Active Learning of GAV Schema Mappings

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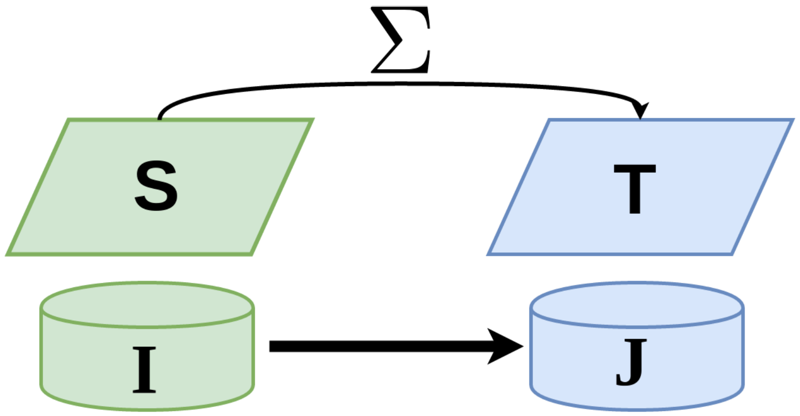
Schema mappings and data exchange

- **Schema Mapping –** a triple $\mathcal{M} = (\mathbf{S}, \mathbf{T}, \Sigma)$, where Σ describes the relationship between a source schema **S** and a target schema **T**



- **Data Exchange Problem** for a schema mapping $\mathcal{M} = (\mathbf{S}, \mathbf{T}, \Sigma)$:
  - Given an **S**-instance $\mathbf{I}$, find a solution for $\mathbf{I}$,i.e., a **T**-instance $\mathbf{J}$ so that $(I, J) \models \Sigma$.
  - Universal solutions are the preferred solutions.

Schema-mapping languages

- The language of GLAV (Global-and-Local-As-View) – A FO logic formula of the form:

$$\forall \mathbf{x} \left(\varphi(\mathbf{x}) \rightarrow \exists \mathbf{y}\ \psi(\mathbf{x}, \mathbf{y}) \right),$$

where $\varphi(\mathbf{x})$ is a conjunction of atoms over $\mathbf{S}$ and $\psi(\mathbf{x})$ is a conjunction of atoms over $\mathbf{T}$.

Example: $\forall s \forall c \left(\mathsf{Student}(s) \wedge \mathsf{Enroll}(s, c) \rightarrow \exists t \exists g \mathsf{Teacher}(t, c) \wedge \mathsf{Grade}(s, c, g) \right)$

- Two important sublanguages
  - **GAV (Global-As-View):** $\forall \mathbf{x}\ (\varphi(\mathbf{x}) \rightarrow T(\mathbf{x}))$:

    Example: $\forall v \forall u\ (\ \mathsf{Node}(v) \wedge \mathsf{Node}(u) \rightarrow \mathsf{Edge}(v, u)\ )$

  - **LAV (Local-As-View):** $\forall \mathbf{x}\ (S(\mathbf{x}) \rightarrow \exists y\ \psi(\mathbf{x}, \mathbf{y}))$:

    Example: $\forall v \forall u\ (\ \mathsf{Edge}(v, u) \rightarrow \exists m\ \mathsf{Edge}(v, m) \wedge \mathsf{Edge}(m, u)\ )$

Deriving schema mappings from examples

- **Problem**: derive a schema mapping $\mathcal{M} = (\mathbf{S}, \mathbf{T}, \Sigma)$ from a given set of data examples, where a data example is a pair (I,J) that satisfies Σ .

- **Learning framework** [ten Cate, Dalmau, Kolaitis 2013]
  - Exact learning algorithm for GAV with equivalence queries and labeling queries

Cast the problem as a computational learning problem.

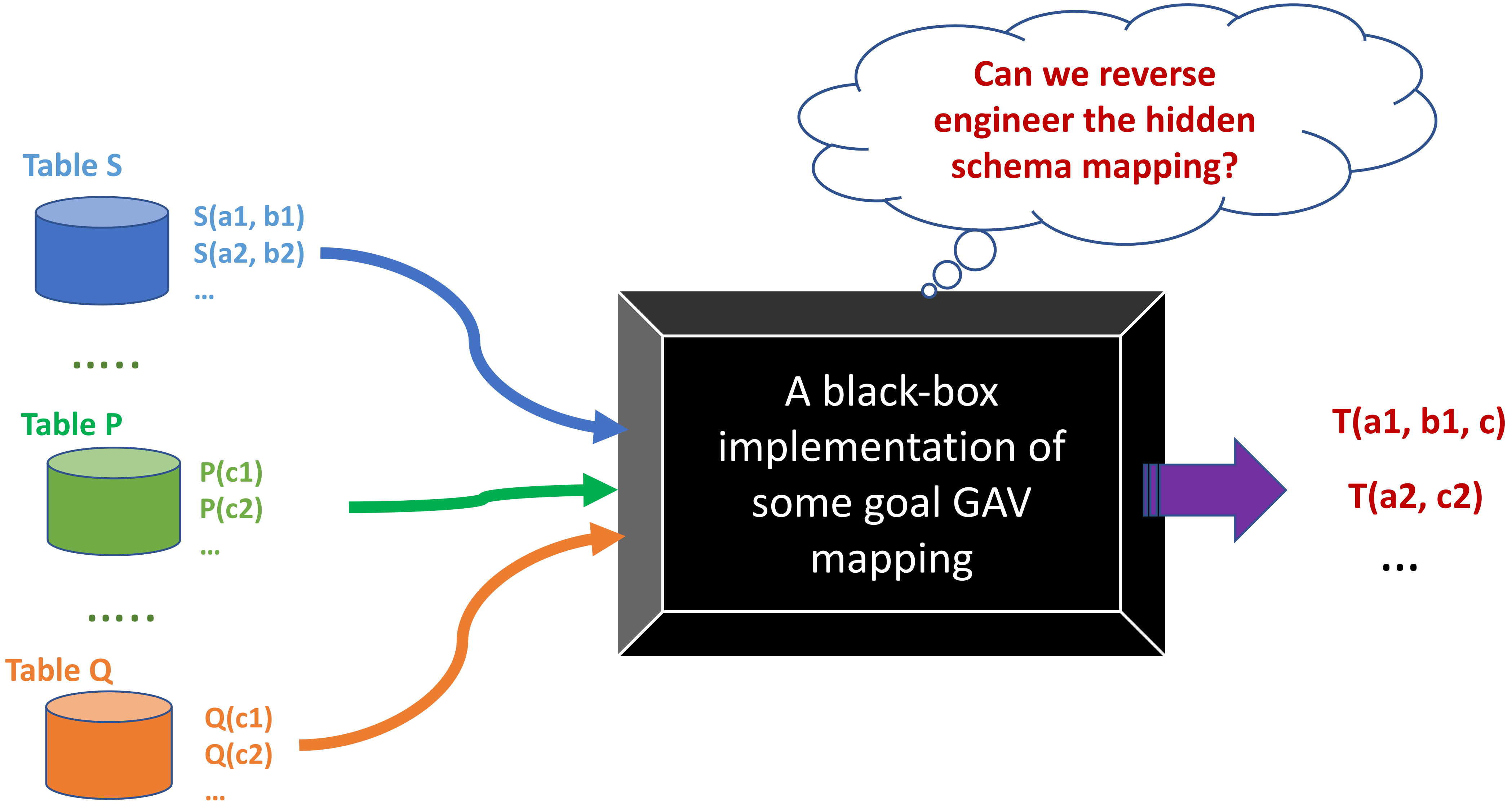
- **Other frameworks**
  - Fitting framework [Alexe, ten Cate, Kolaitis, Tan 2011]
  - Repair framework [Gottlob and Senellart, 2010]
  - Interactive Mapping Specification (IMS) [Bonifati et al., 2017]

Focused on the fitting decision problem for GLAV and GAV. Practical algorithms exist. One of our baselines

Proposed a cost model to measure the "quality" of schema Mappings. No practical algorithm for GAV

Human-in-the-loop approach. No quality guarantees for derived schema mappings

A motivating scenario: GAV reverse engineering



Learning Framework [ten Cate, Dalmau, Kolaitis 2013]

- Cast schema-mapping discovery as a computational learning problem.
  - There is a goal concept (i.e., goal mapping), whose specification needs to be discovered.

- **Theorem ([**ten Cate, Dalmau, Kolaitis 2013**]).**

GAV mappings are efficiently learnable with equivalence and labeling queries.

  - ***Equivalence oracle:*** given two GAV mappings M and M*, check if M and M* are logically equivalent. If not, a counter-example is returned.
  - ***Labeling oracle***: given a source instance I, return the canonical universal solution J for I.

ExactGAV learning algorithm

- The ExactGAV algorithm is hard to implement
  - A black-box implementation can serve as the labeling oracle.
  - However, an equivalence oracle may not be available in practice.

Contributions – the GAVLearn algorithm

- We design an active learning algorithm, called GAVLearn

- Main characteristics:
  - Adapted from the ExactGAV algorithm
  - Assumes a labeling oracle is given by a black-box implementation
  - Replaces the equivalence oracle with **conformance testing**
    - Approximate the equivalence oracle with a set of data examples
  - GAVLearn is an **active learning** algorithm
    - the learning is done by actively doing experiments with intermediate GAV mappings
  - Usefulness of GAVLearn verified through extensive experimentation.

The key ingredients of GAVLearn algorithm

Input: $\mathcal{G}$ - goal mapping (as a labeling oracle);
E - a set of universal examples for $\mathcal{G}$
Output: a mapping that fits E.

$\mathcal{H} \leftarrow \emptyset$
while true **do**
  if each $(I, J) \in E$ is canonical universal for $\mathcal{H}$ **then**
    return $\mathcal{H}$
  end if
  choose an $(I, J) \in E$ such that $J \neq \text{can-sol}_{\mathcal{H}}(I)$
  // In the proof of Thm 13, we show $\text{can-sol}_{\mathcal{H}}(I) \subsetneq J$
  $f \leftarrow$ choose a fact $f \in J \setminus \text{can-sol}_{\mathcal{H}}(I)$
  if $\mathcal{G}$ logically implies $(I, \{f\}) \times C$ for some $C \in \mathcal{H}$ **then**
    Choose $C \in \mathcal{H}$ such that $\mathcal{G}$ logically implies $(I, \{f\}) \times C$
    $\mathcal{H} \leftarrow (\mathcal{H} \setminus \{C\}) \cup \{Crit_{\mathcal{G}}((I, \{f\}) \times C)\}$
  else
    $\mathcal{H} \leftarrow \mathcal{H} \cup \{Crit_{\mathcal{G}}((I, \{f\}))\}$
  end if
end while
return $\mathcal{H}$

Find more details of the algorithm in the paper

Input: **G** – a black-box implementation of the goal GAV mapping
E – a set of universal examples for **G**

randomly created or obtained from domain experts

Output: H – a GAV mapping that fits **E** whose size is at most the size of **G.**

- **Conformance testing**: use **E** to check if **H**'s data exchange behavior conforms to the specification of **G.**
  - **H** semantically conforms to **G** if **H** and **G** agree on **E.**
  - Otherwise, there is one $(I, J) \in$ **E**, on which **H** and **G** disagree.
- Use **active learning** to extract a **critically sound constraint** from a counterexample
  - Actively do experiments with the **counter-example** and the black-box implementation of **G.**

Theoretical Guarantees

Given a set E of universal examples for some hidden goal GAV mapping G, GAVLearn is guaranteed to produce a GAV mapping H that is **consistent with E such that size(H) <= size(G)**

Theorem 1 *GAVLearn is an optimal Occam algorithm for GAV mappings.*

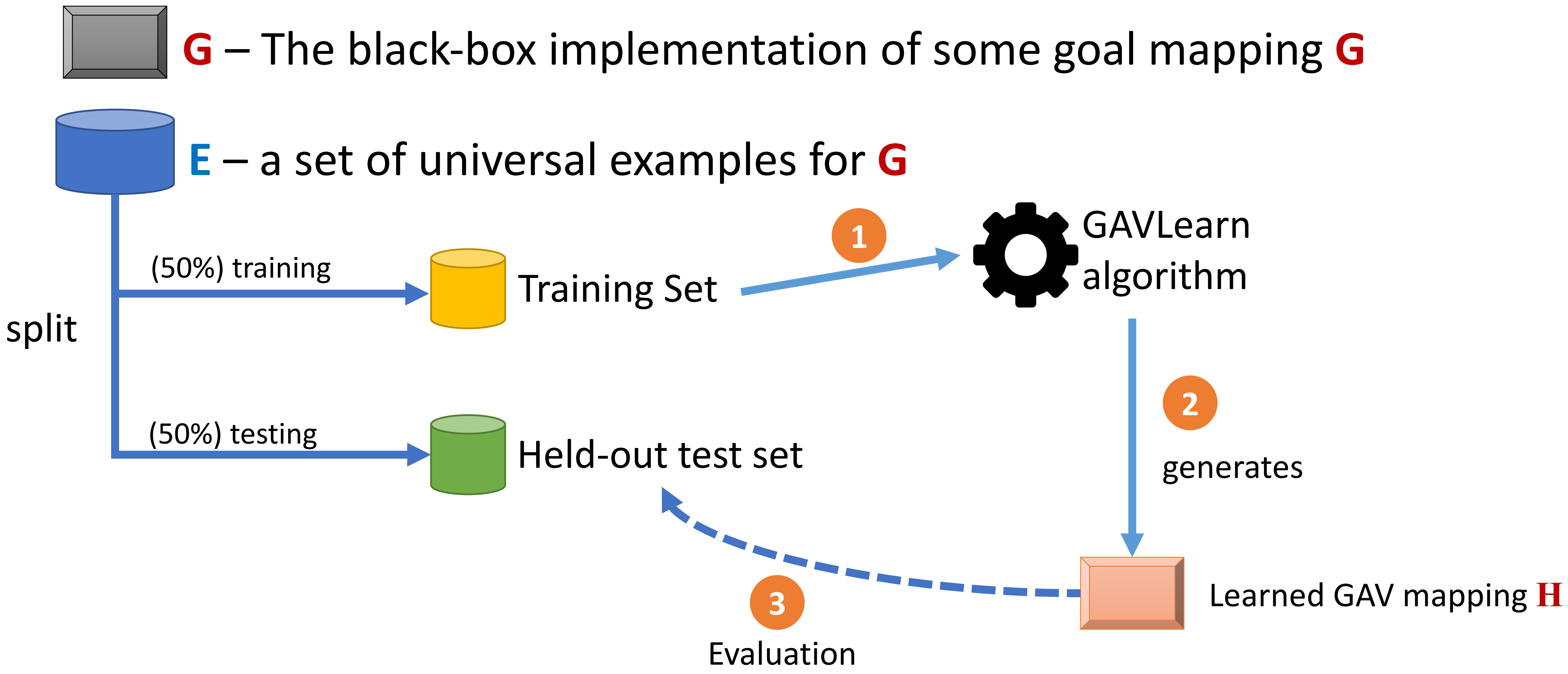
Occam learnability implies PAC learnability (Blumer et al., 1987)

Corollary 1 *GAVLearn is a PAC learning algorithm for GAV mappings*

with **sufficiently large number of random universal examples**, GAVLearn will produce a GAV mapping that is **approximately correct with high probability**

More theoretical results can be found in the paper

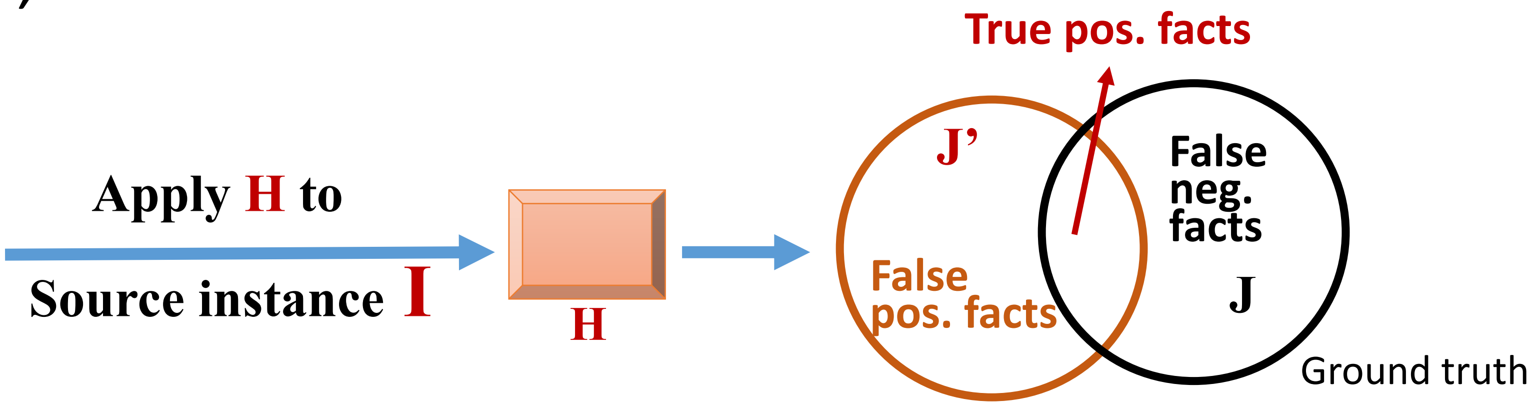
Experimental Evaluation - Methodology



Experimental Evaluation - Metrics

Precision, recall, and F-score

Given a held-out test example **(I,J)**



$$\text{Precision} = \frac{\text{\# True pos. facts}}{\text{\# True pos. facts + \# false pos. facts}}$$

We **DO NOT** report precision because the mappings returned by GAVLearn is always sound w.r.t. the goal mapping

$$\text{Recall} = \frac{\text{True pos. facts}}{\text{\# True pos. facts + \# false neg. facts}}$$

$$\text{F-score} = \frac{\text{2 x Precision x Recall}}{\text{precision + recall}}$$

Evaluation – Schema Mapping and Data Examples

- Schema mappings and data examples were generated by **iBench**
  - A metadata generator ([Arocena, Glavic, Ciucanu, Miller 2015])

- Schema mapping generation: created three types of mapping scenarios:
  - **SIMPLE, MODERATE, COMPLEX**
    using copy, merge, and projection constraints

  - Characteristics

	Copy	Projection	Merge	Join Size
SIMPLE	3	3	4	3
MODERATE	6	6	8	6
COMPLEX	9	9	12	9

- Data example generation: for each schema mapping,
  - generated {10, 30, 50, 70, 90} universal examples
  - used a 50-50 training/testing split

Evaluation – Standalone Evaluation of GAVLearn

Table. Results of GAVLearn on COMPLEX scenarios

α	n	$\|E\|$	$\overline{Comp}$	$\overline{Rep}$	$\overline{Recall}$	F-score	$\overline{\text{Time}}$
0.1	10	5	0.53±5%	0.87±10%	0.882±10%	0.937	17.8s
	30	15	0.60±0%	1	1	1	20.7s
	50	25					17.6s
	70	35					22.4s
	90	45					19.7s
0.3	10	5	0.60±0%	1	1	1	1m26s
	30	15	0.60±1%				1m35s
	50	25	0.60±0%				1m34s
	70	35	0.60±1%				1m33s
	90	45	0.60±0%	0.98±2%	0.999	0.999	1m45s
0.5	10	5	0.63±3%	0.98±2%	0.998±4‰	0.999	4m15s
	30	15	0.64±4%	0.92±5%	0.997±2‰	0.998	4m43s
	50	25	0.69±3%	0.92±4%	0.998±1%	0.999	6m55s
	70	35	0.73±4%	0.87±9%	0.998±1%	0.999	5m44s
	90	45	0.74±2%	0.88±8%	0.998±1%	0.999	10m9s

Results of SIMPLE and MODERATE schema mapping scenarios can be found in the paper

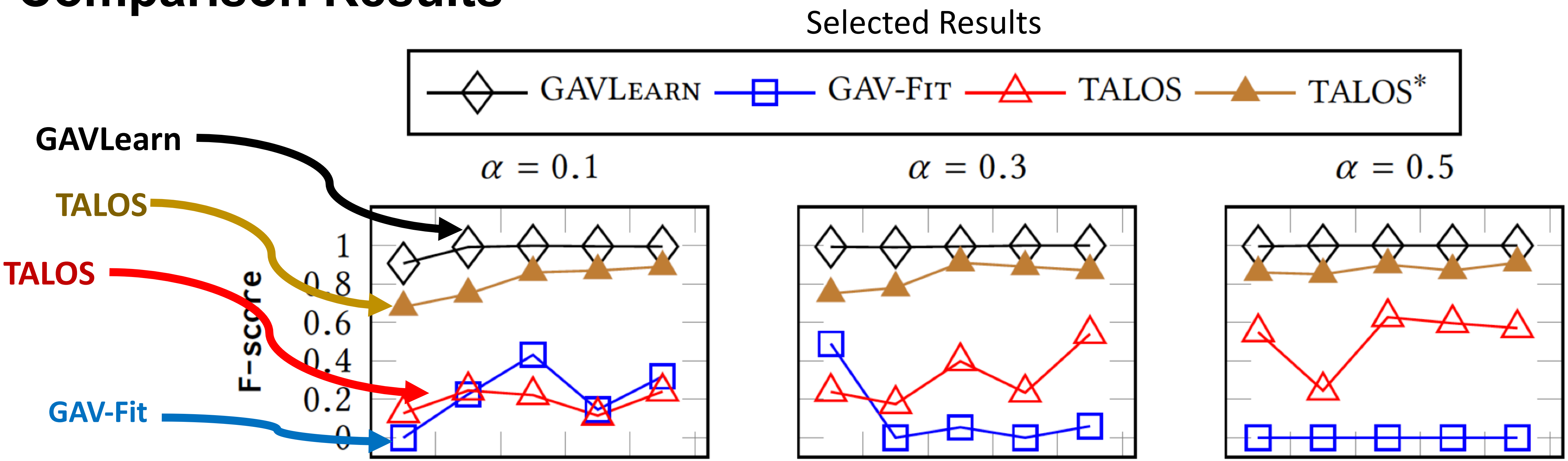
- **Highlights**
  - In all cases, F-scores are above 90% (100% in many cases)
  - Strong correspondence between number of training examples and Runtime
    - Size of training examples determines number of oracle calls

Evaluation – comparing to other algorithms

- Baselines
  - GAV-Fit: Fitting algorithm for GAV mappings [Alexe, ten Cate, Kolaitis, Tan 2011]
  - TALOS: Reverse-engineering algorithm for union of conjunctive queries [Tran et al., 2014]
    - Union of CQs can be viewed as a GAV mapping

Both algorithms have only one input:
a pre-existing set of data examples

Comparison Results



- GAVLearn outperforms both the GAV-Fit and TALOS
  - TALOS outperforms GAV-Fit, but suffers from overffiting
- Explanation: GAVLearn, being an active learning algorithm, can
  - generate "informative" examples that guide the algorithm towards better mappings
  - Both GAV-Fit and TALOS can perform significantly better if we give them the GAVLearn-generated examples.

Concluding Remarks

- Contributions:
  - Designed GAVLearn, an active learning algorithm adapted from an exact learning algorithm.
  - GAVLearn provides theoretical guarantees.
  - Experimental evaluation shows the efficacy of GAVLearn.

- Message
  - Conformance testing can be a good subsitute for an equivalence oracle.

- Open Problems
  - Exact learnability of LAV or GLAV schema mappings.
  - Active learning algorithms for LAV and GLAV.

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Thank you

Backup

Example

$$\mathrm{M}(x,y)\wedge\mathrm{N}(y,z)\rightarrow\mathrm{Q}(x,y,z)$$
$$\mathrm{S}(x,y)\wedge\mathrm{R}(y,z)\rightarrow\mathrm{T}(x,z)$$

Goal Mapping - G

Reveal the specification for presentation purpose

(I,J)

Examples - E

$$\mathrm{I}=\{\underbrace{S(a,b),R(b,c)},\underbrace{M(a,b),N(b,c)}\},$$
$$\mathrm{J}=\{T(a,c),Q(a,b,c)\}$$

Many mappings can perfectly describe the semantics of (I,J)

$$\{\mathrm{M}(x,y)\wedge\mathrm{N}(y,z)\rightarrow\mathrm{T}(x,z),\mathrm{S}(x,y)\wedge\mathrm{R}(y,z)\rightarrow\mathrm{Q}(x,y,z)\}$$
$$\{\mathrm{M}(x,y)\wedge\mathrm{R}(y,z)\rightarrow\mathrm{T}(x,z),\mathrm{S}(x,y)\wedge\mathrm{N}(y,z)\rightarrow\mathrm{Q}(x,y,z)\}$$

…

1st iteration

Run of GAV-Learn algorithm

H = {}, and H and G disagree on (I,J)
Choose F = T(a,c) from J, and form a Counter-example (I,{F})

Active learning

I → {~~S(a,b),~~ R(b,c),M(a,b), N(b,c)} $\xrightarrow{\text{Apply G}}$ {Q(a,b,c)} **Keep S(a,b)**

I → {S(a,b), ~~R(b,c),~~ M(a,b), N(b,c)} $\xrightarrow{\text{Apply G}}$ {Q(a,b,c)} **Keep R(b,c)**

I → {S(a,b), R(b,c), ~~M(a,b)~~, N(b,c)} $\xrightarrow{\text{Apply G}}$ {T(a,c)} **Remove M(a,b)**

I → {S(a,b), R(b,c), ~~M(a,b), N(b,c)~~} $\xrightarrow{\text{Apply G}}$ {T(a,c)} **Remove N(b,c)**

S(a,b), R(b,c) $\xrightarrow{\text{T(a,c)}}$ $\mathrm{S}(x,y)\wedge\mathrm{R}(y,z)\rightarrow\mathrm{T}(x,z)$

H = { $\mathrm{S}(x,y)\wedge\mathrm{R}(y,z)\rightarrow\mathrm{T}(x,z)$ **}**

2nd iteration

H and G still disagree on (I,J). This time we choose F' = Q(a,b,c) from J, and form a Counter-example (I,{F'})

With similar computation in 1st iteration

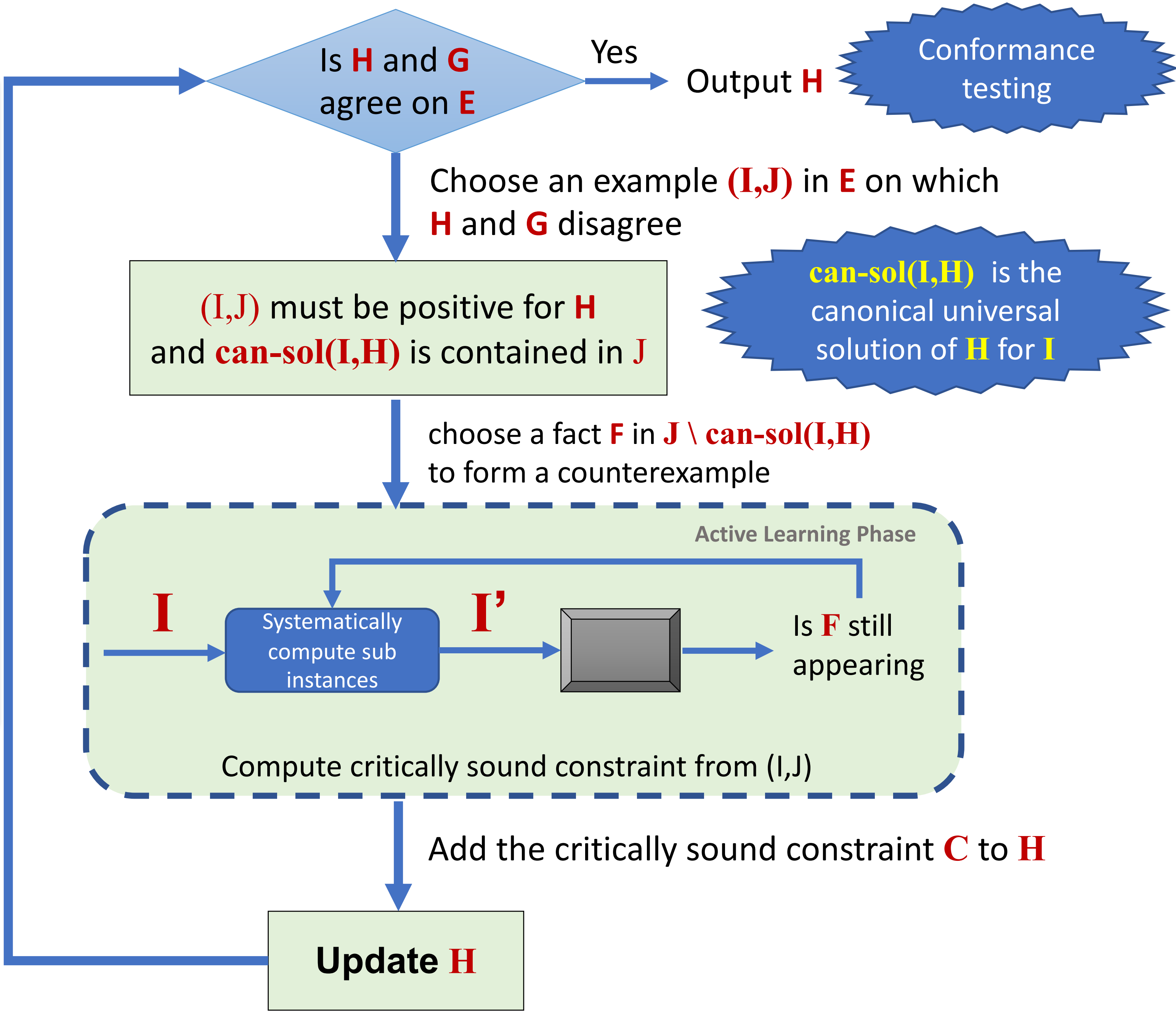
M(a,b), N(b,c) $\xrightarrow{\text{Q(a,b,c)}}$ $\mathrm{M}(x,y)\wedge\mathrm{N}(y,z)\rightarrow\mathrm{Q}(x,y,z)$

H = G

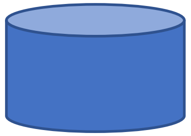
The GAV-Learn Algorithm

Input: $\mathcal{G}$ - goal mapping (as a labeling oracle);
E - a set of universal examples for $\mathcal{G}$
Output: a mapping that fits E.

$\mathcal{H} \leftarrow \emptyset$
while true **do**
  if each $(I, J) \in E$ is canonical universal for $\mathcal{H}$ **then**
    return $\mathcal{H}$
  end if
  choose an $(I, J) \in E$ such that $J \neq \text{can-sol}_{\mathcal{H}}(I)$
  `// In the proof of Thm 13, we show` $\text{can-sol}_{\mathcal{H}}(I) \subsetneq J$
  $f \leftarrow$ choose a fact $f \in J \setminus \text{can-sol}_{\mathcal{H}}(I)$
  if $\mathcal{G}$ logically implies $(I, \{f\}) \times C$ for some $C \in \mathcal{H}$ **then**
    Choose $C \in \mathcal{H}$ such that $\mathcal{G}$ logically implies $(I, \{f\}) \times C$
    $\mathcal{H} \leftarrow (\mathcal{H} \setminus \{C\}) \cup \{Crit_{\mathcal{G}}((I, \{f\}) \times C)\}$
  else
    $\mathcal{H} \leftarrow \mathcal{H} \cup \{Crit_{\mathcal{G}}((I, \{f\}))\}$
  end if
end while
return $\mathcal{H}$



G – The black-box implementation of some goal mapping G



E – a set of universal example for G

H - the intermediate GAV mapping that tries to capture G; initially, it is empty

Occam Learnability

Definition of Occam algorithm and optimal Occam algorithm

Definition 1 *Let $\mathcal{C}$ be a concept class. An Occam algorithm for $\mathcal{C}$ with parameters $0 \leq \alpha \leq 1$ and $k \geq 1$ is an algorithm A that takes as input a collection*

$$(x_1, c(x_1)), \ldots, (x_m, c(x_m))$$

of examples labeled according to some unknown concept $c \in \mathcal{C}$ and produces a hypothesis h consistent with the input of size at most $m^\alpha n^k$, where $n = |c|$ is the size of c. If $\alpha = 0$ and $k = 1$, then A is an optimal Occam algorithm for $\mathcal{C}$

Main Theoretical Result

Theorem 1 *GAVLearn is an optimal Occam algorithm for GAV mappings.*

Given a goal GAV mapping G and a set E of (universal) examples for G, the GAVLearn is guaranteed to returns a GAV mapping H such that, H perfectly describe the semantics of E and the size of H is at most the size of G

Evaluation – Standalone evaluation of GAVLearn

Table 2: Results of GAVLEARN on simple type

α	n	$\|E\|$	$\overline{Comp}$	$\overline{Rep}$	$\overline{Recall}$	F_S	$\overline{Time}$
0.1	10	5	0.52±8%	0.83±20%	0.832±18%	0.907	0.3s
	30	15	0.6±0%	0.91±7%	0.984±1%	0.992	0.7s
	50	25	0.58±16%	0.97±3%	0.998±13%	0.999	1.1s
	70	35	0.66±5%	0.92±5%	0.992±1%	0.996	0.7s
	90	45	0.7±7%	0.89±15%	0.992±1%	0.995	0.7s
0.3	10	5	0.74±31%	0.95±6%	0.988±9%	0.993	2.2s
	30	15	0.88±8%	0.89±7%	0.982±2%	0.991	2.4s
	50	25	0.96±8%	0.96±8%	0.992±1%	0.995	2.3s
	70	35	1	1	1	1	4.2s
	90	45					2.2s
0.5	10	5	0.98±4%	0.97±4%	0.992±1%	0.996	3.4s
	30	35					3.8s
	50	45	1	1	1	1	3.6s
	70	45					4.1s
	90	45					3.8s

Table 3: Results of GAVLEARN on moderate type

α	n	$\|E\|$	$\overline{Comp}$	$\overline{Rep}$	$\overline{Recall}$	F_S	$\overline{Time}$
0.1	10	5	0.59±22%	0.98±4%	0.99±1%	0.996	4.4s
	30	15					4.9s
	50	25	0.60	1	1	1	4.2s
	70	35					4.9s
	90	45					5.4s
0.3	10	5	0.61±2%	0.98±3%	0.998±4‰	0.998	15.2s
	30	15	0.61±2%	1	1	1	16.2s
	50	25	0.65±3%	0.95±6%	0.998±1‰	0.998	25.6s
	70	35	0.63±2%	0.92±5%	0.997±2‰	0.997	13.6s
	90	45	0.65±3%	0.85±4%	0.997±1‰	0.998	18.2s
0.5	10	5	0.72±2%	0.88±8%	0.985±1‰	0.992	28.4s
	30	15	0.89±4%	0.90±3%	0.992±4‰	0.996	38.3s
	50	25	0.92±5%	0.92±5%	0.995±3‰	0.997	39s
	70	35	0.95±5%	0.95±4%	0.997±3‰	0.998	42s
	90	45	1	1	1	1	50s

Table 4: Results of GAVLEARN on complex type

α	n	$\|E\|$	$\overline{Comp}$	$\overline{Rep}$	$\overline{Recall}$	F_S	$\overline{Time}$
0.1	10	5	0.53±5%	0.87±10%	0.882±10%	0.937	17.8s
	30	15					20.7s
	50	25	0.60±0%	1	1	1	17.6s
	70	35					22.4s
	90	45					19.7s
0.3	10	5	0.60±0%				1m26s
	30	15	0.60±1%				1m35s
	50	25	0.60±0%	1	1	1	1m34s
	70	35	0.60±1%				1m33s
	90	45	0.60±0%	0.98±2%	0.999	0.999	1m45s
0.5	10	5	0.63±3%	0.98±2%	0.998±4‰	0.999	4m15s
	30	15	0.64±4%	0.92±5%	0.997±2‰	0.998	4m43s
	50	25	0.69±3%	0.92±4%	0.998±1%	0.999	6m55s
	70	35	0.73±4%	0.87±9%	0.998±1%	0.999	5m44s
	90	45	0.74±2%	0.88±8%	0.998±1%	0.999	10m9s

- **Highlights**
  - In all cases, F-scores are above 90%
    - Achieved 100% in many cases
  - More training examples lead to higher F-scores
  - Strong correspondence between number of training examples and Runtime
    - Size of training examples -> number of oracle calls