Symantec Research Labs

Automatic Generation of String Signatures for Malware Detection

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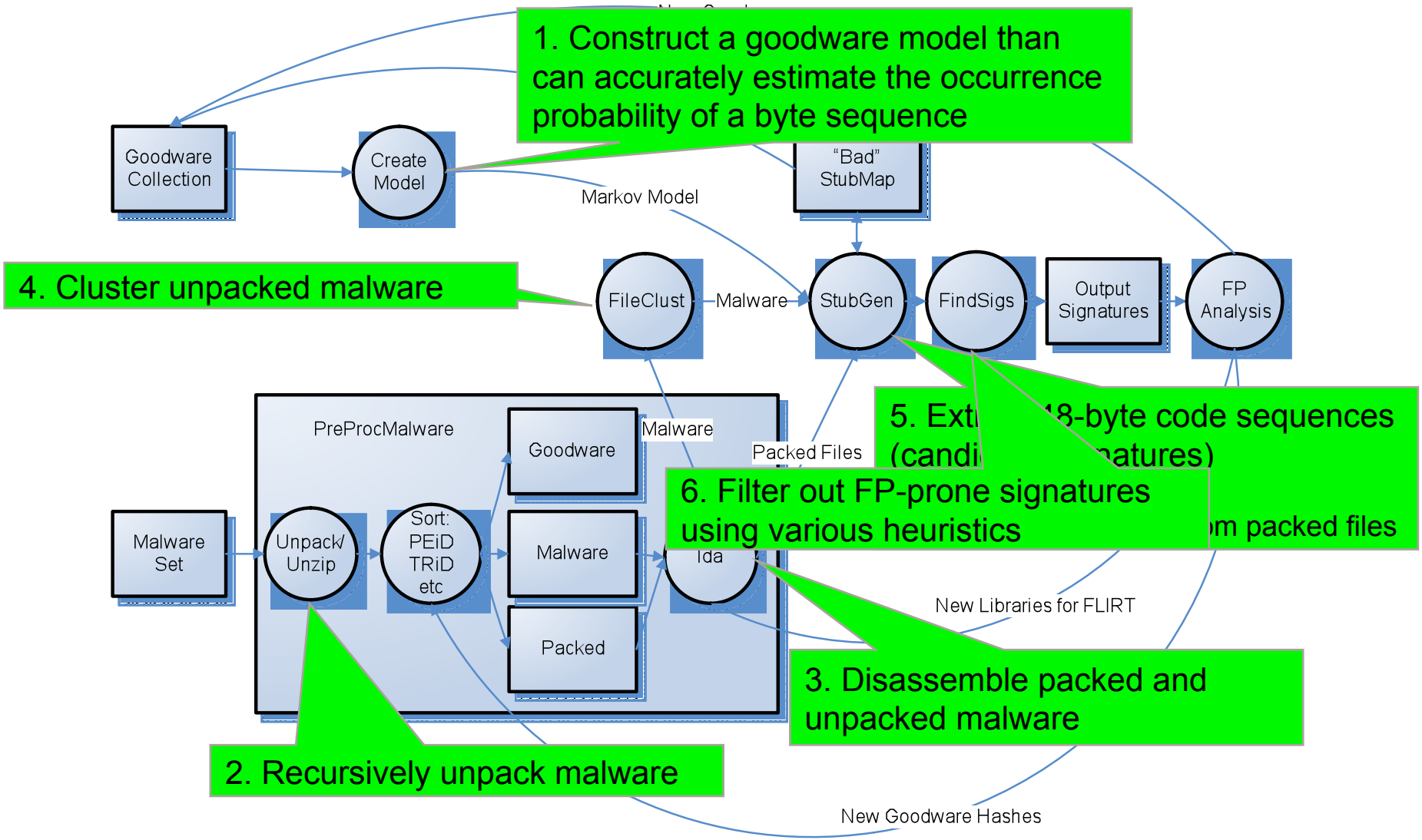
String Signature Generation

- Goal: Given a set of malware samples, derive a minimal set of string signatures that can cover as many malware samples as possible while keeping the FP rate close to zero
  - 48-byte sequences from code
- Why string signatures?
  - Still one of the main techniques for Symantec and other AV companies
  - Higher coverage than file hashes → smaller signature set
  - Currently created manually!

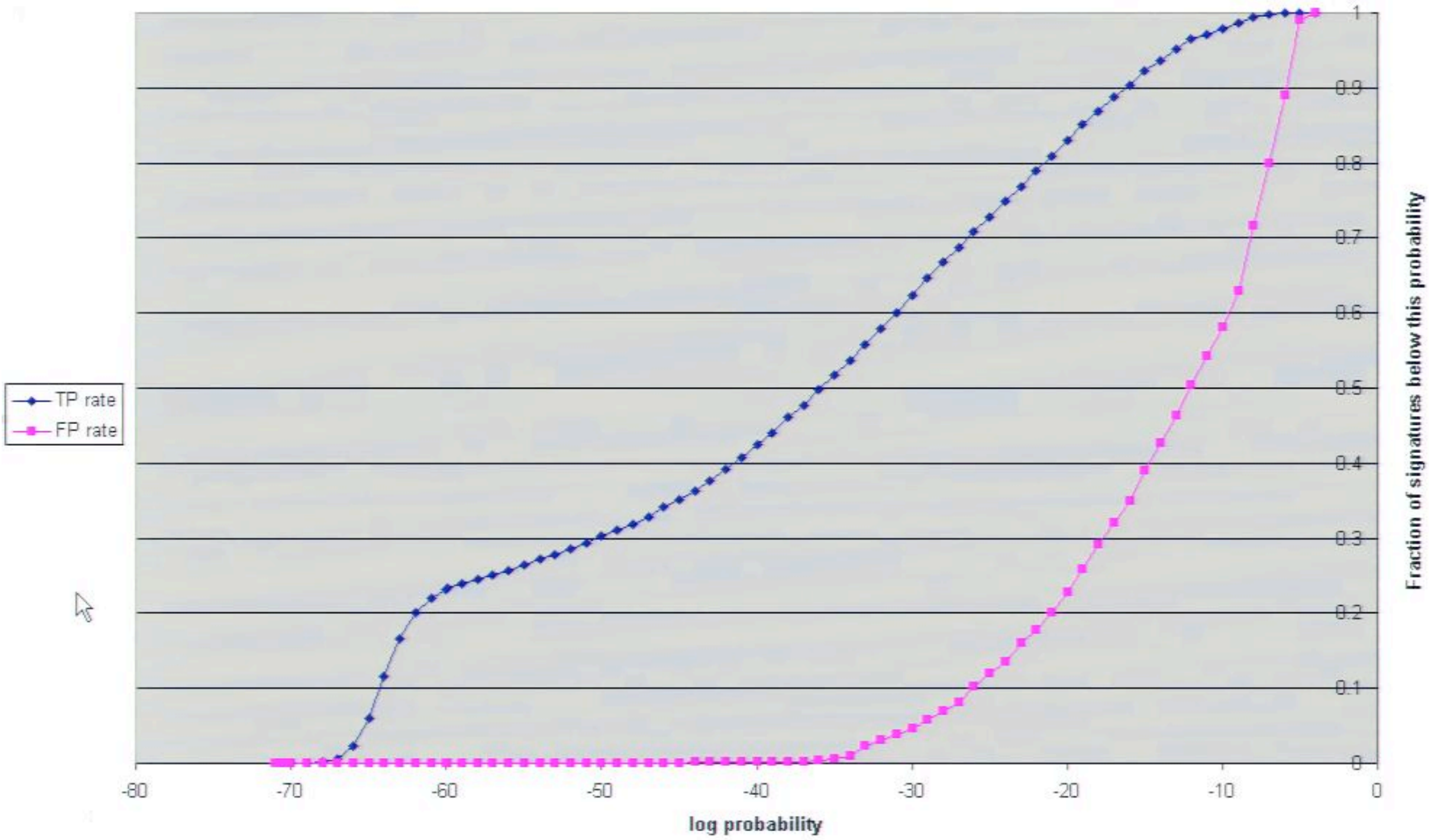
System Overview



Heuristics

- 3 main categories:
  - Probability-based – using a Markov chain model
  - Diversity-based – identifies rare libraries and other reused code
  - Disassembly-based – examines assembly instructions
- Discrimination power
  - The best heuristics have high FP reduction and low coverage reduction
  - $\log (FP_i / FP_f) / \log (Coverage_i / Coverage_f)$
  - Raw vs marginal discrimination power

Goodware Model Effectiveness



Modeling

- Fixed 5-gram Markov chain model
  - Fixed because the rarest byte sequences are the most important
    - LZ-based training backfired
    - Variable-order models use much more memory
- Needed ~100 MB of relevant data to work

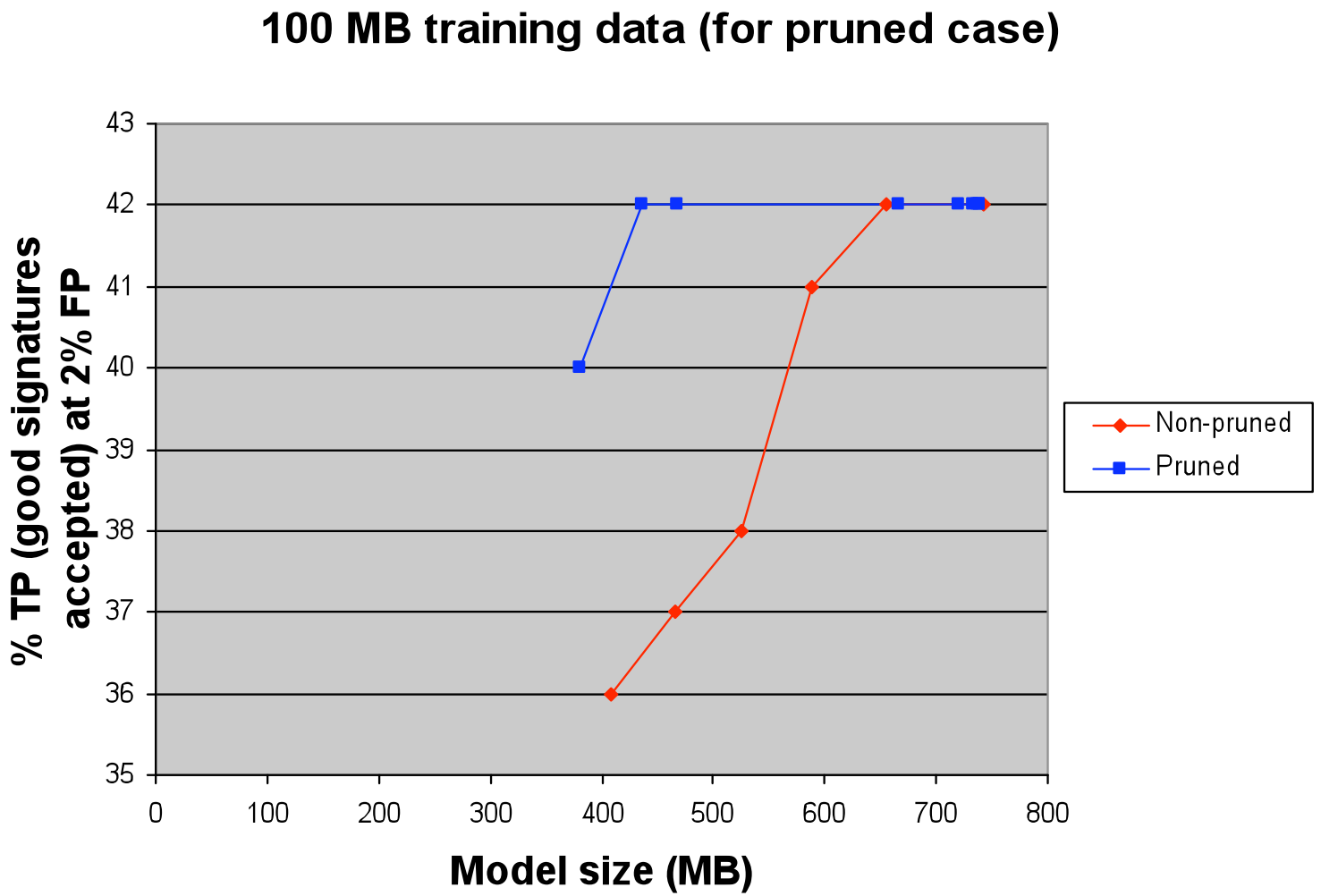
- Probability calculated as in Prediction by Partial Matching
  - $p(c|ab) = [c(abc) / c(ab)] * (1-\varepsilon(c(ab))) + p(c|b) * \varepsilon(c(ab))$
  - $\varepsilon(c) = sqrt(32) / (sqrt(32) + sqrt(c))$

Scaling the Model

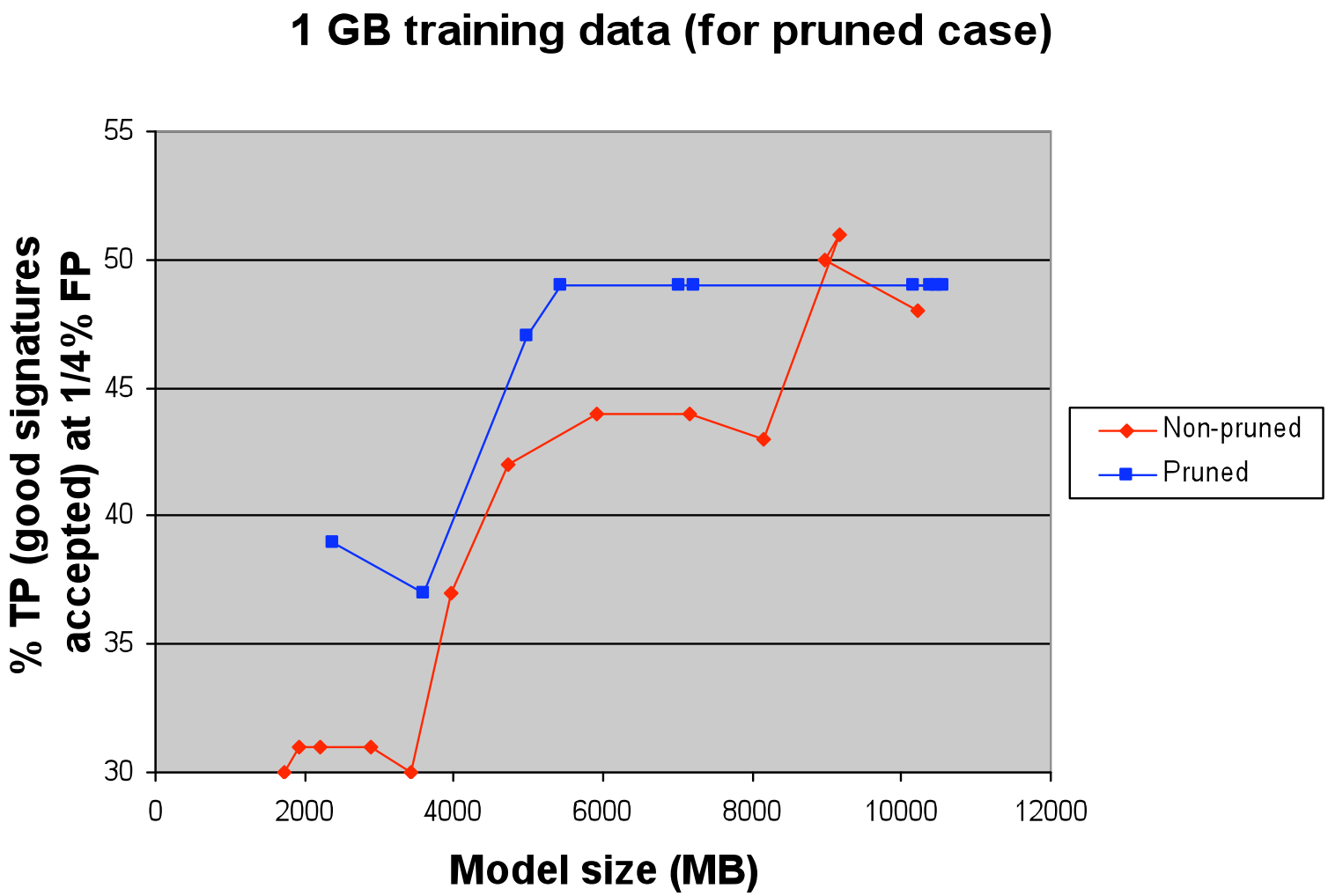
- We have TBytes of training data
  - A model trained on this would use too much memory
  - Solution: create several models, then prune and merge them

- Pruning
  - If p(c|ab) is close to p(c|b), we don't need node abc
  - If |log(p(c|ab)) – log(p(c|b))| < log(threshold), remove abc
    - Thresholds up to 200 preserve most of the model's effectiveness

Pruned Model Results



Pruned Model Results Continued



Diversity-based Heuristics

- High coverage signatures are more likely to be from rare library code
  - Model-only tests had 25-30% FPs
- So we examine the *diversity* of covered malware files
  - If files are from many malware families, it's probably a library

Byte-level Diversity-based Heuristics

- Group count/ratio
  - Cluster malware into families
  - Reject signatures that cover too many groups or have too high a ratio of groups to covered files
- Signature position deviation
  - How much does the signature's position in the files vary?
- Multiple common signatures
  - Find a 2nd signature a fixed distance (≥1kb) away in all covered files

Instruction-level Diversity-based Heuristics

- Enclosing function count
  - Different enclosing functions indicates code reuse
- Several ways of comparing enclosing functions:
  - Exact byte sequences
  - Instruction op codes with some canonicalization
    - e.g. All ADD instructions are treated the same
  - Instruction sequence de-obfuscation
    - e.g. “test esi, esi” and “or esi, esi” is the same

Method	% FP sig.s Remaining	% all sig.s Remaining	Discrimination Power
Exact byte sequences	17%	54%	2.9
Op code canonicalization	78%	90.5%	2.5
Instruction de-obfuscation	89%	94.7%	2.1

Disassembly-based Heuristics

- IDA Pro's FLIRT –
  Fast Library Identification and Recognition Technology
  - Universal FLIRT
  - Library function reference heuristic
  - Address space heuristic

- Code interestingness…

Code Interestingness Heuristic

- Encodes Symantec analysts' intuitions using fuzzy logic
- Targets code that is suspicious and/or unlikely to FP
- Points for
  - Unusual constant values
  - Unusual address offsets
    - May indicate custom structs/classes
  - Local, non-library function calls
  - Math instructions
    - Often done by malware for obfuscation

Results

Thresholds	Coverage	# sigs	# FPs	# Good sigs	# So-so sigs	# Bad sigs
Loose	15.7%	23	0	6	7	1
Normal	14.0%	18	0	6	2	0
Strict	11.7%	11	0	6	0	0
All non-FP	22.6%	220	0	10	11	9

- Used samples for August 2008
  - 2,363 unpacked files

Threshold settings	Prob.	Group ratio	Pos. dev.	# common sig.s	Interesting score	Min. coverage
Loose	-90	0.35	4000	Single	13	3
Normal	-90	0.35	3000	Single	14	4
Strict	-90	0.35	3000	Dual	17	4

Results

- 2007-8 files
  - 46,988 unpacked files

Thresholds	Coverage	# sigs	# FPs
Loose	14.1%	1650	7
Normal	11.7%	767	2
Normal + pos. dev. 1,000	11.3%	715	0
Strict	4.4%	206	0
All non-FP	31.8%	7305	0

Raw Discrimination Power

Heuristic	% FPs Remaining	% Coverage	Discrimination Power
Position deviation (from ∞ to 8,000)	41.7%	96.6%	25
Min File Coverage (from 3 to 4)	6.0%	83.3%	15
Group Ratio (from 1.0 to .6)	2.4%	74.0%	12
*Probability (from -80 to -100)	51.2%	73.7%	2.2
*Interestingness (from 13 to 15)	58.3%	78.2%	2.2
Multiple common sig.s (from 1 to 2)	91.7%	70.2%	0.2
*Universal FLIRT	33.1%	71.7%	3.3
*Library function reference	46.4%	75.7%	2.8
*Address space	30.4%	70.8%	3.5

*Not entirely raw

Marginal Discrimination Power

Heuristic	# FPs	% Coverage
Position deviation (from 3,000 to ∞)	10	121%
Min File Coverage (from 4 to 3)	2	126%
Group Ratio (from 0.35 to 1)	16	162%
Probability (from -90 to -80)	1	123%
Interestingness (from 17 to 13)	2	226%
Multiple common sig.s (from 2 to 1)	0	189%
Universal FLIRT	3	106%
Library function reference	4	108%
Address space	3	109%

Multi-component Signatures

# Components	# Allowed FPs	Coverage	# Signatures	# FPs
2	1	28.9%	76	7
2	0	23.3%	52	2
3	1	26.9%	62	1
3	0	24.2%	44	0
4	1	26.2%	54	0
4	0	18.1%	43	0
5	1	26.2%	54	0
5	0	17.9%	43	0
6	1	25.9%	51	0
6	0	17.6%	41	0

- 16 bytes per component, from code and data
- Tested against a smaller goodware set

Thank You!

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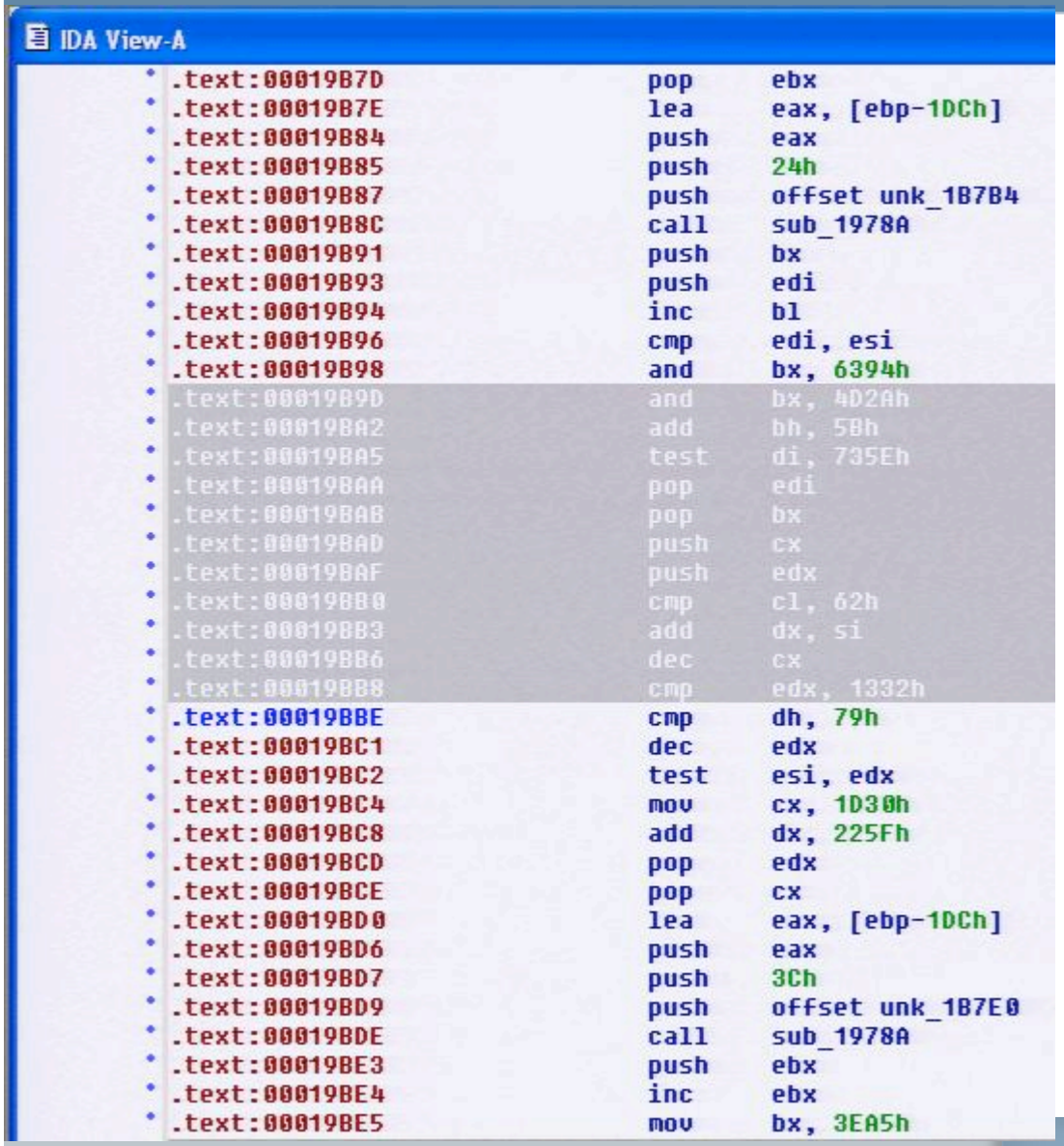
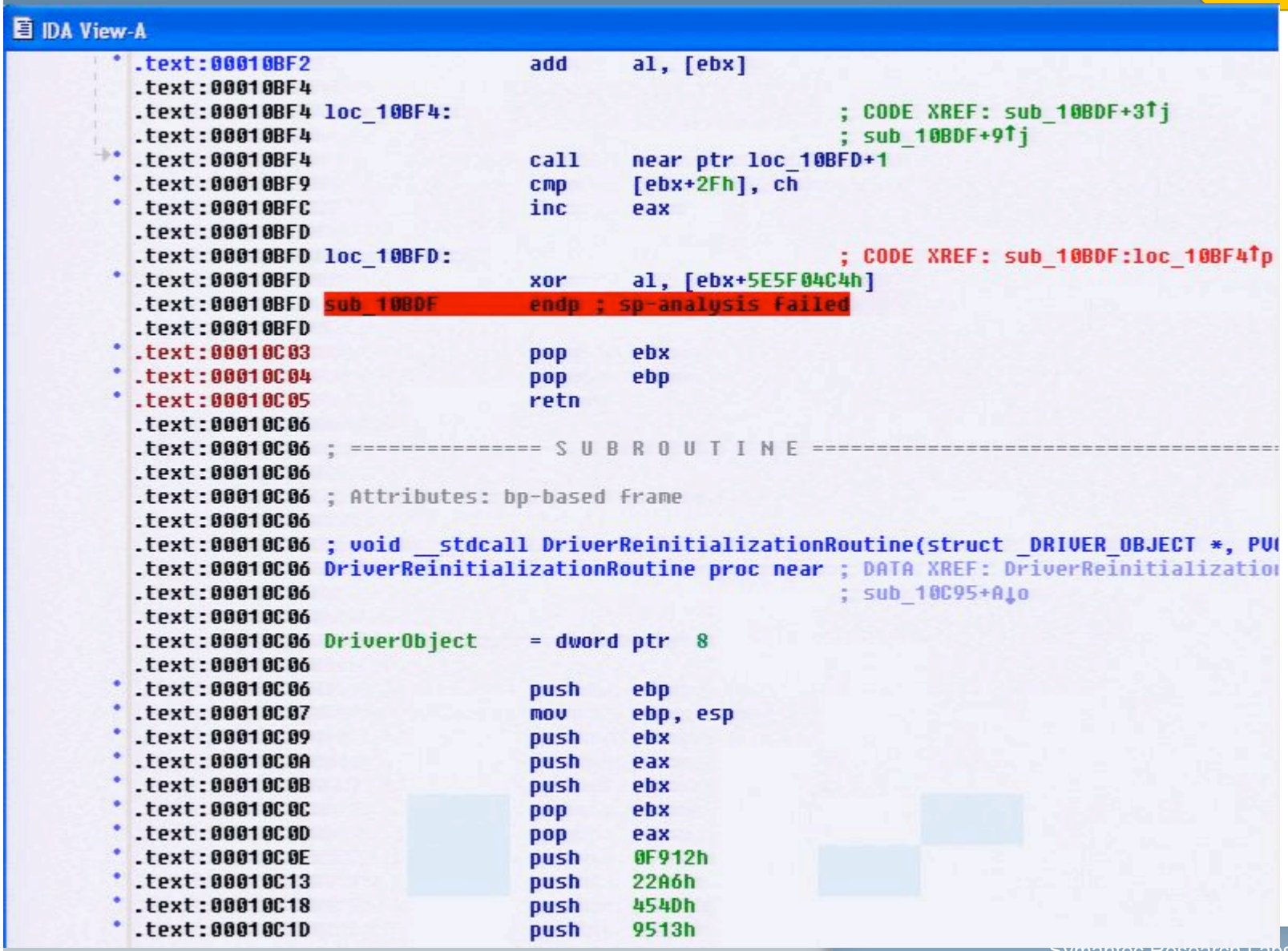
Good Signature #0



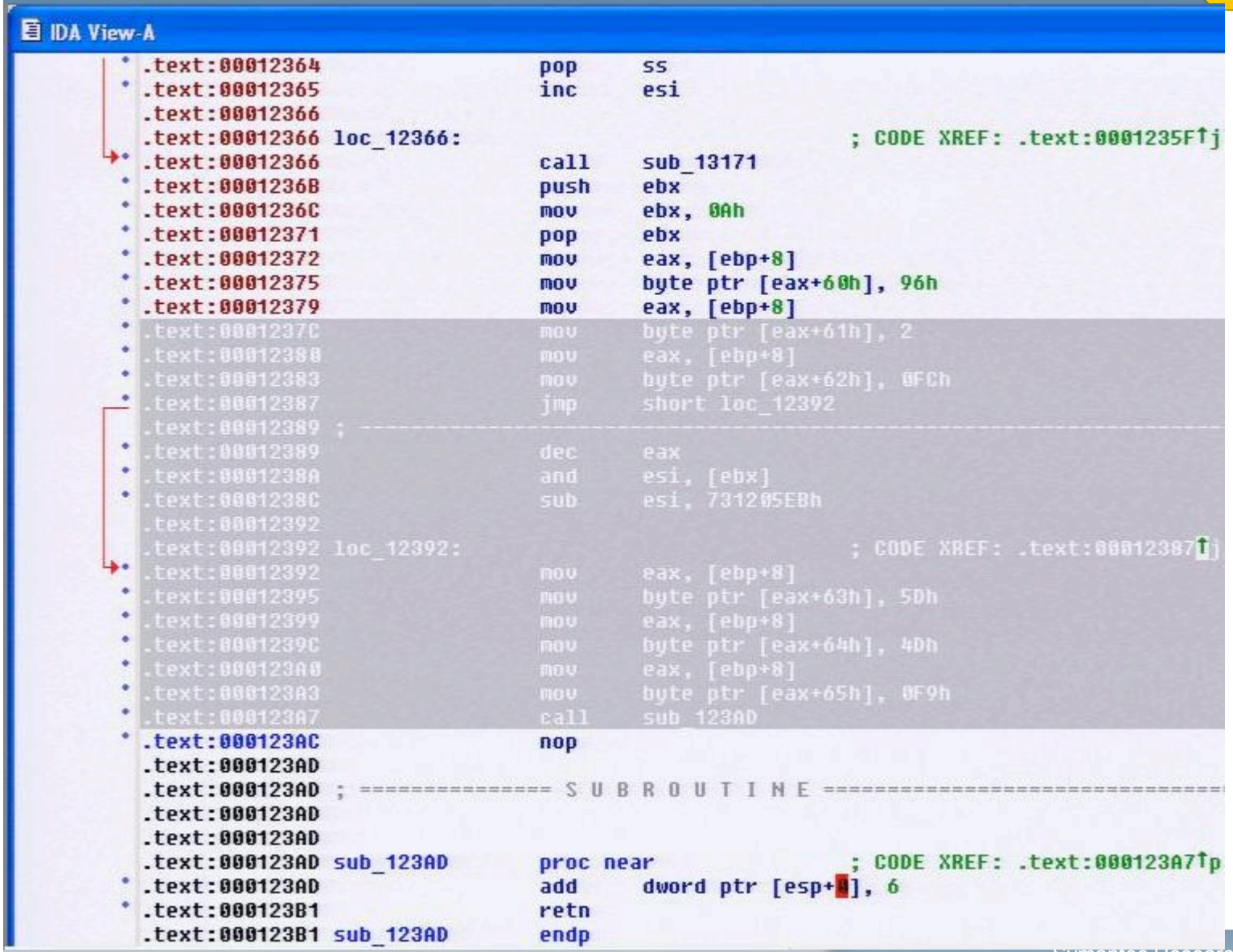
- Uses 16-bit registers
- Several interesting constants
- Covers 73 files in our malware set
- Very low probability (-140)
- High interestingness score (33)
- Perfect diversity scores

Good Signature #1



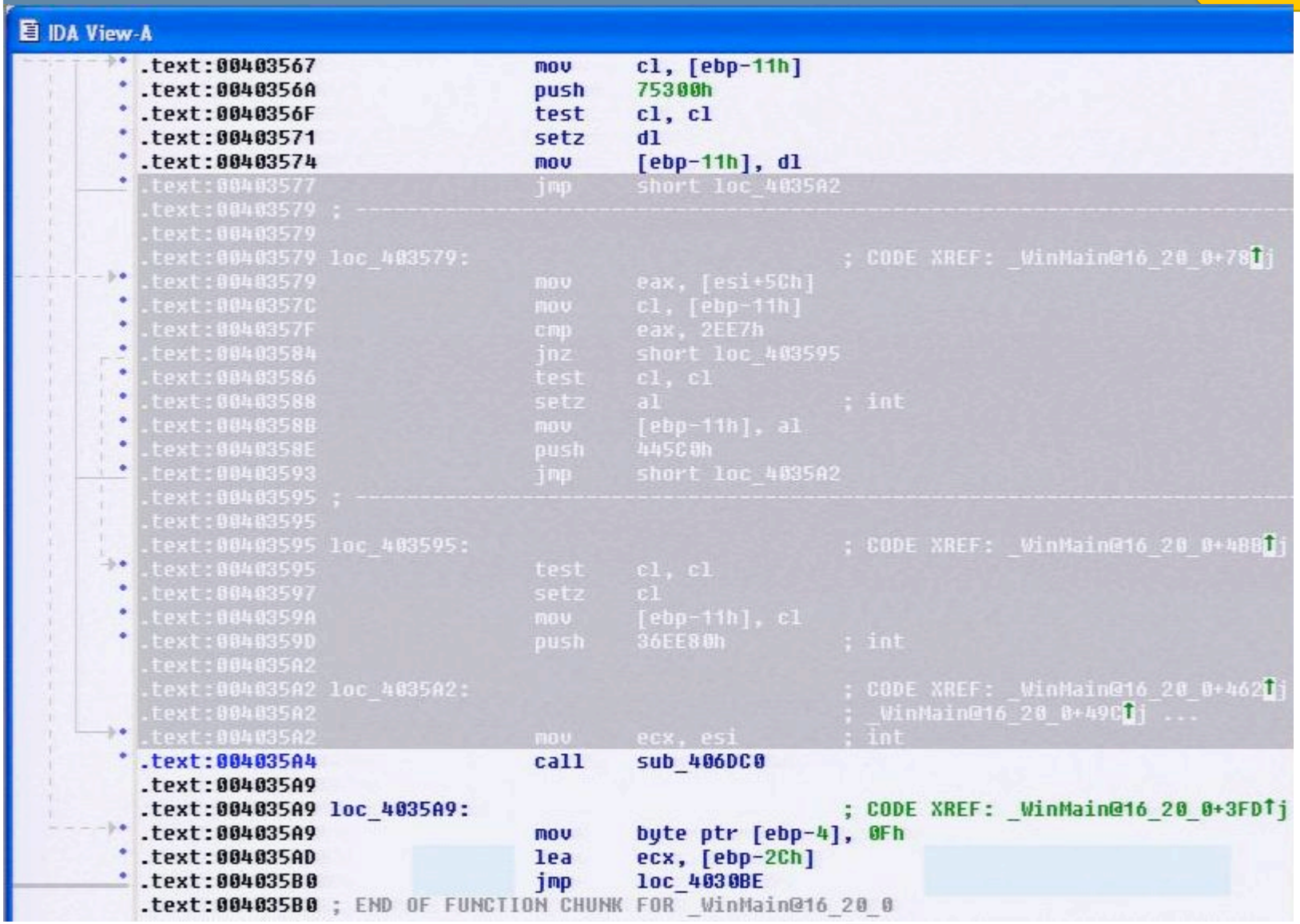
- Several constants
- Covers 65 in our malware set
- Interesting-ness score 19
- Perfect diversity scores

Good Signature #2



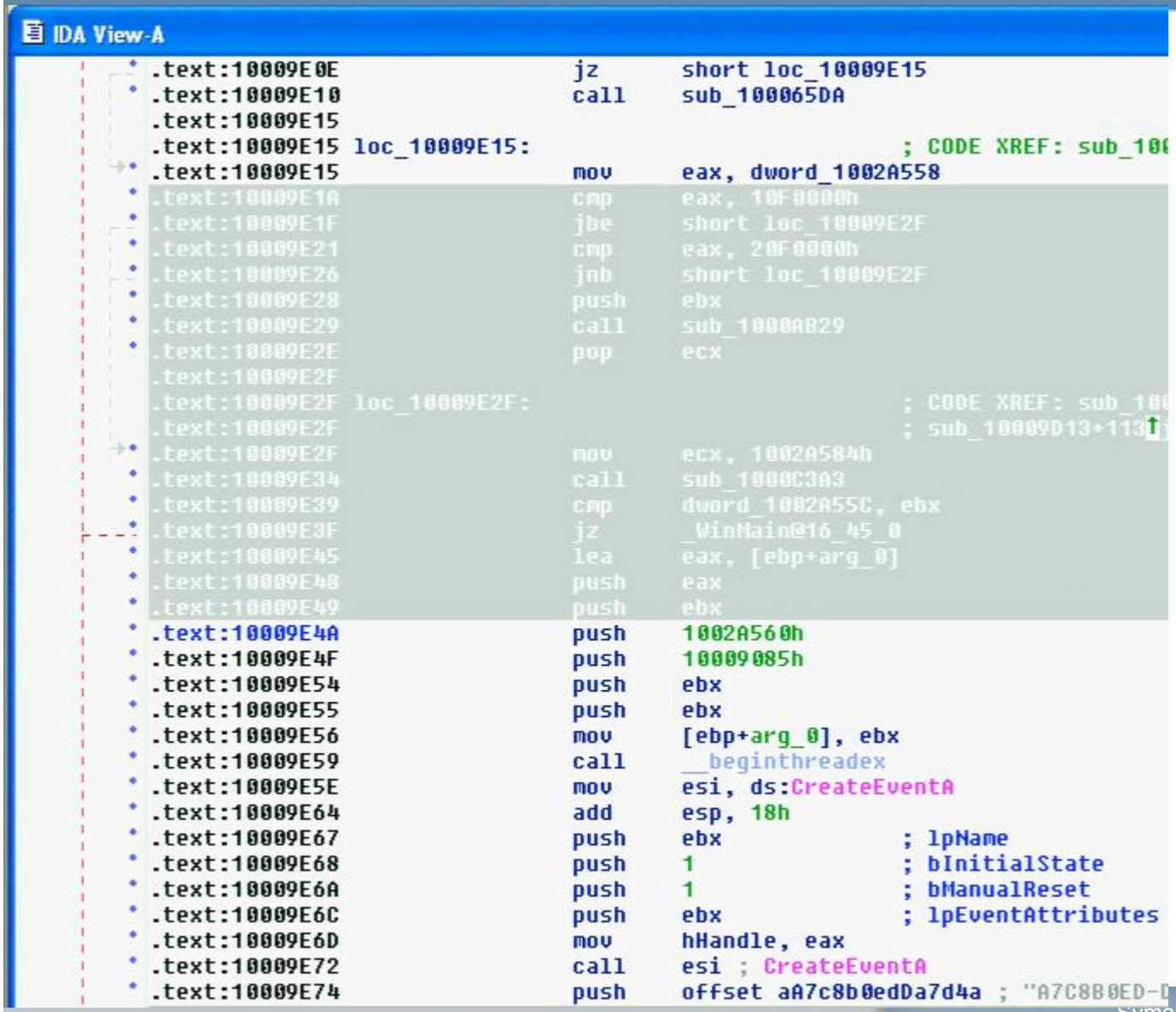
- Several constants
- Covers 63 in our malware set
- Interesting-ness score 21
- Perfect diversity scores

So-so Signature #4



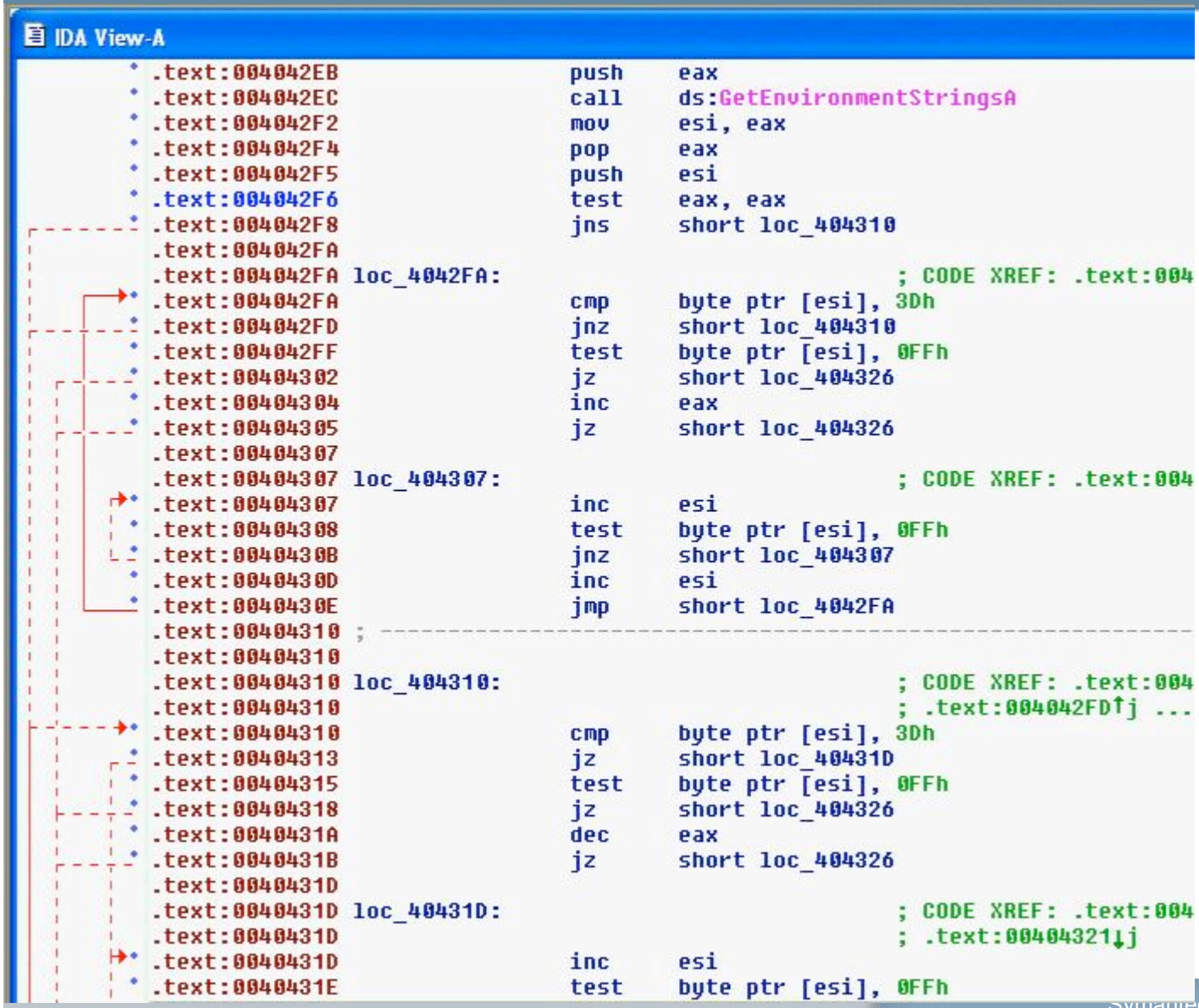
- Suspicious constants – multiples of 10,000
- This sig and variants cover 50+ files
- Interesting-ness score 13
- Good group count, std dev, single sig
- Eliminated by better threshold

So-so Signature #50



- 1 interesting constant
- Covers 4 files in our malware set
- Interestingness score 16
- Good diversity scores
- Eliminated by best thresholds

Bad Signature #16



- Generic logic
- Only 1 interesting 1-byte constant
- Covers 7 files
- Interestingness score 13
- Bad diversity scores