

# Approximate Nearest Neighbor Retrieval

*Task: given a recommendation vector(provided by recommendation algorithm) fetch  $M$ -elements closest to it from the database(containing videos) ensuring at the same time they are not too similar(same content with resolution difference etc.)*

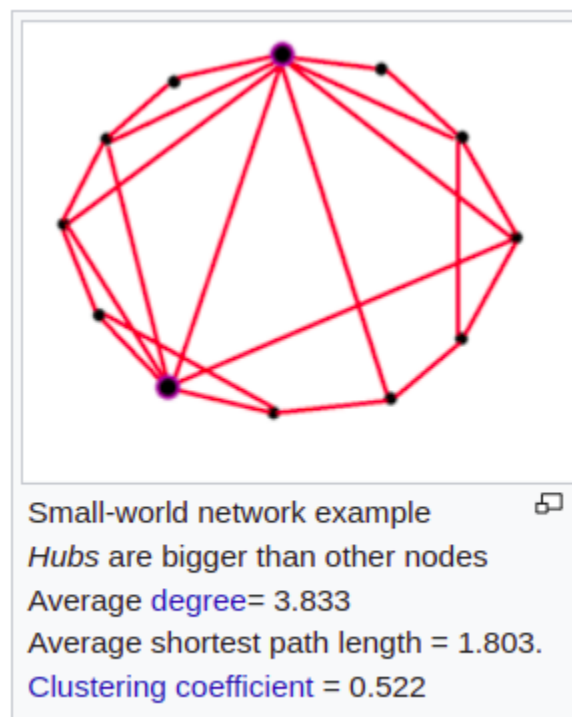
1st approach is based on **Hierarchical Navigable Small World graphs**

## Terminologies:

**proximity graph** : is simply a graph in which two vertices are connected by an edge if and only if the vertices satisfy particular geometric requirements.

**Delaunay triangulation** : for a given set  $\mathbf{P}$  of discrete points in a general position is a triangulation  $DT(\mathbf{P})$  such that no point in  $\mathbf{P}$  is inside the circumcircle of any triangle in  $DT(\mathbf{P})$ .

**small-world graph** : is a type of mathematical graph in which most nodes are not neighbors of one another, but the neighbors of any given node are likely to be neighbors of each other and most nodes can be reached from every other node by a small number of hops or steps. Specifically, a small-world network is defined to be a network where the [typical](#) distance  $L$  between two randomly chosen nodes (the number of steps required) grows proportionally to the [logarithm](#) of the number of nodes  $N$  in the network.



Construction of NSW graph:

The NSW graph is constructed via consecutive insertion of elements in random order by bidirectionally connecting them to the M closest neighbors from the previously inserted elements. The M closest neighbors are found using the structure's search procedure (a variant of a greedy search from multiple random enter nodes). Links to the closest neighbors of the elements inserted in the beginning of the construction later become bridges between the network hubs that keep the overall graph connectivity and allow the logarithmic scaling of the number of hops during greedy routing.

**Key Idea:**

The idea of Hierarchical NSW algorithm is to separate the links according to their length scale into different layers and then search in a multilayer graph. In this case we can evaluate only a needed fixed portion of the connections for each element independently of the networks size, thus allowing a logarithmic scalability. the search starts from the upper layer which has only the longest links. The algorithm greedily traverses through the elements from the upper layer until a local minimum is reached. After that, the search switches to the lower layer(which has shorter links), restarts from the element which was the local minimum in the previous layer and the process repeats. The maximum number of connections per element in all layers can be made constant, thus allowing a logarithmic complexity scaling of routing in a navigable small world network.

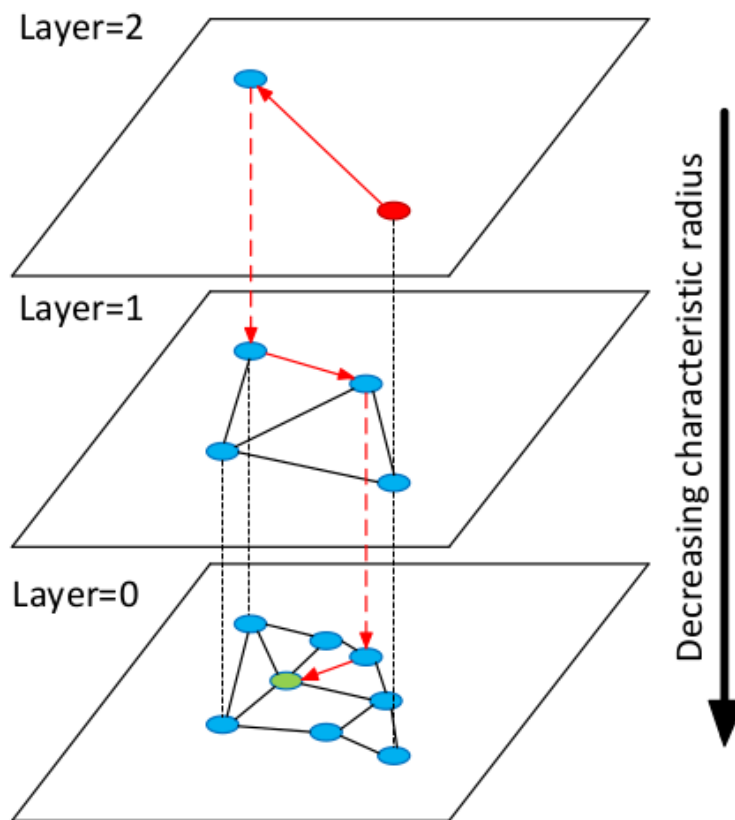


Fig. 1. Illustration of the Hierarchical NSW idea. The search starts from an element from the top layer (shown red). Red arrows show direction of the greedy algorithm from the entry point to the query (shown green).

### Algorithms:

### Algorithm 1

$$\text{INSERT}(hns w, q, M, M_{max}, efConstruction, ml)$$

**Input:** multilayer graph  $hns\omega$ , new element  $q$ , number of established connections  $M$ , maximum number of connections for each element per layer  $M_{max}$ , size of the dynamic candidate list  $efConstruction$ , normalization factor for level generation  $m_L$

**Output:** update *hmsw* inserting element  $q$

```
1  $W \leftarrow \emptyset$  // list for the currently found nearest elements
```

2  $ep \leftarrow$  get enter point for  $hns w$ 

```

3  $L \leftarrow$  level of  $ep$  // top layer for  $hns w$ 

```

```
4  $l \leftarrow \lfloor -\ln(\text{unif}(0..1)) \cdot m_L \rfloor$  // new element's level
```

5 **for**  $l_c \leftarrow L \dots l+1$ 6  $W \leftarrow \text{SEARCH-LAYER}(q, ep, ef=1, lc)$ 

7  $ep \leftarrow$  get the nearest element from  $W$  to  $q$

8 **for**  $l_c \leftarrow \min(L, l) \dots 0$ 

9  $W \leftarrow \text{SEARCH-LAYER}(q, ep, efConstruction, lc)$

10 *neighbors*  $\leftarrow$  SELECT-NEIGHBORS( $q, W, M, l_c$ ) // alg. 3 or alg. 4

```

11  add bidirectionall connections from neighbors to q at layer lc

```

12 **for** each  $e \in neighbors$  // shrink connections if needed13  $eConn \leftarrow \text{neighbourhood}(e)$  at layer  $l_c$ 14    **if**  $|eConn| > M_{max}$  // shrink connections of  $e$ 

```
// if  $l_c = 0$  then  $M_{max} = M_{max0}$ 
```

15  $eNewConn \leftarrow \text{SELECT-NEIGHBORS}(e, eConn, M_{max}, lc)$ 

```
// alg. 3 or alg. 4
```

16     set  $neighbourhood(e)$  at layer  $l_c$  to  $eNewConn$ 17  $ep \leftarrow W$ 18 **if**  $l > L$ 

19 set enter point for *hns* to  $q$

### Algorithm 2

SEARCH-LAYER( $q, ep, ef, l_c$ )

**Input:** query element  $q$ , enter points  $ep$ , number of nearest to  $q$  elements to return  $ef$ , layer number  $l_c$

**Output:**  $ef$  closest neighbors to  $q$

```
1  $v \leftarrow ep$     // set of visited elements
2  $C \leftarrow ep$   // set of candidates
3  $W \leftarrow ep$  // dynamic list of found nearest neighbors
4 while  $|C| > 0$ 
5    $c \leftarrow$  extract nearest element from  $C$  to  $q$ 
6    $f \leftarrow$  get furthest element from  $W$  to  $q$ 
7   if  $distance(c, q) > distance(f, q)$ 
8     break // all elements in  $W$  are evaluated
9   for each  $e \in neighbourhood(c)$  at layer  $l_c$  // update  $C$  and  $W$ 
10    if  $e \notin v$ 
11       $v \leftarrow v \cup e$ 
12       $f \leftarrow$  get furthest element from  $W$  to  $q$ 
13      if  $distance(e, q) < distance(f, q)$  or  $|W| < ef$ 
14         $C \leftarrow C \cup e$ 
15         $W \leftarrow W \cup e$ 
16        if  $|W| > ef$ 
17          remove furthest element from  $W$  to  $q$ 
18 return  $W$ 
```

### Algorithm 3

SELECT-NEIGHBORS-SIMPLE( $q, C, M$ )

**Input:** base element  $q$ , candidate elements  $C$ , number of neighbors to return  $M$

**Output:**  $M$  nearest elements to  $q$

**return**  $M$  nearest elements from  $C$  to  $q$

**Algorithm 4**

SELECT-NEIGHBORS-HEURISTIC( $q, C, M, l_c, extendCandidates, keepPrunedConnections$ )

**Input:** base element  $q$ , candidate elements  $C$ , number of neighbors to return  $M$ , layer number  $l_c$ , flag indicating whether or not to extend candidate list  $extendCandidates$ , flag indicating whether or not to add discarded elements  $keepPrunedConnections$

**Output:**  $M$  elements selected by the heuristic

```
1  $R \leftarrow \emptyset$ 
2  $W \leftarrow C$  // working queue for the candidates
3 if  $extendCandidates$  // extend candidates by their neighbors
4   for each  $e \in C$ 
5     for each  $e_{adj} \in neighbourhood(e)$  at layer  $l_c$ 
6       if  $e_{adj} \notin W$ 
7          $W \leftarrow W \cup e_{adj}$ 
8  $W_d \leftarrow \emptyset$  // queue for the discarded candidates
9 while  $|W| > 0$  and  $|R| < M$ 
10   $e \leftarrow$  extract nearest element from  $W$  to  $q$ 
11  if  $e$  is closer to  $q$  compared to any element from  $R$ 
12     $R \leftarrow R \cup e$ 
13  else
14     $W_d \leftarrow W_d \cup e$ 
15 if  $keepPrunedConnections$  // add some of the discarded
                             // connections from  $W_d$ 
16  while  $|W_d| > 0$  and  $|R| < M$ 
17     $R \leftarrow R \cup$  extract nearest element from  $W_d$  to  $q$ 
18 return  $R$ 
```

**Algorithm 5**

K-NN-SEARCH( $hns w, q, K, ef$ )

**Input:** multilayer graph  $hns w$ , query element  $q$ , number of nearest neighbors to return  $K$ , size of the dynamic candidate list  $ef$

**Output:**  $K$  nearest elements to  $q$

- 1  $W \leftarrow \emptyset$  // set for the current nearest elements
- 2  $ep \leftarrow$  get enter point for  $hns w$
- 3  $L \leftarrow$  level of  $ep$  // top layer for  $hns w$
- 4 **for**  $l_c \leftarrow L \dots 1$
- 5    $W \leftarrow$  SEARCH-LAYER( $q, ep, ef=1, l_c$ )
- 6    $ep \leftarrow$  get nearest element from  $W$  to  $q$
- 7  $W \leftarrow$  SEARCH-LAYER( $q, ep, ef, l_c=0$ )
- 8 **return**  $K$  nearest elements from  $W$  to  $q$