Flask Installation

- Flask is a popular Python web framework, meaning it is a third-party Python library used for developing web applications.

```
$ pip install Flask

mkdir flaskDirectory

cd flaskDirectory
create app.py
Add data.csv

mkdir templates
cd templates
create index.html
```

Sample Code

```
from flask import Flask
app = Flask(__name__)   # creates the Flask instance

@app.route("/") #creates a simple route so you can see the application
                working. It creates a connection between the
                URL /hello and a function that returns a response, the
                string 'Hello, World!' in this case.
def hello():
return "Hello World!"

if __name__ == "__main__": app.run()
```

Creating URL Routes

```
from flask import Flask
app = Flask(__name__)

@app.route("/")
def index():
return "Index!"

@app.route("/hello")
def hello():
return "Hello World!"


@app.route("/members")
def members():
return "Members"


if __name__ == "__main__": app.run()
```

/hello

/members/

Running Server

```
$ python app.py
```

Serving Flask app “dirName"

Environment: development

Debug mode: on

Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)

Restarting with stat

Debugger is active!

Debugger PIN: 855-212-761

Load Data - Back-End

```python
@app.route("/")
def index():
    data = pd.read_csv('data2.csv')
    chart_data = data.to_dict(orient='records')
    chart_data = json.dumps(chart_data, indent=2)
    data = {'chart_data': chart_data}
    return render_template("index.html", data=data)


if __name__ == "__main__":
app.run(debug=True)
```

Load Data to Front-End

```
<!-- Load the d3.js library -->
<script src="http://d3js.org/d3.v3.min.js"></script>
<script src="https://ajax.googleapis.com/ajax/libs/jquery/3.3.1/jquery.min.js"></script>

<script>

var data = {{ data.chart_data | safe }}
console.log(data);
// Set the dimensions of the canvas / graph
var margin = {top: 30, right: 20, bottom: 30, left: 50},
    width = 600 - margin.left - margin.right,
    height = 270 - margin.top - margin.bottom;
```

Process Data – Back-End

```python
import json

from flask import Flask, render_template, request, redirect, Response, jsonify
import pandas as pd

app = Flask(__name__)

@app.route("/", methods = ['POST', 'GET'])
def index():
    #df = pd.read_csv('data.csv').drop('Open', axis=1)
    global df

    data = df[['date','close']]
    chart_data = data.to_dict(orient='records')
    chart_data = json.dumps(chart_data, indent=2)
    data = {'chart_data': chart_data}
    return render_template("index.html", data=data)


if __name__ == "__main__":
    df = pd.read_csv('data2.csv')
    app.run(debug=True)
```

Process Data – Back-End

```python
@app.route("/", methods = ['POST', 'GET'])
def index():
    #df = pd.read_csv('data.csv').drop('Open', axis=1)
    global df
    if request.method == 'POST':
        data = df[['date','open']]
        data = data.rename(columns={'open':'close'})
        print(data)
        print("Hello World!")
        chart_data = data.to_dict(orient='records')
        chart_data = json.dumps(chart_data, indent=2)
        data = {'chart_data': chart_data}
        # data = {'chart_data': chart_data}
        return jsonify(data) # Should be a json string

    data = df[['date','close']]
    chart_data = data.to_dict(orient='records')
    chart_data = json.dumps(chart_data, indent=2)
    data = {'chart_data': chart_data}
    return render_template("index.html", data=data)
```

Connect to Back-End

```
// ** Update data section (Called from the onclick)
function updateData() {

    // Get the data again
      // Request the "" page and send some additional data along
    $.post("", {'data': 'received'}, function(data_infunc){
      // console.log({data_infunc})

      data2 = JSON.parse(data_infunc.chart_data)
      console.log(data2);
      data2.forEach(function(d) {
      d.date = parseDate(d.date);
      d.close = +d.close;
      });
```

Multidimensional Scaling (MDS)

MDS is for irregular structures

- scattered points in high-dimensions (N-D)
- adjacency matrices

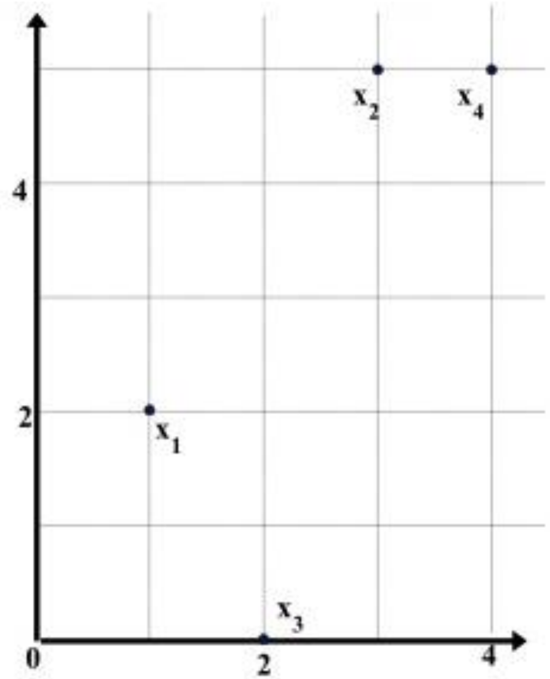
Maps the distances between observations from N-D into low-D (say 2D)

- attempts to ensure that differences between pairs of points in this reduced space match as closely as possible

The input to MDS is a distance (similarity) matrix

- actually, you use the *dissimilarity* matrix because you want similar points mapped closely
- dissimilar point pairs will have greater values and map father apart

The Dissimilarity Matrix



Data Matrix

point	attribute1	attribute2
x1	1	2
x2	3	5
x3	2	0
x4	4	5

Dissimilarity Matrix

(with Euclidean Distance)

	x1	*x2*	*x3*	*x4*
x1	0			
x2	3.61	0		
x3	2.24	5.1	0	
x4	4.24	1	5.39	0

Distance Matrix

MDS turns a distance matrix into a network or point cloud

- correlation, cosine, Euclidian, and so on

Suppose you know a matrix of distances among cities

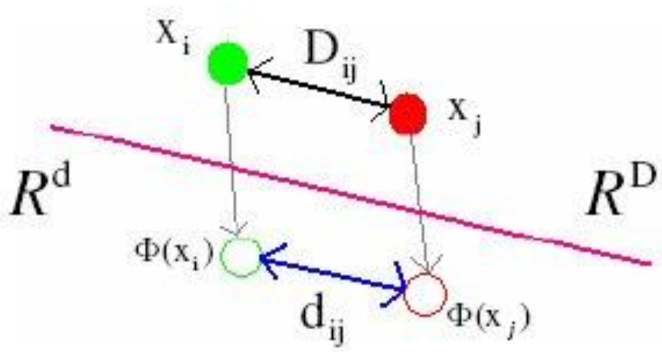
	Chicago	Raleigh	Boston	Seattle	S.F.	Austin	Orlando
Chicago	0						
Raleigh	641	0					
Boston	851	608	0				
Seattle	1733	2363	2488	0			
S.F.	1855	2406	2696	684	0		
Austin	972	1167	1691	1764	1495	0	
Orlando	994	520	1105	2565	2458	1015	0

Result of MDS

COMPARE WITH REAL MAP

MDS Algorithm

- Task:
  - Find that configuration of image points whose pairwise distances are most similar to the original inter-point distances !!!
- Formally:
  - Define: $D_{ij} = \| x_i - x_j \|_D \qquad d_{ij} = \| y_i - y_j \|_d$
  - Claim: $D_{ij} \equiv d_{ij} \qquad \forall i, j \in [1, n]$
- In general: an exact solution is not possible !!!
- Inter Point distances → invariance features



MDS Algorithm

Strategy (of metric MDS):

- iterative procedure to find a good configuration of image points
  - 1) Initialization
    → Begin with some (arbitrary) initial configuration
  - 2) Alter the image points and try to find a configuration of points that minimizes the following sum-of-squares error function:

MDS Algorithm

Strategy (of metric MDS):

- iterative procedure to find a good configuration of image points
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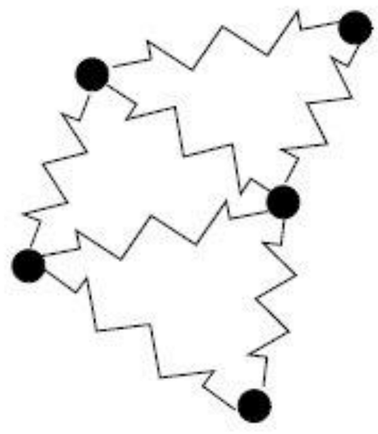
      → Begin with some (arbitrary) initial configuration
    - 2) Alter the image points and try to find a configuration of points that minimizes the following sum-of-squares error function:

$$E = \sum_{i<j}^{N} \left(D_{ij} - d_{ij}\right)^2$$

Force-Directed Algorithm

Spring-like system

- insert springs within each node
- the length of the spring encodes the desired node distance
- start at an initial configuration
- iteratively move nodes until an energy minimum is reached



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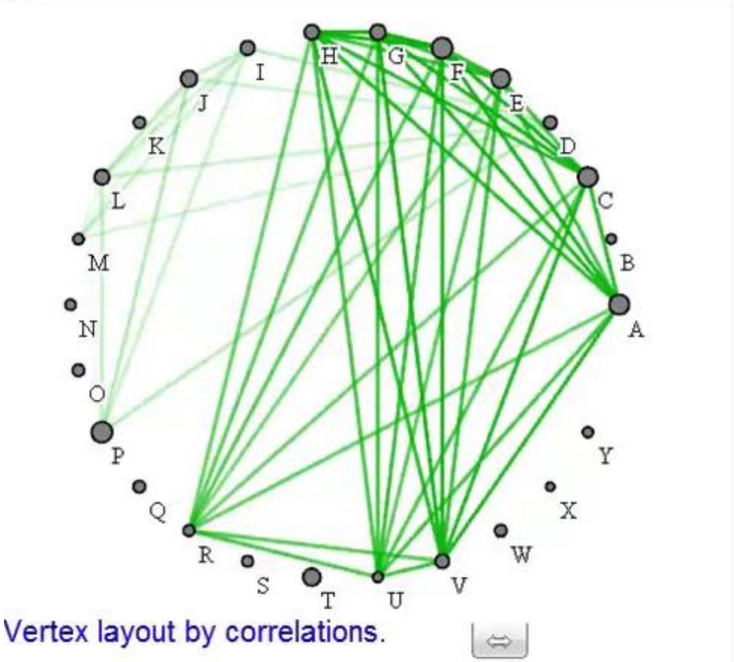


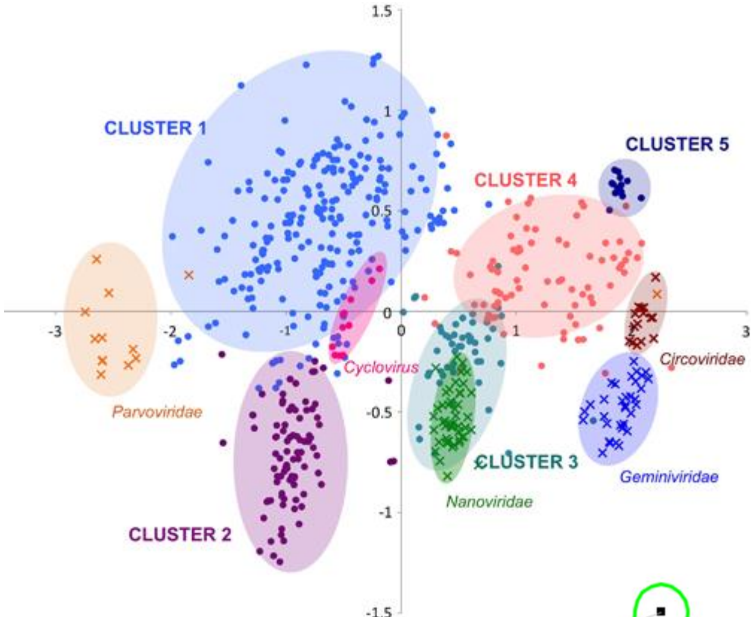
Vertex layout by correlations.

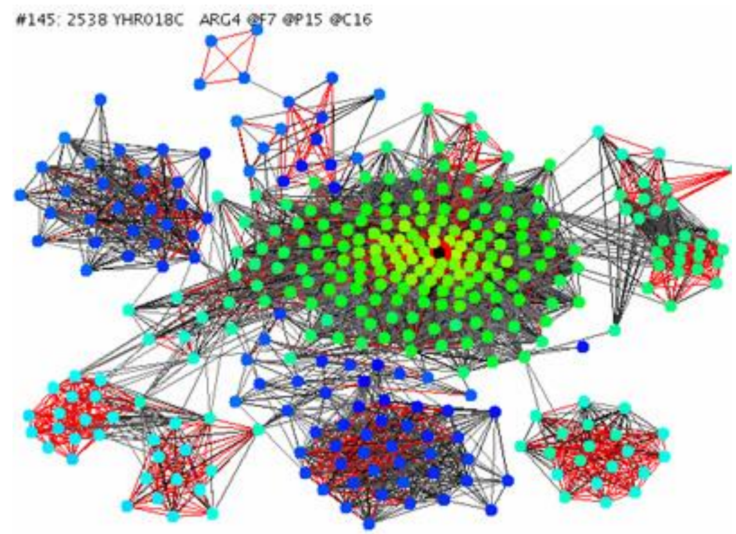
Uses of MDS

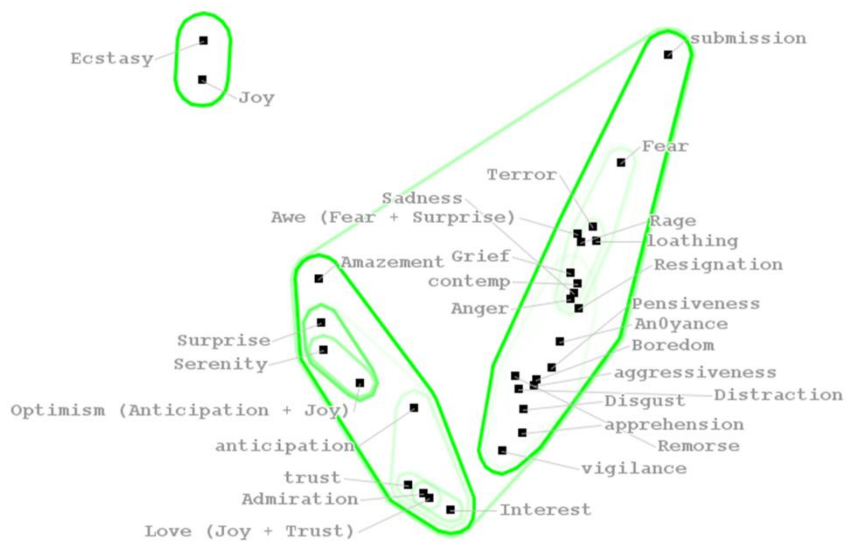
Distance (similarity) metric

- Euclidian distance (best for data)
- Cosine distance (best for data)
- |1-correlation| distance (best for attributes)
- use 1-correlation to move correlated attribute points closer
- use | | if you do not care about positive or negative correlations

MDS Examples







MDS in Scikit-learn

sklearn.manifold.MDS

class `sklearn.manifold.MDS`(*n_components=2, metric=True, n_init=4, max_iter=300, verbose=0, eps=0.001, n_jobs=1, random_state=None, dissimilarity='euclidean'*) [source]

sklearn.manifold.**MDS**(

n_components=2,

metric=True,

n_init=4, Number of time the smacof algorithm will be run with different initialisation.
The final results will be the best output of the n_init consecutive runs in terms of stress.

max_iter=300, Maximum number of iterations of the SMACOF algorithm for a single run

verbose=0,

eps=0.001, relative tolerance w.r.t stress to declare converge

n_jobs=1,

random_state=None,

dissimilarity='euclidean') Which dissimilarity measure to use. Supported are 'euclidean' and 'precomputed'.

The **SMACOF** (Scaling by MAjorizing a COmplicated Function) algorithm is a multidimensional scaling algorithm which minimizes an objective function (the *stress*) using a majorization technique.