Python in Computational Neuroscience & Modular toolkit for Data Processing (MDP)

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Python in Computational Neuroscience

Python

Created in 1991 by Guido van Rossum as a scripting language.
Its characteristics are:

- very concise and readable code, almost like pseudo-code:

```
print "hello world"
```

- garbage collection (memory is freed automatically)
- dynamically typed

```
a = "test"

def increment(value):
    return value + 1

increment(a)  # error at runtime
```

Allows fast implementation, relies on conventions and documentation.
Note that static typing often only catches simple bugs, but not subtle ones (e.g., division by zero).

Python

- whitespaces indicate code blocks

```
for i in range(4):
    line = "Happy Birthday"
    if i % 3:
        line += " to you"
    else:
        line += " dear Guido"
    print line
```

- supports Object Oriented and to some extend Functional programming

```
class Test(object):

    def info(self):
        print "test here"

test = Test()  # create class instance
test.info()  # prints "test here"
```

dynamic nature also enables metaprogramming

Python

- Python code is interpreted by a virtual machine (after being compiled to byte code) or can be written in an interactive interpreter (REPL). Python can be a 100 times slower than C, but relies on external libraries where performance matters (e.g. numerics in Fortran).
- Python is maybe the leading modern dynamic language. (according to TIOBE, when PHP, Pearl and VB are ignored) It is one of three official languages at Google (e.g. Youtube is implemented in Python).
- Python is generally considered to have hit a sweet spot in language design, people just like it.
- Open source ecosystem (language, libraries, IDEs).

Bottom line: Python allows very rapid and enjoyable development.

Python in Computational Neuroscience

Python has gained much popularity in science, thanks to its available libraries and language quality.

- Python is now competitor to Matlab in data analysis and smaller simulations.
- Python is increasingly used to interface with the standard neural simulators (like NEURON, e.g. via PyNN).

Examples of Research groups migrating their code bases to Python.

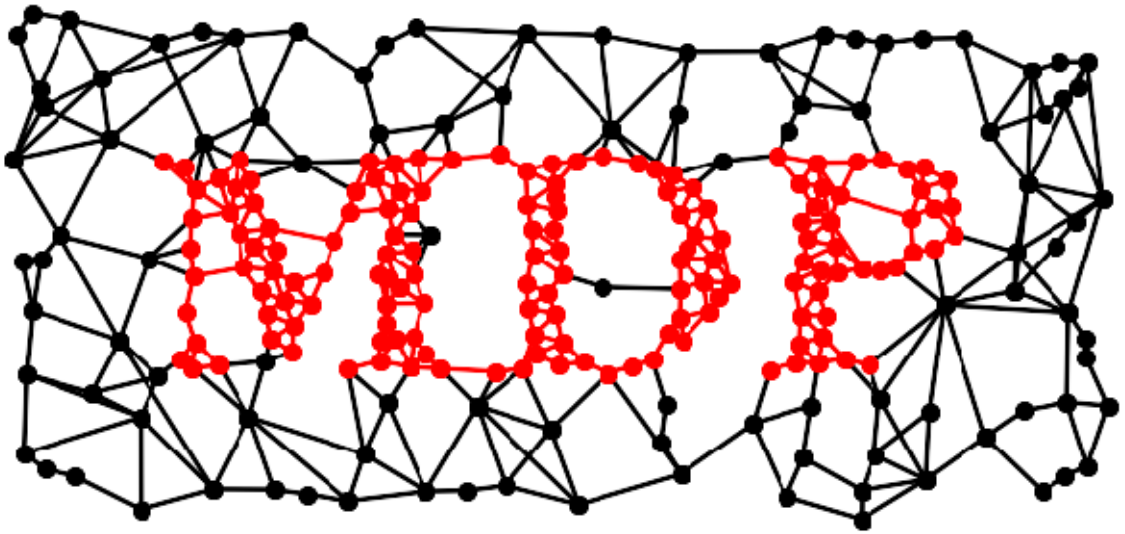
So let's compare Python and Matlab (hopefully in an objective way) ;-)

Python vs. Matlab

Python	Matlab
+ free and open source	- expensive and proprietary
+ very good language design	- poor language design
+ advanced programming tools, scales well	- lack of tools, problems with large projects
- scientific libraries are good and improving	+ scientific libraries superior in several areas (e.g. statistics)
+ huge range of libraries from all areas, very diverse	- restricted to numerical applications
+ easy integration of C code for performance	- interfacing C code problematic

Python is not just a low-cost Matlab clone!

Modular Toolkit for Data Processing



Background

- Open Source library (LGPL)
- first release 2004
- 15k+ downloads, available in Debian, Ubuntu, MacPorts, Python(x,y)
- originated in and supported by research group of Prof. Wiskott, but used outside neuroscience as well

Overview

1. Introducing the basic building blocks of MDP
2. Example
3. Outlook

Building blocks: Node

Node: fundamental data processing element,
node classes represent algorithms, public API:

train (optional)
support for multiple phases, batch, online, chunks, supervised, unsupervised

execute
map n dimensional input to m dimensional output

inverse (optional)
inverse of execute mapping

data format: 2d numpy arrays
(1st index for samples, 2nd index for channels)
automatic checks and conversions (dimensions, dtype).

Building blocks: Node

Example: Principal Component Analysis (PCA)
reduce dimension of data from 10 to 5:

```
>>> import mdp
>>> import numpy as np
>>> data = np.random.random((50,10))  # 50 data points
>>> node = mdp.nodes.PCANode(output_dim=5,
...                          dtype='float32')
>>> node.train(data)
>>> proj_data = node.execute(data)
```

shortcut:

```
>>> import mdp
>>> import numpy as np
>>> data = np.random.random((50,10))  # 50 data points
>>> proj_data = mdp.pca(data, output_dim=5, dtype='float32')
```

Building blocks: Node

Some available nodes:

PCA (standard, NIPALS)
ICA (FastICA, CuBICA, JADE, TDSEP)
Locally Linear Embedding
Hessian Locally Linear Embedding
Fisher Discriminant Analysis
Slow Feature Analysis
Independent Slow Feature Analysis
Restricted Boltzmann Machine
Growing Neural Gas
Factor Analysis
Gaussian Classifiers
Polynomial Expansion
Time Frames
Hit Parades
Noise
...

Or write your own node (and contribute it :-).

Building blocks: Flow

Combine nodes in a **Flow** (data processing pipeline):

```
>>> flow = PCANode() + SFANode() + FastICANode()
>>> flow.train(train_data)
>>> test_result = flow.execute(test_data)
>>> rec_test_data = flow.invert(test_result)
>>> flow += HitParadeNode()
```

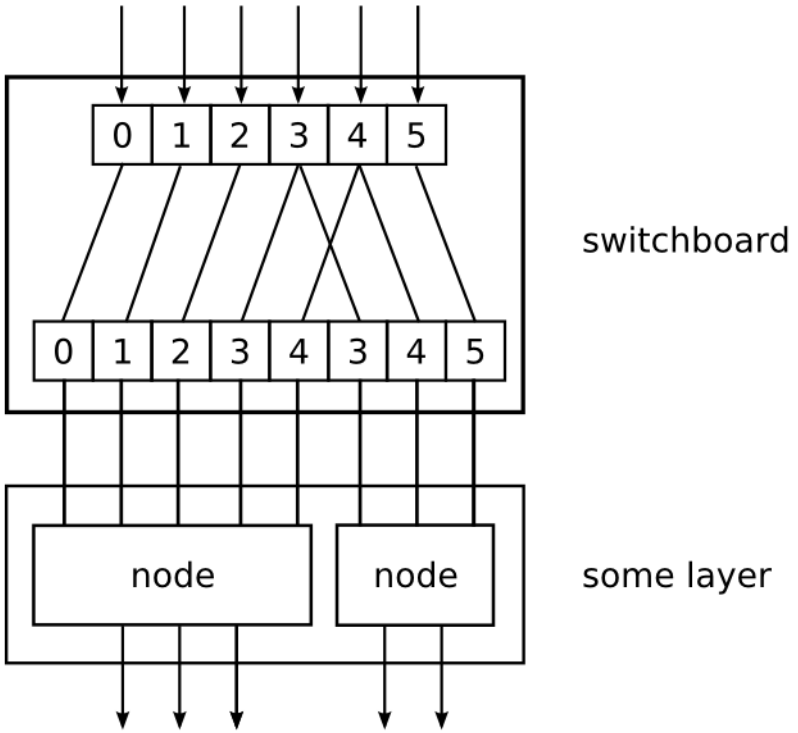
- automatic organization: training, execution, inversion
- automatic checks: dimensions and data formats
- use arrays or iterators
- crash recovery, checkpoints

Building blocks: Network

`mdp.hinet` package for hierarchical networks

Layer (combine nodes horizontally in parallel)
Switchboard (routing between layers)
FlowNode (combine nodes into a "supernode")

All these classes are nodes, combine them as you want.

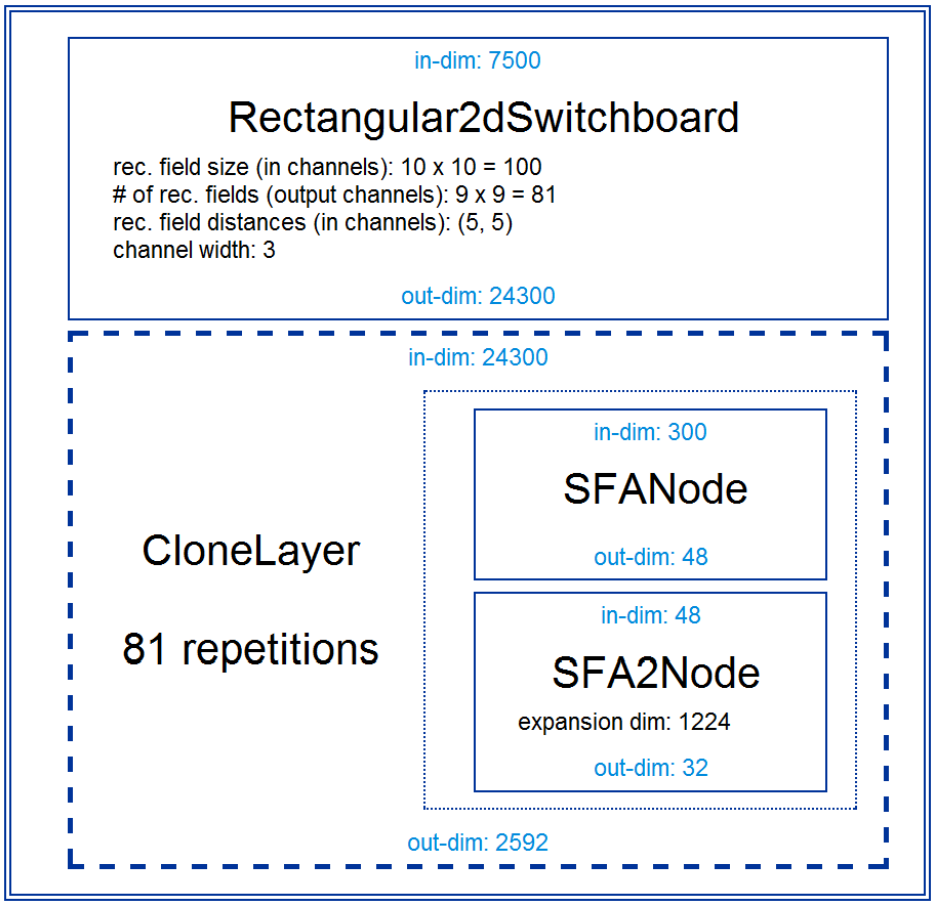


Building blocks: Network

HTML representation of your network:

```
>>> mdp.hinet.show_flow(flow)
```

Use this for debugging, reports or GUI.



Extending MDP: Writing Nodes

Write your own node class:

```
>>> class MyNode(Node):
...     def _train(self, x):
...         ... training code ...
...     def _execute(self, x):
...         ... execution code ...
...
>>> flow = PCANode() + MyNode()
```

- integrate with the existing library
- benefit from automatic checks and conversions
- contribute your node to make it available to a broader audience

Parallelization

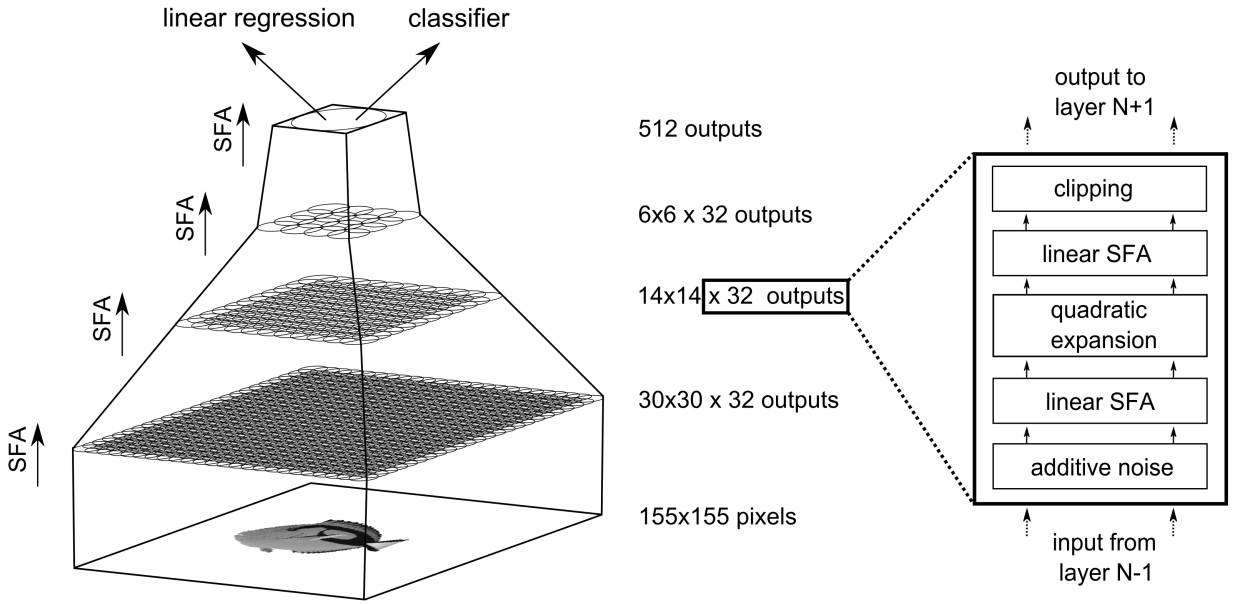
- for "embarrassingly parallel" problems:
  data chunks for node training can be processed independently (fork node), combine results in the end (join node)
- parallel training and execution is automatically handled by `ParallelFlow`
- easy to implement for your own nodes
  (implement `_fork` and `_join` methods)

Example:

```
>>> pflow = mdp.parallel.ParallelFlow([PCANode(), SFANode()])
>>> scheduler = mdp.parallel.ProcessScheduler(n_processes=4)
>>> pflow.train(data, scheduler)
```

Real World Example

- object recognition system,
  working on 155x155 pixel image sequences
- several GB of training data for each training phase.
- hierarchical network with nested nodes,
  900 “supernodes” on lowest layer
- training is parallelized, takes multiple hours on network



[Franzius, M., Wilbert, N., and Wiskott, L., 2008]

Upcoming: BiNet package

`mdp.binet` package will allow data flow in both directions,
enabling for example error backpropagation and loops.

compatible with both the `mpd.parallel` and `mdp.hinet` packages.

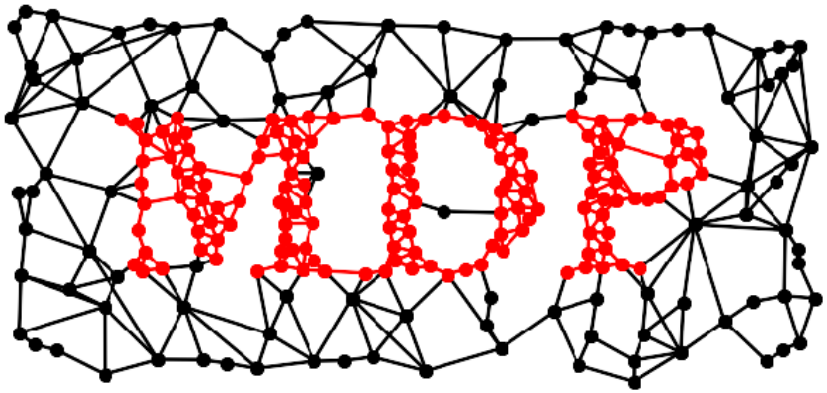
HTML+JS based inspector for debugging and analysing

scheduled for inclusion in MDP 3.0 (maybe end of 2009)

Embedding / Using MDP

- comprehensive documentation:
  tutorial covering basic and advanced usage,
  detailed doc-strings,
  PEP8 compliant, commented, and pylint-clean code
- API is stable and designed for straightforward embedding
- unittest coverage (400+ unit tests)
- minimal dependencies: Python + NumPy
- used by:
  PyMCA (X-ray fluorescence mapping),
  PyMVPA (ML framework for neuroimaging data analysis),
  Chandler (personal organizer application)

Thank you!



mdp-toolkit.sourceforge.net