Hate Speech Detection in an Italian Incel Forum Using Bilingual Data for Pre-Training and Fine-Tuning

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Abstract

English. In this study, we aim to enhance hate speech detection in an Italian incel forum. We pre-train monolingual (Italian) and multilingual Transformer models on corpora built from two incel forums, one in Italian and one in English, using masked language modeling. Then, we fine-tune the models on combinations of English and Italian corpora, binary-annotated for hate speech. Experiments on a hate speech corpus derived from the Italian incel forum show that the best results are achieved by training multilingual models on bilingual data, rather than training monolingual models on Italian-only data. This emphasizes the importance of using training and testing data from a similar linguistic domain, even when the languages differ.

Italiano. *In questo studio, ci proponiamo di migliorare il rilevamento dei discorsi d'odio in un forum italiano di incel. Addestriamo modelli Transformer monolingue (italiano) e multilingue su corpora ottenuti da due forum di incel, uno in italiano e uno in inglese, con il masked language modeling. Facciamo quindi il fine-tuning dei modelli su corpora in italiano e inglese con annotazioni binarie indicanti se un post esprime odio. Sperimentando su un corpus annotato per i discorsi di odio ottenuto da un forum italiano di incel mostriamo che i risultati migliori si ottengono addestrando modelli multilingue su combinazioni bilingue di corpora e non con modelli italiani e dati monolingue. Ciò sottolinea l'importanza di utilizzare dati di addestramento appartenenti a un contesto linguistico simile a quello dei dati di valutazione, anche con lingue differenti.*

1 Introduction

Hate speech, broadly defined as language that expresses hatred towards a targeted group or is intended to be derogatory, humiliating, or insulting to the members of the group (Davidson et al., 2017), has become an increasingly prevalent and dangerous phenomenon (Matamoros-Fernández and Farkas, 2021). A specific area of concern in the realm of hate speech is the online spaces known as the "Manosphere", where misogynous discourse in particular has become increasingly rampant (Ribeiro et al., 2021). Specifically, within the Manosphere, the incel (short for "involuntary celibate") community has been identified as frequently engaging in hateful, misogynous, and racist speech (Nagle, 2017; Jaki et al., 2019).

While there is no scarcity of English-language models and training resources for the detection of hate speech, especially with the recent rise in popularity of this research topic (Alkomah and Ma, 2022), much work can still be done when approaching this problem in other languages. For less-resourced languages, such as Italian, one of the main difficulties of combating this phenomenon is the lack of annotated data (Van, 2023). The problem becomes even more exacerbated when considering the detection of hate speech in niche contexts, such as in forums frequented by incels, which are characterized by the use of specific misogynous and racist lexicon (Gothard, 2020). In particular, it seems no work has yet been done on the detection of hate speech in Italian incel forums.

In this paper, we present a simple approach to improving the performance of hate speech detection models in Italian incel forums. Our contribution is two-fold:

(*i*) Masked language modeling We adapt monolingual Italian models and multilingual models to the linguistic domain of Italian and English incel forums by training them on the masked lan-

guage modeling (MLM) task on the aforementioned unsupervised corpora. We release these novel models, which can be used for further research on the topic.[1]

***(ii)* Hate speech detection** We approach the detection of hate speech in Italian incel forums using monolingual (Italian) and bilingual (Italian–English) combinations of corpora, binary-annotated for hate speech, compiled from incel forums and mainstream social media. We fine-tune the monolingual models on Italian-only combinations of corpora, while the multilingual models are fine-tuned on bilingual combinations. Testing their performance on a supervised hate speech corpus, obtained from the Italian incel forum, shows that the best results are obtained by training the multilingual model on bilingual data taken from both the English and Italian incel forums, using the MLM task, and then fine-tuning it on combinations of English and Italian hate speech corpora.

In the approached scenarios, pre-training and fine-tuning on in-domain incel annotated data may therefore be more effective than training on general target-language supervised corpora, despite part of the training data not being in the language of the downstream task. In addition, the results show that this strategy can be used to improve model performance when in-domain target-language data is scarce, by using in-domain data from other languages.

The rest of the paper is organized as follows: Section 2 presents related work on hate speech detection in Italian and English, as well as multilingual approaches to the problem. Section 3 describes the corpora used in this study. Section 4 presents the models used in this study, while Section 5 describes the experiments conducted and discusses the results.

2 Related Work

Prior work on Italian hate speech detection has been conducted chiefly within the context of EVALITA. The 2018 edition hosted a shared task on hate speech detection (Bosco et al., 2018) based on two corpora, one from Twitter and one from Facebook. The participating teams experimented with a variety of machine-learning and deep-learning algorithms, with the top team relying on an SVM and a BiLSTM (Cimino et al., 2018). The 2020 edition hosted a shared task on the detection of hate speech, especially against migrants, focusing on tweets and news headlines (Basile et al., 2020). In this case, the best results were obtained by using AlBERTo (Polignano et al., 2019) and UmBERTo (Parisi et al., 2020), two Transformer models for Italian. The 2020 edition also hosted a shared task on the automatic identification of misogyny in Italian tweets (Fersini et al., 2020), where an ensemble of BERT models won the competition (Muti and Barrón-Cedeño, 2020).

English-language hate speech detection has been conducted in a variety of ways. Davidson et al. (2017) build a corpus of tweets annotated with multi-class labels ("hate speech", "offensive", "neither") and train logistic regression and linear SVM models on it. Mathew et al. (2021) build a dataset called "HateXplain" from Twitter and Gab posts, annotated with a multi-class label based on whether the post is "offensive", expesses "hate", or is "normal", which they use to fine-tune a BERT hate speech classifier. Caselli et al. (2021) retrain BERT$_{base}$ on the MLM task using a dataset built from hateful and offensive Reddit messages, obtaining a model called "HateBERT", capable of outperforming BERT$_{base}$ on hate speech identification on various benchmark datasets.

In multilingual settings, Pelicon et al. (2021) use a multilingual combination of datasets annotated for hate speech to improve the performance of classifiers in zero-shot, few-shot and well-resourced settings. Gokhale et al. (2022) use MLM training to improve the hate speech detection performance of BERT in Hindi and Marathi, separately. We follow such approaches in attempting to improve the performance of our models.

A: do you compare against them?

P: no, we just apply the approach on another problem

3 Corpora

We leverage three supervised Italian-language corpora from past EVALITA campaigns, along with two supervised corpora compiled from two incel forums, one in English and one in Italian.

EVALITA corpora The first Italian corpus we use was compiled for the first edition of the Hate Speech Detection (HaSpeeDe) shared task, from EVALITA 2018 (Bosco et al., 2018) (henceforth "HSD-FB"), by annotating Facebook posts for hate speech. The second one is from the 2020 HaSpeeDe shared task (Basile et al., 2020) ("HSD-TW"), compiled by adding new data to the HaSpeeDe 2018 Twitter dataset. The third cor-

[1] https://github.com/paolo-gajo/clic23

Table 1: Statistics of the *Incels.is* and *Il forum dei brutti* (*FdB*) unsupervised corpora. Mean length computed at token level.

Corpus	Posts	Threads	Length
Incels.is	4,760k	230k	31.07±70.01
FdB	638k	30k	52.78±80.77

Table 2: Hate speech (HS) annotation statistics for the adopted supervised corpora.

Corpus	HS	%	Non-HS	%
IFS-EN	2,090	40.17	3,113	59.83
IFS-IT	200	40.00	300	60.00
HSD-FB	1,382	46.08	1,617	53.92
HSD-TW	971	32.38	2,028	67.62
AMI-20	2,337	46.74	2,663	53.26

pus is the one compiled for the Automatic Misogyny Identification (AMI) shared task (Fersini et al., 2020) ("AMI-20"), hosted at EVALITA 2020. AMI-20 also contains tweets and is annotated with misogyny labels, which we use in place of hate speech labels.[2] The corpora were split 70/30 between training and development sets (we do not use the test partitions of these shared tasks).

A: why? Why not using the official partitions? That would allow you to eventually compare against them

P: there was only training data in the datasets, so I assume teams had to split the dataset into train and dev themselves for the competitions. i use the train set, split it 70/30 and use it for train/dev. i did not use

Incel corpora. We use two unsupervised corpora compiled by scraping two incel forums: *Incels.is*[3] and *Il forum dei brutti*[4] (Gajo et al., 2023). Table 1 reports the statistics of the two corpora.[5] We build these new resources both due to the lack of freely available incel corpora and the fact that incel language changes rapidly, as outlined in Appendix A, making it worthwhile to compile updated resources.

A subset of the two datasets was annotated for both misogyny and racism. For English, a subset of 50 posts was randomly selected and labeled by three annotators, all with a C2 CEFR level of English, well-versed in linguistics, gender studies, NLP, and data annotation. The Cohen's Kappa inter-annotator agreement (IAA) (Bobicev and Sokolova, 2017) was of 0.77, which is considered high. As such, the remaining instances were annotated by a single annotator. For the Italian dataset, two native speakers of Italian, also experts in the relevant fields, annotated 50 posts as well, reaching an IAA of 0.69. As the IAA was deemed acceptable, the rest of the instances were once again annotated by one annotator.

We refer to these two supervised corpora as IFS-EN (Incel Forum, Supervised, English) and IFS-IT (Incel Forum, Supervised, Italian). IFS-EN is split between training, development and testing partitions with a 70/15/15 split, while IFS-IT is only used for testing. The datasets are annotated for racism and misogyny, since they are the most relevant forms of hate speech in the two forums (Silva et al., 2016; Ging and Siapera, 2018). Posts are annotated as hateful if they are either labeled as misogynous or racist.

The annotation statistics of all the datasets used in this study can be found in Table 2.

4 Models

ABC: I am here (24/07)

With relation to the Italian-only scenario, we use UmBERTo and AlBERTo as our baseline models. We choose these models because they achieved the best performance in previous EVALITA shared tasks on hate speech (Basile et al., 2020) and misogyny (Fersini et al., 2020) identification. We also create MLM-enhanced versions of these two models by training them on the entirety of the contents of IFU-22-IT, for a total of $627k$ posts.[6] We refer to these models as "Incel UmBERTo" and "Incel AlBERTo".

As regards the Italian-English setting, we use mBERT$_{base}$ as our baseline. We also use an MLM-enhanced version of it, "Incel mBERT", which we obtain by training it for one epoch on $500k$ posts sampled from IFU-22-EN and $500k$ posts sampled from IFU-22-IT, for a total of $1M$ posts in Italian and English.

The MLM pre-training process is carried out in all cases by tokenizing post contents using each model's own tokenizer and masking tokens with a probability of 15%. We use a batch size of 32 samples and train the models for one epoch on a single Tesla P100 GPU with 16 GB of VRAM.

5 Experiments and Evaluation

We approach the task of identifying hate speech as a binary classification problem, where a post can either be hateful or not. We train each model

[2] In incel spaces most of the hate speech is expressed in the form of misogyny, making this data useful.

[3] https://incels.is

[4] https://ilforumdeibrutti.forumfree.it

[5] Both corpora are available at: https://zenodo.org/record/8147845.

[6] The number of posts is lower than the total number of posts ($638k$) because we exclude empty posts.

Table 3: Performance when fine-tuning on Italian-only corpora combinations. Epochs (e) selected based on validation performance. Highest scores in bold.

	HSD-FB	HSD-TW	AMI-20	(e)	$\mathbf{F}_{1\ val}$	$\mathbf{R}_{val}$	$\mathbf{P}_{val}$	$\mathbf{F}_{1\ test}$	$\mathbf{R}_{test}$	$\mathbf{P}_{test}$
UmBERTo	■			5	0.855±0.003	0.868	0.843	0.696±0.010	**0.879**	0.576
		■		4	0.754±0.004	0.800	0.713	0.432±0.060	0.319	0.685
			■	4	**0.914±0.004**	**0.931**	**0.899**	0.569±0.031	0.520	0.631
	■	■		4	0.788±0.006	0.824	0.755	0.666±0.024	0.758	0.595
	■		■	5	0.883±0.004	0.900	0.867	**0.697±0.019**	0.747	0.653
		■	■	5	0.828±0.003	0.844	0.814	0.596±0.017	0.526	**0.688**
	■	■	■	5	0.822±0.003	0.836	0.808	0.680±0.016	0.692	0.671
Incel UmBERTo	■			5	0.867±0.006	0.887	0.848	**0.705±0.009**	**0.870**	0.593
		■		4	0.756±0.002	0.810	0.708	0.403±0.024	0.285	0.692
			■	4	**0.918±0.001**	**0.946**	**0.891**	0.652±0.031	0.608	0.705
	■	■		4	0.790±0.003	0.831	0.754	0.660±0.014	0.696	0.627
	■		■	5	0.886±0.002	0.901	0.872	0.704±0.005	0.732	0.678
		■	■	2	0.831±0.003	0.866	0.799	0.648±0.011	0.544	**0.802**
	■	■	■	5	0.828±0.003	0.853	0.804	0.699±0.029	0.718	0.682
AlBERTo	■			4	0.850±0.003	0.899	0.807	0.683±0.006	**0.941**	0.537
		■		1	0.752±0.006	0.817	0.698	0.520±0.089	0.426	**0.716**
			■	2	**0.907±0.004**	**0.952**	**0.866**	0.528±0.022	0.517	0.542
	■	■		2	0.775±0.003	0.803	0.750	0.695±0.007	0.786	0.623
	■		■	3	0.879±0.003	0.918	0.843	**0.705±0.011**	0.803	0.629
		■	■	3	0.820±0.001	0.888	0.762	0.652±0.018	0.645	0.660
	■	■	■	2	0.808±0.011	0.872	0.753	0.684±0.015	0.821	0.587
Incel AlBERTo	■			5	0.847±0.005	0.863	0.831	**0.707±0.007**	**0.791**	0.639
		■		1	0.748±0.002	0.785	0.715	0.506±0.035	0.370	**0.805**
			■	5	**0.912±0.003**	**0.930**	**0.895**	0.617±0.018	0.562	0.685
	■	■		2	0.771±0.004	0.791	0.752	0.673±0.016	0.721	0.632
	■		■	5	0.873±0.003	0.888	0.858	0.668±0.014	0.663	0.674
		■	■	1	0.818±0.004	0.864	0.776	0.656±0.007	0.593	0.736
	■	■	■	4	0.800±0.009	0.828	0.773	0.688±0.017	0.747	0.639

five times on all possible combinations of the previously introduced datasets. We do this in order to make our results more reliable and diminishing the effect of the random initialization of the models. In the monolingual Italian setting we never use IFS-EN, while it is always included when training the multilingual models in the bilingual setting. We select the number of epochs based on the convergence of the performance on the validation set. For each dataset combination, the training and validation sets are the unions of the individual training and validation sets of each merged dataset. The models are then evaluated on IFS-IT.

Table 3 shows the performance in terms of precision, recall and F_1-measure for the Italian-only models and dataset combinations, while Table 4 reports the results for the bilingual setting.

Monolingual setting As regards the Italian-only combinations, the top-performing model is Incel AlBERTo, which achieves a test F_1 score of 0.707 when training solely on HSD-FB. Compared to AlBERTo, this represents an improvement of 2.4 F_1 points. To a lesser degree, the same can be observed with regard to Incel UmBERTo and UmBERTo (+0.9 F_1 points), when using the same combination. In both cases, this shows that pre-training AlBERTo and UmBERTo using MLM on Italian posts extracted from IFU-22-IT is effective in improving their performance.

The worst test results, for all models, are obtained when training solely on HSD-TW, with Incel AlBERTo and Incel UmBERTo performing worse than UmBERTo and AlBERTo, which shows an opposite trend to the one observed when training on HSD-FB. The validation scores are

Table 4: Performance when fine-tuning on monolingual and bilingual combinations of English and Italian supervised corpora. Epochs (e) selected based on validation performance. Highest scores in bold.

		HSD-FB	HSD-TW	AMI-20	IFS-EN	(e)	$\mathbf{F}_{1\ val}$	$\mathbf{R}_{val}$	$\mathbf{P}_{val}$	$\mathbf{F}_{1\ test}$	$\mathbf{R}_{test}$	$\mathbf{P}_{test}$
mBERT	Monolingual	■				4	0.807±0.008	0.846	0.775	0.651±0.013	0.891	0.516
			■			4	0.717±0.012	0.745	0.693	0.493±0.037	0.455	0.540
				■		5	**0.885±0.003**	**0.890**	**0.881**	0.425±0.034	0.384	0.479
		■	■			2	0.732±0.014	0.743	0.724	0.619±0.034	0.711	0.552
		■		■		3	0.844±0.002	0.873	0.818	0.639±0.023	0.747	0.560
			■	■		3	0.789±0.008	0.830	0.754	0.560±0.023	0.621	0.516
		■	■	■		5	0.784±0.002	0.793	0.775	0.600±0.014	0.634	0.569
					■	5	0.846±0.010	0.854	0.837	0.465±0.046	0.345	**0.725**
	Bilingual	■			■	3	0.841±0.004	0.852	0.832	**0.688±0.006**	**0.921**	0.549
			■		■	3	0.846±0.002	0.866	0.827	0.529±0.041	0.482	0.588
				■	■	5	0.844±0.007	0.849	0.838	0.634±0.023	0.587	0.692
		■	■		■	4	0.844±0.006	0.844	0.844	0.616±0.028	0.675	0.568
		■		■	■	5	0.842±0.004	0.844	0.840	0.676±0.012	0.801	0.585
			■	■	■	4	0.847±0.008	0.841	0.853	0.570±0.048	0.535	0.620
		■	■	■	■	5	0.837±0.008	0.829	0.845	0.613±0.019	0.639	0.590
Incel mBERT	Monolingual	■				1	0.817±0.009	0.865	0.777	0.668±0.016	0.841	0.557
			■			5	0.727±0.006	0.757	0.701	0.461±0.032	0.379	0.589
				■		4	**0.895±0.007**	**0.912**	**0.879**	0.574±0.047	0.511	0.666
		■	■			3	0.747±0.007	0.774	0.723	0.605±0.015	0.640	0.574
		■		■		3	0.854±0.004	0.896	0.816	0.654±0.025	0.752	0.583
			■	■		4	0.802±0.003	0.840	0.767	0.645±0.019	0.655	0.639
		■	■	■		3	0.799±0.004	0.825	0.774	0.648±0.022	0.644	0.653
					■	3	0.855±0.003	0.877	0.834	0.516±0.071	0.386	**0.807**
	Bilingual	■			■	5	0.859±0.010	0.853	0.864	0.708±0.007	**0.889**	0.588
			■		■	2	0.861±0.015	0.866	0.856	0.615±0.025	0.558	0.690
				■	■	4	0.853±0.009	0.863	0.844	**0.722±0.028**	0.704	0.746
		■	■		■	5	0.857±0.007	0.855	0.859	0.679±0.014	0.731	0.635
		■		■	■	4	0.856±0.009	0.857	0.856	0.689±0.011	0.707	0.673
			■	■	■	5	0.850±0.007	0.839	0.860	0.644±0.010	0.580	0.725
		■	■	■	■	5	0.869±0.003	0.878	0.861	0.700±0.013	0.702	0.698

also noticeably lower for HSD-TW combinations, compared to combinations including HSD-FB, showing that the models have a harder time learning from HSD-TW. This is coherent with the results obtained by teams participating in the two HaSpeeDe shared tasks (Bosco et al., 2018; Basile et al., 2020) and with the fact that the messages contained in HSD-FB are "longer and more correct than those in Twitter, allowing systems (and humans too) to find more and more clear indications of the presence of HS" (Bosco et al., 2018). The fact that messages in HSD-FB are longer is also coherent with the Italian incel models performing better than the vanilla models when training on HSD-FB, since *Il forum dei brutti* on average contains rather long posts (see Table 1), unlike Twitter datasets, which were limited to 280 characters per tweet prior to 2023. Finally, an additional element which might explain the lower performance when training on HSD-TW is the fact that it contains hate speech against migrants, which might not be as relevant when it comes to identifying hate speech in incel spaces.

As regards combining different Italian datasets, the strategy yields the highest performance for AlBERTo and UmBERTo when training on both HSD-FB and AMI-20. However, once the models are MLM-trained on IFU-22-IT, the performance decreases for some combinations, with MLM pretraining seemingly nullifying the improvements obtained by merging different datasets. Therefore, while some improvement can be observed by merging different datasets, MLM appears to be a more effective strategy for improving the perfor-

mance of the models, although it requires greater computational resources.

Bilingual setting Compared to the best combination using mBERT$_{base}$, which achieves a test F_1 score of 0.688, the best combination using Incel mBERT achieves a test F_1 score of 0.722 (+3.4 F_1 points), which is also the highest score across both language settings. Just like in the monolingual setting, mBERT$_{base}$ performs better when only training it on HSD-FB (in addition to IFS-EN). Conversely, Incel mBERT performs better when training on AMI-20. This is interesting, since the AMI-20 dataset lowered the performance of all Italian-only models, compared to only training on HSD-FB. Since misogyny is the main way hate speech is expressed in *Incels.is* (39.44% of the instances in IFS-EN are misogynous) and we are using posts extracted from this forum to pre-train Incel mBERT, the performance boost could be due to the fact that the model is better at learning about misogynous language compared to mBERT$_{base}$ and the Italian-only models.

On average, the lowest performance is achieved when training separately on IFS-EN and the Italian corpora. When using bilingual data, the worst results are obtained when training on HSD-TW and the combinations containing it, which is coherent with the results obtained in the monolingual setting. For almost all combinations of Italian corpora, performance increases once IFS-EN is added to the training data, i.e., bilingual combinations lead to better performance.

Monolingual vs. bilingual The results of our experiments show that the highest performance is not obtained by fine-tuning on the Italian-only dataset combinations, but on the bilingual ones. Indeed, for five dataset combinations out of seven Incel mBERT's performance is higher than all other models. The only combinations for which Incel mBERT does not beat the others are HSD-FB+AMI-20 and HSD-TW+AMI-20.

Since mBERT was originally pre-trained in 104 languages and AlBERTo and UmBERTo were pre-trained only on Italian corpora, the fact that Incel mBERT can outperform them by pre-training on just $1M$ bilingual instances is rather surprising. Even more interesting is the fact that, although we are testing on an entirely Italian dataset, Incel mBERT also outperforms Incel AlBERTo and Incel UmBERTo. Therefore, in the approached scenarios, using bilingual instances to pre-train a multilingual model using MLM seems to yield higher performance than pre-training Italian models only on Italian posts. Furthermore, the number of Italian posts used to train Incel AlBERTo and Incel UmBERTo is $627k$, which is greater than the $500k$ Italian posts used for Incel mBERT.

As such, we could conclude that the model is learning to spot hate speech more effectively in IFS-IT by learning language-agnostic incel concepts, since Incel mBERT is pre-trained on posts extracted from two incel forums in two different languages. Although the two considered incel communities are distinct, the hateful red pill ideology has spread internationally and is shared by both. This could explain why Incel mBERT performs better than the Italian-only models: the model might be learning about incel hate speech by paying more attention to the sociological concepts underlying the language, and putting less focus on purely linguistic features, ultimately improving its performance.

6 Conclusions

In this paper, we have presented an approach to improve the performance of hate speech detection models within Italian incel forums.

Our experiments show that domain-adapting Transformer models to the contents of incel forums boosts their performance when predicting the hatefulness of incel forum posts, both when using Italian-only and multilingual models. The increase in performance obtained through MLM pre-training is particularly high when using bilingual training data with mBERT$_{base}$, which might indicate that the model is learning about incel hate speech by learning language-agnostic incel concepts. We have also shown that for the base Italian models (AlBERTo and UmBERTo) fine-tuning on combinations of different Italian datasets can lead to a boost in performance. However, this performance boost is nullified after MLM pre-training, which appears to be a more effective strategy for improving the performance of the models.

In future work, we plan to experiment with different resources for MLM-pretraining, using corpora in different languages, since it seems multilingual models such as mBERT$_{base}$ are capable of learning about hate speech in a language-agnostic way from multiple languages. In ad-

dition, with more computational resources, more training epochs could be used to further improve the performance of the models.

References

Fatimah Alkomah and Xiaogang Ma. 2022. A Literature Review of Textual Hate Speech Detection Methods and Datasets. *Information*, 13(6):273, May.

Valerio Basile, Di Maro Maria, Croce Danilo, Lucia C Passaro, et al. 2020. Evalita 2020: Overview of the 7th evaluation campaign of natural language processing and sspeech tools for italian. In *Proceedings of the Seventh Evaluation Campaign of Natural Language Processing and Speech Tools for Italian. Final Workshop (EVALITA 2020)*, pages 1–7. CEUR-ws.

Victoria Bobicev and Marina Sokolova. 2017. Inter-annotator agreement in sentiment analysis: Machine learning perspective. In *International Conference Recent Advances in Natural Language Processing*, pages 97–102.

Cristina Bosco, Felice Dell'Orletta, Fabio Poletto, Manuela Sanguinetti, and Maurizio Tesconi. 2018. Overview of the EVALITA 2018 Hate Speech Detection Task. In Tommaso Caselli, Nicole Novielli, Viviana Patti, and Paolo Rosso, editors, *EVALITA Evaluation of NLP and Speech Tools for Italian*, pages 67–74. Accademia University Press.

Tommaso Caselli, Valerio Basile, Jelena Mitrović, and Michael Granitzer. 2021. HateBERT: Retraining BERT for Abusive Language Detection in English, February.

Andrea Cimino, Lorenzo De Mattei, and Felice Dell'Orletta. 2018. Multi-task learning in deep neural networks at evalita 2018. *Proceedings of the 6th evaluation campaign of Natural Language Processing and Speech tools for Italian (EVALITA'18)*, pages 86–95.

Thomas Davidson, Dana Warmsley, Michael Macy, and Ingmar Weber. 2017. Automated hate speech detection and the problem of offensive language. In *Proceedings of the International AAAI Conference on Web and Social Media*. arXiv, May.

Elisabetta Fersini, Debora Nozza, and Paolo Rosso. 2020. AMI @ EVALITA2020: Automatic Misogyny Identification. In Valerio Basile, Danilo Croce, Maria Maro, and Lucia C. Passaro, editors, *EVALITA Evaluation of NLP and Speech Tools for Italian - December 17th, 2020*, pages 21–28. Accademia University Press.

P. Gajo, A. Muti, K. Korre, S. Bernardini, and A. Barrón-Cedeño. 2023. On the identification and forecasting of hate speech in inceldom. In *Proceedings of the 2023 International Conference on Recent Advances in Natural Language Processing (RANLP 2023)*. In press.

Debbie Ging and Eugenia Siapera. 2018. Special issue on online misogyny. *Feminist Media Studies*, 18(4):515–524.

Omkar Gokhale, Aditya Kane, Shantanu Patankar, Tanmay Chavan, and Raviraj Joshi. 2022. Spread Love Not Hate: Undermining the Importance of Hateful Pre-training for Hate Speech Detection. December. arXiv:2210.04267 [cs].

Kelly C Gothard. 2020. Exploring Incel Language and Subreddit Activity on Reddit.

Sylvia Jaki, Tom De Smedt, Maja Gwóźdź, Rudresh Panchal, Alexander Rossa, and Guy De Pauw. 2019. Online hatred of women in the Incels.me forum: Linguistic analysis and automatic detection. *Journal of Language Aggression and Conflict*, 7(2):240–268, November.

Miloš Jakubíček, Adam Kilgarriff, Vojtěch Kovář, Pavel Rychlý, and Vít Suchomel. 2013. The tenten corpus family. *7th International Corpus Linguistics Conference CL 2013*, 07.

Adam Kilgarriff. 2009. Simple maths for keywords. In *Proc. Corpus Linguistics*.

Lexical Computing Ltd. 2015. Statistic used in sketch engine. `https://www.sketchengine.eu/documentation/statistics-used-in-sketch-engine/`, 7.

Ariadna Matamoros-Fernández and Johan Farkas. 2021. Racism, Hate Speech, and Social Media: A Systematic Review and Critique. *Television & New Media*, 22(2):205–224, February.

Binny Mathew, Punyajoy Saha, Seid Muhie Yimam, Chris Biemann, Pawan Goyal, and Animesh Mukherjee. 2021. Hatexplain: A benchmark dataset for explainable hate speech detection. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 14867–14875.

Arianna Muti and Alberto Barrón-Cedeño. 2020. UniBO @ AMI: A Multi-Class Approach to Misogyny and Aggressiveness Identification on Twitter Posts Using AlBERTo. In Valerio Basile, Danilo Croce, Maria Maro, and Lucia C. Passaro, editors, *EVALITA Evaluation of NLP and Speech Tools for Italian - December 17th, 2020*, pages 29–34. Accademia University Press.

Angela Nagle. 2017. *Kill all normies: Online culture wars from 4chan and Tumblr to Trump and the alt-right.* Zero Books, Winchester, Hampshire, UK, July.

Loreto Parisi, Simone Francia, and Paolo Magnani. 2020. Umberto: an italian language model trained with whole word masking. `https://github.com/musixmatchresearch/umberto`.

Andraž Pelicon, Ravi Shekhar, Blaž Škrlj, Matthew Purver, and Senja Pollak. 2021. Investigating cross-lingual training for offensive language detection. *PeerJ Computer Science*, 7:e559, June.

Björn Pelzer, Lisa Kaati, Katie Cohen, and Johan Fernquist. 2021. Toxic language in online incel communities. *SN Social Sciences*, 1(8):1–22.

Marco Polignano, Pierpaolo Basile, Marco de Gemmis, Giovanni Semeraro, and Valerio Basile. 2019. AlBERTo: Italian BERT Language Understanding Model for NLP Challenging Tasks Based on Tweets. In *Proceedings of the Sixth Italian Conference on Computational Linguistics (CLiC-it 2019)*, volume 2481. CEUR.

Manoel Horta Ribeiro, Jeremy Blackburn, Barry Bradlyn, Emiliano De Cristofaro, Gianluca Stringhini, Summer Long, Stephanie Greenberg, and Savvas Zannettou. 2021. The evolution of the manosphere across the web. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 15, pages 196–207.

Leandro Silva, Mainack Mondal, Denzil Correa, Fabrício Benevenuto, and Ingmar Weber. 2016. Analyzing the targets of hate in online social media. In *Tenth international AAAI conference on web and social media*.

Hoang Van. 2023. Mitigating data scarcity for large language models.

Linda Zhou, Andrew Caines, Ildiko Pete, and Alice Hutchings. 2022. Automated hate speech detection and span extraction in underground hacking and extremist forums. *Natural Language Engineering*, pages 1–28.

A Analysis of Keyness in Incel Forums

We can investigate the difference of relative frequency in word usage between general language and the language used in a specific speech community by building corpora representative of the two groups of speakers. That is, we can use a large *reference corpus*, representing general language usage, and compare its frequencies to a *focus corpus* (Kilgarriff, 2009), built only from texts pertaining to a specific communicative context.

We show the evolution of incel language by studying the change in *keyness* (Kilgarriff, 2009) of specific sets of words, showing how the lexical features of incel communities of speakers of Italian and English change rapidly over time. Keyness indicates which words in a focus corpus are highly frequent compared to a reference corpus. The keyness of a word w is defined as (Lexical Computing Ltd., 2015):

$$keyness(w) = \frac{fpm_f(w) + n}{fpm_r(w) + n} \quad (1)$$

where $fpm_f(w)$ represents the normalized frequency of a focus corpus word per million words, $fpm_r(w)$ refers to the word in the reference corpus, and n is a smoothing parameter (here, $n = 1$).

To study the Italian forum, *Il forum dei brutti*, we consider all of its contents, for a total of $30M$ words (up to 4 December 2022). We do the same for the English-speaking *Incels.is* forum, for a total of $104M$ words (collected up to 18 October 2022). For Italian, we calculate the keyness by using itTenTen20 as the reference corpus, while for English we use enTenTen20 (Jakubíček et al., 2013).

For both forums, in order to compile a list of characteristic incel lexicon the keyness of lexical items was calculated across the entirety of the forums, up to the aforementioned cutoff dates. Preliminary candidates were selected by collecting single- and multi-word items that ranked in the top 500 for keyness, for a total of $1k$ analyzed items. Among these, only terms considered to be typical of incel language were examined.

As regards *Il forum dei brutti*, we studied terms we deemed to be characteristic of the forum's incel language, focusing on 10 terms used to describe other men in negative or positive ways. We chose this approach because the goal of this modern diachronic study is to show that language specific to incels changes over time, regardless of whether it can be considered hateful. Therefore, since in *Il forum dei brutti* we could not find a great amount of overtly hateful jargon, we decided to consider the way men are represented.

Conversely, racism and misogyny are very characteristic elements of the language used in *Incels.is*. As such, a simple way to choose characteristic terms for this speech community is manually evaluating racist and misogynous terms (or terms that are frequently associated to racist and misogynous contexts) and selecting those which are not typically found in general language, i.e., having high keyness scores.

The evaluation of the individual terms was carried out by manually analyzing concordance lines in the corpus with the objective of verifying whether their use could be construed as being hateful. Although human evaluation is unavoidably subjective, we erred on the side of caution and

only selected terms which could unmistakably be used in a hateful manner. Unfortunately, this terminology extraction strategy has the drawback of not directly taking into account terms that get resemanticized and assume a new, offensive meaning. Further work could be carried out to identify such terms in order to have a more comprehensive understanding of the issue.

In order to conduct the study, the contents posted on the *Il forum dei brutti* were divided chronologically by grouping posts by year of creation, from 2009 to 2022, for a total of 14 partitions. With a similar approach, *Incels.is* was divided into 22 chronological partitions, from 2017 to 2022, one for each 100 pages, each page containing 100 threads.

The keyness of each selected term was measured for every partition, calculating the slope m of its regression line as:

$$m = \frac{\sum_{i=1}^{n}(t_i - \bar{t})(k_i - \bar{k})}{\sum_{i=1}^{n}(t_i - \bar{t})^2} \quad (2)$$

where t_i is the i-th time partition, k_i is the i-th keyness score, n is the number of partitions, and $\bar{t}$ and $\bar{k}$ are the means of the two variables. By calculating the slope of the regression line, we are able to find how the keyness of a term changes over time. A positive slope indicates that the use of a term is becoming more frequent, while a negative slope indicates that a term is becoming less prevalent. For each term, the slope was first calculated across all partitions (14 for *Il forum dei brutti* and 22 for *Incels.is*); then, it was divided by the average keyness of the term over all the partitions, thus obtaining the normalized slope. This was done because certain terms may have very high keyness values, while other terms may not be as prevalent, and we wanted to be able to compare the slope of different terms regardless of the absolute value of their keyness.

For each partition, only the keyness of the 500 terms with the highest keyness was recorded. Zero values, produced whenever the item's keyness was not high enough to appear among the top 500 terms of the partition, were ignored both for the calculation of the slope and the average keyness. The number of zero values for for *Il forum dei brutti* was 44.44%, while for *Incels.is* it was 7.16% of the total.

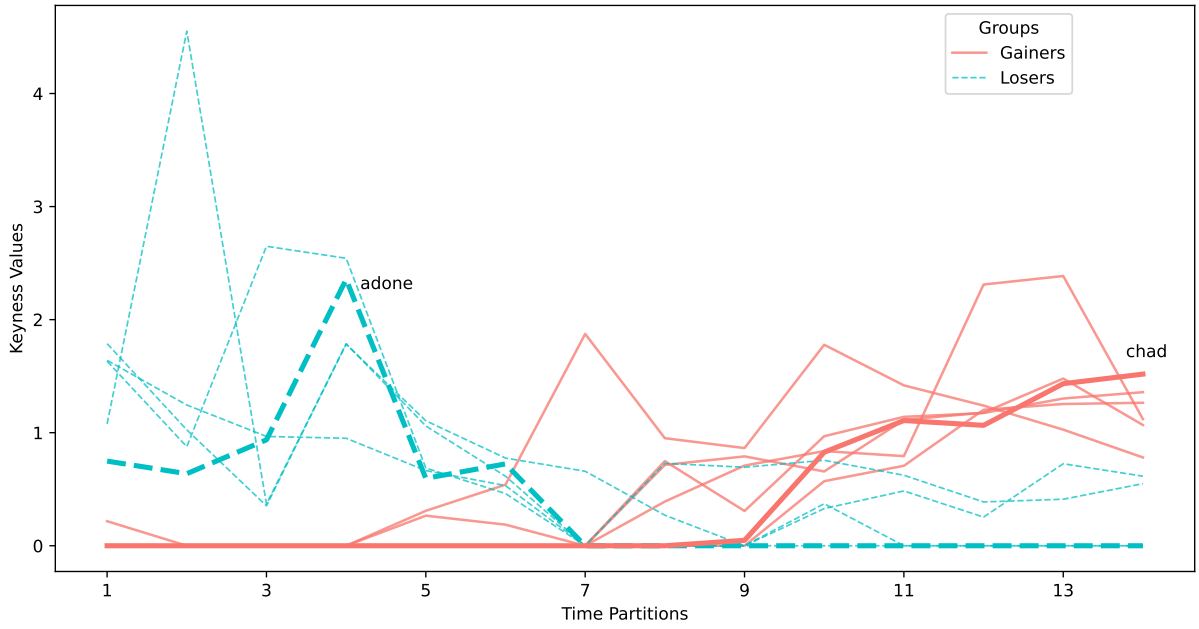
With relation to *Il forum dei brutti* we picked the top and bottom 5 terms with the highest and lowest normalized slope, 10 in total, while for *Incels.is*, we selected the top and bottom 10 terms, 20 in total. The lower number of terms for *Il forum dei brutti* is due to the fact that we could not identify enough relevant terms for the study. For both forums, the mean normalized slope was finally calculated for each group of terms to have a pair of values which could be used to compare the two overall trends.

Table 5: Keyness normalized slopes for *Incels.is* and *Il forum dei brutti*.

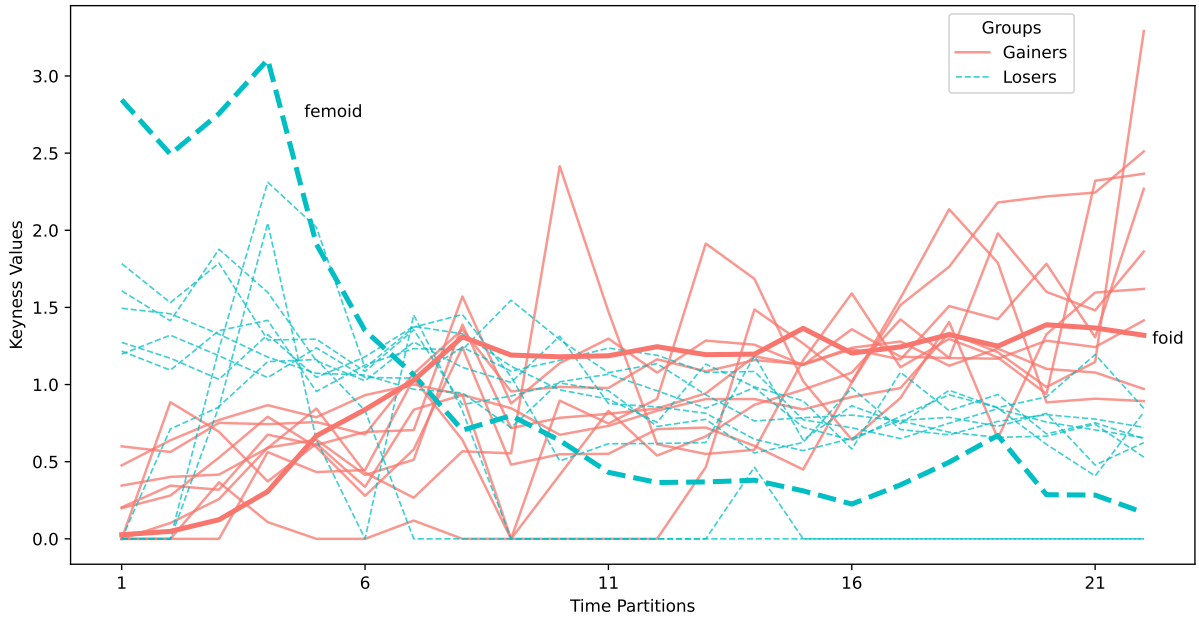
Forum	Gainers		Losers	
	Term	**Slope**	**Term**	**Slope**
Il forum dei brutti	zerbini	0.104	reietto	-0.142
	normie	0.121	strafigo	-0.122
	bv	0.125	figaccione	-0.122
	chad	0.126	attraente	-0.113
	subumano	0.158	adone	-0.103
	Mean	**0.127**	**Mean**	**-0.120**
Incels.is	shitskin	0.093	racepill	-0.019
	deathnic	0.081	stacie	-0.022
	cumskin	0.079	jb	-0.027
	noodlewhore	0.077	chadlite	-0.029
	slav	0.068	whitecels	-0.032
	foid	0.058	cunt	-0.036
	curryland	0.051	slut	-0.046
	aryan	0.048	deathnik	-0.047
	ricecel	0.047	roastie	-0.051
	whore	0.025	femoid	-0.124
	Mean	**0.063**	**Mean**	**-0.043**

Figure 1 shows the over-time trend of the keyness of the terms extracted from *Il forum dei brutti* and *Incels.is* over the partitions of the two forums. The curves show clear opposite trends for the two groups, which we refer to as "gainers" and "losers" of keyness, based on whether their mean normalized slope is positive or negative, respectively. The plots help visualize a widening over-time difference in lexicon, which may cause models trained on dated texts to become increasingly worse at evaluating more recent data. The highlighted terms in the figure also show that certain terms seem to substitute each other over time, although not all of them can be paired in this manner. For example, "adone" is a close synonym of "chad", while "foid" is a contraction of "femoid", and for both pairs we can observe opposite trends with a specific point in time in which one overtakes the other.

Table 5 reports the normalized slopes of the terms obtained from the two forums. In both cases, the mean normalized slopes of the two data series, compared side by side, quantitatively display a clear trend according to which certain terms gain popularity over time, while others become less



(a) *Il forum dei brutti*



(b) *Incels.is*

Figure 1: Keyness over time for the characteristic incel terms extracted from (a) *Il forum dei brutti* and (b) *Incels.is*. Red lines represent the terms that gained keyness over time, while blue lines represent the terms that lost keyness over time.

popular. With regard to *Il forum dei brutti* the difference is 0.247, while for *Incels.is* the difference between the mean normalized slopes is smaller, 0.106, which points at a slower lexical evolution. As regards *Incels.is*, the trends observed for terms such as "foid", "femoid", and "roastie" reflect the time-series data discussed in Gothard (2020), which show certain terms increasing and decreasing in use over the total messages posted in incel subreddits. For both forums, the shift in lexicon needs to be taken into account in order to have a clear picture of the language adopted by each speech community.

As regards *Il forum dei brutti*, we can observe that the way users refer to men changes in a rather clear way. On one hand, positive words that are commonly used in general language, such as "strafigo" and "figaccione" (both meaning "extremely handsome"), are substituted by specialized terms that are more specific to the forum's speech community, e.g., "chad".[7] On the other hand, we can see the same phenomenon for negative words, where "reietto" ("outcast") loses popularity, leaving space to terms with more specialized uses, such as "bv", meaning "brutto vero" (lit. "truly ugly") and "subumano", meaning "subhuman". The first is an acronym, which makes its meaning opaque to outsiders, while the second is a term with a much stronger and denigrating connotation.

With relation to *Incels.is*, as already anticipated through Figure 1, although terms like "foid" and "femoid" have the same meaning (both are used to dehumanize women by associating them to insentient androids[8]), the shorter form has become more popular, while the use of the full form has decreased. This is probably due to the fact that, given the high frequency with which the term is used in the forum, users tend to use the abbreviated version to save time and effort. This might seem like a minor detail, but the sheer amount of misogyny that is expressed in the forum through this term alone makes it important to point out a shift in its use.

Based on the conducted qualitative and quantitative analyses, the same conclusions can be drawn for both forums: the presented terms are arguably characteristic of the incel language used within the two platforms and the change in their usage over time is non-negligible. This implies that language models could become progressively worse at predicting over these domains, were their training resources not be periodically updated. Models rely on training material to learn language, and if the material is outdated, their understanding of the discourse currently produced by a specific speech community could become suboptimal.

Although the hate speech expressed in *Il forum dei brutti* is not as explicit as in *Incels.is*, having updated resources is still valuable, since they can be used to domain-adapt models to improve their contextual embeddings, for example with Transformer models. Of course, when hate speech is expressed through racist and misogynous neologisms, such as in *Incels.is*, having updated lexical resources becomes of paramount importance.

In both scenarios, it is thus arguably desirable, if not necessary, to periodically update corpora to have accurate terminological representations. In some cases, it would arguably make sense to even rebuild resources from scratch, were they too outdated. In our case, given the observed changes in keyness, we estimate that the hereby analyzed time frame could be taken as a reference for how long resources can be considered up-to-date. However, with the aim of obtaining an objective figure, further research could be conducted to quantify how often resources should be updated to keep up with the evolution of the language used in the spaces scrutinized through this study.

The necessity to build such material is also supported by the fact that resources on the topic of incels are rare and limited, and their applicability is often compromised because the linguistic domain of the source data only partially aligns with the one under investigation (Pelzer et al., 2021). An additional cause for such incompatibility of resources can be found in the annotation scheme, which can be inapplicable to the supervised task being approached (Zhou et al., 2022). However, the necessity to build new resources does not mean they will be obsolete soon after being employed, as the time frames we have analyzed in this chapter span various years of forum activity.

[7] https://incels.wiki/w/Chad
[8] https://incels.wiki/w/Femoid