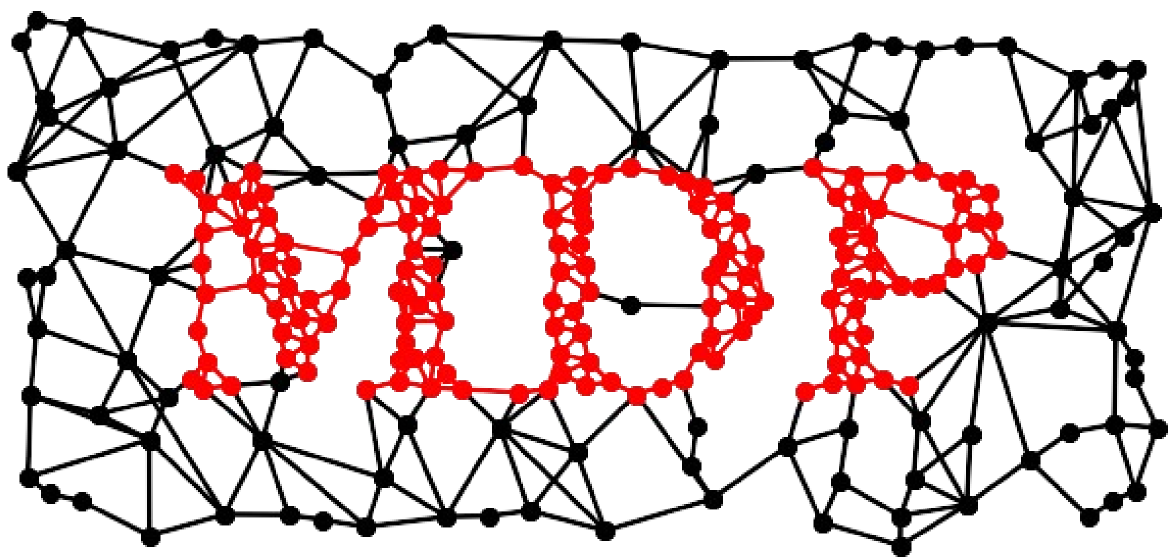
Modular toolkit for Data Processing

a Python data processing framework



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http://mdp-toolkit.sourceforge.net

QOTW

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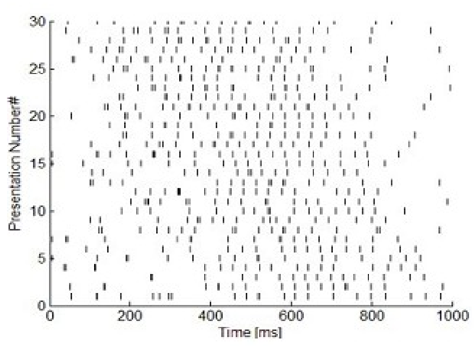
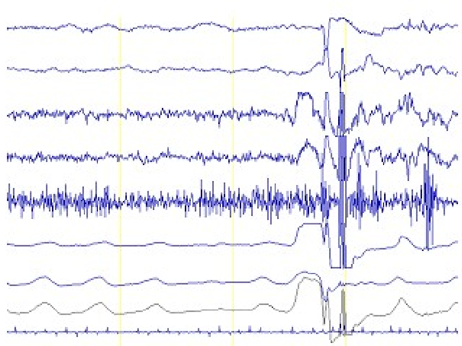
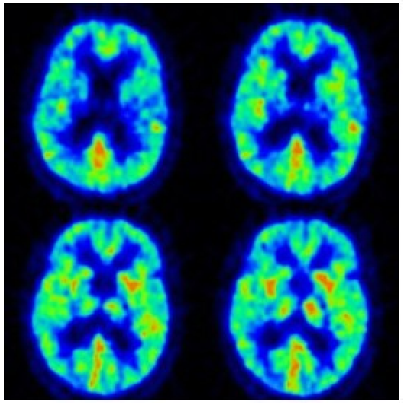
The fact that even bad UIs work at all is a credit to the heuristics, bugs and all, in the meat.

Steven D'Aprano

Background

- Python module, Object Oriented design
- Open Source (LGPL)
- first public release 2004
- 15k+ downloads, available in Debian, Ubuntu, MacPorts, Python(x,y)
- origin in Prof. Wiskott research group...




... but also used outside computational neuroscience

Contents

Building Blocks: Node

- fundamental data processing element

  Node classes correspond to algorithms
- API: train

  support for multiple phases, batch, online, chunks, supervised, unsupervised
- API: execute

  map *n*-dim input to *m*-dim output
- API: inverse

  inverse of execute mapping
- data format: 2-dim numpy arrays
- automatic consistency checks and conversions (dimensions, dtype, ...)

Building Blocks: Node

- example: Principal Component Analysis (PCA)

```
>>> pca = PCANode(output_dim=0.9, dtype='float32')
>>> for x in data_stream:
...     pca.train(x)
>>> out = pca.execute(x)
>>> rec = pca.invert(out)
>>> pca.explained_variance
0.9012761929
>>> pca.output_dim
45
```

- shortcut

```
>>> proj_data = pca(x, output_dim=0.9, dtype='float32')
```

Building Blocks: Node

- PCA (standard, NIPALS)
- ICA (FastICA, CuBICA, JADE, TDSEP, XSFA)
- Locally Linear Embedding
- Hessian Locally Linear Embedding
- Linear Regression
- 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
- ...

Building Blocks: Flow

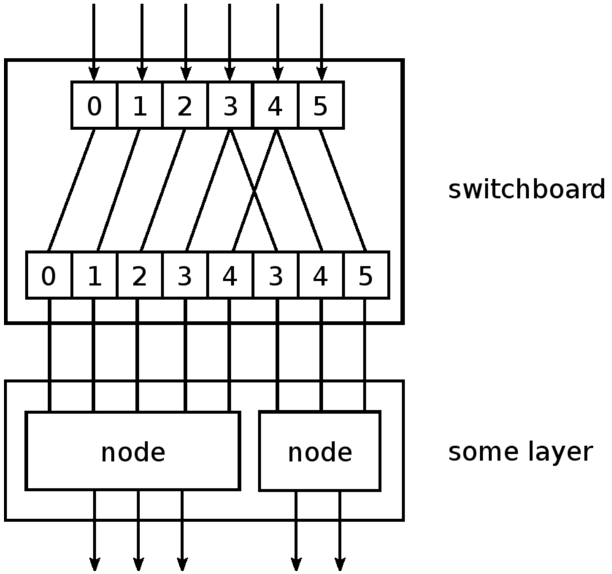
- combine nodes in a pipeline
- API: train, execute, inverse
- automatic training, execution, inversion
- automatic checks: dims and data formats
- Flow is a Python container (list)
- feed on arrays or iterators
- crash recovery, checkpoints

```
>>> flow = PCANode() + SFANode() + FastICANode()
>>> # DataStream is an iterable and returns
>>> # chunks of data (online or offline)
>>> flow.train([DataStream()]*3)
>>> out = flow.execute(x)
>>> rec = flow.inverse(out)
>>> flow += HitParadeNode()
```

Building Blocks: Network

- **mdp.hinet:** hierarchical networks
- **Layer:** combine nodes horizontally in parallel
- **Switchboard:** routing between layers
- **FlowNode:** encapsulate a Flow into a "super" Node
- everything is a Node: combine as you want
- all acyclic graphs can be emulated

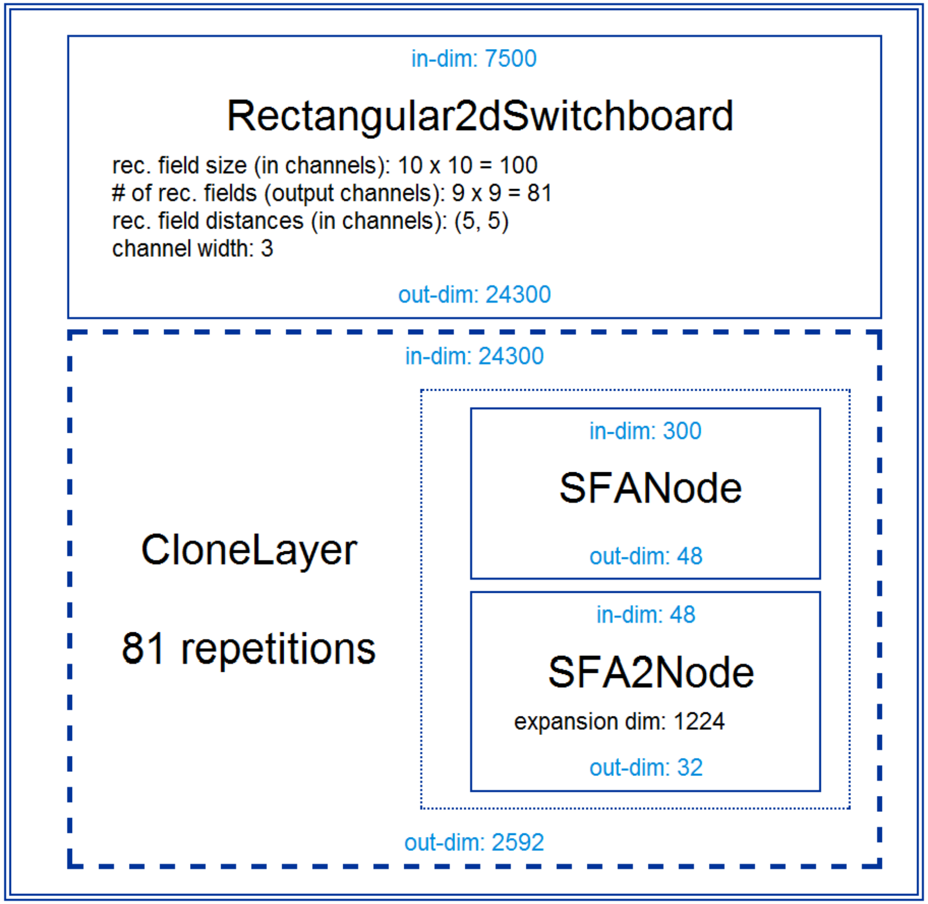
```
>>> layer = Layer([PCANode(),
...                ICANode(), ...])
>>> switch = Switchboard(input_dim=N,
...             connections=[0,3,1,...])
>>> net = switch + layer
>>> net.train(generator())
>>> out = net.execute(x)
```



Building Blocks: Network

- HTML visualization of your network
- Use it for debugging, reports or GUIs

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



Extending MDP: Writing Nodes

- concentrate on the algorithm, MDP takes care of the details
- use MDP utilities in your nodes
- immediately integrate your nodes with the existing library
- contribute your nodes to MDP!

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

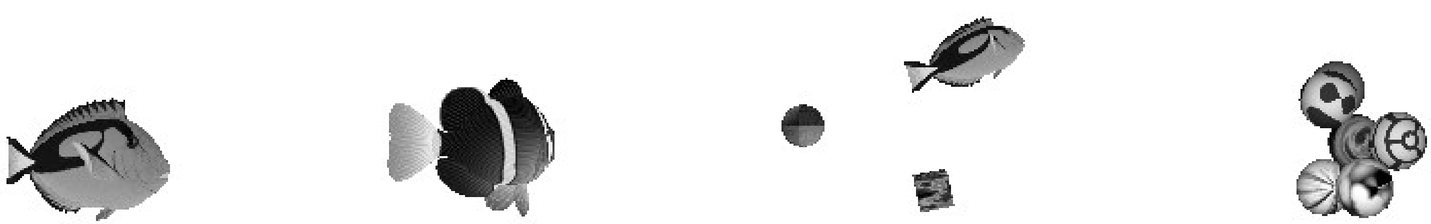
Parallelization

- for *embarrassingly parallel* problems
  - data chunks can be processed independently
- use multiple cores and multiple machines
  - Parallel Python support
- automatic parallelization of serial flows
- use abstract scheduler API
  - write your own adapter
- simple API: write your own parallel nodes
  - implement _fork and _join methods

```
>>> flow = PCANode() + SFANode()
>>> scheduler = ProcessScheduler(n_processes=8)
>>> pflow = make_flow_parallel(flow)
>>> pflow.train(data, scheduler)
```

Real World Example

- object recognition system
  - working on 155x155 pixel image sequences
- several GBs of training data for each training phase
- hierarchical network with nested nodes
  - 900 “super” nodes on lowest layer
- training is distributed over network



[Franzius, Wilbert, Wiskott, 2008]

Software Design Considerations

- Networks in MDP are modular. Why?
  - flexibility
  - distributed complexity = less complexity
  - extensions [e.g. parallelization] are independent from the specific structure of the network
  - higher but "once and for all" implementation cost

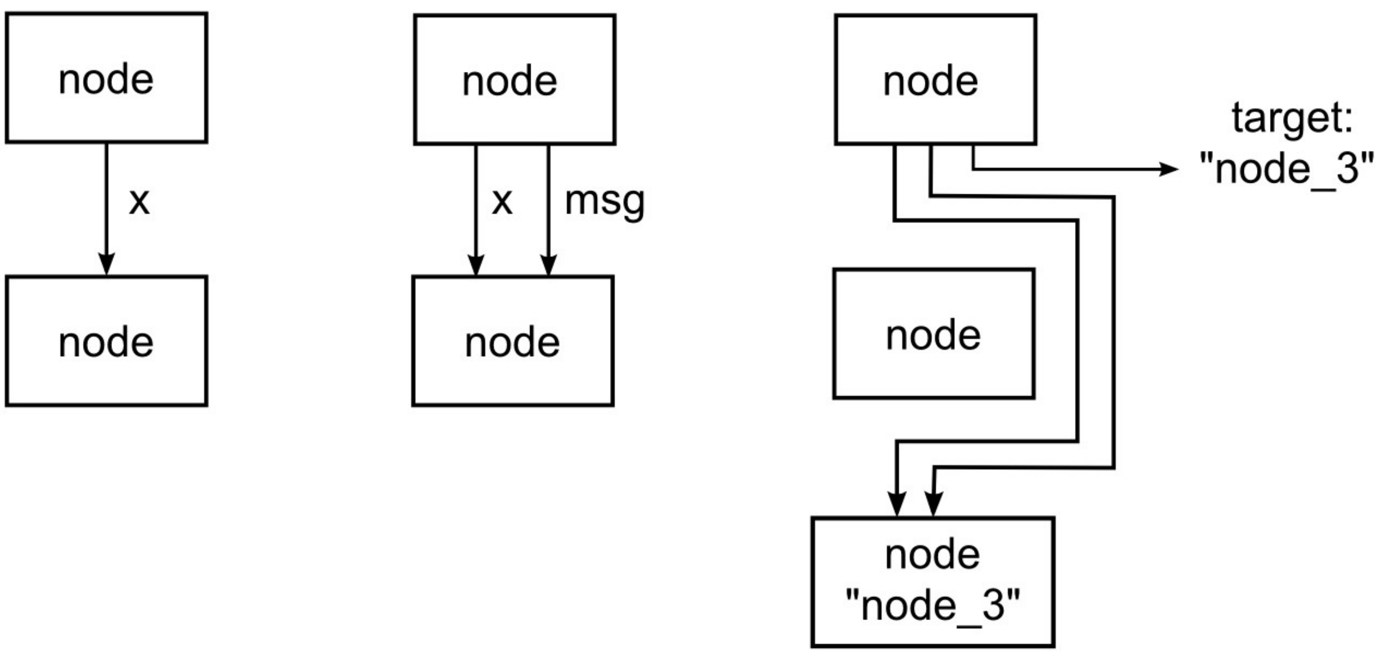
- Comparison with monolithic approach:
  - network structure is hard-coded
  - quick and dirty, not reusable
  - every extension must be hard-coded
  - network changes affect low-level code in different locations

Future Development: the BiNet Package

- mdp.binet allows bi-directional data flow
  - feedback loops, error back-propagation, ...
- compatible with mdp.parallel and mdp.hinet
- HTML+JS inspector for debugging and visualization
- scheduled for MDP 3.0 (end 2009?)

BiNet: Building Blocks

- BiNode and BiFlow: backward compatible
- BiNode has an ID string and can be accessed by this name: `biflow['PCA_node_3']`
- pass a “message” dictionary together with data
- BiNode can specify a target node [GOTO :)]



Using MDP

- comprehensive documentation:
  - tutorial covering basic and advanced usage
  - public objects have detailed doc-strings
  - PEP8 compliant, commented, and pylint-clean code
  - active and responsive user mailing list
- collection of efficient and well tested (390+ unit tests) algorithms
- minimal dependencies: Python + NumPy

Embedding MDP

- input and output just NumPy arrays
- API is stable and designed for straightforward embedding
- PyMCA: X-ray fluorescence mapping
- PyMVPA: ML framework for neuroimaging data analysis
- Chandler: personal organizer application

Future perspectives

- **Architecture:**
  - fully integrate, test, and document BiNet
  - Python 3
  - plugin system
  - GUI
  - automatic graph to BiNet translator
- **Algorithms:**
  - integrate widely used libraries (e.g. SVM)

- **Developers:**
  - Pietro Berkes, Niko Wilbert, Tiziano Zito

- **Contributors:**
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