Downstream Task Performance of BERT Models Pre-Trained Using Automatically De-Identified Clinical Data

Thomas Vakili, Anastasios Lamproidis, Aron Henriksson, Hercules Dalianis
Department of Computer and Systems Sciences (DSV), Stockholm University, Kista, Sweden
{thomas.vakili, anastasios, aronhen, hercules}@dsv.su.se

Abstract

Automatic de-identification is a cost-effective and straightforward way of removing large amounts of personally identifiable information from large and sensitive corpora. However, these systems also introduce errors into datasets due to their imperfect precision. These corruptions of the data may negatively impact the utility of the de-identified dataset. This paper de-identifies a very large clinical corpus in Swedish either by removing entire sentences containing sensitive data or by replacing sensitive words with realistic surrogates. These two datasets are used to perform domain adaptation of a general Swedish BERT model. The impact of the de-identification techniques is assessed by training and evaluating the models using six clinical downstream tasks. The results are then compared to a similar BERT model domain-adapted using an unaltered version of the clinical corpus. The results show that using an automatically de-identified corpus for domain adaptation does not negatively impact downstream performance. We argue that automatic de-identification is an efficient way of reducing the privacy risks of domain-adapted models and that the models created in this paper should be safe to distribute to other academic researchers.

Keywords: Privacy-preserving machine learning, pseudonymization, de-identification, Swedish clinical text, pre-trained language models, BERT, downstream tasks, NER, multi-label classification, domain adaptation

1. Introduction

Natural Language Processing (NLP) research is currently dominated by so-called pre-trained language models based on transformers (Vaswani et al., 2017), which were popularized by the introduction of the BERT model by Devlin et al. (2019). These language models typically consist of millions – even billions – of parameters that are learned from enormous corpora. The success of pre-trained language models in general-domain tasks has prompted research into whether these models also succeed in medical-domain tasks.

Language models are taught to model language by learning the statistical distributions of the words in their training data. However, words often have different meanings depending on in which domain they are used. The word *chest* has a dual meaning in everyday language – something used for storage or a region of the body – but only one of these is relevant in a medical context. A language model which has learned the word *chest* from a general-domain corpus may have a representation of the word that is sub-optimal in the medical domain.

Indeed, many researchers have found that performance on domain-specific tasks is helped by adapting existing language models or pre-training new models using in-domain data (Lee et al., 2019; Beltagy et al., 2019; Lamproidis et al., 2021; Lamproidis et al., 2022a; Lamproidis et al., 2022b). Better performance means that the models will be more useful in helping medical professionals improve patient outcomes.

However, the scale of the data used to train these models means that researchers cannot know what sensitive information the corpora contain. In the medical domain, we can be certain that the texts contain sensitive information. This is cause for concern since pre-trained language models are susceptible to privacy attacks (Bender et al., 2021). This paper examines one way of reducing the privacy risks: automatic de-identification. Two different approaches are studied: pseudonymization (Sweeney, 1996; Dalianis, 2019) and removal of sensitive data.

Two different clinical BERT models are created by applying these techniques to the pre-training data. The impact of automatic de-identification on the performance of the models is then evaluated on downstream tasks.

2. Related Research

The two main topics of this paper are automatic de-identification and the privacy risks of large language models. This section introduces these concepts by providing a brief summary of results related to the topic of this paper.

2.1. Privacy Attacks on Language Models

Large pre-trained language models are susceptible to a wide range of attacks on privacy. One reason for this is due to their size, which gives them a tendency to unintentionally memorize parts of their training data. The attacks can generally be separated into two main categories:

Training data extraction An attacker that successfully mounts a model inversion attack is able to extract details about the training data. One example of a training data extraction attack was mounted by Carlini et al. (2020). They managed to extract entire passages from IRC logs from the model GPT-2 (Radford et al., 2019).
**Membership inference** If an attacker is able to discern whether or not a datapoint was part of the training data, they have successfully mounted a membership inference attack (Shokri et al., 2017). Although these attacks are typically less severe than training data extraction attacks, they can also expose sensitive data.

To the best of our knowledge, there are no examples of successful training data extraction attacks on BERT models. Lehman et al. (2021) and Vakili and Dalianis (2021) found that BERT models are at least less susceptible to such attacks than GPT-2. Both studies attempted to extract training data from a BERT model trained on a version of MIMIC-III (Johnson et al., 2016) which had its masked entities populated with realistic but fake values.

Nakamura et al. (2020) performed a related attack that attempted to re-predict pseudonymized information. They trained a BERT model on a version of the MIMIC-III (with inserted surrogate values) and then re-masked the surrogate entities in this dataset. They then attempted to reconstruct the surrogate names but did not succeed, concluding that this does not seem to be a viable attack.

Lehman et al. (2021) also performed membership inference attacks on their BERT model. Their results indicated a small risk of memorizing patients’ names. At the same time, they were not able to link a patient’s name to any of their conditions. Jagannatha et al. (2021) also performed membership inference attacks on BERT and found that there is a risk of privacy leakage from BERT models. However, this risk is significantly smaller than for models like GPT-2.

### 2.2. De-Identification of Clinical Text Data

The electronic health records (EHRs) used in clinical NLP are inherently sensitive. For example, the data used in this study was found to have an estimated protected health information (PHI) density of 1.57% (Henriksson et al., 2017). However, the PHI density varied considerably across medical specialties and classes of clinical notes. For example, almost 20% of the sentences in discharge summaries contained at least one PHI. The prevalence of PHI has caused many researchers to explore ways of reducing the risks to patient privacy that comes with using their health data. One active area of research is automatic de-identification.

Automatic de-identifiers typically rely on named entity recognition (NER) models to detect sensitive data in datasets. Thus, the recall of the model needs to be balanced against its precision. In this context, the classic precision-recall trade-off translates to one between utility and privacy. Low recall means that a lot of sensitive data will be undetected, but a low precision results in a dataset where a lot of non-sensitive data is corrupted.

Berg et al. (2020) used various high recall models to de-identify several Swedish clinical datasets. This did not seem to lower the utility of the datasets, as training with the datasets did not significantly decrease downstream performance. The authors tried out four strategies for the de-identification: pseudonymization (replacing sensitive data with surrogates), masking the sensitive data, replacing a sensitive word with its class name (e.g., replacing “John” with “First Name”), and removing the sensitive data along with the sentence in which it appeared. All of the downstream tasks were NER tasks and were approached using a machine learning algorithm based on conditional random fields (CRFs). The tasks were clinical entity identification, adverse drug effect identification, and cervical cancer symptom detection. Pseudonymization resulted in the smallest negative impact on the downstream tasks, while the sentence removal strategy resulted in a greater deterioration of the performance.

Vakili and Dalianis (2022) automatically de-identified three Swedish clinical datasets using pseudonymization. Each dataset was associated with a task: two sequence classification tasks (ICD-10 classification and factuality classification) and one NER task (clinical entity recognition). Different BERT models were trained using unaltered and pseudonymized data, and the performances on all tasks were compared. There was no significant difference in the performance of the models trained on unaltered data and the models trained on pseudonymized data.

Obeid et al. (2019) de-identified clinical data and evaluated the impact of this by building detectors of altered mental status (AMS) using a variety of machine learning models. These included Naïve Bayes Classifiers, Single Decision Trees, Random Forests, and Multilayer Perceptrons. The deep learning models performed the strongest, but no model showed any significant deterioration in performance when trained using de-identified text instead of the original text.

No automatic de-identification system has perfect recall, and some sensitive data will remain in a processed corpus. However, pseudonymizing the data makes it difficult to determine which data are real and which data are pseudonymized. Carrell et al. (2019) explored the concept of hiding in plain sight (HIPS). They were able to train a tagger to distinguish between pseudonymized data and data that were HIPS in a pseudonymized dataset. The tagger performed significantly better than random guessing but had a high rate of false positives and false negatives. Thus, the authors concluded that HIPS is still helpful for protecting privacy.

This study applies two of the de-identification approaches outlined in Berg et al. (2021) to a clinical corpus data. However, the data used in this paper is much larger in scale and is used to pre-train language models rather than to build task-specific classifiers.
3. Data

The clinical data used to train and evaluate the BERT models originate from the Karolinska University Hospital. The data are stored in the research infrastructure Health Bank – The Swedish Health Record Research Bank\(^2\) (Dalianis et al., 2015) at DSV/Stockholm University.

### 3.1. EHRs from the Health Bank

The BERT models in this paper were pre-trained using a 17.9 GB subset of the Health Bank. The clinical texts come from a large number of clinical units and encompass over 2 million EHRs\(^3\). This dataset is comparable in size to the general domain Swedish corpus of newspapers, Swedish Wikipedia, and government documents that was used to pre-train *KB-BERT* (Malmsten et al., 2020).

These EHRs were de-identified according to the process outlined in Section 4.1 and the resulting dataset was used to train two BERT models, as will be described in Section 4.2. Lamprodis et al. (2021) also use this dataset in its unaltered form to train the baseline model used for evaluating the impact of de-identifying the pre-training data.

### 3.2. Datasets for Downstream Tasks

Five manually annotated datasets, all created from the Health Bank, were used to evaluate the downstream performance of the models. All of the downstream tasks concern clinical NLP tasks and make it possible to compare the BERT models to each other.

- **Stockholm EPR Gastro ICD-10 Corpus** A Gastro ICD-10 data set consisting of 6,062 gastro-related discharge summaries and their assigned ICD-10 diagnosis codes. The data set encompasses 4,985 unique patients and 795,839 tokens. The data are divided into 10 groups that correspond to different body parts; the ICD-10 codes range from K00 to K99. Each group contains several codes (Remmer et al., 2021).

- **Stockholm EPR PHI Corpus** A PHI data set of 4,480 annotated entities and 380,000 tokens. The PHIs correspond to nine PHI classes: First Name, Last Name, Age, Phone Number, Location, Health Care Unit, Organization, Full Date, and Date Part (Dalianis and Velupillai, 2010).

- **Stockholm EPR Clinical Entity Corpus** A clinical entity data set comprising 70,852 tokens and 7,946 annotated entities corresponding to four clinical entity classes Diagnosis, Findings, Body parts, and Drugs (Skeppsöld et al., 2014).

- **Stockholm EPR Diagnosis Factuality Corpus** A factuality diagnosis data set encompassing six levels of annotations regarding the factuality of a diagnosis. The data set consists of 3,710 samples with 7,066 annotated entities Certainly Positive, Probably Positive, Possibly Positive, Possibly Negative, Probably Negative, and Certainly Negative encompassing 240,000 tokens (Velupillai et al., 2011). The dataset is used for two tasks. One is a NER task where the goal is to identify tokens specifying diagnoses and assigning them a factuality label. The second task treats the sample as a single datapoint and performs a multi-label classification of the entire sample to predict its factuality.

- **Stockholm EPR ADE ICD-10 Corpus** A newly introduced ADE corpus containing 16,858 samples encompassing 634,000 tokens. The samples are distributed over 12 different ICD-10 codes describing adverse drug events. The task is treated as a binary classification task where positive samples have been assigned a specific ICD-10 code that denotes an adverse drug event. Negative samples in each group have been assigned a code describing a similar condition that was not drug-induced. The goal of the task is to determine whether or not the condition defined by the ICD-10 code was induced by an ADE.

4. Experiments

The study encompasses three steps. First, the Health Bank corpus is processed to detect and deal with sensitive data. This leads to two different clinical corpora that are then used for domain-adaptive pre-training. The resulting models are evaluated on downstream tasks, and the results are compared to other models trained on the Health Bank data. This section gives a detailed account of the experiments and their results.

### 4.1. De-Identifying the Health Bank

A NER model was built based on a clinical BERT model trained by Lamprodis et al. (2021) using the *Stockholm EPR PHI Corpus*. The model was used to detect the nine PHI classes described in Section 3.2 and by Dalianis and Velupillai (2010). This model was then applied to the 17.9 GBs of EHRs extracted from the Health Bank. This processing uncovered a large amount of possibly sensitive data. The number of detected instances for each PHI type is listed in Table 1.\(^1\) Two approaches to de-identification were taken, as illustrated in Figure 1. In the first approach, which we refer to as *pseudonymization*, each detected entity was replaced by a realistic surrogate value of the same class. For example, a detected name will be replaced with a realistic surrogate value of the same class.

\(^1\)The Health Bank: [http://dsv.su.se/healthbank](http://dsv.su.se/healthbank)

\(^2\)This research has been approved by the Swedish Ethical Review Authority under permission no. 2019-05679.
Table 1: The PHI types in order of frequency as classified by the de-identification system. The per-class recall and precision for the NER model are also displayed and were calculated on the test data from Dalianis and Velupillai (2010). In total, 83,914,340 sensitive entities are found in 49,715,558 sentences.

| PHI Type             | # Predicted Instances | NER Recall | NER Precision |
|----------------------|------------------------|------------|---------------|
| Health Care Unit     | 19,659,127             | 80%        | 87%           |
| Partial Date         | 19,374,711             | 83%        | 94%           |
| Last Name            | 14,332,309             | 97%        | 96%           |
| First Name           | 12,525,688             | 97%        | 98%           |
| Full Date            | 10,459,935             | 55%        | 77%           |
| Location             | 3,158,031              | 89%        | 85%           |
| Age                  | 2,064,111              | 35%        | 47%           |
| Organisation         | 1,078,115              | 36%        | 71%           |
| Phone Number         | 1,262,313              | 40%        | 63%           |

Figure 1: This hypothetical example illustrates the two approaches taken to de-identify the data. One approach replaces the sensitive data with realistic surrogates and is used to train the model KB-BERT + Pseudo. The other approach instead removes the entire sentence from the dataset and this filtered dataset is used to train the model KB-BERT + Filtered.

learn essentially the same information without exposing any sensitive information.

The second and more aggressive approach is to remove all sentences that contain sensitive entities. This approach removes 49,715,558 out of 364,385,114 sentences in the original dataset. In other words, 13.65% of all sentences were identified as containing sensitive entities. The removal of these sentences reduced the size of the dataset by approximately 19%.

Combined with the total number of entities shown in Table 1 these statistics indicate a slight tendency for sensitive entities to cluster in the same sentences, with around 1.69 entities per sensitive sentence. If this tendency holds for the entire dataset, then removing entire sentences should help remove some additional sensitive entities that the de-identifier has missed.

4.2. Training the BERT Models

The models in this paper are trained using a setup similar to Lamproudis et al. (2021), whose model is used for comparison in this study. Their model was trained using unaltered sensitive EHR data and is referred to as KB-BERT + Real in this paper. The two new models are built using the datasets described in Section 4.1.

KB-BERT + Pseudo The data used to train this model has had all sensitive entities (as listed in Table 1) replaced with realistic surrogates of the same entity class.

KB-BERT + Filtered This model is built using the dataset where all sentences found to contain sensitive data have been removed. This filtered version of the dataset is 19% smaller than the version used to train KB-BERT + Pseudo.

Both models were trained using KB-BERT (Malmsten et al., 2020) as the starting point and are the same size as BERT BASE (Devlin et al., 2019). As in Lamproudis et al. (2021), the vocabularies of both models are identical to that of KB-BERT. Pre-training was resumed for three epochs of the datasets using hyperparameters shown in Table 2.

One way in which the training of these two models differs from KB-BERT + Real is that our training data does not contain any document boundaries. This means that some datapoints in the training data contain two sentences from different clinical notes. In theory, this can harm the training process. As will be shown in Section 4.3, it does not seem to matter very much in practice.

4.3. Evaluating on Downstream Tasks

After training each model for three epochs, the resulting models were fine-tuned and evaluated on each of the six downstream tasks described in Section 3.2. Table 3 displays the results of the downstream evaluation. Each model, except for KB-BERT, is evaluated on all three epochs, and we report the best result of the three evaluations. The best result is selected as the...
aim of this study is not to determine the optimal number of epochs which could vary depending on the de-identification approach.

All three models outperform the non-clinical baseline KB-BERT on every clinical downstream task. This is expected and indicates that the models have adapted to the language of the domain. More surprisingly, de-identification does not lead to any discernible drop in performance. In fact, KB-BERT + Pseudo even outperforms KB-BERT + Real on some tasks.

5. Discussion & Conclusions

The results in Section 5.1 show that performance on downstream tasks is not harmed by de-identifying the data used for domain adaptation of language models. This section contextualizes these findings and provides suggestions for future research.

5.1. Absence of Performance Drops

Automatic de-identification leads to a certain degree of corruption of the training data. The models used in this paper have a strong level of precision for many entity classes, as shown in Table 1. On the other hand, the evaluation indicates that around 15% of all detected locations are actually something else. The de-identification system will then either erroneously replace the word with a location name – corrupting the data – or unnecessarily discard the sentence.

Surprisingly, Table 3 indicates that this does not adversely affect the usefulness of the resulting models on the downstream tasks. KB-BERT + Pseudo is trained on data that is possibly corrupted due to precision issues but still performs similarly to KB-BERT + Real. KB-BERT + Filtered also performs comparably to KB-BERT + Real even though the data is reduced to a non-trivial degree. It does, however, perform noticeably worse on the PHI NER task. This is expected since the de-identification approach aims to remove all such entities from the continued pre-training.

5.2. Reliability of the De-Identification

The NER model used in this paper is evaluated on in-domain clinical NER data. This strongly suggests that the recall and precision estimates are accurate. Nevertheless, the efficacy of the de-identification can only be assessed using the testing data. Due to the very nature of the problem, this means that the amount of sensitive information remaining in the training data can only be estimated.

However, not all entity classes are equally sensitive. Table 3 shows that our system detects and de-identifies 97% of all first and last names which are arguably the most sensitive classes. Furthermore, an attacker cannot target a specific person as they do not know if their names are among the 3% retained in the dataset.

5.3. Releasing the Models?

As explained in Section 2.1, there has been a growing interest in evaluating how susceptible pre-trained language models are to privacy attacks. While GPT-2 has been found to be very susceptible to attacks, BERT seems to be more resilient.

The performance of the de-identification system suggests that the overwhelming majority of sensitive data are removed from the training data of our models. If only 3% of all names in the data used for domain adaptation are sensitive, and the risk of exposing any name is less than 10% [Jagannatha et al., 2021], then the risk of exposing a real name is very small.

Another feature of the approach taken in this paper is that the models use a pre-trained model as their starting point. This means that any memorized names can come both from the Health Bank or the data used to train KB-BERT. This can be viewed as a form of hiding in plain sight (HIPS). Thus, an attacker who has extracted a name not only needs to determine whether or not it is a surrogate but also whether it came from a sensitive or non-sensitive data source.

BERT models have been shown to be quite resistant to training data extraction attacks [Nakamura et al., 2020; Lehman et al., 2021; Vakili and Dalianis, 2021]. Furthermore, the limited susceptibility to membership inference attacks [Lehman et al., 2021; Jagannatha et al., 2021] is likely negligible when most of the data memorized by the model has been made non-sensitive through de-identification. Based on this, as well as other points made in this paper, we believe that the models can safely be shared among academic researchers. The model KB-BERT + Pseudo will be distributed under the name SweDeClin-BERT once we have obtained the necessary permissions from the Swedish Ethical Review Authority.

5.4. Future Research

As noted in Section 5.2, previous research has shown that training on pseudonymized data can adversely impact model performance. In this paper, we show that

This table shows the hyperparameters used for continuing the pre-training with KB-BERT as a starting point. These hyper-parameters were used to train KB-BERT + Real, KB-BERT + Filtered, and KB-BERT + Pseudo.

| Hyperparameter     | Value     |
|--------------------|-----------|
| Max epochs         | 3         |
| Batch size         | 256       |
| Training sequence length | 512         |
| Mask probability   | 15%       |
| Optimizer          | Adam      |
| Learning decay rate| Linear    |
| Learning rate      | 1e-4      |
| Dropout            | 0.1       |
| Warm-up steps      | 10,000    |

This table contains the hyperparameters used for continuing the pre-training with KB-BERT as a starting point. These hyper-parameters were used to train KB-BERT + Real, KB-BERT + Filtered, and KB-BERT + Pseudo.
We suggest that practitioners who use clinical data show a slight increase in performance for some tasks. The results from six clinical downstream tasks show that there is no negative impact from using an automatically de-identified clinical corpus. Indeed, the results indicate that there is no negative impact from using an automat

The consequences for the utility of the de-identified corpus are determined by comparing the downstream performance of the resulting BERT models with a model domain-adapted using an unaltered version of the corpus. The results from six clinical downstream tasks show that there is no negative impact from using an automatically de-identified clinical corpus. Indeed, the results show a slight increase in performance for some tasks. We suggest that practitioners who use clinical data for domain adaptation incorporate automatic de-identification into their workflow to decrease the risk of privacy leaks. Automatic de-identification is an easily implemented measure that reduces the risks of unintentionally memorizing sensitive information without harming utility.

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| Model           | ICD-10 Classification | PHI NER  | Clinical Entity NER  | Factuality Classification | Factuality NER  | ADE Classification |
|-----------------|----------------------|----------|----------------------|---------------------------|----------------|-------------------|
| KB-BERT         | 0.799                | 0.91     | 0.803                | 0.635                     | 0.630          | 0.183             |
| KB-BERT + Real  | 0.833                | 0.941    | 0.858                | 0.732                     | 0.682          | 0.199             |
| KB-BERT + Filtered | 0.833              | 0.929    | 0.854                | 0.731                     | 0.672          | 0.199             |
| KB-BERT + Pseudo | 0.832               | 0.941    | 0.861                | 0.736                     | 0.684          | 0.191             |

Table 3: The table compares the downstream performances of each BERT model. *KB-BERT* and *KB-BERT + Real* are used as baselines. *KB-BERT* is also the starting point for the continued pre-training of all three models, as described in Section 4.2. All values are F1-scores and the best results are bolded.

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5GAN stands for Generative Adversarial Network.
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