## Quantifying Rhythmic Creativity in Classical Music

Keywords: Creativity, Novelty, Influence, Distinctiveness, Musical Rhythm

## **Extended Abstract**

This study quantifies creativity of rhythms in classical piano compositions by examining the connection between novelty and influence—the core elements of creativity—across different historical periods and composers. Focusing on rhythm as both a central musical element and a fundamental aspect of temporal cognition [1], we analyze how composers pursued creativity by navigating the tension between novelty and influence. Using inter-onset interval (IOI) ratios and their transition probabilities, we measure novelty and influence, while introducing distinctiveness to capture combinatorial creativity through unique rhythmic assemblies. This multidimensional framework reconceptualizes creativity as an emergent property encompassing novelty, influence, and distinctiveness.

Our computational framework models each composition  $\zeta$  as a first-order Markov chain network of IOI ratios, following Park et al. [2]. The generation probability of  $\zeta$  is given as  $\Pi(\zeta) = P(r_1)P(r_2|r_1)\dots P(r_m|r_{m-1})$ . Rhythmic novelty is computed as the normalized average information content of these conditional probabilities, while influence is measured as the change in the generation probability of songs of subsequent composer  $\omega$  when a preceding song  $\zeta$  is excluded. Distinctiveness of a composer  $\omega$  is the the mean of all Jensen-Shannon Divergence (JSD) between the transition matrix M constructed from the IOI ratios of the entire data and the transition matrix  $M_{\zeta}$  that excludes a composition  $\zeta$  of composer  $\omega$ .

Novelty(
$$\zeta$$
) =  $\frac{1}{m} \log \frac{1}{\Pi(\zeta)}$  (1)

Influence
$$(\zeta, \omega) = \underset{x \in C_w}{\mathbb{E}} \left[ \frac{1}{m} \log \frac{\Pi_{\zeta}(x)}{\Pi_{\zeta}(x)} \right]$$
 (2)

$$\text{Distinctiveness}(\omega) = \frac{1}{n} \sum_{\zeta \in C_{\omega}} \frac{D_{\text{KL}}(M_{\bar{\zeta}}||M) + D_{\text{KL}}(M||M_{\bar{\zeta}})}{2}, D_{\text{KL}}(P||Q) = \sum_{i} P(i) \log \frac{P(i)}{Q(i)} \quad (3)$$

Figure 1(A) illustrates the relationship between novelty and influence for each composition, revealing an overall weak negative correlation (Pearson correlation coefficient  $r=-0.0567\pm0.0274$ , jackknife error). This negative trend varies across historical periods (Fig. 1(B)), with the Classical era showing the strongest inverse relationship, likely reflecting the constraints of conventional tonal harmony and stable chord structures, which penalized excessively novel rhythmic exploration [3]. While most composers conform to the general inverse pattern between novelty and influence, a subset—ranging from Prokofiev to Haydn (orange region)—defies this trend, with their rhythmic innovations rapidly adopted by subsequent generations (Fig. 1(C)). When comparing novelty with distinctiveness, individual differences emerge: Scriabin and Messiaen, as well as Chopin and Tchaikovsky, represent cases where one composer scores higher in both novelty and distinctiveness, whereas Beethoven and Tchaikovsky, and Sibelius and Messiaen, exemplify cases where the relative ordering between novelty and distinctiveness is reversed.

## References

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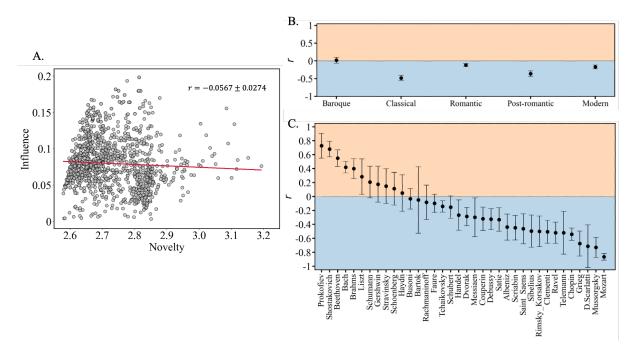


Figure 1: Scatter plot of novelty-influence (A), with points for individual compositions; PCC by musical era (B) and by composer (C).

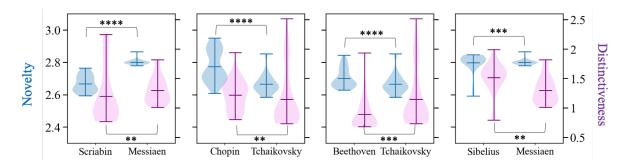


Figure 2: Composer pairs with significant differences in novelty and distinctiveness; asterisks denote p-values: p < 0.05(\*), < 0.01(\*\*\*), < 0.001(\*\*\*), < 0.0001(\*\*\*\*).