

Numerical Aggregation of Trust Evidence: From Foundations to Reasoning Support

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Outline of presentation

- Motivation
- Peal: pluggable evidence aggregation language
- Generating verification conditions for Peal
- Experimental results
- Future work and conclusions

Our Intel project aim

- understand how software annotations can generate trust evidence
- show that such evidence leads to policies that can effectively guard rail executions
 focus of this talk
- do this for both qualitative and/quantitative evidence and develop verification support for this
- study programmers' intent as one source of evidence

Trust evidence

- increasingly, evidence for trust is numeric
- e.g. *reputations* of web sites
- e.g. *age* of software



- e.g. statistical information about past behavior of subjects
- e.g. *probability* of one machine connecting to another



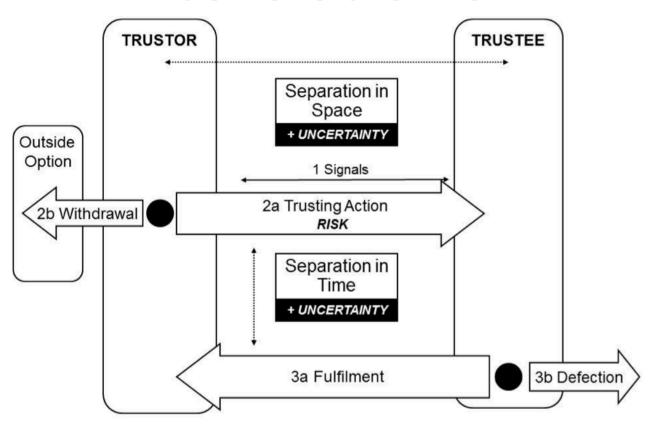
Example

- numeric evidence may be needed even in seemingly qualitative settings
- e.g. you just downloaded the MacTex 2012 package and it does not have a matching hash
- how likely is it that this downloaded software is maliciously corrupted?
- conditional on which browser you use (e.g. Chrome does things to your file!)

Numeric aggregation and its verification

- want to use numeric/non-numeric evidence to produce recommendations or obligations
- which then should inform access-control decisions
- and at all sorts of hardware and software interfaces
 (e.g. forgetful loaders, social networks, infrastructure
 integrity, risk postures of organizations)
- how can we verify such aggregation and what does verification mean here?

Trust-mediated Interactions



Jens Riegelsberger, Martina Angela Sasse, and John D. McCarthy. The mechanics of trust: A framework for research and design. Int. J. Hum.-Comput. Stud., 62(3):381–422, 2005.

Trust & Assurance

- Economic incentive to use trust: assurance techniques are expensive
- But trust signals less reliable in digital domain
- Want to use such signals and combine them with assurance techniques
- ... and in a tuneable manner

Outside

Separation in Space TRUSTEE

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Policies as blocks of aggregated trust signals

- policy (pol) returns a score:
- first, collect all scores of rules in policy whose predicate (i.e. *trust or distrust signal q*) is true
- second, apply op to all these scores to get result; if no q is true, return default score

Full Peal syntax

- op aggregates scores of true predicates in policy
- policy isA policy set, combine policy sets (pSet) with min or max
- cond: compares values of pSet with thresholds

Example

 Alice wants to pay Bob via PayPal on Facebook

```
b_1 = +((if\ (lowCostTransaction\ 0.3)\ (if\ enoughMutualFriends\ 0.1)
(if\ enoughMutualFriendsNormalized\ 0.2))\ default\ 0
b_2 = min((if\ (highCostTransaction\ 0.1)\ (if\ aFriendOfAliceUnfriendedBob\ 0.2)
(if\ aFriendOfAliceVouchesForBob\ 0.6))\ default\ 1
cond = 0.5 < min(b_1, b_2)
```



Analysis example:

Does the behavior of cond change when threshold 0.5 changes to 0.6?

Definition of signals

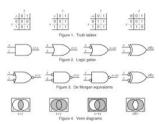
```
lostCostTransaction = (amountAlicePays < 100)
highCostTransaction = (1000 < amountAlicePays)
enoughMutualFriends = (4 < numberOfMutualFriends)
enoughMutualFriendsNormalized = (numberOfBobsFriends < 100 * numberOfMutualFriends)
```

- transaction risk relies on amount that Alice means to pay, amount of 500 does not signal anything!
- other signals also rely on state of relationship graph, e.g. the number of mutual friends
- Last predicate protects against Bob having way too many friends (e.g. celebrity)

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Logical synthesis



- For each cond ("th < pSet" or "pSet <= th"): synthesize propositional formula Φ[cond] over q
- Models = determine truth values of predicates q
- Φ[cond] is true in model iff cond holds in model
- Synthesized Φ[cond] is basis for verification tasks
- predicates q themselves are/representable as formulas of first-order logic

Verification tasks

- Is Φ[cond] always true/false? Vacuity checking
- Do Φ[th < pSet] and Φ[th' < pSet] differ?
 Sensitivity analysis



• Is *cond* persistent, i.e. incomplete requests will grant access only if complete one would?

These and more complex verification tasks reduce to satisfiability checks of $\Phi[cond]$ in logic over predicates q

Analyze instrumentations of Φ[cond]

- Is Φ[cond] always false? Satisfiability checking of that formula, then negate result
- Is Φ[cond] always true? Satisfiability checking of negation of that formula, then negate result
- Do Φ[th < pSet] and Φ[th' < pSet] differ, when th < th'? Satisfiability checking of Φ[th < pSet] && !Φ[th' < pSet]

Etc. But satisfiability checks have to recognize logical dependencies of predicates *q* within *pSet*



SMT solvers

- SMT solvers: combine SAT solvers ("model checking")
 with logical reasoning over theories (theorem proving)
- we have first prototype verification tool using SMT solver Z3 (Microsoft Research)
- below we will explore tradeoff between explicit synthesis of Φ[cond] (space intensive) and synthesis of symbolic version of Φ[cond]
- but first we provide idea and usage of SMT solvers, using Z3 as an example

Simple Z3 code

```
(declare-const a Int) ; example from Z3 documentation
(declare-fun f (Int Bool) Int)
(assert (> a 10))
(assert (< (f a true) 100))
(check-sat)</pre>
```

- declares an integer, and a function that maps an (Int Bool) pair to an integer
- declares two assertions: a is greater than 10, and the value f(a,true) is less than 100
- (check-sat) directive to decide whether there is a model for conjunction of all assertions

Z3 witnesses

```
(declare-const a Int) ; example from Z3 documentation
(declare-fun f (Int Bool) Int)
(assert (> a 10))
(assert (< (f a true) 100))
(check-sat)
(get-model)</pre>
```

(get-model) constructs witness of satisfiability,
 reports exception if no such model exists

```
sat
(model
  (define-fun a () Int
     11)
  (define-fun f ((x!1 Int) (x!2 Bool)) Int
     (ite (and (= x!1 11) (= x!2 true)) 0
          0))
)
```

Scoping in Z3

```
(declare-const x Int); example from Z3 documentation
(declare-const y Int)
(declare-const z Int)
(push)
(assert (= (+ x y) 10))
(assert (= (+ x (* 2 y)) 20))
(check-sat)
(pop); remove the two assertions
(push)
(assert (= (+ (* 3 x) y) 10))
(assert (= (+ (* 2 x) (* 2 y)) 21))
(check-sat)
(declare-const p Bool)
(pop)
(assert p); error, as declaration of p was removed from the stack
```

Each analysis in our tool wrapped in a push/pop frame

Predicate definitions in Z3

 Our tool for Peal verification has text zone in which such domain specifics can be added

Possible Z3 answers

- Some theories and their combination are decidable over first-order logic
- Even if not, conjunction of all assertions may still be decided in instances
- "sat" means that conjunction has model
- "unsat" means that conjunction has no model
- "unknown" means Z3 does not know which is the case

Explicit synthesis

- Generate verification condition Φ[cond] by translating away all references to numerics
- Captures logical nature of condition
- Output is amenable to analysis with an SMT solver
- SMT solver will correctly reflect logical dependencies of predicates within/across policies

Explicit synthesis for pSet composition

- Induction on min/max compositions
- Encodes order properties of min/max

Synthesis of defaults

- pol = op((q1 s1) ... (qn sn)) default s
- reflect whether default is possible or not

$$\begin{array}{lll} \phi[pol \leq th] & \stackrel{\mathrm{def}}{=} & (\bigwedge_{i=1}^{n} \neg q_{i}) \vee \phi_{op}^{ndf}[pol \leq th] & (s \leq th) \\ \\ \phi[pol \leq th] & \stackrel{\mathrm{def}}{=} & (\bigvee_{i=1}^{n} q_{i}) \wedge \phi_{op}^{ndf}[pol \leq th] & (th < s) \\ \\ \phi[th < pol] & \stackrel{\mathrm{def}}{=} & (\bigwedge_{i=1}^{n} \neg q_{i}) \vee \phi_{op}^{ndf}[th < pol] & (th < s) \\ \\ \phi[th < pol] & \stackrel{\mathrm{def}}{=} & (\bigvee_{i=1}^{n} q_{i}) \wedge \phi_{op}^{ndf}[th < pol] & (s \leq th) \\ \end{array}$$

Synthesis of defaults

- default s consistent with threshold:
 conjunction of all negated qi as one disjunct
- otherwise, ensure at least one qi be true

Polarity of synthesis

- want witnessing sets of predicates to be closed under supersets
- X contained in Y implying op(X) <= op(Y)
 means op is monotone; in that case

$$\phi_{op}^{ndf}[pol \le th] \stackrel{\text{def}}{=} \neg \phi_{op}^{ndf}[th < pol]$$

X contained in Y implying op(Y) <= op(X)
means op is anti-tone; in that case

$$\phi_{op}^{ndf}[th < pol] \stackrel{\text{def}}{=} \neg \phi_{op}^{ndf}[pol \leq th]$$

Monotone: op is max

- pol = max((q1 s1) ... (qn sn)) default s
- th < pol if for some qi inequality th < si is true
- last slide: reduce pol <= th to th < pol case

$$\phi_{op}^{ndf}[th < pol] \stackrel{\text{def}}{=} \bigvee_{i|th < s_i} q_i$$

$$\phi_{op}^{ndf}[pol \le th] \stackrel{\text{def}}{=} \neg \phi_{op}^{ndf}[th < pol]$$

Anti-tone: op is min

- pol = min((q1 s1) ... (qn sn)) default s
- pol <= th if there is some qi with si <= th
- now reduce th < pol to pol <= th case

$$\phi_{op}^{ndf}[pol \le th] \stackrel{\text{def}}{=} \bigvee_{i|s_i \le th} q_i$$

$$\phi_{op}^{ndf}[th < pol] \stackrel{\text{def}}{=} \neg \phi_{op}^{ndf}[pol \le th]$$

Monotone: op is +

- let pol be +((q1 s1) ... (qn sn)) default s
- sort predicates qi in pol by ascending score order, e.g. the vector [0.1, 0.2,0.2,0.3,0.5]
- want to find minimal index sets {i,...,j} of predicates
 whose score sum is greater than 0.5 ("0.5 < pol"), say
- here: $M1 = \{\{4,5\}, \{3,5\}, \{2,5\}, \{2,3,4\}, \{1,3,4\}, \{1,2,4\}\}\}$
- explore from highest score, expand only if partial sum ti = s0 + ... + si can get current mass over threshold 0.5

Computing all minimal index sets: M1 explore indexes less than this

```
call enumOne(\{\},0,n+1,+) for n rules where ti = s0 + ... + si
current index set
                         aggregation operator
          enumOne(X, acc, index, op) {
           if (th < acc) \{ output X; \}
           else {
             j = index - 1;
             while ((0 < j) \land (th < op(acc, t_j)))
              enumOne(X \cup \{j\}, op(acc, s_i), j, op);
              j = j - 1; \} \}
```

Example trace

```
th = 0.5, \mathbf{s} = [0.1,0.2,0.2, 0.3, 0.5], \mathbf{t} = [0.1,0.3,0.5,0.8,1.3]
           enumOne(\{\},0,6,+)
             enumOne ({5}, 0.5, 5, +)
                enumOne(\{5,4\},0.8,4,+) --> \{5,4\}
                enumOne(\{5,3\},0.7,3,+) --> \{5,3\}
                enumOne(\{5,2\},0.7,2,+) --> \{5,2\}
                enumOne(\{5,1\},0.6,1,+) --> \{5,1\}
             enumOne(\{4\}, 0.3, 4, +)
                enumOne (\{4,3\},0.5,3,+)
                  enumOne(\{4,3,2\},0.7,2,+) --> \{4,3,2\}
                  enumOne(\{4,3,1\},0.6,1,+) --> \{4,3,1\}
                enumOne (\{4,2\},0.5,2,+)
                  enumOne(\{4,2,1\},0.6,1,+) --> \{4,2,1\}
```

Non-default formula for +

- pol = +((q1 s1) ... (qn sn)) default s
- sort rules so that $s0 \le s1 \le ... \le sn$
- use enumerateOne to generate M1 below

$$\phi_{op}^{ndf}[th < pol] \stackrel{\text{def}}{=} \bigvee_{X \in \mathcal{M}_1} \bigwedge_{i \in X} q_i$$

Anti-tone: op is *

- let pol be *((q1 s1) ... (qn sn)) default s
- Need: scores in [0,1]; so multiplication * is antitone; sort scores in pol by descending order
- find minimal index sets {i,...,j} of qi whose score sum is <= th; M2 = set of such minimal index sets
- explore from lowest score, recurse only if partial product ti can get current mass below threshold th

$$\phi_{op}^{ndf}[pol \le th] \stackrel{\text{def}}{=} \bigvee_{X \in \mathcal{M}_2} \bigwedge_{i \in X} q_i$$

Computing all minimal index sets: *M2*

call enumTwo({},1,n+1,*) for n rules where unit = 1 enumTwo only reverses "th" comparisons of enumOne

```
enumTwo(X, acc, index, op) \ if \ (acc \le th) \ \{ \ output \ X; \ \} \ else \ \{ \ j = index - 1; \ while \ ((0 < j) \land (op(acc, t_j) \le th) \ \{ \ enumTwo(X \cup \{j\}, op(acc, s_j), j, op); \ j = j - 1; \} \} \}
```

Example: Z3 code

 policies b1, b2 composed with max, satisfiability of "cond" explored

```
cond = pSet <= 0.5
b1 = min ((q1 0.2) (q2 0.4) (q3 0.9)) default 1
b2 = + ((q4 0.1) (q5 0.2) (q6 0.2)) default 0
pSet = max(b1, b2)
```

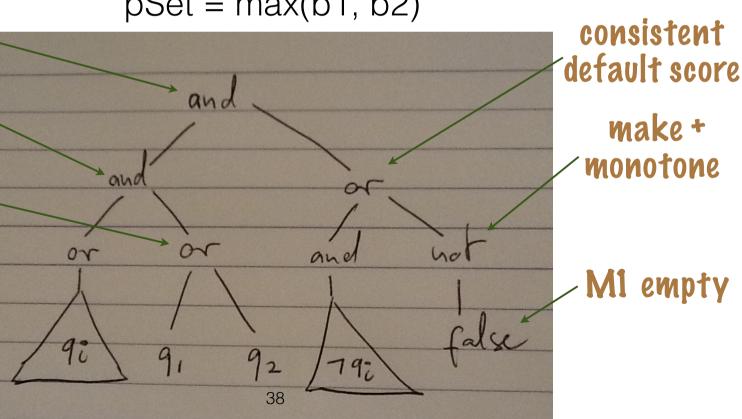
```
(declare-const q4 Bool) ...; declare variables/functions (assert (and (and (or q1 q2 q3) (or q1 q2)) (or (and (not q4) (not q5) (not q6)) (not false)))); synthesised formula in red (check-sat); directive to check for satisfiability (get-model); extraction of witness if satisfiable
```

Parse tree of assertion

cond = pSet <= 0.5 b1 = min ((q1 0.2) (q2 0.4) (q3 0.9)) default 1 b2 = + ((q4 0.1) (q5 0.2) (q6 0.2)) default 0 pSet = max(b1, b2)

inconsistent default score

qi with si <= 0.5



Naming mechanisms

- use simple naming mechanism for all syntactic categories: policies, policy sets, conditions, and analyses
- E.g. we actually bind condition names to formulas in asserts, as in

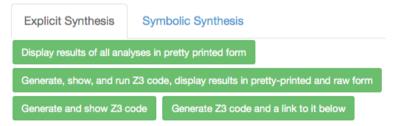
```
(assert (= cond (and (and (or
q1 q2 q3) (or q1 q2)) (or (and
(not q4) (not q5) (not q6)) (not
false)))))
```

DEMO of web app

1. Enter policies, policy sets, conditions, and analyses in the text area below:

Or click on one of the blue buttons to generate a valid input Non-constant score sample Majority-voting sample, n = Constant-score sample Random sample without domain specifics: n, m_min, m_max, m_+, m_*, p, th, delta 5, 5, 4, 3, 2, 7, 0.5, 0.1 Random sample with domain specifics: n, m_min, m_max, m_+, m_*, p, th, delta 2, 3, 1, 1, 1, 9, 0.5, 0.1 Clear text area pSet2 = min(b1, b2)CONDITIONS cond1 = pSet1 <= 0.5cond2 = 0.6 < pSet2cond3 = cond1 && cond2 cond4 = cond1 || cond2 cond5 = !cond4cond6 = true cond7 = false DOMAIN_SPECIFICS (declare-const a Real) (declare-const b Real) (assert (= q1 (< a (+ b 1)))) **ANALYSES** name1 = always_true? cond1 name2 = equivalent? cond1 cond2 name3 = different? cond1 cond2 name4 = implies? cond3 cond4 name5 = always_true? cond3 name6 = always_true? cond4 name7 = always_true? cond5

2. Choose a synthesis method. Then click on one of the green synthesiser buttons:



Non-random benchmark

- Majority voting: pol = +((q1 1/n) (q2 1/n) ... (qn 1/n))
 default 0
- synthesis of 0.5 < pol generates exponentially many disjuncts in set M1
- e.g. for n=27, synthesized formula 0.5 GB!
- satisfiability checks easy, size of formula is real issue here: choose(n,ceilint(n/2)) many terms
- explore space-time trade-offs: symbolic synthesis

Symbolic synthesis

- Hybrid approach: synthesis of min and max composition of rules still done explicitly -linear in input size
- Synthesis of conditions for policy sets makes logical decomposition into conditions for policies explicit
- But synthesis of conditions for policies
 symbolically encodes operational semantics with auxiliary real variables

Simple example

- a policy composed with +
- $b2 = + ((q4 \ 0.1) \ (q5 \ 0.2) \ (q6 \ 0.2)) \ default \ 0$
- declare real variables b2_score_qi for each predicate qi in b2
- assert that these variables have desired operational value
- exploits that + (respectively *) has semantic unit 0 (respectively 1)

Declaring rule effect

```
b2 = + ((q4\ 0.1)\ (q5\ 0.2)\ (q6\ 0.2))\ default\ 0
```

```
(declare-const b2_score_q4 Real) ; reals for b2 (assert (implies q4 (= 0.1 b2_score_q4))) (assert (implies (not (= 0.0 b2_score_q4)) q4)) (declare-const b2_score_q5 Real) (assert (implies q5 (= 0.2 b2_score_q5))) (assert (implies (not (= 0.0 b2 score_q5)) q5))
```

```
(declare-const b2_score_q6 Real)
(assert (implies q6 (= 0.2 b2_score_q6)))
(assert (implies (not (= 0.0 b2_score_q6)) q6))
```

Declaring policy effect

```
b1 = min (...) ...

b2 = + ((q4 0.1) (q5 0.2) (q6 0.2)) default 0

cond2 = 0.6 < min(b1,b2)
```

 effect of policy (here b2) is function of condition, here cond2:

Symbolic synthesis

- Z3 input code linear in size of Peal conditions
- space/time tradeoff: e.g. for majority voting
- explicit synthesis could only deal with n=27 for majority voting
- symbolic synthesis generates and verifies equivalent condition for n=5000 in seconds!

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Experiments

- All experiments test: Z3 code generation and Z3 analysis both take less than five minutes?
- Server funded by this Intel project: 24-core, Linux, 48-GB RAM;
 generated random analyses one single core, here is an example:

```
POLICIES
b0 = max ((q3 \ 0.2602799435758082) (q2 \ 0.8465841883500088) (q1 \ 0.5206939762267451) (q6
0.9230438145042877)) default 0.35448995987981113
b1 = + ((q2\ 0.5067729289557699) (q1\ 0.9809171774005019) (q3\ 0.1957352016220224)) default
0.06811372400781202
b2 = min ((q0 0.3996348599684737) (q6 0.1617558737504945)) default 0.4678754705036007
b3 = * ((q3 0.7832597548785873) (q5 0.5795098955834747)) default 0.4486210823937763
POLICY SETS
p0_1 = min(b0,b1)
p2_3 = min(b2,b3)
p0_3 = max(p0_1, p2_3)
CONDITIONS
cond1 = 0.50 < p0 3
cond2 = 0.60 < p0 3
ANALYSES
analysis1 = always_true? cond1
analysis2 = always_false? cond2
analysis3 = different? cond1 cond2
```

First experiment

- Don't report results on * aggregation of rules in policies for these experiments, see Tech Report for details
- Analyzed sole policy with min or max composition: handle about 2 million rules within five minutes
- Sole policy for + composition: explicit synthesis can handle around 150 rules within five minutes
- Sole policy for + composition: symbolic synthesis can handle about six-thousand(!) rules within five minutes

First experiment + Domain Specifics

- Repeated first experiment but added domain-specific constraints: linear inequalities, and model of method-call graph with in-degree at most 1
- Analyzed sole policy with min or max composition: handle about 7000 (2-million before) rules within five minutes
- Sole policy for + composition: explicit synthesis can handle around 130 (150 before) rules within five minutes
- Sole policy for + composition: symbolic synthesis can handle about two-thousand (6000 before) rules within five minutes

Second experiment

- How many policies analyzable in 5 minutes where each policy has x/10 rules and x was 5-minute bound on number of rules from First Experiment (e.g. x = 200,000 for min and max)
- *min* or *max* composition: handle about 50 policies with about 200,000 rules within five minutes
- + composition: explicit synthesis can handle around 18,000 policies with 14 rules within five minutes
- + composition: symbolic synthesis can handle 24 policies with about six-hundred rules within five minutes

Third experiment

- How many policies n with n rules each can we handle within five minutes?
- *min* or *max* composition: handle about 2000 to 3000 policies with that many rules each within five minutes
- + composition: explicit synthesis can handle about
 100 policies with 100 rules each within five minutes
- + composition: symbolic synthesis can handle about
 160 policies with 160 rules each within five minutes

Alice/Bob example

- cond1 = 0.5 < pSet different from cond2 = 0.6 < pSet
- pretty printed explanation extracted from explicit synthesis analysis (colors added manually):

```
Result of analysis [name1 = different? cond1 cond2] cond1 and cond2 are different

For example, when highCostTransaction is false enoughMutualFriendsNormalized is true lowCostTransaction is true enoughMutualFriends is true aFriendOfAliceUnfriendedBob is false cond2 is false cond1 is true numberOfBobsFriends is 5 amountAlicePays is 2.0 numberOfMutualFriends is 5
```

Alice/Bob explanation

- 0.5 < pSet true, 0.6 < pSet false because
- all predicates in b1 false, so b1 returns 0.6
- first two predicates in b2 true, so b2 returns at least 0.6
- don't care about value of aFriendVouchesForBob
- so pSet = min(b1,b2) returns 0.6

```
b_1 = +((if\ (lowCostTransaction\ 0.3)\ (if\ enoughMutualFriends\ 0.1)
(if\ enoughMutualFriendsNormalized\ 0.2))\ default\ 0
b_2 = min((if\ (highCostTransaction\ 0.1)\ (if\ aFriendOfAliceUnfriendedBob\ 0.2)
(if\ aFriendOfAliceVouchesForBob\ 0.6))\ default\ 1
cond = 0.5 < min(b_1, b_2)
```

Future work

- Comprehensive experimental evaluation
- Case studies that make use of this tool
- Extension to non-constant or negative scores and metrics: symbolic synthesis allows for this
- Independent verification of reported Z3 models, shortening of models for symbolic synthesis
- Implementation of more complex analyses (e.g. computing "threshold spectrum" of policy set)

References

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M. Huth and J. Kuo. PEALT: A reasoning tool for numerical aggregation of trust evidence. Technical Report 2013/7, Imperial College London, Department of Computing, October 2013. ISSN 1469-4166 (Print), ISSN 1469-4174 (Online).

Thank You

Questions?