

# FIGHTING MALWARE WITH MACHINE LEARNING

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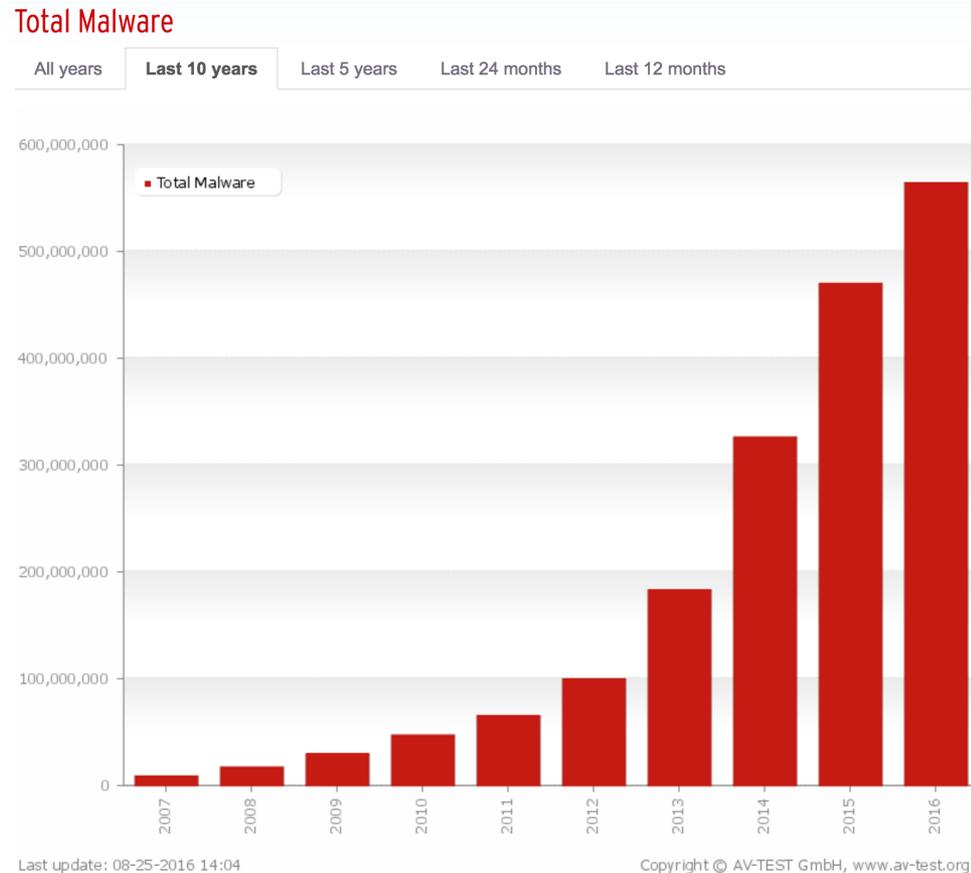
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# Need ML for Malware

- Amount of malware is growing exponentially
- Anti-virus and signature based approaches are reactionary, don't work for novel malware
- Current approaches are labor intensive and require smart analysts
- Machine Learning has the potential for a pro-active solution, but it's a hard problem



# Difficulties with Malware

- Good labeling of data is hard
  - Requires domain expertise
  - Getting good benign data is especially hard
- Variable length and large
  - A *single* binary could be a few KB to 100MB+
  - Scale of individual data points is far beyond work in other domains
- Real life *adversarial scenario*
  - Concept drift++
  - Opponent's behavior is unbounded

# Even More Difficulties with Malware

- No real meaningful transformations
  - Can't do augmented training, can't "resize" a binary, ...
- Many modalities of data
  - Header, code, data, etc, all behave and are represented differently
  - Meaning of a byte is entirely context dependent
- Difficult locality behavior
  - Spatial locality is often disjoint (think branching) and globally invariant (code sections could be re-arranged almost arbitrarily)

# Progress towards ML for Malware

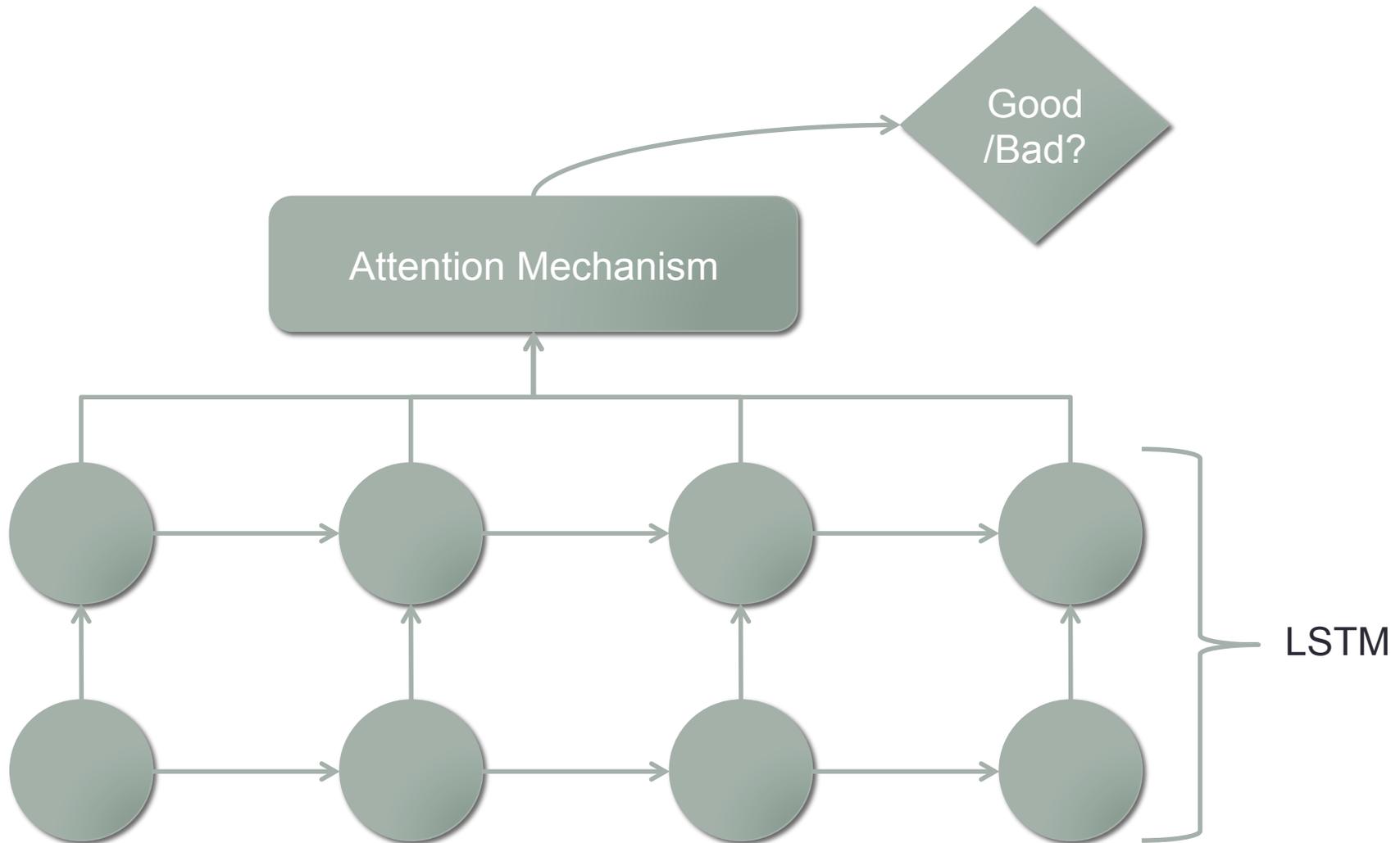
- We want to fight malware using Machine Learning and minimal domain knowledge
  - Its expensive, and malware doesn't always play nice
- Much prior work using things like n-grams, but many results are plagued by data quality issues
  - See: "An Investigation of Byte N-Gram Features for Malware Classification," to appear in *Journal of Computer Virology and Hacking Techniques*
- Deep Learning provides a likely solution
- Short term: Get the easier cases right, and use ML to assist analysts on the harder ones

# Small-Scale Results: Using PE-Headers

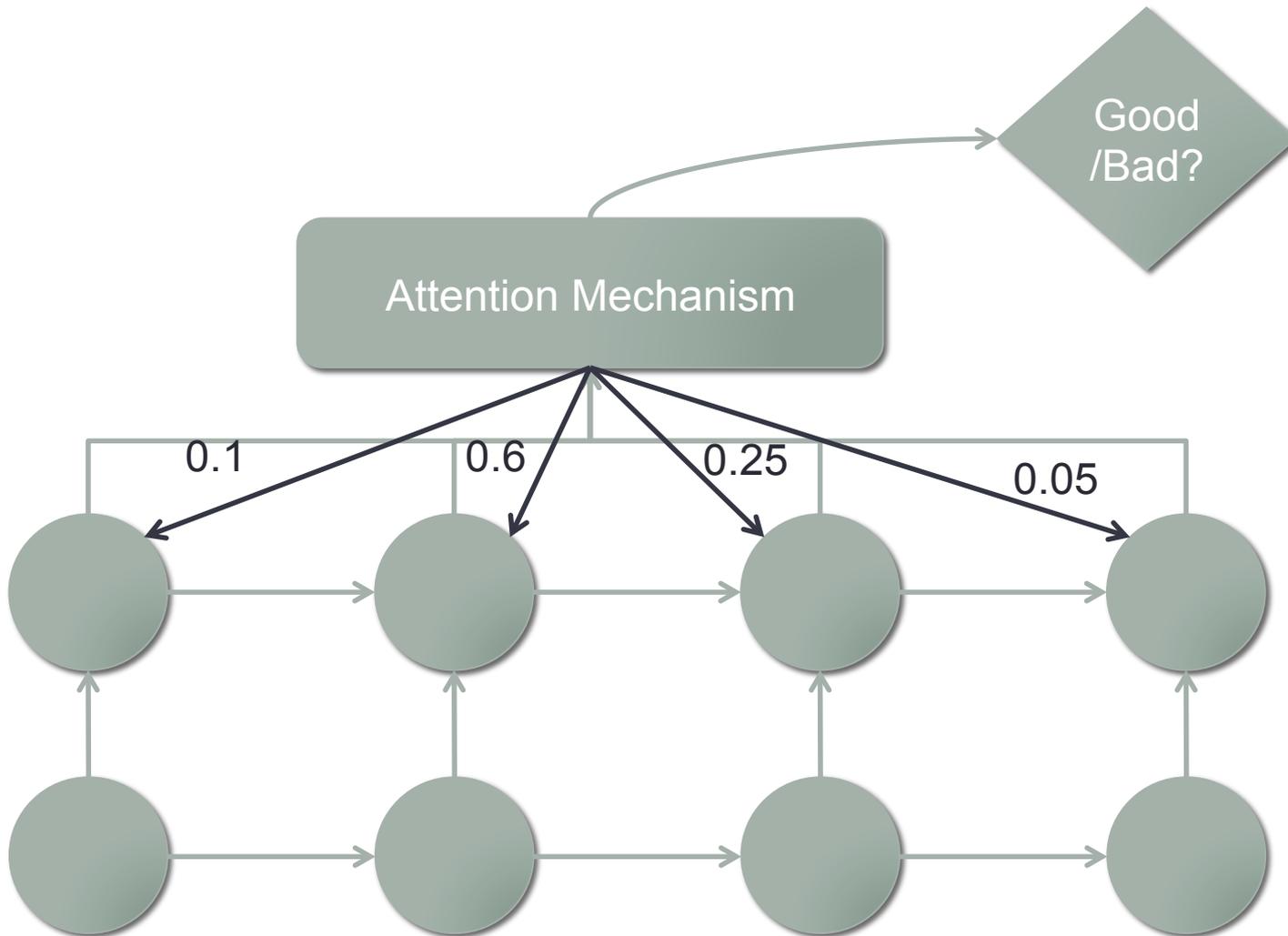
- Compared a Neural Network approach to a Domain Knowledge (DK) using a portion of the PE-Header
  - Neural Networks performed better on every test set
  - Higher AUC provides better rankings
- Validates that neural networks can learn from just byte sequences
- Also trained an attention LSTM, and used the attention to confirm similar items were being learned
  - Took 11 days of training time for each model using a Titan X

Test Set	NN Accuracy	DK Accuracy	NN AUC	DK AUC
A	<b>90.8%</b>	86.4%	<b>0.977</b>	0.972
B	<b>83.7%</b>	80.7%	<b>0.914</b>	0.861

# Why we care about attention



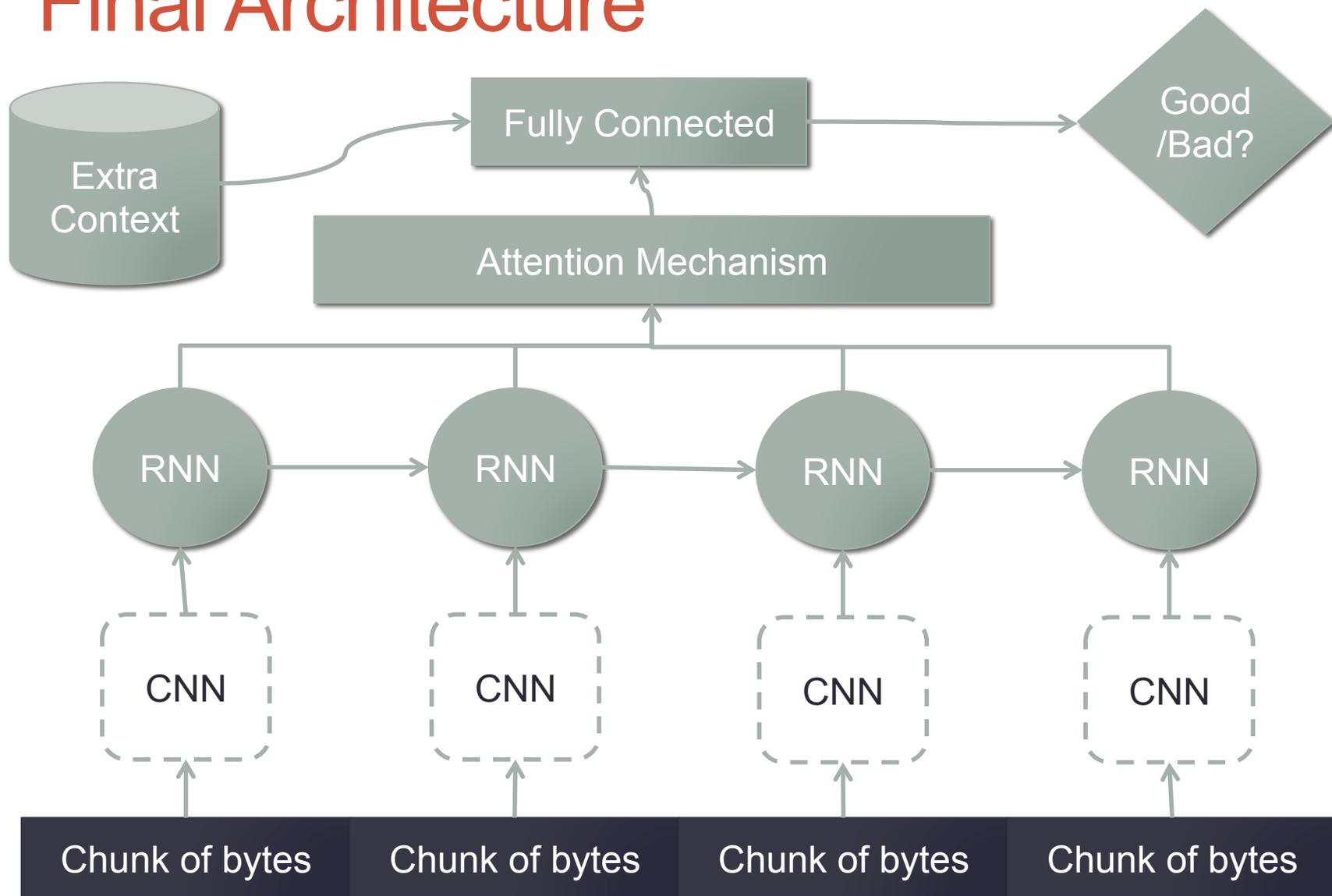
# Why we care about attention



# Current Research and Goals

- Can we replicate this on the entire binary?
- Combine Convolutional & Recurrent Networks
  - Use RNNs to handle the variable length of binaries.
    - Problem is too big to learn byte-by-byte: over 2 million time steps!
  - Use Convolutions to help us process many bytes at a time and exploit the locality we can
- Considering entropy and other high level structure to help infer a decision
- Use attention to ignore parts of the input
  - Helps us infer which portions of a binary may be malicious when trained with only coarse labels

# Final Architecture



# GPUs are 100% necessary

- Our initial tests are pushing the limits of what we can do with GPUs today
  - On 12GB cards, max batch size of 6
- We've already made our model smaller than desired to fit onto a GPU
- Training currently takes over 4 days *for a single epoch* on new M40s