Automated detection of dark patterns in cookie banners: how to do it poorly and why it is hard to do it any other way

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Abstract

Cookie banners, the pop ups that appear to collect your consent for data collection, are a tempting ground for dark patterns. Dark patterns are design elements that are used to influence the user's choice towards an option that is not in their interest. The use of dark patterns renders consent elicitation meaningless and voids the attempts to improve a fair collection and use of data. Can machine learning be used to automatically detect the presence of dark patterns in cookie banners? In this work, a dataset of cookie banners of 300 news websites was used to train a prediction model that does exactly that. The machine learning pipeline we used includes feature engineering, parameter search, training a Gradient Boosted Tree classifier and evaluation. The accuracy of the trained model is promising, but allows a lot of room for improvement. We provide an in-depth analysis of the interdisciplinary challenges that automated dark pattern detection poses to artificial intelligence. The dataset and all the code created using machine learning is available at the url to repository removed for review.

1 Introduction

The digitization of our daily lives has ushered opportunities for the collection of personal data on those activities, which up to recently, were private. Moreover, automated data collection has become almost impossible to escape (Auxier et al., 2019). This data is used in ways that can impact our reality (Slavkovik et al., 2021). Regulations are increasingly put in place to protect our interests. Examples include the European Union’s General Data Protection Regulation (GDPR) (Parlament and Council, 2016) and the California Consumer Privacy Act (CCPA) (Information, 2018). One of the goals of these regulations is to enforce the practice to inform and obtain consent from users about the use of data processing and data trackers (Utz et al., 2019). In Europe, the most
tangible effect of these regulations has been the appearance, and ubiquity, of consent banners on webpages. Cookie banners appear because, according to the GDPR and the ePrivacy Directive (ePD) (the Council of the European Union, 2009), websites, regardless of where they are based, must inform users located in the EU about personal data collection and obtain their consent for certain purposes.

As awareness of data collection and its effects increases, so does the complexity and variety of cookie banners throughout websites and different modalities. Website publishers and their designers, driven by business, marketing needs (Gray and Chivukula, 2019; Chivukula et al., 2019), design user interfaces (UI) deliberately make use of the breadth space they are afforded with regarding UI design. UI design has not been explicitly nor extensively specified in mandatory regulations nor guidelines regarding consent (Santos et al., 2020; Karegar et al., 2020). This gap allows, as several studies have already shown, to make use of (weaponize (Waldman, 2020)) the interface design to steer and manipulate users towards privacy choices they would not normally have an incentive to take. Such interface design is called “dark pattern” used to circumvent the user’s genuine choice and the intent of privacy regulations (Forbrukerrådet, 2018; Chatellier et al., 2019), even when those are explicitly required to protect users, as is the case with cookie banners (Ducato and Marique, 2019). The volume and pervasiveness of questionable cookie banners embedding dark patterns surpasses any human capacity to detect, report and penalize violations for non-compliant practices, either in at desktop web, mobile web and mobile app (Johanna Gunawan, 2021). Several studies measured the presence and behavior of cookie banners on major websites and found that well over 50% contained dark patterns (Nouwens et al., 2020b; Sanchez-Rola et al., 2019; Utz et al., 2019; Soe et al., 2020; Graßl et al., 2021; Bauer et al., 2021; Gray et al., 2021), e.g. when banners present different colors, sizes or shapes of options (violating the unambiguous consent requirement).

Any regulation only constitutes a strong deterrent against any illegal practice, if such regulation can be efficiently enforced at court or regulatory level. Yet, most consent banners embedding dark patterns go undetected and unsanctioned, as data protection regulator’s IT resources are largely insufficient to address all the suspected legal breaches (AccessNow, 2020; Brave, 2020). This reality casts doubts on their real possibilities to investigate these matters efficiently, promptly and on a large scale. Thus, there is a need for technical solutions (algorithms and prototypes) to collect and analyze reliable data on dark patterns, expedite oversight tasks, warn and protect users, expose manipulative practices, and provide proof of unlawful influence to support legal proceedings. Clearly, automatic detection of the presence of dark patterns at scale is pertinent. However, dark pattern detection is a complex cognitive task which makes the use of artificial intelligence (AI) particularly challenging.

1 An example of such cookie banner can be seen in Figure 2 of the Appendix B.
In this paper, we are concerned with this problem of using AI, specifically supervised machine learning (ML), for automating the detection of dark patterns in cookie banners. We present an initial approach. We used a rich manually labeled dataset made available by Soe et al. (2020) and supervised ML to train several prediction models that identify whether or not a cookie banner has a dark pattern. In particular, a cookie banner is represented by a data point. Herewith, we consider a data point to be a set of features of different data type values describing the position of the interface on the screen, amount of text, options given to the user, etc. Each data point is labeled with the following information: whether it has, possibly has, or is confirmed to have one of the 5 dark patterns categories defined by Gray et al. (2018): nagging, obstruction, sneaking, interface interference, and forced action. Thus we have 15 possible different labels. A prediction model we trained assigns one of these 15 possible labels to a new data point (the interface represented as a set of features).

We report the following findings in our experiment. What we present is not a practical approach to detecting dark patterns: our approach relies on being able to encode an interface as a set of feature values before it is fed into the prediction model for dark pattern detection. To obtain values for some features, we relied on supervised and unsupervised machine learning. Some of these used features are such that their values are easy to harvest automatically, but others require human intervention instead. If humans are already looking at the interface, it is most efficient that they are directly tasked with detecting if a dark pattern is present. One can, of course, argue that laymen users cannot necessarily detect a dark pattern and we could still spare the resources for training human dark pattern detectors. Lastly, the accuracy of the predictions we obtained is not particularly high. What we present can therefore be understood as a negative result, but it should still be seen as an advancement towards making automated dark pattern detection a reality - we have learned what does work and particularly why does not work.

We discuss why attempts at automated dark patterns detection such as ours are still insufficient. While our attempt exposes many limitations to the automated detection of dark patterns, it also offers valuable lessons on how we can make progress. Towards this goal, we have made our code, prediction models and data available for anyone to build upon our efforts. We argue that the automatic detection of dark patterns requires not only machine learning, but also refinement of the concept of dark patterns and consequently improvements in regulatory initiatives.
2 Why is dark patterns detection difficult for AI?

The term dark patterns [Gray et al., 2018] has been coined to identify “instances where designers use their knowledge of human behavior (e.g., psychology) and the desires of end users to implement deceptive functionality that is not in the user’s best interest” (Gray et al., 2018). Throughout this work, we use the concept “dark pattern” to refer to types of UI dark designs that have been documented and applied to cookie banners on websites [Gray et al., 2018; Nouwens et al., 2020b].

There is a growing concern that dark patterns can and will be used to i) impede ethical artificial intelligence systems by hampering the explainability and transparency of such systems [Chromik et al., 2019], and to ii) manipulate users into sharing more data with a service than the service needs to operate [Bösch et al., 2016]. In this section, we decompose some of the challenges of automatic detection of dark patterns by AI methods.

2.1 Representation challenges

Artificial intelligence (AI), specifically machine learning, has made considerable breakthroughs in image recognition and natural language processing (NLP) [Benjio et al., 2021]. Despite this progress, AI is deployed successfully when the different cognitive tasks are “emulated” in isolation: image recognition as one task, language processing and sentiment analysis as separate tasks. However, humans perceive a cookie banner, and any other interface, as a single visual-language experience. A dark pattern deceives by forcing the where the user places their attention.

For any algorithm to be able to process any kind of information, that information needs to be represented in a form that can be handled by the algorithm. For cookie banner interfaces, we have 3 representation choices: as image, as text, or as a described phenomenon (a.k.a. factorised representation). We discuss the limitations and advantages of each of these three options.

Images. The input to the algorithm will be the pixels of, effectively, the screenshot of a screen image with the interface active on it.

Advantage. The advantage of using images is that they are easy to collect automatically – a user can easily submit a screenshot and signal whether the image contains a dark pattern or not. A neural network can be trained using such examples of images with and without dark patterns. However, what neural network detects in images is the existence of correlation between pixels.

Limitation. The image representation disregards information from the interface. Dark patterns, such as nagging, exist as an event (one image following another) and would be virtually impossible to capture in an image alone. Information within the text of the interface will also be disregarded. Two images with

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2 The neologism, dark pattern, was coined by user experience designer Harry Brignull in 2010.
different text can easily end up being considered similar by a neural network even if one contains a dark pattern and the other does not. Neural networks can be expected to be successful in identifying how much of the screen does the cookie banner take up, or whether the accept and reject options in a cookie banner are implemented as the same widget. Nevertheless, it is worthwhile empirically verifying the limits of image recognition on the task of identifying visual elements of an interface.

**Text.** The input of the algorithm will be natural language text, or a sequence of texts and treated as a sentiment analysis problem (Chaturvedi et al., 2018).

**Advantage.** NLP techniques (e.g., sentiment analysis) can help to recognize dark patterns that play on linguistic features (e.g., confirmshaming, tricky questions, toyng with emotion, arguments of authority, fear mongering dark patterns) (Kampanos and Shahandashti, 2021). What would considerably further the abilities of an AI algorithm to detect dark patterns is the legal requirement that privacy options and its text (e.g., accept, reject, configure) should be balanced (or equitable) (Article 7(4) of the GDPR, further interpreted by the data protection community (Szpunar, 2019; et Libertés, 2020; Santos et al., 2020)). As so, it possible to automatically detect whether two antonym choices are present in the panel.

**Limitation.** Text, compared to image, is harder to automatically scrap from online applications, particularly if the interface interaction invokes other interfaces. Cookie banners are observed to employ legal and technical jargon (Strycharz et al., 2021; Utz et al., 2019), vague and ambiguous language (Santos et al., 2017), and positive or negative framing (Hausner and Gertz, 2021) which hampers automatic detection of textual expressions. An open question is whether the text of the interface is sufficient to identify a dark pattern. A study that could verify or refute a positive answer to this question would be to compare the insights of one group of study participants tasked to detect dark patterns in an image of an interface, and another group tasked with detecting the dark pattern when only given the text of the interface. Such a study is outside of the scope of this work. Necessarily to denote, however, is the fact that only considering text eliminates the possibility to take into account other impacting visual cues, such as using different colors or salient hues or values representing different privacy options afforded to the user.

**Features.** An option is to identify a set of discerning features of the interface and record the values of those features. This option is the one we used in this paper. A supervised learning algorithm can be used to build a prediction model essentially finding a pattern in the feature values that classifies an interface as either containing or not dark patterns and identifying which one.

**Advantage.** Building on the work of Soe et al. (2020), a large selection of discerning features is used to describe the properties of online cookie banners from news outlets. The advantage of this approach over the other two is that interactive phenomena, such as invoking several interfaces, can be described and both visual and textual cues can be captured in the representation. In Section 3 we describe how the features from the Soe et al. (2020) dataset were processed...
before being used to train a prediction model.

Limitation. The clear disadvantage is that some feature values will be difficult to be automatically “harvested” and virtually all feature values will require different AI post-processing techniques. Namely, after one algorithm (or a human) has identified and scraped the text, another is needed to analyse it. For example, text would require sentiment analysis, and the identification of widgets used would require a image processing. Instead, an ideal approach, and one open problem for future work consists in identifying the features whose values can be automatically scraped and post-processed and which are most relevant to distinguish a dark pattern. The more precise the definition of dark patterns, the easier it is to identify the relevant features. A separate limitation of the features approach is the challenge of humans being able to correctly label the data points with the right dark pattern. We discuss this issue next.

2.2 Detection challenges

Challenges to detect UI of cookie banners The GDPR does not address UI-based elements (the same colors assigned for options, position, design, size, format, location, text, etc.). There is very limited case-law in the EU concerning the use of UI, which refers mainly to the prohibition to use pre-checked boxes (Justice of the European Union 2019). Non-mandatory guidelines from Data Protection Authorities provide further interpretation on UI elements, wherein feature parity is is given priority to. The UK DPA (Office 2019 p. 32) observed that “a consent mechanism that emphasises ‘agree’ or ‘allow’ over ‘reject’ or ‘block’ represents a non-compliant approach, as the online service is influencing users towards the ‘accept’ option.” The French DPA (Chatellier et al. 2019, p. 28) frames as “Attention Diversion” the design choices that draw attention to a point of the site or screen to distract or divert the user from other points that could be useful. This guidance states that visual and color saliency is effective and commonly used, indicating that using a green hue on a “continue” button while leaving the “find out more” or “configure” button smaller or in a lighter shade of grey, users may perceive green as the preferable choice. Conversely, in the US, the Congress (on Digital Platforms 2019) is considering issuing legislation restricting dark patterns, and the CCPA (Information 2018) defines and prohibits dark patterns associated with privacy consent which have a “substantial effect of subverting or impairing a consumer’s choice to opt-out”.

Challenges on a consensual definition of dark patterns. What exactly makes a pattern dark is still a matter of fervent discussion across different communities (Mathur et al. 2021). There is a body of theoretical conceptualization on the definition of dark patterns – researchers unfold diverging definitions and classifications thereof (Mathur et al. 2019, Brignull et al. 2015, Bösch et al. 2016, Chatellier et al. 2019, Chromik et al. 2019, Gray et al. 2018, Zagal et al. 2013, Fritsch 2017) – and their related features – in their own domains, thus even rendering it difficult to communicate about the same.

3 A better term would be obscure.
phenomenon. Pertinent features that determine what makes a certain design “dark”: nudging (Acquisti, 2009), intention, manipulation, influence, persuasion (Cialdini, 2001), deception (Bongard-Blanchy et al., 2021), harm (privacy, financial, time, etc., and evidence thereof) are interpreted with great latitude by different disciplines (law, computer science, cybersecurity, philosophy, ethics) and from different perspectives (e.g., user, designer, developer, lawyer, website publisher, marketer (Gray et al., 2021)) and need to be defined with consensus to build dark patterns detection applications.

Challenges to detect intention and deception. Besides UI-based elements (e.g. feature inequality), there is also the question of whether AI can capture intention and deception in cookie banners. If we define dark pattern’s existence as an attempt for deception, we need to detect whether and when intention to deceive exists. Existence of intention is very difficult to prove and it is hard both for humans and for machines.

Challenges to detect contextual, social and cognitive aspects. Another detection problem refers for context awareness (e.g. temporal, social, cognitive aspects) which are hard to capture. The ability to process all the contextual information at once, holistically remains a hard problem in AI. As of today, AI methods process different types of information differently: for example, text is different than image processing (as mentioned in section 3.1). Within the UI there is a richness of information that is transmitted to the user that needs to be accounted to: the placement of the interface in the screen, the ratio of the interface size vs the screen size, the contrast between different colors used, the finer linguistic nuances of the text used, etc. Herein, the inputs of the HCI community is of essence.

2.3 Summary

Ultimately, dark pattern detection is difficult for AI because it is difficult also for people. It is difficult to capture all the specific instances in which a particular design choice constitutes a dark pattern. The analysis of Soe et al. (2020) reveals that reviewers struggled to agree upon which dark pattern is present in a cookie banner – more than option applied, given a low inter-reviewer reliability. A better, more context specific, definition can contribute to at least eliminate this human labeling uncertainty problem. A common vocabulary for the identification, description and categorization of dark patterns (and in concrete contexts) is needed for its comprehensive detection.

3 Methodology

All of the machine learning tasks, except word embedding, was done using the Scikit-learn library[^4] on a Jupyter notebook. Since the word embedding with Universal Sentence encoder and clustering is more computationally intensive, [^4]: https://scikit-learn.org
the task was performed with Tensor Flow 5 library on the Google Collaboratory 6, a cloud computational platform.

### 3.1 Dataset

**Data collection.** We started with the manually collected and annotated dataset of 300 websites described in [Soe et al. (2020)](https://www.tensorflow.org/). The dataset of the Soe et al. (2020) is available on [https://github.com/videoworkflow/cookiepopup](https://github.com/videoworkflow/cookiepopup).

We split this dataset and use it in training and testing. This data set describes the cookie banners that were encountered in each of the visited websites. Each website was visited on a browser running on a laptop computer in an Incognito mode by a reviewer who recorded information about the websites containing cookie banners. All websites were news outlets, in English or in a Scandinavian language.

The list of features and values from the dataset for the cookie banner from Vice.com is listed in Table 1 and labels are listed in Table 2. The description of the meaning of the features follows.

| Feature name | Value | Feature name | Value | Feature name | Value |
|--------------|-------|--------------|-------|--------------|-------|
| Siteid       | Vice  | Widetleve    | Yes, buttons | Clarityofoptions | Very good: You easily understand what you can opt out from and not. You can opt out from everything possible by one click. |
| Country      | The US | Location     | Middle of page, middle | Cookie categories and their purposes are described in an understandable way. All cookies are listed. |
| Type         | News  | Contentblocking | Yes | Thirdparty | No |
| Notyesoption | Yes   | Optins水源地空 | 89 | Nieworknta-rejectingcookies | Yes |
| Notyesoption | Confirm | Pre-clickreject | 7 | Darkpatternname | Yes |
| Notyesclusters | 3 | | Notyesvisibility | Immediate | Necosumsmessage | No |

Table 1: Sample data-point with features describing the cookie banner of Vice.com retrieved on July 2019.

| Label name | Nagging | Obstruction | Sneaking | Interface Interference | Forced Action |
|------------|---------|-------------|----------|------------------------|---------------|
| Label value | No dark pattern | Confirmed | No dark pattern | Confirmed | Confirmed |

Table 2: Dark pattern labels for Vice.com retrieved on July 2019.

**Information.** The information collected from each website (cookie banner) can be categorized into: basic website information, cookie banner related information and dark patterns. The basic website information consists of an URL, name of the website, country of origin of the website and type of the website.
The data about the cookie banner contains the following information:

- information related to whether a direct reject option is directly available in the interface, or alternatively is the user expected to interact with links to other interfaces or instructions for changing browser settings;
- information on whether the reject option, when available, is of the same type of widget as the accept option (e.g. whether both are buttons or links);
- location of the pop up interface on the screen: up, bottom, centre;
- information on whether the website was accessible while the cookie pop up was active;
- number of clicks required to "reject all" consent choices (whenever such possibility existed).

The dataset also includes the privacy policies and the cookie policies as extracted text. In addition, it includes different cookie types used and explanation of the purpose of the cookie types for which the permission for which use is required. This information was not used in our experiments, but it has been parsed and translated into English using Google Translate and made available in our dataset and in the GitHub link removed for review file as a SQL lite database.

**Dark patterns in cookie banners.** To evaluate the presence and type of dark patterns in the cookie banners in Soe et al. (2020) two reviewers had visited each website and independently recorded the presence of the five park patterns categories from Gray et al. (2018): nagging, obstruction, sneaking, interface interference, and forced action. The description of each of these patterns as given by Gray et al. (2018) and used for data recording in Soe et al. (2020). It is given in Table 6 in the Appendix A.

**Features.** The used dataset of Soe et al. (2020) contains many interesting and potentially relevant features for dark pattern detection. The list of available features in the Soe et al. (2020) dataset and their data types are:

1. Site ID (siteid) - the identifying name of the website;
2. Widget Level (widgetlevel) - the differences in design between the options of "accepting all" and "rejecting all" in cookie banners (this is in the form of semi-structured text);
3. “Not yes” (nameofnotyes) - the text within the first UI element (link or button) that only eventually leads to an opt out from tracking (semi-structured text);
4. Location of the pop up (location) - the location of the cookie pop up on the website (this is a description in the form of semi-structured text);
5. Does the cookie banner disable the website (contentblocking) - whether the website is accessible and scrollable while the pop up is active. It is yes/no (binary) data with some comments;
6. Words number on the option page (optionswordcount) - the number of words on the first "layer" of the cookie banner options (ordinal data integers);

7. Number of clicks required for rejecting all consent (clickstorejectall) - the number of clicks required to reject all possible cookie banners on the website (ordinal data integers);

8. Does the website lists the purpose of the cookies (iscookieusedlisted) - whether the third party cookie list is provided or not (it is binary data with comments);

9. Were there any third party cookies on the website (thirdparty) declared - the number of third party categories used (semi-structured text);

10. Does the website work after rejecting all Cookies (iteworkafterrejectingcookies) - whether the site works after all cookie purposes are rejected (it is binary data with some comments);

In addition to these listed features, the dataset also contains other features herewith mentioned:

**Comments from the data collector** reflecting upon the easiness, clarity and understandability regarding the information presented in the interface. As intentional lack of clarity can be an instrument of deception, and thus indicative of a dark pattern, we considered these reflections to be potentially relevant features that we would like to use in training a supervised model for dark pattern detection;

**Type of widget options.** Lastly, the dataset contains information regarding whether the actionable options are of the same type of widget and what that widget is. To be able to use it, we need to split this information into two features: equality of widget level, and type of widget. This process was used to create the features equality of widget level and type of widget we used a tokenizer and stemmer. This, and other pre-processing is described in Section 3.2.

### 3.2 Feature pre-processing

**Cleaning.** Since manual annotated data contains inconsistencies from typos and comments intended to be read by humans, we cleaned up the data first. Cleaning up of the data was done with using Python scripts and manual correction of some typos on Microsoft Excel. Cleaning reduces the possibility of annotation mistakes degrading the performance of machine learning algorithms on our dataset.

**Text processing.** Text processing included the following steps: translation, sentiment analysis and clustering explained below.

**Translation.** Our dataset contains texts from multiple languages. Therefore, all non-English texts were translated into English language using Google Cloud Translate via its Python API.

[https://cloud.google.com/translate/docs/reference/libraries/v2/python](https://cloud.google.com/translate/docs/reference/libraries/v2/python)
**Tokenization.** To remove the differences in language used in the original websites and hand annotated text, texts are parsed and simplified with NLTK (Natural Language Toolkit) library in Python. In particular, we applied NLTK toolkit’s Tokenizer to remove extra spaces and punctuation marks and NLTK Stemmer to replace different forms of words with their root form (e.g. the root form of does, did and done is “do”).

**Sentiment analysis.** After translation of all the text fields sentiment analysis is performed using Google Cloud Language. Sentiment classification was applied to the collectors reflections in the dataset about the quality of options in the cookie banner. Sentiment classification returns two data points, namely, sentiment and magnitude. The sentiment scores ranges from -1 (negative sentiment) to 1 (positive sentiment). The magnitude represents the magnitude of the sentiment regardless of positive or negative sentiment.

**Clustering.** For ”not yes” options text, we performed a clustering analysis to find groups in different ”not yes” option texts. For that purpose, we used Universal Sentence Encoder to embed phrases used in ”not yes” option into the vector space. The Universal Sentence Encoder ensures that phrases that are similar or closer in meaning are embedded closer together in the vector space. It was necessary to use some form of embedding for the phrases as comparing differences in alphabets between two phrases does not work for finding the similarity in semantics.

**Example of pre-processing.** For illustration purposes, we convey an example on clustering of the “not yes” option text feature. During the data collection, the text that indicates an alternative to accepting consent was collected as a separate text feature regardless of whether the text appeared on a button or as link.

**Translation.** The “not yes” option text in the dataset is unstructured and contains words in multiple languages. To be able to use it for a training machine learning model, we firstly need to translate it into English (as the majority of the data points were in English), which was performed using the Google Cloud Translate API with Python client library. Each “not yes” option text was individually fed into the API to ensure that each of them is processed on its own.

**Clustering.** The translated text was inspected manually, and we observed that the phrasing of the text label “not yes” option varies. A number of different but similar phrases, e.g. “Read more” and “More information”. As per Figure, it would be ”Configure Preferences”, though other options ranges from “Learn More” to “Options” are found in the dataset. Therefore, clustering is applied to discover different categories or clusters of the “not yes” text. First, the “not yes” phrases, now all translated to English, were encoded into vectors using the Universal Sentence Encoder. Text embedding – a popular method used in Natural Language Processing before tasks such as clustering,
translating, classification and similarity –, in our case with Universal Sentence Encoder, converts the phrases into 512 dimensional vectors or an array with 512 values.

*Visualization.* Since it is impossible to visualize 512 dimensions, we used Principle Component Analysis (PCA) to reduce the dimensions to 2 so that the text embedding can be plotted and visually analyzed. It was quite clear from the visualization that the data can be clustered into six clusters. We used K-means method for clustering. The clusters are visualized and the resulting clusters are plotted in Figure 1.

![Figure 1: Clustering of text of “not yes” option with PCA visualization: small circles filled with six different colors correspond to different “not yes” text data points. The color represents membership to a cluster with the same color. The center of each clusters is marked with larger circles in gray color. The x-axis and y-axis are two dimensions computed by PCA from a combination of the initial 512 dimensions.](image)

The rest of the features which are not mentioned in this subsection only required general clean up such as removal of special characters, correction of typos and removal of additional comments from the reviewer. The final set of cleaned and transformed features used to train a prediction model for dark pattern detection is summarized in the Table 3.

### 3.3 Data labeling

The dataset of Soe et al. (Soe et al., 2020) was not collected with the purpose of being used as training data in machine learning. The data points in that dataset were “labeled” with information on the identified types of dark patterns from (Gray et al., 2018). However, the identification of these dark patterns
was done by two independent reviewers for each data-point, who acted without coordinating or agreeing on how to identify the patterns. The reviewers more often than not disagreed on which specific dark pattern was present. As a result, there were a lot of inconclusive results among the reviewers and also some disagreement of whether there was indeed a dark pattern (one reviewer noted the presence of dark pattern, while it was not noted by the other).

We needed to find a way to work with these somewhat ambiguous labels. We adopted the following labelling:

- **No dark pattern usage detected** (Integer value 0) is assigned when both reviewers noted the absence of a dark pattern. No dark pattern usage found by both reviewers.

- **Possible dark pattern usage** (Integer value 1) is assigned when only one reviewer noted the presence of a dark pattern. Possible dark pattern usage.

- **Confirmed dark pattern usage** (Integer value 2) is assigned when both reviewers noted the presence of a dark pattern. Dark pattern usage is confirmed by both reviewers.
In this work, we train the machine learning model with these three labels, thereby classifying the dataset into: samples with no dark pattern usage, samples with possible dark pattern usage (only one reviewer found it), and samples with confirmed dark pattern usage.

The distribution of the labels is depicted in Table 4. Therein, the labels are not evenly distributed, and in particular, nagging and sneaking dark pattern categories have negligible or no confirmed samples. This is the result of the difficulties in detecting these dark patterns mentioned by the collectors of the dataset (Soc et al. 2020).

| Dark Pattern          | No dark pattern - 0 | Possible - 1 | Confirmed - 2 |
|-----------------------|---------------------|--------------|---------------|
| Nagging               | 229                 | 68           | 3             |
| Obstruction           | 50                  | 121          | 129           |
| Sneaking              | 186                 | 114          | 0             |
| Interface Interference| 55                  | 109          | 136           |
| Forced action         | 181                 | 88           | 31            |

Table 4: Number of labels for five dark patterns

3.4 Feature importance measure

The features and labels described are used for feature importance estimation by using the Random Forest Classification model in scikit learn. We used this feature importance measure to help us understand and interpret features and labels, but we did not use this for training machine learning classifiers. The obtained results are depicted in Figures 3a, 3b, 3c, 3d, and 3e. The feature is given in the Y-axis and the feature importance, measured on a scale of 0 to 1, is given on the X-axis.

We observe that not all of the feature importance values were equally useful in interpreting the data. For example, location of the pop up as a feature is estimated to be highly important for identifying the dark pattern nagging, see Figure 3a, which makes sense and already confirmed in the study of Utz et al. (2019), as a pop up that is displaying in the middle of the page can be considered as nagging every time a user browses the web. However, the two features estimated as most important for the dark pattern forced action – the purposes (iscokieusedlised) and clarity of options (clarityofoptions), see Figure 3e do not really make sense.

[1]https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html
4 Classification of dark patterns using machine learning

The type of features and number of data points in the dataset very much dictated the choice of supervised machine learning classifier we could use. We chose to use the Gradient Boosted Tree method for classifying the detected dark patterns as a mix of categorical and continuous features is best solved by decision tree-based classification (Friedman, 2001). Gradient Boosted Tree (Friedman, 2001) for classification uses a combination of many small decision trees in which each small decision trees tries to improve on the results of the combination of previously built trees. Decision tree is a method using branches on each feature to divide the dataset into smaller subsets that contain more homogeneous samples.

The training process involves two steps: tuning the hyper-parameters for the classifier and then training the classifier. The hyper-parameter tuning, finding optimal parameters for Gradient Boosted Tree with our dataset, is done with GridSearch and the following parameters are used learning rate: (0.15, 0.1, 0.05, 0.01, 0.005, 0.001) and n_estimators: (10, 15, 20, 25, 30, 35, 40). This resulted in optimal parameters for our training which are learning_rate: 0.01 and n_estimators: 30.

The dataset is split into training dataset, for which we used two thirds of our dataset, and testing dataset, for which we used one third. The split was done by randomly assigning data points to either the test or training data set. Five different “Gradient Boosted Tree classifiers” are trained, one for each of the five dark patterns. The models are trained independently for each dark pattern and each of the five models attempts to predict whether a presented dark pattern is of three class labels, namely, 0-No dark pattern usage detected, 1-Possible dark pattern usage and 2- Confirmed dark pattern usage. Table 5 list the accuracy score the machine learning models for each type of dark patterns categories. The accuracy score is the mean accuracy score for each of the three class labels in our test dataset weighted by their numbers relative to the total samples in the test dataset. For each of the class label the accuracy score is computed as number of correctly identified samples divided by total numbers of samples with that label in the test dataset. As we can observe, the worst accuracy is obtained for the Interface Interference dark pattern, just 0.535, which is still better than random – a completely random classifier will achieve 0.33 accuracy in this case.

Since we are dealing with a multi-class classification problem, confusion matrices were created for each of the classifiers. These confusion matrices add to the information provided in the accuracy table by displaying the performance in terms of predicted labels and actual labels. The rows are actual labels in our dataset and columns are predicted labels from our machine learning models.

https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.GradientBoostingClassifier.html
https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html
Table 5: Accuracy scores of dark pattern recognition

| Dark Pattern                  | Accuracy score |
|-------------------------------|----------------|
| Nagging                       | 0.720          |
| Obstruction                   | 0.500          |
| Sneaking                      | 0.686          |
| Interface Interference        | 0.570          |
| Forced action                 | 0.628          |

Table 5: Accuracy scores of dark pattern recognition

The cells represent the ratio of actual label that are classified as predicted labels for the corresponding rows and columns. The diagonal line from top left to bottom right represents the values of correct predictions and the rest of the cells are incorrect prediction of different kinds. These matrices are given in Figure 4 in the Appendix B.

5 Discussion

Though the raw numbers from this report are not encouraging, this work reveals a lot for the path towards automatically detection of deceptive UI design in cookie banners. In this section we discuss the most prevalent detected dark patterns type, lessons learned and policy implications.

Prevalence of dark pattern type. During the exercise, it is obvious that Forced action is one of the easiest dark pattern to identify for the reviewers. Consequently, it has the most accurate labels out of all the dark patterns. The accuracy results and confusion matrix scored on the trained classifier for different dark patterns also showed that it is best as detecting this type of dark pattern of forced action. In contrast, nagging and sneaking are most difficult to automatically detect, which is not surprising given the very low number of examples of confirmed presence of these patterns in the dataset. For the rest of the dark patterns, the automated classification is plagued by difficulties for reviewers in identifying the dark patterns, as explained below. Further work would be needed regarding implicit characteristics on the other categories.

Lessons learned. From our experiment and the yielding difficulties observed, we would like to share the most important takeaways that can inform other automated dark pattern detection initiatives based on ML.

1- Labelling dataset and codebook. Any successful automated ML detection depends on tuning dark patterns classifications with concrete features of cookie banners. And an automated approach to assess cookie banners is surely difficult in practice due to their differing designs (Sanchez-Rola et al., 2019; Degeling et al., 2019; Kretschmer et al., 2021). This fact entails that the analysis of cookie banners usually introduces a significant amount of manual labeling effort (Sanchez-Rola et al., 2019; Kretschmer et al., 2021). In fact, the current dataset from Soe et al. (2020) is not yet suitable for automatic analysis. Better
labels are necessary for the dataset and it can be achieved by clarifying the identification of dark patterns by reviewers. Doing so requires a dark pattern classification which is different from [Gray et al. (2018)] and thus more specific and amenable to cookie banners. Accordingly, additional research is needed to improve codebook consensus across dark pattern classification and its inherent characteristics, and alongside accounting for newly identified patterns in future work [Johanna Gunawan (2021)]. On this stance, [Gray et al. (2021)] propose for an holistic, n-dimensional dark patterns analysis in furtherance for such a consensual dark patterns definition.

2- **Guidelines.** Such codebook could be further coupled with guidelines for reviewers quality labels. The guidelines should be specific enough to allow for maximal agreement among reviewers on which dark pattern is present. This in turn imposes again the request for a better definition of dark patterns. There is a limit to how precisely a dark pattern can be defined since when doing so, one can also abolish it. Dark patterns are tricky because “It is rarely possible to foresee which new patterns are going to emerge, and as a result, detection measures are always reactive, and rely on practitioners that constantly update the existing pattern databases as well as engaged consumers that point out new occurrences”. [Hausner and Gertz (2021)]. Thus, guidelines may need to be continuously updated and limited to a particular context of use.

3 - **Clustering.** The process for redefining the dark pattern category for cookie banners could also be done using machine learning by considering a corpus of cookie banners and analyzing clusters within them. Similarity patterns among cookie banners might yield new insights to what new dark pattern definitions can be. We can then use these patterns which are more “visible” to a machine to train a prediction model.

4 - **Mixed approach.** An automated approach combined with manual methods could ensure better results towards detecting dark patterns in cookie banners. As we discussed in the Introduction, some features can be difficult to harvest by machines but can be precisely defined and easily identified by people, even when the people do not necessarily agree on which dark pattern they are looking at. Some dark patterns, such as nagging, would only be detectable with a human observing their behaviour.

5 - **Dark Patterns conceptual refinement.** Need for a refinement of the concept of dark patterns – per dark pattern category (following the cognition of Mathur et al. (2021); Di Geronimo et al. (2020). As Johanna Gunawan (2021) posits, additional research is needed to develop the theory of dark pattern-blindness and potential mitigation strategies in order to detect more accurately the presence of dark patterns.

**Policy and legal implications.** Any AI computational system aiming to detect dark patterns should align to detectable issues that are already deemed illegal by authoritative sources. But there are only few (mandatory) legal rules in Europe constraining the use of dark patterns, and enforcement is slow in holding websites accountable. The only mandatory decision ascertaining any UI based aspect is dated of 2019 forbidding the use of pre-ticked boxes [of Justice...
of the European Union (2019). From Article 7(3) of the GDPR ("it shall be as easy to withdraw as to give consent"), it can be interpreted that privacy choices should be equal (e.g. parity in accept, reject and revoke choices) (Santos et al., 2020; Nouwens et al., 2020b). Parity feature entails i) equal widgets, ii) equal number of times to either accept/reject/revoke consent, iii) across modalities (web, mobile and app setting levels) (Johanna Gunawan, 2021). This reasoning on feature parity needs still to be held definitive by court decisions as well for consistency in all EU. The ePrivacy Regulation draft (https://data.consilium.europa.eu/doc/document/ST-6087-2021-INIT/en/pdf) being discussed in the European Council, as of today, is absent on the definition of dark patterns or UI features, even accepting the use of cookie walls (Council’s version), considered as an onstructive dark pattern (Kretschmer et al., 2021; Gray et al., 2021). Such weak enforcement and the high rate of consent optimization enhanced by using faulty designs in cookie banners (Hils et al., 2020; Santos et al., 2021) at scale, facilitated by the use of consent management platforms, explain the recurrent use of dark patterns in cookie banners. In the future, we need to see a more serious approach to enforcement, either by courts, or by decisions issued by data protection authorities. That is the only way to ensure that automated systems can rely on the necessary legal certainty in identifying dark patterns by identifying concrete characteristics of design.

6 Related Work

Detecting and quantifying the presence of dark patterns has deserved vibrant attention, concretely, within privacy policies (Adjerid et al., 2013), e-commerce websites (Mathur et al., 2021), popular mobile apps (Nouwens et al., 2020b; Sanchez-Rola et al., 2019; Utz et al., 2019; Di Geronimo et al., 2020), video games (Zagal et al., 2013), cookie banners, among other contexts. However, there is little work reporting use of machine learning for automated detection of dark patterns in user interfaces of cookie banners. In this section we analyse automated detection of dark patterns in general and in cookie banners.

Detection of dark patterns in online services. Mathur et al. (2019) analyzed ~53K product pages from ~11K shopping websites, and discovered 1,818 dark pattern instances, together representing 15 types and 7 broader categories. The goal of their work is to present “automated techniques that enable experts to identify dark patterns on a large set of websites in one particular category”. The process presented is done in three steps: The first step is corpus creation through crawling Alexa top websites which are ranked according to monthly web traffic. From that list of top traffic websites, a tool called Webshrinker is used to categorize into shopping or not shopping categories. After that, only English language websites are kept resulting in the final list of 19,455 shopping websites. The second step is data collection of the product checkout pages. The third step is data analysis on the product checkout pages using using Hierarchi-

Density-based Spatial Clustering of Applications with Noise (HDBSCAN)
This is an unsupervised learning method that can form hierarchical clusters from the dataset. Samples from these clusters are then manually examined to identify different categories of dark patterns in product checkout pages.

Curley et al. (2021) developed a framework for automated detection of potential instances of web-based dark patterns. They identify whether or not it is technically possible to automatically detect that particular pattern. They analyze known dark patterns in terms of whether they can be: (1) detected in an automated way (either partially or fully), (2) detected in a manual way (either partially or fully) and (3) cannot be detected at all due to variation in either how the pattern is defined or implemented, there is no direct way of detecting which hampers web crawling and web scraping techniques. Some patterns are easier to detect than others, and some are impossible to detect in an automated fashion. They propose a software tool that can automatically alert users of the presence of web-based dark patterns.

Detection of dark patterns in cookie banners. We focus on related where some attempt for automatic detection of dark patterns was presented. Nouwens et al. (2020b) performed a study on the five most popular CMPs on the top 10,000 websites in the UK which has yielded 680 banners. They aimed to study the impact of various designs of consent banners, user interface design nudges and level of granularity of options. They used a hand-crafted approach for dark patterns detection. The implementation details for using hand-crafted scripts for detection is not available and it only works just for 6.8% of the 10,000 websites crawled. The authors looked at unambiguous, widget level (easiness to reject), presence of pre-ticked boxes. Matte et al. (2020) used semi-automatic methods and only made the content of the cookie banner notifications available to the users via a script and human labour is used to identify four GDPR violations, as depicted in Table 7: consent was stored before the user made the choice, whether a cookie banner offers a way to opt out, whether there were pre-selected choices, if the choice that the user had made was respected at all. Hausner and Gertz (2021) presented ongoing work in the direction of automatic detection of dark patterns on cookie banners. They use the feature representation for cookie banners and automatically extract the feature values. Their goal is to build a general framework to detect dark patterns on arbitrary web pages (regardless of their domain). Unlike us, they do not consider dark patterns as abstract concepts, but focus on widget parity. Their approach does not consider dynamic aspects of dark patterns. By applying the implemented algorithm to more than 4000 German websites extracted from a list of the top one million web sites according to Alexa.com, around 2800 cookie banners were extracted and analyzed. By utilizing features like the HTML tag of elements, they obtained a large amount of clickable elements within the banners. They extracted textual features from those elements, and used clustering techniques to find different groups of buttons with regard to their textual content. Based on the initial clustering and a manual relabeling of critical items, a Support Vector Classifier is trained to distinguish between multiple button types.
The GDPR violations features detected in two of these works in available in Table 7 in the Appendix B.

7 Conclusion

We considered the problem of automatically detecting the five dark patterns of Gray et al. (2018) by training a supervised machine learning model using the data set of Soe et al. (2020). Our approach can be considered naive, since the data set used was relatively small and not well balanced - dark patterns of different type occur with different frequency in the data set. However, as we discussed throughout the paper, creating a training dataset is a considerable challenge in its own right. It requires a combination of human effort, automated extraction of feature values and pre-processing of extracted material using various AI technologies such as clustering and sentiment analysis. Furthermore, unlike related work, we attempt to detect dark patterns directly, rather than specific features that make the pattern dark, like for example widget inequality, which is much less ambitious.

We used this experiment primarily as a spring-board to better understand the problems of using machine learning for automating dark pattern detection. We present a detailed analysis on the challenges involved and consider this our main contribution. Our experiment allows us to clearly outline promising directions of future work.

Clearly, a pipeline of various methods and techniques would eventually need to be constructed for a functioning automated dark pattern detection tool. To construct it we need to decompose the experience: dark patterns into elements that can be automatically, or at least easily processed. This is a task that requires expertise in human-computer interaction and cognitive science. It is also a task that is perhaps easiest tackled when focusing on one specific domain at a time. For example cookie banners should be considered as one domain, whereas privacy settings another.

Visual cues and components of a dark pattern should be explored as an image recognition problem. To this end, we need to construct a common resource, a collection of labeled images, one for each visual cue. For example: one collection of images that contain screenshots of cookie banners with different level widgets.

What the Soe et al. (2020) dataset shows, is that there is a lot of variety in the textual information that describes the purposes of the data collection, cookies, trackers etc. We did not explore how to use this text in our approach, but one should consider that the dark pattern here is the volume and language style of the text, rather than the information it is supposed to convey. As with images, a common resource needs to be created to create training data for a supervised learning algorithm that would label text as confusing or comprehensible, using feature that describe the volume of text and various linguistic cues such as legalese.

In our work, we were not able to identify clear distinguishable features that would discern among the dark patterns. This is because we worked with a
“found” data set. Namely, the features were not engineered to represent a specific dark pattern.

Soe et al. (2020) also suggested 12 refined dark patterns but did not provide a label for these dark patterns in their original dataset. An immediate first step would be to creation a new dataset with similar categories of dark patterns as proposed in (Soe et al. 2020) and features engineered to discern among those dark patterns.

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A Background: dark patterns in cookie banners and their impact in user decision making

In this section we give the preliminary definitions of concepts that we use throughout the paper.

Dark patterns. The term dark patterns (Gray et al., 2018) has been coined to identify “instances where designers use their knowledge of human behavior (e.g., psychology) and the desires of end users to implement deceptive functionality that is not in the user’s best interest” (Gray et al., 2018). Throughout this work, we use the concept “dark pattern” to refer to types of UI dark designs that have been documented and applied to cookie banners on websites (Gray et al., 2018; Nouwens et al., 2020b). Gray et. al. define five dark patterns categories from: nagging, obstruction, sneaking, interface interference, and forced action. The description of each of these patterns as given in Table 6.

| Name                  | Description                                                                                                                                 |
|-----------------------|---------------------------------------------------------------------------------------------------------------------------------------------|
| Nagging               | A minor redirection of expected functionality that may persist over one or more interactions. Nagging often manifests as a repeated intrusion during normal interaction, where the user’s desired task is interrupted one or more times by other tasks not directly related to the one the user is focusing on. |
| Obstruction           | Impending a task flow, making an interaction more difficult than it inherently needs to be with the intent to dissuade an action. Obstruction often manifests as a major barrier to a particular task the user may want to accomplish. |
| Sneaking              | An attempt to hide, disguise, or delay the divulging of information that has relevance to the user. Sneaking often occurs in order to make the user perform an action they may object to if they had the knowledge. |
| Interface interference| Any manipulation of the user interface that privileges specific actions over others, thereby confusing the user or limiting discoverability of important action possibilities. Interface interference manifests as numerous individual visual and interactive deceptions. |
| Forced action         | Any situation in which users are required to perform a specific action to access (or continue to access) specific functionality. This action may manifest as a required step to complete a process, or may appear disguised as an option that the user will greatly benefit from. |

Table 6: Dark pattern types of (Gray et al., 2018) and their definitions

Legal requirements for consent in cookie banners. Consent is defined in Article 4(11) and complemented by Articles 6 and 7 of the GDPR which state that for consent to be valid, it must satisfy the following seven requirements: it must be prior, freely given, specific, informed, unambiguous, must be readable and accessible, and finally, revocable. Unambiguous means that consent must be given through an active behavior of the user through which she indicates acceptance or refusal to online tracking. Such active behaviors can consist

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15The neologism, dark pattern, was coined by user experience designer Harry Brignull in 2010.
"clicking on a link, or a button, box, image or other content on the entry webpage, or by any other active behavior from which a website operator can unambiguously conclude it means consent" (Article 29 Working Party, 2013).

Accordingly, silence, pre-ticked boxes or inactivity should not therefore constitute consent and violate such unambiguous requirement (Recital 32 GDPR, of Justice of the European Union, 2019)). The unambiguous requirement entails that privacy options (accept, reject, revoke, configure, know more) should be balanced (or equitable) (Article 7((4) a contrario, GDPR (Santos et al., 2020; Office, 2019)). Websites failing to comply with these GDPR requirements face fines up to 4% of their annual revenue or 20 million euros (Article 83(5,6)).

Impact of dark patterns in the user decision making process. Deployment of dark patterns by online services are observed to be effective at bending people towards choices that are not in their own interest, impacting their decision-making process.

Studies. The effect of dark patterns is evidenced in a growing studies and experiments. Nouwens et al. (Nouwens et al., 2020b) ran a user study on 40 participants to assess the effect that cookie banner design has on consent and found that there was an approximate 22% of increase in acceptance when the opt-out option was “hidden” behind the initial cookie banner (at least two clicks are needed to opt out).

Di Geronimo et al. (Di Geronimo et al., 2020) coined the term "dark pattern-blindness" motivating why most respondents in their study were not able to recognise dark patterns in mobile applications, though when these were informed of the potential presence of dark patterns in the context at hand, they became more capable of spotting them.

In the same line, Bhoot et al. (Bhoot et al., 2020) observed that if the interface is appealing, respondents tend to experience less frustration and hardly notice manipulative attempts. The experiment shows that certain design elements can influence people’s capacity of identifying and resisting dark patterns.

The study by Utz et al. (Utz et al., 2019) showed that UI design tricks have a very pronounced affect on the decision made by people on whether they will interact with the cookie banners and whether they will accept or reject cookie banners.

Maier and Harr (Maier and Harr, 2020) reveal in the respondents answers awareness, annoyance and resignation, as their participants believed it impossible to avoid online manipulation, and acknowledged that the trade-off (free service) outweighs negative consequences.

Degeling et al. (Degeling et al., 2019) studied how banners design affect users’ choice, and notably finds that the absence of a “refuse” button on the first layer of the banner increases positive consent by about 22%.

Luguri and Strahilevitz (Luguri and Strahilevitz, 2019) found that dark UI caused participants in their survey and experiment to accept costly service almost four times as often as the same interface without dark patterns. Their work showed that subtle dark patterns are easily unnoticed than ostensive ones, and that less-educated people are prone to be influenced than more educated
Kulyk et al. [Kulyk et al., 2018] made an explorative survey with 150 participants in order to study the perception of such cookie banners among the users, as well as the users’ reactions to such a disclaimer and factors that influence these reactions. The study showed that users tend to have a negative perception of cookie banners, either perceiving it as a nuisance or as a threat to their privacy, were distrustful towards textual statements.

Finally, Bongard-Blanchy et al. [Bongard-Blanchy et al., 2021] reveal in their user study that users are able to recognize dark patterns, but fail to understand how manipulative design can concretely harm them. It furthermore hints that a higher ability to discern manipulative designs is positively related to the capacity to self-protect, though it also finds that the most deceptive dark patterns were harder to be identified by users. The authors convey that wrong mental models (about their risks) and grown habituation to such designs make certain dark patterns harder to spot.

| Minimum requirements for GDPR compliance [Nouwens et al., 2020b] | GDPR violations [Matte et al., 2020] |
|---------------------------------------------------------------|-------------------------------------|
| Consent must be unambiguous - Consent must be a clear affirmative action, such as clicking a button or ticking a box (Article 4(11), Recital 32 GDPR) | No way to opt out - The option to refuse consent is not available |
| Accepting all is as easy as rejecting all - Consent must be easy to give as to withdrawal/refuse (Article 7(3) GDPR) | Non-respect of choice - Consent choice made is not respected in the cookie settings |
| No pre-ticked boxes - Consent to tracking purposes must be unchecked by default of Justice of the European Union [2019] | Pre-selected choices - All vendors or purposes choices should not be preselected |
| Prior consent - Consent must be given prior to any data processing (Article 6 (1)(a) GDPR) | Consent stored before choice |

Table 7: Comparisons of GDPR violations measures used in [Matte et al., 2020; Nouwens et al., 2020b]

Solutions. In terms of solutions, Graßl et al. [Graßl et al., 2021] introduced the term bright patterns meaning to redirect users’ consent decisions towards privacy-friendly choices (e.g., pre-selection of ”Do not agree” option). However, they also show that even after removing a nudging and manipulative design choice, a form of routinised conditioning could still persist, ultimately leading users to behave in a certain way, due to an irreflective default behavior.

Summary. Building on this body of knowledge made us realize the following: i) user’s decision making process is impacted by dark patterns; ii) users might be aware and recognize them, though they are unable to resist them, and are bound to the immediate trade-off; iii) some dark patterns are not so easy to be detected by users due to habitation to deceptive design and due to incorrect mental models. As such, automated detection of dark patterns and due reporting to decision-makers (data protection authorities) seems to be the
appropriate and neutral intervention to ease autonomous decision-making and counteract manipulative designs online.

B  Figures

![We Need Your Consent](image)

Figure 2: An example of a cookie banner from vice.com retrieved on July 2019
Figure 3: Feature importance comparisons of different dark patterns
(a) Nagging

(b) Obstruction

(c) Sneaking

(d) Interface Interference

(e) Forced Action

Figure 4: Confusion matrix of different dark patterns
C Description of the data repository

The repository where the work is located contains the following resources

- `clusteringnotyesoption.ipynb` - The python notebook used for clustering of "Not Yes" options for the cookie banners. It is supposed to be uploaded and ran on Google Collab environment.

- `automatedanalysisofdarkpatternscookie.ipynb` - The python notebook used for performing parameter search and training a Gradient Boosted Classifier for the dataset. It is ran on local Jupyter Notebook environment.

- `data-¿banner_data_clean.csv` - The cleaned dataset used in training of the classifier.

- `data-¿banner_data.csv` - The original data from the project it is not used for training.

- `data-¿cookie_consent.db` - The translated dataset for Privacy Policy and Cookie Policy documents.

- `snippets` - The home for all the little snippets created to help in this project.