Why property-based testing matters

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Overview

- A long-standing challenge for software engineering is ensuring software correctness
- Formal verification is (still) expensive and rarely used
- *Tests* are the most commonly used practical technique
- *Unit tests* are the industry-standard for verification “in the small”

This talk

- *Property-based testing*: an automatic testing alternative to unit tests
- A "lightweight" formal method
- Available for many programming languages
- Many successful applications in open-source and some industrial projects
- But still not commonly taught and under-utilized in practice

Slides and demo code:
`https://github.com/pbv/why-pbt-matters`

“Lightweight” formal method?

According to Benjamin Pierce, author of *Types and Programming Languages*

Formal method

“A mathematically rigorous technique for validating the actual behaviour of a program against a description of desired behavious.”

Lightweight formal method

“One that can be applied successfully by someone who doesn’t fully understand it.” ☺

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supports automation

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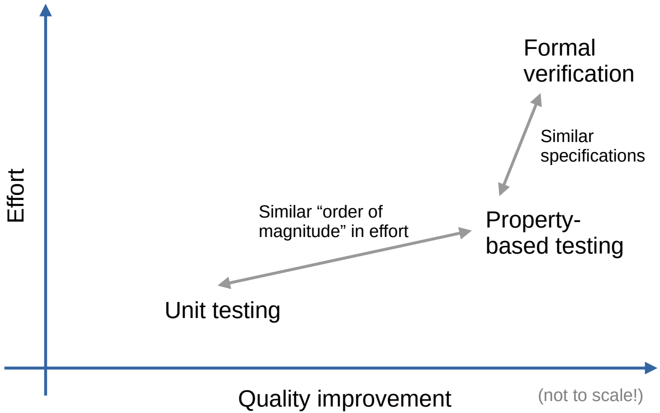
PBT vs unit tests vs formal verification



Unit tests

- Code fragments for testing functions, classes, libraries, etc.
- Express the expected outputs for specific combinations of inputs
- Example: testing an integer square root function in Python

```
def test_isqrt():
    assert isqrt(0) == 0
    assert isqrt(2) == 1
    assert isqrt(4) == 2
    assert isqrt(5) == 2
    assert isqrt(9) == 3
```

Problems with unit tests

Cognitive bias:

- how can we include an edge case in the tests that we didn't consider in the code?

Poor scaling:

- a few unit tests per feature
- for n features, $O(n)$ unit tests
- but testing *interactions* between features requires $O(n^2), O(n^3), \ldots$ unit tests

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Solution:

"Don't write tests — generate them!"

John Hughes, co-author of the *QuickCheck* PBT library

Property-based testing

- Write *properties* instead of specific tests
  - should be universal, i.e. hold for all values
  - should define the expected behaviour for *all* cases
- Specify *generators* for the inputs
- The testings framework runs the property with a large number of inputs
  - testing fails if a counter-example is found
  - otherwise, testing succeeds

Property-based testing (cont.)

- QuickCheck (2000): first PBT library (for Haskell)
- Other implementations:

PropEr	for Erlang
ScalaCheck	for Scala
Hypothesis	for Python
FsCheck	for F#
JUnit-QuickCheck	for Java
RapidCheck	for C++

Many others: `https://en.wikipedia.org/wiki/QuickCheck`

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Let n be an arbitrary non-negative number; let $r = \mathtt{isqrt}(n)$; then

$$r \geq 0 \wedge r^2 \leq n \wedge (r+1)^2 > n$$

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(Cue demo.)

Properties in Hypothesis

- Properties are *functions*...
- ...that should fail if the expected condition is not met
- Arguments are *universally quantified*
- For each property:
  - test with a large number of random values (100 by default)
  - generated using *strategies* (defined by `@given`)
- Module `hypothesis.strategies` provides:
  - *predefined strategies* for basic types
  - methods for *modifying* and *combining* strategies

Strategies

floats()	generate floating-point numbers
integers()	generate integers
booleans()	generate logical values
text()	generate Unicode strings
lists(s)	lists of elements given by strategy s
...	many others

We can also:

- customize strategies using *parameters* (e.g. `min_value`)
- modify strategies by *mapping* and *filtering*
- combine stategies using *combinators*

Generating data

```
>>> integers().example()
848041

>>> lists(integers(min_value=0, max_value=100)).example()
[2, 29, 54, 66, 1, 27, 77, 81, 51, 18, 18]

>>> lists(integers().map(lambda x:x*2)).example()
[6668, -38, 1081651134, -6590]

>>> lists(integers()).map(sorted).example()
[-6913, -59, 37, 77, 90, 25088]

>>> lists(one_of(integers(), booleans())).example()
[True, True, -1318, True, True, -46, -46, True, -46]
```

Another example

Let's test the interaction between *list reverse* and *append*.
Consider x, y two arbitrary lists:

$$reverse(x + y) = \quad ???$$

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Let's test the interaction between *list reverse* and *append*.
Consider x, y two arbitrary lists:

$$reverse(x + y) = reverse(y) + reverse(x)$$

Example:

$$\begin{aligned} reverse([1,2] + [3,4]) &= reverse([3,4]) + reverse([1,2]) \\ &= [4,3] + [2,1] \\ &= [4,3,2,1] \end{aligned}$$

Testing with lists of integers

```
intlist = st.lists(st.integers())
@given(intlist, intlist)
def test_reverse_append(x, y):
    assert reverse(x + y) == reverse(x) + reverse(y)
```

Testing with lists of integers

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intlist = st.lists(st.integers())
@given(intlist, intlist)
def test_reverse_append(x, y):
    assert reverse(x + y) == reverse(x) + reverse(y)
```

```
pytest basic.py -k test_reverse_append
```

```
==================== FAILURES ========================
______________ test_reverse_append _____________________

x = [0], y = [1]
```

What happened. . . ?

Checking expectations

- We've written the property incorrectly!

  ```
  assert reverse(x + y) == reverse(x) + reverse(y)
  ```

  instead of

  ```
  assert reverse(x + y) == reverse(y) + reverse(x)
  ```

- Hypothesis found a counter-example for the wrong property:

$$reverse([0] + [1]) \neq reverse([0]) + reverse([1])$$

- This is the *smallest* counter-example that falsifies the property
- Hypothesis *always* find this counter-example regardless of random generation!

Shrinking

- Hypothesis attempts to simplify counter-examples before presenting; e.g.:
  - removing elements from the lists
  - shrinking elements inside the lists
- This is useful to remove "noise" from randomly generated data
- For the previous example we obtain the *minimal* counter-example
- In general, shrinking only finds a *local minimum*

A real-world example

- Erlang code for SMS text packing at Ericsson
- 7-bit characters transmitted using 8-bit *bytes*
- GSM standard: pack 8 caracteres into 7 bytes
- Two functions (translated to Python):

  ```
  pack(seq: bytes) -> bytes
  unpack(seq: bytes) -> bytes
  ```

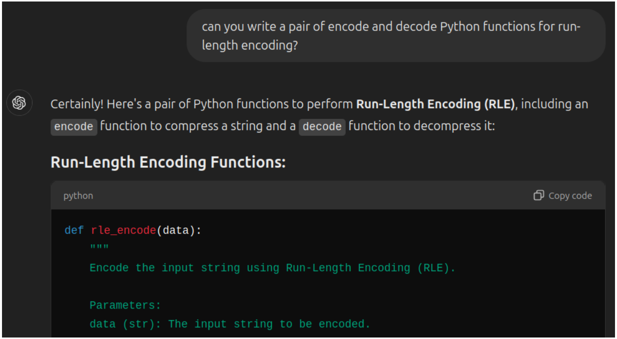
- Roundtrip property: unpack is the inverse of pack

$$unpack(pack(seq)) = seq, \text{ for all } seq$$

A real-world example (cont.)

- John Hughes's company (QuviQ) found a subtle bug affecting strings of length multiple of 8 ending in a `\NUL` character
- The code had been unit tested and was in production

Validating AI generated code



- Let us use Hypothesis to validate AI generated code
- Problem: write a pair of encode/decode functions for run-length encoding

$$\texttt{'AAABBCAAAAA'} \;\underset{\textit{decode}}{\overset{\textit{encode}}{\rightleftarrows}}\; \texttt{'A3B2C1A5'}$$

Testing ChatGPT solution

"Roundtrip" property i.e. decode is the inverse of encode

```
@given(st.text())
def test_decode_encode_1(s):
    assert rle_decode(rle_encode(s)) == s
```

Testing ChatGPT solution

"Roundtrip" property i.e. decode is the inverse of encode

```
@given(st.text())
def test_decode_encode_1(s):
    assert rle_decode(rle_encode(s)) == s
```

```
pytest rle_tests.py -k test_decode_encode_1
==================== FAILURES ===========================
_____________ test_decode_encode_1 _____________________

s = '01'
```

The solution doesn't work for strings with digits!

Characterizing failure

We can check if the generated code works when the string contains no digits:

```
no_digits = st.characters(exclude_categories='N')
@given(st.text(alphabet=no_digits))
def test_decode_encode_2(s):
    assert rle_decode(rle_encode(s)) == s
```

- The property now passes the default 100 tests
- We could now try to fix the solution for digits
- But first: perform some statistics on the testing data

Characterizing test data

```
def longest_count(s: str) -> int:
    "Compute the maximum length of repeated chars."
    ...

@given(st.text(alphabet=no_digits))
def test_decode_encode_3(s):
    event(f'longest = {longest_count(s)}')
    assert rle_decode(rle_encode(s)) == s
```

Characterizing test data (cont.)

```
pytest rle_tests.py -k test_decode_encode_3 \
        --hypothesis-show-statistics

================== Hypothesis Statistics ================
      * 75.70%, longest = 1
      * 22.69%, longest = 2
      * 1.00%, longest = 0
      * 0.60%, longest = 3
```

- 75% of the test cases had no repeats
- 22% had maximum of 2 repeats
- No test case had more than 3 repeats
- Why? Because `text()` chooses each character independently

Improving test data generation

We will use combinators to write a strategy that:

1. generates a long sequence of a *single repeated* character;
2. *or* generates text as before.

```
many_no_digits
  = st.builds(lambda count, char: count*char,
              st.integers(min_value=0, max_value=20),
              no_digits)

combined = st.one_of(many_no_digits,
                     st.text(alphabet=no_digits))
```

Improving test data generation (cont.)

This gives much better test data distribution:

```
* 35.69%, longest = 1
* 12.90%, longest = 2
* 10.48%, longest = 3
* 5.44%, longest = 0
* 4.23%, longest = 20
* 4.23%, longest = 6
* 3.63%, longest = 4
* 3.23%, longest = 7
* 3.02%, longest = 8
* 2.82%, longest = 12
```

```
* 2.82%, longest = 14
* 2.82%, longest = 17
* 1.81%, longest = 9
* 1.61%, longest = 10
* 1.61%, longest = 13
* 1.41%, longest = 15
* 1.21%, longest = 19
* 0.60%, longest = 5
* 0.40%, longest = 18
```

Conclusion

- PBT philosophy: write *properties* and *generate* tests
- Lightweight: implemented as libraries
- Flexible: domain-specific languages (DSLs) for writing data generators and properties
- Scales to realistic software
- Couples executable specifications with code
- Useful for comunicating expectations among developers
- Useful for finding subtle bugs in complex systems

Challenges

- Writting *effective* properties
  - training software engineers to think about pre- and post-conditions, invariants, etc.
  - universities can play a significant role here
  - helping industry adopt a higher-skill technology
- PBT works best with software that is well structured
- Design systems around properties and not the other way around

References

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- D. R. MacIver *et al.* *Hypothesis: A new approach to property-based testing*, The Journal of Open Source Software, 2019. See also `https://hypothesis.readthedocs.io/`
- T. Arts, J. Hughes and J. Johansson *Testing Telecoms Software with Quviq QuickCheck*, ACM Workshop on Erlang, 2006
- T. Arts, J. Hughes, U. Norell and H. Svensson, *Testing AUTOSAR software with QuickCheck*, IEEE ICSTW 2015
- H. Goldstein, *et al.* *Property-Based Testing in Practice*, IEEE/ACM ICSE 2024

Extra slides

Writing properties

equivalence $f(x) = f_{spec}(x)$ e.g. $f(x)$ is an optimized implementation and $f_{spec}(x)$ is a reference implementation.

idempotency $f(f(x)) = f(x)$

inverse $g(f(x)) = x$

associativity $f(x, f(y, z) = f(x, y), z)$

commutativity $f(x, y) = f(y, x)$

right identity $f(x, zero) = x$

left identity $f(zero, x) = x$

Hypothesis can write these kind of properties for you — see `hypothesis.ghostwriter`.

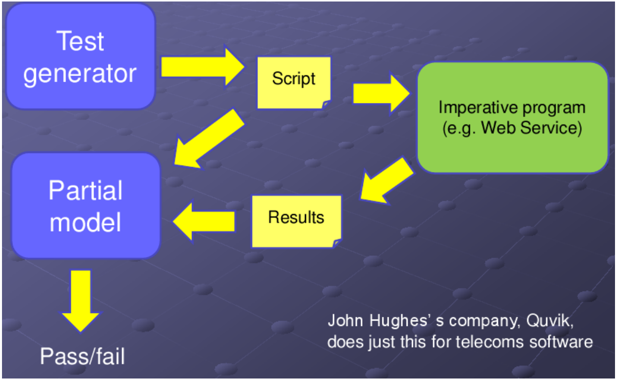
Stateful programs

We can also use PBT to test programs that:

1. modify state;
2. read and write files;
3. use network services, databases, etc.

Testing stateful programs

- Generate sequences of commands
- Specify behaviour using a functional model (state machine)
- Compare the execution against the model



Industrial use example

- Ericsson Media proxy (Java and C++)
- Establish telephony connection throught a firewall
- Tested with Erlang QuickCheck (Quviq.com)
- Adding and removing participants in a call
- Random counterexample with 160 commands
- Shrunk automatically to 7 commands