We present an analysis of the performance of Federated Learning in a paradigmatic natural-language processing task: Named-Entity Recognition (NER). For our evaluation, we use the language-independent CoNLL-2003 dataset as our benchmark dataset and a Bi-LSTM-CRF model as our benchmark NER model. We show that federated training reaches almost the same performance as the centralized model, though with some performance degradation as the learning environments become more heterogeneous. We also show the convergence rate of federated models for NER. Finally, we discuss existing challenges of Federated Learning for NLP applications that can foster future research directions.
and large-scale organizations (cross-silo).

Other approaches have provided convergence guarantees for the original FedAvg algorithm over non-IID data (Li et al., 2019) while others have decoupled the federated optimization problem into global and local optimization (Wang et al., 2021; Reddi et al., 2020) with linear (Mitra et al., 2021; Karimirad et al., 2020) and sub-linear convergence guarantees (Li et al., 2020; Wang et al., 2020) in the presence of different client learning constraints, such as system (different computational capabilities) and statistical heterogeneities (different local dataset distributions).

Even though many federated training approaches have been proposed most of them focus in the context of computer vision and only a handful of them provide a federated solution tailored for NLP applications (Liu et al., 2021; Lin et al., 2021). For instance, federated learning has been applied to tackle the problem of next word keyboard prediction (Hard et al., 2018; Stremmel and Singh, 2021; Yang et al., 2018), speech recognition (Leroy et al., 2019) and health text mining (Liu et al., 2019). In the context of sequence tagging and named entity recognition recent works have investigated the feasibility of a federated learning solution on medical named entity extraction (Ge et al., 2020) and extraction of personally identifiable information elements from text documents (Hathurusinghe et al., 2021).

For the NER task that we investigate in this work, one of the first successful uses of neural networks was the Bi-LSTM (Hochreiter and Schmidhuber, 1997) and CRF (Lafferty et al., 2001) models, with both models combined into a single state-of-the-art deep learning model architecture (Lample et al., 2016) that exhibited superior performance. Other recent works have proposed large transformer-based models such as BERT (Devlin et al., 2019) and XLM (Lample and Conneau, 2019). However, for understanding the impact of federated training in the learning performance of the NER task, in this work we employ the Bi-LSTM-CRF model, similar to (Mathew et al., 2019).

3 NER Model

We use a Bi-LSTM layer which is fed a concatenation of 300-dimension GloVe (Pennington et al., 2014) word embedding and a character embedding that is trained on the data as input. We use dropout during training, set at 0.5. The output of the Bi-LSTM model is then fed into a CRF layer in order to capture neighboring tagging decisions. The CRF layer produces scores for all possible sequences of tags over which we apply the Softmax function to produce the output tag sequence. Figure 1 shows the architecture of the deep learning model used throughout training. The total number of trainable parameters are 322,690.

4 Experiments

For all learning environments (centralized and federated) the random seed was set to 1990. We use Vanilla SGD as the solver of the centralized model and the local model in the federation with a learning rate of 0.01 and batch size of 20.

**Federated Training.** Our federated environments follow a centralized learning topology (Bellavista et al., 2021; Yang et al., 2019; Kairouz et al., 2021) where a single aggregator (server) is responsible to orchestrate the execution of the participating clients. In our experiments, we consider full client participation at every round. We test the performance of the federated model on federation environments consisting of 8, 16 and 32 clients. Each client trained on its local dataset for 4 local epochs in-between federation rounds and each federated experiment was run for a total number of 200 rounds. When merging the local models at the server, we used FedAvg as the merging function. During training clients shared the kernel and bias matrices of the LSTM and dense layers and the transition matrix of the CRF layer. All

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1https://github.com/guillaumegenthial/tf_ner
federated environments were run using the Metis framework (Stripelis and Ambite, 2021).

**Federated Data Distributions.** The CoNLL-2003 (Sang and De Meulder, 2003) is a language-independent newswire dataset developed for the named entity recognition task. The dataset consists of 20,744 sentences (14041 training, 3250 validation, 3453 test) and contains entities referring to locations (LOC), organizations (ORG), people (PER), and miscellaneous (MISC).

We measure that classification performance for all entities. The original tagging scheme is BIO (beginning-intermediate-other). When extracting the named entities two subtasks need to be solved, finding the exact boundaries of an entity, and the entity type. The metrics used to evaluate correct tag (entity) predictions are Precision, Recall and F1. All models were evaluated on the same original test dataset.

To generate the federated environments that we investigate in this work, we split the dataset into equal (Uniform) and unequal (Skewed) sized partitions. For the Uniform environments, we combine the training and validation datasets of the original dataset and split them into approximately equally sized partitions for 8, 16 and 32-clients, such that each partition (client) has almost the same proportion of different tag types. The proportion of tags in each split is approximate, as it can also be seen in Figure 2, since any sentence can have any number of different tags. For the 32-clients and Skewed environment, we randomly partitioned the combined training and validation datasets into 32 splits over an increasing amount of data points (200 to 872 sentences). This increased the data heterogeneity across all partitions with certain partitions containing more unique entity mentions (compared to the Uniform environments); see also Figure 3d.

Figure 2 presents the total number of location, organization and person tags at each client within each federation environment. For Uniform environments, a similar amount of tags has been assigned to each client. For the Skewed environment, the distribution of tags follows a left-skewed assignment. A similar distribution pattern can be observed for tags present in only one client, which we call unique tags. Figure 3 shows the numbers of unique location, organization and person entities each client contains. Finally, Figure 4 shows how many clients contain each entity, that is, how many tags appear simultaneously at K number of clients (e.g., K=5 gives how many tags appear in exactly 5 clients).

![Figure 2: CoNLL-2003 dataset: B-LOC, B-ORG and B-PER entity (tag) distribution for each client within each federation environment.](image)

![Figure 3: CoNLL-2003 dataset: Number of unique B-LOC, B-ORG and B-PER entity (tag) distribution for each client within each federation environment.](image)

**Results.** Table 1 shows the final learning performance of each model for each learning environment. As expected, the centralized model outperforms the federated models. However, the performance degradation is small (~2-3 percentage points). The degradation increases as the federation environments become more challenging, that is, with the number of clients and the heterogeneity of the data. As the number of clients increases, the amount of data available for local training decreases, which makes federated training harder.
We have empirically shown that Federated Learning can be successfully applied in the context of NLP to train deep learning models for Named-Entity Recognition. Across the federated environments that we investigate, the final NER model can reach an acceptable performance when compared to its centralized counterpart. As the federated learning environments become more challenging due to increased statistical heterogeneity and reduced data amount per client, a moderate performance decrease occurs, and more training rounds are required for the federation to converge.

Our immediate future work focuses on training NLP models when the text at each site is private. A critical pre-processing step for training deep NLP models is the creation of a common vocabulary/dictionary that maps each token to a unique identifier. In a centralized setting where all the data are located at a central repository the creation of such a vocabulary is straightforward. However, in a federated setting where the global dataset is split across multiple clients with each client having its own private local dataset, the creation of such a vocabulary is more challenging. Due to privacy concerns, clients need to always keep their data at their original location. They cannot reveal either sentences or individual words/tokens to others. For example, consider an intelligence domain where person names and locations under investigation at a site must be protected. Therefore constructing a common representation that includes all federation tokens needs to be performed in a secure and private way. In our experiments, we assumed that a publicly available vocabulary exists. We are currently investigating hashing methods that can provide a global, but private, vocabulary for federated training in NLP applications.
References

Paolo Bellavista, Luca Foschini, and Alessio Mora. 2021. Decentralised learning in federated deployment environments: A system-level survey. ACM Computing Surveys (CSUR), 54(1):1–38.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Suyu Ge, Fangzhao Wu, Chuhan Wu, Tao Qi, Yongfeng Huang, and Xing Xie. 2020. Fedner: Privacy-preserving medical named entity recognition with federated learning. arXiv preprint arXiv:2003.09288.

Andrew Hard, Kanishka Rao, Rajiv Mathews, Swaroop Ramaswamy, Françoise Beaufays, Sean Augenstein, Hubert Eichert, Chloé Kiddon, and Daniel Ramage. 2018. Federated learning for mobile keyboard prediction. arXiv preprint arXiv:1811.03604.

Rajitha Hathurusinghe, Isar Nejadgholi, and Miodrag Bolic. 2021. A privacy-preserving approach to extraction of personal information through automatic annotation and federated learning. arXiv preprint arXiv:2105.09198.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural Computation, 9:1735–1780.

Peter Kairouz, H Brendan McMahan, Brendan Avent, Aurélien Bellet, Mehdi Bennis, Arjun Nitin Bhagoji, Kallista Bonawitz, Zachary Charles, Graham Cormode, Rachel Cummings, et al. 2021. Advances and open problems in federated learning. Foundations and Trends® in Machine Learning, 14(1–2):1–210.

Sai Praneeth Karimireddy, Satyen Kale, Mehryar Mohri, Sashank Reddi, Sebastian Stich, and Ananda Theertha Suresh. 2020. Scaffold: Stochastic controlled averaging for federated learning. In International Conference on Machine Learning, pages 5132–5143. PMLR.

John D. Lafferty, Andrew McCallum, and Fernando Pereira. 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In ICML.

Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, and Chris Dyer. 2016. Neural architectures for named entity recognition. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 260–270, San Diego, California. Association for Computational Linguistics.

Guillaume Lample and Alexis Conneau. 2019. Cross-lingual language model pretraining. In NeurIPS.

David Leroy, Alice Coucke, Thibaut Lavril, Thibault Gisselbrecht, and Joseph Dureau. 2019. Federated learning for keyword spotting. In ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 6341–6345. IEEE.

Tian Li, Anit Kumar Sahu, Ameet Talwalkar, and Virginia Smith. 2020. Federated learning: Challenges, methods, and future directions. IEEE Signal Processing Magazine, 37(3):50–60.

Xiang Li, Kaixuan Huang, Wenhao Yang, Shusen Wang, and Zhihua Zhang. 2019. On the convergence of fedavg on non-iid data. In International Conference on Learning Representations.

Bill Yuchen Lin, Chaoyang He, Zihang Zeng, Hulin Wang, Yufen Huang, Mahdi Soltanolkotabi, Xiang Ren, and Salman Avestimehr. 2021. Fednlp: Benchmarking federated learning methods for natural language processing tasks. arXiv preprint arXiv:2104.08815.

Dianbo Liu, Dmitriy Diligach, and Timothy Miller. 2019. Two-stage federated phenotyping and patient representation learning. In Proceedings of the Conference. Association for Computational Linguistics. Meeting, volume 2019, page 283. NIH Public Access.

Ming Liu, Stella Ho, Mengqi Wang, Longxiang Gao, Yuan Jin, and He Zhang. 2021. Federated learning meets natural language processing: A survey. arXiv preprint arXiv:2107.12603.

Yi Liu, JQ James, Jiwen Kang, Dusit Niyato, and Shuyu Zhang. 2020a. Privacy-preserving traffic flow prediction: A federated learning approach. IEEE Internet of Things Journal, 7(8):7751–7763.

Yuan Liu, Zhengpeng Ai, Shuai Sun, Shuangfeng Zhang, Zelei Liu, and Han Yu. 2020b. Fedcoin: A peer-to-peer payment system for federated learning. In Federated Learning, pages 125–138. Springer.

Mónica Marrero, Julián Urbano, Sonia Sánchez-Cuadrado, Jorge Morato, and Juan Miguel Gómez-Berbís. 2013. Named entity recognition: fallacies, challenges and opportunities. Computer Standards & Interfaces, 35(5):482–489.

Joel Mathew, Shobeir Fakhræi, and José Luis Ambite. 2019. Biomedical named entity recognition via reference-set augmented bootstrapping. arXiv preprint arXiv:1906.00282.

Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Agueira y Arcas. 2017. Communication-efficient learning of deep networks from decentralized data. In Artificial intelligence and statistics, pages 1273–1282. PMLR.
Aritra Mitra, Rayana Jaafar, George Pappas, and Hamed Hassani. 2021. Linear convergence in federated learning: Tackling client heterogeneity and sparse gradients. Advances in Neural Information Processing Systems, 34.

Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. GloVe: Global vectors for word representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1532–1543, Doha, Qatar. Association for Computational Linguistics.

Sashank J Reddi, Zachary Charles, Manzil Zaheer, Zachary Garrett, Keith Rush, Jakub Konečný, Sanjiv Kumar, and Hugh Brendan McMahan. 2020. Adaptive federated optimization. In International Conference on Learning Representations.

Nicola Rieke, Jonny Hancox, Wenqi Li, Fausto Milletari, Holger R Roth, Shadi Albarqouni, Spyridon Bakas, Mathieu N Galtier, Bennett A Landman, Klaus Maier-Hein, et al. 2020. The future of digital health with federated learning. NPJ digital medicine, 3(1):1–7.

Erik F Sang and Fien De Meulder. 2003. Introduction to the CoNLL-2003 shared task: Language-independent named entity recognition. arXiv preprint cs/0306050.

Micah J Sheller, Brandon Edwards, G Anthony Reina, Jason Martin, Sarthak Pati, Aikaterini Kotrotsou, Mikhail Milchenko, Weilin Xu, Daniel Marcus, Rivka R Colen, et al. 2020. Federated learning in medicine: facilitating multi-institutional collaborations without sharing patient data. Scientific reports, 10(1):1–12.

Joel Stremmel and Arjun Singh. 2021. Pretraining federated text models for next word prediction. In Future of Information and Communication Conference, pages 477–488. Springer.

Dimitris Stripelis and José Luis Ambite. 2021. Semi-synchronous federated learning. arXiv preprint arXiv:2102.02849.

Jianyu Wang, Zachary Charles, Zheng Xu, Gauri Joshi, H Brendan McMahan, Maruan Al-Shedivat, Galen Andrew, Salman Avestimehr, Katharine Daly, Deepesh Data, et al. 2021. A field guide to federated optimization. arXiv preprint arXiv:2107.06917.

Jianyu Wang, Qinghua Liu, Hao Liang, Gauri Joshi, and H Vincent Poor. 2020. Tackling the objective inconsistency problem in heterogeneous federated optimization. Advances in neural information processing systems, 33:7611–7623.

Qiang Yang, Yang Liu, Tianjian Chen, and Yongxin Tong. 2019. Federated machine learning: Concept and applications. ACM Transactions on Intelligent Systems and Technology (TIST), 10(2):1–19.

Timothy Yang, Galen Andrew, Hubert Eichner, Haicheng Sun, Wei Li, Nicholas Kong, Daniel Ramage, and Françoise Beaufays. 2018. Applied federated learning: Improving google keyboard query suggestions. arXiv preprint arXiv:1812.02903.