**InvBERT: Text Reconstruction from Contextualized Embeddings used for Derived Text Formats of Literary Works**

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**ABSTRACT**

Digital Humanities and Computational Literary Studies apply text mining methods to investigate literature. Such automated approaches enable quantitative studies on large corpora which would not be feasible by manual inspection alone. However, due to copyright restrictions, the availability of relevant digitized literary works is limited. Derived Text Formats (DTFs) have been proposed as a solution. Here, textual materials are transformed in such a way that copyright-critical features are removed, but that the use of certain analytical methods remains possible. Contextualized word embeddings produced by transformer-encoders (like BERT) are promising candidates for DTFs because they allow for state-of-the-art performance on various analytical tasks and, at first sight, do not disclose the original text. However, in this paper we demonstrate that under certain conditions the reconstruction of the original copyrighted text becomes feasible and its publication in the form of contextualized word representations is not safe. Our attempts to invert BERT suggest, that publishing parts of the encoder together with the contextualized embeddings is critical, since it allows to generate data to train a decoder with a reconstruction accuracy sufficient to violate copyright laws.

**Introduction**

Due to copyright laws the coverage of text material, specifically literary works, available for scientific purposes is quite limited. Depending on the specific laws there might be some degree of freedom to use protected texts for scientific studies and give reviewers access to them, but in most cases they still can’t be published openly and completely, making it hard for the community to reproduce or build on scientific findings.

This is a fundamental issue for research fields like Digital Humanities (DH) and Computational Literary Studies (CLS), but applies to any analysis of text documents that cannot be made available due to privacy reasons, copyright restrictions or business interests. This, for instance, makes it hard for digital libraries to offer their core service, which is the best possible access to their content. While they provide creative compromise solutions, like data capsules or web-based analysis tools, such access is always limited and complicates subsequent use and reproducibility.

As a consequence, there have been attempts to find a representation formalism which retains as much linguistic information as possible while not disclosing the original text fully. Such text representations have been referred to as Derived Text Formats (DTFs, see [2]). While such DTFs are always a compromise between the degree of obfuscation (non-reconstructibility) and degree of analyzability (retained information), there are DTFs with clear advantages over others.

We investigate if Contextualized Token Embeddings (CTE), like the ones obtained from a transformer encoder stack trained on a self-supervised masked language modeling (MLM) task [3], are a promising candidate for DTFs. On the

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[1] see https://www.hathitrust.org/htrc_access_use
"It takes a great deal of bravery to stand up to our enemies, but just as much to stand up to our friends."

"It takes a great lot of bravery to stand up to our enemies, but just as much to stand up to our friends."

Figure 1: Sample text reconstruction applying InvBERT to a Harry Potter quote [1].

One hand, they are the state-of-the-art text representation for most Natural Language Understanding tasks (see [4] and [5]), including tasks relevant to DH and CLS, like text classification, sentiment analysis, authorship attribution or text re-use [6]. On the other hand, it appears difficult to reconstruct the original text, just from its CTEs. Thus, we pose the following research question:

In which scenarios can protected text documents not be released publicly if encoded as contextualized embeddings since the original content can be reconstructed to an extend that violates copyright laws?

After presenting the related work we will first formalize the components used in a text encoder pipeline in order to describe potential application scenarios in DH or CLS. This allows us to define potential lines of attack that aim at reconstructing the original text. Next, we will discuss the feasibility of each line of attack. In the next section we focus on the most critical line of attack by evaluating it's feasibility empirically, before concluding.

Related Work

First, we look at the very recent field of DTFs, before presenting existing work on text reconstruction beyond copyright protected texts.

Derived Text Formats

DTFs, like n-grams or term-document matrices are an important tool to the Computational Linguistics and Digital Humanities, since they allow the application of quantitative methods to their research objects. However, they have another important advantage: If the publication of an original text is prohibited, DTFs may still enable reproducibility of research (see [6] and [2]). This is especially important for CLS, where there is only a small “window of opportunity” of available manuscripts from the year 1800 to 1920 due to technical issues on the lower and copyright restrictions on the upper boundary. Since this is of permanent concern and an obstacle to free research, tools to widen this window are of great importance to the field. Other approaches to tackle this issue, like granting access to protected texts in a closed room setting, come with their own major drawbacks and still do not enable an unhindered exchange of scientific findings. Therefore, in most cases, DTFs like term-document matrices are the best solution available. The aim of these formats is to retain as much information as possible, while minimizing reconstructibility. In reality, however, the latter most often is achieved by compromising on the former. This leads to the variety of feasible analytical down-stream tasks being narrowed. A format that preserves a noticeable amount of information and is already used as a DTF are word embeddings like Word2Vec [7] or GloVe [8]. However, similar to term-document matrices they can only be applied to document-level tasks. Otherwise, there remains considerable doubt regarding their resilience against reconstruction attempts. A promising attempt to alleviate that is by using contextualized word - or more precise token - embeddings (CTEs) generated by pretrained language models instead, since the search space to identify a token grows exponentially with the length of the sequence containing it. Additionally, these embeddings carry even more information and achieve SOTA results on various down-stream tasks.
Reconstruction of Information from Contextualized Embeddings

Recently, a lot of attention was drawn to privacy and security concerns regarding large language models due to prominent voices in ethics in AI [9], as well as a collaboratory publication of the industry giants Google, OpenAI and Apple [10]. In the latter, the authors demonstrated, that these models memorize training data to such an extend, that it is not only possible to test whether the training data contained a given sequence (membership inference, [11]), but also to directly query samples from it (training data extraction). Other recent research supports these findings and agrees, that this problem is not simply caused by overfitting [12, 13]. Gigantic language models like GPT-3 [14] or T5 [15] were trained on almost the entirety of the available web, which poses a special concern, since sensible information like social security numbers is unintentionally being included. Hence, a majority of the literature focuses on retrieving information about the training data. However, we argue that such attacks are less successful in the case of literary works, since a) the goal in this scenario would usually be the reconstruction of a specific work, and b) the attacks are not suited to recover more than isolated sequences.

A third prominent type of attack which can be performed quite effectively is attribute inference [16,17]. It is also of little relevance, since it aims to infer information like authorship from the embeddings, which is non-confidential in a DTF setting anyways. More so, authorship attribution is actually a relevant field of research in the DHs.

The main threat regarding CTEs as DTFs are embedding inversion attacks, where the goal is the reconstruction of the original textual work they represent. However, research on this topic is still limited and most paper focus on privacy. Therefore, very few go beyond retrieval of isolated sensitive information. E.g. [18] showed, that it is possible to use pattern-recognition and key-word-inference techniques to identify content with fixed format (e.g. birth dates) or specific keywords (e.g. disease sites) with varying degree of success (up to 62% and above 75% avg. precision respectively). However, this is easier and the search space smaller, than reconstructing full sequences drawn from the whole vocabulary.

To the best of our knowledge, retrieval of the full original text is covered only by [17]. Using an RNN with multi-set prediction loss in a setting with access to the encoding model as a black-box, they were able to achieve an in-domain F1 score of 59.76 on BERT embeddings. However, since privacy was their concern, they did not consider word ordering in their evaluation, which is crucial when dealing with literary works. Therefore, and since they failed to improve on their results using a white-box approach as well, we believe that the security of the usage of CTEs as DTFs still remains an unanswered question.

When dealing with partial-white- or black-box scenarios, a final type of attack should be kept in mind: Inferences about the model itself. Even though not the goal here, successful model extraction attacks [19] may transform a black-box situation into a white-box case. However, critical information can even be revealed by fairly easy procedures like model fingerprinting. This was showcased on eight SOTA models by [17], who were able to identify the model based on a respective embedding with 100% accuracy.

Research Question Definition

Since this paper is not about improving an existing model, but inverting it, we will first formalize the standard transformer encoder stack, before instantiating it for our concrete text reconstruction scenarios. This includes a description of likely scenarios and lines of attack that might allow to invert the standard model.

Neural Text Encoder Formalization

A bidirectional-transformer-encoder like BERT can be described as follows: A given textual input sequence \( w = (w_1, ..., w_n) \) is first passed to a subword tokenizer \( \text{tok}() \) and mapped to indices \( x = (x_1, ..., x_n) \) of the learned vocabulary \( V \). Fed to the model \( \text{enc}() \), these are then used to query their respective representations \( z \) in vector space from the embedding layer, where additional information like positional and sequence encodings may be added as well. Those embeddings are then passed through the encoder stack, which returns the contextualized embeddings \( Z = (z_1, ..., z_n) \). These can then be used as input for a wide range of task-specific top layers \( \text{pred}() \), making these kind of models the SOTA approach on a variety of downstream tasks [20].

Text Reconstruction vs. Usefulness as DTFs

Transformer-encoder stacks \( \text{enc}() \) are a promising addition to existing DTFs, since they produce contextualized embeddings \( Z \) known to perform well as input to most downstream tasks \( \text{pred}() \), like sentence or sentiment classification. They are arguably the most versatile and comprehensive representation of machine-interpretable text to date. In addition,
trained models are openly available\textsuperscript{2} However, there is a trade-off in respect to how useful CTEs are as DTFs between what is made public of the encoder model and the risk that the text can be reconstructed.

Formally, the reconstruction task is defined as follows:

**Given:** contextualized token embeddings $Z$ of a copyright protected text document $W$\textsuperscript{3} Potentially, also the the bidirectional-encoder-transformer pipeline $\text{tok}()$ and $\text{enc}()$ used for generating $Z$ is available.

**Searched:** a function or algorithm $\text{inv}(Z) = \hat{W}$ that inverts the model pipeline or approximate its inverse $\text{tok}^{-1}(\text{enc}^{-1}(Z)) = W$. We denote the reconstructed text with $\hat{W}$.

From the perspective of a DH or CLS researcher the following experimental scenarios need to be distinguished:

**WB - White Box Scenario:** The most flexible scenario is given if the encoder $\text{enc}()$, including the neural network’s architecture and learned parameters, and tokenizer $\text{tok}()$ is made openly available in addition to the CTEs. Then, analytical experiments can be conducted that require to adapt/optimize the encoder $\text{enc}()$ and/or the tokenizer $\text{tok}()$.

**BB - Black Box Scenario:** A less flexible scenario is given, when the tokenizer $\text{tok}()$ and the encoder $\text{enc}()$ are made available as a black box only. Then the researcher is still able to generate $X$ from $W$ and $Z$ from $X$, i.e. $(W, Z)$-pairs. Thus, he can label his own training data and use it to optimize $\text{pred}()$ or embed other data not yet available as $Z$ for analysis. However, if provided as a service, the number of queries allowed to be sent to $\text{enc}()$ might be limited. Up to the point that the model is not released at all. Then, existing implementations can be reused in order to perform a standard analytical task on $W$ if the respective task-specific top layer function $\text{pred}()$ is also provided. Still, even without the ability to query $\text{enc}()$ training data can be obtained if original versions of texts are obtained and aligned with the CTEs. Also note, that BB could be turned into WB by successful model extraction attacks.

Obviously in the first scenarios more information is made public, which intuitively also increases the risk, that $W$ might be reconstructed from $Z$. In other words, BB is harder to attack while WB is most prone to successful attacks.

**Attack Vectors**

We consider three lines of attack:

**A1 - Inverting Functions:** Inverting $\text{enc}()$ and $\text{tok}()$ using calculus requires to find a closed-form expression for $\text{tok}^{-1}()$ and $\text{enc}^{-1}()$. Since this requires knowledge of the encoder pipeline, A1 is only applicable to WB.

**A2 - Exhaustive Search:** Sentence-by-sentence combinatorial testing of generated inputs to “guess” the contextualized token embeddings is applicable to WB and BB, as long as an unlimited number of queries to $\text{enc}()$ is allowed.

**A3 - Machine-Learning** Learning an approximation of $\text{tok}^{-1}(\text{enc}^{-1}())$ is feasible as long as training pairs $(W, Z)$ are available. If the encoder $\text{enc}()$ is available and it’s use is not in any way limited, an unlimited number of training pairs can be generated.

**Discussion of Attacks**

In this section we estimate the feasibility of each attack listed in the previous section. We start with the more obvious cases that are less likely to succeed and end with the most promising line of attack.

**A1:** To calculate a closed-form solution that inverts the model it is mandatory to have full knowledge of its underlying function and parameters which is only the case in WB. However, this approach would only be feasible if all functions in question are invertible which is not the case for BERT-like transformer encoder stacks, since they contain matrix multiplications, add and normalization layers.

**A2:** For an exhaustive-search attack it is mandatory to generate the contextualized embeddings for the auxiliary data set, therefore this attack can only be performed in WB and, under the condition of unlimited access, in BB. Even then, however, combinatorial explosion renders this approach infeasible: A sentence of 15 tokens results in $18 \cdot 10^{66}$ possible combinations, assuming a vocabulary size of 30.522 different tokens, like in the case of

\textsuperscript{2}see e.g., https://huggingface.co/transformers/

\textsuperscript{3}Typically a book, containing literary works, like poetry, prose or drama.
BERT\textsubscript{BASE}: Considering inference performance of current chip sets\textsuperscript{4}, a brute-force attack seems not feasible for the foreseeable future.

A3: Previous research on embedding inversion shows that it is possible for an adversary to train a model which allows them to partially map CTEs back to their corresponding plain text. However, the reported results beyond reconstruction of isolated keywords are certainly not good enough to keep the style and spirit of a literary work. Therefore we, assume that an attack is more likely to be successful if some parts of the embedding generating pipeline are given in addition to training pairs. Since BERT-like models are trained on MLM-tasks and weight-tying \textsuperscript{21, 22} is a common and beneficial technique in bigger models, we assume that if the initial embedding matrix is given, the reconstruction quality might be improved considerably.

Empirical Assessment of a Machine Learning Attack in a (partial) White Box Scenario

In this Section, we empirically test a promising attack, namely the learning of a top layer that inverts $enc()$ by outputting the reconstructed text $\hat{W}$. Since it is the prototype of the transformer-encoder-based general language models, we consider BERT the target of the attack. We assume a white-box scenario in which the contextualized token embeddings $Z$, the tokenizer $tok()$ and the initial weight layer are given. As the core of the tokenizer is basically a look-up table, which can be searched from both directions, the inverse $tok^{-1}()$ to $tok()$ is also provided, effectively simplifying the problem from finding an approximation of the inverse $tok^{-1}(enc^{-1}())$ of the whole pipeline to just $enc^{-1}()$. As BERT is the attacked model, we denote the approximation of $enc^{-1}()$ InvBERT.

All our code and data described in the following is publicly available\textsuperscript{5}.

Data

Since we are struggling with the same copyright restrictions DTFs set out to alleviate, we can’t experiment with copyright restricted works while ensuring the reproducibility of our findings. Thus, we choose a text corpus that is openly available, resembles protected works as much as possible (in our experiments we focus on literary works, like prose or drama) and contains a sufficient amount of text documents to generate a suitable training set: We created the auxiliary data set $D_{aux}$ by scraping the Archive of Our Own (AO3)\textsuperscript{6}, an openly available fan fiction repository, using a modified version of AO3Scraper\textsuperscript{7}. We filtered out mature, extreme and non-general audience content using the given tags and cleaned the corpus by deleting duplicates. In total, we collected 27,457 works with at least 15,000 English words each, amounting to 6.7GB of raw text, metadata not counted.

Since there could be differences between in and out of domain training, we then examined the ten most common tags among the scraped data and rated Action and Adventure, Drama and Fluff\textsuperscript{8} as being sufficiently close to common genres, while at the same time being distinct enough from another to represent different domains.

Based on these three tags, we created subsets containing the respective nltk-sentenized\textsuperscript{23} works, divided into train- and test sets in a 80:20 split. Before conducting the split we shuffled the sentences to minimize a) the risk of the test set not being representative for the train set and b) the concerns regarding publishing the data. Other than that, we did no additional cleaning or other preprocessing. The size of and the number of samples in the resulting data sets is displayed in Table I.

Model

We then built our initial model by creating a pretrained BERT\textsubscript{base-uncased} encoder from Huggingface Transformers\textsuperscript{24}, freezing it and putting an untrained masked language modeling network on top. The latter consists of two dense layers with an intermediate gelu activation function plus layer normalization and it outputs predictions over the vocabulary for every CTE, after applying a final softmax function. Those predictions are also used for cross-entropy loss calculation during training.

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\textsuperscript{4}https://developer.nvidia.com/deep-learning-performance-training-inference
\textsuperscript{5}Available on GitHub, once the paper is accepted. For now: https://drive.google.com/drive/folders/1IC88x2J0jFgWlIoWMoZ0O015C1evBL?usp=sharing. We included the full data set for the reviewers’ convenience. However, if accepted, we can’t publish the data due to copyright restrictions. Instead we will publish the IDs of each site used for training/test so that the data set and experiments can be reproduced.
\textsuperscript{6}https://archiveofourown.org
\textsuperscript{7}https://github.com/radiolarian/AO3Scraper
\textsuperscript{8}"Feel good" fan fiction designed to be happy, and nothing else. According to https://en.wikipedia.org/wiki/Fan_fiction
| Tag    | Train Size | Train Samples | Test Size | Test Samples |
|--------|------------|---------------|-----------|-------------|
| Action | 373M       | 5903k         | 94M       | 1476k       |
| Drama  | 305M       | 4855k         | 77M       | 1214k       |
| Fluff  | 328M       | 5251k         | 82M       | 1313k       |

Table 1: Size and number of contained training samples of the collected data sets.

In this setting it was possible to train InvBERT end-to-end using the default language modelling training script provided by Huggingface. Due to the frozen encoder, the base BERT model delivering the embedded input to InvBERT does not change during training. Thereby, an equivalent setting to a separate generation and reconstruction of embeddings is established. An overview of the procedure is given by Algorithm 1.

Algorithm 1: Build InvBERT

Require: BertForMaskedLM, BertConfig

```python
model type ← bert-base-uncased
config ← BertConfig(model type)
untrained mlm ← BertForMaskedLM(config)
untrained mlm.init weights()
InvBERT ← BertForMaskedLM.load pretrained(model type)
untrained mlm.last linear layer.weights ← InvBERT.embedding matrix
InvBERT.top layer ← untrained mlm.top layer
InvBERT.save model()
if about to train then
    InvBERT.freeze encoder()
    InvBERT.freeze last linear layer()
end if
```

While the full model has around 110m parameters, the to-be-trained top layer has only about 24m. By using the embedding matrix as weights for the final dense layer (weight-tying) and freezing them as well, we could further reduce this number to a mere 622,650.

Training

Using a modified version of the basic huggingface script for masked language modeling, which covers freezing the encoder and shared weights, we trained three instances of our model - one for Action and Adventure (InvBERT\textsubscript{action}), Drama (InvBERT\textsubscript{drama}) and Fluff (InvBERT\textsubscript{fluff}), using their respective training data subset. The Training was conducted on a single Tesla V100-PCIE-32GB and we performed no hyperparameter optimization. Beside training for one epoch only, we used the default parameters of the script and trainer class, which lead to runtimes of 4-7 hours, depending on the exact size of the used data set and the computational load caused by other users on the same machine.

To get an estimate for the effect of weight-tying, we created a fourth model (InvBERT\textsubscript{drama-noWeightTying}) which did not have access to the initial layer of weights. Its last weight matrix $W_{out}$ is randomly initialized instead of being cloned from the embedding matrix $W_{emb}$. Beside that, it is identical to the others. We randomly picked one of the three auxiliary datasets for its training, which resulted in it being trained on the same data as InvBERT\textsubscript{drama} and thus having to be evaluated in terms of its performance compared to this model.

Evaluation Metrics

Since the nature of the presented reconstruction task asks for outputs which match the original texts’ tokens and their order as closely as possible, while simultaneously allowing for imperfect matches to a certain degree, common evaluation metrics like precision, recall and F1 scores are not suitable.

Instead, we chose to use the established BLEU metric, since its consideration for n-grams fits our needs more closely: In order to preserve the spirit of literary works it is necessary that the reconstruction resembles the original text as closely as possible in terms of words used as well as their ordering. However, it is also important to allow imperfect

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9 https://github.com/huggingface/transformers/blob/master/examples/pytorch/language-modeling/run_mlm.py
Table 2: BLEU-scores and n-gram precision for in- and out-of-domain evaluation of InvBERT\textsubscript{action}, InvBERT\textsubscript{drama} and InvBERT\textsubscript{fluff} and the InvBERT\textsubscript{drama-noWeightTying}.

| Tag       | 3-gram | 4-gram |
|-----------|--------|--------|
| Action    | 0.9307 | 0.9176 | 0.8919 |
| Drama     | 0.9257 | 0.9118 | 0.8847 |
| Fluff     | 0.9302 | 0.9172 | 0.8917 |
| Action    | 0.9331 | 0.9205 | 0.8956 |
| Drama     | 0.9298 | 0.9167 | 0.8912 |
| Fluff     | 0.9341 | 0.9216 | 0.8972 |

Table 3: BLEU-scores and n-gram precision of actionBERT, dramaBERT and fluffBERT on 15 Harry Potter quotes.

| Model     | 3-gram | 4-gram |
|-----------|--------|--------|
| action    | 0.9421 | 0.9316 | 0.9079 |
| drama     | 0.9363 | 0.9241 | 0.9000 |
| fluff     | 0.9421 | 0.9316 | 0.9079 |

matches to a certain degree, since a few synonyms or one instance of swapped words would surely not be considered a failed text reconstruction attack.

As reference for each predicted candidate sequence, we only provided the corresponding original text and we calculated the achieved score using Huggingface Datasets BLEU implementation\textsuperscript{10} To give more context regarding specifically the performance on multi token sub-sequences, we report achieved tri- and tetra-gram precision as well.

Empirical Results:

Quantitative Evaluation

We quantitatively evaluated the trained models in-domain by calculating their BLEU-score over all samples of their respective test set. Equally, we determined out-of-domain performance by repeating the procedure for our three main models twice - using one of the other two data sets at a time. A few (< 7) samples per set had to be excluded, since they exceeded the 512 token limit of the architecture\textsuperscript{11} The results are presented in Table 2.

As can be seen, all three InvBERT models achieve very high in-domain BLEU-scores of above 0.93 with tri- and tetra-gram precision of at least 0.91 and 0.89 respectively. Even more noticeable, all models deliver near-as-good results out-of-domain, with the worst performing combination of InvBERT\textsubscript{fluff} and action data still achieving a convincing 0.9194 BLEU-score with 0.9044 tri- and 0.8753 tetra-gram precision.

Since we only used the original text and no similar sequences as references for calculating these scores, the values indicate a tremendous degree of word-by-word agreement between \( W \) and \( \hat{W} \), which, as we assume, will not only preserve the vast majority of the semantic content of the work in question, but also keep its spirit by capturing more abstract features like writing style.

\textsuperscript{10} https://huggingface.co/metrics/bleu

\textsuperscript{11} 4 for Action, 5 for Drama, 6 for Fluff
Table 4: Example of a Harry Potter quote [26] and its corresponding predictions. InvBERT predictions are identical for all three models. Differences are highlighted. Missing white space is due to the subword tokenizer and does not indicate miss-prediction.

We also evaluated InvBERT_drama-noWeightTying on the drama test set where it achieved extremely low results. It performed more than a full order of magnitude lower compared to its in-domain competitor InvBERT_drama. This highlights the enormous positive impact of weight-tying and it’s importance for the proposed reconstruction attack.

Qualitative Evaluation

To put our previously made assumption about their reconstruction quality to the test, we applied our models to 15 quotes from the Harry Potter book series[12]. The calculated metrics in table 3 show that the performance on these real-world examples are consistent with the results on our test data.

Of the provided 15 sequences, eight were reconstructed token by token by all of our main InvBERT models. While achieved by the others, a ninth perfect match was missed by InvBERT_action only by a single word (likely instead of sure). On four of the six remaining samples, all three models chose only one (the same) non-identical token. Quite impressive was the performance on the longest sequence, 73 words and 12 punctuation marks over two sentences, where the three models only mistook two dashes for commas as well as InvBERT_drama proposing thrill instead of rush. Overall, only in two instances the reconstructions deviated in a meaningful way from the original text.

The control model on the other hand failed on every sample, producing output identifiable as non-human generated text at first glance. Therefore, its results will only be included in following tables for transparency reasons, but will not be discussed any further.

Since the lack of informational value, we do not showcase any of the perfect reconstructions in this section. Nevertheless, to demonstrate the quality of our embedding inversions, we present one of the four sequences with, in our opinion, neglectable flaws in Table 4.

In the shown example, the preservation of entities like an’, ol’ and botherin’, while only turning ter into to, seems remarkable to us and greatly contributes to our perception of a reconstruction, which, while being imperfect, still captures the spirit of the original work.

To give an impression of a subpar performance, in Table 5 we provide the predictions for one of the two sequences with meaningful deviations from the original. As can be seen, all three InvBERT models fail to reconstruct temptress in the presented case and - even more noticeable - substitute it with a non-word. InvBERT_action and InvBERT_drama go even further by additionally concatenating it and its preceding word flying. The reason for this lies in the subword unit tokenization: Since temptress is an uncommon word, it is split into the three subword tokens te, #htmp and #ress, where # indicates a non-leading part of a word. InvBERT_fluff predicts the first unit wrong, rendering the resulting word meaningless. The other models, however, even predict #pe instead of te, resulting in the tokenizer appending it to the previous token during decoding.

Discussion

Although small-scale, our manual evaluation confirms the results from our quantitative experiments. A trained reconstruction layer can easily produce sentences so close to the original, that copyright violations are immanent. However,

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12Retrieved from https://mashable.com/article/best-harry-potter-quotes
A PREPRINT - SEPTEMBER 22, 2022

| Source                        | Sequence                                      |
|-------------------------------|-----------------------------------------------|
| Original                      | Let us step into the night and pursue that flitty temptress, adventure. |
| Action Drama                  | let us step into the night and pursue that flitty temptress, adventure. |
| Fluff                         | let us step into the night and pursue that flitty temptress, adventure. |
| InvBERT (no weight tying)     | ”i., the, and, the, the the...               |

Table 5: Example pf a Harry Potter quote [27] and its rather bad corresponding predictions. Models in the same row predicted identical sequences. Differences are highlighted.

this could only be achieved if the initial embedding layer, used for weight-tying is known. In a perfect black-box scenario without information about the model itself leaked, such information would not be available.

In conclusion, according to our assessment, scenario WB can not be considered safe. Even a partial WB scenario, where only the tokenizer and the initial embedding layer is known near perfect reconstruction is feasible. For the BB scenarios we cannot give a definite statement, since related work has shown that at least some words are reconstructable. Still, we are not aware of a BB line of attack that produces text that reconstructs the original to a copyright-critical degree. Most interesting is the grey area between BB and WB (aka partial WB): If critical parts of the encoder can be revealed, for instance by a fingerprinting attack that identifies that a standard encoder or tokenizer was used, BB is transformed into WB and attacks become feasible.

Conclusion and Future Work

To conclude, we first summarize our findings, before outlining open research questions.

Summary and Conclusion:

Derived Text Formats (DTFs) are an important topic in Digital Humanities (DH). There, the proposed DTFs rely on deleting important information from the text, e.g., by using term-document matrices or paragraph-wise randomising of word orders. We argue, that Contextualized Token Embeddings (CTEs), as produced by modern language models, are superior in retaining syntactic and semantic information of the original documents. However the use of CTEs for large-scale publishing of copyright protected works as DTFs is hindered by the risk that the original texts can be reconstructed.

In this paper we first identify and describe typical scenarios in DH when analyzing text using CTEs is helpful to different degrees. Next, we list potential attacks to recover the original texts. We theoretical and empirically investigate what attack can be applied in which scenario. Our findings suggest, that publishing only CTEs is most resistant to reconstruction attacks but also limited in its usefulness. In contrast, a white-box scenario, where the encoder stack is made partly transparent, is not advisable, since it allows to recover the original sequences with high precision. Anything in-between, like publishing the encoder as a black box model, requires an individual assessment and more research. Then, fingerprinting or model extraction attacks are possible but might not allow to recover text to an extend that can be considered a copyright violation.

In conclusion, if publishers and digital libraries consider the open publication of their content as CTEs, their generation needs to be carefully planned and supervised, since access to the inner workings of the encoding model allows a copyright-critical reconstruction of content. For instance, the use of openly available pre-trained transformer models might be enough to conduct a successful attack.

Noteworthy though, there are efforts in research to develop defense strategies and hardening techniques against such attacks, which might alleviate some of the aforementioned concerns. For embedding inversion at inference and especially in the given context, this, however, is still uncharted terrain and has therefore not been covered in this work. Without any such effort though, we have to clearly advice against the publication of CTEs generated from copyright protected material in a white-box or partial white-box setting based on the results of our experiments. In a similar fashion we would discourage doing so in other settings without them being extensively researched under the scope of the given context. Especially the black-box scenario marks an interesting area of tension in this regard: It still bears a lot of
potential for applications in a DTF context, while at the same time successful attack vectors do not seem impossible, but in turn might be rendered so by applying the right hardening methods. While it is hard to imagine an approach that enables reconstructions based on the embeddings only, even this should not prematurely be considered safe, since it needs dedicated research to develop methods to put that hypothesis to the test and the field is still in its early stages of development.

Ultimately, it is a legal consideration, if a reconstructed text, e.g., above a certain BLEU-score, violates copyright laws. This is beyond the scope of this paper, as is the benefit of the different scenarios for DH and CLS.

Future Work:

While researchers from the area of DH have to judge the usefulness of CTEs as DTFs themselves, we also see more need for research on DTFs for the field of Natural Language Processing (NLP). So far, CTEs have only been investigated in regards to privacy risks, but not copyright protection. After all, the problem of reproducibility of scientific results from restricted corpora is not restricted to the DHs.

While the purpose of this paper is to define the task of reconstruction text from CTEs and thereby establish a novel research niche, we only covered the most obvious lines of attack. Needless to say, there are more scenarios that require additional investigation:

For instance, a scenario might occur, where only a limited number of tuples \((W, Z)\) and/or \((X, Z)\) might be given to the attacker. How well can \(\text{enc()}\) be reconstructed from that? Also, even if no initial weight layer is given, just \(\text{tok()}\) as in our InvBERT\textsuperscript{drama-noWeightTying}, a reconstruction might become feasible once pre-trained information, like static word embeddings are used as the mapping target instead of tokens.

In addition, potential combinations of different DTFs or metadata might allow new lines of attack, for instance, if n-grams plus CTEs are published for the same text.

Intuitively, the more information is available regarding the generation of CTEs, the more angles for possible attacks are opened, while on the other hand a lack of information about the model might prevent them from being usable for downstream tasks. To find the right balance between those factors will be the most important challenge regarding this topic. Due to the broad range of combinatorial possibilities, it will not be easily solved by a singular study, but will require the combined efforts of further research from the fields of DH, NLP and law instead.

Thereby, the task of NLP is to come up with attacks which, especially in black-box scenarios, put the resilience of CTEs against reconstruction attempts to the test, while at the same time developing strategies to defend against the same. In the course of this, resource demand and ethical aspects should also be monitored and evaluated.

Ultimately, publishers and libraries need to decide if they release DTFs of their inventory. However, we believe that more research in NLP is needed to give an informed answer. For NLP researchers, this is an exciting challenge, since it requires both, theoretical studies regarding computational complexity, but also empirical experiments with real-word corpora in real-world settings.

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