# validclust Documentation

*Release 0.1.1*

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Validate clustering results

# CHAPTER 1

# Motivation

Clustering algorithms often require that the analyst specify the number of clusters that exist in the data, a parameter commonly known as `k`. One approach to determining an appropriate value for `k` is to cluster the data using a range of values for `k`, then evaluate the quality of the resulting clusterings using a cluster validity index (CVI). The value of `k` that results in the best partitioning of the data according to the CVI is then chosen. `validclust` handles this process for the analyst, making it very easy to quickly determine an optimal value for `k`.

# CHAPTER 2

# Installation

You can get the stable version from PyPI:

```
pip install validclust
```

Or the development version from GitHub:

```
pip install git+https://github.com/crew102/validclust.git
```

# CHAPTER 3

# Basic usage

Load libraries.

```
import matplotlib.pyplot as plt
from sklearn.datasets import make_blobs
from validclust import ValidClust
```

Create some synthetic data. The data will be clustered around 4 centers.

```
data, _ = make_blobs(n_samples=500, centers=4, n_features=5, random_state=0)
```

Use `ValidClust` to determine the optimal number of clusters. The code below will partition the data into 2-7 clusters using two different clustering algorithms, then calculate various CVIs across the results.

```
vclust = ValidClust(
    k=list(range(2, 8)),
    methods=['hierarchical', 'kmeans']
)
cvi_vals = vclust.fit_predict(data)
print(cvi_vals)
#>                                   2            3            4            5  \
#> method       index
#> hierarchical silhouette     0.645563     0.633970     0.747064     0.583724
#>              calinski    1007.397799  1399.552836  3611.526187  2832.925655
#>              davies         0.446861     0.567859     0.361996     1.025296
#>              dunn           0.727255     0.475745     0.711415     0.109312
#> kmeans       silhouette     0.645563     0.633970     0.747064     0.602562
#>              calinski    1007.397799  1399.552836  3611.526187  2845.143428
#>              davies         0.446861     0.567859     0.361996     0.988223
#>              dunn           0.727255     0.475745     0.711415     0.115113
#>
#>                                   6            7
#> method       index
#> hierarchical silhouette     0.435456     0.289567
#>              calinski    2371.222506  2055.323553
```

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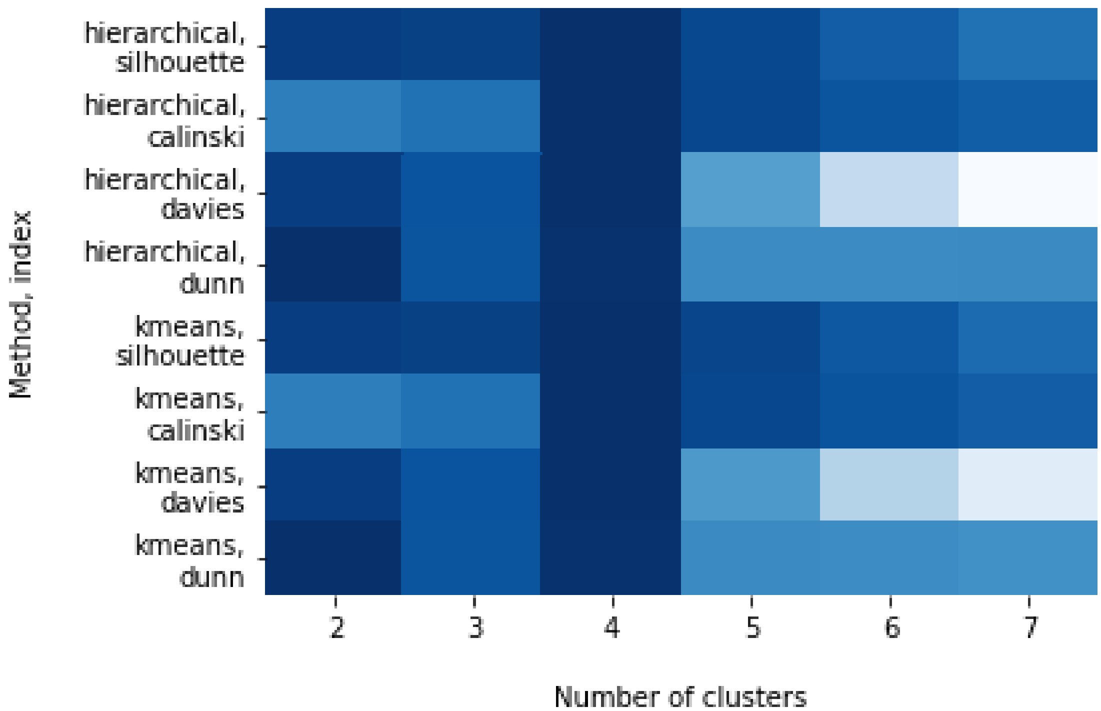
```
#>              davies         1.509404     1.902413
#>              dunn           0.109312     0.116557
#> kmeans       silhouette     0.468945     0.334379
#>              calinski    2389.531071  2096.945591
#>              davies         1.431102     1.722117
#>              dunn           0.098636     0.072423
```

It's hard to see what the optimal value of `k` is from the raw CVI values shown above. Not all of the CVIs are on a 0-1 scale, and lower scores are actually associated with better clusterings for some of the indices. `ValidClust`'s `plot()` method solves this problem by first normalizing the CVIs and then displaying the results in a heatmap.

```
vclust.plot()
```




For each row in the above grid (i.e., for each clustering method/CVI pair), darker cells are associated with higher-quality clusterings. From this plot we can see that each method/index pair seems to be pointing to 4 as being an optimal value for `k`.

# CHAPTER 4

## Reference

- Modules
- Full index