MASTER OF SCIENCE IN ENGINEERING

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MSE - Software Engineering

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Bot Detection and Analysis

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1 Introduction

With the emergence of technology and smart devices, social networks have been present in our daily life for more than two decades. The first social networks were created in the late 1990s and most notably, "The Facebook", was launched in 2004. Those companies have now gathered billions of daily users of various interests, from hobbies to politics. One network of particular importance is Twitter. With 206 million daily users [1], Twitter is one of the largest social networks on the market. Twitter has also over the years become a center-place for political discussion. 64 world leaders are officially verified by Twitter as legitimate users [2]. Former US President Barack Obama is widely considered one of the first leaders to use social media actively in his campaign [Aak], and the decision to ban former US President Donald Trump from the platform is still debated today.

Additionally, billionaire Elon Musk's ongoing negotiations to acquire Twitter are partially motivated by political reasons. With Musk criticizing Twitter's approach to content moderation and removal of hate speech, whilst opponents of the deal are arguing that Musk's proposals may only exacerbate the problems. Musk has also often talked about another issue faced by Twitter : the presence and influence of bots.

To give our study some context, we decided to focus our research and efforts on the 2022 French Presidential Elections. Our goal is therefore to give a brief overview of the usage of bots on Twitter during this election. Additionally, since energetic and environmental aspects were of particular concern for the majority of the candidates, we decided to take a look at how much energy is needed to make bots function.

In this report, we aim to analyze what is referred to as "bot detection". The objective is to automatically determine whether a Twitter user is a bot using a machine learning model trained on openly available data. In a second stage, we apply our model to a dataset of the 2022 French presidential election. Finally we will analyze our results and try to draw conclusions regarding the impact of bots in different domains (energetic and social).

[1] https://www.statista.com/statistics/242606/number-of-active-twitter-users-in-selected-countrie
[2] https://twitter.com/i/lists/15299140

2 State of the art

The topic of social bots has gained widespread attention from the scientific community in the last decade, particularly in the wake of the 2016 United States election that saw a wide use of misinformation and bots to interfere with people's political opinions [GPT21, SFDD18, SCV$^+$18, GJF$^+$19]. According to recent studies, Twitter bots are becoming an increasingly serious threat due to their numbers; Varol et al. [VFD$^+$17] estimated in 2017 that between 9% and 15% of active Twitter users are in fact bots. They came to this conclusion by using the (now deprecated) online bot detection framework created by Davis et al. [DVF$^+$16] that leveraged over a thousand features. Furthermore, as indicated in [VFD$^+$17], Twitter stated in a United States SEC (Securities and Exchange Commission) filed in 2014 that "approximately 8.5% of all active users used third party applications that may have automatically contacted our servers for regular updates without any discernable additional user-initiated action"[1].

Annotated datasets The earliest publicly available dataset (to the best of our knowledge) is due to Cresci et al. [CDPP$^+$15] in 2015. While this dataset contains two classes, genuine and fake Twitter accounts, it does not include what we call "bots". Fake Twitter accounts corresponds to accounts that could be bought online at that time. In a follow up paper by the same authors [CPP$^+$17], they improved their work by including various manually annotated bots in the datasets, such as bots promoting *Amazon.com* products, paid mobile applications, scam URLs and bots accounts automatically retweeting political candidates. A larger dataset was published in 2019 by Yang et al. [YVHM20]; unlike [CPP$^+$17], the authors used automated techniques to label the dataset based on suspicious behaviours. One of the most recent dataset, also the largest one, is TwiBot-20 [FWW$^+$21] which used crowdfunding techniques to label part of the dataset. This dataset also contains a wide variety of Tweets and neighborhood information (i.e. which accounts follows which). In 2022, an improved version of TwiBot-20, named TwiBot-22 [FTW$^+$22], was published by Feng et al.

Bot detection To the best of our knowledge, the earliest research that tackled the problem of Twitter bots detection was done by Yardi et al. in 2010 [YRSdb10] by analyzing behavioral patterns among spam bots compared to legitimate users. After the work by Yardi et al., many other bots detection models were proposed [LEC11, DVF$^+$16, VFD$^+$17, YVHM20].

[1] https://www.sec.gov/Archives/edgar/data/1418091/000156459014003474/twtr-10q_20140630.htm

3 Datasets

In this chapter, we first present an individual analysis of the different datasets that were used in this project, then we present a comparative analysis of those datasets in the section.

3.1 cresci-17 [CPP+17]

We use the name cresci-17 to refer to the dataset created by Cresci et al. [CPP+17] in 2017. The dataset was made available after the publication of their paper on the detection of “spambots”.

3.1.1 Purpose

The initial objective of this dataset was to detect a particular class of bots referred to as “spambots”. The authors describe this class of bots in two ways: accounts that automatically retweets posts by political candidates and bots that promotes products from *Amazon.com*.

3.1.2 Data collection

The first bots in the dataset were first collected by Cresci et al. while observing a candidate in the 2014 Rome Mayoral election.

After a sample of potential spambots were collected, the accounts were analyzed manually by two post-graduate students in order to annotate the dataset. The disagreements between annotations were evaluated by a third annotator, a doctoral student with in-depth knowledge of Twitter. The quality of the annotation was evaluated using the Cohen’s Kappa metric [Coh60] to measure the level of agreement. This yielded mixed results with a κ of 0.824 and 0.351 for retweet bots and *Amazon.com* bots respectively. While the former is considered a strong level of agreement, the latter is considered *minimal* [McH12].

The dataset also contains 3474 users that were verified by asking simple questions and verifying the answer to attest whether or not they are legitimate users.

3.1.3 Data analysis

After loading the datasets and removing some accounts as they were irrelevant for our analysis, we end up with 7543 bot accounts and 3474 legitimate users. The dataset contains the standard Twitter features:

- created_at: When the account was created
- default_profile: True if the default profile theme or background is used
- default_profile_image: True if the default profile image is used
- description: Short personal description
- followers_count: Number of followers
- friends_count: Number of users followed (aka “followings”)
- geo_enabled: (Deprecated) True if the location data is displayed in Tweets
- has_url: True if a URL is included in the profile
- listed_count: The number of public lists containing the user
- location: Location manually defined in the user profile
- name: Custom name of the user
- screen_name: Username / id of the user

- statuses_count: Total number of Tweets (include Retweets)
- url: Url included in the profile
- verified: True if the account is verified[1]

Table 3.3 displays statistics on the numerical features of the dataset. We can see that the bots tend to interact less with Twitter than other users as both the mean and the median are always lower. In this dataset, 50% of bots have no favorites saved, about 10 followers, less than 50 friends and are not listed in public lists. Somewhat surprisingly at first, those bots also have few statuses - 100 times less than users. However, upon further analysis, this makes sense because they would be easily and quickly detected by Twitter if they were to spam statuses; having many bots is a more effective solution.

Table 3.1: cresci-17 numerical features

		favourites	followers	friends	listed	statuses
	mean	29	1004	666	12	1802
Bots	**median**	0	11	45	0	60
	std	827	35212	3508	352	7873
	mean	4670	1393	633	19	16958
Users	**median**	1286	341	319	2	6609
	std	11528	17217	1601	158	30696

We used a PCA analysis with two components on the numerical features of the dataset to visualize the data on a 2D plot, we show this in Figure 3.1. This plot reveals that there are 4 main clusters of points, 3 of those clusters contain both bots and users. This indicates that a good part of the data can be classified relatively easily, but some of the bots appear to be harder to classify as their features appear to be similar to the users'.

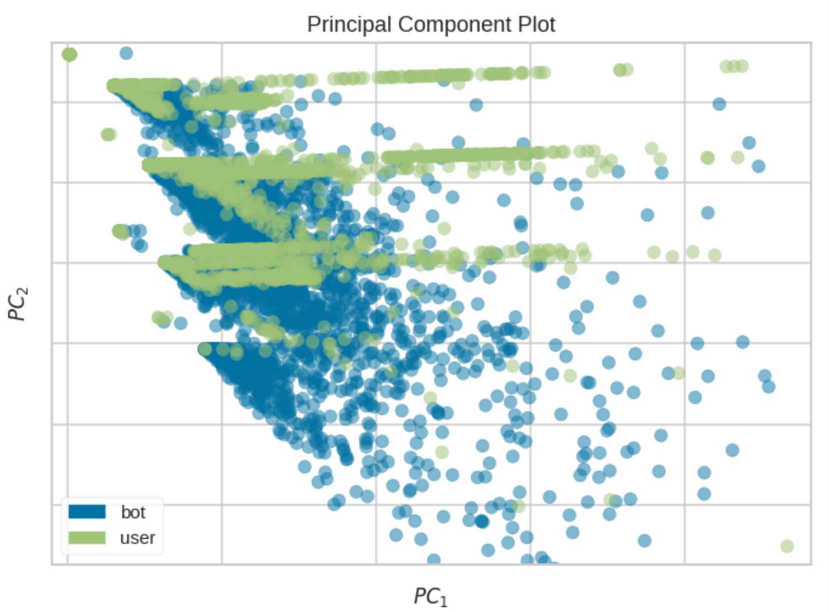


Figure 3.1: Two components PCA analysis of cresci-17 with 3000 users and 3000 bots

[1]A verified account is a popular individual/company that has been manually authenticated by Twitter.

3.2 midterm-2018 [YVHM20]

This dataset was collected by Yang et al. [YVHM20] in 2018 during the U.S. midterm elections.

3.2.1 Purpose

The objective of this dataset was to identify legitimate users and bots that were tweeting political tweets during the 2018 U.S. midterm elections.

3.2.2 Data collection

The dataset was collected in two different ways, Some of the genuine users were manually identified while analyzing the online political discussions. Bots, on the other hand, were classified automatically by

3.2.3 Data analysis

Table 3.2: cresci-17 numerical features

		favourites	followers	friends	listed	statuses
	mean	79	19	76	0	123
Bots	**median**	0	0	1	0	20
	std	757	146	233	1	893
	mean	14043	16428	1424	98	14659
Users	**median**	3984	362	478	7	4352
	std	28919	580301	6540	1119	31666

A PCA analysis, displayed in Figure 3.2, reveals that the users of this dataset behave in a very similar manner as they are grouped together tightly. The bots tend to be quite different than the users.

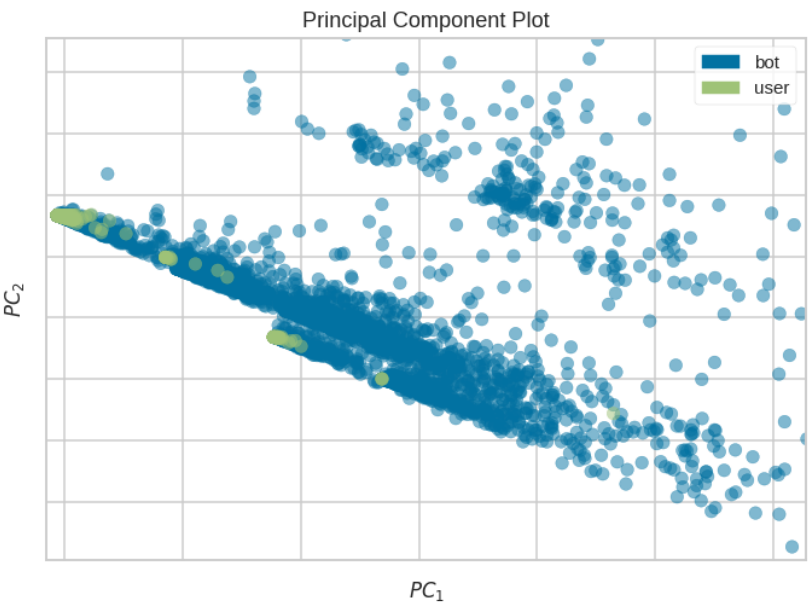


Figure 3.2: Two components PCA analysis of midterm-2018 with 5000 users and 5000 bots

3.3 TwiBot-20 [FWW+21]

The last annotated dataset that we analyzed for this project is called TwiBot-20.

3.3.1 Purpose

The objective of Feng et al. [FWW+21] is to provide a large scale dataset with a diverse population of bots and users to better represent the reality of Twitter.

3.3.2 Data collection

TwiBot-20 was collected from July to September 2020 using a BFS algorithm that iterates through the followers of specific “seed” accounts and stops on the third layers. The algorithm does not filter the accounts and simply stores the data of all discovered users.

To generate a diversified set of users, Feng et al. chose 40 seed users from 4 main disciplines: politics (e.g. Nancy Pelosi), business (e.g. Amazon), entertainment (e.g. Sam Smith) and sports (e.g. Stephen Curry). In addition to this, the authors of TwiBot-20 also sample users that comment on relevant Tweets and hashtags.

The dataset was annotated via a crowdsourcing campaign on the website Appen (`www.appen.com`) and used various methods to ensure the quality of the annotation.

3.3.3 Data analysis

Table 3.3: cresci-17 numerical features

		favourites	followers	friends	listed	statuses
	mean	15157	23514	4967	119	15632
Bots	**median**	1467	713	825	4	2006
	std	45543	211742	22843	719	54097
	mean	10919	1443320	8711	3277	29204
Users	**median**	1711	26809	613	208	6580
	std	32558	6168407	92720	14667	121052

3.4 2022 French presidential election

The "2022 French presidential election" refers to the dataset that we collected during this project. It is composed of 40217 distinct users.

3.4.1 Purpose

The purpose of this dataset is to analyze the behavior of Twitter users the day before the first round of the 2022 French presidential election. After collecting usernames of participants discussing the subject, a deeper data collection was performed to extract each user metadata.

3.4.2 Data collection

The global process to collect the dataset is described in figure 3.4. In order to access the complete Twitter API with bigger rate limits, an academic research application was submitted and was validated by Twitter.

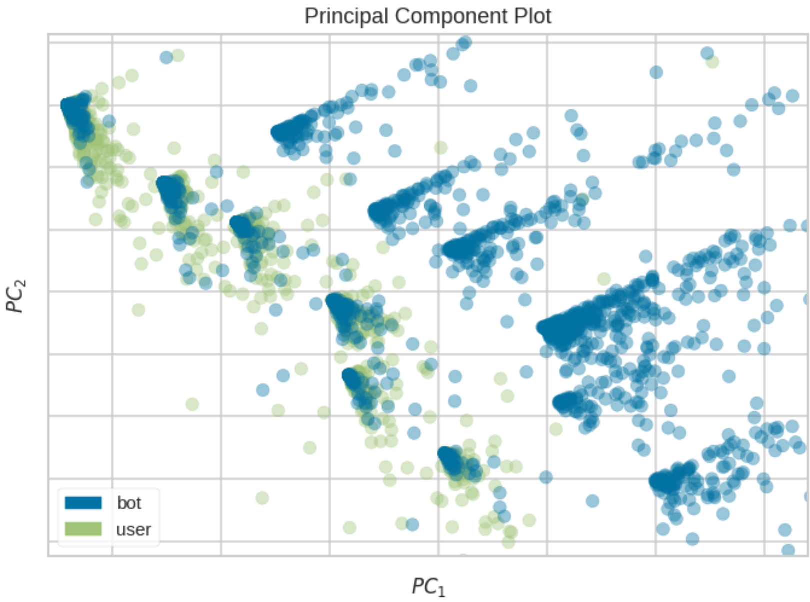
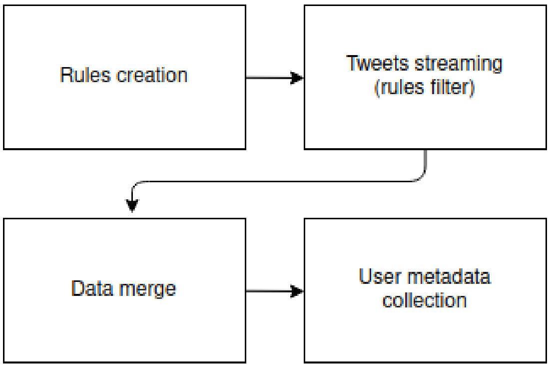


Figure 3.3: Two components PCA analysis of TwiBot-20 with 2000 users and 2000 bots

The end goal is to collect the metadata of each user taking part in the public political debate on Twitter during our scan. To do so, we wish to listen and filter to Twitter live stream according to a set of rule (e.g with a politician mentioned). Then, we merge all the collected tweets in a set of users name and we poll the Twitter API once again to obtain each user metadata.

Figure 3.4: Data collection process



Rules creation

With the help of Twitter context annotation[2], we were able to narrow filter the Tweet stream and to only capture relevant data.

The first step was to manually identify several context annotations that we could use to create rules. For example, by searching "Macron Démission" with Twitter search API, we can find that the context 35.822153632002904064 corresponds to "Politician - Emmanuel Macron". We then try to cover each candidate and create the following ruleset 3.5:

[2] https://developer.twitter.com/en/docs/twitter-api/annotations/overview

Figure 3.5: Definitive ruleset

```
def set_rules(delete):
    # You can adjust the rules if needed
    sample_rules = [
        {"value": "context:38.1483827056597110000", "tag": "French Presidential Elections 2022"},
        {"value": "context:38.1483827056597110787", "tag": "French Presidential Elections 2022 v2"},
        {"value": "context:35.822153632002904064", "tag": "Emmanuel Macron"},
        {"value": "context:35.822417319812943873", "tag": "Nicolas Sarkozy"},
        {"value": "context:35.1466465464691822594", "tag": "Valérie Pécresse"},
        {"value": "context:35.1466058925661245445", "tag": "Jean-Luc Mélenchon"},
        {"value": "context:35.840172130562064384", "tag": "Nathalie Arthaud"},
        {"value": "context:35.1466053355365548040", "tag": "Eric Zemmour"},
        {"value": "context:35.822153193526169600", "tag": "Marine Le Pen"},
        {"value": "context:35.828643761416658944", "tag": "Jean-Luc Melenchon"},
        {"value": "context:35.1118103044795748352", "tag": "Yannick Jadot"},
        {"value": "context:35.840176055679766530", "tag": "Philippe Poutou"},
        {"value": "context:35.1117814891144810497", "tag": "Nicolas Dupont-Aignan"},
        {"value": "context:35.1230925906685771777", "tag": "Anne Hidalgo"},
        {"value": "context:35.1466081450558570498", "tag": "Fabien Roussel"},

    ]
```

One can notices that some candidates appear more than once. For example "Jean-Luc Mélenchon" can be seen twice. It is explained by the fact that Twitter generated to different contexts for about him: one with an accent (Mélenchon) and another without accent (Melenchon). To capture all the public debate, we need to include both version in our ruleset.

Tweets streaming

This step is fairly straightforward. We simply listen to all incoming Tweets filtered by our ruleset until we collected enough data for our experiment. In 67 minutes of scanning, we were able to collect our entire dataset.

Data merge

During data collection, most users tweeted multiple times. In the span of one hour, the mean tweets count is more than five. To limit our future API calls to retrieve metadata, we need to merge those tweets in a single entity. A user now has a tweet count and a set of triggering rules attributes.

User metadata collection

As it is explained in the Model chapter 4, the definitive model only needs some metadata to make a prediction [YVHM20]. To collect those, we use the previous steps output and poll Twitter user API. The final dataset is described in figure 3.6

3.4.3 Data analysis

Since this dataset is not annotated, we had to set a threshold in the random forest model. If the model compute a probability higher than 0.85, the sample is classified as bot. We chose this number manually after testing several thresholds (0.5, 0,75, 0.85, 0.99). This approach allows to decrease the number of false positive. With this exact threshold, our dataset classifies 4% of samples as bots. With a lower thresholds, too many accounts were labeled as bots in consideration of known statistics. We prefer to focus on fewer false positive and higher false negative than the opposite.

The normal distribution is shown in figure 3.8.

```
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   nb_tweets                     40217 non-null  int64
 1   matching_rules                40217 non-null  object
 2   probe_date                    40217 non-null  datetime64[ns, UTC]
 3   statuses_count                40217 non-null  int64
 4   followers_count               40217 non-null  int64
 5   friends_count                 40217 non-null  int64
 6   favourites_count              40217 non-null  int64
 7   listed_count                  40217 non-null  int64
 8   description                   40217 non-null  object
 9   screen_name                   40217 non-null  object
 10  name                          40217 non-null  object
 11  geo_enabled                   40217 non-null  bool
 12  verified                      40217 non-null  bool
 13  created_at                    40217 non-null  datetime64[ns, UTC]
 14  profile_background_tile       40217 non-null  bool
 15  profile_use_background_image  40217 non-null  bool
 16  default_profile               40217 non-null  bool
 17  default_profile_image         40217 non-null  bool
 18  url                           6832 non-null   object
 19  has_location                  40217 non-null  bool
 20  user_age                      40217 non-null  float64
 21  tweet_freq                    40217 non-null  float64
 22  followers_growth_rate         40217 non-null  float64
 23  friends_growth_rate           40217 non-null  float64
 24  favourites_growth_rate        40217 non-null  float64
 25  listed_growth_rate            40217 non-null  float64
 26  followers_friends_ratio       40217 non-null  float64
 27  name_length                   40217 non-null  int64
 28  screen_name_length            40217 non-null  int64
 29  description_length            40217 non-null  int64
 30  num_digits_in_name            40217 non-null  int64
 31  num_digits_in_screen_name     40217 non-null  int64
 32  has_url                       40217 non-null  bool
```

Figure 3.6: Definitive dataset features

The figure 3.7 shows a 2 components PCA. Since the dataset is not annotated, we can not be sure about the sample colours. If they were correct, we could say that bots and user are easily separable but we can't know for sure. We can, however, say that there are 3 main areas alongside the PC2 component with clear borders.

Table 3.4: Presidential22 numerical features

		favourites	followers	friends	listed	statuses
	mean	67861	2276	3156	15	59060
Bots	**median**	36804	1459	2768	3	24166
	std	88907	3102	2953	41	102988
	mean	32816	6385	860	40	35741
Users	**median**	11338	267	392	1	10336
	std	62018	158550	1890	659	88541

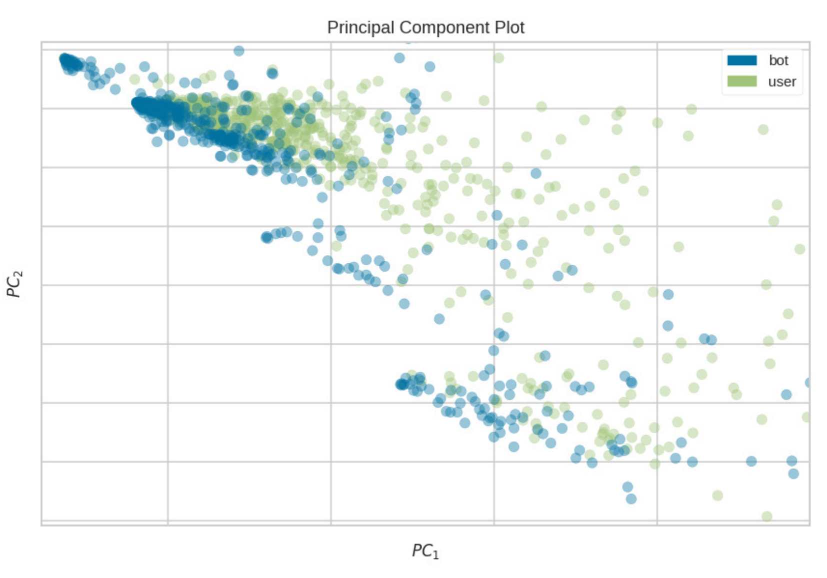


Figure 3.7: Presidential 2022 PCA

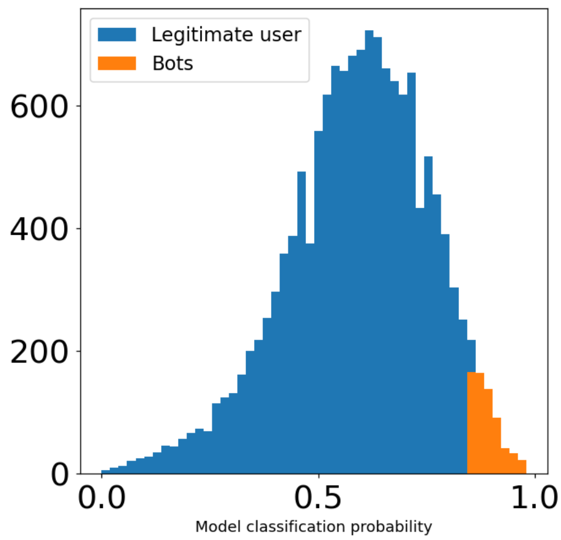


Figure 3.8: Presidential 2022 distribution

4 Models

This chapter explores the various models that we have built using the annotated datasets that we described in the previous chapter.

4.1 Feature engineering

The first step that we executed to build our models is to increase and transform the features of the datasets. Many information of the dataset are non-numerical and cannot be exploited by our models without this step.

We follow the feature engineering methods used by Yang et al. [YVHM20] and extract a number of new features. Those features are either engineered by transforming textual data into numerical data (e.g. length, occurence of numbers), or by deriving new features to generate a frequency (e.g. tweet frequency) over the age of the account. We summarize those new features in Table 4.1.

Table 4.1: List of features obtained via feature engineering

feature	value	description
user_age	probe_date - created_at	The age of the account upon data collection.
tweet_freq	$\frac{\text{statuses\_count}}{\text{user\_age}}$	The frequency of Tweets over the age of the account.
followers_growth_rate	$\frac{\text{followers\_count}}{\text{user\_age}}$	The number of followers over the age of the account.
friends_growth_rate	$\frac{\text{friends\_count}}{\text{user\_age}}$	The number of followers gained over the age of the account.
favourites_growth_rate	$\frac{\text{favourites\_count}}{\text{user\_age}}$	The number of favourites Tweets saved over the age of the account.
listed_growth_rate	$\frac{\text{listed\_count}}{\text{user\_age}}$	The number of times the account appears in a public list over the age of the account.
followers_friends_ratio	$\frac{\text{followers\_count}}{\text{friends\_count}}$	The number of followed accounts over the age of the account.
screen_name_length	len(screen_name)	The length of the screen name.
num_digits_in_screen_name	$\mathsf{len}_{0\text{-}9}$(screen_name)	The number of digits in screen_name.
name_length	len(name)	The length of the custom name.
num_digits_in_name	$\mathsf{len}_{0\text{-}9}$(screen_name)	The number of digits in the custom name.
description_length	len(description)	The length of the description.

4.2 Model type

Several types of models were used in the literature to analyze and discover bots through machine learning. The main type of model used for the problem of bot analysis is a random forest model [LEC11, DVF+16, VFD+17, YVHM20] as they tend to work best for the problem of Twitter bot detection using accounts metadata; therefore, we decided to focus on this type of model.

4.3 Building the model

As described in the previous chapter, the 3 annotated datasets were used in slightly different contexts and thus contain a variety of Twitter bots; some easy to detect and some much harder to detect. In order to bulid a more generalized dataset, we used various experiments while building the model described in Table 4.2. First, we attempted to use a single dataset and compare the generalization capabilities on the other datasets, but this resulted in poor accuracy when testing the model on the other datasets. For instance, training the model using the cresci-17 dataset results in near-perfect performance when testing the model on a test set extracted from the same dataset. When trying to apply the same model to a test set based on midterm-18, we still obtain decent accuracy of 0.68 and a low False Positive Rate (FPR)[1]. However, testing the model on the twibot-20 dataset results in an accuracy below 0.50 and a high FPR. Other models trained on a single dataset tend to behave similarly, but with a higher FPR.

From Table 4.2, we also see that independently of the models, TwiBot-20 tend to have a higher FPR than other datasets, this can indicate that bots tend to behave similarly to legitimate users. Due to the constantly high accuracy and low FPR of cresci-17, we can say that the bots in this dataset are easier to distinguish from legitimate users.

Due to those factors, we decided to train the model on two datasets rather than single one, this is also displayed in Table 4.2. In order to have good performance, we need to include TwiBot-20 in the dataset as it is much harder to train. However, as the bots in cresci-17 are easier to distinguish, we get good performance even if the dataset is not included. The best model was obtained by combining midterm-18 and twibot-20; this model yields great performance on cresci-17 even though it was not trained on this dataset. One downside of this model is the relatively high FPR, 0.11 and 0.24 on midterm-18 and TwiBot-20, respectively.

Table 4.2: Performance of various models

Datasets	cresci-17		midterm-18		TwiBot-20	
	Accuracy	FPR	Accuracy	FPR	Accuracy	FPR
cresci-17	0.99	0.01	0.68	0.01	0.46	0.29
midterm-18	0.32	0.32	0.99	0.01	0.45	0.44
twibot-20	0.71	0.30	0.80	0.16	0.82	0.23
cresci-17 & midterm-18	0.98	0.01	0.99	0.01	0.50	0.33
cresci-17 & twibot-20	0.94	0.01	0.80	0.12	0.81	0.23
midterm-18 & twibot-20	0.93	0.01	0.83	0.11	0.80	0.24

[1]We use this metric because we want to limit the number of legitimate users falsely detected as bots

5 Analysis

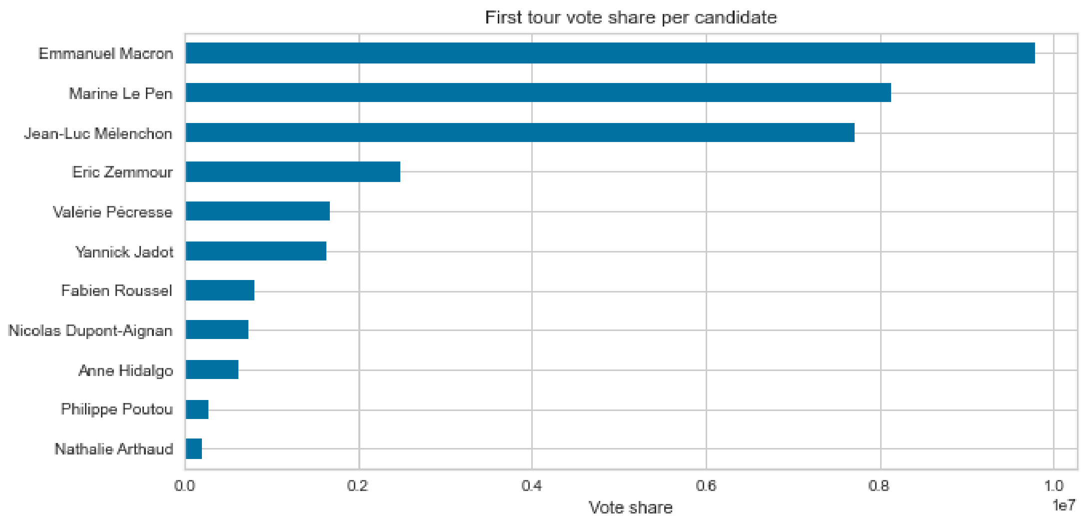
5.1 Analysis of Presidential22 results

This section aims at understanding and evaluating results from our model for the collected dataset "Presidential22".

5.1.1 Candidates representation

Since we did not narrow down our search to any particular candidate, we firstly hypothesized that our dataset should include the same proportion of discussions about each candidate than their vote share. To test this hypothese, we counted how many times each rules (specific to each candidate) were triggered. The figure 5.1 shows official results for the presidential first round.

Figure 5.1: First round vote share



Figures 5.2 and 5.3 show each candidate prevalence in our dataset.

We can make some observations out of these plots. Firstly, we can see that both legitimate users and bots follow the same tendencies for each candidate. The ranking is globally the same and the differences amongst "smaller" candidates is too slim to deduce anything. One explanation could be that bots are mostly used by "bigger" candidate with more funds and winning chances. Another one is that bots did not have a great influence in the public debate.

Secondly, we can the see that the "quantity" of triggers does not directly depict the real results even if there is a correlation. It can be explained by the fact that our analysis does not capture the nature of the triggers (Are the concerned tweets vote intentions or, in contrary, messages that go against the political program of the candidate).

Another explanation is that Twitter users are mostly under 35 years old (more than 62% [twi22]) which is the main age range of Jean Luc Mélenchon electors [TD22].

Figure 5.2: How many times candidate rule was triggered - legitimate users

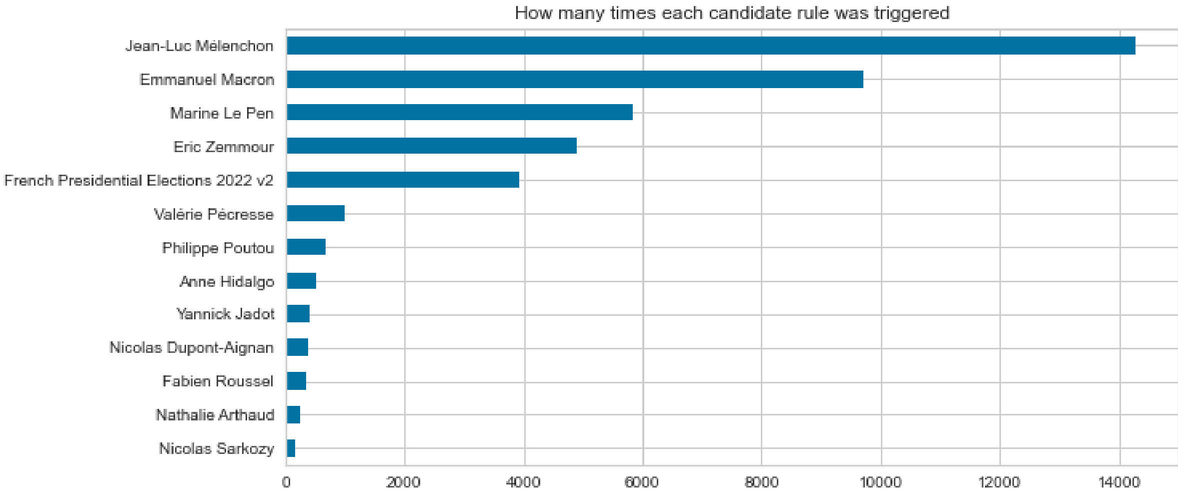
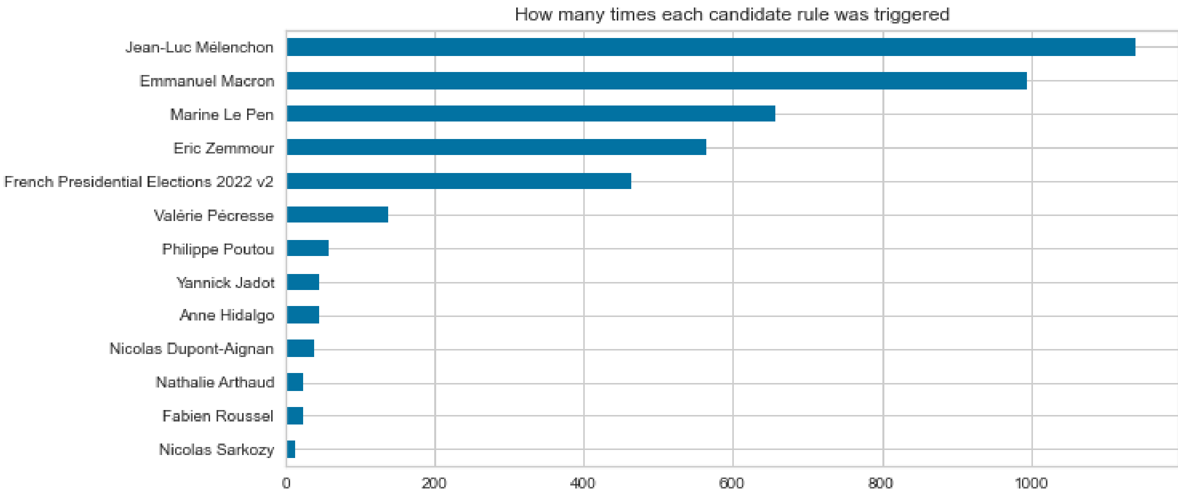


Figure 5.3: How many times candidate rule was triggered - presumed bots



5.1.2 Comparative model analysis

Since we do not have the time to manually annotate our presidential22 dataset, we have have to find other ways to evaluate our model. To do so, we could use another well known model to try and compare results with our model. A lot of studies use Botometer, a well-known model that use over a thousand features to characterize the account's profile, friends, social network structure, temporal activity patterns, language, and sentiment to compute the bot score. [1]

Methodology

In order to compare Botometer and our model, we need to use the Botometer API. Since the API call are limited, we will only retrieve results for 200 samples.

As Botometer returns a global score between 0 and 5 and our model returns a score between 0 and 1, we can compute several linear correlation metrics to see how well our model performed.

[1] https://botometer.osome.iu.edu/faq#how-does-it-works

Figure 5.4 plots the comparative score of 200 samples.

Figure 5.4: Comparative score between Botometer and our model

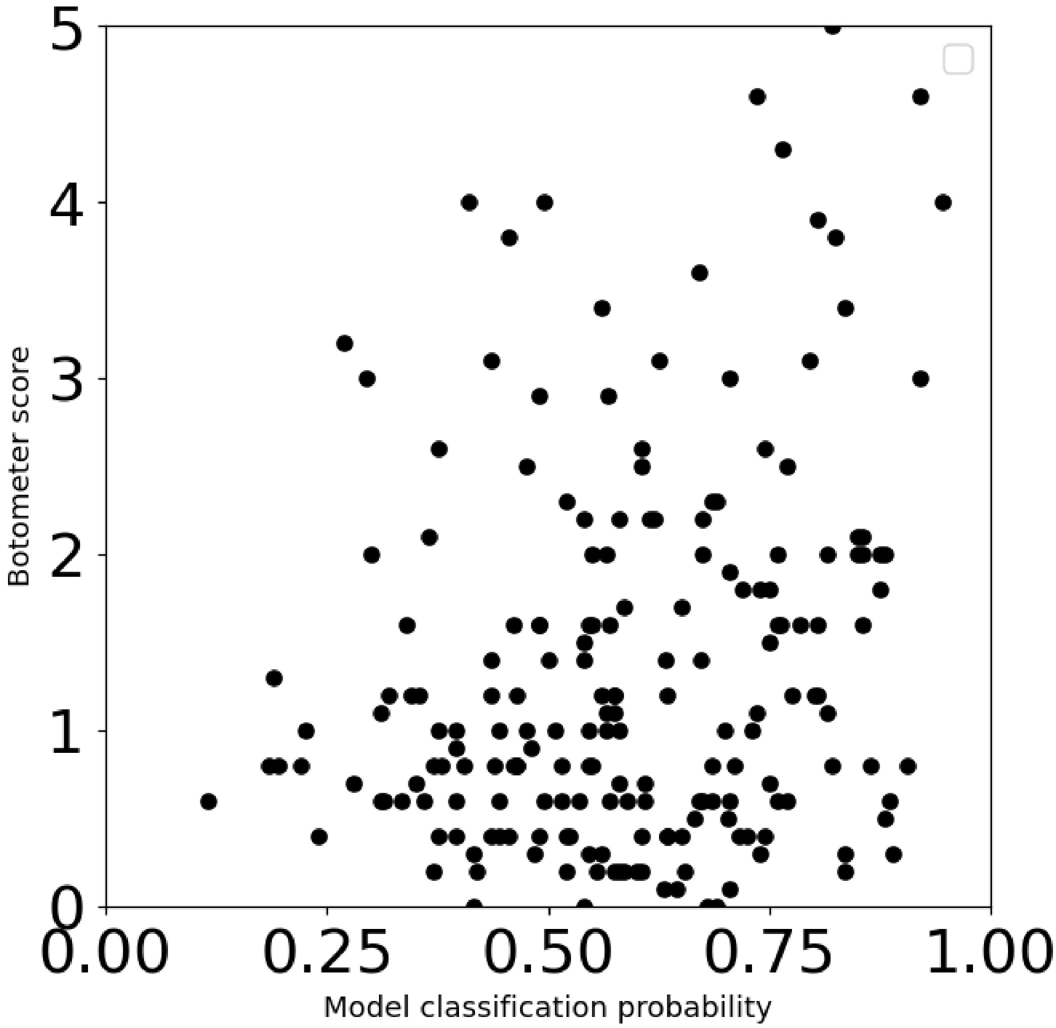


Table 5.1 show the results of 3 correlation metrics score.

Pearson's correlation measures the linear correlation of two variables and is computed by :

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2(y_i - \overline{y})^2}}$$

Spearman's rho, similarly to Pearson's r, measures the monotone correlation of two variables but is not limited to linear correlation. In fact, it is based on the rank of inputs instead of the inputs themselves. It is computed by :

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

where
d = the pairwise distances of the ranks of the variables x_i and y_i
n = the number of samples.

Kendall's tau measures also measures the monotone correlation of two variables and is rank-basked. It is computed by :

$$\tau = \frac{c-d}{c+d} = \frac{S}{\binom{n}{2}} = \frac{2S}{n(n-1)}$$

where
c = the number of concordant pairs
d = the number of discordant pairs

Table 5.1: Correlation metrics

	Result	**P-value**
Pearson's r	0.23	0.001
Spearman's rho	0.18	0.012
Kendall's tau	0.12	0.013

In the case of a linear comparison, Pearson's r seems to be the most relevant metric. With a result of 0.22, we can say that a correlation exist but is quite weak, implying that our model is greatly improvable. Looking at the plot, we can say that strong values (> 0.8) for our model seems to be strong values for Botometer as well. Lower that this threshold, our model seems to predict a lot of false positive.

6 Impact

In this section, we will study the impact the bots on twitter have with regards to two interdisciplinary aspects : energetic and social impact.

6.1 Energetic impact of the bots

We will start by calculating an estimate of how much energy twitter bots use worldwide during a year.
We can estimate the cost of a twitter bot by calculating several different parts : how much a tweet costs; how much do the servers, data centers and network facilities needed to store and treat this tweet cost; how much do the computers of twitter users cost; and finally how much it costs to run a bot on a terminal.
According to [Sch17], Twitter claims a tweet costs 100 joules to post. By comparison, the same source claims a spam email consumes 15 times as much energy. However it is not clear which parts of the process are included in this estimation. Since this value comes directly from Twitter, we can assume it is a low range.
We will give a brief overview of what these costs represent at the end of this section.

6.1.1 Cost of tweets posted by bots

Firstly we take a look at the cost of the tweets tweeted by the bots over a year. In this calculation, we will also take into account the fact that the cost of a tweet is not only the cost of the post itself, but also the cost of the various interactions : replies, likes and retweets. Due to lack of information on the energetic cost of likes and retweets, we will neglect them during this estimation.
As we said previously, Twitter claims a tweet costs 100 joules to write and post. Since we do not know what is included in this cost, we will assume it is only the cost of the post itself. Which means the cost of treatment, storage and diffusion over the web will be studied later.

According to our model, the bots we detected in our dataset posted an average of 5.85 tweets over the course of the time we collected the set (1 hour and 8 minutes).
Assuming the bots keep up this rhythm throughout an entire year, this would mean that those bots post an average of 45’000 tweets a year. To give a comparison, Donald Trump tweeted a total of 57’000 times over the course of 12 years [Mad21].
However a bot does not tweet continuously; the point of a bot is often to increase visibility of the posted or retweeted content, so it makes sense for the bot to only be active at peak hours or during special periods.
In our case, we studied the french presidential election of April 2022. Bots posting about this event were likely not active in January and will likely not be active in December, instead concentrating around the time frame of the elections themselves, which is when we collected our data.
Our value for average tweeting frequency is thus likely biased and not representative of twitter bots as a whole.

We will therefore have to take another approach to find the tweeting frequency of the average bot.

According to [VFD+17], between 9 and 15% of Twitter accounts are bots. If we assume they tweet at around the same average frequency as legitimate users, then between 9 and 15% of tweets are generated by bots.
The number of tweets per day in 2020 was of approximately 200 million [Say20]. Which means 500 billion tweets per year in total. With 9 to 15% being between 45 and 75 billion tweets per year generated by bots.

Now we will consider replies. Since a twitter reply behaves exactly the same way as a tweet, we assume it consumes the same amount of energy. Other interactions on a tweet are neglected due to lack of relevant information as to their energy consumption.
To estimate how many average replies a bot tweet has, we took 10 random bot accounts from our data set, and looked at their 10 last tweets each; averaging the number of replies of the 100 tweets considered.
We found a total of 14 replies total. However 2 of the 10 accounts considered were "retweet" bots, which do not post content and simply share tweets by other users. So we averaged 14 replies for 80 tweets or 0.175 replies per tweet.

A tweet costs 100 joules and has on average 0.175 replies, that means the total costs is of 117.5 joules. And since there were between 45 and 75 billion tweets by bots in 2020, this means they must have consumed between 5.288 and 8.813 Terajoules, or between **1.4 and 2.2 Giga Watt-hour every year.**

6.1.2 Cost of infrastructure, servers and data centers

Until now we have only considered the costs of the tweets themselves; now we will add on the costs of the infrastructure needed to maintain, treat and transfer the data contained in the tweet. To do so, we will take a look at how much the Web consumes as a whole, and try to estimate which percentage of the traffic is from Twitter.

It is nearly impossible to estimate which percentage of Internet traffic is due to Twitter itself. Even websites specialized in web traffic analysis [Fit22] cannot procure an accurate representation.
According to [Neu22], Twitter receives 6.6 billion monthly visits, whereas Google receives 92.5 billion. Additionally, Google is reported [McM13] to receive around 25% of total web traffic (data from 2013). Which would make Twitter receive around 1.8% of total web traffic.

We must now estimate which amount of energy is used by the Internet as a whole, to determine how much energy Twitter requires.
This is a simplification of reality as we make the assumption that all websites consume the same quantity of energy, which is not true. Depending on the data being send, the distance between host and user and several other factors, not all websites use the same amount of energy but we will make this simplification in our study.
According to [cnr], the web uses around 10% of the world's electricity supply. According to [Iea] that was around 25000 Tera Watt-hour in 2019. Which means the Internet consumes approximately 2500 TWh per year.

Since Twitter represents 1.8% of traffic, we assume they require 1.8% of the energy expanded, or around 45 TWh. Considering 9 to 15% or bots, this means between **4.05 and 6.75 TWh of energy used by bots every year.**
This order of magnitude corresponds to the production of a power plant.

But this cost isn't clearly imputable to bots, as this energy is not used because of the bots directly. The costs of infrastructure are present regardless of usage as the system is always "on" and whether there is or isn't data circulating does not change the cost.
Thus we can make the assumption that if bots did not exist on Twitter, a large portion of this energy would still be used to maintain the network.

6.1.3 Cost of Twitter user devices

We will now consider the cost in energy of the devices used by Twitter users. Specifically by legitimate users exposes to bot-made content.

To start this section, we consider that users use either a computer or a mobile phone to browse Twitter.
[Coë22] tells us that around 80% of daily Twitter users use their phone to browse, we will therefore assume the remaining 20% to be computer users.
On average, a phone uses around 10Wh/day of energy [Pie15] or 0.5W, whereas a home computer has an average power of 200W [Rou19]. Which means the average power of a Twitter-using device is :

$$0.8 * 0.5 + 0.2 * 200 = 40.4 Watts \tag{6.1}$$

Now obviously neither a phone nor a computer need full power to open and browse Twitter, but estimating exactly how much is difficult.
Additionally, there are multiple ways to use Twitter. One can use the official Twitter application, or a web browser such as Chrome or Firefox. Each of these possibilities costs a different amount of energy.
Therefore, we will take a simplistic approach to the problem and consider that devices use about 10% of their max power when using Twitter. Trying to get a more accurate representation is unnecessary as we are only trying to get an order of magnitude and not an exact value.

The average daily user spends around 10 minutes per day on Twitter [Roa22], and there are 200 million daily Twitter users. Since bots make up around 12% of all accounts (anywhere between 9 and 15), we are looking at around :

$$EnergyUsed = AveragePower * AverageUseTime * NumberUsers * PercentageBots \tag{6.2}$$

or

$$EnergyUsed = 40.4 * 10/60 * 200 * 10^6 * 0.12 = 161.6 MWh/day \tag{6.3}$$

We multiply that by 365 days and we find **58.9 GWh per year**.

6.1.4 Cost of bot terminals

Now we come to arguably the most directly imputable cost presented so far : how much energy is needed to run the bots themselves.
This is also the hardest estimation to realize since bots vary wildly between each other and precise numeric values are hard to come by, so we will have to assume a lot of the values used here.
Every bot requires a terminal on which to run. A terminal can run several bots, albeit not at once. It is recommended to use different terminals for different bots, or to have them run after one another instead of at the same time. This is possible due to the fact that bots do not need to be active 100% of the time.

As we said previously, there are about 200 millions accounts on Twitter, and between 9 and 15% of bots. Which means between 18 and 30 million bots to run. We will take 25 million as a middle value.

We assume that an average bot is active during 2 hours a day. To reduce monetary costs, we assume each terminal is used at 100% capacity, which means that 12 bots can be run on one machine.
In order to run the 25 million false accounts, one would need around 2 million computers.
The average home computer as an electrical power of about 200W, but portable computers come much lighter at around 30W [Rou19]. We will use 100W as an average value. We will also assume that the computer functions at 100% capacity when running a bot.

We can then calculate :

$$EnergyUsed = AveragePower * AverageUseTime * NumberOfTerminals \tag{6.4}$$

or

$$EnergyUsed = 100 * 24 * 2 * 10^6 = 4.8GWh/day \tag{6.5}$$

Or **1.75 TWh/year**. Which is quite significant. In the next section we will try to analyze what those costs mean and compare them to other energetic applications.

6.1.5 Meaning of these costs

In short, we found the following results (per year) :

1. Cost of posted tweets : 1.4 to 2.2 GWh
2. Cost of necessary web infrastructure : 4.05 to 6.75 TWh
3. Cost of user devices : 58.9 GWh
4. Cost of "provider" devices : 1.75 TWh

Straight up we notice that the two largest costs come from the "provider" and the infrastructure. However, as said previously, the latter cannot be reliably attributed to the existence of bots. The infrastructure on which the web relies (servers, data centers, relays, ...) would exist regardless of the existence of bots and would require the same amount of energy.
So we cannot reasonably consider this cost to be caused by bots.

The amount of energy needed by posted tweets is quite negligible. To give a comparison, [wor] claims that the average Swiss resident consumes 6769 KWh per year. Which means tweets generated by bots consume as much as 200 to 325 Swiss residents.
The cost of user devices is also quite low. Equivalent to 8700 Swiss residents.

The most direct and important cost is therefore, rather unsurprisingly, the cost of the terminal on which the bots are run. It is the only cost we will consider for the rest of this section. Sadly, this estimate is also the most vague of the 4. But we can assume the order of magnitude of the TWh is acceptable.
To give a comparison, according to [fdl21], the total production of hydro-energy in 2020 in Switzerland came at 40.6 TWh.

From a monetary standpoint, the cost of electrical energy is substantial. Over the past few months, the price of energy has risen across Europe [Alv22], from 53.88 € in February 2021 to 208.71 € in February 2022 for 1 MWh of energy.
Which means that Twitter bots today cost around 8385 € just to power up.
Considering this amount powers up to 15 million bots, we can deduce it is quite cheap to use a bot to post or spread content on Twitter. Which makes sense since bots are often used with the intent to make a profit (more on that in part 7.3), so if energy costs were high they would no longer be profitable.

From an environmental standpoint, according to the US Energy Information Administration [USE], in 2020 the US produced an average of 0.85 pounds of CO_2 per kWh of energy, or around 385 grams per kWh.
Considering our 1.75 TWh, this amounts to around 1488 metric tons of CO_2 released per year(Although it should be noted this value was obtained using several approximations, it's order of magnitude is likely correct). According to [swi], Switzerland produced around 40 million tons of CO_2 in 2016. To give another example, the CO_2 cost of bots is equivalent to 750 Bern-New York trips by plane [myc] .

In conclusion, we can say that although the amount of energy required by bots on Twitter may seem large at first, neither its economic nor environmental costs are very substantial.

6.2 Energetic impact of the decisions influenced by the bots

In this short section, we will present the work done towards estimating the influence bots had on political decision making.
During this study, we have focused much of our attention to the French Presidential Election of 2022. The bots posting and tweeting about this topic likely had one of two purposes : either generate clout for themselves by "surfing" on the popular trend, or directly try to impact events by influencing public perception of a candidate (in a positive or negative way).

Initially, we thought the second type of bots would be predominant. Our plan of approach was therefore to do some analysis on these bots that we would find and determine which candidate benefited the most from their influence.
This was also partially influenced by an article from Time Magazine [1] (based on a research publication from the University of California and Swansea University) claiming that votes in the 2016 US Presidential Election might have been boosted by up to 3% by bots. Our initial idea was therefore to take a similar approach and try to determine which percentage of votes for each candidate in the 2022 French Presidential Election was due to bots. We would then estimate what impact each candidate would have (specifically with regards to energy policy), and attribute a percentage of this impact to the influence of bots.

Sadly this proved hard to implement and we preferred to focus our efforts on making sure we could differentiate bots and legitimate users clearly, rather than try to do some further analysis on the bots to try and classify them. Additionally, most of the bots we encountered showed no clear preference towards any candidates, and a large portion of them even appeared to be disconnected from the french politics scene altogether, having likely retweeted one of our key words by accident.

All of this adds up and we could not conclusively establish which candidate benefited the most from bots, nor estimate how much electoral impact they had.

Nevertheless, we had started an analysis of french energy policy based on data from the Ministry of Ecological Transition [sddeesS22]. With the tables in Appendix 1, we developed a report comprising : production, consumption, import and export; detailed by energy type (for production, export and import) or by usage sector (for consumption).

Then we realized several predictions for 2050.

1. A prediction based on data from [dCdlRplA17], itself based on the objectives from the French Law on Energy Transition for 2050.
2. A prediction based on linear regression and extrapolation based on 2016-2019 data (shown in Appendix 2)
3. A prediction based on linear regression and extrapolation based on 2016-2019 data for tendency, applied to 2020 data

Because of the Covid19 crisis, 2020 data was heavily affected and differed too much from expectations to take it into account directly.

[1] https://time.com/5286013/twitter-bots-donald-trump-votes/

Then we analyzed campaign promises from all 12 candidates, compiling those pertinent to energy and environment. Promises were pulled from the french newspaper "Le Monde".

We would then predict what impact those promises would have on our data, by adjusting our prediction based on what was promised. For example, Emmanuel Macron promised to "multiply by 10 solar energy production"; this means that we assume that by 2050, solar energy production will be 10 times higher than in 2020. See Appendix 3 for an example on one scenario for E. Macron, domains where promises where made (and thus numbers adjusted) are shown by the "P" in the right hand side column.

Afterwards, we estimate how much CO2 is created per KWh [2] and we have a rough sketch of how much extra CO2 each candidate is likely to save or create. See Appendix 4 for an example with E. Macron. Then, if we estimate that 1% of the votes are due to bots, we attribute 1% of the CO2 to bots. We stopped work on this section after 4 of the 12 candidates when it appeared clear we would not be able to do this last step.

Even if this analysis had been finished, it presented several shortcomings such as :

1. We assumed that promises would be upheld and would have the desired effects
2. Promises are often vague and must be interpreted
3. We did not wonder if promises were feasible, even the more outlandish ones
4. The data on which we based ourselves is unclear and sometimes inconsistent between sources
5. Not all sources (such as pits of energy) were taken into account
6. We use 4-5 years of data to predict for the next 30 years
7. We use simple linear extrapolation
8. We do not take into account economic policy or potential changes in circumstances between 2020 and 2050
9. and other reasons.

It would have been interesting to find out which candidates where most supported by bots, even without attributing an extra energy cost to this influence. From our experience handling the data we have found a few bots whose support for a candidate was apparent, but determining this equally would mean doing so for all accounts. Impossible to do manually in a timely manner, and as it was not the main objective of our projects we decided to focus on accurate bot detection instead of assigning them preferences, which would have required a lot more work.

[2] https://www.equilibredesenergies.org/12-10-2018-le-contenu-en-co2-du-kwh/

6.3 Types of bots

Over the course of this study, we have discovered several different types of bots. When checking some results manually we also often found ourselves wondering whether the account we were looking at was a bot or a legitimate user. In this section we will give a brief overview of some of the type of bots we have encountered, what their possible uses or goals are, and what problems we ran into regarding their identification.

Firstly we have "explicit" bots. That is, accounts like the one we used for data collection. Twitter allows users to create bot-run accounts as long as the goal is explicitly stated and publicly declared. These are often (but not always) corporate press accounts whose stated purpose is to share news article of their parent company on Twitter in order to increase the reach of said articles. Examples found in our study include the following users : StarvisionNews; P_Mundo; RedditLFI.

On the other side, we find undeclared bots. Those accounts are those we have identified (with our own model, with botometer or by checking manually) as bots. Despite this we cannot confirm with absolute certainty that they are bot-run accounts. Of those we have also found several types :

1. Retweet bots. Those bots only retweet content instead of producing it. Examples include : colinjarrett587; AGrothendick; kagan_sumner; BronyRetweets.
2. Spam bots. These produce only one type of content. Example : CianGaia (this account seems to have switched to a retweet account since we last examined the data).
3. Human like bots. These bots seem like normal twitter users when checked manually, but were detected as bots with good confidence values by both algorithms used in this study. Example : jeanlemarcheur.

From our observations, we can say the general purpose of the average bot on Twitter is akin to an advert. That is, to generate interest (in a company, a topic, or a political candidate as was our focus here). However we did not find a clear use for the spam bots we found, the majority of which seemed to pump out daily, or hourly, cryptic content consisting of seemingly unrelated images with few or no words to explain. The regularity and consistency of those posts tend to confirm their status as automated accounts, but the reason of their existence or their purpose remains evasive.

7 Conclusion

The purpose of this study and report was to try and learn how to identify automated accounts (bots) on Twitter using machine learning algorithms. In a second time, we wanted to apply our findings to a specific topic : the french presidential election of 2022, this newly acquired knowledge would help us to draw conclusions about the political French debate, the use of bots in political campaigns and their social and energetic impact.

For this we used several methods. At first, we studied the state of the art to deduce which kind of model would best suits our problematic. After choosing a random forest model using Twitter accounts metadata, we aimed at generalizing our model by merging multiple datasets during the training phase. With our final model we obtained accuracy metrics between 0.8 and 0.93 and FPR between 0.24 and 0.1 on our annotated datasets.

After creating the model, we used the Twitter API for researchers in order to build our own datasets centered around the French public and political debate. As we did not have enough time and resources to manually annotate our dataset, we used Twitter automated context annotation to retrieve relevant data. Using our pre-trained model, we were able to detect several types of bots. However, a comparative study between Botometer and our model only indicates a low positive correlation (0.23 Pearson's r) and manual researches suggest a high false positive rate.

In parallel, we calculated the energetic impact of bots with regards to energy consumed for their use. We found that the quantity of energy necessary for all twitter bots in the world is "human scale", that is, on the scale of the consumption of a couple thousand people. Negligible on the world scale. Further attempts to deepen this part of the study were scaled back after several unforeseen issues appeared during the course of the project. At the end of the project, we also looked at the different types of bots we found. We did this in order to better understand why and how they are used. Overall we found that few bots actually seem to post, their main use being to spread content that is already on the platform.

Overall this project was a success as we achieved our objectives. Thanks to our custom model and dataset, we managed to obtain some results and draw conclusions regarding bot types, uses and purpose. In order to pursue this project and obtain more precise results, more research would be needed to understand causes and better fit the training model to our specific dataset.

But we could have done better in some regards. Especially concerning our initial objectives as we failed to clearly specify whether classifying the bots found according to their political alignment was a part of the goal or not. Models would have been easier to train if we had picked a problematic based on an English dataset.

Thank you for your attention.

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A Appendix 1 : Report of french energy policy from 2016 to 2020

Production	2016	2017	2018	2019	2020
Nucléaire	1221.8	1207.2	1251.3	1209.1	1072.2
Fossiles	12.1	11.8	11.0	11.8	10.0
Pétrole et produits pétroliers	11.9	11.6	10.9	11.6	9.8
Gaz naturel	0.2	0.2	0.1	0.2	0.2
Charbon	0.0	0.0	0.0	0.0	0.0
Renouvelables	318.0	309.6	335.7	339.2	345.9
Eolien	21.4	24.6	28.6	34.7	40.7
Solaire	8.7	9.6	10.9	12.2	13.6
Hydraulique	59.3	48.6	63.1	55.5	60.8
Autres renouvelables électriques	2.0	1.9	2.5	2.0	2.2
Sous total : renouvelables électriques	91.4	84.7	105.1	104.4	117.3
Renouvelables thermiques	226.6	224.9	230.6	234.8	228.6
TOTAL	1551.9	1528.6	1598.0	1560.1	1428.1

Importations	2016	2017	2018	2019	2020
Nucléaire	0.0	0.0	0.0	0.0	0.0
Fossiles	1733.5	1792.2	1749.0	1762.2	1447.9
Pétrole et produits pétroliers	1154.2	1172.9	1131.1	1108.6	909.1
Gaz naturel	479.6	501.9	510.4	568.8	479.4
Charbon	99.7	117.4	107.5	84.8	59.4
Renouvelables	14.6	18.5	19.0	21.2	15.5
Renouvelables électriques	0.0	0.0	0.0	0.0	0.0
Renouvelables thermiques	14.6	18.5	19.0	21.2	15.5
TOTAL	1748.1	1810.7	1768.0	1783.4	1463.4

Exportations	2016	2017	2018	2019	2020
Nucléaire	0.0	0.0	0.0	0.0	0.0
Fossiles	282.3	303.3	298.3	316.5	247.6
Pétrole et produits pétroliers	242.9	240.2	236.0	203.9	152.5
Gaz naturel	38.8	63.1	61.9	112.6	95.0
Charbon	0.6	0.0	0.4	0.0	0.1
Renouvelables	6.9	7.5	10.9	9.6	8.0
Renouvelables électriques	0.0	0.0	0.0	0.0	0.0
Renouvelables thermiques	6.9	7.5	10.9	9.6	8.0
TOTAL	289.2	310.8	309.2	326.1	255.6

Consommation	2016	2017	2018	2019	2020
Consommation économie	1668.8	1656.8	1633.4	1619.8	1492.2
Industrie	333.5	322.3	329.4	321.4	301.6
Résidentiel	486.5	478.1	462.4	460.8	450.2
Agriculture	51.0	50.5	51.2	50.7	52.3
Tertiaire	266.3	270.2	265.8	262.3	243.5
Transports	531.5	535.7	524.6	524.6	444.6
Consommation branche énergie	1080.9	1083.5	1099.2	1074.3	934.4
Autre consommation	155.4	163.9	154.6	156.4	146.0
TOTAL	2905.1	2904.2	2887.2	2850.5	2572.6

Figure A.1: Report of french energy policy from 2016 to 2020

B Appendix 2 : Neutral prevision of the state of french energy production and use in 2050, ignoring 2020

Production	2016	2019	2020	2025	2030	2035	2040	2045	2050
Nucléaire	1221.8	1209.1	1223.9	1226.9	1229.9	1232.9	1235.9	1238.9	1241.9
Fossiles	12.1	11.8	11.3	10.5	9.7	8.9	8.1	7.3	6.5
Pétrole et produits pétroliers	11.9	11.6	11.1	10.3	9.5	8.7	7.9	7.1	6.3
Gaz naturel	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Charbon	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Renouvelables	318.0	339.2	348.1	392.9	437.7	482.6	527.4	572.3	617.1
Eolien	21.4	34.7	38.3	60.3	82.2	104.2	126.1	148.1	170.0
Solaire	8.7	12.2	13.3	19.2	25.1	31.0	36.9	42.8	48.7
Hydraulique	59.3	55.5	57.4	59.0	60.5	62.1	63.6	65.2	66.7
Autres renouvelables électriques	2.0	2.0	2.3	2.5	2.8	3.1	3.4	3.7	4.0
Sous total : renouvelables électriques	91.4	104.4	111.3	140.9	170.6	200.3	230.0	259.7	289.4
Renouvelables thermiques	226.6	234.8	236.8	252.0	267.1	282.3	297.4	312.6	327.7
TOTAL	1551.9	1560.1	1583.2	1630.2	1677.3	1724.3	1771.4	1818.4	1865.4

Importations	2016	2019	2020	2025	2030	2035	2040	2045	2050
Nucléaire	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Fossiles	1733.5	1762.2	1635.7	1419.2	1202.6	986.0	790.0	650.7	561.4
Pétrole et produits pétroliers	1154.2	1108.6	1097.1	1007.8	918.5	829.2	740.0	650.7	561.4
Gaz naturel	479.6	568.8	450.0	350.0	250.0	150.0	50.0	0.0	0.0
Charbon	99.7	84.8	88.7	61.4	34.1	6.8	0.0	0.0	0.0
Renouvelables	14.6	21.2	23.4	33.6	43.7	53.8	64.0	74.1	84.3
Renouvelables électriques	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Renouvelables thermiques	14.6	21.2	23.4	33.6	43.7	53.8	64.0	74.1	84.3
TOTAL	1748.1	1783.4	1659.1	1452.7	1246.3	1039.9	854.0	724.8	645.7

Exportations	2016	2019	2020	2025	2030	2035	2040	2045	2050
Nucléaire	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Fossiles	282.3	316.5	260.5	169.9	79.3	18.7	0.0	0.0	0.0
Pétrole et produits pétroliers	242.9	203.9	200.5	139.9	79.3	18.7	0.0	0.0	0.0
Gaz naturel	38.8	112.6	60.0	30.0	0.0	0.0	0.0	0.0	0.0
Charbon	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Renouvelables	6.9	9.6	11.6	17.3	23.1	28.8	34.6	40.3	46.1
Renouvelables électriques	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Renouvelables thermiques	6.9	9.6	11.6	17.3	23.1	28.8	34.6	40.3	46.1
TOTAL	289.2	326.1	272.1	187.2	102.4	47.5	34.6	40.3	46.1

Consommation	2016	2019	2020	2025	2030	2035	2040	2045	2050
Consommation économie	1668.8	1619.8	1602.1	1516.9	1431.7	1346.5	1261.3	1176.1	1090.9
Industrie	333.5	321.4	319.3	304.8	290.2	275.5	260.9	246.3	231.7
Résidentiel	486.5	460.8	448.8	402.3	356.0	309.5	263.2	216.8	170.3
Agriculture	51.0	50.7	50.8	50.7	50.6	50.5	50.4	50.3	50.2
Tertiaire	266.3	262.3	262.1	253.9	245.7	237.5	229.3	221.1	212.9
Transports	531.5	524.6	521.2	505.3	489.4	473.5	457.6	441.7	425.8
Consommation branche énergie	1080.9	1074.3	1083.5	1081.4	1079.4	1077.3	1075.3	1073.2	1071.2
Autre consommation	155.4	156.4	156.0	152.9	149.7	146.6	143.4	140.3	137.1
TOTAL	2905.1	2850.5	2841.6	2751.2	2660.8	2570.4	2480.0	2389.6	2299.2

Figure B.1: Neutral prevision of the state of french energy production and use in 2050, ignoring 2020

C Appendix 3 : Prevision of the state of french energy production and use in 2050 for E. Macron, ignoring 2020

Production	2016	2019	2020	2025	2030	2035	2040	2045	2050	
Nucléaire	1221.8	1209.1	1221.4	1283.0	1344.6	1406.2	1467.8	1529.3	1590.9	P
Fossiles	12.1	11.8	11.3	10.5	9.7	8.9	8.1	7.3	6.5	
Pétrole et produits pétroliers	11.9	11.6	11.1	10.3	9.5	8.7	7.9	7.1	6.3	
Gaz naturel	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	
Charbon	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
Renouvelables	318.0	339.2	350.2	406.6	463.0	519.3	575.7	632.0	688.4	
Eolien	21.4	34.7	38.3	60.3	82.2	104.2	126.1	148.1	170.0	
Solaire	8.7	12.2	15.7	33.5	51.2	68.9	86.6	104.3	122.0	P
Hydraulique	59.3	55.5	57.4	59.0	60.5	62.1	63.6	65.2	66.7	
Autres renouvelables électriques	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	
Sous total : renouvelables électriques	91.4	104.4	113.4	154.7	195.9	237.1	278.3	319.5	360.7	
Renouvelables thermiques	226.6	234.8	236.8	252.0	267.1	282.3	297.4	312.6	327.7	
TOTAL	1551.9	1560.1	1583.0	1700.1	1817.2	1934.4	2051.5	2168.7	2285.8	

Importations	2016	2019	2020	2025	2030	2035	2040	2045	2050
Nucléaire	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Fossiles	1733.5	1762.2	1635.7	1365.0	1060.0	780.0	545.0	325.0	105.0
Pétrole et produits pétroliers	1154.2	1108.6	1097.1	965.0	830.0	680.0	545.0	325.0	105.0
Gaz naturel	479.6	568.8	450.0	340.0	200.0	100.0	0.0	0.0	0.0
Charbon	99.7	84.8	88.7	60.0	30.0	0.0	0.0	0.0	0.0
Renouvelables	14.6	21.2	60.0	33.6	43.7	53.8	64.0	74.1	84.3
Renouvelables électriques	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Renouvelables thermiques	14.6	21.2	60.0	33.6	43.7	53.8	64.0	74.1	84.3
TOTAL	1748.1	1783.4	1695.7	1398.6	1103.7	833.9	609.0	399.2	189.3

Exportations	2016	2019	2020	2025	2030	2035	2040	2045	2050
Nucléaire	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Fossiles	282.3	316.5	260.5	169.9	79.3	18.7	0.0	0.0	0.0
Pétrole et produits pétroliers	242.9	203.9	200.5	139.9	79.3	18.7	0.0	0.0	0.0
Gaz naturel	38.8	112.6	60.0	30.0	0.0	0.0	0.0	0.0	0.0
Charbon	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Renouvelables	6.9	9.6	11.6	17.3	23.1	28.8	34.6	40.3	46.1
Renouvelables électriques	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Renouvelables thermiques	6.9	9.6	11.6	17.3	23.1	28.8	34.6	40.3	46.1
TOTAL	289.2	326.1	272.1	187.2	102.4	47.5	34.6	40.3	46.1

Consommation	2016	2019	2020	2025	2030	2035	2040	2045	2050	
Consommation économie	1668.8	1619.8	1601.1	1510.7	1420.3	1329.8	1239.4	1149.0	1058.6	
Industrie	333.5	321.4	319.3	304.8	290.2	275.5	260.9	246.3	231.7	
Résidentiel	486.5	460.8	447.7	396.1	344.5	292.9	241.3	189.7	138.1	P
Agriculture	51.0	50.7	50.8	50.7	50.6	50.5	50.4	50.3	50.2	
Tertiaire	266.3	262.3	262.1	253.9	245.7	237.5	229.3	221.1	212.9	
Transports	531.5	524.6	521.2	505.3	489.4	473.5	457.6	441.7	425.8	
Consommation branche énergie	1080.9	1074.3	1083.5	1081.4	1079.4	1077.3	1075.3	1073.2	1071.2	
Autre consommation	155.4	156.4	156.0	152.9	149.7	146.6	143.4	140.3	137.1	
TOTAL	2905.1	2850.5	2840.5	2744.9	2649.3	2553.7	2458.1	2362.5	2266.9	

Figure C.1: Prevision of the state of french energy production and use in 2050 for E. Macron, ignoring 2020

D Appendix 4 : Calculation of CO2 emissions for Appendix 3 scenario

Taux de conversion en CO2	Nucléaire	Pétrole	Charbon	Gaz	Eolien	Solaire	Hydraulique	Ren. Therm
gCO2/kWh	6	730	1060	418	7	55	6	45
tCO2/TWh	6000	730000	1060000	418000	7000	55000	6000	45000

EXPORTATIONS NON COMPTEES

Scénario 1 : Prévision sans 2020	Nucléaire	Pétrole	Charbon	Gaz	Eolien	Solaire	Hydraulique	Ren. Therm	Total	
Production TWh	1590.9	6.3	0.2	0.0	170.0	122.0	66.7	327.7		
Production tCO2	9545526.3	4599000.0	212000.0	0.0	1190000.0	6710000.0	400200.0	14746500.0	37403226.3	
Importations TWh	0.0	105.0	0.0	0.0	0.0	0.0	0.0	84.3		
Importations tCO2	0.0	76650000.0	0.0	0.0	0.0	0.0	0.0	3793500.0	80443500.0	
Exportations TWh	0.0	0.0	0.0	0.0	0.0	0.0	0.0	46.1		
Exportations tCO2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2074500.0	2074500.0	
									117846726.3	117.8

Consommation totale	2266.9	TWh
Rendement moyen	51986.1	tCO2/TWh
	52.0	gCO2/kWh

Scénario 2 : Prévision 2020 tendance 2019	Nucléaire	Pétrole	Charbon	Gaz	Eolien	Solaire	Hydraulique	Ren. Therm	Total	
Production TWh	1410.8	5.0	0.0	0.0	172.4	136.0	70.1	319.5		
Production tCO2	8464736.8	3650000.0	0.0	0.0	1206800.0	7480000.0	420600.0	14377500.0	35599636.8	
Importations TWh	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
Importations tCO2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
Exportations TWh	0.0	0.0	0.0	0.0	0.0	0.0	0.0	42.5		
Exportations tCO2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1912500.0	1912500.0	
									35599636.8	35.6

Consommation totale	1997.9	TWh
Rendement moyen	17818.2	tCO2/TWh
	17.8	gCO2/kWh

Scénario 3 : Prévision Officielle	Nucléaire	Pétrole	Charbon	Gaz	Eolien	Solaire	Hydraulique	Ren. Therm	Total	
Production TWh	1410.8	6.1	0.2	0.0	300.0	136.0	60.0	230.0		
Production tCO2	8464736.8	4453000.0	212000.0	0.0	2100000.0	7480000.0	360000.0	10350000.0	33419736.8	
Importations TWh	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0		
Importations tCO2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
Exportations TWh	0.0	64.5	10.5	0.0	0.0	0.0	0.0	8.0		
Exportations tCO2	0.0	47085000.0	11130000.0	0.0	0.0	0.0	0.0	360000.0	58575000.0	
									33419736.8	33.4

Consommation totale	1475.0	TWh
Rendement moyen	22657.4	tCO2/TWh
	22.7	gCO2/kWh

Figure D.1: Calculation of CO2 emissions for Appendix 3 scenario