

SMT-Based Weighted Model Integration

Roberto Sebastiani¹

joint work with

Paolo Morettin¹, Andrea Passerini¹

with contributions by

Samuel Kolb², Luc De Raedt², Francesco Sommariva¹, Pedro Zuidberg²

¹ University of Trento, Italy

² KU Leuven; Belgium

– 17th International Workshop on Satisfiability Modulo Theories, SMT 2019 –

– 6th Vampire Workshop, Vampire 2019 –

Context

Goal

- Efficiently perform **probabilistic inference** in **hybrid domains**
 - both Boolean and continuous variables
 - arithmetical and logical constraints
- Using SMT-based **Weighted Model Integration**.

Brief History

- **Weighted Model Counting (WMC)** [10] [Chavira & Darwiche, AU 2008]
 - SAT-based probabilistic inference in Boolean domains
- **Weighted Model Integration (WMI)** [8] [Balla, Passerini & Van den Broeck, IJCAI 2015]
 - SMT-based probabilistic inference in hybrid domains (Boolean+arithmetic)
- **Weighted Model Integration, revisited** [19, 20] [Moretin, Passerini & Sebastiani, IJCAI 2017, AU 2019]
 - WMI reformulated from scratch, novel SMT-based algorithms

Context

Goal

- Efficiently perform **probabilistic inference** in **hybrid domains**
 - both Boolean and continuous variables
 - arithmetical and logical constraints
- Using SMT-based **Weighted Model Integration**.

Brief History

- **Weighted Model Counting (WMC)** [10] [Chavira & Darwiche, AIJ 2008]
 - SAT-based probabilistic inference in Boolean domains
- **Weighted Model Integration (WMI)** [8] [Belle, Passerini & Van den Broeck, IJCAI 2015]
 - SMT-based probabilistic inference in hybrid domains (Boolean+arithmetic)
- **Weighted Model Integration, revisited** [19, 20] [Morettin, Passerini & Sebastiani, IJCAI 2017, AIJ 2019]
 - WMI reformulated from scratch, novel SMT-based algorithms

Context

Goal

- Efficiently perform **probabilistic inference** in **hybrid domains**
 - both Boolean and continuous variables
 - arithmetical and logical constraints
- Using SMT-based **Weighted Model Integration**.

Brief History

- **Weighted Model Counting (WMC)** [10] [Chavira & Darwiche, AIJ 2008]
 - SAT-based probabilistic inference in Boolean domains
- **Weighted Model Integration (WMI)** [8] [Belle, Passerini & Van den Broeck, IJCAI 2015]
 - SMT-based probabilistic inference in hybrid domains (Boolean+arithmetic)
- **Weighted Model Integration, revisited** [19, 20] [Morettin, Passerini & Sebastiani, IJCAI 2017, AIJ 2019]
 - WMI reformulated from scratch, novel SMT-based algorithms

Context

Goal

- Efficiently perform **probabilistic inference** in **hybrid domains**
 - both Boolean and continuous variables
 - arithmetical and logical constraints
- Using SMT-based **Weighted Model Integration**.

Brief History

- **Weighted Model Counting (WMC)** [10] [Chavira & Darwiche, AIJ 2008]
 - SAT-based probabilistic inference in Boolean domains
- **Weighted Model Integration (WMI)** [8] [Belle, Passerini & Van den Broeck, IJCAI 2015]
 - SMT-based probabilistic inference in hybrid domains (Boolean+arithmetic)
- **Weighted Model Integration, revisited** [19, 20] [Morettin, Passerini & Sebastiani, IJCAI 2017, AIJ 2019]
 - WMI reformulated from scratch, novel SMT-based algorithms

Context

Goal

- Efficiently perform **probabilistic inference** in **hybrid domains**
 - both Boolean and continuous variables
 - arithmetical and logical constraints
- Using SMT-based **Weighted Model Integration**.

Brief History

- **Weighted Model Counting (WMC)** [10] [Chavira & Darwiche, AIJ 2008]
 - SAT-based probabilistic inference in Boolean domains
- **Weighted Model Integration (WMI)** [8] [Belle, Passerini & Van den Broeck, IJCAI 2015]
 - SMT-based probabilistic inference in hybrid domains (Boolean+arithmetic)
- **Weighted Model Integration, revisited** [19, 20] [Morettin, Passerini & Sebastiani, IJCAI 2017, AIJ 2019]
 - WMI reformulated from scratch, novel SMT-based algorithms

Outline

- 1 Background
- 2 Weighted Model Integration, Revisited
- 3 SMT-Based WMI Computation
- 4 A Case Study: The Road Network Problem
- 5 Experimental Evaluations
- 6 Ongoing and Future Work

Outline

- 1 Background
- 2 Weighted Model Integration, Revisited
- 3 SMT-Based WMI Computation
- 4 A Case Study: The Road Network Problem
- 5 Experimental Evaluations
- 6 Ongoing and Future Work

Weighted Model Counting

Definition (Weighted Model Count)

Let φ be a propositional formula on $\mathbf{A} \stackrel{\text{def}}{=} \{A_1, \dots, A_M\}$ and let w be a function associating a non-negative weight to each literal on $Atoms(\varphi)$. Then the **Weighted Model Count** of φ is:

$$\text{WMC}(\varphi, w) = \sum_{\mu \in \mathcal{TA}(\varphi)} \prod_{\ell \in \mu} w(\ell).$$

Proposition ([10, 8])

The probability of a query q given evidence e in a Boolean Markov Network N is computed as:

$$Pr_N(q|e) = \frac{\text{WMC}(q \wedge e \wedge \Delta, w)}{\text{WMC}(e \wedge \Delta, w)}, \quad \text{where } \Delta \text{ encodes } N \text{ and } w \text{ the potential.}$$

Many efficient computing techniques

- based on knowledge compilation [12, 21] or exhaustive DPLL search [23]
- improved by component caching techniques [22, 6]

Weighted Model Counting

Definition (Weighted Model Count)

Let φ be a propositional formula on $\mathbf{A} \stackrel{\text{def}}{=} \{A_1, \dots, A_M\}$ and let w be a function associating a non-negative weight to each literal on $Atoms(\varphi)$. Then the **Weighted Model Count** of φ is:

$$\text{WMC}(\varphi, w) = \sum_{\mu \in \mathcal{TA}(\varphi)} \prod_{\ell \in \mu} w(\ell).$$

Proposition ([10, 8])

The probability of a query q given evidence e in a Boolean Markov Network N is computed as:

$$\Pr_N(q|e) = \frac{\text{WMC}(q \wedge e \wedge \Delta, w)}{\text{WMC}(e \wedge \Delta, w)}, \quad \text{where } \Delta \text{ encodes } N \text{ and } w \text{ the potential.}$$

Many efficient computing techniques

- based on knowledge compilation [12, 21] or exhaustive DPLL search [23]
- improved by component caching techniques [22, 6]

Weighted Model Counting

Definition (Weighted Model Count)

Let φ be a propositional formula on $\mathbf{A} \stackrel{\text{def}}{=} \{A_1, \dots, A_M\}$ and let w be a function associating a non-negative weight to each literal on $Atoms(\varphi)$. Then the **Weighted Model Count** of φ is:

$$\text{WMC}(\varphi, w) = \sum_{\mu \in \mathcal{TA}(\varphi)} \prod_{\ell \in \mu} w(\ell).$$

Proposition ([10, 8])

The probability of a query q given evidence e in a Boolean Markov Network N is computed as:

$$Pr_N(q|e) = \frac{\text{WMC}(q \wedge e \wedge \Delta, w)}{\text{WMC}(e \wedge \Delta, w)}, \quad \text{where } \Delta \text{ encodes } N \text{ and } w \text{ the potential.}$$

Many efficient computing techniques

- based on knowledge compilation [12, 21] or exhaustive DPLL search [23]
- improved by component caching techniques [22, 6]

Weighted Model Integration [8]

Definition (Weighted Model Integral [8])

Let φ be a \mathcal{LRA} formula on $\mathbf{x} \stackrel{\text{def}}{=} \{x_1, \dots, x_N\}$ and $\mathbf{A} \stackrel{\text{def}}{=} \{A_1, \dots, A_M\}$. Let w be a function associating an expression (possibly constant) over \mathbf{x} to each literal whose atom occurs in φ . Then the **Weighted Model Integral** of φ is defined as:

$$\text{WMI}_{\text{old}}(\varphi, w) = \sum_{\mu \in \text{TA}(\varphi)} \int_{\mu^{\mathcal{LRA}}} \prod_{\ell \in \mu} w(\ell) \, d\mathbf{x}, \quad \text{s.t. } \mu \stackrel{\text{def}}{=} \mu^{\mathbf{A}} \wedge \mu^{\mathcal{LRA}}$$

Note: $\langle \varphi, w \rangle$ implicitly defines an un-normalized probability distribution

If $P(\mathbf{x})$ is polynomial and $\mu^{\mathcal{LRA}}(\mathbf{x})$ is a conjunction of linear constraints, then $\int_{\mu^{\mathcal{LRA}}} P(\mathbf{x}) \, d\mathbf{x}$ can be exactly computed [7] (e.g., by **LATTE INTEGRALE** [18])

Proposition ([8])

The probability of a query q given evidence e in a **Hybrid** Markov Network N is computed as:

$$\Pr_N(q|e) = \frac{\text{WMI}_{\text{old}}(q \wedge e \wedge \Delta, w)}{\text{WMI}_{\text{old}}(e \wedge \Delta, w)}, \quad \text{where } \Delta \text{ encodes } N \text{ and } w \text{ the potential.}$$

Weighted Model Integration [8]

Definition (Weighted Model Integral [8])

Let φ be a \mathcal{LRA} formula on $\mathbf{x} \stackrel{\text{def}}{=} \{x_1, \dots, x_N\}$ and $\mathbf{A} \stackrel{\text{def}}{=} \{A_1, \dots, A_M\}$. Let w be a function associating an expression (possibly constant) over \mathbf{x} to each literal whose atom occurs in φ . Then the **Weighted Model Integral** of φ is defined as:

$$\text{WMI}_{\text{old}}(\varphi, w) = \sum_{\mu \in \text{TA}(\varphi)} \int_{\mu^{\mathcal{LRA}}} \prod_{\ell \in \mu} w(\ell) \, d\mathbf{x}, \quad \text{s.t. } \mu \stackrel{\text{def}}{=} \mu^{\mathbf{A}} \wedge \mu^{\mathcal{LRA}}$$

Note: $\langle \varphi, w \rangle$ implicitly defines an un-normalized probability distribution

If $P(\mathbf{x})$ is polynomial and $\mu^{\mathcal{LRA}}(\mathbf{x})$ is a conjunction of linear constraints, then $\int_{\mu^{\mathcal{LRA}}} P(\mathbf{x}) \, d\mathbf{x}$ can be exactly computed [7] (e.g., by **LATTE INTEGRALE** [18])

Proposition ([8])

The probability of a query q given evidence e in a **Hybrid** Markov Network N is computed as:

$$\Pr_N(q|e) = \frac{\text{WMI}_{\text{old}}(q \wedge e \wedge \Delta, w)}{\text{WMI}_{\text{old}}(e \wedge \Delta, w)}, \quad \text{where } \Delta \text{ encodes } N \text{ and } w \text{ the potential.}$$

Weighted Model Integration [8]

Definition (Weighted Model Integral [8])

Let φ be a \mathcal{LRA} formula on $\mathbf{x} \stackrel{\text{def}}{=} \{x_1, \dots, x_N\}$ and $\mathbf{A} \stackrel{\text{def}}{=} \{A_1, \dots, A_M\}$. Let w be a function associating an expression (possibly constant) over \mathbf{x} to each literal whose atom occurs in φ . Then the **Weighted Model Integral** of φ is defined as:

$$\text{WMI}_{\text{old}}(\varphi, w) = \sum_{\mu \in \text{TA}(\varphi)} \int_{\mu^{\mathcal{LRA}}} \prod_{\ell \in \mu} w(\ell) \, d\mathbf{x}, \quad \text{s.t. } \mu \stackrel{\text{def}}{=} \mu^{\mathbf{A}} \wedge \mu^{\mathcal{LRA}}$$

Note: $\langle \varphi, w \rangle$ implicitly defines an un-normalized probability distribution

If $P(\mathbf{x})$ is polynomial and $\mu^{\mathcal{LRA}}(\mathbf{x})$ is a conjunction of linear constraints, then $\int_{\mu^{\mathcal{LRA}}} P(\mathbf{x}) \, d\mathbf{x}$ can be exactly computed [7] (e.g., by **LATTE INTEGRALE** [18])

Proposition ([8])

The probability of a query q given evidence e in a **Hybrid** Markov Network N is computed as:

$$\Pr_N(q|e) = \frac{\text{WMI}_{\text{old}}(q \wedge e \wedge \Delta, w)}{\text{WMI}_{\text{old}}(e \wedge \Delta, w)}, \quad \text{where } \Delta \text{ encodes } N \text{ and } w \text{ the potential.}$$

Weighted Model Integration - Example

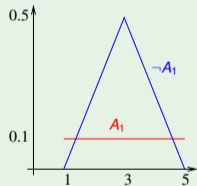
Example

$$\begin{aligned} \varphi &\stackrel{\text{def}}{=} (A_2 \rightarrow ((1 \leq x) \wedge (x \leq 3))) \wedge (A_3 \rightarrow (\neg(x \leq 3) \wedge (x \leq 5))) \\ &\wedge (A_1 \leftrightarrow (\neg A_2 \wedge \neg A_3)) \wedge (1 \leq x) \wedge (x \leq 5). \end{aligned}$$

Let $w(A_1) = 0.1$, $w(A_2) = (0.25 \cdot x - 0.25)$, $w(A_3) = (1.25 - 0.25 \cdot x)$, $w(I) = 1$ for the others.

$$\mathcal{T}\mathcal{A}(\varphi) = \left\{ \begin{array}{l} A_1 \wedge \neg A_2 \wedge \neg A_3 \wedge (1 \leq x) \wedge (x \leq 5) \wedge (x \leq 3), \\ A_1 \wedge \neg A_2 \wedge \neg A_3 \wedge (1 \leq x) \wedge (x \leq 5) \wedge \neg(x \leq 3), \\ \neg A_1 \wedge A_2 \wedge \neg A_3 \wedge (1 \leq x) \wedge (x \leq 5) \wedge (x \leq 3), \\ \neg A_1 \wedge \neg A_2 \wedge A_3 \wedge (1 \leq x) \wedge (x \leq 5) \wedge \neg(x \leq 3) \end{array} \right\}.$$

$$\begin{aligned} \text{WMI}_{\text{old}}(\varphi, w) &= \int_{(1 \leq x) \wedge (x \leq 5) \wedge (x \leq 3)} w(A_1) dx + \int_{(1 \leq x) \wedge (x \leq 5) \wedge \neg(x \leq 3)} w(A_1) dx \\ &+ \int_{(1 \leq x) \wedge (x \leq 5) \wedge (x \leq 3)} w(A_2) dx + \int_{(1 \leq x) \wedge (x \leq 5) \wedge \neg(x \leq 3)} w(A_3) dx \\ &= \int_{[1,3]} 0.1 dx + \int_{(3,5]} 0.1 dx + \int_{[1,3]} 0.25 \cdot x - 0.25 dx + \int_{(3,5]} 1.25 - 0.25 \cdot x dx = (\dots) = 1.4 \end{aligned}$$



Models an unnormalized distribution over x in $[1, 5]$, which:

- is uniform with $w = 0.1$ if A_1 is true
- is modeled as a triangular distribution with mode $w = 0.5$ at $x = 3$ otherwise.

Weighted Model Integration - Example (cont.)

Example

Given the previous unnormalized distribution $\langle \varphi, w \rangle$ and the information that $A_1 = \perp$ (evidence), the probability that $x \leq 2$ (query) is:

$$P_{(\varphi, w)}(x \leq 2 | A_1 = \perp) = \frac{\text{WMI}_{\text{old}}(\varphi \wedge \neg A_1 \wedge (x \leq 2), w)}{\text{WMI}_{\text{old}}(\varphi \wedge \neg A_1, w)} = \frac{0.125}{1.0} = 0.125$$

$$\begin{aligned} \text{WMI}_{\text{old}}(\varphi \wedge \neg A_1, w) &= \int_{(1 \leq x) \wedge (x \leq 5) \wedge (x \leq 3)} w(A_2) dx + \int_{(1 \leq x) \wedge (x \leq 5) \wedge \neg(x \leq 3)} w(A_3) dx \\ &= \int_{[1,3]} 0.25 \cdot x - 0.25 dx + \int_{(3,5]} 1.25 - 0.25 \cdot x dx = (\dots) = 1.0 \end{aligned}$$

$$\begin{aligned} \text{WMI}_{\text{old}}(\varphi \wedge \neg A_1 \wedge (x \leq 2), w) &= \int_{(1 \leq x) \wedge (x \leq 5) \wedge (x \leq 3) \wedge (x \leq 2)} w(A_2) dx \\ &= \int_{[1,2]} 0.25 \cdot x - 0.25 dx = (\dots) = 0.125 \end{aligned}$$

Outline

- 1 Background
- 2 Weighted Model Integration, Revisited**
- 3 SMT-Based WMI Computation
- 4 A Case Study: The Road Network Problem
- 5 Experimental Evaluations
- 6 Ongoing and Future Work

Basic case: WMI Without Atomic Propositions

Definition

Assume φ does not contain atomic propositions and $w : \mathbb{R}^N \mapsto \mathbb{R}^+$. Then we define the **Weighted Model Integral** of w over φ on \mathbf{x} as:

$$\text{WMI}_{\text{nb}}(\varphi, w|\mathbf{x}) \stackrel{\text{def}}{=} \int_{\varphi(\mathbf{x})} w(\mathbf{x}) \, d\mathbf{x},$$

“nb” meaning “no-Booleans”, that is, as the integral of $w(\mathbf{x})$ over the set $\{\mathbf{x} \mid \varphi(\mathbf{x}) \text{ is true}\}$.

Proposition

$$\begin{aligned} \text{WMI}_{\text{nb}}(\varphi, w|\mathbf{x}) &= \sum_{\mu^{\mathcal{LRA}} \in \text{TTA}(\varphi)} \text{WMI}_{\text{nb}}(\mu^{\mathcal{LRA}}, w|\mathbf{x}) \\ &= \sum_{\mu^{\mathcal{LRA}} \in \text{TA}(\varphi)} \text{WMI}_{\text{nb}}(\mu^{\mathcal{LRA}}, w|\mathbf{x}). \end{aligned}$$

Note: $\text{WMI}_{\text{nb}}(\mu^{\mathcal{LRA}}, w|\mathbf{x}) \stackrel{\text{def}}{=} \int_{\mu^{\mathcal{LRA}}(\mathbf{x})} w(\mathbf{x}) \, d\mathbf{x}$ can be computed exactly if $w(\mathbf{x})$ is polynomial [7].

Basic case: WMI Without Atomic Propositions

Definition

Assume φ does not contain atomic propositions and $w : \mathbb{R}^N \mapsto \mathbb{R}^+$. Then we define the **Weighted Model Integral** of w over φ on \mathbf{x} as:

$$\text{WMI}_{\text{nb}}(\varphi, w|\mathbf{x}) \stackrel{\text{def}}{=} \int_{\varphi(\mathbf{x})} w(\mathbf{x}) \, d\mathbf{x},$$

“nb” meaning “no-Booleans”, that is, as the integral of $w(\mathbf{x})$ over the set $\{\mathbf{x} \mid \varphi(\mathbf{x}) \text{ is true}\}$.

Proposition

$$\begin{aligned} \text{WMI}_{\text{nb}}(\varphi, w|\mathbf{x}) &= \sum_{\mu^{\mathcal{LRA}} \in \text{TTA}(\varphi)} \text{WMI}_{\text{nb}}(\mu^{\mathcal{LRA}}, w|\mathbf{x}) \\ &= \sum_{\mu^{\mathcal{LRA}} \in \text{TA}(\varphi)} \text{WMI}_{\text{nb}}(\mu^{\mathcal{LRA}}, w|\mathbf{x}). \end{aligned}$$

Note: $\text{WMI}_{\text{nb}}(\mu^{\mathcal{LRA}}, w|\mathbf{x}) \stackrel{\text{def}}{=} \int_{\mu^{\mathcal{LRA}}(\mathbf{x})} w(\mathbf{x}) \, d\mathbf{x}$ can be computed exactly if $w(\mathbf{x})$ is polynomial [7].

General Case: WMI With Atomic Propositions

Definition

We consider a \mathcal{LRA} -formula $\varphi(\mathbf{x}, \mathbf{A})$ and $w(\mathbf{x}, \mathbf{A})$ s.t. $w : \mathbb{R}^N \times \mathbb{B}^M \mapsto \mathbb{R}^+$.
The **Weighted Model Integral** of w over φ is defined as follows:

$$\text{WMI}(\varphi, w | \mathbf{x}, \mathbf{A}) \stackrel{\text{def}}{=} \sum_{\mu^{\mathbf{A}} \in \mathbb{B}^M} \text{WMI}_{\text{nb}}(\varphi_{[\mu^{\mathbf{A}]}} | \mathbf{x}) = \sum_{\mu^{\mathbf{A}} \in \mathbb{B}^M} \sum_{\mu \in \mathcal{LRA} \in \mathcal{TA}(\varphi_{[\mu^{\mathbf{A}]})} \int_{\mathcal{LRA}(\mathbf{x})} w_{[\mu^{\mathbf{A}]}}(\mathbf{x}) \, d\mathbf{x},$$

- the $\mu^{\mathbf{A}}$'s are all total truth assignments on \mathbf{A} ,
- $\varphi_{[\mu^{\mathbf{A}]}}(\mathbf{x})$ denotes (any formula equivalent to) the formula obtained from φ by substituting every Boolean value A_i with its truth value in $\mu^{\mathbf{A}}$ (thus $\varphi_{[\mu^{\mathbf{A}]}} : \mathbb{R}^N \mapsto \mathbb{B}$)
- $w_{[\mu^{\mathbf{A}]}}(\mathbf{x})$ is w computed on \mathbf{x} and on the truth values of $\mu^{\mathbf{A}}$ ($w_{[\mu^{\mathbf{A}]}} : \mathbb{R}^N \mapsto \mathbb{R}^+$ if $\mu^{\mathbf{A}}$ total)

Note

- $w(\mathbf{x}, \mathbf{A})$ generic, **not restricted in the form of products of weighs on literals of φ** .
- if $w_{[\mu^{\mathbf{A}]}}(\mathbf{x})$ polynomial for every $\mu^{\mathbf{A}}$, then $\int_{\mathcal{LRA}(\mathbf{x})} w_{[\mu^{\mathbf{A}]}}(\mathbf{x}) \, d\mathbf{x}$ can be computed exactly

WMI - Example

Example

Let

- $\varphi \stackrel{\text{def}}{=} (A \leftrightarrow (x \geq 0)) \wedge (x \geq -1) \wedge (x \leq 1)$,
- $w(x, A) \stackrel{\text{def}}{=} \llbracket \text{If } A \text{ Then } x \text{ Else } -x \rrbracket$.

Then:

- If $\mu^A \stackrel{\text{def}}{=} \{\neg A\}$, then $\varphi_{[\mu^A]} = \neg(x \geq 0) \wedge (x \geq -1) \wedge (x \leq 1)$ and $w_{[\mu^A]} = -x$.
- If $\mu^A \stackrel{\text{def}}{=} \{A\}$, then $\varphi_{[\mu^A]} = (x \geq 0) \wedge (x \geq -1) \wedge (x \leq 1)$ and $w_{[\mu^A]} = x$.

Thus,

$$\begin{aligned} \text{WMI}(\varphi, w | \mathbf{x}, \mathbf{A}) &\stackrel{\text{def}}{=} \text{WMI}_{\text{nb}}(\varphi_{[\mu^A]}, w_{[\mu^A]} | \mathbf{x}) + \text{WMI}_{\text{nb}}(\varphi_{[\mu^{\neg A}]}, w_{[\mu^{\neg A}]} | \mathbf{x}) \\ &= \int_{[-1,0)} -x \, dx + \int_{[0,1]} x \, dx \\ &= \frac{1}{2} + \frac{1}{2} = 1. \end{aligned}$$

Some Results on WMI

Proposition

Given \mathbf{x} , \mathbf{A} , $w(\mathbf{x}, \mathbf{A})$, $\varphi(\mathbf{x}, \mathbf{A})$ and $\mathcal{T}\mathcal{T}\mathcal{A}(\varphi)$ as above, we have that:

$$\text{WMI}(\varphi, w|\mathbf{x}, \mathbf{A}) = \sum_{\mu^{\mathbf{A}} \wedge \mu^{\mathcal{L}\mathcal{R}\mathcal{A}} \in \mathcal{T}\mathcal{T}\mathcal{A}(\varphi)} \text{WMI}_{\text{nb}}(\mu^{\mathcal{L}\mathcal{R}\mathcal{A}}, w_{[\mu^{\mathbf{A}]}}|\mathbf{x}) = \sum_{\mu^{\mathbf{A}} \wedge \mu^{\mathcal{L}\mathcal{R}\mathcal{A}} \in \mathcal{T}\mathcal{T}\mathcal{A}(\varphi)} \int_{\mu^{\mathcal{L}\mathcal{R}\mathcal{A}}(\mathbf{x})} w_{[\mu^{\mathbf{A}]}}(\mathbf{x}) \, d\mathbf{x}$$

Proposition

Given \mathbf{x} , \mathbf{A} , $w(\mathbf{x}, \mathbf{A})$, $\varphi(\mathbf{x}, \mathbf{A})$ and $\mathcal{T}\mathcal{T}\mathcal{A}(\varphi)$ as above, we have that:

$$\text{WMI}(\varphi, w|\mathbf{x}, \mathbf{A}) = \sum_{\mu^{\mathbf{A}} \in \mathcal{T}\mathcal{T}\mathcal{A}(\exists \mathbf{x}.\varphi)} \text{WMI}_{\text{nb}}(\varphi_{[\mu^{\mathbf{A}]}}|w_{[\mu^{\mathbf{A}]}}|\mathbf{x}) = \sum_{\mu^{\mathbf{A}} \in \mathcal{T}\mathcal{T}\mathcal{A}(\exists \mathbf{x}.\varphi)} \sum_{\mu^{\mathcal{L}\mathcal{R}\mathcal{A}} \in \mathcal{T}\mathcal{A}(\varphi_{[\mu^{\mathbf{A}]})} \int_{\mu^{\mathcal{L}\mathcal{R}\mathcal{A}}(\mathbf{x})} w_{[\mu^{\mathbf{A}]}}(\mathbf{x}) \, d\mathbf{x},$$

- enumerate only $\mathcal{L}\mathcal{R}\mathcal{A}$ -consistent $\mu^{\mathbf{A}} \wedge \mu^{\mathcal{L}\mathcal{R}\mathcal{A}}$'s propositionally satisfying φ
- enumerate only $\mu^{\mathbf{A}}$'s for which exists a $\mathcal{L}\mathcal{R}\mathcal{A}$ -consistent (partial) $\mu^{\mathcal{L}\mathcal{R}\mathcal{A}}$ s.t. $\mu^{\mathbf{A}} \wedge \mu^{\mathcal{L}\mathcal{R}\mathcal{A}} \models_{\mathbb{B}} \varphi$

Some Results on WMI

Proposition

Given \mathbf{x} , \mathbf{A} , $w(\mathbf{x}, \mathbf{A})$, $\varphi(\mathbf{x}, \mathbf{A})$ and $\mathcal{T}\mathcal{T}\mathcal{A}(\varphi)$ as above, we have that:

$$\text{WMI}(\varphi, w|\mathbf{x}, \mathbf{A}) = \sum_{\mu^{\mathbf{A}} \wedge \mu^{\mathcal{L}\mathcal{R}\mathcal{A}} \in \mathcal{T}\mathcal{T}\mathcal{A}(\varphi)} \text{WMI}_{\text{nb}}(\mu^{\mathcal{L}\mathcal{R}\mathcal{A}}, W_{[\mu^{\mathbf{A}]}}|\mathbf{x}) = \sum_{\mu^{\mathbf{A}} \wedge \mu^{\mathcal{L}\mathcal{R}\mathcal{A}} \in \mathcal{T}\mathcal{T}\mathcal{A}(\varphi)} \int_{\mu^{\mathcal{L}\mathcal{R}\mathcal{A}}(\mathbf{x})} W_{[\mu^{\mathbf{A}]}}(\mathbf{x}) \, d\mathbf{x}$$

Proposition

Given \mathbf{x} , \mathbf{A} , $w(\mathbf{x}, \mathbf{A})$, $\varphi(\mathbf{x}, \mathbf{A})$ and $\mathcal{T}\mathcal{T}\mathcal{A}(\varphi)$ as above, we have that:

$$\text{WMI}(\varphi, w|\mathbf{x}, \mathbf{A}) = \sum_{\mu^{\mathbf{A}} \in \mathcal{T}\mathcal{T}\mathcal{A}(\exists \mathbf{x}.\varphi)} \text{WMI}_{\text{nb}}(\varphi_{[\mu^{\mathbf{A}]}}|\mathbf{x}) = \sum_{\mu^{\mathbf{A}} \in \mathcal{T}\mathcal{T}\mathcal{A}(\exists \mathbf{x}.\varphi)} \sum_{\mu^{\mathcal{L}\mathcal{R}\mathcal{A}} \in \mathcal{T}\mathcal{A}(\varphi_{[\mu^{\mathbf{A}]})} \int_{\mu^{\mathcal{L}\mathcal{R}\mathcal{A}}(\mathbf{x})} W_{[\mu^{\mathbf{A}]}}(\mathbf{x}) \, d\mathbf{x},$$

- enumerate only $\mathcal{L}\mathcal{R}\mathcal{A}$ -consistent $\mu^{\mathbf{A}} \wedge \mu^{\mathcal{L}\mathcal{R}\mathcal{A}}$'s propositionally satisfying φ
- enumerate only $\mu^{\mathbf{A}}$'s for which exists a $\mathcal{L}\mathcal{R}\mathcal{A}$ -consistent (partial) $\mu^{\mathcal{L}\mathcal{R}\mathcal{A}}$ s.t. $\mu^{\mathbf{A}} \wedge \mu^{\mathcal{L}\mathcal{R}\mathcal{A}} \models_{\mathbb{B}} \varphi$

Feasibly computable WMIs: FIUC^{LR \mathcal{A}} weight functions

FI^{LR \mathcal{A}} weight function

A function $f(\mathbf{x})$ is **feasibly integrable on a set of LR \mathcal{A} constraints** (FI^{LR \mathcal{A}}) if exists a procedure that can compute the integral $\int_{\mu^{\text{LR}\mathcal{A}}} f(\mathbf{x}) d\mathbf{x}$, for all $\mu^{\text{LR}\mathcal{A}}$

- example: polynomials [7]

Definition (FIUC^{LR \mathcal{A}} weight function)

Given $\langle \mathbf{x}, \mathbf{A} \rangle$ and

- a set of LR \mathcal{A} -conditions $\Psi \stackrel{\text{def}}{=} \{\psi_1(\mathbf{x}, \mathbf{A}), \dots, \psi_K(\mathbf{x}, \mathbf{A})\}$;
- a support LR \mathcal{A} -formula $\chi(\mathbf{x}, \mathbf{A})$ s.t. $w(\mathbf{x}, \mathbf{A}) = 0$ where $\chi(\mathbf{x}, \mathbf{A})$ holds (\top if not present);

we say that a weight function $w(\mathbf{x}, \mathbf{A})$ is **feasibly integrable under LR \mathcal{A} conditions** (FIUC^{LR \mathcal{A}}) iff, for every total truth-value assignment $\mu^{\mathbf{A}}$ on \mathbf{A} and μ^{Ψ} on Ψ , $w_{[\mu^{\mathbf{A}}, \mu^{\Psi}]}(\mathbf{x})$ is FI^{LR \mathcal{A}} .

Property

$$\text{WMI}(\varphi, w|\mathbf{x}, \mathbf{A}) = \text{WMI}(\varphi \wedge \chi, w|\mathbf{x}, \mathbf{A}).$$

Feasibly computable WMIs: FIUC^{LR \mathcal{A}} weight functions

FI^{LR \mathcal{A}} weight function

A function $f(\mathbf{x})$ is **feasibly integrable on a set of LR \mathcal{A} constraints** (FI^{LR \mathcal{A}}) if exists a procedure that can compute the integral $\int_{\mu^{\text{LR}\mathcal{A}}} f(\mathbf{x}) d\mathbf{x}$, for all $\mu^{\text{LR}\mathcal{A}}$

- example: polynomials [7]

Definition (FIUC^{LR \mathcal{A}} weight function)

Given $\langle \mathbf{x}, \mathbf{A} \rangle$ and

- a set of LR \mathcal{A} -conditions $\Psi \stackrel{\text{def}}{=} \{\psi_1(\mathbf{x}, \mathbf{A}), \dots, \psi_K(\mathbf{x}, \mathbf{A})\}$;
- a support LR \mathcal{A} -formula $\chi(\mathbf{x}, \mathbf{A})$ s.t. $w(\mathbf{x}, \mathbf{A}) = 0$ where $\chi(\mathbf{x}, \mathbf{A})$ holds (\top if not present);

we say that a weight function $w(\mathbf{x}, \mathbf{A})$ is **feasibly integrable under LR \mathcal{A} conditions** (FIUC^{LR \mathcal{A}}) iff, for every total truth-value assignment $\mu^{\mathbf{A}}$ on \mathbf{A} and μ^{Ψ} on Ψ , $w_{[\mu^{\mathbf{A}}, \mu^{\Psi}]}(\mathbf{x})$ is FI^{LR \mathcal{A}} .

Property

$$\text{WMI}(\varphi, w|\mathbf{x}, \mathbf{A}) = \text{WMI}(\varphi \wedge \chi, w|\mathbf{x}, \mathbf{A}).$$

Feasibly computable WMIs: FIUC^{LR \mathcal{A}} weight functions

FI^{LR \mathcal{A}} weight function

A function $f(\mathbf{x})$ is **feasibly integrable on a set of LR \mathcal{A} constraints** (FI^{LR \mathcal{A}}) if exists a procedure that can compute the integral $\int_{\mu^{\text{LR}\mathcal{A}}} f(\mathbf{x}) d\mathbf{x}$, for all $\mu^{\text{LR}\mathcal{A}}$

- example: polynomials [7]

Definition (FIUC^{LR \mathcal{A}} weight function)

Given $\langle \mathbf{x}, \mathbf{A} \rangle$ and

- a set of LR \mathcal{A} -conditions $\Psi \stackrel{\text{def}}{=} \{\psi_1(\mathbf{x}, \mathbf{A}), \dots, \psi_K(\mathbf{x}, \mathbf{A})\}$;
- a support LR \mathcal{A} -formula $\chi(\mathbf{x}, \mathbf{A})$ s.t. $w(\mathbf{x}, \mathbf{A}) = 0$ where $\chi(\mathbf{x}, \mathbf{A})$ holds (\top if not present);

we say that a weight function $w(\mathbf{x}, \mathbf{A})$ is **feasibly integrable under LR \mathcal{A} conditions** (FIUC^{LR \mathcal{A}}) iff, for every total truth-value assignment $\mu^{\mathbf{A}}$ on \mathbf{A} and μ^{Ψ} on Ψ , $w_{[\mu^{\mathbf{A}}, \mu^{\Psi}]}(\mathbf{x})$ is FI^{LR \mathcal{A}} .

Property

$$\text{WMI}(\varphi, w|\mathbf{x}, \mathbf{A}) = \text{WMI}(\varphi \wedge \chi, w|\mathbf{x}, \mathbf{A}).$$

Support of FIUC^{LR}A weight functions: example

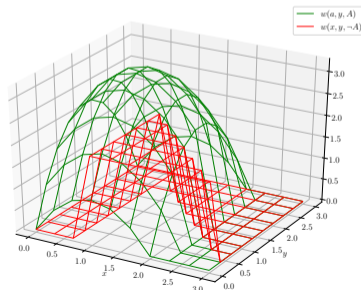
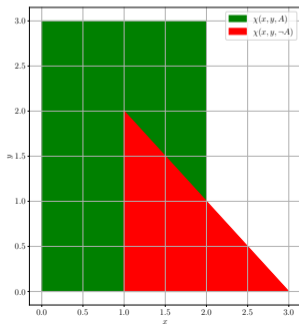
Example

Let $\mathbf{x} \stackrel{\text{def}}{=} \{x, y\}$, $\mathbf{A} \stackrel{\text{def}}{=} \{A\}$,

$$\chi(\mathbf{x}, \mathbf{A}) \stackrel{\text{def}}{=} (A \rightarrow \llbracket x \in [0, 2] \rrbracket) \wedge (\neg A \rightarrow (\llbracket x \in [1, 3] \rrbracket \wedge (x + y \leq 3))) \wedge \llbracket y \in [1, 3] \rrbracket$$

$$w(\mathbf{x}, \mathbf{A}) \stackrel{\text{def}}{=} \llbracket \text{If } A \text{ Then } (-x^2 - y^2 + 2x + 3y) \text{ Else } (-2x - 2y + 6) \rrbracket.$$

(Note that outside the support the two polynomials may acquire negative values.)



A very relevant subcase of $\text{FIUC}^{\mathcal{LRA}}$ functions: $\text{P}^{\mathcal{LRA}}$ functions

Definition ($\text{P}^{\mathcal{LRA}}$ weight function)

Given $\langle \mathbf{x}, \mathbf{A} \rangle$, Ψ and χ as in $\text{FIUC}^{\mathcal{LRA}}$ definition, a weight function $w(\mathbf{x}, \mathbf{A})$ is called **Polynomial under \mathcal{LRA} conditions, $\text{P}^{\mathcal{LRA}}$** iff, for every total assignment $\mu^{\mathbf{A}}$ on \mathbf{A} and μ^{Ψ} on Ψ , $w_{[\mu^{\mathbf{A}} \mu^{\Psi}]}(\mathbf{x})$ is a polynomial whose value is non-negative in the domain defined by μ^{Ψ} .

$\text{P}^{\mathcal{LRA}}$ functions are $\text{FIUC}^{\mathcal{LRA}}$ because polynomials can always be integrated exactly on sets of \mathcal{LRA} literals [7].

We define a grammar to express $\text{P}^{\mathcal{LRA}}$ weight functions:

$$\begin{aligned} w & ::= c \mid x \mid -w \mid (w + w) \mid (w - w) \mid (w \cdot w) \mid \\ & \quad \llbracket \text{If } \varphi \text{ Then } w \text{ Else } w \rrbracket \mid \\ & \quad \llbracket \text{Case } \varphi : w; \varphi : w; \dots \rrbracket \\ \chi & ::= \varphi \end{aligned}$$

where c is a real value, x is a real variable, w is a $\text{P}^{\mathcal{LRA}}$ weight function, φ is an \mathcal{LRA} formula.

A very relevant subcase of FIUC^{LR \mathcal{A}} functions: P^{LR \mathcal{A}} functions

Definition (P^{LR \mathcal{A}} weight function)

Given $\langle \mathbf{x}, \mathbf{A} \rangle$, Ψ and χ as in FIUC^{LR \mathcal{A}} definition, a weight function $w(\mathbf{x}, \mathbf{A})$ is called **Polynomial under LR \mathcal{A} conditions, P^{LR \mathcal{A}}** iff, for every total assignment $\mu^{\mathbf{A}}$ on \mathbf{A} and μ^{Ψ} on Ψ , $w_{[\mu^{\mathbf{A}}, \mu^{\Psi}]}(\mathbf{x})$ is a polynomial whose value is non-negative in the domain defined by μ^{Ψ} .

P^{LR \mathcal{A}} functions are FIUC^{LR \mathcal{A}} because polynomials can always be integrated exactly on sets of LR \mathcal{A} literals [7].

We define a grammar to express P^{LR \mathcal{A}} weight functions:

$$\begin{aligned} w & ::= c \mid x \mid -w \mid (w + w) \mid (w - w) \mid (w \cdot w) \mid \\ & \quad \llbracket \text{If } \varphi \text{ Then } w \text{ Else } w \rrbracket \mid \\ & \quad \llbracket \text{Case } \varphi : w; \varphi : w; \dots \rrbracket \\ \chi & ::= \varphi \end{aligned}$$

where c is a real value, x is a real variable, w is a P^{LR \mathcal{A}} weight function, φ is an LR \mathcal{A} formula.

A very relevant subcase of FIUC^{LR \mathcal{A}} functions: P^{LR \mathcal{A}} functions

Definition (P^{LR \mathcal{A}} weight function)

Given $\langle \mathbf{x}, \mathbf{A} \rangle$, Ψ and χ as in FIUC^{LR \mathcal{A}} definition, a weight function $w(\mathbf{x}, \mathbf{A})$ is called **Polynomial under LR \mathcal{A} conditions, P^{LR \mathcal{A}}** iff, for every total assignment $\mu^{\mathbf{A}}$ on \mathbf{A} and μ^{Ψ} on Ψ , $w_{[\mu^{\mathbf{A}} \mu^{\Psi}]}(\mathbf{x})$ is a polynomial whose value is non-negative in the domain defined by μ^{Ψ} .

P^{LR \mathcal{A}} functions are FIUC^{LR \mathcal{A}} because polynomials can always be integrated exactly on sets of LR \mathcal{A} literals [7].

We define a grammar to express P^{LR \mathcal{A}} weight functions:

$$\begin{aligned} w & ::= c \mid x \mid -w \mid (w + w) \mid (w - w) \mid (w \cdot w) \mid \\ & \quad \llbracket \text{If } \varphi \text{ Then } w \text{ Else } w \rrbracket \mid \\ & \quad \llbracket \text{Case } \varphi : w; \varphi : w; \dots \rrbracket \\ \chi & ::= \varphi \end{aligned}$$

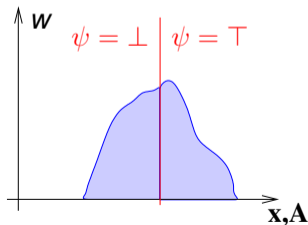
where c is a real value, x is a real variable, w is a P^{LR \mathcal{A}} weight function, φ is an LR \mathcal{A} formula.

Computing WMI with FIUC^{LR,A} weight functions

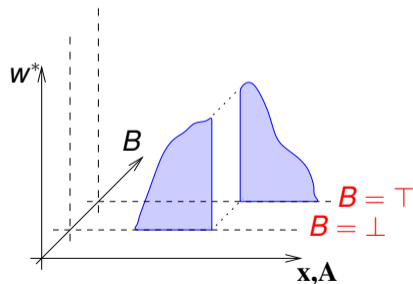
Theorem

Let $w(\mathbf{x}, \mathbf{A})$, $\Psi \stackrel{\text{def}}{=} \{\psi_1, \dots, \psi_K\}$ and χ be as above. Let $\mathbf{B} \stackrel{\text{def}}{=} \{B_1, \dots, B_K\}$ be fresh propositional atoms and let $w^*(\mathbf{x}, \mathbf{A} \cup \mathbf{B})$ be the weight function obtained by substituting in $w(\mathbf{x}, \mathbf{A})$ each condition ψ_k with B_k , for every $k \in [1..K]$. Let $\varphi^* \stackrel{\text{def}}{=} \varphi \wedge \chi \wedge \bigwedge_{k=1}^K (B_k \leftrightarrow \psi_k)$. Then:

$$\text{WMI}(\varphi \wedge \chi, w | \mathbf{x}, \mathbf{A}) = \text{WMI}(\varphi^*, w^* | \mathbf{x}, \mathbf{A} \cup \mathbf{B}).$$



$\text{WMI}(\varphi, w | \mathbf{x}, \mathbf{A})$



$\text{WMI}(\varphi \wedge (B \leftrightarrow \psi), w^* | \mathbf{x}, \mathbf{A} \cup \{B\})$

Computing WMI with FIUC^{LR.A} weight functions - Example

Example

Let

- $\mathbf{A} = \emptyset, \mathbf{x} = \{x\}$
- $\chi \stackrel{\text{def}}{=} \llbracket x \in [-1, 1] \rrbracket$,
- $\varphi \stackrel{\text{def}}{=} \top$,
- $\Psi \stackrel{\text{def}}{=} \{(x \geq 0)\}$,
- $w(x) \stackrel{\text{def}}{=} \llbracket \text{If } (x \geq 0) \text{ Then } x \text{ Else } -x \rrbracket$ (i.e., $w(x) \stackrel{\text{def}}{=} |x|$.)

Then $\text{WMI}(\varphi, w|x, \emptyset) = \text{WMI}_{\text{nb}}(\varphi, w|\mathbf{x}) = \int_{[-1,1]} |x| dx = 1$.

$\varphi^* = \llbracket x \in [-1, 1] \rrbracket \wedge (B \leftrightarrow (x \geq 0))$ and $w^* = \llbracket \text{If } B \text{ Then } x \text{ Else } -x \rrbracket$.

Then $\text{WMI}(\varphi^*, w^*|\mathbf{x}, \mathbf{B}) = 1$.

(See previous example, modulo reordering and variable renaming).

From WMI_{old} to WMI and vice versa

From WMI_{old} to WMI

We can easily express and compute WMI_{old} as WMI by an equivalent FIUC $^{\mathcal{LRA}}$ weight function:

$$WMI(\varphi, \prod_{\psi \in Atoms(\varphi)} \llbracket \text{If } \psi \text{ Then } w(\psi) \text{ Else } w(\neg\psi) \rrbracket | \mathbf{x}, \mathbf{A}).$$

From WMI to WMI_{old} ?

- AFAIK, there is no obvious general way to encode an arbitrary FIUC $^{\mathcal{LRA}}$ weight function into a WMI_{old} one while always preventing an explosion in the size of its representation.
 - Ex: $w(\mathbf{x}, \mathbf{A}) = \sum_{\mathbf{A}_j \in \mathbf{A}} \llbracket \text{If } \mathbf{A}_j \text{ Then } w_{j1}(\mathbf{x}) \text{ Else } w_{j2}(\mathbf{x}) \rrbracket$.
 - a trivial general solution:
 - for every total truth assignment $\mu \in \mathcal{T}TA(\varphi)$ add a fresh Boolean atom B_μ
 - $w(B_\mu) \stackrel{\text{def}}{=} w_\mu(\mathbf{x})$, $w(\neg B_\mu) \stackrel{\text{def}}{=} 1$, $w(l) \stackrel{\text{def}}{=} 1$ for every other literal l .
- \implies blows up in size wrt. $\|\mathbf{A}\|$

From WMI_{old} to WMI and vice versa

From WMI_{old} to WMI

We can easily express and compute WMI_{old} as WMI by an equivalent FIUC $^{\mathcal{LRA}}$ weight function:

$$WMI(\varphi, \prod_{\psi \in Atoms(\varphi)} \llbracket \text{If } \psi \text{ Then } w(\psi) \text{ Else } w(\neg\psi) \rrbracket | \mathbf{x}, \mathbf{A}).$$

From WMI to WMI_{old} ?

- AFAIK, there is no obvious general way to encode an arbitrary FIUC $^{\mathcal{LRA}}$ weight function into a WMI_{old} one while always preventing an explosion in the size of its representation.
 - Ex: $w(\mathbf{x}, \mathbf{A}) = \sum_{\mathbf{A}_j \in \mathbf{A}} \llbracket \text{If } \mathbf{A}_j \text{ Then } w_{j1}(\mathbf{x}) \text{ Else } w_{j2}(\mathbf{x}) \rrbracket$.
 - a trivial general solution:
 - for every total truth assignment $\mu \in TTA(\varphi)$ add a fresh Boolean atom B_μ
 - $w(B_\mu) \stackrel{\text{def}}{=} w_\mu(\mathbf{x})$, $w(\neg B_\mu) \stackrel{\text{def}}{=} 1$, $w(l) \stackrel{\text{def}}{=} 1$ for every other literal l .
- \implies blows up in size wrt. $\|\mathbf{A}\|$

Outline

- 1 Background
- 2 Weighted Model Integration, Revisited
- 3 SMT-Based WMI Computation**
- 4 A Case Study: The Road Network Problem
- 5 Experimental Evaluations
- 6 Ongoing and Future Work

Baseline

The Problem

Compute efficiently the WMI of a FIUC^{LR_A} weight function $w(\mathbf{x}, \mathbf{A})$, with support formula χ and set of conditions $\Psi \stackrel{\text{def}}{=} \{\psi_1, \dots, \psi_K\}$, over a formula $\varphi(\mathbf{x}, \mathbf{A})$.

Preprocessing

The problem is transformed into $\varphi^* \stackrel{\text{def}}{=} \varphi \wedge \chi \wedge \bigwedge_{k=1}^K (B_k \leftrightarrow \psi_k)$, $w^* \stackrel{\text{def}}{=} w[\mathbf{B} \leftarrow \Psi]$, and $\mathbf{A}^* \stackrel{\text{def}}{=} \mathbf{A} \cup \mathbf{B}$ by applying the Theorem: $\text{WMI}(\varphi \wedge \chi, w|\mathbf{x}, \mathbf{A}) = \text{WMI}(\varphi^*, w^*|\mathbf{x}, \mathbf{A} \cup \mathbf{B})$.

Baseline Procedure: WMI-AISMT

- Based on the proposition: $\text{WMI}(\varphi^*, w^*|\mathbf{x}, \mathbf{A}^*) = \sum_{\mu^{\mathbf{A}^*} \wedge \mu^{\text{LR}_{\mathbf{A}}}} \text{WMI}_{\text{nb}}(\mu^{\text{LR}_{\mathbf{A}}}, w_{[\mu^{\mathbf{A}^*}]}^*|\mathbf{x})$.
- $\text{TTA}(\varphi^*)$ is computed by AISMT (e.g., in MATHSAT5) without assignment-reduction
- $\text{WMI}_{\text{nb}}(\mu^{\text{LR}_{\mathbf{A}}}, w_{[\mu^{\mathbf{A}^*}]}^*|\mathbf{x})$ is computed by invoking our background integration procedure for FI^{LR_A} functions (e.g., by LATTE INTEGRALE [18])

Baseline

The Problem

Compute efficiently the WMI of a FIUC^{LR_A} weight function $w(\mathbf{x}, \mathbf{A})$, with support formula χ and set of conditions $\Psi \stackrel{\text{def}}{=} \{\psi_1, \dots, \psi_K\}$, over a formula $\varphi(\mathbf{x}, \mathbf{A})$.

Preprocessing

The problem is transformed into $\varphi^* \stackrel{\text{def}}{=} \varphi \wedge \chi \wedge \bigwedge_{k=1}^K (B_k \leftrightarrow \psi_k)$, $w^* \stackrel{\text{def}}{=} w[\mathbf{B} \leftarrow \Psi]$, and $\mathbf{A}^* \stackrel{\text{def}}{=} \mathbf{A} \cup \mathbf{B}$ by applying the Theorem: $\text{WMI}(\varphi \wedge \chi, w|\mathbf{x}, \mathbf{A}) = \text{WMI}(\varphi^*, w^*|\mathbf{x}, \mathbf{A} \cup \mathbf{B})$.

Baseline Procedure: WMI-AIISMT

- Based on the proposition: $\text{WMI}(\varphi^*, w^*|\mathbf{x}, \mathbf{A}^*) = \sum_{\mu^{\mathbf{A}^*} \wedge \mu^{\text{LR}_{\mathbf{A}}} \in \text{TTA}(\varphi^*)} \text{WMI}_{\text{nb}}(\mu^{\text{LR}_{\mathbf{A}}}, w_{[\mu^{\mathbf{A}^*}]}^*|\mathbf{x})$.
- $\text{TTA}(\varphi^*)$ is computed by AIISMT (e.g., in MATHSAT5) without assignment-reduction
- $\text{WMI}_{\text{nb}}(\mu^{\text{LR}_{\mathbf{A}}}, w_{[\mu^{\mathbf{A}^*}]}^*|\mathbf{x})$ is computed by invoking our background integration procedure for FI^{LR_A} functions (e.g., by LATTE INTEGRALE [18])

Baseline

The Problem

Compute efficiently the WMI of a FIUC ^{\mathcal{LRA}} weight function $w(\mathbf{x}, \mathbf{A})$, with support formula χ and set of conditions $\Psi \stackrel{\text{def}}{=} \{\psi_1, \dots, \psi_K\}$, over a formula $\varphi(\mathbf{x}, \mathbf{A})$.

Preprocessing

The problem is transformed into $\varphi^* \stackrel{\text{def}}{=} \varphi \wedge \chi \wedge \bigwedge_{k=1}^K (B_k \leftrightarrow \psi_k)$, $w^* \stackrel{\text{def}}{=} w[\mathbf{B} \leftarrow \Psi]$, and $\mathbf{A}^* \stackrel{\text{def}}{=} \mathbf{A} \cup \mathbf{B}$ by applying the Theorem: $\text{WMI}(\varphi \wedge \chi, w | \mathbf{x}, \mathbf{A}) = \text{WMI}(\varphi^*, w^* | \mathbf{x}, \mathbf{A} \cup \mathbf{B})$.

Baseline Procedure: WMI-AISMT

- Based on the proposition: $\text{WMI}(\varphi^*, w^* | \mathbf{x}, \mathbf{A}^*) = \sum_{\mu^{\mathbf{A}^*} \wedge \mu^{\mathcal{LRA}} \in \text{TTA}(\varphi^*)} \text{WMI}_{\text{nb}}(\mu^{\mathcal{LRA}}, w_{[\mu^{\mathbf{A}^*}]}^* | \mathbf{x})$.
- $\text{TTA}(\varphi^*)$ is computed by AISMT (e.g., in MATHSAT5) without assignment-reduction
- $\text{WMI}_{\text{nb}}(\mu^{\mathcal{LRA}}, w_{[\mu^{\mathbf{A}^*}]}^* | \mathbf{x})$ is computed by invoking our background integration procedure for FI ^{\mathcal{LRA}} functions (e.g., by LATTE INTEGRALE [18])

Efficient WMI procedure: WMI-PA

Efficient WMI procedure: WMI-PA

- Based on the propositions:

$$\begin{aligned} \text{WMI}(\varphi^*, w^* | \mathbf{x}, \mathbf{A}^*) &= \sum_{\mu^{\mathbf{A}^*} \in \mathcal{T}\mathcal{A}(\exists \mathbf{x}.\varphi^*)} \text{WMI}_{\text{nb}}(\varphi_{[\mu^{\mathbf{A}^*}]}, w_{[\mu^{\mathbf{A}^*}]}^* | \mathbf{x}) \\ \text{WMI}_{\text{nb}}(\varphi_{[\mu^{\mathbf{A}^*}]}, w_{[\mu^{\mathbf{A}^*}]}^* | \mathbf{x}) &= \sum_{\mu^{\mathcal{L}\mathcal{R}\mathcal{A}} \in \mathcal{T}\mathcal{A}(\varphi_{[\mu^{\mathbf{A}^*}]})} \text{WMI}_{\text{nb}}(\mu^{\mathcal{L}\mathcal{R}\mathcal{A}}, w_{[\mu^{\mathbf{A}^*}]}^* | \mathbf{x}). \end{aligned}$$

- $\mathcal{T}\mathcal{A}(\exists \mathbf{x}.\varphi^*)$ is computed by **Predicate Abstraction** $\mathcal{T}\mathcal{A}(\text{PredAbs}_{[\varphi^*]}(\mathbf{A}^*))$ [17] (in **MATHSAT5**)
- $\text{WMI}_{\text{nb}}(\varphi_{[\mu^{\mathbf{A}^*}]}, w_{[\mu^{\mathbf{A}^*}]}^* | \mathbf{x})$ is computed by **AllSMT with assignment-reduction** [17] (in **MATHSAT5**)
- $\varphi_{[\mu^{\mathbf{A}^*}]}$ aggressively simplified before invoking $\mathcal{T}\mathcal{A}()$ on it
 - reduces number of assignments in $\mathcal{T}\mathcal{A}(\varphi_{[\mu^{\mathbf{A}^*}]})$
 - if $\varphi_{[\mu^{\mathbf{A}^*}]}$ reduced to a conjunction of $\mathcal{L}\mathcal{R}\mathcal{A}$ -literals, then no need to invoke $\mathcal{T}\mathcal{A}()$
- $\text{WMI}_{\text{nb}}(\mu^{\mathcal{L}\mathcal{R}\mathcal{A}}, w_{[\mu^{\mathbf{A}^*}]}^* | \mathbf{x})$ can exploit **caching** of integral values

Efficient WMI procedure: WMI-PA (cont.)

WMI-PA($\varphi, w, \mathbf{x}, \mathbf{A}$)

$\langle \varphi^*, w^*, \mathbf{A}^* \rangle \leftarrow \text{LabelConditions}(\varphi, w, \mathbf{x}, \mathbf{A})$ // Apply Theorem

$\mathcal{M}^{\mathbf{A}^*} \leftarrow \text{TtA}(\text{PredAbs}_{[\varphi^*]}(\mathbf{A}^*))$ // $\text{TtA}(\exists \mathbf{x}. \varphi^*)$

$vol \leftarrow 0$

for $\mu^{\mathbf{A}^*} \in \mathcal{M}^{\mathbf{A}^*}$ **do**

 Simplify($\varphi_{[\mu^{\mathbf{A}^*}]}^*$) // remove as many \mathcal{LRA} -atoms as possible from $\varphi_{[\mu^{\mathbf{A}^*}]}^*$

if (IsLiteralConjunction($\varphi_{[\mu^{\mathbf{A}^*}]}^*$)) **then**

$vol \leftarrow vol + \text{WMI}_{\text{nb}}(\varphi_{[\mu^{\mathbf{A}^*}]}^*, w_{[\mu^{\mathbf{A}^*}]}^* | \mathbf{x})$

else

$\mathcal{M}^{\mathcal{LRA}} \leftarrow \text{TA}(\text{PredAbs}_{[\varphi_{[\mu^{\mathbf{A}^*}]}^*]}(\text{Atoms}(\varphi_{[\mu^{\mathbf{A}^*}]}^*)))$ // AllSMT with assignment-reduction

for $\mu^{\mathcal{LRA}} \in \mathcal{M}^{\mathcal{LRA}}$ **do**

$vol \leftarrow vol + \text{WMI}_{\text{nb}}(\mu^{\mathcal{LRA}}, w_{[\mu^{\mathbf{A}^*}]}^* | \mathbf{x})$

end for

end if

end for

return vol

WMI-PA vs. WMI-ALLSMT

WMI-PA decouples the enumeration of the $\mu^{\mathbf{A}^*}$ s from that of the $\mu^{\mathcal{LRA}}$ s

- $\mathcal{TTA}(\exists \mathbf{x}. \varphi^*)$ removes *a priori* all the assignments $\mu^{\mathbf{A}^*}$ which cannot be expanded by any \mathcal{LRA} -satisfiable assignment $\mu^{\mathcal{LRA}}$ s.t. $\mu^{\mathbf{A}^*} \wedge \mu^{\mathcal{LRA}}$ propositionally satisfies φ^*
- $\mathit{Atoms}(\varphi^*_{[\mu^{\mathbf{A}^*}]})$ can be much smaller than $\mathit{Atoms}(\varphi^*)$ by Simplify
 - (E.g., $(x \leq 1) \wedge (A_2 \vee (x \geq 0))$)_[A₂] is simplified into $(x \leq 1)$, so that $(x \geq 0)$ is eliminated.)
 \Rightarrow the number of assignments $\mu^{\mathbf{A}^*} \wedge \mu^{\mathcal{LRA}}$ can be drastically reduced
- search for a set $\mathcal{TA}(\dots)$ of **partial** assignments $\mu^{\mathcal{LRA}}$, each substituting $2^{(\dots)}$ total ones

WMI-PA vs. WMI-ALLSMT: Example

Example

$$w(\mathbf{x}, \mathbf{A}) = \llbracket \text{If } (y \leq 1) \text{ Then } f(x, y) \text{ Else } g(x, y) \rrbracket$$

$$\chi(\mathbf{x}, \mathbf{A}) \wedge (0 \leq y) \wedge (y \leq 2)$$

$$\wedge ((y \leq 1) \rightarrow ((0 \leq x) \wedge (x \leq 2)))$$

$$\wedge (\neg(y \leq 1) \rightarrow ((1 \leq x) \wedge (x \leq 3)))$$

$$\varphi(\mathbf{x}, \mathbf{A}) = \top$$

Note: $f(x, y)$ defined on $x \in [0, 2], y \in [0, 1]$, $g(x, y)$ defined on $x \in [1, 3], y \in [1, 2]$

After labelling

$$w^*(\mathbf{x}, \mathbf{A}^*) = \llbracket \text{If } B_1 \text{ Then } f(x, y) \text{ Else } g(x, y) \rrbracket$$

$$\varphi^*(\mathbf{x}, \mathbf{A}^*) = (B_1 \leftrightarrow (y \leq 1))$$

$$\wedge (0 \leq y) \wedge (y \leq 2)$$

$$\wedge ((y \leq 1) \rightarrow ((0 \leq x) \wedge (x \leq 2)))$$

$$\wedge (\neg(y \leq 1) \rightarrow ((1 \leq x) \wedge (x \leq 3)))$$

WMI-PA vs. WMI-ALLSMT: Example

Example

$$w(\mathbf{x}, \mathbf{A}) = \llbracket \text{If } (y \leq 1) \text{ Then } f(x, y) \text{ Else } g(x, y) \rrbracket$$

$$\chi(\mathbf{x}, \mathbf{A}) \wedge (0 \leq y) \wedge (y \leq 2)$$

$$\wedge ((y \leq 1) \rightarrow ((0 \leq x) \wedge (x \leq 2)))$$

$$\wedge (\neg(y \leq 1) \rightarrow ((1 \leq x) \wedge (x \leq 3)))$$

$$\varphi(\mathbf{x}, \mathbf{A}) = \top$$

Note: $f(x, y)$ defined on $x \in [0, 2], y \in [0, 1]$, $g(x, y)$ defined on $x \in [1, 3], y \in [1, 2]$

After labelling

$$w^*(\mathbf{x}, \mathbf{A}^*) = \llbracket \text{If } B_1 \text{ Then } f(x, y) \text{ Else } g(x, y) \rrbracket$$

$$\varphi^*(\mathbf{x}, \mathbf{A}^*) = (B_1 \leftrightarrow (y \leq 1))$$

$$\wedge (0 \leq y) \wedge (y \leq 2)$$

$$\wedge ((y \leq 1) \rightarrow ((0 \leq x) \wedge (x \leq 2)))$$

$$\wedge (\neg(y \leq 1) \rightarrow ((1 \leq x) \wedge (x \leq 3)))$$

WMI-PA vs. WMI-ALLSMT: Example (cont.)

After labelling

$$w^*(\mathbf{x}, \mathbf{A}^*) = \llbracket \text{If } B_1 \text{ Then } f(x, y) \text{ Else } g(x, y) \rrbracket$$

$$\begin{aligned} \varphi^*(\mathbf{x}, \mathbf{A}^*) = & (B_1 \leftrightarrow (y \leq 1)) \wedge (0 \leq y) \wedge (y \leq 2) \\ & \wedge ((y \leq 1) \rightarrow ((0 \leq x) \wedge (x \leq 2))) \\ & \wedge (\neg(y \leq 1) \rightarrow ((1 \leq x) \wedge (x \leq 3))) \end{aligned}$$

WMI-ALLSMT

- With WMI-ALLSMT, the integration on 4 total truth assignments is needed:

$$\left\{ \begin{array}{l} \{ B_1, (0 \leq y), (y \leq 2), (y \leq 1), (0 \leq x), (x \leq 2), (1 \leq x), (x \leq 3) \} \\ \{ B_1, (0 \leq y), (y \leq 2), (y \leq 1), (0 \leq x), (x \leq 2), \neg(1 \leq x), (x \leq 3) \} \\ \{ \neg B_1, (0 \leq y), (y \leq 2), \neg(y \leq 1), (0 \leq x), (x \leq 2), (1 \leq x), (x \leq 3) \} \\ \{ \neg B_1, (0 \leq y), (y \leq 2), \neg(y \leq 1), (0 \leq x), \neg(x \leq 2), (1 \leq x), (x \leq 3) \} \end{array} \right\}$$

$$\int_0^1 \int_0^1 f(x, y) \, dx \, dy + \int_0^1 \int_1^2 f(x, y) \, dx \, dy + \int_1^2 \int_1^2 g(x, y) \, dx \, dy + \int_1^2 \int_2^3 g(x, y) \, dx \, dy$$

- two useless partitions: on $[0, 1] \times [1, 2]$ and on $[1, 2] \times [2, 3]$

WMI-PA vs. WMI-ALLSMT: Example (cont.)

After labelling

$$w^*(\mathbf{x}, \mathbf{A}^*) = \llbracket \text{If } B_1 \text{ Then } f(x, y) \text{ Else } g(x, y) \rrbracket$$

$$\begin{aligned} \varphi^*(\mathbf{x}, \mathbf{A}^*) = & (B_1 \leftrightarrow (y \leq 1)) \wedge (0 \leq y) \wedge (y \leq 2) \\ & \wedge ((y \leq 1) \rightarrow ((0 \leq x) \wedge (x \leq 2))) \\ & \wedge (\neg(y \leq 1) \rightarrow ((1 \leq x) \wedge (x \leq 3))) \end{aligned}$$

WMI-ALLSMT

- With WMI-ALLSMT, the integration on 4 total truth assignments is needed:

$$\left\{ \begin{array}{l} \{ B_1, (0 \leq y), (y \leq 2), (y \leq 1), (0 \leq x), (x \leq 2), (1 \leq x), (x \leq 3) \} \\ \{ B_1, (0 \leq y), (y \leq 2), (y \leq 1), (0 \leq x), (x \leq 2), \neg(1 \leq x), (x \leq 3) \} \\ \{ \neg B_1, (0 \leq y), (y \leq 2), \neg(y \leq 1), (0 \leq x), (x \leq 2), (1 \leq x), (x \leq 3) \} \\ \{ \neg B_1, (0 \leq y), (y \leq 2), \neg(y \leq 1), (0 \leq x), \neg(x \leq 2), (1 \leq x), (x \leq 3) \} \end{array} \right\}$$

$$\int_0^1 \int_0^1 f(x, y) \, dx \, dy + \int_0^1 \int_1^2 f(x, y) \, dx \, dy + \int_1^2 \int_1^2 g(x, y) \, dx \, dy + \int_1^2 \int_2^3 g(x, y) \, dx \, dy$$

- two useless partitions: on $(1 \leq x)$ and on $(x \leq 2)$

WMI-PA vs. WMI-ALLSMT: Example (cont.)

After labelling

$$w^*(\mathbf{x}, \mathbf{A}^*) = \llbracket \text{If } B_1 \text{ Then } f(x, y) \text{ Else } g(x, y) \rrbracket$$

$$\begin{aligned} \varphi^*(\mathbf{x}, \mathbf{A}^*) = & (B_1 \leftrightarrow (y \leq 1)) \wedge (0 \leq y) \wedge (y \leq 2) \\ & \wedge ((y \leq 1) \rightarrow ((0 \leq x) \wedge (x \leq 2))) \\ & \wedge (\neg(y \leq 1) \rightarrow ((1 \leq x) \wedge (x \leq 3))) \end{aligned}$$

WMI-ALLSMT

- With WMI-ALLSMT, the integration on 4 total truth assignments is needed:

$$\left\{ \begin{array}{l} \{ B_1, (0 \leq y), (y \leq 2), (y \leq 1), (0 \leq x), (x \leq 2), (1 \leq x), (x \leq 3) \} \\ \{ B_1, (0 \leq y), (y \leq 2), (y \leq 1), (0 \leq x), (x \leq 2), \neg(1 \leq x), (x \leq 3) \} \\ \{ \neg B_1, (0 \leq y), (y \leq 2), \neg(y \leq 1), (0 \leq x), (x \leq 2), (1 \leq x), (x \leq 3) \} \\ \{ \neg B_1, (0 \leq y), (y \leq 2), \neg(y \leq 1), (0 \leq x), \neg(x \leq 2), (1 \leq x), (x \leq 3) \} \end{array} \right\}$$
$$\int_0^1 \int_0^1 f(x, y) \, dx \, dy + \int_0^1 \int_1^2 f(x, y) \, dx \, dy + \int_1^2 \int_1^2 g(x, y) \, dx \, dy + \int_1^2 \int_2^3 g(x, y) \, dx \, dy$$

- two useless partitions: on $(1 \leq x)$ and on $(x \leq 2)$

WMI-PA vs. WMI-ALLSMT: Example (cont.)

After labelling

$$w^*(\mathbf{x}, \mathbf{A}^*) = \llbracket \text{If } B_1 \text{ Then } f(x, y) \text{ Else } g(x, y) \rrbracket$$

$$\begin{aligned} \varphi^*(\mathbf{x}, \mathbf{A}^*) = & (B_1 \leftrightarrow (y \leq 1)) \wedge (0 \leq y) \wedge (y \leq 2) \\ & \wedge ((y \leq 1) \rightarrow ((0 \leq x) \wedge (x \leq 2))) \\ & \wedge (\neg(y \leq 1) \rightarrow ((1 \leq x) \wedge (x \leq 3))) \end{aligned}$$

WMI-ALLSMT

- With WMI-ALLSMT, the integration on 4 total truth assignments is needed:

$$\left\{ \begin{array}{l} \{ B_1, (0 \leq y), (y \leq 2), (y \leq 1), (0 \leq x), (x \leq 2), (1 \leq x), (x \leq 3) \} \\ \{ B_1, (0 \leq y), (y \leq 2), (y \leq 1), (0 \leq x), (x \leq 2), \neg(1 \leq x), (x \leq 3) \} \\ \{ \neg B_1, (0 \leq y), (y \leq 2), \neg(y \leq 1), (0 \leq x), (x \leq 2), (1 \leq x), (x \leq 3) \} \\ \{ \neg B_1, (0 \leq y), (y \leq 2), \neg(y \leq 1), (0 \leq x), \neg(x \leq 2), (1 \leq x), (x \leq 3) \} \end{array} \right\}$$

$$\int_0^1 \int_0^1 f(x, y) \, dx \, dy + \int_0^1 \int_1^2 f(x, y) \, dx \, dy + \int_1^2 \int_1^2 g(x, y) \, dx \, dy + \int_1^2 \int_2^3 g(x, y) \, dx \, dy$$

- two useless partitions: on $(1 \leq x)$ and on $(x \leq 2)$

WMI-PA vs. WMI-ALLSMT: Example (cont.)

After labelling

$$w^*(\mathbf{x}, \mathbf{A}^*) = \llbracket \text{If } B_1 \text{ Then } f(x, y) \text{ Else } g(x, y) \rrbracket$$

$$\begin{aligned} \varphi^*(\mathbf{x}, \mathbf{A}^*) = & (B_1 \leftrightarrow (y \leq 1)) \wedge (0 \leq y) \wedge (y \leq 2) \\ & \wedge ((y \leq 1) \rightarrow ((0 \leq x) \wedge (x \leq 2))) \\ & \wedge (\neg(y \leq 1) \rightarrow ((1 \leq x) \wedge (x \leq 3))) \end{aligned}$$

WMI-ALLSMT

- With WMI-ALLSMT, the integration on 4 total truth assignments is needed:

$$\left\{ \begin{array}{l} \{ B_1, (0 \leq y), (y \leq 2), (y \leq 1), (0 \leq x), (x \leq 2), (1 \leq x), (x \leq 3) \} \\ \{ B_1, (0 \leq y), (y \leq 2), (y \leq 1), (0 \leq x), (x \leq 2), \neg(1 \leq x), (x \leq 3) \} \\ \{ \neg B_1, (0 \leq y), (y \leq 2), \neg(y \leq 1), (0 \leq x), (x \leq 2), (1 \leq x), (x \leq 3) \} \\ \{ \neg B_1, (0 \leq y), (y \leq 2), \neg(y \leq 1), (0 \leq x), \neg(x \leq 2), (1 \leq x), (x \leq 3) \} \end{array} \right\}$$

$$\int_0^1 \int_0^1 f(x, y) \, dx \, dy + \int_0^1 \int_1^2 f(x, y) \, dx \, dy + \int_1^2 \int_1^2 g(x, y) \, dx \, dy + \int_1^2 \int_2^3 g(x, y) \, dx \, dy$$

- two useless partitions: on $(1 \leq x)$ and on $(x \leq 2)$

WMI-PA vs. WMI-ALLSMT: Example (cont.)

After labelling

$$w^*(\mathbf{x}, \mathbf{A}^*) = \llbracket \text{If } B_1 \text{ Then } f(x, y) \text{ Else } g(x, y) \rrbracket$$

$$\begin{aligned} \varphi^*(\mathbf{x}, \mathbf{A}^*) = & (B_1 \leftrightarrow (y \leq 1)) \wedge (0 \leq y) \wedge (y \leq 2) \\ & \wedge ((y \leq 1) \rightarrow ((0 \leq x) \wedge (x \leq 2))) \\ & \wedge (\neg(y \leq 1) \rightarrow ((1 \leq x) \wedge (x \leq 3))) \end{aligned}$$

WMI-ALLSMT

- With WMI-ALLSMT, the integration on 4 total truth assignments is needed:

$$\left\{ \begin{array}{l} \{ B_1, (0 \leq y), (y \leq 2), (y \leq 1), (0 \leq x), (x \leq 2), (1 \leq x), (x \leq 3) \} \\ \{ B_1, (0 \leq y), (y \leq 2), (y \leq 1), (0 \leq x), (x \leq 2), \neg(1 \leq x), (x \leq 3) \} \\ \{ \neg B_1, (0 \leq y), (y \leq 2), \neg(y \leq 1), (0 \leq x), (x \leq 2), (1 \leq x), (x \leq 3) \} \\ \{ \neg B_1, (0 \leq y), (y \leq 2), \neg(y \leq 1), (0 \leq x), \neg(x \leq 2), (1 \leq x), (x \leq 3) \} \end{array} \right\}$$

$$\int_0^1 \int_0^1 f(x, y) \, dx \, dy + \int_0^1 \int_1^2 f(x, y) \, dx \, dy + \int_1^2 \int_1^2 g(x, y) \, dx \, dy + \int_1^2 \int_2^3 g(x, y) \, dx \, dy$$

- two useless partitions: on $(1 \leq x)$ and on $(x \leq 2)$

WMI-PA vs. WMI-ALLSMT: Example (cont.)

After labelling

$$w^*(\mathbf{x}, \mathbf{A}^*) = \llbracket \text{If } B_1 \text{ Then } f(x, y) \text{ Else } g(x, y) \rrbracket$$

$$\begin{aligned} \varphi^*(\mathbf{x}, \mathbf{A}^*) = & (B_1 \leftrightarrow (y \leq 1)) \wedge (0 \leq y) \wedge (y \leq 2) \\ & \wedge ((y \leq 1) \rightarrow ((0 \leq x) \wedge (x \leq 2))) \\ & \wedge (\neg(y \leq 1) \rightarrow ((1 \leq x) \wedge (x \leq 3))) \end{aligned}$$

WMI-PA Computation

$$\mathcal{M}^{\mathbf{A}^*} = \{\overbrace{\{B_1\}}^{\mu_1}, \{\neg B_1\}\}$$

$$w_{[\mu_1]}^*(\mathbf{x}, \mathbf{A}^*) = f(x, y)$$

$$\begin{aligned} \varphi_{[\mu_1]}^*(\mathbf{x}, \mathbf{A}^*) = & (\top \leftrightarrow (y \leq 1)) \wedge (0 \leq y) \wedge (y \leq 2) \\ & \wedge ((y \leq 1) \rightarrow ((0 \leq x) \wedge (x \leq 2))) \\ & \wedge (\neg(y \leq 1) \rightarrow ((1 \leq x) \wedge (x \leq 3))) \end{aligned}$$

$$\text{Simplify}(\varphi_{[\mu_1]}^*) = (y \leq 1) \wedge (0 \leq y) \wedge (y \leq 2) \wedge ((0 \leq x) \wedge (x \leq 2))$$

$$\int_{\varphi_{[\mu_1]}^*} w_{[\mu_1]}^* d\mathbf{x} = \int_0^1 \int_0^2 f(x, y) dx dy$$

WMI-PA vs. WMI-ALLSMT: Example (cont.)

After labelling

$$w^*(\mathbf{x}, \mathbf{A}^*) = \llbracket \text{If } B_1 \text{ Then } f(x, y) \text{ Else } g(x, y) \rrbracket$$

$$\begin{aligned} \varphi^*(\mathbf{x}, \mathbf{A}^*) = & (B_1 \leftrightarrow (y \leq 1)) \wedge (0 \leq y) \wedge (y \leq 2) \\ & \wedge ((y \leq 1) \rightarrow ((0 \leq x) \wedge (x \leq 2))) \\ & \wedge (\neg(y \leq 1) \rightarrow ((1 \leq x) \wedge (x \leq 3))) \end{aligned}$$

WMI-PA Computation

$$\mathcal{M}^{\mathbf{A}^*} = \{\{B_1\}, \overbrace{\{\neg B_1\}}^{\mu_2}\}$$

$$w_{[\mu_2]}^*(\mathbf{x}, \mathbf{A}^*) = g(x, y)$$

$$\begin{aligned} \varphi_{[\mu_2]}^*(\mathbf{x}, \mathbf{A}^*) = & (\perp \leftrightarrow (y \leq 1)) \wedge (0 \leq y) \wedge (y \leq 2) \\ & \wedge ((y \leq 1) \rightarrow ((0 \leq x) \wedge (x \leq 2))) \\ & \wedge (\neg(y \leq 1) \rightarrow ((1 \leq x) \wedge (x \leq 3))) \end{aligned}$$

$$\text{Simplify}(\varphi_{[\mu_2]}^*) = \neg(y \leq 1) \wedge (0 \leq y) \wedge (y \leq 2) \wedge ((1 \leq x) \wedge (x \leq 3))$$

$$\int_{\varphi_{[\mu_2]}^*} w_{[\mu_2]}^* d\mathbf{x} = \int_1^2 \int_1^3 g(x, y) dx dy$$

Outline

- 1 Background
- 2 Weighted Model Integration, Revisited
- 3 SMT-Based WMI Computation
- 4 A Case Study: The Road Network Problem**
- 5 Experimental Evaluations
- 6 Ongoing and Future Work

Case Study 1: The Road Network Problem, Fixed Path

Given :

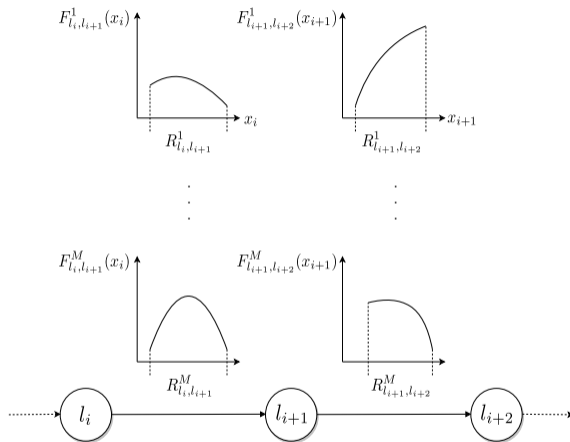
- a path of $N + 1$ consecutive adjacent locations $\{l_0, \dots, l_N\}$ in a road network (implicit)
- (the part of interest of) the day partitioned into disjoint consecutive intervals $\{I^1, \dots, I^M\}$
- for each pair $\langle l_i, l_j \rangle$ of adjacent locations, for each time interval $I^m \stackrel{\text{def}}{=} [c_m, c_{m+1})$, the distribution of the journey time from l_i to l_j at any time $t \in I^m$:
 - $f_{l_i, l_j}^m : \mathbb{R} \mapsto \mathbb{R}^+$ is such distribution
 - $R_{l_i, l_j}^m \stackrel{\text{def}}{=} [a_{l_i, l_j}^m, b_{l_i, l_j}^m)$ is its support.

Note: the time slots I^m s are disjoint, the supports R_{l_i, l_j}^m s are not disjoint.

- two values: departure time t_{dep} and maximum arrival time t_{arr}
- variables: for $n \in [0 \dots N]$,
 - x_n the journey time between l_{n-1} and l_n ,
 - t_n is the time at step n , i.e., $t_n \stackrel{\text{def}}{=} t_0 + \sum_{i=1}^{n-1} x_i$

Query: $P(t_N \leq t_{\text{arr}} \mid t_0 = t_{\text{dep}}, \{l_i\}_{i=0}^N)$. (The locations $\{l_i\}_{i=0}^N$ are left implicit.)

Case Study 1: The Road Network Problem, Fixed Path (cont.)



Journey time densities for a pair of consecutive time steps, from location l_i to l_{i+2} . Each edge shows the corresponding journey time distribution for each of the intervals.

The Road Network Problem, Fixed Path: Encoding

Let $\mathbf{x} \stackrel{\text{def}}{=} \{x_1, \dots, x_N\}$, $\mathbf{A} \stackrel{\text{def}}{=} \emptyset$, and “ t_n ” be a shortcut for the term “ $\sum_{i=1}^n x_i + t_0$ ”. Then:

$$w(\mathbf{x}) \stackrel{\text{def}}{=} \prod_{n=1}^N \left[\text{Case } \llbracket t_{n-1} \in I^1 \rrbracket : f_{l_{n-1}, l_n}^1(x_n); \dots \llbracket t_{n-1} \in I^M \rrbracket : f_{l_{n-1}, l_n}^M(x_n) \right]$$

$$\begin{aligned} \chi(\mathbf{x}) &\stackrel{\text{def}}{=} \bigwedge_{n=0}^N \llbracket t_n \in \bigcup_{m=1}^M I^m \rrbracket \\ &\wedge \bigwedge_{n=1}^N \bigwedge_{m=1}^M (\llbracket t_{n-1} \in I^m \rrbracket \rightarrow \llbracket x_n \in R_{l_{n-1}, l_n}^m \rrbracket) \end{aligned}$$

$$\varphi(\mathbf{x}) \stackrel{\text{def}}{=} \top$$

$$P(t_N \leq t_{\text{arr}} \mid t_0 = t_{\text{dep}}, \{l_i\}_{i=0}^N) = \frac{\text{WMI}_{\text{nb}}(\chi(\mathbf{x}) \wedge (t_N \leq t_{\text{arr}}) \wedge (t_0 = t_{\text{dep}}), w(\mathbf{x}) \mid \mathbf{x})}{\text{WMI}_{\text{nb}}(\chi(\mathbf{x}) \wedge (t_0 = t_{\text{dep}}), w(\mathbf{x}) \mid \mathbf{x})}$$

If each $f_{l_i, l_j}^m(x)$ is polynomial in $x \in R_{l_i, l_j}^m$, then $w(\mathbf{x})$ is $\text{P}^{\mathcal{LRA}}$ and hence $\text{FIUC}^{\mathcal{LRA}}$. Thus we can apply the theorem:

$$\varphi^*(\mathbf{x}, \mathbf{B}) \stackrel{\text{def}}{=} \varphi(\mathbf{x}) \wedge \chi(\mathbf{x}) \wedge \bigwedge_{n=1}^N \bigwedge_{m=1}^M (B_{n-1}^m \leftrightarrow \llbracket t_{n-1} \in I^m \rrbracket)$$

$$w^*(\mathbf{x}, \mathbf{B}) \stackrel{\text{def}}{=} \prod_{n=1}^N \left[\text{Case } B_{n-1}^1 : f_{l_{n-1}, l_n}^1(x_n); \dots B_{n-1}^M : f_{l_{n-1}, l_n}^M(x_n) \right].$$

The Road Network Problem, Fixed Path: Encoding

Let $\mathbf{x} \stackrel{\text{def}}{=} \{x_1, \dots, x_N\}$, $\mathbf{A} \stackrel{\text{def}}{=} \emptyset$, and “ t_n ” be a shortcut for the term “ $\sum_{i=1}^n x_i + t_0$ ”. Then:

$$w(\mathbf{x}) \stackrel{\text{def}}{=} \prod_{n=1}^N \left[\text{Case } \llbracket t_{n-1} \in I^1 \rrbracket : f_{l_{n-1}, l_n}^1(x_n); \dots \llbracket t_{n-1} \in I^M \rrbracket : f_{l_{n-1}, l_n}^M(x_n) \right]$$

$$\begin{aligned} \chi(\mathbf{x}) &\stackrel{\text{def}}{=} \bigwedge_{n=0}^N \llbracket t_n \in \bigcup_{m=1}^M I^m \rrbracket \\ &\wedge \bigwedge_{n=1}^N \bigwedge_{m=1}^M (\llbracket t_{n-1} \in I^m \rrbracket \rightarrow \llbracket x_n \in R_{l_{n-1}, l_n}^m \rrbracket) \end{aligned}$$

$$\varphi(\mathbf{x}) \stackrel{\text{def}}{=} \top$$

$$P(t_N \leq t_{\text{arr}} \mid t_0 = t_{\text{dep}}, \{l_i\}_{i=0}^N) = \frac{\text{WMI}_{\text{nb}}(\chi(\mathbf{x}) \wedge (t_N \leq t_{\text{arr}}) \wedge (t_0 = t_{\text{dep}}), w(\mathbf{x}) \mid \mathbf{x})}{\text{WMI}_{\text{nb}}(\chi(\mathbf{x}) \wedge (t_0 = t_{\text{dep}}), w(\mathbf{x}) \mid \mathbf{x})}$$

If each $f_{l_i, l_j}^m(x)$ is polynomial in $x \in R_{l_i, l_j}^m$, then $w(\mathbf{x})$ is $\text{P}^{\mathcal{LRA}}$ and hence $\text{FIUC}^{\mathcal{LRA}}$. Thus we can apply the theorem:

$$\varphi^*(\mathbf{x}, \mathbf{B}) \stackrel{\text{def}}{=} \varphi(\mathbf{x}) \wedge \chi(\mathbf{x}) \wedge \bigwedge_{n=1}^N \bigwedge_{m=1}^M (B_{n-1}^m \leftrightarrow \llbracket t_{n-1} \in I^m \rrbracket)$$

$$w^*(\mathbf{x}, \mathbf{B}) \stackrel{\text{def}}{=} \prod_{n=1}^N \left[\text{Case } B_{n-1}^1 : f_{l_{n-1}, l_n}^1(x_n); \dots B_{n-1}^M : f_{l_{n-1}, l_n}^M(x_n) \right].$$

The Road Network Problem, Fixed Path: Example

Example

$$\begin{aligned}
 \chi(\mathbf{x}) &\stackrel{\text{def}}{=} \llbracket t_0 \in [7, 10] \rrbracket \\
 &\quad \wedge \llbracket t_0 + x_1 \in [7, 10] \rrbracket \\
 &\quad \wedge \llbracket t_0 \in [7, 8] \rrbracket \rightarrow \llbracket x_1 \in [0.5, 1] \rrbracket \\
 &\quad \wedge \llbracket t_0 \in [8, 9] \rrbracket \rightarrow \llbracket x_1 \in [1, 1.5] \rrbracket \\
 &\quad \wedge \llbracket t_0 \in [9, 10] \rrbracket \rightarrow \llbracket x_1 \in [1, 2] \rrbracket \\
 &\quad \wedge \llbracket t_0 + x_1 \in [7, 8] \rrbracket \rightarrow \llbracket x_2 \in [1, 1.5] \rrbracket \\
 &\quad \wedge \llbracket t_0 + x_1 \in [8, 9] \rrbracket \rightarrow \llbracket x_2 \in [1.5, 2] \rrbracket \\
 &\quad \wedge \llbracket t_0 + x_1 \in [9, 10] \rrbracket \rightarrow \llbracket x_2 \in [1, 2] \rrbracket
 \end{aligned}$$

$$w(\mathbf{x}) \stackrel{\text{def}}{=} \left[\begin{array}{l} \text{Case} \\ \llbracket t_0 \in [7, 8] \rrbracket : w_{[0.5, 1]}^1(x_1); \\ \llbracket t_0 \in [8, 9] \rrbracket : w_{[0.5, 1]}^2(x_1); \\ \llbracket t_0 \in [9, 10] \rrbracket : w_{[0.5, 1]}^3(x_1); \end{array} \right] \cdot \left[\begin{array}{l} \text{Case} \\ \llbracket t_0 + x_1 \in [7, 8] \rrbracket : w_{[1, 1.5]}^1(x_2); \\ \llbracket t_0 + x_1 \in [8, 9] \rrbracket : w_{[1, 1.5]}^2(x_2); \\ \llbracket t_0 + x_1 \in [9, 10] \rrbracket : w_{[1, 1.5]}^3(x_2); \end{array} \right]$$

$$\varphi(\mathbf{x}) \stackrel{\text{def}}{=} \top$$

where the $w_{[l_{n-1}, l_n]}^m(x_n)$ are functions which are integrable and positive in their respective domain stated in $\chi(\mathbf{x})$ (e.g., $w_{[0.5, 1]}^1(x_1)$ is integrable and positive in $\llbracket x_1 \in [0.5, 1] \rrbracket$).

The Road Network Problem, Fixed Path: Example (cont.)

Example

Then, by applying the theorem:

$$\begin{aligned}\varphi^*(\mathbf{x}, \mathbf{B}) &\stackrel{\text{def}}{=} \varphi(\mathbf{x}) \wedge \chi(\mathbf{x}) \\ &\wedge (B_0^1 \leftrightarrow \llbracket t_0 \in [7, 8] \rrbracket) \\ &\wedge \dots \\ &\wedge (B_1^3 \leftrightarrow \llbracket t_0 + x_1 \in [9, 10] \rrbracket)\end{aligned}$$

$$w^*(\mathbf{x}, \mathbf{B}) \stackrel{\text{def}}{=} \left[\begin{array}{l} \text{Case} \\ B_0^1 : w_{[t_0, t_1]}^1(x_1); \\ B_0^2 : w_{[t_0, t_1]}^2(x_1); \\ B_0^3 : w_{[t_0, t_1]}^3(x_1); \end{array} \right] \cdot \left[\begin{array}{l} \text{Case} \\ B_1^1 : w_{[t_1, t_2]}^1(x_2); \\ B_1^2 : w_{[t_1, t_2]}^2(x_2); \\ B_1^3 : w_{[t_1, t_2]}^3(x_2); \end{array} \right]$$

Case Study 2: The Road Network Problem under Conditional Plan

Given:

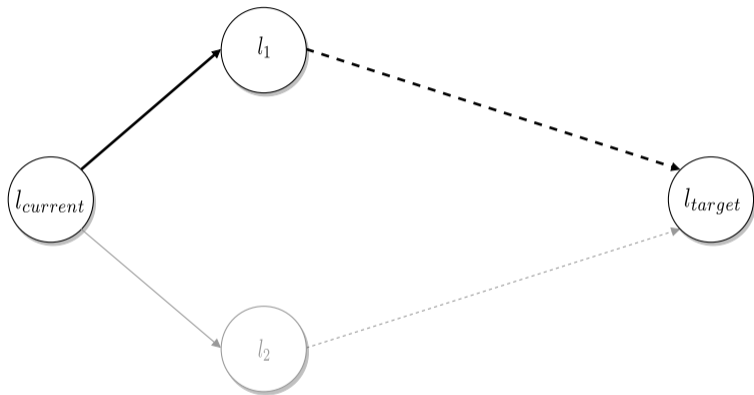
- Time intervals I^m s, variables x_n s and t_n s, values t_{dep} and t_{arr} , distributions of journey times f_{l_i, l_j}^m s and supports R_{l_i, l_j}^m (for all $\langle l_i, l_j \rangle$ s in the network): as with the fixed-path case.
- **The path in the road network is not given in advance.** Instead it is given:
 - a maximum path length N
 - an initial location l_{dep} and final target location l_{target}
 - a **conditional plan**, s.t., for any current location l and time interval index m , $\text{next}(l, m, l_{\text{target}})$ is the next location in the path (mimics empirical knowledge of the driver)

(for l_{target} , $\text{next}(l_{\text{target}}, m, l_{\text{target}}) \stackrel{\text{def}}{=} l_{\text{target}}$ and $R_{l_{\text{target}}, l_{\text{target}}}^m \stackrel{\text{def}}{=} [0, 0]$)

Query: $P(t_N \leq t_{\text{arr}} \mid t_0 = t_{\text{dep}}, l_{\text{dep}}, l_{\text{target}}, \text{next})$.

Case Study 2: The Road Network Problem under Cond. Plan (cont.)

k	$next(l_{current}, k, l_{target})$
1	l_2
m	l_1
M	l_2



Two alternative (sub)paths from l_{curr} to l_{target} .

The successor of l_{curr} is selected according to the time interval at which the node is reached.

The Road Network Problem with Conditional Plan: Encoding

Let $\mathbf{x} \stackrel{\text{def}}{=} \{x_1, \dots, x_N\}$, $\mathbf{A} \stackrel{\text{def}}{=} \{A_{01}, \dots, A_{NL}\}$, and “ t_n ” be a shortcut for the term “ $\sum_{i=1}^n x_i + t_0$ ”.

$$\begin{aligned} \chi(\mathbf{x}, \mathbf{A}) &\stackrel{\text{def}}{=} \bigwedge_{n=0}^N \left[t_n \in \bigcup_{m=1}^M I^m \right] \wedge \bigwedge_{n=0}^N \left[\text{OneOf} \{ A_{n,l} \mid l \in [1, L] \} \right] \\ &\quad \wedge \bigwedge_{n=1}^N \left(\bigwedge_{l=1}^L \left(A_{n-1,l} \rightarrow \bigwedge_{m=1}^M \left(\left[t_{n-1} \in I^m \right] \rightarrow \left[x_n \in R_{l, \text{next}(l,m,t_{\text{target}})}^m \right] \right) \right) \right), \\ \varphi(\mathbf{x}, \mathbf{A}) &\stackrel{\text{def}}{=} A_{0,t_0} \wedge \bigwedge_{n=1}^N \left(\bigwedge_{l=1}^L \left(A_{n-1,l} \rightarrow \bigwedge_{m=1}^M \left(\left[t_{n-1} \in I^m \right] \rightarrow A_{n, \text{next}(l,m,t_{\text{target}})} \right) \right) \right) \end{aligned}$$

$$w(\mathbf{x}, \mathbf{A}) \stackrel{\text{def}}{=} \prod_{n=1}^N \left[\begin{array}{l} \text{Case} \\ (A_{n-1,l_1} \wedge A_{n,l_2}) : \\ \quad \left[\text{Case } \left[t_{n-1} \in I^1 \right] : f_{l_1,l_2}^1(x_n); \dots; \left[t_{n-1} \in I^M \right] : f_{l_1,l_2}^M(x_n) \right]; \\ (A_{n-1,l_1} \wedge A_{n,l_3}) : \\ \quad \left[\text{Case } \left[t_{n-1} \in I^1 \right] : f_{l_1,l_3}^1(x_n); \dots; \left[t_{n-1} \in I^M \right] : f_{l_1,l_3}^M(x_n) \right]; \\ \dots \\ (A_{n-1,l_L} \wedge A_{n,l_{L-1}}) : \\ \quad \left[\text{Case } \left[t_{n-1} \in I^1 \right] : f_{l_L,l_{L-1}}^1(x_n); \dots; \left[t_{n-1} \in I^M \right] : f_{l_L,l_{L-1}}^M(x_n) \right]; \end{array} \right]$$

Note: in $w(\mathbf{x}, \mathbf{A})$ the case “ $A_{n-1,l_i} \wedge A_{n,l_j}$ ” is considered only if $\langle l_i, l_j \rangle$ adjacent and $l_j = \text{next}(l_i, m, t_{\text{target}})$ for some m .

$$P(t_N \leq t_{\text{arr}} \mid t_0 = t_{\text{dep}}, l_{\text{dep}}, l_{\text{target}}, \text{next}) = \frac{\text{WMI}(\varphi(\mathbf{x}, \mathbf{A}) \wedge \chi(\mathbf{x}, \mathbf{A}) \wedge (t_N \leq t_{\text{arr}}) \wedge (t_0 = t_{\text{dep}}), w(\mathbf{x}, \mathbf{A}) \mid \mathbf{x}, \mathbf{A})}{\text{WMI}(\varphi(\mathbf{x}, \mathbf{A}) \wedge \chi(\mathbf{x}, \mathbf{A}) \wedge (t_0 = t_{\text{dep}}), w(\mathbf{x}, \mathbf{A}) \mid \mathbf{x}, \mathbf{A})}$$

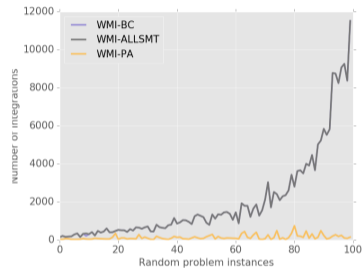
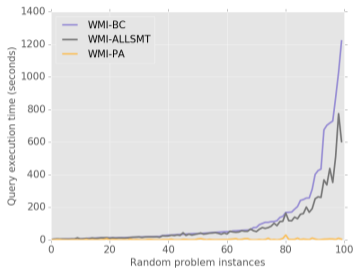
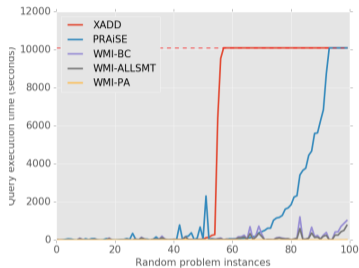
Outline

- 1 Background
- 2 Weighted Model Integration, Revisited
- 3 SMT-Based WMI Computation
- 4 A Case Study: The Road Network Problem
- 5 Experimental Evaluations**
- 6 Ongoing and Future Work

Experimental Evaluation: Description

- We compared the following tools:
 - **WMI-BC** is our re-implementation of the WMI_{old} procedure in [8];
 - **WMI-ALLSMT** and **WMI-PA**;
 - **SVE-XADD** is the tool in [24] we adapted to parse our input format;
 - **PRAISE** is the tool of Probabilistic Inference Modulo Theories [13].
- In WMI-BC, WMI-ALLSMT and WMI-PA we use
 - **MATHSAT5** [11, 1] for SMT reasoning
 - **LATTE INTEGRALE** [18, 2] to compute integrals of polynomials
 - **SYMPY** [3], a Python library for symbolic mathematics, for weight manipulations
- Experiments:
 - **synthetic settings** [19, 20]
 - real-world **Strategic Road Network Dataset** [4] by the English Highways Agency (both fixed-path and conditional-plan)
- run on 7-core Virtual Machine, 2.2 GHz and 94 GB of RAM
- timeout at 10,000 seconds for each $\langle \text{query}, \text{tool} \rangle$ job pair
- **if terminating, all tools returned the same values on the same queries (modulo roundings)**
- tools, data, and scripts used for experiments are publicly available [5]

Results on Synthetic Settings [19]

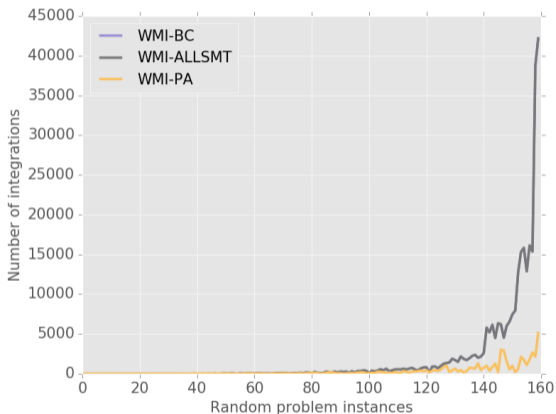
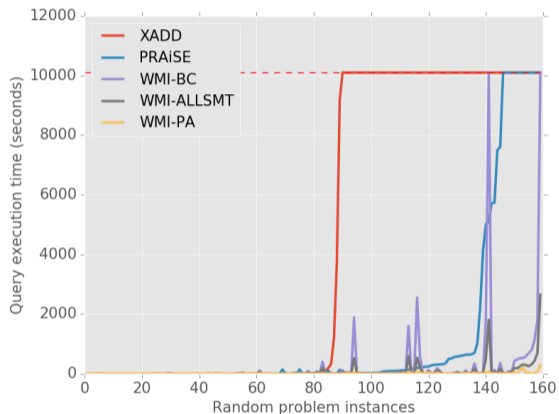


(left): Query execution times for all methods

(center): Query execution times for the three most performing algorithms

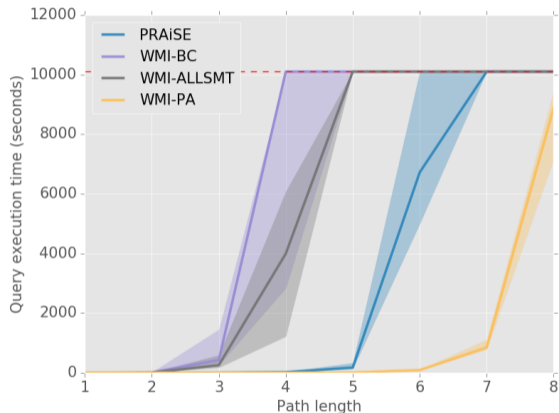
(right): Number of integrals for the three most performing algorithms

Results on Synthetic Settings [20]



(left): **Query execution times** (in seconds) for all methods on the synthetic experiment;
(right): **Number of integrals** for WMI-BC, WMI-ALLSMT and WMI-PA on the same instances.

Strategic Road Network with Fixed Path

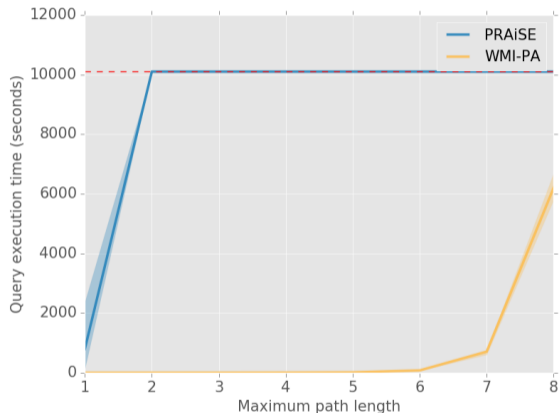


#	PRAiSE	WMI		
		BC	AllSMT	PA
1	2	1	0	0
2	3	10	8	0
3	7	425	253	0
4	22	> 10000	3994	2
5	174	> 10000	> 10000	8
6	6722	> 10000	> 10000	86
7	> 10000	> 10000	> 10000	850
8	> 10000	> 10000	> 10000	8884

(left): Query execution times in seconds (1st quartile, median and 3rd quartile).

(right): Table showing the medians for each length (right).

Strategic Road Network with Conditional Plan



#	PRAiSE	WMI-PA
1	799	1
2	> 10000	2
3	> 10000	4
4	> 10000	6
5	> 10000	14
6	> 10000	77
7	> 10000	708
8	> 10000	6203

(left): Query execution times in seconds (1st quartile, median and 3rd quartile).

(right): Table showing the medians for each length (right).

Outline

- 1 Background
- 2 Weighted Model Integration, Revisited
- 3 SMT-Based WMI Computation
- 4 A Case Study: The Road Network Problem
- 5 Experimental Evaluations
- 6 Ongoing and Future Work**

Conclusion

- **Novel WMI formulation**
 - easily captures the previous definition (not vice versa);
 - works with weight functions $w(\mathbf{x}, \mathbf{A})$ rather than $w(\text{lit}(\mathbf{x}, \mathbf{A}))$
 - w not restricted to products of weights *over literals*
 \implies allows for much more general forms, FIUC ^{\mathcal{LRA}}
- **Novel (WMI-ALLSMT and) WMI-PA procedure**
 - 2 step: predicate abstraction + partial-assignment ALLSMT, interleaved with formula simplification
 \implies reduces drastically the number of integrals to compute
- **Empirical evaluation on both synthetic and real-word problems**
 - WMI-PA outperforms WMI-ALLSMT and previous approaches
- A WMI-ALLSMT & WMI-PA tool available: **pywmi** [16]
(<https://pypi.org/project/pywmi/>)

Note:

CPU times for WMI-PA largely dominated by $\text{WMI}_{\text{nb}}(\mu^{\mathcal{LRA}}, w|\mathbf{x}) \stackrel{\text{def}}{=} \int_{\mu^{\mathcal{LRA}}(\mathbf{x})} w(\mathbf{x}) d\mathbf{x}$ calls
 \implies computation of integrals current bottleneck

Ongoing & Future Work

Efficiency

- look for more efficient basic integrator for $\text{WMI}_{\text{nb}}(\varphi, w|\mathbf{x}) \stackrel{\text{def}}{=} \int_{\mu^{\mathcal{L}\mathcal{R}\mathcal{A}}(\mathbf{x})} w(\mathbf{x}) d\mathbf{x}$
- $\mathcal{TA}(\varphi)$: more effective partial-assignment reduction techniques
- exploiting $w(\mathbf{x}, \mu^{\mathbf{A}})$ with **partial** $\mu^{\mathbf{A}}$ s
- investigate forms of approximated enumeration [14]
- investigate forms of component caching [22, 6]

Expressiveness

- Extend WMI to integers and mixed real/integers
- Extend WMI integration domains to (subcases of) non-linear arithmetic constraints?

Others

- find other applications, other than probabilistic reasoning?



References I

- [1] <http://mathsat.fbk.eu/>.
- [2] [https://www.math.ucdavis.edu/~sim\\$latte/](https://www.math.ucdavis.edu/~sim$latte/).
- [3] <http://www.sympy.org/>.
- [4] <https://data.gov.uk/dataset/dft-eng-srn-routes-journey-times>.
- [5] <https://github.com/unitn-sml/wmi-pa>.
- [6] F. Bacchus, S. Dalmao, and T. Pitassi.
Solving #SAT and Bayesian inference with backtracking search.
Journal of Artificial Intelligence Research, 34(1):391–442, 2009.
- [7] V. Baldoni, N. Berline, J. D. Loera, M. Köppe, and M. Vergne.
How to integrate a polynomial over a simplex.
Mathematics of Computation, 80(273):297–325, 2011.
- [8] V. Belle, A. Passerini, and G. V. den Broeck.
Probabilistic inference in hybrid domains by weighted model integration.
In *IJCAI*, 2015.
- [9] R. Cavada, A. Cimatti, A. Franzén, K. Kalyanasundaram, M. Roveri, and R. Shyamasundar.
Computing Predicate Abstractions by Integrating BDDs and SMT Solvers.
In *FMCAD*, 2007.
- [10] M. Chavira and A. Darwiche.
On probabilistic inference by weighted model counting.
Artificial Intelligence, 172(6-7):772–799, 2008.
- [11] A. Cimatti, A. Griggio, B. J. Schaafsma, and R. Sebastiani.
The MathSAT 5 SMT Solver.
In *TACAS*, 2013.
- [12] A. Darwiche.
New advances in compiling CNF to decomposable negation normal form.
In *Proceedings of ECAI*, pages 328–332, 2004.

References II

- [13] R. de Salvo Braz, C. O'Reilly, V. Gogate, and R. Dechter.
Probabilistic Inference Modulo Theories.
In *IJCAI*, 2016.
- [14] S. Ermon, C. P. Gomes, A. Sabharwal, and B. Selman.
Embed and project: Discrete sampling with universal hashing.
In *NIPS*, pages 2085–2093, 2013.
- [15] S. Graf and H. Saïdi.
Construction of abstract state graphs with pvs.
In *CAV*, 1997.
- [16] S. Kolb, P. Morettin, P. Z. D. Martires, F. Sommariva, A. Passerini, and R. S. L. D. Raedt.
The pywmi framework and toolbox for probabilistic inference using weighted model integration.
In *Proc IJCAI*, 2019.
To appear.
- [17] S. K. Lahiri, R. Nieuwenhuis, and A. Oliveras.
SMT techniques for fast predicate abstraction.
In *CAV*, 2006.
- [18] J. D. Loera, B. Dutra, M. Koeppel, S. Moreinis, G. Pinto, and J. Wu.
Software for exact integration of polynomials over polyhedra.
ACM Communications in Computer Algebra, 45(3/4):169–172, 2012.
- [19] P. Morettin, A. Passerini, and R. Sebastiani.
Efficient weighted model integration via SMT-based predicate abstraction.
In *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI-17*, pages 720–728, 2017.
- [20] P. Morettin, A. Passerini, and R. Sebastiani.
Advanced smt techniques for weighted model integration.
Artificial Intelligence, 2019.
<https://doi.org/10.1016/j.artint.2019.04.003>.
- [21] C. Muise, S. A. McIlraith, J. C. Beck, and E. I. Hsu.
Dsharp: fast d-dnnf compilation with sharpsat.
In *Advances in Artificial Intelligence*, pages 356–361. Springer, 2012.

References III

- [22] T. Sang, F. Bacchus, P. Beame, H. A. Kautz, and T. Pitassi.
Combining component caching and clause learning for effective model counting.
In *SAT*, 2004.
- [23] T. Sang, P. Beame, and H. A. Kautz.
Performing bayesian inference by weighted model counting.
In *AAAI*, volume 5, pages 475–481, 2005.
- [24] S. Sanner, K. V. Delgado, and L. N. de Barros.
Symbolic dynamic programming for discrete and continuous state mdps.
In *UAI 2011, Proceedings of the Twenty-Seventh Conference on Uncertainty in Artificial Intelligence, Barcelona, Spain, July 14-17, 2011*, pages 643–652, 2011.