From Dirt to Shovels:
Inferring PADS descriptions from ASCII Data

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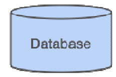
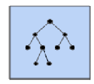
Data,Data,everywhere!

Incredible amounts of data stored in well-behaved formats:

Databases:



XML:



Tools

- Schema
- Browsers
- Query Languages
- Standards
- Libraries
- Books, documentation
- Training courses
- Conversion tools
- Vendor support
- Consultants…

We're not always so lucky!

Vast amounts of chaotic *ad hoc* data:

Tools

- Perl
- Awk
- C
- …

Government stats

```
"MSN","YYYYMM","Publication Value","Publication Unit","Column
Order"
"TEAJBUS",197313,-0.456483,Quadrillion Btu,4
"TEAJBUS",197413,-0.482265,Quadrillion Btu,4
"TEAJBUS",197513,-1.066511,Quadrillion Btu,4
"TEAJBUS",197613,-0.177807,Quadrillion Btu,4
"TEAJBUS",197713,-1.948233,Quadrillion Btu,4
"TEAJBUS",197813,-0.336538,Quadrillion Btu,4
"TEAJBUS",197913,-1.649302,Quadrillion Btu,4
"TEAJBUS",198013,-1.0537,Quadrillion Btu,4
```

Train Stations

```
Southern California Regional Railroad Authority,"Los Angeles, CA",
U,45,46,46,47,49,51,U,45,46,46,47,49,51
Connecticut Department of Transportation ,"New Haven, CT",
U,U,U,U,U,U,8,U,U,U,U,U,U,8
Tri-County Commuter Rail Authority ,"Miami, FL",
U,U,U,U,U,U,18,U,U,U,U,U,U,18
Northeast Illinois Regional Commuter Railroad Corporation,"Chicago,
IL",226,226,226,227,227,227,227,91,104,104,111,115,125,131
Northern Indiana Commuter Transportation District,"Chicago,
IL",18,18,18,18,18,18,20,7,7,7,7,7,7,11
Massachusetts Bay Transportation Authority,"Boston, MA",
U,U,117,119,120,121,124,U,U,67,69,74,75,78
Mass Transit Administration - Maryland DOT ,"Baltimore, MD",
U,U,U,U,U,U,42,U,U,U,U,U,U,22
New Jersey Transit Corporation ,"New York,
NY",158,158,158,162,162,162,167,22,22,41,46,46,46,51
```

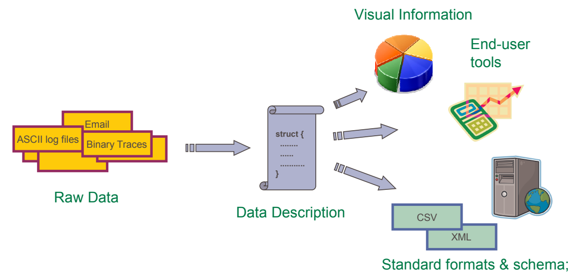
Web logs

```
207.136.97.49 - - [15/Oct/2006:18:46:51 -0700] "GET /turkey/amnty1.gif HTTP/1.0" 200 3013
207.136.97.49 - - [15/Oct/2006:18:46:51 -0700] "GET /turkey/clear.gif HTTP/1.0" 200 76
207.136.97.49 - - [15/Oct/2006:18:46:52 -0700] "GET /turkey/back.gif HTTP/1.0" 200 224
207.136.97.49 - - [15/Oct/2006:18:46:52 -0700] "GET /turkey/women.html HTTP/1.0" 200 17534
208.196.124.26 - Dbuser [15/Oct/2006:18:46:55 -0700] "GET /candatop.html HTTP/1.0" 200 -
208.196.124.26 - - [15/Oct/2006:18:46:57 -0700] "GET /images/done.gif HTTP/1.0" 200 4785
www.att.com - - [15/Oct/2006:18:47:01 -0700] "GET /images/reddash2.gif HTTP/1.0" 200 237
208.196.124.26 - - [15/Oct/2006:18:47:02 -0700] "POST /images/refrun1.gif HTTP/1.0" 200 836
208.196.124.26 - - [15/Oct/2006:18:47:05 -0700] "GET /images/hasene2.gif HTTP/1.0" 200 8833
www.cnn.com - - [15/Oct/2006:18:47:08 -0700] "GET /images/candalog.gif HTTP/1.0" 200 -
208.196.124.26 - - [15/Oct/2006:18:47:09 -0700] "GET /images/nigpost1.gif HTTP/1.0" 200 4429
208.196.124.26 - - [15/Oct/2006:18:47:09 -0700] "GET /images/rally4.jpg HTTP/1.0" 200 7352
128.200.68.71 - - [15/Oct/2006:18:47:11 -0700] "GET /amnesty/usalinks.html HTTP/1.0" 143 10329
208.196.124.26 - - [15/Oct/2006:18:47:11 -0700] "GET /images/reyes.gif HTTP/1.0" 200 10859
```

And many others…

- Gene ontology data
- Cosmology data
- Financial trading data
- Telecom billing data
- Router config files
- System logs
- Call detail data
- Netflow packets
- DNS packets
- Java JAR files
- Jazz recording info
- …

Learning: Goals & Approach



Problem: Producing useful tools for ad hoc data takes a lot of time.
Solution: A learning system to generate data descriptions and tools automatically .

PADS Reminder

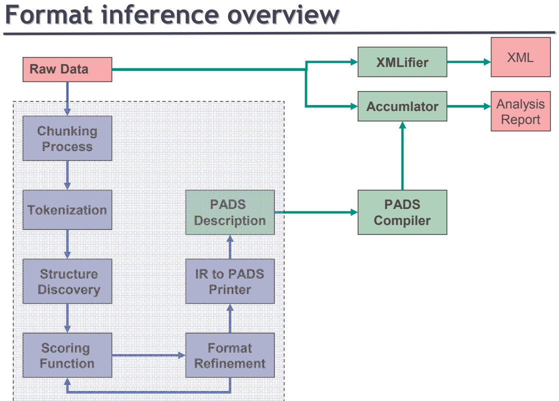
Inferred data formats are described using a specialized language of types

- Provides rich base type library; many specialized for systems data.
  - `Pint8, Puint8, …            // -123, 44`
    `Pstring(:'|':)               // hello |`
    `Pstring_FW(:3:)              // catdog`
    `Pdate, Ptime, Pip, …`
- Provides type constructors to describe data source structure:
  - sequences: `Pstruct, Parray,`
  - choices: `Punion, Penum, Pswitch`
  - constraints: allow arbitrary predicates to describe expected properties.

PADS compiler generates stand-alone tools including xml-conversion, Xquery support & statistical analysis directly from data descriptions.

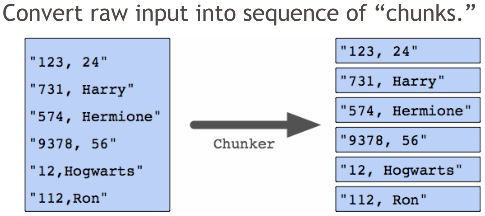
Go to demo

Format inference overview



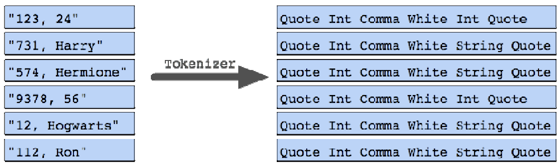
Chunking Process

- Convert raw input into sequence of "chunks."



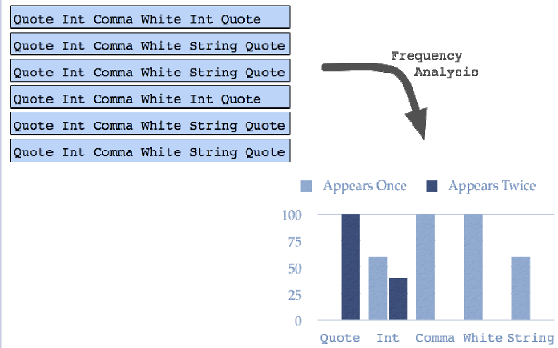
- Supported divisions:
  - Various forms of "newline"
  - File boundaries
- Also possible: user-defined "paragraphs"

Tokenization



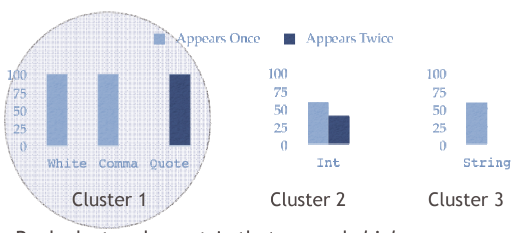
- Tokens expressed as regular expressions.
- **Basic tokens**
  - Integer, white space, punctuation, strings
- **Distinctive tokens**
  - IP addresses, dates, times, MAC addresses, ...

Histograms



Clustering

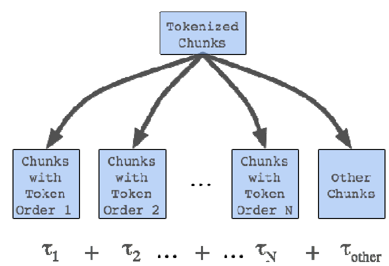
Group clusters with similar frequency distributions



Rank clusters by metric that rewards *high coverage* and narrow distributions. Chose cluster with highest score.

Two frequency distributions are *similar* if they have the same shape (within some error) when the columns are sorted by height.

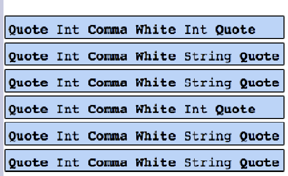
Partition chunks



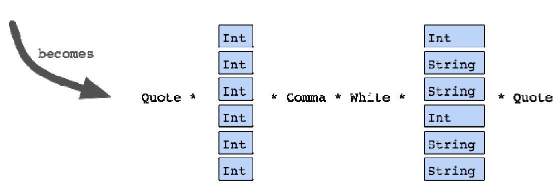
$\tau_1 + \tau_2 \ldots + \ldots \tau_N + \tau_{other}$

In our example, all the tokens appear in the same order in all chunks, so the union is degenerate.

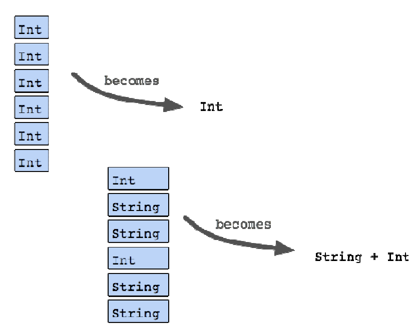
Find subcontexts



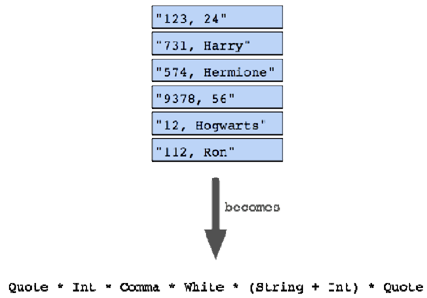
Tokens in selected cluster:
Quote(2) Comma
White



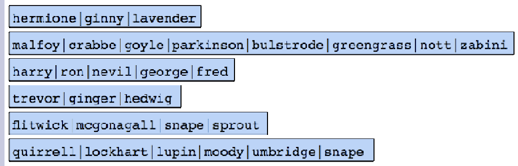
Then Recurse...



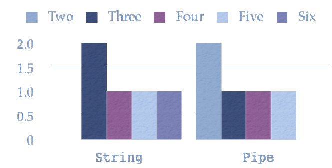
Inferred type



Finding arrays

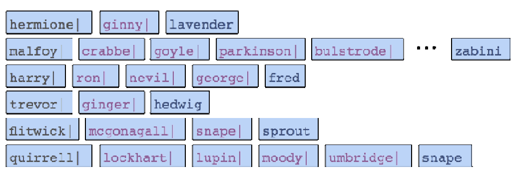


Single cluster with high coverage, but *wide* distribution.



Partitioning

Selected tokens for array cluster: String Pipe



Context 1,2:
String * Pipe

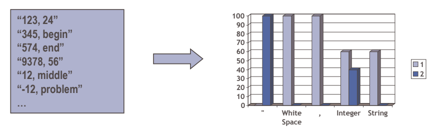
becomes

Context 3: String

String [] sep('|')

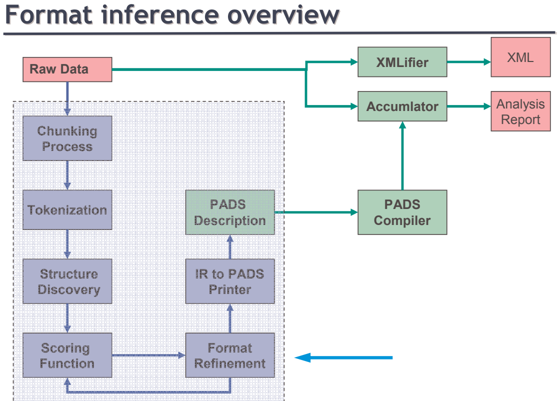
Structure Discovery Review

- Compute frequency distribution for each token.



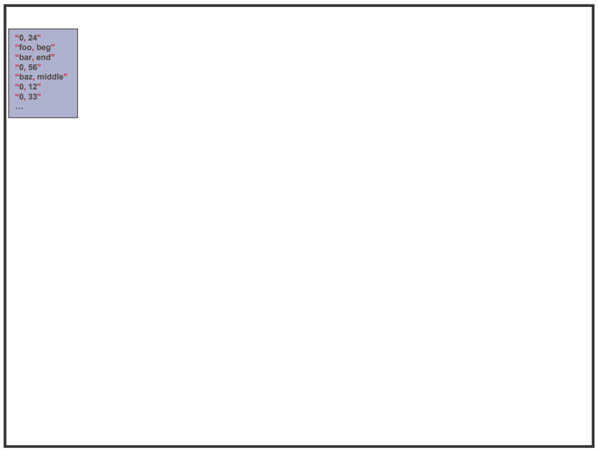
- Cluster tokens with *similar* frequency distributions.
- Create hypothesis about data structure from cluster distributions
  - Struct
  - Array
  - Union
  - Basic type (bottom out)
- Partition data according to hypothesis & recurse

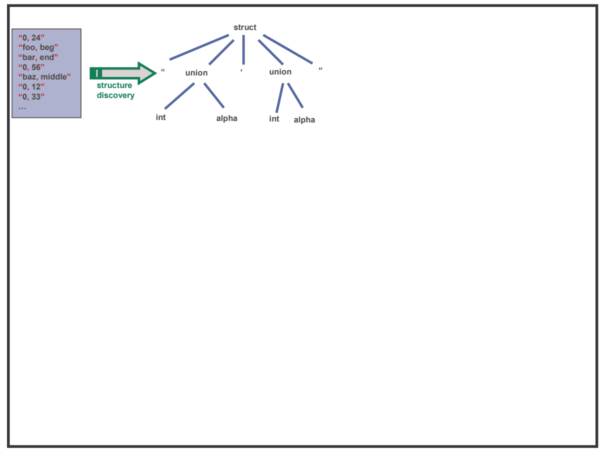
Format inference overview

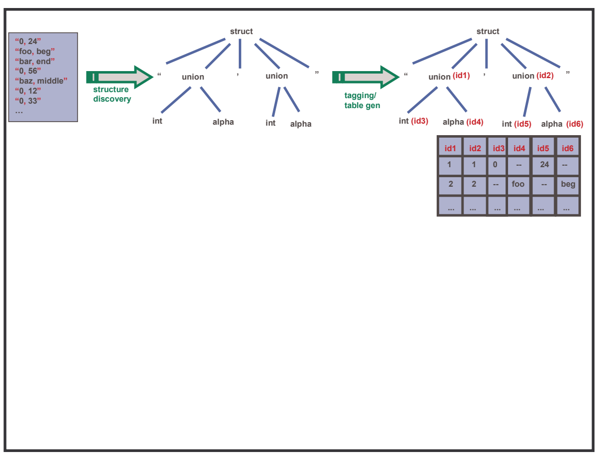


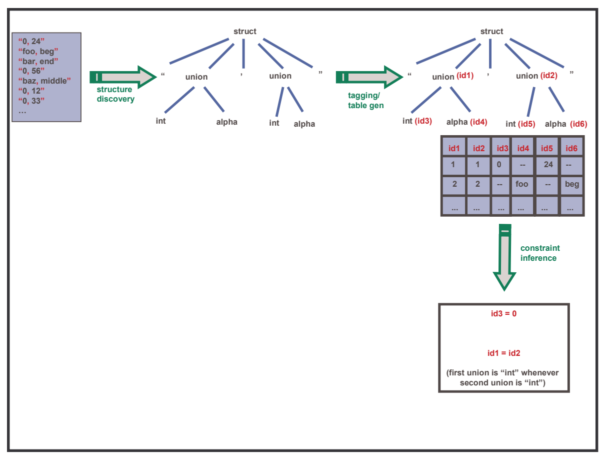
Format Refinement

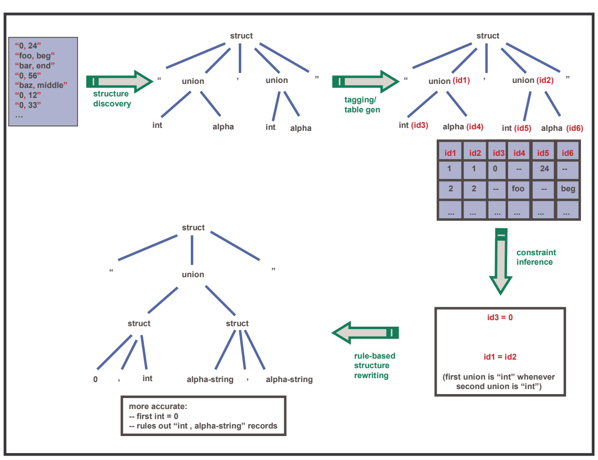
- Rewrite format description to:
  - Optimize information-theoretic complexity
    - Simplify presentation
      - Merge adjacent structures and unions
    - Improve precision
      - Identify constant values
      - Introduce enumerations and dependencies
  - Fill in missing details
    - Find completions where structure discovery stops
    - Refine types
      - Termination conditions for strings
      - Integer sizes
      - Identify array element separators & terminators

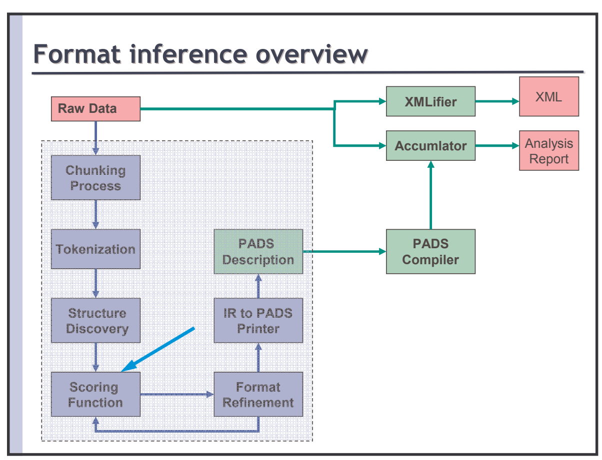

"0, 24"
"foo, beg"
"bar, end"
"0, 56"
"baz, middle"
"0, 12"
"0, 33"
...


"0, 24"
"foo, beg"
"bar, end"
"0, 56"
"baz, middle"
"0, 12"
"0, 33"
...
structure discovery
struct
union
union
int
alpha
int
alpha


structure discovery
tagging/ table gen
struct
union (id1)
union (id2)
int (id3)
alpha (id4)
int (id5)
alpha (id6)
id1 id2 id3 id4 id5 id6
1 1 0 -- 24 --
2 2 -- foo -- beg


structure discovery
tagging/ table gen
constraint inference
id3 = 0
id1 = id2
(first union is "int" whenever second union is "int")


structure discovery
tagging/ table gen
constraint inference
id3 = 0
id1 = id2
(first union is "int" whenever second union is "int")
rule-based structure rewriting
struct
union
struct
struct
0
int
alpha-string
alpha-string
more accurate:
-- first int = 0
-- rules out "int , alpha-string" records


Format inference overview
Raw Data
XMLifier
XML
Accumulator
Analysis Report
Chunking Process
Tokenization
PADS Description
PADS Compiler
Structure Discovery
IR to PADS Printer
Scoring Function
Format Refinement

Scoring

- Goal: A quantitative metric to evaluate the quality of inferred descriptions and drive refinement.
- Challenges:
  - *Underfitting*. Pstring(Peof) describes data, but is too general to be useful.
  - *Overfitting*. Type that exhaustively describes data (‘H’, ‘e’, ‘r’, ‘m’, ‘i’, ‘o’, ‘n’, ‘e’,…) is too precise to be useful.
- Sweet spot: Reward compact descriptions that predict the data well.

Minimum Description Length

- Standard metric from machine learning.
- Cost of transmitting the syntax of a description plus the cost of transmitting the data given the description:

```
cost(T,d) =
   complexity(T) + complexity(d|T)
```

- Functions defined inductively over the structure of the type T and data d respectively.
- Normalized MDL gives compression factor.
- Scoring function triggers rewriting rules.

Testing and Evaluation

- Evaluated overall results qualitatively
  - Compared with Excel -- a manual process with limited facilities for representation of hierarchy or variation
  - Compared with hand-written descriptions -- performance variable depending on tokenization choices & complexity
- Evaluated accuracy quantitatively
  - Implemented infrastructure to use generated accumulator programs to determine inferred description error rates
- Evaluated performance quantitatively
  - Tokenization & rough structure inference perform well: less than 1 second on 300K
  - Dependency analysis can take a long time on complex format (but can be cut down easily).

Benchmark Formats

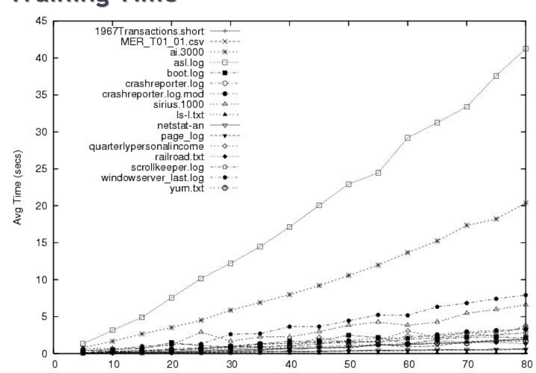
Data source	Chunks	Bytes	Description
1967Transactions.short	999	70929	Transaction records
MER_T01_01.cvs	491	21731	Comma-separated records
Ai.3000	3000	293460	Web server log
Asl.log	1500	279600	Log file of MAC ASL
Boot.log	262	16241	Mac OS boot log
Crashreporter.log	441	50152	Original crashreporter daemon log
Crashreporter.log.mod	441	49255	Modified crashreporter daemon log
Sirius.1000	999	142607	AT&T phone provision data
Ls-l.txt	35	1979	Command ls -l output
Netstat-an	202	14355	Output from netstat -an
Page_log	354	28170	Printer log from CUPS
quarterlypersonalincome	62	10177	Spread sheet
Railroad.txt	67	6218	US Rail road info
Scrollkeeper.log	671	66288	Application log
Windowserver_last.log	680	52394	Log from Mac LoginWindow server
Yum.txt	328	18221	Log from package installer Yum

Execution Times

Data source	SD (s)	Ref (s)	Tot (s)	HW (h)
1967Transactions.short	0.20	2.32	2.56	4.0
MER_T01_01.cvs	0.11	2.82	2.92	0.5
Ai.3000	1.97	26.35	28.64	1.0
Asl.log	2.90	52.07	55.26	1.0
Boot.log	0.11	2.40	2.53	1.0
Crashreporter.log	0.12	3.58	3.73	2.0
Crashreporter.log.mod	0.15	3.83	4.00	2.0
Sirius.1000	2.24	5.69	8.00	1.5
Ls-l.txt	0.01	0.10	0.11	1.0
Netstat-an	0.07	0.74	0.82	1.0
Page_log	0.08	0.55	0.65	0.5
quarterlypersonalincome	0.07	5.11	5.18	48
Railroad.txt	0.06	2.69	2.76	2.0
Scrollkeeper.log	0.13	3.24	3.40	1.0
Windowserver_last.log	0.37	9.65	10.07	1.5
Yum.txt	0.11	1.91	2.03	5.0

SD: structure discovery
Ref: refinement
Tot: total
HW: hand-written

Training Time

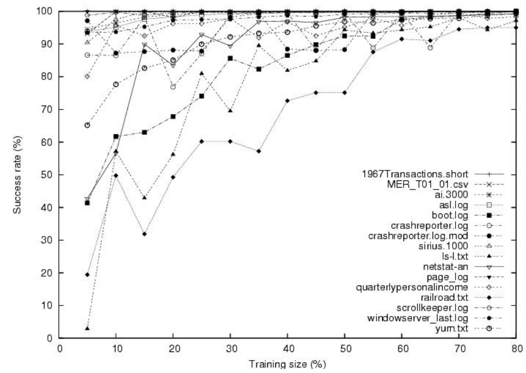


Normalized MDL Scores

Data source	SD	Ref	HW
1967Transactions.short	0.295	0.218	0.268
MER_T01_01.cvs	0.648	0.112	0.138
Ai.3000	0.503	0.332	0.338
Asl.log	0.630	0.267	0.361
Boot.log	0.620	0.481	0.703
Crashreporter.log	0.607	0.328	0.348
Crashreporter.log.mod	0.612	0.329	0.347
Sirius.1000	0.602	0.470	0.438
Ls-l.txt	0.559	0.333	0.401
Netstat-an	0.413	0.394	0.319
Page_log	0.540	0.107	0.353
quarterlypersonalincome	0.544	0.367	0.354
Railroad.txt	0.715	0.506	0.522
Scrollkeeper.log	0.625	0.354	0.352
Windowserver_last.log	0.618	0.241	0.267
Yum.txt	0.827	0.305	0.474

SD: structure discovery
Ref: refinement
HW: hand-written

Training Accuracy



Type Complexity and Min. Training Size

Data source	Norm. Ty Complexity	90%	95%
Sirius.1000	0.0001	5	10
1967Transaction.short	0.0003	5	5
Ai.3000	0.0004	5	10
Asl.log	0.0012	5	10
Scrollkeeper.log	0.0020	5	5
Page_log	0.0032	5	5
MER_T01_01.csv	0.0037	5	5
Crashreporter.log	0.0052	10	15
Crashreporter.log.mod	0.0053	5	15
Windowserver_last.log	0.0084	5	15
Netstat-an	0.0118	25	35
Yum.txt	0.0124	30	45
quarterlypersonalincome	0.0170	10	10
Boot.log	0.0213	45	60
Ls-l.txt	0.0461	50	65
Railroad.txt	0.0485	60	75

Problem: Tokenization

- Technical problem:
  - Different data sources assume different tokenization strategies
  - Useful token definitions sometimes overlap, can be ambiguous, aren't always easily expressed using regular expressions
  - Matching tokenization of underlying data source can make a big difference in structure discovery.
- Current solution:
  - Parameterize learning system with customizable configuration files
  - Automatically generate lexer file & basic token types
- Future solutions:
  - Use existing PADS descriptions and data sources to learn probabilistic tokenizers
  - Incorporate probabilities into back-end rewriting system
    - Back end has more context for making final decisions than the tokenizer, which reads 1 character at a time without look ahead

Structure Discovery Analysis

- Usually identifies top-level structure sufficiently well to be of some use
- When tokenization is accurate, this phase performs well
- When tokenization is inaccurate, this phase performs less well
  - Descriptions are more complex than hand-coded ones
  - Intuitively: one or two well-chosen tokens in a hand-coded description is represented by complex combination of unions, options, arrays and structures
- Technical Problems:
  - When to give up & bottom out
  - Choosing between unions and arrays
- Current Solutions:
  - User-specified recursion depth
  - Structs prioritized over arrays, which are prioritized over unions
- Future Solutions:
  - Information-theory-driven bottoming out
  - Expand infrastructure to enable "search" and evaluation of several options

Format Refinement Analysis

- Overall, refinement substantially improves precision of data format & sometimes improves compactness
- Technical problem 1:
  - Sometimes refinement is overly aggressive, unnecessarily expanding data descriptions without providing added value in terms of precision
- Current solution 1:
  - Do not refine all possible base types -- limit refinements to simplest types (int, string, white space).
  - Refinement of complex types such as dates & URLs is not usually needed by tools or programmers (even when they really are constant) and often leads to overfitting.
- Future solution 1:
  - Tune complexity analysis more finely and use it as a guide for rewriting
  - Identify refinement opportunities for which insufficient data is available

Format Refinement Analysis

- Technical problem 2:
  - Value-space analysis is O(R * T^2) where R is the number of records and T is the number of abstract syntax tree nodes in the description. In some descriptions, T is sufficiently large that value-space analysis grinds to a halt.
- Current solution 2:
  - Bound the size of the table generated from the abstract syntax tree, discarding the chance to find dependencies in some portions of the description
- Future solution 2:
  - Optimize value-space algorithms intelligently
    - Perform left-to-right sweep, ignoring backward dependencies
    - Detect candidate dependencies on small data sets, discard non-candidates & verify candidate feasibility on larger data sets

Scoring Analysis

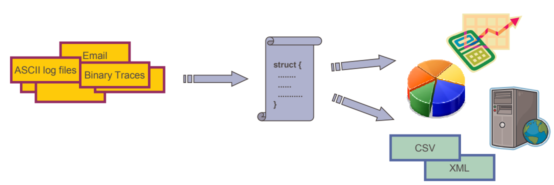
- Technical Problem: It is unclear how to weigh type complexity vs data complexity to predict human preference in description structure
- Current Solution:
  - Final type complexity and final data complexity are weighted equally in the total cost function
  - However, final data complexity grows linearly with the amount of data used in the experiment
- Future Solutions:
  - Observation: some of our experiments suggest that humans weight type complexity more heavily than data complexity
    - introduce a hyper parameter h and perform experiments, varying h until cost of inferred results and expert descriptions match expectations:
      - cost = h*type-complexity + data-complexity
- Bottom Line: Information theory is a powerful and general tool, but more research is needed to tune it to our application domain

Related work

- Grammar Induction
  - *Extracting Structure from Web Pages* [Arasu & Hector-Molena, SigMod, 2003].
  - *Language Identification in the Limit* [Gold, Information and Control, 1968].
  - *Grammatical Inference for Information Extraction and Visualization on the Web* [Hong, PhD Thesis, Imperial College, 2003].
  - *Current Trends in Grammatical Inference* [Higuera, LNCS, 2001].
- Functional dependencies
  - *Tane: An Efficient Algorithm for Discovering Functional and Approximate Dependencies* [Huhtal et al, Computer Journal, 1999].
- Information Theory
  - *Information Theory, Inference, and Learning Algorithms* [Mackay, Cambridge University Press, 2003].
  - *Advances in Minimum Description Length* [Grünwald, MIT Press, 2004].

Technical Summary

- Format inference is feasible for many ASCII data formats
- Our current tools infer sufficient structure that descriptions may be piped into the PADS compiler and used to generate tools for XML conversion and simple statistical analysis.



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