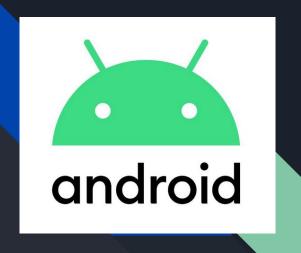
# Multidimensional Fingerprinting

By Dennis Sarovski Project Supervisor PhD. Saed Alrabaee

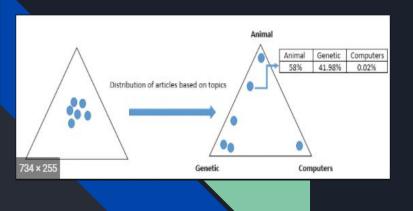




## Background

- 71.81% of mobile users use Android OS
- Mobile & User friendly infrastructure is increasing everyday
- Due to popularity a lot of lot devices use some distribution of android OS
- Malware developers across the world produce over 10k types of malware per day based on a 2019 study.





## What is Multi-Dimensional Fingerprinting



- A way to identify and cluster malware based on unique aspects specific to the malware on different dimensions.
- Like an Police officer looking for evidence (finger prints/DNA) we look for similar things in the code.



- Due to mass innovation in tech industry, many malicious users are flocking to develop technology to take advantage of this rapidly developing industry to cheat their way to success.
- Like in "Big Data" it become increasingly difficult to manually analyze user data. The same is true for malware.
- It is also increasingly difficult to build a one size fits all model due the increasing differences and output of today's malware developers.



## Goal

- Build a model that can
  - Reduce the need to manually analyze malware
  - Fingerprint types of malware to allow us to categorize them in specific families.
  - Be able to detect both known and unseen malware



- My project is based on 2 papers one being:
- Scalable and robust unsupervised android malware fingerprinting using community-based network partitioning (2020) - by ElMouatez Billah Karbab, Mourad Debbabi, Abdelouahid Derhabb, Djedjiga Mouhebc

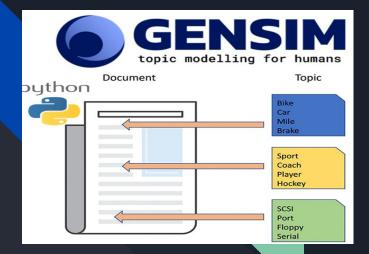
 MalDozer: Automatic framework for android malware detection using deep learning (2018) - by ElMouatez Billah Karbab, Mourad Debbabi, Abdelouahid Derhabb, Djedjiga Mouhebc

#### topic modelling for humans Document Topic buthon Brake Sport Coach Player Hockey SCSI Port Floppy Serial

## Methodology

In order to tackle our goal I decided that the best approach would be to use some sort of Artificial Intelligence that could help automate the process.

- We ended up using LDA (Latent Dirichlet Allocation)
- LDA is a generative statistical model that allows sets of observations to be explained by unobserved groups that explain why some parts of data are similar or different.



Landroid/app/AlarmManager\_Ljava /lang/CharSequence, Landroid/widget /Button, Ljava/io /DataOutputStream\_Landroid /telephony/SmsMessage, Ljava/io /BufferedReader\_Landroid/content /ContentResolver, Lorg/json /JSONException, Landroid/net/Proxy, Landroid/app/Activity, Ljava/io /FileOutputStream, Ljava/net/Proxy, Landroid/app/Service

- LDA imagines a fixed set of topics. Each topic represents a set of words. And the goal of LDA is to map all the documents to the topics in a way, such that the words in each document are mostly captured by those imaginary topics.
- We have chosen topic modeling:
  - The reason we decided to choose topic modeling is because I found that it would be easier to cluster different malware under similar families (topics) due to this similarities or differences in the code.
- In reality the topic modeling becomes more complex than the first example due to not being human readable.
- Once all our data comes together it becomes easier to compare and cluster.

Name	Size	Packed Size	Modified	Created	
assets	228 816	123 655			
	2 273	1 218			
lib	78 612	53 220			
META-INF	30 757	11 266			
res	264 236	167 044			
AndroidManifest.xml	7 880	2 098	2012-05-24 15:15		
classes.dex	825 168	380 232	2012-05-24 15:15		
resources.arsc	98 660	98 660	2012-05-24 15:15		

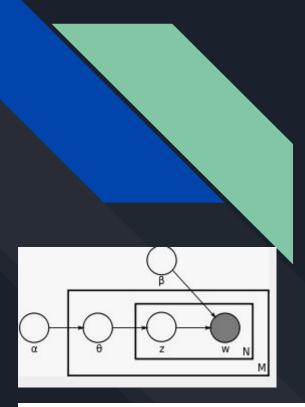
- First step of pre processing our data would be figuring out what is or isn't important!
- The classes.dex is the most important file we use for our model
  - A Dex file contains code which is executed by the android runtime.
  - Every APK has a single classes.dex file which references any classes or methods used within an app.

	134 4 6666 00663305 414	
	a131a4e6ff6a99ff3795e1b1 a4e6ff6a99ff3795e1b17d.c	
Opened '0008C4a131a	14e6ff6a99ff3/95e1D1/d.c	sex , DEX Version 035
	: 'Lcom/androidemu/Che	nats\$item;
Access flags	: 0x0001 (PUBLIC)	
Superclass	: 'Ljava/lang/Object;'	
Interfaces	-	
Static fields		
Instance fields	·	
#0	: (in Lcom/androidemu)	/Cheats\$Item;)
name	: 'code'	
type	: 'Ljava/lang/String;'	•
access	: 0x0001 (PUBLIC)	
#1	: (in Lcom/androidemu)	/Cheats\$Item;)
name	: 'enabled'	
type	: 'Z'	
access	: 0x0001 (PUBLIC)	
#2	: (in Lcom/androidemu)	/Cheats\$Item;)
name	: 'name'	
type	: 'Ljava/lang/String;'	•
access	: 0x0001 (PUBLIC)	
#3	: (in Lcom/androidemus	/Cheats\$Item;)
name	: 'this\$0'	
type	: 'Lcom/androidemu/Che	pats:'
access	: 0x1010 (FINAL SYNTHE	
Direct methods		
#0	: (in Lcom/androidemu)	(CheatsSitem:)
пате	: ' <init>'</init>	
type	: '(Lcom/androidemu/Ch	heats: W'
access	: 0x10001 (PUBLIC CONS	
code	- ONLOGOL (FORLIC COM	
registers	: 2	
ins	: 2	
outs	: 1	
insns size	: 6 16-bit code units	
0140f8;	. 6 10-bit code units	[0140f8] com.androidemu.Cheats\$Item. <init>:(Lcom/androidemu/Cheats:)V</init>
014108: 5b01 5500		1909: inut-object v1, v0, Lcom/androidemu/CheatsSitem; thisS0:Lcom/androidemu/Cheats: // field@0055
	2000	19990: iput-object vi, vo, Lcom/androidemu/cheats;item;.thispo:Lcom/androidemu/cheats; // fielogooss
01410c: 7010 280c 0 014112: 0e00	7000	BOOS: return-void
		18865: return-vold
catches	: (none)	
positions	1	
0x0000 line	2=1/	
locals	_i_	
	x0006 reg=0 this Lcom/ar	
6 - 6969xB	x8086 reg=1 (null) Lcom/	/androidemu/Lheats:

- When we extract the classes.dex file from each malware it is human unreliable so we need to use a dexdump to make it human readable.
- The dex file to the left is the human readable text

Lbsh/This Lbsh/DelayedEvalBshMethod Lco/lvdou/showshow/ui/FragDiscovery Lu/aly/fs Lorg/json/JSONObject Lco/lvdou/showshow/ui/subject/SubjectUtil Lco/lvdou/showshow/ o/lvdou/showshow/model/f/a/ak Lco/lvdou/showshow/diy/combine/OnCombineChangeListener Landroid/support/v4/os/EnvironmentCompatKitKat Ljavax/servlet/http/HttpServletR /lvdou/showshow/service/e Lcom/j256/ormlite/stmt/query/SetValue ZZLjava/lang/String org/sax/properties/lexical ILandroid/support/v4/view/PagerAdapter Lorg/cocos2dx/ ite/stmt/query/IsNull Lco/lvdou/showshow/b/h Ljava/lang/Math Lcom/umeng/socialize/controller/impl/k Lco/lvdou/showshow/a/db ILcom/umeng/socialize/common/ResContaine Exception Lco/lvdou/showshow/g/cd cn/my/wallpaper/shareIt Lco/lvdou/showshow/diy/font/selectbg/ActFontBackground long/2addr cn/app/my/editOtherInfo Landroid/widget/ ssion Lcom/umeng/socialize/net/utils/SocializeNetUtils Lco/lvdou/showshow/div/font/combine/TxtSizeGallervAdapter Lcom/tencent/mm/sdk/constants/ConstantsAPI Lco/lvdo /g/ch Lu/aly/fp cn/trend Lco/lvdou/showshow/util/c/e Landroid/view/View Lcn/zjy/pulltorefreshview/PullToRefreshView Lco/lvdou/showshow/j/c/a/c Lco/lvdou/showshow/mo oid/support/v4/widget/ScrollerCompatGingerbread ILco/lvdou/showshow/diy/combine/OnUpdateFontListListener Lco/lvdou/showshow/util/usersystem/o Lco/lvdou/showshow/a/b /showshow/c/c/e Lco/lvdou/extension/OnNativeCallbackListener Lorg/cocos2dx/lib/Cocos2dxGLSurfaceViewManager Lco/lvdou/showshow/c/g Lcom/umeng/socialize/utils/Statis wshow/files/effect2/ Lco/lvdou/showshow/c/r IIILjava/lang/Object Lco/lvdou/showshow/ui/account/ActRetrieveAccount Lco/lvdou/showshow/c/c/i Lco/lvdou/showshow/model/ odel/e/b Lco/lvdou/showshow/ui/material/ActPicMaterialDetailDelegate Lco/lvdou/showshow/a/av Lco/lvdou/showshow/global/b/d Ljava/io/Closeable Landroid/os/Bundle Lco va/util/zip/GZIPOutputStream Landroid/support/v4/app/TaskStackBuilderHoneycomb Lcom/j256/ormlite/field/types/IntegerObjectType Lco/lvdou/showshow/e/b/e Lco/lvdou/sh s2dx/lib/BaseUnlockService Lco/lvdou/showshow/util/h/k Lcom/umeng/analytics/AnalyticsConfig Lorg/jdom2/output/LineSeparator Lco/lvdou/showshow/receiver/TurntableGam d/support/v4/widget/ContentLoadingProgressBar Lco/lvdou/showshow/view/g Ljava/lang/Object Ljavax/xml/stream/events/EndElement Lco/lvdou/showshow/ui/account/ActRetri /support/StAXStreamProcessor Lcom/j256/ormlite/field/types/BaseEnumType Ljavax/swing/border/MatteBorder Lcom/umeng/socialize/view/aj Lcom/umeng/socialize/bean/SnsAc il/AbstractQueue Lcom/viewpagerindicator/v cn/comment/count Lco/lvdou/showshow/util/wallpaper/OnWallpaperInforListener Lco/lvdou/showshow/view/MuliteColorViewGroup w/SurfaceHolder ILcom/tencent/open/TaskGuide Lco/lvdou/showshow/util/usersystem/k Lu/aly/di Lcom/umeng/socialize/view/s Landroid/os/Parcel Lco/lvdou/showshow/floatw serzone/ActDiyPickPicHead Lco/lvdou/showshow/util/h/m Lco/lvdou/showshow/g/ca Lco/lvdou/a/c/a/a Lbsh/BlockNameSpace Ljavax/swing/JPanel Ljava/util/regex/Pattern Lan id/graphics/Xfermode cn/my/wallpaper/sell Lco/lvdou/showshow/a/dc Lco/lvdou/b/a/u Lco/lvdou/showshow/j/d/d/c IILandroid/graphics/Rect Lco/lvdou/showshow/util/c/c Lc types/DateStringType Lco/lvdou/showshow/j/av Landroid/widget/ImageView Lco/lvdou/extension/LDResLoader JZLco/lvdou/showshow/model/f/h Lcom/umpay/huafubao/h/a Lbsh/

> To preprocess I used regular expressions to collect anything that looked like an API and files that might be specific to the malware and saved it to its own word file.



- Once finished preprocessing, I had to figure out what hyperparameters would best suit the model so I ended up generating multiple models till i found the best coherence.
- Coherence was generated based on how many topics we can choose

#### **Hyper-Parameters**

- $\alpha$  is the parameter of Dirichlet prior on the per-document topic distribution
- $\beta$  is the parameter of the Dirichlet prior on the per-topic word distribution
- K is the number of topics

$$P(oldsymbol{W}, oldsymbol{Z}, oldsymbol{ heta}, oldsymbol{arphi}; lpha, eta) = \prod_{i=1}^K P(arphi_i; eta) \prod_{j=1}^M P( heta_j; lpha) \prod_{t=1}^N P(Z_{j,t} \mid heta_j) P(W_{j,t} \mid arphi_{Z_{j,t}}),$$

Dominant_Topic	Topic_Perc_Contri
23.0	0.9656
3.0	0.9590
0.0	0.0312
27.0	0.9530
15.0	0.9580
25.0	0.9169
0.0	0.0312
0.0	0.0312
22.0	0.9667
27.0	0.9209
20.0	0.7875
0.0	0.0312
13.0	0.9402
23.0	0.9054
0.0	0.0312
2.0	0.9135
0.0	0.0312
0.0	0.0312
15.0	0.9705
0.0	0.0312
13.0	0.9560
3.0	0.9641
0.0	0.0312
27.0	0.9559
27.0	0.9606
26.0	0.9511
2.0	0.9431
21.0	0.9451

- Once we finished with choosing which model best suits our needs I processed our data to get the results.
- I used F1 scores to identify and analyze how well and accurate my data was to see if any anomalies occurred in building my model
- Accuracy: Ratio of the correct labeled subjects to the whole pool of subjects
- Precision: Ratio of correctly positive labels by our program to all the positive labels
- Specificity: Ratio of the correctly negative labels by our program to all the documents who are positive in reality
- Misclassification: how often something is wrong



# Experimental Setup

- For this project we used the maldozer data set which contains 20090 separate malware of which 20040 was used.
- The data set contained 32 different malware.
- This data uncompressed was ~ 200 GB of human readable dex files.
- The framework that was used was Gensim.
  - This was used due to its superior multithreading capabilities and other tools such as using tf-idf.
- Hardware that was used i7-7700 @ 3.60 GHz
- 32 GB DDR4 @ 4000 MHz
- RTX 2080TI
- Based on the hardware it took me ~24h to process my models based on the whole dataset

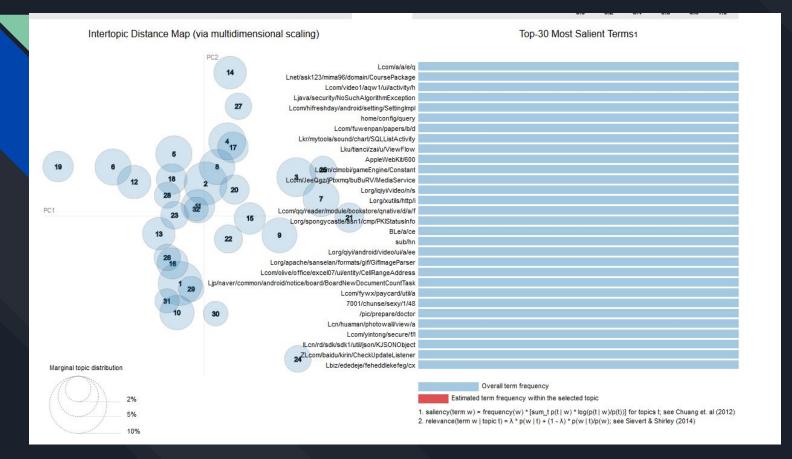
	Document_No	Dominant_Topic	Topic_Perc_Contri
0	0	23.0	0.9656
1	1	3.0	0.9590
2	2	0.0	0.0312
3	3	27.0	0.9530
4	4	15.0	0.9580
5	5	25.0	0.9169
6	6	0.0	0.0312
7	7	0.0	0.0312
8	8	22.0	0.9667
9	9	27.0	0.9209

Landroid/widget/ListAdapter, III.android/os/Bundle, s3/eu, II.com/duomi/superdj/logic/ay, Ligudi/com/ergushi/ap, Lframework/net/DownloadImgEventListener, /data/libr9umd, Lcom/tiqiaa/b/ah, ZCLjava/lang/String, Lbiz/edeiehe-befedeleieiei/bx

### Results

18750d3a30a52e508aa4a03t Adwo	fdada630e-
1874ed85ba7160d4b8002f6 SmsPay	82d8b3102-
1873ebb0538fc2656ea67aa9 FakeInst	3815dba6-
187347fd95d5675ac183f86f Adwo	84097896-
18732dd40714f304cfa8647f SMSReg	d4b2b020-
18648135b9a314e35920ddfi Dowgin	e28db4186-
185f1e54de7b139f56a65c4a FakeInst	8134b39a-
18546fd960ae37cb2d335a90 FakeInst	)8699c94c-
184ce6255faf70d13575784c Plankton	02ed8f52-
184c22371a693f0906f87474 Dowgin	101023a1-

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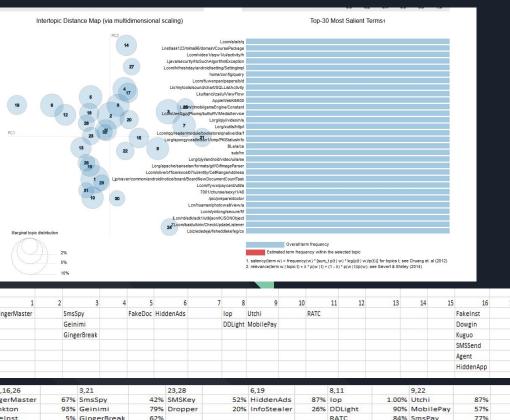


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22 36		127	21	21	69	28	4	6	6	12	4	26	13	16	7	13	10	5	3	1	26	2	40	7	2	1	10	2	1	3	4
23 91		26	9	17	48	5	0	2	0	22	4	28	8	10	4	21	1	8	2	5	12	7	21	3	5	8	6	0	3	7	9
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26 44		60	10	19	92	37	0	3	17	8	5	24	10	16	3	18	6	3	2	2	23	6	20	1	50	5	12	2	3	5	7
27 309	9	40	10	43	54	60	3	3	5	42	6	49	12	17	6	28	34	25	3	4	7	4	18	11	6	2	0	1	4	2	2
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1 1	06 2.526	0.166	2.041	2.137	4.284	2.475	NaN	2.817	3.944 3.597	2.781	2.015 5.253	0.943	2.036	1.278	2.262	2.857	1.818	1.015	1.538	2.314	1.724 0.880	NaN	1.186	3.738	3.883	1.538	3.846	6.250
2 3	50 2.850	0.270	2.332	3.028	1.346	9.406	1.115	1.174	3.944 2.158	4.474	2.519 3.002	3.774	4.525	3.195	1.810	2.857	1.818	3.044	0.769	2.828	4.310 0.880	NaN	2.767	2.336	4.854	1.026	2.885	6.250
3 0	36 2.720	0.187	1.603	2.760	0.367	NaN	3.717	1.643	0.563 3.237	1.814	2.771 2.439	6.604	3.167	0.958	1.810	2.143	3.636	0.830	NaN	2.057	5.172 10.557	NaN	1.976	3.738	7.767	1.026	2.885	NaN
4 1	09 7.254	0.311	4.519	4.497	6.732	15.842	1.115	1.878	1.408 2.158	2.660	3.275 4.503	0.943	3.620	3.514	0.905	10.000	5.455	1.015	4.615	3.213	1.724 2.053	NaN	1.976	1.869	NaN	0.513	4.808	4.861
5 1	73 1.490	0.104	1.458	2.894	1.102	1.980	0.743	4.225	1.408 0.719	2.781	4.282 3.377	1.887	1.357	1.917	2.715	11.429	3.636	1.015	3.077	2.442	3.448 0.880	NaN	0.791	2.804	0.971	0.513	4.808	1.389
6 3	85 2.526	0.270	2.770	2.182	0.734	0.495	0.743	23.709	2.817 0.719	2.056	3.275 1.689	3.774	1.584	1.597	7.240	NaN	NaN	1.661	3.077	2.571	1.724 2.639	NaN	0.395	9.346	1.942	1.538	1.923	2.083
7 0	03 1.425	0.104	0.729	2.004	0.245	NaN	0.372	0.704	2.817 0.719	1.814	2.015 2.251	1.887	1.131	0.958	1.357	2.857	0.909	0.369	NaN	1.542	0.862 1.173	NaN	NaN	0.935	NaN	1.538	1.923	2.083
8 4	25 2.137	0.228	4.227	2.404	1.836	NaN	1.115	2.817	2.817 0.719	2.781	3.275 1.689	2.830	5.204	2.556	4.977	2.143	3.636	1.015	NaN	1.799	3.448 2.346	0.291	0.395	4.206	4.854	1.538	6.731	0.694
9 2	45 2.979	0.270	2.187	3.651	1.102	1.485	3.717	1.174	3.380 2.158	4.595	4.786 1.876	3.774	4.977	1.917	3.620	NaN	4.545	1.845	2.308	3.856	2.586 0.587	NaN	0.791	2.336	2.913	2.051	4.808	7.639
10 4	23 1.360	0.270	2.478	2.449	4.284	5.941	1.487	1.643	1.972 2.878	3.023	2.771 1.313	1.887	1.810	2.236	NaN	1.429	2.727	0.461	3.077	1.414	4.310 0.293	NaN	NaN	2.804	1.942	1.538	3.846	NaN
11 6	71 2.267	0.228	0.875	2.182	0.490	0.990	NaN	1.408	3.380 NaN	4.353	2.267 2.439	1.887	1.584	3.834	1.810	11.429	9.091	1.292	NaN	1.285	0.862 2.053	NaN	0.791	4.206	1.942	NaN	1.923	2.083
12 1	73 1.619	0.166	1.895	1.870	0.734	1.485	0.372	0.704	2.535 1.439	3.265	3.526 1.501	0.943	2.941	0.319	0.452	5.714	1.818	0.923	1.538	1.799	2.586 0.587	NaN	NaN	0.467	0.971	0.513	0.962	2.083
13 1	73 1.813	0.228	0.729	1.825	0.734	4.455	0.743	0.469	2.817 0.360	2.902	2.267 1.876	NaN	2.715	1.917	2.715	2.143	1.818	1.199	NaN	1.799	0.862 4.692	NaN	0.791	0.935	0.971	1.026	3.846	NaN
14 5	61 2.267	0.270	4.956	3.740	1.836	0.495	0.743	3.052	3.380 0.360	3.023	1.763 2.627	2.830	4.977	1.278	7.240	2.857	4.545	2.306	2.308	2.571	2.586 0.587	0.291	0.791	2.336	2.913	NaN	3.846	2.083
15 1	05 1.684	0.187	1.312	1.647	0.612	0.495	0.372	0.469	4.225 NaN	3.628	3.526 2.251	0.943	1.584	1.917	1.357	3.571	1.818	0.738	1.538	2.314	1.724 4.985	NaN	0.395	0.467	0.971	NaN	1.923	2.083
16 3	87 5.959	0.726	5.539	8.816	1.591	7.426	2.230	6.573	7.042 0.360	5.562	4.282 5.066	3.774	9.502	1.917	2.715	3.571	3.636	5.351	2.308	6.170	1.724 3.519	0.291	1.581	13.084	2.913	1.538	1.923	2.083
17 2	81 2.720	0.104	2.041	1.915	0.122	NaN	1.115	4.225	1.127 0.360	2.297	2.267 1.689	1.887	1.357	1.917	0.905	1.429	1.818	1.292	3.077	2.314	2.586 0.293	NaN	NaN	2.336	NaN	0.513	NaN	3.472
<b>18</b> 0	03 1.425	0.166	1.749	1.469	1.469	8.911	NaN	0.235	1.408 0.360	1.693	2.771 1.313	2.830	1.357	1.278	0.905	2.857	3.636	1.199	3.077	2.314	1.724 0.293	NaN	0.395	NaN	0.971	2.051	0.962	4.167
19 2	79 4.987	0.353	2.332	3.651	1.714	0.495	1.487	0.235	2.817 0.719	4.111	3.023 1.876	0.943	1.810	2.556	3.620	6.429	0.909	1.292	0.769	2.057	6.034 1.466	NaN	4.743	2.336	1.942	NaN	2.885	4.861
<b>20</b> 0	71 2.526	0.228	2.187	2.093	0.979	NaN	2.230	0.704	1.972 NaN	2.660	3.526 3.189	NaN	3.846	1.917	2.262	0.714	NaN	1.384	2.308	2.314	2.586 0.880	NaN	0.791	0.467	1.942	0.513	0.962	1.389
21 8	43 2.267	0.270	1.895	2.671	1.346	29.703	3.346	0.704	5.070 4.317	3.265	4.030 2.814	2.830	5.656	6.070	3.620	1.429	3.636	1.199	3.077	2.057	6.897 13.783	NaN	NaN	1.869	5.825	1.538	1.923	0.694
<b>22</b> 2	13 8.225	0.436	3.061	3.072	3.427	1.980	2.230	1.408	3.380 1.439	3.144	3.275 3.002	6.604	2.941	3.195	2.262	2.143	0.909	2.399	1.538	5.141	6.034 0.587	0.291	0.395	4.673	1.942	0.513	2.885	2.778
23 6	99 1.684	0.187	2.478	2.137	0.612	NaN	0.743	NaN	6.197 1.439	3.386	2.015 1.876	3.774	4.751	0.319	3.620	1.429	4.545	1.107	5.385	2.699	2.586 1.466	NaN	3.162	2.804	NaN	1.538	6.731	6.250
24 0	02 7.189	0.270	3.061	1.915	0.122	NaN	2.602	23.239	0.845 1.439	2.056	1.259 1.313	2.830	2.262	2.236	3.167	2.143	NaN	1.661	0.769	4.370	0.862 0.587	0.291	1.581	7.009	NaN	1.538	0.962	0.694
25 1	44 1.231	0.145	0.875	2.404	1.224	NaN	0.372	0.235	1.127 0.360	2.056	2.771 2.251	1.887	1.357	1.597	1.810	3.571	1.818	0.554	1.538	2.185	4.310 0.587	NaN	1.581	1.402	1.942	NaN	5.769	2.083
<b>26</b> 2	49 3.886	0.207	2.770	4.096	4.529	NaN	1.115	3.991	2.254 1.799	2.902	2.519 3.002	2.830	4.072	1.917	1.357	1.429	1.818	2.122	4.615	2.571	0.862 14.663	NaN	1.976	5.607	1.942	1.538	4.808	4.861
<b>27</b> 2	710 2.591	0.207	6.268	2.404	7.344	1.485	1.115	1.174	11.831 2.158	5.925	3.023 3.189	5.660	6.335	10.863	11.312	2.143	3.636	0.646	3.077	2.314	9.483 1.760	NaN	0.791	NaN	0.971	2.051	1.923	1.389
<b>28</b> 2	11 1.101	0.207	4.082	2.093	0.857	1.485	2.974	1.174	1.127 0.360	2.177	2.771 2.439	4.717	2.489	0.639	1.810	0.714	2.727	1.107	0.769	2.442	3.448 0.880	NaN	NaN	2.804	2.913	2.564	0.962	1.389
29 1	73 6.088	0.166	5.394	1.781	31.334	NaN	1.859	NaN	3.662 2.158	3.265	1.763 1.876	4.717	2.036	1.278	3.620	2.143	7.273	1.015	3.077	2.314	2.586 1.466	NaN	0.395	NaN	4.854	0.513	1.923	1.389
30 1	75 1.878	0.270	9.767	2.093	9.670	0.990	1.487	NaN	1.690 NaN	2.781	3.275 1.501	3.774	2.262	2.236	1.810	2.143	1.818	1.661	0.769	2.057	3.448 5.279	NaN	NaN	1.402	2.913	NaN	3.846	1.389
31 1	75 2.461	0.145	1.749	1.870	0.490	0.495	0.372	0.469	3.099 0.360	1.330	3.275 0.938	0.943	1.584	1.597	1.357	2.857	NaN	0.830	2.308	2.828	NaN 6.158	NaN	NaN	0.935	0.971	1.538	0.962	NaN

0	1	2	3	4	5 6	7		В	9 1	.0	11	12	1	3	14	15	16	17	18	1	9	20	21	22	23	24	25 2	5 2	7 28	29	30
(	ingerMaster	SmsSpy		FakeDo	c HiddenAds	le le	ор	Utchi		RATC						F	akelnst		In	foSteale	er	AppQu	anta Sn	msPay :	SMSKey		BaseBridge	Adwo	Dropper		SMSReg
		Geinimi				0	DLigh	t MobilePa	y							[	owgin					FakeA	op					Youmi			
		GingerBrea	<													K	uguo											Wapsx			
																S	MSSend											DroidKungFu	1		
																A	gent											Kmin			
																H	HiddenApp											Mseg			
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Topic_Perc_Contr	ib		Precision	Recall	F1_Score	Accuracy	Specificity	Misclassificatio
0.9656		Adwo	0.9871	0.7702	0.8652	0.9363	0.9964	0.0637
0.9590		SmsPay	0.8898	0.2534	0.3944	0.7753	0.9872	0.2247
0.0312		FakeInst	0.8000	0.0061	0.0121	0.0525	0.9698	0.9475
0.9530		SMSReg	0.9403	0.3580	0.5185	0.8294	0.9922	0.1706
0.9580		Dowgin	0.9646	0.3032	0.4614	0.8014	0.9957	0.1986
0.9169		Plankton	0.9844	0.8182	0.8936	0.9266	0.9921	0.0734
0.0312		AppQuant				201000000000000000000000000000000000000	1.0000	0.0149
( ( ( ( ( ( ( ( ( ( ( ( ( ( ( ( ( ( (		SmsSpy	1.0000				1.0000	0.5799
0.0312		HiddenAd				Contract of the Contract of th	0.9928	0.1221
0.9667		Youmi	0.9048				0.9850	0.1549
0.9209		FakeApp	0.9167				0.9885	0.6511
0.7875		Wapsx	0.9184	0.3261		Control of the Contro	0.9942	0.1173
0.0312		Utchi	0.9474				0.9970	0.1209
0.9402		GingerMast		0.1407			1.0000	0.3208
0.9054		Geinimi	0.8571				0.9873	0.2075
<u> </u>		Kuguo	0.9524		0.7339		0.9947	0.0656
0.0312		DroidKungI					1.0000	0.3642
0.9135		Kmin	0.9600			100000000000000000000000000000000000000	0.9942	0.1222
0.0312		FakeDoc	1.0000				1.0000	0.0571
0.0312		RATC	1.0000	0.3571		120000000000000000000000000000000000000	1.0000	0.1636
0.9705		SMSSend	0.9483				0.9922	0.5959
0.0312		SMSKey	0.8571	0.0896			0.9841	0.4769
0.9560		Agent	0.8333			TO A TOP OF THE PARTY OF THE PA	0.9833	0.3419
		Mseg	1.0000				1.0000	0.0603
0.9641		BaseBridge					0.9960	0.1349
0.0312		Iop I Common	1.0000				1.0000	0.9855
0.9559		InfoStealer		0.0606			1.0000	0.7352
0.9606		HiddenApp				100000000000000000000000000000000000000	1.0000	0.1355
0.9511		GingerBrea	0.6000	0.1556			0.9828	0.3786
0.9431		Dropper DDLight	1.0000				1.0000	0.8000
0.9451		MobilePay	0.6364	0.4118		7.7345.000	0.9500	0.4236
0.5451		MobilePay	0.0304	0.1094	V.100/	0.2704	0.7000	0.4230



0 1	2	3	4	5	6	5	7	8	9	10	11	12	13	14	15	5 16	17	18	19	20	21	2	23	24	25	26	27	2	8 :	29 30	
GingerMaster	SmsS	ру	Fak	keDoc H	iddenAds		lop	Utchi		RATO						FakeInst		InfoSte	eler		AppQuanta	SmsPay	SMSKey			BaseBridge	Adwo	Dropper	Plankto	on SMSReg	
	Gein	imi					DDLigh	ht Mobi	lePay							Dowgin					FakeApp						Youmi				
	Ginge	erBreak														Kuguo											Wapsx				Г
																SMSSend											DroidKungFu				
																Agent											Kmin				
																HiddenApp											Mseg				
1,29,16,26		3,21			23,28			6,1	9		8,11			9,22						2	3		5			2	27		30	0	٩
GingerMaster		SmsSpy	,	429	% SMSK		52		idenAds	87	% lop		1.00%		i	87%			SMS	SKey		52%	FakeDoc		4% Ac				Reg		6
Plankton		Geinim			% Drop				oSteale		% DDI				ilePay									_		oumi	84				
FakeInst	5%	Ginger	Break	629							RAT	c	84%	Sms	Pay	77%									W	apsx	88	96			T
Dowgin	80%	AppQua	anta	989	%																				Dr	roidKungF	u 64	%			
Kuguo	93%	FakeAp	р	359	%																				Kr	min	87	96			
SMSSend	40%																								M	seg	93	%			
Agent	66%																														
HiddenApp	86%																														Ш
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Kuguo		Ginger	Break																						W	apsx					
HiddenApp																									Kr	min					
BaseBridge																									M	seg					$\perp$



In the end i do believe that my models has shown for some of the malware success in clustering different types into families but overall i did feel like there was some limitation,

- Thing I could improve is using a much larger data set where types of malware are equally distributed.
- Using different types of N-Grams to try to form a more holistic model.
- Using different aspects of the Dex file such as the assembly or meta data.
- For the future I can take this model as a precursor for a larger scale framework which is designed to identify malware