# CS5950 - Machine Learning
# Identification of Duplicate Album Covers

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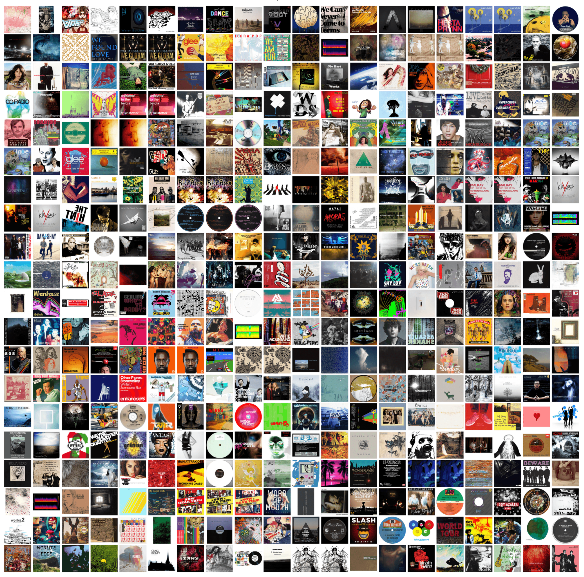

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## 1 Introduction

This paper covers the results of our groups' initial experimentation with the album covers dataset from the Internet Archive, located at:

`https://blog.archive.org/2015/05/27/experiment-with-one-million-album-covers/`

Every album cover used in this paper is from The Internet Archive and is copyright of its respective owners.

The dataset itself contains 997,131 images, which are an assortment of .gif, .jpg, or .png files.

The goal of our project was to identify images within the dataset that were "similar" to each other, meaning images that were not exactly identical.

## 2 First Steps

Initially, our team searched for existing algorithms that we could implement that could be used to detect whether two images were similar. This led us almost immediately to this site:

`http://www.hackerfactor.com/blog/?/archives/432-Looks-Like-It.html`

Most of the ideas in general involved transforming images and converting them ultimately to a number, which could then be compared, or "hashing" the images. The two algorithms detailed on the site we refer to as:

- The Simple Algorithm
- The DCT (discrete-cosine-transform) Algorithm

We will detail these algorithms in the next section. After having some idea of algorithms that may work, while implementing the algorithms we also downloaded the entire dataset onto a computer.

The sizes for each letter directory are detailed in the table below. The download itself took roughly 1.5 days via the torrent download on the site.

| Directory | Size (GB) |
|---|---|
| a | 8.4 |
| b | 7.5 |
| c | 19 |
| d | 7.2 |
| e | 4.5 |
| f | 5.3 |
| g | 4.0 |
| h | 5.3 |
| i | 5.2 |
| j | 1.6 |
| k | 2.1 |
| l | 7.0 |
| m | 7.4 |
| n | 4.1 |
| o | 3.3 |
| p | 5.9 |
| q | .380 |
| r | 5.0 |
| s | 13 |
| t | 6.5 |
| u | 1.7 |
| v | 2.5 |
| w | 4.3 |
| x | .245 |
| y | .769 |
| the | 9.1 |
| total | 140 |

Table 1: Uncompressed Directory Sizes for Album Covers

## 3 Initial Complications

Simply traversing the directory tree was slow and difficult. A simple command:

```
ls a/*.png
```

Will fail because the size overloads the limit for files returned. This made a traditional command fail, like:

```
md5sum a/*
```

We tested several different options, which included:

- find with exec
- find with xargs
- ls -1 with xargs
- Python script using process pools

Using process pools was the fastest method for running our Python-based implementations of the algorithms. We used ls with xargs for the md5sums we ran.

The second major complication was any penalty for bugs. Because running the hash across the entire dataset took on the order of half a day, the first few mistakes took several days to identify and fix. In hindsight, doing extensive testing on a smaller dataset is very necessary before running on the entire dataset.

## 4 The Algorithms

After some initial testing, we were fairly impressed by the algorithms detailed on:

`http://www.hackerfactor.com/blog/?/archives/432-Looks-Like-It.html`

Once again, we refer to them as:

- The Simple Algorithm
- The DCT (discrete-cosine-transform) Algorithm

We now detail these algorithms in pseudo-code. Our Python implementation of these algorithms can be found at:

`http://github.com/jpypi/dup-image-search`

## 4.1 The Simple Algorithm

```
simple_hash(image_filepath):

    img = image.load(image_filepath)
    img.resize(8, 8)  # resize the image to 8x8
    img.convert_to_grayscale()
    arithmetic_mean(img.pixels())

    hash = 0  # hash is 64-bit integer
    index = 0
    for each pixel in img.pixels()
        if pixel > mean
            hash.set_bit(index)

        index += 1
```

## 4.2 The DCT Algorithm

```
dct_hash(image_filepath):

    img = image.load(image_filepath)
    img.resize(32, 32)  # resize the image to 32x32
    img.convert_to_grayscale()

    transformed_matrix = dctII2d(dctII2d(img.pixels().transpose()).transpose

    # take the top-left only
    top_left = transformed_matrix.subset(8, 8)

    # leave out [0, 0]
    arithmetic_mean(top_left - top_left[0, 0])

    hash = 0  # hash is 64-bit integer
    index = 0
    for each pixel in img.pixels()
        if pixel > mean
            hash.set_bit(index)

        index += 1
```

This algorithm uses the 2D Discrete Cosine Transform, detailed here:

`http://en.wikipedia.org/wiki/Discrete_cosine_transform#DCT-II`

Also, per the details found on:

`http://www.hackerfactor.com/blog/?/archives/432-Looks-Like-It.html`

The recommendation was to use the top-left only of the transform and to leave out the [0, 0] term when doing averaging.

## 5 Initial Run - Exact Duplicates

Prior to running our algorithms, first we wanted to reduce the size of the dataset by removing any corrupt (unloadable) images and any exact duplicates. For this, we calculated the MD5 hash of each image and used the Python Image Library (PIL) to verify whether the image was a valid image.

After running this on the dataset (for roughly 10 hours), we were able to identify matching hashes and calculate that, of the 997,131 images:

- 189,567 images (19%, 16.65 GB) were exact duplicates of an image in the remaining set
- 7962 images (about .8%, 221 MB) images were corrupt

## 6 Second Run - Simple and DCT Hashes

After removing the exact duplicates and corrupt images, we then ran each of our hashes on the full dataset. After the runs were complete, we compiled the combined MD5 hash, simple hash, and DCT hash into a SQLite database. We shared this database in a Google Drive folder with the team for use in analysis. We can make this database publicly available, but it is fairly large (the bzip2 compressed database is 63.2 MB).

## 7 Post-run Analysis

Per the algorithms, any image within hamming distance of five should come close to matching. The hamming distance is the number of bit flips two integers are apart. To more easily identify all the images within hamming distance of 5 of any given image, we calculating the hamming weight (the number of ones in the integer) of each image and stored that in the database as well.

From this, we can say that any image within hamming weight of +/- 5 of the select image is a candidate for checking the hamming distance. The problem was with so many images, checking this takes some time - not a lot - but with about 750,000 images the calculation adds up.

We tried another approach of building up a database slowly and checking with each insertion if the added image is within 5 of any image already in the database. That too, was fairly slow (manageable, but slow).

We decided to refocus, instead, on the determination of what the accuracy for hamming distance zero was. It is very easy to calculate the hamming distance of zero, since we only need to check the database for sets of matching hashes.

We then built up a list of DCT hashes and simple hashes that, per the algorithms, should match. All that was left was to manually verify the matches. For this we developed a simple tool that would go through the list and allow the user to select Yes or No if the images matched.

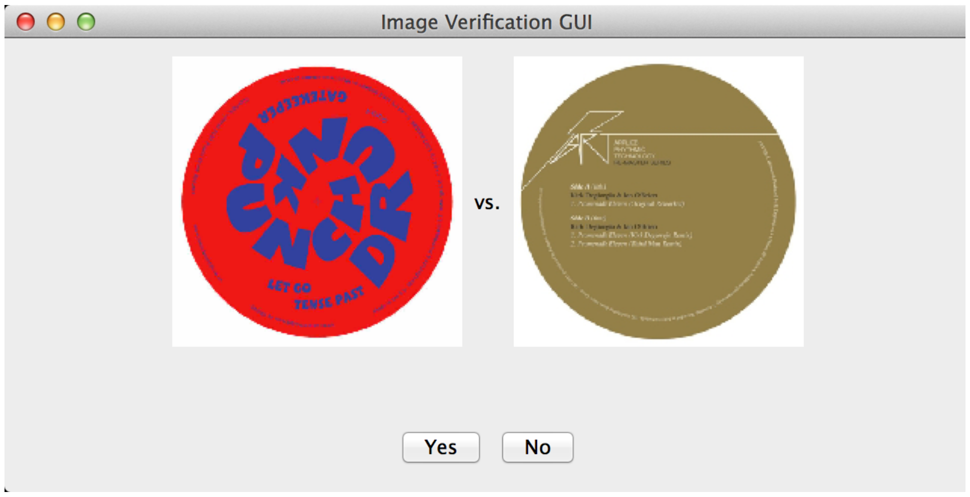

Figure 1: The Image Verification Tool

The tool writes the results out to a file, which we could then use to determine the error rate for false positives. We also fed this into a database for any further analysis that would require user input (at least that small subset of manual user validation would already be done).

We took the matches for simple and matches for DCT and split them into three for each of us to validate. We immediately noticed some large sets that were clearly not matching.

We decided to remove all sets with greater than 4 results as their accuracy was close to 0%. We make note of this in the final numbers.

The final number of sets (between 2 and 5 images each) for the simple algorithm totalled 9031. For DCT, the number of sets was 5302. That was a lot of pictures to sift through using the tool. Further tool enhancements would definitely include:

- Indication of current progress
- Keyboard-based entry (in addition to mouse)
- Ability to go-back and modify a result

We all noticed we had a few misclicks here and there, which will contribute to some error. Also, each individual had a differing definition of what a "similar" album cover would be, which led to some images being accepted by one person that may not otherwise have been accepted by another.

## 8 Results

| Images Scanned | Correct | Incorrect | % Correct |
|---|---|---|---|
| First Set | 1663 | 2008 | 45.3% |
| Second Set | 1315 | 2546 | 34% |
| Third Set | 1204 | 2378 | 33.6% |

Table 2: Results for Simple Algorithm

| Images Scanned | Correct | Incorrect | % Correct |
|---|---|---|---|
| First Set | 1049 | 678 | 60.7% |
| Second Set | 841 | 964 | 46.6% |
| Third Set | 1280 | 420 | 75.3% |
| Already Matched | 807 | 49 | 94.2% |

Table 3: Results for DCT

The "Already Matched" column were images from the database that we had already manually matched from the Simple algorithm analysis that we did not have to re-evaluate. Take note of the fact that we pruned the sets greater than 4, which we assume had zero accuracy.

| Algorithm | Count |
|---|---|
| Simple | 14817 |
| DCT | 2833 |

Table 4: Count of Images in Sets Above Length 4

If we were to introduce other algorithms, we should be able to reduce the sets above 4 to only those that legitimately match.

| Algorithm | Percentage Correct |
|---|---|
| Simple (sets less than 5) | 37% |
| DCT (sets less than 5) | 81% |
| Simple (assuming sets greater than 4 are 0%) | 16% |
| DCT (assuming sets greater than 4 are 0%) | 45% |

Table 5: Combined Results for Each Algorithm

## 9 Analysis of Results

We gained great insight into what the algorithms did and did not see once seeing the images that had matching hashes.

The failing points we saw in the algorithms were:

- The algorithms are color-insensitive. As a result, covers that differ only by color were identified (incorrectly) as matches.
- Small details are not picked up in the algorithm. This includes, for the most part, any text. This had three weak points:

  Many album covers were not covers but rather images of the CD/record. As a result, the round circular image dominated the algorithm and the text to distinguish album covers was the only thing that could differentiate them. A large number of false positives were due to this.

  There were many "compilation" albums, in particular Glee albums and "The Voice" albums, whose only differentiating feature was the song name on the album cover. Those were always matching, which led to a large number of false positives.

  Some albums by the same producer had matching artwork but different artists/-songs. The text was, again, a differentiator here and did not get picked up by either algorithm.

Despite the failings, the algorithms were good (at hamming distance zero) of detecting a number of duplicates.

## 10 Recommendations

Based on what we saw, we would recommend using the DCT algorithm as a first pass (after exact duplicates were removed with MD5), then another algorithm be applied to determine:

- Shape - if it is a circular picture it is likely an image of the album itself (and not a cover). If character recognition is expensive, apply it to these hits first.
- Color - Again, if the DCT algorithm indicates the images are close, then some color-matching algorithm would help to weed out false-positives.

## 11 Next Steps

If we were to continue working on this, we would recommend first the use of a character-recognition algorithm to help sort out false-positives.

We would also tune the image verification program, likely refactoring it as a web page for detecting if the images are equal, to distribute the workload better. We would feed the results directly into a database.

This is also a project which lends itself readily to some massive parallelization step - divide and conquer works well on this as many of the steps are independent (like the individual image hashing). Per some of our discussions, offloading much of the image processing work to a graphics processor would likely significantly speed up the algorithms, as they are tailored to doing these kinds of transformations.

We would also map out the accuracy for hamming weights 1, 2, 3, and 4, to see how rapid the decline in accuracy is. Honestly, this is what we ran out of time to do - in hindsight we would have worked with much smaller datasets first as a training step before moving to the full dataset for testing.