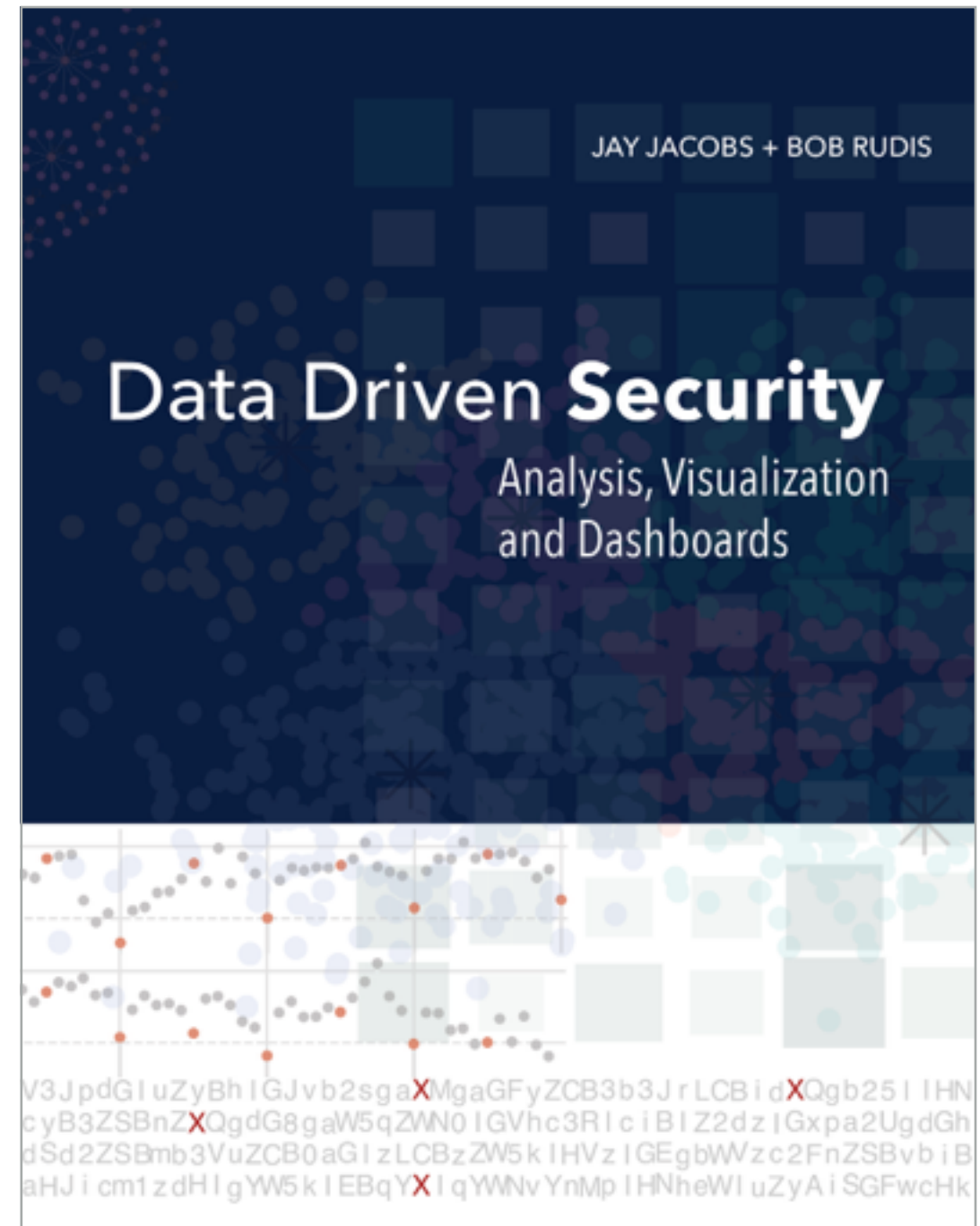


Detecting **Algorithmically** **Generated Domains**

Jay Jacobs
March 7th, 2015
@jayjacobs

Jay Jacobs

Data Driven Security

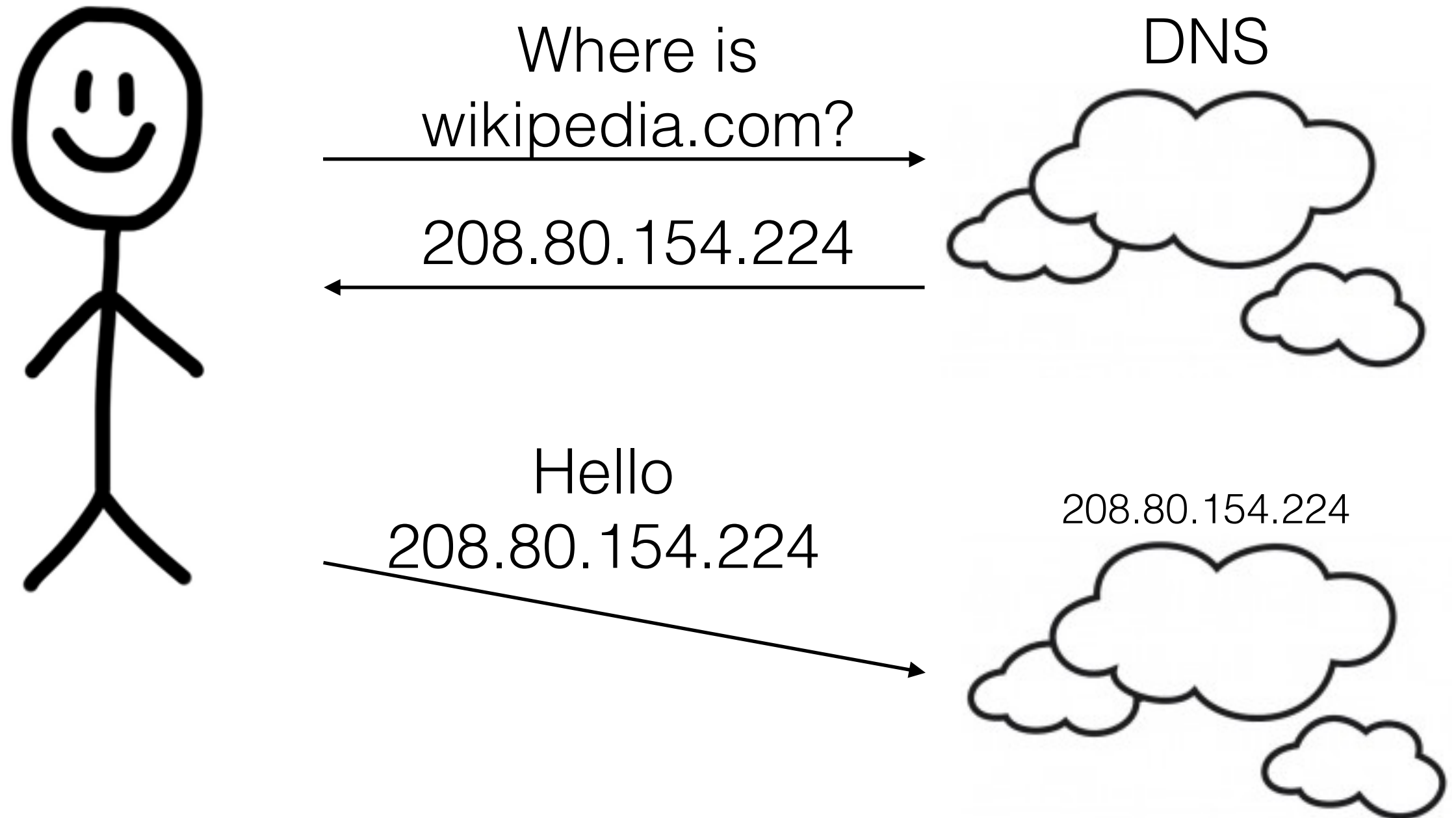


<http://www.verizonenterprise.com/DBIR/>

<http://amzn.to/ddsec>

<http://datadrivensecurity.info/>

IP and Domains



IP and Domains

The early days...

Malicious
Software

201.130.44.18
216.58.216.238
173.194.46.86
badserver1.com
badserver2.com
badserver3.com



Domain Generating Algorithms (DGA)

Algorithms that generate pseudo-random domain names. Used by malware to communicate with a controlling server.

IP and Domains

And Now...

Malicious
Software

xautsghmdtoofnn.com	No
exotugfsphafhxt.com	No
kykwdvibpsccedj.com	No
nmexqpgdqnxysvp.com	No
civtuqeeoqueg.com	No
kmlnfcegedkle.com	No
uailugreagmxe.com	No
cohbwhtwwdrqqv.com	No
dbbsxhljgdexb.com	No
vyqabtoayoheu.com	Yes

Building a Classifier

1. Obtain labelled data
2. Add or derive features
3. Create test/train data sets
4. Run classification algorithm[s] on training data
5. Evaluate model and features on test data

The Challenge

Given a list of domains, classify them as either benign or DGA

hrjiojexjpjodkk.ru
xautsghmdtoofnn.ru
exotugfsphafhxt.ru
kykwdvibpsccedj.ru
nmexqpgdqnxysvp.ru
civtuqeeoqueg.ru
kmlnfcegedkle.ru
uailugreagmxe.ru
cohbw hwwdrqqv.ru
dbbsxhljgdexb.ru

1pbwqpi1599j8ppv1rr11u580qx.com
1k81e0smhotv93pt7c295rr6e.net
1yzkujin8r9xi1mt6ku0bt5n11.biz
xkvy3k2afwwm1baincm1qds8sz.org
ophh561k6a4v13dotmo9fshq5.com
1jf7fx5113uv7obi9k0mqfgyn.net
1e9aiud11ed98c1x4gnp7hi4q8s.org
1drt41a5ndhno93q70cmnwmph.net
6e6bqs1bbmcovukufk3hzhri0.com
1nh8no0q31xv313hzv6xmskrm6.org

3k-5k (3.7k median) malicious domains registered daily in US domains,
about 1% of US domains are malicious

The Solution

For Python:

https://github.com/ClickSecurity/data_hacking [dga_detection]

For R:

<https://github.com/jayjacobs/dga-tutorial>

<https://github.com/jayjacobs/dga>

<http://datadrivensecurity.info/blog/posts/2014/Sep/dga-part1/>

Both locations have labelled data!

Building a Classifier

1. ~~Obtain labelled data~~
- 2. Add or derive features**
3. Create test/train data sets
4. Run classification algorithm[s] on training data
5. Evaluate model and features on test data

Features?

facebook.com	1pbwqpi1599j8ppv1rr11u580qx.com
doubleclick.com	1k81e0smhotv93pt7c295rr6e.net
google-analytics.com	1yzkujin8r9xi1mt6ku0bt5n11.biz
akamaihd.com	xkvy3k2afwwm1baincm1qds8sz.org
twitter.com	ophh561k6a4v13dotmo9fshq5.com
youtube.com	1jf7fx5113uv7obi9k0mqfgyn.net
scorecardresearch.com	1e9aiud11ed98c1x4gnp7hi4q8s.org
microsoft.com	1drt41a5ndhno93q70cmnwmph.net
googletagservices.com	6e6bqs1bbmcovukufk3hzhri0.com
msftncsi.com	1nh8no0q31xv313hzv6xmskrm6.org

Features

- Length

facebook.com
doubleclick.com
google-analytics.com

- Entropy

1pbwqpi1599j8ppv1rrl1u580qx.com
1k81e0smhotv93pt7c295rr6e.net
1yzkujin8r9xi1mt6ku0bt5n11.biz

- n-grams

- dictionary word matches

- and Others

n-grams

3-grams

ing	3.5482
lin	3.4924
ine	3.4743
ter	3.3857
ion	3.3727
ent	3.3471
tor	3.3469
the	3.3031
ers	3.2736
tra	3.2683

4-grams

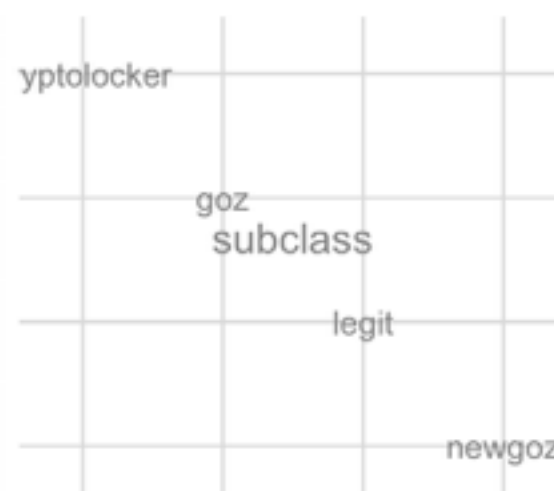
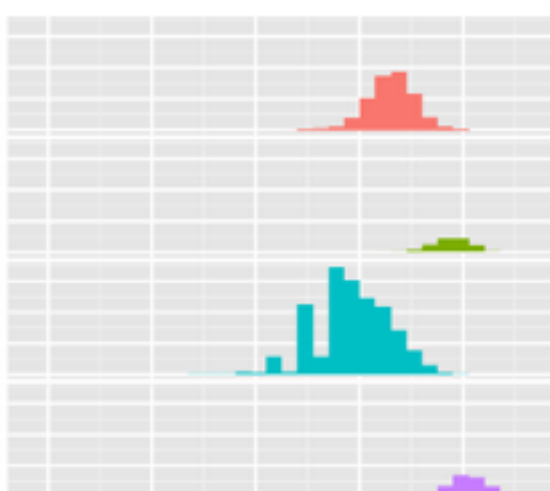
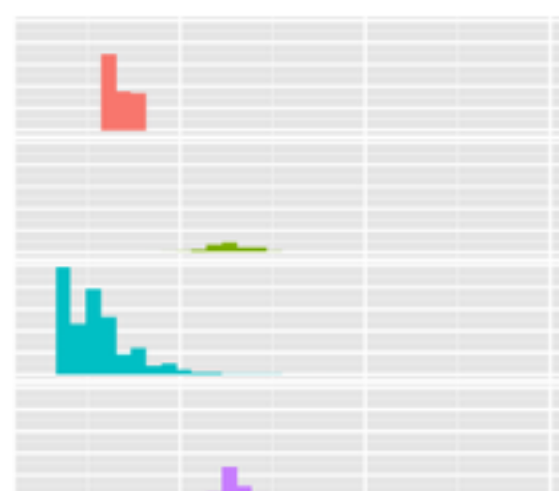
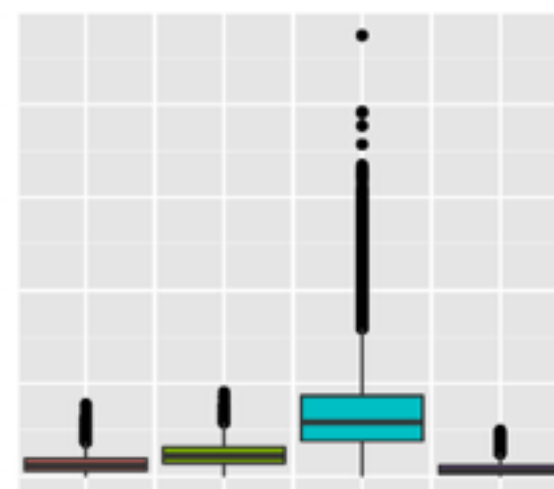
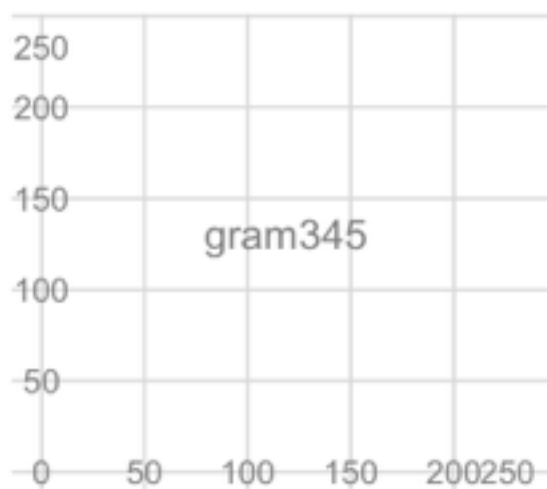
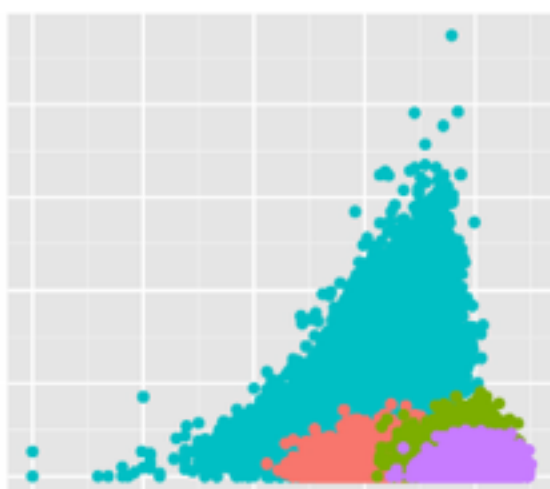
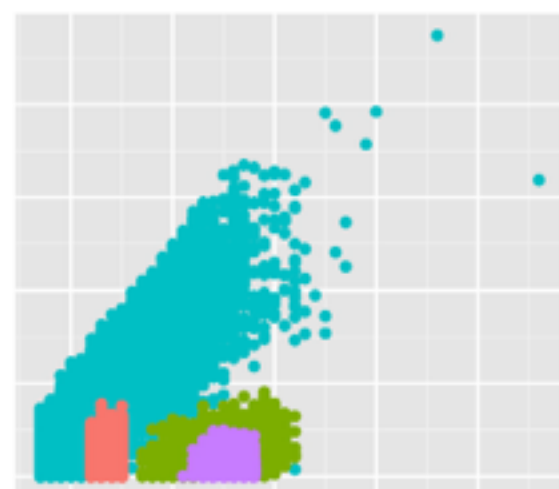
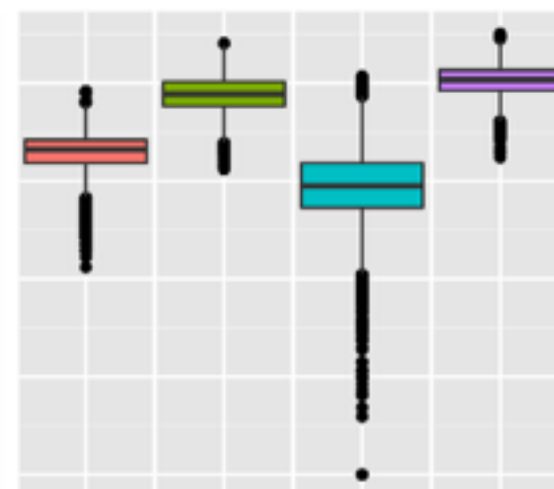
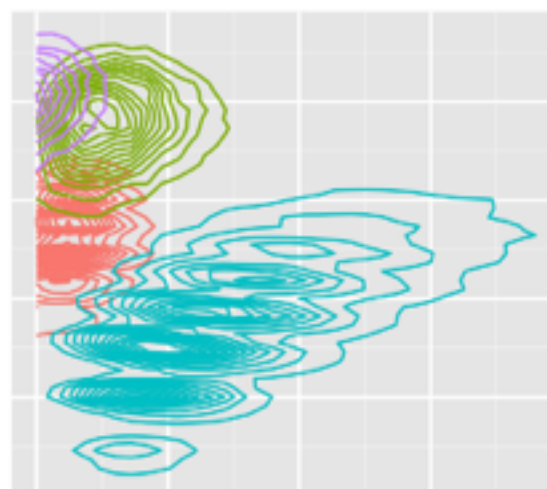
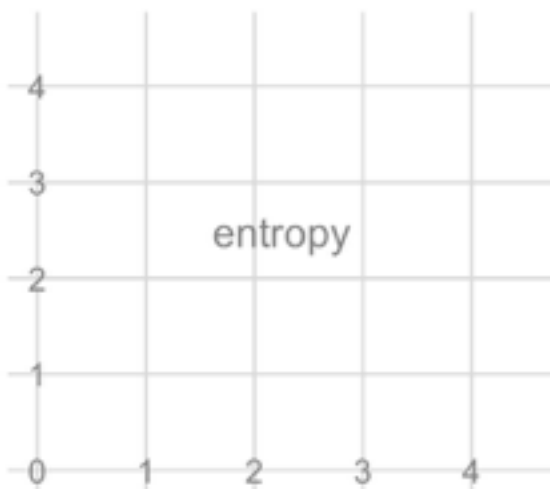
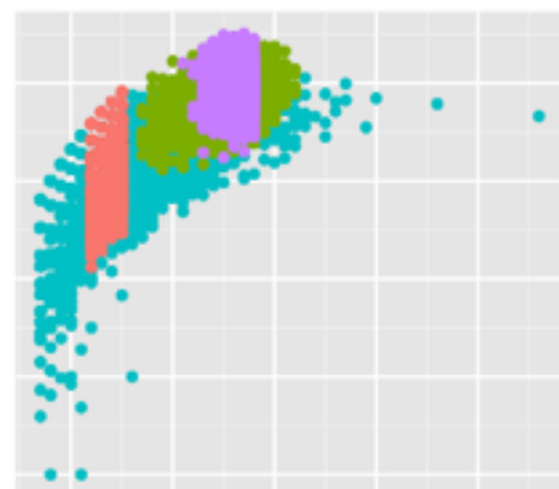
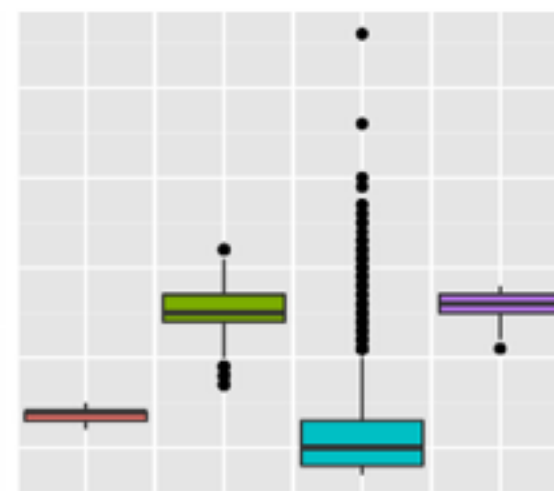
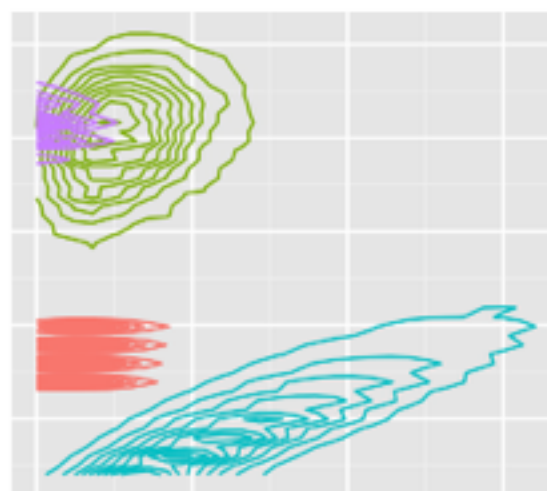
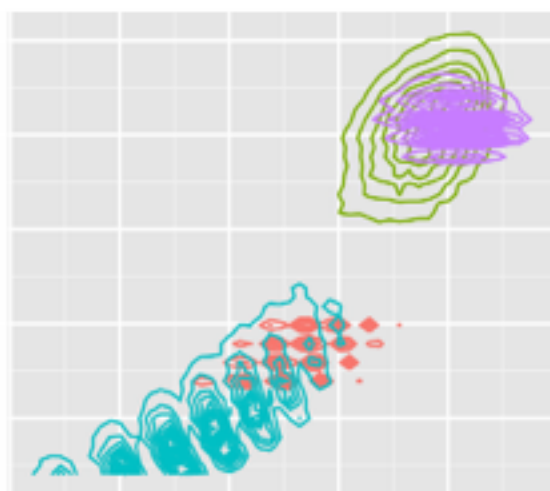
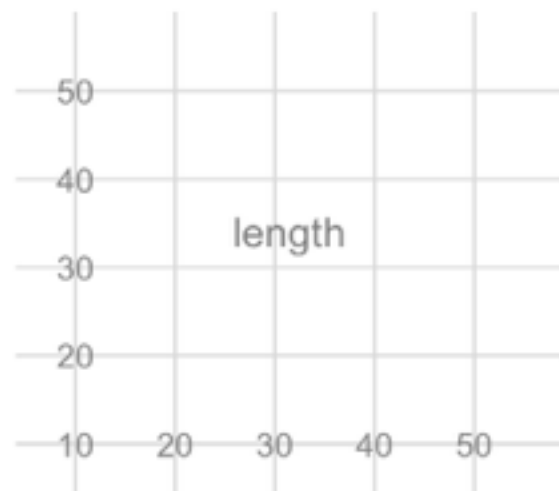
line	3.2148
nlin	3.1595
onli	3.1513
tion	3.1322
free	3.0330
news	3.0051
mark	2.9995
game	2.9978
dire	2.9845
irec	2.9781

4-grams (dga)

eqkb	1.0791
inqo	1.0791
wgyh	1.0791
gylr	1.0413
inqw	1.0413
ljtg	1.0413
lrdq	1.0413
nbyp	1.0413
onba	1.0413
qcws	1.0413

domain	class	length	entropy	onegram	threegram	fourgram	fivegram	gram345
facebook	legit	8	2.750000	36.93176	15.66067	10.39223	6.844194	32.89709
google-analytics	legit	16	3.500000	74.47313	32.33994	16.50915	11.601353	60.45045
akamaihd	legit	8	2.405639	37.22381	11.01290	1.50515	0.000000	12.51805
facebook	legit	8	2.750000	36.93176	15.66067	10.39223	6.844194	32.89709
microsoft	legit	9	2.947703	42.15909	17.11639	11.39665	7.493930	36.00697
googletagservices	legit	17	3.292770	79.98536	36.45091	23.18288	12.778621	72.41240

domain	class	length	entropy	onegram	threegram	fourgram	fivegram	gram345
exotugfsphafhxt	dga	15	3.373557	67.02298	8.673246	0	0	8.673246
civtuqeeoqueg	dga	13	3.026987	57.67474	8.827826	0	0	8.827826
cohbwhwwdrqqv	dga	13	3.026987	54.43738	0.000000	0	0	0.000000
qixyfrsfiyied	dga	13	3.026987	57.37876	9.761103	0	0	9.761103
ptyjwsefmslk	dga	13	3.392747	58.05692	4.670913	0	0	4.670913
hvuwoxwkfpbwy	dga	13	3.334679	55.16979	0.000000	0	0	0.000000



Building a Classifier

1. ~~Obtain labelled data~~
2. ~~Add or derive features~~
3. **Create test/train data sets**
4. Run classification algorithm[s] on training data
5. Evaluate model and features on test data

Train Data

Python

```
# Hold out 10%
hold_out_alex = alexa_dataframe[alexa_total*.9:]
alexa_dataframe = alexa_dataframe[:alexa_total*.9]
hold_out_dga = dga_dataframe[dga_total*.9:]
dga_dataframe = dga_dataframe[:dga_total*.9]

# Pull together our hold out set
hold_out_domains = pd.concat([hold_out_alex, hold_out_dga], ignore_index=True)

# Concatenate the domains in a big pile!
all_domains = pd.concat([alexa_dataframe, dga_dataframe], ignore_index=True)
```

R

```
library(caret)

testindex <- createDataPartition(dgadomain$subclass, p=0.9, list=F)
traindga <- dgadomain[testindex, ]
testdga <- dgadomain[-testindex, ]
```

Building a Classifier

1. ~~Obtain labelled data~~
2. ~~Add or derive features~~
3. ~~Create test/train data sets~~
4. **Run classification algorithm[s] on training data**
5. Evaluate model and features on test data

Run Classifier(s)

Python

```
# List of feature vectors (scikit learn uses 'X' for the matrix of feature vectors)
X = all_domains.as_matrix(['length', 'entropy'])

# Labels (scikit learn uses 'y' for classification labels)
y = np.array(all_domains['class'].tolist()) # Yes, this is weird but it needs
                                           # to be an np.array of strings

import sklearn.ensemble
clf = sklearn.ensemble.RandomForestClassifier(n_estimators=20, compute_importances=True)

# Train on a 80/20 split
from sklearn.cross_validation import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
```

Run Classifier(s)

R

```
# set up Train Control
ctrl <- trainControl(method="repeatedcv", repeats=5, classProbs=TRUE,
                     summaryFunction=twoClassSummary)

# Random Forest
rfFit <- train(class ~ ., data = traindga, metric="ROC",
              method = "rf", trControl = ctrl)

# Support Vector Machine
svmFit <- train(class ~ ., data = traindga, method = "svmRadial",
               preProc = c("center", "scale"), metric="ROC",
               tuneLength = 10, trControl = ctrl)

# C4.5
c45Fit <- train(class ~ ., data = traindga, method = "J48",
               metric="ROC", trControl = ctrl)
```


Building a Classifier

1. ~~Obtain labelled data~~
2. ~~Add or derive features~~
3. ~~Create test/train data sets~~
4. ~~Run classification algorithm[s] on training data~~
5. **Evaluate model and features on test data**

Evaluate Model

R

```
Reference
Prediction  dga legit
dga        39292  282
legit      206 64458
```

```
Accuracy : 0.9953
95% CI : (0.9949, 0.9957)
No Information Rate : 0.6211
P-Value [Acc > NIR] : < 2.2e-16
```

```
Kappa : 0.9869
McNemar's Test P-Value : 0.0006861
```

```
Sensitivity : 0.9948
Specificity : 0.9956
Pos Pred Value : 0.9929
Neg Pred Value : 0.9968
Prevalence : 0.3789
Detection Rate : 0.3769
Detection Prevalence : 0.3797
Balanced Accuracy : 0.9952
```

Evaluate Model

Confusion Matrix Stats

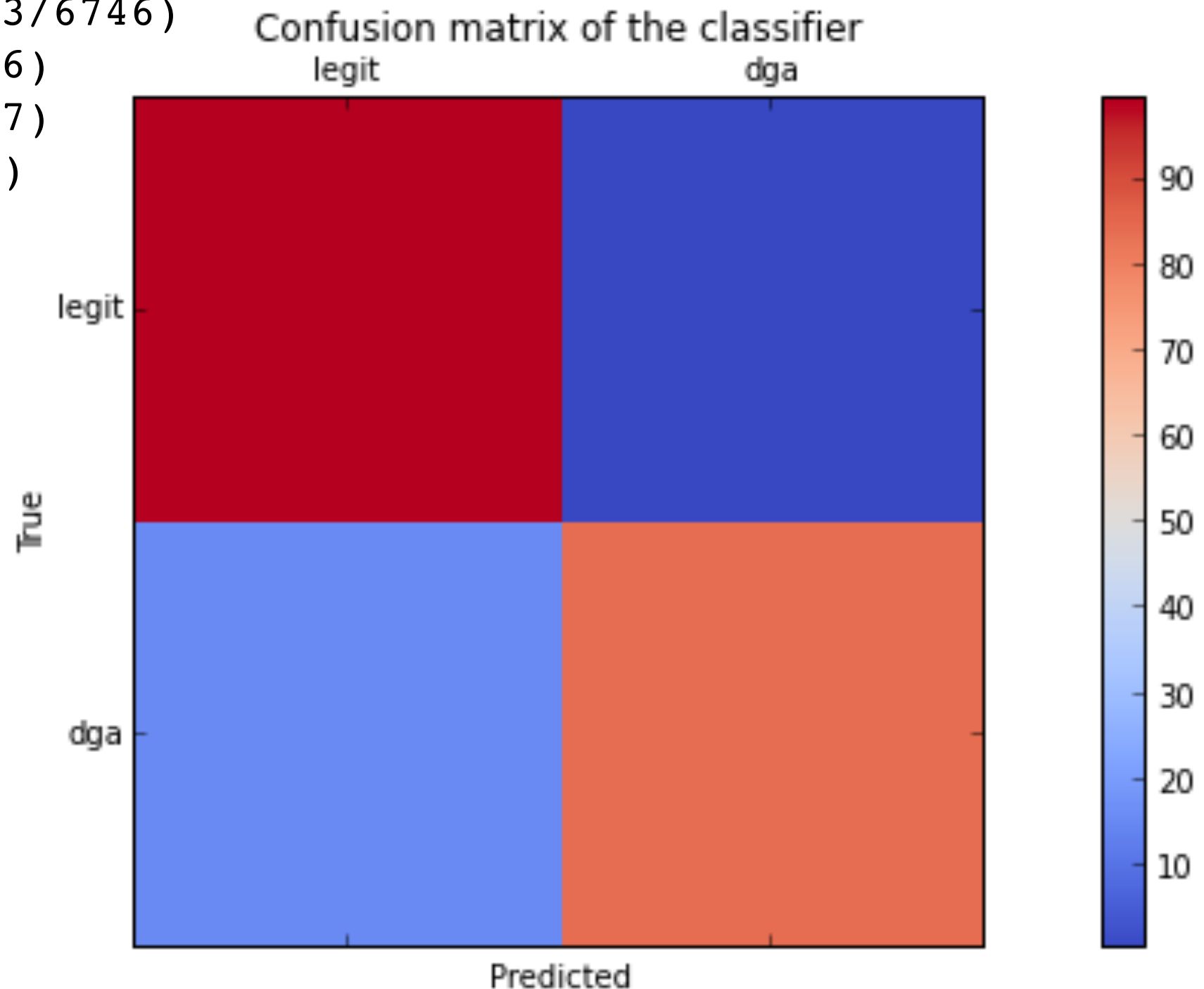
legit/legit: 99.51% (6713/6746)

legit/dga: 0.49% (33/6746)

dga/legit: 15.73% (42/267)

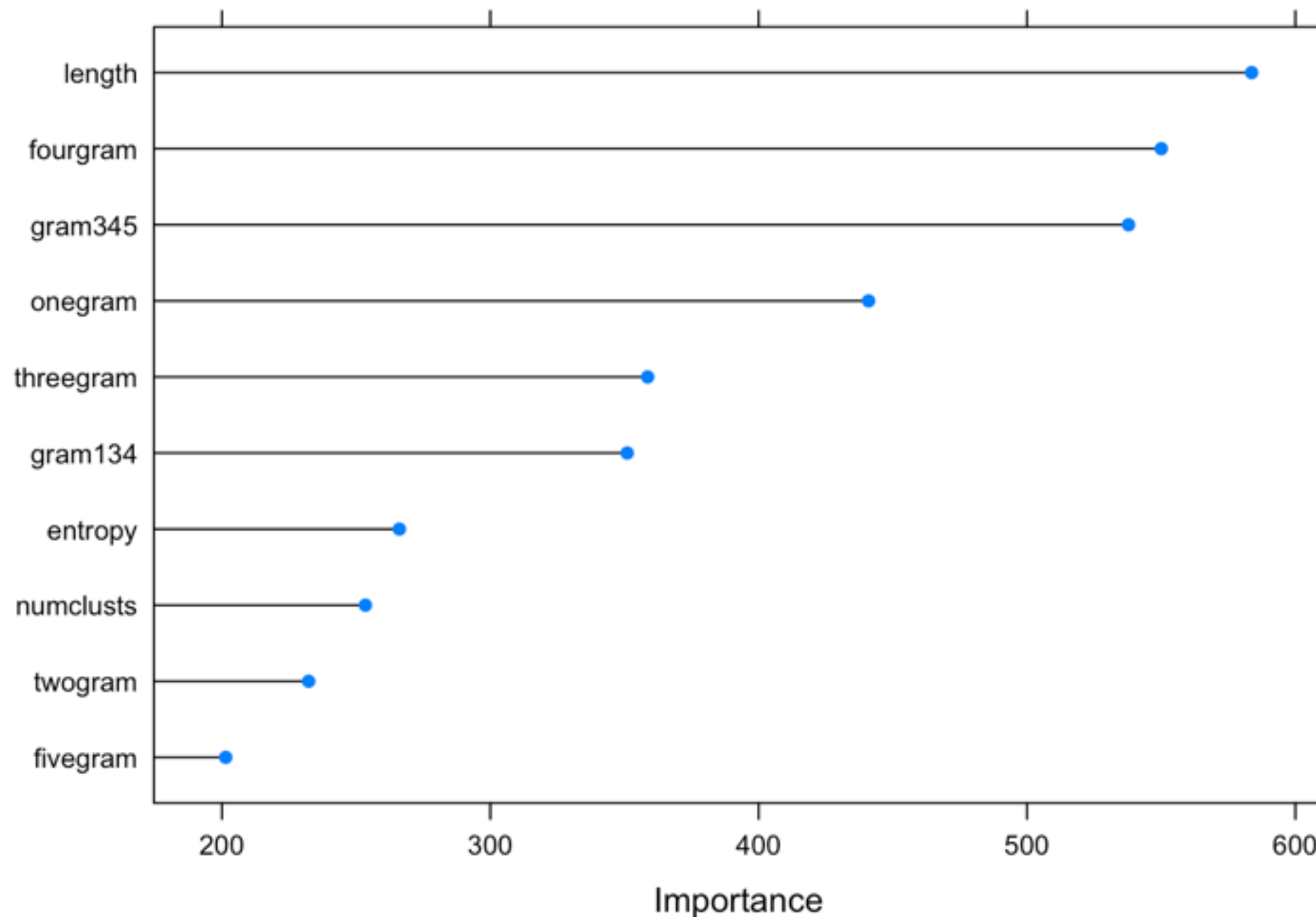
dga/dga: 84.27% (225/267)

Python



Evaluating Features

```
rf.importance <- varImp(rfFit, scale=F)  
plot(rf.importance)
```



Building a Classifier

1. Obtain labelled data
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More Evaluation

	dga	legit	domain
2	0.000	1.000	doubleclick
5	0.000	1.000	googlesyndication
6	0.000	1.000	googleapis
7	0.000	1.000	googleadservices
8	0.000	1.000	twitter
10	0.000	1.000	youtube
11	0.000	1.000	scorecardresearch
14	0.000	1.000	googleusercontent
17	0.006	0.994	msftncsi
22	0.000	1.000	verisign
24	0.000	1.000	quantserve
25	0.000	1.000	bluekai
31	0.000	1.000	digicert
34	0.000	1.000	pubmatic
36	0.000	1.000	adadvisor
43	0.006	0.994	yahooapis
47	0.000	1.000	googletagmanager
48	0.008	0.992	crwdcntrl
49	0.000	1.000	mookie1
54	0.000	1.000	imrworldwide

	dga	legit	domain
138957	1.000	0.000	7sy3v81toy7vim3br0410212pg
138958	1.000	0.000	i8hkuf1wwfc8wlg25u0110vx6w3
138959	1.000	0.000	etvp9c12ixta51jko7ba18xgd3
138961	1.000	0.000	bw25th1nsiukt1344bch1gwgr1h
138965	1.000	0.000	1opr1mm13rpbbm1iy7sdr1572kdu
138967	1.000	0.000	hhnp8p1732n9113wcdb2no89fb
138968	1.000	0.000	155xuit1i4td2bkc2t18qes6me
138969	1.000	0.000	5jndc1t1bvy811hk5ntxk6r4j
138971	1.000	0.000	p5b9an1lo4kybhsghp2inlq58
138973	1.000	0.000	12sjxntztid4mh6snh1dpqc3z
138974	0.998	0.002	15rrp3pyeoms11dbgsqurati8
138975	1.000	0.000	1wguzv3ddl1tf9lwm6og2s6qkv
138976	1.000	0.000	1wvyjf21f8ve5967taqgpkpgvz
138977	1.000	0.000	r16k3i172flcb1u5d8vh1u7yfw
138978	1.000	0.000	1a3i2bq1cjka6s19kdymf1411282
138979	1.000	0.000	qcnqm211790taqp8h54eb9w85
138981	1.000	0.000	1ccvakyzxp80o1ij99er1d5yt56
138982	1.000	0.000	naihsdncxgv8e3eivnx2qmg0
138983	1.000	0.000	5yeo3813dmjen17zzsxtployhn
138984	0.992	0.008	1gl0zqzcqo5futz9ead2vj6e3

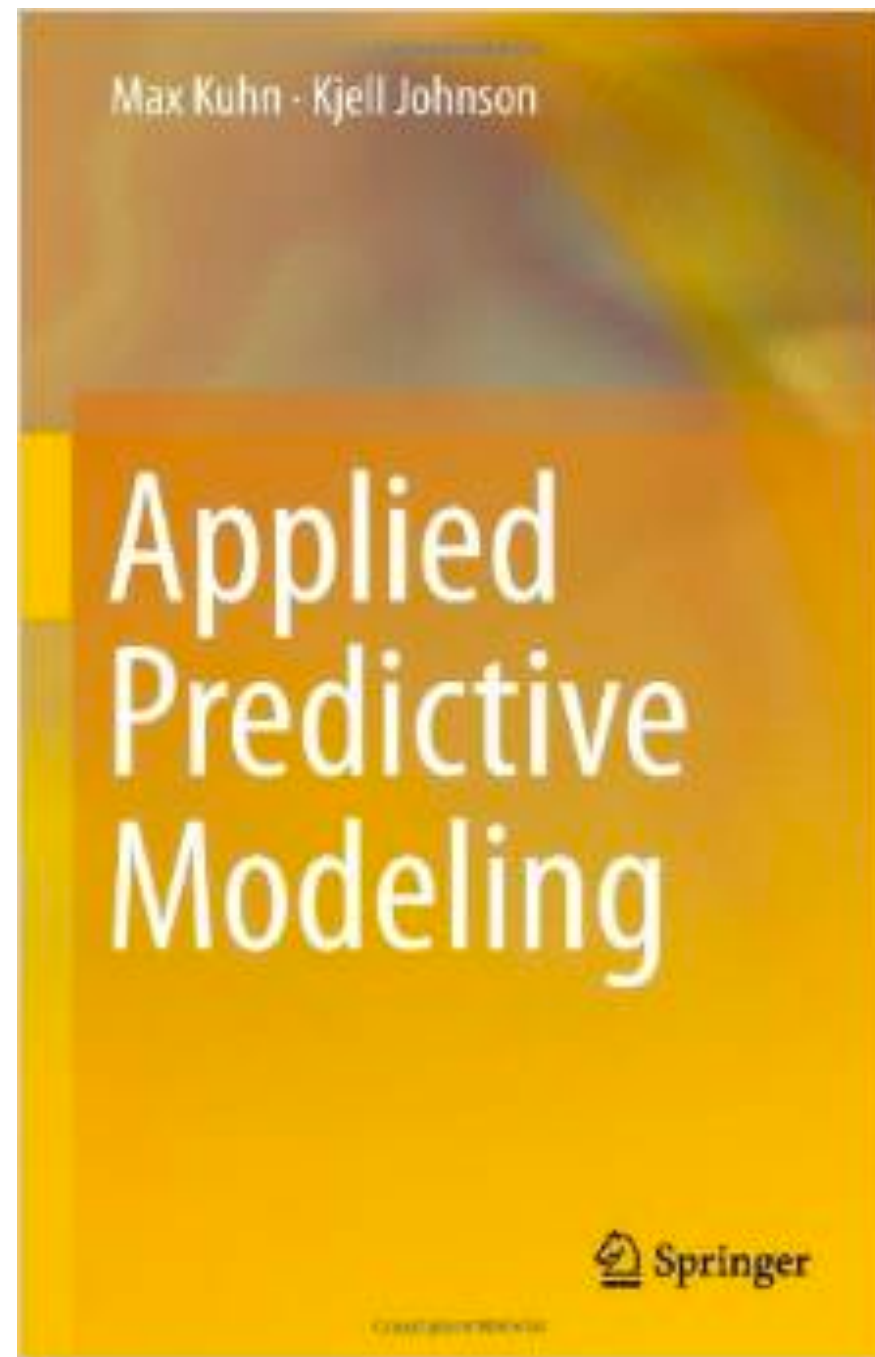
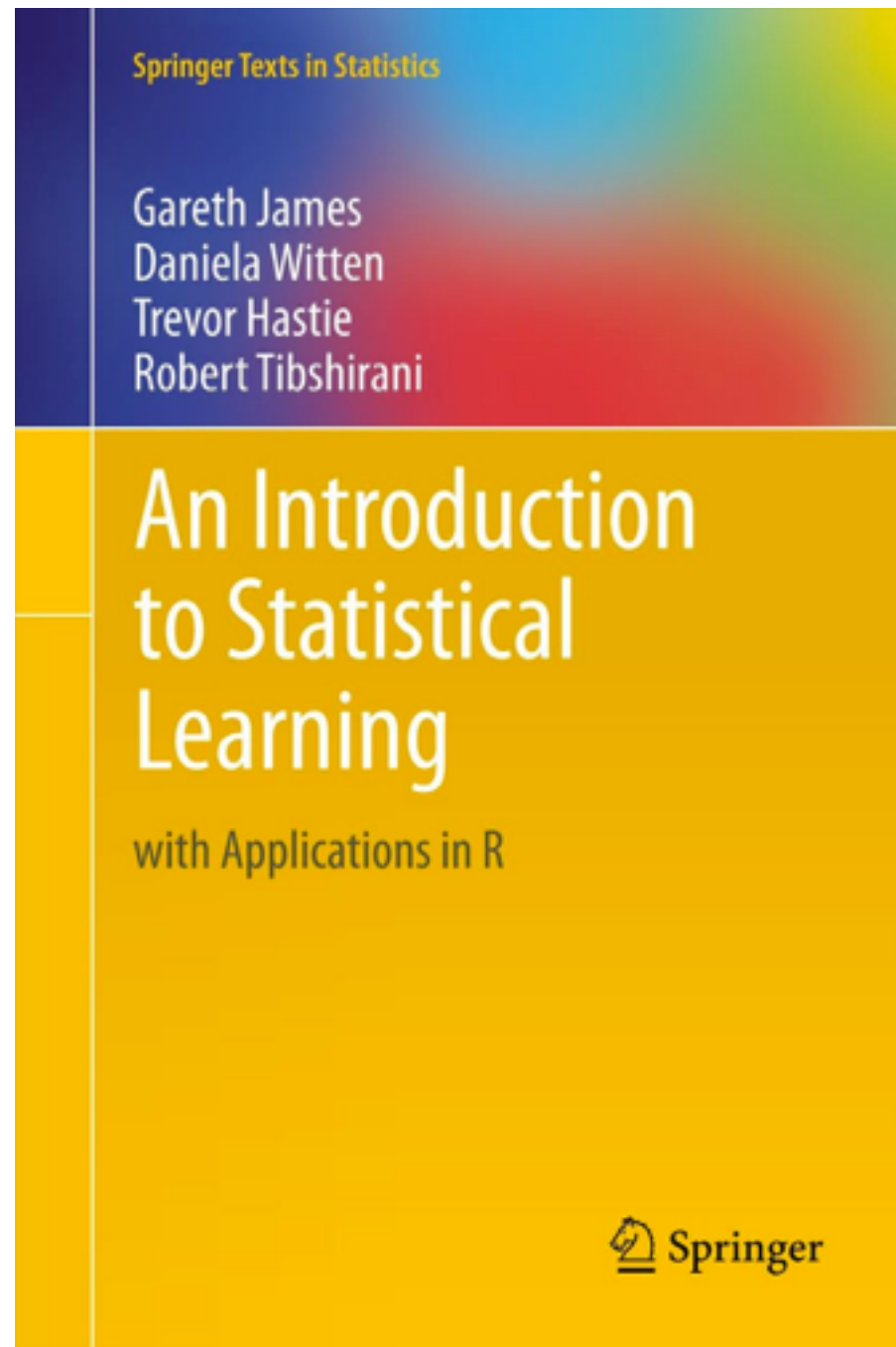
	dga	legit	domain
96375	0.532	0.468	muskel schmiede
96739	0.492	0.508	cendrawasih11
97182	0.506	0.494	empayar-pemuda
97824	0.506	0.494	avto-flagman
26011	0.534	0.466	semilukskaya-crb
25273	0.502	0.498	amovpnforoosh11
27955	0.482	0.518	fairheadkenya
3356	0.536	0.464	m3mieszkania
35484	0.524	0.476	stukadoorsbedrijfvannoord
3876	0.504	0.496	pik-equipment
41173	0.520	0.480	oxfordlawtrove
71022	0.546	0.454	inezandvinoodh
72228	0.528	0.472	voiceofdaegu
99001	0.536	0.464	sacdokulmesi-tr
878461	0.452	0.548	viokbmsinerce
878951	0.512	0.488	hebsphsplitih
886501	0.504	0.496	hotodfonwpougi
890121	0.544	0.456	vgcjamateggut
897231	0.504	0.496	bjoseiraicgty
912801	0.470	0.530	ewebgestbocrus
916521	0.496	0.504	dseemngarkpll
919051	0.528	0.472	ojmeatrfojec
924721	0.478	0.522	plletrsadpawy
936541	0.528	0.472	fbyantymmandfxh
93780	0.514	0.486	yreapptcabych

Evaluating visually

Data Driven
Security

Recommendations

Data Driven
Security



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