

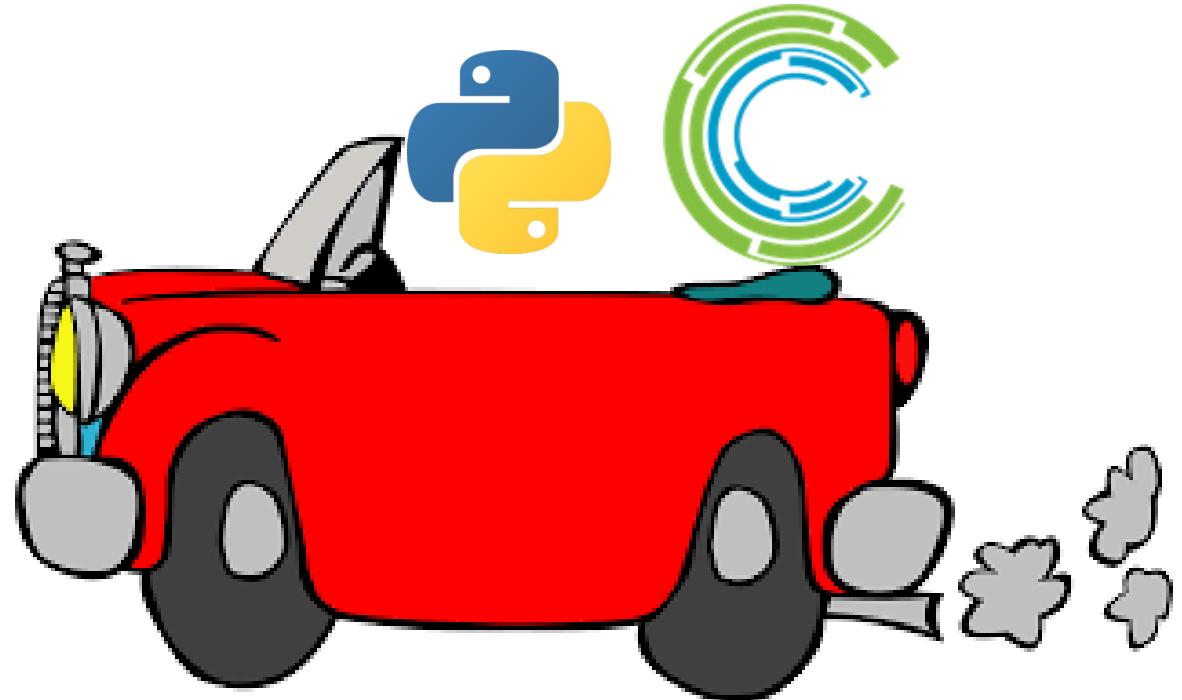
If it walks like Python and quacks like Python, it must be....Chapel?

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What are we talking about?

- For a long time you could call Chapel from Python
 - Compile Chapel to a shared library, load it from Python
 - Python is the “driver”
- Can we put Chapel in the driver seat?
 - Yes!
- Outline
 - [Motivating Example](#)
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Python isn't a high-performance language, why?

- Dynamic execution!
 - Change your program without recompiling
 - Embed a fully fledged interpreter in your application
 - Do funky dynamic execution not possible in Chapel
- Massive ecosystem of easy-to-use libraries
 - pytorch
 - tensorflow
 - scikit-learn
 - your-favorite-ai-library



Example Time!

Motivating Example

```
proc square(x: int): int do return x * x;
```

A Chapel function to
“apply” to an array

```
use BlockDist;  
config const n = 16;  
var myArr = blockDist.createArray(1..n, int);  
myArr = myArr.domain;
```

Create a block-distributed array
named ‘myArray’

```
writeln("myArr before: ", myArr);
```

```
forall x in myArr do  
    myArr[x] = square(x);
```

```
writeln("myArr after: ", myArr);
```

For each element in the array,
call ‘square()’

The computation is both
distributed and parallel

How do we make this dynamic?

Dynamic Execution Part 1

```
const square = """
    def square(x):
        return x * x
""".dedent();

import Python;
record funcPerLocale {
    var i = new Python.Interpreter();
    forwarding var func = i.createModule(square).get("square");
}

// ...

coforall l in myArr.targetLocales() do on l {
    var f = new funcPerLocale();
    for i in myArr.localSubdomain() do
        myArr[i] = f(myArr[i]): int;
}
```

Calls 'f()' like any normal Chapel function!

The result is a generic Value,
the explicit cast extracts the
integer value

The Python equivalent function,
embedded as a Chapel string in the source code

A Chapel widget that handles
the book-keeping needed to
load and call Python

Create a new Python module
and get 'square()' as a handle
to a Python Value

Explicitly distributes execution
like 'forall', creating a function
'f()' for each locale

The computation is distributed,
not parallel

Dynamic Execution Part 2

```
config const modName = "func";
config const funcName = "func";

import Python;
record funcPerLocale {
    var i = new Python.Interpreter();
    forwarding var func = i.importModule(modName).get(funcName);
}

// ...

coforall l in myArr.targetLocales() do on l {
    var f = new funcPerLocale();
    for i in myArr.localSubdomain() do
        myArr[i] = f(myArr[i]): int;
}
```

Instead of embedding the Python code in the program, extract it out to a file

```
func.py
def func(x):
    return x

def square(x):
    return x * x

def cube(x):
    return square(x) * x
```

The behavior is now fully editable at runtime

```
$ ./example -n14

$ ./example -n14 --funcName=cube

$ ./example -n14 --modName=numpy --funcName=negative
```

Integrated Example

Integrated Example

- We started by showing you calling out to a Python file
 - This next example is going to show you how to intermingle Python calls with your Chapel code using Parquet
 - It will show a variety of features available in the Python module:
 - Importing modules
 - Calling functions
 - Accessing fields on Python types
 - Using both generic and specific Python types
 - Including Python/NumPy arrays
 - Casting to supported Chapel types
 - Iterating over Python types
 - Interoperating with NumPy arrays through Parquet
- We're not going to focus on the details of reading a Parquet file



Integrated Example

- To start, we'll want to import the Parquet module:

```
var pa = interp.importModule("pyarrow");
var pq = interp.importModule("pyarrow.parquet");
```

- We'll open a Parquet file...

```
var parquet_file = pq.call("ParquetFile", filename);
```

- We can get the columns in that file using field accesses via the 'get()' call

- We then can cast the Python-type result to a Chapel list of strings

```
var columns = parquet_file.get("schema").get("names") : list(string);
```



Integrated Example

- We will then iterate over the file and store its contents into an array of Chapel lists of ambiguous Python types

```
var data_chunks: [0..<columns.size] list(owned Value?);
```

Create the array of lists

```
for batch in parquet_file.call("iter_batches", kwargs={"batch_size" => 300}) {  
    for (col, idx) in zip(columns, 0..) {  
        data_chunks[idx].pushBack(batch.call("__getitem__", col));  
    }  
}
```

Iterate over the Python Parquet file type

Store the Python Value into the relevant Chapel list



Integrated Example

- Next, we'll iterate over the columns and determine the sum

```
var num_rows = parquet_file.get("metadata").get("num_rows") : int;  
var schema_arrow = parquet_file.get("schema_arrow");  
  
for (col, idx) in zip(columns, 0..) {  
    var rowType = schema_arrow.call("field", col).get("type");  
  
    if pa.call("int64") == rowType {  
        var arr = getArray(int(64), data_chunks[idx], num_rows);  
        writeln("Column: ", col, " Sum: ", + reduce arr);  
    } else if pa.call("float64") == rowType {  
        var arr = getArray(real(64), data_chunks[idx], num_rows);  
        writeln("Column: ", col, " Sum: ", + reduce arr);  
    }  
}
```

Get a string description of the Python type stored

Iterate over the Chapel list type

If statement because Python's type is dynamic

Calls to a Chapel function that will use numpy

Integrated Example

- Finally, let's dive into 'getArray()'

```
proc getArray(type eltType, ref data_chunks: list(owned Value?), num_rows: int) {  
    var arr: [0..<num_rows] eltType;  
    var i = 0;  
    for chunk in data_chunks {  
        var chunk_arr = chunk!.call(owned PyArray(eltType, 1), "to_numpy",  
            kwargs=["zero_copy_only" => false,  
                    "writable" => true]);  
        arr[i..#chunk_arr.size] = chunk_arr.array();  
        i += chunk_arr.size;  
    }  
    return arr;  
}
```

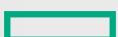
Traverse the Chapel list of Python Values

Call a Python method, returning a handle to a NumPy array

'.array()' returns a reference, but storing into the Chapel array is a copy



Internals

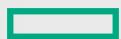


Internals

- The Python interpreter is embedded into the Chapel application
 - Manages the GIL, when present
 - Increments and decrements references to Python objects, ensuring they stay alive and get cleaned up
- Library itself actively converts between Chapel and Python types
 - Arguments to library calls can be of either type, library need to convert to the appropriate type
 - Can register custom types, enabling their use
 - Python objects are referenced rather than copied, including arrays
- Vast majority of implementation is Chapel module code
 - Relies on C interoperability to access Python's C API
 - Some additional Chapel-specific C functions and macros were necessary
 - But otherwise Chapel language features were sufficient
 - Could potentially be used as a blueprint for interoperability with other interpreted languages?



What's Next?



What's Next?

- New features in both Chapel and Python can enable better multi-threaded performance
 - GIL-less Python – Python is inherently single threaded because of the GIL, removing it is “free” performance
 - Chapel function pointer support can enable tight integration with Python JIT libraries like ‘numba’
- GPU’s
 - Using Chapel’s GPU support, we can call Python GPU functions, like kernels from ‘cupy’
- Shave off the sharp edges
 - Multiple libraries could all try to start Python interop, this will fall over
 - Interoperability with some Python libraries can fall over
 - This is due to internal Python C API incompatibilities
 - We may never be able to make this better
- Investigate ways to improve the syntax for interoperating with Python



Thank You

