Part 2: Stochastic Gradient (1/3)

- **Stochastic Gradient Method (SGM).**
 - **Principle:** it is possible to obtain an unbiased estimate of the gradient by taking the average gradient on a minibatch of m examples drawn i.i.d. from the training dataset.
 - **Procedure:** depends on parameters $\alpha_0^{SG} > 0$ and γ_1^{SG} , $\gamma_2^{SG} \in [0,1]$
 - Sample a minibatch $S = \{s_1, s_2, ..., s_m\}$ of $m = |\gamma_1^{SG} p| \ll p$ observations from the training dataset:

$$X_{\mathbf{s}}^{TR} = \begin{bmatrix} x_{\mathbf{s_1}}^{TR}, x_{\mathbf{s_2}}^{TR}, \dots, x_{\mathbf{s_m}}^{TR} \end{bmatrix}; \ y_{\mathbf{s}}^{TR} = \begin{bmatrix} y_{\mathbf{s_1}}^{TR} & y_{\mathbf{s_2}}^{TR} & \cdots & y_{\mathbf{s_m}}^{TR} \end{bmatrix}^T$$

Compute search direction through the <u>gradient</u> estimate: ii.

$$d^k \leftarrow -\frac{1}{m} \nabla \tilde{L}(w; X_s^{TR}, y_s^{TR}, \lambda)$$

Update the parametres: $w^k \leftarrow w^k + \alpha^k d^k$ with **learning rate** α^k iii.

$$\alpha^k \coloneqq \begin{cases} \left(1 - \frac{k}{k^{SG}}\right) \alpha_0^{SG} + \frac{k}{k^{SG}} \alpha^{SG} & \text{if } k \leq k^{SG} \\ \alpha^{SG} & \text{if } k > k^{SG} \end{cases}, \qquad \begin{cases} \alpha^{SG} \approx 0.01 \cdot \alpha_0^{SG} \\ k^{SG} \coloneqq \left\lfloor \frac{\gamma_2^{SG}}{2} \cdot k^{max} \right\rfloor \end{cases}$$





Part 2: Stochastic Gradient (2/3)

Script uo_nn_solve.m must be extended to include the SGM:

```
uo nn main.m : recognition of num target digits.
clear;
% Parameters for dataset generation
num target =[3];
tr freq
           = .5;
         = 250;
tr p
          = 250;
te q
tr seed = 123456;
te seed
         = 789101;
% Parameters for optimization
la = 1.0;
                                                              % L2 regularization.
epsG = 10^-6; kmax = 10000;
                                                              % Stopping criterium.
ils=3; ialmax = 2; kmaxBLS=30; epsal=10^-3;c1=0.01; c2=0.45; % Linesearch (ils=3 -> uo BLSNW32).
isd = 7; icg = 2; irc = 2; nu = 1.0;
                                                              % Search direction.
sg ga1 = 0.05; sg a10=2; sg ga2=0.3;
                                                              % Stochastic gradient
% Optimization
t1=clock;
[Xtr,ytr,wo,fo,tr acc,Xte,yte,te acc,niter,tex]=uo nn solve(num target,
tr freq,tr seed,tr p,te seed,te q,la,epsG,kmax,ils,ialmax,kmaxBLS,epsal,c1,c2,isd,sg gal,sg al0,sg ga2,icg,irc,nu)
t2=clock;
fprintf('wall time = %6.1d s.\n', etime(t2,t1));
```





Part 2: Stochastic Gradient (3/3)

```
>> uo nn Xyplot(Xtr,ytr,wo)
        Pattern recognition with neural networks (OM/GCED).
[uo nn] Training data set generation
           num target = 3
[uo nn]
                                                Rigth positive
[uo nn]
           tr freq
                       = 0.50
                       = 250
[uo nn]
           tr p
[uo nn]
           tr seed
                       = 123456
                                               Rigth negative
[uo nn] Optimization
[uo nn]
           L2 \text{ reg. } lambda = 1.00
[uo nn]
           epsG= 1.0e-06, kmax= 10000
           ils= 3, ialmax= 2, kmaxBLS= 30, epsBLS= 1.0e-03,
[uo nn]
[uo nn]
           c1=0.01, c2=0.45, isd=7
           sq qa1= 0.05, sq a10= 2.0, sq qa2= 0.30
[uo nn]
[uo nn]
                                                          Hall
               2.00e+00
                              -1.46e+02
                                           6.25e+01
                                                      4.95e+01
[uo nn]
[uo nn]
               2.00e+00
                             -7.03e+01
                                           1.63e+02
                                                      8.46e+00
               2.00e+00
                              -6.90e+01
                                           1.56e+02
                                                      8.31e+00
[uo nn]
               2.00e-02
[uo nn] 9998
                           0 -4.71e+01
                                           2.68e+01
                                                      2.69e+01
[uo nn] 9999
               2.00e-02
                             +1.65e+00
                                           2.64e+01
                                                      1.94e+01
[uo nn]10000
                                           2.68e+01
                                                      2.49e+01
           k
                      al iW
                                   g'*d
                                                  £
                                                          Hall
[uo nn]
[uo nn]
                 -1.5e-01,+6.0e-02,-1.6e-01,-2.6e-02,-2.0e-01
[uo nn]
[uo nn]
                 +1.9e-01,-1.0e-01,-6.7e-02,-5.8e-02,+1.1e-01
                 -4.6e-01,-1.0e-01,-1.5e-01,-1.3e-01,+1.3e-01
[uo nn]
                 -1.9e-01,-3.1e-01,+3.2e-01,+1.3e-01,-3.4e-01
[uo nn]
                 -2.8e-01,-1.3e-03,-3.3e-01,-6.7e-02,+1.3e-01
[uo nn]
                 +3.1e-01,-1.7e-01,-9.9e-02,-1.5e-02,+1.7e-01
[uo nn]
[uo nn]
                 -1.7e-01,-1.7e-02,+2.4e-02,-4.0e-03,-1.2e-01
[uo nn]
[uo nn] Test data set generation.
[uo nn]
           te q
           te seed = 789101
[uo nn]
[uo nn] tr accuracy = 96.4
[uo nn] te accuracy = 87.2
>> uo nn Xyplot(wo,0,[])
```





Part 3: computational study (1/3)

- In this third part we want to conduct a series of computational experiments to study:
 - i. How the regularization parameter λ affects the results.
 - ii. The relative performance of the different algorithms (GM, QNM,SGM)
- To this end, an instance of the SLNN problem must be solved:
 - For every one of the individual digits, 0 to 9.
 - For every value of the regularization parameter $\lambda \in \{0.0, 1.0, 10.0\}$.
 - For every optimization algorithm: GM, QNM and SGM.

That makes a total of $10 \times 3 \times 4 = 120$ instances to be solved.





Part 3: computational study (2/3)

To organize the computational experiments you can use function uo_nn_batch.m:

```
uo_nn_batch.m : run a batch of SLNN instances.
```

```
function uo nn batch(tr seed, te seed)
% Parameters.
tr p = 250; te q = 250; tr freq = .5;
                                                               % Datasets generation
epsG = 10^-6; kmax = 1000;
                                                              % Stopping criterium.
ils=3; ialmax = 2; kmaxBLS=10; epsal=10^-3; c1=0.01; c2=0.45; % Linesearch (ils=3 -> uo BLSNW32).
icg = 2; irc = 2; nu = 1.0;
                                                               % Search direction.
sg ga1 = 0.05; sg a10=2; sg ga2=0.3;
                                                              % Stochastic gradient
% Optimization
iheader = 1;
csvfile = strcat('uo nn batch ',num2str(tr seed),'-',num2str(te seed),'.csv');
fileID = fopen(csvfile ,'w');
t1=clock;
for num target = 1:10
    for la = [0.0, 1.0, 10.0]
        for isd = [1,3,7]
            [Xtr,ytr,wo,fo,tr acc,Xte,yte,te acc,niter,tex]=uo nn solve(num target,
tr freq,tr seed,tr p,te seed,te q,la,epsG,kmax,ils,ialmax,kmaxBLS,epsal,c1,c2,sd,sg ga1,sg al0,sg ga2,icg,i
rc, nu, iheader);
            if iheader == 1 fprintf(fileID, 'num target; la; isd; niter; tex; tr acc; te acc; L*\n');
end
                                    %1i; %4.1f; %1i; %4i; %7.4f; %5.1f; %5.1f; %8.2e;\n',
            fprintf(fileID, '
mod(num target,10), la, isd, niter, tex, tr acc, te acc, fo);
            iheader=0;
        end
    end
end
t2=clock;
fprintf(' wall time = %6.1d s.\n', etime(t2,t1));
fclose(fileID);
end
```