Data Mining: Learning from Large Data Sets - Spring Semester 2014 Project 1

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Approximate near-duplicate search using Locality Sensitive Hashing

This document explains the implementation of project 1. In this first project we were supposed to find near-duplicate videos using Locality Sensitive Hashing. The videos were given as a number of shingles that could be compared. The implementation was done in Python to be used in combination with the hadoop infrastructure. This means we implemented a mapper and a reducer that read from stdin and write to stdout. In the following two sections we explain the functionality of the mapper and the reducer each.

mapper.py

The mapper creates a signature vector of a video. This signature vector is afterwards subdivided into b bands having r elements that get hashed. Each band and its hash are then emitted.

These are the steps in more detail:

- 1. As Figure 1 shows, choosing b=32 and r=8 forgets no true positives.
- 2. We create $k = b \cdot r$ hashfunctions of the form $a_p x + b_p \mod c_p$ where $a_p = rand(0,999), b_p = rand(0,9999), c_p = 10000$ and rand(x,y) is random variable drawn from a uniform distribution between x and y. These hashfunctions are used to calculate the permutations in min-hashing.
- 3. We create r hashfunctions of the form $a_bx+b_b \mod c_b$ where $a_b=rand(0,999), b_b=rand(0,999),$ $c_b=1000$ and rand(x,y) is random variable drawn from a uniform distribution between x and y. These hashfunctions are used to calculate the band hashes before emitting.
- 4. The signature is then created according to 1
- 5. Calculate the band hash and emit the band hash and the band as key, and the video with its corresponding shingles as value according to 2

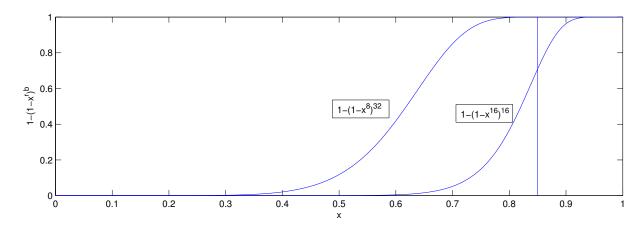


Figure 1: $1 - (1 - x^r)^b$

Algorithm 1 Create signature

```
\begin{aligned} signature &= \infty \\ \textbf{for all } shingle \ in \ shingles \ \textbf{do} \\ \textbf{for } i \ in \ range(k) \ \textbf{do} \\ signature[i] &= min(a_{p_i} \cdot shingle + b_{p_i} \mod c_p, signature[i]) \\ \textbf{end for} \\ \textbf{end for} \end{aligned}
```

Algorithm 2 Emit keys and values

```
\label{eq:continuous_problem} \begin{split} & \textbf{for} \; \text{band in range(b)} \; \textbf{do} \\ & \textit{vector} = signature[band \cdot r : band \cdot r + r] \\ & \textit{bandhash} = \sum_{i=1}^{len(vector)} a_{bi} \cdot vector[i] + b_{bi} \; \; \text{mod} \; c \\ & \text{emit} \; key = [bandhash, band] \; value = [video\_id, shingles] \\ & \textbf{end for} \end{split}
```

reducer.py

The main task of the reducer is to get rid of the false positives by comparing the reported similar videos using the jaccard distance:

- 1. gather all videos with the same key in a collection duplicates
- 2. emit similar videos like shown in 3

Algorithm 3 Emit similar videos

```
for i=0 to len(duplicates) do

for j=i+1 to len(duplicates) do

if duplicates[i].video_id < duplicates[j].video_id then

shingles_left = duplicates[i].shingles

shingles_right = duplicates[j].shingles

distance = |shingles_left∩shingles_right|
|shingles_left∪shingles_right|

if distance > 0.85 then

emit duplicates[i].video_id duplicates[j].video_id

end if

end for

end for
```