Principal Component Analysis

Matthew Cocci

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1 Overview

Principal Component Analysis is a type of *feature extraction* that takes a number of "features" or independent variables, then uses them in combination to build and rank new variables which explain the largest share of variability in some response (or dependent) variable. This differs from *feature selection* which takes a list of features and selects a subset to use as is (free of any combination or modification).

Principal Component Analysis can also be used to combat the *curse of dimensionality*. Loosely speaking, this technical problem arises when you have many features or independent variables that might explain some dependent variable. As the number of features grows, the data becomes ever sparser in a higher dimensional space.[1] Principal Component Analysis can be used to combine features, rank them in order or importance, and throw out features that don't explain much variance in the dependent variable.

2 Intuition

Principal Component Analysis really just finds new ways to look at the data by changing the axes. Imagine we had the following data.

PCA highlights the fact that there is nothing sacred about the axes I have drawn there. We can express the data points relative to a new set of axes so that the variation along different dimensions is more explicit.

[1] Say that an outcome y is dependent upon the roll of N dice, $\{x_1, \ldots, x_N\}$. As N increases, there are exponentially more outcomes that might result–6^N to be precise. So as N increases, the space of your data grows exponentially, which typically necessitates exponentially larger samples to match the explanatory power you would have in dimensions with lower N.