

Multivariate time series classification

Oct 12, 2015

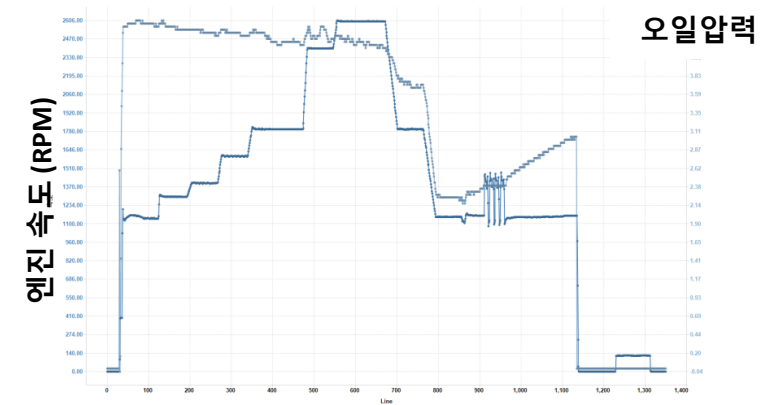
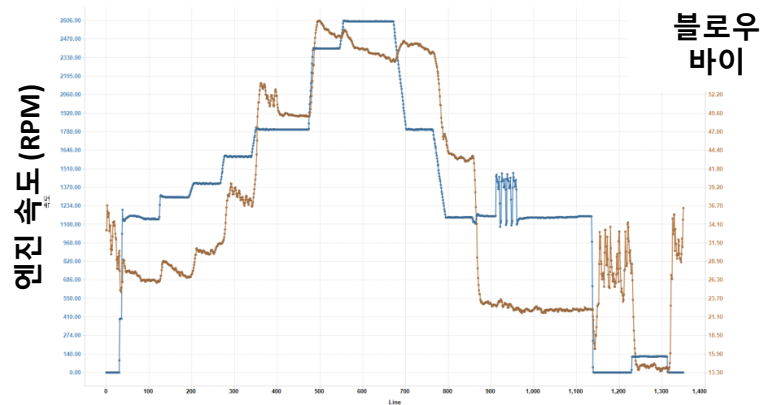
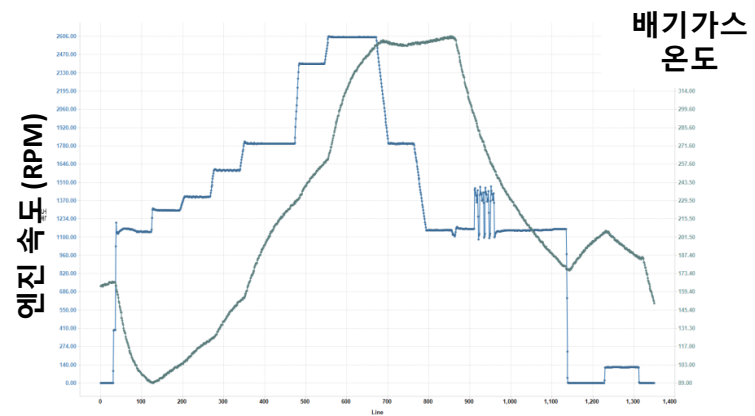
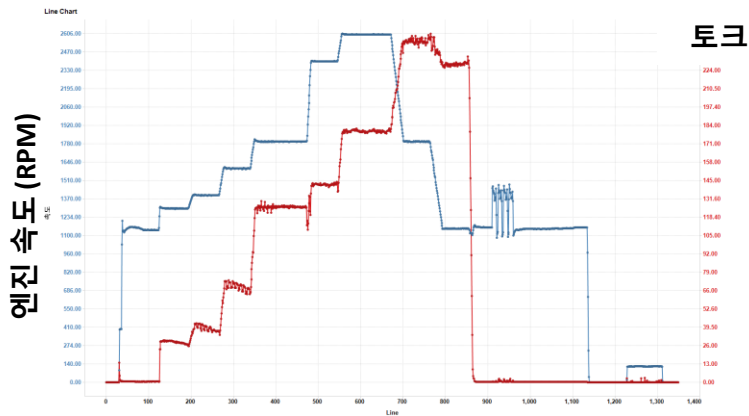
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Data

• Characteristics

- 엔진 속도를 step으로 변화시키면서, 여러 항목이 어떻게 변화하는지 측정
- Multivariate Time series data



Questions

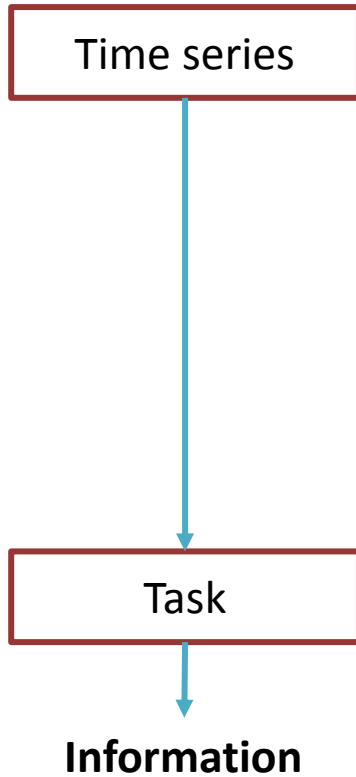
- **1. How to deal with multivariate time series data?**
 - Before the anomaly detection problem, how to solve classification problem?
 - classify multivariate time series
 - Spiegel, Stephan et al.(2011): classify multivariate time series
- **2. How to apply shapelet method to multivariate time series data?**
 - Ghalwash et al.(2012): multi-shapelet in bioinformatics
 - But what if the important feature is not obvious?
- **3. What if the important feature is not in each step?**
 - Only extracted features for each step
 - In the gap between two steps
 - Spiegel, Stephan et al.(2011): Segmentation and clustering using SVD
- **4. It has various different length. How to deal with this problem?**
 - ...

Section 1

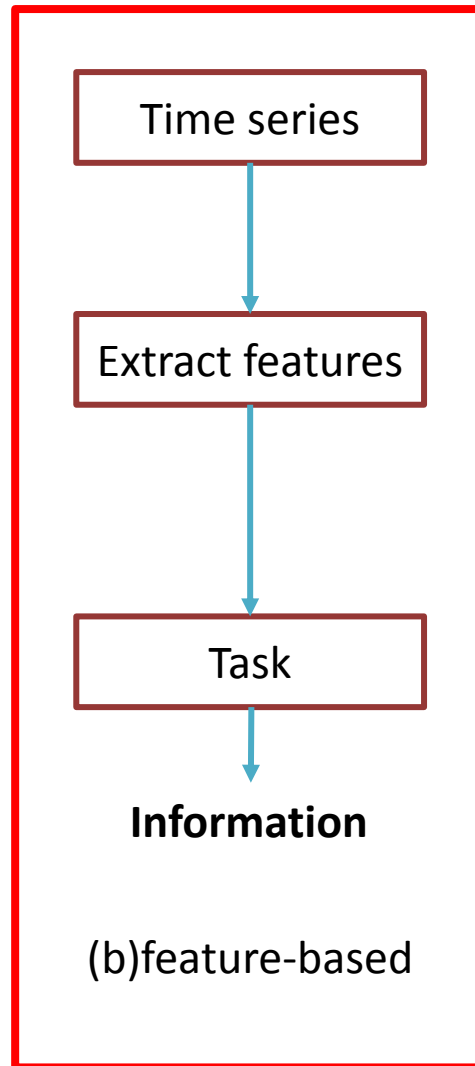
EARLY CLASSIFICATION OF MULTIVARIATE TIME SERIES BY SHAPELET

Ghalwash, Mohamed F., and Zoran Obradovic. "Early classification of multivariate temporal observations by extraction of interpretable shapelets." *BMC bioinformatics* 13.1 (2012): 195.

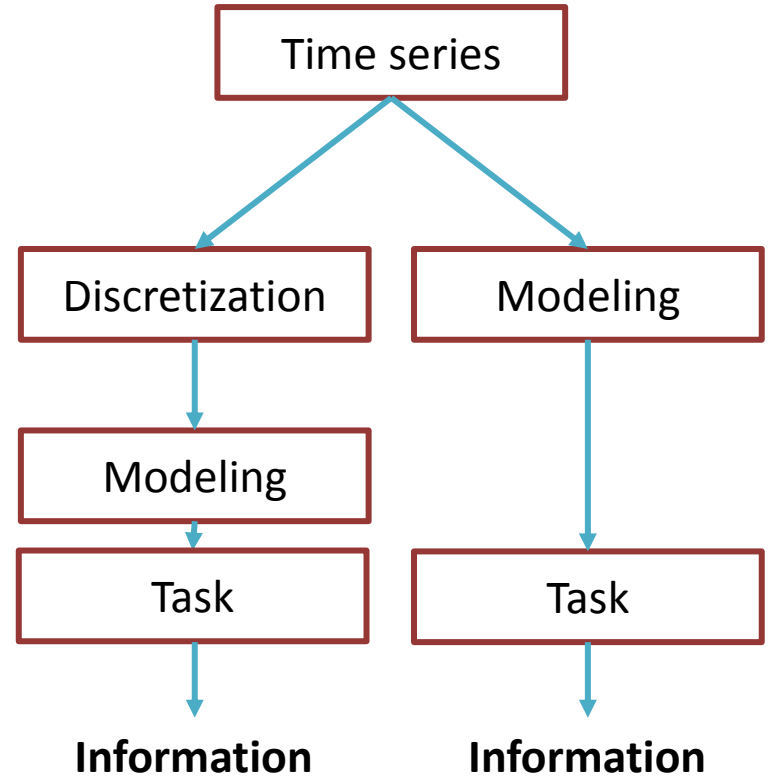
Time series data mining



(a) raw-data-based



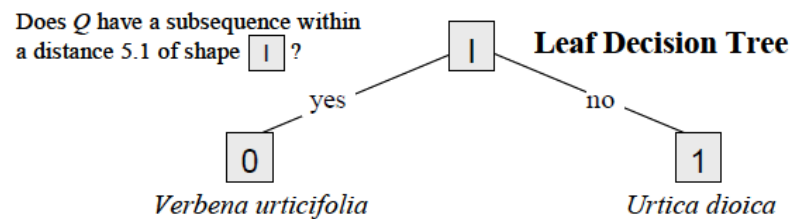
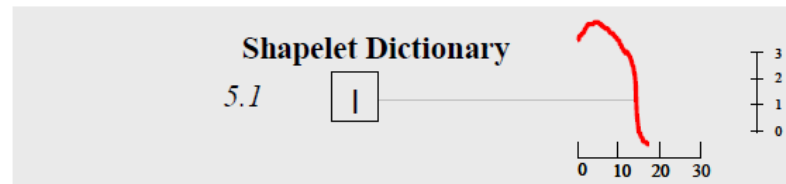
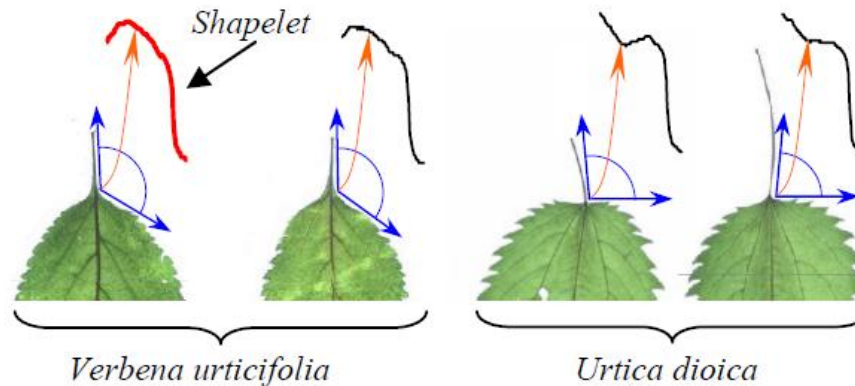
(b) feature-based



(c) model-based

Shapelet

- **Shapelet**
 - Subsequences which are maximally representative of a class
 - **Motif of sequences**



Research

- Shapelet concept had been studied only in univariate study
- In this study,
 - Extend the concept of shapelet to multivariate case
 - Information-gain based distance threshold
 - Weighted information-gain based utility score of a shapelet

Univariate Shapelet

- **Formal definition**

- T: Sequence data
- S_p^l : subsequence that has starting point p, length l
- S_T^l : subsequences set. $S_T^l = \{S_p^l \text{ of } T, \text{ for } 1 \leq p \leq m - l + 1\}$
- Subsequence distance ($Subdist(T, S)$)
 - $Subdist(T, S) = \min(Dist(S, S')), \text{ where } S' \in S_T^{|S|}$
 - Minimum distance between S and subsequences of T which has length |S|
- Entropy $I(D)$
 - $I(D) = -p(A) \log(p(A)) - p(B) \log(p(B))$
- Information Gain
 - Entropy difference when D is split into D_1, D_2 by split strategy sp
 - $Gain(sp) = I(D) - (f(D_1)I(D_1) + f(D_2)I(D_2))$

Univariate Shapelet

- **Formal definition**

- Shapelet is a kind of motif
 - Subsequence distance plays a important role in similarity measure
 - **How to set a starting point and length?**
- How to classify Time series data
 - Data set \mathbf{D} 는 class가 \mathbf{A} 와 \mathbf{B} 인 data point들로 구성됨
 - Classification Rule : $class = \begin{cases} \mathbf{D}_1, & \text{subsequenceDist}(T_{1,i}, S) < d_{th} \\ \mathbf{D}_2, & \text{subsequenceDist}(T_{1,i}, S) \geq d_{th} \end{cases}$
 - 분류된 class와 실제 class가 비슷한 distance threshold d_{th} 를 찾아야
- **Optimal split point** ($OSP(\mathbf{D}, S)$)
 - Time series data set \mathbf{D} 가 class \mathbf{A}, \mathbf{B} 들로 이루어져 있다고 하자
 - A Shapelet candidate S 에 대해서, 가장 분류를 잘하는 distance threshold
 - $Gain(S, d_{OSP(\mathbf{D}, S)}) \geq Gain(S, d'_{th})$, for any other distance threshold d'_{th}
- **Shapelet** ($Shapelet(\mathbf{D})$)
 - 모든 candidate subsequence들과, 해당 OSP들 중, 가장 분류를 잘하는 subsequence
 - $Gain(Shapelet(\mathbf{D}), d_{OSP(\mathbf{D}, Shapelet(\mathbf{D}))}) \geq Gain(S, d'_{th})$

Multivariate Shapelet

- **Formal definition**

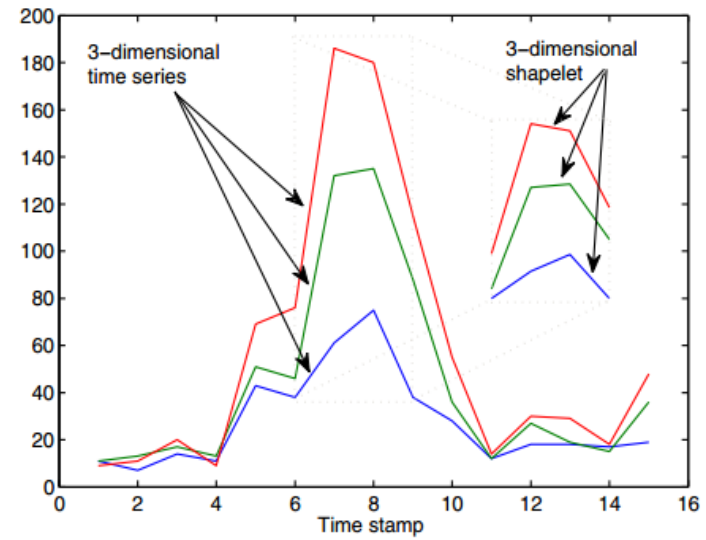
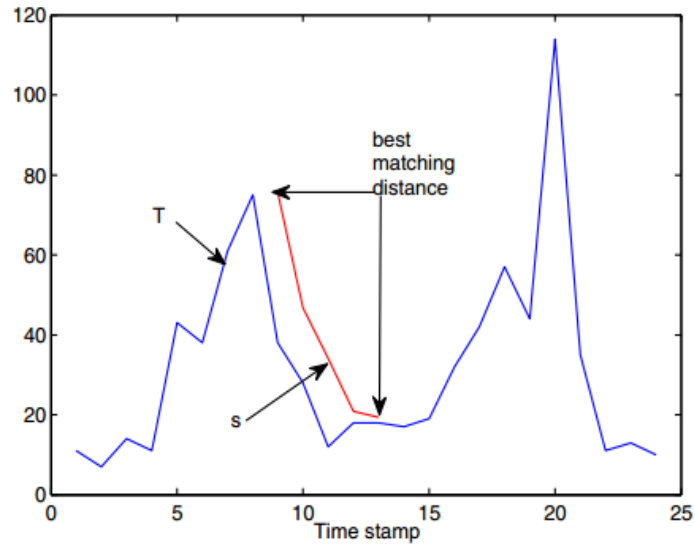
- $T = [T^1, T^2, \dots, T^N]$: N-dimensional sequence data
- s^j : Subsequence of j^{th} dimension factor
- Subsequence distance ($Subdist(S, T)$)
 - $Subdist(s, T) = [\mathbf{dist}(s^1, T^1), \mathbf{dist}(s^2, T^2), \dots, \mathbf{dist}(s^N, T^N)]$
 - Minimum distance between S and subsequences of T which has length $|s^i|$

Multivariate Shapelet

- **Formal definition**

- Shapelet is a kind of motif
 - Subsequence distance plays a important role in similarity measure
- How to classify Time series data
 - Data set \mathbf{D} 는 class가 \mathbf{A} 와 \mathbf{B} 인 data point들로 구성됨
 - Classification Rule : $class = \begin{cases} \mathbf{D}_1, & \text{subsequenceDist}(T_{1,i}, S) <_{perc} \mathbf{d}_{th} \\ \mathbf{D}_2, & \text{subsequenceDist}(T_{1,i}, S) \geq_{perc} \mathbf{d}_{th} \end{cases}$
 - $d_1 <_{perc} d_2: d_1^{qj} < d_2^{qj}, \forall j = 1 \dots perc \times N, perc \in [0,1]$
 - 분류된 class와 실제 class가 비슷한 distance threshold \mathbf{d}_{th} 를 찾아야
- **Optimal split point** ($OSP(\mathbf{D}, S)$)
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- **Shapelet** ($Shapelet(\mathbf{D})$)
 - 모든 candidate subsequence들과, 해당 OSP들 중, 가장 분류를 잘하는 subsequence
 - $Gain(Shapelet(\mathbf{D}), \mathbf{d}_{OSP(\mathbf{D}, Shapelet(\mathbf{D}))}) \geq Gain(S, \mathbf{d}'_{th})$
 - 여기서, 각 변수의 starting point는 같은 지점으로 함

Example



(Left): Univariate case, (Right): Multivariate case

Shapelet - BruteForce Algorithm

GenerateCandidates (dataset \mathbf{D} , $MAXLEN$, $MINLEN$)	
1	$pool \leftarrow \emptyset$
2	$l \leftarrow MAXLEN$
3	While $l \geq MINLEN$
4	For T in \mathbf{D}
5	$pool \leftarrow pool \cup S_T^l$
6	EndFor
7	$l \leftarrow l - 1$
8	EndWhile
9	Return $pool$

CheckCandidate (dataset \mathbf{D} , shapelet candidate S)	
1	$objects_histogram \leftarrow \emptyset$
2	For each T in \mathbf{D}
3	$dist \leftarrow \text{SubsequenceDist}(T, S)$
4	insert T into $objects_histogram$ by the key $dist$
5	EndFor
6	Return $\text{CalculateInformationGain}(objects_histogram)$

- **Generate Candidate**

- 모든 shapelet 후보 생성

- **Check Candidate**

- 후보 shapelet과의 dist계산
- 이 dist들로 histogram 생성

Shapelet - BruteForce Algorithm

CalculateInformationGain (distance histogram <i>obj_hist</i>)	
1	<i>split_dist</i> \leftarrow OptimalSplitPoint(<i>obj_hist</i>)
2	$\mathbf{D}_1 \leftarrow \emptyset, \mathbf{D}_2 \leftarrow \emptyset$
3	For <i>d</i> in <i>obj_hist</i>
4	If <i>d.dist</i> $<$ <i>split_dist</i>
5	$\mathbf{D}_1 \leftarrow \mathbf{D}_1 \cup d.objects$
6	Else
7	$\mathbf{D}_2 \leftarrow \mathbf{D}_2 \cup d.objects$
8	EndIf
9	EndFor
10	Return $I(\mathbf{D}) - \hat{I}(\mathbf{D})$

FindingShapeletBF (dataset \mathbf{D} , <i>MAXLEN</i> , <i>MINLEN</i>)	
1	<i>candidates</i> \leftarrow GenerateCandidates(\mathbf{D} , <i>MAXLEN</i> , <i>MINLEN</i>)
2	<i>bsf_gain</i> \leftarrow 0
3	For each <i>S</i> in <i>candidates</i>
4	<i>gain</i> \leftarrow CheckCandidate(\mathbf{D} , <i>S</i>)
5	If <i>gain</i> $>$ <i>bsf_gain</i>
6	<i>bsf_gain</i> \leftarrow <i>gain</i>
7	<i>bsf_shapelet</i> \leftarrow <i>S</i>
8	EndIf
9	EndFor
10	Return <i>bsf_shapelet</i>

- **CalculateInformationGain**
 - Split distribution set 생성
 - 각 split마다 분류
 - 각각 Information Gain 산출

- **FindingShapeletBF**
 - 후보 shapelet 생성
 - 매 후보마다 IG 계산
 - IG, Shapelet 업데이트

Classification

- Score the shapelet candidates w.r.t. weighted information gain
 - Consider both early classification and accuracy
- If highest score can cover the current test time series
 - Classified as the class of the shapelet
 - Else, next highest score and repeats the process again
- (Maybe, it's not a good classification method)

Experiments

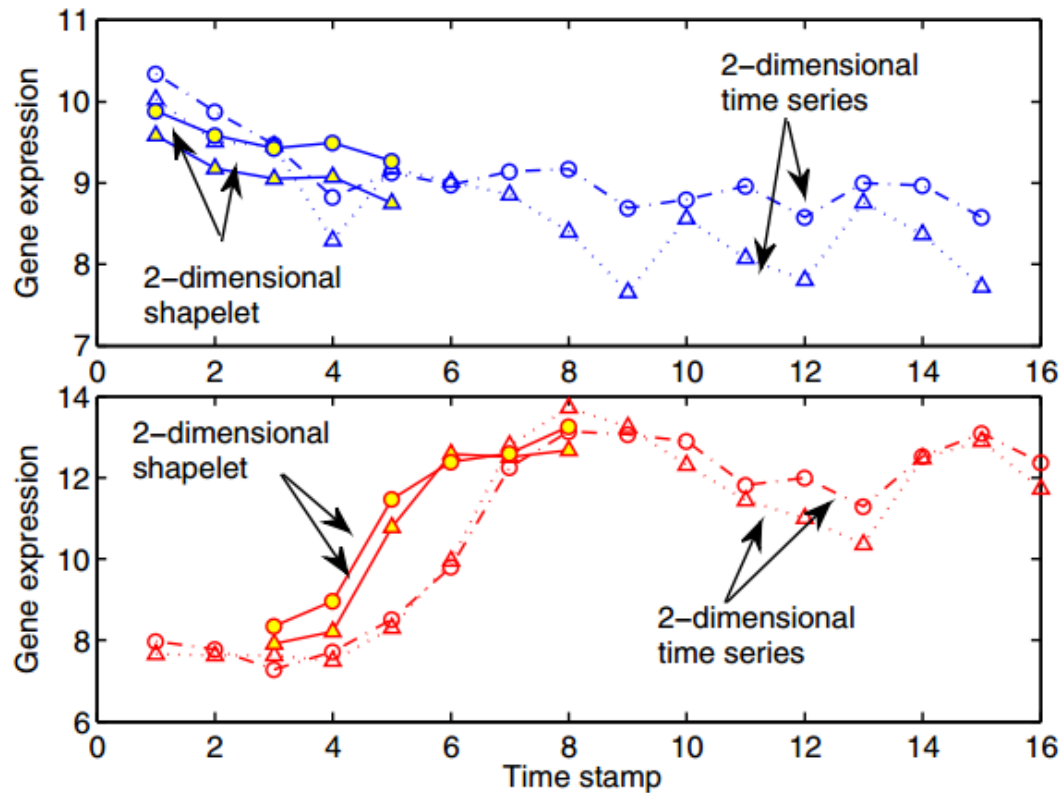
- 3 data sets
 - **Blood gene expression dataset** from human viral studies with influenza A (H3N2)
 - 17 subjects: 9 symptomatic, 8 asymptomatic
 - Blood samples taken from 16 time points
 - Used 23 unique genes from Zaas et al.(2009)
 - **HRV dataset** to distinguish acute respiratory infections
 - 20 subjects: 10 symptomatic, 10 asymptomatic
 - Blood samples taken from 14 time points
 - Used 26 unique genes from Zaas et al.(2009)
 - **Drug Response datasets** for drug therapy with IFN β from Baranzini et al.(2005)
 - 52 patients: 33 good responders, 19 bad responders to the drug
 - Every 3 months in the first year, and every 6 months in the second year
 - Generated data (Baranzini 3A, 3B, 6, 12)
 - 9 genes that was founded from discriminative HMM study (Lin et al.(2008))
 - 17 relevant genes from mixture of HMM study (Costa et al.(2009))

Experiments

- Settings
 - Length : 3~60% of time series length
 - Bootstrapping for generalization error estimation
 - Sample with replacement from original dataset(75%)
 - Test with the others
 - Report the median of the accuracy
 - Report components
 - Accuracy
 - Coverage (percentage of the time series covered by the method)
 - Earliness (fraction of the time series length used for classification)
 - $F_1 = 2 \frac{Acc(1-Ear)}{(1-Ear)+Acc}, 0 < F_1 < 1$

Experiments

- Results
 - Effectiveness of the MSD method on a case from H3N2 dataset
 - Used first half of the earliest time stamp
 - (Top): 2-D H3N2 asymptomatic test subject
 - (Bottom): 2-D H3N2 symptomatic test subject
 - Both used RSAD2 and IFI44L genes in each time step



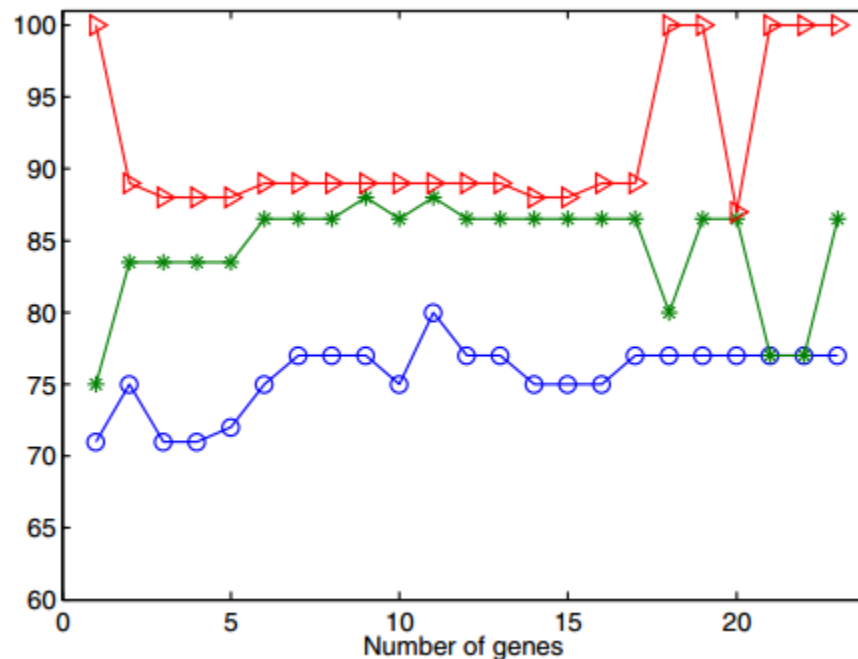
Experiments

- Results
 - Performance of the MSD method on each dataset
 - Relatively good performance with a small fraction of the time series

Dataset	Number of genes	Accuracy	Relative accuracy	Coverage	Earliness	F_1
H3N2	23	77.78	85.71	100	62.50	0.5060
HRV	26	70.00	71.43	100	40.00	0.6462
Baranzini3A	3	70.00	73.91	95.83	46.26	0.6080
Baranzini3B	3	66.67	68.00	100	44.81	0.6039
Baranzini6	6	70.83	70.83	100	42.86	0.6325
Baranzini12	12	66.67	66.67	100	42.86	0.6154
Lin9	9	67.86	69.57	100	44.00	0.6136
Costa17	17	68.00	69.23	100	45.24	0.6067

Experiments

- Results
 - Performance of MSD on H3N2 dataset using top genes
 - Using some of the top genes rather than whole genes to get better performance
 - Top genes are studied by Zaas et al(2009)



(Red): Coverage, (Green): Relative Accuracy, (Blue): Accuracy

Experiments

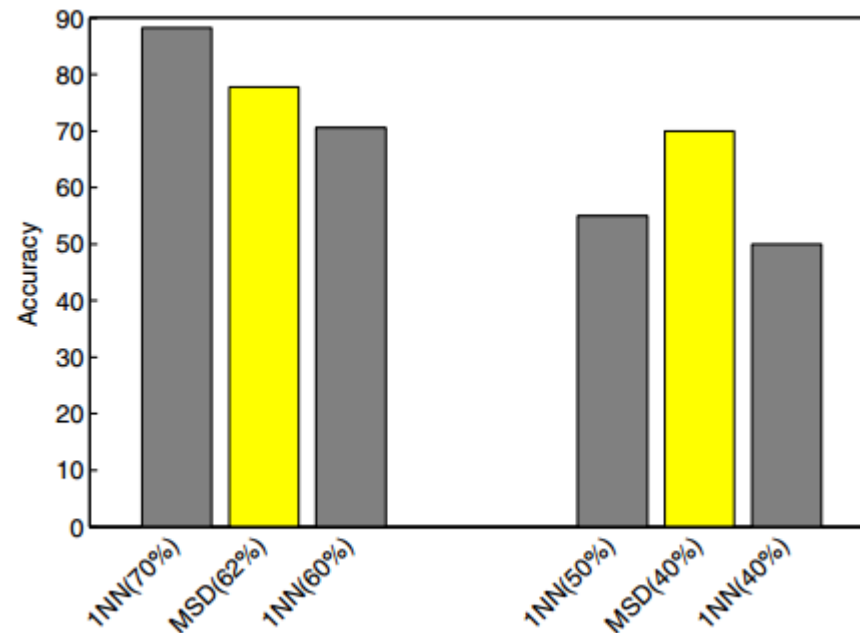
- Results
 - Comparing the MSD method with the univariate method
 - Without H3N2, MSD outperformed the univariate method
 - (Top): MSD method
 - (Bottom): Univariate method

Dataset	genes	Accuracy	Relative accuracy	Coverage	Earliness	F_1
H3N2	Top 11 genes	80.00	87.50	88.89	64.29	0.4938
HRV	RSAD2	71.43	75.00	100	38.89	0.6587
Baranzini3A	Caspase 10	75.00	76.00	100	45.45	0.6316
Baranzini3B	Caspase 2, Caspase 3	75.00	76.19	100	44.05	0.6409
Baranzini6	Caspase 10, IL-4Ra	75.00	76.00	100	43.45	0.6448
Lin9	Caspase 2, Caspase 3, Jak2	81.82	82.61	100	43.43	0.6689

Dataset	gene	Accuracy	Relative accuracy	Coverage	Earliness	F_1
H3N2	LOC26010	77.78	85.71	100	38.34	0.6879
HRV	RSAD2	42.86	80.00	55.56	52.50	0.4506
Baranzini3A	Caspase 10	12.00	100.00	12.25	42.86	0.1983
Baranzini3B	Caspase 3	26.09	80.00	31.38	40.26	0.3632
Baranzini6	Caspase 10	12.00	100.00	12.25	42.86	0.1983
Baranzini12	Caspase 3	26.09	80.00	31.38	40.26	0.3632
Lin9	Caspase 3	26.09	80.00	31.38	40.26	0.3632
Costa17	Caspase 3	26.09	80.00	31.38	40.26	0.3632

Experiments

- Results
 - Comparing to conventional method
 - Comparing 1NN method with DTW which is exceptionally difficult to beat
 - To consider the earliness, used shorter time series
 - For the early classification task, MSD can be better than 1NN-DTW



Conclusion

- Shapelet method in multivariate time series is done
 - With simple concept
- This method is useful in early detection task
- Too much computation cost
 - Bruteforce approach: $O(k^2 \bar{m}^3)$, k : number of subsequence, \bar{m} : *average length*
 - Only can be applied in short time series
 - Need more efficient algorithm

To dos

- Only for independence among attributes
- Too much computational cost for original task
- Difference in time series length
- How can DTW replace the Euclidean distance?
- Focusing on small data set with classification task

References

- Baranzini, Sergio E., et al. "Transcription-based prediction of response to IFN β using supervised computational methods." (2004): e2.
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- Zaas, Aimee K., et al. "Gene expression signatures diagnose influenza and other symptomatic respiratory viral infections in humans." *Cell host & microbe* 6.3 (2009): 207-217.