
DevDays, Lithuania, 17th May 2017

# Cognitive IoT Anomaly Detector with DeepLearning4J on IoT Sensor Data

@romeokienzler



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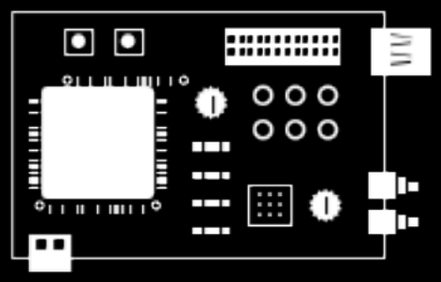
- 6000+ clients
- $200 million investment
- Partners including
  - Avnet, BNP Paribas, EEBus, Capgemini, Tech Mahindra, Vodafone, BMW, Visa, Bosch, Indiegogo, French national railway SNCF,Arrow Electronics, Intel, Cisco

# Why IoT (now) ?

- 15 Billion connected devices in 2015
- 40 Billion connected devices in 2020
- World population 7.4 Billion in 2016

Now you can believe the hype

# OASIS makes MQTT gold standard for Internet of Things



## Your device or gateway

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To find out how to get it connected, search our recipes.

## MQTT & HTTP

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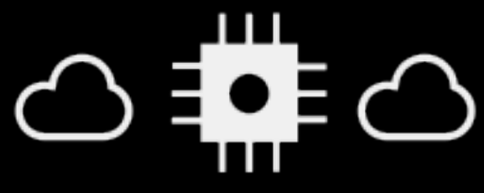

## IBM Watson IoT Platform

This is the hub of all things IBM IoT. This is where you can
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## Your application and analytics

Create applications within IBM Bluemix, another cloud,
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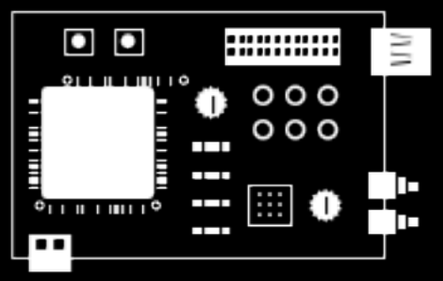

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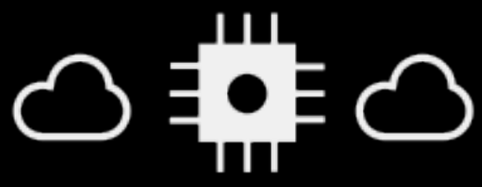

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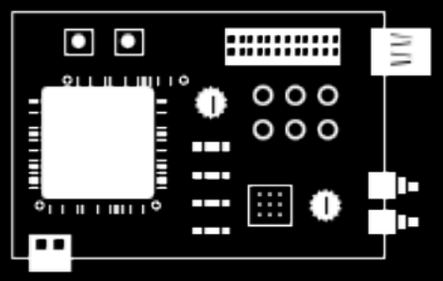

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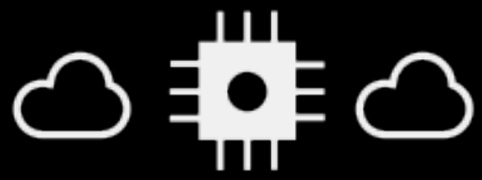

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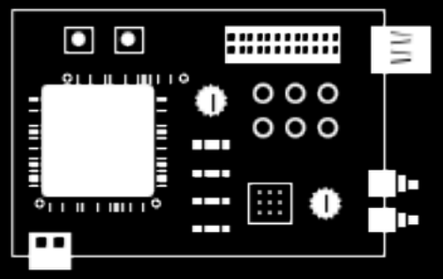

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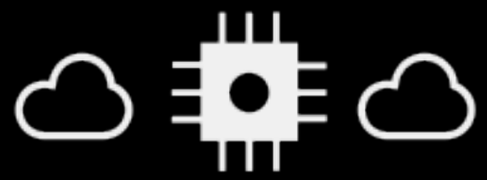

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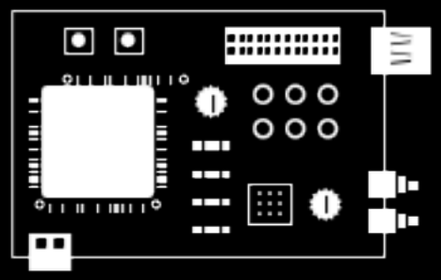

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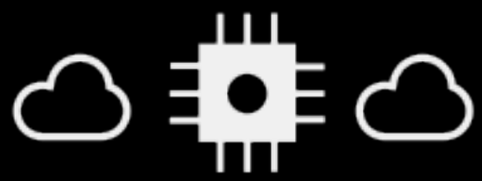

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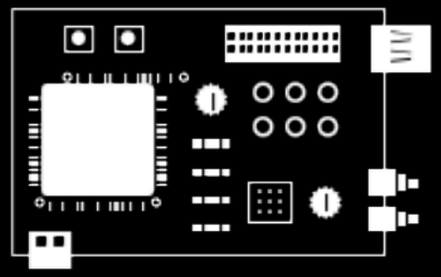

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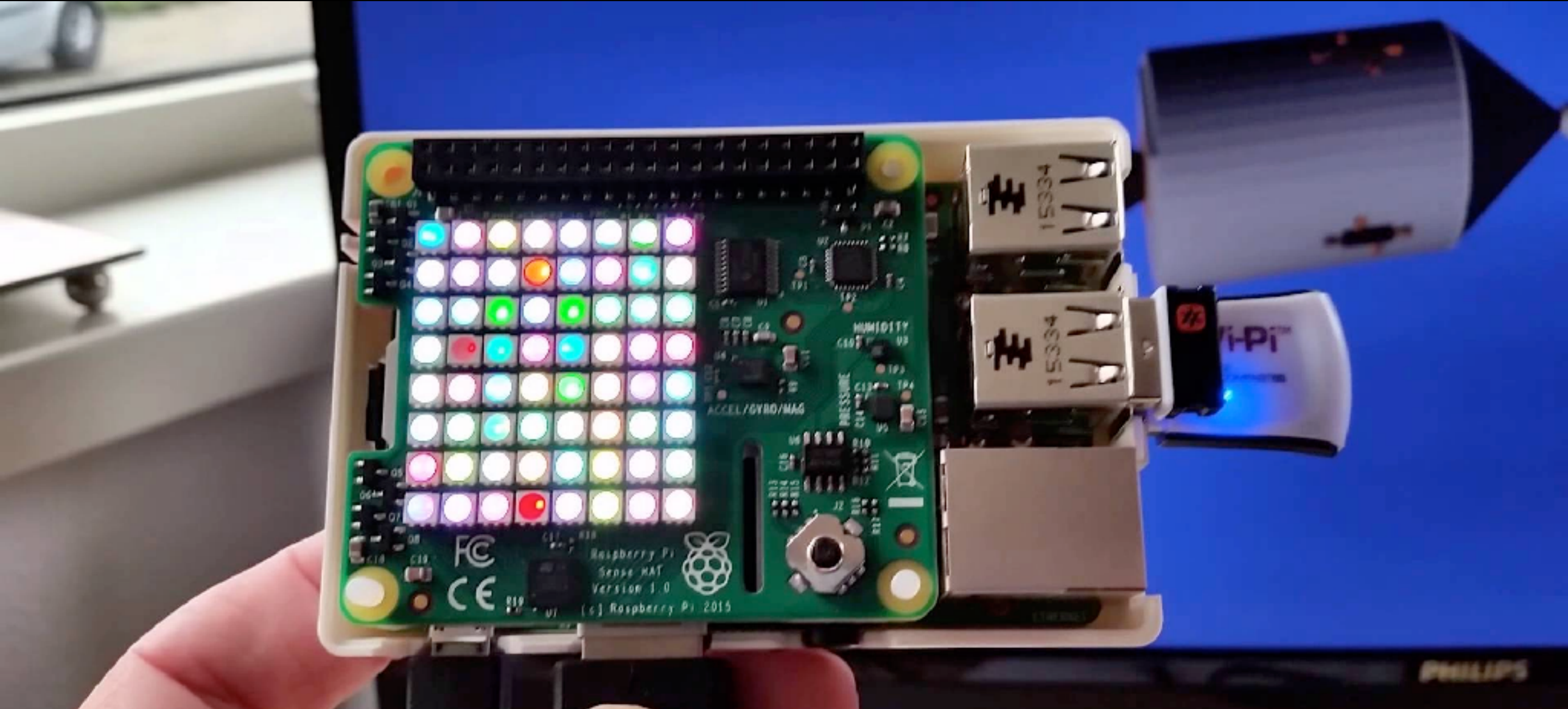


```python
import ibmiotf.gateway
from sense_hat import SenseHat
gatewayOptions = {"auth-method": "token", "auth-token": "s*)3uX"}
gatewayCli = ibmiotf.gateway.Client(gatewayOptions)
gatewayCli.connect()
sense = SenseHat()

temp = sense.get_temperature()
myData = {'temp' : temp}
gatewayCli.publishDeviceEvent(myData,qos=2)
```


# A developer's guide to the Internet of Things (IoT)

IBM

coursera

A developer's guide to the Internet of Things (IoT)

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Starting May 2016

# A developer's guide to Exploring and Visualizing IoT Data

**Created by:** IBM

A developer's guide to Exploring and Visualizing IoT Data

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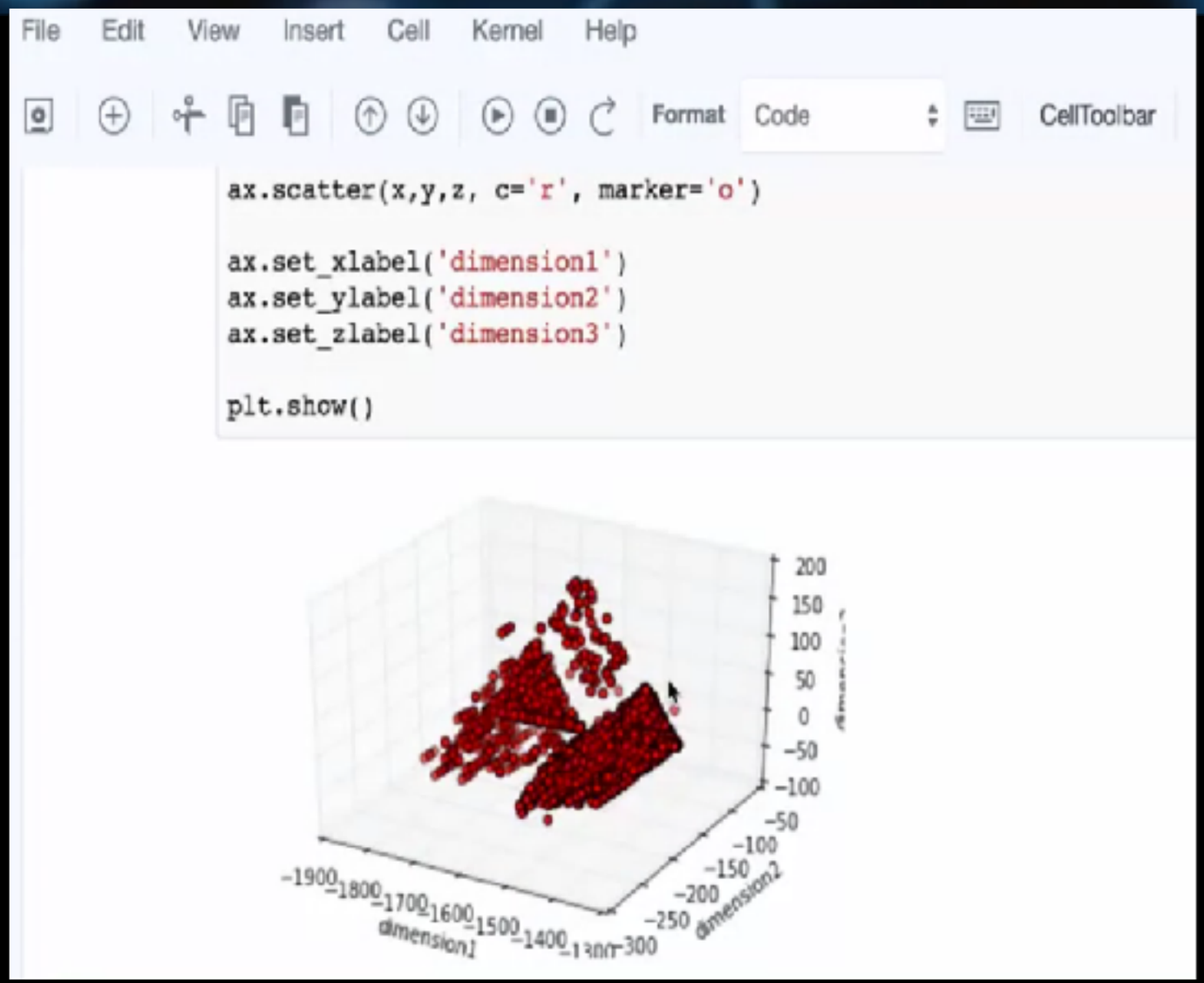
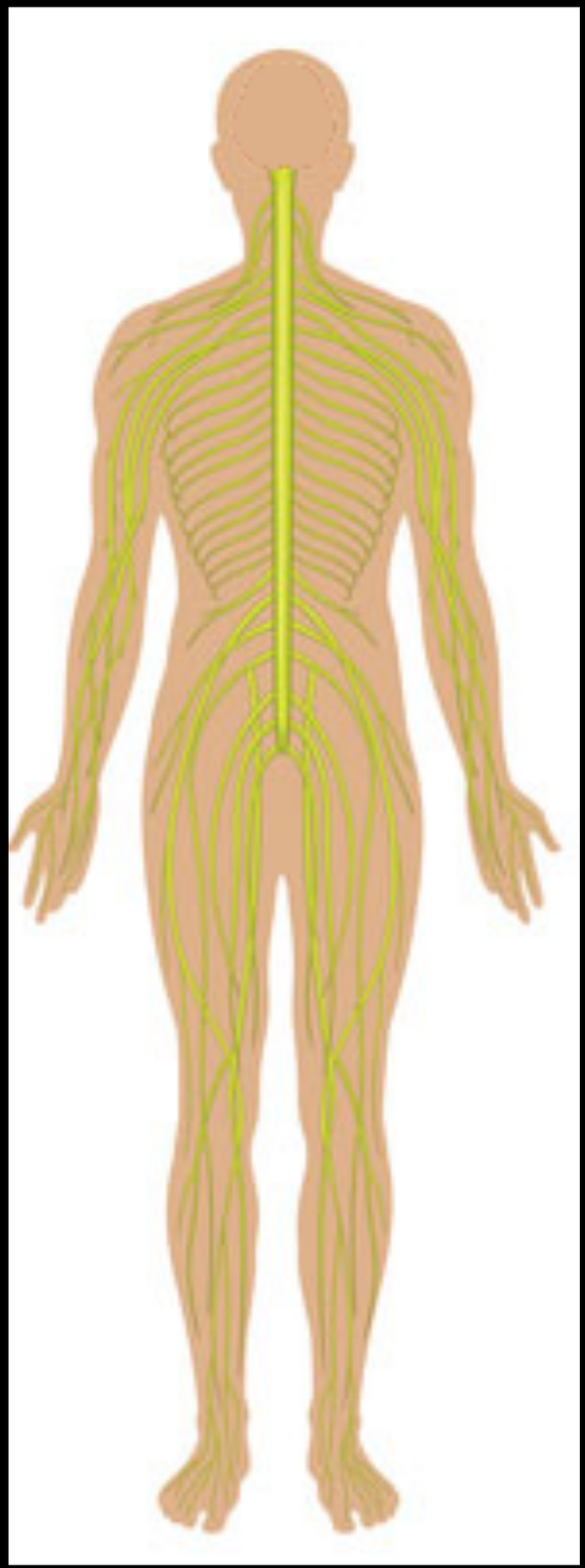
Starting January 9, 2017

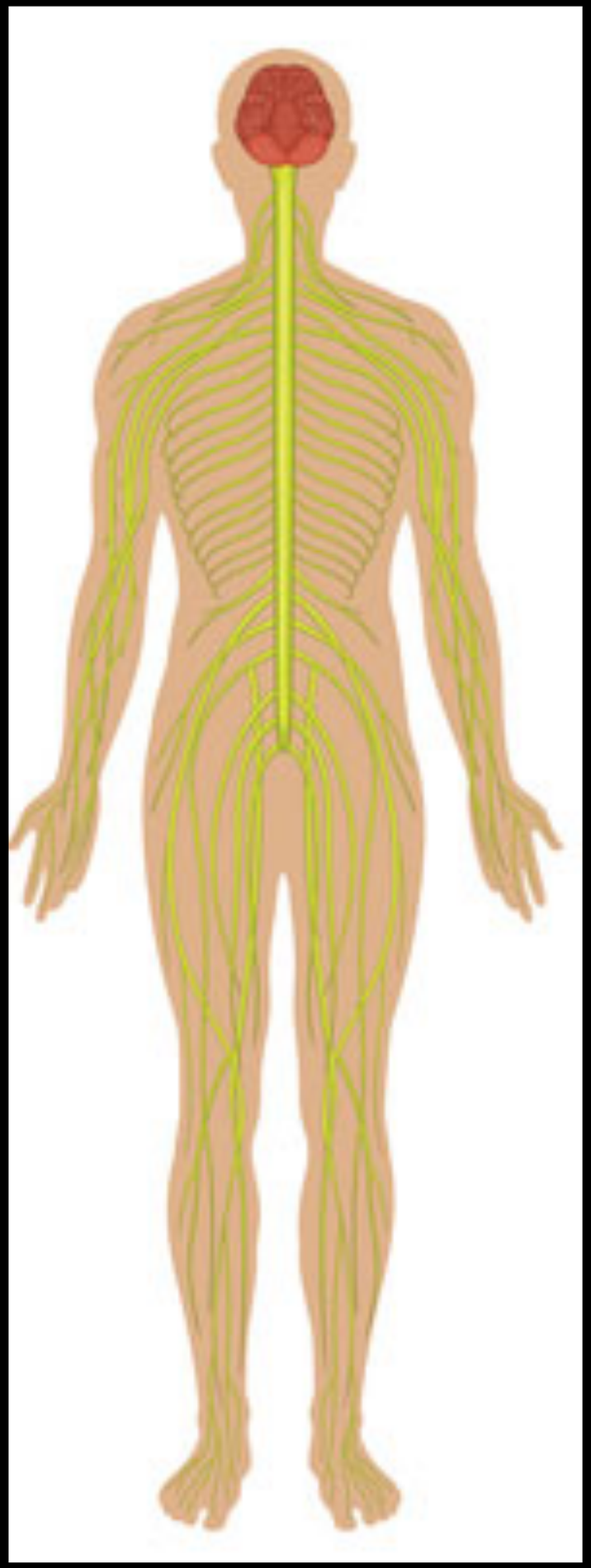
**Taught by:** Romeo Kienzler, Chief Data Scientist

IBM Watson IoT

# A developer's guide to Exploring and Visualizing IoT Data







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**Webseite (URL)**

http://ibm.biz/boomboomshakeshake

Statisch Dynamisch ( Was bedeutet Dynamisch? )

QR Code erstellen

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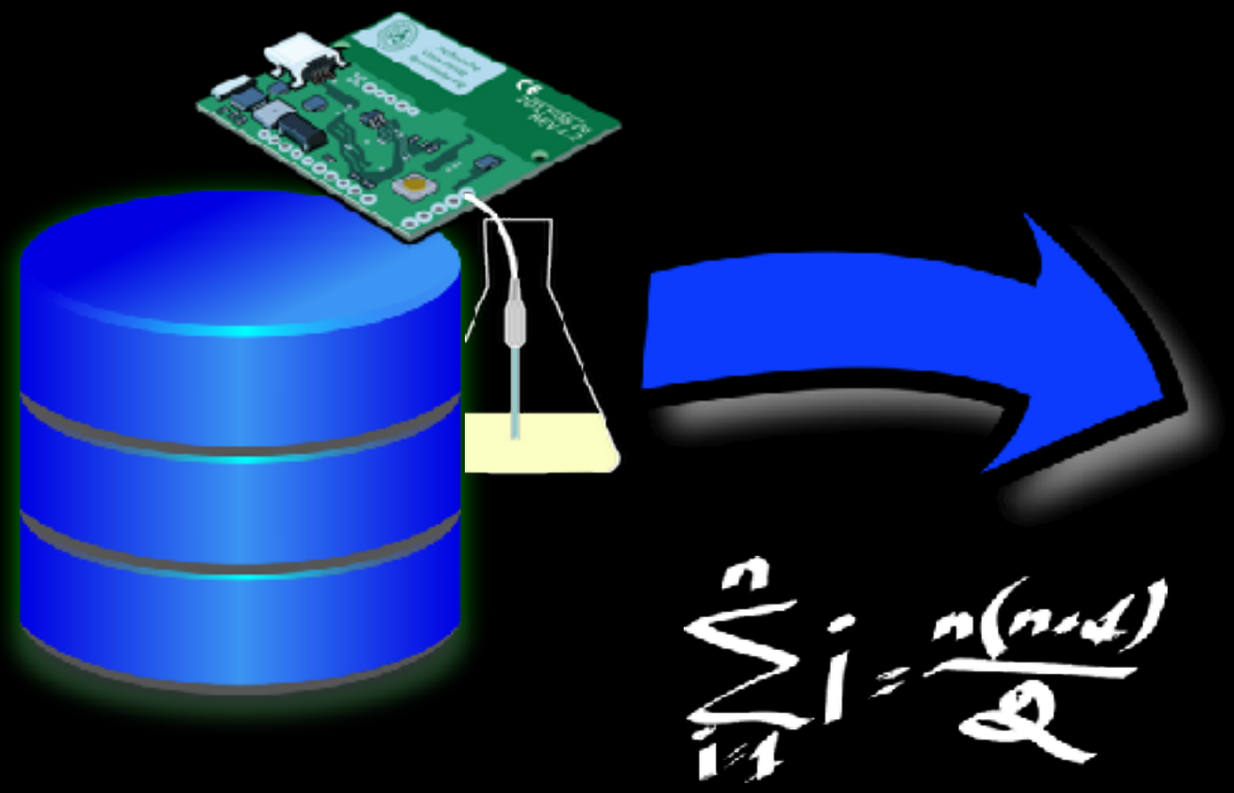
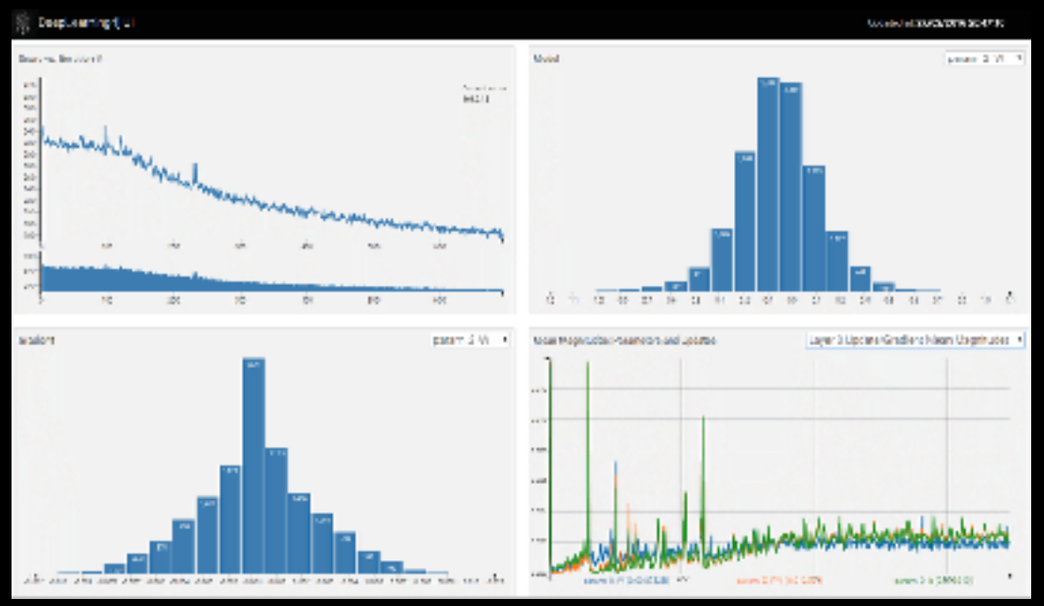
Herunterladen

QRCode einbetten

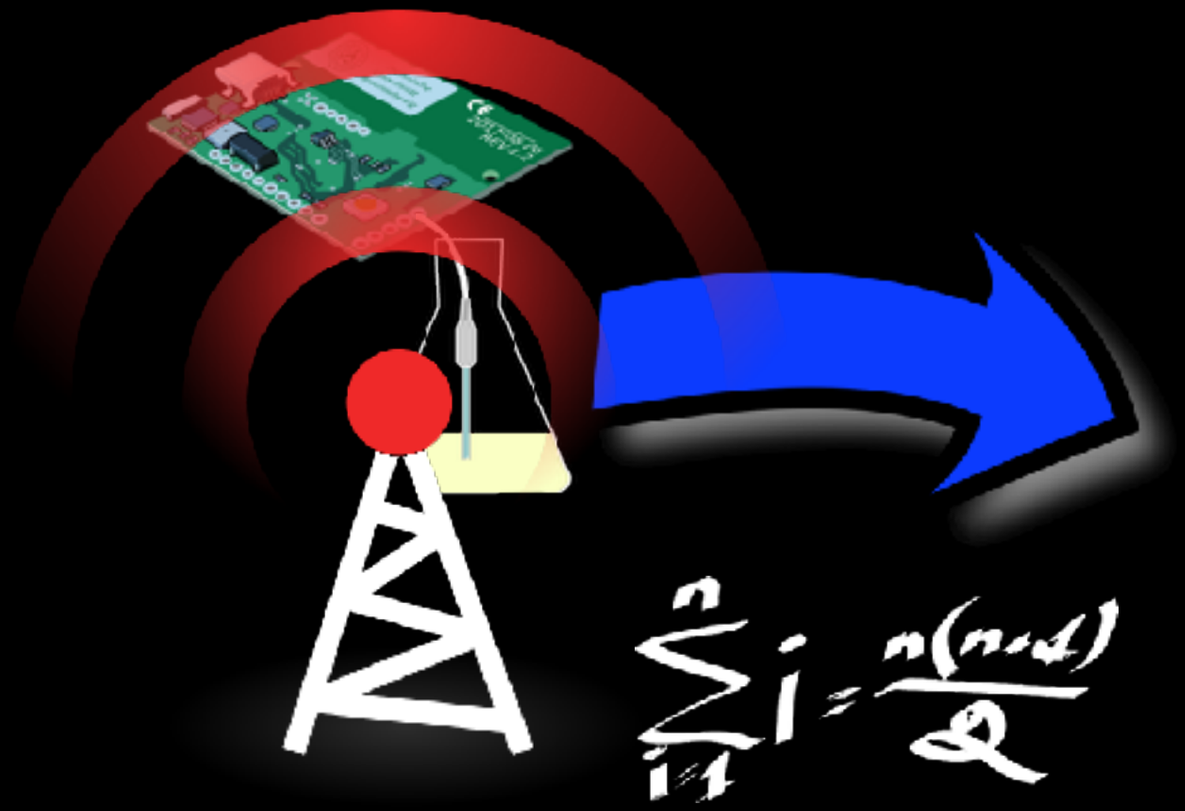
# Machine Learning on historic data

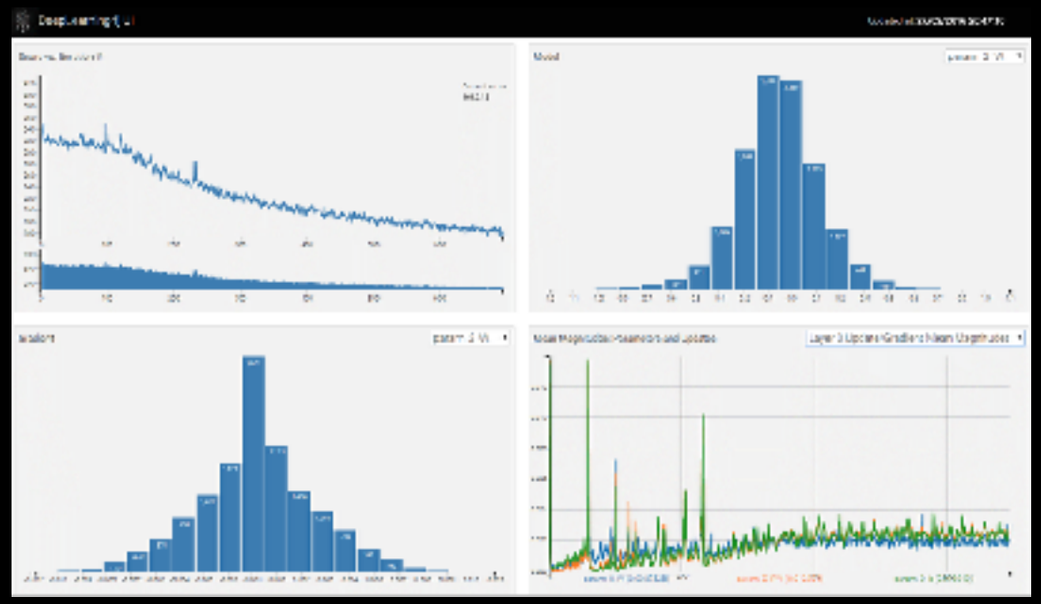




Source: deeplearning4j.org

# Online Learning



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# online vs. historic

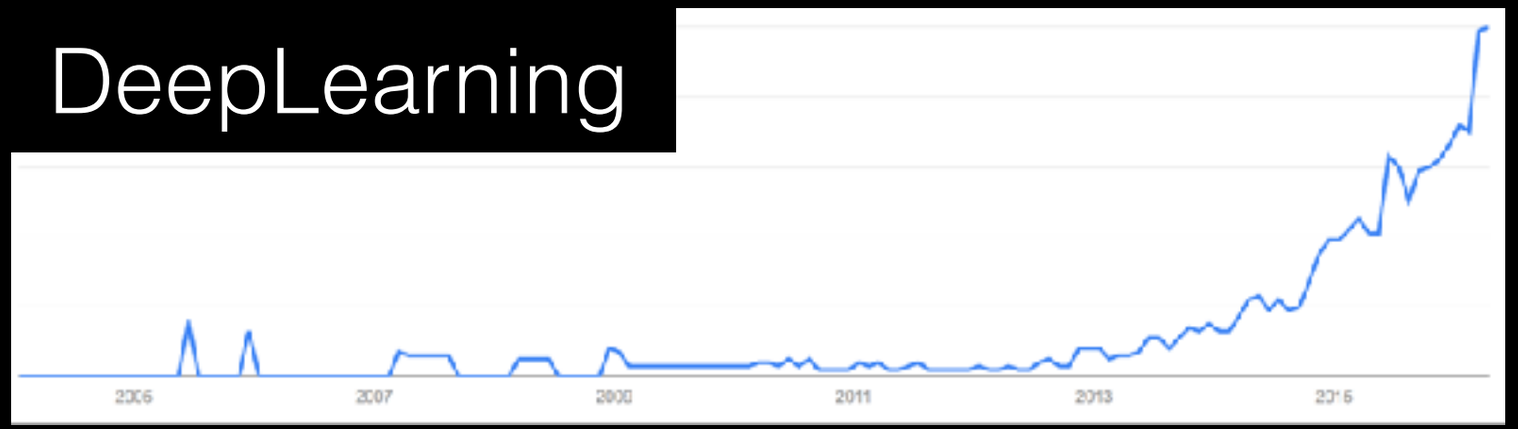
- Pros
  - low storage costs
  - real-time model update
- Cons
  - algorithm support
  - software support
  - no algorithmic improvement
  - compute power to be inline with data rate

- Pros
  - all algorithms
  - abundance of software
  - model re-scoring / re-parameterisation (algorithmic improvement)
  - batch processing
- Cons
  - high storage costs
  - batch model update

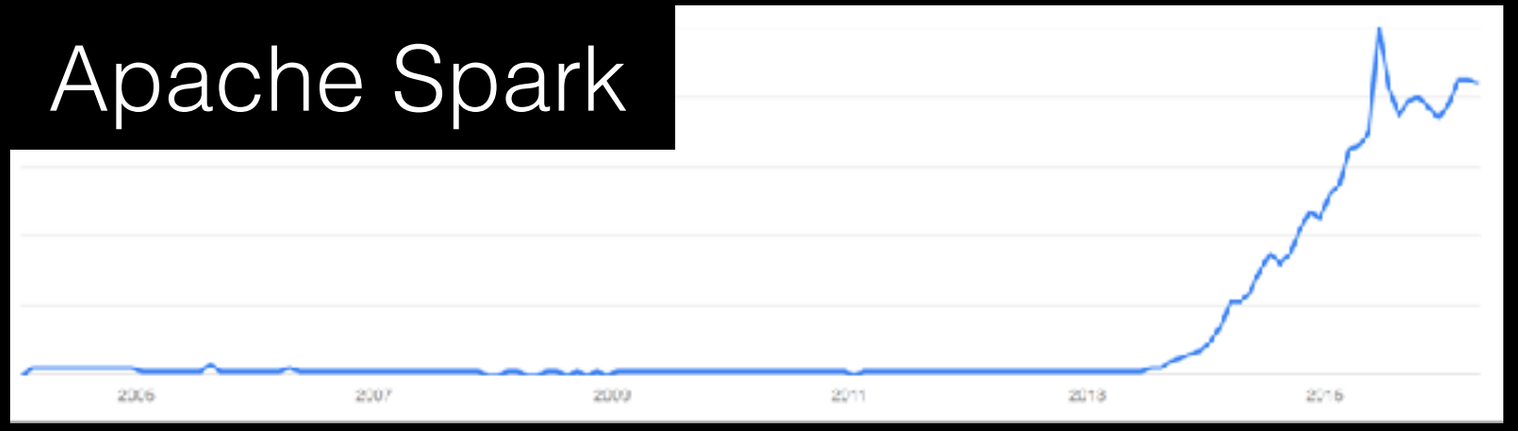
$$\hat{y}_t = \mu + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q}$$

# DeepLearning

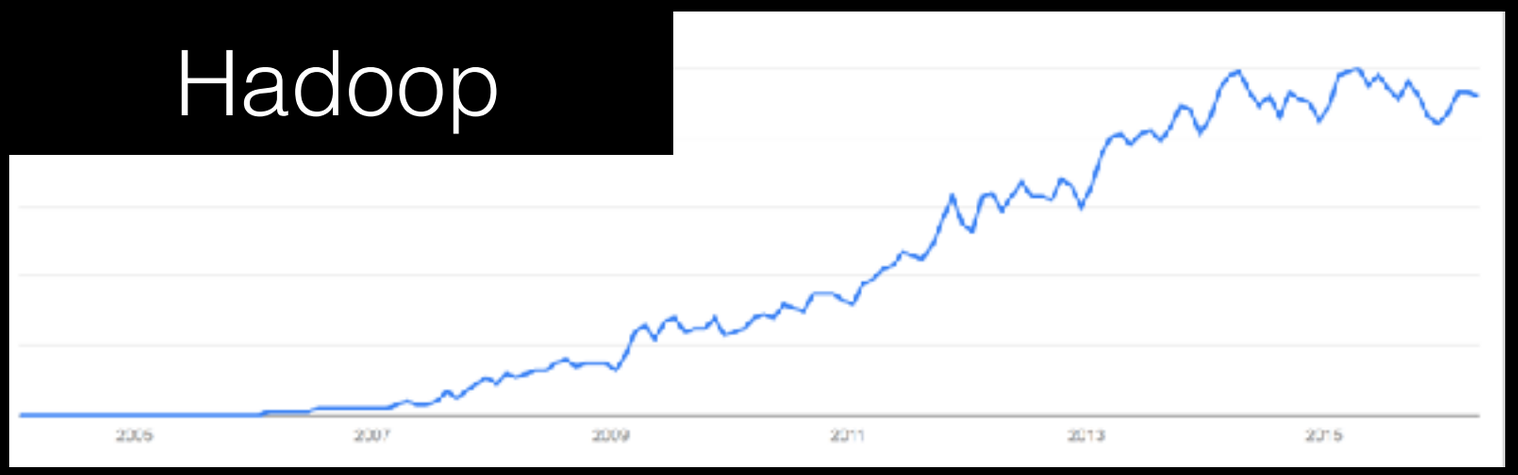
DeepLearning



Apache Spark



Hadoop



# Neural Networks

| Part No. | Max Temp. 1 | Min Temp 1 | Max Vibration 1 | Outcome |
|---|---|---|---|---|
| 100 | 35 | 35 | 12 | 1 |
| 101 | 46 | 35 | 21 | 1 |
| 130 | 56 | 46 | 3412 | 0 |

# Neural Networks

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|---|---|---|---|---|
| 100 | 35 | 35 | 12 | 1 |
| 101 | 46 | 35 | 21 | 1 |
| 130 | 56 | 46 | 3412 | 0 |

```
def predict(datapoint):
    if datapoint.MaxVibration1>100:
        return 0
    else:
        return 1
```

# Neural Networks

| Part No. | Max Temp. 1 | Min Temp 1 | Max Vibration 1 | Outcome |
|---|---|---|---|---|
| 100 | 35 | 35 | 12 | 1 |
| 101 | 46 | 35 | 21 | 1 |
| 130 | 56 | 46 | 3412 | 0 |

```
def predict(dp):
    return a+b*dp.MaxTemp1+c*dp.MinTemp1+d*dp.MaxVibration1
```

# Neural Networks

| Part No. | Max Temp. 1 | Min Temp 1 | Max Vibration 1 | Outcome |
|---|---|---|---|---|
| 100 | 35 | 35 | 12 | 1 |
| 101 | 46 | 35 | 21 | 1 |
| 130 | 56 | 46 | 3412 | 0 |

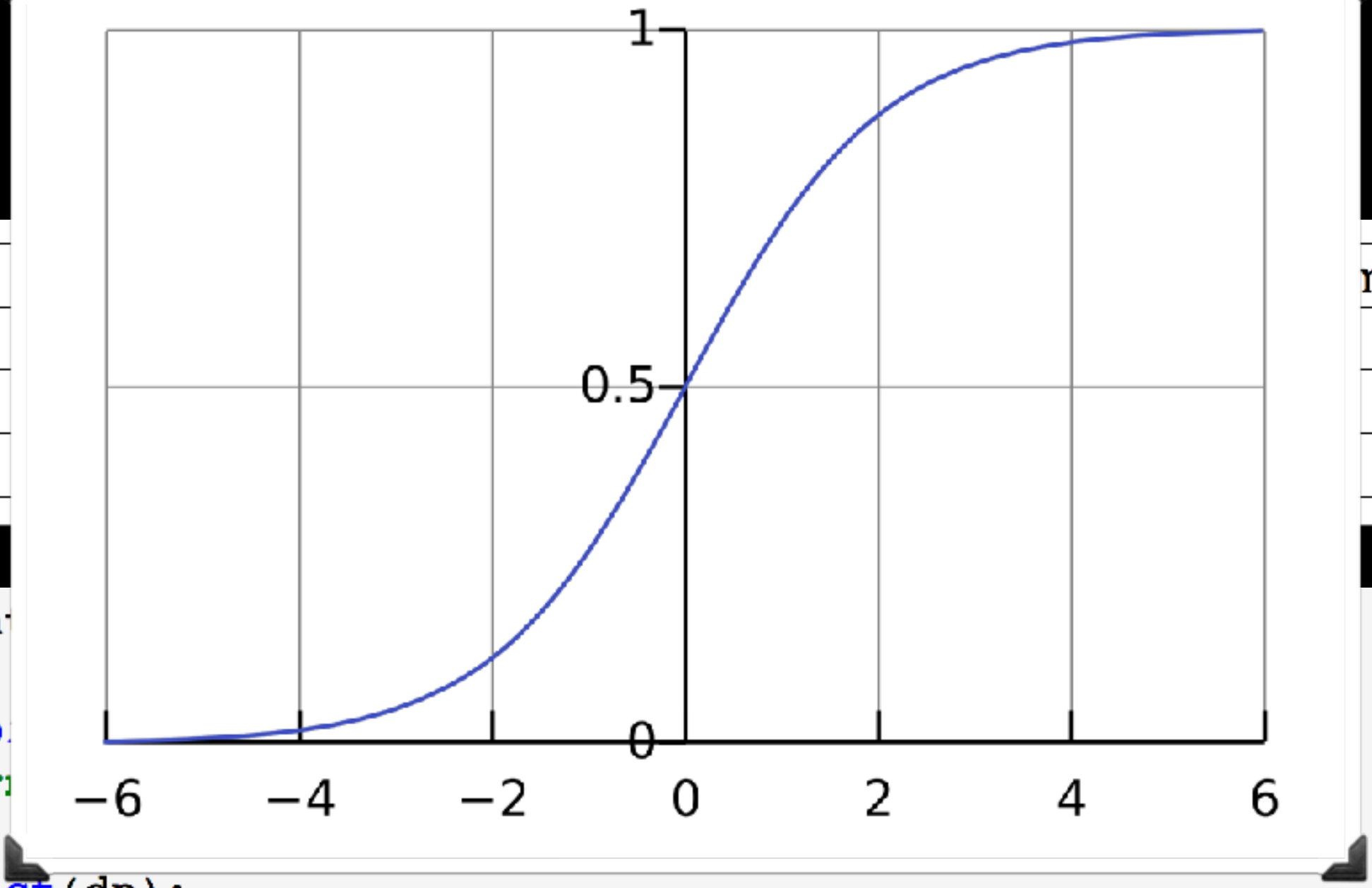
```
import math

def sigmoid(x):
    return 1 / (1 + math.exp(-x))

def predict(dp):
    return sigmoid(a+b*dp.MaxTemp1+c*dp.MinTemp1+d*dp.MaxVibration1)
```

# Neural Networks

| Part No. | ne |
|---|---|
| 100 | |
| 101 | |
| 130 | |




```
import ma

def sigmo
    retur

def predict(dp):
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```

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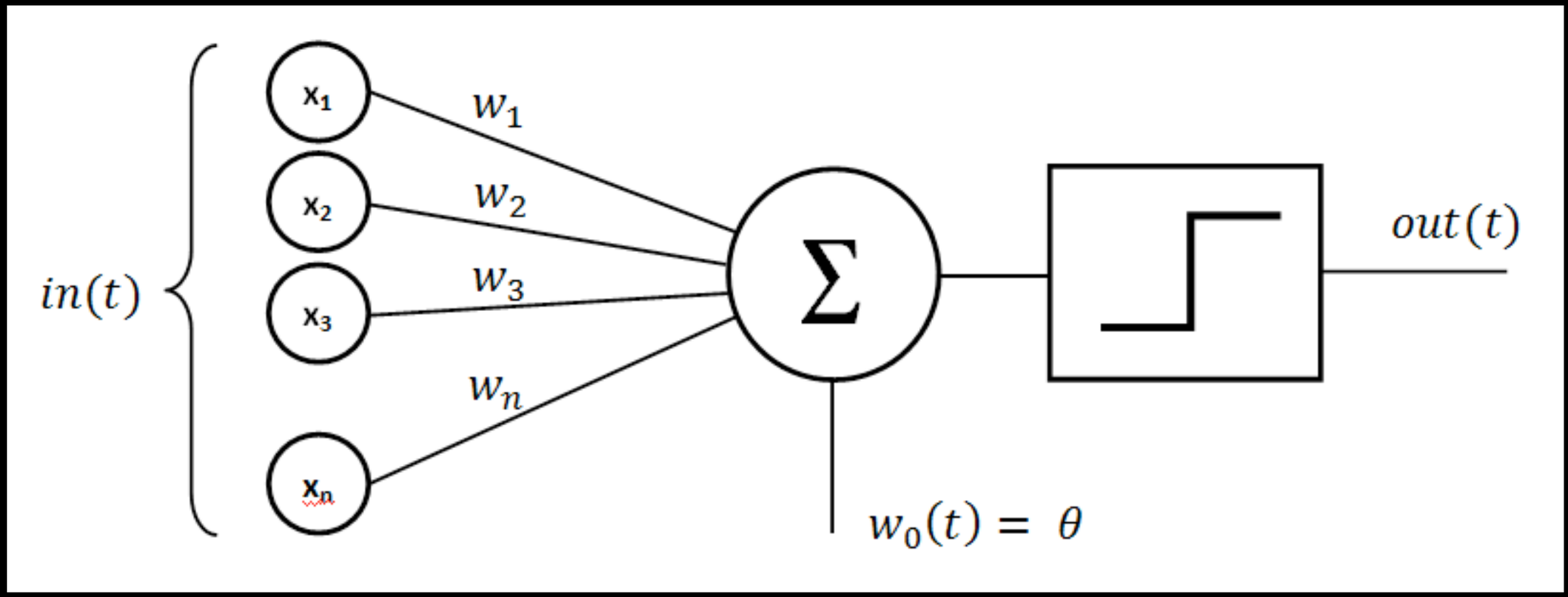

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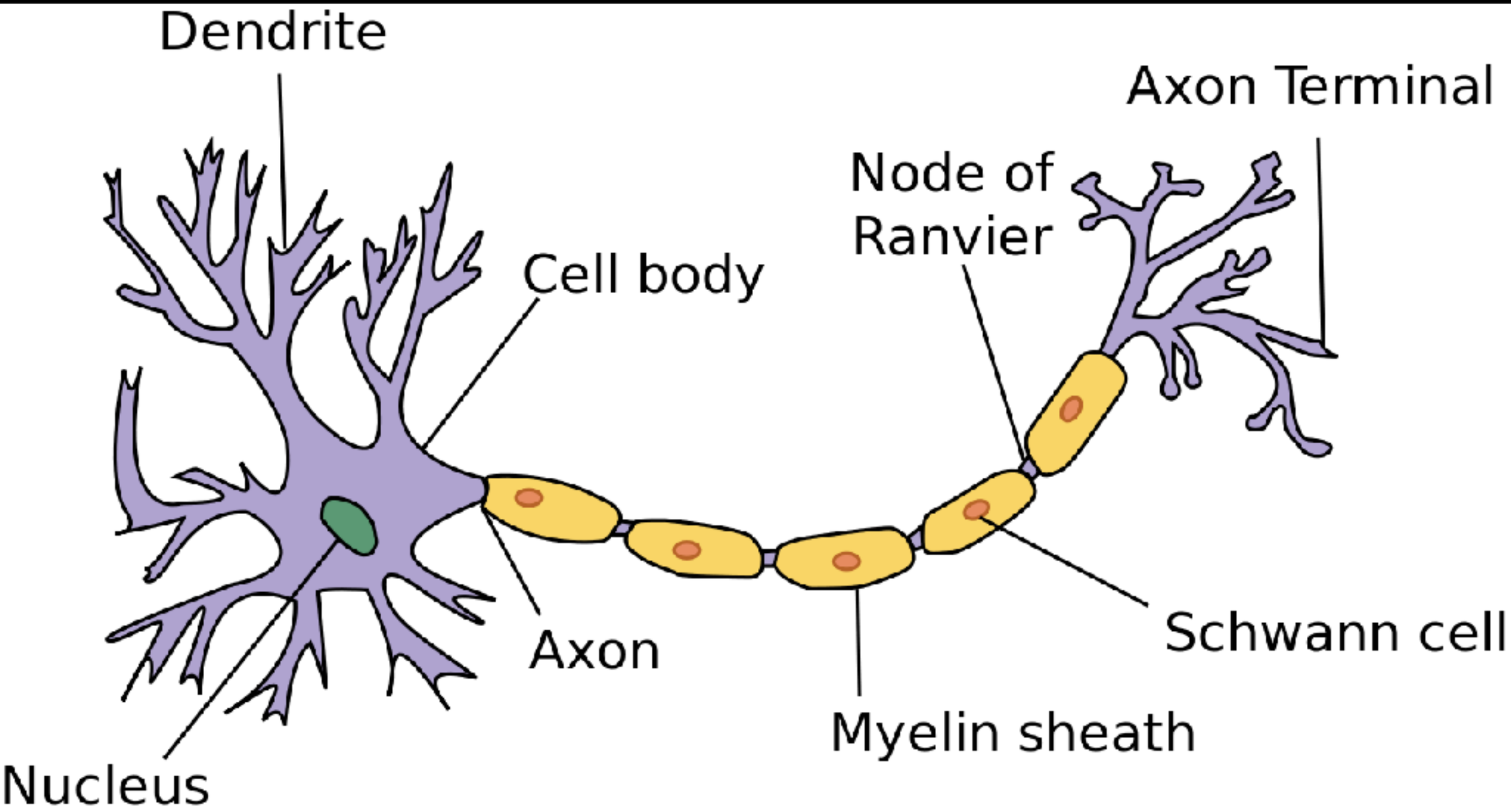

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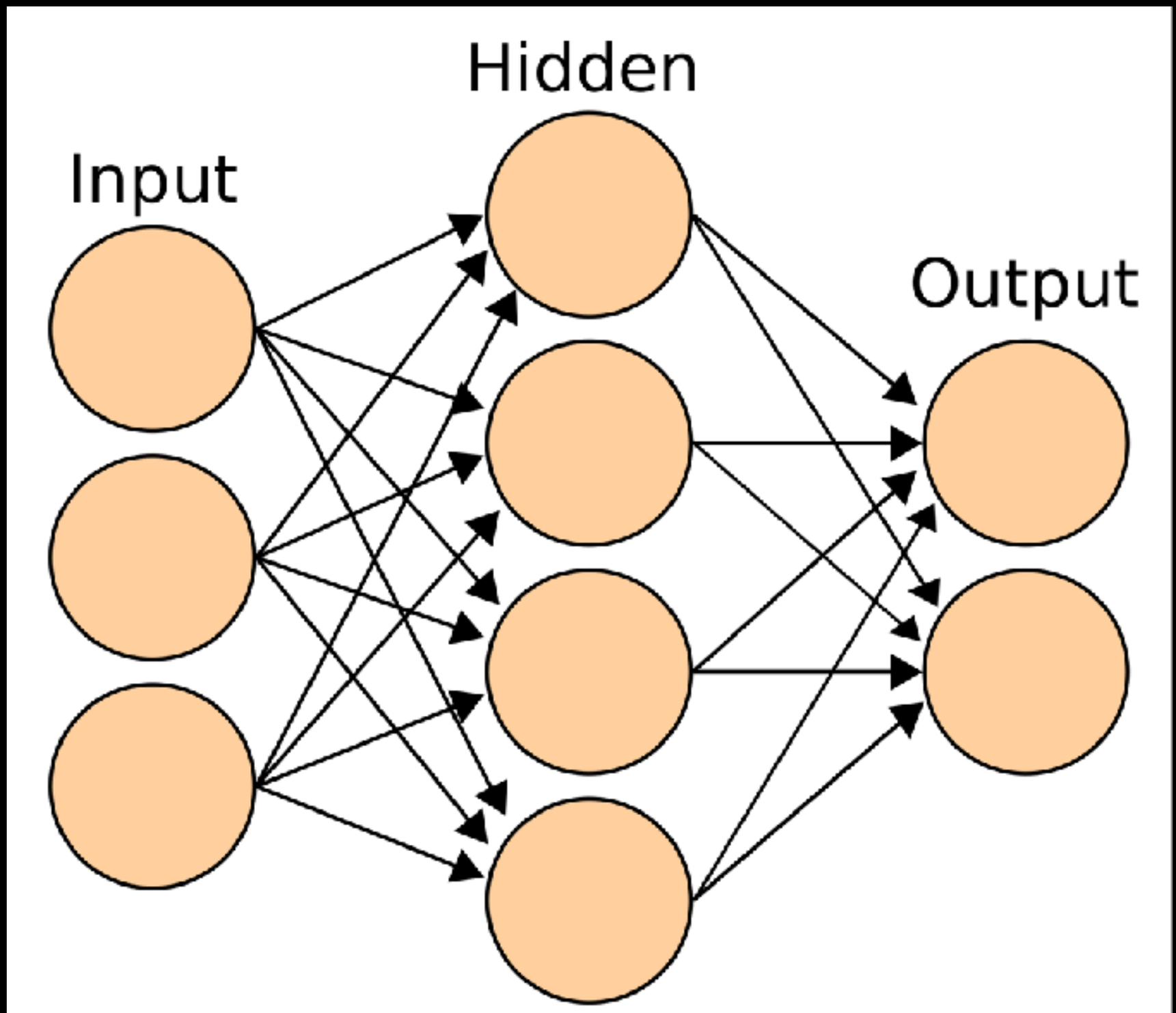


# Neural Networks

```
import numpy as np

datapoint = {"MaxTemp1":35, "MinTemp1":35, "MaxVibration1":12}

#radomly initialize weigts
w_layer1 = np.random.rand(4)
```

```
def neuron1(dp):
    x = np.array([1,dp["MaxTemp1"],dp["MinTemp1"],dp["MaxVibration1"]])
    return sigmoid(x.dot(w_layer1))


print(neuron1(datapoint))
```

# Neural Networks

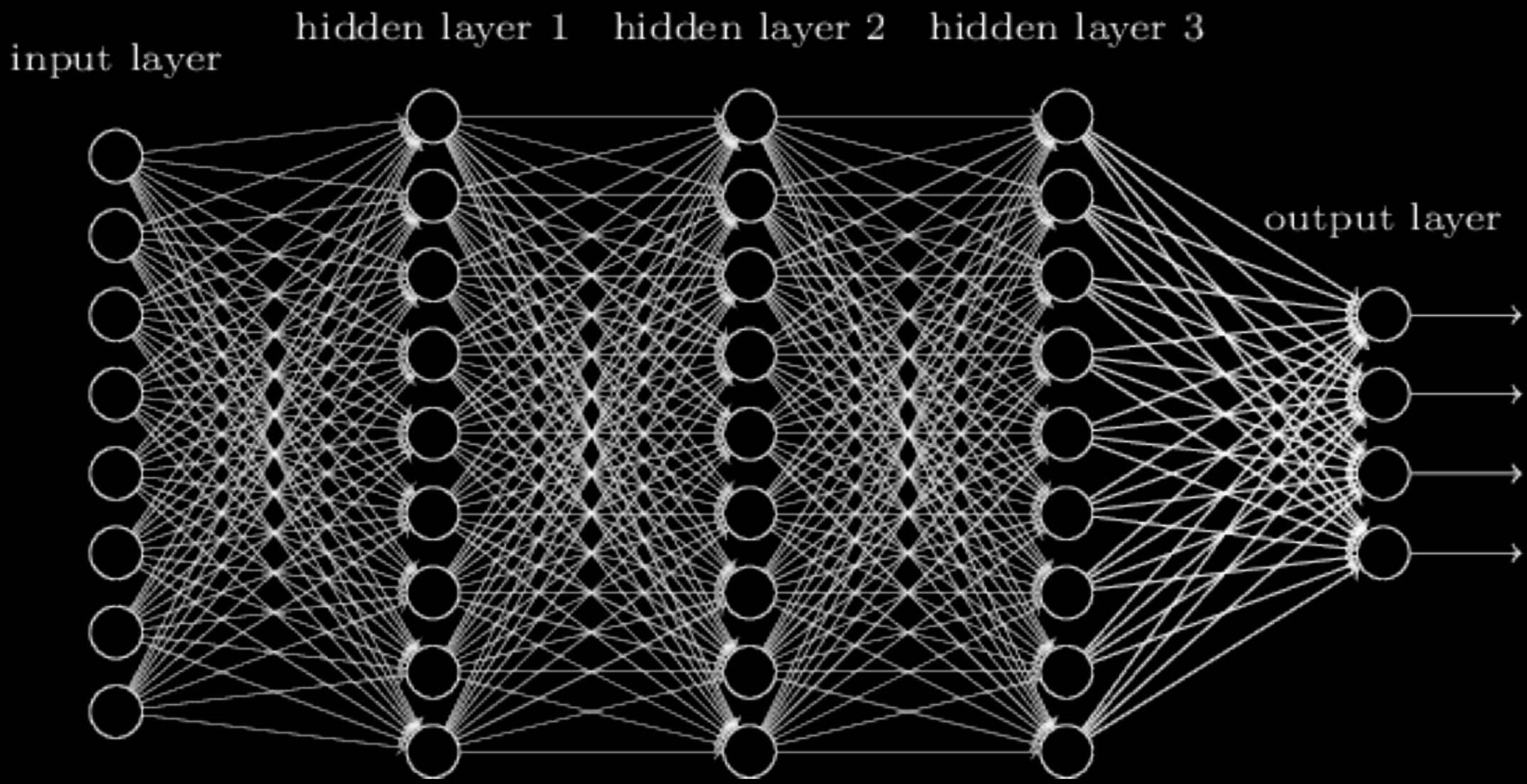
```
import numpy as np

#make sigmoid function applicable to vectors instead of scalars only
def sigmoid(z):
    s = 1.0 / (1.0 + np.exp(-1.0 * z))
    return s

datapoint = {"MaxTemp1":35, "MinTemp1":35, "MaxVibration1":12}
```

```
#radomly initialize weigts, now as a matrix for the four hidden layer neurons
w_layer1 = np.random.rand(4,4)

def layer1(dp):
    x = np.array([1,dp["MaxTemp1"],dp["MinTemp1"],dp["MaxVibration1"]])
    return sigmoid(x.dot(w_layer1))


print(layer1(datapoint))
```

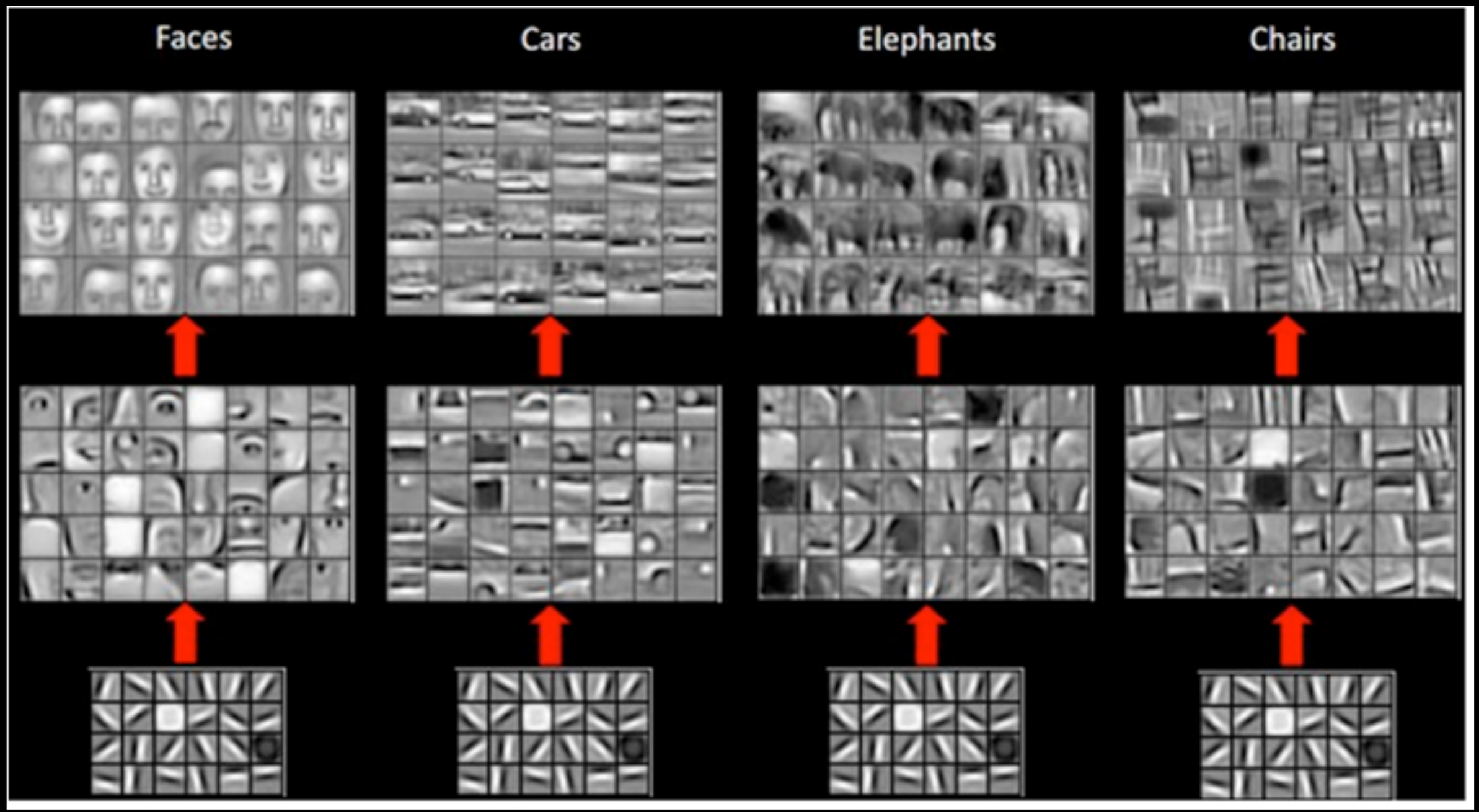
# Neural Networks

```
w_layer2 = np.random.rand(5,2)

def layer2(x):
    x = np.concatenate(([1],x))
    return sigmoid(x.dot(w_layer2))

print(layer2(layer1(datapoint)))
```

# Deeper (more) Layers



# Convolutional

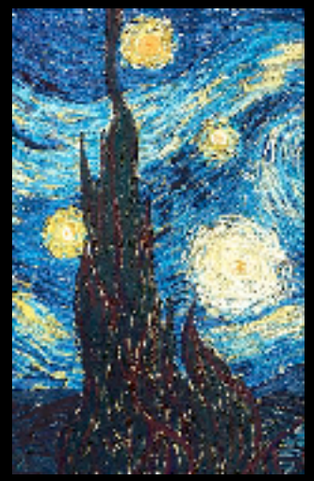


# Convolutional

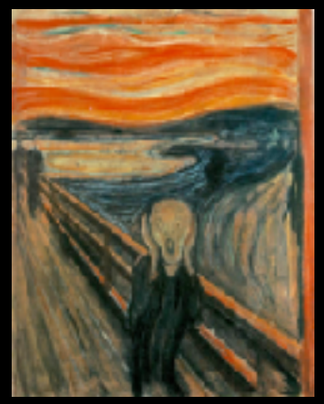
+


=

# Convolutional













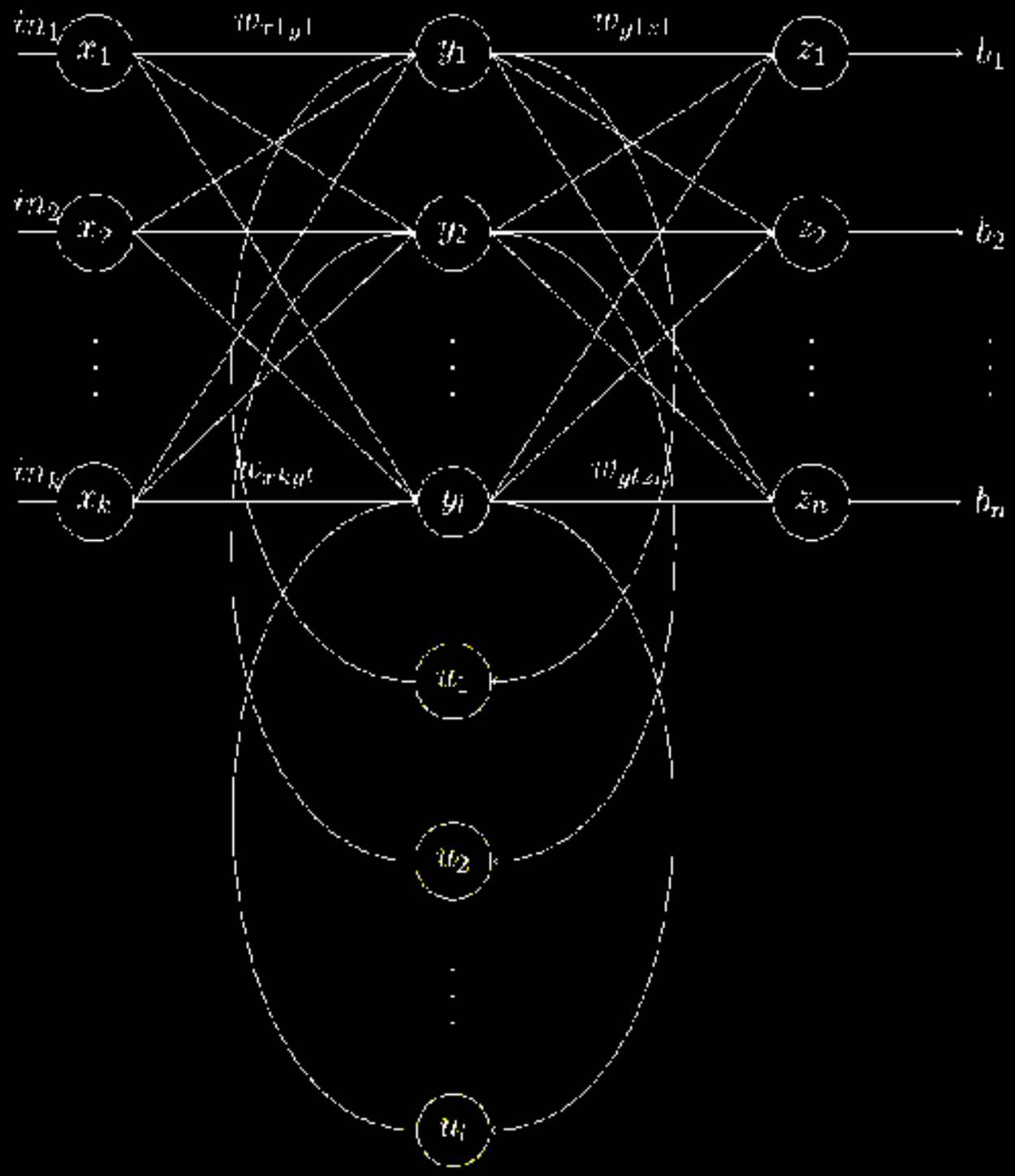




# Learning of a function

*A neural network can basically learn any mathematical function*

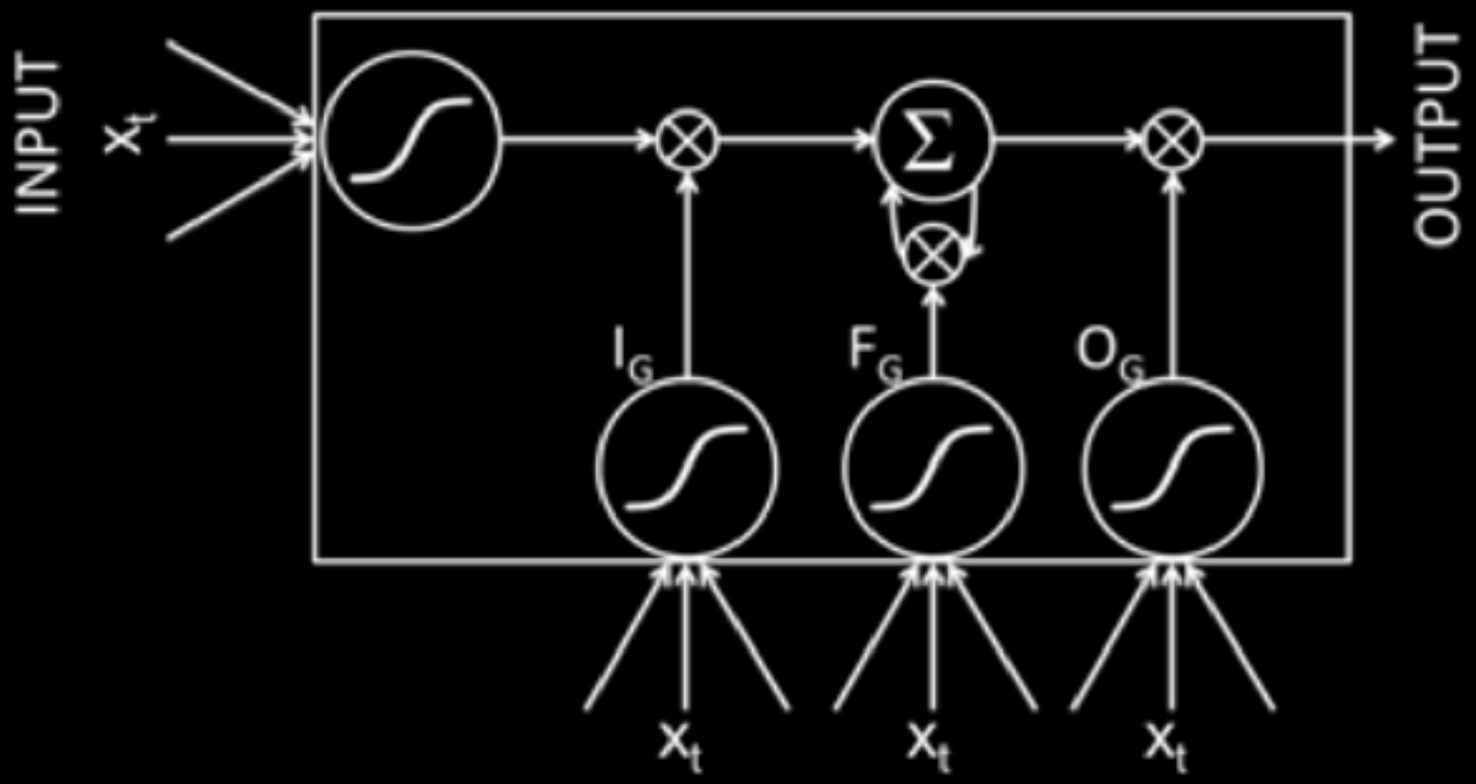
# Recurrent


$in_1$
$x_1$
$w_{x1|y1}$
$y_1$
$w_{y1|z1}$
$z_1$
$b_1$
$in_2$
$x_2$
$y_2$
$z_2$
$b_2$
$in_k$
$x_k$
$w_{xk|yl}$
$y_l$
$w_{yl|zn}$
$z_n$
$b_n$
$u_2$
$u_1$

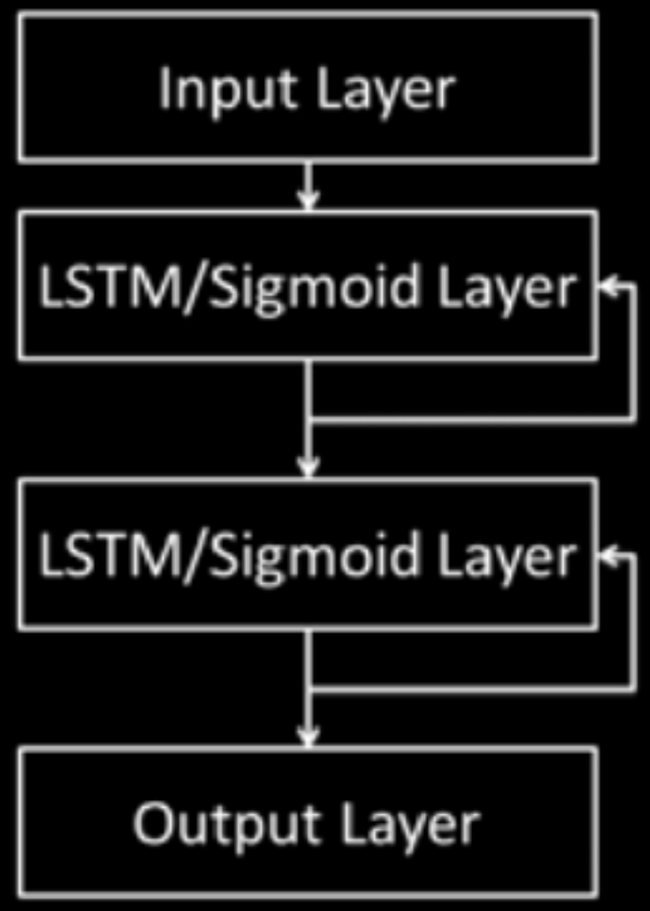
http://www.theverge.com/2015/7/17/8985699/stanford-neural-networks-image-recognition-google-study

http://www.media.uzh.ch/en/Press-Releases/2016/drohnen-suchen-selbstaendig-auf-waldwegen-nach-vermissten-.html

# LSTM




(a)




(b)

"vanishing gradient problem" == influence of past inputs decay quickly over time

PANDARUS:
Alas, I think he shall be come approached and the day
When little srain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:
They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:
Well, your wit is in the care of side and that.

Second Lord:
They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

Clown:
Come, sir, I will make did behold your worship.

VIOLA:
I'll drink it.

http://karpathy.github.io/2015/05/21/rnn-effectiveness/

VIOLA:
Why, Salisbury must find his flesh and thought
That which I am not aps, not a man and in fire,
To show the reining of the raven and the wars
To grace my hand reproach within, and not a fair are hand,
That Caesar and my goodly father's world;
When I was heaven of presence and our fleets,
We spare with hours, but cut thy council I am great,
Murdered and by thy master's ready there
My power to give thee but so much as hell:
Some service in the noble bondman here,
Would show him to her wine.

KING LEAR:
O, if you were a feeble sight, the courtesy of your law,
Your sight and several breath, will wear the gods
With his heads, and my hands are wonder'd at the deeds,
So drop upon your lordship's head, and your opinion
Shall be against your honour.

For $\bigoplus_{n=1,\ldots,m}$ where $\mathcal{L}_{m_\bullet} = 0$, hence we can find a closed subset $\mathcal{H}$ in $\mathcal{H}$ and any sets $\mathcal{F}$ on $X$, $U$ is a closed immersion of $S$, then $U \to T$ is a separated algebraic space.

*Proof.* Proof of (1). It also start we get

$$S = \mathrm{Spec}(R) = U \times_X U \times_X U$$

and the comparicoly in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \to V$. Consider the maps $M$ along the set of points $Sch_{fppf}$ and $U \to U$ is the fibre category of $S$ in $U$ in Section, ?? and the fact that any $U$ affine, see Morphisms, Lemma ??. Hence we obtain a scheme $S$ and any open subset $W \subset U$ in $Sh(G)$ such that $\mathrm{Spec}(R') \to S$ is smooth or an

$$U = \bigcup U_i \times_{S_i} U_i$$

which has a nonzero morphism we may assume that $f_i$ is of finite presentation over $S$. We claim that $\mathcal{O}_{X,x}$ is a scheme where $x, x', s'' \in S'$ such that $\mathcal{O}_{X,x'} \to \mathcal{O}'_{X',x'}$ is separated. By Algebra, Lemma ?? we can define a map of complexes $\mathrm{GL}_{S'}(x'/S'')$ and we win. □

To prove study we see that $\mathcal{F}|_U$ is a covering of $\mathcal{X}'$, and $\mathcal{T}_i$ is an object of $\mathcal{F}_{X/S}$ for $i > 0$ and $\mathcal{F}_p$ exists and let $\mathcal{F}_i$ be a presheaf of $\mathcal{O}_X$-modules on $\mathcal{C}$ as a $\mathcal{F}$-module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

$$\widetilde{M}^\bullet = \mathcal{I}^\bullet \otimes_{\mathrm{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1}\mathcal{F})$$

is a unique morphism of algebraic stacks. Note that

$$\mathrm{Arrows} = (Sch/S)^{opp}_{fppf}, (Sch/S)_{fppf}$$

and

$$V = \Gamma(S, \mathcal{O}) \longrightarrow (U, \mathrm{Spec}(A))$$

is an open subset of $X$. Thus $U$ is affine. This is a continuous map of $X$ is the inverse, the groupoid scheme $S$.

*Proof.* See discussion of sheaves of sets. □

The result for prove any open covering follows from the less of Example ??. It may replace $S$ by $X_{spaces,\acute{e}tale}$ which gives an open subspace of $X$ and $T$ equal to $S_{Zar}$, see Descent, Lemma ??. Namely, by Lemma ?? we see that $R$ is geometrically regular over $S$.

**Lemma 0.1.** *Assume (3) and (3) by the construction in the description.*

*Suppose* $X = \lim |X|$ *(by the formal open covering* $X$ *and a single map* $\underline{Proj}_X(\mathcal{A}) = \mathrm{Spec}(B)$ *over* $U$ *compatible with the complex*

$$Set(\mathcal{A}) = \Gamma(X, \mathcal{O}_{X,\mathcal{O}_X}).$$

*When in this case of to show that* $\mathcal{Q} \to \mathcal{C}_{Z/X}$ *is stable under the following result in the second conditions of (1), and (3). This finishes the proof. By Definition ?? (without element is when the closed subschemes are catenary. If* $T$ *is surjective we may assume that* $T$ *is connected with residue fields of* $S$*. Moreover there exists a closed subspace* $Z \subset X$ *of* $X$ *where* $U$ *in* $X'$ *is proper (some defining as a closed subset of the uniqueness it suffices to check the fact that the following theorem*

(1) $f$ *is locally of finite type. Since* $S = \mathrm{Spec}(R)$ *and* $Y = \mathrm{Spec}(R)$.

*Proof.* This is form all sheaves of sheaves on $X$. But given a scheme $U$ and a surjective étale morphism $U \to X$. Let $U \cap U = \coprod_{i=1,\ldots,n} U_i$ be the scheme $X$ over $S$ at the schemes $X_i \to X$ and $U = \lim_i X_i$. □

The following lemma surjective restrocomposes of this implies that $\mathcal{F}_{x_0} = \mathcal{F}_{x_0} = \mathcal{F}_{X,\ldots,0}$.

**Lemma 0.2.** *Let* $X$ *be a locally Noetherian scheme over* $S$, $E = \mathcal{F}_{X/S}$. *Set* $\mathcal{I} = \mathcal{J}_1 \subset \mathcal{I}'_n$. *Since* $\mathcal{I}^n \subset \mathcal{I}^n$ *are nonzero over* $i_0 \leq \mathfrak{p}$ *is a subset of* $\mathcal{J}_{n,0} \circ \overline{A}_2$ *works.*

**Lemma 0.3.** *In Situation ??. Hence we may assume* $\mathfrak{q}' = 0$.

*Proof.* We will use the property we see that $\mathfrak{p}$ is the mext functor (??). On the other hand, by Lemma ?? we see that

$$D(\mathcal{O}_{X'}) = \mathcal{O}_X(D)$$

where $K$ is an $F$-algebra where $\delta_{n+1}$ is a scheme over $S$. □

```
/*
 * Increment the size file of the new incorrect UI_FILTER group information
 * of the size generatively.
 */
static int indicate_policy(void)
{
  int error;
  if (fd == MARN_EPT) {
    /*
     * The kernel blank will coeld it to userspace.
     */
    if (ss->segment < mem_total)
      unblock_graph_and_set_blocked();
    else
      ret = 1;
    goto bail;
  }
  segaddr = in_SB(in.addr);
  selector = seg / 16;
  setup_works = true;
  for (i = 0; i < blocks; i++) {
    seq = buf[i++];
    bpf = bd->bd.next + i * search;
    if (fd) {
      current = blocked;
    }
  }
  rw->name = "Getjbbregs";
  bprm_self_clearl(&iv->version);
  regs->new = blocks[(BPF_STATS << info->historidac)] | PFMR_CLOBATHINC_SECONDS << 12;
  return segtable;
}
```

https://m.soundcloud.com/optometrist-prime/recurrence-music-written-by-a-recurrent-neural-network

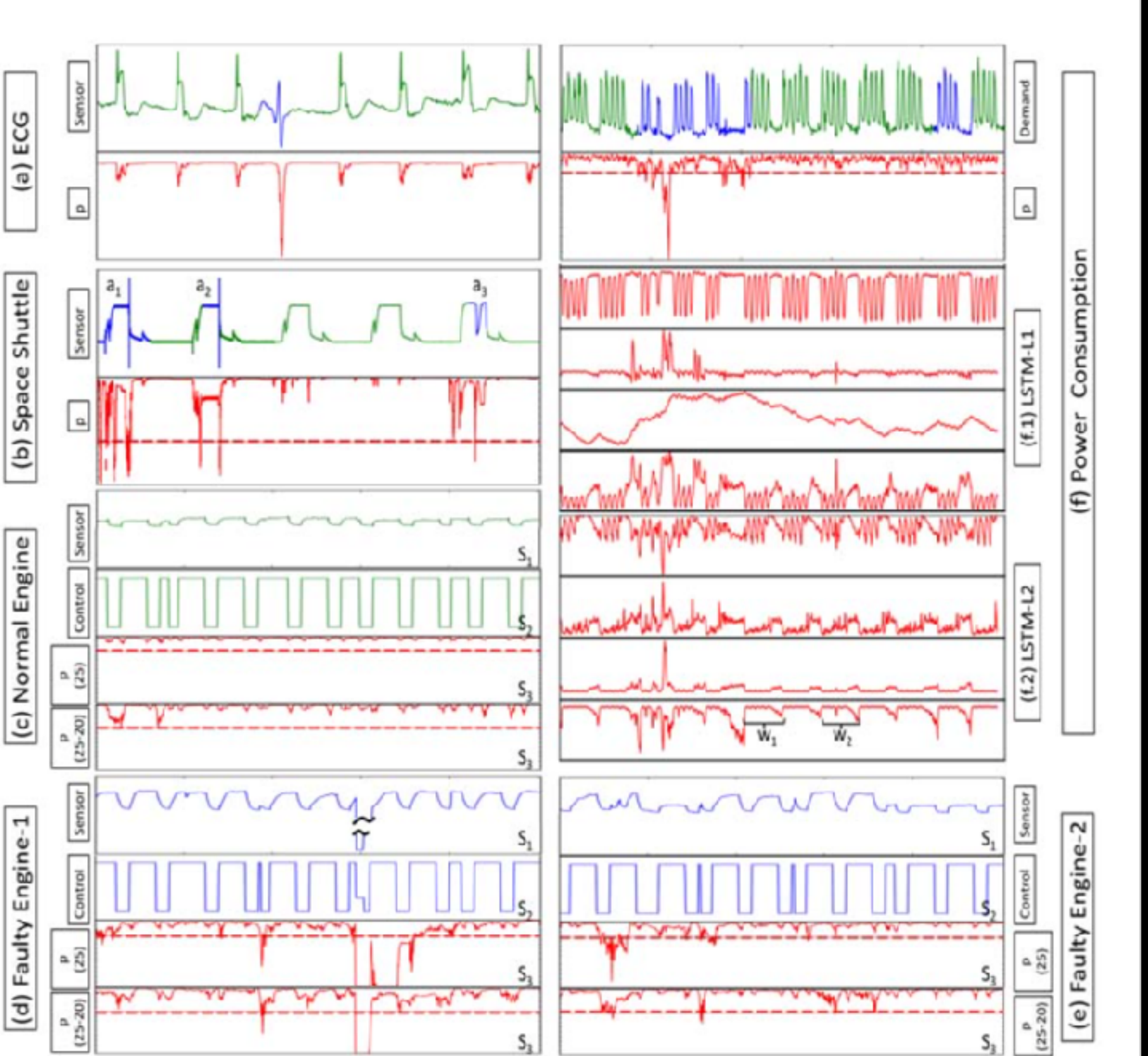
# Long Short Term Memory Networks for Anomaly Detection in Time Series

Pankaj Malhotra[1], Lovekesh Vig[2], Gautam Shroff[1], Puneet Agarwal[1]

1- TCS Research, Delhi, India

2- Jawaharlal Nehru University, New Delhi, India

- Outperformed traditional methods, such as
  - cumulative sum (CUSUM)
  - exponentially weighted moving average (EWMA)
  - Hidden Markov Models (HMM)
- Learned what “Normal” is
- Raised error if time series pattern haven't been seen before

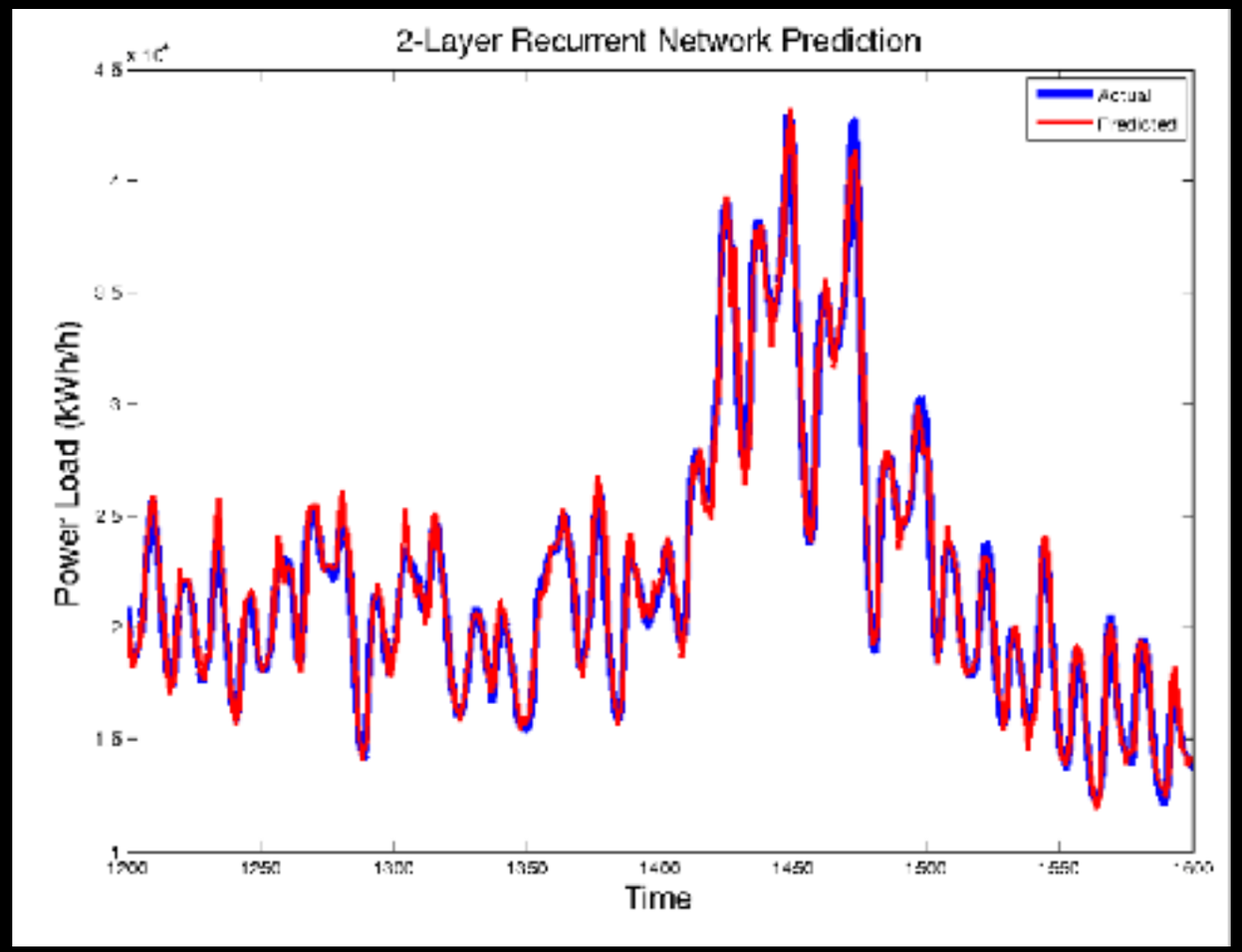



ESANN 2015 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 22-24 April 2015, i6doc.com publ., ISBN 978-287587014-8. Available from http://www.i6doc.com/en/.

# Deep Learning for Time Series Modeling

## CS 229 Final Project Report

Enzo Busseti, Ian Osband, Scott Wong




| Learning Method | RMSE | % RMSE |
|---|---|---|
| Kernelized Regression | 1,540 | 8.3% |
| Frequency NN | 1,251 | 6.7% |
| Deep Feedforward NN | 1,103 | 5.9% |
| Deep Recurrent NN | 530 | 2.8% |

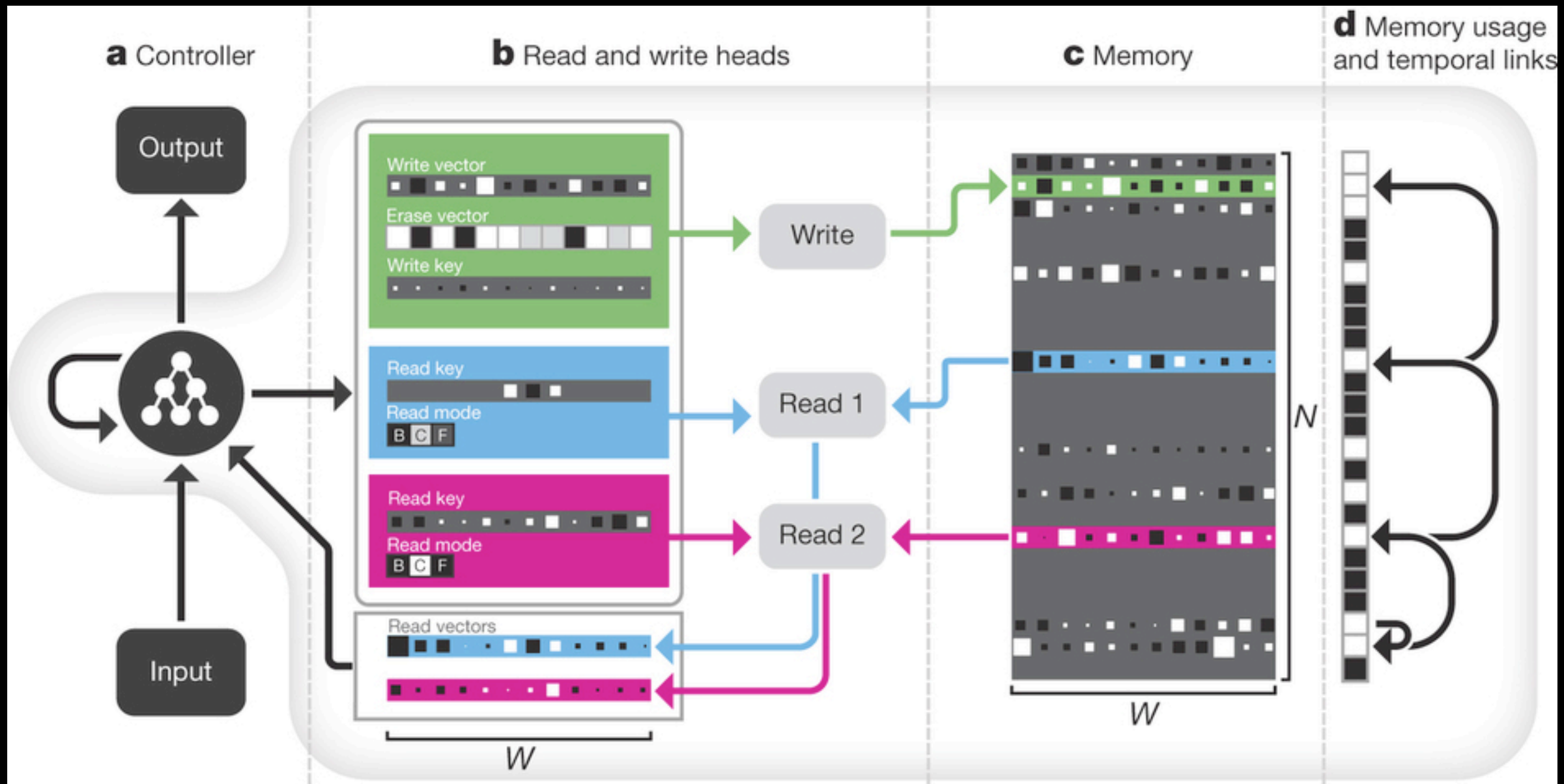
# Learning of an algorithm

*A LSTM network is Turing complete*[1]

1: http://binds.cs.umass.edu/papers/1995_Siegelmann_Science.pdf

# Learning of an algorithm V2

*The Differentiable Neural Computer*



# Problems

- Neural Networks are computationally very complex
  - especially during training
  - but also during scoring

CPU (2009)

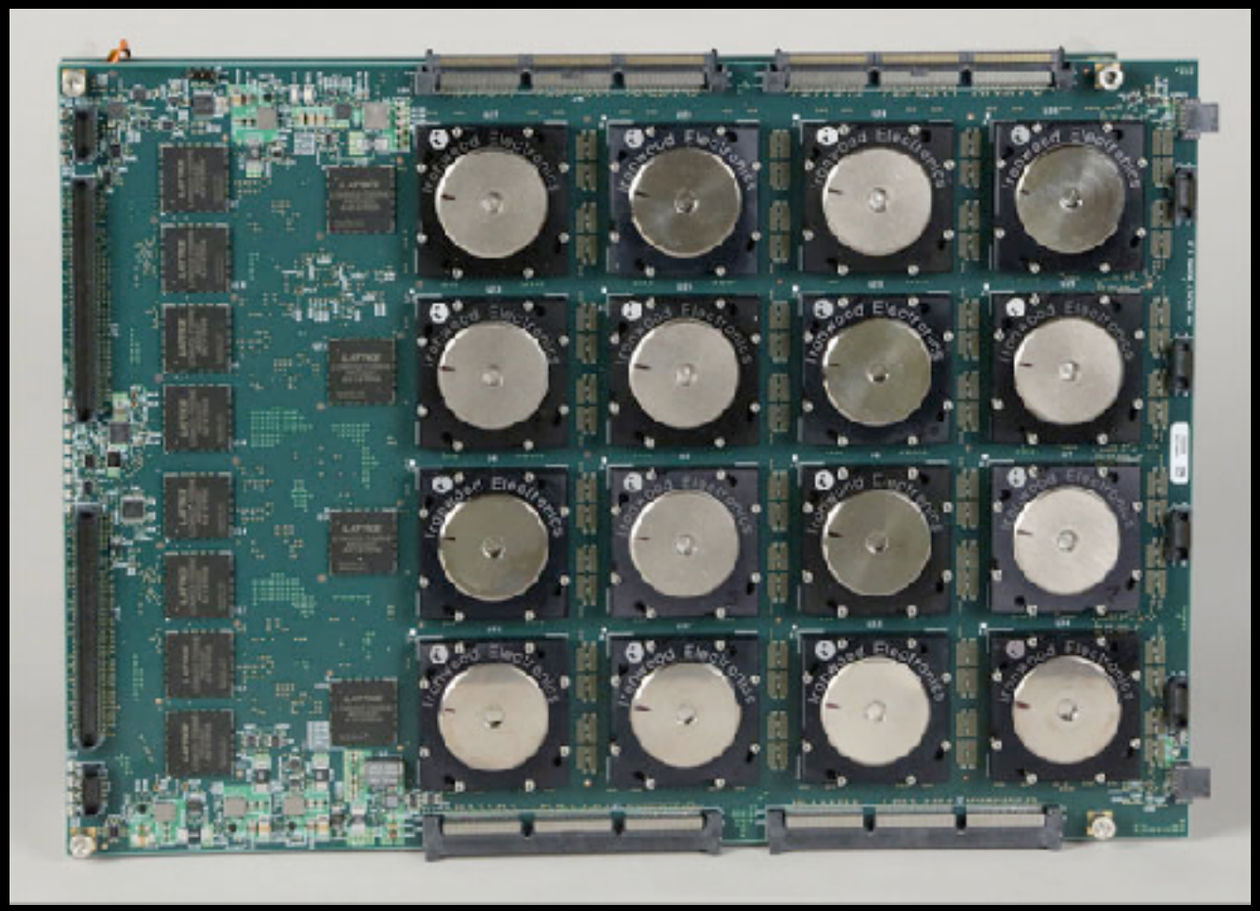

GPU (2016)


IBM TrueNorth (2017)

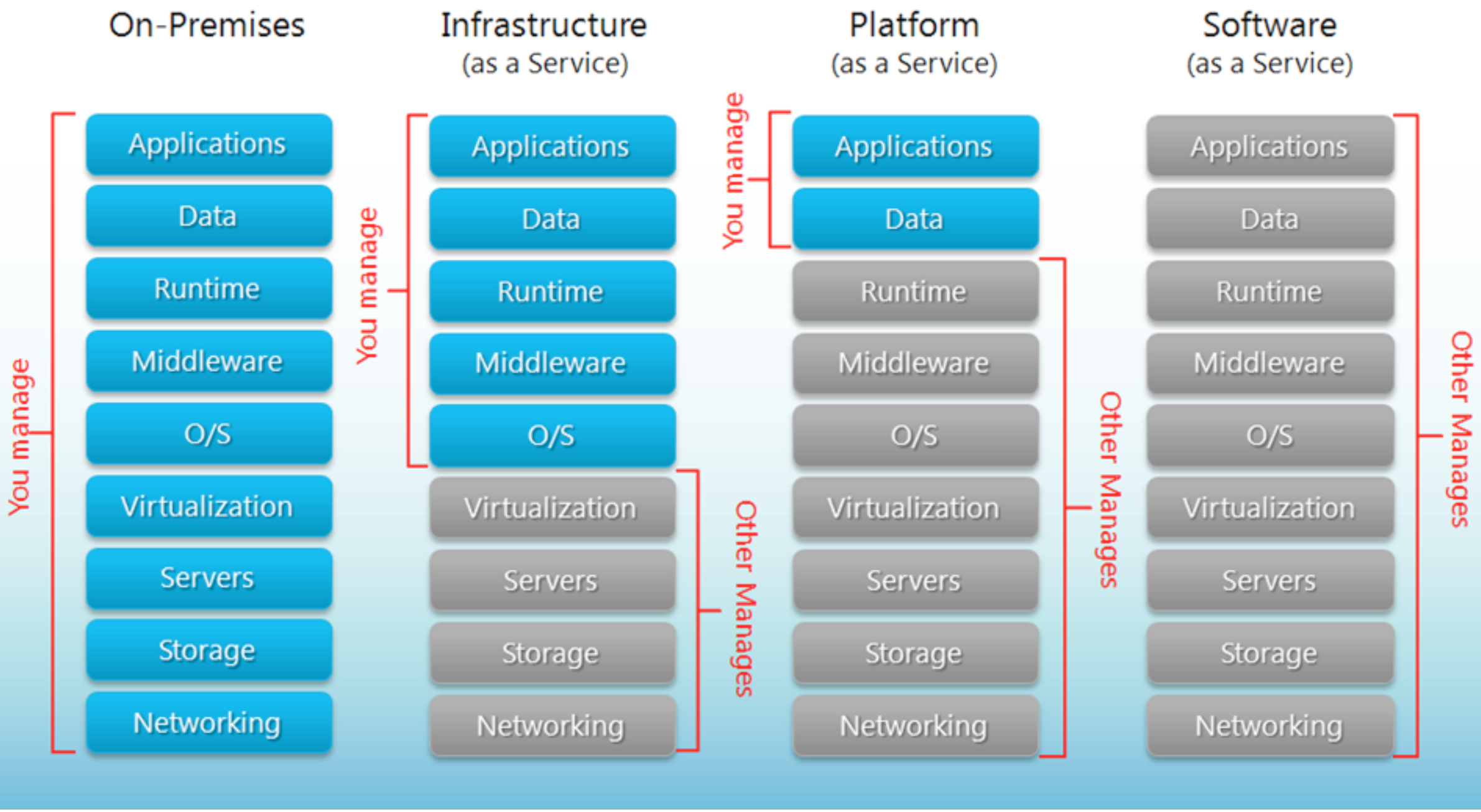
# IBM TrueNorth

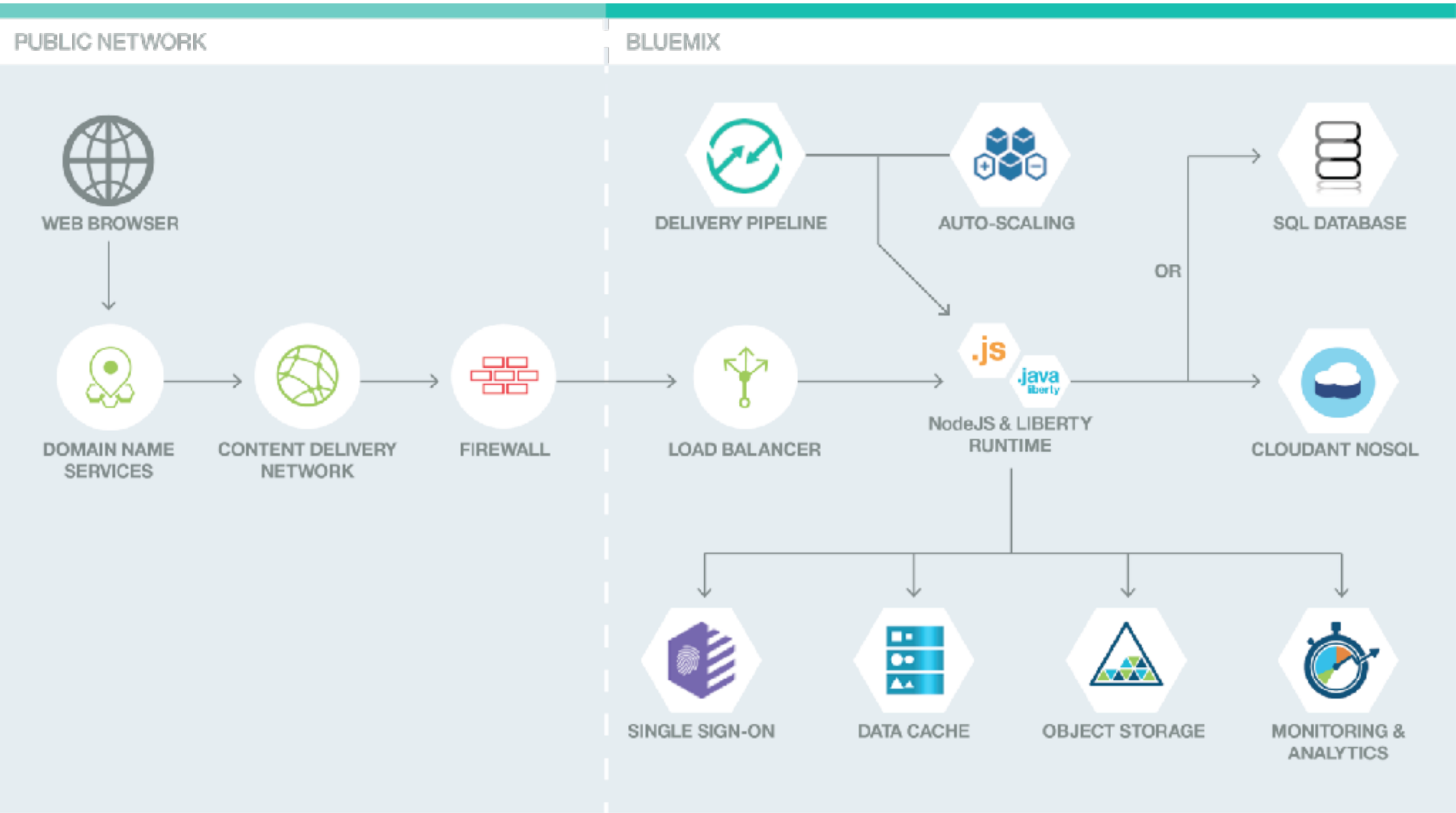
- Scalable
- Parallel
- Distributed
- Fault Tolerant
- No Clock ! :)
- IBM Cluster
  - 4.096 chips
  - 4 billion neurons
  - 1 trillion synapses
- Human Brain
  - 100 billion neurons
  - 100 trillion synapses

- 1.000.000 neurons
- 250.000.000 synapses



# Separation of Responsibilities




PUBLIC NETWORK
BLUEMIX
WEB BROWSER
DOMAIN NAME SERVICES
CONTENT DELIVERY NETWORK
FIREWALL
LOAD BALANCER
DELIVERY PIPELINE
AUTO-SCALING
SQL DATABASE
OR
.js
.java
liberty
NodeJS & LIBERTY RUNTIME
CLOUDANT NOSQL
SINGLE SIGN-ON
DATA CACHE
OBJECT STORAGE
MONITORING & ANALYTICS

| | Watson IoT | Watson Cognitive Services | Analytics |
|---|---|---|---|
| **Model + API** | Driver Behaviour | Personality Insights | |
| **Trainable Model + API** | IoT for Insurance | Visual Recognition | |
| **Customizable Model + API** | | | Watson Machine Learning |
| **Data Science Platform as a Service** | | | Data Science Experience |

# DeepLearning4J

# Components

- DeepLearning4J
  Enterprise Grade DeepLearning Library

- DataVec
  CSV/Audio/Video/Image/… => Vector

- ND4J / ND4S (NumPy for the JVM)

# ND4J

- Tensor support (Linear Buffer + Stride)
- Multiple implementations, one interface
  - vectorized c++ code (JavaCPP), off-heap data storage, BLAS (OpenBLAS, Intel MKL, cuBLAS)
  - GPU (CUDA 7.5)

# turn on GPU

```
<name>DeepLearning4j Examples Parent</name>
<description>Examples of training different data sets</description>
<properties>
    <nd4j.backend>nd4j-native-platform</nd4j.backend>
```

```
    <nd4j.backend>nd4j-cuda-7.5-platform</<nd4j.backend>
```

# DL4J parallelisation

- TensorFlow on ApacheSpark =>
  - Scoring
  - Multi-model hyper-parameter tuning
  - Parallel training since V r0.8
- DeepLearning4J =>
  - Scoring, Multi-model hyper-parameter tuning
  - Parallel training
    “Jeff Dean style parameter averaging”

"Code local vs spark"

```
new MultiLayerNetwork(conf);
```

vs.

```
new SparkDl4jMultiLayer(sc, conf, tm);
```

```
TrainingMaster tm = new ParameterAveragingTrainingMaster.Builder(int dataSetObjectSize)
        ... (your configuration here)
        .build();
```

# Demo

IoT / Industry / Predictive Maintenance Use Case

**Romeo Kienzler** @romeokienzler 11:19

@raver119 @agibsonccc One Q. Today evening in my talk I'm planning to state that DL4J is the only FW capable of training NN in Jeff Dean Style Parameter Averaging on ApacheSpark (+ GPU support +support for all sorts of NN topologies) Is this correct? IMHO TensorFrames doesn't support parallel Parameter Averaging , correct?

**Adam Gibson** @agibsonccc 11:19

yup

so tensorframes only allows ETL

The main thing it had going for it was the catalyst compiler for tensorflow ops

It *also* hasn't seem a commit since august

We also support configuring everything from a spark job

Tensorframes for their JNI support used javacpp (which we maintain)

So main differences: Community and Distributed

**Romeo Kienzler** @romeokienzler 11:23

Thanks a lot @agibsonccc

**Adam Gibson** @agibsonccc 11:23

sure 😃

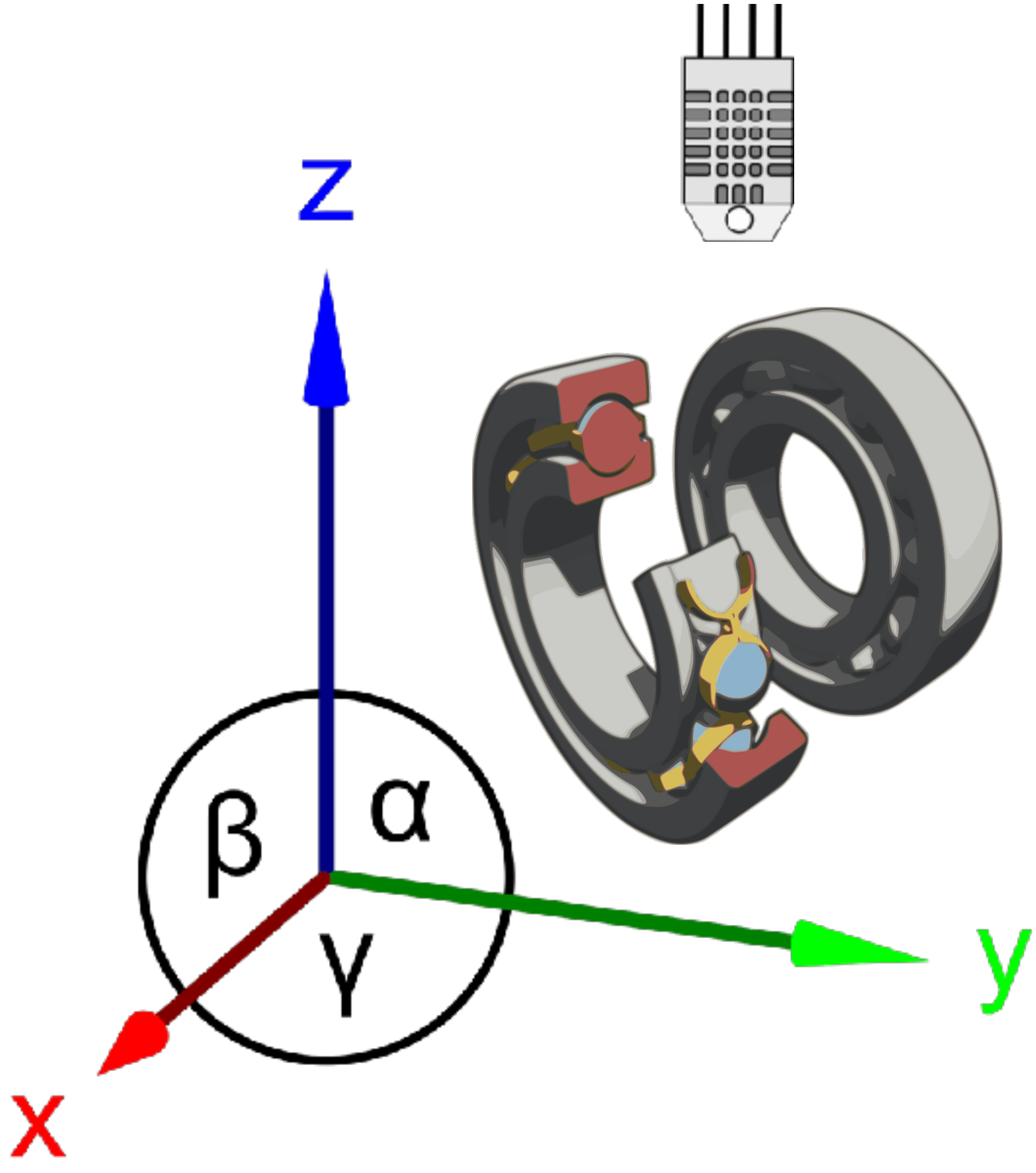
**Alex Black** @AlexDBlack 11:28

also tensorframes is based on dataframes, so no variable length data (images, time series etc) afaik

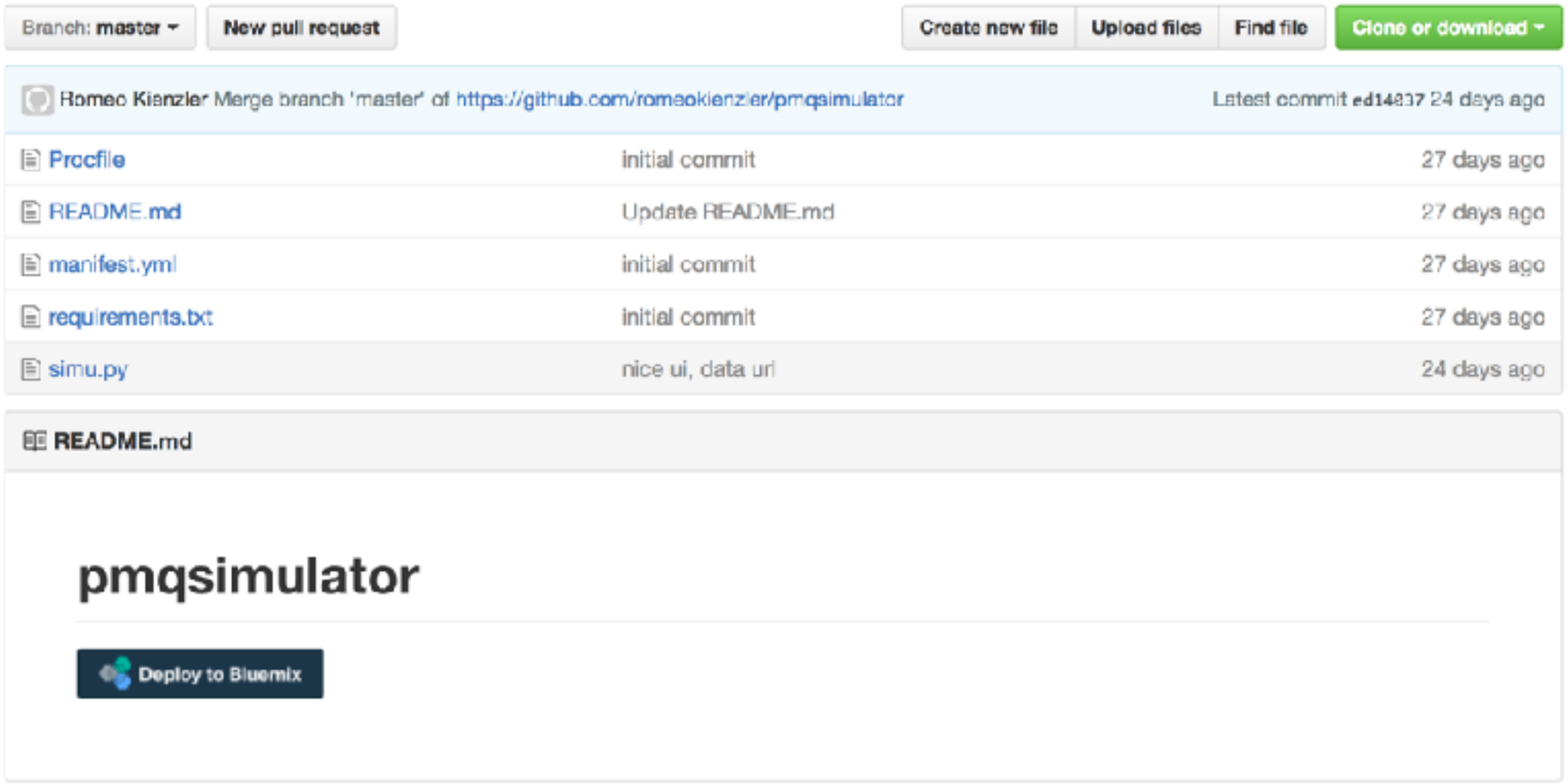
**Adam Gibson** @agibsonccc 11:44

right

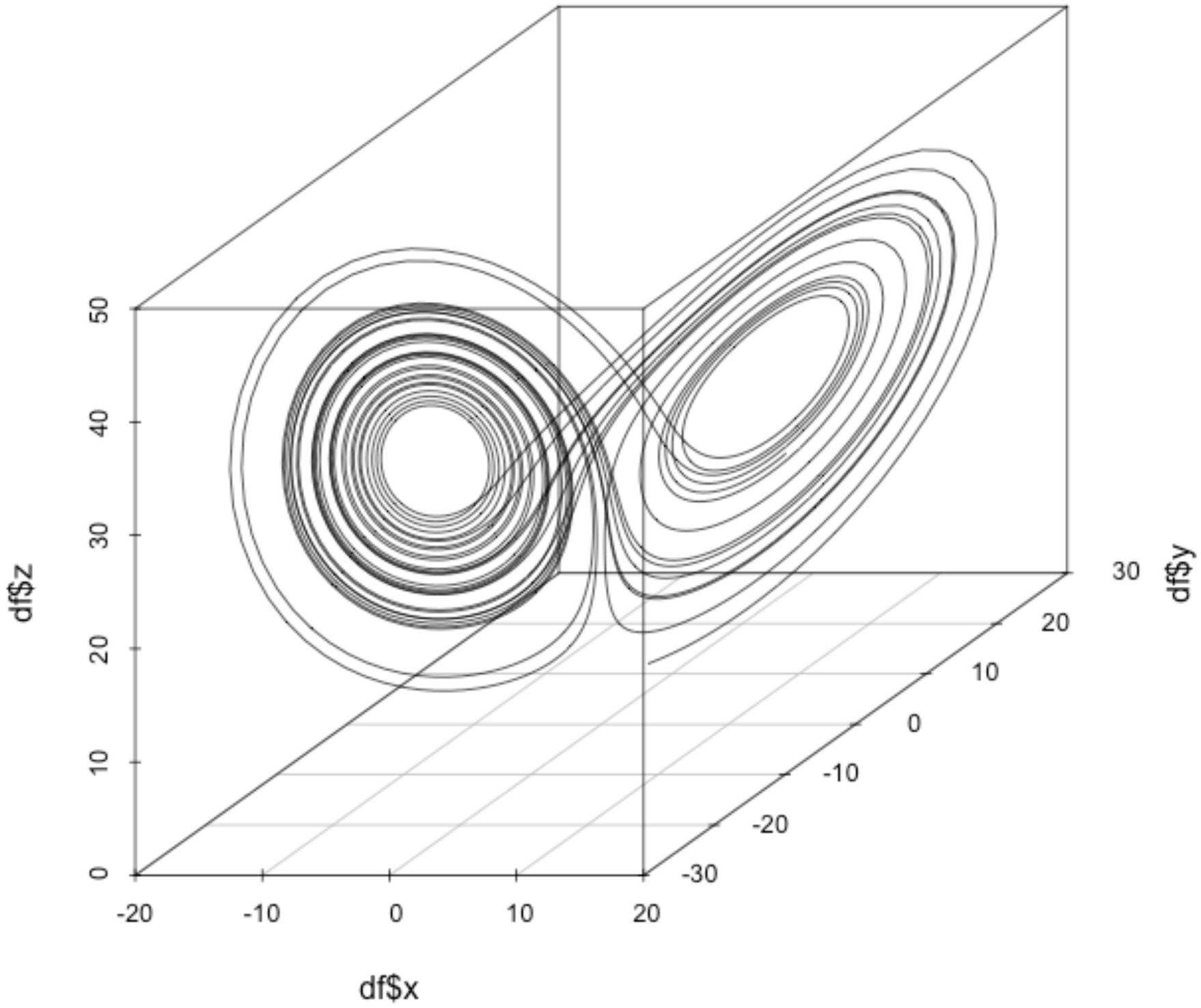
26 UNREAD

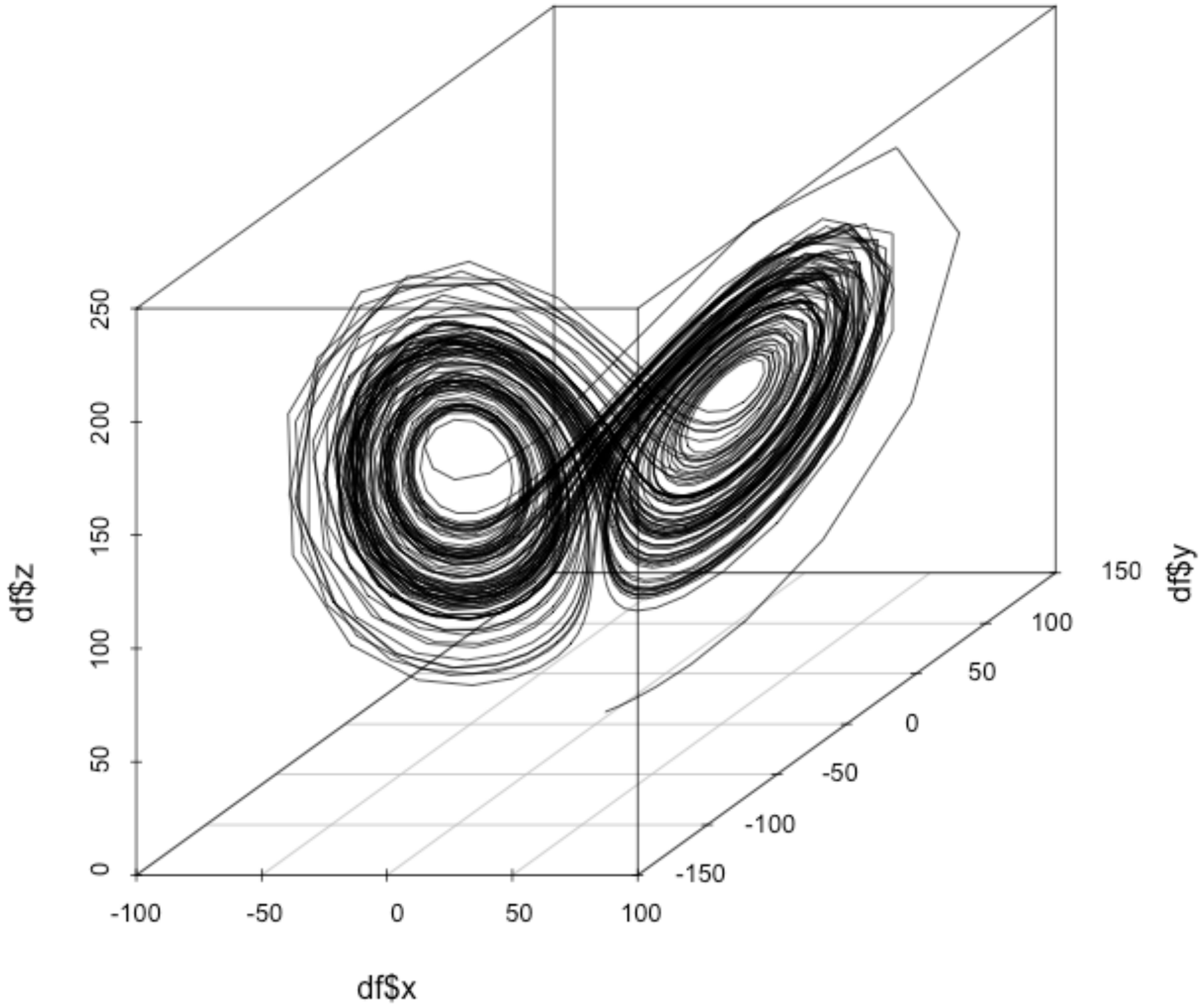

Z
β
α
γ
y
x

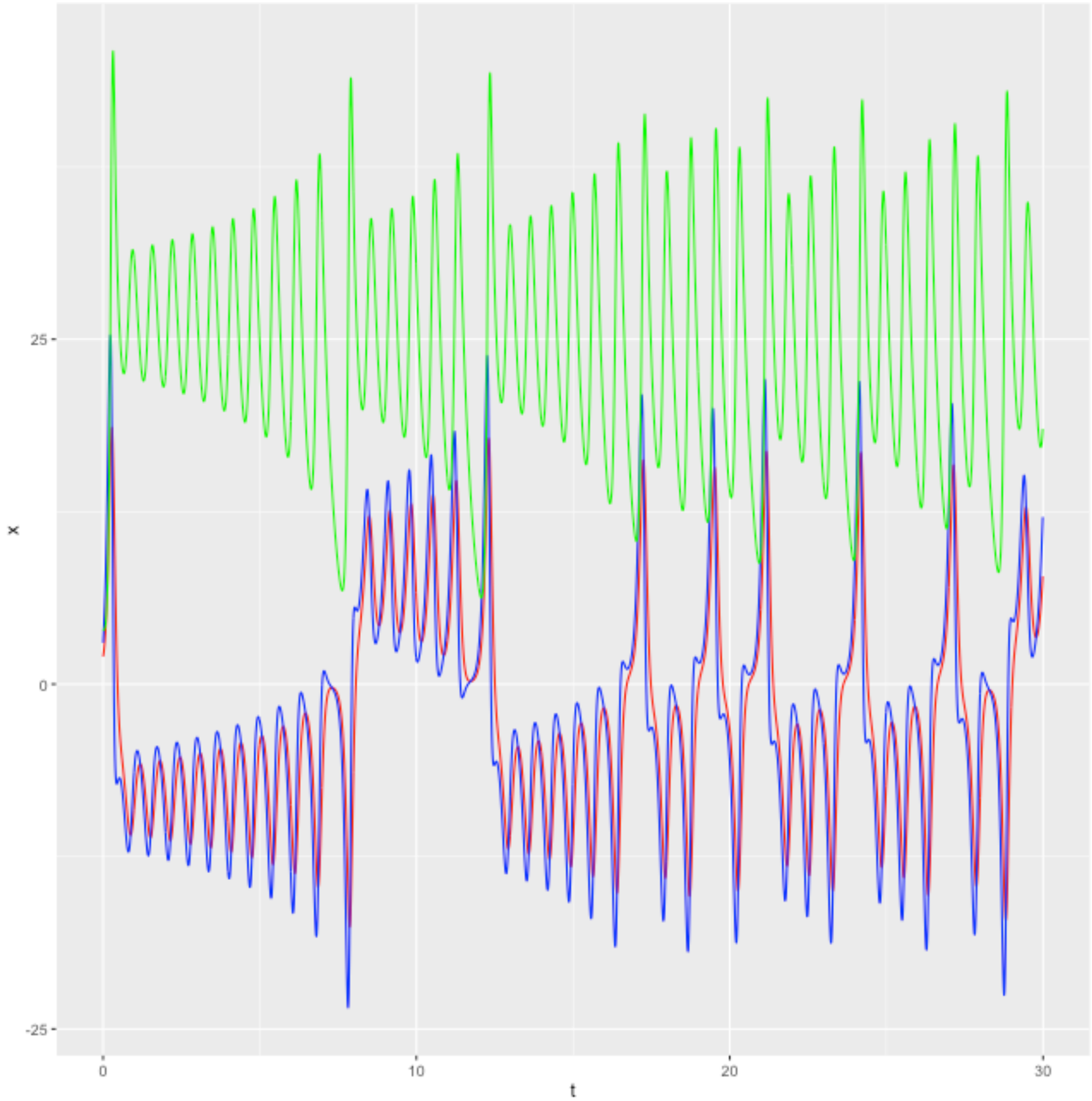
# data

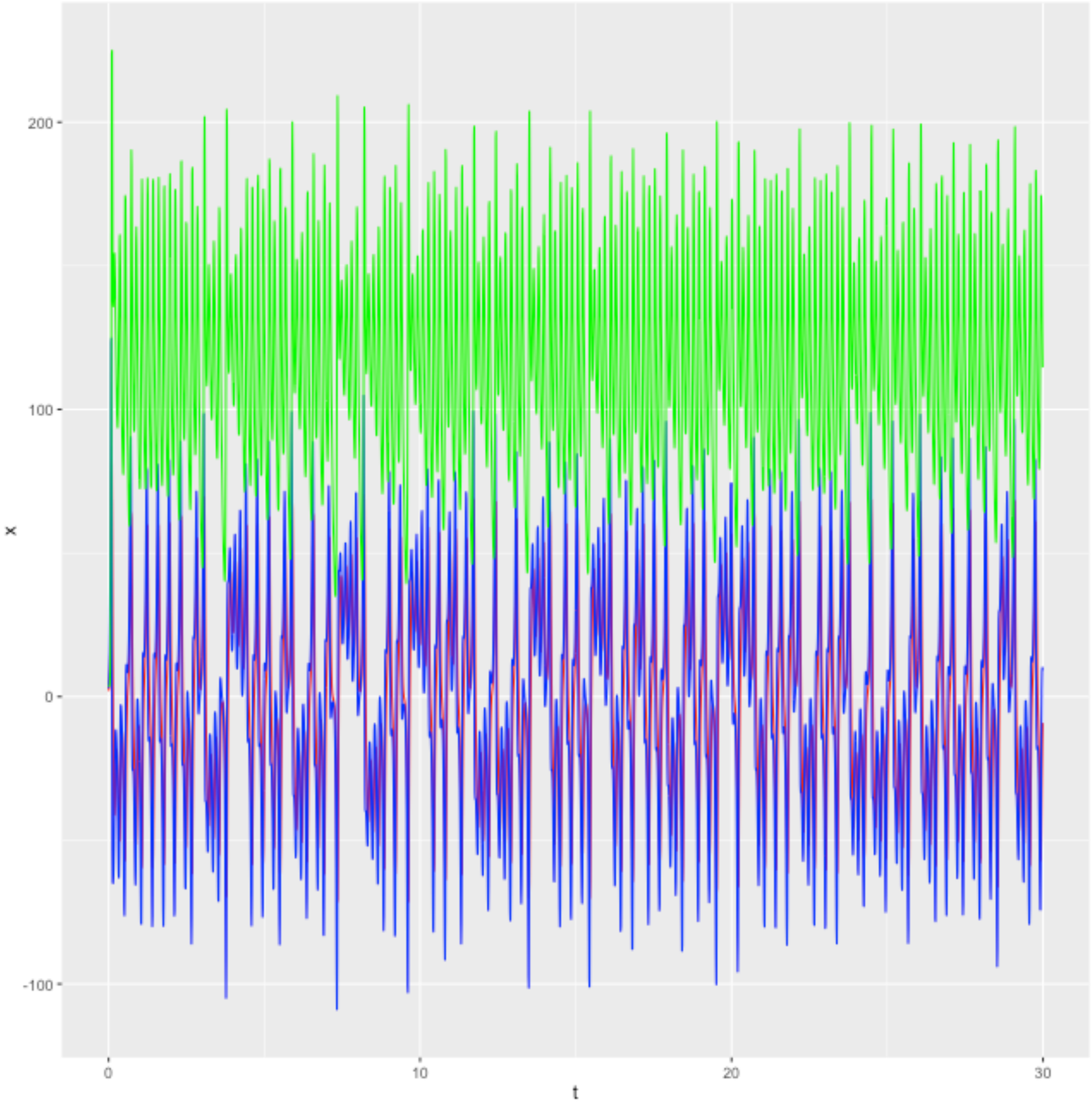


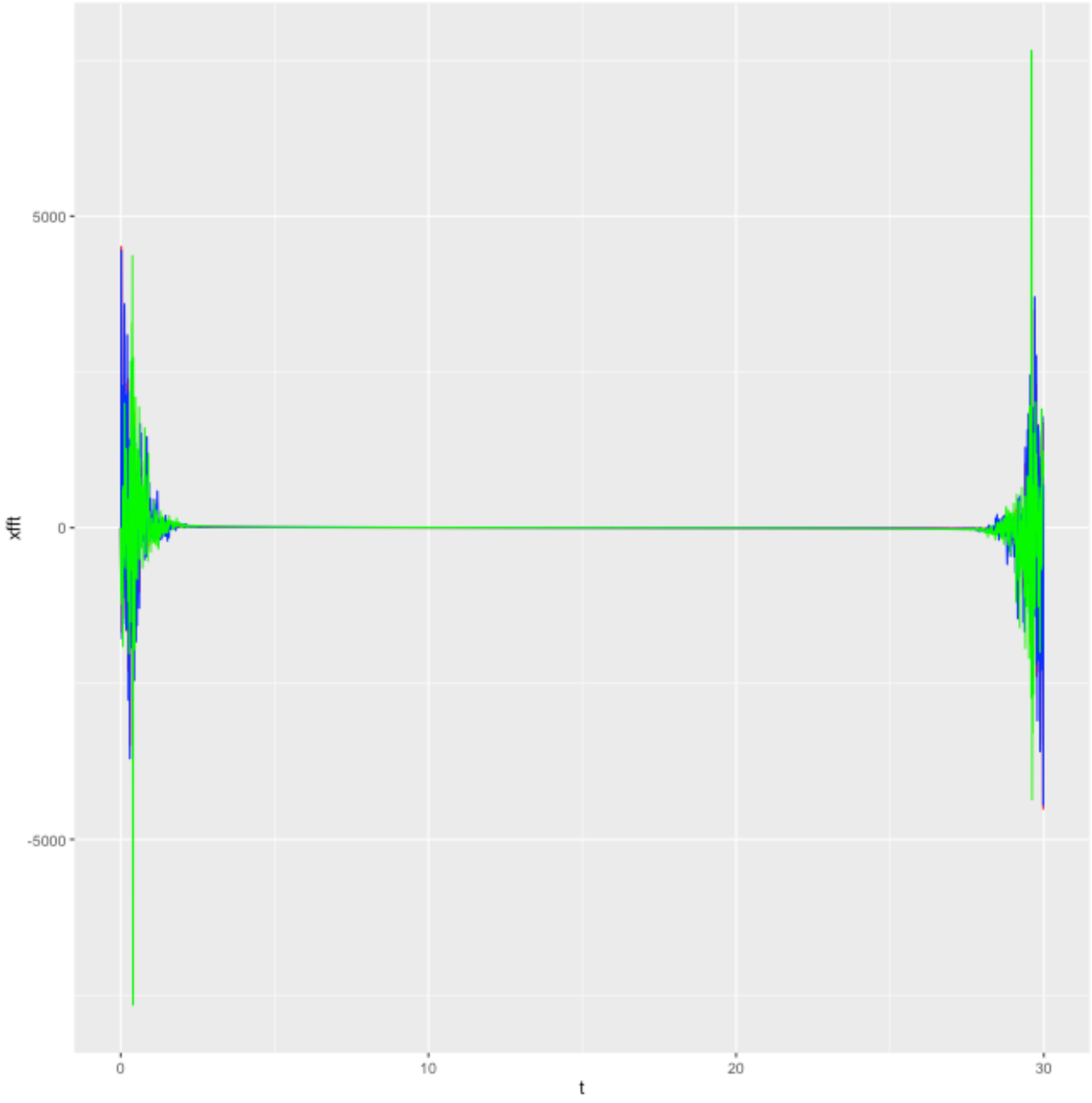

https://github.com/romeokienzler/pmqsimulator
https://ibm.biz/joinIBMCloud

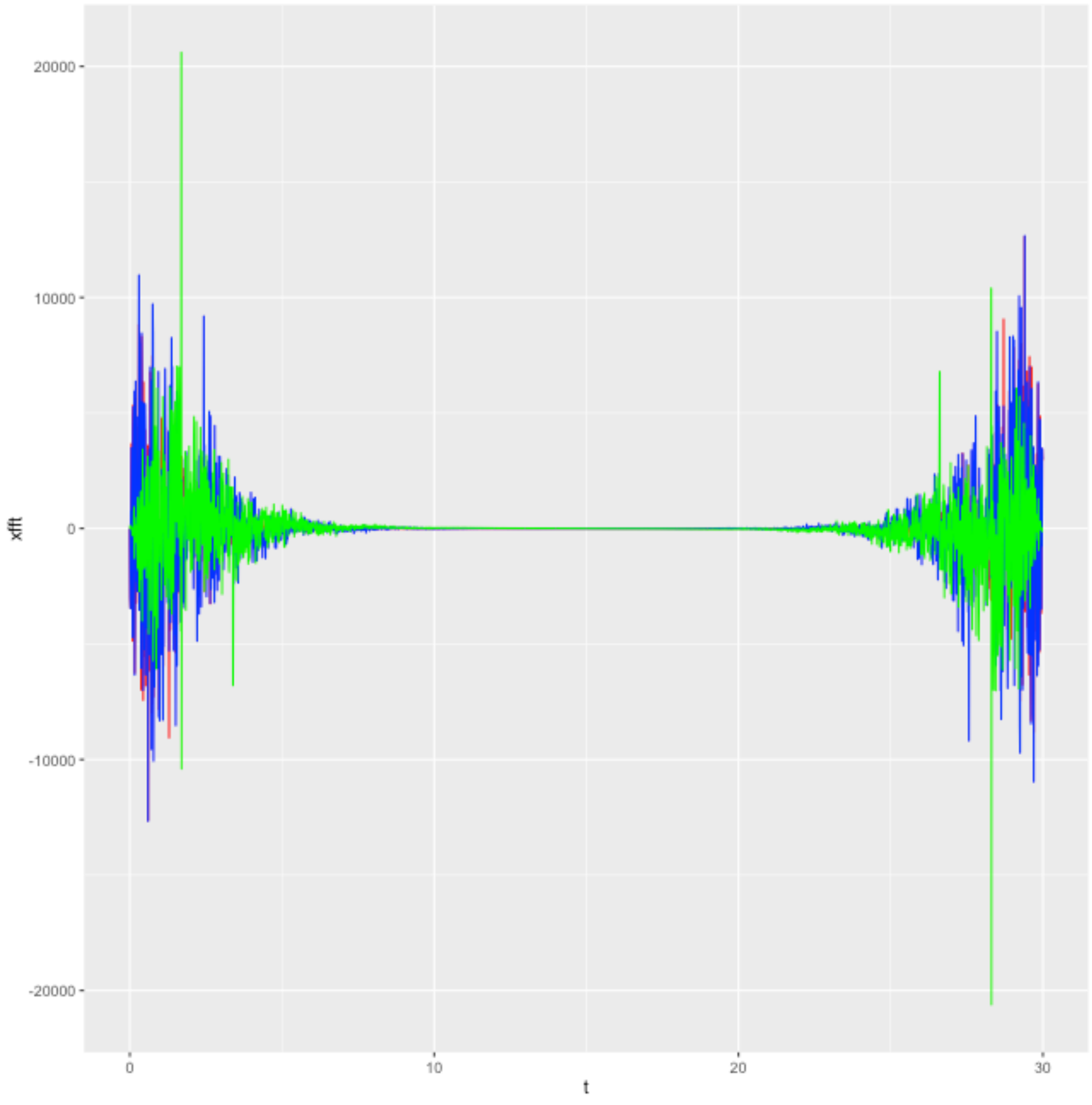

df$z
50
40
30
20
10
0
-20
-10
0
10
20
df$x
30
20
10
0
-10
-20
-30
df$y

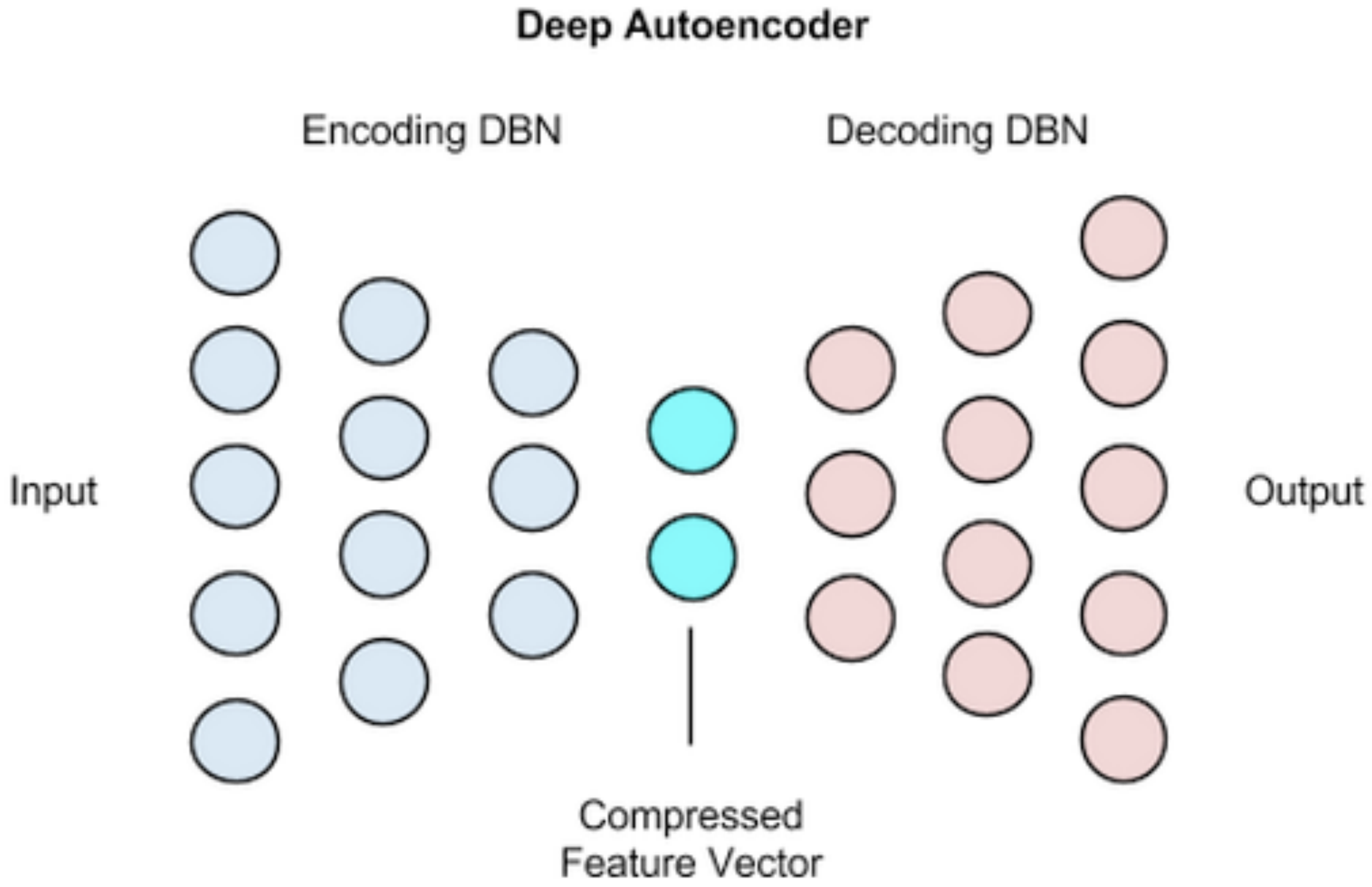

df$z
250
200
150
100
50
0
-100
-50
0
50
100
df$x
150
100
50
0
-50
-100
-150
df$y


25
0
-25
x
0
10
20
30
t


200
100
0
-100
x
0
10
20
30
t


5000
0
-5000
xfft
0
10
20
30
t


20000
10000
0
-10000
-20000
xfft
0
10
20
30
t


Deep Autoencoder
Encoding DBN
Decoding DBN
Input
Output
Compressed
Feature Vector