

MSc Project Report

Implementing Learned Indexes on 1 and 2 Dimensional Data

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Databases use indexes to find records efficiently. Among these indexes, B-tree and KD-tree are the two indexes used for 1-dimensional and 2-dimensional data. In this project, we first implement these two indexes from scratch and then we implemented the learned indexes, including a fully connected neural network and a recursive model for 1-dimensional data [KBC⁺18] and the LISA model for 2-dimensional data [LLZ⁺20]. Afterwards, we conduct several experiments to evaluate the performance of learned indexes. In addition to the implementation and evaluation, we then theoretically analyse some properties that the learned indexes hold. Beyond that, we also explore and discuss the properties that the learned indexes should hold.

As an extension to the existing learned indexes, we explore the possibilities of using convolution operation and convolutional neural network as learned indexes.

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1. Introduction

Over the years, indexes have been widely used in databases to improve the speed of data retrieval. In the past decades, the database indexes generally fall into the hand-engineered data structures, such as B-Tree, KD-Tree, etc. These indexes have played a crucial role in databases and have been used widely in modern data management systems (DBMS) such as PostgreSQL. Despite their huge success, a shortcoming of these data structures is the lack of consideration of how the database records distributed. We use an example to demonstrate how distributions can affect the efficiency of database indexes.

Example 1.1 For example, if the dataset contains integers from 1 to 1 million, then the keys can be used directly as offsets. With the keys used as offsets, the value with a given key can be retrieved in $\mathcal{O}(1)$ time complexity while B-Tree requires $\mathcal{O}(\log n)$ time complexity for the same query. From the perspective of space complexity, we do not need any extra overhead by using the key as an offset directly, while the B-Tree needs extra $\mathcal{O}(n)$ space complexity to save the tree.

From the above example, we found that there are two promising advantages of leveraging the distribution of the data:

1. It may be faster when performing queries, especially when the number of entries in the database are rather huge.
2. It may take less memory space, as we only need to save the model with constant size.

Nowadays, to learn the distribution and apply it to database indexes, researchers proposed learned indexes [KBC⁺18], where machine learning techniques are applied to automatically learn the distribution of the database entries and build the data-driven indexes. In this project, we implemented hand-engineered indexes and the learned index. After that, we explore the possibilities of using complex convolutional neural networks as database indexes. This report is organised into the following chapters:

1. **Introduction.** In this chapter, we illustrate the organisation of this report. Besides, we go through the modern computer systems and introduce the general information about database indexes.
2. **Implementation.** In this chapter, we thoroughly describe the implementation of one and two dimensional indexes, including B-Tree, baseline learned index, recursive model, KD-Tree and LISA.

3. **Evaluation.** In this chapter, we perform evaluation among the indexes we implemented with different evaluation dataset.
4. **Insights and Findings.** We demonstrate our findings during the implementation in this chapter. Besides, we also discuss the advantages and disadvantages of different indexes.
5. **Convolution and CNN for Learned Indexes.** In this chapter we explore the possibilities of using convolution operation and convolutional neural network to build learned indexes.
6. **Conclusions.**

1.1. Notations

In this report, we will use the following notations:

Sets and Spaces

\mathbb{R}

The set of real numbers

\mathbb{R}^d

The set of d dimensional real space

Random Variables

\mathbf{X}

A vector or matrix

x

A single value in \mathbf{X}

(x, y)

A tuple contains two values

Hyper-Parameters

N

A pre-set hyper parameter

Functions

\mathcal{LR}

Linear Regression Function

\mathcal{P}

Polynomial Function

\mathcal{M}

Mapping Function

\mathcal{O}

Big-O notation for complexity

\mathcal{SP}

Shard Prediction Function

\mathcal{Q}

Range Query

\mathcal{K}

KNN Query

1.2. Terminologies

In the following chapters, we will use the following terminologies

Index model is a function that maps the index of a row of data into the location (e.g. page index) of the data. For example, in one-dimensional case, the index models include B-Tree, Linear Regression models, etc.

Key is a special attribute in the database that could identify a record. In our work, the key could be a scalar in one-dimensional case, or a (x, y) pair in two-dimensional case.

Order of a tree is the maximum number of children that a node can have.

Internal node is any node of a tree that has child nodes and is not a root node.

Leaf node is any node that does not have child nodes.

Level of a node is defined as the number of edges between this node and the root node.

1.3. Assumptions

Formally, we define the index of each record as x and the corresponding location as y and we represent the whole data as (X, Y) pairs with the total number of pairs defined as N . We could then normalise the Y into $\tilde{Y} \in [0, 1]$ so that the \tilde{y} represents the portion of the y among the whole Y . With these definitions, we can then define a function $F : X \rightarrow \tilde{Y}$ that maps the index into the portion of the y . We have $y = F(x) * N$. As the output of this function can be considered as the probability of $X \leq x$, we can regard this function $F(x)$ as the cumulative distribution function (CDF) of X , i.e. $F(x) = \mathbb{P}(X \leq x)$. Now that N is determined by the length of data records, we only need to learn such CDF and we called the learned CDF function as **learned index model**.

Example 1.2 From the perspective of the distribution of data records, our previous example can be rephrased as following. Our data records are (X, Y) pairs with a linear relation, i.e. $y = x, \forall y \in Y$. We are looking for a function F such that $y = x = F(x) * N$, and hence we end up with $F(x) = \frac{1}{N} * x$. If we use this linear function $F(x)$ as the index model, then we could locate the data within $\mathcal{O}(1)$ time complexity and we only need to store the total number of records as the only parameter. Compared with B-Tree and other indexes, the advantages are enormous.

In order to ensure the learned index model to be the desired CDF, we need to make the following assumptions:

1. All data records are stored statically in database, hence we do not take insertion and deletion into consideration. If there is some insertion or deletion, then the total size of the data records, N , will be different. Therefore, if insertion or deletion are involved, we cannot calculate the position as we show above.
2. All data records are sorted according to their keys X . Only when the data records are sorted according to the keys, we can regard the index model as CDF, i.e. $F(x) = \mathbb{P}(X \leq x)$.
3. For simplicity, we assume that our data records are stored in a continuous memory space. In other words, the indices of pages in this project is continuous integers and all the data records are loaded into memory.

2. Implementation

2.1. One Dimensional Data

2.1.1. B-Tree

B-Tree and its variants have been widely used as indexes in databases. B-Trees can be considered as a generalisation of binary search tree: In binary search tree, there is only one key and two children at most in the internal node. B-Tree extends the nodes such that each node can contain several keys and children. The keys in a node serve as dividing points and separate the range of keys. With this structure, we make a multi-way decision based on comparisons with the keys stored at the node x .

In this section, we introduce the construction and search processes of B-Trees and then analyse their properties.

Attributes

Each node in a B-Tree has the following attributes:

- $x.n$ is the number of keys currently stored in the node x .
- Inside each node, the keys are sorted in non decreasing order, so that we have $x.keys_1 \leq x.keys_2 \leq \dots \leq x.keys_{x.n}$.
- $x.leaf$, a Boolean value determines if current node is a leaf node.

With these properties, A B-Tree T whose root is $T.root$ have the following properties:

- Each internal node x contains $x.n+1$ children. We assume the children are $x.c_1, \dots, x.c_{x.n+1}$.
- The nodes in the tree have lower and upper bounds on the number of keys that can contain. These bounds can be expressed in terms of a fixed integer t .

When inserting keys into a binary search tree, we search for the leaf position at which to insert the new key. However, with B-Tree, we cannot simply find the position, create a new node and insert the value because the tree will be imbalanced again. Hence, in this section, we illustrate an operation that splits a full node around its median key

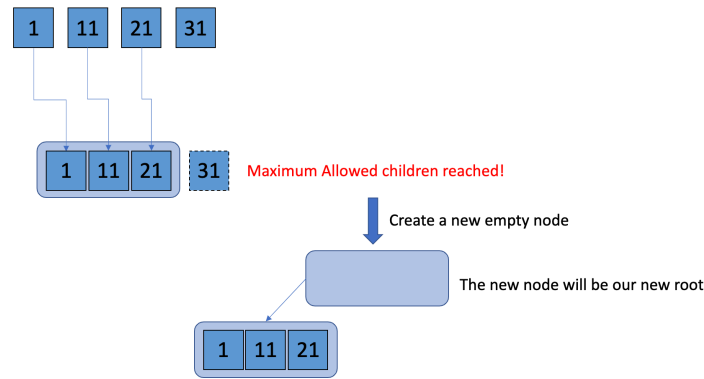


Figure 2.1.: B-Tree key insertion

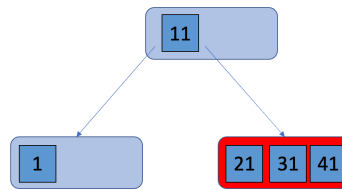


Figure 2.2.: B-Tree key insertion

Insertion in a B-Tree

Algorithm 1: Algorithm for B-Tree insertion

Input: m :order_of_tree , (k,v) : (key, value), N :Node;
Output: B-Tree

```

1 if  $N$  is a leaf and not yet full then
2   | insert  $(k,v)$  into  $N$ 
3 else
4   | create new Node  $N'$ 
5   | Find the median of the node
6   | Add the value at the median location to the new node  $N'$ 
7 end
8 if  $N$  is root with no children and not full then
9   | insert  $(k,v)$  into  $N$ 
10 end
```

There are two conditions in insertion:

- **When the node is empty or not created at all:** In the algorithm, initially when the first key is inserted and there is no root to the tree it will check the condition if there are any nodes and if not create a new one. It will insert the new key in the node and keeps inserting the new keys until it is one less than the order of the B-Tree being created.
- **When the node is full:** As soon as the maximum number of allowed children has reached for the root node a new empty node is created. Suppose we have inserted

[1,11,21] to a node of a B-Tree with degree 4. Now if we want to insert a new value 31 into the tree, since it has reached the maximum number of children it will find the median of the existing node [1,11,21] which is 11 and increase the level of the B-tree to 2 and make [1] and [21] child nodes of [11]. So now if a new value is to be inserted it can be inserted. Splitting of the node happens each time it reaches its maximum allowed keys. Now 31 will be compared with 11 and since $31 > 11$ it will be inserted in the right child and it will have an updated value of [21,31]. More keys can then be inserted until it reaches its maximum and splits again. Once the node is split its parent is also updated to the median value i.e., [11] in this case for nodes [1] and [21,31,41] as can be seen in 2.2.

2.1.2. Baseline Learned Index

Overview

The B-Tree can be regarded as a function \mathcal{F} that maps the key x into its corresponding page index y . It is known to us that the pages are allocated in a way that the every S entries are allocated in a page where S is a pre-defined parameter. For example, if we set S to be 10 items per page, then the first page will contain the first 10 keys and their corresponding values. Similarly, the second 10 keys and their corresponding values will be allocated to the second page.

If we know the CDF of X as $F(X \leq x)$ and the total number of entries N , then the position of x can be estimated as $p = F(x) * N$ and the page index where it should be allocated to is given by

$$y = \lfloor \frac{p}{S} \rfloor = \lfloor \frac{F(x) * N}{S} \rfloor$$

Example 2.1 For example, if the keys are uniformly distributed from 0 to 1000, i.e. the CDF of X is defined as $F(X \leq x) = \frac{x}{1000}$ and we set $S = 10$, $N = 1001$. Then for any key x , we immediately know it will be allocated into $y = \lfloor \frac{1000}{10} * \frac{x}{1000} \rfloor = \lfloor \frac{x}{10} \rfloor$. Assume that we have a key 698, then we can calculate $y = \lfloor \frac{698}{10} \rfloor = 69$. By doing so, the page index is calculated in constant time and space.

In this example, we see that the distribution of X is essential and our goal of learned index in one-dimensional data is to learn such distribution. To do so, we apply two different techniques as the baseline, the polynomial regression and fully connected neural network.

To train such a learned index, we first manually generate the X with respect to a certain distribution. We then save the generated X into a dense array with the length N . Then we use the proportional index, i.e. the index of each x divided by N as the expected output y .

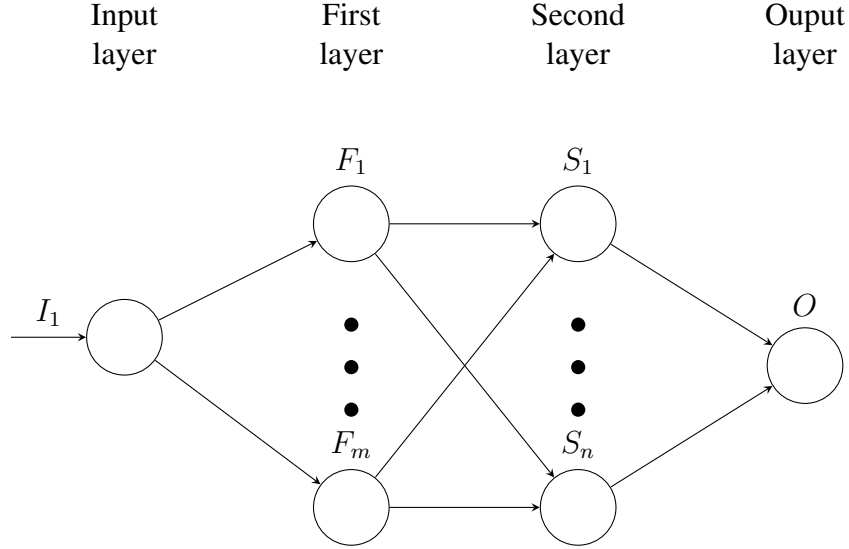


Figure 2.3.: The architecture of the fully connected neural network used as baseline learned index. In this neural network, we use only 2 fully connected layers. The input of this neural network is only one neuron such that it represents the given query key. The output of this neural network is limited to 1 neuron such that it represents the predicted proportional position of the key-value pair.

Fully Connected Neural Network

After generating the training dataset X and its corresponding Y , we build a fully connected neural network as the baseline learned index. The architecture of the fully connected neural network is illustrated in Figure 2.3.

We apply the Rectified Linear Unit (ReLU) activation function at the end of F_i and S_i . Formally, assume the output of F_i is \mathbf{a} , then we define the output of $\text{ReLU}(F_i)$ as $y = \max(\mathbf{a}, 0)$ where \max returns the larger value between each entry of \mathbf{a} and 0. Then we train this fully connected neural network with standard stochastic gradient descent (SGD), and we set the learning rate to be $\alpha = 0.001$. We use the mean square error (MSE) $\ell = \frac{1}{n} \sum (y - \hat{y})^2$ as the loss function.

Formally, we can induce the output of this fully connected neural network as following:

1. In the input layer, we have the input as a scalar value x .
2. The first fully connected layer has m nodes, and the output is defined as $\mathbf{y}_1 = \mathbf{w}_1 x + \mathbf{b}_1$ where \mathbf{w}_1 and \mathbf{b}_1 is a $m \times 1$ matrix. Hence, the output of the first fully connected layer is a $m \times 1$ matrix. Then we apply the ReLU activation function to \mathbf{y}_1 and we get $\mathbf{z}_1 = \max(\mathbf{y}_1, 0)$.
3. The second fully connected layer has n nodes, and the output is defined as $\mathbf{y}_2 = \mathbf{w}_2 \mathbf{z}_1 + \mathbf{b}_2$. Similarly, after the ReLU operation, we get $\mathbf{z}_2 = \max(\mathbf{y}_2, 0)$.
4. For the output layer, in order to get a scalar as output, we apply a n node fully connected layer here. The final output is defined as $\hat{y} = \mathbf{w}_3 \mathbf{z}_2 + \mathbf{b}_3$ where \mathbf{w}_3 is a $1 \times n$ matrix.

In summary, the output of the fully connected neural network can be calculated as

$$\hat{y} = \mathbf{w}_3 \max(\mathbf{w}_2 \max(\mathbf{w}_1 x + \mathbf{b}_1, 0) + \mathbf{b}_2, 0) + \mathbf{b}_3 \quad (2.1)$$

In the above fully connected neural network, there are 6 parameters to optimise: $\mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3$ and $\mathbf{b}_1, \mathbf{b}_2, \mathbf{b}_3$ and we apply the gradient descent and back propagation to optimise them. Formally, the steps are illustrated below:

1. **Initialisation.** For \mathbf{w}_i and \mathbf{b}_i of the shape $m \times n$, we randomly initialise the values of each entry using a uniform distribution $U(-\frac{1}{\sqrt{n}}, \frac{1}{\sqrt{n}})$.
2. **Forward Pass.** With the initialised \mathbf{w}_i and \mathbf{b}_i , we calculate the output as formulated by the equation 2.1. We then calculate the error as $\ell = \frac{1}{n} \sum (y - \hat{y})^2$.
3. **Backward Pass.** After getting the error, we start from the last layer to perform the backward propagation operation. Formally, we do the following operations:
 - a) We first calculate the partial derivatives: $\frac{\partial \ell}{\partial \mathbf{w}_3} = \mathbf{z}_2^T$, $\frac{\partial \ell}{\partial \mathbf{b}_3} = 1$ and $\nabla_3 = \frac{\partial \ell}{\partial \mathbf{z}_2} = \mathbf{w}_3^T$. Then we can update \mathbf{w}_3 and \mathbf{b}_3 as $\mathbf{w}_3^{\text{new}} = \mathbf{w}_3 - \alpha * \frac{\partial \ell}{\partial \mathbf{w}_3}$ and $\mathbf{b}_3^{\text{new}} = \mathbf{b}_3 - \alpha * \frac{\partial \ell}{\partial \mathbf{b}_3}$.
 - b) Then we pass the ∇_3 to previous layer, and calculate the partial derivatives as $\frac{\partial \ell}{\partial \mathbf{w}_2} = \mathbf{z}_2^T \nabla_3$, $\frac{\partial \ell}{\partial \mathbf{b}_2} = \nabla_3$ and $\nabla_2 = \frac{\partial \ell}{\partial \mathbf{z}_1} = \nabla_3 \mathbf{w}_2^T$. Then we update \mathbf{w}_2 and \mathbf{b}_2 .
 - c) After that, we pass the ∇_2 to the first layer, and calculate the partial derivatives as $\frac{\partial \ell}{\partial \mathbf{w}_1} = x^T \nabla_2$, $\frac{\partial \ell}{\partial \mathbf{b}_1} = \nabla_2$. Then we update \mathbf{w}_1 and \mathbf{b}_1 .
4. **Loop between 2 and 3.** We perform the forward pass and the backward several times until the loss is acceptable or a maximum number of loops reached.

We will discuss more findings and insights about the baseline model in the *Chapter 4*.

2.1.3. Recursive Model Index

In our baseline models, it is not very difficult to reduce the mean square error from millions to thousands. However, it is much harder to reduce it from thousands to tens. This is the so called last-mile problem.

In order to solve this problem, recursive model index was proposed [KBC⁺18]. The idea is to split the whole set of data into smaller pieces and assign each piece an index model. By doing so, each model is only responsible for a small range of keys. Ideally, in each smaller range, the keys are distributed in a way that is easier to be learned by our index models, such as polynomial model, fully connected model or even traditional B-Tree model.

As shown in Fig. 2.4. A recursive model can be regarded as a tree structure, which contains a root model that receives the full dataset for training. Then the root model will split the dataset into several parts. Each sub-model will then receive one part of the full dataset. Then we train the sub-models one by one with the partial training dataset.

Example 2.2 For example, in the Fig. 2.4, the full dataset will be split into three parts and each sub-model receives one part. To train this recursive model, we first train the root model with the whole dataset. Then the root model will split the dataset into 3 parts according to the predicted value of each data point in the dataset. Then each sub-model will receive one part and we train the sub-model accordingly.

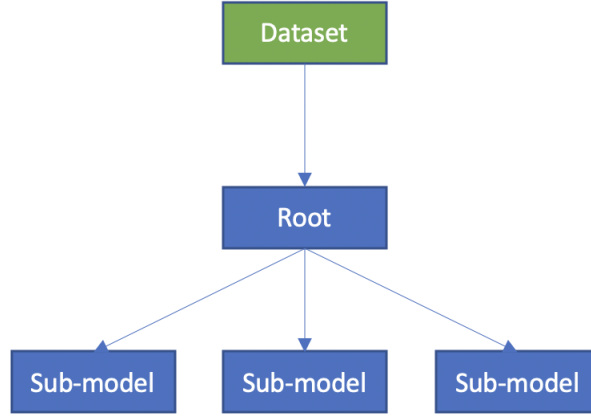


Figure 2.4.: An example recursive model index with one root model and three leaf model.

Properties

Similar to a tree, we define the following terms in a recursive model:

1. **Node Model.** Every node is responsible for making decisions with given input data. In one dimensional case, it can be regarded as a function $f : \mathbb{R} \rightarrow \mathbb{R}, x \rightarrow y$ where x is the input index and y is the corresponding page block. In principle, each node can be implemented as any machine learning model, from linear regression to neural network, or a traditional tree-based model, such as B-Tree.
2. **Internal Node Model.** Internal nodes are all nodes except for leaf nodes and the root node. Every internal node receives a certain part of training data from the full dataset, and train a model on it.

In the following sections, we will use the notations defined below:

1. $N_M^{(i)}$ is the number of models in the i th stage.

Training

In order to construct a recursive model, we need to have several parameters listed below:

1. The training dataset, notated as (X, Y) with entries notated as (x, y) .

2. The number of stages, notated as N_S . It is an integer variable.
3. The number of models at each stage, notated as N_M . It is a list of integer variable.
 $N_M^{(i+1)}$ represents the number of models in the i th stage.

The training process of recursive model is an up-bottom process. There will be only one root model that receives the whole training data. After the root model is trained, we iterate over all the training data and predict the page by the root model. After the iteration, we get a new set of pairs (X, Y_0) . Then we map $\forall y_0 \in Y_0$ into the selected model id in next stage by $\text{next} = y_0 * N_M^{(i+1)} / \max(Y)$.

Algorithm 2: Training of Recursive Model Index

```

input: num_of_stages; num_of_models; types_of_models; x; y
1 trainset=[[ (x,y) ]]
2 stage← 0
3 while stage < num_of_stages do
4   while model < num_of_models[stage] do
5     model.train(trainset[stage][model])
6     models[stage].append(model)
7   end
8   if not last stage then
9     for i ← 0 to len(x) do
10      model=models[output from previous stage]
11      output=model.predict(x[i])
12      next=output * num_of_models[stage+1]/max_y
13      trainset[stage+1][next].add((x[i],y[i]))
14    end
15 end

```

Polynomial Internal Models

In the recursive model index, we use internal models to learn the CDF of a part of the full training data. In order to learn the CDF, we need to know or assume the distribution of a specific part of the data. In this report, we support the following distributions.

Linear Regression	$w x + b$
Quadratic Regression	$a x^2 + b x + c$
B-Tree	N/A
Fully Connected Neural Network	N/A

Here we describe how we fit a polynomial model.

The polynomial regression model with degree m can be formalised as

$$\hat{y}_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \cdots + \beta_m x_i^m$$

and it can be expressed in a matrix form as below

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & x_1^2 & \cdots & x_1^m \\ 1 & x_2 & x_2^2 & \cdots & x_2^m \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_n & x_n^2 & \cdots & x_n^m \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_m \end{bmatrix}$$

which can be written as $Y = \mathbf{X}\beta$.

Proof 2.1 Our goal is to find β such that the sum of squared error, i.e.

$$S(\beta) = \sum_{i=1}^n (\hat{y} - y)^2$$

is minimal. This optimisation problem can be resolved by ordinary least square estimation as shown below.

First we have the error as

$$\begin{aligned} S(\beta) &= \|\mathbf{y} - \mathbf{X}\beta\|^2 = (\mathbf{y} - \mathbf{X}\beta)^T (\mathbf{y} - \mathbf{X}\beta) \\ &= \mathbf{y}^T \mathbf{y} - \beta^T \mathbf{X}^T \mathbf{y} - \mathbf{y}^T \mathbf{X} \beta + \beta^T \mathbf{X}^T \mathbf{X} \beta \end{aligned} \quad (2.2)$$

Here we know that $(\beta^T \mathbf{X}^T \mathbf{y})^T = \mathbf{y}^T \mathbf{X} \beta$ is a 1×1 matrix, i.e. a scalar. Hence it is equal to its own transpose. As a result we could simplify the error as

$$S(\beta) = \mathbf{y}^T \mathbf{y} - 2\beta^T \mathbf{X}^T \mathbf{y} + \beta^T \mathbf{X}^T \mathbf{X} \beta \quad (2.3)$$

In order to find the minimum of $S(\beta)$, we differentiate it with respect to β as

$$\nabla_{\beta} S = -2\mathbf{X}^T \mathbf{y} + 2(\mathbf{X}^T \mathbf{X})\beta \quad (2.4)$$

By let it to be zero, we end up with

$$\begin{aligned} -\mathbf{X}^T \mathbf{y} + (\mathbf{X}^T \mathbf{X})\beta &= 0 \\ \implies \beta &= (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} \end{aligned} \quad (2.5)$$

■

2.2. Two Dimensional Data

2.2.1. KD-Tree

KD-Tree is a space partitioning structure that can be used to organise data points in k dimensional space. We have fixed our dimensions of data points to 2-dimensions and their values

are stored as a scalar. In our implementation, *KD-Tree* is a binary tree with every node having data points partitioned in 2-dimensional space. A *KD-Tree* is a binary tree since each node has two children and when the keys are multidimensional each node is partitioned at split axis based on the depth of the tree and the dimension of the key which in turn determines the number of split axis the tree will have. For example for a 3-dimensional space the first split axis is x-coordinate and then at the next level it will be y-coordinate and lastly z-coordinate.

Properties

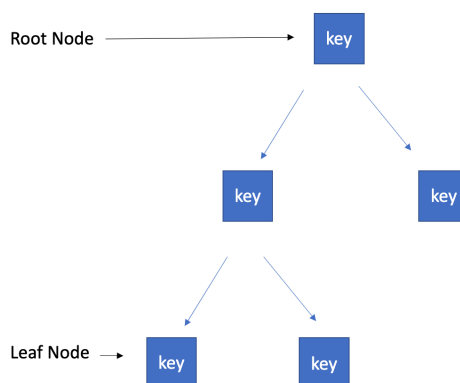


Figure 2.5.: *KD-Tree*

1. **Node:** Node of a *KD-Tree* is essentially a 2-dimensional data point. It can be k -dimensional for *KD-Tree*. Node is called a Root Node when it is at the top level as can be seen in Fig. 2.5 and does not have a parent. A node is called a Leaf Node when it has no children and is at the bottom level.
2. **Levels:** Nodes are at the same level when they have the same distance from root. Hence, a level increases as the distance of the nodes increase from root. In the 2.5 we can see the key at root is at level 1 and then we have level 2 and level 3.
3. **Dimensions:** Every *KD-Tree* can be structured in such a way that the data points are divided into k -dimensions. Each node is recursively cut into as many dimensions as is mentioned in the dimensions. In our case the data points are 2-dimensional and hence the space is divided into 2-dimensions alternatively until a leaf is reached.
4. **Cell:** The subdivision of space consists of rectangular regions, called cells (possibly unbounded).

Algorithm 3: Construction Algorithm for *KD-Tree*

Input : pointList; Keys= $[(x, y); x \in \mathbb{R}; y \in \mathbb{R}]$, dimension = 2, split_axis; 0 or 1

Output: *KD-Tree*

```
1 for  $i \leftarrow 0$  to  $\text{len}(\text{pointList})$  do
2    $\text{int split\_axis} := \text{split\_axis} \bmod \text{dimension}$  // Select the split_axis
   based on depth
3   Sort point list and choose median
4   Create node at median
5    $\text{node.leftChild} := \text{kdtree}(\text{points in pointList before}$ 
   median,  $\text{split\_axis}+1$ ); //SubTree Creation
6    $\text{node.rightChild} := \text{kdtree}(\text{points in pointList after}$ 
   median,  $\text{split\_axis}+1$ );
7   return node
8 end
```

For constructing the *KD-Tree* we have the following constraints:

1. As one moves down the tree, one cycles through the axes used to select the splitting planes. For example, in a 2-dimensional plane we split the data on x-axis at the root and then split it on y-axis for its children. We then split the grandchildren on x-axis again and so on.
2. Points are inserted by selecting the median of the points being put into the subtree, with respect to their coordinates in the axis being used to create the splitting plane. This ensures that the tree is balanced. A balanced tree is the one in which leaf node is approximately the same distance from the root.

In the algorithm above, we first sort all the values obtained in the Point list. We initialise the first split axis to 0 and then toggle between 0 and 1 as we increase the depth. Once the data points are sorted, their median is chosen.

Example 2.3 For example if we have points sorted as

$((1, 2), (3, 4), (5, 6), (7, 8), (9, 10))$

we will take the median as $(5, 6)$ and assign $(3, 4)$ to the left and $(7, 8)$ to the right. The reason $\text{node.leftChild} = (3, 4)$ is because $3 < 5$ and $\text{node.rightChild} = (7, 8)$ is because $7 > 5$ i.e., we compare the x-axis of the points to the root when we create the subsequent nodes. Now if we want to add point $[1, 2]$ to the above tree it will check the x-coordinate at the root and since $1 < 5$ it will go the left. In the left since we already have a node $(3, 4)$ it will check the y-coordinate of the points i.e., $4 > 2$ and so it will go and check in the left of the node if this point can be added there and since it's empty it is added in the left. Further points are added in the same way by checking the x-coordinate and y-coordinate alternatively. This process is then carried out recursively and subtrees are created on the left and right until all the points are added to the tree. Similarly point $(9, 10)$ is added in the right subtree as the rightChild of node $(7, 8)$. (*None*) is added when the rightChild or

leftChild of the node is empty. The tree will now look like

$((1, 2), (None), (3, 4)), ((None), (9, 10), (7, 8)), (5, 6))$

Points are added to left and right subtree as follows:

left subtree points: $((1, 2)(3, 4))$,

right subtree points: $(7, 8), (9, 10)$

centre being the root: $(5, 6)$.

$([Left\ Subtree, Right\ subtree, Root\ Point])$

Construction time and space complexity of 2-dimensional KD-Tree:

The most expensive part of the construction of KD-Tree is sorting the points on both the axis. Instead of working with more complex algorithm to find the median we first presorted the values on x-axis and then on y-axis.

$T(n) = O(n)$, if $n = 1$

$O(n) + 2T(n/2)$, if $n > 1$

The above equations then solve to $O(n \log n)$.

Since KD-Tree is A binary tree, and every leaf and internal node uses $O(1)$ storage, hence the total storage is $O(n)$.

2.2.2. LISA: Learned Index for Spatial Data

Spatial data and query processing have become ubiquitous due to proliferation of location-based services such as digital mapping, location-based social networking, and geo-targeted advertising. Motivated by the performance benefits of learned indices for one-dimensional data, this section explores the application of learned index for spatial data. The main motivation is to map spatial data into one-dimensional data through several steps and apply machine learning techniques to generate a learned index for the one-dimensional data.

Motivation

In the last section, we described a recursive model index (RMI) that consists of a number of machine learning models staged into a hierarchy to enable synthesis of specialised index structures, termed learned indexes. Provided with a search key x , RMI predicts the position of x 's data with some error bound, by learning the CDF over the key search space. However, the idea of RMI is not applicable in the context of spatial data as spatial data invalidates the assumption required by RMI that the data is sorted by key and that any imprecision can be easily corrected by a localised search. Although it is possible to learn multi-dimensional CDFs, such CDFs will result in searching local regions qualified on one dimension but not all dimensions.

For the one-dimensional data, we can learn the CDF by using a recursive model as shown in previous section. However, when the data is two-dimensional, the learned CDF (the marginal

CDF) through recursive model cannot be applied directly to predict the position of the key. Formally, we could learn the marginal CDF for each dimension by using recursive model, i.e. $F(X)$ and $F(Y)$. However, to predict the position of a 2-dimensional key, we need to joint CDF $F(X, Y)$, which cannot be induced from the marginal CDFs. We show an example as below to illustrate this limitation.

Example 2.4 Assume that X and Y are distributed as shown in Fig 2.6. In this example, we have $F(x \leq A) = \frac{1}{3}$, which means that the point A should be assigned into the first third pages. With learned indexes in one-dimensional, then there comes the problem below:

1. There will be duplicate keys. In this example, if we only consider the X axis, we will get an array $[0.7, 0.7, 1.5]$ which contains duplicate keys.
2. If we remove the duplicate keys, then $F(x \leq A) = \frac{1}{2}$, which is not what we expect.
3. If we do not remove the duplicate keys, then $F(x \leq A) = F(x \leq B)$, which is still not we expect.

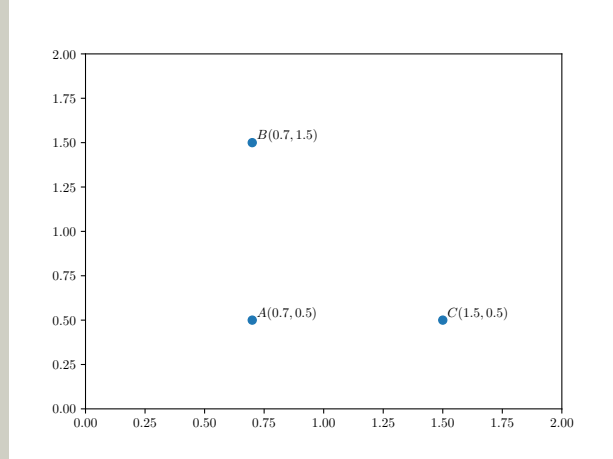


Figure 2.6.: An example demonstrating the limitations of one-dimensional learned index in two-dimensional data. In this graph we have $F(x \leq A) = \frac{1}{3}$ but with learned index in one-dimensional, we cannot learned such joint CDF.

LISA solves this problem by partitioning search space into a series of grid cells based on the data distribution and building a function map the data from \mathbb{R}^d into \mathbb{R} , in our case, we have $d = 2$. We call this function as *Mapping Function*.

Definitions

This section presents the definition

1. **Key.** A key k is a unique identifier for a data record with $k = (x_0, x_1) \in \mathbb{R}^2$.

2. **Cell.** A grid cell is a rectangle whose lower and upper corners are points (l_0, l_1) and (u_0, u_1) , i.e., $\text{cell} = (l_0, u_0) \times [l_1, u_1)$.
3. **Mapping Function.** A mapping function \mathcal{M} is a function on the domain \mathbb{R}^2 to the non-negative range, i.e $M : [0, X_0] \times [0, X_1] \rightarrow [0, +\infty)$ such that $M(x_0, x_1) \leq \mathcal{M}(y_0, y_1)$ when $x_0 \leq y_0$ and $x_1 \leq y_1$.

2.2.3. Baseline Method

We can extend the learned index method for range queries on spatial data by using a mapping function. This baseline method works as follows. We first sort all keys according to their mapped values and divide the mapped values into some cells such that each cell contains the same number of keys (except the last one). If a point (x, y) 's mapped value is larger than those of the keys stored in the first i cells, i.e. $\mathcal{M}(x, y) > \sup \bigcup_{j=0}^{i-1} M(C_j)$, we store (x, y) in the $(i + 1)$ th cell.

For a range query, we have a query rectangle $qr = [l_0, u_0) \times [l_1, u_1)$, we only need to predict the indices of (l_0, l_1) and (u_0, u_1) namely i_1 and i_2 respectively. Then we scan the keys in $i_2 - i_1 + 1$ cells, and find those keys that fall in the query rectangle qr .

Example 2.5 As shown in Fig. 2.7, the key space is divided into 3 cells using the mapping function $\mathcal{M}((x, y)) = x + y$. The query rectangle consisting of only 1 key, falls inside the second part. During prediction, we need to find out the cells to which our query rectangle belongs (the 2^{nd} cell in our example). Once the cell is found, we need to compare the key of the query point, against all the possible keys in that cell until a match is found. This results in 8 irrelevant points accessed for the range query that only contains one relevant key.

Training

The training dataset for the baseline model can be notated as (\mathbf{X}, Y) with entries notated as (\mathbf{x}, y) . \mathbf{X} represents the two dimensional key coordinates, and Y represents the corresponding data item.

In order to construct the baseline model, we need to have several parameters listed below:

1. N , which represents the number of cells into which the key's mapped value space will be divided.

As described in Algorithm 6, during training, we perform the following operations:

1. Sort all keys according to their mapped values.
2. Divide the keys into equal sized cells

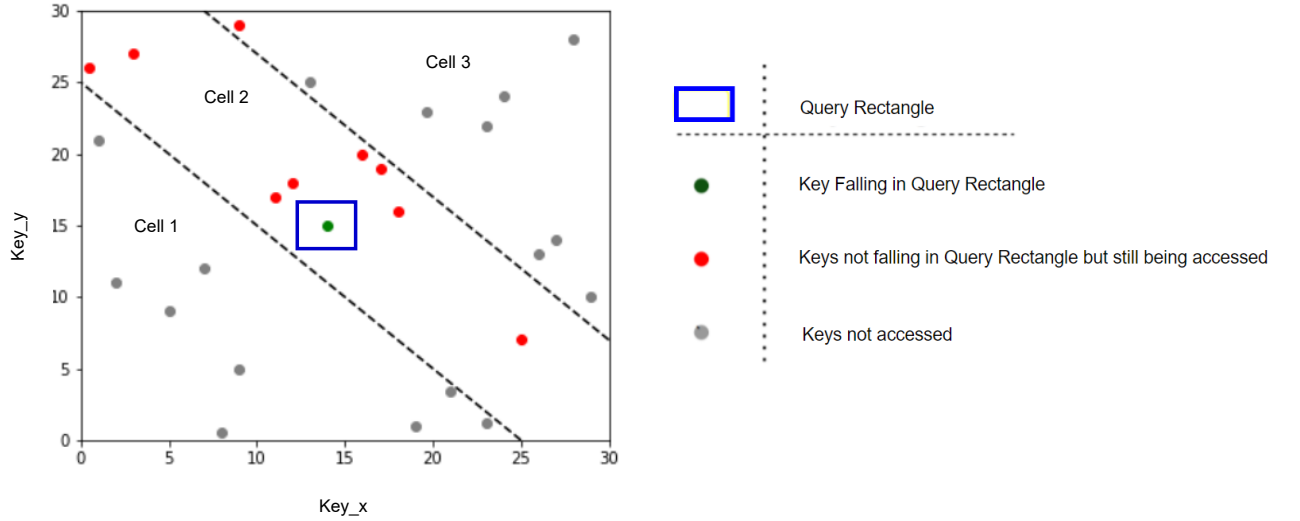


Figure 2.7.: LISA Baseline Method

- a) Key space is divided into 3 cells with equal number of keys
- b) To search for a query, we first need to find out the cell which contain the query point
- c) Once the query point is found, we need to compare the query point key values with all the keys in the cell until a match is found

3. Store the mapped values of first and last key for each cell into an array

Algorithm 4: Training Algorithm for Lisa Baseline Method

```

input :  $N$ ; trainset= $[(x, y); x \in \mathbb{R}^2; y \in \mathbb{R}]$ 
Output: M: Mapped Function
1 for  $i \leftarrow 0$  to  $len(x)$  do
2    $x[i].mapped\_value = x[i][0] + x[i][1]$ 
3 end
4  $sortXBasedOnMappedValue()$ 
5 divide  $x$  into equal size pages according to  $num\_of\_cells$ 
6 Store mapped value of first and last key for each page
7 for  $i \leftarrow 0$  to  $num\_of\_cells$  do
8    $denseArray[i].lower = \text{first key in page } i$ 
9    $denseArray[i].upper = \text{last key in page } i$ 
10 end

```

For prediction, we find the cell corresponding to mapped value of the query point using binary search, scan this cell sequentially and compare the values of keys in the cell against the query point, until a match is found.

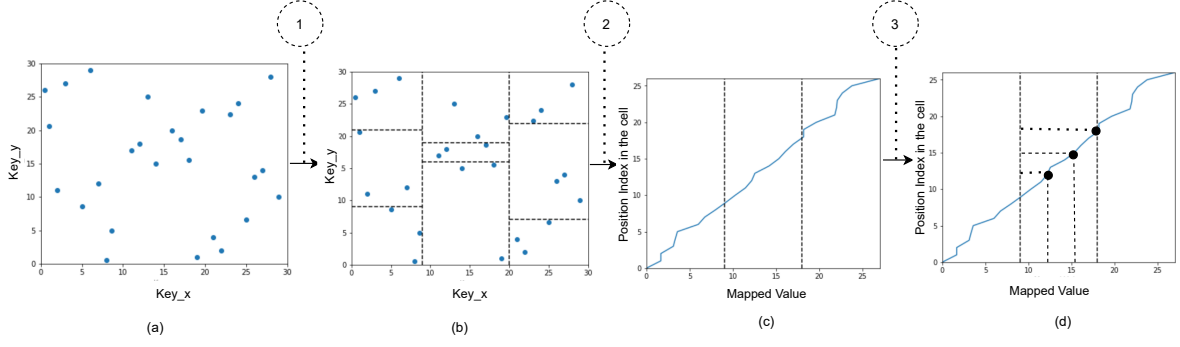


Figure 2.8.: Lisa Framework

- 1) Generate grid cells, and apply Lebesgue Measure to each cell to map two dimensional key value to a scalar.
- 2) Sort mapped values and divide them across equal length intervals termed as mapped intervals(3 in the figure)
- 3) For each mapped interval, divide the mapped value range in shards(3 in the figure) and learn a linear regression function per shard

Prediction

Algorithm 5: Prediction Algorithm for Lisa Baseline Model

input: x_test : Key; d : the denseArray

```

1  $x\_test.mapped\_value = x\_test[0] + x\_test[1]$ 
2 for  $i \leftarrow 0$  to  $len(denseArray)$  do
3   if  $\mathcal{M}(x\_test) \in [d[i].lower, d[i].upper]$  then
4     | Key is in Page i
5     | break
6   end
7 end
8 Sequentially search for  $x\_test$  in page j

```

2.2.4. Lisa Overview

Given a spatial dataset, we generate the mapping function \mathcal{M} , the shard prediction function \mathcal{SP} . Based on them, we build our index structure, LISA, to process range query and KNN query. LISA consists of four parts: the representation of grid cells, the mapping function \mathcal{M} , the shard prediction function \mathcal{SP} , and the local models for all shards. As illustrated in the Fig 2.8. the procedure of building LISA is composed of four parts.

1. Grid cell partition.
2. Mapping spatial coordinates into scalars, i.e. $\mathbb{R}^d \rightarrow \mathbb{R}$.
3. Build shard prediction function \mathcal{SP} .

4. Build local models.

Definitions

This section presents the additional definition specific to Lisa implementation.

4. **Shard.** The shard S is the pre-image of an interval $[a, b) \subseteq [0, +1)$ under the mapping function \mathcal{M} , i.e., $S = M^{-1}([a, b))$.

Given an initial data set, we divide the key space into cell grids based on the data distribution, map keys values to an one dimensional space using mapping function, followed by learning several monotonic shard prediction functions. After sorted, the one dimensional mapped value space is then divided into equal-length intervals, and one shard prediction function is learned for each interval, to partition the keys belonging to a particular interval, into different shards. As keys are sorted by mapped values before partitioning them into equal sized intervals, and all shards exhibit a total order with respect to their corresponding intervals in the mapped range(Shard Prediction function for each interval is monotonically increasing), following relationship holds

$$\inf(M(S_i)) > \sup(M(S_j)) \text{ when } i > j.$$

5. **Local Model.** Local model L_i is a model that processes operations within a shard S_i . It keeps dynamic structures such as the addresses of pages contained by S_i .

2.2.5. Design and Implementation Details

Grid Cells Generation

The first task in Lisa implementation is to partition the 2 dimensional key space into a series of grid cells based on the data distribution along a sequence of axes. Then we number the cells along these axes as well. The principal idea behind this partition strategy is to divide the key space into cell boundaries and apply a mapping function to create monotonically increasing mapping values at the cell boundaries.

$$M(x_i \in V) < M(x_j \in V) \text{ when } i < j, \text{ where } x_i \in C_i \text{ and } x_j \in C_j$$

i.e. mapped value of a key in cell i will always be less than mapped values of a key in cell j , if $i < j$.

Example 2.6 Consider the example shown in the figure 2.9: 27 keys are partitioned into 9 cell, resulting in 3 keys per cell. To partition the key space, we first sort the keys values according to 1st dimension and divide the keys into 3 vertical columns each containing 9 keys. Then for each vertical column of 9 keys, we sort the keys again according to 2nd dimension, and divide the keys in each column into 3 new cells. The number of cells N into which the keys space is divided, is a hyper-parameter and found empirically using grid search.

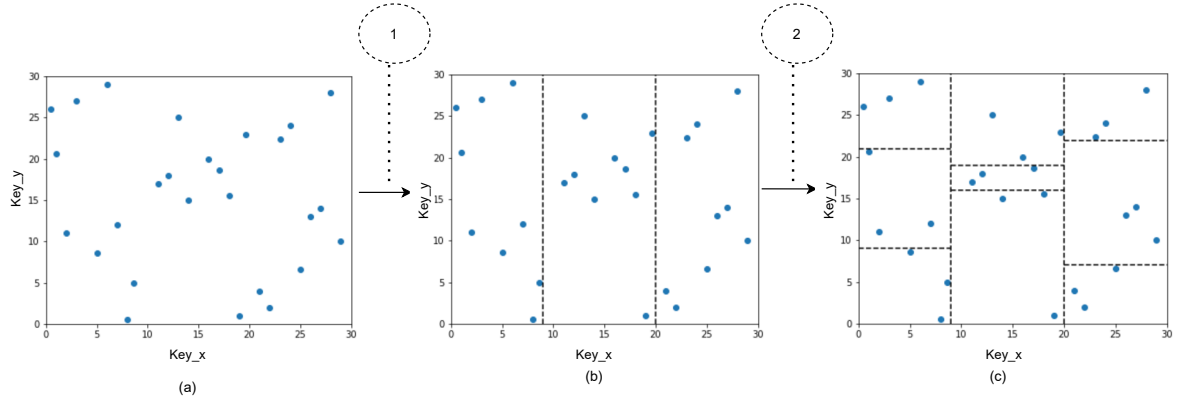


Figure 2.9.: Cell Partition Strategy:

- 1) : Sort Keys on x dimension and divide into 3 vertical columns each containing 9 keys
- 2) : Sort each vertical column keys on y dimension and divide into 3 horizontal columns each containing 3 keys

We need to sort the key space along the sequence of axis before we partition the keys value along that axis to make sure that cells don't contain overlapping keys.

Algorithm 6: Grid Cell Generation Algorithm for Lisa Method

```

input: num_of_cells; x; y
1 trainset=[(x,y); x ∈ ℝ2; y ∈ ℝ]
2 keysPerPage = len(x)/num_of_cells
3 Sort x based on first dimension x[:,[0]]
4 In first for loop, divide the keys into equal size subsets
  based on first dimension
5 for i ← 0 to √(num_of_cells) do
6   | Store the 1st dimensional coordinates of first and last
   | key for each cell. Each such cell will contain
   | keysPerPage * sqrt(num_of_cells) keys
7 end
8 Sort keys in each cell based on 2nd dimension, x[:,[1]]
9 for i ← 0 to √num_of_cells do
10  | for j ← 0 to √(num_of_cells) do
11  | |
12  | end
13  | Store the 2nd dimensional coordinates of first and last
    | key for each cell.
14 end

```

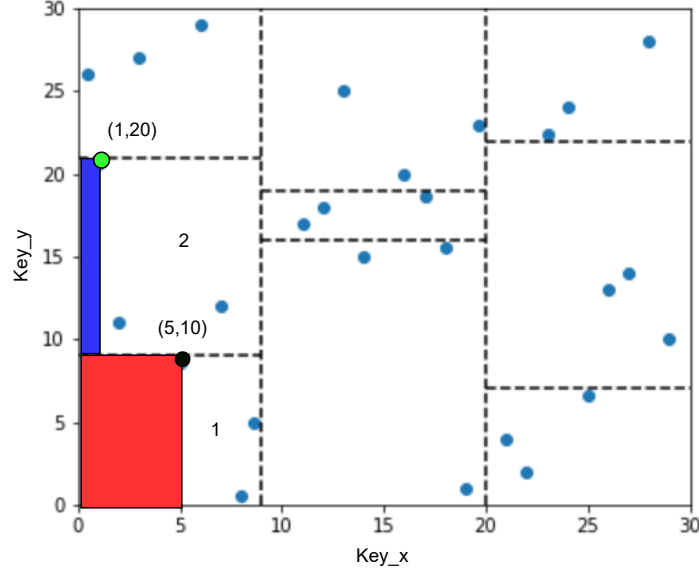


Figure 2.10.: Lebesgue Measure Representation for 2 dimensional data

1) Lebesgue Measure for the black point in first cell will be ratio of area of red rectangle divided by the total area of 1st cell = $50/100 = 0.5$

1) Lebesgue Measure for the green point in second cell will be ratio of area of blue rectangle divided by the total area of 2nd cell = $20/100 = 0.2$

Mapping Function

A mapping function \mathcal{M} is a function on the domain \mathbb{R}^2 to the non-negative range, i.e $M : [0, X_0] \times [0, X_1] \rightarrow [0, +\infty)$ such that $M(x_i \in V) < M(x_j \in V)$ if $i < j$, where $x_i \in C_i$ and $x_j \in C_j$. That means the mapped value of a key in cell i will always be less than mapped values of a key in cell j , if $i < j$.

Suppose $x = (x_0, x_1)$ and $x \in C_i = [\theta_{i_0}^{(0)}, \theta_{i_0+1}^{(0)}) \times [\theta_{i_1}^{(1)}, \theta_{i_1+1}^{(1)})$ then we define

$$M(x) = i + \frac{\mu(H_i)}{\mu(C_i)}$$

where $H_i = [\theta_{i_0}^{(0)}, x_0) \times [\theta_{i_1}^{(1)}, x_1)$ and μ is the Lebesgue measure on \mathbb{R}^2 .

As shown in figure 2.10, in 2-dimensional case, $\frac{\mu(H_i)}{\mu(C_i)}$ represents the fraction of the area covered by the key (x_0, x_1) to the total area of the cell. Since we are adding i , the index of the cell, to this fraction, the mapped value of a key in cell i will always be less than mapped values of a key in cell j , if $i < j$. After calculating the mapped values of the data set, we sort the keys in each cell according to the mapped value. This results in the whole key space to be sorted according to the mapped value. Figure 2.11 shows the mapping of 2 dimensional key space to one dimensional CDF.

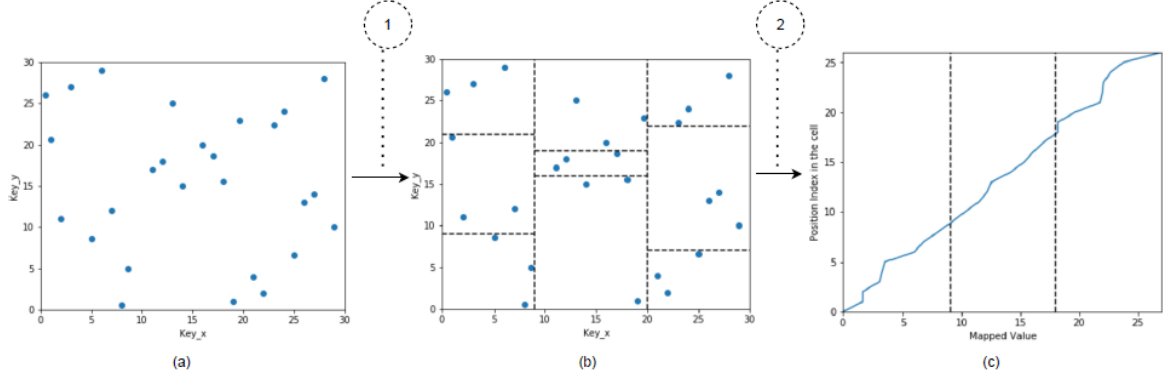


Figure 2.11.: Mapping 2 dimensional key Values to one dimensional cdf

- 1) Generate grid cells, and apply Lebesgue Measure to each cell.
- 2) Sort key in each cell according to mapped value. Mapped values in consecutive cells are already sorted by mapping function definition. Plot the cdf of mapped values.

Shard Prediction Function

After the mapping function, we get a dense array of mapped values. Then we partition them evenly into U parts and let $M_p = [m_1, \dots, m_U]$. We train linear regression functions \mathcal{F}_i on each interval and suppose $V + 1$ is the number of mapped values that each \mathcal{F}_i needs to process and Ψ is the average number of keys falling in a shard. With these definitions, we know that each \mathcal{F}_i generates $D = \lceil \frac{V+1}{\Psi} \rceil$ shards.

Example 2.7 For example, assume we have a dense array of mapped values as

$$[1, 1.2, 2.2, 3, 3.4, 4]$$

We want to partition it into 2 parts, so we have $M_p = [3]$ and $V + 1 = 3$. In this case we will train 2 linear regression functions. Suppose that the average number of keys in a shard is $\Psi = 2$, then each \mathcal{F}_i generates $D = \lceil \frac{V+1}{\Psi} \rceil = \lceil \frac{3}{2} \rceil = 2$ shards.

Then with a given x , the predicted shard is given by $\mathcal{SP}(x) = \mathcal{F}_i(x) + i \times D$, where $i = \text{binary-search}(M_p, x)$. More specifically, we first determine i by using binary search. The result tells which interval this x should belong to. Then we find the corresponding linear regression function \mathcal{F}_i and calculate $\mathcal{F}_i(x)$, which is the predicted shard.

Example 2.8 In the above example, given a key $x = 2.2$, we first perform binary search in M_p and we found $i = 1$. Then we find the first linear regression function \mathcal{F}_1 and calculate $\mathcal{F}_1(x)$. Since each linear regression function will yield $D = \lceil \frac{V+1}{\Psi} \rceil = 2$ shards, the shards that the first linear regression function generates will be from 0 to 1 and the shards that the second linear regression function generates will be from 2 to 3. Hence, the predicted shard id is given by

$$\mathcal{SP}(x) = \mathcal{F}_i(x) + i \times D$$

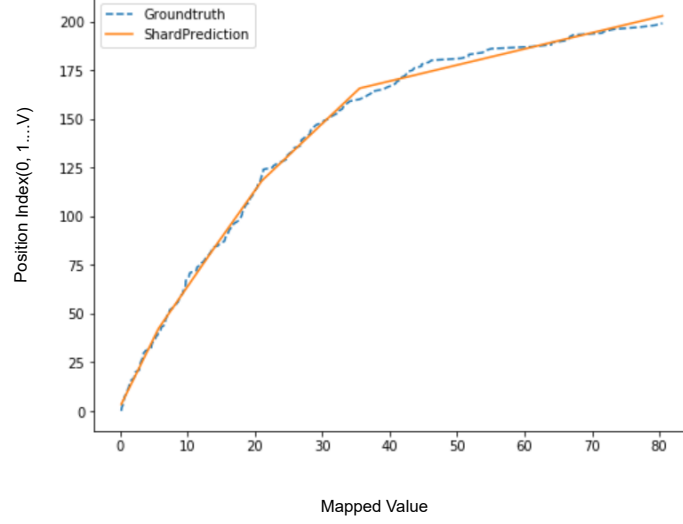


Figure 2.12.: Piecewise linear regression functions learnt by ShardTrainingAlgorithm, V is the number of keys per mapped interval

Then the problem left is to train the linear regression functions \mathcal{F}_i . Let $\mathbf{x} = (x_0, \dots, x_v)$ be the keys' mapped value that fall in $[m_{i-1}, m_i)$. Suppose that \mathbf{x} is sorted, i.e. $x_i \leq x_j, \forall 0 \leq i < j \leq v$. Let $\mathbf{y} = (0, \dots, V)$. Then we build a piecewise linear regression function f_i with inputs \mathbf{x} and ground truth \mathbf{y} . For a given point with mapped value $m \in [m_{i-1}, m_i)$, its shard id is given by $\lceil \frac{f_i(m)}{\Psi} \rceil + i \times D$, i.e. $\mathcal{F}_i(x) = \frac{f_i(m)}{\Psi}$.

Example 2.9 In our previous example, in the interval $[0, 3)$, we have $\mathbf{x} = (1, 1.2, 2.2)$ and $\mathbf{y} = (0, 1, 2)$. Then for a point with the mapped value $m = 1.2$, the expected output will be $f_i(m) = 1$ and the shard id is given by $\lceil \frac{1}{2} \rceil + 0 \times 2 = 1$. Hence, the point with mapped value $m = 1.2$ will be allocated to the first shard. Then the problem is to train a continuous piecewise linear regression function in each interval. We constrain the piecewise linear regression function to be continuous so that it is guaranteed be monotonic as shown in Figure 2.12.

Formally, a piecewise linear function can be described as

$$f(x) = \begin{cases} b_0 + \alpha_0(x - \beta_0) & \beta_0 \leq x < \beta_1 \\ b_1 + \alpha_1(x - \beta_1) & \beta_1 \leq x < \beta_2 \\ \vdots & \\ b_\sigma + \alpha_\sigma(x - \beta_\sigma) & \beta_\sigma \leq x \end{cases} \quad (2.6)$$

In order to make this piecewise linear function continuous, the slopes and intercepts of each linear region depend on previous values. Formally, let $\bar{a} = b_0$, then Eq. (2.6) reduces to

$$f(x) = \begin{cases} \bar{\alpha} + \alpha_0(x - \beta_0) & \beta_0 \leq x < \beta_1 \\ \bar{\alpha} + \alpha_0(x - \beta_0) + \alpha_1(x - \beta_1) & \beta_1 \leq x < \beta_2 \\ \dots & \dots \\ \bar{\alpha} + \alpha_0(x - \beta_0) + \alpha_1(x - \beta_1) + \dots + \alpha_\sigma(x - \beta_\sigma) & \beta_\sigma \leq x \end{cases} \quad (2.7)$$

Then to make Eq. (2.7) monotonically increasing, we only need to ensure that

$$\sum_{i=0}^{\eta} \alpha_i \geq 0, \forall 0 \leq \eta \leq \sigma$$

Let $\alpha = (\bar{\alpha}, \alpha_0, \dots, \alpha_\sigma)$, the square loss function $L(\alpha, \beta) = \sum_{i=1}^V (f(x_i) - y_i)^2$. We then optimise α and β iteratively.

Assume that $\beta = \hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_\sigma)$ is fixed, then α can be regarded as the least square solution of the linear equation $A\alpha = y$, where

$$A = \begin{bmatrix} 1 & x_0 - \hat{\beta}_0 & (x_0 - \hat{\beta}_1) 1_{x_0 \geq \hat{\beta}_1} & \dots & (x_0 - \hat{\beta}_\sigma) 1_{x_0 \geq \hat{\beta}_\sigma} \\ 1 & x_1 - \hat{\beta}_0 & (x_1 - \hat{\beta}_1) 1_{x_1 \geq \hat{\beta}_1} & \dots & (x_1 - \hat{\beta}_\sigma) 1_{x_1 \geq \hat{\beta}_\sigma} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_N - \hat{\beta}_0 & (x_N - \hat{\beta}_1) 1_{x_N \geq \hat{\beta}_1} & \dots & (x_N - \hat{\beta}_\sigma) 1_{x_N \geq \hat{\beta}_\sigma} \end{bmatrix}$$

where $1_{x_0 \geq \hat{\beta}_1}$ equals to 1 if $x_0 \geq \hat{\beta}_1$, otherwise it equals to 0.

We have

$$\begin{aligned} L(\alpha, \beta) &= (y - A\alpha)^T (y - A\alpha) = y^T y - \alpha^T A^T y - y^T A\alpha + \alpha^T A^T A\alpha \\ &= y^T y - 2\alpha^T A^T y + \alpha^T A^T A\alpha \end{aligned} \quad (2.8)$$

and if we let

$$\begin{aligned} \frac{\partial L(\alpha, \beta)}{\partial \alpha} &= 2A^T A\alpha - 2A^T y = 0 \\ \implies \alpha &= (A^T A)^{-1} A^T y \end{aligned} \quad (2.9)$$

we get the α with the given fixed β . Clearly, different β give rise to different optimal parameters. Let $\alpha^*(\beta)$ be the optimal α for a particular β , then we want to find β such that

$$L(\alpha^*(\beta^*), \beta^*) = \min\{L(\alpha^*(\beta), \beta) | \beta \in \mathbb{R}^{\sigma+1}\} \quad (2.10)$$

For β , we define $r = A\alpha - y$ and

$$\mathbf{K} = \text{diag}(\bar{\alpha}, \alpha_0, \dots, \alpha_\sigma), \mathbf{G} = \begin{bmatrix} -1 & -1 & \dots & -1 \\ p_0^{(0)} & p_0^{(1)} & \dots & p_0^{(V)} \\ p_1^{(0)} & p_1^{(1)} & \dots & p_1^{(V)} \\ \vdots & \vdots & \ddots & \vdots \\ p_\sigma^{(0)} & p_\sigma^{(1)} & \dots & p_\sigma^{(V)} \end{bmatrix}$$

where $p_i^{(l)} = -1_{x_i \geq \beta_i}$. Then

$$\mathbf{KG} = \begin{bmatrix} -\bar{\alpha} & -\bar{\alpha} & \dots & -\bar{\alpha} \\ 0 & \alpha_0 p_0^{(1)} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \alpha_\sigma p_\sigma^{(V)} \end{bmatrix}$$

then we have

$$g = \frac{\partial L(\alpha, \beta)}{\partial \beta} = 2\mathbf{KG}r, Y = \frac{\partial g}{\partial \beta} = 2\mathbf{KG}\mathbf{G}^T\mathbf{K}^T \quad (2.11)$$

Show how these are calculated

As $g = \nabla_\beta L$, $-g$ specifies the steepest descent direction of β for L . However, the convergence rate of $-g$ is low as it does not consider the second order derivative of L . Hence, we use Newton's method to perform the update along the direction of second derivative, $s = -\mathbf{Y}^{-1}g$. Newton's method assumes that the loss L is twice differentiable and uses the approximation with Hessian. The geometric interpretation of Newton's method is that at each iteration, it amounts to the fitting of a paraboloid to the surface of $L(\alpha, \beta)$ at the trial value β_k , having the same slopes and curvature as the surface at that point, and then proceeding to the maximum or minimum of that paraboloid. Hessian matrix, \mathbf{Y} in our case is positive semidefinite and hence can be inverted.

$$Y = \frac{\partial g}{\partial \beta} = 2\mathbf{KG}\mathbf{G}^T\mathbf{K}^T = 2(\mathbf{KG})(\mathbf{G}^T\mathbf{K}^T) = 2(\mathbf{G}^T\mathbf{K}^T)^T(\mathbf{G}^T\mathbf{K}^T) = 2(\mathbf{M}^T\mathbf{M}) \quad (2.12)$$

Show how these are calculated \mathbf{Y} is a full rank matrix as columns of \mathbf{Y} are linearly independent (all keys are independent of each other). To prove that \mathbf{Y} is positive definite, we need to show that $x^T \mathbf{Y} x > 0, \forall x \neq 0$.

$$x^T \mathbf{Y} x = x^T \mathbf{M}^T \mathbf{M} x = (\mathbf{M}x)^T (\mathbf{M}x) = \|\mathbf{M}x\|_2^2 \geq 0, \forall x \neq 0$$

In the beginning, we set $\beta^{(0)} = x_0$ and $\beta_i^{(0)} = x_{\lfloor i \times \frac{V}{\Psi} \rfloor}, \forall i \in [1, \sigma]$. Then we can obtain α by solving Eq. (2.9). Then at each step, we perform a grid search to find the step $lr^{(k)}$ such that the loss L is minimal. Then at the next iteration, we increase k by one and set

$$\beta^{(k+1)} = \beta^{(k)} + lr^{(k)} s^{(k)}$$

As described in Algorithm 7, we perform following operations during shard training, :

1. Divide the sorted mapped values into equal sized U intervals.

2. Suppose $V + 1$ is the number of mapped values in each interval and ψ is the estimated average number of keys falling in a shard.
3. For each interval, we want to build a monotonic regression model \mathcal{F}_i whose domain is $[m_{i-1}, m_i]$
4. Each \mathcal{F}_i generates $D = \lceil \frac{V+1}{\psi} \rceil$ number of shards
5. $x = [x_0, \dots, x_V]$ specifies the keys' mapped values in interval i , $[m_{i-1}, m_i]$
6. Given $V + 1$ sorted mapped values $x = [x_0, \dots, x_V]$ and their indices $y = [0, \dots, V]$, each \mathcal{F}_i is built and trained with the procedure mentioned in the algorithm 7.

Algorithm 7: Shard Training Algorithm

input: M_p, Ψ, U

```

1 Partition  $M_p$  into equal length  $U$  intervals  $\mathbf{M}_p = [m_1, \dots, m_U]$ 
  for  $i \leftarrow 0$  to  $U$  do
2    $x = [x_0, \dots, x_V]$  be the keys' mapped values in interval  $i$ 
3    $y = [0, \dots, V]$ 
4   Initialize  $\beta^{(0)}$  as  $\beta^{(0)} = x_0$  and  $\beta_i^{(0)} = x_{\lfloor i \times \frac{V}{\Psi} \rfloor}, \forall i \in [1, \sigma]$ 
5   while  $k < 1000$  do
6     Initialize  $A^{(k)}$  according to (2.7)
7      $\alpha^{(k)} = ((A^{(k)})^T A^{(k)})^{-1} (A^{(k)})^T y$ 
8     Calculate  $g^{(k)}, Y^{(k)}$ 
9      $s^k = -(Y^{(k)})^{-1} g^{(k)},$ 
10    Find update step  $lr^{(k)}$  such that
11     $L(\alpha^*(\beta^k + lr^{(k)} s^k), \beta^k + lr^{(k)} s^k) = \min\{L(\alpha^*(\beta^k + lr^{(k)} s^k), \beta^k + lr^{(k)} s^k)\}$ 
12     $\beta^{k+1} = \beta^k + lr^{(k)} s^k$ 
13  end
  end

```

Local Models for Shards

Local models are not relevant to our implementation as full data-set is loaded in the main memory.

2.3. Queries

2.3.1. Point Query

A point query is a database operation that finds the records that exactly match our query conditions. In this project, we perform point query on 1-dimensional data and 2 dimensional data. We assign the database records into pages, predict the page index with the index models

and then perform sequential search on the predicted page. In order to evaluate the errors that different index models are making, we focus on predicting the page indices and ignore the sequential search operation on a specific page.

Example 2.10 For example, assume we have an 1-dimensional array $[1, 2, 3, 4]$ and two pages such that $[1, 2] \in P_0$ and $[3, 4] \in P_1$. A point query for $x = 2$ is expected to return 0 as the page index.

Point Query with B-Tree

Point query in a B-Tree is to search the key with the exact same value of key in the tree. By searching in a Tree structure we can exploit the structure of tree to search for the key much faster. We do not have to linearly search the entire key space for the key anymore.

If the root node is a leaf node as well then it will simply search linearly and return an exact match of the key. If it doesn't find the key it will not return any value.

Since keys in B-tree are much larger in number and are usually of few levels we traverse the tree until we reach a leaf node and then search for an exact match to the point key in the leaf node.

To do this, firstly, we compare the point key with each key in the root node and find a key value which is greater than the point key in the root node. It will then traverse and search in the child of the key before it. We do this because we know that there is no possibility of finding the key in the child node associated with the keys which have a value higher than the Point query key. We then recursively keep traversing down the tree until we reach the desired leaf node. We then search for the key linearly in the leaf node.

Example 2.11 For example if we were to search for $\mathcal{K}(x)$ (41) in the example 1 of the B-Tree above, we would first compare point query (41) and the only $\mathcal{K}(x)$ in root node is (11). Since $(11) < (31)$ and there are no keys greater than this in the root node it will search in the right child of the root node. It will then linearly search the node and since there is an exact match it will return the associated value with it.

Algorithm 8: Algorithm for B-Tree Search

Input: $\mathcal{K}(x); [x \in \mathbb{R}]$, root ; Root of the B-Tree
Output: Value associated with key

```
1 for  $i \leftarrow 0$  to  $\text{len}(\text{RootNode})$  do
2   if keys in root greater than  $k$  then
3     SEARCH_CHILD ( $\mathcal{K}(x, y)$ ) //Search linearly the child associated with the key
      location one before
4     if Child is a leaf then
5       | Linearly search until the  $\mathcal{K}(x, y)$  is reached
6     else
7       | SEARCH_CHILD ( $\mathcal{K}(x, y)$ )
8     end
9   end
10 end
```

Point Query with KD-Tree Model Index

Algorithm 9: Point Query Algorithm for KD-Tree

Input : TestPoint $\mathcal{T}(x, y); [x \in \mathbb{R}; y \in \mathbb{R}]$, dim; 2, split_axis; 0/1 (0;
x_axis and 1; y_axis)
Output: Value associated with $\mathcal{T}(x, y)$

```
1 SEARCH_POINT_QUERY (dim, split_axis)
2 Start at root
3 if node is leaf then
4   | return value associated with node
5 else
6   if  $\mathcal{T}(x, y)$  A split_axis value > node split_axis value then
7     | Traverse to node.rightChild
8     | SEARCH_POINT_QUERY (dim, (split_axis + 1)%dim)
9   else
10    | Traverse to node.leftChild
11    | SEARCH_POINT_QUERY (dim, (split_axis + 1)%dim)
12  end
13 end
```

In algorithm 9

1. Start traversing the tree from the root to look for the location of $\mathcal{T}(x, y)$.
2. Check if the point is a leaf. If it is a leaf then we can simply return the value associated with the point.
3. If root point is not a leaf then we make a decision weather to go left or right.

4. We make this decision based on the *split_axis* value associated with the point. At the root, we start with *split_axis* as 0 (*x_axis*). We then recursively call the function `SEARCH_POINT_QUERY()` and update the *split_axis* between 0 and 1 alternatively as we increase levels until we reach a leaf.

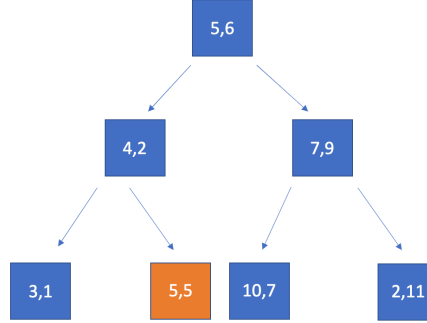


Figure 2.13.: KD-Tree for Point Query (TestPoint $\mathcal{T}(\mathbf{x}, \mathbf{y}) = (5, 5)$ is highlighted in orange)

Example 2.12 Case 1 : For example we have a tree with Point list as

$$((5, 6), (4, 2), (7, 9), (3, 1), (5, 5), (10, 7), (2, 11))$$

Suppose we are looking for $\mathcal{T}(\mathbf{x}, \mathbf{y}) = (5, 5)$.

We start with root point $(5, 6)$ and *split_axis* as 0. Hence, we compare the *x_axis* of the $\mathcal{T}(\mathbf{x}, \mathbf{y})$ and root node. Since $5 = 5$ we move left of the root node.

Next, we increase the *split_axis* to 1 and so will compare the *y_axis* of point $(4, 2)$ and $\mathcal{T}(\mathbf{x}, \mathbf{y})$. Since $5 > 2$, we move to the right of the tree. Since node $(5, 5)$ is a leaf and is the point we were searching for we return the value associated with the point.

Point Query with Baseline Index Model

The point query with baseline model is the same with forward pass in the training process. As the baseline model is a two-layer fully connected neural network with `ReLU` activation functions, we calculate the output of a given input x with the equation below:

$$\hat{y} = w_3 \max(w_2 \max(w_1 x + b_1, 0) + b_2, 0) + b_3 \quad (2.13)$$

As we assumed, the baseline model is approximating the CDF of X . Hence, for a certain x , the output is the probability that $F(X \leq x)$. Since we are working with a static array without insertion and deletion, we can assume that we know the total number of records as N . We also define the page size to be S as a parameter. Then we can calculate the position of this key as $\hat{p} = \lfloor \hat{y} * N \rfloor$.

After knowing the position of the key in the static array, we then calculate the page where it should be allocated to as below

$$\hat{o} = \lfloor \frac{\hat{p}}{S} \rfloor = \lfloor \frac{\hat{y} * N}{S} \rfloor \quad (2.14)$$

Complexity Analysis

For any key, the computation complexities of \hat{o} are the same, as there are only fixed number of computations needed. Hence, the time complexity of query with the baseline model is $\mathcal{O}(1)$, i.e. constant for any training data size.

Point Query with Recursive Model Index

The point query of recursive model is a top-down process. With a given x , the root model will first predict an output that represents the probability that $F(X \leq x)$. Then we map this output into the index of models in the next stage. Afterwards, we use that model to predict an output with the given x . We iterate these steps until the last stage in which we use the output as the final output. The above process is described in Algorithm. 10

Algorithm 10: Point Query With Recursive Model Index

```

input:  $x$ ; models; num_of_stages
1 stage  $\leftarrow$  0
2 next_model  $\leftarrow$  0
3 while stage < num_of_stages do
4   model = models[stage][next_model]
5   output = model.predict( $x$ )
6   if stage == num_of_stages - 1 then
7     | y = output
8   else
9     | next_model = output * len(models[stage+1])
10    | stage = stage + 1
11  end
12 end
13 return y

```

In the query algorithm, we have three inputs: x as the query key, trained models and the number of stages.

On line 1–2, we first initialise the *stage* and *next_model* to be 0, so that we use the root model at the very beginning. Then on line 3, we iterate over all stages. In each stage, we perform the following actions:

1. On line 4, we access the model at *stage* whose index is *next_model*.
2. On line 5, we perform the prediction with the query key x and the model selected by the previous step.
3. On line 6, we check if current stage is the last stage.
 - a) If it is, then we get the final output, which equals to the output from line 5.

- b) If it is not the last stage, then we map the output from previous step into the index of the model in the next stage. As there are $\text{len}(\text{models}[\text{stage}+1])$ models in the next stage and the output represents some probability (hence, $\text{output} \in [0, 1]$), we multiply them and find the next_model . In the meanwhile, we add 1 to the stage.
4. At the end, we return the final output, which is the output from the model in the last stage.

After calculating the output as described in the Algorithm. 10, we calculate the page index in a same way as we described in the baseline model.

Point Query with Lisa

Point query search in LISA is composed of following steps.

1. Find the cell to which point query belongs by comparing the query key value with first and last key in each cell. This search will be linear in the number of grid cells.
2. Calculate mapped value of the query key as mentioned in the section 14
3. Find the mapped interval to which point query's mapped value belongs using binary search.
4. Predict the shard Id for calculated mapped interval. Predicted shard Id can differ from ground-truth value by 1 for keys falling near the shard boundaries.
5. Search for the query key in the predicted shard by sequentially comparing against all the keys in the shard until a match is found. If case of no match, search in adjacent left and right shards as predicted shard Id can have an error of 1 .

2.3.2. Range Query

A range query is a database operation that retrieves all the records that lies in a range. In this project, we perform range query on 2-dimensional data only. In addition, we only consider a range query where the range is defined as a rectangle. Under these assumptions, a range query can be formalised as a query $Q(l, u)$ where $l, u \in \mathbb{R}^2$.

Example 2.13 For example, assume we have the points

$$[(1, 2), (3, 4), (3.5, 4), (5, 6)]$$

and the range query $Q((2, 3), (5, 5))$, as shown below:

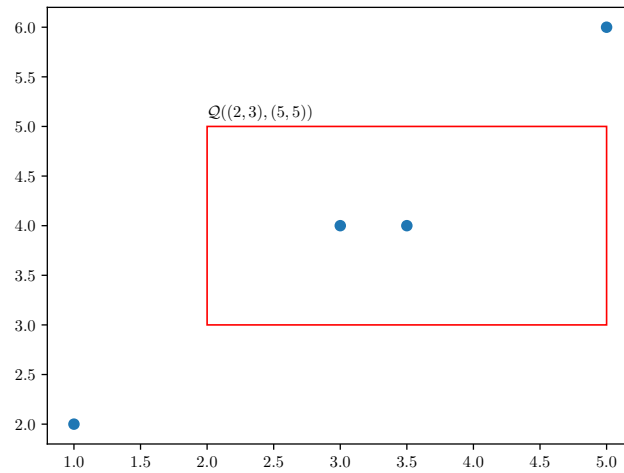


Figure 2.14.: A Range Query Example where $Q(l, u) = Q((2, 3), (5, 5))$

In this example, the range query should return the points that lies inside the red rectangle, i.e. $((3, 4), (3.5, 4))$.

Range Query with *KD*-Tree

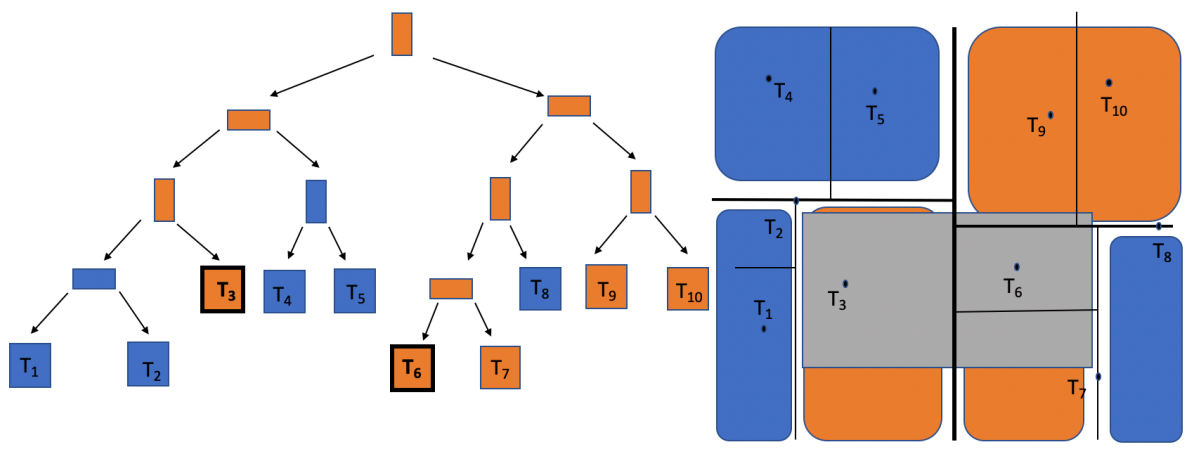


Figure 2.15.: *KD*-Tree for Range Query Algorithm (Orange color are the visited points and blue color are the points not visited) 1) Tree representation of points.
2) Subdivision of space into cells.(Orange color are the visited cells and blue color are the cells not visited)

Algorithm 11: Range Query Algorithm for KD-Tree

Input : Rectangle range (Lower; l and upper; u) $Q(l, u)$; [$l \in \mathbb{R}; u \in \mathbb{R}$]
Output: List of points within $Q(l, u)$

```
1 SEARCH_RANGE_QUERY ( $Q(l, u)$ )
2 if node.leftChild is leaf then
3   if  $cell(v) \subseteq Q(l, u)$  then
4     | add all points within cell to list
5   end
6   if  $cell(v) \cap Q(l, u) = \emptyset$  then
7     | add nothing to list
8   else
9     | add all points reported within  $cell(v) \cap Q(l, u)$ 
10  end
11 else
12  | SEARCH_RANGE_QUERY ( $Q(l, u)$ ) //Recursively function is called
13 end
14 Similarly, steps are repeated for node.rightChild
```

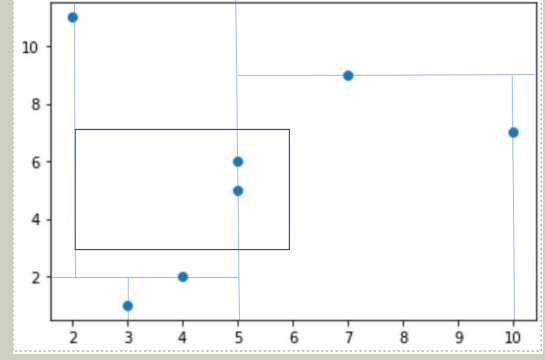
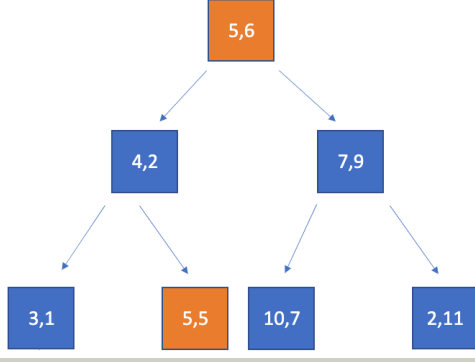
In algorithm 11

first check the root of the tree in the function SEARCH_RANGE_QUERY(). We pass $Q(l)$ and $Q(u)$ and check if the point at the root falls within $Q(l, u)$. If the point falls within $Q(l, u)$ then the point is added to the result list. In fig 2.15 we see how the space is partitioned on x-axis and y-axis alternatively. The subdivision consists of rectangular regions, called cells (possibly unbounded). Suppose current splitting line is vertical. Let v, w be left and right children nodes. After checking the root, v is searched to see if it is a leaf node. Since v is not a leaf node a decision to traverse the right or left subtree is made by checking its x-axis, y-axis and split axis. In fig 2.15 we can see that all cells that intersect $Q(l, u)$ are checked and all the cells that are not intersected by $Q(l, u)$ are pruned. This improves the performance of the range query and hence results in much faster query.

There are two cases in range query search:

1. **Case 1:** When an entire subtree lie within $Q(l, u)$.
2. **Case 2:** When only a part of the subtree lie within $Q(l, u)$.

Example 2.14



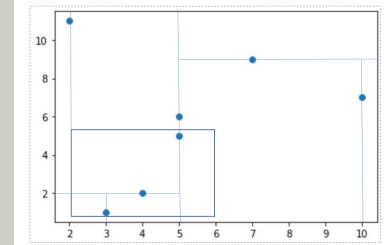
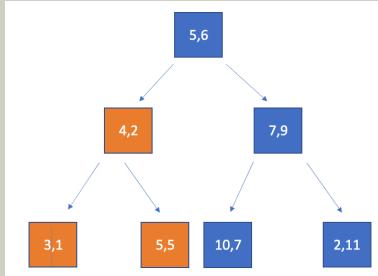
1. **Case 1 :** For example we have a tree with Point list as

$$((5, 6), (4, 2), (7, 9), (3, 1), (5, 5), (10, 7), (2, 11))$$

with $Q(l) = (2, 3)$ and $Q(u) = (6, 7)$.

We can see the points along with $Q(l, u)$ plotted in 14. Firstly, the root point is checked and since the x-axis and y-axis both lie within $Q(l, u)$ i.e., $2 > 5 > 6$ and $3 > 6 > 7$, it is added to the result list.

Secondly, we have to check whether to traverse left or right of tree. To do this, we then check if the x-axis of root is greater than or equal to the $Q(l)$ x-axis. Since this value is larger ($5 > 2$), it will then traverse to the left. We have root.leftChild to be (4, 2). Next, we will check if both the axis lie within $Q(l, u)$. Since the y-axis doesn't lie in $Q(l, u)$, this point is not selected ($2 \notin [3, 7]$). Similarly, it recursively traverses the tree and checks if the point lie within $Q(l, u)$ until it reaches a leaf.



2. **Case 2 :** For example, we have a tree with Point list as

$$((5, 6), (4, 2), (7, 9), (3, 1), (5, 5), (10, 7), (2, 11))$$

with $Q(l) = (2, 0.5)$ and $Q(u) = (6, 4.75)$.

We can see the points along with $Q(l, u)$ plotted in 1. Firstly, the root point is checked and since both x-axis and y-axis do not lie within $Q(l, u)$ i.e., $6 \notin [0.5, 4.75]$ it is not added to the list.

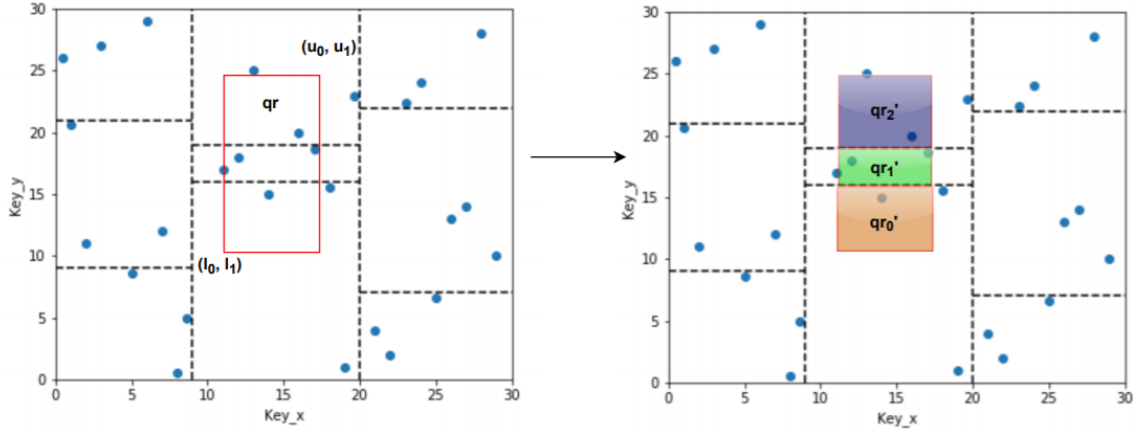


Figure 2.16.: Range Query Search in Lisa. 1) Find the cells that overlap with $Q(l, u)$.
 2) Decompose $Q(l, u)$ into the unions of smaller query rectangles, each of which intersect only one cell.
 3) Find shards corresponding to lower and upper coordinates for each $Q(l, u)$, and perform a sequential search.

Secondly, we will check whether to traverse left or right of the tree. To do this, we then checks if the x-axis of root is greater than or equal to $Q(l)$ x-axis. Since the value is larger ($5 > 2$), it will then traverse to the left. Root.leftChild node is (4, 2). Since both, x-axis and y-axis lie within $Q(l, u)$ it is added to the result list. Since all the points in this cell lie within $Q(l, u)$, they are all added to the list.

Range Query with LISA

For a range query $Q(l, u)$, we first find the cells that overlap with Q . Then we decompose Q into the union of smaller query rectangles $\bigcup Q_i$ such that each smaller query rectangles intersects only one cell, as shown in the Fig. 2.16.

Suppose that $Q = \bigcup Q_i$ where $Q_i = [l_{i0}, u_{i0}) \times [l_{i1}, u_{i1})$, i.e. we have Q_i representing the i th smaller query rectangles of one cell C_j .

Then we can calculate the mapped values of Q_i , i.e. $\mathcal{M}(l_{i0}, l_{i1})$ and $\mathcal{M}(u_{i0}, u_{i1})$. For simplicity, we use $m_l^{(i)}$ and $m_u^{(i)}$ to denote $\mathcal{M}(l_{i0}, l_{i1})$ and $\mathcal{M}(u_{i0}, u_{i1})$ respectively.

After creating corresponding mapped values, we then apply the shard prediction function $\mathcal{SP}(m_l^i)$ and $\mathcal{SP}(m_u^i)$ to predict the shard that could possibly contain keys that lie in the query rectangle Q_i . Then in each shard, we perform a sequential search to find the desired keys.

2.3.3. KNN Query

K -Nearest Neighbours (KNN), as the name suggests, is the process of finding K nearest neighbours to a given query point. In this project, KNN query is only performed on 2-dimensional data. We use ℓ_2 norm as the distance metric. A KNN query will be formalised as $\mathcal{K}(\mathbf{X})$ where $\mathbf{X} \in \mathbb{R}^2$.

KNN query with KD-Tree

Algorithm 12: KNN Query Algorithm for KD-Tree

Input : K ; Number of nearest neighbour, List of TestPoints; $\mathcal{P}(x, y)$; $[x \in \mathbb{R}; y \in \mathbb{R}]$
Output: List of K nearest points (ResultList)

```

1 for  $i \leftarrow 0$  to  $\text{len}(\text{TestPoints})$  do
2   Start at root
3   Traverse subtree where the  $\mathcal{P}(x, y)_i$  can be added.
4   Find the leaf; Calculate the distance and store it as  $d$ 
5   if  $\text{len}(\text{ResultList}) < K$  then
6     if Perpendicular distance of Parent with  $\mathcal{P}(x, y)$   $\leq d$  then
7       Go on the other side of subtree
8     else
9       Go up another level
10    end
11  else
12    return ResultList
13  end
14 end

```

In algorithm 12,

1. Start with the root to traverse the tree until we reach the leaf. We find the subtree where the new $\mathcal{P}(x, y)$ could be added and finally reach the leaf of this subtree.
2. Calculate the square of the euclidean distance of this point from the $\mathcal{P}(x, y)$. We add it to the list and push and pop values from the list depending on the distances we calculate while traversing the tree upwards from here.
3. The main advantage of KD-Tree is that we can exploit the tree structure and prune the points we don't think will have distance smaller than the ones we have already calculated. We do this by checking if we should either go up another level or go the other side of the subtree to get a point that could have a distance smaller than the last best calculated distance in the list.

As a baseline, we first perform KNN query with KD-tree.

Example 2.15 For example, we have Point list as

$$((5, 4), (2, 6), (13, 3), (8, 7), (3, 1), (10, 2))]$$

test point $(9, 4)$, we will have a tree structure as shown in 2.17 and it's plot on 2-dimensional plane is shown in 2.18.

In fig 2.18 we can see that although point $(8, 7)$ is the leaf we will reach when we traverse the tree to search where test point $(9, 4)$ can be added, it is not in fact the nearest point to the test point.

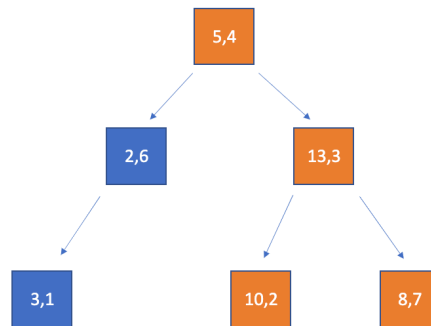


Figure 2.17.: *KD-Tree for KNN Query*

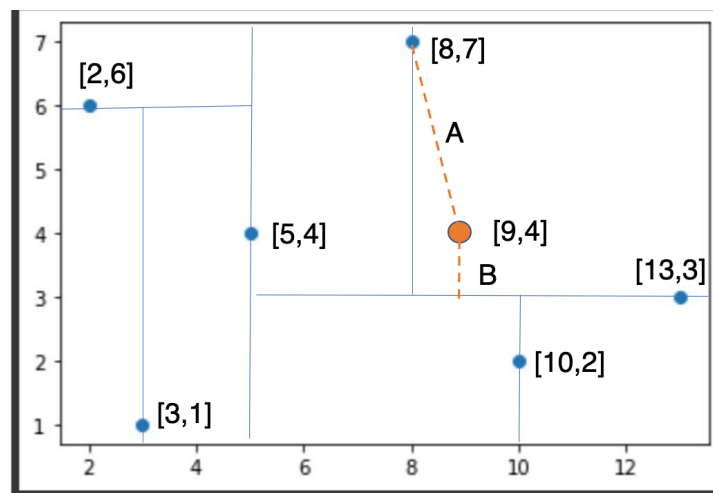


Figure 2.18.: *KD-Tree KNN Plot on 2-dimentional plane*

In this case if we want to look for 4 nearest neighbour, we will first traverse to (8, 7) and then make a decision whether to traverse to the other side of the subtree to point (10, 2). We decide this by checking the perpendicular distance of (13, 3) with test point (9, 4) and compare this with the distance of (8, 7) and test point (9, 4). We do this to verify if there is even a possibility to find a point smaller than the last best distance on the other side of the subtree. Since the perpendicular distance is smaller than the best calculated distance we will check the distance of test point (9, 4) and (10, 2) on the other side of the subtree ($A > B$). This distance in our case is indeed smaller than the best calculated distance of test point (9, 4) with (8, 7) so far and so point (10, 2) will be added to the list. Similarly, we traverse until we have K nearest neighbour to the test point in the list.

***K*NN Query with LISA**

It is difficult to apply traditional *K*NN query pruning strategies applicable for *KD*-Trees, to LISA model as it doesn't maintain a tree like structure with all nodes and entries based on MBRs and parent-children relationships. Shard boundaries are learned per mapped interval and no data structure is maintained to refer to shards in adjacent mapped intervals. LISA paper suggests Lattice Regression model to learn an appropriate distance bound from underlying training data for every query point and specific value of K . This distance bound is used to convert the *K*NN query to range query. The key idea in the *K*NN query is to convert it into a range query by estimating an appropriate query range. The query range is augmented if less than K neighbors are found in a range query. LISA paper

Consider a query point $q_{knn} = (x_0, x_1)$, let $x' \in V$ be the K th nearest key to x in database at a distance value $\delta = \|x' - q_{knn}\|_2$. Let's define $\mathcal{Q}(q_{knn}, \delta) \triangleq [x_0 - \delta, x_0 + \delta] \times [x_1 - \delta, x_1 + \delta]$ and $\mathcal{B}(q_{knn}, \delta) \triangleq \{p \in V \mid \|q_{knn} - p\|_2 \leq \delta\}$. We can create a query rectangle $qr = \mathcal{Q}(q_{knn}, \delta + \epsilon)$ where $\epsilon \rightarrow 0$. As shown in Fig. 2.19, K nearest keys to q_{knn} are all in $\mathcal{B}(q_{knn}, \delta)$ and thus in \mathcal{Q} . *K*NN query can be solved using the range query if we can estimate an appropriate distance bound δ for every query point.

In our experiments, we find the δ empirically. We try with different values of δ and choose the one for which we get the best results.

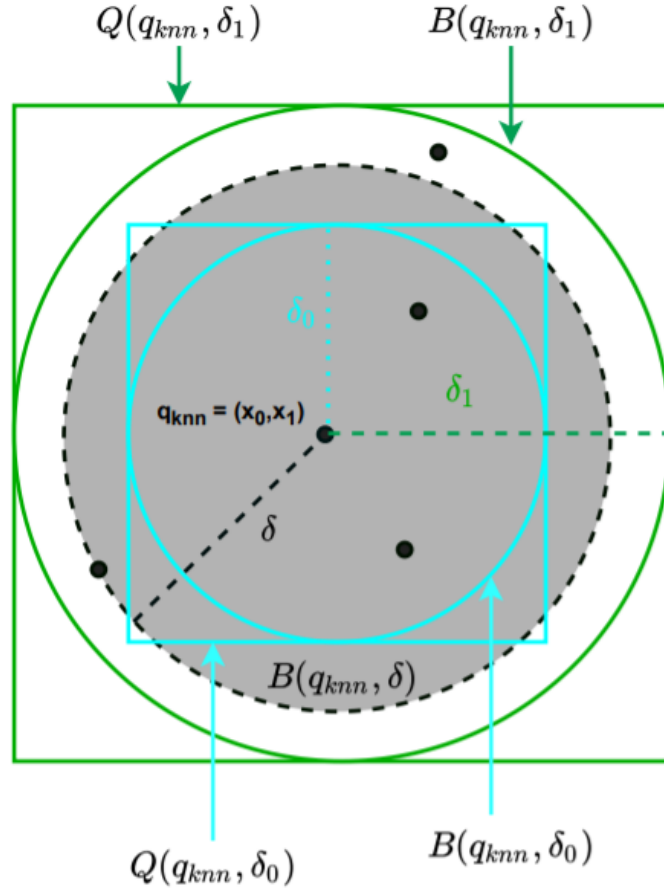


Figure 2.19.: KNN Query Implementation in Lisa(K=3)

- 1) q_{knn} represents the query point, $\mathcal{Q}(x, \delta) \triangleq [x_0 - \delta, x_0 + \delta) \times [x_1 - \delta, x_1 + \delta)$, represents query rectangle and $\mathcal{B}(x, \delta)$ represents the key space at distance δ containing K nearest keys.
- 2) KNN query can be solved by range query if we can estimate an appropriate distance bound δ for every query point

3. Evaluation

In order to evaluate the performance, we perform the evaluation on manually synthesised dataset.

3.1. One Dimensional Data and Indexes

For one dimensional data, the evaluation covers the following tasks:

- Find a structure for recursive model index empirically.
- Compares the performance between baseline model, recursive model and traditional B-Tree.

3.1.1. Dataset

For one dimensional case, we manually generate two columns of the data:

- The first column contains the keys X , which is randomly sampled from a given distribution.
- Then we assign the keys into different pages according to a preset parameter N_{page} for page size. Specifically, the first N_{page} keys will be assigned into the first page, the second N_{page} keys will be assigned into the second page and so on so forth. After the assignments, we set the second column Y to be the page index of the corresponding x .

3.1.2. Small Lognormal Data

We first generate 10,000 data points where X is from a lognormal distribution $\text{Lognormal}(0, 4)$. In the Fig 3.1, we illustrate the $x - y$ relations where X is randomly sampled from a lognormal distribution.

We use three groups to find the best recursive model for lognormal data.

- All models are fully connected neural networks. The number of second-level models are 200, 400, and 600 respectively. The number of third-level models are 2000, 4000 and 6000 for each number of second-level models.
- All models are linear regression models. The number of second-level models are 200, 400, and 600 respectively. The number of third-level models are 2000, 4000 and 6000 for each number of second-level models.

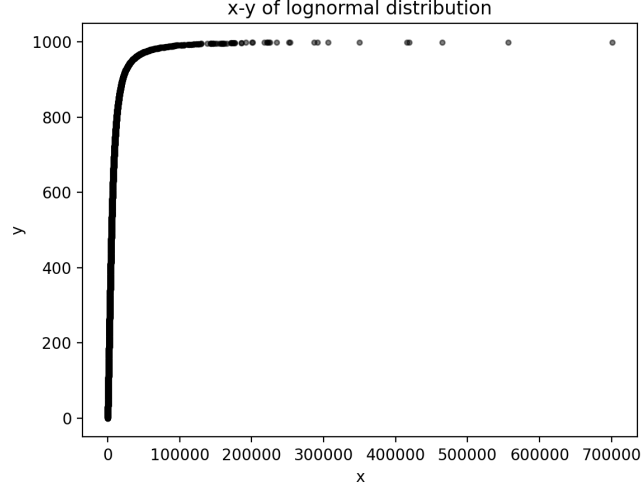


Figure 3.1.: The x-y graph where x is randomly sampled from a lognormal distribution

- Models are combinations of fully connected neural networks and linear regression models. The numbers of second-level and third-level models are determined by the best settings in previous two group.

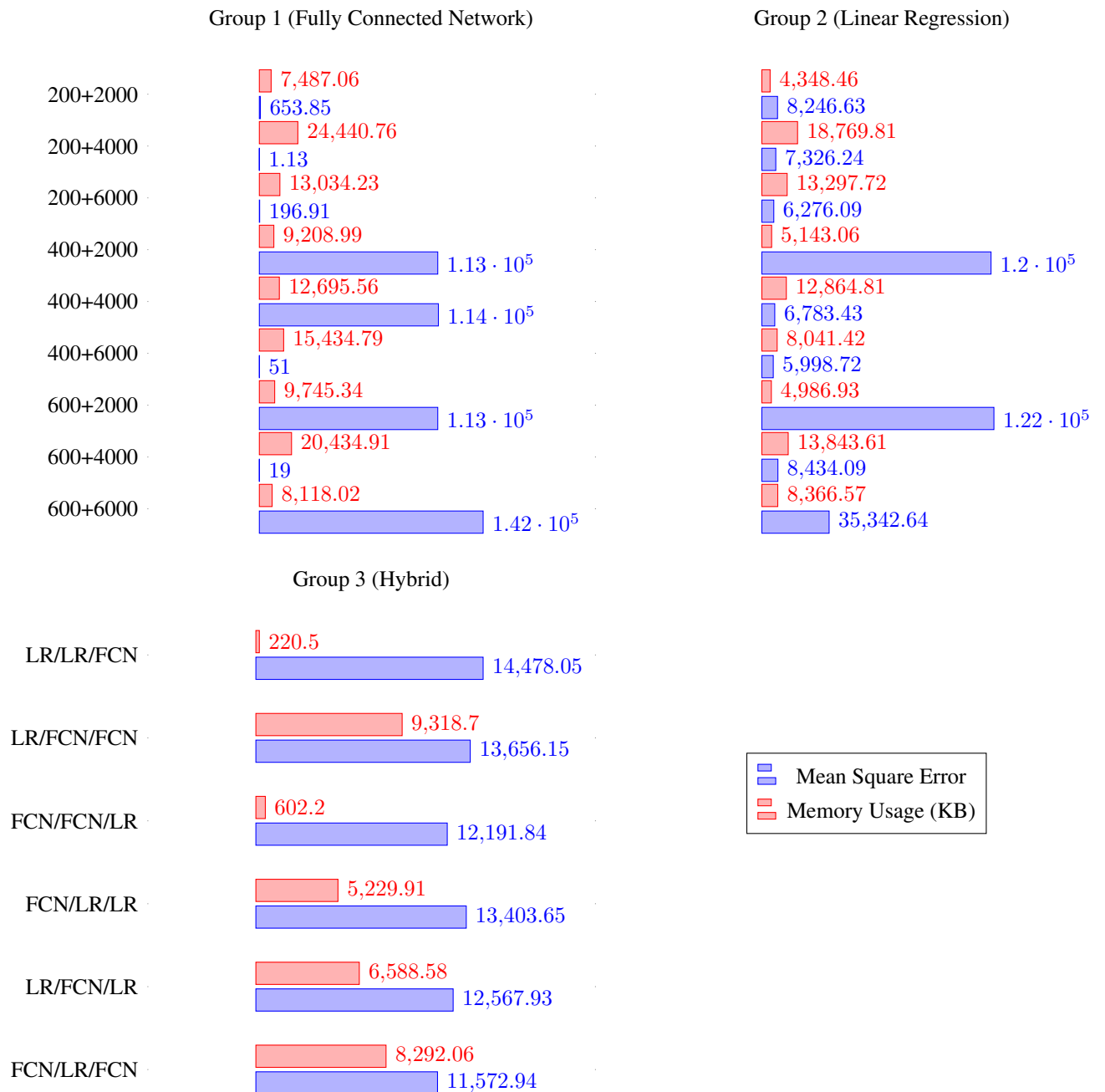
From the experiment results, we found that the second setting in group 1 (1 FCN model as root, 200 FCN models as second level models and 4000 FCN models as third level models) is the best regarding the mean square error. We also have the following findings in this searching process.

- Generally, the average error in group 1, where all models are fully connected neural networks is less than the error in group 2. Fully connected neural networks have a potential to be more accurate, i.e. it could achieve a small error if we tuned the models parameters properly.
- Tuning a model is tedious and can be costly. There are lots of hyper-parameters to choose from, such as the number of models in each level, types of models in each level, number of levels, and the internal hyper-parameters in each model. Using grid search, as we did in this experiment can be costly and time-consuming.

3.1.3. Various Distributions and Sizes

After the search process for a recursive model, we then conduct experiments on several different distributions and sizes datasets. During this process, we use the following settings:

- The X is generated from *uniform*, *normal* and *lognormal* distribution.
- For each distribution, we generate 1 thousand, 10 thousands, 100 thousands and 1 million data points. We then assign the generated data points into pages where $N_{page} = 10$.



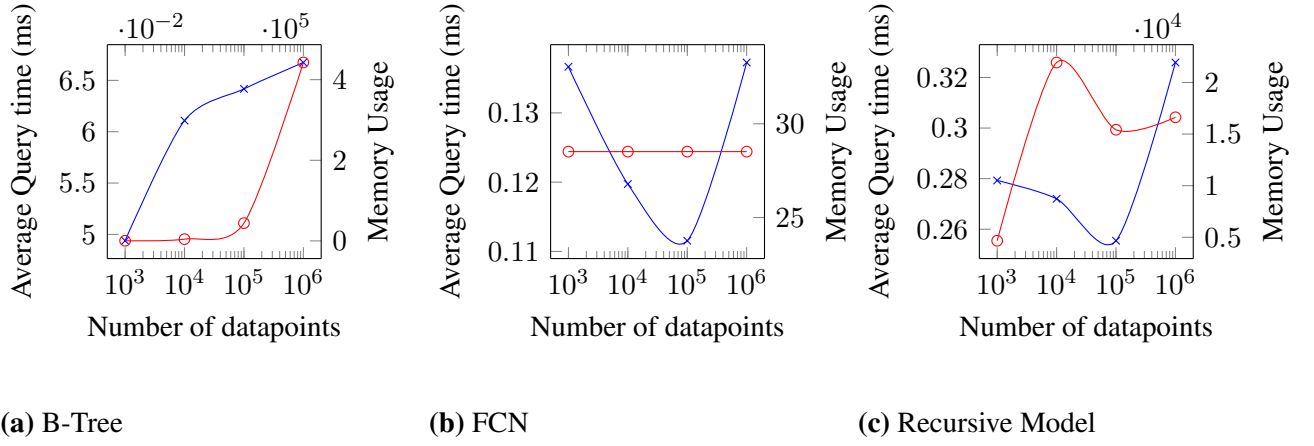


Figure 3.2.: The relations between the number of data points, average query time and the memory usage among three different indexes. The blue line represents the average query time and the red line represents the memory usage

- We use a B-Tree with degree=20, a fully connected neural network with two layers and 32 nodes per layer, and a recursive model with 200 second-layer models and 4000 third-layer models.

We compare the following performance metrics:

- The query time per key and the memory usage among three index models.
- The mean square error caused by fully connected network and recursive models, across different distributions.
- The construction time among three index models.

Conclusion 3.1 From Fig 3.2, we analysed the time complexities for query and the space complexity for storing three different index models.

1. From Fig 3.2a, we verified that the average query time per key for a B-Tree is growing as the number of data points is increasing. It grows with a complexity of $\mathcal{O}(\log n)$, i.e. it grows slower when there are more data points.
2. From Fig 3.2b, we found that the memory usage of a fully connected neural network is significantly less than the memory usage of B-Tree. Meanwhile, the fully connected neural network takes constant memory usage, as there are fixed number of nodes in the neural network. Similarly, the average query time is also a constant in theory. In the experiments, the average query time is changing, but very likely caused by turbulence.
3. From Fig 3.2c, we found that the memory usage of a recursive model is significantly

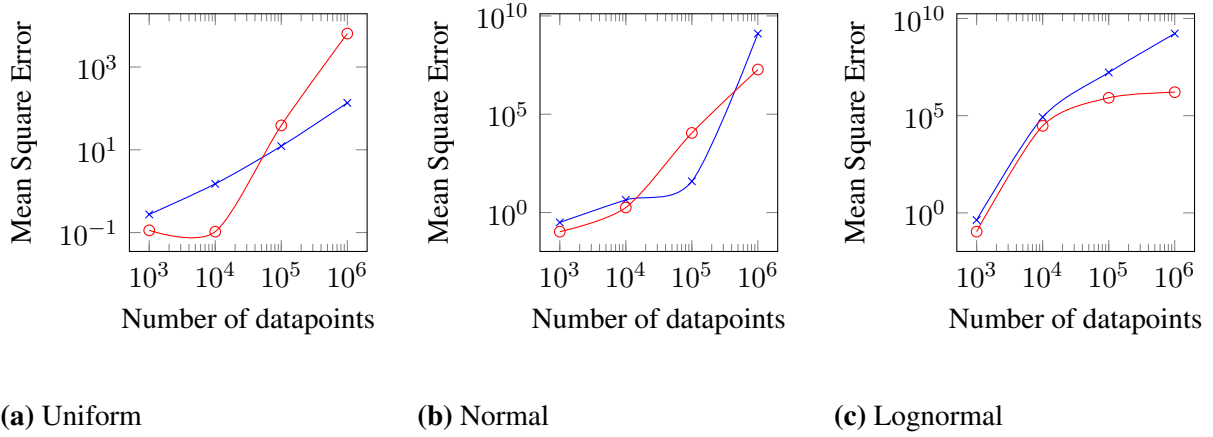


Figure 3.3.: The relations between the number of data points and the mean square error in three different distributions. The blue line represents the fully connected network and the red line represents the recursive model

higher than the memory usage of a fully connected neural network, but still less than a B-Tree, which is because the recursive model consists of thousands fully connected network. The memory usage of a recursive model is fluctuating, as the actually used number of fully connected network varies. The query time is higher than B-Tree and single fully connected network, but still a constant in theory, as there are only fixed number of computations.

Conclusion 3.2 From Fig 3.3, we analysed the errors of fully connected neural network and recursive model on different distributed dataset.

1. From Fig 3.3a, we found that both fully connected neural network and recursive model are capable of modelling uniformly distributed dataset with a rather low error. In the mean while, fully connected neural network could achieve less error, especially when there is large amount of data.
2. From Fig 3.3b, we found that the error is increasing exponentially as the number of data points is increasing. The error in fully connected neural network is significantly higher than recursive model.
3. From Fig 3.3c, we found that the error from recursive model is significantly less than the error in fully connected neural network. Combined with 3.3b and 3.3a, we conclude that the recursive model could surpass fully connected network when the data is not uniformly distributed. That means, the fully connected network is suitable for uniformly distributed data. We will analyse this property in more detail in the chapter *Insights and Findings*.

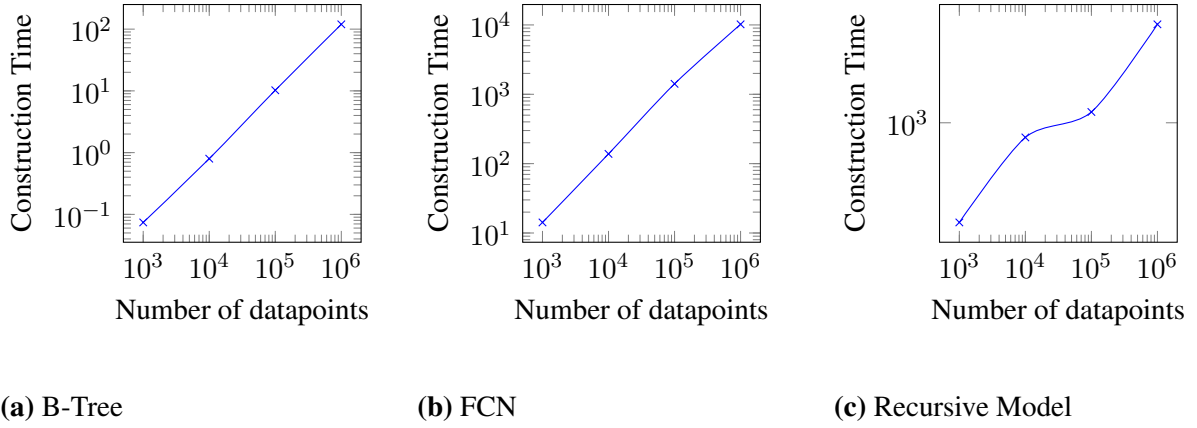


Figure 3.4.: The relations between the number of data points and the construction time among three different index models.

Conclusion 3.3 In 3.4, we analysed the construction time of different models.

1. As shown in 3.4a and 3.4b, the construction time of both B-Tree and fully connected neural network is increasing almost linearly as the number of datapoints is increasing. Theoretically, the construction time for B-Tree is $\mathcal{O}(n \log n)$ and $\mathcal{O}(n)$ for fully connected neural network.
2. In 3.4c, we found that the construction time of recursive model is increasing as well. The time in construction varies by two factors:
 - The number of data points will affect the construction time.
 - As we need to iterate over all possible models in each layer to assign training set, the number of models in each layer will affect the construction time as well.

3.1.4. 190M Lognormal Distributed Data

The last and largest dataset that we used is a large dataset that contains 190 million key value pairs that are distributed under lognormal distribution. There are two challenges in this task:

1. The training set is too large to be trained and tuned. As our implementation only supports single process, it would take a tediously long time to train the recursive model.
2. It takes super long time (several days in our settings) to evaluate on the very large dataset, as only one CPU thread will be used.

To tackle these challenges, we take the following strategies:

Training on Sampled Dataset We first randomly and uniformly sample from the whole training dataset. By sampling uniformly, we could keep the shape of the distribution unchanged. Assume we sampled S data pairs from the whole training dataset which contains N

pairs, then we define the sampling ratio as $R = \frac{S}{N}$. We then map the output \tilde{y} from our index model to its approximate position by $\hat{y} = \frac{\tilde{y}}{R}$. An example is illustrated in Example 3.1.

Example 3.1 Assume the X in training set is exponentially distributed as

$$[1, 2, 4, 8, 16, 32, 64, 128]$$

and we use a sample size $S = 4$. As we know the size of the fully training dataset is $N = 8$, we have $R = \frac{S}{N} = 0.5$. We uniformly sample from the training set and we will get $[1, 4, 16, 64]$. Then we train an index model based on

$$[(1, 0), (4, 1), (16, 2), (64, 3)]$$

For the key 32 as an example, ideally, we want our index model \mathcal{F} to have an output such that $\tilde{y} = \mathcal{F}(32) = 2.5$. Then the original index of the key 32 can be calculated as $\hat{y} = \frac{\tilde{y}}{R} = \frac{2.5}{0.5} = 5$, which is exactly the index of 32 in the original full training dataset.

Evaluation with Multiple Processes To evaluate our models on the full training set would take several days to complete because there is only one process working on it. As the query is independent from each other, we utilise multiple processes to work on it by taking the following steps:

1. We first train our model on the sampled dataset with $S = 100,000$.
2. Then we split the full training set into 10 pieces such that each piece contains only 19 million pairs.
3. Afterwards, we perform the point query with the trained model on each piece in parallel.
4. Finally, we collect the query time from 10 pieces and sum them to get the total query time of the full training set. Then we divide it by the number of pairs in total, i.e. 19 million and get the average query time per key. For the mean square error, we take the average of errors from each piece.

With these two approaches, we achieved the results as shown below:

Model	Construction Time (s)	Avery Query Time	Memory Usage (MB)
B-Tree (degree=20)	26356 (1.00x)	0.3489 (1.00x)	96912 ¹
Recursive Model	334 (0.013x)	2.6505 (7.60x)	8.836

Table 3.1.: The construction time, average query time and memory usage of a B-Tree (with a degree=20) and a recursive model.

¹The memory usage of each node is larger than previous experiments. It is because the tools for measuring memory usage (pympler) requires extra memory, and caused the program to be killed when there is not enough memory. Hence we use a different tool (top) to measure an approximate memory usage.

Conclusion 3.4 From Table 3.1, we have the following conclusions:

1. The construction time of recursive model can be significantly less than the construction of B-Tree, for two reasons:
 - We sampled from the training dataset, and avoid iterating over all the data points. In contrast, B-Tree has to iterate all the data points and insert them one-by-one.
 - The recursive model trains relatively fast as it can converge in one to a few passes over the data points.
2. Then query time for recursive model is higher than B-Tree, but not significantly higher. The computation costs is mainly on the calculation in fully connected neural networks. The query time for recursive model can be improved by either using a well-established library, such as PyTorch, that provides faster matrix computation, or using faster hardware, such as GPU to improve the query.
3. The memory usage of B-Tree is significantly higher than the recursive model. As we showed above, the memory usage of B-Tree is $\mathcal{O}(n)$ and hence growing linearly. For recursive model, the memory usage is mainly depends on how many models in each layer. Therefore, the memory usage of recursive model has an upper bound (if all models are used), and then does not grow as the number of data points is growing.

3.2. Two Dimensional Data and Indexes

For two dimensional data, the evaluation covers the following tasks:

- Find hyper-parameters for the LISA Baseline model empirically.
- Find the hyper-parameters for the LISA model empirically.
- Compares the performance between *KD*-tree, LISA Baseline and LISA models for point query.
- Compare the performance between *KD*-tree, LISA Baseline and LISA models for range query.
- Compare the performance between *KD*-tree and LISA models for KNN query. KNN Query has not been implemented for LISA Baseline as there is no description of KNN Query for Baseline model in the paper.

3.2.1. Dataset

For two dimensional case, we manually generate three columns of the data:

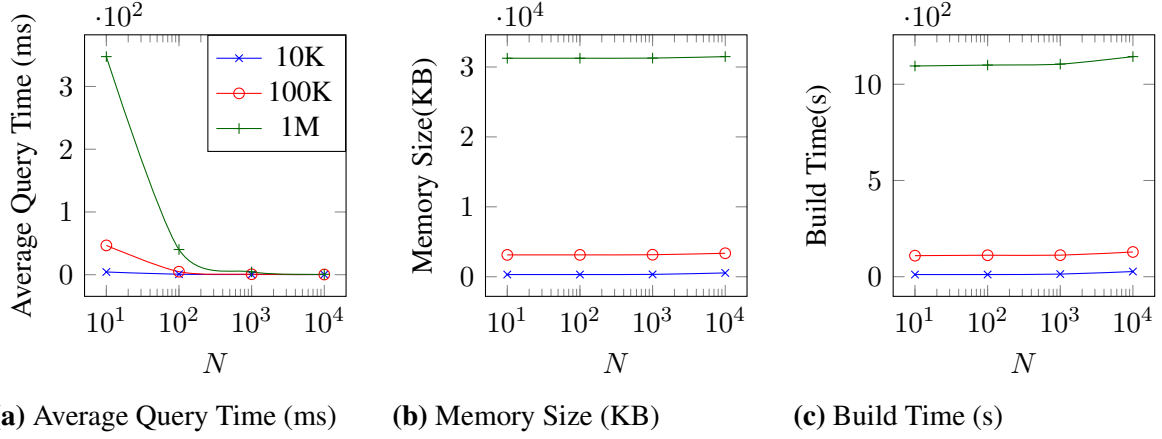


Figure 3.5.: Hyper-parameter search in LISA Baseline for training sizes 10K, 100K and 1M.

- The first two columns contain the 2 dimensional keys $\mathbf{X} \in \mathbb{R}^2$, which are independently sampled from a given distribution.
- Then we assign the keys into different pages according to a preset parameter N_{page} for page size. Specifically, the first N_{page} keys will be assigned into the first page, the second N_{page} keys will be assigned into the second page and so on so forth. After the assignments, we set the second column Y to be the page index of the corresponding x .

3.2.2. Hyper-parameters Search

After generating dataset as mentioned in previous section, we sample a smaller subset from it. We repeat our experiments for 3 different sample sizes of 10000, 100000 and 1000000 points. Test data is a copy of training data for all our experiments. For Baseline and Lisa models, final prediction is given by linear search through a range of values (identified as a Cell for Baseline and Shard for LISA model) and mean square error (MSE) is zero as test points are already learned during training. This is where Learned Index models differ from traditional machine learning models where model performance is evaluated on unseen data.

Hyper-parameter search for the LISA Baseline implementation

Baseline model has one hyper-parameter: N (Number of cells specifying the number of equal length intervals into which mapped values are divided). The point query search consists of two parts, first is binary search to locate the cell into which the query key is located, followed by sequentially comparison of the query key value with keys in the found cell until a match is found. The time complexity of first search is $\log_2 N_1$, where N_1 is the number of cells. The time complexity of second search is $\lceil N_2/2 \rceil$, where N_2 is the number of keys per cell.

Conclusion 3.5 Following conclusions can be drawn from experimental results shown in table A.1 and Fig. 3.5

1. Optimum value of hyper-parameter N will be equal to number of points in the training data-set, resulting in 1 key per cell and search query time of $O(\log_2 N)$.
2. Average Query Time : Average Query Time decreases with increase in value of N as number of keys per cell decreases.
3. Build time : Build time increases with increase in value of N , as metadata for additional cells needs to be calculated.
4. Memory Size : Memory requirements of the model increases with increase in value of N , as metadata for additional cells needs to be stored. Increase in memory size is not significant with increase in N as we maintain only two values per cell, mapped value of first key in the cell and mapped value of last key in the cell.

Hyper-parameter search for the LISA implementation

For LISA model, we have 3 hyper parameters:

1. G : The size of the grid cell. Number of grid cells into which the key space is divided. In our implementation, we use a square grid cell, and total number of cells is given by $G \times G$.
2. N : Number of equal length intervals into which mapped value range is divided. During our experiments, we found that shard prediction algorithm gives better performance if mapped interval boundaries are aligned to grid cell boundaries. That's why this parameter is always initialised to $N=G \times G$
3. S : Number of shards to learn per mapped interval.

Conclusion 3.6 Following conclusions can be drawn from experiments results shown in tables A.3, A.4 and A.5.

1. For a particular value of G , average query time decreases and memory size increases with increase in value of S . This is expected as increasing S , will result in lesser number of keys per shard, thereby reducing the sequential search cost of scanning the query key through the Shard.
2. Average query time decreases and memory size increases with increase in values of G and S .
3. We need to choose S such that there are at least 40 keys per shard. We may see mean square errors(mse) if number of keys per shard are less than 45 for following reasons.

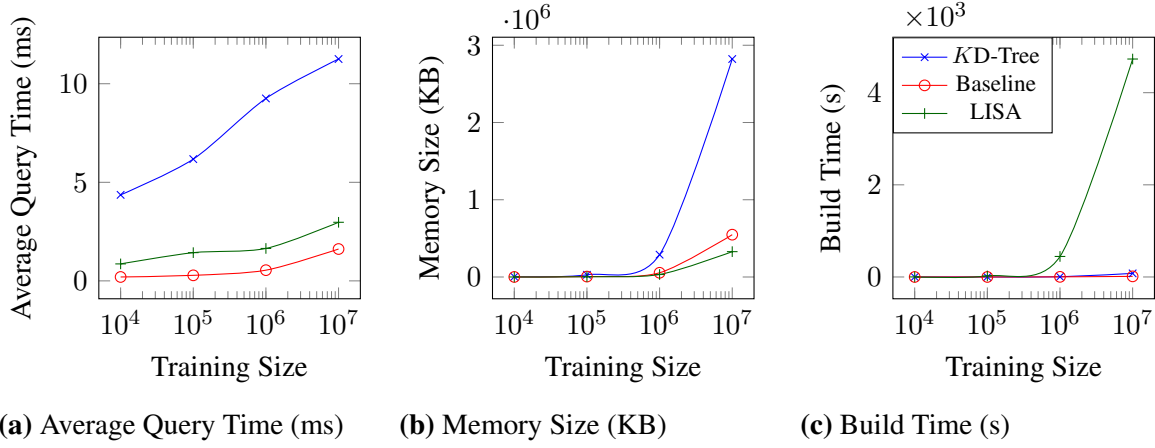


Figure 3.6.: Point Query experimental results for *KD-Tree*, Baseline and LISA models.

- a) For point query search, we first predict a shard and then sequentially compare the query point key values with all the keys in the predicted shard until a match is found
- b) For query points near the shard boundaries, there can be a mismatch in ground truth shardId and predicted shardId. If the query point is not found in the predicted shard, we continue our search in adjacent left and right shards in an empirically found range.

During test experiments, we found that if shard size is less than 40 keys, then sometimes shard prediction error can be greater than 1 and point query search can fail resulting in MSE errors.

3.2.3. Comparisons Across Models

During following experiments, for each training data size, we have used hyper-parameters optimized for that particular data set size.

Point Query Comparison

Table A.6 and Fig. 3.6 shows the performance evaluation for *KD-Tree*, LISA-Baseline and LISA Models for different training data sizes. For a given training set, we perform point query evaluation for every point in the data-set and take the average.

Conclusion 3.7 The following conclusions can be concluded:

1. LISA outperforms *KD-tree* in terms of average query time. Search complexity of *KD-Tree* and LISA baseline is $O(N)$, and $O(\log_2 N)$ respectively where N is the number of points in the training data-set. On the other hand point query search cost in LISA is a combination of 3 costs.

- a) Search cost to find the grid cell to which point query belongs. This cost increase linearly with increase in number of grid cells.
 - b) Find the shard Id to which point query belongs. This cost is constant as shard prediction function weights are already learned during the build process.
 - c) Once the shard Id is found, search sequentially in the shard interval by comparing query point key value with all the keys in the shard until a match is found. This cost is relatively constant with respect to increase in training data-size as we try initialize our hyper-parameters in such a way that number of keys per shard remain close to 50.
2. LISA outperforms *KD*-tree in terms of memory size requirements, however its build time is significantly higher than *KD*-Tree and LISA Baseline. The storage consumption of LISA is considerably smaller than *KD*-Tree that has to construct a tree with all nodes and entries based on MBRs and parent-children relationships. In contrast, LISA only keeps the parameters of *M* and *SP*. Specifically, *M*'s parameters contain several numbers and a small list only, and *SP* is composed of a series of piecewise linear functions whose parameters are a number of coefficients.

Range Query Experiments

Table A.7 shows evaluation results for LISA, Baseline and *KD*-tree models for range sizes of 10, 100, 1000 for different training sizes. For a given range query size, we perform 20 trials and take the average. For each trial, we sample a random point from the test set and find the range from sampled point to the range query size. Average query time for each range is further divided by the range size to compare the query time across various ranges. As shown in the Fig. 3.7, LISA outperforms *KD*-tree for range query size of 10000 for all training sizes, however its range query time for smaller range sizes is significantly higher than *KD*-Tree.

KNN Query Experiments

Table A.8 shows evaluation results for LISA and *KD*-tree models for *KNN* Queries for various value of *K* and training sizes. For a given *K* value, we perform 20 trials and take the average of query time. For each trial, we sample a random point from the test set and find *K* neighbours around that point. Average query Time is further divided by *K* to compare the Query time across various values of *K*. As shown in the Fig. 3.8, LISA outperforms *KD*-tree for different training sizes and *K* values.

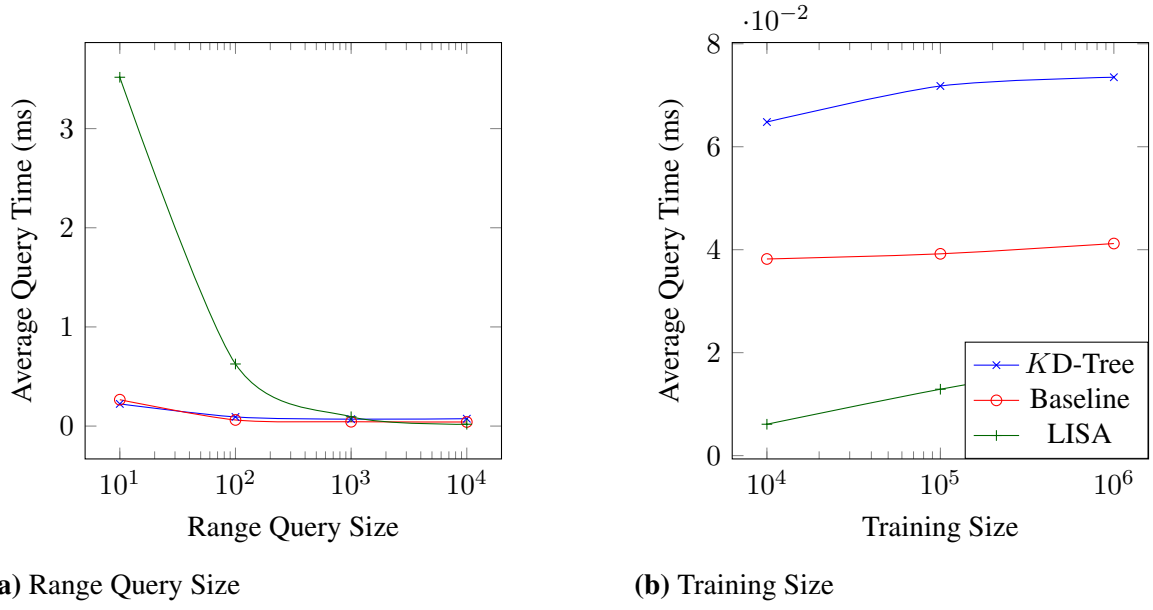


Figure 3.7.: Range Query experimental results for *KD-Tree*, *Baseline* and *LISA* models.
a) Plot A shows average range query time for a fixed training size of 1M points.
b) Plot B shows average range query time for a fixed range query of size 10000 for various training sizes.

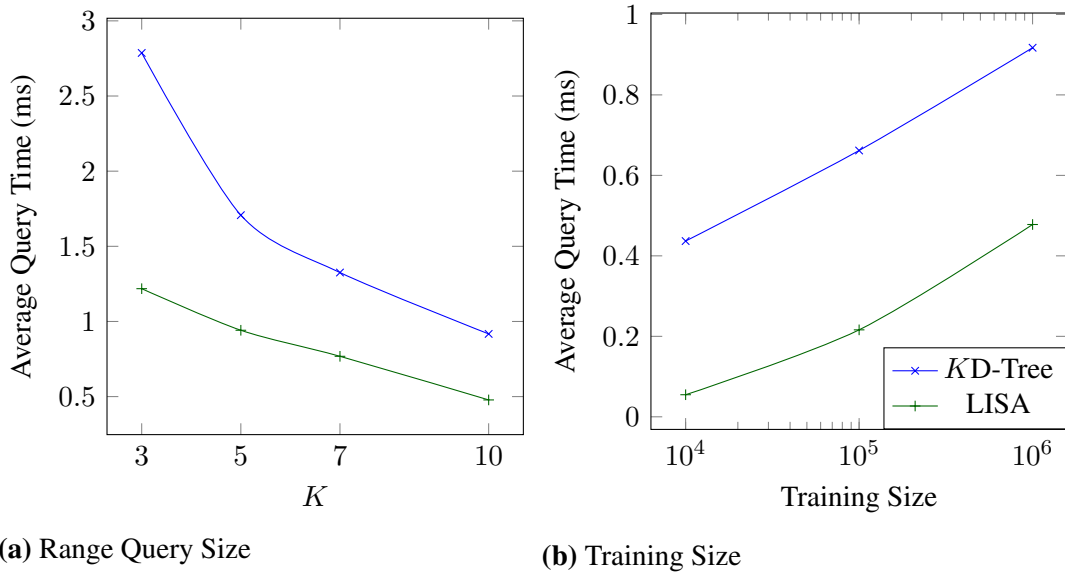


Figure 3.8.: KNN Query experimental results for *KD-Tree* and *LISA* models.
a) Plot A shows average *KNN* query time for a fixed training size of 1M points for different values of K .
b) Plot B shows average *KNN* query time for various training sizes with $K = 10$.

4. Insights and Findings

4.1. General Discussions

Limitations

Though the learned index model, especially the recursive model has a potential to greatly reduce the memory usage and cost less time in making the query. It is still limited in several perspective.

- **Read-only database.** Current recursive model index assumes that the data is a static, read-only array. Only when this assumption is hold, we can regard the database index as the CDF. However, in reality, we usually need to insert and delete the data in the array and violates this assumption.

Requirements

For a learned index.

4.2. One Dimensional Learned Index

4.2.1. Baseline Learned Index

Activation Functions

- If we use identity activation function, i.e. $z^{(i)}(x) = x$, then no matter how many layers are there, the fully connected neural network falls back to a linear regression.

Proof: The output of the first layer, with identity activation function, will be $z^{(1)}(w^{(1)}x + b^{(1)}) = w^{(1)}x + b^{(1)}$. Then the output will be the input of the next layer, and hence the output of the second layer will be $z^{(2)}(w^{(2)}(w^{(1)}x + b^{(1)}) + b^{(2)}) = w^{(2)}w^{(1)}x + w^{(2)}b^{(1)} + b^{(2)}$. Similar induction can be obtained for multiple layers. Hence if we use identity activation, the trained neural network will fall back to a linear regression. The visualization below shows our lemma is correct.

- With ReLU (Rectified Linear Unit) as activation function i.e. $z^{(i)}(x) = \max(0, x)$, then the fully connected neural network falls back to a piecewise linear function.

Proof: The output with ReLU activation function, will be $z^{(1)}(w^{(1)}x + b^{(1)}) = \max(w^{(1)}x + b^{(1)}, 0)$. Then the output will be the input of the next layer, and hence the output of the second layer will be $z^{(2)}(w^{(2)}(w^{(1)}x + b^{(1)}) + b^{(2)}) = \max(w^{(2)}w^{(1)}x + w^{(2)}b^{(1)} + b^{(2)}, 0)$.

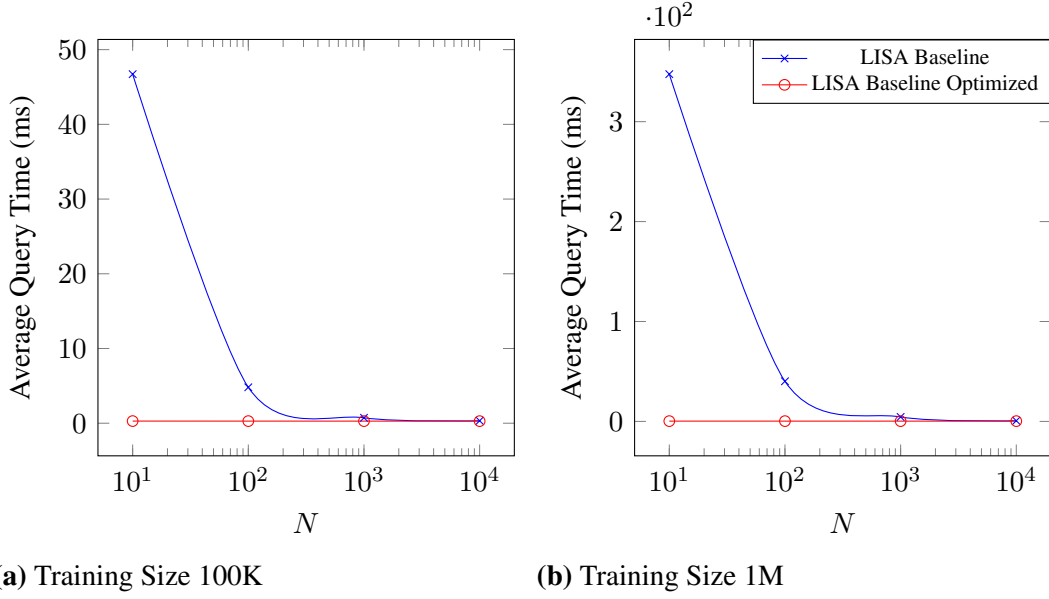


Figure 4.1.: Point query results comparison between LISA Baseline and Optimized Model for different training sizes.

Similar induction can be obtained for multiple layers. Hence if we use identity activation, the trained neural network will fall back to a piecewise linear function. The visualization below shows our lemma is correct.

4.3. Two Dimensional Learned Index

LISA Baseline model search optimization for smaller values of N

In case of high dimensional key values, key with in a cell can not be searched with mapped value, as a large number of keys can have the same mapped value. However for the 2 dimensional scenario, we can get considerable savings in search cost by replacing sequential scan based on keys values to binary search based on mapped value. As in the original method, search process will consist of two parts.

1. Find the cell which contains the query key based on mapped value using binary search.
2. With in the cell, replace sequential search based on query key value with the binary search based on query key mapped value. Once mapped value is found, do a lookup in the neighbourhood of the found key based on query key 2 dimensional value.

As shown in Fig. 4.1, we get significant savings in the query time with this approach for smaller values of N . As the value of N increases, number of Keys per cell decreases, and savings in avoiding sequential search gets normalized.

4.4. Future Work

Future work

In current work, we have implemented RMI and LISA, two novel learned index structures for one and two dimensional data respectively. This work opens up several directions for future research on learned indexes for database systems. We are listing some of them here.

1. Read only and in-memory database are two major constraints applicable to our LISA implementation that are supported by the original paper. Adding support for insertion, deletion and disk resident training data will be taken in next phase.
2. LISA paper supports Lattice Regression model to learn an appropriate distance bound from underlying training data for every query point and specific value of K . This distance bound is used to convert the K NN query to range query. It will be interesting to add support for the Lattice Regression Implementation in future work.
3. It will be interesting to study other query types (e.g., spatial joins and closest pairs) using LISA

5. Convolution and CNN for Learned Indexes

From the previous discussion, we summarise that both one-dimensional and two-dimensional indexes requires to learn a function from a one-dimensional array.

1. In one dimensional data, the learned function is used directly as an approximation to the CDF. We use a fully connected neural network or a recursive model to learn such function.
2. In two dimensional data, the learned function is used to predict the corresponding shard. We use a piecewise linear function to achieve this task.

These models in our previous chapters have their shortcomings:

1. The fully connected neural network (with ReLU as activation functions) is essentially a continuous piecewise linear function. The training of such neural network is unstable and highly dependent on the initial values, well-tuned hyper-parameters, etc. Meanwhile, it requires more work if we want to ensure the monotonicity.
2. The recursive model takes more memory than a single neural network, and there are many more parameters to tune than neural network.
3. The training method for a piecewise linear function is an iteration-based method. If we choose a large number of break points, then the training time will be long.

In fact, in order to train the piecewise linear function, we only need to know either the slope of each segments or the position of the breakpoints. If we know any one of them, we can learn the other in a closed form, as we shown in the shard prediction section. In this chapter, we present a method to learn the position of breakpoints.

Learning the position of breakpoints can be regarded as a binary point-wise classification problem. That means, for each point in our X , we want to learn to classify it to be 1 if it is a breakpoint, otherwise we want it to be 0. Then we classify all the points in our X and each point is classified to be 1 with a confidence. Afterwards, we only need to filter the top- K points to be the breakpoints.

This task is similar to the image segmentation in computer vision, which essentially tries to classify every pixel in the image. One successful technique in image segmentation is by using the convolution and convolution transpose network [LSD15]. Inspired by this, we propose a similar network to perform binary point-wise classification. Due to the page limit, we will only describe the most important steps in this chapter.

5.1. Training

6. Conclusion

Acknowledgement

We would like to express our sincere gratitude to Prof. Dr. Michael Böhlen, and Mr. Qing Chen for their commitment in supervising this project. Our appreciation extends to Dr. Sven Helmer in reading our report and arranging discussion and presentation of this project.

Appendices

A. Appendix

Training/Test Data Size	Model	N	Build Time (ms)	Avg Query Time (ms)	Memory Size (KB)
10,000	Lisa Baseline	10	11.17	4.3426	313
10,000	LISA Baseline	100	11.25	0.7189	315
10,000	LISA Baseline	1000	13.54	0.3283	336
10,000	LISA Baseline	10000	26.83	0.2415	547
100,000	LISA Baseline	10	109.28	46.7173	3126
100,000	LISA Baseline	100	111.59	4.8086	3128
100,000	LISA Baseline	1000	111.97	0.7271	3149
100,000	LISA Baseline	10000	128.49	0.3301	3360
100,000	LISA Baseline	100000	272.93	0.2381	5469
1,000,000	LISA Baseline	10	1094.85	347.5613	31251
1,000,000	LISA Baseline	100	1099.38	40.1451	31253
1,000,000	LISA Baseline	1000	1104.65	4.4732	31274
1,000,000	LISA Baseline	10000	1143.65	0.6697	31485
1,000,000	LISA Baseline	100000	1273.56	0.2944	33594
1,000,000	LISA Baseline	1000000	2717.65	0.2436	54688

Table A.1.: Hyper-parameters Search LISA Baseline Model for training sizes $10K$, $100K$ and $1M$

Training/Test Data Size	Model	N	Build Time(ms)	Avg Query Time(ms)	Memory Size(KB)
10,000	LISA Baseline Optimized	10	11.1208	0.2841	313
10,000	LISA Baseline Optimized	100	12.0108	0.2779	315
10,000	LISA Baseline Optimized	1000	12.7589	0.2765	336
10,000	LISA Baseline Optimized	10000	25.8732	0.2752	547
100,000	LISA Baseline Optimized	10	112.973	0.2855	3126
100,000	LISA Baseline Optimized	100	114.318	0.2823	3128
100,000	LISA Baseline Optimized	1000	116.699	0.2806	3149
100,000	LISA Baseline Optimized	10000	129.514	0.2794	3360
1,000,000	LISA Baseline Optimized	10	1116.51	0.2905	31251
1,000,000	LISA Baseline Optimized	100	1118.85	0.2858	31253
1,000,000	LISA Baseline Optimized	1000	1134.88	0.2844	31274
1,000,000	LISA Baseline Optimized	10000	1134.88	0.2831	31485

Table A.2.: Experimental results for LISA Baseline model with search optimization

Training/Test Data Size	Model	G	S	Build Time(s)	Avg Query Time(ms)	Memory Size(KB)	mse
10,000	LISA	4*4=16	5	4.335	1.13135	324.72	0
10,000	LISA	4*4=16	10	3.370	0.96036	329.07	0
10,000	LISA	4*4=16	20	1.127	0.86184	337.85	0
10,000	LISA	4*4=16	30	3.478	0.74339	346.63	5729

Table A.3.: Hyper-parameters Search LISA Model: Training Size:10,000 Points.

a) For the last row, Numbers of keys= 10000

b) Keys per cell= $10000 \setminus (4 \times 4) = 625$

c) Keys per shard = $625 \setminus 30 = 20$ keys per shard, resulting in mse errors

Training/Test Data Size	Model	GridCellSize	No of Shards	Build Time(s)	Avg Query Time(ms)	Memory Size(KB)	mse
100,000	LISA	4*4=16	50	122.64	1.51173	3176.6	0
100,000	Lisa	4*4=16	100	30.211	1.44084	3220.3	0
100,000	LISA	4*4=16	150	142.13	1.15491	3264.1	297234
100,000	Lisa	6*6=36	50	66.375	1.55903	3238.1	0
100,000	LISA	6*6=36	75	72.491	1.43043	3287.2	0
100,000	Lisa	6*6=36	100	60.929	1.64881	3336.4	5.6e+07
100,000	LISA	8*8=64	20	35.638	1.54029	3218.7	0
100,000	LISA	8*8=64	50	45.014	1.52117	3323.6	0

Table A.4.: Hyper-parameters Search LISA Model: Training Size:100,000 Points

Training/Test Data Size	Model	GridCellSize	No of Shards	Build Time(s)	Avg Query Time(ms)	Memory Size(KB)	mse
1,000,000	Lisa	10*10=100	50	743.29	1.77751	31558.9	0
1,000,000	Lisa	10*10=100	100	1077.89	1.63397	31832.3	0
1,000,000	Lisa	20*20=400	25	365.49	2.53317	31930.8	0
1,000,000	Lisa	20*20=400	50	609.32	1.44526	32477.6	0
1,000,000	Lisa	25*25=625	25	240.22	1.56227	32779.8	0
1,000,000	Lisa	30*30=900	25	205.18	1.79839	33010.3	0

Table A.5.: Hyper-parameters Search LISA Model: Training Size:1,000,000 Points

Training/Test Data Size	Model	Build Time (s)	Avg Query Time (ms)	Memory Size (KB)
10,000	KD-Tree	0.023	4.363	2890
10,000	Baseline	0.026	0.198	547
10,000	LISA	1.127	0.861	337
100,000	KD-Tree	0.340	6.176	28906
100,000	Baseline	0.324	0.241	5469
100,000	LISA	22.491	1.43	3169
1,000,000	KD-Tree	4.124	9.254	289062
1,000,000	Baseline	2.718	0.343	54688
1,000,000	LISA	445.324	1.445	32477

Table A.6.: Point Query experimental results for KDTree, Baseline and LISA models

Training/Test Data Size	Range Query Size	Avg Query Time (ms) (<i>KD</i> -tree)	Avg Query Time (ms) (Baseline)	Avg Query Time (ms) (LISA)
10,000	10	0.1361	0.1113	0.8204
10,000	100	0.0533	0.0451	0.1201
10,000	1000	0.0438	0.0399	0.0294
10,000	10000	0.0648	0.0382	0.0061
100,000	10	0.1392	0.1298	2.8961
100,000	100	0.0539	0.0505	0.2792
100,000	1000	0.043	0.0428	0.0563
100,000	10000	0.0718	0.0392	0.0129
1,000,000	10	0.2238	0.2661	3.5181
1,000,000	100	0.0922	0.0617	0.6263
1,000,000	1000	0.0744	0.0437	0.0939
1,000,000	10000	0.0735	0.0412	0.0186

Table A.7.: Range Query experimental results for *KD*-tree, Baseline and LISA models

Training/Test Data Size	K	Avg Query Time(ms)(<i>KD</i> -tree)	Avg Query Time(ms)(LISA)
10,000	3	1.4069	0.2020
10,000	5	0.8753	0.1181
10,000	7	0.6333	0.0811
10,000	10	0.4368	0.0549
100,000	3	2.0325	0.5867
100,000	5	1.2004	0.3549
100,000	7	0.8812	0.2779
100,000	10	0.6618	0.2161
1,000,000	3	2.7865	1.218
1,000,000	5	1.7072	0.9414
1,000,000	7	1.3255	0.7681
1,000,000	10	0.9172	0.5779

Table A.8.: KNN Query experimental results for *KD*-tree and LISA model

# id	Distributions	root model	second model	third models	Build Time (s)	Query Time (ms)	Evaluation Error (MSE)	Memory Size (KB)
1	log_normal	fcn	200 fcn	2000 fcn	418.9493798	0.970932583	653.853667	7487.059896
2		fcn	200 fcn	4000 fcn	1141.521194	0.9675528	1.13416667	24440.75523
3		fcn	200 fcn	6000 fcn	688.8004486	1.07512705	196.9116667	13034.22656
4		fcn	400 fcn	2000 fcn	483.1734781	1.158343717	113246.196	9208.992183
5		fcn	400 fcn	4000 fcn	636.8463397	1.339095933	113652.3212	12695.55731
6		fcn	400 fcn	6000 fcn	742.0712694	1.243333667	51.00183333	15434.78905
7		fcn	600 fcn	2000 fcn	504.959355	1.06512235	113246.2647	9745.335942
8		fcn	600 fcn	4000 fcn	879.6010201	0.973031833	18.99766667	20434.90626
9		fcn	600 fcn	6000 fcn	373.6126809	1.11725315	142041.6877	8118.023442
10		lr	200 lr	2000 lr	262.5089284	1.280502367	8246.633985	4348.463542
11		lr	200 lr	4000 lr	869.7494701	1.304096217	7326.238372	18769.81252
12		lr	200 lr	6000 lr	655.0431077	1.318176683	6276.09111	13297.72135
13		lr	400 lr	2000 lr	275.3925674	1.31789575	120427.9247	5143.059892
14		lr	400 lr	4000 lr	601.7362665	1.453903583	6783.428749	12864.80731
15		lr	400 lr	6000 lr	388.5866734	1.623972083	5998.720313	8041.416654
16		lr	600 lr	2000 lr	267.8966881	1.861582733	121932.5051	4986.927088
17		lr	600 lr	4000 lr	558.531068	1.52717965	8434.091306	13843.60678
18		lr	600 lr	6000 lr	337.0881814	1.28034995	35342.6365	8366.570317
19		lr	200 lr	4000 fcn	34.86059083	1.63086885	14478.05283	220.4973958
20		lr	200 fcn	4000 fcn	410.2378013	1.653916983	13656.1507	9318.697933
21		fcn	200 fcn	4000 lr	38.131223	1.667702583	12191.8397	602.2005208
22		fcn	200 lr	4000 lr	238.9569197	1.663567483	13403.64758	5229.914058
23		lr	200 fcn	4000 lr	290.6430138	1.657428583	12567.93278	6588.58335
24		fcn	200 lr	4000 fcn	352.6849412	1.909310833	11572.93555	8292.059883

Table 6.9.

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