

Learning Tree to Word Transducers

LATA 2014

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Learning Tree Transductions

Transforming structured datas

```
- <movie>
  <title>The Lego Movie</title>
  <year>2014</year>
  <imdbid>tt1490017</imdbid>
  <rating>8.4</rating>
  <runtime>100min</runtime>
  <genres>Animation, Adventure, Comedy,
  Family, Fantasy</genres>
  - <synopsis>
    An ordinary LEGO minifigure, mistakenly
    thought to be the extraordinary
    MasterBuilder, is recruited to join a quest
    to stop an evil LEGO tyrant from gluing the
    universe together.
  </synopsis>
</movie>
```



The Lego Movie (2014) 2

100 min - Animation | Adventure | Comedy -
19 February 2014 (France)

Your rating: 7/10

8.4 Ratings: 8,4/10 from 42 083 users Metascore: 82/100
Reviews: 194 user · 230 critic · 41 from Metacritic.com

An ordinary LEGO minifigure, mistakenly thought to be the extraordinary MasterBuilder, is recruited to join a quest to stop an evil LEGO tyrant from gluing the universe together.

Directors: [Phil Lord](#), [Christopher Miller](#)

Writers: [Dan Hageman](#) (story), [Kevin Hageman](#) (story), 4 more credits »

Stars: [Will Arnett](#), [Elizabeth Banks](#), [Alison Brie](#) | See full cast and crew »

[Watch Trailer](#) [Share...](#)

Example of XSLT transformation : from XML to XHTML

- Many applications, many formalisms...
- requires some expertise
- One solution : infer the transformation

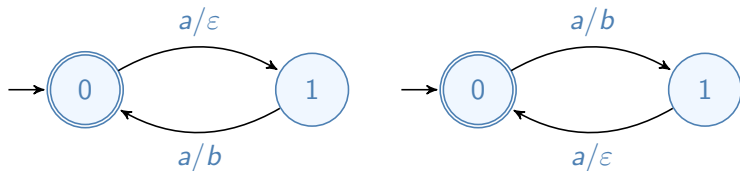
Learning Subsequential Transducer

Learning Subsequential Transducer [OncinaGarciaVidal93]

Subsequential transducers are learnable from examples with polynomial time and data (Gold Model [Gold78])

Two main ideas:

- Onward normal form [Choffrut79] : produce the output as soon as possible



Two subsequential transducers for $\tau(a^{2n}) = b^n$

- State merging algorithm : OSTIA [OncinaGarciaVidal93]

- **Rational Functions** [BoiretLemayNiehren12]
 - ▶ Represented by Subsequential transducers w. deterministic look-ahead
 - ▶ Normal form (inspired by bimachines [ReteunauerSchutzenberger92])
 - ▶ Learning algorithm \simeq learn the look-ahead, then apply OSTIA
- **Top-Down Tree-to-Tree Transducers** [LemayManethNiehren11]
 - ▶ Earliest normal form [EngelfrietManethSeidl09] : earliest production (produce as 'up' as possible),
 - ▶ Myhill-Nerode kind of theorem in [LemayManethNiehren11]
 - ▶ Learning based on a state merging algorithm

Toward learning MSO tree transformations ?

MSO tree Transformation [Courcelle92] : an interesting target for learning tree transformation !

The big picture

MSO tree transformations

\simeq Macro Tree Transducers w. regular look-ahead (MTT^R)

[EngelfrietManeth03]

\simeq Top-Down + **Concatenation** + Look-ahead

- Top-Down Tree transducers : learnable ✓
- Look-ahead : learnable ✓
 - ▶ not extended to trees yet
- Concatenation in the output : ?

- 1 Tree to Word Transducers
- 2 Normal Form
- 3 A Myhill-Nerode Theorem
- 4 learning Algorithm

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Tree to Word Transducers - An example

XML-like Serialization

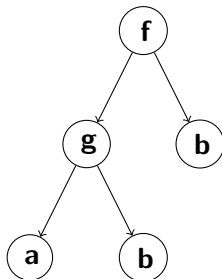
Axiom : $q(x_0)$

$q(f(x_1, x_2)) \rightarrow \langle f \rangle \cdot q(x_1) \cdot q(x_2) \langle /f \rangle$

$q(g(x_1, x_2)) \rightarrow \langle g \rangle \cdot q(x_1) \cdot q(x_2) \langle /g \rangle$

$q(a) \rightarrow \langle a \rangle$

$q(b) \rightarrow \langle b \rangle$



Tree to Word Transducers - An example

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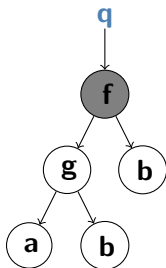
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Tree to Word Transducers - An example

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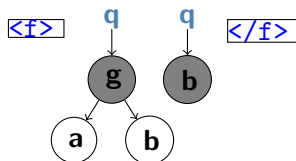
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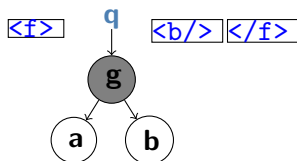
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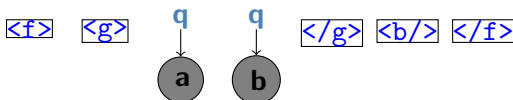
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$q(a) \rightarrow \langle a/ \rangle$

$q(b) \rightarrow \langle b/ \rangle$

$\langle f \rangle$ $\langle g \rangle$ $\langle a/ \rangle$ $\langle b/ \rangle$ $\langle /g \rangle$ $\langle b/ \rangle$ $\langle /f \rangle$

Tree to word Transducers - Presentation

Axiom: $u_0 \cdot q(x_0) \cdot u_1$

Rules: $q(f(x_1, x_2)) \rightarrow u_0 \cdot q_1(x_1) \cdot u_1 \cdot q_2(x_2) \cdot u_2$

Three Restrictions

- Deterministic
- Linear (no copy)
- Ordered (no swap)

Deterministic Sequential Tree to Words (STW)

Outline

- 1 Tree to Word Transducers
- 2 Normal Form**
- 3 A Myhill-Nerode Theorem
- 4 learning Algorithm

Normal Form

Earliest STW : produce as soon as possible

Example transformation : count the number of symbols.

$$\tau_{count}(f(a, f(a, b))) = #####$$

An STW for τ_{count}

Axiom: q

$$q(f) \rightarrow \#q(x_1)q(x_2)$$

$$q(a) \rightarrow \#$$

$$q(b) \rightarrow \#$$

Not earliest ! At least one '#' could be output from the beginning.

Normal Form

Another STW for τ_{count} :

Axiom: $\#q$

$q(f) \rightarrow \#q(x_1)\#q(x_2)$

$q(a) \rightarrow \varepsilon$

$q(b) \rightarrow \varepsilon$

Earliest (Rule 1)

Produce as 'up' as possible

Normal Form

We want a unique normal form :

Do we want : $q(f) \rightarrow \#q(x_1)\#q(x_2)$

or $q(f) \rightarrow \#\#q(x_1)q(x_2)$

(or another choice ?)

Earliest - Rule 2

produce as 'left' as possible

Normal Form

Earliest STW (eSTW) : produce as 'up' and as 'left' as possible

Theorem [LaurenceLemayNiehrenStaworkoTommasi11]

For any STW, there exists an equivalent unique minimal eSTW

Possibly of exponential size

The minimal eSTW of \mathcal{T}_{count}

Axiom: $\#q$

$q(f) \rightarrow \#\#q(x_1)q(x_2)$

$q(a) \rightarrow \varepsilon$

$q(b) \rightarrow \varepsilon$

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A Myhill-Nerode Theorem for STW

- constructive algorithm for $can(\tau)$ (minimal eSTW for τ)
- builds for each input path p a τ_p
- $p \simeq p'$ iff $\tau_p = \tau_{p'}$

Myhill-Nerode Theorem for STW

τ is represented by a STW

$\Leftrightarrow \simeq$ is of Finite Index

$\Leftrightarrow can(\tau)$ is the minimal eSTW of τ

Building Axiom

Axiom : $lcp(\text{range}(\tau)) \cdot q_\epsilon \cdot lcs'(\text{range}(\tau))$

lcp : longest common prefix

lcs' : longest common suffix (minus what is in lcp)

For τ_{count} :

$lcp(\text{range}(\tau_{count})) = \#$

$lcs'(\text{range}(\tau_{count})) = \epsilon$

Axiom : $\#q_\epsilon$

Building τ_ϵ

Axiom : $\#q_\epsilon$

We define τ_ϵ :

For any t , $\tau_\epsilon(t) = \#^{-1}\tau_{count}(t)$

Defining τ_ϵ

$a \rightarrow \epsilon$

$b \rightarrow \epsilon$

$f(a, a) \rightarrow \#^2$

...

$f(f(a, b), a) \rightarrow \#^4$

...

$\tau_\epsilon(t) : \#^{|t|-1}$

Building Rules for Leaf Symbols

Rules from state q_ϵ

For leaf symbols :

$$\tau_\epsilon(a) \rightarrow \epsilon$$

$$\tau_\epsilon(b) \rightarrow \epsilon$$

Rules

$$q_\epsilon(a) \rightarrow \epsilon$$

$$q_\epsilon(b) \rightarrow \epsilon$$

Building Other Rules (1)

build the rule $q_{\epsilon}(f(x_1, x_2)) \rightarrow u_0 \cdot q_{(f,1)} \cdot u_1 \cdot q_{(f,2)} \cdot u_2$

First, $u_0 = \text{lcp}(\{\tau_{\epsilon}(f(?, ?))\})$

Compute u_0 from $\tau_{\epsilon}(f(?, ?))$

$f(a, a) \rightarrow \#^2$

...

$f(f(a, b), a) \rightarrow \#^4$

...

$u_0 = \#^2$

$q_{\epsilon}(f(x_1, x_2)) \rightarrow \#^2 \cdot q_{(f,1)} \cdot u_1 \cdot q_{(f,2)} \cdot u_2$

Building Other Rules (2)

$$q_{\varepsilon}(f(x_1, x_2)) \rightarrow \#^2 \cdot q_{(f,1)} \cdot u_1 \cdot q_{(f,2)} \cdot u_2$$

To have $\tau_{(f,1)}(t)$, take the lcp of $\tau_{\varepsilon}(f(t, ?))$

Compute $\tau_{(f,1)}(a)$ from $\tau_{\varepsilon}(f(a, ?))$

$$\tau_{\varepsilon}(f(a, a)) = \#^2$$

$$\tau_{\varepsilon}(f(a, b)) = \#^2$$

$$\tau_{\varepsilon}(f(a, f(a, a))) = \#^4$$

...

$$\tau_{\varepsilon}(f(a, f(a, f(a, a)))) = \#^6$$

$\text{lcp}(\tau_{\varepsilon}(f(a, ?))) = \#^2 = u_0 \tau_{(f,1)}(a) u_1$ (guaranteed by earliness)

As $u_0 = \#^2$, $\tau_{(f,1)}(a) = u_1 = \varepsilon$

Building Other Rules (3)

Compute $\tau_{(f,1)}$

$$\tau_{(f,1)}(a) = \varepsilon$$

$$\tau_{(f,1)}(b) = \varepsilon$$

$$\tau_{(f,1)}(f(a, a)) = \#^2$$

...

$$\tau_{(f,1)}(f(a, f(a, f(a, a)))) = \#^4$$

...

$$\tau_{(f,1)} : t \rightarrow \#^{|t|-1}$$

State Equivalence

$$\tau_\varepsilon : t \rightarrow \#^{|t|-1}$$

$$\tau_{(f,1)} : t \rightarrow \#^{|t|-1}$$

$$\varepsilon \simeq (f, 1) \text{ So : } q_\varepsilon = q_{(f,1)}$$

Similarly $u_2 = u_1 = \varepsilon$ and $(f, 2) \simeq \varepsilon$

eSTW $\text{Can}(\tau)$

Axiom : $\#q_\varepsilon$

$$q_\varepsilon(a) \rightarrow \varepsilon$$

$$q_\varepsilon(b) \rightarrow \varepsilon$$

$$q_\varepsilon(f(x_1, x_2)) \rightarrow \#\#q_\varepsilon q_\varepsilon$$

minimal eSTW for τ_{count}

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Learning algorithm $Learn_{STW}(S)$

- Essentially the same as the construction algorithm
 - ▶ Input : a finite sample $S \subseteq \tau$
 - ▶ from each path p , compute S_p (approximation of τ_p)
 - ▶ $p \simeq p'$ if S_p does not contradict with $S_{p'}$
- $Learn_{STW}(S)$ answers in polynomial time
- For any STW τ , there exists a sample CS_τ of polynomial cardinality such that $Learn_{STW}(S) = Can(\tau)$ if $CS_\tau \subseteq S$

Consistency Problem

Consistency Issues

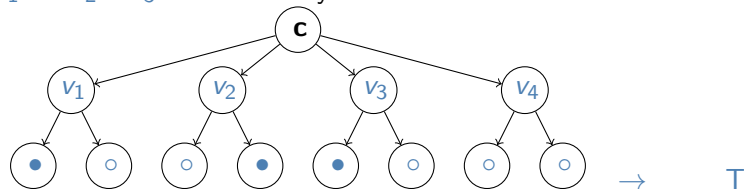
Checking if there exists an STW consistent with a given sample is NP-complete.

Idea : Encoding 1-in-3 SAT Problem

1-in-3 SAT : Variant of 3-SAT with exactly 1 literal satisfied per clause
NP-Complete [Schaefer78]

Consistency Problem

Example with a 4 literal formulas $(v_1 \vee \neg v_2 \vee v_3) \wedge (v_2 \vee \neg v_3 \vee v_4)$
 $v_1 \vee \neg v_2 \vee v_3$ is encoded by:



Consistency Problem

The encoding of $(v_1 \vee \neg v_2 \vee v_3) \wedge (v_2 \vee \neg v_3 \vee v_4)$

$(v_1 \vee \neg v_2 \vee v_3)$:	$c(v_1(\bullet, \circ), v_2(\circ, \bullet), v_3(\bullet, \circ), v_4(\circ, \circ))$	\rightarrow	T
$(v_2 \vee \neg v_3 \vee v_4)$:	$c(v_1(\circ, \circ), v_2(\bullet, \circ), v_3(\circ, \bullet), v_4(\bullet, \circ))$	\rightarrow	T
$(v_1 \vee \neg v_1)$:	$c(v_1(\bullet, \bullet), v_2(\circ, \circ), v_3(\circ, \circ), v_4(\circ, \circ))$	\rightarrow	T
$(v_2 \vee \neg v_2)$:	$c(v_1(\circ, \circ), v_2(\bullet, \bullet), v_3(\circ, \circ), v_4(\circ, \circ))$	\rightarrow	T
$(v_3 \vee \neg v_3)$:	$c(v_1(\circ, \circ), v_2(\circ, \circ), v_3(\bullet, \bullet), v_4(\circ, \circ))$	\rightarrow	T
$(v_4 \vee \neg v_4)$:	$c(v_1(\circ, \circ), v_2(\circ, \circ), v_3(\circ, \circ), v_4(\bullet, \bullet))$	\rightarrow	T
		$c(v_1(\circ, \circ), v_2(\circ, \circ), v_3(\circ, \circ), v_4(\circ, \circ))$	\rightarrow	ε

Idea: An eSTW that recognizes this sample encodes a solution of SAT one-in-three.

Consistency Problem

Unique STW solution

Axiom : q

$$q(c(x_1, \dots, x_n)) \rightarrow q_1(x_1) \dots q_n(x_n)$$

$$q_i(v_i(x_1, x_2)) \rightarrow q_i^L(x_1)q_i^R(x_2)$$

$$q_i^{L/R}(\circ) \rightarrow \varepsilon$$

$$\text{if } v_i \text{ is true : } q_i^L(\bullet) \rightarrow T \text{ and } q_i^R(\bullet) \rightarrow \varepsilon$$

$$\text{if } v_i \text{ is false : } q_i^L(\bullet) \rightarrow \varepsilon \text{ and } q_i^R(\bullet) \rightarrow T$$

Idea : one state q_i per variable v_i , and

$v_i(\bullet, \circ)$ produces T iff v_i is true

$v_i(\circ, \bullet)$ produces T iff v_i is false

Learning Theorem

Learning Theorem

The Class of STW represented by eSTW is learnable from examples with polynomial time and data with abstain.

With abstain : the algorithm may not answer (non characteristic sample)

Results

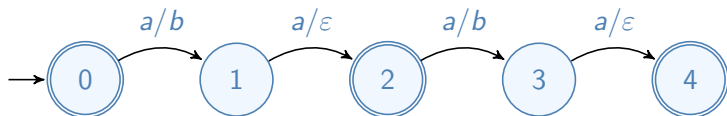
- Sequential Tree to Word Transducers :
 - ▶ A Myhill-Nerode Theorem
 - ▶ learnable in a Gold-like Model

Future Works

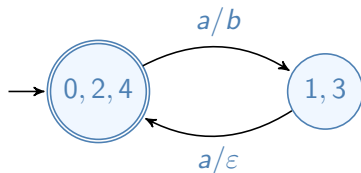
- extension to non-ordered : good hope !
- extension to non-linear : bad hope ...
- toward a learning algorithm for MSO tree transduction ?

Example Input : $S = \{(\epsilon, \epsilon), (aa, b), (aaaa, bb)\}$

- 1 Align Input / output in an onward way, and build initial transducer



- 2 Perform State merging in an ordered way



S characteristic for $\tau \Rightarrow \text{OSTIA}(S)$: canonical subsequential of τ