Paper Title

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ABSTRACT

300 word description of the project

PVLDB Reference Format:

Jaouhara Chanchaf and Karima Echihabi. Paper Title, 15(10): XXX-XXX, 2022.

doi:XX.XX/XXX.XX

1 INTRODUCTION

• Use case 1: Keyword Query

A data scientist wants to retrieve datasets with information related to Biomass Power Companies. Initially, The user decides to start the search with a keyword-query $Q_{0,0} = (\{\text{"biomass"}, \text{"power"}, \text{"companies"}\}, k = 10)$. The search engine returns thirty datasets but none seem relevant to the user. To retrieve more results the user decides to run the same query and increase k, $Q_{0,1} = (\{\text{"biomass"}, \text{"power"}, \text{"companies"}\}, k = 20)$. After the second attempt the search engine returns Table 1 (at position #31) which contains data about biomass power plants per company. The user decides to keep Table 1 and continue to search for other relevant tables.

• Use case 2: Join Query Table 1 is relevant to $Q_{0,1}$ as it contains a list of biomass power plants, their location and capacity in Mega-Watt. However the user wants to include other information related to the prime mover of each plant, its status (operational or not), its start date etc. For that the user selects a set of plants based in California, and perform a join query on the "Plant" column in Table 1 to explore other tables that may complement Table 1 with more information.

To avoid running the join query multiple times, the user chooses a high k value at the expense of query time. $Q_{1,0} = (\sigma_{Location} = \%CA\%$ (Table 1), Join column : "Plant", k = 100). The search engine returned 381 results. After skimming through the list of result, the user finds Table 2 at position #315. Table 2 can be joined with Table 1 on column "Plant name".

Proceedings of the VLDB Endowment, Vol. 15, No. 10 ISSN 2150-8097.

doi:XX.XX/XXX.XX

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Because the user has no prior knowledge of the total dataset size nor the optimal k value to retrieve relevant results in the least time possible, the user chooses k values randomly until he/she finds a relevant table.

In use case 2 the user is unaware that the same result could be retrieved at position #5 with k = 10.

Due to a large number of results, It is also possible that the user does not notice the desired result and decides to further increase k. For example, suppose that in use case 2 the user did not notice the result at position #315 and decided to submit $Q_{1,1} = (\sigma_{Location="\%CA\%"}(\text{Table 1})$, Join column: "Plant", k = 200). The search engine will return 755 results, and Table 2 would be at position #235.

2 LITERATURE REVIEW

Dataset Discovery.

Keyword and Join Queries.

Incremental Query Answering.

3 PROPOSED APPROACH

Algorithm 1: BuildIndex

Algorithm 2: HEURISTICKNNSEARCH

```
Input: A query vector q, and k.

Output: k Nearest vectors to q.

1 KnnResults[k] \leftarrow \{\infty_1, ..., \infty_k\};

2 initialize stack \leftarrow \{\};

3 N_{curr} = N_{root};

4 while !N_{curr}.IsLeaf() do
```

```
4 while !!N_{curr}.!SLeaf() do

5 SP = N_{curr}.SplitPolicy();

6 N_{curr} = N_{curr}.routeToChild(q, SP);

7 KnnResults \leftarrow GetNeirestVectors(N_{curr}, q, k);
```

8 return KnnResutls;

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```
Algorithm 4: EXACTKNNSEARCH
```

```
Input: A sequence of query vectors Q = \{q_1, ..., q_n\}, k.
   Output: k * n Nearest vectors to the query vectors.
 1 Array KnnResults[n][k] \leftarrow
    \{\{+\infty_1,...,+\infty_k\}_{q_1},...,\{+\infty_1,...,+\infty_k\}_{q_n}\};
 2 Queue pq_1, ..., pq_n;
 з foreach q_i \in Q do
    KnnResults[i] \leftarrow HEURISTICKNNSEARCH(q_i);
 5 WorkerThread reaches SendUpdatesBarrier;
   // update knn results in global array
 6 foreach a in Q do
    ArrayCopy(AllKnnResults[i], KnnResults[i]);
   // initialize priority queues
 s foreach q_i in Q do
       pq_i \leftarrow \{\};
      pq_i.Add(N_{root}, D_{lb}(N_{root}, q[i]));
10
   while !Finished and \exists q_j \in Q, !pq_j.Empty() do
11
       foreach q_i in Q do
12
           N_{curr} = pq_i.Pop();
13
           if N_{curr}.IsLeaf() then
14
               d_{curr} = calcMinDist(N_{curr}, q_i);
15
               if d_{curr} < KnnResults[i][k-1] then
16
                   UpdateKnnResults(N_curr, KnnResults[i]);
17
           else
18
               foreach N_{child} in N_{curr}.ChildNodes() do
19
                   if D_{lb}(N_{child}, q_i) < KnnResults[i][k-1]
20
21
                       pq_i.Add(N_{child}, D_{lb}(N_{child}, q[i]));
       WorkerThread reaches SendUpdatesBarrier;
22
       // update knn results in global array
       foreach q_i in Q do
23
24
           ArrayCopy(AllKnnResults[i], KnnResutls[i]);
25 Finished \leftarrow True;
```

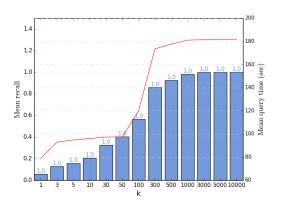
Algorithm 3: Kashif: ParallelIncremental-QueryAnswering

```
Input: A sequence of query vectors Q = \{q_1, ..., q_n\}, k and
            the recall threashold r_{th}.
   Output: k * n Nearest vectors to the query vectors.
 1 Shared Array AllKnnResults[n][k] \leftarrow
     \{\{+\infty_1,...,+\infty_k\}_{q_1},...,\{+\infty_1,...,+\infty_k\}_{q_n}\};
 2 Shared Boolead Finished \leftarrow False;
 3 Float CurrentRecall \leftarrow 0;
 4 Barrier SendUpdatesBarrier for workerThread;
 5 Barrier GetUpdatesBarrier for CoordinatorThread;
 6 initialize WorkerThread;
 7 WorkerThread runs an instance of ExactKnnSearch(Q, k);
   do
       CoordinatorThread blocks on GetUpdatesBarrier;
       CurrentRecall \leftarrow ComputeRecall(AllKnnResults);
10
11 while !Finished and CurrentRecall < r_{th};
12 Finished \leftarrow True;
```

4 EXPERIMENTAL EVALUATION

13 return AllKnnResutls;

Figure 1: Query-time recall and precision, Experiment on 100k tables $\approx 500 k$ columns and 25M vectors



ACKNOWLEDGMENTS

We sincerely thank X, Y and Z.

REFERENCES

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Company	Plant	Location	Feedstock	Capacity (MW)	
Wheelabrator Technologies Inc.	Wheelabrator Shasta Energy Co. Inc.	Anderson - CA	Logging and Mill Residue/Ag Residue	50	
Greenleaf Power LLC	Desert View	Mecca - CA	Ag Residue/Urban Wood Waste	47	
Greenleaf Power LLC	Honey Lake	Wendel - CA	Mill and Logging Residue/Forest Thinning/Urban Woodwaste	30	
Covanta	Covanta Delano	Delano - CA	Orchard and Vineyard Prunings/Nut Shells/Stone Fruit Pits	58	

Table 1: U.S. Biomass Power Plants

Category	Plant ID	Plant Name	Unit	Status	Start Date	Retire Date	Prime mover ID	Prime Mover Description	Capacity	net MWh
Е	E0027	Desert View Power (Mecca Plant)	GEN1	OP	1991/11/1	-	ST	Steam Tur- bine	54.15	351291
Е	E0041	HL Power Company (Honey Lake)	GEN 1	OP	1989/7/26	-	ST	Steam Tur- bine	35.5	200712
Е	E0029	Covanta Delano, Inc	Delano 1-2	OP	1990/6/12	-	ST	Steam Tur- bine	58	322731
Е	E0086	Wheelabrator Shasta	Units 1-3	OP	1987/1/1	-	ST	Steam Tur- bine	54.9	405628
•••				•••						

Table 2: Annual Generation - Plant Unit