“Quantum” Classification of Malware

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- Actively studying/researching infosec for about three years (mostly academic)
- Currently an intern for CyberPoint International

Outline

- The D-Wave Controversy
- How to play around on a D-Wave
- Building a malware classifier on a D-Wave 2
- What did we find?

https://blog.kaspersky.com/quantum-computers-and-the-end-of-security/

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LET ME DOWN MIGhTILY

What you might have heard (and why it's wrong)

- FALSE: The D-Wave can solve NP-Complete problems in polynomial time.
- FALSE: The D-Wave is already "better" than classical computing for hard problems.

The Current State of Affairs

Quantum effects are happening…

…but that might not be interesting

We don't know whether the D-Wave uses quantum effects for computation.

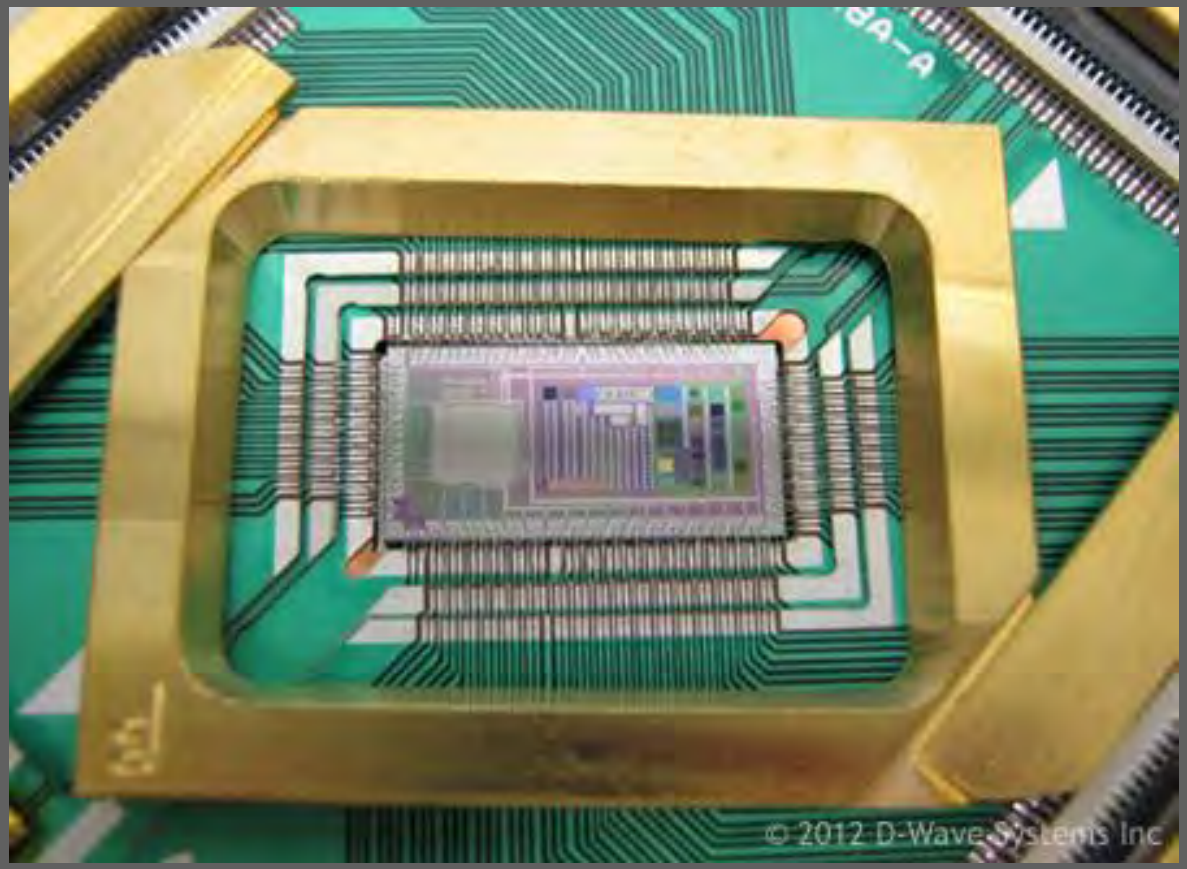
Regardless, it cannot run Shor's/Grovers/QKD.

http://www.dwavesys.com/

http://www.nytimes.com/

Kim Stallknecht for The New York Times

http://www.nytimes.com/



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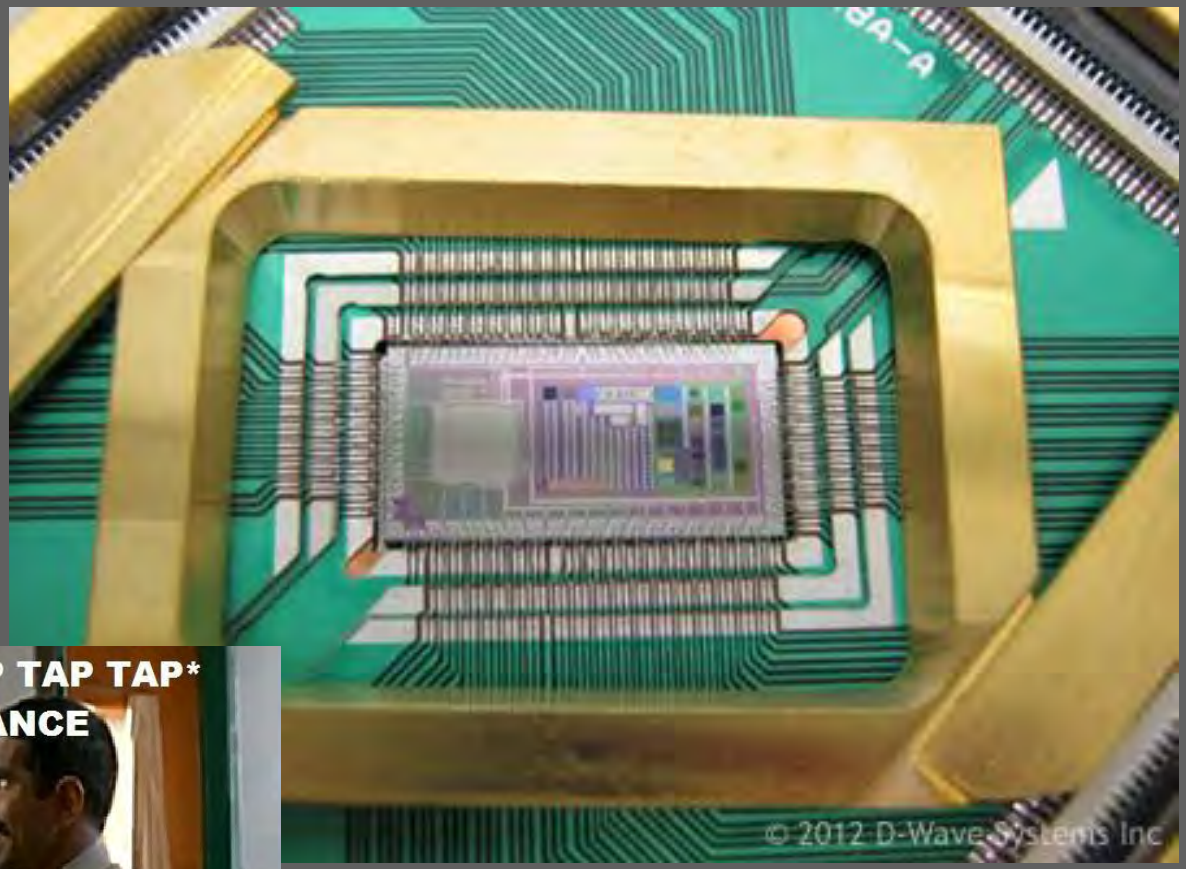

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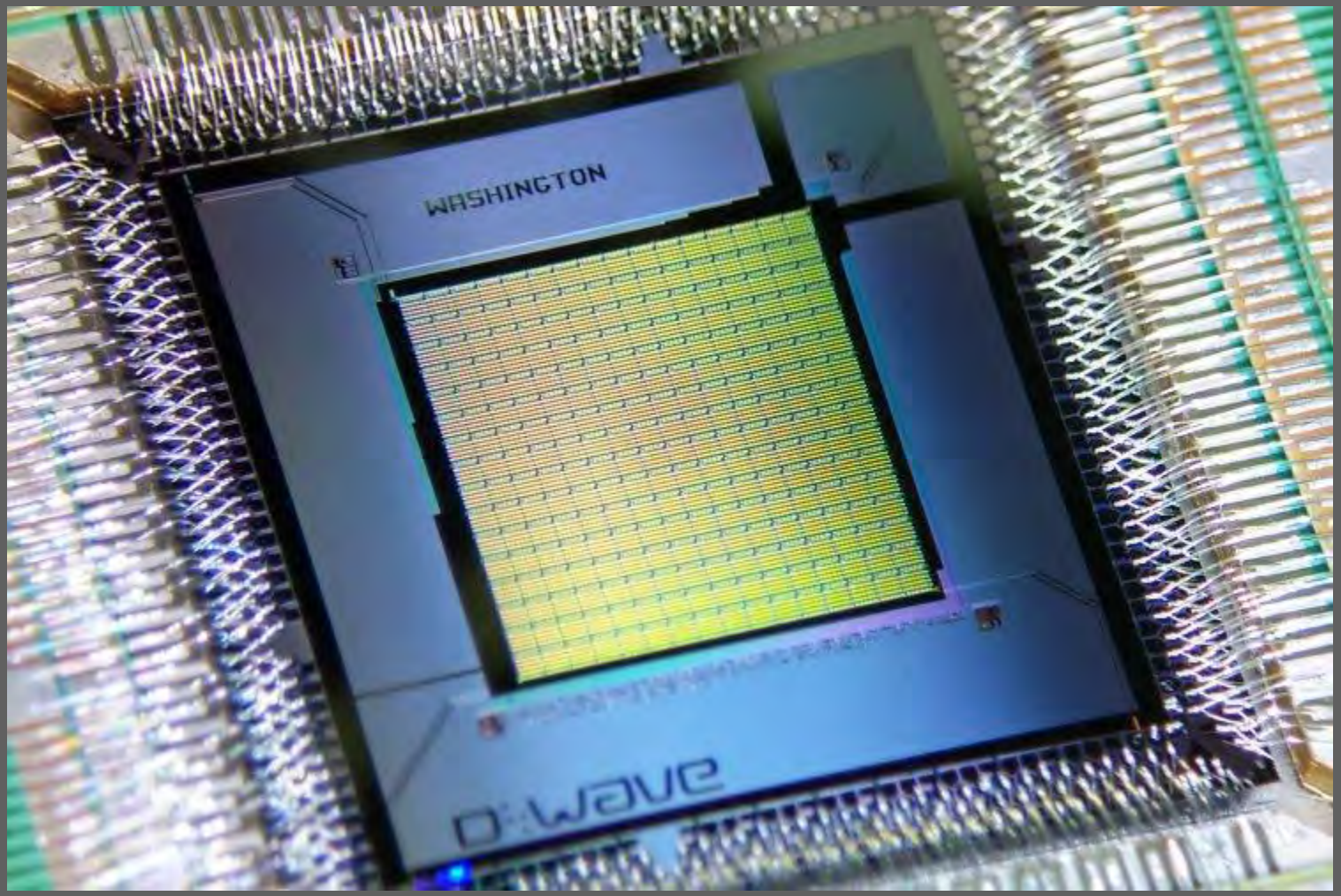

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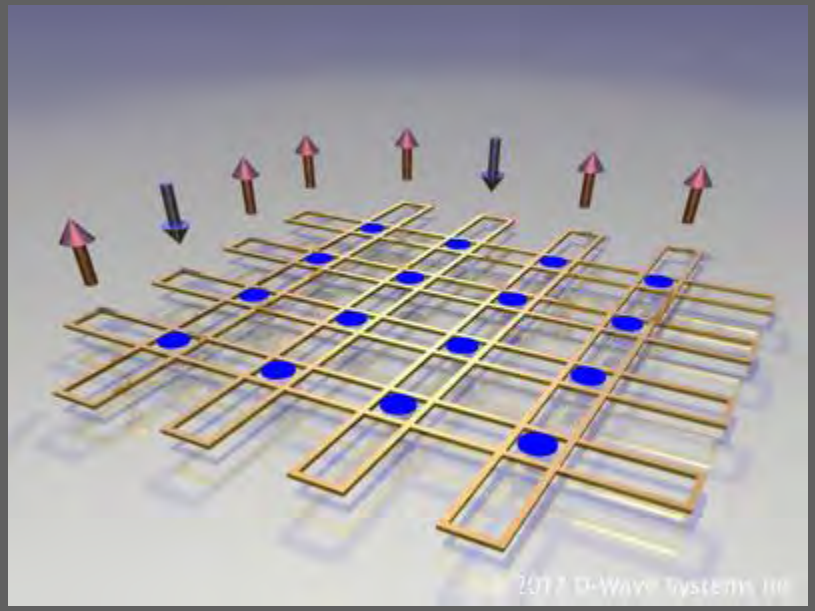
D-Wave chips consist of:

- niobium loops
- couplers



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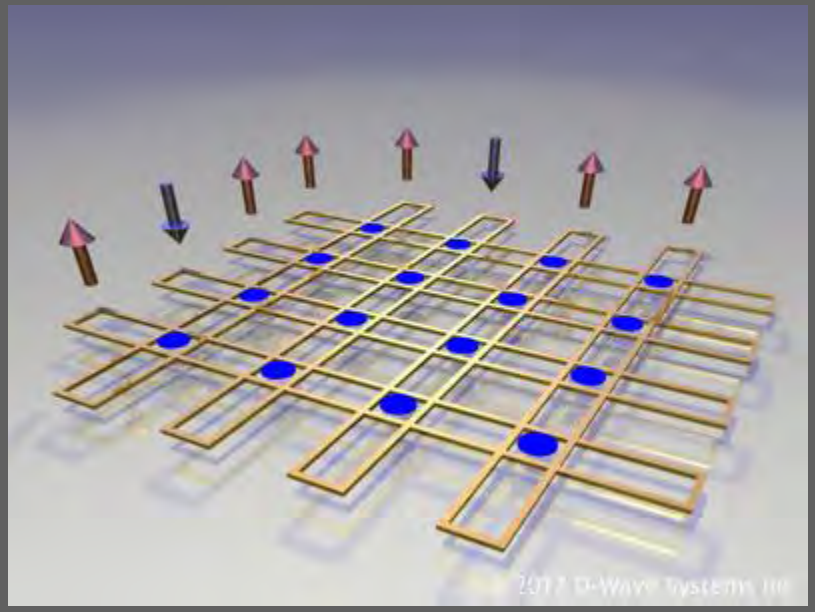
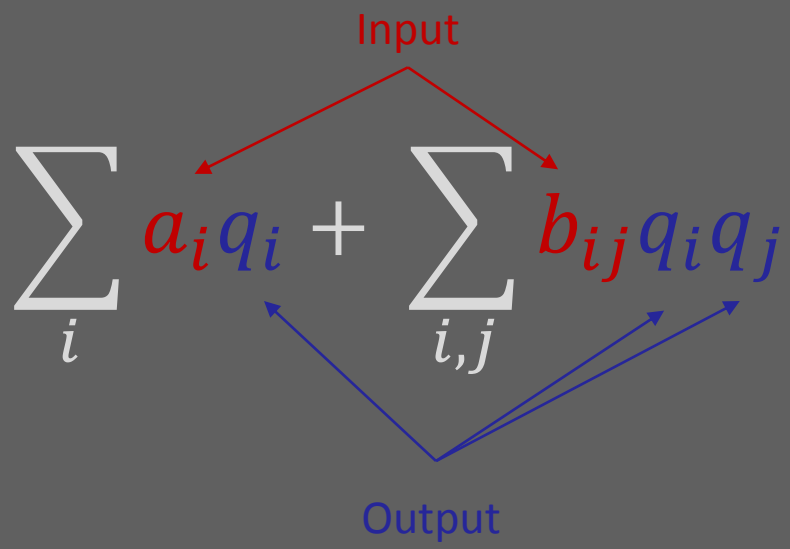


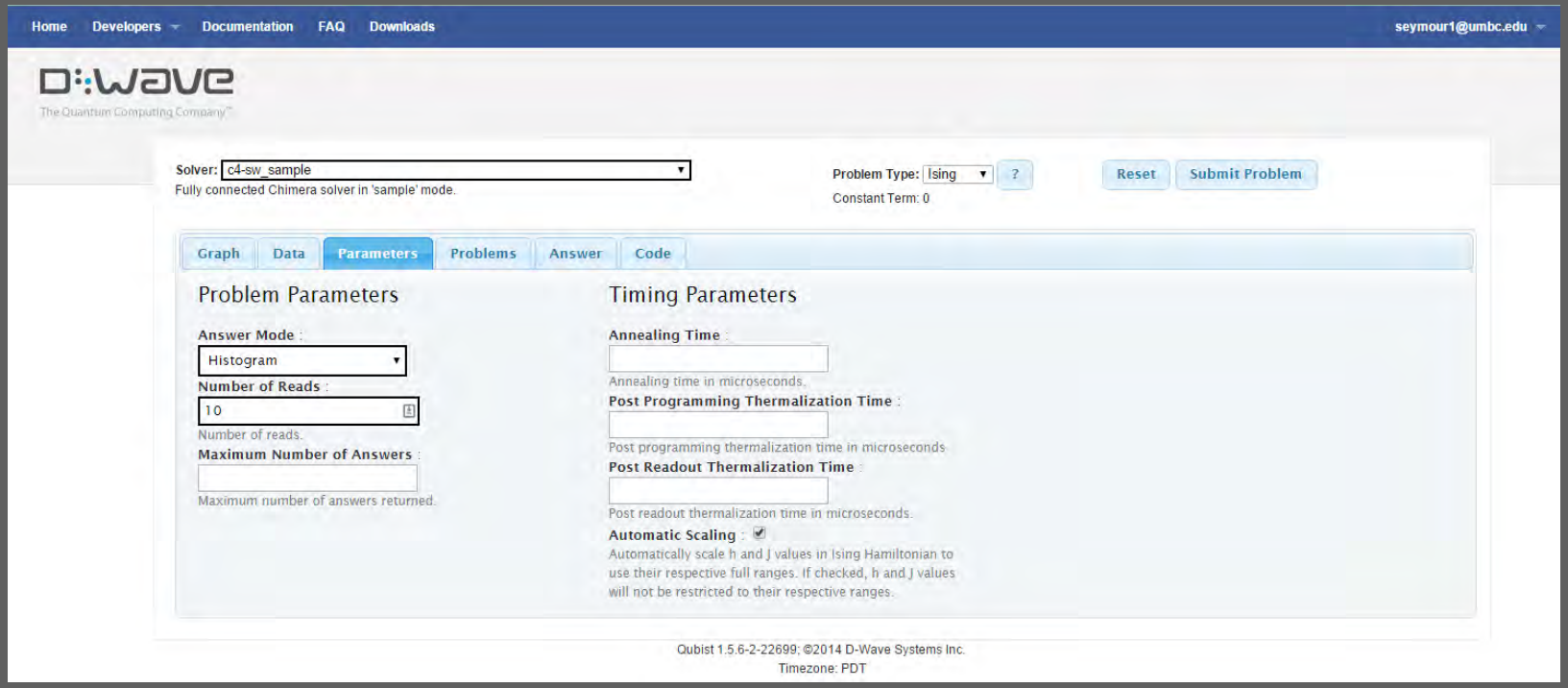
http://www.dwavesys.com/

The D-Wave QUBO

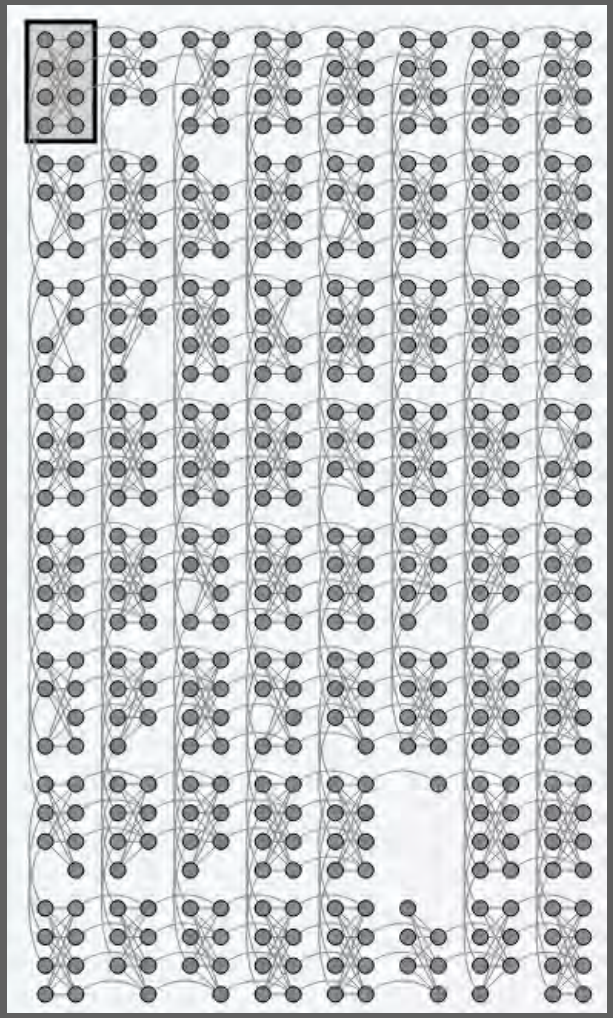


"Quadratic Unconstrained Binary Optimization"

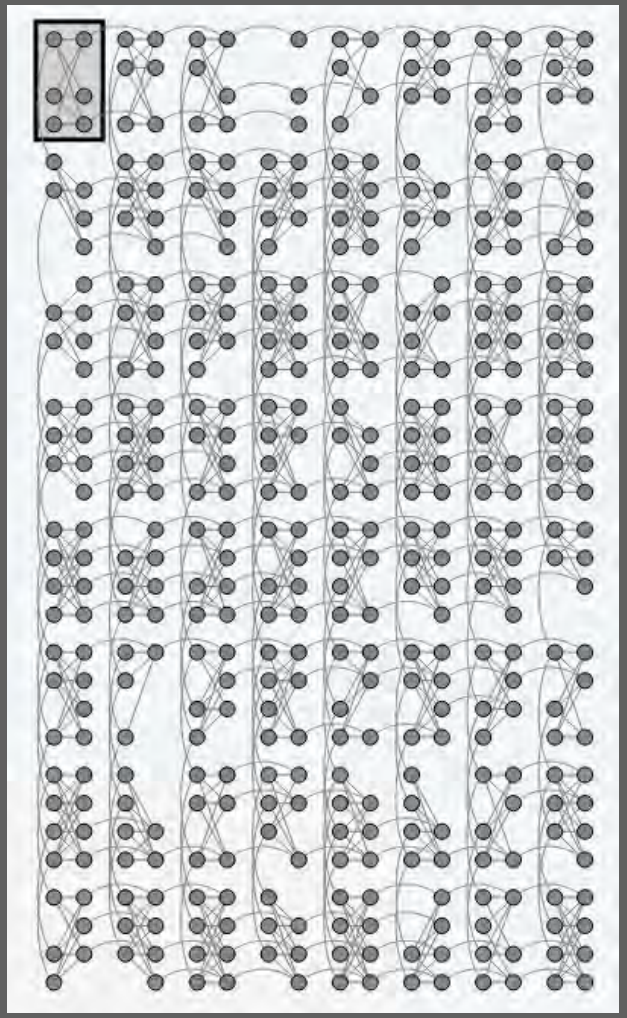
They’ve got a website. To do stuff on and stuff.



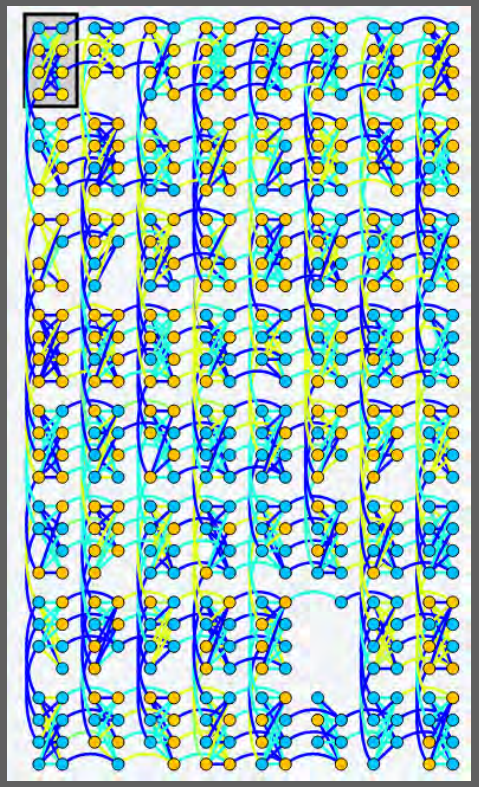
System 6



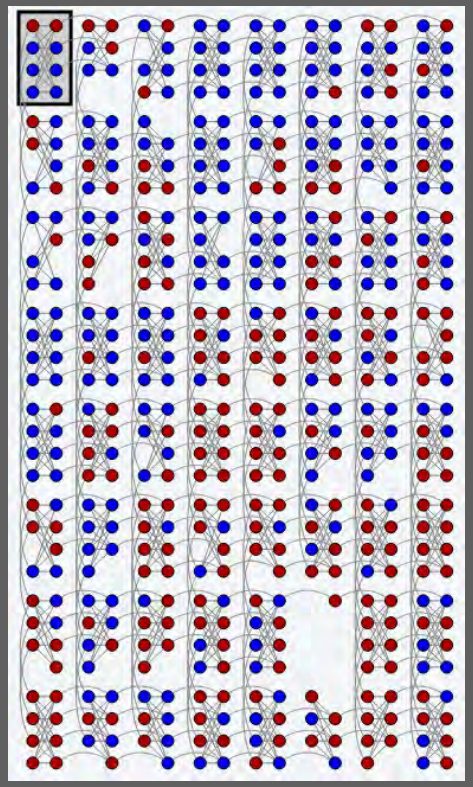
System 13



One D-Wave Run



Input



Output

Blackbox/ToQ

- Software, developed by D-Wave
- Turns arbitrary problems into QUBOs
- Heuristic (problem is NP-Complete)
- Conversation between classical machine and D-Wave

So what can it do?

D-Wave claims applications: classification, protein-folding models, finding close-to-optimal solutions to NPC problems (e.g. Traveling Salesman)

Crash Course in Machine Learning
(At least what's relevant to this)

Boosting - using combinations of weak classifiers

- 3 binary classifiers with 70% accuracy

All Correct: **0.7 * 0.7 * 0.7 = 0.3429**	**Two Correct:** **3 * 0.7 * 0.7 * 0.3 = 0.4409**
Two Wrong: 3 * 0.3 * 0.3 * 0.7 = 0.189	All Wrong: 0.3 * 0.3 * 0.3 = 0.027

- Majority vote can increase your accuracy to 0.7838! (Hint: add up the top row)
- Most boosting algorithms also allow weights for these classifiers.

http://mlwave.com/kaggle-ensembling-guide/

Loss

- Want to minimize:
  - Number of misclassifications
  - Complexity of the model

$$G(w) = \frac{1}{4}\sum_{s=1}^{S}(sign[\sum_{j=1}^{D} w_j F_j(x_s)] - y_s)^2 + \lambda \sum_{j=1}^{D} w_j$$

N-Grams

- Sliding window over text

$$DEADBEEF$$

N-Grams

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N-Grams

- Sliding window over text

$$DEADBEEF$$

- Easy to generate
- Used before in malware with good results
- Easy to turn into weak classifiers
- Complex enough to compare classifiers

Building the “Quantum” Malware Classifier

QBoost

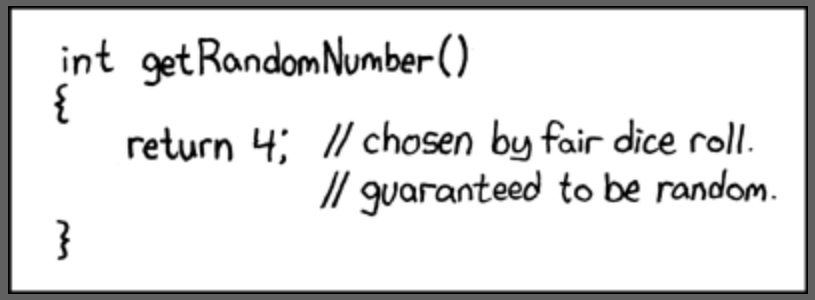
- Outperforms Adaboost
- Robust to label noise
  - Will generally still learn even if training data is mislabeled
  - Good for learning malware: ground truth is hard!

Dataset used

- Plenty of malicious datasets to choose from
  - Vx Heaven, VirusShare, scraping the web
  - We used Vx Heaven (fairly standard but old)
- No standard for benign dataset
  - Problematic
  - Windows + Cygwin + Sourceforge
    - No adware was used in the making of this classifier

(Classical) Preprocessing

- Resample corpus to be balanced
  - Side-effects: Less time to train, lose information



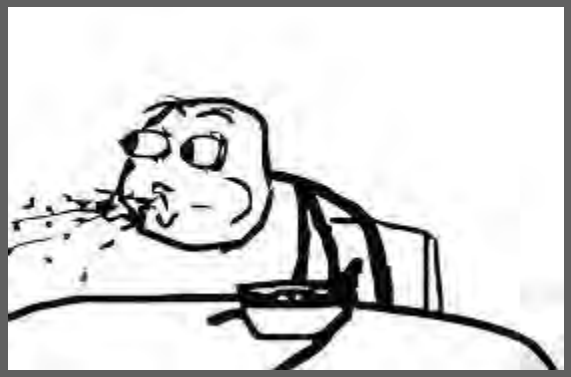
HTTP://XKCD.COM/221/

- Extract Features (3-gram bytes)

At first, D-Wave solutions were no better than random chance

Next question: how long do we need to let the D-Wave run?

- Previous work says 30 minute timeout



- Pilot Experiment to find how long it should take
  - Even on small problems, it takes 10 minutes to find decent solutions
  - Larger problems require even more time

- Limited to 32 features
  - We used 16 malware and 16 benign n-grams
  - Implemented QBoost with 10-fold cross-validation
    - Both on D-Wave and using a simulator
- Compared to several models from WEKA
  - Adaboost
  - J48 Decision Tree
  - Random Forest

Results

Classifier	Cross-fold Accuracy	Average Time to Build (Seconds)
D-Wave	0.80	536.32
D-Wave Simulator	0.802	451.62
Adaboost	0.768	0.02
J48	0.796	0.03
RandomForest	0.814	0.05

Table 1: Cross-fold accuracy and time to build classifiers.

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Interesting Result 1: takes a LOT of time

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Table 1: Cross-fold accuracy and time to build classifiers.

Interesting Result 2: Simulator > actual chip

So, to recap:

- Blackbox/D-Wave CAN learn a malware classifier
- Accuracy comparable to classical algorithms using same features.
- Significant overhead and must restrict problem substantially

Future Work

- How much better is the next D-Wave chip?
- Possible to embed directly onto chip, rather than use Blackbox?
- Better for another task?
  - e.g. feature or instance selection

- Machine Learning standards for Malware Analysis

Thank you!

Questions?

References

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