

Sampling Size 1

```
sm11326_nyu_edu@nyu-dataproc-m:~$ hadoop fs -cat output2/part-r-00000
@@51669441 <p> The commissioner said the Almajiris who were recently deported by Kan
the community . <p> Meanwhile , the Kaduna State government said the , " Installatio
e NCDC , this will increase to three the number of COVID-19 testing labs activated i
ed the people of Kaduna state for their sacrifice and cooperation in enduring Quarant
m other states and avert the nightmare of community transmission " . <p> The governm
ted by robust enforcement of boundary lockdowns . <p> Advertisement <p> " This will
f Kaduna State Quarantine Orders and the prohibition of inter-state travel by the Fe
El-Rufai.
sm11326_nyu_edu@nyu-dataproc-m:~$ █
```

Explanation – ReservoirSampling.java

In this Hadoop MapReduce program for reservoir sampling, the **Mapper** reads each input line and simply passes it as a key-value pair to the **Reducer**, where all lines are grouped under a single key ("sample"). The **Reducer** implements the reservoir sampling algorithm, which is designed to randomly select a subset of k lines (default 900) from the input data. It iterates through all the input lines, filling the reservoir until it reaches k elements, and then replacing elements in the reservoir with a certain probability as more lines are encountered. Finally, the **Driver** class configures and runs the MapReduce job, setting paths for the input and output directories, specifying the Mapper and Reducer classes, and ensuring that only one Reducer task is used (`job.setNumReduceTasks(1)`) for simplicity. The job then processes the input data and outputs a random sample of lines to the specified output directory.

Note : I Have the driver class, reducer class and mapper class chained within the

same ReservoirSampling.java class for ease of use.

Question 2) Spark – Language Models - in Spark - 50 points

To find the probability of the third word occurring in a trigram given that two words have already occurred,

- I am using the formula = $P(w_3 | w_1 w_2) = \text{count}(\text{trigrams}(w_1 w_2 w_3)) / \text{count}(\text{bigrams}(w_1 w_2))$
- I have three versions –
- Version 1 : without applying any regex or filtering and extracting meaningless trigram probabilities.

```
spark.SparkContext
```

trigram	trigram_count	conditional_probability
[@, @, @]	113349	0.8886563021850084
[., <p>, "]	7959	0.16716022934912733
[., <p>, The]	6287	0.13204376955873395
[., ", <p>]	4810	0.4664468580294802
[said, ., <p>]	2415	0.5625436757512229
[,, ", he]	1487	0.16955530216647663
[<p>, ", We]	1376	0.15076147693656186
[., <p>, In]	1321	0.02774452355449142
[the, spread, of]	1180	0.9161490683229814
[,, ", said]	1142	0.13021664766248575

- Version 2 : Filtering out everything apart from [A-z a-z 0-9]

trigram	trigram_count	conditional_probability
[the, spread, of]	1180	0.9161490683229814
[of, the, coronavirus]	854	0.04978430686720298
[as, well, as]	824	0.7285587975243147
[the, number, of]	819	0.9457274826789839
[one, of, the]	791	0.6233254531126872
[spread, of, the]	772	0.5482954545454546
[due, to, the]	719	0.42244418331374856
[the, coronavirus, pandemic]	711	0.20887191539365452
[of, the, virus]	691	0.04028214993587501
[the, end, of]	615	0.9057437407952872

- Version 3 : Applying Broadcasting and making it even faster as Professor suggested in the class.

trigram	trigram_count	conditional_probability
[the, spread, of]	1180	0.9161490683229814
[of, the, coronavirus]	854	0.04978430686720298
[as, well, as]	824	0.7285587975243147
[the, number, of]	819	0.9457274826789839
[one, of, the]	791	0.6233254531126872
[spread, of, the]	772	0.5482954545454546
[due, to, the]	719	0.42244418331374856
[the, coronavirus, pandemic]	711	0.20887191539365452
[of, the, virus]	691	0.04028214993587501
[the, end, of]	615	0.9057437407952872

Code Explanation :

In this code, I am building a trigram language model using PySpark to calculate the conditional probability of a third word, given the first two words in a sequence.

The input text is read from text files and split into words. I then filter out any sequences that contain non-alphanumeric words, ensuring that only valid words remain. Using explode and transform, I generate bigrams (pairs of consecutive words) and trigrams (triplets of consecutive words) from the word sequences.

I calculate the counts of each bigram and trigram, and then create prefixes for the trigrams to match them with their corresponding bigrams. After joining the trigram counts with the bigram counts, I compute the conditional probability of a trigram by dividing its count by the count of its bigram prefix. Finally, I order the trigrams by their count in descending order and display the top 10 trigrams along with their respective conditional probabilities. This gives insights into which word triplets are most likely to occur together in the text.

Question 3) Ranking over Partitions – in Spark. - 50 points

In this code, I am analyzing bakery sales data to find the top 3 items purchased during different parts of the day (morning, noon, afternoon, and evening). First, I read the data and convert the "Time" column into a timestamp, then create a new column "Daypart" to categorize each entry into one of the four time periods based on the hour of the day. After grouping the data by "Daypart" and "Item", I count the number of sales for each item within each daypart. Using a window function, I rank the items within each daypart by their sales count. I then filter to get the top 3 items per daypart and aggregate them into a list, which is displayed as the final result.

This process leverages Spark's window functions and groupings to efficiently compute the top 3 items per daypart in large datasets. The window function partitions the data by "Daypart" and orders it by the item sales count, while the rank() function helps identify the top 3 items. Finally, collect_list() is used to gather these top items for each daypart into a list, making it easy to view the most popular items for each period of the day.

Daypart	TopItems
afternoon	[Coffee, Bread, Tea]
evening	[Coffee, Bread, Tea]
morning	[Coffee, Bread, Pastry]
noon	[Coffee, Bread, Tea]

Manual Verification :

Top 3 Items per Daypart (Ranked):

Daypart	TopItems
afternoon	[Coffee, Bread, Tea]
evening	[Coffee, Bread, Tea]
morning	[Coffee, Bread, Pastry]
noon	[Coffee, Bread, Tea]

Verification: Raw counts for the top 3 items per daypart:

Daypart	Item	count
afternoon	Coffee	1476
afternoon	Bread	847
afternoon	Tea	566
evening	Coffee	87
evening	Bread	55
evening	Tea	49
morning	Coffee	1615
morning	Bread	1081
morning	Pastry	453
noon	Coffee	2293
noon	Bread	1342
noon	Tea	540

Question 4) : Duplicate Detection with Minhash – 50 points

Top 5 Urls - MINHASH LSH using Approx Nearest Neighbours algorithm which uses Jaccard Similarity

[Stage 22:=====]>			(1 + 1) / 2]
link	category	short_description	
https://www.huffingtonpost.com/entry/mom-hilariously-nails-what-getting-ready-looks-like-for-mothers_us_595666f0e4b0da2c73230b40	PARENTS	"Maybe she's born with it ... Maybe she's a tired mom who doesn't have time for this."	
https://www.huffingtonpost.com/entry/how-to-make-the-perfect-c_us_5b9dc24ee4b03a1dcc8c8503	FOOD & DRINK	A cookie with the perfect combination of fat, flavor, and comfort. Who needs detox?	
https://www.huffingtonpost.com/entry/andrew-garfield-lip-syncs-whitney-houston-in-epic-drag-show-act_us_592ff5d1e4b0540ffc84b79b	ENTERTAINMENT	With a back flip and everything.	
https://www.huffingtonpost.com/entry/linked-by-their-choice-to-become-single-mothers-two-women-share-their-stories_us_59b91b63e4b0edff9717de69	PARENTS	The stories of an Idaho mom who gave birth and a California mom who adopted.	
https://www.huffingtonpost.com/entry/carol-brady_us_5b9c5c92e4b03a1dcc7e15be	PARENTING	Here's the story of a lovely lady — who somehow kept six kids, a husband, a housekeeper and a dog in perfect order with	

Method 2 : Done by manually calculating Jaccard Similarity (Used as verification for the first!)

Top 5 items using Manual Jaccard Similarity:		
link	category	short_description
https://www.huffingtonpost.com/entry/mom-hilariously-nails-what-getting-ready-looks-like-for-mothers_us_595666f0e4b0da2c73230b40	PARENTS	"Maybe she's born with it ... Maybe she's a tired mom who doesn't have time for this."
https://www.huffingtonpost.com/entry/how-to-make-the-perfect-c_us_5b9dc24ee4b03a1dcc8c8503	FOOD & DRINK	A cookie with the perfect combination of fat, flavor, and comfort. Who needs detox?
https://www.huffingtonpost.com/entry/andrew-garfield-lip-syncs-whitney-houston-in-epic-drag-show-act_us_592ff5d1e4b0540ffc84b79b	ENTERTAINMENT	With a back flip and everything.
https://www.huffingtonpost.com/entry/linked-by-their-choice-to-become-single-mothers-two-women-share-their-stories_us_59b91b63e4b0edff9717de69	PARENTS	The stories of an Idaho mom who gave birth and a California mom who adopted.
https://www.huffingtonpost.com/entry/carol-brady_us_5b9c5c92e4b03a1dcc7e15be	PARENTING	Here's the story of a lovely lady — who somehow kept six kids, a husband, a housekeeper and a dog in perfect order with

Step 1: Data Preparation and Tokenization

I started by loading a dataset of HuffPost articles and a base article description. I used Tokenizer to split each article's short_description into individual words,

creating a words column in the DataFrame. Tokenization was essential here, as it allowed me to compare articles based on shared words.

Step 2: Vectorization Using HashingTF

To enable the MinHashLSH model to work with this text data, I converted the tokenized words into feature vectors using HashingTF. This step generated a fixed-length feature vector for each article's words, allowing the model to perform efficient similarity calculations. HashingTF effectively reduced the dimensionality of the text data by hashing words into a numerical representation of a specific length (numFeatures=10000), capturing word frequency information while avoiding the computational expense of more complex embeddings.

Step 3: Finding Similar Items with MinHashLSH

With feature vectors in place, I applied MinHashLSH to find approximate nearest neighbors to the base article. MinHashLSH is particularly useful in high-dimensional data, as it groups similar items by hashing, allowing for fast and approximate similarity calculations. After fitting the MinHashLSH model to the data, I queried the model for the top 5 articles with the highest similarity to the base article. This gave me a set of candidates with similar content based on hash proximity, approximating Jaccard similarity efficiently.

Step 4: Validation Using Manual Jaccard Similarity

To validate the accuracy of the MinHashLSH results, I manually calculated the Jaccard similarity between the base article and each article in the dataset. I used a custom UDF (User Defined Function) to compute Jaccard similarity by finding the intersection and union of word sets for each article and the base description. I then selected the top 5 articles with the highest Jaccard similarity, creating a second list of most similar items based on exact similarity.

Results Comparison

Finally, I displayed the top 5 similar articles based on both MinHashLSH and manual Jaccard similarity. This allowed me to evaluate how closely the approximate similarity matched the exact Jaccard results, illustrating the balance between accuracy and computational efficiency offered by MinHashLSH in large datasets. This dual approach highlights the practical utility of MinHashLSH as a fast, scalable approximation for Jaccard similarity in text-based similarity tasks.

AI Acknowledgement

I have used ChatGPT & Perplexity to understand Jaccard Similarity, 1.MinHash LSH and HashingTF in Q4 because I didn't know this before. Also I used it to generate a validation code for my existing code in Q3, just to check if my answers are correct. I also used GPT to figure out Hadoop .jar compilation commands, and also to verify my Reducer, as it was erroneous in the beginning in Q1.

THANK YOU!

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