ReservoirPy: Efficient Training of Recurrent Neural Networks for Timeseries Processing

Xavier Hinaut, Nathan Trouvain

reservoirpy

Efficient Training of Recurrent Neural Networks for Timeseries Processing

Xavier Hinaut[1,2,3*], Nathan Trouvain[1,2,3]

[1]Inria, Bordeaux, France. [2]LaBRI, UMR 5800, Talence, France.
[3]Neurodegeneratives Diseases Institute, UMR 5293, Bordeaux, France. *xavier.hinaut@inria.fr

github.com/reservoirpy

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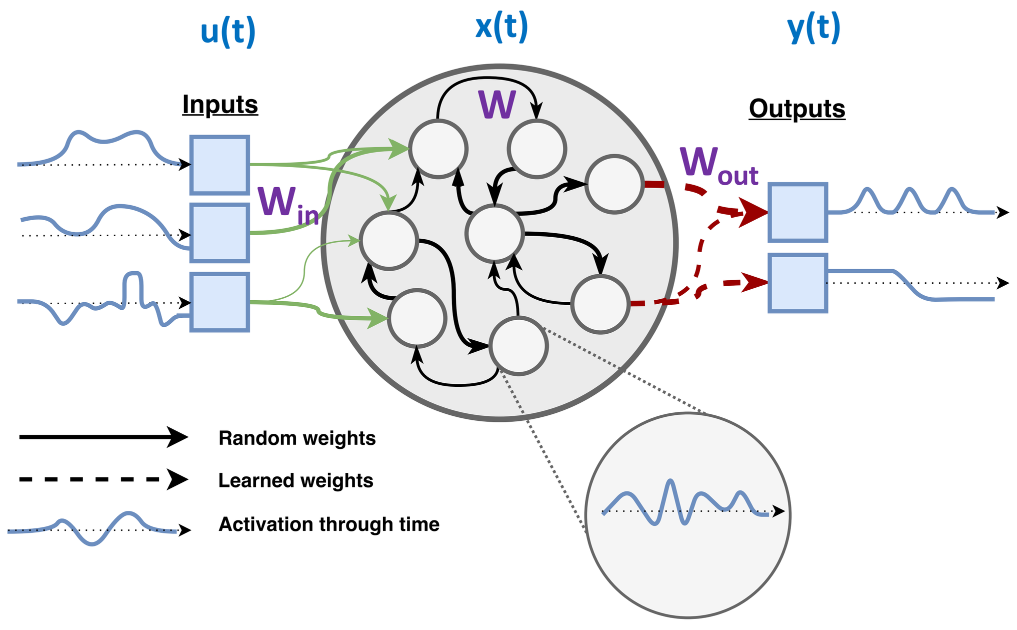
Abstract

ReservoirPy is a simple user-friendly library based on Python scientific modules. It provides a flexible interface to implement efficient Reservoir Computing (RC) [2] architectures with a particular focus on Echo State Networks (ESN) [1]. Advanced features of ReservoirPy allow to improve computation time efficiency on a simple laptop compared to basic Python implementation. Some of its features are: offline and online training, parallel implementation, sparse matrix computation, fast spectral initialization, advanced learning rules (e.g. Intrinsic Plasticity) etc. It also makes possible to easily create complex architectures with multiple reservoirs (e.g. deep reservoirs), readouts, and complex feedback loops. Moreover, graphical tools are included to easily explore hyperparameters with the help of the hyperopt library. It includes several tutorials exploring exotic architectures and examples of scientific papers reproduction.

Reservoir Computing paradigm



Reservoir state update

$$x(t) = \left(1 - \frac{1}{\tau}\right) x(t-1) + \frac{1}{\tau} f(W^{in}u(t) + Wx(t-1))$$

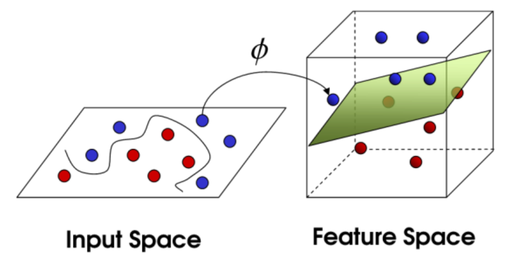
Output (« read-out ») update

$$y(t) = W^{out}x(t)$$

- $u(t)$: inputs
- W^{in}, W, W^{out}: input, recurrent, output matrices
- W^{in} and W matrices are kept random
- Only W^{out} is trained (e.g. ridge regression)
- τ : time constant of reservoir units
  - *leak rate* (LR) is often used instead of $\frac{1}{\tau}$
- f : activation function (usually $tanh$)

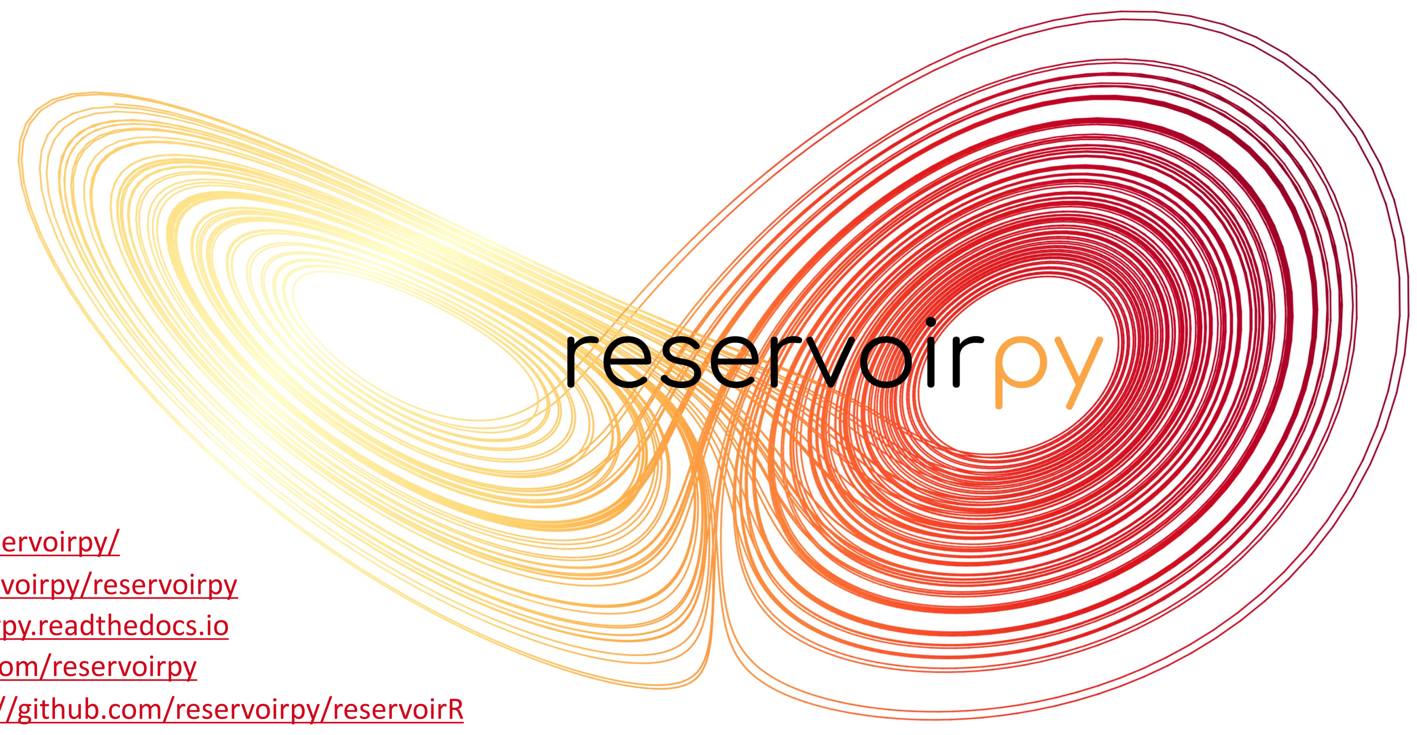
(see [1;2] for more details)

Similar to temporal Support Vector Machines (SVMs)



Intuition

The names "reservoir" for the recurrent layer, and "read-out" for the output layer, come from the fact that a lot of input combinations are made inside the recurrent layer (thanks to random projections):
the "reservoir" is literally a reservoir of calculations
(= "reservoir computing") that are non-linear.
From this "reservoir" one linearly decodes (= "reads-out") the combinations that will be useful for the task to be solved.
Reservoirs can be implemented on various kinds of physical substrates [9] (e.g. electronic, photonic, mechanical RC).



Founded at:

Inria

pypi: https://pypi.org/project/reservoirpy/
GitHub: https://github.com/reservoirpy/reservoirpy
Documentation: https://reservoirpy.readthedocs.io
Related projects: https://github.com/reservoirpy
R interface to ReservoirPy: https://github.com/reservoirpy/reservoirR

Why reservoirpy ?

- Few **dedicated, modern, reusable** tools.
- Last available dedicated tool: Oger (2012, Python 2).
- Other open source tools: *PyRCN*, *EchoTorch*, standalone scripts...
- Possibility of using existing machine learning frameworks:

Machine Learning
Scikit-learn (2011, Python 3)
and extensions like Sktime (2019, Python 3)
→ High quality codebase
→ Lack of flexibility for RC purpose

Deep Learning
Tensorflow/Keras (2015, Python 3)
PyTorch (2016, Python 3)
→ Flexible
→ Heavy codebase and unadapted

Project philosophy

Python 3.8+ "*scikit*" tools:
only based on **Python standard scientific stack.**
Everything is a ***recurrent network****, everything is a* ***timeseries.***
Create **complex models** with **simple building blocks.**
Reach **high computational efficiency.**
Community driven developement
(tests, documentation, tutorials...).

Targeted users

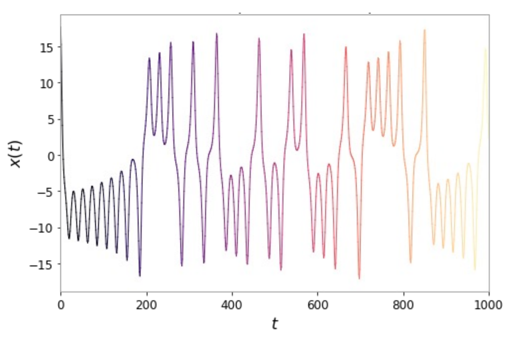
→ Academic researchers
→ Industry
→ *Machine learning students/beginners*

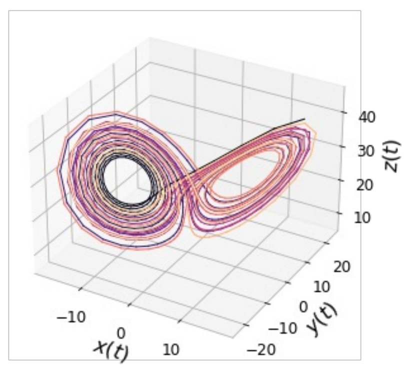
A simple application: Chaotic timeseries prediction

Importing the dataset (Lorenz attractor)

```
from reservoirpy.datasets import lorenz
X = lorenz(2500)
```

Given *x[t], y[t], z[t]*, can we predict *x[t+10], y[t+10], z[t+10]* ?

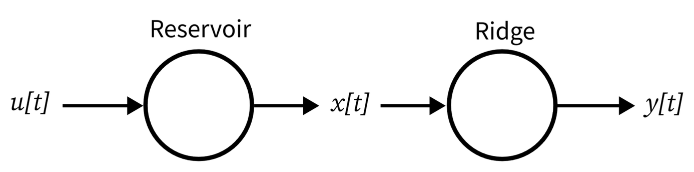




Node & model creation

A *node* is an independent operator, that applies a function on some data, potentially in a recurrent way.
A *model* connects nodes together to compose operators.
ESN = *Echo State Network* (a specific instance of Reservoir Computing with firing rate neurons)

```
from reservoirpy.nodes import Reservoir, Ridge
reservoir = Reservoir(100, lr=0.3, sr=1.25, input_scaling=0.1)
readout = Ridge(ridge=1e-5)
esn = reservoir >> readout
```



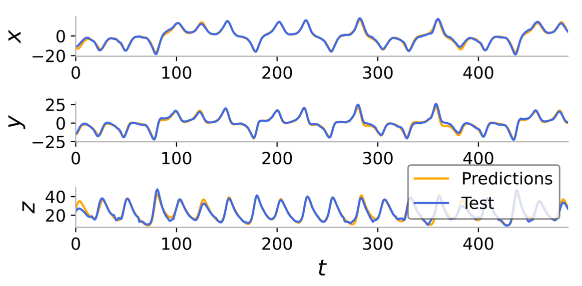
Model offline training & Evaluation

Offline training using linear regression:
the model is trained **in one shot on all available data.**

```
esn.fit(X_train, Y_train)
```

Evaluation

```
predictions = esn.run(X_) test
```



Model online training

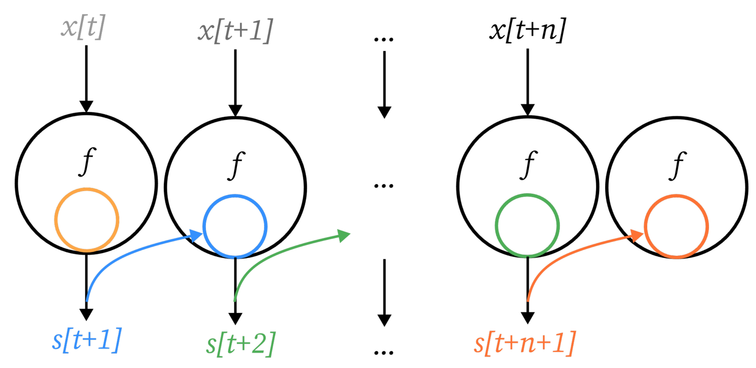
Online using Recursive Least Squares (RLS) or Least Mean Squares (LMS).

```
esn.train(X_train, Y_train)
```

Building blocks

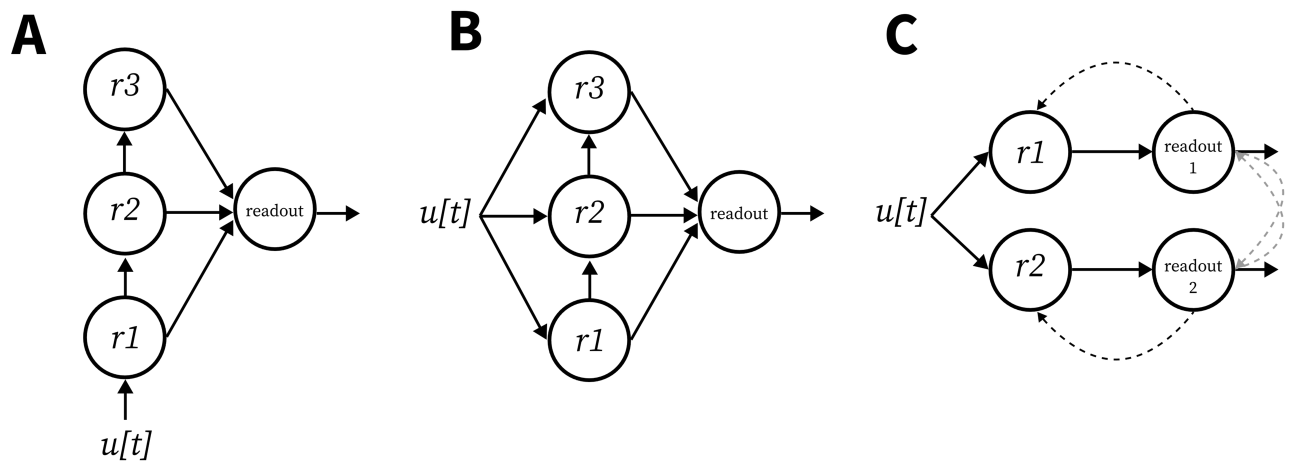
Node

Base object used to apply functions defined as ***f: s[t], x[t] -> s[t+1]*** to inputs ***x*** and modifying a state ***s***.
Can be parametrized and carry a learning rule to fit its parameters.



Model

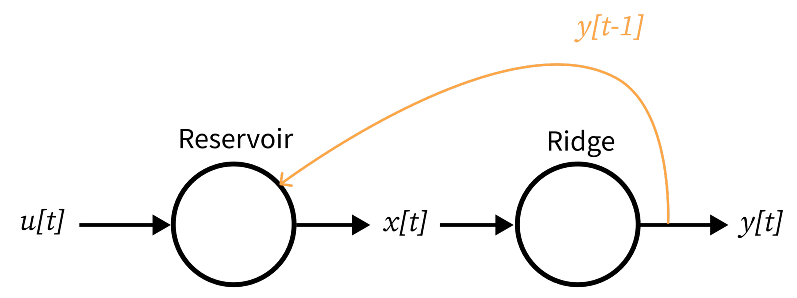
Composition of *Nodes*



Delayed connections (Feedback loops)

Can propagate different kind of information:
→ unit activities, error signals, yield ground truth values from an operator (teacher nodes), ...
Can also be used just to add a delay in the network.

```
reservoir_with_fb = reservoir << readout
```

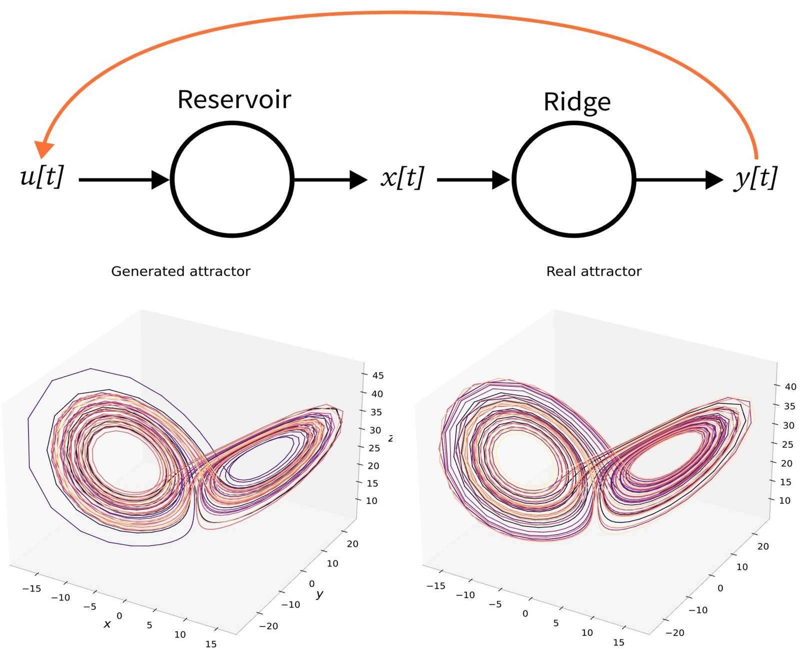


Generative mode

Timeseries generation: Lorenz attractor

Generation of 2000 timesteps (consecutive to training timeseries).

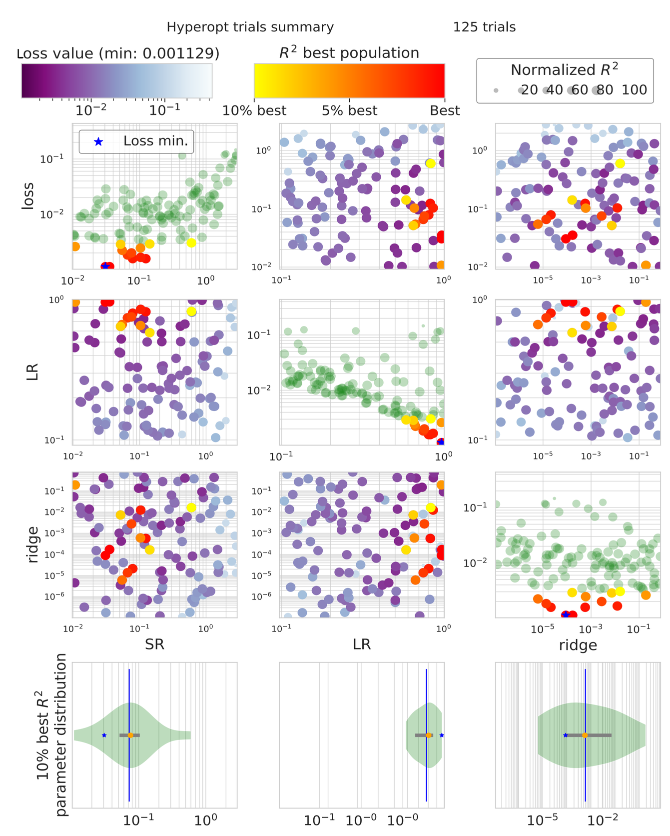
```
N = 2000
y_gen = np.zeros((N, 3))
y = X_test[0]

for i in range(N):
  y = model(y)
  y_gen[i] = y
```



Hyperparameter exploration

Random search on Lorenz attractor
Graphical tools to explore hyperparameters are included (using Hyperopt [6]).
With 125 random sets of HPs you can already have a good idea of the landscape.
SR: *spectral radius*
LR: *leak rate*
ridge: regularization param.

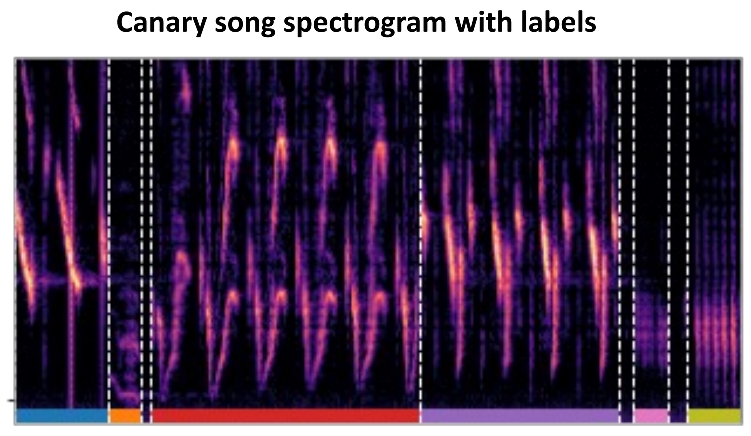
See [4] for more details on a general method to optimize HPs for reservoirs.
See [7] to understand why random search is better than grid search.



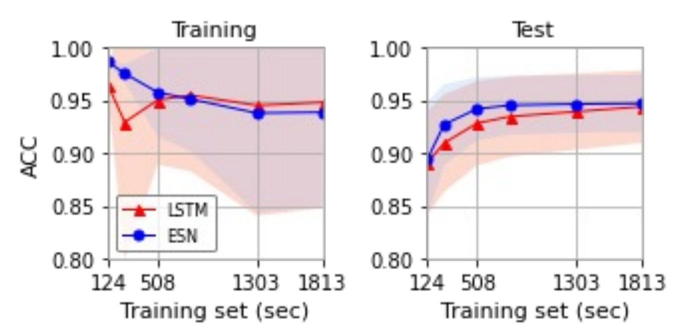
Sound classification example [5]

Dataset [9]
- 459 canary songs
- 40 labels
- MFCC preproc.

Canary song spectrogram with labels



Train/test frame accuracies*: LSTM vs. Reservoir
Reservoir learn with less data than LSTM (with equal number of trainable parameters)
*avg. 5 fold-CV;



CPU training time* (sec.): LSTM vs. Reservoir
Reservoir benefited from distributed states computation of *reservoirpy*.
*Trained on 2h40 of songs on Intel i7-9850H with 12 cores at 2.60GHz and 32GB RAM

Model	LSTM	ESN
Average training time (s)	2930 ± 222	35 ± 1

Summary

Dedicated framework for Reservoir Computing
- **Online/Offline** learning
- **Complex feedback loops**
- Hierarchical models, ***deep reservoir computing***
- **Parallel** computing
- Inspired from *scikit-learn, Thinc* and *Keras*

Reservoir Computing models toolbox
- *Reservoir, Autoregressive reservoir (NVAR), Ridge regression, FORCE learning (RLS & LMS), Intrinsic Plasticity, ...*

Complementary features
- Datasets, metrics, hyperoptimization tools using *Hyperopt*...
- Tutorials, examples, documentation...

Perspectives

Upgrade framework capabilities
- Spiking neural networks (e.g. *Liquid State Machines*)
- Extended distributed computation strategies
- GPU hardware exploitation
- *Scikit-learn* tools integration

Reservoir Computing Community
- Sharing and reuse models across community
- Replicate scientific results
- Implement new tools
- Find new use cases

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