اصول پردازش تصویر

Principles of Image Processing

مصطفی کمالی تبریزی

۲۴ آبان ۱۳۹۹

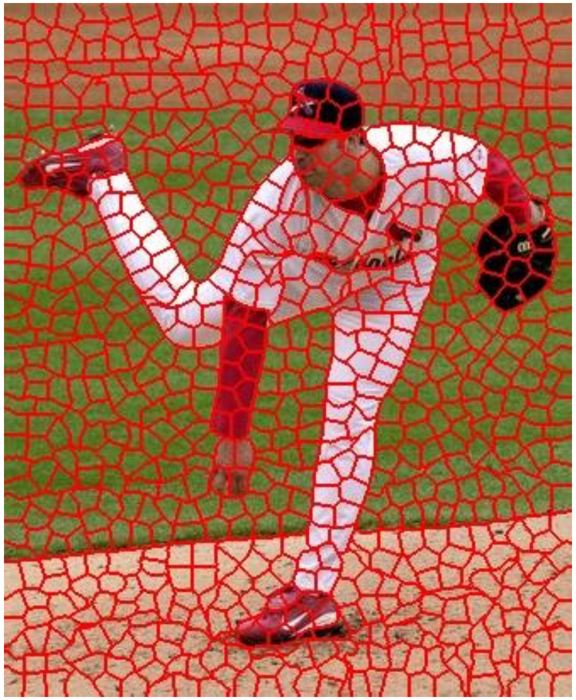
جلسه شانزدهم

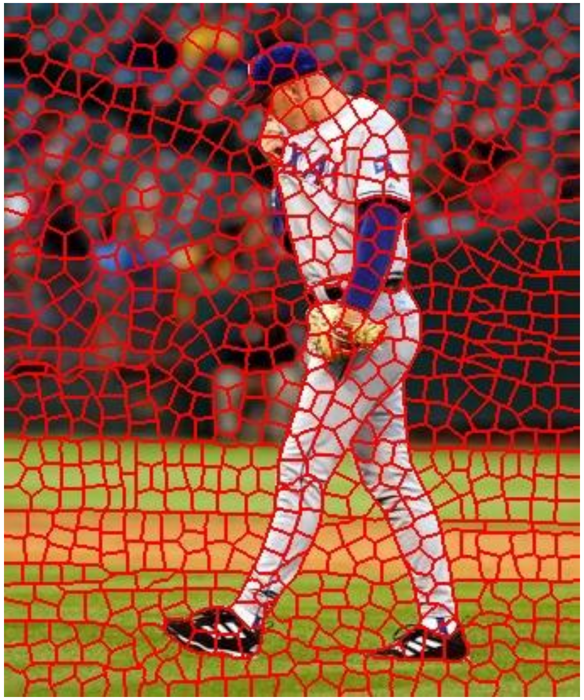
Oversegmentation & Superpixels

Oversegmentation

- Group together similar-looking pixels for efficiency of further processing
  - "Bottom-up" process
  - Unsupervised

"superpixels"





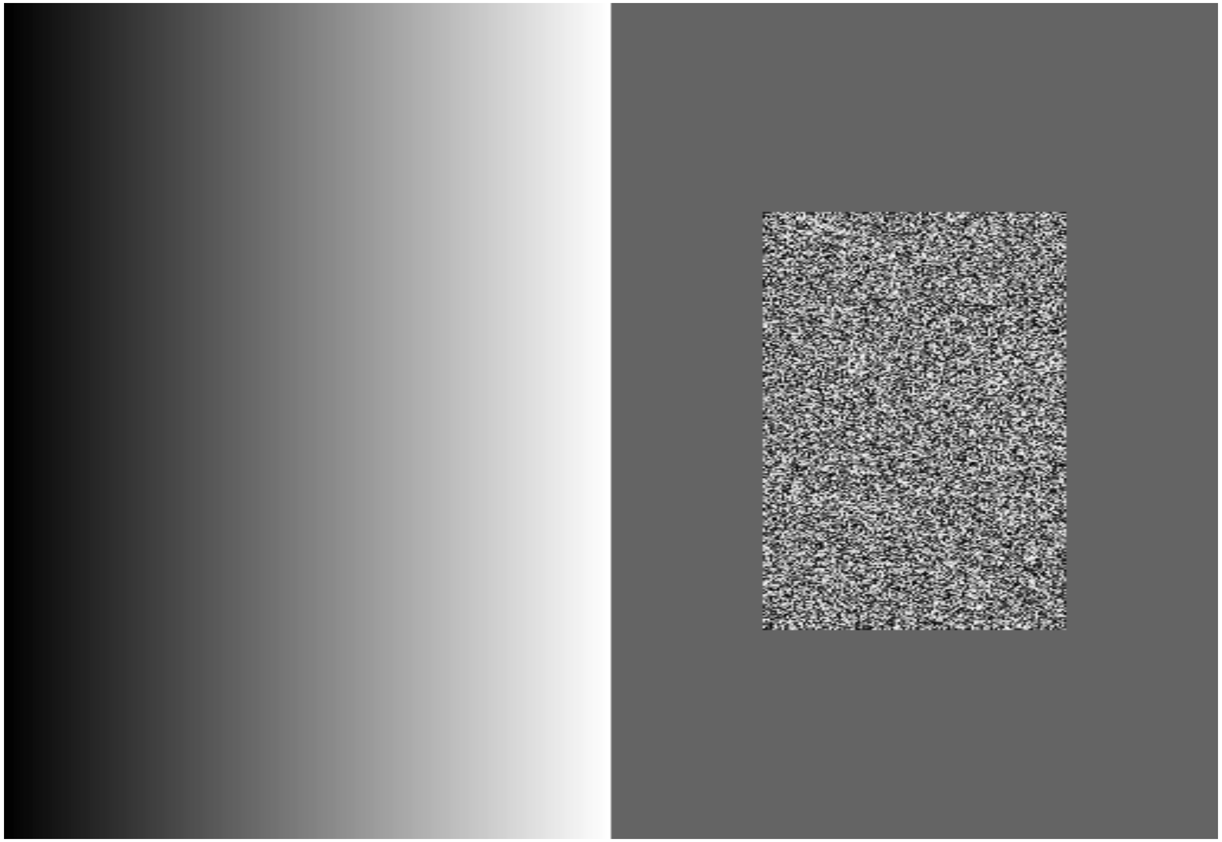
Xiaofeng Ren and Jitendra Malik
Learning a classification model for segmentation,
International Conference on Computer Vision (ICCV), 2003.

Slide Credit: Svetlana Lazebnik

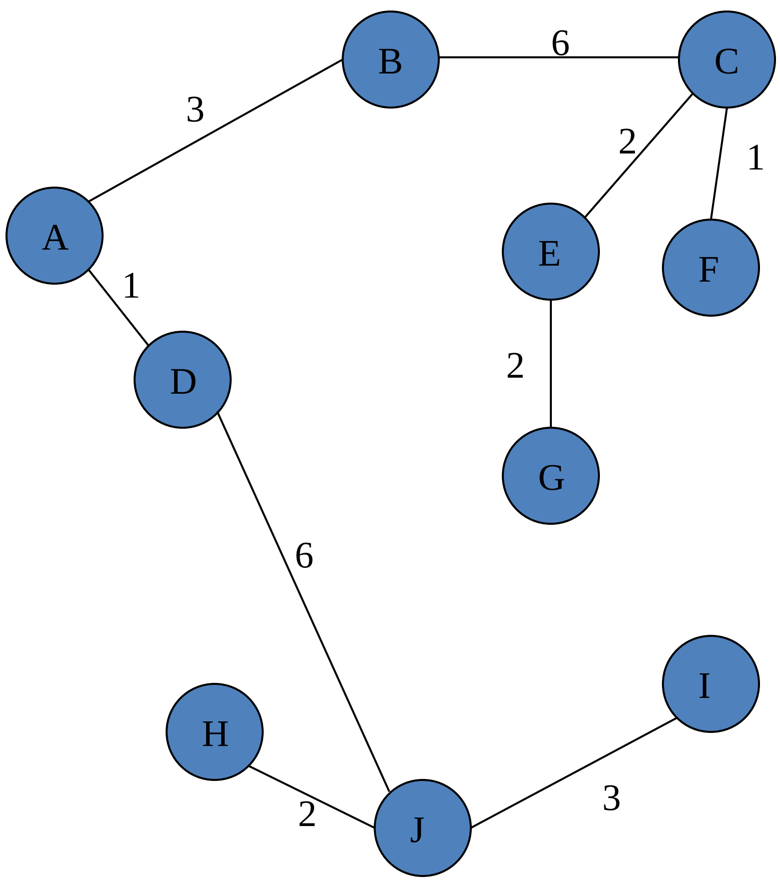
Graph-Based Oversegmentation

Pedro F. Felzenszwalb and Daniel P. Huttenlocher
Efficient Graph-Based Image Segmentation
International Journal of Computer Vision (IJCV), 2004.

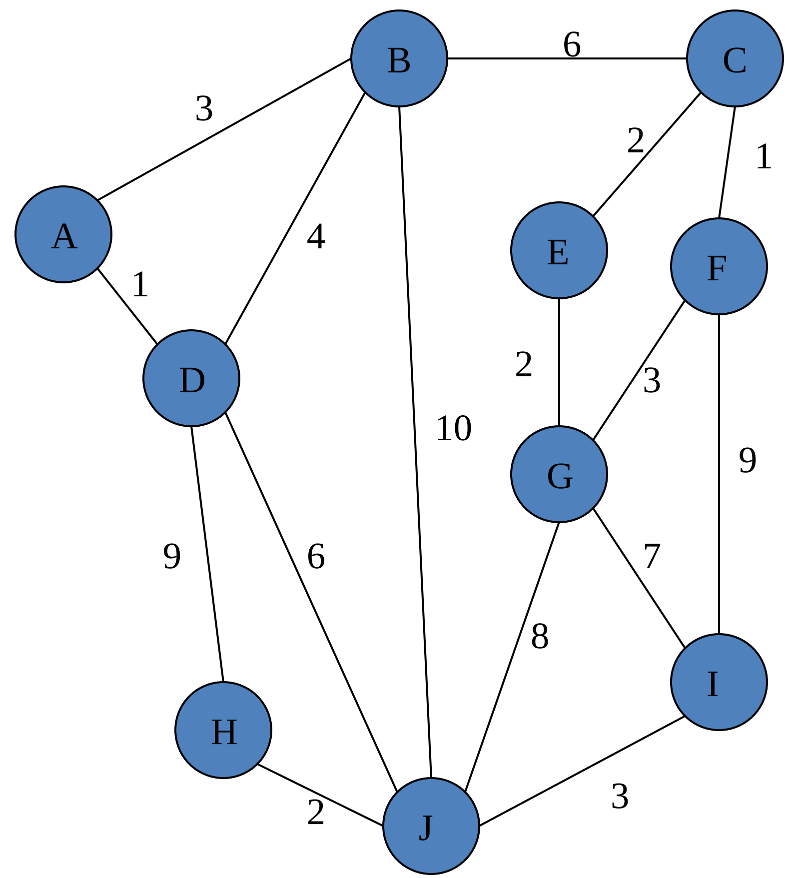
Challenging Example



Minimum Spanning Tree
(Kruskal Algorithm)



Complete Graph



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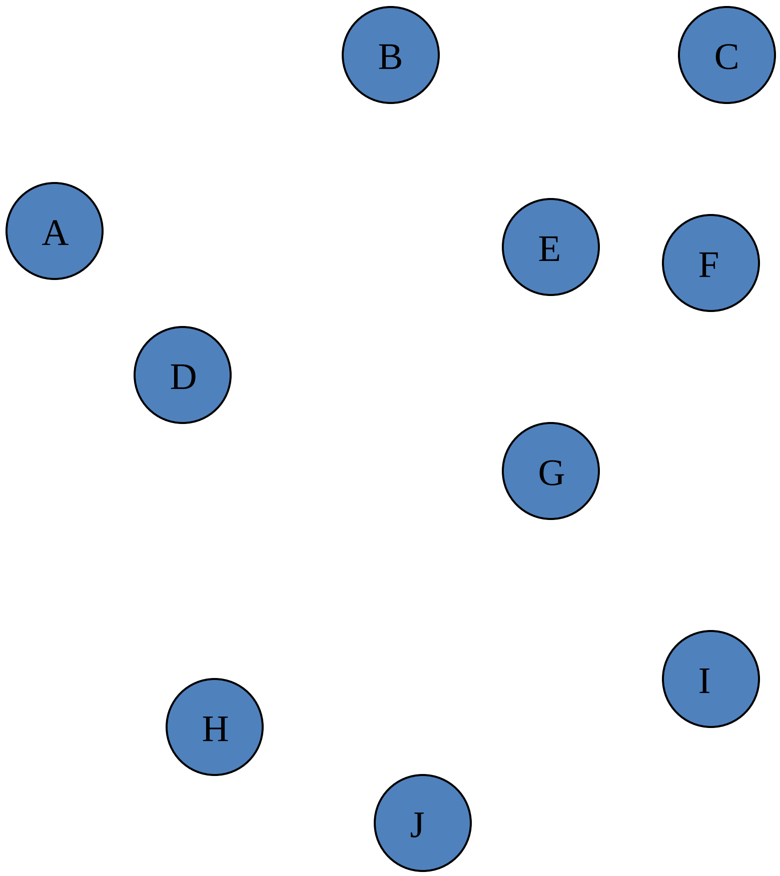

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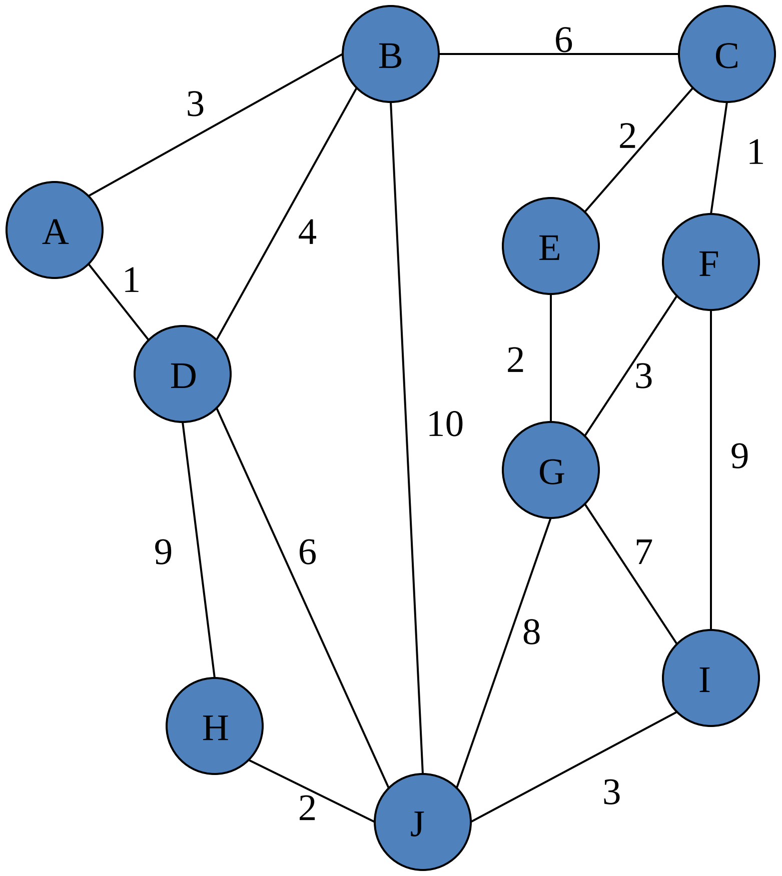

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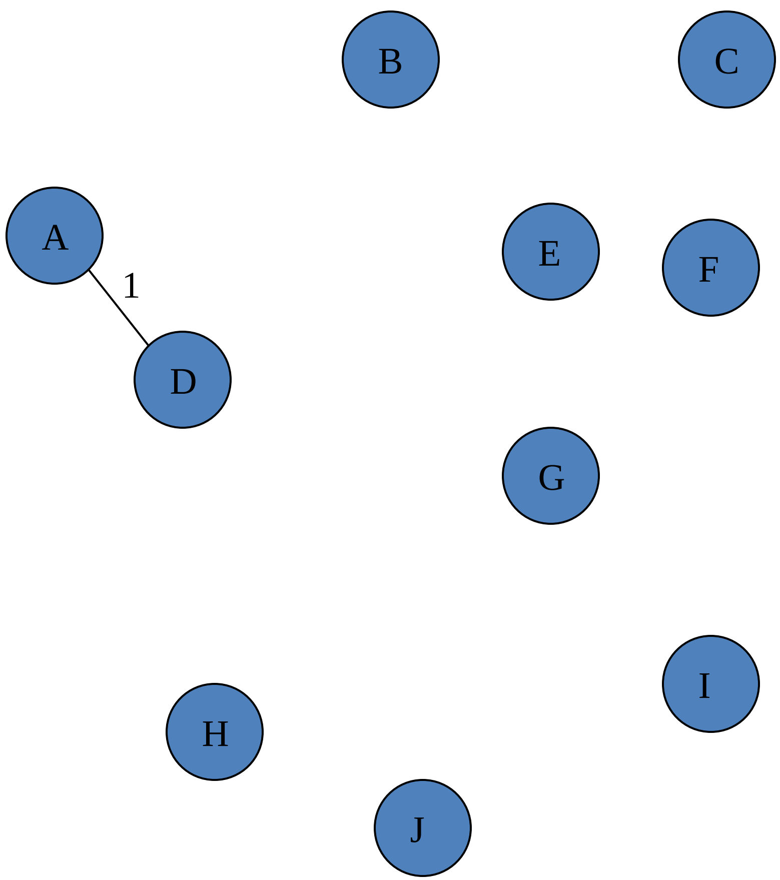

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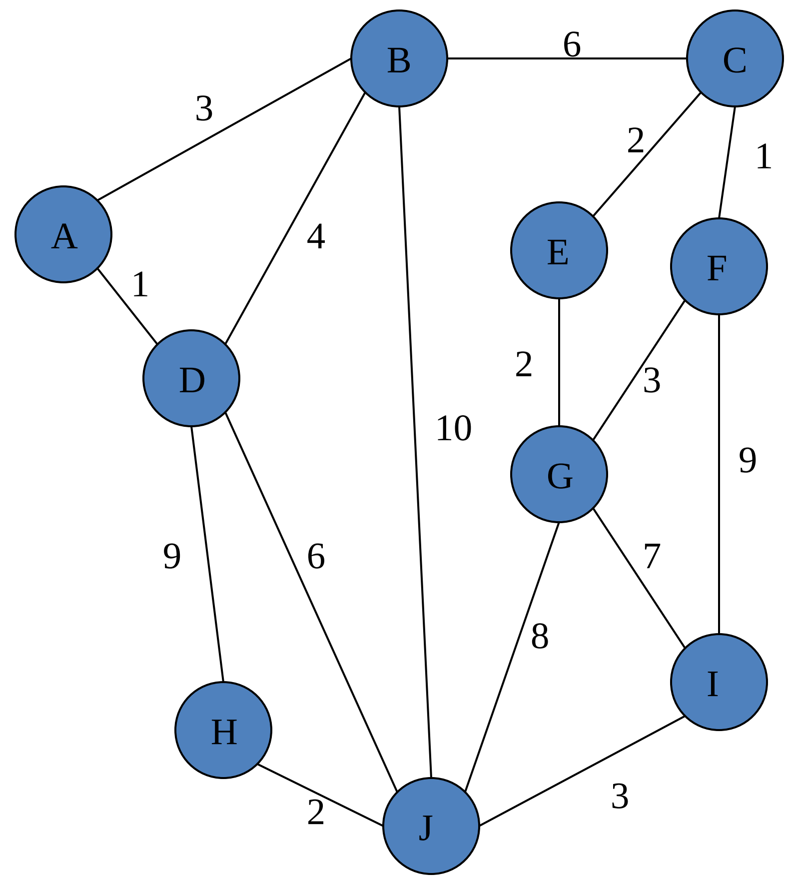

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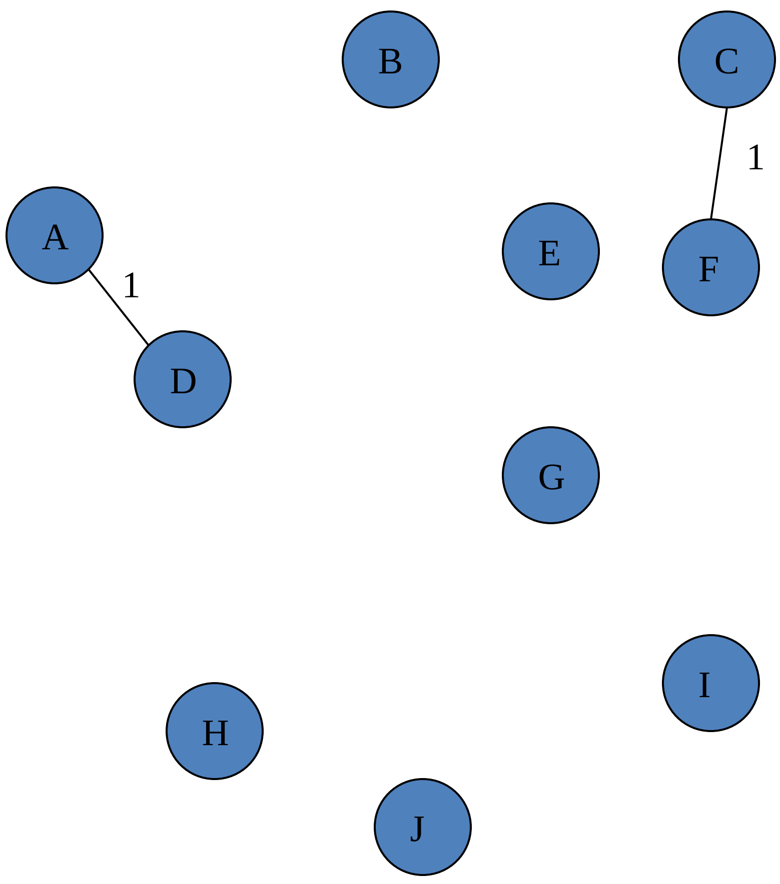

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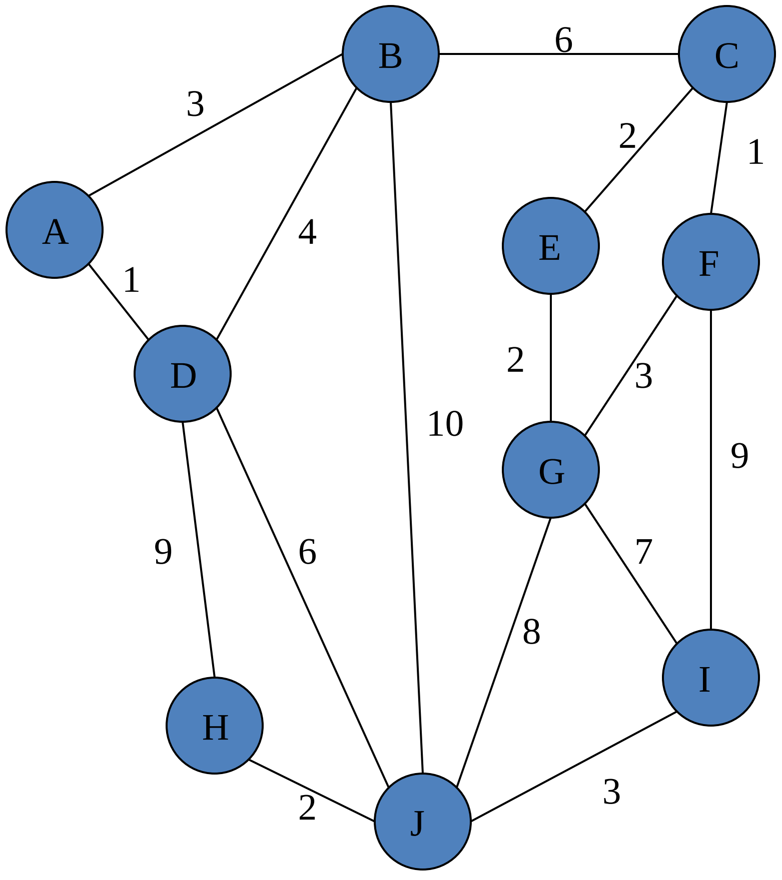

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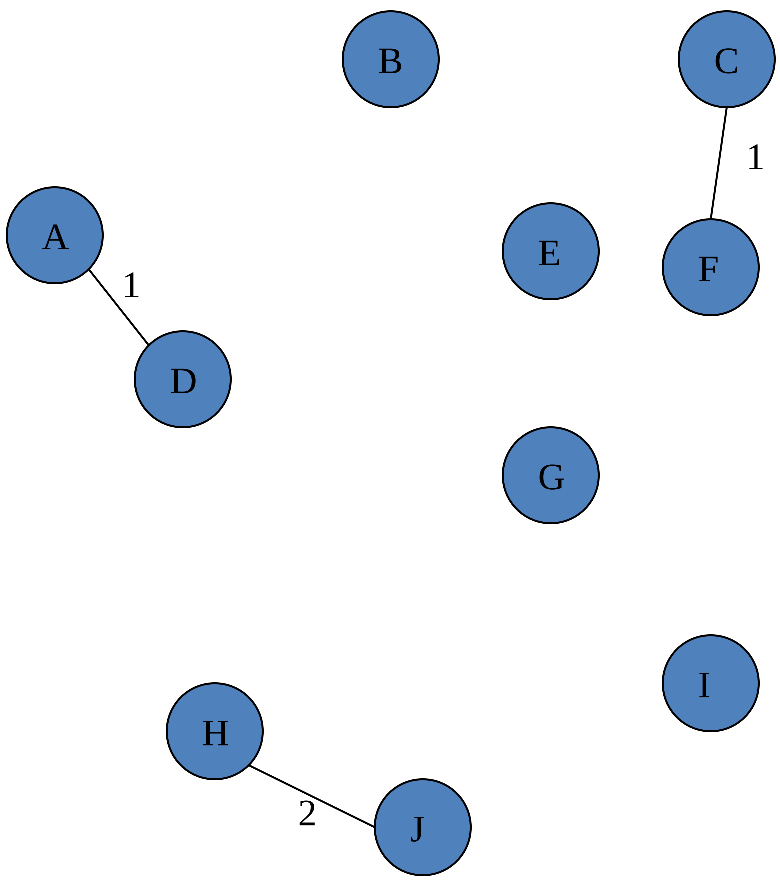

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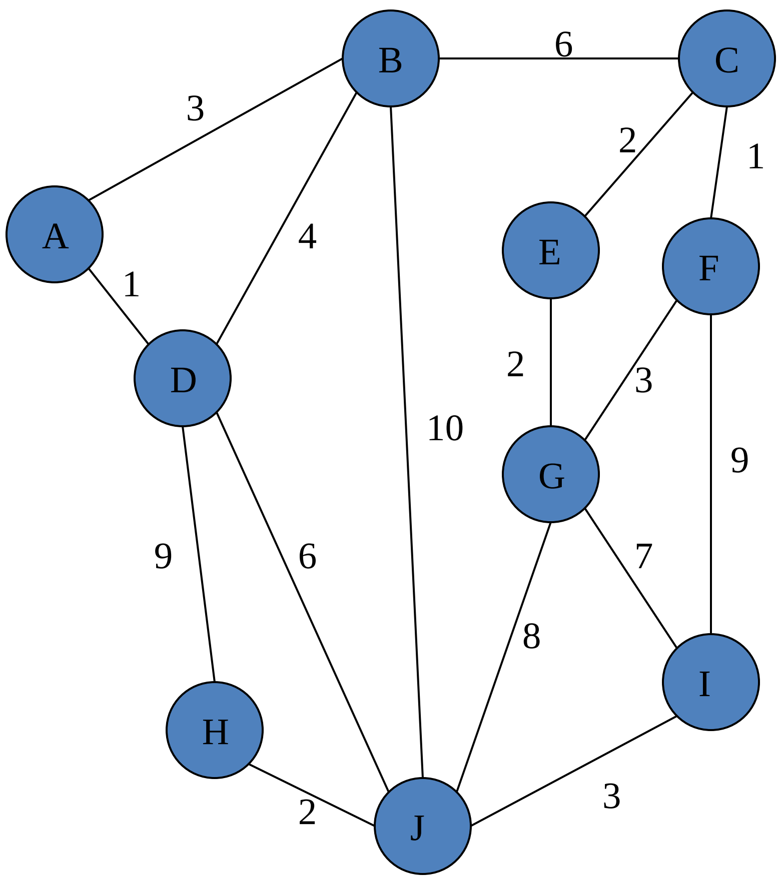

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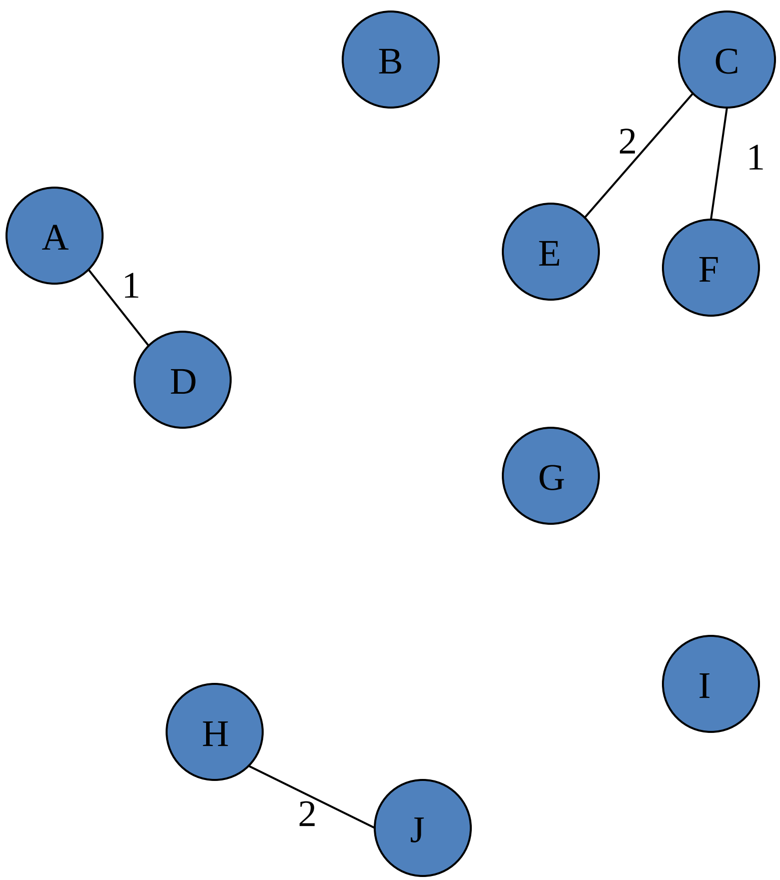

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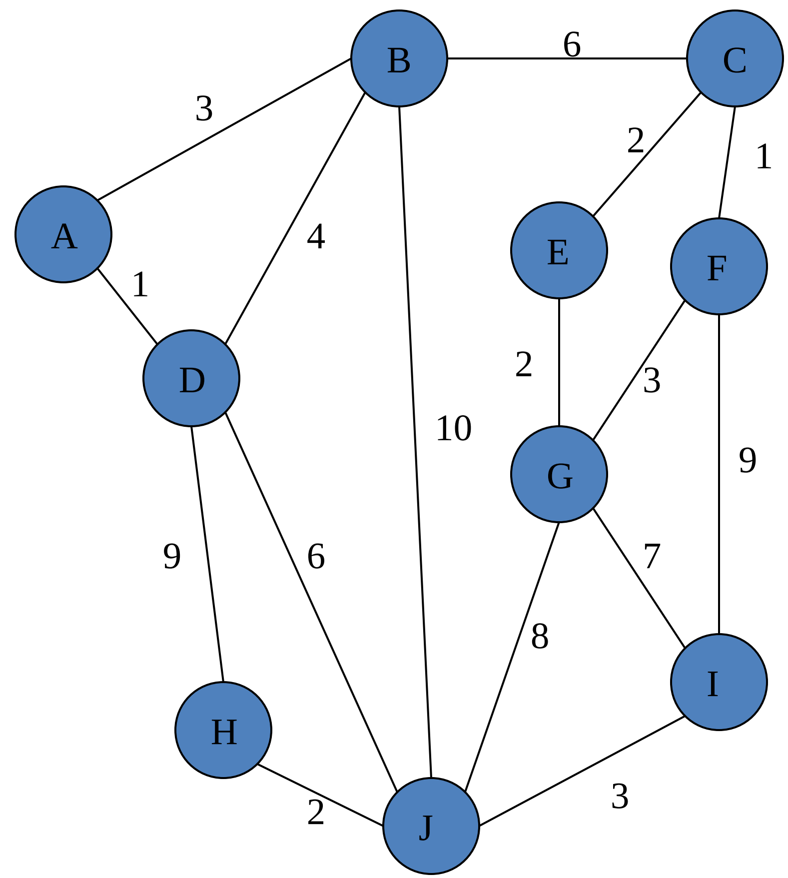

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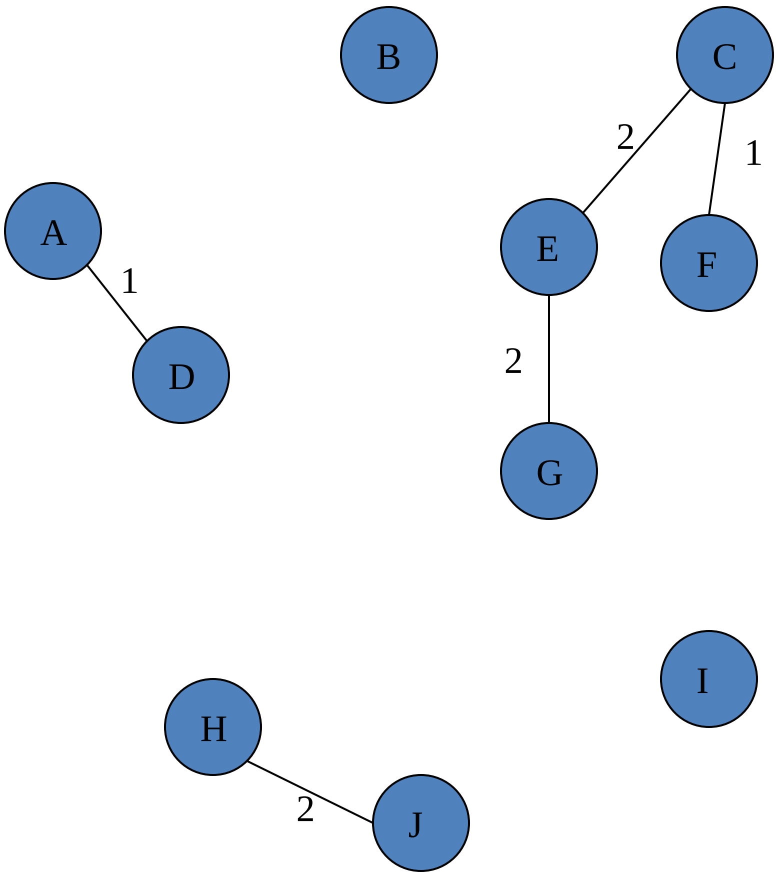

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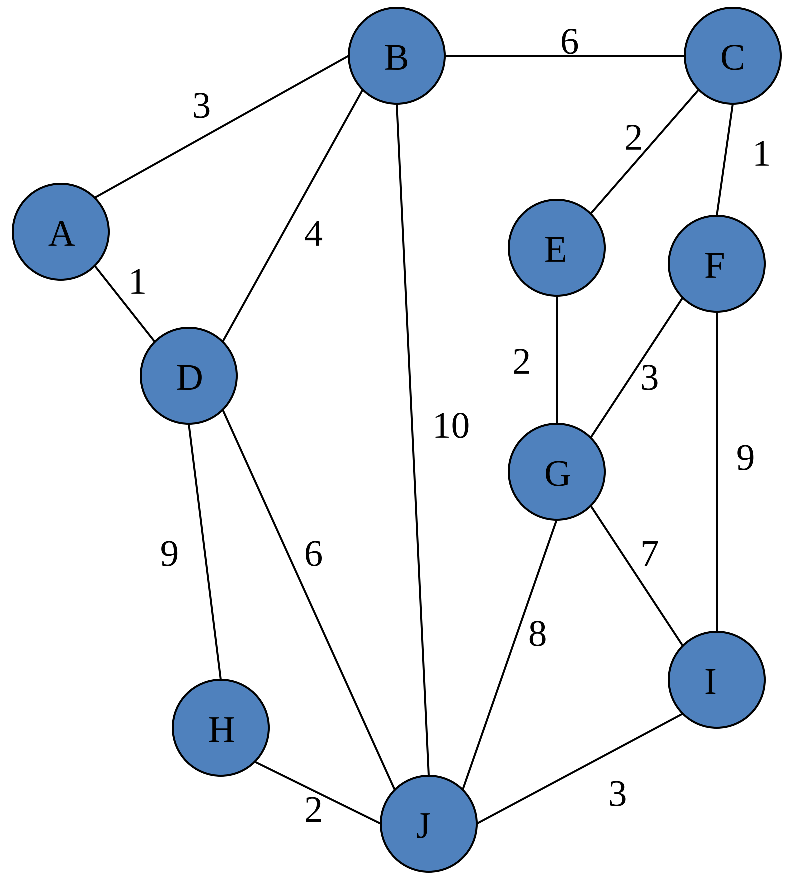

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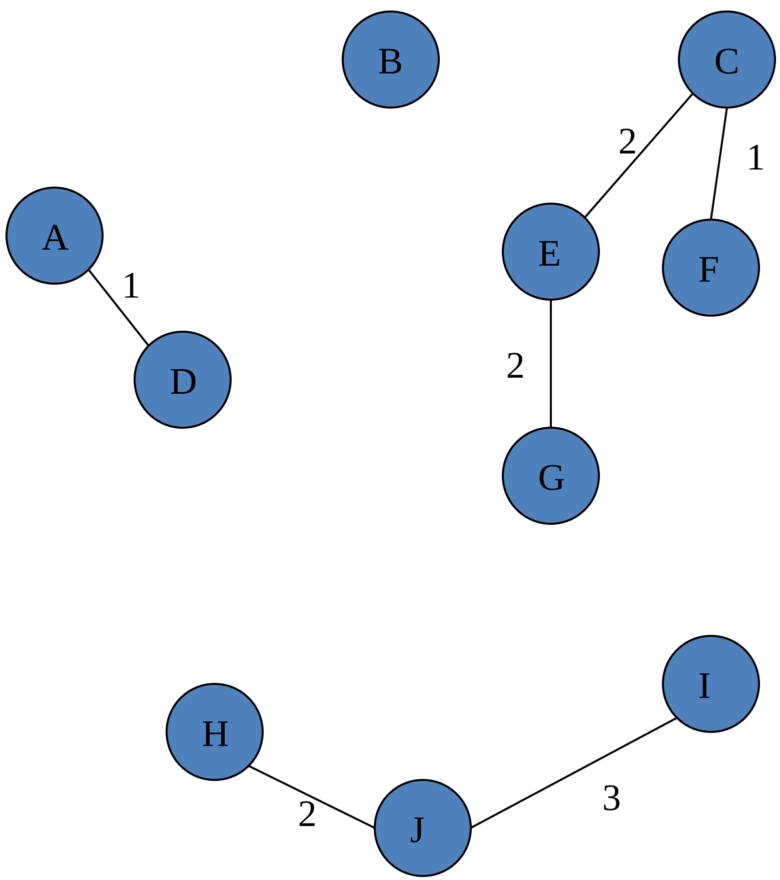

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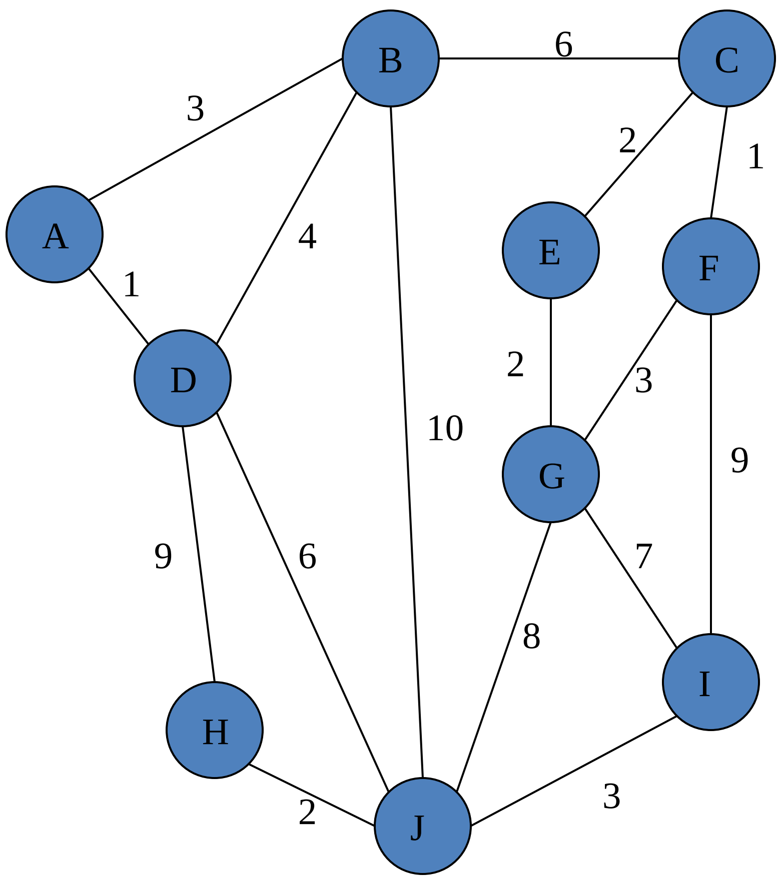

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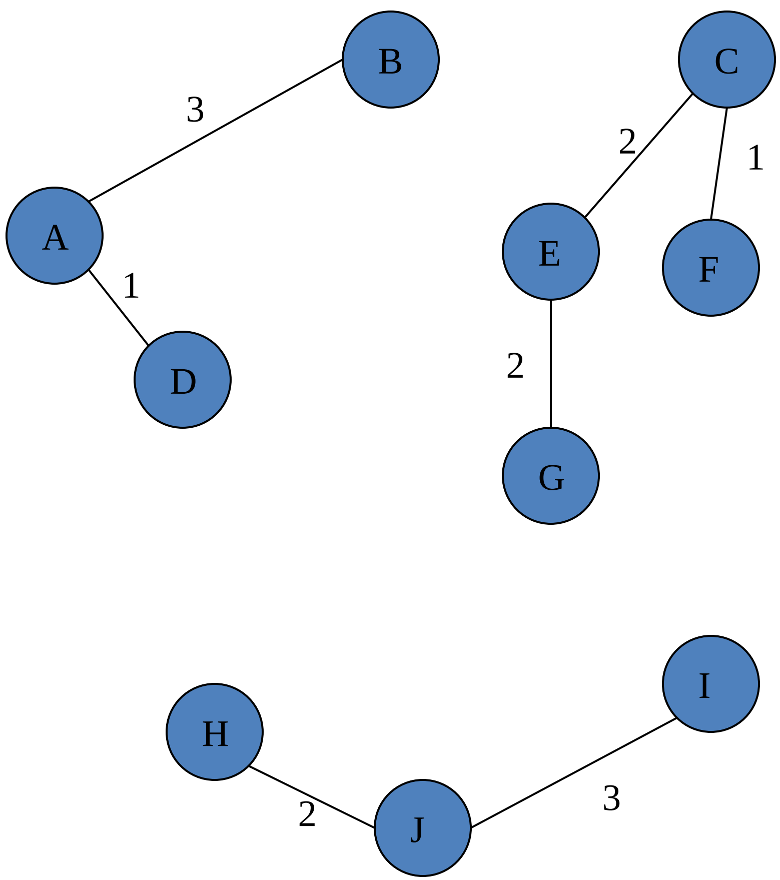

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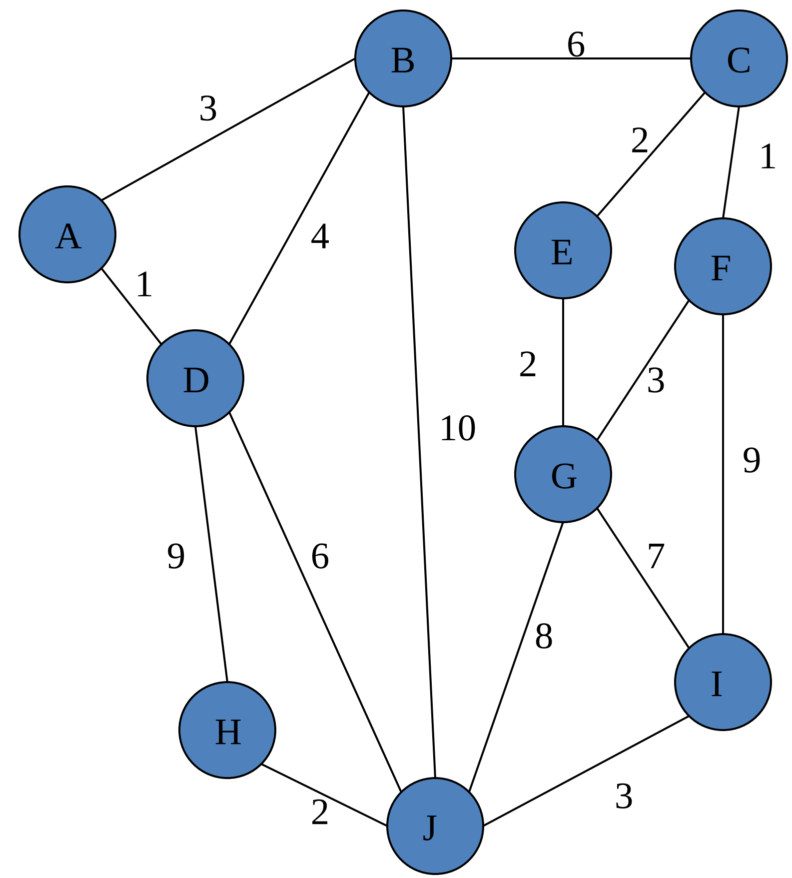

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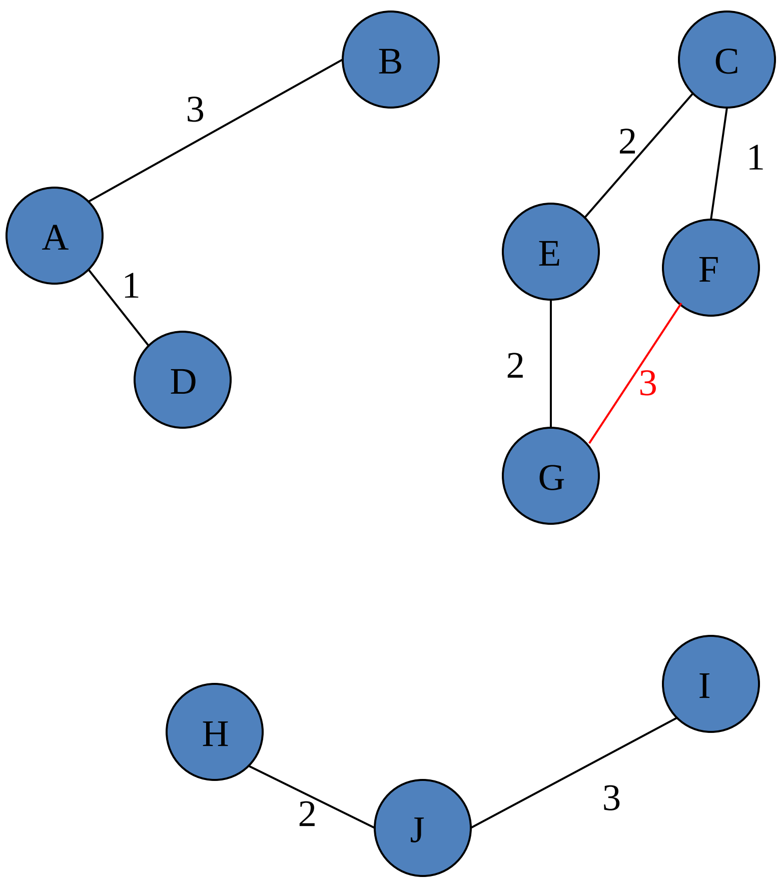

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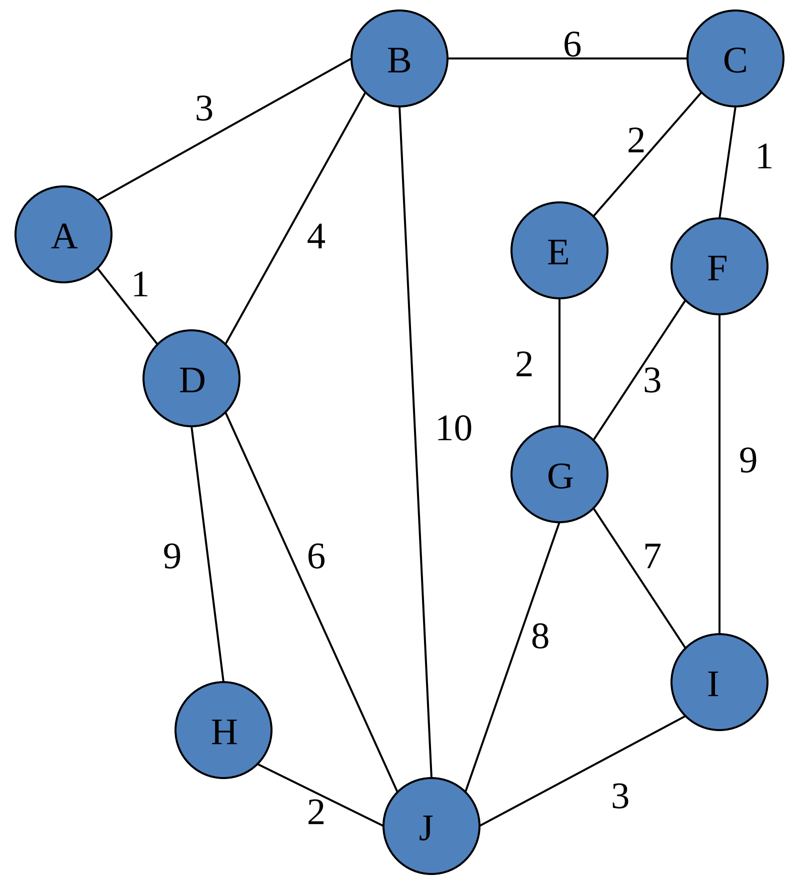

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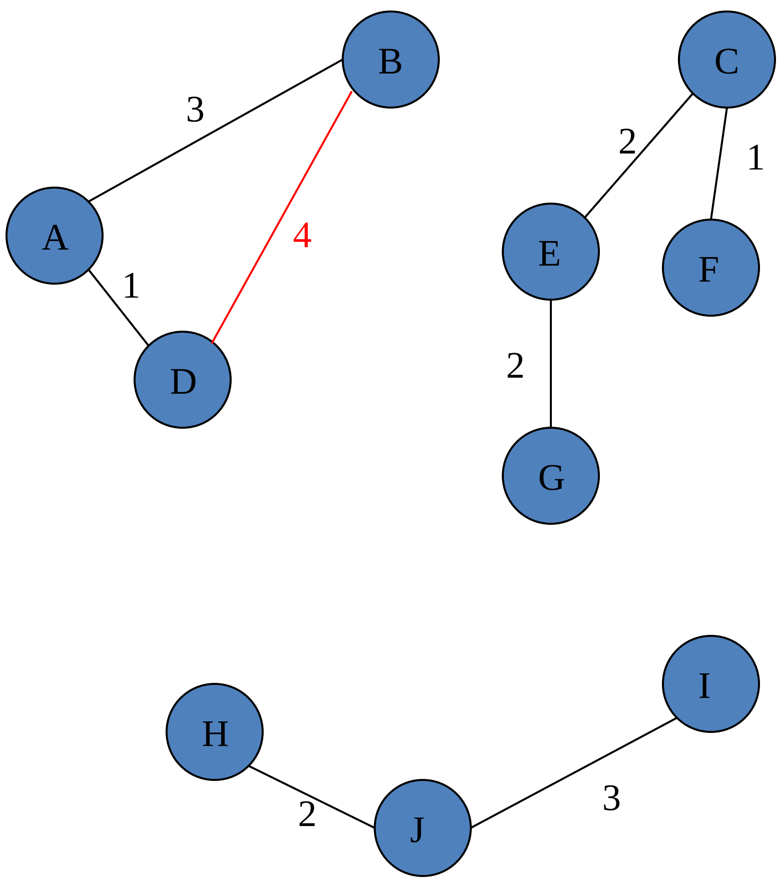

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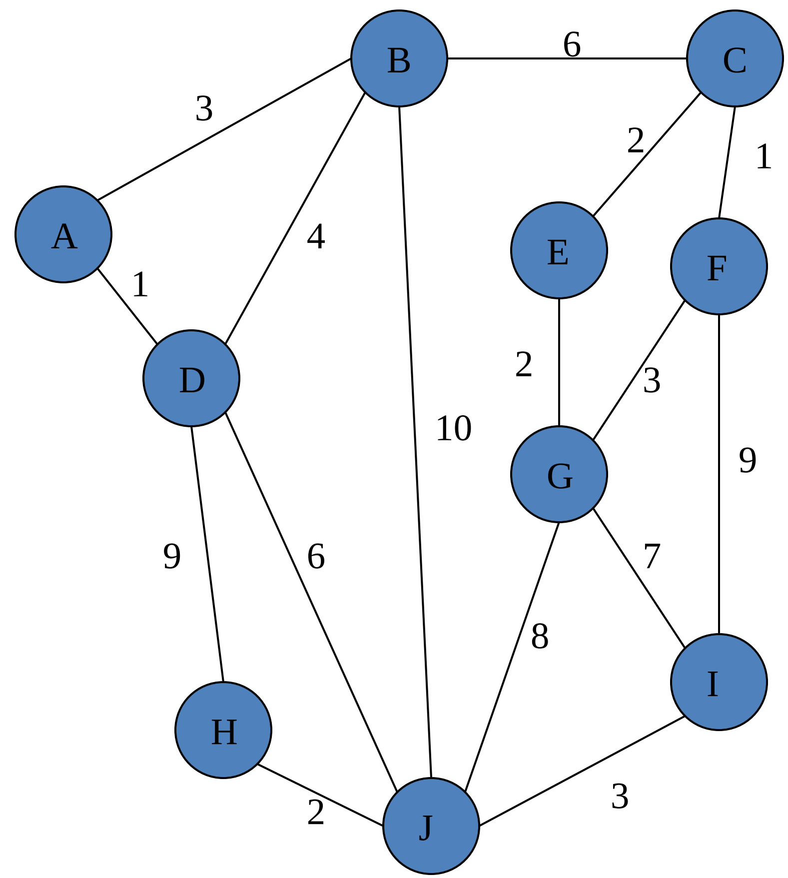

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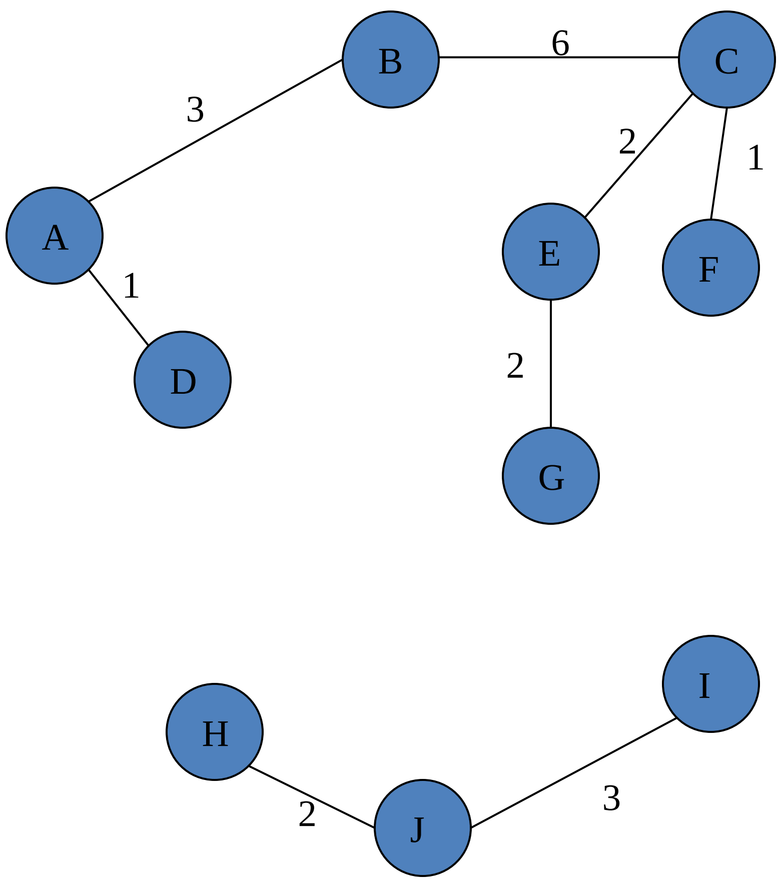

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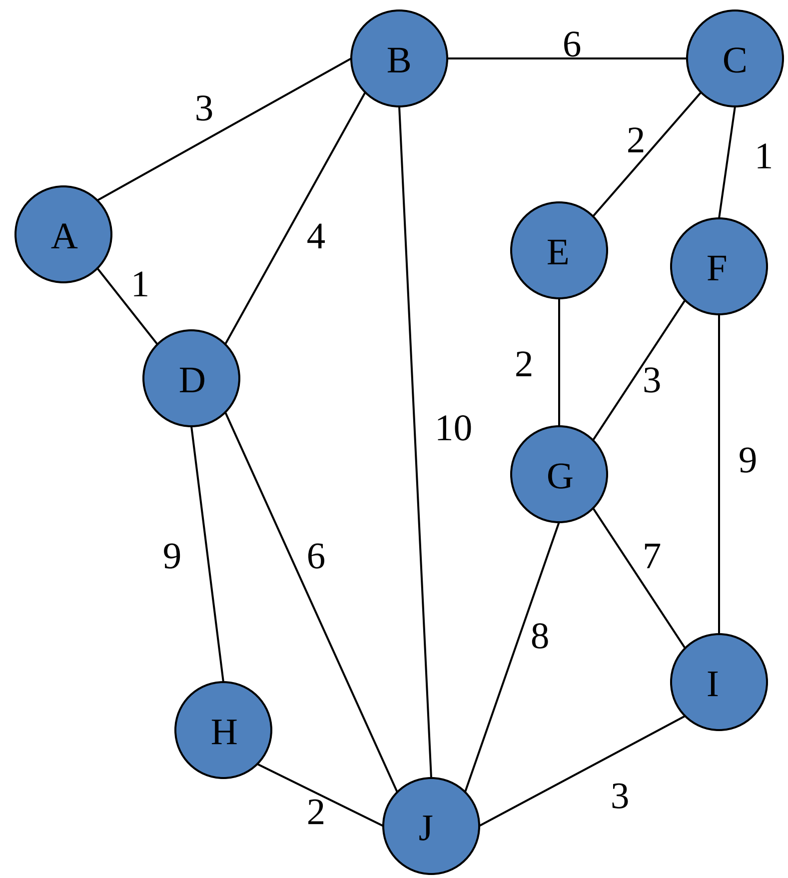

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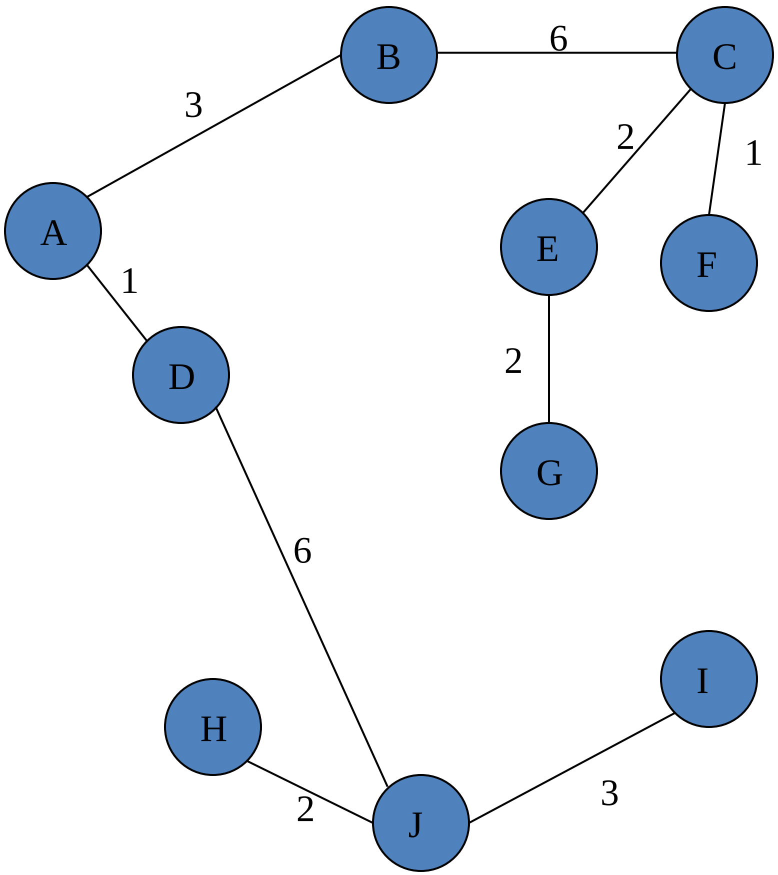

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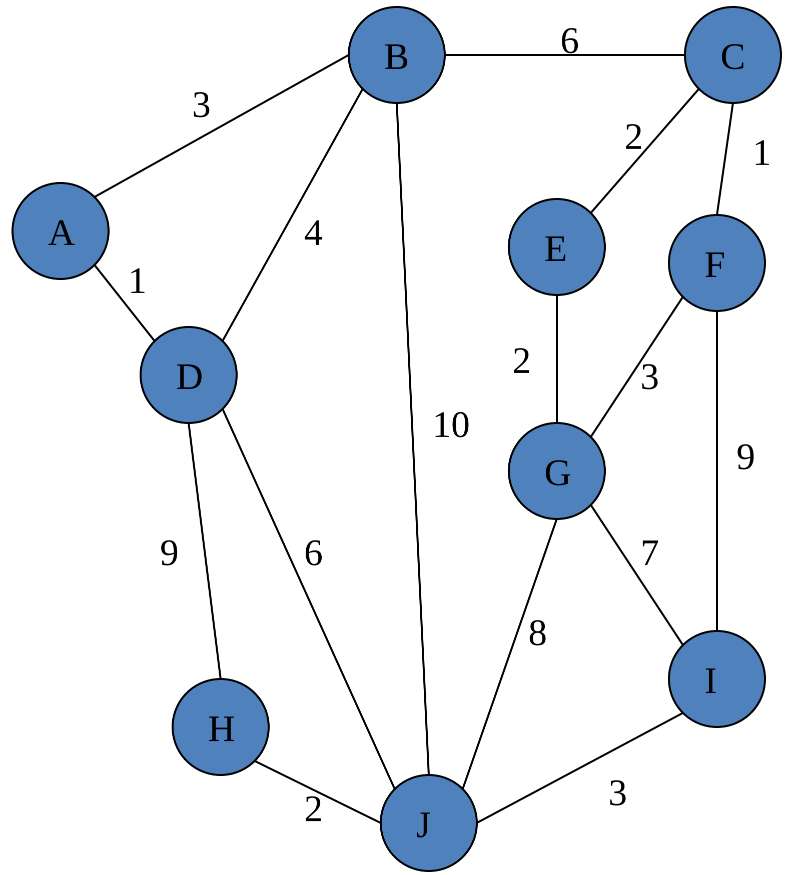

Efficient Graph-Based Image Segmentation (Felzenswalb & Huttenlocher)

Consider undirected graph $G = (V\ , E)$ with characteristics below:

- Vertices $v_i \in V$ are descriptors of pixels p_i
- Edges $\left(v_i, v_j\right) \in E$ pair neighboring vertices
- Weights $w\left(\left(v_i, v_j\right)\right)$ are non-negative measures of dissimilarity between neighboring elements v_i and v_j.

Segmentation $S = \{C_1, C_2, \dots, C_n\}$ is a partition of V so that:

- Each C_i is a connected component in graph $G_i = (V, E_i)$
- $E_i \subseteq E$

Efficient Graph-Based Image Segmentation (Felzenswalb & Huttenlocher)

Objective:

Finding a segmentation so that:
elements in a component to be similar, and
elements in different components to be dissimilar.

In other words:
Low weights of edges in a component, and
High weights of edges between two different components.

Efficient Graph-Based Image Segmentation (Felzenswalb & Huttenlocher)

Internal difference of a component $C \subseteq V$:

$$Int(C) = \max_{e \in MST(C,E)} w(e)$$

The largest weight in the minimum spanning tree of C, $MST(C, E)$.

Difference between two components $C_1, C_2 \subseteq V$:

$$Dif(C_1, C_2) = \min_{\substack{v_i \in C_1,\ v_j \in C_2 \\ (v_i, v_j) \in E}} w\left((v_i, v_j)\right)$$

The minimum weight edge connecting two components.

Minimum internal difference of two components C_1 and C_2:

$$MInt(C_1, C_2) = \min(\, Int(C_1) + \tau(C_1)\, ,\, Int(C_2) + \tau(C_2)\,)$$

Efficient Graph-Based Image Segmentation (Felzenswalb & Huttenlocher)

Pairwise comparison predicate:

$$D(C_1, C_2) = \begin{cases} true & Dif(C_1, C_2) < MInt(C_1, C_2) \\ false & otherwise \end{cases}$$

True = Merging two components

False = Not merging two components

Algorithm $\boxed{n log(n) \ where \ n \ is \ the \ number \ of \ pixels}$

Objective:

Finding segmentation $S = (C_1, C_2, \dots, C_r)$

1. Sort E into $(o_1, o_2, \dots, o_m)$ by non-decreasing edge weights.
2. Start with S^0, where each vertex v_i is a component.
3. Repeat steps below for $q = 1, \dots, m$ to construct S^q given S^{q-1}:
    1. Let v_i in C_i^{q-1} and v_j in C_j^{q-1} denote the vertices connected by the q-th edge in the ordering, i.e., $o_q = (v_i, v_j)$.
    2. If $C_i^{q-1} \neq C_j^{q-1}$ and $w(o_q) \leq MInt(C_i^{q-1}, C_j^{q-1})$ then merge two components.
4. *Return* $S = S^m$.

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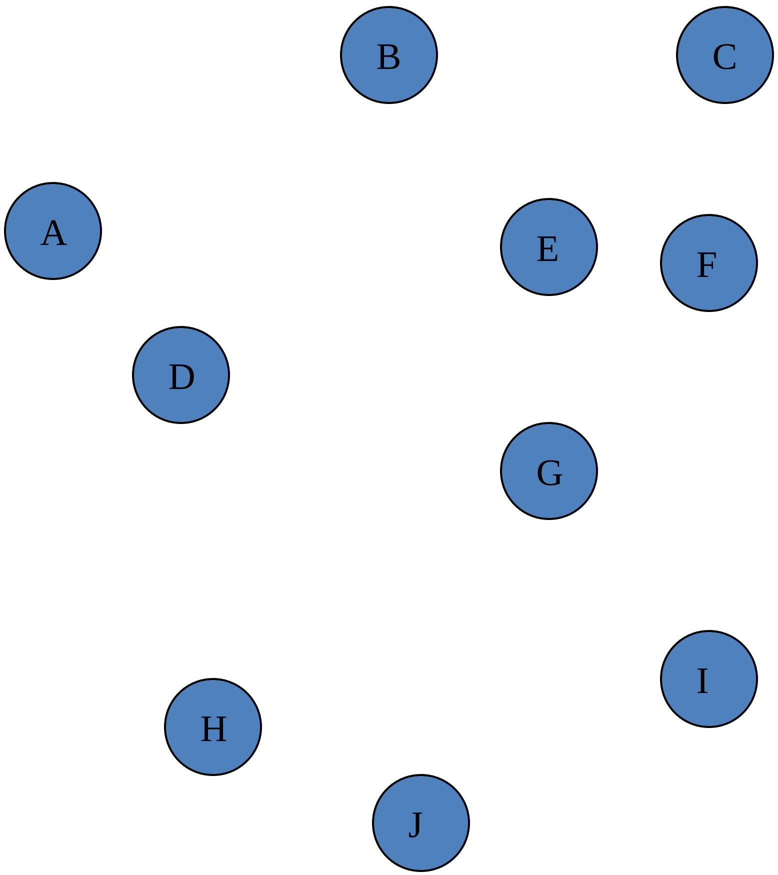
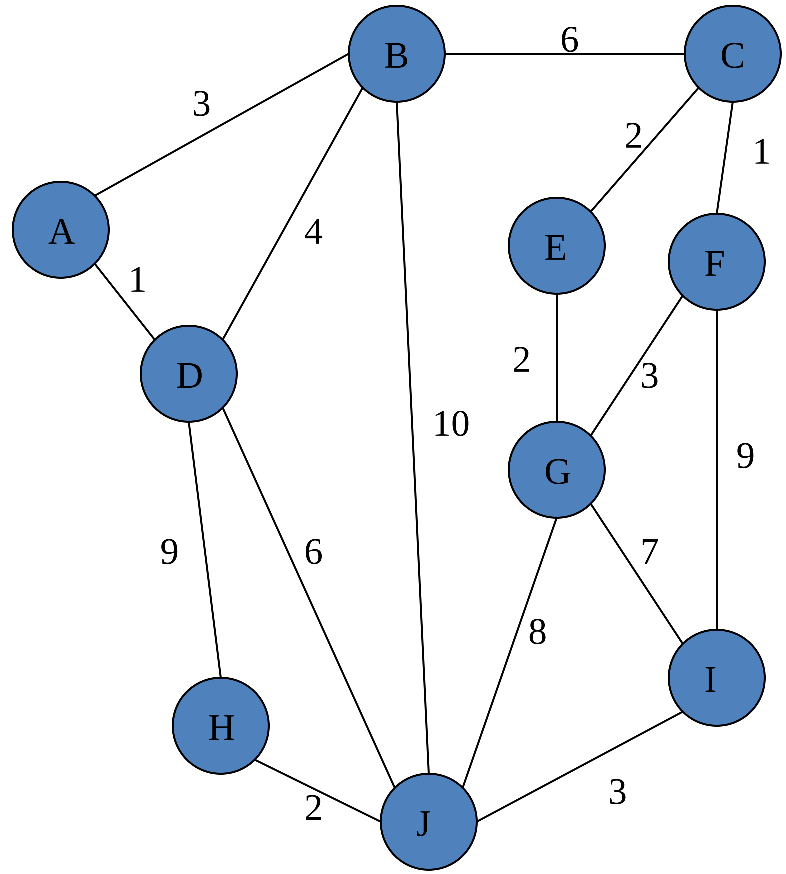


$\boxed{\tau = 2}$

Complete Graph



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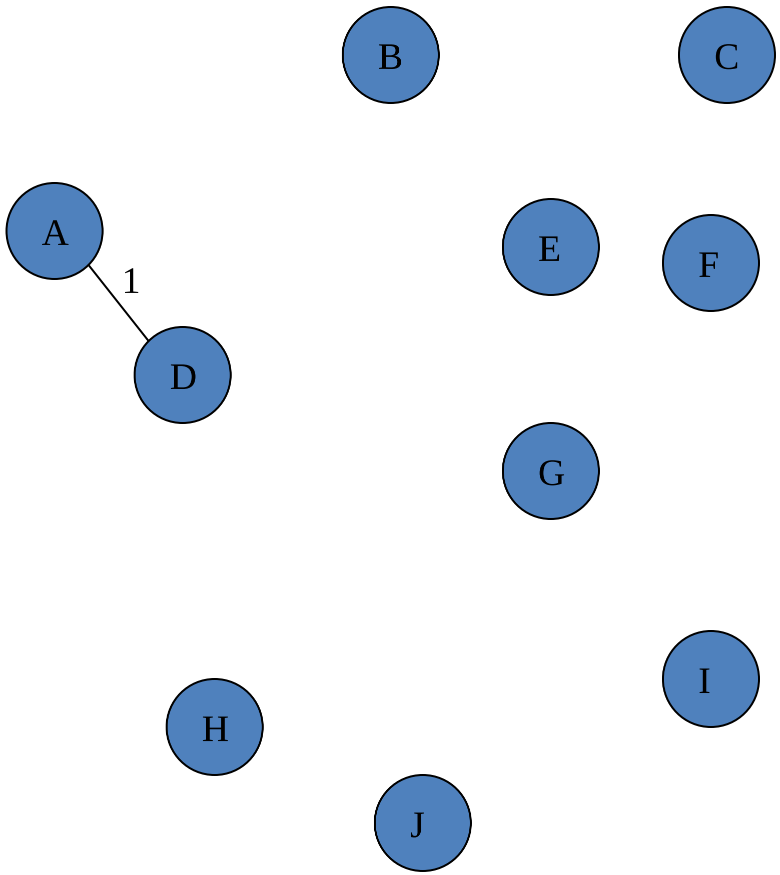

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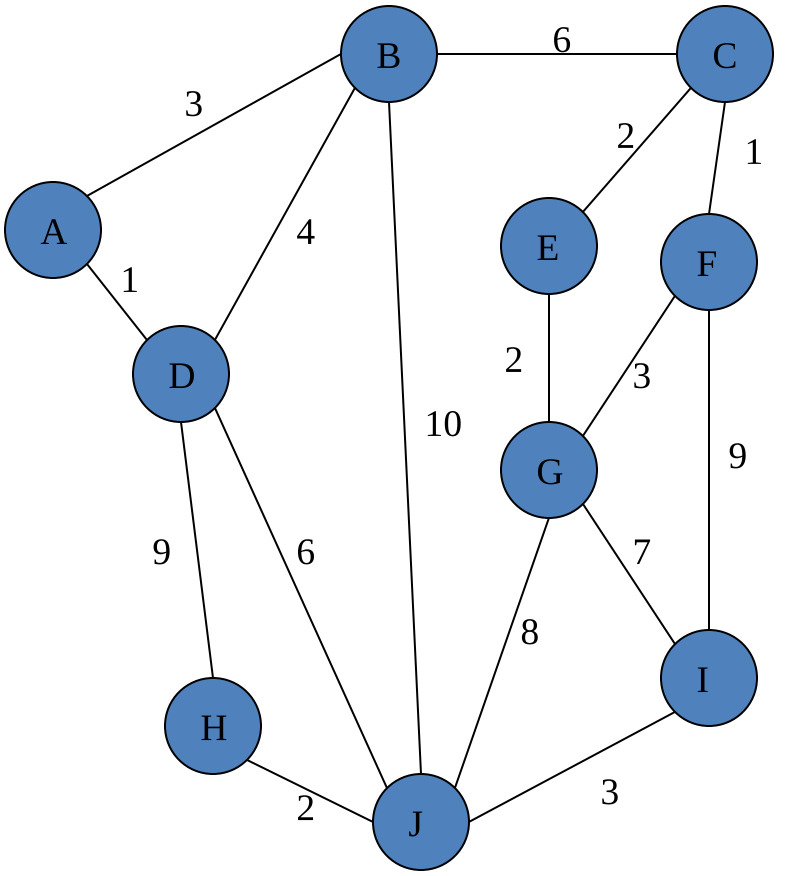

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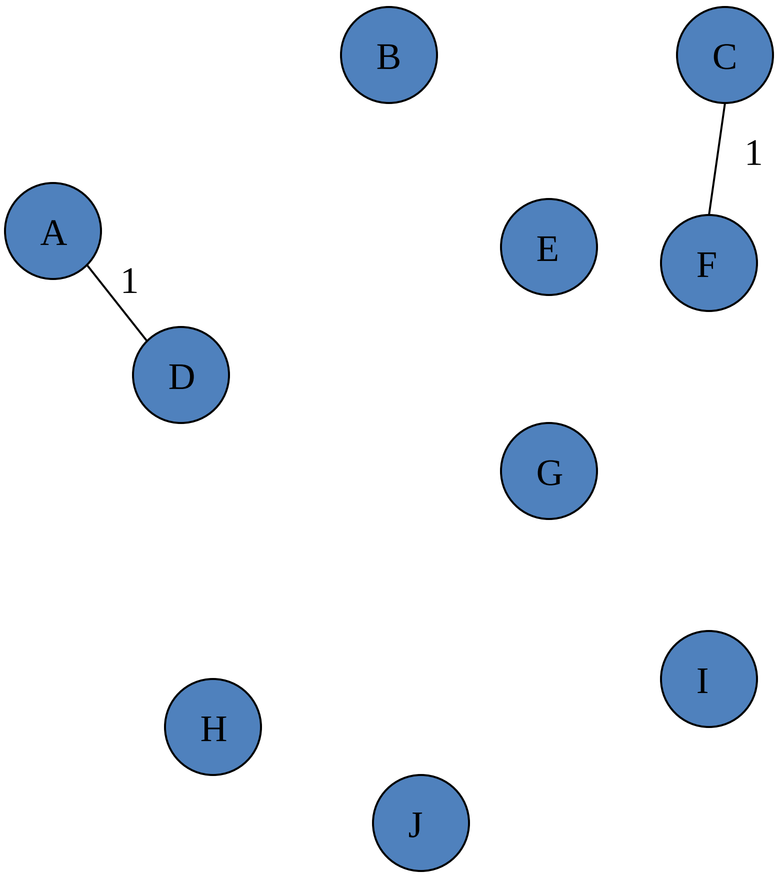

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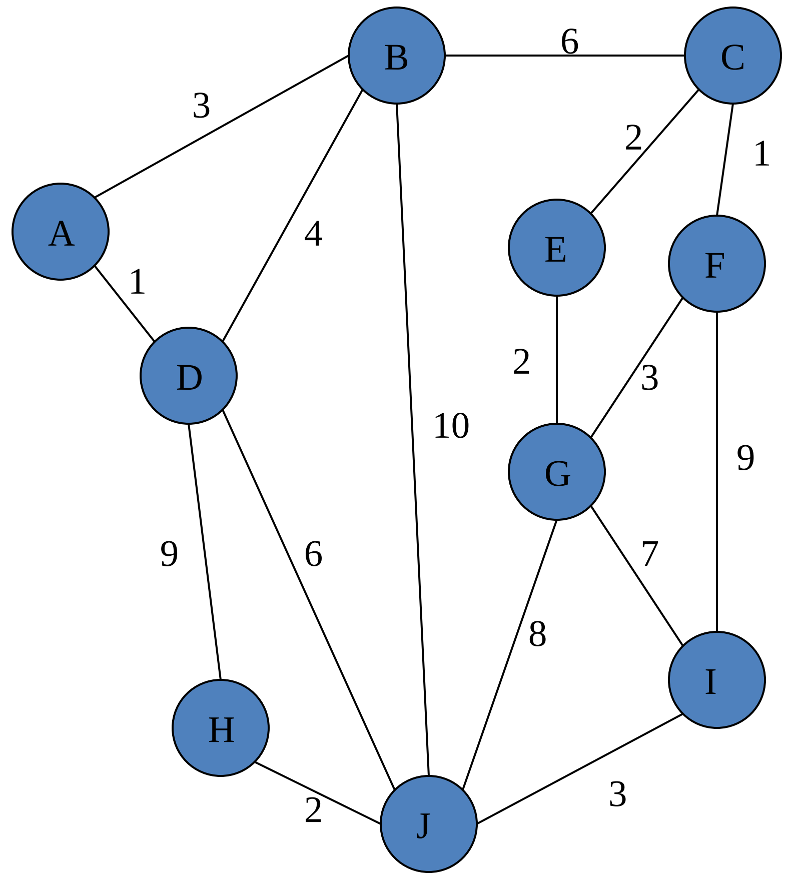

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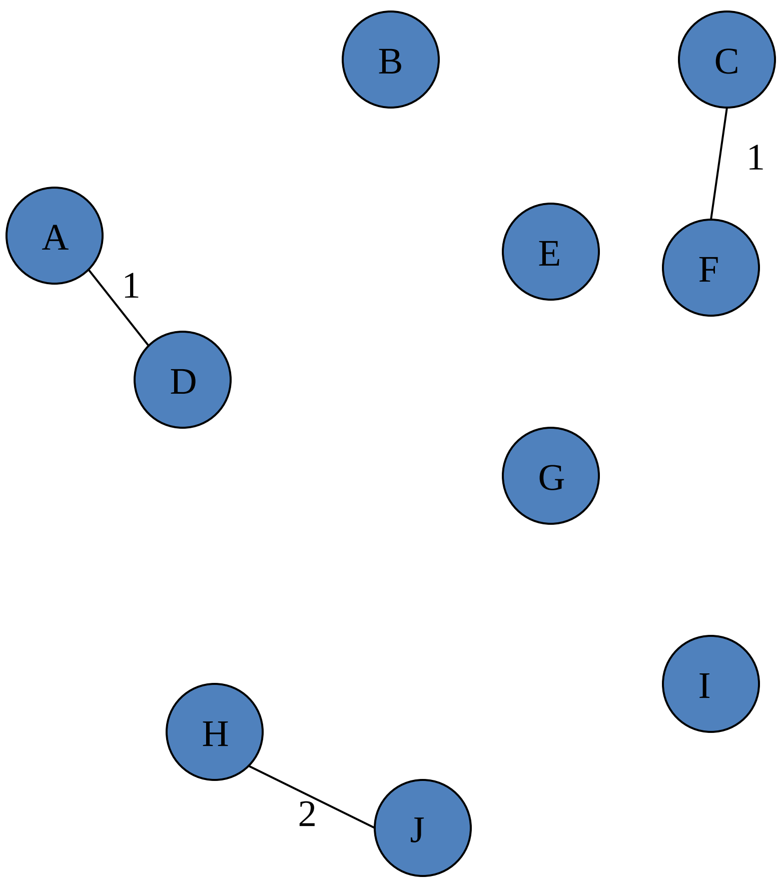

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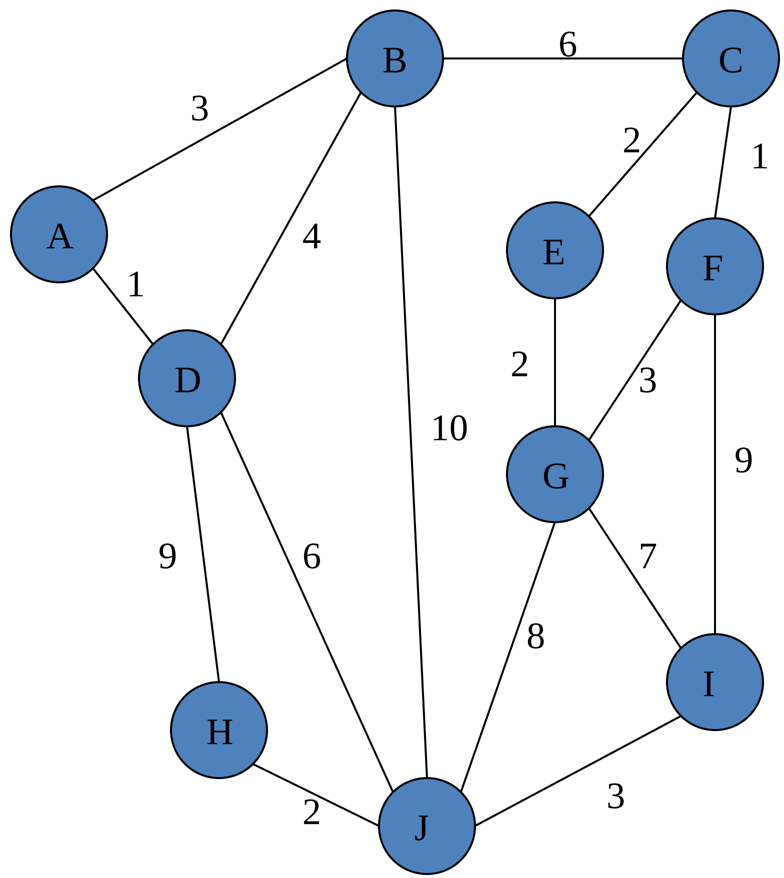

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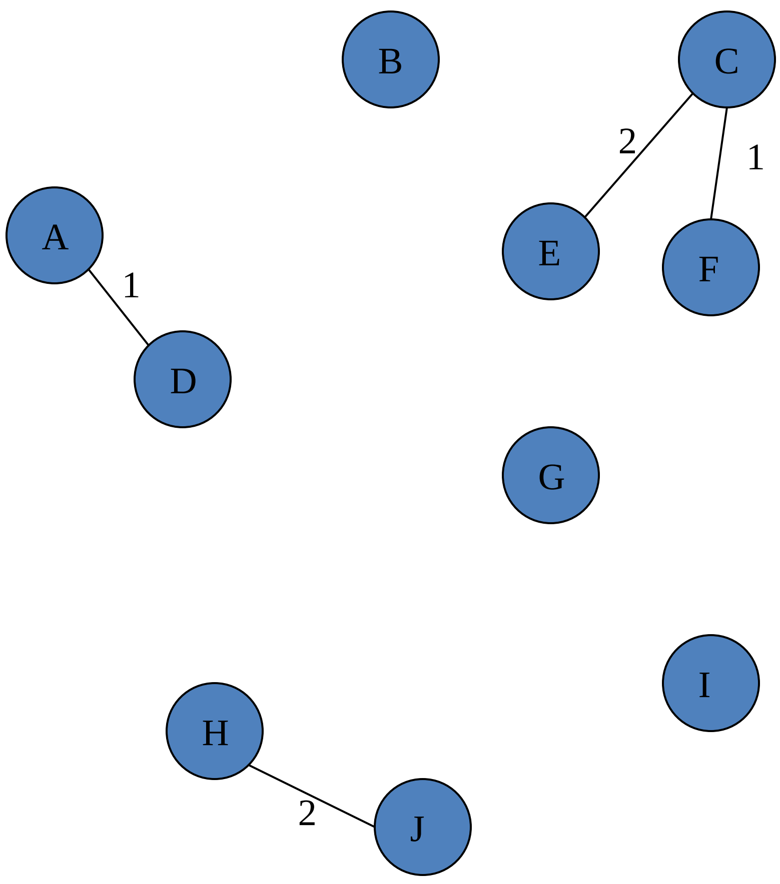

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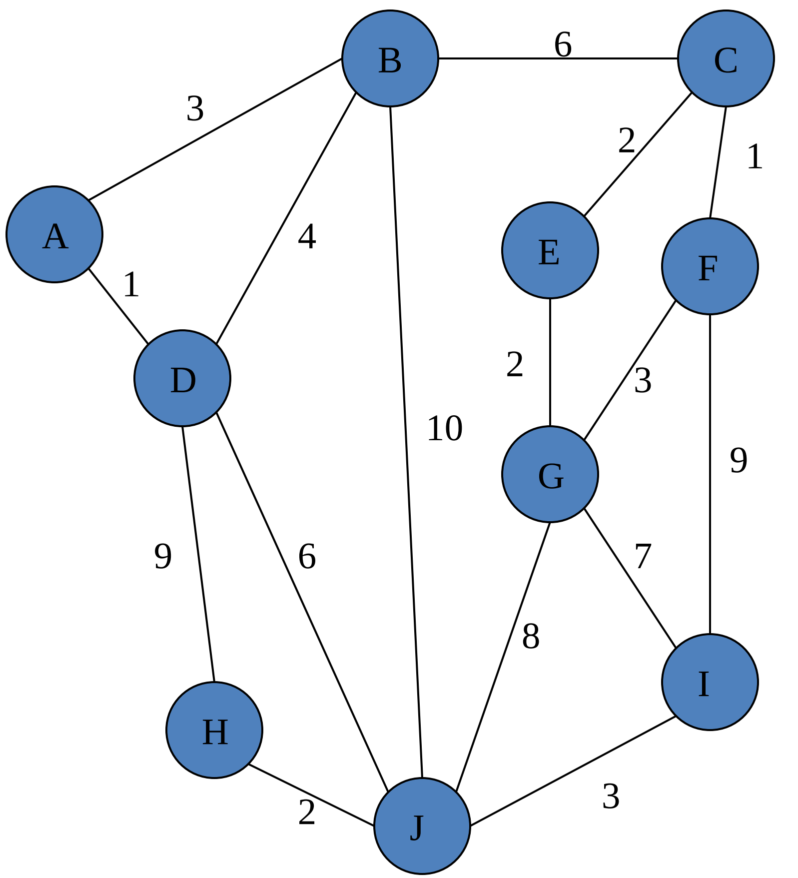

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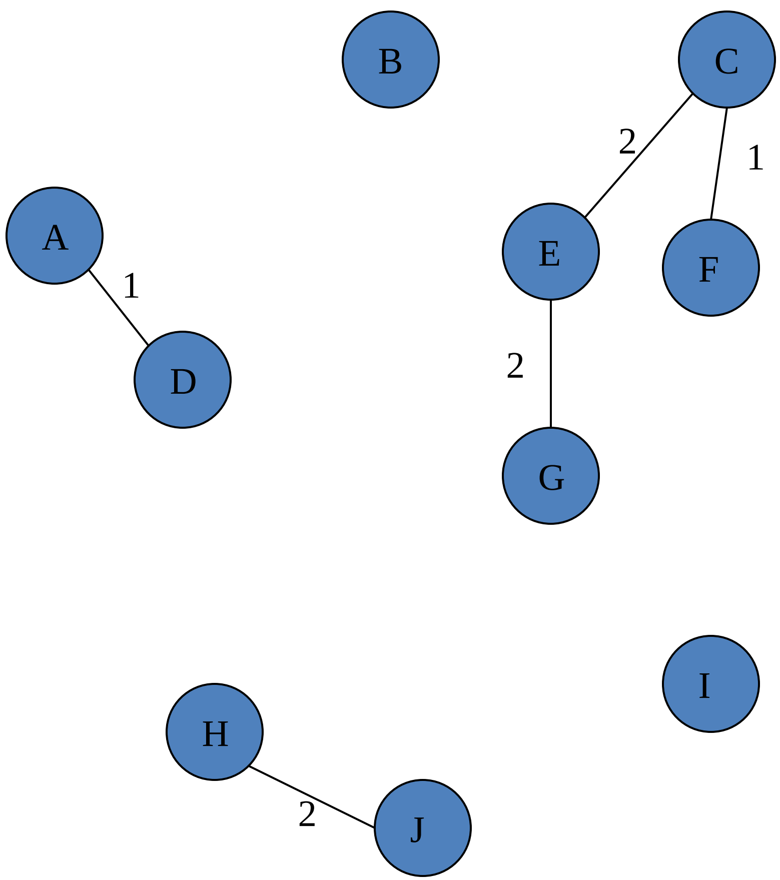

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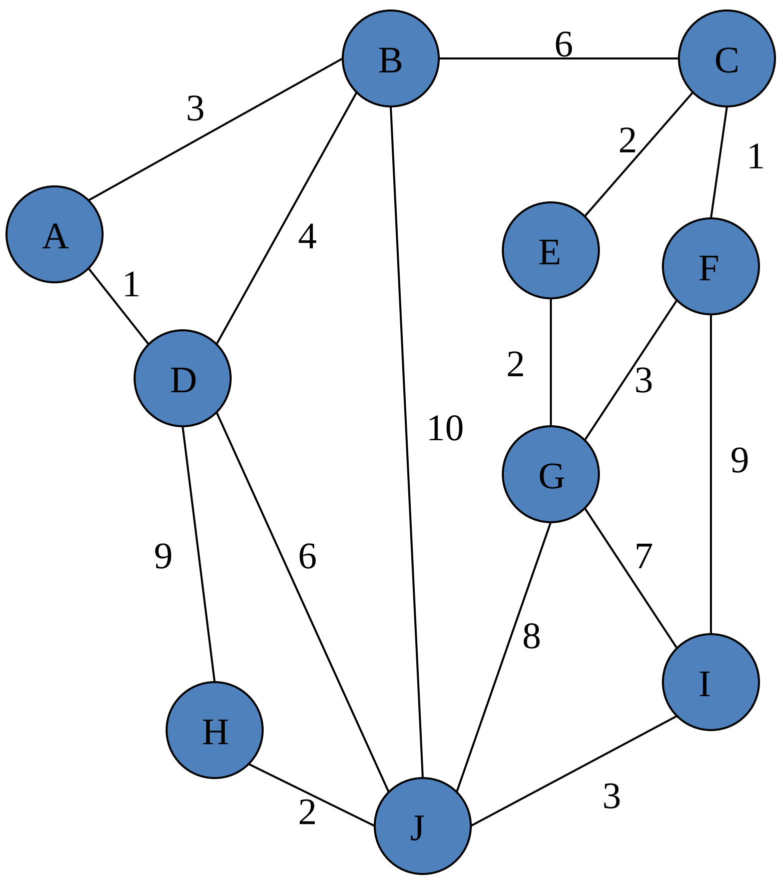

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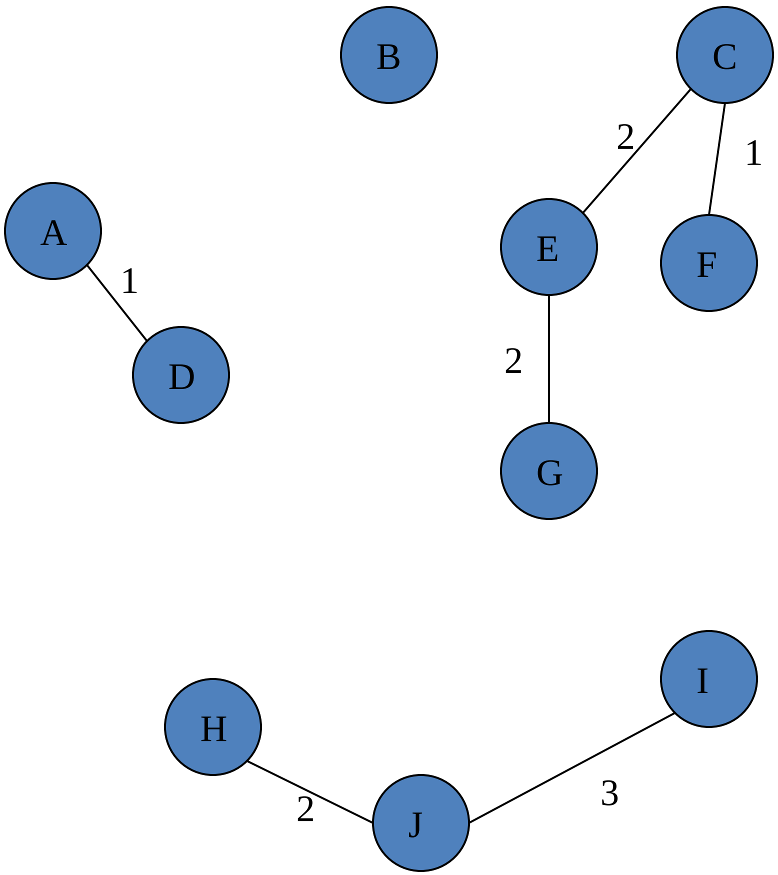

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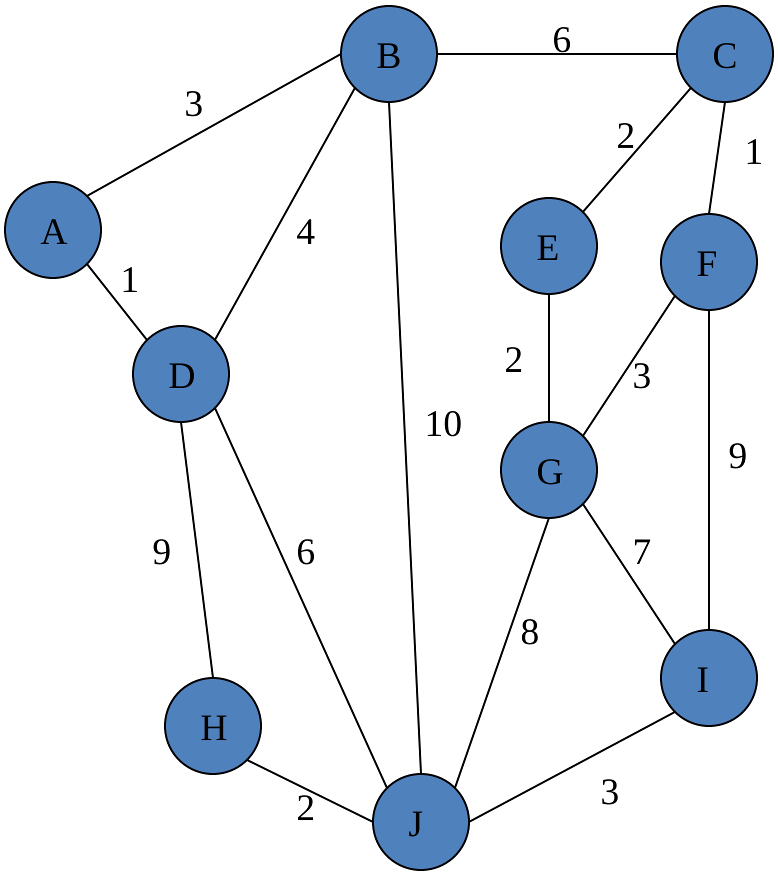

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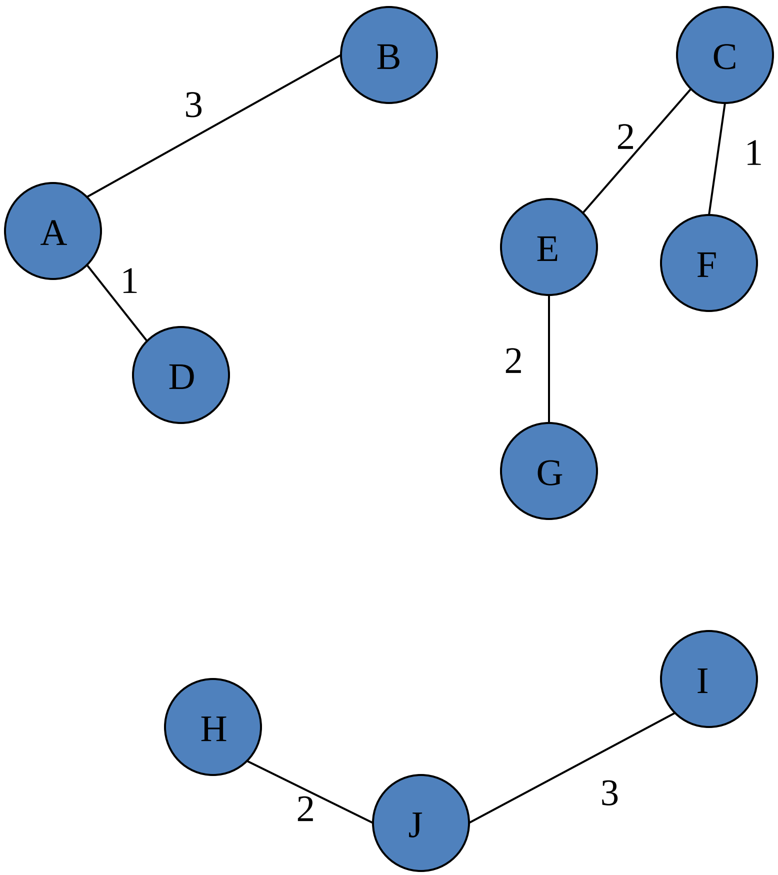

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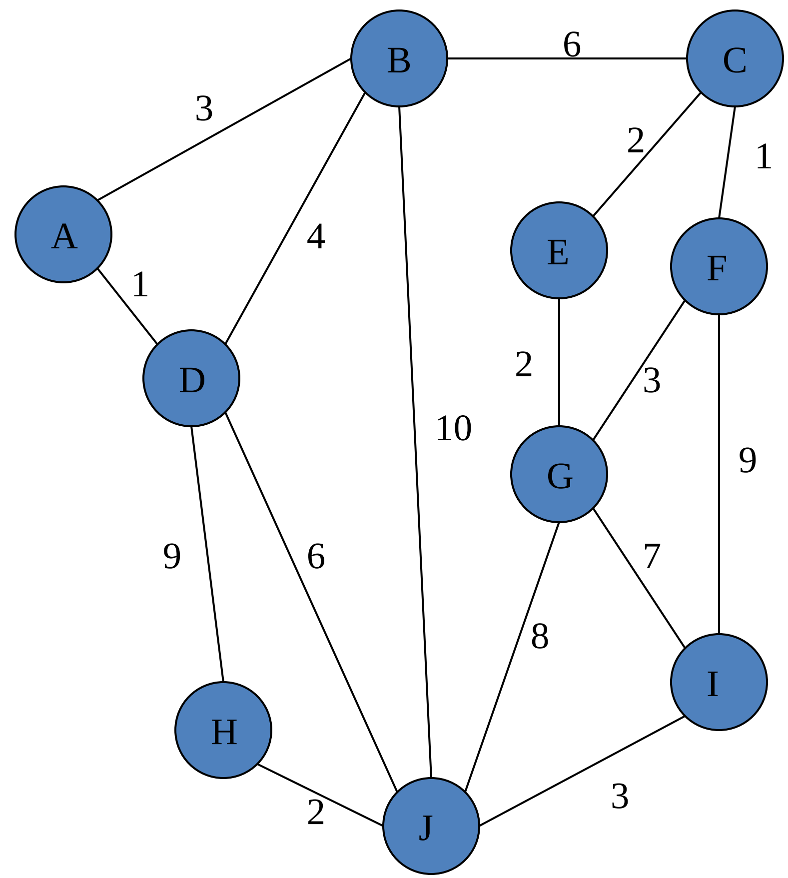

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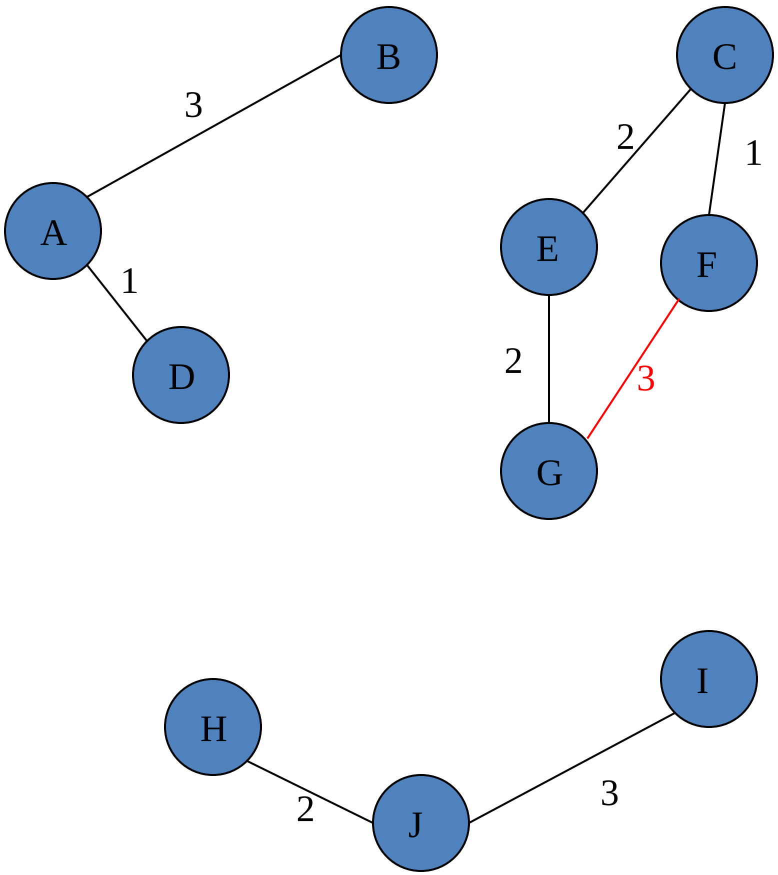

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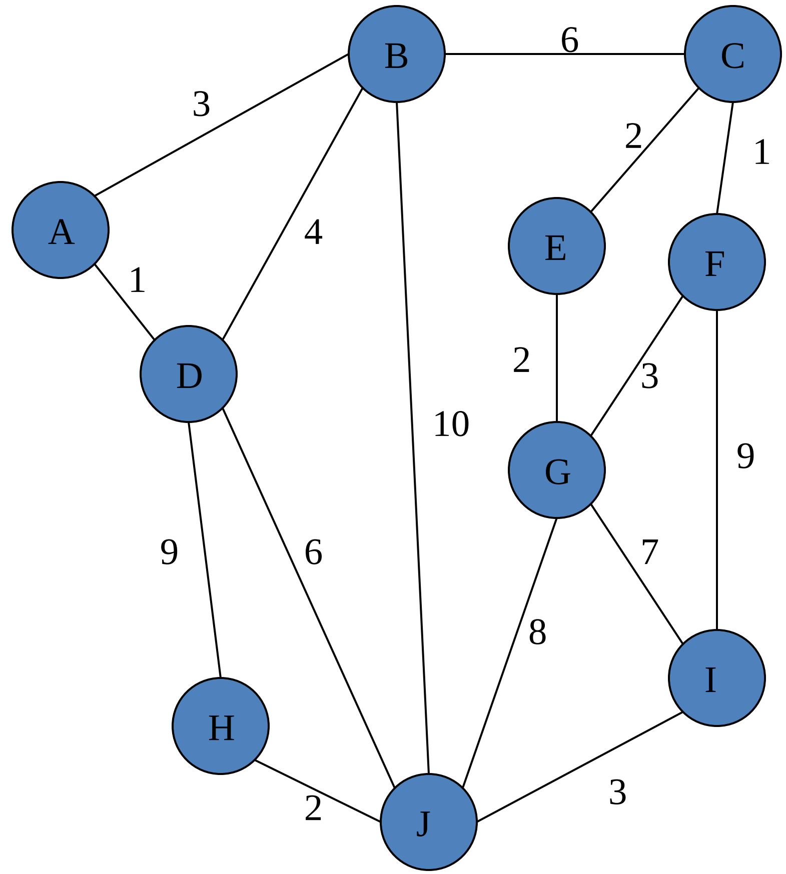

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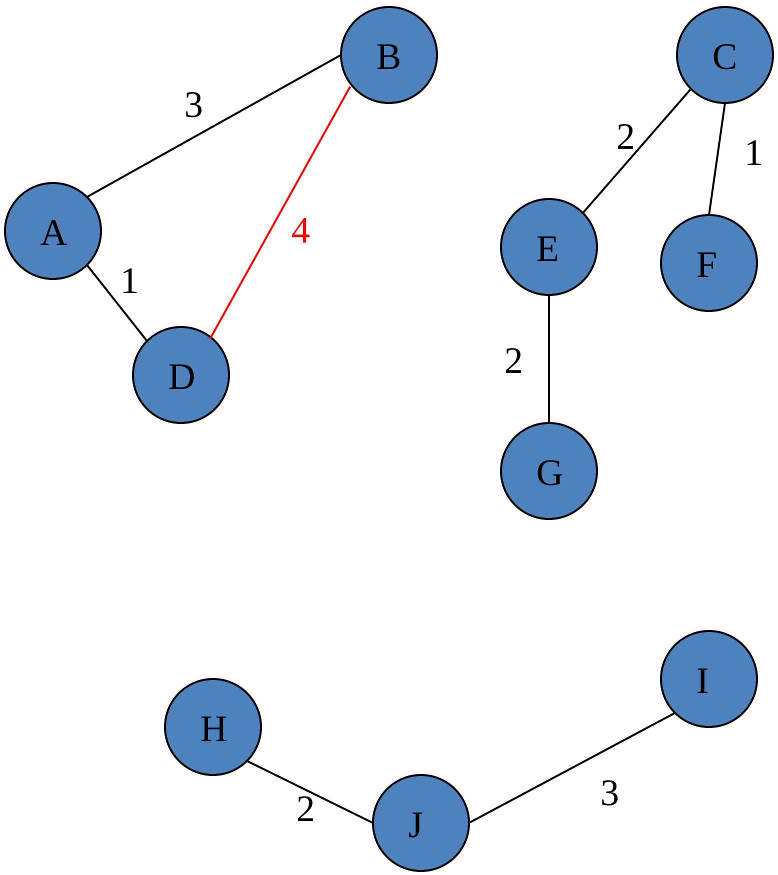

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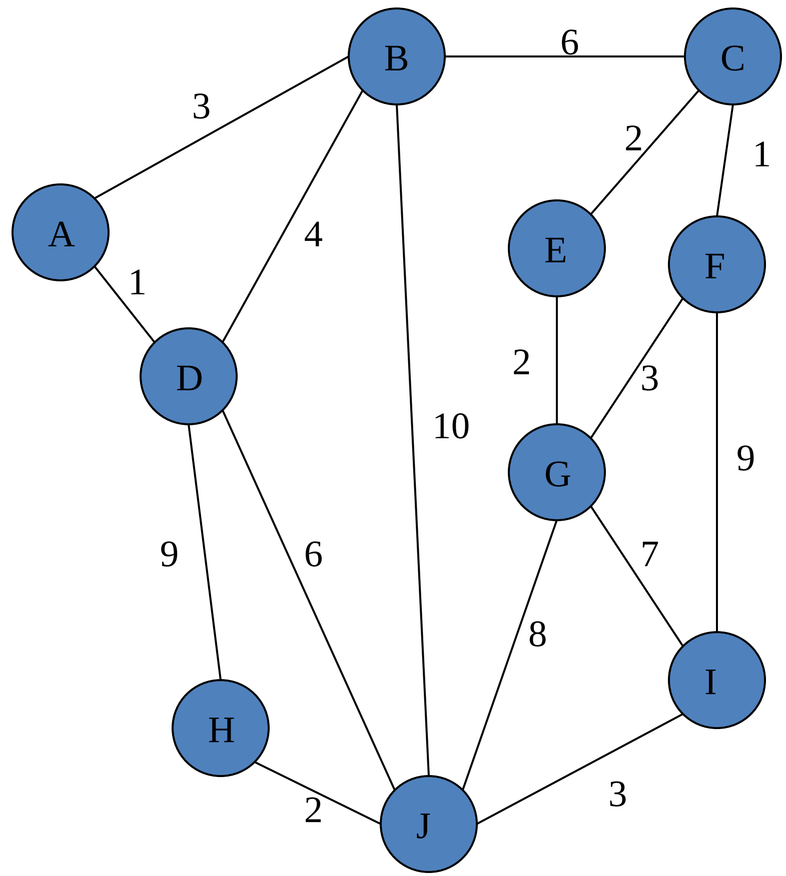

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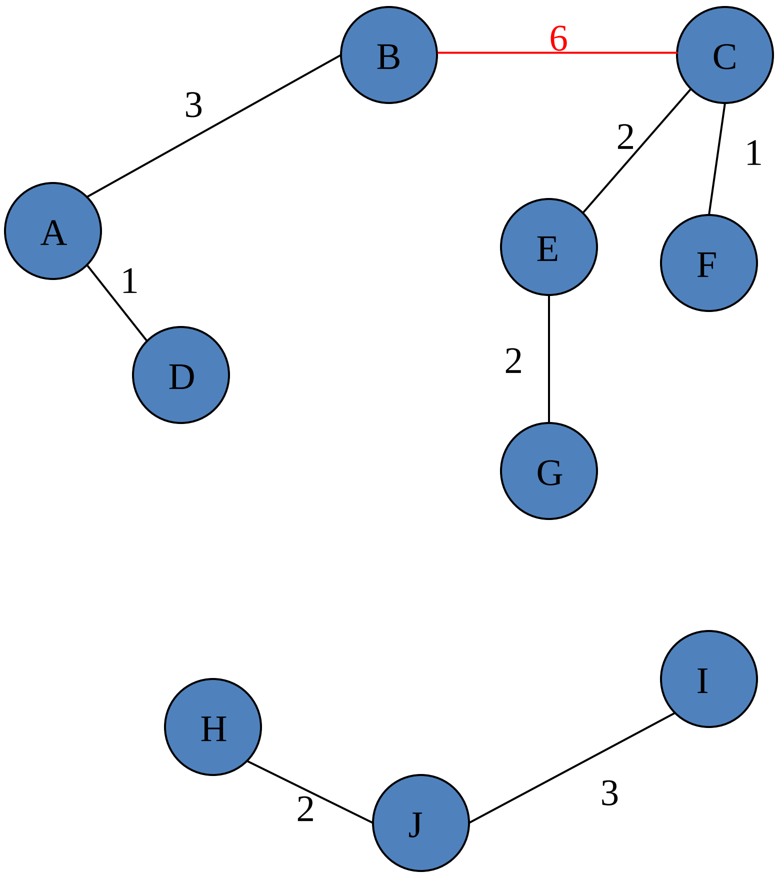

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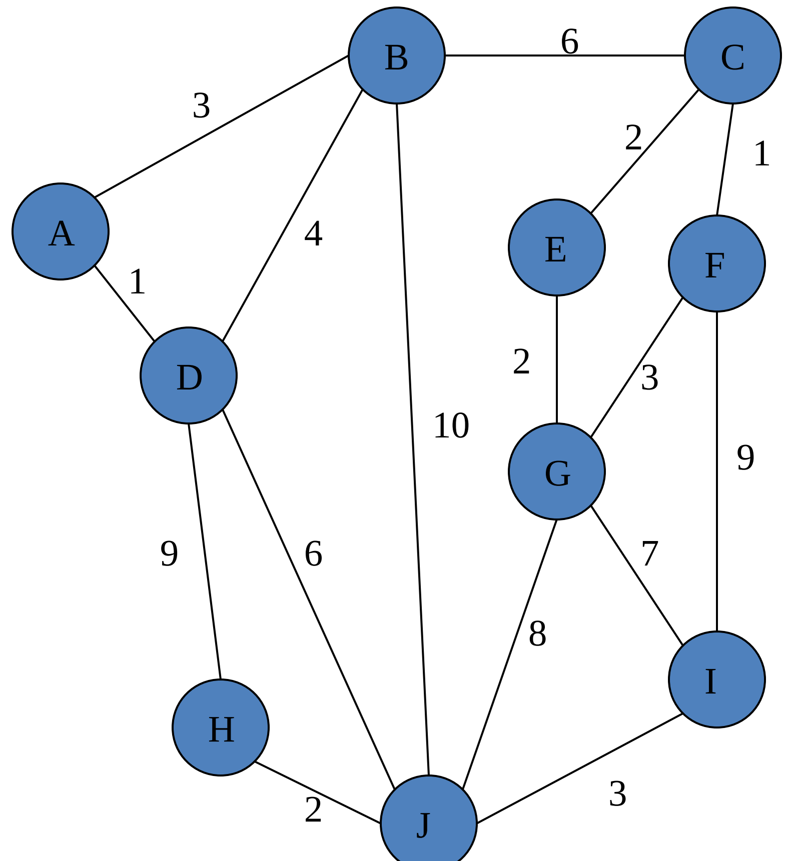

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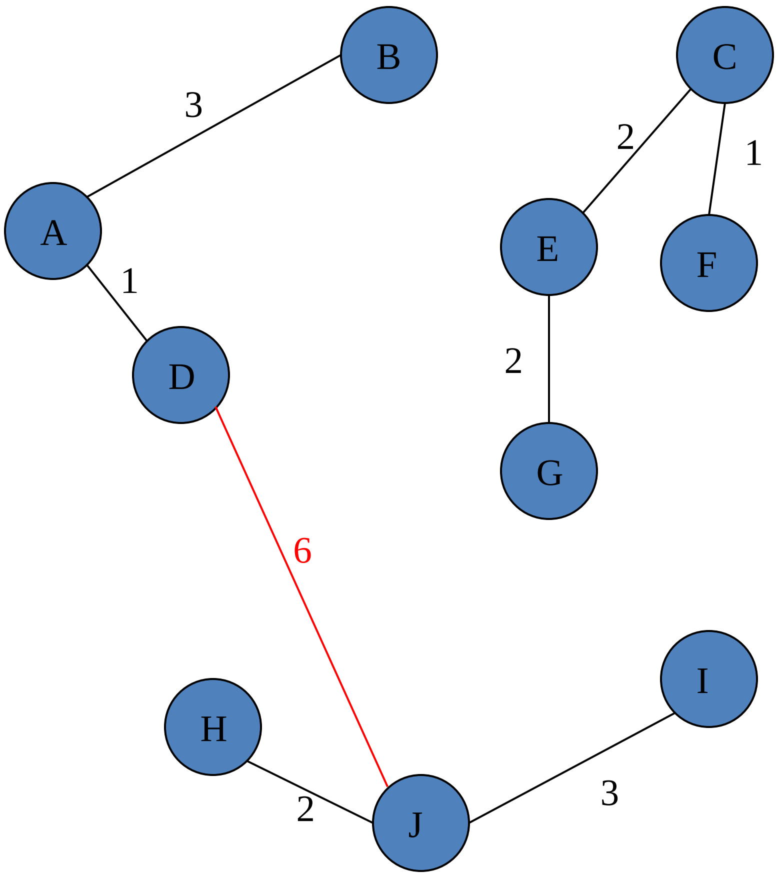

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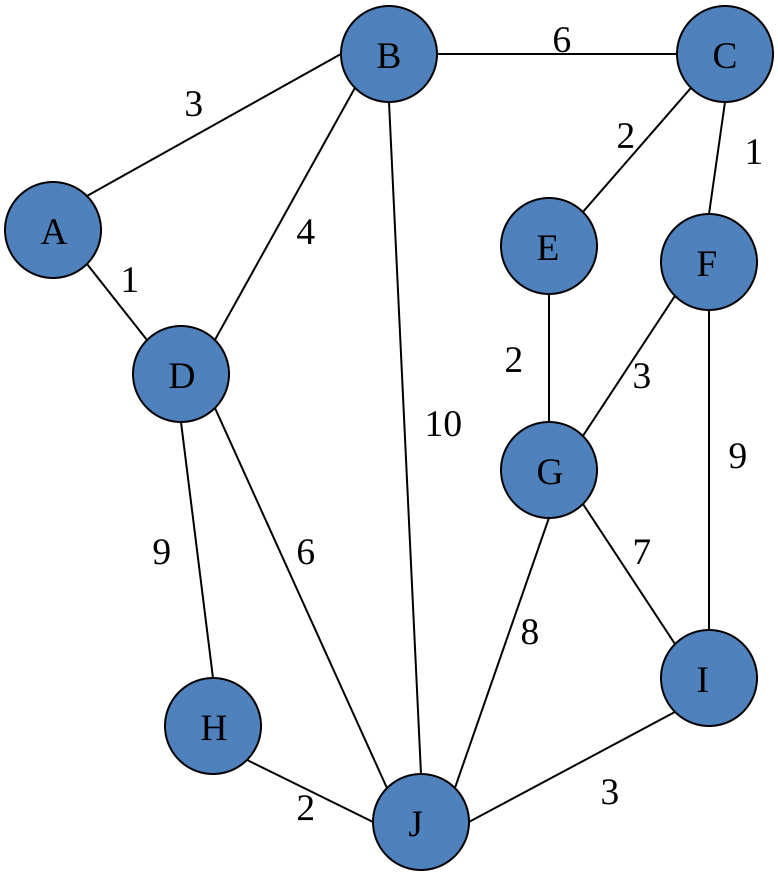

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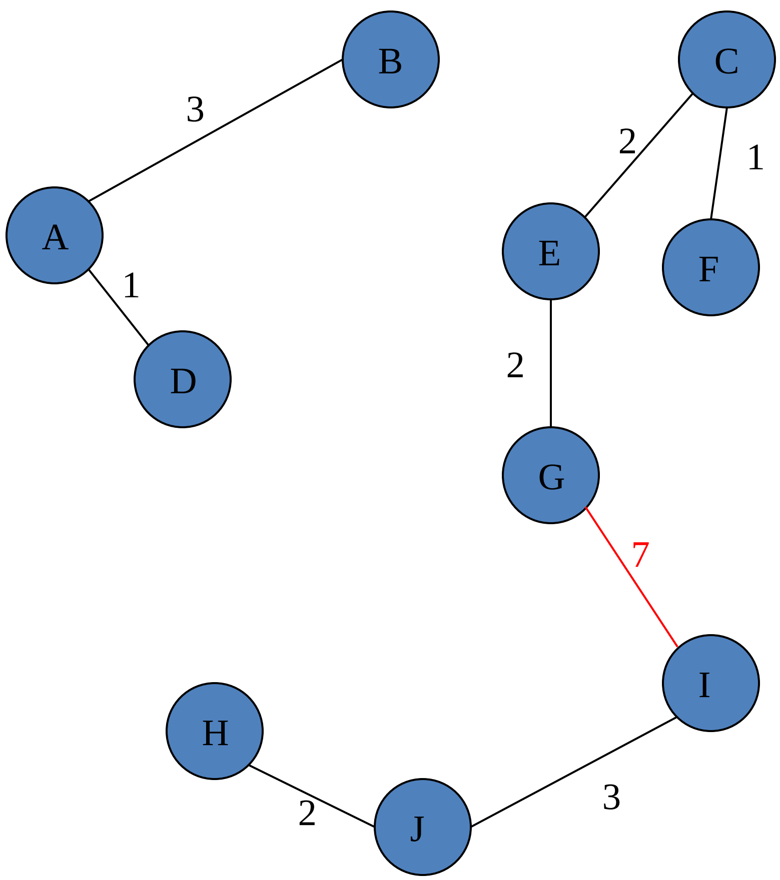

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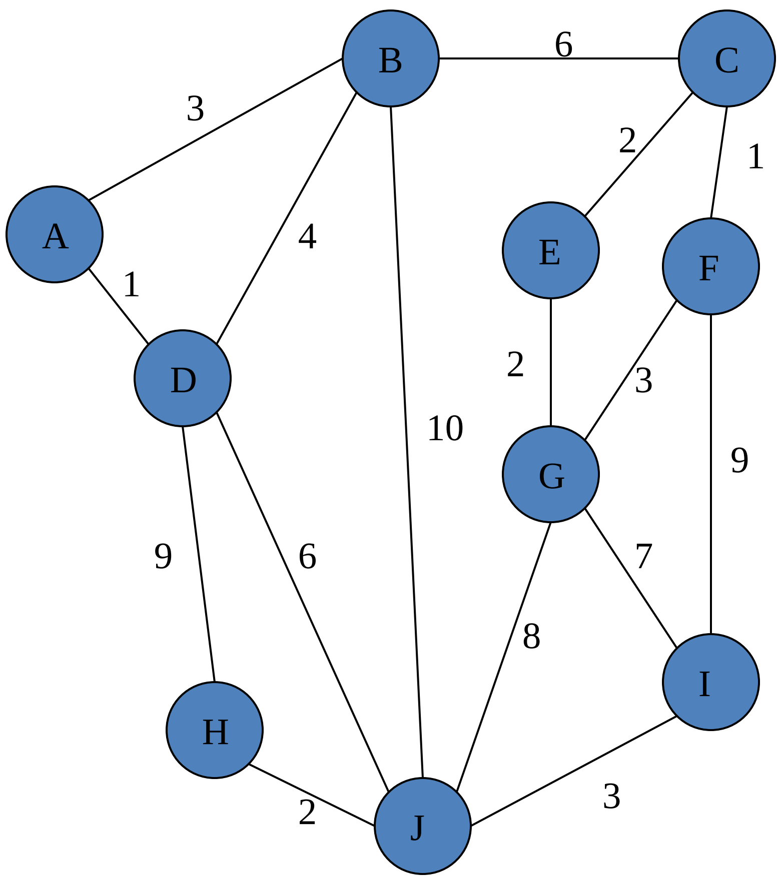

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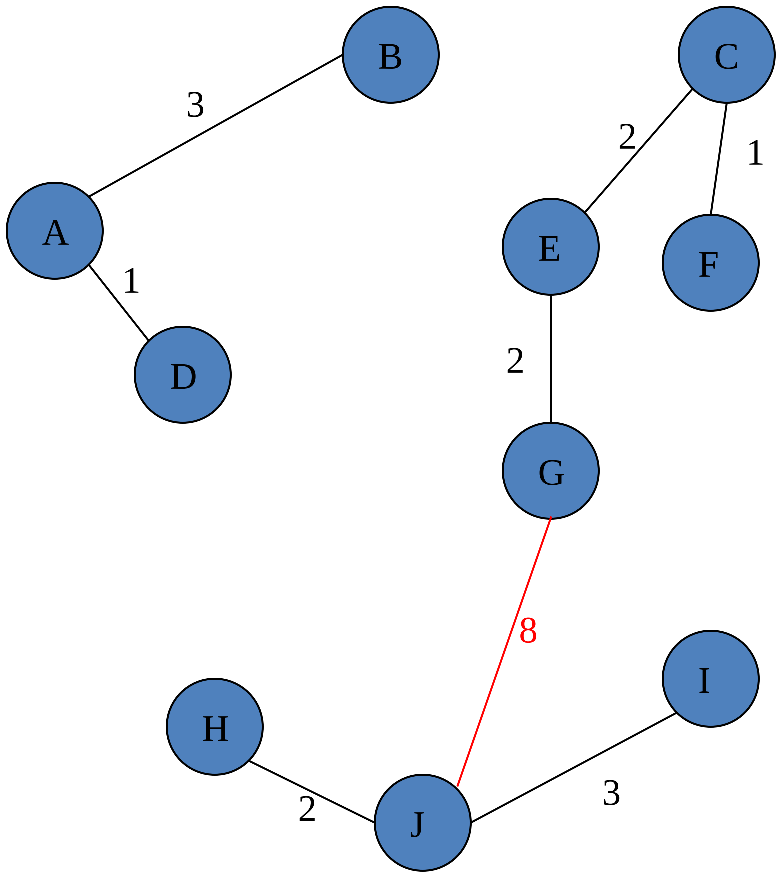

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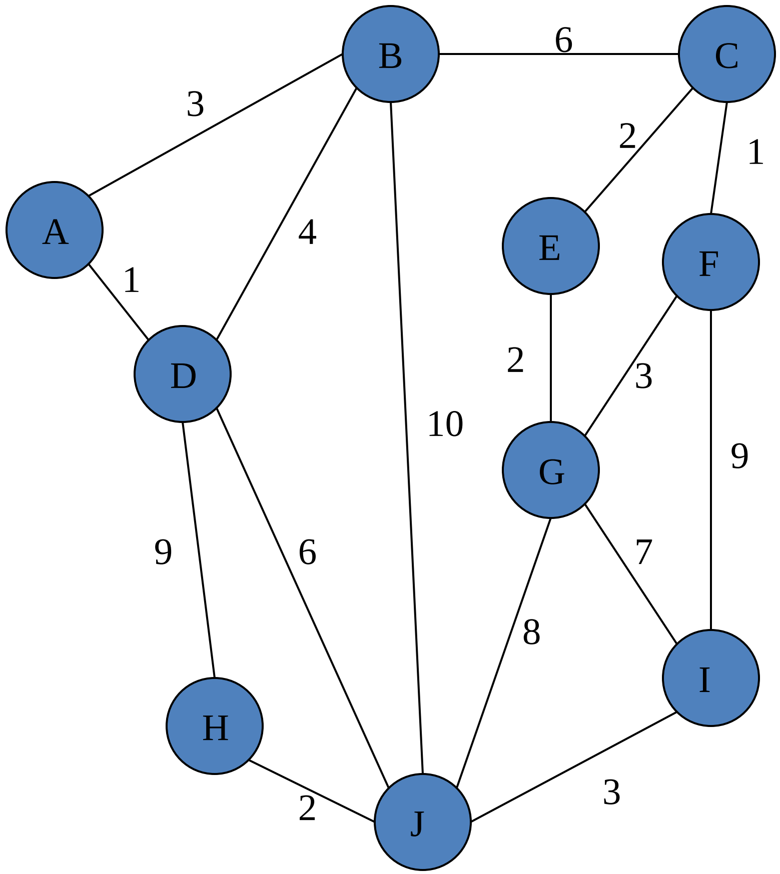

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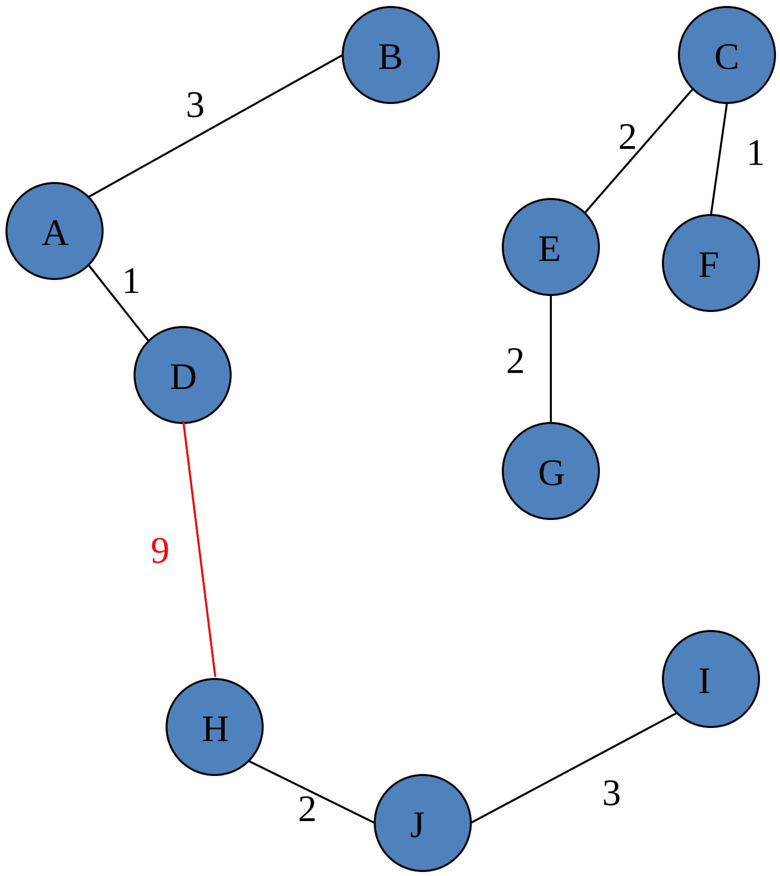

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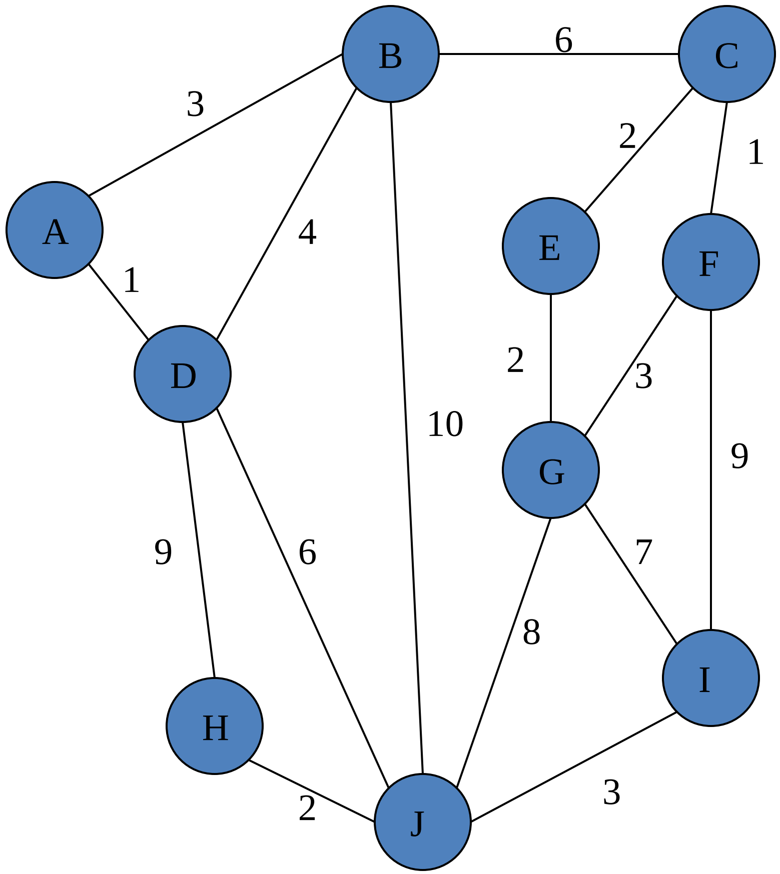

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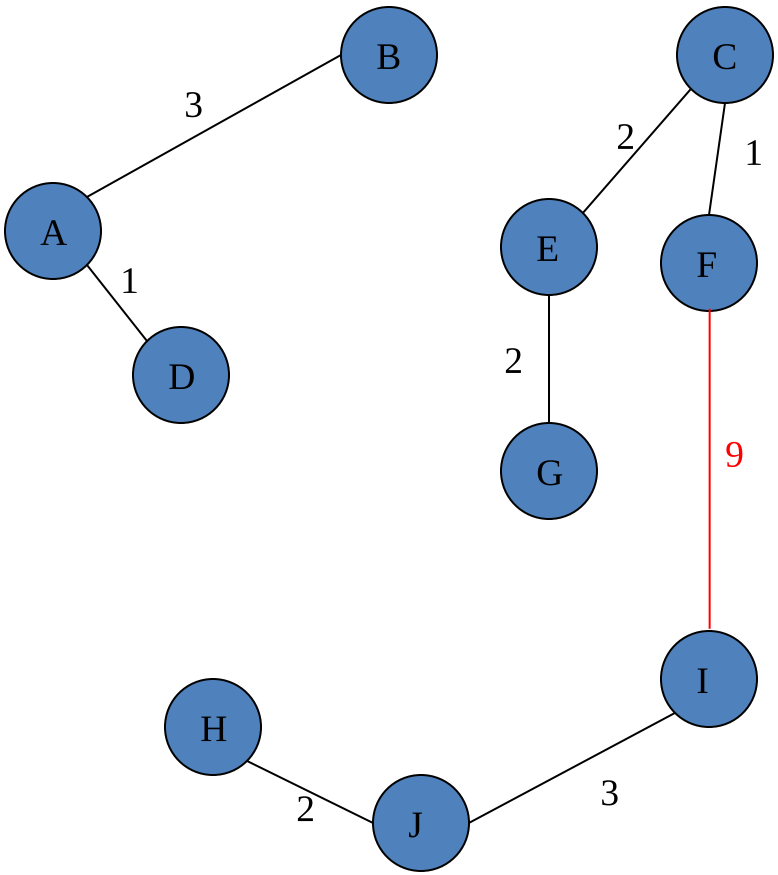

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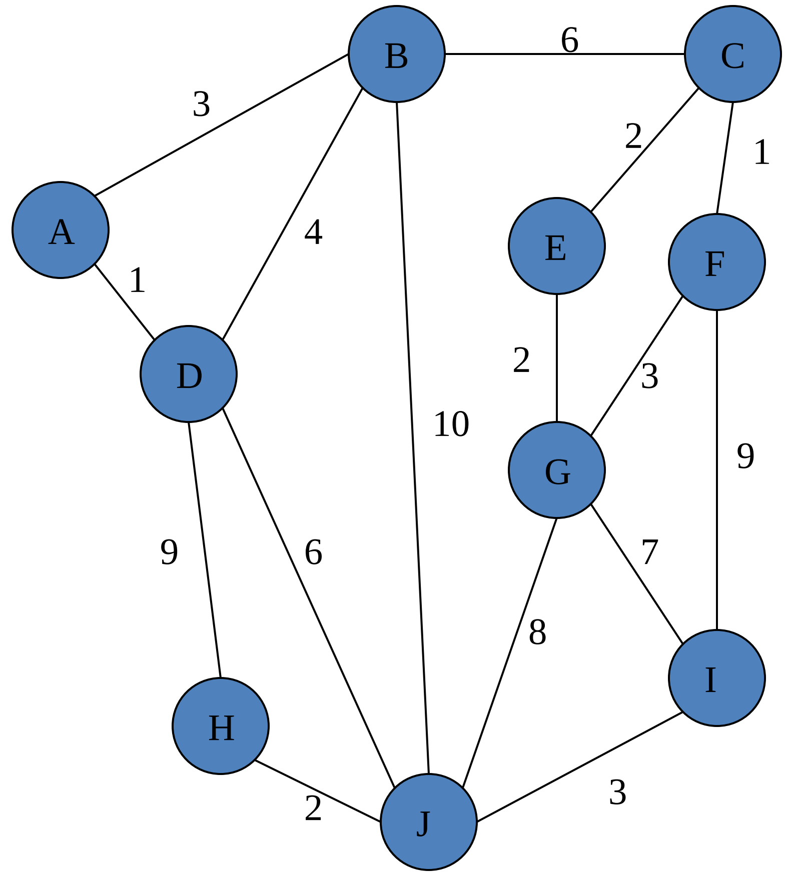
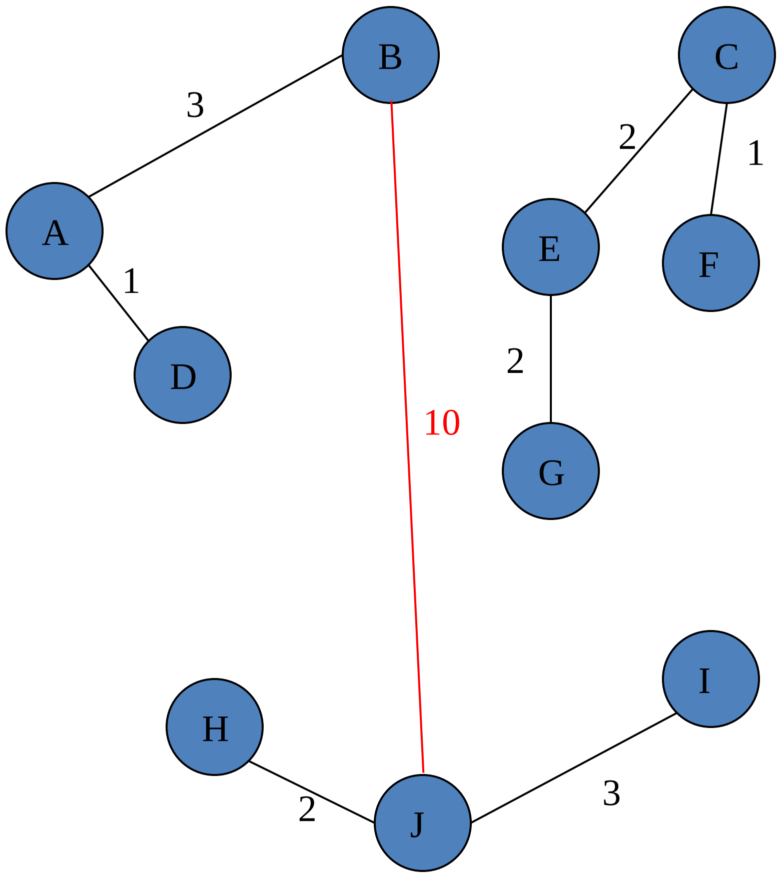


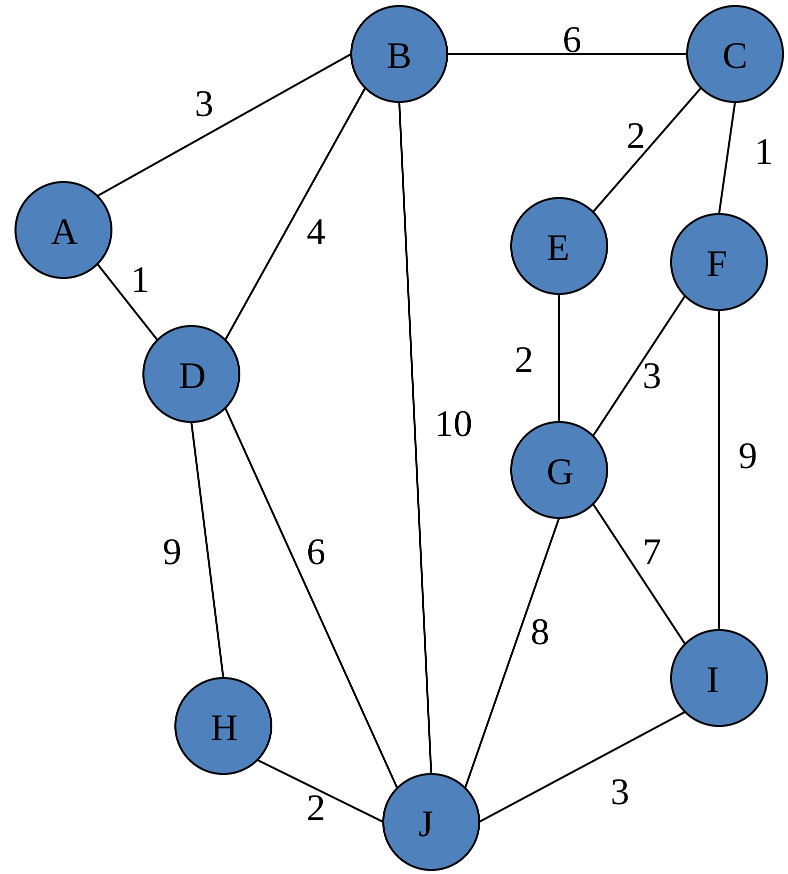
Minimum Spanning Tree

(Kruskal Algorithm)



$\boxed{\tau = 2}$

Complete Graph



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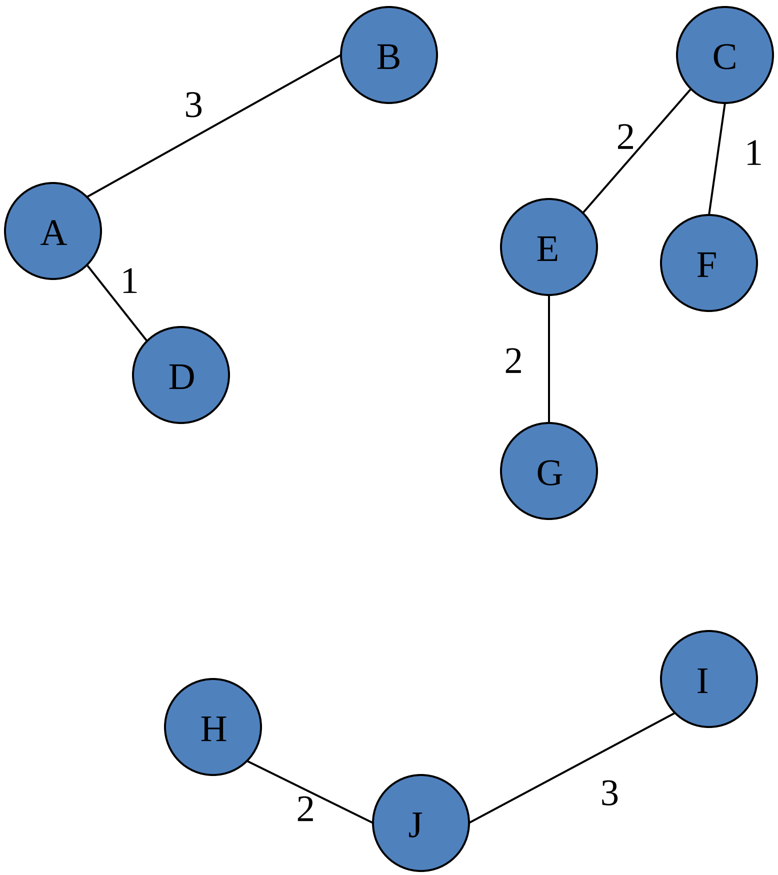
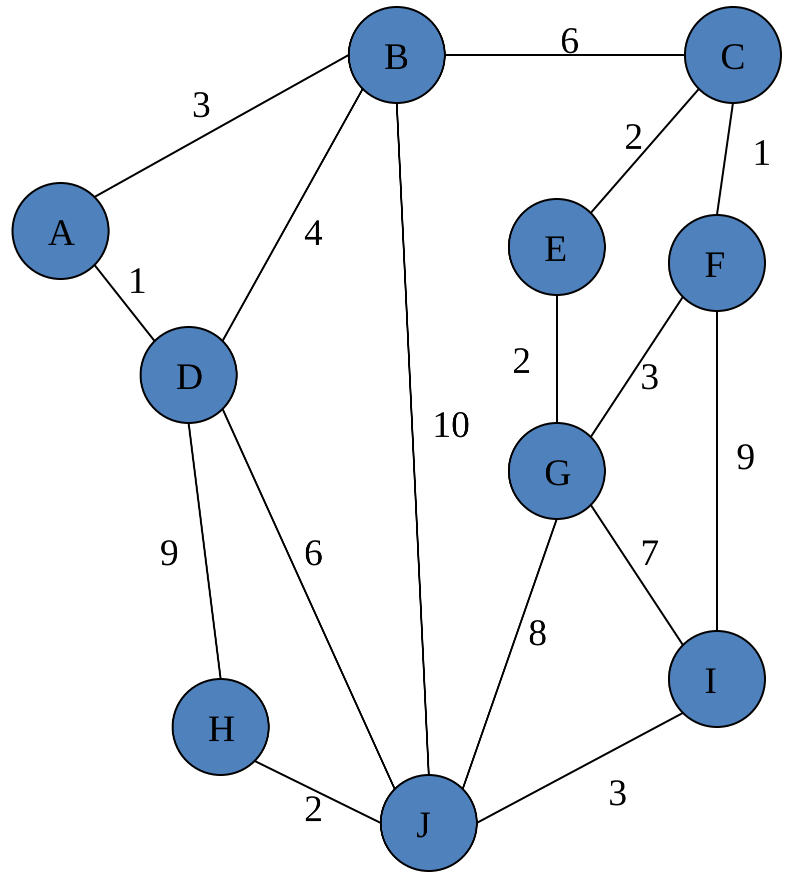
(Kruskal Algorithm)

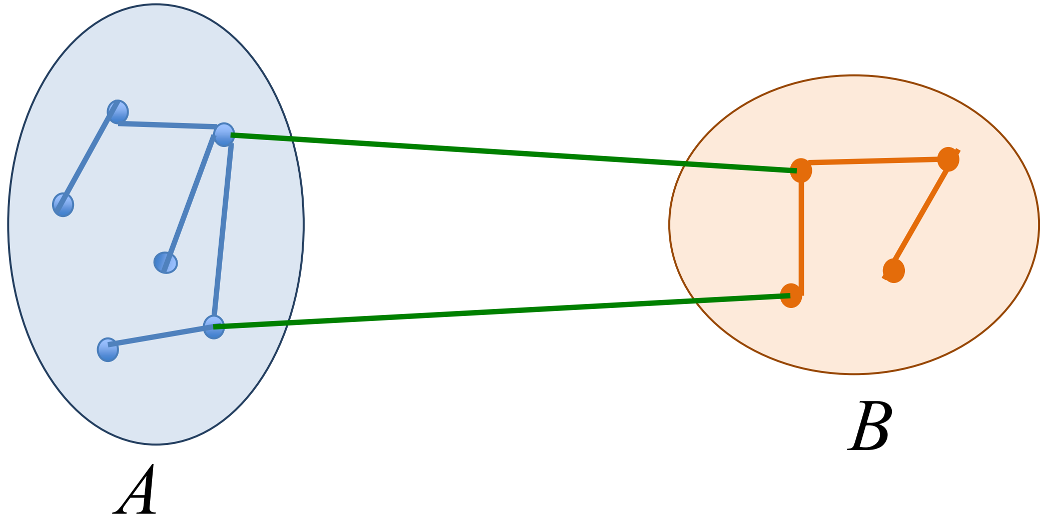


$\tau = 2$

Complete Graph



Optional



$$Int(A) = \max_{e \in MST(A,E)} w(e) \qquad Int(B) = \max_{e \in MST(A,E)} w(B)$$

$$MInt(A, B\ ) = \min(\ Int(A) + \tau(A)\ ,\ Int(B) + \tau(B)\ )$$

$$Dif(A, B) = \min_{\substack{v_i \in A,\ v_j \in B \\ (v_i, v_j) \in E}} w\big((v_i, v_j)\big)$$

$$\begin{cases} if\ Dif(A,B) < MInt(A,B) & Merge \\ if\ Dif(A,B) \geq MInt(A,B) & Don't\ merge \end{cases}$$

Refinement: Segmentation T is a refinement of segmentation S when each component of T is contained in S.

Too Fine: A segmentation is *too fine* if there is some pair of regions for which there is no evidence for a boundary between them.

Too Coarse: A segmentation is *too coarse* when there exists a proper refinement that is not too fine.

For any graph, there exists a segmentation that is neither too fine nor too coarse.

Lemma: In the algorithm, if two distinct components are considered and not merged, then one of these components will be in the final segmentation.

Optional

Theorem: The segmentation produced by the algorithm is neither too coarse nor too fine.

Theorem: The segmentation produced by the algorithm does not depend on which non-decreasing weight order of the edge is used.

Efficient Graph-Based Image Segmentation (Felzenswalb & Huttenlocher)

http://www.cs.brown.edu/~pff/segment/

+ Good for thin regions
+ Fast
+ Easy to control coarseness of segmentations
+ Can include both large and small regions

 - Often creates regions with strange shapes
 - Sometimes makes very large errors