Mobile Causes Cancer: A Data Mining Case Study

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Abstract – Mobile phones play a crucial role in their life and they use them for a variety of communication and mediarelated activities such as accessing news, listening to music and taking pictures. The Mobile phone use and always accompanied by the issue of health implications for human. Brain tumor risk among children and adolescents. In an Environmental Health, an increased brain tumor risk in relation to wireless phone use. There is no plausible explanation of how a notably increased risk from use of wireless phones would correspond to the relatively stable incidence time trends for brain tumors' among children and adolescents. Nevertheless, an increased risk restricted to heavy mobile phone use, to very early life exposure, thus further monitoring of childhood brain tumor incidence rate time trends is warranted. Previous research studies show no evidence of the impacts of mobile phones to human health. New studies suggest that mobile radiation might double the risk of developing cancer on the side of the head used, increase brain activity, can cause damage to nerves around ears and, more importantly.

I. Introduction

Mobile Phones are used for personal communication and entertainment activities. Media and government institutions are also using mobile phones to reach out to young people. News and entertainment companies are engaging young audience by incorporating text messaging into television programs. Young people are also using mobile phones as public communication medium to engage and collaborate on social and political issues. This wide use of mobile technology has often raised the question about if there are health implications for human. Electromagnetic radiation is "energy radiated in the form of a wave as a result of the motion of electric charges". It produced electromagnetic wave is both a transverse and a polarized wave (2008). More importantly, "electromagnetic radiation does not require a material medium and can travel through a vacuum". Radio frequency induces RF electric fields in tissue a part of the radiated energy will be absorbed in tissues. Exposure to mobile phone radiation causes a stress. Effects on blood pressure in human volunteers exposed to a conventional GSM digital mobile phone positioned close to the right side of the head. After 35 minutes of exposure, heart rate, blood pressure was measured with standing for 60 seconds.

II. Problem Definition and Description

A. Statement of the problem

This paper provides some evidence for the socio-cultural shaping of mobile phone usage. The promotion of mobile phones as attractive devices by industry plays a role in the adoption and use of mobile phones by young people. Children use cell phones to watch TV, play games, make phone calls, and send text messages. Many older kids and teens have their own cell phones, which they are attached to 24/7. But are there risks to such frequent use by children.

B. Objectives of the study

• Mobile phone companies monitor the results of mobile phones and cancer studies carefully.

• The amount of time the person is on the phone.

• The person is using the speaker mode on the phone or a hands-free device.

• The distance and path to the nearest cell phone tower.

• The amount of cell phone traffic in the area at the time. Higher traffic may require more energy to get a good signal.

III. RESEARCH METHODOLOGY

A. Methodology

The case study will consist of deferent stages, roughly following the cross industry standard procedure CRISP-DM. Firstly, the business understanding phase has to be carried out. In this phase, the project objectives and requirements are stated and reined and the resulting data mining problem is formulated. The results of this phase are summarized in the previous sections. Although the collection of additional data results in a richer data set and is therefore likely to give better results, model acting on a data set that is already automatically kept-to-data is potentially a much useful tool.

B. Algorithm used

Cluster Analysis

Cluster analysis is a multivariate analysis that attempts to form groups or "clusters" of objects (Sample Plots in our case) that are "similar" to each other but which differ among clusters. The exact definition of "similar" is variable among algorithms. But has a generic basis. The methods of forming clusters also vary, but follow a few general blueprints.

K-means clustering

The most common partitioning method is the K-means cluster analysis. Conceptually, the K-means algorithm:

Selects K cancroids (K rows chosen at random)

• Assigns each data point to its closest centroid.

• Recalculates the centroids as the average of all data points in a cluster (i.e., the centroids are p-length mean vectors, where p is the number of variables)

• Assigns data points to their closest centroids.

• Continues step 3 and 4 until the observations are not reassigned or the maximum number of iterations(R uses 10 as a default) is reached.

C. Tools for the study

i) Cluster Analysis in R

R has an amazing variety of function for cluster analysis. In this section, we use three of the many approaches: hierarchical agglomerative, partitioning, and model base.

Data preparation: Prior to clustering data, you may want to remove or estimate missing data and rescale variables for comparability.

Partitioning: K-means clustering is the most popular partitioning methods. It requires the analyst to specify the number of cluster to extract. A plot of the within groups sum of squares by number of cluster extracted can help determine the appropriate number of cluster. The analyst looks for a bend in the plot similar to a screen test in factor analysis.

Hierarchical Agglomerative: There are a wide range of hierarchical clustering approaches. The pvclust() function in the pvclust package provides p-values for hierarchical

clustering based on multi scale bootstrap resembling. Clusters that are highly supported by the data will have large p values. Be aware that pvsclust clusters column, not rows. Transpose your data before using.

#Ward Hierarchical Clustering with Bootstrapped p values

Model based: Model based approaches assume a variety of data models and apply maximum like hood Estimation and bayes criteria to identify the most likely model and number of cluster. Specifically, the Mclust() function in the mclust package selects the optimal model according to BIC for EM initialized by hierarchical clustering for parameterized Gaussian mixture model. One chooses the model and number of clusters with the largest BIC.

Plotting Cluster solution: It is always a good idea to look at the cluster result.

#k-means clustering with 5 clusters.

Validating cluster solution: The function cluster. Status () in the fpc package provides a mechanism for comparing the similarity of two cluster solutions using a variety of validation criteria.

#comparing 2 cluster solutions

Library (fpc)

Cluster. Stats(d,fit1\$cluster,fit2\$cluster)

Where d is a distance matrix among objects, and fit cluster and fit2 cluster are integer vectors containing classification results from two different clusters of the same data.

IV. RESULTS AND DISCUSSION

A. Analysis of data

The data has been collected from 500 samples all over Theni district. After collecting the information, all the details are fed into the software and checked and outlier. The cleaned data was analyzed using single attribute and multiple attributes. Names, Age, Gender. To process the data, we installed the libraries such as pvclust, mcclust, cluster, FPC and NBclust from cloud storage. Then the dataset was inserted into the R tool for processing.

Data Preparation >mydata<- na.omit (tab1)

>mydata<-scale (mydata)

Partitioning

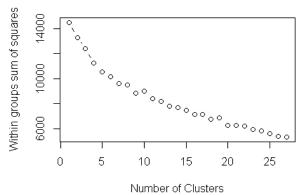
>wss<- (nrow(mydata)-1)*sum(apply(mydata,2,var))

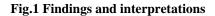
>print (wss)
[1] 14471
> fit <- kmeans (mydata, 5)
>aggregate (mydata, by=list(fit\$cluster),FUN=mean)
Group.1 V1 V2 V3 V4
1 1 0.06016017 -0.005721312 0.04002828 -0.031675543
2 2 -0.00776986 0.011827357 -0.07809936 0.113390253
3 3 0.08885063 0.094321276 0.10987640 -0.165829550
4 4-0.05668964-0.036055108-0.13293860-0.008186842
5 5 -0.11647224 -0.067565170 0.05152981 0.059277296
V5 V6 V7 V8 V9
1 0.5016582 -0.3550737 0.7701993 -0.6117310 0.7368332
2 0.2860602 -0.3503436 -0.2617512 0.3950607 -0.3831149
3 0.6353624 1.1116318 -0.7173806 0.7887521 0.4242590
4 -0.9446961 -0.4398748 0.3698878 0.2058483 -0.5460314
5 -0.9510606 0.3030673 -0.4118035 -0.5498370 -0.5274594
V10 V11 V12 V13 V14
1 -0.1383308 0.3060777 0.3135022 0.2662896
0.2751673544
2 0.1829293 0.6827839 -0.2463231 0.5654228
0.1832815504
3 1.1061354 -0.9311893 0.5553553 -0.3332337
0.0009512883 4 -0.7525047 -0.3039593 -0.1999397 -0.7694570
-0.7323047 -0.3039393 -0.1999397 -0.7094370 0.6112541691
5 -0.4722248 -0.2324971 -0.4970020 -0.1992840 -
1.1643769084
V15 V16 V17 V18 V19
1 -0.41297962 0.7246721 0.03315864 0.3005126 -
0.47112692
2 1.04194564 -0.4286844 -0.45151912 -0.6518160
0.49623103 3 0.04537734 0.4374042 1.18144187 -0.7162565
0.46264414
4 -0.08556797 -0.2256576 -0.27761331 1.0154739
0.05431999
5 -0.76455293 -0.7269133 -0.33790810 0.2728875 -
0.45734160
V20 V21 V22 V23 V24
1 -0.009431525 -0.4285989 1.1659379 0.19780759 - 0.1004056
0.1004056

```
2 0.723423433
                 0.7525047 -0.6125841
                                         0.07328842 -
0.5227683
3 0.377051064
                -0.1523596
                               0.2486996
                                           -0.08890041
1.3480703
4 -1.265877333
                  0.7244136 -0.6436871 -0.69161504 -
0.5983128
5 -0.268991781
                 -0.8357478
                             -0.6056216
                                           0.26776218
0.0637630
```

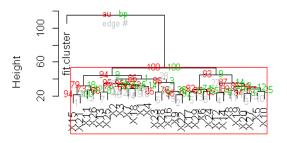
V. FINDING, INTERPRETATION,

RECOMMENDATIONS AND SUGGESTIONS





Cluster dendrogram with AU/BP values (%)



Distance: euclidean Cluster method: ward.D

Fig. 2 Hierarchical Agglomerative

p-value vs standard error plot

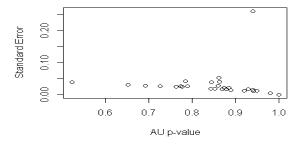
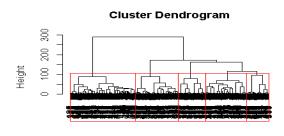


Fig. 3 Finding standard Errors



d hclust (*, "ward.D") Fig. 4 Cluster Dendrogran

Mobile cause cancer factor

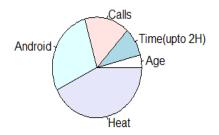


Fig. 5 Mobile cause cancer factor Conclusion

This study reveals that all category people of society using mobile phones for coordinating studies, entertainment, communications, maintaining relationships.

• Social media taking to lead role of bringing knowledge and must to be reduce the time of using mobile phones step by step.

• To know the risk from the causes the cancer and aware to others and try to be using hand held devices.

Suggestions for further study

Mobile phone is an integral part of life. It strongly related to age, with the highest incidence rates overall being in childhood, adults. In future we extend our research all over the India, women how to prevent for Breast cancer. To know the service provider given frequency stay from the 2watt, but it may increase use of mobile phones make diseases. This study is to be extend governments take action about people's health, and service provider must have limits of the frequency not increased. An Alternative device, people which level used.

VI. BIBLIOGRAPHY

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