Elements Of Data Science - S2022

Week 11: Clustering and Recommendation Systems

4/19/2022

TODOs

- Readings:
    - Recommended: DSFS: **Chap 9: Getting Data**
    - Recommended: DSFS: **Chap 23: Databases and SQL**

Catch up reading on clustering

- Recommended: DSFS: **Chap 19: Clustering**
- Recommended: DSFS: **Chap 22: Recommender Systems**

Catch up reading on text analysis

- Recommended: DSFS: **Chap 20: Natural Lanuage Processing**

- **HW4: due Monday May 2nd 11:59pm**

- **Quiz 11: due Monday April 25th, 11:59pm ET**

Today

- **Clustering**
- **Recommendation Systems**
- Start **Time-Series Data?**

Questions?

Environment Setup

In [1]:

```
import numpy
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from mlxtend.plotting import plot_decision_regions

import warnings
warnings.filterwarnings('ignore')

sns.set_style('darkgrid')
%matplotlib inline
```

Clustering

- Can we group our data based on the features alone?
- **Unsupervised:** There is no label/target y
- Use similarity to group X into k clusters
- Many methods:
    - **k-Means**
    - **Heirarchical Agglomerative Clustering**
    - Spectral Clustering
    - DBScan
    - ...

Why do Clustering?

- Exploratory data analysis
- Group media: images, music, news articles,...
- Group people: social network
- Science applications: gene families, psychological groups,...
- Image segmentation: group pixels, regions, ...
- ...

Clustering: K-Means

- Not to be confused with k-NN!
- Idea:
    - Finds k points in space as cluster centers (means)
    - Assigns datapoints to their closest cluster mean
- Need to specify the number of clusters k up front
- sklearn uses euclidean distance to judge similarity

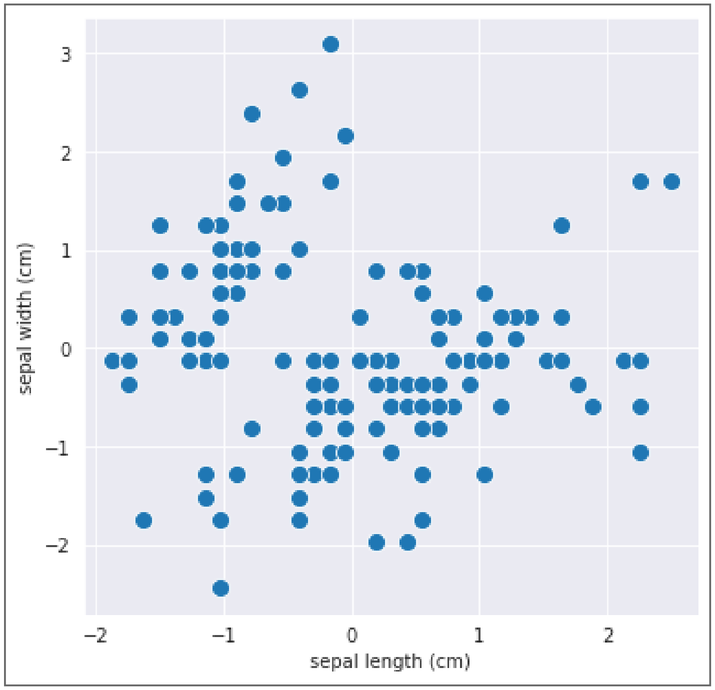
k-Means: How it works

```
FIRST: choose initial k points (means)

A: fix means -> assign all datapoints to their closest mean

B: fix cluster assignments -> recalculate means

RETURN TO A and Repeat until convergence!
```

Load Example Data

In [2]:

```
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler
iris = load_iris()
X_iris = StandardScaler().fit_transform(iris.data[:,:2])
X_iris = pd.DataFrame(X_iris,columns=iris.feature_names[:2])
fig,ax = plt.subplots(1,1,figsize=(6,6))
sns.scatterplot(x='sepal length (cm)',y='sepal width (cm)',data=X_iris,s=100);
```



KMeans in sklearn

In [3]:

```
from sklearn.cluster import KMeans

km = KMeans(n_clusters=2, init='random', random_state=0) # default init=k-means++

c = km.fit_predict(X_iris)
```

In [4]:

```
# cluster assignments
tmp = X_iris.copy()
tmp['cluster_assignments'] = c
tmp.sample(5,random_state=0)
```

Out[4]:

	sepal length (cm)	sepal width (cm)	cluster_assignments
114	-0.052506	-0.592373	1
62	0.189830	-1.973554	1
33	-0.416010	2.630382	0
107	1.765012	-0.362176	1
7	-1.021849	0.788808	0

In [5]:

```
# cluster centers
km.cluster_centers_
```

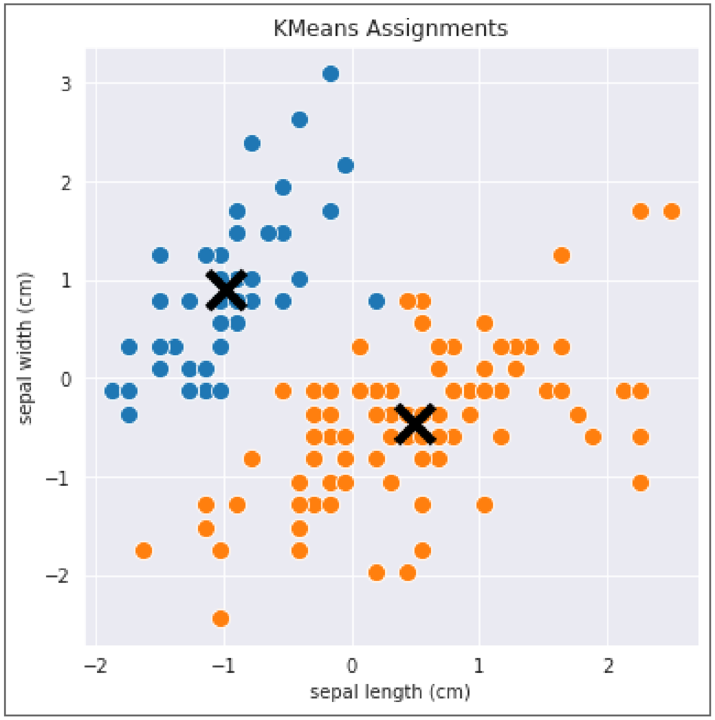
Out[5]:

```
array([[-0.97822861,  0.90390597],
       [ 0.4891143 , -0.45195298]])
```

Plotting clusters and centers

In [6]:

```
# plot data colored by cluster assignment
def plot_clusters(X,c=None,km=None,title=None,ax=None,marker_size=100):
    if not ax:
        fig,ax = plt.subplots(1,1,figsize=(6,6))
    if km:
        c = km.fit_predict(X)
    for i in range(np.max(c)+1):
        X_cluster = X[c == i]
        sns.scatterplot(x=X_cluster.iloc[:,0],y=X_cluster.iloc[:,1],s=marker_size,ax=ax);
    if km:
        for m in km.cluster_centers_:
            ax.plot(m[0],m[1], marker='x',c='k', ms=20, mew=5)
    if title:
        ax.set_title(title)

plot_clusters(X_iris,km=km,title="KMeans Assignments")
```


KMeans Assignments
sepal width (cm)
sepal length (cm)
3
2
1
0
−1
−2
−2
−1
0
1
2

K-Means: How good are the clusters?

- One way: **Within Cluster Sum of Squared Distances**
- How close is every point to it's assigned cluster center?
  $SSD = \sum_{k=1}^{K} \sum_{x_i \in C_k} \| x_i - \mu_k \|_2^2$
  where $\| x - \mu \|_2 = \sqrt{\sum_{j=1}^{d} (x_j - \mu_j)^2}$
- If this is high, items in cluster are far from their means.
- If this is low, items in cluster are close to their means.

In [8]:

```
# SSD stored in KMeans as `.inertia_`
round(km.inertia_,2)
```

Out[8]:

```
166.95
```

KMeans in Action

In [9]:

```
import ipywidgets as widgets
kmeans_video = widgets.Video.from_file('images/kmeans.mp4', width=750, autoplay=False, controls=True)
kmeans_video
```

From **https://dashee87.github.io/data%20science/general/Clustering-with-Scikit-with-GIFs/**

Things you need to define for KMeans

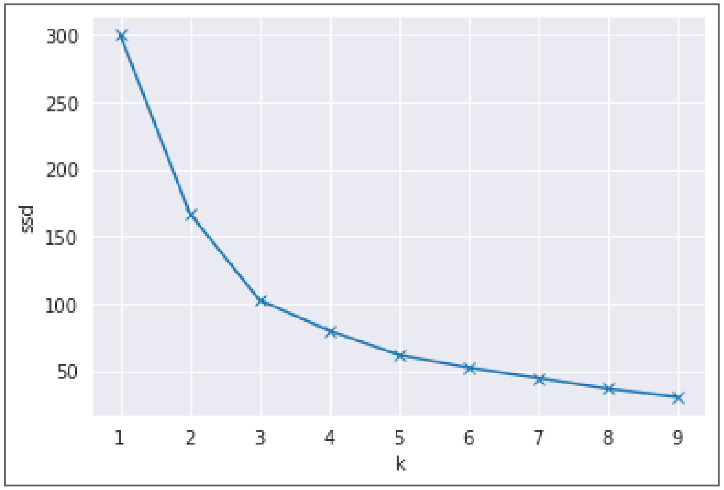
- number of clusters k or `n_clusters`
- initial locations of means
    - random
    - k-means++ (pick starting points far apart from each other)

How to choose k or `n_clusters`?

- One way: use "elbow" in sum of squared distances (SSD) or `KMeans.inertia_`
- "elbow" is where SSD ceases to drop rapidly

In [10]:

```
ssd = []
for i in range(1,10):
    ssd.append(KMeans(n_clusters=i).fit(X_iris).inertia_)
fig,ax=plt.subplots(1,1,figsize=(6,4))
ax.plot(range(1,10),ssd,marker='x');
ax.set_xlabel('k');ax.set_ylabel('ssd');
```

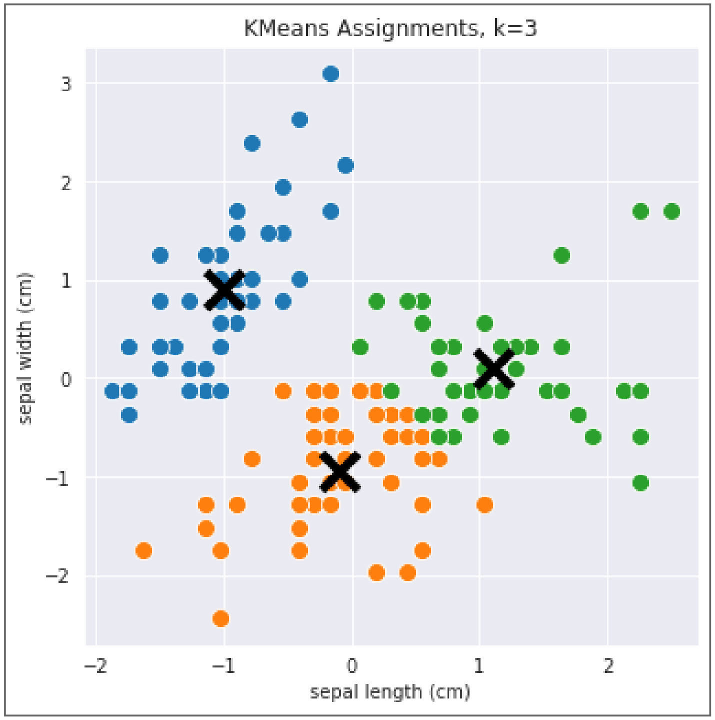


- Question: What value k will minimize SSD?

Refitting with k=3

In [11]:

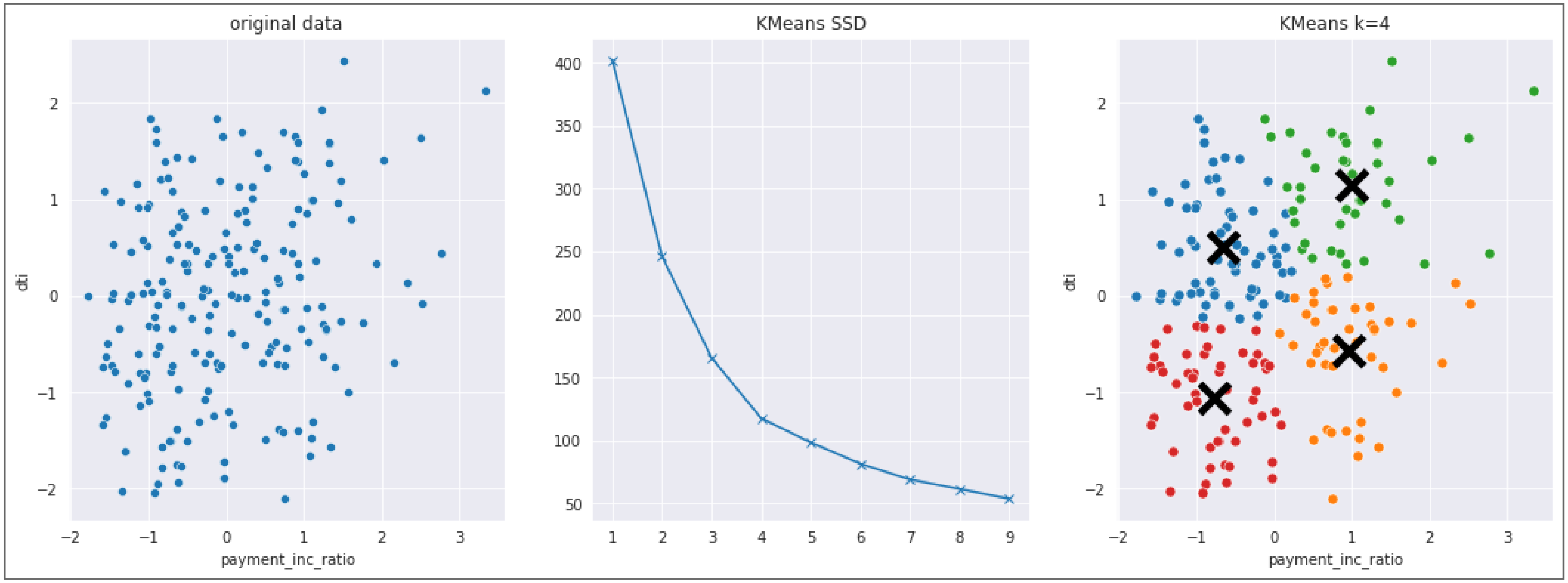
```
plot_clusters(X_iris,km=KMeans(n_clusters=3,random_state=0),title="KMeans Assignments, k=3")
```



KMeans: Another Example

In [13]:

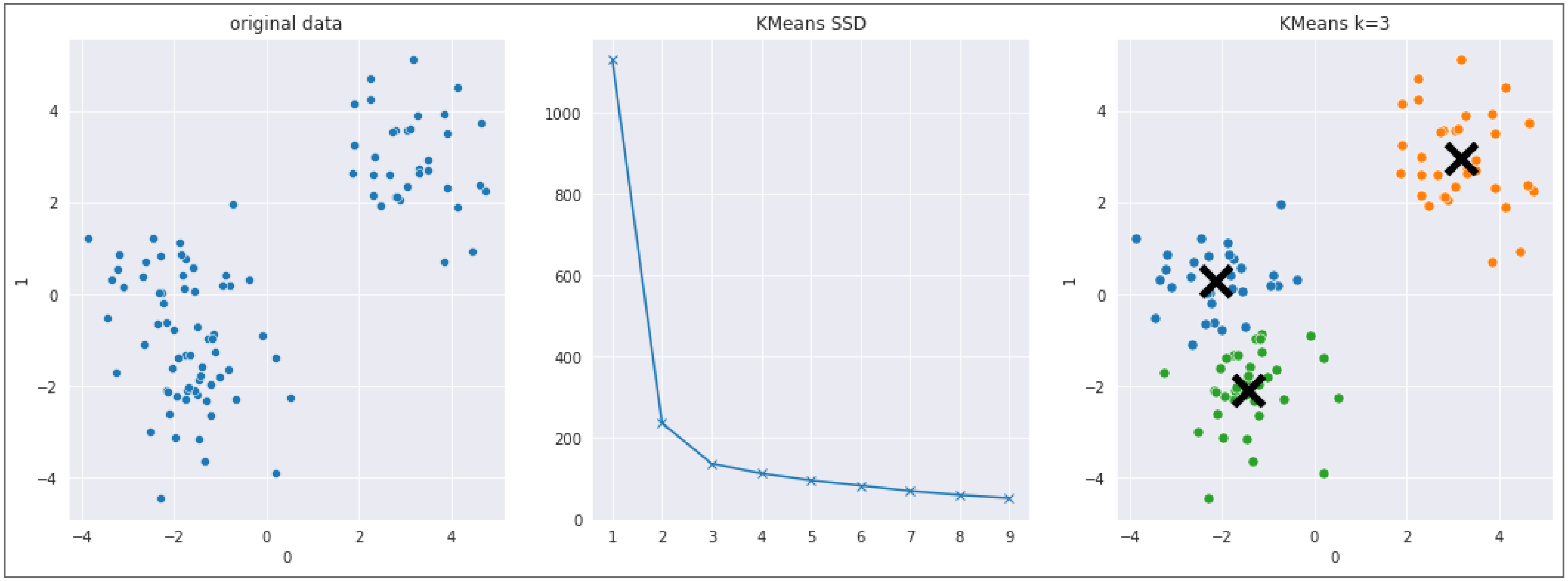
```
# Loading and plotting the data
data = pd.read_csv('../data/loan200.csv')[['payment_inc_ratio','dti']]
from sklearn.preprocessing import StandardScaler
X_loan = pd.DataFrame(StandardScaler().fit_transform(data),columns=data.columns)

fig,ax = plt.subplots(1,3,figsize=(18,6))
sns.scatterplot(x=X_loan.iloc[:,0],y=X_loan.iloc[:,1],ax=ax[0]);
ax[0].set_title('original data');

ssd = [KMeans(n_clusters=i).fit(X_loan).inertia_ for i in range(1,10)]
ax[1].plot(range(1,10),ssd,marker='x');
ax[1].set_title('KMeans SSD');

plot_clusters(X_loan,km=KMeans(n_clusters=4, random_state=0),title='KMeans k=4',marker_size=50,ax=ax[2])
```


original data
KMeans SSD
KMeans k=4
payment_inc_ratio
dti
payment_inc_ratio
dti

KMeans: Synthetic Example

In [14]:

```
from sklearn.datasets import make_blobs
X_blobs,y_blobs = make_blobs(centers=[(3,3),(-2,0),(-2,-2)],random_state=1)
X_blobs = pd.DataFrame(X_blobs)

fig,ax = plt.subplots(1,3,figsize=(18,6))

sns.scatterplot(x=X_blobs.iloc[:,0],y=X_blobs.iloc[:,1],ax=ax[0]);
ax[0].set_title('original data');

ssd = [KMeans(n_clusters=i).fit(X_blobs).inertia_ for i in range(1,10)]
ax[1].plot(range(1,10),ssd,marker='x');
ax[1].set_title('KMeans SSD')

plot_clusters(X_blobs,km=KMeans(n_clusters=3, random_state=0),title='KMeans k=3',marker_size=50,ax=ax[2])
```


original data
KMeans SSD
KMeans k=3
0
1

Hierarchical Agglomerative Clustering (HAC)

- group clusters together from the bottom up
- don't have to specify number of clusters up front
- generates binary tree over data

HAC: How it works

```
FIRST: every point is it's own cluster

A: Find pair of clusters that are "closest"

B: Merge into single cluster

GOTO A and Repeat till there is a single cluster
```

HAC in Action

In [15]:

```
import ipywidgets as widgets
hac_video = widgets.Video.from_file('images/hac.mp4', width=750, autoplay=False, controls=True)
hac_video
```

From **https://dashee87.github.io/data%20science/general/Clustering-with-Scikit-with-GIFs/**

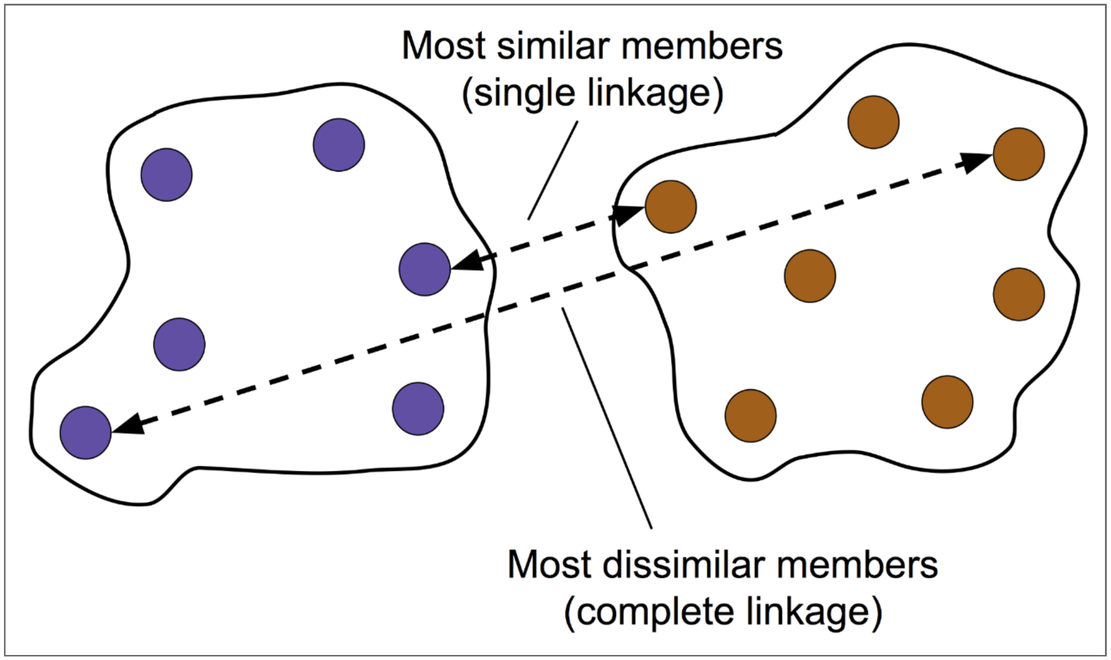
What is ”close”?

- Need to define what we mean by "closeness" by choosing
    - distance metric (how to measure distance)
    - linkage criteria (how to compare clusters)

Need to define: Distance Metric

- **Euclidean** : $\sqrt{\sum_{i=1}^{n} (a_i - b_i)^2}$
    - easy to use analyitically, sensitive to outliers
- **Manhattan** : $\sum_{i=1}^{n} | a_i - b_i|$
    - more difficult to use analytically, robust to outliers
- **Cosine** : $1 - \frac{\sum a_i b_i}{\|a_i\|_2 \|b_i\|_2}$
    - angle between vectors while ignoring their scale
- many more (see **https://numerics.mathdotnet.com/Distance.html**

Need to define: **Linkage**

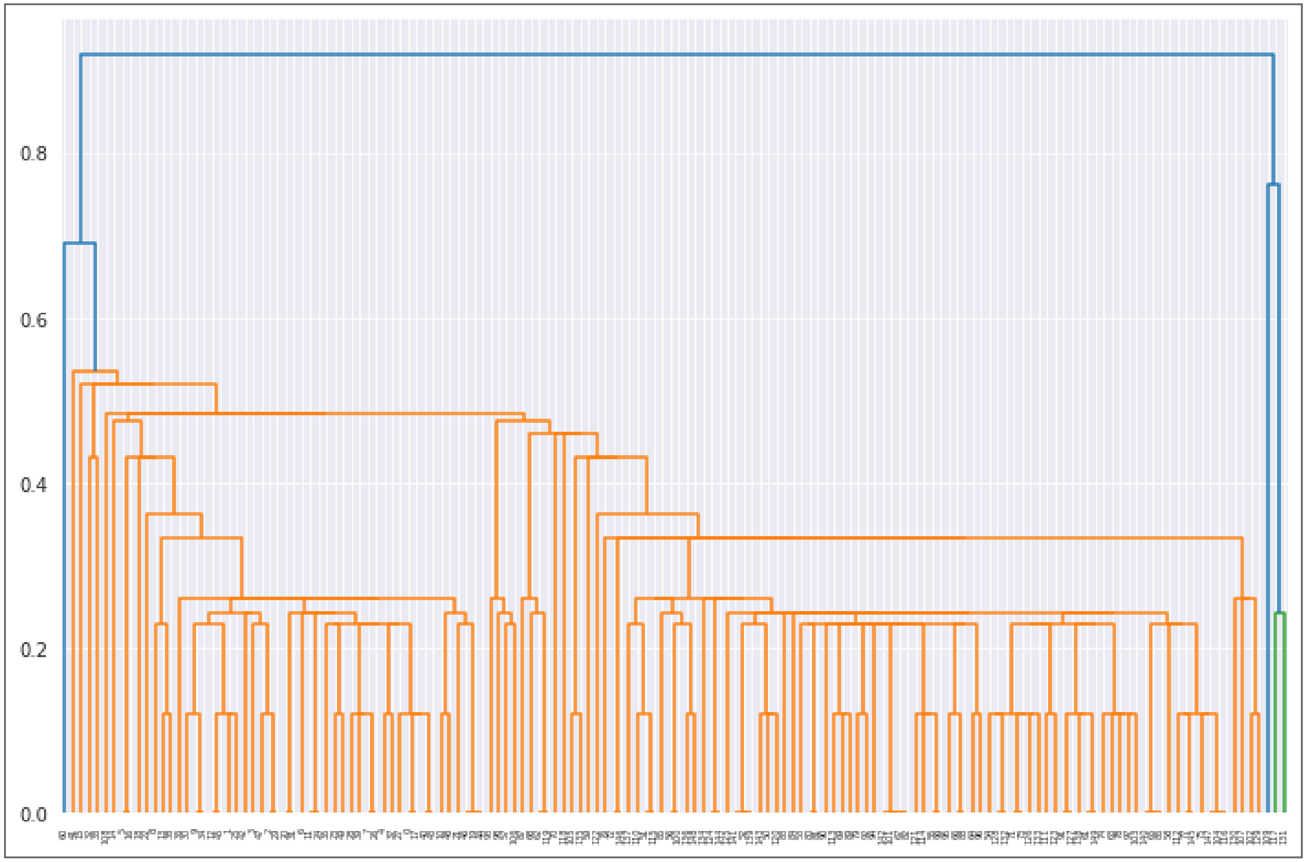


single : shortest distance from item of one cluster to item of the other
complete : greatest distance from item of one cluster to item of the other
average : average distance of items in one cluster to items in the other
ward : minimize variance of clusters being merged (only euclidean metric)

HAC and Dendrograms: Single Linkage

In [16]:

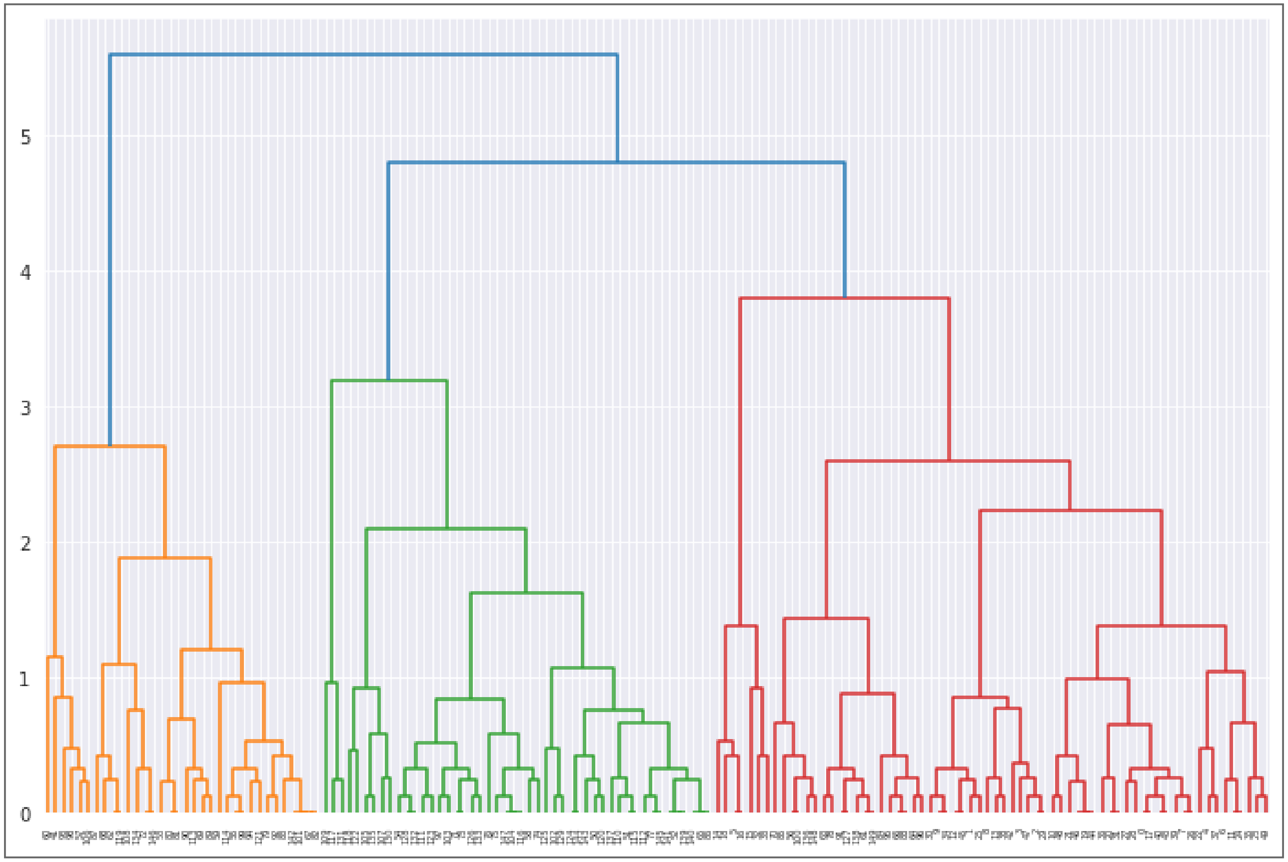
```
# nice helper function for creating a dendrogram
from scipy.cluster import hierarchy

Z = hierarchy.linkage(X_iris,'single')
fig = plt.figure(figsize=(12,8)); hierarchy.dendrogram(Z);
```


0.8
0.6
0.4
0.2
0.0

HAC and Dendrograms: Complete Linkage

In [17]:

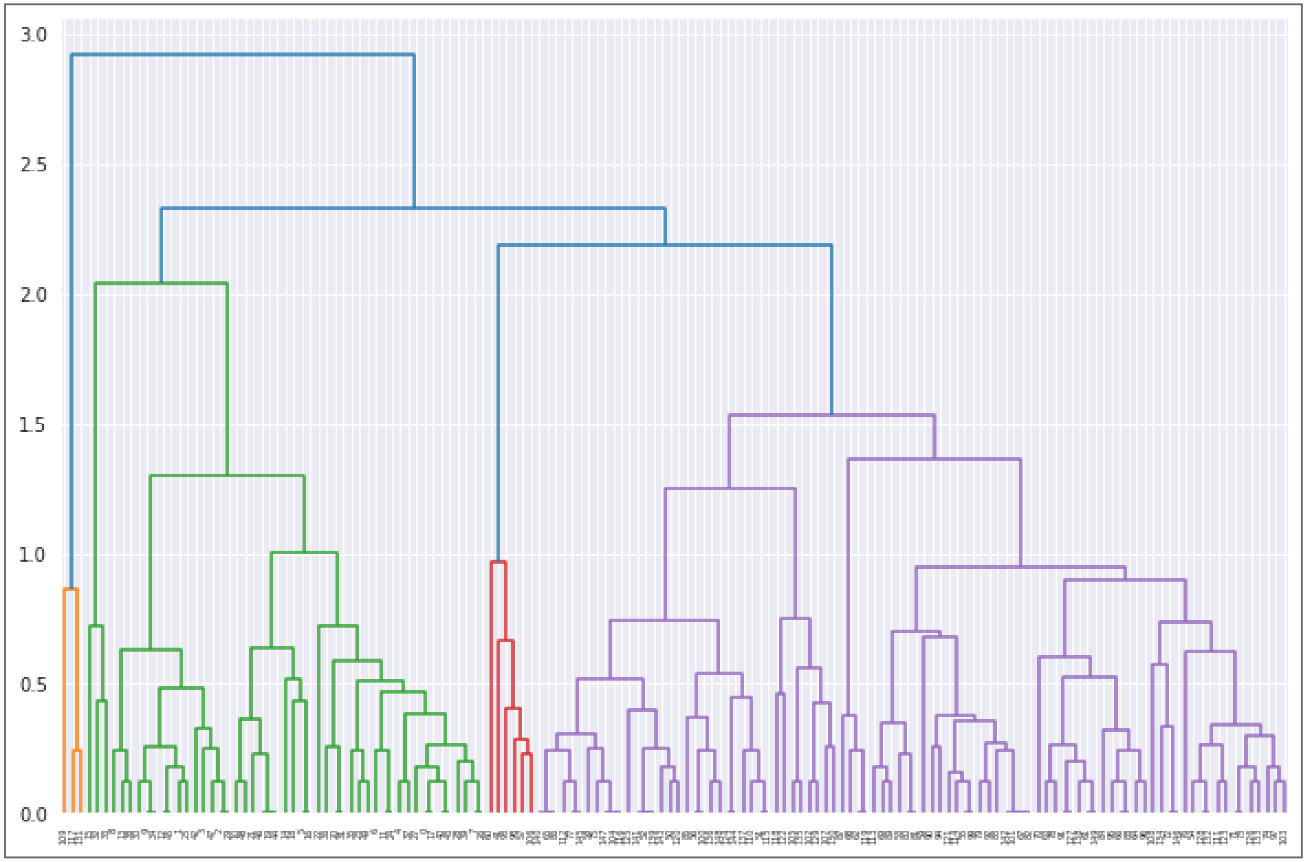
```
Z = hierarchy.linkage(X_iris,'complete')
fig = plt.figure(figsize=(12,8)); hierarchy.dendrogram(Z);
```



HAC and Dendrograms: Average Linkage

In [18]:

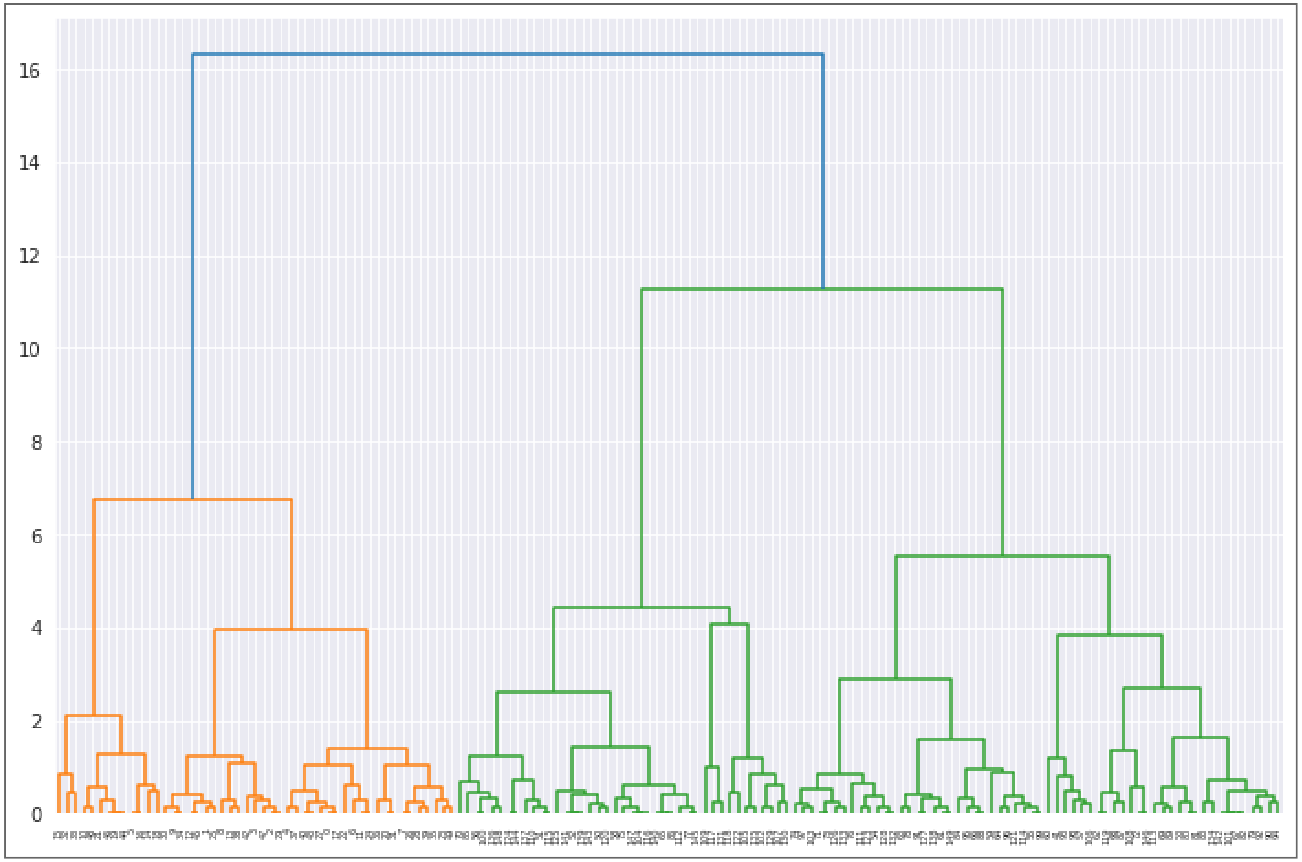
```
Z = hierarchy.linkage(X_iris,'average')
fig = plt.figure(figsize=(12,8)); hierarchy.dendrogram(Z);
```



HAC and Dendrograms: Ward Linkage

In [19]:

```
Z = hierarchy.linkage(X_iris,'ward')
fig = plt.figure(figsize=(12,8)); hierarchy.dendrogram(Z);
```



HAC in sklearn

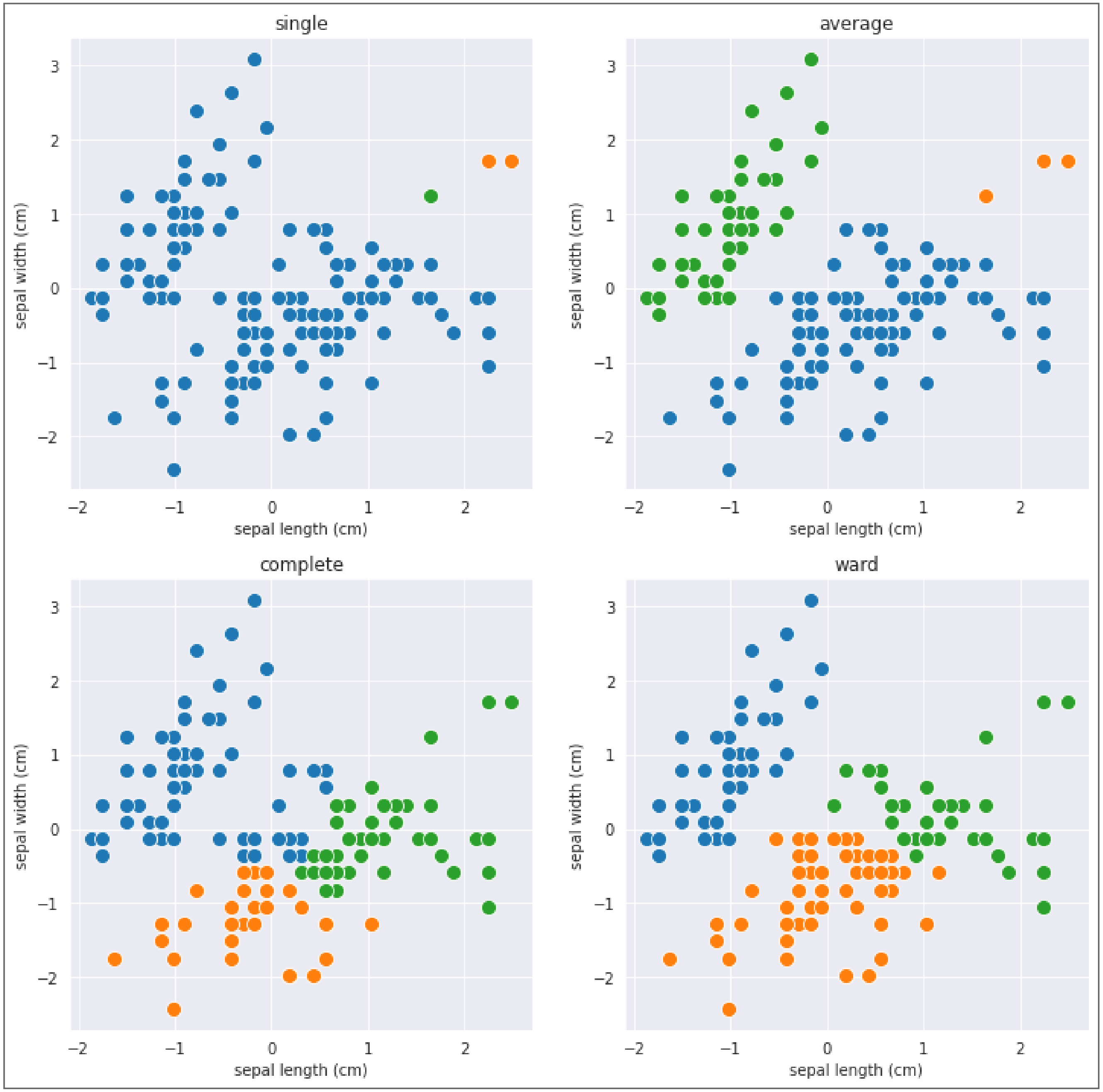
In [20]:

```
from sklearn.cluster import AgglomerativeClustering

hac = AgglomerativeClustering(linkage='single',
                              affinity='euclidean',
                              n_clusters=4)
c_single = hac.fit_predict(X_iris)

# generate models and assignments for all linkages
models,assignments = [],[]
linkages = ['single','average','complete','ward']
for linkage in linkages:
    models.append(AgglomerativeClustering(linkage=linkage,affinity='euclidean',n_clusters=3))
    assignments.append(models[-1].fit_predict(X_iris))

# plot on the next slide
```

HAC in sklearn

In [21]:

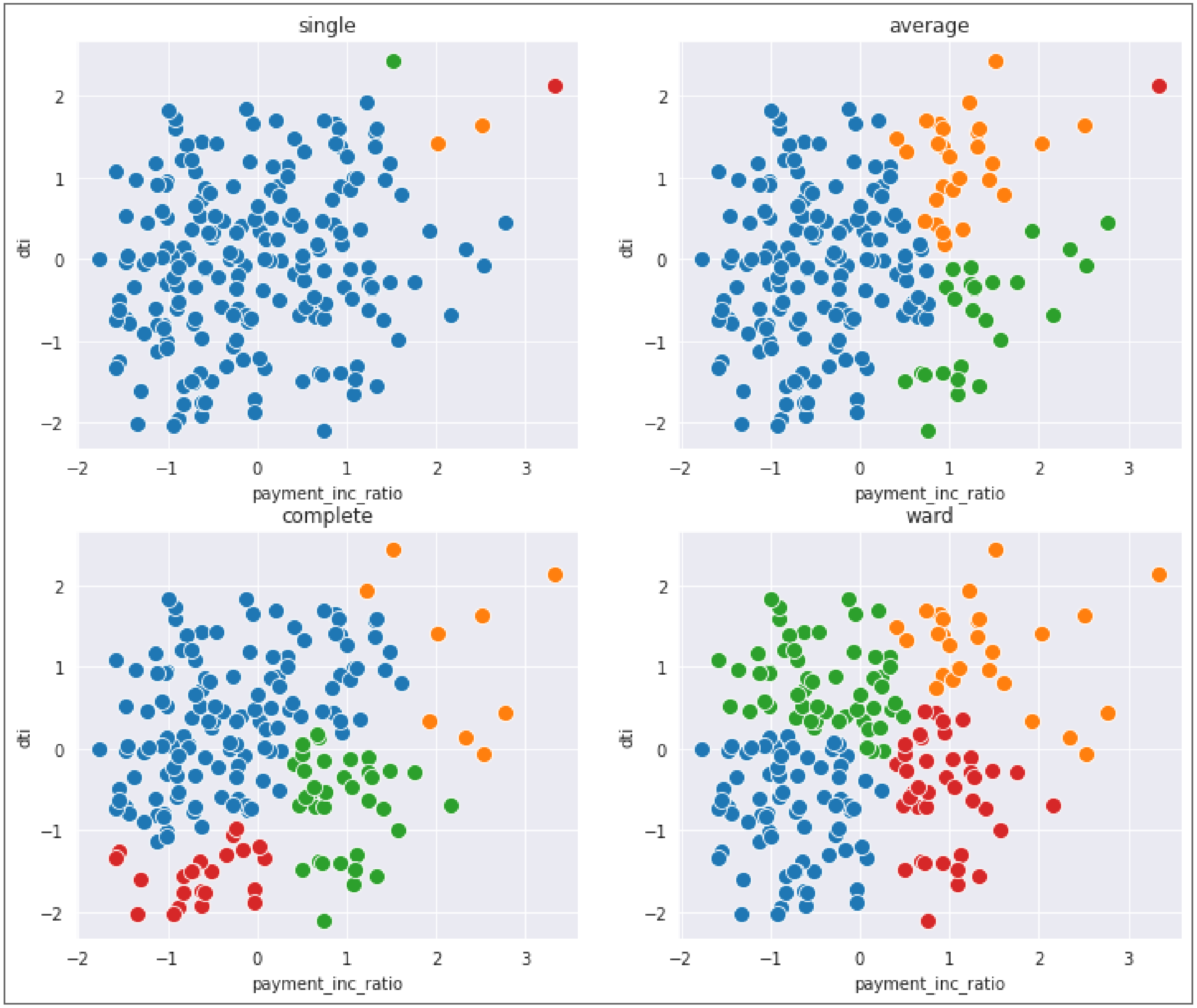
```
fig,ax = plt.subplots(2,2,figsize=(12,12))
axs = ax.flatten()
for i in range(len(linkage)):
    plot_clusters(X_iris,assignments[i],title=linkages[i],ax=axs[i])
```


single
average
complete
ward
sepal width (cm)
sepal length (cm)
3
2
1
0
−1
−2
−2
−1
0
1
2

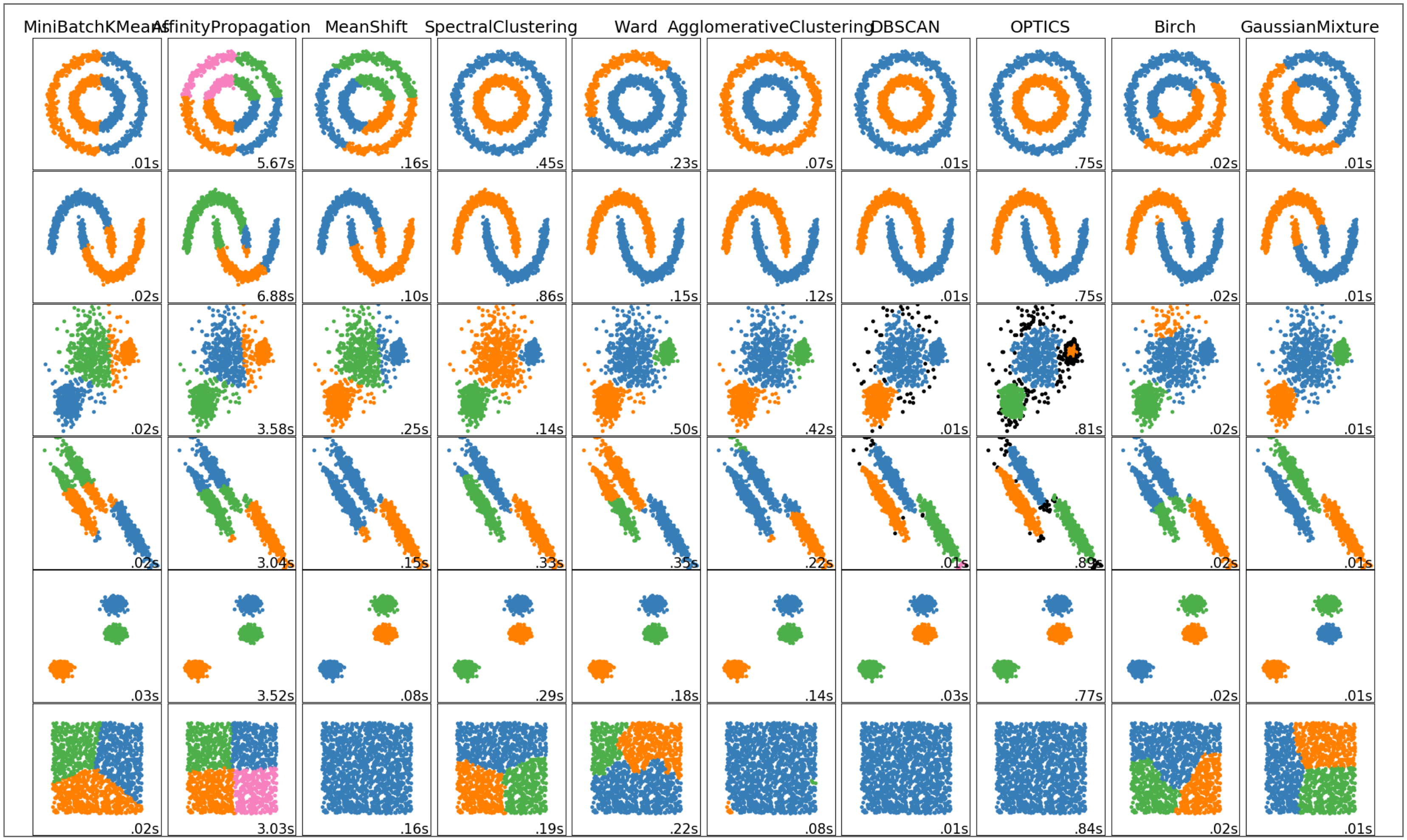
HAC: Another Example

In [22]:

```
models,assignments,linkages = [],[],['single','average','complete','ward']
for linkage in linkages:
    models.append(AgglomerativeClustering(linkage=linkage,affinity='euclidean',n_clusters=4))
    assignments.append(models[-1].fit_predict(X_loan))
fig,ax = plt.subplots(2,2,figsize=(12,10))
axs = ax.flatten()
for i in range(len(linkage)):
    plot_clusters(X_loan,assignments[i],title=linkages[i],ax=axs[i])
```


single
average
complete
ward
dti
payment_inc_ratio

Clustering: Many Other Methods



From **https://scikit-learn.org/stable/modules/clustering.html**

How to evaluate clustering?

- Within Cluster Sum of Squared Distances (SSD)
- If we have labels
    - How "pure" are the clusters? Homogeneity
    - Mutual Information
- Silhouette plots (see PML)
- many others (**see sklearn**)

Clustering Review

- k-Means
- Heirarchical Agglomerative Clustering
    - linkages
    - distance metrics
- Evaluating

Questions re Clustering?

Recommendation Engines

- Given a user and a set of items to recommend (or rank):
    - Recommend things **similar to the things I've liked**
        - Content-Based Filtering
    - Recommend things **that people with similar tastes have liked**
        - Collaborative Filtering
    - Hybrid/Ensemble

Example: Housing Data

In [23]:

```
df_house = pd.read_csv('../data/house_sales_subset.csv')
df_house = df_house.iloc[:10].loc[:,['SqFtTotLiving','SqFtLot','AdjSalePrice']]
X_house_scaled = StandardScaler().fit_transform(df_house)
df_house_scaled = pd.DataFrame(X_house_scaled,columns=['SqFtTotLiving_scaled','SqFtLot_scaled','AdjSalePrice_scaled'])
df_house_scaled.head()
```

Out[23]:

	SqFtTotLiving_scaled	SqFtLot_scaled	AdjSalePrice_scaled
0	0.399969	-0.466145	-0.699629
1	2.030444	0.647921	2.479556
2	-0.006455	1.255424	1.190602
3	1.356259	-0.544149	-0.120423
4	-0.412878	-0.543943	-0.714964

Content-Based Filtering

- Find **other things** similar to **the things I've liked**
- Assume: If I like product A, and product B is like product A, I'll like product B
- Use similarity of items
- Matrix: items x items
- Values: Similarity of items

Calculate Distances

- to maximize similarity → minimize distance

In [24]:

```
# using euclidean distance
from sklearn.metrics.pairwise import euclidean_distances

# calculate all pairwise distances between houses
dists = euclidean_distances(X_house_scaled)

np.round(dists,2)
```

Out[24]:

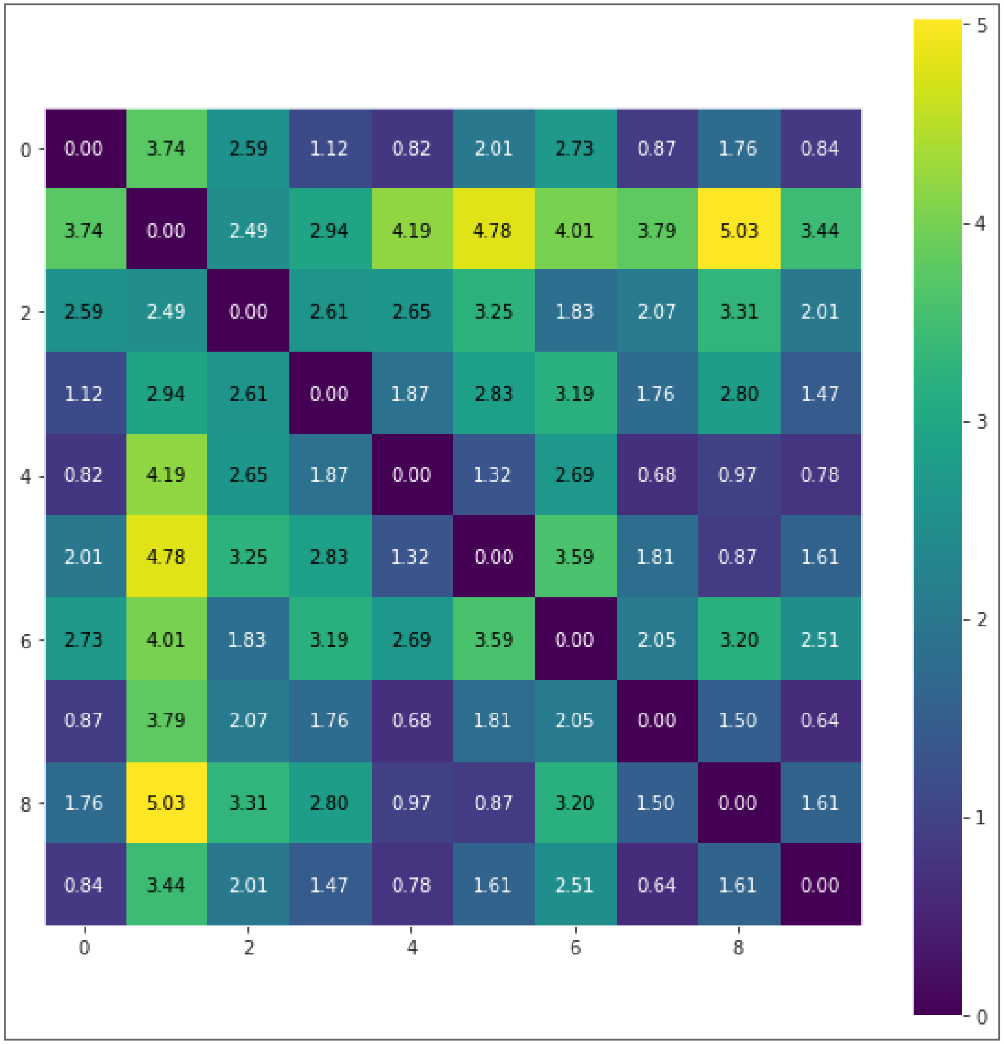
```
array([[0.  , 3.74, 2.59, 1.12, 0.82, 2.01, 2.
73, 0.87, 1.76, 0.84],
       [3.74, 0.  , 2.49, 2.94, 4.19, 4.78, 4.
01, 3.79, 5.03, 3.44],
       [2.59, 2.49, 0.  , 2.61, 2.65, 3.25, 1.
83, 2.07, 3.31, 2.01],
       [1.12, 2.94, 2.61, 0.  , 1.87, 2.83, 3.
```

```
19, 1.76, 2.8 , 1.47],
        [0.82, 4.19, 2.65, 1.87, 0.  , 1.32, 2.
69, 0.68, 0.97, 0.78],
        [2.01, 4.78, 3.25, 2.83, 1.32, 0.  , 3.
59, 1.81, 0.87, 1.61],
        [2.73, 4.01, 1.83, 3.19, 2.69, 3.59, 0.
, 2.05, 3.2 , 2.51],
        [0.87, 3.79, 2.07, 1.76, 0.68, 1.81, 2.
05, 0.  , 1.5 , 0.64],
        [1.76, 5.03, 3.31, 2.8 , 0.97, 0.87, 3.
2 , 1.5 , 0.  , 1.61],
        [0.84, 3.44, 2.01, 1.47, 0.78, 1.61, 2.
51, 0.64, 1.61, 0.  ]])
```

Visualizing Distances With a Heatmap

In [25]:

```
from mlxtend.plotting import heatmap
heatmap(np.round(dists,2),figsize=(10,10));
```


0.00 3.74 2.59 1.12 0.82 2.01 2.73 0.87 1.76 0.84
3.74 0.00 2.49 2.94 4.19 4.78 4.01 3.79 5.03 3.44
2.59 2.49 0.00 2.61 2.65 3.25 1.83 2.07 3.31 2.01
1.12 2.94 2.61 0.00 1.87 2.83 3.19 1.76 2.80 1.47
0.82 4.19 2.65 1.87 0.00 1.32 2.69 0.68 0.97 0.78
2.01 4.78 3.25 2.83 1.32 0.00 3.59 1.81 0.87 1.61
2.73 4.01 1.83 3.19 2.69 3.59 0.00 2.05 3.20 2.51
0.87 3.79 2.07 1.76 0.68 1.81 2.05 0.00 1.50 0.64
1.76 5.03 3.31 2.80 0.97 0.87 3.20 1.50 0.00 1.61
0.84 3.44 2.01 1.47 0.78 1.61 2.51 0.64 1.61 0.00
0
2
4
6
8
0
1
2
3
4
5

Query For Similarity

- Imagine I like house 5
- What houses are similar to house 5?

In [26]:

```
query_idx = 5
df_house.iloc[query_idx]
```

Out[26]:

```
SqFtTotLiving        930.0
SqFtLot             1012.0
AdjSalePrice      411781.0
Name: 5, dtype: float64
```

In [27]:

```
# Distances to house 5
[f'{x:0.1f}' for x in dists[query_idx]]
```

Out[27]:

```
['2.0', '4.8', '3.3', '2.8', '1.3', '0.0', '3.
6', '1.8', '0.9', '1.6']
```

Query For Similarity Cont.

In [28]:

```
# find indexes of best scores (for distances, want ascending)
best_idxs_asc = np.argsort(dists[query_idx])
best_idxs_asc
```

Out[28]:

```
array([5, 8, 4, 9, 7, 0, 3, 2, 6, 1])
```

In [29]:

```
# the top 10 recommendations with their distances
list(zip(['house '+str(x) for x in best_idxs_asc],
         np.round(dists[query_idx][best_idxs_asc],2)
        )
    )
```

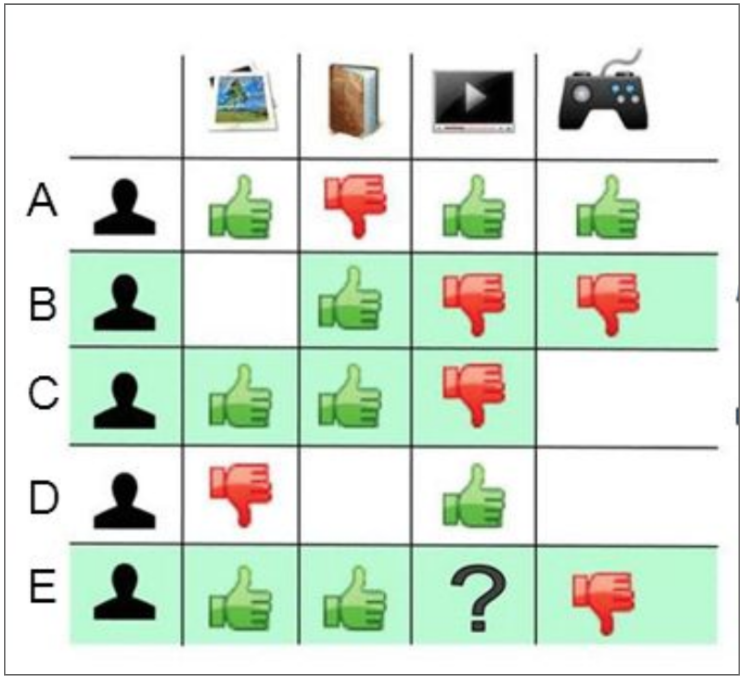
Out[29]:

```
[('house 5', 0.0),
 ('house 8', 0.87),
 ('house 4', 1.32),
 ('house 9', 1.61),
```

```
 ('house 7', 1.81),
 ('house 0', 2.01),
 ('house 3', 2.83),
 ('house 2', 3.25),
 ('house 6', 3.59),
 ('house 1', 4.78)]
```

(User Based) Collaborative Filtering

- Recommend things **that people with similar tastes have liked**
- Assume: If both you and I like Movie A, and you like Movie B, I'll like movie B
- Use similarity of user preferences
- Matrix: Users x Items
- Values: Rankings


A
B
C
D
E
?

Example: User Interests

Can we recommend topics based on a users existing interests?

In [30]:

```
# from Data Science from Scratch by Joel Grus
#https://github.com/joelgrus/data-science-from-scratch.git

users_interests = [
    ["Hadoop", "Big Data", "HBase", "Java", "Spark", "Storm", "Cassandra"],
    ["NoSQL", "MongoDB", "Cassandra", "HBase", "Postgres"],
    ["Python", "scikit-learn", "scipy", "numpy", "statsmodels", "pandas"],
    ["R", "Python", "statistics", "regression", "probability"],
    ["machine learning", "regression", "decision trees", "libsvm"],
    ["Python", "R", "Java", "C++", "Haskell", "programming languages"],
    ["statistics", "probability", "mathematics", "theory"],
    ["machine learning", "scikit-learn", "Mahout", "neural networks"],
    ["neural networks", "deep learning", "Big Data", "artificial intelligence"],
    ["Hadoop", "Java", "MapReduce", "Big Data"],
    ["statistics", "R", "statsmodels"],
    ["C++", "deep learning", "artificial intelligence", "probability"],
    ["pandas", "R", "Python"],
    ["databases", "HBase", "Postgres", "MySQL", "MongoDB"],
    ["libsvm", "regression", "support vector machines"]
]
```

In [31]:

```
# interests of user0
sorted(users_interests[0])
```

Out[31]:

```
['Big Data', 'Cassandra', 'HBase', 'Hadoop',
'Java', 'Spark', 'Storm']
```

All Unique Interests

In [32]:

```
# get a sorted list of unique interests (here using set)
unique_interests = sorted({interest
                           for user_interests in users_interests
                           for interest in user_interests})

# the first 5 unique interests
unique_interests
```

Out[32]:

```
['Big Data',
 'C++',
 'Cassandra',
 'HBase',
 'Hadoop',
 'Haskell',
 'Java',
 'Mahout',
 'MapReduce',
```

```
 'MongoDB',
 'MySQL',
 'NoSQL',
 'Postgres',
 'Python',
 'R',
 'Spark',
 'Storm',
 'artificial intelligence',
 'databases',
 'decision trees',
 'deep learning',
 'libsvm',
 'machine learning',
 'mathematics',
 'neural networks',
 'numpy',
 'pandas',
 'probability',
```

```
'programming languages',
'regression',
'scikit-learn',
'scipy',
'statistics',
'statsmodels',
'support vector machines',
'theory']
```

Transform User Interest Matrix

In [33]:

```
# Transform between lists of strings and fixed length lists of ints
from sklearn.preprocessing import MultiLabelBinarizer

mlb = MultiLabelBinarizer(classes=unique_interests)

# a matrix of "user" rows and "interest" columns
user_interest_matrix = mlb.fit_transform(users_interests)

# The interests for user0
user_interest_matrix[0]
```

Out[33]:

```
array([1, 0, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

In [34]:

```
# transforming back from interest matrix to list of interests
mlb.inverse_transform(user_interest_matrix)[0]
```

Out[34]:

```
('Big Data', 'Cassandra', 'HBase', 'Hadoop',
'Java', 'Spark', 'Storm')
```

Calculate Similarity

In [35]:

```
from sklearn.metrics.pairwise import cosine_similarity

# using similarity, higher values are better
user_similarities = cosine_similarity(user_interest_matrix)

# what are the similarites for user0 to other users?
user_similarities[0]
```

Out[35]:

```
array([1.        , 0.3380617 , 0.        , 0.        , 0.        ,
       0.15430335, 0.        , 0.        , 0.18898224, 0.56694671,
       0.        , 0.        , 0.        , 0.16903085, 0.        ])
```

In [36]:

```
# what users does user0 share interests with?
np.where(user_similarities[0])[0]
```

Out[36]:

```
array([ 0,  1,  5,  8,  9, 13])
```

Find Similar Users

In [37]:

```
# return a sorted list of users based on similarity
# skip query user and similarity == 0
def most_similar_users_to(query_idx):
    users_scores = [(idx,np.round(sim,4))
                    for idx,sim in enumerate(user_similarities[query_idx])
                    if idx != query_idx and sim > 0]
    return sorted(users_scores, key=lambda x:x[1])

most_similar_users_to(0)
```

Out[37]:

```
[(5, 0.1543), (13, 0.169), (8, 0.189), (1, 0.3
381), (9, 0.5669)]
```

Recommend Based On User Similarity

- Want to return items sorted by the similarity of other users

In [38]:

```
from collections import defaultdict

def user_based_suggestions(user_idx):
    suggestions = defaultdict(float)

    # iterate over interests of similar users
    for other_idx, sim in most_similar_users_to(user_idx):
        for interest in users_interests[other_idx]:
            suggestions[interest] += sim

    # sort suggestions based on weight
    suggestions = sorted(suggestions.items(),
                         key=lambda x:x[1],
                         reverse=True)

    # return only new interests
    return [(suggestion,weight)
            for suggestion,weight in suggestions
            if suggestion not in users_interests[user_idx]]
```

Recommend Based On User Similarity

In [39]:

```
# reminder: original interests
users_interests[0]
```

Out[39]:

```
['Hadoop', 'Big Data', 'HBase', 'Java', 'Spar
k', 'Storm', 'Cassandra']
```

In [40]:

```
# top 5 new recommended interests
user_based_suggestions(0)[:5]
```

Out[40]:

```
[('MapReduce', 0.5669),
 ('Postgres', 0.5071),
 ('MongoDB', 0.5071),
 ('NoSQL', 0.3381),
 ('neural networks', 0.189)]
```

Issues with Collab. Filtering

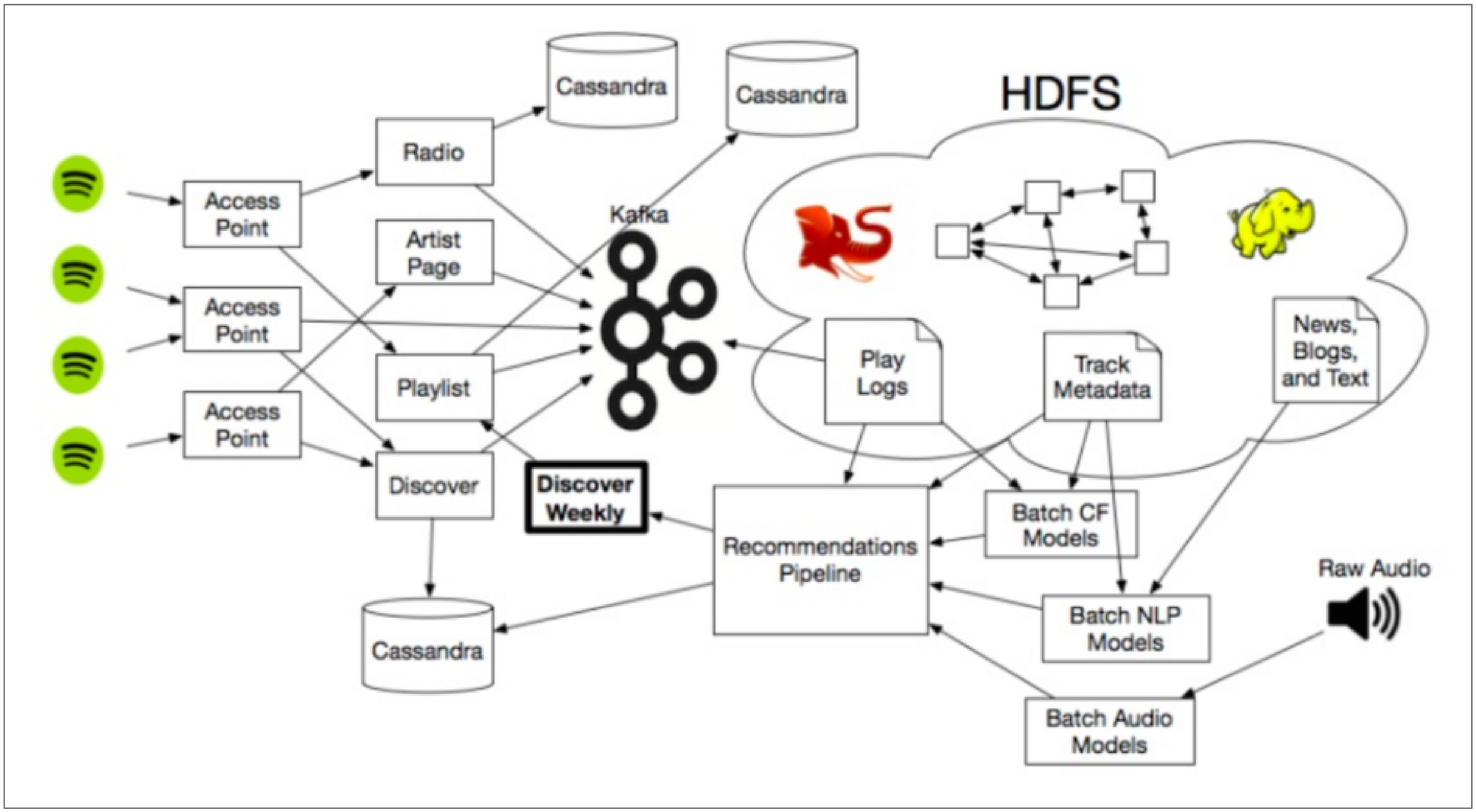
- **the cold start problem** : What if it's your first time?
- **sparcity** : How to recommend movies no one's seen?

Evaluating Rec. Systems

- **Precision@N**: Out of top N, how many were true?
- **Recall@N**: Out of all true, how many were in top N
- Surprise/Novelty?
- Diversity?

Spotify’s Recommendation Engine

How Does Spotify Know You So Well?



Recommendation Engines Review

- Content-Based
- User-Based Collaborative Filtering
- Issues
- Evaluating

Questions re Recommendation Engines?

Time Series

- Data ordered in time
- Applications
    - Financial
    - Economic
    - Scientific
    - etc.

Time Series Differences

- **Non-i.i.d.** : not independent and identically distributed
- not independent
    - Ex: Stock price
- not-identically distributed
    - Ex: Seasonality
- Order matters

Representing Time in Python

- `datetime` library
- Pandas `Timestamp`

`datetime.date`

In [41]:

```
from datetime import date

friday = date(2020,12,4) # year,month,day
friday
```

Out[41]:

```
datetime.date(2020, 12, 4)
```

In [42]:

```
today = date.today()
today
```

Out[42]:

```
datetime.date(2021, 11, 29)
```

In [43]:

```
today.year
```

Out[43]:

2021

`datetime.time`

In [44]:

```
from datetime import time

noon = time(12,0,0) # hour,minute,second,microsecond
noon
```

Out[44]:

```
datetime.time(12, 0)
```

In [45]:

```
noon.hour
```

Out[45]:

```
12
```

`datetime.datetime`

In [46]:

```
from datetime import datetime

# year,month,day,hour,minute,second,microsecond
monday_afternoon = datetime(2020,11,30,19,10)
monday_afternoon
```

Out[46]:

```
datetime.datetime(2020, 11, 30, 19, 10)
```

In [47]:

```
now = datetime.now()
now
```

Out[47]:

```
datetime.datetime(2021, 11, 29, 19, 0, 46, 674
886)
```

`datetime.timedelta`

In [48]:

```
diff = datetime(2020,11,30,1) - datetime(2020,11,29,0)
diff
```

Out[48]:

```
datetime.timedelta(days=1, seconds=3600)
```

In [49]:

```
diff.total_seconds()
```

Out[49]:

```
90000.0
```

In [50]:

```
from datetime import timedelta

#days,seconds,microseconds,milliseconds,minutes,hours,weeks
one_day = timedelta(1)

date(2020,11,30) + 2*one_day
```

Out[50]:

```
datetime.date(2020, 12, 2)
```

Printing Datetimes: `strftime()`

In [51]:

```
print(now)
```

```
2021-11-29 19:00:46.674886
```

In [52]:

```
now.strftime('%a %h %d, %Y %I:%M %p')
```

Out[52]:

```
'Mon Nov 29, 2021 07:00 PM'
```

%Y 4-digit year %y 2-digit year %m 2-digit month %d 2-digit day %H Hour (24-hour) %M 2-digit minute %S 2-digit second

See **strftime.org**

Parsing Datetimes: `pandas.to_datetime()`

- `dateutil.parser` available
- pandas has parser built in: `pd.to_datetime()`

In [53]:

```
pd.to_datetime('11/22/2019 2:36pm')
```

Out[53]:

```
Timestamp('2019-11-22 14:36:00')
```

In [54]:

```
dt_index = pd.to_datetime([datetime(2020, 11, 26),
                           '27th of November, 2020',
                           '2020-Nov-28',
                           '11-29-2030',
                           '20201130',
                           None
                          ])
dt_index
```

Out[54]:

```
DatetimeIndex(['2020-11-26', '2020-11-27', '20
20-11-28', '2030-11-29',
               '2020-11-30', 'NaT'],
              dtype='datetime64[ns]', freq=Non
e)
```

`pandas.Timestamp`

- like datetime.datetime
- can include **timezone** and **frequency** info
- can handle a missing time: `NaT`
- can be used anywhere datetime can be used
- an array of Timestamps can be used as an index

In [55]:

```
dt_index[0]
```

Out[55]:

```
Timestamp('2020-11-26 00:00:00')
```

Accessing Datetime Components with `.dt`

In [56]:

```
df_taxi = pd.read_csv('../data/yellowcab_tripdata_2017-01_subset10000rows.csv',
                      parse_dates=['tpep_pickup_datetime']).head(3)
df_taxi.tpep_pickup_datetime
```

Out[56]:

```
0   2017-01-10 18:37:59
1   2017-01-05 15:14:52
2   2017-01-11 14:47:52
Name: tpep_pickup_datetime, dtype: datetime64
[ns]
```

In [57]:

```
df_taxi.tpep_pickup_datetime.dt.day
```

Out[57]:

```
0    10
1     5
```

```
2    11
Name: tpep_pickup_datetime, dtype: int64
```

In [58]:

```
df_taxi.tpep_pickup_datetime.dt.day_of_week
```

Out[58]:

```
0    1
1    3
2    2
Name: tpep_pickup_datetime, dtype: int64
```

In [59]:

```
df_taxi.tpep_pickup_datetime.dt.hour
```

Out[59]:

```
0    18
1    15
2    14
Name: tpep_pickup_datetime, dtype: int64
```

DateIndex Indexing/Selecting/Slicing

In [60]:

```
s = pd.Series([101,102,103],
              index=pd.to_datetime(['20191201','20200101','20200201']))
s
```

Out[60]:

```
2019-12-01    101
2020-01-01    102
2020-02-01    103
dtype: int64
```

In [61]:

```
# can index normally using iloc
s.iloc[0:2]
```

Out[61]:

```
2019-12-01    101
2020-01-01    102
dtype: int64
```

DateIndex Indexing/Selecting/Slicing Cont.

In [62]:

```
# only rows from the year 2020
s.loc['2020']
```

Out[62]:

```
2020-01-01    102
2020-02-01    103
dtype: int64
```

In [63]:

```
# only rows from January 2020
s.loc['2020-01']
```

Out[63]:

```
2020-01-01    102
dtype: int64
```

In [64]:

```
# only rows between Jan 1st 2019 and Jan 1st 2020, inclusive
s.loc['01/01/2019':'01/01/2020']
```

Out[64]:

```
2019-12-01    101
2020-01-01    102
dtype: int64
```

In [65]:

```
# can use the indexing shortcut
s['2020']
```

Out[65]:

```
2020-01-01    102
2020-02-01    103
dtype: int64
```

Datetimes in DataFrames

In [66]:

```
df = pd.DataFrame([['12/1/2020',101,'A'],
                   ['1/1/2021',102,'B']],columns=['col1','col2','col3'])
df.col1 = pd.to_datetime(df.col1)
df.set_index('col1',drop=True,inplace=True)
df
```

Out[66]:

col1	col2	col3
2020-12-01	101	A
2021-01-01	102	B

In [67]:

```
# only return rows from 2020
df.loc['2020']
```

Out[67]:

col1	col2	col3
2020-12-01	101	A

Timestamp Index: Setting Frequency

In [68]:

```
s = pd.Series([101,103],index=pd.to_datetime(['20201201','20201203']))
s
```

Out[68]:

```
2020-12-01    101
2020-12-03    103
dtype: int64
```

In [69]:

```
# Use resample() and asfreq() to set frequency
s.resample('D').asfreq()
```

Out[69]:

```
2020-12-01    101.0
2020-12-02      NaN
2020-12-03    103.0
Freq: D, dtype: float64
```

In [70]:

```
pd.to_datetime(['20191201','20191203'])
```

Out[70]:

```
DatetimeIndex(['2019-12-01', '2019-12-03'], dtype='datetime64[ns]', freq=None)
```

In [71]:

```
# Use date_range with freq to get a range of dates of a certain frequency
pd.date_range(start='20191201',end='20191203',freq='D')
```

Out[71]:

```
DatetimeIndex(['2019-12-01', '2019-12-02', '2019-12-03'], dtype='datetime64[ns]', freq='D')
```

Sample of Available Frequencies B business day frequency D calendar day frequency W weekly frequency M month end frequency BM business month end frequency ... Q quarter end frequency BQ business quarter end frequency ... Y year end frequency BY business year end frequency ... BH business hour frequency H hourly frequency T,min minutely frequency S secondly frequency L,ms milliseconds U,us microseconds N nanoseconds https://pandas.pydata.org/pandas-docs/stable/user_guide/timeseries.html#timeseries-offset-aliases

Timezones

- Handled by `pytz` library

In [72]:

```
import pytz

[x for x in pytz.common_timezones if x.startswith('U')]
```

Out[72]:

```
['US/Alaska',
 'US/Arizona',
 'US/Central',
 'US/Eastern',
 'US/Hawaii',
 'US/Mountain',
 'US/Pacific',
 'UTC']
```

UTC: coordinated universal time (EST is 5 hours behind, -5:00)

Timezones Cont.

In [73]:

```
ts = pd.date_range('11/2/2019 9:30am',periods=2,freq='D')
ts
```

Out[73]:

```
DatetimeIndex(['2019-11-02 09:30:00', '2019-11-03 09:30:00'], dtype='datetime64[ns]', freq='D')
```

In [74]:

```
# Set timezone using .localize()
ts_utc = ts.tz_localize('UTC')
ts_utc
```

Out[74]:

```
DatetimeIndex(['2019-11-02 09:30:00+00:00', '2019-11-03 09:30:00+00:00'], dtype='datetime64[ns, UTC]', freq='D')
```

In [75]:

```
# Change timezones using .tz_convert()
ts_utc.tz_convert('US/Eastern')
```

Out[75]:

```
DatetimeIndex(['2019-11-02 05:30:00-04:00', '2019-11-03 04:30:00-05:00'], dtype='datetime64[ns, US/Eastern]', freq='D')
```

Timeseries in Python so far:

- `datetime .date .time .datetime .timedelta`
- format with `.strftime()`
- parse time with `pd.to_datetime()`
- `pandas Timestamp Timedelta DatetimeIndex`
- Indexing with `DatetimeIndex`
- Frequencies
- Timezones

Additional pandas functionality we won't discuss:

- `Period` and `PeriodIndex`
- `Panels`

Next: Operations on Time Series data

Questions re Datetimes in Python?