

Mesure :

$$\mu\left(\bigcup_{k=1}^{\infty} E_k\right)=\sum_{k=1}^{\infty} \mu\left(E_k\right)$$

Théorème de Vaschy-Buckingham (Pi) :

$$\begin{aligned} f\left(q_1, q_2, \ldots, q_n\right) &= 0 \\ F\left(\pi_1, \pi_2, \ldots, \pi_p\right) &= 0 \\ \pi_i &= q_1^{a_1} q_2^{a_2} \cdots q_n^{a_n} \end{aligned}$$

```
# solver method
pi = sympy.solve(Symbol('x')**2-1, Symbol('x'))
# numeric method
g = lambda x : (x^a)*(x^b)
pi = scipy.fsolve(g,[i,1])
```

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Un choc élastique (3 loi de conservations) :

$$\left\{\begin{array}{l} \vec{\mathbf{r}}_1 \wedge m_1 \vec{\mathbf{v}}_1 + \vec{\mathbf{r}}_2 \wedge m_2 \vec{\mathbf{v}}_2 = \vec{\mathbf{r}}_1' \wedge m_1 \vec{\mathbf{v}}_1' + \vec{\mathbf{r}}_2' \wedge m_2 \vec{\mathbf{v}}_2' \\ m_1 \vec{\mathbf{v}}_1 + m_2 \vec{\mathbf{v}}_2 = m_1 \vec{\mathbf{v}}_1' + m_2 \vec{\mathbf{v}}_2' \\ m_1 \mathbf{v}_1^2 + m_2 \mathbf{v}_2^2 = m_1 \mathbf{v}_1'^2 + m_2 \mathbf{v}_2'^2 \end{array}\right.$$

Solution vectorielle :

$$\begin{aligned} \mathbf{v}_1' &= \mathbf{v}_1 - \frac{2m_2}{m_1 + m_2} \frac{\langle \mathbf{v}_1 - \mathbf{v}_2, \mathbf{x}_1 - \mathbf{x}_2 \rangle}{\|\mathbf{x}_1 - \mathbf{x}_2\|^2} (\mathbf{x}_1 - \mathbf{x}_2), \\ \mathbf{v}_2' &= \mathbf{v}_2 - \frac{2m_1}{m_1 + m_2} \frac{\langle \mathbf{v}_2 - \mathbf{v}_1, \mathbf{x}_2 - \mathbf{x}_1 \rangle}{\|\mathbf{x}_2 - \mathbf{x}_1\|^2} (\mathbf{x}_2 - \mathbf{x}_1) \end{aligned}$$

```
# consevation law
d = np.linalg.norm(ri - rj)**2
ui = vi - 2*mj / M * np.dot(vi-vj, ri-rj) / d * (ri - rj)
```

Symétrie par rotation :

$$R(\theta) . \vec{\mathbf{x}} = \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix} . \vec{\mathbf{x}}$$

Champs de force global (PFD) :

$$m \frac{\mathrm{d} \vec{\mathbf{v}}}{\mathrm{d} t}=m \vec{\Gamma}(\vec{\mathbf{x}}) \Leftrightarrow \mathbf{v}_{t+1}=\vec{\mathbf{v}}_t+d t . \vec{\Gamma}(\vec{\mathbf{x}})$$

Champes de force local (Vicsek) :

$$\begin{aligned} v(\mathbf{r}, \Theta) &= \mathbf{r} . e^{i \Theta} = \Re(v) + i \Im(v) \\ \Theta_i(t+\Delta t) &= \left\langle \Theta_j \right\rangle_{\left| r_i-r_j \right| < R} + \eta_i(t) \\ \mathbf{r}_i(t+\Delta t) &= \mathbf{r}_i(t) + v \Delta t \begin{pmatrix} \cos \Theta_i(t) \\ \sin \Theta_i(t) \end{pmatrix} \end{aligned}$$

```
# field perturbation (euler method)
v[0] += dt*(lambda x,y : (x*y, 9.81 + x+y))
# local field (complex)
U = v[0]+1j*v[1]; d = np.absolute(u - U)
```

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Potentiel thermodynamique :

$$\mu_i=\left(\frac{\partial U}{\partial n_i}\right)_{V, S, n_j \neq i}=\left(\frac{\partial G}{\partial n_i}\right)_{P, T, n_j \neq i} \quad \mathrm{d} U=-P \mathrm{d} V+T \mathrm{d} S+\sum_{i=1}^N \mu_i \mathrm{d} n_i G=V \mathrm{d} P-S \mathrm{d} T+\sum_{i=1}^N \mu_i \mathrm{d} n_i$$

Equation locale de diffusion (loi de Fick) :

$$c(t+1, x_i)=h+D \sum_{r < R} c(t, x_j)=h+D\left(c(t, x_{i+1})+c(t, x_{i-1})\right)$$

Diffusion locale avec réactif (Turing) :

$$c(t+1, x_i) = \text{sign} \left[ h + \sum_k D_k \sum_{r < R_k} c(t, x_j) \right]$$

```
# local diffusion
d = np.linalg.norm(X - X[i], axis=1)
c_i += d*np.sum(C[d<r])
new_C[c] = np.sign(h+c_i)
```

Réseau de Bravais :

$$\mathbf{R} = n_1 \mathbf{a}_1 + n_2 \mathbf{a}_2$$

Méthodes d'approximation des milieux continus (serie de Taylor) :

$$f(x_0 + a) = f(x_0) + a \frac{df(x_0)}{dx} + \frac{a^2}{2} \frac{d^2f(x_0)}{dx^2} + O(n)$$

Equation de la diffusion :

$$\frac{\partial c}{\partial t} = D \frac{\partial^2 c}{\partial x^2}$$

Schéma d'Euler (Laplacien) :

$$u''(x, y) = \frac{1}{h^2} \begin{bmatrix} 1 & -4 & 1 \\ -1 & 4 & -1 \end{bmatrix} u(x, y)$$

Résolution dans l'espace propre du systeme :

$$\frac{U_{n+1} - U_n}{dt} - \frac{1}{h^2} \begin{bmatrix} 2 & -1 & & & \\ -1 & 2 & -1 & & \\ & -1 & 2 & -1 & \\ & & & 2 & -1 \\ & & & -1 & 2 \end{bmatrix} U_n = 0 \Leftrightarrow U_{n+1} = M \cdot U_n$$

```
# local and global laplacian
LAP = signal.convolve2d(U, kernel, boundary='symm', mode='same')
M = spdiags(main,[0],N*M,N*M) + spdiags(upper,[1],N*M,N*M)+spdiags(lower,[-1],N*M,N*M)
LAP = (new_U-U).reshape(LAP)
```

Cinétique chimique de  $2A + B \xrightarrow{k} 2C$  :

$$\frac{d[A]}{dx} = \frac{d[B]}{dx} = -\frac{d[C]}{dx} = -k[A]^2[B]^1$$

Modèle de Gray-Scott :

$$\left\{ \begin{array}{l} U + 2V \xrightarrow{1} 3V \\ P \xrightarrow{f} U \\ V \xrightarrow{f+k} P \\ U \xrightarrow{f} P \end{array} \right. \Leftrightarrow \left\{ \begin{array}{l} \frac{\partial u}{\partial t} = -uv^2 + f(1-u) \\ \frac{\partial v}{\partial t} = +uv^2 - (f+k)v \end{array} \right.$$

Marche aléatoire (Chaine de Markov) :

$$\mathbb{P}\left(X_{n+1} = j \mid X_0 = i_0, X_1 = i_1, \dots, X_{n-1} = i_{n-1}, X_n = i\right) = \mathbb{P}(X_{n+1} = j \mid X_n = i).$$

```
# new position of walker with continuum noise
WAY = 2*np.pi*(np.random.randint(0,4,N_WALKER)/4.)
VAR = delta*(np.random.random(WALKER_NUMBER) - 0.5)
```

Force électromagnétique :

$$\vec{F} = q\vec{E} + q\vec{v} \wedge \vec{B} \Leftrightarrow X < R \Rightarrow X_{t+1} = X_t$$

Dimension Fractale (autosimilarité) :

$$a^{D_h} ; D_h = \frac{\ln(N)}{\ln(\frac{1}{r})}$$

## Évolution du rapport de dimension :

$$C(r) \equiv N^{-1} \sum_{r'} \rho(r') \rho(r' + r)$$

```
# calculate distance for each node
```

```
G = nx.from_pandas_dataframe(tree, 'min_dist_index', 'initial_index')
```

```
SHORT_PATH = nx.shortest_path(G)
```

## Entropie (theorie de l'information) :

$$H_b(X) = -\mathbb{E}[\log_b P(X)] = \sum_{i=1}^n P_i \log_b \left( \frac{1}{P_i} \right) = - \sum_{i=1}^n P_i \log_b P_i$$

## Lagrangien (symetrie de Noether) :

$$L = E_c - E_p = T - V$$

$$\frac{d}{dt} \frac{\partial \mathcal{L}}{\partial \dot{q}_k} = \frac{\partial \mathcal{L}}{\partial q_k}$$

## Double pendule (Espace des phases $\dot{\theta}(\theta)$ ):

$$\dot{p}_{\theta_1} = \frac{\partial L}{\partial \theta_1} = -\frac{1}{2} m l^2 \left( \dot{\theta}_1 \dot{\theta}_2 \sin(\theta_1 - \theta_2) + 3 \frac{g}{l} \sin \theta_1 \right)$$

$$\dot{p}_{\theta_2} = \frac{\partial L}{\partial \theta_2} = -\frac{1}{2} m l^2 \left( -\dot{\theta}_1 \dot{\theta}_2 \sin(\theta_1 - \theta_2) + \frac{g}{l} \sin \theta_2 \right)$$

```
# differential equation solver method
```

```
res = integrate.odeint(derivs, state, t)
```

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## Fonction de transfert :

$$Y(s) = H(s) X(s)$$

## Réponse impulsionnelle :

$$y(t) = \int_{-\infty}^{\infty} h(t - \tau) u(\tau) d\tau = \int_{-\infty}^{\infty} h(\tau) u(t - \tau) d\tau.$$

## Transformations en Z :

$$H[z] = \frac{Y[z]}{X[z]} = \frac{1 - z^{-1}}{T_e}$$

```
# transfert signal
```

```
H = scipy.signal.firwin()
```

```
freq = scipy.signal.freqz(b,a)
```

```
conv = scipy.signal.convolve()
```

## Series de Fourier (Diffusion) :

$$\frac{Y'(t)}{\alpha Y(t)} = \frac{X''(x)}{X(x)} T(x, t) = \sum_{n=1}^{+\infty} D_n \sin\left(\frac{n\pi x}{L}\right) e^{-\frac{n^2 \pi^2 \alpha t}{L^2}}$$

## Coefficient de Fourier (Parseval) :

$$\sum_{n=-\infty}^{+\infty} |c_n(f)|^2 = \frac{1}{T} \int_T |f(t)|^2 dt = \|f\|^2$$

## Harmonique d'un signal :

$$c_n(f) = \frac{1}{T} \int_T f(t) e^{-i2\pi \frac{n}{T} t} dt$$

```
# integration method
```

```
cf += [[sims(X[1]*np.exp(-1j*2*n*np.pi*X[0]/T)/T, X[0]), sims(X[2]*np.exp(-1j*2*n*np.pi*X[0]/T)/T, X[0])]
```

```
# direct method
```

```
freq = np.fftfreq(x.size, d=1/rate)
```

**Filtre passe-bande (second ordre) :**

$$h(jw) = \frac{A_0}{1 + j \cdot Q \cdot (x - \frac{1}{x})}$$

**Filtre de Kalman (  $X_t = X_{t-1} + v_{(x,t-1)} \cdot dt$  ) :**

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{F}_k \hat{\mathbf{x}}_{k-1|k-1} + \mathbf{B}_k \mathbf{u}_k + \mathbf{w}_k \mathbf{P}_{k|k-1} = \mathbf{F}_k \mathbf{P}_{k-1|k-1} \mathbf{F}_k^T + \mathbf{Q}_k$$

**Régulateur PID :**

$$u(t) = K_p \epsilon(t) + K_i \int_0^t \epsilon(\tau) d\tau + K_d \frac{d\epsilon(t)}{dt}$$

**Commande linéaire quadratique :**

$$\dot{\mathbf{x}}(t) = A(t)\mathbf{x}(t) + B(t)\mathbf{u}(t) + \mathbf{v}(t)\mathbf{y}(t) = C(t)\mathbf{x}(t) + \mathbf{w}(t)$$

```
# control
PID = x
```

---

**Méthodes Monte-Carlo (Theorement de transfert) :**

$$\mathbb{E}[\varphi(X)] \stackrel{\text{def.}}{=} \int_{\Omega} \varphi(X(\omega)) \mathbb{P}(d\omega) = \int_{\mathbb{R}} \varphi(x) \mathbb{P}_X(dx)$$

**Fonction d'un transition d'etats optimum :**

$$V^*(s) = \max_{a \in A} \sum_{s' \in S} [R(s, \pi(s), s') + \gamma V^*(s')] T(s, a, s')$$

**Equation de Bellman :**

$$Q^*(s, a) = \sum_{s' \in S} [R(s, a, s') + \gamma \max_{a' \in A} Q^*(s', a')] T(s, a, s')$$

```
# update Q(s,a)
max_future_q = np.max(q_table[new_discrete_state])
current_q = q_table[discrete_state][action]
new_q = (1-alpha)*current_q+alpha*(reward+gamma*max_future_q)
q_table[discrete_state][action]=new_q
```

**Récompense et Regret (Exploration/Exploitation) :**

$$r_n = n\mu^* - \sum_{k=1}^n \mathbb{E}(\mu_{I_k})$$