The Language of Legal and Illegal Activity on the Darknet

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What is the Dark Web?

- The non-indexed parts of the Internet
- Anonymous activities
- Both legal and illegal activities

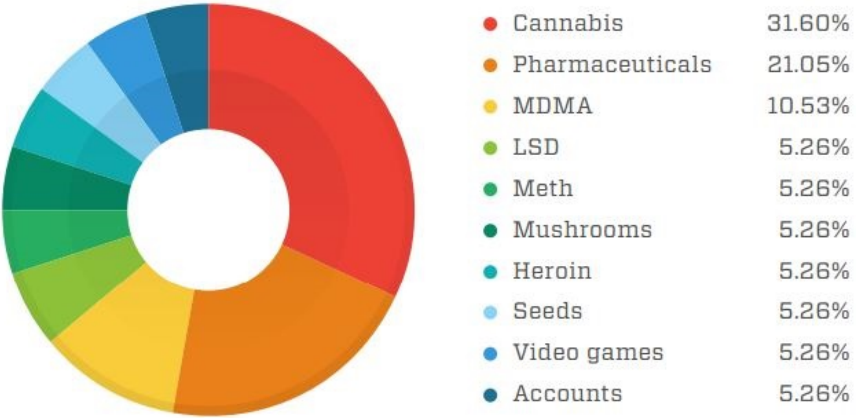
Darknet

Used interchangeably in this work:

- **Dark Web**
- **Darknet**
- **Tor** network (Tor: an encrypted browser)
- **Onion** network (.onion top-level domain)

Hosts: **onion services** (hidden services).

Darknet Markets



[1] Paganini (2015). "The Deep Web and Its Darknets".

Language of the Darknet

How well do NLP tools work on Darknet text?

Language of the Darknet

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spaCy flair

NLTK Reference Guide

AllenNLP NLP ARCHITECT

Can we automatically identify illegal activity?

Outline

1. Data: Darknet & eBay
2. Domain Differences: Vocabulary & Named Entities
3. Classification: Legal & Illegal Drugs, eBay
4. Cross-Domain Classification: Legal & Illegal Forums

DUTA-10K

Dataset of 10367 Onion Services text pages [Al Nabki et al., 2019].

- 20% categorized as illegal and 48% as legal (32% unavailable).
- Of the illegal (suspicious) websites, 23% concern illegal **drugs**.

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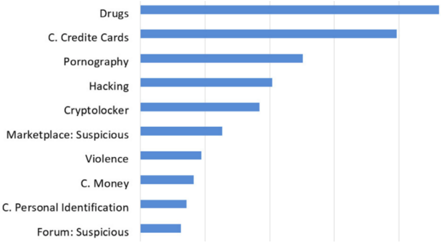
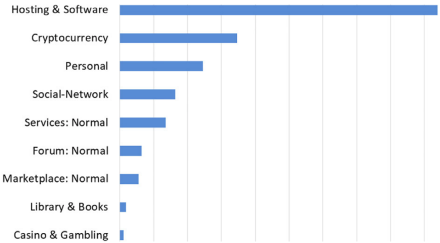
Distribution of categories:



Illegal



Legal

Control Data: eBay

Product descriptions acquired by searching for drug-related terms.
Do not sell actual drugs, but rather drug-related products.

```
3 Layers  Chip Style Herb Herbal Tobacco Grinder Weed Grinders
Description:
Quantity: 1
Type : Tobacco Crusher
Feature: Stocked,Eco-Friendly
Material: plastic
Size: 42*26mm
Package include:
1PC  Tobacco Crusher
```

Data

	Public Web	Dark Web
Legal	**eBay** (188 pages, 35,799 words)	**Legal Onion** (35 pages, 61,655 words)
Illegal		**Illegal Onion** (255 pages, 1,438,351 words)

Cleaning

- Remove non-linguistic content: buttons, encryption keys, metadata, URLs.
- Split to paragraphs and join paragraphs to single lines.
- Remove duplicate paragraphs.

```
Finest organic cannabis grown by proffessional growers in the
netherlands.
We double seal all packages for odor less delivery.
Shipping within 24 hours!
              Product                       Price           Quantity
1g Original Haze                     15 EUR = 0.025 ฿ 1_ X Buy now
5g Original Haze                     65 EUR = 0.108 ฿ 1_ X Buy now
1g Bubblegum                         10 EUR = 0.017 ฿ 1_ X Buy now
5g Bubblegum                         45 EUR = 0.075 ฿ 1_ X Buy now
1g Jack Herer                        14 EUR = 0.023 ฿ 1_ X Buy now
5g Jack Herer                        60 EUR = 0.099 ฿ 1_ X Buy now
1g Chronic                           9 EUR = 0.015 ฿  1_ X Buy now
5g Chronic                           40 EUR = 0.066 ฿ 1_ X Buy now
1g Banana Kush                       11 EUR = 0.018 ฿ 1_ X Buy now
```

Clean Data

Sampled 571 paragraphs from each, for comparable size.

	Public Web	Dark Web
Legal	**eBay** (14,276 words)	**Legal Onion** (14,802 words)
Illegal		**Illegal Onion** (15,049 words)

Outline

Vocabulary

Distance between word frequencies distributions, measured by:

- Jensen-Shannon divergence.
- L1 distance.

Splitting each dataset in half, we find small “self-distances”, but the different domains are about equidistant.

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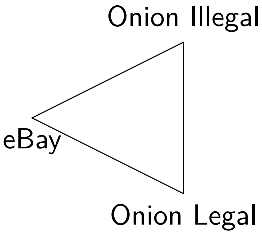

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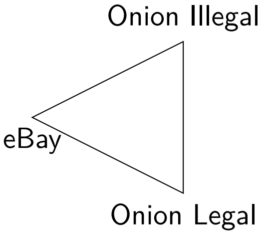
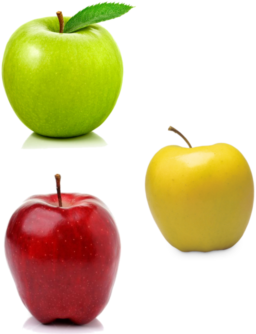


Legal and illegal Onion should be considered different domains.

Characteristics of Darknet Data

Diverse: sub-domains are distinguishable.

Unique: distinguishable from other domains.



Named Entities and Wikification

NE extraction [spaCy] + Wikification [Bunescu and Pașca, 2006].

	% Wikifiable
eBay	38.6 ± 2.00
Illegal Onion	32.5 ± 1.35
Legal Onion	50.8 ± 2.31

By manual inspection, NE precision and recall are low for Illegal Onion.
For example: slang words for drugs (e.g., “kush”) falsely picked up as NEs.

$\Rightarrow$ Standard NLP is not suited for this domain.

Outline

Classes

We identified three domains. Two binary classification settings:

{ eBay, **Legal Onion** }

{ **Legal Onion**, **Illegal Onion** }

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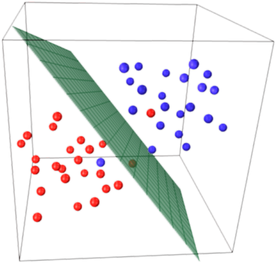
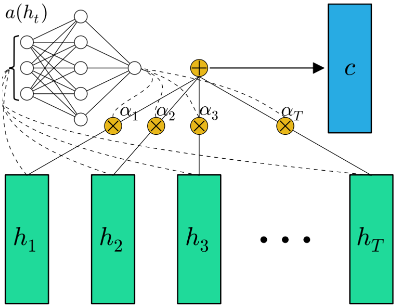
What are the linguistic features distinguishing them?



Classifiers

- NB: Naive Bayes (bag of words)
- SVM: Support Vector Machine
- BoE: sum/average GloVe + MLP
- seq2vec: BiLSTM + MLP
- attention: ELMo + BCN (self-attention)



Manipulations

- Full original text

- Drop **content** words
- Drop **function** words

- Replace **content** words with their POS
- Replace **function** words with their POS

$$\{\text{ADJ},\ \text{ADV},\ \text{NOUN},\ \text{PROPN},\ \text{VERB},\ \text{X},\ \text{NUM}\}$$

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Generic	Viagra	(	Oral	Jelly	)	is	used	for	Erectile	Dysfunction
PROPN	PROPN	(	PROPN	PROPN	)	VERB	VERB	for	PROPN	PROPN

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PROPN	PROPN	(	PROPN	PROPN	)	VERB	VERB	for	PROPN	PROPN

Welcome	to	SnowKings	Good	Quality	Cocaine	!
VERB	to	PROPN	PROPN	PROPN	PROPN	!

Results: eBay vs. Legal Onion Drugs

Clear separation by content (by NB), but also by function (by SVM).

	full	drop content	drop function	pos content	pos function
NB	91.4	57.8	90.5	56.9	92.2
SVM	63.8	64.7	63.8	68.1	63.8
BoE_{sum}	66.4	56.0	63.8	50.9	76.7
$\text{BoE}_{\text{average}}$	75.0	55.2	59.5	50.0	75.0
seq2vec	73.3	53.8	65.5	65.5	75.0
attention	82.8	57.5	85.3	62.1	82.8

Results: Legal vs. Illegal Onion Drugs

Harder to distinguish by content, easier by POS distribution (SVM again).

	full	drop content	drop function	pos content	pos function
NB	77.6	53.4	87.9	51.7	77.6
SVM	63.8	66.4	63.8	70.7	63.8
BoE_{sum}	52.6	61.2	74.1	50.9	51.7
$\text{BoE}_{\text{average}}$	57.8	57.8	52.6	55.2	50.9
seq2vec	56.9	55.0	54.3	59.5	49.1
attention	64.7	51.4	62.9	55.2	69.0

Classification Challenges

Simple classifiers (NB, SVM) work best.

- Small training data.
- Non-standard language.
- Understudied domain.

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Darknet Forums

Can we generalize beyond drugs?

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DUTA-10K also contain Legal Forums and Illegal Forums.
Multi-topic and user-generated.

Results: Legal vs. Illegal Onion Forums

Harder for most classifiers, but SVM succeeds using content and function.

	full	drop content	drop function	pos content	pos function
NB	74.1	50.9	78.4	50.9	72.4
SVM	85.3	75.9	56.0	81.9	81.0
BoE_{sum}	25.9	32.8	21.6	36.2	35.3
$\text{BoE}_{\text{average}}$	40.5	42.2	31.9	48.3	53.4
seq2vec	50.0	48.9	50.9	28.4	51.7
attention	31.0	37.2	33.6	27.6	30.2

Results: Trained on Drugs, Tested on Forums

Effective cross-domain generalization even with bag-of-words.

	full	drop content	drop function	pos content	pos function
NB	78.4	63.8	89.7	63.8	79.3
SVM	62.1	69.0	54.3	69.8	62.1
BoE_{sum}	45.7	50.9	49.1	50.9	50.0
$\text{BoE}_{\text{average}}$	49.1	51.7	51.7	52.6	58.6
seq2vec	51.7	61.1	51.7	54.3	57.8
attention	65.5	59.2	65.5	50.9	66.4

Conclusion

Differences between legal and illegal Darknet sites:

- Vocabulary
- Shallow syntax (POS)
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Code: https://github.com/huji-nlp/cyber
Data: dan.eldad1@mail.huji.ac.il

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Thanks!

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