#maskUp: Selective Attribute Encryption for Sensitive Vocalization for English language on Social Media Platforms

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Abstract

Social media has become a platform for people to stand up and raise their voices against social and criminal acts. Vocalization of such information has allowed the investigation and identification of criminals. However, revealing such sensitive information may jeopardize the victim’s safety. We propose #maskUp, a safe method for information communication in a secure fashion to the relevant authorities, discouraging potential bullying of the victim. This would ensure security by conserving their privacy through natural language processing supplemented with selective encryption for sensitive attribute masking. To our knowledge, this is the first work that aims to protect the privacy of the victims by masking their private details as well as emboldening them to come forward to report crimes. The use of masking technology allows only binding authorities to view/un-mask this data. We construct and evaluate the proposed methodology on continual learning tasks, allowing practical implementation of the same in a real-world scenario. #maskUp successfully demonstrates this integration on sample datasets validating the presented objective.

Introduction

The rise in gender-based crimes has been alarmingly high over the past few years. Reports show that globally, 1 in 3 women experience physical and/or sexual violence in their lifetime (WHO). However, the willingness of survivors to report such heinous crimes is very low (Kishor and Johnson 2004). Less than 10 per cent of women who experience violence seek help from the concerned authorities. This lack of vocalization not only encourages criminals to harm again without fear but also allows such occurrences to continue and be prolonged.

Societal and structural barriers like societal stigma and shame, distrust of institutions, fear of retaliation by the perpetrator, misuse of power by concerned authorities and prolonged trials, prevent women from coming forward and reporting crimes (Kishor and Johnson 2004). Therefore, a platform to voice opinions without fear of societal judgment, devoid of misuse of power by institutions, is required to encourage women to speak up. Social media giants like Twitter, Facebook, Instagram, and Reddit have been very instrumental in being such a platform.

However, one must understand that information relayed on topics as volatile as Sexual Harassment and Crimes (Koss 1993) can leak sensitive information and cause disastrous outcomes. Victims of sexual assault are often held culpable for the assault and face tremendous backlash and personal attacks (Suvarna and Bhalla 2020). With the rise of such crimes, it is essential to devise a computational framework that can identify and prevent the online victimization of sexual assault survivors who choose to report the crime.

In our construction of the problem statement, we aim to estimate and accurately retrieve such information and provide security for the vocalization of crimes. While previous literature and implementation focus on the identification of victim-blaming language and overall data encryption, they do not account for the impact these messages may have and the inherent fear amongst victims to come forward. It also does not account for how essential it is to communicate said information.

Therefore, a methodology that only encrypts vital information that may be limited to characteristic names, locations, or other sensitive aspects of the texts is proposed. For this, we offer a streamlined pipeline that augments Named Entity Recognition with Selective Encryption to formalize Selective Attribute Encryption for Sensitive Vocalization on Social Media Platforms. To our knowledge, this is the first work in the field of computational social science that aims to protect the privacy of the victims by masking their confidential details.
Related Work

Selective Encryption

Selective encryption, a recently popularized field of Cryptography, proposes a trade-off between security and computational complexity. It is based on the constitution that encrypting only the sensitive aspects of the complete data gives enough encryption to conserve data privacy. Previous literature has proposed a multitude of methodologies that encrypt and secure texts, such as (Kushwaha, Sharma, and Ambhaikar 2016; Etaiwi and Hraiz 2018), which uses a symmetric-key-based encryption algorithm for selective encryption of text over a mobile ad hoc network. On the other hand, (Kushwaha, Sharma, and Ambhaikar 2018) uses natural language processing to optimize selective encryption for sensitive aspects of text sent over the same medium. However, these encryption systems are still computationally expensive, and although they retain their selective nature, the content may still be perceptible in some instances. Therefore, it becomes imperative that an updateable retrieval function be applied for sensitive attribute extraction.

Named Entity Recognition

Named entity recognition has been an effective way of identifying and classifying names of person (PER), location (LOC), organization (ORG). Research on NER started with the use of handcraft features (Zhou and Su 2002; Chieu and Ng 2002; Bender, Och, and Ney 2003; Settles 2004), supervised learning techniques (Roy 2021) joint structured CRF models (Durrett and Klein 2014) and transitioned to semi-supervised learning methods (Nadeau, Turney, and Matwin 2006; Yangarber, Lin, and Grishman 2002; Riloff and Jones 1999; Cucchiarelli and Velardi 2001; Pasca et al. 2006) due to limited structured data. Recently, deep learning methods came to light since they significantly showed progress by automatically extracting high-level features and performing sequence tagging with neural networks (Santos and Guimarães 2015; Chiu and Nichols 2015; Lample et al. 2016; Yadav and Bethard 2019). The rise of transformers brought promising results for, (Yan et al. 2019) proposed TENER, a NER architecture adopting an adapted Transformer Encoder to model the character-level features and word-level features. Thus, utilizing the best technique for NER, in our proposed algorithm, we use the NERDA Framework, an open-sourced tool that fine-tunes transformers for NER tasks for any arbitrary language to identify sensitive information from text.

Continual Learning

Continual learning refers to the ability to continually learn over time by accommodating new knowledge while retaining previously learned experiences (Paris et al. 2019). Research in this field has found significant development by utilizing the concept of regularisation. Joint learning, an implementation accommodating the procedures of continual learning, requires interleaving samples from each task (Caruana 1997). However, this methodology becomes increasingly cumbersome as the number of tasks increases making it resource-constraining.

This led to the development of Learning without Forgetting ($LwF$) (Li and Hoiem 2017), which only required samples form the task-at-hand for learning. Although similar to joint training, the method does not require old data or reference points; instead, it uses regularisation techniques such as, Elastic Weight Consolidation, to compensate for the network forgetting an entire sequence of old data. By using the $LwF$ algorithm, the model is able to retain the previous performance learnt on the old tasks as well as gradually learn and update for newer tasks. However, this methodology still does not account for gradient flow and may restrain the training over the current task. Therefore, we restrict the training only to those neurons which have shown value in previous tasks. This idea was proposed in the "Overcoming catastrophic forgetting in neural networks" paper which discusses the integration of the Fisher information matrix as a regularizer for the loss function (Kirkpatrick et al. 2016). We provide said equation 1 and integrate it into the training of our proposed #maskUp algorithm.

$$\mathcal{L}(\theta) = \mathcal{L}_B(\theta) + \sum_i \frac{\lambda}{2} F_i(\theta_i - \theta_{A,i})^2$$

where $\mathcal{L}_B(\theta)$ is the loss for task $B$ only, $\lambda$ defines how important the old task is compared to the new one and $i$ labels each parameter.

With the introduction of continual learning, we add a dimension of adaptability and robustness against domain shifts for our algorithm.

Proposed Methodology

We consider our primary problem statement to be the construction of an NER based sensitive information encryption system. The retrieval system must incorporate privacy leakage terms such as names of individuals involved in the incident, as well as, any locations/organizations that may be used to retrace or reconstruct user identity. We present our algorithmic flowchart in Fig 1. Through #maskUp, we aim to achieve the following objectives:

1. Extract sensitive phrases/words from given paragraph/post/tweet (further referred to as a document).
2. Enable Continual Learning using EWC paradigm for targeted neuron training.
3. Selectively encrypt only those aspects of the document which may be sensitive to the users (such as names, locations, organizations, among others.).
4. Provide a mechanism for criminal authorities to decrypt all user data (Master-Key Module).

We demonstrate a flow of data and encryption keys through our proposed methodology.

Continual NER

For the active and continual deployment of #maskUp, we recognized the need for integration with online learning paradigms. As language and grammatical structures tend to shift, it becomes imperative for said model to incorporate and augment its parameters with this new data.
Figure 1: Algorithmic flow chart of #maskUp detailing flow of data and encryption keys for given objectives. Included are the
(1) Sensitive-Entity-Retrieval System (2) User Based Symmetric-Key Encryption Mechanism (3) Master-Key Module. Here,
A and B simply act as connectors co-joining Asymmetric-key Encryption with encrypted session-key storage and Platform
Database with encrypted session-key storage.

• B-PER  • I-PER  • B-ORG  • I-ORG
• B-LOC  • I-LOC  • B-MISC  • I-MISC

Named Entity Recognition becomes an important aspect
of our proposed methodology as it seeks to retrieve those en-
tities which may leak victim privacy. Our objective aims to
fine-tune an NER for the task of sensitive feature retrieval.
We train the NER on the CoNLL-2003 Dataset, a benchmark
in NER tasks. The CoNLL-2003 is a named entity recogni-
tion dataset released as a part of CoNLL-2003 shared task:
language-independent named entity recognition. Following
are the entities the model learns to distinguish with respect
to said dataset. The dataset follows a prescribed template
where the words tagged with O are outside of the named
entities while the I − XXX tag is used for words inside a
named entity of type XXX. Whenever two entities of type
XXX are immediately next to each other, the first word
of the second entity will be tagged B − XXX in order to
show that it starts another entity. The data includes entities
of four types: persons (PER), organizations (ORG), loca-
tions (LOC) and miscellaneous names (MISC) as men-
tioned above. Each of which are relevant to our extraction of
sensitive attributes.

This enables the model to retrieve only those aspects
of the dataset which may include personal details, such as
names, associated organizations, locations, among other sen-
sitive attributes. Utilizing the depth and variety of CoNLL-
2003 dataset, allows us assurance over our collection.

We aim to integrate a rectification feature, whereby users
may choose to use/not use certain words selected by them,
allowing our models to utilize the concept of EWC for pro-
gressive learning overtime (Kirkpatrick et al. 2016). This
corrective feature would further allow users to include their
own words, making the model synchronous with the users’
linguistics.

Selective Attribute Encryption
Selective attribute encryption is enabled as the base
mechanism for privacy-preservation within #maskUp. We employ AES—Symmetric Key Encryption system
for securing said data. The symmetric-key is gen-
erated for every user independent of others, it uti-
lizes their given PLATFORM_PASSWORD and em-
ployes a NOISE_TRANSFORMATION coupled with
DOUBLE_ENCRYPTION of the output, generating a
key of KEY_SIZE = 128bits. This key is then utilized for
selective encryption of target entities within the user text.
The rest of the document is returned as user-provided and
no changes are made to it. We choose to employ AES for
the encryption mechanism due to its wide usage, as well as
its ingrained security.

Master-Key Module
While the utilization of symmetric key encryption pro-
vides validity and safety in securing user data, it does
not account for visibility to civic authorities. It becomes
important that legally binding authorities understand and
evaluate concerns regarding said posts, and therefore,
a Master-Key module is created which makes use of
asymmetric-key encryption system. We specifically employ
## Table 1: Performance of Complete AES Encryption against Selective AES Encryption. Relayed Time Taken in ms and Memory Utilization (kB). Performance generalized over 30 articles in each instance of comparison.

| Algorithm Name   | Time Taken - Encryption | Time Taken - Decryption | Memory Utilized |
|------------------|-------------------------|--------------------------|-----------------|
| Full AES Encryption | 2038.5                  | 1970.4                   | 1.406           |
| #maskUp          | 211.6                    | 207.5                    | 0.553           |

## Table 2: Performance of 5-Fold Cross Validation of Google’s electra-small-discriminator model for NER on the CoNLL-2003 dataset.

| Level     | F1-Score | Precision | Recall |
|-----------|----------|-----------|--------|
| B-PER     | 0.949689 | 0.953242  | 0.946163|
| I-PER     | 0.984483 | 0.980258  | 0.988745|
| B-ORG     | 0.868681 | 0.890082  | 0.848284|
| I-ORG     | 0.839024 | 0.854658  | 0.823952 |
| B-LOC     | 0.914252 | 0.901458  | 0.927415 |
| I-LOC     | 0.811808 | 0.769231  | 0.859375 |
| B-MISC    | 0.807584 | 0.796399  | 0.819088 |
| I-MISC    | 0.64488 | 0.609053  | 0.685185 |
| AVG_MICRO | 0.894215 | ---        | ---      |
| AVG_MICRO | 0.85255 | ---        | ---      |

RSA-encryption for encrypting the symmetric keys of every user. The platform utilizes $PUBLIC_K.EY$ provided by the legally binding authority of that country/state. A $PRIVATE_K.EY$ is used by the authorities to decrypt the said symmetric key. Since the authorities aren’t aware of the NOISE_TRANSFORMATION coupled with DOUBLE_ENCRYPTION mechanism, we ensure the privacy of User passwords. This ability acts as a master key, allowing users to easily navigate their own accounts independently of other users. However, authorities can overlook and decrypt sensitive attributes from whichever account they wish to pull.

### Result Analysis

For our implementation, we incorporate the NERDA library for NER-model training. We specifically utilize the “google/electra-small-discriminator” model for its state-of-the-art electra implementation as well its comparatively smaller base. We provide in Table 2 its training over the CoNLL-2003 corpora.

We provide a comparative analysis in Table 1 for complete encryption and selective encryption of data by #maskUp. The execution time was averaged over 30 distinct articles giving us a generalized overview of time-memory utilization.

The experiments clearly distinguish performance of selective encryption from complete encryption. With an optimization of up to 89.1% for time-taken during encryption and 60.7% for memory consumed, #maskUp considerably reduces deployment costs on edge-devices. The further integration of continual learning also supplements the privacy-preserving features of this proposal. Our utilization of EWC is inspired by the NERDA—Con python library (Vijay and Priyanshu 2022), which is a pipeline for training NERs with LLM bases by incorporating the concept of Elastic Weight Consolidation (EWC) into the NER fine-tuning NERDA pipeline.

### Ethical Considerations

We work with the aim to help vocalize victims of gender-based crimes on social media to expedite the process of seeking assistance from the concerned authorities. We acknowledge that sensitive information may be subjective and open for interpretation. We take further precautions to ensure data doesn’t get leaked and is directly accessible to only authorities who possess the master key. However, we recognize that it is almost impossible to prevent abuse of released technology even when developed with good intentions (Hovy and Spruit 2016). All the examples shown in this paper have been taken from online reports, ensuring anonymization and paraphrasing for user privacy. We further acknowledge that our named entity recognition pipeline may be susceptible to allocation bias, regularity bias and bias against certain demographics (Ghaddar et al. 2021; Mishra, He, and Belli 2020). However, the essence of our work is to create a safe space for abuse victims to come forward and voice their incidents directly to the authorities without having to fear the spread of information or societal stigma. Furthermore, it is essential that the authorities aren’t overburdened by falsified complaints that hinder the road to justice.

### Conclusion

With a motivation to provide a safe space for victims of gender-based crimes and for authorities to investigate the identification of said criminals, we present #maskUp, a method for information to be conveyed securely to the relevant authorities. #maskUp utilizes masking technology to selectively encrypt sensitive information and continuously train on new data using continual learning. Sampled datasets are used to validate and ensure the working of the same. Future work can try to focus on the multilingual aspect of vocalization as well to include victims of all languages. We believe this method will help embolden victims to come forward and report incidents without any fear of societal judgement or misuse of power.

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Figure 2: Algorithmic flow of a User’s post through #maskUp.