



Active-Learning driven Testing of RESTful web APIs

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Contents



- Context
 - REST APIs
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work

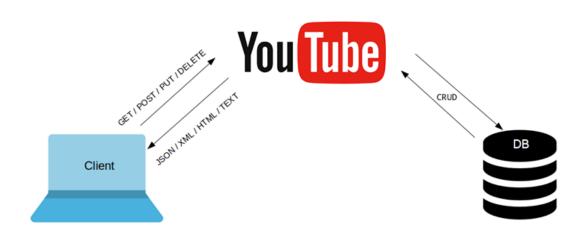
Contents



- Context
 - REST APIs
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work

REST APIs





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- Approach
 - Example
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 - PI1
 - PI2
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Dependencies





videoDuration

string

The **videoDuration** parameter filters video search results based on their duration. If you specify a value for this parameter, you must also set the **type** parameter's value to **video**.

custom object

The custom amount to apply to an invoice. If you include a label, you must include a custom amount.





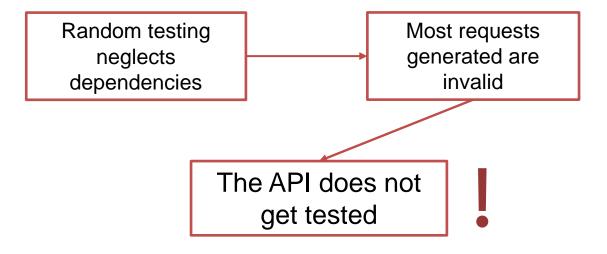
browse

Find venues within a given area. Unlike the checkin intent, browse searches an entire region instead of only finding venues closest to a point. A region to search can be defined by including either the 11 and radius parameters, or the sw and ne. The region will be circular if you include the II and radius parameters, or a bounding box if you include the sw and ne parameters.

- Context
 - REST APIs
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work

Dependencies





98% faulty test cases in



- Context
 - REST APIs
 - Dependencies
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- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
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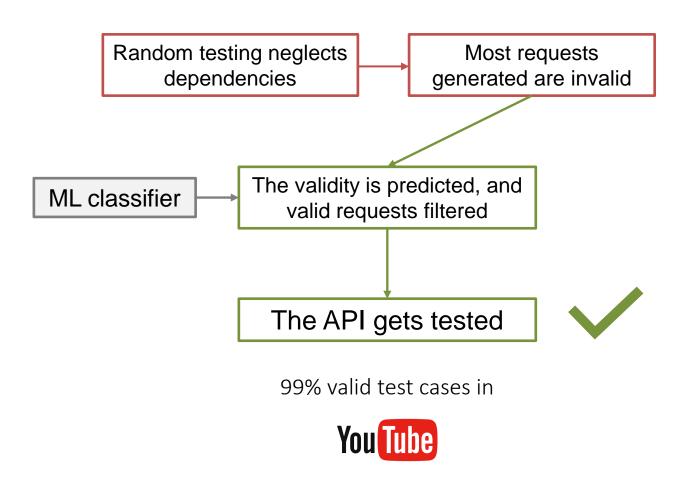


Automated test case generation for RESTful APIs with unspecified dependencies

- Context
 - **REST APIs**
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work

ML-based prediction of requests validity





- Context
 - REST APIs
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work

ML-based prediction of requests validity



Deep Learning-Based Prediction of Test Input Validity for RESTful APIs

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International Workshop on Testing for Deep Learning and Deep Learning for Testing, 2021.

- Context
 - REST APIs
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work

ML-based prediction of requests validity



		р	arameters			valid
visi	bility	affiliation	direction	sort	type	fault
all				full_name	all	
priva	ate	collaborator,owner				
			desc		all	
publ	ic			full_name	public	
all					private	
publ	ic	owner	desc	updated		



- Context
 - REST APIs
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work

ML-based prediction of requests validity



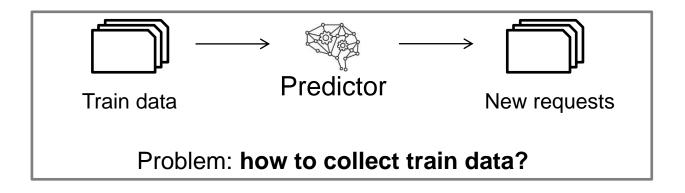
		ра	rameters			valid
visib	oility	affiliation	direction	sort	type	fault
all				full_name	all	Tru
priva	te	collaborator,owner				Fals
			desc		all	Fals
publi	С			full_name	public	Tru
all					private	Tru
publi	С	owner	desc	updated		Fals
				<u> </u>		<u></u>



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 - REST APIs
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work

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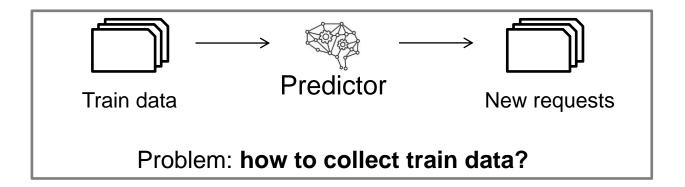


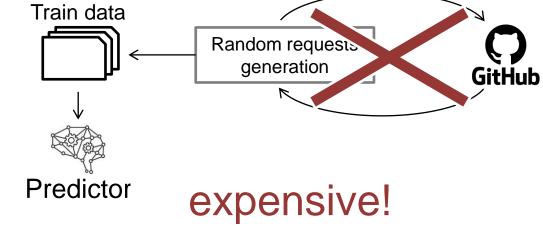


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 - REST APIs
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work

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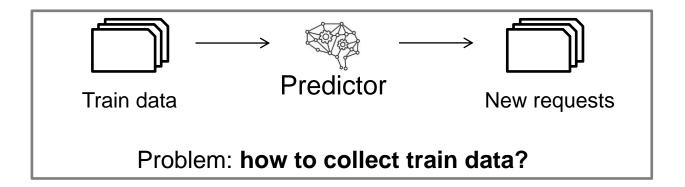


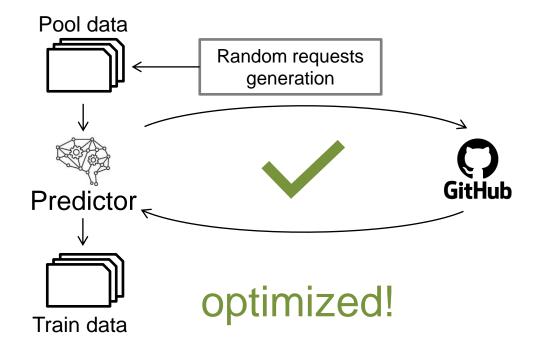




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 - **REST APIs**
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work







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 - Dependencies
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- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work

Example



parameters

visibility affiliation direction sort type all full_name all private collaborator,owner desc all all pushed all private public updated owner desc

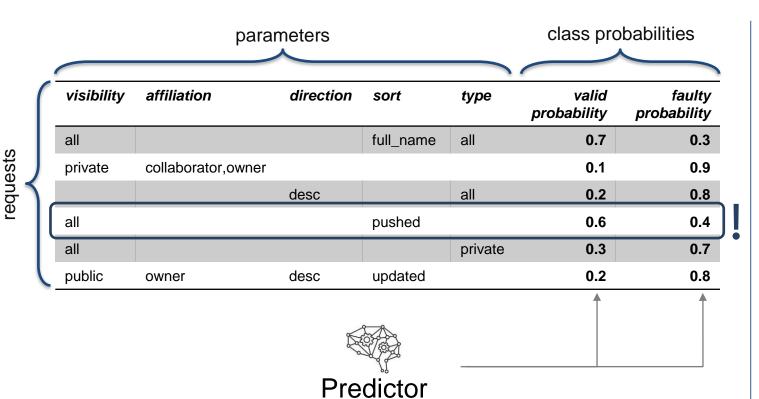
requests

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- **REST APIs**
- Dependencies
- ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work

Example





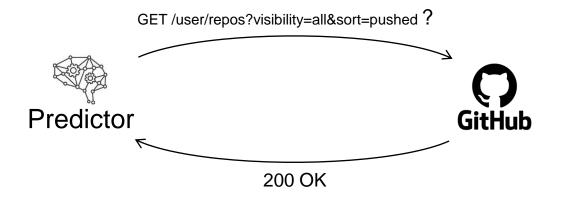
- Context
 - REST APIs
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
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 - PI1
 - PI2
- Future Work

Example



		parai	meters			class pro	babilities
	visibility	affiliation	direction	sort	type	valid probability	faulty probability
ı	all			full_name	all	0.7	0.3
	private	collaborator,owner				0.1	0.9
1			desc		all	0.2	0.8
ı	all			pushed		0.6	0.4
ı	all				private	0.3	0.7
1	public	owner	desc	updated		0.2	0.8

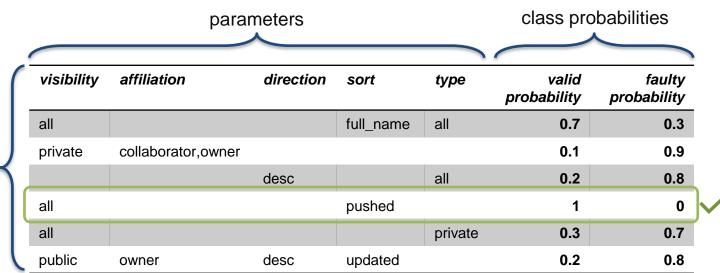
requests



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 - REST APIs
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work

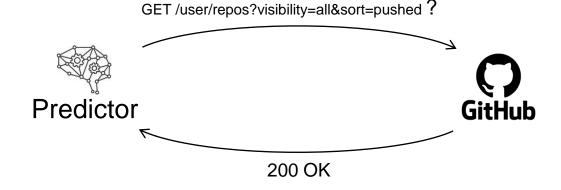
Example





requests

- - PI1
 - PI2
 - **Future Work**



Context

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- Dependencies
- ML-based prediction of requests validity

Example

- Problem
- Approach
- Evaluation

Evaluation



RQ1: How effective is this approach in generating valid requests compared to a random testing baseline?

RQ2: What is the fault-detection capability of this approach compared to a random testing baseline?

- Context
 - **REST APIs**
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work

Evaluation

RQ1



RQ1: How effective is this approach in generating valid requests compared to a random testing baseline?

Comico	Valid requests (%)		
Service	Random testing	AL-driven testing	
GitHub	62.1	98.7	
Stripe-CC	13.7	97.4	
Stripe-CP	55.8	99.3	
Yelp	44.2	83.7	
YouTube-GCT	13.4	85.0	
YouTube-VID	25.3	99.0	
YouTube-SRC	3.0	89.2	
Mean	31.3	93.2	

The ratio of valid requests obtained is **93%**, three times more than random testing baseline (31%).

- Context
 - REST APIs
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
 - PI1
 - PI2
- Future Work

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RQ2



RQ2: What is the fault-detection capability of this approach compared to a random testing baseline?

Comico	Specification Faults			
Service	Random testing	AL-driven testing		
GitHub	313	1159		
Stripe-CC	0	0		
Stripe-CP	104	284		
Yelp	29	60		
YouTube-GCT	0	262		
YouTube-VID	45	442		
YouTube-SRC	30	742		
Mean	74	421		

The number of faults detected is **421**, more than five times the faults detected with random testing baseline (74).

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 - Dependencies
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- Approach
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- Evaluation
 - PI1
 - PI2
- Future Work

Future Work



Human-readable dependencies inference

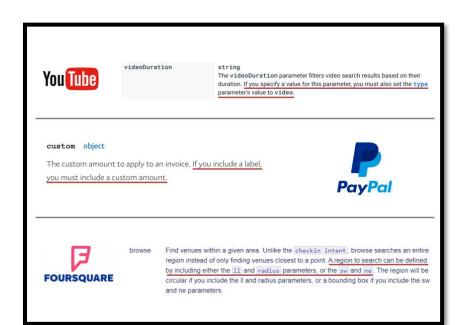
IF type=='private' THEN NOT visibility=='all';

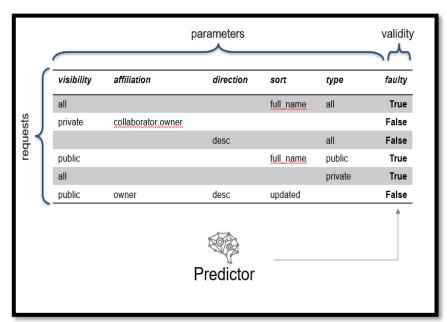
IF type=='public' THEN visibility;

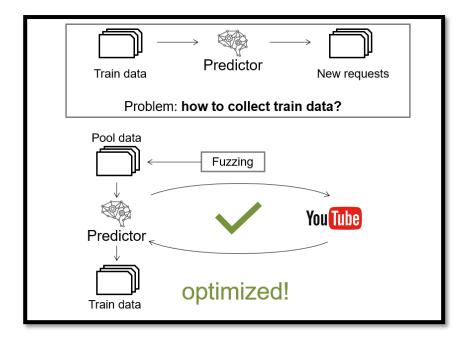
IF type=='public' THEN NOT visibility=='private';

ZeroOrOne(type, visibility)

- Context
 - REST APIs
 - Dependencies
 - ML-based prediction of requests validity
- Problem
- Approach
 - Example
- Evaluation
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 - PI2
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PI2: What is the fault-detection capability of this approach compared to a fuzzing baseline?

	OAS Faults		
Service	Random testing	AL-driven testing	
GitHub	313	1159	
Stripe-CC	0	0	
Stripe-CP	104	284	
Yelp	29	60	
YouTube-GCT	0	262	
YouTube-GV	45	442	
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Mean	74	421	

The number of faults detected is **421**, more than five times the faults detected with random testing techniques (74).





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