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Using Principal Component Analysis to support students' performance prediction and data analysis

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Outline

- Introduction/Motivation
- Proposed method
- Experimental results
- Conclusion

Introduction/Motivation

Introduction

- Educational Data Mining (EDM) has emerged with techniques and strategies to process, interpret and obtain useful and implicit knowledge on educational data

- Several EDM tasks have been explored by the EDM community [1]:
  - Students' performances prediction
  - Students' drop-out rates
  - Learning achievements

[1] BAKER, Ryan Shaun; INVENTADO, Paul Salvador. Educational data mining and learning analytics. In: Learning analytics. Springer, New York, NY, 2014. p. 61-75.

Problem description

- Educational datasets can present several attributes, denoting high dimensionality
- Generally, state-of-art EDM methods deal with high dimensional data by:
  - Removing manually data attributes
  - Automatically selecting the relevant attributes [2]
- Another possibility refers to the dimensionality reduction by attribute transformation
  - It is not well-explored in EDM tasks

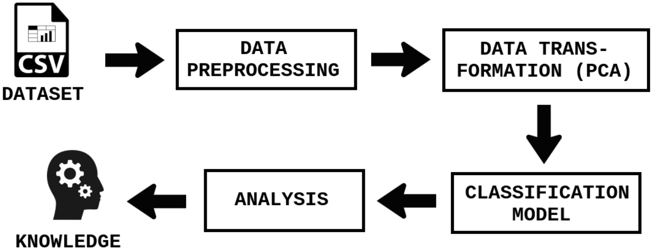
[2] BARADWAJ, Brijesh Kumar; PAL, Saurabh. Mining educational data to analyze students' performance. arXiv preprint arXiv:1201.3417, 2012.

Problem description

- A well-known technique for data transformation is Principal component analysis (PCA)
- PCA is a technique that can be simultaneously useful for:
  - Dimensionality reduction
  - Data analysis
- Succesfully applied in other knowledge domains

Proposed method

Proposed method



Dataset

- Data describes student achievements in secondary education of two Portuguese schools [3]
- Studens are described according to scholar, financial, social and personal attributes (33)
  - The first dataset (Dataset I) contains 649 students of the Portuguese subject
  - The second dataset (Dataset II) refers to final achievements of 394 students in the Math subject;

[3] CORTEZ, Paulo; SILVA, Alice Maria Gonçalves. Using data mining to predict secondary school student performance. 2008.

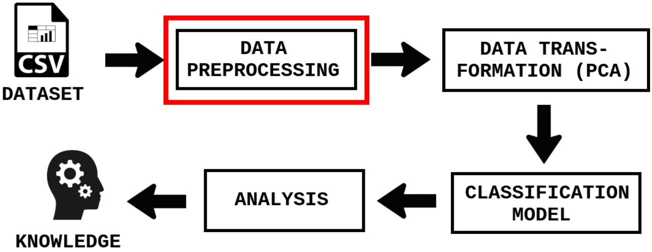
Dataset

- Scholar attributes
  - Midterms exams grades (G1 and G2)
  - Final exam grade (G3)
  - Past failures
  - Absences
- Personal attributes
  - Daily and weekly alcohol consumption
  - free time
  - romantic relationship
  - wants to take higher education (higher)

Dataset

- Familiar attributes
  - Mother and father education
  - Mother and father jobs
  - Student's guardian
- Other attributes
  - Travel time to school (in hours)
  - Address
  - Age, genre...

Proposed method



Preprocessing

- Transform categorical attributes to dummy variables [4]
- Obtain the categorical values $\{v_1, ..., v_k\}$ of an attribute A_i

Attribute i
A
B
B
C
A

[4] LEBART, Ludovic. Correspondence analysis. In: Data Science, Classification, and Related Methods: Proceedings of the Fifth Conference of the International Federation of Classification Societies (IFCS-96), Kobe, Japan, 1996. Springer Science & Business Media, 2013. p. 423.

Preprocessing

- Transform categorical attributes to dummy variables
- Create a new attribute $A_i = v_j$ for each categorical value v_j of A_i

Attribute i	**Attribute i =** A
A	1
B	0
B	0
C	0
A	1

Preprocessing

- Transform categorical attributes to dummy variables

Attribute i	Attribute i = *A*
A	1
B	0
B	0
C	0
A	1

- Transform categorical attributes to dummy variables

Attribute i	**Attribute i =** *A*	**Attribute i =** *B*
A	1	0
B	0	1
B	0	1
C	0	0
A	1	0

Preprocessing

- Transform categorical attributes to dummy variables

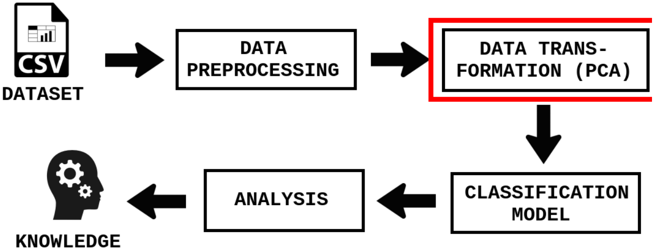
Attribute i	**Attribute i =** *A*	**Attribute i =** *B*
A	1	0
B	0	1
B	0	1
C	0	0
A	1	0

Preprocessing

- Final preprocessing result

Attribute i = A	**Attribute i =** B	**Attribute i =** C
1	0	0
0	1	0
0	1	0
0	0	1
1	0	0

Proposed method

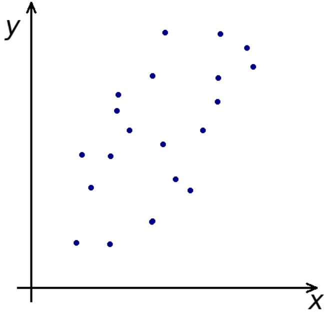


Data transformation

- Principal component analysis (PCA) [5]
- PCA performs a linear mapping of the data in a high dimensional space to a lower-dimensional space
  - so that data's variance is maximized

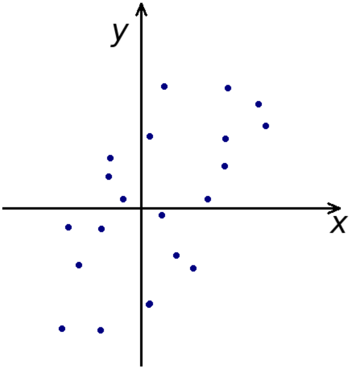
[5] JOLLIFFE, Ian. Principal component analysis. In: International encyclopedia of statistical science. Springer, Berlin, Heidelberg, 2011. p. 1094-1096.

- Consider the following dataset $\mathbf{X} = \{\mathbf{x}_1, ..., \mathbf{x}_N\}$, in which $\mathbf{x}_i = \{x_i, y_i\}$:



- 1. Center the data instances $\mathbf{x}_i$ in relation to the mean μ:

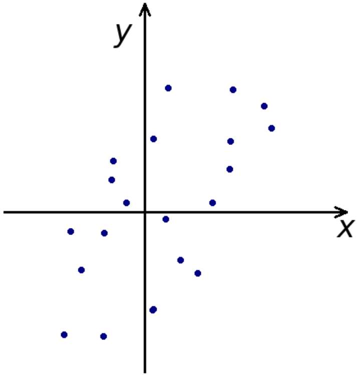
$$z_i = \mathbf{x}_i - \mu \tag{1}$$



Principal component analysis

- 2. Compute the covariance matrix Σ for centered data $Z = \{z_1, ..., z_N\}$:

$$\Sigma = Z^T Z \tag{2}$$



$$\Sigma = \begin{bmatrix} \sigma_x^2 & \sigma_x \sigma_y \\ \sigma_x \sigma_y & \sigma_y^2 \end{bmatrix}$$

- 3. From the decomposition of Compute the covariance matrix Σ such as

$$\Sigma = \mathbf{V} A \mathbf{V}^{-1} \tag{3}$$

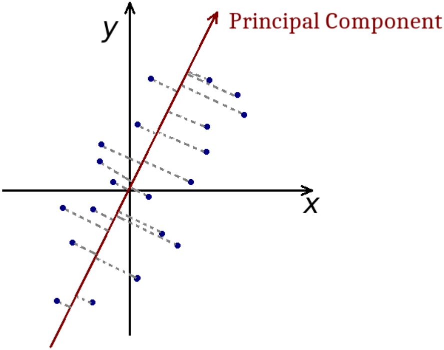
- obtain:
  - the eigenvalues $\lambda = \{\lambda_1, ..., \lambda_D\}$
  - the eigenvectors $\mathbf{V} = \{\mathbf{v_1}, ..., \mathbf{v_D}\}$
- The eigenvalues on the diagonal of A correspond the columns in $\mathbf{V}$

Principal component analysis

- Sort the eigenvalues in descending order;
- Select the k eigenvectors associated to the k largest eigenvalues
  - k is the number of dimensions of low-dimensional space (reduced space)
- Each eigenvector is associated to a principal component (PC)

Principal component analysis

- Generation of a principal component (the eigenvector associated to the higher eigenvalue):

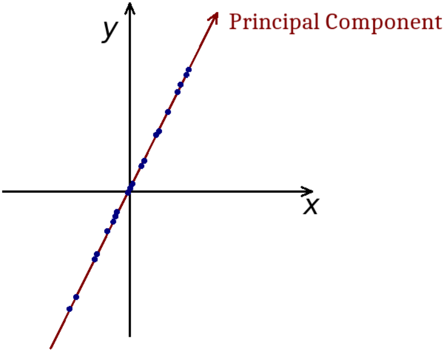


Principal component analysis

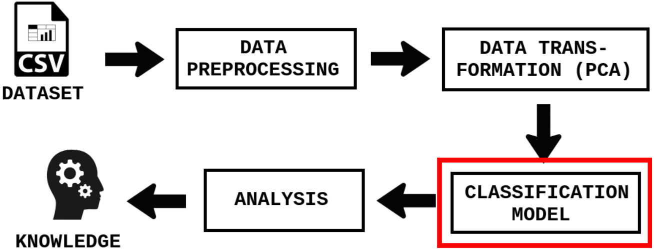
- Transforming original data $\mathbf{x}_i = \{x_{i,1}, ..., x_{i,D}\}$ to the principal component values

$$PC_l = c_{l,1}x_1 + c_{1,2}x_2 + ... + c_{1,D}x_D \tag{4}$$

in which $c_{l,j}$ is a coefficient of PC_l



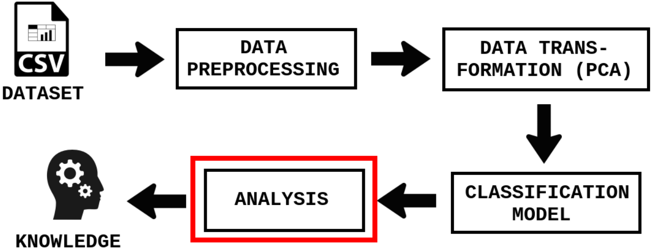
Proposed method



Classification

- The prediction of students' performances is deal as a classification problem
  - predicts if a student is approved or fail at the end of the scholar year
- Support vector machines (SVM)
  - SVM was set using a Radial Basis Function (RBF)
  - RBF width set as 2.0
- Naive Bayes
  - Probabilistic classification model on the Bayes theorem

Proposed method



Experiments and results

Experiments and results

- Experiments were conducted uing the Weka 3.9.1 environment
  - Holdout cross-validation
  - 66% of data instances are used for training, while 34% are used for test
- F-Score is the evaluation measure:

$$F_1 = \frac{2 \times TP}{2 \times TP + FP + FN}. \tag{5}$$

- F1-Scores obtained by the SVM classifier

Dataset	High	2 PCs	5 PCs	10 PCs
Dataset I (Portuguese)	0.776	**0.893**	0.773	0.776
Dataset II (Math)	0.511	**0.790**	0.511	0.511

Experiments and results

- F1-Scores obtained by the Naive-Bayes classifier

Dataset	High	2 PC's	5 PC's	10 PC's
Dataset I (Portuguese)	0.930	**0.992**	0.883	0.895
Dataset II (Math)	0.849	**0.917**	0.909	0.915

- Coefficients of the two principal components for the Portuguese subject
- PC1: positive correlation and negative correlation

PC1	PC2
Midterm exam 1 (-0.3)	Daily alcohol cons.="1" (0.357)
Midterm exam 2 (-0.294)	Weekly alcohol cons.="1" (0.279)
Mother educ. = "4" (-0.259)	sex="M" (-0.265)
wants higher educ.="no" (0.222)	Weekly alcohol cons.="5" (-0.219)
Mother educ. = "1" (0.221)	Weekly alcohol cons.="4" (-0.216)

Experiments and results

- Top-5 coefficients of the two principal components for the Portuguese subject
- PC2: positive correlation and negative correlation

PC1	PC2
Midterm exam 1 (-0.3)	Daily alcohol cons. =“1” (0.357)
Midterm exam 2 (-0.294)	Weekly alcohol cons.=“1” (0.279)
Mother educ. = “4” (-0.259)	sex=“M” (-0.265)
wants higher educ. =“no” (0.222)	Weekly alcohol cons.=“5” (-0.219)
Mother educ. = “1” (0.221)	Weekly alcohol cons.=“4” (-0.216)

Discussion (Educational perspective)

- The midterm exams and the higher educational degree of mother:
  - Vary together in PC1, so higher PC1 values are associated to lower values of such attributes
  - Mother education is related to the students' performances on midterms

- Mother education also influences students when deciding to take higher education

- Frequent alcohol consumption is more related to male students
  - Such attributes vary together in PC2
  - Higher values for PC2 are associated to lower alcohol consumption

- Top-5 coefficients of the two principal components for the Math subject
- PC1: positive correlation and negative correlation

PC1	PC2
absences (-0.998)	Midterm exam 2 (-0.752)
age (-0.029)	Midterm exam 1 (-0.649)
Midterm exam 2 (0.024)	failures (0.058)
Weekly alcohol cons. (-0.023)	go out (0.04)
Midterm exam 1 (0.021)	absences (-0.034)

Experiments and results

- Top-5 coefficients of the two principal components for the Math subject
- PC2: positive correlation and negative correlation

PC1	PC2
absences (-0.998)	Midterm exam 2 (-0.752)
age (-0.029)	Midterm exam 1 (-0.649)
Midterm exam 2 (0.024)	failures (0.058)
Weekly alcohol cons. (-0.023)	goout (0.04)
Midterm exam 1 (0.021)	absences (-0.034)

Discussion (Educational perspective)

- The first component (PC1) is strongly affected by the students' absences
  - Higher values in PC1 denotes lower absences values
- The student's absences, age and weekly alcohol consumption vary together
- The midterms exams are strongly correlated to the second principal component
  - Higher values in PC2 are related to lower values of midterm exams

Conclusion

Conclusion

- Method based on PCA for students' performance prediction tasks:
  - Retained or improved the prediction F-Scores when compared to the high dimensional spaces
  - PCA results provided information for data analysis
- Limitations
  - Choose the number of principal components (k) to consider in the low dimensional space
- Future works
  - Use Brazilian educational datasets
  - Consider other classification models (Neural networks, decision trees) and visualization techniques

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