

A decorative graphic on the left side of the slide consisting of two overlapping parallelograms. The front one is blue and the back one is a light green color. They are positioned diagonally, with the blue one partially covering the green one.

Data Reduction Techniques

Diane DeOcampo - Data_607.001



What is Data Reduction?

Ch 12, pg 304 - Data Science for Business textbook

Data Reduction - A large/wide set of data and replace with a smaller set that preserves much of the important information

Also known as Dimensionality Reduction

Pros: easier to process, less resource extensive

Tradeoff: details in insight for manageability gained for the information lost



Data Reduction Technique: Missing Values Ratio

Determining data columns with too many missing values

Columns with missing data greater than a threshold can be removed

The higher the threshold, the more aggressive the reduction



Data Reduction Technique: Low Variance Filtering

The variance is range dependent, favors wide variance

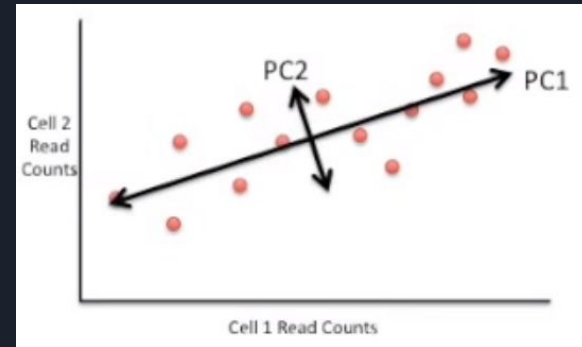
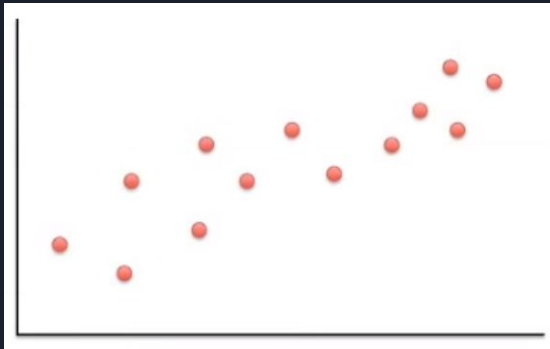
Similar to Missing Values Ratio, the higher the set threshold, the more aggressive the data reduction


Data Reduction Technique: Principal Component Analysis (PCA)

Linear mapping original variables

where the greatest variance is important variables (first principal component) and second greatest variance is on the second coord, etc

The data is normalized to be on the same scale





Principal Component Analysis (PCA) Example

Usage of `prcomp` (from `stats` package) returns Standard Deviation and Cumulative Proportion

```
1 | pca_res <- prcomp(gapminder_life, scale=TRUE)
```

```
1 | summary(pca_res)
2 |
3 | ## Importance of components:
4 | ##              PC1      PC2      PC3      PC4      PC5
5 | ## Standard deviation    3.360 0.69114 0.40463 0.19246 0.11371
6 | ## Proportion of Variance 0.941 0.03981 0.01364 0.00309 0.00108
7 | ## Cumulative Proportion 0.941 0.98083 0.99448 0.99756 0.99864
```

```
1 | names(pca_res)
2 |
3 | [1] "sdev"      "rotation" "center"   "scale"    "x"
```

Principal Component Analysis (PCA) Example

```
1  pca_res$x[1:5,1:3]
2
3  ##                PC1                PC2                PC3
4  ## Africa_Algeria    0.4518264 -1.3208553  0.3848907
5  ## Africa_Angola    -5.2217443  0.2876153 -0.2574503
6  ## Africa_Benin     -2.2956809 -0.2847236  0.0080484
7  ## Africa_Botswana  -0.6460076  1.1788076  0.8922150
8  ## Africa_Burkina Faso -3.3832822 -0.3287683  0.1598156
```

```
1  pca_res$center[1:5]
2
3  ## lifeExp_1952 lifeExp_1957 lifeExp_1962 lifeExp_1967 lifeExp_1972
4  ##      48.38172      50.57246      52.54620      54.26249      55.98415
```

```
1  head(pca_res$scale^2, n=5)
2
3  ## lifeExp_1952 lifeExp_1957 lifeExp_1962 lifeExp_1967 lifeExp_1972
4  ##      181.2131      181.8949      177.7479      168.3315      157.4524
```



Other Data Reduction Techniques

Random Forests

Backward Feature Elimination

Forward Feature Construction

High Correlation Filter



Reference/Additional Readings:

Prcomp function:

<https://www.rdocumentation.org/packages/stats/versions/3.6.1/topics/prcomp>

PCA in R: <https://blog.learningtree.com/dimensionality-reduction-in-r/>

<https://www.r-bloggers.com/principal-component-analysis-using-r/>

<https://cmdlinetips.com/2019/04/introduction-to-pca-with-r-using-prcomp/>

Dimensionality Reduction Techniques (with Python codes):

<https://www.analyticsvidhya.com/blog/2018/08/dimensionality-reduction-techniques-python/>