MALWARE DETECTION BY EATING A WHOLE EXE

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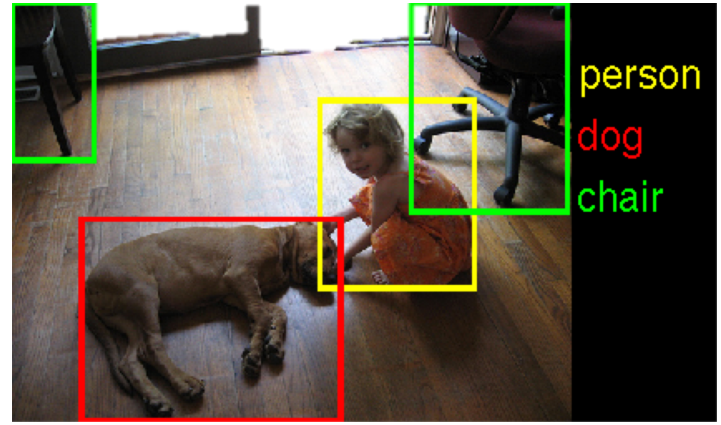
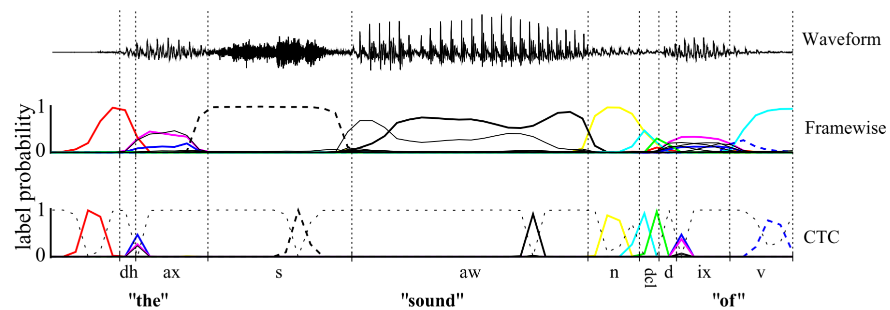
Malware Detection? Don't AVs do that?

- Single incidents of malware are now causing millions in damages.
  - Potential impact is growing, see: WannaCry, Petya
  - Lives can be on the line, especially when older hospital infrastructures get infected
- AV products are built around a Signature Based approach
  - Essentially extended RegExs for binaries
  - Do some fancy stuff too, but often not as much
  - Makes the approach reactionary
  - Signatures have high specificity, but low generalization

Sounds like a Standard Classification Problem…

- Machine Learning has enjoyed huge success in recent years at predicting things
  - What is in this picture? (Object Detection)
  - What did you say? (Speech-to-text, Alexa, Siri)
  - What did you mean? (Sentiment Analysis)
- But Malware is more challenging for several reasons





I found this to be a charming adaptation, very lively and full of fun. With the exception of a couple of major errors, the cast is wonderful. I have to echo some of the earlier comments -- Chynna Phillips is horribly miscast as a teenager. At 27, she's just too old (and, yes, it DOES show), and lacks the singing "chops" for Broadway-style music. Vanessa Williams is a decent-enough singer and, for a non-dancer, she's adequate. However, she is NOT Latina, and her character definitely is. She's also very STRIDENT throughout, which gets tiresome. The girls of Sweet Apple's Conrad Birdie fan club really sparkle -- with special kudos to Brigitta Dau and Chiara Zanni. I also enjoyed Tyne Daly's performance, though I'm not generally a fan of her work. Finally, the dancing Shriners are a riot, especially the dorky three in the bar. The movie is suitable for the whole family, and I highly recommend it.

Binaries Lack Spatial Consistency

- Jumps and Calls add weird locality
- Spatial correlation ends at function boundaries
  - Except for when it doesn't
- Multiple hierarchies of relationships
  - Basic-block level
  - Function level
  - Function composition into classes

```
jmp 0x4010eb
push 0x10024b78
lea ecx, dword ptr [esp + 4]
call dword ptr [MFC71.DLL:None]
push ebx
push esi
push edi
push 0x10024c05
lea ecx, dword ptr [esp + 0x14]
call dword ptr [MFC71.DLL:None]
lea ecx, dword ptr [esp + 0x24]
mov ebx, 1
push ecx
mov byte ptr [esp + 0x20], bl
call 0x41f8ec
mov edx, dword ptr [eax]
```

Malware Complicates *Everything*

- Malware may intentionally break rules / format specifications
  - Bug that is part of an exploit
  - Intentionally trying to obfuscate itself
    - Attribution, purpose, that it is even malware
- x86 code gives you the freedom to make your programs, gives malware the freedom to be weird
  - Binaries with no “code”
  - Binaries with only code
  - Binaries within binaries
  - Binaries composed of only the x86 mov instruction.
  - Binaries that can detect if they are in a VM

Complication Makes Feature Extraction Difficult

- Simple things like getting values from the PE header are non-trivial
  - We’ve tested multiple libraries with disagreements on header content
  - Windows doesn't even follow the PE-spec
- A number of companies have followed through on this domain-knowledge based path
  - Expensive proprietary feature extraction systems
    - Reverse engineering the windows loader
    - Hooking deep into the OS
    - Enhanced emulated execution
  - Huge amount of effort and person-hours just for features
- What if we want to work for any new format?

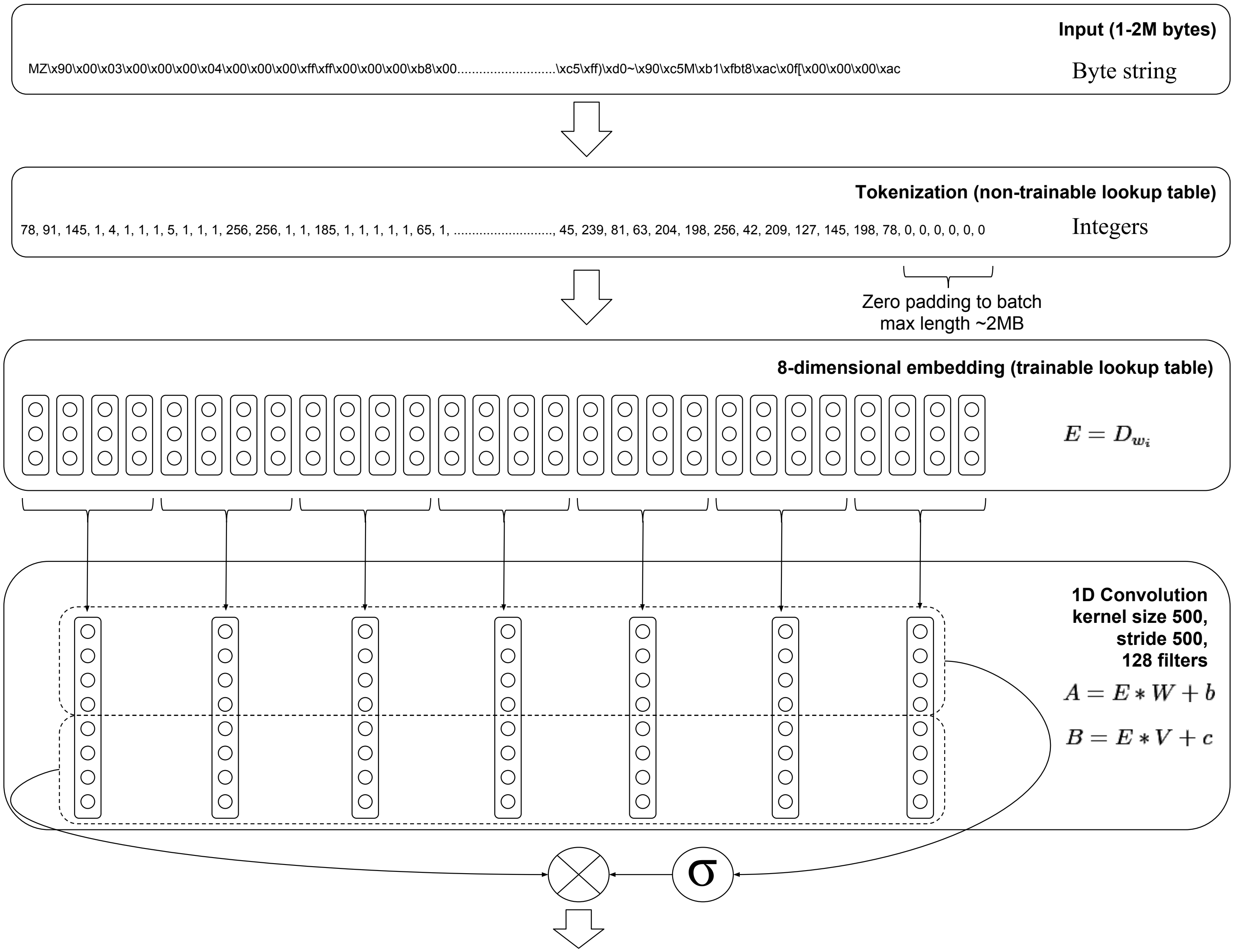
A Domain Knowledge Free Approach

- DK-free means we don't encode any knowledge about the file format in the solution: Looking at raw bytes.
  - Means we are going to be doing static analysis.
- DK-free means we can adapt to new file formats (given data).
  - Build new models for PDFs, RTFs, etc., as they become a problem.
  - Ready to work for any new file format as it arises.
  - Save time on feature extraction, time-to-solution reduced.
- DK-free means we get rid of old problems, but also introduce new ones. That's what we tackle in this work.
- We think a neural-network based solution is most likely to succeed.

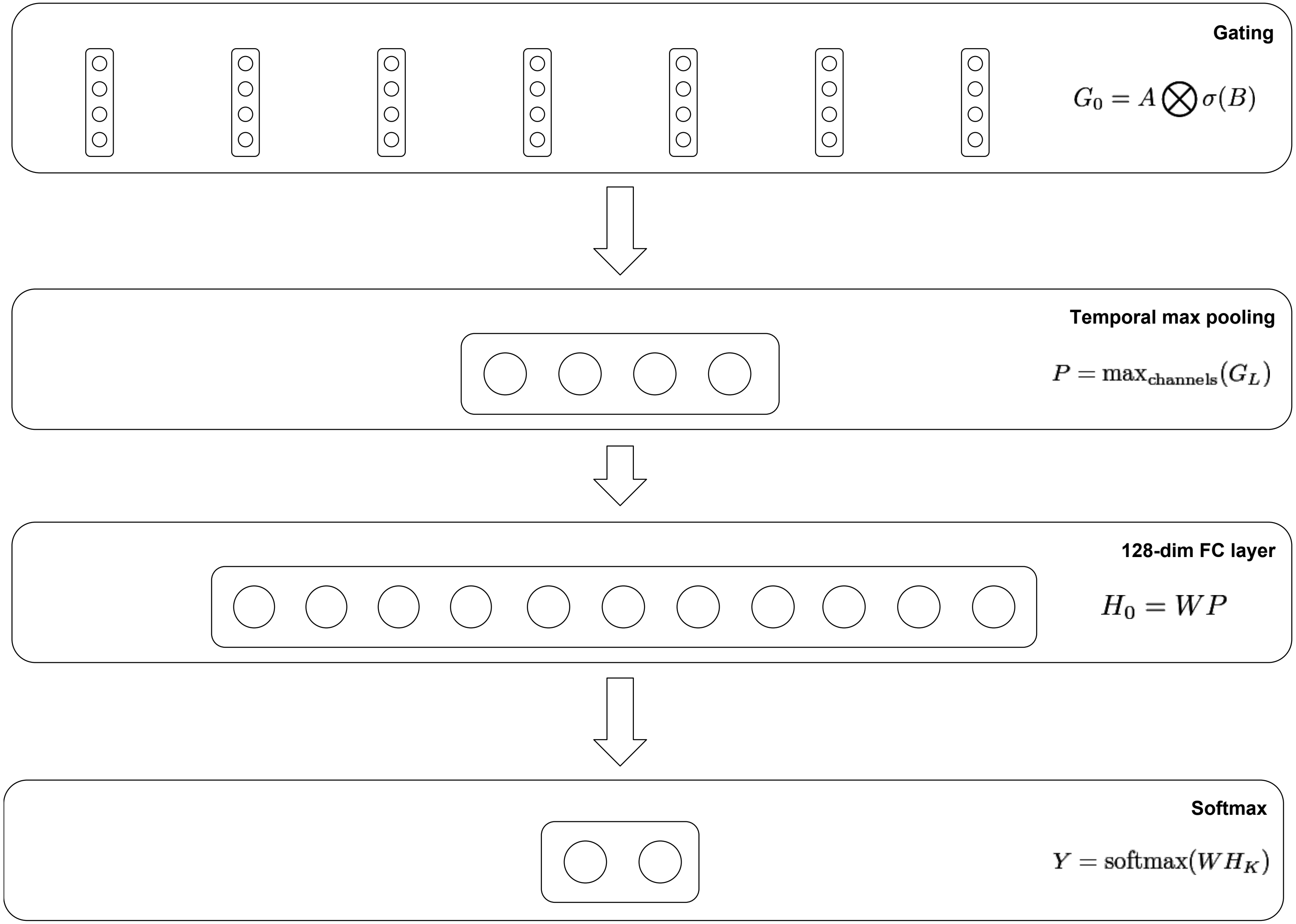
How do we Make a Neural Net Process a Whole Binary?

- Problems:
  - Binaries are variable length
  - Binaries are large
  - Binaries can store many things
- We found that many best-practices in the image domain didn't translate to our space
  - We needed to make our network shallow instead of deep
  - We needed to use large filter sizes instead of small
  - We needed to be very careful in how we handle variable length
- Memory constraints are the primary bottle neck
  - Modern frameworks were never designed for inputs of *2 million* time steps!
  - Just the first convolution uses >40GB of RAM for backpropagation

MalConv Architecture, Part 1



MalConv Architecture, Part 2



Data and Evaluation

- Using two test sets, Groups "A" and "B"
  - Allow us to better test generalization
  - The I.I.D. assumption is strongly violated by malware
    - Cross-Validation will over-estimate your accuracy!
  - Group A is public data, benign comes from Microsoft Windows
  - Group B is private AV data, real-world
- Training, we use two private datasets from our AV partner
  - 400k training set, used in prior work.
  - 2 million training set, over 2 TB in size!

Primary Results

- We have a model and we have data. Now for some results!
- 1) How accurate is MalConv?
  - Is it better than what we could do before?
- 2) What does MalConv learn?
  - Does it learn more than what prior results did?
- 3) What have *we* learned?
  - A lot of ML practice does not easily transfer to this new domain!

MalConv Results

	MalConv		Byte n-grams		PE-Header Network	
Test Set	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
Group A	*88.1*	**98.5**	87.0	*98.4*	**90.8**	97.7
Group B	*89.6*	*95.8*	**92.5**	**97.9**	83.7	91.4

- Trained on 400,000 binaries
- Evaluated on two datasets
- MalConv has best holistic performance
  - Outperformed our prior work looking at just the PE-Header
  - Smallest gap between two test sets, indicates robustness to features

MalConv Results

	MalConv		Byte n-grams	
Test Set	Accuracy	AUC	Accuracy	AUC
Group A	**94.0**	**98.1**	82.6	93.4
Group B	90.9	**98.2**	**91.6**	97.0

- Trained on a larger corpus of 2 million binaries
  - Took *a month* on a DGX-1
  - N-grams took one month to count using 12 servers.
- MalConv performance improved, Byte n-grams *decreased*
  - MalConv still has growth on the learning curve
  - N-grams are overfitting

What is MalConv Learning?

- Our prior work has found that byte n-grams really only learn the PE-Header.
  - We expect PE-Header to make a big portion of any model, because it's the easiest to learn.
- Because MalConv has temporal max-pooling, we can look back and see which areas of the binary will respond.
  - Produces a sparse set of 128 regions each of 500 bytes per binary.
- Using tools to parse the PE-Header, we can look at what sections the blocks were found in.
  - Gives us an idea about the type of features it is learning.

What is MalConv Learning?

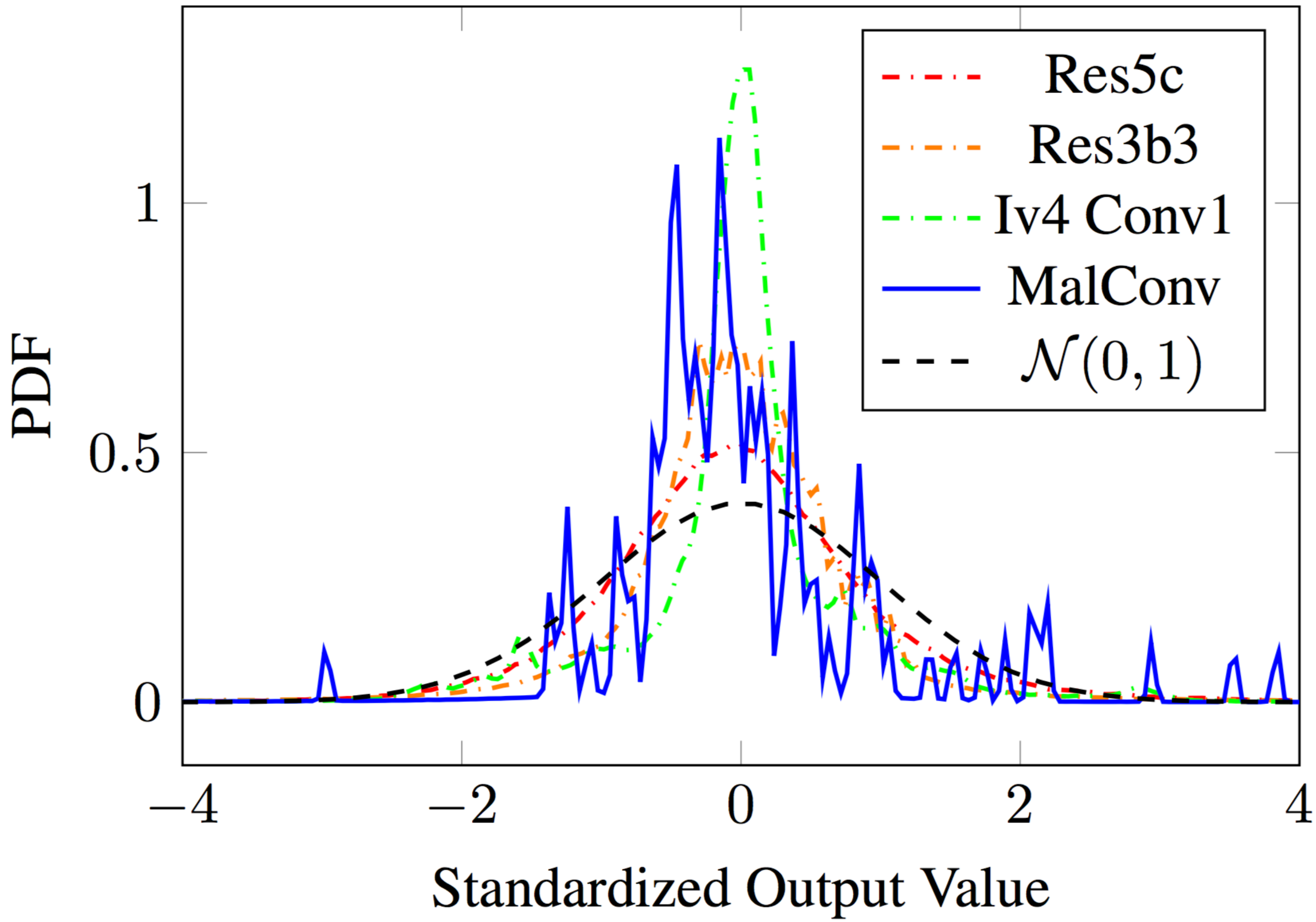
Section	Total	PE-Header	.rsrc	.text	UPX1	CODE	.data	.rdata	.reloc
Malicious	26,232	15,871	3,315	2,878	697	615	669	383	214
Benign	19,290	11,183	2,653	2,414	596	505	423	243	77

- Blocks can indicate they were used to recognize benign-ness or maliciousness.
  - The PE-Header makes up ~60% of regions used. PE-Header properties are a strong indicator of maliciousness to domain experts.
  - Lots of new regions we weren't learning from before!
- UPX1 for both benign and malicious is interesting.
  - UPX is a packer, and many models degrade to saying packers are always malicious.
- Significant use of resource and code sections
  - Strong indication that we are learning to extract far more information than previous approaches.

What Didn’t Work: BatchNorm

- Sacrilege warning: BatchNorm doesn’t always work.
- Issue with data modality. Every pixel in an image is a pixel. Meaning doesn’t change.
- Byte meaning is *context sensitive*
- When we trained with BatchNorm, models failed to ever learn.
  - Training accuracy would reach 60% at best.
  - Testing would be 50% random guessing.
  - Happened with *every* architecture we tested.

The Failure of BatchNorm



Questions?

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"Malware Detection by Eating a Whole EXE"
https://arxiv.org/abs/1710.09435