

Analysis Write-up

Gleb Furman¹

¹ Who Kneads a PH.D. Bakery

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Cluster Analysis

Population Frame

The population frame is composed of data from three sources: (1) the Common Core of Data (CCD), (2) publically available accountability data, and (3) the U.S. Census. The CCD is a comprehensive database housing anually collected national statistics of all public schools and districts. Accountability data was used to calculate the proportion of students within each school performing at or above proficiency in Math and ELA. Finally, local median income was obtained from the U.S. Census and was matched to each school by zipcode. School level data was aggregated to get district level variables. These are reported in Table @ref(tab:tbl_desc)

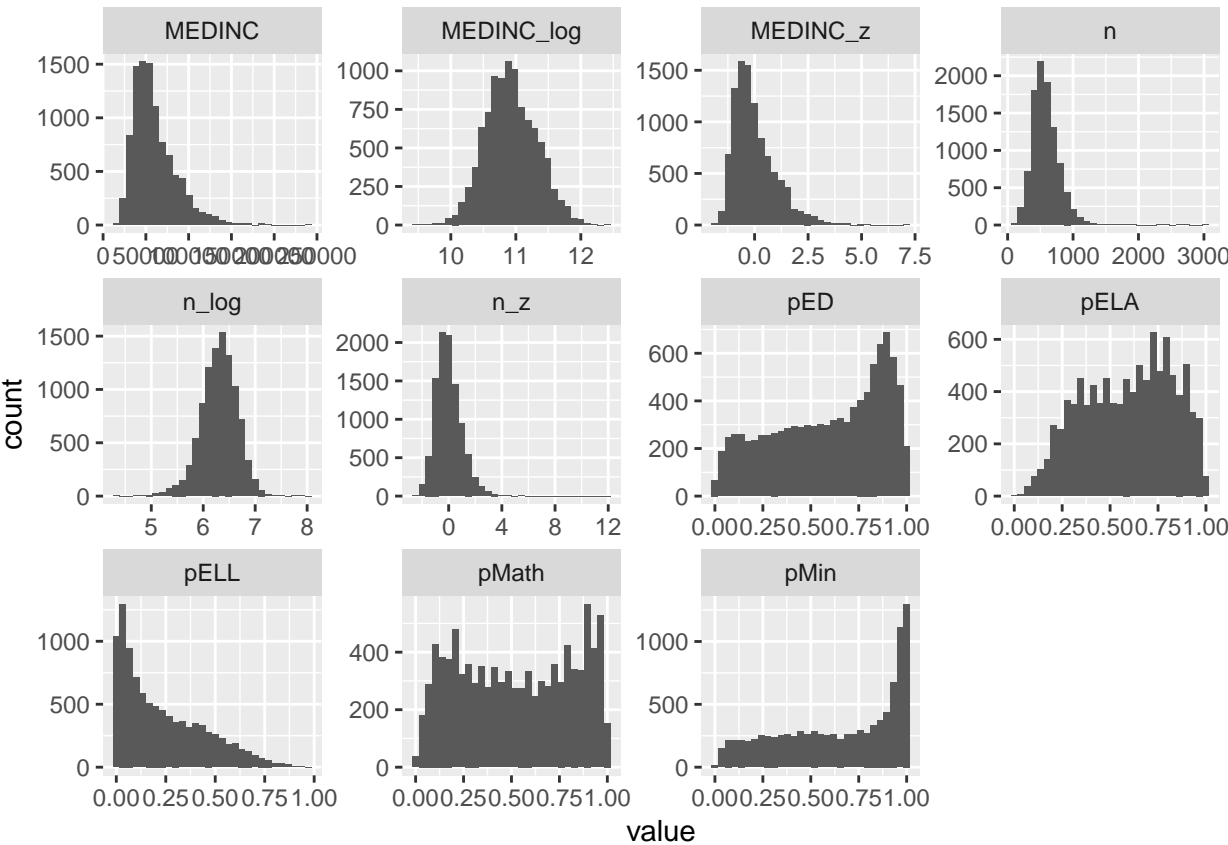
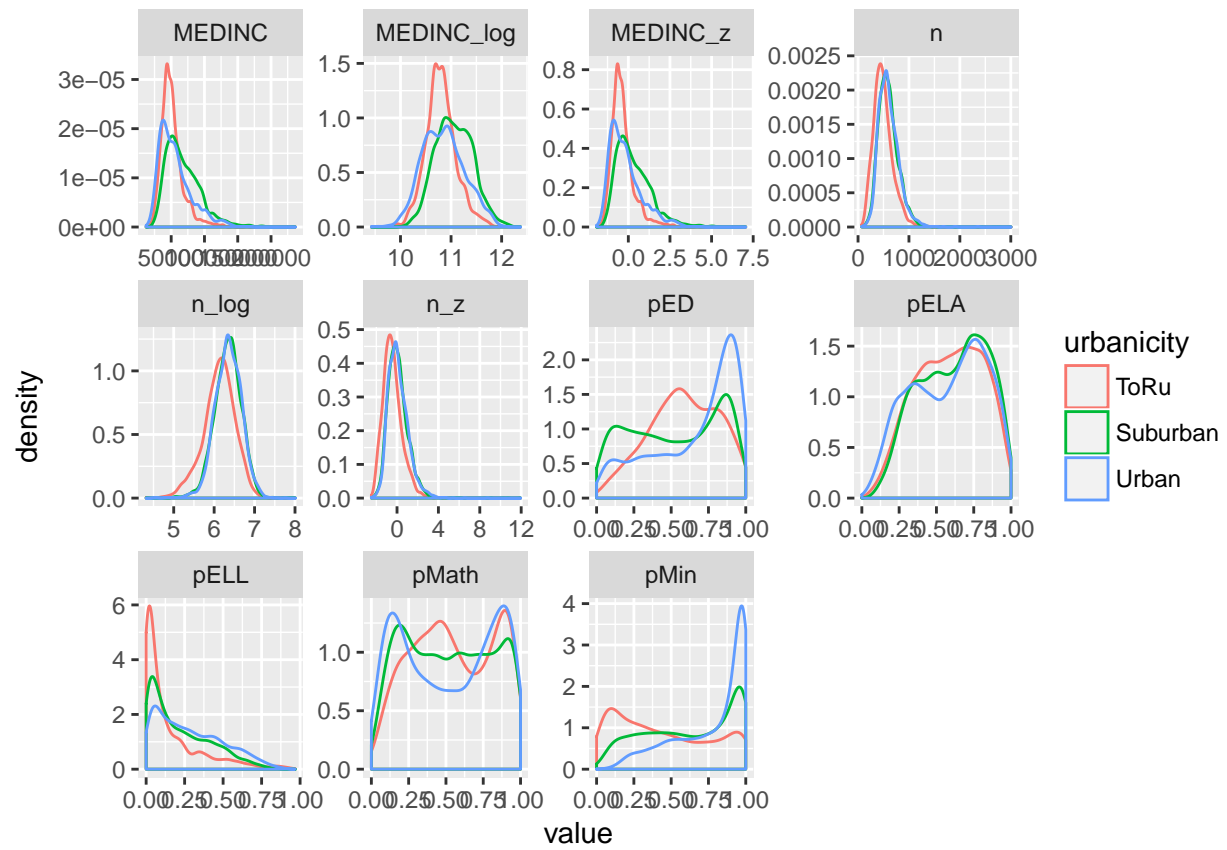


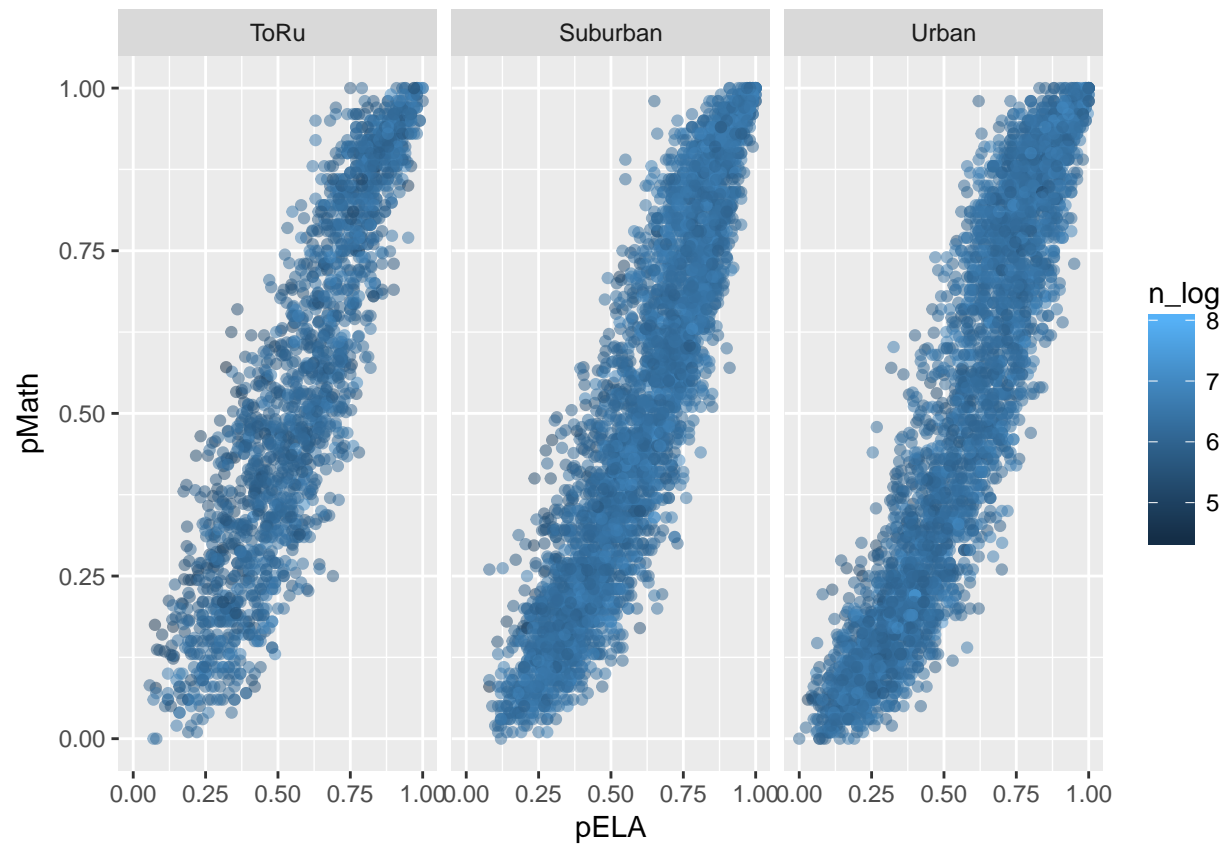
Table 1

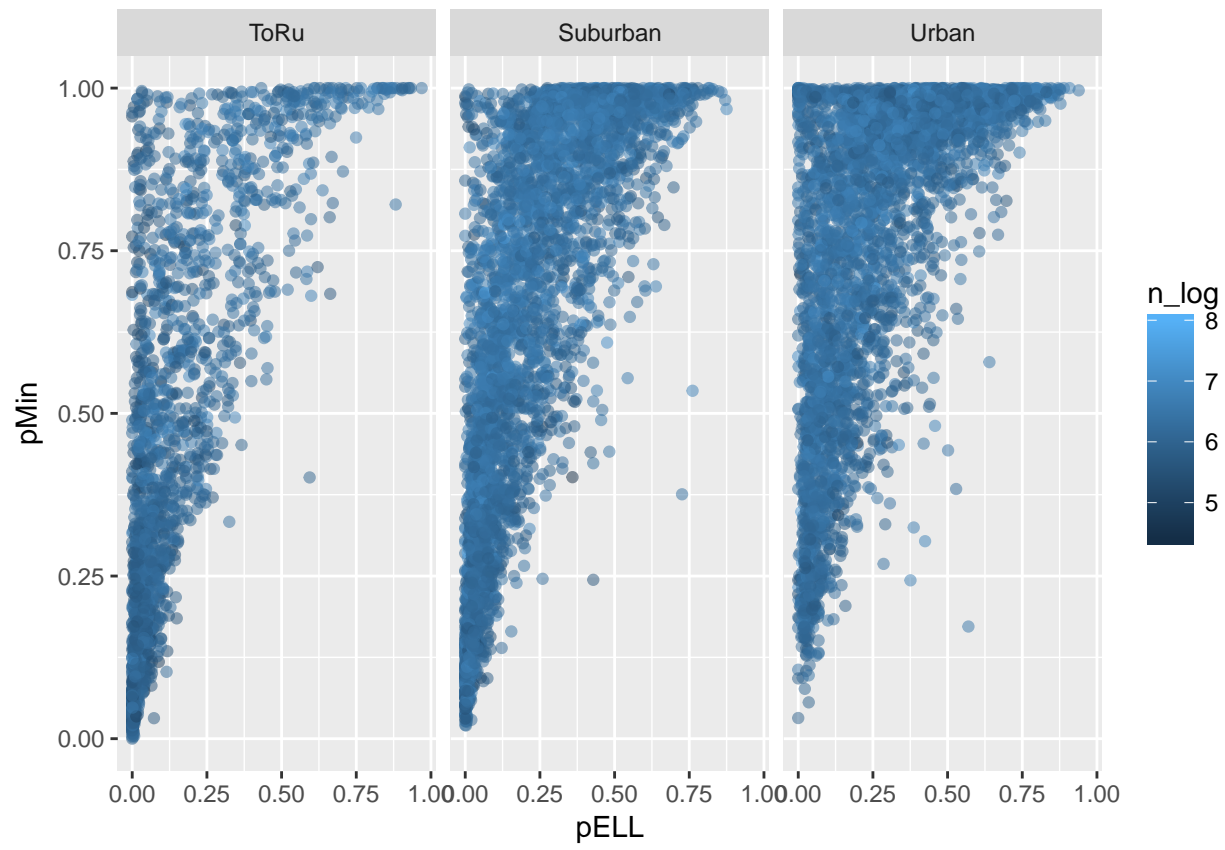
Descriptives of variables

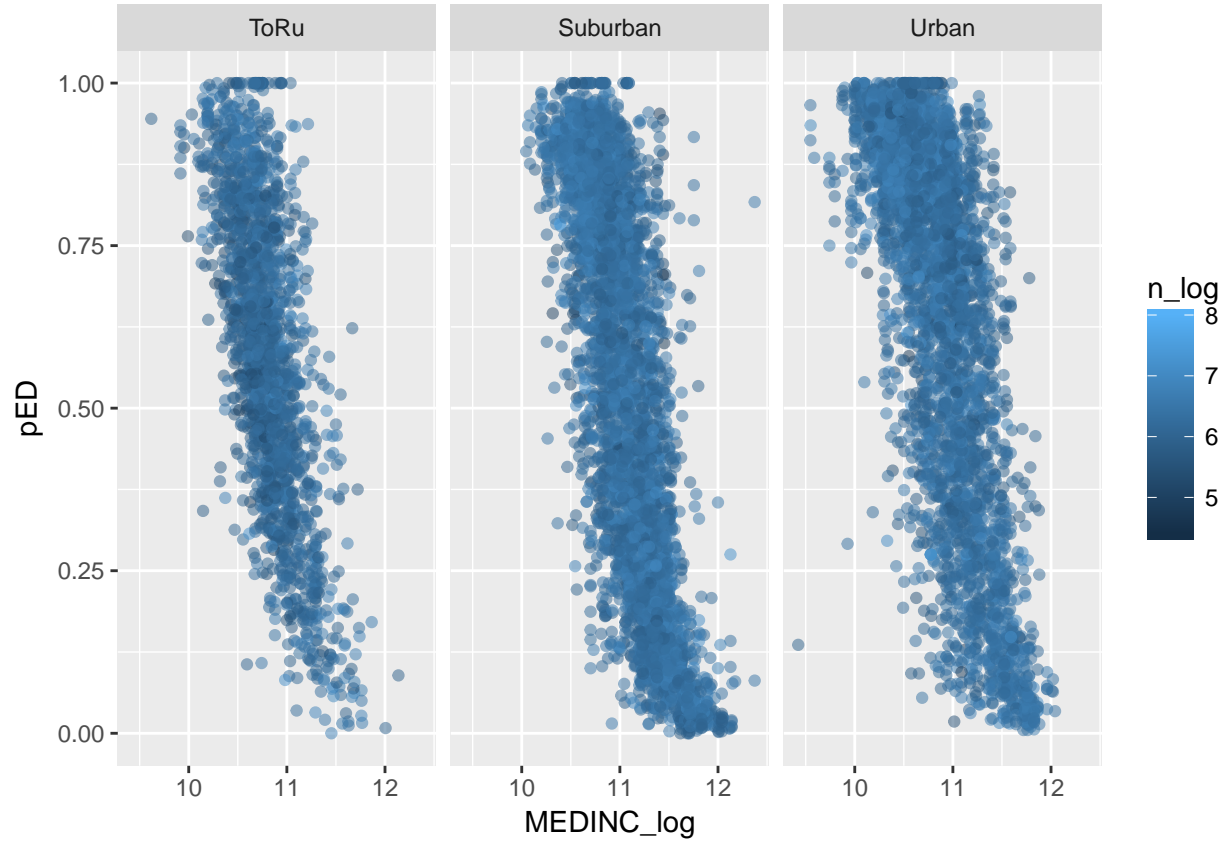
Variables	School		District Weighted		District Unweighted	
	Mean	SD	Mean	SD	Mean	SD
Number of Schools	NA	NA	9,875.00	0.00	4.84	12.72
School Size	579.07	203.19	534.77	225.34	534.77	225.34
Median Income	60,084.98	25,007.61	56,710.63	20,804.82	56,648.44	20,750.06
Average Proportions						
ELA Proficiency	0.59	0.23	0.60	0.20	0.60	0.20
Math Proficiency	0.53	0.29	0.54	0.26	0.54	0.26
Economically Disadvantaged	0.59	0.29	0.54	0.24	0.54	0.24
English Language Learners	0.23	0.21	0.14	0.17	0.14	0.17
Minority Status	0.65	0.30	0.46	0.32	0.46	0.32
Total/Free/Reduced Lunch	0.59	0.29	0.53	0.24	0.53	0.23
Indicators						
Urban	0.40	0.49	0.15	0.33	0.15	0.33
Suburban	0.41	0.49	0.33	0.44	0.33	0.44
Town or Rural	0.19	0.39	0.51	0.48	0.51	0.48

Note. District variables are derived as aggregate means of school variables









SUBS

Stratification using balanced sampling (SUBS) was performed prior to simulation because the group of schools in each strata would be static across conditions except where the balancing model is manipulated. The set of covariates in both the full model (SUBS-F) and the omitted variable model (SUBS-OV) include binary indicator variables

Number of Clusters. Selecting the number of clusters, k , is one of the most difficult problems in cluster analysis (Steinley, 2006). To date, the most extensive investigation of methods for determining k was conducted by Milligan and Cooper (1985) who analyzed 30 methods. However, aside from the limited generalizability of this study, many methods are also inappropriate in the context of non-hierarchical and thus do not support k-means clustering. Hennig and Liao (2013) argue that the method of selecting k should depend on the context of the clustering and frame the issue as one of obtaining an

appropriate subject-matter-dependent definition of rather than a statistical estimation.

- Everitt (2011), p126
- clusterSim
- Continuous data?
 - Calinski and Harabasz (1974)
 - Duda and Hart (1973)
- Steinley, D. (2006a) K-means clustering: a half-century synthesis. British Journal of Mathematical & Statistical Psychology, 59, 1–34.
- Milligan and Cooper (1984)
- list 30

Subs-Full.

Subs-OV.

```
## # A tibble: 11 x 8
##   cluster_full_10  `1`  `2`  `3`  `4`  `5`  `6`  `20`
##           <dbl> <int> <int> <int> <int> <int> <int> <int>
## 1             1.   978   NA    NA   176   NA    NA  1154
## 2             2.    NA    NA    NA    NA    NA  1241  1241
## 3             3.    NA    NA    NA    NA   658    NA   658
## 4             4.    NA   957   193    NA    NA    NA  1150
## 5             5.    NA    NA     2    NA   667    NA   669
## 6             6.   283    59    NA    NA   217    NA   559
## 7             7.    NA     6  1368    NA    NA    NA  1374
## 8             8.    NA  1458    NA    NA    NA    NA  1458
```

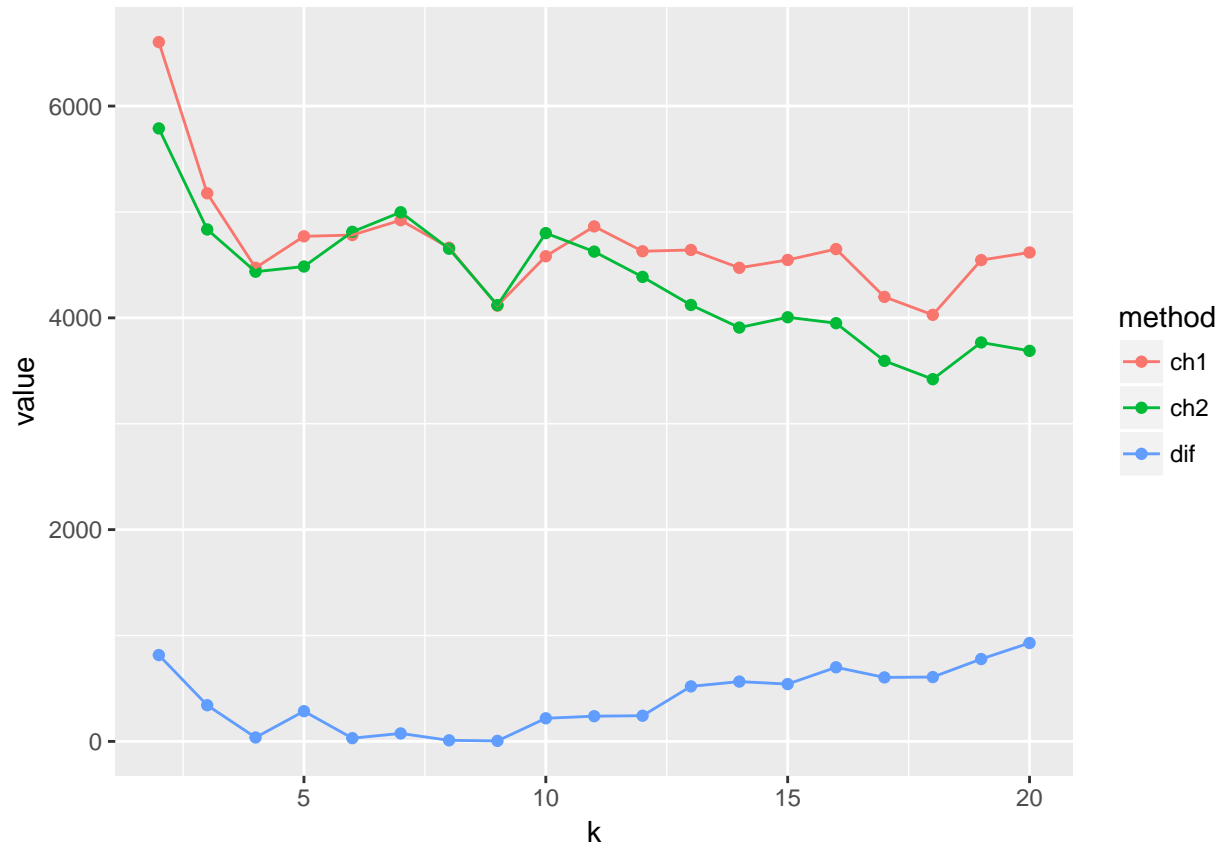



Figure 1

```
## 9          9.    NA    NA    NA    749    NA    319  1068
## 10         10.    45    NA    NA    495    NA     4    544
## 11         20.  1306  2480  1563  1420  1542  1564    NA
```

```
## # A tibble: 11 x 8
```

```
##   cluster_OV_10  `1`  `2`  `3`  `4`  `5`  `6`  `20`
##           <dbl> <int> <int> <int> <int> <int> <int> <int>
## 1             1.    NA    NA  1372    NA    NA    NA  1372
## 2             2.    NA    36    NA    47    10   247   340
## 3             3.    NA    NA    NA    NA  1106    NA  1106
## 4             4.    NA   597    NA    54     5    NA   656
## 5             5.    NA   888    NA    NA    NA    NA   888
```

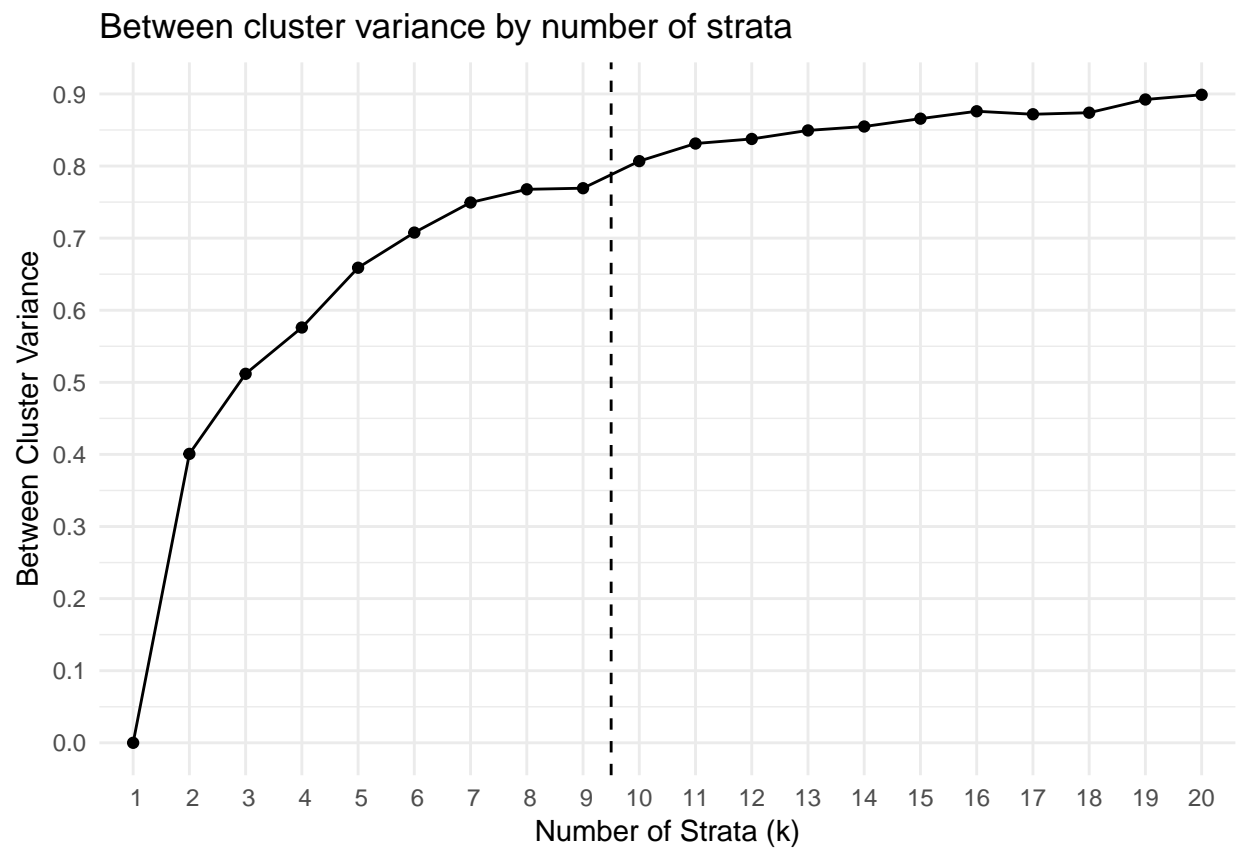


Figure 2

##	6	6.	NA	NA	573	NA	368	NA	941
##	7	7.	NA	NA	NA	10	NA	1455	1465
##	8	8.	12	NA	NA	1178	NA	NA	1190
##	9	9.	1328	NA	NA	NA	NA	1	1329
##	10	10.	NA	NA	185	NA	403	NA	588
##	11	20.	1340	1521	2130	1289	1892	1703	NA

##	#	A tibble: 7 x 8						
##	cluster_OV_6	`1`	`2`	`3`	`4`	`5`	`6`	`20`
##		<dbl>	<int>	<int>	<int>	<int>	<int>	<int>
##	1	1.	NA	8	1332	NA	NA	1340
##	2	2.	20	NA	NA	NA	1501	1521

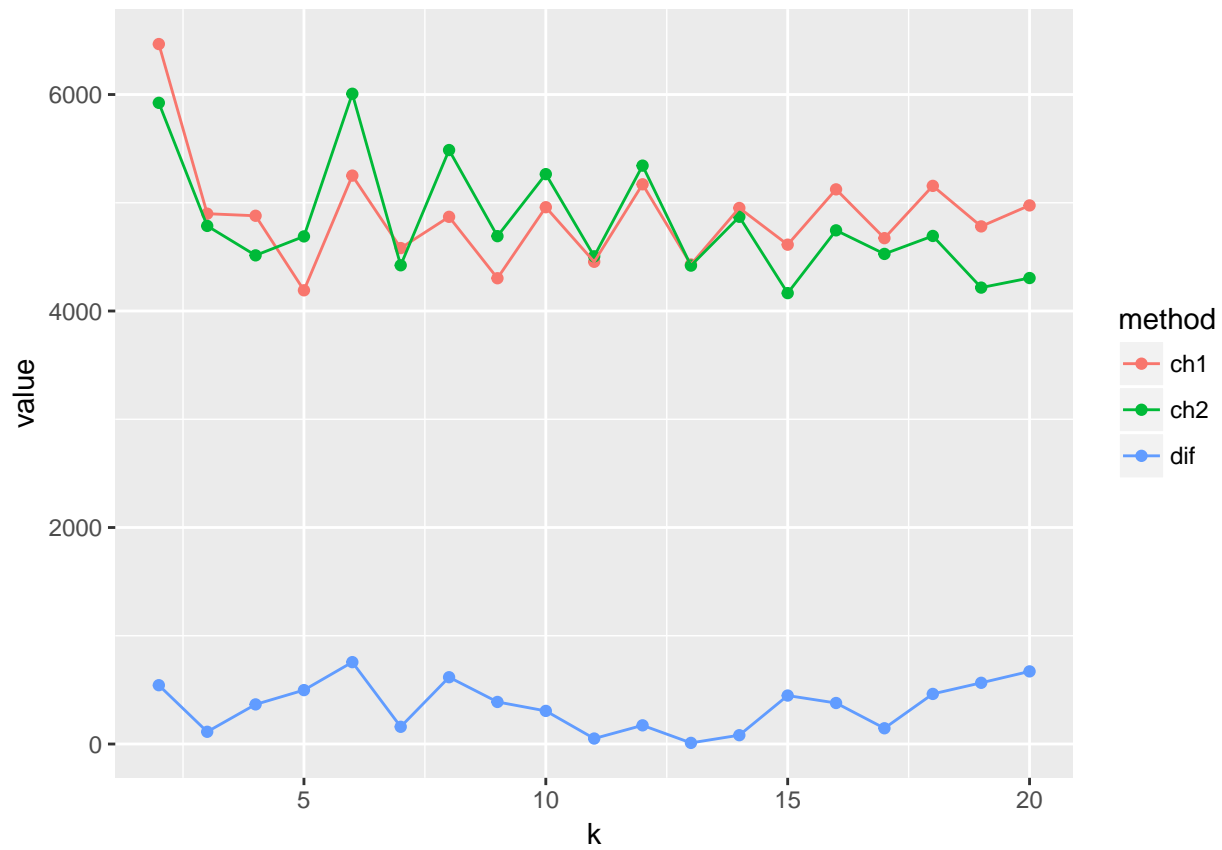


Figure 3

```
## 3      3.    NA    NA    NA    566    NA   1564   2130
## 4      4.      1  1019   228    NA     41    NA   1289
## 5      5.   1038    NA    NA    854    NA    NA   1892
## 6      6.    247  1453     3    NA    NA    NA   1703
## 7     20.   1306  2480  1563  1420  1542  1564    NA
```

```
## # A tibble: 11 x 12
```

```
##   cluster_OV_10  `1`  `2`  `3`  `4`  `5`  `6`  `7`  `8`  `9`
##           <dbl> <int> <int> <int> <int> <int> <int> <int> <int> <int>
## 1             1.    NA  1218    NA    NA    NA    NA    NA    NA   153
## 2             2.    NA    NA     1    NA    NA   339    NA    NA    NA
## 3             3.  1104    NA    NA    NA    NA    NA    NA    NA    NA
```



##	4		4.	NA	NA	300	NA	136	220	NA	NA	NA
##	5		5.	NA	NA	357	NA	531	NA	NA	NA	NA
##	6		6.	50	NA	NA	NA	NA	NA	NA	NA	878
##	7		7.	NA	NA	NA	8	NA	NA	5	1452	NA
##	8		8.	NA	NA	NA	1130	NA	NA	57	3	NA
##	9		9.	NA	NA	NA	12	2	NA	1312	3	NA
##	10		10.	NA	23	NA	NA	NA	NA	NA	NA	37
##	11		20.	1154	1241	658	1150	669	559	1374	1458	1068
##	#	... with 2 more variables: `10` <int>, `20` <int>										

References