

Exercise #1

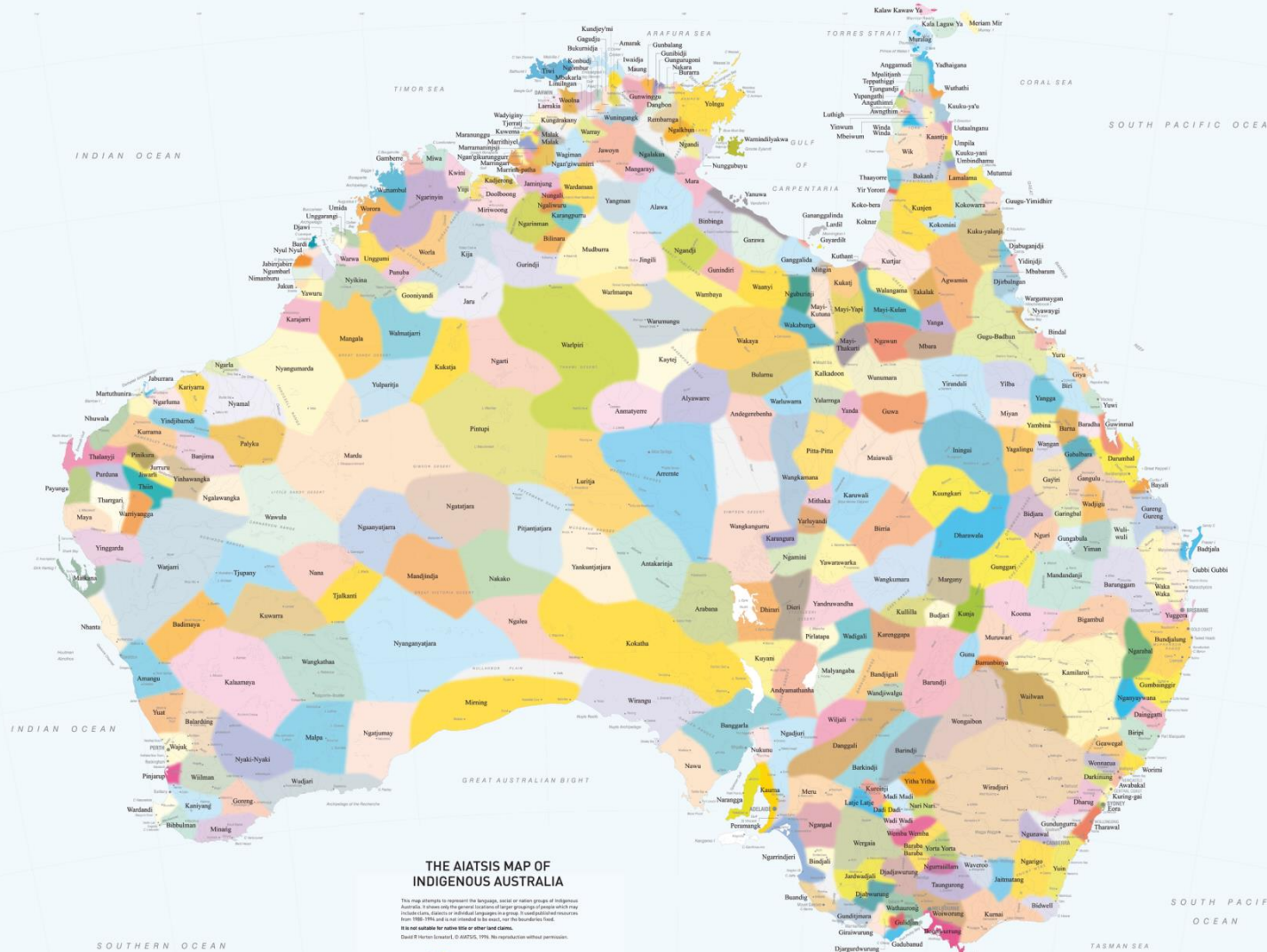


- Clone repo: tiny.cc/zhd-workshop
github.com/Zac-HD/escape-from-automannual-testing
- `pip install pytest hypothesis`
- `pytest *.py`
 - to check that it's all installed 😊



Escape from auto-manual testing with Hypothesis!

Zac Hatfield-Dodds

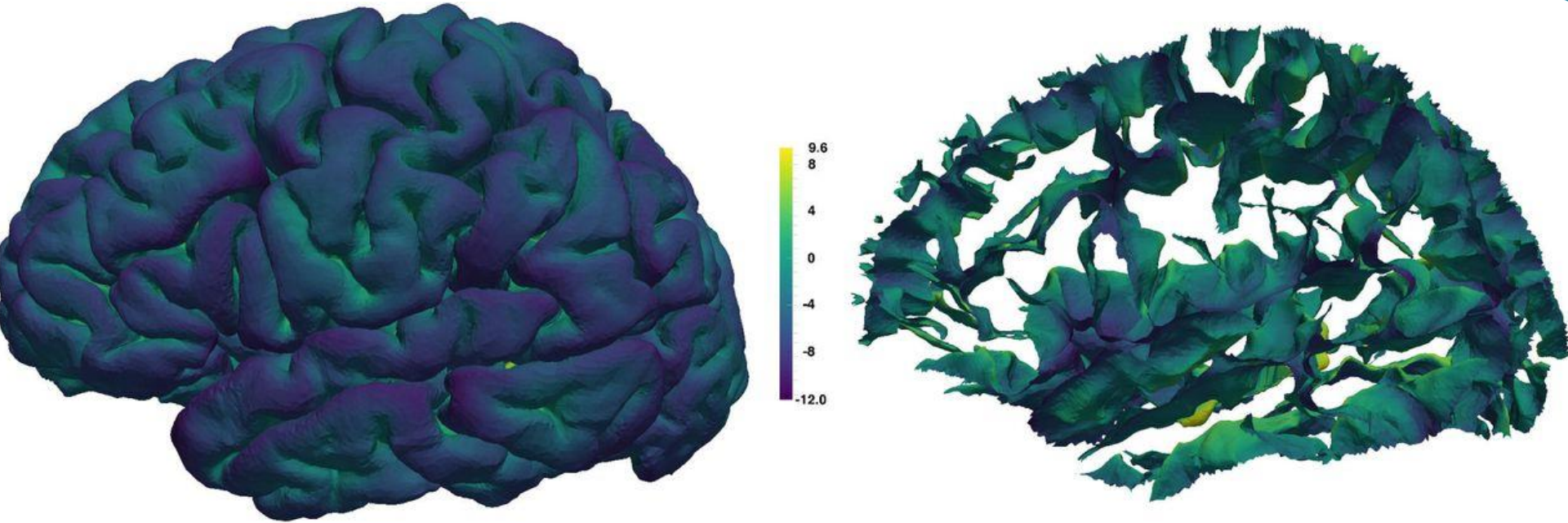


Outline



1. Motivation
2. Writing testable code
3. Property-based testing 101 *Ex 1*
4. Describing data with Hypothesis *Ex 2*
5. Testing tactics *Ex 3*

“This is your brain on software”





... any reported scientific result could be wrong if data have passed through a computer, and these errors may remain largely undetected ...

-- Soergal (2015) <https://dx.doi.org/10.12688%2Ff1000research.5930.2>

Why are we here?



- Code has become critical to our research
 - Open source libraries
 - One-off analyses
- We need faster, better ways to test it
 - Still with me? Great!



Secretly the most important part:

WRITING TESTABLE CODE

Design for testability



- Deterministic behaviour
- Immutable data
- Canonical data
- Keep I/O out of logic
- Lots of assertions

What is an assertion?



“an expression in a program
which is **always true**
unless there is a bug.”

<http://wiki.c2.com/?WhatAreAssertions>

What should a test do?



- Execute the “system under test”
 - “arrange, act, assert”
 - “given, when, then”
- Fail iff a bug is introduced

“Auto-manual tests”



- Humans
 - Decide the input
 - Write the test function
 - Determine and check expected results
- Doing it in code is *repeatable*, not *automated*

Other kinds of tests



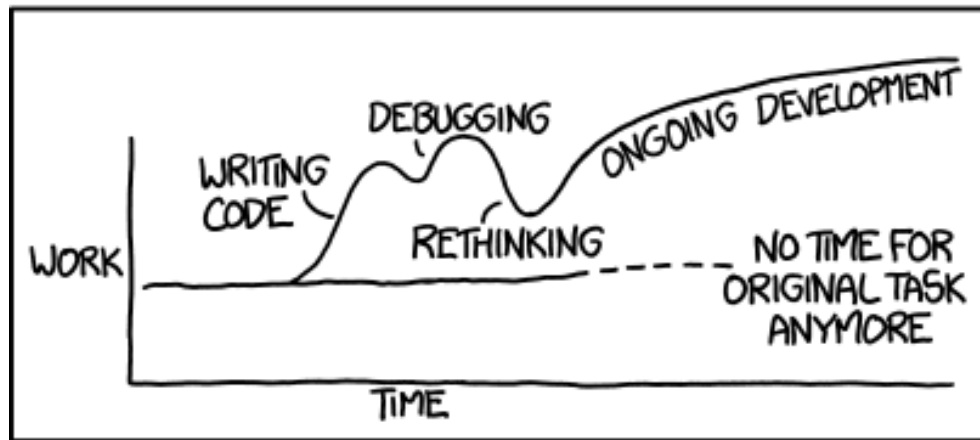
- Diff tests
 - Does new version reproduce known output?
- Doctests
 - Check that examples in docs still work
- Coverage tests
 - Identify unexecuted parts of your code
 - Use number, not percentage, of uncovered lines

Property-based testing



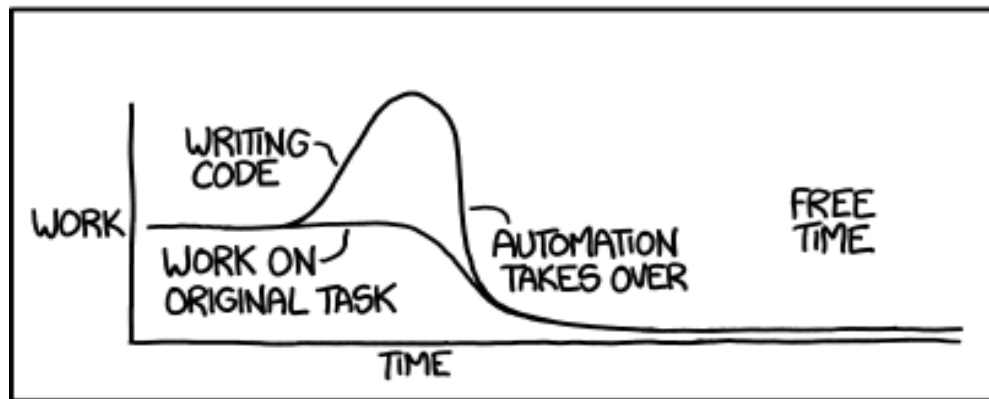
- User:
 - Describes valid inputs
 - Writes a test that passes for any valid input
- Engine:
 - Generates many *test cases*
 - Runs your test for each input
 - Reports minimal failing inputs (usually)

"I SPEND A LOT OF TIME writing tests
I SHOULD WRITE A PROGRAM AUTOMATING IT!"



PROPERTY-BASED TESTING 101

"I SPEND A LOT OF TIME writing tests
I SHOULD WRITE A PROGRAM AUTOMATING IT!"



PROPERTY-BASED TESTING 101


```
from hypothesis import given, strategies as st
```

```
@given(  
    st.lists(st.integers(), min_size=1)  
)
```

```
def test_a_sort_function(ls):
```

```
    # we can compare to a trusted implementation,
```

```
    assert dubious_sort(ls) == sorted(ls)
```

```
    # or check the properties of dubious_sort directly.
```

```
    assert Counter(out) == Counter(ls)
```

```
    assert all(a<=b for a, b in zip(out, out[1:]))
```



Exercise #1



- Clone repo: tiny.cc/zhd-workshop
github.com/Zac-HD/escape-from-automannual-testing
- `pip install pytest hypothesis`
 - In your preferred environment, py2 or py3
- `pytest pbt-101.py`
- Open file, edit per comments, re-run tests



DESCRIBING DATA

hypothesis.strategies



- Describes inputs for `@given` to generate
- Only construct strategies via the public API
 - SearchStrategy type is only public for type hints
 - Composing factories is nicer anyway!

Values



- Simplest strategies are for values
 - None, bools, numbers, Unicode or binary strings...
- Finer-grained than types
 - Optional bounds for value or length
 - Arguments like `allow_nan` or `timezones`

Collections



- Lists, sets, dicts, iterables, etc.
 - Take a strategy for elements (or keys/values)
 - Optional min_size and max_size

Map and Filter methods



`s.map(f)`

- applies function f to example
- shrinks *before* mapping

`s.filter(f)`

- retry unless $f(ex)$
- mostly for edge cases

```
s = integers()
s.map(str) # strings of digits
```

```
# even integers
s.map(lambda x: x * 2)
# odd ints, slowly
s.filter(lambda x: x % 2)
```

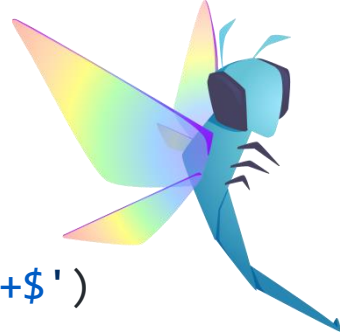
```
# Lists with some unique numbers
lists(s, 2).filter(
    lambda x: len(set(x)) >= 2
)
```


Complicated data



- Got a list of values?
 - `sampled_from` or `permutations` can help
- Recursive strategies just work
 - At least three ways to define them
- Combine strategies:
 - `integers()` | `text()`
 - Can't take intersection though.
- Call anything with `builds()`

Inferring strategies



A schema is a machine-readable description:

- Used for validating input
- Can generate input instead!

This tests both validation and logic.

*regex, array dtype, django model,
attrs classes, type hints, database...*

```
>>> from_regex(r'^[A-Z]\w+$')  
'Fgjdfas'  
'D榕譲Ć斎\n'
```

```
>>> from_dtype('f4,f4,f4')  
(-9.00713e+15, 1.19209e-07, nan)  
(0.5, 0.0, -1.9)
```

```
>>> def f(a: int): return str(a)  
>>> builds(f)  
'20091'  
'-507'
```

Beyond the standard library



- hypothesis.extra
 - Django, Numpy, Pandas, Lark, pytz, dateutil...
- Also many third-party extensions, e.g.
 - Geojson, SQLAlchemy, networkx, jsonschema, Lollipop, Mongoengine, protobuf...

Data dependencies



Custom strategies

- Similar to interactive data in tests

```
@composite
def str_and_index(draw, min_size):
    s = draw(text(min_size=min_size))
    i = draw(integers(0, len(s) - 1))
    return (s, i)

str_and_index().example()
```

Interactive data

- Run part of a test, then get more input
- Useful with complex dataflow

```
@given(data())
def test_something(data):
    i = data.draw(integers(...))
```

Minimal examples



- Strategies shrink
 - From the inside out
 - i.e. before map or filter are applied
 - Towards the smallest and shortest example
 - Based on the strategy definition
- Multiple errors possible per test!

Inline `st.data()`



- Draw more data *within* the test function
 - Great for complex or stateful systems
 - Use `@composite` instead if you can

```
@given(st.data())
def a_test(data):
    x = data.draw(integers(0, 100), label="First number")
    y = data.draw(integers(x, 100), label="Second number")
    # Do something with `x` and `y`
```



TACTICS FOR TESTS

Tactics: what do we test?



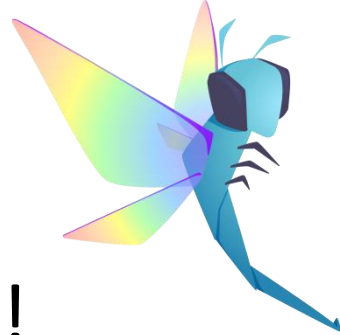
- “Auto-manual” testing
 - `output == expected`
- Oracle tests (full specification)
 - Does a magic “oracle” function say output is OK?
- Partial specification
 - Can identify some but not all failures
- Metamorphic testing
- Hyper-properties

Oracles



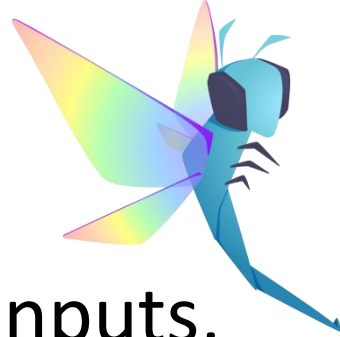
- Fantastic for refactoring or testing performance optimisations
- “reverse oracles”
 - Generate an answer, ask the oracle for a matching question, test that code gets the answer
- You may need to test the Oracle too

Partial specification



- We don't need an exact answer for tests!
 - $\min(xs) \leq \text{mean}(xs) \leq \max(xs)$
- Lots of serialisation specs are like this
 - In fact almost all specs are partial

Special-case oracles



- If your oracle only works for some valid inputs, that's still useful to test those inputs
- Or a more precise test for a subset of inputs
 - Monotonic functions, positive numbers, etc.
 - Varying just one parameter to simplify results

Common properties



- Shared by lots of code
 - Often good API design generally
 - Or worth it just for testability

“Does not crash”



- Just call your function with valid input:

```
@given(lists(integers()))  
def test_fuzz_max(xs):  
    max(xs) # no assertions in the test!
```

- This is embarrassingly effective.

Invariants



`Counter(ls) == Counter(sorted(ls))`



`ls != set(ls) == set(set(ls))`

Round-trips

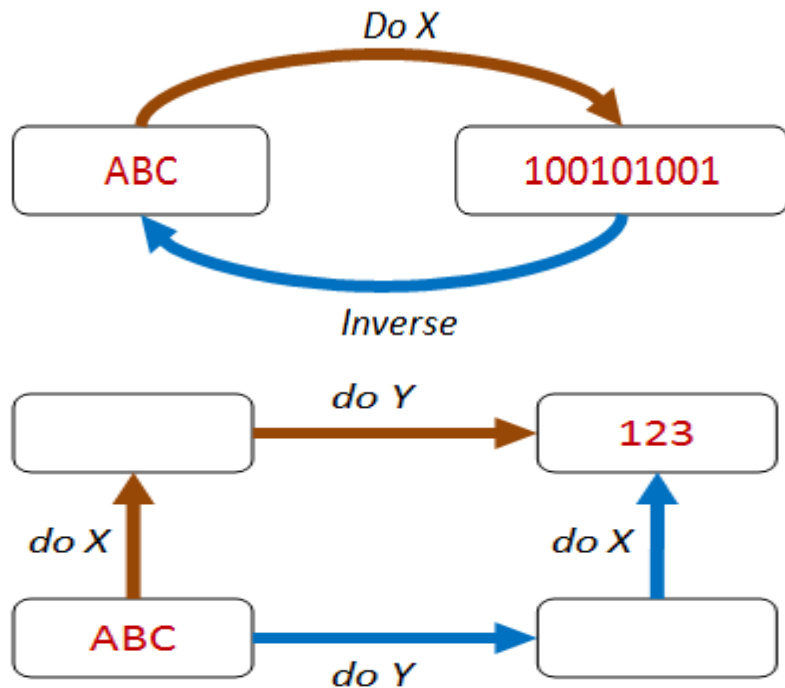


“inverse functions”

- `add` / `subtract`
- `json.dumps` / `json.loads`

or just related:

- `factorize` / `multiply`
- `set_x` / `get_x`
- `list.append` / `list.index`



Exercise #2



- Same plan as last time:
 - `pytest strategies-and-tactics.py`
 - Open, edit, re-test



Metamorphic Relations

TESTING BLACK BOXES

Metamorphic relations?



- We don't know how input relates to output
- BUT
 - Given an input and corresponding output
 - Make a known change to the input
 - We might know how the output should change (or not change)
- That's it – but this is really, really powerful

Compilers



- Very popular technique for compilers!
 - Generate valid program
 - Use many different compilers and settings
 - Run and compare results
 - Any difference == there's a bug somewhere
- A kind of differential testing

Neural Networks

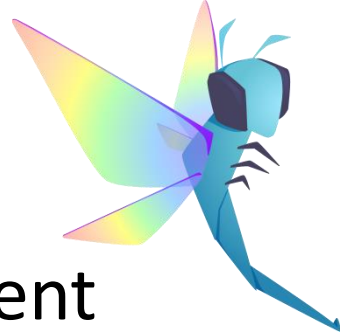


Neural Networks



- Testing for implementation errors is rare
 - Embed lots of assertions
 - Use simple properties across single steps
- Testing things like...
 - Training steps change neuron weights
 - Bounds on inputs and outputs
 - Converges when expected to

Computer vision



- Cars should not confidently choose a different action if the camera feed has
 - slight changes in contrast or brightness or scale
 - a small skew or offset or blur added
 - light rain or fog added
- <https://deeplearningtest.github.io/deepTest/>
 - Luckily there aren't many on the road (yet)

Exercise #3



- Same plan as last time, choice of two files:
 - `pytest scientific-hypothesis.py`
 - `pytest test-the-untestable.py`
 - Open, edit, re-test



In which we discuss all the other things that you might want to know.

PERFORMANCE, CONFIGURATION, AND COMMUNITY

Observability



- `-hypothesis-show-statistics`
 - Shows timing stats, perf breakdown, exit reasons
 - Add custom entries by calling `event()` in a test
- Use `note()` if you like print-debugging
 - Only prints for minimal failing example
 - Details controlled by `verbosity` setting

Performance (generation)



- All pretty obvious in generation phase:
 - Calling slow things or many things is slow
 - Generating larger data takes longer
 - Filter more, and getting output takes longer
- Otherwise Hypothesis is pretty fast!

Performance (shrinking)



- Composition of shrinking
 - If any part shrinks, the whole should shrink
 - Order of recursive terms is important!
- Keep things local
 - Put filters (or assume) as far in as possible
 - Avoid drawing a size, then that many things
- Don't waste more tuning than you save!

Configuration



- `hypothesis.settings`
- Per-test decorator or whole-suite profiles
- Lots of options
 - `deadline`, `max_examples`, `report_multiple_bugs`, `database`, etc.

Reproducing failures



- Hypothesis tests should **never** be flaky.
 - We detect most user-caused flakiness too
- Failures cached and retried until fixed
 - for local dev, reproducibility is automatic
- Printed seed to re-run failures from CI
- Explicit decorator for really tough cases

Update early & often!



- Hypothesis releases every pull request.
 - All bug fixes are available in ~30 minutes
 - As are features, performance improvements, ...
 - We use strict semver and code review
 - (and have a fantastic test suite 😊)
- So stay up to date – for your own sake!

Who uses Hypothesis?



- 4% of all Pythonistas (PSF survey)
- Many companies
- ~2000 open source projects (github stats)

Consulting Services



- Want exciting new features?
 - Want Hypothesis training for your team?
 - Want your tests (and code) reviewed?
-
- Zac Hatfield-Dodds and David MacIver
 - Say hi via hello@hypothesis.works

About the project



- MPL-2.0 license
- New contributors welcome!
 - most remaining issues are non-trivial
 - using or extending Hypothesis is valued too
- Tries to be *legible*
 - we design APIs and errors to teach users
 - does what you expect; or explains why not