DEEP LEARNING FOR MUSICAL FORM: RECOGNITION AND ANALYSIS

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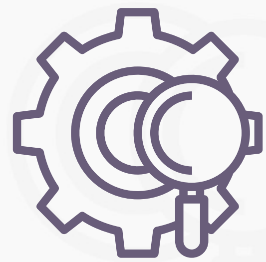
Introduction

- [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**



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Motivation

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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**

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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

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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 uses live recordings rather than basing timestamps on the score

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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

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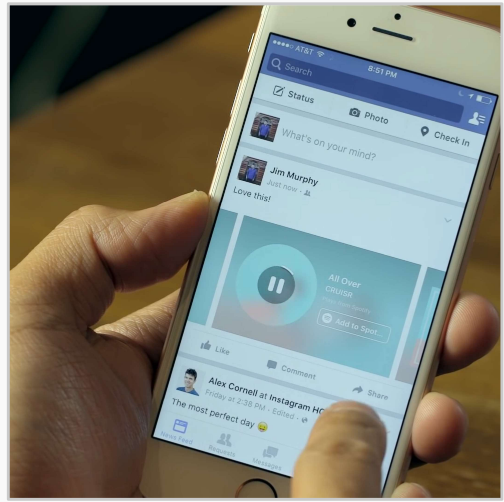
Motivation – Potential Applications

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/

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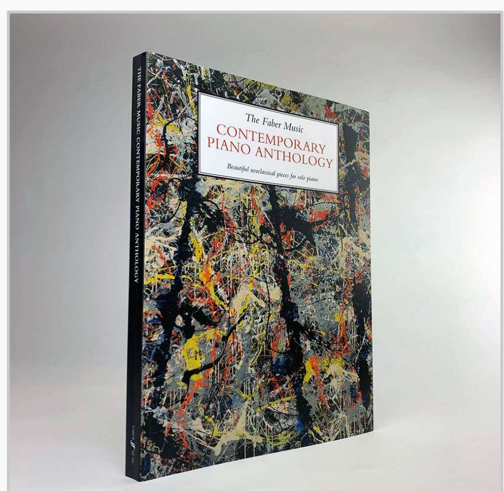
Motivation – Potential Applications

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

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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

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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)

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Literature Review

System	Description
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

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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

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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)

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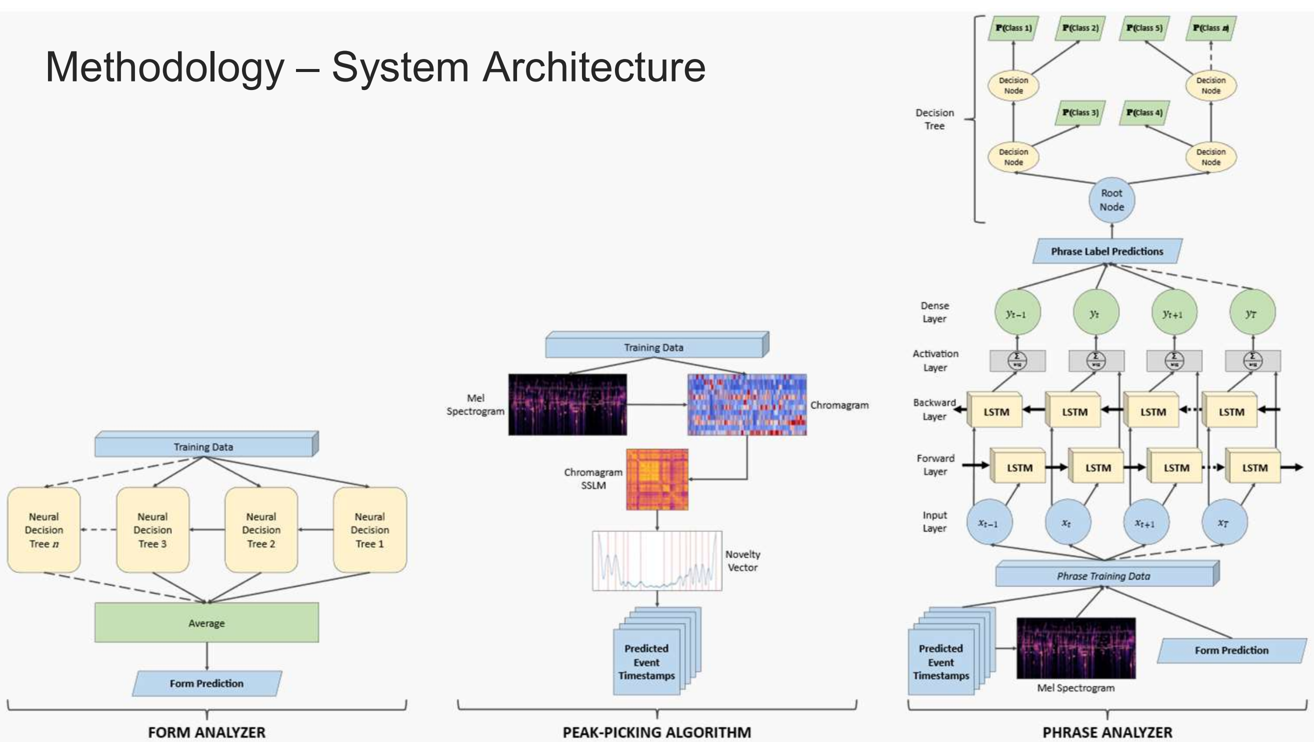
Methodology – System Architecture



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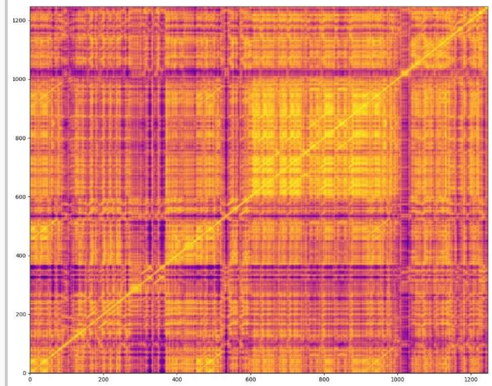
Data Extraction and Preparation

- 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 ($X = \frac{X - \min(X)}{\max(X) - \mathrm{m}\ \ (X)}$).



Mel Spectrogram SSM

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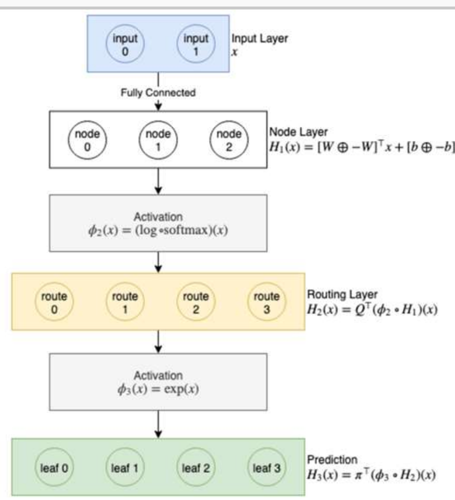
Form Analyzer Architecture – TreeGrad

- 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

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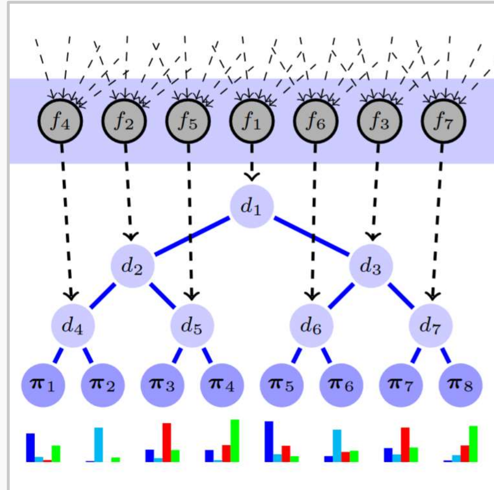
Form Analyzer Architecture – TreeGrad

- Each tree is 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

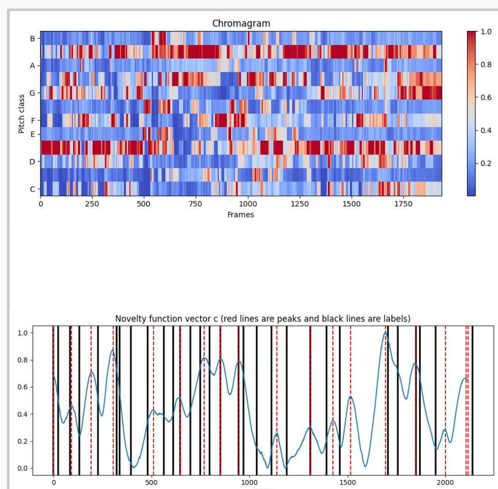
	# Of Leaves (Per Tree)	Max Depth	Learning Rate	# Of Estimators (Trees)	Batch Size	Refit Splits?
Value	31	-1 (∞)	0.1	100	32	True



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)



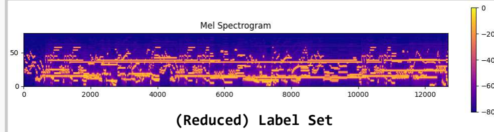
Example Chromagram and Novelty Vector

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

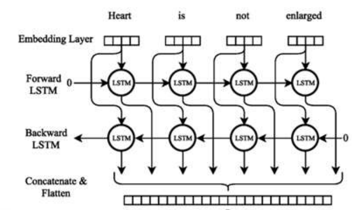


(Reduced) Label Set

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

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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)
- The Phrase Analyzer thus receives the predicted form classification and the peak-picked timestamps (along with each of their Mel spectrograms), predicting the **Part** and/or **Phrase labels for each timestamp** in chronological order
- In the full prediction system, both outputs are combined to provide a **full musical analysis**

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

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

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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

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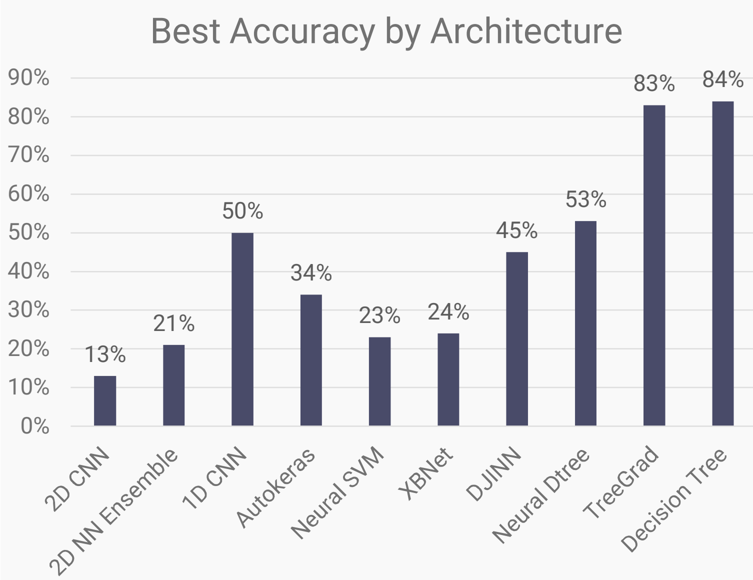
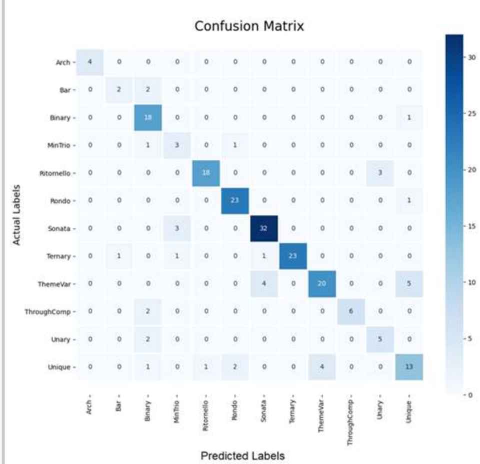
Results – Form Analyzer





TreeGrad Confusion matrix

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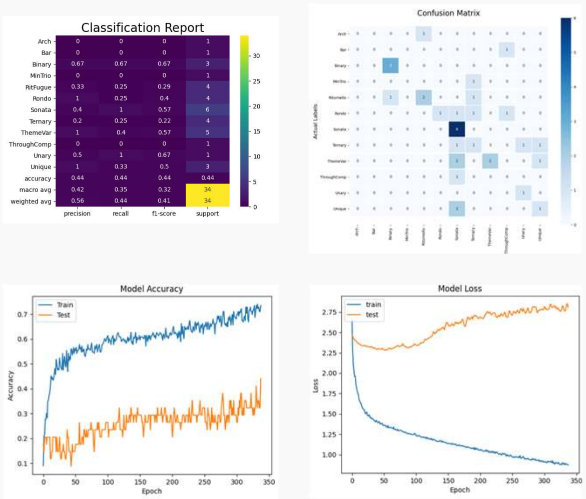
Results – Architecture Comparison



Best CNN model performance compared to TreeGrad

Form Analyzer	Phrase Analyzer
83% Validation Accuracy (Jaccard Score)	**100%** Accuracy (Hamming Score)

Form Analyzer	Form Analyzer
84% Precision	**82%** Recall & F1

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Evaluation – Peak-Picking Algorithm

- The authors of the full algorithm propose further modifications for segment-segment comparisons, but these **greatly increase the number of matrix computations** and add substantial overhead
- Results were found to be **identical or nearly the same** for most pieces of music regardless of the proposed additions
- 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

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Evaluation – 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

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Evaluation – Phrase Analyzer

- The Phrase Analyzer was evaluated using both training accuracy (Jaccard score) as well as Hamming Score. However, 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**
  - 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**
  - 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
  - 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)
  - 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

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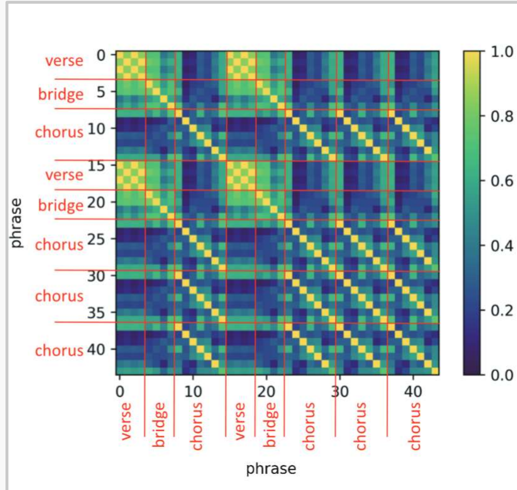
Evaluation – Phrase Analyzer

- 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[5]

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

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Evaluation – 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
- TreeGrad was left in for comparison to show the result of attempting to reduce the problem to **single-label classification**, rather than multilabel
- 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

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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

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Conclusion

We have devised a system for the task of automatic musical form recognition and analysis using hybrid Neural Decision Tree models that significantly outperformed standard neural architectures and greatly reduced overfitting

This system completely analyses a piece of classical music, including locating the points of musical events, labeling them according to their formal part and/or phrase classification, and classifying the piece by its large form structure

We also presented a new dataset that seeks to correct the errors presented by previous commonly used databases, also providing both pre-computed spectral data to speed up the training process of future models and the form classification of each piece of music

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

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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

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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

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Thank you!

DEEP LEARNING FOR MUSICAL FORM: RECOGNITION AND ANALYSIS

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