SHOW ME YOUR PROPERTIES!
THE POTENTIAL OF PROPERTY-BASED TESTING IN AGENT-BASED SIMULATION

Jonathan Thaler
Peer Olaf Siebers

School Of Computer Science
University of Nottingham
7301 Wollaton Rd
Nottingham, United Kingdom
{jonathan.thaler,peer-olaf.siebers}@nottingham.ac.uk

ABSTRACT

This paper presents property-based testing, an approach for testing implementations of agent-based simulations (ABS), never considered so far in this field. It is a complementary technique to unit-testing and allows to test specifications and laws of an implementation directly in code which is then checked using *automated* test-data generation. As case-studies, we present two different models, an agent-based SIR model and the SugarScape model, in which we will show how to apply property-based testing to explanatory and exploratory agent-based models and what its limits are.

Keywords: Agent-Based Simulation, Validation & Verification, Property-Based Testing, Haskell.

1 INTRODUCTION

When implementing an Agent-Based Simulation (ABS) it is of fundamental importance that the implementation is correct up to some specification and that this specification matches the real world in some way. This process is called verification and validation (V&V), where *validation* is the process of ensuring that a model or specification is sufficiently accurate for the purpose at hand, whereas *verification* is the process of ensuring that the model design has been transformed into a computer model with sufficient accuracy (Robinson 2014). In other words, validation determines if we are we building the *right model* and verification if we are building the *model right* (Balci 1998).

One can argue that ABS should require more rigorous programming standards than other computer simulations (Polhill, Izquierdo, and Gotts 2005). Because researchers in ABS look for an emergent behaviour in the dynamics of the simulation, they are always tempted to look for some surprising behaviour and expect something unexpected from their simulation. Also, due to ABS mostly exploratory nature, there exists some amount of uncertainty about the dynamics the simulation will produce before running it. The authors (Ormerod and Rosewell 2006) see the current process of building ABS as a discovery process where often models of an ABS lack an analytical solution (in general) which makes verification much harder if there is no such solution. Thus it is often very difficult to judge whether an unexpected outcome can be attributed to the model or has in fact its roots in a subtle programming error (Galán, Izquierdo, Izquierdo, Santos, del Olmo, López-Paredes, and Edmonds 2009).

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In general this implies that we can only *raise the confidence* in the correctness of the simulation: it is not possible to prove that a model is valid, instead one should think of confidence in its validity. Therefore, the process of V&V is not the proof that a model is correct but the process of trying to prove that the model is incorrect. The more checks one carries out which show that it is not incorrect, the more confidence we can place on the models validity. To tackle such a problem in software, software engineers have developed the concept of test-driven development (TDD).

Test-Driven Development (TDD) was rediscovered in the early 00s by Kent Beck (Beck 2002) as a way to a more agile approach to software-engineering, where instead of doing each step (requirements, implementation, testing,...) as separated from each other, all of them are combined in shorter cycles. Put shortly, in TDD tests are written for each feature before actually implementing it, then the feature is fully implemented and the tests for it should pass. This cycle is repeated until the implementation of all requirements has finished. Traditionally TDD relies on so-called unit-tests which can be understood as a piece of code which when run isolated, tests some functionality of an implementation. Thus we can say that test-driven development in general and unit-testing together with code-coverage in particular, guarantee the correctness of an implementation to some informal degree, which has been proven to be sufficiently enough through years of practice in the software industry all over the world.

In this paper our aim is to introduce and discuss property-based testing, a complementary method of testing the implementation of an ABS, which allows to directly express model-specifications and laws in code and test them through *automated* test-data generation. We see it as an addition to TDD where it works in combination with unit-testing to verify and validate a simulation to increase the confidence in its correctness and is a useful tool for expressing regression tests. To our best knowledge property-based testing has never been looked at in the context of ABS and this paper is the first one to do so.

Property-based testing has its origins (Claessen and Hughes 2000, Claessen and Hughes 2002, Runciman, Naylor, and Lindblad 2008) in the pure functional programming language Haskell (Hudak, Hughes, Peyton Jones, and Wadler 2007) where it was first conceived and implemented. It has been successfully used for testing Haskell code for years and also been proven to be useful in the industry (Hughes 2007). To make this paper sufficiently self-contained we avoid discussing it from a Haskell perspective and present it more on a conceptual level.

We claim that property-based testing is a natural fit for ABS and a valuable addition to the already existing testing methods in this field. To substantiate and test our claims, we present two case-studies. First, the agent-based SIR model (Macal 2010), which is of explanatory nature, where we show how to express formal model-specifications in property-tests. Second, the SugarScape model (Epstein and Axtell 1996), which is of exploratory nature, where we show how to express hypotheses in property-tests and how to property-test agent functionality.

Further we claim that our research is not only applicable to theoretical models like the ones mentioned above but has also importance for Internet of Things (IoT), currently a hot topic in the field of Multi-Agent Systems (MAS) and ABS. ABS is conceptually related to IoT due to both having roots in MAS: in IoT as well as in ABS *things* interact locally with each other, out of which the whole system behaviour emerges. Thus ABS allows to model and simulate large IoT systems and networks before installing them, acting as a kind of prototype and *validation & verification* mechanism. As our paper is focused on exactly that topic, we claim that it is highly relevant for IoT as well.

The structure of the paper is as follows: First we present related work in Section 2. Then we give a more in-depth explanation of property-based testing in Section 3. Next we shortly discuss how to conceptually apply property-based testing to ABS in Section 4. The heart of the paper are the two case-studies, which we present in Section 5 and 6. Finally, we conclude and discuss further research in Section 7.

2 RELATED WORK

Research on TDD of ABS is quite new and thus there exist relative few publications. The work (Collier and Ozik 2013) is the first to discusses how to apply TDD to ABS, using unit-testing to verify the correctness of the implementation up to a certain level. They show how to implement unit-tests within the RePast Framework (North, Collier, Ozik, Tatara, Macal, Bragen, and Sydelko 2013) and make the important point that such a software needs to be designed to be sufficiently modular otherwise testing becomes too cumbersome and involves too many parts. The paper (Asta, Özcan, and Siebers 2014) discusses a similar approach to DES in the AnyLogic software toolkit.

The paper (Onggo and Karatas 2016) proposes Test Driven Simulation Modelling (TDSM) which combines techniques from TDD to simulation modelling. The authors present a case study for maritime search-operations where they employ ABS. They emphasise that simulation modelling is an iterative process, where changes are made to existing parts, making a TDD approach to simulation modelling a good match. They present how to validate their model against analytical solutions from theory using unit-tests by running the whole simulation within a unit-test and then perform a statistical comparison against a formal specification. This approach is important for our SIR and Sugarscape case studies.

The paper (Gurcan, Dikenelli, and Bernon 2013) gives an in-depth and detailed overview over verification, validation and testing of agent-based models and simulations and proposes a generic framework for it. The authors present a generic UML class-model for their framework which they then implement in the two ABS frameworks RePast and MASON. Both of them are implemented in Java and the authors provide a detailed description how their generic testing framework architecture works and how it utilises JUnit to run automated tests. To demonstrate their framework they provide also a case study of an agent-base simulation of synaptic connectivity where they provide an in-depth explanation of their levels of test together with code.

Although the work on TDD is scarce in ABS, there exists quite some research on applying TDD and unit-testing to Multi-Agent Systems (MAS). Although MAS is a different discipline than ABS, the latter one has derived many technical concepts from the former one, thus testing concepts applied to MAS might also be applicable to ABS. The paper (Nguyen, Perini, Bernon, Pavón, and Thangarajah 2011) is a survey of testing in MAS. It distinguishes between unit-tests of parts that make up an agent, agent tests which test the combined functionality of parts that make up an agent, integration tests which test the interaction of agents within an environment and observe emergent behaviour, system tests which test the MAS as a system running at the target environment and acceptance test in which stakeholders verify that the software meets their goal. Although not all ABS simulations need acceptance and system tests, still this classification gives a good direction and can be directly transferred to ABS.

The work (Onggo and Karatas 2016) explicitly mentions the problem of test coverage, which would often require to write a large number of tests manually to cover the parameter ranges sufficiently enough - property-based testing addresses exactly this problem by *automating* the test-data generation. Note that this is closely related to data-generators (Gurcan, Dikenelli, and Bernon 2013) and load generators and random testing (Burnstein 2010) but property-based testing goes one step further by integrating this into a specification language directly into code, emphasising a declarative approach and pushing the generators behind the scenes, making them transparent and focusing on the specification rather than on the data-generation.

3 PROPERTY-BASED TESTING

Property-based testing allows to formulate *functional specifications* in code which then a property-based testing library tries to falsify by *automatically* generating test-data, covering as many cases as possible. When a case is found for which the property fails, the library then reduces the test-data to its simplest form for which the test still fails e.g. shrinking a list to a smaller size. It is clear to see that this kind of testing

is especially suited to ABS, because we can formulate specifications, meaning we describe *what* to test instead of *how* to test. Also the deductive nature of falsification in property-based testing suits very well the constructive and exploratory nature of ABS. Further, the automatic test-generation can make testing of large scenarios in ABS, which is almost always stochastic by nature, feasible as it does not require the programmer to specify all test-cases by hand, as is required in traditional unit-tests.

Property-based testing was invented by the authors of (Claessen and Hughes 2000, Claessen and Hughes 2002) in which they present the QuickCheck library in Haskell, which tries to falsify the specifications by *randomly* sampling the space. We argue, that the stochastic sampling nature of this approach is particularly well suited to ABS, because it is itself almost always driven by stochastic events and randomness in the agents behaviour, thus this correlation should make it straight-forward to map ABS to property-testing. A challenge when using QuickCheck is to write *custom* test-data generators for agents and the environment, which cover the space sufficiently enough to not miss out on important test-cases. According to the authors of QuickCheck *"The major limitation is that there is no measurement of test coverage."* (Claessen and Hughes 2000). QuickCheck provides help to report the distribution of test-cases but still it could be the case that simple test-cases which would fail are never tested because of the stochastic nature of QuickCheck.

To give a rough idea on how property-based testing works in Haskell, we give a few examples of properties on lists, which are directly expressed as functions in Haskell. Such a function has to return a *Bool*, which indicates *True* in case the test succeeds or *False* if not and can take input arguments which data is automatically generated by QuickCheck. Note that the first line of each function defines its name, its inputs (*[Int]* is a list of integers) and the output which is the last type (*Bool*). Note that the *(++)* operator concatenates two lists, *reverse* simply reverses a list.

```
-- concatenation operator (++) is associative
append_associative :: [Int] -> [Int] -> [Int] -> Bool
append_associative xs ys zs = (xs ++ ys) ++ zs == xs ++ (ys ++ zs)

-- reverse is distributive over concatenation (++)
-- xs and ys need to be swapped on the right-hand side!
reverse_distributive :: [Int] -> [Int] -> Bool
reverse_distributive xs ys = reverse (xs ++ ys) == reverse ys ++ reverse xs

-- the reverse of a reversed list is the original list
reverse_reverse :: [Int] -> Bool
reverse_reverse xs = reverse (reverse xs) == xs
```

As a remedy for the potential sampling difficulties of QuickCheck, there exists also a deterministic property-testing library called SmallCheck (Runciman, Naylor, and Lindblad 2008), which instead of randomly sampling the test-space, enumerates test-cases exhaustively up to some depth. It is based on two observations, derived from model-checking, that (1) *"If a program fails to meet its specification in some cases, it almost always fails in some simple case"* and (2) *"If a program does not fail in any simple case, it hardly ever fails in any case* (Runciman, Naylor, and Lindblad 2008). This non-stochastic approach to property-based testing might be a complementary addition in some cases, where the tests are of non-stochastic nature with a search-space which is too large to implement manually by unit-tests but is relatively easy and small enough to enumerate exhaustively. The main difficulty and weakness of using SmallCheck is to reduce the dimensionality of the test-case depth search to prevent combinatorial explosion, which would lead to an exponential number of cases. Thus, one can see QuickCheck and SmallCheck as complementary instead of in opposition to each other. Note that in this paper we only use QuickCheck due to the match of ABS stochastic nature and the random test generation. Also note that we regard property-based testing as *complementary* to unit-tests and not in opposition - we see it as an addition in the TDD process of developing an ABS.

4 TESTING ABS IMPLEMENTATIONS

Generally we need to distinguish between two types of testing / verification in ABS.

1. Testing / verification of models for which we have real-world data or an analytical solution which can act as a ground-truth - examples for such models are the SIR model, stock-market simulations, social simulations of all kind.
2. Testing / verification of models which are of exploratory nature, inspired by real-world phenomena but for which no ground-truth per se exists - examples for such models is the Sugarscape (Epstein and Axtell 1996) or Agent_Zero model (Epstein 2014).

The baseline is that either one has an analytical model as the foundation of an agent-based model or one does not. In the former case, e.g. the SIR model, one can very easily validate the dynamics generated by the simulation to the one generated by the analytical solution through System Dynamics. In the latter case one has basically no idea or description of the emergent behaviour of the system prior to its execution e.g. SugarScape. In this case it is important to have some hypothesis about the emergent property / dynamics. The question is how verification / validation works in this setting as there is no formal description of the expected behaviour: we don't have a ground-truth against which we can compare our simulation dynamics.

One distinguishes between black-box and white-box verification where in white-box verification one looks directly at code and reasons about it whereas in black-box verification one generally feeds input to the software / functions / methods and compares it to expected output. Black-box verification is our primary concern in this paper as property-based testing is an instance of black-box verification. In the case of ABS we have the following levels of black-box tests:

1. Isolated and interacting agent behaviour parts - test the individual parts which make up the agent behaviour under given inputs and test if interaction between agents are correct. For this we can use traditional unit-tests as shown by (Collier and Ozik 2013) and also property-based testing as we will show in the use-cases.
2. Simulation dynamics - compare emergent dynamics of the ABS as a whole under given inputs to an analytical solution or real-world dynamics in case there exists some, using statistical tests. We see this type of tests conceptually as property-tests as well because we are testing properties of the model / simulation as we will see in the use-cases. Technically speaking we can both use traditional unit-tests and also property-based tests to implement them - conceptually they are property-tests.
3. Hypotheses - test whether hypotheses about the model are valid or invalid. This is very similar to the previous point but without comparing it to analytical solutions or real-world dynamics but only to some hypothetical values.

5 CASE STUDY I: SIR

As first use-case we discuss property-based testing for the *explanatory* agent-based SIR model. It is a very well studied and understood compartment model from epidemiology (Kermack and McKendrick 1927) which allows to simulate the dynamics of an infectious disease like influenza, tuberculosis, chicken pox, rubella and measles spreading through a population. We implemented an agent-based version of this model [1], inspired by (Macal 2010).

[1]The code is accessible from https://github.com/thalerjonathan/haskell-sir

In this model, people in a population of size N can be in either one of three states *Susceptible*, *Infected* or *Recovered* at a particular time, where it is assumed that initially there is at least one infected person in the population. People interact *on average* with a given rate of β other people per time-unit and become infected with a given probability γ when interacting with an infected person. When infected, a person recovers *on average* after δ time-units and is then immune to further infections. An interaction between infected persons does not lead to re-infection, thus these interactions are ignored in this model. Due to the models' origin in System Dynamics (SD) (Porter 1962), there exists a top-down formalisation in SD with the following equations:

$$\begin{aligned} \frac{\mathrm{d}S}{\mathrm{d}t} &= -infectionRate & infectionRate &= \frac{I\beta S\gamma}{N} \\ \frac{\mathrm{d}I}{\mathrm{d}t} &= infectionRate - recoveryRate & recoveryRate &= \frac{I}{\delta} \\ \frac{\mathrm{d}R}{\mathrm{d}t} &= recoveryRate \end{aligned} \tag{1}$$

5.1 Deriving a property

Our goal is to derive a property which connects the agent-based implementation to the SD equations. The foundation are both the infection- and recovery-rate where the infection-rate determines how many *Susceptible* agents per time-unit become *Infected* and the recovery-rate determines how many *Infected* agents per time-unit become *Recovered*. Let's look at the algorithm of the susceptible agent behaviour, which is key for the infection-rate:

generate on average β make-contact events per time-unit;
if *make-contact event* **then**
  select random agent *randA* from population;
  if *agent randA infected* **then**
    become infected with probability γ;
  end
end

Algorithm 1: Susceptible behaviour

Per time-unit, a susceptible agent makes *on average* contact with β other agents, where in the case of a contact with an infected agent, the susceptible agent becomes infected with a given probability γ. In this description there is another probability hidden, the probability of making contact with an infected agent, which is simply the ratio of number of infected agents to number non-infected agents. We can now derive the formula for the probability of a *Susceptible* agent to become infected: $\frac{\beta * \gamma * \text{number of infected (I)}}{\text{number of non-infected (N)}}$. When we look at the formula we can see that it is conceptually the same representation of the *infection-rate* of the SD specification as shown above - except that it only considers a single *Susceptible* agent instead of the aggregate of S susceptible agents. We have now a property we can check using a property-test.

5.2 Constructing the property-based test

Having a property (law), we want to construct a property-test for it. The formula is invariant under random population mixes and thus should hold for varying agent populations where the mix of *Susceptible, Infected*

and Recovered agents is random - thus we use QuickCheck to generate the population randomly, the property must still hold.

Obviously we need to pay attention to the fact that we are dealing with a stochastic system thus we can only talk about averages and thus it does not suffice to only run a single agent but we are repeating this for 1,000 *Susceptible* agents (all with different random-number seeds). We thus compute the simulated infection-rate simply by counting the agents which got infected and divide it by the number of total replications N = 1,000. To check whether the test has passed we run it 100 times and use a two-sided T-test to check if the sample infection-rate is statistically significant equal to the hypothetical infection-rate. When executing the tests, QuickCheck generates 100 test-cases by randomly generating 100 different *randAs* inputs to the test. All have to pass for the whole property-test to pass. See Algorithm 2 for the pseudo-code of this property-based test.

```
input : List randAs of random agent-population generated by QuickCheck
populationCount = length randAs;
infectedCount = count Infected in randAs;
hypInfRate = infectivity * contactRate * (infectedCount / populationCount);
sampleRateList = empty list;
for i ← 1 to 100 do
    susceptibles = create 1000 Susceptible agents;
    countInfected = 0;
    for each agent sa in susceptibles do
        run agent sa for 1.0 time-unit, with list randAs as input;
        if agent sa became Infected then
            countInfected = countInfected + 1;
        end
    end
    avgInfRate = countInfected / (length susceptibles);
    insert avgInfRate into sampleRateList;
end
tTestPass = perform 2-sided t-test comparing hypInfRate with sampleRateList on a 0.95 interval;
if tTestPass then
    PASS;
else
    FAIL;
end
```

Algorithm 2: Property-based test for infection-rate.

This is the very power which property-based testing is offering us: we directly express the specification of the original SD model in a test of our agent-based implementation and let QuickCheck generate random test cases for us. This closely ties our implementation to the original specification and raises the confidence to a very high level that it is actually a valid and correct implementation. Also using this test we can determine the *optimal* Δt for running our simulation: because the SIR model is a time-driven one, we need to select a sufficiently small Δt to avoid sampling issues (Thaler, Altenkirch, and Siebers 2018). Using this property-test one can start out with an initial Δt, halving it until the tests pass. Further, by using property-tests we found out about a special case we haven't covered in the implementation of the Susceptible agent behaviour. This shows that property-based testing is not only useful for encoding specifications for regression tests but that is indeed also a valuable tool in finding real bugs e.g. due to missed edge-cases.

6 CASE STUDY II: SUGARSCAPE

We now look at how property-based testing can be made of use in the *exploratory* Sugarscape model (Epstein and Axtell 1996). It was one of the first models in ABS, with the aim to *grow* an artificial society by simulation and connect observations in their simulation to phenomenon observed in real-world societies. In this model a population of agents move around in a discrete 2D environment, where sugar grows, and interact with each other and the environment in many different ways. The main features of this model are (amongst others): searching, harvesting and consuming of resources, wealth and age distributions, population dynamics under sexual reproduction, cultural processes and transmission, combat and assimilation, bilateral decentralized trading (bartering) between agents with endogenous demand and supply, disease processes transmission and immunology. For our research we undertook a *full and validated* implementation of the Sugarscape model [2]. We validated of our implementation against the book (Epstein and Axtell 1996) and a NetLogo implementation (Weaver 2009) [3] during which we also implemented property tests [4].

Whereas in the explanatory SIR case-study we had an analytical solution, inspired by the SD origins of the model, the fundamental difference in the exploratory Sugarscape model is that no such analytical solutions exist. This raises the question, which properties we can actually test in such a model - we propose the following:

- Environment behaviour - the Sugarscape environment has its own behaviour which boils down to regrowing of resources. The correct working can be tested using property-tests by generating random environments and checking laws governing the regrowth.
- Agent behaviour - obviously full agent behaviour could be tested with property-tests, using randomly generated agents (with random values in their properties). It turned out to be quite difficult to derive properties for full agent behaviour, thus in this paper we restricted ourselves to test parts of agent behaviour and also left out testing of agent interactions.
- Emergent behaviour - although we don't have analytical descriptions of properties of our model in the case of Sugarscape, there still exist informal descriptions and more formal hypotheses about emergent properties. Property-testing can be used to check them and if proved to be valid can be seen as regression tests.

6.1 Environment behaviour

The environment in the Sugarscape model has some very simple behaviour: each site has a sugar level and when harvested by an agent, it regrows back to the full level over time. Depending on the configuration of the model it either grows back immediately within 1 tick or over multiple ticks. We can construct simple property-tests for these behaviours. In the case the sugar grows back immediately, we let QuickCheck generate a random environment and then run the environment behaviour for 1 tick and then check the property that all sites have to be back to their maximum sugar level. In the case of regrow over multiple ticks, we also use QuickCheck to generate a random environment but additionally a random *positive* rate (which is a floating point number) which we then use to calculate the number of ticks until full regrowth. After running the random environment for the given number of ticks all sites have to be back to full sugar level - see Algorithm 3 for this case.

[2] The code can be accessed freely from https://github.com/thalerjonathan/haskell-sugarscape

[3] https://www2.le.ac.uk/departments/interdisciplinary-science/research/replicating-sugarscape

[4] A description of this process can be found in a separate Appendix at https://github.com/thalerjonathan/phd/blob/master/public/propabs/appendix_validating_sugarscape.pdf

Note that QuickCheck initially doesn't know how to generate a random environment because each site consists of a custom data-structure for which QuickCheck is not able to generate random instances by default. This problem is solved by writing a custom data-generator, for which existing QuickCheck functions can be used e.g. picking the current sugar level of a site from a random range.

input : Random environment *env* generated by QuickCheck
input : Random regrowth rate *randRate* generated by QuickCheck
maxTicks = maxSugarCapacityOnSites / randRate;
env' = runEnvironmentTicks maxTicks env;
sites = getEnvironmentSites env';
if *all sites maxSugarLevel* **then**
  PASS;
else
  FAIL;
end

Algorithm 3: Property-based test for rate-based regrow of sugar on all sites.

The Sugarscape environment is a torus where the coordinates wrap around in both dimensions. To check whether the implementation of the wrapping calculation is correct we used both unit- and property-tests. With the unit-tests we carefully constructed all possible cases we could think of and came up with 13 test-cases. With the property-based test we simply defined a single test-case where we expressed the property, that after wrapping *any* random coordinates supplied by QuickCheck, the wrapped coordinates have to be within bounds. See Algorithm 4.

input : Random 2D discrete coordinate *randCoord* generated by QuickCheck
(x, y) = wrapCoordinates randCoord;
if *($x \geq 0$ and $x \leq$ environmentDimX) and ($y \geq 0$ and $y \leq$ environmentDimY)* **then**
  PASS;
else
  FAIL;
end

Algorithm 4: Property-based test for wrap-coordinates functionality.

6.2 Agent behaviour

We implemented a number of property-tests for agent functions which just cover a part of an agents behaviour: checks whether an agent has died of age or starved to death, the metabolism, immunisation step, check if an agent is a potential borrower or fertile, lookout, trading transactions. We provided custom data-generators for the agents and let QuickCheck generate the random data and us running the agent with the provided data, checking for the properties.

As an example, provided in Algorithm 5, we give the property-test of an agent dying of age, which happens when the agents age is greater or equal its maximum age. It might look trivial but property-based testing helps us here to clearly state the invariants (properties) and relieves us from constructing all possible edge-cases because we rely on QuickChecks abilities to cover them for us.

input : Random agent *ag* with random age generated by QuickCheck
died = hasAgentDiedOfAge ag;
if *died == (age ag >= maxAge ag)* **then**
  PASS;
else
  FAIL;
end

Algorithm 5: Property-based test for agent dying of age.

6.3 Emergent properties

In the validation and verification process of our Sugarscape implementation we put informal descriptions and hypotheses about emergent properties from the Sugarscape book into formal property-tests. Examples for such hypotheses / informal descriptions of emergent properties are e.g. the carrying capacity becomes stable after 100 steps; when agents trade with each other, after 1,000 steps the standard deviation of trading prices is less than 0.05; when there are cultures, after 2,700 steps either one culture dominates the other or both are equally present.

The property we test for is whether *the emergent property under test is stable under varying random-number seeds* or not. Put another way, we let QuickCheck generate random number streams and require that the tests all pass. Unfortunately, this revealed that this property doesn't hold for all hypotheses. The problem is that QuickCheck generates by default 100 test-cases for each property-test where all need to pass for the whole property-test to pass - this wasn't the case, where most of the 100 test-cases passed but unfortunately not all. Thus in this case a different approach is required: instead of requiring *every* test to pass we require that *most* tests pass, which can be achieved using a T-test with a confidence interval of e.g. 95%. This means we won't use QuickCheck anymore and resort to a normal unit-test where we run the simulation 100 times with different random number streams each time and then performing a T-test with a 95% confidence interval. Note that we are now technically speaking of a unit-test but conceptually it is still a property-test.

In Algorithm 6 we show a property-test for checking whether after 1,000 steps the standard deviation of trading prices is less than 0.05. The test passes if out of 100 runs a 95% confidence interval is reached using a T-test.

7 CONCLUSIONS

We found property-based testing particularly well suited for ABS firstly due to ABS stochastic nature and second because we can formulate specifications, meaning we describe *what* to test instead of *how* to test. Also the deductive nature of falsification in property-based testing suits very well the constructive and often exploratory nature of ABS.

Although property-based testing has its origins in Haskell, similar libraries have been developed for other languages e.g. Java, Python, C++ as well and we hope that our research has sparked an interest in applying property-based testing to the established object-oriented languages in ABS as well.

We didn't look into testing full agent and interacting agent behaviour using property-tests due to its complexity which would justify a whole paper alone. Due to its inherent stateful nature with complex dependencies between valid states and agents actions we need a more sophisticated approach as outlined in (De Vries 2019), where the authors show how to build a meta-model and commands which allow to specify properties and valid state-transitions which can be generated automatically. We leave this for further research.

```
maxTicks = 1000;
replications = 100;
stdAverage = 0.05;
tradingPriceStdsList = empty list;
for i ← 1 to replications do
    rng = new random number generator;
    simContext = initSimulation rng;
    out = runSimulation maxTicks simContext;
    tps = extractTradingPrices out;
    tpsStd = calculate standard deviation of tps;
    insert tpsStd into tradingPriceStdsList;
end
tTestPass = perform 1-sided t-test comparing stdAverage with tradingPriceStdsList on a 0.95 interval;
if tTestPass then
    PASS;
else
    FAIL;
end
```

Algorithm 6: Property-based test for trading prices.

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