DEEP LEARNING FOR MUSICAL FORM: RECOGNITION AND ANALYSIS

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Master Thesis
MS Computer Science

April 2022
University of Wisconsin - Whitewater

Outline of Presentation

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Introduction

- [Classical] **Musical form analysis** is a rigorous task that frequently challenges the expertise of human analysts and signal processing algorithms alike

- While numerous systems have been proposed to perform the tasks of **musical segmentation**, **genre classification**, and **single-label segment classification** in **popular music**, none have specifically focused on the analytical process used by classical musicians

- As well, **current datasets** used for related research tasks **lack standardized analytical conventions**, including **form classification**, and suffer from **erroneous annotations** and **extensibility** due to the data sources used for the music

- We propose a new system to perform the task of **automatic musical form analysis** using deep learning models, as well as a new **standardized dataset**

Motivation

X

Problem Definition

Several attempts to **autonomously analyze and segment musical form** using artificial intelligence algorithms have been made (including novelty methods, community detection algorithms, and neural networks), but **none have proven to be sufficient**

1

Limitation #1

Current systems focus on **popular music tasks**, such as **Verse-Chorus segmentation/classification** and **genre classification** – although attempts have been made to segment classical music by phrases without classifying

2

Limitation #2

The only existing datasets of phrase-analyzed classical music (SALAMI) feature numerous errors, **lack standardized analytical conventions** (to allow for genre flexibility), and use live recordings rather than basing timestamps on the score

3

Limitation #3

No such tool exists for **automatic** (or **computer assisted**) classical form analysis – this time-consuming task must be done entirely by hand, and translating this to an AI-usable format requires a double analysis of **both the sheet music and a reliable audio file** for timestamping

Motivation – Potential Applications

1 **Music Rehearsal and Pedagogy**

Music practice and analysis tools, such as **dividing a piece by themes** for rehearsal, **assignment generation** using peak-picking, or a **grading system** for human-analyzed scores

2 **Audio Thumbnails and Fingerprints**

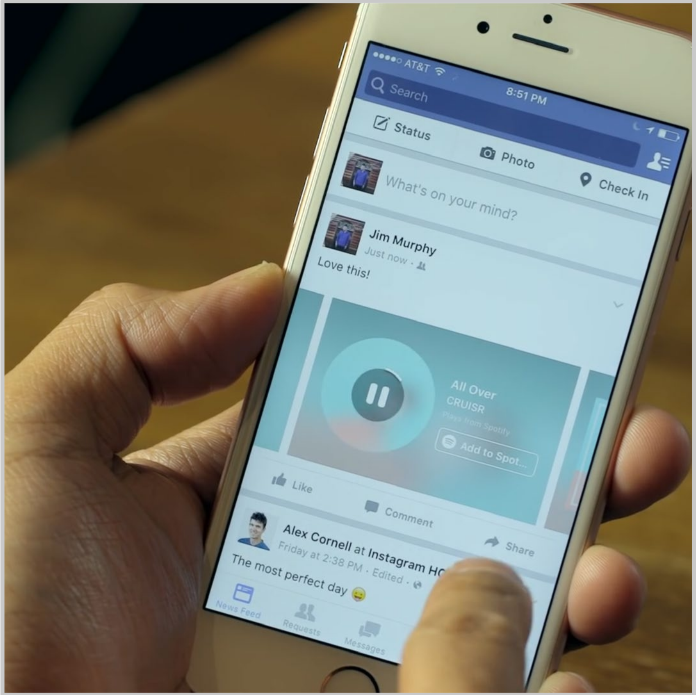
Audio thumbnail/fingerprint generation, as applicable for a **streaming service or web store** (iTunes, Facebook Music Sharing, Amazon music)

3 **Forensics and Copyright Detection**

Forensic Musicology, where the analysis may be used to **compare numerous pieces of music** for similar or exact replications of musical phrases, motives, or other structures

4 **Audio-Video Analysis**

Extension to video analysis to apply both **visual and audio cues** to the **media's structure**, whether formal in design (such as a music video, musical, etc.) or not (a movie/TV show)



Facebook's audio sharing feature for Spotify /iTunes[1] (Plays a 30 second song preview)

[1] Image Source: https://digiday.com/media/facebook-now-lets-users-share-music-listen-30-second-song-snippets/

Motivation – Potential Applications

5

Generalized Audio Structure Analysis

Performing structural analysis on any given audio or waveform, including **spoken audio** where patterns of repeated language may be used (i.e., poetry, forensic investigation, lecture, neuro-linguistic programming, **Natural Language Processing (NLP)** problems)

6

Optical Music Recognition and Analysis

Optical Music Recognition (OMR) – analyzing a piece using the sheet music, much like a human analyst, or correcting optical sheet music transcriptions using formal structures

7

Audio and Spoken Language Classification

Audio classification by content, with or without music (e.g., for **sorting a web database**, hearing-impaired **accessibility tools**, **language classification** from audio recordings [NLP])

8

Lacking Musicology Research

Production of **musical form/analysis-based anthologies**, alongside other fields of musicology that lack significant research and technological advancement

Anthology books are widely used in all fields of music[2] – though Form Analysis has very few

[2] Image Source: https://www.amazon.com/Faber-Music-Contemporary-Piano-Anthology/dp/0571541585

Goals and Objectives

Goal #1

Provide a new model to **perform full form analysis** (form classification, segmentation, part/phrase labeling), rather than simply peak-picking and segmentation, and **expand upon existing model architecture designs** using recurrent memory cells to better recognize repeated audio patterns

Goal #2

Develop **a new, musically accurate dataset** by common analytical conventions, including categorical divisions by large musical form, and provide appropriate **evaluation metrics** and **accurate model performance** results

Goal #3

Present a more accurate deep learning model to perform both **form-level** and **part/phrase-level analysis** using suitable algorithms for the network architecture and signal processing by extensive and exhaustive research

Goal #4

Examine the previous work done in the field through **extensive background research** and **contribute to the literature** by obtaining improved results from previous studies in the formal analysis of music using machine learning and peak picking methods

Background

- Classical music form analysis facilitates a combination of classification and segmentation tasks, including **form classification**, **structural segmentation**, and **multilabel large-** and **small-segment classification** – tasks that lack feasible algorithms, machine learning models, and extensive research

- Classical pieces are broken down hierarchically by their **large form** (two-part/binary, three-part/ternary, ...), **Part** divisions (part A, B, A', Development, CODA, …), and **Phrases** (a, a', b, c, theme, variation, transition, section, …) – though many additional labels may be employed, including for other sub-structures

- Form analysis has many applications in the world of music (especially for directors), and a viable analytical system would greatly benefit **performing musicians** and **academic researchers**, both in musicology and signal processing

- One of the greatest difficulties in musical analysis is the **lack of complete ground truth** – pieces of music are frequently interpreted differently by different analysts, and **may be classified or even analyzed differently** at the phrase or part levels

Analysis of Bourrée from J.S. Bach's BWV 996 (Rounded Binary form)

Literature Review

System 1 (1998)	Melody and harmony generator using **Feed-forward Neural Networks**; unable to learn higher-level musical structures occurring simultaneously and at multiple time scales or recognize melodic vs. harmonic context of notes and intervals
System 2 (2007)	Automatic musical style recognition through classification of harmonic, melodic, and rhythmic descriptors using **k-NN**, **Self-Organizing Maps**, and **Bayesian classification**; SOMs may be useful for formal analysis, system designed to recognize low-level features only
System 3 (2014, 2015, 2016)	Boundary recognition using **Convolutional Neural networks**, **Mel Spectrogram**, and **Self-Similarity Lag Matrices** to estimate fixed-depth segmentations based on SALAMI annotation levels; boundaries evaluated by time tolerance. Also used to generate audio thumbnails
System 4 (2020)	Automatic musical structure detection and segmentation using **multi-resolution community detection** and **graph theory** to perform boundary detection and structural grouping, yielding a structural hierarchy. Noted that CNNs will continue to lack improvement without recurrent layers

Methodology – Main Contributions

Develop a system of three components: Form Analyzer, Peak-Picking Algorithm, and Phrase Analyzer

Use hybrid Neural-Decision Tree models to train quickly and reduce overfitting

Dataset built from 200 manually classified MIDIs, augmented with 5 different sets of permutations to expand dataset to 1,200

Methodology – System Components

Form Analyzer

- Classify classical piece as one of 12 possible forms:
  - Arch
  - Bar
  - Binary
  - Minuet & Trio
  - Ritornello
  - Rondo
  - Sonata
  - Ternary
  - Theme & Variation
  - Through Composed
  - Unary/Strophic
  - Unique

Peak-Picking Alg.

- Break down audio file using Onset Detection methods to discover the peak event audio frames
- Return this set of frames as a series of timestamps representing the musical phrases

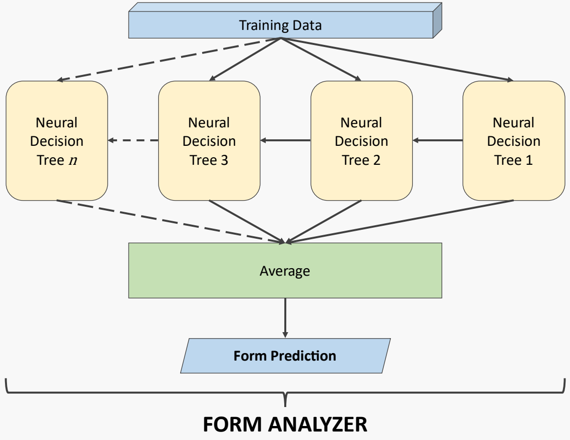
Phrase Analyzer

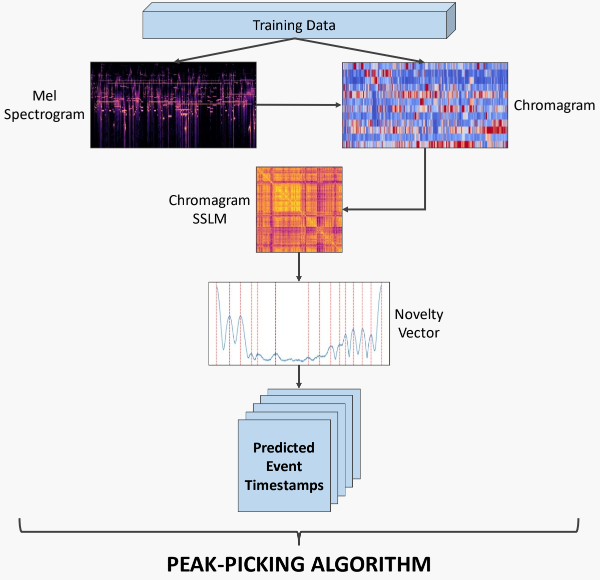
- Using the form classification and phrase timestamps, classify each timestamp sequentially
- Timestamps may include multiple labels (part and phrase) or individual (transition, phrase, etc.)

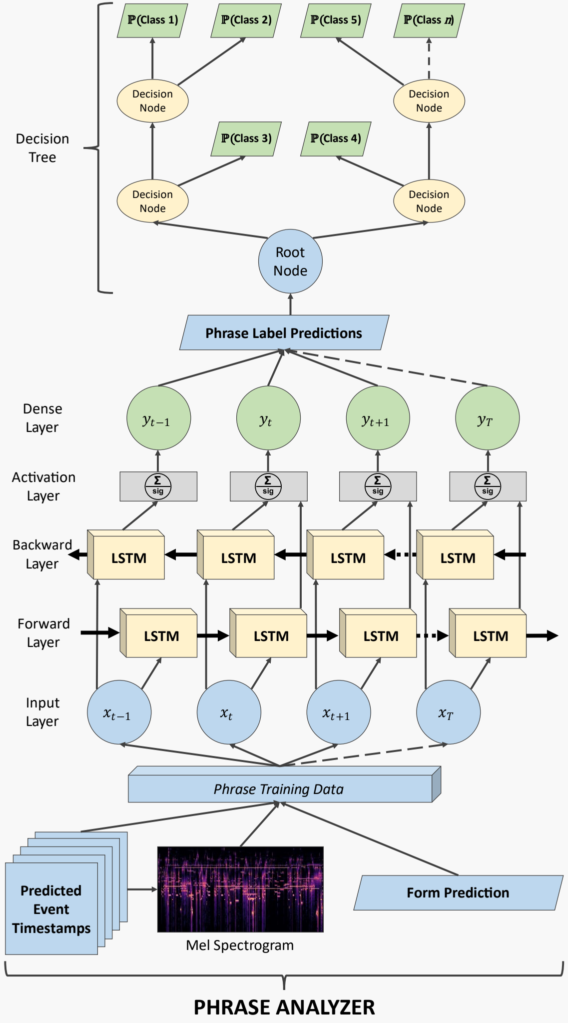
Prediction System

- Combine the outputs of all 3 major components
- Present final analysis formatted to match the training data (filename, form, and labeled timestamps)

Methodology – System Architecture







Data Extraction and Preparation

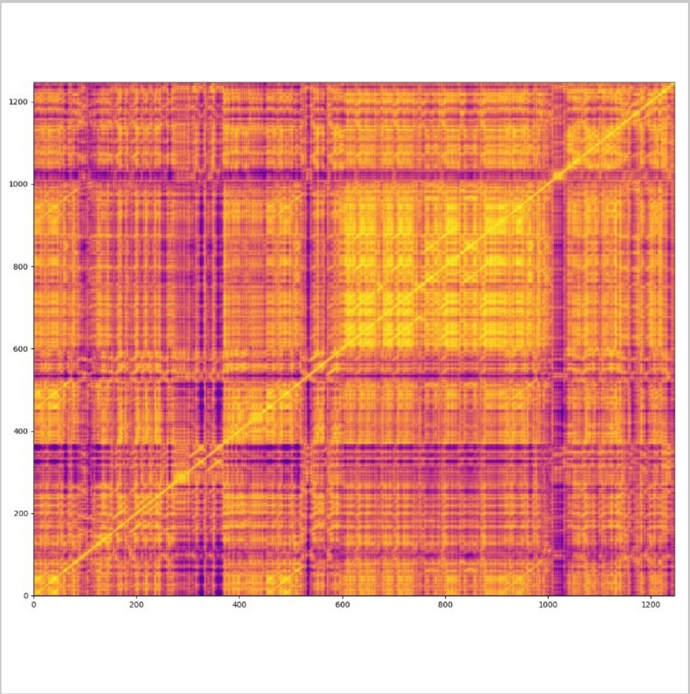
- Using feature selection and elimination methods, we found that the two most important data features for Form Classification were the **music duration** and the **Self-Similarity Matrix (SSM) of the (Mel) Spectrogram**

- The dataset was **augmented** using **pitch, time, speed**, and **starting-point shifting** methods to expand the 200-piece dataset to 1200 – the data is publicly available on GitHub for extended contribution (https://github.com/danielathome19/Form-NN/tree/master/Data)

- Each piece of music was converted to its **Spectrogram SSM**, and the mean and variance were used to reduce the 2D array into 1D – a common approach for **feature scaling** and **dimensionality reduction** in signal processing

- This set of data (including the duration and numerous unused pre-calculated features) was stored as a **data table** for ease of extensibility and reduced computation time during training

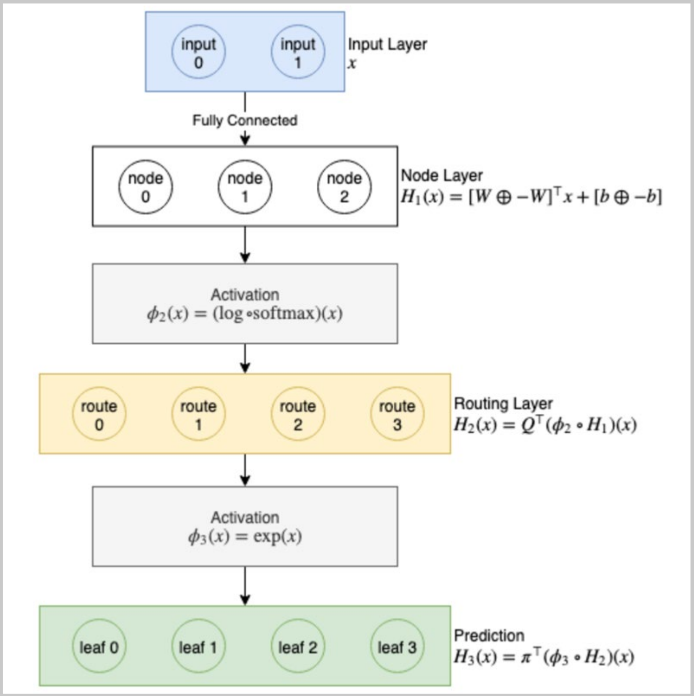
- The data for the Form Analyzer was scaled using $X = \frac{(X - mean(X))}{std(x)}$, and using **Min-Max Scaling** for the Phrase Analyzer ($X = \frac{X - \min(X)}{\max(X) - \min(X)}$).



Mel Spectrogram SSM

Form Analyzer Architecture – TreeGrad

- A hybrid **Deep Neural-Decision Forest** architecture (known as **TreeGrad**) was used to fit the dataset as an ensemble network using Stacking
- This model trained extremely quickly and fit to the dataset with **high accuracy and low error** – hence, overfitting was not an issue compared to **non-hybrid models** (CNN, DNN, etc.)
- **Duration** was found to be the most important feature in **classifying the form**, a hint well-used by human analysts
- Labels were encoded using **Integer encoding**
- To combat overfitting using the **pruning methods** employed by decision trees, TreeGrad models each tree in the ensemble as a three-layer neural network to create a **Neural Decision Tree**
- Each Neural Decision Tree is comprised of a **Decision (Input) Layer**, **Node/Routing (Hidden) Layer** which controls the branching of each node in the tree, and a **Prediction (Output) Layer**



TreeGrad Architecture

Form Analyzer Architecture – TreeGrad

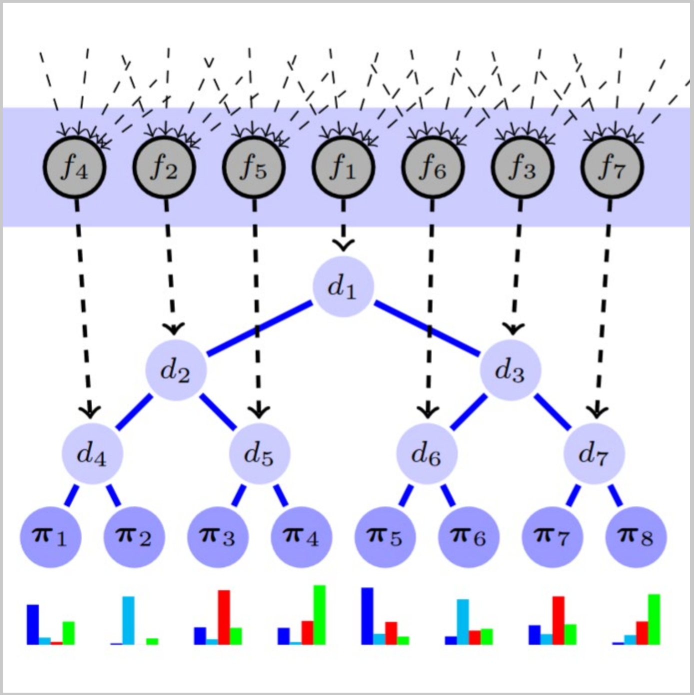
- Each tree in the TreeGrad forest uses probabilistic routing computed by the **sigmoid function**, replicating the probabilistic output of a **Dense Neural Network**

- Both the **Input** and **Dense** layers are trainable, allowing the weights of each layer to be bounded by the $\ell_p - norm$ with $p \geq 1$, conforming the model to the **AdaNet Generalization Bounds** (creating better comparisons between the complexities of models in an ensemble and the overall training loss)

- All trees in the forest are combined into a **Stacked** ensemble, where multiple well-performing models are combined, and the **average** of their output is returned as the final prediction

Form Analyzer Parameters

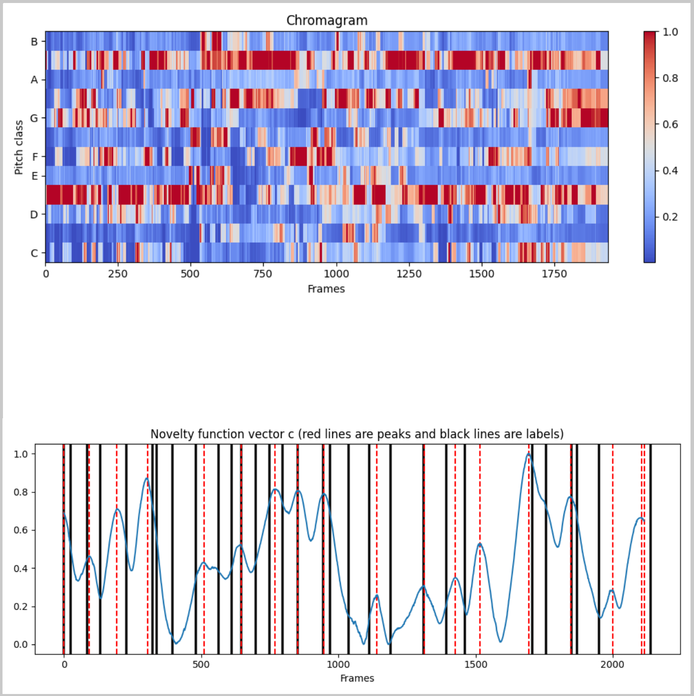
	# Of Leaves (Per Tree)	Max Depth	Learning Rate	# Of Estimators (Trees)	Batch Size	Refit Splits?
Value	31	-1 (∞)	0.1	100	32	True



Probabilistic routing and output of a Neural Decision Tree modeled as a CNN [92]

Peak-Picking Algorithm – Onset Detection

- The Peak-Picking (also called "**Onset Detection**") algorithm uses the **Mel Spectrogram** and **Self-Similarity Lag Matrix (SSLM) Chromagram** (a graph of pitch class distribution by time) to detect peaks in the audio
- The Chromagram SSLM is computed using **k-Nearest Neighbors** to cluster pitches in the Mel Spectrogram
- The **computed vector of peaks**, represented by audio frames captured by the Short-Time Fourier Transform (STFT), is returned as **an array of timestamps**
- While the algorithm **does not employ machine learning techniques** to perform the peak-detection directly, it was **found to be comparable to other CNN architectures** discovered in the literature review and greatly reduced system design time (given the lack of training necessary to perform the calculations)



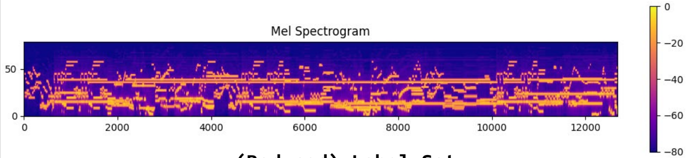
Example Chromagram and Novelty Vector

Phrase Analyzer Architecture – LSTM-Tree

- Data for the Phrase Analyzer is divided into **a series of timestamps** which are used to slice the audio into segments between these points
- The features selected for the Phrase Analyzer include the **Form classification**, **timestamp**, **audio slice duration**, and the **Mel Spectrogram**. Hence, prediction requires both an accurate Form prediction and Peak-Picking results. Labels were encoded using **One-Hot Encoding**
- The model was implemented using a hybrid architecture – a **Bidirectional LSTM** (a form of Recurrent Neural Network) is fit to the data, then the output of the last hidden (Dense) layer is used to fit a **Decision Tree** to perform the final prediction (referred to as **LSTM-Tree**)

Phrase Analyzer Parameters

	LSTM Units	LSTM Dropout	Merge Mode	Loss	Activation	Optimizer	Batch Size	Epochs
Value	4	0.2	Concat	Binary Cross-entropy	Sigmoid	Adam	1	5

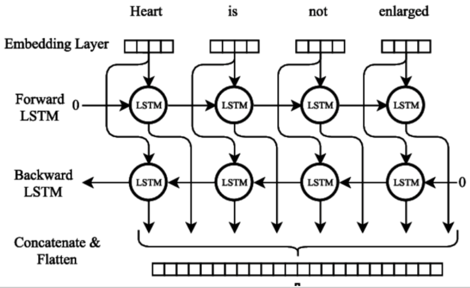


(Reduced) Label Set

Large Parts = { A, B, C, D, Theme, Variation, CODA, End, Silence }

Phrases = { a, b, c, d, e, f, transition, codetta, section (abbr. “sec”) }

Theme Variations = { characteristic, figural, melodic, ornamental, simplifying }



Example Mel Spectrogram, Label Set Universe, and Bi-LSTM Architecture

Evaluation – Experimental Results

- For the Form Analyzer, the TreeGrad model simply takes in the SSM and duration of a piece of music and outputs the **predicted classification**, which is compared against the **ground truth label**

- For a musicologist, this system alone could be used to discover **when and why** a composer may choose a particular form over another, for example

- While the Peak-Picking Algorithm was not evaluated using a formal metric, the algorithm was tested against the training data and the output timestamps were often found to be **nearly identical** or **had a low enough difference** to be subjectively true (similar to human bias)

- Using the **timestamps** provided by the Peak-Picking Algorithm and the **labels** output from the Phrase Analyzer, the piece of music can be **score studied** (i.e., analyzed within the sheet music) much quicker for rehearsal and research use, for example

A person performing music analysis using the sheet music for the piece[3]

[3] Image Source: https://makingmusicmag.com/music-analysis-essay/

Evaluation – Form Analyzer

- The full (augmented) dataset was split into **83.1% training** and **16.9% testing** (or validation)
- The Form Analyzer was evaluated using both validation accuracy (or **Jaccard score** in this case) as well as **Precision/Recall/F1** scores
- The final model solely uses the TreeGrad model to perform the prediction – the **Mel Spectrogram SSM** is calculated on the fly, then passed to the model along with the **duration**
- The output provided by the prediction is **the large form classification** expected by the model, which was found to be 83% accurate – a surprisingly good performance given the **subjective nature** of the form classification

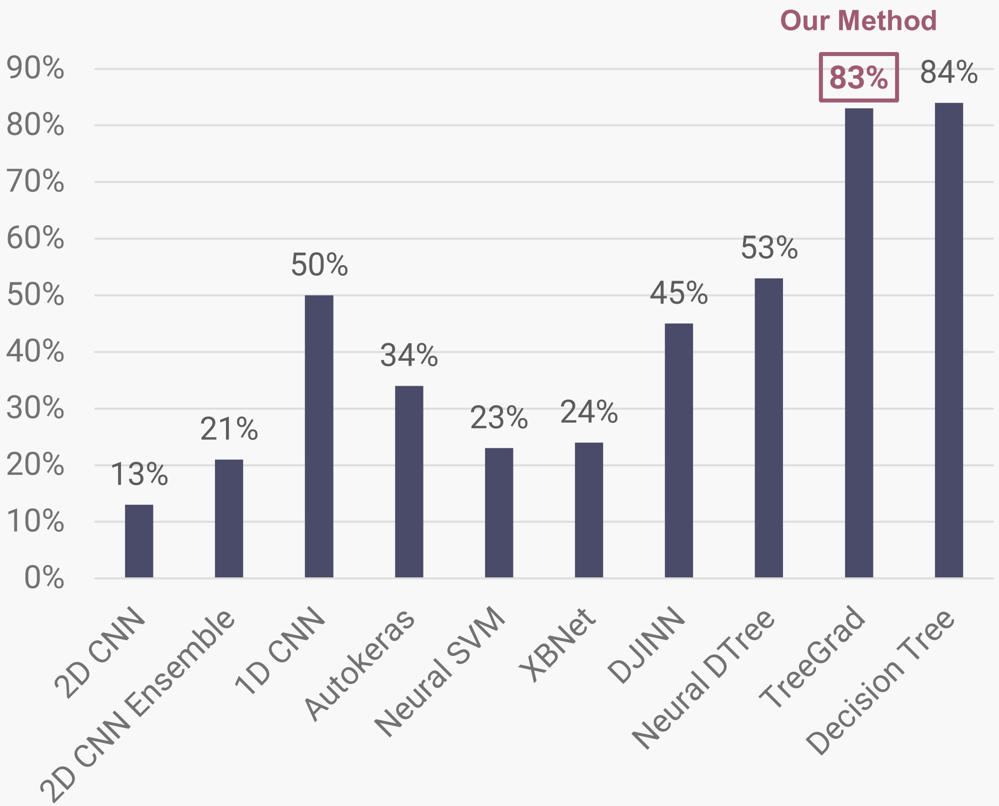
Result #1

The final Form Analyzer model achieved a **maximum accuracy of 83%** -- precision and recall were closely correlated to this score. May perform better as an **ensemble**

```
Performing predictions on anna-magdalena_book_14
                                        Predicted form: Unary
Performing predictions on brahms_opus117_1
                                        Predicted form: Ternary
Performing predictions on faure_nocturne_99_no10
                                        Predicted form: Sonata
Performing predictions on bthvn_pno_concerto_2_19_3
                                        Predicted form: Rondo
Performing predictions on schubert_D935_2
                                        Predicted form: Ternary
Performing predictions on schumann_evening_song
                                        Predicted form: Rondo
Performing predictions on schbrt_strquartet_13-mvt3
                                        Predicted form: MinTrio
Performing predictions on tchaik_nocturne_19_4
                                        Predicted form: Binary
```

Sample prediction output from Form Analyzer

Results – Form Analyzer Compared to Other Methods



Form Analyzer

83%
Validation Accuracy (Jaccard Score)

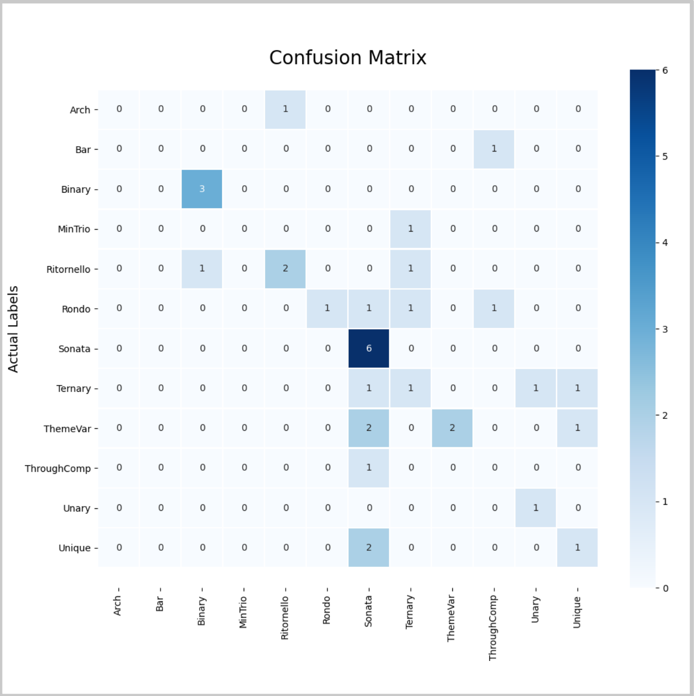
Form Analyzer

84%
Precision

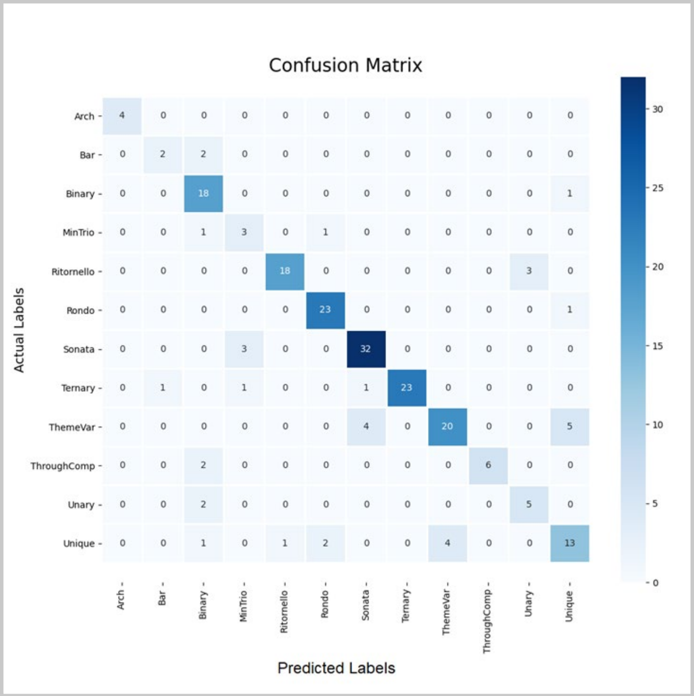
Form Analyzer

82%
Recall & F1

Results – Form Analyzer Compared to Other Methods



Best CNN Confusion Matrix
(50% Accuracy, 56% Precision, 44% Recall, 41% F1)



TreeGrad Confusion matrix
(83% Accuracy, 84% Precision, 82% Recall & F1)

Evaluation – Peak-Picking Algorithm

- The authors of the full algorithm propose further modifications for segment-segment comparisons [80], but these **greatly increase the number of matrix computations** and add substantial overhead
- Results were found to be **identical** for almost all pieces of music regardless of the proposed additions — since the timestamps are independent of the classification analysis, a segment-segment comparison is unnecessary for onset detection
- The output of the novelty function was compared to **numerous hand-labeled pieces** from the dataset, and we found that the **difference was negligible**

```
Event: 0:00:00          Ground Truth: 0:00:00          Difference:  0.000000
Event: 0:00:13.235374   Ground Truth: 0:00:01.150000   Difference: -12.085374
Event: 0:00:28.560544   Ground Truth: 0:00:23.995000   Difference: -4.565544
Event: 0:00:40.124082   Ground Truth: 0:00:29.945000   Difference: -10.179082
Event: 0:01:00.186122   Ground Truth: 0:00:37.545000   Difference: -22.641122
Event: 0:01:18.715646   Ground Truth: 0:00:48.645000   Difference: -30.070646
Event: 0:01:42.678639   Ground Truth: 0:00:56.495000   Difference: -46.183639
Event: 0:01:54.102857   Ground Truth: 0:01:40.195000   Difference: -13.907857
Event: 0:02:14.443537   Ground Truth: 0:01:59.161000   Difference: -15.282537
Event: 0:02:27.678912   Ground Truth: 0:02:22.011000   Difference: -5.667912
Event: 0:02:44.397279   Ground Truth: 0:02:52.811000   Difference:  8.413721
Event: 0:02:56.100136   Ground Truth: 0:03:19.611000   Difference:  23.510864
Event: 0:03:09.196190   Ground Truth: 0:03:32.411000   Difference:  23.214810
Event: 0:03:22.292245   Ground Truth: 0:03:51.761000   Difference:  29.468755
Event: 0:03:36.642177   Ground Truth: 0:04:10.761000   Difference:  34.118823
Event: 0:03:59.072653   Ground Truth: 0:04:24.211000   Difference:  25.138347
Event: 0:04:15.233741   Ground Truth: 0:04:30.761000   Difference:  15.527259
Event: 0:04:31.255510   Ground Truth: 0:04:38.761000   Difference:  7.505490
Event: 0:04:41.983129   Ground Truth: 0:04:47.761000   Difference:  5.777871
Event: 0:05:01.209252   Ground Truth: 0:04:59.911000   Difference: -1.298252
Event: 0:05:19.878095   Ground Truth: 0:05:06.511000   Difference: -13.367095
Event: 0:05:34.228027   Ground Truth: 0:05:31.761000   Difference: -2.467027
Event: 0:05:48.438639   Ground Truth: 0:05:43.861000   Difference: -4.577639
Event: 0:06:08.918639   Ground Truth: 0:06:08.001000   Difference: -0.917639
Average (absolute) time difference: ±14.828637755102045
```

Demonstration of peak-picking algorithm compared to ground truth annotation

Results – Peak-Picking Algorithm

- Based on our comparisons, it was **more feasible** (and both faster and accurate) **to use the algorithm than to train a CNN** to perform the same task
- One issue the algorithm faces is that some pieces of music that are exceptionally short in duration **only return the onset of the start and end** of the piece – for such examples, the halfway point (*duration* / 2) is added to the novelty vector

Result #2

The Peak-Picking algorithm proved **comparable to other machine learning approaches** (CNN, Self-Organizing Maps), as even pre-labeled data points were nearly identical to those marked by a human analyst

A demonstration of harmonic analysis, part of the intuition behind analyzing musical phrase segmentation[4]

[4] Image Source: https://www.pycosom.com/music-theory.html

Evaluation – Phrase Analyzer

Associated Challenges

- This model is **much more difficult to score programmatically**, as numerous factors affect the final system
- The model receives the timestamps from the Peak-Picking algorithm, which is also difficult to compare to a human annotated ground truth due to **integrative disagreement**
- The labels are often **highly subjective**, and **some labels are implicit** (part A continues until timestamp *n* but is normally only labeled at the first occurrence)

Phrase Analyzer

100%

Accuracy
(Hamming Score)

Formal Plan of Vivaldi's "Winter," Op. 8, No. 4, Second Movement

Sections	[__________ A __________]				[____________ B ____________]				
Measure #'s	1-2	3-5	5-7	7-8	9-10	11	12-13	14-16	17-18
Phrases	a	b	ext.	---------	a′	ext.	b′	ext.	---------
Harmonic Motion (Phrase Level)	I-V-I	V^6 ________	$^5_3$		=V	V^7 I	IV V	V	I
		=	I	V-I	I-V-I				
Keys	E♭		B♭			E♭			
Large-Scale Harmonic Plan	I		V			I		V	I

A full analysis example, displaying the carryover of the Part labels and the repetition of Phrase labels[5]

[5] Figure Source: https://apcentral.collegeboard.org/courses/ap-music-theory/classroom-resources/teaching-score-analysis-ap-music-theory

Evaluation – Phrase Analyzer

Associated Challenges

- Form analysis, especially onset detection, operates on **fuzzy logic rules**, so the peak-picking algorithm and phrase analyzer may or may not be considered accurate based on the bias of a human analyst and/or their conventions
- If the data was split into a test set, the results would likely be less truthful of the model's performance due to **poor generalizing**
- The dataset is too small to split well into training and testing proportions – however, expanding the dataset would require many analysts all trained on the same methodology **analyzing each piece individually** before reaching an agreement for the ground truth labels (two analysts may even label varying numbers of events)

```
brahms_opus117_1
         Ternary
        Guesser: LSTMTree   DcnTree TreeGrad
             0.0  Silence   Silence  Silence
             0.1   [A, a]       [A]        B
          21.177      [A]       [B]        B
           38.87 [A, sec] [CODA, f]        B
          57.121 [A, sec] [CODA, f]        B
          67.013      [A]  [A, sec]        B
           96.27      [B]  [A, sec]        B
         150.187      [b]       [A]        B
         167.741      [a]  [A, sec]        B
          186.41 [B, sec]       [B]        B
         200.899   [B, c]       [A]        B
         210.512   [CODA]       [A]        B
         223.608   [CODA]  [A, sec]        B
         237.958      [A]  [A, sec]        B
         252.029      [A]       [A]        B
         269.444      End       End      End
```

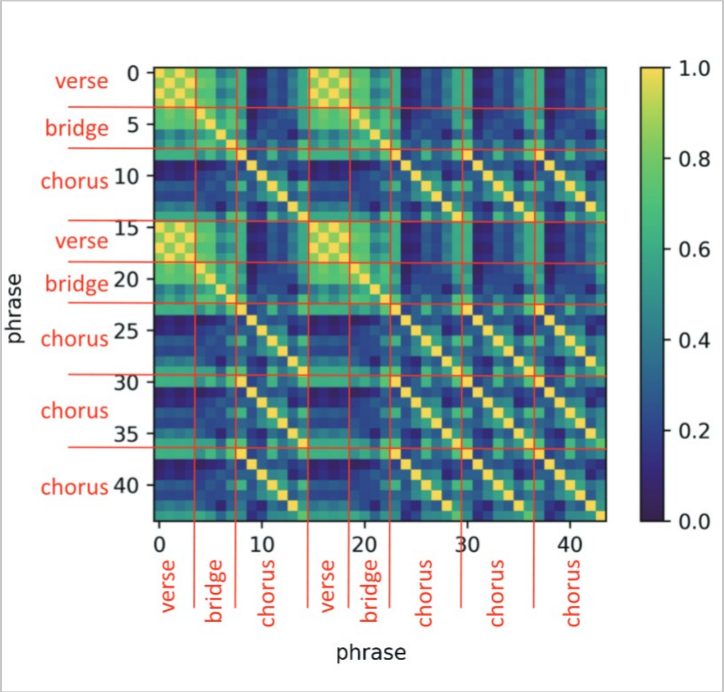
Final prediction system output includes Decision Tree and TreeGrad for comparison

Results – Phrase Analyzer

- While there was currently little room for improving the model outside of **manually expanding the dataset** (after optimizing the hyper-parameters), we found that output of the final model was **objectively comparable** to our ground-truth analyses

- As such, the model is practical enough to be used as an **assisting tool** for human analyses (such as for expanding the dataset), and was thus considered as good as currently possible

- Given the evaluation constraints for the phrase analysis, we found that the **LSTM-Tree** was sufficient to avoid harsh overfitting compared to other attempted models (DNN, RNN, TreeGrad), likely the result of the **boosting** from the decision tree



A Self-Similarity Matrix of a popular-form piece of music analyzed using an extended Word2Vec model[6]

[6] Image Source: http://dx.doi.org/10.2197/ipsjjip.27.278

Results – Phrase Analyzer

- Other machine learning algorithms such as **Random Forest** and **Extra Trees** were attempted, but provided unusable or highly-overfit output due to the Multilabel Classification

- The LSTM-Tree also appears to **prioritize the large form labels**, and often tends to leave out the phrase label or generalizes it as a “section” without a unique letter

Result #3

In comparison to other models, **LSTM-Tree outperformed** both individual NNs (DNN, CNN), ML algorithms (decision tree, random forest), and TreeGrad

Result #4

Using a **hybrid NN-Decision Tree approach** greatly reduced overfitting and thus increased accuracy for both Form and Phrase analyzers

Discussion

Discussion #1

The LSTM-Tree may benefit from using a **Curriculum Learning** approach, much like that of a traditional Form and Analysis class. An Autoencoder or Seq2Seq model may be useful in creating a more accurate/faster system

Discussion #2

The final Form-NN system is currently accurate enough to be implemented as the backend of a **higher-level system** such as an **assisted grading tool** for human-analyzed scores or a musical practice tool

Discussion #3

The Peak-Picking algorithm could be used to train a more accurate **music segmentation network**, allowing the entire system to be treated as one large Deep Learning system

Discussion #4

The **current dataset features class imbalance**; anthologies of classical music classified by form are lacking, though this system could be used to assist in compiling such a work

Conclusion

Methodology

We have devised a system for the task of automatic musical form recognition and analysis using hybrid Neural Network-Decision Tree models

Intuition

This system completely analyses a piece of classical music, including locating the points of musical events, labeling them by their structural classification, and classifying the piece by its large form structure

Contribution

We presented a new dataset that seeks to correct the errors presented by previous commonly used databases, including pre-computed spectral data (for training) and the form classification for each piece

Extension

The final system is in a usable state for individual use, anthology development, or implementation into a more complex piece of software

Conclusion

In this thesis, we proposed a new system to perform the task of automatic musical form analysis using deep learning models, as well as a new standardized dataset

Future Work

Suggestion #1

While the current system is specific to classical music analysis, it could be extended to allow for the **classification of additional forms** including those found in popular music and more complex hybrid forms

Suggestion #2

Optical Music Recognition is another difficult task lacking substantial research – our methods could be potentially extended to perform visual music analysis and perform the segmentation/classification on the score

Suggestion #3

The system may be extendable for use in **Forensic Musicology**, using the system’s output analysis in the comparison of multiple pieces of music for potentially similar or exact replications of musical phrases

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QUESTIONS

Thank you!

DEEP LEARNING FOR MUSICAL FORM:
RECOGNITION AND ANALYSIS

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Master Thesis
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April 2022
University of Wisconsin - Whitewater