FastLAS: Scalable Inductive Logic Programming, incorporating Domain-specific Optimisation Criteria

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Inductive Logic Programming

Input: background knowledge B and examples E^+ and E^-.

Output: a hypothesis H s.t.

1. $\forall e^+ \in E^+ : B \cup H \models e^+$
2. $\forall e^- \in E^- : B \cup H \not\models e^-$.

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The paper contains two main contributions:

- FastLAS, an ASP-based ILP system which is scalable w.r.t. the size of the hypothesis space.
- A new approach to supporting domain specific optimisation criteria in the search.

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Optimisation Criteria

In some domains, false negatives are more dangerous than false positives.

Event detection

Medical diagnosis

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Depending on the domain, different optimisation criteria may be required!

Optimisation Criteria in ILP

Many ILP systems aim to find the simplest solution.

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- The number of ground instances of rules in H.
- The number of variables in H.
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A general *scoring function* takes as input a learning task T and a hypothesis H and returns a *score* in $\mathbb{R}_{\geq 0}$.

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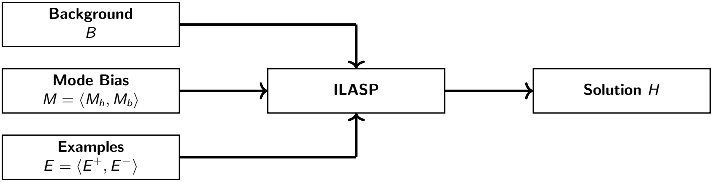
FastLAS currently supports *decomposable* scoring functions. These can be evaluated on each rule independently.

FastLAS Learning Task

The FastLAS task T is based on the ILASP (Law et al. 2015) task:



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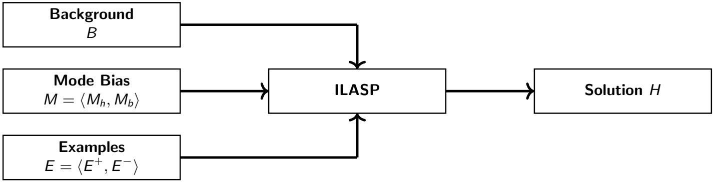
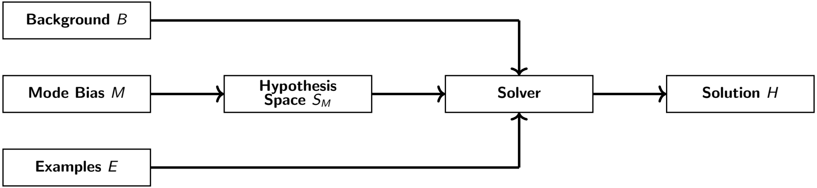


FastLAS has two major restrictions:

- All programs have a single answer set.
- No predicate in M_h occurs in M_b or any rule in T.

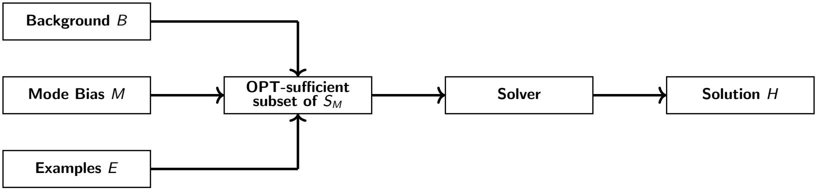
FastLAS: Overview

ILASP begins by computing the hypothesis space S_M, which contains every rule that is compatible with the mode bias M.



FastLAS: Overview

FastLAS instead begins by computing an *OPT-sufficient* subset of the hypothesis space, which is often significantly smaller than S_M.



FastLAS

Initial Construction

Generalisation

Optimisation

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Generate the set of all “maximal” rules which could be useful.

$\mathcal{C}^{+}(T)$ contains the “maximal” rules that prove something we **should** prove.
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Example:

$$B = \emptyset \qquad M_h = \{\texttt{p}, \texttt{q}\} \qquad M_b = \left\{ \begin{array}{c} \texttt{r}, \texttt{not r}, \\ \texttt{s}, \texttt{not s} \\ \texttt{t}, \texttt{u} \end{array} \right\}$$

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$$\text{Find } H \text{ s.t. } \left\{ \begin{array}{cc} H \models \texttt{q}, & H \not\models \texttt{p}, \\ H \cup \{\texttt{r. t.}\} \models \texttt{p}, & H \cup \{\texttt{r. t.}\} \not\models \texttt{q}, \\ H \cup \{\texttt{r. u.}\} \models \texttt{p}, & H \cup \{\texttt{r. u.}\} \not\models \texttt{q} \end{array} \right\}$$

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$$\mathcal{C}^+(T) = \left\{ \begin{array}{l} \texttt{q :- not r, not s.} \\ \texttt{p :- r, not s, t.} \\ \texttt{p :- r, not s, u.} \end{array} \right\} \quad \mathcal{C}^-(T) = \left\{ \begin{array}{l} \texttt{p :- not r, not s.} \\ \texttt{q :- r, not s, t.} \\ \texttt{q :- r, not s, u.} \end{array} \right\}$$

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$\mathcal{G}(T)$ contains the maximal subrules of rules in $\mathcal{C}^+(T)$ that are subrules of as many rules in $\mathcal{C}^+(T)$ as possible.

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For each $R \in \mathcal{G}(T)$, compute *one* optimal subrule of R w.r.t. $\mathcal{S}$ that is not a subrule of any rule in $\mathcal{C}^{-}(T)$.

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The full hypothesis space (computed by ILASP) contains 72 rules.

Evaluation

Sentence Chunking

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System	F_1	Running Time
INSPIRE	0.712	>1800s in some cases
ILASP3	0.777	1051.4s
FastLAS	0.768	4.5s

Policy Learning II

We evaluated FastLAS on access control datasets.

- We used three scoring functions, $\mathcal{S}_{len}$, $\mathcal{S}_{cov}$ and $\mathcal{S}_{uni}$, which encouraged learning progressively more general hypotheses.

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Learning rules for *accept*:

Scoring function	Recall	Precision
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Learning rules for *reject*:

Scoring function	Recall	Precision
$\mathcal{S}_{len}$	0.974	0.935
$\mathcal{S}_{cov}$	0.969	0.941
$\mathcal{S}_{uni}$	0.966	0.965

Conclusion

FastLAS is a new ASP-based ILP system.

- Far more scalable than ILASP.
- Supports domain-specific optimisation criteria, through scoring functions.

Future research directions include:

- Lifting current restrictions, to allow recursion, non-observational predicate learning, predicate invention and programs with multiple answer sets.
- Non-decomposable scoring functions.

Backup Slides

Sentence Chunking Results

100 examples:

System	F_1	Running Time
INSPIRE	0.733	–
ILASP3	0.757	210.4s
FastLAS	0.751	0.909s

500 examples:

System	F_1	Running Time
INSPIRE	0.712	–
ILASP3	0.777	1051.4s
FastLAS	0.768	4.5s

CAVIAR

The CAVIAR dataset (generated by the EC Funded CAVIAR project/IST 2001 37540) consists of manually annotated video streams.

The task is to detect events by learning initiating/terminating conditions. We compared FastLAS to OLED (Katzouris et al. 2016) and ILASP3 (Law et al. 2015) on the task of detecting people meeting.

CAVIAR Results

System	F_1	Running Time
OLED	0.792	107s
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Due to the larger search space, FastLAS achieved an F_1 score of 0.923 compared to ILASPs 0.842.

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In (Cotrini et al. 2018), a new metric, *universal* F_1 was proposed, which uses a modified version of *precision* ($P = \frac{tp}{tp+fp}$), $UP = \frac{tp}{tp+fp+u}$, where $\mathtt{u}$ is the set of users who have not requested access to the resource.

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Method	Resource 25993	Resource 4675	Resource 75078	Resource 79092
Rhapsody	0.04	0.10	0.10	0.04
CTA	0.04	**0.12**	0.10	0.04
FastLAS: $\mathcal{S}_{len}$	0.02	0.04	0.02	0.02
FastLAS: $\mathcal{S}_{cov}$	0.02	0.04	0.02	0.02
FastLAS: $\mathcal{S}_{uni}$	0.01	0.04	0.02	0.02
FastLAS: $\mathcal{S}_{UF_1}$	**0.07**	0.10	**0.11**	**0.05**

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