

Proving Productivity, part 2

extended formats, variants of productivity, and complexity

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The End of *Infinity*

VU Amsterdam, December 15, 2009

Overview

- ▶ Extended stream formats
 - ▶ for a **special** class of **stream functions**
(simulation by **open pebbleflow nets**)
 - ▶ for **larger classes** of stream specifications
(using **data-oblivious productivity**)
- ▶ Productivity and variant definitions in TRSs
- ▶ Complexity of productivity and its variants

Overview

1. Extended stream formats
2. Variants of Productivity
3. Computational Complexity

Overview

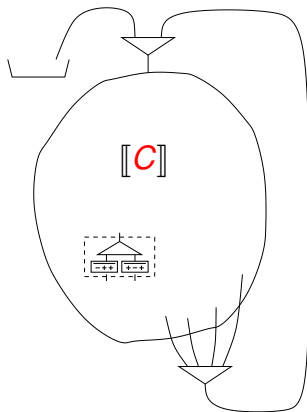
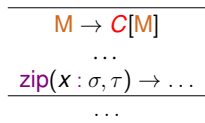
1. Extended stream formats

A format for stream function specifications
Extended formats for stream specifications

2. Variants of Productivity

3. Computational Complexity

Deciding productivity via pebbleflow



(PSF)

pure stream **constant** spec

\longrightarrow
translation

pebbleflow net

\longrightarrow
computation of production

pebble source

Pure stream **constant** specification

Example

$$M \rightarrow \text{zip}(0 : M, M)$$

stream layer

$$\text{zip}(x : \sigma, \tau) \rightarrow x : \text{zip}(\tau, \sigma)$$

data layer

Suppose that $\text{nats} \rightsquigarrow 0 : 1 : 2 : \dots$. Then it holds:

$$f(\text{nats}) \rightsquigarrow 0 : 0 : 1 : 0 : 2 : 1 : 3 : 0 : 4 : 2 : 5 : 1 : 6 : 3 : 7 : 0 : 8 : \dots =: \mathbf{a}$$

For all n : $\mathbf{a}(2n) = n$, $\mathbf{a}(2n + 1) = \mathbf{a}(n)$ (Sequence A025480).

stream function specification

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$$f(\sigma) \rightarrow \text{zip}(\sigma, f(\sigma))$$

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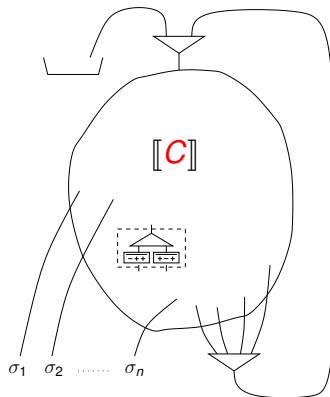
Recognising productivity via pebbleflow

$$f(\sigma) \rightarrow C[\sigma, f(\sigma)]$$

...

$$\text{zip}(x : \sigma, \tau) \rightarrow \dots$$

...

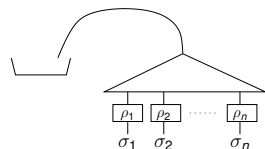
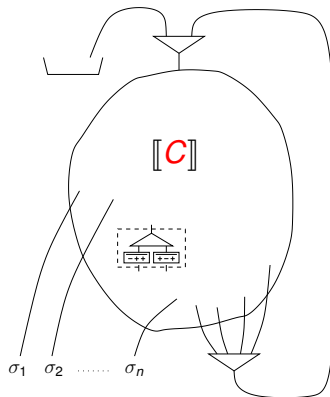


stream **function** spec

\longmapsto **open** pebbleflow net
translation

Recognising productivity via pebbleflow

$f(\sigma) \rightarrow C[\sigma, f(\sigma)]$
 ...
 $\text{zip}(x : \sigma, \tau) \rightarrow \dots$
 ...



stream **function** spec

\longmapsto
 translation

open pebbleflow net

\longmapsto
 computation of **throughput**

gate

Recognising productivity of some stream functions

Let \mathcal{S} be a specification for a stream function f .

- 1 Try to transform \mathcal{S} into a stream constant spec in PSF with stream parameters. If unsuccessful, answer: “sorry, don’t know”.
- 2 Build the corresponding open pebbleflow net.
- 3 Collapse the pebbleflow net into a gate γ (*ProPro*-extension by Niels Rademaker using the I/O-list infimum operation).
- 4 If either of the I/O-lists in the gate γ is finite, answer: “ \mathcal{S} is not productive for f ”; else “ \mathcal{S} is productive for f ”.

Recognising productivity of some stream functions

Let S be a specification for a stream function f .

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Recognising productivity of some stream functions

$$\begin{aligned} f(\sigma_1, \sigma_2) &\rightarrow \text{zip}(\sigma_1, \text{zip}(\sigma_2, g(\sigma_1))) \\ g(\sigma_1) &\rightarrow \text{zip}(\text{even}(f(\sigma_1, \sigma_1)), g(\sigma_1)) \end{aligned}$$

By introducing a new stream function $f_1(\sigma_1) := f(\sigma_1, \sigma_1)$, we obtain:

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Now, by letting $M := f(\sigma_1, \sigma_2)$, $M_1 := f_1(\sigma_1)$, $N := g(\sigma_1)$, we obtain:

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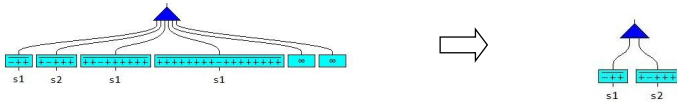
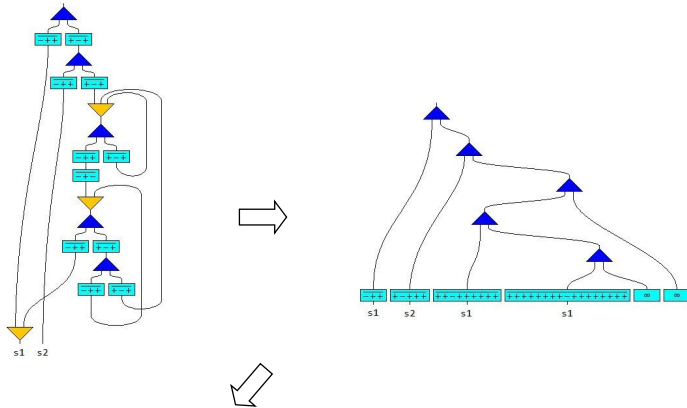
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How special is this class of stream functions?

Very restrictive. Their defining rules are of the form (simplified):

$$\begin{aligned} f_1(\sigma) &\rightarrow C_1[\sigma, f_1(\sigma), \dots, f_n(\sigma)] \\ &\dots \\ f_n(\sigma) &\rightarrow C_n[\sigma, f_1(\sigma), \dots, f_n(\sigma)] \end{aligned}$$

where C_1, \dots, C_n are stream contexts consisting of pure stream functions (like `zip`, `even`, `...`).

In their defining rules:

- ▶ no consumption of data-elements from stream parameters
- ▶ consequently also no additional supply of consumed

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Extended formats for stream specifications

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Extending PSF

Example (poor man's pat-mat)

$$\begin{array}{l}
 \hline
 T \rightarrow 0 : 1 : f(\text{tail}(T)) \\
 \underline{f}(0 : \sigma) \rightarrow 0 : 1 : f(\sigma) \quad \textit{stream layer} \\
 \underline{f}(1 : \sigma) \rightarrow 1 : 0 : f(\sigma) \\
 \text{tail}(x : \sigma) \rightarrow \sigma \\
 \hline
 \textit{data layer} \\
 \hline
 \end{array}$$

is a **productive** stream definition of the **Thue–Morse stream**:

$$T \rightsquigarrow 0 : 1 : 1 : 0 : 1 : 0 : 0 : 1 : 1 : 0 : 0 : 1 : 0 : 1 : 1 : 0 : \dots$$

Extending PSF

- ▶ In **extended-pure** specifications, the **rules for stream functions** allow:
 - ▶ a **restricted** form of exhaustive **pattern matching**
 - ▶ **duplication** of stream variables

$$f(\sigma) \rightarrow g(\sigma, \sigma).$$
 - ▶ **additional supply** in stream variables is allowed

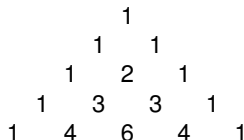
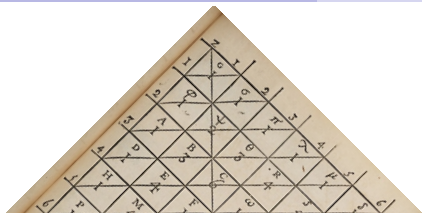
$$\text{diff}(x : y : \sigma) \rightarrow \text{xor}(x, y) : \text{diff}(y : \sigma)$$
 - ▶ use of **non-productive** stream functions

$$\text{onlyread2}(x : y : \sigma) \rightarrow x : y : \text{idle}(\sigma) \quad \text{idle}(\sigma) \rightarrow \text{idle}(\sigma)$$

- ▶ In **flat** specifications, additional feature:
 - ▶ exhaustive **pattern matching** on constructors

Extending PSF

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Example (Pascal's triangle)

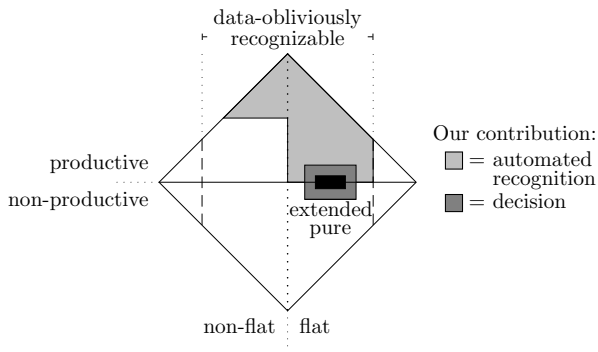
$$\begin{array}{l}
 \hline
 P \rightarrow 0 : s(0) : g(P) \\
 g(\underline{s(x)} : \underline{y} : \sigma) \rightarrow a(s(x), y) : g(y : \sigma) \quad \textit{stream layer} \\
 g(\underline{0} : \sigma) \rightarrow 0 : s(0) : g(\sigma) \\
 \hline
 a(x, s(y)) \rightarrow s(a(x, y)) \\
 a(x, 0) \rightarrow x \quad \textit{data layer} \\
 \hline
 \end{array}$$

is a **productive** stream specification of the **Pascal's triangle**:

$$P \rightsquigarrow 0 : 1 : 0 : 1 : 1 : 0 : 1 : 2 : 1 : 0 : 1 : 3 : 3 : 1 : 0 : \dots$$

New concepts and definitions

- ▶ stream specification formats: **ext. pure** \subsetneq **flat** \subsetneq **friendly-nesting**;
- ▶ **data-oblivious rewriting**;
- ▶ **data-oblivious productivity**.



Data-Oblivious Analysis

Example (Pascal's triangle)

$$\begin{aligned}
 P &\rightarrow 0 : s(0) : g(P) \\
 g(s(x) : y : \sigma) &\rightarrow a(s(x), y) : g(y : \sigma) \\
 g(0 : \sigma) &\rightarrow 0 : s(0) : g(\sigma)
 \end{aligned}$$

data abstracted we have:

$$\begin{aligned}
 P' &\rightarrow \bullet : \bullet : g(P') \\
 g(\bullet : \bullet : \sigma) &\rightarrow \bullet : g(\bullet : \sigma) \\
 g(\bullet : \sigma) &\rightarrow \bullet : \bullet : g(\sigma)
 \end{aligned}$$

The data oblivious lower/upper bounds on the production of g are:

$$n \mapsto n \div 1 \quad / \quad n \mapsto 2n$$

The lower bound implies productivity of P' follows; we say: P is data-obliviously productive. This implies productivity of P .

Data-Oblivious Productivity

$\Pi_S(t) := \sup\{n \in \overline{\mathbb{N}} \mid t \twoheadrightarrow s_1 : \dots : s_n : r\}$ **data-aware production** of t .

Definition

The **data-oblivious production range** ($\subseteq \overline{\mathbb{N}}$) of a term t :

$\overline{do}_S(t) :=$ set of all productions of t under **outermost-fair data-oblivious** rewrite sequences starting at t

The **d-o lower/upper bounds**:

$$\underline{do}_S(t) := \inf \overline{do}_S(t) \qquad \overline{do}_S(t) := \sup \underline{do}_S(t)$$

A term t is **data-obliviously productive** if $\underline{do}_S(t) = \infty$.

Proposition (Data-oblivious productivity implies productivity)

$$\underline{do}_S(t) \leq \Pi_S(t) \leq \overline{do}_S(t)$$

Stream specifications

For stream specifications we consider:

- ▶ $\{S, D\}$ -sorted, **orthogonal**, **constructor TRSs** $R = \langle \Sigma, R \rangle$
- ▶ Σ_S **stream symbols** and Σ_D **data symbols**

Definition (Stream Specification)

$$\frac{R_S \quad \textit{stream layer}}{R_D \quad \textit{data layer}}$$

- 1 $M_0 \in \Sigma_S$ with arity 0, the **root of R** .
- 2 $\langle \Sigma_D, R_D \rangle$ is a **terminating**, D -sorted TRS, the **data layer of R** .
- 3 R is **exhaustive**

Flat stream spec's

R is called **flat**: in rules for stream functions, **no nested occurrences** of stream function rules on their right hand sides.

Theorem

*For flat stream spec's we can **decide data-oblivious productivity**.*

Extended-pure stream spec's

R is called **extended-pure**: the defining rules for a stream function all have the same **data abstraction**.

Example

$$\text{inv}(0 : \sigma) \rightarrow 1 : \text{inv}(\sigma)$$

$$\text{inv}(1 : \sigma) \rightarrow 0 : \text{inv}(\sigma)$$

$$\text{inv}(\bullet : \sigma) \rightarrow \bullet : \text{inv}(\sigma)$$

Non-example: $\mathbf{g}(0 : x : \sigma) \rightarrow x : x : \mathbf{g}(\sigma)$

$$\mathbf{g}(1 : x : \sigma) \rightarrow x : \mathbf{g}(\sigma)$$

$$\mathbf{g}(\bullet : \bullet : \sigma) \rightarrow \bullet : \bullet : \mathbf{g}(\sigma)$$

$$\mathbf{g}(\bullet : \bullet : \sigma) \rightarrow \bullet : \mathbf{g}(\sigma) .$$

Proposition

For pure stream spec's: productivity = data-oblivious productivity.

Theorem

*We can **decide productivity** of extended-pure stream specifications.*

Stream specification (friendly-nesting)

The **convolution product** \times is the stream operation $\times : \mathbb{R}^\omega \times \mathbb{R}^\omega \rightarrow \mathbb{R}^\omega$:

$$(\sigma \times \tau)(i) = \sum_{j=0}^i \sigma(j) \cdot \tau(i-j) \quad (\text{for all } i \in \mathbb{N})$$

Hence: $(x : \sigma') \times (y : \tau') = (x.y) : (x \cdot \tau' + \sigma' \times (y : \tau'))$.

Example

$\text{nats} \rightarrow 0 : \times(\text{ones}, \text{ones})$

$\text{ones} \rightarrow s(0) : \text{ones}$

$\times(x : \sigma', y : \tau') \rightarrow m(x, y) : \text{add}(\text{times}(\tau', x), \times(\sigma', y : \tau'))$ *stream layer*

$\text{times}(x : \sigma', y) \rightarrow m(x, y) : \text{times}(\sigma', y)$

$\text{add}(x : \sigma', y : \tau') \rightarrow a(x, y) : \text{add}(\sigma', \tau')$

$a(x, 0) \rightarrow x$ $a(x, s(y)) \rightarrow s(a(x, y))$

$m(x, 0) \rightarrow 0$ $m(x, s(y)) \rightarrow a(m(x, y), x)$

data layer

Stream specification (friendly-nesting)

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$$\begin{aligned}(\sigma \times \tau)(0) &:= \sigma(0) \cdot \tau(0) \\ (\sigma \times \tau)' &:= \sigma(0) \cdot \tau' + \sigma' \times \tau\end{aligned}$$

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Example

nats \rightarrow **0** : \times (**ones**, **ones**)

ones \rightarrow **s**(0) : **ones**

$\times(x : \sigma', y : \tau') \rightarrow$ **m**(x, y) : **add**(**times**(τ' , x), $\times(\sigma', y : \tau')$) *stream layer*

times($x : \sigma', y$) \rightarrow **m**(x, y) : **times**(σ', y)

add($x : \sigma', y : \tau'$) \rightarrow **a**(x, y) : **add**(σ', τ')

a($x, 0$) \rightarrow x **a**($x, \mathbf{s}(y)$) \rightarrow **s**(**a**(x, y))

m($x, 0$) \rightarrow **0** **m**($x, \mathbf{s}(y)$) \rightarrow **a**(**m**(x, y), x)

data layer

Friendly-nesting stream spec's

Friendly-nesting stream specifications are extensions of flat ones with **friendly (nesting) rules** γ :

- ▶ γ consumes in each argument at most one stream element,
- ▶ it produces at least one stream element, and
- ▶ the defining rules of stream function symbols on the right hand side are friendly again.

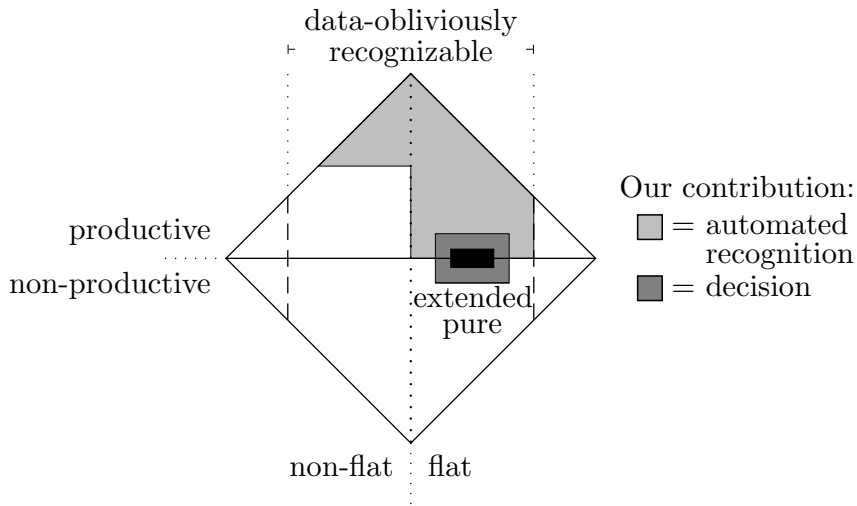
Example

$$\begin{aligned}f(x : \sigma, \tau) &\rightarrow x : x : g(f(\sigma, x : \tau)) \\g(x : \sigma) &\rightarrow x : g(x : f(\sigma, \sigma))\end{aligned}$$

Theorem (For friendly nesting stream specifications ...)

... we have a sufficient condition for (data-oblivious) productivity.

Map of stream specifications



Overview

1. Extended stream formats
2. Variants of Productivity
3. Computational Complexity

Productivity and variants

1

$\text{zeros} \rightarrow 0 : \text{zeros}$

- ▶ **productive**: there is only one maximal rewrite sequence:
 $\text{zeros} \rightarrow 0 : \text{zeros} \rightarrow 0 : 0 : \text{zeros} \rightarrow \dots \rightsquigarrow 0 : 0 : 0 : \dots$

2

$\text{zeros} \rightarrow 0 : \text{id}(\text{zeros})$

$\text{id}(\sigma) \rightarrow \sigma$

- ▶ $\text{zeros} \rightsquigarrow 0 : \text{id}(0 : \text{id}(0 : \text{id}(\dots)))$
- ▶ still **productive**, since for all max. **outermost-fair** rewrite sequences:
 $\text{zeros} \rightsquigarrow 0 : 0 : 0 : \dots$

Even for well-behaved spec's (orthogonal TRSs), productivity should be based on a **fair treatment of outermost redexes**.

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$\text{id}(\sigma) \rightarrow \sigma$

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$\text{id}(\sigma) \rightarrow \sigma$

- ▶ $\text{zeros} \rightsquigarrow 0 : \text{id}(0 : \text{id}(0 : \text{id}(\dots)))$
- ▶ still **productive**, since for all max. **outermost-fair** rewrite sequences:
 $\text{zeros} \rightsquigarrow 0 : 0 : 0 : \dots$

Even for well-behaved spec's (orthogonal TRSs), productivity **should** be based on a **fair treatment of outermost redexes**.

Productivity and variants

3 maybe $\rightarrow 0 : \text{maybe}$ maybe $\rightarrow \text{sink}$ sink $\rightarrow \text{sink}$

- ▶ productive or not, dependent on the chosen strategy
- ▶ ‘weakly productive’: maybe $\twoheadrightarrow 0 : 0 : 0 : \dots$
- ▶ not ‘strongly productive’: e.g. maybe $\rightarrow \text{sink} \rightarrow \text{sink} \rightarrow \dots$

4 bitstream $\rightarrow 0 : \text{bitstream}$ bitstream $\rightarrow 1 : \text{bitstream}$

- ▶ productive independent of the strategy chosen
- ▶ ‘weakly’ and ‘strongly productive’
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- ▶ **productive** independent of the strategy chosen
- ▶ ‘**weakly**’ and ‘**strongly productive**’
- ▶ **infinite normal forms not unique**

Productivity w.r.t. computable strategies

Let R be a TRS.

A **strategy** for a rewrite relation \rightarrow_R is a relation $\rightsquigarrow \subseteq \rightarrow_R$ with the same normal forms as \rightarrow_R .

Definition

A term t is called **productive w.r.t. a strategy** \rightsquigarrow if all maximal \rightsquigarrow -rewrite sequences starting from t end in a **constructor normal form**.

Strong and weak productivity

Definition

A term t in a TRS R is called

- ▶ **strongly productive**: all maximal **outermost-fair** rewrite sequences starting from t end in a **constructor normal form**.
- ▶ **weakly productive**: if there exists a rewrite sequence starting from t that ends in a **constructor normal form**.

Definition of productivity in general TRSs

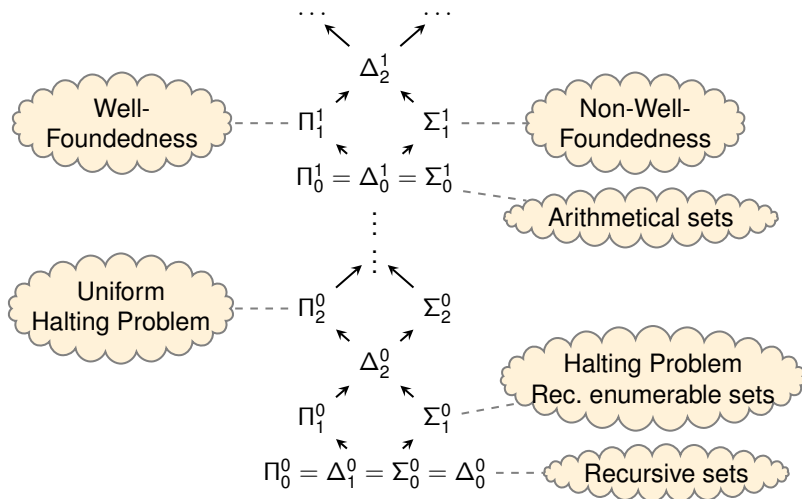
We think:

- ▶ For non-well-behaved spec's (non-orthogonal TRSs), productivity has to be defined relative to a given rewrite strategy.
- ▶ Strategy-independent variants (strong, weak productivity) are of limited general interest.
- ▶ Uniqueness of (infinite) normal form UN^∞ should be considered to be a separate property, independent of productivity. (In orthogonal TRSs, UN^∞ is guaranteed.)

Overview

1. Extended stream formats
2. Variants of Productivity
3. Computational Complexity

The arithmetical and analytical hierarchies



Productivity w.r.t. computable strategies

PRODUCTIVITY PROBLEM w.r.t. a family \mathcal{S} of computable strategies

Instance: Encodings of a finite TRS R , a strategy $\rightsquigarrow \in \mathcal{S}(R)$,
and a term t in R .

Question: Is t productive w.r.t. \rightsquigarrow ?

We say that:

- ▶ such a family \mathcal{S} is *admissible*: if R is orthogonal, $\mathcal{S}(R) \neq \emptyset$.

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Productivity w.r.t. computable strategies

Theorem

For every family of admissible, computable strategies \mathcal{S} , the productivity problem w.r.t. \mathcal{S} is Π_2^0 -complete.

Proof.

Contained in Π_2^0 : a term t is productive w.r.t. $\sim \in \mathcal{S}(R)$ iff

$\{ \forall d \in \mathbb{N}. \exists n \in \mathbb{N}. \text{ every } n\text{-step } \sim\text{-reduct of } t \text{ is a constructor normal form up to depth } d \} \in \Pi_2^0$

Π_2^0 -complete: By reducing the totality problem for Turing-machines, which is Π_2^0 -complete, to the productivity problem here. \square

Corollary

In orthogonal TRSs, productivity w.r.t. lazy (outermost-fair) evaluation is Π_2^0 -complete.

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Strong and weak productivity

Theorem

The recognition problem for

- ▶ *strong productivity is Π_1^1 -complete;*
- ▶ *weak productivity is Σ_1^1 -complete.*

Proof (Idea).

Π_1^1 -hardness (Σ_1^1 -hardness): reducing the
– recognition problem for well-founded (for non-well-founded)
binary relations over \mathbb{N} , which is Π_1^1 -complete (Σ_1^1 -complete), to the
– to the recognition problem of strong (weak) productivity. \square

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Uniqueness of infinite normal form

Theorem

The problem of recognising, for TRSs R and terms t in R , whether t has a unique (finite or infinite) normal form is Π_1^1 -complete.

Changes due to adding the condition **uniqueness of normal form**:

- (i) w.r.t. family of strategies:
 - ▶ uniqueness of normal forms w.r.t. \rightsquigarrow : Π_2^0 -complete.
 - ▶ uniqueness of normal forms generally: Π_1^1 -complete.
- (ii) strong productivity: Π_1^1 -complete
- (iii) weak productivity: now $(\Pi_1^1 \cup \Sigma_1^1)$ -hard

Uniqueness of infinite normal form

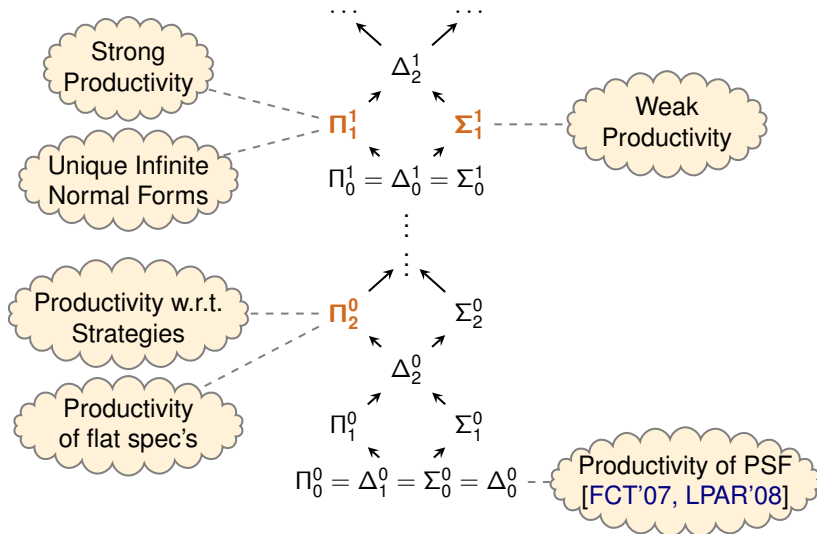
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Complexity of productivity



Summary

- ▶ Extended stream formats
 - ▶ for a **special** class of **stream functions**
(simulation by **open pebbleflow nets**)
 - ▶ for **larger classes** of stream specifications:
flat, **extended-pure**, **friendly-nesting**
(using **data-oblivious productivity**)
- ▶ Productivity and variant definitions in TRSs
 - ▶ **productivity with respect to strategies**
 - ▶ **weak and strong productivity**
- ▶ Complexity of productivity and its variants

The End of *Infinity*?

The End of **Infinity**? Yes, but the idea catches on . . .



Infinity Groep BV, **Toetsenbordweg** 48, 1033 MZ Amsterdam

Realising Optimal Sharing (ROS)

NWO-Project (2009–2012/13) at Utrecht University linking:

- ▶ Dept. of Philosophy (Theor. Philosophy)
- ▶ Dept. of Computer Science (Functional Languages)

Aims

- ▶ Study **optimal-sharing implementations** of the λ -calculus
- ▶ Try to incorporate optimal-sharing techniques in the **Utrecht Haskell Compiler (UHC)**

People

- ▶ Phil: **Vincent van Oostrom** (principal investigator),
CG (postdoc/3 years)
- ▶ CS: **Doaitse Swierstra** and **Atze Dijkstra**,
Jan Rochel (PhD student)