Hashing and Anonymizing Datasets

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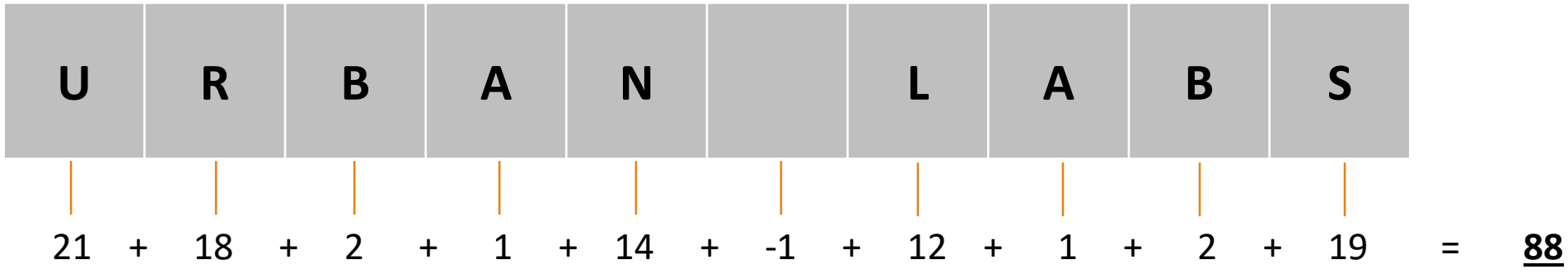
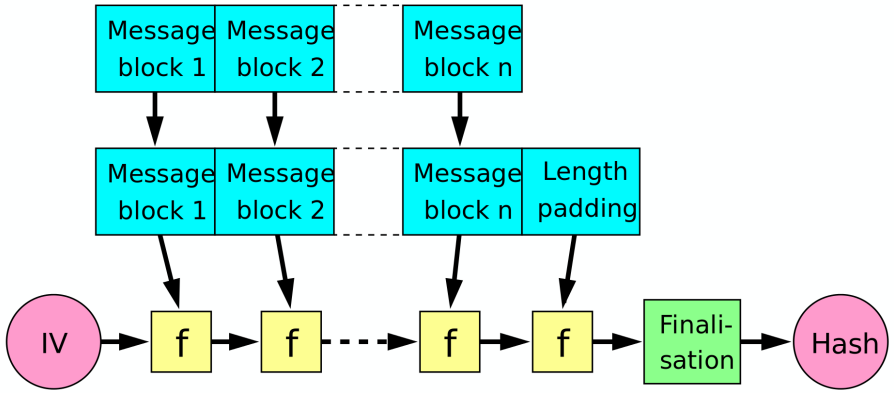
What is “hashing”?

- A **hash** is a value that is obtained from the **transformation of a string of characters by a certain function**.
- This function can be anything – including something as simple as taking the index of each alphabet in a word and summing them up.



What is “hashing”?

- In encryption, much more complicated functions are used to ensure:
  - **Minimal collisions** (Two different strings should not map to the same value)
  - **Difficulty of reversing the hash** without using ‘brute-force’ methods
- Some types:
  - MD5
  - SHA0
  - SHA1
  - SHA256
  - etc.



Merkle-Damgard construction

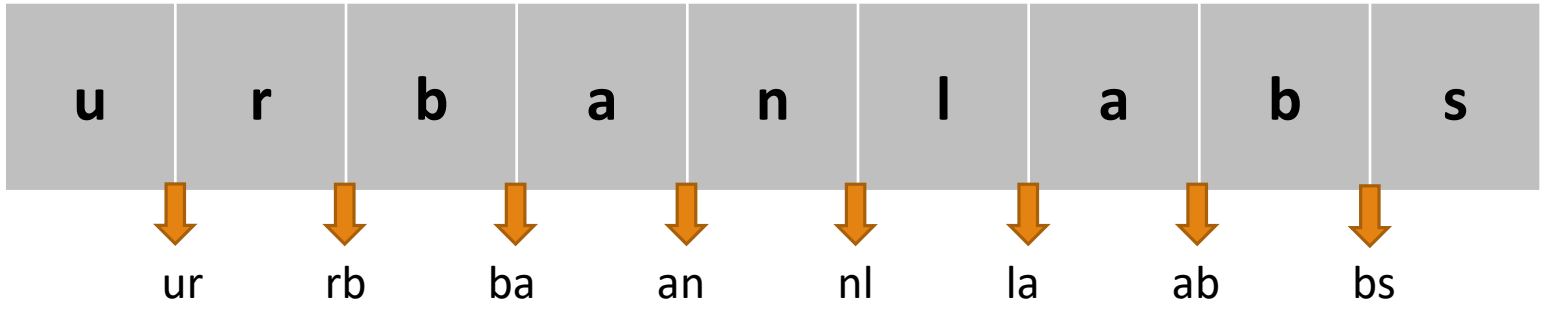
Image: Wikipedia

What is “hashing”?

- *But wait, if the hash function produces the same value for a string every time, won’t it be easy to reverse the algorithm or keep track of values that correspond to particular words?*
  - Cryptographic functions are designed to be **non-reversible**
  - One type of brute-force decryption involves “rainbow tables”
- This is where a **‘salt’** becomes useful (hidden/random value appended to the string before hashing)

Protocol (from CCAC project)

- MD5, ‘Salted’, and Locality-Sensitive Hashing
- Locality-Sensitive Hashing (LSH)
  - **MinHash** (min-wise independent permutations)
  - Collect **minimum values** from hashing bigrams of the identifiable information (name), each time changing the hash value permutations by adding the iteration number to the
    - **150**



Protocol (from CCAC project)

- **Required Preparation**
  - Date-shifting and Dataset Truncation
    - Prevent identification/record linkage by date or ordering
    - **Shift all dates in the dataset by a random number of days** (to preserve temporal relationship)
    - Truncate random number of data points from front and back
  - The Salt
    - **Keyword, to be known only by analysts hashing the datasets**
    - Preferably read salt into script from another secure file
  - Password-Protected Folders
    - For data transfer between analysts
    - Use **randomly generated password**

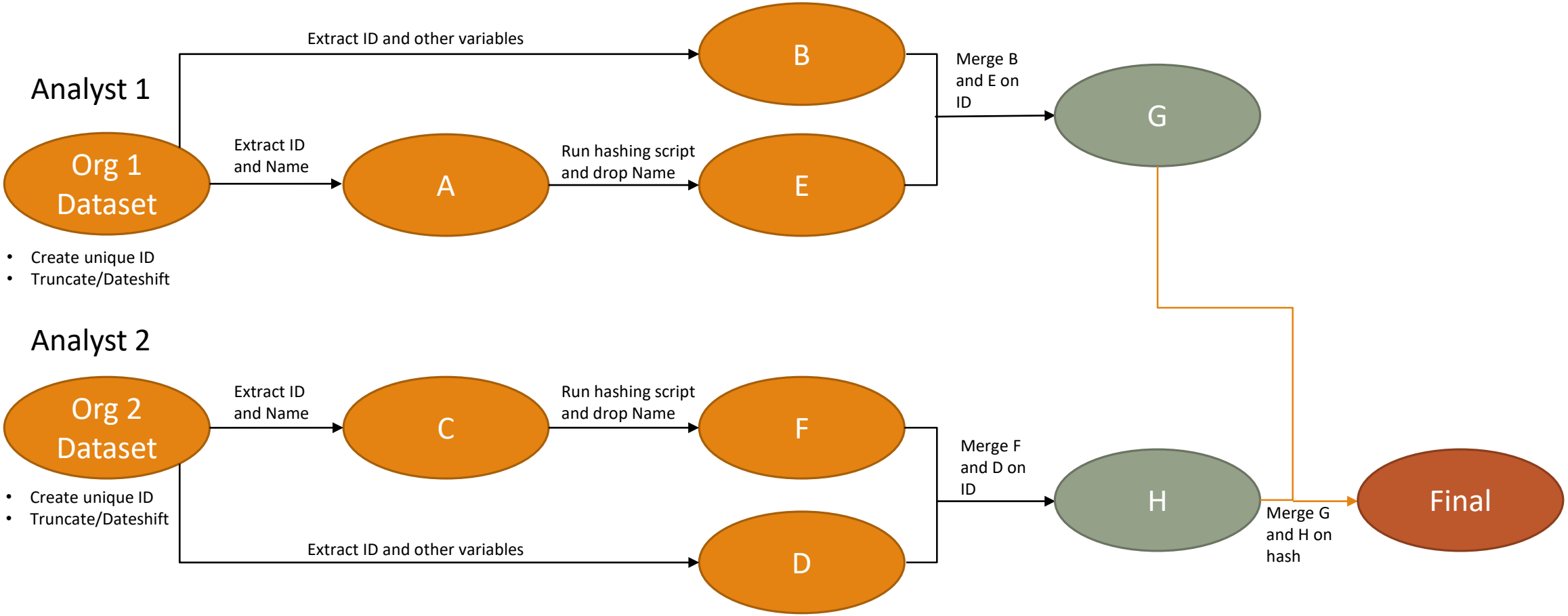
Protocol (from CCAC project)

- Analyst 1 handles sensitive dataset from Organization 1
  - Create a unique ID for each row
  - Truncate and Date-shift as necessary
  - Extract the name field and ID field into a separate dataset (Dataset A)
  - Extract the ID field and the other variables of interest into a separate dataset (Dataset B)
- Analyst 1 then communicates the salt and the value of the date-shift to Analyst 2 securely
- Analyst 2 handles sensitive Dataset from Organization
  - Perform the same steps as the dataset from Organization 1 to get Dataset C and Dataset D
- Analyst 1 runs the hashing script on Dataset A, drops the name column (Dataset E)
- Analyst 2 runs the hashing script on Dataset C, drops the name column (Dataset F)

Protocol (from CCAC project)

- Analyst 1 merges Dataset E with Dataset B using the unique ID (Dataset G)
- Analyst 2 merges Dataset F with Dataset D using the unique ID (Dataset H)
- Now, Dataset G is a dataset from Organization 1 with hashed names and Dataset H is a dataset from Organization 2 with hashed names
- Finally, Analyst 1 securely transfers Dataset G to Analyst 2, who can then perform the merging using the hashed names!

Protocol (from CCAC project)



Actual Code

Code Flow

- run script with **python gen_hash.py [csv filename] 150**
- code reads in the csv, stores name column and other variables into separate lists
  - cleans the names by lowercasing and removing all spaces
- code splits each name into **2-shingles**
- for each 2-shingle, the **salt is appended to the front and back, the iteration number, and then a hash value is obtained**
- in each iteration till 150, we take the **minimum of the these values**
- we end up with a series of **150 minhashes, which we call the signature**.
- code then outputs the names, cleaned names, the hash signature, and other relevant variables into a csv
- **remember to drop the names afterwards!** They are there just for checking purposes!

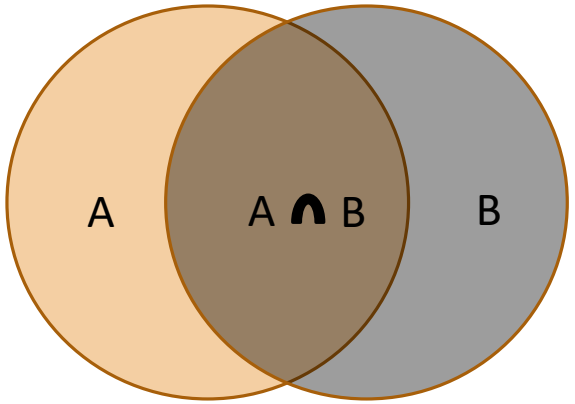
Merging

- Compare the hash signatures (vector of 150 hashes)
- As mentioned, two strings which are exactly the same should produce the exact same vector

Leona'rd Bloo#mfield	[4627305473336, 5086361082474, 19804513338981, 1
Wilhelm Wundt#	[4627305473336, 2940959422940, 5011493785980, 88
William James	[49637563509771, 3743988101286, 27797746129796,

Merging

- **Jaccard Similarity**



$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

Shared values / Total unique values

Currently, we have used a modified similarity score that is the **intersection divided by the width (150),** which gives us a more intuitive score closer to 1. Basically this measures the ratio of shared values to non-shared ones.

Merging

- Optimal threshold is difficult to determine (we've tried 0.9, 0.95)
- Currently in R, but we can also develop a Python script for it
  - And vice versa, the hashing is done in Python, but it may be possible to port it to other programming languages (There's a version made for SQL Studio, with the help of Dejan)
- Next week, we'll see if we can try it out on a sample dataset!

Validation

- Difficult to definitively validate due to impossibility of accessing ground truth (viewing true names from both datasets)
- Proxy validation with “fake data”
  - Try to merge two hashed datasets of created names with some variation
  - Check if merging works as intended
  - This is what we did with Dejan at IDPH

ID	NAME	HASH (DEJAN)	HASH (LEOSON)	EQUAL
1	Leona'rd Bloo#mfield	[4627305473336, 5086361082474, 19804513338981, 1573	[4627305473336, 5086361082474, 19804513338981, 15	TRUE
2	Wilhelm Wundt#	[4627305473336, 2940959422940, 5011493785980, 88145	[4627305473336, 2940959422940, 5011493785980, 881	TRUE