

DATA-DRIVEN IDENTIFICATION

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Find $(\mathbf{u}, \boldsymbol{\sigma})$ such that

Admissibility for \mathbf{u}

$$\mathbf{u} = \mathbf{u}_d \text{ on } \Gamma_u + \text{regularity}$$

Balance of momentum

$$\text{div}(\boldsymbol{\sigma}) = 0$$

Compatibility

$$\boldsymbol{\epsilon} = \frac{1}{2}(\nabla \mathbf{u} + \nabla^T \mathbf{u})$$

Balance of external forces

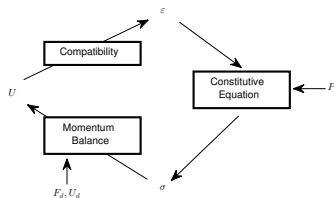
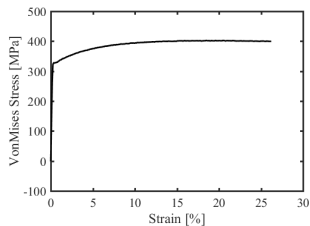
$$\boldsymbol{\sigma}(\mathbf{n}) = \mathbf{F}_d \text{ on } \Gamma_F$$

Regularization

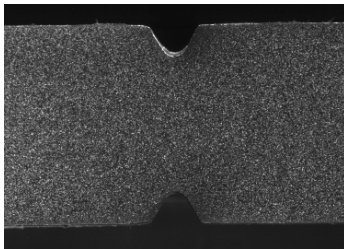
Sample with a geometry such that the solution is unique.
Usual specimen geometry for uni-, bi-, tri-axial testing,...

IDENTIFICATION OF CONSTITUTIVE LAWS

► “Engineering” approach

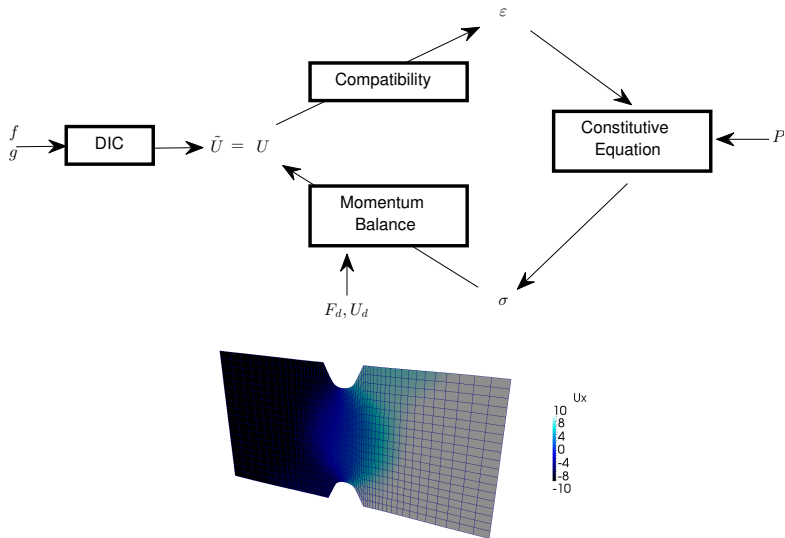


► Validation ?

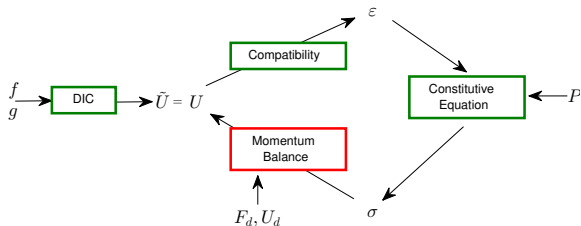


by G. Portemont at ONERA Lille

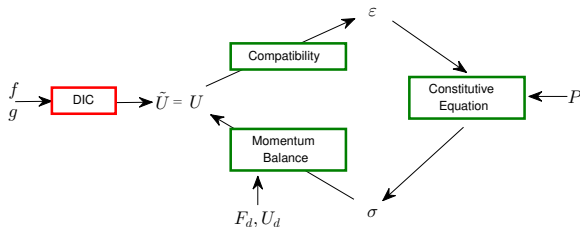
► Photomechanics



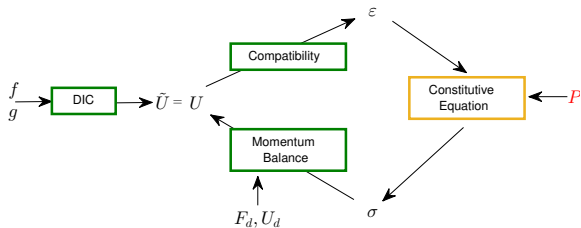
► Stress calculation



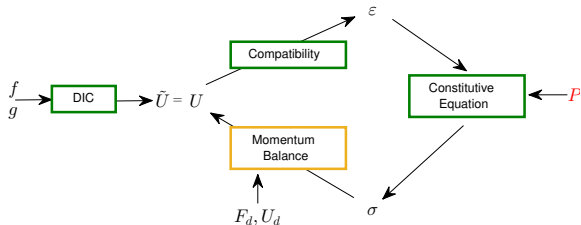
► Numerical simulation



► Constitutive Equation Gap [Chrysochoos *et al.*]

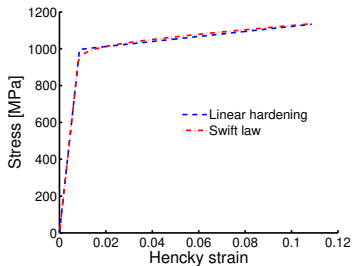
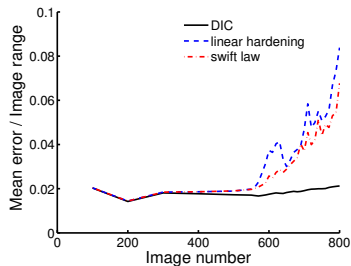
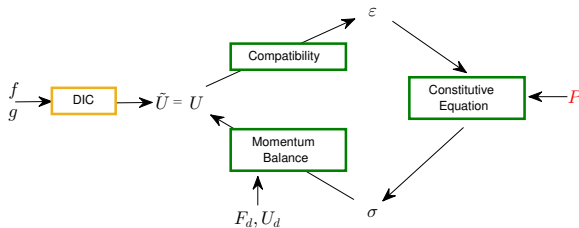


► Equilibrium gap [Claire *et al.*, 2004], VFM [Grédiac *et al.*, 2006]

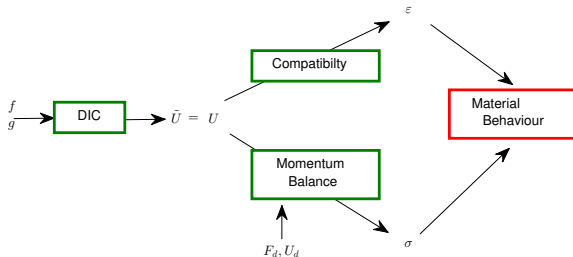


IDENTIFICATION OF CONSTITUTIVE LAWS

- FEMU [Lecompte et al., 2007, Leclerc et al., 2009]...

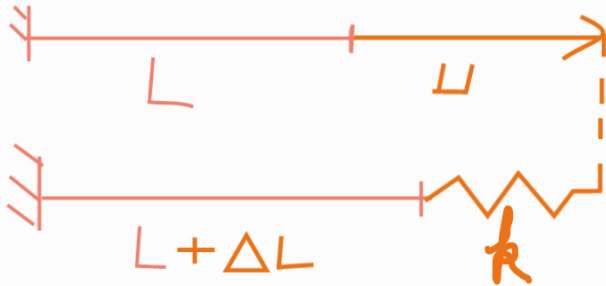


- ▶ Parametric techniques (using a constitutive equation)
 - + provide for the optimal set of parameters
 - +/- tell that the constitutive equation is not correct
 - how to improve it
 - kinematically consistent direct FEA
- ▶ Non-parametric (without using a constitutive equation)



SIMPLE PROBLEM

Problem definition

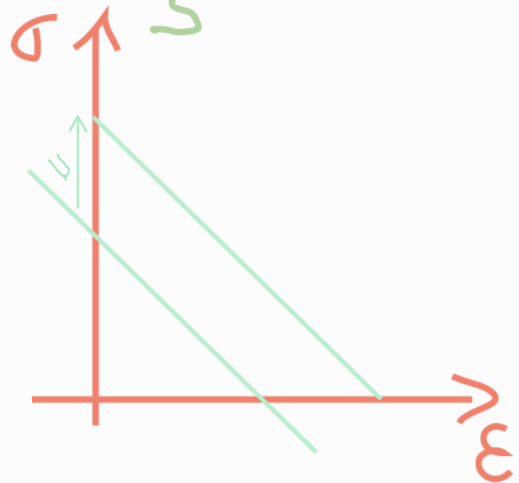


Balance of momentum

$$\sigma = \frac{(L - \Delta L)k}{S}$$
$$\sigma = \frac{Lk}{S} - \epsilon \frac{Lk}{S}$$

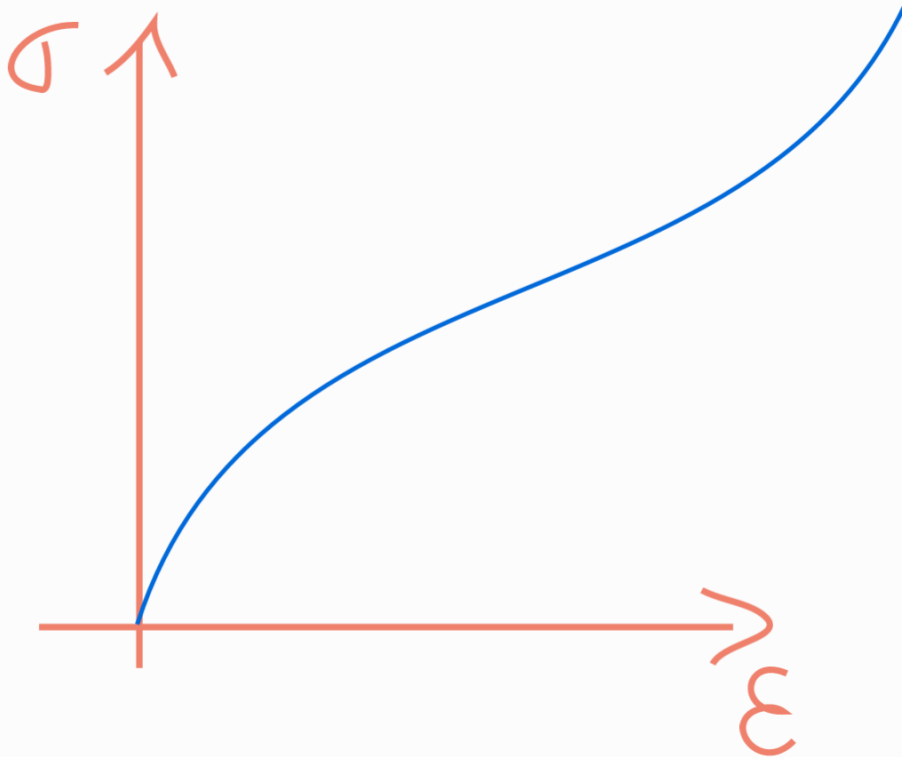
Compatibility

$$\epsilon = \frac{\Delta L}{L}$$



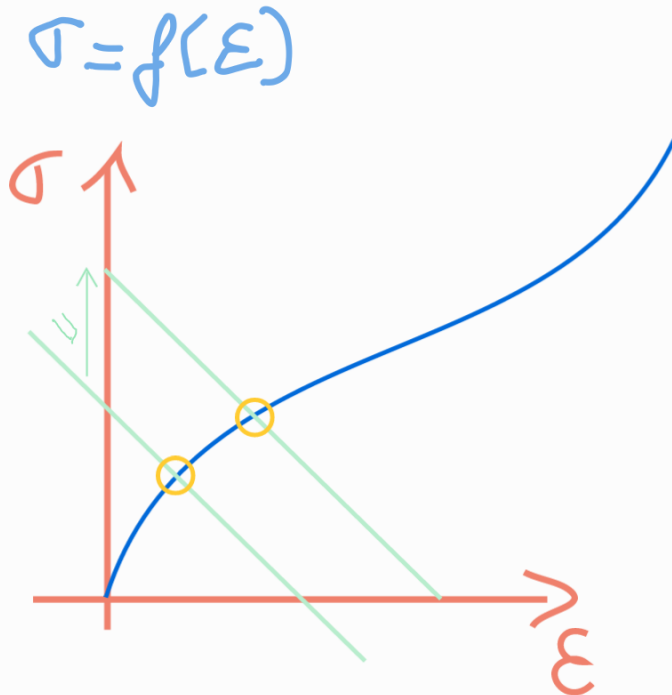
CONSTITUTIVE LAW

$$\sigma = f(\varepsilon)$$

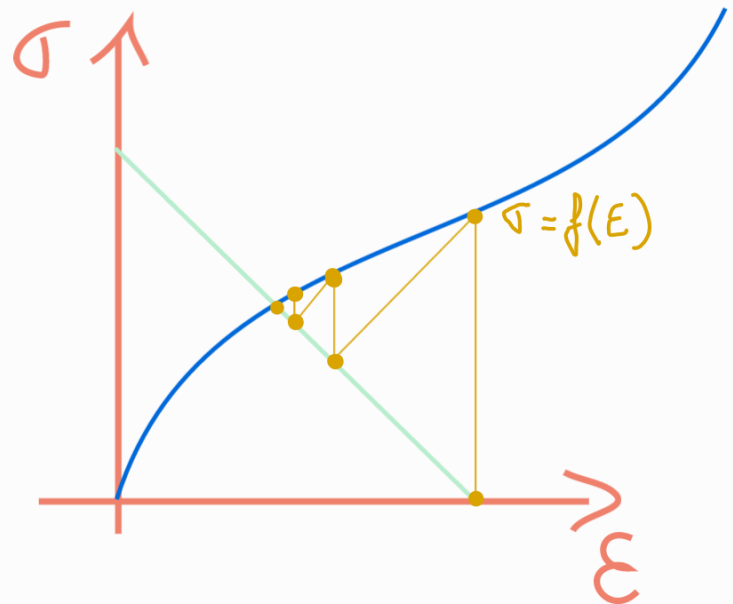


RESOLUTION

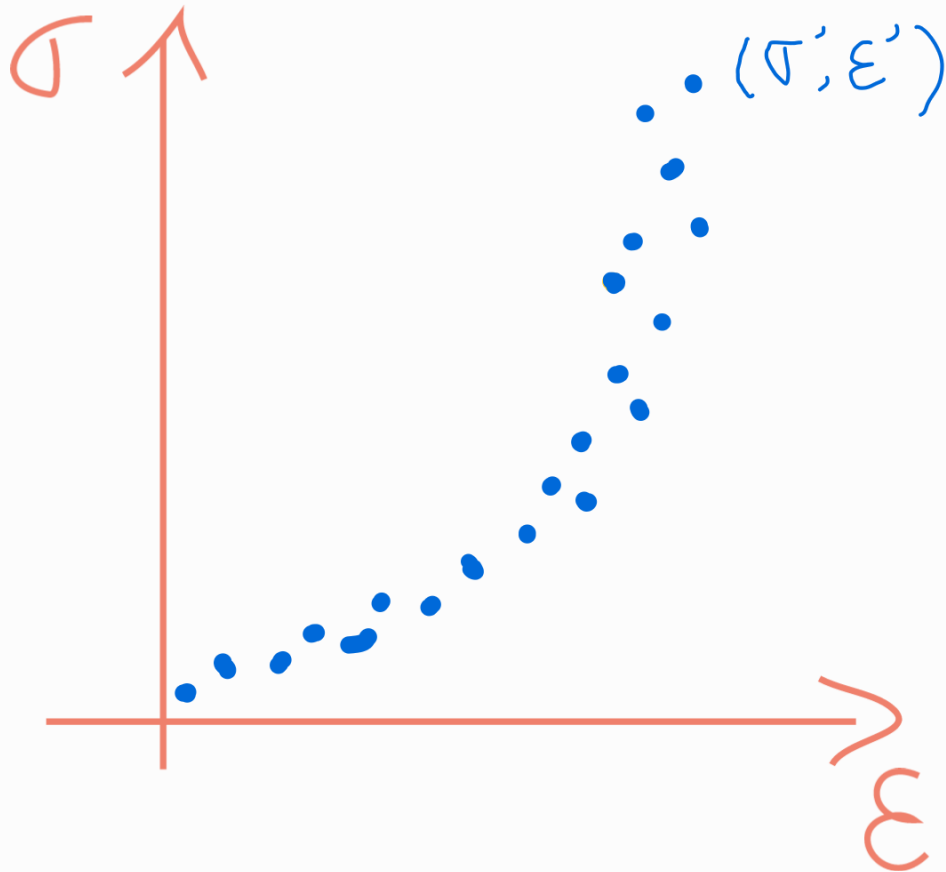
Expected solution



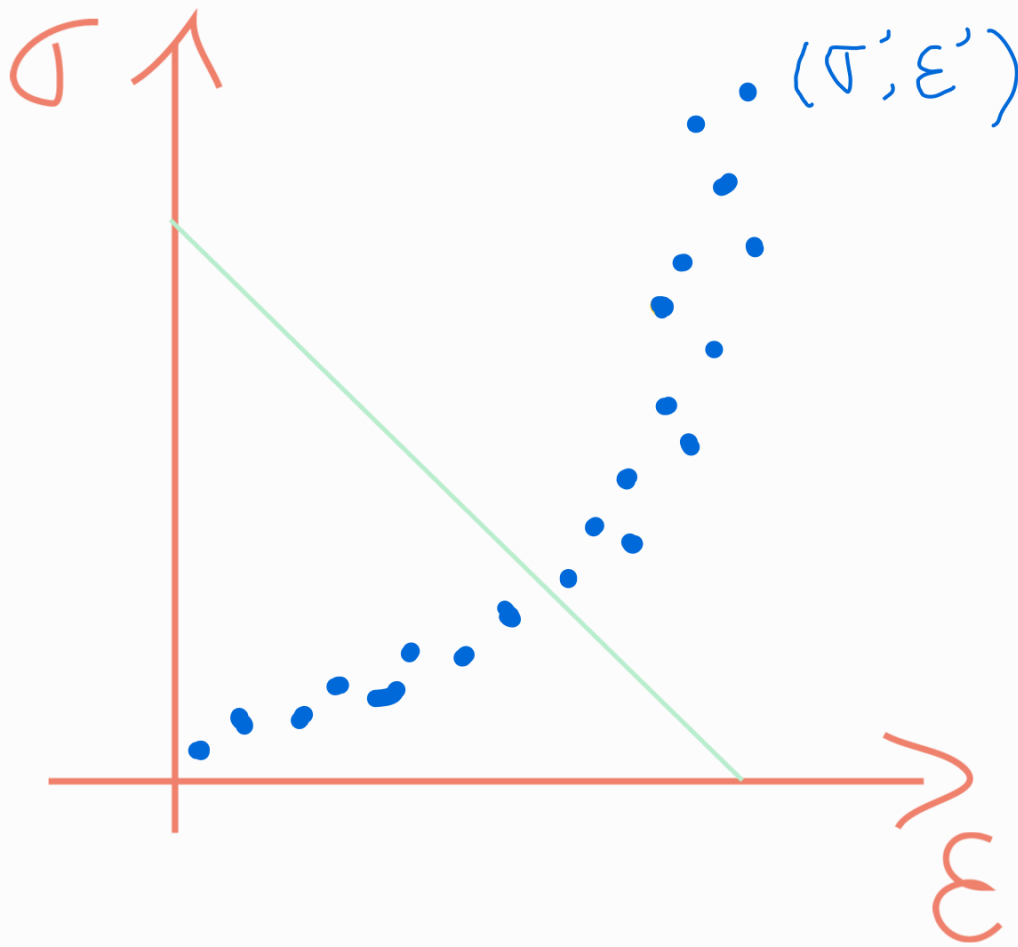
Non linear problem resolution



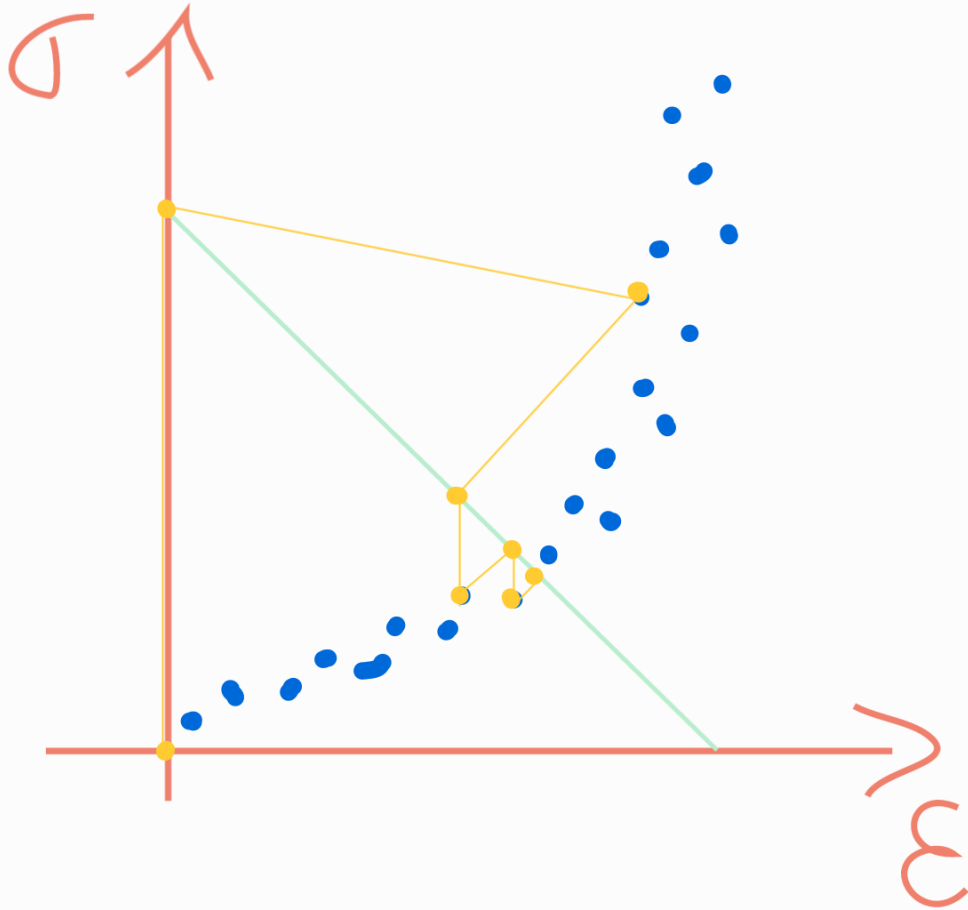
CONSTITUTIVE DATA



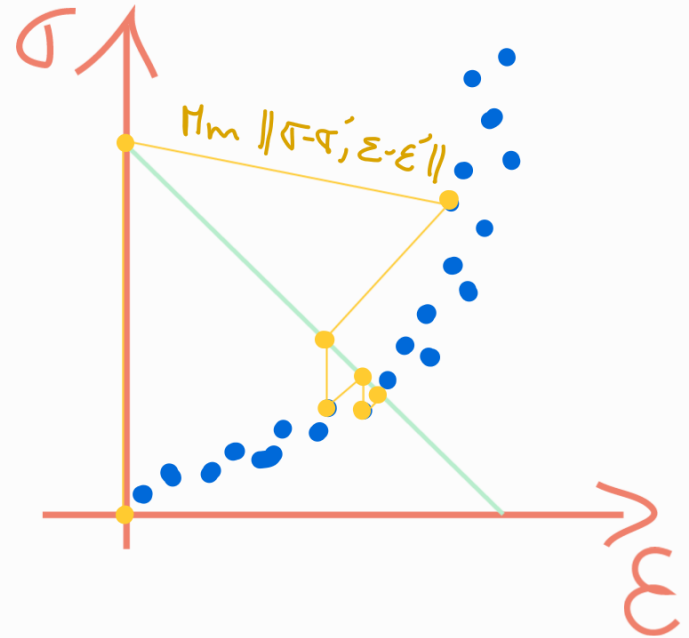
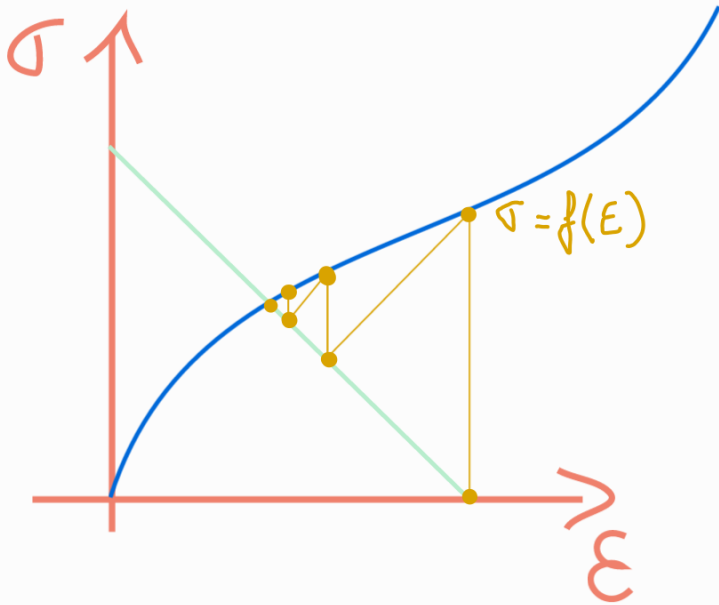
DATA-DRIVEN COMPUTATIONAL MECHANICS



DATA-DRIVEN SOLVER



INTRINSIC DIFFERENCE



Find $(\mathbf{u}, \boldsymbol{\sigma})$ such that:

Admissibility for \mathbf{u}

$$\mathbf{u} = \mathbf{u}_d \text{ on } \Gamma_u + \text{regularity}$$

Balance of momentum

$$\text{div}(\boldsymbol{\sigma}) = 0$$

Compatibility

$$\boldsymbol{\epsilon} = \frac{1}{2}(\nabla \mathbf{u} + \nabla^T \mathbf{u})$$

Balance of external forces

$$\boldsymbol{\sigma}(\mathbf{n}) = \mathbf{F}_d \text{ on } \Gamma_F$$

Regularization

Sample with a geometry such that the solution is unique.
Usual specimen geometry for uni-, bi-, tri-axial testing,...

Find $(\mathbf{u}, \boldsymbol{\sigma})$ such that:

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$$\operatorname{div}(\boldsymbol{\sigma}) = 0$$

Compatibility

$$\boldsymbol{\epsilon} = \frac{1}{2}(\nabla \mathbf{u} + \nabla^T \mathbf{u})$$

Balance of external forces

$$\boldsymbol{\sigma}(\mathbf{n}) = \mathbf{F}_d \text{ on } \Gamma_F$$

Regularization

Constitutive relation

$$\boldsymbol{\sigma} = f(\boldsymbol{\epsilon}, \dots)$$

NON-PARAMETRIC IDENTIFICATION

From a measured \mathbf{u} , find $(\boldsymbol{\sigma})$ such that:

Admissibility for \mathbf{u}

$$\mathbf{u} = \mathbf{u}_d \text{ on } \Gamma_u + \text{regularity}$$

Balance of momentum

$$\text{div}(\boldsymbol{\sigma}) = 0$$

Compatibility

$$\boldsymbol{\epsilon} = \frac{1}{2}(\nabla \mathbf{u} + \nabla^T \mathbf{u})$$

Balance of external forces

$$\boldsymbol{\sigma}(\mathbf{n}) = \mathbf{F}_d \text{ on } \Gamma_F$$

Regularization

Minimizing the deviation (energy norm in the phase space) from the mean response $(\boldsymbol{\epsilon}^*, \boldsymbol{\sigma}^*)$.

IMPLEMENTATION

DDI_implementation

October 9, 2025

1 How DDI Works ?

Authors : Outlaw Group, Centrale Nantes, France

[Leygue et al., Data-based derivation of material response, CMAME 2018]

1.1 Basics and an illustrative example

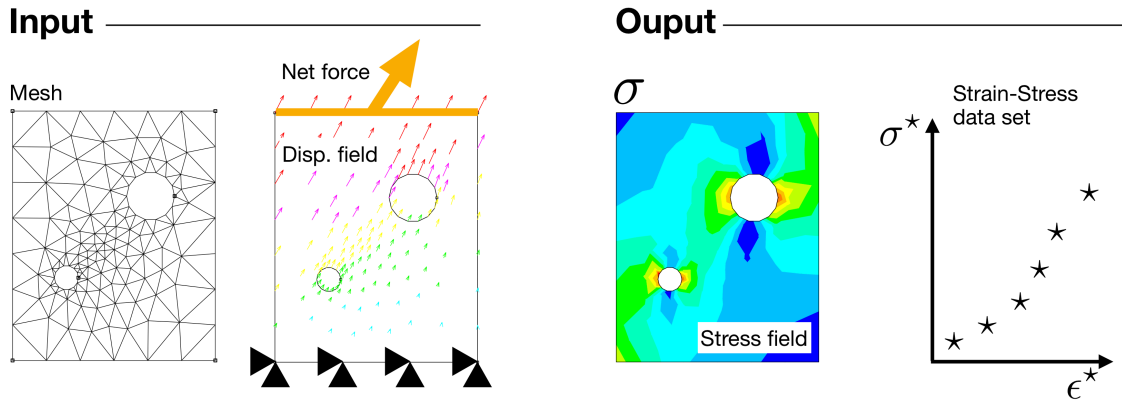
1.1.1 DDI at a glance

Data Driven Identification (DDI) aims at computing stresses on a structure where displacement field (u) and applied forces (f) are known but not the mechanical behaviour law. DDI gives us, first, the **balanced stress field** (σ) in the structure (stress tensor in each element) and second, a **Strain-Stress data set** (ε^*, σ^*). The Strain-Stress data set is needed to solve the ill-posed problem of equilibrium in the absence of a material law, its size, (N_{ss}), is smaller than the number of elements (N_e) of the structure. This data set can also be seen as an attractor allowing the minimisation of the variance of the stress field.

Input * 2D mesh of a structure * Node displacement field u of size N_e - Typically from DIC * Applied net forces - Typically from a load cell

Output * Stress field (σ) - preserving balance of momentum * Clusterized Strain-Stress data base (ε^*, σ^*) of size N_{ss}

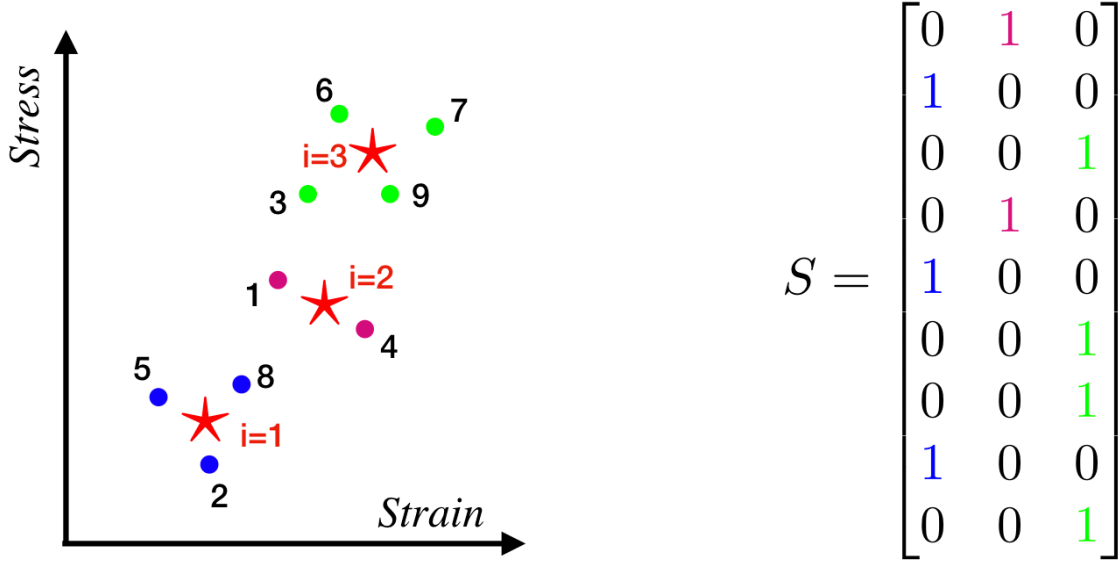
Parameters 1. r : clustering ratio [no unit] ($r = \frac{N_e}{N_{ss}}$) 2. \mathcal{C}_0 : Algorithmic stiffness [Pa]



1.2 Definitions, Problem & Equations to be solved

1.2.1 1. Definitions:

- **The Clustering** is the pairing between each couple $(\varepsilon, \sigma)_e$ of an element e with a couple i of the data-set $(\varepsilon^*, \sigma^*)_i$. $(\varepsilon^*, \sigma^*)$ is a weighted average of a subset of (ε, σ) . Obviously, $N_e > N_{ss}$.
- Clusterization is defined by the pairing operator S such as $\sigma_e^* = P_{ie} \sigma_i^*$. S is an unknown of the problem.
- Illustration of S :



- \mathcal{C}_0 **norm** is define on a couple (\mathbf{a}, \mathbf{b}) of tensors of order 2 (typically a strain and a stress) by the definition :

$$\|\mathbf{a}, \mathbf{b}\|_{\mathcal{C}_0} = [\mathbf{a} : \mathcal{C}_0 : \mathbf{a} + \mathbf{b} : \mathcal{C}_0^{-1} : \mathbf{b}]^{\frac{1}{2}}, \quad \mathcal{C}_0 \text{ a 4th order symmetric positive definite tensor.}$$

1.2.2 2. Problem:

ε and f being known, find $(\sigma, \varepsilon^*, \sigma^*, S)$ minimizing the \mathcal{C}_0 norm between (ε, σ) and $(\varepsilon^*, \sigma^*)$ and which preserve the equilibrium of the structure.

- $$\|\varepsilon - S\varepsilon^*, \sigma - S\sigma^*\|_{\mathcal{C}_0} = [(\varepsilon - S\varepsilon^*) : \mathcal{C}_0 : (\varepsilon - S\varepsilon^*) + (\sigma - S\sigma^*) : \mathcal{C}_0^{-1} : (\sigma - S\sigma^*)]^{\frac{1}{2}},$$
- $$\text{and } \text{div } \sigma = f, \quad \forall M \in \text{Structure}$$

\mathcal{C}_0 has the dimension of a stiffness tensor.

That can be rewritten in a variational form:

Find, $(\sigma, \varepsilon^*, \sigma^*, \eta)$ that make the following functional stationary, for a given S

$$\mathcal{E}(\sigma, \varepsilon^*, \sigma^*, S, \eta) = \frac{1}{2} \int_V [\|\varepsilon - S\varepsilon^*, \sigma - S\sigma^*\|_{\mathcal{C}_0}^2 - (\operatorname{div} \sigma - f) \eta] dV$$

With η a Lagrange Multiplier (dimension of a displacement vector in [m]).

1.2.3 3. Derivation of variational equation:

The derivation of the above functional $\delta \mathcal{E} = 0$ gives us the following equations needed to find the unknowns $(\sigma, \varepsilon^*, \sigma^*, \eta)$:

$$\delta \varepsilon^* \Rightarrow \int_V \mathcal{C}_0 : (\varepsilon - S\varepsilon^*) dV = 0 \quad \forall V \quad (1)$$

$$\delta \sigma^* \Rightarrow \int_V \mathcal{C}_0^{-1} : (\sigma - S\sigma^*) dV = 0 \quad \forall V \quad (2)$$

$$\delta \eta \Rightarrow \int_V (\operatorname{div} \sigma - f) dV = 0 \quad \forall V \quad (3)$$

$$\delta \sigma \Rightarrow (\sigma - S\sigma^*) = \mathcal{C}_0 : \operatorname{grad}^s(\eta) \quad \forall M \quad (4)$$

- Equations 1 and 2 state that ε^* (resp. σ^*) is a weighted average of a cluster of ε (resp. σ)
- Equation 3 is the standard balance of momentum equation on the whole structure.
- Equation 4 states the distance between σ and σ^* is proportional to the gradient of η (a kind of strain)

1.3 Discrete format

In 1D using bar elements (instead 2D elements): ε, σ become scalar (instead of tensors) \mathcal{C}_0 is just a scalar C_0 - Only one snapshot is considered - the bar elements are assigned a unit height - the unit for length is pixel

The variational form can be rewritten as:

$$\begin{aligned} \mathcal{E}(S_e, E^*, S^*, S, L) = & \frac{1}{2} C_0 [E_e - S E^*]^T W [E_e - S E^*] \\ & + \frac{1}{2} C_0^{-1} [S_e - S S^*]^T W [S_e - S S^*] \\ & - [B^T W S_e - F_{ext}]^T L \end{aligned}$$

where B is such that $E_e = B U$, U being a vector collecting the nodal displacements (data), W is a diagonal matrix collecting the surface of each bar element (E_e, S_e) are vectors collecting the strain and stress in each element, (S^*, S^*) are vectors containing the values of $(\varepsilon^*, \sigma^*)$ and L a vector collecting the value of nodal Lagrange multipliers. The stationarity conditions recast as:

$$\begin{aligned}
\delta E^* &\Rightarrow (S^T S)E^* = S^T E_e & (I) \\
\delta S^* &\Rightarrow (S^T S)S^* = S^T S_e & (II) \\
\delta L &\Rightarrow B^T W S_e = F_{ext} & (III) \\
\delta S_e &\Rightarrow C_0^{-1}W (S_e - S S^*) + W B L = 0 & (IV)
\end{aligned} \tag{1}$$

In practice the full F_{ext} vector is not known. Only one component of the resulting force applied on one side of the sample can be measured. A two matrices D and D_c are introduced.

$$D = B^T W \quad D_c = \Lambda B^T W$$

where Λ is such that: >- the lines of D corresponding to vanishing nodal forces are kept, >- the lines of D corresponding to non-vanishing nodal forces are removed, >- lines corresponding to measuring resulting force (sum of one component of nodal forces along one edge e.g.) are added. The external force vector is modified accordingly and named \bar{F}_{ext} .

The first two systems of equations (I, II):

$$(S^T S)E^* = S^T E_e \tag{2}$$

$$(S^T S)S^* = S^T S_e \tag{3}$$

$$\tag{4}$$

are easily solved independently as $(S^T S)$ is diagonal. In the following they will be solved together when updating S the selection matrix obtained from the labelling of a k-means algorithm.

The two next lines (III, IV) are included in the following linear system

$$\begin{bmatrix} C_0^{-1}W & D_c^T \\ D_c & 0 \end{bmatrix} \begin{bmatrix} S_e \\ L \end{bmatrix} = \begin{bmatrix} C_0^{-1}W S S^* \\ \bar{F}_{ext} \end{bmatrix}$$

The resolution is performed by computing first the Lagrange multipliers L :

$$(Dc W^{-1} Dc^T)L = Dc S S^* - \bar{F}_{ext}$$

and then the stress:

$$S_e = S S^* - C_0 W^{-1} D_c^T L$$

The following algorithm is used latter on >- ##### While > - Update S using k-means > - Solve $(S^T S)E^* = S^T E_e$ > - Solve $(S^T S)S^* = S^T S_e$ > - Solve $(Dc W^{-1} Dc^T)L = Dc S S^* - \bar{F}_{ext}$ > - Update $S_e = S S^* - C_0 W^{-1} D_c^T L$

Note that the three steps could be performed in a single one but, usually k-means function use a L_2 norm for evaluating the distance between clusters and samples. Here the norm for this distance is $\|\mathbf{a}, \mathbf{b}\|_{C_0}$. K-means is thus called with $(E_e \sqrt{C_0}, S_e / \sqrt{C_0})$ instead of (E_e, S_e) as input. The coordinates of the clusters (E^*, S^*) are thus not a direct output of kmeans. Their are updated by solving systems (I, II) using the new S .

1.4 Numerical implementation

```
[1]: # Import Libraries
import numpy as np
import matplotlib.pyplot as plt
import scipy
from scipy import ndimage
from scipy.sparse import csr_matrix as smatrix
import scipy.sparse.linalg as splinalg
import h5py
import scipy.io as sio
from sklearn.cluster import KMeans
import fem
```

1.4.1 Application parameters

```
[2]: # Units m->pixel=m/pix2m
# Pa=kg/m/s^2->kg/pixel/s^2=Pa*pix2m
# N = kg.m/s^2->kg.pixel/s^2=N/pix2m
# N/m = kg/s^2->kg/s^2=N/m
stdu=0.1 # noise level displacement in pixel
stdf=.0 # N noise level on force
pix2m=25.e-6; # pixel to m conversion
thickness=3e-3 # specimen thickness in m
```

1.4.2 DDI parameters

```
[3]: Ns=50 # number of material states
inp='dic-coarse.res'# input file
(X,conn)=fem.readDICmesh(inp)# loading the mesh
model=fem.FEModel() # instantiating a model
model.X=X # Nodes
model.conn=conn # Connectivity
Nnodes=X.shape[0]
Nelems=conn.shape[0]

model.Assemble() # Assembly
W=model.W # Weighting matrix
B=model.B # B matrix for computing strain from displacement

npz=np.load('fem-from-dic.npz')
U=npz['U'] # Input displacement from FE simulation
Fres=(npz['Fres']+stdf)/thickness # Input force from FE simulation
Sref=npz['Sref']*pix2m # Stress field from the FE simulation used as input data
E_e=B.dot(U) # Input strain
Eref=E_e # considered as the reference
dE_e=B.dot(stdu*np.random.randn(U.size))# noise
E_e=Eref+dE_e # strain to be considered as input for DDI
```

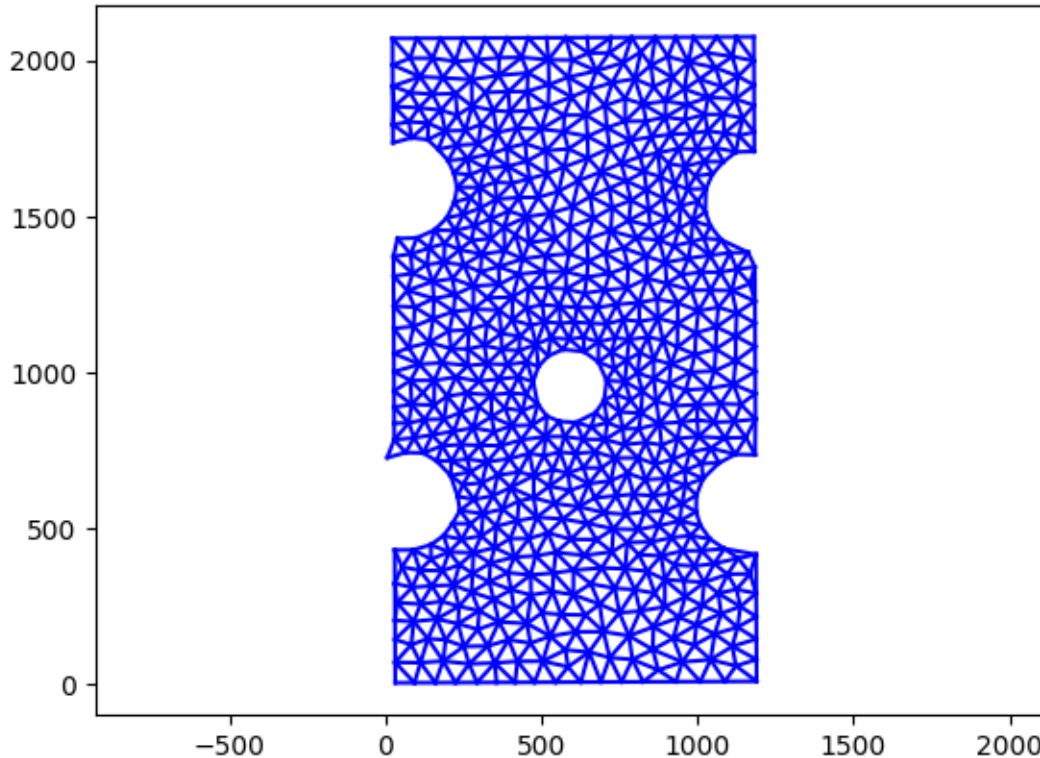


```

# Setting the algorithmic stiffness
L=max(X[:,1])-min(X[:,1])
dL=np.max(U[Nnodes:,:])-np.min(U[Nnodes:,:])
section=max(X[:,0])-min(X[:,0])
Co=(Fres/section)/(dL/L)*pix2m

# Display the sample
plt.plot(X[conn,0].T,X[conn,1].T,'b-');
plt.axis('equal');

```



1.4.3 Boundary conditions

The internal force vector is 0 everywhere except: >- on the bottom where the distribution of its x component is unknown >- on the bottom where the distribution of its y component is unknown >- on the top where the distribution of its x component is unknown >- on the top where the sum of the distribution of its y component equals the measured load

```

[4]: top=X[:,1]>max(X[:,1])*0.99
     bot=X[:,1]<max(X[:,1])*0.01

     nodes_index=np.arange(Nnodes)
     top_nodes=nodes_index[top]

```

```

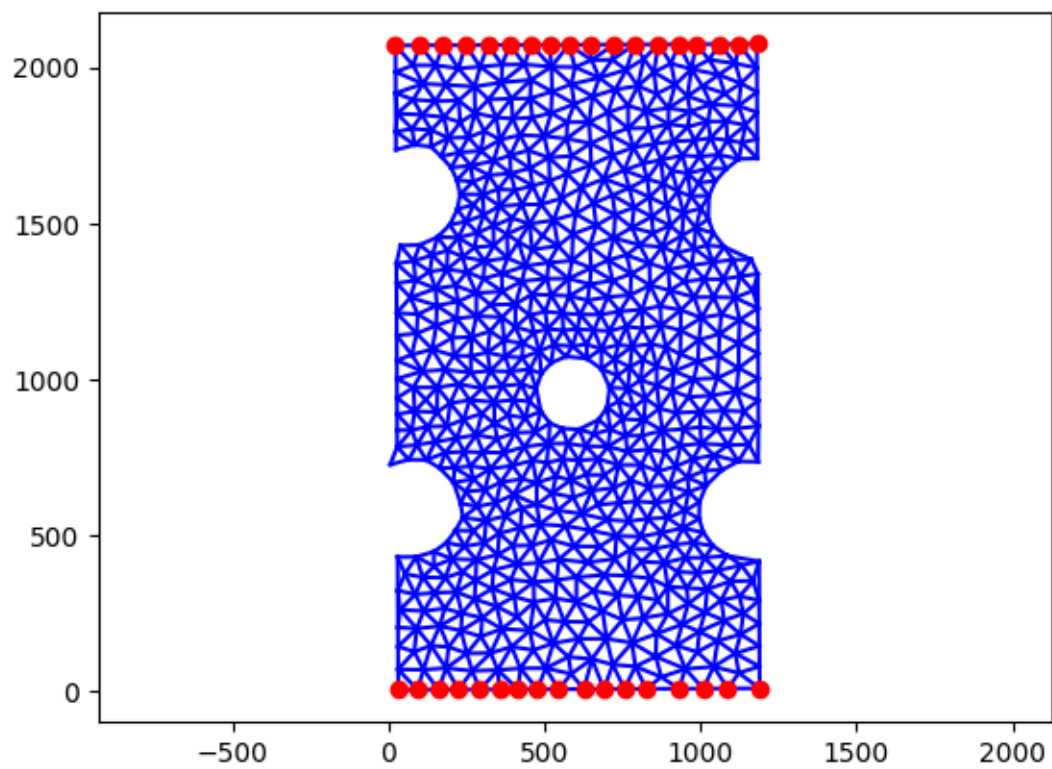
ntop=top_nodes.size
free=np.logical_not(np.logical_or(top, bot))
free_nodes=nodes_index[free]
nfree=free_nodes.size
Free_x=smatrix((np.ones(nfree),(np.
    ↪arange(nfree),free_nodes))),shape=(2*nfree+1,2*Nnodes))
Free_y=smatrix((np.ones(nfree),(np.
    ↪arange(nfree)+nfree,free_nodes+Nnodes))),shape=(2*nfree+1,2*Nnodes))
Const_y=smatrix((np.ones(ntop),(2*nfree*np.
    ↪ones(ntop),top_nodes+Nnodes))),shape=(2*nfree+1,2*Nnodes))

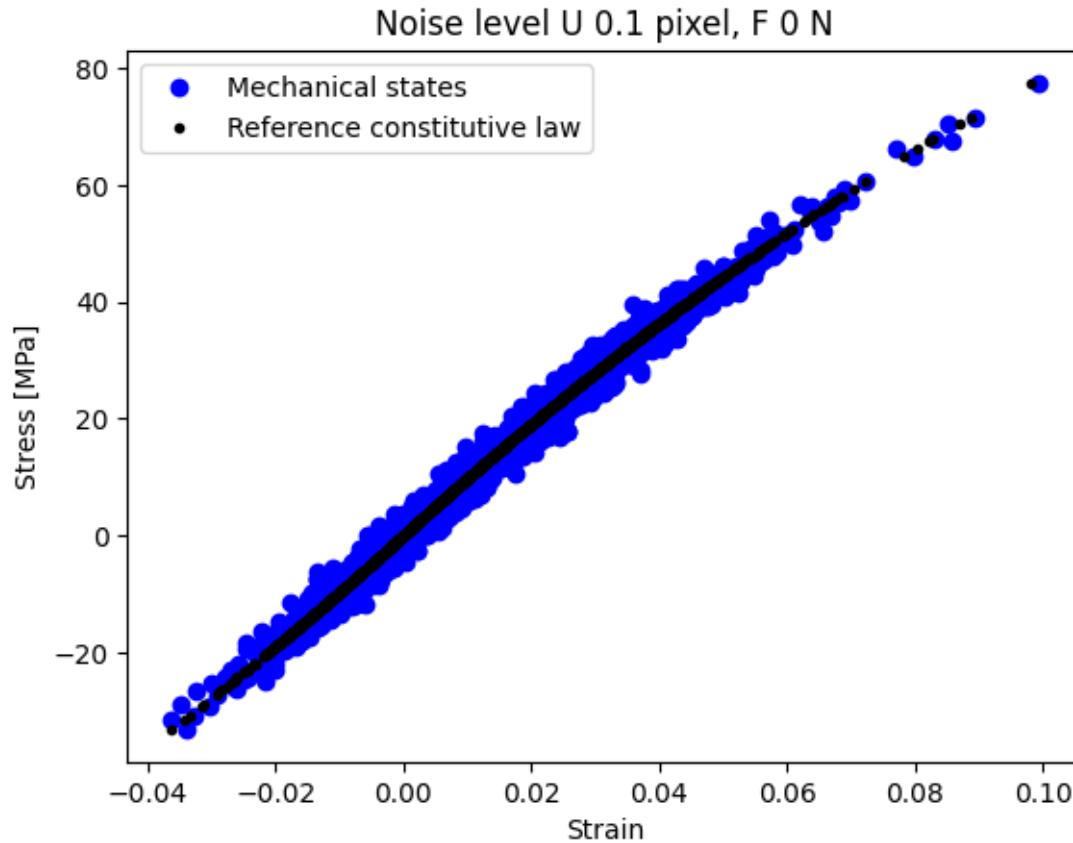
plt.plot(X[conn,0].T,X[conn,1].T,'b-');
plt.plot(X[top,0],X[top,1].T,'ro');
plt.plot(X[bot,0],X[bot,1].T,'ro');

plt.axis('equal');

ff=plt.figure()
plt.plot(E_e,Sref/pix2m*1.e-6,'bo',label='Mechanical states')
plt.plot(Eref,Sref/pix2m*1.e-6,'k.',label='Reference constitutive law');
plt.xlabel('Strain')
plt.ylabel('Stress [MPa]');
plt.title('Noise level U %g pixel, F %g N' % (stdu,stdf))
plt.legend();

```





```
[5]: # Operator assembly
D=B.T*W
Dc=(Free_x+Free_y+Const_y)*(B.T*W)
Fext=np.zeros(2*nfree+1)
Fext[-1]=Fres

iW=scipy.sparse.spdiags(1/W.diagonal(),0,Nelems,Nelems)
C=Dc*(iW*Dc.T)
LU=splinalg.splu(C)
```

```
/tmp/ipykernel_81593/876515232.py:9: SparseEfficiencyWarning: splu converted its
input to CSC format
    LU=splinalg.splu(C)
```

1.4.4 Resolution

```
[6]: # Initialisation
E_e=B.dot(U)
S_e=np.zeros(Nelems)
```

```

E_e=Eref+dE_e
#ff=plt.figure()
#plt.yscale('log')
#plt.ylabel('DDI norm')
#plt.xlabel('Number of iteration')
ic=0
for resampling in range(5):
    ## selection matrix from k-means
    samples=np.c_[np.squeeze(E_e*np.sqrt(Co)),np.squeeze(S_e/np.sqrt(Co))]
    kmeans = KMeans(Ns).fit(samples)
    #.reshape(-1,1))
    ie=kmeans.labels_
    val=np.ones(Nelems)
    ii=np.arange(Nelems)
    S=smatrix((val,(ii,ie)),shape=(Nelems,Ns))
    STS=S.T*S
    STS=STS.diagonal()

    ## Material states
    Estar=S.T.dot(E_e)/STS
    Sstar=S.T.dot(S_e)/STS
    ff=plt.figure()
    plt.subplot(121)
    plt.plot(E_e,S_e/pix2m*1.e-6,'bo',label='Mechanical states')
    plt.plot(Estar,Sstar/pix2m*1.e-6,'r+',label='Material states');
    plt.xlabel('Strain')
    plt.ylabel('Stress [MPa]');
    plt.title('Iteration %d after clustering' % (resampling))
    plt.legend();

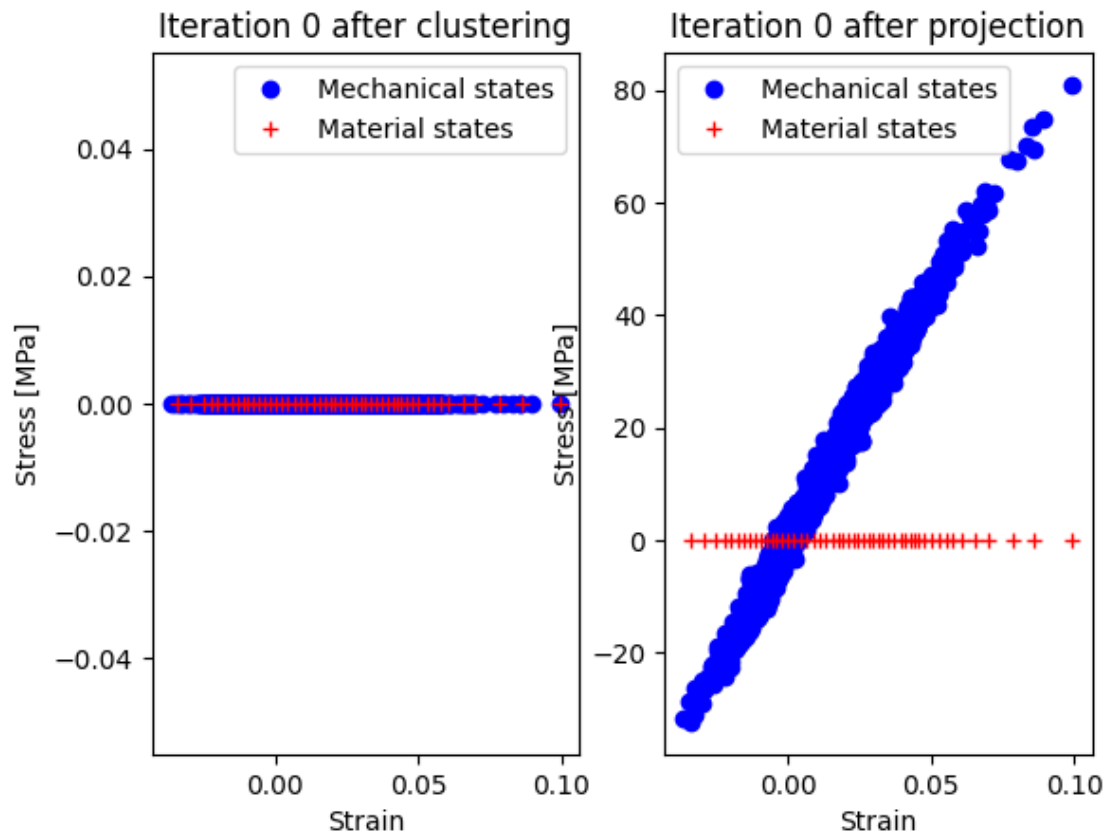
    # Projection
    Estar_e=S.dot(Estar)
    Sstar_e=S.dot(Sstar)
    b=Dc.dot(Sstar_e)-Fext
    Lag=LU.solve(b)
    S_e=Sstar_e-iW*(Dc.T.dot(Lag))

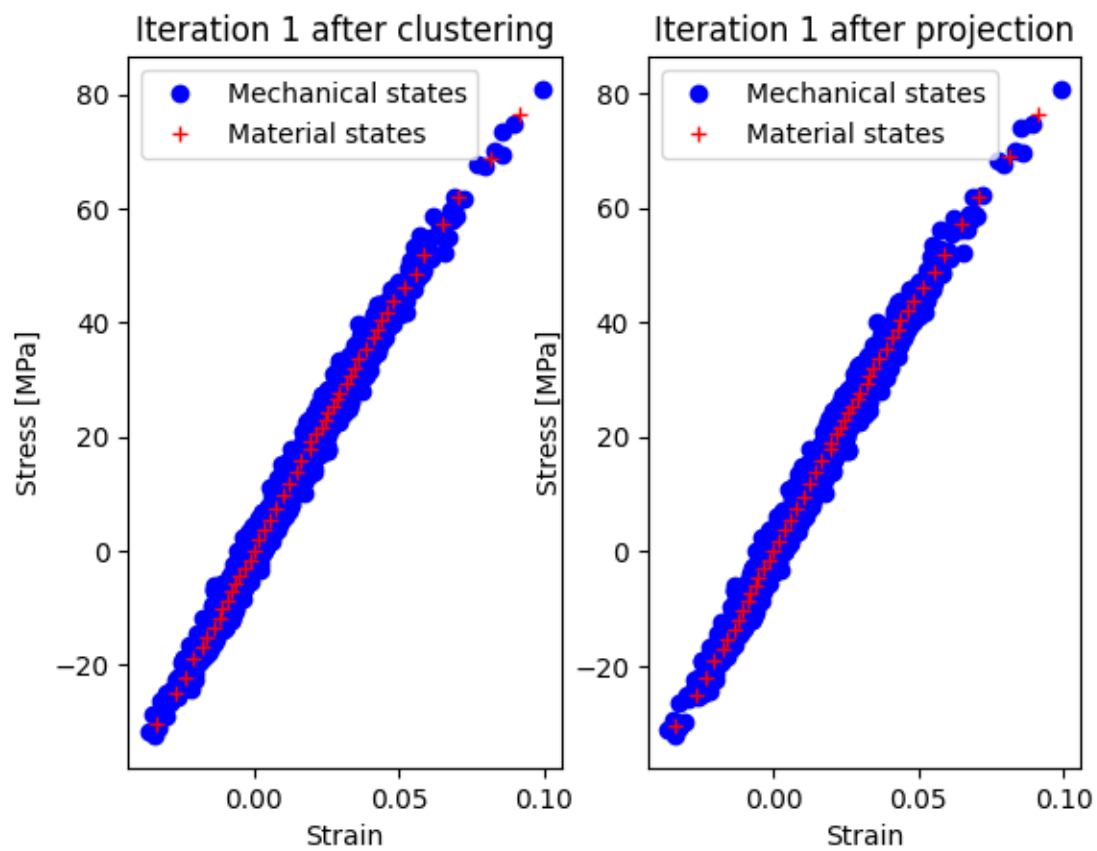
    Estar_e=S.dot(Estar)
    Sstar_e=S.dot(Sstar)
    ddi_norm=0.5*(Co*np.dot(E_e-Estar_e,W.dot(E_e-Estar_e))+1/Co*np.
    ↪dot(S_e-Sstar_e,W.dot(S_e-Sstar_e)))
    print('***DDI loop Iteration %02d: DDI norm %6.3e ***' %_
    ↪(resampling,ddi_norm))
    plt.subplot(122)
    plt.plot(E_e,S_e/pix2m*1.e-6,'bo',label='Mechanical states')
    plt.plot(Estar,Sstar/pix2m*1.e-6,'r+',label='Material states');
    plt.xlabel('Strain')

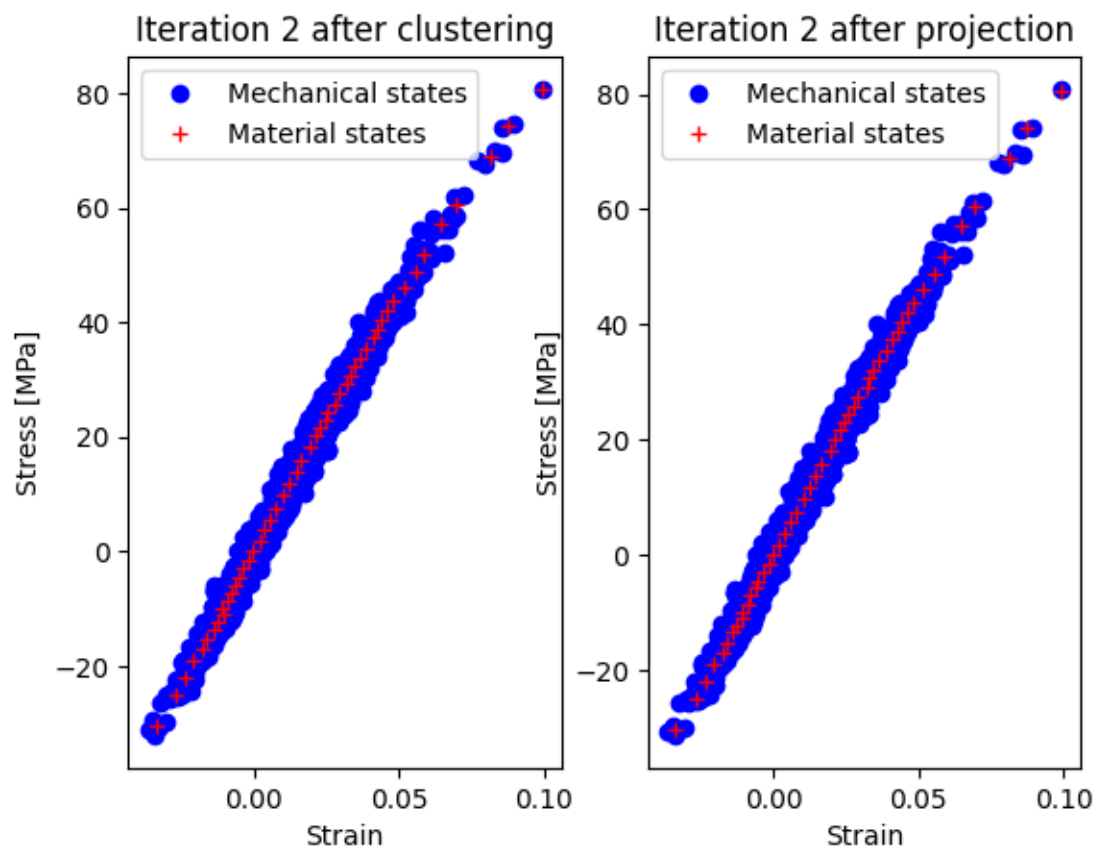
```

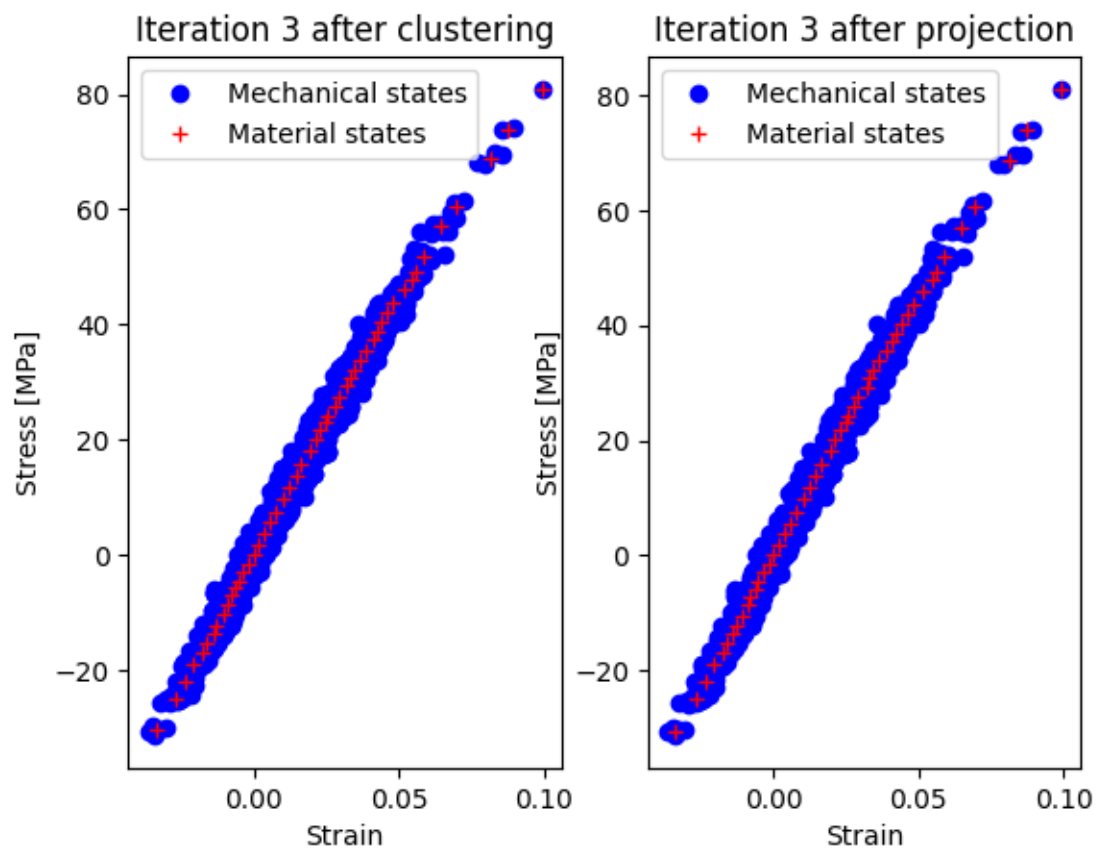
```
plt.ylabel('Stress [MPa]');
plt.title('Iteration %d after projection' % (resampling))
plt.legend();
```

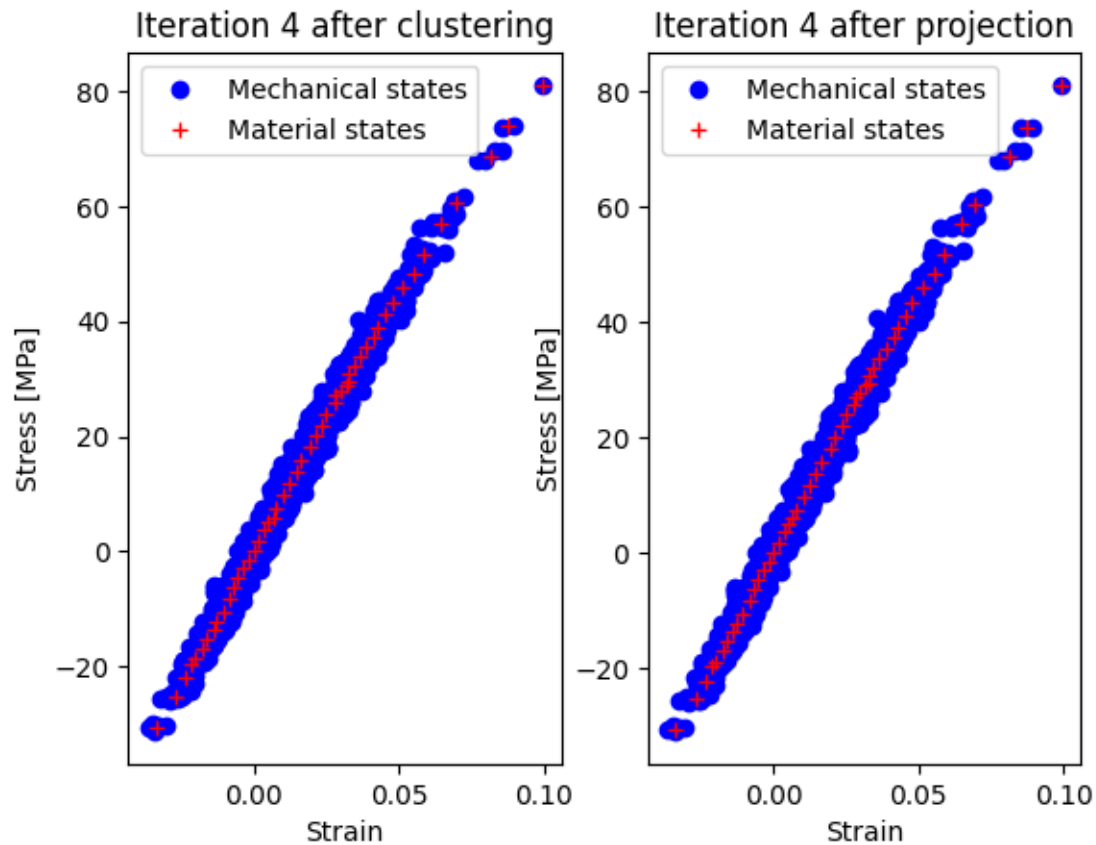
```
***DDI loop Iteration 00: DDI norm 2.619e+12 ***
***DDI loop Iteration 01: DDI norm 9.214e+08 ***
***DDI loop Iteration 02: DDI norm 7.138e+08 ***
***DDI loop Iteration 03: DDI norm 6.544e+08 ***
***DDI loop Iteration 04: DDI norm 6.437e+08 ***
```





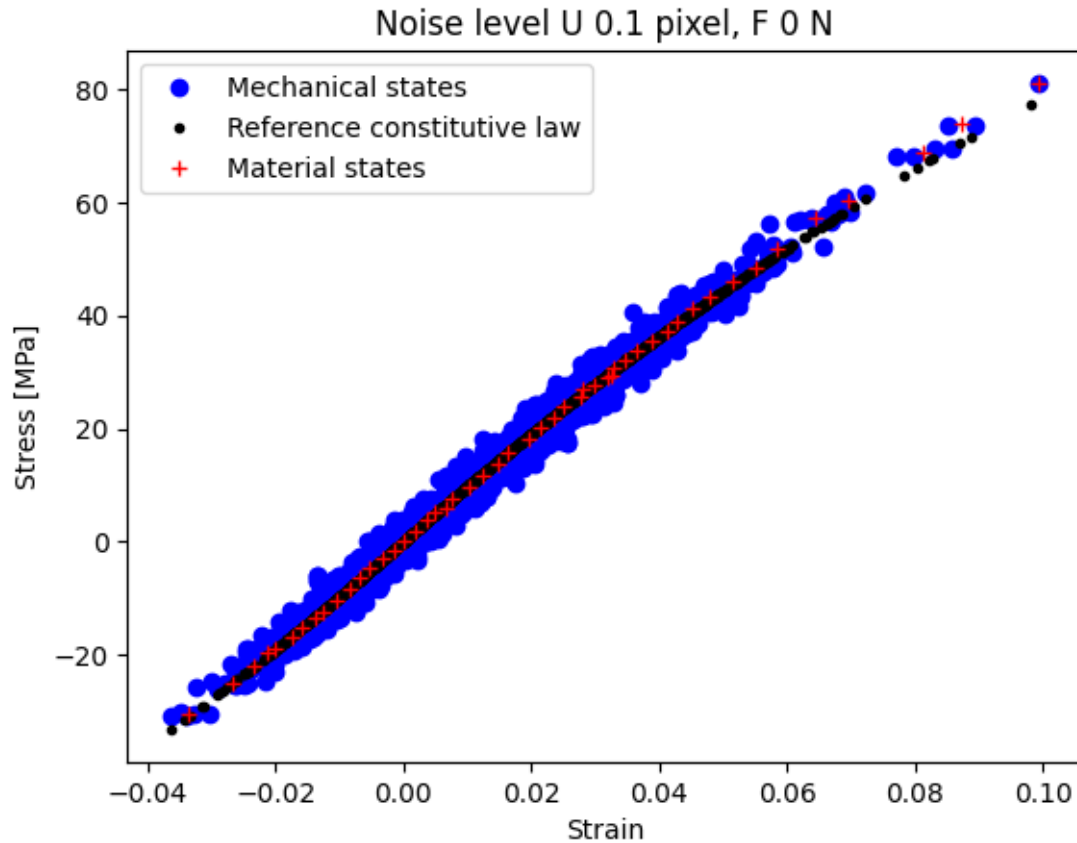






2 Comparison with refernece

```
[7]: ff=plt.figure()
plt.plot(E_e,S_e/pix2m*1.e-6,'bo',label='Mechanical states')
plt.plot(Eref,Sref/pix2m*1.e-6,'k.',label='Reference constitutive law');
plt.plot(Estar,Sstar/pix2m*1.e-6,'r+',label='Material states');
plt.xlabel('Strain')
plt.ylabel('Stress [MPa]');
plt.title('Noise level U %g pixel, F %g N' % (stdu,stdf))
plt.legend();
```

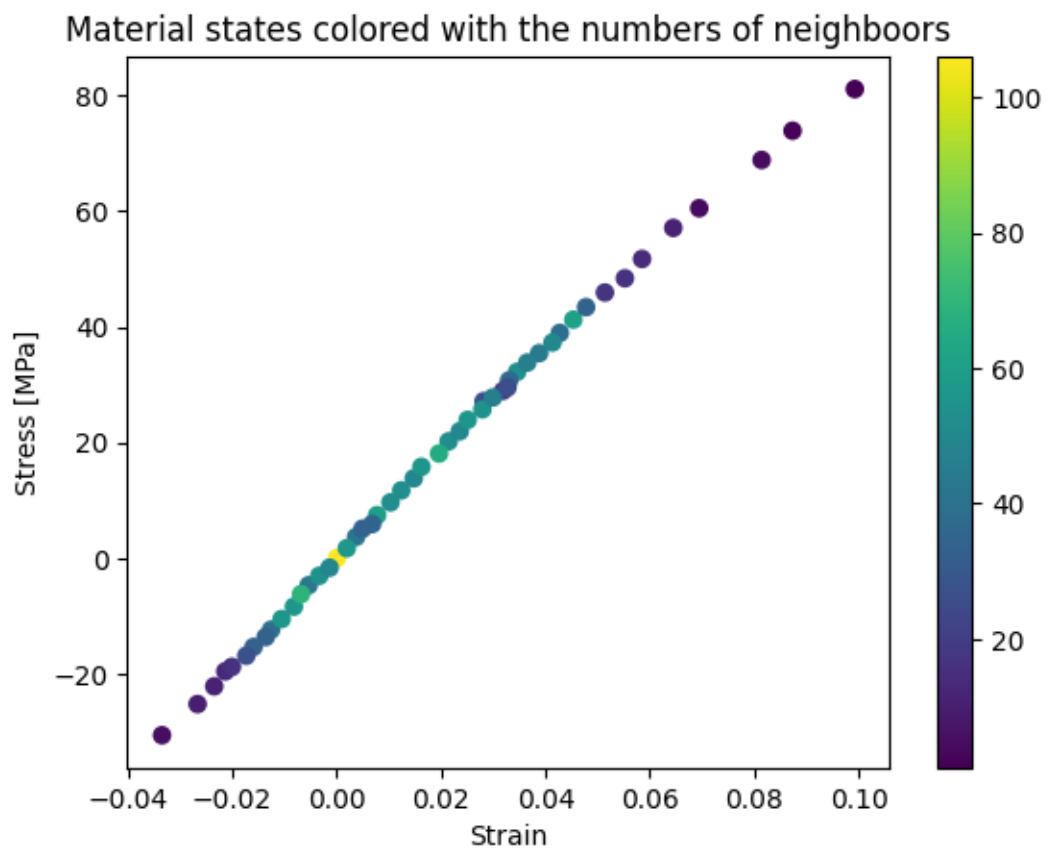


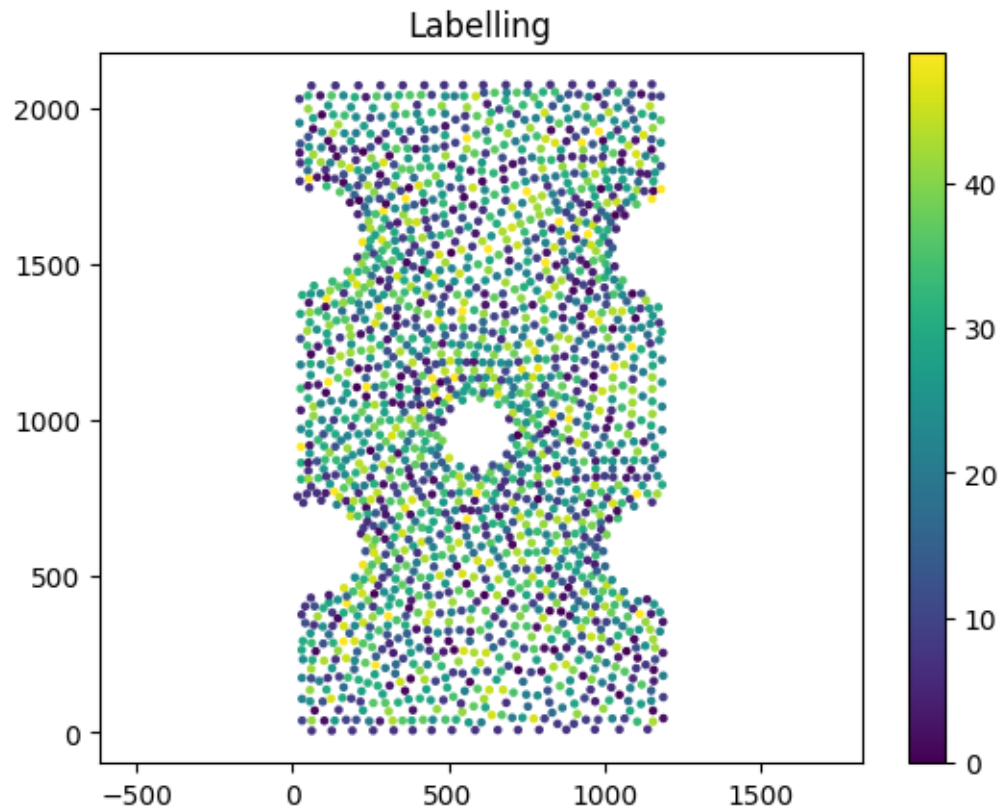
2.1 Illustrations

```
[8]: STS=S.T*S
iSTS=STS.diagonal()
ff=plt.figure()
plt.scatter(Estar,Sstar/pix2m*1.e-6,c=iSTS);
plt.xlabel('Strain')
plt.ylabel('Stress [MPa]');
plt.title('Material states colored with the numbers of neighbors')
plt.colorbar();

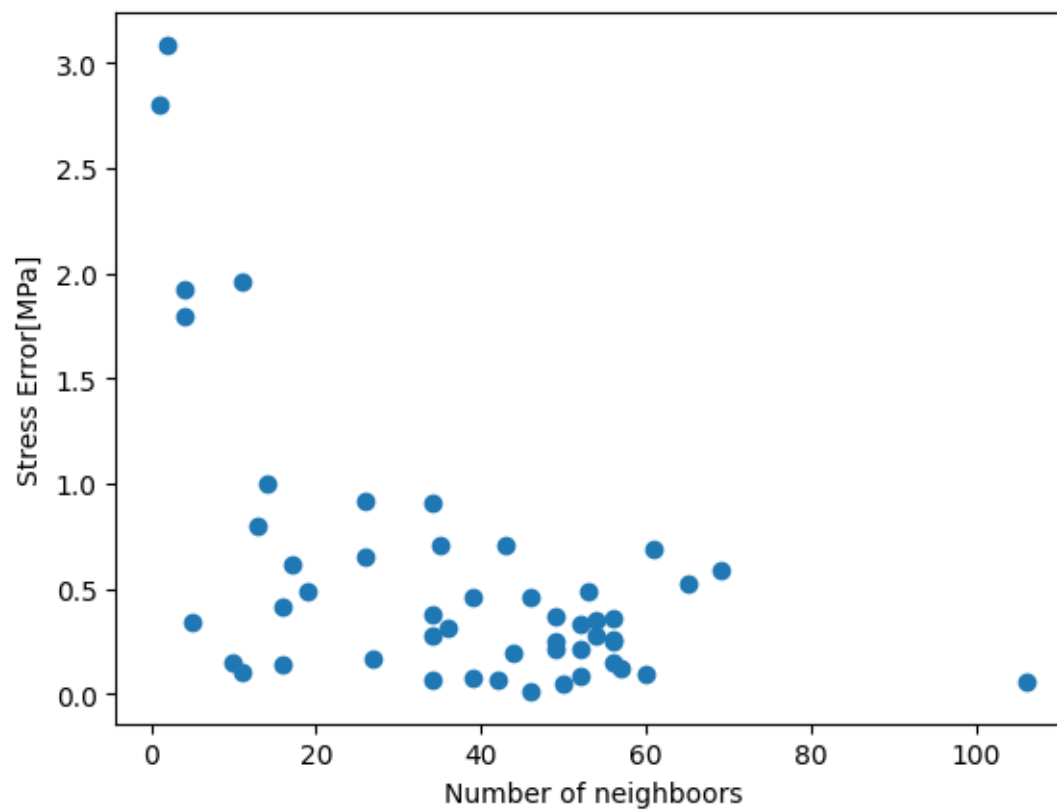
Xg=0.5*(X[conn[:,0]]+X[conn[:,1]])
ff=plt.figure();
plt.scatter(Xg[:,0],Xg[:,1],c=ie,s=5);
plt.colorbar();
plt.axis('equal');
plt.title('Labelling')
```

```
[8]: Text(0.5, 1.0, 'Labelling')
```











```
[9]: Sref=2e8*(1-np.exp(-np.abs(Estar)/0.2))*np.sign(Estar)*pix2m
plt.scatter(iSTS,np.abs(Sref-Sstar)/pix2m*1.e-6);
plt.xlabel('Number of neighbors')
plt.ylabel('Stress Error[MPa]');
```



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