PINNs Description:   
“In PINNs, a fully connected network is built to approximate concentration in multilayer human skin by putting distance x and time t as inputs. Multilayer human skin with different layers has different neural network structures, the number of hidden layers and the number of neurons in each layer are determined by the number of layers of the composite medium, and then we substitute all initial conditions, boundary conditions, continuity conditions at interfaces and governing equations into loss function. Meanwhile, we choose tanh as the activation function.

The core of PINNs is to add the above physical information to approximate the actual concentration distributions, and the loss function is optimized to minimize the total value. The loss function should include the corresponding four parts:

\begin{aligned}

&Loss=MSE\_e+\gamma\_b M S E\_b+\gamma\_i M S E\_i+\gamma\_c M S E\_c\\

&\begin{aligned}

MSE\_e=\frac{1}{N\_{e\_1}} \sum\_{i=1}^{N\_{e\_1}}\left\|\frac{\partial C\_{veh}(x, t ; \theta)}{\partial t}-D\_{veh} \frac{\partial^2 C\_{veh}(x, t ; \theta)}{\partial x^2}\right\|^2+\frac{1}{N\_{e\_2}} \sum\_{i=1}^{N\_{e\_2}}\left\|\frac{\partial C\_{sc}(x, t ; \theta)}{\partial t}-D\_{sc} \frac{\partial^2 C\_{sc}(x, t ; \theta)}{\partial x^2}\right\|^2+\frac{1}{N\_{e\_3}} \sum\_{i=1}^{N\_{e\_3}}\left\|\frac{\partial C\_{ep}(x, t ; \theta)}{\partial t}-D\_{ep} \frac{\partial^2 C\_{ep}(x, t ; \theta)}{\partial x^2}\right\|^2 +\frac{1}{N\_{e\_4}} \sum\_{i=1}^{N\_{e\_4}}\left\|\frac{\partial C\_{de}(x, t ; \theta)}{\partial t}-D\_{de} \frac{\partial^2 C\_{de}(x, t ; \theta)}{\partial x^2}\right\|^2

\end{aligned}\\

MSE\_b=\frac{1}{N\_{b\_1}} \sum\_{i=1}^{N\_{b\_1}}\left\|C\_{veh}(x=0, t ; \theta) - C\_1\right\|^2+\frac{1}{N\_{b\_2}} \sum\_{i=1}^{N\_{b\_2}}\left\|C\_{de}(x=1, t ; \theta)-0\right\|^2 \\

M S E\_i=\frac{1}{N\_{i\_1}} \sum\_{i=1}^{N\_{i\_1}}\left\|C\_{veh}(x, t=0 ; \theta)-C\_1\right\|^2+\frac{1}{N\_{i\_1}} \sum\_{i=1}^{N\_{i\_1}}\left\|C\_{sc}(x, t=0 ; \theta)-0\right\|^2 +\frac{1}{N\_{i\_1}} \sum\_{i=1}^{N\_{i\_1}}\left\|C\_{ep}(x, t=0 ; \theta)-0\right\|^2+\frac{1}{N\_{i\_1}} \sum\_{i=1}^{N\_{i\_1}}\left\|C\_{de}(x, t=0 ; \theta)-0\right\|^2\\

MSE\_c = \frac{1}{N\_c} \sum\_{i=1}^{N\_c}\left\|\frac{C\_{veh}\left(x=x\_{veh}, t ; \theta\right)}{K\_{veh}}-\frac{C\_{sc}\left(x=x\_{veh}, t ; \theta\right)}{K\_{sc}}\right\|^2+\frac{1}{N\_c} \sum\_{i=1}^{N\_c}\left\|D\_{veh} \frac{\partial C\_{veh}\left(x=x\_{veh}, t ; \theta\right)}{\partial x}-D\_{sc} \frac{\partial C\_{sc}\left(x=x\_{veh}, t ; \theta\right)}{\partial x}\right\|^2+\\

\frac{1}{N\_c} \sum\_{i=1}^{N\_c}\left\|\frac{C\_{sc}\left(x=x\_{sc}, t ; \theta\right)}{K\_{sc}}-\frac{C\_{ep}\left(x=x\_{sc}, t ; \theta\right)}{K\_{ep}}\right\|^2+\frac{1}{N\_c} \sum\_{i=1}^{N\_c}\left\|D\_{sc} \frac{\partial C\_{sc}\left(x=x\_{sc}, t ; \theta\right)}{\partial x}-D\_{ep} \frac{\partial C\_{ep}\left(x=x\_{sc}, t ; \theta\right)}{\partial x}\right\|^2+\\

\frac{1}{N\_c} \sum\_{i=1}^{N\_c}\left\|\frac{C\_{ep}\left(x=x\_{ep}, t ; \theta\right)}{K\_{ep}}-\frac{C\_{de}\left(x=x\_{ep}, t ; \theta\right)}{K\_{de}}\right\|^2+\frac{1}{N\_c} \sum\_{i=1}^{N\_c}\left\|D\_{ep} \frac{\partial C\_{ep}\left(x=x\_{ep}, t ; \theta\right)}{\partial x}-D\_{de} \frac{\partial C\_{de}\left(x=x\_{ep}, t ; \theta\right)}{\partial x}\right\|^2

where MSE\_e, MSE\_b, MSE\_i and MSE\_c represent mean square errors corresponding to the governing of the diffusion equations, boundary, initial and continuity conditions respectively; Ne, Nb, Ni and Nc denote the number of training data for different terms; c\_i(x, t; θ), c\_i(x = 0, t; θ), c\_i(x, t = 0; θ) are the given concentration corresponding to each data point in region, on the boundaries and at the initial time, respectively; δ(t) and f(x) are the boundary and initial conditions; γ\_b, γ\_i and γ\_c represent weighting coefficients, which are used to balance different terms of the loss function and accelerate convergence in training process.