INDEX

Note: Page numbers referring to figures and tables are followed by an italicized f or t respectively.

A

activation functions common, 178*t*-180*t* defined. 178 add edge function, 41 add_node function, 49–50 add question function, 112 add arithmetic instruction, 15 ADS (Alternate Data Streams), 29 Advanced Persistent Threat 1 attacker group. See APT1 attacker group advanced persistent threats (APTs), 60 Allaple.A malware family, 157, 157f Alternate Data Streams (ADS), 29 anti-disassembly techniques, 22 API calls, 32-33, 33f apply_hashing_trick function, 138 APT1 (Advanced Persistent Threat 1) attacker group, 37-39, 38f, 45-47, 45*f*-47*f*, 61, 61*f*, 76, 76*f*, 86, 222–223 APTs (advanced persistent threats), 60 ArchSMS family of Trojans, 55 area under the curve (AUC), 209-210, 210f, 213 arithmetic instructions, 15, 15t .asarray method, 142 assembly language, defined, 12. See also x86 assembly language AT&T. 43 AT&T syntax, 13 attributes, 37 adding to nodes and edges, 42 and edges, 48-51 AUC (area under the curve), 209-210, 210f, 213

autoencoder neural networks, 194–195, 195f automatic feature generation, 188

B

backpropagation, 190–192, 190*f*–191*f* bag of features model, 62–64, 63f features, defined, 62 Jaccard index and, 65 N-grams, 63-64, 64f order information and, 63-64 overview, 62–63 bar charts (histograms), 168-170, 168*f*-169*f* base virtual memory address, 6 basic blocks, 19-20 bias parameter, 104 bias term, 178, 181 bipartite networks, 37–39, 38f bitcoin mining, 158, 160-161, 168f, 172*f*-173*f*, 173

C

callbacks built-in (Keras package), 212 creating shared callback relationship network, 51-54 custom, 213-214, 214f call instruction, 17-18 capstone module, 20 Carerra, Ero, 5 chain rule, 191-192 cmp instruction, 18 CNNs (convolutional neural networks), 193-194, 194f coarsenings, 46 color attribute, 49 comment sample function, 82-84 COMMENT mode, 229 compile method, 202

compressed_data_weight parameter, 103 compressed data parameter, 103-104 conditional branches, defined, 15 control flow, 17 graphs, 19-20, 19f instructions, 17-18 registers, 14-15 convolutional neural networks (CNNs), 193-194, 194f CPU registers, 13-15, 14f general-purpose registers, 13-14 stack and control flow registers, 14 - 15cross validation module, 151 cross-validation, 150-153, 151f, 153f CuckooBox software platform, 27, 33 - 34, 59"curse of dimensionality," 92 cv_evaluate function, 151

D

dapato malware family, 62, 67f-68f, 70*f*-72*f* DataFrame objects, 158-161 data movement instructions, 15-20, 16t basic blocks, 19-20, 19f control flow graphs, 19-20, 19f control flow instructions, 17-18 stack instructions, 16-17 data science, iii, iv applying to malware, v importance of, iv-v .data section (in PE file format), 4 dateutil package, 164 dec arithmetic instruction, 15 decision boundaries, 93-98, 95f-98f identifying with k-nearest neighbors, 97-98, 97f-98f identifying with logistic regression, 96-97, 96*f*-97*f* overfit machine-learning model, 100, 101f underfit machine-learning model, 99, 99f well-fit machine-learning model, 100, 100f decision thresholds, 149 DecisionTreeClassifier class, 130

decision trees, 109-115, 109f-110f, 113f - 114fdecision tree-based detectors, 129 importing modules, 129 initializing sample training data, 130 instantiating classes, 130 sample code, 133-134 training, 130-131 visualizing, 131–133, 132f follow-up questions, 111 limiting depth or number of questions, 111-112 pseudocode for, 112-113 root node, 110-111 when to use, 114-115 deep learning, 175-197, 216. See also neural networks automatic feature generation, 188 building neural networks, 182-188 neurons, 176 anatomy of, 177-180 networks of, 180-181 overview, 176-177 training neural networks, 189-193 types of neural networks, 193-197 universal approximation theorem, 181-182 deep neural networks. See neural networks Dense function, 200-201 describe method, 159 detection accuracy evaluation, 119-126, 146 - 153base rates and precision, 124-126 effect of base rate on precision, 124 - 125estimating precision in deployment environment, 125 - 126with cross-validation, 150-153, 151f, 153f neural networks, 209-211, 210f-211f possible detection outcomes, 120, 120f with ROC curves, 123-124, 123f, 147-150, 150f true and false positive rates, 120 - 124relationship between, 121-122, 121*f*-122*f* ROC curves, 123-124, 123f

DictVectorizer class, 128–130 directed graphs, 180 distance functions, 107 DLLs (dynamic-link libraries), 13 DOS header (in PE file format), 3 .dot format, 42 dynamically downloaded data, 22-23 dynamic analysis, 25-34 bag of features model, 63 dataset for, 222 for disassembly, 26 limitations of, 33-34 for malware data science. 26 typical malware behaviors, 27 using malwr.com, 26-33 analyzing results, 28-33 limitations, 33 loading files, 27-28 dynamic API call-based similarity, 72, 72f dynamic-link libraries (DLLs), 13

E

EAX register, 14 EBP register, 14 EBX register, 14 ECX register, 14 edges, 37 adding attributes, 42 adding to shared relationship networks, 41 adding visual attributes to, 48-51 color, 49, 49f text labels, 50-51 width, 48-49, 48f EDX register, 14 EFLAGS register, 15 EIP register, 14-15 ELU activation function, 179t entry point, 3, 19 epochs parameter, 206 ESP register, 14 euclidean distance function, 107 Euclidean distance, 107 evaluate function, 148 evaluate mode, 231-232 evaluating malware detection systems. See detection accuracy evaluation export graphviz function, 132 extract features function, 204-205 ExtractImages helper class, 56-57

F

fakepdfmalware.exe, 7 false negatives, defined, 120, 120f false positives, 120, 120f base rates and precision, 124-126 false positive rate, 121 relationship between true and false positive rates, 121-122, 121*f*-122*f* ROC curves, 123–124, 123f fdp tool, 43-45, 45f, 76 feature_extraction module, 129 feature extraction, 134-138 Import Address Table features, 136 machine learning-based malware detectors, 90-92, 141-142 N-grams, 136-137 Portable Executable header features, 135-136 shared code analysis, 73, 75 string features, 135 training neural networks with Keras package, 203-204 why all possible features can't be used at once, 137-138 FeatureHasher class, 140–141 feature hashing. See hashing trick feature spaces, 93-98, 94f-98f feed-forward neural networks, 181, 181f, 193 fit generator function, 204–206, 208, 212, 214 fit method, 130-131, 142 flags, defined, 15 format strings, 70 forward propagation, 189-190

G

Gaussian activation function, 179*t* generative adversarial networks (GANs), 195–196 generator parameter, 206 get_database function, 80–82 get_string_features function, 141–142, 144 get_strings function, 82 get_training_data function, 143 get_training_paths function, 143 GETMAIL utility, 223 getstrings function, 73–74 -G flag, 44 gini index, 132, 132f gradient descent, 105, 190 Graph constructor, 41, 52–53 graphical image analysis, 7-8 converting extracted .ico files to .png graphics, 8 creating directory to hold extracted images, 7-8 extracting image resources using wrestool, 8 GraphViz, 76 decision tree-based detectors, 131-133, 132f malware network analysis, 43-51 adding visual attributes to nodes and edges, 48-51 fdp tool, 44-45, 45f neato tool, 47-48, 47f parameters, 44 sfdp tool, 46-47, 46f similarity graphs, 76 ground_truth variable, 130

H

hashing trick (feature hashing), 138–141 complete code for, 139–140 FeatureHasher class, 140–141 implementing, 138–139 hidden layer, 181 histograms (bar charts), 168–170, 168*f*–169*f* hostname_projection argument, 225 hyperplanes, 96, 97*f*

I

IAT. See Import Address Table icoutils toolkit, 5 IDA Pro, 12 .idata section (imports) (in PE file format), 4 Identity activation function, 178t Import Address Table (IAT), 4 dumping using pefile, 6–7 extracting features, 136 similarity analysis based on, 71, 71f imports analysis, 6–7 inc arithmetic instruction, 15 information gain, 113 Input function, 200–201 instruction sequence–based similarity, 68*f* limitations of, 68–70 overview, 67–68 Intel syntax, 13 Internet Relay Chat (IRC), 2 int function, 148 inverted indexing, 82 *ircbot.exe* bot, 2 disassembling, 20–21 dissecting, 5–7 dumping IAT, 6–7 strings analysis, 9–10

J

jaccard_index_threshold argument, 227–228 jaccard function, 73 Jaccard index, 61, 65, 65*f* building similarity graphs, 73–75 dynamic API call–based similarity, 72 instruction sequence–based similarity, 68 minhash method, 77–79 scaling similarity comparisons, 77 strings-based similarity, 70 jge instruction, 18 jmp instructions, 18 jointplot function, 171–172

K

Kaspersky, 62 Keras package, building neural networks with, 199-214 compiling model, 202–203, 202f defining architecture of model, 200-202 evaluating model, 209-211, 210f - 211flayers, 200 saving and loading model, 209 syntaxes, 200 training model, 203-209, 211-214 built-in callbacks, 212 custom callbacks, 213-214, 214f data generators, 204-207, 207f feature extraction, 203-204 validation data, 207-209, 208f keyloggers, 158, 168f, 172f-173f, 173

KFold class, 151–152
K-fold cross-validation, 151
k-nearest neighbors, 105–109, 106*f*, 108*f*identifying decision boundaries
with, 97–98, 97*f*–98*f*logistic regression vs., 108–109
math behind, 107
pseudocode for, 107
when to use, 109

L

label attribute, 50-51 layers submodule, 200-201 lea instruction, 16 Leaky ReLU activation function, 179t learned_parameters parameter, 103 linear disassembly, 12 limitation of, 12 shared code analysis, 67-68 LOAD mode, 229 logistic function function, 103-104, 104flogistic regression function, 103 logistic regression, 102-105, 103f-104f, 154 gradient descent, 105 identifying decision boundaries with, 96-97, 96f-97f k-nearest neighbors vs., 108-109 limitation of, 102 math behind, 103-104 plot of logistic function, 104f pseudocode for, 103 when to use, 105 long short-term memory (LSTM) networks, 196 Los Alamos National Laboratory, 41 loss parameter, 201-202

M

machine learning–based malware detectors, 89–117, 127–154 building basic detectors, 129 sample code, 133–134 training, 130–131 visualizing, 131–133, 132*f* building overview, 90–93 collecting training examples, 90–91 designing good features, 92

extracting features, 90-92 reasons for, 89-90 testing system, 90, 93 training system, 90, 92-93 building real-world detectors, 141-146 complete code for, 144-146 feature extraction, 141-142 running detector on new binaries, 144 training, 142-143 dataset for, 224 decision boundaries, 93–98, 95f-98f evaluating detector performance, 146 cross-validation, 150–153, 151f, 153f ROC curves, 147–150, 150f splitting data into training and test sets, 148-149 feature extraction, 134–138 Import Address Table features, 136 N-grams, 136–137 Portable Executable header features, 135-136 string features, 135 why all possible features can't be used at once, 137–138 feature spaces, 93–98, 94*f*–98*f* hashing trick, 138-141 complete code for, 139-140 FeatureHasher class, 140-141 implementing, 138-139 overfitting and underfitting, 98-99, 99f - 101fsupervised vs. unsupervised algorithms, 93 terminology and concepts, 128-129 tool for, 230-232, 231f traditional algorithms vs., 90 types of algorithms, 101, 102f decision trees, 109–115, 109f-110f, 113f-114f k-nearest neighbors, 97–98, 97f-98f, 105-109, 106f, 108f logistic regression, 96-97, 96f-97f, 102-105, 103f-104f random forest, 115-116, 116f malware projection argument, 52, 225 - 227

malware detection evaluation. See detection accuracy evaluation malware network analysis, 35–58, 36f attributes, defined, 37 bipartite networks, 37-39, 38f creating shared callback relationship network, 51-54, 225-226, 226f code for, 52-54 importing modules, 51-52 parsing command line arguments, 52 saving networks to disk, 54 creating shared image relationship networks, 54-58, 55f, 226 - 227extracting graphical assets, 57 parsing initial argument and file-loading code, 55-57 saving networks to disk, 58 dataset for, 222-223 edges, defined, 37 GraphViz, creating visualizations with, 43-51 fdp tool, 44-45, 45f neato tool, 47-48, 47f parameters, 44 sfdp tool, 46-47, 46f visual attributes, 48-51 NetworkX library, creating networks with, 40-43 adding attributes, 42 adding nodes and edges, 41 saving networks to disk, 42-43 nodes, defined, 37 projections, 38 shared code analysis and, 60-61 visualization challenges, 39-40 distortion problem, 39-40, 40f force-directed algorithms, 40 network layout, 39-40 malware samples, 61-62, 222-224 malwr.com, 26-33, 28f analyzing results on, 28-33 API calls, 32-33, 33f modified system objects, 30-32 Screenshots panel, 30, 30f Signatures panel, 29-30, 29f Summary panel, 30–32, 31f–32f limitations of, 33 loading files on, 27-28

Mandiant, 61, 76, 223 MAPIGET utility, 223 Mastercard, iii matplotlib library, 148-150, 162–167, 162f plotting ransomware and worm detection rates, 165-167, 166f plotting ransomware detection rates, 164–165, 165f plotting relationship between malware size and detection, 162 - 163max function, 160 mean function, 160-161 memory cells, 196 metrics module, 147-148 metrics parameter, 201-202 min function, 81, 160 minhash approach combined with sketching, 79 math behind, 78-79, 78f overview, 77-78 minhash function, 82 ModelCheckpoint callback, 212 Model class, 201 models submodule, 201-202 mov instruction, 15-16 murmur module, 80, 82 mutexes, defined, 32 my generator function, 205, 207-208 MyCallback class, 213-214

N

neato tool, 47-48, 47f Nemucod.FG malware family, 157, 157f NetworkX library, 40-43 creating shared relationship networks, 41-42 overview, 41 saving networks to disk, 42-43 neural networks, 176, 177-188 automatic feature generation, 188 building with four neurons, 186-188, 186f-187f, 187t with three neurons, 184-186, 185f-186f, 185t with two neurons, 182-184, 182f-184f, 183t-184t

building with Keras package, 199 - 214compiling model, 202-203, 202f defining architecture of model, 200-202 evaluating model, 209-211, 210*f*-211*f* saving and loading model, 209 training model, 203-209, 211 - 214dataset for, 224 neurons, 176 anatomy of, 177–180, 177*f*, 178t-180t networks of, 180-181, 181f training, 189-193 using backpropagation, 190-192, 190f-191f using forward propagation, 189 - 190vanishing gradient problem, 192 - 193types of, 193–197 autoencoder, 194–195, 195f convolutional, 193–194, 194*f* feed-forward, 193 generative adversarial, 195-196 recurrent, 196 ResNet, 196-197 universal approximation theorem, 181-182, 182f neurons, 176 anatomy of, 177-180, 177f, 178t-180t networks of, 180-181, 181f next method, 205, 208 N-grams, 63-64, 64f dynamic API call-based similarity, 72 extracting features, 136-137 instruction sequence-based similarity, 67-68 nodes, 37 adding attributes, 42 adding to shared relationship networks, 41 adding visual attributes to, 48-51 color, 49, 49f shape, 49-50, 50f text labels, 50-51 width, 48-49 in decision trees, 110–111 NUM_MINHASHES constant, 80-81

0

objective function, 189 optimizer parameter, 201–202 optional header (in PE file format), 3–4 output_dot_file argument, 227–228 output_file argument, 52, 225, 227 overfit machine-learning models, 98–99, 101*f* overlap parameter, 44

P

packing, 21 difficulty of disassembling packed malware, 26 legitimate uses of, 22 pandas package, 158-161 filtering data using conditions, 161 loading data, 158-159 manipulating DataFrame, 159-161 Parkour, Mila, 61 pasta malware family, 62, 67f-68f, 70f - 72fPE. See Portable Executable file format PE (Portable Executable) header, 3, 135 - 136pecheck function, 73-74 pefile module, 5-7 disassembly using, 20 dumping IAT, 6-7 installing, 5, 20 opening and parsing files, 5-6 pulling information from PE fields, 6 pefile PE parsing module, 51–52 penwidth attribute, 48-49 persistent malware similarity search systems, 79-87 building allowing users to search for and comment on samples, 82-84 implementing database functionality, 80-81 importing packages, 80 indexing samples into system's database, 82 loading samples, 85 obtaining minhashes and sketches, 81-82 parsing user command line arguments, 84-85

persistent malware similarity search systems, continued commenting on samples, 86 sample output, 86-87 searching for similar samples, 86 wiping database, 86 pick best question function, 112-113 pickle module, 143-144 plot function, 162-163, 167 .png format, 43 pooling layer, 194 pop instruction, 16–17 Portable Executable (PE) file format, 2-5 dissecting files using pefile, 5-7entry point, 3 file structure, 2–5, 3f DOS header, 3 optional header, 3-4 PE header, 3 section headers, 4-5 sections, defined, 4 Portable Executable (PE) header, 3, 135 - 136position independence, 5 precision, 124-126 effect of base rate on, 124-125 estimating in deployment environment, 125-126 predict proba method, 144, 149 PReLU activation function, 179t program stack, defined, 14 projected graph function, 54 projections, 38 push instruction, 16-17 pyplot module, 148-149, 163

R

random forest overview, 115–116, 116*f* random forest–based detectors, 141–146 complete code for, 144–146 running detector on new binaries, 144 training, 142–143 RandomForestClassifier class, 143, 152 ransomware, 30–31, 31f, 155–158, 156*f*, 158, 164–168, 165*f*–166*f*, 168*f*, 172–173, 172*f*–173*f* .rdata section (in PE file format), 4 **Receiver Operating Characteristic** curves. See ROC curves rectified linear unit (ReLU) activation function, 177f, 178t, 180, 182f, 183-185, 201 recurrent neural networks (RNNs), 196 registry keys, 32 .reloc section (in PE file format), 5 ReLU (rectified linear unit) activation function, 177f, 178t, 180, 182f, 183-185, 201 ResNets (residual networks), 196-197 resource projection argument, 52, 227 resource obfuscation, 22 ret instruction, 17-18 reverse engineering, 12 anti-disassembly techniques, 22 dynamic analysis for, 26 methods for, 12 shared code analysis, 60 using pefile and capstone, 20-21 RNNs (recurrent neural networks), 196 ROC (Receiver Operating Characteristic) curves, 123-124, 123f, 126, 147-150, 230-231, 231f computing, 147–150 cross-validation, 151-152, 153f neural networks, 209-210, 210f - 211fvisualizing, 149, 150f roc curve function, 149, 210 .rsrc section (resources) (in PE file format), 4-5

S

sandbox, 26 Sanders, Hillary, 216 savefig function, 165 scan_file function, 144 scan mode, 230–231 scikit-learn (sklearn) machine learning package, 127–128 building basic decision tree–based detectors, 129–134 building random forest–based detectors, 141–146 evaluating detector performance, 146–153 feature extraction, 134–135 hashing trick, 140–141

terminology and concepts, 128-129 classifiers, 129 fit, 129 label vectors, 128-129 prediction, 129 vectors, 128 seaborn package, 168–174, 168f creating violin plots, 172-174, 172*f*–173*f* plotting distribution of antivirus detections, 169-172, 169f, 171f search_sample function, 82-84 SEARCH mode, 229 section headers (in PE file format), 4-5 .data section. 4 .idata section (imports), 4 .rdata section, 4 .reloc section, 5 .rsrc section (resources), 4-5 .text section, 4 security data scientists, 215-220 expanding knowledge of methods, 219 - 220paths to becoming, 216 traits of effective, 218-219 curiosity, 218-219 obsession with results, 219 open-mindedness, 218 skepticism of results, 219 willingness to learn, 216 workflow of, 216-218, 217f data feed identification, 218 dealing with stakeholders, 217 deployment, 218 problem identification, 217-218 solution building and evaluation, 218 self-modifying code, 12 set_axis_labels function, 172 sfdp tool, 46-47, 46f shape attribute, 49-50 shared attribute analysis. See malware network analysis shared code analysis (similarity analysis), 59–87, 60, 61f bag of features model, 62-64, 63f features, defined, 62 N-grams, 63–64, 64f order information and, 63-64 overview, 62-63 dataset for, 223

Jaccard index, 64–65, 65f persistent malware similarity search systems, 79-87 allowing users to search for and comment on samples, 82-84 commenting on samples, 86 implementing database functionality, 80-81 importing packages, 80 indexing samples into system database, 82 loading samples, 85 obtaining minhashes and sketches, 81-82 parsing user command line arguments, 84-85 sample output, 86-87 searching for similar samples, 86 wiping database, 86 scaling similarity comparisons, 77 - 79difficulties with, 77 minhash method, 77-79, 78f similarity graphs, 73-76, 76f declaring utility functions, 73 - 74extracting features, 73, 75 importing libraries, 73 iterating through pairs, 75 Jaccard index threshold, 73 parsing user's command line arguments, 74 visualizing graphs, 76 similarity matrices, 66-72, 66f-67f concept of, 66 dynamic API call-based similarity, 72, 72f Import Address Table-based similarity, 71, 71f instruction sequence-based similarity, 67-70, 68f strings-based similarity, 70-71, 70f tools for, 227–230, 228f shared image relationship networks, 54-58, 55f, 226-227 extracting graphical assets, 57 parsing initial argument and fileloading code, 55-57 saving networks to disk, 58 shelve module, 80 show function, 152, 163, 165, 168

Sigmoid activation function, 180t, 201 sim graph module, 80, 82 similarity analysis. See shared code analysis similarity functions, 64-65 similarity graphs, 73–76, 76f declaring utility functions, 73-74 extracting features, 73, 75 importing libraries, 73 iterating through pairs, 75 Jaccard index threshold, 73 parsing user's command line arguments, 74 visualizing graphs, 76 similarity matrices, 66–72, 66f–67f dynamic API call-based similarity, 72, 72f Import Address Table-based similarity, 71, 71f instruction sequence-based similarity, 67–70, 68f strings-based similarity, 70-71, 70f SKETCH RATIO constant, 80, 82 sklearn. See scikit-learn machine learning package skor malware family, 62, 67f-68f, 70*f*–72*f* Softmax activation function, 180t Sophos, 216 splines parameter, 44 split regex expression, 203-204 stack, defined, 16 stack instructions, 16-17 stack management registers, 14-15 static malware analysis, 1-23 dataset for, 222 disassembly and reverse engineering, 12 methods for, 12 using pefile and capstone, 20 - 21graphical image analysis, 7-8 imports analysis, 6-7 limitations of, 21-23 anti-disassembly techniques, 22 dynamically downloaded data, 22 - 23packing, 21-22 resource obfuscation, 22 pefile module, 5-7 Portable Executable file format, 2-5 strings analysis, 8-10

std function, 160 Step activation function, 179t steps per epoch parameter, 206 string hash function, 81-82strings defined, 8 feature extraction, 135, 141–142 strings analysis, 8-10 analyzing printable strings, 8-10 information revealed through, 8 printing all strings in a file to terminal, 8-9 strings-based similarity, 70-71, 70f strings tool, 8-10 sub arithmetic instruction, 15 summary function, 202–203, 202*f* supernodes, 46 suspicious_calls parameter, 103-104 suspiciousness scores, 121-122, 121*f*-122*f*

T

Target, iii target_directory argument, 227-228 target_path argument, 52, 225, 227 TensorFlow, 200, 207 .text section (in PE file format), 4 threat scores, 147 .todense method, 142 train detector function, 143 training examples variable, 130 transform method, 131, 140 tree module, 129 Trojans, 54–55, 55f, 158–161, 168f, 172*f*-173*f*, 173 true negatives, defined, 120, 120f true positives, 120, 120f base rates and precision, 124-126 relationship between true and false positive rates, 121–122, 121*f*-122*f* ROC curves, 123–124, 123f true positive rate, 121

U

underfit machine-learning models, 98–99, 99*f* universal approximation theorem, 181–182, 182*f* UPX packer, 29

V

validation labels object, 210-211 validation_scores object, 210 vanishing gradient problem, 192-193 vbna malware family, 62, 67f-68f, 70*f*–72*f* vectors, 128 violin plots, 172–174, 172f–173f VirtualBox, vii-viii, 222 virtual size, 6 VirusTotal.com, 29, 59 visualization, 155-174 basic machine learning-based malware detectors. 131-133, 132f dataset for, 224 importance of, 156-158, 157f malware network analysis challenges to, 40f creating with GraphViz, 45f-47f network analysis challenges to, 39-40 creating with GraphViz, 43-51 ROC curves, 149, 150f, 152-153, 153f shared code analysis, 76 using matplotlib, 162–167, 162f plotting ransomware and worm detection rates, 165-167, 166f plotting ransomware detection rates, 164-165, 165f plotting relationship between malware size and detection, 162 - 163using pandas, 158-161 filtering data using conditions, 161 loading data, 158-159 manipulating DataFrame, 159 - 161using seaborn, 168-174, 168f creating violin plots, 172-174, 172f - 173fplotting distribution of antivirus detections, 169-172, 169f, 171f

W

webprefix malware family, 62, 67*f*–68*f*, 70*f*–72*f* weight attribute, 37 weight parameter, 178, 181 Wells Fargo, iii Wikipedia, 220 wipe_database function, 80–81 wipe mode, 229 work method, 57 worms, 158–161, 165–167, 166*f*, 168*f*, 172, 172*f*–173*f* wrestool tool, 55 downloading, 8 extracting image resources, 7–8 write_dot function, 42–43

X

x86 assembly language, 12-20 arithmetic instructions, 15, 15t CPU registers, 13–15, 14*f* general-purpose registers, 13 - 14stack and control flow registers, 14 - 15data movement instructions, 15-20.16tbasic blocks and control flow graphs, 19-20, 19f control flow instructions, 17-18 stack instructions, 16-17 dialects of, 13 shared code analysis, 67 xtoober malware family, 62, 67f-68f, 70*f*-72*f*

Y

yield statement, 205

Z

zango malware family, 62, 67*f*–68*f*, 70*f*–72*f*