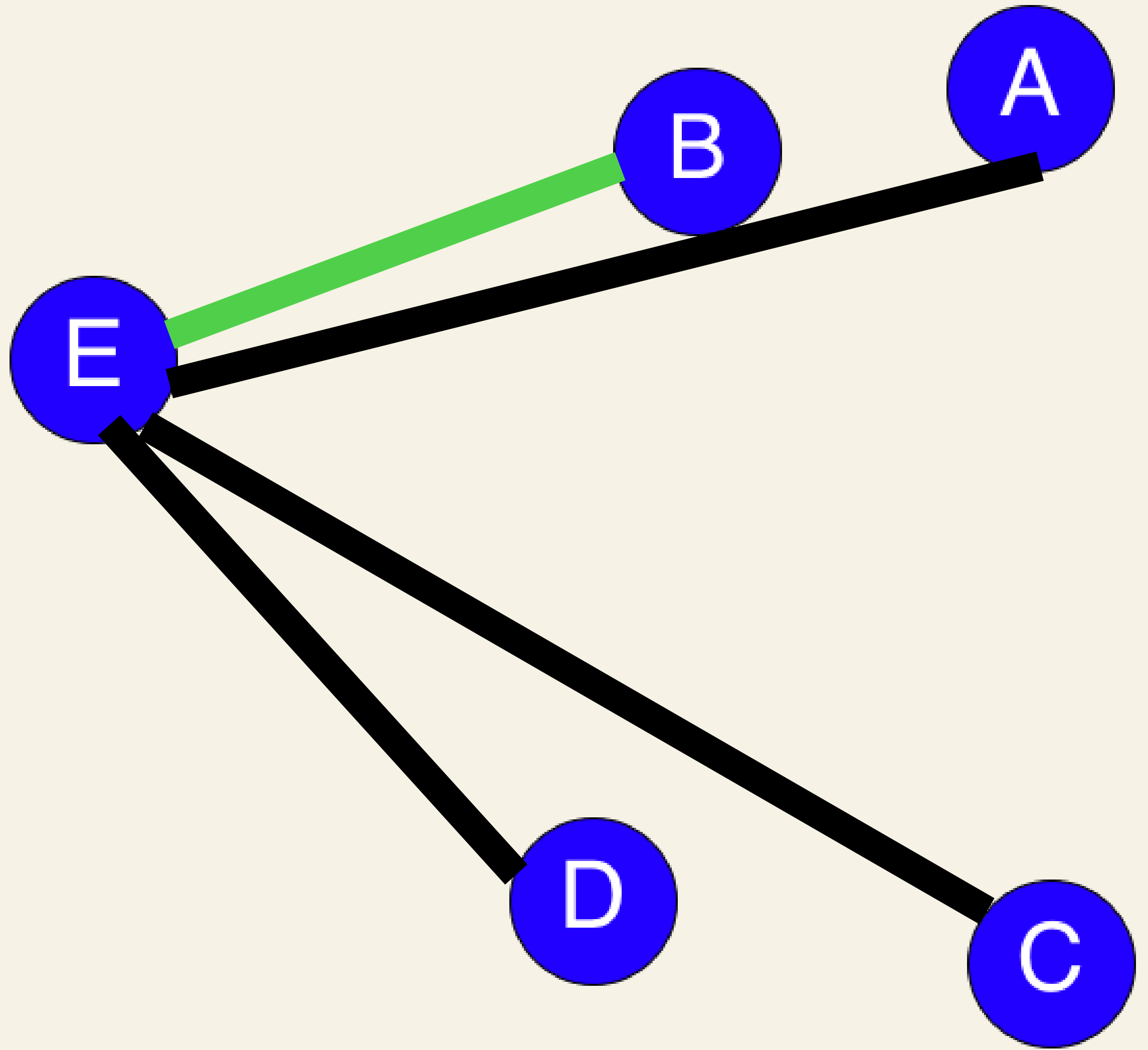
Distances

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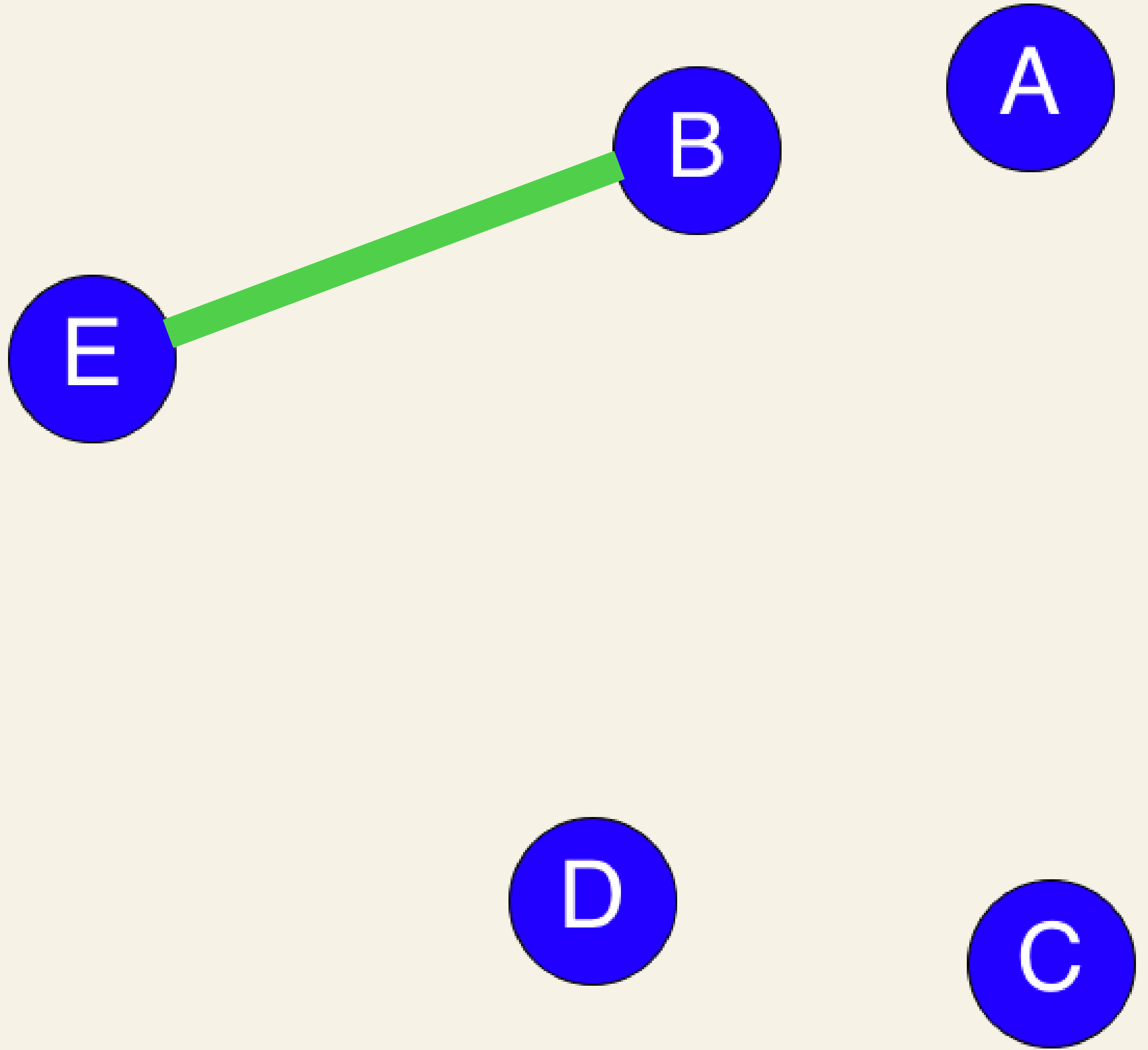
Distances

A: 6

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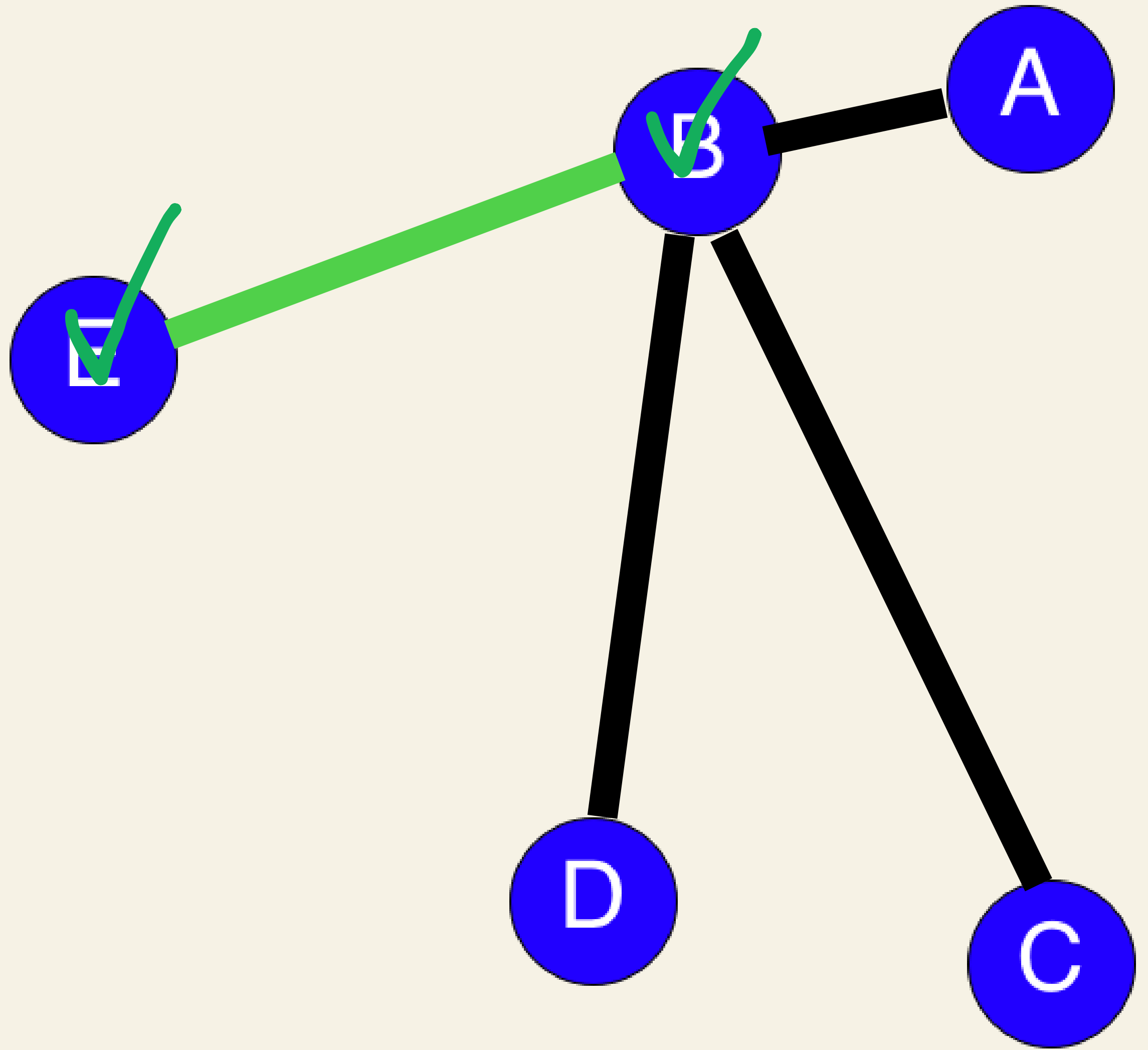


Distances

A: 2

C: 6.5

D: 5 (from E)

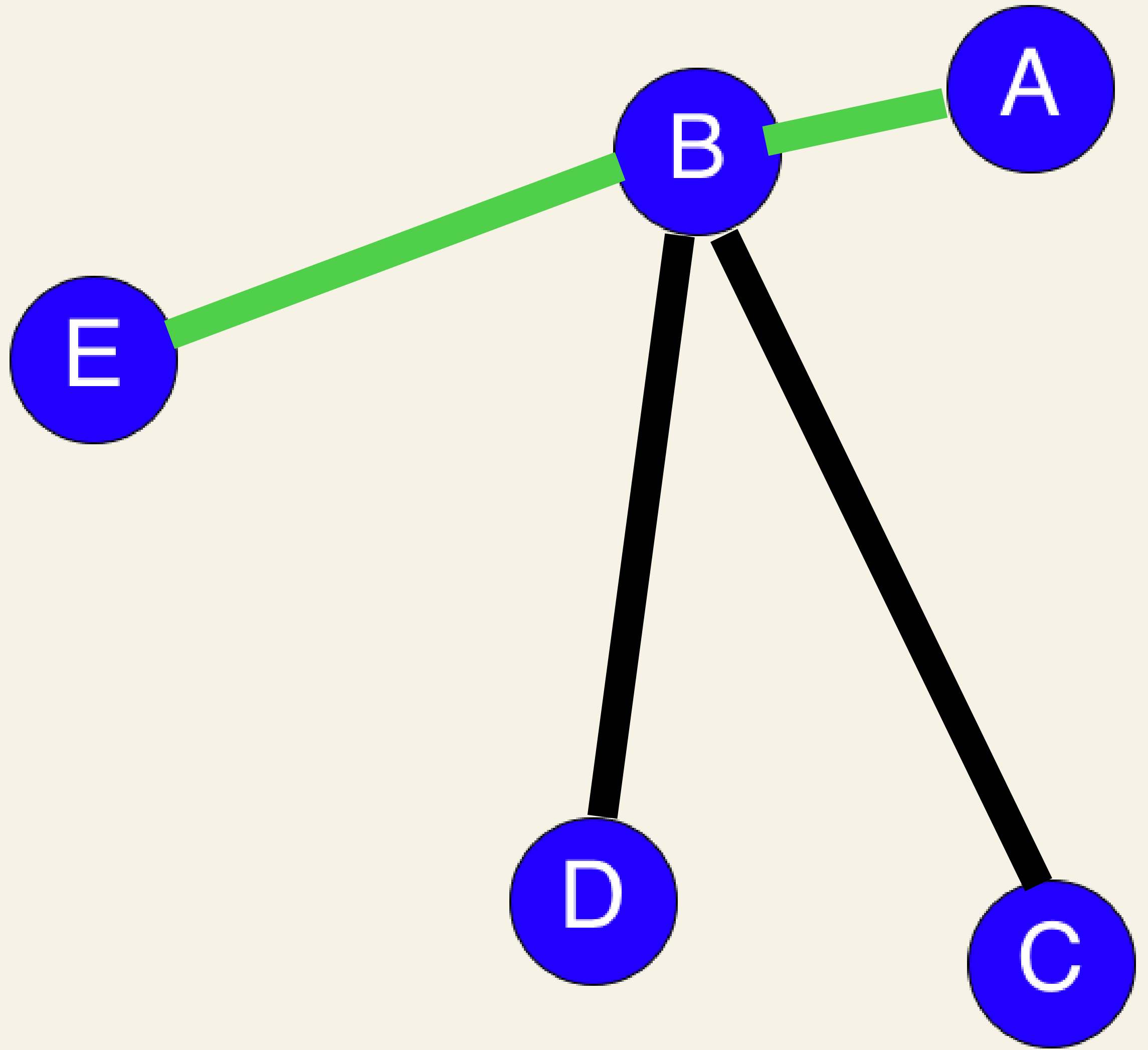


Distances

A: 2

C: 6.5

D: 5 (from E)

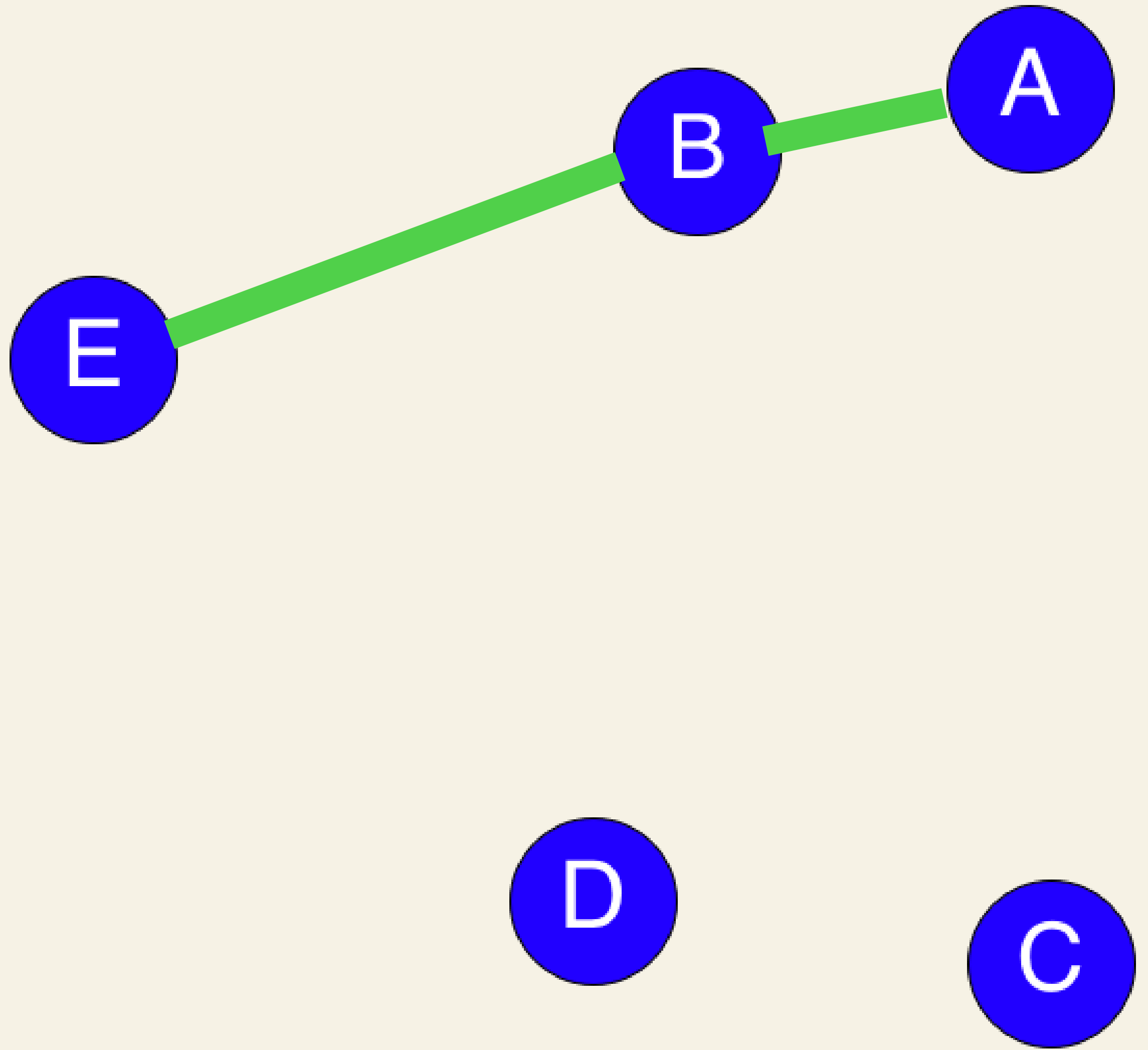


Distances

A: 2

C: 6.5

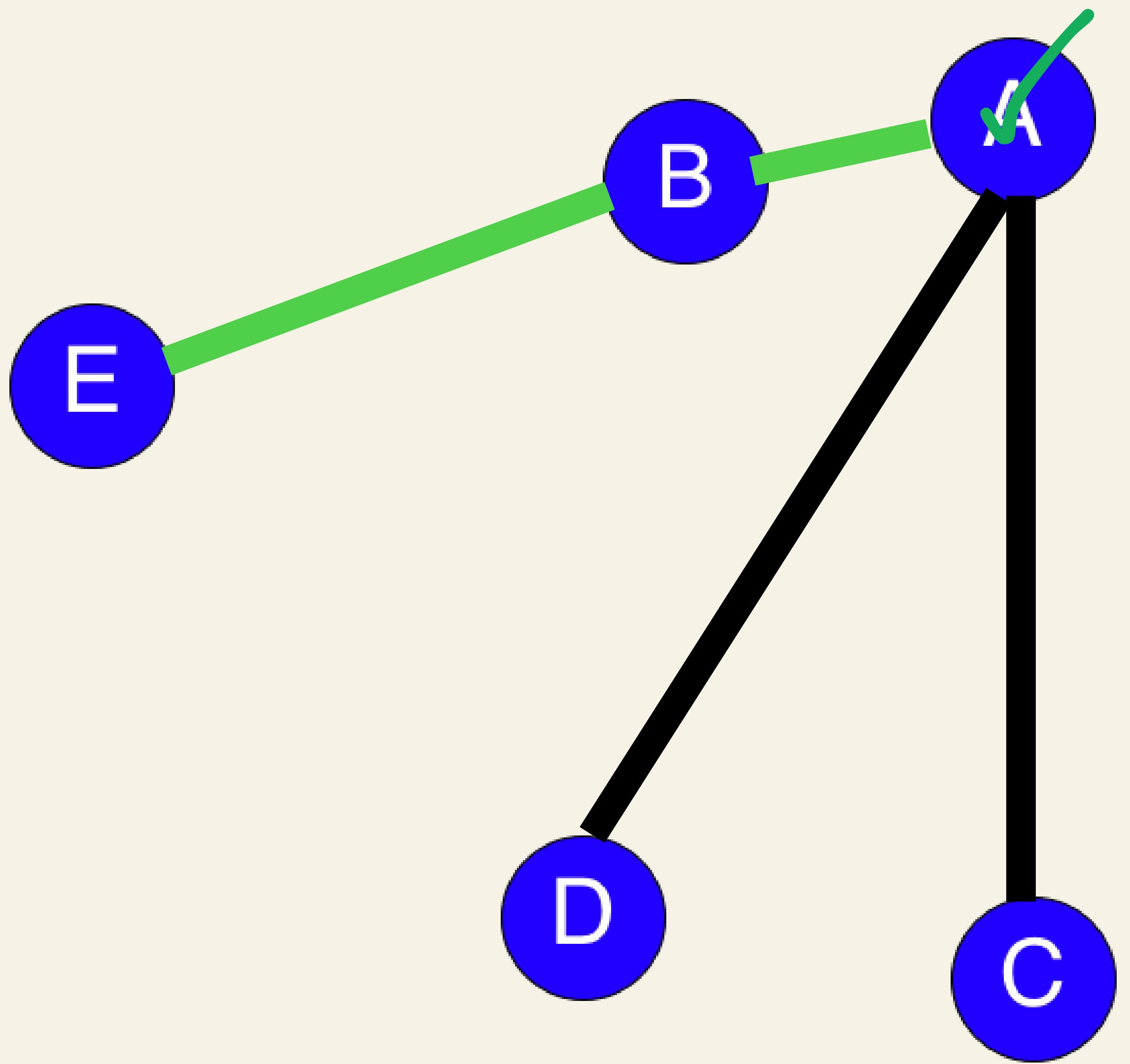
D: 5 (from E)



Distances

C: 6.5 (from B)

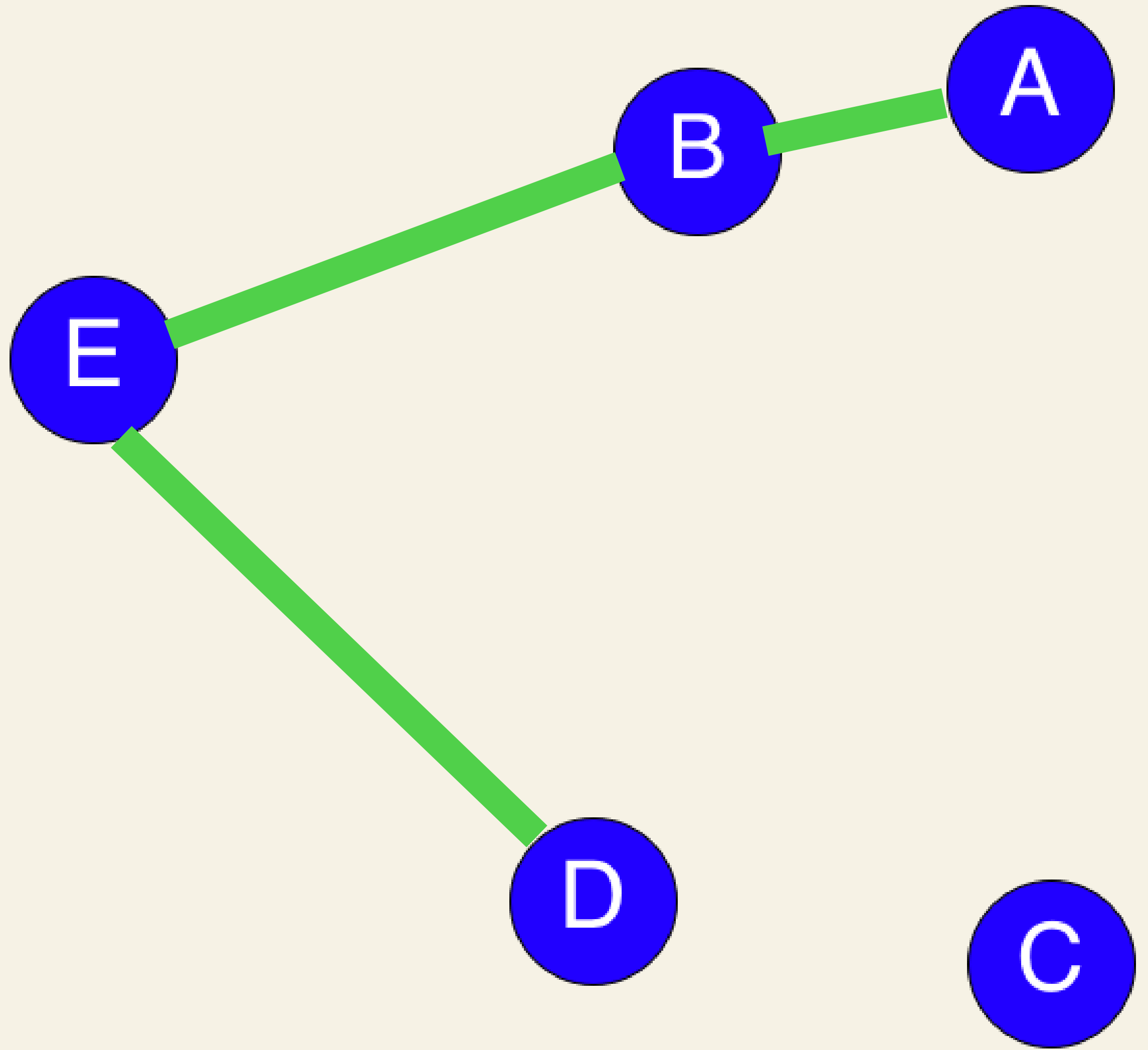
D: 5 (from E)



Distances

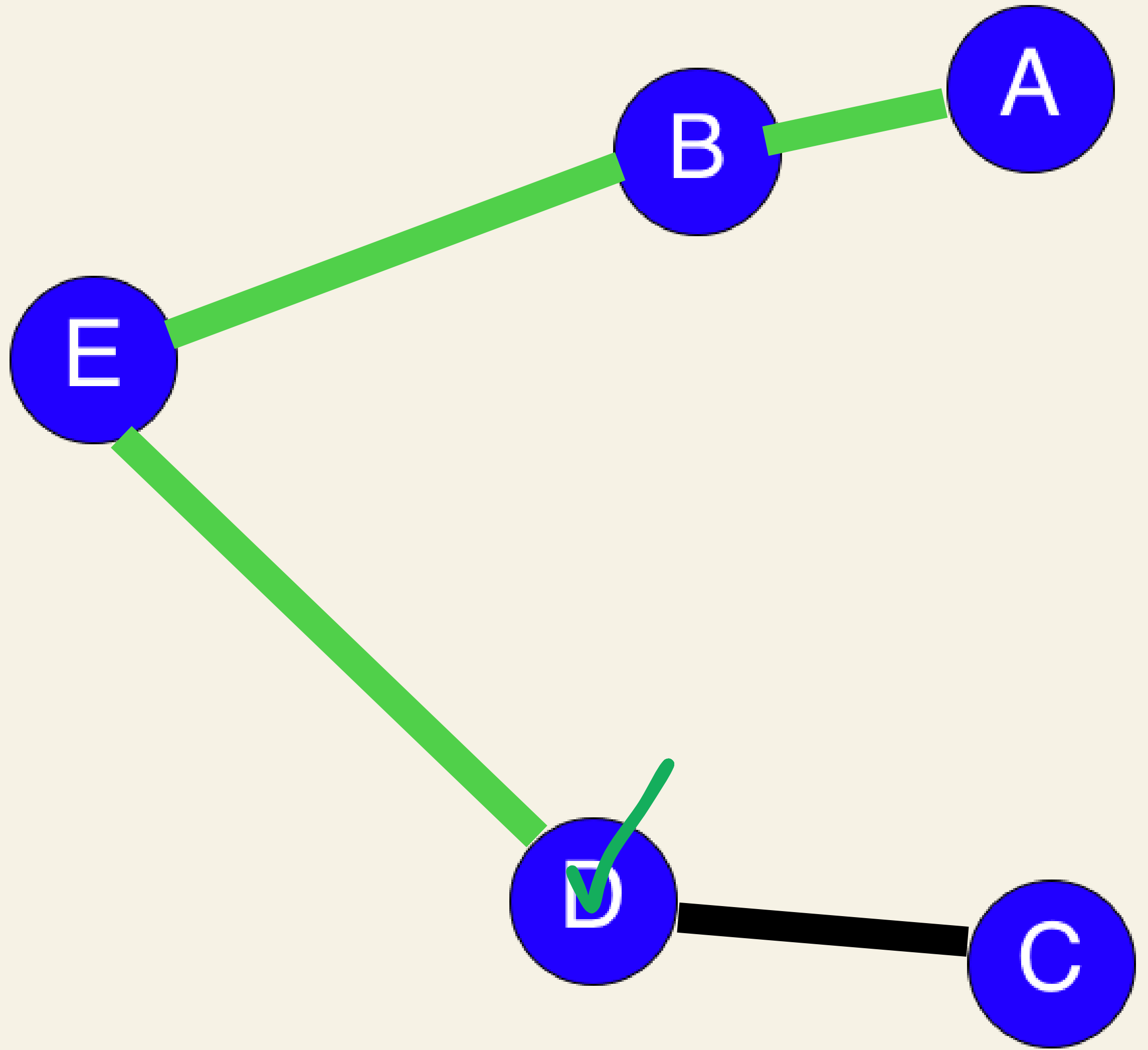
C: 6.5 (from B)

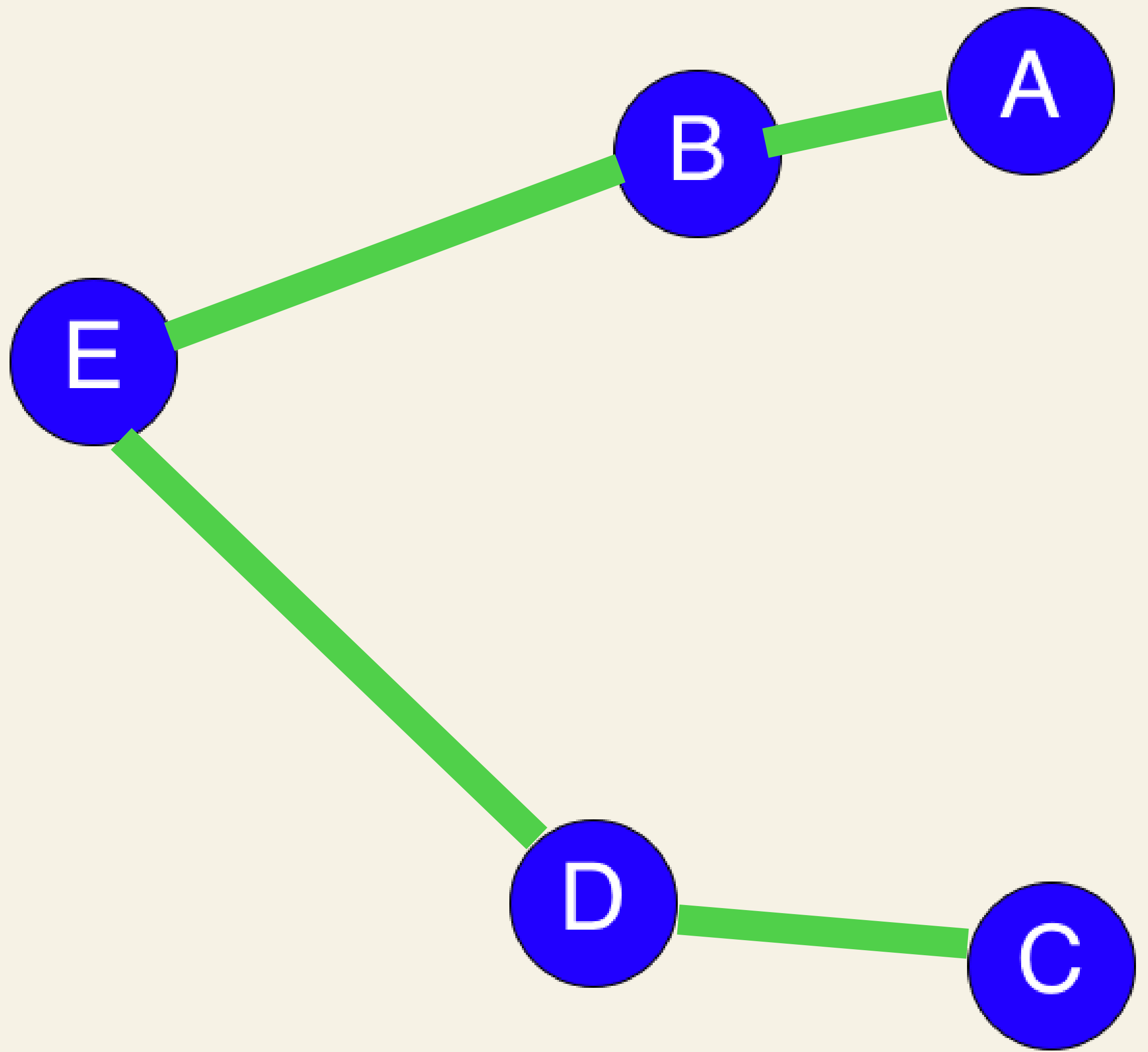
D: 5 (from E)



Distances

C: 2.5





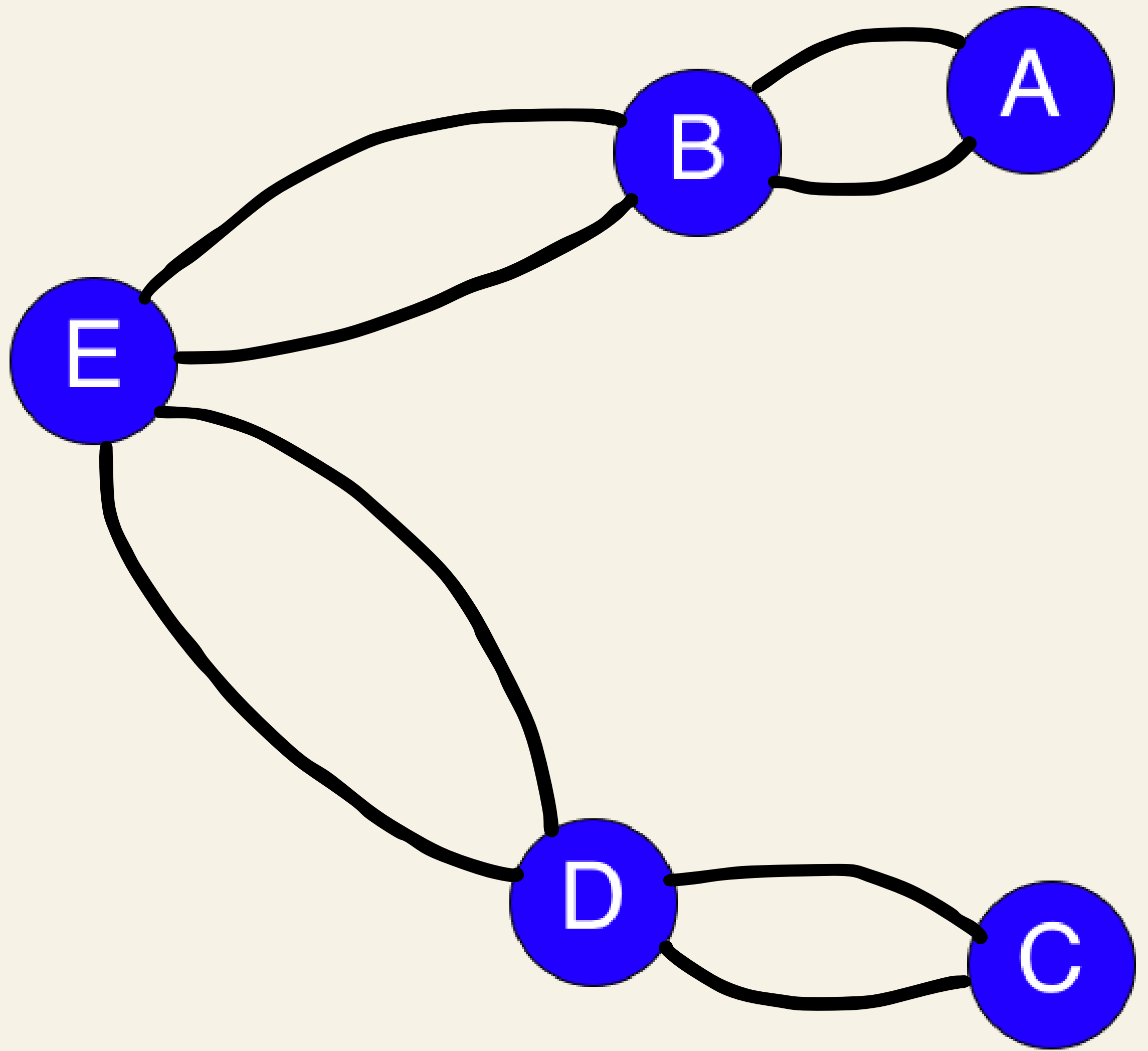
Complexity

- $O(n^2)$
- Bounds the whole algorithm
- MST is OPT for approximation

DOUBLING THE EDGES

Why do this?

- Even degree requirement
- Minimum Weight Perfect Matching on odd degree vertices

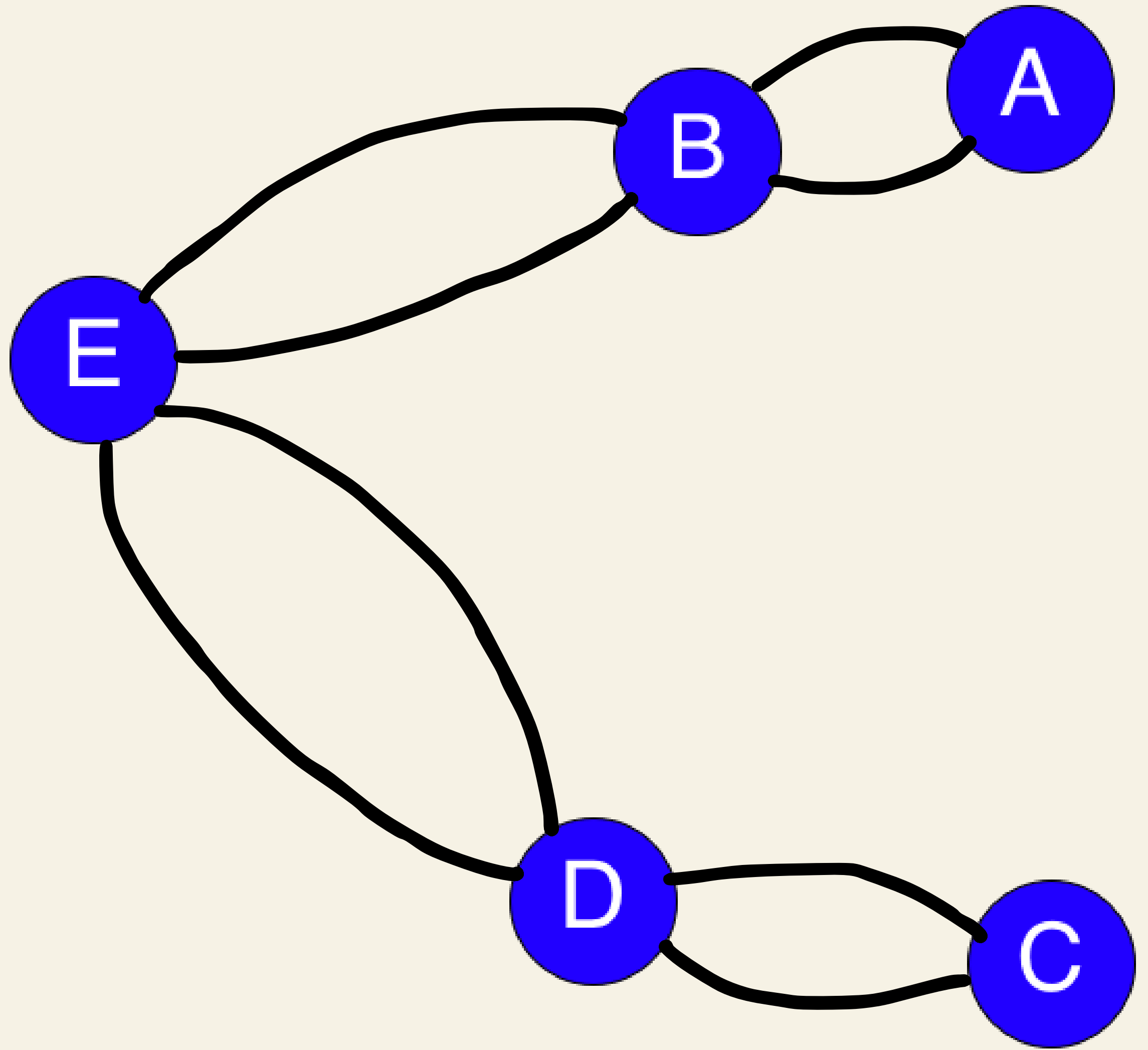


EULERIAN CIRCUIT HIERHOLZER'S ALGORITHM

Eulerian Circuit

- An Eulerian circuit is a circuit that visits every edge in the graph exactly once and returns back to a starting vertex.

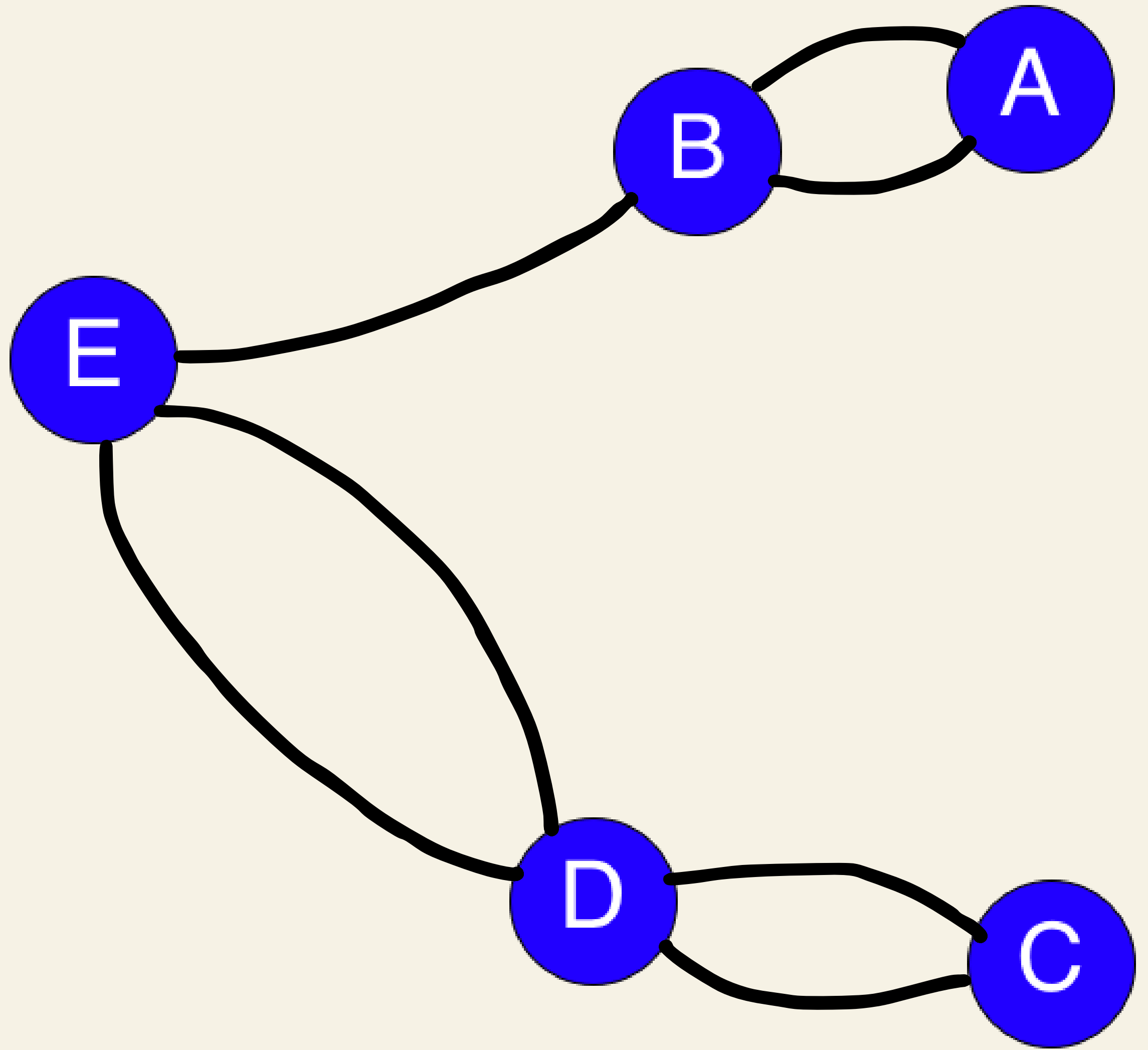
Stack
E



Stack

B

E

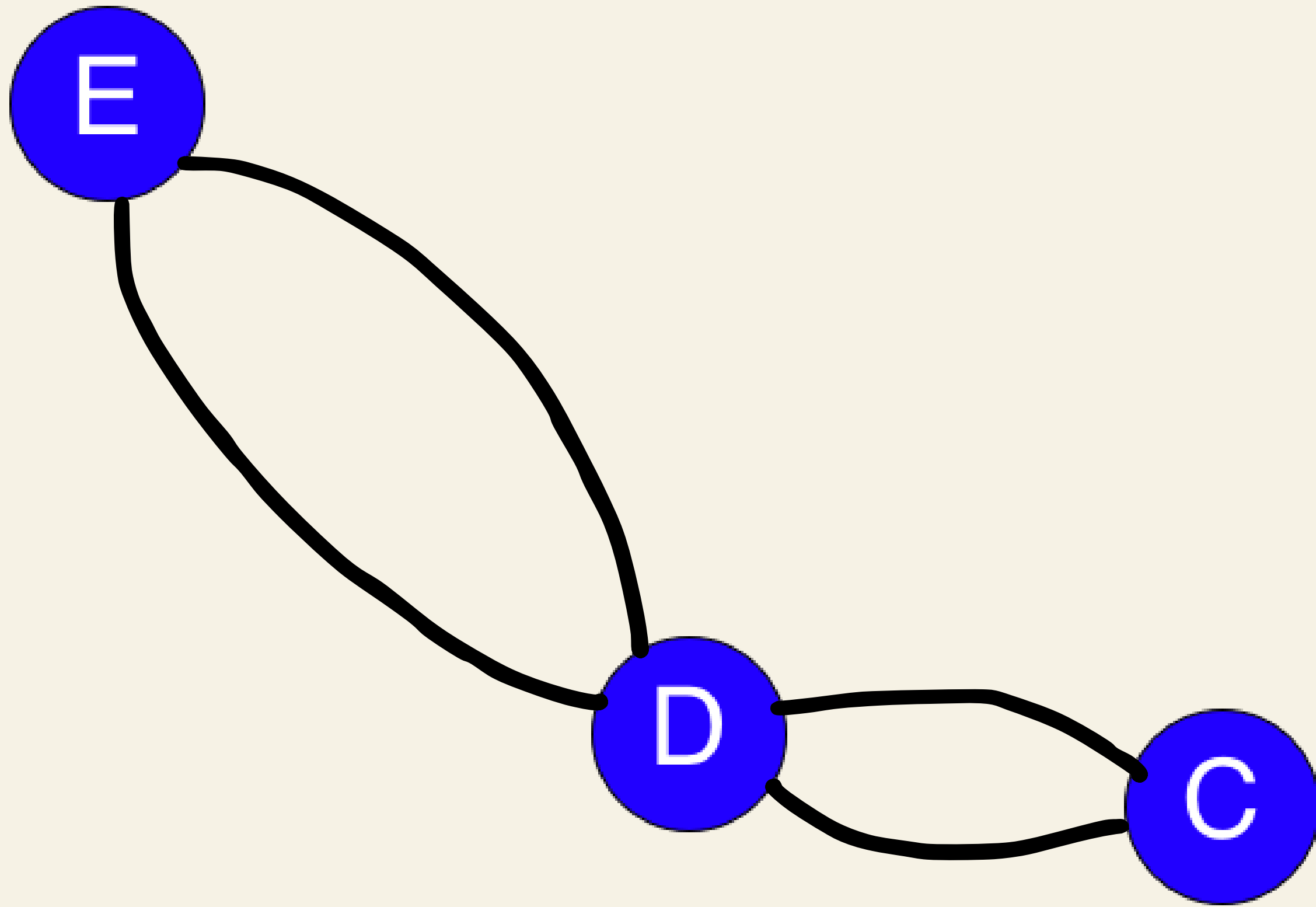
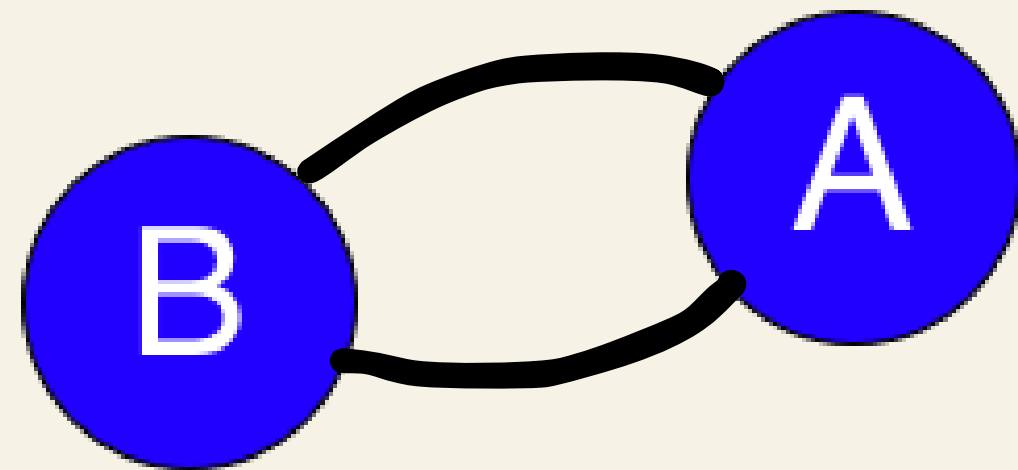
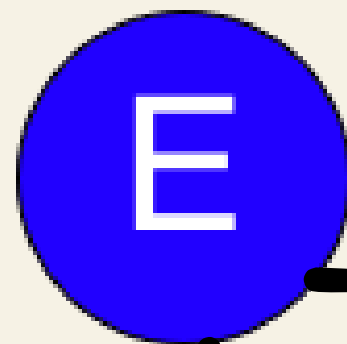


Stack

E

B

E



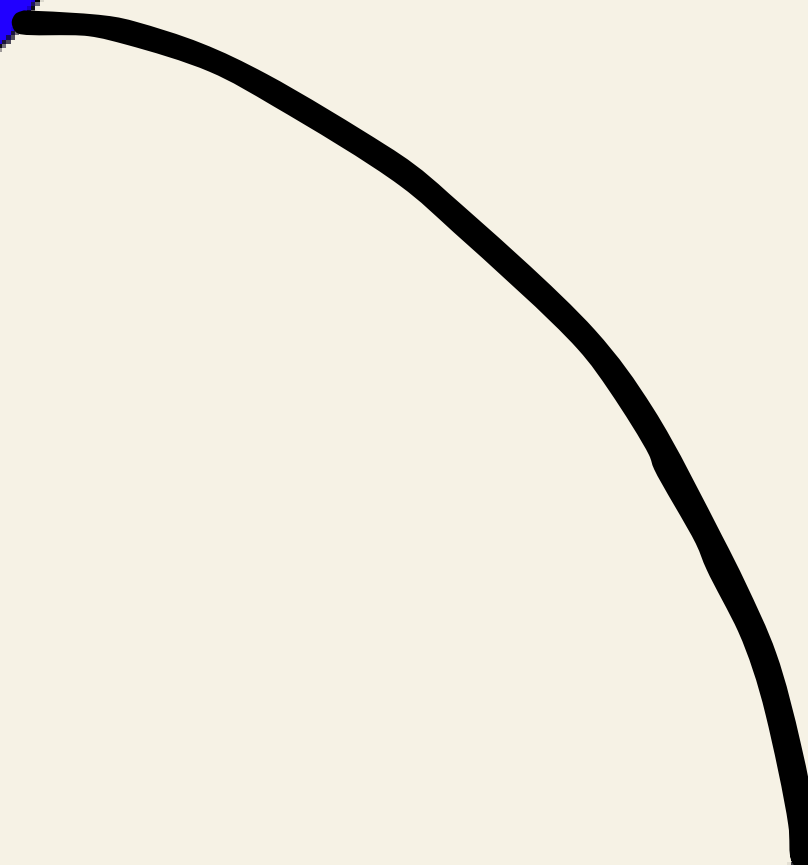
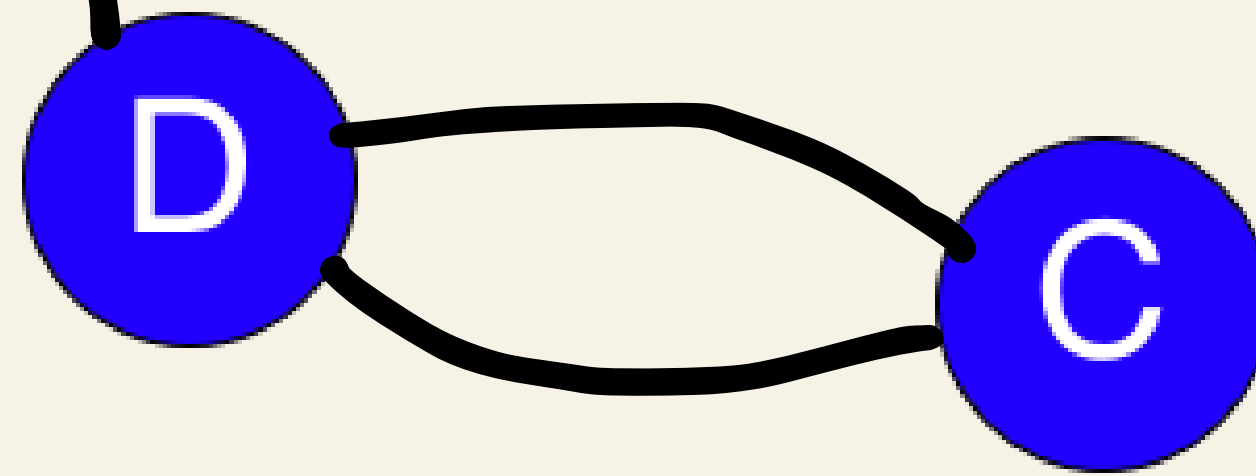
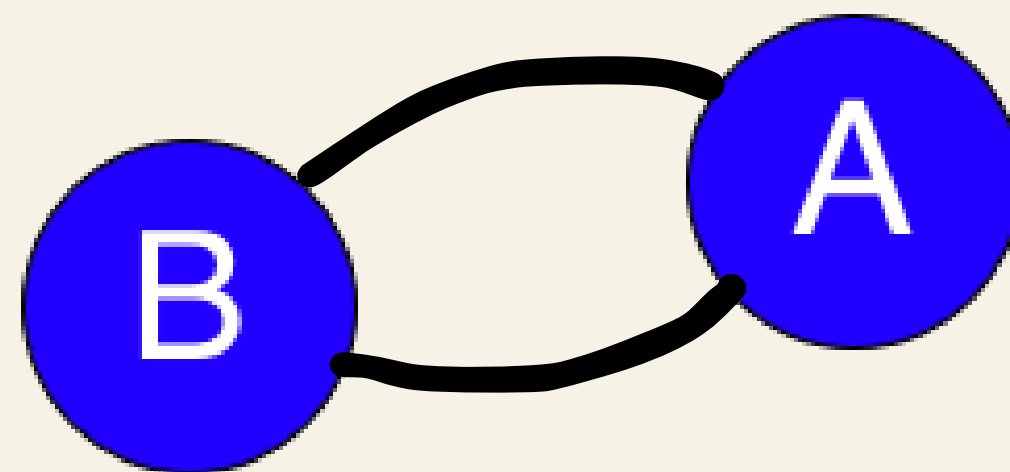
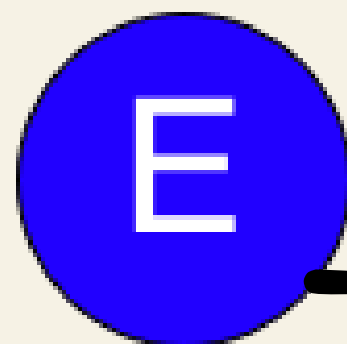
Stack

D

E

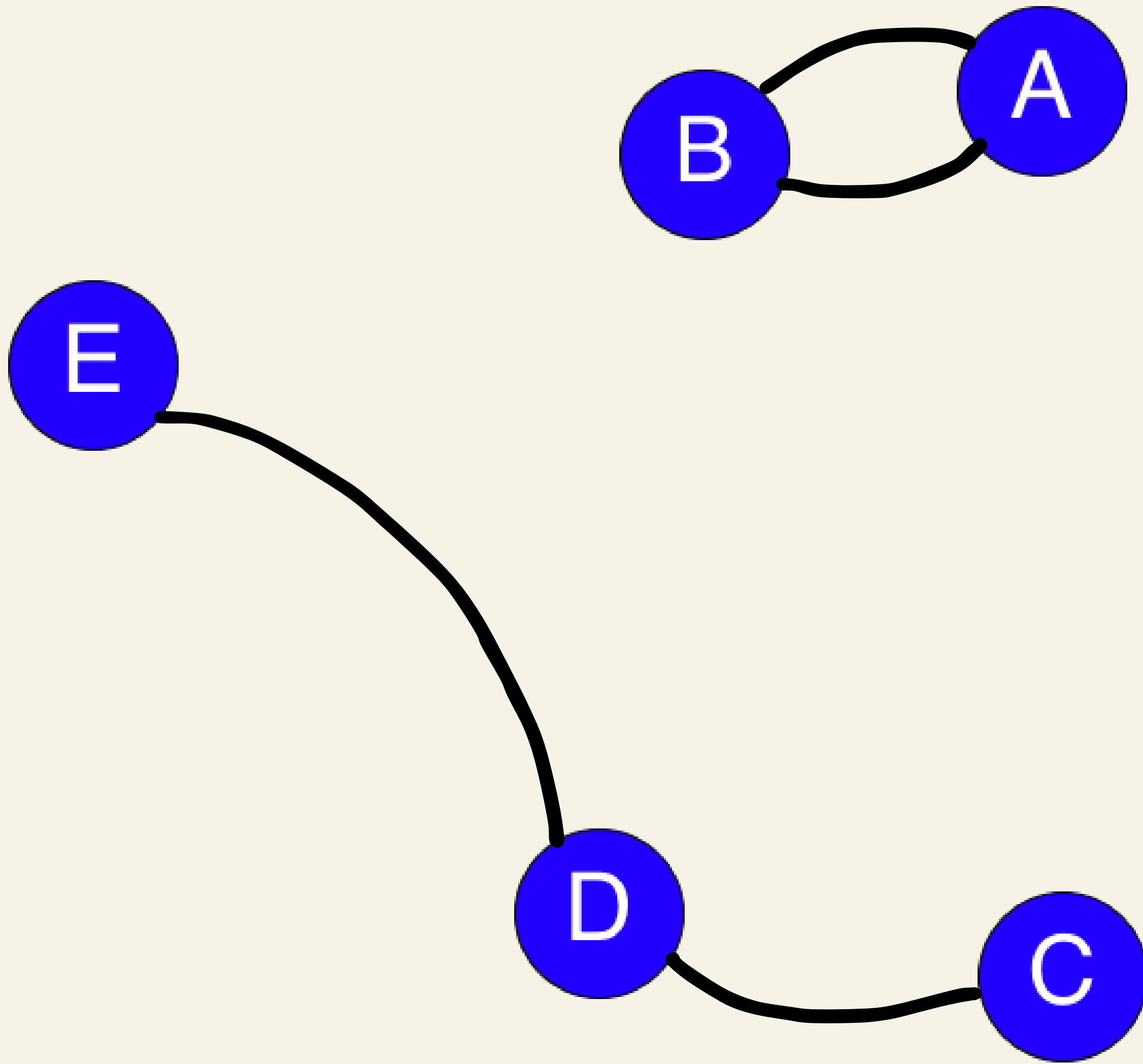
B

E



Stack

C
D
E
B
E



Stack

D

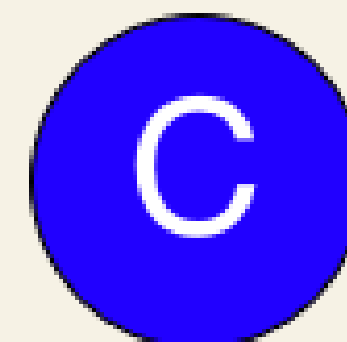
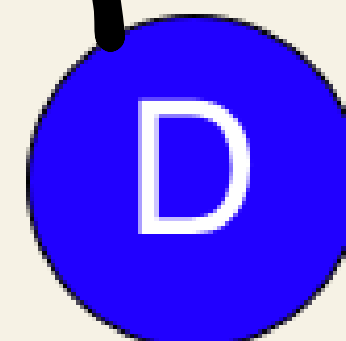
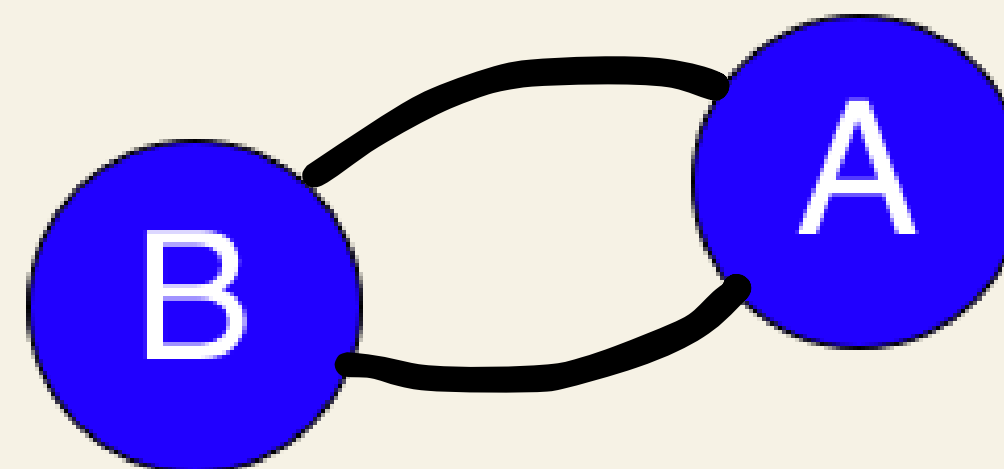
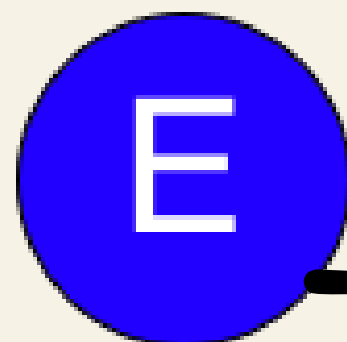
C

D

E

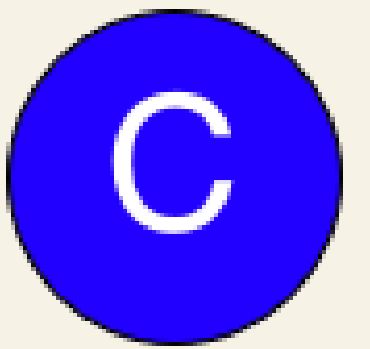
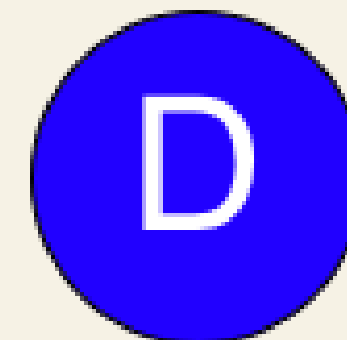
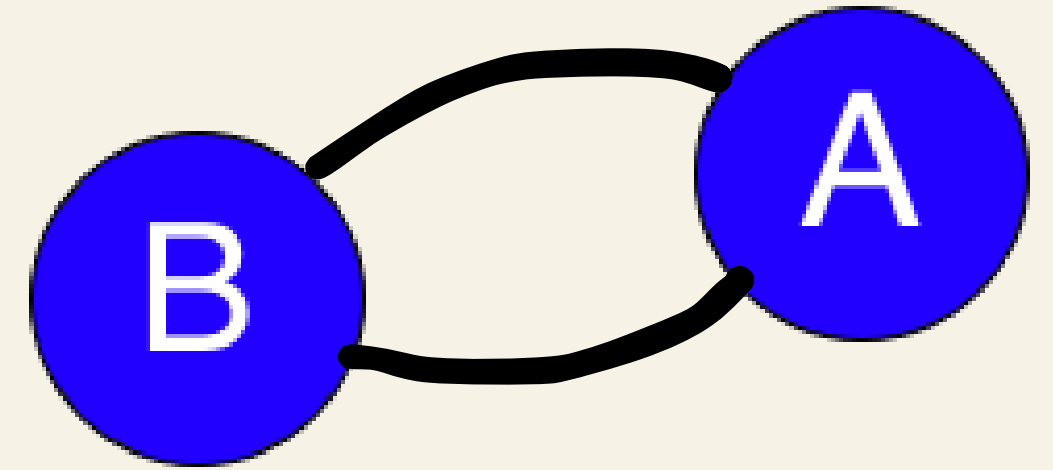
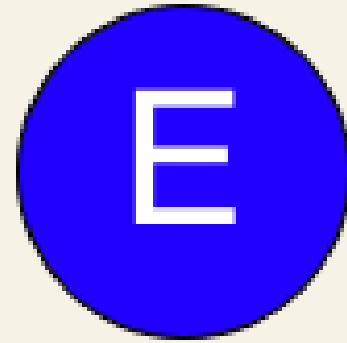
B

E



Stack

E
D
C
D
E
B
E

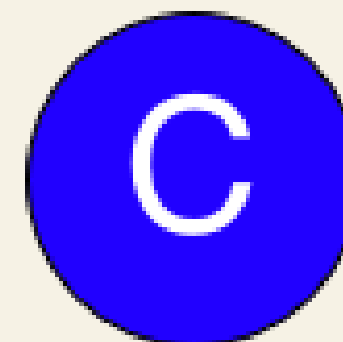
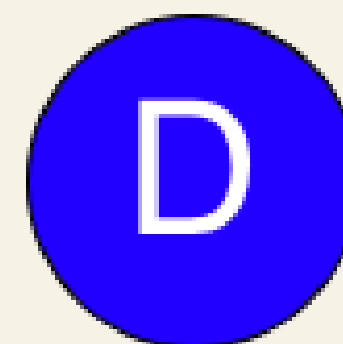
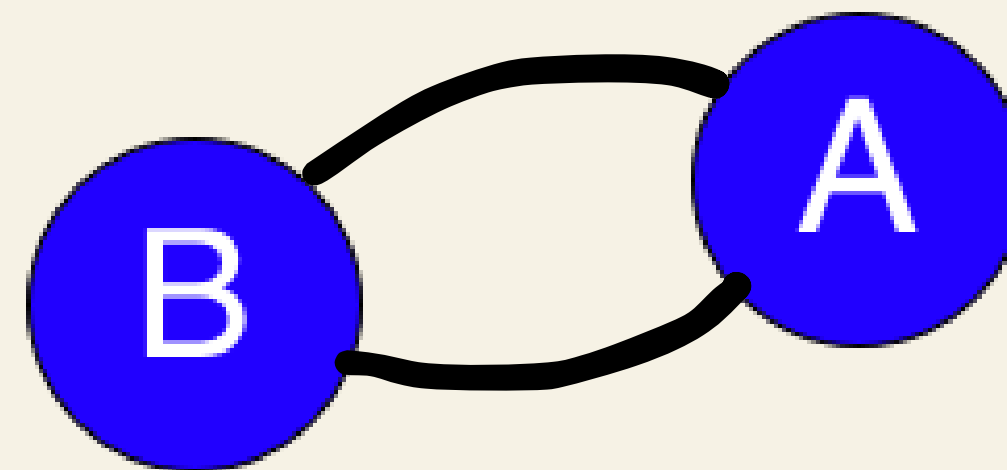
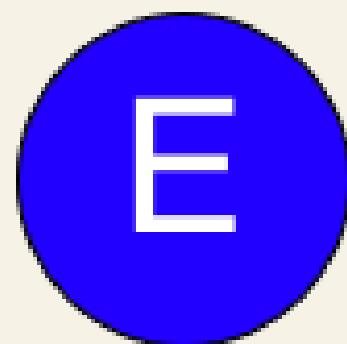


Stack

D
C
D
E
B
E

Circuit

E

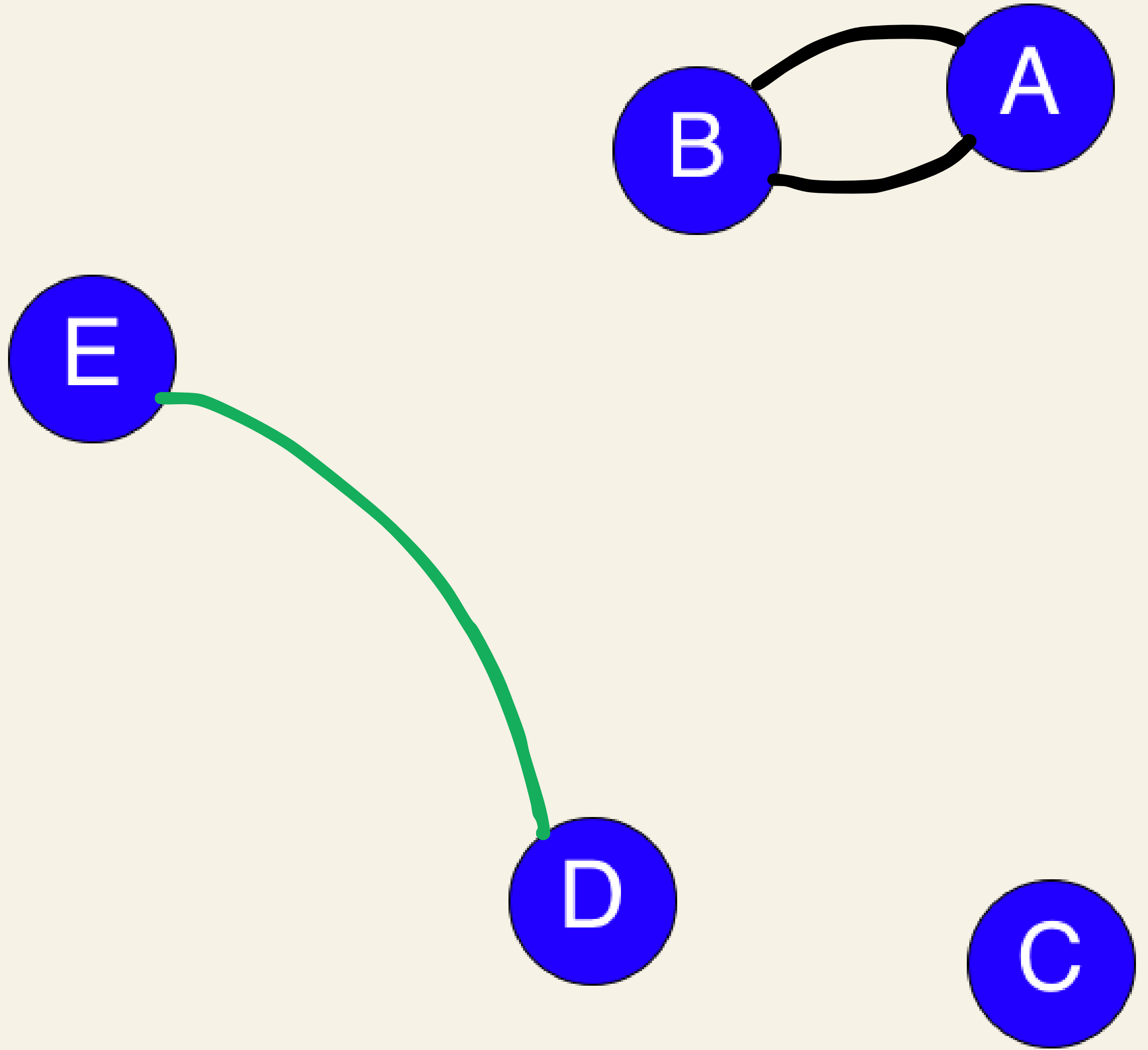


Stack

C
D
E
B
E

Circuit

E, D

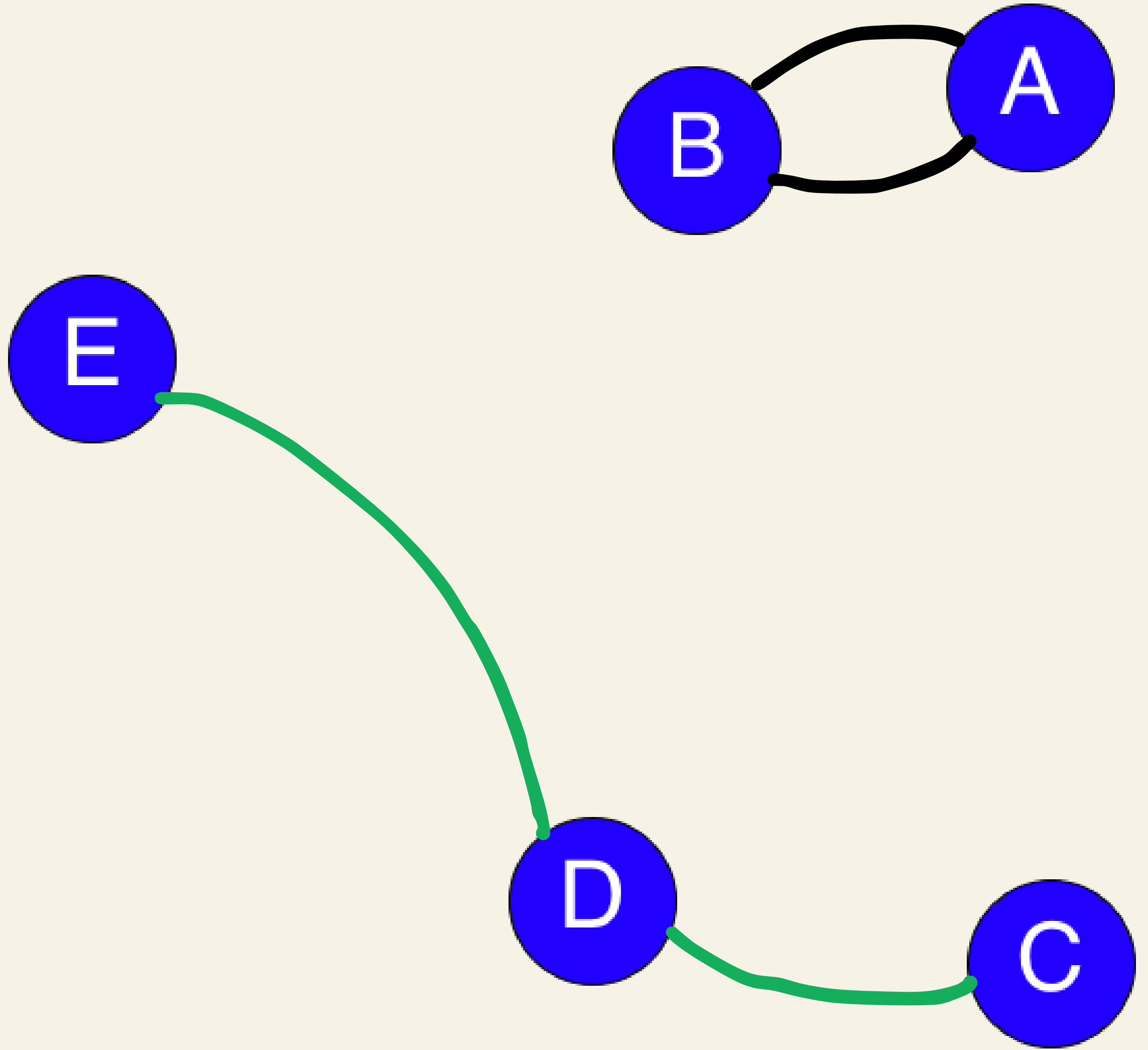


Stack

D
E
B
E

Circuit

E, D, C

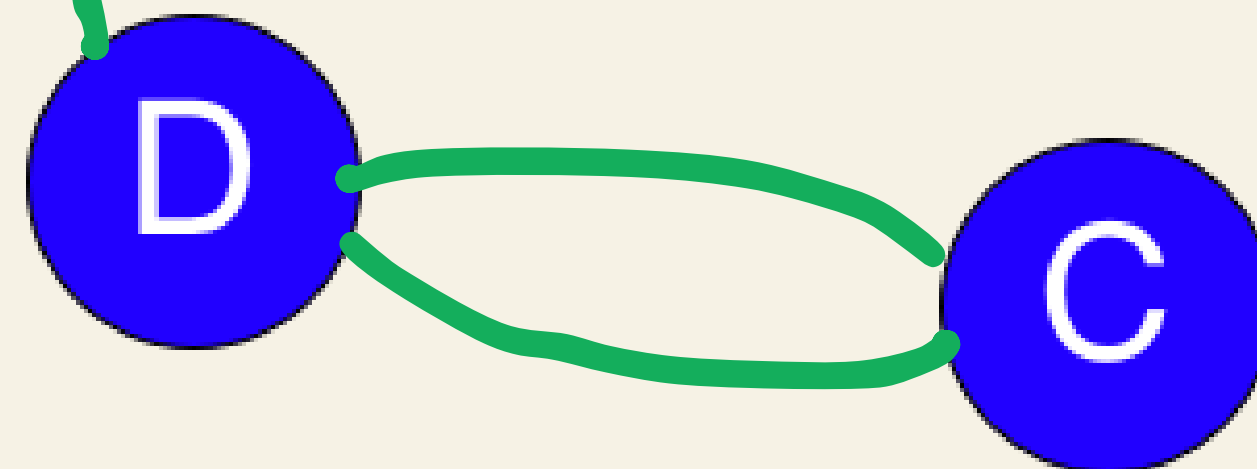
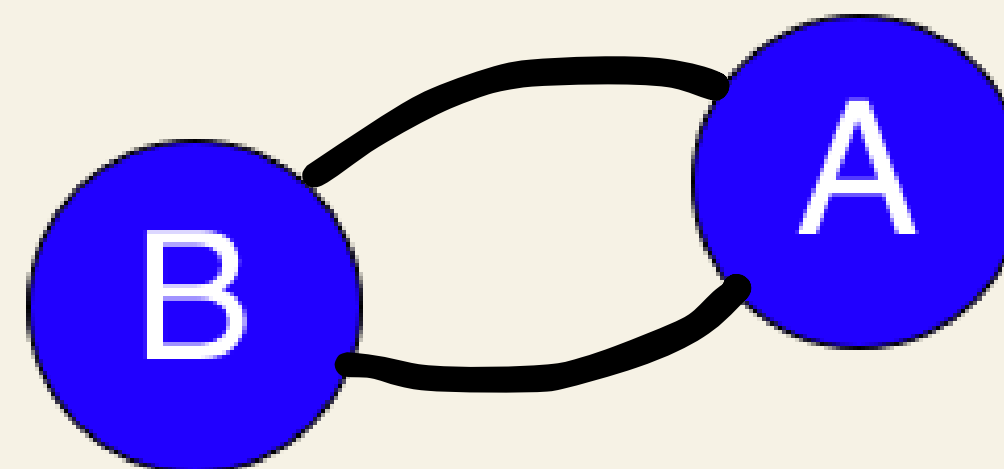
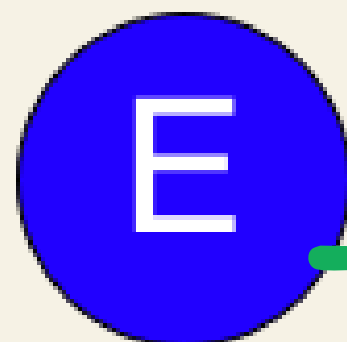


Stack

E
B
E

Circuit

E, D, C, D



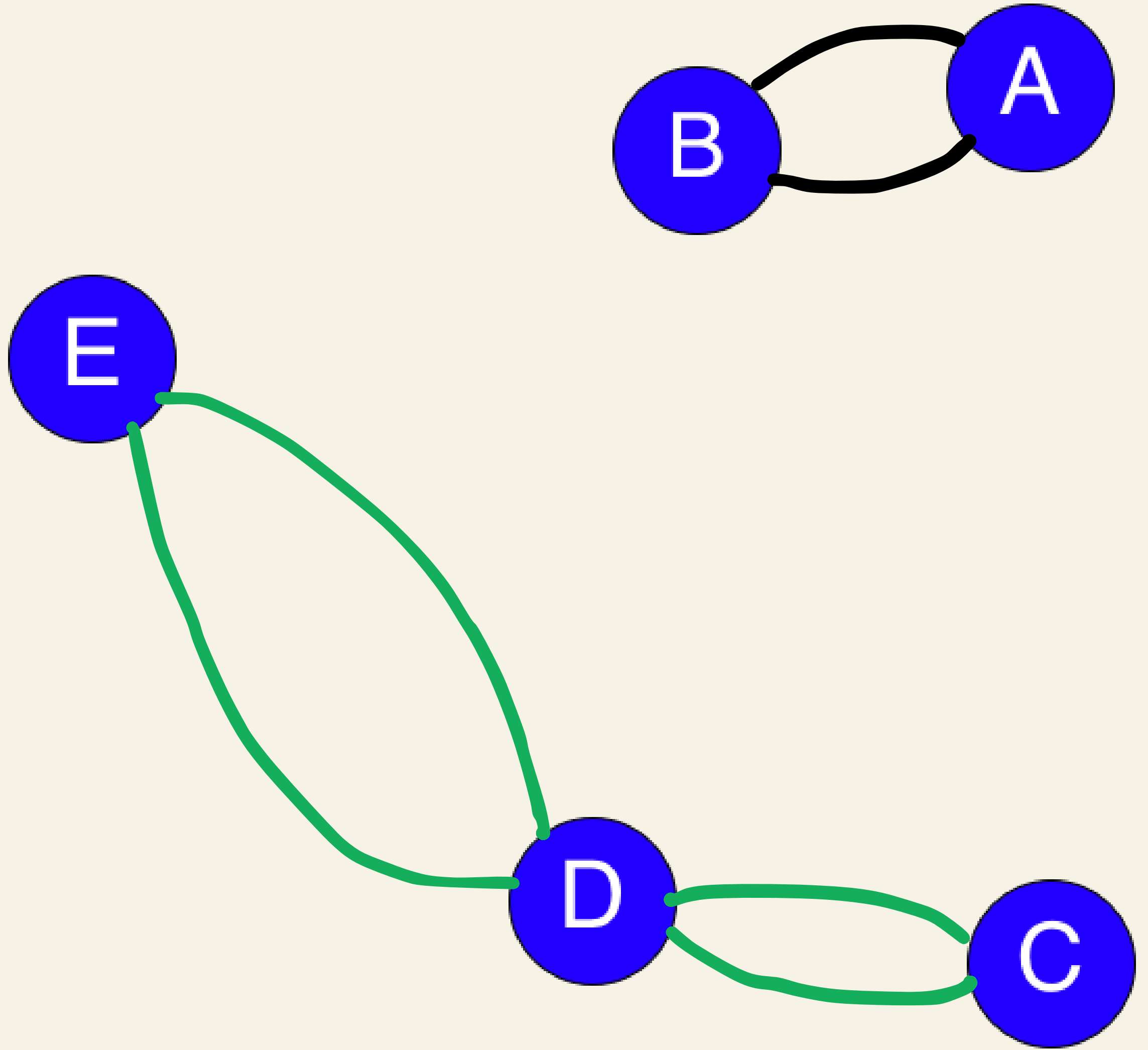
Stack

B

E

Circuit

E, D, C, D, E

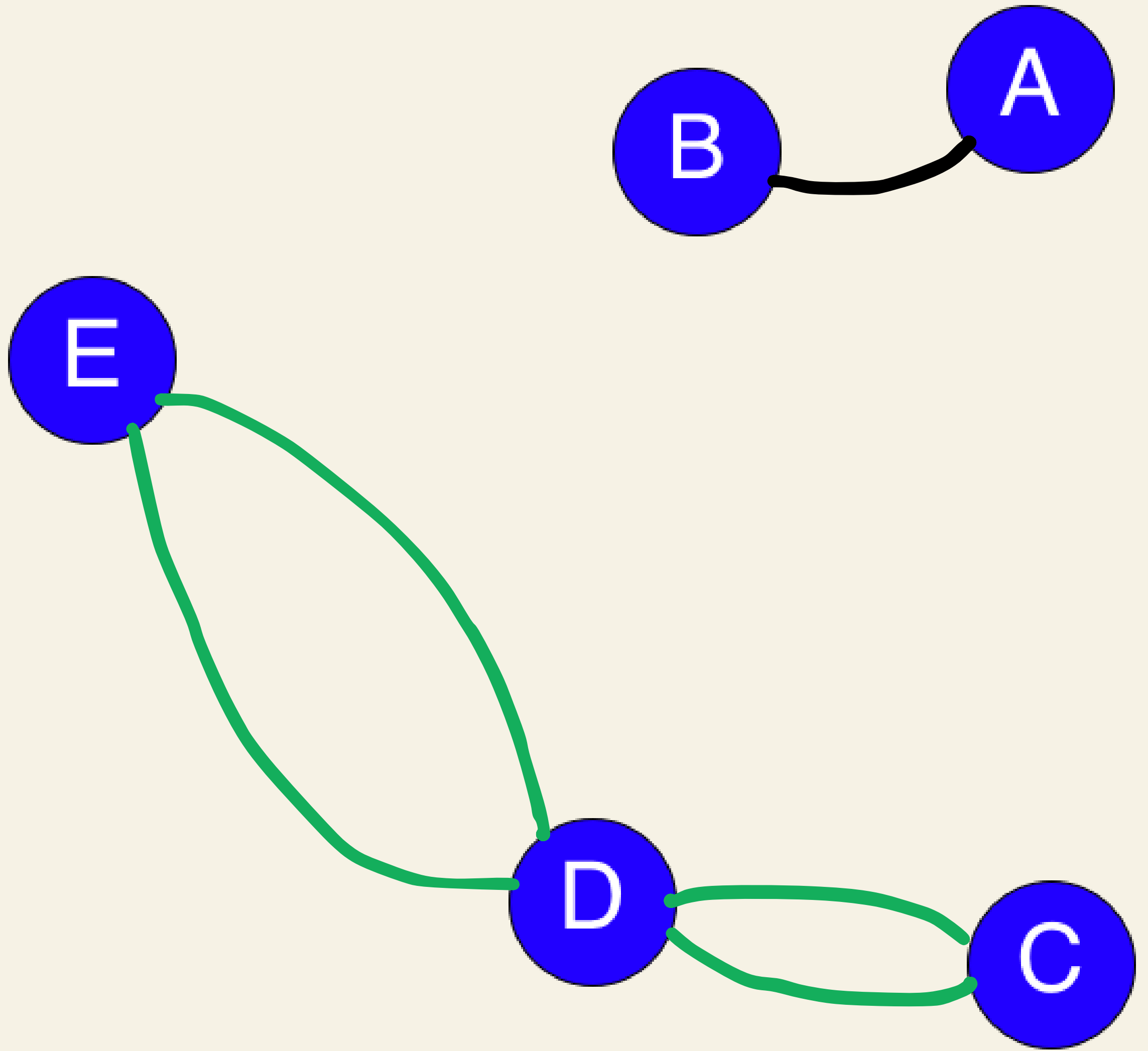


Stack

A
B
E

Circuit

E, D, C, D, E

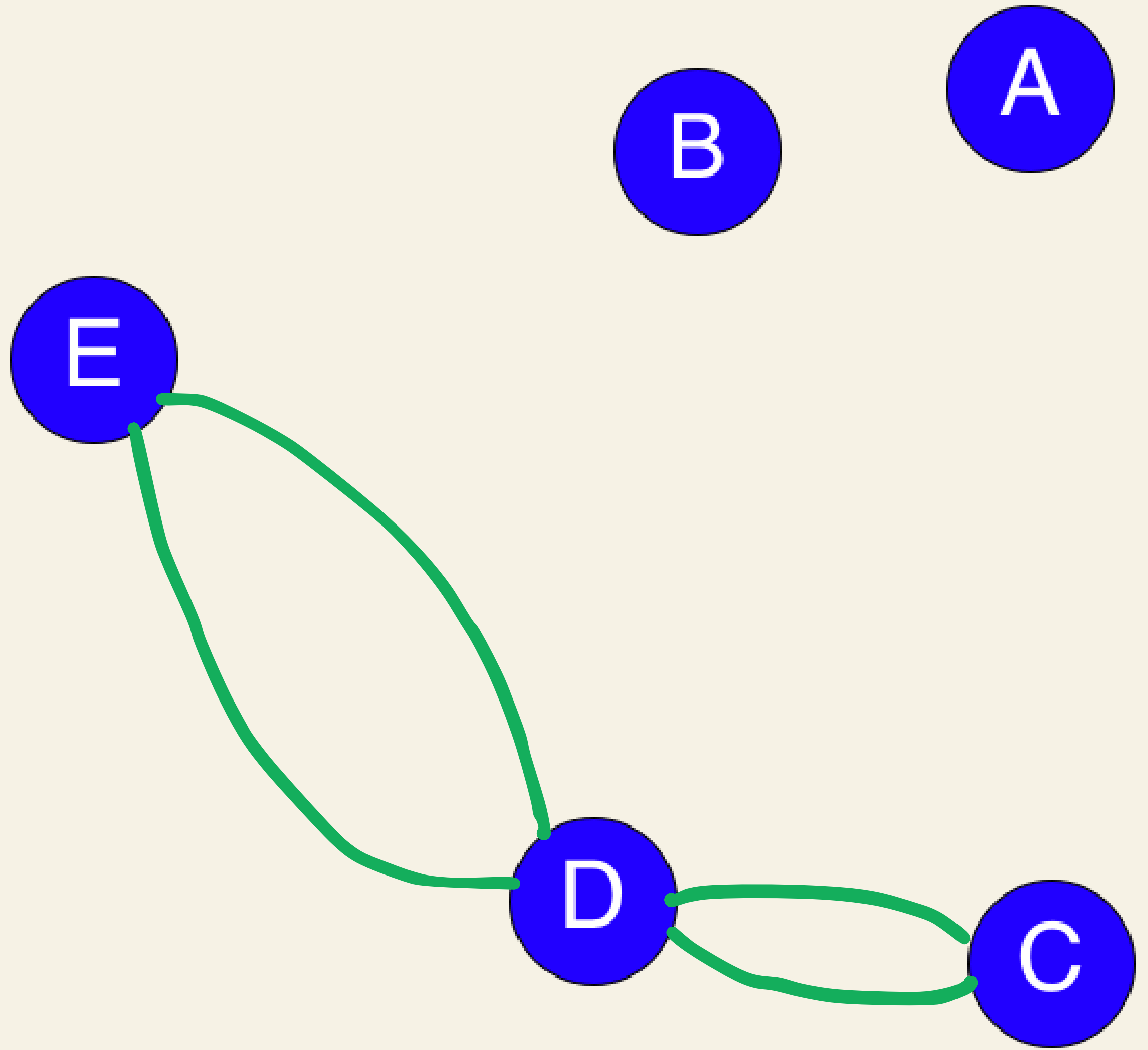


Stack

B
A
B
E

Circuit

E, D, C, D, E

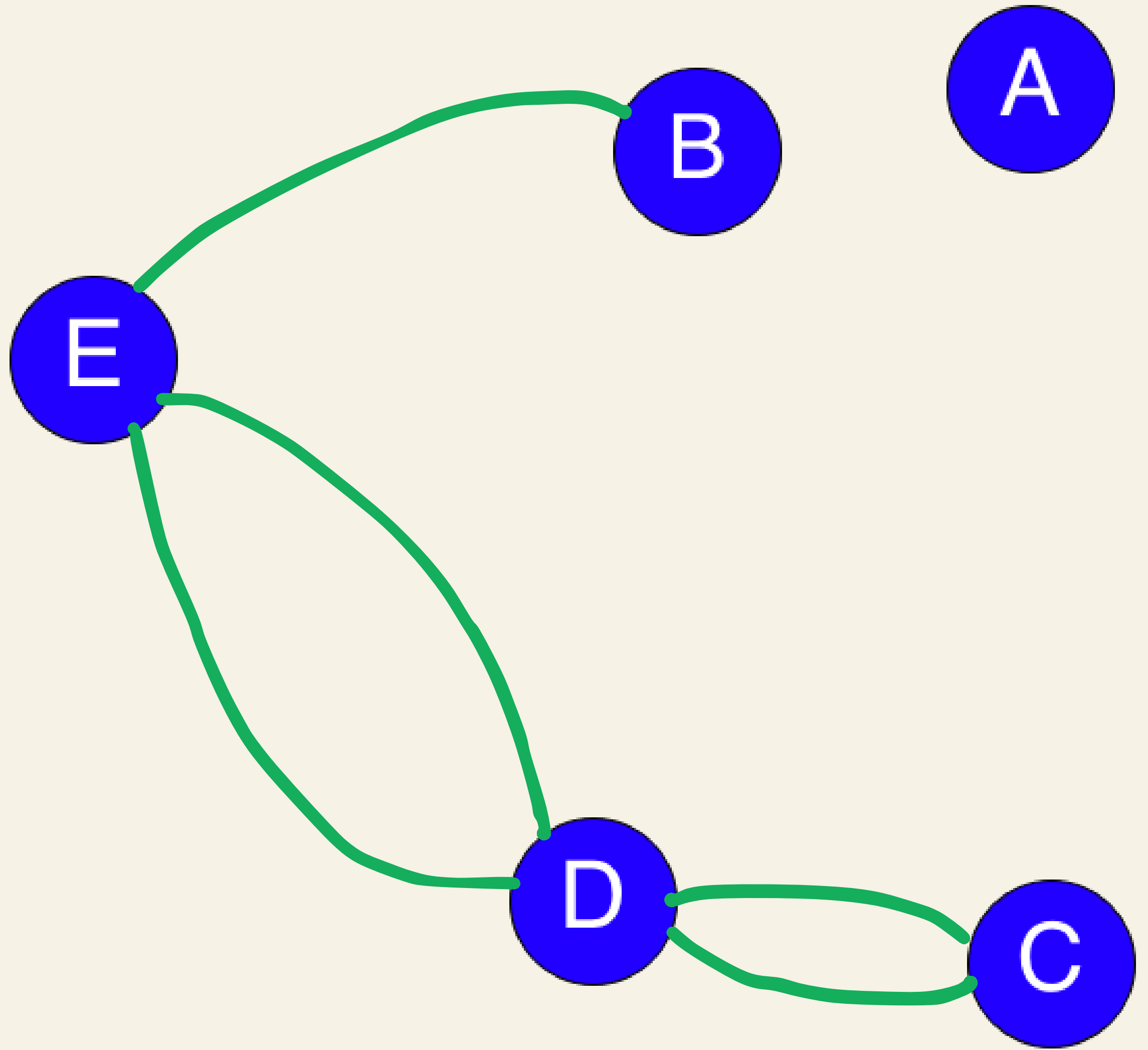


Stack

A
B
E

Circuit

E, D, C, D, E, B

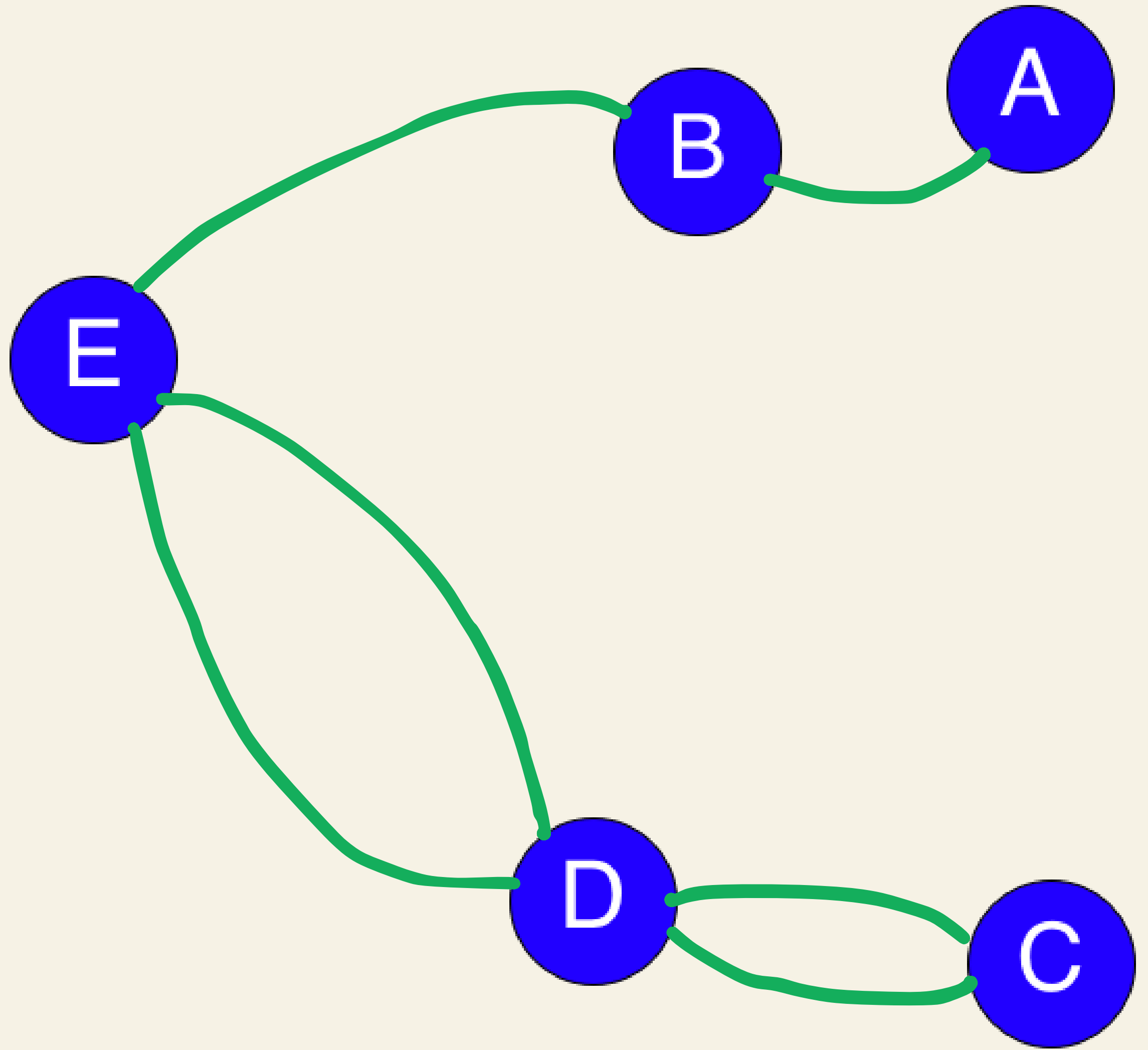


Stack

B
E

Circuit

E, D, C, D, E, B, A

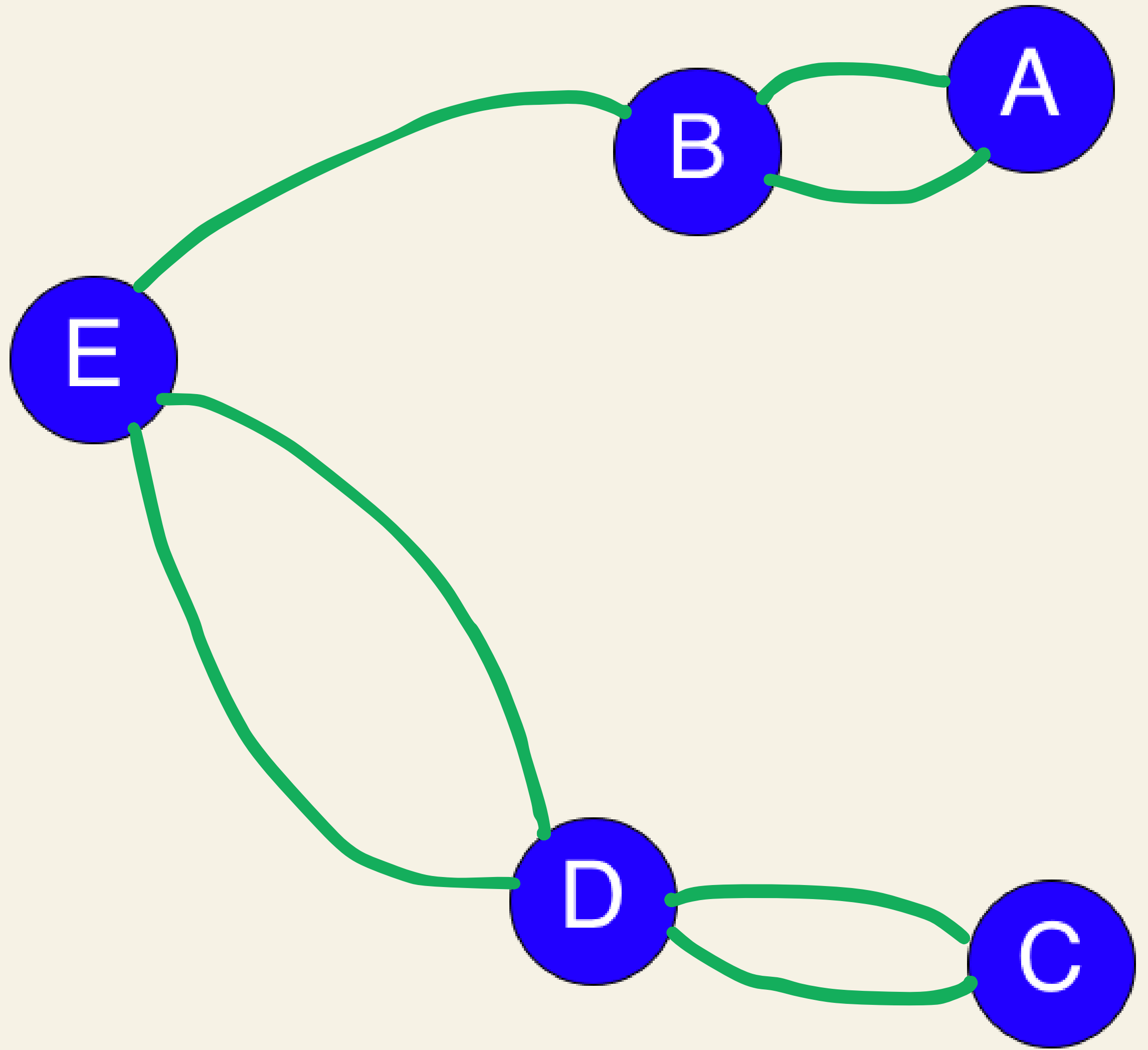


Stack

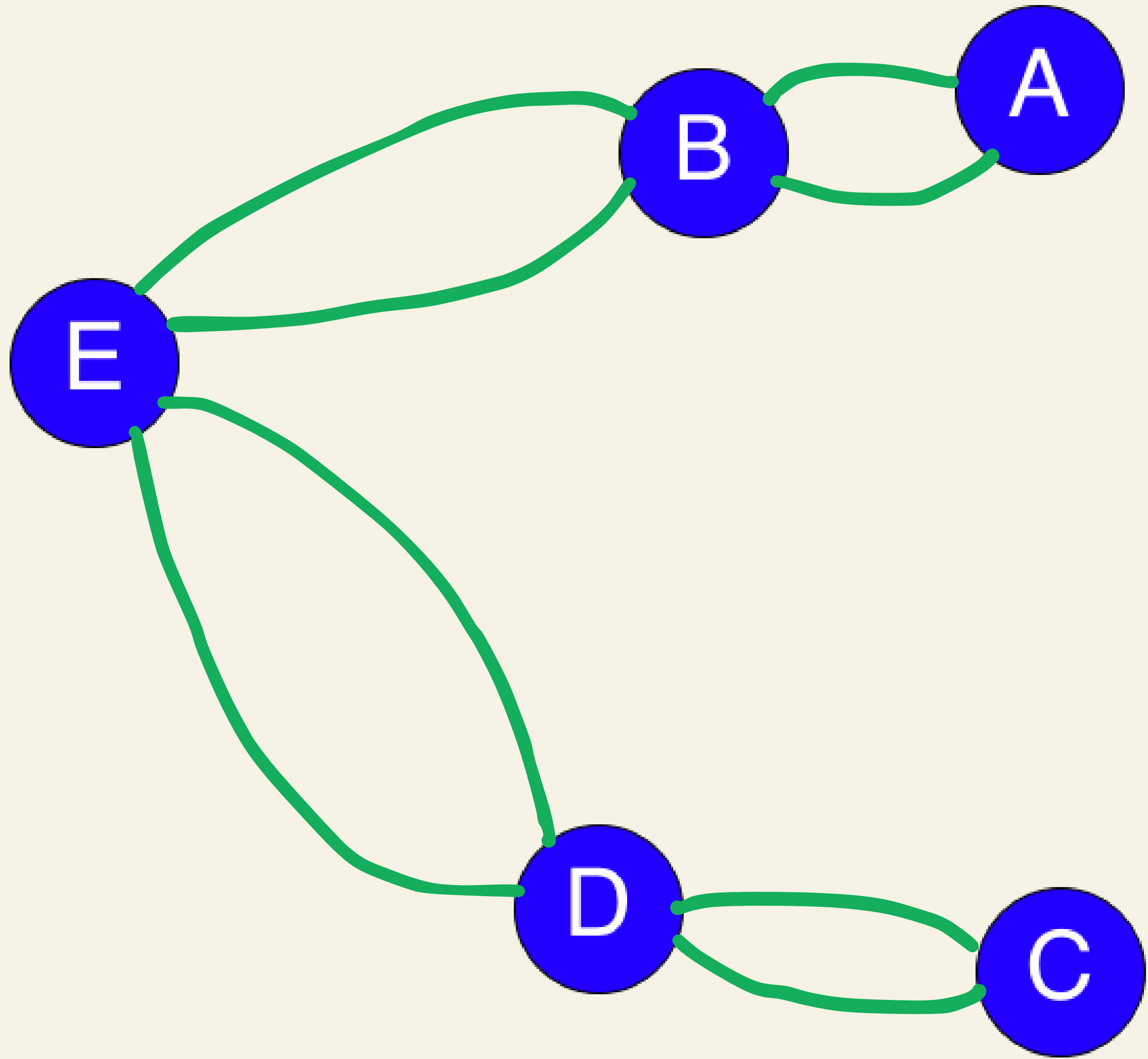
E

Circuit

E, D, C, D, E, B, A, B



Stack



Circuit

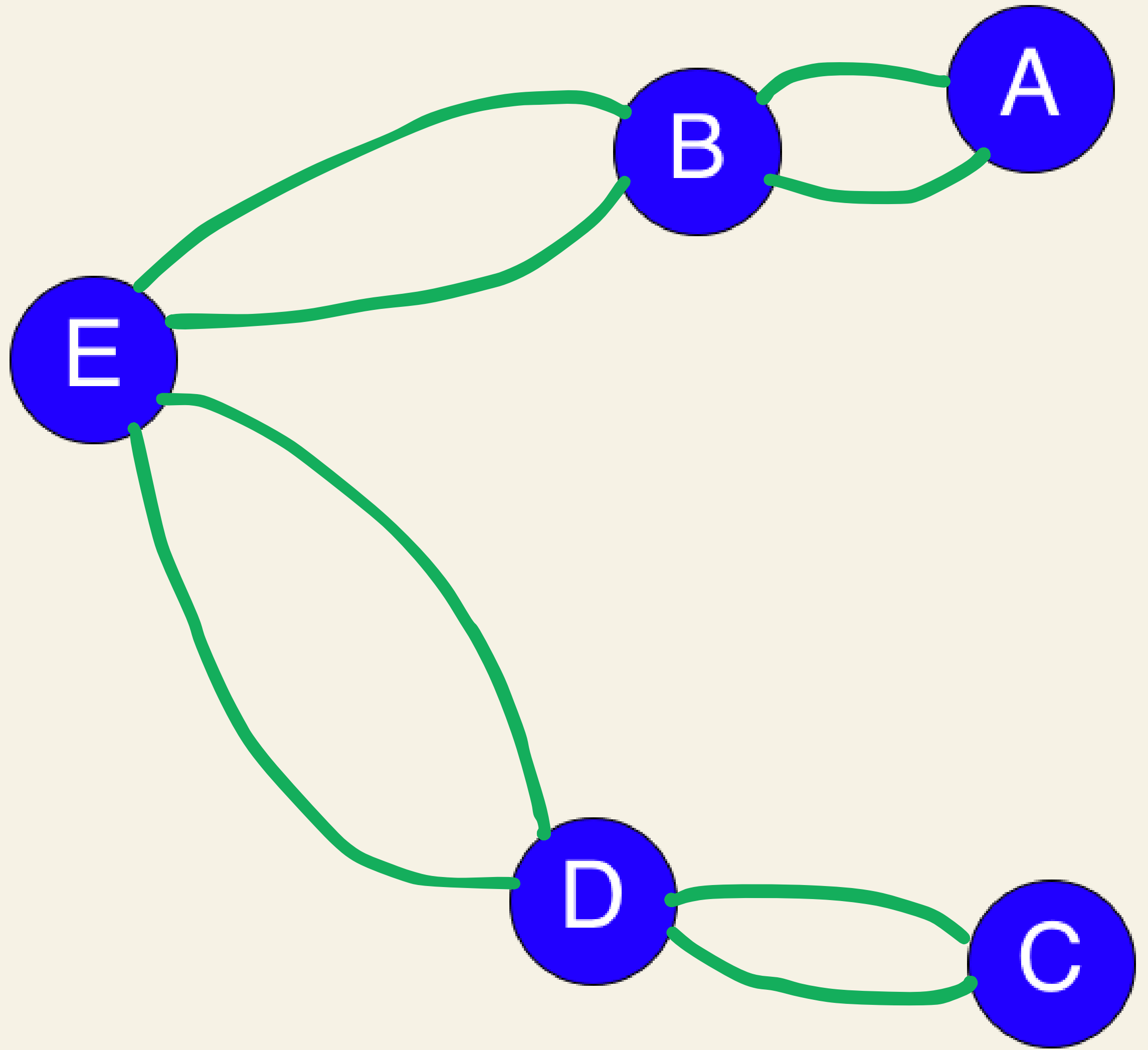
E, D, C, D, E, B, A, B,
E

Circuit

E, D, C, D, E, B, A, B,
E

Reversed

E, B, A, B, E, D, C, D,
E



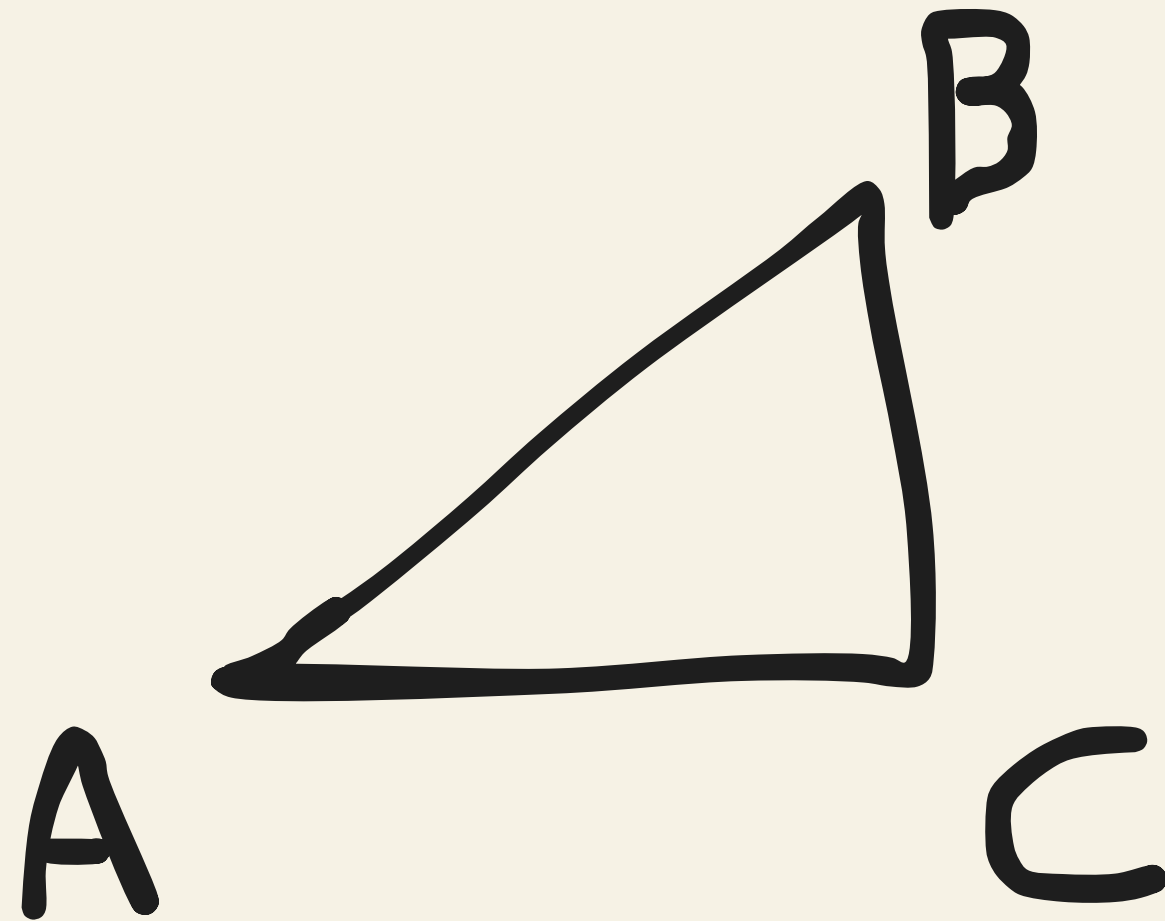
SHORTCUTTING HAMILTONIAN TOUR

Hamiltonian Tour

- A Hamiltonian tour is a cycle that visits every vertex exactly once.

Shortcutting

- Triangle inequality
- Complete graph

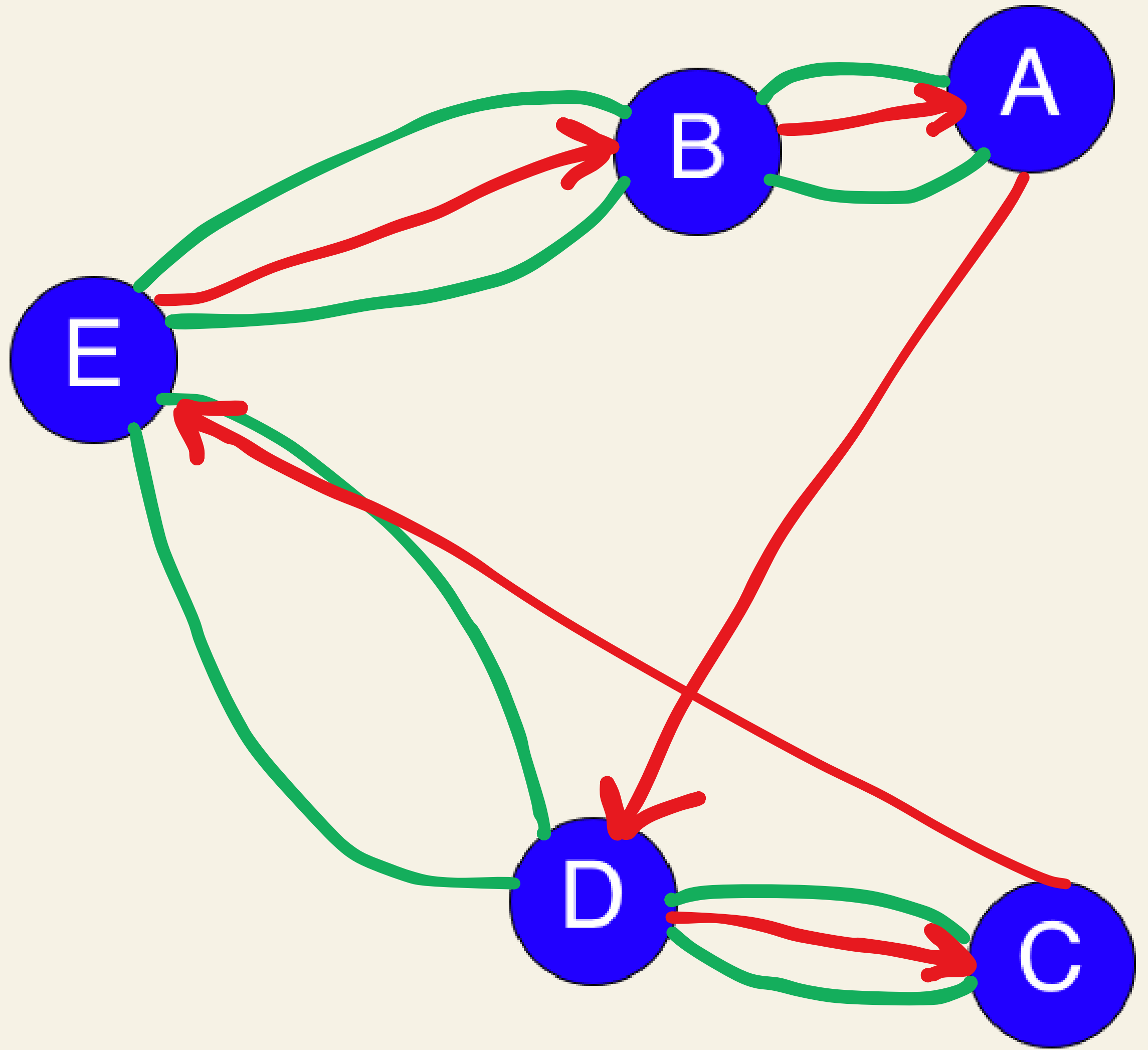


Eulerian Circuit

E, B, A, B, E, D, C, D, E

Hamiltonian Tour

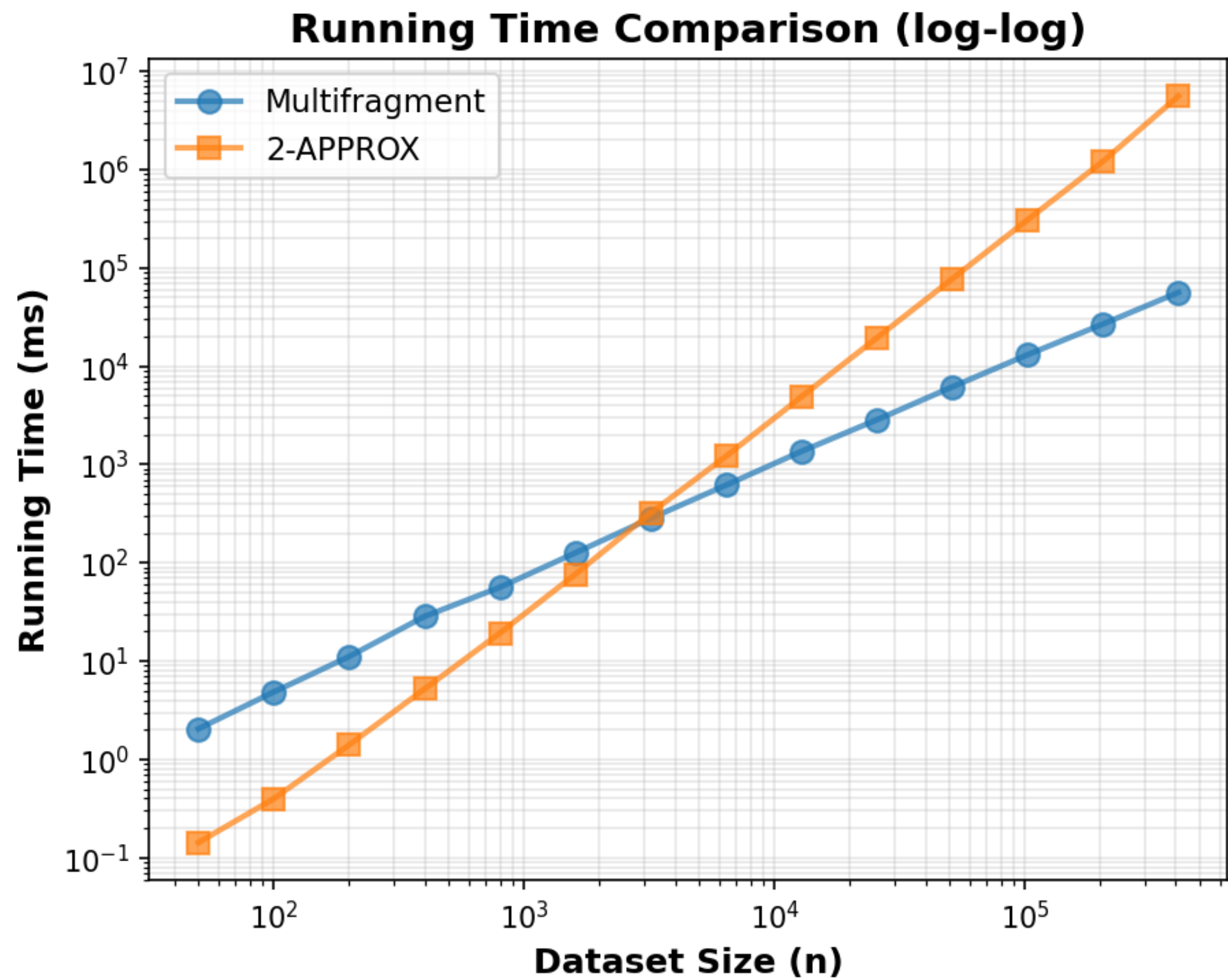
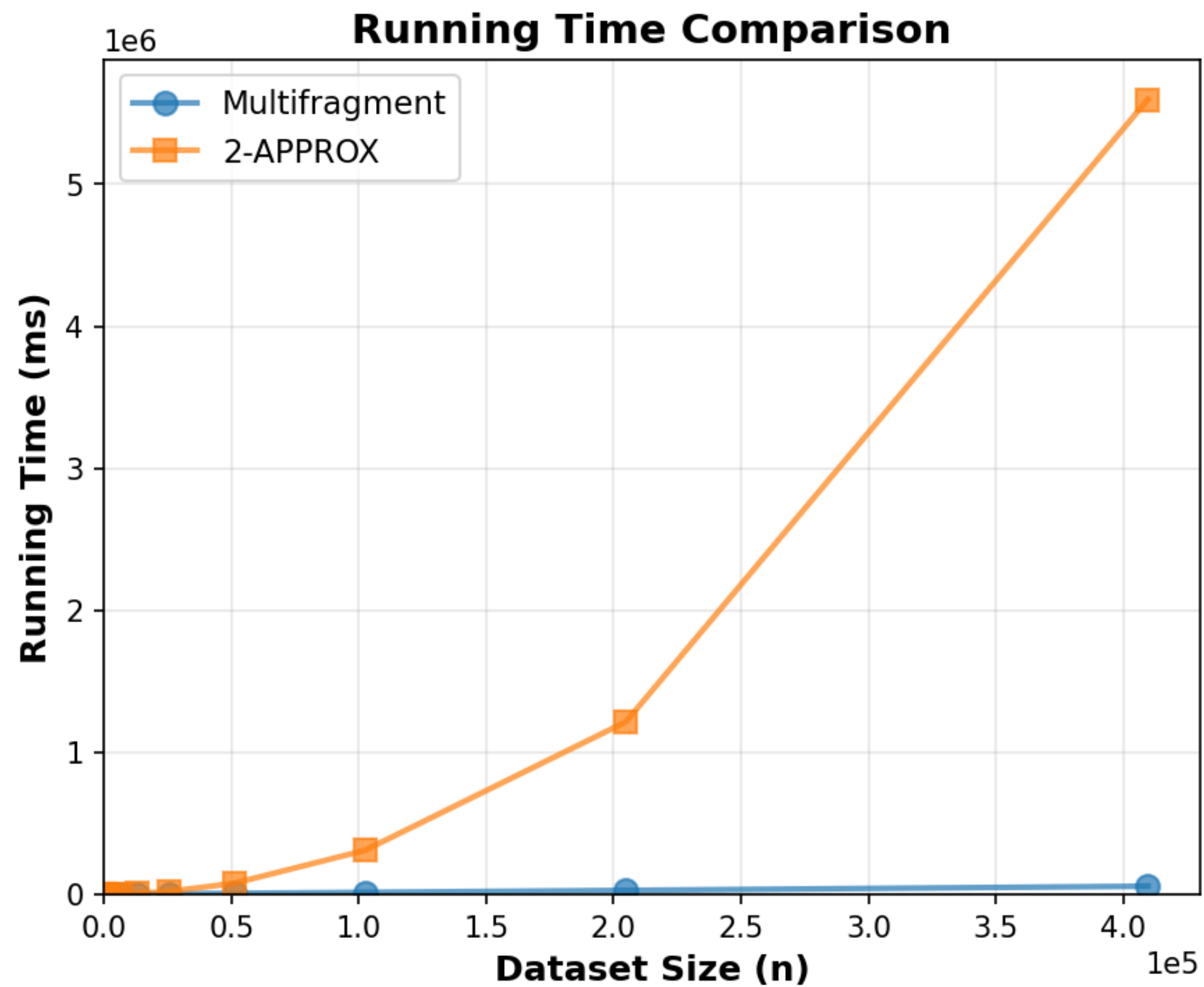
E, B, A, D, C



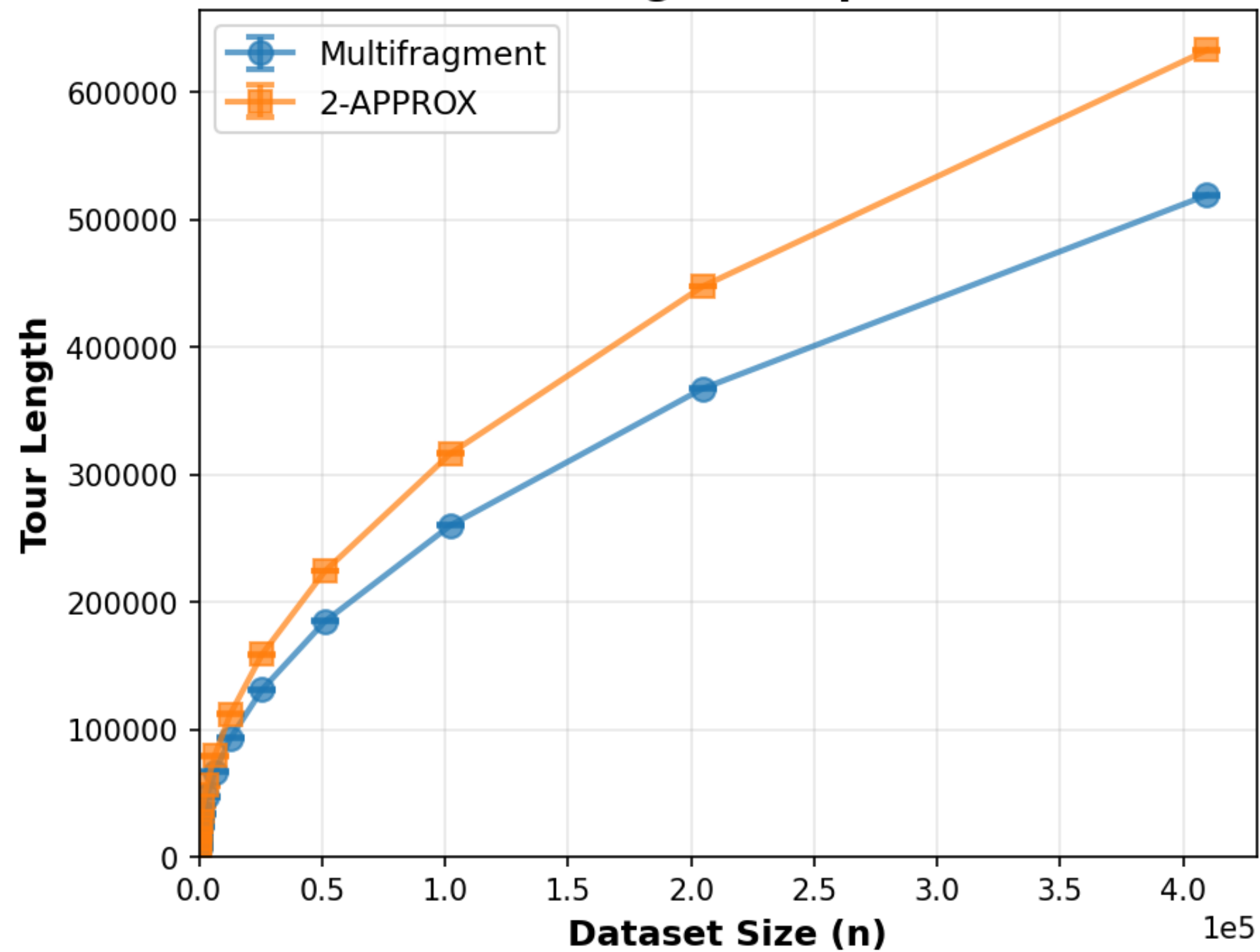
EXPERIMENTS RANDOM + TSPLIB

Random Point Sets

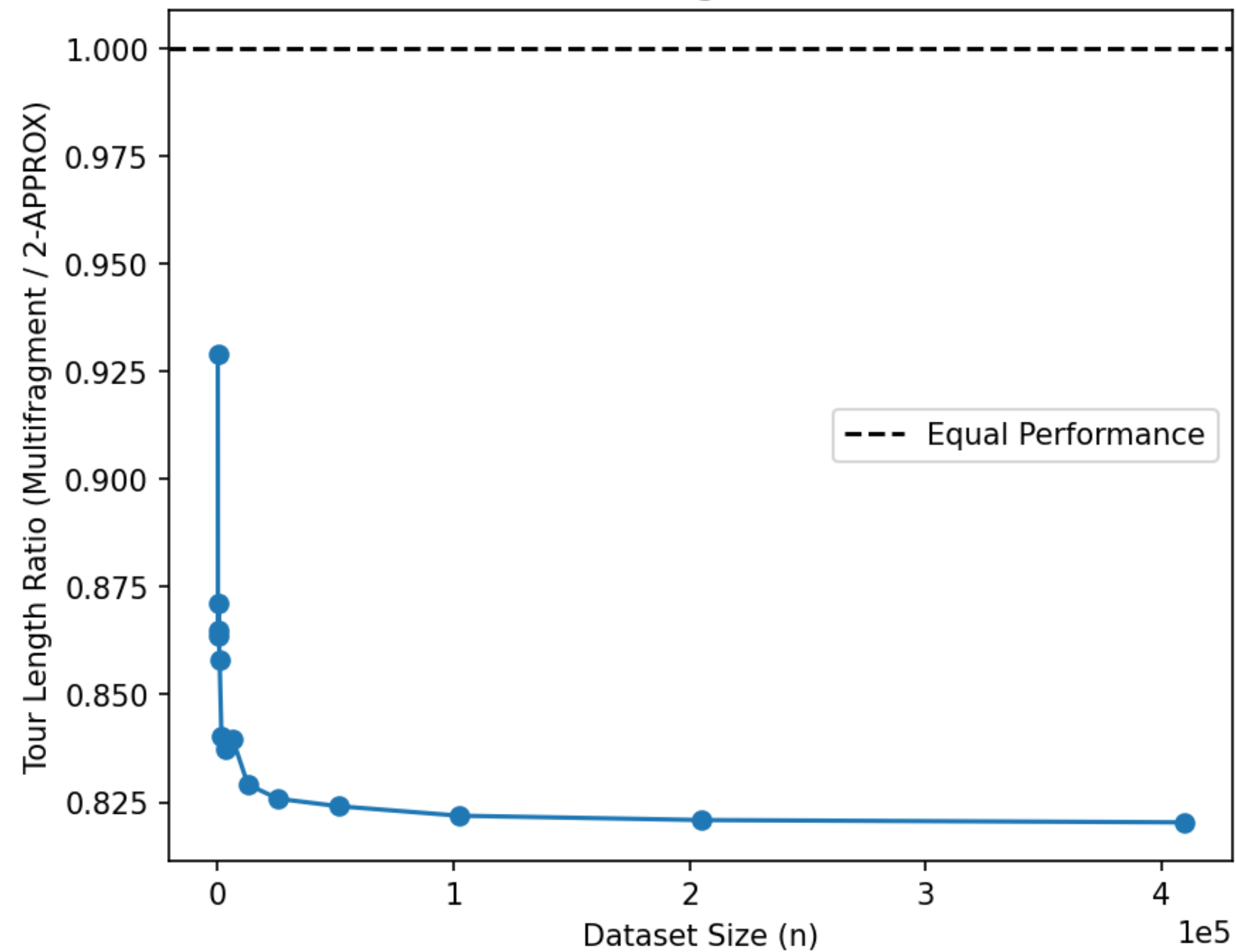
- $n = 50$ continuously doubled up to 409,600
- 10 trials for all n except 409,600
- 5 trials for 409,600



Tour Length Comparison



Tour Length Ratio



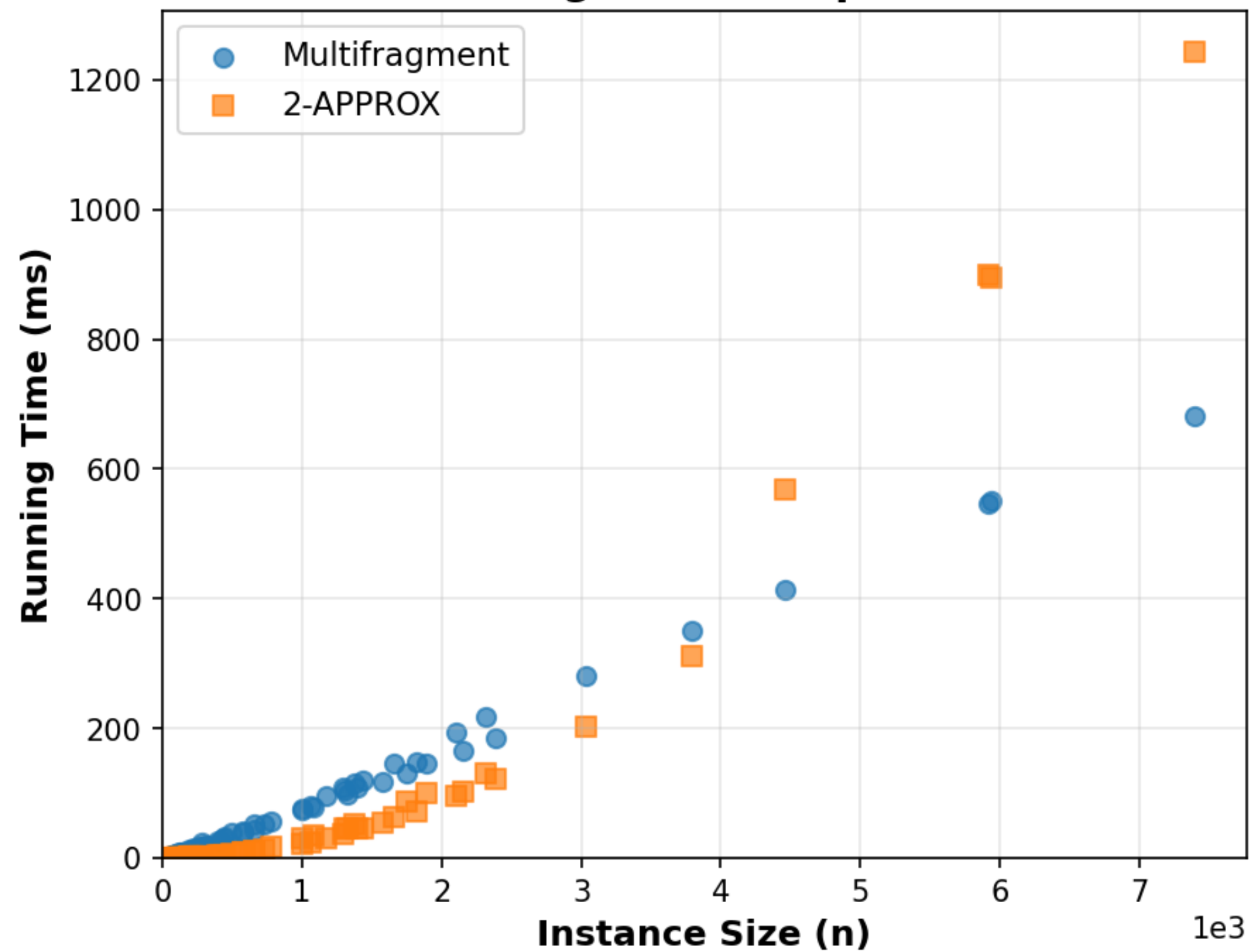
TSPLIB

- Various categories
- 73 instances used

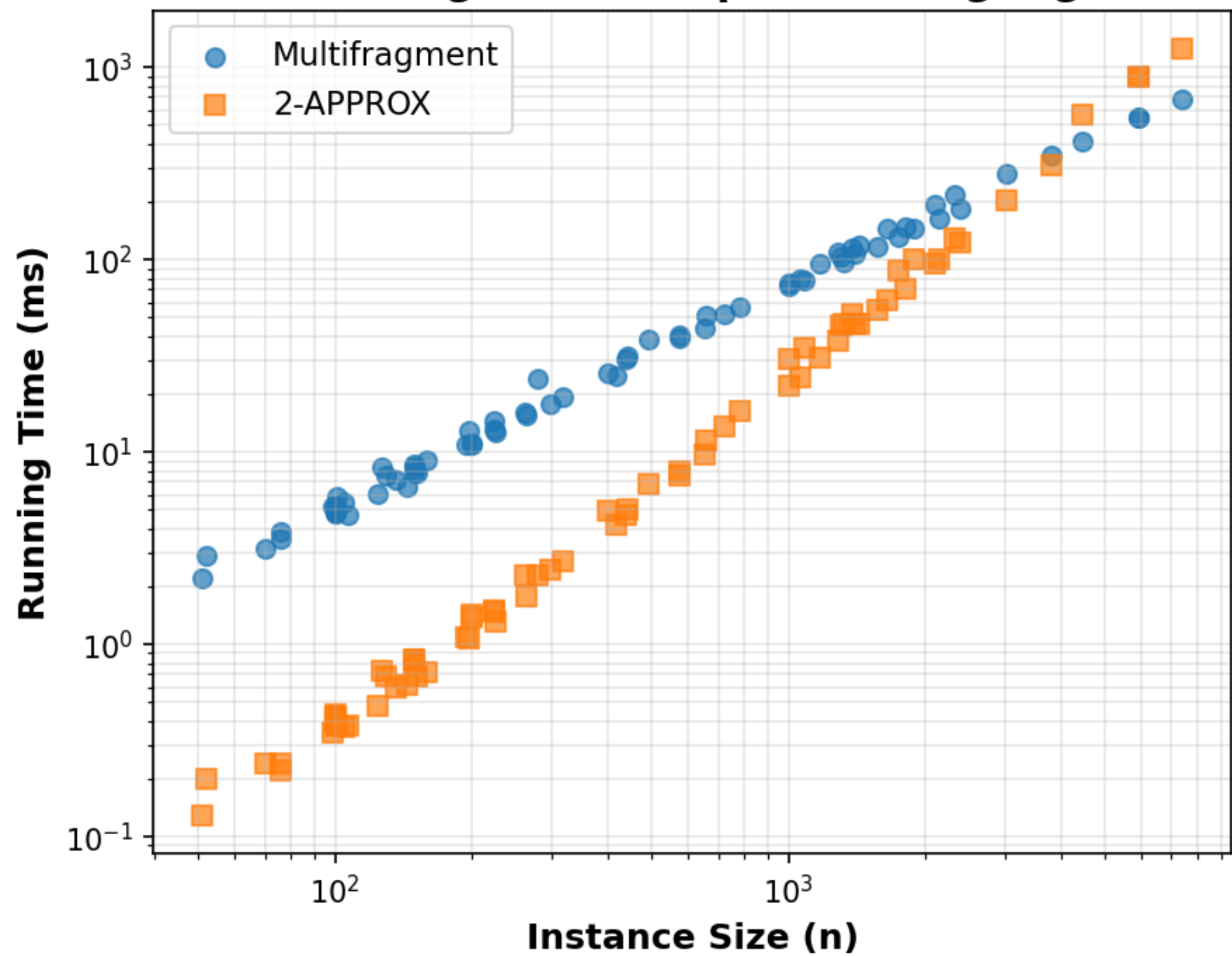
Table 3.1: Sample TSPLIB Instances

Category	Size range	Representative instances
Geographic	52–4461	berlin52, nrw1379, fnl4461
PCB drilling	159–3795	a280, d493, pcb1173, f11577
VLSI placement	1084–7397	vm1084, r11304, pla7397
Padberg/Rinaldi	76–2392	pr76, pr439, pr2392
Rattled grid	99–783	rat99, rat575, rat783
Random / synthetic	51–1000	eil151, kroA100, lin318, dsj1000

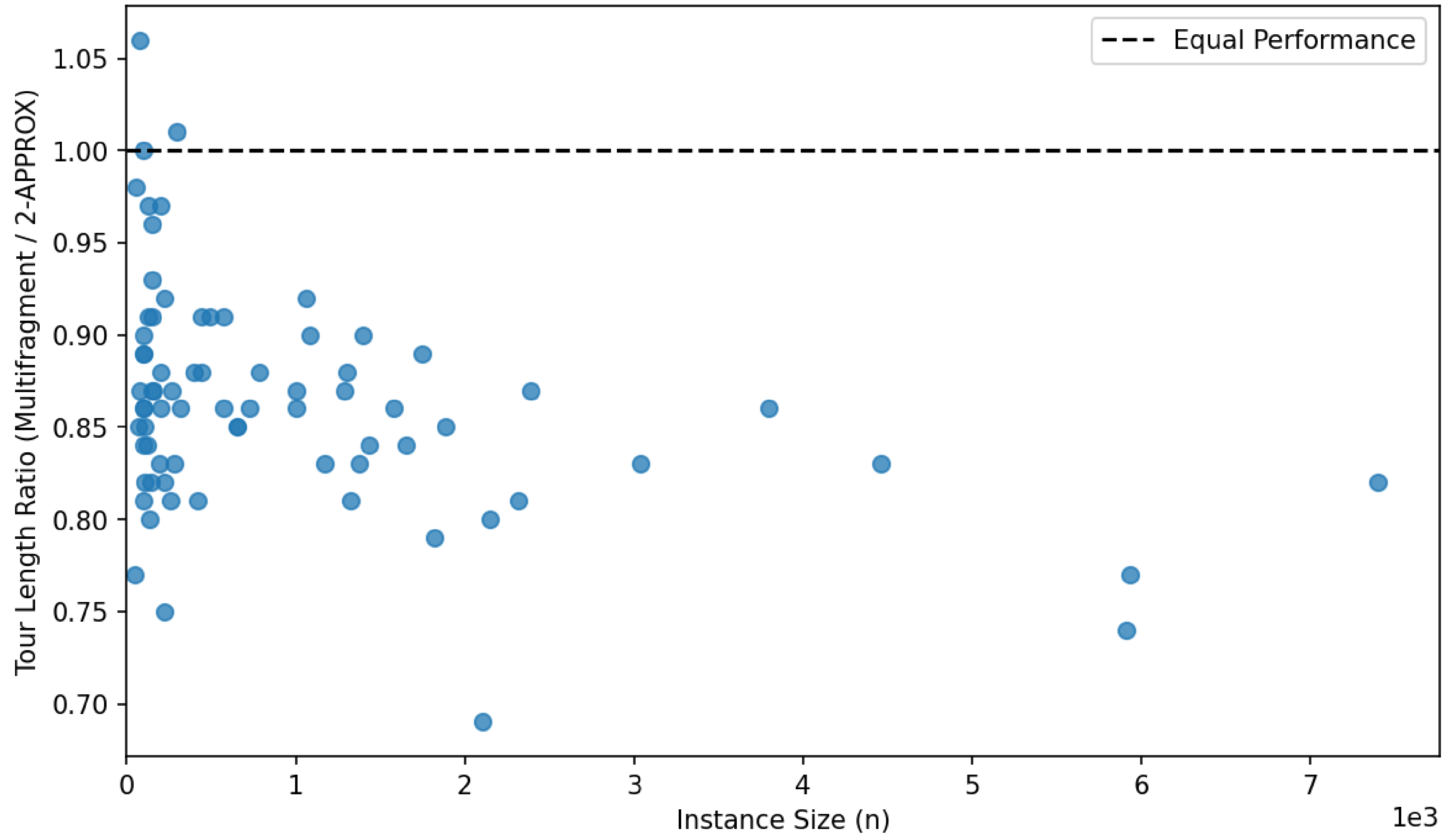
Running Time Comparison



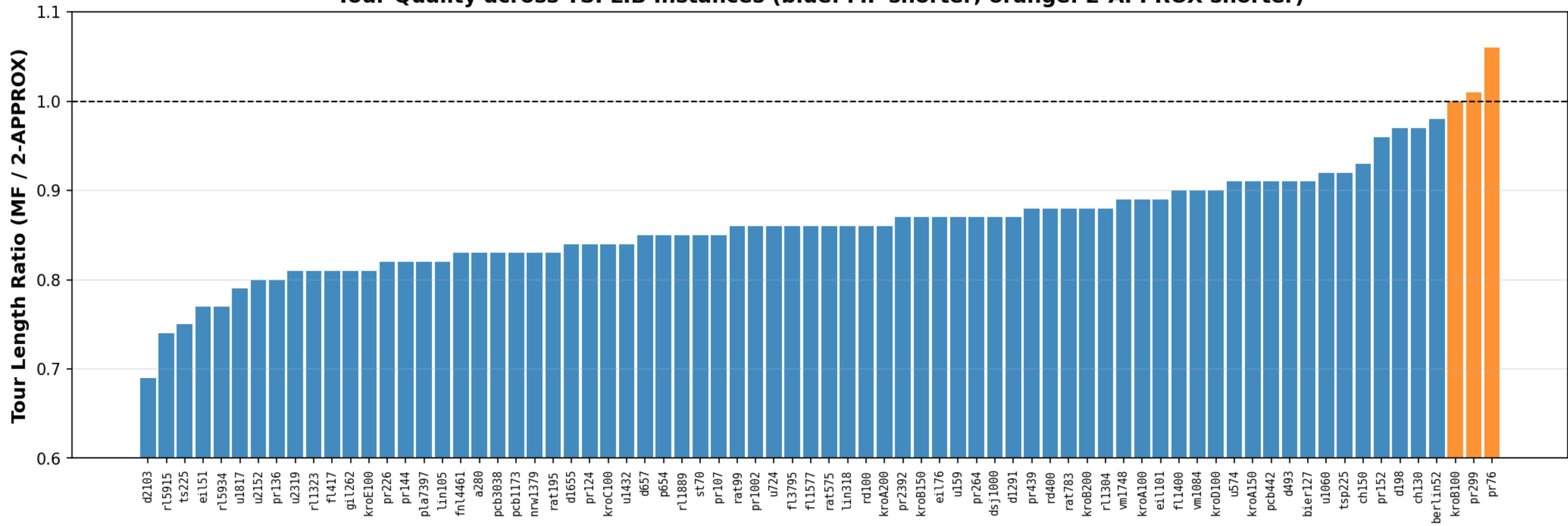
Running Time Comparison (log-log)



Tour Length Ratio



Tour Quality across TSPLIB Instances (blue: MF shorter; orange: 2-APPROX shorter)



Summary of Experiments

- Multifragment outperforms 2-approx in both runtime and in tour length

CONCLUSIONS + FUTURE WORK

Research Question 1

- RQ1: In practice, what are the tradeoffs in approximation performance, runtime, and implementation simplicity between these algorithms?

Research Question 2

- RQ2: In theory, NNC gives a speedup for the MFH. In practice, how much of a speedup is there?

Future Work

- Fully implement Christofides
- More robust experimentation
- Test in higher dimensions

Conclusions

- Worst case theoretical bound doesn't mean an algorithm performs that way in the real world