1. Biographical sketch : James C. Bezdek

PhD, Applied Mathematics, Cornell, 1973; past president - NAFIPS, IFSA and IEEE CIS; founding editor - Int'l. Jo. Approximate Reasoning, IEEE Transactions on Fuzzy Systems; Life fellow - IEEE and IFSA; awards : IEEE 3rd Millennium, IEEE CIS Fuzzy Systems Pioneer, IEEE Frank Rosenblatt TFA, IPMU Kempe de Feret Award. Retired in 2007. Honorary senior fellow, U. of Melbourne, 2005-present.

IEEE plenary/keynote/ invited talks in past 4 years:

CIS Distinguished Lecturer Program (Canada)	(Plenary)	Toronto	12/15
CIS Distinguished Lecturer Program (Canada)	(Plenary)	Ottawa	12/15
CIS Distinguished Lecturer Program (Australia)	(Plenary)	Canberra	03/16
CIS WCCI FUZZ-IEEE	(Plenary)	Vancouver	07/16
CIS Distinguished Lecturer Program (Bulgaria)	(Plenary)	Sofia	09/16
SMC summer school, Intelligent systems (Bulgaria)	(Plenary)	Sofia	09/16
CIS Distinguished Lecturer Program (Germany)	(Plenary)	Magdeburg	09/16
CIS Distinguished Lecturer Program (USA)	(Plenary)	Dallas	12/16
CIS Distinguished Lecturer Program (Argentina)	(Plenary)	Buenos Aires	09/17
SMC Distinguished Lecturer Program (USA)	(Plenary)	New York City	02/18
CIS Distinguished Lecturer Program (Ecuador)	(Plenary)	Guayaquil	11/19

Google Scholar Profile (Nov. 27, 2019)

James C. Bezdek		All	Since 2014
Honorary Senior Fellow, Univ. of Melbourne, Australia	**citations**	63,595	19,993
Verified email unimelb.edu.au	**H index**	89	50
	i10 index	243	151

2 Abstracts of two lectures

2.1 Every picture tells a story: Visual Cluster Assessment in Square and Rectangular Relational Data

The VAT/iVAT, algorithms are the parents of a large family of visual assessment models. Outline for a 2-hour talk (can be shortened as required):

1. The three canonical problems of cluster analysis in Static data sets: tendency assessment, clustering, and cluster validity.
2. History of Visual Clustering. Cluster Heat Maps from the past. The basic VAT and iVAT algorithms.

3.siVAT: scalable iVAT; Approximate cluster heat maps for big data. This is the basis of clusiVAT and clusiVAT+ for clustering in big data.

4. coiVAT: co-clustering tendency in the four clustering problems associated with rectangular relational data.

5. inciVAT: visual representation of possible structure and changes in online streaming data.

Applications: IBRL lab environmental sensor data. GSB weather data, Heron Island weather data, anomaly detection in wireless sensor networks, image segmentation, neural spike detection, smart city sensor data, fibroblast treatments in gene expression data.

2.2 How big is too big? Clustering in (static) BIG DATA with the Fantastic 4

For this talk "big" refers to the number of samples (N) and/or number of dimensions (P) in static sets of feature vector data; or the size of (NxN) (similarity or distance) matrices for relational clustering. Outline for a 2-hour talk (can be shortened as required)

Objectives of clustering in static sets of big numerical data are *acceleration* for loadable data and *approximation* for non-loadable data. The Fantastic Four are four basic (aka "naïve") classical clustering methods:

Gaussian Mixture Decomposition (GMD, 1898)
Hard c-means (often called "k-means," HCM, 1956)
Fuzzy c-means (reduces to hard k-means in the limit, FCM, 1973)
SAHN Clustering (principally single linkage (SL, 1909))

This talk describes approximation of literal clusters in non-loadable static data. The method is sampling followed by very fast (usually 1-2% of the overall processing time) non-iterative extension to the remainder of the data with the nearest prototype rule. Three methods of sampling are covered: random, progressive, and MaxiMin. The first three models apply to feature vector data and find partitions by approximately optimizing objective function models with alternating optimization (known as expectation-maximization (EM) for GMD). Numerical examples using various synthetic and real data sets (big but loadable) compare this approach to incremental methods (spH/FCM and olH/FCM) that process data chunks sequentially.

The SAHN models are deterministic, and operate in a very different way. Clustering in big relational data by sampling and non-iterative extension begins with visual assessment of clustering tendency (VAT/iVAT). Extension of iVAT to scalable iVAT (siVAT) for arbitrarily large square data is done with Maximin sampling, and affords a means for visually estimating the number of clusters in the literal MST of the sample. siVAT then marries quite naturally to single linkage (SL), resulting in two offspring: (exact) scalable SL in a special case; and clusiVAT for the more general case. Time and accuracy comparisons of clusiVAT are made to crisp versions of three HCM models; HCM (k-means), spHCM and olHCM; and to CURE. Experiments synthetic data sets of Gaussian clusters, and various real world (big, but loadable) are presented.

3. Statement about availability for delivering lectures.

I am available and willing to give SMC DL lectures at any time. I do have commitments that might exclude certain times, but I have enough flexibility that the proposed date of any DL lecture can be negotiated, no problem.