# **Paper Title**

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#### ABSTRACT

300 word description of the project

#### **PVLDB** Reference Format:

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#### 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. to explore other tables that may complement Table 1 with more information, the data scientist selects a subset of plants based in California (from Table 1), and performs a join query on the "Plant" column.

To avoid running the join query multiple times, the user chooses a high k value at the expense of query time.  $Q_{1,0} = (\sigma_{Location="\%CA\%"}(\text{Table 1})$ , 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 the "Plant name" column.

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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  $N_{curr} = N_{root}$ ;
- 3 while  $!N_{curr}.IsLeaf()$  do
- 4  $SP = N_{curr}.SplitPolicy();$
- $N_{curr} = N_{curr}.RouteToChildNode(q, SP);$
- 6  $KnnResults \leftarrow GetNearestVectors(N_{curr}, q, k);$
- 7 return KnnResutls;

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```
Algorithm 4: EXACTKNNSEARCH
```

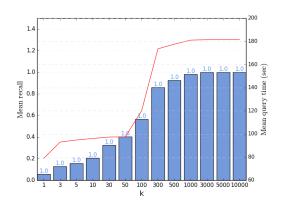
```
Input: A sequence of query vectors Q = \{q_1, ..., q_n\}, k.
   Output: k * n Nearest vectors to the query vectors.
 1 Array KnnResults[n][k] \leftarrow
    \{\{+\infty_1, ..., +\infty_k\}_{q_1}, ..., \{+\infty_1, ..., +\infty_k\}_{q_n}\};
 2 Queue pq_1, ..., pq_n;
   /* perform heuristic search and update knn results
      in global array
 3 foreach q_i \in Q do
       ArrayCopy(KnnResutls[i], HEURISTICKNNSEARCH(q_i);
       ArrayCopy(AllKnnResults[i],KnnResutls[i]);\\
 6 WorkerThread reaches SendUpdatesBarrier;
   /* initialize priority queues
 7 foreach q_i \in Q do
       pq_i \leftarrow \{\};
       pq_i.Add(N_{root}, D_{lb}(N_{root}, q_i));
   while !Finished and \exists q_j \in Q, !pq_j.Empty() do
11
       foreach q_i \in Q do
           N_{curr} = pq_i.Pop();
12
           if N_{curr}.IsLeaf() then
13
               d_{curr} = calcMinDist(N_{curr}, q_i);
14
               if d_{curr} < KnnResults[i][k-1] then
15
                   UpdateKnnResults(N_curr, KnnResults[i]);
16
           else
17
               for
each N_{child} in N_{curr}.ChildNodes() do
18
                   if D_{lb}(N_{child}, q_i) < KnnResults[i][k-1]
19
                     then
                       pq_i.Add(N_{child}, D_{lb}(N_{child}, q[i]));
20
       /* update knn results in global array
       foreach q_i in Q do
21
           ArrayCopy(AllKnnResults[i], KnnResutls[i]);
22
       WorkerThread reaches SendUpdatesBarrier;
23
24 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 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);
 8
   do
       CoordinatorThread blocks on GetUpdatesBarrier;
       CurrentRecall \leftarrow ComputeRecall(AllKnnResults);
10
11 while !Finished and CurrentRecall < r_{th};
12 Finished \leftarrow True;
13 return AllKnnResutls;
```

#### EXPERIMENTAL EVALUATION

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



## ACKNOWLEDGMENTS

We sincerely thank X, Y and Z.

## REFERENCES

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- [2] PhDComics. Graduate Student Work Output. https:// phdcomics.com/comics/archive.php?comicid=124, 2022.

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