Implementations and Applications of Toeplitz Inverse Covariance-Based Clustering

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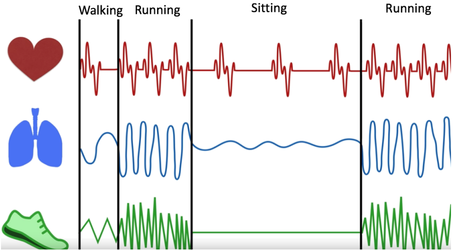
Outline

Time Series Clustering

Represent long time series as a sequence of temporal states

Example

Wearable sensor data.



Introduction
Challenges and Related Work

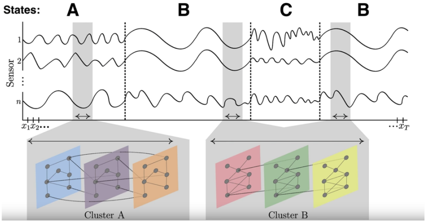
- Challenge: Identify the states and the split simultaneously
- Related methods
  - Distance-based: KMeans
  - Shape-based: Dynamic Time Wrapping
  - EM-based methods

Toeplitz Inverse Covariance-Based Clustering (TICC)

- Represent the states in structural network relationship
- Simultaneous segmentation and clustering
- Multivariate time series

Example

Car sensor dataset.



Outline

- Human Activity Data set
  - Accelerometer and gyroscope readings in smart phones
  - 6 different activities: Standing, Sitting, Biking, Walking, Stairs Up and Stairs Down
- Gesture Sensor Dataset
  - Spatial recordings of left and right hands, head, spine and left and right wrists
  - 5 different gestures: Rest, Preparation, Stroke, Hold and Retraction
  - Smaller clusters

Dataset selections

- Well-labeled multivariate time series
- Completeness
- Real world interpretations

Outline

Implementation and Model Comparison

Baseline

Comparing with baseline

- K-Means Clustering
- Gaussian Mixture Model (GMM)

Comparing Focus

- Clustering accuracy with ground truth

Example

- Human Activity Dataset.
- Gesture Dataset

Human Activity Dataset

- TICC better than K-means and GMM in terms of clustering accuracy
- TICC classify each subsequence a a whole

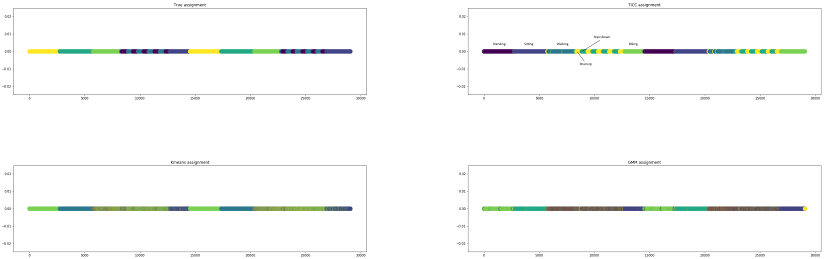


Figure: Cluster assignment of (a) True Labels (b) TICC (c) KMeans (d) GMM. Each different color represent a unique label in the time series.

Implementation and Model Comparison

Baseline

Human Activity Dataset: Confusion Matrix

- TICC: perfectly clustered the 6 classes of activities
- K-means: classify some subsequences, miss-interpretations exist
- GMM: Standing, Stairs down and Walking are best recognized

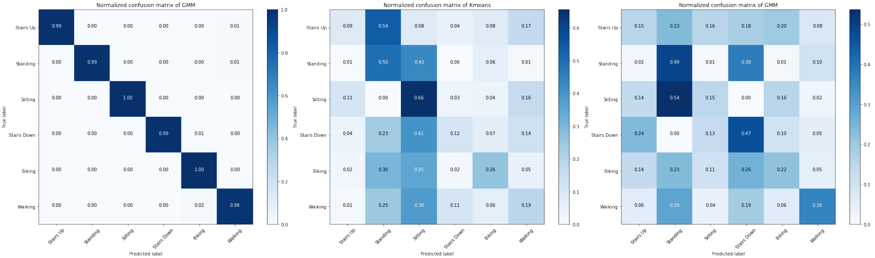


Figure: Confusion Matrix of (a) TICC (b) KMeans (c) GMM. Each different color represent a unique label in the time series.

Gesture Dataset

- TICC: unsatisfactory results
- Time series gesture changes frequently
- KMeans and GMM perform even worse

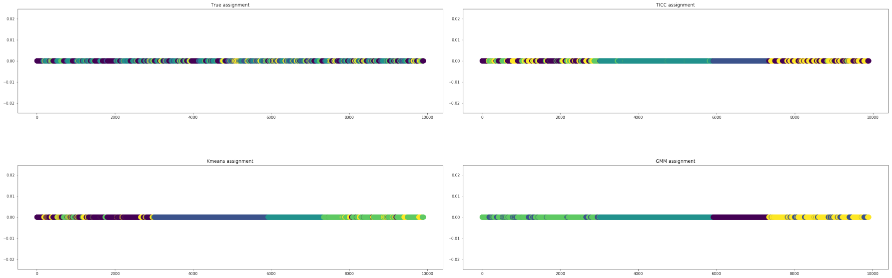


Figure: Gesture Cluster assignment of (a) True Labels (b) TICC (c) KMeans (d) GMM

Summary for two datasets

- TICC: better performance in general
- More experiments are needed

Model	Human Activity Dataset	Gesture Dataset
TICC	92.88%	14.21%
KMeans	42.69%	3.11%
GMM	58.76%	4.98%

Table: Comparison of Accuracy between different models on two datasets

Outline

Model

- Recurrent Neural Networks (RNN) classification model
- Long Short-Term Memory cells (LSTM cells)

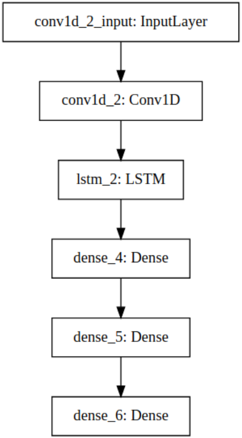


Figure: Structure of LSTM RNN for comparison

LSTM RNN Results: Gesture Data

- LSTM RNN: validation accuracy around 0.42
- TICC: validation accuracy at 0.14

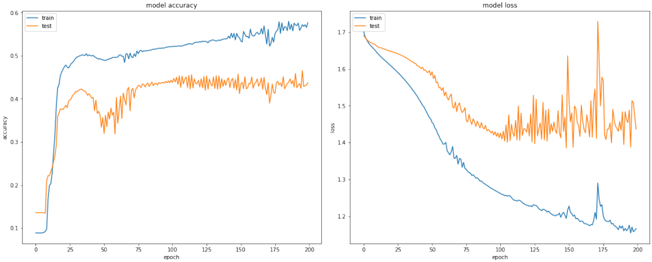


Figure: Accuracy and loss v.s. epochs for LSTM on gesture data

LSTM RNN Results: Human Activity Data

- LSTM RNN: validation accuracy around 0.45
- TICC: validation accuracy at 0.92

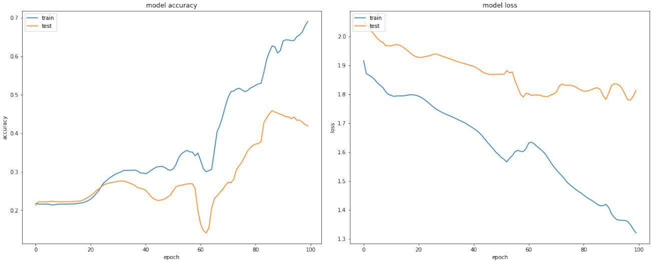


Figure: Accuracy and loss v.s. epochs for LSTM on human activity data

Outline

Hyper-Parameter Tuning

Smoothing Penalty

Effects of Smoothing Penalty

- Determines the number of segment of a time series

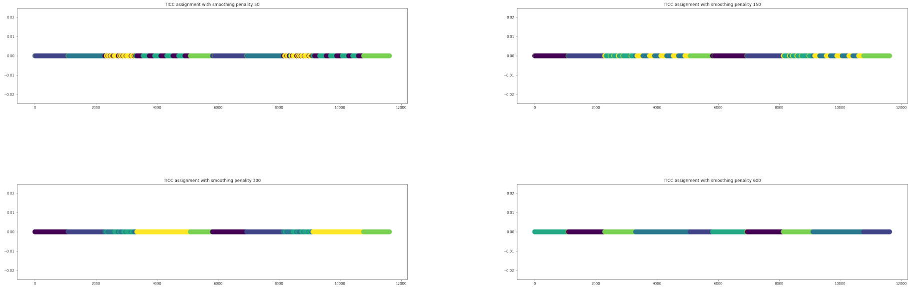


Figure: Human Activity Cluster assignment of smoothing penalty equals to (a) 50 (b) 150 (c) 300 (d) 600

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Effects of Regularization

- Regularizes sparsity level of MRF graph characterizing each cluster

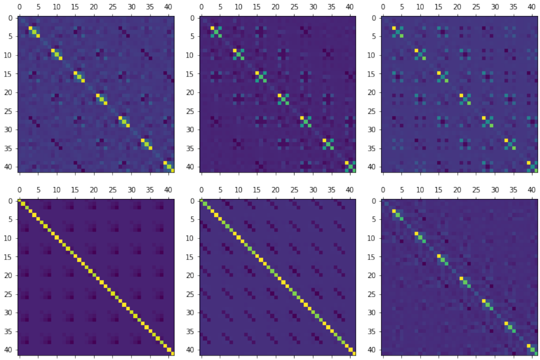

Figure: MRF of (a) Walk (b) Stairs Up (c) Stairs Down (d) Sit (e) Stand (f) Bike

Effects of Regularization

- Regularizes sparsity level of MRF graph characterizing each cluster

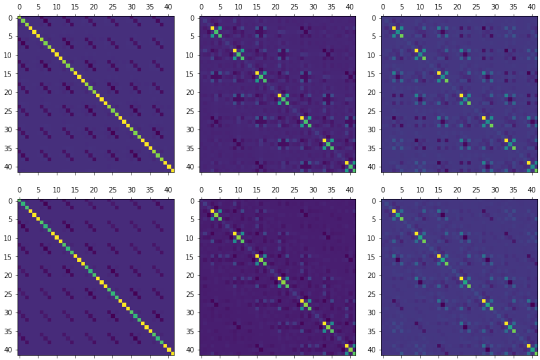

Figure: MRF with regularization = 0.00011(upper row)/0.011(lower row) of (a) Stand (b) Stairs Up (c) Stairs Down

Outline

Effects of Window Size and Dataset Size

- Controls the consideration of cross-time correlation
- Sensor reading at time t affect some sensor readings at time t + w (window size)

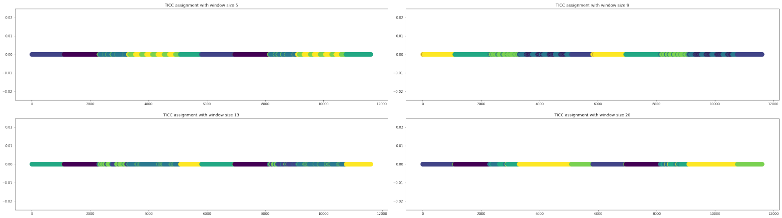

Figure: Human Activity Cluster assignment of window size w equals to (a) 5 (b) 9 (c) 13 (d) 20

Discussion

- Baseline Comparisons
  - TICC performs better in general
  - TICC, K-means and GMM clustered did not generate satisfactory results on the dataset with short segmentations
- Comparison with RNN using LSTM
  - TICC fails to capture the small sub-sequences
  - LSTM on truncated sample sequences generally work
- Choosing the Hyper-Parameters
  - In our case, smaller window size and smallersmoothing penalty could be employed, but in general it depends on the application.
  - For more general solution, larger regularization parameter can be set.