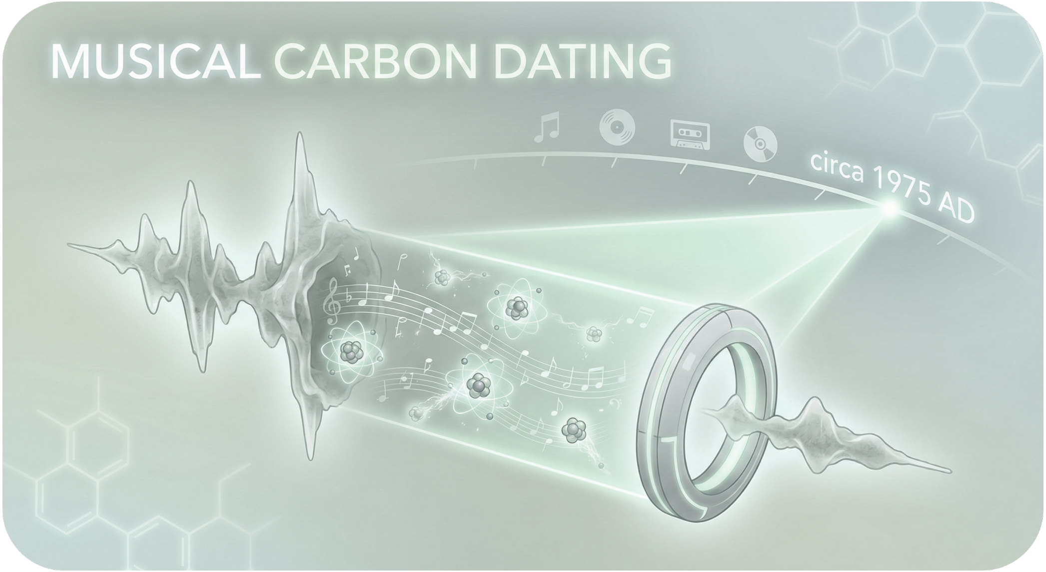
Musical Carbon Dating

A Statistical Feature Recognition Approach (1960-2020)

Group Presentation

University Statistical Analysis Project

December 23, 2025


MUSICAL CARBON DATING
circa 1975 AD

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The Research Question

Feature Recognition

"Can we determine the vintage of a musical recording purely from its acoustic properties?"

Objective: To build a regression model that maps audio features to release year, quantifying the "Arrow of Time" in music production.

Hypothesis: Musical eras have distinct, quantifiable acoustic fingerprints (e.g., the "dryness" of 70s rock vs. the "compression" of 2000s pop).

The Data: Spotify 600k Tracks

Data Filtering Strategy:

- **Source**: Spotify 600k Tracks Dataset (Kaggle).
- **Filter 1**: Timeframe $1960 \leq T \leq 2020$ (Modern Era).
- **Filter 2**: `popularity > 30` (Focus on culturally significant music).
- **Final Sample**: $N = \mathbf{250,971}$ tracks.

Validation Strategy:

- **Random Split**: 80% Training / 20% Test.
- *Rationale*: We are testing "feature recognition" (interpolating styles), not future forecasting (extrapolating time).

The Feature Set (p=13)

We utilized all 13 available audio features.

Physical Features

1. Loudness (dB)
2. Tempo (BPM)
3. Duration (ms)

Musical Features

4. Key (0-11)
5. Mode (Major/Minor)
6. Time Signature

Perceptual Features

7. Acousticness
8. Danceability
9. Energy
10. Instrumentalness
11. Liveness
12. Speechiness
13. Valence (Positivity)

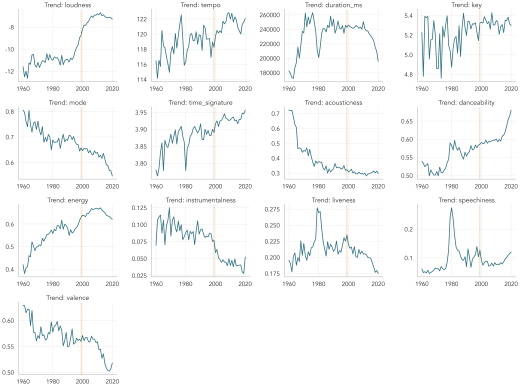
The Regression Pipeline

We followed a rigorous 5-phase statistical workflow:

1. **Phase I: Simple Linear Regression (SLR)** *Hypothesis testing: The "Loudness War".*
2. **Data Standardization** *Z-Score Normalization ($x' = \frac{x-\mu}{\sigma}$) to ensure scale invariance.*
3. **Phase II: Multiple Linear Regression (MLR)** *Baseline model using all $p = 13$ features.*
4. **Phase III: The Diagnostic Audit** (Critical Step) *Testing Linearity, Multicollinearity, Normality, and Homoscedasticity.*
5. **Phase IV: Model Selection** *Stepwise AIC vs LASSO comparison.*
6. **Phase V: Refinement (WLS)** *Weighted Least Squares to correct for Heteroscedasticity.*

Phase I: The "Loudness War" (SLR)

$$Year_i = \beta_0 + \beta_{loud} \cdot Loudness_i + \varepsilon_i$$



Results:

- t-stat: **159.4** (Highly Significant).
- $\beta_{loud} \approx 4.98$ years/dB (Standardized).
- $R^2 = 0.130$.

Conclusion: Tracks have consistently gotten louder, but Loudness alone explains only 14% of the variance.

Phase II: Multiple Linear Regression (Baseline)

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

- **Algorithm**: Ordinary Least Squares (OLS) with all 13 features.
- **Result (R^2)**: **0.238**
- **RMSE**: 12.05 years.

Why so low?

An R^2 of 0.3 suggests we are missing non-linear patterns or violating OLS assumptions. We initiated a **Diagnostic Audit**.

Phase III: Diagnostic Audit (1/2)

Test 1: Independence of Errors

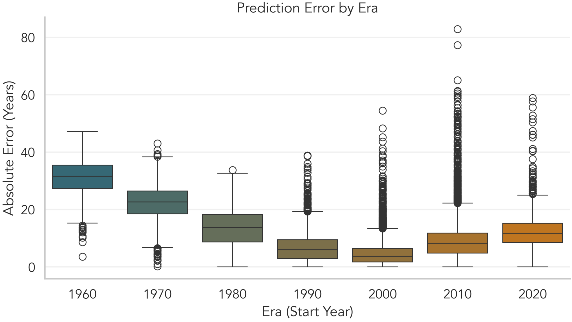
- **Method**: Durbin-Watson Statistic.
- **Result**: $DW \approx 2.001$. (Target $=$ 2.0)
- **Finding**: Assumption Met. No autocorrelation. Each song is statistically unique.

Test 2: Multicollinearity

- **Method**: Variance Inflation Factor (VIF).
- **Concern**: High correlation between Loudness and Energy ($r = 0.74$).
- **Result**: Max VIF (Energy) $=$ **3.62**. All VIFs < 5.0.
- **Finding**: Assumption Met. No severe multicollinearity.

Phase III: Diagnostic Audit (2/2)

Test 3: Homoscedasticity (Constant Variance)



- **Visual**: Dispersed variance (Right) vs Tight variance (Left).
- **Insight**: "Stylistic Entropy". The definition of specific eras has blurred over time due to technology.
- **Statistic**: $\chi^2 = \mathbf{19,567}$ (Breusch-Pagan).
- **Conclusion**: Variance is expanding. OLS fails because it treats 1960 and 2020 as equally predictable.

Solution: We must weight the model to trust the "consistent" eras more than the "chaotic" ones. **Enter WLS.**

Phase IV: Model Selection

We compared two methods to identify the "True" feature set:

Method	Selected Features	Key Difference
Stepwise (AIC)	12 Features	Dropped `Key`
LASSO (L_1)	**13 Features**	**Kept All Acoustic Features**

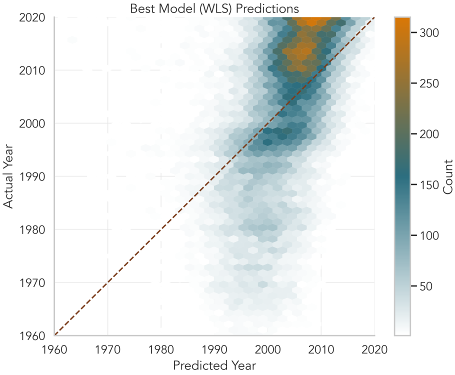
Decision: We utilized the full acoustic feature set.

- Removing variables offered negligible AIC improvement.
- Retaining subtle features (Key, Mode) ensures we capture harmonic evolution.

Phase V: Weighted Least Squares (WLS)

To cure Heteroscedasticity, we implemented WLS:

$$\min_{\beta} \sum_{i=1}^{n} w_i (y_i - \mathbf{x}_i^T \beta)^2, \quad \text{where } w_i \propto \frac{1}{\mathrm{Var}(\varepsilon_i)}$$



What WLS Fixes

- **Valid p-values** & confidence intervals.
- **Efficient coefficient estimates**.

Metrics:

- Weighted R^2: **0.763** (Trend Fit)
- F-statistic: $\mathbf{4.19 \times 10^4}$ (Highly Significant)
- Unweighted Test R^2: ≈ 0.24 (Raw Data)
- Test **RMSE**: 12.05 years
- Test **MAE**: 9.31 years

Note: The jump to 0.77 reflects weighting down outliers, not miraculously predicting them. The raw prediction power

Phase VI-A: Technological Drivers ("The Sound of Efficiency")

Regression reveals the impact of technology on composition ($p < 0.001$).

- **The Loudness-Energy Paradox (Multicollinearity Insight)**:
  - Mean `Loudness` has skyrocketed over time ($\beta_{loud} \approx +6.51$).
  - Yet, `Energy`'s coefficient is **negative** ($\beta_{energy} \approx -1.20$) when controlling for Loudness.
  - **Interpretation**: Modern tracks are "loud" due to compression (technological), not raw musical energy (compositional).
- **The Attention Economy (Duration)**:
  - Coefficient $\beta_{duration} \approx -0.89$ (Negative).
  - Songs are getting statistically shorter, likely driven by streaming incentives and skipping behavior.
- **Instrumentalness** ($\beta \approx +0.58$): A shift towards beat-driven (Hip-Hop/EDM) production over vocal-centric ballads.

Phase VI-B: Cultural Evolution ("The Mood of an Era")

Applying Statistical Inference to Cultural Theory.

- **The "Sad Banger" Phenomenon**:
  - **Danceability** ($\beta \approx +3.86$): The single strongest predictor. Rhythm is the defining feature of modernity.
  - **Valence** ($\beta \approx -4.14$): Optimism has collapsed.
  - **Synthesis**: We are dancing more, but feeling less.
- **The Acousticness Paradox (Ceteris Paribus)**:
  - Raw Correlation: Negative ($r \approx -0.12$).
  - WLS Coefficient: **Positive** ($\beta \approx +0.62$).
  - **Discovery**: *Controlling for Loudness*, modern music actually retains significant acoustic elements (Indie, Lo-Fi), hidden by the "Wall of Sound".

Analytical Triumph

By using **Partial Regression Coefficients**, we uncovered trends (like the Acousticness reversal) that simple correlation would have missed.

The Nostalgia Index

"One man's error is another man's feature."
We define the **Nostalgia Index** as the model's prediction error:

$$\text{Index} = |\hat{Y}_{predicted} - Y_{actual}|$$

High index = A song that "sounds" like it belongs to a different era.

Distribution Stats:

- Mean: **9.31** yrs
- Median: **7.58** yrs
- Max: **82.88** yrs (extreme retro outliers)

Validation: Detecting "Time Travelers"

We validated the index on tracks known for their retro aesthetic.

Song	Year	Predicted	Index	Diagnosis
Uptown Funk (Ronson)	2015	2013.1	**1.9**	Modern Construction
Physical (Dua Lipa)	2020	2009.0	**11.0**	**Retro Aesthetic**
Blinding Lights (Weeknd)	2019	2004.2	**14.8**	**80s Revival**

Conclusion: The model correctly identifies these hits as "sounding old", proving it captures aesthetic style rather than just memorizing release dates.

Conclusion

1. **Recognition**: We can date music to within ± 9 years purely from audio.
2. **Rigor**: Diagnostics proved OLS is insufficient; WLS is required.
3. **Insight**: Musical evolution is quantifiable.
4. **Value**: The Nostalgia Index provides a commercial metric for "Vibe".

Thank You.