



UNSUPERVISED LEARNING IN PYTHON

Visualizing hierarchies



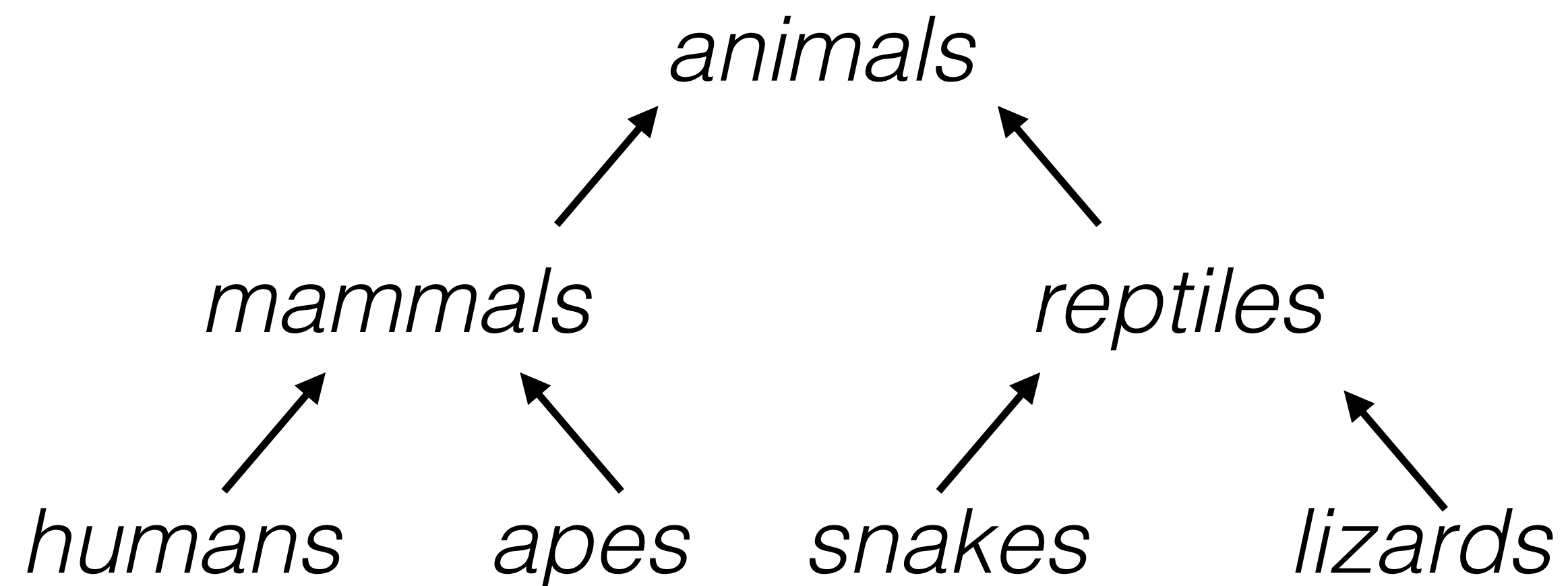
Visualisations communicate insight

- "t-SNE" : Creates a 2D map of a dataset (later)
- "Hierarchical clustering" (this video)



A hierarchy of groups

- Groups of living things can form a hierarchy
- Clusters are contained in one another





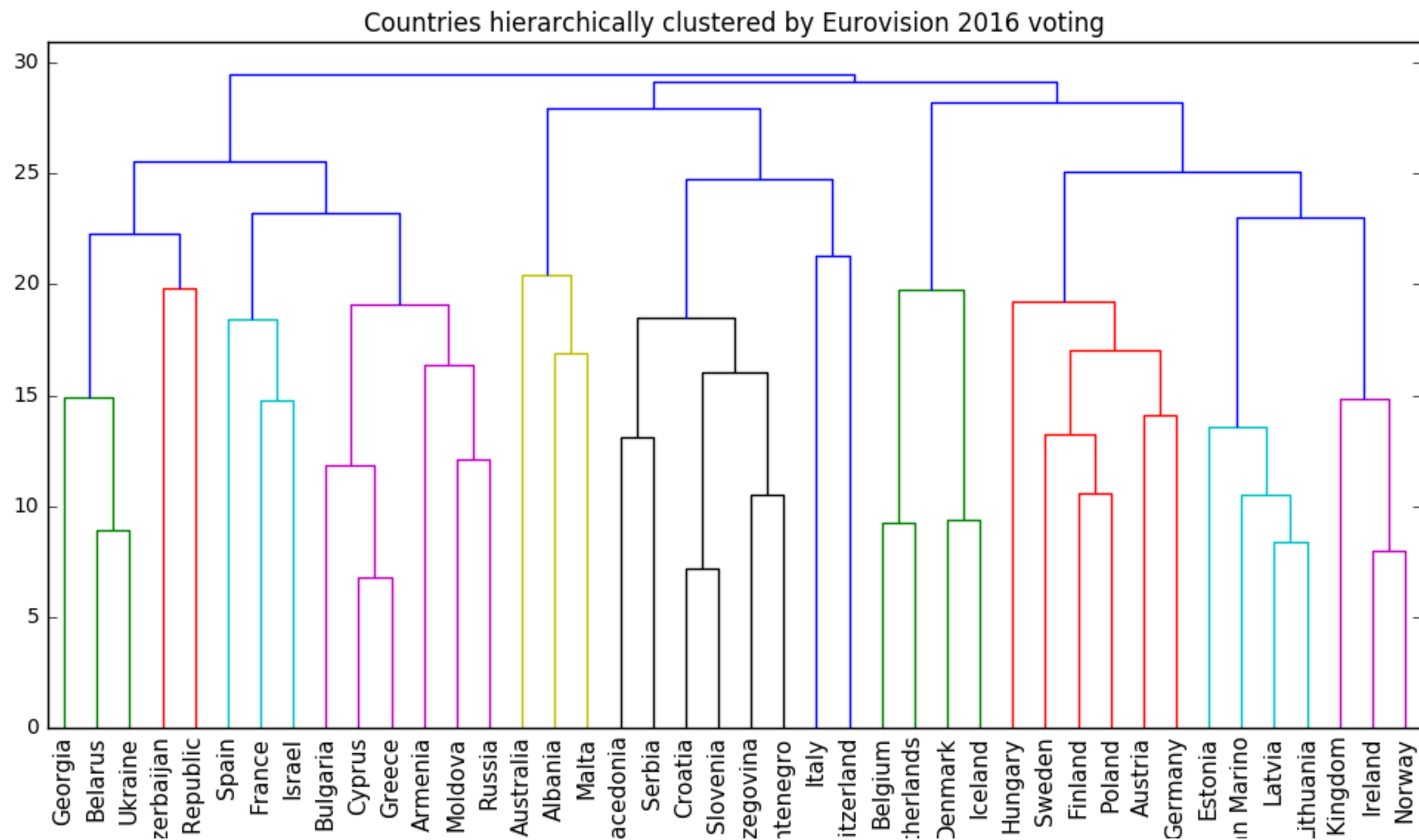
Eurovision scoring dataset

- Countries gave scores to songs performed at the Eurovision 2016
- 2D array of scores
- Rows are countries, columns are songs

	song0	song1	.	.	.	song25
Albania						
Armenia						
	0	7	...			4
United Kingdom						



Hierarchical clustering of voting countries





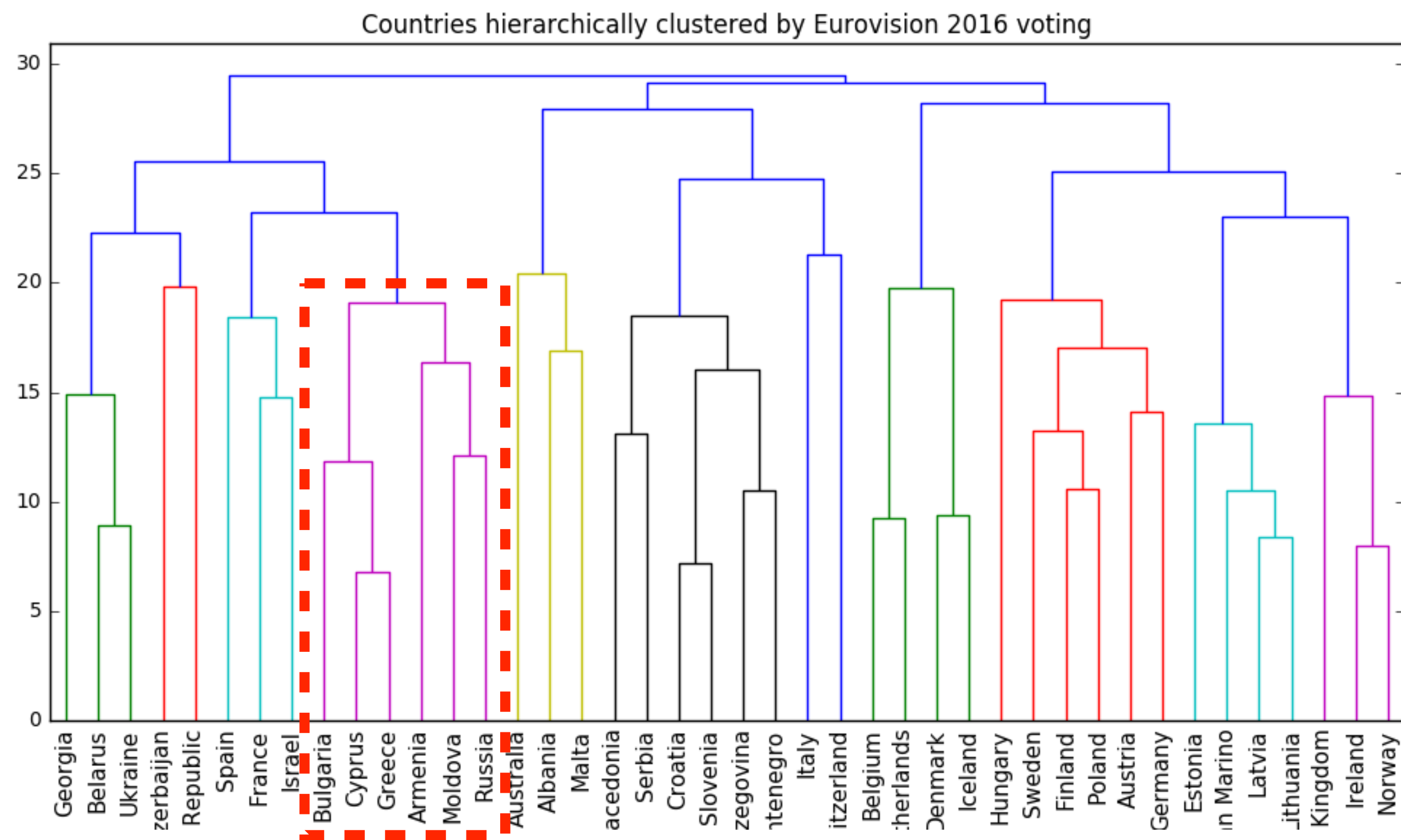
Hierarchical clustering

- Every country begins in a separate cluster
- At each step, the two closest clusters are merged
- Continue until all countries in a single cluster
- This is “agglomerative” hierarchical clustering



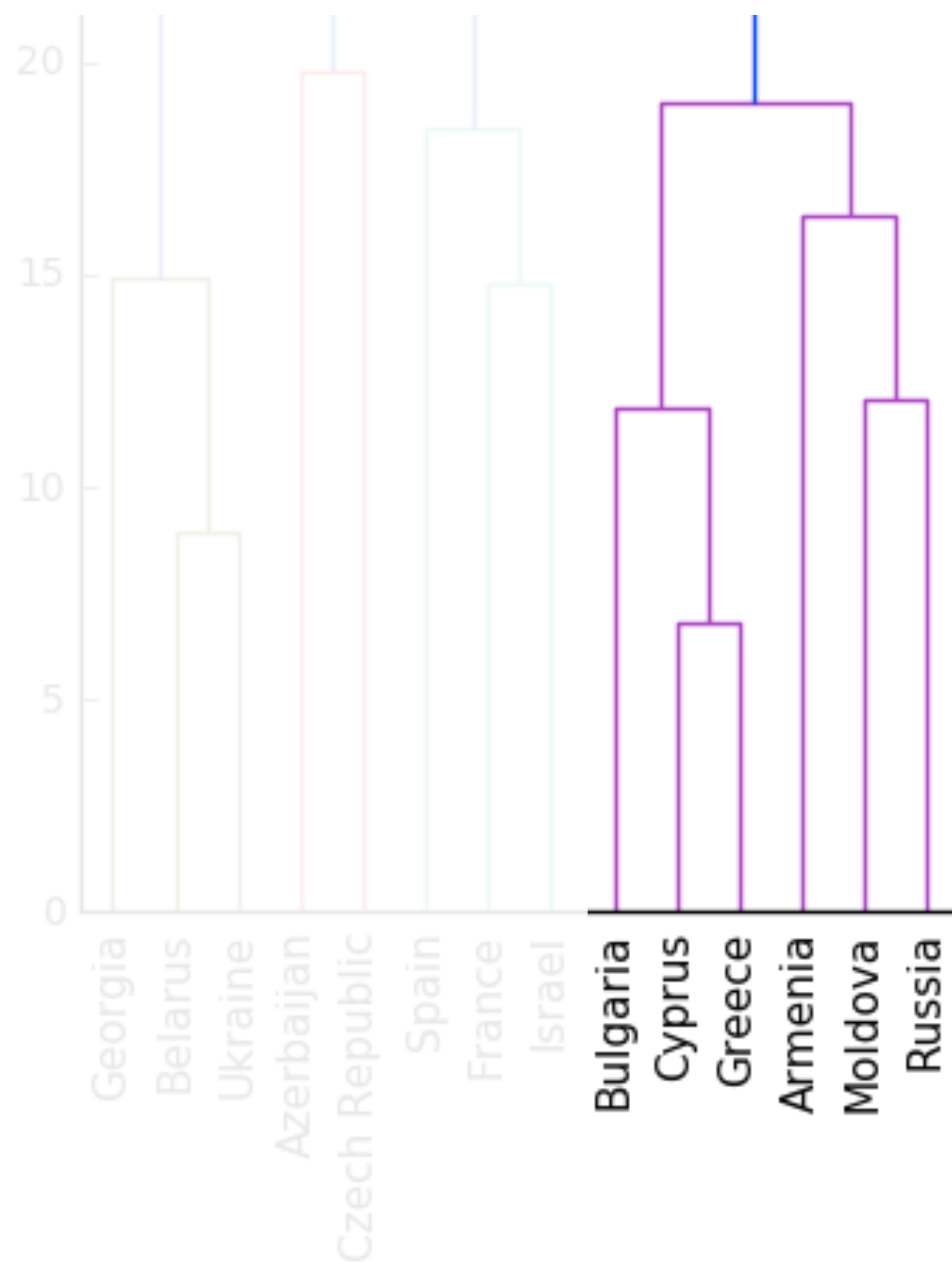
The dendrogram of a hierarchical clustering

- Read from the bottom up
- Vertical lines represent clusters



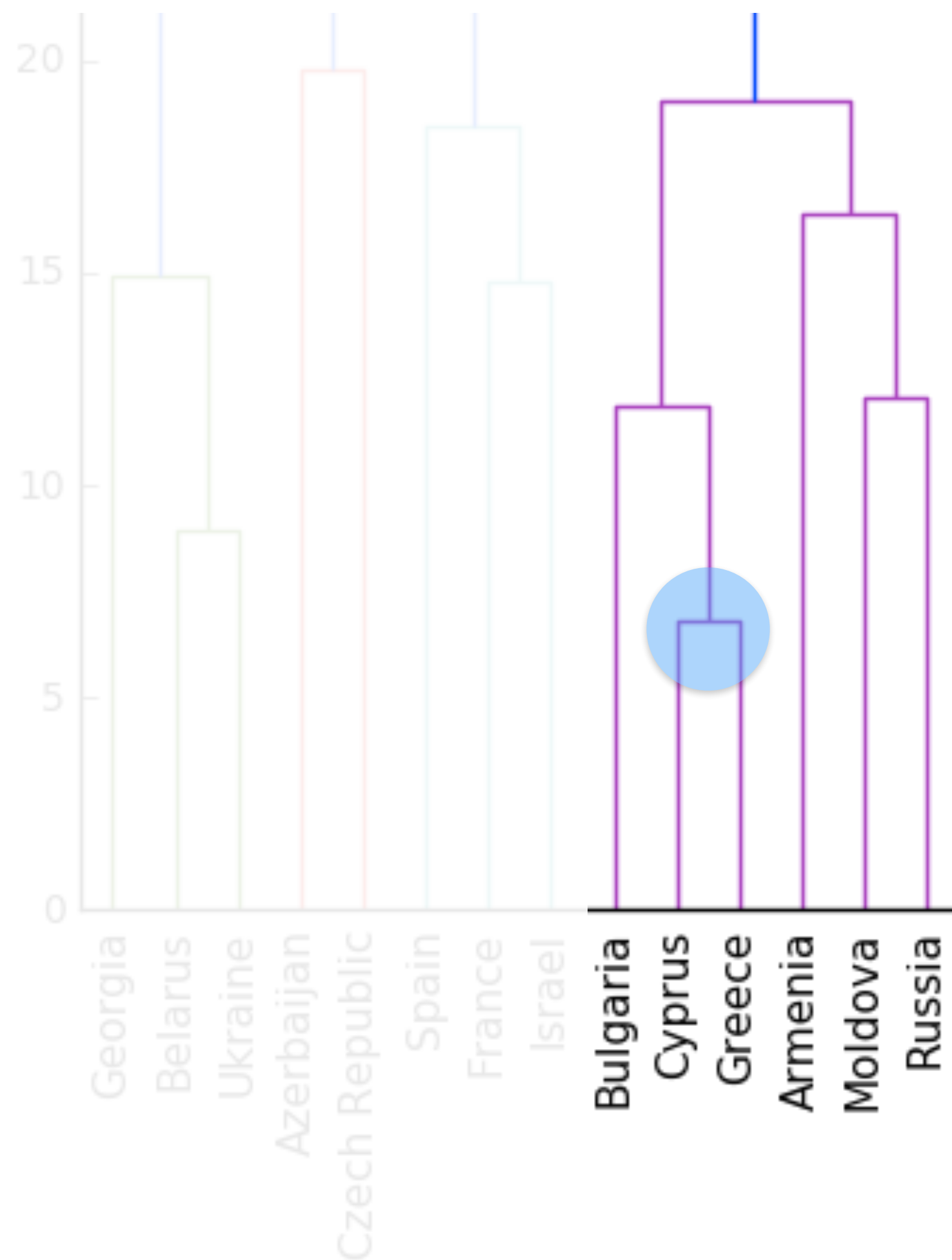


Dendrograms, step-by-step



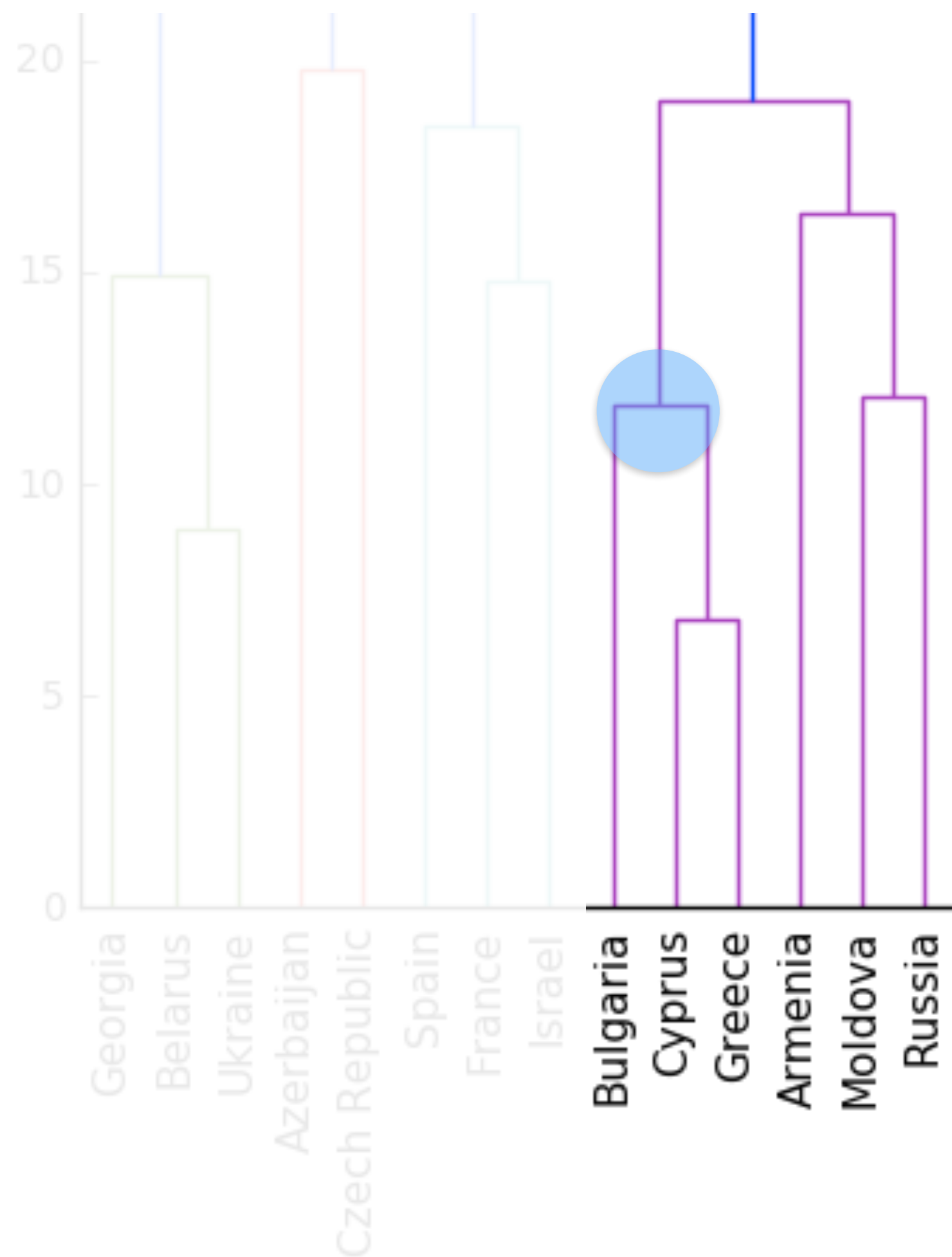


Dendrograms, step-by-step



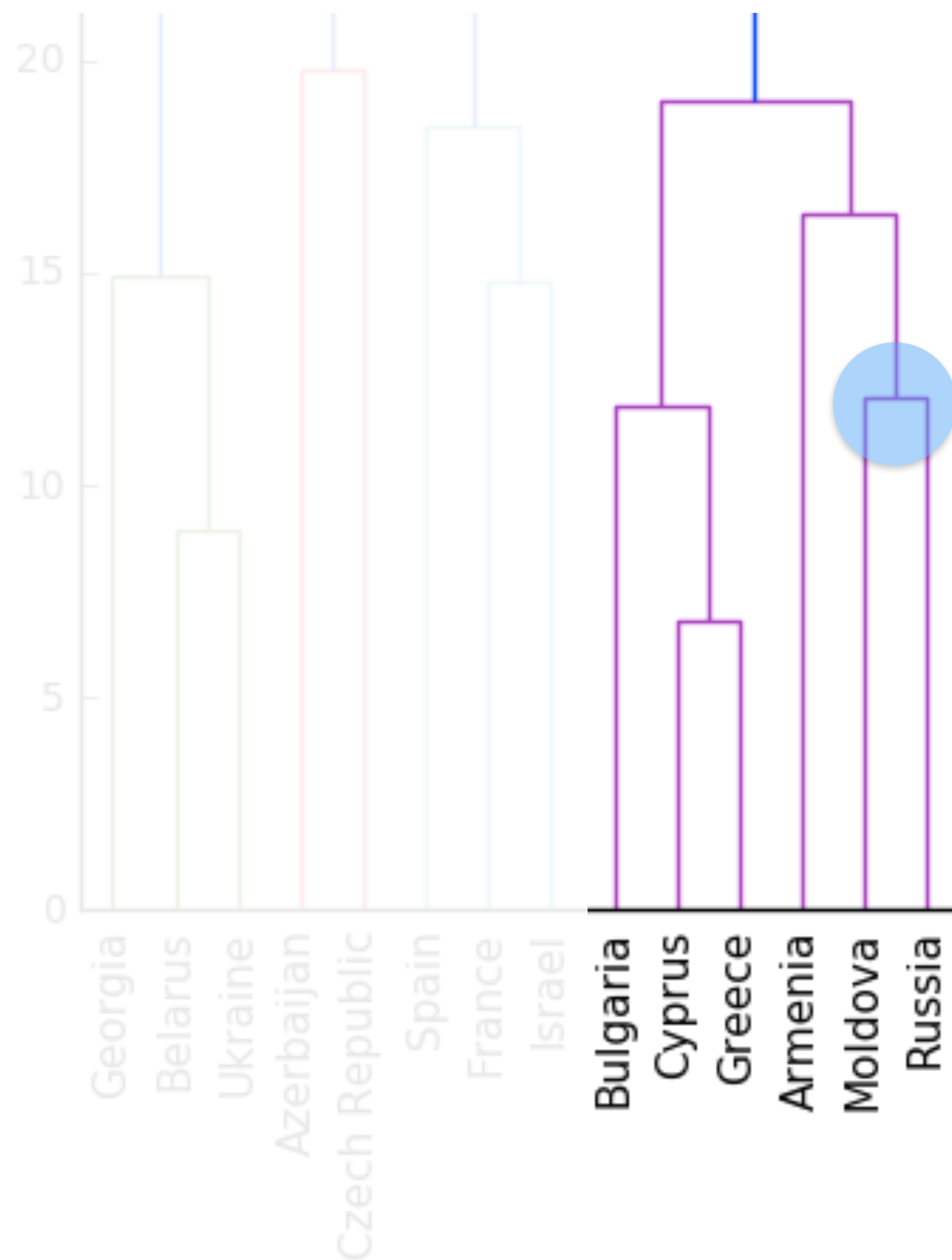


Dendrograms, step-by-step



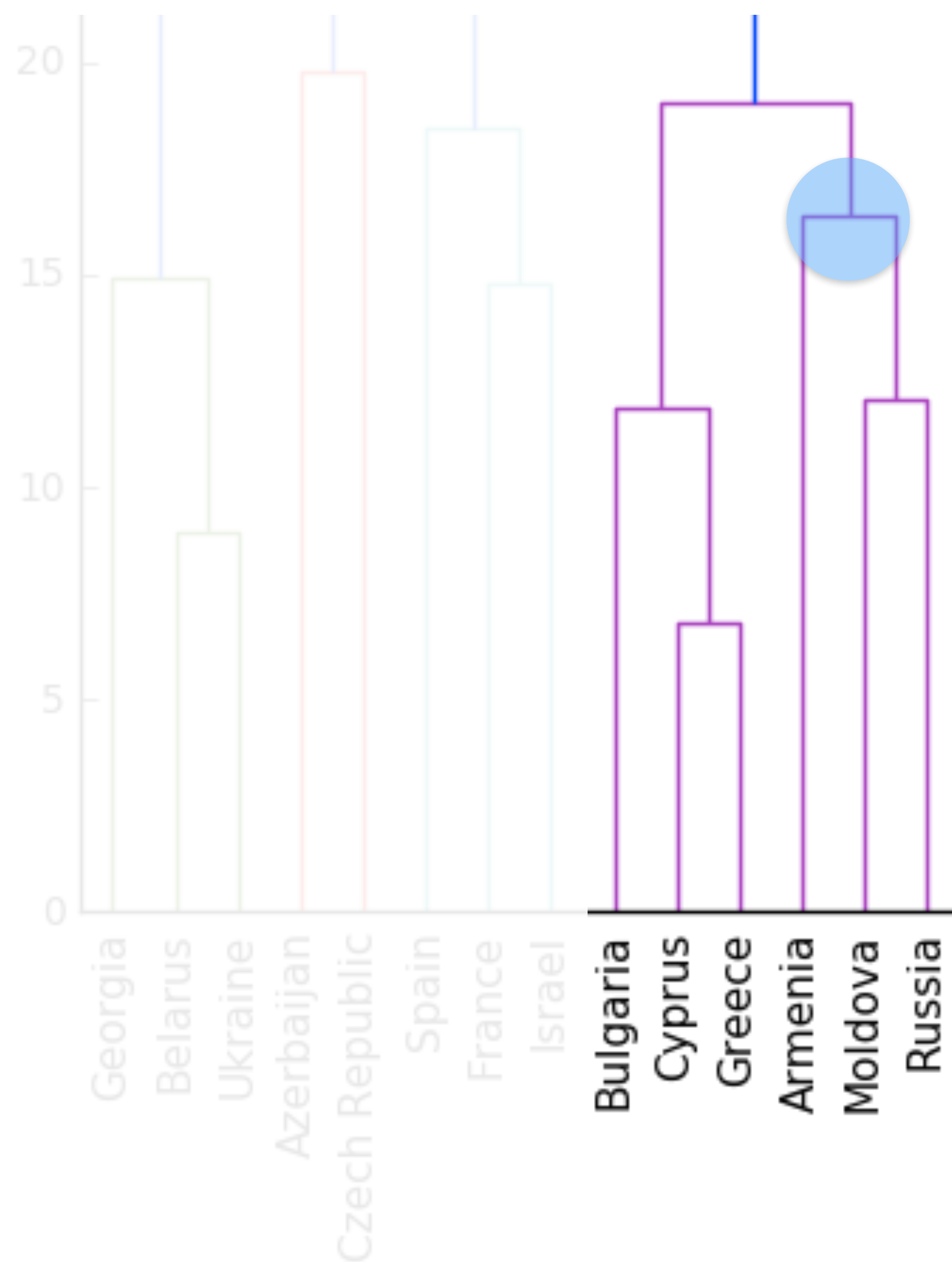


Dendrograms, step-by-step



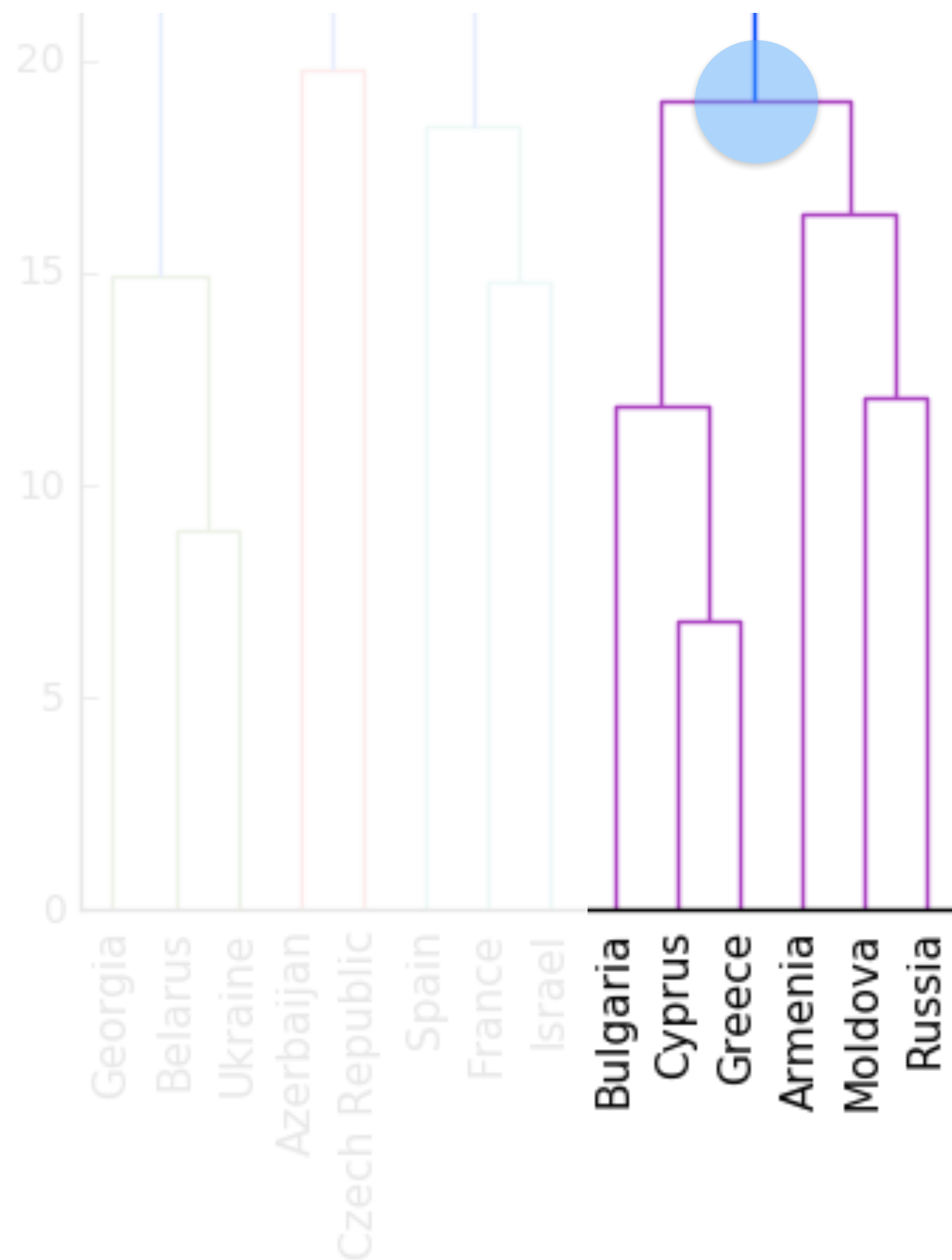


Dendrograms, step-by-step



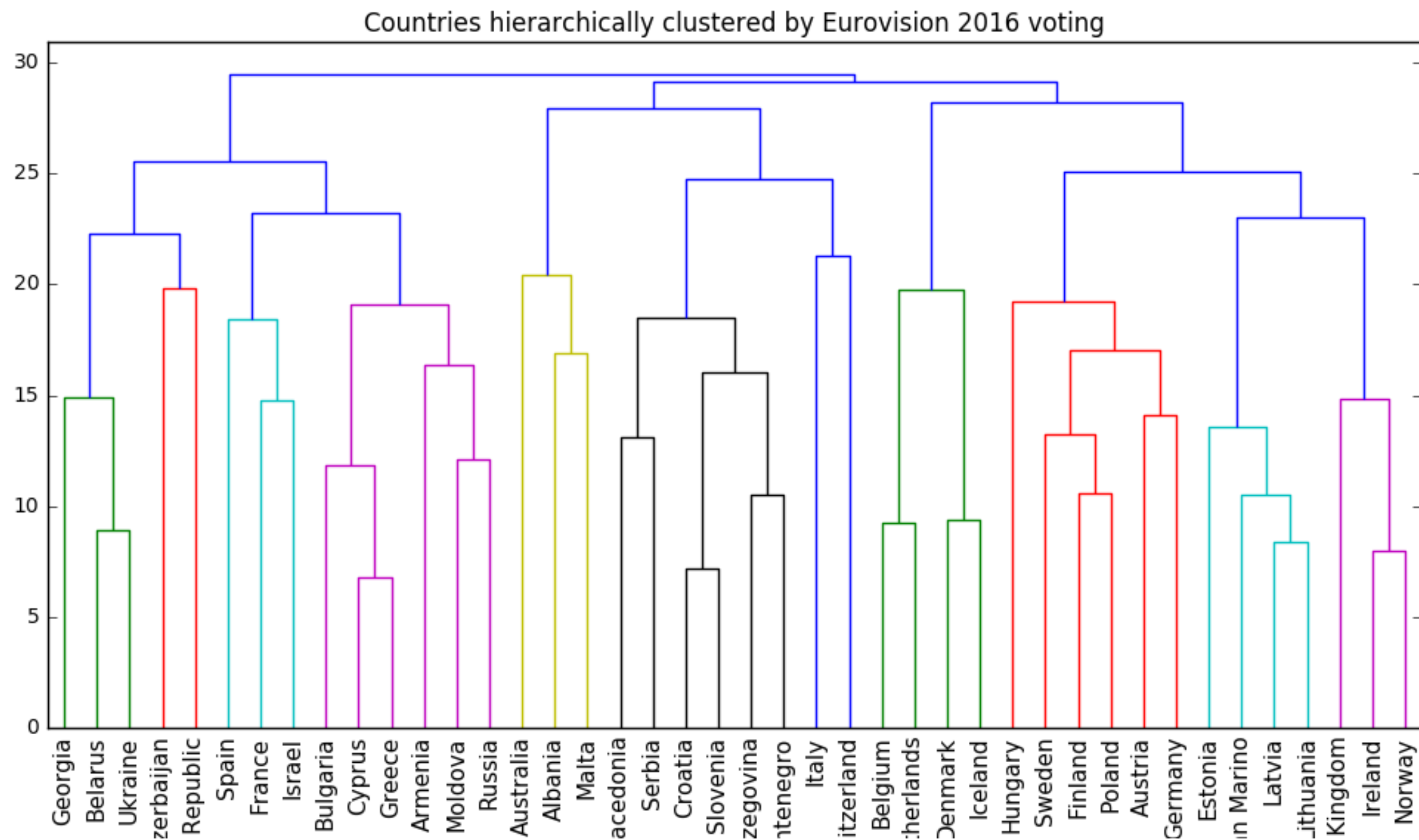


Dendrograms, step-by-step





Dendrograms, step-by-step





Hierarchical clustering with SciPy

- Given `samples` (the array of scores), and `country_names`

```
In [1]: import matplotlib.pyplot as plt
```

```
In [2]: from scipy.cluster.hierarchy import linkage, dendrogram
```

```
In [3]: mergings = linkage(samples, method='complete')
```

```
In [4]: dendrogram(mergings,  
...:               labels=country_names,  
...:               leaf_rotation=90,  
...:               leaf_font_size=6)
```

```
In [5]: plt.show()
```



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Let's practice!



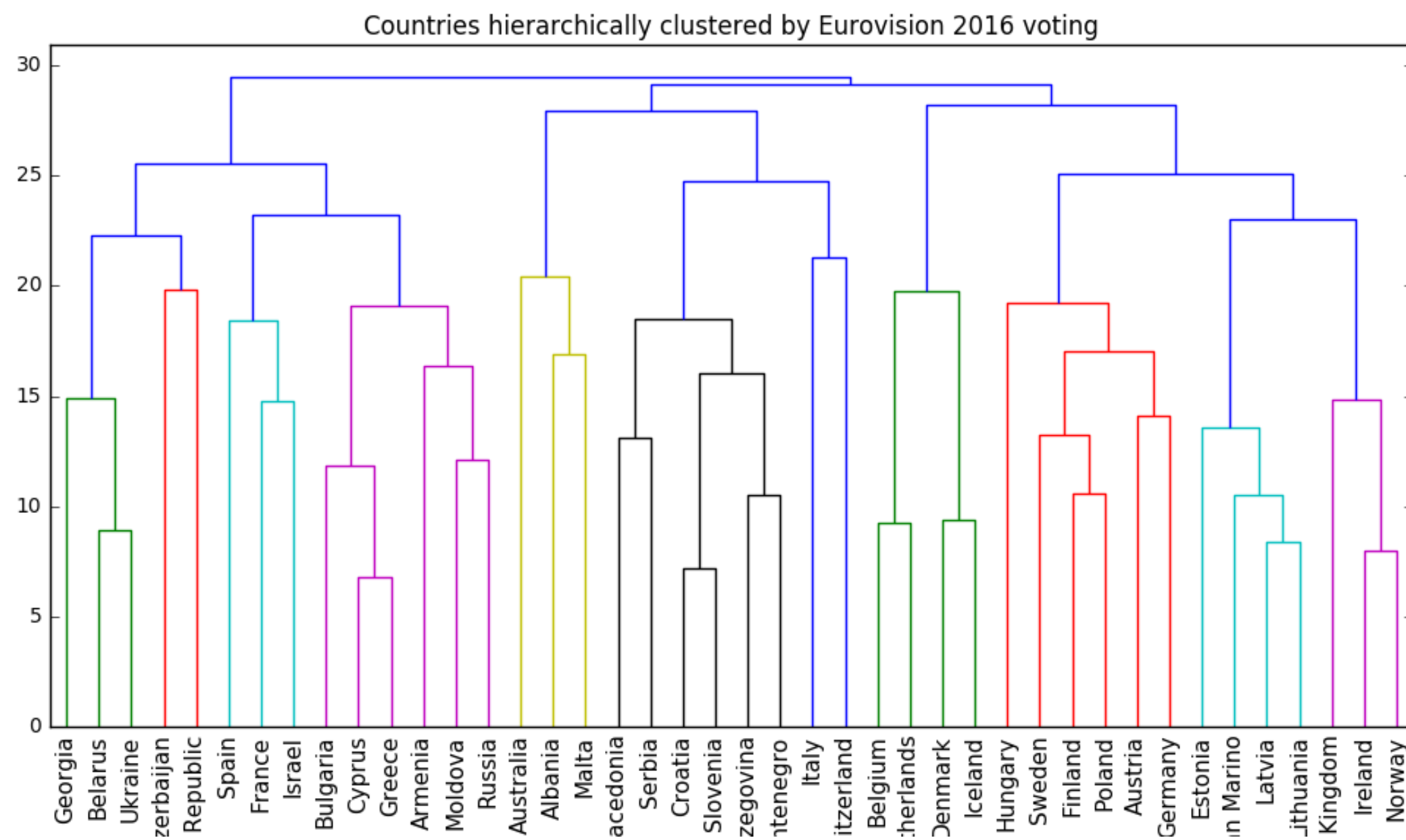
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Cluster labels in hierarchical clustering



Cluster labels in hierarchical clustering

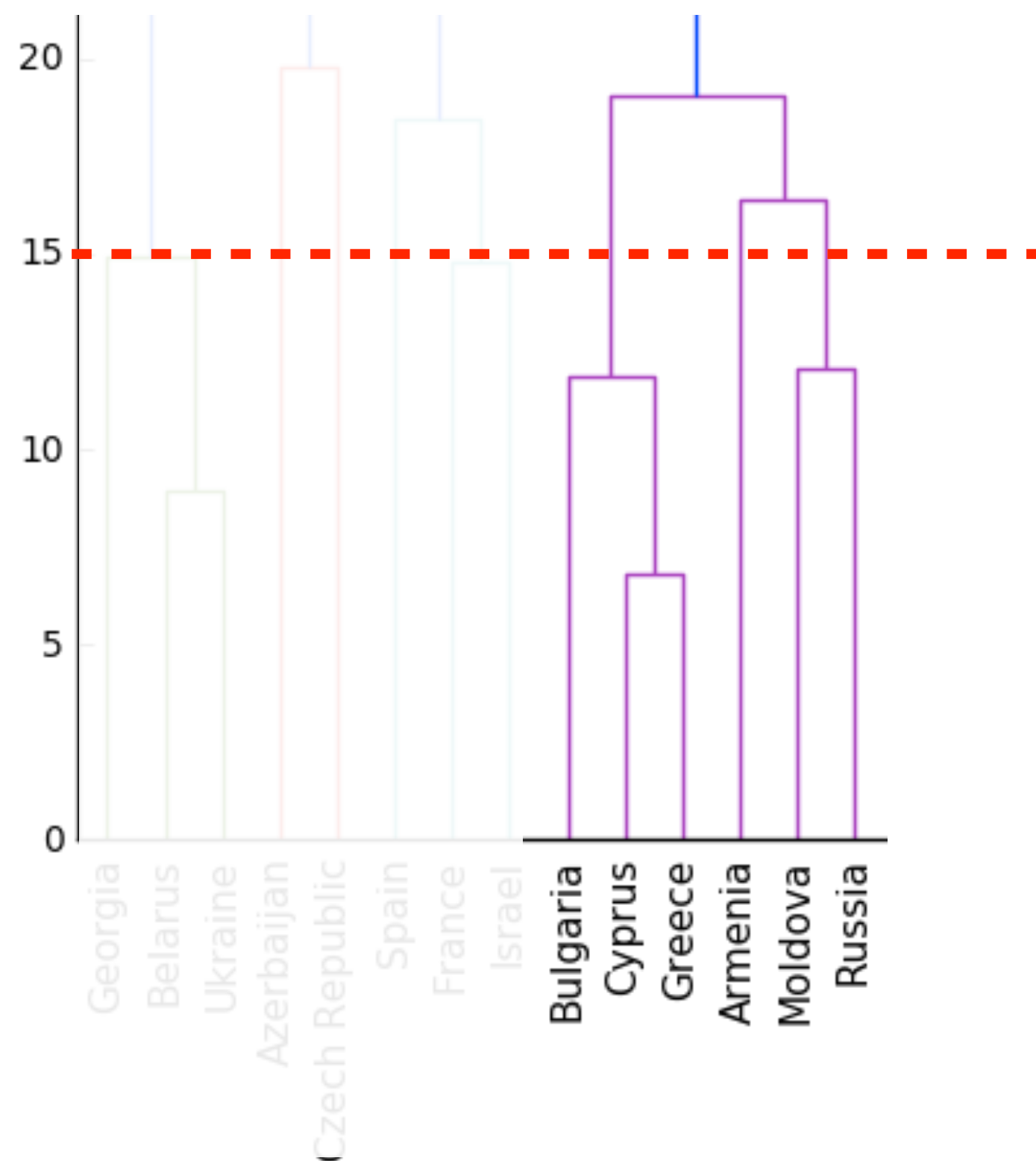
- Not only a visualisation tool!
- Cluster labels at any intermediate stage can be recovered
- For use in e.g. cross-tabulations





Intermediate clusterings & height on dendrogram

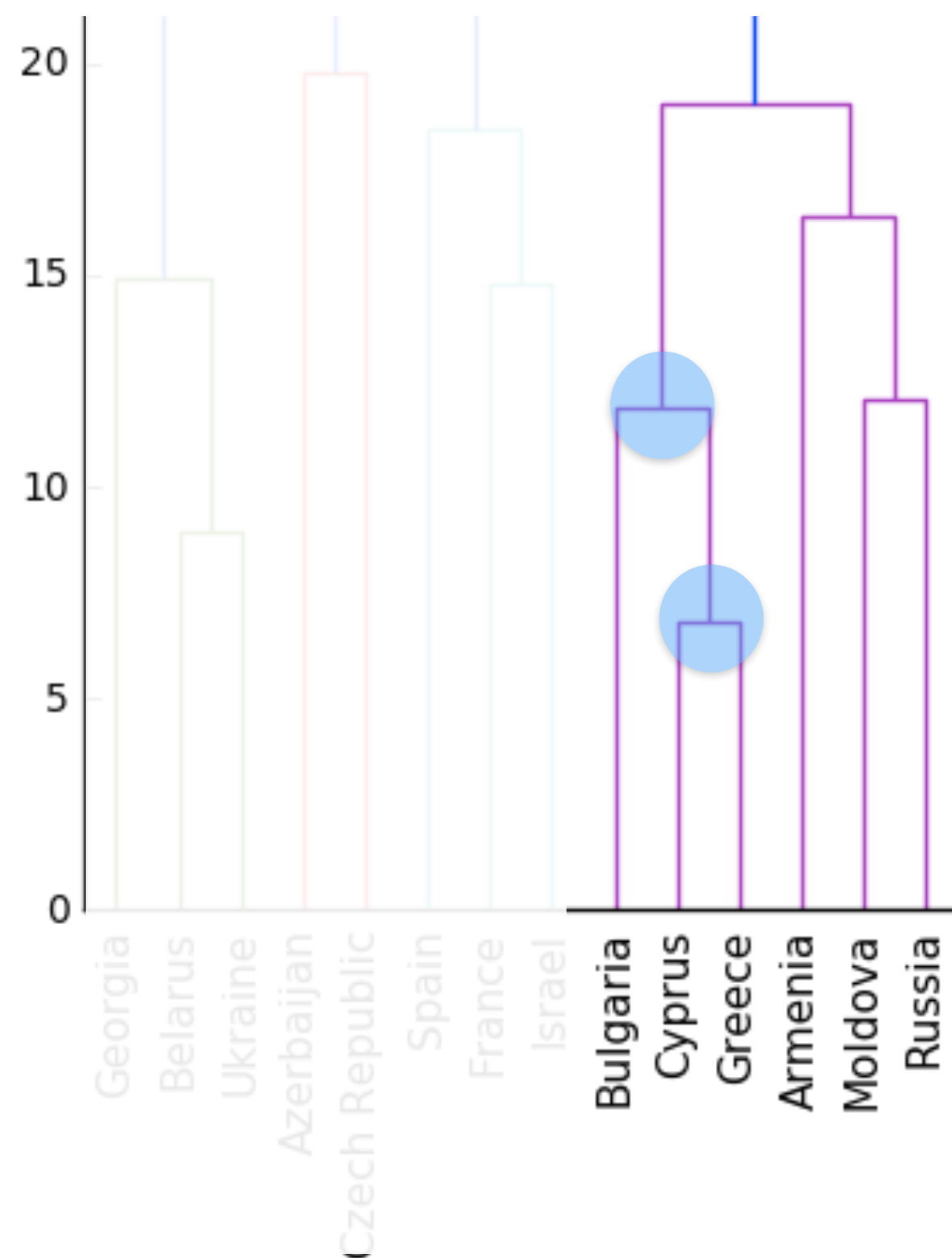
- E.g. at height 15: Bulgaria, Cyprus, Greece are one cluster
- Russia and Moldova are another
- Armenia in a cluster on its own





Dendrograms show cluster distances

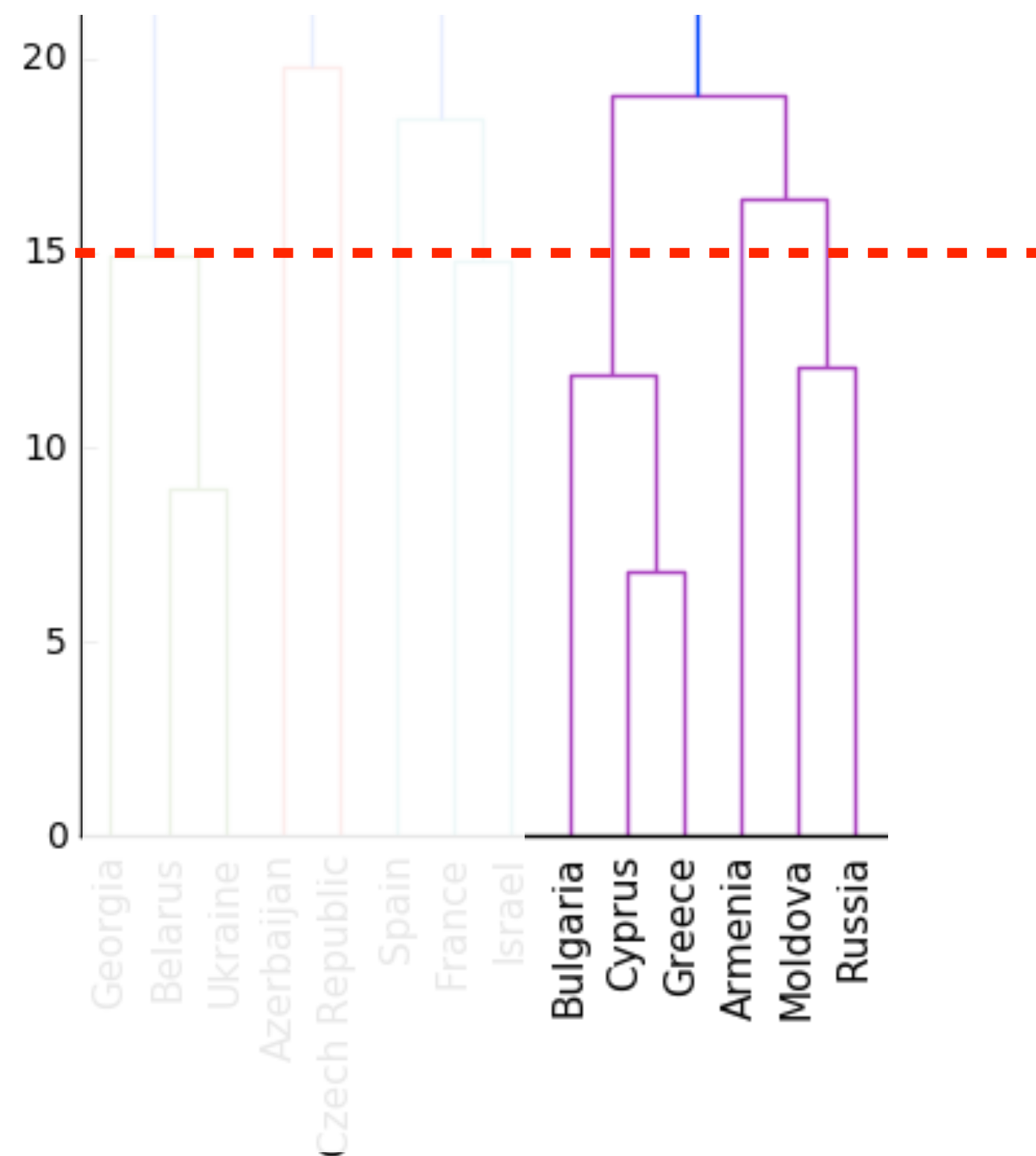
- Height on dendrogram = distance between merging clusters
- E.g. clusters with only Cyprus and Greece had distance approx. 6
- This new cluster distance approx. 12 from cluster with only Bulgaria





Intermediate clusterings & height on dendrogram

- Height on dendrogram specifies max. distance between merging clusters
- Don't merge clusters further apart than this (e.g. 15)



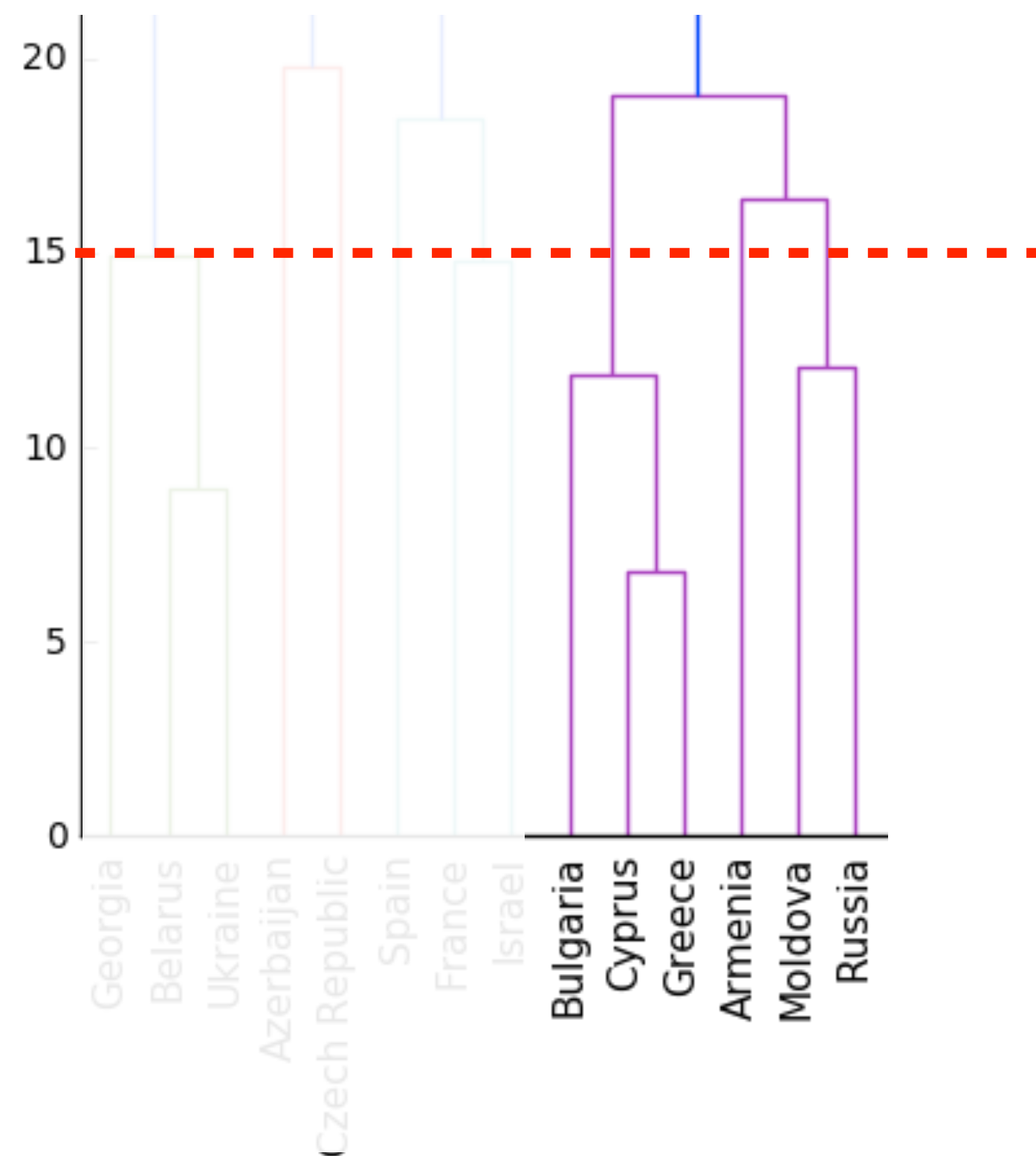
Distance between clusters

- Defined by a "linkage method"
- Specified via method parameter, e.g. `linkage(samples, method="complete")`
- In "complete" linkage: distance between clusters is max. distance between their samples
- Different linkage method, different hierarchical clustering!



Extracting cluster labels

- Use the `fcluster` method
- Returns a NumPy array of cluster labels





Extracting cluster labels using fcluster

```
In [1]: from scipy.cluster.hierarchy import linkage

In [2]: mergings = linkage(samples, method='complete')

In [3]: from scipy.cluster.hierarchy import fcluster

In [4]: labels = fcluster(mergings, 15, criterion='distance')

In [5]: print(labels)
[ 9  8 11 20  2  1 17 14 ... ]
```




Aligning cluster labels with country names

- Given a list of strings `country_names`:

```
In [1]: import pandas as pd
```

```
In [2]: pairs = pd.DataFrame({'labels': labels,  
    ....:                    'countries': country_names})
```

```
In [3]: print(pairs.sort_values('labels'))
```

	countries	labels
5	Belarus	1
40	Ukraine	1
17	Georgia	1
...		
36	Spain	5
8	Bulgaria	6
19	Greece	6
10	Cyprus	6
28	Moldova	7
...		



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Let's practice!



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t-SNE for 2-dimensional maps

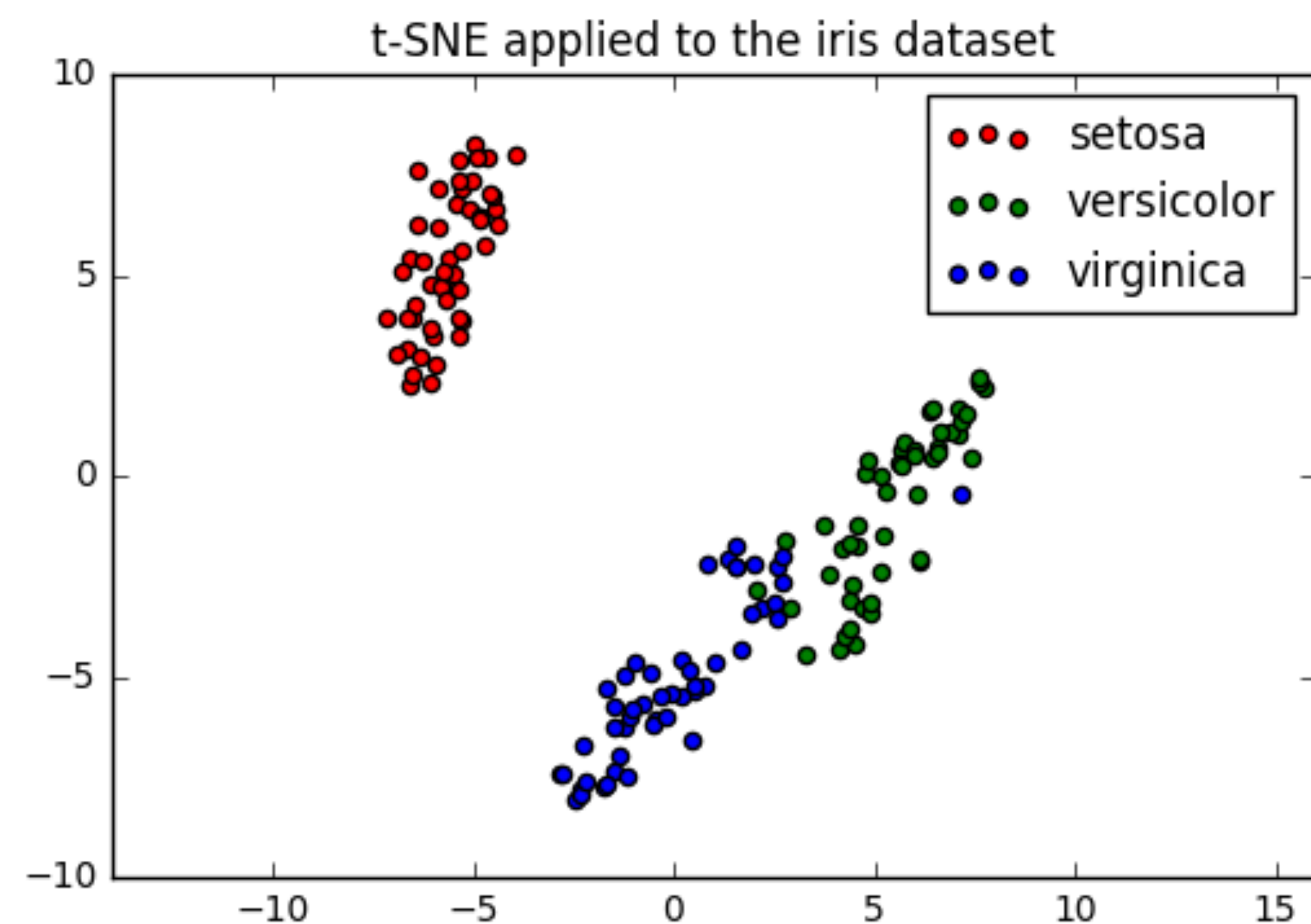
t-SNE for 2-dimensional maps

- t-SNE = “t-distributed stochastic neighbor embedding”
- Maps samples to 2D space (or 3D)
- Map approximately preserves nearness of samples
- Great for inspecting datasets



t-SNE on the iris dataset

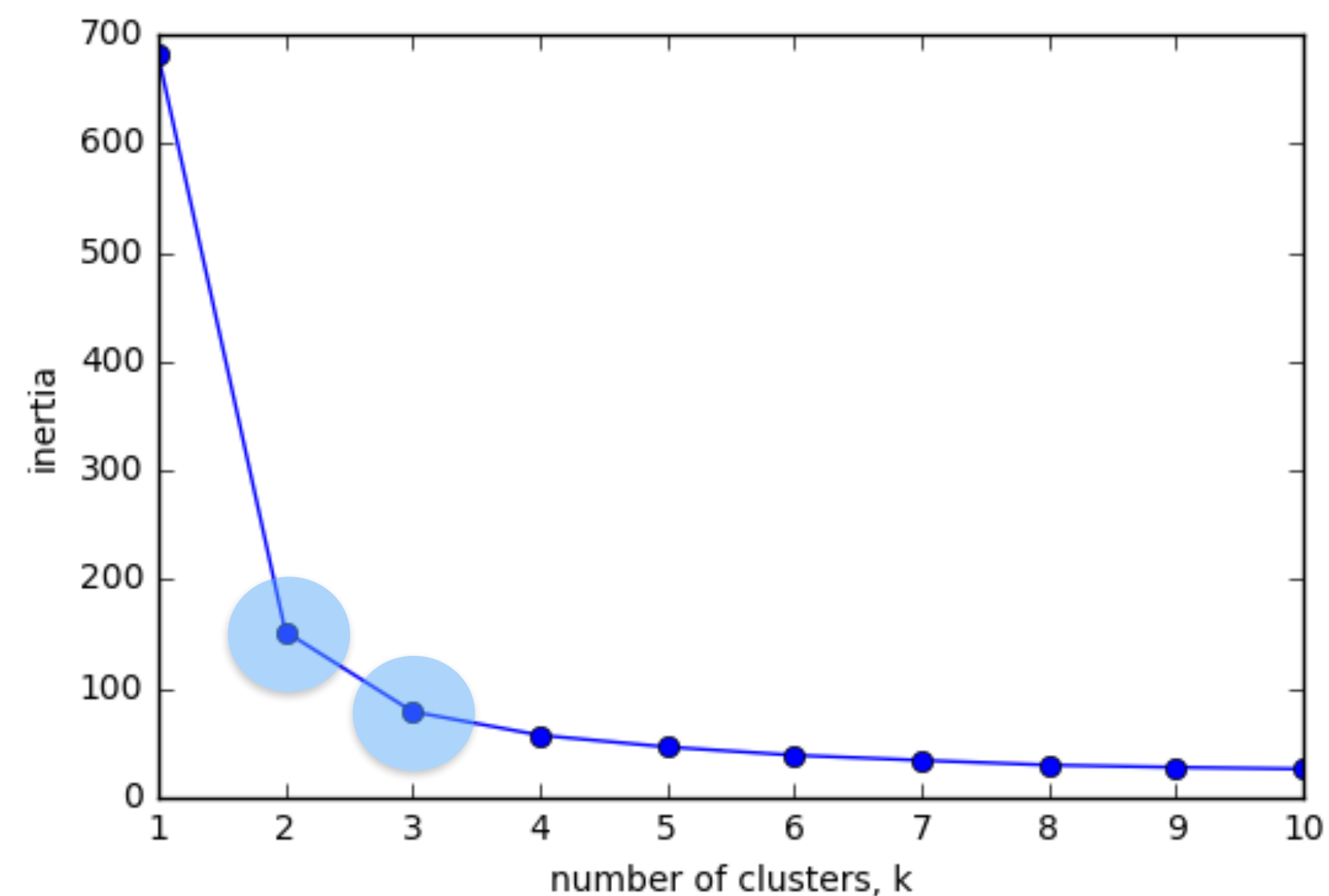
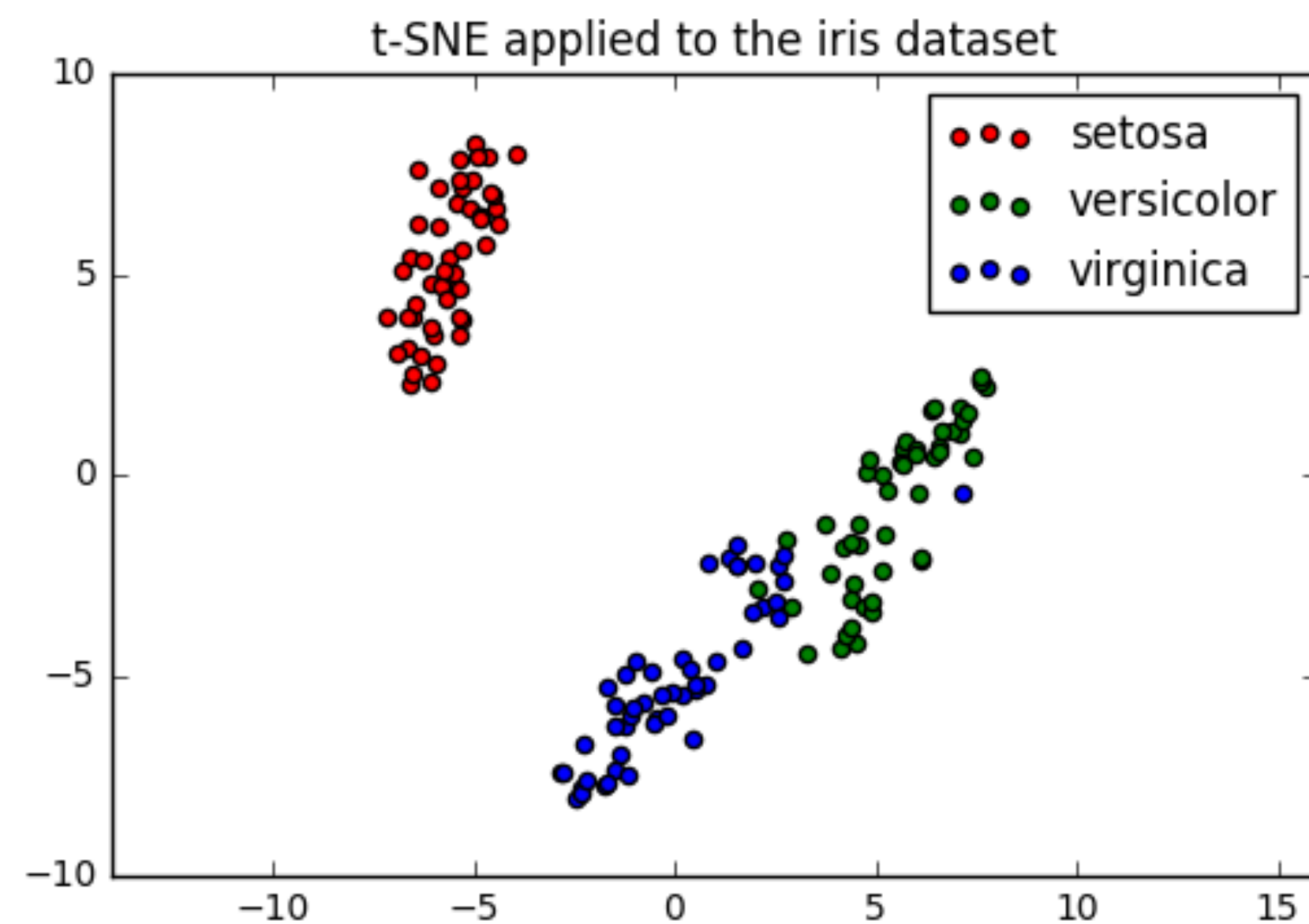
- Iris dataset has 4 measurements, so samples are 4-dimensional
- t-SNE maps samples to 2D space
- t-SNE didn't know that there were different species
- ... yet kept the species mostly separate





Interpreting t-SNE scatter plots

- “versicolor” and “virginica” harder to distinguish from one another
- Consistent with k-means inertia plot: could argue for 2 clusters, or for 3





t-SNE in sklearn

- 2D NumPy array samples
- List **species** giving species of labels as number (0, 1, or 2)

```
In [1]: print(samples)
[[ 5.   3.3  1.4  0.2]
 [ 5.   3.5  1.3  0.3]
 [ 4.9  2.4  3.3  1. ]
 [ 6.3  2.8  5.1  1.5]
 ...
 [ 4.9  3.1  1.5  0.1]]
```

```
In [2]: print(species)
[0, 0, 1, 2, ..., 0]
```



t-SNE in sklearn

```
In [3]: import matplotlib.pyplot as plt
```

```
In [4]: from sklearn.manifold import TSNE
```

```
In [5]: model = TSNE(learning_rate=100)
```

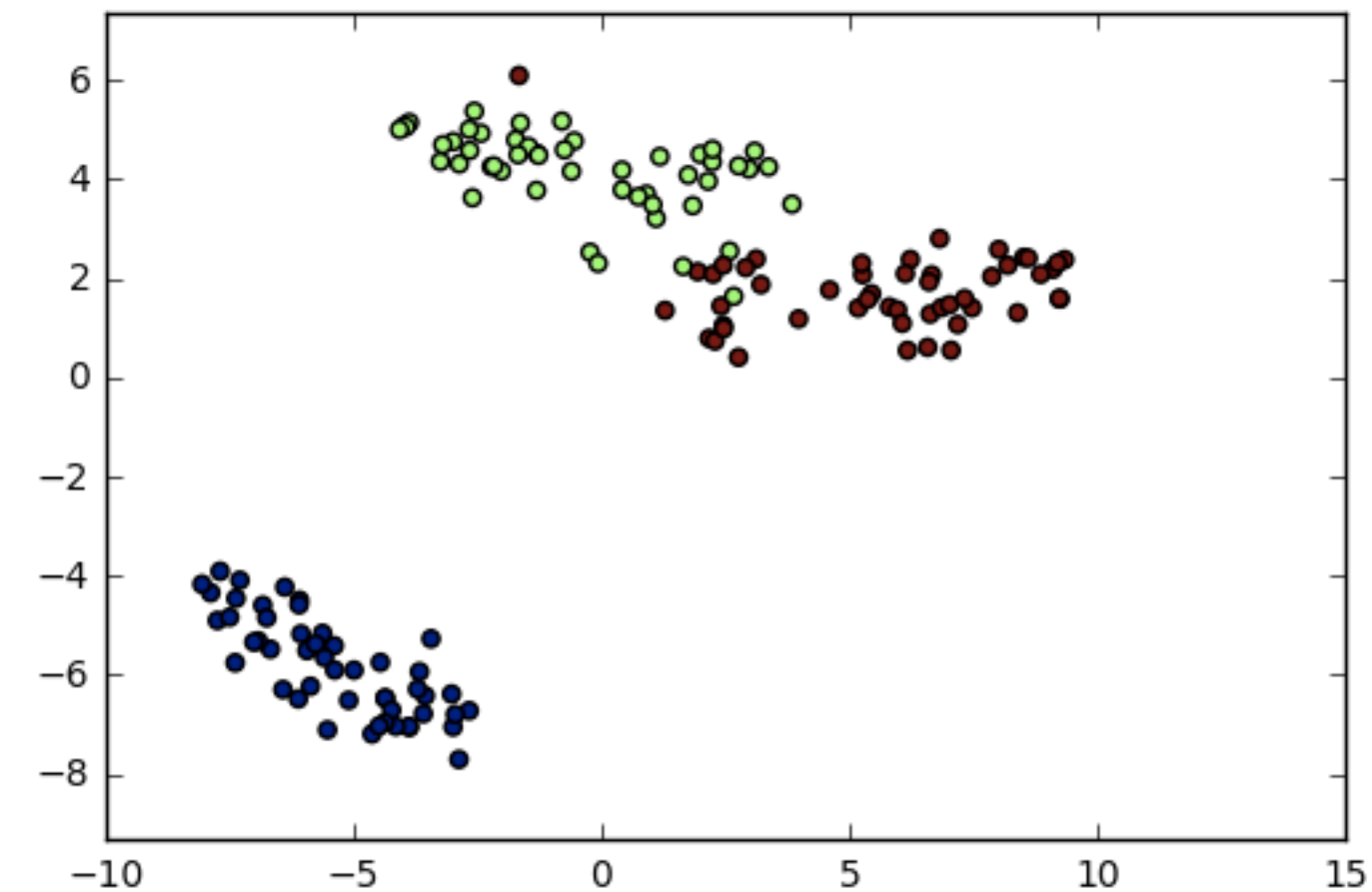
```
In [5]: transformed = model.fit_transform(samples)
```

```
In [6]: xs = transformed[:,0]
```

```
In [7]: ys = transformed[:,1]
```

```
In [8]: plt.scatter(xs, ys, c=species)
```

```
In [9]: plt.show()
```



t-SNE has only `fit_transform()`

- Has a `fit_transform()` method
- Simultaneously fits the model and transforms the data
- Has no separate `fit()` or `transform()` methods
- Can't extend the map to include new data samples
- Must start over each time!



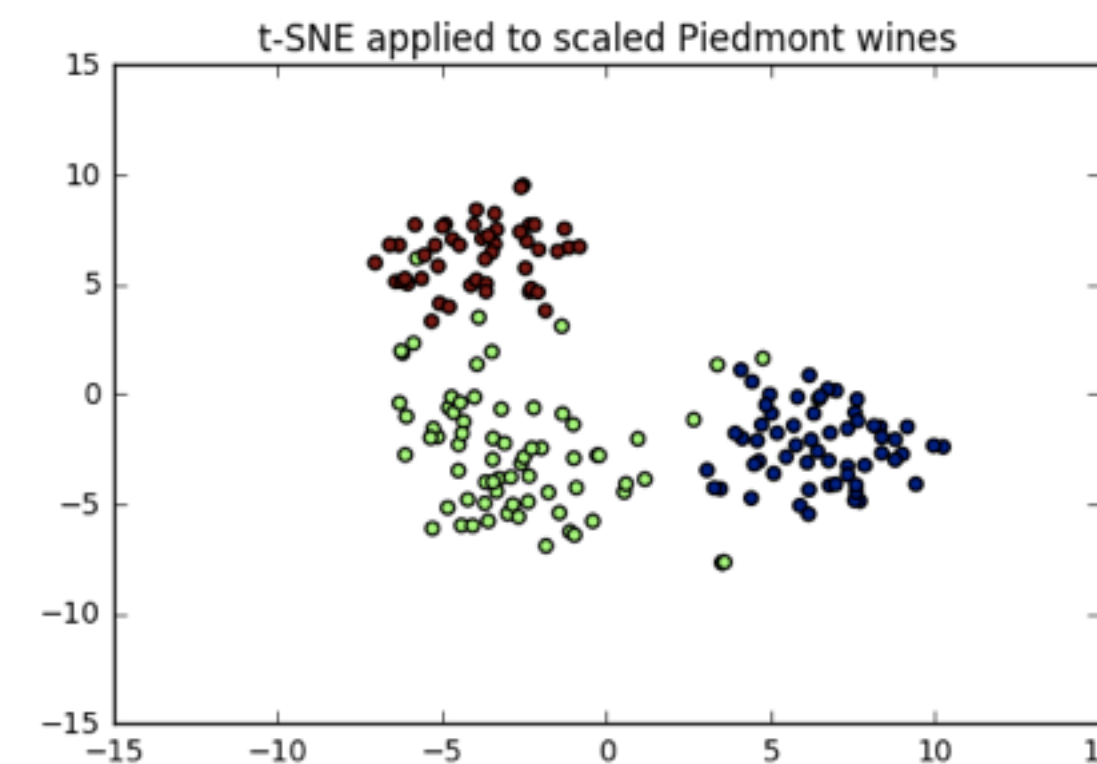
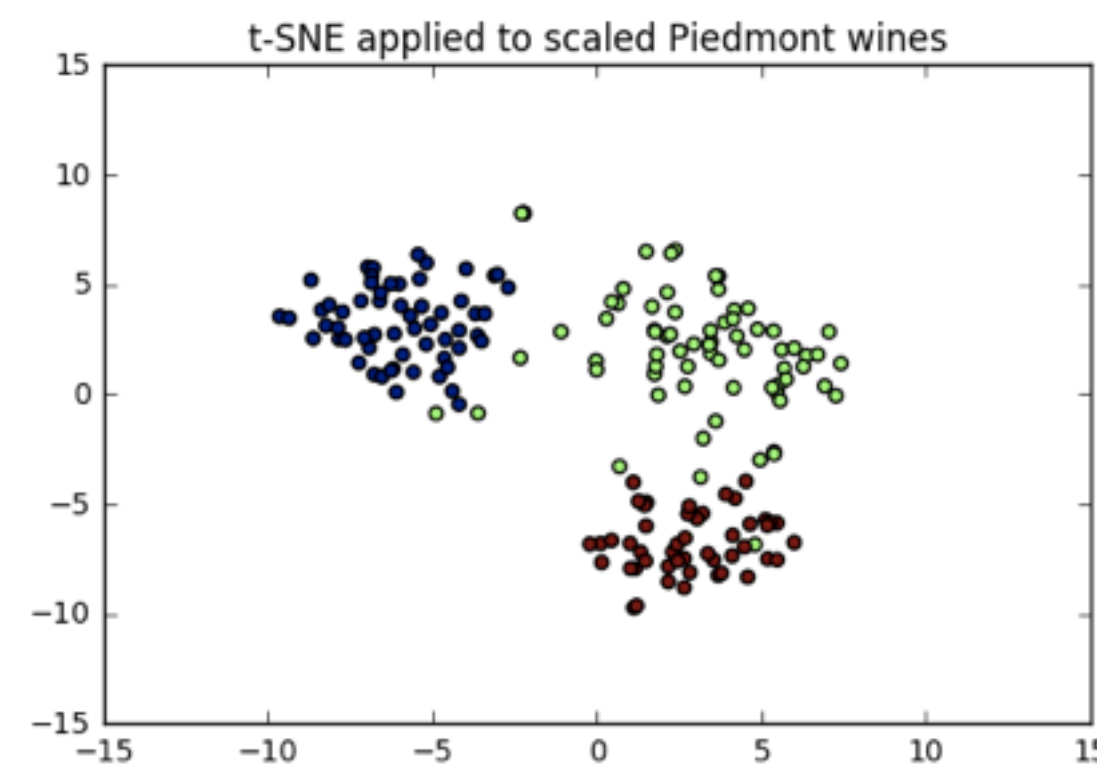
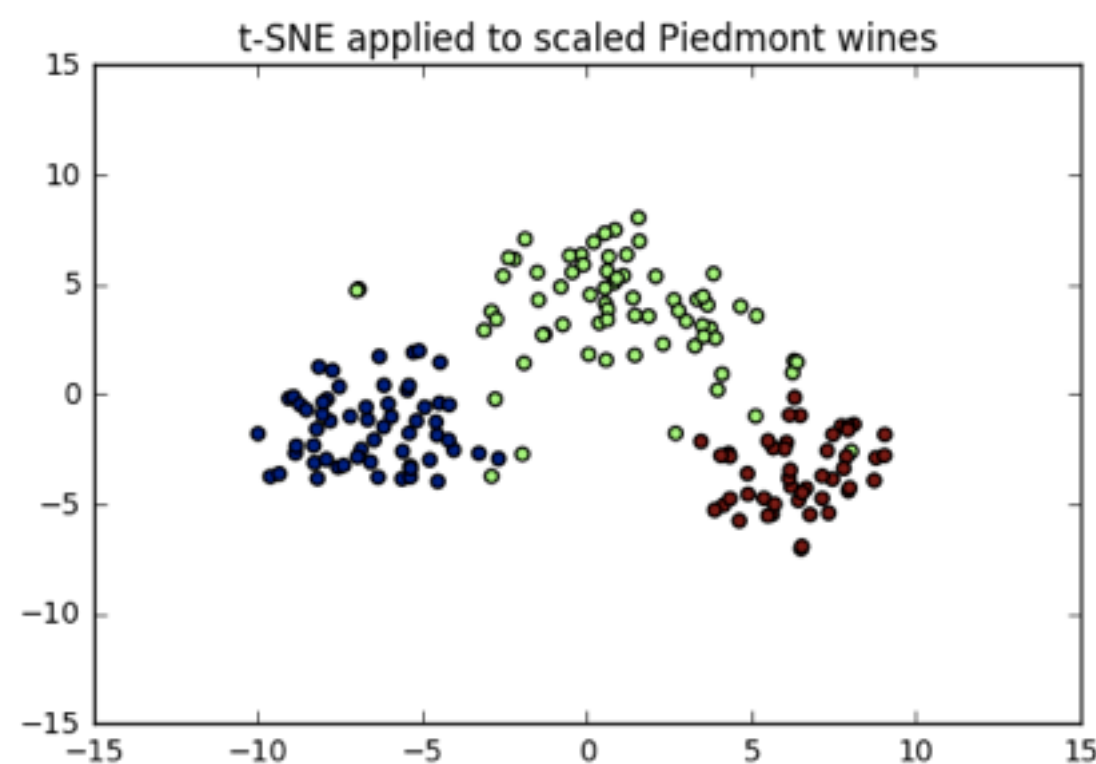
t-SNE learning rate

- Choose learning rate for the dataset
- Wrong choice: points bunch together
- Try values between 50 and 200



Different every time

- t-SNE features are different every time
- Piedmont wines, 3 runs, 3 different scatter plots!
- ... however: The wine varieties (=colors) have same position relative to one another





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