Comp: Please increase the point size of the Listing Heads to make them stand out more.

Au: Please check the following:
*chapter cross-refs (highlighted)
*The light grey code is italic in the other chapters. In Chap.3 it is not. Should it be italic here?
If so, Global all to be italic?
*Code listings have been marked to move lines of code so that there are no lines spaces at the bottom of a page where they are not obvious.

AR: XREFs checked & OK
AR: code should be italic; should i change that?
AR: code listings: ACK; thx

3

Learning the "Hello World" of Security Data Analysis

delete em dash (consistency)

"From one thing, know ten thousand things."

—Miyamoto Musashi, ***The Book of Five Rings***

If you've ever tried to learn a new programming language there's a good chance you started off with a "Hello World" example that quickly introduces basic language structure and code execution. The immediate sense of accomplishment as the syntax is verified by the compiler/interpreter and the familiar two-word output is displayed becomes a catalyst for the notion that, soon, you shall have the ability to bend this new language to your will.

This chapter takes the "Hello World" concept and expands it to a walk-through of a self-contained, introductory security data analysis use case that you will be able to follow along with, execute, and take concepts from as you start to perform your own analyses. There are parallel examples in Python and R to provide a somewhat agnostic view of the similarities, strengths, and differences between both languages in a real-life data analysis context. If you're not familiar with one or both of those languages, you should read Chapter 2 and at least skim some of the external resources referenced there.

AR:VERIFIED REF

This is a good place to reinforce the recommendation to use IPython Notebooks or RStudio for your analyses and exploration as they provide very robust and forgiving environments, which means you will be much more productive compared to the alternative of writing, saving, and executing scripts within the bare interpreter shells. Remember, all the source code, sample data, and visualizations are on the book's website (`www.wiley.com/go/datadrivensecurity`), so there's no need for transcription. You can just cut/paste and focus on the flow and concepts presented in the examples. Listings 3-0 and 3-1 provide you with the setup code for this chapter.

because / ? / delete: is / ?

AR: "because" would work instead of "as"

LISTING 3-0

```
# This is for the R code in the chapter
# set working directory to chapter location
# (change for where you set up files in ch 2)
setwd("~/book/ch03")
# make sure the packages for this chapter
# are installed, install if necessary
pkg <- c("ggplot2", "scales", "maptools",
         "sp", "maps", "grid", "car" )
new.pkg <- pkg[!(pkg %in% installed.packages())]
if (length(new.pkg)) {
  install.packages(new.pkg)
}
```

LISTING 3-1

```
# This is for the Python code in the chapter
# loads the necessary Python library for chdir
import os
# set working directory to chapter location
# (change for where you set up files in ch 2)
os.chdir(os.path.expanduser("~") + "/book/ch03")
```

Solving a Problem

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Chapter 1 emphasized the criticality of developing a solid research question before going off and "playing with data." For this "Hello World" example, you are working on a problem given to you by the manager

of the Security Operations Center (SOC). It seems the SOC analysts are becoming inundated with "trivial" alerts ever since a new data set of indicators was introduced into the Security Information and Event Management (SIEM) system. They have asked for your help in reducing the number of "trivial" alerts without sacrificing visibility.

This is a good problem to tackle through data analysis, and we should be able to form a solid, practical question to ask after we perform some exploratory data analysis and hopefully arrive at an answer that helps out the SOC.

Getting Data

We are entering the age of data in information security. The challenge is no longer where to get data from, but what to do with it. And, the kind of information in each data set will drive the type of research you perform.

For this example, the SOC chose to integrate AlienVault's IP Reputation Database (`http://labs.alienvault.com/labs/index.php/projects/open-source-ip-reputation-portal/download-ip-reputation-database/`) into the SIEM. AlienVault itself develops OSSIM—an open source security information manager—and a proprietary unified security management (USM) product, both of which make use of this freely available data set that contains information on various types of "badness" across the Internet. AlienVault provides this data in numerous formats free of charge. The version you work with is the OSSIM Format (`http://reputation.alienvault.com/reputation.data`) since it provides the richest information of all the available formats.

lc / ? (style sheet) / rebreak

rebreak

> ***Note***
>
> *AlienVault updates their IP reputation data set hourly and produces a companion "revision" file (`http://reputation.alienvault.com/reputation.rev`), enabling you to ensure you are working with the latest data set or keep a history of data sets. If you plan on performing a long term analysis of this data set—often referred to as a* longitudinal study*—it's a good idea to script some code to perform this check to see if it's time to download a new one, even in scheduled jobs.*

Au: monofont not italic /

AR: I don't thin we were the ones who made it italic. Keep it consistent w/InlineURL pls.

When performing an exploratory analysis or getting a first look at a data set, you might find it helpful to perform an initial download via browser (or use `wget`/`curl` if you are handy on the command line). The AlienVault database hovers near 16MB, so it may take a minute or two to download on slower connections. When you download the AlienVault IP reputation database and examine the first few data elements, you can get an idea of the contents and format, which will come in handy when you start to read in and work with the data. In the following code, you use some simple Linux/UNIX commands to inspect the download:

Cap

```
$ head -10 reputation.data # look at the first few lines in the file
222.76.212.189#4#2#Scanning Host#CN#Xiamen#24.479799270,118.08190155#11
222.76.212.185#4#2#Scanning Host#CN#Xiamen#24.479799270,118.08190155#11
222.76.212.186#4#2#Scanning Host#CN#Xiamen#24.479799270,118.08190155#11
5.34.246.67#6#3#Spamming#US##38.0,-97.0#12
```

```
178.94.97.176#4#5#Scanning Host#UA#Merefa#49.823001861,36.0507011414#11
66.2.49.232#4#2#Scanning Host#US#Union City#37.59629821,-122.0656966#11
222.76.212.173#4#2#Scanning Host#CN#Xiamen#24.479799270,118.08190155#11
222.76.212.172#4#2#Scanning Host#CN#Xiamen#24.479799270,118.08190155#11
222.76.212.171#4#2#Scanning Host#CN#Xiamen#24.479799270,118.08190155#11
174.142.46.19#6#3#Spamming###24.4797992706,118.08190155#12
```

Comp: CodeColorRed2Bold

```
$ wc -l reputation.data # see how many total records there are
  258626 reputation.data
```

For most projects, it's better to get into the habit of retrieving the data source directly from your analysis scripts. If you still prefer to download files manually you should provide some type of comment in your programs that provides details about where the source data comes from and when you retrieved the data for your current analysis. These comments make it easier to repeat the analyses at a later date, and trust us, you'll revisit your code and analyses more often than you think.

The following examples (Listings 3-2 and 3-3) show how to perform the data retrieval in both R and Python. If you are following along with RStudio or IPython, all the code examples assume a working directory of the top level of the project structure (such as executing in the `book/ch03` directory that was suggested in Chapter 2, which you either manually created or created using the `prep` script we provided). Code blocks are, for the most part, self-contained, but each block expects this first snippet and the snippet in the next section on "Reading in Data" to have been executed in the running RStudio or IPython session.

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LISTING 3-2

```
# URL for the AlienVault IP Reputation Database (OSSIM format)
# storing the URL in a variable makes it easier to modify later
# if it changes. NOTE: we are using a specific version of the data
# in these examples, so we are pulling it from an alternate
# book-specific location.
avURL <-
  "http://datadrivensecurity.info/book/ch03/data/reputation.data"

# use relative path for the downloaded data
avRep <- "data/reputation.data"

# using an if{}-wrapped test with download.file() vs read.xxx()
# directly avoids having to re-download a 16MB file every time
# we run the script
if (file.access(avRep)) {
  download.file(avURL, avRep)
}
## trying URL 'http://datadrivensecurity…/ch03/data/reputation.data'
## Content type 'application/octet-stream' length 17668227 bytes
## opened URL
## ==================================================
## downloaded 16.8 Mb
```

LISTING 3-3

```
# URL for the AlienVault IP Reputation Database (OSSIM format)
# storing the URL in a variable makes it easier to modify later
# if it changes. NOTE: we are using a specific version of the data
# in these examples, so we are pulling it from an alternate
# book-specific location.
import urllib
import os.path

avURL = "http://datadrivensecurity.info/book/ch03/data/reputation.data"

# relative path for the downloaded data
avRep = "data/reputation.data"

# using an if-wrapped test with urllib.urlretrieve() vs direct read
# via panads avoids having to re-download a 16MB file every time we
# run the script
if not os.path.isfile(avRep):
    urllib.urlretrieve(avURL, filename=avRep)
```

The R and Python code looks very similar and follow the same basic structure: using variables whenever possible for URL and filenames plus testing for the existence of the data file before downloading it again. These are good habits to get into and we'll be underscoring other suggested good practices throughout the rest of the book.

With the IP reputation data in hand, it's now time to read in the data so you can begin to work with it.

Reading In Data

R and Python (especially with pandas) abstract quite a bit of complexity when it comes to reading and parsing data into structures for processing. R's `read.table()`, `read.csv()`, and `read.delim()` functions and pandas' `read_csv()` function cover nearly all your delimited file-reading needs and provide robust configuration options for even the most gnarly input file. Both tools, as you learn in later chapters, also provide ways to retrieve data from SQL and NoSQL databases, HDFS "big data" setups, and even handle unstructured data quite well.

AR:VERIFIED

The Revolution Will Be Properly Delimited!

Base R and Python's pandas package both excel at reading in delimited files. Although they are also both agnostic when it comes to what that delimiter is, there is a general acceptance in the data science community that it should be either a comma-separated value (CSV) or a tab-separated value (TSV), and the majority of the sample data sets available to practice with come in one of those two flavors. The CSV format is thoroughly defined in RFC 4180 (`http://www.rfc-editor.org/rfc/rfc4180.txt`) and has the following high-level attributes:

apostrophe

- There should only be one record per line.
- Data files can include an optional header line.

Comp: Insert thin rule - underneath put *(continues)*

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Insert thin rule above and put the continued line above it.

(Continued)

- Header and data rows have fields separated by commas (or tabs).
- Each line should have the same number of fields.
- Spaces in fields should be treated as significant.

Though RFC 4180 explicitly specifies the comma as the separator, the same rules apply when using tabs (there is no corresponding RFC for tab-separated files).

Many tools in the security domain can import and export CSV-formatted files. If you intend to do any work in environments like Hadoop, you have to become familiar with CSV/TSV.

Another established format is JSON (JavaScript Object Notation), which has grown to become the preferred way to transport data between servers and browsers. As you'll see in Chapter 8, it is also the foundational data format behind many NoSQL database environments/tools. The JSON format is defined in RFC 4627 (`http://www.rfc-editor.org/rfc/rfc4627.txt`) and has two primary structures:

AR: VERIFIED REF

- A collection of name/value pairs (a "dictionary")
- An ordered list of values (an "array")

JSON enables richer and more complex data representation than CSV/TSV and is rapidly superseding another popular, structured format—the Extensible Markup Language (XML)—as the preferred ***data exchange*** representation. This is because it's syntactically less verbose, much easier to parse, and (usually) more readable. XML has and will continue to excel at document representation, but you should strongly consider using JSON for your structured data-processing needs.

From a cursory examination of the downloaded file, you can see the AlienVault data has a fairly straightforward record format with eight primary fields using a # as the field separator/delimiter.

```
222.76.212.189#4#2#Scanning Host#CN#Xiamen#24.479799270,118.08190155#11
```

Notice also that the reputation data file lacks the optional header, so the example code segment assigns more meaningful column names manually. This is a completely optional step, but it helps avoid confusion as you expand your analyses and, as you see in later chapters, helps build consistency across data frames if you bring in additional data sets.

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The consistency in the record format makes the consumption of the data equally as straightforward in each language. In each language/environment, we follow a typical pattern of:

- Reading in data
- Assigning meaningful column names (if necessary)
- Using built-in functions to get an overview of the structure of the data
- Taking a look at the first few rows of data, typically with the `head()` function

that we'll cover in more detail in Chapter 4.

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The code that follows (Listings 3-4 and 3-5) builds on the code from the previous section. It won't work correctly otherwise. This is the pattern we will follow in the book, so you should load and run the code in each chapter sequentially.

LISTING 3-4

```
# read in the IP reputation db into a data frame
# this data file has no header, so set header=FALSE
av <- read.csv(avRep,sep="#", header=FALSE)

# assign more readable column names since we didn't pick
# any up from the header
colnames(av) <- c("IP", "Reliability", "Risk", "Type",
                  "Country", "Locale", "Coords", "x")

str(av) # get an overview of the data frame
## 'data.frame': 258626 obs. of  8 variables:
## $ IP : Factor w/ 258626 levels "1.0.232.167",..: 154069 154065
##    154066 171110 64223 197880 154052 154051 154050 56741 ...
## $ Reliability: int 4 4 4 6 4 4 4 4 4 6 ...
## $ Risk : int 2 2 2 3 5 2 2 2 2 3 ...
## $ Type : Factor w/ 34 levels "APT;Malware Domain",..: 25 25 25 31 25
##    25 25 25 25 31 ...
## $ Country : Factor w/ 153 levels "","A1","A2","AE",..: 34 34 34 143
##    141 143 34 34 34 1 ...
## $ Locale : Factor w/ 2573 levels "","Aachen","Aarhus",..: 2506 2506
##    2506 1 1374 2342 2506 2506 2506 1 ...
## $ Coords : Factor w/ 3140 levels "-0.139500007033,98.1859970093",..:
##    489 489 489 1426 2676 1384 489 489 489 489 ...
## $ x : Factor w/ 34 levels "11","11;12","11;2",..: 1 1 1 7 1 1 1 1 1
##    7 ...

head(av) # take a quick look at the first few rows of data
##               IP Reliability Risk          Type Country     Locale
## 1 222.76.212.189           4    2 Scanning Host      CN     Xiamen
## 2 222.76.212.185           4    2 Scanning Host      CN     Xiamen
## 3 222.76.212.186           4    2 Scanning Host      CN     Xiamen
## 4    5.34.246.67           6    3      Spamming      US
## 5  178.94.97.176           4    5 Scanning Host      UA     Merefa
## 6    66.2.49.232           4    2 Scanning Host      US Union City
##                        Coords  x
## 1   24.4797992706,118.08190155 11
## 2   24.4797992706,118.08190155 11
## 3   24.4797992706,118.08190155 11
## 4                 38.0,-97.0 12
## 5  49.8230018616,36.0507011414 11
## 6 37.5962982178,-122.065696716 11
```

Au: check if the ##s should be CodeHighlight as in Listing 3-5.

AR: Yes. All code lines beginning with a double "##" should have the darker color

LISTING 3-5

```
# first time using the pandas library so we need to import it
import pandas as pd
# read in the data into a pandas data frame
av = pd.read_csv(avRep,sep="#")
# make smarter column names
av.columns = ["IP","Reliability","Risk","Type","Country",
              "Locale","Coords","x"]
print(av) # take a quick look at the data structure
## <class 'pandas.core.frame.DataFrame'>
## Int64Index: 258626 entries, 0 to 258625
## Data columns (total 8 columns):
## IP             258626  non-null values
## Reliability    258626  non-null values
## Risk           258626  non-null values
## Type           258626  non-null values
## Country        248571  non-null values
## Locale         184556  non-null values
## Coords         258626  non-null values
## x              258626  non-null values
## dtypes: int64(2), object(6)

# take a look at the first 10 rows
av.head().to_csv(sys.stdout)
## ,IP,Reliability,Risk,Type,Country,Locale,Coords,x
## 0,222.76.212.189,4,2,Scanning Host,CN,Xiamen,"24.4797992706,
## 118.08190155",11
## 1,222.76.212.185,4,2,Scanning Host,CN,Xiamen,"24.4797992706,
## 118.08190155",11
## 2,222.76.212.186,4,2,Scanning Host,CN,Xiamen,"24.4797992706,
## 118.08190155",11
## 3,5.34.246.67,6,3,Spamming,US,,"38.0,-97.0",12
## 4,178.94.97.176,4,5,Scanning Host,UA,Merefa,"49.8230018616,
## 36.0507011414",11
```

Within Canopy, IPython has a set of functions to output data to a more viewer-friendly HTML format (see Listing 3-6) that can be used to make the `head()` output in Listing 3-5 much easier to read (see Figure 3-1).

LISTING 3-6

```
# require object: av (3-5)
# See corresponding output in Figure 3-1
# import the capability to display Python objects as formatted HTML
from IPython.display import HTML
# display the first 10 lines of the dataframe as formatted HTML
HTML(av.head(10).to_html())
```

	IP	Reliability	Risk	Type	Country	Locale	Coords	x
0	222.76.212.189	4	2	Scanning Host	CN	Xiamen	24.4797992706,118.08190155	11
1	222.76.212.185	4	2	Scanning Host	CN	Xiamen	24.4797992706,118.08190155	11
2	222.76.212.186	4	2	Scanning Host	CN	Xiamen	24.4797992706,118.08190155	11
3	5.34.246.67	6	3	Spamming	US	NaN	38.0,-97.0	12
4	178.94.97.176	4	5	Scanning Host	UA	Merefa	49.8230018616,36.0507011414	11
5	66.2.49.232	4	2	Scanning Host	US	Union City	37.5962982178,-122.065696716	11
6	222.76.212.173	4	2	Scanning Host	CN	Xiamen	24.4797992706,118.08190155	11
7	222.76.212.172	4	2	Scanning Host	CN	Xiamen	24.4797992706,118.08190155	11
8	222.76.212.171	4	2	Scanning Host	CN	Xiamen	24.4797992706,118.08190155	11
9	174.142.46.19	6	3	Spamming	NaN	NaN	24.4797992706,118.08190155	12

Text

FIGURE 3-1 *IPython HTML head() output*

Exploring Data

Now that you have a general idea of the variables and how they look, it's time to bring your security domain expertise into the mix to explore and discover what is interesting about the data. This will enable you to form good questions to ask and answer. Despite having almost 260,000 records, you have many tools at your disposal to help get a feel for what it contains.

Before going any deeper into the data, however, there are some tidbits of information you know about the data, so we will summarize them here:

- `Reliability`, `Risk`, and `x` are ***integers***.
- `IP`, `Type`, `Country`, `Locale`, and `Coords` are ***character strings***.
- The IP address is stored in the dotted-quad notation, not in hostnames or decimal format.
- Each record is associated with a unique IP address, so there are 258,626 IP addresses (in this download).
- Each IP address has been geo-located into the latitude and longitude pair in the `Coords` field, but they are in a single field separated by a comma. You will have to parse that further if you want to use that field.

When you have quantitative variables (which is a fancy way to say "numbers representing a quantity"), a good first exploratory step is to look at the basic ***descriptive statistics*** on the variables. These are comprised of the following:

- ***Minimum*** and ***maximum*** values; taking the difference of these will give you the ***range*** (***range*** = ***max*** - ***min***)
- ***Median*** (the value at the middle of the data set)
- ***First*** and ***third quartiles*** (the 25th and 75th percentiles, or you could think of it as the median value of the first and last halves of the data, respectively)
- ***Mean*** (sum of all values divided by the number of count)

rebreak

You may see the min, max, median, and quartiles referred to as the ***five number summary*** of a data set (as developed by Tukey), and both languages have built-in functions to calculate them—`summary()` in R and `describe()` in Python— along with the mean. Take a look at the summary on the two primary numeric columns: `Reliability` and `Risk` (Listings 3-7 and 3-8).

LISTING 3-7

```
# require object: av (3-4)
summary(av$Reliability)
## Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 1.000   2.000   2.000   2.798   4.000  10.000

summary(av$Risk)
## Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 1.000   2.000   2.000   2.221   2.000   7.000
```

LISTING 3-8

```
# require object: av (3-5)
av['Reliability'].describe()
## count    258626.000000
## mean          2.798040
## std           1.130419
## min           1.000000
## 25%           2.000000
## 50%           2.000000
## 75%           4.000000
## max          10.000000
## Length: 8, dtype: float64

av['Risk'].describe()
## count    258626.000000
## mean          2.221362
## std           0.531571
## min           1.000000
## 25%           2.000000
## 50%           2.000000
## 75%           2.000000
## max           7.000000
## Length: 8, dtype: float64
```

As you look at these results, note that the `Reliability` column spreads across the ***documented*** potential range of [1…10] (Slide 10 of `http://www.slideshare.net/alienvault/building-an-ip-reputation-engine-tracking-the-miscreants`), but the `Risk` column—which AlienVault says has a documented potential range of [1…10]—only has a spread of [1…7]. You can also see that both `Risk` and `Reliability` appear to center on a value of 2.

rebreak & delete hyphen

You can now dig a bit deeper and use the fact that the `Reliability`, `Risk`, `Type`, and `Country` fields can be used together to define data set categories. Even though we just treated `Reliability`

and `Risk` as numbers, they actually are ordinal, meaning each entry is assigned an integer and a value of 4 is not necessarily twice the Reliability or Risk of 2. It only means that Reliability or Risk that is scored 4 is higher than that scored 2. In other words, the number is has more meaning as a label than a measurement. Categorical data may also be referred to as ***nominal values***, ***factors***, or in some cases, ***qualitative variables***.

comma

delete: is

Isn't "Data" Just "Data"?

You may be used to treating data holistically, thinking that the contents of a log file or database extract is just, well, ***data***. If you're used to working with data in spreadsheet form (like Microsoft Excel), you aren't really encouraged to think of it any other way. Individual data elements can, however, be broken down into two broad categories: ***quantitative*** and ***qualitative***. Quantitative data elements represent actual quantities whereas qualitative (or ***categorical***) data elements are more descriptive in nature.

TCP or UDP port numbers may be numeric, but they don't actually represent a quantity; they are just parts of a category, in this case numerically named entities. Port "22" is not truly greater or less port "7070." Conversely, "number of bytes transferred" or "number of infected hosts" represents actual quantities that can be compared numerically.

Categorical data is easily manipulated in R as `factors` and in Python as a pandas `Categorical` class. In fact, both R and Python have extensive functions that allow you to group, split, extract, and perform analysis on and with factors. You can see in Listing 3-4 that R made a correct educated guess that `IP`, `Type`, `Country`, and `Locale` were all categorical in nature as it scanned through the AlienVault IP reputation data file. Country names and malware types are easily identified as just classifications (***nominal*** data in statistics terms). You can also see that R did ***not*** properly recognize that `Reliability` and `Risk` were both qualitative in nature. Even though there is a meaningful sequence to them—risk level "5" is greater than "1"—the numeric, ***ordinal*** arrangement is not expressing quantity (that is, you should not try to calculate the mean of the `Risk` values or subtract one `Risk` value from another).

apostrophe

Within R, the difference between the two is automatically handled by the `summary()` function (Listing 3-9), and it displays the count for each category. This doesn't work on the quantitative variables though. In order to get a count of those, you can use the `table()` function if there are not too many unique values in the variable. Within Python, you can create a short function that leverages pandas to convert a data frame column (which is just an array) into a very appropriately named `Categorical` object (Listing 3-10), which you can tweak a bit to give you similar helpful output.

Listing 3-9

```
# require object: av (3-4)
table(av$Reliability)
## 1         2      3      4      5      6      7      8      9
## 5612 149117  10892  87040      7   4758    297     21    686
##  10
## 196
```

Comp: Move this line of code and the line of space beneath it to the top of the next page (page 50).

(continues)

Listing 3-9 *(continued)*

```
table(av$Risk)
## 1       2      3      4      5      6      7
## 39 213852  33719   9588   1328     90     10

# summary sorts by the counts by default
# maxsum sets how many factors to display
summary(av$Type, maxsum=10)
##                 Scanning Host                Malware Domain
##                        234180                          9274
##                    Malware IP                Malicious Host
##                          6470                          3770
##                      Spamming                           C&C
##                          3487                           610
## Scanning Host;Malicious Host    Malware Domain;Malware IP
##                           215                           173
## Malicious Host;Scanning Host                     (Other)
##                           163                           284

summary(av$Country, maxsum=40)
##      CN      US      TR      RU      DE      NL      RO      GB
##   68583   50387   13958   10055    9953    7931    6346    6293
##      IN      FR      TW      BR      UA      RO      KR      CA
##    5480    5449    4399    3811    3443    3274    3101    3051
##      AR      MX      TH      IT      HK      ES      CL      AE
##    3046    3039    2572    2448    2361    1929    1896    1827
##      JP      HU      PL      VE      EG      ID      RS      PK
##    1811    1636    1610    1589    1452    1378    1323    1309
##      VN      LV      NO      CZ      BG      SG      IR (Other)
##    1203    1056     958     928     871     868     866   15136
```

Au: country / ?

LISTING 3-10

```
# require object: av (3-5)
# factor_col(col)
#
# helper function to mimic R's "summary()" function
# for pandas "columns" (which are really just Python arrays)

def factor_col(col):
    factor = pd.Categorical.from_array(col)
    return pd.value_counts(factor,sort=True).reindex(factor.levels)

rel_ct = pd.value_counts(av['Reliability'])
risk_ct = pd.value_counts(av['Risk'])
type_ct = pd.value_counts(av['Type'])
country_ct = pd.value_counts(av['Country'])
```

Comp: Move this line of code and the line of space beneath it to the top of the next page (page 51).

```
print factor_col(av['Reliability'])
## 1       5612
## 2     149117
## 3      10892
## 4      87040
## 5          7
## 6       4758
## 7        297
## 8         21
## 9        686
## 10       196
## Length: 10, dtype: int64

print factor_col(av['Risk'])
## 1        39
## 2    213852
## 3     33719
## 4      9588
## 5      1328
## 6        90
## 7        10
## Length: 7, dtype: int64

print factor_col(av['Type']).head(n=10)
## APT;Malware Domain                  1
## C&C                               610
## C&C;Malware Domain                 31
## C&C;Malware IP                     20
## C&C;Scanning Host                   7
## Malicious Host                   3770
## Malicious Host;Malware Domain       4
## Malicious Host;Malware IP           2
## Malicious Host;Scanning Host      163
## Malware Domain                   9274
## Length: 10, dtype: int64

print factor_col(av['Country']).head(n=10)
## A1     267
## A2       2
## AE    1827
## AL       4
## AM       6
## AN       3
## AO     256
## AR    3046
## AT      51
```

Comp: Can these lines of code fit on the previous page?
If not, need continued Listing.

```
## AU     155
## Length: 10, dtype: int64
```

oftentimes

Risk (monofont), and Reliability (monofont)

These numerical tables help you get a general view of the data, but a graph of the distribution of the data has the potential to provide a whole new perspective, often times giving insights that numbers alone cannot reveal. We start with a simple bar chart to get a very quick visual overview of the `Country`, `Reliability`, and `Risk` factors (see Figures 3-2 through 3-4, respectively). You'll need to execute each R code listing individually (Listings 3-11, 3-12, and 3-13) to see each graph.

LISTING 3-11

```
# require object: av (3-4)
# We need to load the ggplot2 library to make the graphs
# See corresponding output in Figure 3-2
# NOTE: Graphing the data shows there are a number of entries without
#       a corresponding country code, hence the blank entry
library(ggplot2)

# Bar graph of counts (sorted) by Country (top 20)
# get the top 20 countries' names
country.top20 <- names(summary(av$Country))[1:20]
# give ggplot a subset of our data (the top 20 countries)
# map the x value to a sorted count of country
gg <- ggplot(data=subset(av,Country %in% country.top20),
             aes(x=reorder(Country, Country, length)))
# tell ggplot we want a bar chart
gg <- gg + geom_bar(fill="#000099")
# ensure we have decent labels
gg <- gg + labs(title="Country Counts", x="Country", y="Count")
# rotate the chart to make this one more readable
gg <- gg + coord_flip()
# remove "chart junk"
gg <- gg + theme(panel.grid=element_blank(),
                 panel.background=element_blank())
# display the image
print(gg)
```

LISTING 3-12

```
# requires packages: ggplot2
# require object: av (3-4)
# See corresponding output in Figure 3-3
# Bar graph of counts by Risk
gg <- ggplot(data=av, aes(x=Risk))
gg <- gg + geom_bar(fill="#000099")
# force an X scale to be just the limits of the data
# and to be discrete vs continuous
gg <- gg + scale_x_discrete(limits=seq(max(av$Risk)))
```

Comp: Can these lines of code move to the previous page?

```
gg <- gg + labs(title="'Risk' Counts", x="Risk Score", y="Count")
gg <- gg + theme(panel.grid=element_blank(),
                 panel.background=element_blank())
print(gg)
```

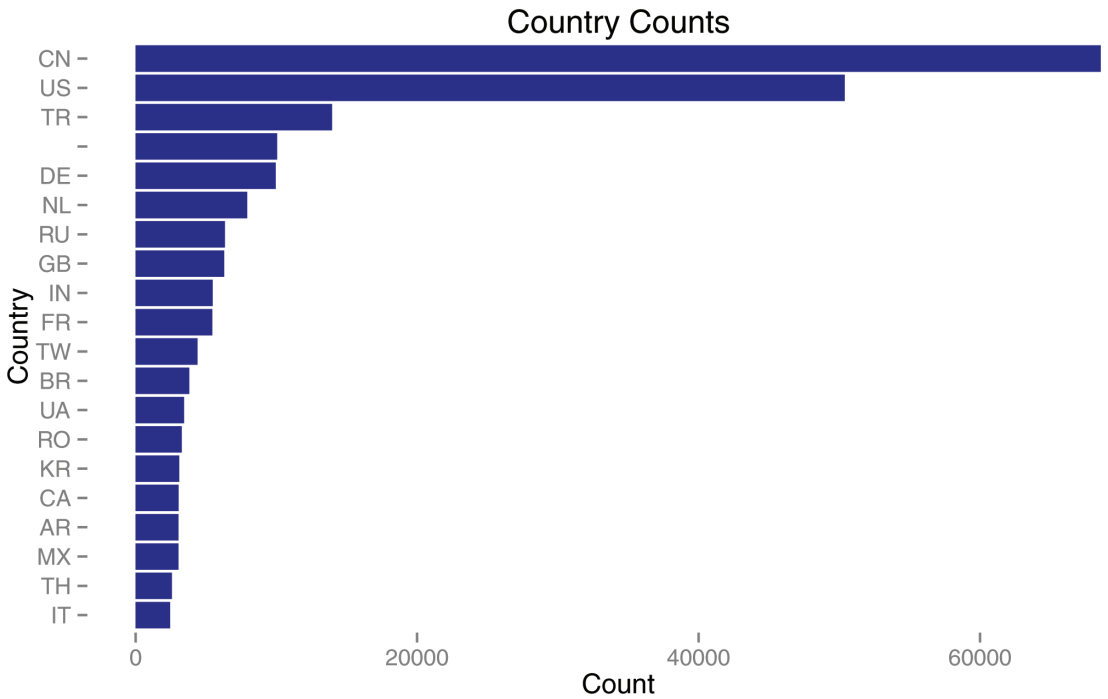


FIGURE 3-2 *Country factor bar chart (R)*

LISTING 3-13

```
# requires packages: ggplot2
# require object: av (3-4)
# See corresponding output in Figure 3-4
# Bar graph of counts by Reliability
gg <- ggplot(data=av, aes(x=Reliability))
gg <- gg + geom_bar(fill="#000099")
gg <- gg + scale_x_discrete(limits=seq(max(av$Reliability)))
gg <- gg + labs(title="'Reliabiity' Counts", x="Reliability Score",
                y="Count")
gg <- gg + theme(panel.grid=element_blank(),
                 panel.background=element_blank())
print(gg)
```

The Python version (Listings 3-14, 3-15 and 3-16) uses

comma

Move this text to top of page 55.

Au: Are we missing text?

AR: This is an errant artifact of an old cut/paste. Please remove

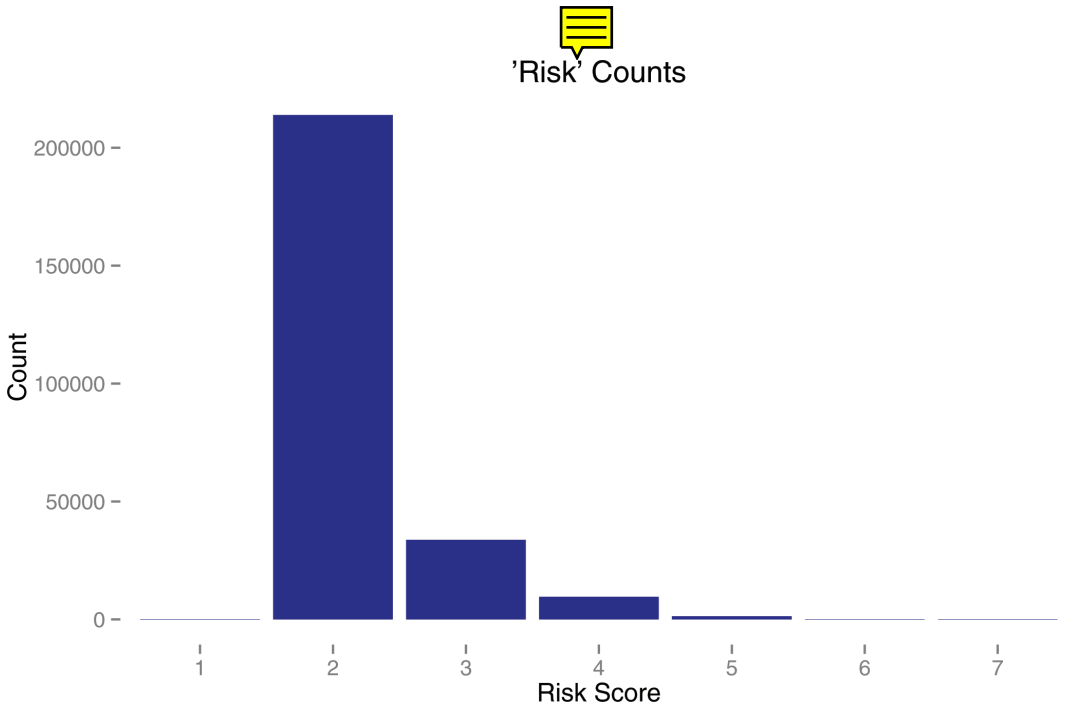


FIGURE 3-3 *Risk factor bar chart (R)*

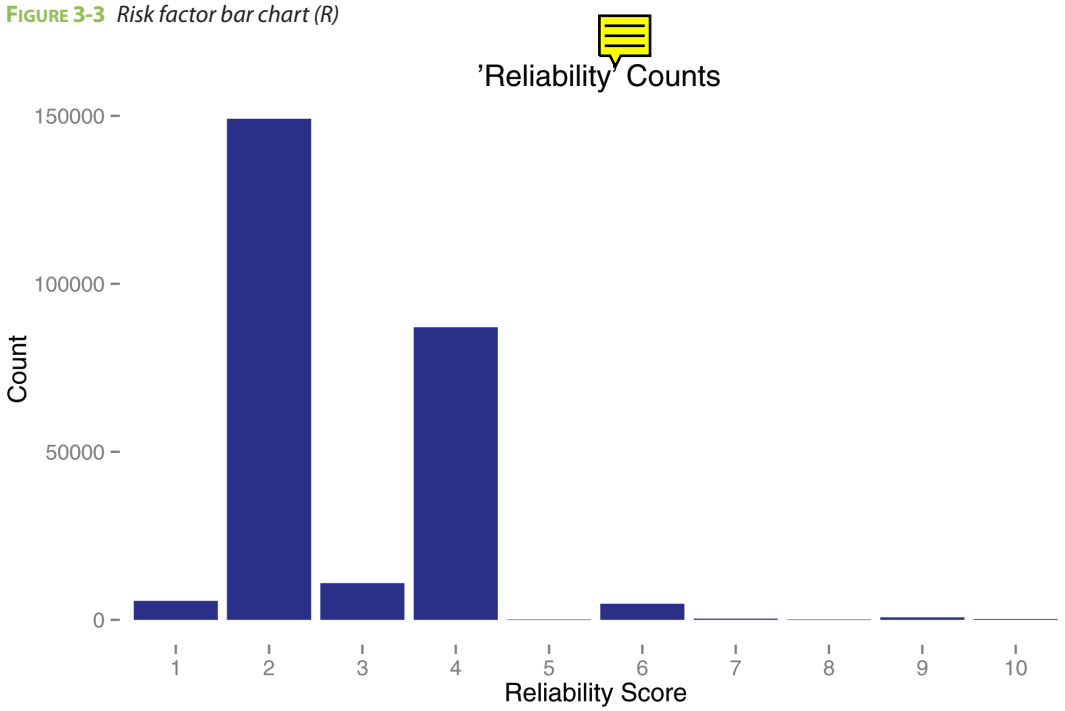


FIGURE 3-4 *Reliability factor bar chart (R)*

LISTING 3-14

```
# require object: av (3-5), factor_col (3-10)
# See corresponding output in Figure 3-5
# NOTE: Notice the significant differnce in the Python graph in that the
#       blank/empty country code entries are not in the graph
# need some functions from matplotlib to help reduce 'chart junk'
import matplotlib.pyplot as plt
# sort by country
country_ct = pd.value_counts(av['Country'])

# plot the data
plt.axes(frameon=0) # reduce chart junk
country_ct[:20].plot(kind='bar',
   rot=0, title="Summary By Country", figsize=(8,5)).grid(False)
```

LISTING 3-15

```
# require object: av (3-5), factor_col (3-10)
# See corresponding output in Figure 3-6
plt.axes(frameon=0) # reduce chart junk
factor_col(av['Reliability']).plot(kind='bar', rot=0,
           title="Summary By 'Reliability'", figsize=(8,5)).grid(False)
```

LISTING 3-16

```
# require object: av (3-5), factor_col (3-10)
# See corresponding output in Figure 3-7
plt.axes(frameon=0) # reduce chart junk
factor_col(av['Risk']).plot(kind='bar', rot=0,
           title="Summary By 'Risk'", figsize=(8,5)).grid(False)
```

The `Country` chart, as shown in Figure 3-5, shows there are definitely some countries that are contributing more significantly to the number of malicious nodes, and you can go back to numbers for a moment to look at the percentages for the top ten in the list (Listings 3-17 and 3-18):

LISTING 3-17

```
# require object: av (3-4)
country10 <- summary(av$Country, maxsum=10)
# now convert to a percentage by dividing by number of rows
country.perc10 <- country10/nrow(av)
# and print it
print(country.perc10)
##         CN         US         TR                    DE         NL
## 0.26518215 0.19482573 0.05396983 0.03887854 0.03848414 0.03066590
##         RU         GB         IN    (Other)
## 0.02453736 0.02433243 0.02118890 0.30793501
```

Au: country?

AR: the blank is correct. it's a blank field in the data file. thx.

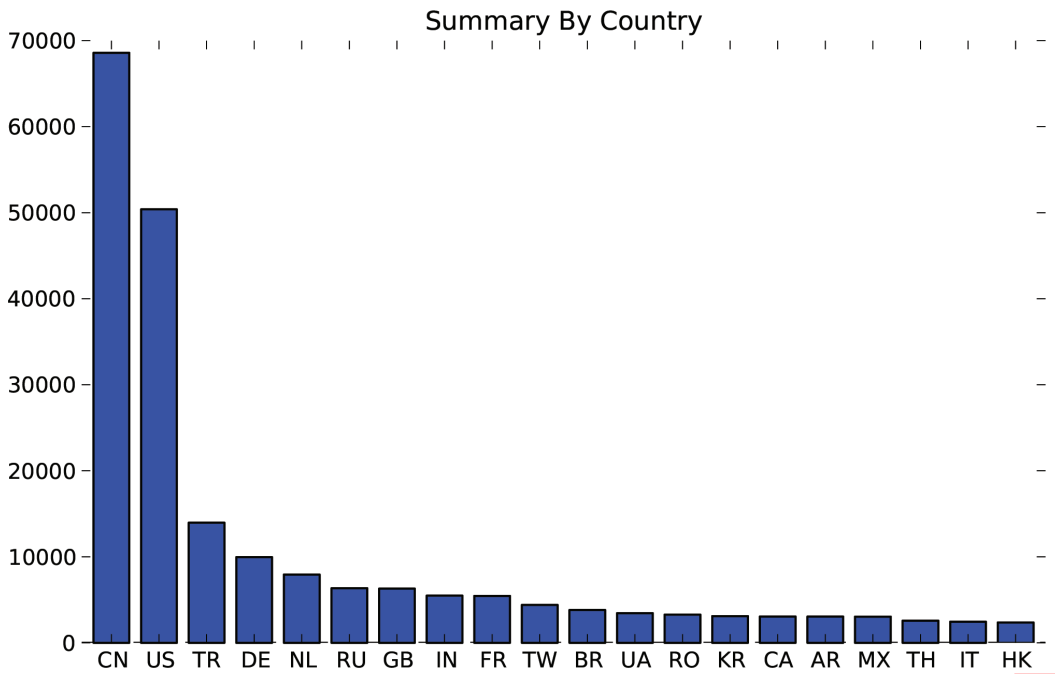
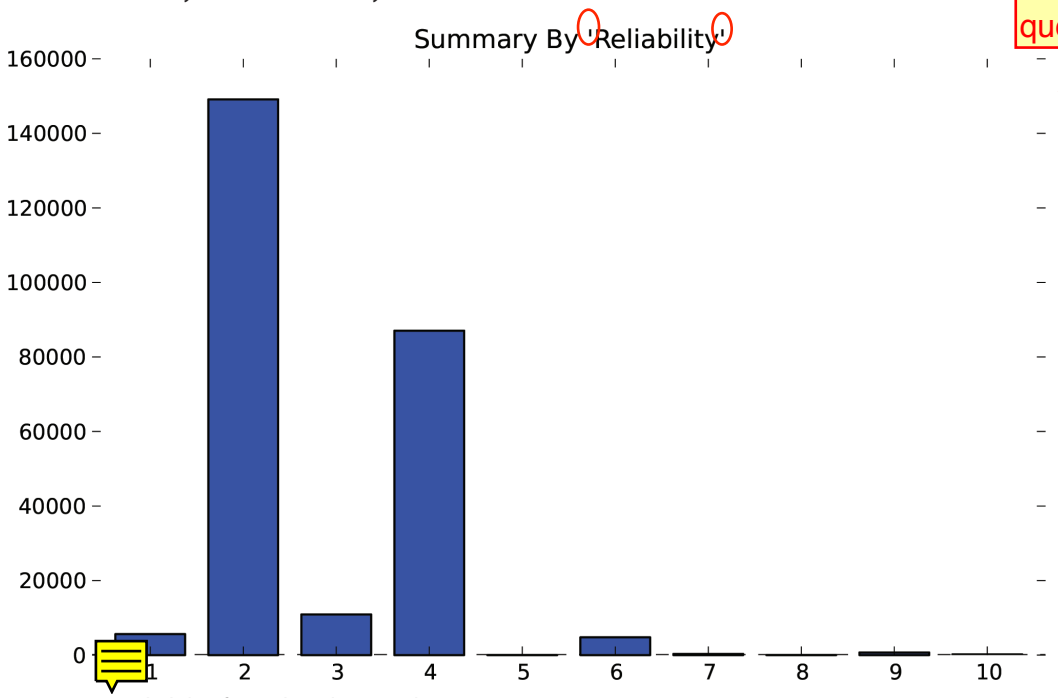


FIGURE 3-5 *Country factor bar chart (Python)*

Au: single straight quotes as wanted?

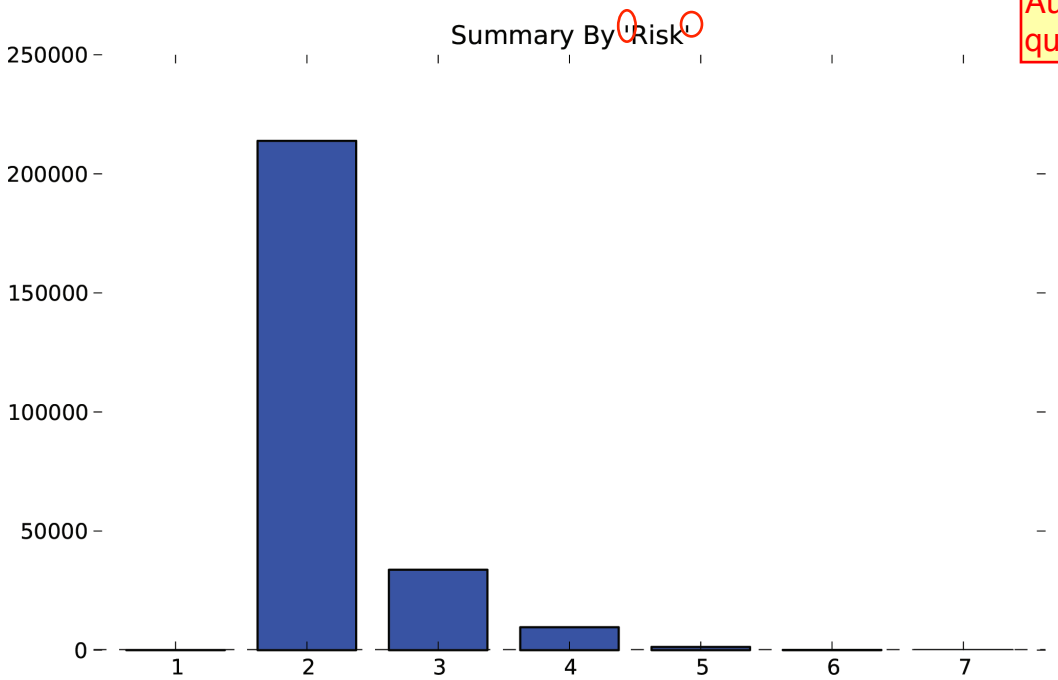
AR: Yes. thx.



Au: Fig.3-6 is cited in Listing 3-15, but not in the text. OK?

FIGURE 3-6 *Reliability factor bar chart (Python)*

Au: single straight quotes as wanted?



Au: Fig.3-7 is cited in Listing 3-16, but not in the text. OK?

AR: Yes. thx.

FIGURE 3-7 *Risk factor bar chart (Python)*

LISTING 3-18

```
# require object: av (3-5)
# extract the top 10 most prevalent countries
top10 = pd.value_counts(av['Country'])[0:9]
# calculate the % for each of the top 10
top10.astype(float) / len(av['Country'])
## CN    0.265182
## US    0.194826
## TR    0.053970
## DE    0.038484
## NL    0.030666
## RU    0.024537
## GB    0.024332
## IN    0.021189
## FR    0.021069
## Length: 9, dtype: float64
```

These quick calculations show that China and the United States together account for almost 46 percent of the malicious nodes in the list, and Russia accounts for just 2.4 percent. One avenue to explore here is to see how this compares with various industry reports since you would expect many of these countries to be in the top ten. However, the amount that some countries contribute suggest that there might be some bias in the data set. You can also see that 3 percent of the nodes cannot be geo-located (in the R output, \(Other)/ category).

[/]

AR: VERIFIED REF

> ***Note***
>
> *Chapter 5 covers the challenges and pitfalls of IP address geo-location, so we'll refrain from exploring that further here.*

geolocation (style sheet)

Looking at the `Risk` variable, you can see that the level of risk of most of the nodes is ***negligible*** (that is, so low that they can be disregarded). There are other elements that stand out with this data though, foremost being that practically no endpoints are in categories 1, 5, 6, or 7, and none in the rest of the defined possible range [8–10]. This anomaly is a sign to you that it is worth digging a bit deeper, but the anomaly is significant evidence of bias in the data set.

Finally, the `Reliability` rating of the nodes also appears to be a bit skewed (that is, the distribution is extended to one side of the mean or central tendency). The values are mostly clustered in levels 2 and 4, with not many ratings above level 4. The fact that it completely skips a reliability rating of 3 should raise some questions in your mind. It could indicate a systemic flaw in the assignment of the rating, or it could be that you have at least two distinct data sets. Either way, that large quantity of 2s and 4s and low quantity of 3s is a clear sign that you should investigate further, because it's just a little odd and surprising.

You now have some leads to pursue and a much better idea of the makeup of the key components of the data. This preliminary analysis gives you enough information to formulate a research question.

Homing In on a Question

Consider both the problem and the primary use case for the AlienVault reputation data: importing it into a SEIM or Intrusion Detection System/Intrusion Prevention System (IDS/IPS) to alert incident response team members or to log/block malicious activity. How can this quick overview of the reputation data influence the configuration of the SIEM in this setting to ensure that the least number of "trivial" alerts are generated?

Cap

Let's take a slightly more practical view of those questions by asking, "Which nodes from the reputation database represent a potentially real threat?"

comma

There ***is*** a reason AlienVault included both `Risk` and `Reliability` fields, and you should be able to use these attributes to classify nodes into two categories: 1) the nodes you really care about, and 2) everything else. The definition of "really care about" can be somewhat subjective, but it is unrealistic to believe you would want to generate an alert on all detected activity by one of these 258,626 nodes. Some form of prioritization triage and prioritization ***must*** occur, and it is a far better approach to base the triage and prioritization on statistical analysis of data and evidence rather than a "gut call" or solely on "expert opinion" alone.

comma

It's possible to see which nodes should get your attention by comparing the `Risk` and `Reliability` factors. To do this, you use a ***contingency table***, which is a tabular view of the multivariate frequency distribution of specific variables. In other words, a contingency table helps show relationships between two variables. After building a contingency table, you can take both a numeric and graphical look at the results to see where the AlienVault nodes "cluster".

tr

The output from the R code in Listing 3-19 is Figure 3-8, which shows the output of the contingency table as a level plot and uses size and color to show quantity, whereas the Python code in Listing 3-20 is used to generate a standard heat map (Figure 3-9) that relies on color alone to show quantity. (A ***heat map***

heatmap x2 (style sheet)

is a graphical representation of data where the individual values contained in a matrix are represented as colors. See `http://en.wikipedia.org/wiki/Heat_map` for more information.) With both factors combined, it is very apparent that the values in this data set bias are concentrated around [2, 2], which might be a sign of bias.

Listing 3-19

```
# require object: av (3-4)
# See corresponding output in Figure 3-8
# compute contingency table for Risk/Reliability factors which
# produces a matrix of counts of rows that have attributes at
# each (x, y) location
rr.tab <- xtabs(~Risk+Reliability, data=av)
ftable(rr.tab) # print table
## virtually identical output to pandas (See Listing 3-20)

# graphical view of levelplot
# need to use levelplot function from lattice package
library(lattice)
# cast the table into a data frame
rr.df = data.frame(table(av$Risk, av$Reliability))
# set the column names since table uses "Var1" and "Var2"
colnames(rr.df) <- c("Risk", "Reliability", "Freq")
# now create a level plot with readable labels
levelplot(Freq~Risk*Reliability, data=rr.df, main="Risk ~ Reliabilty",
          ylab="Reliability", xlab = "Risk", shrink = c(0.5, 1),
          col.regions = colorRampPalette(c("#F5F5F5", "#01665E"))(20))
```

Listing 3-20

```
# require object: av (3-5)
# See corresponding output in Figure 3-9
# compute contingency table for Risk/Reliability factors which
# produces a matrix of counts of rows that have attributes at
# each (x, y) location
# need cm for basic colors
# need arange to modify axes display
from matplotlib import cm
from numpy import arange

pd.crosstab(av['Risk'], av['Reliability'])

## Reliability    1       2     3      4   5     6    7   8    9   10
## Risk
## 1              0       0    16      7   0     8    8   0    0   0
## 2            804  149114  3670  57653   4  2084   85  11  345  82
## 3           2225       3  6668  22168   2  2151  156   7  260  79
## 4           2129       0   481   6447   0   404   43   2   58  24
## 5            432       0    55    700   1   103    5   1   20  11
```

(continues)

Listing 3-20 *(continued)*

```
## 6              19       0       2      60       0       8       0       0       1       0
## 7               3       0       0       5       0       0       0       0       2       0
```

Au: Need the Reliability col. heads above these lines of cold?

```
# graphical view of contingency table (swapping risk/reliability)
xtab = pd.crosstab(av['Reliability'], av['Risk'])
plt.pcolor(xtab,cmap=cm.Greens)
plt.yticks(arange(0.5,len(xtab.index), 1),xtab.index)
plt.xticks(arange(0.5,len(xtab.columns), 1),xtab.columns)
```

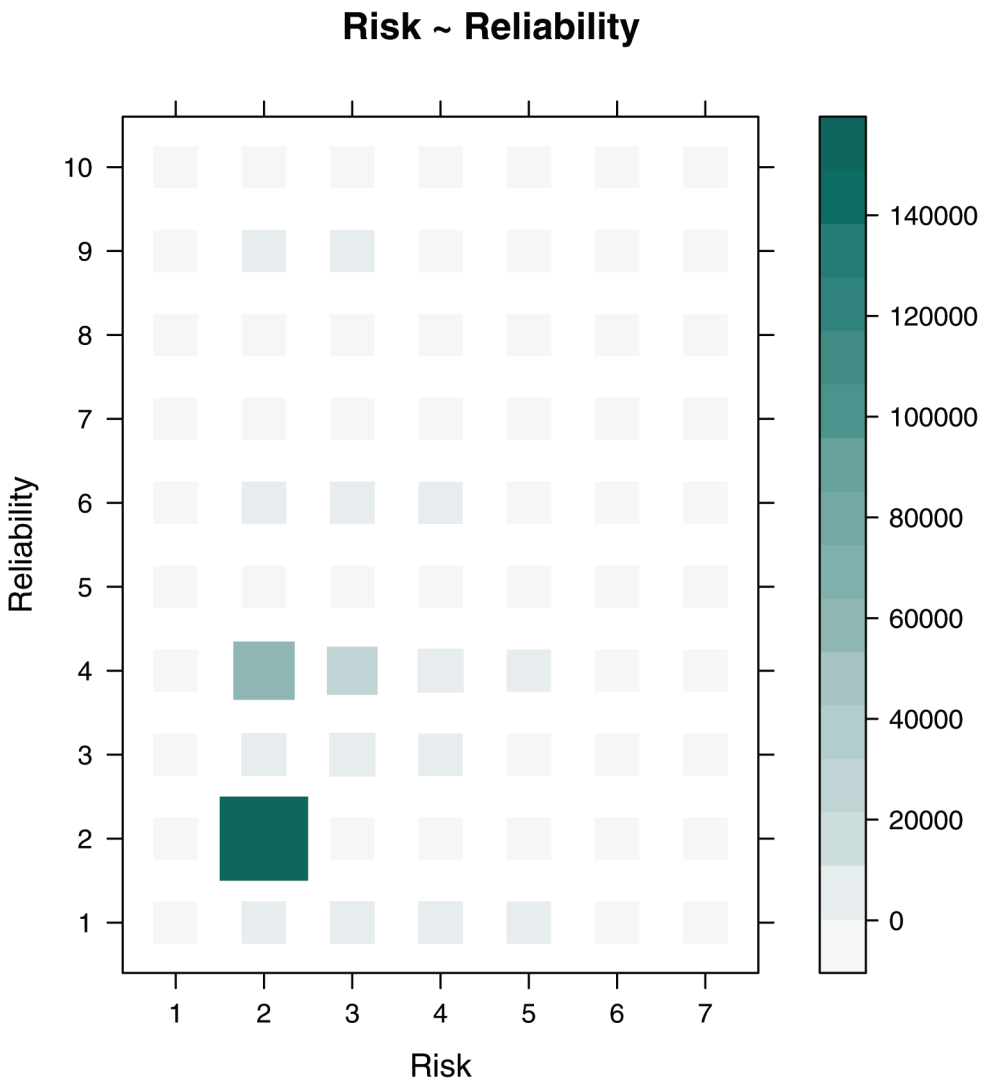
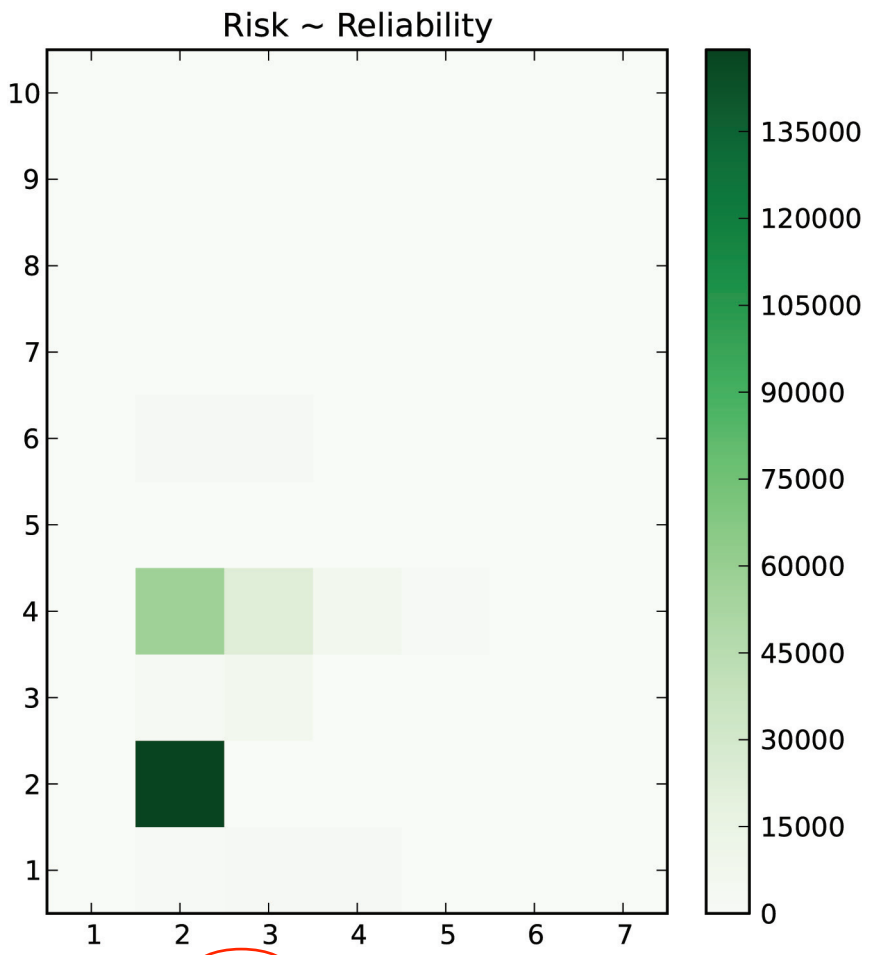


FIGURE 3-8 *Risk/reliability contingency table level plot (R)*



heatmap

FIGURE 3-9 *Risk/reliability contingency table heat map (Python)*

Comp: move to end of listing 3-20.

```
plt.colorbar()
```

Comp: CodeColorRed2

As a fun aside, you can determine whether the patterns you're seeing are occurring by chance, or whether there is some underlying meaning to them. Although you could do some fancy-pants statistics here and maybe apply Fisher's exact test, you don't need to get crazy. What if you assumed that every value of `Risk` and `Reliability` had an equal chance of occurring? What would the level plot look like? You should expect some amount of natural variation—both in the systems and the data collection process—so some combinations would naturally occur more often than others. But how different would it look from the current data?

You can use the `sample()` function to generate random samples from a Uniform distribution [1, 7] and [1, 10] and then build a contingency table from those random samples. Running this multiple times should produce a different set of random tables each time. Each run is called a ***realization*** of the random processes.

The R code in Listing 3-21 produces the levelplot in Figure 3-10 and shows two things. First, you can make some pretty and colorful random boxes with a few lines of code. Second, there is definitely something pulling nodes into the lower `Risk` and `Reliability` categories (that is, toward zero for each). It could be because the world just has low risk and reliability or the sampling method or scoring system is introducing the skew.

Move figure 3-10 here.

LISTING 3-21

```
# require object: av (3-4), lattice (3-19)
# See corresponding output in Figure 3-10
# generate random samples for risk & reliability and re-run xtab
# starting PRNG from reproducable point
set.seed(1492) # as it leads to discovery
# generate 260,000 random samples
rel=sample(1:7, 260000, replace=T)
rsk=sample(1:10, 260000, replace=T)
# cast table into data frame
tmp.df = data.frame(table(factor(rsk), factor(rel)))
colnames(tmp.df) <- c("Risk", "Reliability", "Freq")
levelplot(Freq~Reliability*Risk, data=tmp.df, main="Risk ~ Reliabilty",
          ylab="Reliability", xlab = "Risk", shrink = c(0.5, 1),
          col.regions = colorRampPalette(c("#F5F5F5", "#01665E"))(20))
```

Now turn your attention to the `Type` variable to see if you can't establish a relationship with the `Risk` and `Reliability` ratings. Looking closely at the `Type` variable, you notice that some entries have more than type assigned to them and they are separated by a semicolon (there are 215 `Scanning Host;Malicious Host` values, for example). Since you want to see how those types compare, those with a combination of types shouldn't be mixed with other types. So, rather than try to parse out the nodes with multiple types, you can just reassign all of them into a category of `Multiples` to show that they were assigned more than one type. Then you can create a three-way contingency table and see how that looks. Pull in the `Type` column and see how that impacts the view.

comma

The R code in Listing 3-22 produces the three-way contingency table lattice graph in Figure 3-11, enabling you to visually compare the amount of impact `Type` has on the `Risk` and `Reliability` classifications. The Python code in 3-23 also computes the three-way contingency table, but shows an alternate output representation in a simple bar chart (Figure 3-12).

LISTING 3-22

```
# require object: av (3-4), lattice (3-19)
# See corresponding output in Figure 3-11
# Create a new varible called "simpletype"
# replacing mutiple categories with label of "Multiples"
av$simpletype <- as.character(av$Type)
# Group all nodes with mutiple categories into a new category
av$simpletype[grep(';', av$simpletype)] <- "Multiples"
# Turn it into a factor again
av$simpletype <- factor(av$simpletype)
```

Comp: Move this line of code and the line of space beneath it to the top of the next page (page 63).

```
rrt.df = data.frame(table(av$Risk, av$Reliability, av$simpletype))
colnames(rrt.df) <- c("Risk", "Reliability", "simpletype", "Freq")
levelplot(Freq ~ Reliability*Risk|simpletype, data =rrt.df,
          main="Risk ~ Reliabilty | Type", ylab = "Risk",
          xlab = "Reliability", shrink = c(0.5, 1),
          col.regions = colorRampPalette(c("#F5F5F5","#01665E"))(20))
```

Move this figure to previous page where indicated.

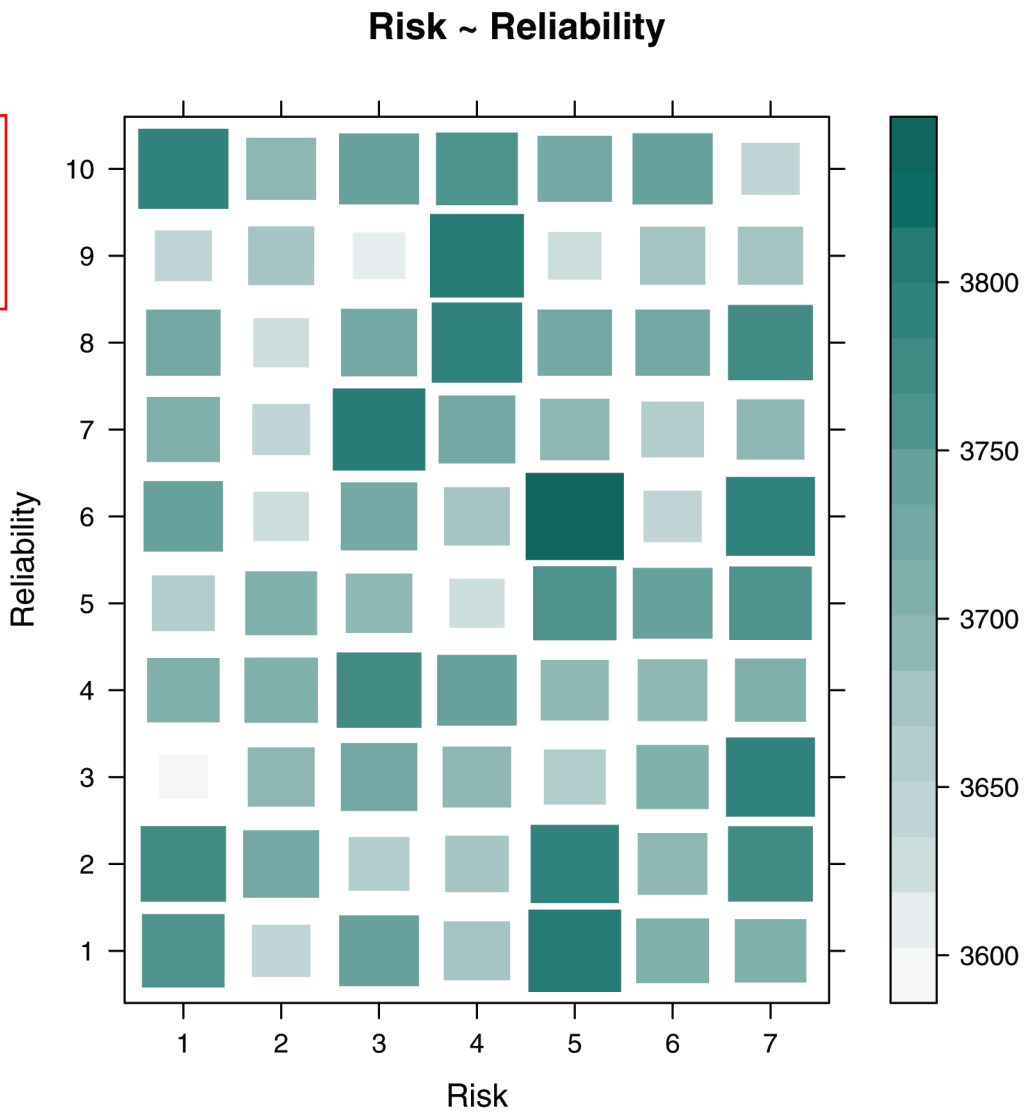


FIGURE 3-10 *"Unbiased" risk/reliability contingency table (R)*

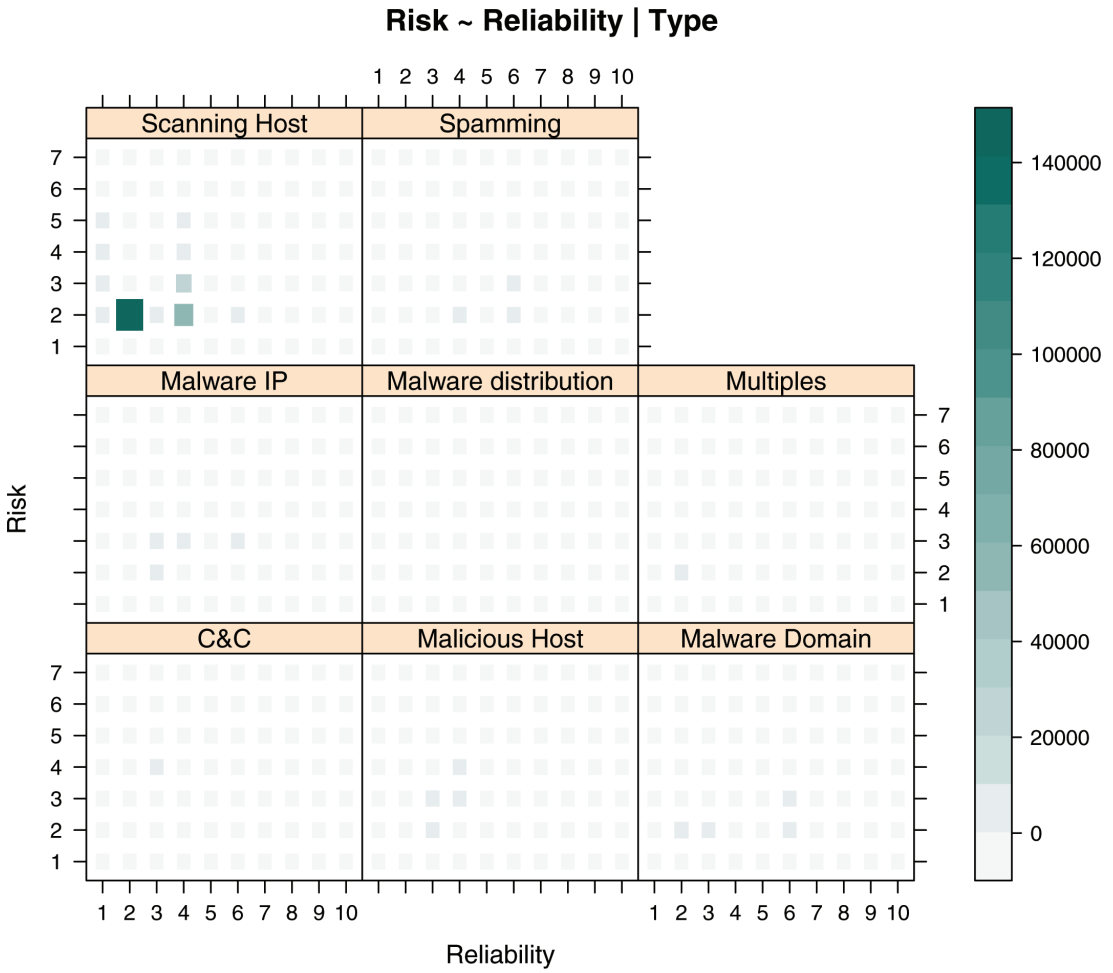


FIGURE 3-11 *Three-way risk/reliability/type contingency table (R)*

LISTING 3-23

```
# require object: av (3-5)
# See corresponding output in Figure 3-12
# compute contingency table for Risk/Reliability factors which
# produces a matrix of counts of rows that have attributes at

# create new column as a copy of Type column
av['newtype'] = av['Type']

# replace multi-Type entries with Multiples
av[av['newtype'].str.contains(";")] = "Multiples"
```

Comp: Move this line of code and the line of space beneath it to the top of the next page (page 65).

```
# setup new crosstab structures
typ = av['newtype']
rel = av['Reliability']
rsk = av['Risk']

# compute crosstab making it split on the
# new type column
xtab = pd.crosstab(typ, [ rel, rsk ],
          rownames=['typ'], colnames=['rel', 'rsk'])

# the following print statement will show a huge text
# representation of the contingency table. The output
# is too large for the book, but is worth looking at
# as you run through the exercise to see how useful
# visualizations can be over raw text/numeric output
print xtab.to_string() #output not shown

xtab.plot(kind='bar',legend=False,
   title="Risk ~ Reliabilty | Type").grid(False)
```

move to top of page 66

They say a picture is worth a thousand words, but in this case it's worth about 234,000 data points in the `Scanning Hosts` category (about 90 percent of the entries are classified as scanning hosts).

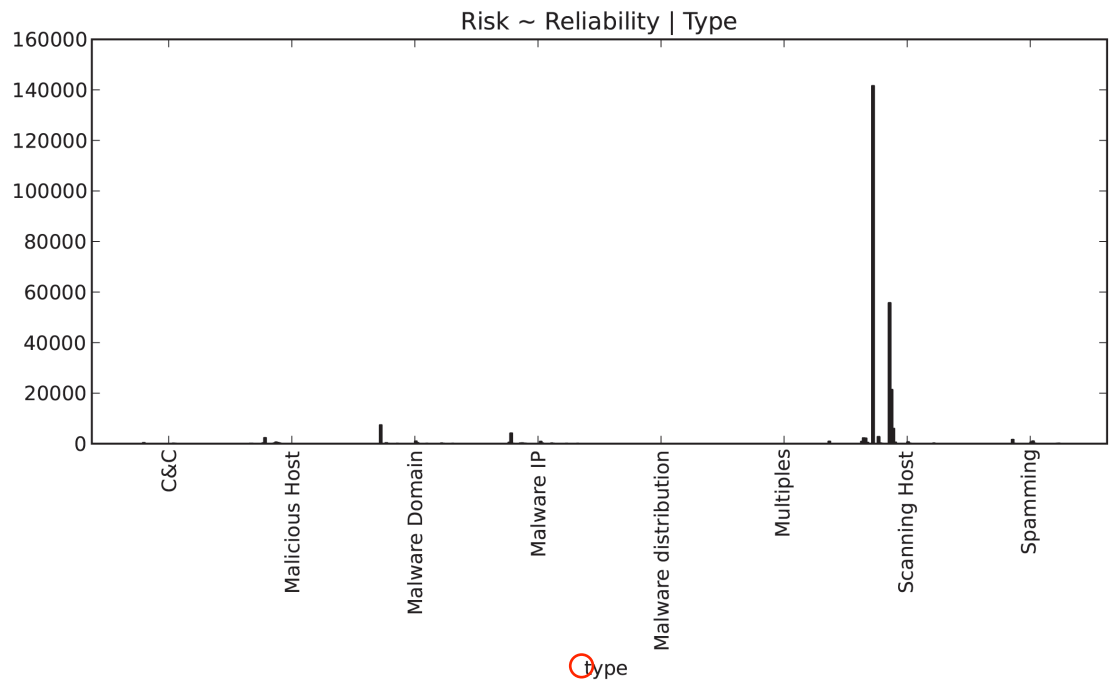


FIGURE 3-12 *Three-way risk/reliability/type contingency table bar chart (Python)*

Cap / ?

AR: yes. it's what readers will see when they work with the raw data file. thx

That category is so large and generally low risk that it is overshadowing the rest of the categories. Remove it from the `Type` factors and regenerate the image. This isn't to say the `Scanning Hosts` category isn't important, but remember you are trying to understand which of these entries you really care about. Nodes with low risk and reliability ratings are things you don't want to be woken up from your nap for. You want to peel those away and look at the relationships that exist underneath the scanning hosts. We continue the examples from Listings 3-22 and 3-23 and generate new corresponding Figures 3-13 (R lattice) and 3-14 (Python bar chart) in Listings 3-24 and 3-25.

LISTING 3-24

```
# require object: av (3-4), lattice (3-19)
# See corresponding output in Figure 3-13
# from the existing rrt.df, filter out 'Scanning Host'
rrt.df <- subset(rrt.df, simpletype != "Scanning Host")
levelplot(Freq ~ Reliability*Risk|simpletype, data =rrt.df,
          main="Risk ~ Reliabilty | Type", ylab = "Risk",
          xlab = "Reliability", shrink = c(0.5, 1),
          col.regions = colorRampPalette(c("#F5F5F5","#01665E"))(20))
```

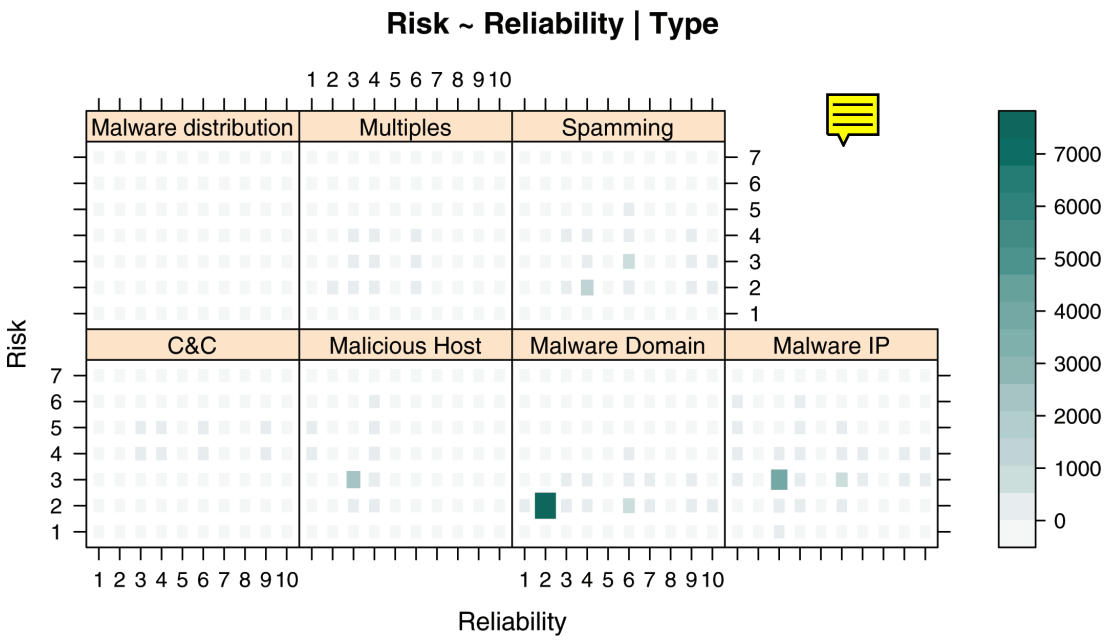


FIGURE 3-13 *Three-way risk/reliability/type contingency table without "Scanning Host" (R)*

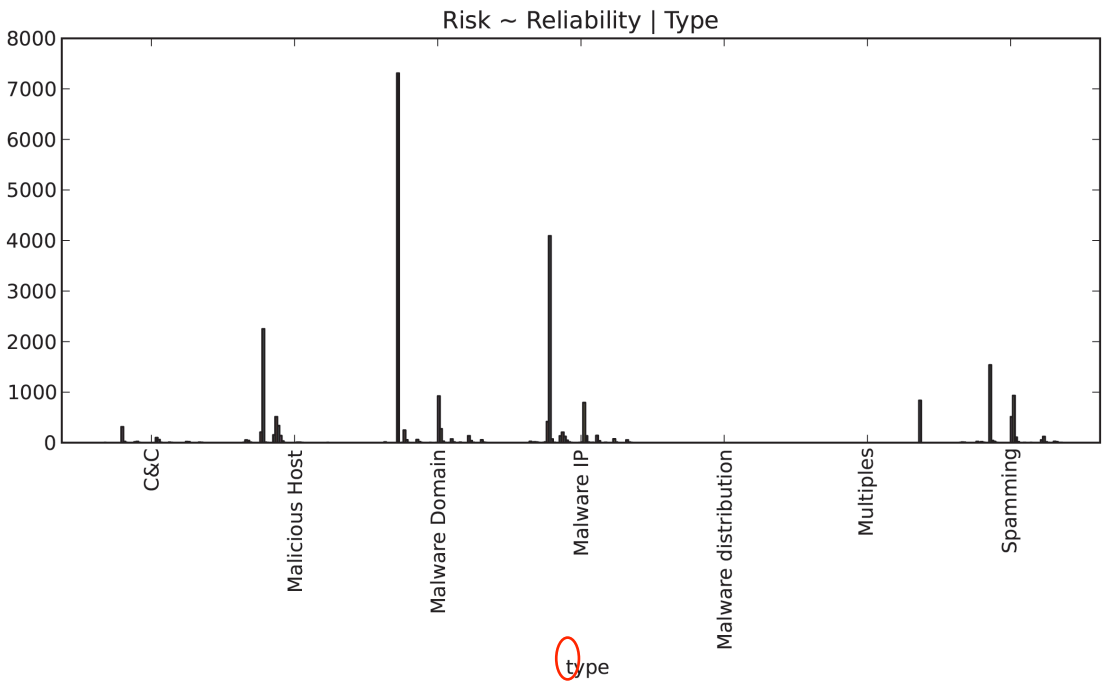
LISTING 3-25

```
# require object: av (3-5)
# See corresponding output in Figure 3-14
# filter out all "Scanning Hosts"
```

```
rrt_df = av[av['newtype'] != "Scanning Host"]
typ = rrt_df['newtype']
rel = rrt_df['Reliability']
rsk = rrt_df['Risk']
xtab = pd.crosstab(typ, [ rel, rsk ],
       rownames=['typ'], colnames=['rel', 'rsk'])
xtab.plot(kind='bar',legend=False,
   title="Risk ~ Reliabilty | Type").grid(False)
```

Now you are getting somewhere. In Figure 3-13, you can see the `Malware domain` type has risk ratings limited to 2s and 3s, and the reliability is focused around 2, but spreads the range of values. You can also start to see the patterns in the other categories as well even in Figure 3-14, but it's time to regenerate the graphics once more after you remove the `Malware domain`. Also, it looks like `Malware distribution` does not seem to be contributing any risk, so you can filter that factor out of the remaining types as well (in Listings 3-26 and 3-27) to get the final results in Figure 3-15 (R lattice plot) and Figure 3-16 (Python bar chart).

rebreak & delete hyphen



Cap / ?

FIGURE 3-14 *Three-way risk/reliability/type contingency table bar chart without "Scanning Host" (Python)*

LISTING 3-26

```
# require object: av (3-4), lattice (3-19), rrt.df (3-24)
# See corresponding output in Figure 3-15
rrt.df = subset(rrt.df,
           !(simpletype %in% c("Malware distribution",
                               "Malware Domain")))
```

(continues)

Listing 3-26 *(continued)*

```
sprintf("Count: %d; Percent: %2.1f%%",
        sum(rrt.df$Freq),
        100*sum(rrt.df$Freq)/nrow(av))
## [1] Count: 15171; Percent: 5.9%

levelplot(Freq ~ Reliability*Risk|simpletype, data =rrt.df,
          main="Risk ~ Reliabilty | Type", ylab = "Risk",
          xlab = "Reliability", shrink = c(0.5, 1),
          col.regions = colorRampPalette(c("#F5F5F5","#01665E"))(20))
```

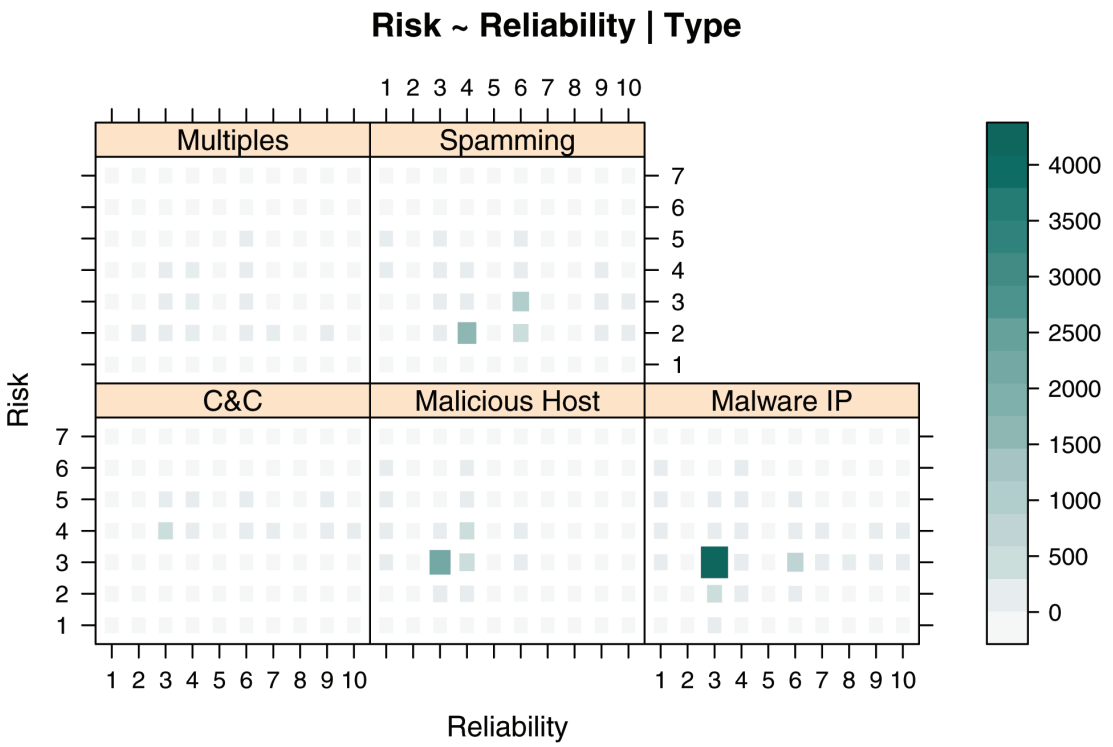


FIGURE 3-15 *3-Way risk/reliability/type contingency table—final (R)*

LISTING 3-27

```
# require object: av (3-5), rrt_df (3-25)
# See corresponding output in Figure 3-16
rrt_df = rrt_df[rrt_df['newtype'] != "Malware distribution" ]
rrt_df = rrt_df[rrt_df['newtype'] != "Malware Domain" ]
typ = rrt_df['newtype']
rel = rrt_df['Reliability']
rsk = rrt_df['Risk']
```

```
xtab = pd.crosstab(typ, [ rel, rsk ],
        rownames=['typ'], colnames=['rel', 'rsk'])

print "Count: %d; Percent: %2.1f%%" % (len(rrt_df), (float(len(rrt_df))
   / len(av)) * 100)
## Count: 15171; Percent: 5.9%

xtab.plot(kind='bar',legend=False)
```

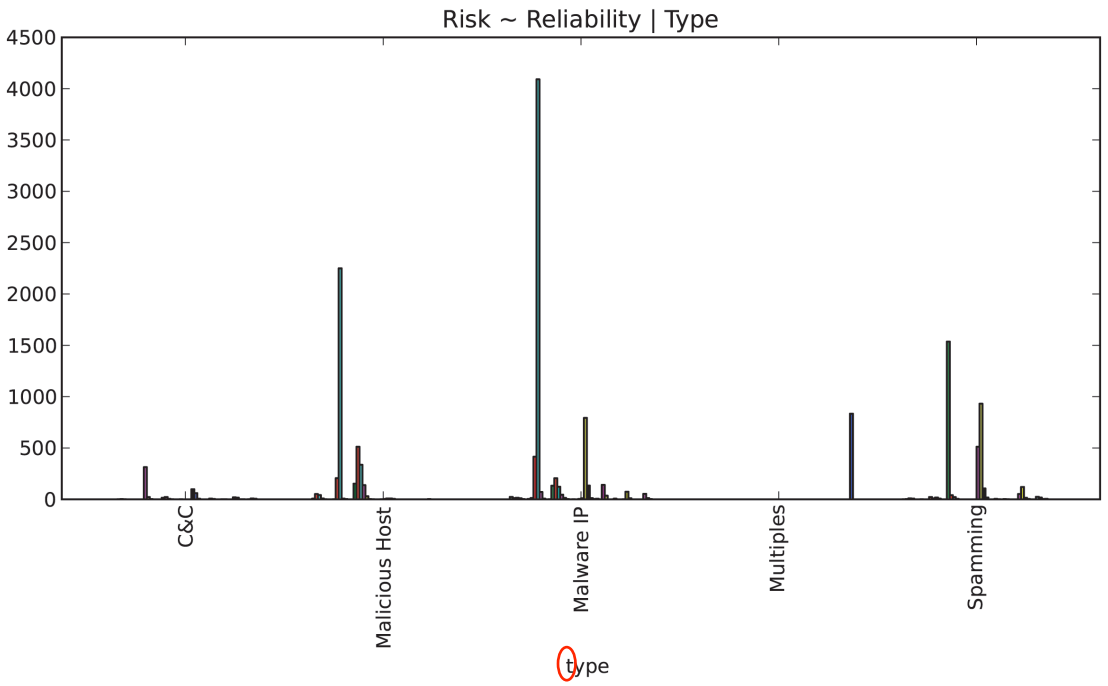


FIGURE 3-16 *3-Way risk/reliability/type contingency table—final (Python)*

Cap / ?
AR: yes. it's what readers will face when working with the raw data file. thx.

With this final bit of filtering, you've reduced the list to less than 6 percent of the original and have honed in fairly well on the nodes representing the ones you really should care about. If you wanted to further reduce the scope, you could filter by various combinations of `Reliability` and/or `Risk`. Perhaps you want to go back to the categories you filtered out and bring a subset of those back in.

The rather simple parsing and slicing done here doesn't show which variables are most important; it simply helps you understand the relationships and the frequency with which they occur. Just because 90 percent of the data was Scanning Hosts, perhaps you only want to filter those hosts with a risk of 2 or below. This analysis has merely helped you identify a set of nodes on which you can generate higher priority alerts. You can still capture the other types into a lower priority or into an informational log.

Since AlienVault updates this list hourly, you can create a script to do this filtering before importing new revisions into your security tools. You can then keep track of the percentage of nodes filtered out as a flag

for the need to potentially readjust the rules. Furthermore, you should strongly consider performing this exploratory analysis on a semi-frequent basis. This will help you determine whether you need to re-think your perspective on what constitutes non-trivial nodes.

Summary

This chapter introduced the core structure and concepts of data analyses in Python and R. It incorporated basic statistics, foundational scripting/analysis patterns, and introductory visualizations to help you ask and answer a pertinent question. In addition, each example demonstrated the similarity of Python (with pandas) and R coding techniques and generated output. The steps presented are just one direction this particular analysis could lead. Every situation is different and will require you to pull in different tools and techniques as needed.

AR: VERIFIED REF Future chapters focus mainly on R code, with some Python sprinkled in on occasion. If you are familiar with Python/pandas, the previous examples should help you translate between the two languages. If you are new to both R and Python, the standardization of future examples in one language should help you follow along with less confusion and help you learn R a bit better.

Recommended Reading

The following are some recommended readings that can further your understanding on some of the topics we touch on in this chapter. For full information on these recommendations and for the sources we cite in the chapter, please see Appendix B. AR: VERIFIED REF

Statistics and Data with R: An Applied Approach Through Examples **by Yosef Cohen and Jeremiah Y. Cohen**

Python for Data Analysis **by Wes McKinney**