⊧ dupi -- design

Dupi is a tool for finding duplicated data in a large and noisy set of documents.

This document describes the design of dupi.

Background

In this section we describe some background concepts.

Inverted Index

An inverted index takes as input a set of documents and produces a list of posts for elements in each document.

For example, given

```
1. There are lots of duplicate Go packages.
2. There are lots of cool and interesting Go modules.
3. I like Go.
4. And who doesn't?
```

An inverted index may look like this

```
there: 1, 2
are: 1, 2
lots: 1, 2
of: 1, 2
duplicate: 1
go: 1, 2, 3
packages: 1
cool: 2
and: 2, 4
interesting: 2
modules: 2
i: 3
like: 3
who: 4
doesn't: 4
```

Documents

Documents may be files, web pages, chat posts, ...

Elements

Note that there are always questions of identifying the elements in the documents: are they words? Are they case-folded? What about punctuation?

Some common ways of treating this are:

- use trigrams (like [codesearch])
- detect language, tokenize and stem the input (like [Lucene])
  - use named entity recognition.
  - use part of speech tagging.

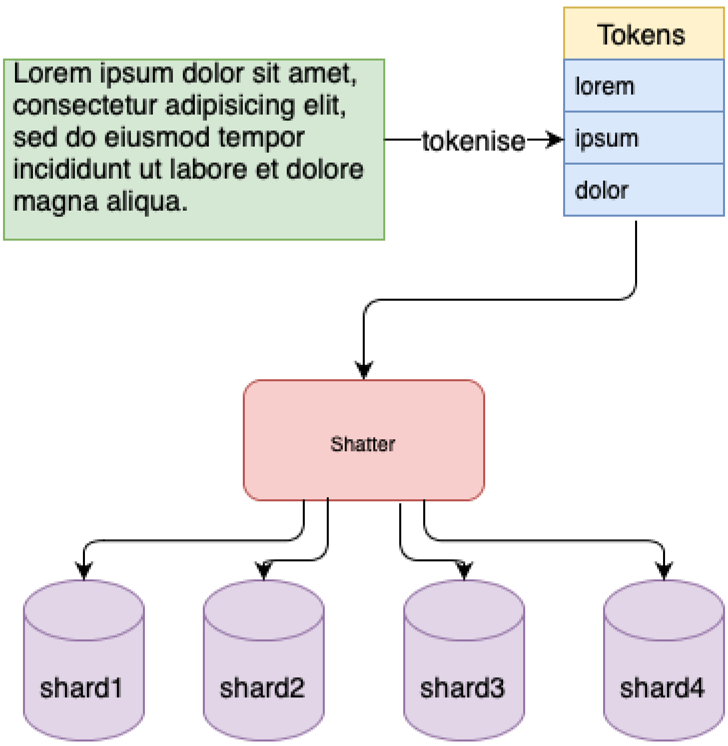
Post lists

Representation of posting lists is a field of study because they tend to present challenges. They can grow to be very large. There tends to be an exponential distribution of elements which are indexed. Exactly which set of words may be interesting is challenging (for example if we exclude "the" because it is too common, will we be able to find the band "The The"?).

Post lists are most commonly compressed by storing differences between successive document ids in sorted order with a variable length encoding.

dupi Overview

dupi works in the paradigm above of inverted indices, with a few substantial twists. Here is the flow for creating a dupi index from a document:



Tokenisation

The first step tokenizes the input. Different tokenisation schemes can be used for different kinds of input. For example, a simple case fold and filtering of all non alphanumerics can be a simple, generic tokeniser. Using Go's unicode support, this should work accross languages.

Other tokenisation schemes can be interesting as well. For example, to find duplicative code, we could include tokens for '{([])}' and operators, and map variable names to names for their types. Dupi provides extendable and pluggable tokenizers.

Fingerprinting (blots)

Dupi *shatters* each document accross a set of shards by translating each document into a sequence of micro-fingerprints called *blots*.

Blots

Blots must be roughly evenly distributed for a document set. As a result, one cannot use letters or words as the defining parameters of a blot, as letters and words generally occur in exponential distribution. If blots are not roughly evenly distributed, then the space of potential duplicates increases, which is undesireable.

This can in principle be accomplished any number of ways, and Dupi allows extending and pluging in blotter.T objects of any sort. A few basic blottering techniques are provided.

First, dupi *tiles* the token stream into tiles of sufficient size to have near-uniform distribution. Second, dupi computes a blot for each tile, as indicated in the digram below.

Tokens
lorem
ipsum
dolor
sit
amet

t_1	t_2	t_3	blot
lorem	ipsum	dolor	2db9
ipsum	dolor	sit	c479
dolot	sit	amet	f1f9

k-Circular Hash Xor

The blot computation uses a k-circular hash mechanism as follows. Let t_1 t_2 t_3 ... be a stream of tokens and f_h be a hash function from tokens to uint32s.

The hash value of a k-window of tokens rooted at token 1 is defined to be

$$h_1 \doteq f_h(t_1) \oplus f_h(t_2) \oplus \ldots \oplus f_h(t_k)$$

We can then advance to the next hash value with

$$h_{i+1} \doteq h_i \oplus f_h(t_i) \oplus f_h(t_{k+1})$$

This can be easily implemented in a circular buffer of hash values.

This provides us with a translation from a document to a stream of fingerprints of windows of text. Small values of 'k', like 2-3, may lead to a sharper frequency distribution of the fingerprints. However, such values do not provide much information about duplicative text, so let's assume 'k' is large enough to provide near-uniform distribution of the fingerprints over the documents. Later, we can exploit this property.

Interleaving k-Circular Hash Xor

While the fingerprints above probably would capture cut-and-paste duplicates or message quotes with a simple tokenisation scheme, it is not so robust for noisier duplicates, such as would occur with OCR scanning errors or different treatment of "doesn't", due to the apostrophe, in different contexts. In this section, we present an alternative blotting scheme which is more robust to such fuzzy matches.

The idea is simple: Given a tokenized document, we create 2 fingerprint streams based on even and odd indexed tokens, so one stream does a k-circular hash of even tokens and the other a k-circular hash of odd tokens. When we process an even token, we output the fingerprint from the even stream and likewise for the odd stream. A query will then consider a possible match either of the two streams matches.

Example

Suppose we are looking at code documentation for 10 million LoC distributed over a few million source code files and maybe a 1 million documented items in the code. Let's consider a dupi document to be a documented item in this code base.

So we estimate 1m dupi documents, each of which is fairly short. dupi uses hash based fingerprinting of a sliding window of text. So let's say on average we can assume there will be 100 fingerprints per document. That gives us 100 million posts which is the product of the fingerprints per document and the number of documents.

Suppose we allow for 2^{18} distinct fingerprint values, as is the current default for dupi. Then on average we will have about 200 documents per blot, and each document will contain about 100 blots, making the expected number of possible documents with duplicate blots 20000, independent of their actual content.

By looking up the 200 or so documents associated with a blot, we have ruled out 999800 documents having a duplicate of the text associated with the blot.
Exploiting this fact to efficiently find all duplicate text is discussed in the extraction and query sections below, where relatively cheap per-blot processing can be iterated over all or a subset of blots. By focusing on the data blot-wise, we effectively reduce the N^2 nature of the find all duplicates query to worst case |blots|x|per-blot-processing-time| query, which in this example is much smaller than N^2.

Posting Lists

Dupi posting lists are the main component of shards in dupi. Each shard contains a posting list, and each *blot* indicates a pair of a shard and a value associated with documents in the posting list.

Posting lists are then an on-disk storage which maps blot shard values (16 bits) to lists of document ids. This is accomplished in dupi by an on-disk linked list which allows each blot value to store chunks of compressed integers at each list node. On-disk linked list allows for fast appends and reasonable iteration through blot data.

The document ids are by construction increasing in value, so they are delta-encoded and then varuint encoded to save space.

Along with posting lists, dupi stores the size of each list. As in [^lucene] posting lists are built in a limited memory fashion allowing the indexing of large document sets.

On plain English text, the posting lists take about 25% the size of the input data.

Extraction

Dupi provides a command to extract duplicates or candidate duplicates from a set of indexed documents.

On startup, dupi sorts the blots in descending order of frequency of associated documents, based on the idea that a blot with many documents is more likely to represent duplicate text than a blot with an expected number of associated documents just based on the document number and size and the uniform-ish distribution of shattering.

The extraction mechanism visits the blots in descending order, skipping any blots of size 1 or 0. It can output the associated documents one per line, or in json format, giving a consumer a much-reduced set of pairs of documents to analyse. This raw form can produce a lot of documents of documents an does not by itself show or test the associated text.

Blot filtering

TBD: filtering

Query

Query works exactly like extraction, except we restrict the set of blots visited to those which have a hit for the input document or set of documents.

Concurrent Design

The indexing engine has 2 components which operate concurrently. First, the index is broken into shards, and there is one goroutine for adding to each shard. Second, the tokenisation and shattering operates with several goroutines. These elements are coordinated with channels.

On the query side, each query has a dedicated gorouting and multiple such queries can be executed at once. Queries present an iterative interface allowing back-and-forth communication between the a client, such as the command line, and the index server.

All i/o operations on the query side are concurrent safe, so many queries share the underlying file descriptor for every shard.

Future Work

Workflows

Some large document set review workflows need a feedback

Go

Generic programming languages

Improved Blotting

Blotting gives a function which is blind to the order of the tile to which it is applied.

Explore DNA sequence duplicates

Dupi is built for large data sets, and looking at things like BLAST [blast] it seems this kind of token-shatter-index architecture could be applied with success at the DNA sequence level.

Related Work

[lsh] Locality sensitive hashing was first used to remove similar items from altavista search in the late 90s. Dupi is designed to find duplicative text, such as results of cut and paste, with associated formatting noise. While duplicative text is very similar, it can be embedded in documents which are very disimilar. As a result, LSH would need to be applied at a micro level for dupi, which does not seem to scale.

From a broader perspective, dupi creates an index which makes it easy to rule out possible pairs of documents which contain duplicative text, whereas LSH is generally applied in a context where one searches for similar documents. By focusing on ruling out possible document pairs, dupi scales more easily.

Bloom filters [bloomfilters] have an interesting relationship to Dupi. In fact, we started out with (and then rejected) Bloom filter based posting lists for blots. However, a Dupi index is very much like a bloom filters. Bloom filters are parameterized on a number of bits, m, and a number of elements used to identify elements in the set, k, with k less than m. Two elements are in a set if their k true bits are all true in the set's m-bit representation.

If one thinks of the space of values of (shard, blot) tuples, one gets |shards| x |blots| bits which can be true or false in a document. Unlike a Bloom filter, a document does not have a fixed number of k bits true. Rather, longer documents will have more blot values, and membership in a set of candidate paired documents can be established, rejected, and estimated by looking at the degree of overlap of blots. Like a Bloom filter, Dupi indices can safely *reject* a large set of possibly duplicative documents, as all those documents whose blots do not overlap.

Conclusions

dupi is novel, fast, flexible, effective and scalable mechanism for finding duplicates over large sets of data. Currently a beefy machine can easily scale to a billion documents. dupi is not yet however distributed so we do not yet scale to hundreds or thousands of terabytes of documents. For future work, we plan on examining peer to peer xor based protocols to address this.

References

codesearch Russ Cox's codesearch.

codesearchblog

^lucene: Apache Lucene.

bloomfilters Wikipedia on Bloom filters.

bloomcalc Bloom Filter parameter calculator.

lsh Locality Sensitive Hashing. Wikipedia article

mg Managing Gigabytes: Compressing and Indexing Documents and Images by Ian H. Witten, Alistair Moffat, and Timothy C. Bell, was published in May 1999 by Morgan Kaufmann Publishing, San Francisco (now a component of Elsevier Publishing), ISBN 1-55860-570-3.

zoekt. Zoekt code search.

lshforest LSH Forest: Self-Tuning Indexes for Similarity Search. Mayank Bawa, Tyson Condie, Prasana Ganesan

blast BLAST basic local alignment search tool.