GenrELM: An ELM Approach to Automatic Music Genre Classification using Bass Lines

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Outline

- Introduction
- Literature Review
- Statement of the Problem
- Objectives
- Proposed Approach
- Experiments and Results
- Conclusion and Future Works


Introduction

Music

- "the science or art of ordering tones or sounds in succession, in combination, and in temporal relationships to produce a composition having unity and continuity" *(Merriam-Webster)*

Elements of Music

- Rhythm
- Melody
- Harmony
- Texture
- Dynamics
- Tone Color

Elements of Music

- Rhythm
  - element of “time”
  - beat

Elements of Music

- Melody
  - horizontal representation of pitch
  - tune

Elements of Music

- Harmony
  – vertical representation of pitch

Elements of Music

- Texture
  - number of individual melodies and their relationships
    - monophonic
    - polyphonic
    - homophonic

Elements of Music

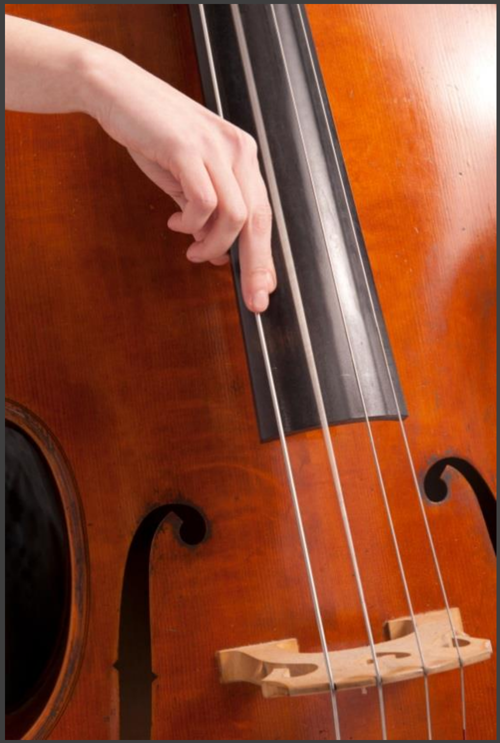
- Dynamics
  – relative loudness and softness of music

Elements of Music

- Tone Color
  - timbre/ quality of sound

Bass Lines

- a monophonic instrumental melody
- played by instruments having a low-pitched sound (*i.e. bass guitar, double bass*)



Bass Lines

- bridges together melodic and rhythmic sections in most musical styles
- "...the groundwork or foundation upon which all musical composition is to be erected." (Christopher Simpson)

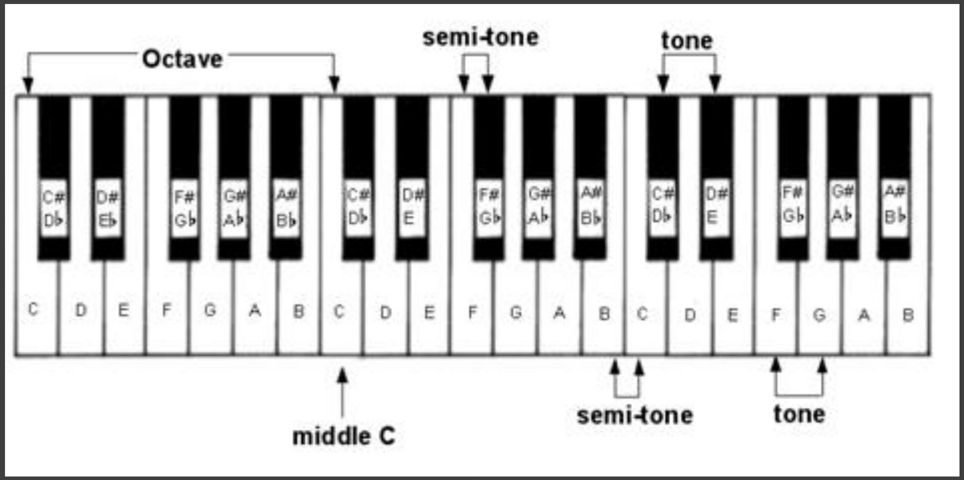
Bass Lines

- can establish rhythm
- has tune
- does not harmonize in itself alone
- monophonic
- low-pitched sound

Melodic Intervals

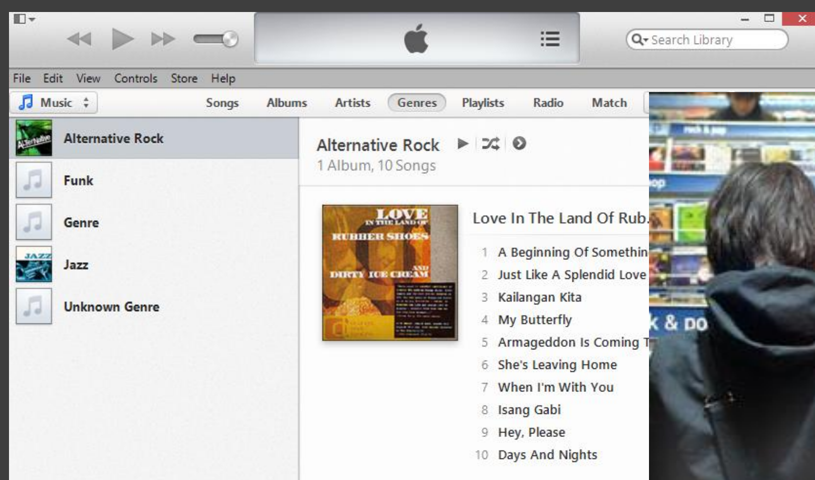
- represents the number of semitones in a given time interval

  semitone – half-step-distance between two adjacent notes



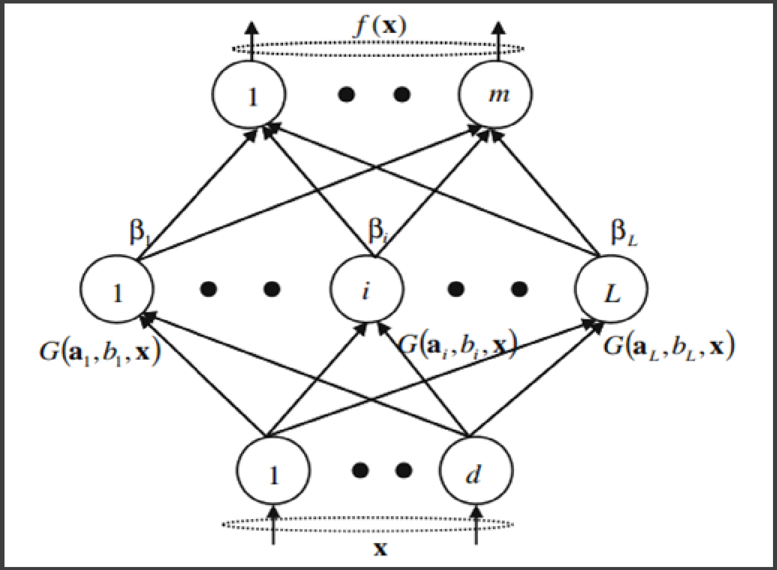
Genre

- a way of organizing, classifying, and grouping music
- a kind of music (Franco Fabbri)



Extreme Learning Machine (ELM)

- machine learning algorithm
- created for single-hidden layer feed forward networks



Extreme Learning Machine (ELM)

- tries to overcome the challenges encountered among traditional computing techniques such as SVMs and NNs
  - slow learning speed
  - over training
  - local optima entrapment

Extreme Learning Machine (ELM)

Given a training set , hidden node output function , and hidden node number *L*,

step 1 Randomly generate hidden parameters (a_i, b_i), *i* = 1,…,*L*.

step 2 Calculate the hidden layer output matrix **H**.

step 3 Calculate the output weight vector **β**:

$$\boldsymbol{\beta} = \mathbf{H}^{\dagger}\mathbf{T}, \text{ where}$$

$$\mathbf{T} = [\boldsymbol{t}_1, \dots, \boldsymbol{t}_N]^{\mathrm{T}}.$$

Literature Review

Literature Review

- Karpov, I.: *Hidden Markov Classification for Musical Genres* (2002)
- McKay, C. and Fujinaga, I.: *Automatic Genre Classification using Large High-Level Musical Feature Sets* (2004)

Literature Review

- Haggblade, M., Hong, Y., and Kao, K.: *Music Genre Classification* (2011)
  - K-Nearest Neighbour, K-means, multiclass SVM, and neural networks

Literature Review

- Meng, A., et al.: *Temporal Feature Integration for Music Genre Classification* (2007)
- Şimşekli, U.: *Automatic Music Genre Classification using Bass Lines* (2010)
  - K-nearest neighbor classifier

Statement of the Problem

Statement of the Problem

- to create a platform for automatic music genre classification using information on bass lines

Objectives

Objectives

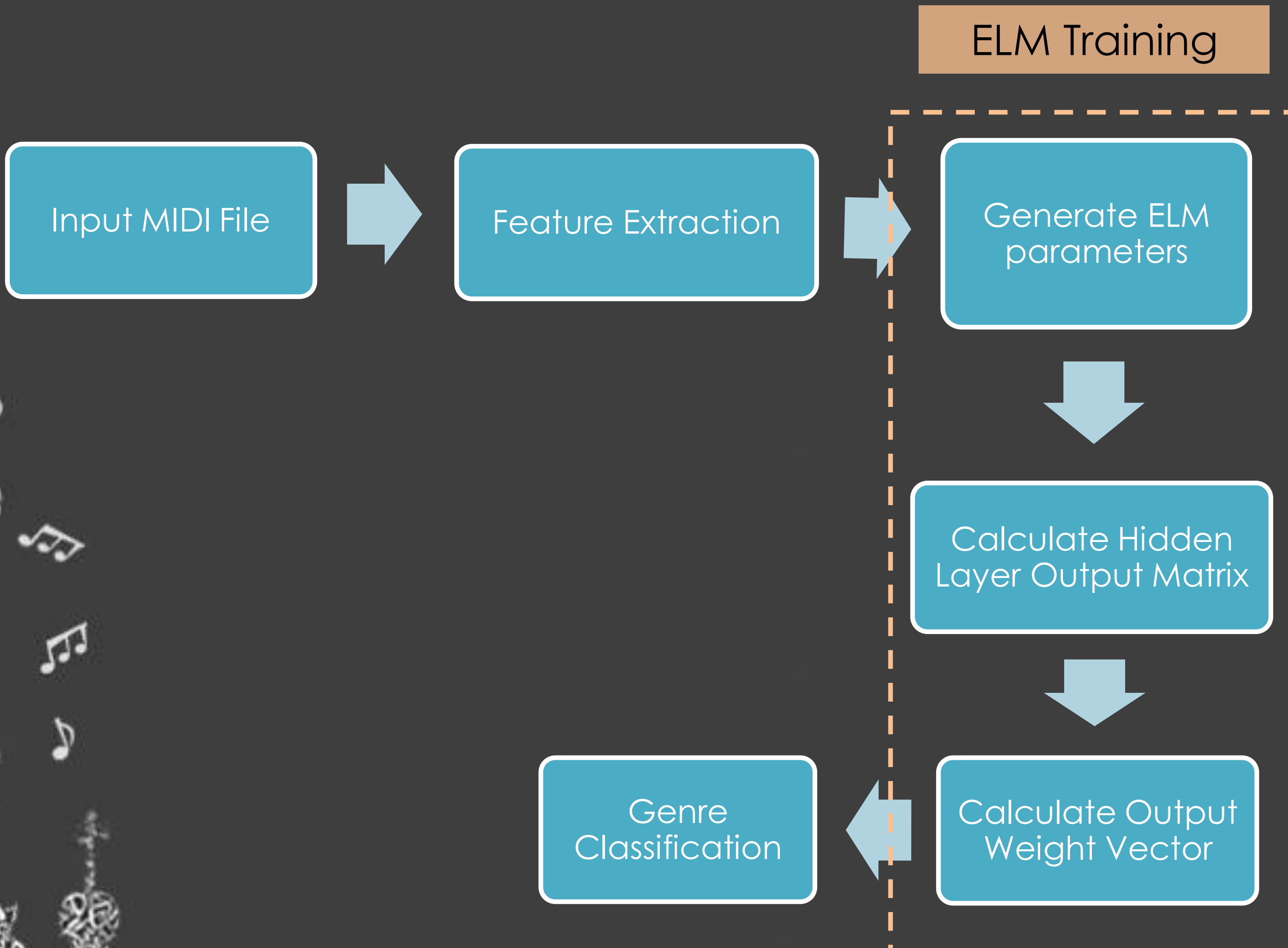
- to apply the ELM algorithm to music genre classification
- to evaluate the performance of ELM in genre classification by varying the number of its hidden nodes,

Objectives

- to evaluate the performance of ELM in genre classification by introducing a regularization coefficient, and
- to evaluate the performance of ELM in genre classification by altering the network structure.

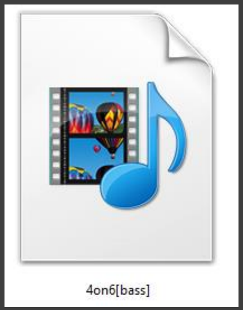
Proposed Approach

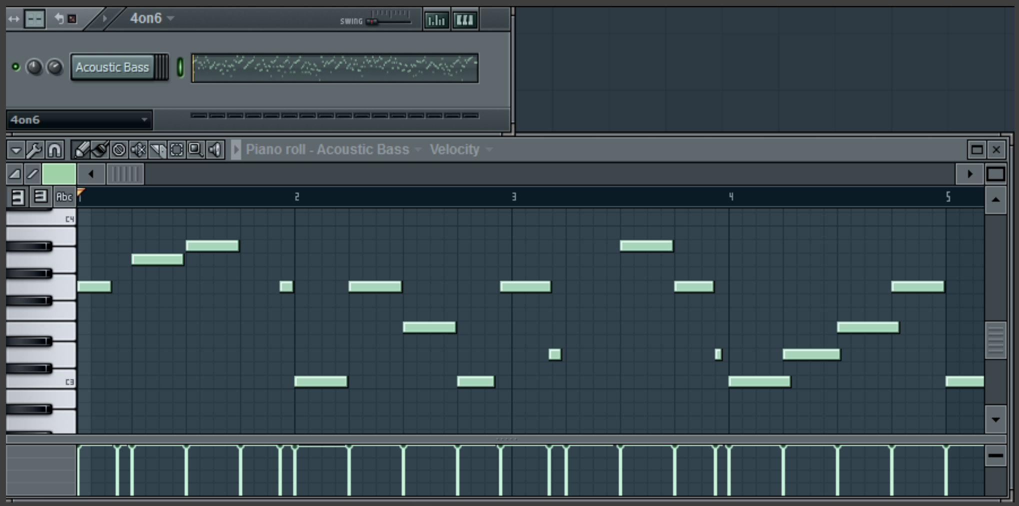
General Flow



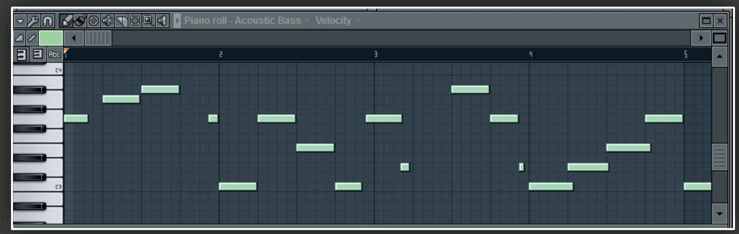
Input

- MIDI file containing bass lines only
- Any length

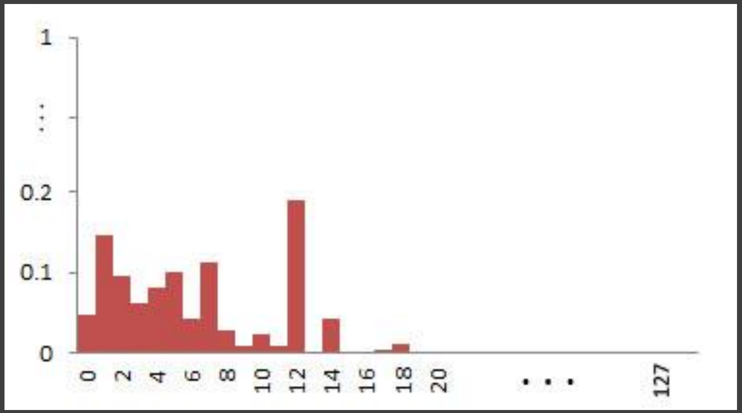




Feature Extraction



MIDI Bass Line



Melodic Interval Histogram

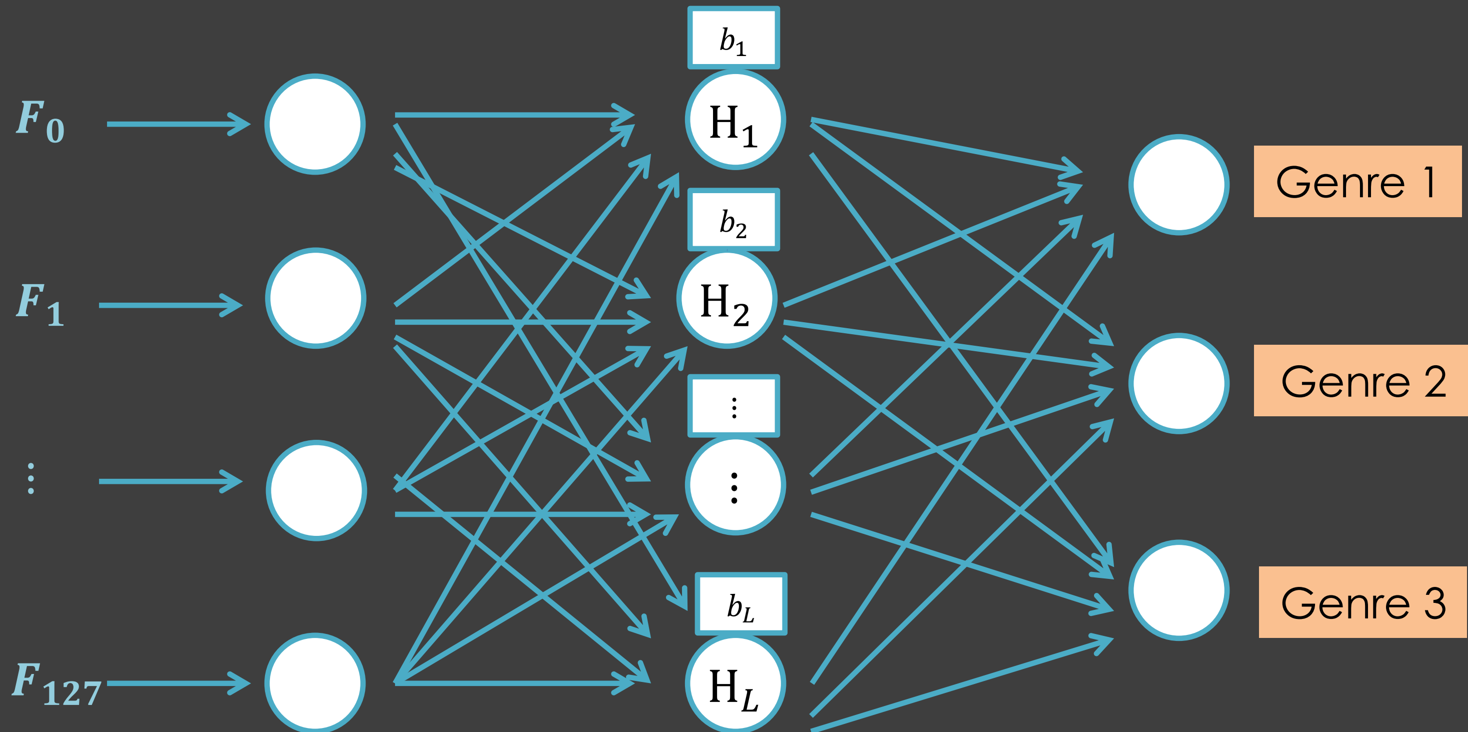
0.046	0.147	0.097	0.062	0.081	0.100	0.042	0.112	0.027	0.008	0.023	0.008	0.189	0	0.042	0	0	0.004	0.012	0	0	0
0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	...	127

feature vector (*F*)

Genre Taxonomy

Jazz	Rhythm & Blues	Rock	- root genre
Bebop	Blues Rock	Hard Rock	{ leaf genres
Swing	Funk	Metal	
Bossa Nova	Rock 'n Roll	Alternative Rock	

ELM Training



L - no. of hidden nodes

ELM Training

- Generate Hidden Node Parameters
  - random-generated integers from -1 to 1
  - input layer to hidden layer

$$a = \begin{bmatrix} -0.804 & \cdots & -0.855 \\ \vdots & \ddots & \vdots \\ -0.299 & \cdots & -0.181 \end{bmatrix}_{d\ x\ L}$$

input weights

$$b = \begin{bmatrix} 0.528 \\ \vdots \\ -0.269 \end{bmatrix}_{L}$$

bias

d – input vector length
L – no.of hidden nodes

ELM Training

- Calculate Hidden Layer Output Matrix

$$H = \begin{bmatrix} G(\boldsymbol{a}_i, b_i, \boldsymbol{x}_1) & \cdots & G(\boldsymbol{a}_L, b_L, \boldsymbol{x}_1) \\ \vdots & \cdots & \vdots \\ G(\boldsymbol{a}_i, b_i, \boldsymbol{x}_N) & \cdots & G(\boldsymbol{a}_L, b_L, \boldsymbol{x}_N) \end{bmatrix}_{N\ x\ L} \qquad \begin{matrix} j \in 1, 2, \dots, N \\ i \in 1, 2, \dots, L \end{matrix}$$

$$f(x) = \frac{1}{1 + \exp(-w)}$$

activation function

$$w = \left(\sum F_i * a \right) + \mathrm{b}$$

ELM Training

- Calculate Output Weight Vector

$$\boldsymbol{\beta} = \boldsymbol{H}^{\dagger}\,\boldsymbol{T}$$

$$\boldsymbol{T} = \begin{bmatrix} 1 & 0 & 0 \\ \vdots & \cdots & \vdots \\ 0 & 0 & 1 \end{bmatrix}_{N\,x\,m}$$

$$\boldsymbol{\beta} = \begin{bmatrix} \cdots & \cdots & \cdots \\ \vdots & \cdots & \vdots \\ \cdots & \cdots & \cdots \end{bmatrix}_{L\,x\,m}$$

L – no. of hidden nodes
N – training set size
m – no. of output nodes

ELM Training

- w/ regularization parameter
  - any positive number C

$$\boldsymbol{\beta} = \mathbf{H}^{\mathbf{T}}\left(\frac{I}{C} + \mathbf{H}\mathbf{H}^{\mathbf{T}}\right)^{-1}\mathbf{T}$$

ELM Training

- Target Output Mapping

Genre	Node 1	Node 2	Node 3
Jazz	1	0	0
Rhythm & Blues	0	1	0
Rock	0	0	1

Genre (Root: Jazz)	Node 1	Node 2	Node 3
Bebop	1	0	0
Swing	0	1	0
Bossa Nova	0	0	1

ELM Training

- Target Output Mapping (cont'd)

Genre (Root: RnB)	Node 1	Node 2	Node 3
Blues Rock	1	0	0
Funk	0	1	0
Rock 'n Roll	0	0	1

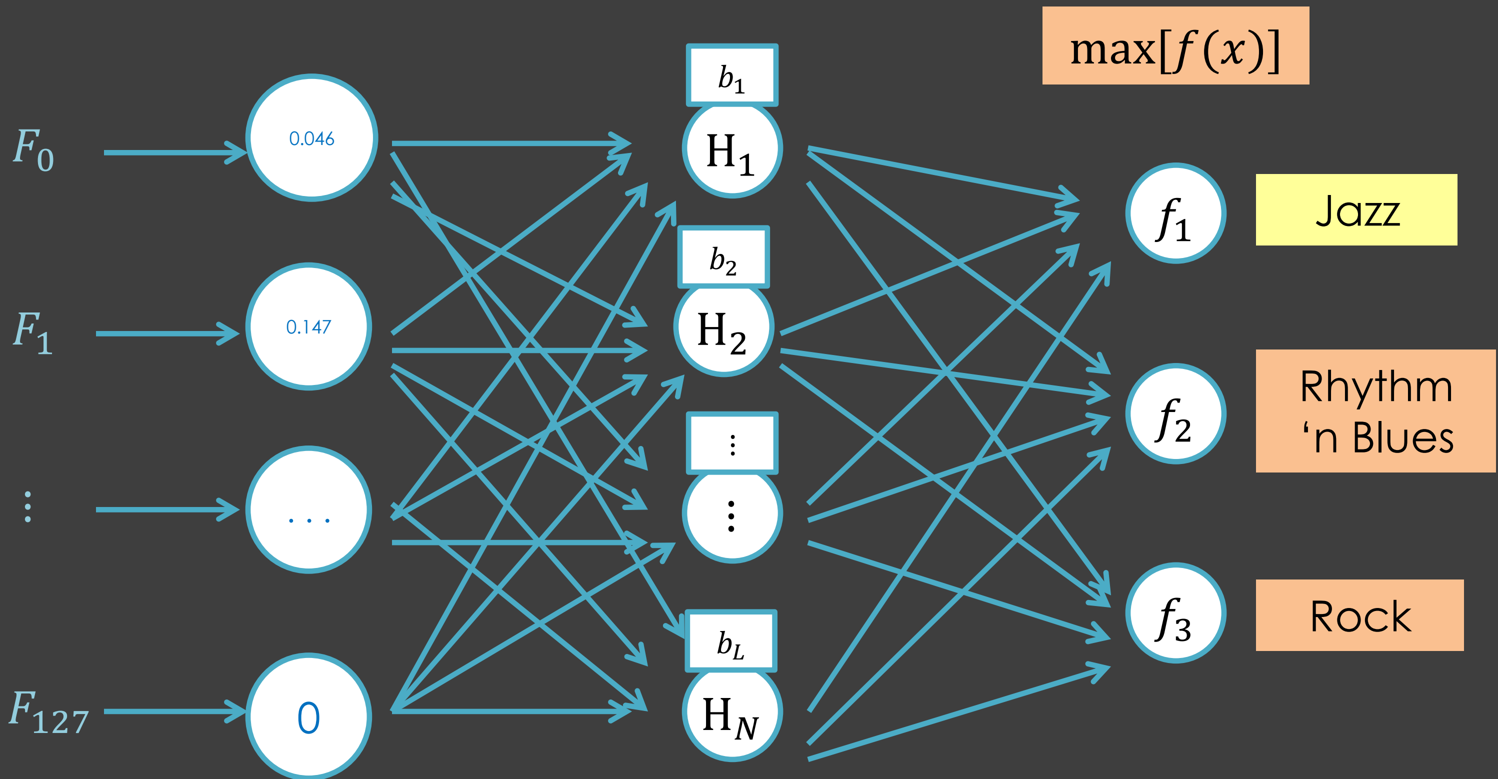
Genre (Root: Rock)	Node 1	Node 2	Node 3
Hard Rock	1	0	0
Metal	0	1	0
Alternative Rock	0	0	1

Output

- two-step manner
  1. Classify according to root genre
  2. Based on result in step 1, classify according to its corresponding leaf genres
- output function

$$f(x) = \mathrm{H}(x)\beta$$

Output


max[f(x)]
F_0
F_1
⋮
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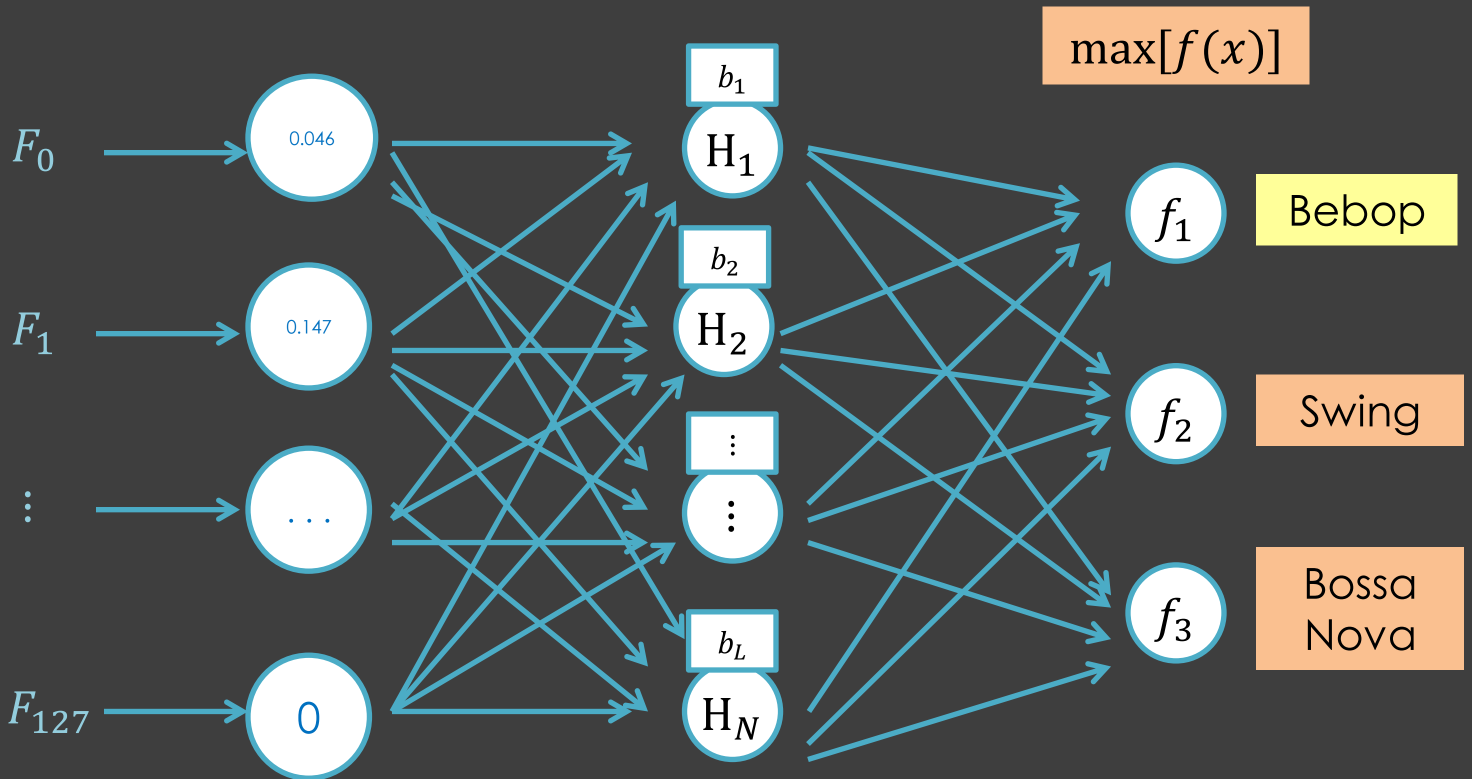
b_1
b_2
⋮
b_L
H_1
H_2
⋮
H_N
f_1
f_2
f_3
Jazz
Rhythm 'n Blues
Rock

Genre Taxonomy

Jazz	Rhythm & Blues	Rock	- root genre
Bebop	Blues Rock	Hard Rock	{ leaf genres
Swing	Funk	Metal	
Bossa Nova	Rock 'n Roll	Alternative Rock	

Output



F_0
F_1
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0.046
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H_1
b_2
H_2
⋮
b_L
H_N
$\max[f(x)]$
f_1
f_2
f_3
Bebop
Swing
Bossa Nova

Output

- Max. Output Node-to-Genre Mapping

Output Node with Max. Value	Genre
1	Jazz
2	Rhythm & Blues
3	Rock

Output Node with Max. Value	Genre (Jazz)
1	Bebop
2	Swing
3	Bossa Nova

Output

- Max. Output Node-to-Genre Mapping (cont'd)

Output Node with Max. Value	Genre (R'nB)
1	Blues Rock
2	Funk
3	Rock 'n Roll

Output Node with Max. Value	Genre (Rock)
1	Hard Rock
2	Metal
3	Alternative Rock

Experiments and Results

Experiments and Results

- System Specifications
  - Hardware
    - Intel Core i5 CPU M 460 @ 2.53GHz
    - 2048MB RAM
  - Software:
    - Windows 8 Pro 32-bit (6.2, Build 9200)
    - Eclipse Juno IDE
    - Java Virtual Machine

Experiments and Results

- Experimental Setups
  - Variation in training and test sets used
  - Variation in number of hidden nodes
  - Introduction of a regularization parameter
    - Variation in reg. coeff values

Experiments and Results

- Experimental Setups
  - Variation in network structure *(i.e. no. of output nodes)*
  - Comparison with existing study

Experiments and Results

- Experimental Settings
  - 30 trials per setup
  - Dataset
    - 225 MIDI Files
      - Training: 80%
      - Testing: 20%
    - Random-stratified

Experiments and Results

- Experimental Settings
  - Dataset (cont'd.)

	Training	Testing
Jazz	60	15
R'nB	60	15
Rock	60	15
Root	**180**	**45**

Experiments and Results

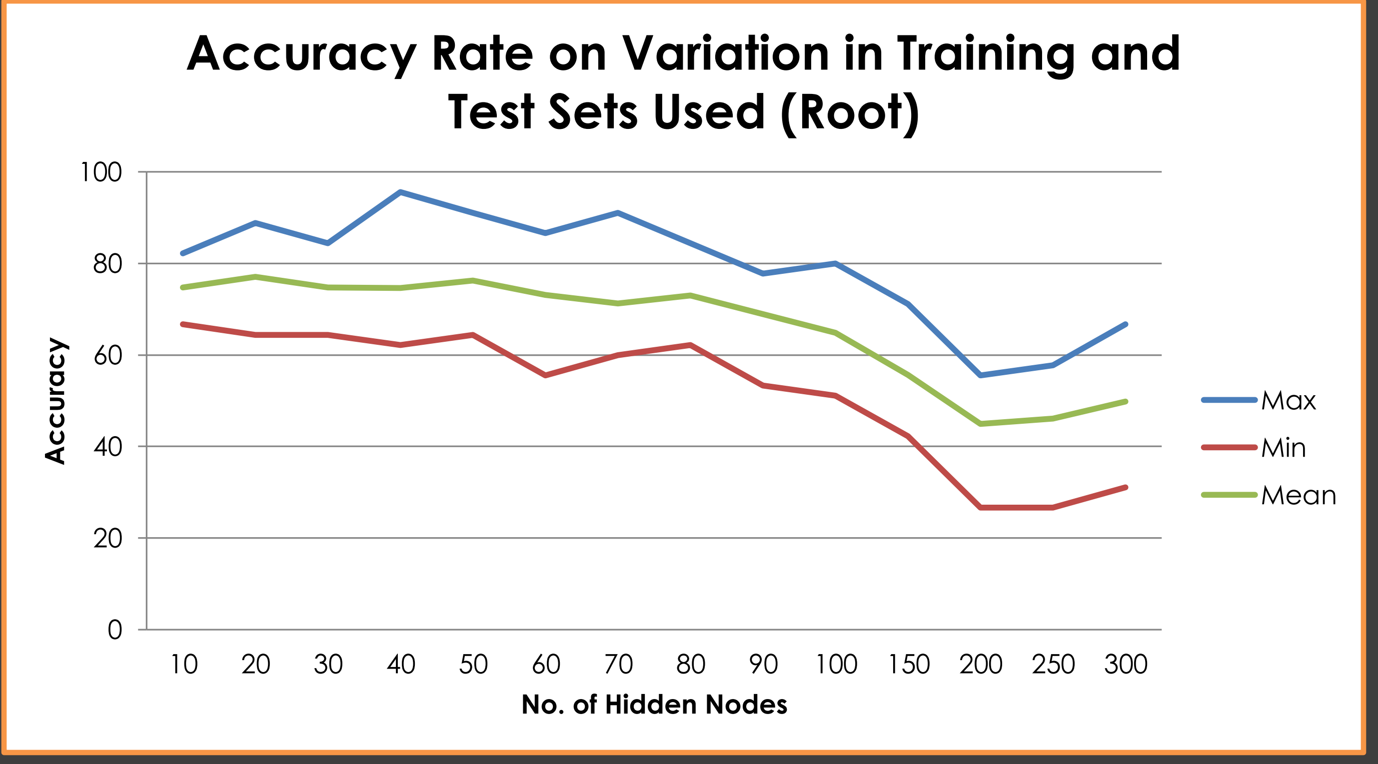
- Experimental Settings
  - Dataset (cont'd.)

		Training	Testing
Jazz	Bebop	20	5
	Swing	20	5
	Bossa Nova	20	5
R'nB	Blues Rock	20	5
	Funk	20	5
	Rock 'n Roll	20	5
Rock	Hard Rock	20	5
	Metal	20	5
	Alternative	20	5

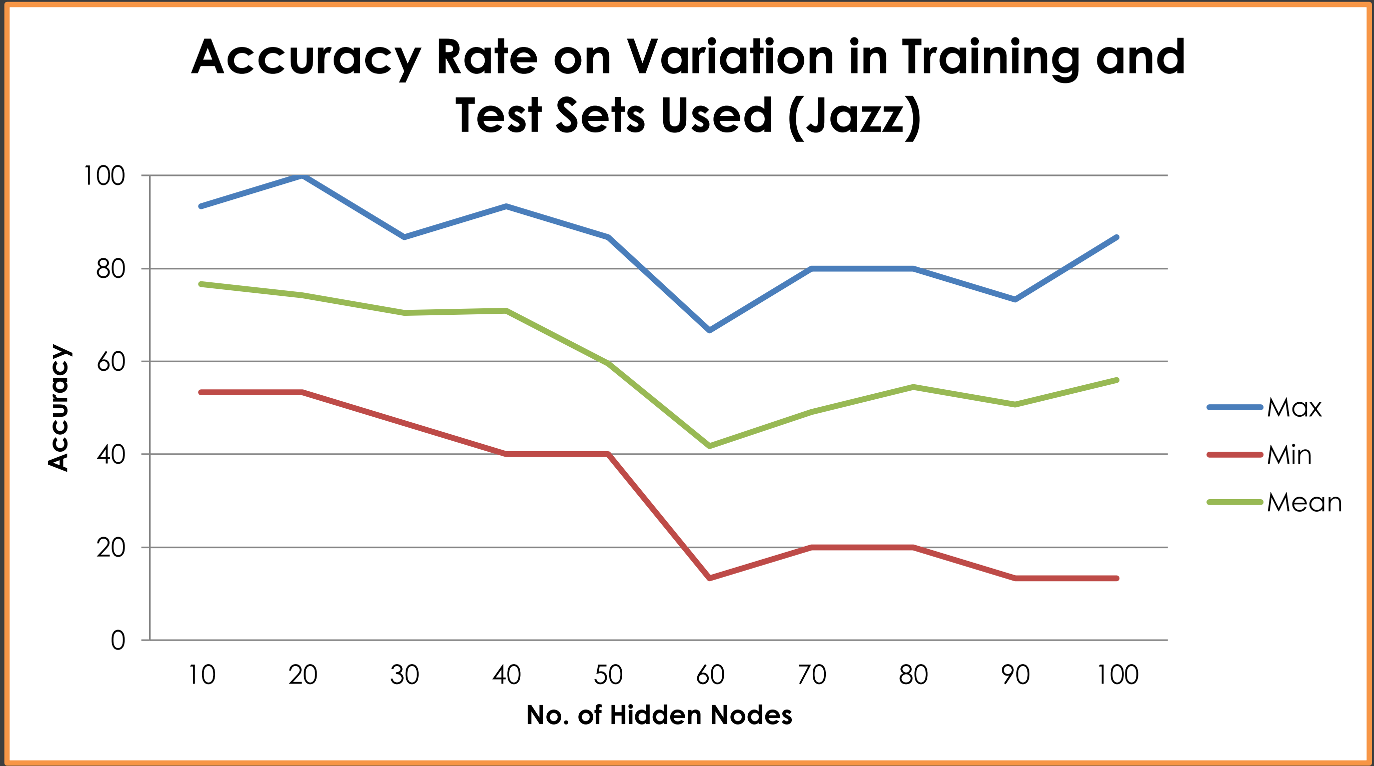
Experiments and Results

- Experimental Settings
  - initial parameters
    - Basic ELM
      - No. of hidden nodes 10
    - ELM w/ regularization parameter
      - Regularization coeff 0.2
  - dataset
    - random partitioning of dataset
    - fixed dataset

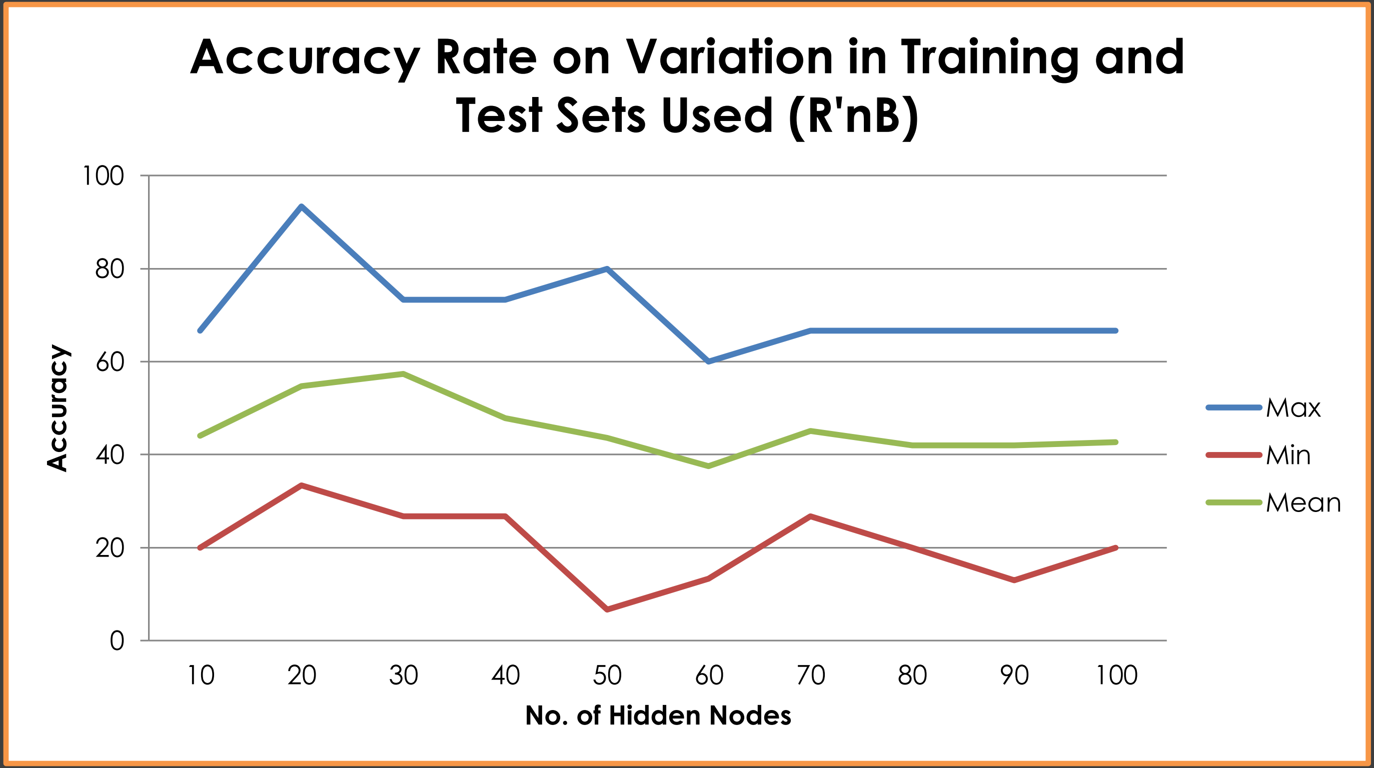
Experiments and Results



Experiments and Results



Experiments and Results



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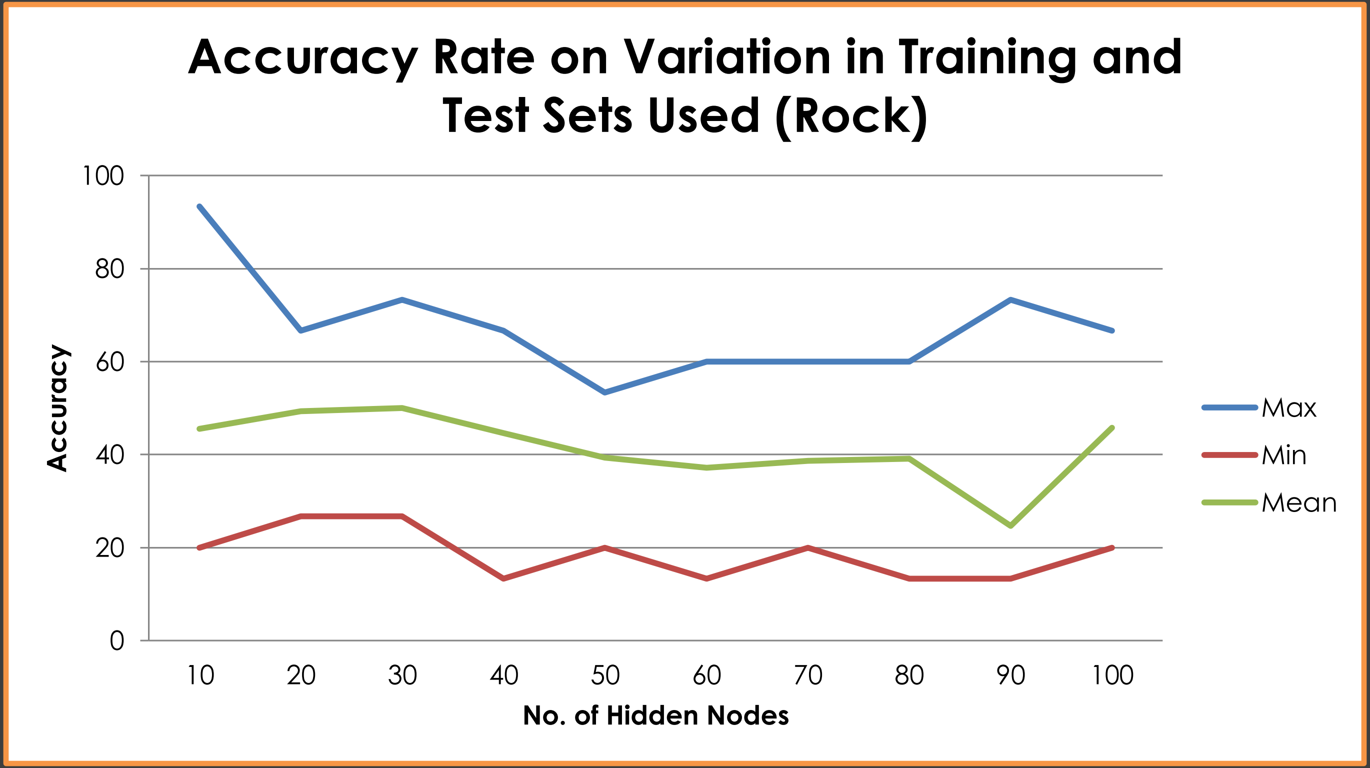
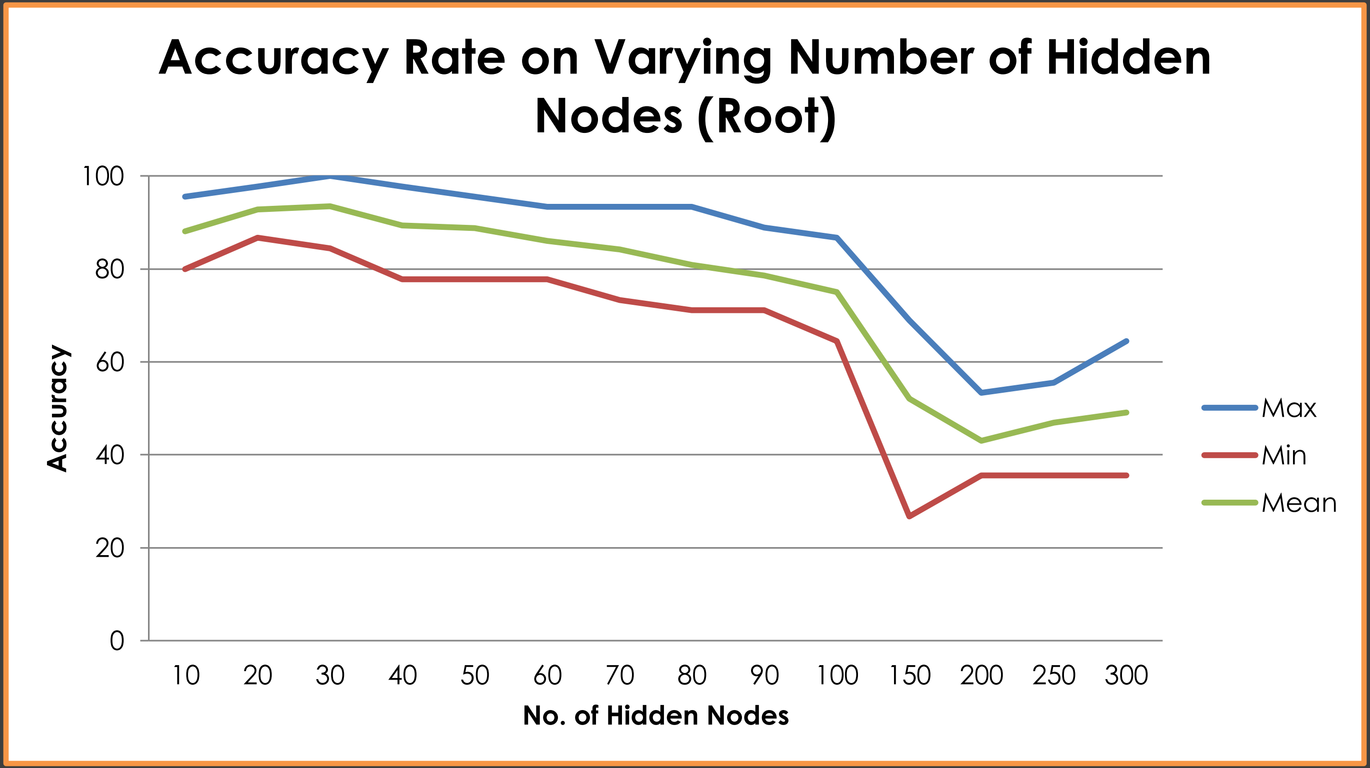


Experiments and Results



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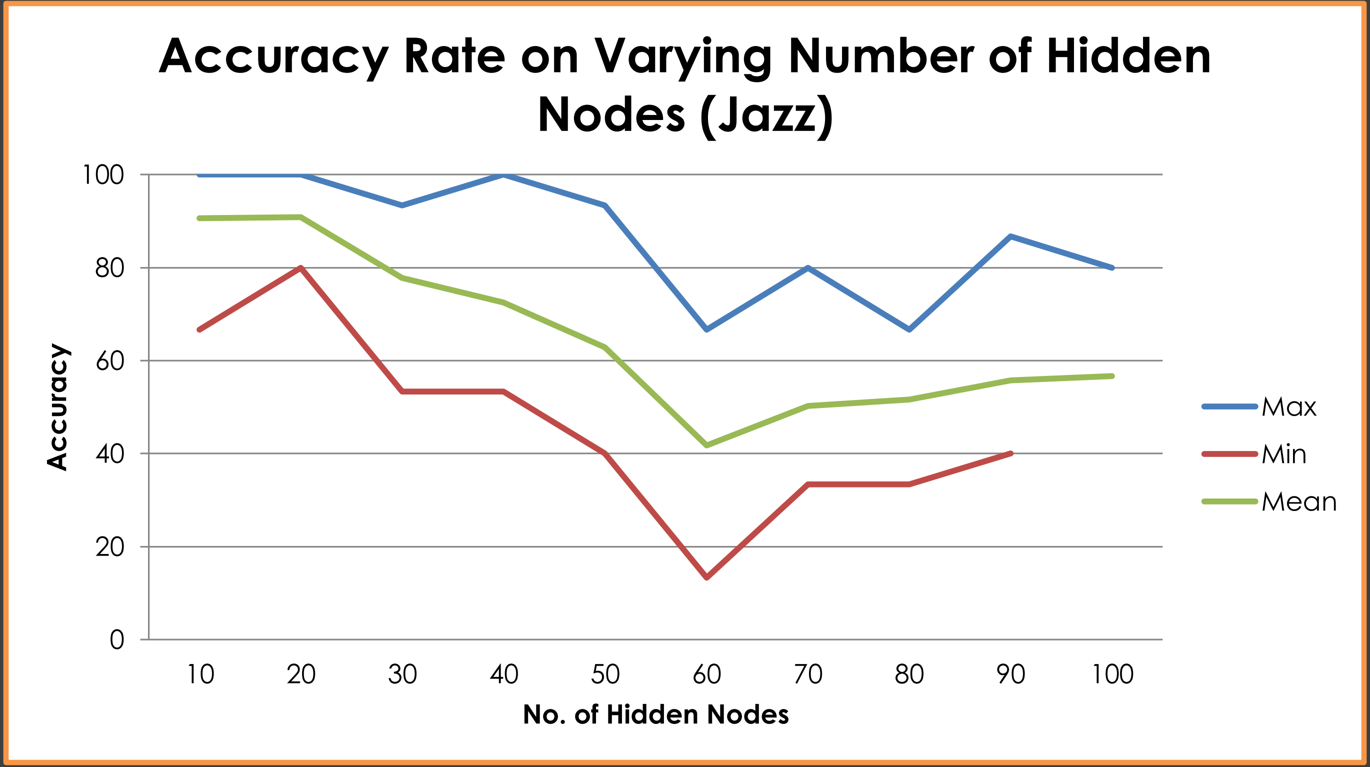
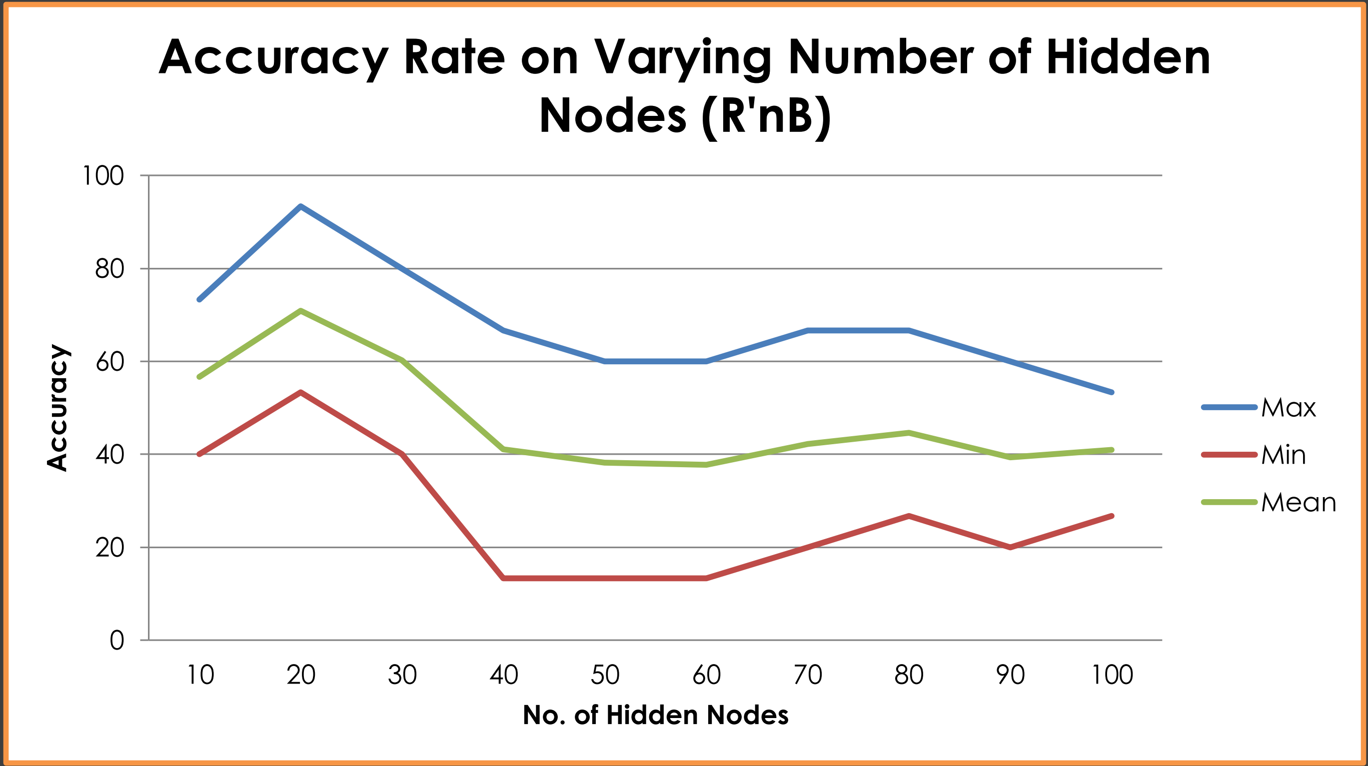
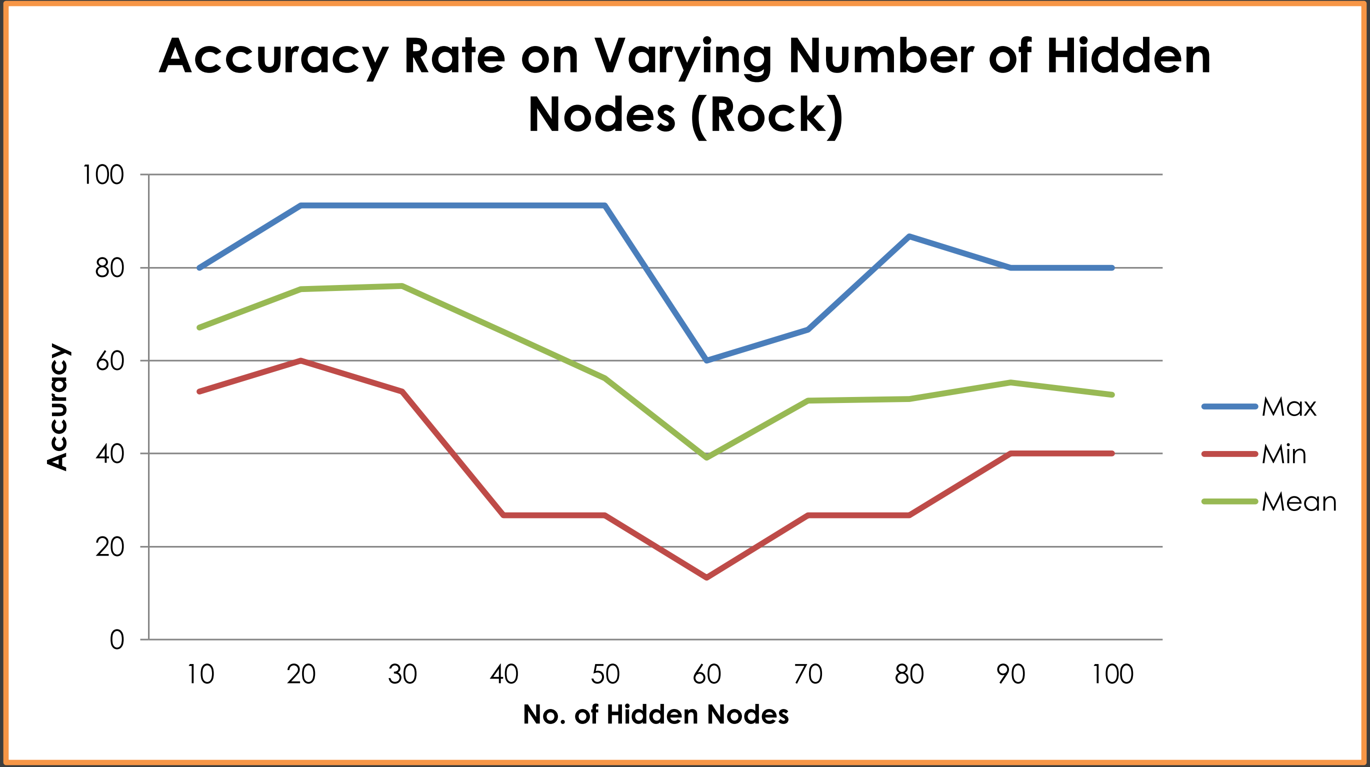


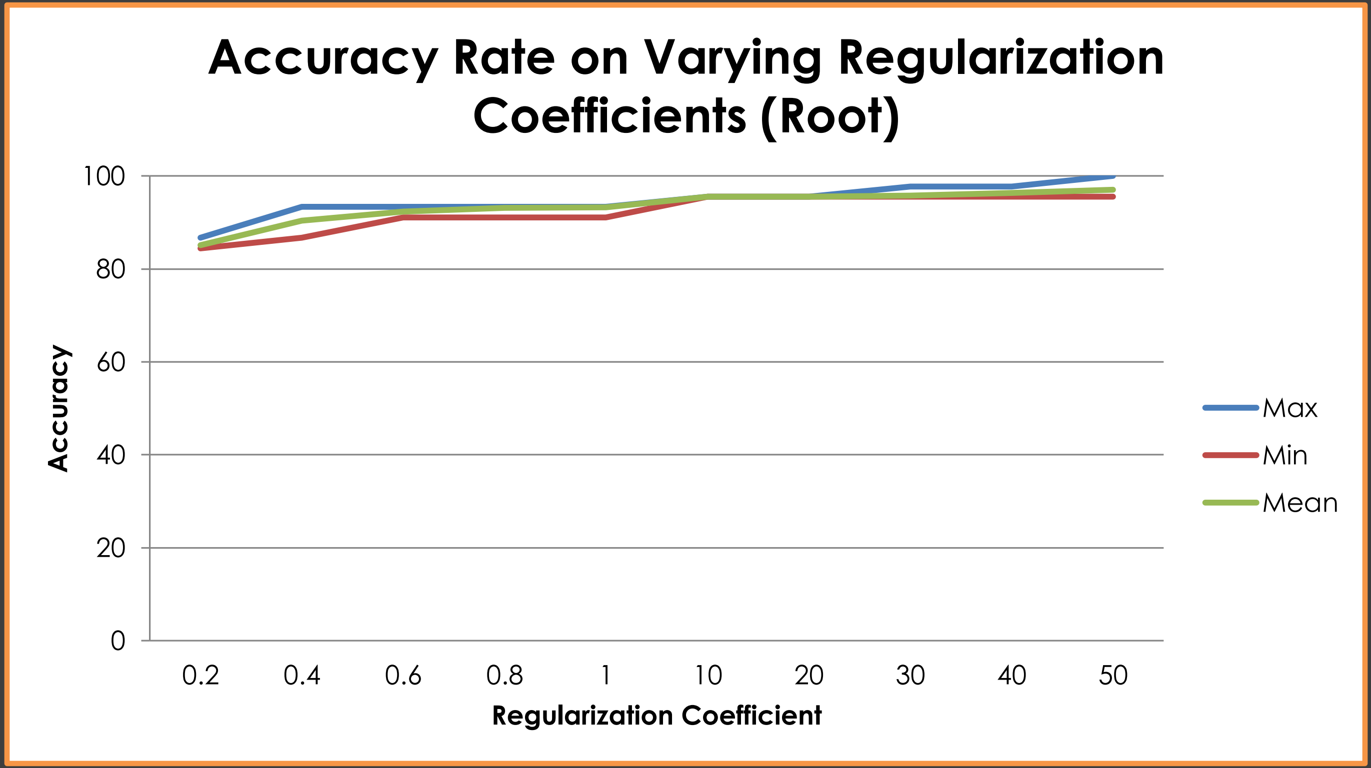
Experiments and Results



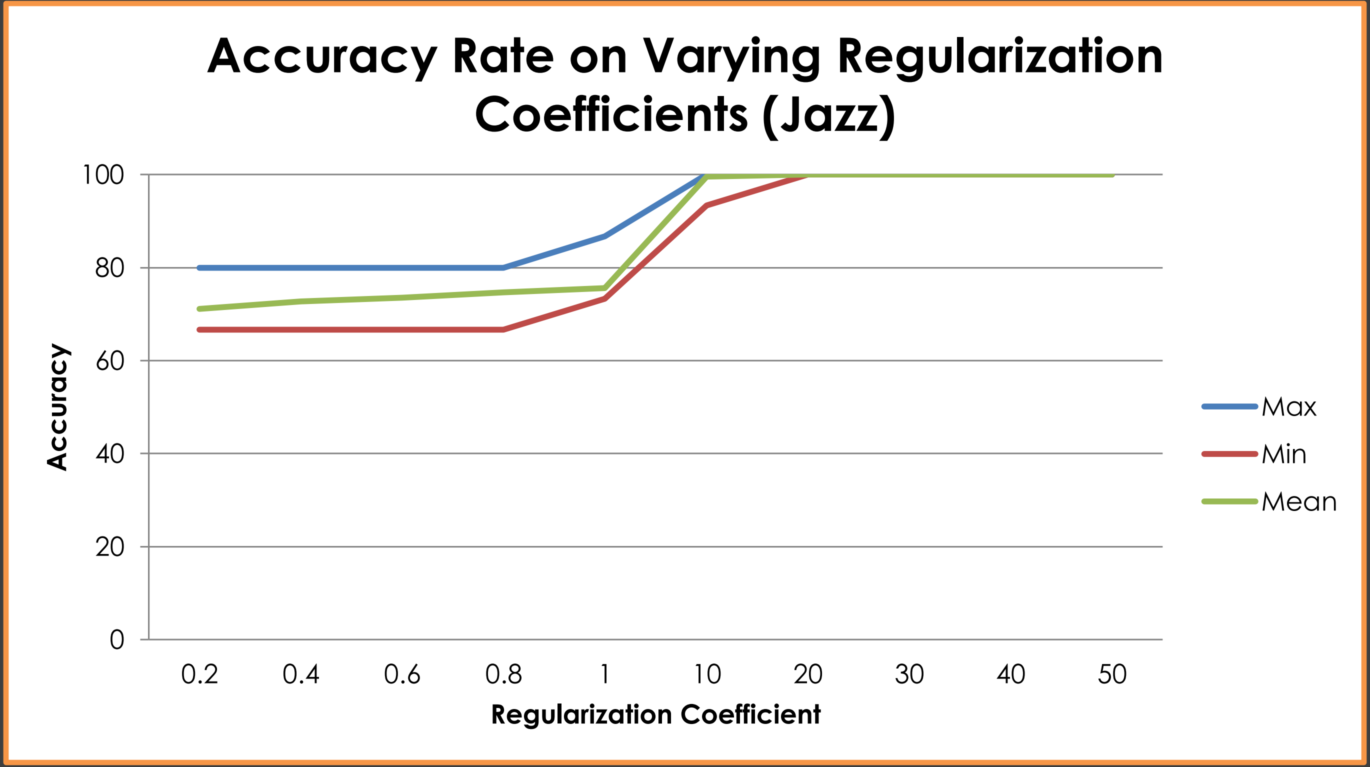
Experiments and Results



Experiments and Results



Experiments and Results



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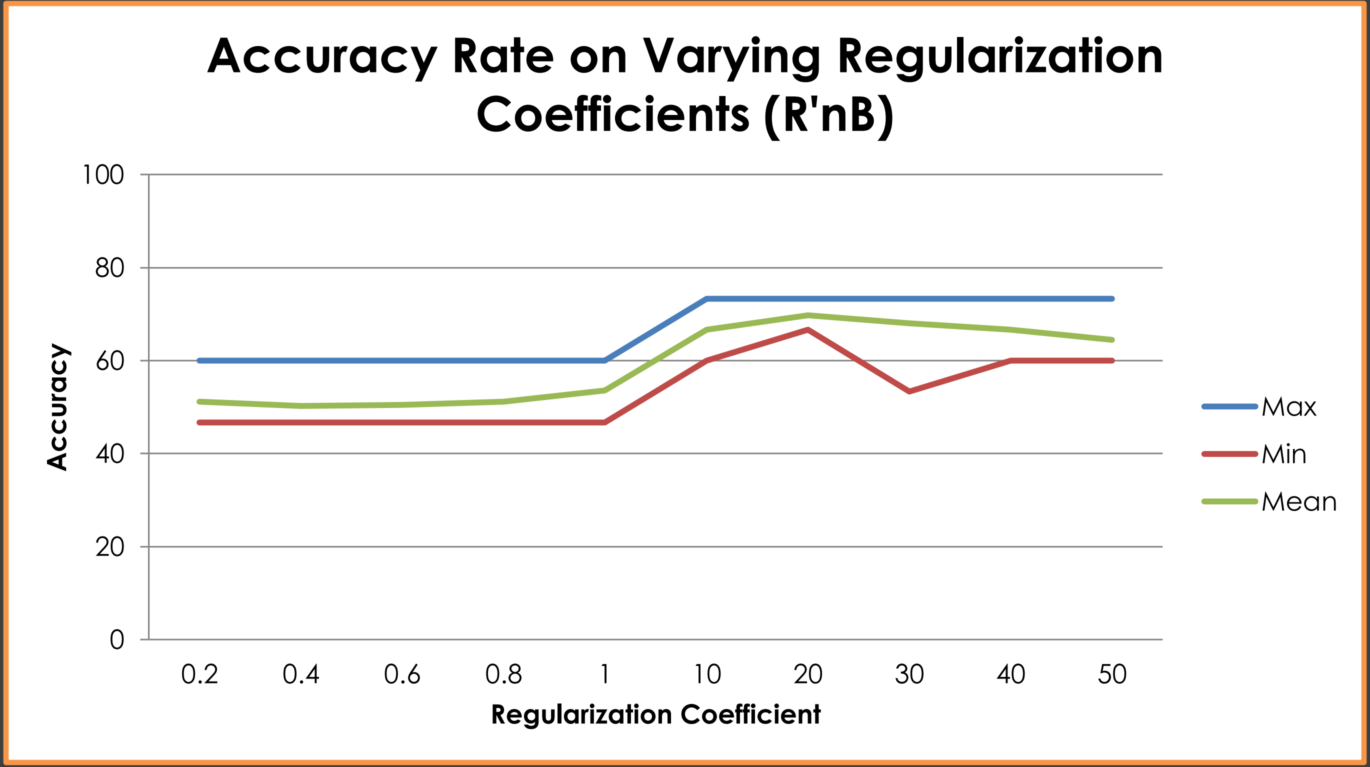

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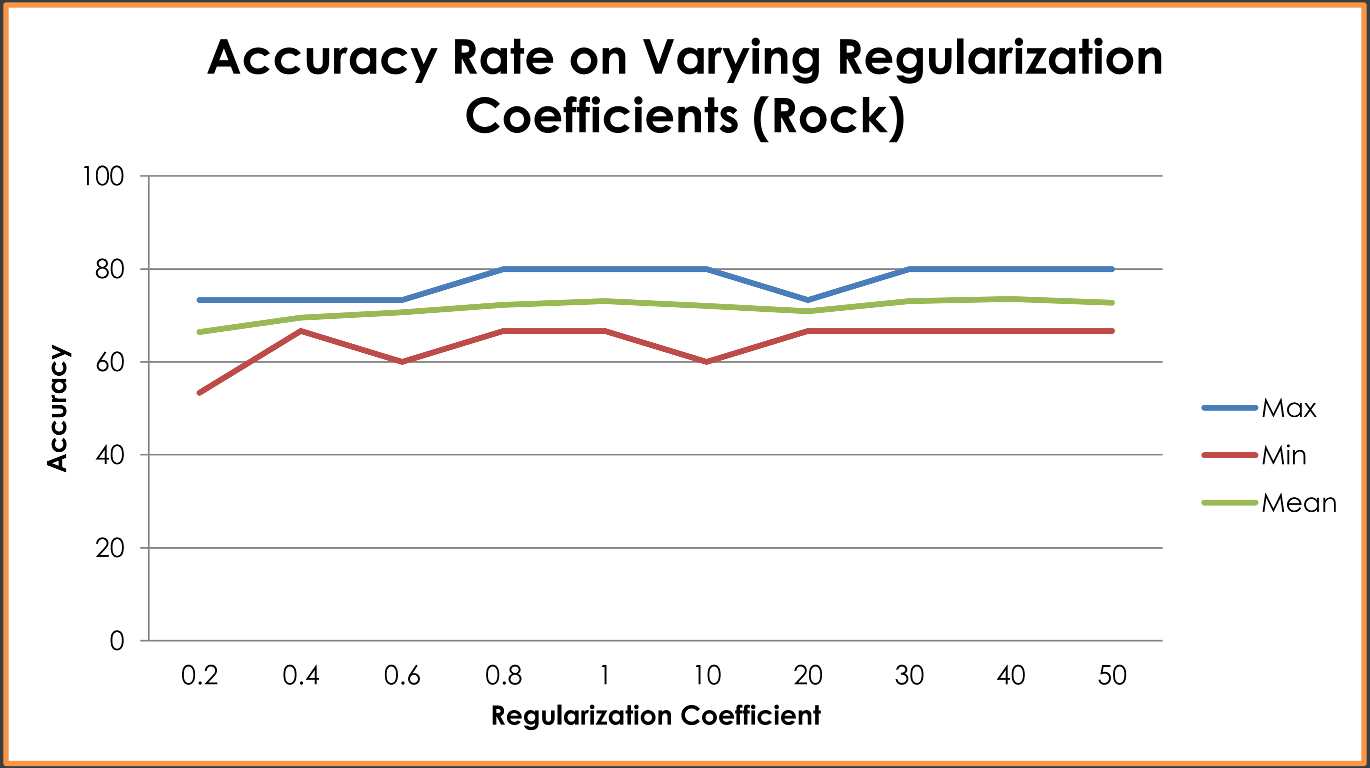
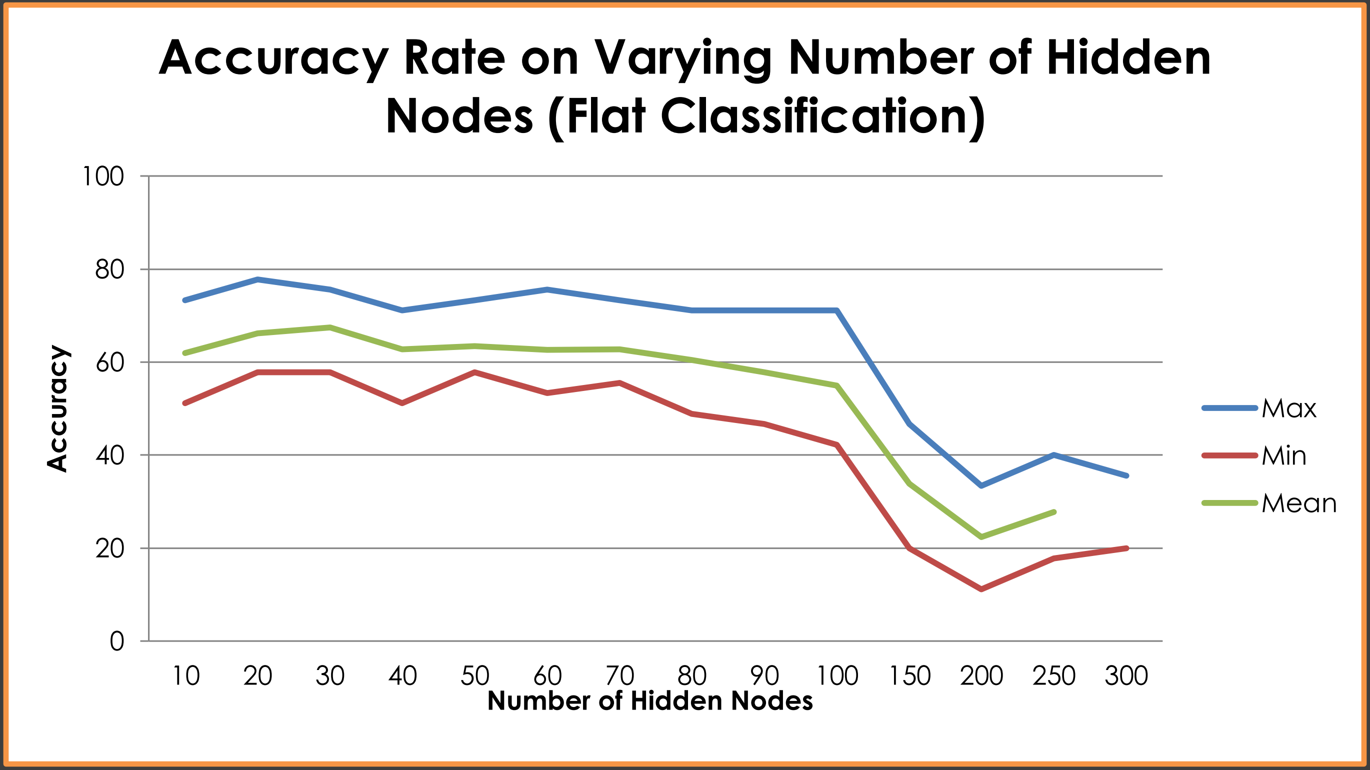


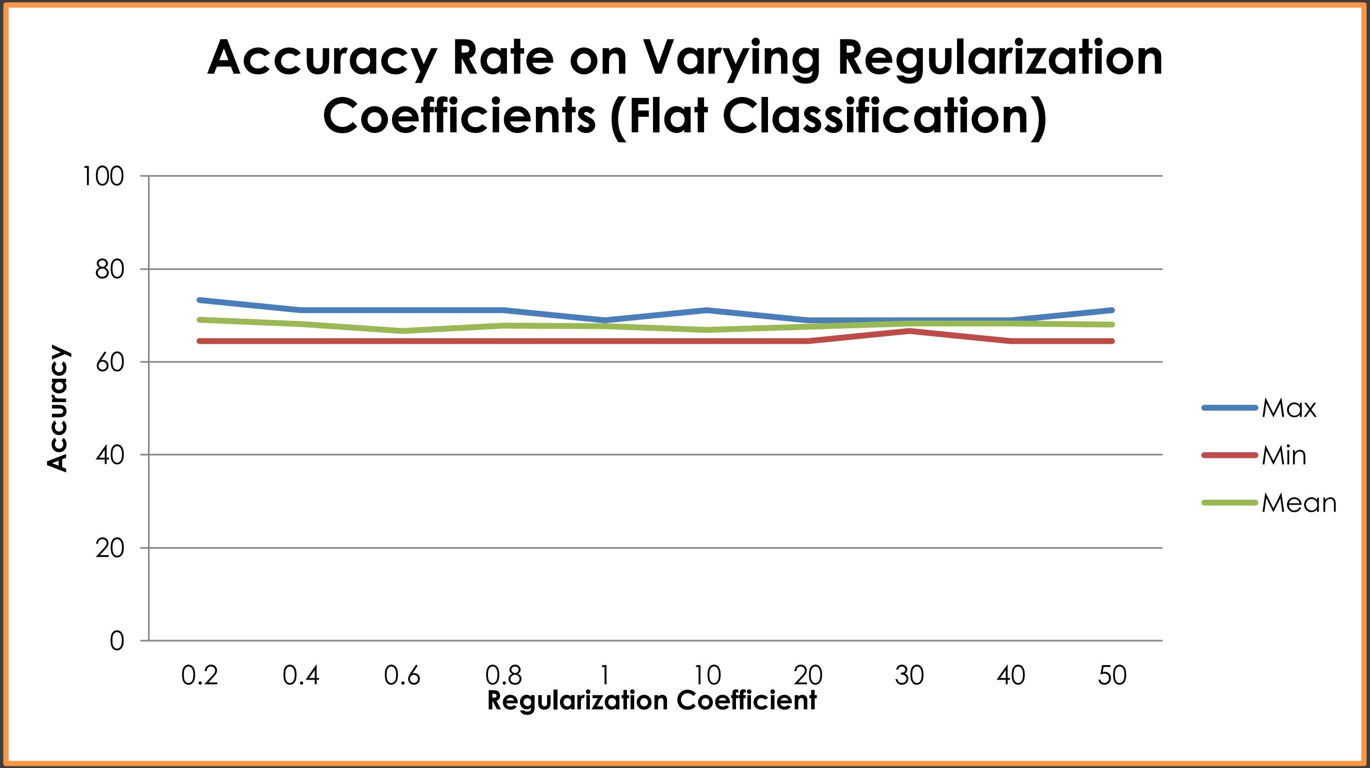
Experiments and Results

	Root (300 hidden nodes)	Leaf (100 hidden nodes)
Basic ELM	49.11%	50.08%
ELM w/ reg. coeff (C. @ 0.2)	**85.11%**	**62.96%**

Experiments and Results



Experiments and Results



Experiments and Results

Algorithm	Distance Metric / Type	Root Accuracy (%)	Leaf Accuracy (%)
KNN	ED	97.78	84.44
	EMD	93.33	80.00
	KL_2D	93.33	80.00
	NCD	75.56	66.67
	PWED	**100**	86.67
ELM	---	**100**	**95.56**

Conclusion and Future Works

Conclusion

- ELM is robust
  - good for music genre classification
- ELM is able to make good generalizations even with just a few hidden nodes, but declines when the number of hidden nodes is increased

Conclusion

- Adding a regularization parameter makes the ELM more stable.
- Hierarchical approach is better than flat classification

Future Works

- Online-Sequential ELM (OS-ELM)
  - No need for retraining when data/training set is updated
- Larger dataset
- Bassline Transcription