[[1]](#footnote-1)

Enlighten DarkWeb Markets with Data Mining

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*Abstract*—These instructions give you guidelines for preparing papers for IEEE Transactions and Journals*.* Use this document as a template if you are using Microsoft *Word* 6.0 or later. Otherwise, use this document as an instruction set. The electronic file of your paper will be formatted further at IEEE. Paper titles should be written in uppercase and lowercase letters, not all uppercase. Avoid writing long formulas with subscripts in the title; short formulas that identify the elements are fine (e.g., "Nd–Fe–B"). Do not write “(Invited)” in the title. Full names of authors are preferred in the author field, but are not required. Put a space between authors’ initials. The abstract must be a concise yet comprehensive reflection of what is in your article. In particular, the abstract must be self-contained, without abbreviations, footnotes, or references. It should be a microcosm of the full article. The abstract must be between 150–250 words. Be sure that you adhere to these limits; otherwise, you will need to edit your abstract accordingly. The abstract must be written as one paragraph, and should not contain displayed mathematical equations or tabular material. The abstract should include three or four different keywords or phrases, as this will help readers to find it. It is important to avoid over-repetition of such phrases as this can result in a page being rejected by search engines. Ensure that your abstract reads well and is grammatically correct.

*Index Terms*—dark web, marketplace, data mining, text mining, statistic, prediction, analysis, drugs

# INTRODUCTION

P

OLICE forces have been fighting strenuously against illegal websites (e.g., Megaupload [1]), but new ones resurface or re-migrate frequently [2]. This is also happening on the dark web. As a matter of fact, plenty of marketplaces have been shut down, however there are still a lot of them online at the time of this research [3]. On top of that, currently, we don't really know in detail how these websites operate.

This paper presents a research carried out between June and September 2017 on the largest web market at the time (especially for drugs) on Internet, AlphaBay. This web market has caught the attention of governmental agencies since two teenagers aged of 13 and 18 died after overdosing on a powerful synthetic opioid. It has been shut down on July 2017, at the same time of Hansa, as a part of a law enforcement operation by the Federal Bureau of Investigation, the Drugs Enforcement Administration and European law enforcement agencies acting through Europol. [4] [5]

According to US Attorney General Jeff Sessions the aim of this action was to caution criminals from thinking that they could evade prosecution by using the dark web. Looking at previous large shut down marketplaces it is widely believed that other web markets will take the place of AlphaBay. By the way, the popularity of AlphaBay can be explained by the shutdown of Silk Road 2.0 on 2013 since it has been launched on September 2014.

This paper reports on the last weeks of life of Alphabay. Its nature, its different countries of origin, its main sellers, and its predominance of items will be analyzed.

# Method

[AB part].

During a first phase basic statistics will be carried out on the database, in order to discover the web market and to point out its trends. Then, experimental results of data mining techniques will be discussed.

# Technical Implementation

## Software Stack

There is a number of technologies and programming languages that can be used for Data Analysis. The 3 main programming languages for this kind of research are Python, SAS and R. [6] Since we would like to use open-source languages, we exclude SAS and eventually chose R.

Beside standard libraries, we have made extensive use of:

### units: Unit library including solution for conversion.

### rpart: Package that contains a wide library for decision tree method.

### arules: Used for association rules.

### e1071: Bayesian Naive implementation library.

### bnlearn: Library including solution for Bayesian network creation and visualization.

We have used RStudio for implementing code. As for publishing the results, we have used R Notebooks. [7]

## Code Repository

All the code is publicly available in the GitHub project "Data Mining - Dark Web Market". The repository is accessible from the following link: <https://github.com/SimonDele/Enlighten-DarkWeb-Markets-with-Data-Mining>

You can also find the whole list of packages used in the GitHub repository.

## Detailed Diagram

This is the representation of the technical implementation taking place during this project:

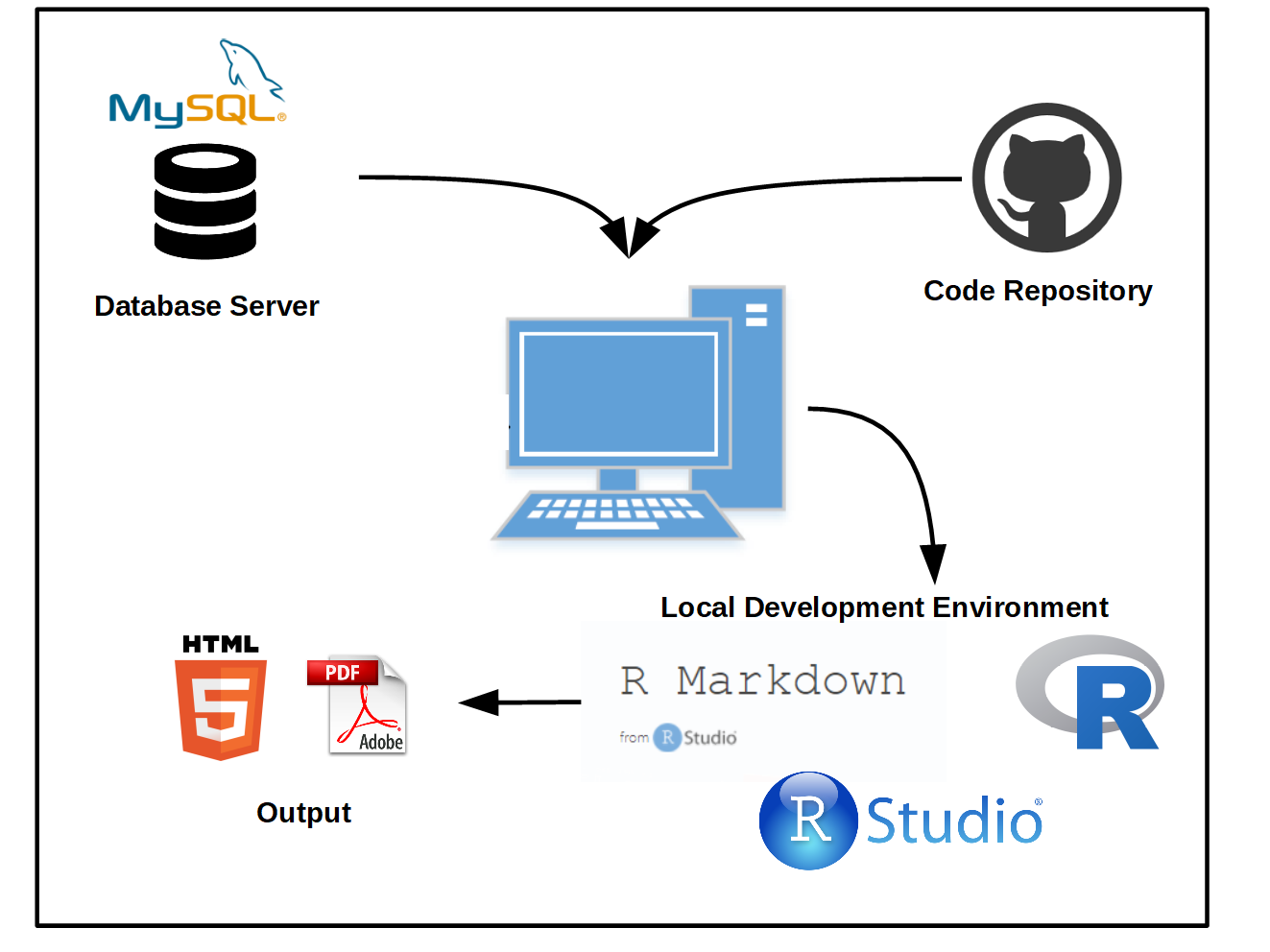


Fig. 1. Technical implementation

# Data Retrieval

For each product we have collected and analyzed ad title, description, price (in USD), URL, seller, payment, origin, destination, category, collection timestamp, date of posting and number of products sold.

[AB to refine] The data represents approximately \*1/10\* of the Web Market, but gives a pretty good representation since the uploaded ads were fairly distributed.

Thus, the first step was to clean the data and to make it readable in a computer way. This is our pipelines:

### Removing special characters, switching in lowercase.

### Finding in the title or description of the ads the amount (number and mass) of the product.

### Calculating the price of one unit of one dose (1 gram) each time.

# Alphabay Market

As it has been said in the INTRODUCTION, AlphaBay, due to its popularity, drew the police forces attentions. As a matter of fact its reputation can be reflected by looking at Google search statistics with the keywords Alphabay and dream market between January 2015 until June 2017. [8]

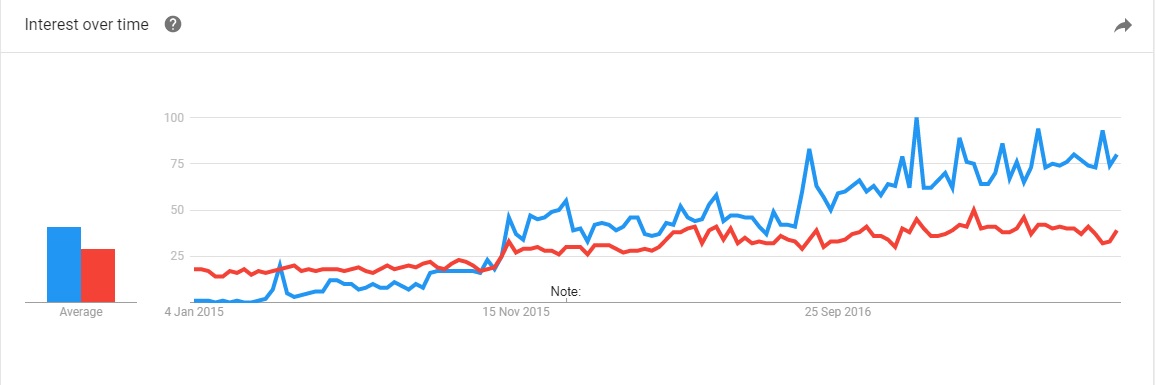


Fig. 2 Evolution of AlphaBay and Dream Market Google researches

On this graph, AlphaBay is in blue and Dream Market is in red, which is another dark web market still operating. AlphaBay has become more and more popular since the demise of Agora, and before being shut down, it was the most popular dark web market. [9]

Let's now try to look at the evolution of the market with the collected data on AlphaBay. Here you can see the number of ads posted per month from January 2015 until June 2017.

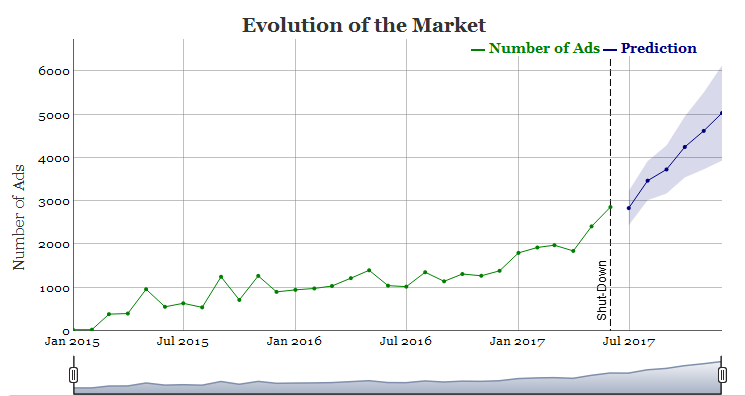


Fig. 3 Evolution f AlphaBay web market

The overall appearance and the growing popularity can be again pointed out with this graph. Between 2015 and 2016, there was a significant jump, the amount of ads rose from 7,712 up to14,161. Nevertheless the most surprising thing is that the number of ads that have been posted during the six first months of 2017 (before the closing) is 12,878 which is almost the same that in the whole 2016.

In order to see how the market would have looked like in the end of 2017 a prediction also has been added on this graph. Therefore, according to prognoses, the amount of ads would have reached a pick of 5,000 ads by the end of year.

# Basic Statistics

As it has been said before, basic statistics have been first realized. Let's see the general distribution and trend of the market.

## General Distribution

### Global View of Ads Distribution

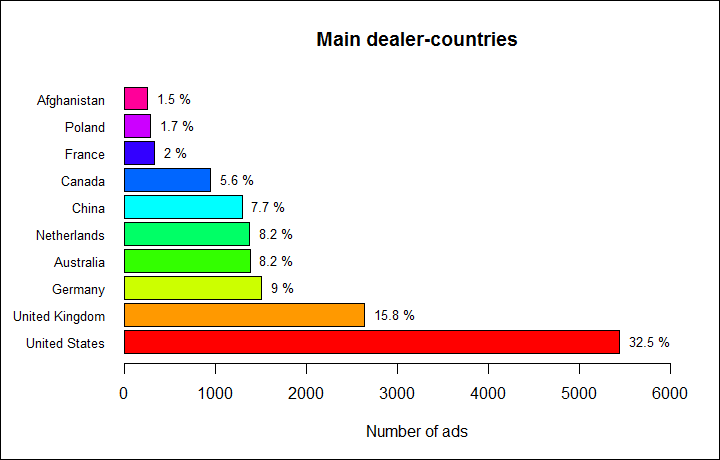


Fig. 4 Main dealer countries

This bar-chart represents the 10 main countries in the world regarding the number of ads. As we can see, United States are the biggest dealer far ahead of the rest. Their number of ads is more than twice as the number of the second one, United Kingdom.

Moreover, it is noticeable that most of these countries have strong economies. Five of the top 10 countries belong to the Group of Seven (G7), only Japan and Italy are not present. And other ones are also located in powerful areas where a lot of trade are made with other countries.

Furthermore it is worth pointing out that the first four countries are exactly the ones where the word "AlphaBay" is the most researched on Google! [10]

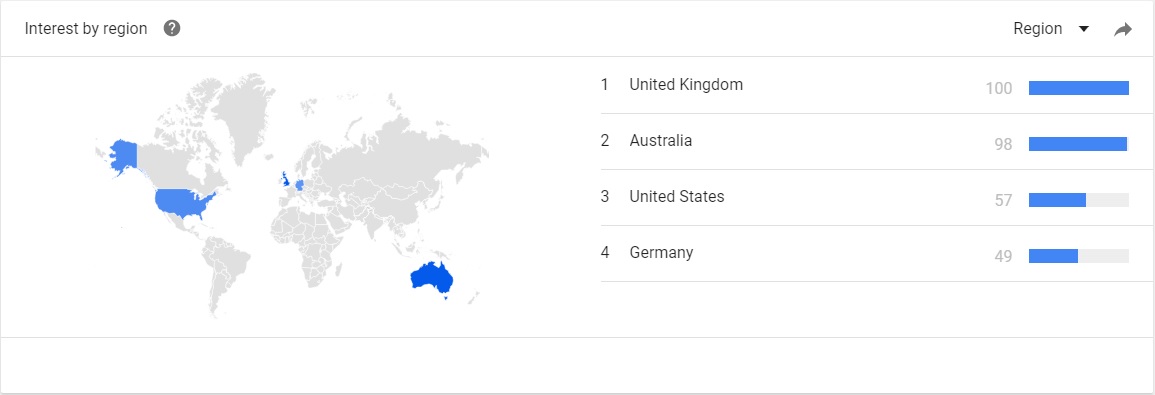


Fig. 5 AlphaBay world Google researches

### Distribution of Ads per Category

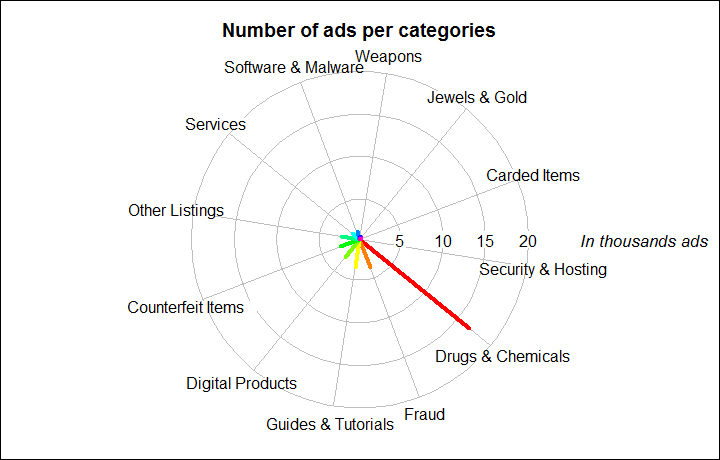


Fig. 6 Distribution of the market

There are 12 main categories in this web marketplace. "Drugs and Chemicals" group is the largest one, representing 45.64 % of the global market.

It is also worth noting that the second most popular category is "Fraud", that is to say all the ads regarding impersonation, deception papers and accounts. It represents 13.5 % of the market. Eventually, all other items (digital product, weapons, jewelry ...) represent a small rate of the marketplace.

## Drug Market

AlphaBay core focus is clearly on Drugs (cf., Fig. 6.).

### Distribution of Drugs

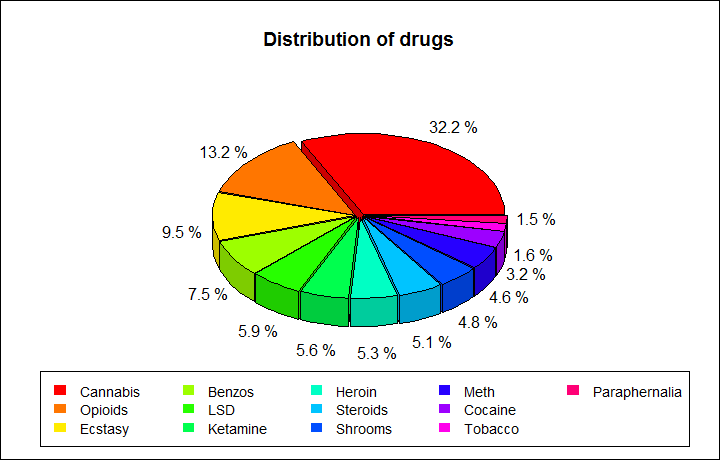


Fig. 7 Drug distribution

AlphaBay includes 13 subcategories for drugs. That said, Cannabis, Opioids and Ecstasy cover more than 50 % of the market.

### World Distribution of Drugs

When looking at drug-related ads by country, it is worth noting that the distribution of Figure 8 has a strong resemblance with the overall ad distribution by country on AlphaBay (Fig. 4). This is coherent, indeed, by comparing the ratio between drugs ads and the total number of ads, it is intelligible that they are mainly dealing drugs.

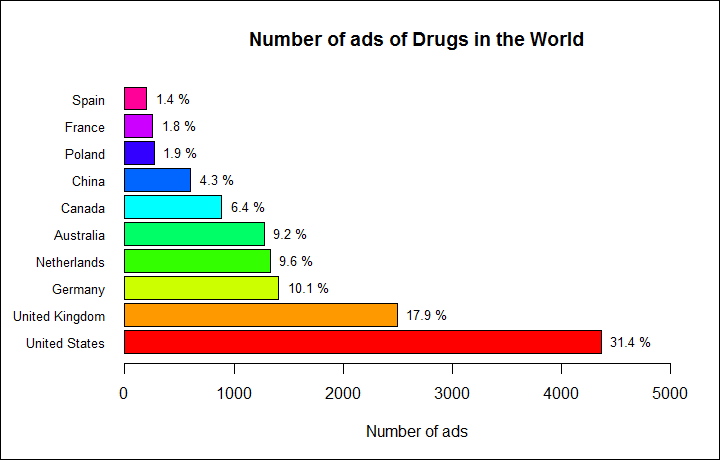


Fig. 8 Main drug dealer countries

So far it is possible to conclude that the market of drugs is gathered in Europe and the north of America.

### Global View of the Drugs Market in Europe

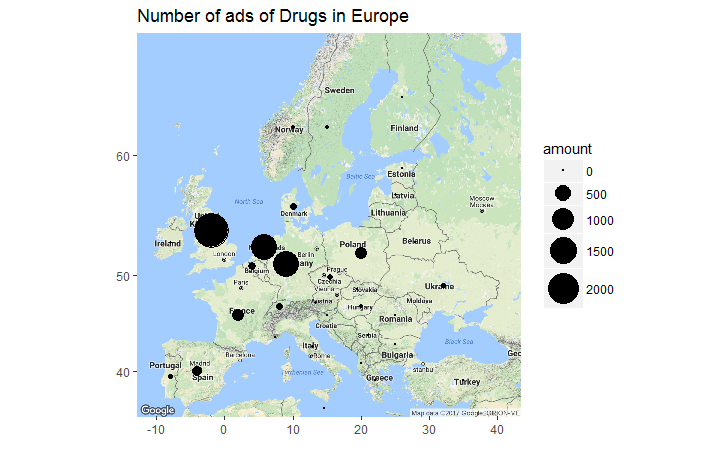


Fig. 9 European drug dealers

Circles show the amount of ads concerning drugs. The map confirms previous assumptions that the majority of the products is supposedly originating from United Kingdom, Netherlands and Germany.

It appears that dealer-countries are located on the Atlantic Coast and own huge harbours where there is important merchant shipping. Whereas on the East part there are not a lot of activities. This is probably due to the fact that dealers are using international commercial maritime traffics in order to dispatch their drugs all around the world. Maritime transport is an option increasingly used since it allows them to carry large quantities at one time. Drugs can be transported in small and fast boats (Go-Fast-Boat between countries border) or in containers on commercial vessels. Thus, significant seaports in Europe such as Rotterdam in Netherlands or Antwerp in Belgium are key points for this type of trafficking. In 2014 “Dutch police estimated that 25-50 % of the cocaine reaching Europe now enters via the port, which handles around 11 million containers a year.” [11]

## Product Flow By Country

Let’s now focus more specifically on different countries and study their trend. To do so, export and import flows of the country have been investigated.

### United Kingdom Exportation

The chart below (Fig. 10) represents the repartition of each category that United Kingdom supposedly exports.

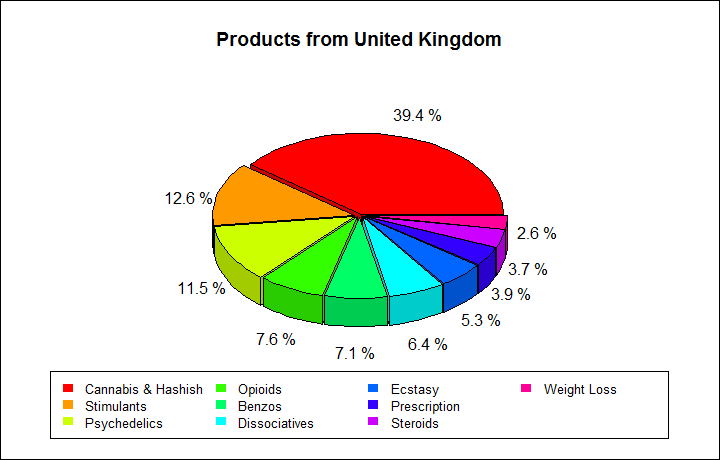


Fig. 10 Products from United Kingdom

Once again this chart shows the market diversity. Although a huge part concerns “Cannabis & Hashish” category, “Stimulants” and other illegal drugs are significantly present as well.

Most of European countries follows the same pattern as United Kingdom and this confirms previous assumptions.

### Products from Afghanistan

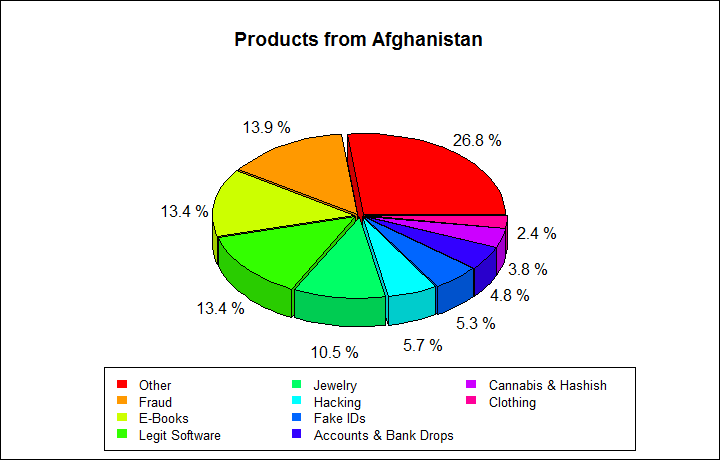


Fig. 11 Products from Afghanistan

It is interesting to notice that, unlike most of countries, Afghanistan doesn’t really retail drugs on AlphaBay market. Actually, a vast majority of exported products are false identity, deception accounts… Afghanistan is also dealing electronic devices or software.

### France Export & Import Flows

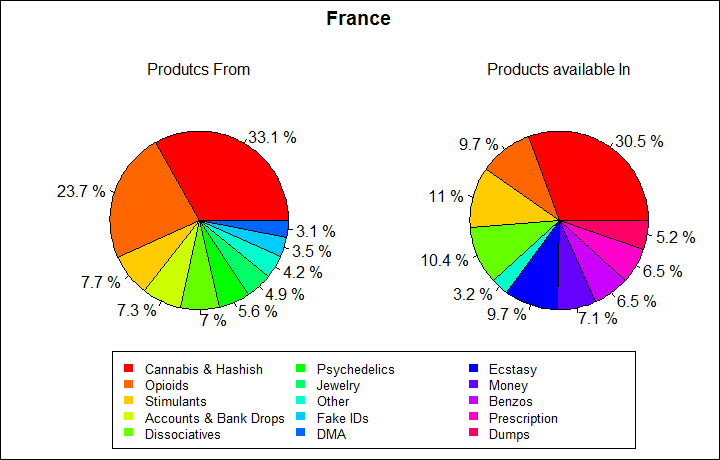


Fig. 12 Products from and available in France

It is noticeable that both charts are different. The percentages of each category are not equal and some of them don’t appear systematically in the other chart.

Nevertheless these conclusions should be moderated since targeting one particular country reduces significantly the number of information used for statistics.

## Market Prices

After analyzing general trend and flows, one interesting topic to analyze is market prices. One may ask if sold products in AlphaBay are cheaper than in the streets.

### Average Prices

Firstly, the median price of one gram of the most common drugs has been calculated and results below has been obtained.

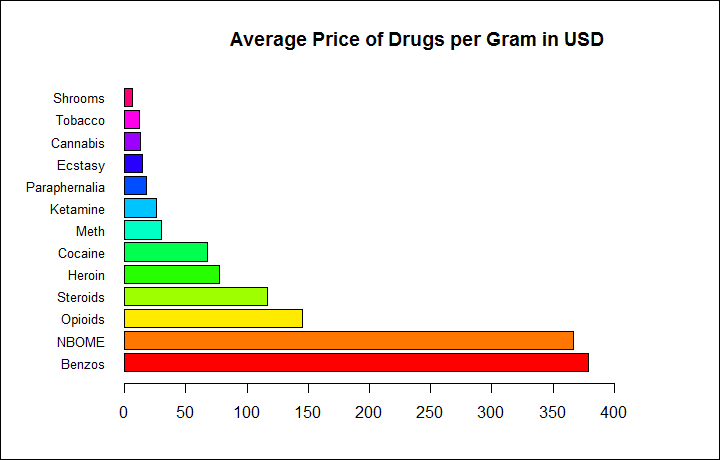


Fig. 13 AlphaBay drug prices

### Comparison with the “Street”

Information on street prices for commonly available drugs have been collected on websites.

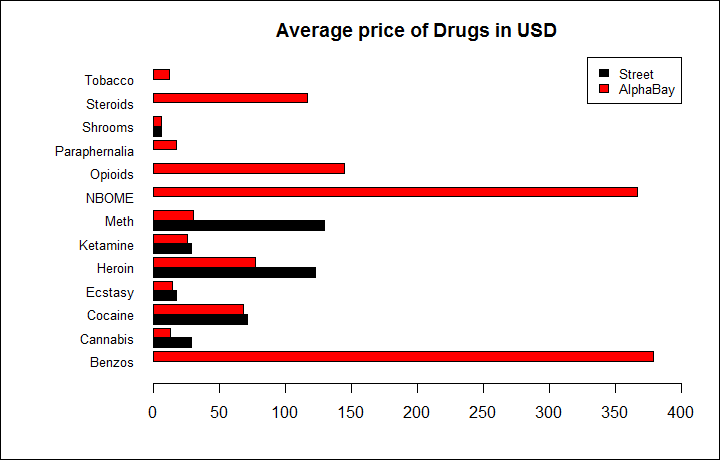


Fig. 14 Comparison of prices between AlphaBay and Street

Globally, it appears that prices of street sellers are often largely higher than AlphaBay ads. In few cases both prices tend to be similar. (Please find in the last section all references used: [12] [13] [14] [15] [16])

# Drugs on AlphaBay - Exploration Analysis

Secondly, data mining techniques have been performed in order to discover hidden rules and correlations in the database.

## Sellers Predictions

The first thing to wonder is how to guess the seller of an ad. This knowledge could enable to identify sellers in other web market. To answer this question, different data mining methods have been used, especially decision tree and Bayesian classification.

Algorithm has been run on a subset of the database with by rows ads and by columns the origin, category, seller and price. The aim is to predict who is selling each ads. By training the algorithm on one half of the data, predictions could be made on other half. Given that most of sellers own just few ads (occasional advertisements) only the main ones were selected, which represent at best the market. Otherwise, data mining techniques will fail in finding rules for them.

To check efficiency of the algorithm a measure of accuracy must be calculated. It is obtain by comparing the prediction of decision tree method with the true value.

### Decision Tree

Using rpart package, which is based on the CART Algorithm, a decision tree has been created. Thanks to it, predictions of the seller could be made. Prognoses on the five most significant sellers and the related tree can be found below.

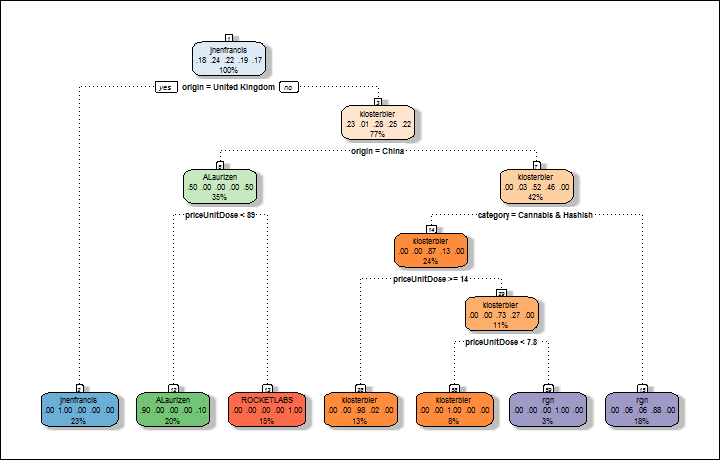


Fig. 15 Seller prediction - Decision tree

The accuracy is: 94.27%. It is striking to realize that predictions are very reliable since the accuracy is very high.

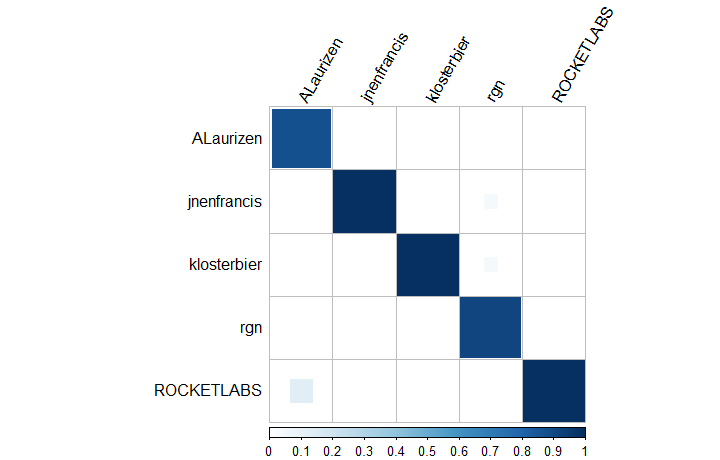


Fig. 16 Confusion matrix – Decision tree

The confusion matrix (Fig. 16) presents the different results of the prognoses, by row you can find the real sellers and by column our predictions. The color scale shows our precision out of one. In other words the diagonal shows the correct predictions (1 mean 100% of success) and all other values are mistakes made by the algorithm.

The tree enables to have a good visual aspect and gives a lot of essential information on these five main sellers.

Predictions have been done here on only five sellers in order to have a readable tree (otherwise the size of the tree is too big for being plotted). However, prognoses with more sellers can be made and with still a good accuracy. For instance, with 10 sellers the accuracy is: 88.79%.

### Bayesian Classification - Naive Algorithm

Bayesian classification has been used in the same objective as decision tree, making predictions. When running Bayesian naive algorithm with the same data, the results are:

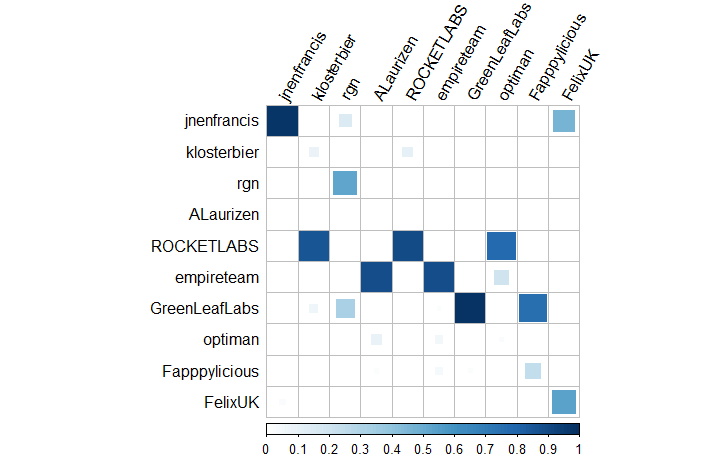


Fig. 17 Confusion matrix - Bayesian classification

The accuracy is 56.37% which is not very good comparing to decision tree. One way to improve the prognosis is to add new variables to the data which could be relevant like the number of ads already sold and the creation date of the ad.

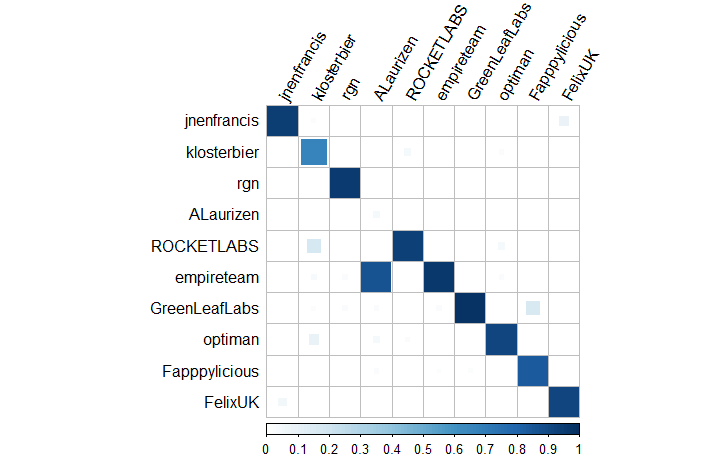


Fig. 18 Confusion matrix - Bayesian classification 2

Results show that the algorithm succeeds in predicting most of the sellers. The accuracy is 79.8%. Which is still a little bit less than with decision tree. However with more sellers (i.e., more than 40 sellers for instance), this algorithm tends to be more accurate than the one based on decision tree method.

Later in the section Prediction of ads profitability, it will be discussed how to exploit at best this two values: the creation date of ads and the number of sold products.

### Text Mining

One last method, but not least: text mining. It can be used for text classification (determination the topic, the tone, etc.), but here it will be used for predicting who has written the text (i.e., sellers).

The main interest comparing to previous methods is that it is only based on the words used by the sellers. Thus, it is possible to identify the seller according to his writing style in other type websites, such as social network. What previous methods cannot do because they are trained with variables specific to AlphaBay. Furthermore, there is no need to explain the interest of identifying in social network illegal sellers…

The method consists in training the algorithm with words from the ad description of each seller. Then, it is tested with a part of the data which has not been used for training. The algorithm chosen for this method is Support Vector Machine but other algorithms have been tested such as decision tree and random forest and results are similar. The result below has been obtained with a data containing the ads description from the 50 main sellers.

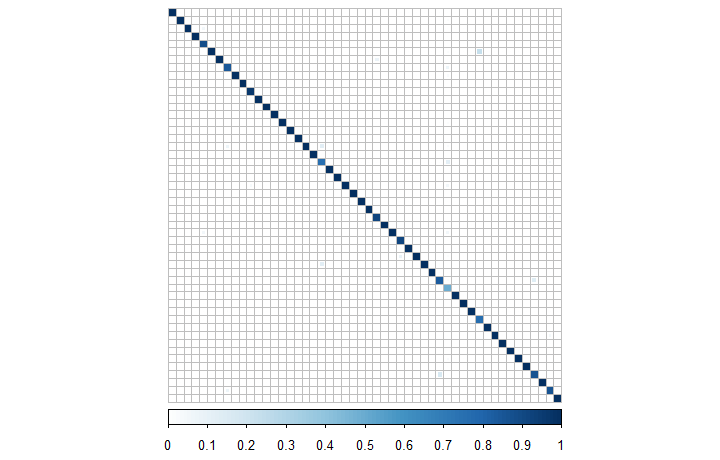


Fig. 19 Confusion matrix - Text mining

The accuracy is 93.83% which is very high. For more sellers, (which own enough ads, in order to have some of them in the training dataset) the accuracy decreased but it is still very high. For instance for 150 main sellers it is around 90%.

However, this accuracy has to be taken with precaution. Indeed, most of the ads descriptions from one seller are very similar. The reason is that they create various ads for the same product with different quantities. Thus, ads description are almost the same. That is why, it is not surprising that the accuracy is so high.

Anyway, that show us that the algorithm is working properly and it can be used in order to find hidden identities of one seller in AlphaBay or in other website and eventually discover his real identity.

## Clustering of Drugs

Secondly, one can wonder if there were links between some drugs. That is to say, if this is possible to cluster some drugs.

To do so, firstly, a new data frame has been created with by rows sellers and by columns different sub-categories of “Drugs & Chemicals”. In each cell, value is true or false if the dealer has already sold something in this sub-category or not. Then, Apriori algorithm of association rules has been used. One drug has been selected that must be in the item set. Here it is Ecstasy and results can be seen below.

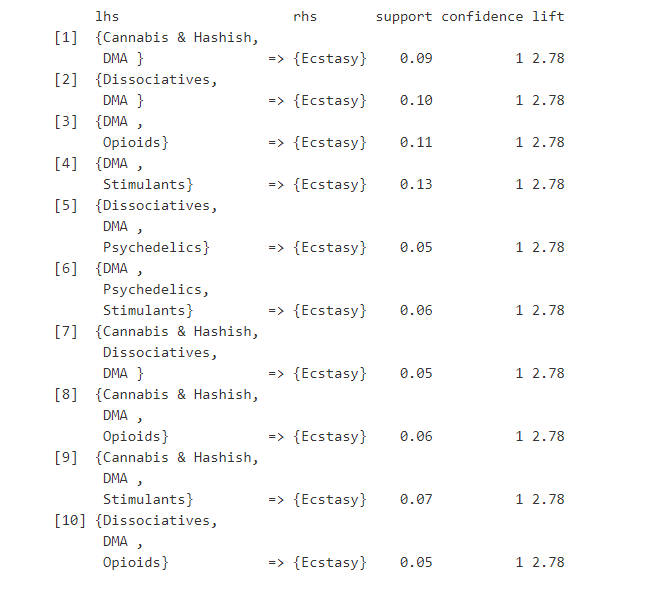


Fig. 20 Cluster of drugs - Association rules

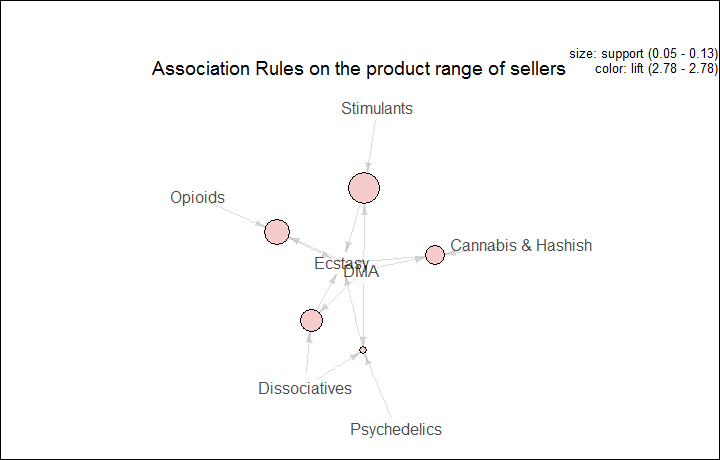


Fig. 21 Cluster of drugs - Association rules 2

The algorithm succeeds in finding some rules in the data frame. That means that some drugs can effectively be clustered. The support is between 5% and 15% so it is frequent to have these item sets. Moreover the confidence is more than 80%. In other words, if there is the item set on the left we are most likely to have the drug on the right.

These rules can be interpreted as follows: sellers often deal more than one product. And these products can be clustered by type.

## Prediction of Ads Origin

After trying to make predictions on sellers (cf. Sellers Predictions), prognoses on the origin of the ads have been made using decision tree method and association rules.

### Decision Tree

Looking at prices and categories, a decision tree has been created in order to predict the origin. In the same way the algorithm has been trained on one half of the data, and predictions made on the other half.

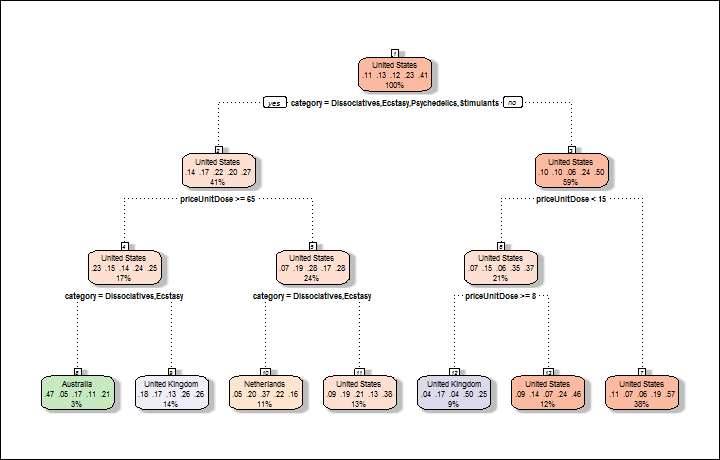


Fig. 22 Origins prediction - Decision tree

Results don’t seem to be very good, the accuracy is 45.33 % which is lower than previously. It turns out that without sellers, which give a lot of information on the origin, prognoses are not very reliable.

### Correlations between Categories and Origins

To do so, association rules method has been run with 2 variables: category and origin. Thus, one may be able to make a link with predictions of above decision tree. One country has been fixed, here United States.

TABLE I

Origin prediction - Association rules

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Category | Origin | Support | Confidence | Lift |
| Cannabis & Hashish/ Concentrates | United States | 0.028 | 0.76 | 2.95 |
| Cannabis & Hashish/ Topical & Others | United States | 0.002 | 0.68 | 2.63 |
| Stimulants/ Adderal & Vyvanse | United States | 0.001 | 0.67 | 2.58 |
| Cannabis & Hashish/ Edibles | United States | 0.023 | 0.65 | 2.51 |
| Opioids/Pills | United States | 0.020 | 0.53 | 2.07 |
| Paraphernalia/ Paraphernalia | United States | 0.006 | 0.52 | 2.01 |

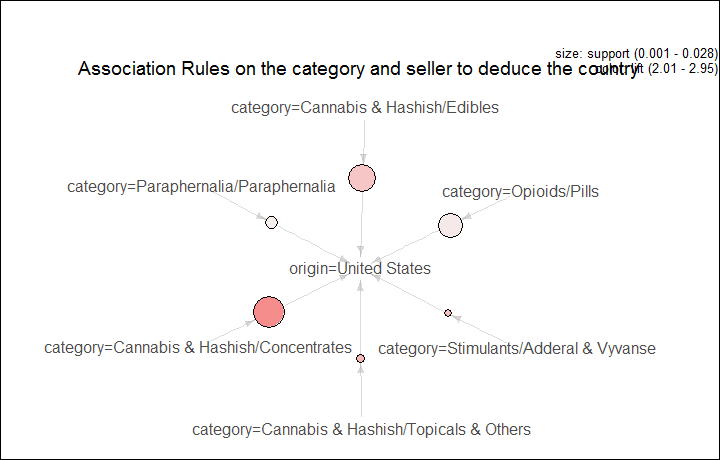


Fig. 23 Origin prediction - Association rules 2

The results show that when there is an ad of the category on the left, it is likely to come from United States with a confidence higher than 50%. Thus, ads from United States are often on Cannabis & Hashish, this can be easily confirmed by plotting a pie chart of United States exportations, as in the section before.

It is striking to see that Cannabis & Hashish seems to be the main rule. This can be explained by the legalization of Cannabis in some states. Thus, the sales of these products is easy in United States and may interest people from other countries where they are not legalized.

## Prediction of ads profitability

Secondly, it is worth predicting the profitability of an ad. That is to say, given an ad to predict if it will be sold a lot or not. Each ad have information on the category, origin, seller, price and a rate of profitability. This rate is calculated by dividing the number of product sold by the current lifetime of the ad and by times 30 to have a number of ads sold monthly. Bayesian neural network algorithm has been accomplished on this new data.

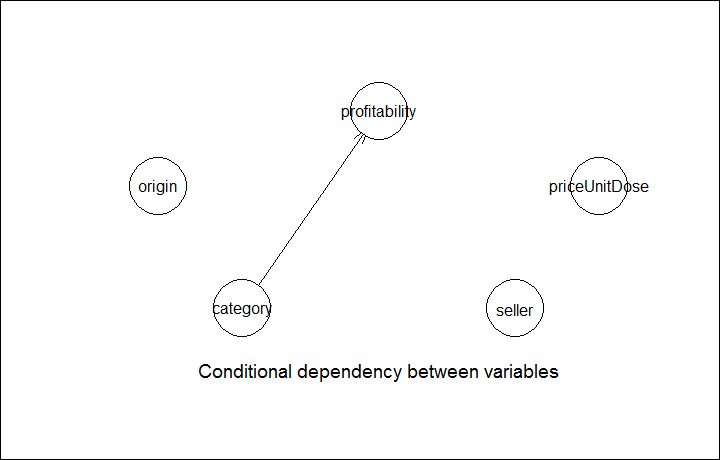


Fig. 24 Variable dependencies - Bayesian neural network

Neural network shows that the profitability is conditionally dependent to category. That is to say category has a significant impact on profitability. Conditional probabilities are shown in the array. It is surprising that price and seller have no impacts on profitability.

Furthermore, expectancy of each event profitability X given category Y has been calculated. Thus, we can find the most profitable products to sell. Apparently it seems to be prescription, steroid and opioids. May be they are more profitable because they are not “common products” (and still wanted) contrary to Cannabis or Cocaine which can be found more easily on the street.

TABLE II

Expectancies of category profitability

|  |  |
| --- | --- |
| Category | Expectancy |
| Benzos | [1.48 , 30.75] |
| Cannabis & Hashish | [2.88 , 114.89] |
| Dissociative | [1.77 , 74.75] |
| DMA | [1.56 , 84.02] |
| Ecstasy | [3.24 , 103.68] |
| Opioids | [3.28 , 128.07] |
| Other | [0.86 , 28.41] |
| Paraphernalia | [0.71 , 29.57] |
| Prescription | [3.67 , 226.93] |
| Psychedelics | [1.26 , 56.99] |
| Steroids | [3.86 , 152.38] |
| Stimulants | [3.81 , 100.74] |
| Tobacco | [1.16 , 49.7] |
| Weight Loss | [0.96 , 26] |

# Conclusion

The understanding of such illegal market is crucial to fight it. Information gathered in those websites, allow to identify which are the most wanted ads for the consumer and where they come from. Therefore it might be possible to detect the footprint of each seller and, thus, help governmental agencies to identify recurrent sellers with various hidden identities.

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