Accelerating Symbolic Analysis for Android Apps

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Motivation

Unsatisfiable path
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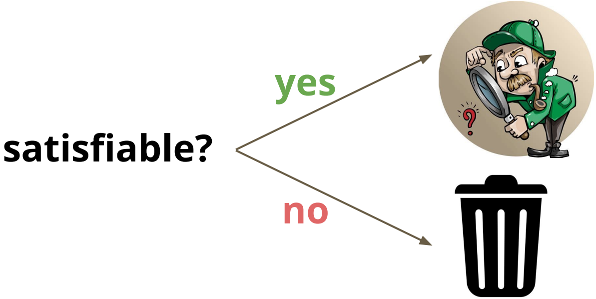
No time to analyze :(

Satisfiable path

- Symbolic execution challenge: **path explosion**
- **Unsatisfiable** paths: no input can trigger
- Require constraint collection & solving to find out satisfiability (expensive!)

Idea



- **Predict** satisfiability => skip potentially unsatisfiable paths
- Criteria:
  - Satisfiable recall: miss fewer (potentially malicious) satisfiable paths
  - Satisfiable precision: better speedup
  - Security-related analysis => **satisfiable recall** more important than **satisfiable precision**

- Use **program features** instead of constraint features
  - More info about code functionality
  - Save constraint collection time

Analysis Platform

- TIRO: symbolic analysis on Android apps
- Overall, only 29.8% of satisfiable paths (258,510 / 868,474)
    - From 127 out of 200 popular Google Playstore apps

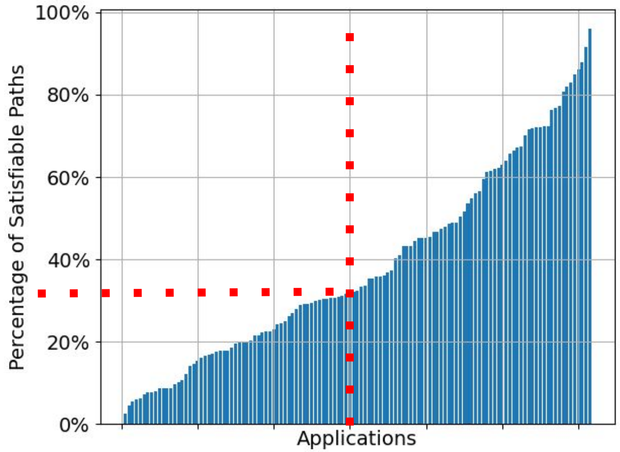
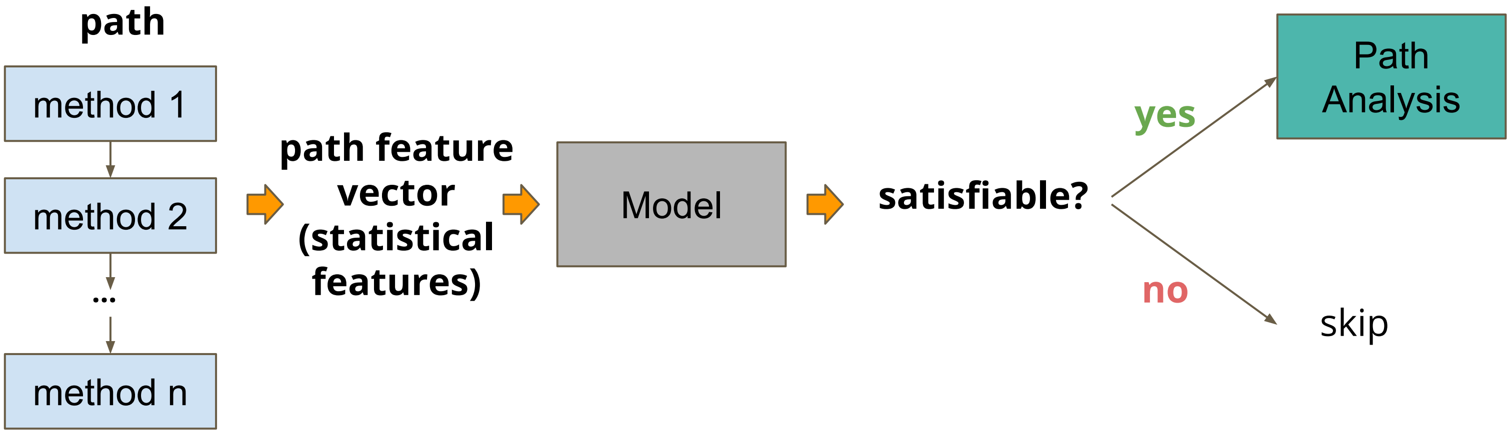


TABLE I
PATH PROCESSING TIME

	mean (ms)	std (ms)
Unsatisfiable Path Analysis	1720	15026
Overall Path Finding	32	107

path analysis cost >> path finding cost

Approach



- Statistical features (specific to Jimple IR)
- Simple models: logistic regression & random forest
    - more complex model as future work (require more data; time-consuming to collect)

Approach: Statistical Features Used

Complex data reference => hard for solve

Method-level features: **complex execution => satisfiability**

Control Flow

# of If / Goto / LookupSwitch / TableSwitch
# of loops, # of statements in loop
# of returns / void returns

Method Invocation

# of method invocation, # of methods invoked

Operation

# of identity statements / assign statements
# of cast expressions
# of arithmetic / logical / shift / cmp operations

Program Size / Structure

# of nop statements ← **program style**
# of blocks, # of units

Variables & Expressions

# of defs / uses / locals
# of new arrays, # of new expressions
# of array references, # of arrays referred
# of field references, # of fields referred
# of length expressions
# of class constants / concrete value constants / nulls

Others

# of enter monitors / exit monitors
# of throw statements

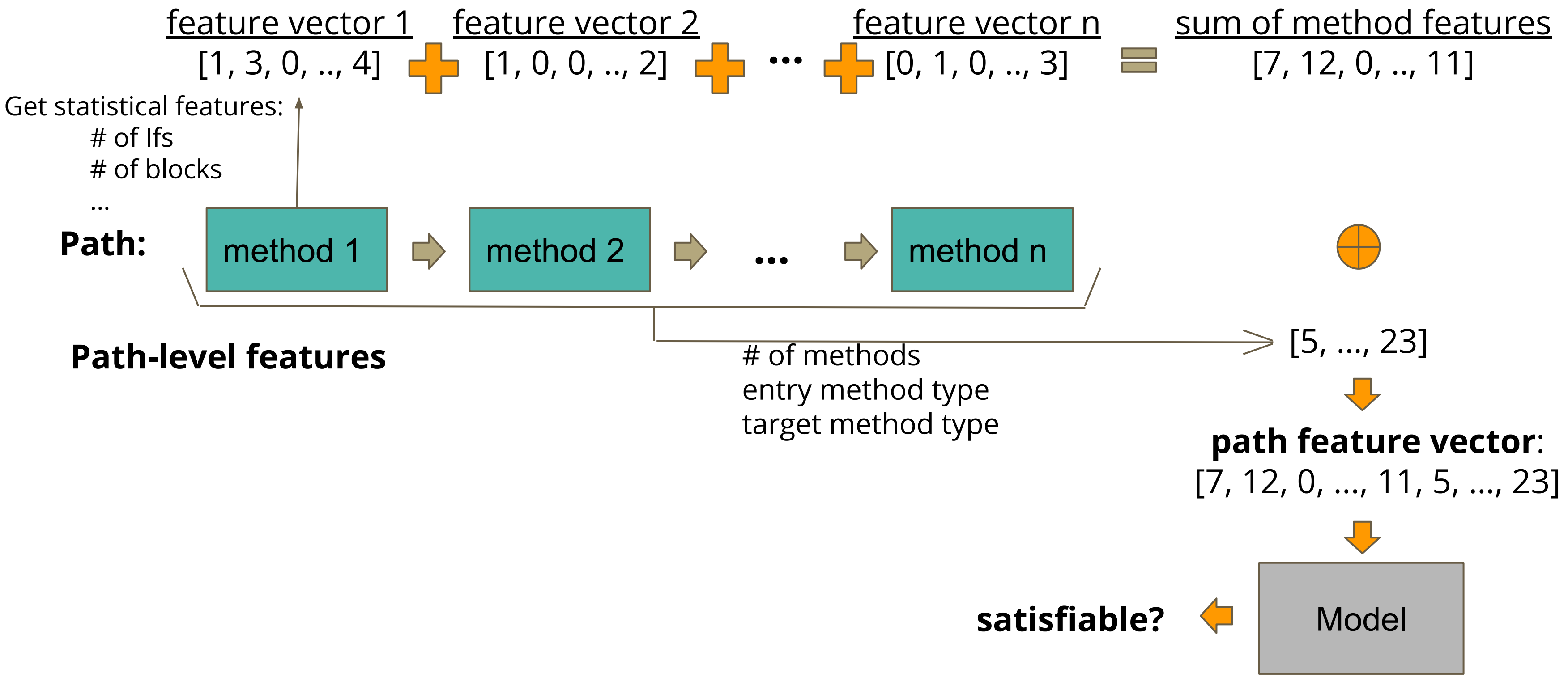
Path-level features:

# of methods in path
entry method type (if common)
target method type (if common)

certain entry easier to reach certain target

Approach: Feature Vector Construction

Method-level features



Evaluation: Google Playstore apps

- Dataset: 127 out of 200 most popular apps in Google Playstore (July 2019)

- **All Apps**: Randomly split all paths into 5 groups & do 5-fold cross validation
    - Paths in training & test set could be from **same** app

Evaluation	Model	Satisfiable Precision	Satisfiable Recall	Unsatisfiable Precision	Unsatisfiable Recall	Average Accuracy	Balanced Accuracy
All Apps (Section IV-B)	LogReg	0.820	0.883	0.939	0.902	0.896	0.893
	RandForest	0.913	0.947	0.973	0.955	0.952	0.951
Cross-App (Section IV-C)	LogReg	0.743	0.895	0.949	0.858	0.872	0.877
	RandForest	0.751	0.914	0.956	0.864	0.880	0.889

- **Cross-App**: predict paths for **unseen** apps; more realistic scenario
    - Randomly split all apps into 5 groups for 5 runs
    - In each run, pick 1 group as test set & other groups as training set
- Random forest overfits for specific apps
- Satisfiable class: higher recall than precision (without tuning)
    - Higher satisfiable recall: <u>miss fewer (potentially malicious</u>) satisfiable paths

Cross-app evaluation: different path types

Inspect paths used in previous cross-app validation (popular Google Playstore apps)

Path Time	Num Paths		Max Save Time	Total Time
	Sat : Unsat	Total Paths		
<10ms	4651:7088 (0.66)	11739 (1.4%)	48 (0.00063%)	67 (0.00088%)
10ms-100ms	3857:135175 (0.029)	139032 (16.0%)	7092 (0.093%)	7231 (0.095%)
100ms-1s	13670:320514 (0.043)	334184 (38.5%)	122830 (1.61%)	130343 (1.71%)
1s-10s	105522:135863 (0.78)	241385 (27.8%)	368698 (4.84%)	888698 (11.7%)
10s-100s	119996:10168 (11.8)	130164 (15.0%)	270983 (3.56%)	3924772 (51.5%)
>100s	10814:1156 (9.4)	11970 (1.4%)	279367 (3.67%)	2667137 (35.0%)

Cross-app evaluation: different path types

Inspect paths used in previous cross-app validation (popular Google Playstore apps)

Path Prediction Type		Sat Performance		Unsat Performance		Confidence			
Path Time	Model	Precision	Recall	Precision	Recall		Total Paths	Saved Time	Max Save Time
<10ms	LogReg	0.463	1.000	0.999	0.239	0.826	11739 (1.4%)	13.6 (0.00018%)	48 (0.00063%)
	RandForest	0.543	0.994	0.991	0.452	0.828		24 (0.00031%)	
10ms-100ms	LogReg	0.079	0.982	0.999	0.671	0.817	139032 (16.0%)	5110 (0.067%)	7092 (0.093%)
	RandForest	0.079	0.980	0.999	0.675	0.746		5148 (0.068%)	
100ms-1s	LogReg	0.346	0.996	1.000	0.920	0.926	334184 (38.5%)	115711 (1.52%)	122830 (1.61%)
	RandForest	0.337	0.985	0.999	0.917	0.861		115245 (1.51%)	
1s-10s	LogReg	0.958	0.933	0.949	0.968	0.921	241385 (27.8%)	356483 (4.68%)	368698 (4.84%)
	RandForest	0.950	0.956	0.966	0.961	0.889		352983 (4.63%)	
10s-100s	LogReg	0.984	0.852	0.323	0.836	0.814	130164 (15.0%)	209206 (2.75%)	270983 (3.56%)
	RandForest	0.985	0.874	0.363	0.846	0.789		213817 (2.81%)	
>100s	LogReg	0.987	0.778	0.304	0.907	0.809	11970 (1.4%)	240624 (3.16%)	279367 (3.67%)
	RandForest	0.977	0.786	0.291	0.825	0.745		221619 (2.91%)	

direction of increase

For better satisfiable recall >10s: can increase overall confidence threshold

Cross-application speedup

- Project speedup for Google Playstore apps

- Additional prediction overhead: feature extraction + model prediction
    - Method-level feature: save extracted features for encountered methods into hash-map; later retrieve (only retrieval overhead)

    - Presented as proportion of total path analysis time
    - Added overhead **negligible**

Model	Prediction Time
	Added Prediction Overhead
LogReg	0.021%
RandForest	0.022%

Cross-application speedup

Threshold	Model	Unsatisfiable Path Savings			
		Saved Analysis Time	Max Achievable Analysis Time	Saved Paths	Max Achievable Paths
0.5	LogReg	**13.9%**	15.9%	**51.7%**	61.4%
0.7		13.2%		47.3%	
0.9		**12.1%**		**40.5%**	
0.5	RandForest	**13.9%**		**51.2%**	
0.6		13.0%		47.5%	
0.7		**11.7%**		**43.0%**	
0.9		7.4%		26.9%	

Threshold	Model	Satisfiable Path Savings	
		Missed Analysis Time	Missed Paths
0.5	LogReg	**13.8%**	**3.6%**
0.7		6.8%	1.6%
0.9		**1.9%**	**0.49%**
0.5	RandForest	**12.4%**	**3.1%**
0.6		7.18%	1.8%
0.7		**3.8%**	**0.97%**
0.9		0.53%	0.17%

- Saved analysis time close to max achievable
- Some time-consuming paths are missed
- Adjust confidence threshold
  - Find points that balance missed path rate & saved analysis time

Cross-application speedup

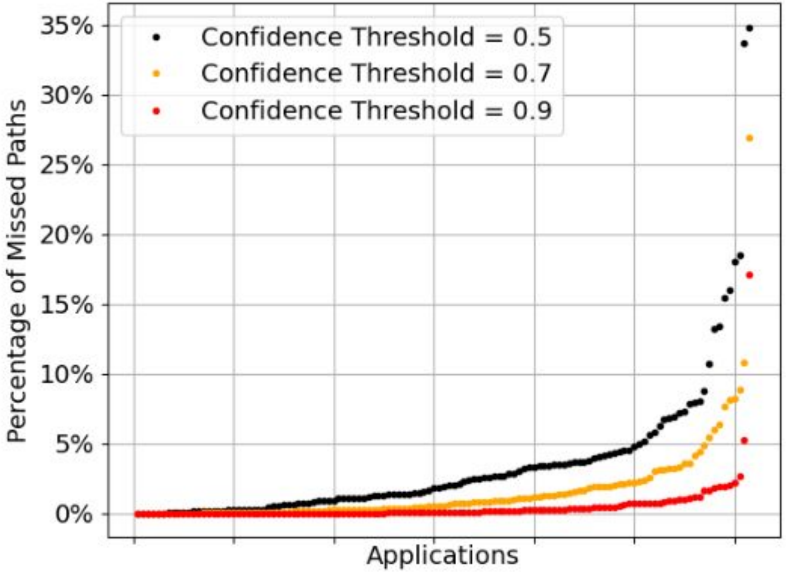


Fig. 2. Sorted Percentage of Missed Paths per App (Logistic Regression)

Cross-app evaluation on malware

- Train on benign apps & test on malware (Genome dataset)
- Malware: important **not to miss paths** (potentially malicious) => require **high satisfiable recall**
    - 61% of malware paths are satisfiable

TABLE V
CROSS-APPLICATION PERFORMANCE ON MALWARE

Threshold	Model	Satisfiable Precision	Satisfiable Recall
0.5	LogReg	0.765	0.934
	RandForest	0.723	0.967
0.7	LogReg	0.714	0.976
	RandForest	0.647	0.998
0.9	LogReg	0.657	0.995
	RandForest	0.621	1

Conclusion

- **Reduce path explosion**: predict unsatisfiable paths with ML classifiers
- Use statistical features with **path-level** program analysis info

- Evaluation: TIRO deobfuscation tool for Android
- Able to generalize patterns about satisfiability to unseen apps & malware
- Saved analysis time close to max achievable save time
- Miss a small number of time-consuming satisfiable paths
    - Adjust confidence threshold: trade-off small amount of saved analysis time => reduce missed satisfiable paths

Thank you!

Related Work

- Use ***constraint features*** to predict best constraint solver / satisfiability: *[DeepSolver, Path Constraint Classifier(PCC), SMTimer]*
    - Still need to run constraint collection
    - We use ***program features*** before constraint collection: more info about code functionality
- Predict satisfying values for constraints that are difficult to solve: *[NeuEx, MLB]*
- Android program analysis tools: *[IntelliDroid, AppIntent, AppAudit]*
    - find paths statically and then dynamically execute them
    - also path explosion: can apply our technique
- Reduce path explosion: *[Statsym, Fitnex, Mutation-based Validation Paradigm (MVP)]*
    - Instead of filter out unsatisfiable ones, use path search algorithm to select paths matching specific objectives

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