

# Exploratory Data Analysis: Real vs Automatically Generated Irish Folk Tunes

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# Research problem



# Research Questions

- Use features to discover **differences** and **commonalities** between the original songs from *The Session* and the computer-generated songs with *Folk-RNN* and use those features to do classification.
- Which features can tell us about the **artificialness** of the generated tunes?

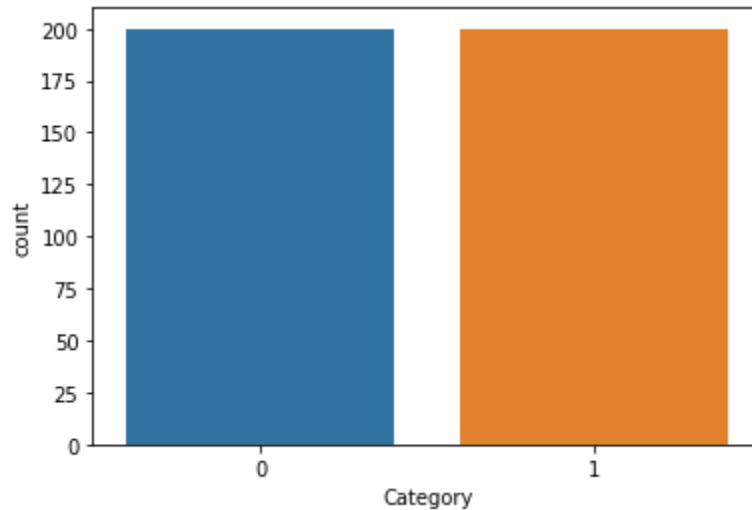
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Data



# Dataset

- 200 real tunes from **The Session**
  - 200 generated tunes from **Folk-RNN**
- 
- Generated = 0
  - Real = 1



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# Methods



# Methods

- Folk-RNN (already trained recurrent neural network)
  - 3 LSTM layers with 512 units
  - Using mini-batch size of 50 and dropout of 0.5
- jSymbolic
  - Feature extraction (1495 features)
- Preprocessing
  - Drop columns with **standard deviation = 0**
  - Feature scaling for classification purposes (MinMax Scaler)
- 1495 features reduced to 10-30 features

Generating tunes

Feature  
extraction

Feature  
preprocessing

Knowledge  
discovery



# Results





# jSymbolic Feature Definitions

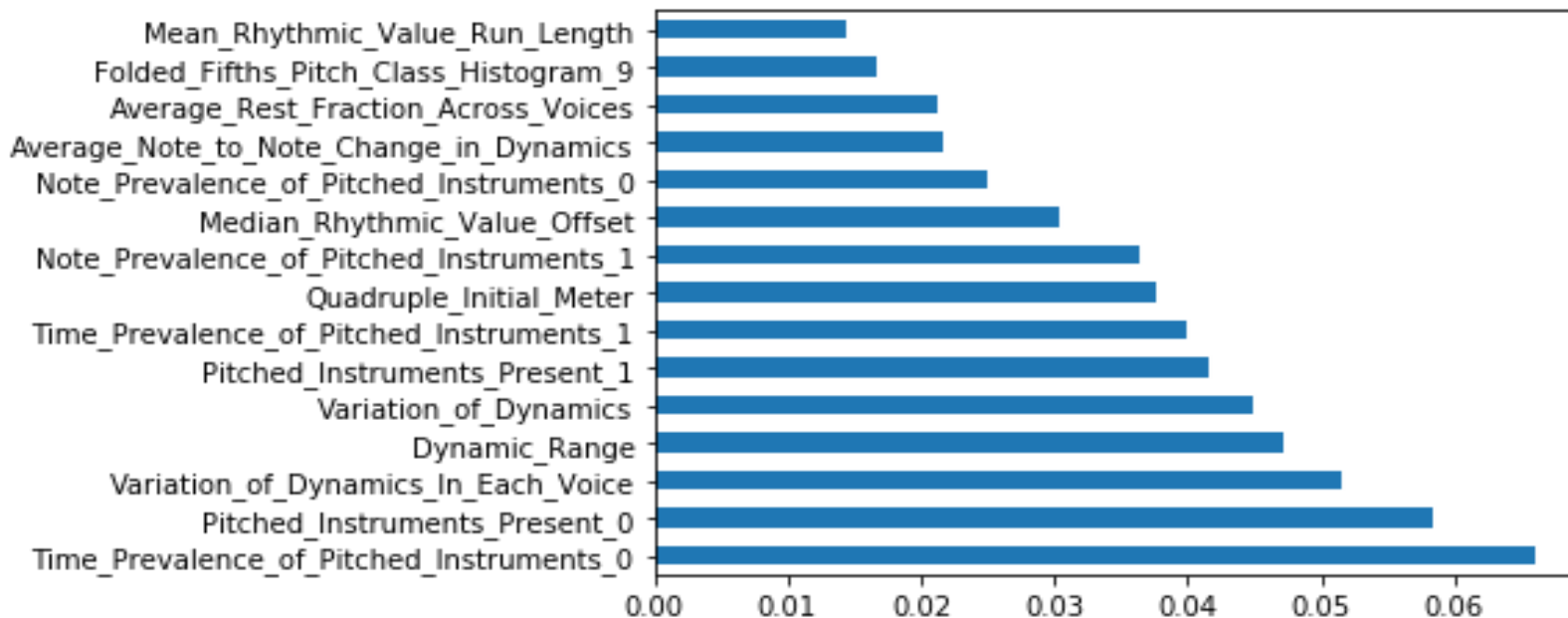
- **Number of Pitches**
  - Number of unique pitches that occur at least once in the piece. Enharmonic equivalents are grouped together for the purpose of this calculation.
- **Range**
  - Difference in semitones between the highest and lowest pitches.



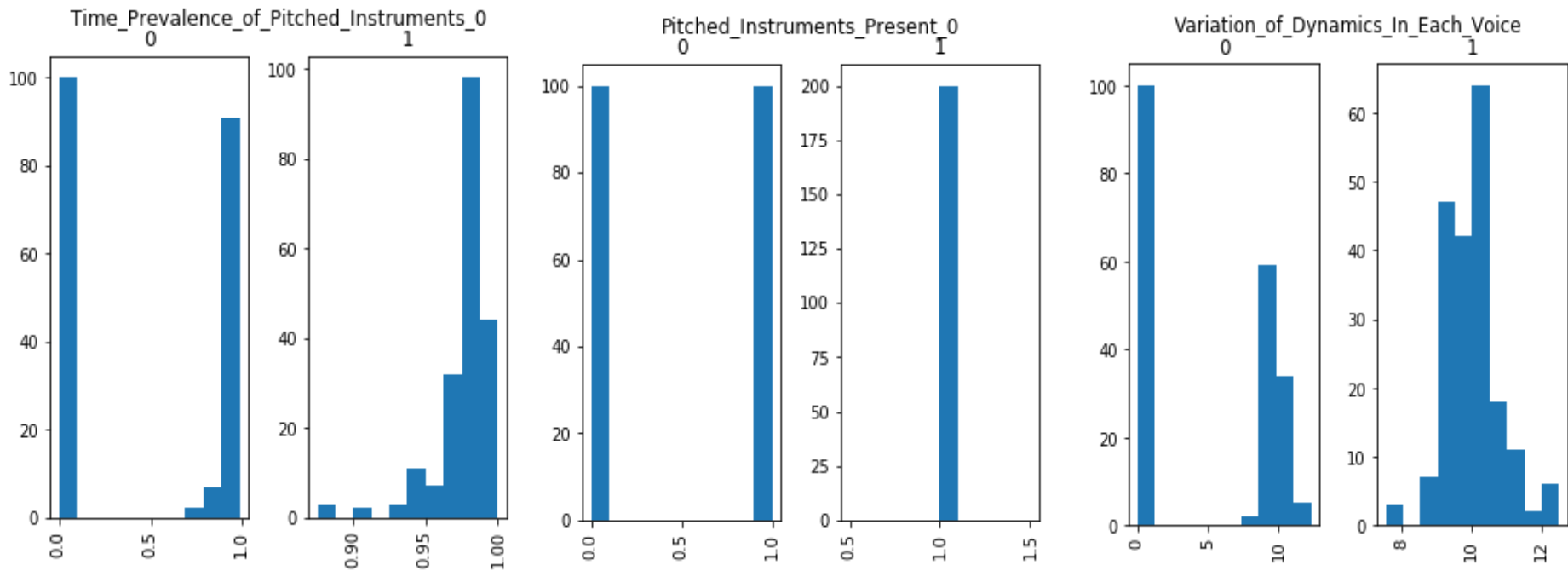
# Feature importance

- We were left with **683** features after preprocessing.
  - The other **811** features didn't give any information about the tunes.
- Techniques for feature selection/importance:
  - **Extra Trees Classifier** for Feature Selection
  - Feature Selection based on **Pearson Correlation**
  - **Univariate Feature Selection** using Chi-Squared statistical test

# Extra Trees Classifier - Top 15 Features



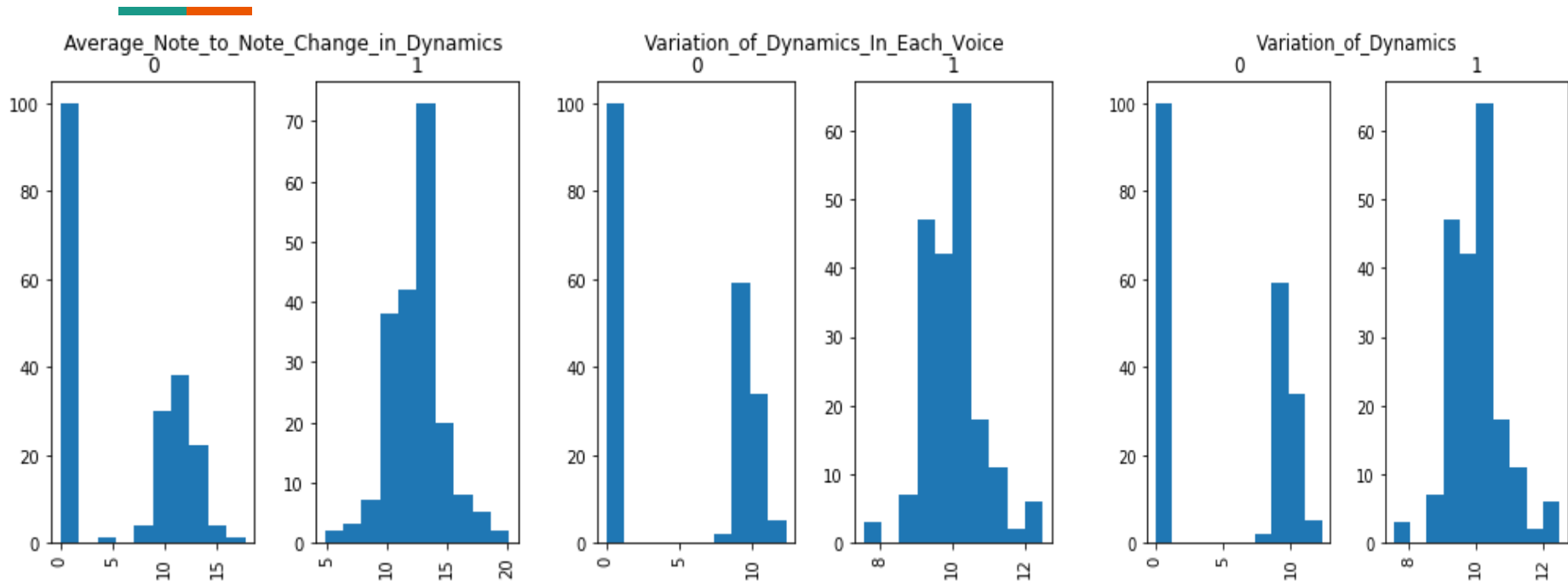
# Extra Trees Classifier - Top 3 Features



# Pearson Correlation - Features with Corr > 0.5

Target variable: Category	Condition: corr > 0.5		
		Feature name:	Correlation value:
		Average_Note_to_Note_Change_in_Dynamics	0.620820
		Variation_of_Dynamics_In_Each_Voice	0.592151
		Variation_of_Dynamics	0.592151
		Dynamic_Range	0.577350
		Time_Prevalence_of_Pitched_Instruments_1	0.577121
		Time_Prevalence_of_Pitched_Instruments_0	0.606889
		Note_Prevalence_of_Pitched_Instruments_1	0.577350
		Note_Prevalence_of_Pitched_Instruments_0	0.577350
		Pitched_Instruments_Present_1	0.577350
		Pitched_Instruments_Present_0	0.577350
		Quadruple_Initial_Meter	0.510394
		Folded_Fifths_Pitch_Class_Histogram_10	0.542638

# Pearson Correlation - Top 3 Features

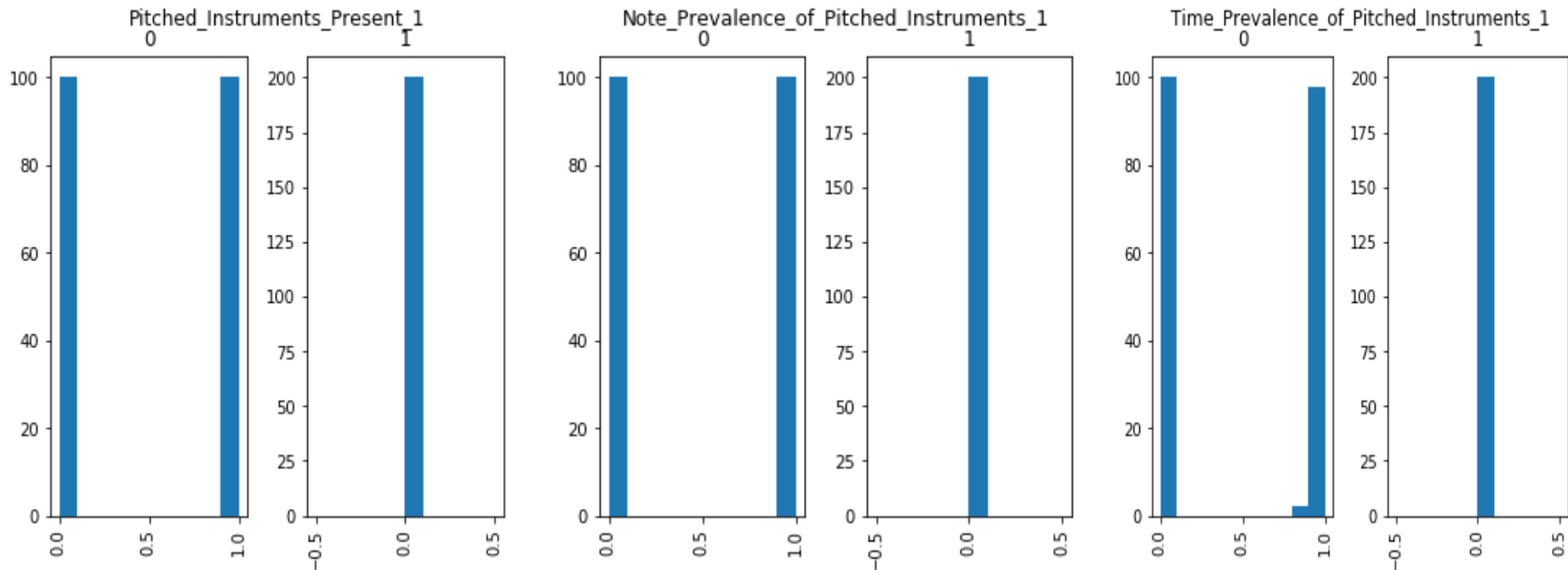


# Univariate Feature Selection - Top 10 Features



Feature name:	Score:
Pitched_Instruments_Present_1	100.000000
Note_Prevalence_of_Pitched_Instruments_1	100.000000
Time_Prevalence_of_Pitched_Instruments_1	98.067700
Quadruple_Initial_Meter	44.545852
Compound_Initial_Meter	43.200000
Duple_Initial_Meter	40.163934
Median_Rhythmic_Value_Run_Length	39.384593
Folded_Fifths_Pitch_Class_Histogram_10	38.936623
Mean_Rhythmic_Value_Run_Length	37.542055
Folded_Fifths_Pitch_Class_Histogram_9	36.581359

# Univariate Feature Selection - Top 3







## Classification - Using all 683 Features

- Classifier: **SVM**
- **Train** set = 280 tunes
- **Test** set = 120 tunes

[[39 15] [ 1 65]]		precision	recall	f1-score	support
0		0.97	0.72	0.83	54
1		0.81	0.98	0.89	66
accuracy				0.87	120
macro avg		0.89	0.85	0.86	120
weighted avg		0.89	0.87	0.86	120



## Classification - Using Top 15 Features of ETC

- Classifier: **SVM**
- **Train** set = 280 tunes
- **Test** set = 120 tunes

```
[[48  6]
 [ 1 65]]
```

	precision	recall	f1-score	support
0	0.98	0.89	0.93	54
1	0.92	0.98	0.95	66
accuracy			0.94	120
macro avg	0.95	0.94	0.94	120
weighted avg	0.94	0.94	0.94	120



## Classification - Using 12 Features of PC

- Classifier: **SVM**
- **Train** set = 280 tunes
- **Test** set = 120 tunes

```
[[54  0]
 [ 0 66]]
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	54
1	1.00	1.00	1.00	66
accuracy			1.00	120
macro avg	1.00	1.00	1.00	120
weighted avg	1.00	1.00	1.00	120



# Classification - Using Top 10 Features of UFS

- Classifier: **SVM**
- **Train** set = 280 tunes
- **Test** set = 120 tunes

[[54 0] [ 0 66]]		precision	recall	f1-score	support
0	1.00	1.00	1.00	1.00	54
1	1.00	1.00	1.00	1.00	66
accuracy				1.00	120
macro avg		1.00	1.00	1.00	120
weighted avg		1.00	1.00	1.00	120



# Common Features between Real and Generated

- Used the combined dataset of 400 songs (real + generated)
- Analysed and selected the features that have a **very low standard deviation**
- The resulting set was **30** common features

# Common Features between Real and Generated

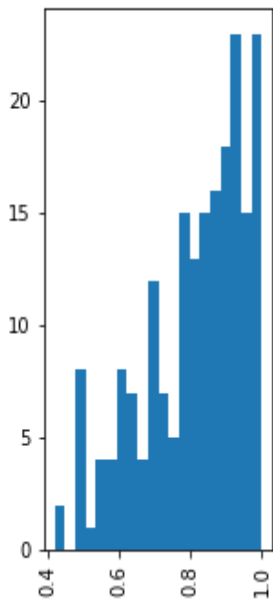


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'Relative_Prevalence_of_Top_Pitches',  
'Relative_Prevalence_of_Top_Pitch_Classes',  
'Melodic_Interval_Histogram_2',  
'Prevalence_of_Most_Common_Melodic_Interval',  
'Relative_Prevalence_of_Most_Common_Melodic_Intervals',  
'Amount_of_Arpeggiation', 'Stepwise_Motion',  
'Vertical_Interval_Histogram_12',  
'Wrapped_Vertical_Interval_Histogram_0',  
'Wrapped_Vertical_Interval_Histogram_5',  
'Variability_of_Number_of_Simultaneous_Pitch_Classes',  
'Variability_of_Number_of_Simultaneous_Pitches',  
'Prevalence_of_Second_Most_Common_Vertical_Interval', 'Vertical_Thirds',  
'Vertical_Perfect_Fourths', 'Vertical_Sixths', 'Vertical_Octaves',  
'Non-Standard_Chords', 'Rhythmic_Value_Histogram_4',  
'Shortest_Rhythmic_Value', 'Mean_Rhythmic_Value',  
'Most_Common_Rhythmic_Value',  
'Prevalence_of_Most_Common_Rhythmic_Value',  
'Rhythmic_Value_Median_Run_Lengths_Histogram_1',  
'Rhythmic_Value_Median_Run_Lengths_Histogram_4',  
'Variability_of_Complete_Rest_Durations',  
'Variability_of_Partial_Rest_Durations',  
'Polyrhythms_-_Tempo_Standardized', 'Polyrhythms', 'Similar_Motion',
```

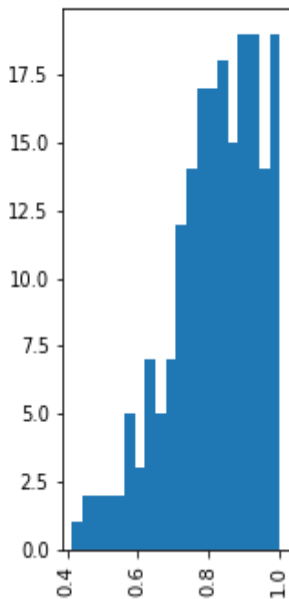
# Common Features between Real and Generated



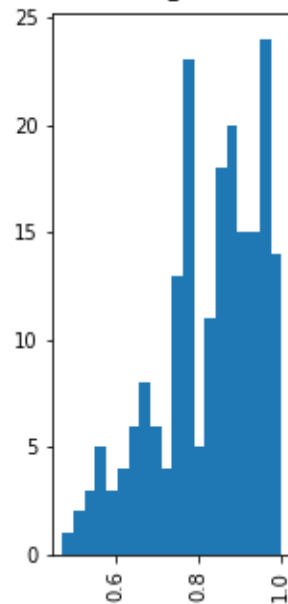
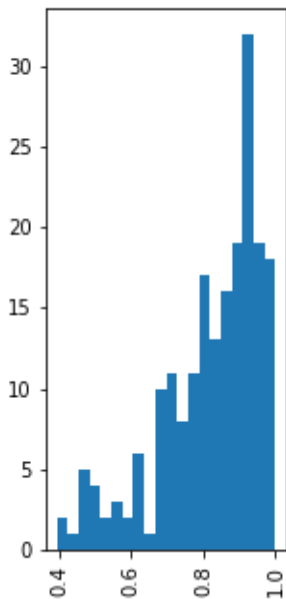
Relative\_Prevalence\_of\_Top\_Pitches  
0



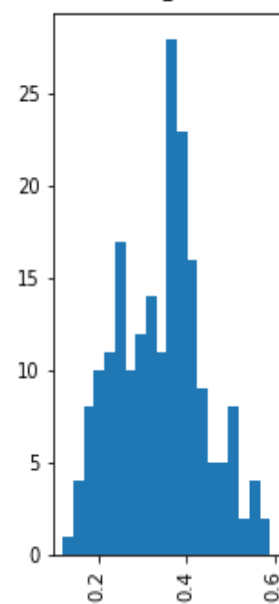
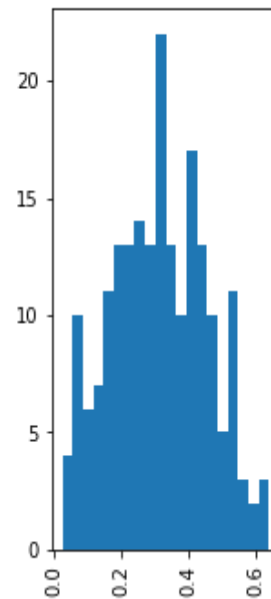
Relative\_Prevalence\_of\_Top\_Pitch\_Classes  
1



Relative\_Prevalence\_of\_Top\_Pitch\_Classes  
0



Melodic\_Interval\_Histogram\_2  
0





# Artificialness of the Generated Tunes

- We calculated the **means** of all relevant **features** for both **Real and Generated** tunes.
- Then we calculated the **differences** between those **means**
  - $\text{difference} = \text{generated}[x].\text{mean}() - \text{real}[x].\text{mean}()$
- We took the features with **difference > 0.5** as features indicating **artificialness** of tunes.
- Reason: **Folk-RNN** tune generator **focused more** on those features than a real person does when creating real tunes.



# Artificialness of the Generated Tunes - 20 Features

Feature name:	Difference:
Number_of_Pitches	3.99
Number_of_Pitch_Classes	1.0250000000000004
Range	4.675000000000001
Interval_Between_Most_Prevalent_Pitches	0.6749999999999998
Pitch_Variability	0.6441450000000008
Pitch_Class_Variability_After_Folding	0.7808850000000009
First_Pitch	0.7849999999999996
Mean_Melodic_Interval	0.8861700000000008
Average_Interval_Spanned_by_Melodic_Arcs	1.1191399999999999
Most_Common_Vertical_Interval	0.605

Feature name:	Difference:
Second_Most_Common_Vertical_Interval	0.56
Distance_Between_Two_Most_Common_Vertical_Intervals	0.655
Quadruple_Initial_Meter	0.5049999999999999
Mean_Rhythmic_Value_Run_Length	51.740030000000004
Median_Rhythmic_Value_Run_Length	50.64
Variability_in_Rhythmic_Value_Run_Lengths	1.8352150000000025
Strongest_Rhythmic_Pulse_-_Tempo_Standardized	18.755000000000001
Second_Strongest_Rhythmic_Pulse_-_Tempo_Standardized	8.414999999999992
Strongest_Rhythmic_Pulse	18.755000000000001
Second_Strongest_Rhythmic_Pulse	8.414999999999992

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# Future work



# Future Work

- Team up with a more **musically inclined** individual to gather more insight.
- **Analyse** the **artificialness** of the features in a more detailed way and from other points of view.
- Writing the obtained results and answering the research questions in the project report.

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Thank you!