

#### Creating a distributed python wrapper with otwrapy

HPC and Uncertainty Treatment

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Outline

- Basic skeleton of a wrapper
- In use tools
- Parallelization
- Conclusion



#### Introduction

- What is a wrapper?
  - ▶ a python interface with your external code.
  - able to take advantage of multi-core computers and HPC clusters, to distribute multiple evaluations of your code.
- Presentation goal: Show you how to create a distributed wrapper to efficiently carry on uncertainty studies.
- Based on the module otwrapy available at GitHub. Initially developed at Phimeca engineering.
- A good working example can be found on the otwrapy repository example.



# What makes a good wrapper?

- It is distributed and avoids conflict between runs.
- You can use it as a script (argsparse module):

```
>> python wrapper.py -X 170 3 0.05
```

- It is able to run on different environments:
  - Workstation
  - Office made heterogeneous clusters -> e.g. IPyparallel or dispy
  - ► HPC through submission scripts -> e.g. TGCC or Poincare
  - ► Cloud solutions -> e.g. Simulagora or DominoUp
- It catches and logs errors for easy debugging.
- ☑ It can either run or simply prepare runs → useful when running on clusters.

All of this might seem complex, but wrappers are repetitive and otwrapy is here for you!



### Basic skeleton of a wrapper

- Assumption: you want to wrap an external code not written in Python.
- An OpenTURNS wrapper is a subclass of ot.OpenTURNSPythonFunction for which at least the method \_exec(X) should be overloaded. Additionally, you can overload \_exec\_sample(X), but with otwrapy.Parallelizer() there is no need to.
- If your code handles the gradient and the hessian, you can respectively overload \_gradient(X) and \_hessian(X).

```
class Wrapper(ot.OpenTURNSPythonFunction):
    """Wrapper of my external code.
    """

def __init__(self):
    """Tnitialize the wrapper with 4 and 1 as input and output dimension.
    """
    super(Wrapper, self).__init__(4, 1)
    # Do other stuff if necessary

def __exec(self, X):
    """Run the model in the shell for the input vector X
    """
    pass
```



- \_exec is the default OpenTURNS method that executes the function on a given point.
- Semantically speaking, the function is divided on three parts:
  - 1. Prepare the input parameters, e.g., create an input file.
  - 2. Run the external code, e.g., on the shell.
  - 3. Get the output parameters by parsing the output given by the code.
- The three steps are executed on a temporary working directory using otwrapy. TempWorkDir

```
def _exec(self, X):
    """Run the model in the shell for the input vector X
    """

# Move to temp work dir. Cleanup at the end
with otw.TempWorkDir(cleanup=True):
    # Prepare the input
    self._prepare_input(X)
    # Run the external code
    self._run_code(X)
    # Parse the output parameters
    Y = self._parse_output()
```



#### Temporary working directory

- Efficiently and safely work on temporary directories with otwrapy. TempWorkDir
  - Avoid conflict between simulations running in parallel.
  - ▶ If an exception is raised during execution, the Python interpreter should come back to the preceding current directories.
  - Cleanup the temporary working directories upon exit. Or don't if you want a full backup of the simulations.
  - Transfer necessary files needed by the external code

#### Example:

```
import otwrapy as otw
# I'm on a given dir, e.g. ~/beam-wrapper
with otw.TempWorkDir(base_temp_work_dir='/tmp', prefix='run-', cleanup=True, transfer=None):
    """
    ...
    Do stuff safely on an exclusive temporary directory and erase it afterwards
    ...
    """
    # The current working directory is something like /tmp/run-pZYpzQ
# Back on ~/beam-wrapper and /tmp/run-pZYpzQ does not exist anymore
```



- For each simulation, your wrapper must communicate the input parameters to the external code.
- Most scientific codes use input files that describe, among other thing, the parameters of your model/simulation.
- Using OpenTURNS coupling tools, the values of the vector X are placed on an input template file that have tokens/placeholders for where the expected parameters should be.

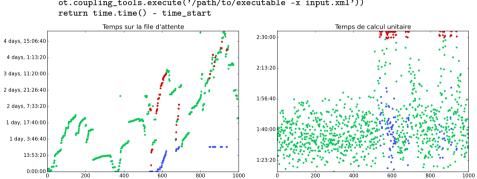
```
def _prepare_input(self, X):
    """Create the input file required by the code.
    """
    ot.coupling_tools.replace(
        infile='input_templatefile.xml',
        outfile='input.xml',
        tokens=['@X1','@X2','@X3','@X4'],
        values=X)
```



#### Run the external code

- Most of the time this is a fairly straightforward call to an executable with an input file.
- Sometimes, it is useful to time your runtime.

```
def _run_code(self):
   time_start = time.time()
   ot.coupling_tools.execute('/path/to/executable -x input.xml'))
   return time.time() - time_start
```





# Parse output parameters 1/2

- Common practice among scientific code is to create output files with the results of the simulation.
- The output should then be parsed in order to get the output parameters of interest.
- If it is a .csv file
  - pandas.read csv is the fastest option, but it introduces pandas as a dependency.
  - if speed is not an issue, try ot.coupling\_tools.get\_value,
  - or numpy.loadttxt.



# Parse output parameters 2/2

- For .xml files minidom package from the python standard library does the trick.
- If by any chance the external code returns the output parameters of interest to STDOUT. set get\_stdout=True when calling ot.coupling\_tools.execute(...). (or use subprocess.check output)
- For standard binary formats, there are python interfaces to netcdf and HDF5.
- Otherwise, be creative and pythonic!

```
def _parse_output(self):
   # Retrieve output (see also )
   xmldoc = minidom.parse('outputs.xml')
   itemlist = xmldoc.getElementsByTagName('outputs')
   Y = float(itemlist[0].attributes['Y1'].value)
   return [Y]
```



#### Managing data backups

- Uncertainty studies tend to be expensive in computational time, it is then in your best interest to backup your simulation results!
- otwrapy has two useful functions to do so: otwrapy.dump\_array and otwrapy.load\_array
- They are faster than a simple pickle.dump and pickle.load (because they use protocol=2)
- They offer the possibility to compress data with the gzip library. If the extension is 'pklz', it compresses by default.
- Advice: Convert your ot.Sample to a np.array before dumping. An np.array is lighter!
- Example: dump and compress

```
import otwrapy as otw
otw.dump_array(np.array(X), 'InputSample.pklz', compress=True)
```

... and load

```
import otwrapy as otw
import openturns as ot
X = otw.load_array('InputSample.pklz')
X = ot.Sample(X)
```



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## Catch exceptions when your code fails

- In order to catch exceptions use the decorator otwrapy. Debug()!
- It encloses what happens inside a function into a try/catch structure and logs Exceptions when they are raised.
- Useful when your wrapper is not used on an interactive environment like IPython or a Jupyter notebook.

```
import otwrapy as otw
class Wrapper(ot.OpenTURNSPvthonFunction):
   @otw.Debug('wrapper.log')
   def exec(self. X):
        #Do stuff
        return Y
```



#### Creating a CLI for your wrapper

- A command line interface allows you to run your wrapper in detached mode, e.g., through submission scripts on HPC clusters.
- The argparse library might seem complicated, but they have a great cookbook and there are good chances that a simple copy/paste will be enough.
- Take a look at the beam wrapper for an example of a CLI interface

```
if __name__ == '__main__':
    import argparse
    parser = argparse.ArgumentParser(description="Python wrapper example.")
    parser.add_argument('-X', nargs=3, metavar=('X1', 'X2', 'X3'),
        help='Vector on which the model will be evaluated')
    args = parser.parse_args()

model = Wrapper(3, 1)
    X = ot.NumericalPoint([float(x) for x in args.X])
    Y = model(X)
    dump_array(X, 'InputSample.pkl')
    dump_array(Y, 'OutputSample.pkl')
```

You can then execute your code from the command line:
python wrapper.py -X 170 3 0.05



#### Parallelizing the wrapper

- Uncertainty studies fall into what we call embarrassingly parallel (or pleasantly parallel) patterns -> Repeat similar non communicating tasks over and over.
- Good news, this means that they are very simple to parallelize.
- But don't bother... just let the magic happen with otwrapy.Parallelizer() !!

```
import otwrapy as otw
from otwrapy.examples.beam import Wrapper
parallelized_beam_wrapper = otw.Parallelizer(Wrapper())
```



#### Distributing calls on clusters or the cloud

- But what if you want to distribute your wrapper calls on the cloud or on a cluster?
- otw.Parallelizer is no longer the way to go, for the moment...
- You can manage to make an heterogeneous office cluster with IPyparallel or dispy
- For clusters and the cloud, rely on a good CLI interface of your wrapper and distribute your calls through submission scripts or cloud APIs (e.g., Simulagora or Domino)



#### Conclusion

- Take away message: Making a wrapper is all about preparing the input, executing the code and parsing the output on isolated working directories. Don't forget, in a multi-core era you don't have a choice, make your wrapper distributed!
- By creating a CLI of your wrapper, you can easily distribute your calls on a cluster or on cloud platforms.
- It is important to protect your wrapper with otw.Debug() so that you can have a traceback of raised Exceptions.
- ot.PythonFunction() is a simpler alternative to ot.OpenTURNSPythonFunction(), but you loose the ability to parameterize your wrapper when instantiating it.
- otwrapy is here for you! Use it to avoid code boilerplate or as a simple cookbook.



#### Thank you for your attention



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