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A Comparative analysis of the ordinary Correspondence Analysis (CA) and the Robust CA: The Nigerian Crime Data Example

Kingsley U. Ajoku[1], Chisimkwuo John[2] and Catherine U. Okereke[3]

[123]Department of Mathematics, Michael Okpara University of Agriculture, Umudike

*Corresponding author: ajokuprince123@gmail.com

Abstract

Correspondence Analysis is widely used for analyzing contingency tables. In this paper, the ordinary Singular Value Decomposition (SVD) based Correspondence Analysis (CA) was compared with the Robust SVD CA by discussing the theoretical procedures involved in the two procedures from first principle, and analyzing the 2018 Nigerian crime data. The Robust CA version that is based on the L1-Norm SVD which utilizes the median loss function was adopted to handle the noisy residual matrices from the contingency table. Hypothesis testing methods (including the quality of the biplot display measure) were utilized. Applying this on the reported Nigerian crime data, the ordinary CA and the Robust CA biplots shows that certain crimes are inherent to specific states, while some are general across the states. Comparatively, the Robust CA seems to produce a higher biplot adequacy measure suggesting that it is more suitable for contaminated datasets.

Keywords: Correspondence Analysis (CA), Singular Value Decomposition (SVD), Biplots

1 Introduction

Crime is an act that brings about offences and it is punishable under the law (Oguntunde et al, 2018). According to the Demographic Statistics Bulletin 2020 of the National Bureau of Statistics, the population of Nigeria in 2018 was estimated at 204.9million. With a population growth rate of over 2%, Nigeria's population is projected to be 242.4million by mid-year 2026. This high population in addition to corrupt leadership, high poverty rates, unemployment, weak under-funded institutions and justice system, porous borders, inadequate policing, break down of social/family values etc., are the factors whose interaction fuel various crimes and make Nigeria a multi-crime prone nation. Crime analysis is essential for understanding societal patterns and informing policy decisions. In Nigeria, crime statistics compiled by the National Bureau of Statistics provide valuable insights into the distribution and types of reported offences. According to the 2018 report, a total of 135,556 crime cases were recorded, with offences against property accounting for the largest share, followed by offences against persons and lawful authority. Additionally, significant regional disparities exist, with Lagos State contributing approximately 37.6Multivariate techniques such as Correspondence

Analysis (CA) are commonly used to explore relationships between categorical variables like crime type and location. However, classical CA relies on Singular Value Decomposition and is sensitive to outliers. This motivates the use of Robust Correspondence Analysis (RCA), which mitigates such effects. This study aims to:

- Compare SVD-based CA and RCA
- Apply both methods to Nigerian crime data
- Evaluate robustness, interpretability, and statistical reliability.

2 Literature Review

Crime analysis in Nigeria has evolved from predominantly qualitative assessments to more quantitative and data-driven approaches. Early studies such as Adebayo (2013) emphasized socio-economic determinants of crime, linking criminal activities to poverty, unemployment, and urbanization. While these studies provided valuable insights into the causes of crime, they often lacked rigorous statistical modeling. Similarly, Ojo (2014) examined crime trends in Nigeria using basic descriptive and trend analysis techniques. Although useful for identifying general patterns, such approaches were limited in uncovering deeper relationships among crime variables. In contrast, Oguntunde et al. (2018) introduced a more robust statistical framework for analyzing selected crime data in Nigeria. Using data from the National Bureau of Statistics spanning 1999 to 2013, the study applied descriptive statistics, correlation analysis, and principal component analysis (PCA) to examine crime patterns. The dataset covered major offences such as murder, armed robbery, assault, burglary, bribery, and corruption. Their findings revealed that assault and burglary were among the most prevalent crimes, while manslaughter had the lowest occurrence. More importantly, the study demonstrated that crime variables are interrelated and can be reduced into underlying components, highlighting the structural nature of criminal activities. Overall, the study represents a significant step toward evidence-based crime analysis in Nigeria, bridging the gap between descriptive crime statistics and advanced analytical modelling. As a tool for analyzing contingency tables, Correspondence Analysis decomposes chi-square distances into orthogonal components. It is closely related to Principal Component Analysis but more suitable for categorical data. However, several studies and literatures indicate the following as major limitations of Correspondence Analysis: • Sensitivity to outliers • Distortion in sparse datasets • Overemphasis on high-frequency categories Applications of crime data analysis in Nigeria (e.g., Oguntunde et al., 2018) show that crime types such as robbery, fraud, and burglary dominate datasets, often exhibiting skewness and extreme values. To mitigate the effect of these limitations on CA output, robust methods are introduced for a more reliable and statistically interpretable results. Hence, robust methods extend ordinary CA by incorporating the following into the CA algorithm: • M-estimation (using the median or myriad as the robust estimator) • Weighted influence functions • Outlier down-weighting • Boostrapping The outcome of this extension is the Robust Correspondence Analysis (RCA).

3 Methodology

3.1 The Ordinary SVD CA Approach

Correspondence Analysis (CA) is a multivariate technique for exploring associations in an $I \times J$ contingency table $\mathbf{N} = (n_{ij})$. Let $n = \mathbf{1}_I^\top \mathbf{N} \mathbf{1}_J$ be the grand total, where $\mathbf{1}_k$ denotes the k-vector of ones. Define the row masses vector $\mathbf{r} = \mathbf{N}\mathbf{1}_J/n \in \mathbb{R}^I$ and column masses $\mathbf{c} = \mathbf{N}^\top \mathbf{1}_I/n \in \mathbb{R}^J$. The correspondence matrix is

$$\mathbf{P} = \frac{1}{n}\mathbf{N}. \tag{1}$$

The expected matrix under row–column independence is $\mathbf{r}\mathbf{c}^\top$. The *standardized residual matrix* (Pearson residuals scaled by masses) is

$$\mathbf{S} = \mathbf{D}_r^{-1/2}(\mathbf{P} - \mathbf{r}\mathbf{c}^\top)\mathbf{D}_c^{-1/2}, \tag{2}$$

where $\mathbf{D}_r = \mathrm{diag}(\mathbf{r})$ and $\mathbf{D}_c = \mathrm{diag}(\mathbf{c})$. Classical CA performs the singular value decomposition (SVD)

$$\mathbf{S} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^\top, \tag{3}$$

with $\mathbf{U}^\top\mathbf{U} = \mathbf{I}_K$, $\mathbf{V}^\top\mathbf{V} = \mathbf{I}_K$ ($K = \min(I-1, J-1)$), and $\mathbf{\Sigma} = \mathrm{diag}(\sigma_1, \ldots, \sigma_K)$, $\sigma_k \geq 0$ non-increasing. The total inertia is $\Phi^2 = \|\mathbf{S}\|_F^2 = \sum_k \sigma_k^2$.

For *Robust CA*, we replace the classical SVD of $\mathbf{S}$ with the Hawkins et al. (2001) AL1-SVD (L1-norm alternating regression SVD) to obtain robust singular vectors $\tilde{\mathbf{U}}$, $\tilde{\mathbf{V}}$ and L1-eigenvalues $\tilde{\mathbf{\Sigma}}$ that are resistant to cell-wise outliers. The query specifies the version with *median weights*, which arises naturally as the L1 regressions reduce to weighted medians (detailed below). We derive the full procedure, including replications for successive components (deflation).

All matrices are replicated explicitly in notation (e.g., $\mathbf{S}^{(0)} = \mathbf{S}$, $\mathbf{S}^{(k)} = \mathbf{S}^{(k-1)} - \tilde{\lambda}_k \tilde{\mathbf{u}}_k \tilde{\mathbf{b}}_k^\top$ for the k-th component).

3.2 Deriving the Classical CA

Definition 1 (Chi-Squared Distance in CA)**.** *The chi-squared distance between row profiles i and i' is*

$$d^2(i, i') = \sum_{j=1}^{J} \frac{1}{c_j}\left(\frac{p_{ij}}{r_i} - \frac{p_{i'j}}{r_{i'}}\right)^2. \tag{4}$$

This equals the squared Euclidean distance between rows of

$$\mathbf{D}_r^{-1/2}(\mathbf{P} - \mathbf{r}\mathbf{c}^\top)\mathbf{D}_c^{-1/2}. \tag{5}$$

Theorem 1 (Inertia Equals Pearson Chi-Squared Statistic)**.** *The total inertia satisfies*

$$n\Phi^2 = \sum_{i=1}^{I}\sum_{j=1}^{J} \frac{(n_{ij} - e_{ij})^2}{e_{ij}} = X^2, \tag{6}$$

where $e_{ij} = nr_ic_j$ are expected frequencies under independence.

Proof.

$$\Phi^2 = \operatorname{tr}(\mathbf{S}^\top \mathbf{S}) = \sum_{i,j} s_{ij}^2 = \sum_{i,j} \frac{(p_{ij} - r_i c_j)^2}{r_i c_j} = \frac{1}{n} \sum_{i,j} \frac{(n_{ij} - e_{ij})^2}{e_{ij}}. \tag{7}$$

Multiplying by n yields X^2. The proof follows directly from the definition of $\mathbf{S}$ and the Frobenius norm. □

The row principal coordinates are $\mathbf{F} = \mathbf{D}_r^{-1/2}\mathbf{U}\mathbf{\Sigma}$, and column principal coordinates $\mathbf{G} = \mathbf{D}_c^{-1/2}\mathbf{V}\mathbf{\Sigma}$. These satisfy the transition formulas (replication of matrix notation):

$$\mathbf{F} = \mathbf{D}_r^{-1/2}\mathbf{P}\mathbf{D}_c^{-1/2}\mathbf{G}\mathbf{\Sigma}^{-1}, \quad \mathbf{G} = \mathbf{D}_c^{-1/2}\mathbf{P}^\top\mathbf{D}_r^{-1/2}\mathbf{F}\mathbf{\Sigma}^{-1}. \tag{8}$$

4 The Robust Correspondence Analysis

Since our classical CA approach was based on the ordinary SVD. It is apt to derive a comparative robust CA approach using a suitable robust SVD approach. Hawkins et al. (2001) used the median weights to replace the mean weights (L2 criterion) used in the ordinary SVD since the median is more robust to outliers when compared to the mean. They termed this alternative approach the L1-criterion and this merits discussion.

4.1 The Hawkins (2001) L1-Norm SVD with Median Weights

Hawkins et al. (2001) replace the L2 criterion $\min \|\mathbf{X} - \lambda\mathbf{a}\mathbf{b}^\top\|_F^2$ (classical SVD) with the L1 criterion

$$\min_{\mathbf{a},\mathbf{b},\lambda} \sum_{i=1}^{n}\sum_{j=1}^{p} |x_{ij} - \lambda a_i b_j|, \tag{9}$$

subject to $\|\mathbf{a}\|_2 = \|\mathbf{b}\|_2 = 1$. This is solved via *alternating L1 regressions* (AL1-SVD). The solution uses weighted medians, hence "median weights."

Lemma 1 (L1 Regression Reduces to Weighted Median)**.** *Consider the univariate L1 regression* $\min_c \sum_{k=1}^m w_k|y_k - cx_k|$ *with* $w_k > 0$*. The minimizer is*

$$c^* = \textit{weighted median of } \left\{\frac{y_k}{x_k}\right\}_{k=1}^m \textit{ with weights } |x_k|w_k. \tag{10}$$

Proof. The subgradient of the objective w.r.t. c is

$$\partial L(c) = -\sum_{k:y_k > cx_k} w_k|x_k| + \sum_{k:y_k < cx_k} w_k|x_k| + \text{boundary terms at equality.}$$

Setting the subgradient to contain zero requires the weighted sum of signs to balance at zero, which occurs precisely when c is the weighted median of the ratios y_k/x_k (weights $|x_k|w_k$). For the

no-intercept case with $w_k = 1$, this is the stated form. The proof is standard in robust statistics (see Hawkins et al., 2001, Technical Report 122). □

4.1.1 The AL1-SVD Algorithm

Let $\mathbf{X}^{(0)} = \mathbf{X}$ (here $\mathbf{X} \equiv \mathbf{S}$ for Robust CA). For the k-th component ($k = 1, 2, \ldots, K$):

- **Initialization:** Set $\mathbf{a}_1^{(0)}$ as the normalized vector of row-wise median absolute deviations:

$$a_{1i}^{(0)} = \frac{\text{median}_j\, |x_{ij}^{(k-1)}|}{\| \text{median}_j\, |x_{ij}^{(k-1)}| \|_2}.$$

- **Update Right Vector (Weighted Median Replication):** For each $j = 1, \ldots, p$,

$$c_j = \text{weighted median of } \left\{ \frac{x_{ij}^{(k-1)}}{a_{1i}^{(m)}} \right\}_{i=1}^{n} \text{ with weights } |a_{1i}^{(m)}|.$$

  Then $\mathbf{b}_1^{(m+1)} = \mathbf{c}/\|\mathbf{c}\|_2$.

- **Update Left Vector:** Symmetrically,

$$d_i = \text{weighted median of } \left\{ \frac{x_{ij}^{(k-1)}}{b_{1j}^{(m+1)}} \right\}_{j=1}^{p} \text{ with weights } |b_{1j}^{(m+1)}|,$$

  $\mathbf{a}_1^{(m+1)} = \mathbf{d}/\|\mathbf{d}\|_2$.

- Iterate until $\|\mathbf{a}_1^{(m+1)} - \mathbf{a}_1^{(m)}\|_2 < \epsilon$ (e.g., $\epsilon = 10^{-8}$). Denote converged vectors $\tilde{\mathbf{a}}_k$, $\tilde{\mathbf{b}}_k$.

- **L1-Eigenvalue (Single-Parameter Weighted Median):**

$$\tilde{\lambda}_k = \arg\min_{\lambda} \sum_{i,j} |x_{ij}^{(k-1)} - \lambda \tilde{a}_{ki} \tilde{b}_{kj}|,$$

  solved as the weighted median of $\{x_{ij}^{(k-1)}/(\tilde{a}_{ki}\tilde{b}_{kj})\}$ with weights $|\tilde{a}_{ki}\tilde{b}_{kj}|$.

- **Deflation (Replication for Next Component):**

$$\mathbf{X}^{(k)} = \mathbf{X}^{(k-1)} - \tilde{\lambda}_k \tilde{\mathbf{a}}_k \tilde{\mathbf{b}}_k^{\top}.$$

Theorem 2 (Monotonicity and Convergence of AL1-SVD)**.** *Each iteration decreases the L1 criterion* $L(\mathbf{a}, \mathbf{b}) = \sum_{i,j} |x_{ij} - \lambda a_i b_j|$. *The sequence converges to a stationary point.*

Proof. The alternating regressions are coordinate-wise L1 minimizations; by the property of medians, each step strictly reduces L unless at a fixed point. Deflation preserves the L1 approximation property for successive residuals (Hawkins et al., 2001). □

4.2 The Robust Correspondence Analysis Procedure

Apply AL1-SVD to $\mathbf{S}$ (the classical CA matrix) to obtain robust $\tilde{\mathbf{U}}$, $\tilde{\mathbf{\Sigma}}$, $\tilde{\mathbf{V}}$. Robust row coordinates: $\tilde{\mathbf{F}} = \mathbf{D}_r^{-1/2}\tilde{\mathbf{U}}\tilde{\mathbf{\Sigma}}^{1/2}$; robust column coordinates: $\tilde{\mathbf{G}} = \mathbf{D}_c^{-1/2}\tilde{\mathbf{V}}\tilde{\mathbf{\Sigma}}^{1/2}$. The robust inertia is $\tilde{\Phi}^2 = \sum_k \tilde{\sigma}_k^2$ (L1 analogue, not necessarily equal to classical X^2).

In a nutshell, the steps to implement Robust CA are:

- Compute $\mathbf{S}$.
- Apply AL1-SVD (steps in Section 3) with median-weight L1 regressions on $\mathbf{S}$.
- Deflate for second component (replication).
- Compare to classical SVD: the outlier distorts classical σ_1 heavily; AL1-SVD (via weighted medians) downweights it, recovering the underlying structure.

In practice, code the weighted median function and iterate (convergence in < 10 steps typical).

The full Robust CA algorithm replicates the classical steps but substitutes the SVD block with AL1-SVD on $\mathbf{S}$.

4.3 CA and RobCA Hypothesis Testing Methods

4.3.1 Classical CA Independence Test

Theorem 3 (Asymptotic Chi-Squared Test)**.** *Under H_0: row–column independence, $n\Phi^2 \xrightarrow{d} \chi^2_{(I-1)(J-1)}$.*

Proof. The vectorized Pearson residuals $\sqrt{n}\,\mathrm{vec}(\mathbf{S})$ is asymptotically normal with covariance structure projecting onto the orthogonal complement of the independence subspace (Agresti, 2013). The quadratic form $n\Phi^2$ is the sum of squares of these residuals, yielding the stated χ^2 limit by the continuous mapping theorem. □

4.3.2 Robust Hypothesis using Permutation Test

For Robust CA, use a permutation test on the robust inertia $\tilde{\Phi}^2$:

- Permute the cells of $\mathbf{N}$ under H_0 (fix margins or use full permutation).
- Recompute $\tilde{\Phi}^2$ via AL1-SVD on each permuted $\mathbf{S}^*$.

proposition 1 (Consistency of Permutation Test)**.** *The test is exact under exchangeability and consistent against fixed alternatives as $n \to \infty$.*

Proof. Under H_0, the distribution of the test statistic is invariant to permutation. Power follows from the consistency of the L1 approximation to the signal subspace (Hawkins et al., 2001; standard robust statistics arguments). □

Sequential tests for dimensionality follow analogously by testing successive $\tilde{\lambda}_k = 0$.

4.3.3 Inference using the CA and RobCA Biplot Quality

The CA biplot is discussed fully in Greenacre, 2010. The procedure of the biplot construction of the robust CA is indifferent from the ordinary CA procedure. The Robust CA biplot uses markers $\tilde{\mathbf{F}}$ (rows) and $\tilde{\mathbf{G}}$ (columns) in the plane spanned by the first two robust components.

Definition 2 (Biplot Matrix Form)**.** *Let* $\tilde{\mathbf{L}} = \tilde{\mathbf{F}}_{[:,1:2]}$, $\tilde{\mathbf{R}} = \tilde{\mathbf{G}}_{[:,1:2]}$. *The low-rank approximation is*

$$\mathbf{S} \approx \tilde{\mathbf{L}}\tilde{\mathbf{R}}^{\top} \quad \textit{(in L1 sense).} \tag{11}$$

Theorem 4 (Inner-Product Interpretation)**.** *The inner product* $\tilde{f}_{i\ell}\tilde{g}_{j\ell}$ *approximates the* (i, j)*-entry of the standardized residual* s_{ij} *(robustified).*

Proof. From the AL1-SVD reconstruction $\mathbf{S} \approx \sum_k \tilde{\lambda}_k \tilde{\mathbf{u}}_k \tilde{\mathbf{b}}_k^{\top}$ and the coordinate scalings, the inner product recovers the bilinear form exactly in the L1-minimizing subspace. □

Drawing the Biplot (Step-by-Step):

- Compute $\tilde{\mathbf{F}}$ and $\tilde{\mathbf{G}}$ as above (principal scaling).
- Plot row points at coordinates $(\tilde{F}_{i1}, \tilde{F}_{i2})$; column points at $(\tilde{G}_{j1}, \tilde{G}_{j2})$.
- Scale axes by singular values for aspect ratio preservation.
- Interpret: proximity of row i to column j indicates positive association (robust to outliers); angles reflect correlations.

The adequacy (quality) of a Correspondence Analysis (CA) biplot is given by

$$\text{Biplot Adequacy} = \frac{\lambda_1 + \lambda_2 + \cdots + \lambda_k}{\sum_{i=1}^{p} \lambda_i} \times 100\% \tag{12}$$

where: λ_i = eigenvalue (principal inertia) of the ith dimension, k = number of displayed dimensions, and p = total number of dimensions. For a two–dimensional CA biplot,

$$\text{Biplot Adequacy} = \frac{\lambda_1 + \lambda_2}{\sum_{i=1}^{p} \lambda_i} \times 100\% \tag{13}$$

In the empirical example that follows in Section 6, Nigerian Crime data (particularly offenses against persons) from the National Bureau of Statistics (2018) will be used and we envisaged that the robust biplot isolates the outlier cell while recovering the diagonal association pattern (classical biplot collapses).

5 The Nigerian Crime Data Application

5.1 The Nigerian Crime Data: Offences against persons

Table 1: excerpt of the crime statistics data by state (NBS 2018)

STATE	AROB	WWME	THST	BURG	HBRE	SBRE	FRCH	FOGE	RSPR	UNPO	ARSON	OO
FCT	384	0	2586	32	129	16	518	7	288	0	12	188
ABIA	88	0	570	23	576	23	544	4	9	49	345	89
ADAMAWA	45	0	825	0	62	24	106	5	65	28	0	246
..	.	.	.	.	.	.	.	.	.	.	.	.
..	.	.	.	.	.	.	.	.	.	.	.	.
..	.	.	.	.	.	.	.	.	.	.	.	.
YOBE	32	0	355	0	6	2	45	7	38	13	15	77
ZAMFARA	46	0	155	0	19	2	21	1	29	6	0	39

For the dataset presented in Table 1, is the 2018 Crime data for crimes or offences agaist persons with the variables AROB = ARMED ROBBERY, WWME = WOUNDING WITH MENACE, THST = THEFT/STEALING, BURG = BRGLARY, HBRE = HOUSE BREAKING, SBRE = STORE BREAKING, FRCH = FRAUD/CHEATING, FOGE = FOGERY, RSPR = RECEIVING STOLEN PROPERTY, UNPO = UNLAWFUL POSSESSION, ARSON = ARSON, and OO = OTHER OFFENCES.

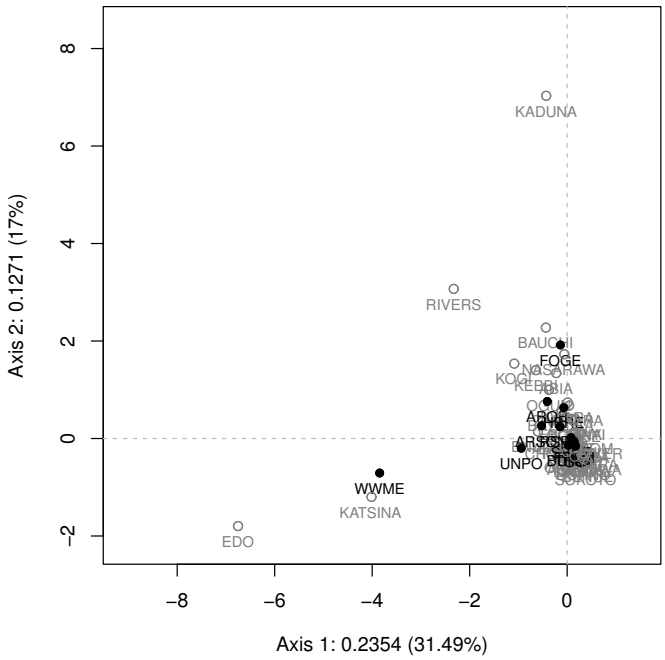


Figure 1: CA biplot using the ordinary SVD

5.2 The Exploratory Data Analysis (EDA) Plots

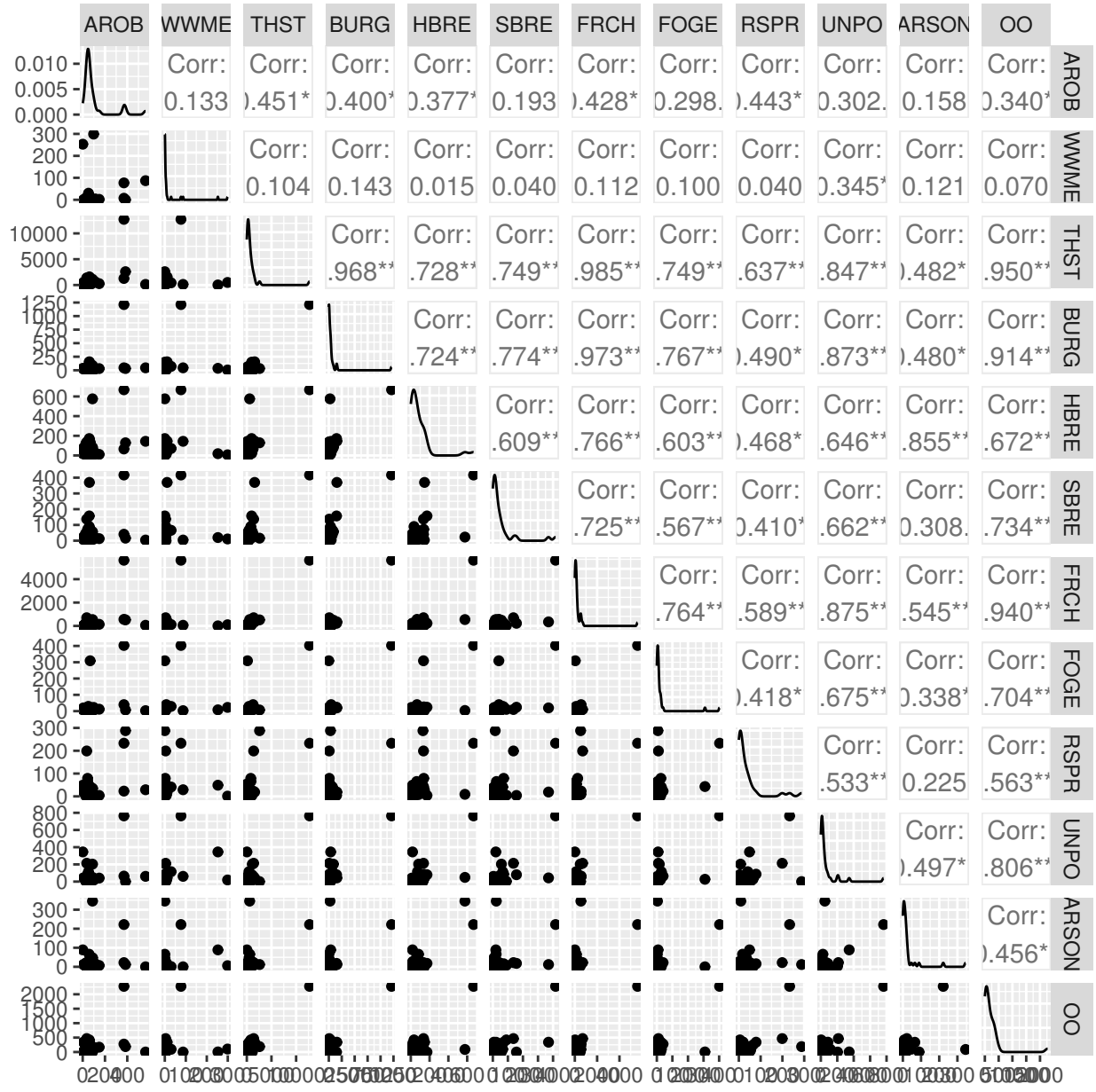


Figure 2: Sample graph of results

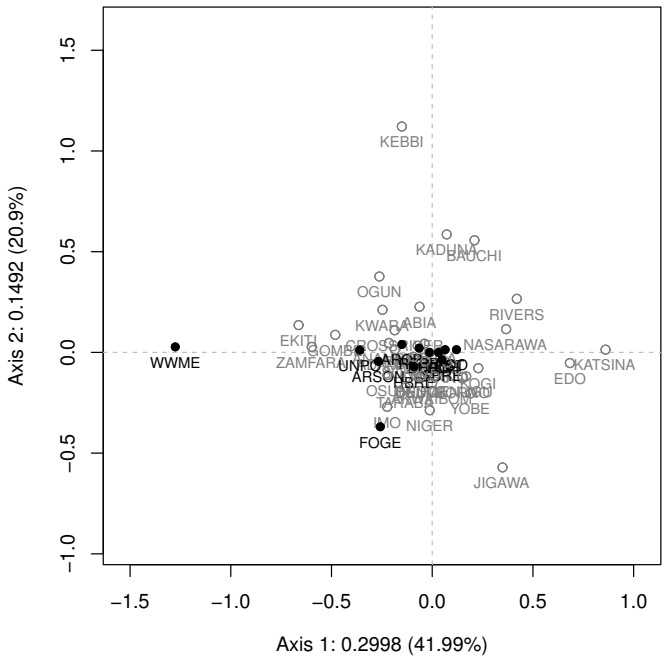


Figure 3: CA biplot using the robust SVD

5.3 Discussions and Comparative analysis

The EDA plots presented in Figures 1, 2, and 3 showcases the correlation plots, the CA biplot and the Robust CA biplot respectively. It is observable from Figure 1 that there exist strong significant correlation between certain crimes and each other, while some correlated weakly with no observable significance.

Table 2: Comparison of CA with SVD and Robust SVD in terms of Quality of the Display

	Row Axis	Column Axis	Total
CA with SVD	31.49%	17%	48.49%
CA with Robust SVD	31.99%	20.90%	52.89%

A good inferential statistic that will reveal the a fair comparative approach is the Quality or Adequacy of the CA biplot display. This is showcased in Table 2. It is observable from Table 2 that the quality or adequacy of the Robust CA biplot is higher than that of the ordinary CA biplot for the Nigerian crime data.

Meanwhile, the general structure of Figures 2 and 3 shows how states differ in crime patterns. States close together implies that they have similar crime profiles and the crime variables act like directional indicators. Note that states that are closer together has similar profles. From dimension 1 (horizontal

axis) separates high-total-crime states vs low/moderate ones States far right from Figure 3 suggests high involvement in dominant crimes (e.g., WWME, FOGE) and states near origin indicates average crime distribution. Viewing from dimension 2 (vertical axis), it exposes or separates types of crime emphasis. Upper region suggests states associated with certain violent/property crimes while the lower region pinpoints states associated with others (e.g., WWME, UNPO). Pinpointing few states for interpretation guide, IMO likely positioned far from origin has strong associated with FOG and this implies that IMO has a high concentration of dominant forgery crime types. Another indicative observation is that some northern states like Kebbi, Kaduna, Bauchi, Katsina lies far from the origin as well as the crime WWME suggesting that those states are susceptible to the dominant crime wounding with menace.

In the overall, the map reveals clusters and dominant crime profiles of states. It helps identify groups of states with similar crime structures and the main crime structures that defines those differences and in conclusion, the highlights shows that while crime concentration differs across states, many crimes dominate the structure with the cluster based on crime profiles. Also, some states are outliers (unique crime patterns) and finally, the Robust CA construction (with the Robust SVD) seems to produce a better CA profile structure compared to the standard CA construction using ordinary SVD.

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