Hush-hush Gradients: A Review of Differential Privacy for Deep Learning

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Introduction

The field of Deep Learning (DL) is for many subfields moving towards a setup where large multi-purpose foundation models are developed and trained at major companies or research instutitions, and then released for engineers to adapt to specific applications [Bom+21, pp. 3]. This application of the open-source principle to pre-trained models improves scientific reproduction ability [HO20, pp. 3] and technology accessibility [Bom+21, pp. 139]. One risk, however, is an adversarial actor exploiting a property of DL models: Parts of training data is generally recoverable from model weights [NSH19; Sho+17]. This might expose proprietary data or the private data of individuals as exemplified for Natural Language Processing (nlp) language models in Figure 1. As large-scale data sets are here to stay [Sun+17], algorithmic methods for improving the privacy of foundation models are required. The methods of Differential Privacy (DP) are suitable for this task and the relevant concepts, algorithms and problems will here be reviewed.

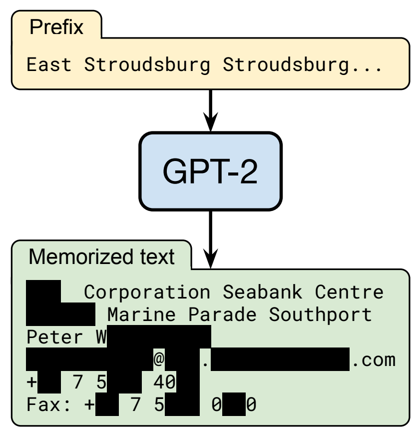

Figure 1: The extraction attack performed on GPT-2 [Car+21, Fig. 1] (private data redacted).

Fundamental Concepts

Achieving DP corresponds to making a promise of hiding information about individuals when publishing quantitative patterns about groups [DR14, pp. 5]. This general problem is historically faced in releases of statistical data analyses by e.g. official organizations [Dal77; Wik22]. An algorithm is thus differentially private if a third party observer cannot extract individual information from its' computation. In this context, a Machine Learning (ML) model $f(x|w) = \hat{y} \approx y$ trained on a data set $\mathcal{D}$ exposes data patterns when either its' parametrization w or predictions $(x, \hat{y})$ are released.

State of the Art

Open Problems

References

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