Sprawozdanie 2

Eksploracja danych

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Spis treści

1 ZADANIE 1 (Dyskretyzacja(przedziałowanie) cech ciągłych)

1.1 a) Dane: iris (R-pakiet datasets).

3 Pierwsze wiersze z pakietu iris

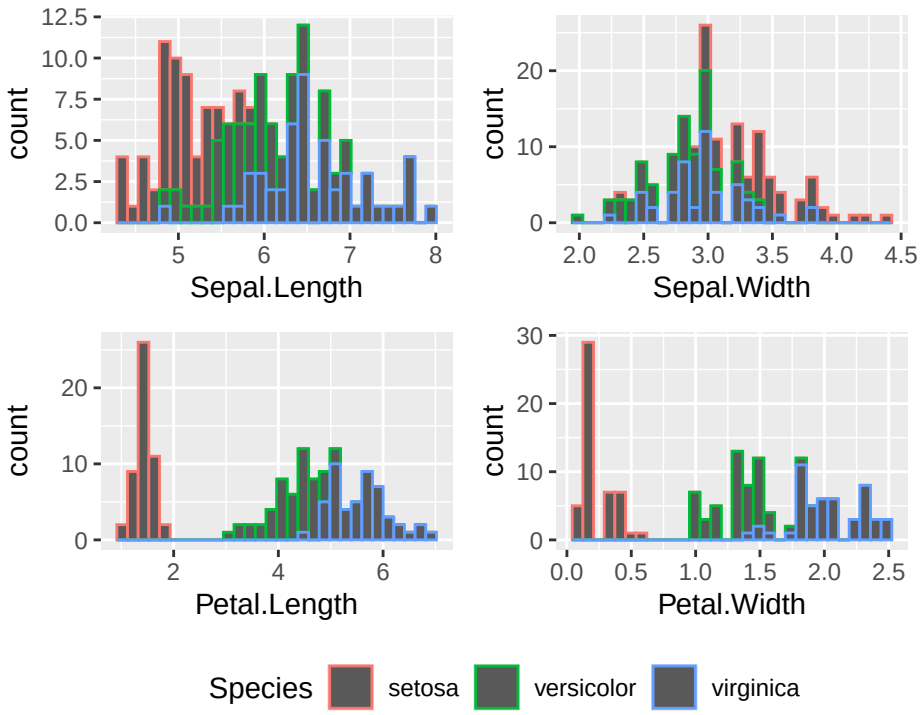
Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
5.1	3.5	1.4	0.2	setosa
4.9	3.0	1.4	0.2	setosa
4.7	3.2	1.3	0.2	setosa

Zbiór danych zawiera wyniki pomiarów uzyskanych dla **trzech gatunków irysów** (tj. setosa, versicolor i virginica) i został **udostępniony przez Ronalda Fishera w roku 1936.**

– **Pomiary** dotyczą **długości oraz szerokości** dwóch różnych części kwiatu– działki **kielicha (ang. sepal) oraz płatka (ang. petal).**

1.2 b) Wybór cech

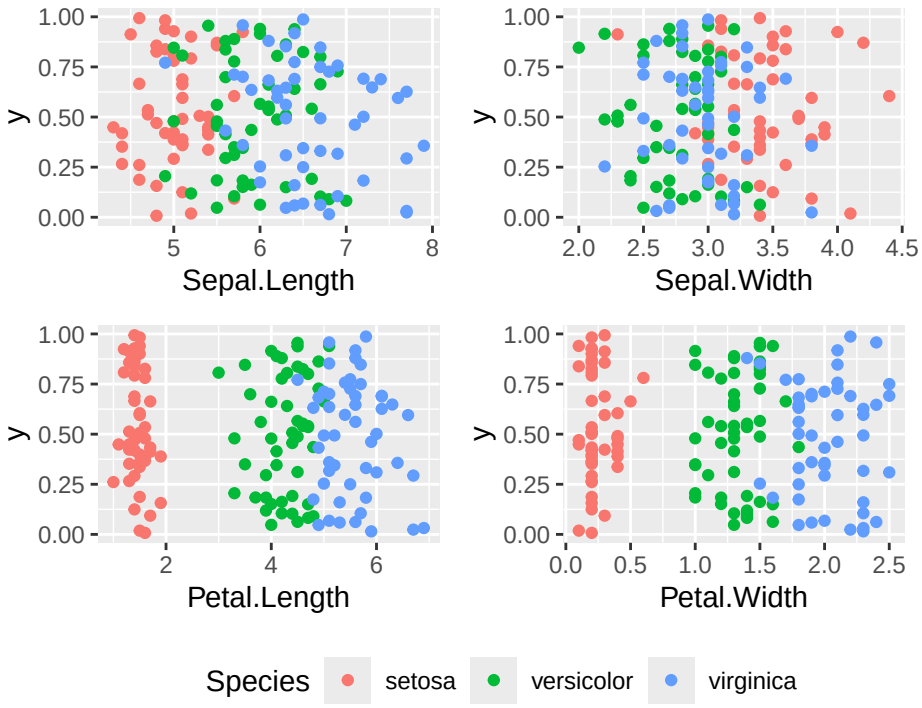
Cechy, inaczej właściwie możemy to rozstrzygać jako kolumny, które charakteryzują się **największym zróżnicowaniem** w stosunku do rodzaju gatunku



Po przeanalizowaniu histogramów, widać ,że warto zwrócić uwagę na takie cechy jak **Petal.Length i Petal.Width**, ponieważ

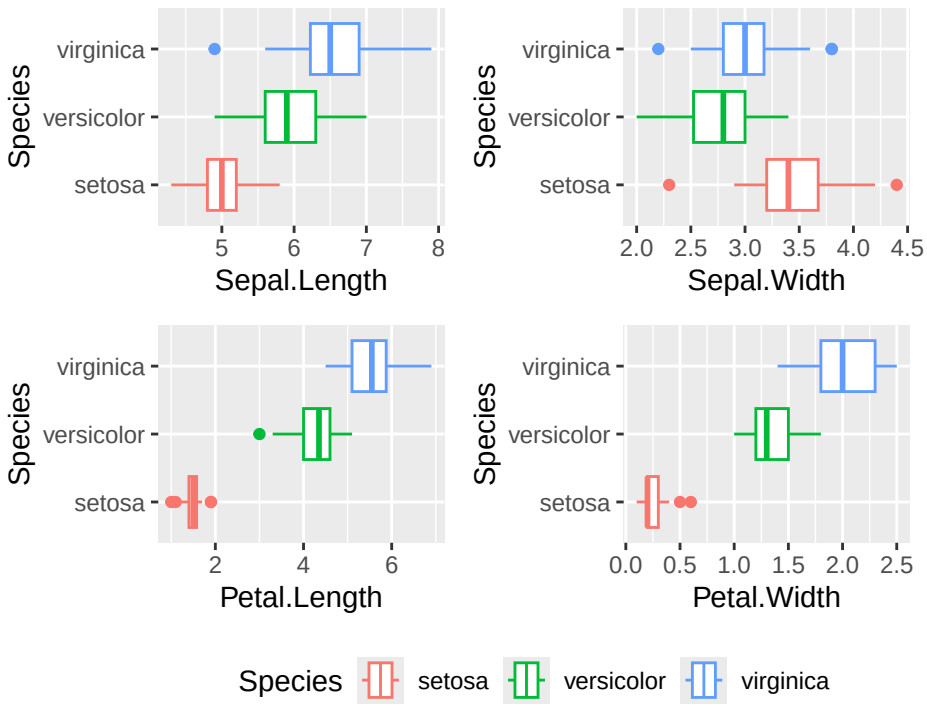
widać dobrze zaznaczone przedziały w których występuje większość kwiatków danego gatunku.

Dalej warto jest też spojrzeć na to jak nasze *obserwawcje* teoretycznie rozkładają się w przestrzeni 2D, aby to zrobić dodajemy jedną dodatkową kolumnę y, wypełnioną losowymi liczbami od 0 do 1 (rozkład jednostajny)



Wykresy typu scatter-plot potwierdzają ,że **Petal.Length i Petal.Width** są bardzo dobry wyborem cech, które mogłyby być wyznacznikami gatunków roślin.

Musimy jednak wybrać wartości najlepsze i najgorsze, aby to zrobić przeanalizujemy jeszcze boxploty.

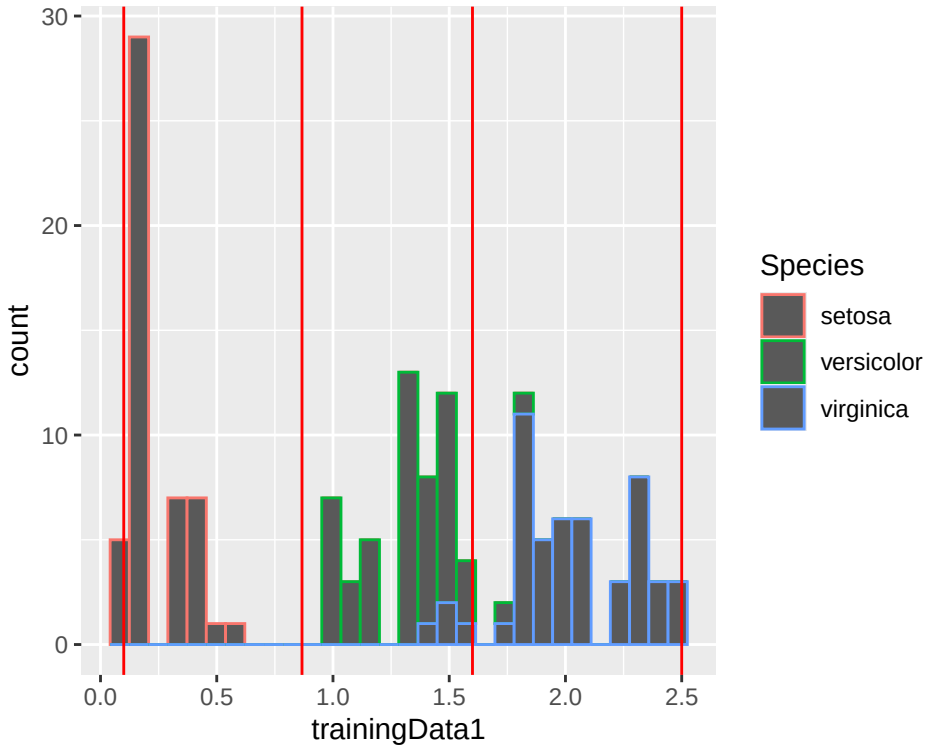


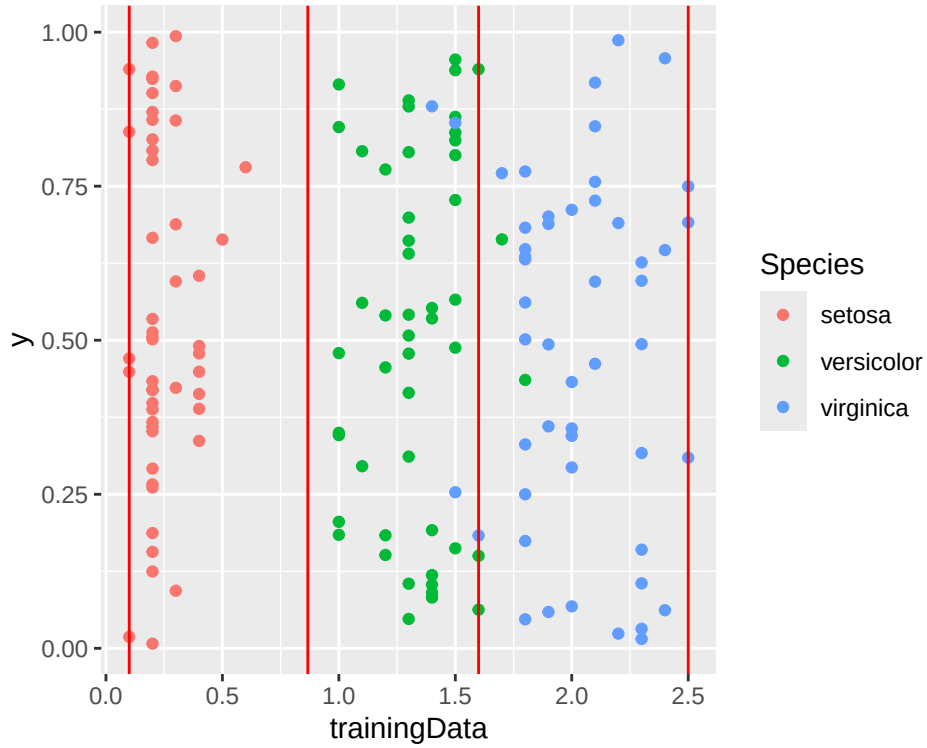
Na ich podstawaie możemy uznać, że Petal.Width może stanowić najlepszy wyznacznik gatunku roślin Najgorszym natomiast jest Sepal.Width, tutaj duża część gatunków dzieli te same wartości tej cechy.

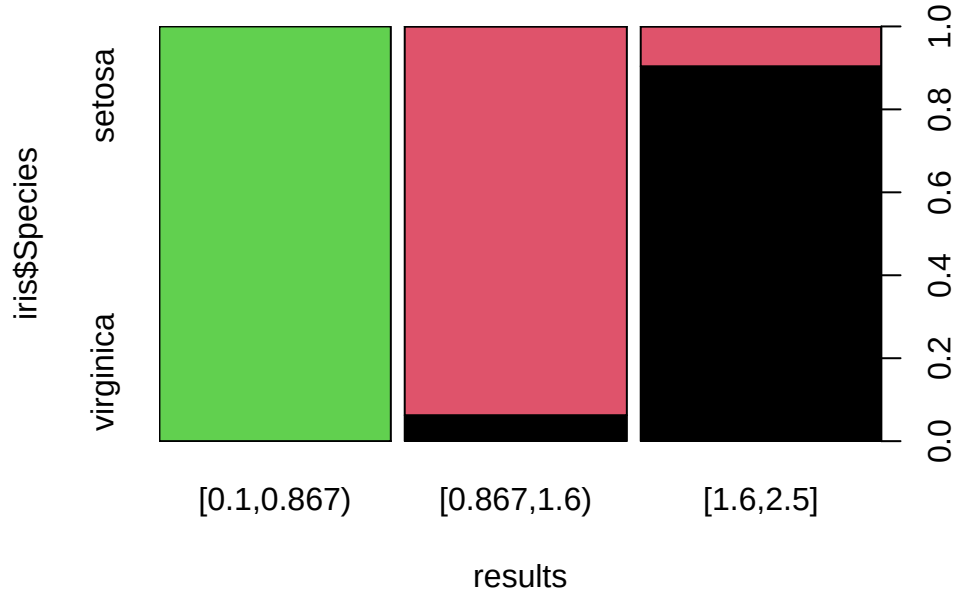
1.3 c) Porównanie nienadzorowanych metod dyskretyzacji

1.3.1 Równe częstości

1.3.1.1 Dla najlepszej

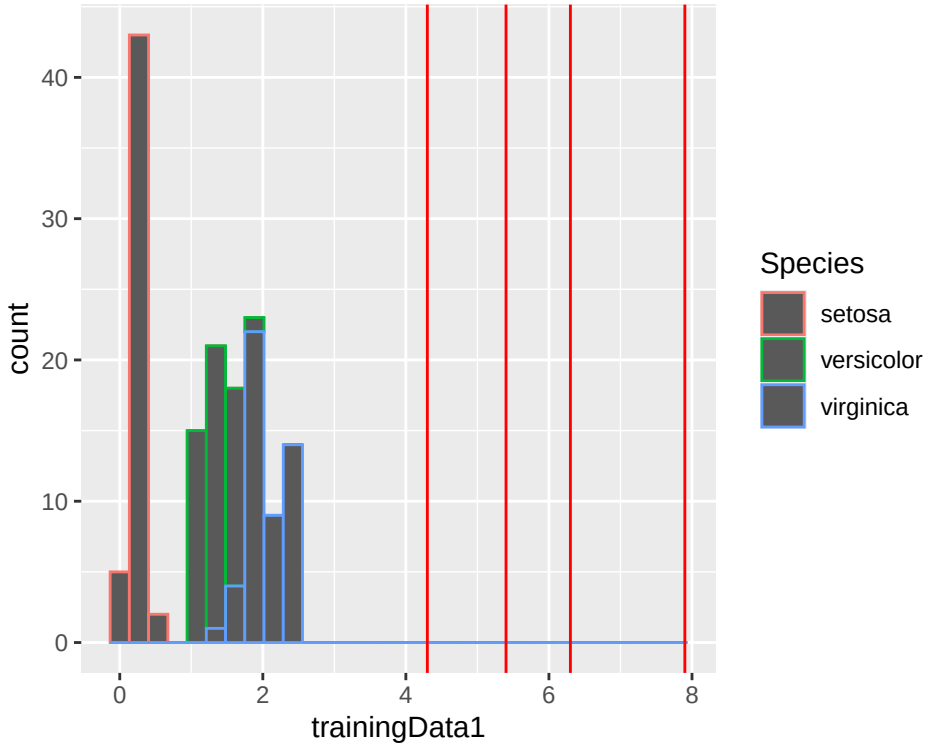

30
20
10
0
count
0.0
0.5
1.0
1.5
2.0
2.5
trainingData1
Species
setosa
versicolor
virginica

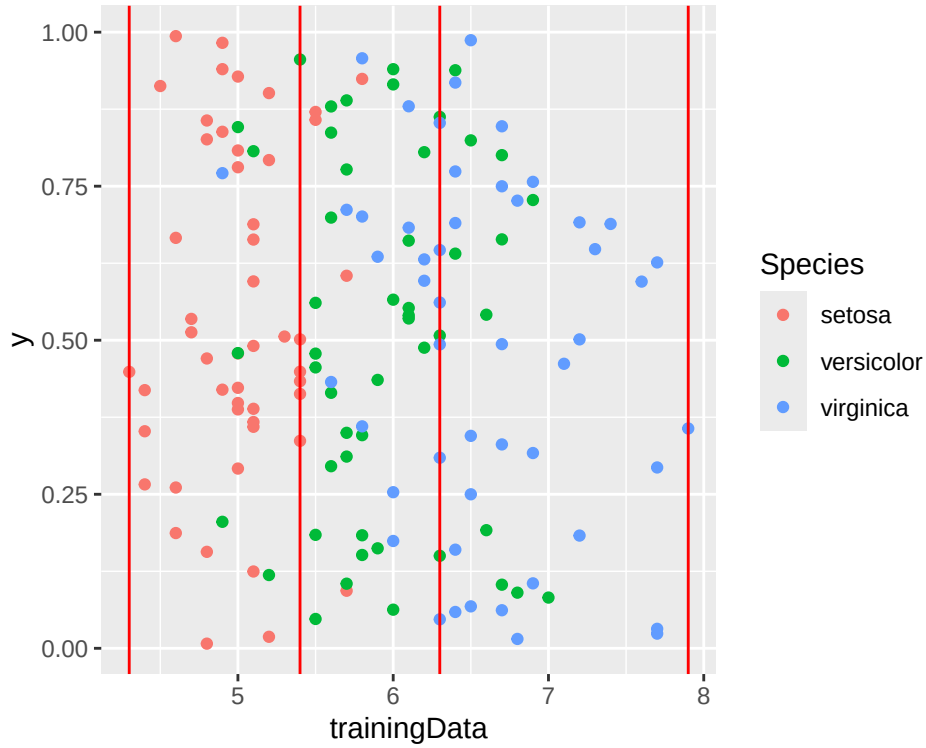

1.00
0.75
0.50
0.25
0.00
y
0.0
0.5
1.0
1.5
2.0
2.5
trainingData
Species
setosa
versicolor
virginica

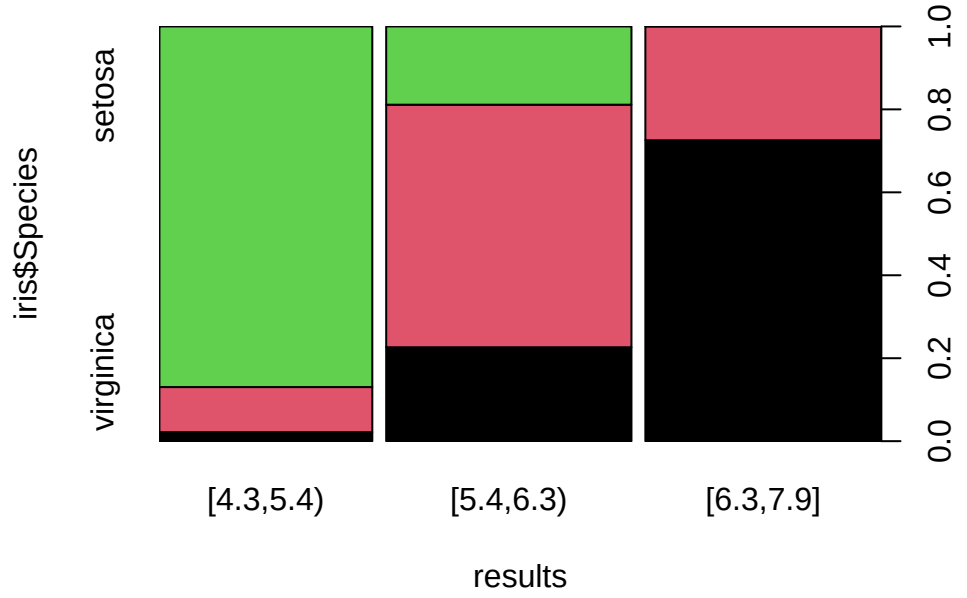



```
##           [,1]
## [1,] 0.9466667
```

1.3.1.2 Dla najgorszej


count
40
30
20
10
0
0
2
4
6
8
trainingData1
Species
setosa
versicolor
virginica

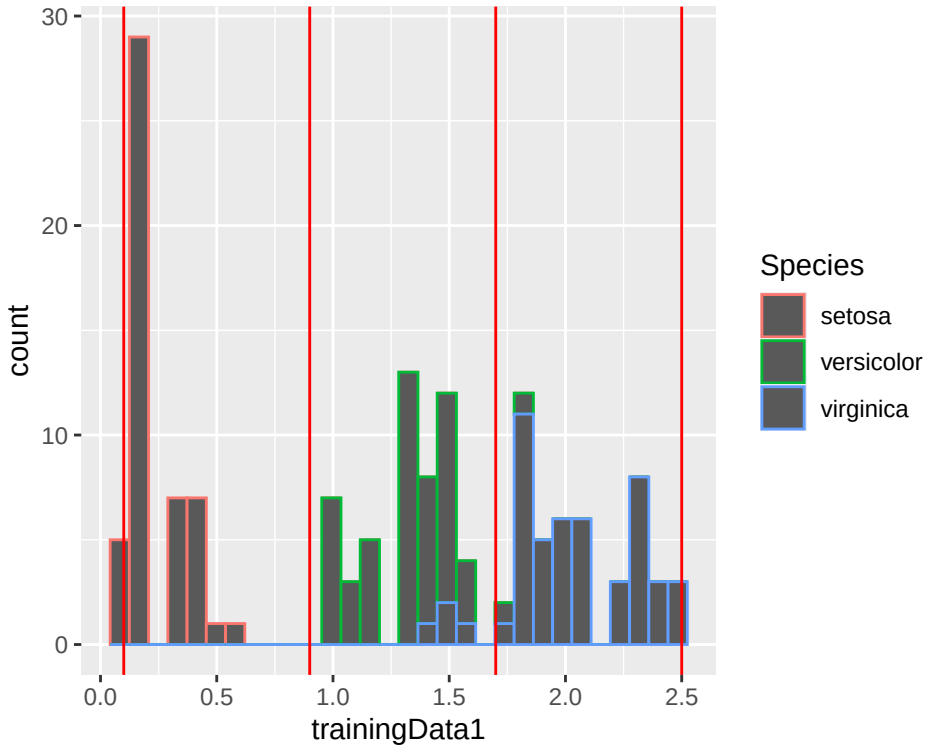

y
1.00
0.75
0.50
0.25
0.00
5
6
7
8
trainingData
Species
setosa
versicolor
virginica

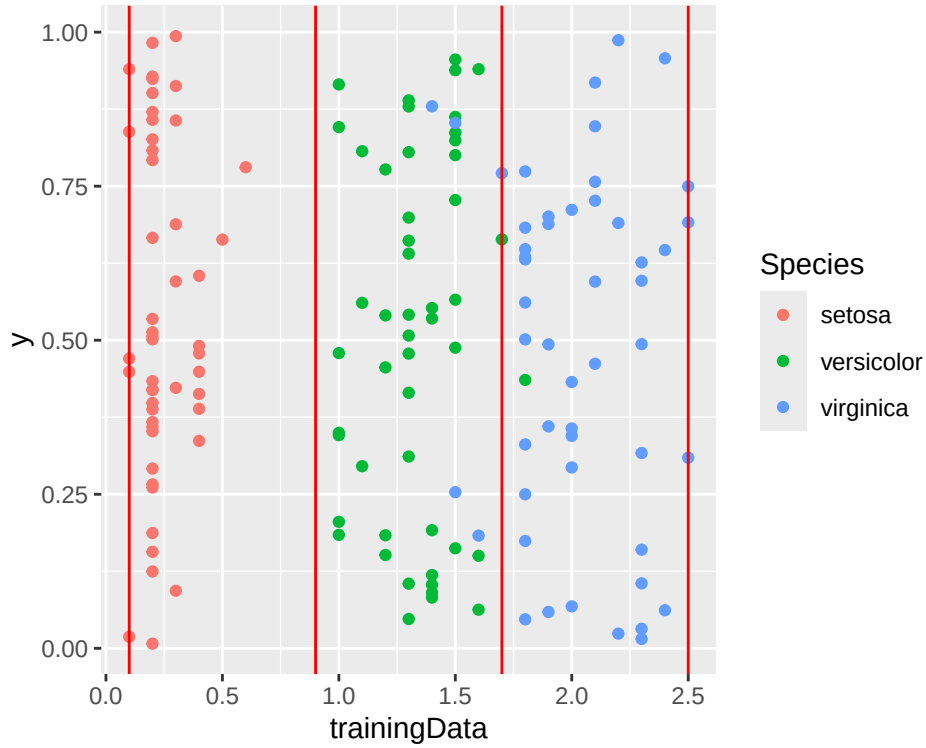


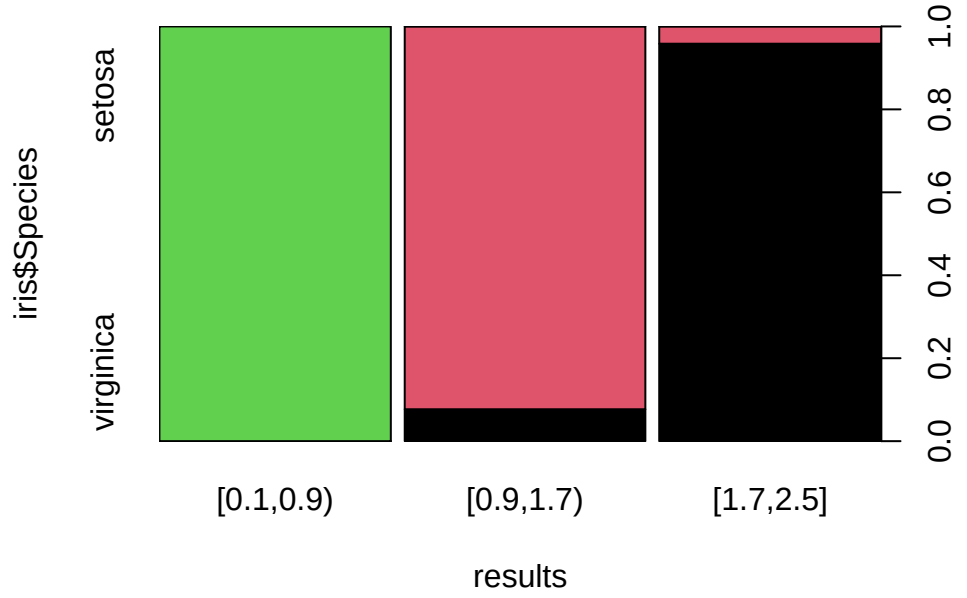

```
##      [,1]
## [1,] 0.72
```

1.3.2 Równe szerokości

1.3.2.1 Dla najlepszej

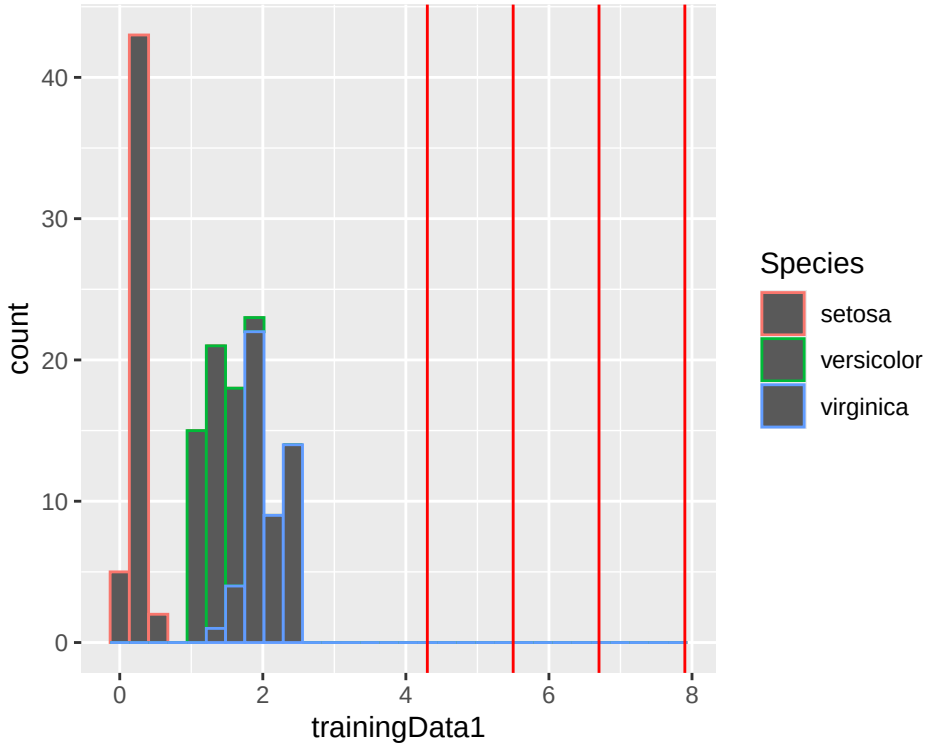

30
20
10
0
count
0.0
0.5
1.0
1.5
2.0
2.5
trainingData1
Species
setosa
versicolor
virginica

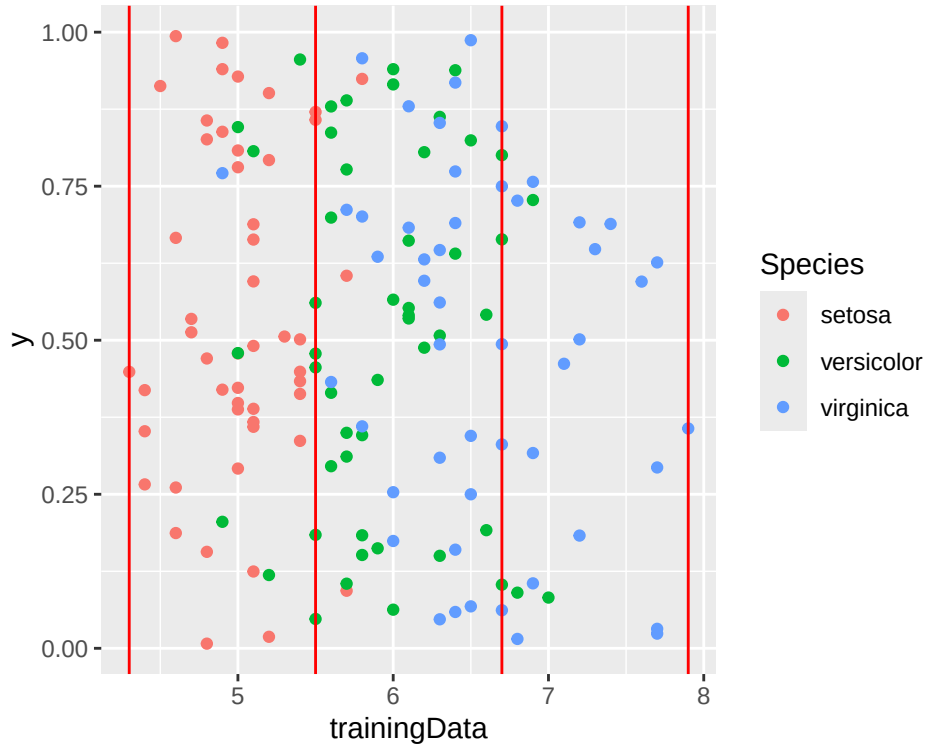

1.00
0.75
0.50
0.25
0.00
y
0.0
0.5
1.0
1.5
2.0
2.5
trainingData
Species
setosa
versicolor
virginica

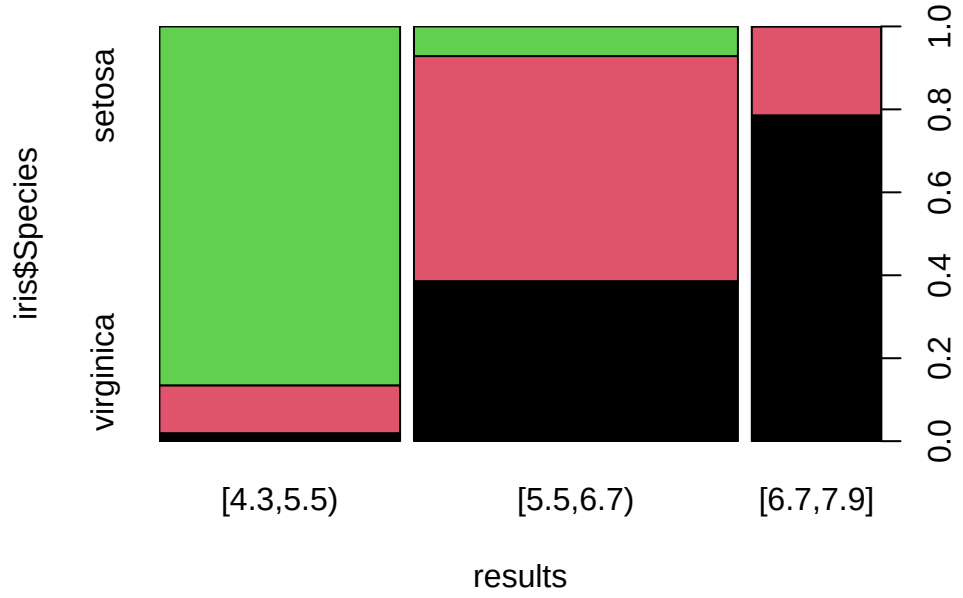



```
##      [,1]
## [1,] 0.96
```

1.3.2.2 Dla najgorszej


count
40
30
20
10
0
0
2
4
6
8
trainingData1
Species
setosa
versicolor
virginica

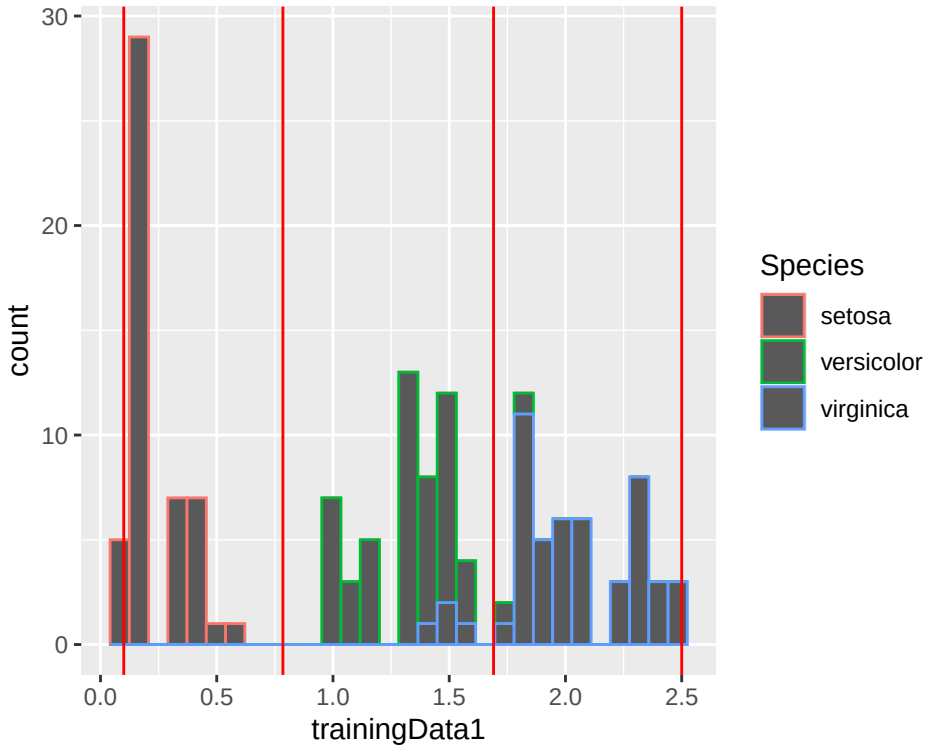

y
1.00
0.75
0.50
0.25
0.00
5
6
7
8
trainingData
Species
setosa
versicolor
virginica

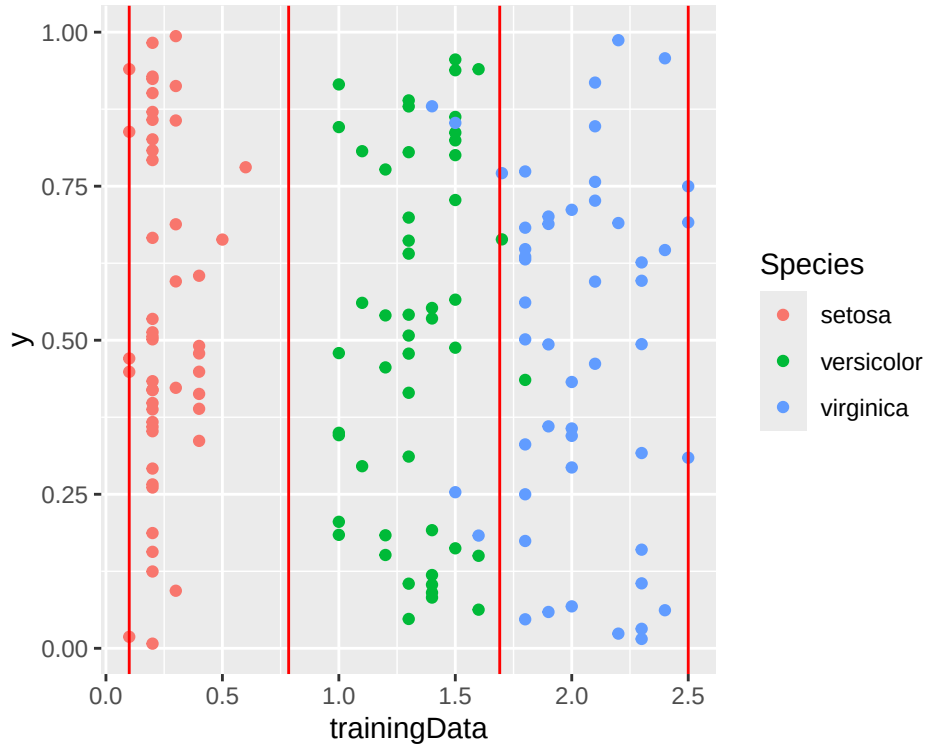


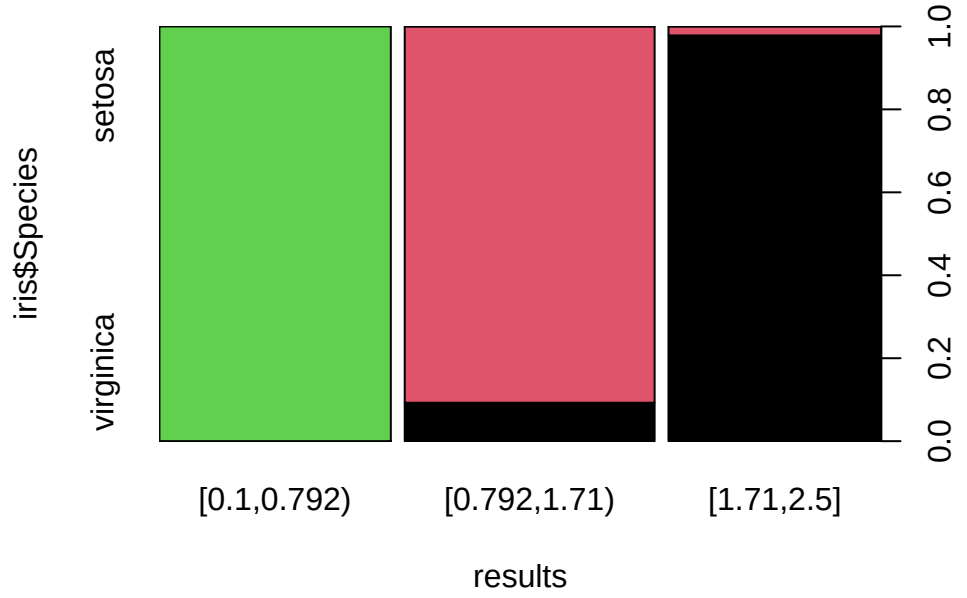

```
##           [,1]
## [1,] 0.5729167
```

1.3.3 K-means

1.3.3.1 Dla najlepszej

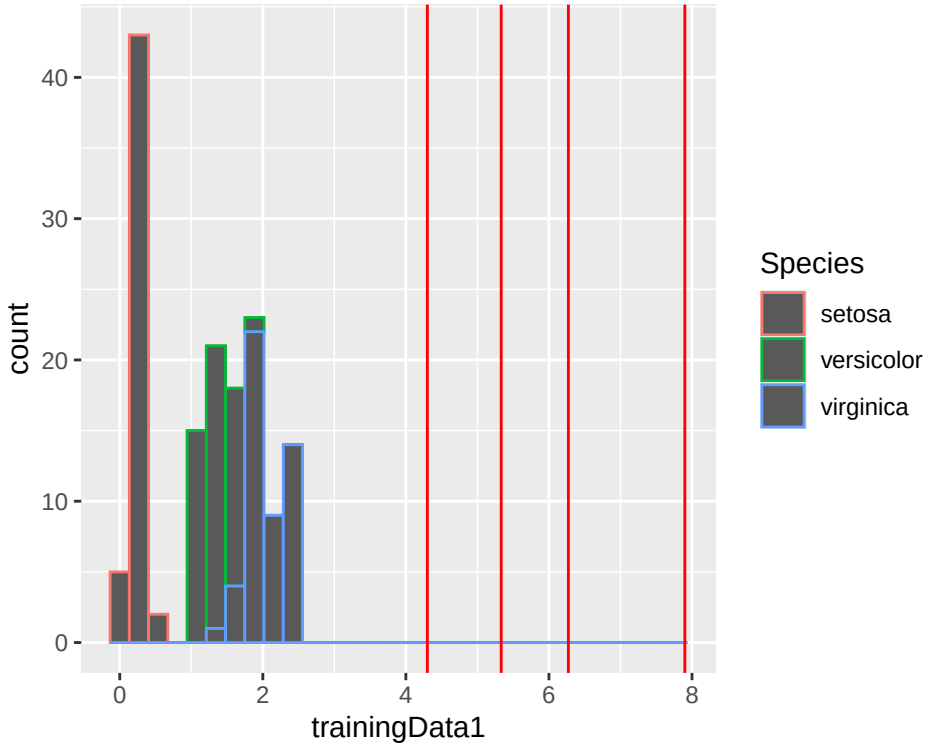

30
20
10
0
count
0.0
0.5
1.0
1.5
2.0
2.5
trainingData1
Species
setosa
versicolor
virginica

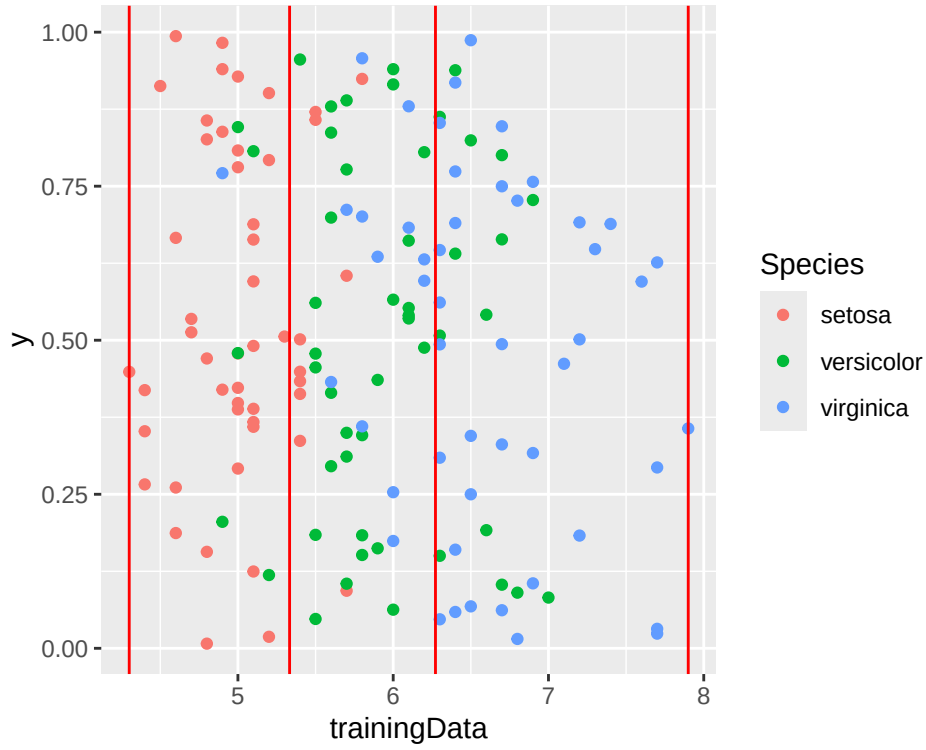

1.00
0.75
0.50
0.25
0.00
y
0.0
0.5
1.0
1.5
2.0
2.5
trainingData
Species
setosa
versicolor
virginica

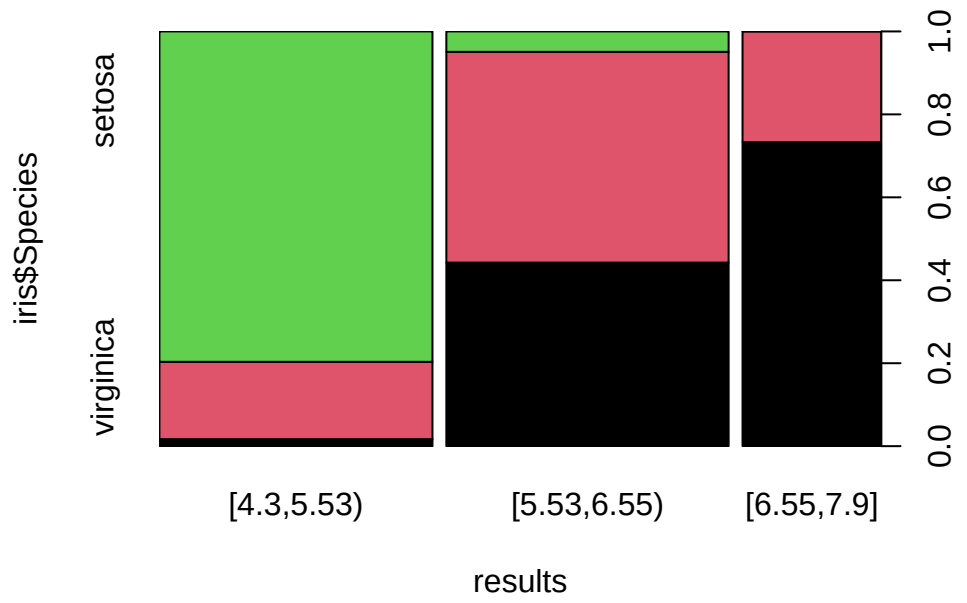



```
##      [,1]
## [1,] 0.96
```

1.3.3.2 Dla najgorszej


count
40
30
20
10
0
0
2
4
6
8
trainingData1
Species
setosa
versicolor
virginica

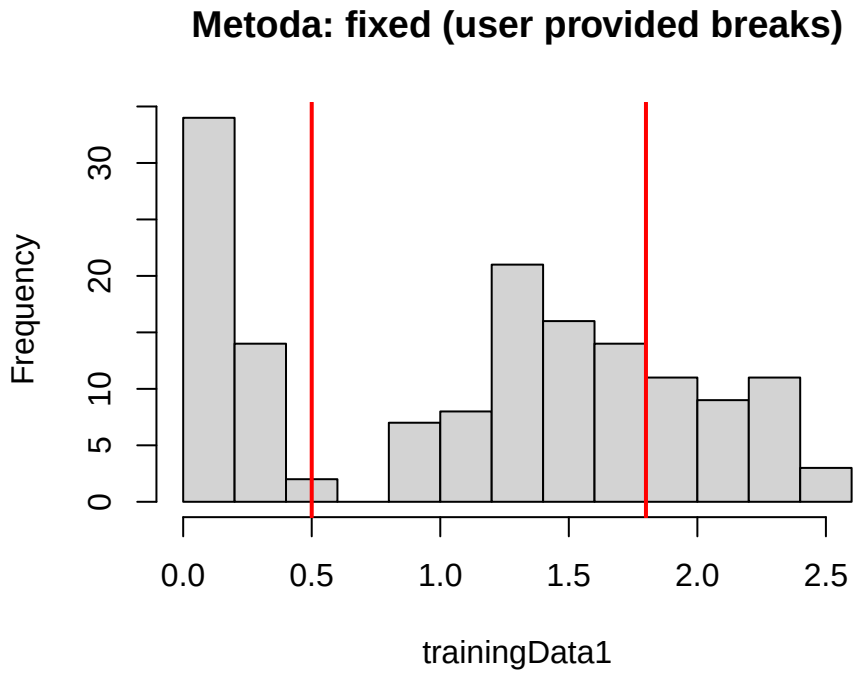

y
1.00
0.75
0.50
0.25
0.00
5
6
7
8
trainingData
Species
setosa
versicolor
virginica

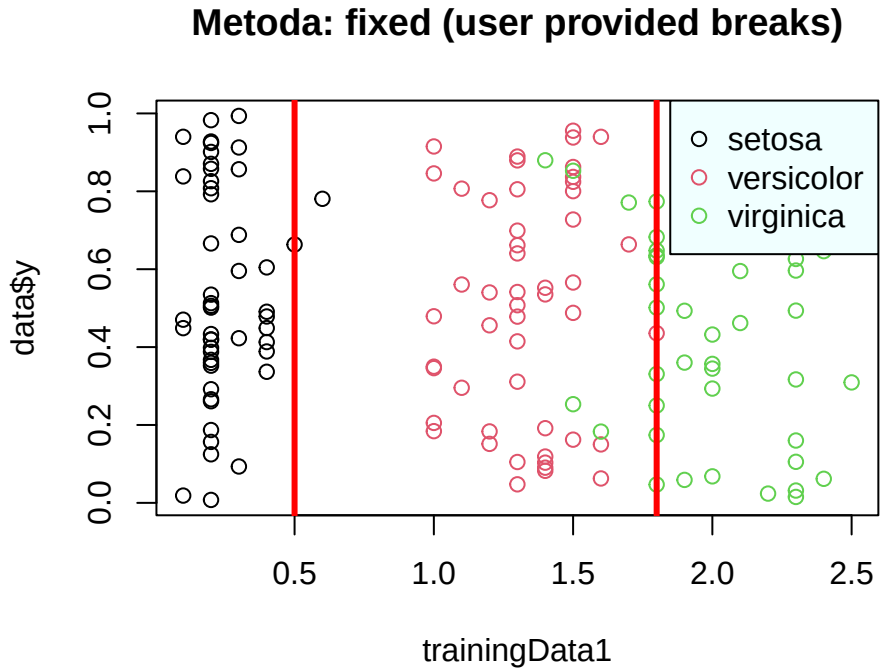


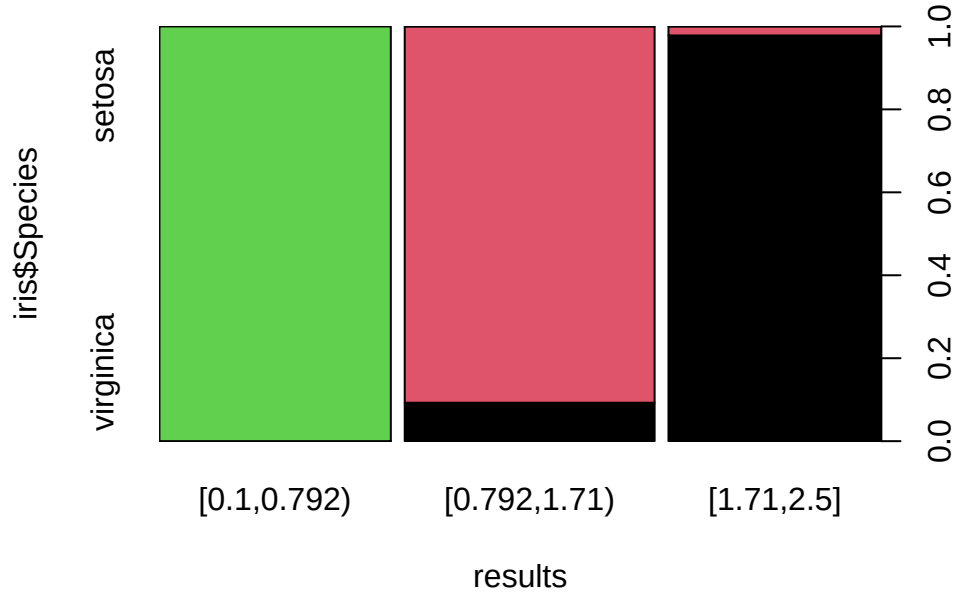

```
## [1] 0.5801105
```

1.3.4 Dyskretyzacja z przedziałami zadanymi przez urzytkownika

1.3.4.1 Dla najlepszej

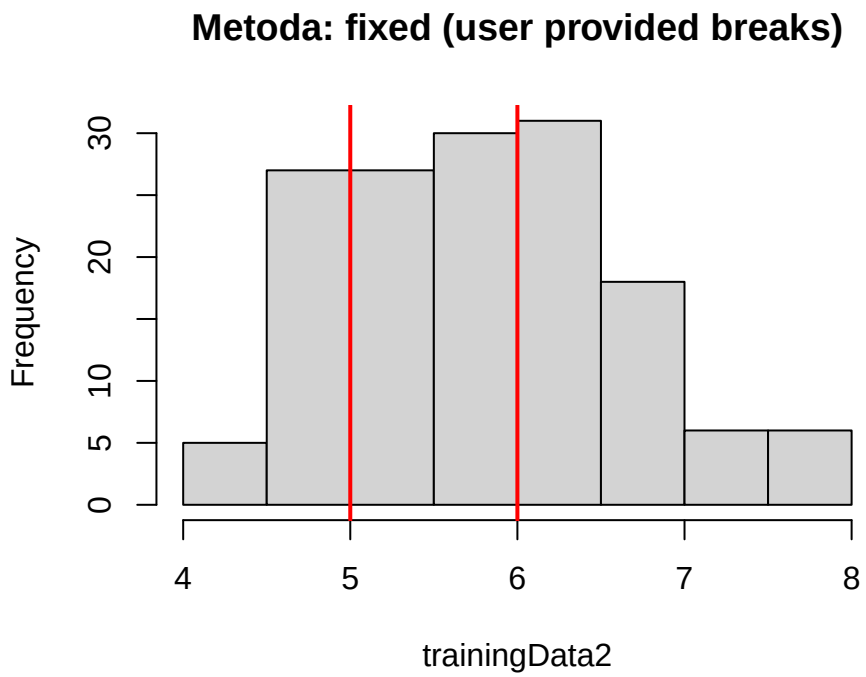

Metoda: fixed (user provided breaks)
Frequency
0
5
10
20
30
0.0
0.5
1.0
1.5
2.0
2.5
trainingData1

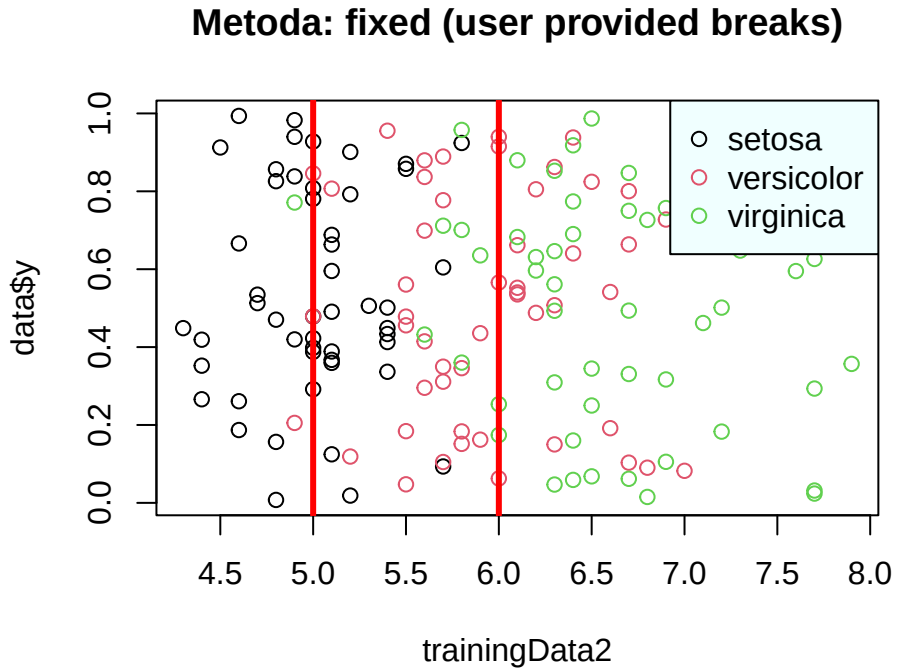

Metoda: fixed (user provided breaks)
data$y
0.0
0.2
0.4
0.6
0.8
1.0
0.5
1.0
1.5
2.0
2.5
trainingData1
setosa
versicolor
virginica

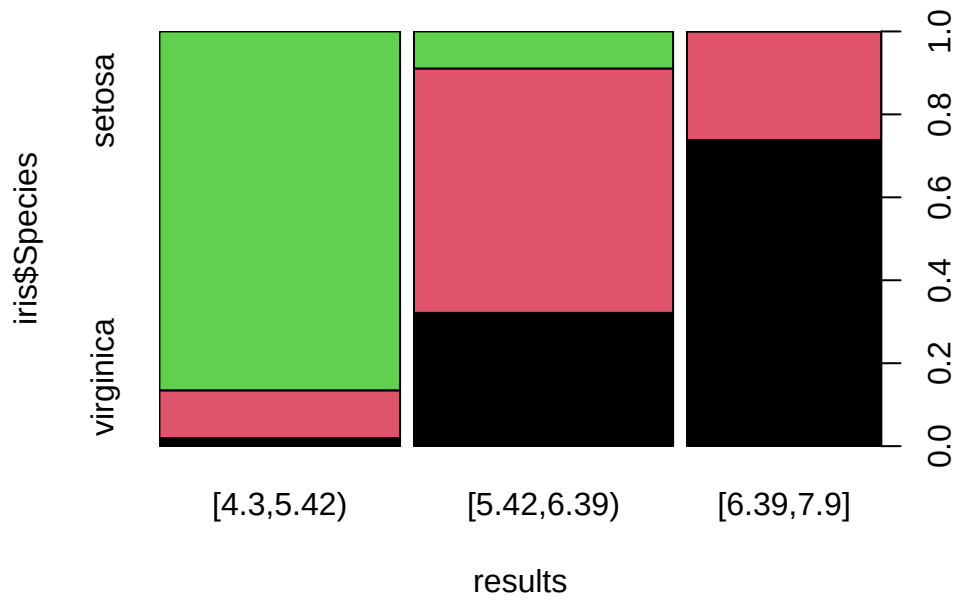



```
##      [,1]
## [1,] 0.96
```

1.3.4.2 Dla najgorszej


Metoda: fixed (user provided breaks)
Frequency
0
5
10
20
30
4
5
6
7
8
trainingData2


Metoda: fixed (user provided breaks)
data$y
0.0
0.2
0.4
0.6
0.8
1.0
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
setosa
versicolor
virginica
trainingData2




```
##           [,1]
## [1,] 0.7266667
```

2 ZADANIE 2 (Analizaskładowych głównych (Principal Component Analysis (PCA)))

2.1 a) Przygotowanie danych

Tabela 2: Typy danych w zbiorze

	Type
X	integer
UA_Name	character
UA_Country	character
UA_Continent	character
Housing	numeric
Cost.of.Living	numeric
Startups	numeric
Venture.Capital	numeric
Travel.Connectivity	numeric

	Type
Commute	numeric
Business.Freedom	numeric
Safety	numeric
Healthcare	numeric
Education	numeric
Environmental.Quality	numeric
Economy	numeric
Taxation	numeric
Internet.Access	numeric
Leisure. . . Culture	numeric
Tolerance	numeric
Outdoors	numeric

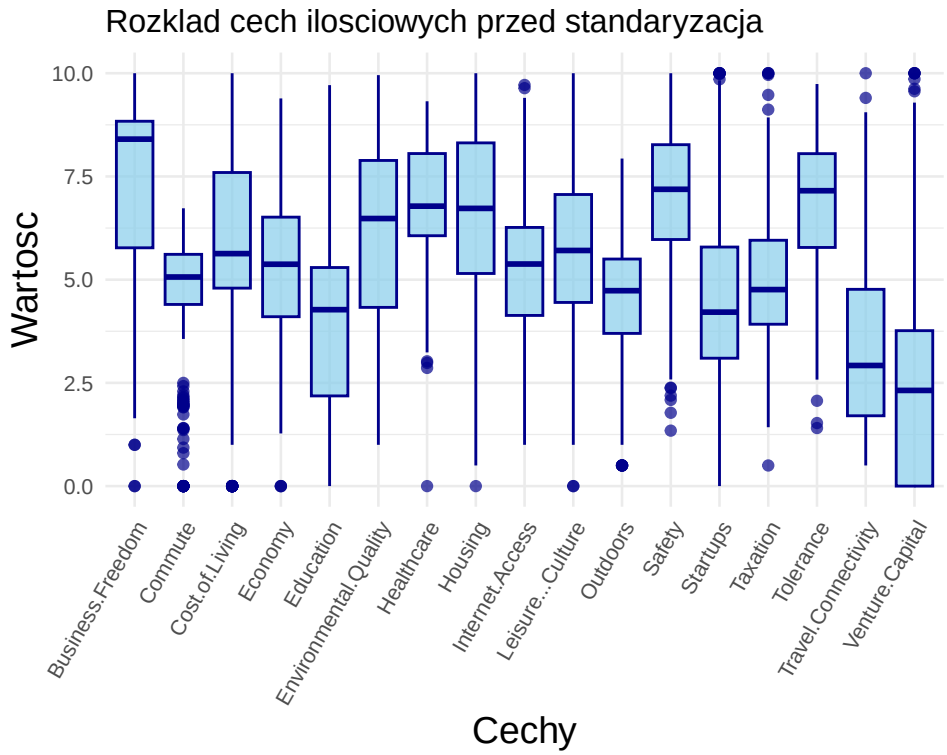
X	UA_Name	UA_Country	UA_Continent	Housing	Cost.of.Living
0	Aarhus	Denmark	Europe	6.132	4.015
1	Adelaide	Australia	Oceania	6.310	4.692
2	Albuquerque	New Mexico	North America	7.262	6.059
3	Almaty	Kazakhstan	Asia	9.282	9.333
4	Amsterdam	Netherlands	Europe	3.053	3.824
5	Anchorage	Alaska	North America	5.434	3.141

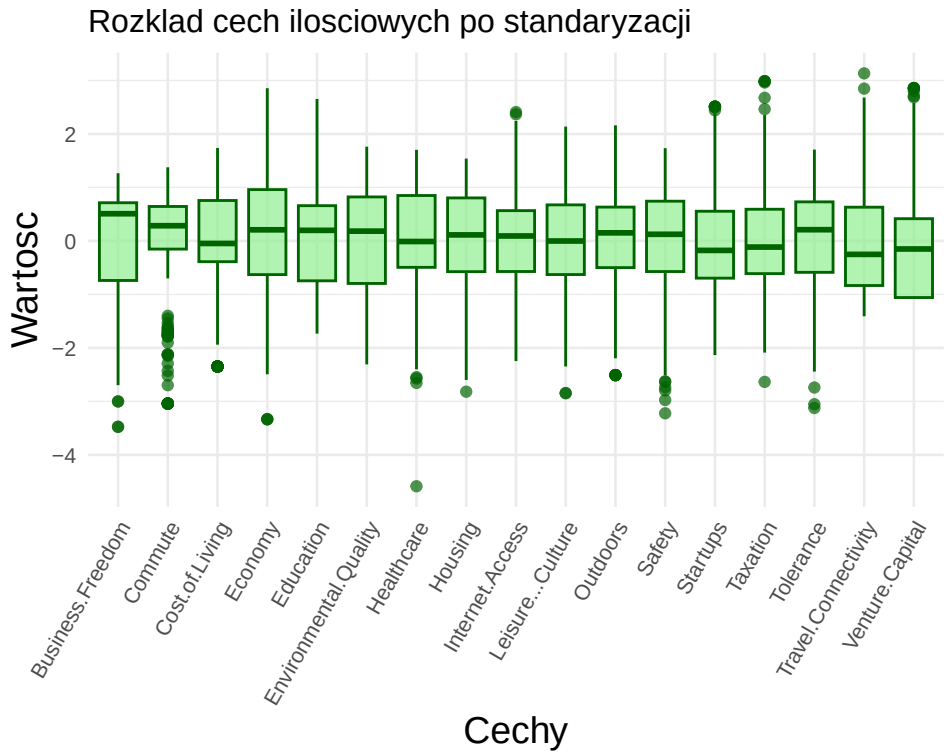
X	Startups	Venture.Capital	Travel.Connectivity	Commute	Business.Freedom
0	2.827	2.512	3.536	6.312	9.940
1	3.136	2.640	1.777	5.336	9.400
2	3.772	1.493	1.456	5.056	8.671
3	2.458	0.000	4.592	5.871	5.568
4	7.972	6.107	8.325	6.118	8.837
5	2.795	0.000	1.738	4.715	8.671

X	Safety	Healthcare	Education	Environmental.Quality	Economy
0	9.617	8.704	5.367	7.633	4.887
1	7.926	7.937	5.142	8.331	6.070
2	1.343	6.430	4.152	7.319	6.514
3	7.309	4.546	2.283	3.857	5.269
4	8.504	7.907	6.180	7.597	5.053
5	3.470	6.060	3.624	9.272	6.514

X	Taxation	Internet.Access	Leisure. . . Culture	Tolerance	Outdoors
0	5.068	8.373	3.187	9.739	4.130
1	4.588	4.341	4.328	7.822	5.531
2	4.346	5.396	4.890	7.028	3.515
3	8.522	2.886	2.937	6.540	5.500
4	4.955	4.523	8.874	8.368	5.307
5	4.772	4.964	3.266	7.093	5.358

	Wariancja
Housing	5.265
Cost.of.Living	5.988
Startups	4.635
Venture.Capital	6.520
Travel.Connectivity	4.375
Commute	2.320
Business.Freedom	4.450
Safety	3.051
Healthcare	2.196
Education	4.897
Environmental.Quality	4.840
Economy	2.302
Taxation	2.855
Internet.Access	3.505
Leisure. . . Culture	4.027
Tolerance	2.974
Outdoors	2.534





2.2 b) Wyznaczenie składowych głównych

Tabela 8: Podsumowanie analizy PCA

Składowa	Odchylenie_standardowe	Procent_wariancji	Kumulatywna_wariancja
PC1	2.251	29.80	29.80
PC2	1.606	15.16	44.96
PC3	1.443	12.25	57.21
PC4	1.140	7.65	64.86
PC5	1.095	7.05	71.90
PC6	0.980	5.65	77.55
PC7	0.831	4.06	81.62
PC8	0.815	3.90	85.52
PC9	0.764	3.43	88.95
PC10	0.651	2.50	91.45
PC11	0.569	1.90	93.35
PC12	0.539	1.71	95.06
PC13	0.524	1.62	96.68
PC14	0.434	1.11	97.79
PC15	0.393	0.91	98.69
PC16	0.352	0.73	99.42
PC17	0.313	0.58	100.00

2.3 c) Zmienność odpowiadająca poszczególnym składowym

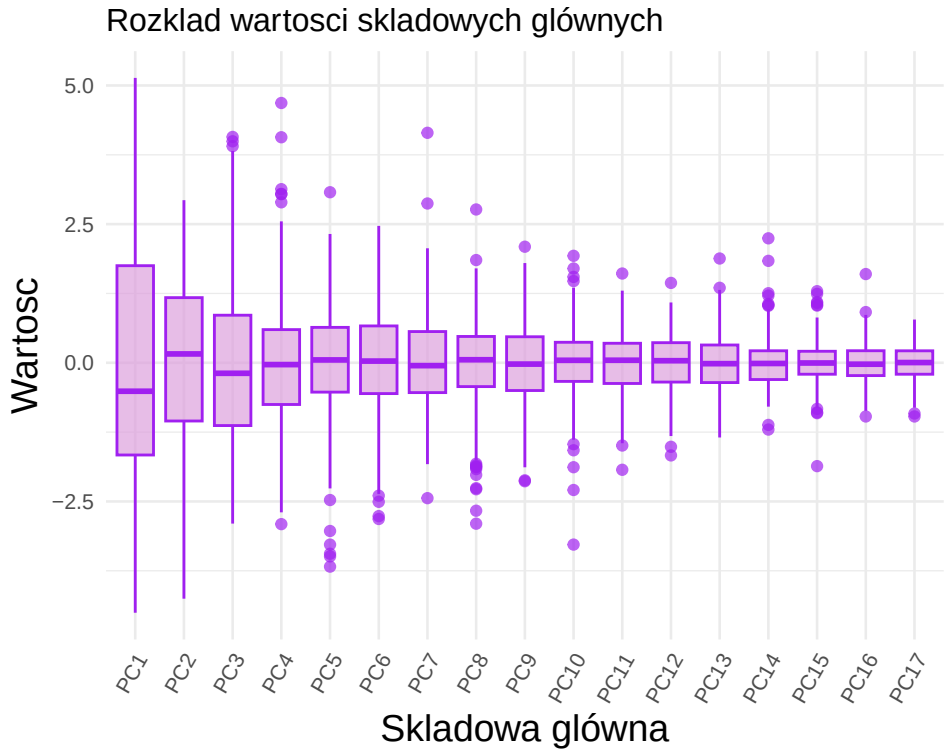
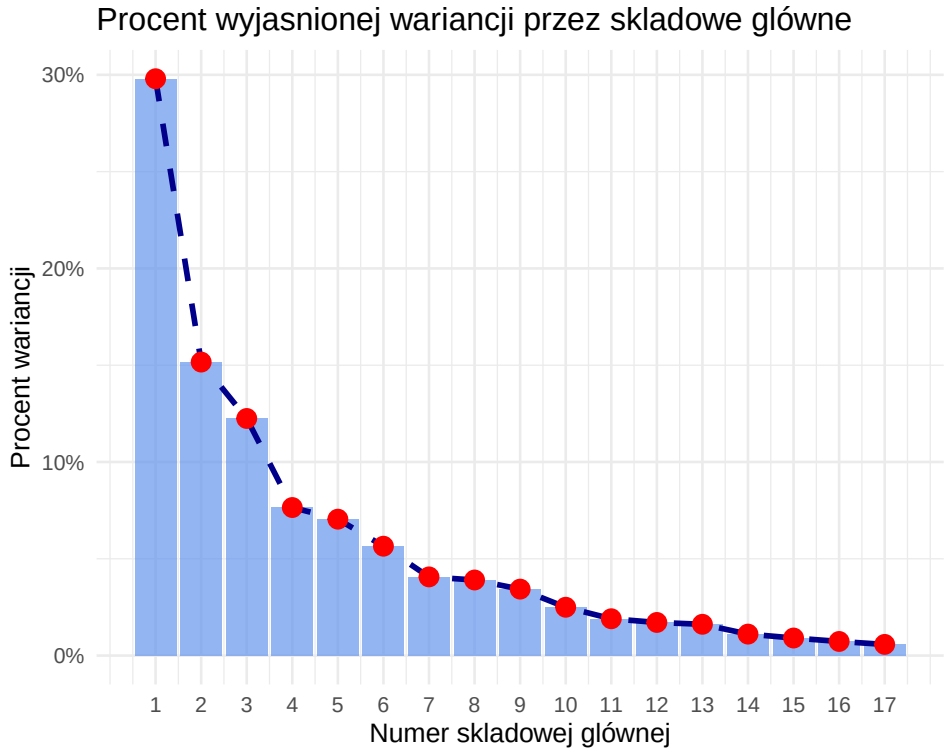
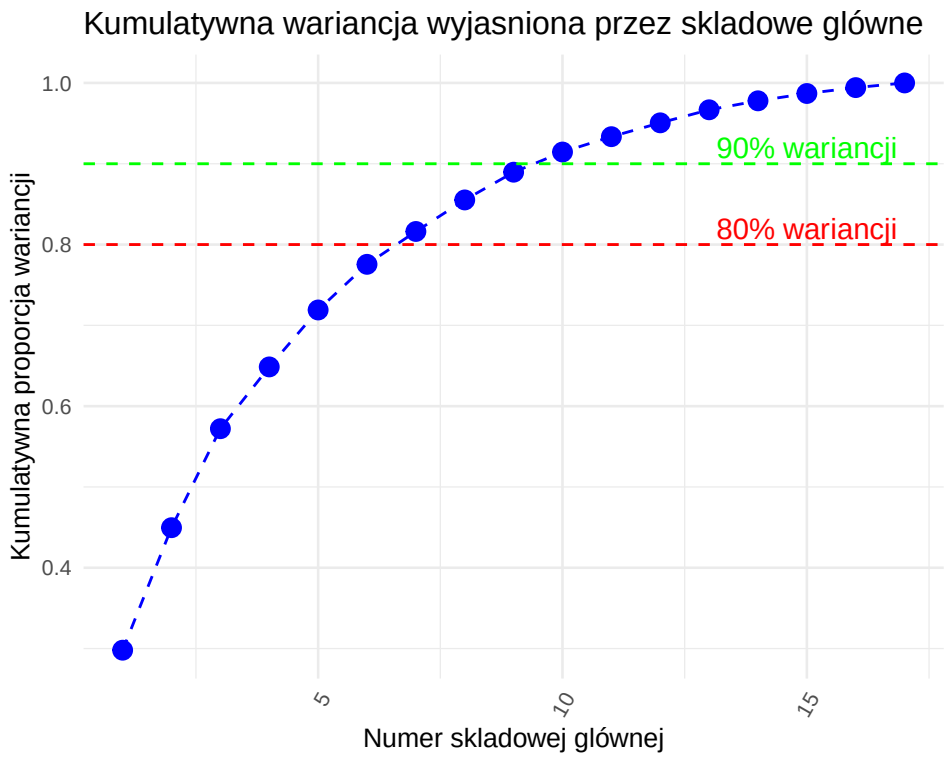


Tabela 9: Wektory ładunków dla PC1, PC2 i PC3

	PC1	PC2	PC3
Housing	0.3078251	0.0533534	-0.3135465
Cost.of.Living	0.2596091	-0.1757815	-0.3305352
Startups	-0.1802385	-0.4834415	0.0061000
Venture.Capital	-0.2365974	-0.4274509	0.0148768
Travel.Connectivity	-0.2094543	-0.1353067	-0.3397760
Commute	-0.1142045	0.0259310	-0.5057359
Business.Freedom	-0.3772809	0.0982196	0.0241046
Safety	-0.0389355	0.2871039	-0.3330100
Healthcare	-0.2803590	0.2419482	-0.2810248
Education	-0.4025620	-0.0490795	-0.0738645
Environmental.Quality	-0.3262220	0.2525355	0.0535717
Economy	-0.2731752	-0.0740033	0.3086705
Taxation	0.0262992	0.1074151	-0.0201849
Internet.Access	-0.2761922	0.0227056	0.0284416
Leisure...Culture	-0.0744466	-0.3647324	-0.3050545
Tolerance	-0.1897496	0.3550911	-0.1027251
Outdoors	-0.0915866	-0.1933825	-0.1485868





Liczba składowych głównych wyjaśniających **80%** wariancji: **7**
Liczba składowych głównych wyjaśniających **90%** wariancji: **10**

2.4 d) Wizualizacja danych wielowymiarowych

2.5 e) Korelacja zmiennych

2.6 f) Końcowe wnioski

3 ZADANIE 3 (Skalowaniewielowymiarowe (Multidimensional Scaling (MDS)))

3.1 a) Dane: titanic_train (R-pakiet titanic)

3.2 b) Przygotowanie danych

3.3 c) Redukcja wymiaru na bazie MDS

3.4 d) Wizualizacja danych