Results

December 12, 2018

1 Results of feature importance evaluations

1.1 Imports

```
In [1]: ## generals
        import pandas as pd
        import numpy as np
        import timeit
        from functools import partial
        import matplotlib.pyplot as plt
        from scipy.io import loadmat
        import matplotlib.pyplot as plt
        import time

        ## hoggorm
        import hoggorm as ho

        ##sklearn
        from sklearn.cross_decomposition import PLSRegression
        import sklearn.datasets
        from sklearn.exceptions import NotFittedError
        from sklearn.linear_model import Ridge
        from sklearn.model_selection import train_test_split
        from sklearn.metrics import mean_absolute_error

        ## mlxtend
        from mlxtend.feature_selection import ExhaustiveFeatureSelector as EFS

        ##selfmade
        from VIP import VIP
        from sMCf import sMC
        from IPW import IPW
```

1.2 VIP

1.2.1 intuitive vrs implemented

In [2]:
```
def VIP_implemented(pls,opt=None,p=None):
    """
    Computes the importances to the data given

    Get a quantified importance value for each parameter in the matrix X
    a set of column vectors equal in length to the number of variables
    included in the model. It contains one column of VIP scores for each
    predicted y-block column.

    Parameters
    ----------
    pls : object
        object from PLS regression with atributes y_loadings_, x_scores_
        and x_weights_.

    opt : int
        optimal number of components of PLS model.

    p : int
        number of variables in PLS model.


    Returns
    -------
    :returns value: a nx1 vector, where n are the number of features in x
    :type value: vector

    """
    pls = pls
    p = len(pls.coef_) if p is None else p
    opt = None if opt is None else opt

    q = pls.y_loadings_
    t = pls.x_scores_
    W = pls.x_weights_

    WW = np.divide(W*W ,np.ones((p,1))*sum(W*W)) # evt np.sum(W*W,axis=0)
    Q2TT = (np.dot(np.dot((q*q)[0:opt],t[:,0:opt].T),t[:,0:opt]))
    importances = np.sqrt(p*np.sum(np.ones((p,1))*Q2TT*WW[:,:opt],axis=1)/np.sum(Q2TT)

    return importances


def vip_git(model):
```

```
    """
    Aquired from https://github.com/scikit-learn/scikit-learn/issues/7050
    """
    t = model.x_scores_
    w = model.x_weights_
    q = model.y_loadings_
    p, h = w.shape
    vips = np.zeros((p,))
    s = np.diag(t.T @ t @ q.T @ q).reshape(h, -1)
    total_s = np.sum(s)
    for i in range(p):
        #weight = np.array([ (w[i,j] / np.linalg.norm(w[:,j]))**2 for j in range(h) ])
        #weight = np.array([ (w[i,j] / np.linalg.norm(w[:,j]))**2 for j in range(h) ])
        #weight = np.divide(w[i,:],np.linalg.norm(w))**2
        #inni = 2*s.T @np.divide(w[i,:],np.linalg.norm(w))**2
        #vips[i] = np.sqrt(p*(inni)/total_s)
        weight = np.array([ (w[i,j] / np.linalg.norm(w[:,j]))**2 for j in range(h) ])
        vips[i] = np.sqrt(p*(s.T @ weight)/total_s)
        #vips[i] = np.sqrt(p*(s.T @ weight)/total_s)
    return vips
```

```
In [3]: data = sklearn.datasets.load_boston()
        X = data['data']
        y = data['target']
        pls = PLSRegression()
        pls.fit(X,y)
        vip1 = VIP_implemented(pls)
        vip2 = vip_git(pls)
```

1.2.2 VIP scores

```
In [4]: np.round(vip1,14) == np.round(vip2,14)

Out[4]: array([ True,  True,  True,  True,  True,  True,  True,  True,  True,
                True,  True,  True,  True])
```

1.2.3 Speed

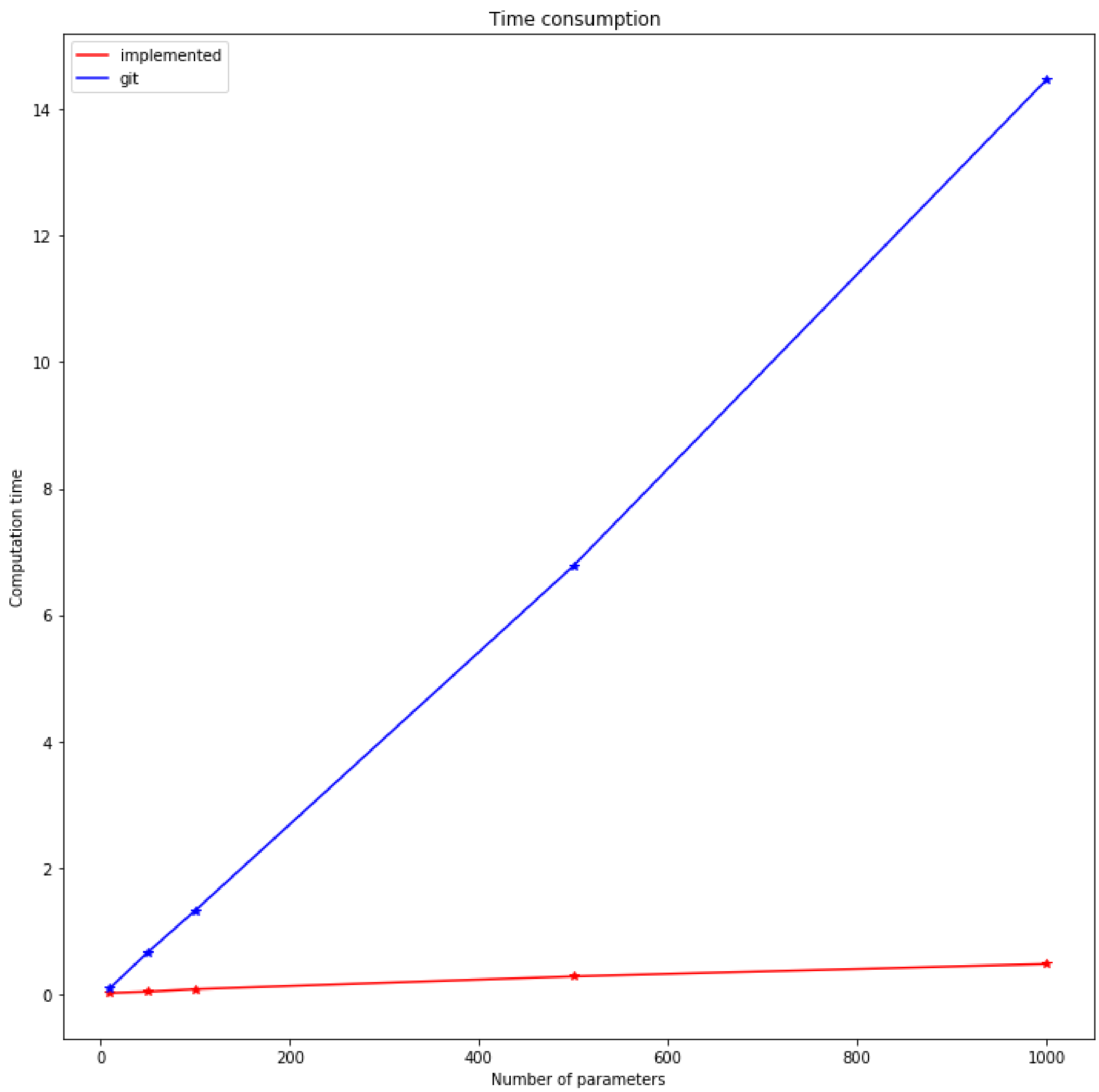
```
In [5]: times1 = timeit.Timer(partial(VIP_implemented, pls)).repeat(3, 1000)
        times2 = timeit.Timer(partial(vip_git, pls)).repeat(3, 1000)
        times1[0] /times2[0]
```

```
In [ ]: time_imp = []
        time_git = []
        params = [10,50,100,500,1000]#,1000,10000]#,100000]
        samples = 506
        for no_params in params:
            X_test = np.random.rand(samples,no_params)
            pls.fit(X_test,y)
```

```
        time_imp.append(timeit.Timer(partial(VIP_implemented, pls)).repeat(3, 500)[0])
        time_git.append(timeit.Timer(partial(vip_git, pls)).repeat(3, 500)[0])
```

```
In [51]: plt.figure(figsize=(12,12))
         plt.plot(params,time_imp,'r-',label='implemented')
         plt.plot(params,time_imp,'r*')
         plt.plot(params,time_git,'b-',label='git')
         plt.plot(params,time_git,'b*')

         plt.legend(loc='upper left')
         plt.title('Time consumption ')
         plt.xlabel('Number of parameters')
         plt.ylabel('Computation time [s]')
         plt.show()
```



```
In [54]: slope_imp = [(time_imp[i]-time_imp[i-1])/(params[i]-params[i-1]) for i in range(1,len
         slope_git = a = [(time_git[i]-time_git[i-1])/(params[i]-params[i-1]) for i in range(1
         print(np.mean(slope_imp),np.mean(slope_git),np.mean(slope_imp)/np.mean(slope_git))
```

1.3 score on Boston Housing Dataset

1.3.1 VIP

```
In [9]: ##Sklearn
        Importance_Boston_VIP = pd.DataFrame(index =data['feature_names'])
        vip = VIP()
        pls_sklearn = PLSRegression(scale=False)
        pls_sklearn.fit(X,y)
        vip.fit(pls_sklearn)
        Importance_Boston_VIP['sklearn pls'] = vip.importances

        #Values from Matlab
        #Stored values from the VIP process in matlab as vipscores1.mat in the validering fold
        Importance_Boston_VIP['Matlab VIP'] =  loadmat('./validering/vipscores1.mat')['values']

        # values in python from matlab PLS atributes
        #Stored values of X scores as xs.mat and weigts as w.mat from matlab pls method in the
        pls.y_loadings_ = np.array([[101.729463326136,34.0591751857485]]) # extracted y_loadin
        pls.x_scores_ = loadmat('./validering/xs.mat')['Xs']
        pls.x_weights_ = loadmat('./validering/W.mat')['W']
        vip.fit(pls)
        Importance_Boston_VIP['matlab pls'] =vip.importances

        #hoggorm PLS
        pls_ho =  ho.nipalsPLS1(X, y.reshape(506,1), cvType=['loo'], numComp=2)
        vip.fit(pls_ho)
        Importance_Boston_VIP['hoggorm pls'] =vip.importances

        # extracted from r
        Importance_Boston_VIP['R-VIP nipals pls'] = pd.Series([0.171312472, 0.709292976, 0.177
                                                         0.002431485, 0.056888702, 0.6
                                                         0.152825608, 3.160193230, 0.0
                                                         0.496683595] ,index=data['fea

        Importance_Boston_VIP

loo
loo
```

Out[9]:

	sklearn pls	Matlab VIP	matlab pls	hoggorm pls	R-VIP nipals pls
CRIM	0.171312	0.173715	0.173715	0.171312	0.171312
ZN	0.709293	0.716212	0.716212	0.709293	0.709293

INDUS	0.177492	0.179978	0.179978	0.177492	0.177492
CHAS	0.005766	0.005796	0.005796	0.005766	0.005766
NOX	0.002431	0.002465	0.002465	0.002431	0.002431
RM	0.056889	0.057243	0.057243	0.056889	0.056889
AGE	0.618079	0.626494	0.626494	0.618079	0.618079
DIS	0.021929	0.021727	0.021727	0.021929	0.021929
RAD	0.152826	0.150566	0.150566	0.152826	0.152826
TAX	3.160193	3.149395	3.149395	3.160193	3.160193
PTRATIO	0.095656	0.096555	0.096555	0.095656	0.095656
B	1.335759	1.351521	1.351521	1.335759	1.335759
LSTAT	0.496684	0.500895	0.500895	0.496684	0.496684

1.3.2 sMC

In [10]:
```
# sklearn
Importance_Boston_sMC = pd.DataFrame(index = data['feature_names'])
pls = PLSRegression(scale=False)
pls.fit(X,y)
smc = sMC()
smc.fit(pls,X)
Importance_Boston_sMC['sklearn pls'] = smc.importances

# values from matlab
#Stored values from the sMC process in matlab as values_smc_1.mat in the validering f
Importance_Boston_sMC['Matlab sMC'] = loadmat('./validering/values_smc_1_centered.mat

# values in python from matlab coefficients
# beta values from matlab are stored as beta_1 in the validering folder
pls = PLSRegression()
pls.fit(X,y)
coef = loadmat('./validering/beta_1_centered.mat')['BETA']
pls.coef_ = coef[1:] # remove interception
smc = sMC()
smc.fit(pls,X)
Importance_Boston_sMC['Matlab coef']= smc.importances

# hoggorm pls
#from sMCf import sMC
pls =  ho.nipalsPLS1(X, y.reshape(506,1), cvType=['loo'], numComp=2)
smc.fit(pls,X)
Importance_Boston_sMC['hoggorm pls'] =smc.importances

# Values from R
# extracted from r
Importance_Boston_sMC['R sMC w/nipals pls'] = pd.Series([7.209326e+02, 6.146978e+02,
                                                         3.883885e+02, 9.805696e+02,
                                                         7.607644e+02, 2.350280e-03,
                                                         5.910422e+01, 6.033948e+02,
```

```
6.270982e+02], index=data['fe
```

```
Importance_Boston_sMC
```

```
loo
loo
```

```
Out[10]:          sklearn pls   Matlab sMC  Matlab coef  hoggorm pls  \
         CRIM      720.932559   720.932559   720.932559   720.932559
         ZN        614.697833   614.697833   614.697833   614.697833
         INDUS    1001.570191  1001.570191  1001.570191  1001.570191
         CHAS      388.388473   388.388473   388.388473   388.388473
         NOX       980.569572   980.569572   980.569572   980.569572
         RM        542.168964   542.168964   542.168964   542.168964
         AGE       760.764384   760.764384   760.764384   760.764384
         DIS         0.002350     0.002350     0.002350     0.002350
         RAD        27.029754    27.029754    27.029754    27.029754
         TAX        59.104216    59.104216    59.104216    59.104216
         PTRATIO   603.394756   603.394756   603.394756   603.394756
         B         757.993942   757.993942   757.993942   757.993942
         LSTAT     627.098220   627.098220   627.098220   627.098220

                  R sMC w/nipals pls
         CRIM               720.93260
         ZN                 614.69780
         INDUS             1001.57000
         CHAS               388.38850
         NOX                980.56960
         RM                 542.16900
         AGE                760.76440
         DIS                  0.00235
         RAD                 27.02975
         TAX                 59.10422
         PTRATIO            603.39480
         B                  757.99390
         LSTAT              627.09820
```

1.3.3 IPW

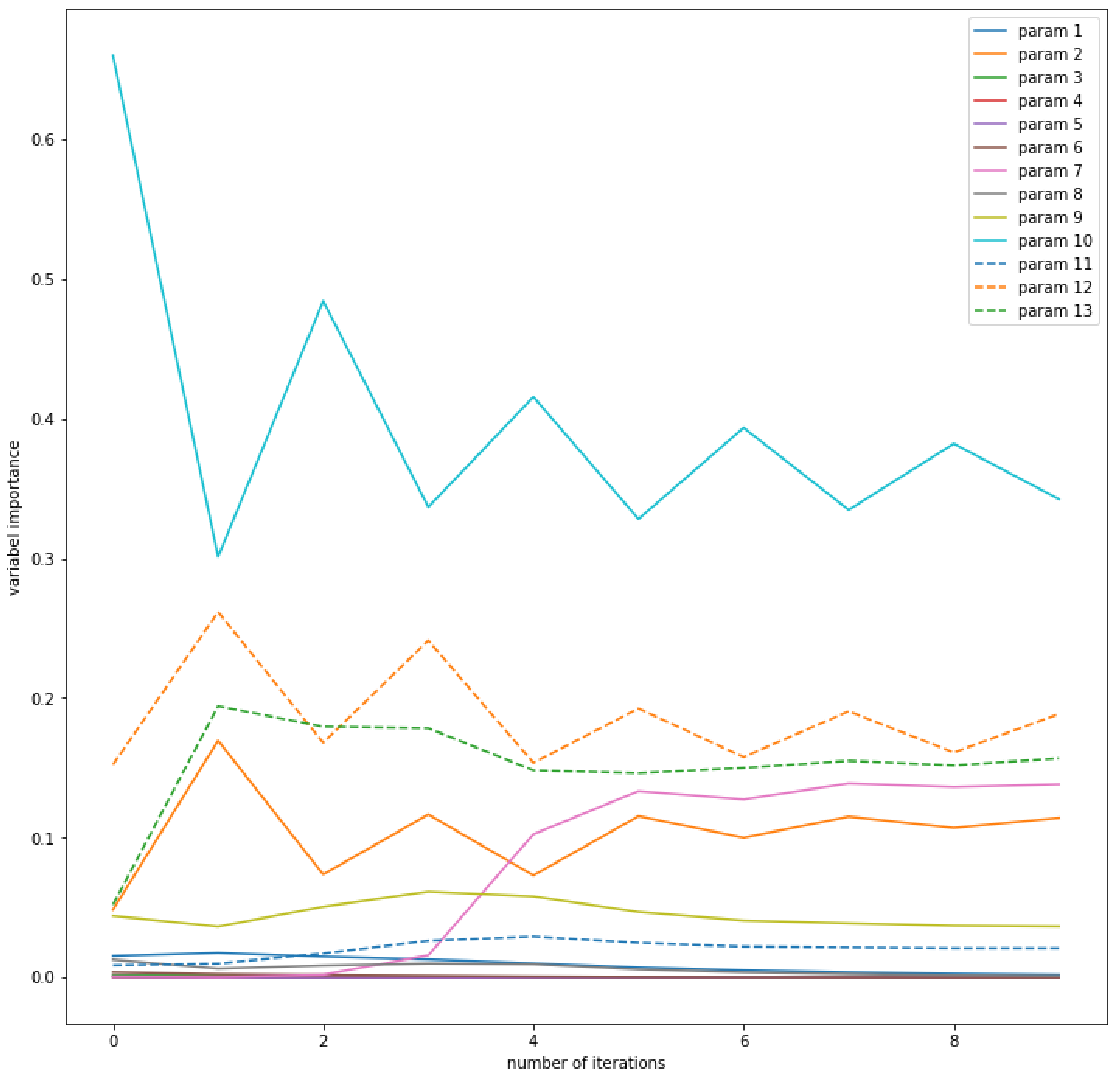
sklearn

```
In [11]: Importance_Boston_IPW = pd.DataFrame(index = data['feature_names'])
         r = Ridge()
         ipw = IPW()
         ipw.fit(r,X,y,threshold=0)
         Importance_Boston_IPW['sklearn Ridge'] = ipw.importances
```

```
In [12]: Importance_Boston_IPW
```

```
Out[12]:          sklearn Ridge
         CRIM      1.799166e-03
         ZN        1.141085e-01
         INDUS     1.665880e-10
         CHAS      1.910537e-13
         NOX       3.736411e-26
         RM        1.713835e-05
         AGE       1.381398e-01
         DIS       1.086916e-03
         RAD       3.639848e-02
         TAX       3.423726e-01
         PTRATIO   2.087235e-02
         B         1.885313e-01
         LSTAT     1.566738e-01
```

```
In [13]: ipw.plot_development()
```



1.4 Comparison

The comparioson is done with Sklearn and Hoggorm, which as been done to indicate the diffrent result with and without scaling.

Shown Below is the results obtained with scaling wich is done with sklearn and without scaling which is done with Hoggorm.

Tables of both the rank and the measure of importance have been included for both cases

1.4.1 sklearn

In [24]:
```
Importance_Boston_Comp = pd.DataFrame(index =data['feature_names'])
vip = VIP()
smc = sMC()
ipw = IPW()
r = Ridge()
pls = PLSRegression(scale=True)
pls.fit(X,y)

vip.fit(pls)
Importance_Boston_Comp['VIP sklearn'] = vip.importances
smc.fit(pls,X)
Importance_Boston_Comp['sMC sklearn'] = smc.importances

ipw.fit(r,X,y,threshold=0)
Importance_Boston_Comp['IPW sklearn Ridge'] = ipw.importances
Importance_Boston_Comp
```

Out[24]:

	VIP sklearn	sMC sklearn	IPW sklearn Ridge
CRIM	0.733727	7.962739e+01	1.799166e-03
ZN	0.717301	3.118435e+00	1.141085e-01
INDUS	0.970405	8.159210e+01	1.665880e-10
CHAS	0.570576	5.055341e+02	1.910537e-13
NOX	0.924612	6.285301e+02	3.736411e-26
RM	1.635932	5.192550e+02	1.713835e-05
AGE	0.854793	1.654036e-07	1.381398e-01
DIS	1.051266	3.151353e+02	1.086916e-03
RAD	0.907570	2.132675e+00	3.639848e-02
TAX	0.950611	6.668559e-02	3.423726e-01
PTRATIO	1.012233	6.008149e+02	2.087235e-02
B	0.619090	6.739726e-01	1.885313e-01
LSTAT	1.475682	8.972325e+02	1.566738e-01

In [25]:
```
Importance_Boston_Comp_no = pd.DataFrame(index =data['feature_names'])
Importance_Boston_Comp_no['VIP sklearn pls'] = np.argsort(np.argsort(vip.importances)
Importance_Boston_Comp_no['sMC sklearn pls'] = np.argsort(np.argsort(smc.importances)
```

```
Importance_Boston_Comp_no['IPW sklearn Ridge'] = np.argsort(np.argsort(ipw.importances
Importance_Boston_Comp_no
```

Out[25]:

	VIP sklearn pls	sMC sklearn pls	IPW sklearn Ridge
CRIM	10	8	8
ZN	11	9	5
INDUS	5	7	11
CHAS	13	5	12
NOX	7	2	13
RM	1	4	10
AGE	9	13	4
DIS	3	6	9
RAD	8	10	6
TAX	6	12	1
PTRATIO	4	3	7
B	12	11	2
LSTAT	2	1	3

1.4.2 Hoggorm

In [26]:

```
Importance_Boston_Comp = pd.DataFrame(index =data['feature_names'])
vip = VIP()
smc = sMC()
ipw = IPW()
r = Ridge()
#pls = PLSRegression()
#pls.fit(X,y)
pls =  ho.nipalsPLS1(X, y.reshape(506,1), cvType=['loo'], numComp=2,Xstand=False)

vip.fit(pls)
Importance_Boston_Comp['VIP sklearn'] = vip.importances
smc.fit(pls,X)
Importance_Boston_Comp['sMC sklearn'] = smc.importances

ipw.fit(r,X,y,threshold=0)
Importance_Boston_Comp['IPW sklearn Ridge'] = ipw.importances
Importance_Boston_Comp
```

```
loo
loo
```

Out[26]:

	VIP sklearn	sMC sklearn	IPW sklearn Ridge
CRIM	0.171312	720.932559	1.799166e-03
ZN	0.709293	614.697833	1.141085e-01
INDUS	0.177492	1001.570191	1.665880e-10
CHAS	0.005766	388.388473	1.910537e-13
NOX	0.002431	980.569572	3.736411e-26
RM	0.056889	542.168964	1.713835e-05

```
AGE         0.618079   760.764384       1.381398e-01
DIS         0.021929     0.002350       1.086916e-03
RAD         0.152826    27.029754       3.639848e-02
TAX         3.160193    59.104216       3.423726e-01
PTRATIO     0.095656   603.394756       2.087235e-02
B           1.335759   757.993942       1.885313e-01
LSTAT       0.496684   627.098220       1.566738e-01
```

```
In [27]: Importance_Boston_Comp_no = pd.DataFrame(index =data['feature_names'])
         Importance_Boston_Comp_no['VIP hoggorm pls'] = np.argsort(np.argsort(vip.importances)
         Importance_Boston_Comp_no['sMC hoggorm pls'] = np.argsort(np.argsort(smc.importances)
         Importance_Boston_Comp_no['IPW sklearn Ridge'] = np.argsort(np.argsort(ipw.importance
         Importance_Boston_Comp_no
```

Out[27]:

	VIP hoggorm pls	sMC hoggorm pls	IPW sklearn Ridge
CRIM	7	5	8
ZN	3	7	5
INDUS	6	1	11
CHAS	12	10	12
NOX	13	2	13
RM	10	9	10
AGE	4	3	4
DIS	11	13	9
RAD	8	12	6
TAX	1	11	1
PTRATIO	9	8	7
B	2	4	2
LSTAT	5	6	3

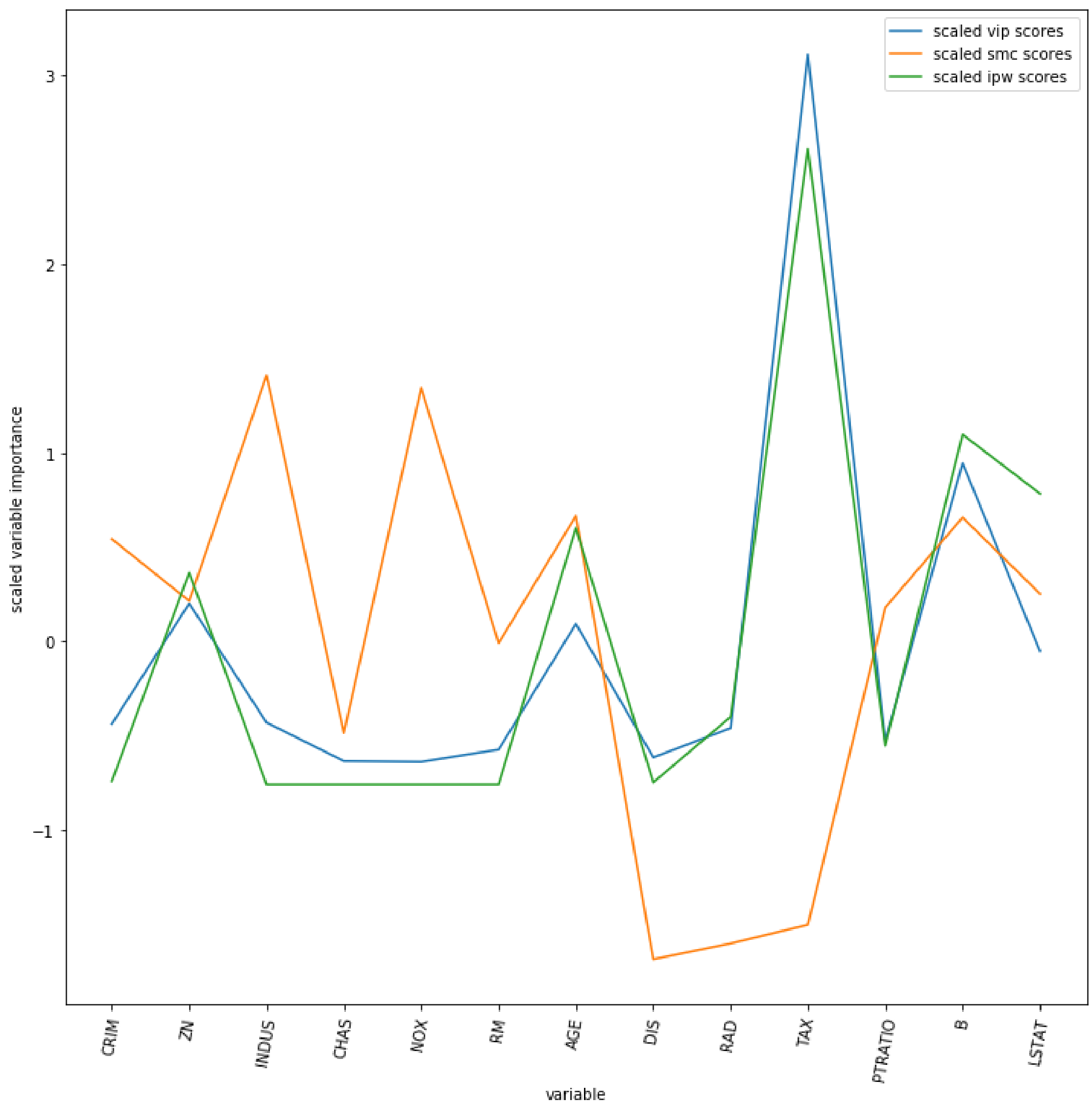
1.4.3 Visulization

Scaling

```
In [29]: vip_scaled = (vip.importances - np.mean(vip.importances))/np.std(vip.importances)
         smc_scaled = (smc.importances - np.mean(smc.importances))/np.std(smc.importances)
         ipw_scaled = (ipw.importances - np.mean(ipw.importances))/np.std(ipw.importances)
```

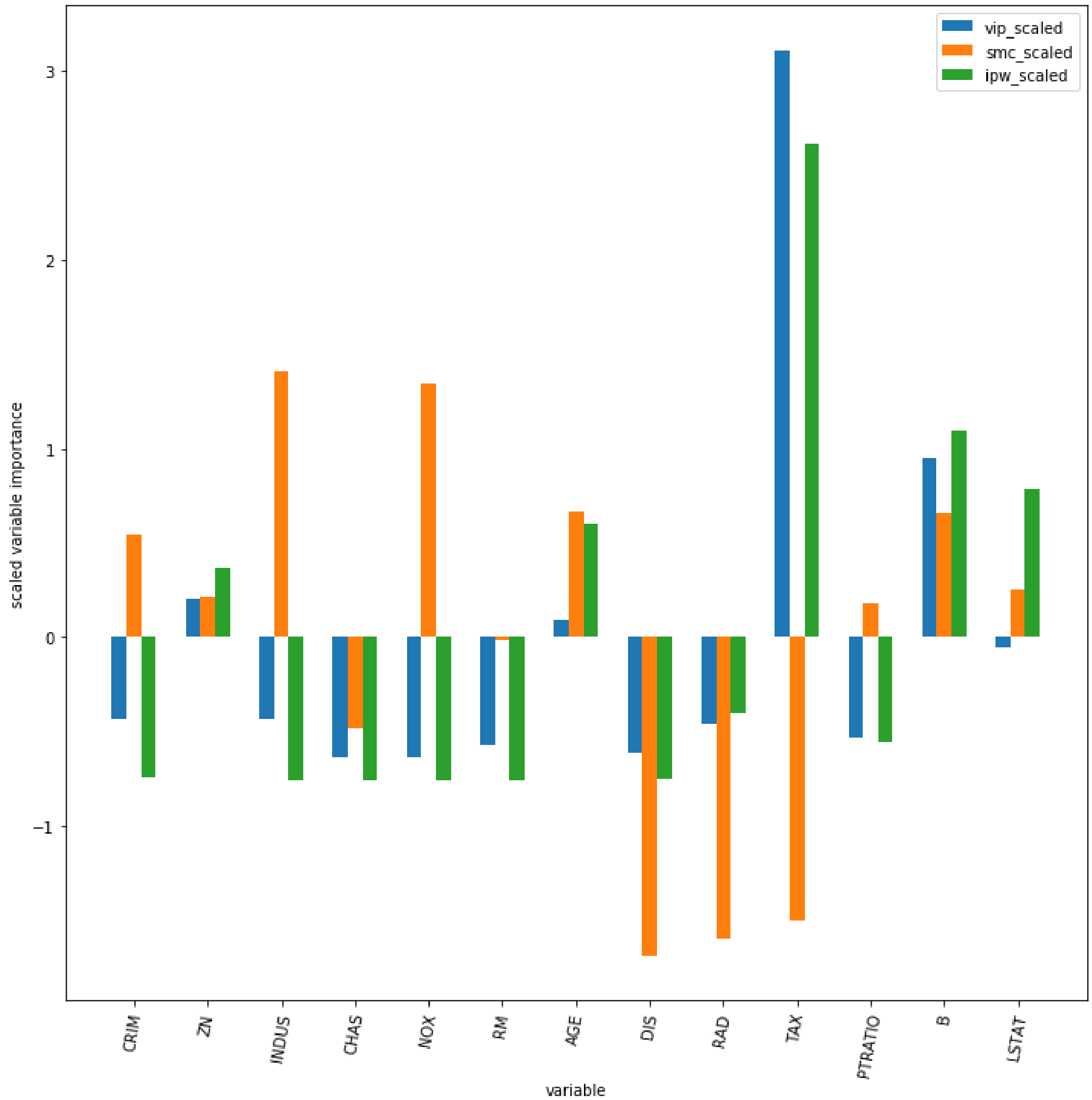
graf

```
In [30]: plt.figure(figsize=(12,12))
         plt.plot(range(0,13),vip_scaled,label = 'scaled vip scores')
         plt.plot(range(0,13),smc_scaled,label = 'scaled smc scores')
         plt.plot(range(0,13),ipw_scaled,label = 'scaled ipw scores')
         plt.legend(loc='upper right')
         plt.xticks(range(X.shape[1]), data['feature_names'], rotation=80)
         plt.xlabel('variable')
         plt.ylabel('scaled variable importance')
         plt.show()
```



histogram

In [55]:
```
plt.figure(figsize=(12,12))
w = 0.2
plt.bar(np.arange(len(vip_scaled))-w, vip_scaled,width=w, label ='vip_scaled')
plt.bar(np.arange(len(smc_scaled)), smc_scaled,width=w, label ='smc_scaled')
plt.bar(np.arange(len(ipw_scaled))+w, ipw_scaled,width=w, label ='ipw_scaled')
plt.xticks(range(X.shape[1]), data['feature_names'], rotation=80)
plt.yticks(size=10)
plt.legend(loc='upper right')
plt.xlabel('variable')
plt.ylabel('scaled variable importance')
plt.show()
```



1.5 Effects on Key Peformance Indicators

```
In [311]: ## introducing efs
          r = Ridge()

          efs1 = EFS(r,
                     min_features=1,
                     max_features=13,
                     scoring='neg_mean_absolute_error',#'neg_mean_squared_error',
                     print_progress=True,
                     cv=5)

          #efs1.fit(X_train, y_train)
```

```
Features: 8191/8191
```

Out[311]:
```
ExhaustiveFeatureSelector(clone_estimator=True, cv=5,
                estimator=Ridge(alpha=1.0, copy_X=True, fit_intercept=True, max_iter=No
      normalize=False, random_state=None, solver='auto', tol=0.001),
                max_features=13, min_features=1, n_jobs=1,
                pre_dispatch='2*n_jobs', print_progress=True,
                scoring='neg_mean_absolute_error')
```

In [ ]:
```python
## introducing efs
r1 = Ridge()

efs1 = EFS(r1,
           min_features=1,
           max_features=13,
           scoring='mean_absolute_error'#'neg_mean_squared_error',
           print_progress=True,
           cv=5)

## Models
baseline = Ridge()
vip_model = Ridge()
smc_model = Ridge()
ipw_model = Ridge()
r_efs = Ridge()
r = Ridge() # for readability used inside the IPW

## score storage
baseline_scores = []
vip_scores = []
smc_scores = []
ipw_scores = []
efs_score = []

## number of parameters storage
no_param_vip = []
no_param_smc = []
no_param_ipw = []
no_param_efs = []

## time consumption storage
time_vip = []
time_smc = []
time_ipw = []
efs_times = []

storage = {}
for state in range(100):
```

```
X_train, X_test, y_train, y_test = train_test_split(X,
                                                     y,
                                                    test_size=0.3,
                                                    random_state=state)

pls = ho.nipalsPLS1(X_train, y_train.reshape(np.shape(y_train)[0],1), cvType=['loo
vip = VIP()
smc = sMC()
ipw = IPW()

#time fit_tranform efs
t0_efs1 = time.time()
efs1.fit(X_train, y_train)
t1_efs1 = time.time()
efs_times.append(t1_efs1-t0_efs1)

#time fit_tranform vip
t0 = time.time()
vip_trans = vip.fit_transform(pls,X_train,threshold=1)
t1 = time.time()
time_vip.append(t1-t0)

#time fit_tranform smc
t0 = time.time()
smc_trans = smc.fit_transform(pls,X_train,alpha_mc=0.001)
t1 = time.time()
time_smc.append(t1-t0)

#time fit_tranform IPW
t0 = time.time()
ipw_trans = ipw.fit_transform(r,X_train,y_train,no_iter=40,threshold=0.05)
t1 = time.time()
time_ipw.append(t1-t0)

#Storage of number of parameters
no_param_vip.append(np.shape(vip_trans)[1])
no_param_smc.append(np.shape(smc_trans)[1])
no_param_ipw.append(np.shape(ipw_trans)[1])
no_param_efs.append(len(efs1.best_idx_))

#transform test data
vip_test = vip.transform(X_test,threshold=1)
smc_test = smc.transform(X_test)
ipw_test = ipw.transform(X_test)

#fit different models to given data
baseline.fit(X_train,y_train)
vip_model.fit(vip_trans,y_train)
```

```
    smc_model.fit(smc_trans,y_train)
    ipw_model.fit(ipw_trans,y_train)
    r_efs.fit(X_train[:,efs1.best_idx_],y_train)

    storage[str(state)] = data['feature_names'][vip.importances>1]

    baseline_scores.append(mean_absolute_error(y_test, baseline.predict(X_test)))
    vip_scores.append(mean_absolute_error(y_test,vip_model.predict(vip_test)))
    smc_scores.append(mean_absolute_error(y_test,smc_model.predict(smc_test)))
    ipw_scores.append(mean_absolute_error(y_test,ipw_model.predict(ipw_test)))
    efs_score.append(mean_absolute_error(y_test, r_efs.predict(X_test[:,efs1.best_idx_
```

In [296]:
```
print('    avrage mean squared error for baseline model is {0:4f} with std +/-{1:4f}
print('    avrage mean squared error for vip selection is {0:4f} with std +/-{1:4f}'
print('    avrage mean squared error for smc selection is {0:4f} with std +/-{1:4f}'
print('    avrage mean squared error for ipw selection is {0:4f} with std +/-{1:4f}'
print('    avrage mean squared error for efs model is {0:4f} with std +/-{1:4f}'.forr
```

```
    avrage mean squared error for baseline model is 8.264785 with std +/-3.701695
    avrage mean squared error for vip selection is 5.861383 with std +/-0.379991
    avrage mean squared error for smc selection is 7.227898 with std +/-3.752635
    avrage mean squared error for ipw selection is 6.045653 with std +/-0.650087
    avrage mean squared error for baseline model is 3.453203 with std +/-0.244792
```

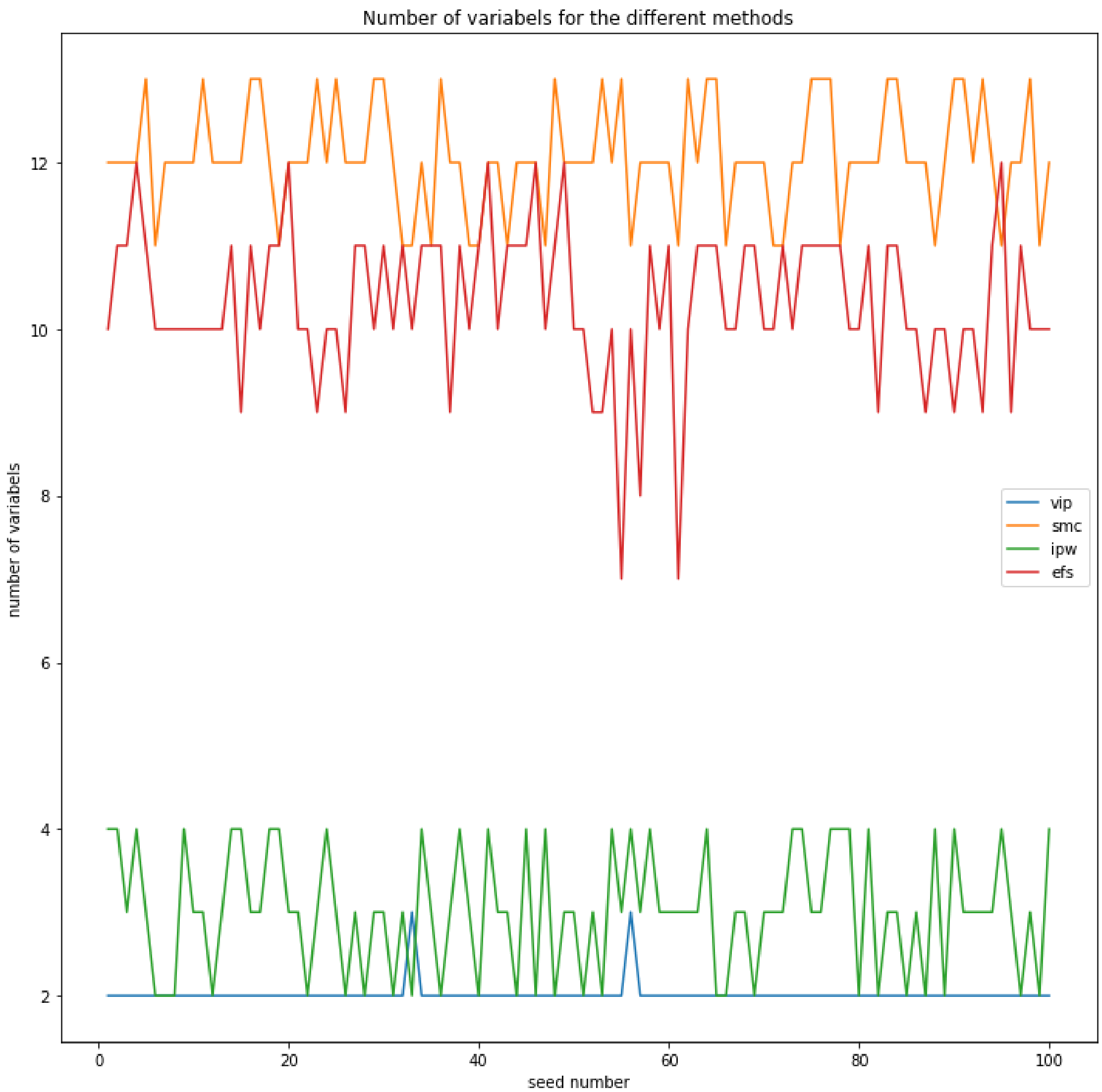
In [304]:
```
col_names= ['Average mse', 'Standard deviation', 'Average number of features','averag
KPI = pd.DataFrame(index =col_names)
KPI['Baseline'] = pd.Series([np.mean(baseline_scores),np.std(baseline_scores),13,0],i
KPI['VIP'] = pd.Series([np.mean(vip_scores),np.std(vip_scores),np.mean(no_param_vip)
KPI['sMC'] = pd.Series([np.mean(smc_scores),np.std(smc_scores),np.mean(no_param_smc)
KPI['IPW'] = pd.Series([np.mean(ipw_scores),np.std(ipw_scores),np.mean(no_param_ipw)
KPI['EFS'] = pd.Series([np.mean(efs_score),np.std(efs_score),np.mean(no_param_efs),np
KPI
```

Out[304]:
```
                             Baseline       VIP        sMC       IPW  \
Average mse                  8.264785  5.861383   7.227898  6.045653
Standard deviation           3.701695  0.379991   3.752635  0.650087
Average number of features  13.000000  2.020000  12.060000  3.020000
average time fit_transform   0.000000  0.000210   0.000791  0.025638

                                  EFS
Average mse                  3.453203
Standard deviation           0.244792
Average number of features  10.310000
average time fit_transform  54.709215
```

In [247]:
```
plt.figure(figsize=(12,12))
plt.plot(range(1,101),no_param_vip,label='vip')
plt.plot(range(1,101),no_param_smc,label='smc')
```

```
plt.plot(range(1,101),no_param_ipw,label='ipw')
plt.plot(range(1,101),no_param_efs,label='efs')
plt.legend(loc='best')
plt.xlabel('seed number')
plt.ylabel('number of variabels')
plt.title('Number of variabels for the different methods')
plt.show()
```



1.5.1 Output from the different PLS algorithms

In [ ]:

```
X = data['data']
y = data['target']
pls_sklearn = PLSRegression(n_components=13,scale=False)
```

```
    pls_sklearn.fit(X,y)
    pls_ho = ho.nipalsPLS1(X,y.reshape(506,1),numComp=13,Xstand=False)
```

```
In [ ]: #Cleared output
        print(np.divide(pls_sklearn.x_weights_,pls_ho.arrW))
        print(np.divide(pls_sklearn.x_scores_,pls_ho.arrT))
        print(pls_sklearn.y_loadings_/pls_ho.arrQ)
```