Thwarting Bobby Droptables: Adapting a TF-IDF HTTP Classifier to Embedded Hardware

September 2, 2009

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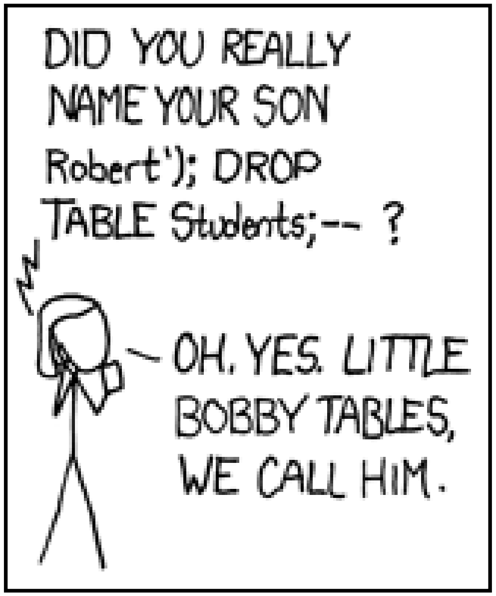
Network Security is Challenging

- Mixed requirements in server security
  - Provide flexible web services
  - Do so on top of existing standards
  - Thwart malicious behavior
- HTTP is conduit for web traffic
  - Simple, plain-text formatting
  - Gateway to databases, files, executables
- Malicious users also use these interfaces
  - Query a DB, invoke commands
  - Obfuscate commands, game network filters
- Can we embed more intelligent filtering in the network?



From xkcd, Randall Munroe
http://xkcd.com/327

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Overview

- LLNL work on HTTP attack classification
- Can this be converted to run on embedded network hardware?
  - Tilera or FPGAs: limited memory, operate in streaming manner
  - Need to convert 160MB dictionary to ~128 KB
- Our approach
  - Hypothesis: number of terms more useful than exact probabilities
  - Compress dataset via truncation and hashing tricks
- Status
  - Implemented core hardware design for FPGAs
  - Porting C version to Tilera

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ECML/PKDD 2007 Discovery Challenge

- HTTP Traffic Classification
  - Apply machine learning to identify malicious activity in HTTP
- Hand-labeled datasets of HTTP flows
  - Training: 50K inputs, 30% attacks
  - Competition: 70K inputs, 40% attacks
  - 7 Attack Types XSS, SQL/LDAP/XPATH injection, path traversal, command execution, and SSI

Flow Example

odbc connect statement drop table

```
GET /eH/first_str/2hFnull6/oixsotcwrseamgit2/38PrR_Lkmmzo.htm
Host: www.a215Een.st:15
Connection: close
Accept: */*
Accept-Charset: *;q=0.4
Accept-Encoding: *
Accept-Language: boHEor-sen0, gte-htmse4      oS, 3TeoUsHn-asrao;q=0.2, paly-wreihi, 78iiqths-ar;q=0.3
Cache-Control: no-store
Client-ip: 200.91.18.159
Cookie: uciy2kleicl=%3C%21--+%23odbc++++++++++++++connect%3D%226at8h%2CHcteil%2CeHnNa%22+++++statement%3D%22drop+table+elkbO…
```

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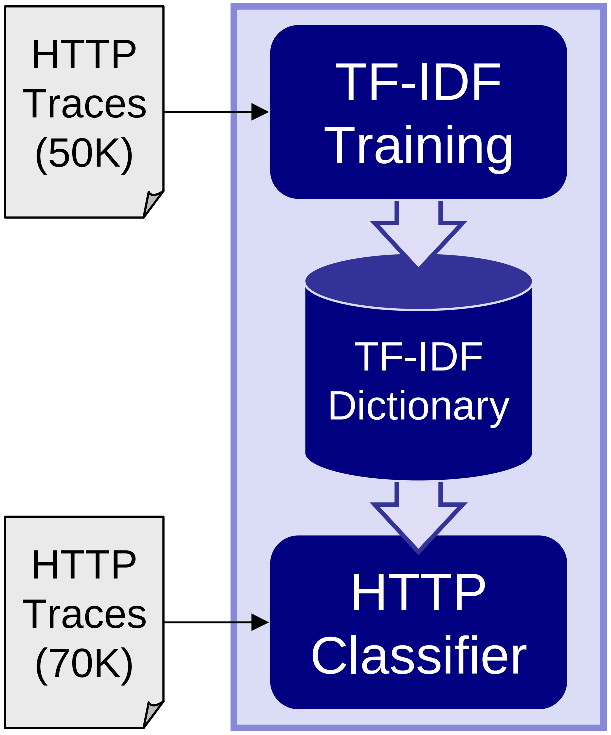
LLNL Work Achieved 99% Accuracy

- Brian Gallagher and Tina Eliassi-Rad
- Vector approach
  - Tokenize input
  - Assign weights to tokens via TF-IDF
  - Cosine similarity for vector comparison
- Relies on a data dictionary
  - Generate term statistics during training
  - Reference statistics at runtime



Top 3 SSI Classifier Terms

Term	IDF	Weight
odbc	2.079	0.0134
statement	2.079	0.0134
--	0.988	0.0126

Top 3 OS Commanding Classifier Terms

Term	IDF	Weight
..	1.386	0.0057
dir	2.079	0.0053
/c	2.079	0.0051

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Equations

- Term-Frequency, Inverse Document Frequency
  - TF: How often does each term appear in an attack?
  - IDF: How specific is the term to an attack?

$$tfidf(t,d) = \underbrace{\frac{count(t,d)}{\sum_{v \in d} count(v,d)}}_{\text{Term Frequency}} \cdot \underbrace{\log \frac{|D|}{|\{d_j : t \in d_j\}|}}_{\text{Inverse Document Frequency}}$$

- Cosine Similarity
  - Vector dot product to estimate angle between input and attack

$$\text{sim}_{\cos}(a,R) = \frac{\vec{a} \cdot \vec{R}}{\|\vec{a}\| \cdot \|\vec{R}\|} = \frac{\sum_{t \in a \cap R} tfidf(t,a) \cdot tfidf(t,R)}{\sqrt{\sum_{t \in a} tfidf(t,a)^2} \cdot \sqrt{\sum_{t \in R} tfidf(t,R)^2}}$$

Equations for Programmers

$$score[classifier] = \frac{\sum_{t \in a \cap R} \frac{count[t]}{\#\,input\ terms} \cdot idf[t] \cdot ClassLabelTfidf[classifier][t]}{\sqrt{\sum_{t \in a} \left(\frac{count[t]}{\#\,input\ terms} \cdot idf[t]\right)^2} \cdot DocMagnitude[classifier]}$$

Equations for Programmers

Lookup IDF for term
in dictionary

Lookup weight for term
in dictionary

Count each term in Input

$$score[classifier] = \frac{\sum_{t\in a\cap R} \boxed{\frac{count[t]}{\#input\ terms}} \cdot \boxed{idf[t]} \cdot \boxed{ClassLabelTfidf[classifier][t]}}{\boxed{\sqrt{\sum_{t\in a}\left(\frac{count[t]}{\#input\ terms} \cdot idf[t]\right)^2}} \cdot \boxed{DocMagnitude[classifier]}}$$

Scale based on TF-IDFs found
by ALL classifiers

Adjust based on weight
of classifier

Equations for Programmers

Lookup IDF for term in dictionary

Lookup weight for term in dictionary

Count each term in Input

$$score[classifier] = \frac{\sum_{t \in a \cap B} \cancel{\boxed{\frac{count[t]}{\#\,input\ terms}}} \cdot \boxed{idf[t]} \cdot \boxed{ClassLabelTfidf[classifier][t]}}{\cancel{\boxed{\sqrt{\sum_{t \in a} \left(\frac{count[t]}{\#\,input\ terms} \cdot idf[t]\right)^2}}} \cdot \boxed{DocMagnitude[classifier]}}$$

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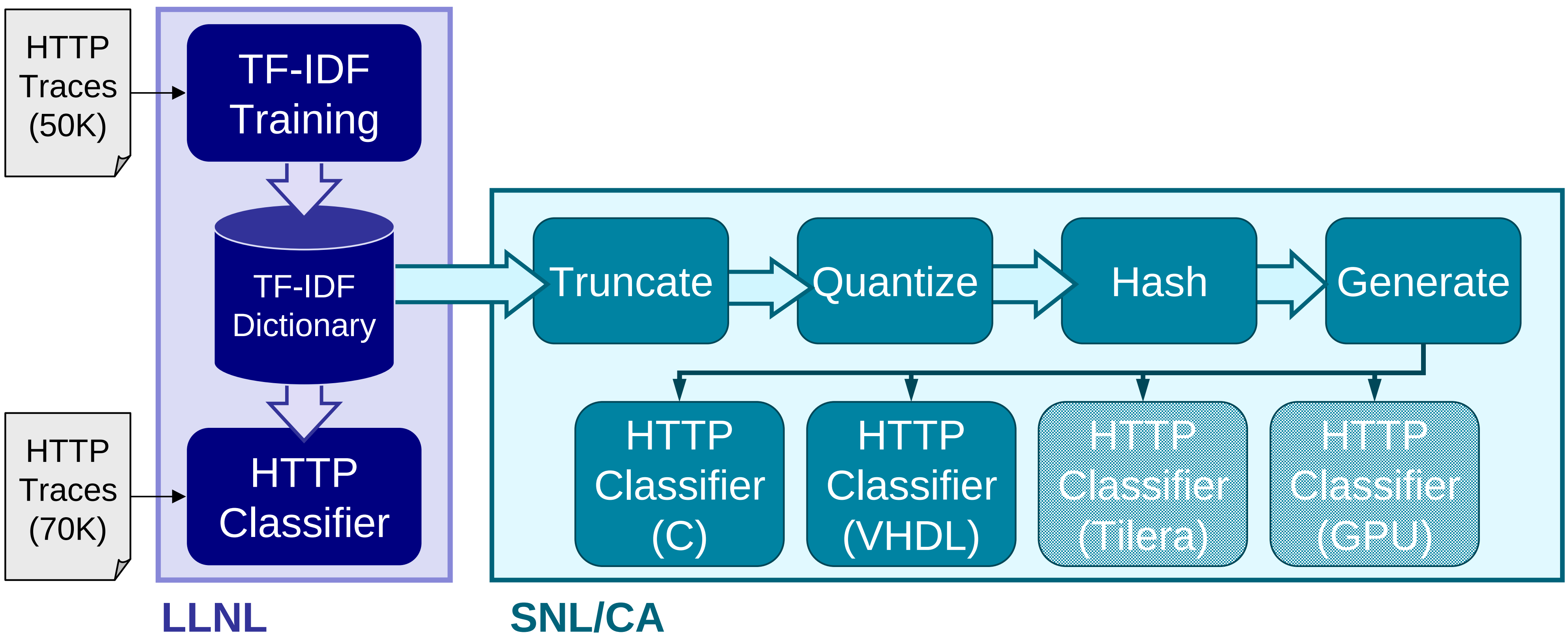
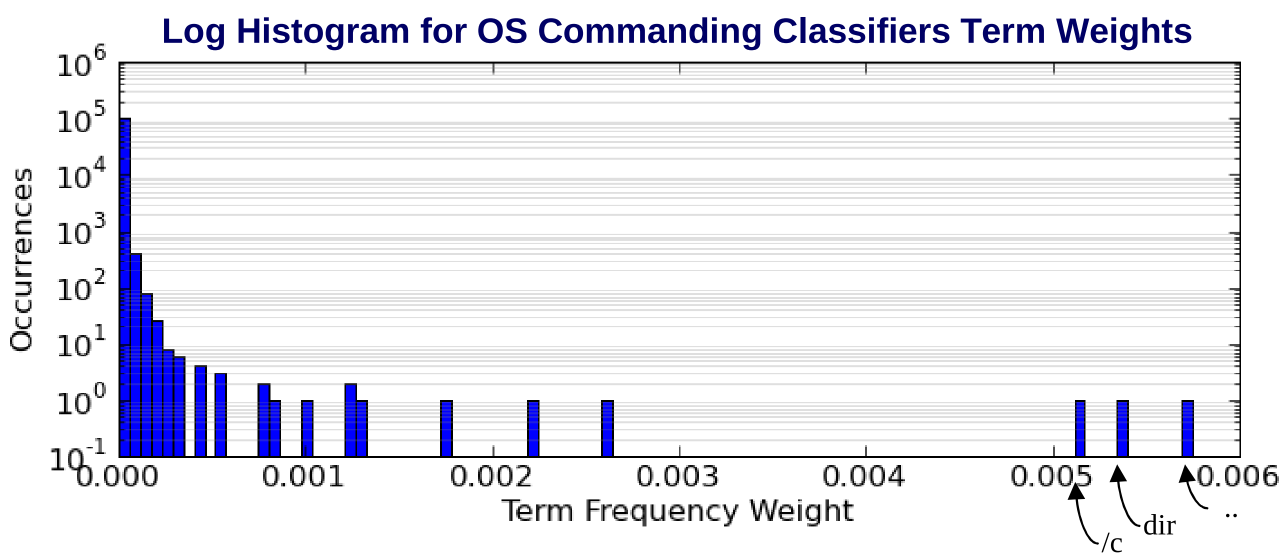
The Path to Embedded Hardware



Dictionary Observations

- Many terms in the dictionary
  - 1.8M terms (46MB text, 128MB data)
  - Many terms are junk (“rv:0.7.8”), but they also get very low weight
- Data values are not very diverse
  - Total unique values is < 2% of population
  - Eg: OSC Classifier has 102K terms, but only *415* unique weights



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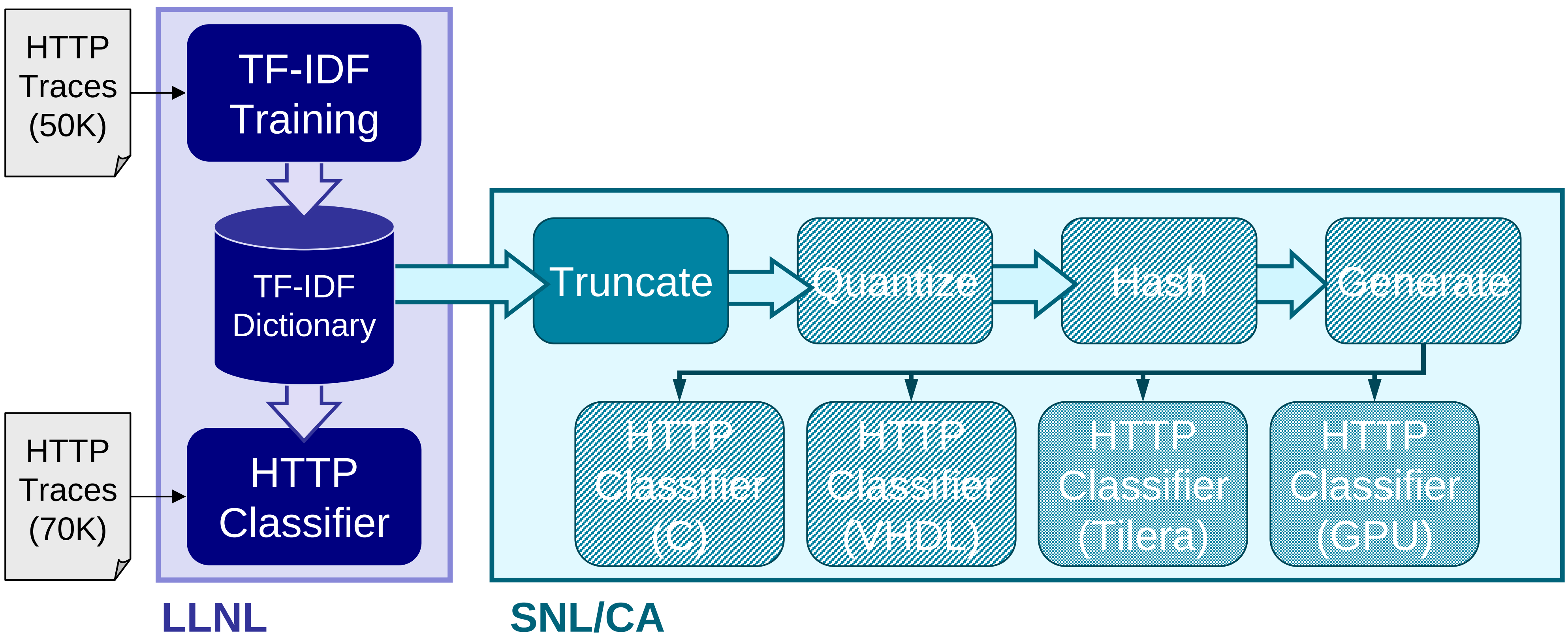

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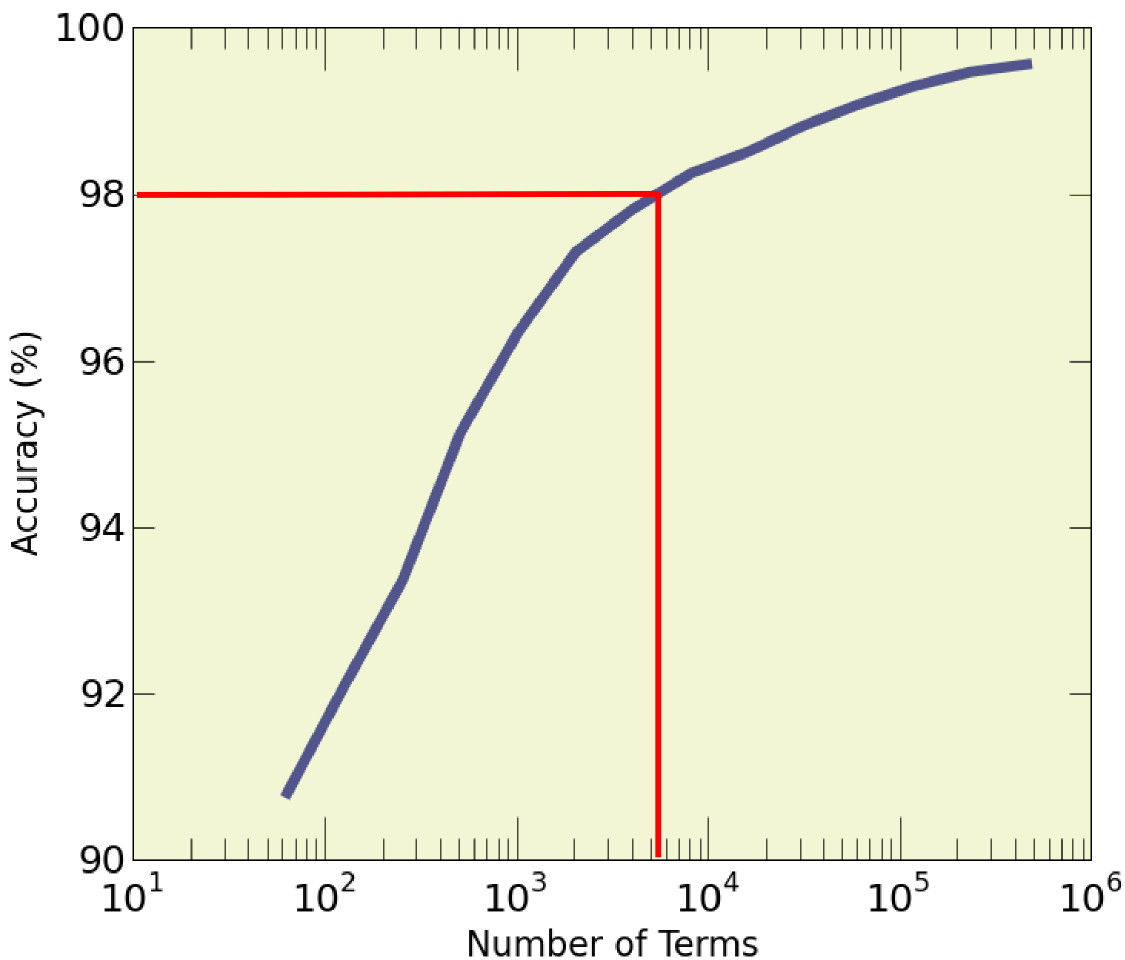
Easy: Truncate the Dictionary



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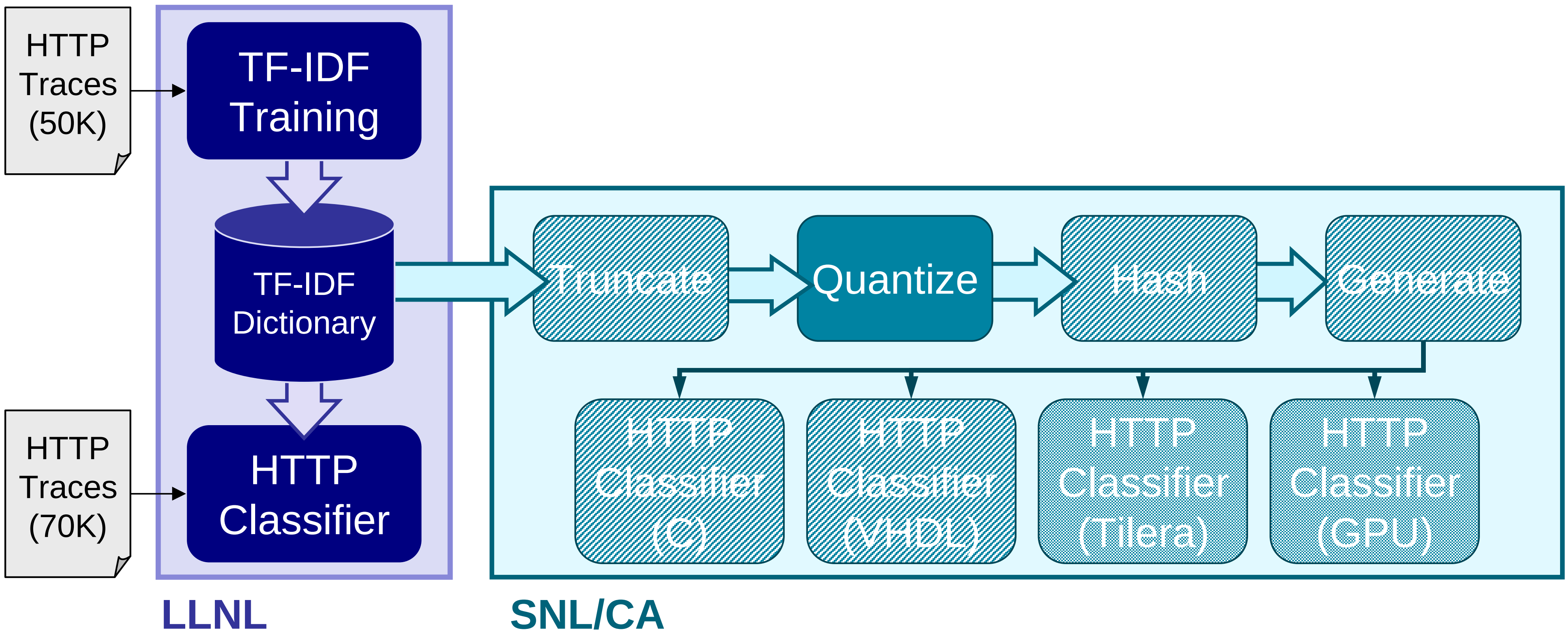

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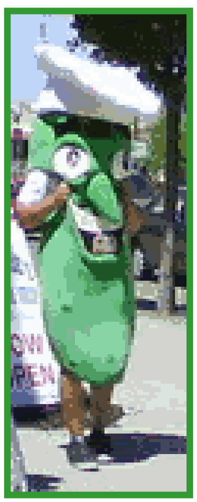
Quantize Dictionary Data Values

- How accurate do data values in dictionary need to be?
- Does IDF(“ODBC”) = 0.500001 give more accurate results than..
  - 0.500002?   0.488886?   0.03?
- Experiment:
  - Reduce unique data values in dictionary, measure accuracy impact



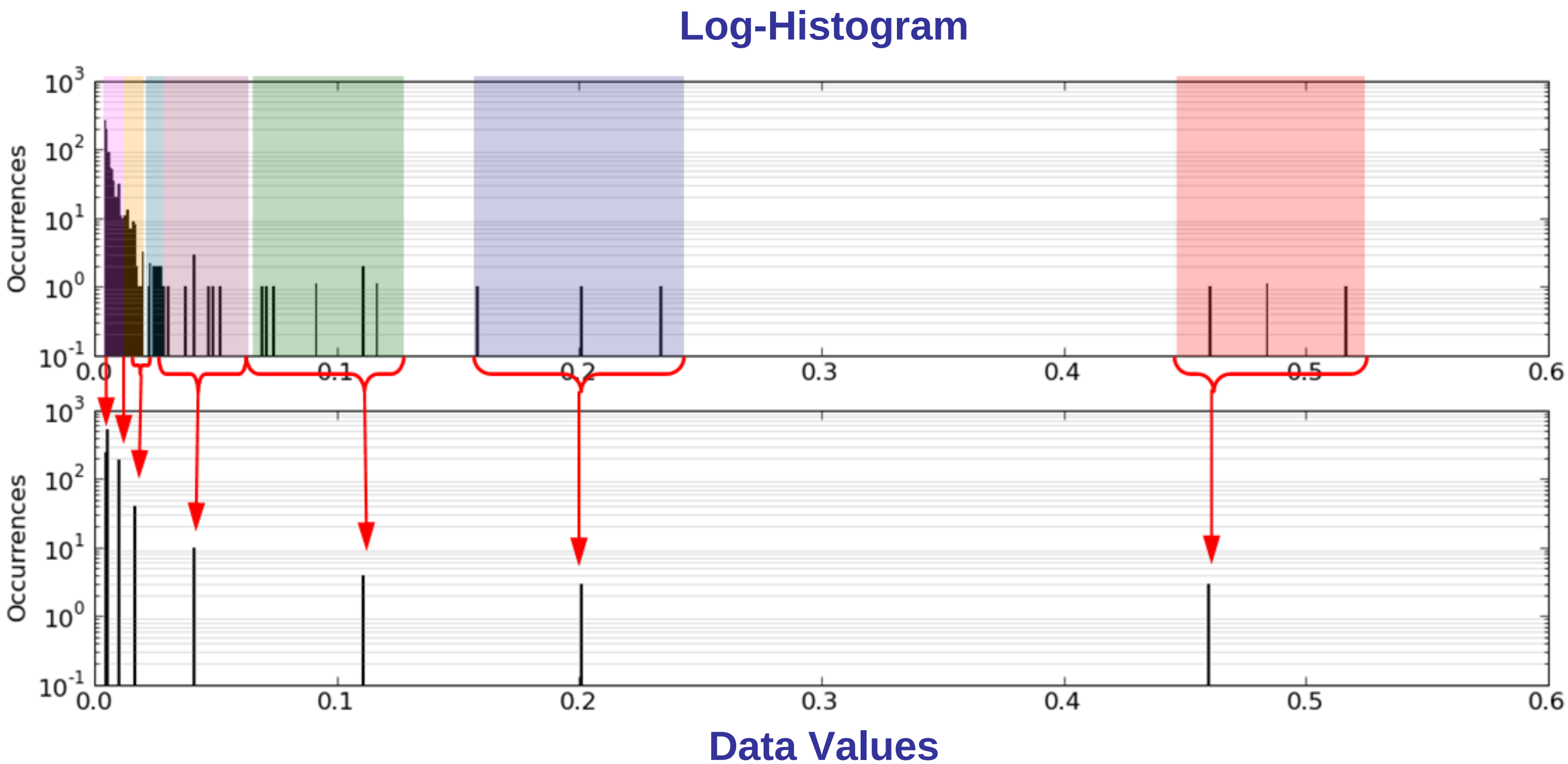
256 Colors

64 Colors

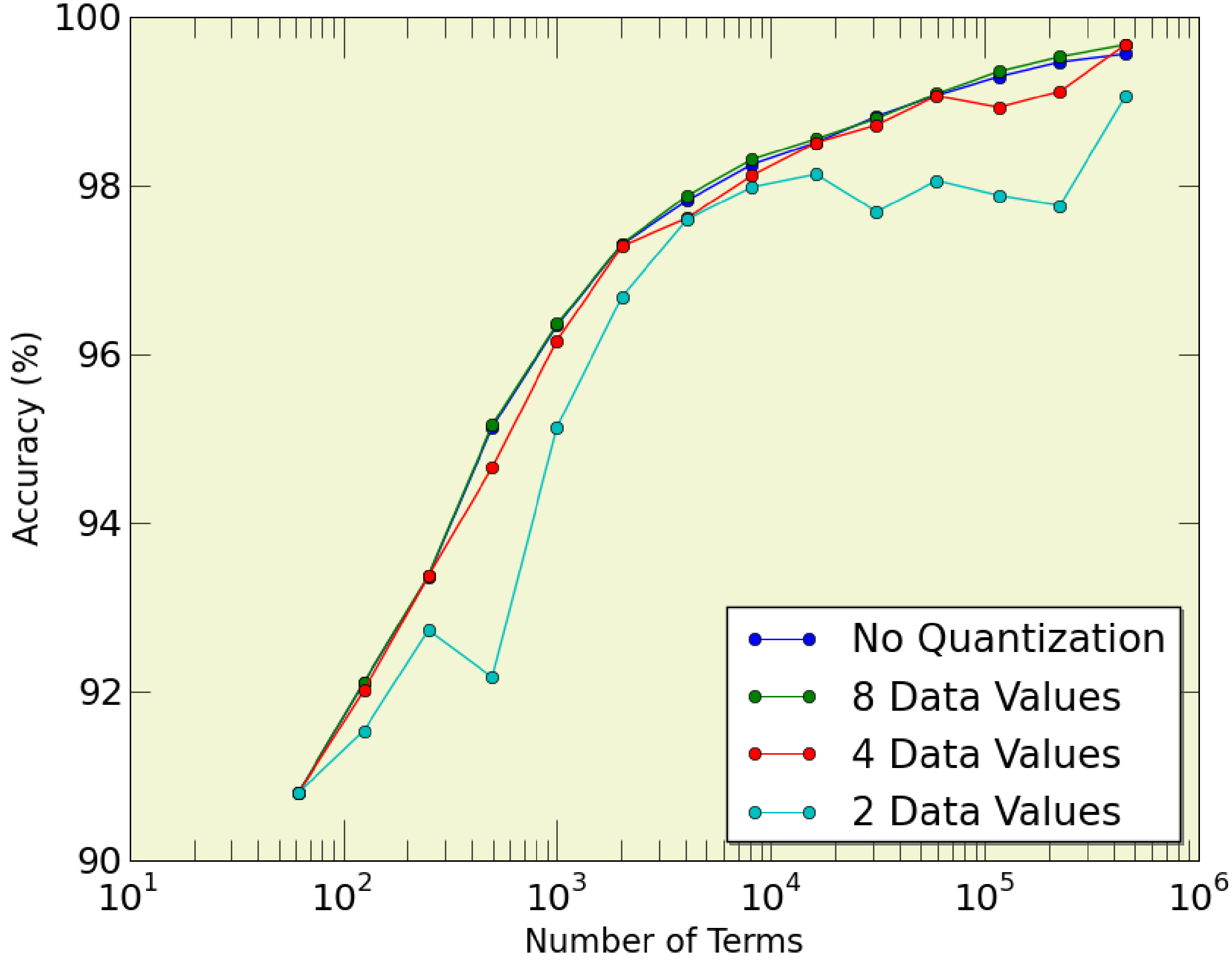
16 Colors

2 Colors

Re-Quantizing Data



Quantization Impact on End Accuracy



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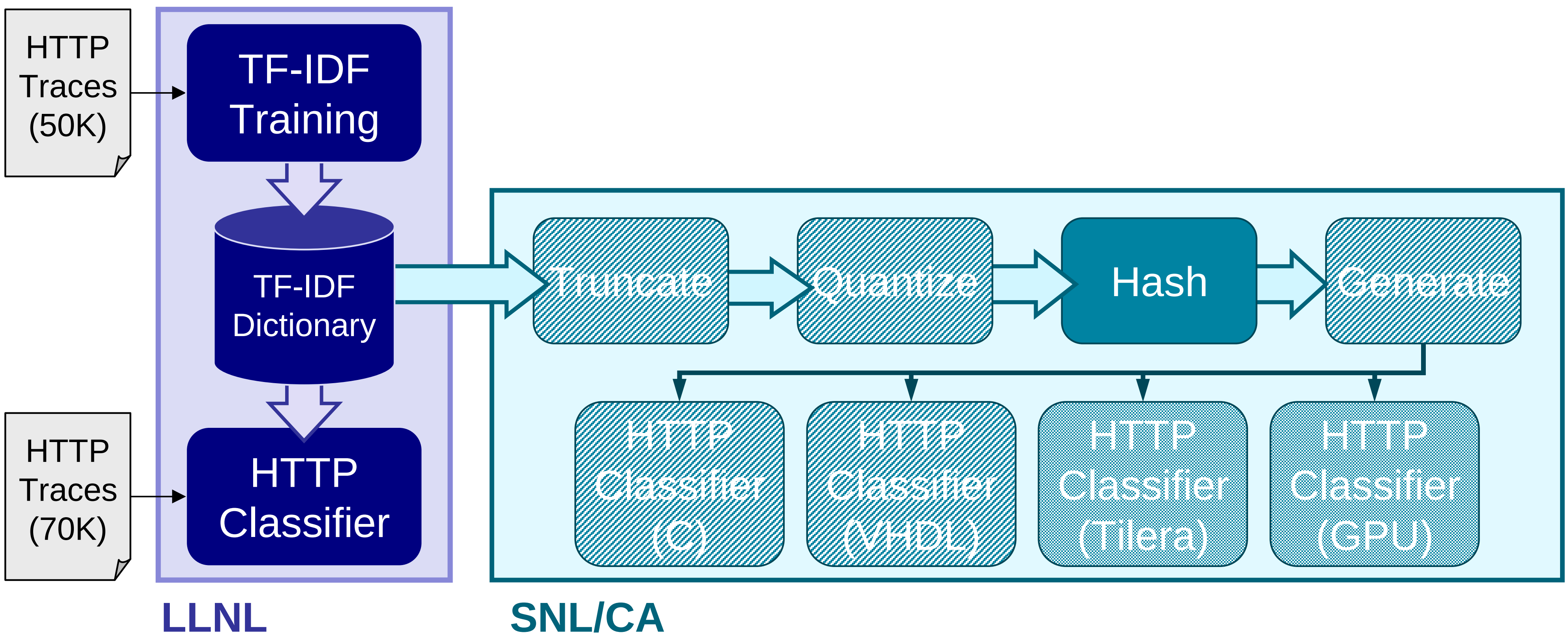

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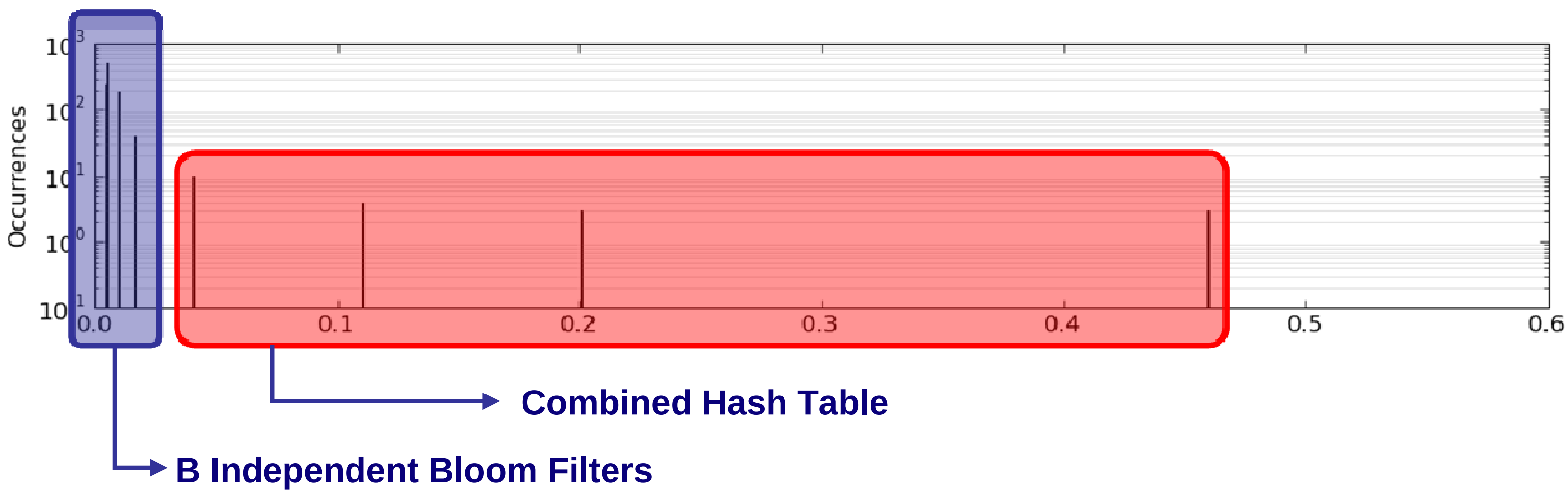
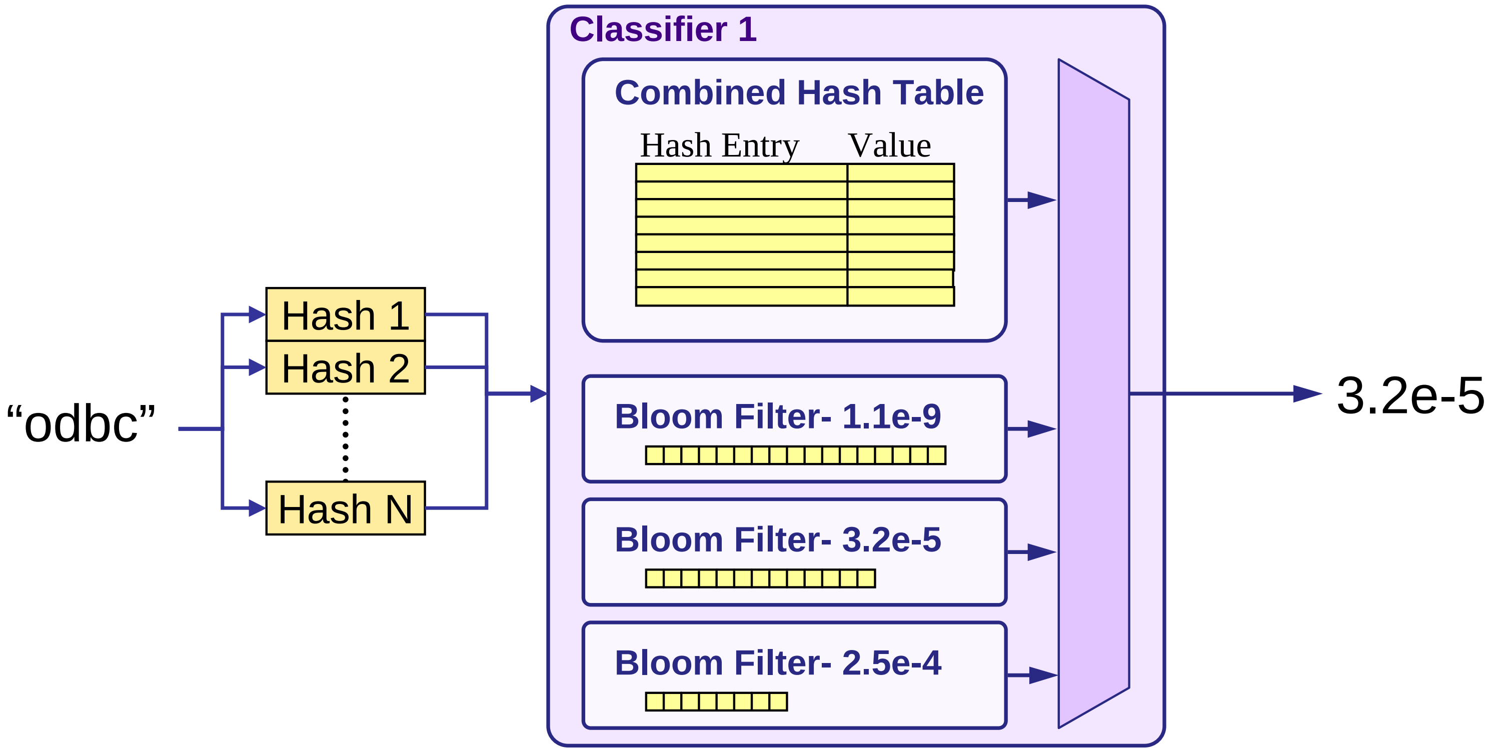
Hashing Tricks

- Small sets: combine into a single hash table
  - Brute-force packing sufficient for small tables
- Large sets: Array of Bloom filters
  - Bloom filters: space-efficient way to determine set membership
  - No false negatives, but can have false positives



Hashing Replaces Dictionary

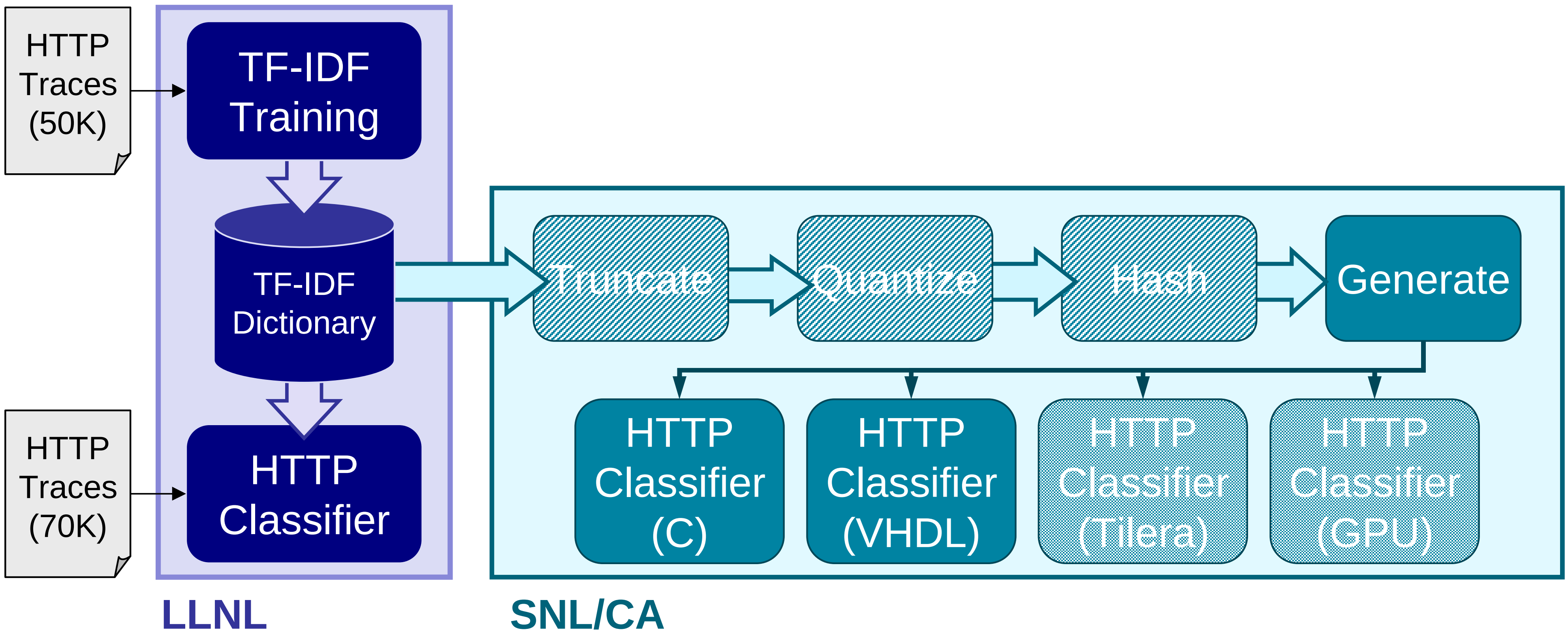


For 2KB Memory Block:

256 Hash table entries

~1K Bloom Filter members

The Path to Embedded Hardware



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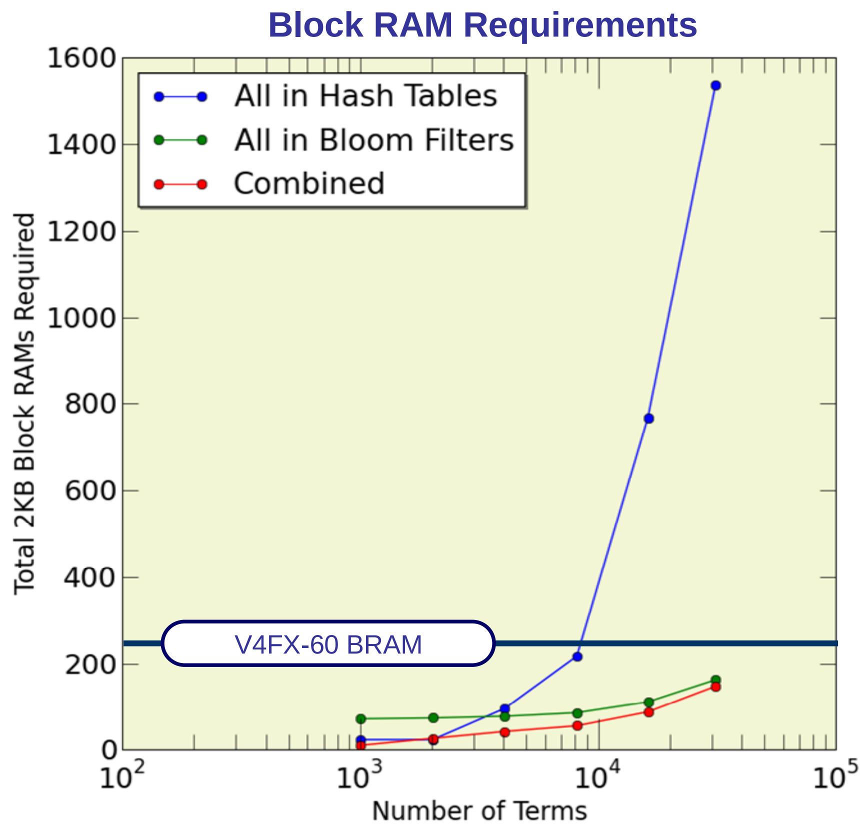
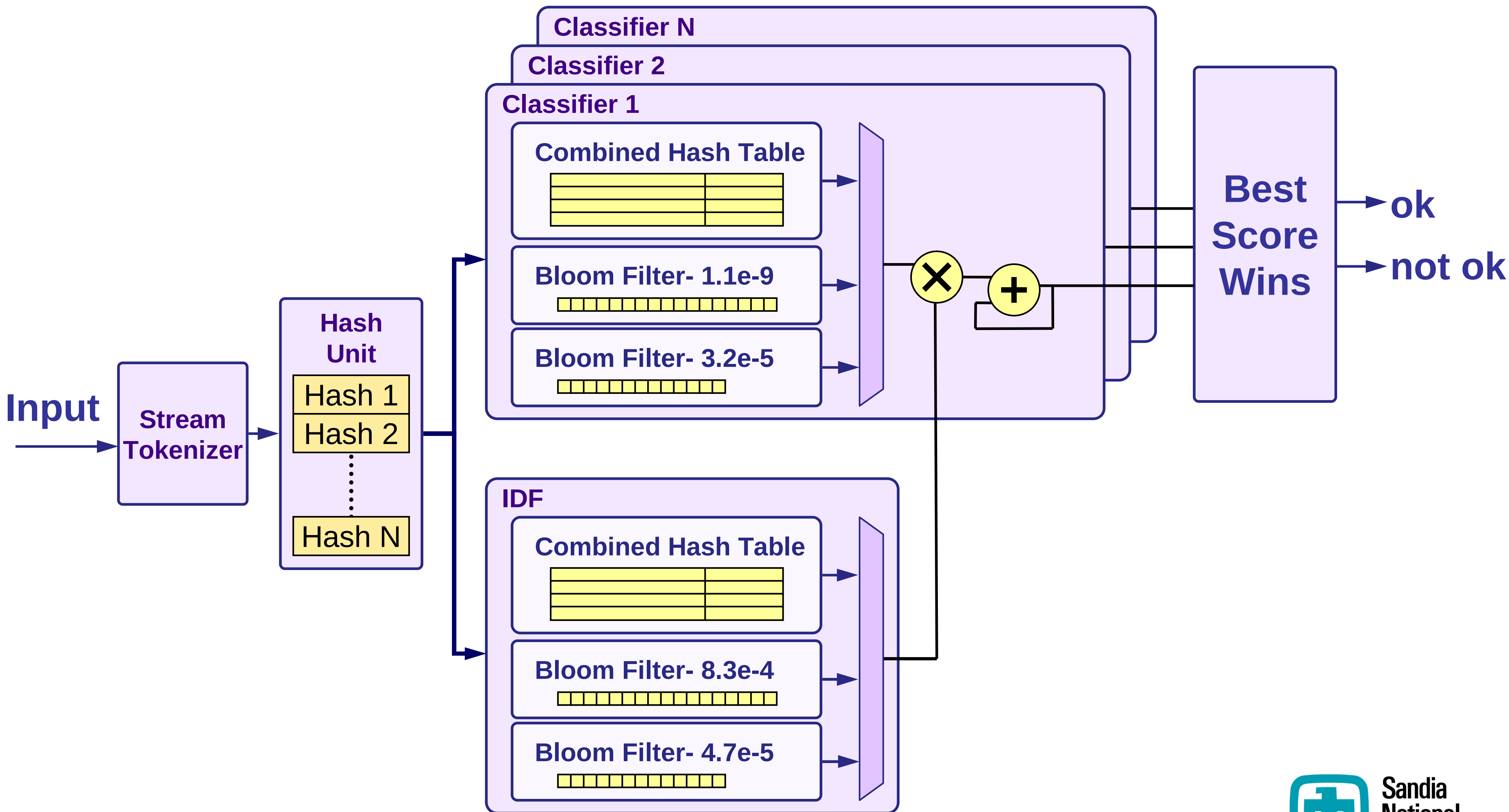
Generating Hardware

- Implemented flexible hardware design
  - Perl script converts data to parameters
- Piecewise testing
  - Full design in simulation software
  - Testing on new Virtex5 board
- Estimated speeds
  - 140MHz, >100MB/s
  - Bottleneck stream tokenizer



Hardware Data Flow



Summary

- Adapted an HTTP classifier to embedded platforms
  - Confirmed and took advantage of wiggle room in dictionary
  - Hybrid approach to hashing works well
- Relevant in other classification applications
  - TF-IDF/Cosine Similarity is a standard approach
- Ongoing/Future Work
  - Finish out a demo system by the end of FY
  - Investigate port to Tilera and GPUs

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