

Survey Monkey Customer Feedback Data Analysis Report

OSSIC

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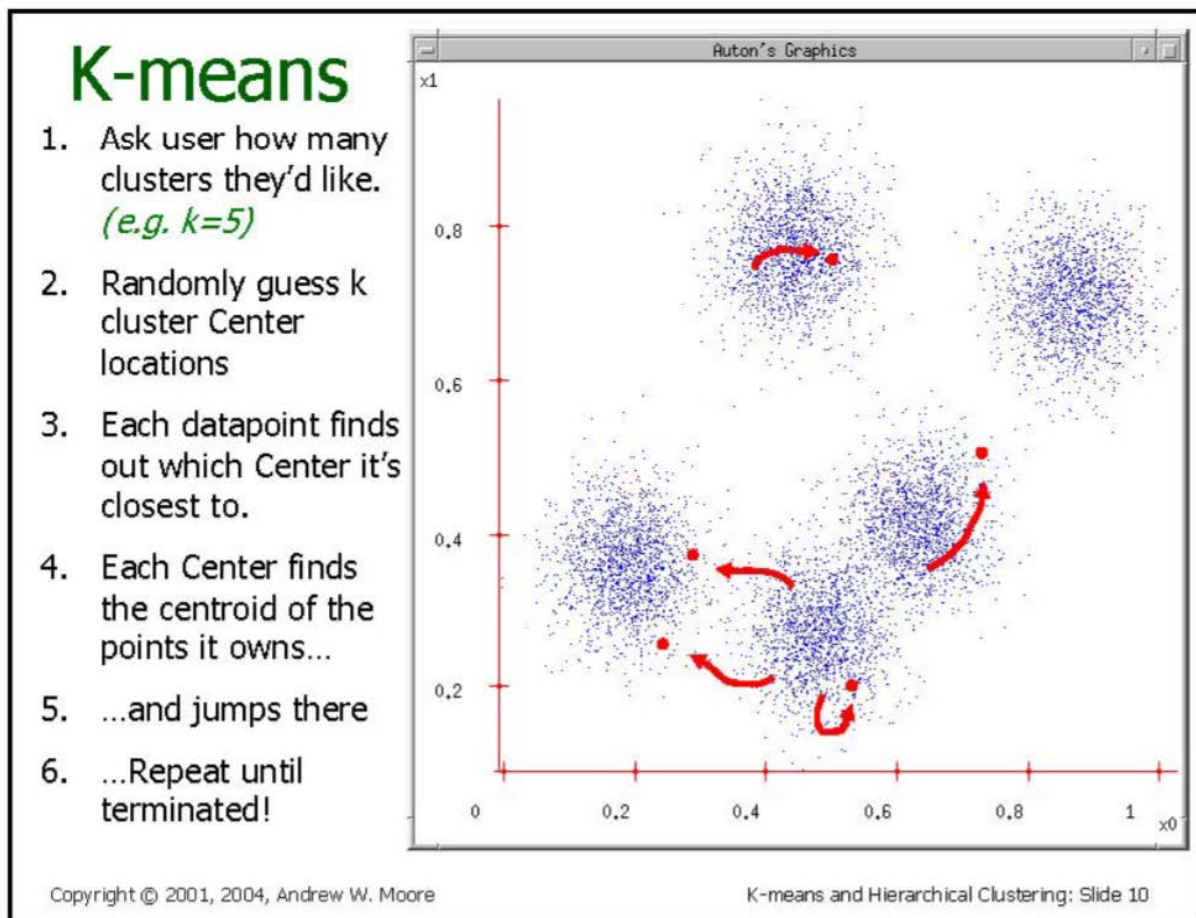
1. Methodology

1.1 About the method used to analyze the data

Jump to page XX for the insights and conclusion of the analysis. The body of this report contains detailed information about the methodology used to analyze the data.

The Machine Learning technique used for this analysis is commonly known as k-means. It consists of an unsupervised learning method that clusters the data set based on the distance between each data point and a sample point of each class. This distance can be calculated in various ways and the data can be clustered in n different classes. In this analysis, the distance was calculated by the Euclidean method with 3, 4, 5 and 6 clusters and also by the Mahalanobis method with 2, 3, 4, 5(*) clusters. *Three different k-mean procedures were used for 5 clusters with Mahalanobis distance.

The following image explains, in a summarized way, how the k-means algorithm works. Note that the initialization technique for the analysis of this data is different than the one showed in the picture. Random initialization is usually not optimal so for this application mean-splitting initialization was utilized.



1.2. Software and how to re-run the code

The software script used for analysis was entirely written in MATLAB. There are a total of 14 scripts used to interpret the data, but when re-running the code only two of them need to be executed (MaiscriptOSSICsurvey.m and surveydatamatrix). Other scripts work as specific functions that are called inside MaiscriptOSSICsurvey. Please refer to the following description of each script:

MaiscriptOSSICsurvey.m

Main script, should be opened and ran according to instructions bellow.

surveydatamatrix.m

Converts the imported Excel spreadsheet into numeric array that can be interpreted by the other scripts. Should be open and ran according to instructions bellow.

overall_data_vis.m

Display graphs of the distributions of each dimension, their mean and variance.

Inputs: music, moviestv, gaming, vr, cmusicp, clivem, csound, caudioeng, camed, cvr, cfilm, clives, age

Outputs: None

Print: Distribution graphs of each dimension (13 graphs total)

linear_transformation_analysis.m

Generates the linear transformation of each data set and analyses it. Ln transform, sqrt transform and inverse transform are performed.

Inputs: data set that must be analyzed

Outputs: None

Print: Graphs for the distribution of each transform (4 total).

classifier_euclidean_3.m

function that returns 3 clusters using an Euclidian classifier.

Inputs: processed survey matrix

Outputs: mean values of each class, standard deviation of each class, size of each class

Print: Image with the mean of each class for each dimension

classifier_euclidean.m

function that returns 4 clusters using an Euclidian classifier.

Inputs: processed survey matrix

Outputs: mean values of each class, standard deviation of each class, size of each class

Print: Image with the mean of each class for each dimension

classifier_euclidean_5.m

function that returns 5 clusters using an Euclidian classifier.

Inputs: processed survey matrix

Outputs: mean values of each class, standard deviation of each class, size of each class

Print: Image with the mean of each class for each dimension

classifier_euclidean_6.m

function that returns 6 clusters using an Euclidian classifier.

Inputs: processed survey matrix

Outputs: mean values of each class, standard deviation of each class, size of each class

Print: Image with the mean of each class for each dimension

classifier_gaussian_2.m

function that returns 2 clusters using a Gaussian classifier.

Inputs: processed survey matrix

Outputs: mean values of each class, standard deviation of each class, size of each class

Print: Image with the mean of each class for each dimension

classifier_gaussian_3.m

function that returns 3 clusters using a Gaussian classifier.

Inputs: processed survey matrix

Outputs: mean values of each class, standard deviation of each class, size of each class

Print: Image with the mean of each class for each dimension

classifier_gaussian.m

function that returns 4 clusters using a Gaussian classifier.

Inputs: processed survey matrix

Outputs: mean values of each class, standard deviation of each class, size of each class

Print: Image with the mean of each class for each dimension

classifier_gaussian_5.m

function that returns 5 clusters using a Gaussian classifier using initialization methodology 1.

Inputs: processed survey matrix

Outputs: mean values of each class, standard deviation of each class, size of each class

Print: Image with the mean of each class for each dimension

classifier_gaussian_52.m

function that returns 5 clusters using a Gaussian classifier using initialization methodology 2.

Inputs: processed survey matrix

Outputs: mean values of each class, standard deviation of each class, size of each class

Print: Image with the mean of each class for each dimension

classifier_gaussian_53.m

function that returns 5 clusters using a Gaussian classifier using initialization methodology 3.

Inputs: processed survey matrix

Outputs: mean values of each class, standard deviation of each class, size of each class

Print: Image with the mean of each class for each dimension

There are two simple steps you need to take to re-run the code:

Step1: running surveydatamatrix.m

Open surveydatamatrix.m on MATLAB, on the tab HOME (top left corner) click on Import Data and open Sheet_1.xls. Select columns J K L M T U V W X Y Z AA and AC. Change import type to Cell Array and add rule: Replace unimportable cells with NaN. Once imported, the Cell array should appear on the list of variables (on the right), rename it to OSSICsurvey2 and finally run the script.

Step2: running MaiscriptOSSICsurvey

Open MaiscriptOSSICsurvey. Remove comment marks (%) from appropriate areas according to the information you are trying to display (as described in the script). Run the script.

1.3. Opportunities for improvement of the algorithm

The results of this analysis can certainly be improved if we perform some more robust machine learning techniques. For instance, I believe that utilizing an Expectation Maximization algorithm to predict the mixture distribution of each class and then utilizing a probabilistic classifier instead of a distance one would yield a more accurate clustering. Performing a Principal Component Analysis with sigma threshold at 70-85% before the Expectation Maximization step would possibly also improve the results. The objective of this analysis is not to be extremely accurate when classifying, but rather to identify what are the clusters and estimate their specific characteristic. Because of that I judge a waste of time performing very complex calculations that would yield similar, slightly more accurate, results.

2. Overview of Data Dimensions

The decision of using Euclidean and Mahalanobis methods was made based on the shape of the data distribution of each dimension (A dimension is equivalent to a question in this analysis). In this section we will go over how each data dimension is distributed.

2.1. Hour Allocation for OSSIC

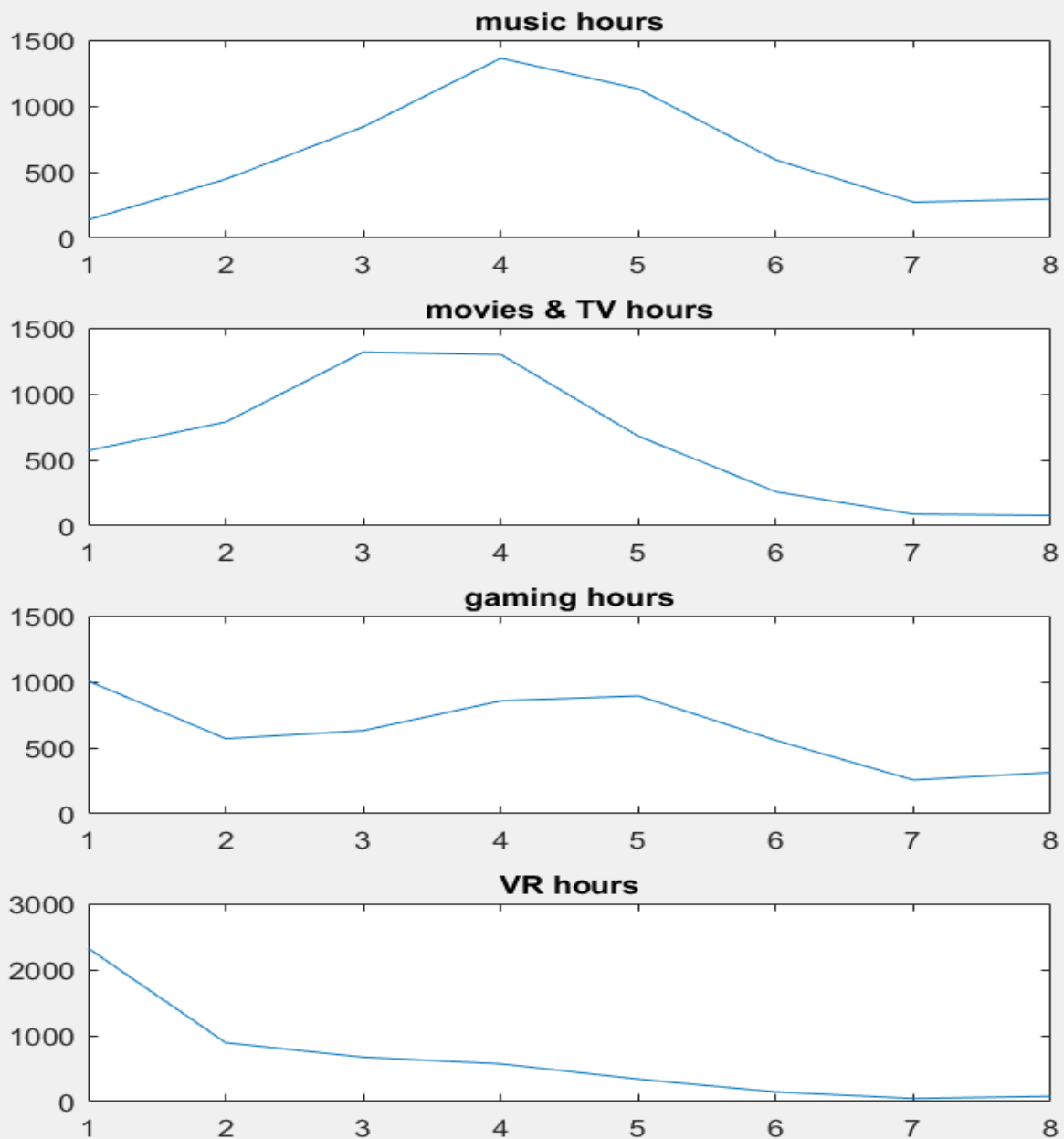
The following graphs reports the distribution for each of the following questions:

Do you plan on listening to music using your OSSIC X? If so, for how many hours per week?

Do you plan on watching movies or TV shows using your OSSIC X? If so, for how many hours per week?

Do you plan on using your OSSIC X for gaming? If so, for how many hours per week?

Do you plan on using your OSSIC X with virtual reality? If so, for how many hours per week?



2.2. Content Creation Proficiency 1

The following graphs reports the distribution for each of the following questions:

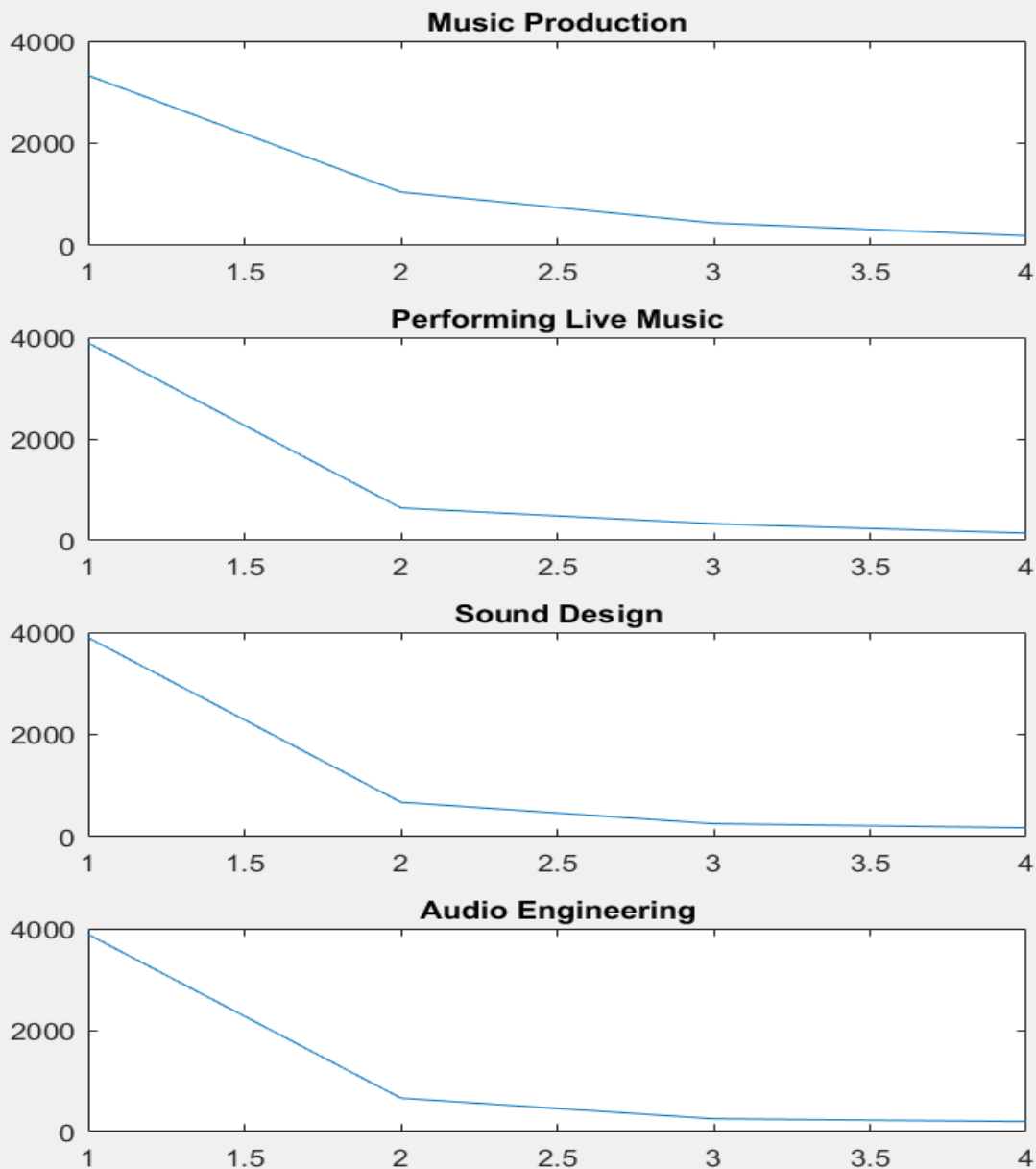
To what level do you create content in the following?

Music production

Performing live music (band, DJ, singer etc.)

Sound design

Audio engineering



2.3. Content Creation Proficiency 2

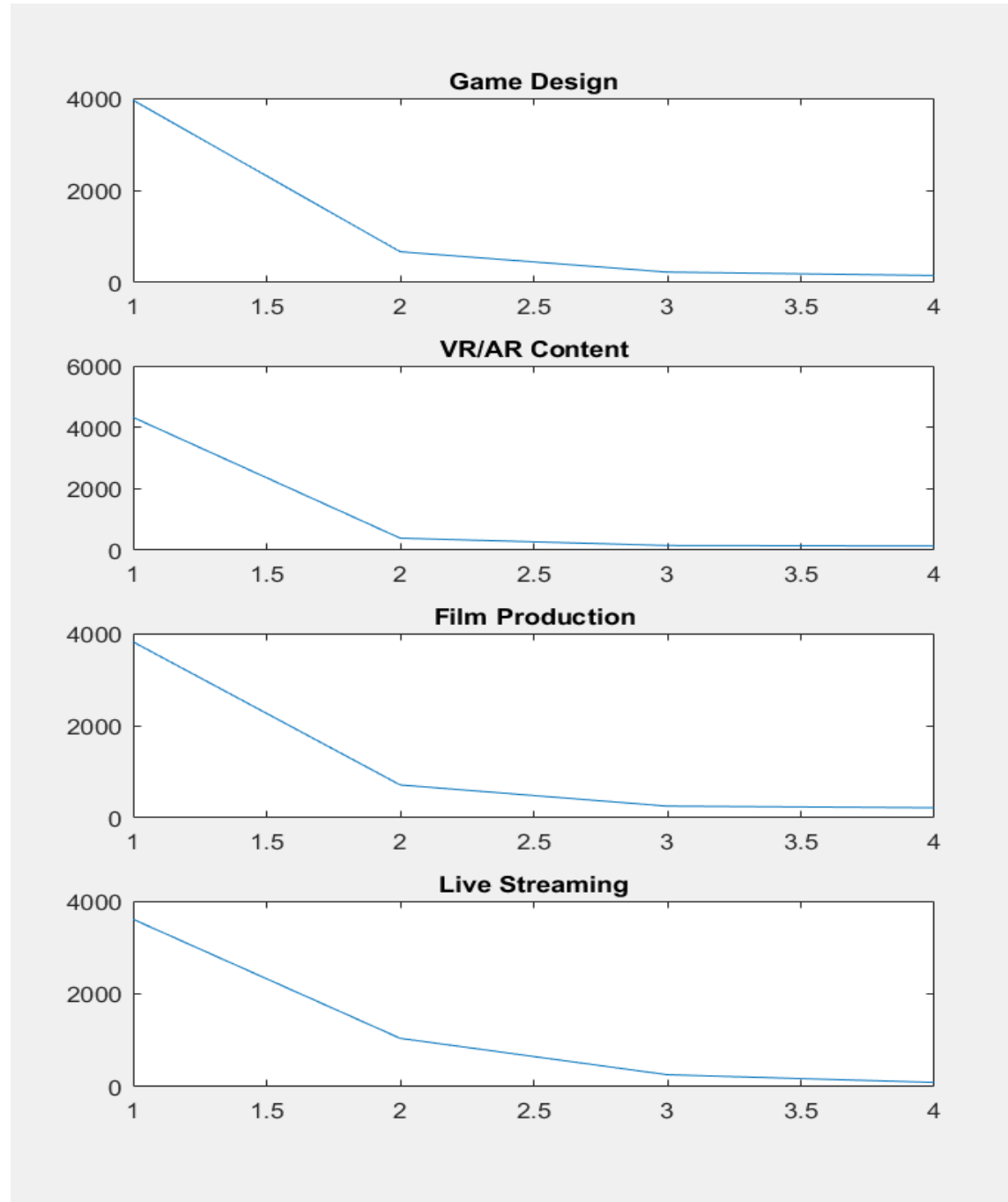
The following graphs reports the distribution for each of the following questions:
To what level do you create content in the following?

Game design

VR/AR content creation

Film production

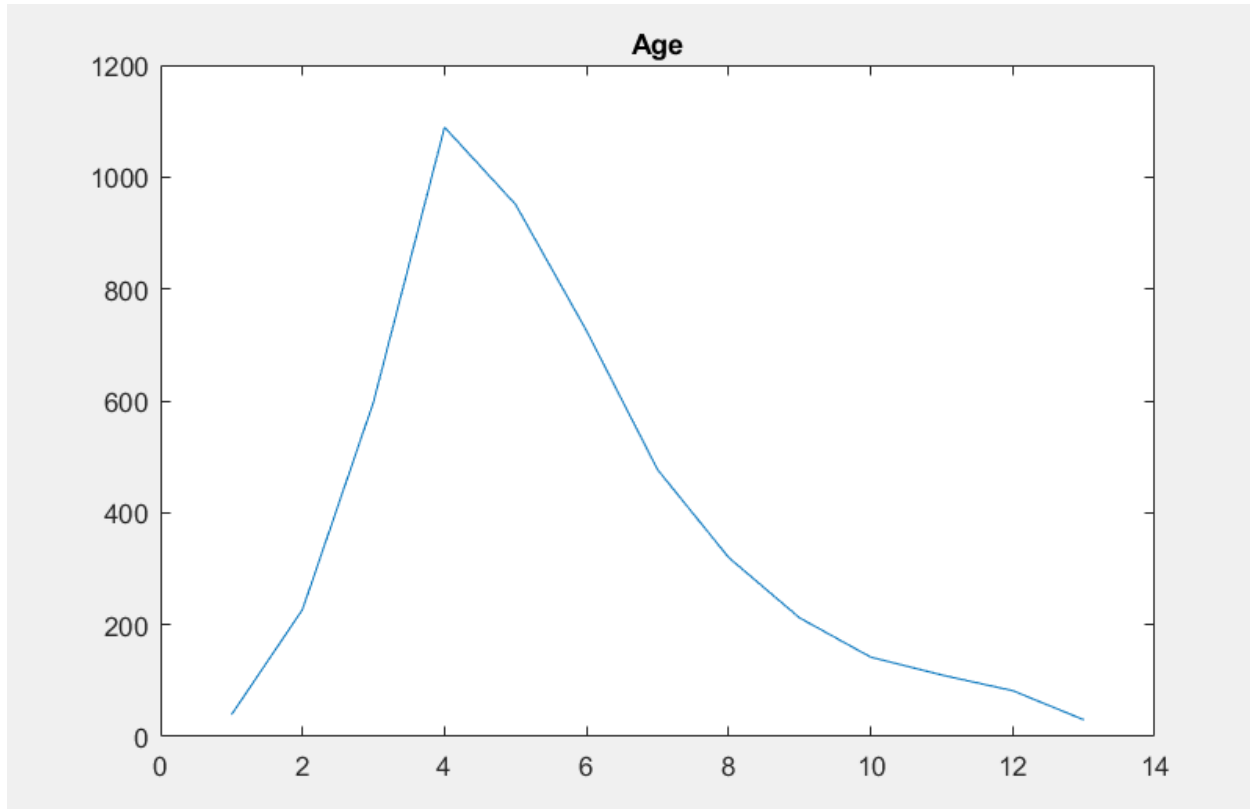
Live Streaming



2.4. Age Distribution

The following graphs reports the distribution for each of the following questions:

Your age



For all the graphs the y axis represents the number of responses for that particular answer.

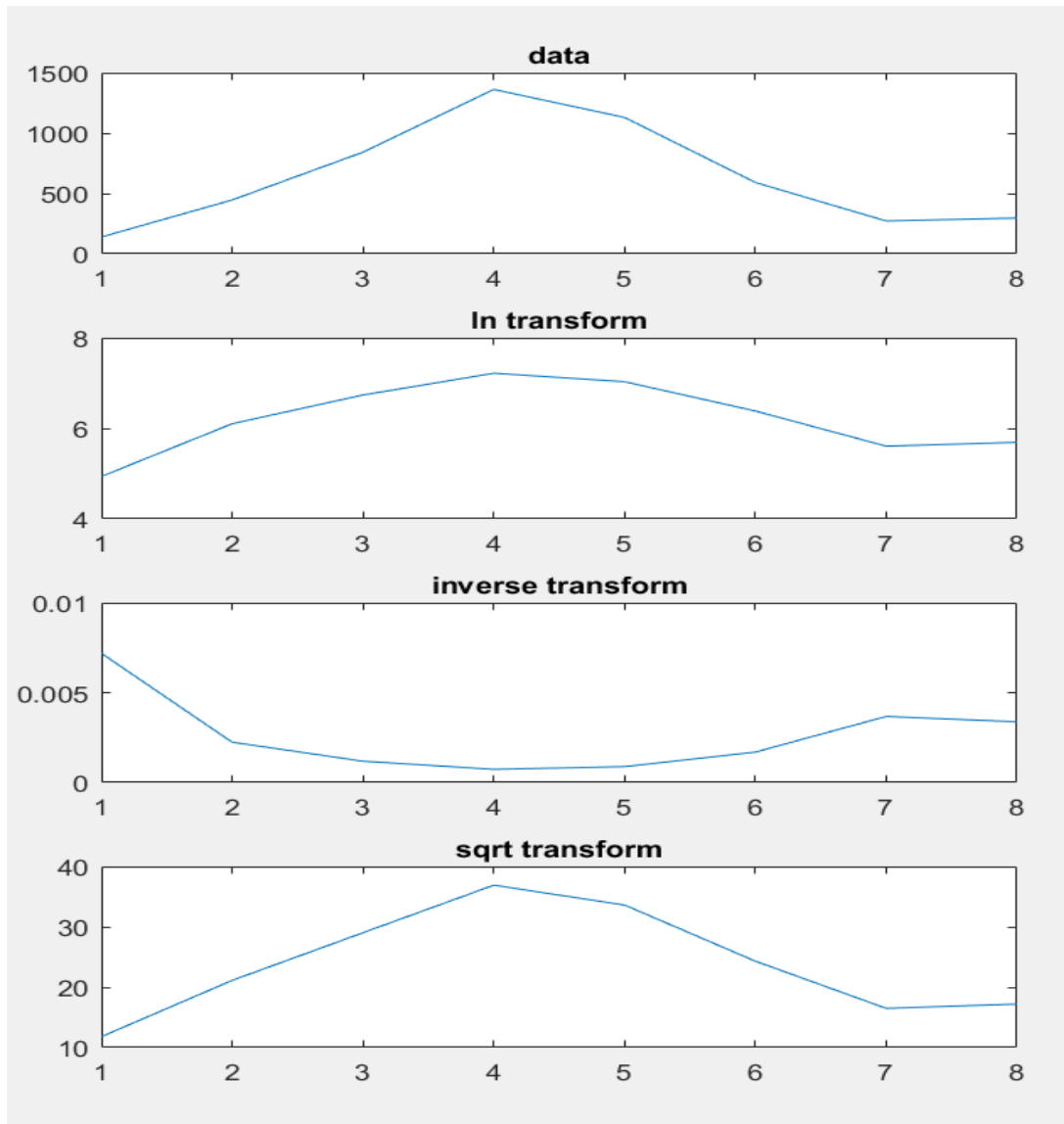
For the first four graphs the x axis is labeled as follows:

Label	0	1	2	3	4	5	6	7	8	9	10	11	12
Graphs 1-4	No 0 hours	1 – 2 hours	2 – 4 hours	4 – 8 hours	8 – 16 hours	16 – 24 hours	24 – 35 hours	35+ hours	-				
Graphs 5-14	-	None	Amateur	Serious Hobbyist	Professional	-	-	-	-				
Graph 15	I prefer not to answer	17 or younger	18-20	21-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64	65+

3. Analysis of Linear Transformation of each vector and choice for optimal dimension

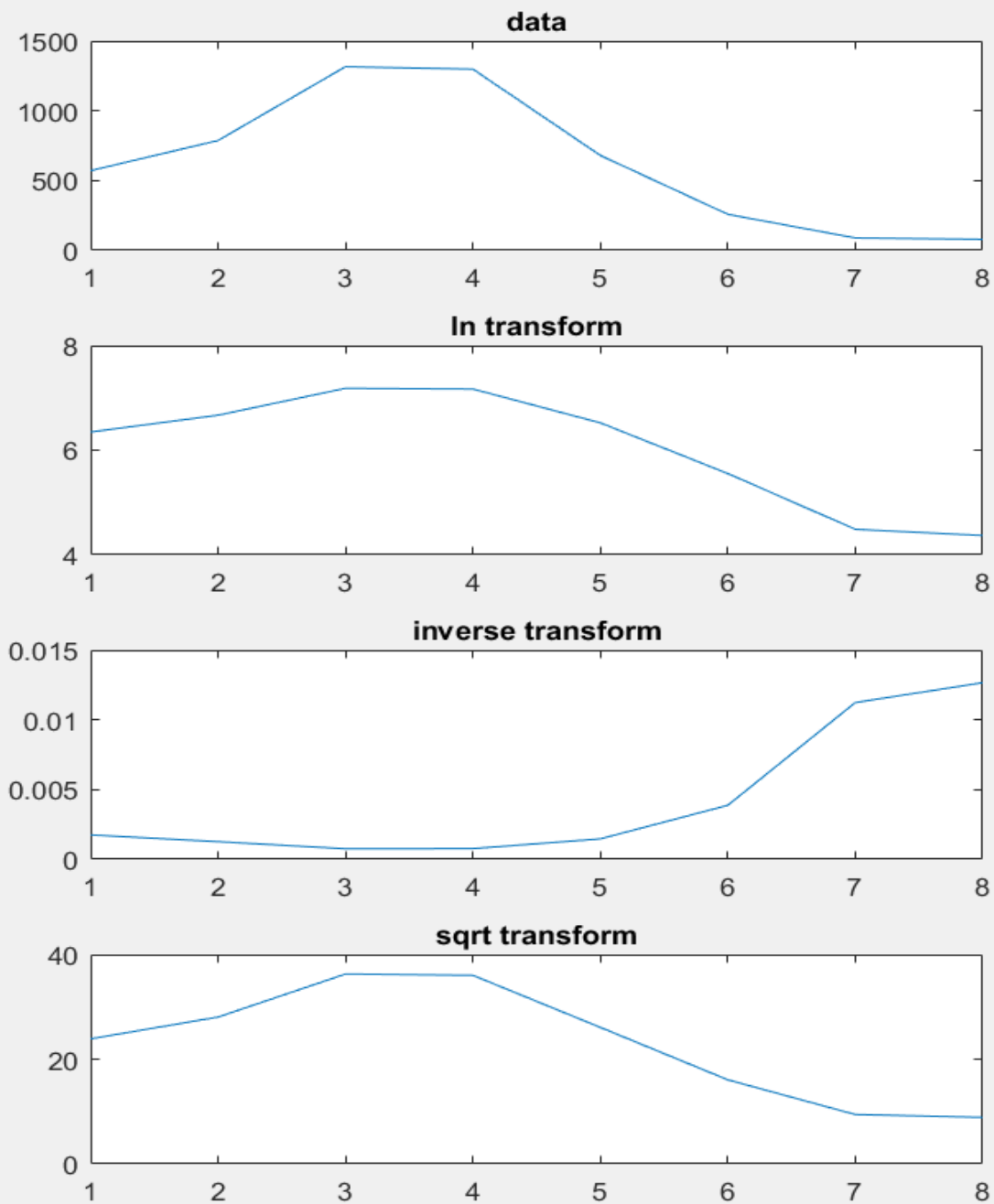
The following graphs depict a detailed picture of the data distribution in each dimension and the linear transformation of that distribution. The linear transformations applied here were: natural log, inverse and squareroot. Each dimension analysis also contains data regarding standard deviation and mean.

3.1. Music hours



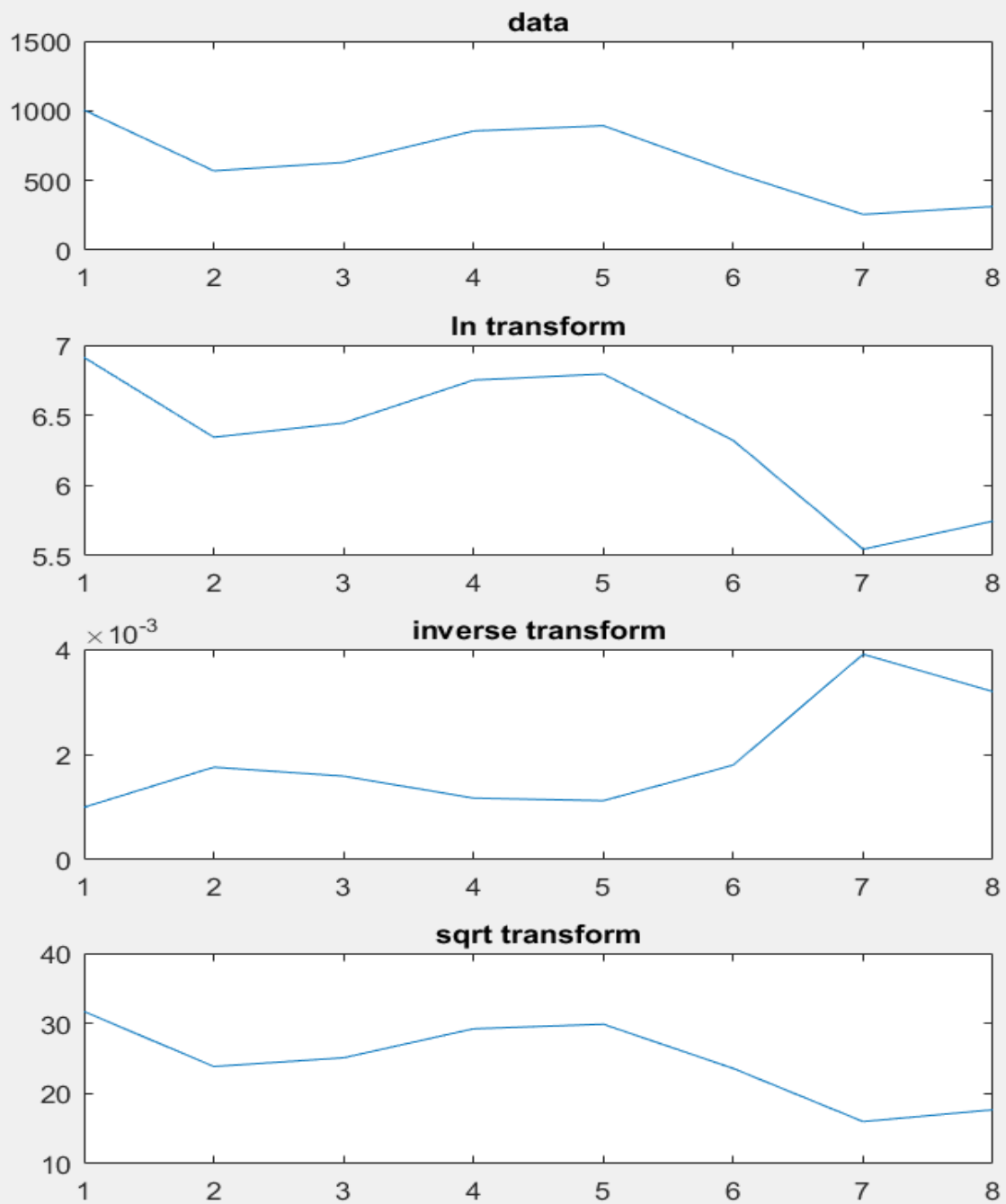
original:	$\sigma^2=2.685184$		mean=4.426
ln transform:	$\sigma^2=4.756620$		mean=4.516
inv transform:	$\sigma^2=8.079250$		mean=4.074
sqrt:	$\sigma^2=3.821710$		mean=4.493

3.2. Movies & TV Hours



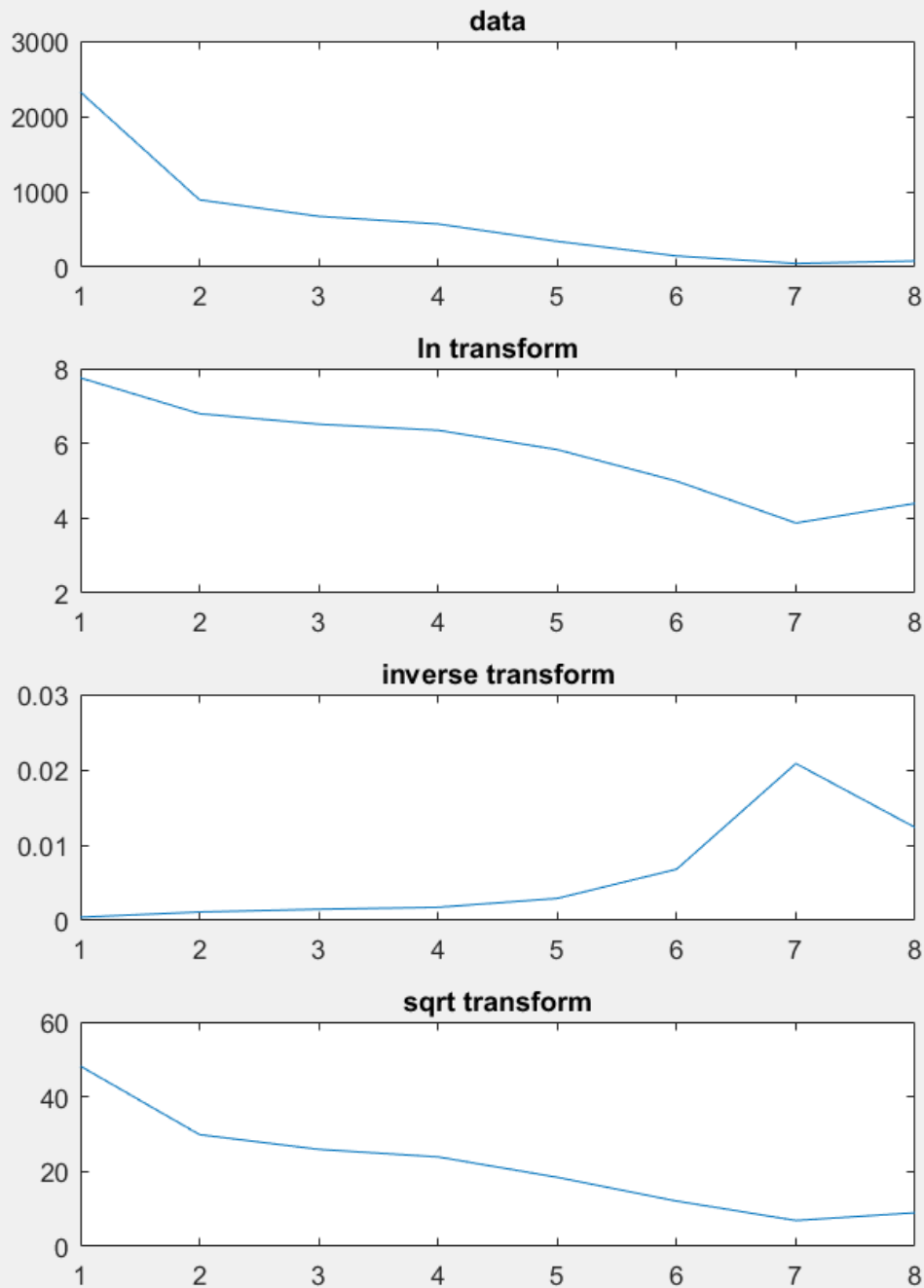
original: $\sigma^2=2.325621$ || mean=3.444
ln transform: $\sigma^2=4.727641$ || mean=4.187
inv transform: $\sigma^2=3.799341$ || mean=6.516
sqrt: $\sigma^2=3.634996$ || mean=3.773

3.3. Gaming Hours



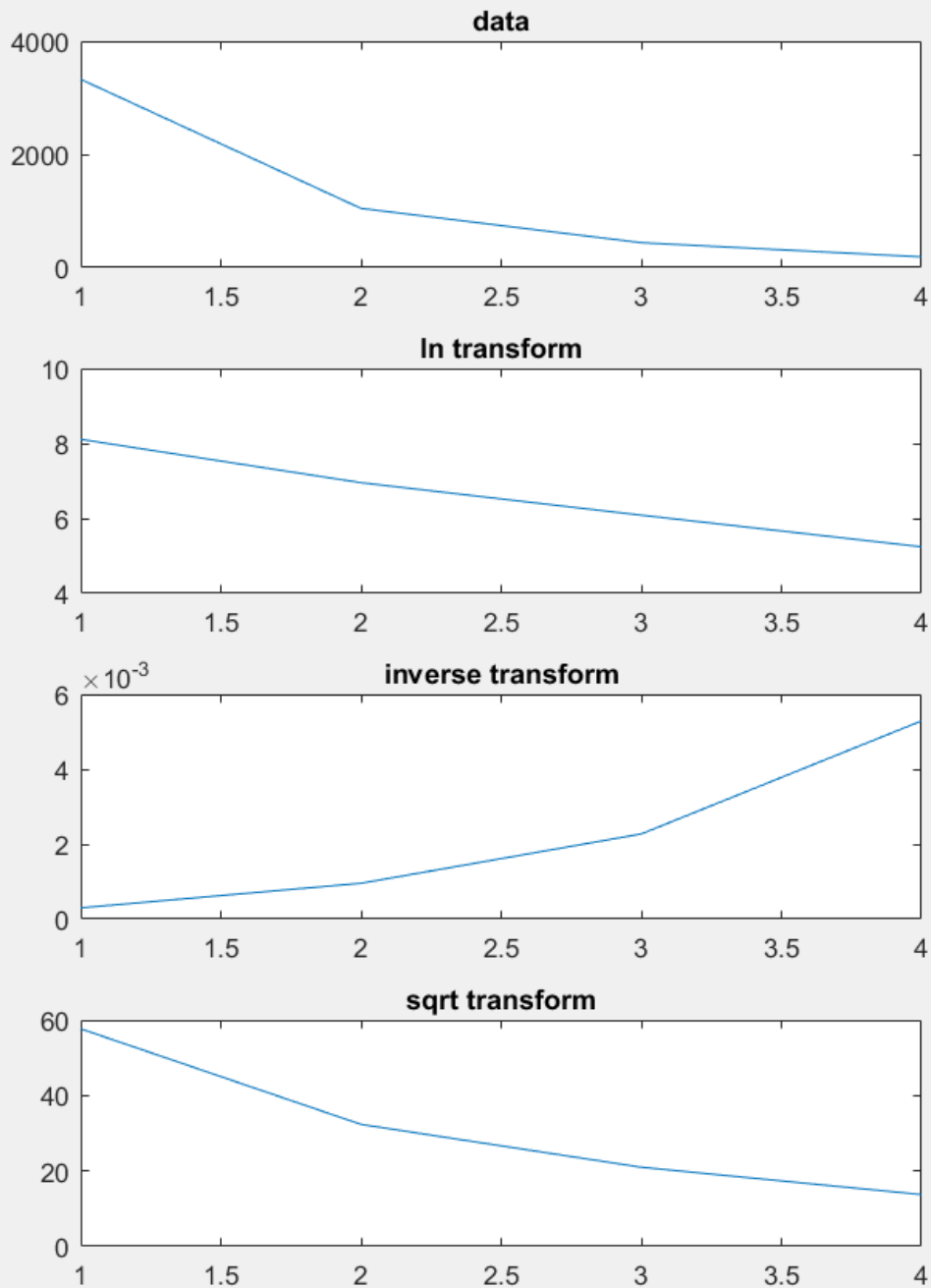
original: $\sigma^2=4.386561$ || mean=3.850
ln transform: $\sigma^2=5.126389$ || mean=4.377
inv transform: $\sigma^2=5.370740$ || mean=5.361
sqrt: $\sigma^2=4.837502$ || mean=4.141

3.4. VR hours



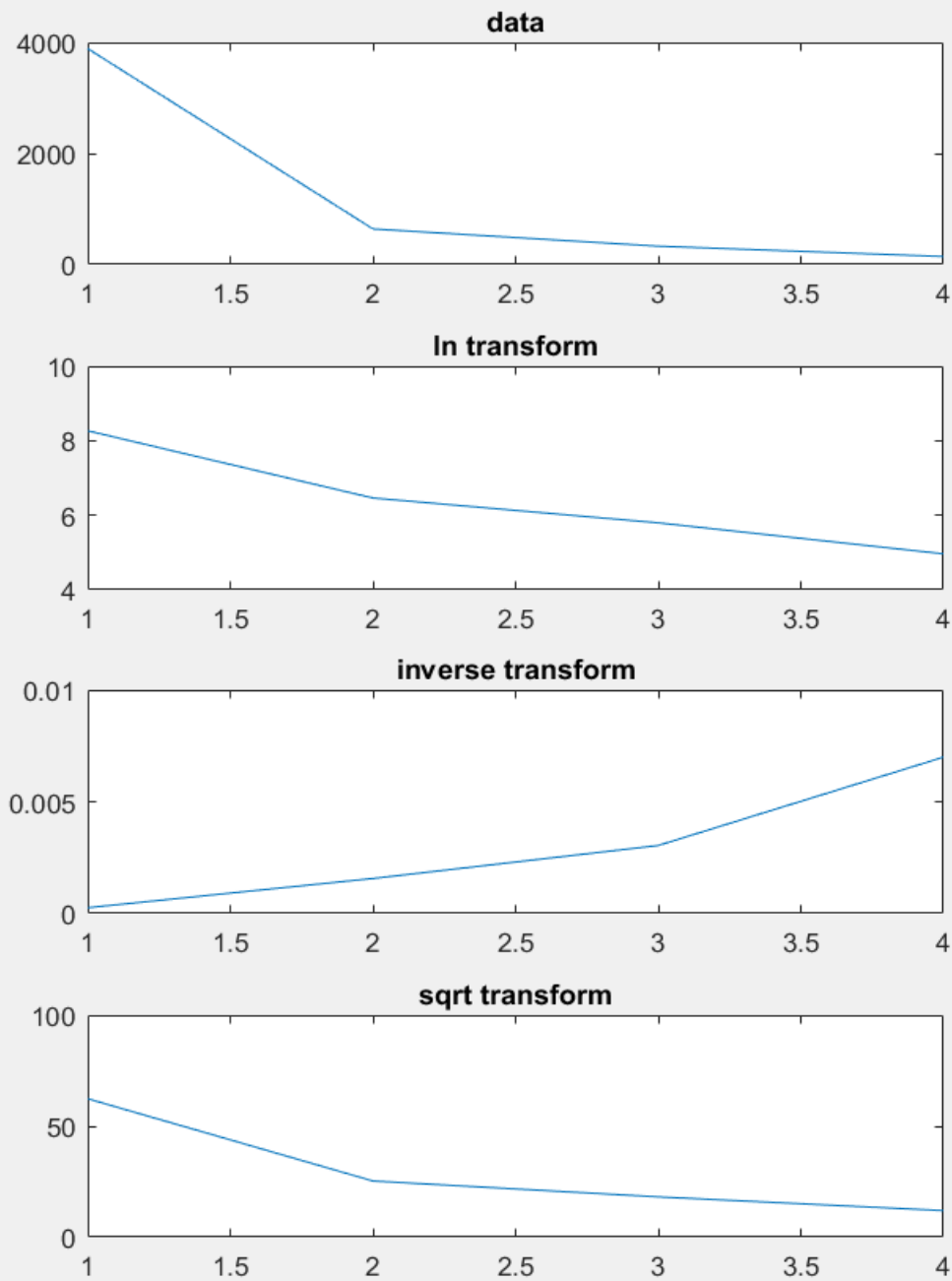
original: $\sigma^2=2.788993$ || mean=2.360
ln transform: $\sigma^2=5.040115$ || mean=4.036
inv transform: $\sigma^2=2.217418$ || mean=6.587
sqrt: $\sigma^2=4.325130$ || mean=3.250

3.5. Music Production



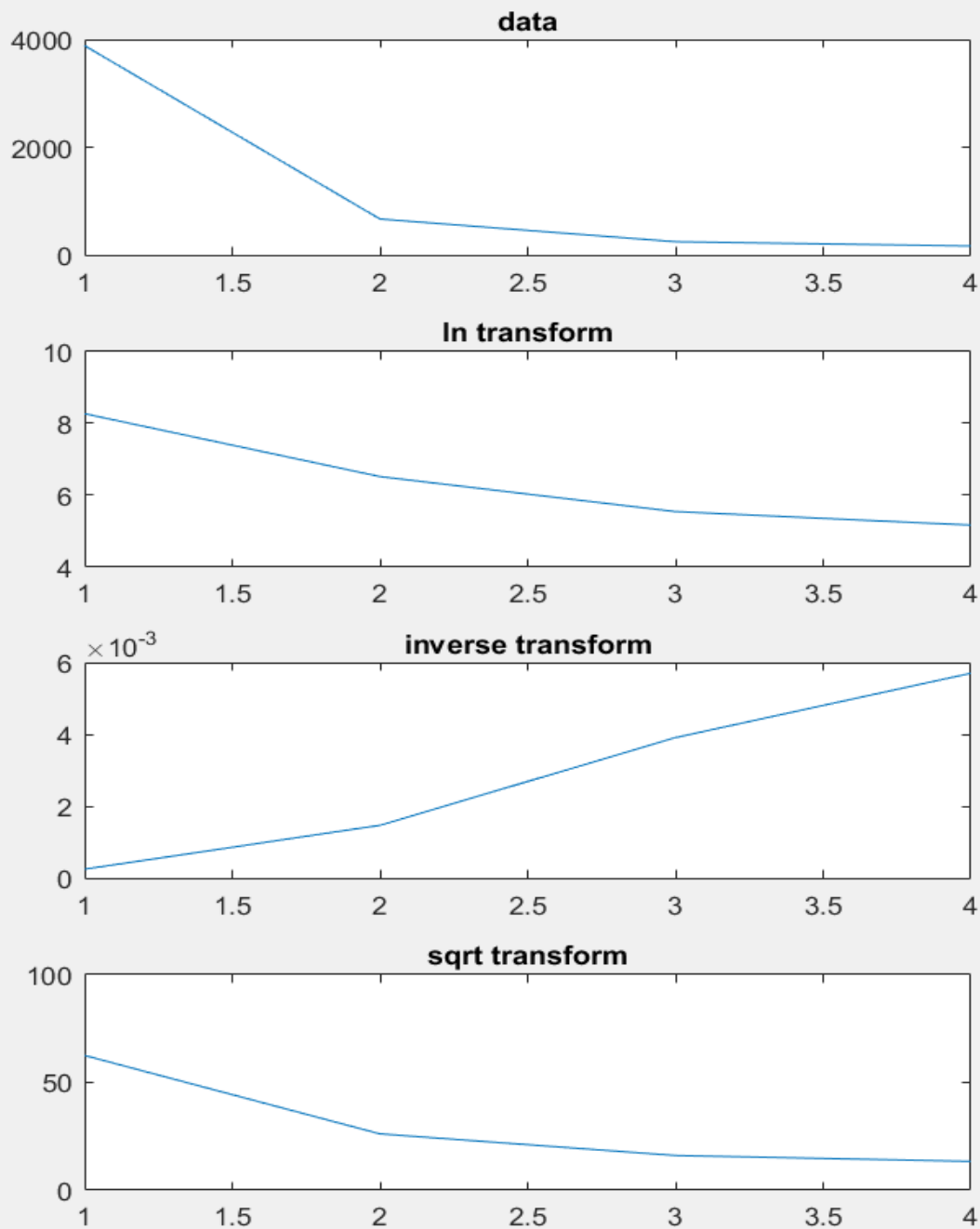
original: $\sigma^2=0.652636$ || mean=1.498
ln transform: $\sigma^2=1.229633$ || mean=2.321
inv transform: $\sigma^2=0.665360$ || mean=3.423
sqrt: $\sigma^2=1.065906$ || mean=1.926

3.6.Live Music



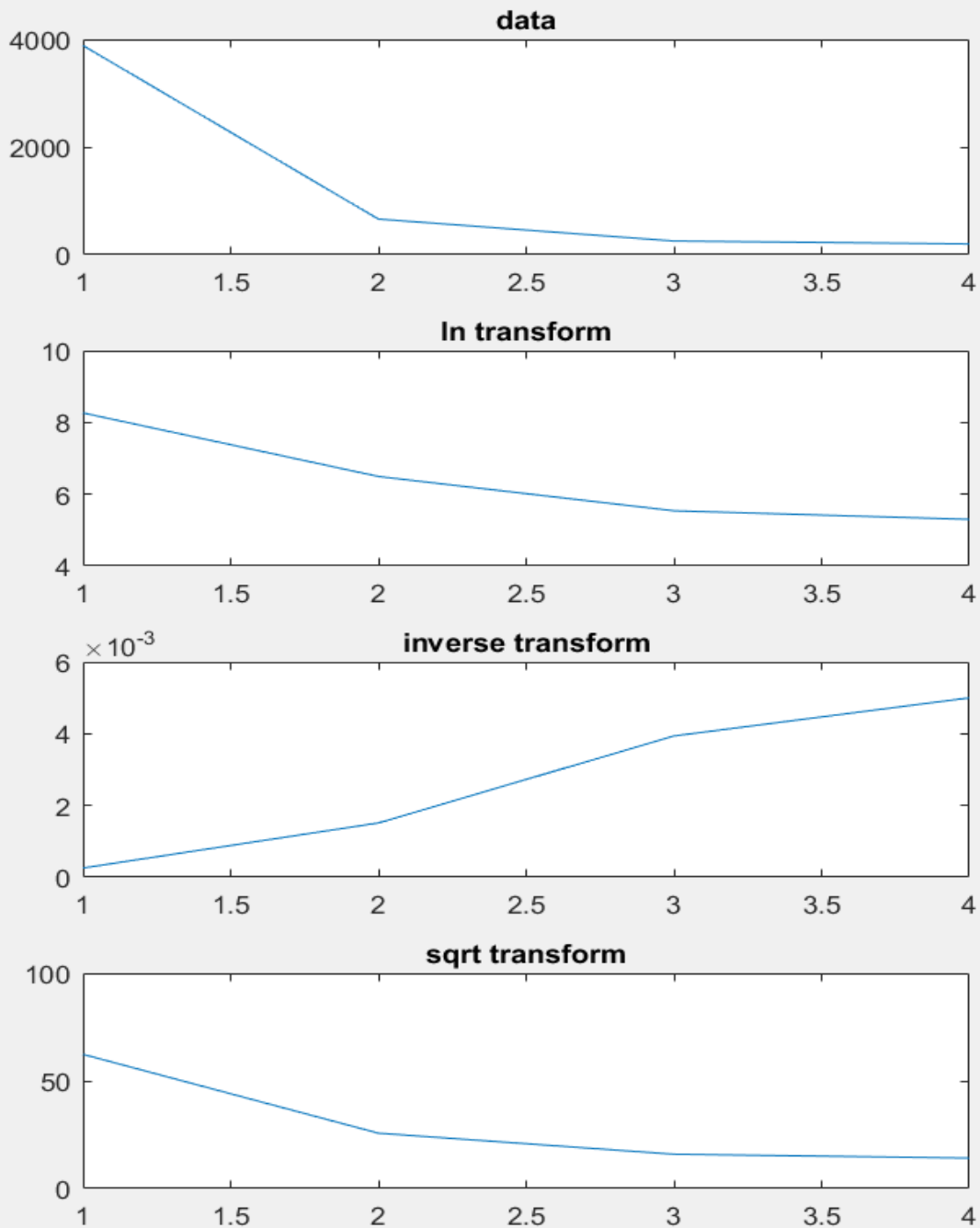
original:	$\sigma^2=0.529135$		mean=1.345
ln transform:	$\sigma^2=1.245074$		mean=2.293
inv transform:	$\sigma^2=0.636548$		mean=3.415
sqrt:	$\sigma^2=1.060053$		mean=1.827

3.7. Sound Design



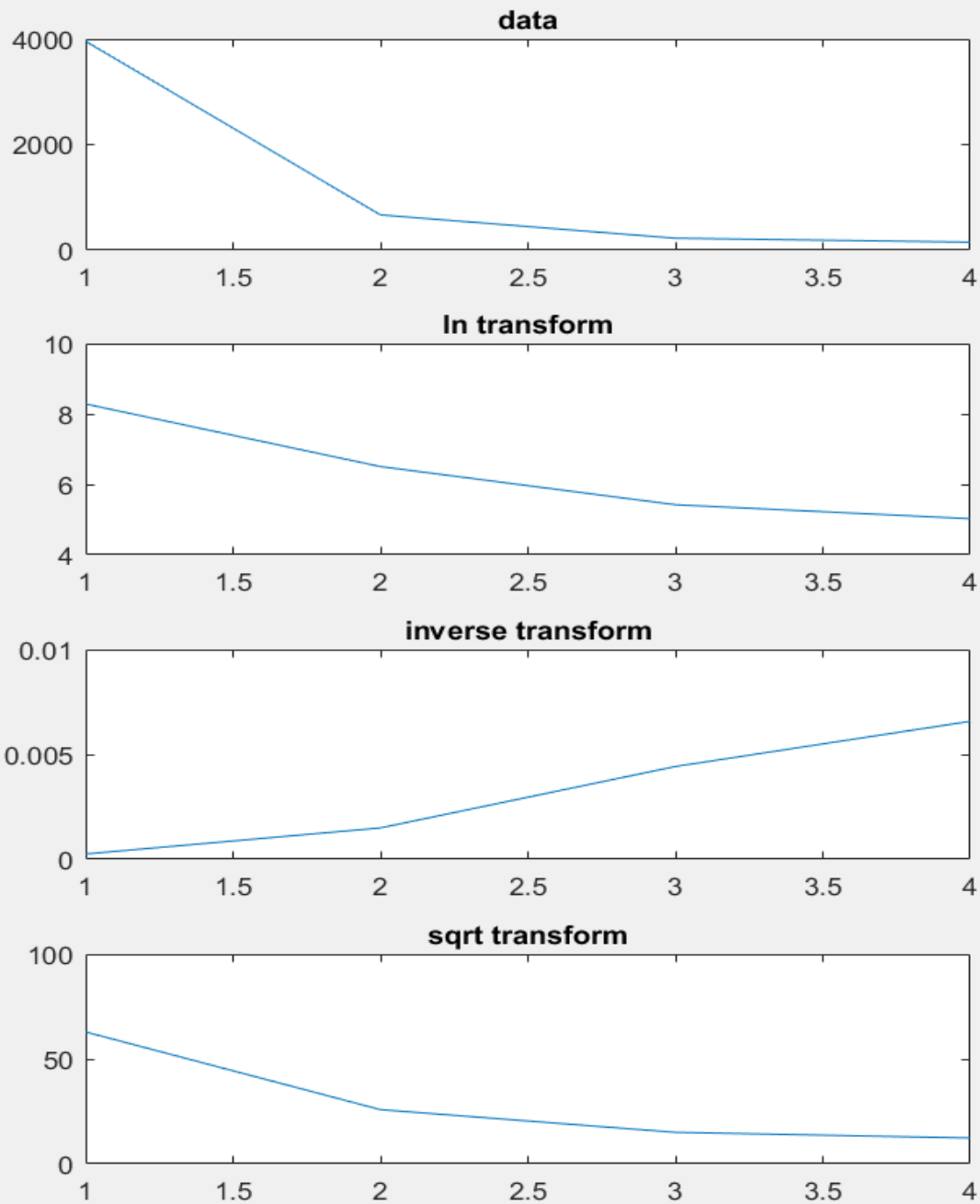
original: $\sigma^2=0.536931$ || mean=1.342
ln transform: $\sigma^2=1.263253$ || mean=2.298
inv transform: $\sigma^2=0.615758$ || mean=3.327
sqrt: $\sigma^2=1.087473$ || mean=1.830

3.8. Audio Engineering



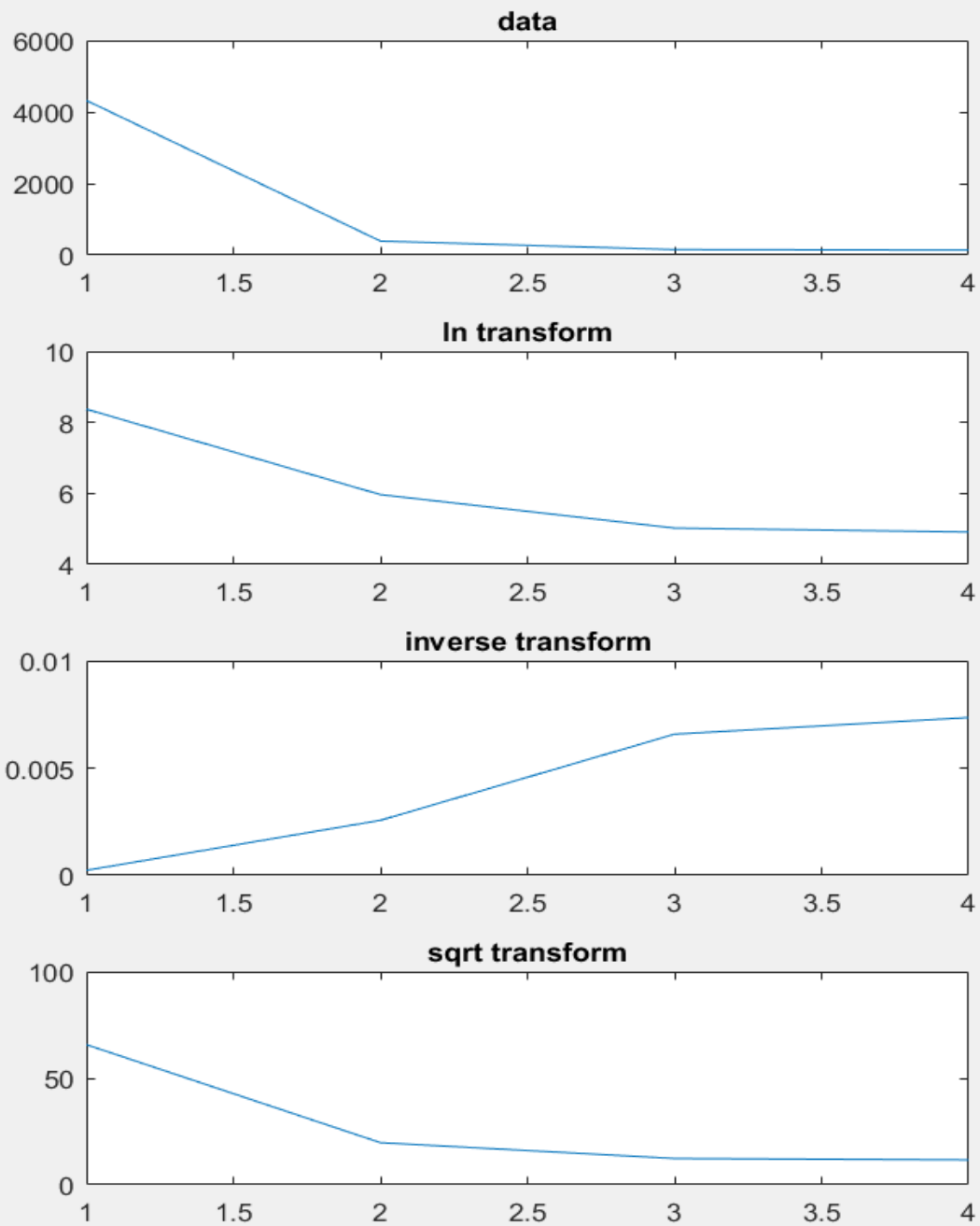
original: $\sigma^2=0.570048$ || mean=1.354
ln transform: $\sigma^2=1.272797$ || mean=2.307
inv transform: $\sigma^2=0.627306$ || mean=3.278
sqrt: $\sigma^2=1.117966$ || mean=1.847

3.9. Game Design



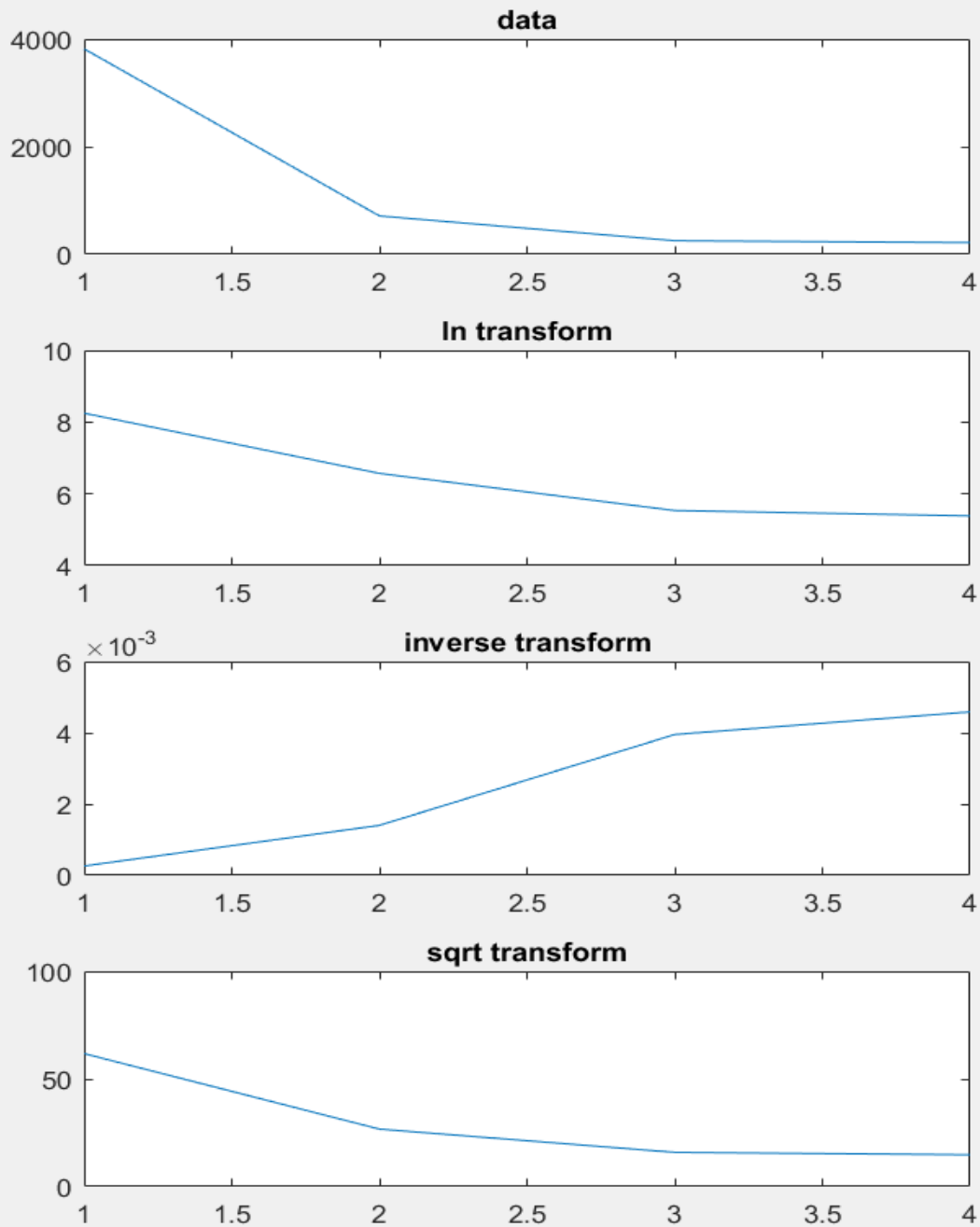
original: $\sigma^2=0.488493$ || mean=1.315
ln transform: $\sigma^2=1.258452$ || mean=2.285
inv transform: $\sigma^2=0.583754$ || mean=3.359
sqrt: $\sigma^2=1.056007$ || mean=1.800

3.10. VR/AR Content



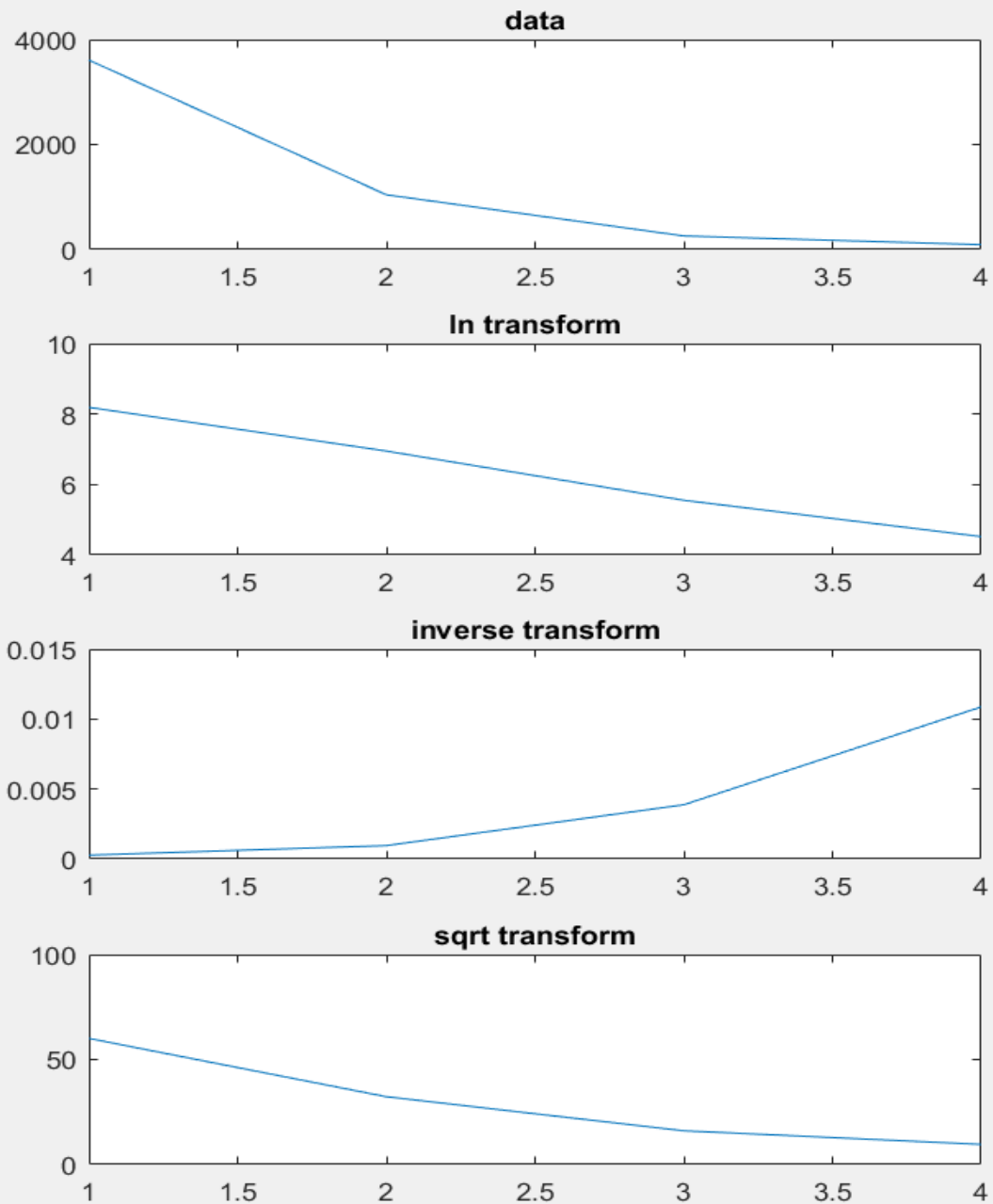
original: $\sigma^2=0.395685$ || mean=1.220
ln transform: $\sigma^2=1.290158$ || mean=2.267
inv transform: $\sigma^2=0.581277$ || mean=3.259
sqrt: $\sigma^2=1.063568$ || mean=1.725

3.11. Film Production



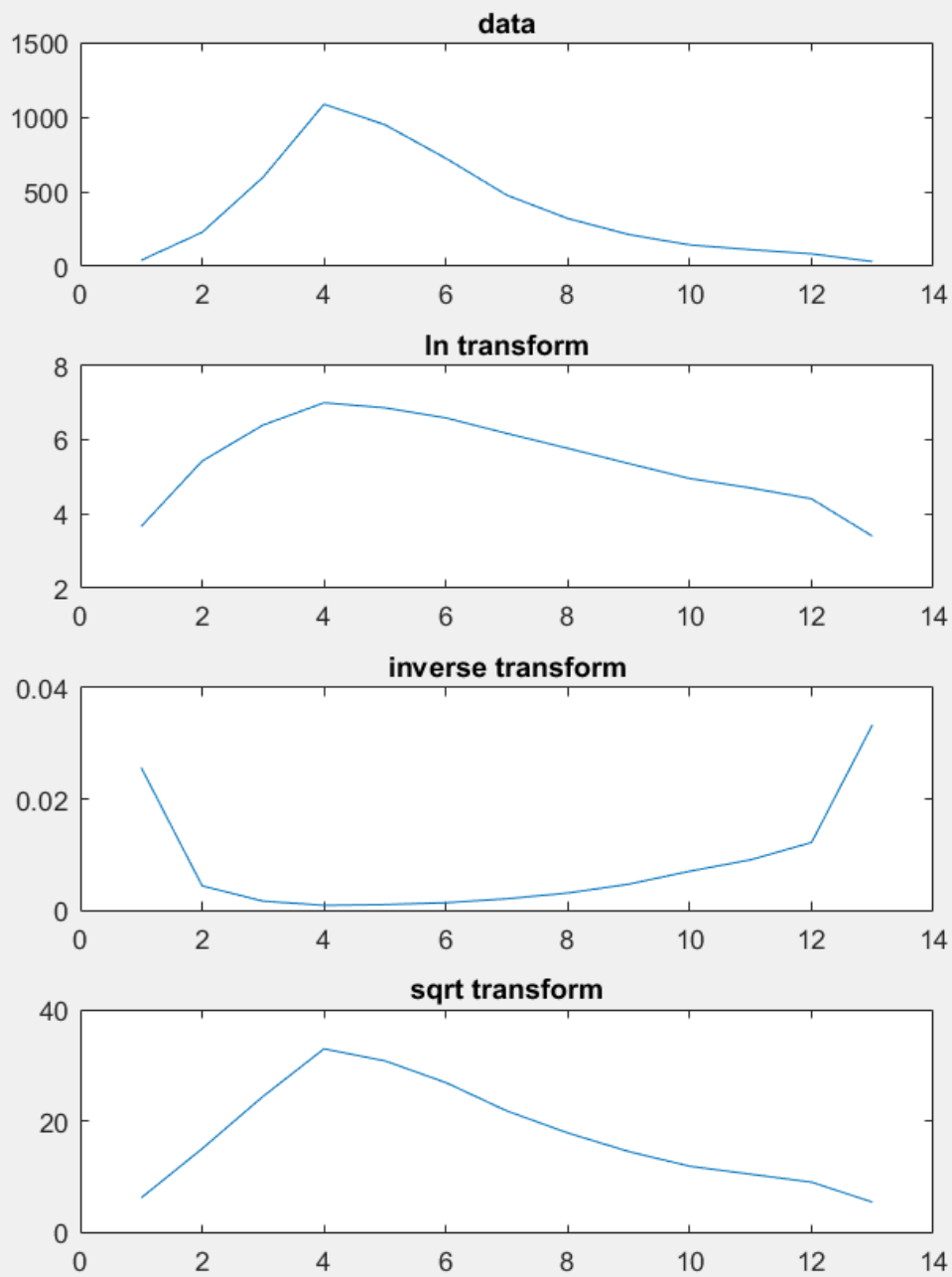
original: $\sigma^2=0.596892$ || mean=1.374
ln transform: $\sigma^2=1.274447$ || mean=2.313
inv transform: $\sigma^2=0.621661$ || mean=3.261
sqrt: $\sigma^2=1.128798$ || mean=1.863

3.12. Live Streaming



original: $\sigma^2=0.445787$ || mean=1.367
ln transform: $\sigma^2=1.197829$ || mean=2.254
inv transform: $\sigma^2=0.466709$ || mean=3.585
sqrt: $\sigma^2=0.925914$ || mean=1.790

3.13. Age Distribution



original: $\sigma^2=355.521484$ || mean=384.769
ln transform: $\sigma^2=1.170818$ || mean=5.437
inv transform: $\sigma^2=0.010152$ || mean=0.008
sqrt: $\sigma^2=9.182369$ || mean=17.520

3.14. Summary of data and linear transformation distributions

dataset		Original data		
type	specific	sigma^2	mean	ratio
hours	Music	2.685184	4.426	0.606684139
	Movies & TV	2.325621	3.444	0.675267422
	Gaming	4.386561	3.85	1.139366494
	VR	2.788993	2.36	1.181776695
Creation	Music Production	0.652636	1.498	0.435671562
	Performing Live Music	0.529135	1.345	0.393408922
	Sound Design	0.536931	1.342	0.400097615
	Audio Engineering	0.570048	1.354	0.42101034
	Game Design	0.488493	1.315	0.371477567
	VR/AR Content	0.395685	1.22	0.324331967
	Film Production	0.596892	1.374	0.434419214
	Livre Streaming	0.445787	1.367	0.326106072
Misc	Age Group	5.438233	5.51	0.986975136

dataset		In transform		
type	specific	sigma^2	mean	ratio
hours	Music	4.75662	4.516	1.053281665
	Movies & TV	4.727641	4.187	1.129123716
	Gaming	5.126389	4.377	1.171210647
	VR	5.040115	4.036	1.248789643
Creation	Music Production	1.229633	2.321	0.529785868
	Performing Live Music	1.245074	2.293	0.542989097
	Sound Design	1.263253	2.298	0.549718451
	Audio Engineering	1.272797	2.307	0.55171088
	Game Design	1.258452	2.285	0.550744858
	VR/AR Content	1.290158	2.267	0.569103661
	Film Production	1.274447	2.313	0.550993083
	Livre Streaming	1.197829	2.254	0.531423691
Misc	Age Group	11.866237	6.669	1.779312791

dataset		inv transform		
type	specific	sigma^2	mean	ratio
hours	Music	8.07925	4.074	1.983124693
	Movies & TV	3.799341	6.516	0.583078729
	Gaming	5.37074	5.361	1.001816825
	VR	2.217418	6.587	0.336635494
Creation	Music Production	0.66536	3.423	0.1943792
	Performing Live Music	0.636548	3.415	0.186397657
	Sound Design	0.615758	3.327	0.18507905
	Audio Engineering	0.627306	3.278	0.191368517
	Game Design	0.583754	3.359	0.173788032
	VR/AR Content	0.581277	3.259	0.17836054
	Film Production	0.621661	3.261	0.190635081
	Livre Streaming	0.466709	3.585	0.130183821
Misc	Age Group	24.561157	8.333	2.947456738

dataset		sqrt transform		
type	specific	sigma^2	mean	ratio
hours	Music	3.82171	4.493	0.850592032
	Movies & TV	3.634996	3.773	0.963423271
	Gaming	4.837502	4.141	1.168196571
	VR	4.32513	3.25	1.330809231
Creation	Music Production	1.065906	1.926	0.553429907
	Performing Live Music	1.060053	1.827	0.580215107
	Sound Design	1.087473	1.83	0.594247541
	Audio Engineering	1.117966	1.847	0.605287493
	Game Design	1.056007	1.8	0.586670556
	VR/AR Content	1.063568	1.725	0.616561159
	Film Production	1.128798	1.863	0.605903382
	Livre Streaming	0.925914	1.79	0.517270391
Misc	Age Group	8.988518	6.142	1.463451319

It is noticeable that at least one of each transformations for a given data dimension looks similar to a Gaussian distribution or to a La Placian distribution. This conclusion results in the choice of the Euclidean and Manhalabis methods.

The excel sheet with the complete summary of the linear transformation analysis can be found on the spread sheet [linear transformation analysis.xlsx](#)

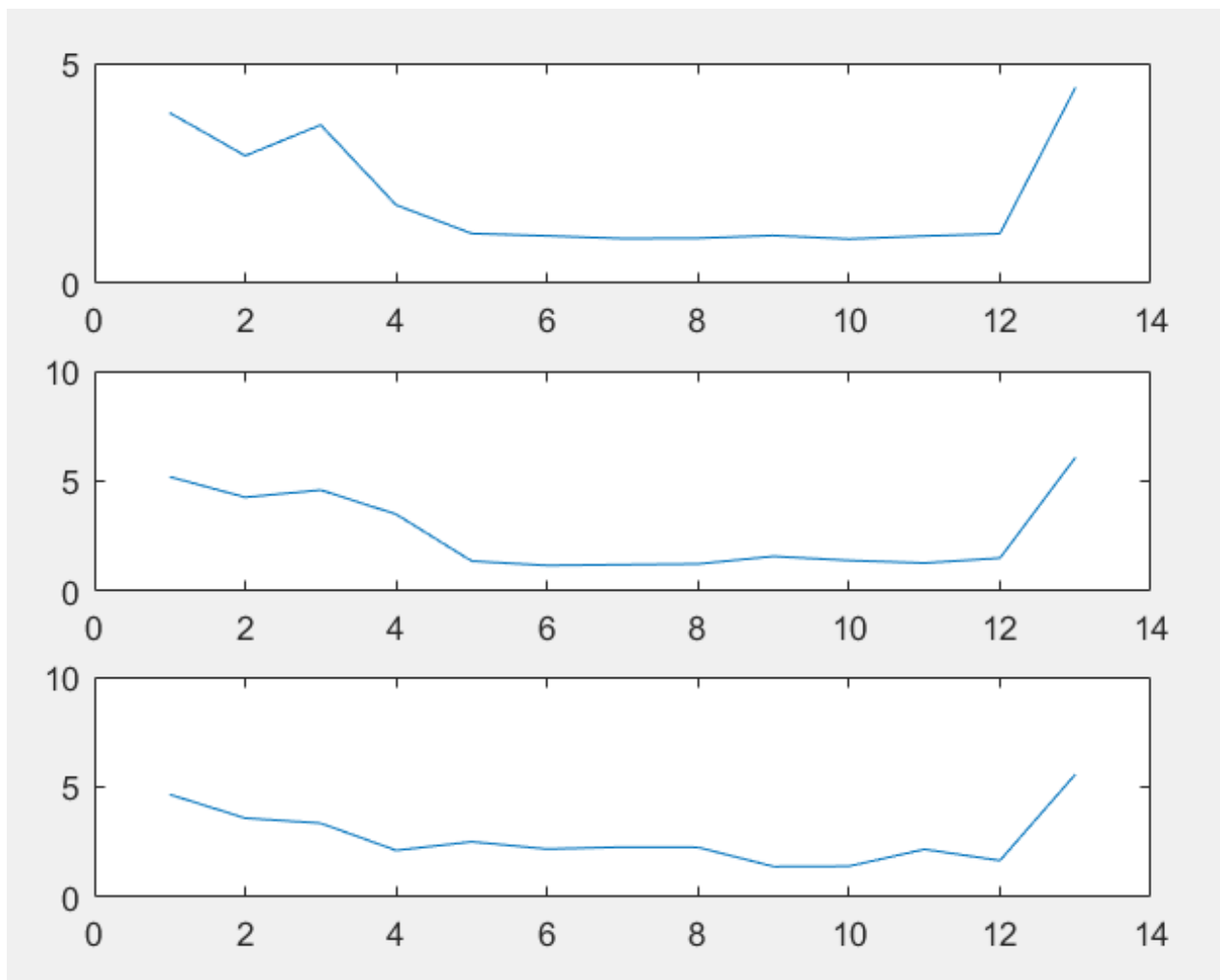
4. Results: Euclidean distance vs Mahalanobis distance

In this section, we will analyze the clusters that resulted from the Euclidean k-mean method and Mahalanobis k-mean method. The main difference between the two is that the Mahalanobis utilizes the inverse of the covariance matrix as a weighting factor to calculate the distance between the classifier mean and the data points.

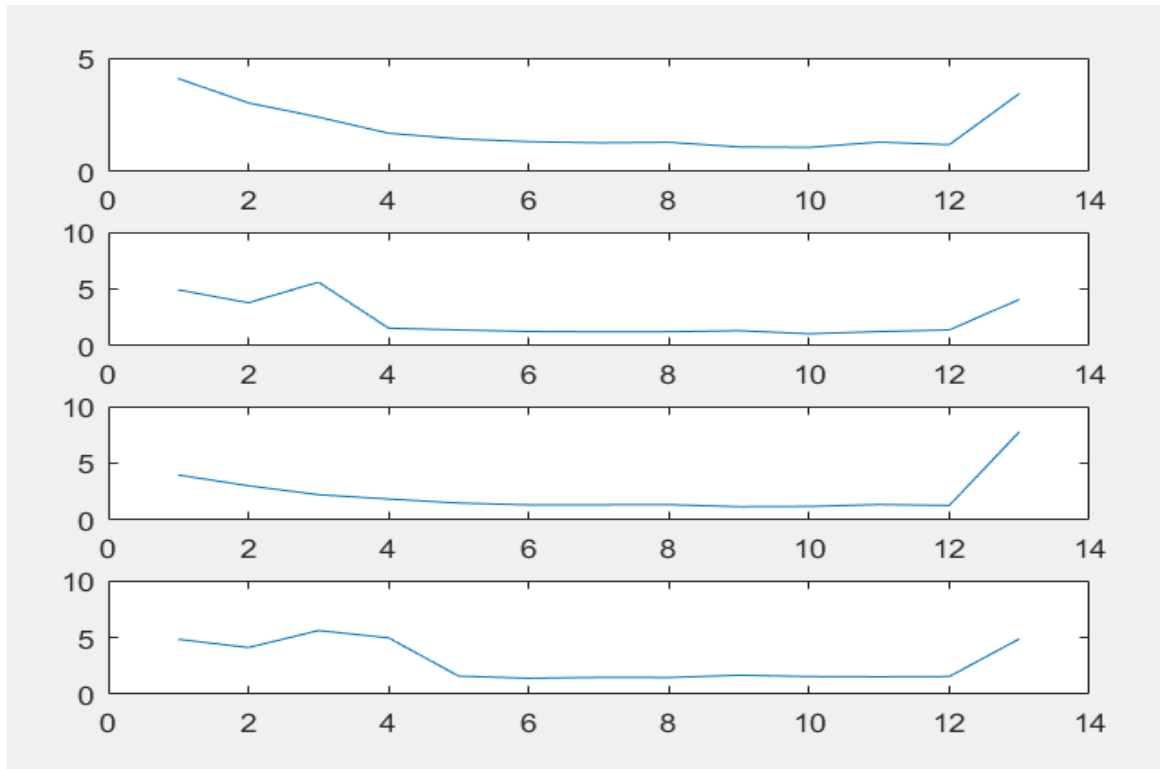
In the following graphs the x axis represents the number of the question (dimension ordered in the same way as the previous sections) and the y-axis represents the response value (equivalent to the x-axis on page XX).

The final results of this analysis is elaborated on the document: [Final Analysis.xlsx](#)

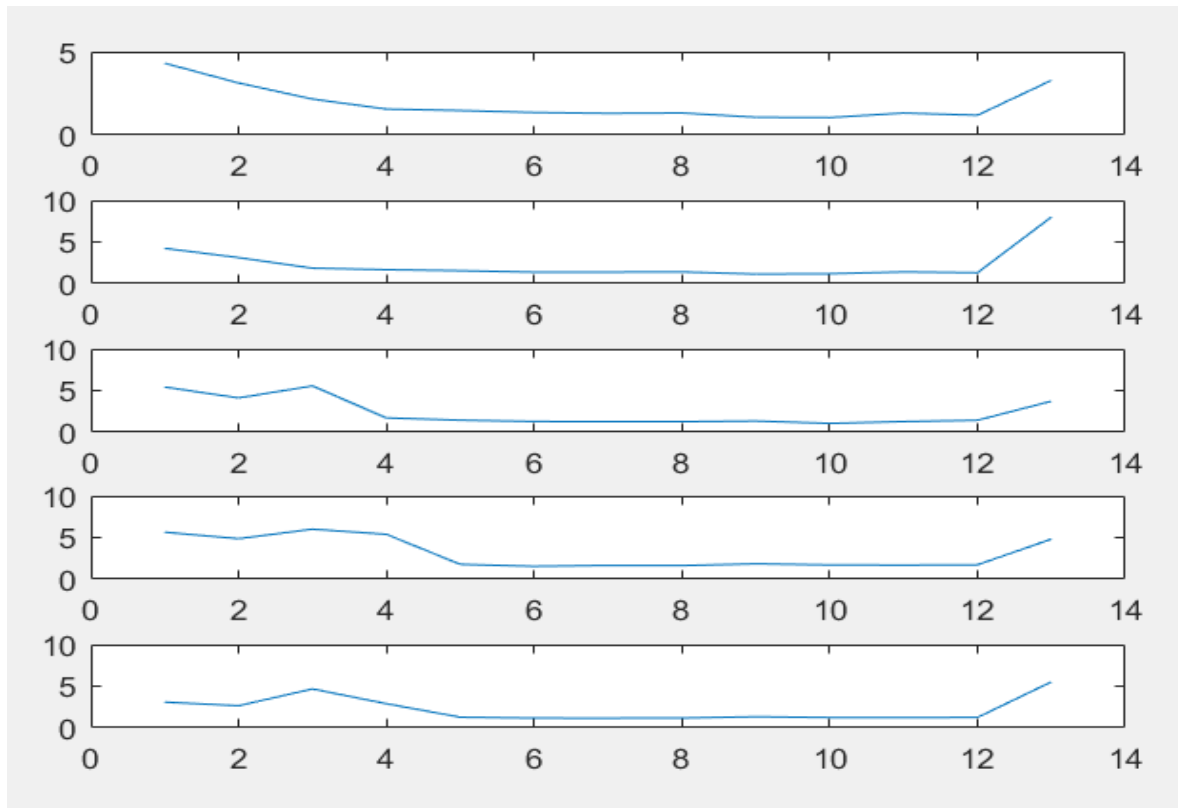
4.1. Euclidean distance with 3 clusters, resulting cluster averages:



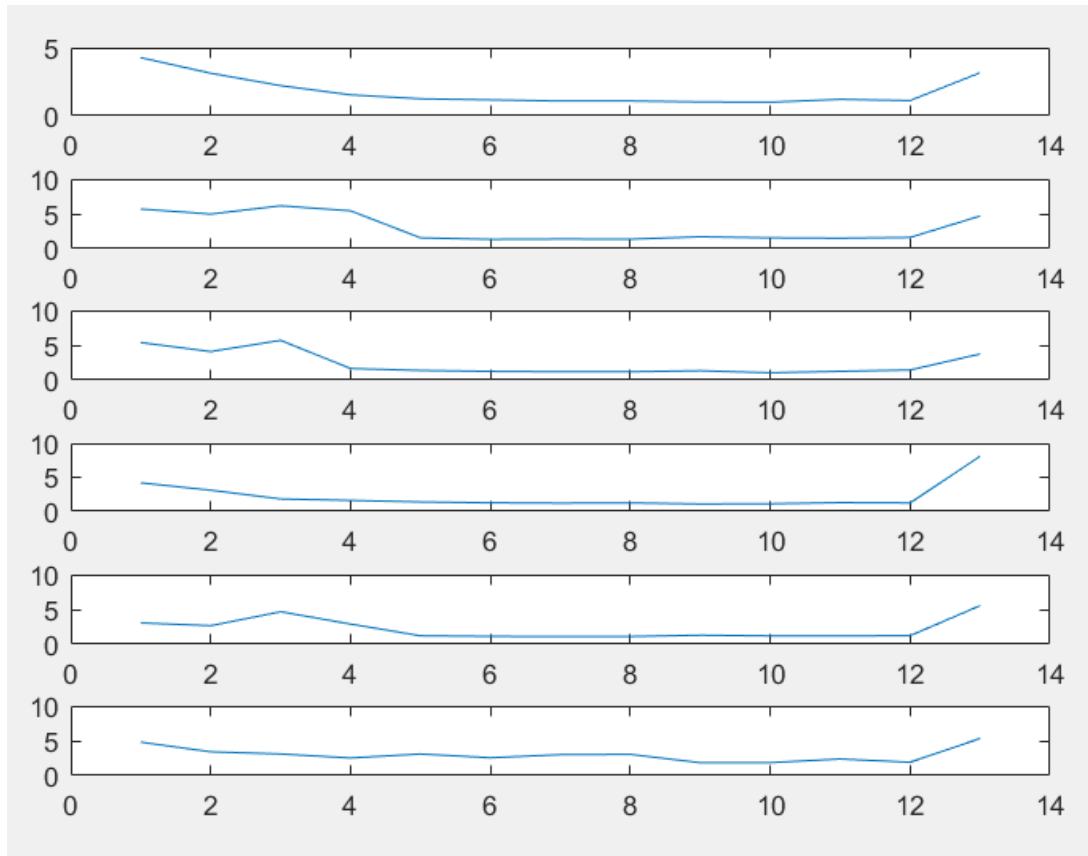
4.2. Euclidean distance with 4 clusters, resulting cluster averages:



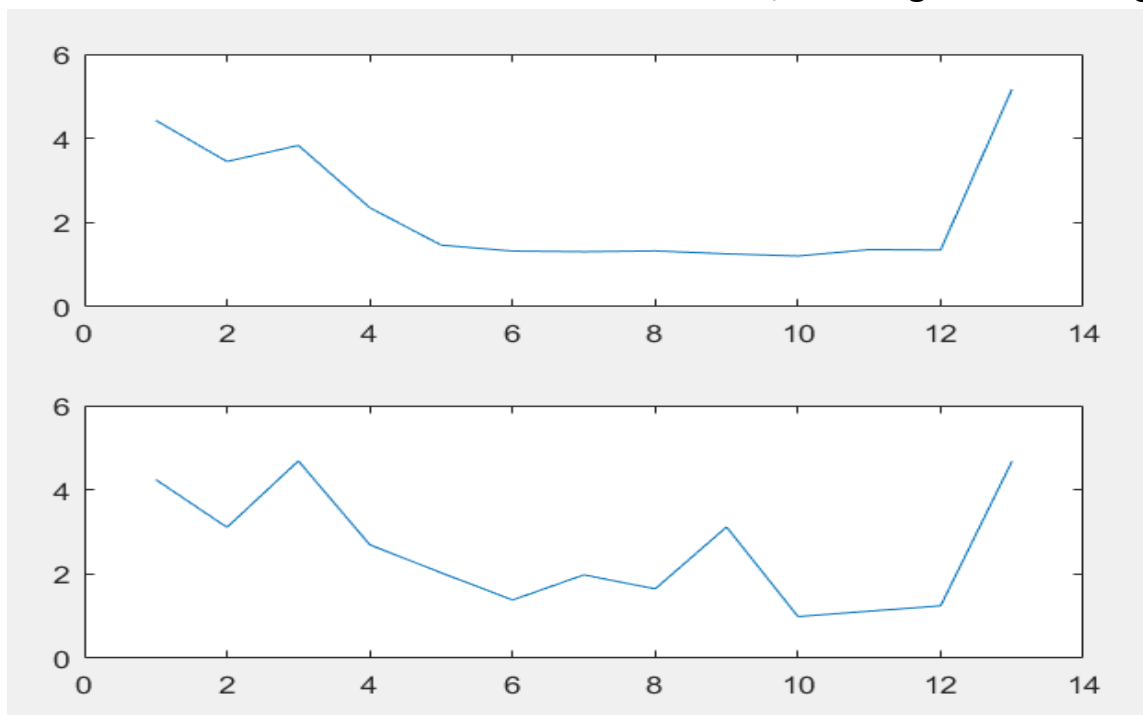
4.3. Euclidean distance with 5 clusters, resulting cluster averages:



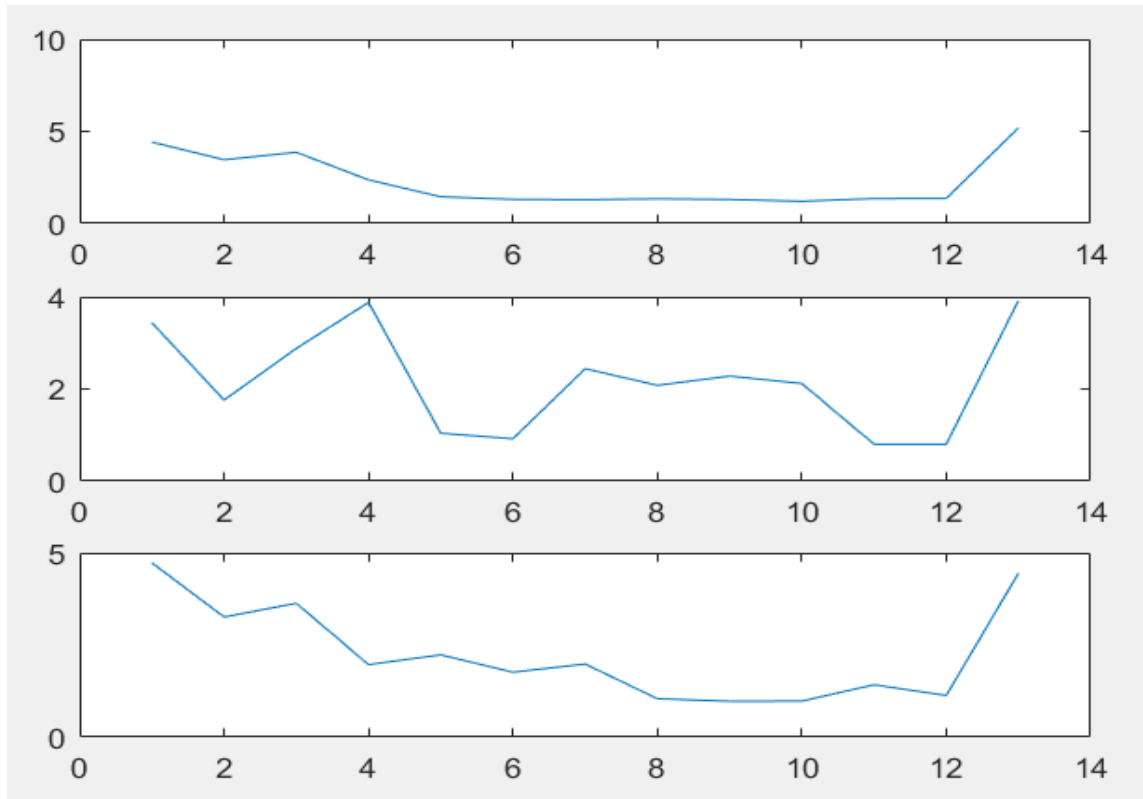
4.4. Euclidean distance with 6 clusters, resulting cluster averages:



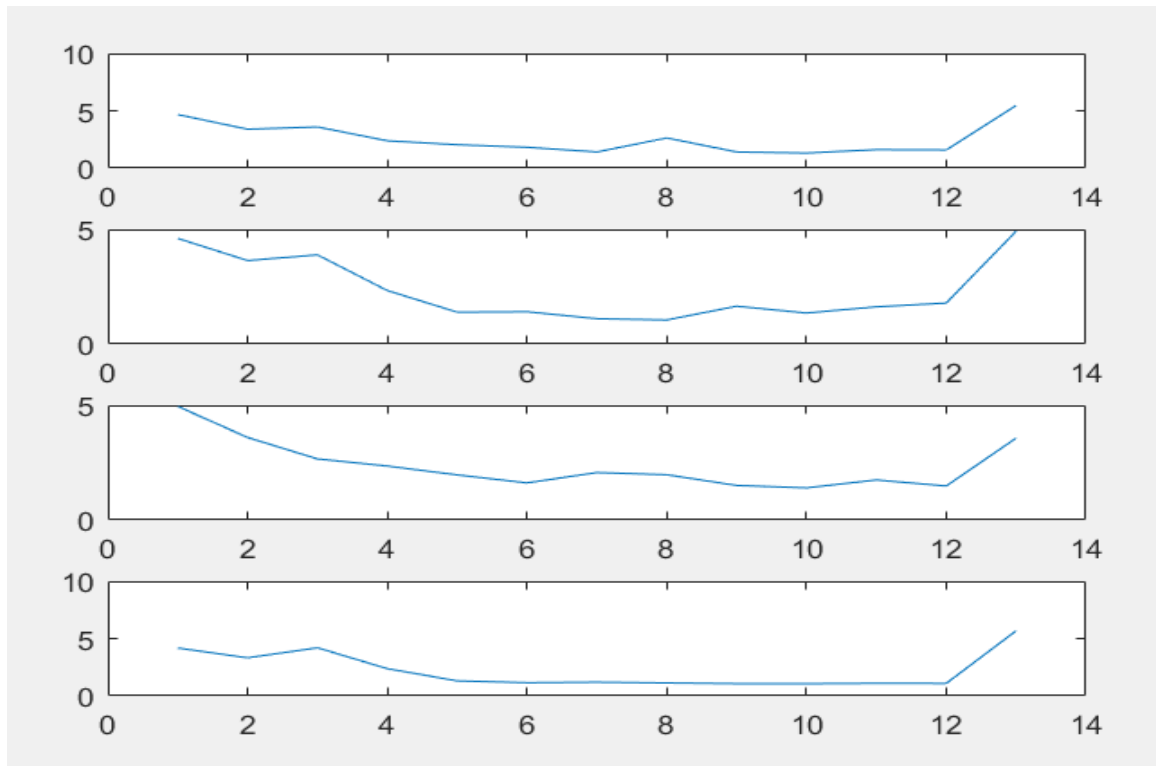
4.5. Mahalanobis distance with 2 clusters, resulting cluster averages:



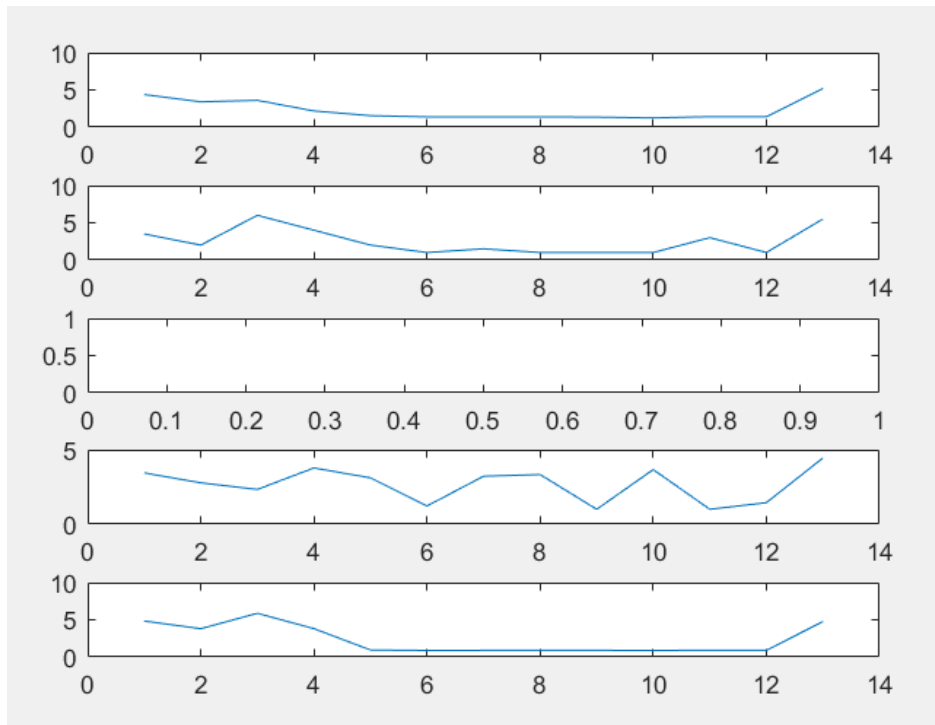
4.6. Mahalanobis distance with 3 clusters, resulting cluster averages:



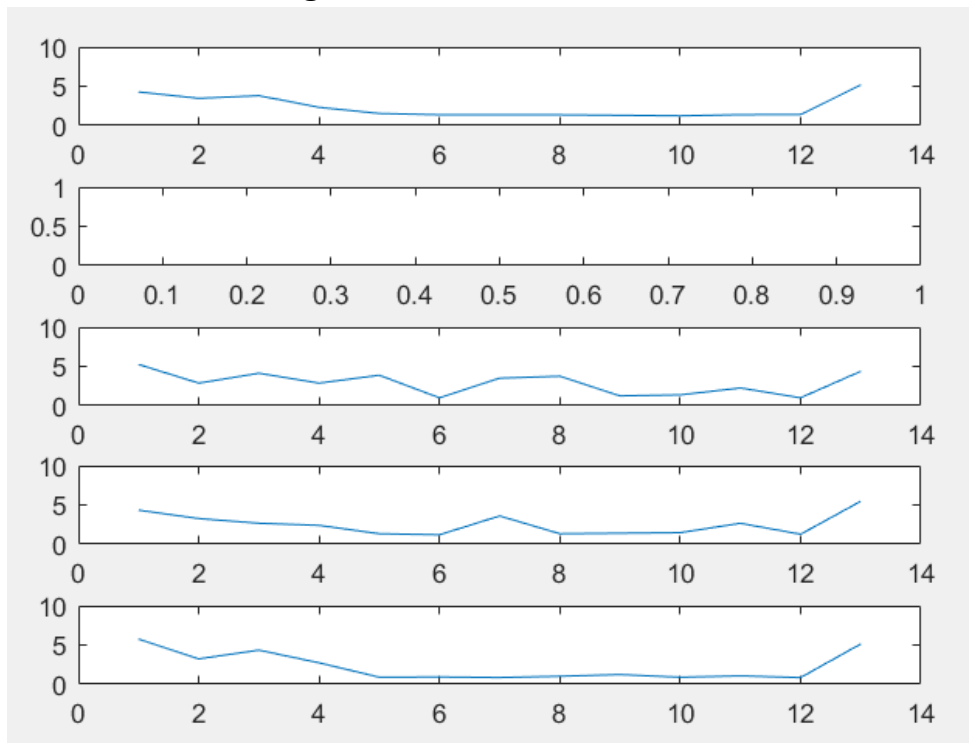
4.7. Mahalanobis distance with 4 clusters, resulting cluster averages:



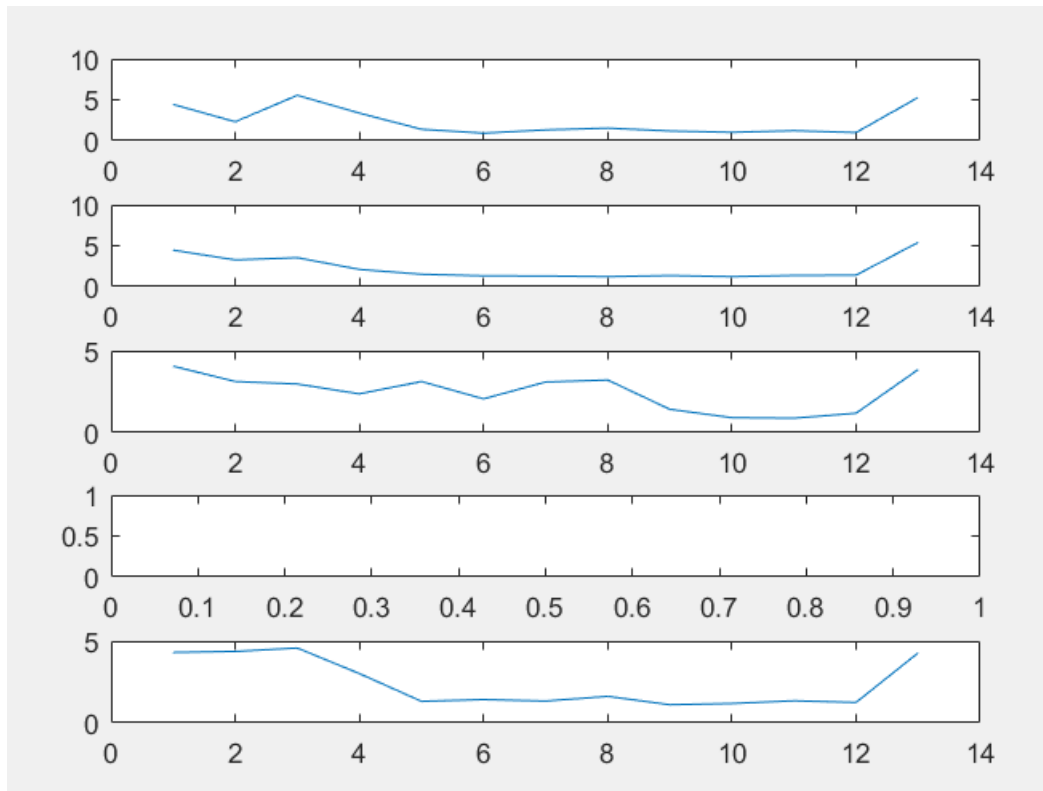
4.8. Mahalanobis distance with 5 clusters (k-means method 1), resulting cluster averages:



4.9. Mahalanobis distance with 5 clusters (k-means method 2), resulting cluster averages:



4.10. Mahalanobis distance with 5 clusters (k-means method 3), resulting cluster averages:



4.11. Choice of Results

Choice of clustering analysis **Euclidean distance with 4 clusters**. The choice was based on the nicely distribution of class sizes (24%, 27%, 29% and 20%) as well as the value of the standard deviation of each class, which is smaller than that of Euclidean with 3 classifiers and also smaller than that of Euclidean with 5 classifiers. We also note that the

Gaussian classifier did not work very well (given distribution sizes and standard deviations). I believe that has happened because the data for dimensions 5 to 12 are distributed in a very steep La Placian manner. This has probably set the weight of the covariance matrix way off which caused the distributions to be so uneven.

Euclidean Classifiers												
	Class 1			Class 2			Class 3			Class 4		
	size	is % of	stdv	size	is % of	stdv	size	is % of	stdv	size	is % of	stdv
Euclidean Classifier 3 Classes	2555	50%	14.498	1521	30%	22.684	1002	20%	23.0222			
Euclidean Classifier 4 Classes	1229	24%	12.943	1352	27%	12.011	1472	29%	13.0672	1025	20%	18.799
Euclidean Classifier 5 Classes	1037	20%	12.796	1192	23%	12.49	1139	22%	11.8962	588	12%	19.477
Euclidean Classifier 6 Classes	946	19%	10.964	550	11%	16.701	1036	20%	10.8704	1074	21%	10.489

Gaussian Classifiers												
	Class 1			Class 2			Class 3			Class 4		
	size	size as % of	stdv	size	size as % of	stdv	size	size as % of	stdv	size	size as % of	stdv
Gaussian Classifier 2 Classes	4976	98%	21.744	102	2%	23.92						
Gaussian Classifier 3 Classes	4868	96%	21.585	25	0%	31.853	185	4%	24.6407			
Gaussian Classifier 4 Classes	310	6%	23.306	1208	24%	9.2574	780	15%	128.614	2780	55%	11.248
Gaussian Classifier 5 Classes initialization 1	4505	89%	20.601	2	0%	6.75	0	0%	0	9	0%	17.086
Gaussian Classifier 5 Classes initialization 2	4551	90%	20.84	0	0%	0	8	0%	19.4063	15	0%	23.147
Gaussian Classifier 5 Classes initialization 3	263	5%	25.584	3736	74%	19.672	33	1%	29.124	0	0%	0

5. Insights & Conclusion

5.1. Overview of Best Result

According to this analysis there are likely 4 main types of buyers who purchased OSSIC headphones on Kickstarter (output from Euclidean Classifier with 4 Classes yields best results, check previous section). Each of these buyers' characteristics are represented by the mean of their respective classes.

Means:

Class 1

4.0928 3.0269 2.3987 1.6900 1.4426 1.3173 1.2685 1.2913 1.0862 1.0643
1.2986 1.1847 3.4386

Class 2

4.9231 3.7892 5.6050 1.5525 1.3964 1.2641 1.2308 1.2426 1.3336 1.0621
1.2544 1.3994 4.0873

Class 3

3.9613 3.0129 2.2283 1.8499 1.4946 1.3322 1.3390 1.3546 1.1726 1.1957
1.3628 1.2833 7.7683

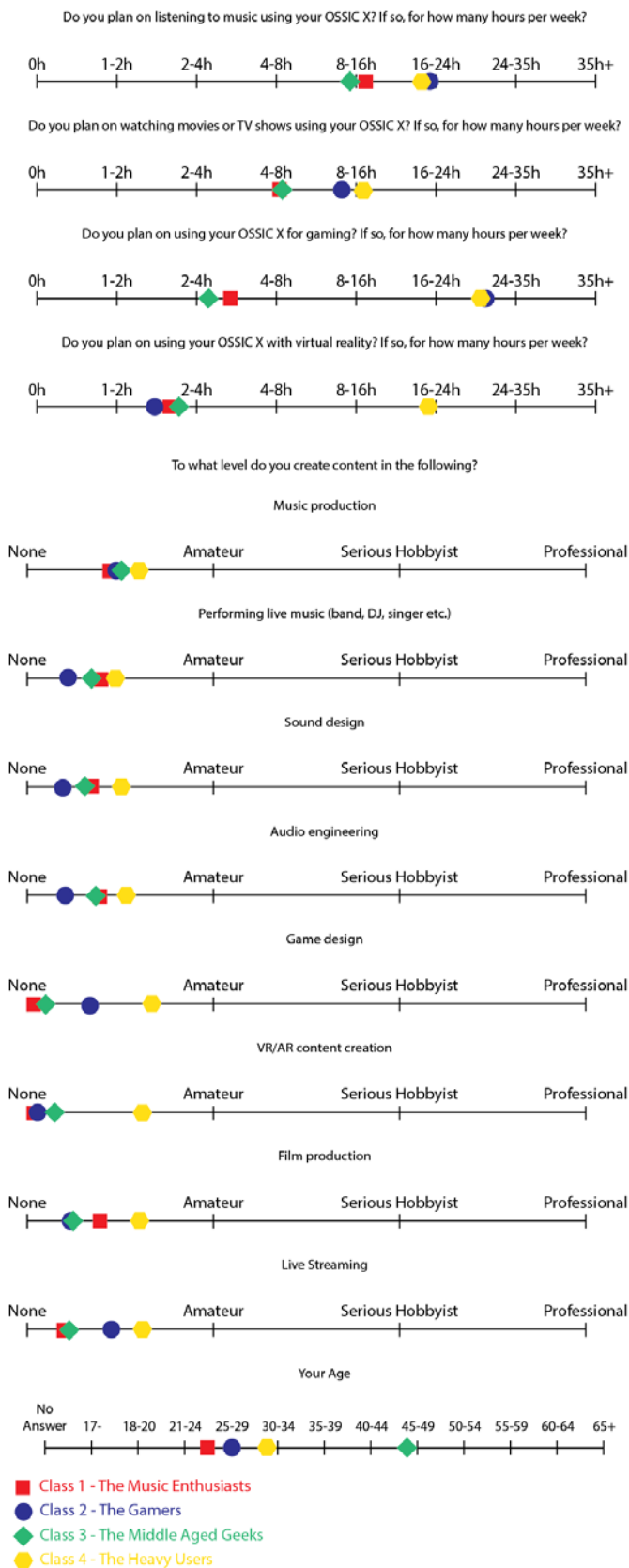
Class 4

4.8351 4.1073 5.6049 4.9629 1.5941 1.4049 1.4820 1.4732 1.6722 1.5610
1.5385 1.5610 4.8761

Class distributions:

Class 1 size			Class 2 size			Class 3 size			Class 4 size		
size	as % of	stdv	size	as % of	stdv	size	as % of	stdv	size	as % of	stdv
12		12.9	13		12.01	14		13.06	10		18.79
29	24%	43	52	27%	09	72	29%	72	25	20%	92

Let's now translate each of the means to readable response values:



5.2. Class 1 – The Music Enthusiasts

This Group of customers represent 24% of all Kickstarter backers. Their most prominent characteristic is their high interest for music. They estimate using OSSIC to listen to music above anything else and have Amateur Proficiency in Music Production, Performing Live Music, Sound Design, Audio Engineering and Film Production. It is interesting to note that they seem to not spend as much time connected as the other 3 classes, even for hours listening to music they rank below classes 3 and 4. They are in their late 20s/early 30s.

Size

1229

Size as % of total

24%

Standard Deviation (stdv is a measure of accuracy of the classifier, smaller stdv = better classifier)

12.943 = 1 average error over all dimensions

Detailed answers

Do you plan on listening to music using your OSSIC X? If so, for how many hours per week?

4.0928 = 8.5-16.5h

Do you plan on watching movies or TV shows using your OSSIC X? If so, for how many hours per week?

3.0269 = 4-8h

Do you plan on using your OSSIC X for gaming? If so, for how many hours per week?

2.3987 = 3-6h

Do you plan on using your OSSIC X with virtual reality? If so, for how many hours per week?

1.6900 = 1.5-3h

To what level do you create content in the following?

Music production

1.4426 = Amateur

Performing live music (band, DJ, singer etc.)

1.3173 = Amateur/None

Sound design
1.2685 = None

Audio engineering
1.2913 = Amateur/None

Game design
1.0862 = None

VR/AR content creation
1.0643 = None

Film production
1.2986 = Amateur/None

Live Streaming
1.1847 = None

Your Age
3.4386 = 28-33 Years Old



5.3. Class 2 – The Gamers

This Group of customers is the second largest of all four and represent 27% of Kickstarter backers. Their most prominent characteristic is their high interest for games. They have the highest time allocation for using OSSIC to game (even above the heavy users) and have Amateur Proficiency in Music Production, Game Design and Live Streaming. It is interesting to note that this class plans on allocating a lot of time to watching movies or TVs also, which probably means that they are very active on platforms like Netflix. Their interest in Live Streaming also gives us insights in how to reach them through platforms like twitch. They are in their mid-20s.

Size

1352

Size as % of total

27%

Standard Deviation (stdv is a measure of accuracy of the classifier, smaller stdv = better classifier)

12.0109 = 0.96 average error over all dimensions

Do you plan on listening to music using your OSSIC X? If so, for how many hours per week?

4.9231 = 16-24h

Do you plan on watching movies or TV shows using your OSSIC X? If so, for how many hours per week?

3.7892 = 7-14h

Do you plan on using your OSSIC X for gaming? If so, for how many hours per week?

5.6050 = 20-30h

Do you plan on using your OSSIC X with virtual reality? If so, for how many hours per week?

1.5525 = 1.5-3h

To what level do you create content in the following?

Music production

1.3964 = Amateur

Performing live music (band, DJ, singer etc.)

1.2641 = Amateur/None

Sound design

1.2308 = Amateur/None

Audio engineering

1.2426 = Amateur/None

Game design

1.3336 = Amateur/None

VR/AR content creation

1.0621 = None

Film production

1.2544 = Amateur/None

Live Streaming

1.3994 = Amateur

Your Age

4.0873 = 25-29yo



5.4. Class 3 – The Middle-Aged Enthusiasts

This Group of customers is the largest among all four and represent 29% of Kickstarter backers. Their most prominent characteristic is their age that averages around 40 to 50 years old. They rank low in hours allocated to all 4 options (music, tv, gaming and VR) which is probably a consequence of their relatively older age. They are particularly not interested in gaming and their two highest allocations of time are music and TV/Movies respectively. Their interests are relatively similar to those of class 1 (Music Enthusiasts) having amateur proficiency in Music Production, Performing Live Music, Sound Design, Audio Engineering and Film Production.

Size

1472

Size as % of total

29%

Standard Deviation (stdv is a measure of accuracy of the classifier, smaller stdv = better classifier)

13.0672 = 1 average error over all dimensions

Do you plan on listening to music using your OSSIC X? If so, for how many hours per week?

3.9613 = 8-16h

Do you plan on watching movies or TV shows using your OSSIC X? If so, for how many hours per week?

3.0129 = 4-8h

Do you plan on using your OSSIC X for gaming? If so, for how many hours per week?

2.2283 = 2.2-5h

Do you plan on using your OSSIC X with virtual reality? If so, for how many hours per week?

1.8499 = 1.8-3.5h

To what level do you create content in the following?

Music production

1.4946 = Amateur

Performing live music (band, DJ, singer etc.)

1.3322 = Amateur/None

Sound design

1.3390 = Amateur/None

Audio engineering

1.3546 = Amateur/None

Game design

1.1726 = None

VR/AR content creation

1.1957 = Amateur/None

Film production

1.3628 = Amateur/None

Live Streaming

1.2833 = Amateur/None

Your Age

7.7683 = 43-48 Years Old



5.5. Class 4 – The Heavy Users/VR Enthusiasts

This Group of customers represent 20% of all Kickstarter backers and is the smallest among the four. This group seems to have classic characteristics of early adopters and their most prominent feature is their high interest for all applications of OSSIC, specially VR. Their estimate of time allocation for Virtual Reality is incredibly high when compared to all other classes and they are the only ones who demonstrate proficiency in VR/AR content development. They also demonstrate a higher level of proficiency, when compared to all other classes, in content development for all applications, having a particularly high proficiency in game design. They are in their early/mid 30s.

Size

1025

Size as % of total

20%

Standard Deviation (stdv is a measure of accuracy of the classifier, smaller stdv = better classifier)

18.7992 = 1.2025 average error over all dimensions

Do you plan on listening to music using your OSSIC X? If so, for how many hours per week?

4.8351 = 14-22h

Do you plan on watching movies or TV shows using your OSSIC X? If so, for how many hours per week?

4.1073 = 9-18h

Do you plan on using your OSSIC X for gaming? If so, for how many hours per week?

5.6049 = 20-30h

Do you plan on using your OSSIC X with virtual reality? If so, for how many hours per week?

4.9629 = 16-24h

To what level do you create content in the following?

Music production

1.5941 = Amateur

Performing live music (band, DJ, singer etc.)

1.4049 = Amateur

Sound design
1.4820 = Amateur

Audio engineering
1.4732 = Amateur

Game design
1.6722 = Amateur

VR/AR content creation
1.5610 = Amateur

Film production
1.5385 = Amateur

Live Streaming
1.5610 = Amateur

Your Age
4.8761 = 29-33 Years Old



5.6. Overall Insights

- 92% of all Kickstarter backers are males
- Most classes don't plan on using OSSIC for VR applications (80% of total) for more than 1.5 hour/week. This doesn't mean that they are not interested in VR but might give us some interesting insights on how to allocate marketing budgets to better reach our audience.
- The fact that the launch was done on Kickstarter probably affected the results of this analysis. For instance, half of the backers have the music enthusiast profile (class 1 and 3). My guess is that this happened because we launched the product under the headphone/music category (naturally music enthusiasts would find the product at this specific platform). This gives us an insight that selling OSSIC through crowdfunding platforms might not effectively reach all the other groups of consumers. My gut feeling is that gamers are more numerous than music enthusiast (which is not the case for this survey result) but we are not effectively reaching them through this crowdfunding platform.
- The results of this analysis are most likely a representation of our innovators market segment. The demographic characteristics and distribution of our consumers will likely change as our product becomes more mainstream.

