Malingering Scraper: A novel framework to reconstruct honest profiles from malingerer psychopathological tests.

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Abstract. Malingered responses to psychological testing are frequent when monetary incentives or other forms of rewards are at stake. Psychological symptoms are usually identified through clinical questionnaires which, however, may be easily inflated by malingered responses (fake-bad). A fake-bad response style is usually identified through specialized scales embedded in the personality questionnaires, but no procedure is currently available that reconstructs honest responses from malingered responses.

In this paper, we present a technique for the Millon (MCMI-III) questionnaire a widely used test for investigating psychopathology. This technique detects malingered MCMI-III profiles (malingering detector) and removes the intentionally inflated test results (malingering remover). We demonstrate that by applying machine learning to the validity scales of MCMI-III we can discriminate between malingerer and honest profiles with 90% accuracy. Moreover, our results show that by applying regression models to malingerer tests, we are able to well reconstruct the original honest profile. Our models decrease the RMSE (Root Mean Square Error) of the reconstruction up to 19% compared to base correction procedures. Finally, applying the malingering detector to the reconstructed scales, we show that only 9% were classified as malingerers, demonstrating the validity of the proposed approach.

Keywords: Malingering Remover · Millon · Machine Learning

1 Introduction

Deception to direct questions may take two different forms: faking-bad and faking-good. Faking-bad characterizes some forensic settings (e.g., criminal, insurance claims) in which the examinee is likely to exaggerate or make up his psychological disorder [18]. Clinical interviews generally yield low detection rates of malingerers, meaning that many cases will be misclassified if clinicians rely solely on their subjective judgement [17]. Indeed, intuitive clinical judgment yields detection rates of faking-bad that are comparable to the disappointingly low hit rates (i.e., 60%) found for intuitive judgment in the broader deception–detection literature [22].

Malingering is the dishonest and intentional production or exaggeration of physical or psychological symptoms to obtain external gain [20]. Despite it being categorically coded by both ICD10 [13] and DSM5 [1], malingering is not a binary “present” or “absent” phenomenon: it must be considered within specific domains (e.g., psychological, cognitive, and medical), often coexists with genuine disorders and can be classified into different types. Due to these considerable variations, appraising the prevalence of malingering in clinical and forensic populations is difficult. Furthermore, according to estimates by forensic practitioners, malingering likely occurs in 15–17% of forensic cases [16,24].

Usually, psychological symptoms are identified, in psychopathological inventories, through responses to direct questions where the examinee is required to respond YES/NO to sentences targeting relevant symptoms. However, the evaluation based only on responses to direct questions is failing miserably in some contexts. Specifically, the responder has an incentive to aggravate his symptoms to gain economic advantage or any other form of gain. To counter this problem, a wide array of tests has been developed that provide scores on the credibility level of the endorsed symptoms. When employing these instruments, empirically-based cut-offs aid in determining whether symptoms are likely to be genuine or not [11].

As regards the detection of malingering, several detection techniques for psychological testing are based on validity scales embedded in general psychopathological questionnaires (e.g., MMPI-II [3] and MCMI-III [12] - the most used tests to evaluate psychiatric disorders) or specific tests (e.g., SIMS [19]) as reported by [14] and [10]. Such detection strategies usually evaluate the endorsement of very atypical symptoms. For example, the SIMS may distinguish malingerers from honest responding with good accuracy [21], collecting responses to questions that cover a broad spectrum of pseudo-psychopathology (e.g., items indexing atypical depression, improbable memory problems, pseudo-neurological symptoms, hyperbolic signs of mental retardation).

Malingering is a continuous variable and the level of malingering is modulated by the stake and by the strategy under the implicit or explicit control of the malingerer. For this reason, efforts have been made to develop specific tests that flag the responder as a faker. Such tests may be specific (e.g., SIMS) or may take the form of a validity scale embedded in a psychopathological questionnaire (e.g., MMPI-II, MCMI-III). While such procedures may spot the faker with decent accuracy, to the best of our knowledge, no procedure has been proposed to reconstruct the honest response profile once a faker has been identified and only the faked profile is available. In short, a non-depressed subject who wants to appear depressed may be spotted as a faker. However, there is no valid procedure that may be used to uncover his true level of depression resulting from honest responses.

Main contributions

- We propose a new framework for detecting malingered MCMI-III profiles and removing the intentionally inflated test results.
- We demonstrate our approach with an extensive data collection on 100 volunteers participating in the MCMI-III questionnaire.
- We make our dataset publicly available [5] to the research community. We hope this is beneficial to investigate the problem further and propose new possible solutions.

2 Method

The MCMI-III is a widely used questionnaire-type test that assesses a variety of psychopathological dimensions. The format of the test requires the examinee to respond to sentences that index psychopathological symptoms. Statements addressing homogeneous psychopathological symptoms (e.g., depression) are added together, leading to a high scale score in the case of psychopathology and a lower range for non-pathological subjects. Malingerers can easily alter their true response from non-pathological to pathological, thus inflating the pathological significance of the resulting score. To highlight the effect of such intentional (and unintentional) distortions, the MCMI-III is equipped with a number of validity scales. As with other modern psychological tests, the MCMI-III has three validity scales devised to capture exaggeration (X scale) and symptoms denial, also called social desirability (Y scale). It has been shown that from scores at these two scales, the faker can be identified with an accuracy that depends on several factors [5]. Apart from the three validity scales reported above, the MCMI-III has 11 scales indexing personality patterns, three scales indexing severe personality disorders, three severe clinical syndromes, and finally, seven clinical syndromes for a total of 24 clinical scales.

Our work aims to reconstruct honest MCMI-III profiles starting from dishonest malingered profiles. The procedure we propose consists of two steps: the Malingerer Detection and the Malingerer Removing, as reported in Figure 1. The malingerer detector takes in input the 24 clinical and the three validity scales of the MCMI-III questionnaire. This first step consists of a binary classifier that labels the input in honest or malingerer. If the profile is classified as honest, no further elaborations are needed, and the final output corresponds to the original output of clinical and validity scales. On the contrary, the original scales are processed by the malingering remover if a malingerer profile is identified. The malingering remover consists of a regression algorithm that filters the input, removing the malingering distortion and providing a reconstructed honest profile as output.

[5] `https://spritz.math.unipd.it/datasets/malingerer_removal/MalingererRemoval.zip`

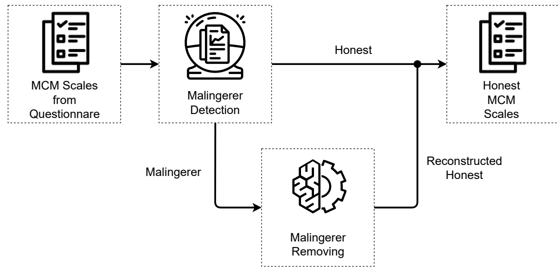


Fig. 1: Workflow of the proposed approach. The malingering removing step is applied only to those profiles classified as malingered from the Malingerer Detection step.

2.1 Data collection

One hundred healthy participants were required to respond to the MCMI-III honestly and also to respond faking depression in order to sustain an insurance compensation seeking claim. 40 participants were males and 60 females. Age ranged between 20 and 61 years (mean = 27.45, sd = 7.87) and schooling between 8 and 22 years (mean = 16.56 and sd = 2.67). All the participants were Italian native speakers, and the MCMI-III was given in Italian [25]. All the subjects did not report previous psychological or psychiatric assessments. Half of them responded in the honest condition first and half in the honest condition second. The participant responses were collected using a computer presentation of the MCMI-III with one of the experimenters supervising in the room. Instructions for the condition requiring malingering were the following: *"You are now asked to fake a severe depression due to a family mourning. Please, respond to the questionnaire pretending to be depressed. The final goal is to obtain insurance compensation for the psychological damage you had after the mourning. Be careful to respond in a way that the depression is credible"*.

At the end, for each participant, two MCMI-III raw results were available. The first with standard instructions was regarded as honest responding and was used as ground truth in the development of the malingering remover. The second collected with fake-bad instructions was regarded as the malingered MCMI-III to be corrected by the model. After being informed about the study's goals and the confidentiality and anonymity of the data, all participants provided written informed consent for their volunteer participation. The present research was designed in accordance with the Declaration of Helsinki and approved by the ethics committee for psychological research at the University of Padova (protocol number 2023).

Using G*Power software, it has been calculated that applying a matched pairs Wilcoxon signed-rank test, a statistical power of $(1-\beta) > 0.95$ may be achieved with a sample size of 100, given a significance level (α) of 0.05 and a large effect size (d) of 0.47 [6].

3 Experimental results

This section first gives insight into the dataset analyzing the statistical distribution of honest and malingerer profiles. We then evaluate the results of different malingerer detection classifiers. Finally, we report and compare the performance of different approaches for the malingering remover.

3.1 Descriptive statistics

A first analysis was carried out by examining the statistical differences between malingerer and honest tests. We applied Kolmogorov-Smirnov test [9] (with α fixed to 0.05), which rejects the null hypothesis, suggesting that the scales were not normally distributed. For this reason, honest and malingered test results were compared using (i) the Wilcoxon signed-rank test [23], and (ii) the Cliff's d effect-size measure [4]. As recommended by the guidelines given by [8], we interpret the effect size as *small* for $|d| < 0.33$, *medium* for $0.33 \leq |d| < 0.474$, and *large* for $|d| \geq 0.474$.

The Wilcoxon signed-rank test resulted in significant differences on all the scales ($p < 0.05$) except for Scale N (Bipolar Disorder), suggesting that, when faking a depression, also scales not related to depression change significantly. As regards the effect size, 17 out of 24 scales showed large values of d. In particular, scales CC (Major Depression) and D (Persistent Depression) reported the highest effect size (0.96 and 0.95 respectively), confirming that participants have successfully faked a depression profile in the malingered test. Small values of d were reported for four scales: 6A (Antisocial), 6B (Aggressive), T (Drug Use), and PP (Delusional Disorder). Finally, only Scale 7 (Compulsive) presented a medium effect size. As reported in Figure 2, most scales present higher scores in malingering tests. Further, two scales had a reduction in score after malingering: Scale 5 (Narcissistic) and Scale SS (Thought Disorder).

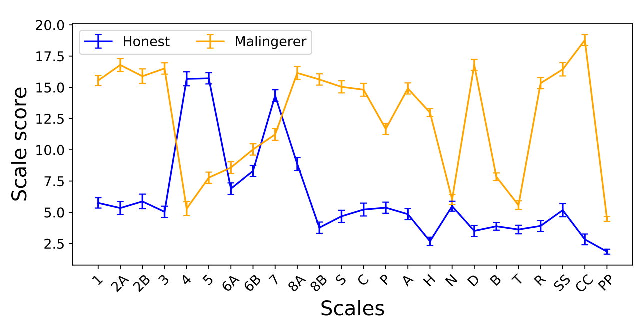
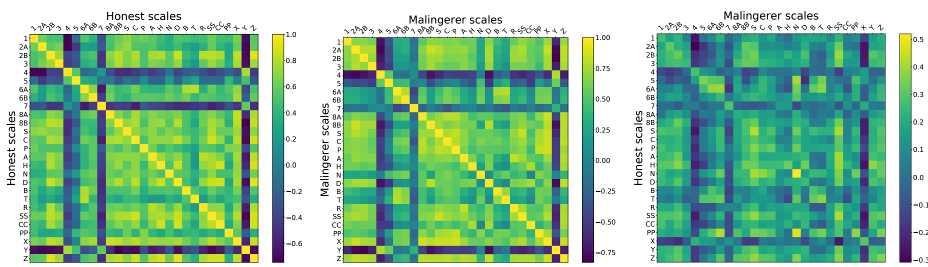


Fig. 2: Average profile of the 100 participants (with the corresponding standard error) responding to the MCMI-III questionnaire for the 24 clinical scales.

A correlation analysis was carried out to assess if the dependencies between scales change in malingerer and honest condition. Figure 3a depicts the scales correlation in honest condition. In particular, the 5 couples of scales that present highest r values are: Z (Debasement) - D (Persistent Depression) $r = 0.93$, Z (Debasement) - 2B (Melancholic) $r = 0.92$, Z (Debasement) - H (Somatic Symptom) $r = 0.89$, CC (Major Depression) - D (Persistent Depression) $r = 0.89$, and CC (Major Depression) - H (Somatic Symptom) $r = 0.88$.

Similarly, we analyzed the correlation matrix in the malingering condition (see Figure 3c). The results are the following: X (Disclosure) - 8A (Negativistic) $r = 0.87$, X (Disclosure) - P (Paranoid) $r = 0.86$, 8B (Masochistic) - 2A (Avoidant) $r = 0.86$, X (Disclosure) - Z (Debasement) $r = 0.86$, and S (Schyzotypal) - SS (Thought Disorder) $r = 0.85$. If we compare the two correlation matrices, there are no pairs of scales in common between the two top-5 correlations, suggesting a different response strategy depending on the task (honest vs malingering) that alters the correlation structure among the scales.



(a) *Autocorrelation honest.* (b) *Autocorrelation malingering.* (c) *Honest-malingering correlation.*

Fig. 3: Correlation matrices for the MCMI-III clinical and validity scales in honest and malingering.

Analyzing the cross-correlation between honest and malingering, it is possible to notice how the values of r drop significantly. The five pairs of scales with the highest r values are respectively: N_honest (Bipolar Disorder) - N_malingerer (Bipolar Disorder) $r = 0.52$, PP_honest (Delusional Disorder) - N_malingerer (Bipolar Disorder) $r = 0.49$, PP_honest (Delusional Disorder) - 6B_malingerer (Sadistic) $r = 0.43$, S_honest (Schizotypal) - S_malingerer (Schizotypal) $r = 0.43$, and SS_honest (Thought Disorder) - SS_malingerer (Thought Disorder) $r = 0.42$. There are no strong correlations between corresponding scales in the two conditions, indicating that the reconstruction of the honest profile from the malingering profile cannot be based on a clear relation between corresponding scales.

3.2 Malingering detection

The discrimination of honest and malingerer profiles represents the first step of our method (see Figure 1). To perform this task, five machine learning (ML) algorithms were tested using leave-one-out cross-validation (LOOCV) on the collected dataset: decision tree, logistic regression, Support Vector Machine (SVM), random forest, and KNN. Further, an inner 5-fold cross-validation was used on the training set to tune the hyper-parameters using grid search. In particular, for the decision tree *max_depth* was set in $[2, 3, 4]$, for the logistic regression *penalty* was set in [l1, l2], for the SVM C was set in $\{10^{-3}, 10^{-2}, \ldots, 10^{2}\}$ and γ in $\{10^{-4}, 10^{-3}, \ldots, 10^{1}\}$, for the random forest *max_depth* was set in $[3, 4, 5]$ and *n_estimators* in $[5, 10, 20, 50, 100]$, and finally, for the KNN *n_neighbors* was set in $\{3, \ldots, 12\}$. Malingering detector was trained using only the three validity scales X, Y, and Z.

Our results show that honest-malingerer discrimination is a simple task for the considered ML classifiers. Indeed, all the models achieved an accuracy higher than 87%. In particular, decision tree and SVM (kernel RBF) classifiers showed the best performance, achieving 90% of accuracy. Similar performance is also achieved in validation for the two models. Because of its simplicity and intelligibility, we have chosen to use the decision tree for our framework.

3.3 Malingering remover

In clinical and forensic evaluations, good accuracy at the single-subject level is required. This objective is essential given that it has been shown, in many datasets, that the number of single cases that behave differently from the trend observed in the group is high [7]. As already mentioned, an important but unaddressed issue in malingering research is the reconstruction of the honest test profile on the sole basis of the malingered test profile. To deal with this problem, we introduced two malingering removing algorithms: average removing and multi-output regressor. We applied the LOOCV procedure in all the reported analyses. One honest and one malingerer test of the same participant were excluded iteratively from the training set. The malingerer trial was used as test while honest as the ground truth. The training set consisted of the remaining 99 malingering trials and the corresponding 99 honest trials. In the following, we describe the two proposed malingering removing techniques.

Average removing A simple malingering removing technique consists of correcting each malingered profile by subtracting the average score of the honest responses for each scale. To avoid inconsistency, values that were out of their specific scale range were set to the closer scale bound (i.e., values lower than 0 were set to 0). Consider, for example, how Scale 1 for subject one is corrected with the average removing. Subject one had a score of 11 on Scale 1, and the average of malingered responses of this same scale is 15.6. The average for honest responses is 5.7. The estimated corrected score for subject one is 1.1 (11-(15.6-5.7)). In short, this method assumes that, on each specific scale, malingering has the same effect for all the participants. Moreover, possible correlations between scales are not considered using this method. The average Root Mean Square Error (RMSE) achieved by this trivial technique is 4.05 ± 1.78.

Multi-output regressor A multi-output regressor was developed to predict all the honest scales based on the malingered test results of the same participant. The multi-output regressor estimates the honest scale scores one by one. As reported in Table 1, we tested different regression models using a grid-search with an inner 5-fold cross-validation on the training set to tune the hyper-parameters. The best performing model resulted to be a Support Vector Regressor (SVR) with Radial Basis Function (RBF) kernel, achieving in test an average RMSE of 3.27 ± 1.51.

Table 1: Performance and hyper-parameters ranges for the tested regression models.

Model	**Parameters**	**Values**	**AVG RMSE on test**
Random Forest	n_estimators max_depth	[10, 20, 30] [4, ..., 7]	3.41
Ridge	α	$[200, 225, \ldots, 500]$	3.38
SVR RBF	c γ	$[10^{-3}, 10^{-1}, 1, 10^2]$ $[10^{-4}, 10^{-3}, 10^{-1}, 10^0, 10^1]$	**3.27**
KNN Regressor	n_neighbors	$[2, \ldots, 12]$	3.34

3.4 Reconstruction performance analysis

In Table 2 we compare the reconstruction performance of average removing and SVM RBF, considering several metrics. Firstly, we compared the average RMSEs between the reconstructed profiles and the honest profiles. In particular, the SVR RBF showed an improvement of 19% in the RMSE metric compared to the average remover. Our results confirm what was suggested by the statistical analysis (Section 3.1), which highlighted the presence of moderate correlations between honest scales and malingered scales. Another method to evaluate the quality of the reconstruction is to perform the malingering detection to the reconstructed honest profile. If a malinger removing technique succeeds, the malingering detector should classify the reconstructed profile as honest. Our results show that 78% of reconstructed profiles with average removing were classified as honest, while 91% of reconstructed profiles with SVR were classified as honest.

Finally, in evaluating the MCMI-III questionnaires, one factor that is commonly considered is the order of the scales when rearranged by increasing value. Based on this consideration, we developed a metric that evaluates the capacity of our malingerer removing algorithms to reproduce the order of the honest profile scales. This metric uses the Top N accuracy defined in [2]. Firstly, we normalized the scales on their upper-bound value in the MCMI-III questionnaire. Then, we calculated the Top N accuracy as the percentage of common Top N scales between honest and reconstructed profiles. In Figure 4, we show the Top N accuracy results for the two proposed malingerer removing algorithms. The metric has been calculated for values of N ranging from 1 to 5. This choice is motivated by the consideration that, among the ordered scales. We also report the Top N accuracy values obtained by directly comparing the honest profiles with the malingerer profiles (without using any malingering remover). The results obtained show that the Top N accuracy calculated on the malingerer profiles is significantly lower than those calculated for the two malingering removing methods. This result confirms that the order of the scales changes significantly between the honest and malingerer tests. Regarding the methods of malingering removing, we can see how SVR always obtains better performance when compared with the average remover. For values of N up to 3 (which are the most interesting), SVR performs significantly better than average removal (18% improvement).

Figure 5 depicts the average accuracy of our approach in reconstructing the honest profile.

Table 2: Performance comparison of malingerer removing techniques.

Model	**Average RMSE**	**Reconstuction Accuracy (%)**	**Top 3 Scales Accuracy (%)**
Average	4.05	78	54
SVR RBF	**3.27**	**91**	**72**

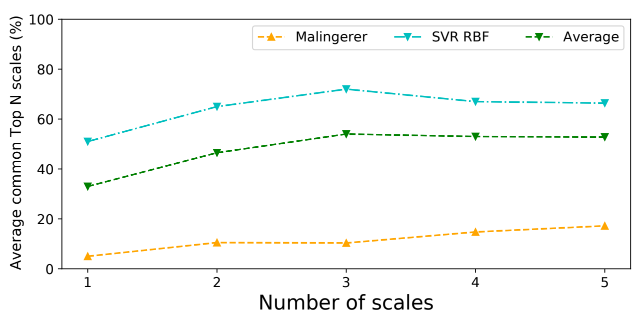


Fig. 4: Percentage of average common Top N scales between honest/reconstructed profiles and honest/malingerer profiles.

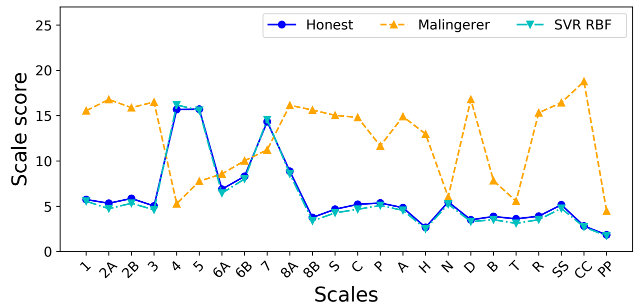


Fig. 5: Average values of the 24 clinical scales for honest, malingerer and reconstructed profiles with SVR.

4 Conclusion

In this paper, we presented a proof-of-concept using the MCMI-III, a widely used test for investigating psychopathology that is complemented with validity scales used to detect malingering. Hundred healthy participants were required to complete the MCMI-III both with standard honest instructions and faking-bad instructions to appear depressed in a hypothetical insurance claim for personal damages. From the statistical analysis on the collected dataset, we found that malingering is not only confined to depression-related scales (e.g., CC, D), but also extends to other scales (e.g., P, C). Moreover, after malingering, the order of the original scales is altered. In particular, the scale with the highest honest score is never also the scale with the highest score after malingering.

We developed a framework composed of two steps: malingerer detection and malingerer removing. The proposed framework takes in input the scores of the 24 MCMI-III clinical scales and three validity scales (i.e., X, Y, and Z). We demonstrate that using decision three as a malingerer detector, we achieve an accuracy of 90% in discriminating between honest and malingerer profiles. Further, the main results regarding the malingering removal procedures were:

– The malingered profile, after malingering removal, is identified by a classifier as an honest profile with high accuracy (91% for SVM regressor);
– ML models were very good at group level in removing malingering and approximating the honest test results;
– In predicting individual responses, ML-based models were better than a simple correction strategy (average removing) consisting of subtracting to the subjects' scale score the average difference between the group score in the honest and malingerer condition. In short, ML models succeeded in personalizing the process of malingering removal;
– The ranking of the scales in the honest condition was mostly maintained after malingering removal. The highest three scales were identified correctly 72% of the times.

It is relevant to stress that the malingering removers proposed here permit individualized modulation of the prediction. This is relevant to the current debate about the lack of group-to-individual generalizability that has been shown to undermine the validity of scientific research in many fields [7]. It has been shown that the credence that an effect at group level generalizes at single-subject level is greatly unfounded given that *"Only 68% of all individual correlational values fall within a range that would be predicted by group data to cover 99.7% of all possible correlations–a discrepancy of nearly 32%."* In short, the ML models used for malingering removal have shown extremely good reconstruction accuracy at the group level and good reconstruction accuracy at the individual level. Given the correction of the ML models, SVR reduces the error by 19% with respect to the correction using the average remover (i.e., correcting all the subjects with the same procedure), we can say that this strategy gives the desired individualized predictions. It is worth noting that the personalization of results is not a trivial task, given that different subjects may fake with different levels of intensity and on different symptoms for a variety of reasons.

Future work A qualitative analysis conducted on single case profiles indicated that the few subjects with poor reconstruction results failed to follow the instructions and had a faked MCMI-III profile that overlapped the honest profile. The proof-of-concept reported here shows that removing malingering from psychological tests may be achieved using ML models. ML models are entering the psychometric field and may now be considered as part of the psychometric toolbox [15]. Once this avenue of research has been established, further steps are required to develop a fully functional model of malingering removal. Specifically, extending the data collection and showing that malingering removal is possible also for other pathological cases that aggravate rather than blatantly fake their profile. Moreover, the malingering remover should also be evaluated in other conditions of malingering (e.g., faking anxiety or post-traumatic stress disorder), since malingered responses change given different malingering objectives.

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