

ACM

February 5, 2021

```
In [2]: #chargement des donnees - index_col = 0 pour indiquer que la colonne n°0 est un label
import pandas
D = pandas.read_excel("ACM.xlsx",sheet_name="ACM",index_col=0)
```

```
In [3]: #affichage des caracteristiques
print(D.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 8 entries, Beauceron to Labrador
Data columns (total 3 columns):
Taille      8 non-null object
Vitesse     8 non-null object
Affection   8 non-null object
dtypes: object(3)
memory usage: 256.0+ bytes
None
```

```
In [5]: #recuperation des variables actives
DActives = D[['Taille','Vitesse','Affection']]
print(DActives)
```

| | Taille | Vitesse | Affection |
|-------------|----------|-----------|-----------|
| Chien | | | |
| Beauceron | Taille++ | Vitesse++ | Affec+ |
| Basset | Taille- | Vitesse- | Affe- |
| Berger-All | Taille++ | Vitesse++ | Affec+ |
| Boxer | Taille+ | Vitesse+ | Affec+ |
| Bull-Dog | Taille- | Vitesse- | Affec+ |
| Bull-Mastif | Taille++ | Vitesse- | Affe- |
| Caniche | Taille- | Vitesse+ | Affec+ |
| Labrador | Taille+ | Vitesse+ | Affec+ |

```
In [6]: #recuperation des infos -
#nombre de variables
p = DActives.shape[1]
#nombre d'observations
n = DActives.shape[0]
```

```
In [7]: #codage en 0/1 les noms de modalites sont explicites
        #pas necessaire de prefixer les indicatrices par les noms de variables
        X = pandas.get_dummies(DActives,prefix='',prefix_sep='')
        print(X)
```

| | Taill- | Taille+ | Taille++ | Velo- | Veloc+ | Veloc++ | Affe- | Affec+ |
|-------------|--------|---------|----------|-------|--------|---------|-------|--------|
| Chien | | | | | | | | |
| Beauceron | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 |
| Basset | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 |
| Berger-All | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 |
| Boxer | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 |
| Bull-Dog | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 |
| Bull-Mastif | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 |
| Caniche | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| Labrador | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 |

```
In [9]: #librairie numpy
        import numpy
        #profil individu moyen
        ind_moy = numpy.sum(X.values,axis=0)/(n*p)
        print(ind_moy)
```

```
[ 0.125      0.08333333 0.125      0.125      0.125      0.08333333
 0.08333333 0.25      ]
```

```
In [11]: #distance du KHI-2 entre beauceron (nř0) et basset (nř1)
        print(numpy.sum(1/ind_moy*(X.values[0,:]/p-X.values[1,:]/p)**2))

        #idem entre basset(nř1) et caniche(nř6)
        print(numpy.sum(1/ind_moy*(X.values[1,:]/p-X.values[6,:]/p)**2))
```

```
5.777777777778
3.555555555556
```

```
In [13]: #distance a l'origine du basset (nř1)
        print(numpy.sum(1/ind_moy*(X.values[1,:]/p-ind_moy)**2))
        #distance a l'origine du caniche (nř6)
        print(numpy.sum(1/ind_moy*(X.values[6,:]/p-ind_moy)**2))
```

```
2.111111111111
1.222222222222
```

```
In [14]: #distance a l'origine des individus (obs.)
        disto_ind = numpy.apply_along_axis(arr=X.values,axis=1,func1d=lambda x:numpy.sum(1 / i
        #poids des obs.
```

```

poids_ind = numpy.ones(X.shape[0])/n
#inertie
inertie_ind = poids_ind*disto_ind
#afffichage
print(pandas.DataFrame(numpy.transpose([poids_ind,disto_ind,inertie_ind]),index=D.ind
#poids (1/n), leurs distances a lorigine, leurs inerties [1/2()])

```

| | 0 | 1 | 2 |
|-------------|-------|----------|----------|
| Chien | | | |
| Beauceron | 0.125 | 1.666667 | 0.208333 |
| Basset | 0.125 | 2.111111 | 0.263889 |
| Berger-All | 0.125 | 1.666667 | 0.208333 |
| Boxer | 0.125 | 1.666667 | 0.208333 |
| Bull-Dog | 0.125 | 1.222222 | 0.152778 |
| Bull-Mastif | 0.125 | 2.111111 | 0.263889 |
| Caniche | 0.125 | 1.222222 | 0.152778 |
| Labrador | 0.125 | 1.666667 | 0.208333 |

```

In [15]: #inertie totale
inertie_tot_ind = numpy.sum(inertie_ind)
print(inertie_tot_ind)

```

```

1.666666666667

```

```

In [ ]: #Linformation totale portee par les donnees, comptabilisee via les distances entre ind

```

```

In [ ]: # 2 Analyse des associations entre les modalites

```

```

In [ ]: #Distance entre modalites

```

```

In [17]: #somme en colonne
somme_col = numpy.sum(X.values,axis=0)
print(somme_col)

```

```

[3 2 3 3 3 2 2 6]

```

```

In [78]: # avec les listes , slicing ne fonctionne pas
M=[[1,2,3],[4,5,6],[7,8,9]]
M[:, 0]

```

```

-----

TypeError                                Traceback (most recent call last)

<ipython-input-78-57336eea6fa7> in <module>()

```

```

1 # avec les listes , slicing ne fonctionne pas
2 M=[[1,2,3],[4,5,6],[7,8,9]]
----> 3 M[: , 0]

```

TypeError: list indices must be integers or slices, not tuple

```

In [76]: # on doit travailler avec array (Tableau) ( ca marche tres bien)
M=numpy.array([[1,2,3],[4,5,6],[7,8,9]])
M[: , 0]

```

```

Out[76]: array([1, 4, 7])

```

```

In [18]: #distance entre taille- (2) et velocite- (5)
print(numpy.sum(n*((X.values[:,2]/somme_col[2]-X.values[:,5]/somme_col[5])**2)))

1.333333333333

```

```

In [19]: #distance entre taille- (2) et velocite+ (3)
print(numpy.sum(n*((X.values[:,2]/somme_col[2]-X.values[:,3]/somme_col[3])**2)))

3.555555555556

```

```

In [ ]: #Distance a l'origine

```

```

In [21]: #profil moyen des variables-modalites
moda_moy = numpy.ones(X.shape[0])/n
#distance a l'origine taille-
print(numpy.sum(n*((X.values[:,0]/somme_col[0]-moda_moy)**2)))

1.666666666667

```

```

In [22]: #distance a l'origine taille+
print(numpy.sum(n*((X.values[:,1]/somme_col[1]-moda_moy)**2)))

3.0

```

```

In [ ]: #Inertie totale

```

```

In [25]: #poids des variables_modalites (points modalites)
poids_moda = somme_col/(n*p)
#distance a l'origine des points modalites
disto_moda = numpy.apply_along_axis(arr=X.values/somme_col,axis=0,func1d=lambda x: nu
#inertie
inertie_moda = poids_moda * disto_moda
#affichage
print(pandas.DataFrame(numpy.transpose([poids_moda,disto_moda,inertie_moda]),index =X

```

| | Poids | Disto | Inertie |
|----------|----------|----------|----------|
| Taill- | 0.125000 | 1.666667 | 0.208333 |
| Taille+ | 0.083333 | 3.000000 | 0.250000 |
| Taille++ | 0.125000 | 1.666667 | 0.208333 |
| Velo- | 0.125000 | 1.666667 | 0.208333 |
| Veloc+ | 0.125000 | 1.666667 | 0.208333 |
| Veloc++ | 0.083333 | 3.000000 | 0.250000 |
| Affe- | 0.083333 | 3.000000 | 0.250000 |
| Affec+ | 0.250000 | 0.333333 | 0.083333 |

```
In [ ]: #Remarque
```

```
#La valeur de linertie totale obtenue via le point de vue des modalites est strictemen  
#exprimee a partir de lanalyse des proximities entre les individus .  
#Nous avons deux manieres dapprehender les donnees, mais il sagit bien des memes donne  
#Nous constatons de surcroit que les modalites (Taille+, Veloc++, Affec-) sont celles  
#contribuent le plus a linformation globale.
```

```
In [27]: #inertie totale des points-modalites
```

```
inertie_tot_moda = numpy.sum(inertie_moda)  
print(inertie_tot_moda)
```

```
1.666666666667
```

```
In [24]: #ACM via une ACP sur le tableau des profils
```

```
In [ ]: #Nous reduisons les variables par la racine carree de leur variance c.-a-d. lecart-typ
```

```
In [29]: profil = numpy.apply_along_axis(arr=X.values,axis=1,func1d=lambda x:x/numpy.sum(x))  
print(pandas.DataFrame(profil,index=X.index,columns=X.columns))
```

| | Taill- | Taille+ | Taille++ | Velo- | Veloc+ | Veloc++ | \ |
|-------------|----------|----------|----------|----------|----------|----------|---|
| Chien | | | | | | | |
| Beauceron | 0.000000 | 0.000000 | 0.333333 | 0.000000 | 0.000000 | 0.333333 | |
| Basset | 0.333333 | 0.000000 | 0.000000 | 0.333333 | 0.000000 | 0.000000 | |
| Berger-All | 0.000000 | 0.000000 | 0.333333 | 0.000000 | 0.000000 | 0.333333 | |
| Boxer | 0.000000 | 0.333333 | 0.000000 | 0.000000 | 0.333333 | 0.000000 | |
| Bull-Dog | 0.333333 | 0.000000 | 0.000000 | 0.333333 | 0.000000 | 0.000000 | |
| Bull-Mastif | 0.000000 | 0.000000 | 0.333333 | 0.333333 | 0.000000 | 0.000000 | |
| Caniche | 0.333333 | 0.000000 | 0.000000 | 0.000000 | 0.333333 | 0.000000 | |
| Labrador | 0.000000 | 0.333333 | 0.000000 | 0.000000 | 0.333333 | 0.000000 | |

| | Affe- | Affec+ |
|------------|----------|----------|
| Chien | | |
| Beauceron | 0.000000 | 0.333333 |
| Basset | 0.333333 | 0.000000 |
| Berger-All | 0.000000 | 0.333333 |
| Boxer | 0.000000 | 0.333333 |

```

Bull-Dog      0.000000  0.333333
Bull-Mastif   0.333333  0.000000
Caniche       0.000000  0.333333
Labrador      0.000000  0.333333

```

```

In [30]: #Nous reduisons les variables par la racine carree de leur variance c.-a-d. lecart-ty
         #reduire les profils
         profil = profil/numpy.std(profil,axis=0,ddof=0)
         print(profil)

```

```

[[ 0.          0.          2.06559112  0.          0.          2.30940108
   0.          2.30940108]
 [ 2.06559112  0.          0.          2.06559112  0.          0.
   2.30940108  0.          ]
 [ 0.          0.          2.06559112  0.          0.          2.30940108
   0.          2.30940108]
 [ 0.          2.30940108  0.          0.          2.06559112  0.          0.
   2.30940108]
 [ 2.06559112  0.          0.          2.06559112  0.          0.          0.
   2.30940108]
 [ 0.          0.          2.06559112  2.06559112  0.          0.
   2.30940108  0.          ]
 [ 2.06559112  0.          0.          0.          2.06559112  0.          0.
   2.30940108]
 [ 0.          2.30940108  0.          0.          2.06559112  0.          0.
   2.30940108]]

```

```

In [31]: #ponderation des modalites
         pond_moda = (n-somme_col)/(n*p)
         print(pond_moda)

```

```

[ 0.20833333  0.25          0.20833333  0.20833333  0.20833333  0.25          0.25
  0.08333333]

```

```

In [32]: #appliquer la ponderation aux profils
         profil = profil*numpy.sqrt(pond_moda)
         print(profil)

```

```

[[ 0.          0.          0.94280904  0.          0.          1.15470054
   0.          0.66666667]
 [ 0.94280904  0.          0.          0.94280904  0.          0.
   1.15470054  0.          ]
 [ 0.          0.          0.94280904  0.          0.          1.15470054
   0.          0.66666667]
 [ 0.          1.15470054  0.          0.          0.94280904  0.          0.
   0.66666667]]

```

```
[ 0.94280904  0.          0.          0.94280904  0.          0.          0.
 0.66666667]
[ 0.          0.          0.94280904  0.94280904  0.          0.
 1.15470054  0.          ]
[ 0.94280904  0.          0.          0.          0.94280904  0.          0.
 0.66666667]
[ 0.          1.15470054  0.          0.          0.94280904  0.          0.
 0.66666667]]
```

```
In [ ]: #numpy.linalg.eig
#
```

```
In [35]: R=numpy.corrcoef(X.values,rowvar=False)
```

```
In [36]: pr=numpy.linalg.eig(R)
print(pr)
```

```
(array([ 3.56910019e+00,  2.65189894e+00,  1.27835795e+00,
        -1.50908880e-16,  3.40048343e-01,  1.60594584e-01,
         7.53627951e-17,  0.00000000e+00]), array([[ -1.97572068e-01,   3.51721627e-01,   6.3
        -5.97614305e-01,   2.23488183e-01,   1.75104646e-01,
         5.30093358e-02,   3.01605041e-17],
        [ 3.62565037e-01,   2.39130868e-01,  -4.89295285e-01,
        -5.34522484e-01,  -3.89068180e-01,   3.67239448e-01,
         4.74129913e-02,   6.69823572e-17],
        [-1.26715960e-01,  -5.65606777e-01,  -1.94425636e-01,
        -5.97614305e-01,   1.24504976e-01,  -5.03573594e-01,
         5.30093358e-02,  -4.71717356e-17],
        [-4.71079787e-01,   1.79135691e-01,   2.21190999e-02,
         4.00891461e-16,  -5.77583745e-01,  -2.34006718e-01,
        -5.95258656e-01,  -1.51851997e-17],
        [ 3.96335443e-01,   3.37794725e-01,  -1.64530188e-01,
         1.14945139e-16,   5.10772644e-01,  -2.89328891e-01,
        -5.95258656e-01,  -2.94097915e-17],
        [ 8.35667175e-02,  -5.77945774e-01,   1.59220436e-01,
        -1.24706289e-15,   7.46970818e-02,   5.85106998e-01,
        -5.32415528e-01,   5.76014892e-17],
        [-4.62316770e-01,   9.74194769e-02,  -3.67676828e-01,
        -4.65480057e-16,   3.02577398e-01,   2.23681287e-01,
         1.84450459e-16,   7.07106781e-01],
        [ 4.62316770e-01,  -9.74194769e-02,   3.67676828e-01,
         4.65480057e-16,  -3.02577398e-01,  -2.23681287e-01,
         9.59407461e-17,   7.07106781e-01]]))
```

```
In [38]: t=sorted(pr[0],reverse=True)
v=t/sum(t)
w=numpy.cumsum(v)
```

```
t=[t,v,w]
print(pandas.DataFrame(numpy.transpose(t),columns=['Val.P', '%','cumsum %'],index=range(8)))
```

| | Val.P | % | cumsum % |
|---|---------------|---------------|----------|
| 0 | 3.569100e+00 | 4.461375e-01 | 0.446138 |
| 1 | 2.651899e+00 | 3.314874e-01 | 0.777625 |
| 2 | 1.278358e+00 | 1.597947e-01 | 0.937420 |
| 3 | 3.400483e-01 | 4.250604e-02 | 0.979926 |
| 4 | 1.605946e-01 | 2.007432e-02 | 1.000000 |
| 5 | 7.536280e-17 | 9.420349e-18 | 1.000000 |
| 6 | 0.000000e+00 | 0.000000e+00 | 1.000000 |
| 7 | -1.509089e-16 | -1.886361e-17 | 1.000000 |

```
In [ ]: #LACP ne sait pas quil y a des redondances artificielles dans les
#donnees, dou les facteurs aux variances nulles en excédent.
```

```
In [40]: #coordonnees fact. des observations (1er plan)
print(pandas.DataFrame(pr[1][:,:2],index=X.index,columns=['Fact.1','Fact.2']))
```

| | Fact.1 | Fact.2 |
|-------------|-----------|-----------|
| Chien | | |
| Beauceron | -0.197572 | 0.351722 |
| Basset | 0.362565 | 0.239131 |
| Berger-All | -0.126716 | -0.565607 |
| Boxer | -0.471080 | 0.179136 |
| Bull-Dog | 0.396335 | 0.337795 |
| Bull-Mastif | 0.083567 | -0.577946 |
| Caniche | -0.462317 | 0.097419 |
| Labrador | 0.462317 | -0.097419 |