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Research Article

Application of Principal Component Analysis to Vehicle Sales: case study at IBM company

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Abstract

Principal Component Analysis (PCA) is a fundamental statistical technique used fordimensionality reduction and data transformation. It is providing an overview of PCA's principles, methodology, and applications. PCA aims to capture the most important information in high-dimensional data by transforming it into a new coordinate system defined by its principal components. These components are linear combinations of the original variables, ordered by the amount of variance they explain. The data has been taken from original data from (IBM) company on car sales. According to a real-world example, sales of cars are based on (car type, sales in thousands, 4-year resale value, price in thousands, engine size, horsepower, wheelbase, width and length, curb weight, fuel capacity, fuel economy, and log-transformed sale), these data used in SPSS program for this purpose.The result indicates that the first and second components (Wheelbase, Engine size, Price in thousands, Horsepower, and Sales in thousands) factors together represent the total variances % (75.8(45%) in the model, which uses appropriate sampling and contains two components in total with up to 12 variables added.It is recommended that drivers should have automobiles that are more comfortable for divers and with (high-quality horsepower Wheelbase, Engine size, Price in thousands, Horsepower, and Sales in thousands) of cars.

About the Journal
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1. Introduction

PCA is used to create predictive models and for exploratory data analysis. It is frequently used to acquire lower-dimensional data while retaining the most of the data's variation by projecting each data point onto only the first few principal components. The path that maximises the variance of the projected data can also be used to define the first main component (Elhaik, 2022). Finding structural abnormalities of a community made up of p-variables and a large quantity of data (big sample size) is the goal of the factor analysis (FA) method. (Chatfield C.,and Collins A.J., 1980)

1.1The Objective of study

1-Determine the most important variables that lead to the phenomenon of inflation, according to the opinions of the research sample, car sales
2-Principal component analysis is used to interpret the results

1.2 Problem of research

The research problem is summarized Vehicle Sales, including car type, sales in thousands, 4-year resale value, price in thousands, engine size, horsepower, wheelbase, width, and length, curb weight, fuel capacity, fuel economy, and log-transformed sale. Knowing each of them are effect on Vehicle Sales.

1.3 Hypotheses testing

1-Factorial analysis can be used to choose the validity of the hypotheses related to the pattern of factors affecting a group of variables, based on the matrix of factors.
2- Null hypotheses equal to the model is not adequacy sampling model
Alternative hypotheses equal to the model is adequacy sampling model

2. Literature Review

Rizgar M. Ahmed, Nida S. MalaYounis (2023), they applied to electric power data from the Erbil Gas Power Plant, principal components analysis, one of the methods of multivariate analysis for time series models (Box-Jenkins Model) was found to be effective in condensing multiple time series data and yielding the best models according to statistical criteria. As a consequence, ARIMA $(2,2,2)x(2,2,0)^{12}$ is the best model that has been suggested for forecasting data on electrical energy production in the City of Erbil. (Rizgar M.Ahmed, Nida S. Mala Younis, 2023)

Eran Elhaik (2022), used Principal Component technique (PCA) is a multivariate technique that lessens dataset complexity while maintaining data covariance. Colorful scatterplots can be used to display the results, ideally with little information loss. The most important analyses in population genetics and related fields (such as animal and plant or medical genetics) are PCA applications, which are implemented in well-cited packages like EIGENSOFT and PLINK. The results of PCA are used to guide study design, identify and describe people and populations, and derive historical and ethnobiological conclusions on origins, evolution, dispersion, and relatedness. She came to the conclusion that 32,000–216,000 genetic studies should be reevaluated and that PCA may play a biassing effect in genetic investigations. A different mixed-admixture population genetic model is discussed. (Elhaik, 2022).

Sasan K., Shahidan M. Abdullah, Azizah A., Manaf, Mazdak Z., Alireza H. (2013), they used the principal component analysis (PCA) is a kind of algorithms in biometrics. It is a statistic technical and used orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables. PCA also is a tool to reduce multidimensional data to lower dimensions while retaining most of the information. It covers standard deviation, covariance, and eigenvectors. As a result, background knowledge is meant to make the PCA section very straightforward, but can be skipped if the concepts are already familiar. (Sasan Karamizadeh , 2013)

3. Methods and Materials

3.1 Data Collection

The data have taken data (Original data) in SPSS program on car_ sales for principal component analysis application, and including 12 variables on sales cars is (dependent variable) Sales in thousands, 4-year resale value, Price in thousands, Engine size, Horsepower, Wheelbase, Width, Length, Curb weight, Fuel capacity, Fuel efficiency and Log-transformed sales and types of cars are (independent variables), including (157) observations variable,

3.2 Methodology

3.2.1 In this section, the theoretical aspect of the research is presented, as well as how to analysis of the principal components and Kaiser-Meyer-Olkin Measure of Sampling Adequacy, Bartlett's Test of Sphericity, Eigen values, loading and scree plot.

3.2.2. This research depends on an inductive approach which depends on the collection of information related to the main elements of the research by analyzing and interpreting provided data in order to build a theoretical framework by relying on principal component Analysis. The data achieved from original data from IBM company for car sales, it contains (116) Automobiles and (41) trucks. For this purpose, we have used Principal component Analysis in order to achieve which factors are more effect on car- sales among (12) factors, SPSS program used to analyze provided answers from the research samples.

3.3 Eigen Vectors

The linear composition coefficients of the main components are called the coefficients of the original variables of the main components and are symbolized by (a) (Lan T. Jolliffe , Jorge Cadima, 2016).

3.4 Eigen Values

It is the variation of the main elements and is illustrated by (λj)

3.5 Loading

The load (Ljj ^ ') represents the simple correlation coefficient between the values of component j and the values of variable j ^' as follows. (Lan T. Jolliffe , Jorge Cadima, 2016) (Dillon, W.R,Goldstein M., 1984) (Hotelling, 1933)

$$L_{jj'} = (\underline{a}_j)\sqrt{\lambda_j}$$

3.6 Main Component Model

The model of the main components is that the characteristic vectors are placed as factors in the linear structure of the random variables studied (Xj) (j = 1,2,3, ..., p) and can be expressed as follows:

$$\mathrm{PC_j} = \mathrm{a_{1j}X_1 + a_{2j}X_2 + \cdots + a_{pj}X_p} \ldots \quad (4)$$

$$\mathrm{PC_j} = \sum_{k=1}^{p} \mathrm{a_{kj}X_k} \qquad (\mathrm{j, k} = 1,2,3, \ldots, \mathrm{p})$$

Whereas:

PCj principal component (j).

A $_{kj}$: The parameter (k) in component (j) is the characteristic vector values (aj) associated with the characteristic roots (λj).

Using matrix style. (Amanuel, 2002) (Dillon, W.R,Goldstein M., 1984)

3.7 Characteristics of the principal components

The main properties of the principal components can be summarized as follows:
1. All the characteristic roots of the S and R matrix are positive values because both S and Rare positive matrix.
2. The sum of the characteristic roots is the sum of the values of the country elements of the matrix used

$$\mathrm{trace}(s) = \sum_{j=1}^{p} \lambda_j = \sum_{j=1}^{p} \mathrm{var}(X_j) \dots (5)$$

S: represents the matrix of variance and common contrast.
Var (Xj): represents the variation of the variable (Xj).
When using the R matrix,

$$\mathrm{trace}(R) = \sum_{j=1}^{p} \lambda_j = p$$

Where:
p: number of variables.
R: represents the correlation matrix.
3. The array parameter used is equal
$| R | = (\lambda 1) (\lambda 2) (\lambda 3) \dots (\lambda p)$
4. The characteristic vectors are orthogonal (1 = length) between them

$\underline{a}_j \underline{a}_{j'} = 1 \qquad j' = j$

$\underline{a}_j \underline{a}_{j'} = 0 \qquad j' \neq j$

This property can be achieved if a kj is the Eigen Vector Normalized values associated with the Eigen Values (Amanuel, 2002). (Hotelling, 1933

3.8 Factor Analysis

Is a method for modelling observed variables, and their covariance structure, in terms of a smaller number of underlying unobservable (latent) "factors." The factors typically are viewed as broad concepts or ideas that may describe an observed phenomenon. For example, a basic desire of obtaining a certain social level might explain most of the consumption behaviour. These unobserved factors are more interesting to the social scientist than the observed quantitative measurements. Factor analysis is generally an exploratory (descriptive) method that involves many subjective judgments by the user. It is a widely used tool, but it can be controversial because of the models, methods, and subjectivity are so flexible that debates about interpretations may occur. (Amanuel, 2002)

3.9 Method of Calculating the Principal Components

First, if the variables have different measurement units, the main components are calculated through the correlation matrix R, which is shown as follows:

$$R = \begin{bmatrix} 1 & r_{12} & r_{13} & \cdots r_{1p} \\ r_{21} & 1 & r_{23} & \cdots r_{2p} \\ \vdots & \vdots & \vdots & \cdots \vdots \\ r_{p1} & r_{p2} & r_{p3} & \cdots 1 \end{bmatrix}$$

Correlation Matrix
Symmetric Matrix

$$r_{jk} = \frac{Cov(xj,xk)}{\sqrt{var(x_j)}\ \sqrt{var(x_k)}} = \frac{\sum_{i=1}^{n}(x_{ij}-\bar{y})(x_{ik}-\bar{x}_k)}{\sqrt{\sum(x_{ij}-\bar{x}_j)^2\ \sum(x_{ik}-\bar{x}_k)^2}} \quad , \ -1 \leq r_{jk} \leq +1$$

$$\Sigma = S = \begin{bmatrix} var(xi) & cov(x1,x2)K & cov(x1,xp) \\ cov(x2,x1) & var(x2)K & cov(x2,xp) \\ cov(xp,xi) & cov(xp,x2) & var(p) \end{bmatrix}_{p*p}$$ Covariance Matrix

We find the characteristic equation through the following.

$| R-\lambda I | = 0$

In order to solve this equation, we obtain (p) from the characteristic roots and arrange these roots so that.

$\lambda 1> \lambda 2> \cdots> \lambda p> 0$

Each characteristic root λj has a dimension (p × 1) and is found after the compensation of the characteristic λj root values by the following relationship.

$| R-\lambda I | Aj = 0$

The principal components are calculated according to the following formula.

$PC_j = a_{1j}\, x_1 + a_{2j} x_2 + \cdots + a_{pj}\, x_p.$

Second, if the variables have identical units of measurement, the principal components are calculated through the matrix of variance and common contrast S (same as above with matrix R change in matrix S) (Jolliffe, 2002)

3.10 Methods to Choose the Number of Main Components

1- (Kaiser, 1960). It is based on the selection of the number of major components equal to the number of characteristic roots greater than the correct one (λ> 1). It should be noted that this criterion is used if the variables studied have different units of measurement Use the correlation matrix to calculate the principal components).

2-Standard of interpreted contrast ratio

3-Standard graphic display. (Jolliffe, 2002) (Amanuel, 2002)

3.11 Rotation of Axes

The objective of the analysis is to give a clear image of the nature of the interrelationships between the variables by highlighting the factors underlying these relations and describing them and interpreting them in light of the data. The explanation of the factors in the nature of their nature depends on their duration, their independence, or their correlation. This requires identifying the characteristics in which each group of high-probability variables shares one of the factors. The objective of the rotation of the axes is to gain factors whose coefficients are easy to interpret and have significant significance (do not change from one analysis to another). The method of rotation depends on the correlation or independence of the factors. The researcher should choose the appropriate method of rotation. A non-rounded matrix into a matrix called a simple structure of the matrix of extracted factors. (Lan T. Jolliffe , Jorge Cadima, 2016)

3.12 Rotators Axes

Varimax method, the Quartimax method was designed to simplify the description of each row of variables. In contrast, Kaiser was trying to simplify the columns of the matrix of factors. In an attempt to obtain simple structure, Varimax was proposed by Keizer (1958), an amendment to Quartimax, for simple installation, it is one of the most common orthodontic methods.

The basic rule of this method is based on the fact that the most factors subject to Altiris is that factor, which has some of the high and some of the small and a small percentage of the values of medium-precursors can be clarified and simplified the worker through the different boxes of loading as follows (Jolliffe, 2002)

$$S_p^2 = \frac{1}{n}\sum_{j=1}^{n}(a_{jp}^2) - \frac{1}{n^2}\left(\sum_{j=1}^{n} a_{jp}^2\right)^2 \qquad P = 1,2,\ldots,m$$

If equation (S_p^2) is combined for all the factors

$$S = \sum_{p=1}^{m} s_p^2 = \frac{1}{n}\sum_{p=1}^{m}\sum_{j=1}^{n} a_{jp}^4 - \frac{1}{n^2}\sum_{p=1}^{m}\left(\sum_{j=1}^{n} a_{jp}^2\right)^2$$

3.13 Factor loadings

A factor loading is calculated for each combination of variable and extracted factor. These values are useful for seeing the pattern of which variables are likely to be explained by which factor. The factor loading can be thought of as the coefficient of the correlation between the component and the variable thus the larger the number, the more likely it is that the component underlies that variable. Loadings may be positive or negative.

3.14 Rotation

A factor analysis prior to rotation provides an explanation of how many factors underline the variable; for some purposes this is sufficient. In psychology, however, we normally wish to understand what it all means, because we want to launch whether any psychological constructs might underline the variables. Rotation is a mathematical technique available in factor analysis that arrives at the simplest pattern of factor loadings. (AndersonT., 1984)

3.15 Factor Analysis Methods

1-Principal component Method.
2- Principal Factor Method.
3-Maximum Likelihood Method.
4- Image Method.
5- Unweight Least Squares.
6- Generalized Least squares.
7- Alpha Method.
8- The Centered Method.
9- Rao Method.

Kaiser Measurement

Kaiser-Meyer-Olkin (KMO) Test is a measure of how suited your data is for **Factor Analysis**. It is used for test measures sampling adequacy for each variable in the model **and** for the whole model. The statistic is a measure of the amount of variance between variables that might be common variance. The lower the proportion, the more suited your data is to Factor Analysis.

Bartlett's test of Sphericity

tests the hypothesis that your correlation matrix is an identity matrix, which would indicate that your variables are unrelated and therefore unsuitable for structure detection. Small values (less than 0.05) of the significance level indicate that a factor analysis may be valuable with your data.

Scree Plot

Cattell’s Scree Plot is a graphical representation of the factors and their corresponding eigenvalues. The x-axes represent the factors (components) and the eigenvalues are along the y-axes, because the first component accounts for the greatest amount of variance, it has the highest eigenvalues. The eigenvalues continually decrease resulting in a picture that often called (elbow) shape. The scree plot cutoff is quite subjective, requiring that the number of factors be limited to those occurring before the bend in the elbow**.** (Chatfield C.,and Collins A.J., 1980)

4.Result and interpretation

This chapter covers the statistical analysis of original data from IBM company for car sales, that were distributed to descriptive statistics and result of principal component analysis and contains (12) factors for each contains (157) observations. Including (116) automobiles and

(41) trucks. The main objective that, which factors are more effect on car- sales among (12) factors.

Table 1 statistical description

Vehicle type					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Automobile	116	73.9	73.9	73.9
	Truck	41	26.1	26.1	100.0
	Total	157	100.0	100.0	

Source: applying original data (IBM) based on the SPSS statistical program

Table (1) shows that Automobile (116) is bigger than Truck (41), drives are more comfortable than Truck to purchase (Automobile).

Table 2 Statistics for 12 variables

Statistics													
		Manufacturer	Sales in thousands	4-year resale value	Vehicle type	Price in thousands	Engine size	Horse power	Wheel base	Width	Length	Curb weight	Fuel capacity	Fuel efficiency
N	Valid	157	157	121	157	155	156	156	156	156	156	155	156	154
	Missing	0	0	36	0	2	1	1	1	1	1	2	1	3
Mean			52.99808	18.07298	.26	27.39075	3.061	185.95	107.487	71.150	187.344	3.37803	17.952	23.84
Std. Deviation			68.029422	11.453384	.441	14.351653	1.0447	56.700	7.6413	3.4519	13.4318	.630502	3.8879	4.283
Sum			8320.698	2186.830	41	4245.567	477.5	29008	16768.0	11099.4	29225.6	523.594	2800.5	3672

Source: applying original data (IBM) based on the SPSS statistical program

Table (2) illustrates that the average of length (187.344) and horsepower (185.95) are more attractive for drives to purchase.

Table 3 KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.802
Bartlett's Test of Sphericity	Approx. Chi-Square	1627.036
	df	66
	Sig.	.000

Source: applying original data (IBM) based on the SPSS statistical program

Table (3) shows the value of KMO is equal to (0.802) is greater than 0.5 that means this model is suitable for Adequacy sampling model, and Bartlett's Test of Sphericity is used for goodness of fit (chi-square) because the value of p-value is equal to (0.000) is smaller than the value of chi-square that means is high significant, this tests the null hypothesis that the correlation matrix is an identity matrix. An identity matrix is matrix in which all of the diagonal elements are 1 and all off diagonal elements are zero. i.e: we reject null hypothesis (H_0=the model is not adequacy sampling model).

Table 4 Communalities

variables	Initial	Extraction
Sales in thousands	1.000	.530
4-year resale value	1.000	.809
Price in thousands	1.000	.860
Engine size	1.000	.791
Horsepower	1.000	.838
Wheelbase	1.000	.816
Width	1.000	.731
Length	1.000	.737
Curb weight	1.000	.858
Fuel capacity	1.000	.738
Fuel efficiency	1.000	.705
Log-transformed sales	1.000	.692

Source: applying original data (IBM) based on the SPSS statistical program

Table (4) shows the amount of prevalence of the studied variables, and the closer its value is to the correct one, this is indication of the effect of the variables on the phenomenon (which explains the effect of the variable on the studied phenomenon)

Table 5 Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.047	50.390	50.390	6.047	50.390	50.390	5.618	46.821	46.821
2	3.058	25.484	75.874	3.058	25.484	75.874	3.486	29.053	**75.874**
3	.913	7.608	83.482						
4	.640	5.332	88.813						
5	.432	3.596	92.410						
6	.265	2.204	94.614						
7	.235	1.960	96.574						
8	.139	1.161	97.735						
9	.111	.928	98.663						
10	.088	.731	99.394						
11	.051	.423	99.817						
12	.022	.183	100.000						

Source: applying original data (IBM) based on the SPSS statistical program

Table (5) illustrates the interpretation of the total of the extracted components, where (2) main components were extracted, which together explain (**75.874** %) of the total variance, depending on the root characteristic of the components that is greater than one the correct. For illustration, the first component explains the total variance by (46.821%), which is the highest explanation of the total variance. And the last (second) component, which explains (29.053%) of the total variance.

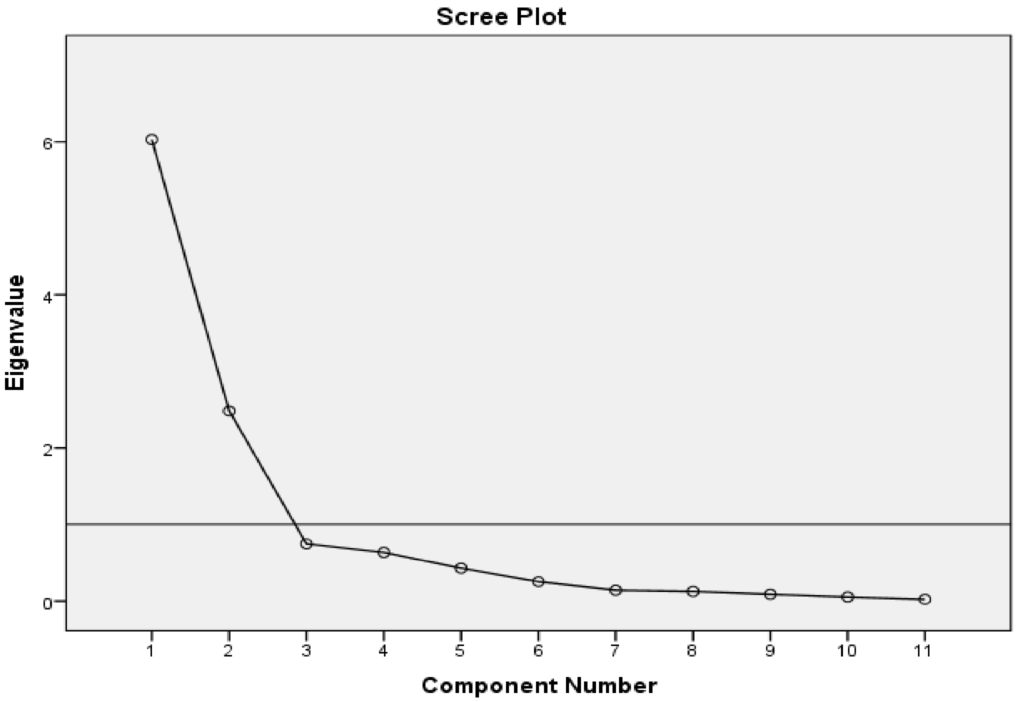

Figure 1 Scree Plot

Figure 1 shows that (2) components were extracted from a total of (11) components, and the components that are taken into account and the components that $\lambda > 1$ that are neglected, because the value of (Eigen value) $\lambda < 1$ for them is between (1-0), meaning that their interpretation of the total variance is small, i.e. (they have little effect on the phenomenon)

Table 6 Component Matrix

	Component	
	1	2
Curb weight	.913	
Engine size	.883	
Fuel efficiency	-.839	
Fuel capacity	.836	
Horsepower	.815	-.416
Width	.795	.315
Length	.704	.492
Price in thousands	.692	-.618
Wheelbase	.641	.636
Log-transformed sales		.819
Sales in thousands		.726
4-year resale value	.571	-.695

Source: applying original data (IBM) based on the SPSS statistical program

Table (6) illustrates the extracted components matrix, which is (2) components, and the matrix represents the degree of relationship each variable has between the studied variables and main components, i.e the numbers in the matrix represent (the load) a large load (we have taken greater than (0.5) into consideration has an effect on the component that is located in it

Table 7 Rotated component matrix

	Component	
	1	2
Curb weight	.905	0.3<
Width	.855	
Fuel capacity	.849	
Length	.838	
Wheelbase	.834	-.346
Fuel efficiency	-.788	
Engine size	.775	.437
4-year resale value		.860
Price in thousands	.406	.834
Log-transformed sales		-.813
Horsepower	.597	.694
Sales in thousands	.329	-.649

Rotation converged in 3 iterations (Source: applying original data (IBM) based on the SPSS statistical program)

Table (7) shows the rotated factor loadings (factor pattern matrix), which represent both how the variables are weighted for each factor but also the correlation between the variables and the factor. Because these are correlations, possible values range from -1 to +1. On the format subcommand, we used the option blank **(0.30)**, which tells SPSS not to print any of the correlations that are .3 or less.

First Component includes (curb weight, width, fuel capacity, length, wheelbase, fuel efficiency, engine size, horsepower, and sales in thousands).

Second Component includes (wheelbase, Engine size, 4-year resale value, price in thousands, log- transformed sales, Horsepower and Sales in thousands)

5.Conclusion

1-Using Automobiles are the most popular than trucks according to the study.

2-The average of length and horsepower are more attractive for drives to purchase for any types of cars

3-The value of KMO is greater than 0.5 that means this model is suitable for Adequacy sampling model.

4- Bartlett's Test of Sphericity is used for goodness of fit (chi-square) because the value is smaller than the value of chi-square that means is high significant, tests the null hypothesis that the correlation matrix is an identity matrix.

5- The result indicates that the first and second factors (75.874%) together represent the total variances in the model, which uses appropriate sampling and contains two components in total with up to 12 variables added.

6-First Component includes (curb weight, width, fuel capacity, length, wheelbase, fuel efficiency, engine size, horsepower, and sales in thousands).

Second Component includes (wheelbase, Engine size, 4-year resale value, price in thousands, log- transformed sales, Horsepower and Sales in thousands), because of the correlations between variables are bigger than 0.30.
7- The main two components include (Wheelbase, Engine size, Price in thousands, Horsepower, and Sales in thousands), after rotation converged in 3 iterations.

6.Recommandation

The recommendations can be summarized as follow:
1-The important of applying Principal components Analysis to determine the most important variables that lead to the phenomenon of inflation.
2-I recommended that for this study, drives can use more automobiles than truck, it is more comfortable for divers.

3- If you want to buy any cars, make sure on (Wheelbase, Engine size, Price in thousands, Horsepower, and Sales in thousands) of cars.
4- If data stored in time, you can use principal component analyses with time series to select the best model.

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Appendices

Original data from Company (IBM) for car-sales (Part One)

No.	Sales	Resale	Type	Price	Engine-size	Horse power	Wheelbase
1	16.919	16.36	Automobile	21.5	1.8	140	101.2
2	39.384	19.875	Automobile	28.4	3.2	225	108.1
3	14.114	18.225	Automobile		3.2	225	106.9
4	8.588	29.725	Automobile	42	3.5	210	114.6
5	20.397	22.255	Automobile	23.99	1.8	150	102.6
6	18.78	23.555	Automobile	33.95	2.8	200	108.7
7	1.38	39	Automobile	62	4.2	310	113
8	19.747	0	Automobile	26.99	2.5	170	107.3
9	9.231	28.675	Automobile	33.4	2.8	193	107.3
10	17.527	36.125	Automobile	38.9	2.8	193	111.4
11	91.561	12.475	Automobile	21.975	3.1	175	109
12	39.35	13.74	Automobile	25.3	3.8	240	109
13	27.851	20.19	Automobile	31.965	3.8	205	113.8
14	83.257	13.36	Automobile	27.885	3.8	205	112.2
15	63.729	22.525	Automobile	39.895	4.6	275	115.3
16	15.943	27.1	Automobile	44.475	4.6	275	112.2
17	6.536	25.725	Automobile	39.665	4.6	275	108
18	11.185	18.225	Automobile	31.01	3	200	107.4
19	14.785	0	Truck	46.225	5.7	255	117.5
20	145.519	9.25	Automobile	13.26	2.2	115	104.1
21	135.126	11.225	Automobile	16.535	3.1	170	107
22	24.629	10.31	Automobile	18.89	3.1	175	107.5
23	42.593	11.525	Automobile	19.39	3.4	180	110.5
24	26.402	13.025	Automobile	24.34	3.8	200	101.1
25	17.947	36.225	Automobile	45.705	5.7	345	104.5
26	32.299	9.125	Automobile	13.96	1.8	120	97.1
27	21.855	5.16	Automobile	9.235	1	55	93.1
28	107.995	0	Automobile	18.89	3.4	180	110.5
29	7.854	12.36	Automobile	19.84	2.5	163	103.7
30	32.775	14.18	Automobile	24.495	2.5	168	106
31	31.148	13.725	Automobile	22.245	2.7	200	113
32	32.306	12.64	Automobile	16.48	2	132	108
33	13.462	17.325	Automobile	28.34	3.5	253	113
34	53.48	19.54	Truck	0	0	0	0
35	30.696		Automobile	29.185	3.5	253	113
36	76.034	7.75	Automobile	12.64	2	132	105
37	4.734	12.545	Automobile	19.045	2.5	163	103.7
38	71.186	10.185	Automobile	20.23	2.5	168	108
39	88.028	12.275	Automobile	22.505	2.7	202	113
40	0.916	58.47	Automobile	69.725	8	450	96.2
41	227.061	15.06	Truck	19.46	5.2	230	138.7
42	16.767	15.51	Truck	21.315	3.9	175	109.6
43	31.038	13.425	Truck	18.575	3.9	175	127.2
44	111.313	11.26	Truck	16.98	2.5	120	131
45	101.323	0	Truck	26.31	5.2	230	115.7
46	181.749	12.025	Truck	19.565	2.4	150	113.3
47	70.227	7.425	Automobile	12.07	2	110	98.4
48	113.369	12.76	Automobile	21.56	3.8	190	101.3
49	35.068	8.835	Automobile	17.035	2.5	170	106.5
50	245.815	10.055	Automobile	17.885	3	155	108.5

51	175.67	0	Automobile	12.315	2	107	103
52	63.403	14.21	Automobile	22.195	4.6	200	114.7
53	276.747	16.64	Truck	31.93	4	210	111.6
54	155.787	13.175	Truck	21.41	3	150	120.7
55	125.338	23.575	Truck	36.135	4.6	240	119
56	220.65	7.85	Truck	12.05	2.5	119	117.5
57	540.561	15.075	Truck	26.935	4.6	220	138.5
58	199.685	9.85	Automobile	12.885	1.6	106	103.2
59	230.902	13.21	Automobile	15.35	2.3	135	106.9
60	73.203	17.71	Truck	20.55	2	146	103.2
61	12.855	17.525	Truck	26.6	3.2	205	106.4
62	76.029	19.49	Truck	26	3.5	210	118.1
63	41.184	5.86	Automobile	9.699	1.5	92	96.1
64	66.692	7.825	Automobile	11.799	2	140	100.4
65	29.45	8.91	Automobile	14.999	2.4	148	106.3
66	23.713	19.69	Automobile	29.465	3	227	108.3
67	15.467		Automobile	42.8	3	240	114.5
68	55.557	13.475	Truck	14.46	2.5	120	93.4
69	80.556	13.775	Truck	21.62	4	190	101.4
70	157.04	18.81	Truck	26.895	4	195	105.9
71	24.072	26.975	Automobile	31.505	3	210	105.1
72	12.698	32.075	Automobile	37.805	3	225	110.2
73	3.334	0	Automobile	46.305	4	300	110.2
74	6.375	40.375	Automobile	54.005	4	290	112.2
75	9.126	0	Truck	60.105	4.7	230	112.2
76	51.238	0	Truck	34.605	3	220	103
77	13.798	20.525	Automobile	39.08	4.6	275	109
78	48.911	21.725	Automobile	43.33	4.6	215	117.7
79	22.925	0	Truck	42.66	5.4	300	119
80	26.232	8.325	Automobile	13.987	1.8	113	98.4
81	42.541	10.395	Automobile	19.047	2.4	154	100.8
82	55.616	10.595	Automobile	17.357	2.4	145	103.7
83	5.711	16.575	Automobile	24.997	3.5	210	107.1
84	0.11	20.94	Automobile	25.45	3	161	97.2
85	11.337	19.125	Truck	31.807	3.5	200	107.3
86	39.348	13.88	Truck	22.527	3	173	107.3
87	14.351	8.8	Automobile	16.24	2	125	106.5
88	26.529	13.89	Automobile	16.54	2	125	106.4
89	67.956	11.03	Automobile	19.035	3	153	108.5
90	81.174	14.875	Automobile	22.605	4.6	200	114.7
91	27.609	20.43	Truck	27.56	4	210	111.6
92	20.38	14.795	Truck	22.51	3.3	170	112.2
93	18.392	26.05	Automobile	31.75	2.3	185	105.9
94	27.602	41.45	Automobile	49.9	3.2	221	111.5
95	16.774	50.375	Automobile	69.7	4.3	275	121.5
96	3.311	58.6	Automobile	82.6	5	302	99
97	7.998	0	Automobile	38.9	2.3	190	94.5
98	1.526	0	Automobile	41	2.3	185	94.5
99	11.592	0	Automobile	41.6	3.2	215	105.9
100	0.954	0	Automobile	85.5	5	302	113.6
101	28.976	0	Truck	35.3	3.2	215	111
102	42.643	8.45	Automobile	13.499	1.8	126	99.8
103	88.094	11.295	Automobile	20.39	2.4	155	103.1
104	79.853	15.125	Automobile	26.249	3	222	108.3

105	27.308	15.38	Truck	26.399	3.3	170	112.2
106	42.574	17.81	Truck	29.299	3.3	170	106.3
107	54.158	0	Truck	22.799	3.3	170	104.3
108	65.005	0	Truck	17.89	3.3	170	116.1
109	1.112	11.24	Automobile	18.145	3.1	150	107
110	38.554	0	Automobile	24.15	3.5	215	109
111	80.255	0	Automobile	18.27	2.4	150	107
112	14.69	19.89	Automobile	36.229	4	250	113.8
113	20.017	19.925	Truck	31.598	4.3	190	107
114	24.361	15.24	Truck	25.345	3.4	185	120
115	32.734	7.75	Automobile	12.64	2	132	105
116	5.24	9.8	Automobile	16.08	2	132	108
117	24.155	12.025	Truck	18.85	2.4	150	113.3
118	1.872	0	Automobile	43	3.5	253	113.3
119	51.645	13.79	Automobile	21.61	2.4	150	104.1
120	131.097	10.29	Automobile	19.72	3.4	175	107
121	19.911	17.805	Automobile	25.31	3.8	200	101.1
122	92.364	14.01	Automobile	21.665	3.8	195	110.5
123	35.945	13.225	Automobile	23.755	3.8	205	112.2
124	39.572	0	Truck	25.635	3.4	185	120
125	8.982	41.25	Automobile	41.43	2.7	217	95.2
126	1.28	60.625	Automobile	71.02	3.4	300	92.6
127	1.866	67.55	Automobile	74.97	3.4	300	92.6
128	9.191	0	Automobile	33.12	2.3	170	106.4
129	12.115	0	Automobile	26.1	2	185	102.6
130	80.62	9.2	Automobile	10.685	1.9	100	102.4
131	24.546	10.59	Automobile	12.535	1.9	100	102.4
132	5.223	10.79	Automobile	14.29	1.9	124	102.4
133	8.472	0	Automobile	18.835	2.2	137	106.5
134	49.989	0	Automobile	15.01	2.2	137	106.5
135	47.107	0	Automobile	22.695	2.5	165	103.5
136	33.028	0	Truck	20.095	2.5	165	99.4
137	142.535	10.025	Automobile	13.108	1.8	120	97
138	247.994	13.245	Automobile	17.518	2.2	133	105.2
139	63.849	18.14	Automobile	25.545	3	210	107.1
140	33.269	15.445	Automobile	16.875	1.8	140	102.4
141	84.087	9.575	Truck	11.528	2.4	142	103.3
142	65.119	0	Truck	22.368	3	194	114.2
143	25.106	13.325	Truck	16.888	2	127	94.9
144	68.411	19.425	Truck	22.288	2.7	150	105.3
145	9.835	34.08	Truck	51.728	4.7	230	112.2
146	9.761	11.425	Automobile	14.9	2	115	98.9
147	83.721	13.24	Automobile	16.7	2	115	98.9
148	51.102	16.725	Automobile	21.2	1.8	150	106.4
149	9.569	16.575	Automobile	19.99	2	115	97.4
150	5.596	13.76	Automobile	17.5	2	115	98.9
151	49.463	0	Automobile	15.9	2	115	98.9
152	16.957	0	Automobile	23.4	1.9	160	100.5
153	3.545	0	Automobile	24.4	1.9	160	100.5
154	15.245	0	Automobile	27.5	2.4	168	104.9
155	17.531	0	Automobile	28.8	2.4	168	104.9
156	3.493	0	Automobile	45.5	2.3	236	104.9
157	18.969	0	Automobile	36	2.9	201	109.9

Original data from Company (IBM) for car-sales (Part Two)

No.	Width	Curb-weight	Length	Fuel-cap	Mpg	Manufact
1	67.3	2.639	172.4	13.2	28	Acura
2	70.3	3.517	192.9	17.2	25	Acura
3	70.6	3.47	192	17.2	26	Acura
4	71.4	3.85	196.6	18	22	Acura
5	68.2	2.998	178	16.4	27	Audi
6	76.1	3.561	192	18.5	22	Audi
7	74	3.902	198.2	23.7	21	Audi
8	68.4	3.179	176	16.6	26	BMW
9	68.5	3.197	176	16.6	24	BMW
10	70.9	3.472	188	18.5	25	BMW
11	72.7	3.368	194.6	17.5	25	Buick
12	72.7	3.543	196.2	17.5	23	Buick
13	74.7	3.778	206.8	18.5	24	Buick
14	73.5	3.591	200	17.5	25	Buick
15	74.5	3.978	207.2	18.5	22	Cadillac
16	75	0	201	18.5	22	Cadillac
17	75.5	3.843	200.6	19	22	Cadillac
18	70.3	3.77	194.8	18	22	Cadillac
19	77	5.572	201.2	30	15	Cadillac
20	67.9	2.676	180.9	14.3	27	Chevrolet
21	69.4	3.051	190.4	15	25	Chevrolet
22	72.5	3.33	200.9	16.6	25	Chevrolet
23	72.7	3.34	197.9	17	27	Chevrolet
24	74.1	3.5	193.2	16.8	25	Chevrolet
25	73.6	3.21	179.7	19.1	22	Chevrolet
26	66.7	2.398	174.3	13.2	33	Chevrolet
27	62.6	1.895	149.4	10.3	45	Chevrolet
28	73	3.389	200	17	27	Chevrolet
29	69.7	2.967	190.9	15.9	24	Chrysler
30	69.2	3.332	193	16	24	Chrysler
31	74.4	3.452	209.1	17	26	Chrysler
32	71	2.911	186	16	27	Chrysler
33	74.4	3.564	207.7	17	23	Chrysler
34	0	0	0	0	0	Chrysler
35	74.4	3.567	197.8	17	23	Chrysler
36	74.4	2.567	174.4	12.5	29	Dodge
37	69.1	2.879	190.2	15.9	24	Dodge
38	71	3.058	186	16	24	Dodge
39	74.7	3.489	203.7	17		Dodge
40	75.7	3.375	176.7	19	16	Dodge
41	79.3	4.47	224.2	26	17	Dodge
42	78.8	4.245	192.6	32	15	Dodge
43	78.8	4.298	208.5	32	16	Dodge
44	71.5	3.557	215	22	19	Dodge
45	71.7	4.394	193.5	25	17	Dodge
46	76.8	3.533	186.3	20	24	Dodge
47	67	2.468	174.7	12.7	30	Ford
48	73.1	3.203	183.2	15.7	24	Ford
49	69.1	2.769	184.6	15	25	Ford
50	73	3.368	197.6	16	24	Ford

51	66.9	2.564	174.8	13.2	30	Ford
52	78.2	3.908	212	19	21	Ford
53	70.2	3.876	190.7	21	19	Ford
54	76.6	3.761	200.9	26	21	Ford
55	78.7	4.808	204.6	26	16	Ford
56	69.4	3.086	200.7	20	23	Ford
57	79.1	4.241	224.5	25.1	18	Ford
58	67.1	2.339	175.1	11.9	32	Honda
59	70.3	2.932	188.8	17.1	27	Honda
60	68.9	3.219	177.6	15.3	24	Honda
61	70.4	3.857	178.2	21.1	19	Honda
62	75.6	4.288	201.2	20	23	Honda
63	65.7	2.24	166.7	11.9	31	Hyundai
64	66.9	2.626	174	14.5	27	Hyundai
65	71.6	3.072	185.4	17.2	25	Hyundai
66	70.2	3.342	193.7	18.5	25	Infiniti
67	71.6	3.65	191.3	18.4	21	Jaguar
68	66.7	3.045	152	19	17	Jeep
69	69.4	3.194	167.5	20	20	Jeep
70	72.3	3.88	181.5	20.5	19	Jeep
71	70.5	3.373	190.2	18.5	23	Lexus
72	70.9	3.638	189.2	19.8	23	Lexus
73	70.9	3.693	189.2	19.8	21	Lexus
74	72	3.89	196.7	22.5	22	Lexus
75	76.4	5.401	192.5	25.4	15	Lexus
76	71.5	3.9	180.1	17.2	21	Lexus
77	73.6	3.868	208.5	20	22	Lincoln
78	78.2	4.121	215.3	19	21	Lincoln
79	79.9	5.393	204.8	30	15	Lincoln
80	66.5	2.25	173.6	13.2	30	Mitsubishi
81	68.9	2.91	175.4	15.9	24	Mitsubishi
82	68.5	2.945	187.8	16.3	25	Mitsubishi
83	70.3	3.443	194.1	19	22	Mitsubishi
84	72.4	3.131	180.3	19.8	21	Mitsubishi
85	69.9	4.52	186.6	24.3	18	Mitsubishi
86	66.7	3.51	178.3	19.5	20	Mitsubishi
87	69.1	2.769	184.8	15	28	Mercury
88	69.6	2.892	185	16	30	Mercury
89	73	3.379	199.7	16	24	Mercury
90	78.2	3.958	212	19	21	Mercury
91	70.2	3.876	190.1	21	18	Mercury
92	74.9	3.944	194.7	20	21	Mercury
93	67.7	3.25	177.4	16.4	26	Mercedes-Benz
94	70.8	3.823	189.4	21.1	25	Mercedes-Benz
95	73.1	4.133	203.1	23.2	21	Mercedes-Benz
96	71.3	4.125	177.1	21.1	20	Mercedes-Benz
97	67.5	3.055	157.9	15.9	26	Mercedes-Benz
98	67.5	2.975	157.3	14	27	Mercedes-Benz
99	67.8	3.213	180.3	16.4	26	Mercedes-Benz
100	73.1	4.115	196.6	23.2	20	Mercedes-Benz
101	72.2	4.387	180.6	19	20	Mercedes-Benz
102	67.3	2.593	177.5	13.2	30	Nissan

103	69.1	3.012	183.5	15.9	25	Nissan
104	70.3	3.294	190.5	18.5	25	Nissan
105	74.9	3.991	194.8	20	21	Nissan
106	71.7	3.947	182.6	21	19	Nissan
107	70.4	3.821	178	19.4	18	Nissan
108	66.5	3.217	196.1	19.4	18	Nissan
109	69.4	3.102	192	15.2	25	Oldsmobile
110	73.6	3.455	195.9	18		Oldsmobile
111	70.1	2.958	186.7	15	27	Oldsmobile
112	74.4	3.967	205.4	18.5	22	Oldsmobile
113	67.8	4.068	181.2	17.5	19	Oldsmobile
114	72.2	3.948	201.4	25	22	Oldsmobile
115	74.4	2.559	174.4	12.5	29	Plymouth
116	71	2.942	186.3	16	27	Plymouth
117	76.8	3.528	186.3	20	24	Plymouth
118	76.3	2.85	165.4	12	21	Plymouth
119	68.4	2.906	181.9	15	27	Pontiac
120	70.4	3.091	186.3	15.2	25	Pontiac
121	74.5	3.492	193.4	16.8	25	Pontiac
122	72.7	3.396	196.5	18	25	Pontiac
123	72.6	3.59	202.5	17.5	24	Pontiac
124	72.7	3.942	201.3	25	23	Pontiac
125	70.1	2.778	171	17	22	Porsche
126	69.5	3.032	174.5	17	21	Porsche
127	69.5	3.075	174.5	17	23	Porsche
128	70.6	3.28	189.2	18.5	23	Saab
129	67.4	2.99	182.2	16.9	23	Saab
130	66.4	2.332	176.9	12.1	33	Saturn
131	66.4	2.367	180	12.1	33	Saturn
132	66.4	2.452	176.9	12.1	31	Saturn
133	69	3.075	190.4	13.1	27	Saturn
134	69	2.91	190.4	13.1	28	Saturn
135	67.5	3.415	185.8	16.9	25	Subaru
136	68.3	3.125	175.2	15.9	24	Subaru
137	66.7	2.42	174	13.2	33	Toyota
138	70.1	2.998	188.5	18.5	27	Toyota
139	71.7	3.417	191.9	18.5	26	Toyota
140	68.3	2.425	170.5	14.5	31	Toyota
141	66.5	2.58	178.7	15.1	23	Toyota
142	73.4	3.759	193.5	20.9	22	Toyota
143	66.7	2.668	163.8	15.3	27	Toyota
144	66.5	3.44	183.3	18.5	23	Toyota
145	76.4	5.115	192.5	25.4	15	Toyota
146	68.3	2.767	163.3	14.5	26	Volkswagen
147	68.3	2.853	172.3	14.5	26	Volkswagen
148	68.5	3.043	184.1	16.4	27	Volkswagen
149	66.7	3.079	160.4	13.7	26	Volkswagen
150	68.3	2.762	163.3	14.6	26	Volkswagen

151	67.9	2.769	161.1	14.5	26	Volkswagen
152	67.6	2.998	176.6	15.8	25	Volvo
153	67.6	3.042	176.6	15.8	25	Volvo
154	69.3	3.208	185.9	17.9	25	Volvo
155	69.3	3.259	186.2	17.9	25	Volvo
156	71.5	3.601	185.7	18.5	23	Volvo
157	72.1	3.6	189.8	21.1	24	Volvo

تطبيق تحليل المكونات الرئيسية على مبيعات السيارات: دراسة حالة شركة IBM

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ملخص

يعد تحليل المكون الرئيسي (PCA) تقنية إحصائية أساسية تستخدم لتقليل الأبعاد وتحويل البيانات. يقدم نظرة عامة على مبادئ PCA ومنهجه وتطبيقاته. يهدف PCA إلى التقاط المعلومات الأكثر أهمية في البيانات ذات الأبعاد العالية من خلال تحويلها إلى نظام إحداثيات جديد يعرف بمكوناته الرئيسية. هذه المكونات هي تركيبات خطية للمتغيرات الأصلية، مرتبة حسب كمية التباين التي تفسرها. تم أخذ البيانات من بيانات أصلية لشركة (IBM) حول مبيعات السيارات. ووفقًا لمثال حقيقي في العالم الحقيقي، تعتمد مبيعات السيارات على (نوع السيارة، مبيعات بالآلاف، قيمة إعادة البيع لمدة 4 سنوات، السعر بالآلاف، حجم المحرك، القوة الحصانية، قاعدة العجلات، العرض والطول، وزن السيارة، سعة الوقود، استهلاك الوقود والبيع المحول), تم التحليل هذه البيانات باستخدام البرنامج الاحصائي الشهير (SPSS). وتشير النتيجة إلى أن العاملين الأول والثاني (قاعدة العجلات ، حجم المحرك ، السعر بالآلاف ، القدرة بالحصان ، والمبيعات بالآلاف) تمثلان معًا الفروق الإجمالية (75.874٪) في النموذج ، والذي يستخدم أخذ العينات المناسب ويحتوي على مكونين إجمالاً مع إضافة ما يصل إلى 12 متغيراً. من المستحسن أن يكون لدى السائقين سيارات أكثر راحة لمختلف أنواع السيارات (قاعدة عجلات ذات قوة حصانية عالية ، وحجم المحرك ، والسعر بالآلاف ، وقوة حصان ، والمبيعات بالآلاف) من السيارات.

الكلمات مفتاحية: تحليل المكونات الرئيسية, التحميل , تحليل العوامل, الدوران, Varimax .

بەکارهێنانی شیکاری پێکهاتە سەرەکییەکان بۆ فرۆشتنی ئۆتۆمبێل: توێژینەوەی کەیس لە کۆمپانیایIBM

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پوختە

شیکاری پێکهاتەی سەرەکی (PCA) تەکنیکێکی ئاماری بنەڕەتییە کە بەکاردێت بۆ کەمکردنەوەی ڕەهەند وگۆڕینی داتا وە تێڕوانینێکی گشتی لە بنەماکانی شیکاری PCA و بەکارهێنانەکانی دەدات. ئامانجی PCA گرنگترین زانیارییە لە داتا ڕەهەندە بەرزەکاندا بە گۆڕینی بۆ سیستەمێکی نوێی ڕێکخستن کە بە پێکهاتە سەرەکییەکانی ناسراوە. ئەم پێکهاتانە پێکهاتەی هێڵی گۆڕاوە بنچینەکانن بەپێی بڕی جیاوازی ڕووندەکرێنەوەو ڕێکدەخرێن بە هێشتنەوەی بەشێک لەم پێکهاتانە. داتاکان لە داتا ڕەسەنەکانی کۆمپانیای IBM سەبارەت بە فرۆشتنی ئۆتۆمبێل وەرگیراون. بەگوێرەی نموونەیەکی جیهانی ڕاستەقینە، گۆڕاوەکانی داتای فرۆشتنی ئۆتۆمبێل کە لەو توێژینەوەیە بەکار هاتوون بریتین لە (جۆری ئۆتۆمبێل، فرۆشتن بە هەزاران، بەهای دووبارە فرۆشتنەوەی 4 ساڵ، نرخ بە هەزاران، قەبارەی بزوێنەر، هێزی ئەسپ، ویلبایس، پانی و درێژی، کێشی ئۆتۆمبێل، توانای سووتەمەنی، بەکارهێنانی سووتەمەنی و گۆڕینی فرۆشتن). کە ژمارەیان (١٢) دوازدە گۆڕاوە و بە بەکارهێنانی بەرنامەی ئاماری بەناوبانگ (SPSS) شیکراونەتەوە. ئەنجامەکە ئاماژە بەوە دەکات کە فاکتەری چوارەم و شەشەم و هەشتەم و دەیەم و یازدەهەم (فرۆشتن بە هەزاران و توانای سووتەمەنی ویلبایس و هێزی ئەسپ و نرخ بە هەزاران) ئۆتۆمبیل پێکەوە نوێنەرایەتی کۆی جیاوازییەکانی (75.874%) ناو مۆدێلەکە دەکەن، کە نمونەگرتنی گونجاو بەکاردەهێنێت و دوو پێکهاتە بە گشتی لەخۆدەگرێت بەشیکار کردنی ١٢ گۆڕاو. وە پێشنیار دەکەم کە شۆفێران ئەو ئۆتۆمبێلانە بەکاربهێنن کە خاوەن توانای هێزی ئەسپیان بەرزەو فرۆشتن بە هەزاران و توانای سووتەمەنی ویلبایس و نرخ بە هەزاران.

وشە سەرەکییەکان: شیکاری پێکهاتەی سەرەکی ، بارکردن، شیکاری فاکتۆر، خولانەوەی، Varimax .