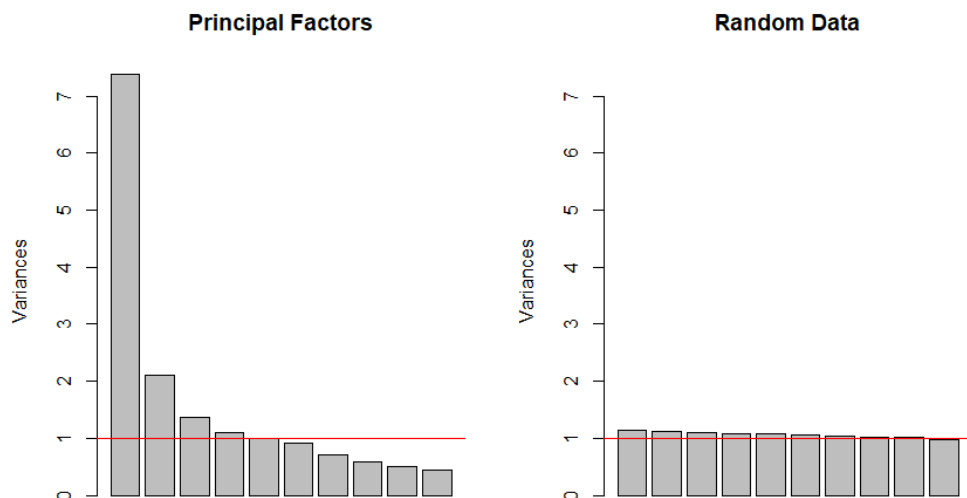


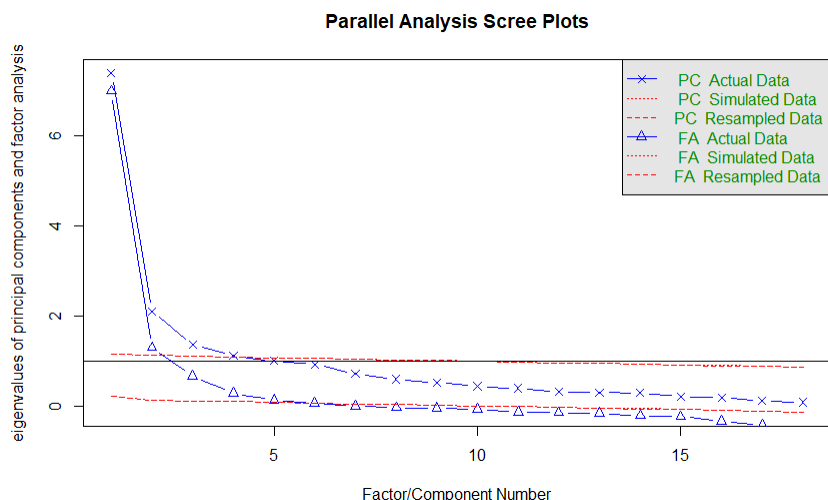
The first Eigen vectors and Eigen values were calculated from a correlation matrix using the prcomp function to try to determine how many principal factors should be used in the principal factor analysis. The first four principal factors account for 66% of all the variance captured by a total of eighteen factors, as can be seen in the Figure below.

Importance of components:												
	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12
Standard deviation	2.7157	1.4484	1.16508	1.05256	0.99956	0.96126	0.84349	0.77094	0.71638	0.66091	0.62692	0.55870
Proportion of Variance	0.4097	0.1166	0.07541	0.06155	0.05551	0.05133	0.03953	0.03302	0.02851	0.02427	0.02183	0.01734
Cumulative Proportion	0.4097	0.5263	0.60170	0.66325	0.71875	0.77009	0.80961	0.84263	0.87114	0.89541	0.91725	0.93459
	PC13	PC14	PC15	PC16	PC17	PC18						
Standard deviation	0.5500	0.53464	0.45911	0.42101	0.34358	0.28814						
Proportion of Variance	0.0168	0.01588	0.01171	0.00985	0.00656	0.00461						
Cumulative Proportion	0.9514	0.96727	0.97898	0.98883	0.99539	1.00000						

Thirty random matrices were generated and the average for each one of their corresponding elements was calculated. The variance explained by each one of the columns of said matrix was plotted on the graph to the right on the figure below. A red line was drawn at variance equals one, allowing a comparison between the variance explained by randomly generated data, or noise, and the variance explained by each of the principal factors calculated, on the left. This figure indicates that four, maybe five, principal factors should explain more variance than just noise would and, therefore, can be used in the analysis.



A parallel analysis using the fa.parallel function was conducted, resulting in the figure below. The “PC Actual Data” line is the one corresponding to the variance explained by the principal factors previously calculated and the “PC Simulated Data” is the equivalent to the randomly generated data. Not only can the parallel analysis be used to confirm what the figure above indicated, as far as how many principal factors to use in the principal factor analysis, but also gives us insight regarding variance explained by each principal factor calculated by common factor analysis, which will be introduced as an alternative to principal factor analysis later on.



The principal factors were re-calculated using the principal function from the psych package with, in the middle, and without, on the left, the VARIMAX rotation. As can be seen in the figure below the loadings in the middle are much easier to interpret than the ones on the left as they are not spread over as many components. A common factor analysis was calculated using the factanal function, producing the factors seen on the right, which have even more multi factor loadings than the principal factors calculated without VARIMAX. Considering that the purpose of this analysis is driving understanding from the principal factors and their loadings, a principal factor analysis using VARIMAX seems to be the best option.

Loadings:					Loadings:					Loadings:				
	PC1	PC2	PC3	PC4		RC1	RC2	RC3	RC4		Factor1	Factor2	Factor3	Factor4
Kidhome	-0.660				Kidhome	-0.550				logp1_Income	0.693			
logp1_Income	0.785				logp1_Income	0.682				logp1_MntMeatProducts	0.704	0.621		
logp1_MntFishProducts	0.761				logp1_MntFishProducts	0.791				logp1_MntWines	0.896			
logp1_MntFruits	0.765				logp1_MntFruits	0.793				logp1_NumCatalogPurchases	0.674	0.547		
logp1_MntGoldProds	0.699				logp1_MntGoldProds	0.749				logp1_NumStorePurchases	0.656	0.460		
logp1_MntMeatProducts	0.931				logp1_MntMeatProducts	0.915				logp1_NumWebPurchases	0.628	0.410	0.406	
logp1_MntSweetProducts	0.755				logp1_MntSweetProducts	0.786				logp1_MntFishProducts		0.752		
logp1_MntWines	0.868				logp1_MntWines	0.816				logp1_MntFruits		0.750		
logp1_NumCatalogPurchases	0.892				logp1_NumCatalogPurchases	0.844				logp1_MntGoldProds	0.404	0.566		
logp1_NumStorePurchases	0.817				logp1_NumStorePurchases	0.803				logp1_MntSweetProducts		0.746		
logp1_NumWebPurchases	0.718	0.406			logp1_NumWebPurchases	0.761				Teenhome			0.928	
logp1_NumWebVisitsMonth	-0.583	0.432	0.434		logp1_NumDealsPurchases		0.857			logp1_NumDealsPurchases				0.646
Teenhome		0.797			logp1_NumWebVisitsMonth	-0.457	0.716			logp1_NumWebVisitsMonth				0.720
logp1_NumDealsPurchases		0.763	0.450		Year_Birth			-0.765		Year_Birth			-0.414	
Year_Birth		-0.438	0.607		Teenhome		0.417	0.729		Kidhome	-0.444			
Recency				0.688	Recency				-0.677	Recency				
Tot_Accepted				-0.683	Tot_Accepted				0.732	Complain				
Complain					Complain					Tot_Accepted				
	PC1	PC2	PC3	PC4		RC1	RC2	RC3	RC4		Factor1	Factor2	Factor3	Factor4
SS loadings	7.375	2.098	1.357	1.108	SS loadings	6.939	1.957	1.805	1.237	SS loadings	4.032	3.568	1.409	1.403
Proportion Var	0.410	0.117	0.075	0.062	Proportion Var	0.386	0.109	0.100	0.069	Proportion Var	0.224	0.198	0.078	0.078
Cumulative Var	0.410	0.526	0.602	0.663	Cumulative Var	0.386	0.494	0.595	0.663	Cumulative Var	0.224	0.422	0.500	0.578

Correlation matrix and principal factor analysis seem to indicate that the more kids at home a customer has the less purchases they are likely to make, especially meat and wine products. These customers are also much less likely to make purchases either at the store or from a catalog, preferring to visit the website and make deal purchases. It can also be inferred that customers who visit the website are usually looking for deals whether they have kids or not. On the other hand, even though customers who buy at the store and from the catalog might also buy online it is clear that the higher the income of a customer, the less likely they are to check the website and the more likely they are to buy at the store or from a catalog. It stems from this analysis that it could be beneficial to have mostly deals on the website as well as a section dedicated to families with kids.

