Federated Learning for Person Re-Identification

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Safety and security have always been critical issues in our world, but with the ever-growing technology of the modern world, maintaining them now is more important than ever. Person Re-Identification is a technology that can enhance both safety and security through applications such as tracking down criminals and finding missing persons. Typical machine learning techniques use centralized data collection to train models. Personal data, such as surveillance footage, leaving devices and moving to the cloud violates people's privacy. We use Federated Learning to implement the task of Person Re- identification to eliminate privacy concerns.

Literature Review

The use of federated learning in person Re-ID is fairly novel and unexplored. One of the first implementations was proposed by Zhuang et al. [1] in October 2020, in which a new benchmark was introduced for FedReID by using nine datasets of broad differences in identity & image numbers, amount of camera views, etc. to simulate the challenges of such a system in real-world. They explored the different algorithms of FL, two dif- ferent federated scenarios and proposed an FL algorithm called Federated Partial Averaging (FedPav) which allows clients of partially different models to be trained in a federated way. The federated scenarios were representing two architectures: client-edge-cloud architecture and client-server architecture. The benchmark analysis results proved the client-edge- cloud, the federated-by-dataset scenario, to have better performance. For the Re-ID, the model structure was the IDE model. The performance metrics were divided into two categories. The first was Re-ID evaluation metrics represented by the customary metrics such as the CMC and mAP [2]. The second category was the communication cost calculated by the number of communication rounds times twice the model size. To enhance performance, two techniques were suggested: knowledge distillation and dynamic weight adjustment. The effectiveness of these techniques to ease convergence and attain better performance has been backed up by numerical results.

Methodology

Analysis concerning the effects of different image recognition models, as well as the various size of datasets, in the task of FedReID was conducted.

Re-ID Model Structure:
ID-discriminative embedding (IDE) with a ResNet backbone.

The FedReID implementation experimented on is by Performance Optimization for Federated Person Re- identification via Benchmark Analysis by Zhuang et al. [1]

Datasets used: MSMT17 [3], Market1501 [4], DukeMTMC-reID [5], CUHK03 [6], 3DPeS [7], VIPeR [8] , PRID2011 [9], CUHK01 [6] and iLIDS- VID [10].

Federated Learning Algorithm: Federated Partial Averaging (FedPav)

Experiment A: ResNet Comparison
Federated model trained on 9 clients using the following models:

- ResNet18
- ResNet50

Experiment B: Dataset Size Comparison
Federated model is trained using different sized datasets as clients to analyze the effects of client size. The model is tested on 2 control datasets using the following combinations as clients on which the model is trained:

- 3 small datasets
- 3 large datasets
- 2 small datasets + 1 large dataset

Results

A

a probability score that the prediction is Rank-k depicts the probability that the query exists in the returned galley of k images. mAP returns correct.

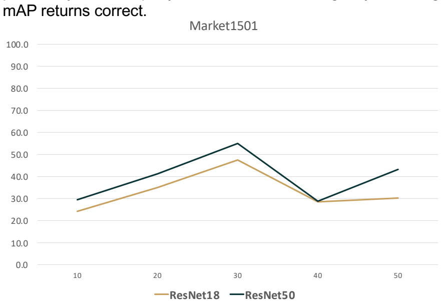

Figure 1.1: mAP score in percentage results using ResNet18 and ResNet50 on Market1501 for 50 rounds

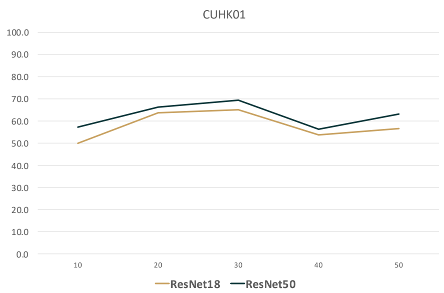

Figure 1.2: mAP score in percentage results using ResNet18 and ResNet50 on CUHK01 for 50 rounds

B

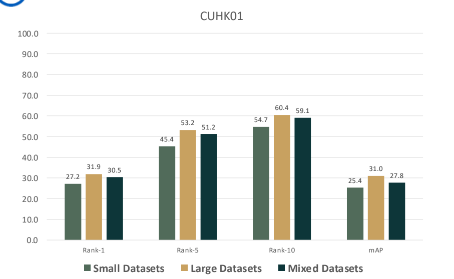

Figure 2.1: CMC and mAP percentage results on CUHK01 using different sizes of clients

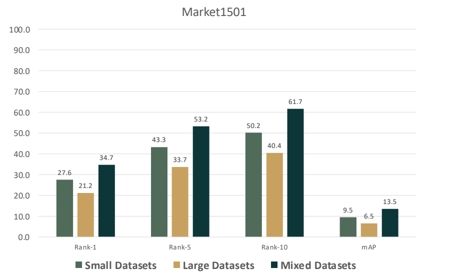

Figure 2.2: CMC and mAP percentage results on Market1501 using different sizes of clients

Conclusion

This study was carried out in the mission of achieving both privacy and accuracy in the task of Person Re- Identification through Federated Learning. The results have revealed that the ResNet50 model performs better than ResNet18, supported by the findings in the graphs, as well as the effect of the size of the clients' dataset. Further work will include analysis of more image recognition models in FedReID.

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