Exploring Seismocardiogram Biometrics with Wavelet Transform

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Outline

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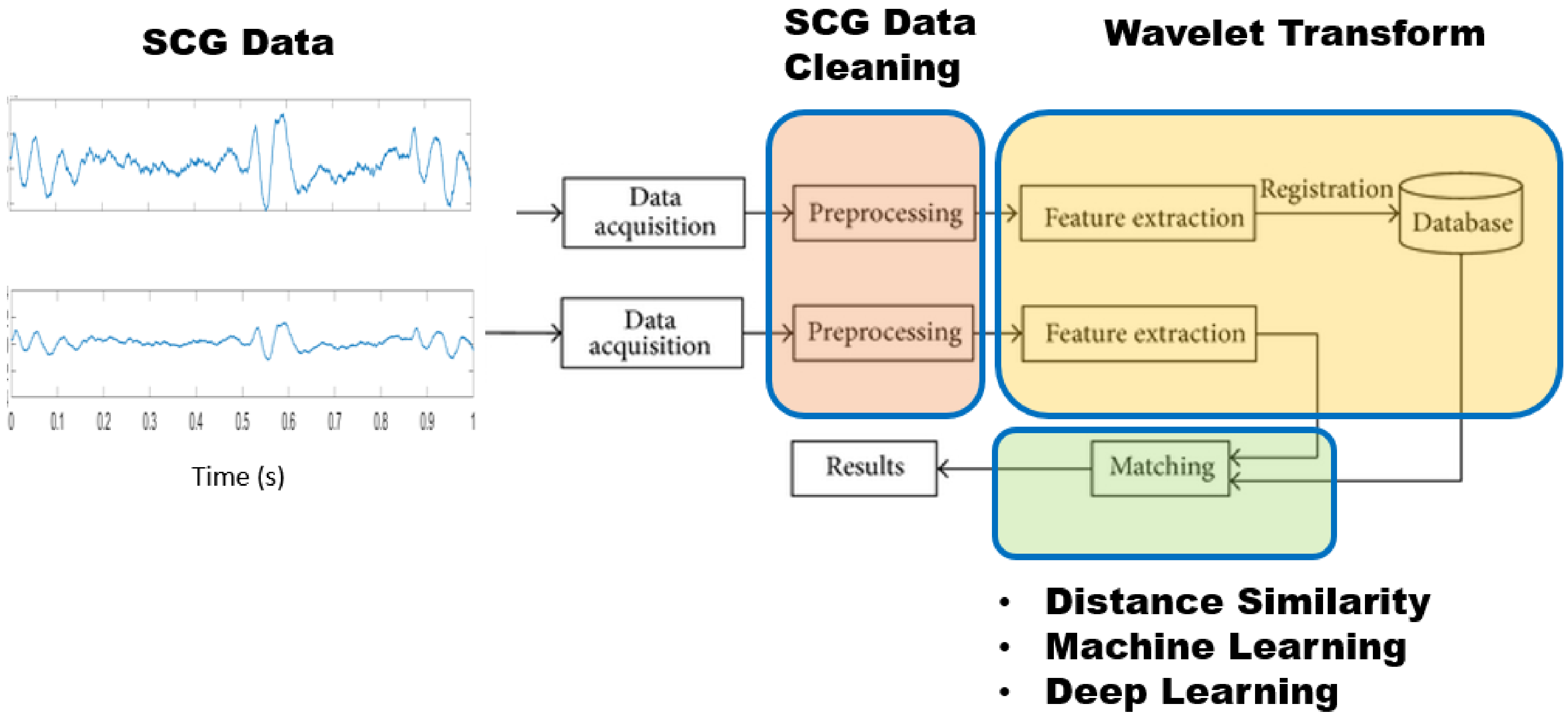
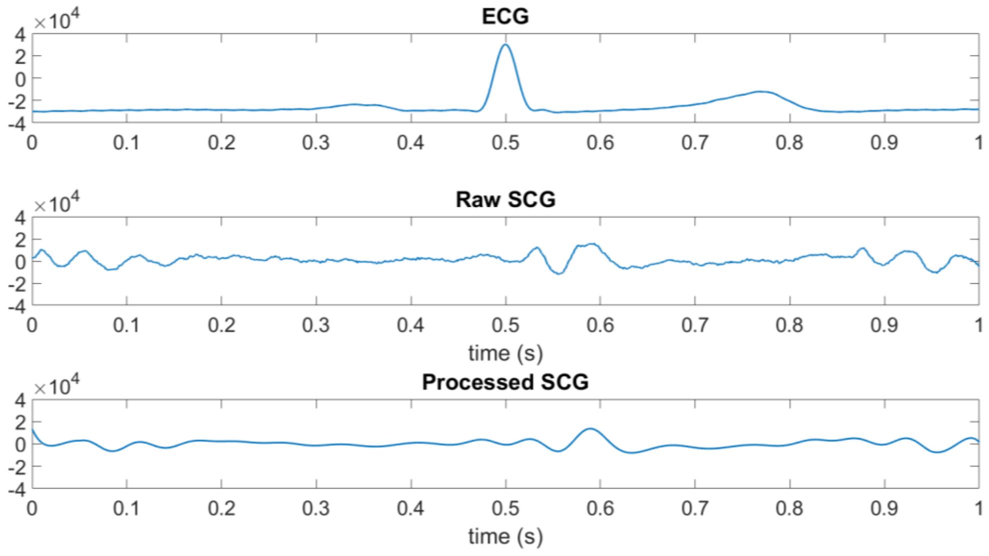
Objective

- Explore the opportunities to utilize Seismocardiograms (SCG) as biometrics



Background

- External biometrics: fingerprints, iris, faces [1]
  - Convenient
  - Mature technology compared to internal biometrics
- Internal biometrics: ECG, SCG [2-4]
  - Against spoofing attacks
  - Contain physiological health information



Background

- ECG Biometrics:
  - Reported in several studies [4-7]
  - State-of-the-art models: 2D-CNN [4,7]
- SCG Biometrics:
  - State-of-the-art model: PCA-based SCG biometric model [8]
  - 98.89% recognition rate is reported, but equal error rate (EER) is not

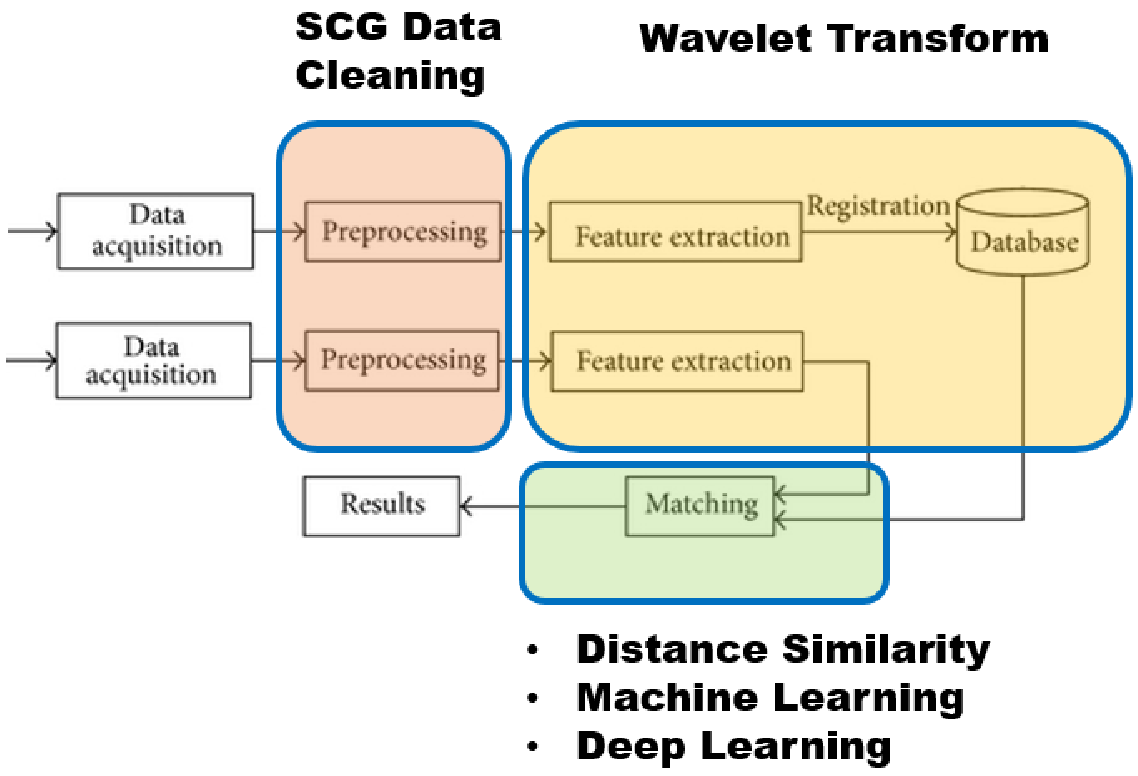
Methods

- Dataset: publicly available SCG data from PhysioBank, 20 subjects' steady posture data of 5 minutes, with each before and after listening to music
- Biometric Modules:

➢SCG Data Cleaning
  - Savitzky-Golay filtering
  - Heartbeat detection

➢Feature Extraction
  - Continuous wavelet transform (CWT)

➢Data Matching
  - General distance metric: L1 norm, L2 norm
  - Machine learning algorithms
  - Deep learning models



Methods

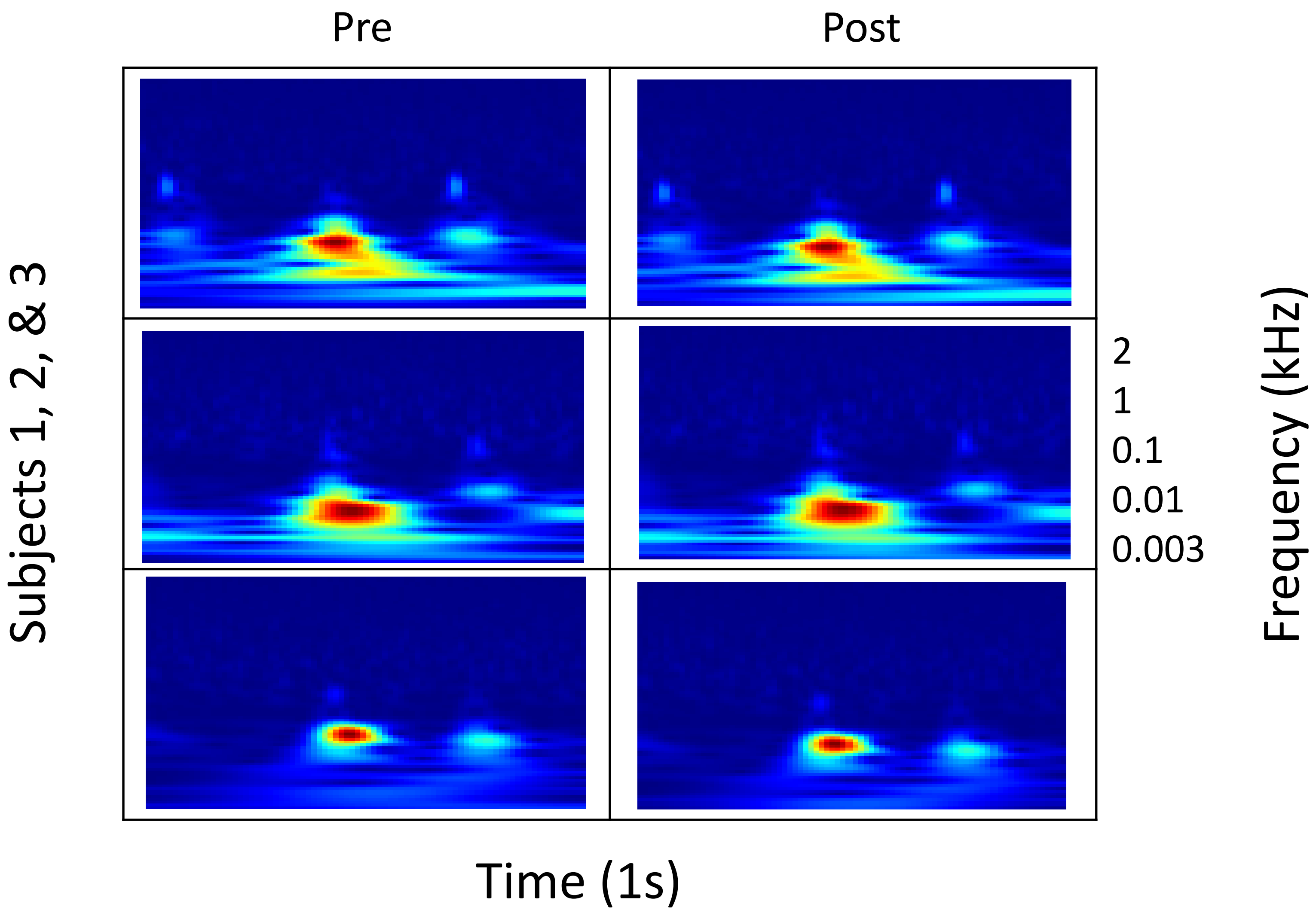
Signal Processing & Peak Detection

Wavelet Transform

$$X_\omega(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\bar{\psi}(\frac{t-b}{a})$$

Biometric Matching

Scalograms



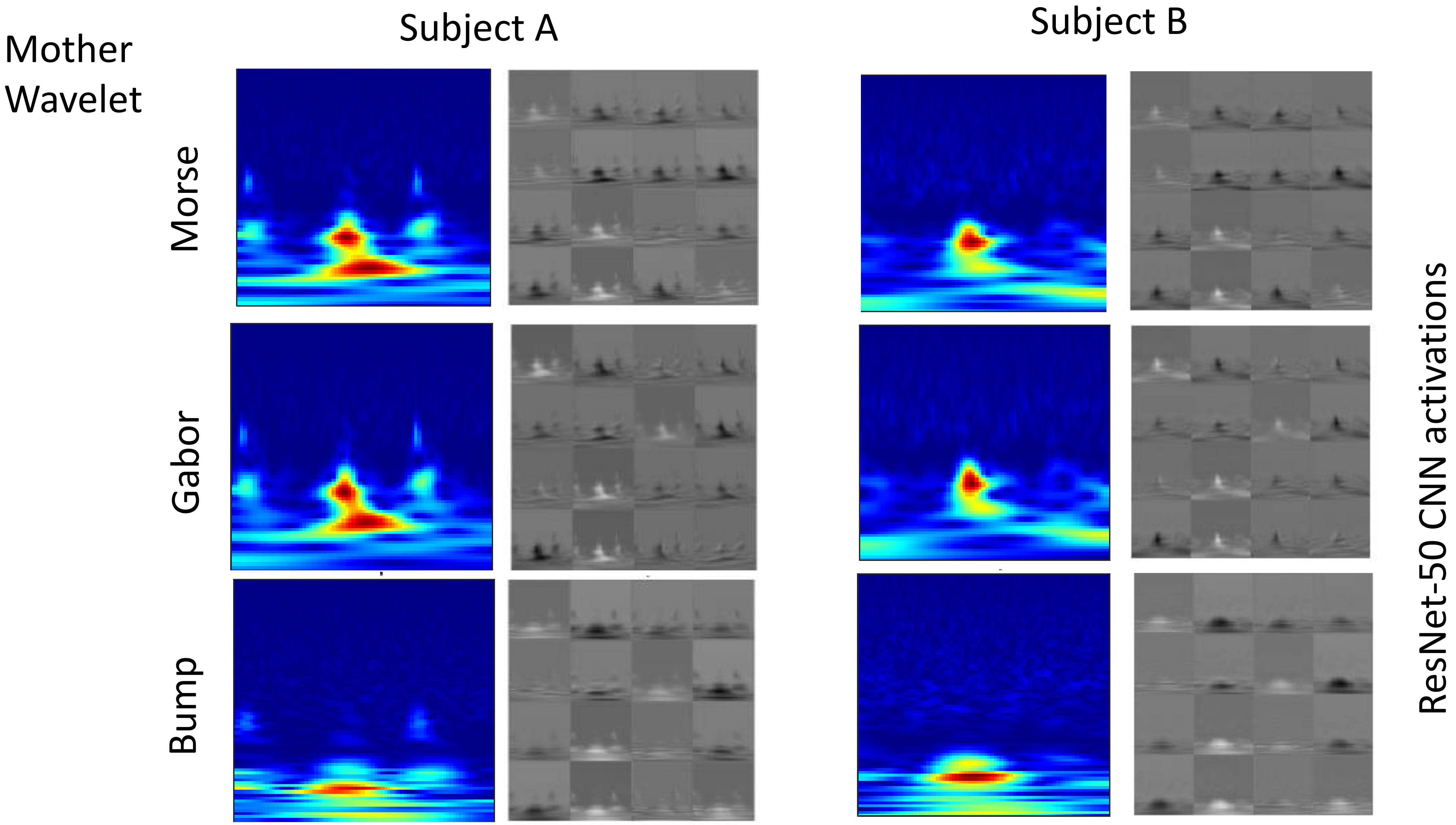
Results

Work	Equal Error Rate (%)
PCA + Machine Learning Classifier [8]	1% (estimated)
Ours	**<0.01%**

Equal Error Rate

- Similarity approach: ≈ 1%
- Machine Learning classifiers: <0.01%
- Deep CNN classifiers: <0.01%

Seismocardiography (SCG) Biometric - Visualization



Summary

- Seismocardiogram can potentially become a biometric
- Research on Motion Artifact Resilient SCG Biometric is highly required for generalized SCG biometrics
- Extend to other applications, e.g. posture recognition

References

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