FlashProfile

A Framework for Synthesizing Data Profiles

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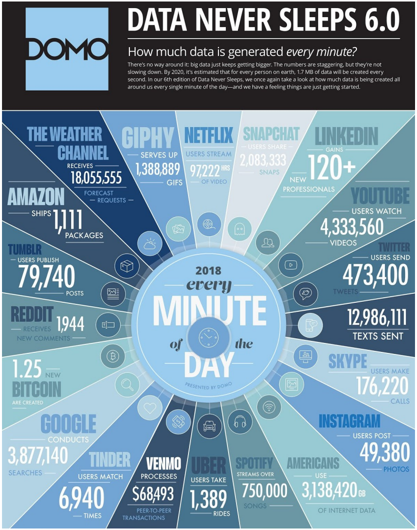
SPLASH BOSTON 2018

(OOPSLA)

† Contributed during an internship with PROSE team at Microsoft

The Challenges of “Big” Data



The Challenges of “Big” Data

High *Volume*

> 2.5 M TB of data generated *every day*!

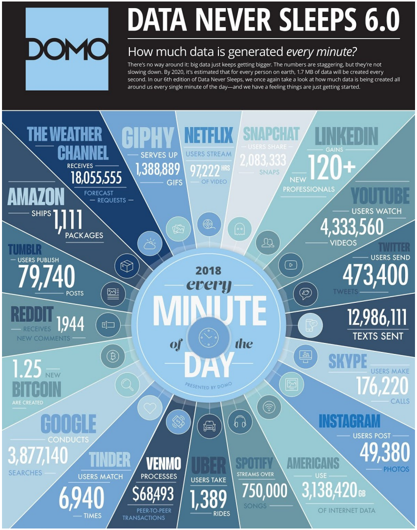
High *Velocity*

~ 4 M Google searches, ~ ½ M tweets,
> 1 K Amazon shipments … *per minute*!

High *Variety*

90 % of generated data is unstructured!

Data may be incomplete, inconsistent,
may contain multiple formats …



State of The Art

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Interactive refinement to gradually drill into data:

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  - Clustering, with similarity ≈ Pattern *score*
- *Exponentially* many ways of generalizing strings to a pattern
  - Efficient synthesis of complex patterns

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Main Contributions

An application of a supervised learning technique (inductive program synthesis) to the unsupervised learning problem of syntactic profiling.

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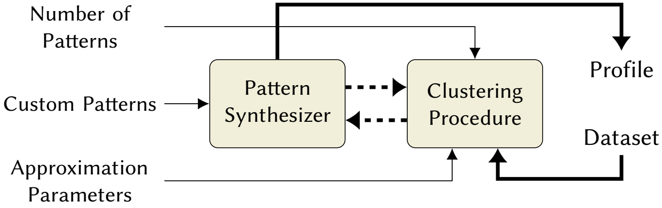
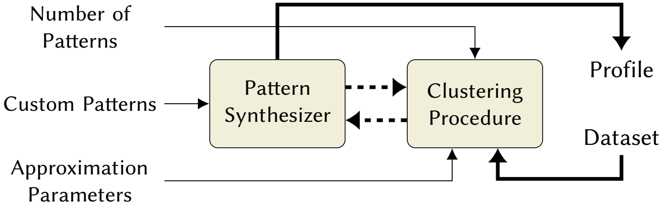
- FlashProfile, and evaluation of its performance and accuracy
- profile-guided interaction for traditional PBE workflows

Overview of FlashProfile





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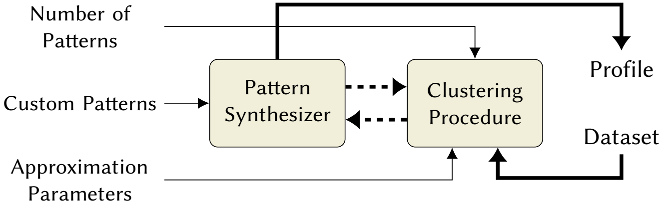

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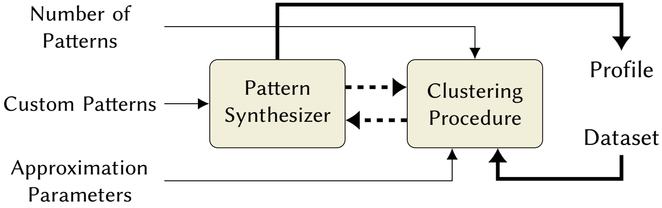

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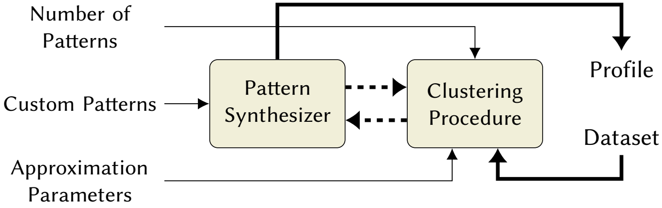

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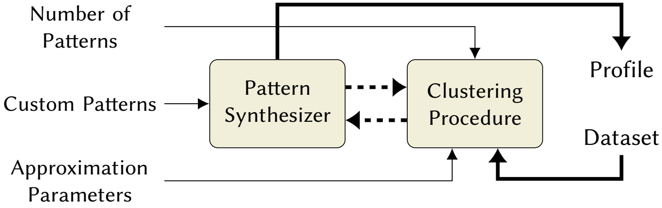

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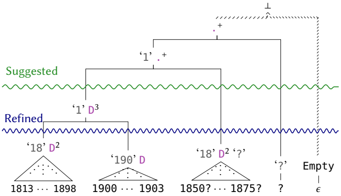
FlashProfile is publicly-available as a cross-platform C# library (`Matching.Text`), as part of the Microsoft PROSE SDK.

Profiling via Clustering



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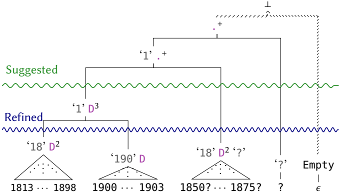
- Pattern-Aware Partitioning
  - *Clustering:* Agglomerative hierarchical clustering
  - *Objective:* Minimize the cost of describing partitions
  - *Similarity:* Minimum cost of describing 2 strings



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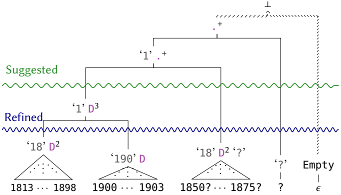
  - A pattern learner $\mathcal{L}$
  - A cost function $\mathcal{C}$



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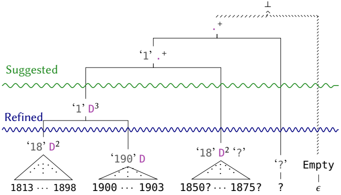
- Optimizations
  - Approximate similarity using previous patterns
  - Profiling small chunks → Full profile



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Pattern Synthesis

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  - *recursively reduces* a synthesis problem
  - sound and complete over a given set of atoms
- A Cost Function C_{FP}
  - tradeoff between specificity and simplicity
  - *weighted sum* of costs of individual atoms

(see our paper for details)

Profile-Guided Interaction for PBE

Traditional PBE Interaction	*Profile-Guided Interaction*
Users typically provide their desired outputs *sequentially*	System *proactively requests* outputs for syntactically discrepant inputs

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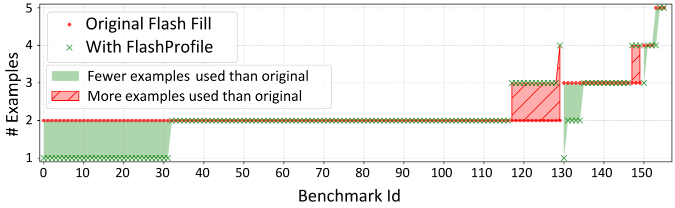

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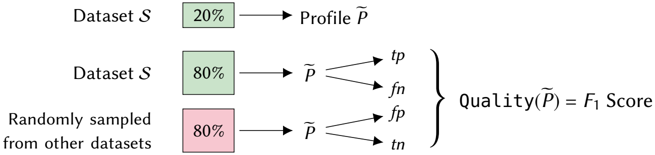

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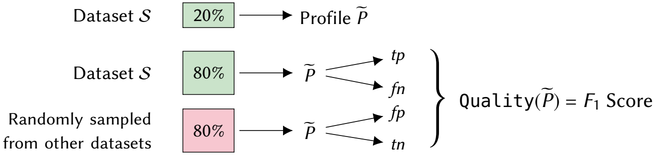
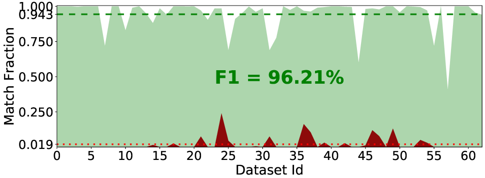
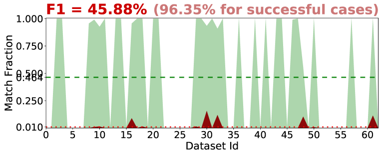
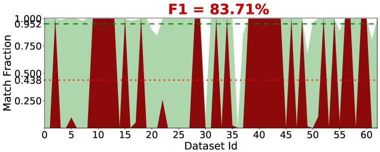




Quality of profiles generated by FlashProfile

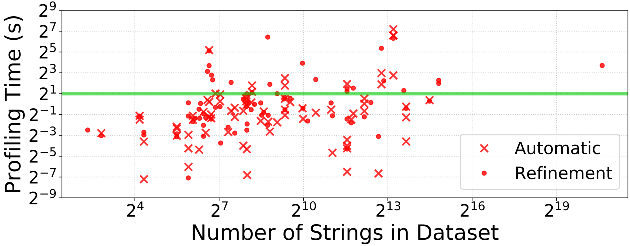


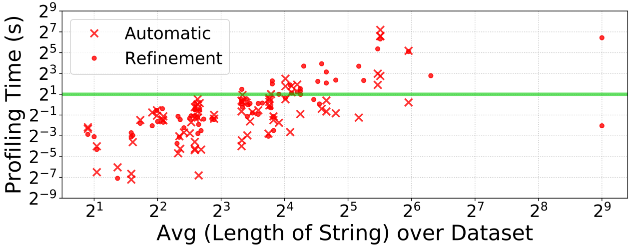
Ataccama One



Microsoft SSDT

End-to-End Profiling Performance





Related Work

- Microsoft SQL Server Data Tools (SSDT) [https://docs.microsoft.com/en-us/sql/ssdt]
  - Recognizes constants and fixed-width atoms.
  - Not extensible. No refinement. Profiles are sometimes not comprehensive.
- Ataccama One [https://one.ataccama.com/]
  - Comprehensive profiles. Recognizes fixed-width atoms.
  - A small fixed set of atoms. No refinement. Does not recognize constants.
- Trifacta Wrangler [https://cloud.trifacta.com]
  - Recognizes fixed-width atoms. Generates readable profiles.
  - Not extensible. No refinement. Does not recognize constants.
- Google OpenRefine [http://openrefine.org/]
  - No patterns, only clusters based on character-wise similarity.
- Potter's Wheel [Vijayshankar Raman and Joseph M. Hellerstein. *VLDB 2001*]
  - Extensible set of atoms.
  - Only learns the most-frequent pattern and shows outliers, not a profile.
- LearnPADS++ [Kathleen Fisher *et al. SIGMOD 2008* ; Kenny Q. Zhu *et al. PADL 2012*]
  - Not extensible. No refinement. Generates C-style structures.

Conclusion & Future Work

A novel composition of hierarchical clustering and program synthesis techniques for efficient pattern-based data profiling

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  - Machine-learnt costs to maximize the *quality* of profiles
- Alternate approximation strategies with better guarantees
  - Compute the overall "goodness" of an approximation and refine if needed
- Identify and classify semantic entities as well
  - For example, combine with *named-entity recognition* (NER) techniques

Publicly-Available Artifacts

- The Matching.Text NuGet package:
  https://www.nuget.org/packages/Microsoft.ProgramSynthesis.Matching.Text/
- Documentation for Matching.Text library:
  https://microsoft.github.io/prose/documentation/matching-text/intro/
- OOPSLA artifacts (a C# app showing Matching.Text API usage):
  https://github.com/SaswatPadhi/FlashProfileDemo
- Contact: padhi@cs.ucla.edu