

# team11 final project report

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## Implement

### 1. IVF\_SQ8\_DIRECT

系統架構: 參考PASE的IVF\_FLAT以及VanillaDB既有的Index寫法(例如 HashIndex、IndexSelectPlan、ConstantRange、SearchKey、executeTrainIndex等等), 不一樣的地方例如我們不用meta page(而是只從vanilladb.properties取得)、我們的centroid page使用spanned record、我們的数据 page包含原table所有的field(原來只包含key跟record id; 這樣在搜尋資料的時候比較連續, 可以降低I/O的次數)。我們另外實作了InsertionSortPlan, 在知道KNN的K很小的情形下, 不需要在disk上跑merge sort才能知道前K名是誰。SQ8\_DIRECT: 我們發現sift.txt裡面都是介於0~218的整數, 所以應該可以做適當的quantization。我們一度以為直接用8個bit來存是作弊, 但我們後來發現Faiss根本也有類似的東西:

```
enum QuantizerType {
    QT_8bit,          ///< 8 bits per component
    QT_4bit,          ///< 4 bits per component
    QT_8bit_uniform,  ///< same, shared range for all dimensions
    QT_4bit_uniform,
    QT_fp16,
    QT_8bit_direct,   ///< fast indexing of uint8s
    QT_6bit,          ///< 6 bits per component
    QT_bf16,
};
```

換句話說, 我們可以在完全不犧牲recall的情形下, 進一步降低I/O的次數。所以, 我們新增了ByteVector相關的type跟method, 來符合我們的要求。我們只有quantize存在data page的vector, centroid vector一樣是用float來存。

### 2. Kmeans: 首先使用來RandomNonRepeatGenerator來從0~899999選不重複的數字

```
74 RandomNonRepeatGenerator RNRG = new RandomNonRepeatGenerator(SiftBenchConstants.NUM_ITEMS);
75 Map<Integer, Integer> M = new HashMap<>();
76 for (int i = 0; i < IVFFlatIndex.NUM_CENTROIDS; ++i){
77     int random_number = RNRG.next();
78     M.put(random_number, i);
79 }
```

接著掃過table, 如果遇到剛剛選到的點, 就把他設為一個cluster的中心

```

81 Plan test_tp = new TablePlan(tableName, tx);
82 Scan test_ts = test_tp.open();
83 test_ts.beforeFirst();
84 while(test_ts.next()){
85     int index = (Integer)test_ts.getVal(fldName:"i_id").asJavaVal();
86     if(M.containsKey(index)){
87         VectorConstant v = new VectorConstant((float[])test_ts.getVal(fldName:"i_emb").asJavaVal());
88         idx.setCentroidVector(M.get(index), v);
89     }
90 }
91 test_ts.close();

```

接著refine剛剛選到的中心iteration次, 每次refine都會掃過整個table一次

```

93 // TODO: refine the centroids by K-means. It is recommended to log each iteration
94 int iteration = 2;
95
96 for (int i = 0; i < iteration; i++){
97     System.err.print("Iteration " + i + "\n");
98     Plan tp = new TablePlan(tableName, tx);
99     Scan ts = tp.open();

```

### 3. SIMD

我們使用了sub、fma來計算Euclidean distance, 其中針對除以SPECIES.length()的餘數部分再計算一次差平方做加總, 最後開根號並回傳

```

@Override
protected double calculateDistance(VectorConstant vec) {
    int i = 0;
    FloatVector sum = FloatVector.zero(SPECIES);
    for (; i < SPECIES.loopBound(vec.dimension()); i += SPECIES.length()) {
        FloatVector v = FloatVector.fromArray(SPECIES, vec.asJavaVal(), i);
        FloatVector q = FloatVector.fromArray(SPECIES, query.asJavaVal(), i);
        FloatVector diff = v.sub(q);
        sum = diff.fma(diff, sum);
    }
    double sum_d = sum.reduceLanes(VectorOperators.ADD);

    for (i=0 ; i < vec.dimension(); i++) {
        double diff = query.get(i) - vec.get(i);
        sum_d += diff * diff;
    }

    return Math.sqrt(sum_d);
}

```

## Other improvement

1. 我們發現public VectorConstant(byte[] bytes)是CPU效能瓶頸, 如下圖。我們一度想把這個constructor也SIMD化, 但後來發現用java.nio優化比較好。

```

27 Top methods over 60013 ms (0 ms paused), with 26653 counts:
28 Rank   Self   Stack  Method
29 1  21% 21% org.vanilladb.core.sql.VectorConstant.<init>
30 2  11% 11% org.vanilladb.core.storage.file.io.javanio.JavaNioFileChannel.write
31 3   9%  9% org.vanilladb.core.storage.file.io.javanio.JavaNioFileChannel.append
32 4   6%  6% org.vanilladb.core.storage.file.io.javanio.JavaNioFileChannel.<init>
33 5   5% 19% org.vanilladb.core.storage.buffer.BufferMgr.pin
34 6   3%  3% org.vanilladb.core.sql.VectorConstant.asBytes
35 7   3%  4% org.vanilladb.core.storage.tx.concurrency.LockTable.sLock
36 8   2% 27% org.vanilladb.core.storage.file.Page.getVal
37 9   2%  4% org.vanilladb.core.storage.tx.concurrency.LockTable.isLock
38 10  2% 24% org.vanilladb.core.sql.Constant.newInstance
39 11  2%  2% org.vanilladb.core.storage.tx.concurrency.LockTable.releaseLock
40 12  2%  2% org.vanilladb.core.storage.file.io.javanio.JavaNioFileChannel.read
41 13  1%  1% org.vanilladb.core.storage.tx.concurrency.LockTable.getAnchor
42 14  1%  1% org.vanilladb.core.storage.file.io.javanio.JavaNioFileChannel.close
43 15  1%  3% org.vanilladb.core.storage.file.FileMgr.delete
44 16  1%  1% org.vanilladb.core.storage.record.RecordPage.close
45 16  1% 19% org.vanilladb.core.storage.record.RecordPage.<init>
46 17  1%  1% org.vanilladb.core.storage.tx.concurrency.LockTable.prepareLockers

```

2. 我們一度想要讓尋找最接近的centroid這個操作在多個thread上跑，因為它是”CPU”效能瓶頸之一。結果因為實作寫得不好，不小心pin了太多buffer，只好作罷。
3. 在原版Kmean做refine的時候，我們一開始是掃過整個table才更新一次centroid，但這樣更新一次要快將近20分鐘，centroid更新效率不高。因此，我們做了簡單的優化，做法是每掃10000個record就更新一次centroid，這樣只需掃一次table就能更新90次centroid。

## Experiments

Environment:

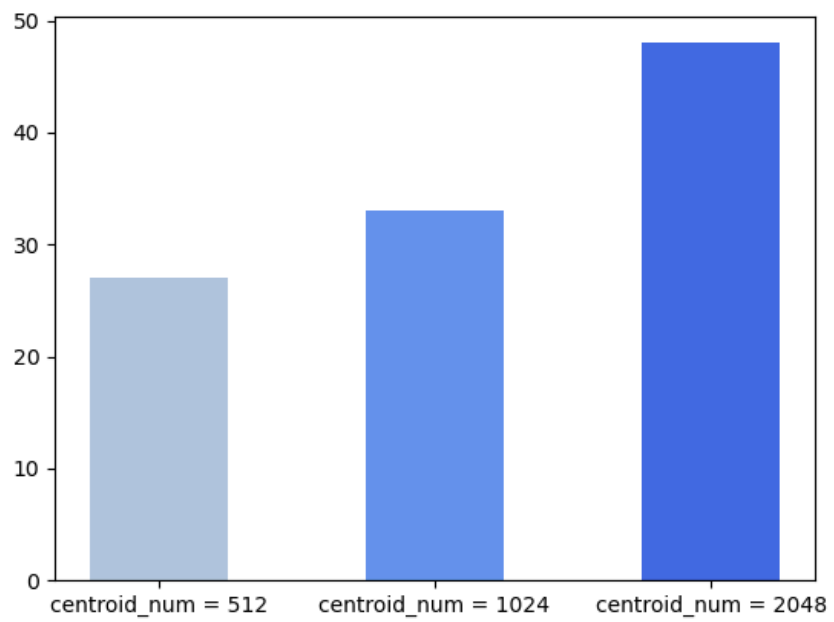
Intel Core i5-6400 CPU @ 2.7GHz, 16 GB RAM, 224 GB SSD, Windows 11

### Different centroid\_num (probe bucket = 8)

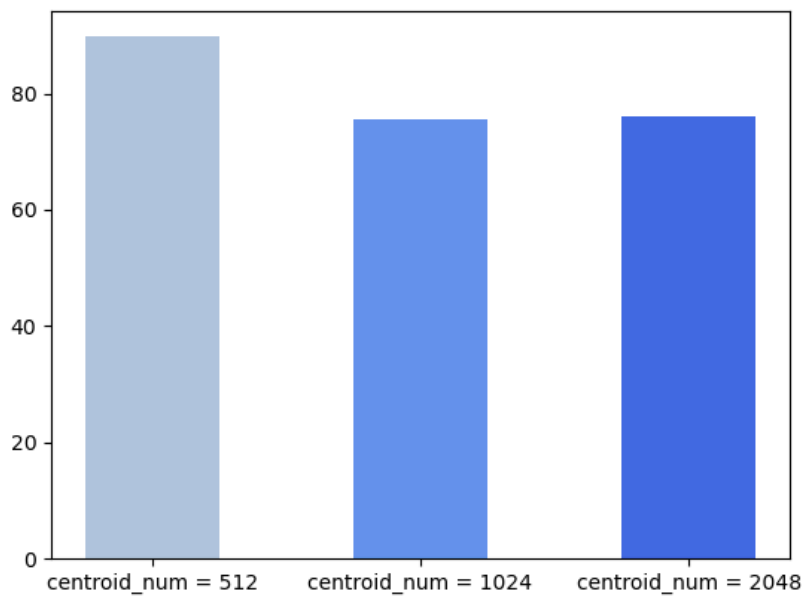
Results:

cen_num	512	1024	2048
commit	27	33	48
recall	89.77%	75.46%	75.95%

Graph(Committed):



Graph(Recall):

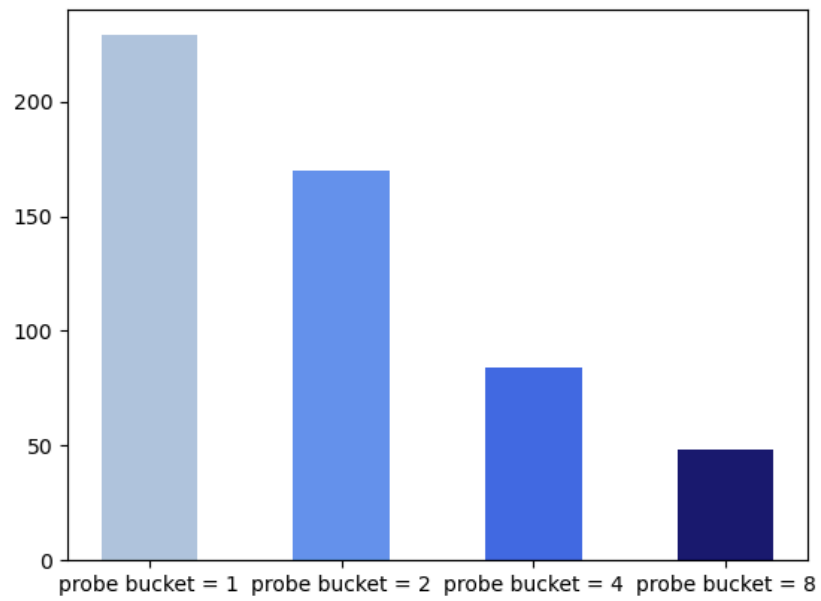


**Different probe bucket (centroid\_num = 2048)**

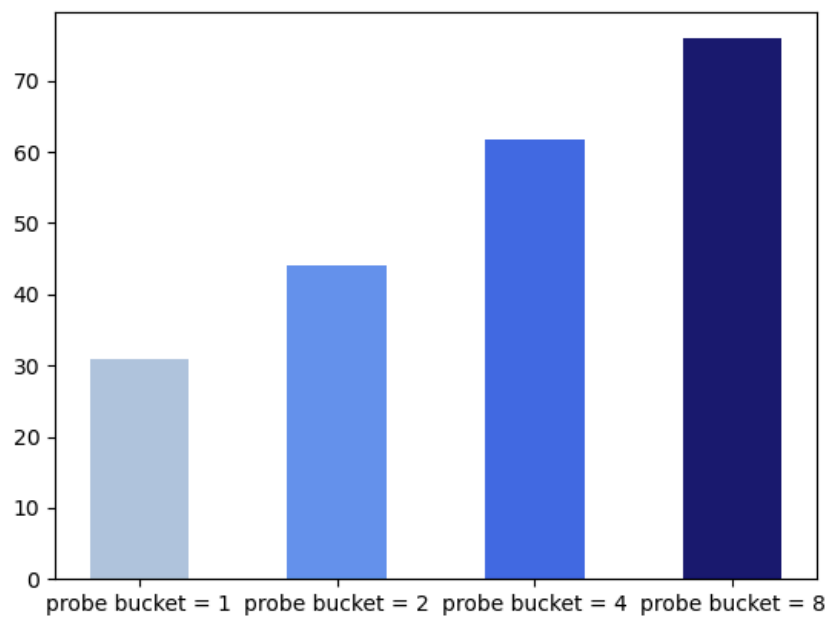
Result:

pro_bucket	1	2	4	8
commit	229	170	84	48
recall	30.94%	44.10%	61.72%	75.95%

Graph(Committed):

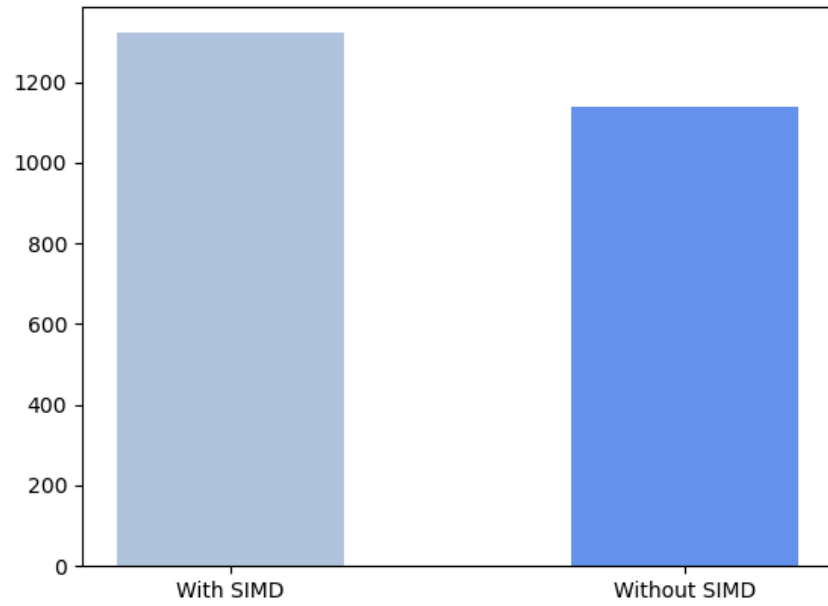


Graph(Recall):

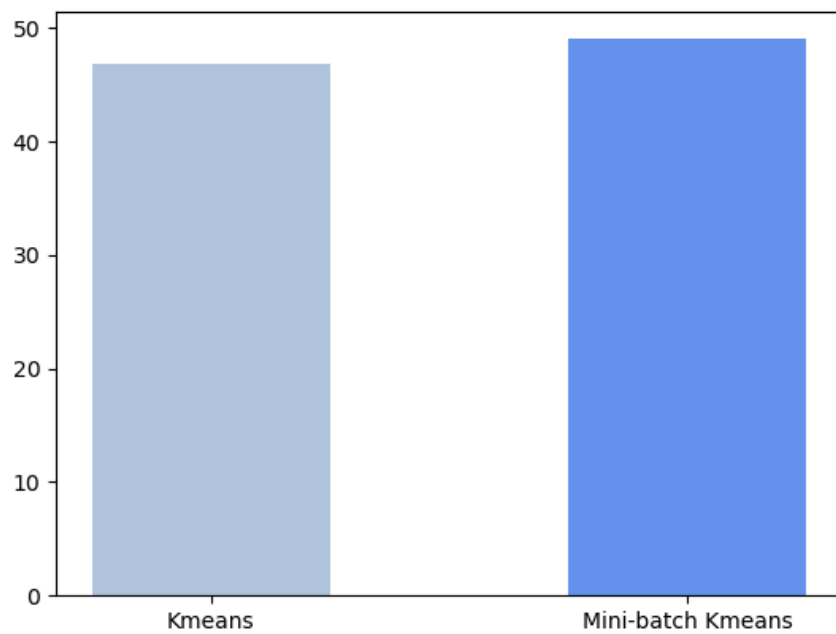


**With/Without SIMD (centroid\_num = 512, probe bucket = 8)**

Graph(Committed):



**Kmeans/Mini-Batch Kmeans (centroid\_num = 512, probe bucket = 8)**  
Graph(Recall):



## Conclusion

1. For centroid\_num

- a. centroid\_num越低, recall就越高。因為當cluster切的越大塊, KNN搜索的範圍就會越大, 找到實際最近的機率就會越高
  - b. centroid\_num越低, committed就越低。因為搜索範圍越大塊, 要接觸到的vector就會越多
- 2. For probe bucket
  - a. probe bucket越高, recall就越高。因為找的cluster越多, 表示搜索範圍越大
  - b. probe bucket越高, committed就越低。因為搜索範圍越大塊, 要接觸到的vector就會越多
- 3. 由實驗結果可以看出有做SIMD能有效增加commit的txn
- 4. Mini-Batch Kmeans之recall比Kmeans高3%左右, 這是因為Mini-Batch較頻繁更新centroid, 故其收斂較快