FluCoMa

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FluCoMa: Fluid Corpus Manipulation

- “*enable techno-fluent musicians to use machine listening and machine learning in their creative practices*”
- Integrating Machine Listening and Machine Learning in…
- Max, SuperCollider & Pure Data
- Learning Resources (learn.flucoma.org)
- Discourse Community (discourse.flucoma.org)

Ted Moore, (James Bradbury, Owen Green, Jacob Hart, Gerard Roma, & Pierre Alexandre Tremblay)
University of Huddersfield | UK

FluCoMa: Fluid Corpus Manipulation

Slice Audio
- onset slice
- transient slice
- novelty slice
- amplitude slice
- amplitude gate

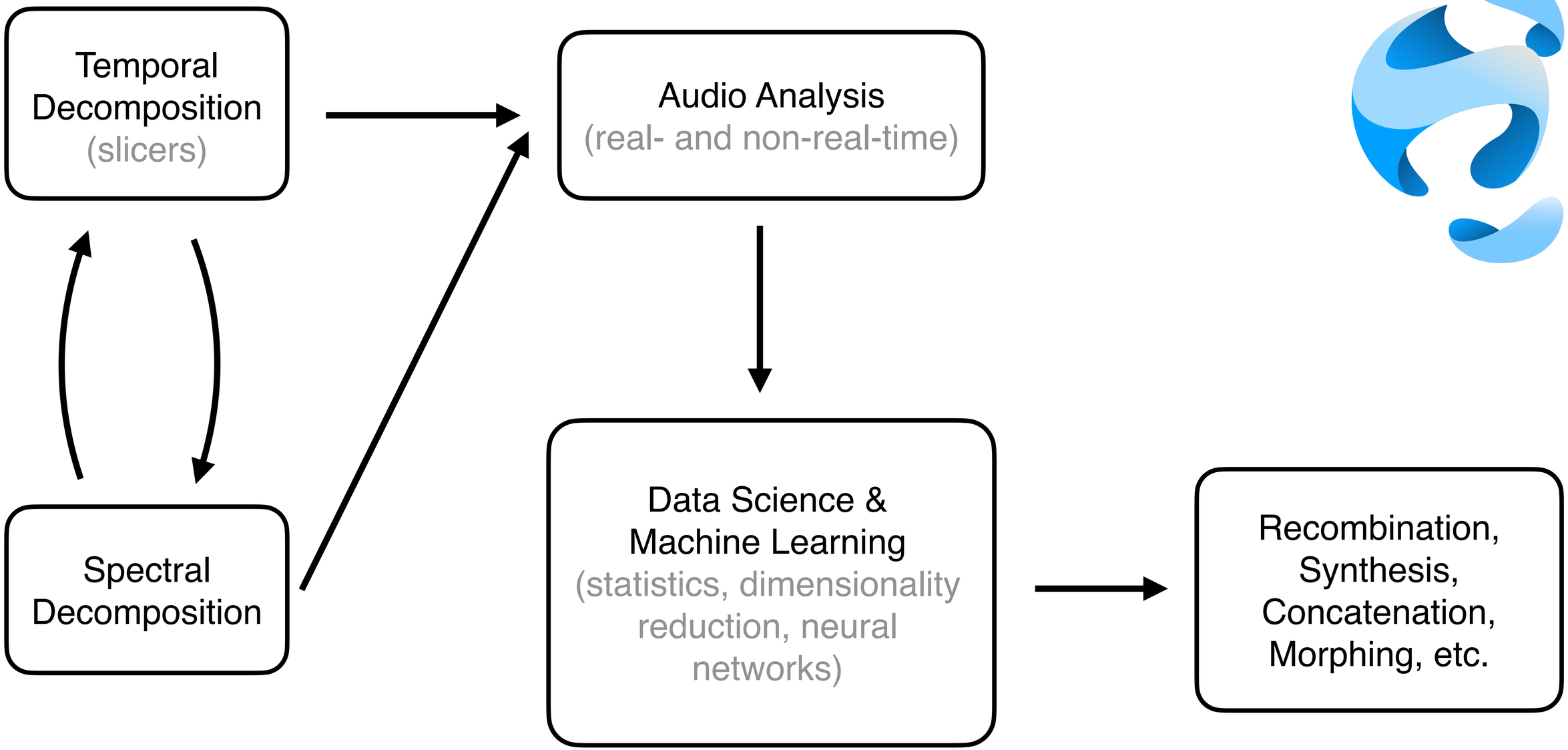
Decompose Audio
- extract transients
- harmonic/percussive separation
- model as sine waves
- non-negative matrix factorisation

Analyse Audio
- pitch
- loudness
- mel-bands
- mel-frequency cepstral coefficients
- spectral centroid
- spectral flatness
- chromagram

Transform Audio
- audio transport
- non-negative matrix factorisation filters & morphing

Analyse Data
- datasets
- labelsets
- statistical analyses
- normalization
- standardization
- robust scaler
- principal component analysis
- MDS
- KDTree
- K Nearest Neighbours
- neural networks
- SQL-type query
- KMeans
- UMAP
- grid

… and more


Temporal Decomposition (slicers)
Audio Analysis (real- and non-real-time)
Spectral Decomposition
Data Science & Machine Learning (statistics, dimensionality reduction, neural networks)
Recombination, Synthesis, Concatenation, Morphing, etc.

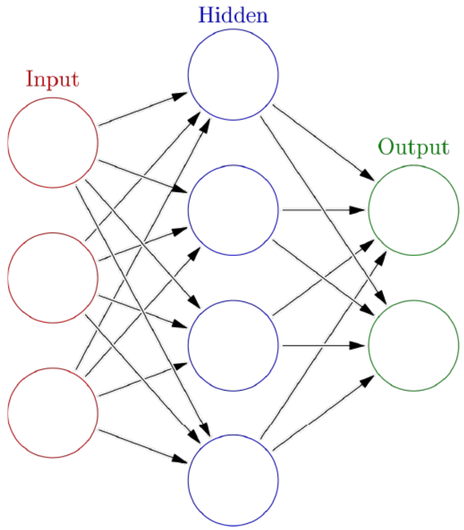
MLPRegressor

control *many* synthesizer parameters from a smaller control space

fluid.mlpregressor~

Neural Network *Training a Regressor*

identifier	input examples		output examples
“a”:	[0.1, 0.5, 1]	→	[0.5, 0.7]
“b”:	[0, 1, 1]	→	[0.1, 0.1]
“c”:	[1, 0, 1]	→	[0.5, 0.6]
“d”:	[0.2, 0, 1]	→	[0.3, 0.9]
“e”:	[0, 0, 0.5]	→	[0.4, 0]
“f”:	[0.8, 0.2, 1]	→	[0.2, 0.7]
“g”:	[0.9, 0.3, 0]	→	[0.5, 0.6]
“h”:	[0.4, 1, 0.7]	→	[0.6, 0.1]
“i”:	[0.2, 0.3, 1]	→	[0.5, 0.3]
“j”:	[0.1, 1, 0.1]	→	[0.5, 0.7]
“k”:	[0, 1, 1]	→	[0.1, 0.8]
“l”:	[0, 1, 1]	→	[0.5, 0.1]
“m”:	[0, 0, 1]	→	[0.4, 0.2]
“n”:	[0, 0, 1]	→	[0.1, 0.8]



Neural Network *Training a Regressor*

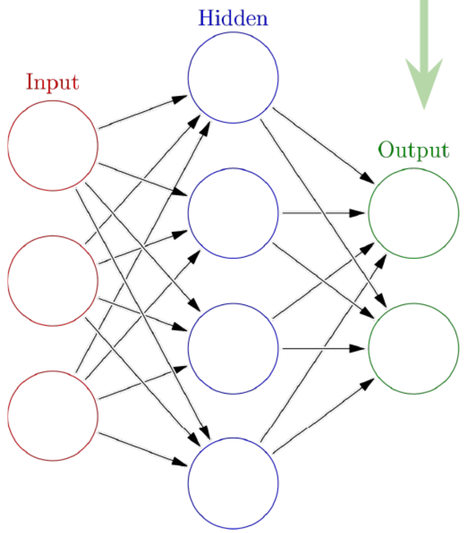
identifier

input examples

output examples

"please return these output values"

"when I input these values…"



Makes a guess on every example and determines how it was wrong. Improves a bit every time.

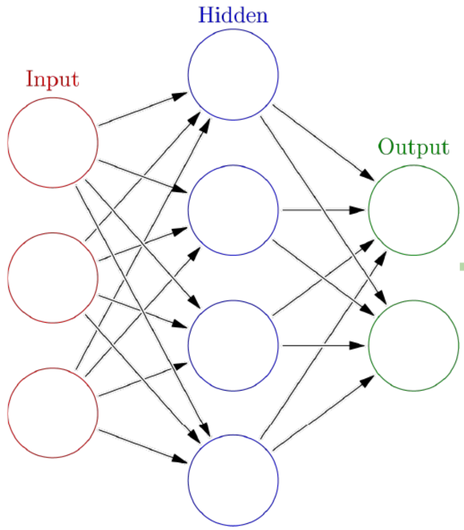
Neural Network *Predicting with Regression*

input examples

output examples

“here are some values you’ve maybe never seen before”

[0.6, 0.2, 0.4]



“here’s an output that would ‘fit’ in your training data”

[0.9, 0.8]

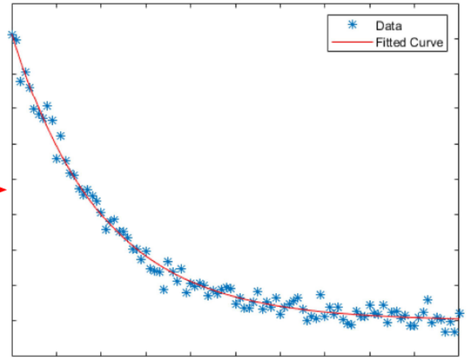
Neural Network *Predicting with Regression*

input examples

output examples

"here are some values you've maybe never seen before"

[0.6, 0.2, 0.4]



"here's an output that would 'fit' in your training data"

[0.9, 0.8]

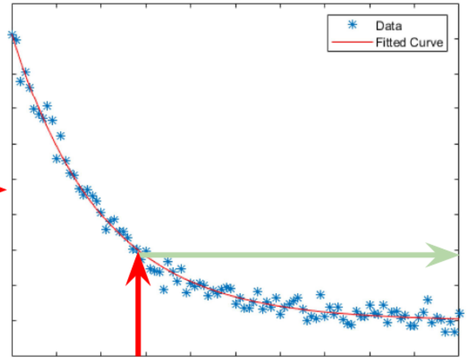
Neural Network *Predicting with Regression*

input examples

output examples

"here are some values you've maybe never seen before"

[0.6, 0.2, 0.4]



"here's an output that would 'fit' in your training data"

[0.9, 0.8]

Neural Network *Predicting with Regression*

"a": [0.1, 0.5, 1]
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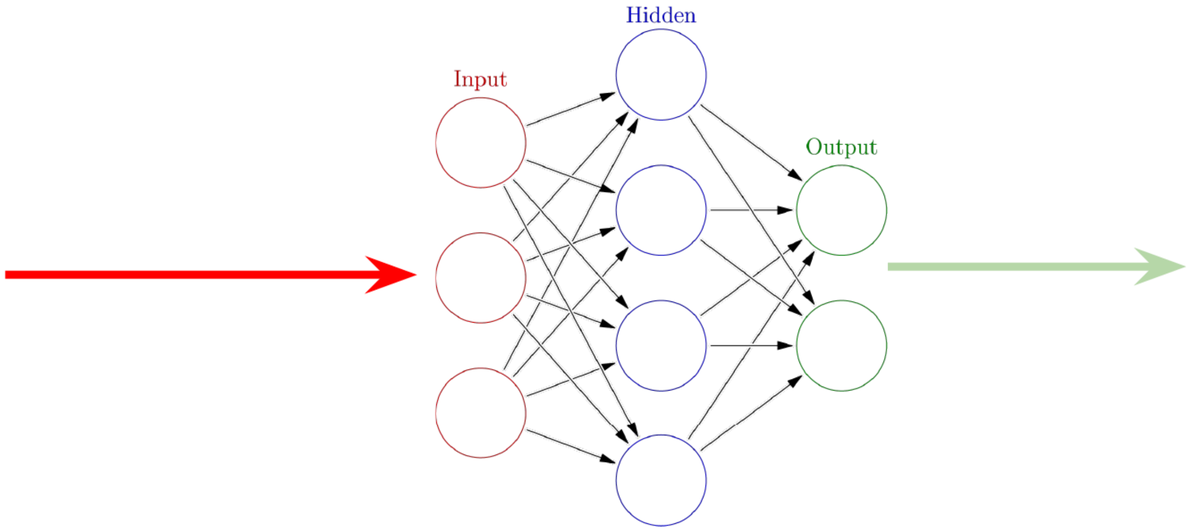
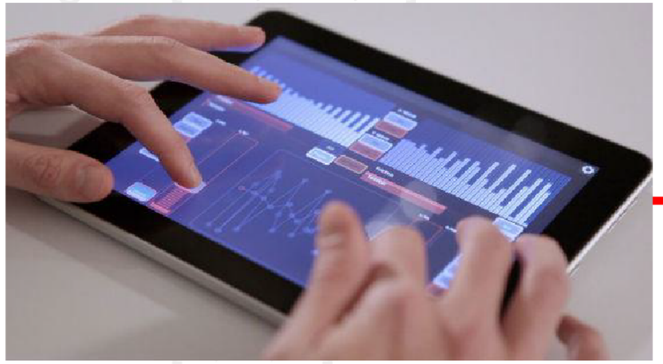
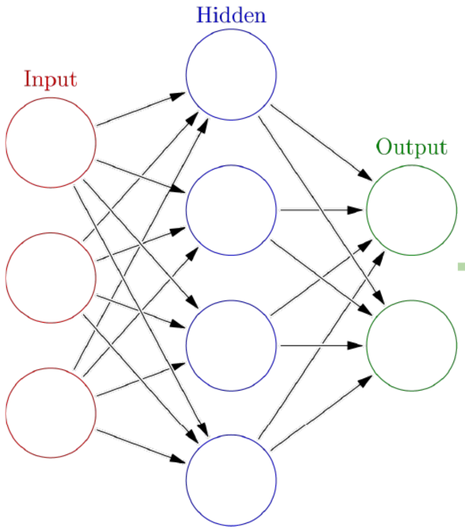
"d": [0.2, 0, 1]
"e": [0, 0, 0.5]
"f": [0.8, 0.2, 1]
"g": [0.9, 0.3, 0]
"h": [0.4, 1, 0.7]
"i": [0.2, 0.3, 1]
"j": [0.1, 1, 0.1]
"k": [0, 1, 1]
"l": [0, 1, 1]
"m": [0, 0, 1]
"n": [0.4, 1, 0.7]
"o": [0.2, 0.3, 1]
"p": [0.1, 1, 0.1]
"q": [0, 1, 1]
"r": [0, 1, 1]

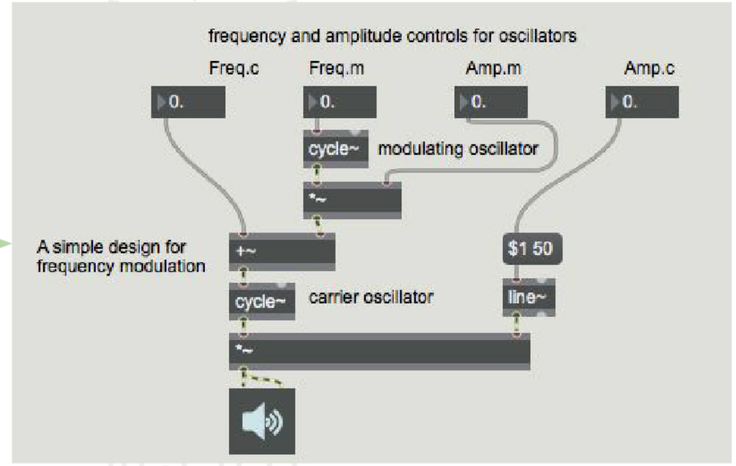


[0.5, 0.7]
[0.1, 0.1]
[0.5, 0.6]
[0.3, 0.9]
[0.4, 0]
[0.2, 0.7]
[0.5, 0.6]
[0.6, 0.1]
[0.5, 0.3]
[0.5, 0.7]
[0.1, 0.8]
[0.5, 0.1]
[0.4, 0.2]
[0.1, 0.8]
[0.5, 0.6]
[0.3, 0.9]
[0.4, 0.3]
[0.2, 0.7]

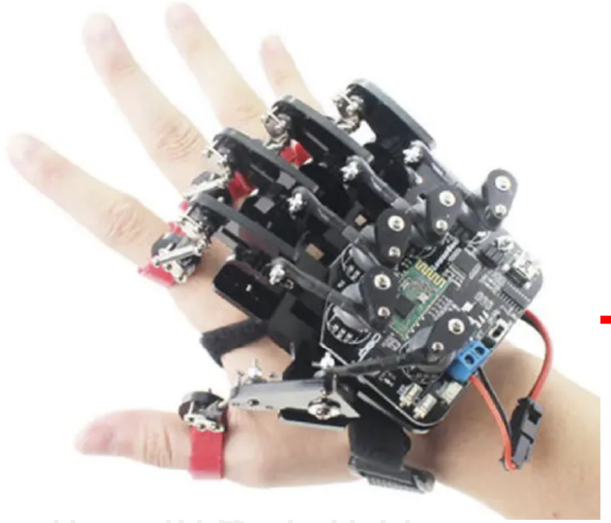
Neural Network *Predicting with Regression*

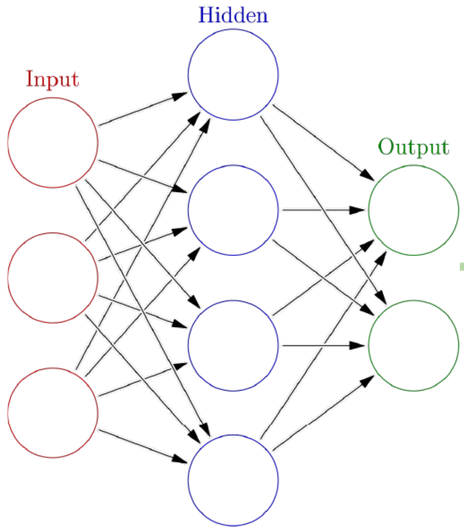


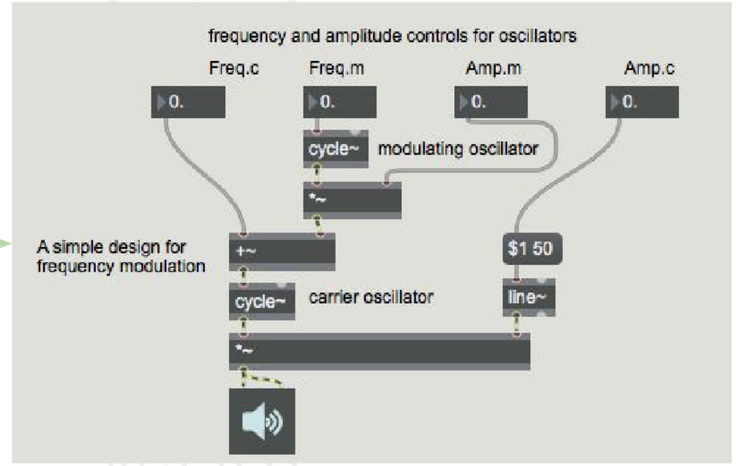




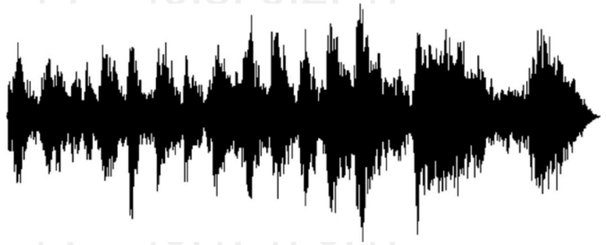
Neural Network *Predicting with Regression*



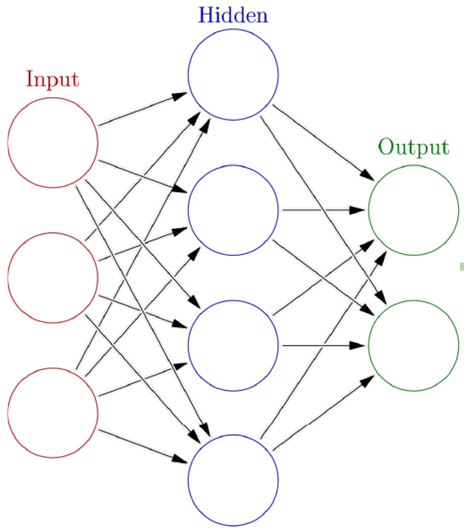


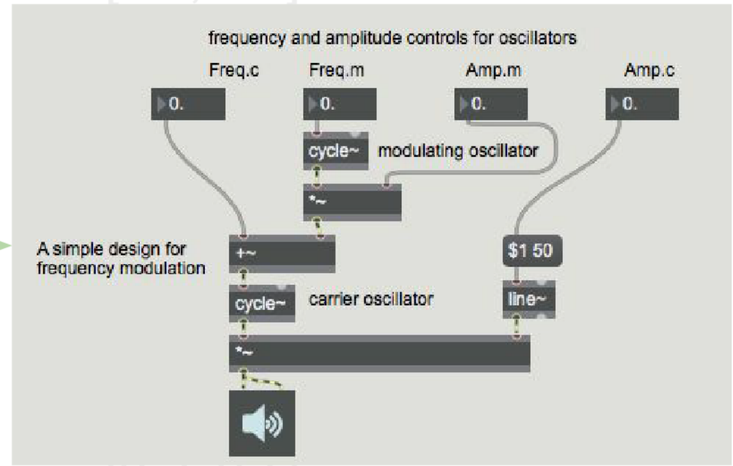


Neural Network *Predicting with Regression*

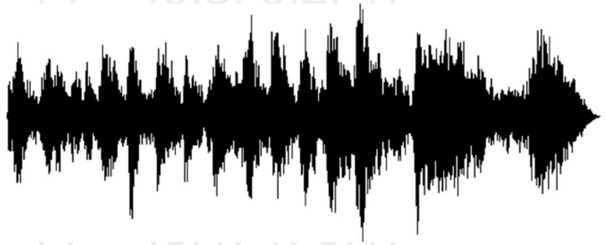


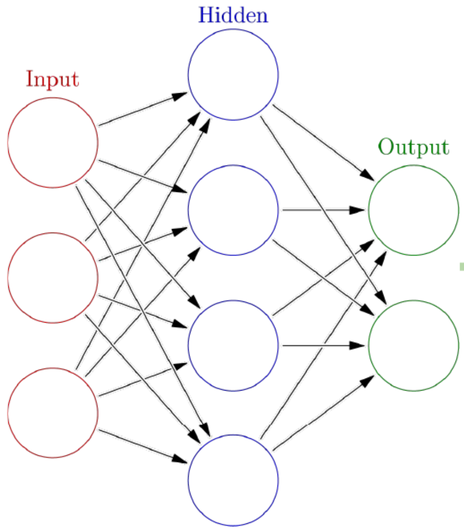
e.g.:
pitch
loudness
spectral centroid
spectral flatness





Neural Network *Predicting with Regression*





Neural Network *Predicting with Regression*

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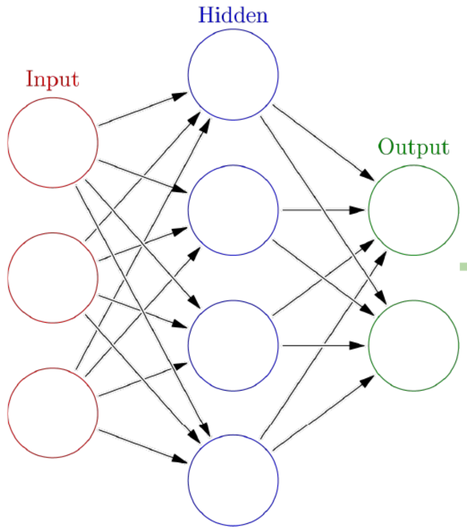
“o”: [0.2, 0.3, 1]
“p”: [0.1, 1, 0.1]
“q”: [0, 1, 1]
“r”: [0, 1, 1]

?



?

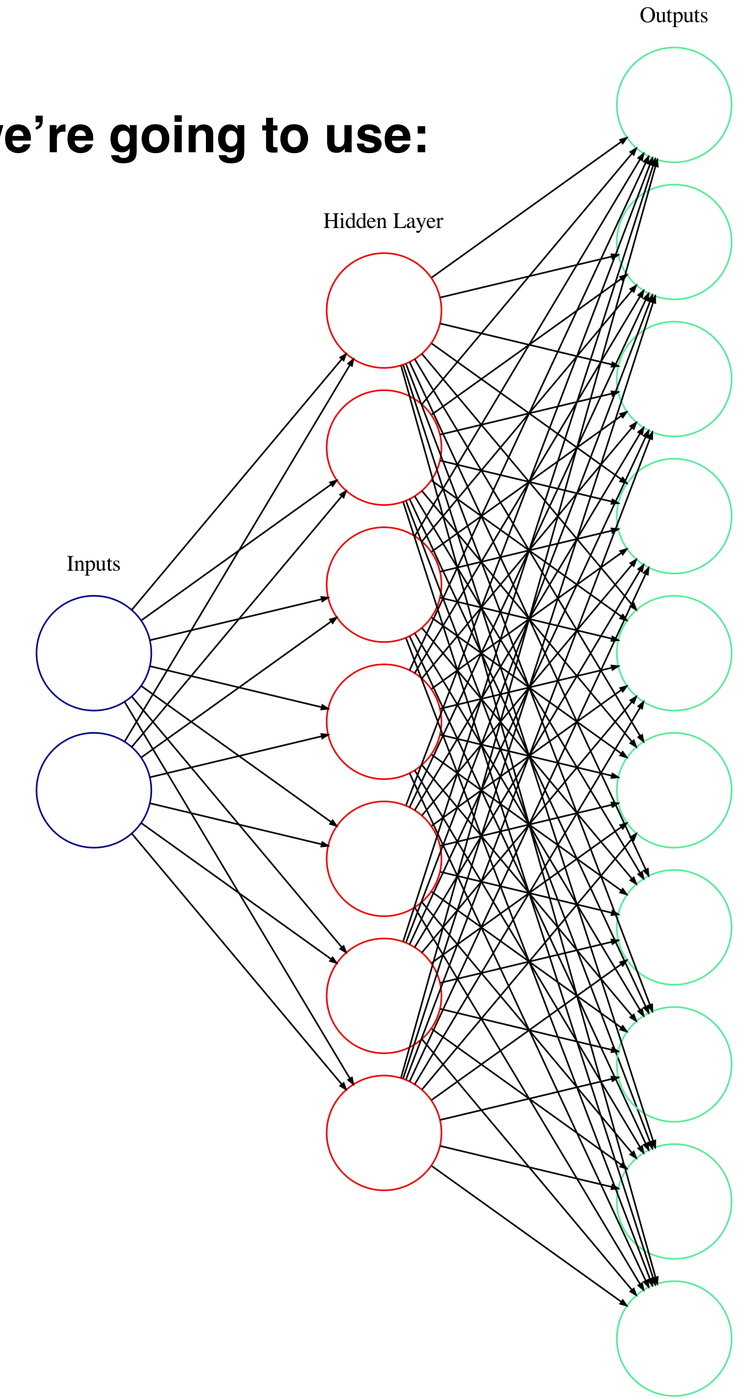
[0.5, 0.7]
[0.1, 0.1]
[0.5, 0.6]
[0.3, 0.9]
[0.4, 0]
[0.2, 0.7]
[0.5, 0.6]
[0.5, 0.7]
[0.1, 0.1]
[0.5, 0.6]
[0.2, 0.7]
[0.6, 0.1]
[0.5, 0.3]
[0.5, 0.7]
[0.1, 0.8]
[0.5, 0.1]
[0.4, 0.2]
[0.1, 0.8]

Structure of the neural network we're going to use:

2 inputs

1 hidden layer of 7 nodes

10 outputs



fluid.mlpregressor~

There are certain things that we care about, as musicians for example, that are really hard to articulate in code. It's hard for me to talk about what kind of quality of sound I want and then translate that into a set of filter coefficients. It's hard for me to talk about how I want a performer to move on stage and then translate that into some sort of mathematical equation for their trajectory. But it's a lot easier for me to either find examples of sounds that have a particular quality or to give examples of movements or if I'm using other types of modalities, often curating or creating examples are just way easier for us as people. And this relates to the types of tacit knowledge and embodied knowledge we bring to creative practices.

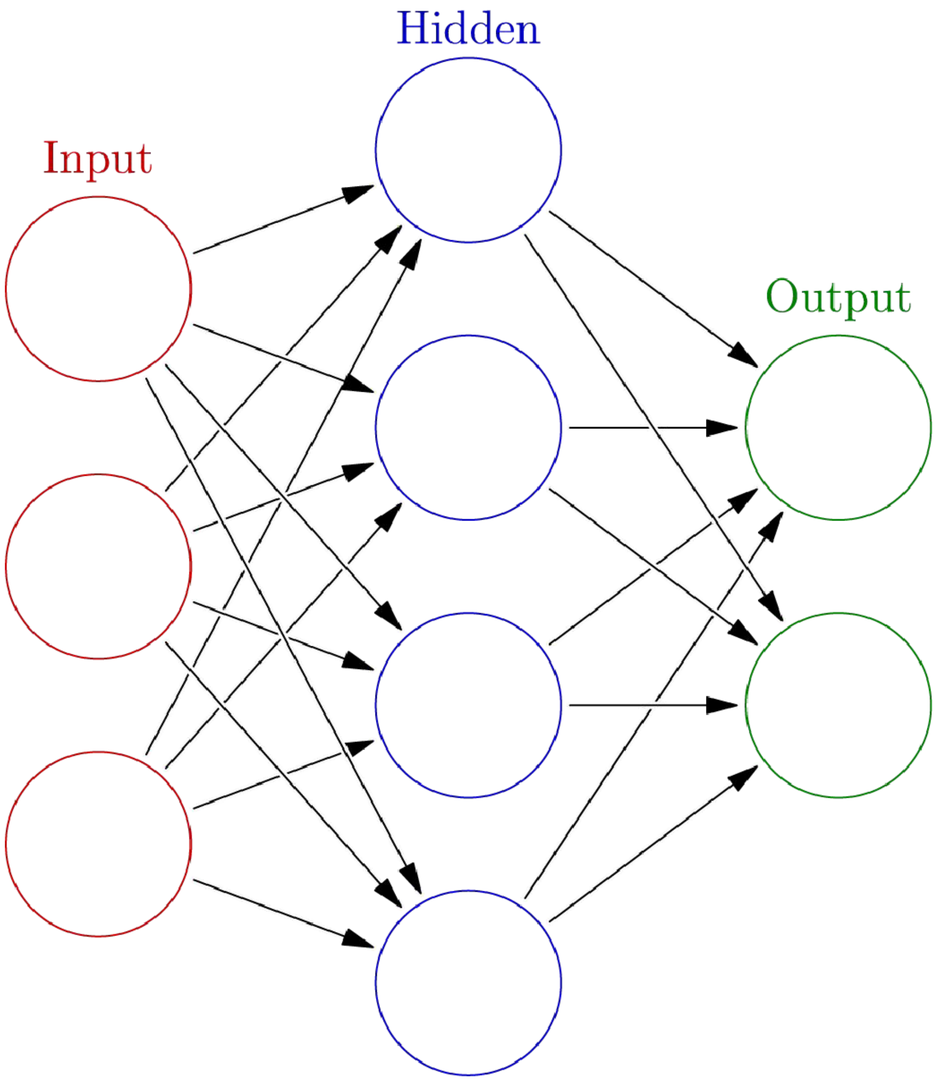
-Rebecca Fiebrink

CeReNeM. 2019. Rebecca Fiebrink: Machine Learning as Creative Design Tool. Centre for Research in New Music. YouTube. Visited on 11/23/2020. https://www.youtube.com/watch?v=Qo6n8MuEgdQ.

FluidMLPClassifier

classify sounds by timbre in real-time

Neural Network (Multi-Layer Perceptron)

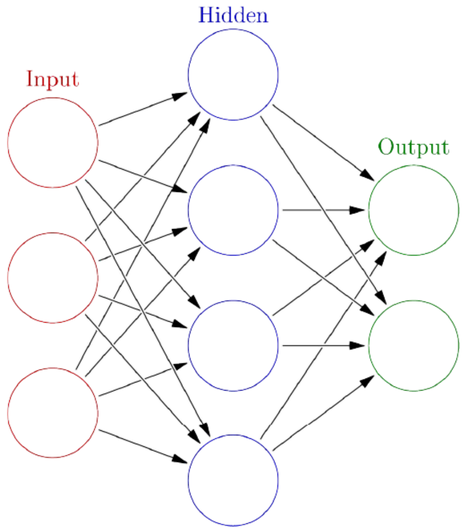


<u>Classification:</u>
a neural network predicts

which category (or “class”) an input belongs to

Neural Network *Training a Classifier*

trombone examples	oboe examples



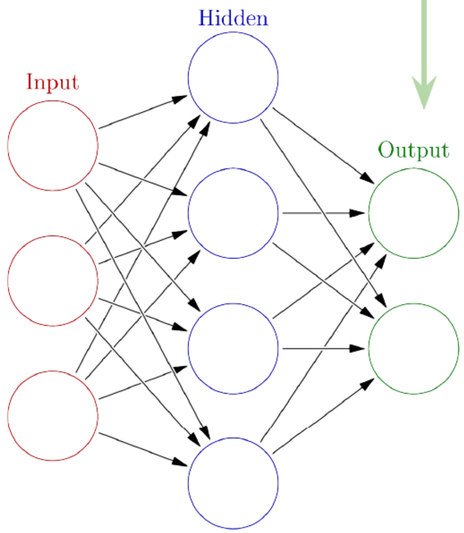
Neural Network *Training a Classifier*

trombone examples

oboe examples

"this example is a trombone"

audio analysis of example (e.g., pitch, brightness, noisiness)



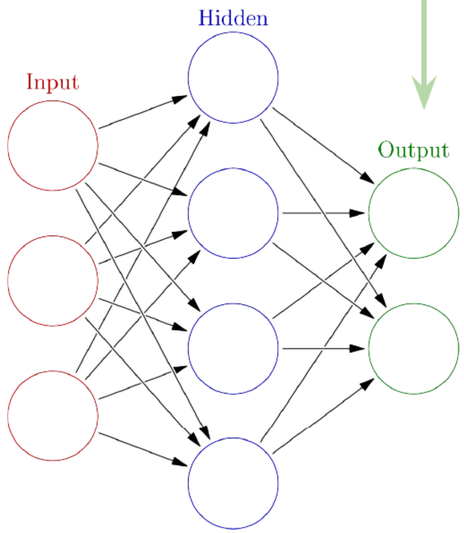
Neural Network *Training a Classifier*

trombone examples

oboe examples

"this example is an oboe"

audio analysis of example (e.g., pitch, brightness, noisiness)



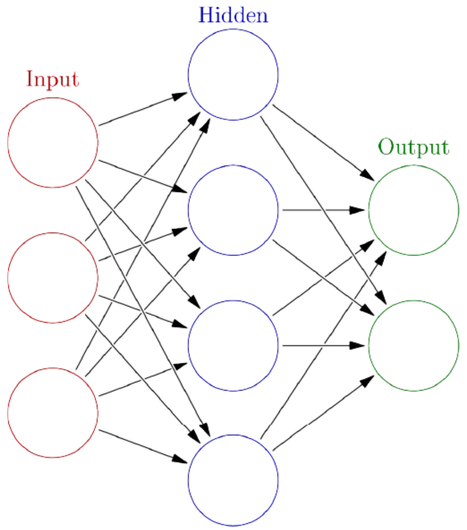
Neural Network *Predicting a Classification*

trombone examples

oboe examples

new example it has never seen before

audio analysis of example (e.g., pitch, brightness, noisiness)



“this new example is most like the oboe examples you showed me before”

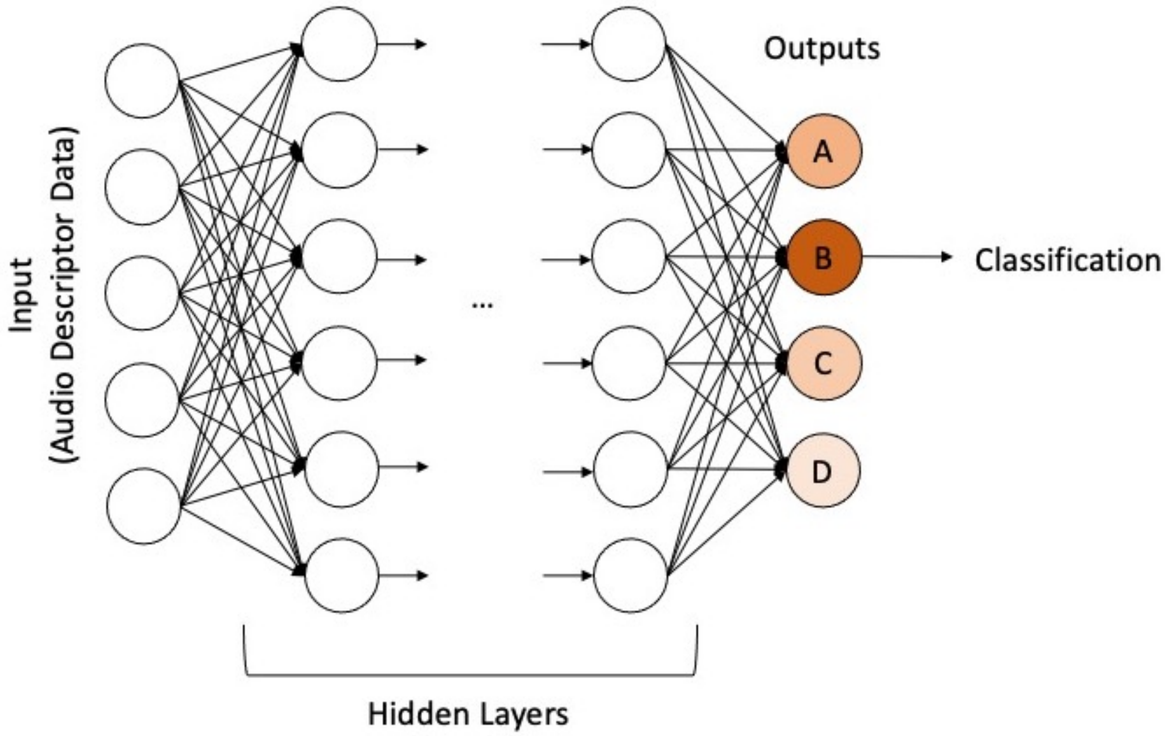
(or trombone…)

fluid.mlpclassifier~

fluid.mlpclassifier~

validation

- **overfitting**
  - excellent on training data, poor on anything else
- **underfitting**
  - poor on everything…keep training!

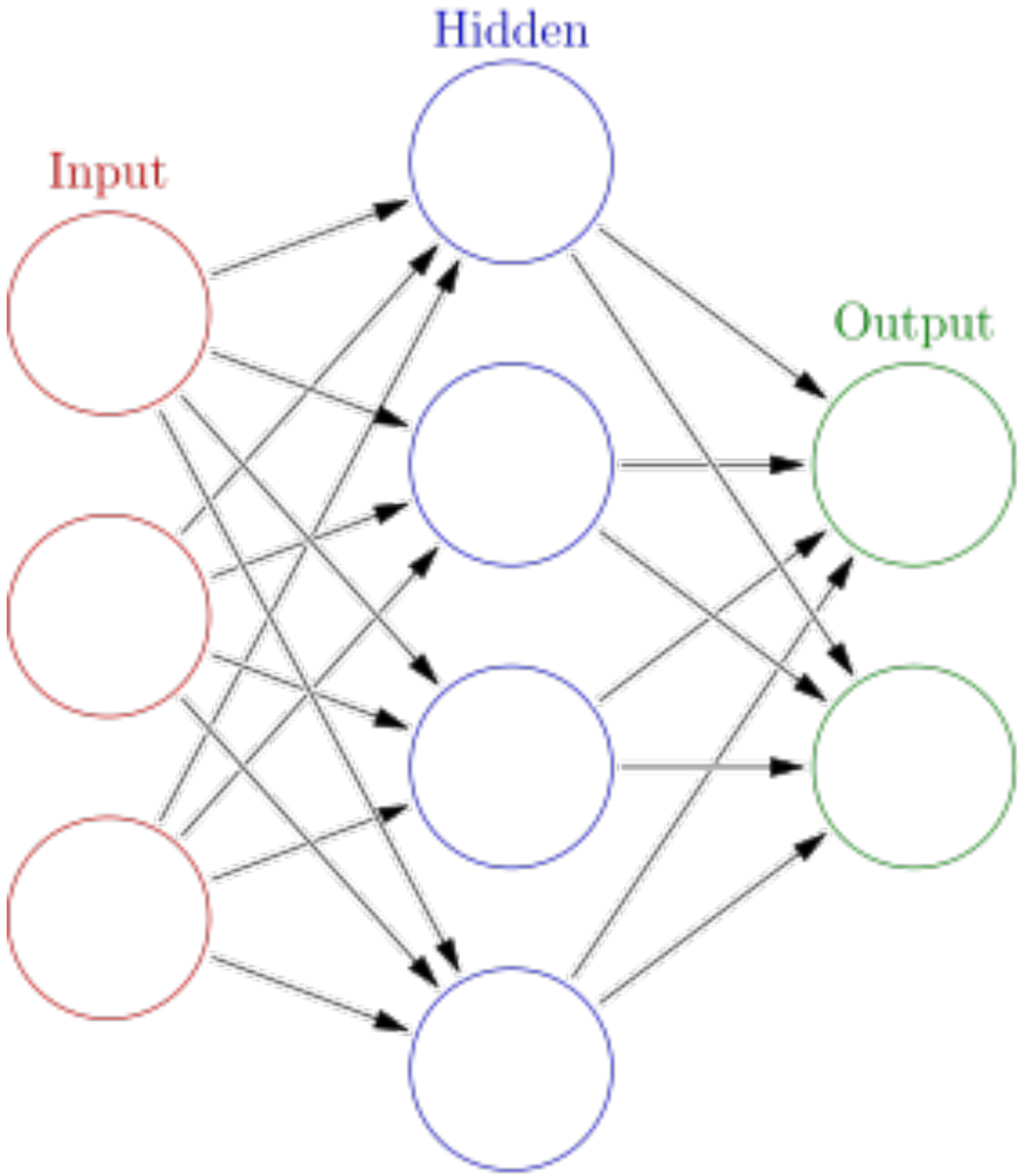


Drift Shadow
by Alex Harker

learn.flucoma.org/explore/harker

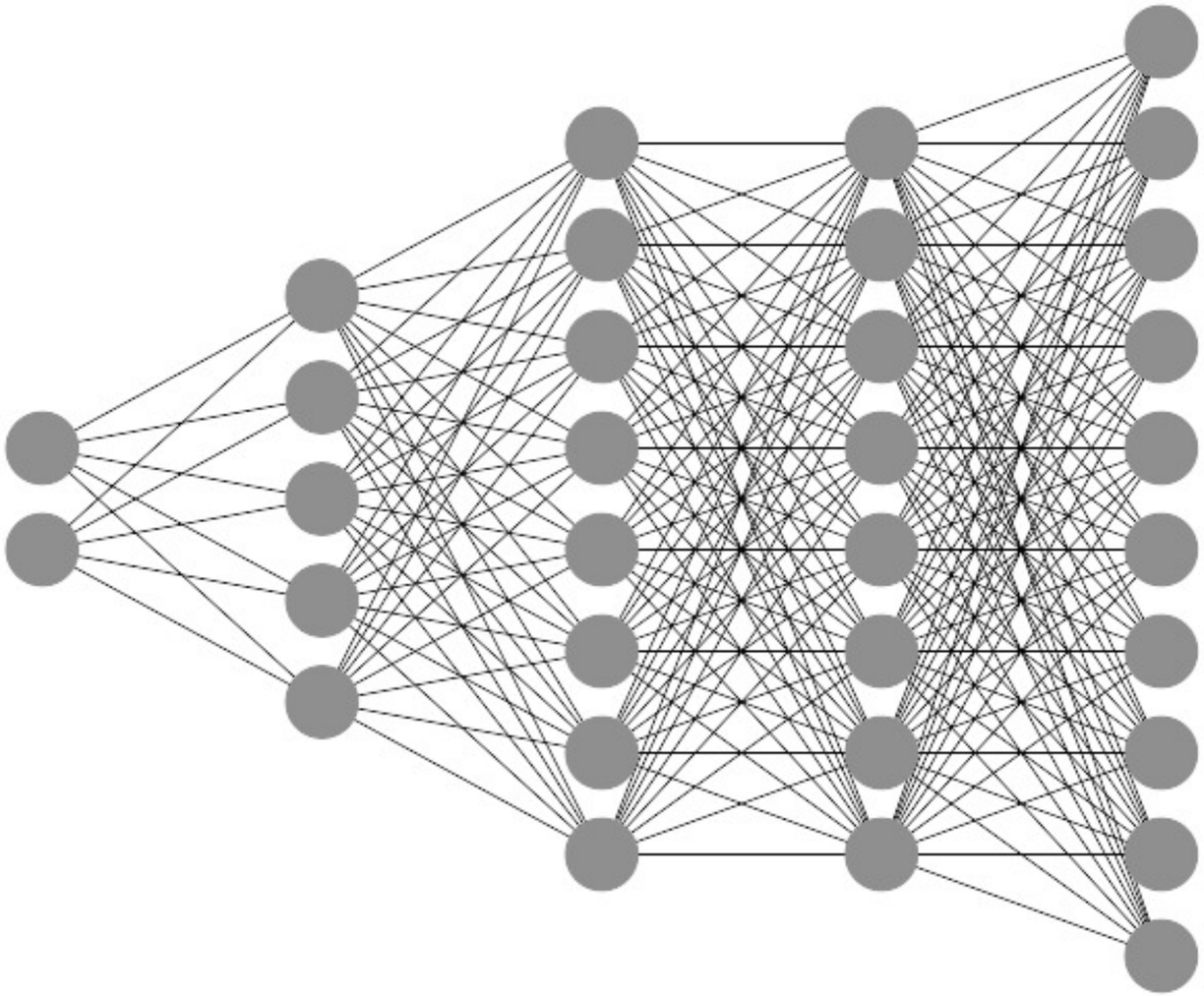
MLP Parameters

@hiddenlayers (list)
n elements = n layers
integers = n neurons

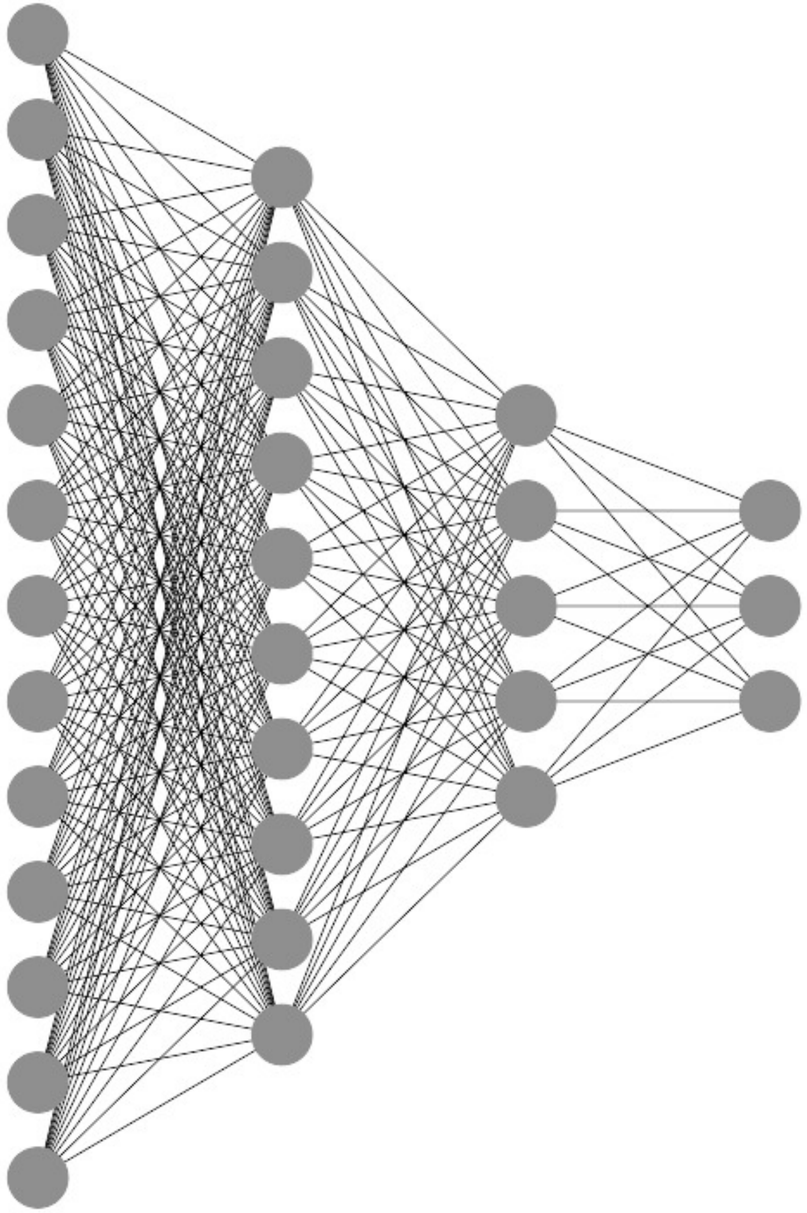


(@hiddenlayers 4)

will reset network



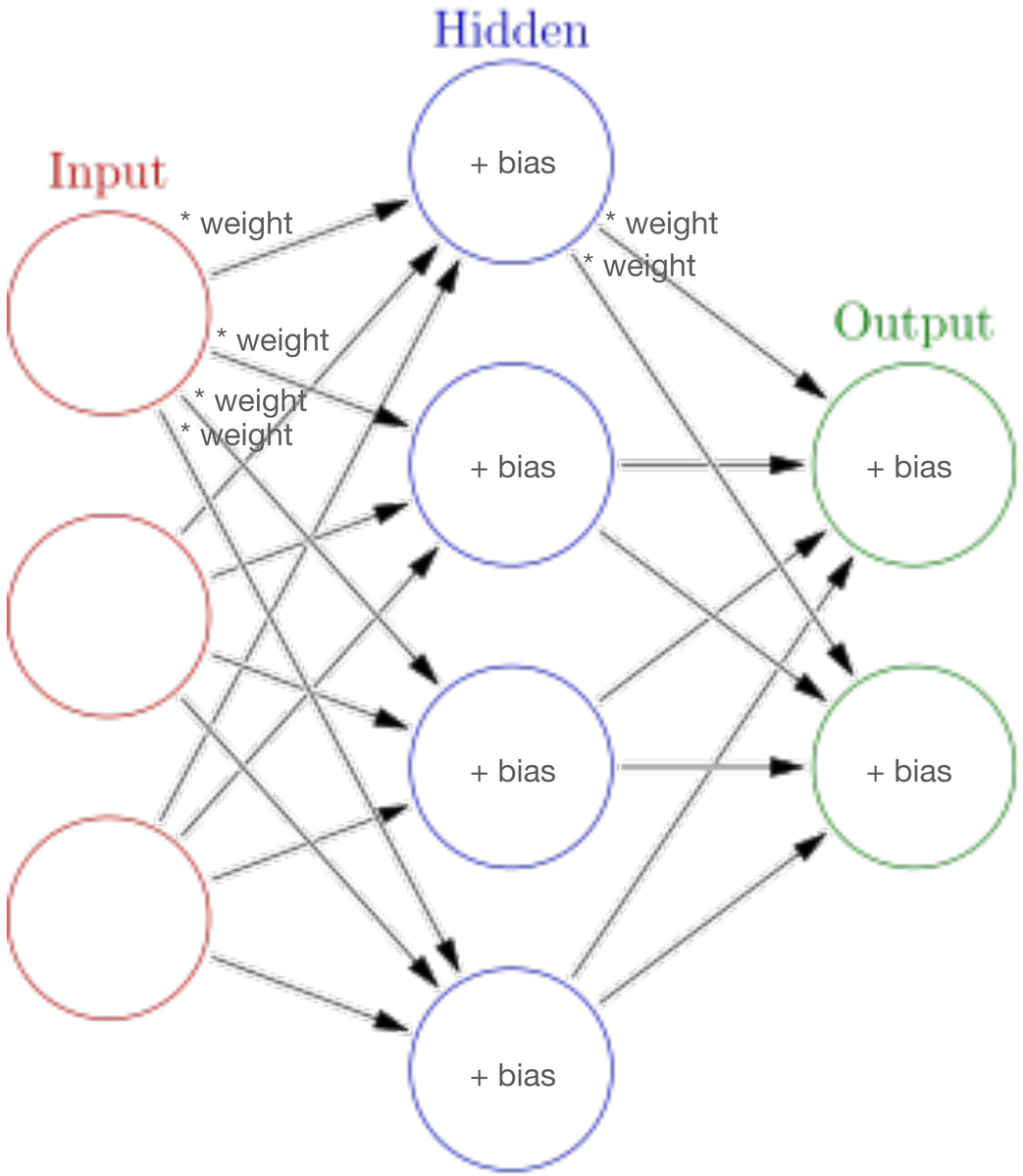
(@hiddenlayers 5 8 8)



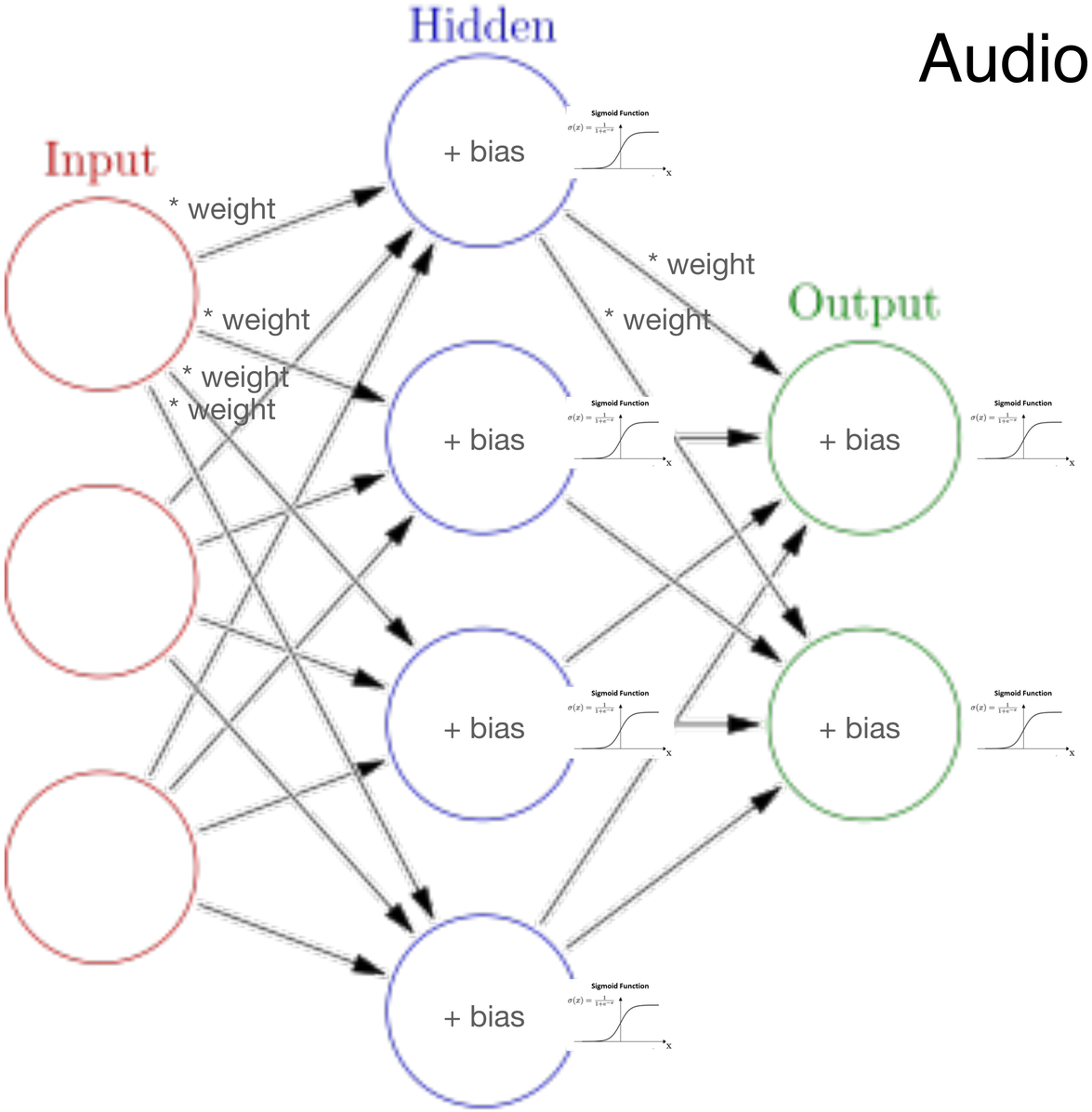
(@hiddenlayers 10 5)

Internal Parameters

weights & biases



@activation
@outputactivation

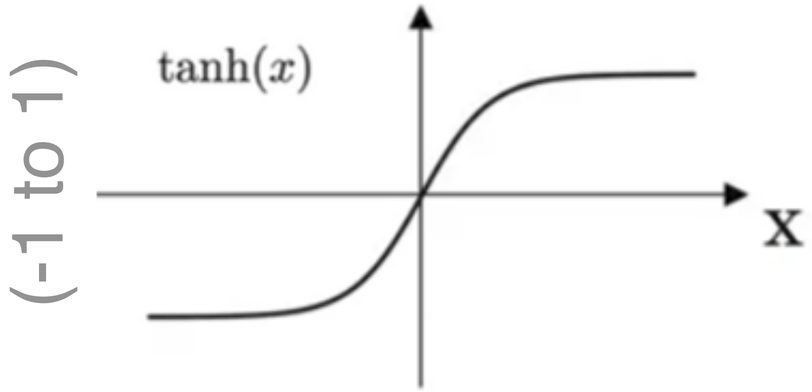


Audio Mixer Metaphor

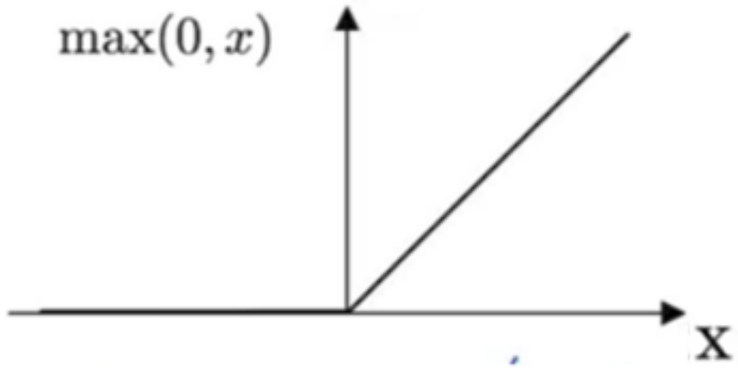
will reset network

@activation
@outputactivation

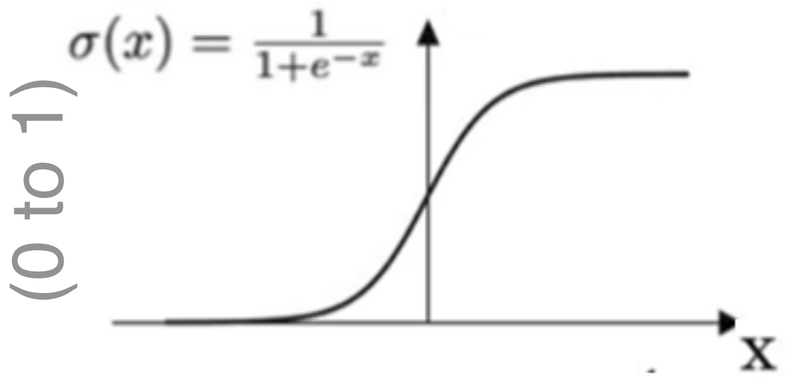
(3) **Hyper Tangent Function**



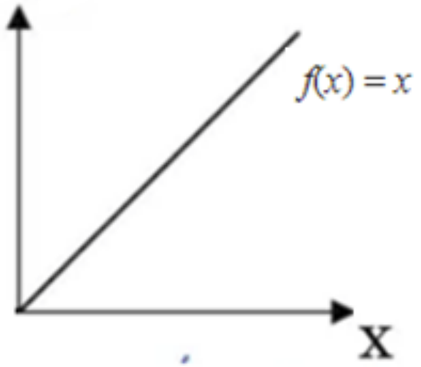
(2) **ReLU Function**



(1) **Sigmoid Function**



(0) **Identity Function**

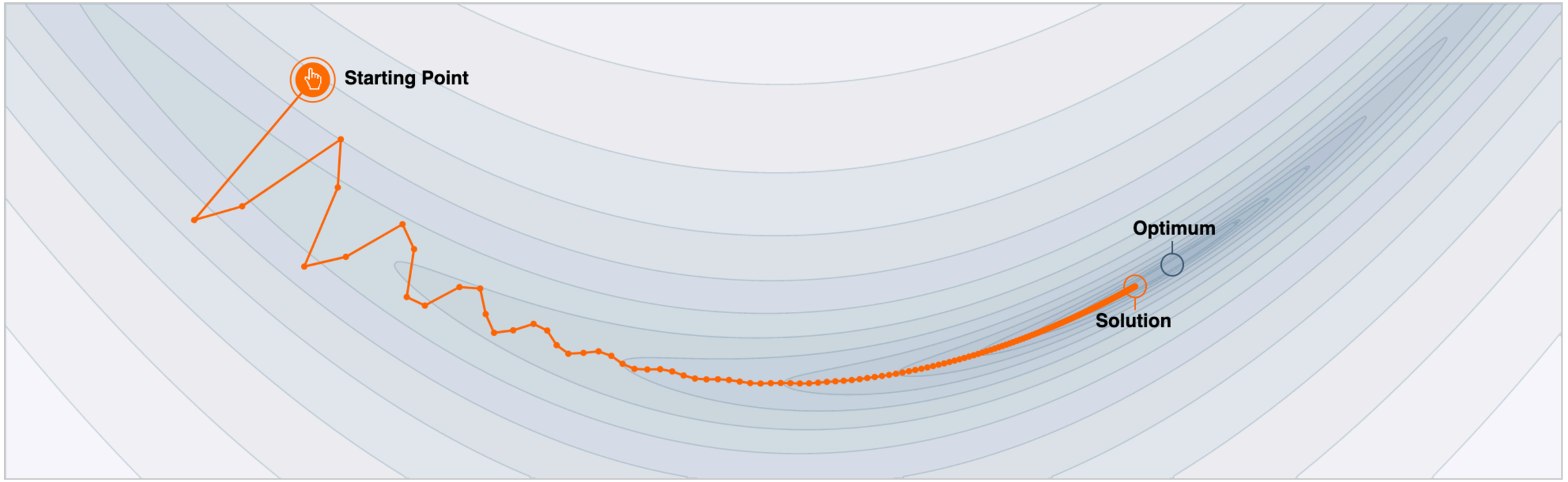


(input = output)

will reset network

@learnrate	a scalar for indicating how much the neural network should adjust its internal parameters during training (during back-propagation)—starting around 0.1 and decreasing over time is usually a good start
@maxiter	number of times to use all the examples on each “fit” message—also called an “epoch”
@batchsize	number of input examples feed-foward before checking their output pairs and adjusting
@validation	percentage (as a decimal) of training data to hold back (not train on) then test with—when there’s *lots* of data, may be helpful to prevent overfitting

@momentum apply smoothing adjustments

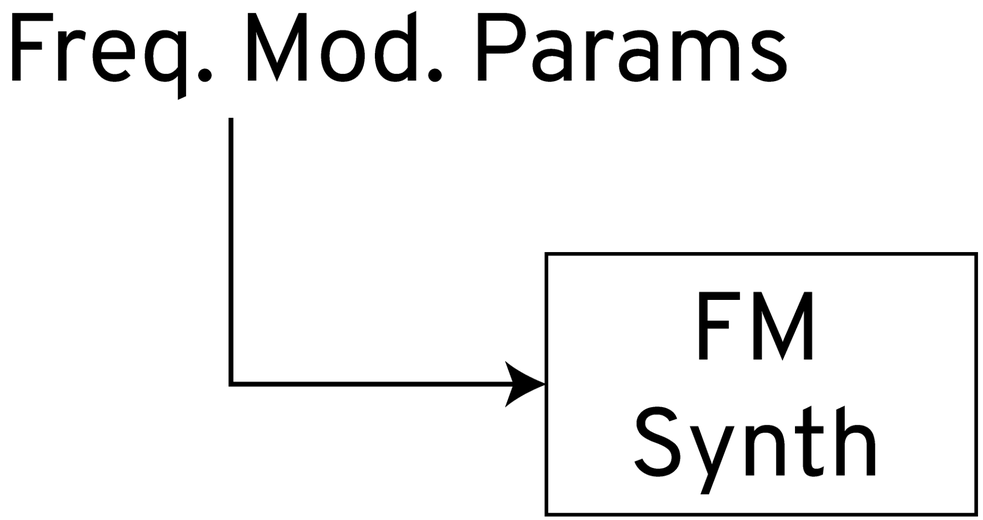


Regression with Audio Analyses

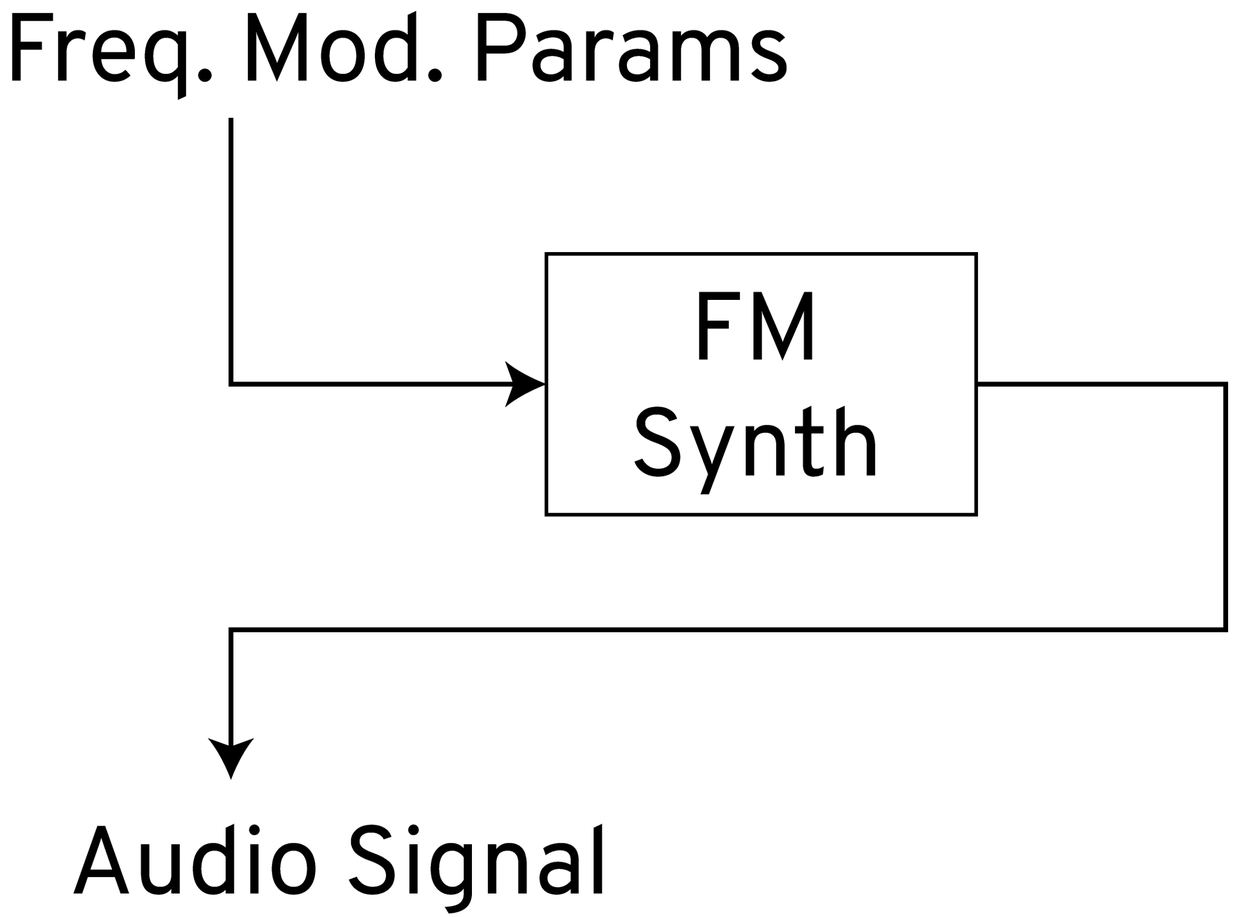
Making the Datasets

Freq. Mod. Params

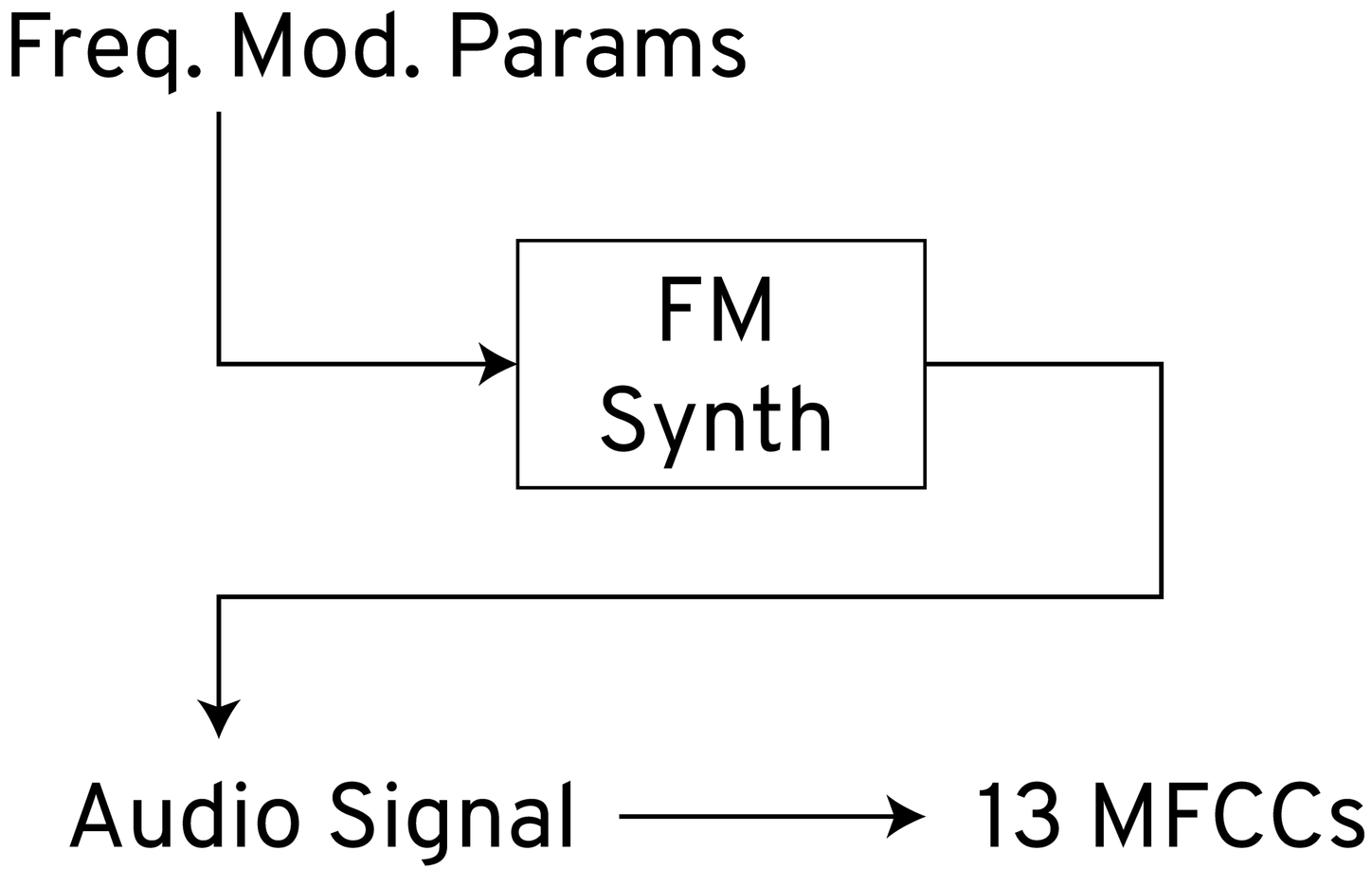
Making the Datasets



Making the Datasets



Making the Datasets



Making the Datasets

Freq. Mod. Params

13 MFCCs

Making the Datasets

Freq. Mod. Params

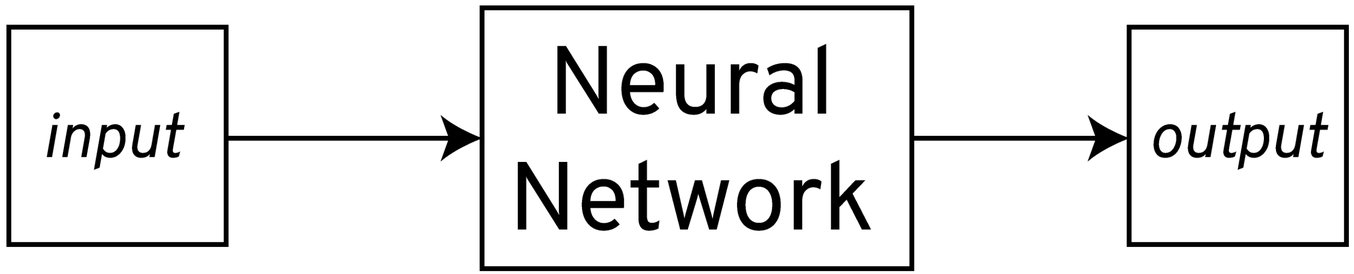
```
DataSet 64:
rows: 100 cols: 3
point-0     2411.1    206.48    3.9116
point-1     69.214    65.334     3.862
point-2      214.7    67.041    6.1554
        ...
point-97     2114.2    82.574    7.8388
point-98     307.08    307.08    15.905
point-99     3797.7    60.559    15.826
```

```
DataSet 63:
rows: 100 cols: 13
point-0     183.98   -204.99    -97.85       ...    17.116    6.7544   -2.6597
point-1     238.64    92.367    67.025       ...   -2.1895   0.26965    3.3148
point-2     279.43     96.95     44.27       ...    9.4531    2.0989   -1.2892
        ...
point-97     162.65   -185.08   -142.91       ...   -19.588    9.1036    14.504
point-98     171.71   -210.44    64.047       ...    0.6732    -15.17   -8.3311
point-99      4.409   -235.47    69.209       ...   -12.299   -6.0117    28.718
```

13 MFCCs

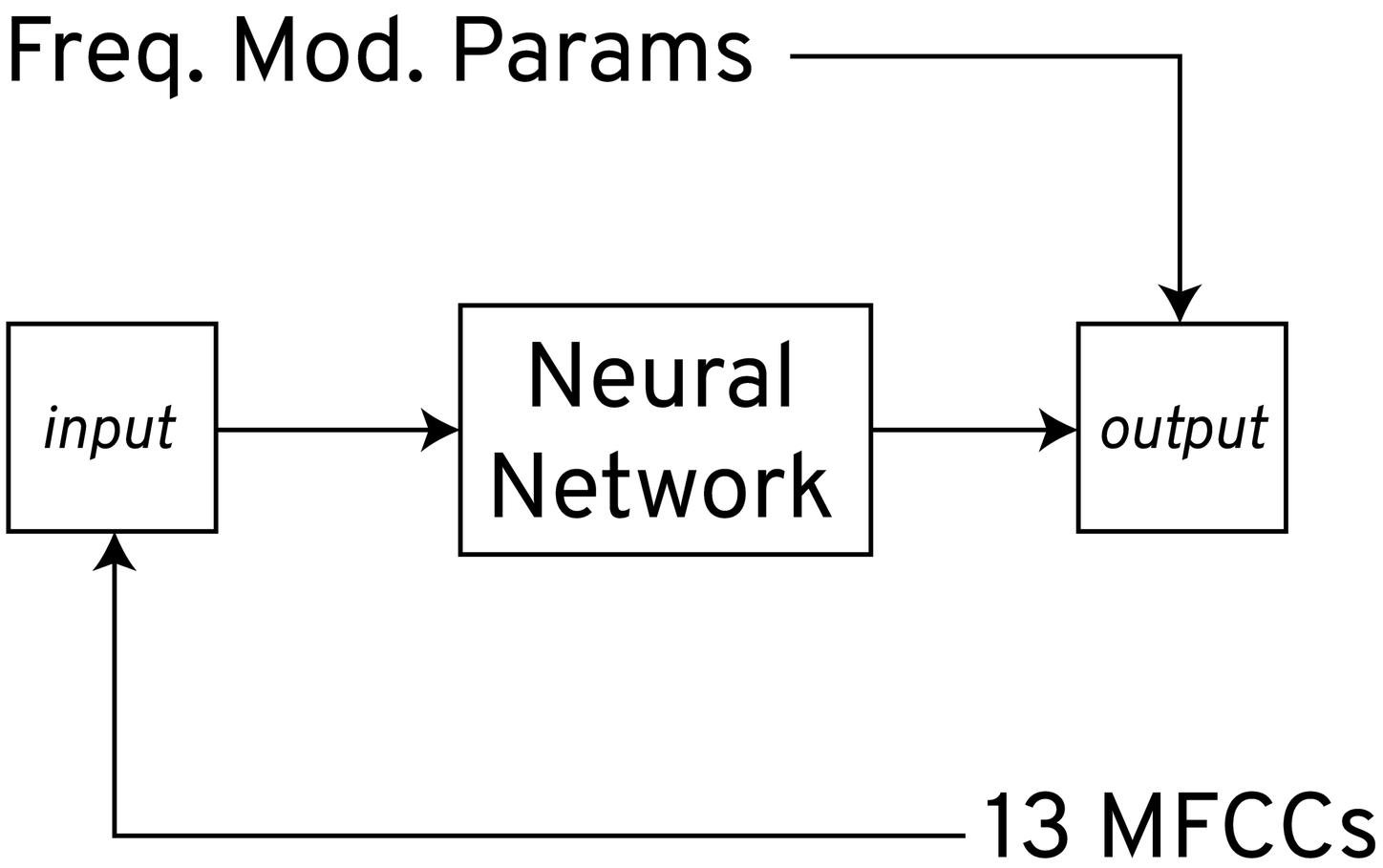
Training

Freq. Mod. Params

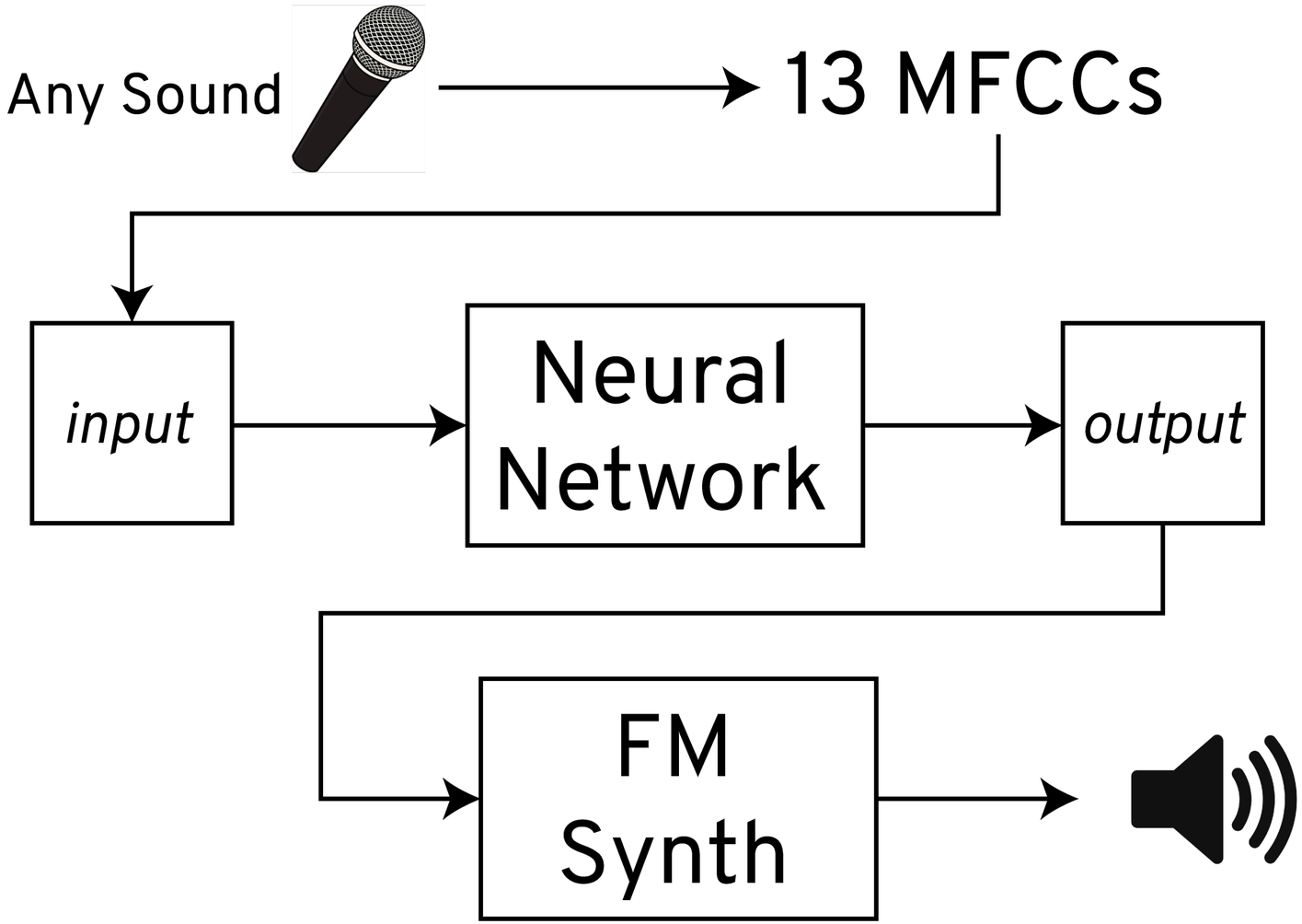


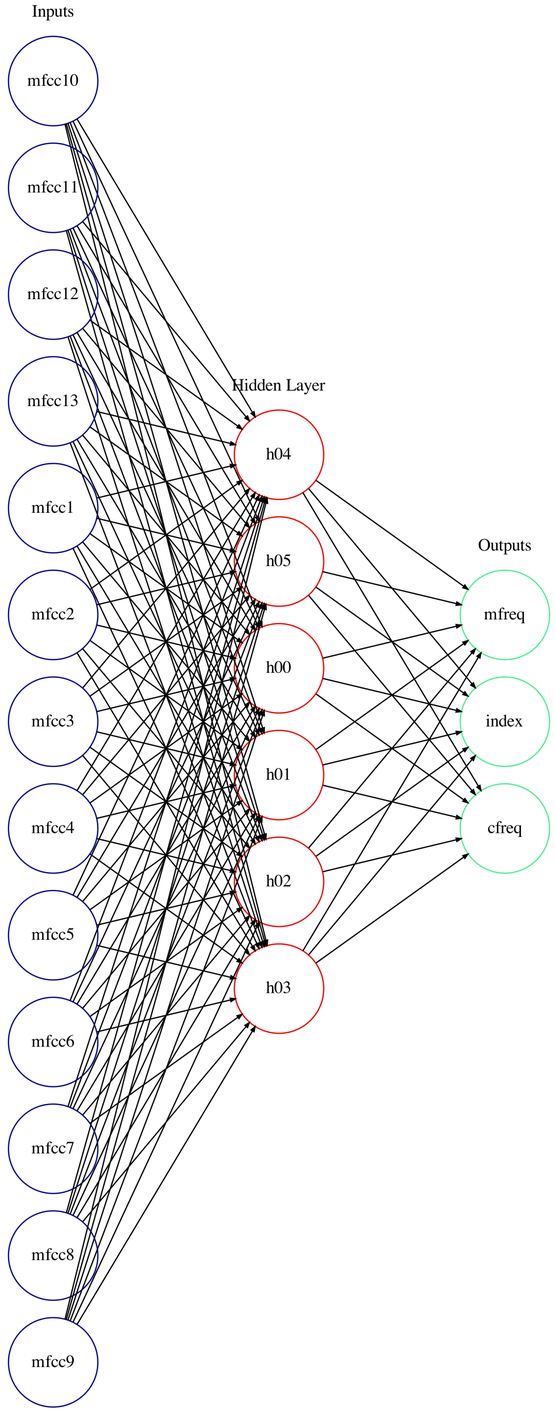
13 MFCCs

Training



Performing




Inputs
mfcc10
mfcc11
mfcc12
mfcc13
mfcc1
mfcc2
mfcc3
mfcc4
mfcc5
mfcc6
mfcc7
mfcc8
mfcc9
Hidden Layer
h04
h05
h00
h01
h02
h03
Outputs
mfreq
index
cfreq