Project 1: PCA on a Birth Weight Dataset

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I. Introduction

Although low birth weighted infants can be healthy, under improper care or other circumstances, it can cause serious long-term health problems. A low birth weight is defined as being below 2.5kg. It can be caused by a multitude of factors —poor socioeconomic situation, premature birth, a mother's pre-existing health conditions, and more. In this project, we will highlight how smoking and other factors can cause low birth weights in infants in comparison to non-smoking parents.

We want to find out what variables related to smoking and birth data are related to eachother and how strong those relationship is. In order to answer this, we will be using principal component analysis to analyze the data. PCA is a statistical technique that reduces a dimensionality of a dataset to make it interpretable while also preserving the variability of the data. We can use it to see what variables group together, identify possible outliers, recognize correlations between variables, and more.

II. Summary of Data

Before conducting PCA onto a dataset, we must first examine the data and decide on what variables we want to specifically look at by looking at different plots and summaries.

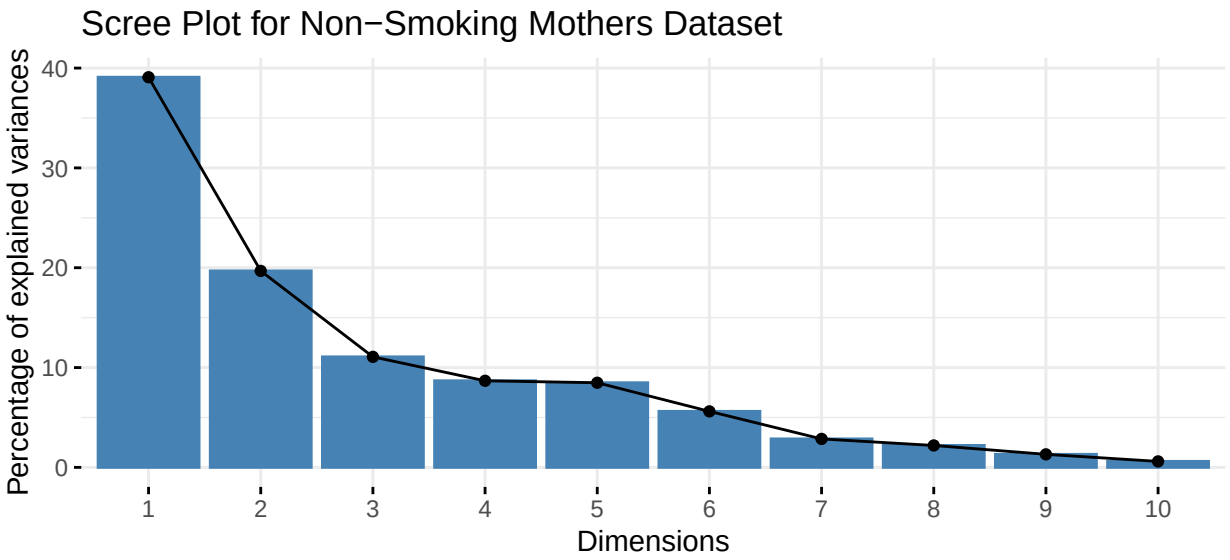
The plot above shows....

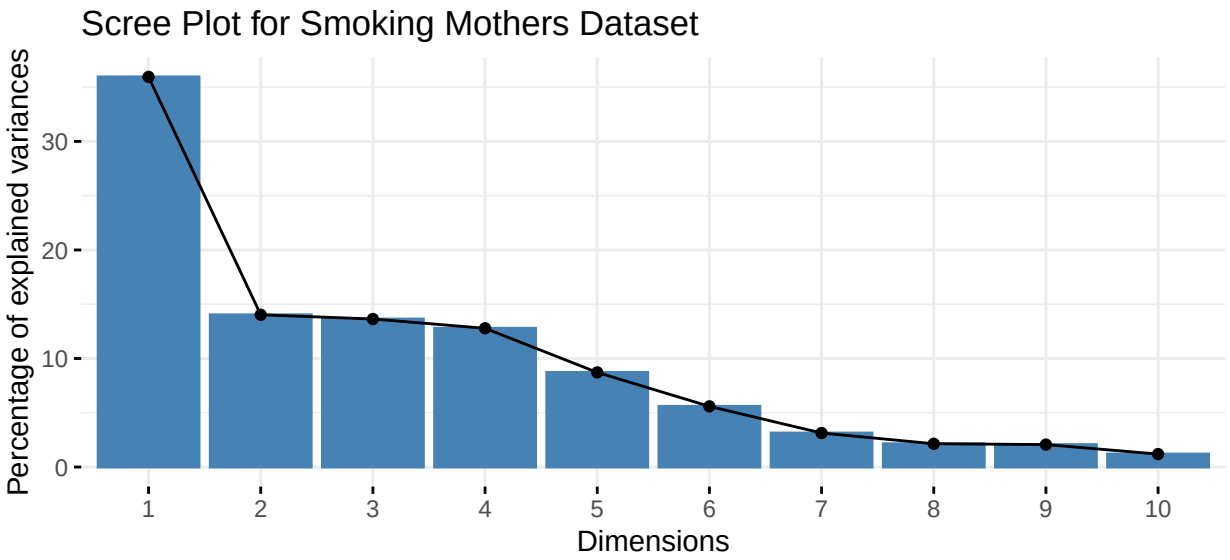
When conducting the analysis, we also want to know if we want to use the covariance matrix or the correlation matrix. [Discuss the positive and negative aspects of using the covariance matrix for a PCA rather than the correlation matrix.]

III. Analysis

If we compared babies according the their mother's smoking status, we can see what factors influence each other in both groups and compare them to see if they are different or similar. If there is a difference, it shows that a mother's smoking status does play a role in influencing their infant's growth. However, if they are similar, then something other than the mother's smoking status is causing a difference in an infant's growth.

When analyzing the data via PCA, we found that both datasets only needed the first 6 PCs to achieve over 90% explanation of the variance. The majority of the variance is explained by the first PC at about 40% as seen from both scree plots below. From there it tapers off and after the 6th principal component, it reaches a plateau and each of the remaining PCs explains less than 3% of the total variance.





The non-smoking mothers dataset shows that the first PC is based mainly on the positive correlation of body measurements of the baby, mother, and father; specifically, the gestation period, the parents' heights, and the infant's weight and length are the most significant here. This means that genetics and longer gestation period is correlated with a healthier baby. In comparison to the smoking mothers dataset, although they are similar, there is more emphasis on the parent's age than height. Overall, both confirm that gestation plays an important role in a healthier baby.

For the second PC, in the non-smoking dataset, it was positively influenced by the parent's age. This highlights that both datasets agree that the parent's age is important in determining a healthy baby. For the smoking data set, the second PC negatively correlates the mother's height, pregnancy weight, and number of cigarettes together. This correlation is saying that an increase in these values means an unhealthy baby. But in PC 1 for the non-smoking dataset, a mother's height meant it would positively impact the baby's health. This confirms that smoking status does in fact effect a baby's health.

Non-Smoking Mothers Loadings

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6
Length	0.413			0.219	0.295	
Birthweight	0.380			0.510		
Headcirc	0.297	0.310	-0.479	0.110	-0.134	-0.296
Gestation	0.396		0.152	0.194	0.257	0.483
mage		0.589	0.296			-0.284
mheight	0.384	0.173	-0.115	-0.125	-0.419	-0.198
mppwt	0.306	0.147	0.363	-0.356	-0.440	0.118
fage	-0.133	0.526	0.367	0.240		0.317
fedyrs	-0.122	0.432	-0.370	-0.242	0.481	
fnocig	0.234	-0.192	0.466	-0.179	0.420	-0.576
fheight	0.325		-0.141	-0.593	0.203	0.323

Smoking Mothers Loadings

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6
Length	0.384	0.135	0.271			
Birthweight	0.408	0.235	0.241			
Headcirc	0.326	0.414		0.194	0.134	0.146
Gestation	0.336	0.238	0.171	-0.379	-0.280	
mage	0.282	-0.138	-0.540			-0.214
mnocig	0.191	-0.398	-0.136	-0.131	-0.261	0.808
mheight	0.179	-0.478	0.341	0.302	0.225	
mppwt	0.322	-0.363	0.111	0.265	0.270	-0.200
fage	0.339	0.177	-0.469	0.182		-0.100
fedyrs	0.284	-0.340		-0.244	-0.359	-0.379
fnocig		0.118	-0.190	0.678	-0.265	0.190
fheight	-0.106		0.365	0.285	-0.707	-0.203

For PCs 3-6, the most notable similarity between the two groups is that they agree that the father's number of cigarettes has a negative influence on the health of the baby. In the smoking dataset, the parent's number of cigarettes predominantly impacts the baby's health negatively. Whereas in the non-smoking dataset, the significant variables seem relatively spread out across the PCs and it becomes harder to interpret them.

Overall, because there is a difference in which variables impact the PCs, it highlights that a mother's smoking status does impact an infant's growth.

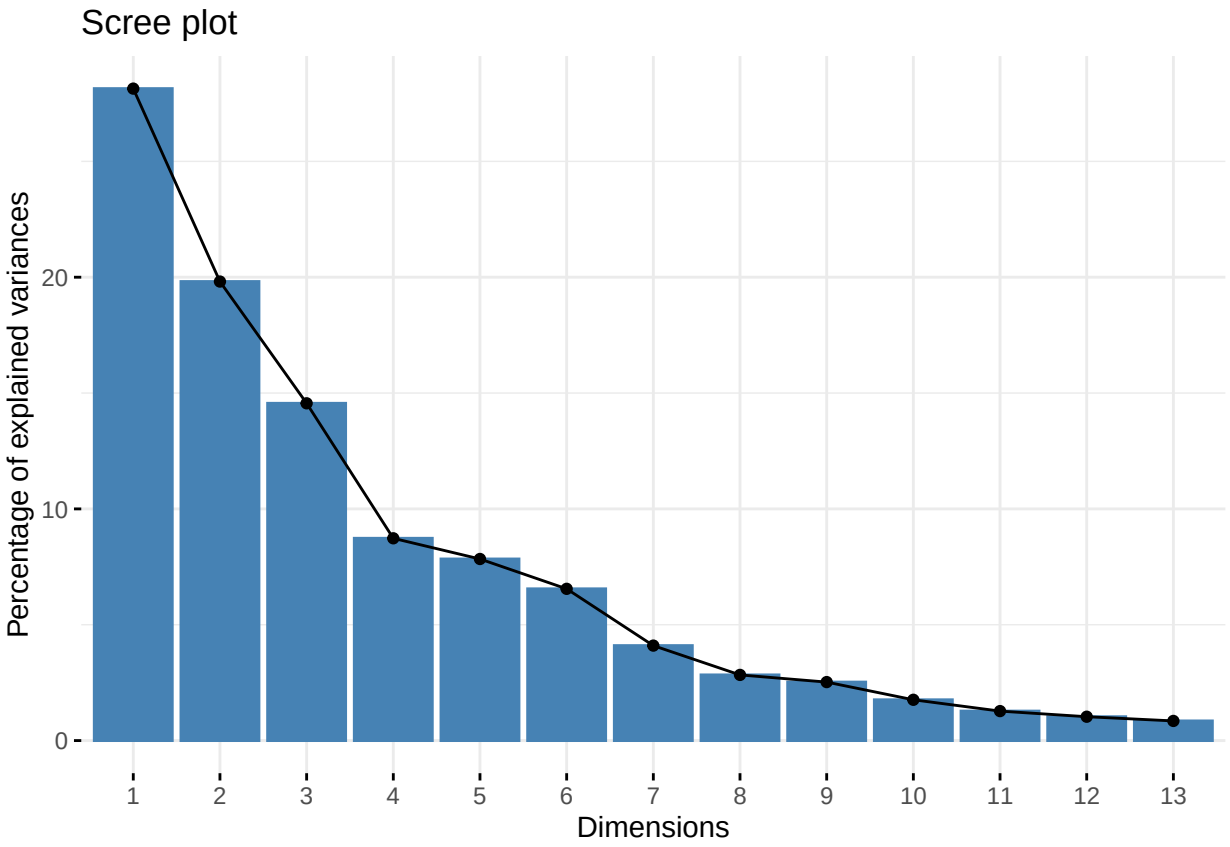
It is further notable that smoking is not beneficial for babies based on the PC analysis of the dataset as a whole. When the Principle Components are found on the dataset using the correlation matrix, we find the following:

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7
Standard deviation	1.912632	1.604867	1.3756776	1.0653791	1.0094043	0.9227677	0.7300199
Proportion of Variance	0.281397	0.198123	0.1455761	0.0873102	0.0783767	0.0655000	0.0409945
Cumulative Proportion	0.281397	0.479520	0.6250961	0.7124063	0.7907830	0.8562830	0.8972775

	Comp.8	Comp.9	Comp.10	Comp.11	Comp.12	Comp.13
Standard deviation	0.6070519	0.5729325	0.4785064	0.4067690	0.3659491	0.3320844
Proportion of Variance	0.0283471	0.0252501	0.0176129	0.0127278	0.0103014	0.0084831
Cumulative Proportion	0.9256246	0.9508748	0.9684877	0.9812155	0.9915169	1.0000000

The number of PCs needed using the correlation matrix is only the first 8. Using only these 8 we are able to explain 92.56% of the variance of the data.

This is further visualized using the following scree plot:



In this plot we are able to see that the elbow curve at the 8th dimension reflects the calculations results showing a need of only 8 dimensions to preserve at least 90% of the variance of the data.

Based on the loadings with a cutoff value of 0.15:

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7
Length	0.444						
Birthweight	0.447	0.166		0.212			
Headcirc	0.389			0.203			-0.767
Gestation	0.382			0.272	0.432	0.163	0.387
smoker		-0.445	0.329		0.157	0.280	-0.232
mage		-0.476	-0.289			-0.230	0.166
mnocig		-0.474	0.224		0.279	0.405	
mheight	0.317		0.304	-0.493	-0.254		
mppwt	0.340			-0.442	-0.327		0.280
fage	0.183	-0.423	-0.321	0.261	-0.188	-0.153	

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7
fedyrs		-0.222	-0.293	-0.381	0.512	-0.340	-0.175
fnocig		-0.231	0.439	0.375	-0.319	-0.347	
fheight			0.497		0.306	-0.610	

	Comp.8	Comp.9	Comp.10	Comp.11	Comp.12	Comp.13
Length	0.224	0.543	0.396	0.458		
Birthweight	-0.335		-0.236	-0.276	0.660	-0.155
Headcirc		-0.168			-0.334	
Gestation		-0.196		-0.289	-0.530	
smoker		-0.202	0.564	-0.287	0.177	
mage	0.362	0.178	-0.201			-0.592
mnocig			-0.544	0.382		
mheight	0.254	0.264		-0.465		0.319
mppwt	-0.301	-0.439	0.203	0.315		-0.190
fage		-0.246				0.660
fedyrs	-0.429	0.202	0.207			
fnocig	-0.485	0.303			-0.206	
fheight	0.288	-0.311	-0.165		0.217	

we can see that when the physical features of the baby are all positive, as seen in the first four features of Comp. 1,

Length	Birthweight	Headcirc	Gestation
0.4442198	0.4465604	0.3891197	0.3822305

that means that these features all correlate with eachother, meaning that a long gestation period is well correlated with a larger and healthier baby.

That said, when birthweight is positive and another score in the component is negative, as seen with smoker in Comp. 2:

Birthweight	smoker
0.1655971	-0.4446873

that is a sign that the attribute of being a smoker is not beneficial for the baby, since it will impact the physical features.

As seen based on the PC analysis, these correlations become weaker as we iterate through the components This means that the later components contradicting that birth weight and smoking are actually the same sign score, such as in Comp.11:

Birthweight	smoker
-0.2764383	-0.2871868

are negligible, since the later components explain very little proportion of the overall data variance. Comp. 11 itself only explains about 1.2% of the variance, so findings such as this are far less relevant as in Comp. 2

which explains almost 20% of the variance.

We can also see that the number of cigarettes smoked per day by mothers and fathers are both, as expected, well correlated with the smoking status of the mother. This is also visible with the mother and father's ages, as seen by the data in Comp.2:

smoker	mage	mnocig	fage	fnocig
-0.4446873	-0.4756988	-0.4735367	-0.4231726	-0.2310304

Based on these Principle Components of the correlation matrix, it is clear that a larger gestational period is a beneficial thing for a baby's health, however a greater count of smoked cigarettes is not. It is also clear that the father's smoking status, as shown by the number of cigarettes he smokes per day, is well correlated with the mothers.

What is further interesting about this analysis is the lack of correlation of the physical attributes of the parents with the physical attributes of their newborn in comparison to that of the smoking features. While in Comp.1 we see that the physical features of the child and the physical features of the mother are similar scores:

Birthweight	Headcirc	Gestation	mheight	mppwt
0.4465604	0.3891197	0.3822305	0.3169582	0.3404202

we see only three principle components later in Comp.4 a contradiction:

Birthweight	Headcirc	Gestation	mheight	mppwt
0.2124146	0.2030967	0.2719839	-0.4928765	-0.4417855

This contradiction may be in a later component, however it is still a component that explains 8.7% of the overall variance of the data, and is relatively significant. It shows a reduced importance of the mother's physical features in explaining the physical features of her child, and a comparative increase in the impact of smoking.

IV. Interpretation

Based on the analysis we can understand an estimation of what the physical features of a new baby not considered in this analysis will be using only a few features of the parents. For example, if the father is older he is more likely to smoke multiple cigarettes per day. In this case, based on the Principle Component Analysis we could expect that the mother also smokes multiple per day, and as such is marked as a smoker in the data. If this is in fact true we can predict that the gestation period will be shorter and the head circumference, birth weight, and length of this newborn baby will all be lower than expected.

We would also see that the physical features of the father and mother such as their height and weight do not factor into the features of their child nearly as much as their actions do when it comes to smoking or not. Based on only these Principle Components we are able to understand how the smoking features of the father and mother have a direct impact on the features of their baby, and subsequently the healthiness of their baby.

Let's also take for an example with the baby features as follows:

length	birthweight	headcirc	gestation	smoker	motherage	mnocig	mheight	mppwt	fage
61	5.1	36	43	0	43	7	165	64	38

fedyrs	fnocig	fheight
19	45	189

From the PC analysis, we can understand how well this new data point matches with the data we have previously seen. The number of cigarettes smoked by the mother is 7, yet she is marked as a nonsmoker, which is unlike any data we have previously seen and doesn't really make sense. 7 is around the average amount for the mothers in our dataset to smoke, however the father is on the upper end of the dataset. Other physical characteristics of the parents are average based on what we have previously seen. Based on all of this, we would expect the baby to physically be smaller than the average child. However, the baby is in the 75th percentile for all of its physical characteristics (gestational period, length, birthweight, and head circumference), which is highly unusual especially giving the parent data. Because of this, we would conclude that this child is an outlier and does not match with the rest of the data in this Principle Component Analysis study.

V. Conclusion

Generally, this analysis shows that while physical features of the parents do explain the physical features of their children, features regarding their smoking habits seems to be a stronger influence. We also see that the smoking actions of the father may correlate with the smoking actions of the mother, meaning that it is likely if one smokes so does the other. This is interesting because it disproves any assumption that the actions of the father do not influence the characteristics of his child.

In future analysis of this topic, it would be interesting to include alcohol consumption as another feature, as it has also been shown to have impacts on child gestation and birth features. We could also further analyze any correlation between the mother and father's non-physical features with each other, such as seeing if the more positive actions of the father in activities such as exercise or sleep influence the actions of the mother in similar ways that smoking does. Father's education level is also a feature in this dataset that does not correlate with other features and wasn't heavily analyzed, however maybe the addition of Mother's education level would show some deeper results.

Appendix: R Script

```
knitr::opts_chunk$set(echo = F)
library(factoextra)
library(knitr)
#data
smok = read.csv("data/Birthweight_reduced_kg_R.csv")
smok = smok[,2:14]

new_print_loadings = function (x, digits = 3L, cutoff = 0.1, sort = FALSE, ...)
{
  ## code from the original print.loadings function, without printing the variances
    Lambda <- unclass(x)
    p <- nrow(Lambda)
    factors <- ncol(Lambda)
    if (sort) {
        mx <- max.col(abs(Lambda))
        ind <- cbind(1L:p, mx)
        mx[abs(Lambda[ind]) < 0.5] <- factors + 1
        Lambda <- Lambda[order(mx, 1L:p), ]
    }
    fx <- setNames(format(round(Lambda, digits)), NULL)
    nc <- nchar(fx[1L], type = "c")
    fx[abs(Lambda) < cutoff] <- strrep(" ", nc)
    return(fx)
}

new_print_sum = function (x, digits = 3L, loadings = x$print.loadings, cutoff = x$cutoff,
    ...)
{
    vars <- x$sdev^2
    vars <- vars/sum(vars)
    return(rbind(‘Standard deviation‘ = x$sdev, ‘Proportion of Variance‘ = vars,
        ‘Cumulative Proportion‘ = cumsum(vars)))
}

#Plots




######[If the overall goal is to compare babies according with their
###### mother’s smoking status, how would you proceed ?]

#split the data
nonsmoke = subset(smok, smoker == 0, select = -c(5, 7))
smoke = subset(smok, smoker == 1, select = -c(5))

#pca and summary
##nonsmoking mothers
pca.nonsmoke =  princomp(nonsmoke, cor = TRUE)
t = summary(pca.nonsmoke, loadings = TRUE, cutoff = 0.1)$loadings
```

```r
##smoking mothers
pca.smoke = princomp(smoke, cor = TRUE)
u = summary(pca.smoke, loadings = TRUE, cutoff = 0.1)$loadings

#scree plots for nonsmoking vs. smoking mothers datasets
library(factoextra)

fviz_eig(pca.nonsmoke, main = "Scree Plot for Non-Smoking Mothers Dataset")
fviz_eig(pca.smoke, main = "Scree Plot for Smoking Mothers Dataset")

kable(new_print_loadings(t, cutoff = 0.1)[,1:6])
kable(new_print_loadings(u, cutoff = 0.1)[,1:6])
## PCA Analysis on whole data
c = princomp(smok, cor = TRUE)
l = summary(c, loadings = TRUE, cutoff = 0.15)$loadings
kable(new_print_sum(c, cutoff = 0.15)[,1:7])
kable(new_print_sum(c, cutoff = 0.15)[,8:13])
fviz_eig(c, ncp = 13)
kable(new_print_loadings(l, cutoff = 0.15)[,1:7])
kable(new_print_loadings(l, cutoff = 0.15)[,8:13])
vars = l[,1][1:4]
kable(matrix(as.numeric(vars), ncol = length(vars)), col.names = names(vars))

vars = c(l[,2]['Birthweight'], l[, 2]['smoker'])
kable(matrix(as.numeric(vars), ncol = length(vars)), col.names = names(vars))

vars = c(l[,11]['Birthweight'], l[, 11]['smoker'])
kable(matrix(as.numeric(vars), ncol = length(vars)), col.names = names(vars))

vars = c(l[,2][5:7], l[, 2][10], l[, 2][12])
kable(matrix(as.numeric(vars), ncol = length(vars)), col.names = names(vars))
vars = c(l[,1][2:4], l[,1][8:9])
kable(matrix(as.numeric(vars), ncol = length(vars)), col.names = names(vars))
vars = c(l[,4][2:4], l[,4][8:9])
kable(matrix(as.numeric(vars), ncol = length(vars)), col.names = names(vars))

kable(matrix(c(61, 5.1, 36, 43, 0, 43, 7, 165, 64, 38), ncol = 10),  col.names = c("length", "birthweigh
kable(matrix(c( 19, 45, 189), ncol = 3), col.names = c("fedyrs", "fnocig", "fheight"))
```