[2]

```
%matplotlib inline
from os import listdir
from os.path import isfile, join
import matplotlib.pyplot as plt
from collections import Counter
import math
from collections import Counter
import numpy as np
from scipy.special import comb
import itertools as it
%load_ext line_profiler
from imp import reload
import itertools as it
import pandas as pd
import seaborn as sns
import sys
sys.path.insert(0, '../mallows kendall')
import mallows_kendall as mk
import cego_lop as cego

from IPython.core.display import display, HTML
display(HTML("<style>.container { width:90% !important; }
</style>"))
```

References

- http://www.spotseven.de/wp-content/papercite-data/pdf/zaef14c.pdf
- https://dl.acm.org/doi/pdf/10.1145/2576768.2598282
- https://pubsonline.informs.org/doi/10.1287/ijoc.1120.0506
- https://link.springer.com/article/10.1007/s11721-015-0106-x
- http://iridia.ulb.ac.be/supp/IridiaSupp2015-004/index.html#Scenarios
- instances LOLIB: http://grafo.etsii.urjc.es/optsicom/lolib/#instances
- bayesian opt tutorial: https://arxiv.org/pdf/1012.2599.pdf
- VEGO package: https://cran.r-project.org/web/packages/CEGO/CEGO.pdf

  falta encontrar donde habia uno con el LOP

LOP instance generator

The instances M follow this distribution $M_\phi[i,j]$

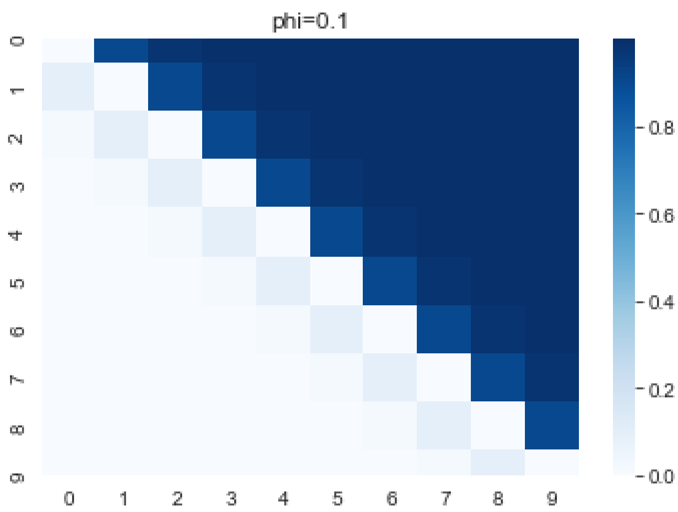
$$M_\phi[i,j] = h(j-i+1,\phi) - h(j-i,\phi),$$

where

$$h(k,\phi)=k/(1-\phi^k).$$

Taking different values of ϕ we controll the uniformity of M:

[49]
```
def h(k,phi):
  if (1-phi**k) == 0 :
    return 0
  return k/(1-phi**k)
  #h(k,\phi)=k/(1-\phi^k)
def mij(i,j,phi):
  return h(j-i+1,phi) - h(j-i,phi)
      #h(j-i+1,\phi) - h(j-i,\phi)
n = 10
for phi in [0.1,0.5,0.7,0.9,0.999]:
  M = np.zeros((n,n))
  for i in range(n):
    for j in range(i+1,n):
      M[i,j] = mij(i,j,phi)
      M[j,i] = 1-M[i,j]
  g = sns.heatmap(M, cmap="Blues")
  g.set_title("phi="+str(phi))
  plt.show()
```



running experimtns

How to run one experiment with a particular parameter configuration

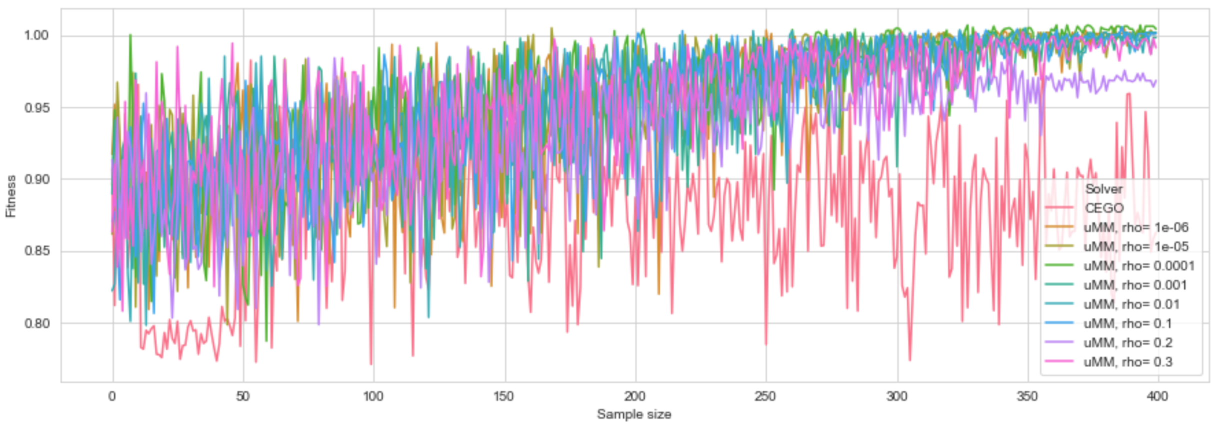
[19]

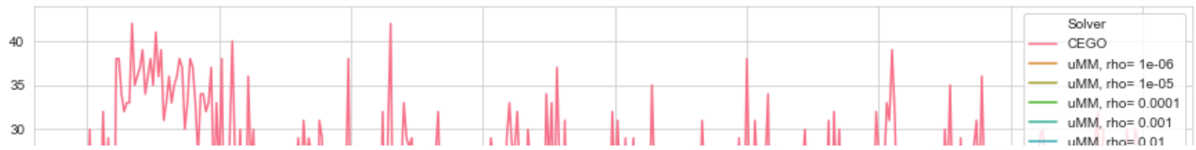
```
reload(cego)
n = 10
m_max = 400
repe = 0
#m_ini = 10
phi_instance = 0.9
budgetGA = 100

cego.run_and_save(n,repe,phi_instance, budgetGA,m_max=m_max)
```

[20]

```
df = pd.read_pickle('pickles/pickLocal.pkl')#pick275670.pkl
color_variable = 'Solver'
y_variables = ['Fitness','Distance']
palette = sns.color_palette("husl",
len(df[color_variable].drop_duplicates()))
for y_variable in y_variables:
    plt.figure(figsize=(15,5))
    sns.lineplot(x='Sample
size',y=y_variable,hue='Solver',data=df, palette=palette)
    plt.show()
```





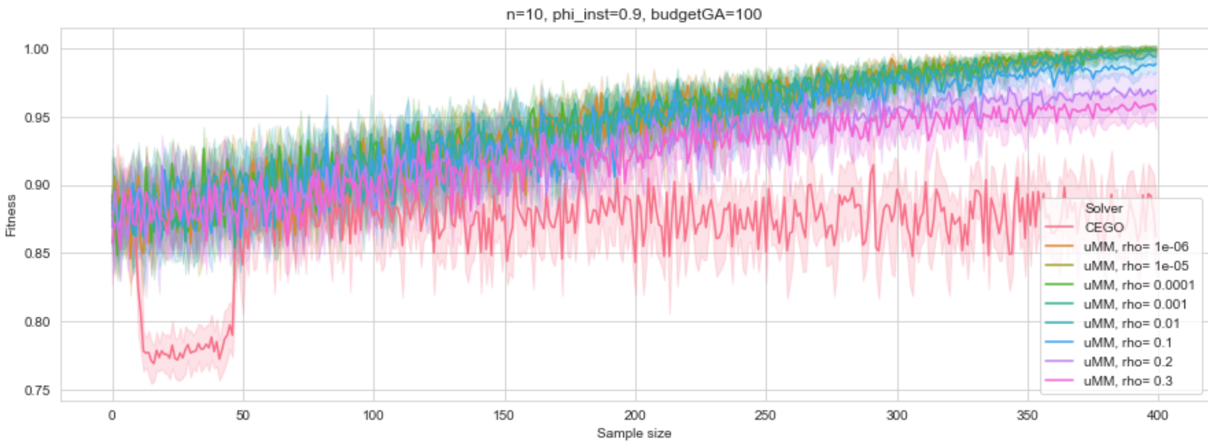
Plot the results

[21]

```
df = pd.concat([pd.read_pickle("pickles/"+f) for f in
listdir("pickles") if (f.endswith(".pkl")and "Local" not in f)]
)
df.head()
```

	Fitness	Problem	Solver	Sample size	repe	Distance	run
0	0.910130	LOP	CEGO	0	3	20	11759.7
1	0.891536	LOP	CEGO	1	3	18	11759.7
2	0.810963	LOP	CEGO	2	3	30	11759.7
3	0.815224	LOP	CEGO	3	3	30	11759.7
4	0.885725	LOP	CEGO	4	3	20	11759.7

[14]
```
sns.set_style("whitegrid")
color_variable = 'Solver'
y_variables = ['Fitness','Distance']
palette = sns.color_palette("husl",
len(df[color_variable].drop_duplicates()))
for phi_i in df.phi_instance.drop_duplicates().values:
  for n in df.n.drop_duplicates().values:
    for budgetGA in df.budgetGA.drop_duplicates().values:
      for y_variable in y_variables:
          plt.figure(figsize=(15,5))
          aux = df[(df.phi_instance==phi_i) & (df.n==n) &
(df.budgetGA==budgetGA)] #& (df.repe==0)
          g = sns.lineplot(x='Sample
size',y=y_variable,hue='Solver',data=aux, palette=palette)
          namestr = 'n='+str(n)+', phi_inst='+str(phi_i)+',
budgetGA='+str(budgetGA)
          g.set_title(namestr)
          plt.savefig("img/"+y_variable+"_"+namestr+".jpg")
          plt.show()
```



Running times

[18]

```
phi_i, n, budgetGA = 0.9,10,1000
df[(df.phi_instance==phi_i) & (df.n==n) &
(df.budgetGA==budgetGA) ].repe.unique()
df = pd.read_pickle("pickles/pick282522.pkl")
df
```

	Fitness	Problem	Solver	Sample size	repe	Distance	r
0	0.665983	LOP	CEGO	0	0	72	8738
1	0.469618	LOP	CEGO	1	0	108	8738
2	0.556589	LOP	CEGO	2	0	92	8738
3	0.498859	LOP	CEGO	3	0	102	8738
4	0.526713	LOP	CEGO	4	0	99	8738
...	...	...	...	...	...	...	...

[15]

```
aux =
df[['Solver','run_time','n','budgetGA']].drop_duplicates().copy
()
aux.loc[aux.Solver.str.contains("uMM"),'Solver'] = "uMM"
aux.groupby(['Solver','n','budgetGA']).mean()/3600
```

			run_time
Solver	**n**	**budgetGA**	
CEGO	**10**	**100**	2.305674
		1000	6.867011
	20	**100**	4.385581
		1000	23.406106
uMM	**10**	**100**	0.004871
		1000	0.001678

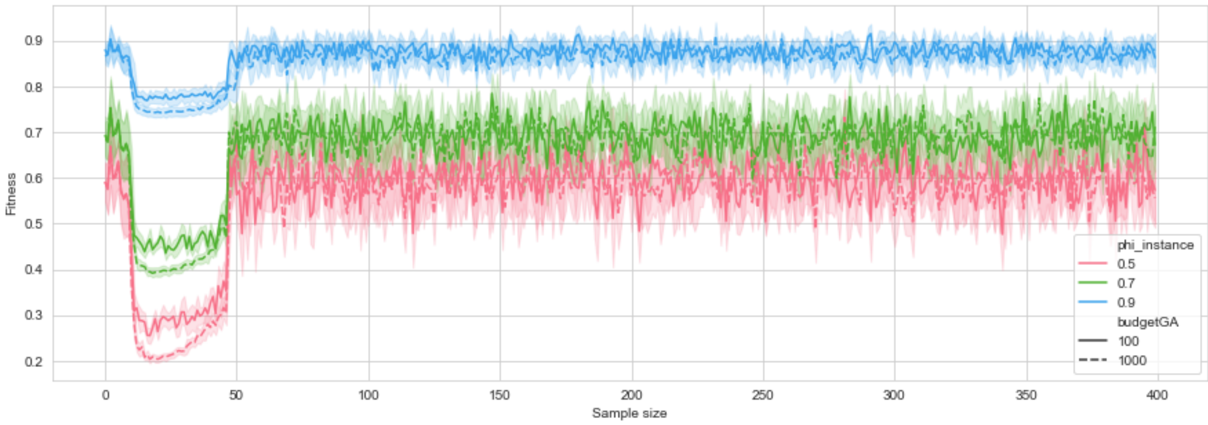
Effect of increasing budget in GA

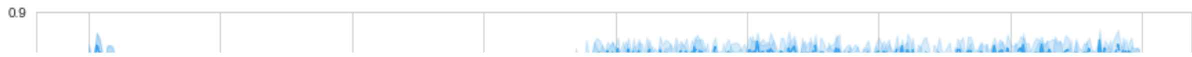
- the performance decreases with the budget
- better results for uniform that for easy, does it do anything?
- why that drop in the 20th iteration?

[56]

```
aux = df[df.Solver=='CEGO']
#aux = aux.groupby(['phi_instance','budgetGA','Sample size'])
['Fitness'].mean().reset_index()##.plot()
aux##[aux.budgetGA==100]g = sns.lineplot(x='Sample
size',y=y_variable,hue='Solver',data=aux, palette=palette)
palette = sns.color_palette("husl", 3)
plt.figure(figsize=(15,5))
sns.lineplot(x='Sample size',y='Fitness',
style='budgetGA',hue='phi_instance', data=aux[aux.n==10],
palette=palette)#ci=None,
plt.figure(figsize=(15,5))
sns.lineplot(x='Sample size',y='Fitness',
style='budgetGA',hue='phi_instance', data=aux[aux.n==20],
palette=palette)#ci=None,
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x136b617d0>
```





Do similar permutations have similar fitness?

In this experiment we analyse the relation between similarity in Kendall distance and in fitness funtion evaluation in the LOP instances. The process is as follows:

do 100 times:

1. a,b = generate two u.a.r. permutations
2. $x = d(a, b)$
3. $y = |f(a) - f(b)|$
4. draw a point in (x, y)

We see that:

- close permutations have similar fitness
- distant permutations have high variance in fitness

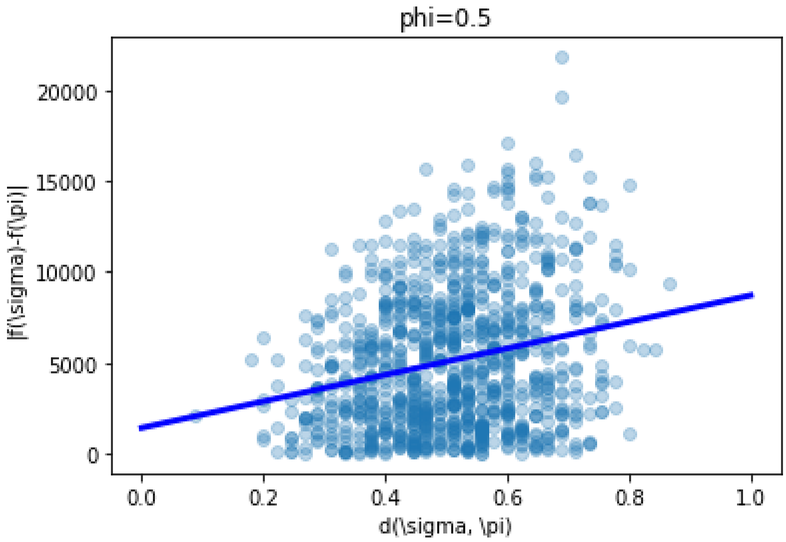
Kriging assumptions:

- stationarity (yes)
- constant variogram (no)

[32]

```
from sklearn import datasets, linear_model
from sklearn.metrics import mean_squared_error, r2_score
n = 10
for phi in [0.5,0.7,0.9]:
  instance = cego.synthetic_LOP(n,1000,phi)
  xs, ys = [],[]
  for repes in range(1000):
    a,b =
np.random.permutation(range(n)),np.random.permutation(range(n))
    ys.append(abs(cego.get_fitness(a, instance,"LOP") -
cego.get_fitness(b, instance,"LOP")))
    #xs.append(mk.kendallTau(np.argsort(a),np.argsort(b)))
#similar
    xs.append(mk.kendallTau(a,b)/(n*(n-1)/2))
  plt.scatter(xs,ys,alpha=0.3)
  regr = linear_model.LinearRegression()
  regr.fit([[x] for x in xs], ys)
  pred = regr.predict([[x] for x in np.linspace(0,1)])
  plt.plot(np.linspace(0,1), pred, color='blue', linewidth=3)

  plt.ylabel(r'|f(\sigma)-f(\pi)|')
  plt.xlabel(r'd(\sigma, \pi)')
  plt.title("phi="+str(phi))
  plt.show()
```



TODO

- meter más problemas: **PFSP**, TSP, ...
- comparar con otras alternativas: LS?
- el símil con la optimización bayesiana no está claro, cómo se traslada aquí la función de utilidad?
- demostración de convergencia rápida
- escribir draft para tener el modelo claro
- maximize (squarre) sum of distances for ini

```
[ ]
```

```
[ ]
```

Empty markdown cell, double click me to add content.