Assignment 4

Clustering Languages

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I: Feature extraction

II: K-means clustering

III: Principal component analysis

IV: Evaluation with gold-standard labels

V: Calculating distances

VI: Hierarchical clustering

I: Feature extraction

fin	s i l m æ
fin	k ɔ r ʋ ɑ
fin	n ɛ n æ
fin	s u u
...	
cmn	t^h ʊ ŋ t ʂ ɨ
cmn	ɻ ə n n a ɪ

I: Feature extraction

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fin	k ɔ r ʋ ɑ
fin	n ɛ n æ
fin	s u u
...	
cmn	tʰ ʊ ŋ t ʂ ɨ
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- 80 languages × 272 IPA segments

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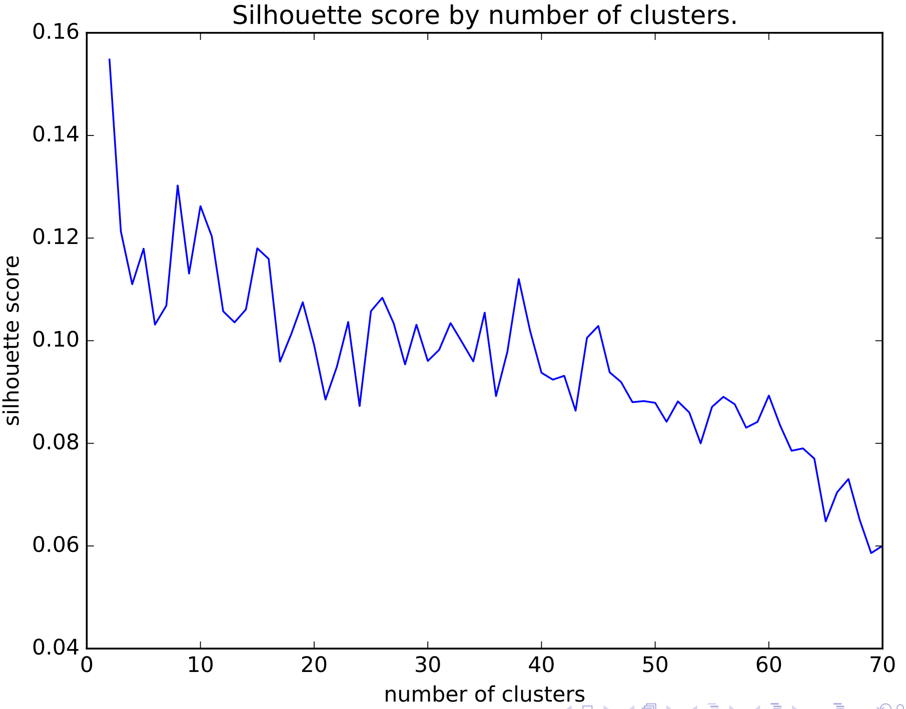
  - $[-1, +1]$, higher scores are better


Silhouette score by number of clusters.
silhouette score
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0
10
20
30
40
50
60
70
number of clusters

II: K-means clustering

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- error function
  - sum of squared distances from the closest centroids
    `kmeans.inertia_`

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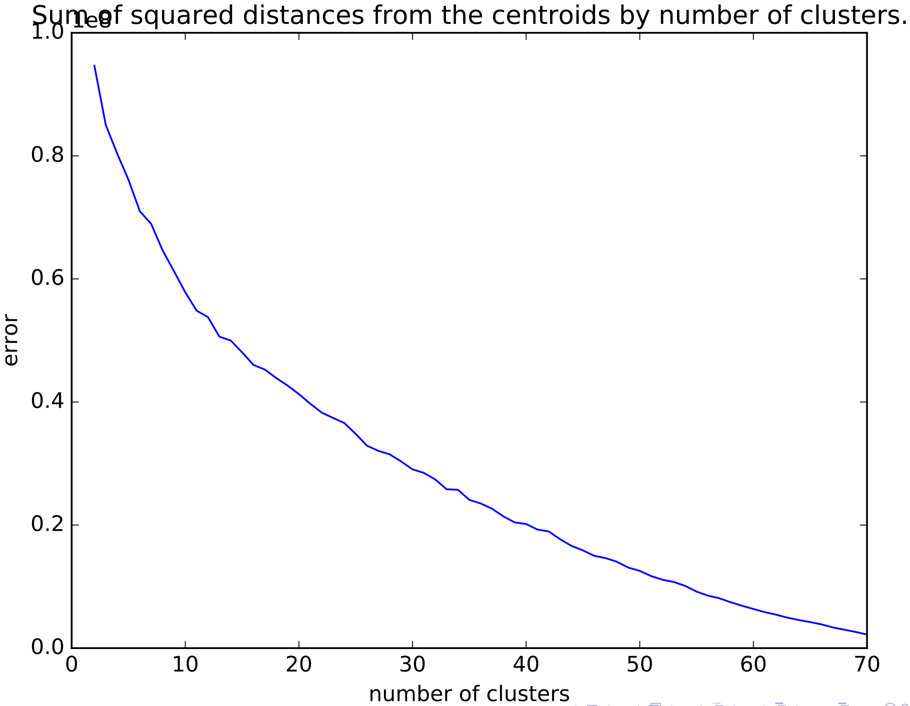
- error function
  - sum of squared distances from the closest centroids `kmeans.inertia_`
  - What is a good number of clusters? $\rightarrow$ elbow method


Sum of squared distances from the centroids by number of clusters.
1e8
1.0
0.8
0.6
0.4
0.2
0.0
error
0
10
20
30
40
50
60
70
number of clusters

III: Principal component analysis

- remove redundant features

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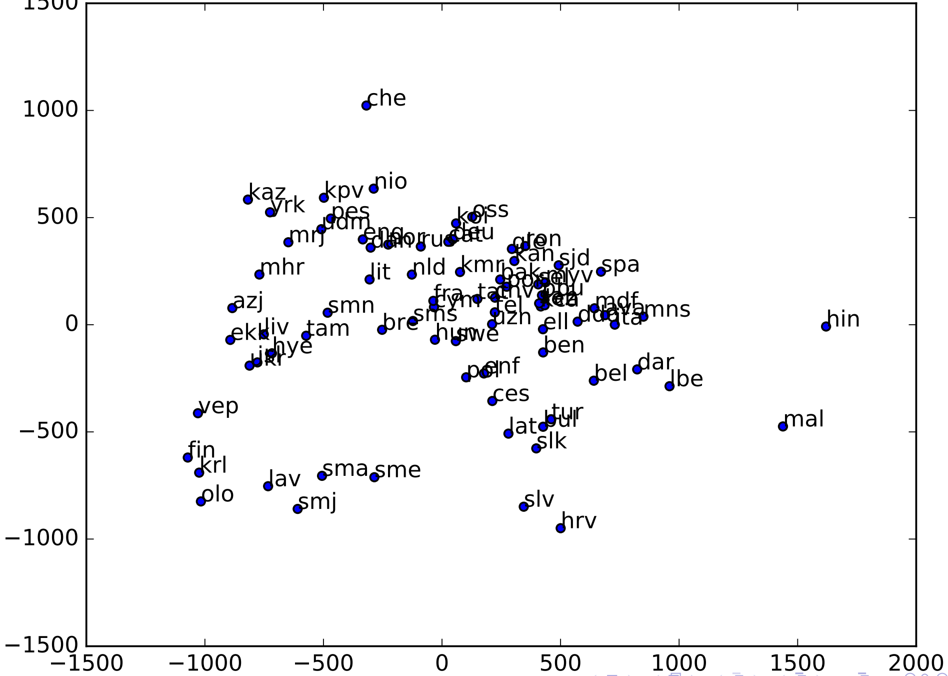
- remove redundant features
  - remove noise
  - train machine learning models more quickly

Feature vectors scaled down to 2 dimensions.



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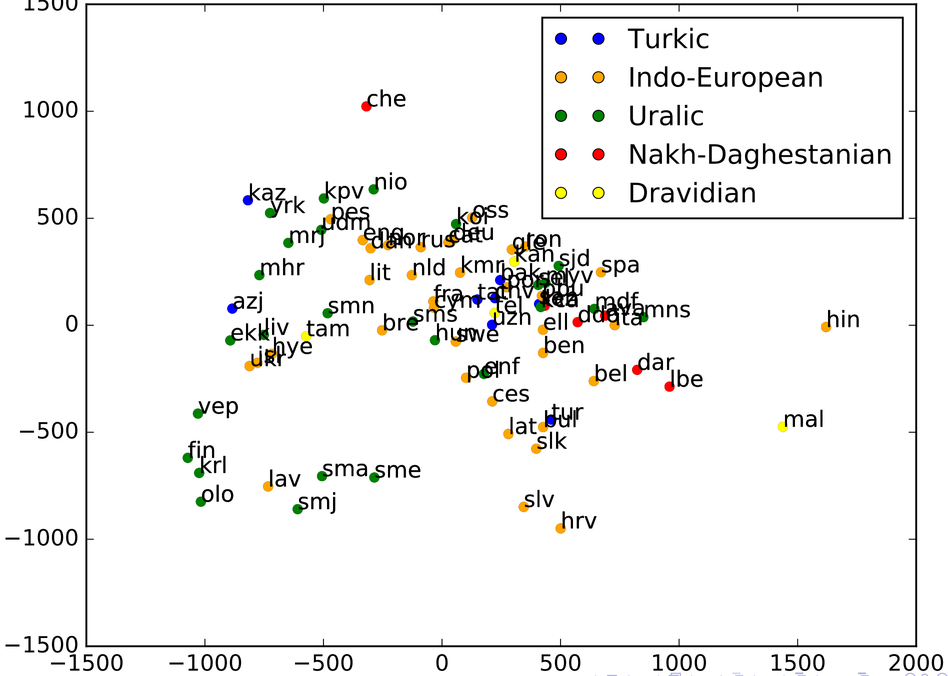

III: Principal component analysis

```
pca = PCA(features.shape[1])
d = 0
var_explained = 0
while var_explained < 0.9:
    var_explained += pca.explained_variance_ratio_[d]
    d += 1


featuresPCA = PCA(d).fit_transform(features)
```

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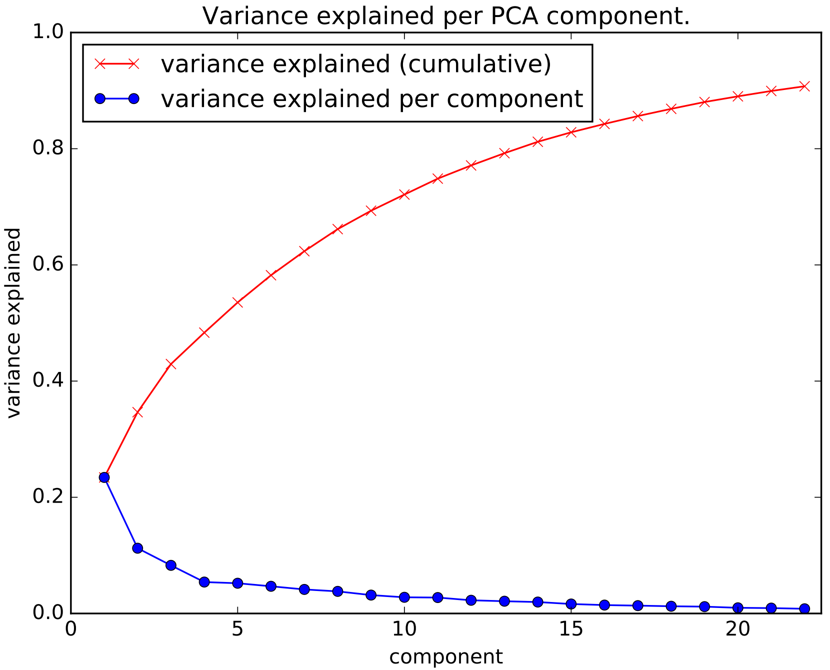
```

```
pca = PCA(0.9)
print(pca.n_components_)
```


Variance explained per PCA component.
variance explained (cumulative)
variance explained per component
variance explained
component
0.0
0.2
0.4
0.6
0.8
1.0
0
5
10
15
20

IV: Evaluation with gold-standard labels

```
n_fam = len(set(family))
pred_all = KMeans(n_fam).fit_predict(features)
pred_pca = KMeans(n_fam).fit_predict(featuresPCA)
```

IV: Evaluation with gold-standard labels

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```

```
lang    all    pca    family
----------------------------------------
kan     2      4      Dravidian
tam     3      0      Dravidian
tel     4      0      Dravidian
mal     4      2      Dravidian
bul     0      1      Indo-European
ces     0      1      Indo-European
...
```

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- $[0, 1]$ higher is better

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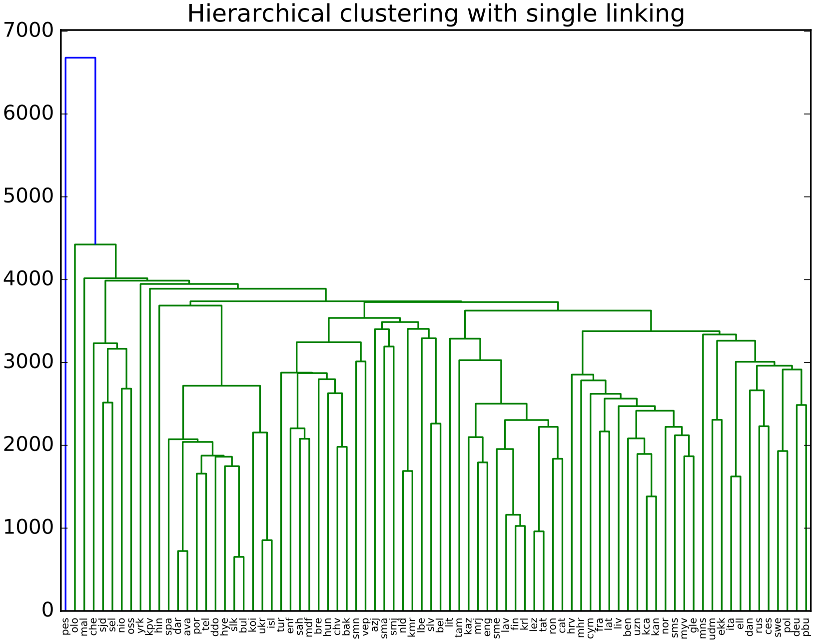
```
all   H: 0.1707   C: 0.1461   V: 0.1575
PCA   H: 0.1728   C: 0.1572   V: 0.1646
```

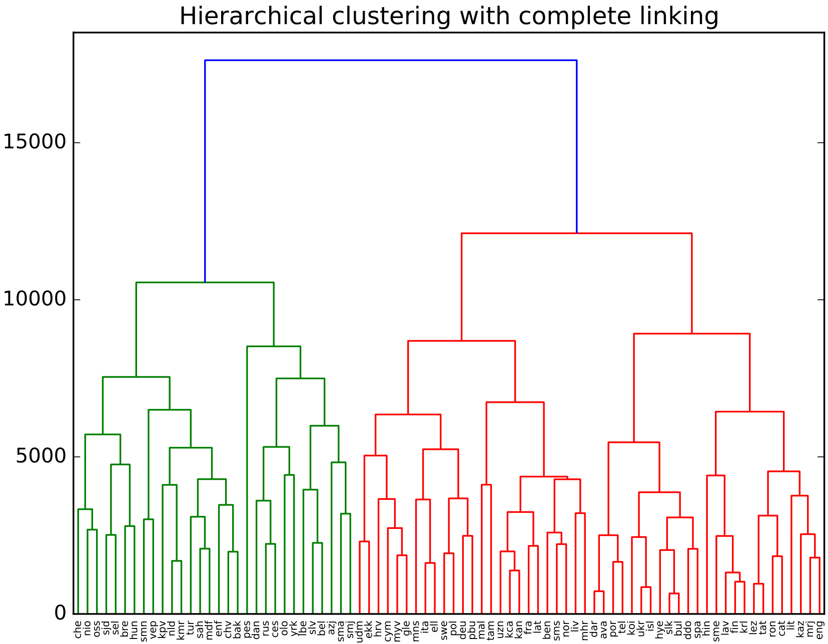
V: Calculating distances

	A	B	C	D	E	
		123	452	10	572	A
			342	370	908	B
				127	754	C
					23	D
						E

VI: Hierarchical clustering

```
for m in ['single', 'complete', 'average']:
    fig, ax = plt.subplots()
    z = scipy.cluster.hierarchy.linkage(dist, method=m)
    scipy.cluster.hierarchy.dendrogram(z, labels=languages)
    fig.savefig('dendrogram-{}.pdf'.format(method))
```


Hierarchical clustering with single linking
7000
6000
5000
4000
3000
2000
1000
0
pes olo mal che sjd sel nio oss yrk kpv hin spa dar ava por tel ddo hye slk bul koi ukr isl tur enf sah mdf bre hun chv bak smn vep azj sma smj nld kmr lbe slv bel lit tam kaz mrj eng sme lav fin krl lez tat ron cat hrv mhr cym fra lat liv ben uzn kca kan nor sms myv gle mns udm ekk ita ell dan rus ces swe pol deu pbu



Hierarchical clustering with complete linking
15000
10000
5000
0
che nio oss sjd sel bre hun smn vep kpv nld kmr tur sah mdf enf chv bak pes dan rus ces olo yrk lbe slv bel azj sma smj udm ekk hrv cym myv gle mns ita ell swe pol deu pbu mal tam uzn kca kan fra lat ben sms nor liv mhr dar ava por tel koi ukr isl hye slk bul ddo spa hin sme lav fin krl lez tat ron cat lit kaz mrj eng

Hierarchical clustering with average linking