

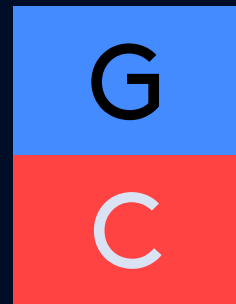
R3.A.09

# Real-Time Identification of Simple and Extended Musical Chords using Artificial Neural Networks

Coronel, Lesli Natasha A.  
Navarro, Joachim Alfonso A.

# Musical Chords

# BACKGROUND



2 or more  
notes



Played  
together



Follow “rules of  
harmony”

(Leino, Brattico, Tervaniemi, & Vurst, 2007)

# Musical Chords

# BACKGROUND

Each  
has a  
name

C5
G
C

Amaj
E
C#
A

D7
C
A
F#
D

# Musical Chords

# BACKGROUND

Each  
has a  
root  
note

C5
G
C

A <sup>maj</sup>
E
C <sup>#</sup>
A

D <sup>7</sup>
C
A
F <sup>#</sup>
D

# Musical Chords

# BACKGROUND

Each  
has a  
type

C <sup>5</sup>
G
C

A <sup>maj</sup>
E
C <sup>#</sup>
A

D <sup>7</sup>
C
A
F <sup>#</sup>
D

# Musical Chords

# BACKGROUND

Simple vs  
Extended

Chord types

Am

E

C

A

Simple

More common chord type

# Musical Chords

# BACKGROUND

Simple vs  
Extended

Chord types

AmM7

G#

Extension

E

C

A

Extended

Less common chord type

# Chord Identification DEFINITION

The determination of the name of the chord from the notes that constitute it

Definition of chord identification



# Chord Identification

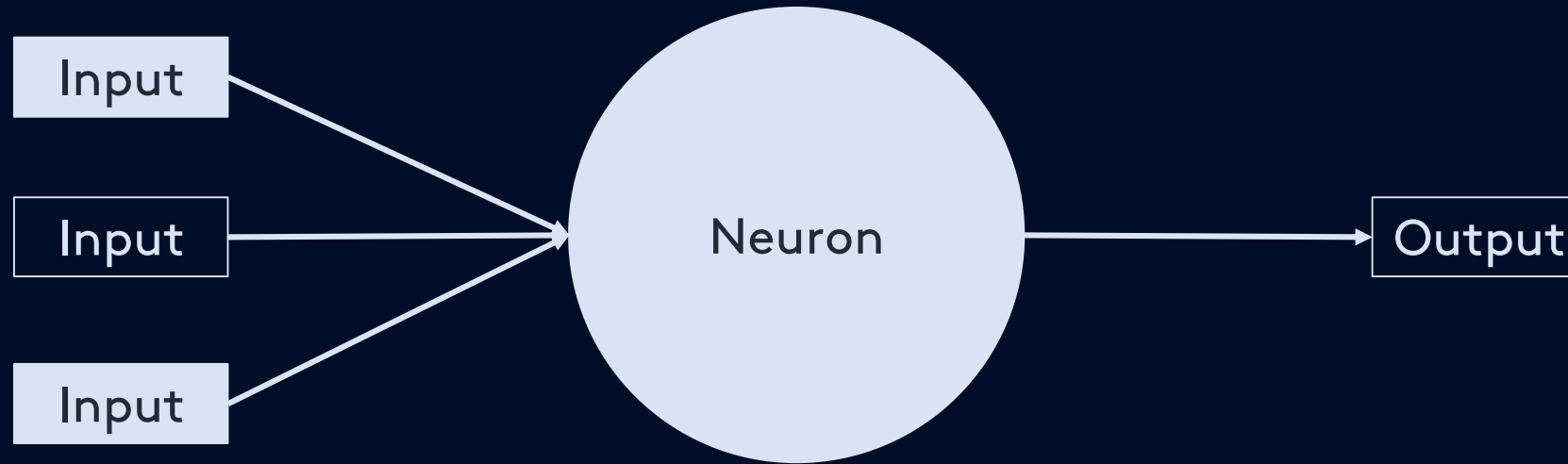
# PROBLEM

Majority of general music learning public **can't do this by themselves** due to **lack of skill** or training

Situation with chord identification

# Neural networks

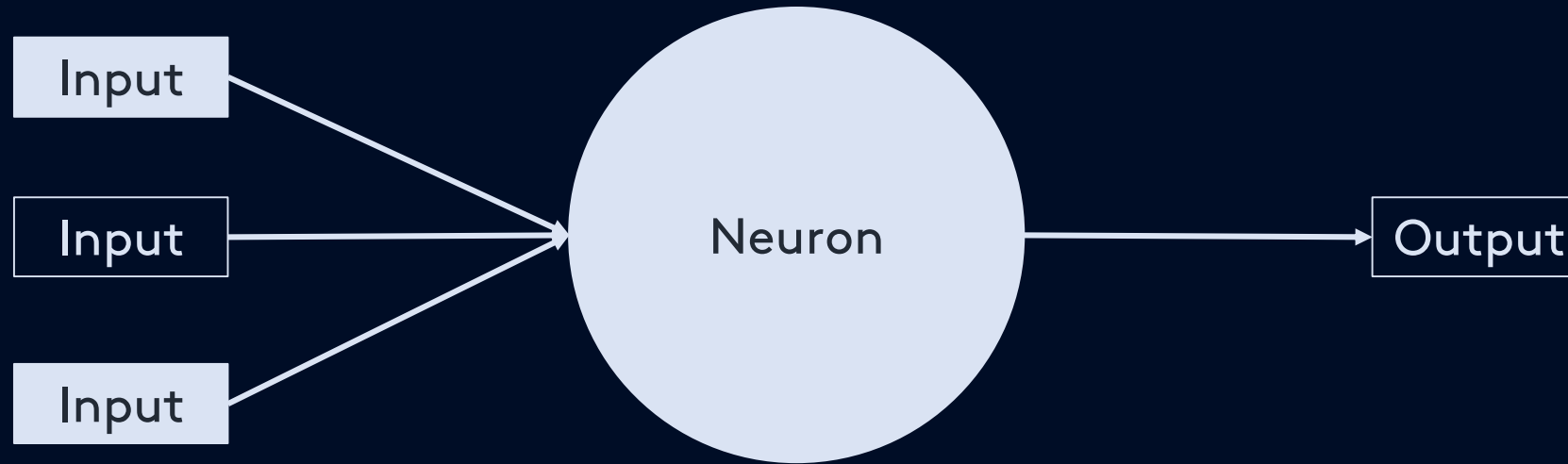
# DEFINITION



Computational model of neurons in a brain

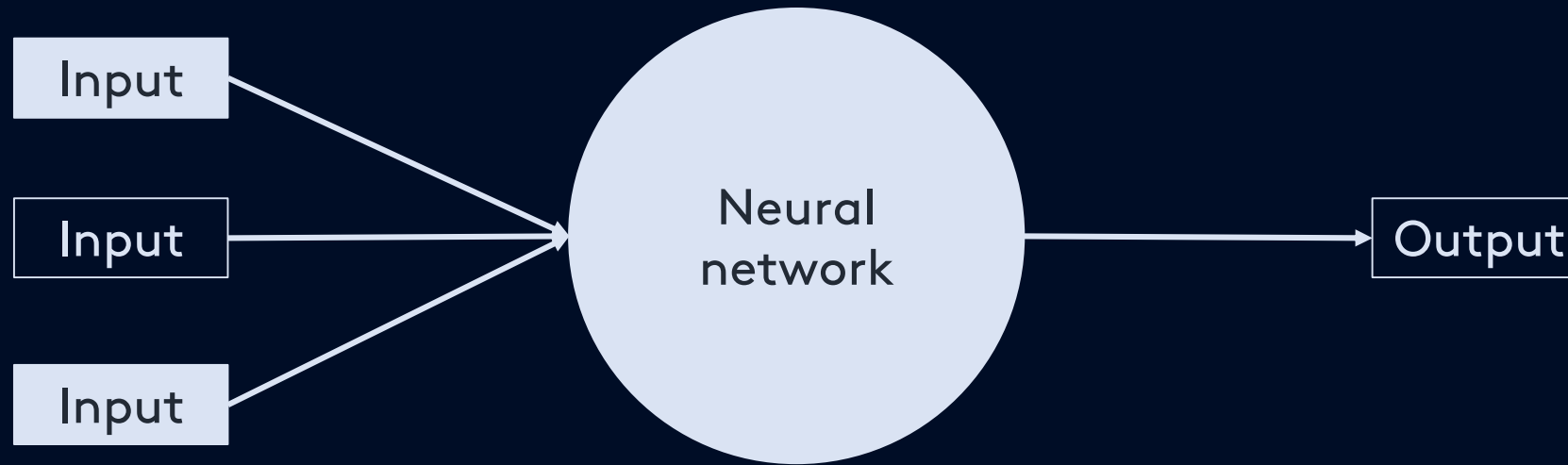
# Neural networks

# DEFINITION



Many neurons = neural network

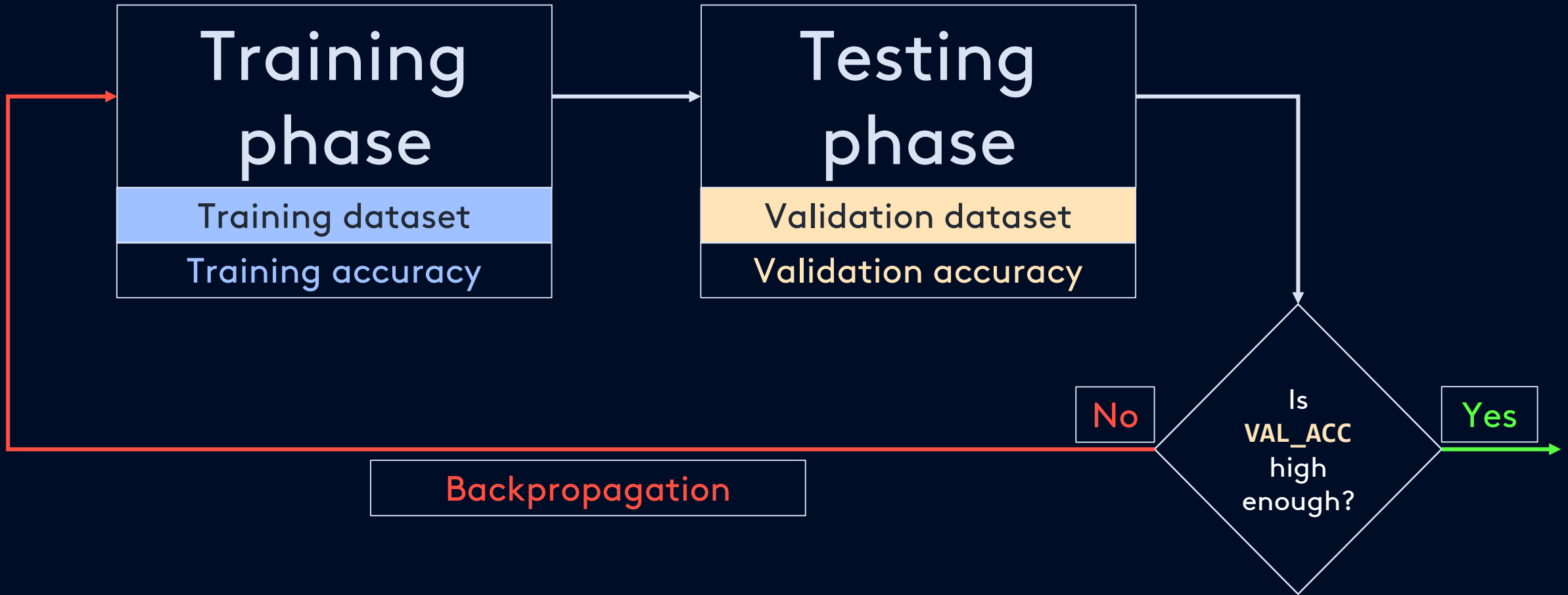
# Artificial Neural Networks (ANNs)



ANN learns by repetitive training

Colina, Perez, & Paraan, 2017

# ANN training & testing



# Why neural networks? PROBLEM

Previous studies with neural network implementations have **not included extended chords in their research**

Osmalskyj, Embrechts, Piérard, & Van Droogenbroeck, 2012  
Perera & Kodithuwakku, 2005  
Zhou & Lerch, 2015

Using neural networks to  
identify both common and  
extended chords is  
**unexplored**

Osmalskyj, Embrechts, Piérard, & Van Droogenbroeck, 2012

Perera & Kodithuwakku, 2005

Zhou & Lerch, 2015

Develop a neural network  
that **quickly** identifies  
**simple and extended**  
musical **chords**



Input is a group of **3 or more**  
**MIDI note signals** played in  
**real-time**

Input chords have **one root note** and are **not inverted**

Identification must be quick  
enough to be used in **live  
performance (<40ms)**

Greeff, 2016

Implemented in  
programming languages  
with **neural network, real-  
time MIDI, and GPU  
processing** libraries

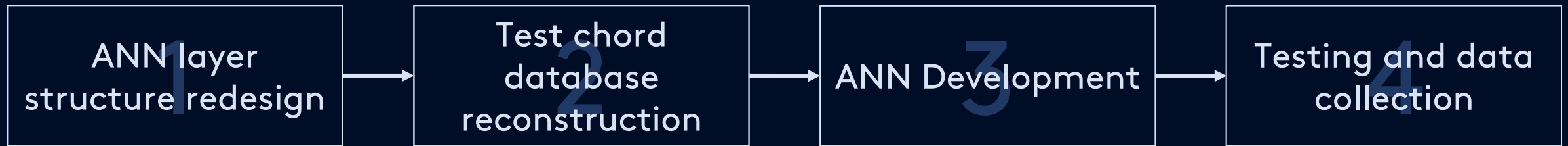
thestk, 2017; Bretschneider, 2017

Neural network must be run  
on a GPU for efficient  
processing

Nickolls, Buck, Garland, & Skadron, 2008

# Level 0

# PROCESS



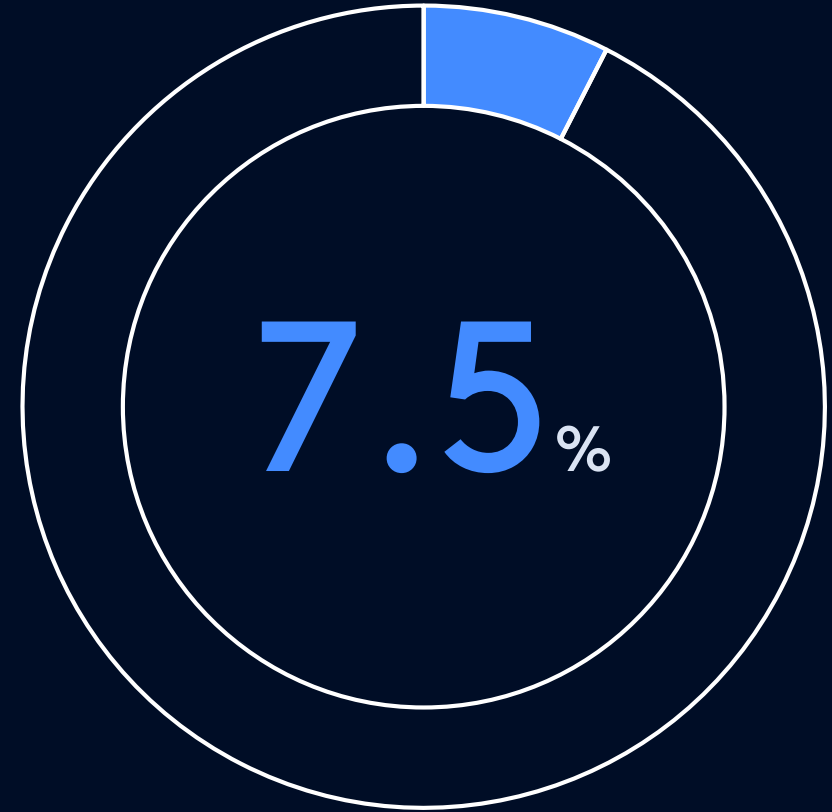
# Performance

Peak validation accuracy after 30K epochs



# RESULTS

Peak training accuracy after 30K epochs



Real-Time Identification of  
Simple and Extended Musical Chords  
using Artificial Neural Networks

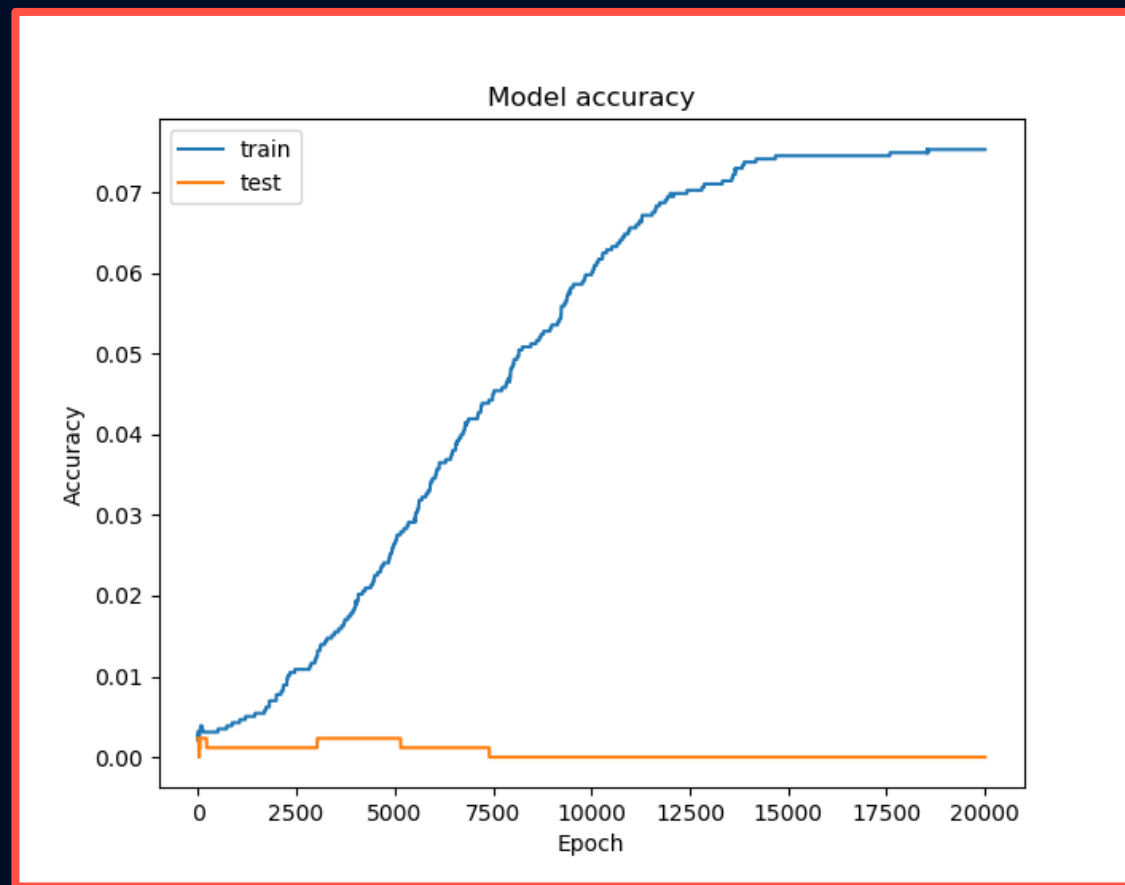
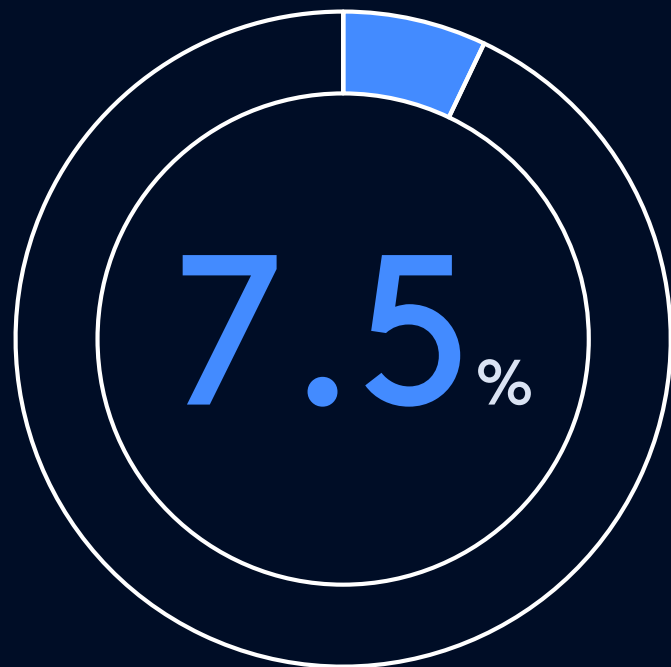
Coronel  
Navarro

R3.A.09

# Performance

# RESULTS

Peak training accuracy  
after 30K epochs



Plateaus  
on  
learning  
training  
dataset

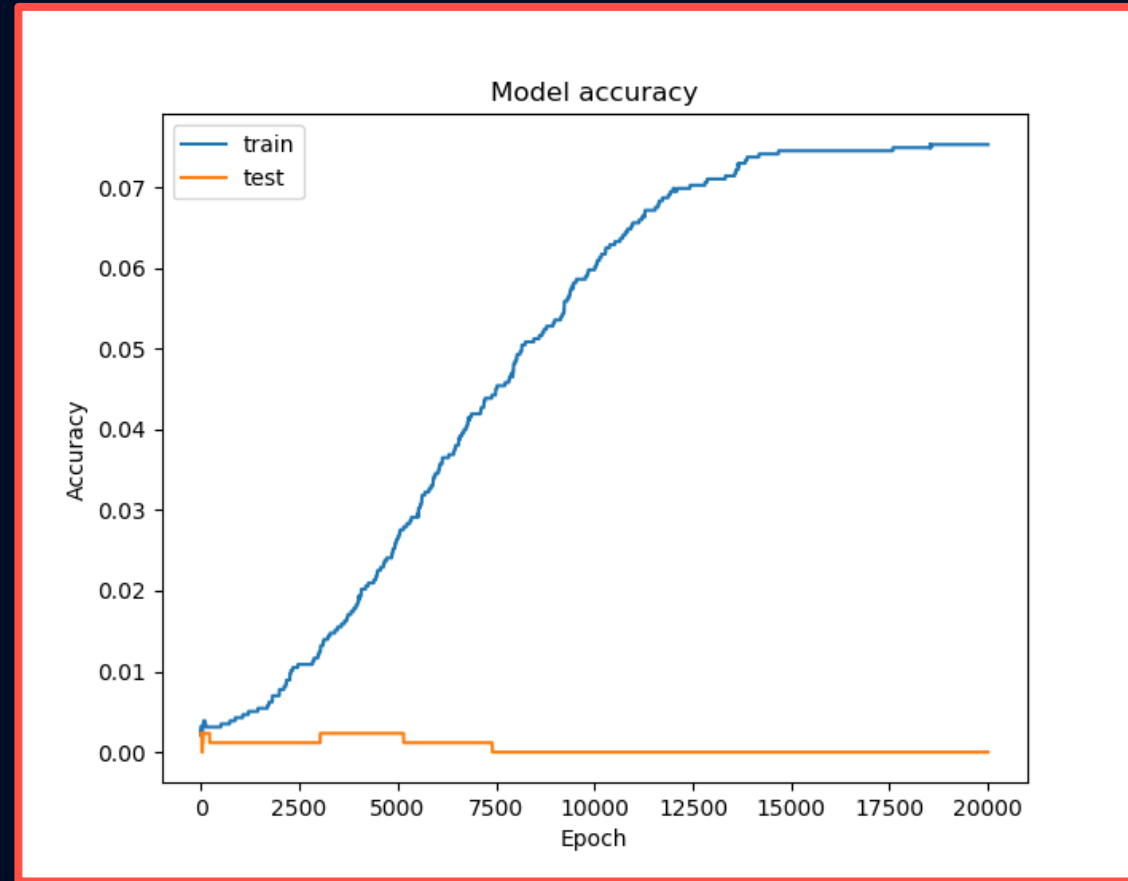
Trend



# Performance

# RESULTS

Peak validation accuracy  
after 2800 epochs

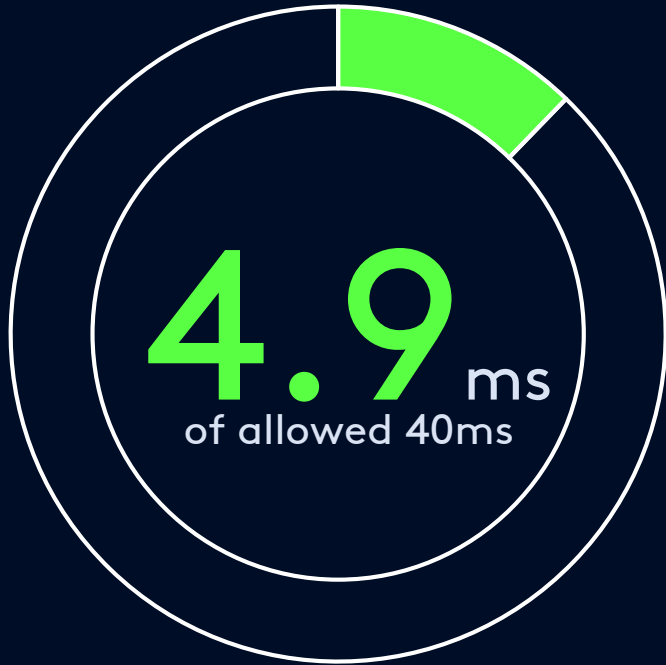


Over-  
fitting on  
training  
dataset

Reason

# Performance

Mean total response time,  
30 samples



# RESULTS

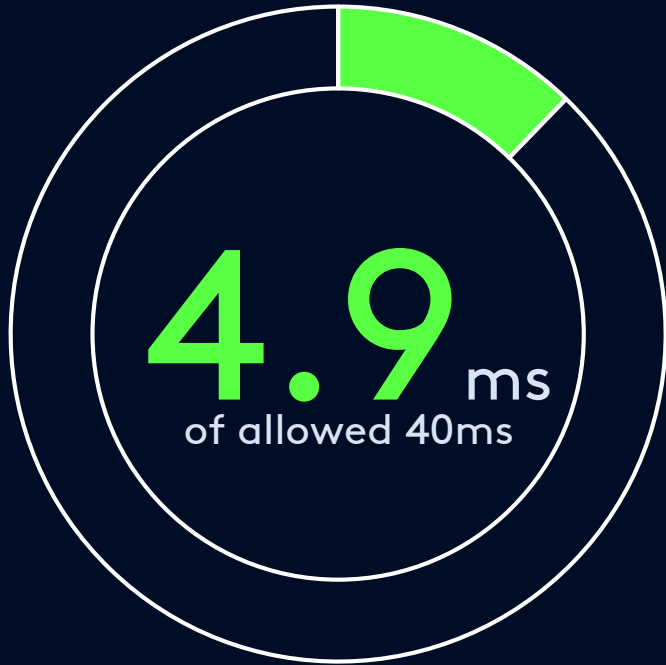
Null hypothesis	Alternative hypothesis
$r \geq 40\text{ms}$	$r < 40\text{ms}$

## T-test for one mean

Sample size = 30; Significance = 5%

# Performance

Mean total response time,  
30 samples



# RESULTS

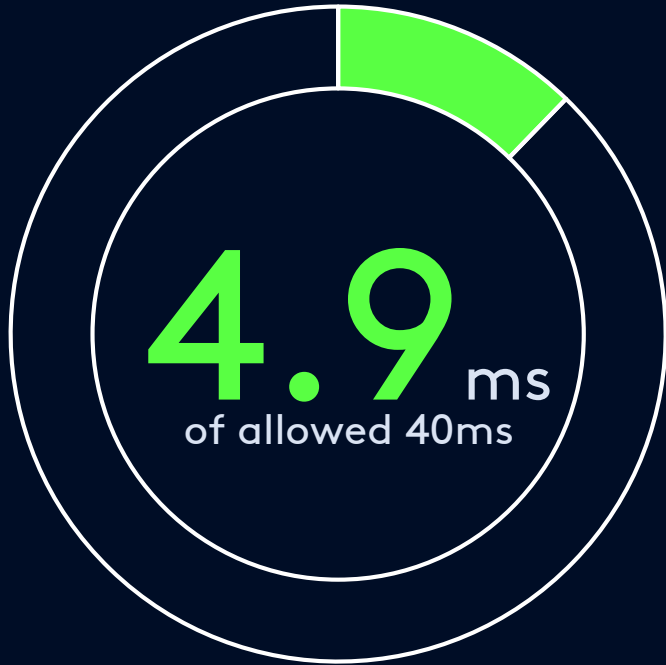
Null hypothesis	Alternative hypothesis
$t \geq -1.699$	$t < -1.699$

## T-test for one mean

Sample size = 30; Significance = 5%

# Performance

Mean total response time,  
30 samples



# RESULTS

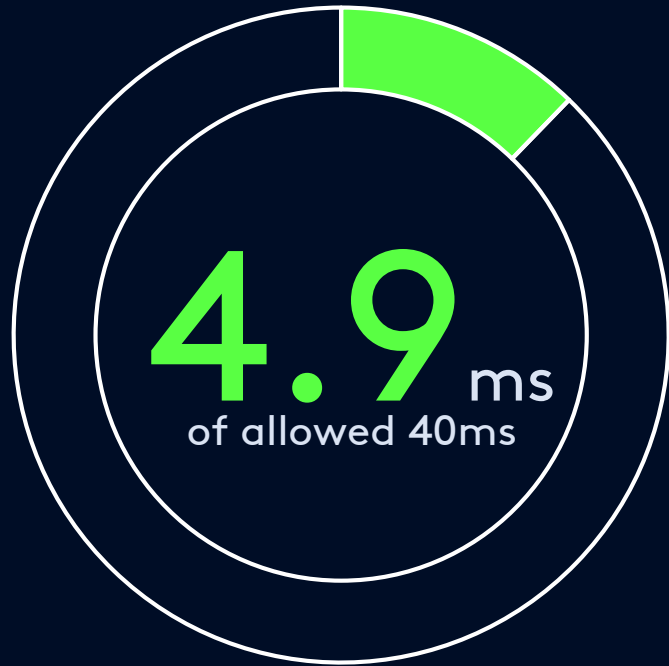
Null hypothesis	Alternative hypothesis
$t \geq -1.699$	$t < -1.699$
$t_{4.9\text{ms}} = -3.17$	

## T-test for one mean

Sample size = 30; Significance = 5%

# Performance

Mean total response time,  
30 samples



# RESULTS

Null hypothesis	Alternative hypothesis
$t \geq 1.699$	$t < -1.699$
NN is faster than standard!	

## T-test for one mean

Sample size = 30; Significance = 5%

# Conclusion

Our chords are too complex for NN...



# CLOSING

...but NNs are fast enough



# Recommendations

CLOSING

Other  
machine  
learning  
algorithms

1

Simplified  
set of  
chords

2

Use audio  
rather than  
MIDI as  
input

3

T	H	E	Rev. C1	E	N	D
Thank you!						



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