## SYMBOLIC MUSIC REPRESENTATIONS FOR CLASSIFICATION TASKS: A SYSTEMATIC EVALUATION

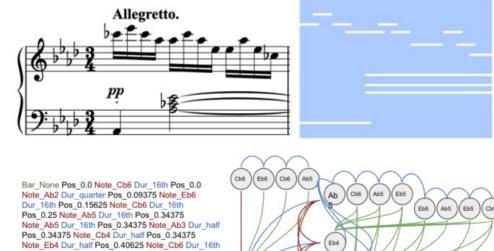
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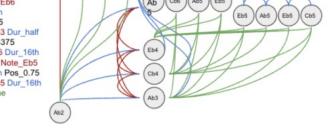
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#### **Contributions**

- We investigate the performance and complexity of matrix, sequence and graph input representations, and their corresponding neural architectures (CNN, Transformer, GCN)
- We compare the impact that the different information contained in symbolic scores and performances has on different piece-level classification tasks.
- We introduce a new graph representation for symbolic </> performances and explore the capability of graph representations in classification tasks.



Pos\_0.5 Note\_Ab5 Dur\_16th Pos\_0.59375 Note\_Eb5 Dur\_16th Pos\_0.65625 Note\_Eb5 Dur\_16th Pos\_0.75 Note\_Ab5 Dur\_16th Pos\_0.84375 Note\_Eb5 Dur\_16th Pos\_0.90625 Note\_Cb5 Dur\_16th Bar\_None



Excerpt of Schubert's Impromptu Op. 90 No.4 and its input visualizations (from left to right): generic matrix, sequence (REMI-like) and graph.

## 3. Results

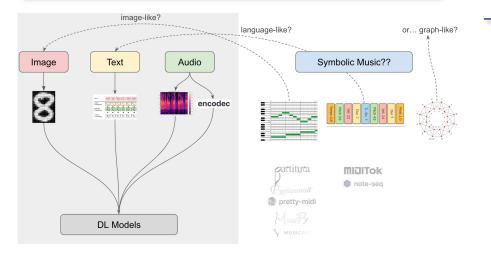
Composer classification results for all representations, on all target subsets of our datasets on the composer classification task using only basic level features.

		ASAP-performance		ASAP-score		ATEPP-performance		ATEPP-score	
		ACC	F1	ACC	F1	ACC	F1	ACC	F1
Mat	rix								
Resl	Chnl								
400	On+Fm	$0.59 \pm 0.04$	$0.18 \pm 0.02$	$0.59 \pm 0.03$	$0.18 \pm 0.01$	0.24±0.05	$0.20 \pm 0.04$	$0.25 \pm 0.02$	0.16±0.03
600	On+Fm	$0.62 \pm 0.06$	0.21±0.03	0.61±0.07	$0.19 \pm 0.02$	$0.28 \pm 0.01$	0.22±0.03	$0.24 \pm 0.02$	0.16±0.04
800	Fm	$0.62 \pm 0.04$	$0.21 \pm 0.02$	$0.58 \pm 0.06$	0.18±0.03	0.22±0.03	0.17±0.01	$0.22 \pm 0.02$	0.18±0.03
800	On+Fm	0.63±0.04	$0.20 \pm 0.01$	$0.57 \pm 0.04$	0.18±0.03	$0.28 \pm 0.02$	$0.22 \pm 0.01$	$0.22 \pm 0.04$	0.14±0.02
Sequ	ence								
Tokn	BPE								
MidiLike	×	$0.53 \pm 0.05$	$0.16 \pm 0.02$	N/A	N/A	$0.18 \pm 0.04$	$0.10 \pm 0.02$	N/A	N/A
REMI	×	$0.51 \pm 0.04$	$0.15 \pm 0.02$	$0.43 \pm 0.04$	$0.14 \pm 0.01$	0.23±0.04	$0.10 \pm 0.02$	$0.23 \pm 0.04$	0.13±0.02
СР	×	$0.48 \pm 0.02$	$0.09 \pm 0.05$	$0.45 \pm 0.05$	$0.10 \pm 0.01$	0.11±0.02	$0.09 \pm 0.01$	0.17±0.06	0.11±0.04
MidiLike	4	$0.52 \pm 0.04$	$0.15 \pm 0.02$	N/A	N/A	0.17±0.03	$0.12 \pm 0.01$	N/A	N/A
REMI	4	$0.51 \pm 0.02$	$0.15 \pm 0.01$	0.43±0.03	0.13±0.01	0.21±0.01	0.13±0.03	0.23±0.03	0.13±0.01
Gra	ph								
Bi-dir	Multi-rel								
×	×	$0.56 \pm 0.01$	$0.17 \pm 0.02$	$0.51 \pm 0.05$	$0.16 \pm 0.02$	$0.22 \pm 0.02$	0.10±0.03	0.23±0.03	0.21±0.05
×	$\checkmark$	0.58±0.03	$0.19 \pm 0.01$	$0.54 \pm 0.05$	0.17±0.02	0.27±0.03	$0.13 \pm 0.02$	0.29±0.10	0.18±0.06
$\checkmark$	$\checkmark$	0.62±0.02	0.21±0.01	$0.50 \pm 0.04$	$0.17 \pm 0.01$	$0.23 \pm 0.04$	0.16±0.03	$0.27 \pm 0.06$	0.22±0.03

# 4. Conclusion & Takeaways

- Performance:
  - Matrix ≈ Graph > Sequence, but overall achieves similar level of acc
  - Matrix approach trains more robustly, while graph approach the least
  - Graph structures benefit the most from voicing information

## 1. Motivation



### 2. Methodology

- Representation configuration:
  - Matrix:
    - Resolution and channels
  - Sequence:
    - Encodings
    - Byte pair encoding
  - Graph:
    - Bi-directions
    - Edge relationships

- Information level:
  - Basic: Pitch, onset, duration
  - Advanced: Voicing, markings (score), velocity (perf)
- Architecture •
  - Frontend:
    - Matrix ResNet family
    - Sequence Transformer
    - Graph GCN from GraphSAGE blocks
  - Backend: Multihead attention block
- Dataset: ATEPP / ASAP ٠
  - Performance MIDI & Score MusicXML
  - Classification tasks: Composer, Performer, Difficulty

• Model complexity:

- Sequence (12.8M) >> Matrix (4.3M) > Graph (1.3M) (Minimal model that achieve the same result)
- Transformer vs. GNN: Are we learning the same set of musical edges?
  - Not entirely, but we observed some structural similarities
- The Album Effect:
  - Multiple interpretations of the same composition may cause information leakage. Happens in existing literature already! (~30% acc boost)

https://github.com/anusfoil/SymRep

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