

Higher-dimensional Data Analysis Using Autocorrelation Wavelets via Julia

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Introduction

Task:

- ▶ Extend the autocorrelation wavelet transform to higher dimensions in the Julia programming language
- ▶ Perform denoising experiments on images and analyze multiple time series using autocorrelation wavelets

Signals and Filters

- ▶ Signal: A function carrying information, often with respect to time
- ▶ Filter: A function to extract certain information or feature from a signal (usually represented as a vector). Applied on a signal using sliding dot product
- ▶ Signal Operations
 - ▶ Cross Correlation
 - ▶ Measures the similarity between a filter and an input signal (Note: a filter could be yet another input signal)
 - ▶ Autocorrelation
 - ▶ Correlation of a signal with a delayed copy of itself
 - ▶ Autocorrelation function is symmetric

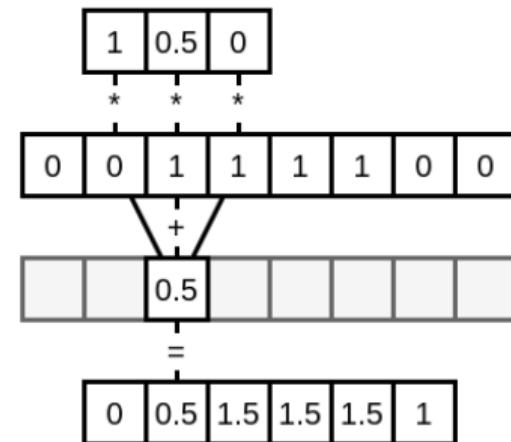
Discrete Correlation

f:

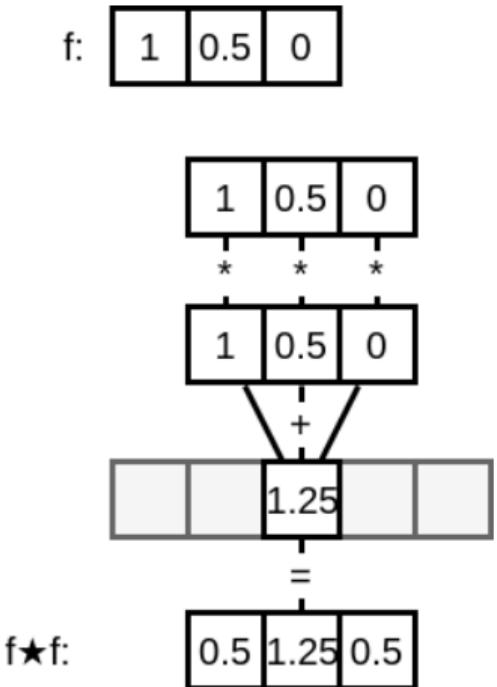
| | | |
|---|-----|---|
| 1 | 0.5 | 0 |
|---|-----|---|

g:

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 |
|---|---|---|---|---|---|---|---|

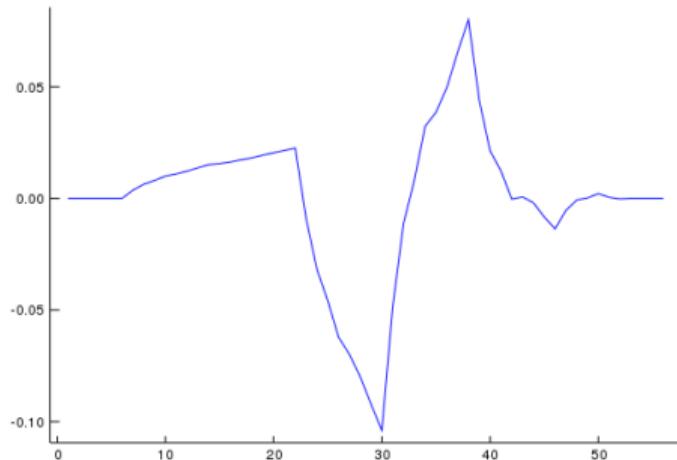


Discrete Autocorrelation

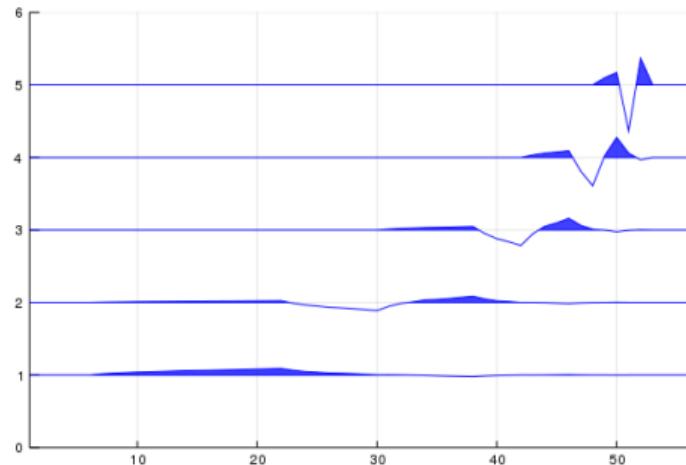


Wavelets

- ▶ Wavelet: A function that resembles a single oscillation of a wave
- ▶ Wavelets have both frequency and time domain info



Daubechies Wavelet



Daubechies Wavelets of various scales

Wavelet Transforms

- ▶ Represent a signal as a linear combination of wavelet basis functions

$$f(t) = \sum_{i=1}^n a_i \phi_i(t)$$

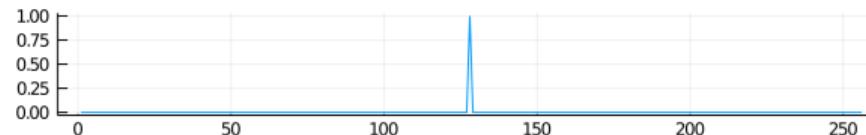
where a_i are expansion coefficients and $\phi(t)$ are the basis functions

- ▶ Wavelet transform deconstructs the signal using the same wavelet at different scales

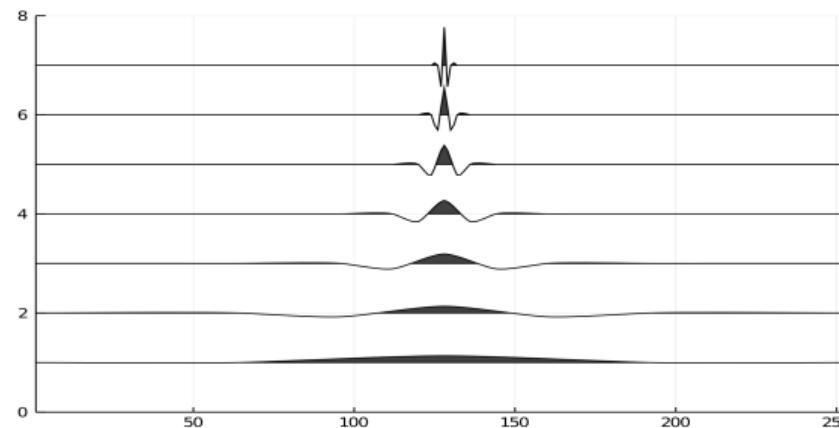
1D Autocorrelation Wavelet Transform

- ▶ Redundant wavelet transform
- ▶ Autocorrelation properties: shift-invariant **and** symmetric

Original Signal



Autocorrelation Functions of Wavelets



2D Autocorrelation

Auto-correlation Wavelets

2 Dimensional Decomposition Heatmap

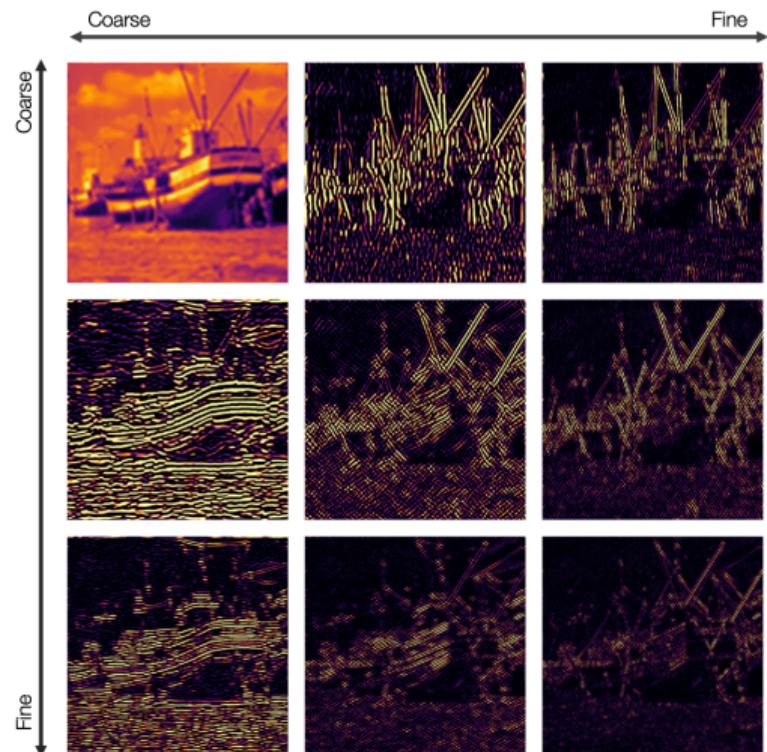


Image De-noising

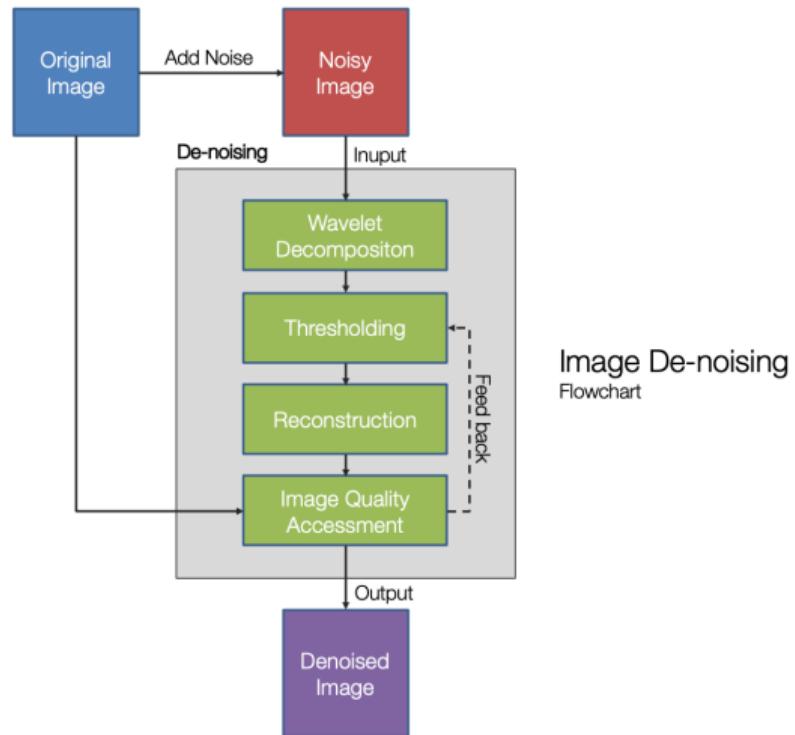
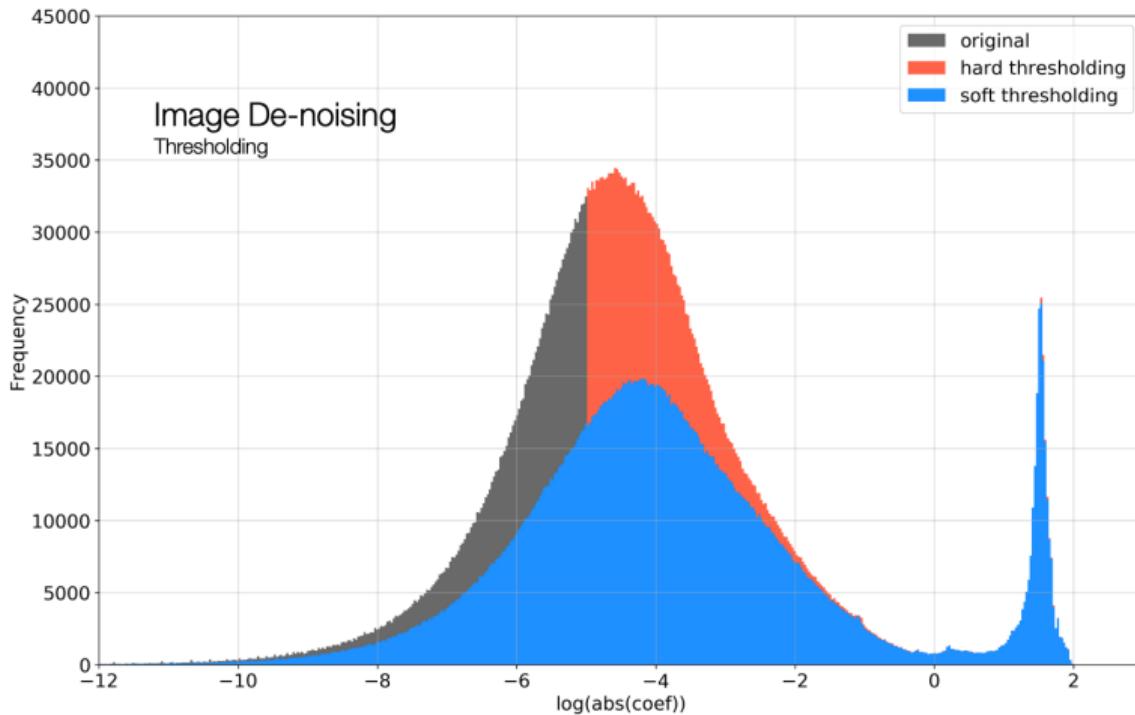


Image De-noising



Note: This thresholding value is not used in any subsequent plots. It is for illustration purposes only.

De-noising: Peak Signal to Noise Ratio (PSNR)

Peak Signal to Noise Ratio (PSNR)

- ▶ Ratio between maximum power of a signal and maximum power of corrupting noise
- ▶ Quantifies image quality degradation

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2 \quad (1)$$

$$PSNR = 20 \log_{10} \left(\frac{MAX_I}{\sqrt{MSE}} \right) \quad (2)$$

- ▶ I, K, MAX_I : original image, denoised image and the maximum possible pixel value of I
- ▶ The smaller the MSE , the larger the value

De-noising: Peak Signal to Noise Ratio (PSNR)

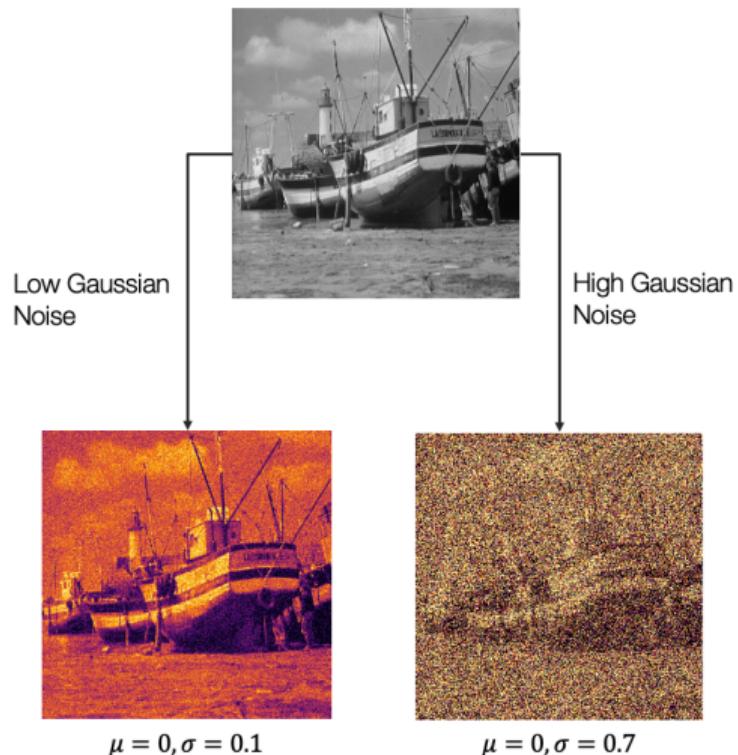
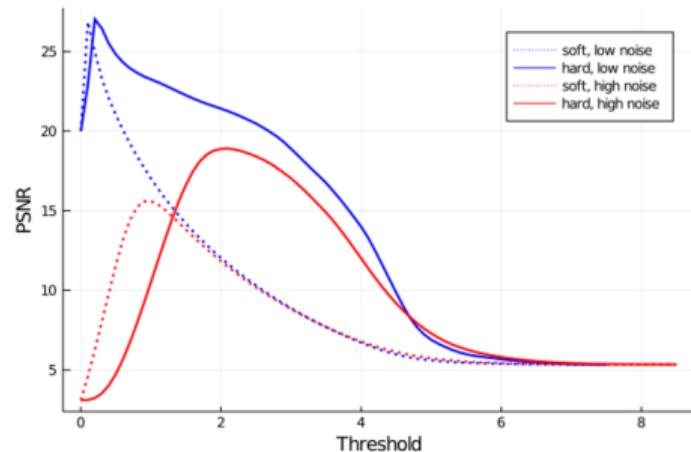


Image De-noising
PSNR Curve

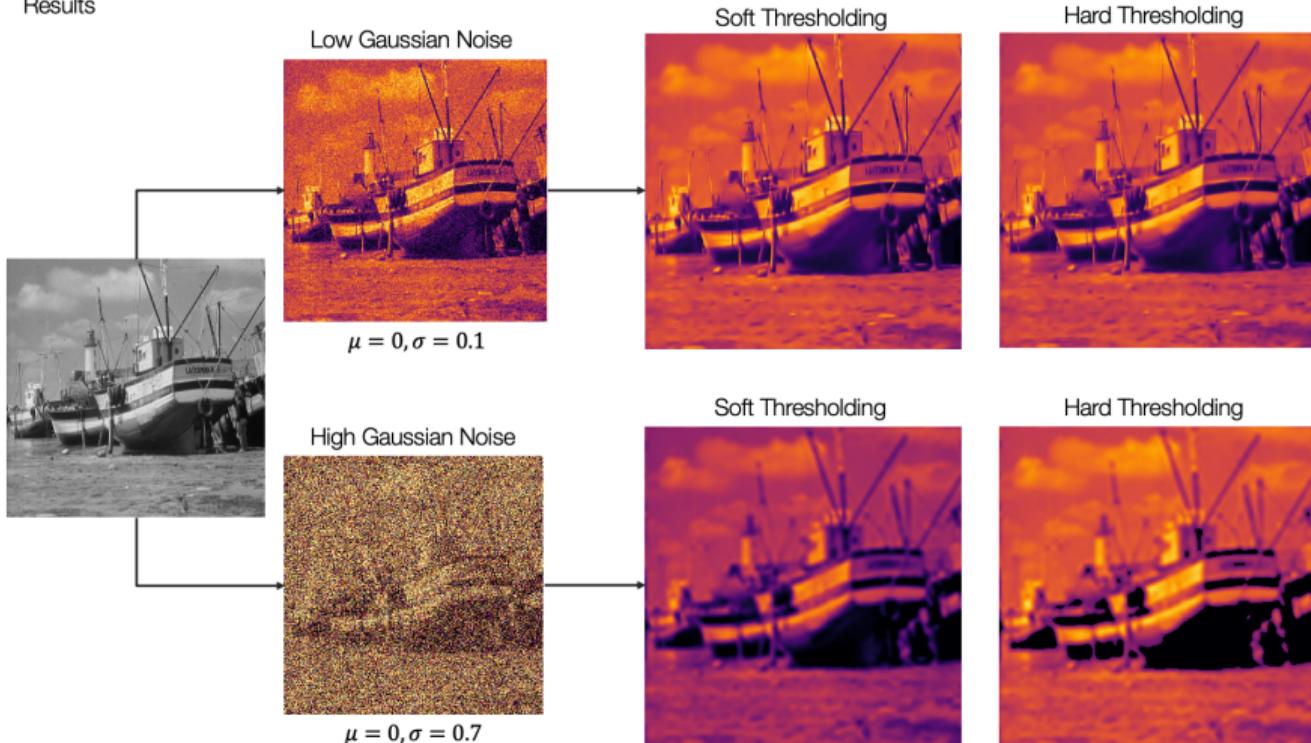


Use the threshold corresponding to the largest PSNR value

De-noising: Peak Signal to Noise Ratio (PSNR)

Image De-noising

Results

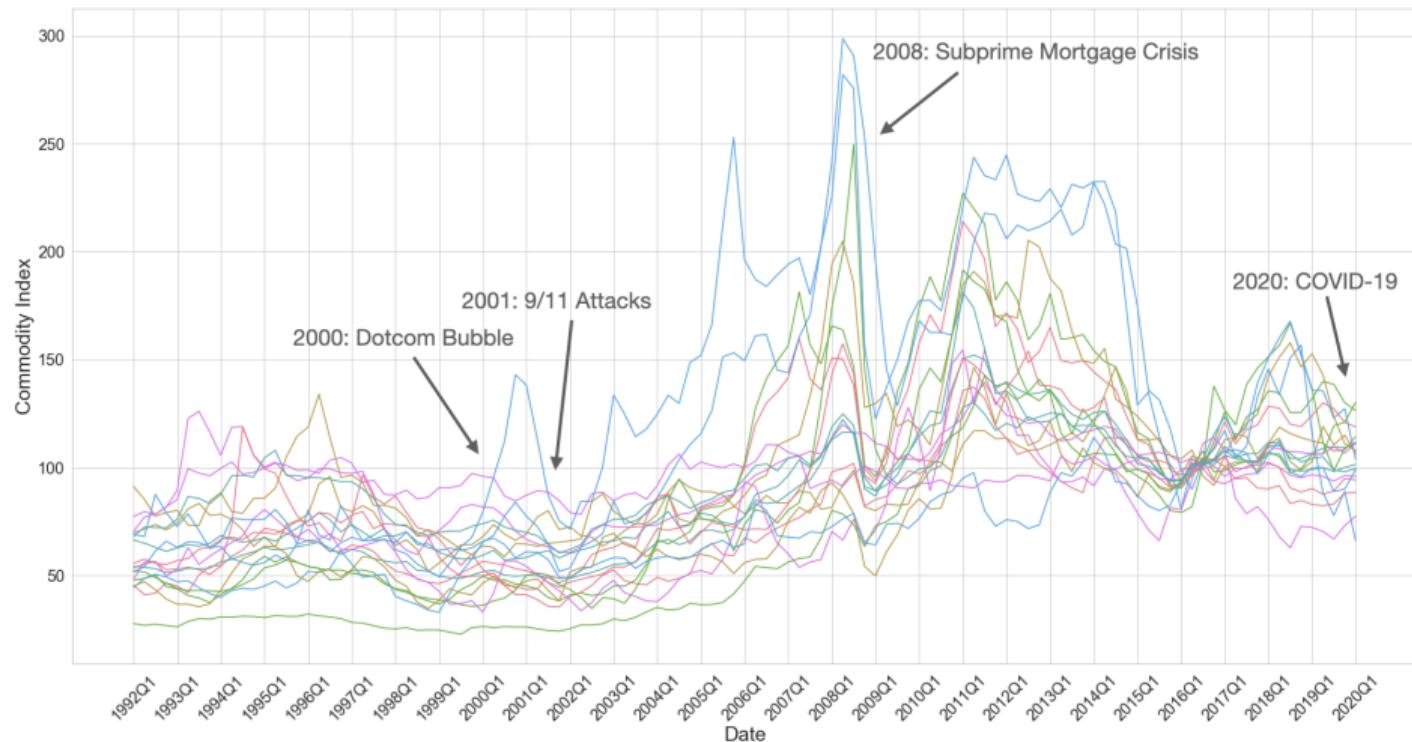


Data Analysis 1: Commodity Prices

- ▶ Commodity index: weighted average of the prices of a selected basket of goods relative to their prices in some base year
- ▶ Source: International Monetary Fund
 - ▶ Includes commodity indices such as Industrial Materials Index, Food Index, Energy Index, etc.
 - ▶ Quarterly data which spans from 1992Q1 to 2020Q1
- ▶ The indices are based in 2016
 - ▶ Example

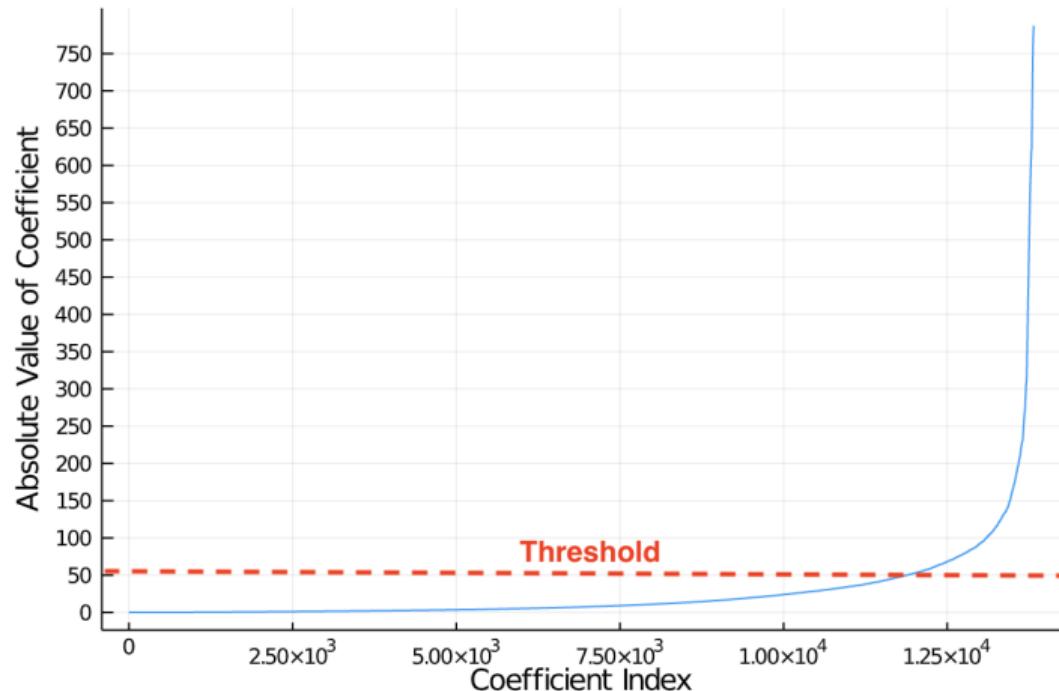
$$\text{Commodity Index for 2020} = \frac{\text{Price of Basket in 2020}}{\text{Price of Basket in 2016}} * 100$$

Data Analysis 1: Commodity Prices



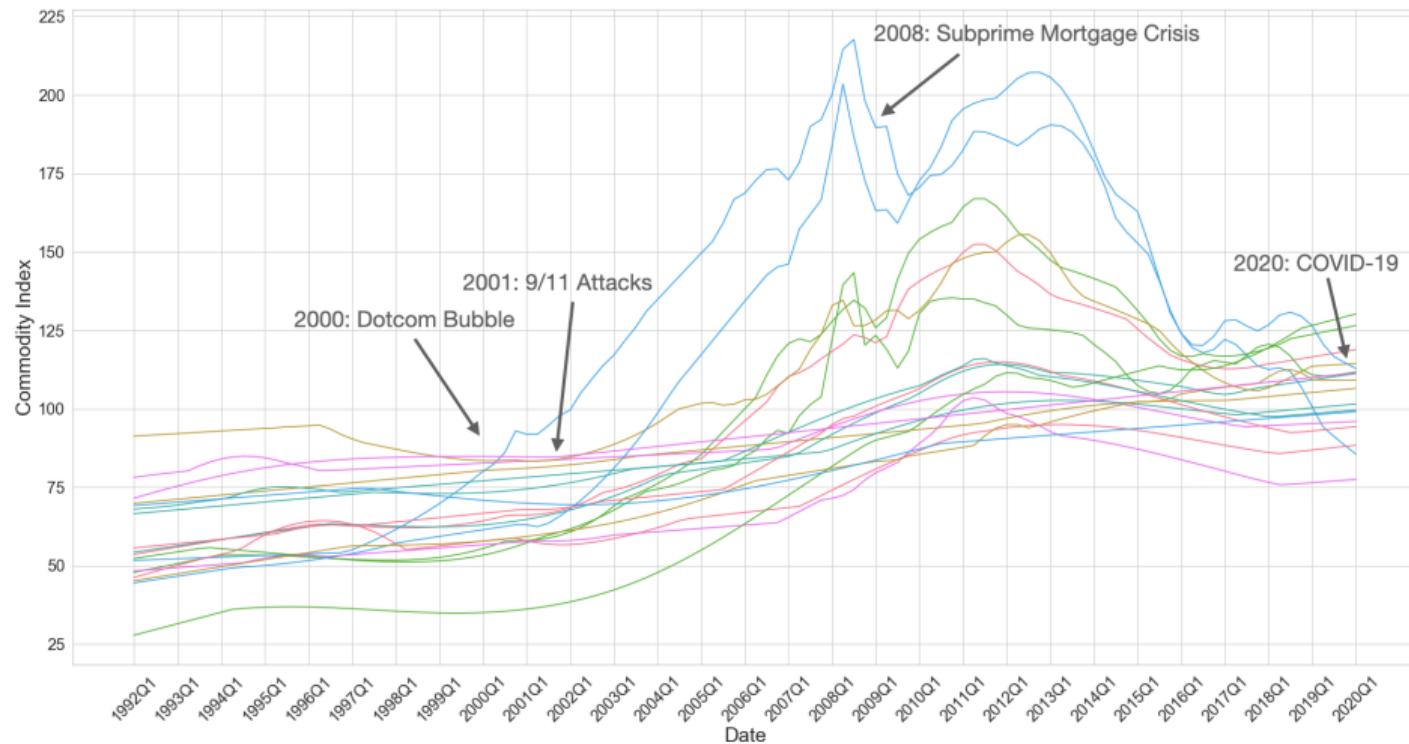
Data Analysis 1: Commodity Prices

- Goal: denoise the data by thresholding the coefficients obtained from the autocorrelation wavelet transform



Data Analysis 1: Commodity Prices

After thresholding:

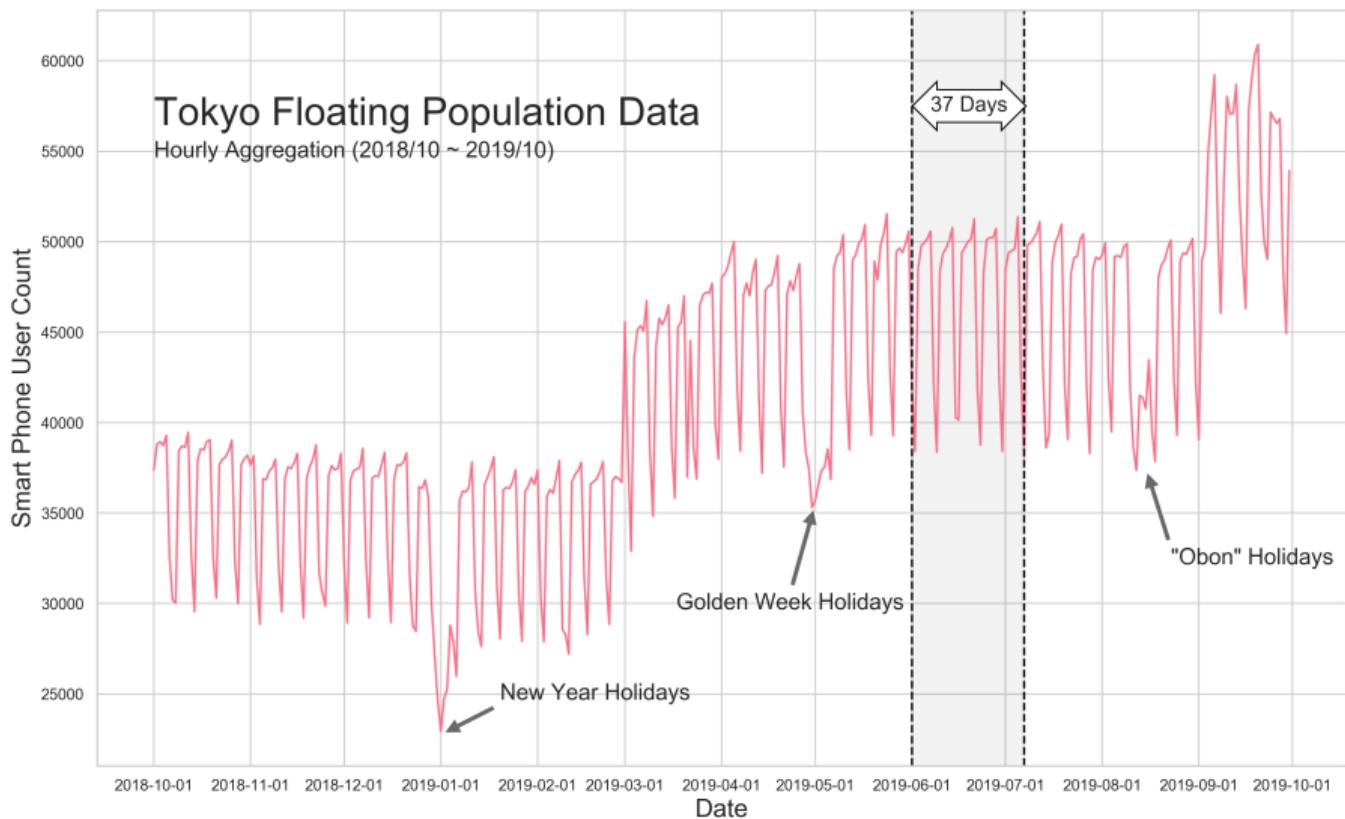


Data Analysis 2: Floating Population

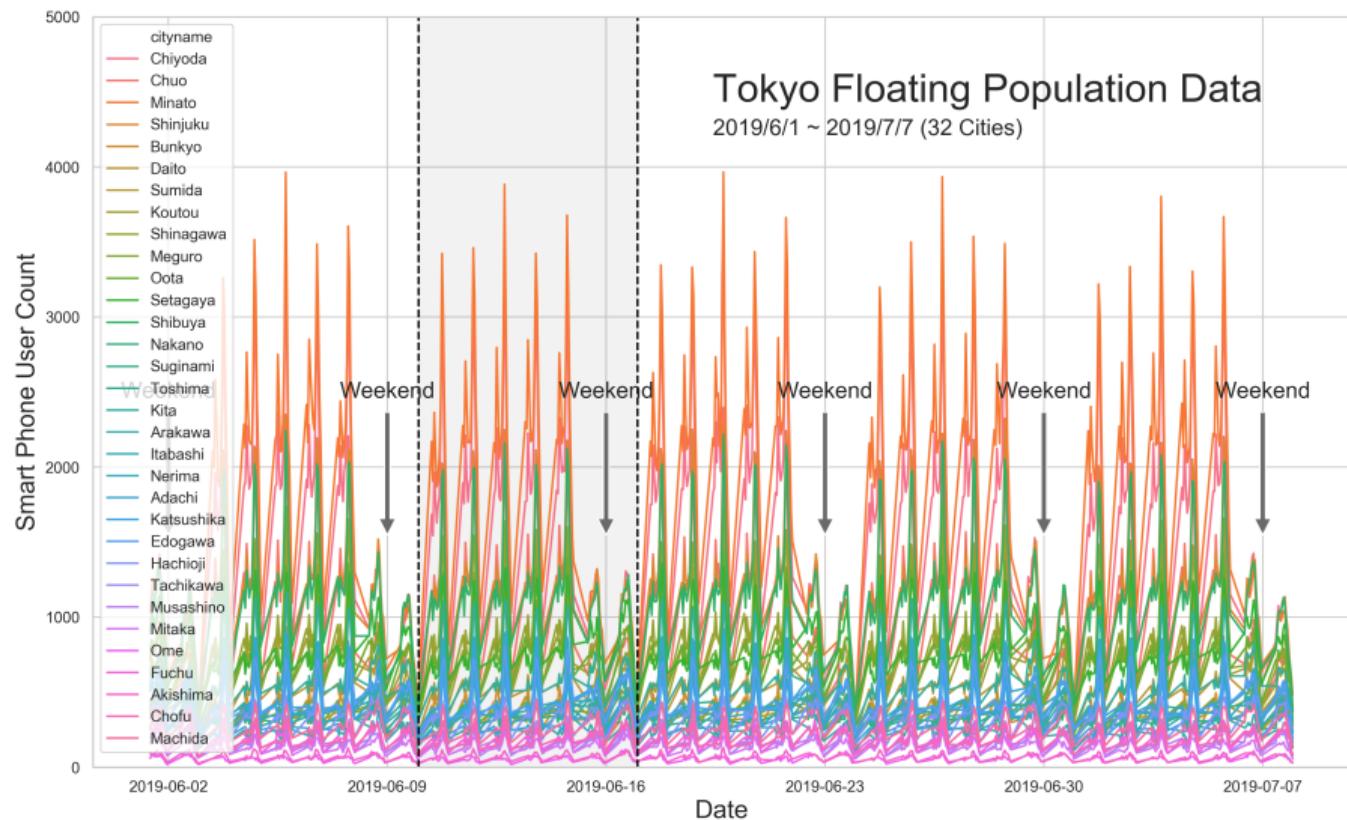
Floating Population Data

- ▶ Source: Tokyo Public Transportation Open Data Challenge
 - ▶ Agoop: Subsidiary of SoftBank(Largest network provider in Japan)
- ▶ Smart Phone Log Data (2018/10 to 2019/10)
 - ▶ Date
 - ▶ Location
 - ▶ Gender
 - ▶ Various Settings e.g. Currency, Language, Country
- ▶ Goal: Use 2D auto-correlation wavelet decomposition to find trends in the flow of people.

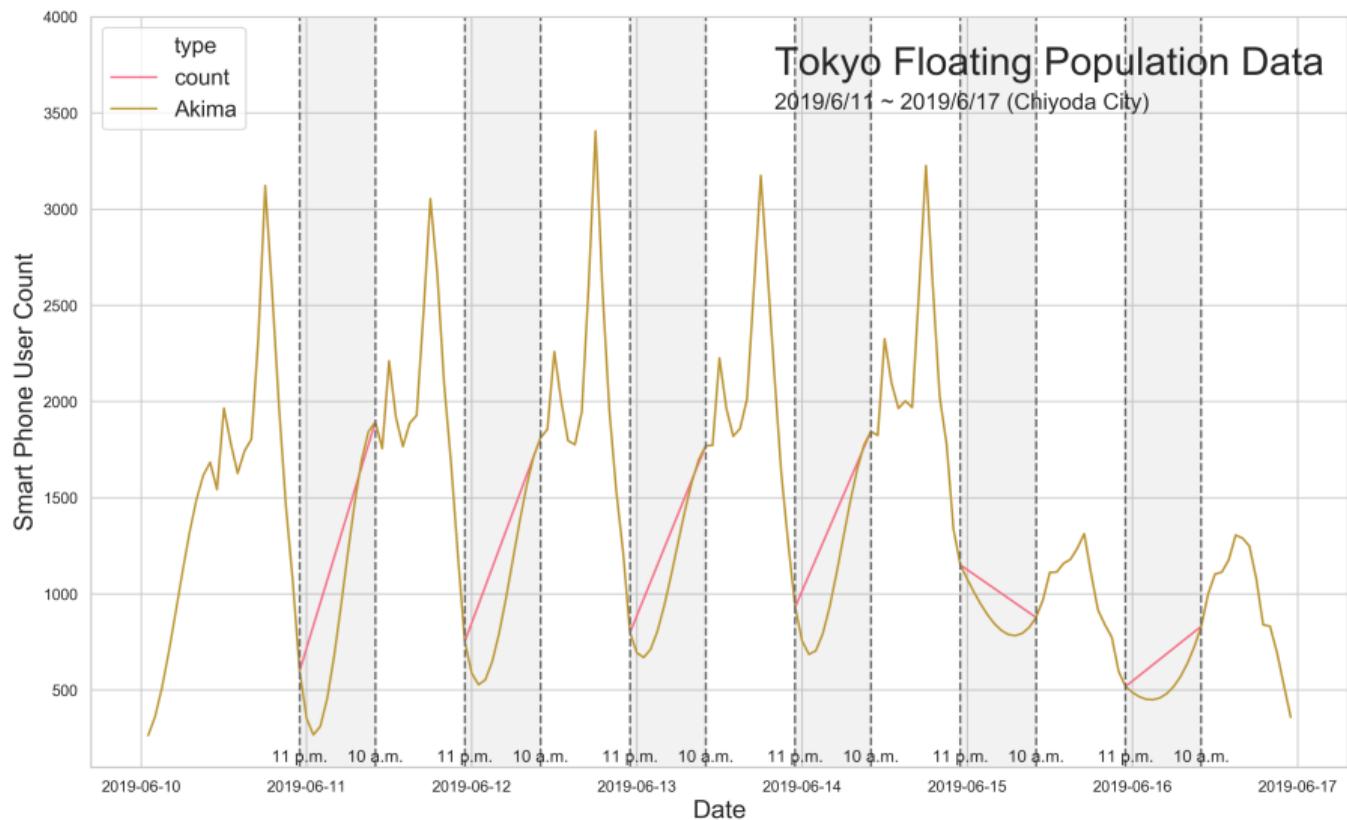
Data Analysis 2: Floating Population



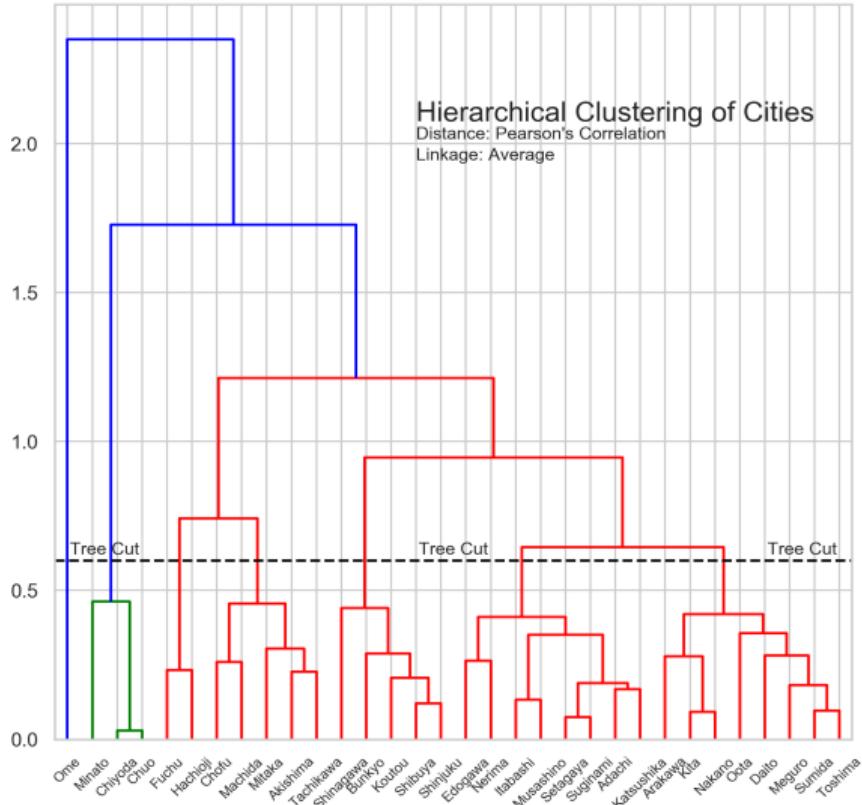
Data Analysis 2: Floating Population



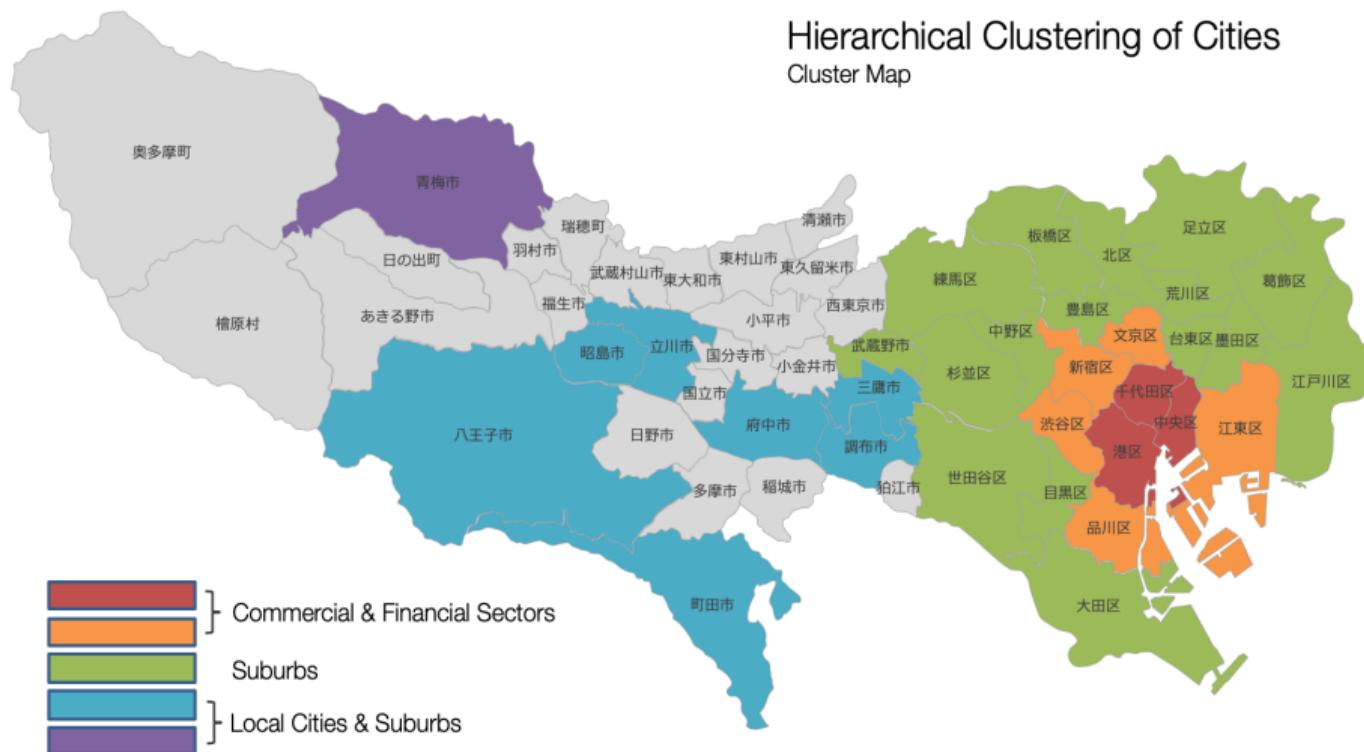
Data Analysis 2: Floating Population



Data Analysis 2: Floating Population



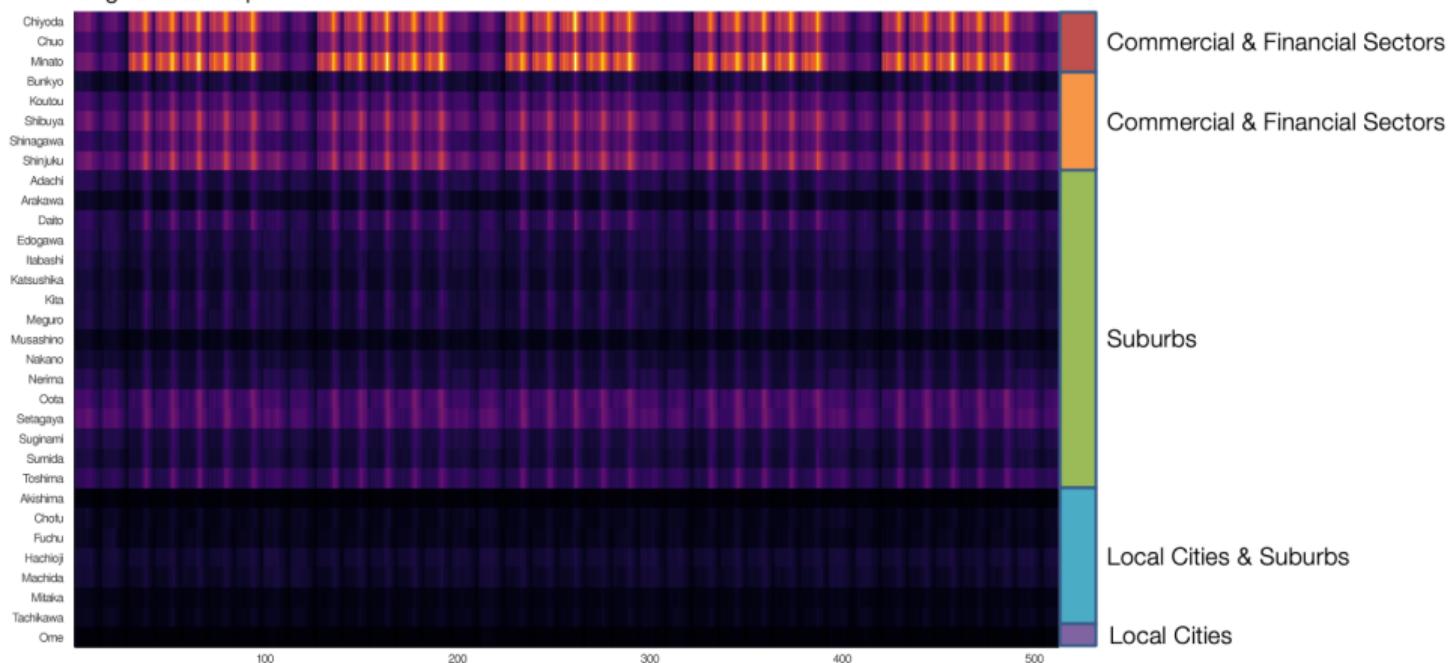
Data Analysis 2: Floating Population



Data Analysis 2: Floating Population

Tokyo Floating Population

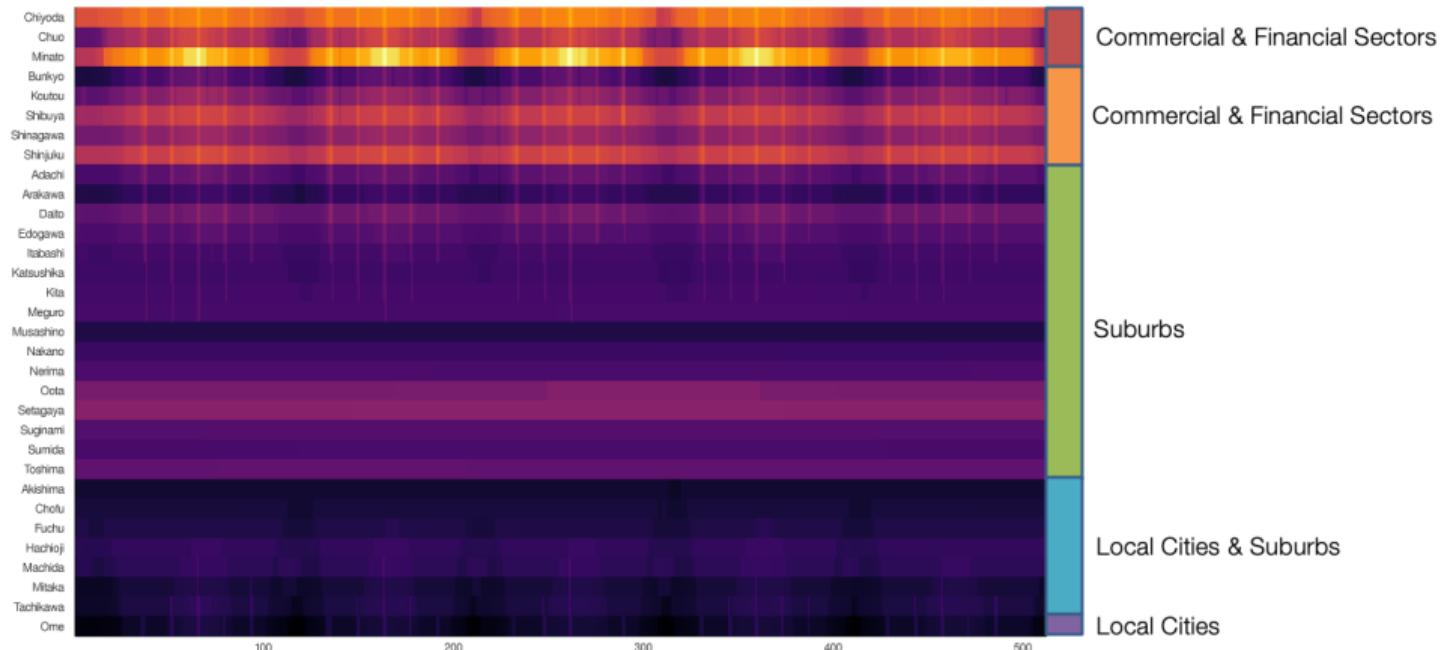
Original Heatmap



Data Analysis 2: Floating Population

Tokyo Floating Population

Thresholded Heatmap (90% Quantile)



Summary

- ▶ Wavelets are functions that contain frequency and time information
- ▶ We can represent signals with a basis of wavelets
- ▶ The advantages of the autocorrelation wavelet transform is that it is both shift-invariant and symmetric
- ▶ Some useful applications of the 2D autocorrelation wavelet transform are denoising and trend analysis