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PUNE INSTITUTE OF COMPUTER TECHNOLOGY, DHANKAWADI PUNE-43. A Seminar Report On Similarity Search Algorithms on Embeddings in Face Recognition SUBMITTED BY NAME: Apoorv Dixit ROLL NO: 31106 CLASS: TE-1 GUIDED BY PROF. P. S. Vidap COMPUTER ENGINEERING DEPARTMENT Academic Year: 2019-20

PUNE INSTITUTE OF COMPUTER TECHNOLOGY, DHANKAWADI PUNE-43. CERTIFICATE This is to certify that

Mr. Apoorv Dixit , Roll No. 31106 a student of T.E. (Computer Engineering Department) Batch 2019-2020, has satisfactorily completed a seminar report on "Similarity Search Algorithms on Embeddings in Face Recognition" under the guidance of Prof. P. S.Vidap towards the partial ful- fillment of the

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third year Computer Engineering Semester II of Pune University. Prof. P. S. Vidap Dr. R.B.Ingle Internal Guide Head of Department, Computer Engineering Date:

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Abstract: Face Recognition

is a challenging task in computer vision in which researchers from all over the world have made great strides owing to the development of more robust and accurate deep learning models. These frameworks have come a long way from hand engineered systems to the end-to-end mapped models that are state of the art today. However, implementing faster similarity search of face features is an increasingly important problem. There is a dire need to address this issue in order to make the face recognition pipelines scalable and more suited for real time applications. This seminar aims to benchmark di erent similarity search algorithms on face embeddings generated from a standard face dataset. The benchmarking will help other users choose a nearest neighbour search method for their face recognition models. Keywords: Face recognition, computer vision, deep learning model, nearest neigh- bor search, embeddings, similarity search, benchmark.

Similarity Search Algorithms on Embeddings in Face Recognition Contents

Similarity Search Algorithms on Embedding in Face Recognition 6 1 INTRODUCTION Face Recognition is the task

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of identifying a person from either a digital image or a frame from a video.

This task is typically accomplished by obtaining facial features of a face from a given image and subsequently comparing it with other faces stored in a database. It finds its appli- cation in a wide variety of fields like robotics, access controls in security systems, commercial identification, marketing tool, human computer interaction, video surveillance, biometrics and many more. Face Recognition's contactless and non-invasive process is what sets it apart from other biometric technologies like iris recognition and fingerprint recognition. Face Recognition is a task that can be performed trivially by humans, but can prove to be a daunting challenge for machines. It has remained so for computer vision problems until recently. There have been major strides in the development of more accurate and robust systems in face recognition owing to the advent of artificial intelligence in the past two decades. We have come a long way from the hand engineered models used in the beginning of the 21 st century to the deep learning pipelines that are pretty much the state of the art today. It is only in recent times that these state of the art models have matched, if not surpassed, the human accuracy. The deep learning systems employed take into consideration various variable conditions like light textures, pose and orientation of the person's face, age of the person, the varying facial hair and much more. Face Recognition Pipelines are primarily broken down into the following major subtasks – Face Detection, Face Alignment, Feature Extraction and finally, the recognition task. The Modern deep learning pipelines for facial recognition systems deploy deep learning models for the first three subtasks, and use an Approximate Nearest Neighbour Search Algorithm (ANN) for the recognition. This report will be focusing on face embeddings and various ANN, which will cater to Feature Extraction and Recognition respectively. Figure 1: Face Recognition Pipeline Architecture 1.1 Motivation While accuracy is not that big of a problem in Face Recognition Systems anymore, making them more suited for real time tasks is. The deep learning models that we see today have been trained on millions of faces. The memory footprint of these models is way too heavy to be used for real time systems. Moreover deep learning pipelines are composed of more than one "Department of Computer Engineering, PICT Pune" P:F/SMR-UG/08/R0

Similarity Search Algorithms on Embedding in Face Recognition 7 deep learning model, to perform the di erent subtasks like Face Detection, Face Alignment and Feature Extraction. This makes them too slow for achieving the overall objective. This issue can be tackled in two ways. The first way is to design a more light weight deep learning model for feature extraction. The second way is to select a fast ANN for the final recognition subtask. This final subtask involves comparing the extracted features of the face obtained with that of faces stored in a database. This subtask returns the ID of the person the face resembles the closest to, thereby recognizing the person. The database typically stores the extracted features of faces rather than the images of the faces themselves. The comparison is done by an ANN. 1.2 Literature Survey 1.2.1 Proprietary Feature Extracting Models Most of the proprietary deep learning models for embedding generation which are state of the art are proprietary. Their saved models are not readily available. 1.2.2 Older ANNs are implemented in Python 2 Many of the older ANNs have been implemented in Python 2. Due to which they cannot be benchmarked against Python 3 ANNs. Python 2.x is generally faster than Python 3.x, which gives the former an unfair advantage. 1.2.3 Need better GPUs for generating a larger embedding dataset A larger embedding dataset will enable us to capture the performance of ANNs more e ec- tively, thereby making the results more accurate. 1.3 Challenges 1.3.1 Proprietary Feature Extracting Models Most of the proprietary deep learning models for embedding generation which are state of the art are proprietary. Their saved models are not readily available. 1.3.2 Older ANNs are implemented in Python 2 Many of the older ANNs have been implemented in Python 2. Due to which they cannot be benchmarked against Python 3 ANNs. Python 2.x is generally faster than Python 3.x, which gives the former an unfair advantage. 1.3.3 Need better GPUs for generating a larger embedding dataset A larger embedding dataset will enable us to capture the performance of ANNs more e ec- tively, thereby making the results more accurate. “Department of Computer Engineering, PICT Pune” P:F/SMR-UG/08/R0

Similarity Search Algorithms on Embedding in Face Recognition 8 2 FACE EMBEDDINGS For Feature extraction, the deep learning model trains itself to extract features of a given di- mension from millions of images. The input for these neural network models are face images which are cropped and aligned for better performance. The output of these models is a vector of a given dimension which encompasses the features of the face. These are called face em- beddings. Thus, the embedding of the person in question is generated, which is then compared against the embeddings of the faces stored in the database. Needless to say, embeddings stored in the database are generated from the same deep learning model. FaceNet is the

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deep convolutional network trained to directly optimize the embedding itself.

FaceNet accelerated the research in Face Recognition and most of the State of the Art Face Embedding generators find their base in FaceNet. These modern derivatives of FaceNet are State of the Art albeit proprietary models. DR-GAN, on the other hand, approaches pose invariant face recognition with a novel represen- tation. This representation is generative and discriminative in nature which leverages the face frontalization of DR-GAN. This pose invariant representation shows promising results in face recognition research. In this report, we have generated face embeddings for a dataset, created a database out of the same and then benchmarked various ANN on the database synthesized. We have generated embeddings using FaceNet and DR-GAN. The dataset used for this seminar is VGGFace2. VGGFace2 is a large-scale face recognition dataset. This dataset has large variations in pose, age, illumination, ethnicity and profession. DR-GAN was trained on VGGFace2. It is interesting to note when t-SNE technique is applied on the FaceNet Embeddings, the em- beddings of the same person group together, since they are similar. Thus FaceNet embeddings portray an impressive cluster analysis. DR-GAN on the other hand does not show significant clustering under t-SNE. “Department of Computer Engineering, PICT Pune” P:F/SMR-UG/08/R0

Similarity Search Algorithms on Embedding in Face Recognition 9 Figure 2: TSNE Analysis on FaceNet Embeddings Figure 3: TSNE Analysis on DR-GAN Embeddings “Department of Computer Engineering, PICT Pune” P:F/SMR-UG/08/R0

Similarity Search Algorithms on Embedding in Face Recognition 10 3 APPROXIMATE NEAREST NEIGHBOURS Nearest neighbor search (NNS) is the optimization problemof finding the point in a given set that is closest (or most similar) to a given point. Closeness is typically expressed in terms of a dissimilarity function: the less similar the objects, the larger the function values. In some applications it may be acceptable to retrieve a "good guess" of the nearest neighbor. In those cases, we can use an algorithm which doesn’t guarantee to return the actual nearest neighbor in every case, in return for improved speed or memory savings. These algorithms are called Approximate Nearest Neighbour Search (ANN). The recognition subtask involves comparing the embedding of the face obtained with that of faces stored in a database. This subtask returns the ID of the person the face resembles the closest to, thereby recognizing the person. The database typically stores the face embeddings rather than the images of the faces themselves. The comparison is done by an ANN. In this report, I have benchmarked various ANN algorithms on the basis of queries executed versus Time. This benchmarking has been done on the FaceNet embeddings. The ANN algo- rithms either have a python wrapper, a python package or were cloned from Github. Moreover, some ANN algorithms support batch processing. 4 IMPLEMENTATION 4.1 Platforms and Technologies Google Colaboratory - It is a free Jupyternotebook environment that runs in the cloud and stores its notebooks on Google Drive. The implementation is done on Google Colaboratory (Colab) under Python 3 environment. 4.2 Python Libraries Core Libraries Time numpy pandas sklearn 2to3 keras_facenet Matplotlib “Department of Computer Engineering, PICT Pune” P:F/SMR-UG/08/R0

Similarity Search Algorithms on Embedding in Face Recognition 11 ANN Python Libraries annoy nearpy ngt pyflann mrpt pynndescent faiss rpforest hnswlib nmslib n2 DolphinnPy FALCONN nanopq 4.3 Process Description Figure 4: Report Implementation Overview For the first part of this report two sets of embeddings have been generated for 5000 test images of VGGFace2. These 5000 images include 10 images each of 500 people. The two sets of embeddings are the FaceNet embeddings and DR-GAN’s pose invariant embeddings. FaceNet embeddings have been generated using a Python library of the same. On the other hand, DR-GAN's embeddings have been generated using the demo test code on their o cial site. After the demo of the embedding, we have benchmarked 20 ANN algorithms on the basis of queries executed versus Time. This benchmarking has been done on the FaceNet embeddings generated in the previous part. The ANN algorithms either have a python wrapper, a python package or were cloned from Github. Moreover, some ANN algorithms support batch processing. Some of the older ANNs which were implemented in Python 2 were converted to equivalent Python 3 code using Python 2to3 refactoring tool. This benchmarking has been done on Google Colab. "Department of Computer Engineering, PICT Pune" P:F/SMR-UG/08/R0

Similarity Search Algorithms on Embedding in Face Recognition 12 4.4 Source Code Figure 5: Source Code for FaceNet Embedding Generation This Python 3 script was used to create a database which contains FaceNet Embeddings of 5,000 faces. 10 images each were selected for 500 persons. This database was subsequently saved as a CSV file as "database.csv" . A similar Python 3 script was used to create a database of DR-GAN Embeddings as well "Department of Computer Engineering, PICT Pune" P:F/SMR-UG/08/R0

Similarity Search Algorithms on Embedding in Face Recognition 13 Figure 6: Source Code for Retrieving FaceNet Embeddings This Python 3 Cell in Google Colaboratory Notebook was used to load the FaceNet Embed- dings from "database.csv" and initialize various other parameters. A similar cell was used for DR-GAN Embeddings as well. "Department of Computer Engineering, PICT Pune" P:F/SMR-UG/08/R0

Similarity Search Algorithms on Embedding in Face Recognition 14 Figure 7: Benchmarking ANN with batch processing This Python 3 Cell in Google Colaboratory Notebook is an example of the benchmarking of an ANN which does not facilitate batch processing. Figure 8: Benchmarking ANN without batch processing This Python 3 Cell in Google Colaboratory Notebook is an example of the benchmarking of an ANN which facilitates batch processing. "Department of Computer Engineering, PICT Pune" P:F/SMR-UG/08/R0

Similarity Search Algorithms on Embedding in Face Recognition 15 4.4 Output 20 ANN libraries in Python 3 have been benchmarked on FaceNet embeddings on 5000 images of VGGFace2 dataset successfully and the results are tabulated below: Table 1: ANN Benchmarks Figure 9: Queries vs Time graph "Department of Computer Engineering, PICT Pune" P:F/SMR-UG/08/R0

Similarity Search Algorithms on Embedding in Face Recognition 16 5 CONCLUSION AND FUTURE SCOPE 5.1 Conclusion Face Recognition is an active area of research and making it more suited for real time applica- tion still proves to be a challenging task. This report provides an insight on generation of face embeddings and analysis of performance of various Approximate Nearest Neighbour Libraries. The results generated establish that while ANNOY ANN is the fastest ANN for a single query, PyNNDescent delivers the fastest results for multiple queries, given that it can facilitate batch processing as well. Some other fast ANNs are HNSWLib, NMSLib, MRPT and NGT. The results generated will help developers to choose a suitable ANN for their Face Recognition Pipeline. 5.2 Future Scope Even though the results generated are satisfactory, to make this project more comprehensive, the following points can be added. Include more Deep Learning Models for Embedding Generators. Include ANN algorithms written in Python2 by converting their code to Python3 and further optimise their performance with the new features of Python3. A larger Embedding Dataset can be generated to capture the performance of ANN more accurately. References [1] M. Aumüller, E. Bernhardsson and

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