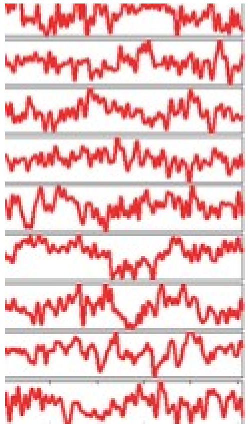
Dimension Selection for Multivariate Time Series Classification for HIVE-COTEv2 (HC2)

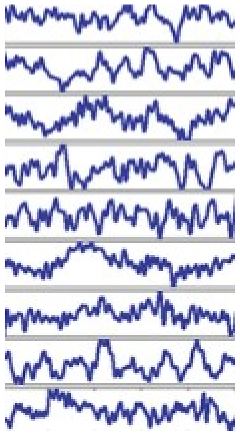
Alejandro Pasos Ruiz and Anthony Bagnall
a.pasos-ruiz@uea.ac.uk and ajb@uea.ac.uk

School of Computing Science
University of East Anglia

Multivariate Time Series Classification



Early Onset Dementia patient



Healthy patient

Time Series Classifier

Make prediction

Often characterised by high number of dimensions (channels)

EEG/MEG often have more than 100 dimensions

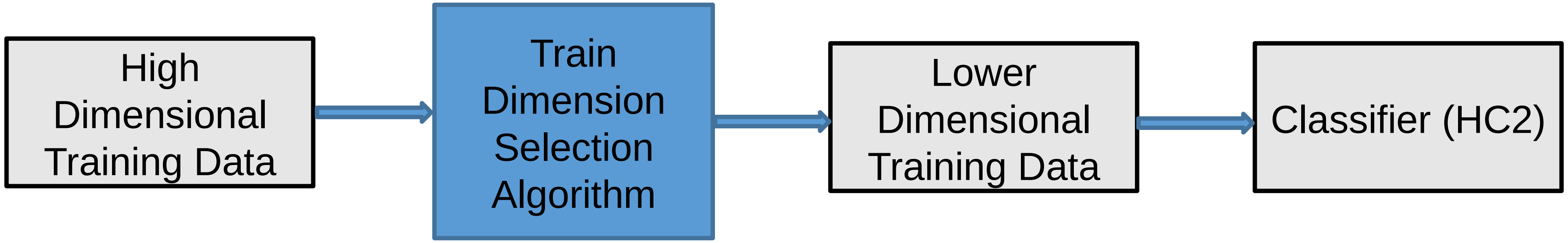
High dimensionality can cause classifiers problems

Research Question

- HIVE-COTEv2 (HC2) [1] is the most accurate algorithm on the UEA multivariate time series (MTS) classification.
- HC2 is quite slow with high dimensional MTS problems.
- ROCKET [2] is a very good MTS classifier, and is very fast [3]
- **Can we speed up HC2 using ROCKET to select dimensions without loss of accuracy?**

[1] HIVE-COTE 2.0: a new meta ensemble for time series classification, MACH. 2021
[2] ROCKET: exceptionally fast and accurate time series classification using random convolutional kernels DAMI 2020
[3] The great multivariate time series classification bake off. DAMI 2021

Why Use a Feature/Dimension Selection Pipeline?



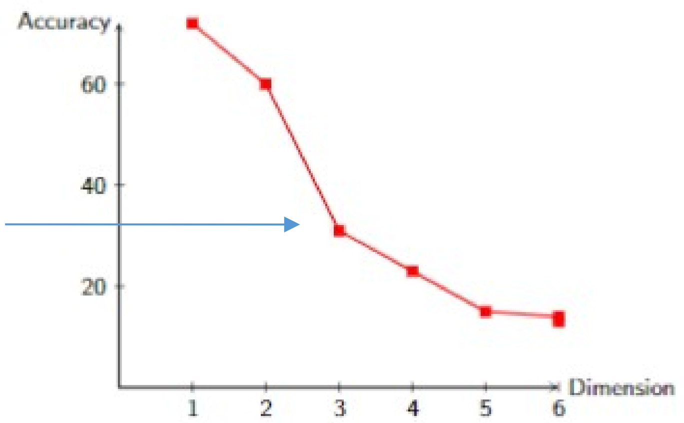
- Feature selection or creation may improve average accuracy
- **It may speed up training without a significant reduction in accuracy**

We focus on feature selection pipelines rather than wrappers or feature creation because our priority is increasing speed and reducing memory for HC2

Related Work

- Merit score function (MSTS) [1,2]. Score dimensions based on 1-NN DTW predictions, select a subset of dimensions
- Kmeans, Elbow Class Sum (ECS), Elbow Class Pairwise (ECP) [3]: dimensions are selected based on distances between series within classes

Elbow Point, select first three dimensions



[1] A feature selection method for multi dimension time series data. 5th AALTD (2020)
[2] Feature subset selection for detecting fatigue in runners using time series sensor data. ICPRAI (2022)
[3] Fast channel selection for scalable multivariate time series classification. 6th AALTD (2021)

Dimension selection using ROCKET filters

Score each dimension independently using the super fast Mini-ROCKET classifier with three fold cross validation, then filter using the elbow method used in ECP/ECS

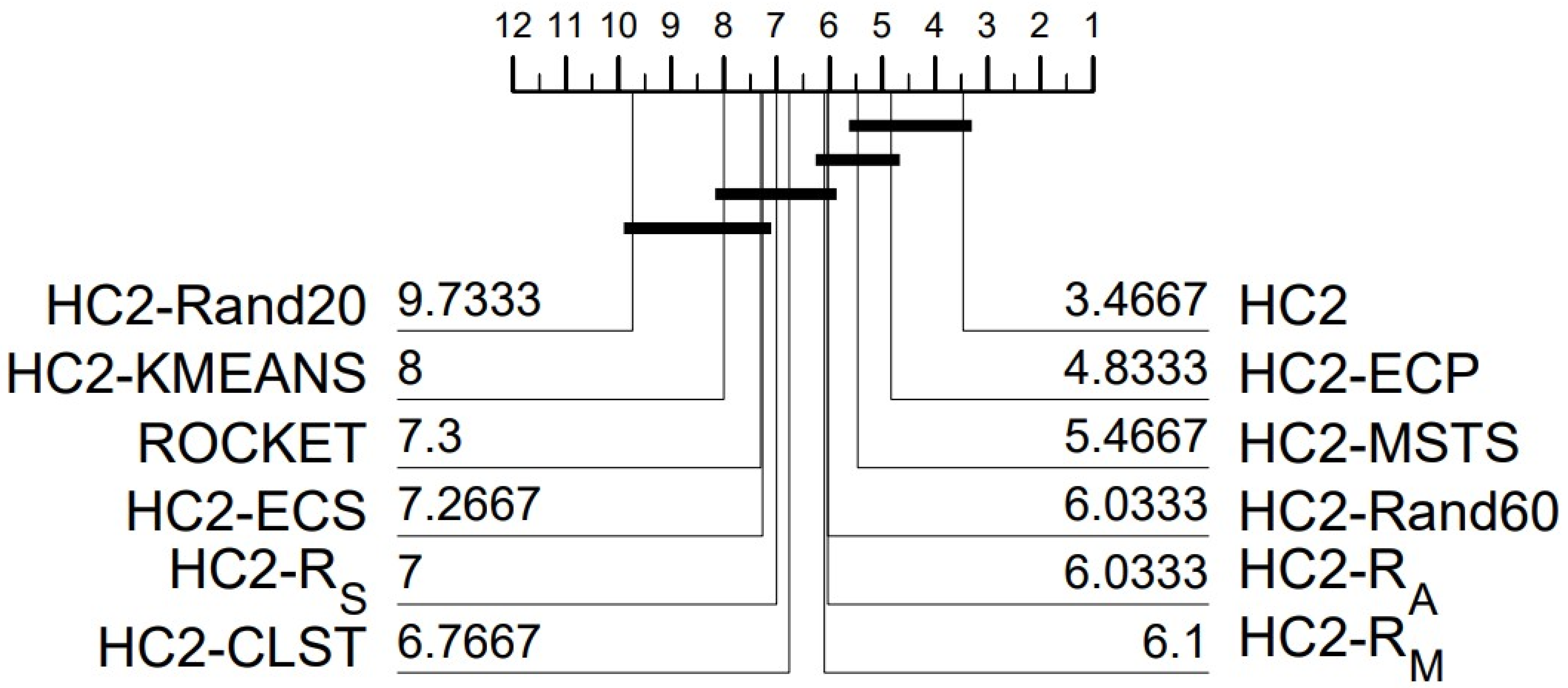
RandomX: Choose X% of features randomly
ROCKET: three scoring methods from single dimension rocket predictions
ECS. Sum of difference between centroid pair distance
ECP. Union of sum of individual centroid pair distances
MSTC. Use ROCKET for predictions instead of 1-NN DTW

15 “high” dimensional data

Name	Train size	Test size	Dimensions	Dim. length	Classes
ArticularyWordRecognition	275	300	9	144	25
DuckDuckGeese	50	50	1345	270	5
EMO	1093	50	30	180	3
FingerMovements	316	100	28	50	2
HAR	217	144	12	200	6
HandMovementDirection	160	74	10	400	4
Heartbeat	204	205	61	405	2
JapaneseVowels	270	370	12	25	9
MindReading	727	653	204	200	5
MotorImagery	278	100	64	3000	2
NATOPS	180	180	24	51	6
PEMS-SF	267	173	963	144	7
PhonemeSpectra	3315	3353	11	217	39
Siemens	700	395	39	180	10
SpokenArabicDigits	6599	2199	13	65	10

We have added four problems to the MTSC Archive

Results


12 11 10 9 8 7 6 5 4 3 2 1
HC2-Rand20 9.7333
HC2-KMEANS 8
ROCKET 7.3
HC2-ECS 7.2667
HC2-R_S 7
HC2-CLST 6.7667
3.4667 HC2
4.8333 HC2-ECP
5.4667 HC2-MSTS
6.0333 HC2-Rand60
6.0333 HC2-R_A
6.1 HC2-R_M

Dimensions selected

Name	d	HC2-ECP	HC2-MSTS	HC2-R_A
ArticularyWordRecognition	9	100	**55.17**	57.09
DuckDuckGeese	1345	29.93	**2.48**	21.08
EMOPain	30	55.29	**31.72**	35.52
FingerMovements	28	38.18	**17.49**	50.49
MotionSenseHAR	12	86.78	**30.75**	65.8
HandMovementDirection	10	83.1	**44.14**	56.21
Heartbeat	61	15.38	**13.85**	45.56
JapaneseVowelsEq	12	75.57	97.41	**62.07**
MotorImagery	64	25.11	**6.25**	54.8
MindReading	204	61.56	**12.81**	16.23
NATOPS	24	79.31	**45.98**	63.07
PEMS-SF	963	35.03	**1.38**	13.8
PhonemeSpectra	11	**18.18**	100	59.25
Siemens	39	30.77	**10.88**	55.61
SpokenArabicDigitsEq	13	53.85	**53.85**	54.91
Average		52.54	**34.94**	47.43

Conclusion

- The three ROCKET variants are significantly worse than HC2, and no better than randomly selecting 60% of dimensions
- Only ECP and MSTS reduce dimensionality without reducing the accuracy of HC2 significantly (but are not much better than selecting 60% randomly)
- On average, HC2-MSTS selects fewer dimensions
- There is little difference in time between the three algorithms

Next: Add more high dimensional problems to the repository, look at the effect of filtering on each HC2 component, look at feature creation (e.g. PCA based), compare to contracting.