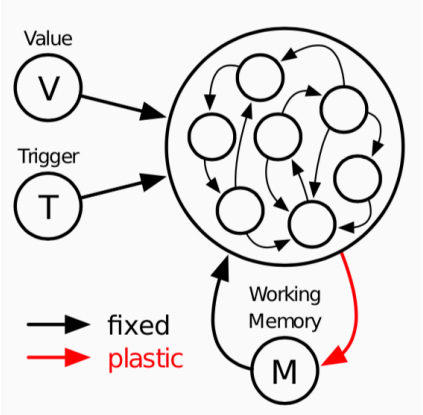
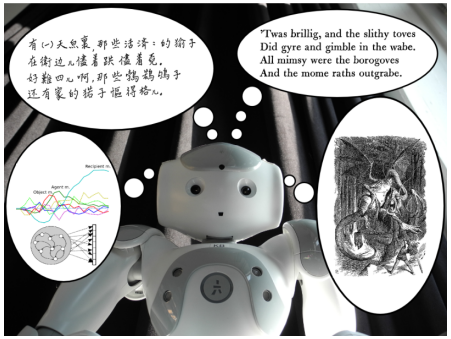
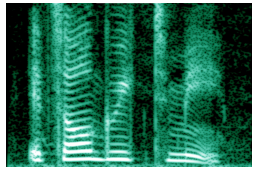






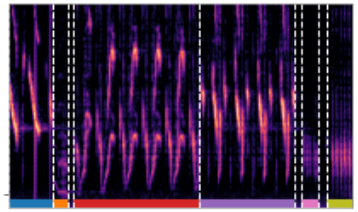
Xavier Hinaut & Paul Bernard

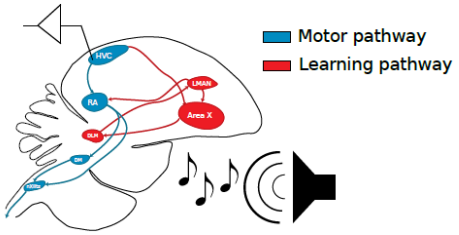
Researcher & Engineer @Inria, Bordeaux, France

{xavier.hinaut / paul.bernard}@inria.fr

@neuronalX & @PAUL-BERNARD

@hinaut @reservoirpy





RÉPUBLIQUE FRANÇAISE
Liberté Égalité Fraternité

Inria LaBRI université de BORDEAUX

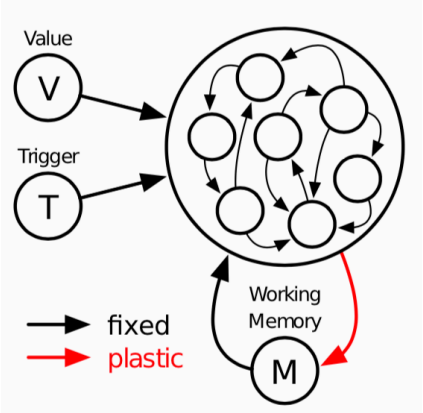
BORDEAUX neurocampus IMN

HACK1 ROBO


HACK1
ROBO
WHERE DID I COME FROM?
WHERE SHOULD I GO?
reservoirpy
RoboCup'23
Mon Fab Lab :
la fabrique à projets

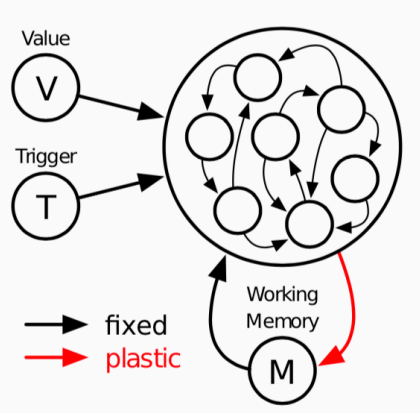
Have you ever dreamed of being a DJ?

Alison Wonderland



?

Alison Wonderland

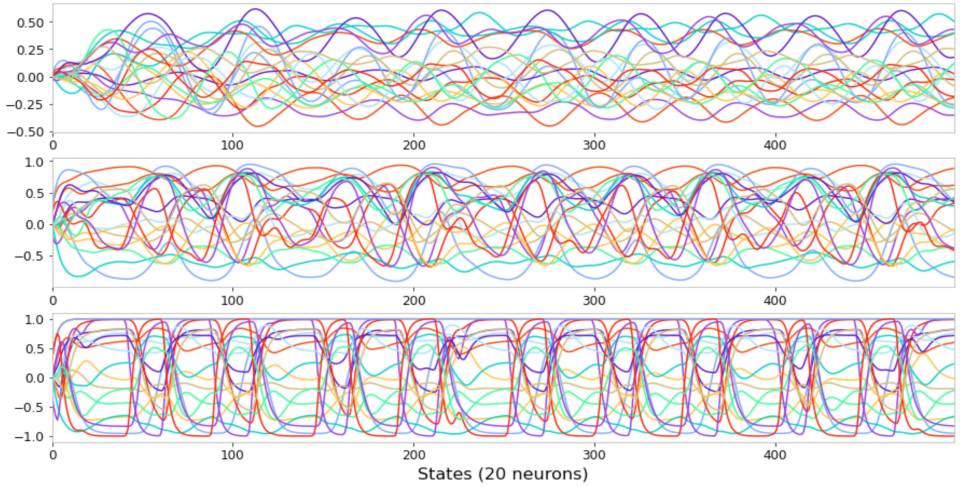


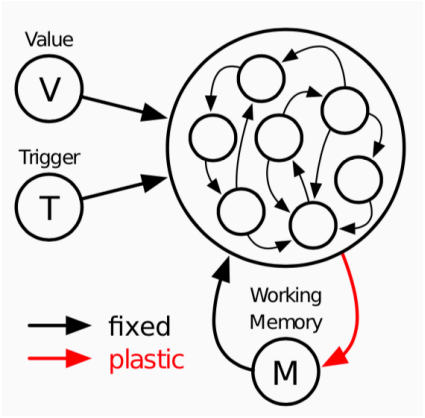
```
from reservoirpy.nodes import Reservoir, Ridge, Input

data = Input(input_dim=1)
reservoir = Reservoir(100, lr=0.3, sr=1.1)
readout = Ridge(ridge=1e-6)

esn = data >> reservoir >> readout

forecast = esn.fit(X, y).run(timeseries)
```

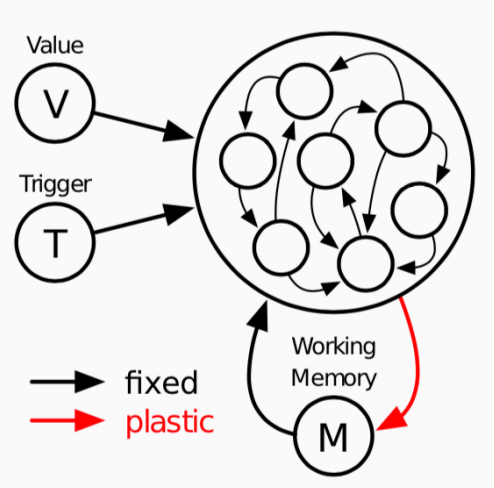


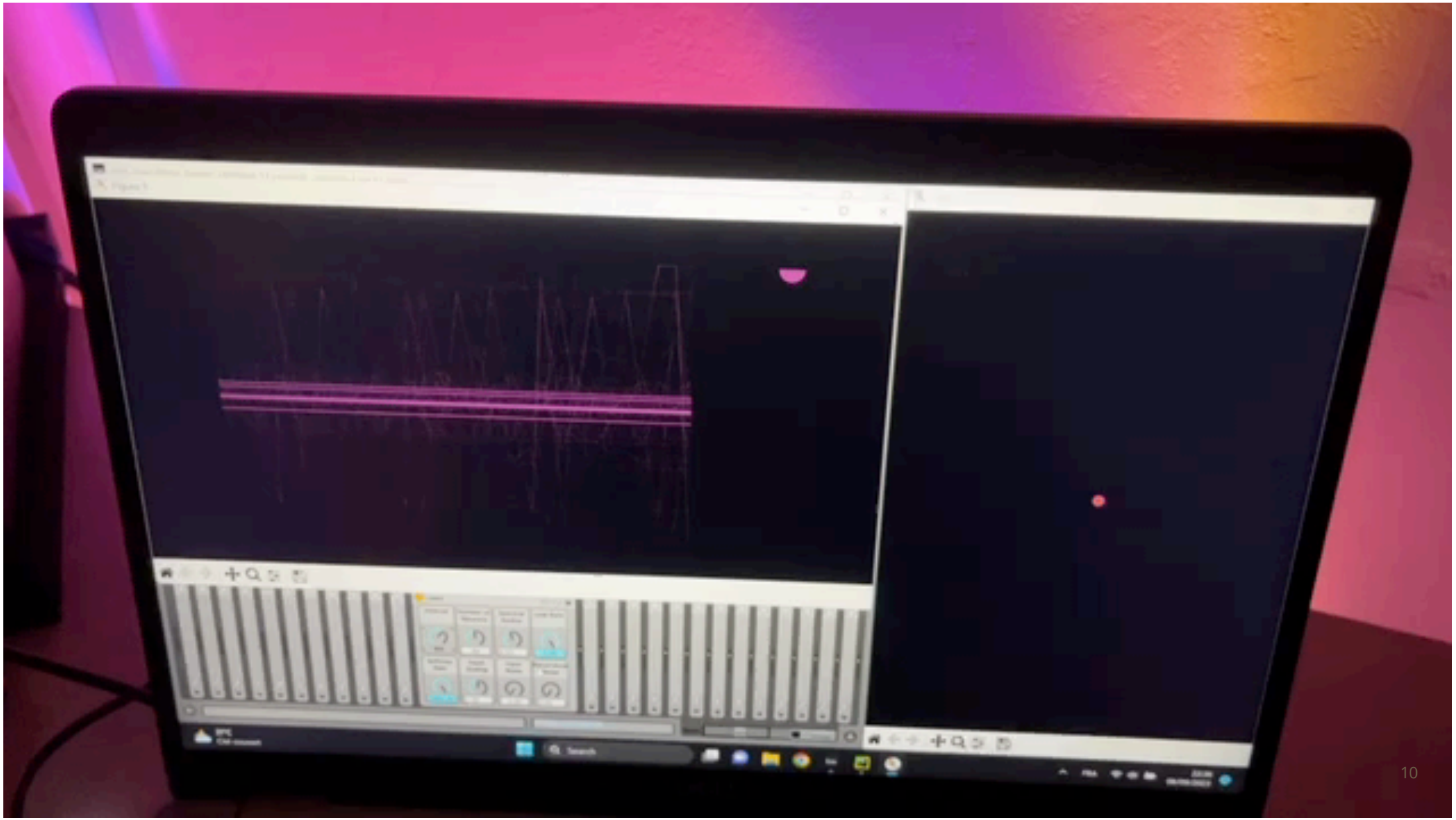

Value
V
Trigger
T
Working
Memory
M
fixed
plastic


SEQUENTIAL

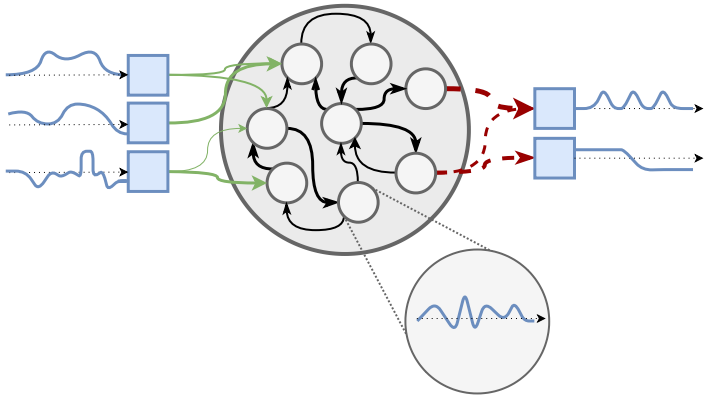

SEQUENTIAL

Have you ever dreamed of playing with a reservoir?

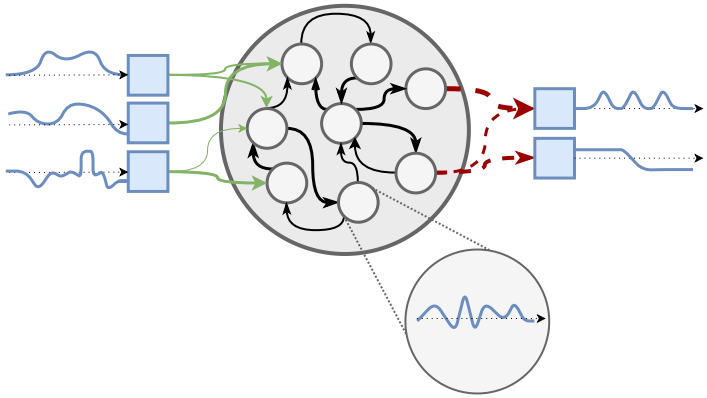




Random networks can generate fascinating dynamics

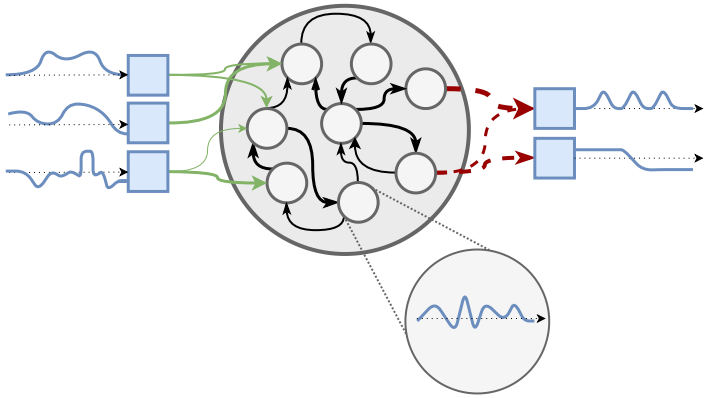


Random networks can generate fascinating dynamics



Reservoir Computing exploits
natural dynamics of random networks

Random networks can generate fascinating dynamics



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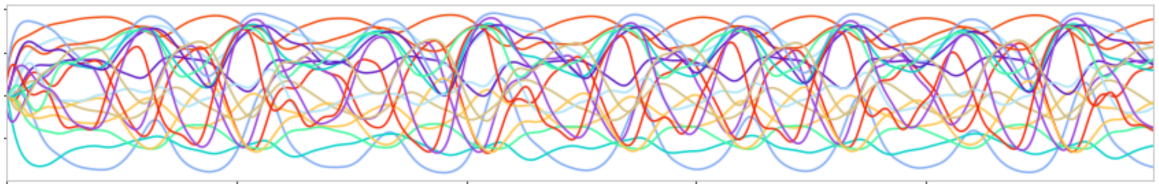
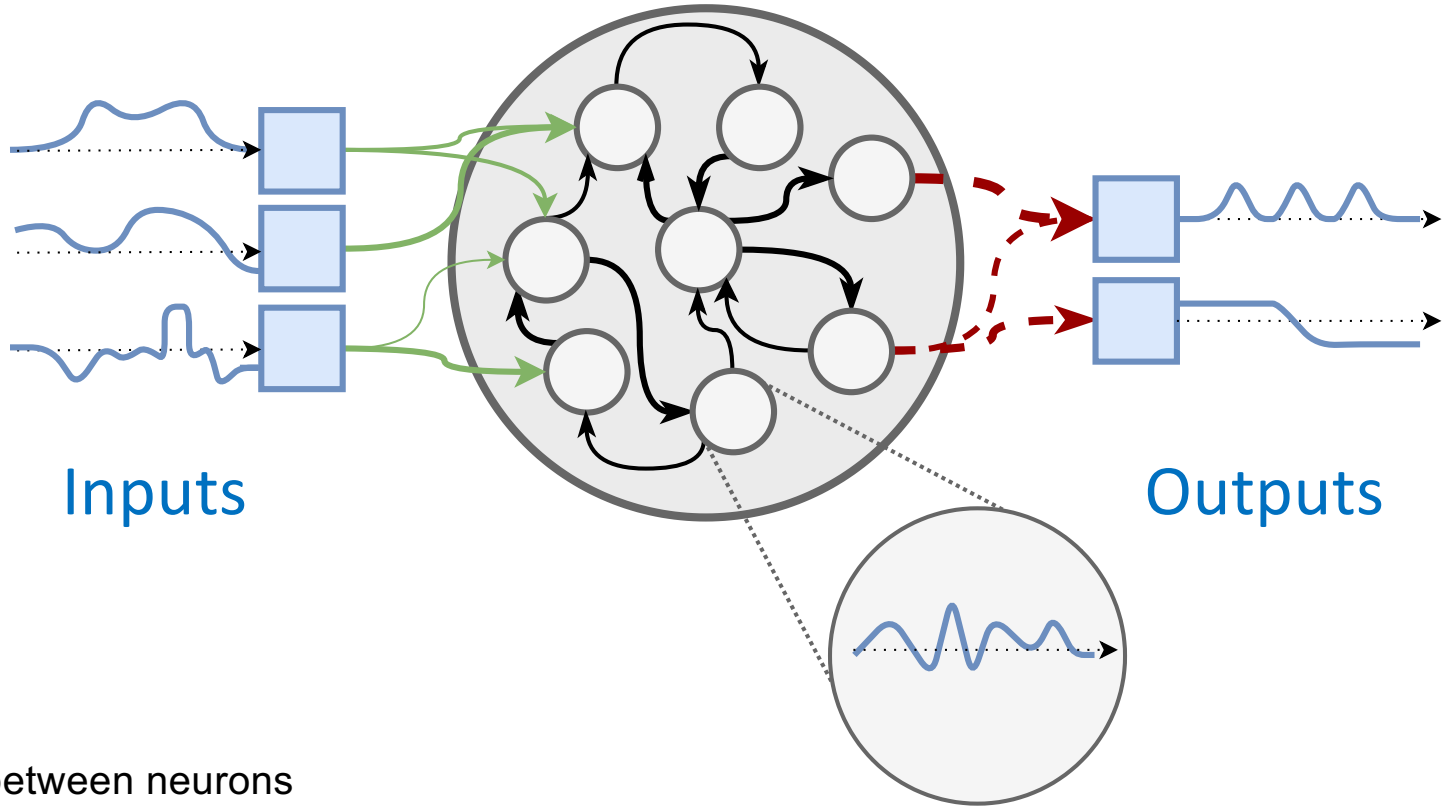


Quick installation for ReservoirPy demo

https://github.com/reservoirpy/reservoirpy

pip install reservoirpy[hyper]

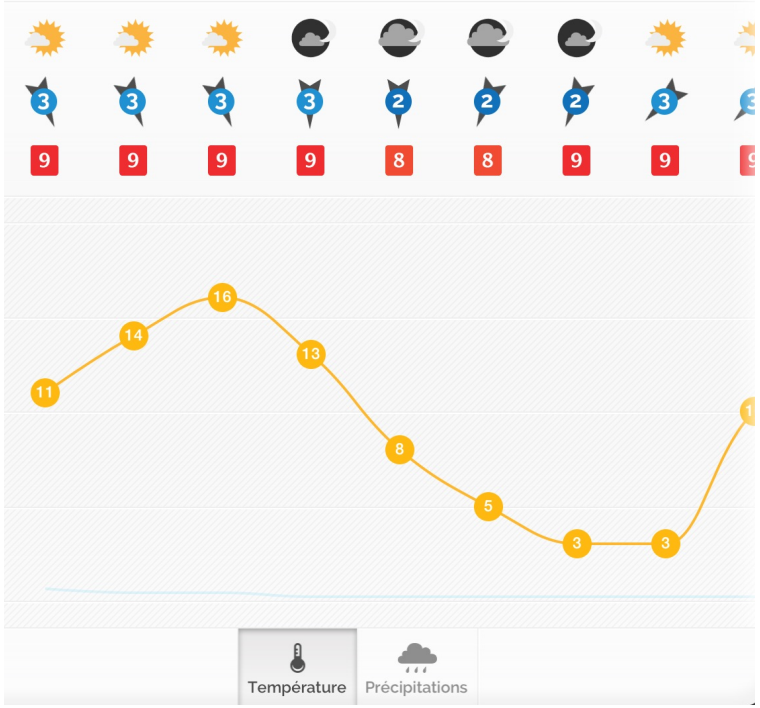
Reservoir Computing



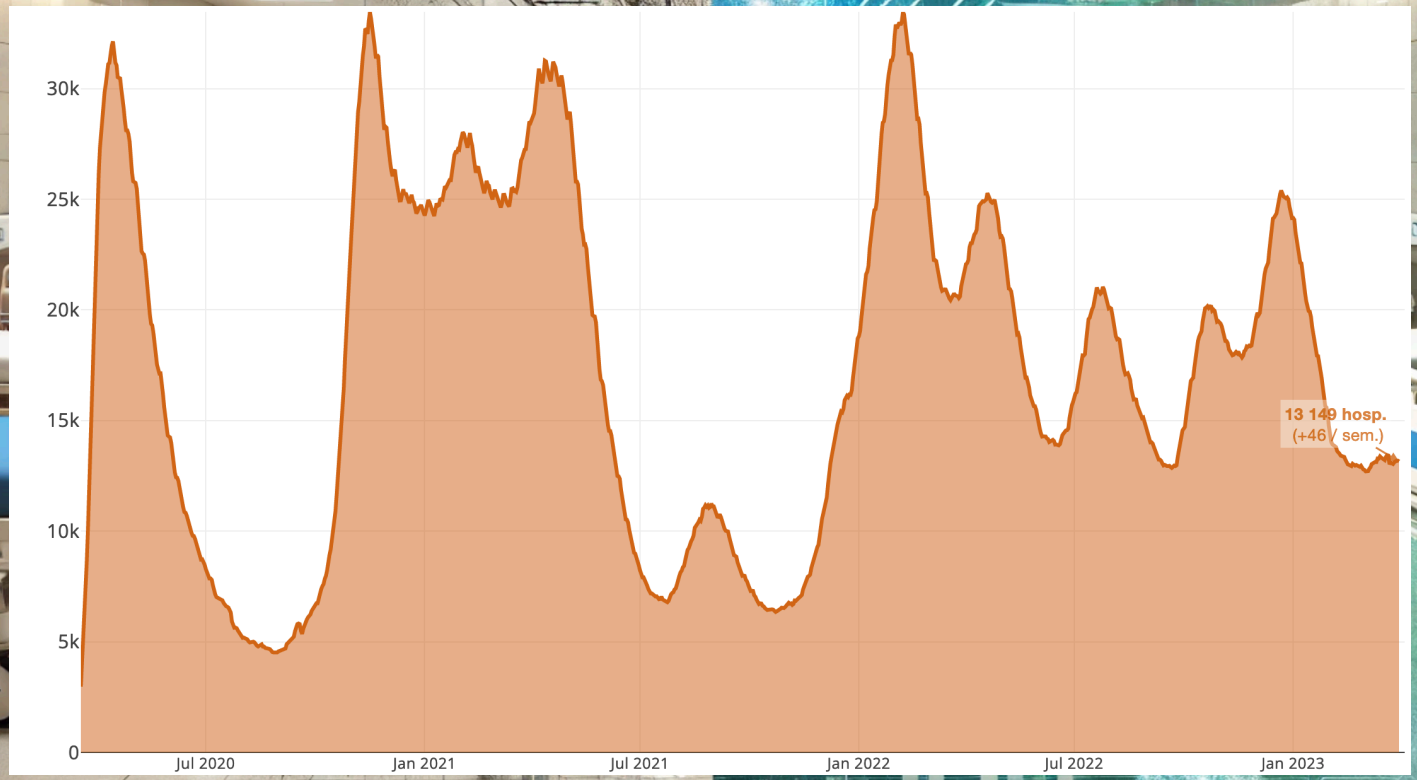
Neuron

Connection between neurons

Time series prediction



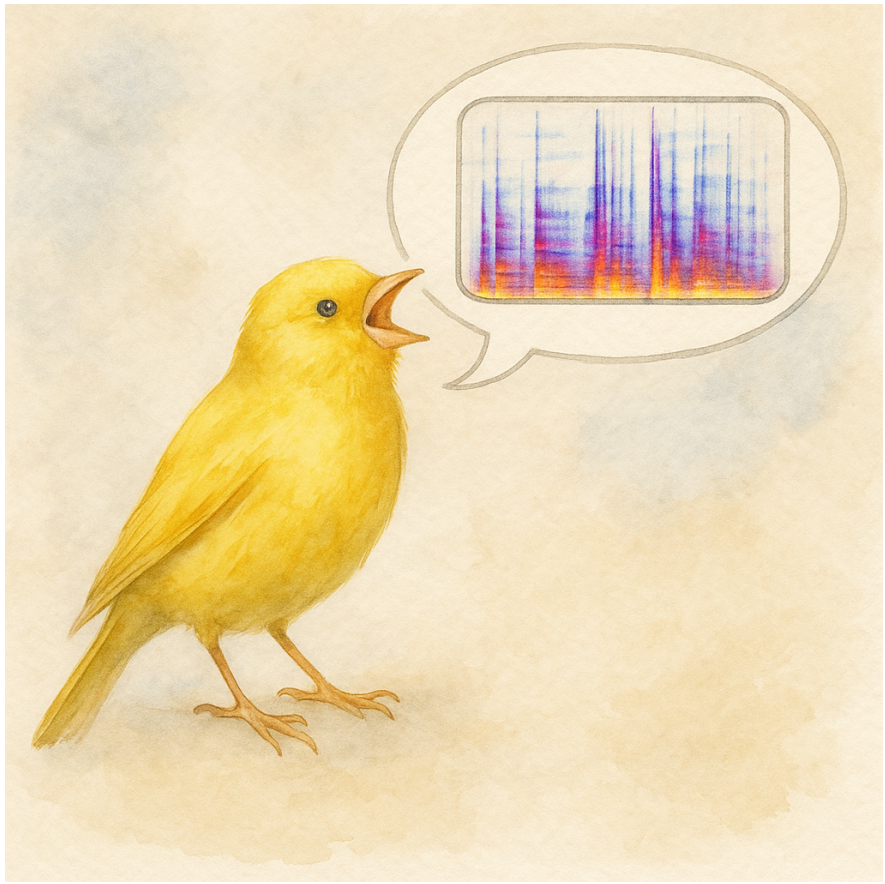
2 week forecasting of COVID hospitalisations

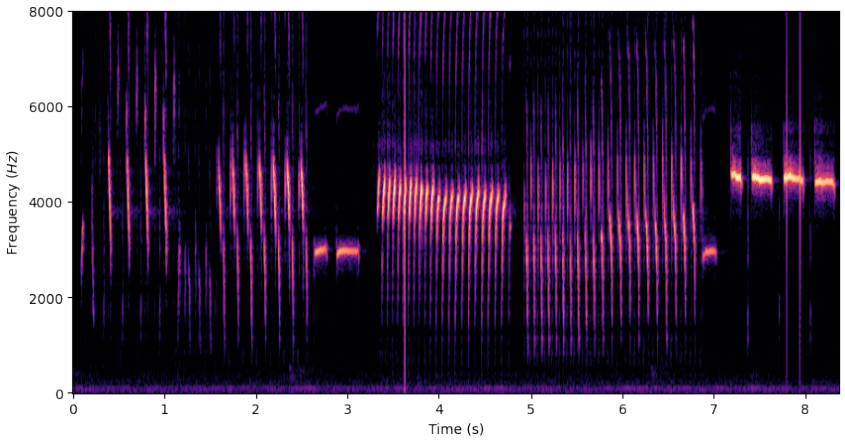


https://covidtracker.fr/france/#hospitalisations

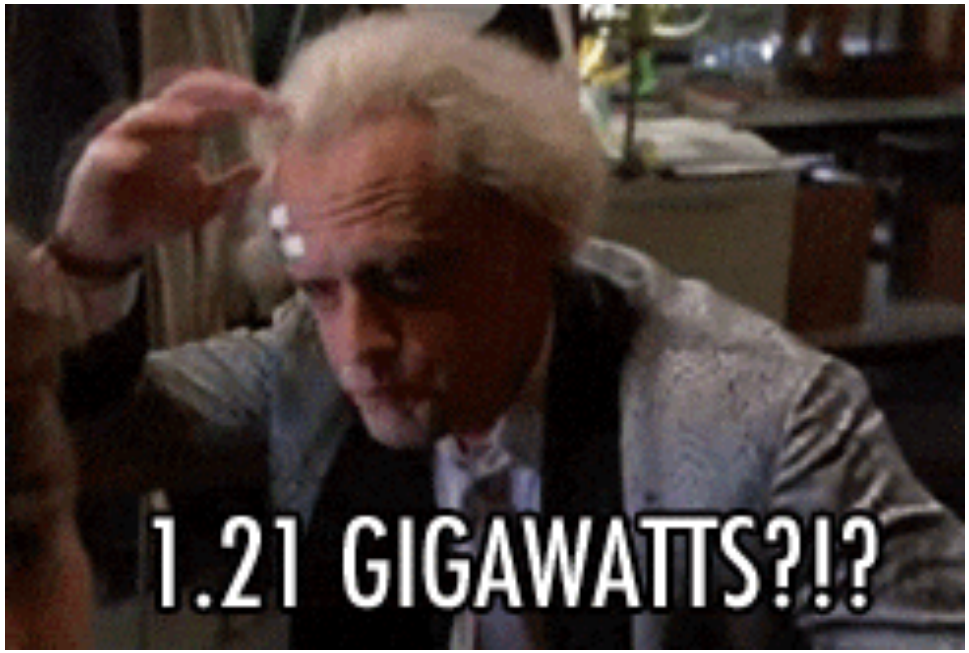
Catégoriser des sons

(“discriminer” des syllabes de canari)





Training a recurrent network is expensive!



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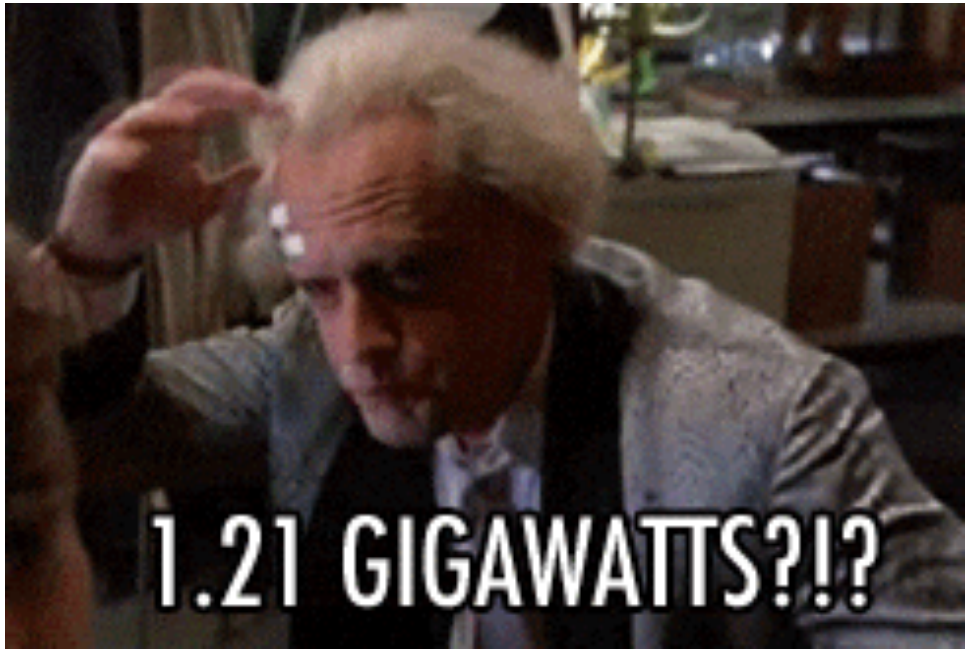
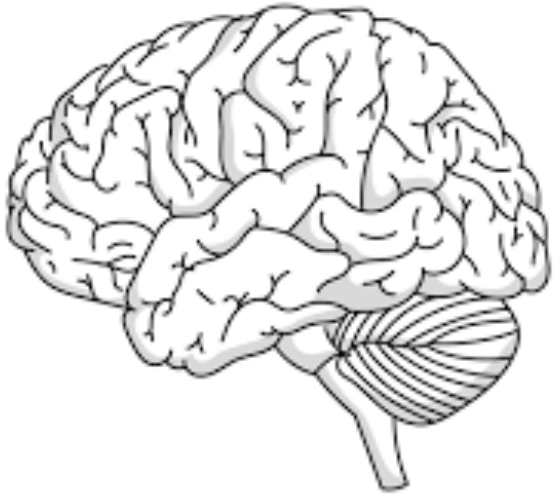
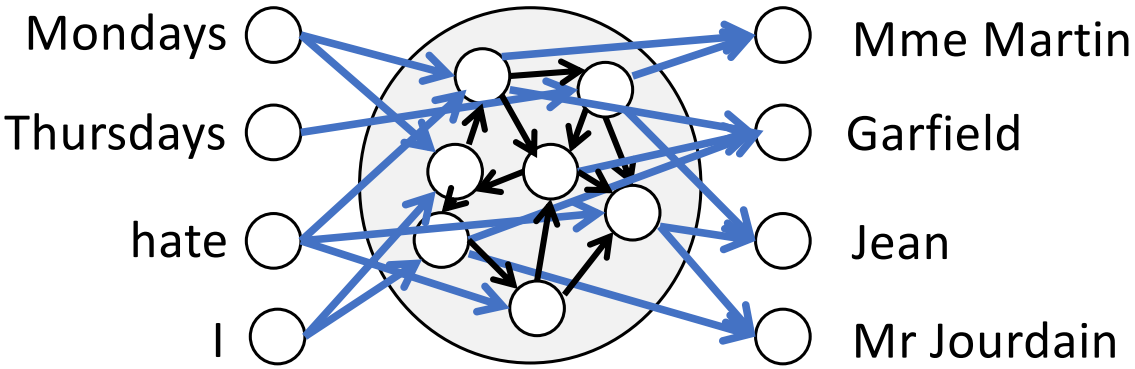




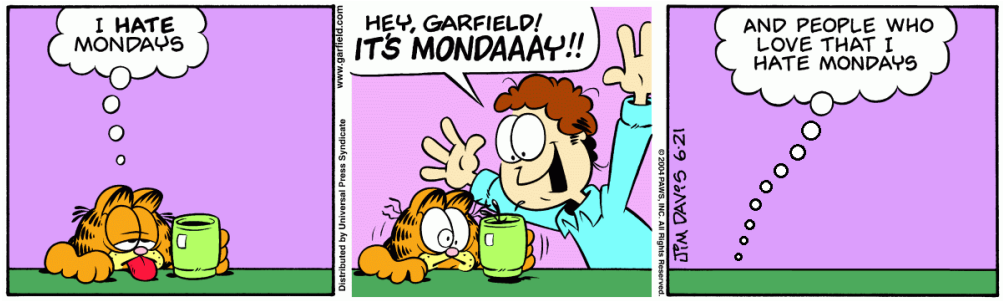
Only 20 W !
(2 energy-saving light bulbs)

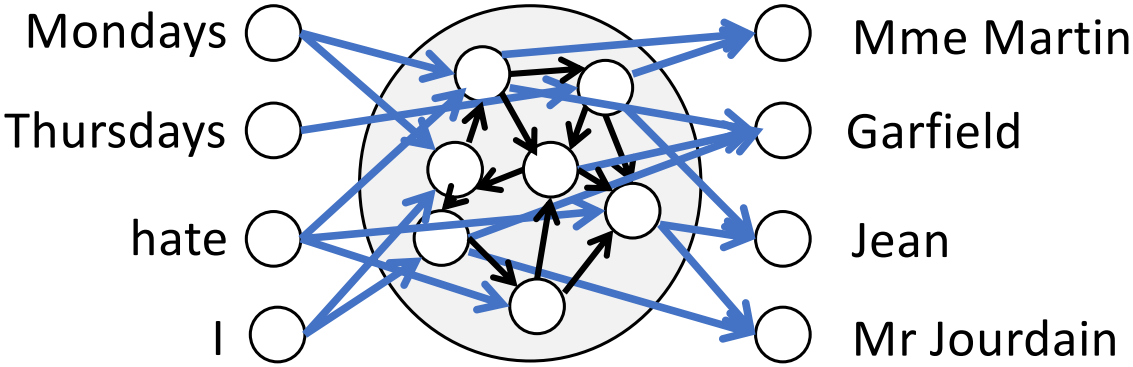
-> How to balance performance and energy?

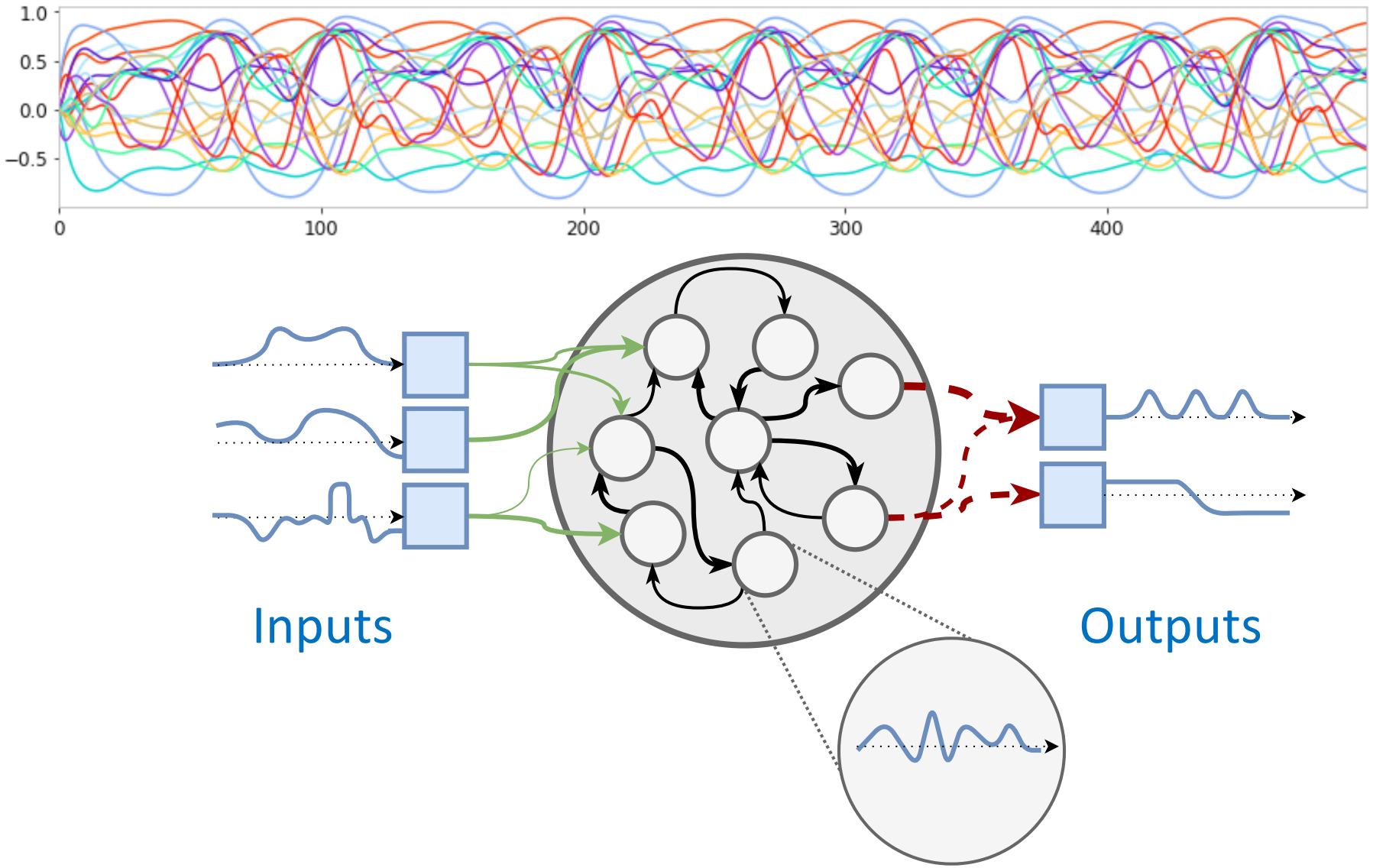
Reservoir Computing exploits natural dynamics of a recurrent neural network



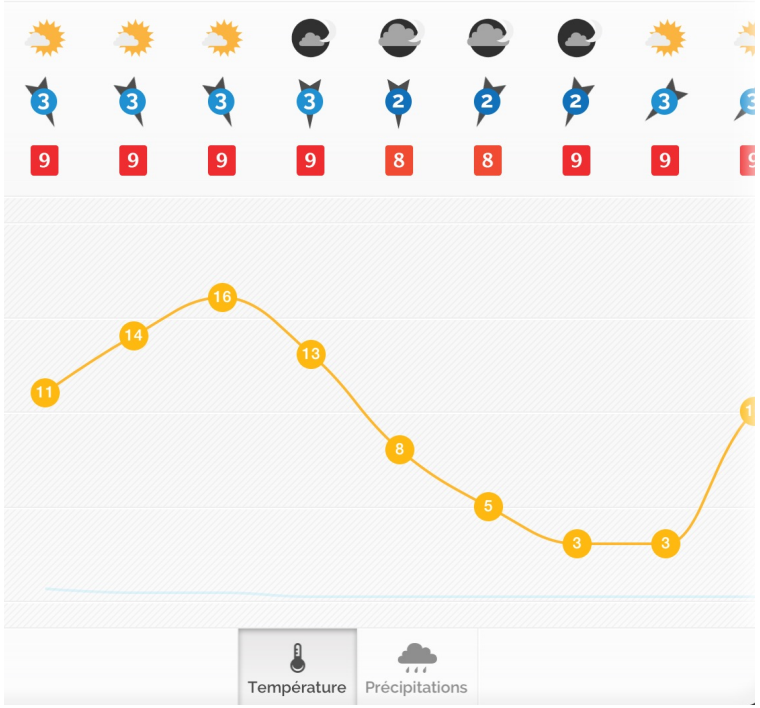
Reservoir Computing exploits natural dynamics of a recurrent neural network



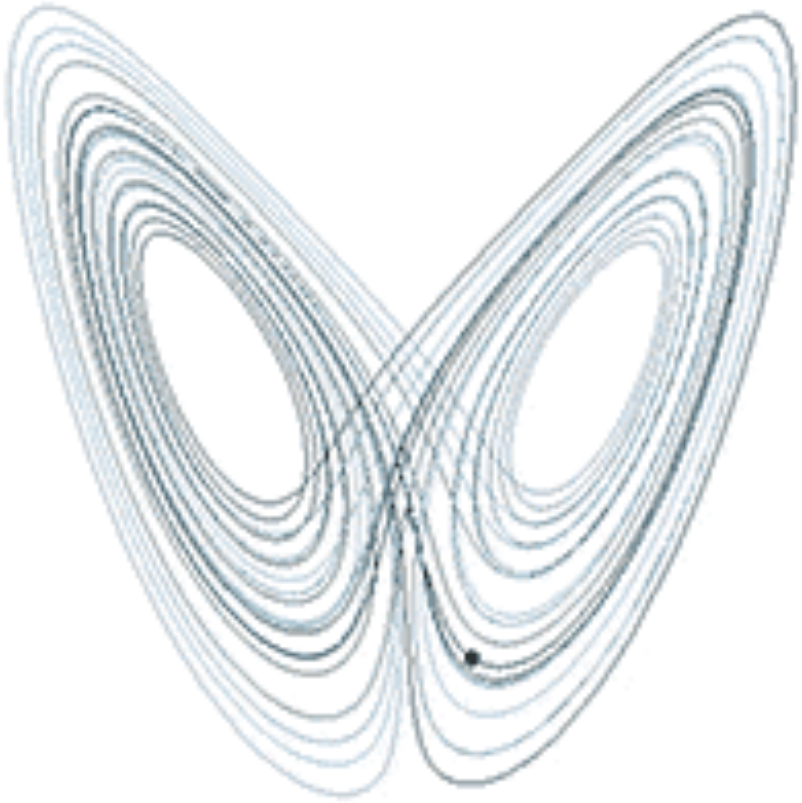



1.0
0.5
0.0
−0.5
0
100
200
300
400
Inputs
Outputs

Time series prediction



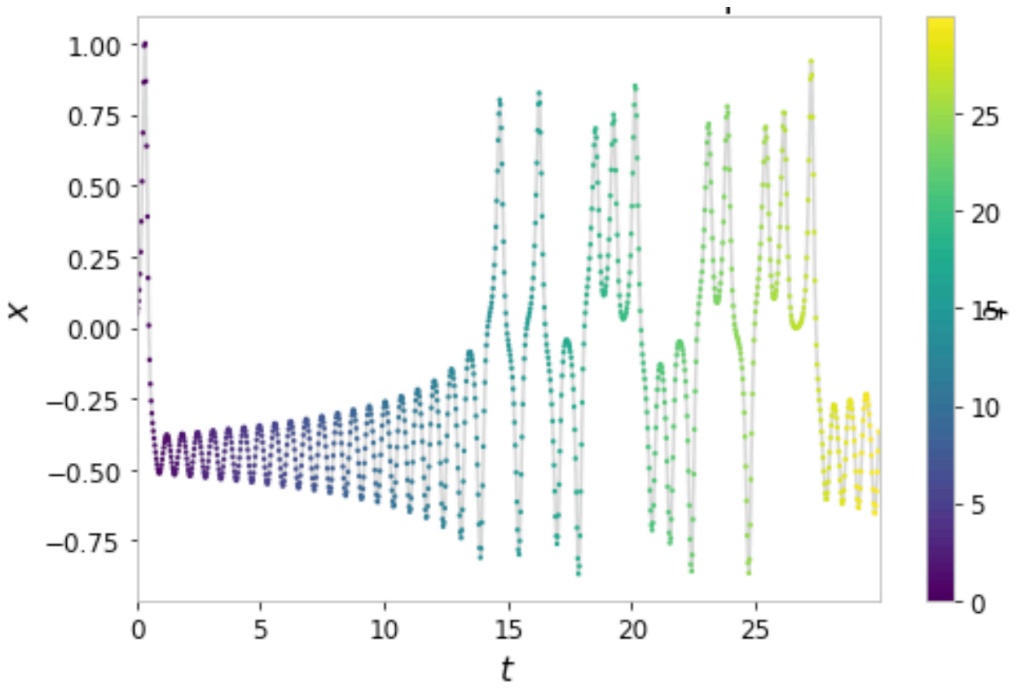
Lorenz chaotic strange attractor

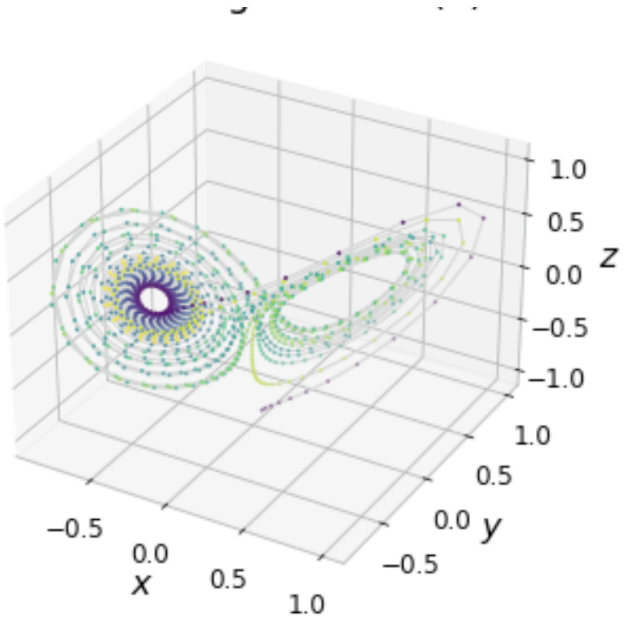


Lorenz chaotic strange attractor

- We try to predict one of the values of the Lorenz dynamical system defined by 3 variables (x, y, z) that change over time

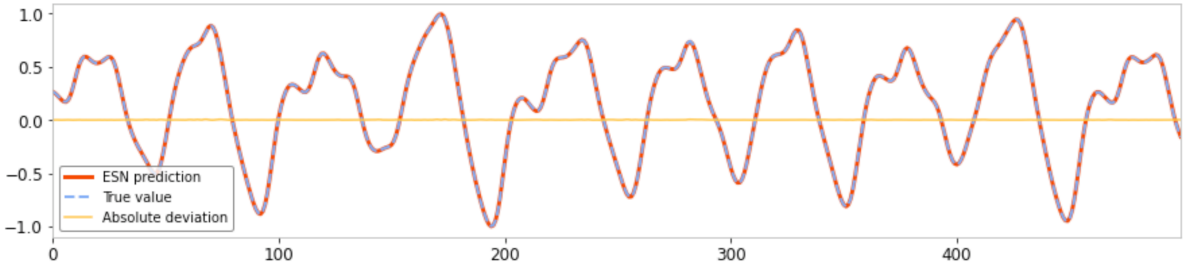
Here we want to predict x across time



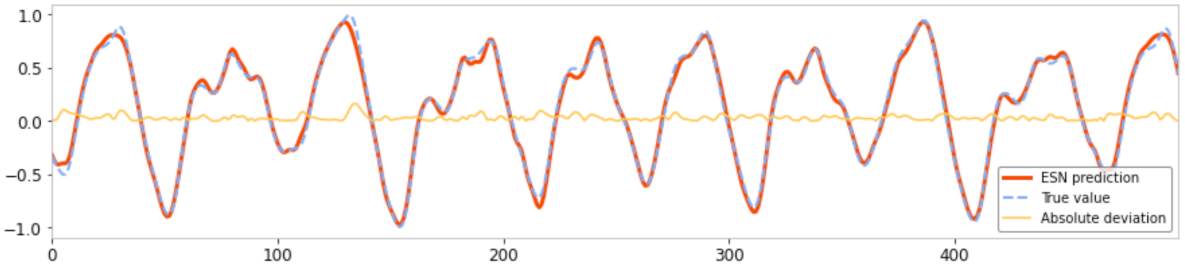


Time series prediction

– Predictions obtained for 10 steps ahead (T+10)



- Predictions obtained for 10 steps ahead (T+50)



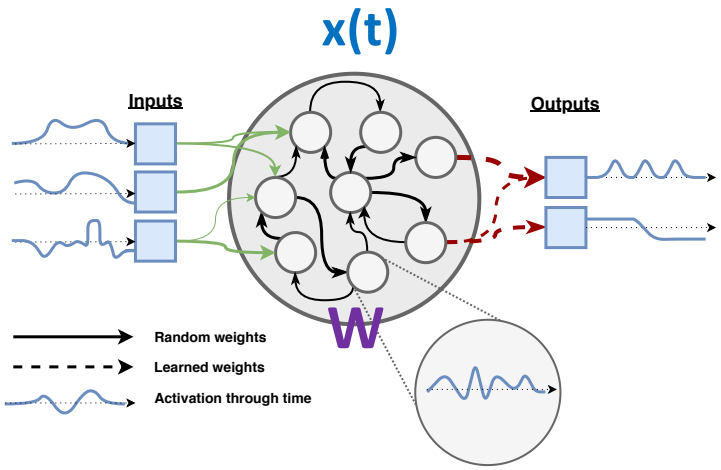
Why does it work?

Why does it work?

Why does it work?

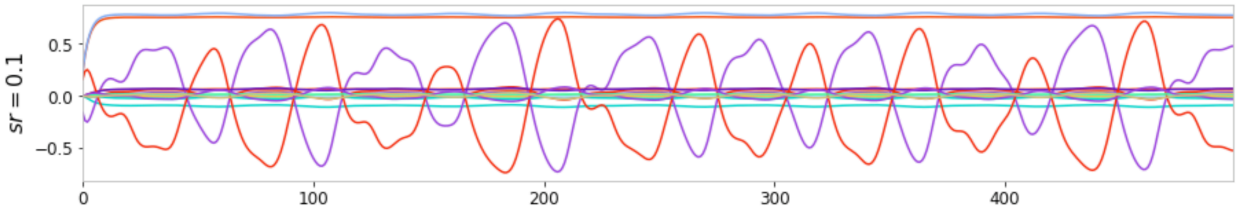
Spectral Radius (SR)

= scaling of recurrent connections

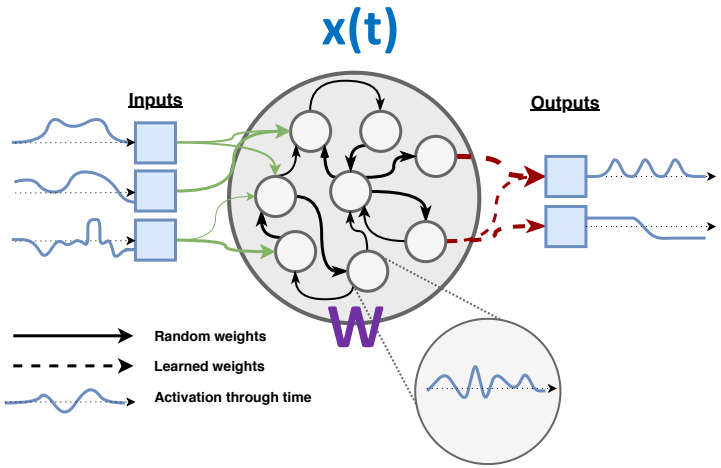


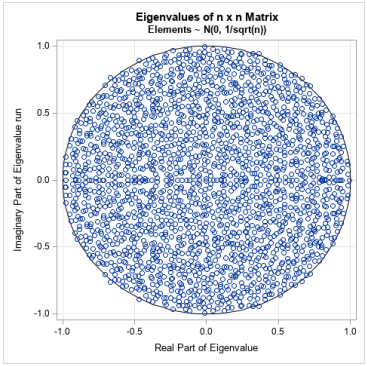
Spectral Radius (SR)

= scaling of recurrent connections



x(t)



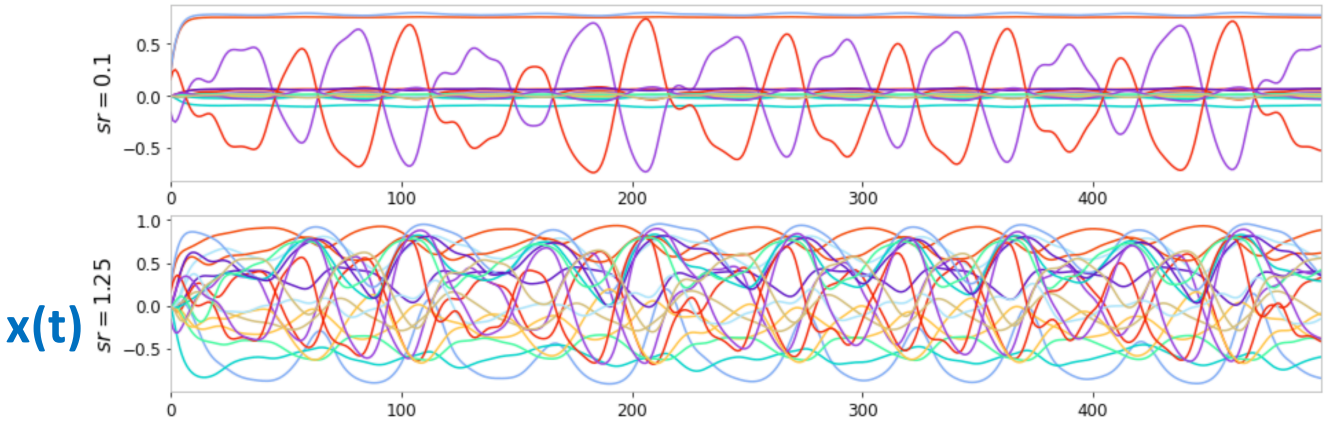


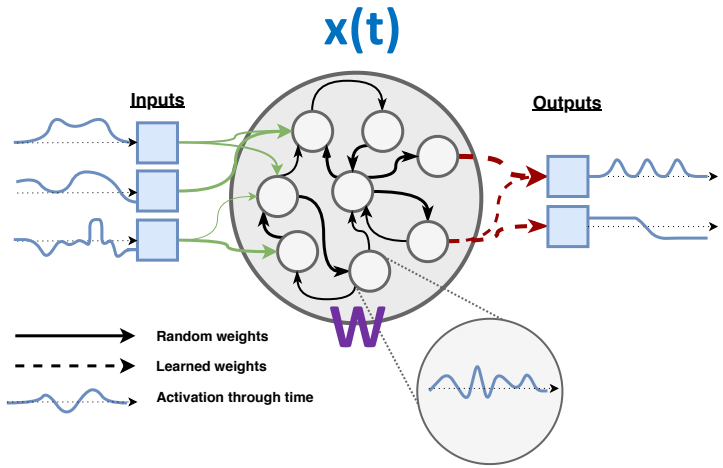
Rayon spectral de la matrice W

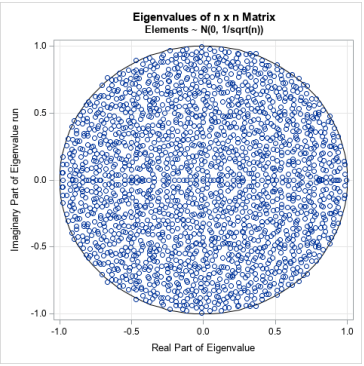
https://blogs.sas.com/content/iml/2020/04/27/circular-law-eigenvalues.html

Spectral Radius (SR)

= scaling of recurrent connections







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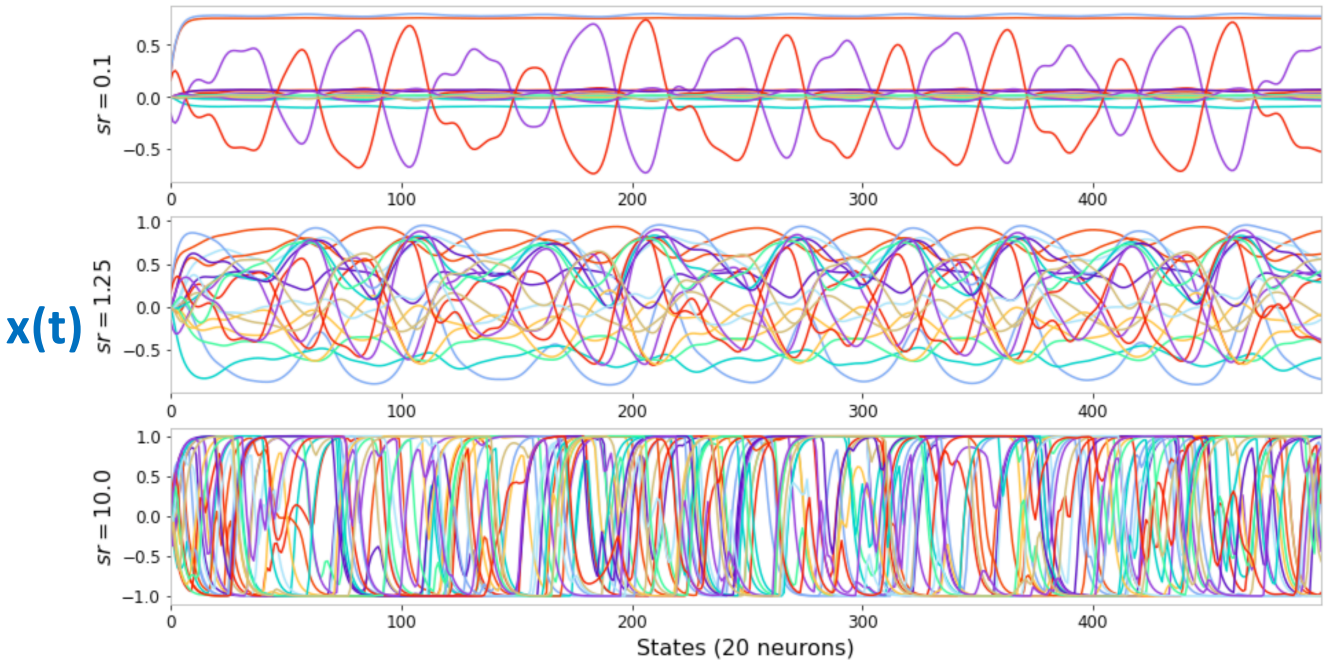

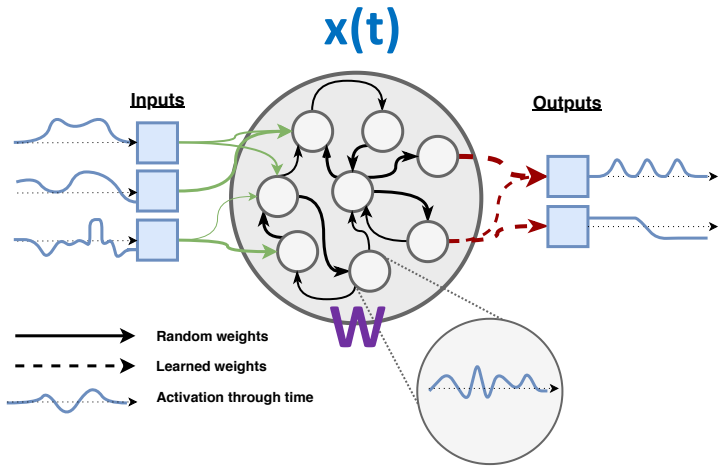

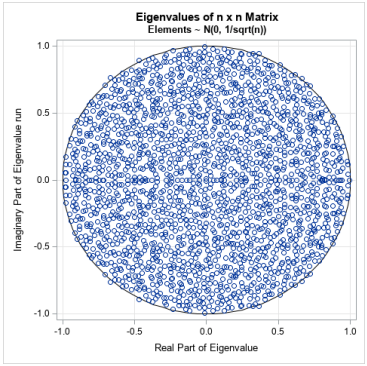

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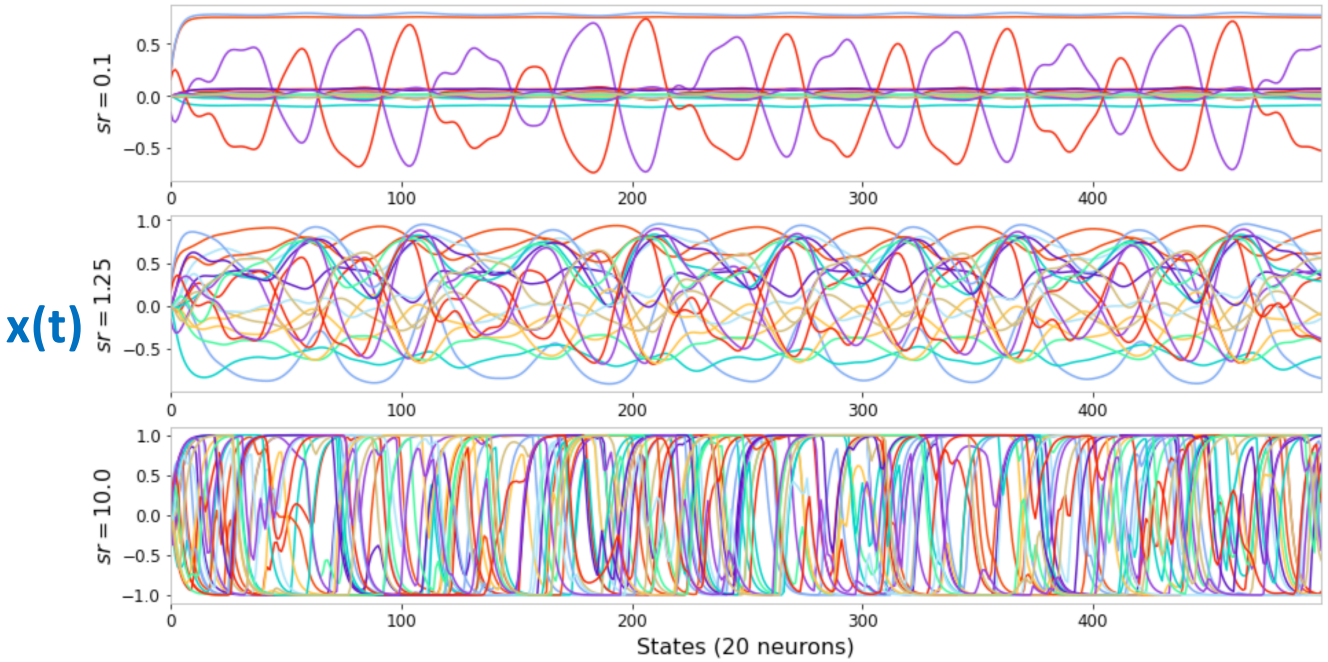
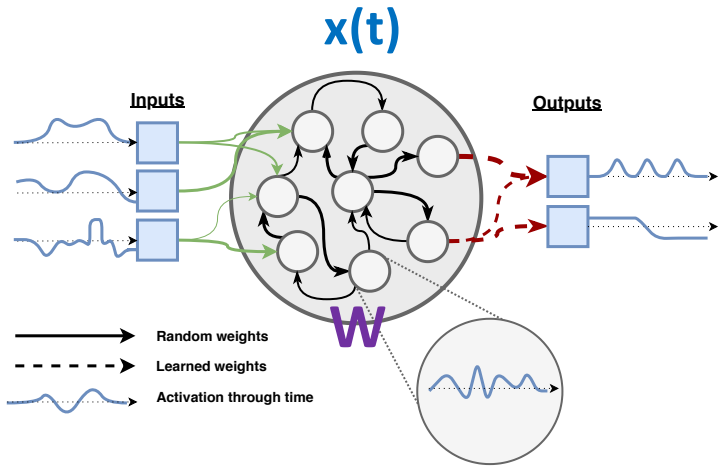
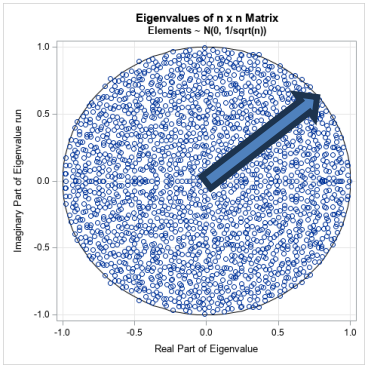




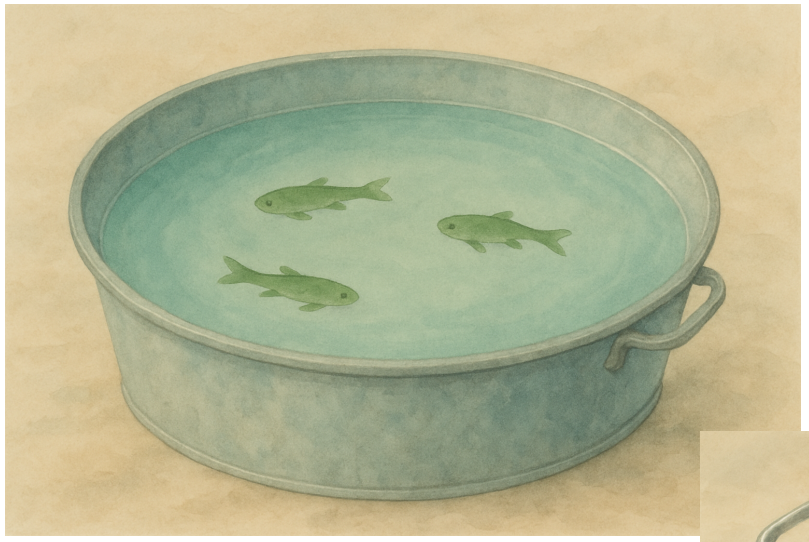


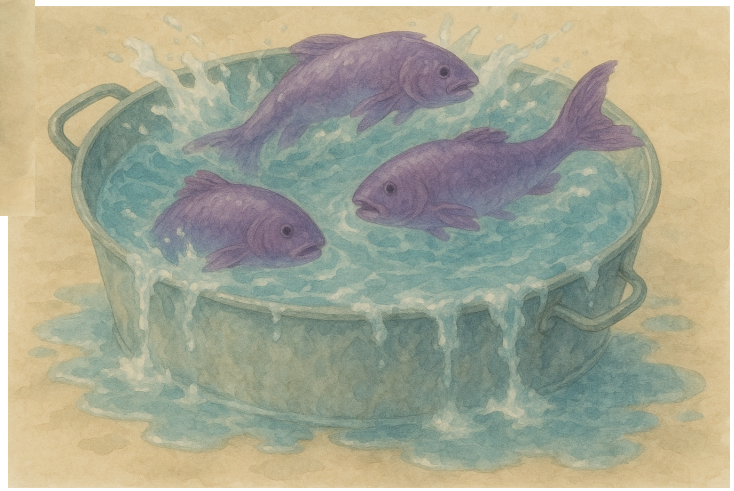
Rayon spectral de la matrice W

— spectral radius → **stable** dynamics

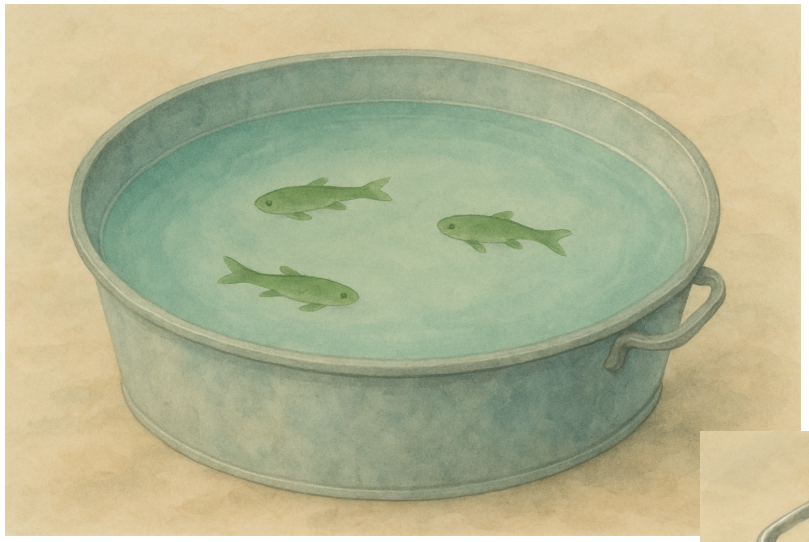
+ spectral radius → **chaotic** dynamics

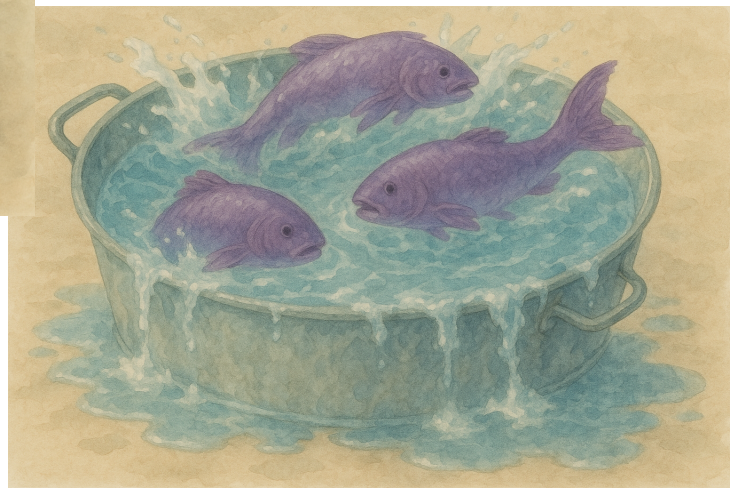
https://blogs.sas.com/content/iml/2020/04/27/circular-law-eigenvalues.html





and in practice?
(are there other
“Hypster-parameters”?)



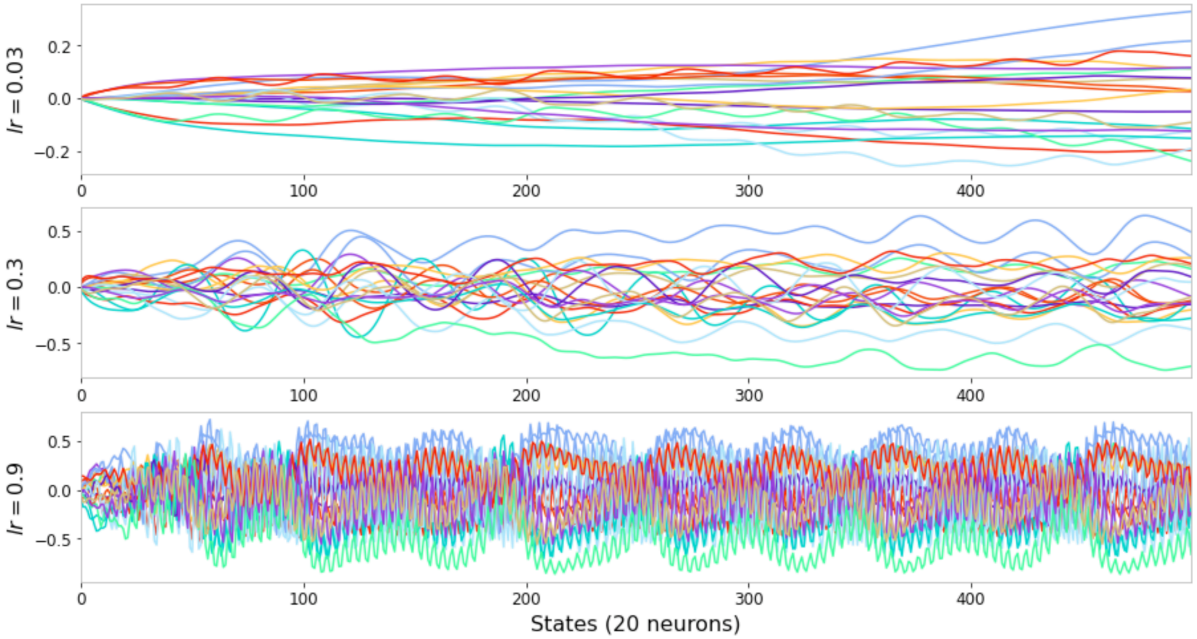


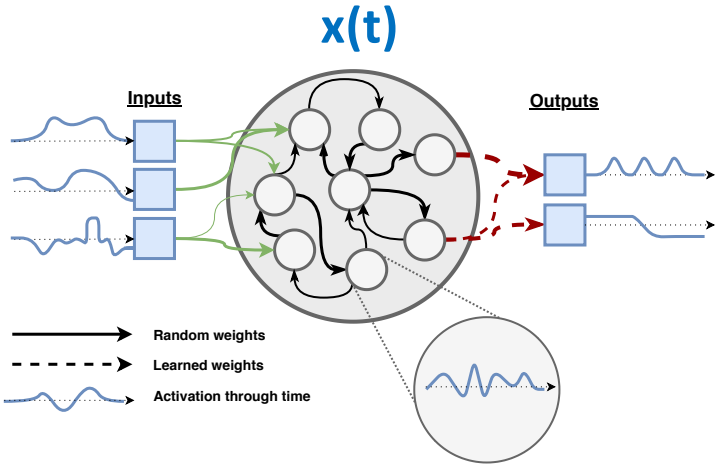
For instance, are there other hyperparameters that could “tame chaos”?

Leak(ing)-rate (LR)

= inverse of a time constant

x(t)





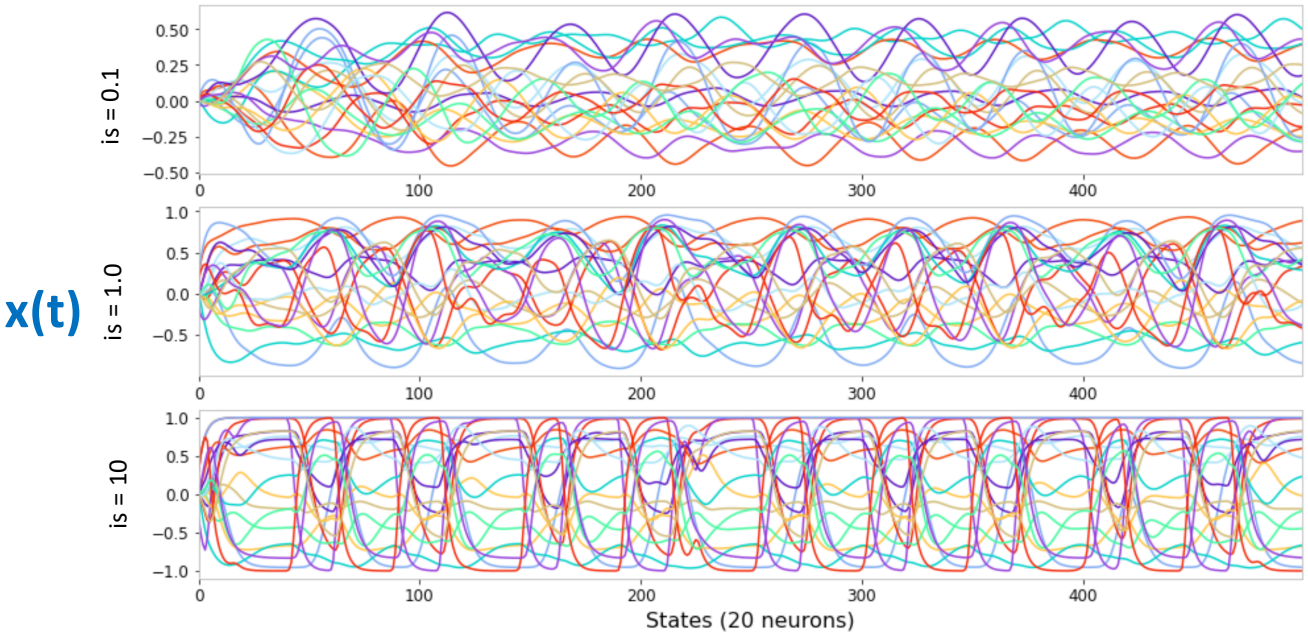
The leaking rate (α) controls the "memory feedback" of the ESN. The ESN states are indeed computed as:

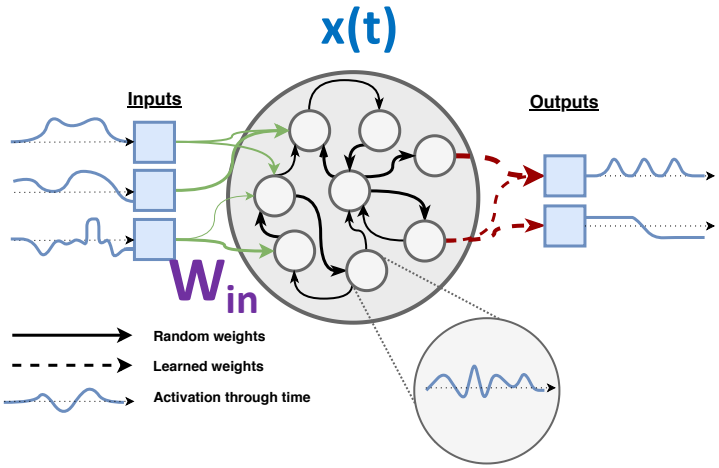
$$s(t+1) = \underbrace{(1-\alpha)s(t)}_{\text{previous states}} + \underbrace{\alpha f(u(t+1), s(t))}_{\text{new states}}$$

- $+$ leaking rate $\rightarrow$ **low inertia**, little memory of previous states
- $-$ leaking rate $\rightarrow$ **high inertia**, big memory of previous states

Input Scaling (IS)

= scaling of input connections





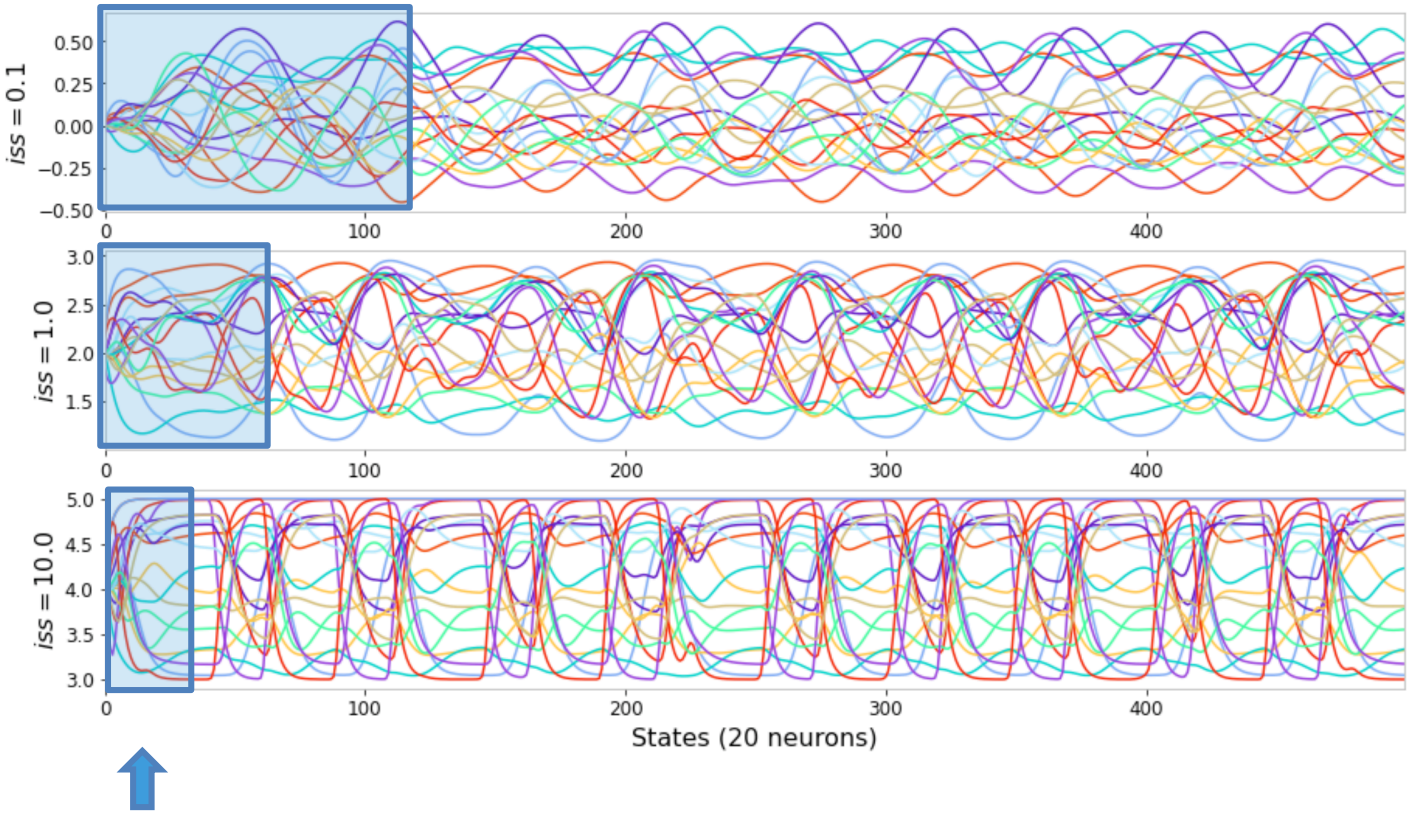
The input scaling controls how the ESN interact with the inputs. It is a coefficient appliyed to the input matrix W_{in}.

- $+$ input scaling $\rightarrow$ **input-driven** activities
- $-$ input scaling $\rightarrow$ **free** activities

The input scaling can also be used to rescale the inputs and ajust their influences.

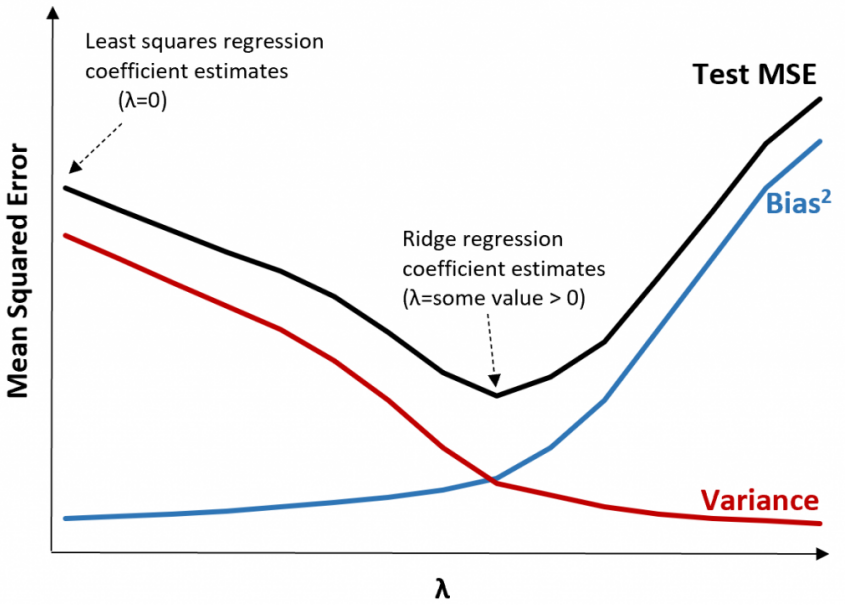
Warm(ing)-up

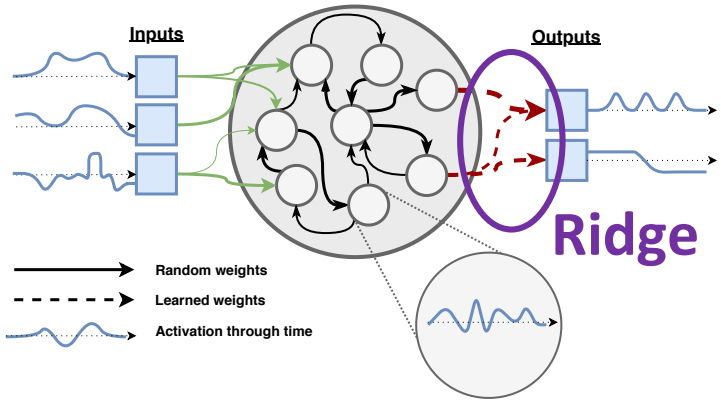
= transitory period during the « heating » of the system



Ridge

= regularisation of the read-out linear regression

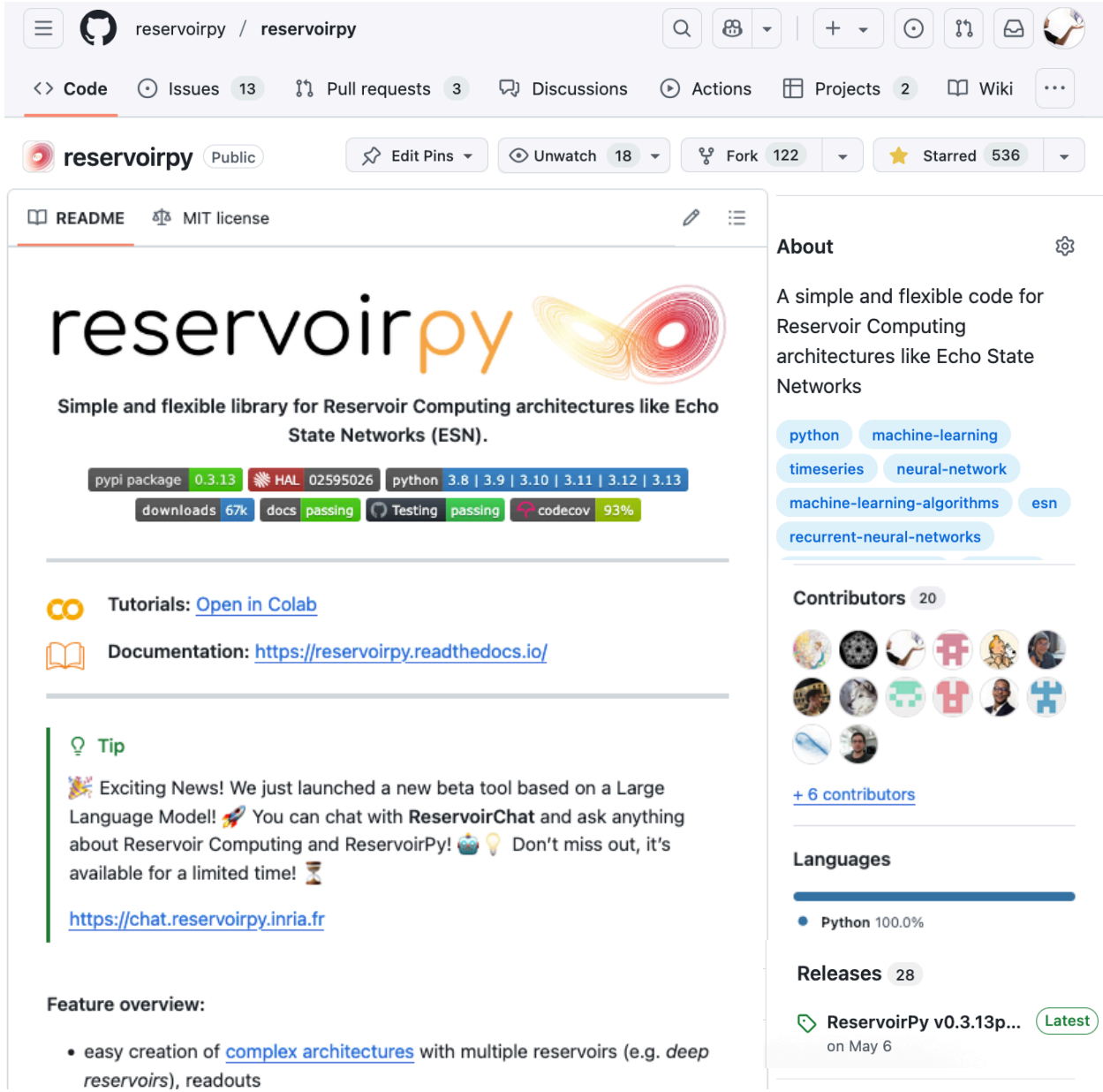




ReservoirPy

ReservoirPy
Pure Python scientific libraries

Few dependencies: mainly **Numpy** (+ optional **JAX backend** very soon!)



github.com/reservoirpy/reservoirpy

Library	Main dependency	Last release	Doc.	Tests	On.	Fb.	Model type
★ **reservoirpy (this package)**	`numpy, jax` (optional)	May 2025	✓	✓	✓	✓	ESN, DeepESN, NVAR Intrinsic Plasticity, LSM, Local Plasticity
EchoTorch	`PyTorch`	Jan. 2021	✓	✓	✓	✓	ESN, DeepESN Conceptor
★ reservoir-computing [1]	`numpy`	Jan. 2025	✓	×	×	×	ESN, state reduction
★ ReservoirComputing.jl	`Julia`	Mar. 2025	✓	✓	×	×	ESN, DeepESN, HybridESN
easyesn	`numpy / CuPy / PyTorch`	Jan. 2021	×	×	×	✓	ESN, Spatio-Temporal ESN
DeepESN	`numpy`	Apr. 2025	×	×	×	×	DeepESN
PyRCN	`scikit-learn`	Jul. 2024	✓	✓	✓	×	ESN, EulerSN
echoes	`scikit-learn`	Jun. 2025	✓	✓	×	×	ESN
RcTorch	`PyTorch`	Jul. 2022	✓	×	✓	×	ESN

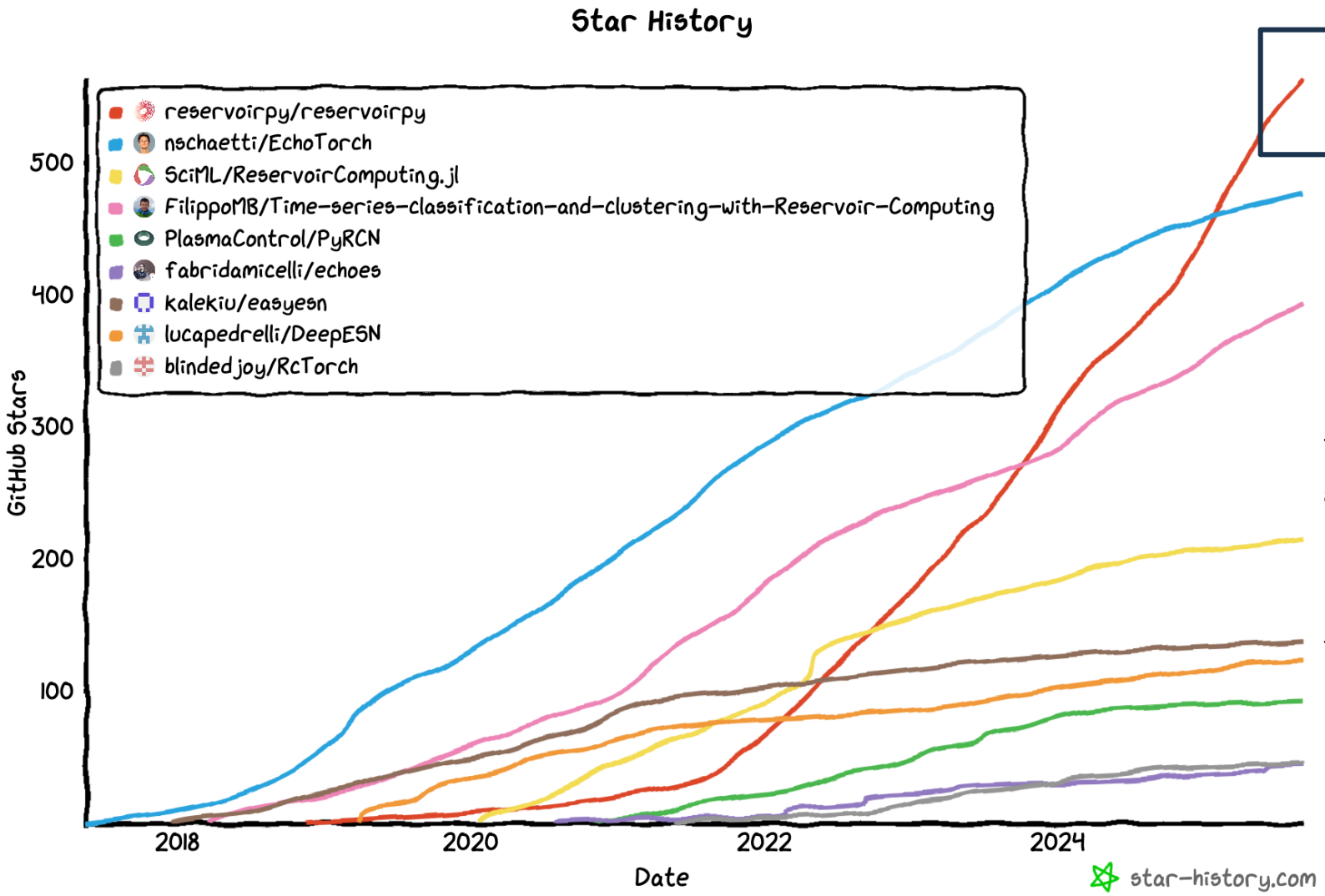
Table 1: Comparative table of some open source software for Reservoir Computing. This table might not be exhaustive. **Doc.** Complete documentation. **On.** Online learning strategies included. **Fb.** Feedback and delayed connections. **Deep** The software allows the design of complex models where basic RC elements such as reservoirs and readouts can be stacked to form so-called "deep" networks.

★ Projects with recent major updates

1: https://github.com/FilippoMB/Time-series-classification-and-clustering-with-Reservoir-Computing

Trouvain, Bernard* & Hinaut* (preprint)

78



→ ReservoirPy offers a solution that supports steady and lasting growth.

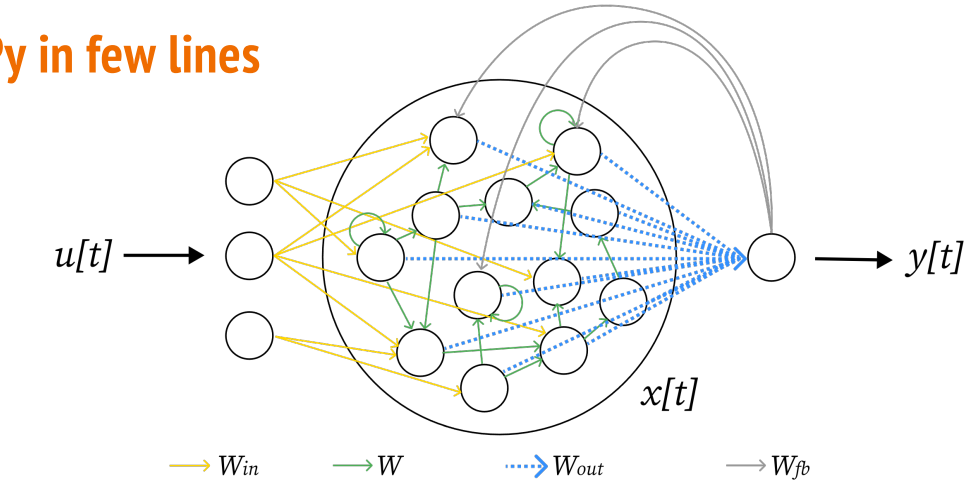
→ 2 times for citations in 2024 than in 2023 (G. Scholar)

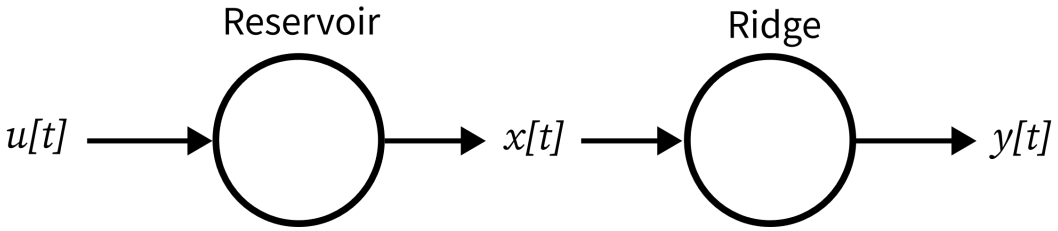
[Image source "star history"]

ReservoirPy in few lines

Node creation

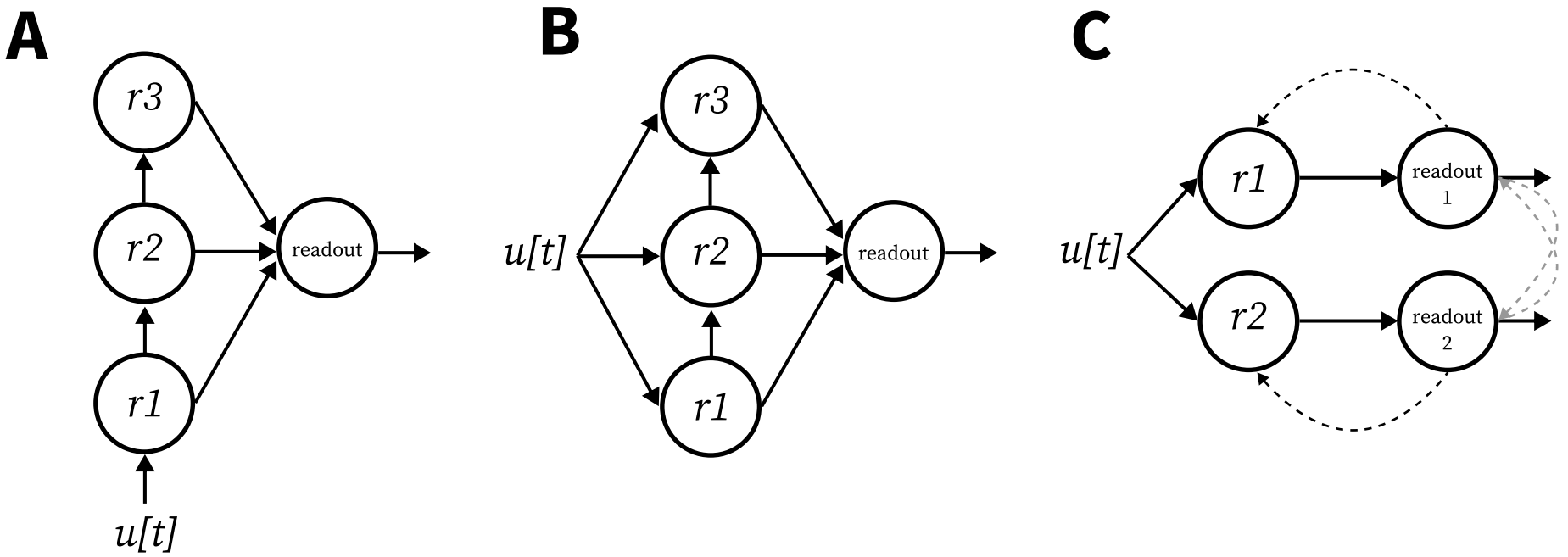
A *node* is an independent operator, that applies a function on some data, potentially in a recurrent way.

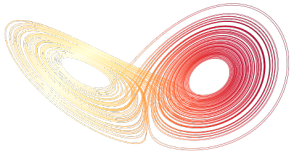





```
from reservoirpy.nodes import Reservoir, Ridge

reservoir = Reservoir(100, lr=0.3, sr=1.25, input_scaling=0.1)
readout = Ridge(ridge=1e-5)
```

Enable complex architectures



reservoirpy  v0.4.0

Reservoir dedicated framework

- **Online/Offline** learning
- **Feedback loops**
- **Hierarchical** models
  - *e.g. Deep Reservoir Computing*
- **Parallel** computing
- R language, (interface)
- Datasets, metrics, …
  - e.g. Memory Capacity
- Hyperoptimization tools
- ***ReservoirR***: interface in R language
- Tutorials, examples, documentation, …

➡️ Share your models in ReservoirPy

Reservoir models

- Echo State Networks (ESN)
- Autoregressive reservoir (NVAR)
- Ridge regression
- FORCE learning
- Intrinsic Plasticity
- Usual reservoir topologies (ring, orthogonal, …)
- Scikit-learn models, (interface)
- Simulated physical models (optical RC)

New • ES^{2}N
New • Local Plasticity (github contribution @Finebouche)
New • Arbitrary delays (between nodes)
New • LIF spiking neurons
New • Cluster & Small-world topologies
New • **v0.4: main refactoring and speed-up**
Soon! • (end Sept 2025) JAX backend

Hands-on ReservoirPy

Follow with the Introduction Notebook

github.com/reservoirpy/presentations/…

main presentations / ICANN-2025 /

PAUL-BERNARD Renamed files + improve README e226ec0 · 29 minutes ago

Name	Last commit message	Last commit date
..		
01_Introduction.ipynb	Renamed files + improve README	29 minutes ago
02_Hackathon.ipynb	Renamed files + improve README	29 minutes ago
README.md	Renamed files + improve README	29 minutes ago

README.md

ICANN 2025 - Tutorial on ReservoirPy

This is a Tutorial presented at the 3rd Reservoir Computing workshop held at ICANN 2025.

The aim is to:

- make participant familiar with the key concepts of Reservoir Computing;
- make participant familiar with ReservoirPy library the most popular reservoir library in Python;
- give you quick insights on ReservoirPy key features;
- show you how to optimize dynamically your hyperparameter search
- propose a quick hackathon and see which participant manages to reach the best performances while testing other reservoir nodes:
  - ES2N node
  - Intrinsic Plasticity
  - Next Generation Reservoir Computing

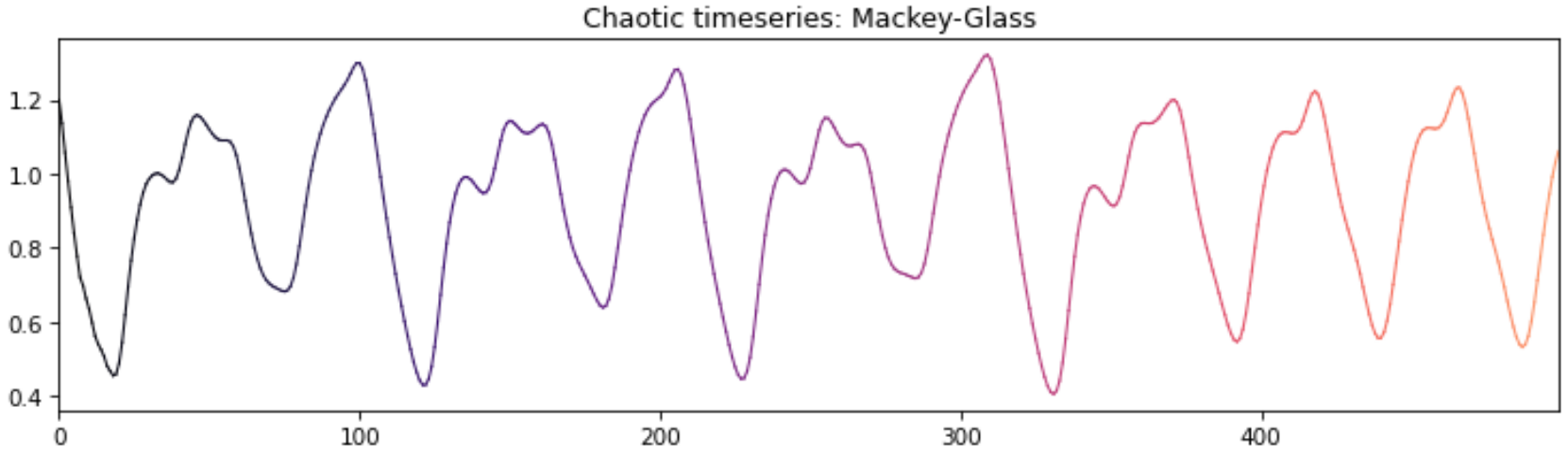
Data format

Everything is a numpy array.
shape = (timesteps, features)

```
from reservoirpy.datasets import mackey_glass

timeseries = mackey_glass(n_timesteps=2_000)
timeseries.shape
```

✓ 0.0s Python

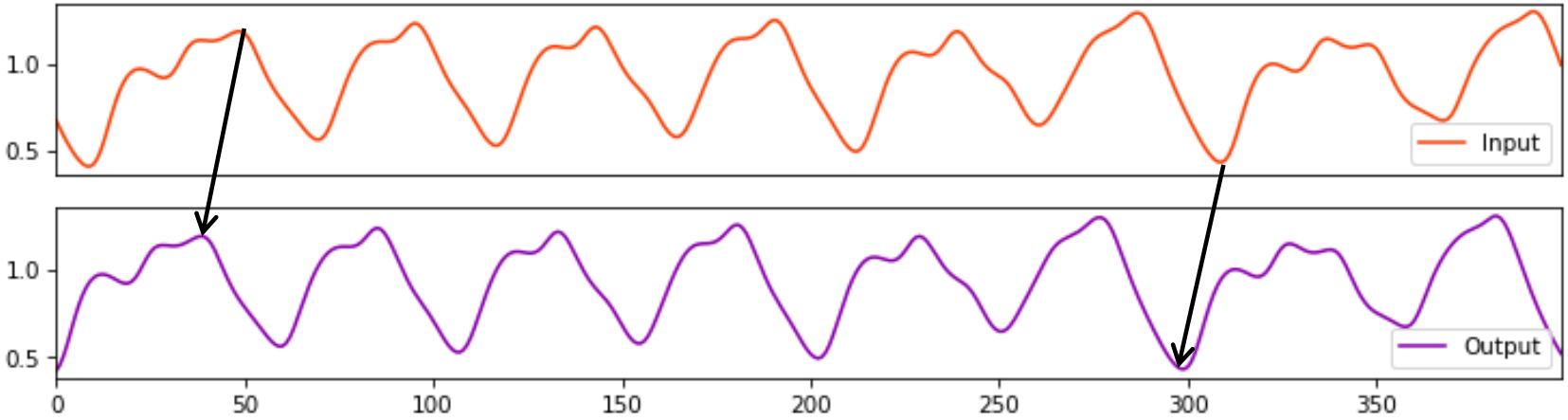
```
(2000, 1)
```



Data pre-processing

```
from reservoirpy.datasets import to_forecasting

dataset = to_forecasting(X, forecast=10, test_size=0.2)
x_train, x_test, y_train, y_test = dataset
```

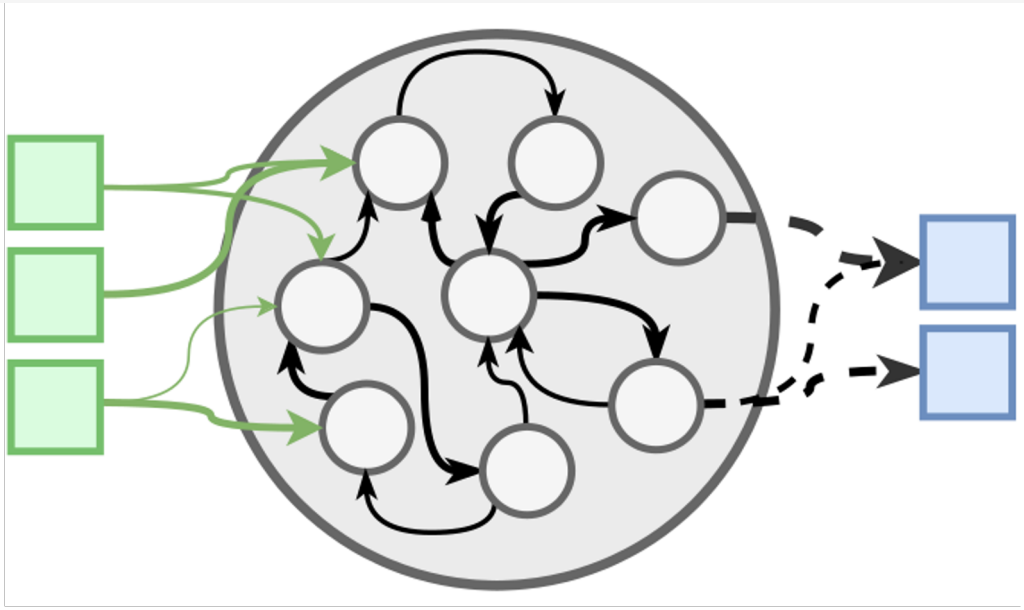
✓ 0.0s Python



Echo State Network creation

```
model = ESN(
    units=100, # neurons inside the reservoir
    lr=0.3, # leak rate
    sr=1.25, # spectral radius of the weight matrix
    ridge=1e-8) # Regularization parameter
```

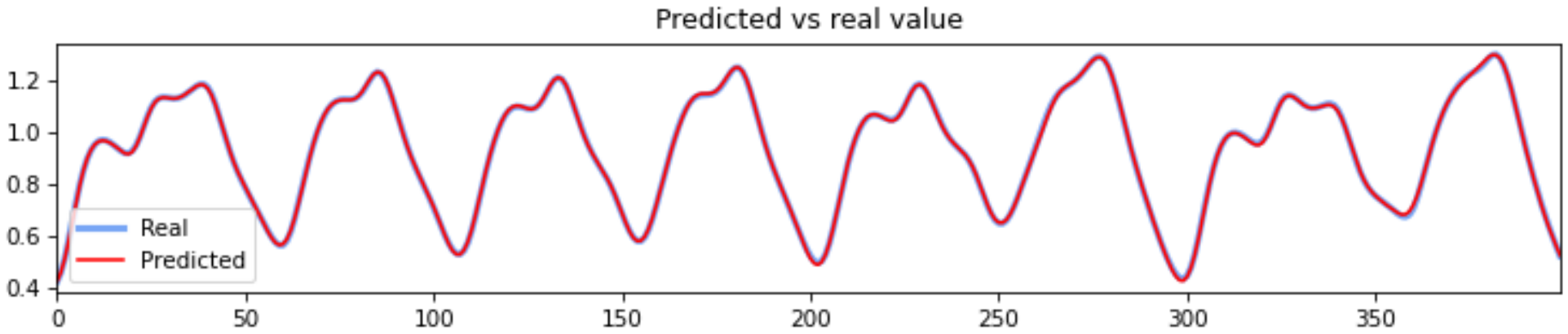
✓ 0.0s Python



Fit and run the model

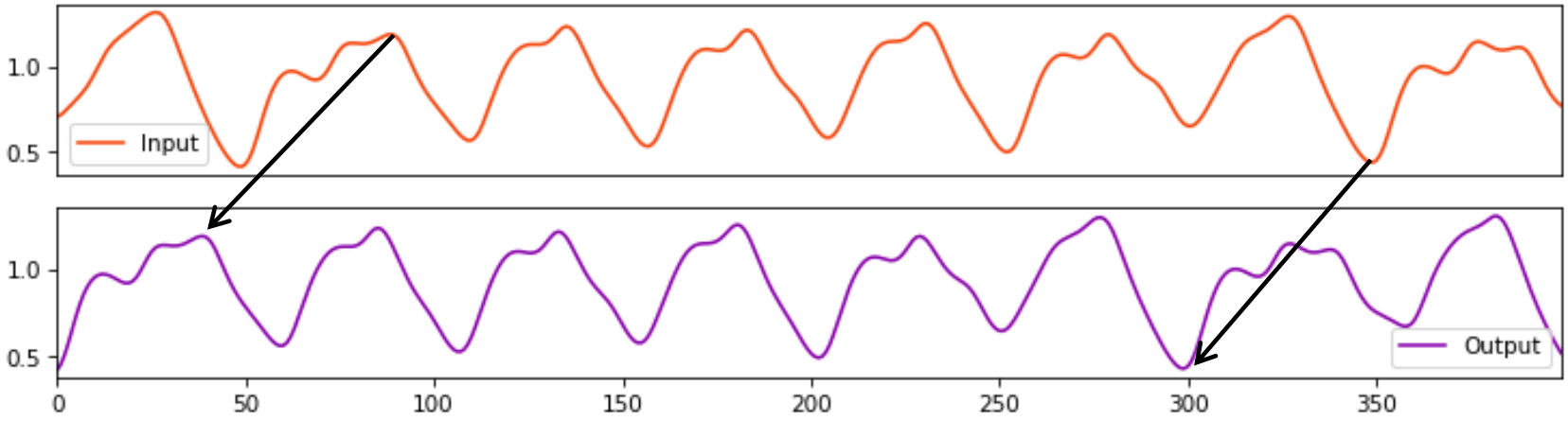
```
model.fit(x_train, y_train) # Learning phase
y_pred = model.run(x_test) # Prediction
```

✓ 0.5s Python



… what about a t+50 prediction?

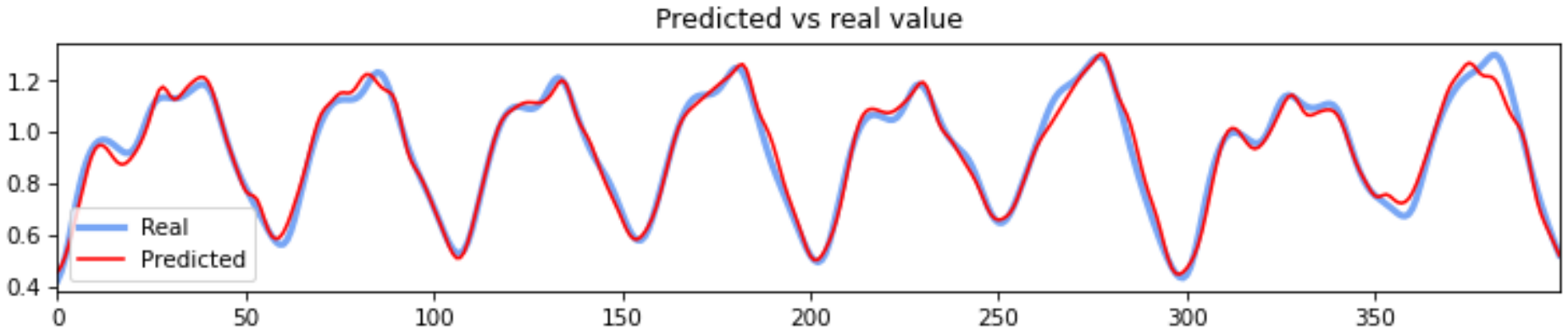
```
dataset = to_forecasting(X, forecast=50, test_size=0.2)
x_train, x_test, y_train, y_test = dataset
```



… what about a t+50 prediction?
The result

```
# Fitting the model
model.fit(x_train, y_train)
# Testing the model
y_pred = model.run(x_test)
```

✓ 0.4s Python



Summary

```python
model = ESN(
    units=100, # neurons inside the reservoir
    lr=0.3, # leak rate
    sr=1.25, # spectral radius of the weight matrix
    ridge=1e-8, # Regularization parameter
)

# Fitting the model
model.fit(x_train, y_train)
# Testing the model
y_pred = model.run(x_test)
```

✓ 0.3s Python

What is happening inside the reservoir?

```
activity = model.reservoir.run(x_test)
```

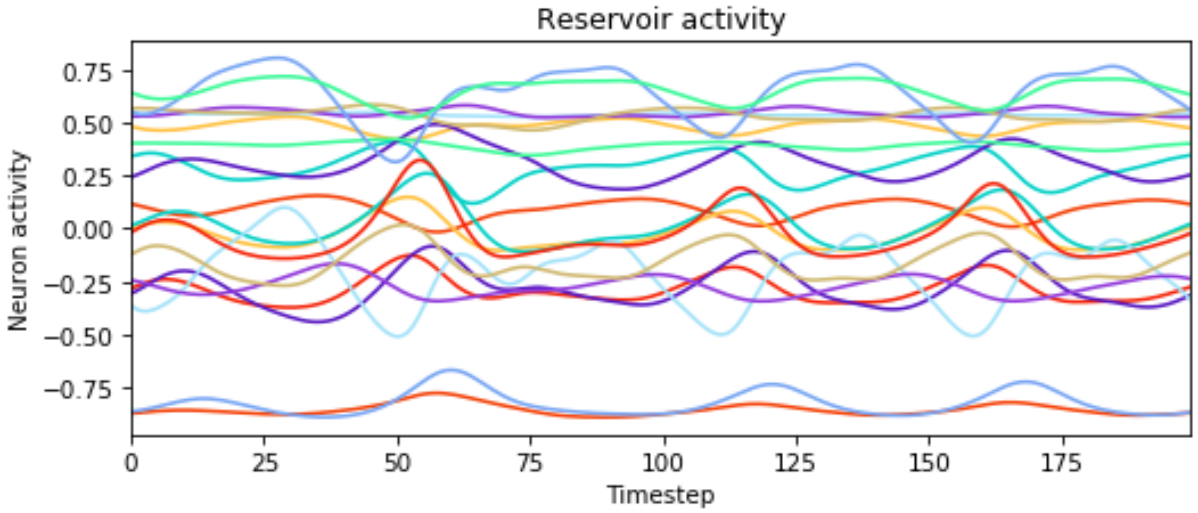
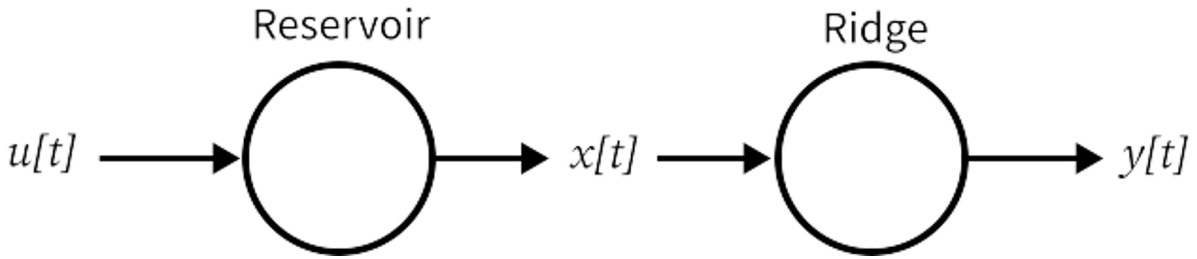


Image credits : Wikimedia

The nodes

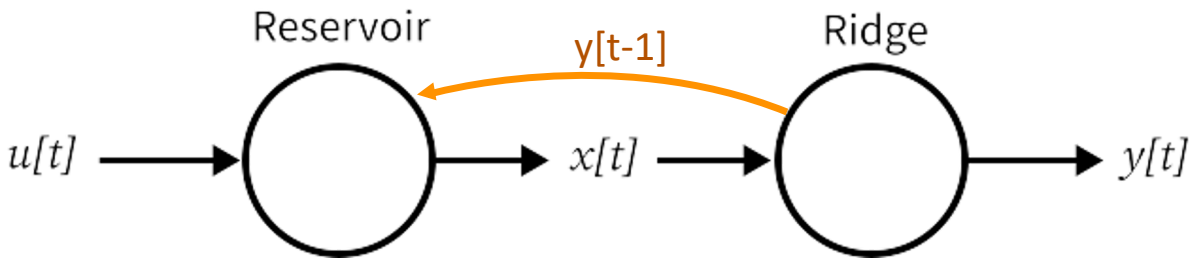
```
from reservoirpy.nodes import Reservoir, Ridge

reservoir = Reservoir(units=10)
readout = Ridge(ridge=1e-4)

model = reservoir >> readout
```

✓ 0.0s Python



Feedback connections

```
reservoir = Reservoir(units=10)
readout = Ridge(ridge=1e-4)

# create feedback
model = (reservoir >> readout) & (reservoir << readout)
```

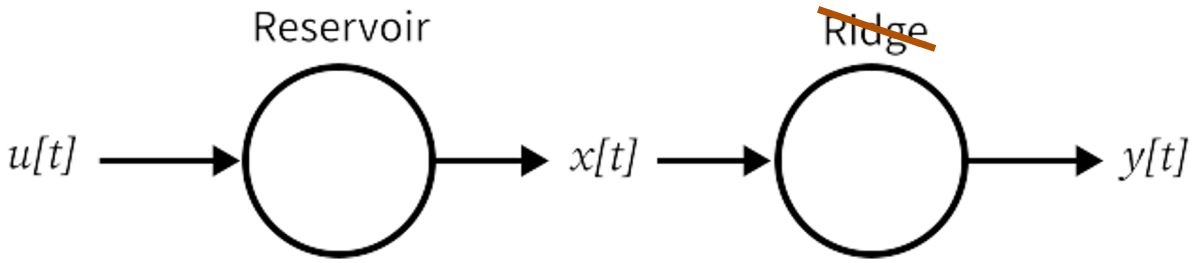


The scikit-learn node

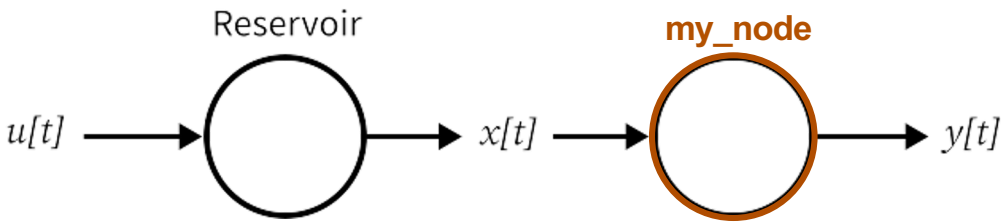
```python
from reservoirpy.nodes import ScikitLearnNode
from sklearn.linear_model import (
    RidgeClassifier,
    LogisticRegression,
)
reservoir = Reservoir(units=10)

classifier = ScikitLearnNode(RidgeClassifier)
logistic_regressor = ScikitLearnNode(LogisticRegression)

model1 = reservoir >> classifier
model2 = reservoir >> logistic_regressor
```

✓ 0.0s Python

Any scikit-learn model

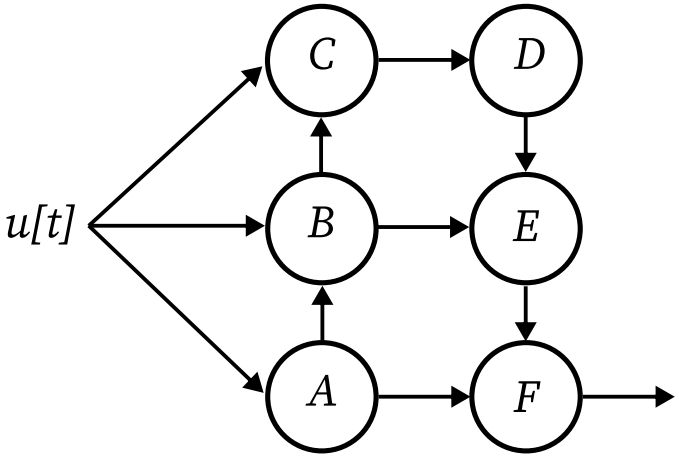


Create custom node




```python
from reservoirpy import Node


class MyNode(Node):
    def __init__(self, param1, param2):
        ...

    def initialize(self, x):
        ...

    def _step(self, state, x):
        ...
```

Enable complex architectures




```python
from reservoirpy.nodes import Input, Output

A, B, C, D, E, F = (Node() for _ in range(6))

path1, path2 = A >> F, B >> E
# One-to-many connection using a list
path3 = Input() >> [A, B, C]
# Chain of connections
path4 = A >> B >> C >> D >> E >> F >> Output()
# Merge all pathways to create the full computational graph
model = path1 & path2 & path3 & path4
```

Tools for Hyperparameter (HP) optimization

Let’s make hyperparameter search easy and reproducible!

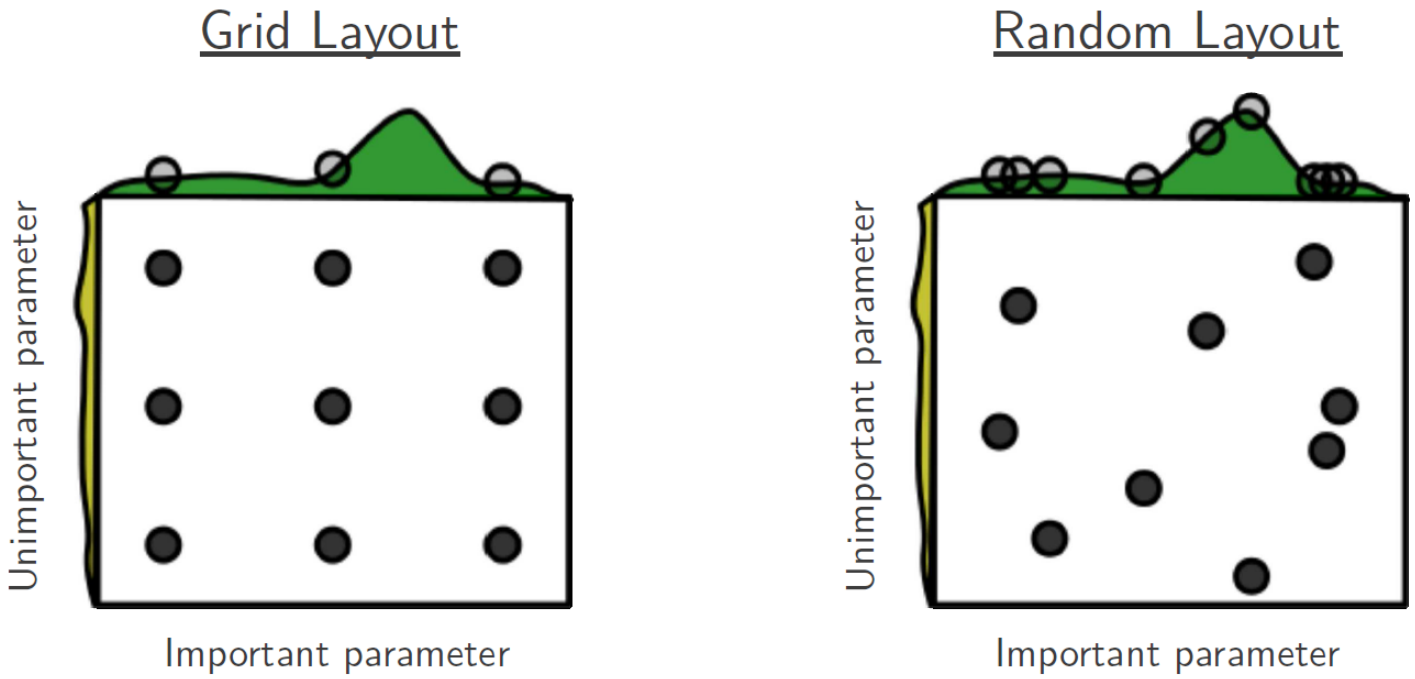
Don’t try at home without proper tools!

(🙏 don’t use grid search!)

Practical advices for parameter optimization

➡️ Grid search often fails in high dimension spaces

- « Grid search allocate **too many trials** to the exploration of **dimensions that do not matter …**
- … and suffer from **poor coverage in dimensions that are important**. » (Bergstra, 2012)



Which Hyperparameters (HP) should you tune?

- Important hyperparameters
  - Number of neurons (N)
  - **Spectral Radius (sr)**
  - **Leak-Rate (lr**)
  - **Input Scaling (input_scaling)**
  - **Ridge** (ridge)
  - Warm-up (= « transitory phase »)
  - (Feedback scaling)

Most important ones

Which Hyperparameters (HP) should you tune?

- Important hyperparameters
  - Number of neurons (N)
  - **Spectral Radius (sr)**
  - **Leak-Rate (lr)**
  - **Input Scaling (input_scaling)**
  - **Ridge** (ridge)
  - Warm-up (= « transitory phase »)
  - (Feedback scaling)

Most important ones

```
# Build your model given the input parameters
reservoir = Reservoir(
    units=N,
    sr=sr,
    lr=lr,
    input_scaling=input_scaling,
    seed=variable_seed
)

readout = Ridge(ridge=ridge)

model = reservoir >> readout
```

Which Hyperparameters (HP) should you tune?

- Important hyperparameters
  - Number of neurons (N)
  - **Spectral Radius (sr)**
  - **Leak-Rate (lr)**
  - **Input Scaling (input_scaling)**
  - **Ridge** (ridge)
  - Warm-up (= « transitory phase »)
  - (Feedback scaling)

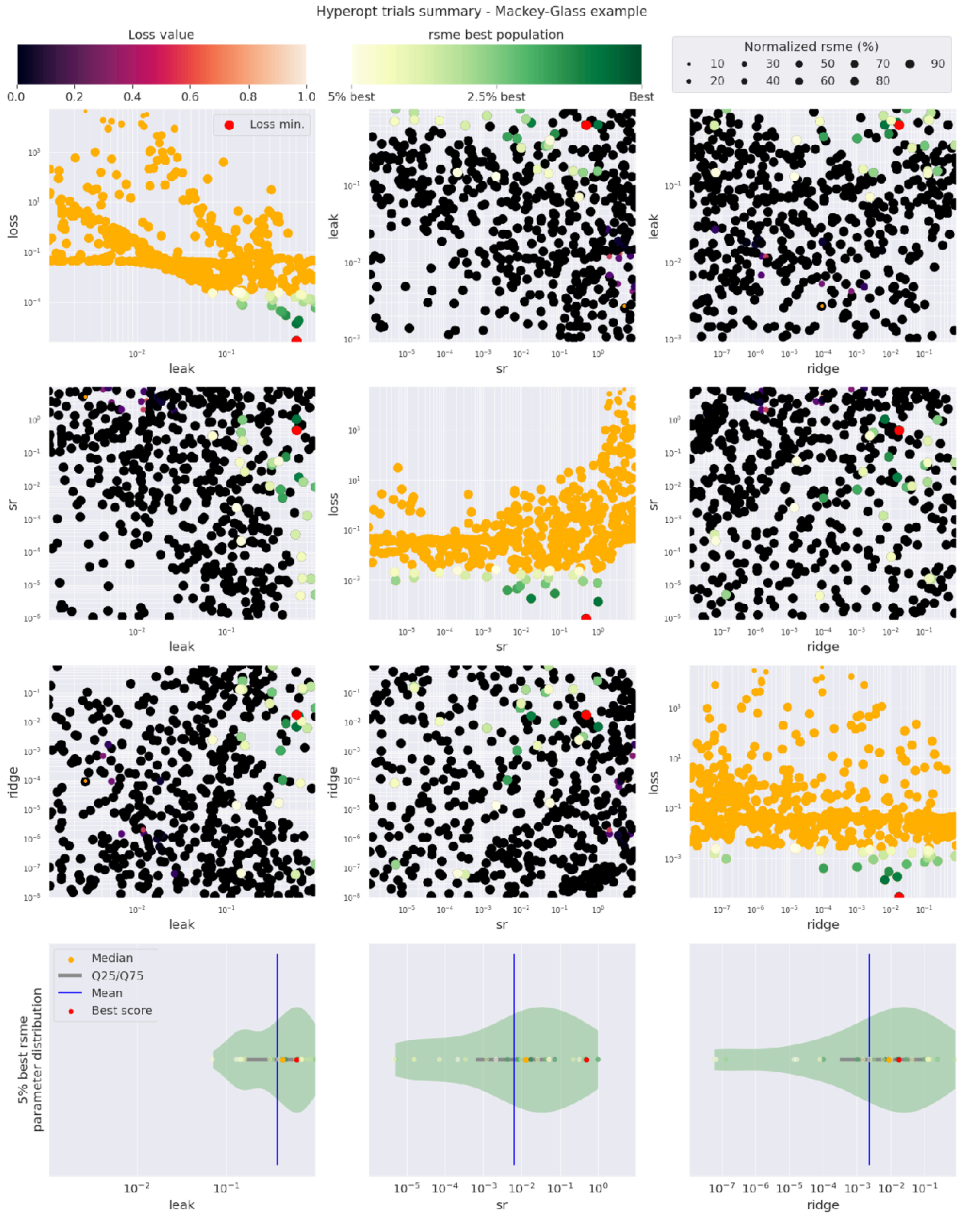
Most important ones

```python
# Build your model given the input parameters
reservoir = Reservoir(
    units=N,
    sr=sr,
    lr=lr,
    input_scaling=input_scaling,
    seed=variable_seed
)

readout = Ridge(ridge=ridge)

model = reservoir >> readout
```

Define logarithmic ranges & fix some HP
(e.g. N and input_scaling)

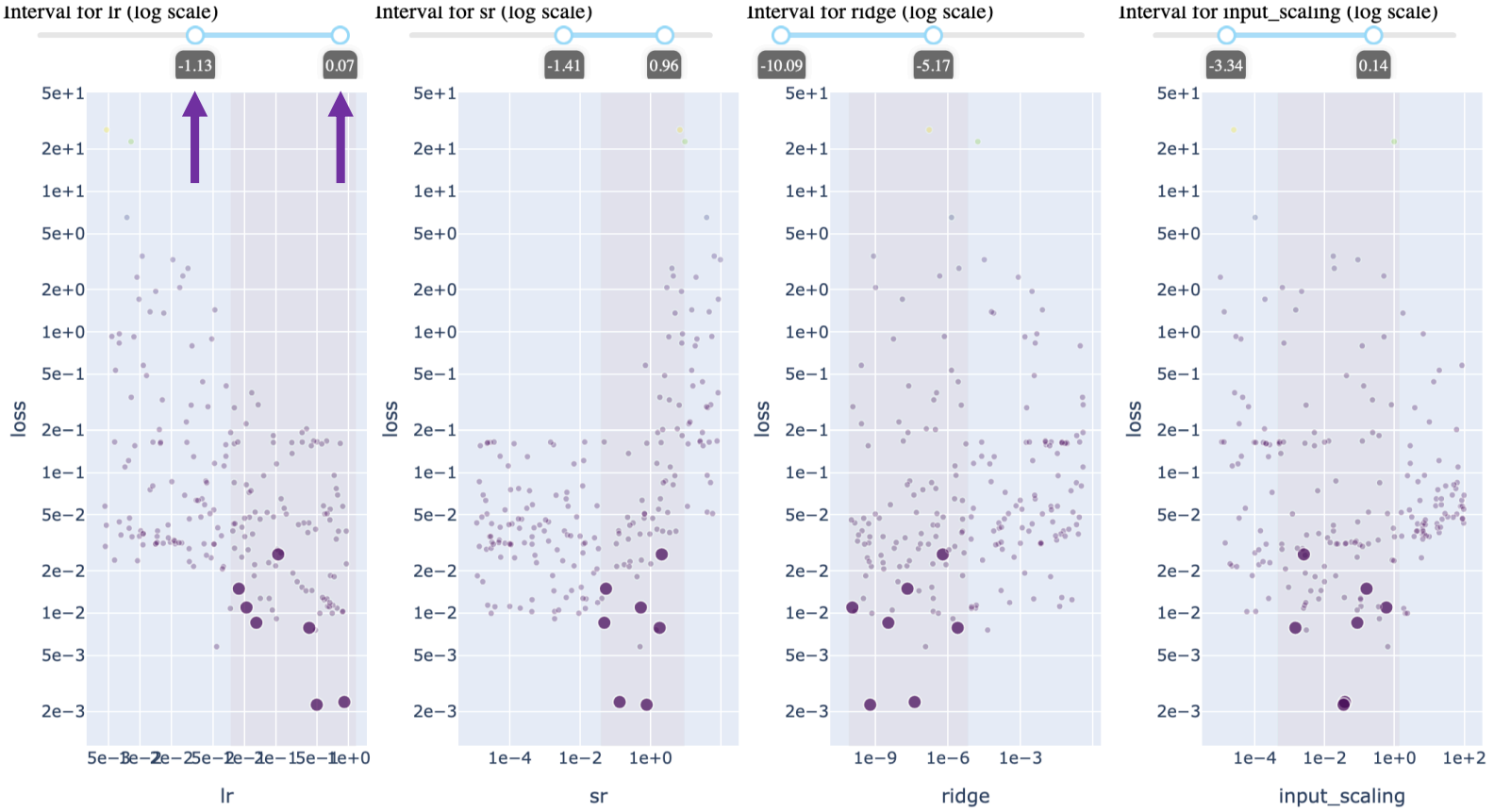
```python
hyperopt_config = {
    "exp": "hyperopt-doublescroll",    # the experimentation name
    "hp_max_evals": 200,               # the number of differents sets of parameters hyperopt has to try
    "hp_method": "random",             # the method used by hyperopt to chose those sets (see below)
    "seed": 42,                        # the random state seed, to ensure reproducibility
    "instances_per_trial": 1,          # how many random ESN will be tried with each sets of parameters
    "hp_space": {                      # what are the ranges of parameters explored
        "N": ["choice", 100],              # the number of neurons is fixed to 100
        "sr": ["loguniform", 1e-5, 1e2],   # the spectral radius is log-uniformly distributed from 1e-5 and 100
        "lr": ["loguniform", 1e-5, 1.0],    # idem with the leaking rate, from 1e-5 to 1
        "input_scaling": ["choice", 1.0],   # the input scaling is fixed
        "ridge": ["loguniform", 1e-6, 1e6],        # regularization parameter is explored widely
        "seed": ["randint", 0, 2**32]          # seeds used for random initialisation of weights matrices
    }
}
```

Graphical view of hyperparameter optimization



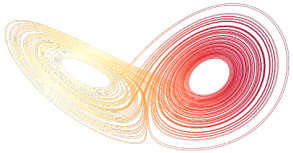
Hyperparameter Dynamic Exploration

```
interactive_report(hyperopt_config['exp'], ['lr', 'sr', 'ridge', 'input_scaling'], log_loss=True, out_path='limit.json')
```



→ quick & robust selection of hyperparameters ranges

Discussion

reservoirpy  v0.4.0

Reservoir dedicated framework

- **Online/Offline** learning
- **Feedback loops**
- **Hierarchical** models
  - *e.g. Deep Reservoir Computing*
- **Parallel** computing
- R language, (interface)
- Datasets, metrics, ...
  - e.g. Memory Capacity
- Hyperoptimization tools
- ***ReservoirR***: interface in R language
- Tutorials, examples, documentation, ...

➡️ Share your models in ReservoirPy

Reservoir models

- Echo State Networks (ESN)
- Autoregressive reservoir (NVAR)
- Ridge regression
- FORCE learning
- Intrinsic Plasticity
- Usual reservoir topologies (ring, orthogonal, ...)
- Scikit-learn models, (interface)
- Simulated physical models (optical RC)

New • ES^{2}N
New • Local Plasticity (github contribution @Finebouche)
New • Arbitrary delays (between nodes)
New • LIF spiking neurons
New • Cluster & Small-world topologies
New • **v0.4: main refactoring and speed-up**
Soon! • (end Sept 2025) JAX backend

Perspectives

Upgrade framework capabilities

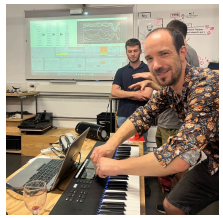
- **JAX back-end** (Sept 2025)
  - Extended distributed computation
  - GPU acceleration

- **Simulated physical Reservoir models**
  - More optical reservoir models
  - Bacterial reservoir (collab with MICALIS, INRAE, Paris-South)

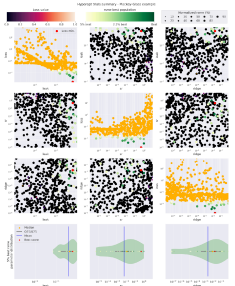
Sharing wihin RC community

- Replicate scientific results
- Implement new tools
- Increase user and expert community
- **Find new use cases**

Summary on reservoirpy



- Easy and quick to use
- Rich documentation and many tutorials (e.g. HPs optim.)



- Rich set of features + Upcoming new features
- Possible to interface with other languages
- We can build advanced and robust architectures by sharing models

https://github.com/reservoirpy/reservoirpy


Many thanks to
Nathan Trouvain
& Paul Bernard
+ all developers

⚠ Looking for a post-doc!

Thank you!

➡ Share your models in ReservoirPy
➡ Ideas of new features to implement?

xavier.hinaut@inria.fr & paul.bernard@inria.fr
@neuronalX & @PAUL-BERNARD
@hinaut @reservoirpy

➡ Add papers on the
Reservoir "Awesome list" ➡

github.com/reservoirpy/awesome-reservoir-computing

Play with the Hackathon Notebook

github.com/reservoirpy/presentations/…

main presentations / ICANN-2025 /

PAUL-BERNARD Renamed files + improve README e226ec0 · 29 minutes ago

Name	Last commit message	Last commit date
..		
01_Introduction.ipynb	Renamed files + improve README	29 minutes ago
02_Hackathon.ipynb	Renamed files + improve README	29 minutes ago
README.md	Renamed files + improve README	29 minutes ago

README.md

ICANN 2025 - Tutorial on ReservoirPy

This is a Tutorial presented at the 3rd Reservoir Computing workshop held at ICANN 2025.

The aim is to:

- make participant familiar with the key concepts of Reservoir Computing;
- make participant familiar with ReservoirPy library the most popular reservoir library in Python;
- give you quick insights on ReservoirPy key features;
- show you how to optimize dynamically your hyperparameter search
- propose a quick hackathon and see which participant manages to reach the best performances while testing other reservoir nodes:
  - ES2N node
  - Intrinsic Plasticity
  - Next Generation Reservoir Computing

Some references using ReservoirPy

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