MDP: Modular toolkit for Data Processing (and its new features)

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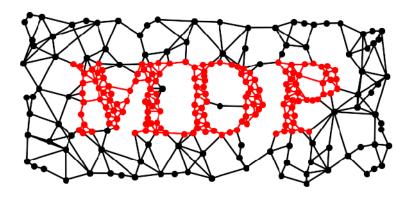






Background

- Library of widely used data processing algorithms, and a framework to combine them according to a pipeline analogy.
- origin: Computational Neuroscience and Machine Learning, supported by Prof. Laurenz Wiskott (HU Berlin, now Bochum)
- documentation and unittest coverage, tutorial on homepage
- first release 2004, 15k+ downloads, available in Debian, MacPorts and Python(x,y)



Talk Overview

- Introducing the basic building blocks:
 - ◆ Nodes and Flows
 - ◆ Hierarchical Networks
 - ◆ Parallelization
- New features:
 - Node Extensions
 - ◆ bidirectional data flow with BiMDP

Node represents data processing algorithm, interface methods:

train (optional) support for multiple phases, chunks, supervised training

execute

map n dimensional input to m dimensional output

inverse (optional)
 inverse of execute method

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

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)
>>> node.train(data)
>>> proj_data = node.execute(data)
```

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 :-).

Write your own node class:

```
class MyNode(Node):
    def _train(self, x):
        # training code

def _execute(self, x):
        # execution code
```

Node base class takes care of the rest.

Building blocks: Flow

Combine nodes in a **Flow**:

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

- management of training, execution, inversion
- arrays or iterables for input

Building blocks: Network

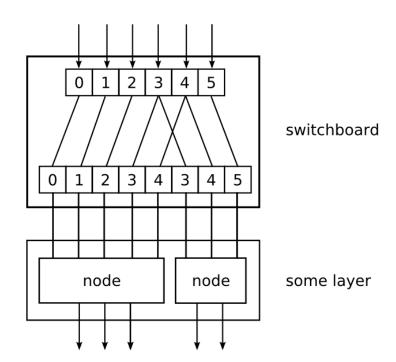
mdp.hinet package for hierarchical networks

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.

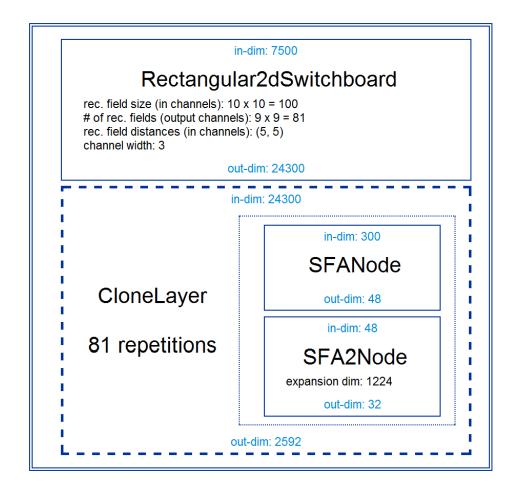


Building blocks: Network

HTML representation of your network:

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

Use this in your reports or GUI.



Parallelization

- training: nodes provide _fork and _join methods, fork → parallel training → join ("embarrassingly parallel" problem)
- execution: node copies are used
- use multiple cores or multiple machines (e.g. via Parallel Python library)
- abstract scheduler API (easy to write adaptor)

Example:

```
>>> nodes = [PCANode(output_dim=10), SFANode()]
>>> flow = mdp.parallel.ParallelFlow(nodes)
>>> scheduler = mdp.parallel.ProcessScheduler() # one process per core
>>> flow.train(data, scheduler)
```

Real World Example

- object recognition system,
 working on 155x155 pixel image sequences
- hierarchical network with nested nodes
- several GB of training data for each layer
- training is distributed over network, takes multiple hours



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

New feature: Node Extensions

Problem: How to add new aspects to nodes?

- Parallelization: add _fork and _join methods to node classes
- HTML representation: add _html_representation method

Solution: Node Extension Mechanism

inside ParallelFlow:

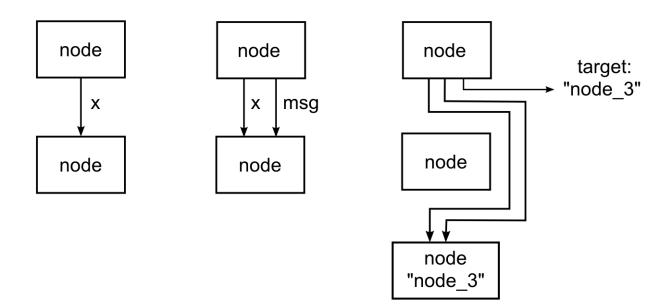
```
>>> mdp.activate_extension("parallel")
>>> # do parallel stuff with the new fork and join methods
>>> mdp.deactivate_extension("parallel")
```

Dynamically add class attributes (methods) to the supported node classes.

Define your own custom extensions

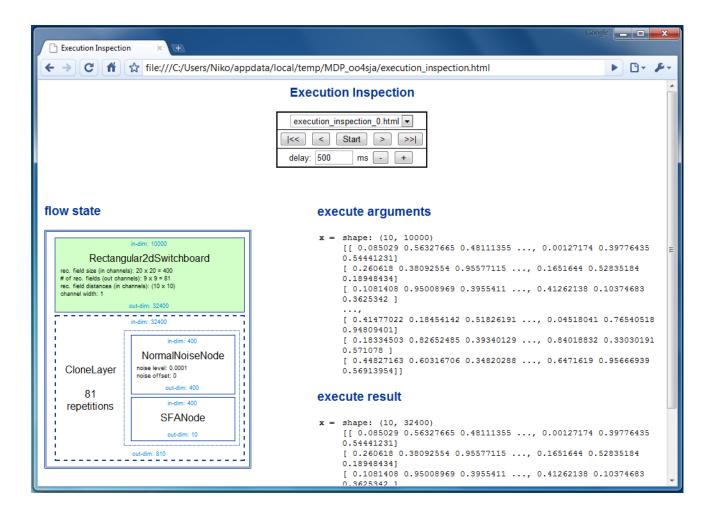
New feature: BiMDP

- transport additional information in msg dictionary,
- nodes can specify a target node, enabling error backpropagation and loops
- helpful functionality to get the data to the right node
- compatible with mpd.parallel and mdp.hinet package



New feature: BiMDP

HTML+JS based inspector for debugging and analysing



works in all browsers (Chrome 5.0 currently with restriction)

Thank you!

Upcoming: MDP Sprint

Join us for a coding sprint in Berlin.

 19^{th} - 23^{th} July 2010

More information on the MDP homepage (or ask us).









New feature: Node Extensions

How to define extension methods for a Node class?

■ Use multiple inheritance:

```
class ParallelPCANode(ParallelExtensionNode, mdp.nodes.PCANode):
    def _join(self, forked_node):
        # join code goes here
```

Metaclass magic to register which methods are available.

Use the function decorator for single methods:

```
@mdp.extension_method("parallel", mdp.nodes.PCANode)
def _join(self, forked_node):
    # join code goes here
```