Predicting the Performance of ATL Model Transformations

Raffaela Groner, Peter Bellmann, Stefan Höppner, Patrick Thiam, Friedhelm Schwenker and Matthias Tichy | 18.04.2023

Software Engineering
Programming Languages

Neural Information
Processing

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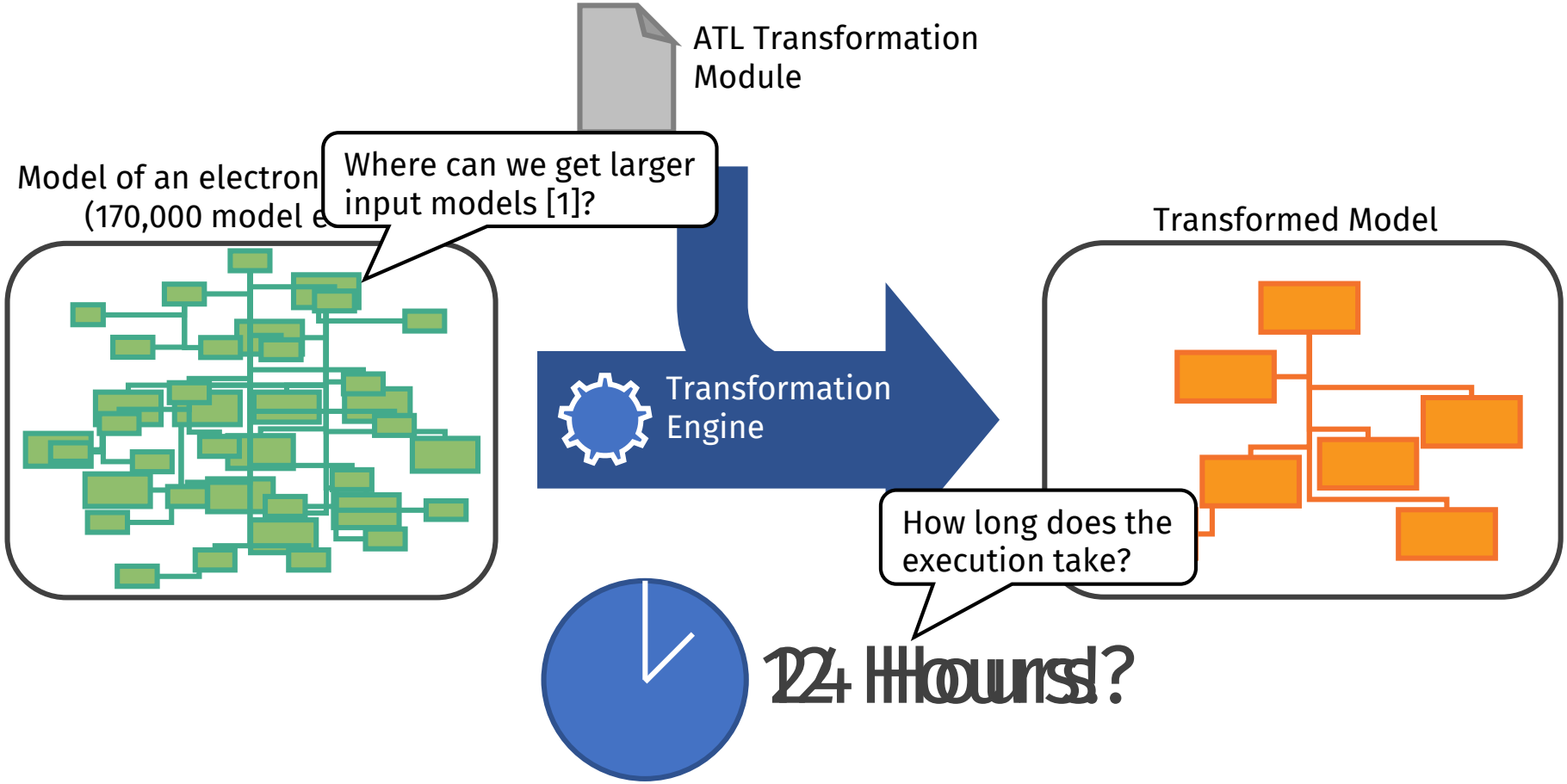
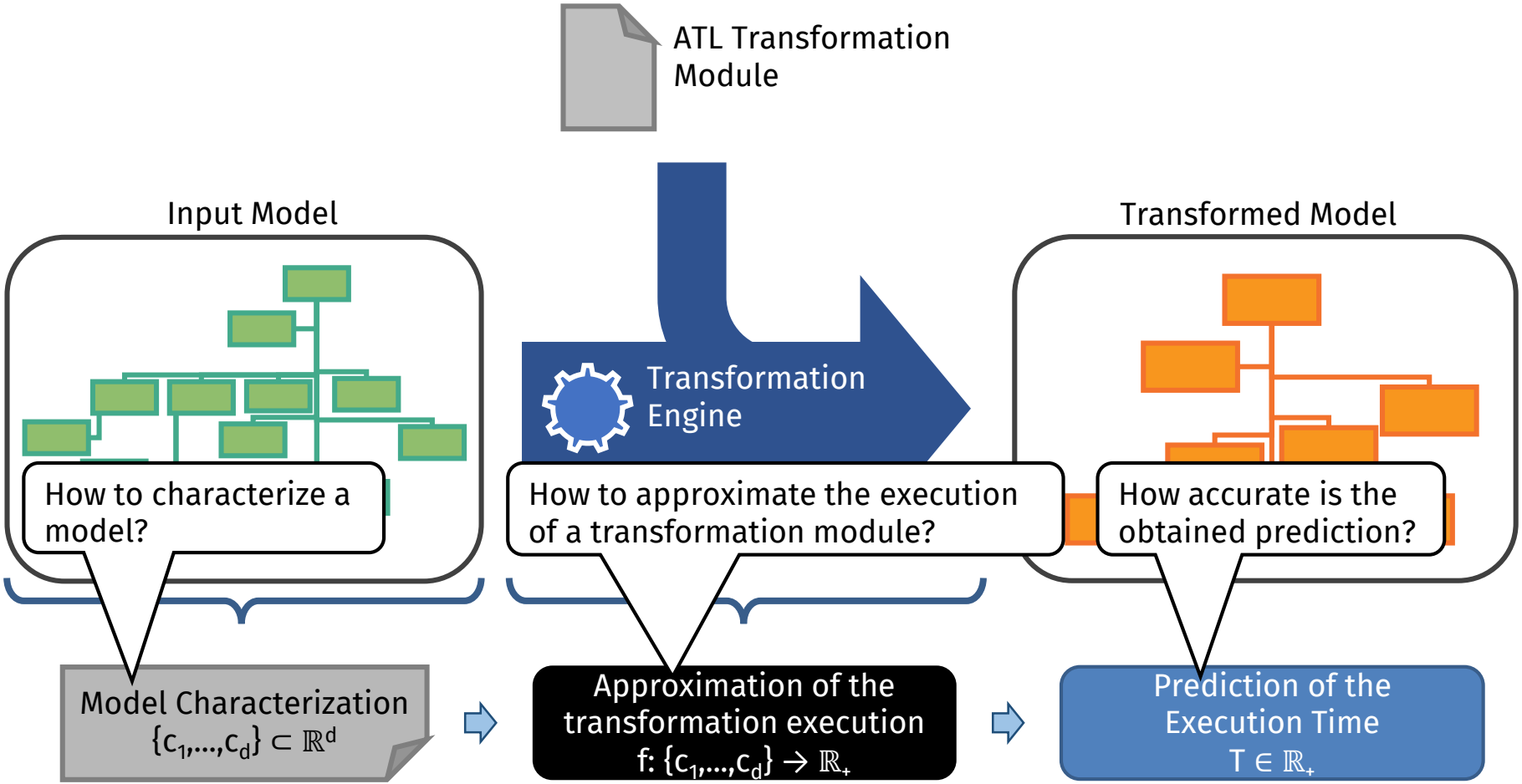
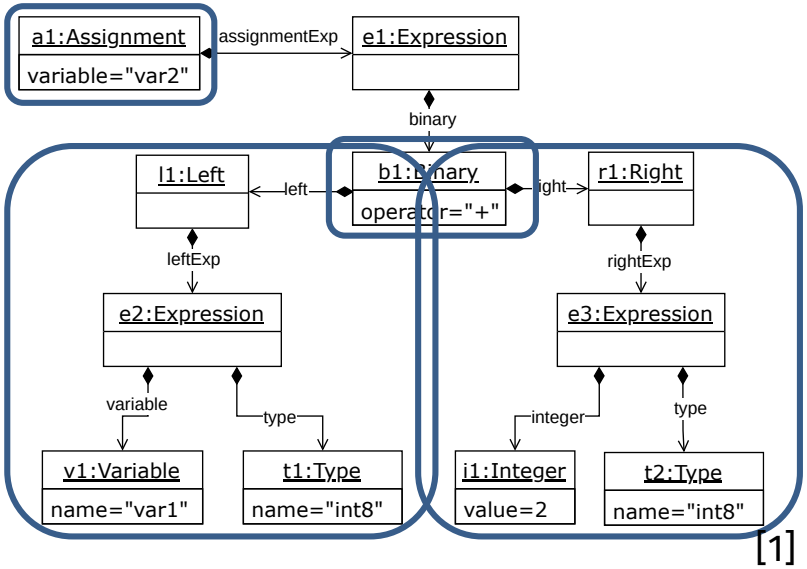


[1] Groner, Raffaela, et al. "An exploratory study on performance engineering in model transformations." *Proceedings of the 23rd acm/ieee international conference on model driven engineering languages and systems*. 2020.


ATL Transformation Module
Input Model
Transformed Model
Transformation Engine
How to characterize a model?
How to approximate the execution of a transformation module?
How accurate is the obtained prediction?
Model Characterization
$\{c_1,...,c_d\} \subset \mathbb{R}^d$
Approximation of the transformation execution
$f: \{c_1,...,c_d\} \rightarrow \mathbb{R}_+$
Prediction of the Execution Time
$T \in \mathbb{R}_+$

var2 = var1 + 2

var = 2 + 3



[1]

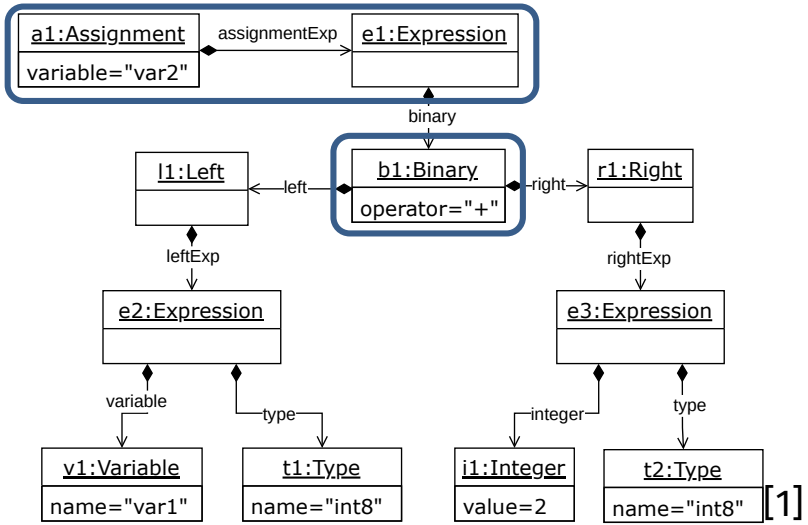
```
23 rule constantFoldingAddition {
24     from
25         expression : AST!Expression (expression.checkExpressionElement())
26     to
27         outExpression : AST!Expression (
28                 integer<- newInteger
29         ),
30
31         newInteger : AST!Integer (
32             value <- expression.binary.left.leftExp.integer.value +
33                         expression.binary.right.rightExp.integer.value
34         )
35
36 }
37
38 rule dropBinary {
39     from
40         binary : AST!Binary (binary.checkBinary())
41     to
42         drop
43 }
44
```

[1] Groner, Raffaela, Sophie Gylstorff, and Matthias Tichy. "A profiler for the matching process of Henshin." *Proceedings of the 23rd ACM/IEEE International Conference on Model Driven Engineering Languages and Systems: Companion Proceedings*. 2020.

- Two types of information:
  a) Structural information
  b) Type information

- Zoom-in metaphor

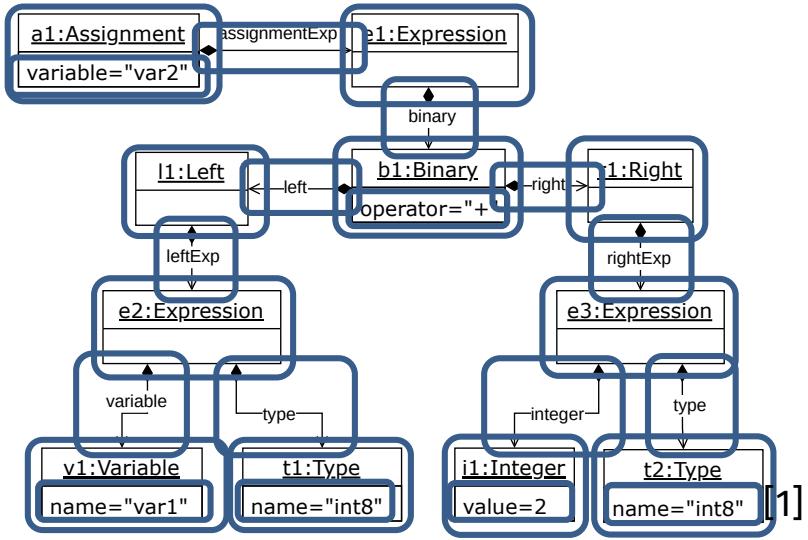
➡ 8 Feature Sets (FS1-8)



[1]

[1] Groner, Raffaela, Sophie Gylstorff, and Matthias Tichy. "A profiler for the matching process of Henshin." *Proceedings of the 23rd ACM/IEEE International Conference on Model Driven Engineering Languages and Systems: Companion Proceedings*. 2020.

- 11 Model elements
- 10 References
- 6 Attributes



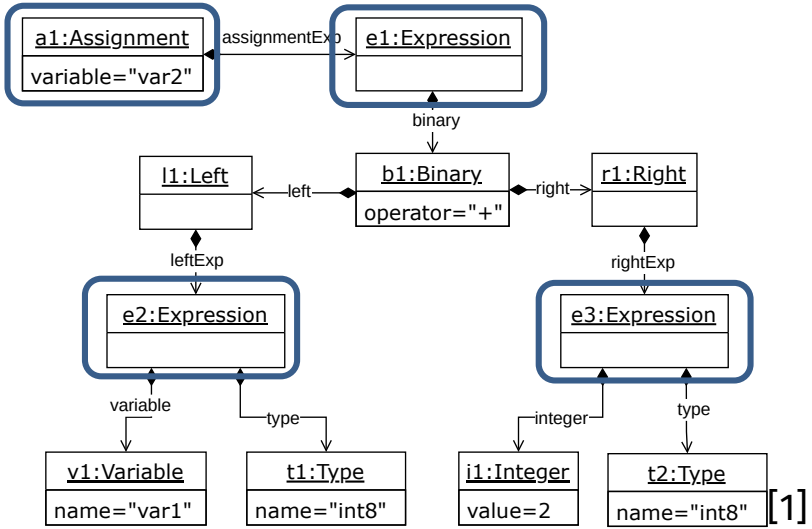
[1]

Feature \ Feature Set (FS)	1
Number of Model Elements	x
Number of References	
Number of Attributes	

[1] Groner, Raffaela, Sophie Gylstorff, and Matthias Tichy. "A profiler for the matching process of Henshin." *Proceedings of the 23rd ACM/IEEE International Conference on Model Driven Engineering Languages and Systems: Companion Proceedings*. 2020.

Characterization

- 1 Assignment, 3 Expressions, …

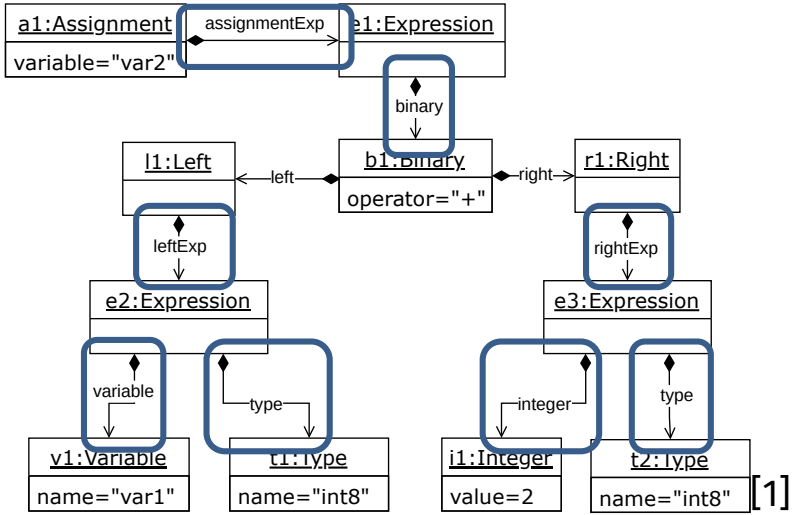


[1]

Feature \ Feature Set (FS)	4
Number of Model Elements per Model Element Type	x
Ø Fan-In/Fan-Out per Model Element Type	
Number of Attributes per Attribute Type	

[1] Groner, Raffaela, Sophie Gylstorff, and Matthias Tichy. "A profiler for the matching process of Henshin." *Proceedings of the 23rd ACM/IEEE International Conference on Model Driven Engineering Languages and Systems: Companion Proceedings*. 2020.

- 1 Assignment, 3 Expressions, …
- 1 Ø Fan-In per Model Element Type Expression, …
  - 3 Expressions
  - 3 Incoming references
  - $\frac{3\ Incoming\ references}{3\ Expressions} = 1$

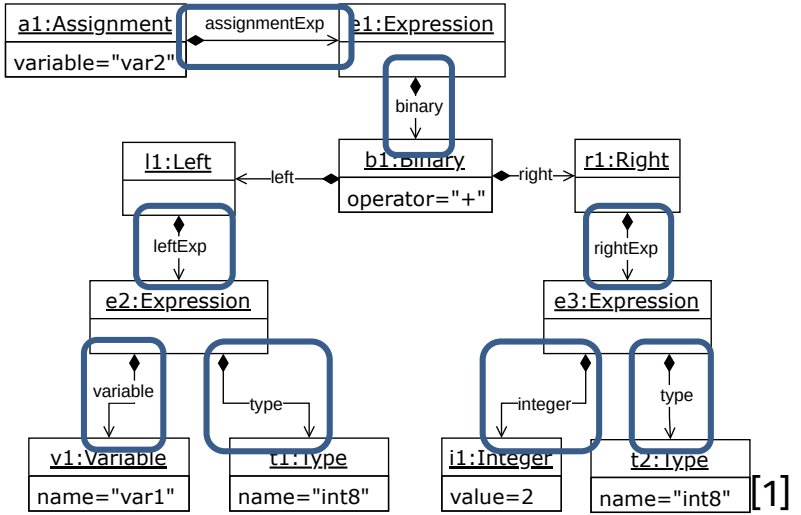


[1]

Feature \ Feature Set (FS)	4	5
Number of Model Elements per Model Element Type	x	x
Ø Fan-In/Fan-Out per Model Element Type		x
Number of Attributes per Attribute Type		

[1] Groner, Raffaela, Sophie Gylstorff, and Matthias Tichy. "A profiler for the matching process of Henshin." *Proceedings of the 23rd ACM/IEEE International Conference on Model Driven Engineering Languages and Systems: Companion Proceedings*. 2020.

- 1 Assignment, 3 Expressions, …
- 1 Ø Fan-In per Model Element Type Expression, …
- 1.67 Ø Fan-Out per Model Element Type Expression, …
  - 3 Expressions
  - 5 Outgoing references
  - $\frac{5\ Outgoing\ references}{3\ Expressions} = 1.67$

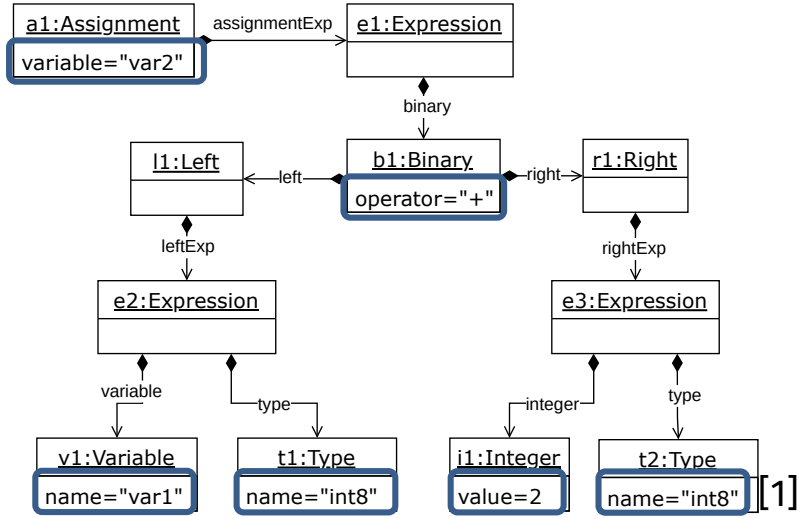


[1]

Feature \ Feature Set (FS)	4	5
Number of Model Elements per Model Element Type	x	x
Ø Fan-In/Fan-Out per Model Element Type		x
Number of Attributes per Attribute Type		

[1] Groner, Raffaela, Sophie Gylstorff, and Matthias Tichy. "A profiler for the matching process of Henshin." *Proceedings of the 23rd ACM/IEEE International Conference on Model Driven Engineering Languages and Systems: Companion Proceedings*. 2020.

- 1 Assignment, 3 Expressions, …
- 1 Ø Fan-In per Model Element Type Expression, …
- 1.67 Ø Fan-Out per Model Element Type Expression, …
- 5 Strings, 1 Integer



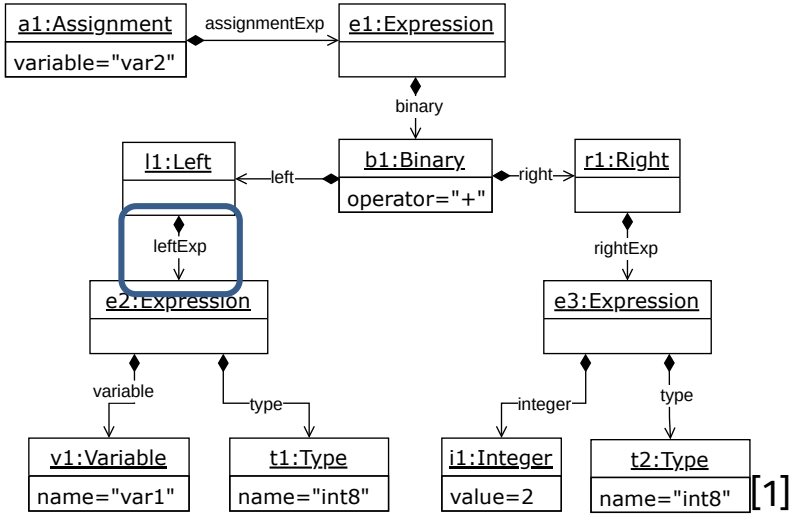
[1]

Feature \ Feature Set (FS)	4	5	6
Number of Model Elements per Model Element Type	x	x	x
Ø Fan-In/Fan-Out per Model Element Type		x	x
Number of Attributes per Attribute Type			x

[1] Groner, Raffaela, Sophie Gylstorff, and Matthias Tichy. "A profiler for the matching process of Henshin." *Proceedings of the 23rd ACM/IEEE International Conference on Model Driven Engineering Languages and Systems: Companion Proceedings*. 2020.

Characterization

- 1 Assignment, 3 Expressions, …
- 0.33 Ø Fan-In per Model Element Type Expression per Reference Type “leftExp”, …
  - 3 Expressions
  - 1 Incoming references “leftExp”
  - $\frac{1\ Incoming\ references\ "leftExp"}{3\ Expressions} = 0.33$

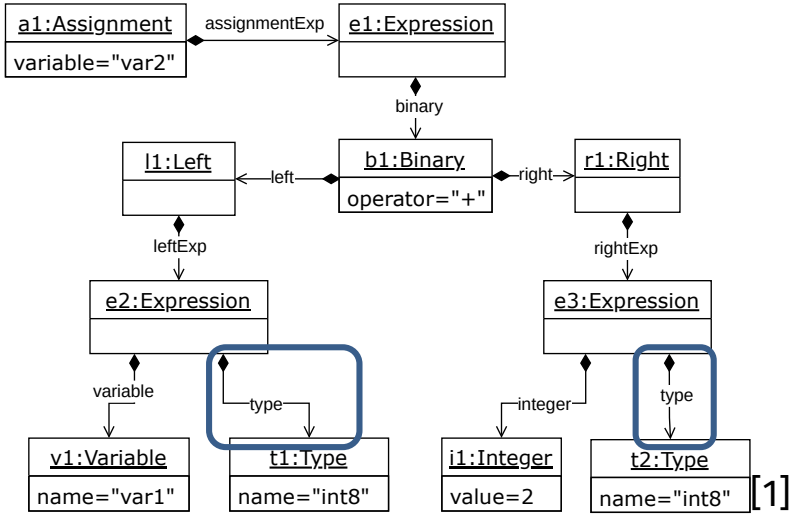


[1]

Feature \ Feature Set (FS)	7
Number of Model Elements per Model Element Type	x
Ø Fan-In/Fan-Out per Model Element Type per Reference Type	x
Ø Number of Attributes per Attribute Type per Model Element Type	

[1] Groner, Raffaela, Sophie Gylstorff, and Matthias Tichy. "A profiler for the matching process of Henshin." *Proceedings of the 23rd ACM/IEEE International Conference on Model Driven Engineering Languages and Systems: Companion Proceedings*. 2020.

- 1 Assignment, 3 Expressions, …
- 0.33 Ø Fan-In per Model Element Type Expression per Reference Type “leftExp”, …
- 1.67 Ø Fan-Out per Model Element Type Expression per Reference Type “type”, …
  - 3 Expressions
  - 2 Outgoing references “type”
  - $\frac{2\ Outgoing\ references\ "type"}{3\ Expressions} = 0.67$

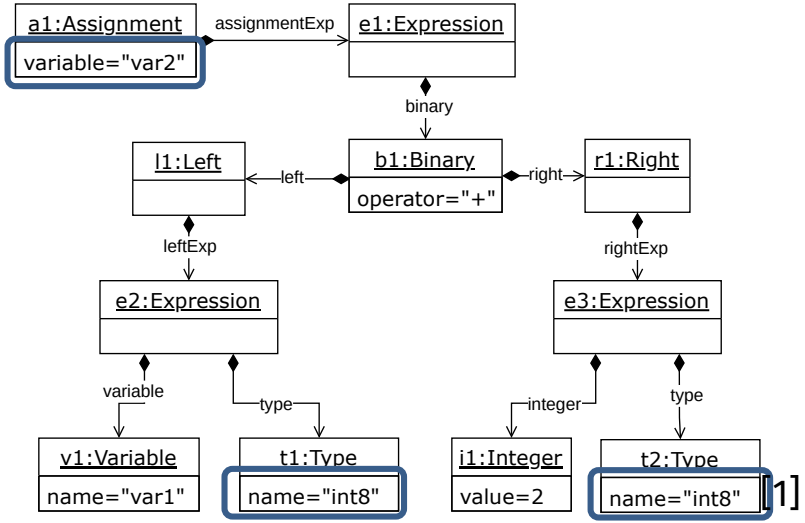


[1]

Feature \ Feature Set (FS)	7
Number of Model Elements per Model Element Type	x
Ø Fan-In/Fan-Out per Model Element Type per Reference Type	x
Ø Number of Attributes per Attribute Type per Model Element Type	

[1] Groner, Raffaela, Sophie Gylstorff, and Matthias Tichy. "A profiler for the matching process of Henshin." *Proceedings of the 23rd ACM/IEEE International Conference on Model Driven Engineering Languages and Systems: Companion Proceedings*. 2020.

- 1 Assignment, 3 Expressions, …
- 0.33 Ø Fan-In per Model Element Type Expression per Reference Type “leftExp”, …
- 1.67 Ø Fan-Out per Model Element Type Expression per Reference Type “type”, …
- 1 String Assignment, 1 String Type, …



[1]

Feature \ Feature Set (FS)	7	8
Number of Model Elements per Model Element Type	x	x
Ø Fan-In/Fan-Out per Model Element Type per Reference Type	x	x
Ø Number of Attributes per Attribute Type per Model Element Type		x

[1] Groner, Raffaela, Sophie Gylstorff, and Matthias Tichy. "A profiler for the matching process of Henshin." *Proceedings of the 23rd ACM/IEEE International Conference on Model Driven Engineering Languages and Systems: Companion Proceedings*. 2020.

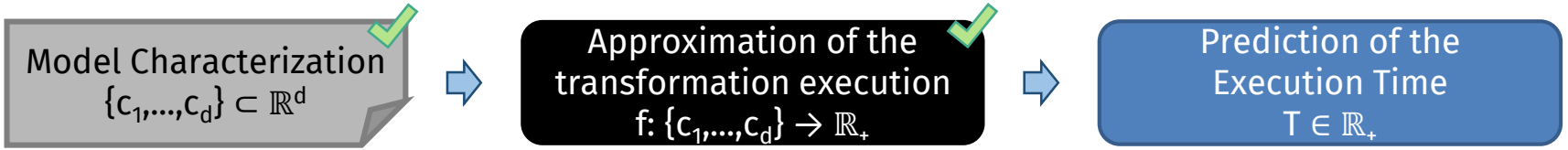
Feature \ Feature Set (FS)	1	2	3	4	5	6	7	8
Number of Model Elements	x	x	x					
Number of References		x	x					
Number of Attributes			x					
Number of Model Elements per Model Element Type				x	x	x	x	x
Ø Fan-In/Fan-Out per Model Element					x	x		

Model Characterization
$\{c_1,\ldots,c_d\} \subset \mathbb{R}^d$

Approximation of the transformation execution
$f: \{c_1,\ldots,c_d\} \rightarrow \mathbb{R}_+$

Prediction of the Execution Time
$T \in \mathbb{R}_+$

- Ordinary Least Squares Linear Regression (LR)
- Support Vector Regression combined with a radial basis function kernel (SVR)
- Random Forests (RF)



Characterization | Approximation

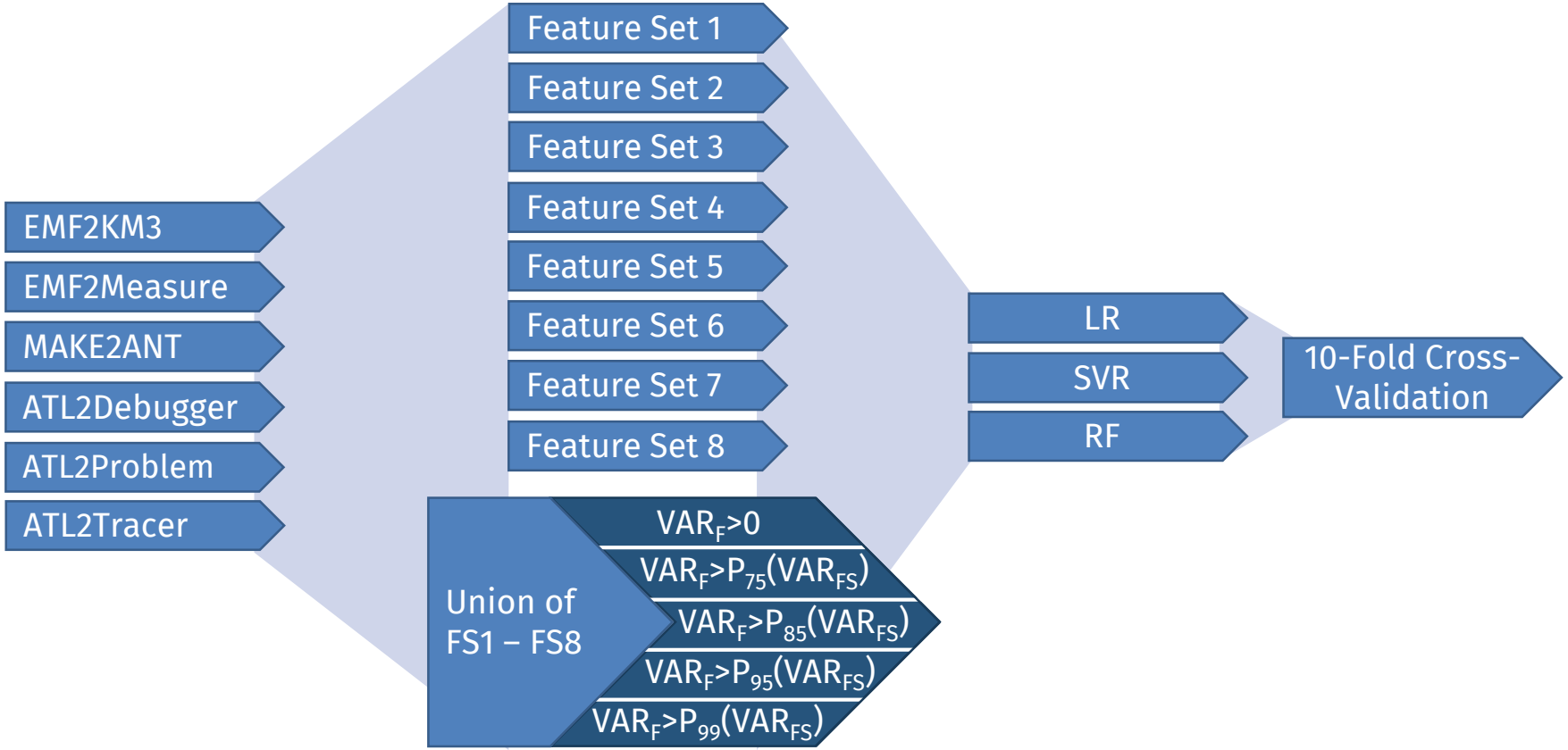
1. Selection of ATL modules and models
2. Time measurements with the help of the JMH [1] framework
3. Determination of the relevant model element types
4. Collection of the metrics of the models for the feature sets

```
rule constantFoldingAddition {
    from
        expression : AST!Expression (expression.checkExpressionElement())
    to
        outExpression : AST!Expression (
                integer<- newInteger
        ),

        newInteger : AST!Integer (
            value <- expression.binary.left.leftExp.integer.value +
                        expression.binary.right.rightExp.integer.value
        )

}

rule dropBinary {
    from
        binary : AST!Binary (binary.checkBinary())
    to
        drop
}
```

[1] Java Microbenchmark Harness https://openjdk.java.net/projects/code-tools/jmh/ (Accessed: 13.02.2022)

Module	Origin of the models	#Models	#Model elements Min	#Model elements Max	Execution time [ms] Min	Execution time [ms] Max	Feature set size Min	Feature set size Max
EMF2KM3	[1]	4,804	1	17,453	3.0	309.2	1	158
MAKE2ANT	[2]	247	1	196	0.9	2.16	1	48
ATL2Tracer	[3]	220	15	7,574	13.0	2,484.0	1	297
ATL2Debugger	[3]	220	1	3,441	0.8	1,371.7	1	66
ATL2Problem	[3]	220	20	11,674	4.0	10,104.0	1	1,964
EMF2Measure	[1]	4,797	1	13,401	5.0	47,707.2	1	107

[1] Stefan Kögel and Matthias Tichy. 2018. Dataset of EMF Models from Eclipse Projects. https://doi.org/10.18725/OPARU-9850
[2] GitHub q=language:makefile 22.04.2021
[3] ATL Transformation Zoo https://www.eclipse.org/atl/atlTransformations/ (Accessed: 03.02.2021)


EMF2KM3
EMF2Measure
MAKE2ANT
ATL2Debugger
ATL2Problem
ATL2Tracer
Feature Set 1
Feature Set 2
Feature Set 3
Feature Set 4
Feature Set 5
Feature Set 6
Feature Set 7
Feature Set 8
Union of FS1 – FS8
VAR_F>0
VAR_F>P_75(VAR_FS)
VAR_F>P_85(VAR_FS)
VAR_F>P_95(VAR_FS)
VAR_F>P_99(VAR_FS)
LR
SVR
RF
10-Fold Cross-Validation

- MAPE and P_{95}(APE)

  - Mean Absolute Percentage Error
  - On average the prediction is off by the given percentage

  - 95^{th} percentile of the Absolute Percentage Error
  - 95% of the predictions yield a smaller absolute error in percent than the given absolute error in percent

- Combination of machine learning approach and feature set that provides the highest accuracy

  ⇨ Small values for the MAPE

  ⇨ Small values for the P_{95}(APE)

Module	Approach	Feature Set (FS)	Variance Threshold	MAPE [%]	P_{95}(APE) [%]
EMF2KM3	LR	FS5	-	1.54	4.17
MAKE2ANT	LR	FS5, FS6	-	1.68	5.01
ATL2Tracer	LR	FS1-8	$VAR_F > P_{85}(VAR_{FS})$	1,187.59	6,134.3
ATL2Debugger	LR	FS2	-	259.23	1,403.23
ATL2Problem	LR	FS1-8	$VAR_F > P_{95}(VAR_{FS})$	243.3	722.23
EMF2Measure	LR	FS2	-	236.55	809.13

➡ Not always a linear relationship exists

- FS2: Number of model elements & number of references
- FS5: Number of model elements per type, Ø Fan-In/Fan-Out per model element type
- FS6: Number of model elements per type, Ø Fan-In/Fan-Out per model element type & number of attributes per attribute type
- $VAR_F > P_{85}(VAR_{FS})$: All features are removed whose variance is less than the 85th percentile of the variances of all features
- $VAR_F > P_{95}(VAR_{FS})$: All features are removed whose variance is less than the 95th percentile of the variances of all features

- MAPE and P_{95}(APE) over all Modules **excluding ATL2Tracer**

Approach	Feature Set (FS)	Variance Threshold	MAPE [%]	P_{95}(APE) [%]	MAPE [%] Min	MAPE [%] Max
RF	FS6	-	4.25	6.6	1.13	10.38
RF	FS1-8	$VAR_F > P_{95}(VAR_{FS})$	3.92	8.63	1.1	9.97
SVR	FS3	-	4.45	11.49	2.07	10.63
SVR	FS1-8	$VAR_F > P_{85}(VAR_{FS})$	3.52	6.71	1.67	26.58

- FS3: Number of model elements, number of references & number of attributes
- FS6: Number of model elements per type, Ø Fan-In/Fan-Out per model element type & number of attributes per attribute type
- $VAR_F > P_{85}(VAR_{FS})$: All features are removed whose variance is less than the 85th percentile of the variances of all features
- $VAR_F > P_{95}(VAR_{FS})$: All features are removed whose variance is less than the 95th percentile of the variances of all features

- MAPE and P_{95}(APE) over all Modules **excluding ATL2Tracer**

Approach	Feature Set (FS)	Variance Threshold	MAPE [%]	P_{95}(APE) [%]	MAPE [%] Min	MAPE [%] Max
RF	FS6	-	4.25	6.6	1.13	10.38
RF	FS1-8	$VAR_F > P_{95}(VAR_{FS})$	3.92	8.63	1.1	9.97
SVR	FS3	-	4.45	11.49	2.07	10.63
SVR	FS1-8	$VAR_F > P_{85}(VAR_{FS})$	3.52	6.71	1.67	26.58

- MAPE and P_{95}(APE) for ATL2Tracer

Approach	Feature Set (FS)	Variance Threshold	MAPE [%]	P_{95}(APE) [%]
RF	FS1-8	$VAR_F > 0$	1,010.91	5,036.55

- FS3: Number of model elements, number of references & number of attributes
- FS6: Number of model elements per type, Ø Fan-In/Fan-Out per model element type & number of attributes per attribute type
- $VAR_F > 0$: All features are removed whose variance is less or equal 0
- $VAR_F > P_{85}(VAR_{FS})$: All features are removed whose variance is less than the 85th percentile of the variances of all features
- $VAR_F > P_{95}(VAR_{FS})$: All features are removed whose variance is less than the 95th percentile of the variances of all features

```
module ATL2Tracer;
create OUT : ATL refining IN : ATL;

rule Module {
    from
        s : ATL!Module
    to
        t : ATL!Module (
            name <- s.name,
            libraries <- s.libraries,
            isRefining <- s.isRefining,
            inModels <- s.inModels,
            outModels <- s.outModels->including(traceModel),
            elements <- s.elements,

            location <- s.location,
            commentsBefore <- s.commentsBefore,
            commentsAfter <- s.commentsAfter
        ),
        traceModel : ATL!OclModel (
            name <- 'trace',
            metamodel <- traceMetamodel
        ),
        traceMetamodel : ATL!OclModel (
            name <- 'Trace'
        )
}
```

ATL2Tracer [1]

```
--@atlcompiler atl2006

-------------------------------------------------------------------------------
-- Transforms an XML metamodel into a R2ML metamodel.
-- Created as part of M.Sc. theses at GOOD OLD AI Research Group
-- Author: Milan Milanovic (milan@milanovic.org), Marko Ribaric (marko.ribaric@gmail.com)
-- Works for R2ML XML Schema and Metamodel v0.5-beta
-------------------------------------------------------------------------------
-- Version: 2.0 (General, Integrity & Derivation rule elements) - 6.11.2006.
-- Version: 2.1 (Reaction rule elements) - 01.02.2007.
--
-- TODO:
--  1) Add support for Production rules
--
-- ANNOTATION: With MDR, Enumerations must be located in top-most package
-------------------------------------------------------------------------------
module XML2R2ML;
create OUT : R2ML from IN : XML;

uses XMLHelpers; -- General XML metamodel helpers

-------------------------------------------------------------------------------
-- HELPERS ----------------------------------------------------------------
-------------------------------------------------------------------------------

```

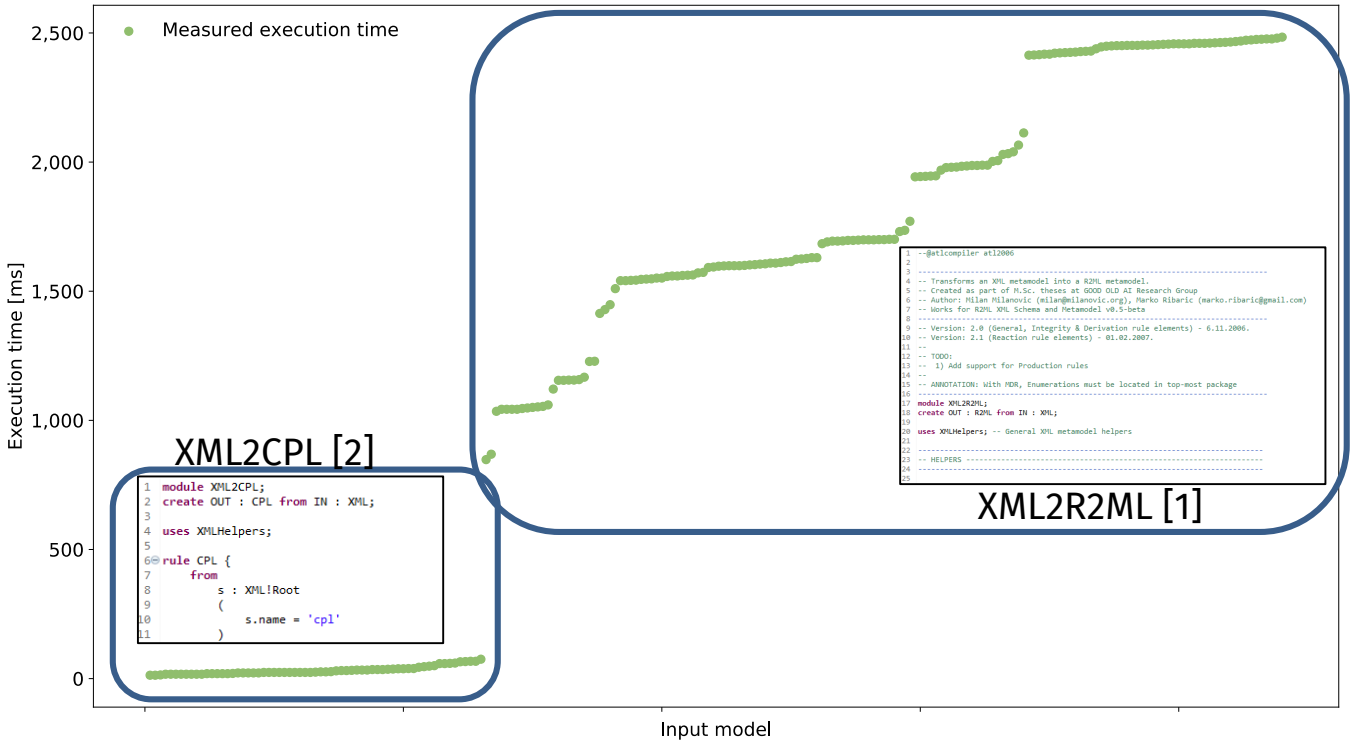
XML2R2ML [2]

```
module XML2CPL;
create OUT : CPL from IN : XML;

uses XMLHelpers;

rule CPL {
    from
        s : XML!Root
        (
            s.name = 'cpl'
        )
```

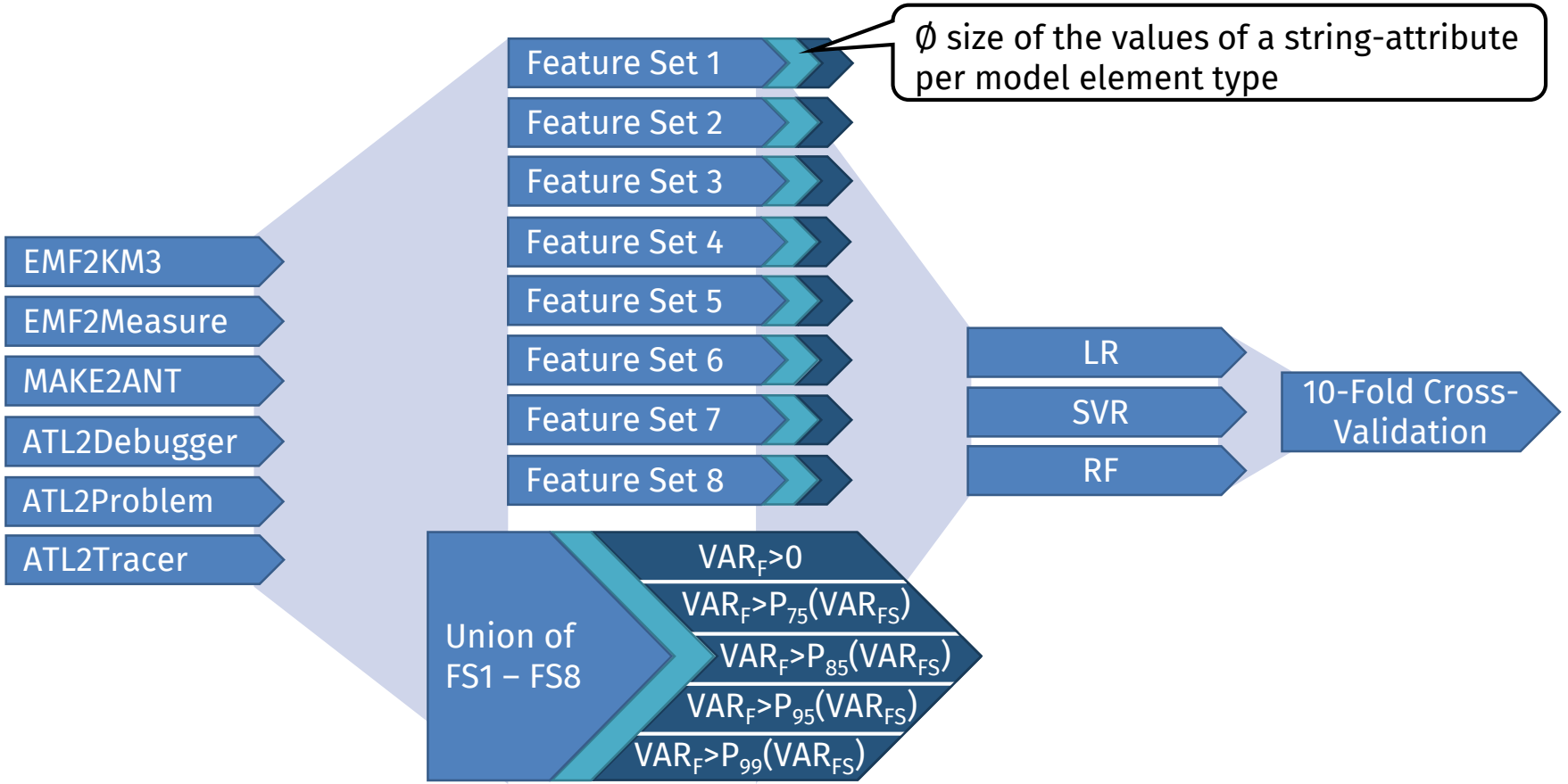
XML2CPL [3]

[1] https://www.eclipse.org/atl/atlTransformations/#ATL2Tracer (Accessed: 06.04.2023)
[2] https://www.eclipse.org/atl/atlTransformations/#WSDL2R2ML (Accessed: 06.04.2023)
[3] https://www.eclipse.org/atl/atlTransformations/#CPL2SPL (Accessed: 06.04.2023)

Measured execution times of ATL2Tracer



[1] https://www.eclipse.org/atl/atlTransformations/#WSDL2R2ML (Accessed: 06.04.2023)
[2] https://www.eclipse.org/atl/atlTransformations/#CPL2SPL (Accessed: 06.04.2023)


Ø size of the values of a string-attribute per model element type
Feature Set 1
Feature Set 2
Feature Set 3
Feature Set 4
Feature Set 5
Feature Set 6
Feature Set 7
Feature Set 8
EMF2KM3
EMF2Measure
MAKE2ANT
ATL2Debugger
ATL2Problem
ATL2Tracer
LR
SVR
RF
10-Fold Cross-Validation
Union of FS1 – FS8
VAR_F>0
VAR_F>P_75(VAR_FS)
VAR_F>P_85(VAR_FS)
VAR_F>P_95(VAR_FS)
VAR_F>P_99(VAR_FS)

- MAPE and P_{95}(APE) over all modules **including ATL2Tracer**

Approach	Feature Set (FS)	Variance Threshold	MAPE [%]	P_{95}(APE) [%]	MAPE [%] Min	MAPE [%] Max
RF	FS3	$VAR_F > P_{85}(VAR_{FS})$	5.07	12.45	1.12	34.53
RF	FS1-8	$VAR_F > P_{95}(VAR_{FS})$	4.55	10.23	1.1	20.53
SVR	FS3	$VAR_F > P_{85}(VAR_{FS})$	6.24	15.85	1.76	63.81
SVR	FS1-8	$VAR_F > P_{95}(VAR_{FS})$	8.37	12.42	2.05	185.99

- MAPE and P_{95}(APE) for ATL2Tracer

Approach	Feature Set (FS)	Variance Threshold	MAPE [%]	P_{95}(APE) [%]
RF	FS4	$VAR_F > 0$	10.47	47.84

- FS3: Number of model elements, number of references & number of attributes
- FS4: Number of model elements per model element type
- $VAR_F > 0$: All features are removed whose variance is less or equal 0
- $VAR_F > P_{85}(VAR_{FS})$: All features are removed whose variance is less than the 85th percentile of the variances of all features
- $VAR_F > P_{95}(VAR_{FS})$: All features are removed whose variance is less than the 95th percentile of the variances of all features

- MAPE and P_{95}(APE) over all modules including ATL2Tracer

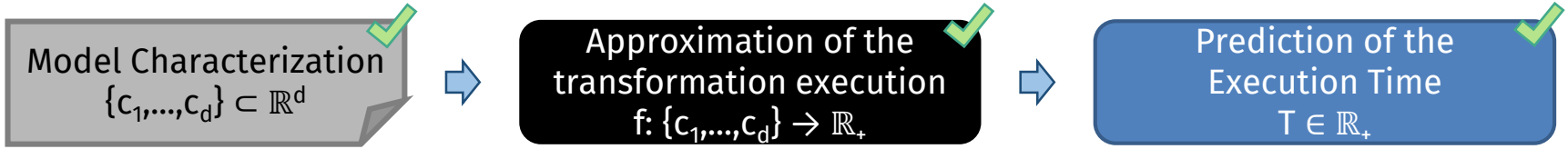
Approach	Feature Set (FS)	Variance Threshold	MAPE [%]	P_{95}(APE) [%]	MAPE [%] Min	MAPE [%] Max
RF	FS3	$VAR_F > P_{85}(VAR_{FS})$	5.07	12.45	1.12	34.53
RF	FS1-8	$VAR_F > P_{95}(VAR_{FS})$	4.55	10.23	1.1	20.53
SVR	FS3	$VAR_F > P_{85}(VAR_{FS})$	6.24	15.85	1.76	63.81
SVR	FS1-8	$VAR_F > P_{95}(VAR_{FS})$	8.37	12.42	2.05	185.99

- Performance prediction of:
  - Jupyter Notebook about 12.8% [1]
  - Spark cloud applications 2.4%-35% [2]

[1] *"Performance Prediction of Jupyter Notebook in JupyterHub using Machine Learning."* P. Prathanrat, and C. Polprasert. In International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS), vol. 3, pp. 157-162, 2018.
[2] "Machine learning for performance prediction of spark cloud applications." A. Maros, F. Murai, A. P. C. da Silva, J. M. Almeida, M. Lattuada, E. Gianniti, M. Hosseini, and D. Ardagna. In IEEE 12th International Conference on Cloud Computing (CLOUD), pp. 99-106, 2019.

- MAPE and P_{95}(APE) over all modules including ATL2Tracer

Approach	Feature Set (FS)	Variance Threshold	MAPE [%]	P_{95}(APE) [%]	MAPE [%] Min	MAPE [%] Max
RF	FS3	$VAR_F > P_{85}(VAR_{FS})$	5.07	12.45	1.12	34.53
RF	FS1-8	$VAR_F > P_{95}(VAR_{FS})$	4.55	10.23	1.1	20.53
SVR	FS3	$VAR_F > P_{85}(VAR_{FS})$	6.24	15.85	1.76	63.81
SVR	FS1-8	$VAR_F > P_{95}(VAR_{FS})$	8.37	12.42	2.05	185.99

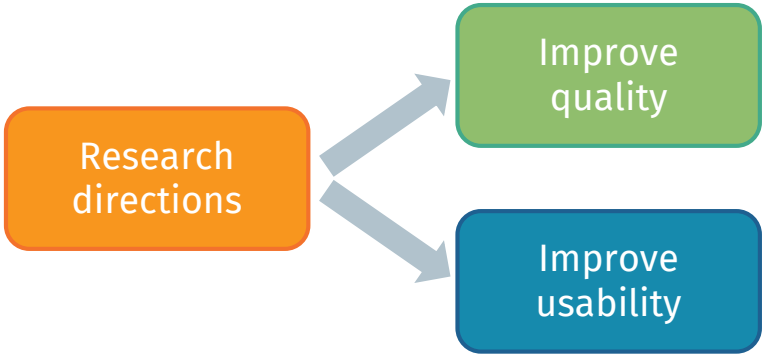


- Performance prediction
  - Multilayer neural networks to predict the performance of SMG2000 applications within 5-7% error [1]

- What-if Analysis
  - What-if analysis in decision-support-system models [2]
  - E-commerce to support decision making for consumers [3]

- Machine Learning and Model Transformations
  - Long Short-Term Memory neural networks to infer model transformations from input-output model pairs [4]

[1] Ipek, Engin, et al. An approach to performance prediction for parallel applications. Vol. 3648. No. UCRL-CONF-212365. Lawrence Livermore National Lab.(LLNL), Livermore, CA (United States), 2005.
[2] Philippakis, Andrew S. "Structured what if analysis in DSS models.“ Proceedings of the Twenty-First Annual Hawaii International Conference on System Sciences. Volume III: Decision Support and Knowledge Based Systems Track. Vol. 3. IEEE, 1988.
[3] Bhargava, Hemant K., Ramayya Krishnan, and Rudolf Müller. "Electronic commerce in decision technologies: A business cycle analysis." International Journal of Electronic Commerce 1.4 (1997): 109-127.
[4] Burgueño, Loli, Jordi Cabot, and Sébastien Gérard. "An LSTM-based neural network architecture for model transformations." 2019 ACM/IEEE 22nd International Conference on Model Driven Engineering Languages and Systems (MODELS). IEEE, 2019.



Approach	Feature Set (FS)	Variance Threshold	MAPE [%]	P_{95}(APE) [%]	MAPE [%] Min	MAPE [%] Max
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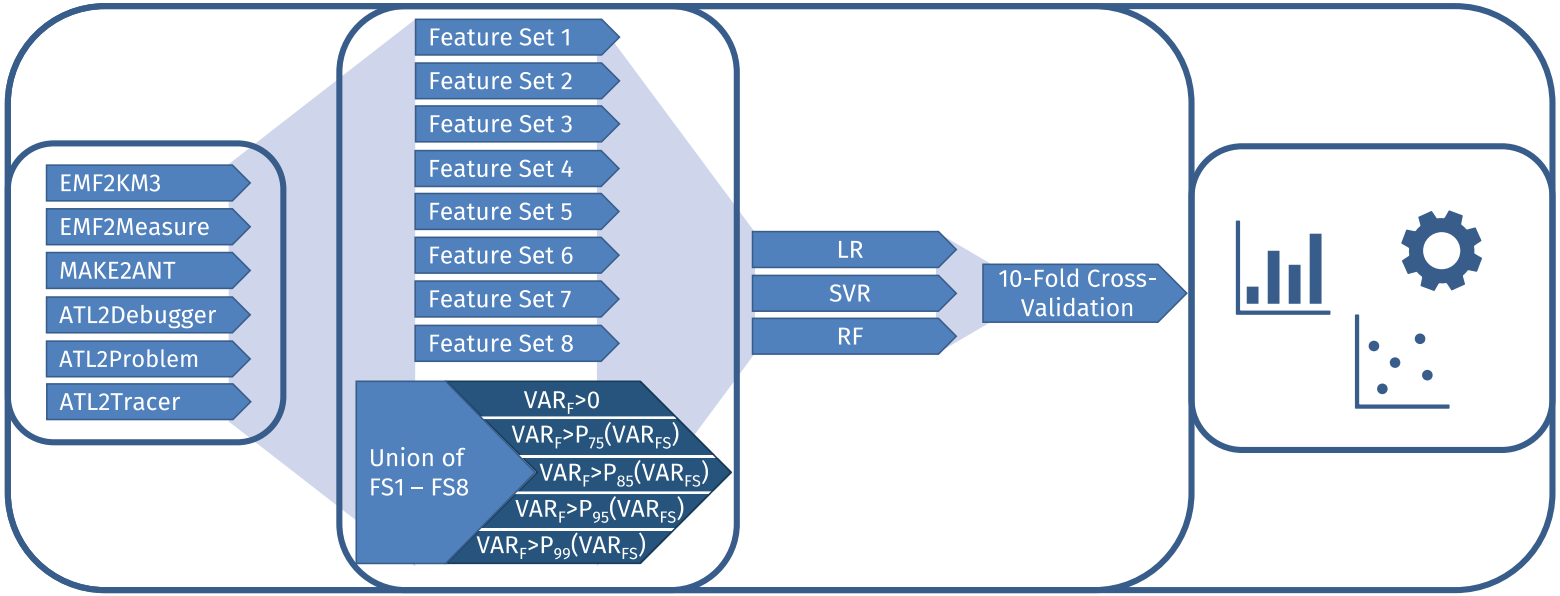
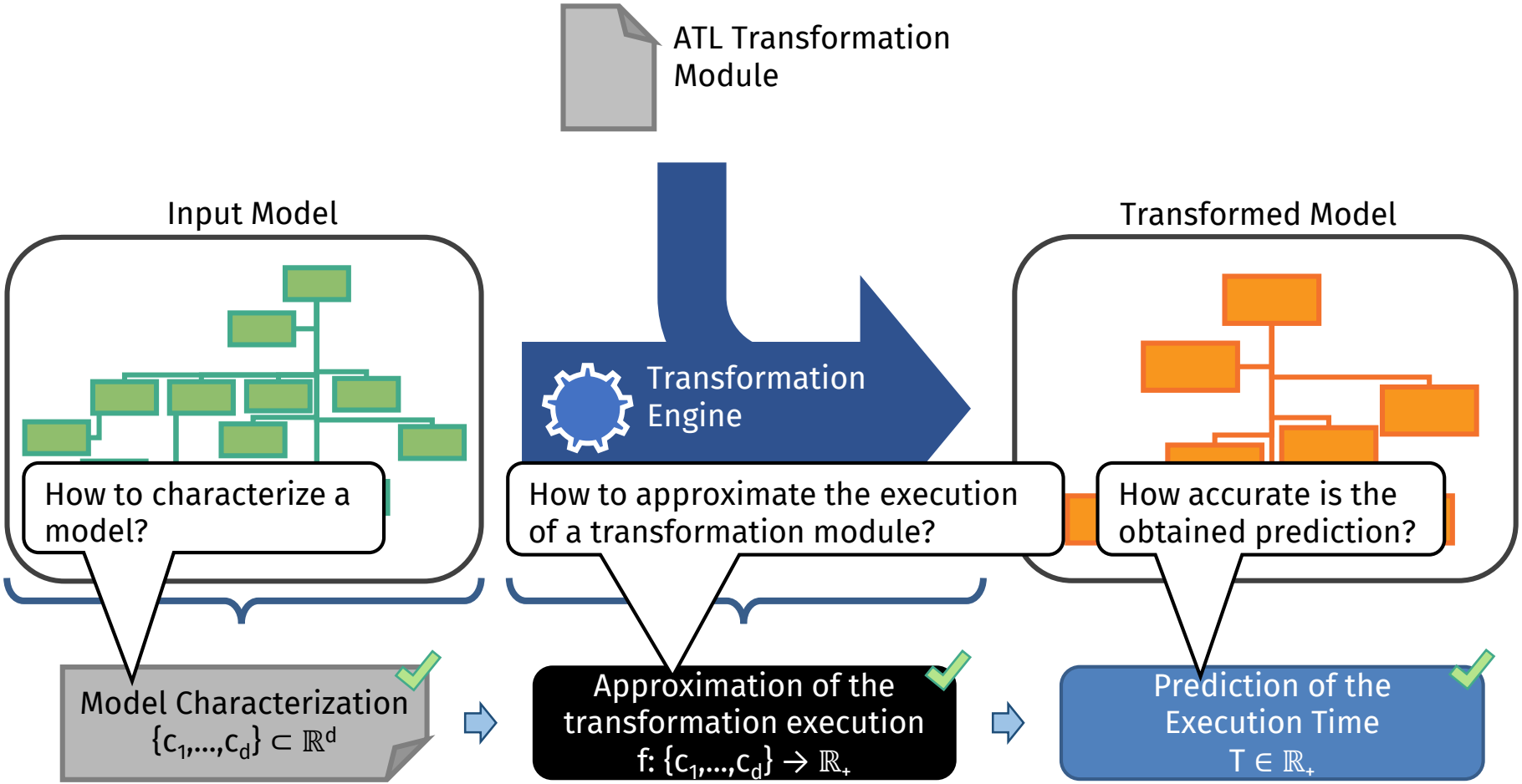


- Documentation of the modules used
- Skeletons of the JMH [1] projects used to measure the execution time
- Eclipse Plugin to collect the model characteristics
- Scripts and raw data to execute our experiments
- Results of our experiments
- Documentation

[1] Java Microbenchmark Harness https://openjdk.java.net/projects/code-tools/jmh/ (Accessed: 13.02.2022)


ATL Transformation Module
Input Model
Transformed Model
Transformation Engine
How to characterize a model?
How to approximate the execution of a transformation module?
How accurate is the obtained prediction?
Model Characterization
$\{c_1,...,c_d\} \subset \mathbb{R}^d$
Approximation of the transformation execution
$f: \{c_1,...,c_d\} \rightarrow \mathbb{R}_+$
Prediction of the Execution Time
$T \in \mathbb{R}_+$