

A Data Driven Approach for Boolean Functional Synthesis

Priyanka Golia ^{1,2}

Joint work with: Friedrich Slivovsky ³, Subhajit Roy ² and Kuldeep S. Meel ¹



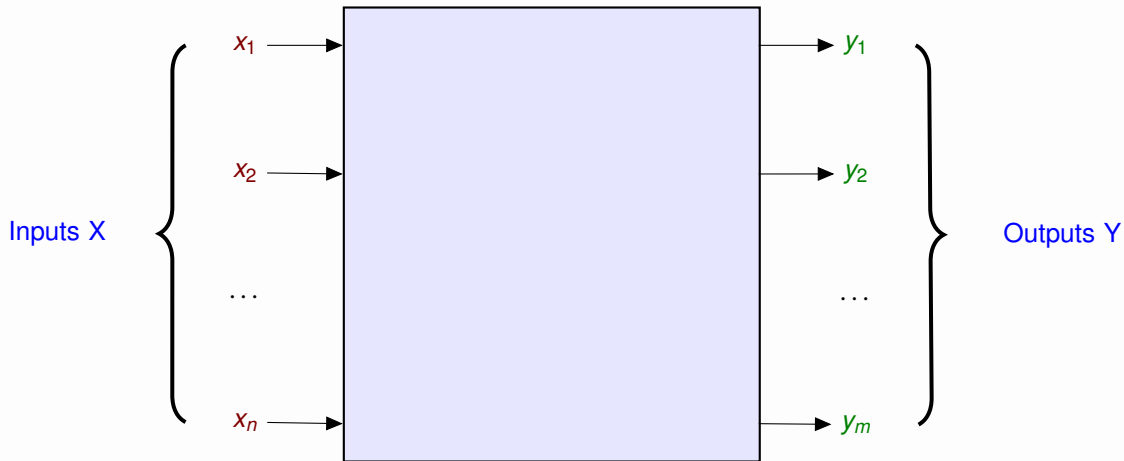
¹National University of Singapore

²Indian Institute of Technology Kanpur

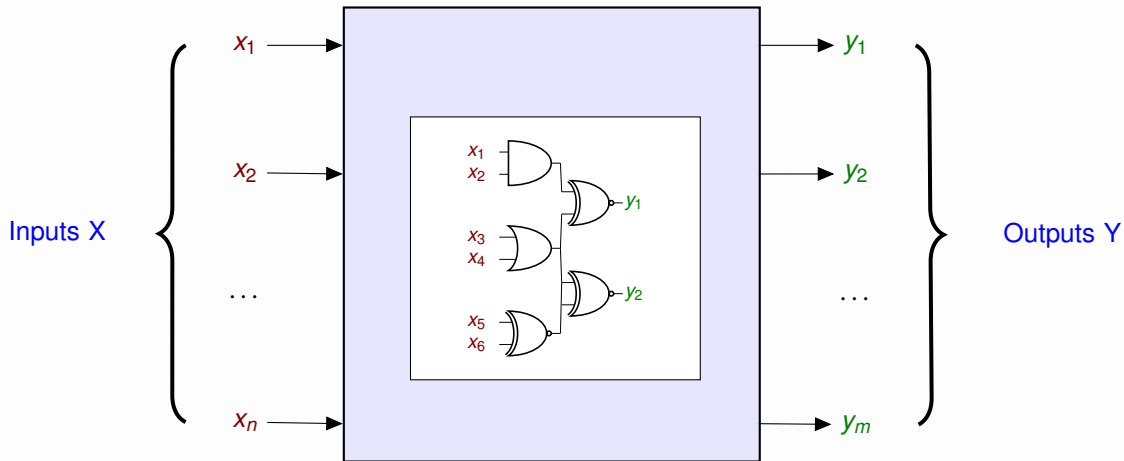
³TU Wien

Corresponding Papers: CAV-20, ICCAD-21 (Best Paper Award Nomination)

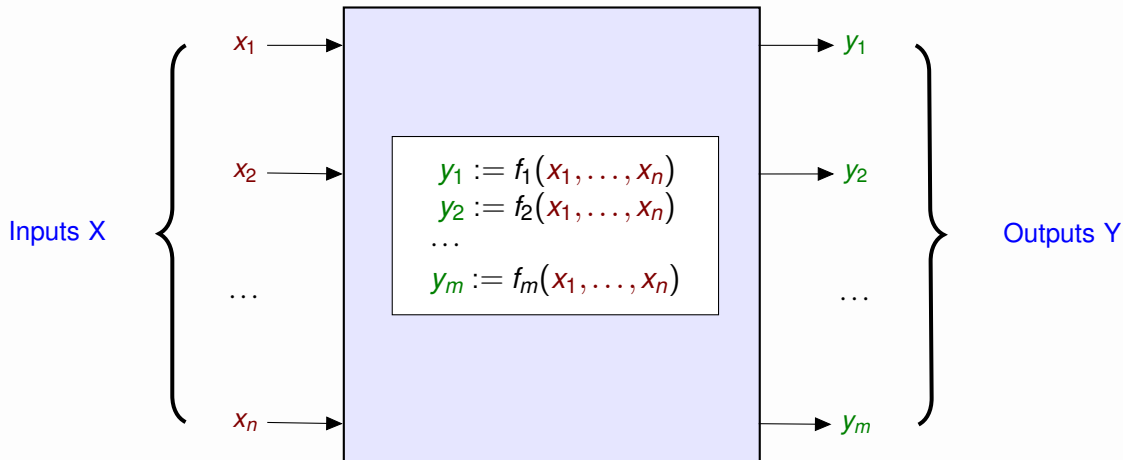
Specification: Relation $\phi(X, Y)$



Specification: Relation $\phi(X, Y)$

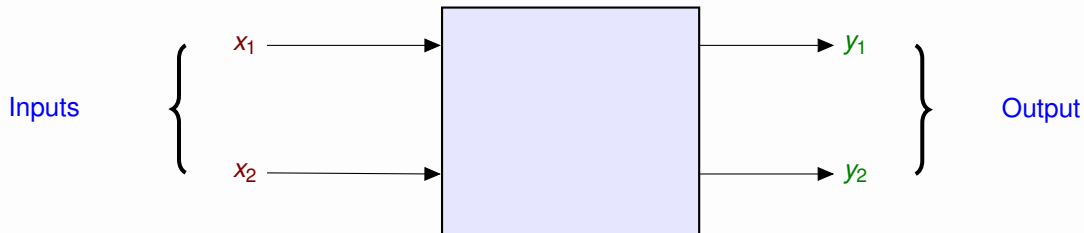


Specification: Relation $\phi(X, Y)$

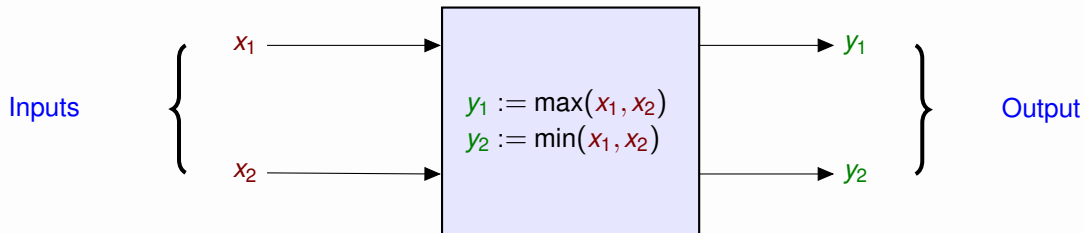


Synthesis – Example

$$\begin{aligned}\varphi(X, Y) = & (y_1 \geq x_1) \wedge (y_1 \geq x_2) \wedge ((y_1 = x_1) \vee (y_1 = x_2)) \\ & \wedge (y_2 \leq x_1) \wedge (y_2 \leq x_2) \wedge ((y_2 = x_1) \vee (y_2 = x_2))\end{aligned}$$



$$\begin{aligned}\varphi(X, Y) = & (y_1 \geq x_1) \wedge (y_1 \geq x_2) \wedge ((y_1 = x_1) \vee (y_1 = x_2)) \\ & \wedge (y_2 \leq x_1) \wedge (y_2 \leq x_2) \wedge ((y_2 = x_1) \vee (y_2 = x_2))\end{aligned}$$



Given $\varphi(X, Y)$ over inputs $X = \{x_1, x_2, \dots, x_n\}$ and outputs $Y = \{y_1, y_2, \dots, y_m\}$.

Synthesize A function vector $F = \{f_1, f_2, \dots, f_m\}$, such that $y_i := f_i(x_1, \dots, x_n)$ such that:

$$\exists Y \varphi(X, Y) \equiv \varphi(X, F(X))$$

Each f_i is called Skolem function and F is called Skolem function vector.

Key Challenge: $\varphi(X, Y)$ is a relation

Non-uniqueness of Skolem Functions

Let $X = \{x_1, x_2\}$, $Y = \{y_1\}$ and $\varphi(X, Y) = x_1 \vee x_2 \vee y_1$

Possible Skolem function: $f(x_1, x_2) := \neg(x_1 \vee x_2)$

Non-uniqueness of Skolem Functions

Let $X = \{x_1, x_2\}$, $Y = \{y_1\}$ and $\varphi(X, Y) = x_1 \vee x_2 \vee y_1$

Possible Skolem function: $f(x_1, x_2) := \neg(x_1 \vee x_2)$

$$\varphi(X, F(X)) = x_1 \vee x_2 \vee (\neg(x_1 \vee x_2))$$

X	$\exists Y \varphi(X, Y)$	$\varphi(X, F(X))$	} $\exists Y \varphi(X, Y) \equiv \varphi(X, F(X))$
$x_1 = 0, x_2 = 0$	$y_1 = 1$ True	True	
$x_1 = 0, x_2 = 1$	$y_1 = 1$ True	True	
$x_1 = 1, x_2 = 0$	$y_1 = 1$ True	True	
$x_1 = 1, x_2 = 1$	$y_1 = 1$ True	True	

Non-uniqueness of Skolem Functions

Let $X = \{x_1, x_2\}$, $Y = \{y_1\}$ and $\varphi(X, Y) = x_1 \vee x_2 \vee y_1$

Possible Skolem function: $f(x_1, x_2) := \neg(x_1 \vee x_2)$

$$\varphi(X, F(X)) = x_1 \vee x_2 \vee (\neg(x_1 \vee x_2))$$

X	$\exists Y \varphi(X, Y)$	$\varphi(X, F(X))$	} $\exists Y \varphi(X, Y) \equiv \varphi(X, F(X))$
$x_1 = 0, x_2 = 0$	$y_1 = 1$ True	True	
$x_1 = 0, x_2 = 1$	$y_1 = 1$ True	True	
$x_1 = 1, x_2 = 0$	$y_1 = 1$ True	True	
$x_1 = 1, x_2 = 1$	$y_1 = 1$ True	True	

Other possible Skolem functions: $f_1(x_1, x_2) = \neg x_1$ $f_2(x_1, x_2) = \neg x_2$ $f_3(x_1, x_2) = 1$

- From the proof of validity of $\forall X \exists Y \varphi(X, Y)$

(Bendetti et al., 2005)

(Jussilla et al., 2007)

(Heule et al., 2014)

- Quantifier instantiation in SMT solvers

(Barrett et al., 2015)

(Bierre et al., 2017)

- Input-Output Separation

(Chakraborty et al., 2018)

- Knowledge representation

(Kukula et al., 2000)

(Trivedi et al., 2003)

(Jiang, 2009)

(Kuncak et al., 2010)

(Balabanov and Jiang, 2011)

(John et al., 2015)

(Fried, Tabajara, Vardi, 2016, 2017)

(Akshay et al., 2017, 2018)

(Chakraborty et al., 2019)

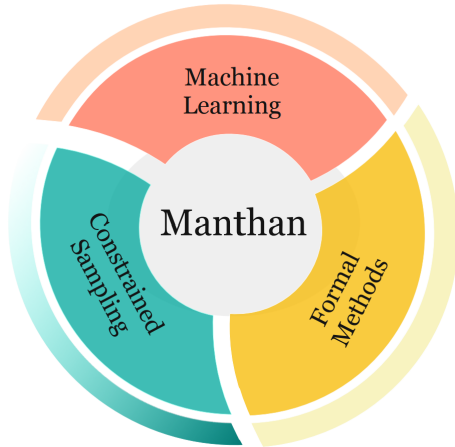
- Incremental determinization

(Rabe et al., 2015, 2018, 2019)

- From the proof of validity of $\forall X \exists Y \varphi(X, Y)$
 - (Bendetti et al., 2005)
 - (Jussilla et al., 2007)
 - (Heule et al., 2014)
- Quantifier instantiation in SMT solvers
 - (Barrett et al., 2015)
 - (Bierre et al., 2017)
- Input-Output Separation
 - (Chakraborty et al., 2018)
- Knowledge representation
 - (Kukula et al., 2000)
 - (Trivedi et al., 2003)
 - (Jiang, 2009)
 - (Kuncak et al., 2010)
 - (Balabanov and Jiang, 2011)
 - (John et al., 2015)
 - (Fried, Tabajara, Vardi, 2016, 2017)
 - (Akshay et al., 2017, 2018)
 - (Chakraborty et al., 2019)
- Incremental determinization
 - (Rabe et al., 2015, 2018, 2019)

Scalability remains the holy grail

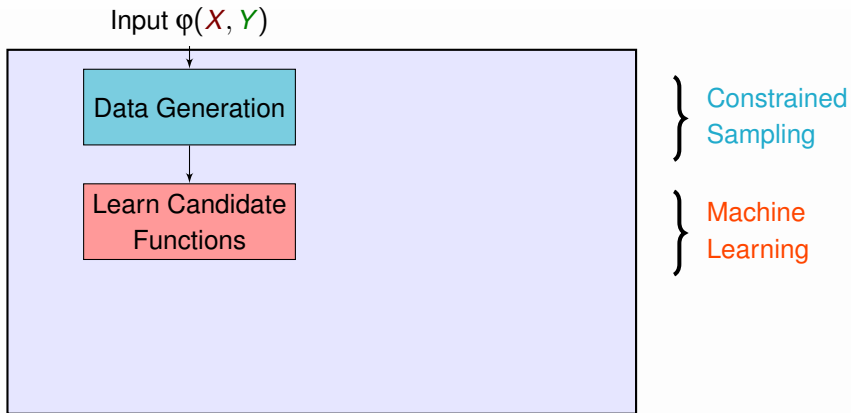
A Data-Driven Approach for Boolean Functional Synthesis

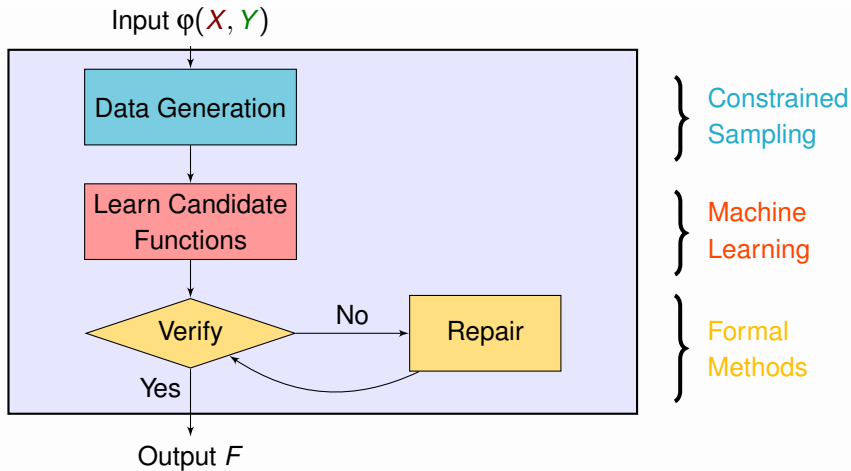


Input $\phi(\textcolor{red}{X}, \textcolor{green}{Y})$

Data Generation

} Constrained
Sampling





Data Generation

Standing on the Shoulders of Constrained Samplers

$\varphi(x_1, x_2, y_1, y_2)$

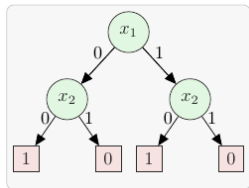


x_1	x_2	y_1	y_2
0	0	1	0
0	1	0	1
1	0	1	1
1	1	0	0

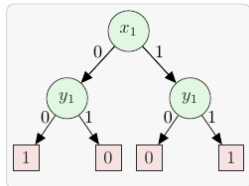
Learn Candidate Functions

Taming the Curse of Abstractions via Learning with Errors

x_1	x_2	y_1	y_2
0	0	1	0
0	1	0	1
1	0	1	1
1	1	0	0



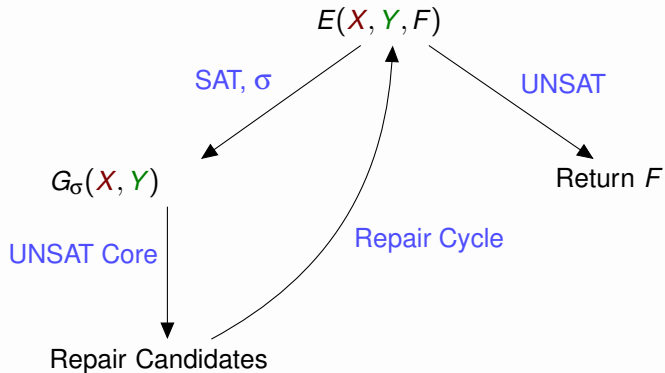
$p_1 := (\neg x_1 \wedge \neg x_2)$,
 $p_2 := (x_1 \wedge \neg x_2)$
 $f_1 =$ if p_1 then 1
 elif p_2 then 1
 else 0

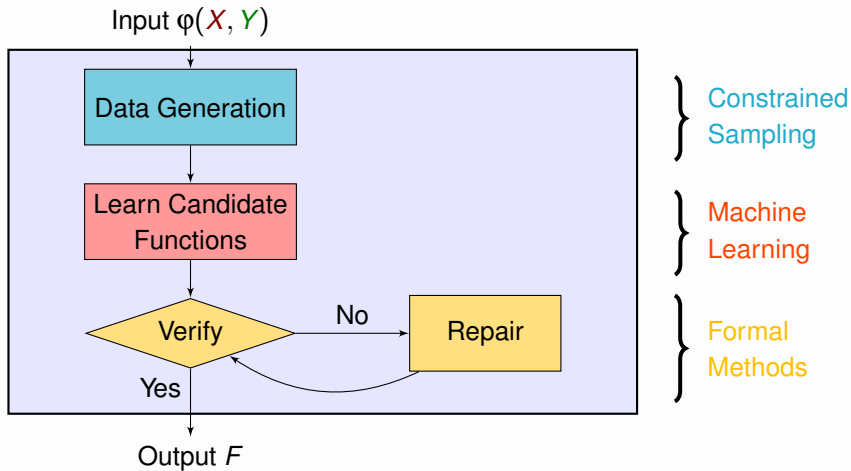


$p_1 := (\neg x_1 \wedge \neg y_1)$,
 $p_2 := (x_1 \wedge y_1)$
 $f_2 =$ if p_1 then 1
 elif p_2 then 1
 else 0

Repair of Approximations

Reaping the Fruits of Formal Methods Revolution





Potential Strategy: Randomly sample satisfying assignment of $\phi(X, Y)$.

Challenge: Multiple valuations of y_1, y_2 for same valuation of x_1, x_2 .

Potential Strategy: Randomly sample satisfying assignment of $\varphi(X, Y)$.


Challenge: Multiple valuations of y_1, y_2 for same valuation of x_1, x_2 .

$$\varphi(x_1, x_2, y_1, y_2) : (x_1 \vee x_2 \vee y_1) \wedge (\neg x_1 \vee \neg x_2 \vee \neg y_2)$$

x_1	x_2	y_1	y_2
0	0	1	0/1
0	1	0/1	0/1
1	0	0/1	0/1
1	1	0/1	0

$$\varphi(x_1, x_2, y_1, y_2) : (x_1 \vee x_2 \vee y_1) \wedge (\neg x_1 \vee \neg x_2 \vee \neg y_2)$$

x_1	x_2	y_1	y_2
0	0	1	0/1
0	1	0/1	0/1
1	0	0/1	0/1
1	1	0/1	0

Uniform Sampler 

x_1	x_2	y_1	y_2
0	0	1	1
0	1	0	1
1	0	0	1
1	1	0	0

$$\varphi(x_1, x_2, y_1, y_2) : (x_1 \vee x_2 \vee y_1) \wedge (\neg x_1 \vee \neg x_2 \vee \neg y_2)$$

x_1	x_2	y_1	y_2		x_1	x_2	y_1	y_2
0	0	1	0/1	Uniform Sampler →	0	0	1	1
0	1	0/1	0/1		0	1	0	1
1	0	0/1	0/1		1	0	0	1
1	1	0/1	0		1	1	0	0

- Possible Skolem functions:

- $f_1(x_1, x_2) = \neg(x_1 \vee x_2)$
- $f_2(x_1, x_2) = \neg(x_1 \wedge x_2)$

$$\varphi(x_1, x_2, y_1, y_2) : (x_1 \vee x_2 \vee y_1) \wedge (\neg x_1 \vee \neg x_2 \vee \neg y_2)$$

x_1	x_2	y_1	y_2		x_1	x_2	y_1	y_2
0	0	1	0/1	Uniform Sampler \rightarrow	0	0	1	1
0	1	0/1	0/1		0	1	0	1
1	0	0/1	0/1		1	0	0	1
1	1	0/1	0		1	1	0	0

- Possible Skolem functions:

- $f_1(x_1, x_2) = \neg(x_1 \vee x_2)$ $f_1(x_1, x_2) = \neg x_1$ $f_1(x_1, x_2) = \neg x_2$ $f_1(x_1, x_2) = 1$
- $f_2(x_1, x_2) = \neg(x_1 \wedge x_2)$ $f_2(x_1, x_2) = \neg x_1$ $f_2(x_1, x_2) = \neg x_2$ $f_2(x_1, x_2) = 0$

$$\varphi(x_1, x_2, y_1, y_2) : (x_1 \vee x_2 \vee y_1) \wedge (\neg x_1 \vee \neg x_2 \vee \neg y_2)$$

x_1	x_2	y_1	y_2		x_1	x_2	y_1	y_2
0	0	1	0/1	Magical Sampler \rightarrow	0	0	1	0
0	1	0/1	0/1		0	1	1	0
1	0	0/1	0/1		1	0	1	0
1	1	0/1	0		1	1	1	0

- Possible Skolem functions:

- $f_1(x_1, x_2) = \neg(x_1 \vee x_2)$ $f_1(x_1, x_2) = \neg x_1$ $f_1(x_1, x_2) = \neg x_2$ $f_1(x_1, x_2) = 1$
- $f_2(x_1, x_2) = \neg(x_1 \wedge x_2)$ $f_2(x_1, x_2) = \neg x_1$ $f_2(x_1, x_2) = \neg x_2$ $f_2(x_1, x_2) = 0$

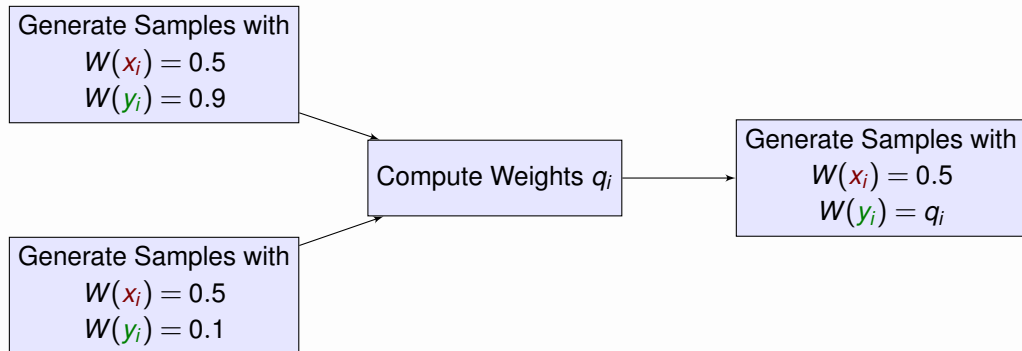
- $W : X \cup Y \mapsto [0, 1]$
- The probability of getting an assignment is proportional to its weight.

$$W(\sigma) = \prod_{\sigma(z_i)=1} W(z_i) \prod_{\sigma(z_i)=0} (1 - W(z_i))$$

- Example: $W(x_1) = 0.5$ $W(x_2) = 0.5$ $W(y_1) = 0.9$ $W(y_2) = 0.1$
 $\sigma_1 = \{x_1 \mapsto 1, x_2 \mapsto 0, y_1 \mapsto 0, y_2 \mapsto 1\}$

$$W(\sigma_1) = 0.5 \times (1 - 0.5) \times (1 - 0.9) \times 0.1 = 0.0025$$

- Uniform sampling is a special case where all variables are assigned weight of 0.5.



- Knowledge representation based techniques

(Yuan,Shultz, Pixley,Miller,Aziz 1999)

(Yuan,Aziz, Pixley,Albin, 2004)

(Kukula and Shiple, 2000)

(Sharma, Gupta, M., Roy, 2018)

(Gupta, Sharma, M., Roy, 2019)

- Hashing based techniques

(Chakraborty, M., and Vardi 2013, 2014,2015)

(Soos, M., and Gocht 2020)

- Mutation based techniques

(Dutra, Laeuffer, Bachrach, Sen, 2018)

- Markov Chain Monte Carlo based techniques

(Wei and Selman,2005)

(Kitchen,2010)

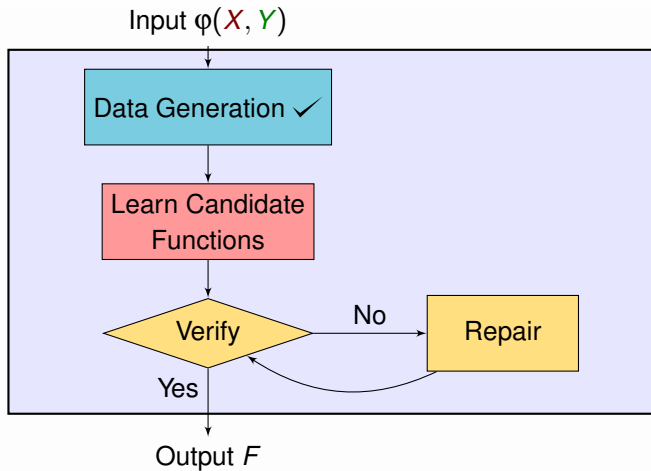
- Constraint solver based techniques

(Ermon, Gomes, Sabharwal, Selman,2012)

- Belief networks based techniques

(Dechter, Kask, Bin, Emek,2002)

(Gogate and Dechter,2006)



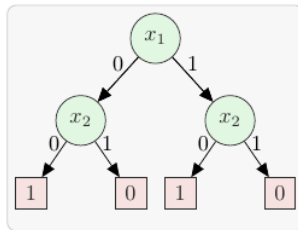
$$\phi(x_1, x_2, y_1, y_2) : (x_1 \vee x_2 \vee y_1) \wedge (\neg x_1 \vee \neg x_2 \vee \neg y_2)$$

- To learn y_2
 - Feature set: valuation of x_1, x_2, y_1
 - Label: valuation of y_2
 - Learn decision tree to represent y_2 in terms of x_1, x_2, y_1
- To learn y_1
 - Feature set: valuation of x_1, x_2
 - Label: valuation of y_1
 - Learn decision tree to represent y_1 in terms of x_1, x_2

x_1	x_2	y_1	y_2
0	0	1	0
0	1	0	1
1	0	1	1
1	1	0	0

Learning Candidate Functions

x_1	x_2	y_1	y_2
0	0	1	0
0	1	0	1
1	0	1	1
1	1	0	0



$$p_1 := (\neg x_1 \wedge \neg x_2),$$

$$p_2 := (x_1 \wedge \neg x_2)$$

$f_1 =$ if p_1 then 1
 elif p_2 then 1
 else 0

$$E(X, Y, Y') := \varphi(X, Y) \wedge \neg \varphi(X, Y') \wedge (Y' \leftrightarrow F(X))$$

(JSCTA'15)

- If $E(X, Y, Y')$ is UNSAT: $\exists Y \varphi(X, Y) \equiv \varphi(X, F(X))$
 - Return F
- If $E(X, Y, Y')$ is SAT: $\exists Y \varphi(X, Y) \not\equiv \varphi(X, F(X))$
 - Let $\sigma \models E(X, Y, Y')$ be a counterexample to fix.

$$E(X, Y, Y') := \varphi(X, Y) \wedge \neg \varphi(X, Y') \wedge (Y' \leftrightarrow F(X))$$

$\sigma \models E(X, Y, Y')$ be a counterexample to fix.

- Let $\sigma := \{x_1 \mapsto 1, x_2 \mapsto 1, y_1 \mapsto 1, y_2 \mapsto 1, y'_1 \mapsto 0, y'_2 \mapsto 0\}$.
- Potential repair candidates: All y_i where $\sigma[y_i] \neq \sigma[y'_i]$.

$$E(X, Y, Y') := \varphi(X, Y) \wedge \neg \varphi(X, Y') \wedge (Y' \leftrightarrow F(X))$$

$\sigma \models E(X, Y, Y')$ be a counterexample to fix.

- Let $\sigma := \{x_1 \mapsto 1, x_2 \mapsto 1, y_1 \mapsto 1, y_2 \mapsto 1, y'_1 \mapsto 0, y'_2 \mapsto 0\}$.
- Potential repair candidates: All y_i where $\sigma[y_i] \neq \sigma[y'_i]$.
- $\varphi(X, Y)$ is Boolean Relation.
 - So it can be $\hat{\sigma} = \{x_1 \mapsto 1, x_2 \mapsto 1, y_1 \mapsto 0, y_2 \mapsto 1, y'_1 \mapsto 0, y'_2 \mapsto 0\}$
 - We would not repair f_1 .

$$E(X, Y, Y') := \varphi(X, Y) \wedge \neg \varphi(X, Y') \wedge (Y' \leftrightarrow F(X))$$

$\sigma \models E(X, Y, Y')$ be a counterexample to fix.

- Let $\sigma := \{x_1 \mapsto 1, x_2 \mapsto 1, y_1 \mapsto 1, y_2 \mapsto 1, y'_1 \mapsto 0, y'_2 \mapsto 0\}$.
- Potential repair candidates: All y_i where $\sigma[y_i] \neq \sigma[y'_i]$.
- $\varphi(X, Y)$ is Boolean Relation.
 - So it can be $\hat{\sigma} = \{x_1 \mapsto 1, x_2 \mapsto 1, y_1 \mapsto 0, y_2 \mapsto 1, y'_1 \mapsto 0, y'_2 \mapsto 0\}$
 - We would not repair f_1 .
- MaxSAT-based Identification of *nice counterexamples*:
 - Hard Clauses $\varphi(X, Y) \wedge (X \leftrightarrow \sigma[X])$.
 - Soft Clauses $(Y \leftrightarrow \sigma[Y'])$.
- Candidates to repair: Y variables in the violated soft clauses

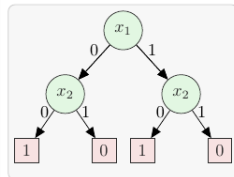
- $\sigma = \{x_1 \mapsto 1, x_2 \mapsto 1, y_1 \mapsto 0, y_2 \mapsto 1, y'_1 \mapsto 0, y'_2 \mapsto 0\}$, and we want to repair f_2 .
- **Potential Repair:** If $\underbrace{x_1 \wedge x_2 \wedge \neg y_1}_{\beta = \{x_1, x_2, \neg y_1\}}$ then $y_2 = 1$
- Would be nice to have $\beta = \{x_1, x_2\}$ or even $\beta = \{x_1\}$
- **Challenge:** How do we find small β ?
 - $G_\sigma(X, Y) := \varphi(X, Y) \wedge x_1 \wedge x_2 \wedge \neg y_1 \wedge (y_2 = 0)$
 - $\beta :=$ Literals in UNSAT Core of $G_\sigma(X, Y)$

$\varphi(X, Y)$
 $X = \{x_1, x_2\}$
 $Y = \{y_1, y_2\}$

Data Generation

x_1	x_2	y_1	y_2
0	0	1	0
0	1	0	1
1	0	1	0
1	1	0	1

Learn Candidates



Verify Candidates

Check Satisfiability
of $E(X, Y, Y')$

SAT, σ
 $G_\sigma(X, Y)$

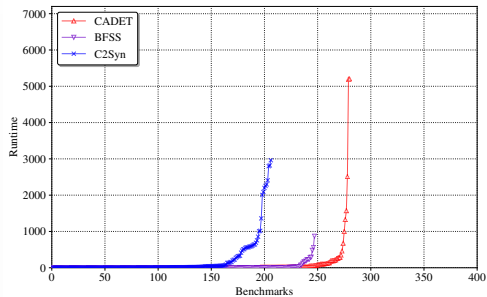
UNSAT Core-based Repair

UNSAT

Return F

- 609 Benchmarks from:
 - QBFEval competition
 - Arithmetic
 - Disjunctive decomposition
 - Factorization
- Compared Manthan with State-of-the-art tools: CADET ([Rabe et al., 2019](#)), BFSS ([Akshay et al. ,2018](#)), C2Syn ([Chakraborty et al., 2019](#)).
- Timeout: 7200 seconds.

Experimental Evaluations

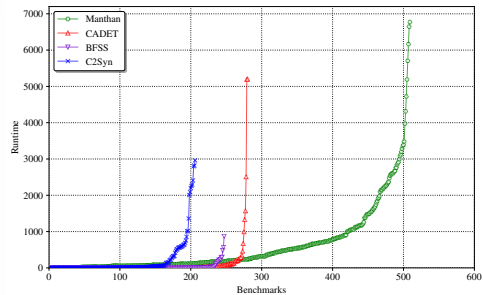


C2Syn
206

BFSS
247

CADET
280

Experimental Evaluations



C2Syn
206

BFSS
247

CADET
280

Manthan
509

An increase of 223 benchmarks.

- Learning Theoretic Foundations for Functional Synthesis
 - What is the ideal distribution to generate the data?
 - Mistake bounds/complexity of learning functions from relations?
- The Future of Formal Methods (FM) +Machine Learning (ML)
 - The proposed solutions by ML do not need to be fully correct.
 - Use FM for correctness and ML to quickly find the solution.

Manthan: A Data-Driven Approach for Boolean Functional Synthesis.



Constrained Sampling



Solves 509 benchmarks — state of the art
could solve 280



Decision List Classifier



Formal Methods



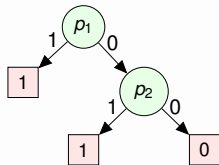
<https://github.com/meelgroup/manthan>

Thanks!

Repair: Adding Level to Decision List

- Candidates are from one level decision list:
 - Say we have paths p_1, p_2 with the leaf node label as 1.
 - Learned decision tree: If p_1 then 1, elif p_2 then 1, else 0.
 - p_1, p_2 can be reordered.

Can reorder p_1, p_2 }



Repair: Adding Level to Decision List

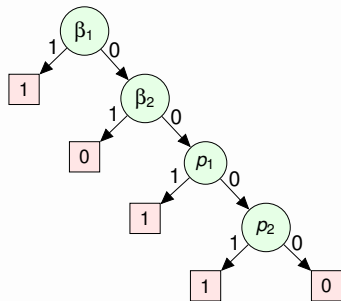
- Candidates are from one level decision list:
 - Say we have paths p_1, p_2 with the leaf node label as 1.
 - Learned decision tree: If p_1 then 1, elif p_2 then 1, else 0.
 - p_1, p_2 can be reordered.

Can reorder β_1, β_2 }

Can reorder p_1, p_2 }

- Suppose in repair iterations, we have learned: If β_1 then 1, ... β_2 then 0
.....

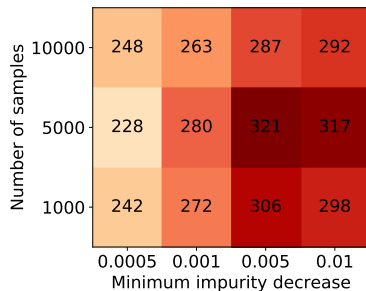
- β_1 and β_2 can be reordered.
- From one level decision list to two decision list.



Impact of different sampling schemes and the quality of samplers.

Sampler	Instances Solved with No Repair	Total Instances Solved
CryptoMiniSAT	14	271
QuickSampler	28	275
Uniform Sampler	51	345
Weighted Sampler	66	356

Learning Candidate Functions: Experimental Evaluations(I)



- Learning without any errors on sampled data: Manthan could only solve 162 instances.
- Manthan decides the number of samples as per cardinality of Y variables, and uses 0.005 as minimum impurity decrease parameter.

- Let $X = \{x_1, x_2\}$, and $Y = \{y_1, y_2\}$
- $\varphi(X, Y) := (y_1 \leftrightarrow (x_1 \vee x_2)) \wedge (y_2 \leftrightarrow (x_1 \wedge (x_2 \vee y_1)))$
- Skolem Functions:
 - $f_1(x_1, x_2) := (x_1 \vee x_2)$
 - $f_2(x_1, x_2, y_1) := (x_1 \wedge (x_2 \vee y_1))$
 $f_2(x_1, x_2, y_1) := (x_1 \wedge (x_2 \vee (x_1 \vee x_2)))$
 $f_2(x_1, x_2, y_1) := x_1$


$$\exists Y \varphi(X, Y) \equiv \varphi(X, F(X))$$

Example: Data Generation

Let $X = \{x_1, x_2\}$, and $Y = \{y_1, y_2\}$

$$\phi(X, Y) := (y_1 \leftrightarrow (x_1 \vee x_2)) \wedge (y_2 \leftrightarrow (x_1 \wedge (x_2 \vee y_1)))$$

Constrained Sampler



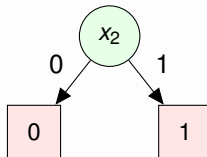
x_1	x_2	y_1	y_2
0	0	0	0
0	1	1	0
1	1	1	1

Example: Learning Candidate Functions

$$\varphi(X, Y) := (y_1 \leftrightarrow (x_1 \vee x_2)) \wedge (y_2 \leftrightarrow (x_1 \wedge (x_2 \vee y_1)))$$

- Learn candidate function f_1 .
- Feature set for $y_1 := \{x_1, x_2\}$

x_1	x_2	y_1
0	0	0
0	1	1
1	1	1



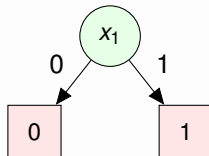
$$f_1(x_1, x_2) := x_2$$

Example: Learning Candidate Functions

$$\varphi(X, Y) := (y_1 \leftrightarrow (x_1 \vee x_2)) \wedge (y_2 \leftrightarrow (x_1 \wedge (x_2 \vee y_1)))$$

- Learn candidate function f_2 .
- Feature set for $y_2 := \{x_1, x_2, y_1\}$

x_1	x_2	y_1	y_2
0	0	0	0
0	1	1	0
1	1	1	1



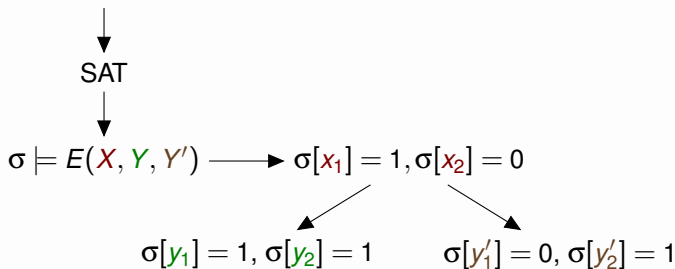
$$f_2(x_1, x_2, y_1) := x_1$$

Example: Verification of Candidate Functions

$$\varphi(X, Y) := (y_1 \leftrightarrow (x_1 \vee x_2)) \wedge (y_2 \leftrightarrow (x_1 \wedge (x_2 \vee y_1)))$$

- $E(X, Y, Y') := \varphi(X, Y) \wedge \neg \varphi(X, Y') \wedge (Y' \leftrightarrow F(X))$

$$E(X, Y, Y') := \varphi(x_1, x_2, y_1, y_2) \wedge \neg \varphi(x_1, x_2, y'_1, y'_2) \wedge (y'_1 \leftrightarrow x_2) \wedge (y'_2 \leftrightarrow x_1)$$



Example: Verification of Candidate Functions

$$\varphi(X, Y) := (y_1 \leftrightarrow (x_1 \vee x_2)) \wedge (y_2 \leftrightarrow (x_1 \wedge (x_2 \vee y_1)))$$

- $E(X, Y, Y') := \varphi(X, Y) \wedge \neg \varphi(X, Y') \wedge (Y' \leftrightarrow F(X))$

$$E(X, Y, Y') := \varphi(x_1, x_2, y_1, y_2) \wedge \neg \varphi(x_1, x_2, y'_1, y'_2) \wedge (y'_1 \leftrightarrow x_2) \wedge (y'_2 \leftrightarrow x_1)$$

↓

SAT

↓

$$\sigma \models E(X, Y, Y') \longrightarrow \sigma[x_1] = 1, \sigma[x_2] = 0$$

↙

↘

$$\sigma[y_1 = 1], \sigma[y_2] = 1$$

$$\sigma[y'_1 = 0], \sigma[y'_2] = 1$$

$$\sigma[y_1] \neq \sigma[y'_1]$$

Candidate to repair f_1

Example: Repairing candidate functions (I)

$$\varphi(X, Y) := (y_1 \leftrightarrow (x_1 \vee x_2)) \wedge (y_2 \leftrightarrow (x_1 \wedge (x_2 \vee y_1)))$$

- $G_1(X, Y) = \varphi(X, Y) \wedge (X \leftrightarrow \sigma[X]) \wedge (y_1 \leftrightarrow \sigma[y_1'])$.
- $G_1(X, Y) = \varphi(X, Y) \wedge (x_1 \leftrightarrow 1) \wedge (x_2 \leftrightarrow 0) \wedge (y_1 \leftrightarrow 0)$.
- UNSAT core of $G_1(X, Y) = \varphi(X, Y) \wedge (x_1 \leftrightarrow 1) \wedge (y_1 \leftrightarrow 0)$
- Repair formula $\beta = x_1$.

Example: Repairing candidate functions (II)

$$\varphi(\textcolor{red}{X}, \textcolor{green}{Y}) := (\textcolor{green}{y}_1 \leftrightarrow (\textcolor{red}{x}_1 \vee \textcolor{red}{x}_2)) \wedge (\textcolor{green}{y}_2 \leftrightarrow (\textcolor{red}{x}_1 \wedge (\textcolor{red}{x}_2 \vee \textcolor{green}{y}_1)))$$

Before repair	Repair	After repair
$f_1(\sigma[\textcolor{red}{X}]) \mapsto 0$	$f_1(\textcolor{red}{X}) \leftarrow f_1(\textcolor{red}{X}) \vee \beta$ $f_1(\textcolor{red}{X}) \leftarrow \textcolor{red}{x}_2 \vee \textcolor{red}{x}_1$	$f_1(\textcolor{red}{X}) \mapsto 1$

Example: Verification of Candidate Functions

$$\varphi(X, Y) := (y_1 \leftrightarrow (x_1 \vee x_2)) \wedge (y_2 \leftrightarrow (x_1 \wedge (x_2 \vee y_1)))$$

- $E(X, Y, Y') := \varphi(X, Y) \wedge \neg \varphi(X, Y') \wedge (Y' \leftrightarrow F(X))$

$$E(X, Y, Y') := \varphi(x_1, x_2, y_1, y_2) \wedge \neg \varphi(x_1, x_2, y'_1, y'_2) \wedge (y'_1 \leftrightarrow x_2 \vee x_1) \wedge (y'_2 \leftrightarrow x_1)$$



UNSAT



Manthan returns F

- $\Sigma_1 :=$ Sample 500 data point with $W(\mathbf{x}_i) = 0.5$ and $W(\mathbf{y}_i) = 0.9$.

$$w_1(i) = \frac{\text{Count}(\Sigma_1 \cap (\mathbf{y}_i = 1))}{500}$$

- $\Sigma_2 :=$ Sample 500 data point with $W(\mathbf{x}_i) = 0.5$ and $W(\mathbf{y}_i) = 0.1$.

$$w_2(i) = \frac{\text{Count}(\Sigma_2 \cap (\mathbf{y}_i = 0))}{500}$$

- If $0.35 < w_1(i) < 0.65$ and $0.35 < w_2(i) < 0.65$, then $q_i = w_1(i)$, else $q_i = 0.9$.