Southern University of Science and Technology

Statistical Learning of the Giant Panda (Ailuropoda Melanoleuca) Ethology

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Contents

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Background of the Giant Panda Research

Scientific facts

Diet, predators, conservation, ecology, human interactions, genes, biofuel and etc..

Living history

Evolution, population, diplomacy and etc..

Behavior research

Gender (Ding-zhen et al.), age (Hong et al.), vocalization (Charlton et al.), oestrus (Kleiman et al.) and etc..

Behavioral Research Methodology

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- Exploratory statistics: correlation, scatter plots, and graphical visualization.
- Statistical inference and analysis:
  - parametric tests: t-test, z-test, ANOVA.
  - non-parametric tests: Mann-Whitney, chi-square test etc..
- Models for representing phenomenon: regression model, non-linear models, clustering, network models
- Newly promoted methods: random resampling, robust problems, missing data, meta-analysis, and other optimizations

Dataset Description

- From March 14^{th}, 2000 to July 28^{th}, 2000. 35 observation days, mostly 3 days between each interval. On observed days, use scanning method.

Internal Relationships

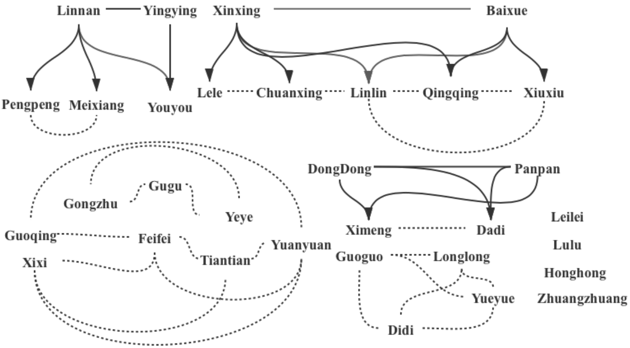


Figure: **Relationships among observed individuals.** Dashed lines for siblings, and solid lines for kinship.

Graphical displays

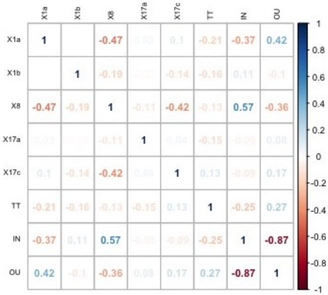


Figure: **Correlation plot.**
8 highest variables selected, only $\rho_{inout} = -0.87 < -0.8$.

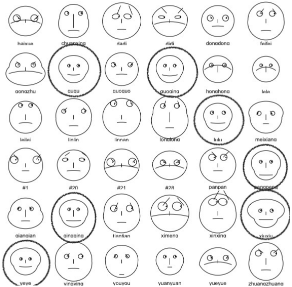


Figure: **Chernoff faces**

Autoregressive Integrated Moving Average (ARIMA)

- Use panda No.20's eating bamboos frequency (x_{1a}) with general class of model $ARIMA(p, d, q)$ including "autoregressive", "moving average" and "difference" terms are used for simulation.
- x_{1a} has autocorrelation function (ACF) almost truncated at $lag = 3$, partial autocorrelation function (PACF) decreased geometrically.
- $AIC = 151.72$,$AIC_C = 153.60$, $BIC = 159.91$ provides an $AR(3)$ model: $X_t = 0.18X_{t-1} + 0.15X_{t-2} + 0.44X_{t-3} + 2.88$
- Ljung-Box of forecasting residuals has Q-statistic equals 17.104 (p-value$= 0.646 > 0.05$). Residuals are white noise.

Autoregressive Integrated Moving Average (ARIMA)

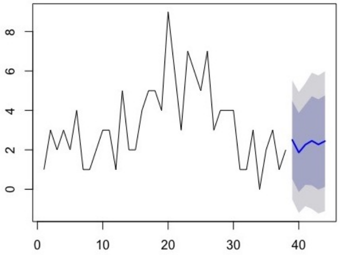


Figure: $AR(3)$ forecast of bamboo eating for panda No.20.

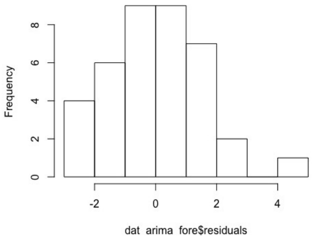


Figure: Residual distribution

Neural Network Auto-Regressive Model (NNAR)

- *ARIMA* forecast of rest performs poorly with $ARIMA(0,1,1)$ as exponential smoothing model.
- Procedures: lagged inputs are used in feed forward network, generating $z_j = b_j + \sum_{i=1}^{j} \omega_{i,j} x_i$ to the next hidden layer. Hidden layer uses $s(z) = \frac{1}{1+e^{-z}}$ as input to output layer, and reduce outliers. Output layer calculates back propagation errors to update $\omega_{i,j}$.
- The NNAR model retrieves results based on optimal number of lags according to AIC.
- Notation: NNAR(p, k) is a neural network with $\{y_{t-1}, y_{t-2}, \ldots, y_{t-p}\}$ as lagged inputs are k nodes in the hidden layer.

Prediction Intervals

- Predictions made through bootstrapped residuals.
- Fitted neural network: $y_t = f(y_{t-1}) + \epsilon_t$. Where f is a neural network 1 node in 1 hidden layer, the series $\{\epsilon_t\}$ are equal variance.
- Iteratively, by resampling ϵ_t from Gaussian distribution, $y^*_{T+1} = f(y_T) + \epsilon^*_{T+1}$,y^*_{T+2} =$f(y_{T+1}) + \epsilon^*_{T+2}, \cdots$. All possible future values are generated.

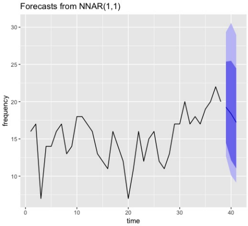


Figure: $NNAR(1,1)$ forecast of rest behavior

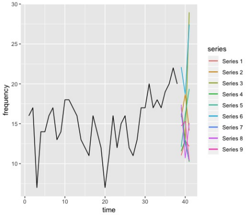


Figure: 9 future series

Bagging Time Series Model

- Bootstrapped time series: introduced uncertainty additionally from changing data generating model.
- For each bootstrapped series, an exponential smoothing $x_{i+1} = \alpha \sum_{j=0}^{i} (1-\alpha)^j x_{ij}$ is applied.
- $RMSE_{Bagging} = 6.14$, $RMSE_{NNAR} = 3.12$. $NNAR$ has better forcast. While prediction intervals of bagging forecast are always wider than others.

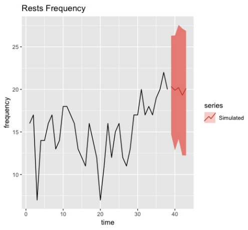


Figure: Bagging forecast

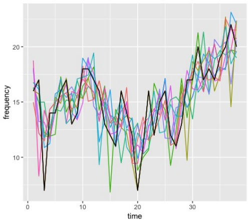


Figure: 10 bootstrapped series

Prediction Intervals

Table: Prediction band of **NNAR** forecast

Label	Forecast	Low 95	High 95
39	19.259	14.475	25.575
40	18.378	12.211	25.998
41	17.223	11.472	25.236

Table: Prediction band of **bagged** forecast

Label	Forecast	Low 95	High 95
39	20.087	14.036	26.443
40	19.882	13.813	25.450
41	20.086	12.607	26.772

- Bagged forecast has a wider prediction interval.

Sub-adults and Adults Individuals

Table: Effects of sex in captive sub-adults

Behavior	Male	Female	p-value
Eating bamboo (x_{1a})	4.25	3.55	0.2631
Rest (x_8)	9.75	12.90	0.0646
Investigating (x_{17a})	1.75	0.80	0.455

Table: Effects of sex in semi-ranging adults

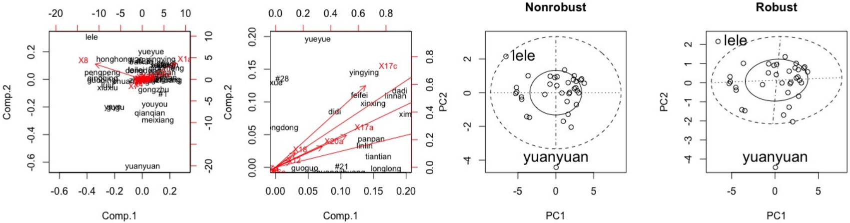
Behavior	Male	Female	p-value
Eating bamboo (x_{1a})	5.25	2.31	0.0211
Rest (x_8)	11.5	4.00	0.0002
Investigating (x_{17a})	0.75	0.365	0.5352

- Semi-ranging adults have significance difference in eating bamboos ($p\text{-}value = 0.0211$), and rest behavior ($p\text{-}value = 0.0002$).

Principal Components Analysis

Preparations for clustering

- The first 4 principal components account for 98.5% of variances (coefficients less than 0.4 omitted):
  - PC1: $0.551X_{1a} - 0.759X_8$ (eating bamboos versus rest)
  - PC2: $0.677X_{1a} + 0.635X_8$ (eating bamboos and rest)
  - PC3: $-0.771X_2 + 0.536X_{17c}$ (sitting versus walking)
  - PC4: $0.438X_{1a} - 0.407X_{1b} - 0.477X_2 - 0.511X_{17c}$ (eating bamboos versus eating others, walking and sitting)



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Factor Analysis

Preparations for clustering

- Aim: find latent factors to simplify interpretation through oblique rotation from principal scores:

$$F_1^* = d_{11}F_1 + d_{12}F_2 + \ldots + d_{1m}F_m$$

$$F_2^* = d_{21}F_1 + d_{22}F_2 + \ldots + d_{2m}F_m$$

$$\ldots$$

$$F_m^* = d_{m1}F_1 + d_{m2}F_2 + \ldots + d_{mm}F_m$$

- Rough rule of thumb (Kaiser criterion) suggests 4 factors, accounting for 62% of total variance, with $\chi^2 = 41.17$, $p\text{-}value = 0.463 > 0.05$.

Output of Factor Scores

Preparations for clustering

Table: Loadings of 4 factors (< 0.5 omitted)

	Factor1	Factor2	Factor3	Factor4
x_{1a}	0.519	0.635	0.523	
x_{1b}	0.824			
x_2		0.795		
x_4	-0.684			
x_{6g1}		-0.560		
x_{6g2}			-0.734	
x_{6a}				-0.503
x_7	-0.801			
x_8				
x_{12}		0.605		
x_{17a}	0.662			
x_{17c}	0.945			
x_{18}		0.503		
x_{20a}		0.577		

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Naming of Factors

Preparations for clustering

- Factor 1: **tense**. Eating bamboos, eating others, sitting straight and investigating versus climbing and playing. It shows restraint in movement and posture, carrying body stiffly.
- Factor 2: **oestrus**. Eating bamboos, pacing around, sniffing, drinking water and bleating versus licking. It is the intensity of demonstrated oestrus behavior.
- Factor 3: **oblivious**. Eating bamboos versus licking, unresponsive to events, and situations.
- Factor 4: **calm**. Minus scratching, not easily disturbed by changes in environment.

Agglomerative Clustering

- Intercluster dissimilarity measures:
  - single linkage: $d_{AB} = min\{d_{ij} | i \in A, j \in B\}$
  - complete linkage: $d_{AB} = max\{d_{ij} | i \in A, j \in B\}$
  - average linkage: $d_{AB} = n_A^{-1} n_B^{-1} \sum_{i \in A} \sum_{j \in B}$

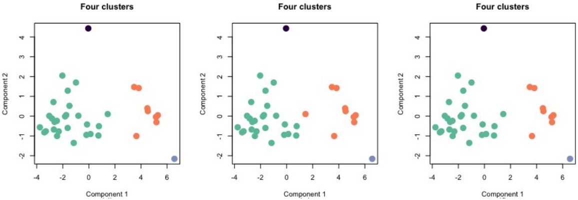

Figure: **Agglomerative clustering with 3 linkages** (from left to right: single, complete and average). Single linkage elongates, complete linkage creates ball-shaped, average linkage balance them two.

Partitional Clustering

- Methodology:
  - K-means
  - K-means++
  - Bisecting K-means
- Clustering evaluation criteria:
  - Average silhouette score (ASS): $s(i) = \frac{b(i)-a(i)}{max(a(i),b(i))}$, where $a(i) = \frac{1}{|C_i|-1} \sum_{j \in C_i, i \leq j} d(i,j)$, $b(i) = min_{k \leq i} \frac{1}{|C_k|} \sum_{j \in C_k} d(i,j)$.
  - Error sum of squares (SSE): $SSE = \sum_{k=1}^{K} \sum_{i=1}^{n_k} (x_{ik} - \bar{x_k})^2$. Which is the same calculation as within cluster sum of squares (WSS) in this research.
  - Calinski-Harabasz index (CHI): $s(k) = \frac{tr(B_k)}{tr(W_k)} \frac{m-k}{k-1}$, where m points have k clusters, B_k is between cluster covariance matrix, W_k as within-cluster covariance.

K-means Clustering

- Probability of a point belonging to each cluster: $\prod_{j=1}^{k}\prod_{i=1}^{N_j}\frac{1}{\sigma^2}exp(-\frac{||x_i-\mu_j||^2}{2\sigma^2})$
- Loss function: $J(\mu_1,\mu_2,\ldots,\mu_k)=\frac{1}{2}\sum_{j=1}^{k}\sum_{i=1}^{N_j}(x_i-\mu_j)^2$.
- Cluster centroids: $\mu_j=\frac{\sum_{i=1}^{N_j}x_i}{N_j}$.
- Procedures:
  - (1): Select initial partition from agglomerative hierarchical clustering with average linkage.
  - (2): Calculates SSE (loss function) in each step.
  - (3): Repeat step (2) by yielding the largest improvement until no changes occur.

K-means++ Clustering

- K-means++ improves the initialization of clustering centers by careful seeding.
- Procedures:
  - (1): Randomly select a point from the dataset as the initial position c_i.
  - (2): Calculate smallest distance between the point to the closest center $D(x)$. Then, select the next center c_i with probability $\frac{D(x)^2}{\sum_x D(x)^2}$.
  - (3): continue with same process as (2) and (3) in k-means clustering.

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Bisecting K-means Clustering

- Bisecting K-means is a hybrid algorithm between hierarchical clustering and K-means. It improves calculation efficiency by bisecting through k-means.
- Procedures:
  - (1): Compute the centroid w of the dataset, select a point c_L randomly and compute $c_R = w - (c_L - w)$.
  - (2): Divide the data M into two clusters M_L and M_R according to:

$$\begin{cases} x_i \in M_L, when \ ||x_i - c_i|| \leq ||x_i - c_R|| \\ x_i \in M_R, when \ ||x_i - c_i|| > ||x_i - c_R|| \end{cases} \tag{1}$$

  - (3): Calculate centroids of M_L and M_R, noted as w_L and w_R.
  - (4): If $w_L = c_L$ and $w_R = c_R$ then stop, else repeat steps (2) and (3).

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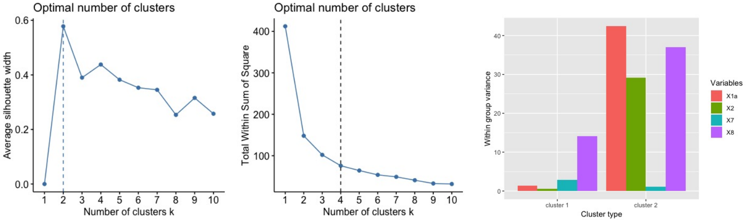
K-means Clustering Results

Best clustering of mean behavior

- $ASS = 0.58$, $SSE = 148.095$, $CHI = 60.68$ suggests a 2-means clustering.
- Cluster 1: labeled as **inactive**, for few variances of eating bamboos, $s_1(x_{1a}) = 1.36$ and walking around, $s_1(x_2) = 0.62$ comparing with rest, $s_1(x_8) = 14.09$.
- Cluster 2: labeled as **active**, large variance in both eating bamboo, walking around and having rest.



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K-means Clustering Results

Best clustering of mean behavior

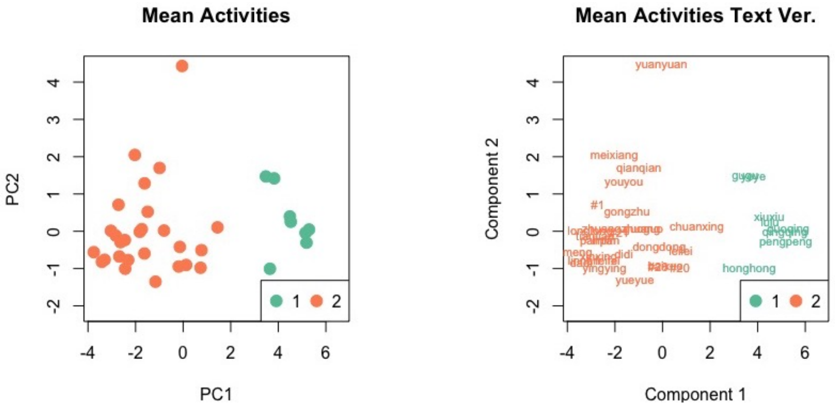

Figure: **Results of 2-means clustering.** Projected on two PCs.

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DBSCAN

- *MinPts*: minimum number of points clustered together in a specific neighbor. When $MinPts \leq 2$, the result is same as agglomerative hierarchical clustering.
- EPS (ϵ): distance that contains *MinPts* neighbour points.
- Procedures:
  - (1) Randomly pick up a point c_L from the dataset.
  - (2) If at least *MinPts* points placed within neighbor with distance ϵ, labeled as the same cluster.
  - (3) Iteratively repeat process until every point picked.

HDBSCAN

- Improvements:
  - (1) Mutual reachability distance:
    $d_{mreach-k}(a,b) = max\{core_k(a), core_k(b), distance(a,b)\}$
  - (2) Minimum spanning tree (MST)
  - (3) Stability of cluster C_i: $\sum_{x_j \in C_i}(\lambda_{x_j} - \lambda_{birth})$
- Procedures:
  - (1) Compute $d_{mreach-k}$ for all points in the dataset.
  - (2) Compute the MST based on mutual reachability graph.
  - (3) Extend MST with edges, connecting to MST_{ext}.
  - (4) Make dendrogram and cut tree by extracting HDBSCAN hierarchy MST_{ext}.

HDBSCAN Results

A possible clustering of factor scores

- $CHI = 21.24$, $ASS = 0.27$.
- Top 5 members: Meixiang, Tiantian, Feifei. Linlin, Youyou.
- Top 5 outliers: Quoqing, Lele, No.1, Yueyue, Xinxing.

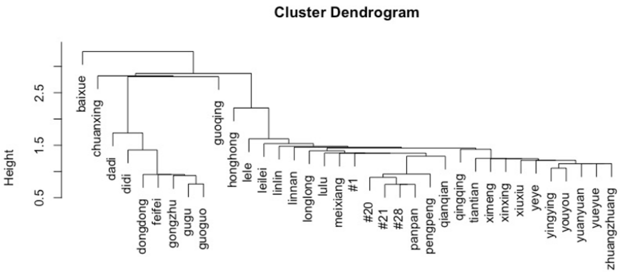

Figure: **HDBSCAN Dendrogram.** Two obvious clusters are fond.

HDBSCAN Results

A possible clustering of factor scores

- Cluster 1: labeled as **unhealthy**. Less tense and low oestrus behavior intensity.
- Cluster 2: labeled as **healthy**. High tense and above average oestrus behavior intensity. 72.2% of all individuals.

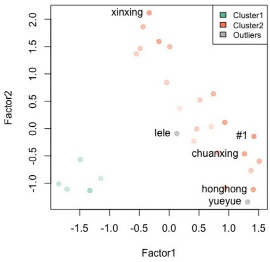

Figure: HDBSCAN of 2 clusters.

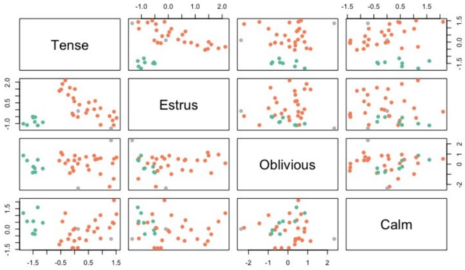

Figure: Scatterplot Matrix.

Spectral Clustering

- Developed from the graph theory, it identifies communities from the links between them.
- Procedures:
  - (1) Calculate the affinity matrix A by

$$\begin{cases} A_{ij} = exp(\frac{||s_i - s_j||^2}{2\sigma^2}), & when\ i \neq j \\ A_{ij} = 0, & when\ i = j \end{cases} \tag{2}$$

  - (2) Calculate the matrix $L = D^{-\frac{1}{2}} A D^{-\frac{1}{2}}$, where D has sum of matrix A's.
  - (3) Find first k eigenvalues and eigenvectors, normalize to form matrix X.
  - (4) Apply k-means to each row of X for clustering.

Spectral Clustering Results

Best clustering of factor scores

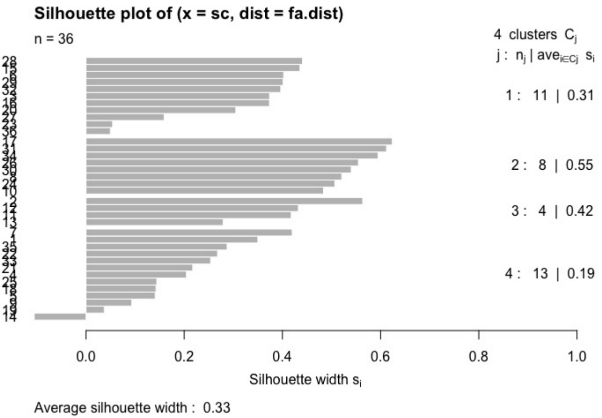

Figure: **Silhouette Plot.** With only abnormality of Linlin.

Spectral Clustering Results

Best clustering of factor scores

- Cluster 1: less tense, high intensity of oestrus behavior.
- Cluster 2: high tense and oestrus behavior. Mostly age in this group is larger than 6 (adults).
- Cluster 3: highly tense, less oestrus and oblivious.
- Cluster 4: highly tense, less oestrus and more oblivious. Age is significantly less than cluster 3 ($p\text{-}value = 0.034 < 0.05$).

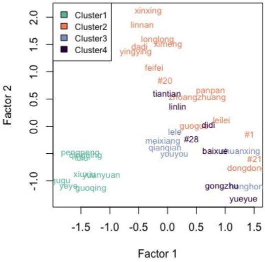

Figure: Spectral clustering results

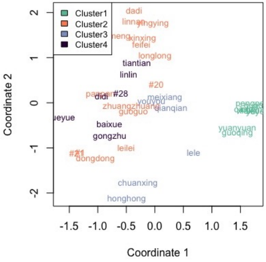

Figure: Results through MDS

Distance Measures

- Euclidean distance: $d(x, y) = ||x, y||_2$.
- Dynamic time warping: $DTW_p(x, y) = (\sum \frac{m_\phi lcm(k)^p}{M_\phi})^{\frac{1}{p}}$. Where lcm is the local cost matrix.
- Shape-based distance: $SBD(x, y) = 1 - \frac{max(NCC_c(x,y))}{||x||_2||y||_2}$. Where NCC_c is the cross-correlation with coefficient normalization of two time-series.
- Global alignment kernel: $k_{GA}(x, y) = \sum_\pi \prod_{i=1}^{|\pi|} \kappa(x_{\pi_1(i)}, y_{\pi_2(i)})$. Where κ is the local similarity function. Triangular global kernel is used to reduce GA kernel's complexity.

Intrinsic Measures of Clustering

For data not labeled in advance:

- Score function: $SF(c) = 1 - \frac{1}{e^{e^{betweeness+within}}}$
- Davies-Bouldin index: $DB(C) = \frac{1}{k}\sum max\{\frac{S(C_k)+S(C_l)}{d(\bar{C}_k,\bar{C}_l)}\}$. Where $S(C_k) = \frac{1}{|C_k|}\sum d(x_i, \bar{C}_k)$.
- Dunn index: $D(C) = \frac{min_{c_k\in c}\{min_{c_l\in C}\delta(c_k)\}}{max_{c_k\in c}\{\Delta(c_k)\}}$.
- COP index: $COP(C) = \frac{1}{N}\sum \frac{\sum d(x_i,\bar{C}_k)}{|C_k| min_{x_i\notin C_k} max_{x_j\notin C_k} d(x_i.x_j)}$.
- For fuzzy clustering using other criteria: MPC, K, T, SC and PBMF.

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Clustering Outcomes

Table: intrinsic criteria of clustering

	ASS	SF	CHI	DB	D	COP
Hclus+L_2	0.12	0.00	10.67	1.61	0.64	0.64
Hclus+SBD	0.19	0.35	3.33	1.16	0.67	0.67
P+DTW	0.40	0.11	23.35	0.88	0.24	0.45
P+DTW_2+DBA	0.25	0.00	29.29	1.52	0.39	0.48
k-shape	0.11	0.41	17.96	1.63	0.39	0.55
P+GAK	0.60	0.63	49.64	0.34	0.11	0.18

- P: partitional clustering; Hclus: hierarchical clustering; L_2: Euclidean distance.

Partitional clustering using GAK Distance

Best time-series clustering of rest behavior

- Procedures:
  - (1) randomly select a series from the dataset as initial position c_i.
  - (2) calculate smallest distance between the series by GAK distance. Then update the cluster centroids.
  - (3) repeat step (2) until no improvement occurs.
- Cluster results:
  - Cluster 1: have fluctuated rest frequency. $\frac{7}{9}$ of the cluster are same to cluster 1 from spectral clustering.
  - Cluster 2: react to an upward variation of time. $\frac{26}{27}$ of the cluster are the same to cluster 2 from bisecting 2-means on mean behavior.

Partitional clustering using GAK Distance

Best time-series clustering of rest behavior

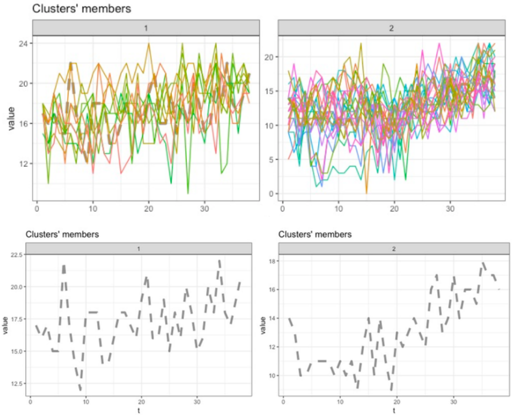

Figure: **Partitional clustering of GAK distance.** Grey lines are obtained prototypes.

Fuzzy Clustering

- Fuzzy clustering provides members of clusters to a certain degree. It is carried out through an iterative optimization of the objective function $\sum_{p=1}^{N}\sum_{c=1}^{k}\mu_{p,c}^{m}d_{p,c}^{2}$.
- Procedures:
  - (1) Initialize $U=[u_{p,c}]$ randomly.
  - (2) Calculate centers vectors $C_j=\frac{\sum_{p=1}^{N}\mu_{p,c}^{m}x_{p,i}}{\sum_{p=1}^{N}\mu_{p,c}^{m}}$.
  - (3) Update U by minimizing the objective function with GAK distance, until nearly no further improvements are made.
- Intrinsic measures $MPC=0.17$, $K=22.75$.

Fuzzy Clustering Outputs

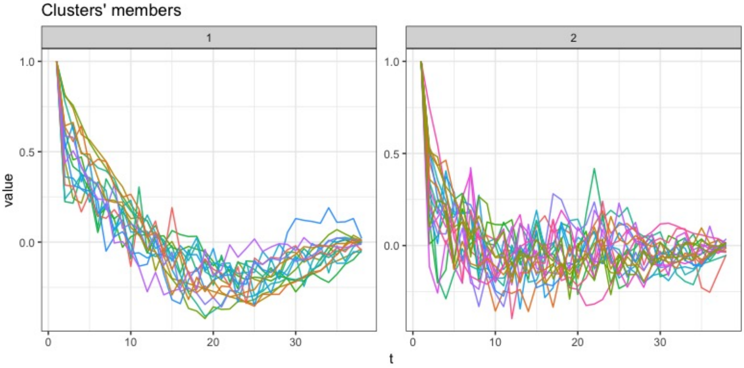

Figure: **Fuzzy clustering of GAK**. Lag-reaction to time is observed. Cluster 1: $\frac{2}{3}$ are female. Cluster 2: $\frac{11}{17}$ are male. Independent t-test has $p\text{-}value = 0.0167 < 0.05$.

Conclusion

- Work presented:
  - NNAR $\Rightarrow$ rest frequency prediction
  - Factor analysis $\Rightarrow$ 4 latent factors
  - K-means based on hierarchical clustering $\Rightarrow$ best clustering on mean behavior
  - Spectral clustering $\Rightarrow$ best clustering on factor scores
  - Partitional time series clustering with GAK $\Rightarrow$ rest variation with previous clustering result
  - Fuzzy time series clustering with GAK $\Rightarrow$ rest variation with gender
- Future research:
  - Integrate semi-supervision learning and sub-spaces of the giant pandas' behavior.
  - Naming of each cluster and factor.

Thank you for listening! Open for discussions.