## **Imports**

```
import random
import numpy as np
from data_process import get_FASHION_data, get_RICE_data
from scipy.spatial import distance
from models import Perceptron, SVM, Softmax, Logistic
from kaggle_submission import output_submission_csv
%matplotlib inline

# For auto-reloading external modules
# See http://stackoverflow.com/questions/1907993/autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2
```

# **Loading Fashion-MNIST**

In the following cells we determine the number of images for each split and load the images. TRAIN IMAGES + VAL IMAGES = (0, 60000], TEST IMAGES = 10000

```
In [2]: # You can change these numbers for experimentation
    # For submission we will use the default values
    TRAIN_IMAGES = 50000
    VAL_IMAGES = 10000
    normalize = True

In [3]: data = get_FASHION_data(TRAIN_IMAGES, VAL_IMAGES, normalize=normalize)
    X_train_fashion, y_train_fashion = data['X_train'], data['y_train']
    X_val_fashion, y_val_fashion = data['X_val'], data['y_val']
    X_test_fashion, y_test_fashion = data['X_test'], data['y_test']
    n_class_fashion = len(np.unique(y_test_fashion))
```

# **Loading Rice**

```
In [4]: # Loads train / test / val splits of 80%, 20%, 20%
data = get_RICE_data()
X_train_RICE, y_train_RICE = data['X_train'], data['y_train']
X_val_RICE, y_val_RICE = data['X_val'], data['y_val']
X_test_RICE, y_test_RICE = data['X_test'], data['y_test']
n_class_RICE = len(np.unique(y_test_RICE))

print("Number of train samples: ", X_train_RICE.shape[0])
print("Number of test samples: ", X_val_RICE.shape[0])
Number of train samples: 10911
Number of val samples: 3637
Number of test samples: 3637
```

## **Get Accuracy**

This function computes how well your model performs using accuracy as a metric.

```
In [5]: def get_acc(pred, y_test):
    return np.sum(y_test == pred) / len(y_test) * 100
```

## Perceptron

Perceptron has 2 hyperparameters that you can experiment with:

- Learning rate controls how much we change the current weights of the classifier during each update. We set it at a default value of 0.5, but you should experiment with different values. We recommend changing the learning rate by factors of 10 and observing how the performance of the classifier changes. You should also try adding a decay which slowly reduces the learning rate over each epoch.
- Number of Epochs An epoch is a complete iterative pass over all of the data in the
  dataset. During an epoch we predict a label using the classifier and then update the
  weights of the classifier according to the perceptron update rule for each sample in the
  training set. You should try different values for the number of training epochs and report
  your results.

You will implement the Perceptron classifier in the **models/perceptron.py** 

The following code:

- Creates an instance of the Perceptron classifier class
- The train function of the Perceptron class is trained on the training data
- We use the predict function to find the training accuracy as well as the testing accuracy

## Train Perceptron on Fashion-MNIST

```
In [7]: pred_percept = percept_fashion.predict(X_train_fashion)
    print('The training accuracy is given by: %f' % (get_acc(pred_percept, y_train_fashion)
    The training accuracy is given by: 84.082000
```

### Validate Perceptron on Fashion-MNIST

```
In [8]: pred_percept = percept_fashion.predict(X_val_fashion)
    print('The validation accuracy is given by: %f' % (get_acc(pred_percept, y_val_fashion)
    The validation accuracy is given by: 82.020000
```

### **Test Perceptron on Fashion-MNIST**

```
In [9]: pred_percept = percept_fashion.predict(X_test_fashion)
    print('The testing accuracy is given by: %f' % (get_acc(pred_percept, y_test_fashion))
    The testing accuracy is given by: 81.880000
```

## Perceptron\_Fashion-MNIST Kaggle Submission

Once you are satisfied with your solution and test accuracy, output a file to submit your test set predictions to the Kaggle for Assignment 1 Fashion-MNIST. Use the following code to do so:

```
In [10]: output_submission_csv('kaggle/perceptron_submission_fashion.csv', percept_fashion.pred
```

## **Train Perceptron on Rice**

```
In [11]: |1r = 0.3|
         n = 20
         percept RICE = Perceptron(n class RICE, lr, n epochs)
         percept_RICE.train(X_train_RICE, y_train_RICE)
         Epoch 0 Accuracy 54.779580240124645
         Epoch 1 Accuracy 94.94088534506461
         Epoch 2 Accuracy 99.8166987443864
         Epoch 3 Accuracy 99.89918430941252
         Epoch 4 Accuracy 99.89918430941252
         Epoch 5 Accuracy 99.89918430941252
         Epoch 6 Accuracy 99.89918430941252
         Epoch 7 Accuracy 99.89918430941252
         Epoch 8 Accuracy 99.89918430941252
         Epoch 9 Accuracy 99.89918430941252
         Epoch 10 Accuracy 99.89918430941252
         Epoch 11 Accuracy 99.89918430941252
         Epoch 12 Accuracy 99.89918430941252
         Epoch 13 Accuracy 99.89918430941252
         Epoch 14 Accuracy 99.89918430941252
         Epoch 15 Accuracy 99.89918430941252
         Epoch 16 Accuracy 99.89918430941252
         Epoch 17 Accuracy 99.89918430941252
         Epoch 18 Accuracy 99.89918430941252
         Epoch 19 Accuracy 99.89918430941252
```

```
In [12]: pred_percept = percept_RICE.predict(X_train_RICE)
    print('The training accuracy is given by: %f' % (get_acc(pred_percept, y_train_RICE)))
The training accuracy is given by: 99.899184
```

### Validate Perceptron on Rice

```
In [13]: pred_percept = percept_RICE.predict(X_val_RICE)
    print('The validation accuracy is given by: %f' % (get_acc(pred_percept, y_val_RICE)))
The validation accuracy is given by: 99.835029
```

### **Test Perceptron on Rice**

```
In [14]: pred_percept = percept_RICE.predict(X_test_RICE)
    print('The testing accuracy is given by: %f' % (get_acc(pred_percept, y_test_RICE)))
The testing accuracy is given by: 99.835029
```

## **Support Vector Machines (with SGD)**

Next, you will implement a "soft margin" SVM. In this formulation you will maximize the margin between positive and negative training examples and penalize margin violations using a hinge loss.

We will optimize the SVM loss using SGD. This means you must compute the loss function with respect to model weights. You will use this gradient to update the model weights.

SVM optimized with SGD has 3 hyperparameters that you can experiment with:

- **Learning rate** similar to as defined above in Perceptron, this parameter scales by how much the weights are changed according to the calculated gradient update.
- **Epochs** similar to as defined above in Perceptron.
- **Regularization constant** Hyperparameter to determine the strength of regularization. In this case it is a coefficient on the term which maximizes the margin. You could try different values. The default value is set to 0.05.

You will implement the SVM using SGD in the **models/svm.py** 

The following code:

- Creates an instance of the SVM classifier class
- The train function of the SVM class is trained on the training data
- We use the predict function to find the training accuracy as well as the testing accuracy

## Train SVM on Fashion-MNIST

```
In [15]: 1r = 1
         n = 30
         reg const = 0.05
         svm fashion = SVM(n class fashion, lr, n epochs, reg const)
         svm_fashion.train(X_train_fashion, y_train_fashion)
         Epoch 0 Accuracy 9.69399999999999
         Epoch 1 Accuracy 77.282
         Epoch 2 Accuracy 74.698
         Epoch 3 Accuracy 82.054
         Epoch 4 Accuracy 79.814
         Epoch 5 Accuracy 83.834
         Epoch 6 Accuracy 82.296
         Epoch 7 Accuracy 83.97
         Epoch 8 Accuracy 84.218
         Epoch 9 Accuracy 84.372
         Epoch 10 Accuracy 84.298
         Epoch 11 Accuracy 84.24000000000001
         Epoch 12 Accuracy 84.186
         Epoch 13 Accuracy 84.314
         Epoch 14 Accuracy 84.296
         Epoch 15 Accuracy 84.3860000000001
         Epoch 16 Accuracy 84.348
         Epoch 17 Accuracy 84.294
         Epoch 18 Accuracy 84.298
         Epoch 19 Accuracy 84.32600000000001
         Epoch 20 Accuracy 84.32
         Epoch 21 Accuracy 84.32
         Epoch 22 Accuracy 84.336
         Epoch 23 Accuracy 84.328
         Epoch 24 Accuracy 84.322
         Epoch 25 Accuracy 84.316
         Epoch 26 Accuracy 84.316
         Epoch 27 Accuracy 84.314
         Epoch 28 Accuracy 84.31
         Epoch 29 Accuracy 84.308
In [16]: pred svm = svm fashion.predict(X train fashion)
         print('The training accuracy is given by: %f' % (get_acc(pred_svm, y_train_fashion)))
         The training accuracy is given by: 84.308000
         Validate SVM on Fashion-MNIST
```

```
In [17]: pred_svm = svm_fashion.predict(X_val_fashion)
    print('The validation accuracy is given by: %f' % (get_acc(pred_svm, y_val_fashion)))
The validation accuracy is given by: 82.840000
```

#### Test SVM on Fashion-MNIST

```
In [18]: pred_svm = svm_fashion.predict(X_test_fashion)
    print('The testing accuracy is given by: %f' % (get_acc(pred_svm, y_test_fashion)))
The testing accuracy is given by: 82.140000
```

## SVM\_Fashion-MNIST Kaggle Submission

Once you are satisfied with your solution and test accuracy output a file to submit your test set predictions to the Kaggle for Assignment 1 Fashion-MNIST. Use the following code to do so:

```
In [19]: output_submission_csv('kaggle/svm_submission_fashion.csv', svm_fashion.predict(X_test_
```

## Train SVM on Rice

```
In [20]: lr = 1
    n_epochs = 50
    reg_const = 0.05

svm_RICE = SVM(n_class_RICE, lr, n_epochs, reg_const)
svm_RICE.train(X_train_RICE, y_train_RICE)
```

```
Epoch 0 Accuracy 54.779580240124645
         Epoch 1 Accuracy 59.160480249289705
         Epoch 2 Accuracy 62.423242599211804
         Epoch 3 Accuracy 74.60361103473558
         Epoch 4 Accuracy 77.49977087343048
         Epoch 5 Accuracy 79.08532673448812
         Epoch 6 Accuracy 78.41627715149849
         Epoch 7 Accuracy 78.7278892860416
         Epoch 8 Accuracy 78.27880120978828
         Epoch 9 Accuracy 79.0944917972688
         Epoch 10 Accuracy 78.98451104390065
         Epoch 11 Accuracy 78.94785079277793
         Epoch 12 Accuracy 79.13115204839153
         Epoch 13 Accuracy 79.07616167170745
         Epoch 14 Accuracy 79.08532673448812
         Epoch 15 Accuracy 79.05783154614609
         Epoch 16 Accuracy 79.00284116946202
         Epoch 17 Accuracy 79.00284116946202
         Epoch 18 Accuracy 79.00284116946202
         Epoch 19 Accuracy 79.0120062322427
         Epoch 20 Accuracy 79.03950142058474
         Epoch 21 Accuracy 79.04866648336541
         Epoch 22 Accuracy 79.04866648336541
         Epoch 23 Accuracy 79.04866648336541
         Epoch 24 Accuracy 79.04866648336541
         Epoch 25 Accuracy 79.04866648336541
         Epoch 26 Accuracy 79.04866648336541
         Epoch 27 Accuracy 79.03033635780406
         Epoch 28 Accuracy 79.04866648336541
         Epoch 29 Accuracy 79.04866648336541
         Epoch 30 Accuracy 79.04866648336541
         Epoch 31 Accuracy 79.04866648336541
         Epoch 32 Accuracy 79.04866648336541
         Epoch 33 Accuracy 79.04866648336541
         Epoch 34 Accuracy 79.04866648336541
         Epoch 35 Accuracy 79.04866648336541
         Epoch 36 Accuracy 79.04866648336541
         Epoch 37 Accuracy 79.04866648336541
         Epoch 38 Accuracy 79.04866648336541
         Epoch 39 Accuracy 79.04866648336541
         Epoch 40 Accuracy 79.04866648336541
         Epoch 41 Accuracy 79.04866648336541
         Epoch 42 Accuracy 79.04866648336541
         Epoch 43 Accuracy 79.04866648336541
         Epoch 44 Accuracy 79.04866648336541
         Epoch 45 Accuracy 79.04866648336541
         Epoch 46 Accuracy 79.04866648336541
         Epoch 47 Accuracy 79.04866648336541
         Epoch 48 Accuracy 79.04866648336541
         Epoch 49 Accuracy 79.04866648336541
In [21]: pred svm = svm RICE.predict(X train RICE)
         print('The training accuracy is given by: %f' % (get_acc(pred_svm, y_train_RICE)))
         The training accuracy is given by: 79.048666
```

#### Validate SVM on Rice

```
In [22]: pred_svm = svm_RICE.predict(X_val_RICE)
print('The validation accuracy is given by: %f' % (get_acc(pred_svm, y_val_RICE)))
```

The validation accuracy is given by: 78.581248

#### Test SVM on Rice

```
In [23]: pred_svm = svm_RICE.predict(X_test_RICE)
print('The testing accuracy is given by: %f' % (get_acc(pred_svm, y_test_RICE)))
```

The testing accuracy is given by: 79.323618

## Softmax Classifier (with SGD)

Next, you will train a Softmax classifier. This classifier consists of a linear function of the input data followed by a softmax function which outputs a vector of dimension C (number of classes) for each data point. Each entry of the softmax output vector corresponds to a confidence in one of the C classes, and like a probability distribution, the entries of the output vector sum to 1. We use a cross-entropy loss on this sotmax output to train the model.

Check the following link as an additional resource on softmax classification: http://cs231n.github.io/linear-classify/#softmax

Once again we will train the classifier with SGD. This means you need to compute the gradients of the softmax cross-entropy loss function according to the weights and update the weights using this gradient. Check the following link to help with implementing the gradient updates: https://deepnotes.io/softmax-crossentropy

The softmax classifier has 3 hyperparameters that you can experiment with:

- **Learning rate** As above, this controls how much the model weights are updated with respect to their gradient.
- **Number of Epochs** As described for perceptron.
- Regularization constant Hyperparameter to determine the strength of regularization. In
  this case, we minimize the L2 norm of the model weights as regularization, so the
  regularization constant is a coefficient on the L2 norm in the combined cross-entropy and
  regularization objective.

You will implement a softmax classifier using SGD in the models/softmax.py

The following code:

- Creates an instance of the Softmax classifier class
- The train function of the Softmax class is trained on the training data
- We use the predict function to find the training accuracy as well as the testing accuracy

## **Train Softmax on Fashion-MNIST**

```
In [24]: lr = 0.0005
    n_epochs = 200
    reg_const = 1

softmax_fashion = Softmax(n_class_fashion, lr, n_epochs, reg_const)
    softmax_fashion.train(X_train_fashion, y_train_fashion)
```

```
Epoch 0 Accuracy 6.39
```

- Epoch 1 Accuracy 75.994
- Epoch 2 Accuracy 78.276
- Epoch 3 Accuracy 78.798
- Epoch 4 Accuracy 79.994
- Epoch 5 Accuracy 80.05
- Epoch 6 Accuracy 81.186
- Epoch 7 Accuracy 79.1019999999999
- Epoch 8 Accuracy 81.462
- Epoch 9 Accuracy 82.592
- Epoch 10 Accuracy 78.572
- Epoch 11 Accuracy 82.238
- Epoch 12 Accuracy 80.822
- Epoch 13 Accuracy 81.734
- Epoch 14 Accuracy 85.356
- Epoch 15 Accuracy 83.084
- Epoch 16 Accuracy 82.988
- Epoch 17 Accuracy 83.248
- Epoch 18 Accuracy 82.35
- Epoch 19 Accuracy 82.462
- Epoch 20 Accuracy 81.4100000000001
- Epoch 21 Accuracy 78.676
- Epoch 22 Accuracy 77.5399999999999
- Epoch 23 Accuracy 82.446
- Epoch 24 Accuracy 82.91
- Epoch 25 Accuracy 83.978
- Epoch 26 Accuracy 83.8
- Epoch 27 Accuracy 82.048
- Epoch 28 Accuracy 77.8440000000001
- Epoch 29 Accuracy 82.734
- Epoch 30 Accuracy 76.94
- Epoch 31 Accuracy 84.3
- Epoch 32 Accuracy 83.364
- Epoch 33 Accuracy 85.112
- Epoch 34 Accuracy 85.504
- Epoch 35 Accuracy 77.45
- Epoch 36 Accuracy 80.444 Epoch 37 Accuracy 79.164
- Epoch 38 Accuracy 81.498
- Epoch 39 Accuracy 83.492
- Epoch 40 Accuracy 76.86
- Epoch 41 Accuracy 82.812
- Epoch 42 Accuracy 82.798
- Epoch 43 Accuracy 85.524
- Epoch 44 Accuracy 82.95
- Epoch 45 Accuracy 83.366
- Epoch 46 Accuracy 84.574
- Epoch 47 Accuracy 84.922
- Epoch 48 Accuracy 85.91
- Epoch 49 Accuracy 85.658
- Epoch 50 Accuracy 85.48
- Epoch 51 Accuracy 84.084
- Epoch 52 Accuracy 83.692
- Epoch 53 Accuracy 83.096
- Epoch 54 Accuracy 86.2280000000001
- Epoch 55 Accuracy 84.77
- Epoch 56 Accuracy 85.464
- Epoch 57 Accuracy 85.58
- Epoch 58 Accuracy 81.77600000000001
- Epoch 59 Accuracy 86.65

```
Epoch 60 Accuracy 85.992
```

- Epoch 61 Accuracy 86.824
- Epoch 62 Accuracy 86.92
- Epoch 63 Accuracy 87.238
- Epoch 64 Accuracy 87.24
- Epoch 65 Accuracy 87.148
- Epoch 66 Accuracy 85.274
- Epoch 67 Accuracy 87.16000000000001
- Epoch 68 Accuracy 88.016
- Epoch 69 Accuracy 86.982
- Epoch 70 Accuracy 86.19
- Epoch 71 Accuracy 87.786
- Epoch 72 Accuracy 87.646
- Epoch 73 Accuracy 88.0519999999999
- Epoch 74 Accuracy 87.3140000000001
- Epoch 75 Accuracy 87.9619999999999
- Epoch 76 Accuracy 87.6499999999999
- Epoch 77 Accuracy 87.28
- Epoch 78 Accuracy 88.008
- Epoch 79 Accuracy 87.972
- Epoch 80 Accuracy 87.756
- Epoch 81 Accuracy 88.064
- Epoch 82 Accuracy 88.0399999999999
- Epoch 83 Accuracy 88.05
- Epoch 84 Accuracy 87.688
- Epoch 85 Accuracy 88.168
- Epoch 86 Accuracy 88.03
- Epoch 87 Accuracy 87.6619999999999
- Epoch 88 Accuracy 88.108
- Epoch 89 Accuracy 88.212
- Epoch 90 Accuracy 88.13
- Epoch 91 Accuracy 88.32
- Epoch 92 Accuracy 88.22
- Epoch 93 Accuracy 88.276
- Epoch 94 Accuracy 88.0
- Epoch 95 Accuracy 88.3939999999999
- Epoch 96 Accuracy 88.164
- Epoch 97 Accuracy 87.8380000000001
- Epoch 98 Accuracy 88.228
- Epoch 99 Accuracy 88.0380000000001
- Epoch 100 Accuracy 88.354
- Epoch 101 Accuracy 88.348
- Epoch 102 Accuracy 88.22
- Epoch 103 Accuracy 88.262
- Epoch 104 Accuracy 88.292
- Epoch 105 Accuracy 88.3079999999999
- Epoch 106 Accuracy 88.318
- Epoch 107 Accuracy 88.304
- Epoch 108 Accuracy 88.31599999999999
- Epoch 109 Accuracy 88.2700000000001
- Epoch 110 Accuracy 88.366
- Epoch 111 Accuracy 88.372
- Epoch 112 Accuracy 88.372
- Epoch 113 Accuracy 88.3159999999999
- Epoch 114 Accuracy 88.336
- Epoch 115 Accuracy 88.402
- Epoch 116 Accuracy 88.426
- Epoch 117 Accuracy 88.412
- Epoch 118 Accuracy 88.426
- Epoch 119 Accuracy 88.20400000000001

```
Epoch 120 Accuracy 88,408
```

- Epoch 121 Accuracy 88.354
- Epoch 122 Accuracy 88.432
- Epoch 123 Accuracy 88.388
- Epoch 124 Accuracy 88.4600000000001
- Epoch 125 Accuracy 88.332
- Epoch 126 Accuracy 88.376
- Epoch 127 Accuracy 88.434
- Epoch 128 Accuracy 88.478
- Epoch 129 Accuracy 88.446
- Epoch 130 Accuracy 88.378
- Epoch 131 Accuracy 88.426
- Epoch 132 Accuracy 88.472
- Epoch 133 Accuracy 88.414
- Epoch 134 Accuracy 88.466
- Epoch 135 Accuracy 88.44
- Epoch 136 Accuracy 88.416
- Epoch 137 Accuracy 88.498
- Epoch 138 Accuracy 88.426
- Epoch 139 Accuracy 88.442
- Epoch 140 Accuracy 88.414
- Epoch 141 Accuracy 88.446
- Epoch 142 Accuracy 88.412
- Epoch 143 Accuracy 88.426
- Epoch 145 Accuracy 88.442
- Epoch 146 Accuracy 88.456
- Epoch 147 Accuracy 88.474
- Epoch 148 Accuracy 88.414
- Epoch 149 Accuracy 88.416
- Epoch 150 Accuracy 88.402
- Epoch 151 Accuracy 88.414
- Epoch 152 Accuracy 88.42
- Epoch 153 Accuracy 88.426
- Epoch 154 Accuracy 88.442
- Epoch 155 Accuracy 88.4619999999999
- Epoch 156 Accuracy 88.454
- Epoch 157 Accuracy 88.428
- Epoch 158 Accuracy 88.434
- Epoch 159 Accuracy 88.472
- Epoch 160 Accuracy 88.464
- Epoch 161 Accuracy 88.4480000000001
- Epoch 162 Accuracy 88.41
- Epoch 163 Accuracy 88.414
- Epoch 164 Accuracy 88.4179999999999
- Epoch 165 Accuracy 88.444
- Epoch 166 Accuracy 88.4
- Epoch 167 Accuracy 88.4179999999999
- Epoch 168 Accuracy 88.412
- Epoch 169 Accuracy 88.416
- Epoch 170 Accuracy 88.4040000000001
- Epoch 171 Accuracy 88.442
- Epoch 172 Accuracy 88.42
- Epoch 173 Accuracy 88.428
- Epoch 174 Accuracy 88.456
- Epoch 175 Accuracy 88.426
- Epoch 176 Accuracy 88.432
- Epoch 177 Accuracy 88.44
- Epoch 178 Accuracy 88.426
- Epoch 179 Accuracy 88.436

```
Epoch 180 Accuracy 88.438
        Epoch 181 Accuracy 88.438
        Epoch 182 Accuracy 88.436
        Epoch 183 Accuracy 88.432
        Epoch 184 Accuracy 88.438
        Epoch 185 Accuracy 88.44
        Epoch 186 Accuracy 88.44
        Epoch 187 Accuracy 88.436
        Epoch 188 Accuracy 88.436
        Epoch 191 Accuracy 88.432
        Epoch 192 Accuracy 88.436
        Epoch 193 Accuracy 88.428
        Epoch 194 Accuracy 88.432
        Epoch 195 Accuracy 88.436
        Epoch 196 Accuracy 88.432
        Epoch 197 Accuracy 88.436
        Epoch 198 Accuracy 88.436
        Epoch 199 Accuracy 88.438
In [25]: pred_softmax = softmax_fashion.predict(X_train_fashion)
        print('The training accuracy is given by: %f' % (get_acc(pred_softmax, y_train_fashior
        The training accuracy is given by: 88.436000
```

#### Validate Softmax on Fashion-MNIST

```
In [26]: pred_softmax = softmax_fashion.predict(X_val_fashion)
    print('The validation accuracy is given by: %f' % (get_acc(pred_softmax, y_val_fashion))
The validation accuracy is given by: 84.540000
```

## **Testing Softmax on Fashion-MNIST**

```
In [27]: pred_softmax = softmax_fashion.predict(X_test_fashion)
    print('The testing accuracy is given by: %f' % (get_acc(pred_softmax, y_test_fashion))
    The testing accuracy is given by: 83.530000
```

### Softmax\_Fashion-MNIST Kaggle Submission

Once you are satisfied with your solution and test accuracy output a file to submit your test set predictions to the Kaggle for Assignment 1 Fashion-MNIST. Use the following code to do so:

```
In [28]: output_submission_csv('kaggle/softmax_submission_fashion.csv', softmax_fashion.predict
```

## Train Softmax on Rice

```
In [29]: lr = 0.5
    n_epochs = 200
    reg_const = 1

softmax_RICE = Softmax(n_class_RICE, lr, n_epochs, reg_const)
    softmax_RICE.train(X_train_RICE, y_train_RICE)
```

```
Epoch 0 Accuracy 47.28255888552837
```

- Epoch 1 Accuracy 45.220419759875355
- Epoch 2 Accuracy 54.779580240124645
- Epoch 3 Accuracy 54.779580240124645
- Epoch 4 Accuracy 45.220419759875355
- Epoch 5 Accuracy 45.220419759875355
- Epoch 6 Accuracy 45.220419759875355
- Epoch 7 Accuracy 60.141141966822474
- Epoch 8 Accuracy 45.220419759875355
- Epoch 9 Accuracy 54.779580240124645
- Epoch 10 Accuracy 64.89780954999543
- Epoch 11 Accuracy 45.220419759875355
- Epoch 12 Accuracy 76.711575474292
- Epoch 13 Accuracy 54.779580240124645
- Epoch 14 Accuracy 45.220419759875355
- Epoch 15 Accuracy 75.55677756392632
- Epoch 16 Accuracy 76.253322335258
- Epoch 17 Accuracy 45.220419759875355
- Epoch 18 Accuracy 56.29181559893686
- Epoch 19 Accuracy 73.71459994500962
- Epoch 20 Accuracy 56.695078361286775
- Epoch 21 Accuracy 45.220419759875355
- Epoch 22 Accuracy 78.40711208871781
- Epoch 23 Accuracy 78.33379158647237
- Epoch 24 Accuracy 60.05865640179635
- Epoch 25 Accuracy 54.779580240124645
- Epoch 26 Accuracy 51.76427458528091
- Epoch 27 Accuracy 45.220419759875355
- Epoch 28 Accuracy 45.220419759875355
- Epoch 29 Accuracy 45.220419759875355
- Epoch 30 Accuracy 45.220419759875355
- Epoch 31 Accuracy 52.01173128035927
- Epoch 32 Accuracy 72.61479241132803
- Epoch 33 Accuracy 45.220419759875355
- Epoch 34 Accuracy 57.61158463935479
- Epoch 35 Accuracy 57.061680872513975
- Epoch 36 Accuracy 45.220419759875355
- Epoch 37 Accuracy 67.61066813307671
- Epoch 38 Accuracy 54.779580240124645 Epoch 39 Accuracy 77.82054807075428
- Epoch 40 Accuracy 59.618733388323705
- Epoch 41 Accuracy 79.15864723673357
- ----- 42 A----- 45 22041075007525
- Epoch 42 Accuracy 45.220419759875355
- Epoch 43 Accuracy 55.21950325359729
- Epoch 44 Accuracy 55.622766015947214
- Epoch 45 Accuracy 76.54660434423975
- Epoch 46 Accuracy 71.78993676106681
- Epoch 47 Accuracy 50.09623315919715
- Epoch 48 Accuracy 63.46805975620933
- Epoch 49 Accuracy 63.633030886261565
- Epoch 50 Accuracy 55.476125011456325
- Epoch 51 Accuracy 66.75831729447347
- Epoch 52 Accuracy 56.695078361286775
- Epoch 53 Accuracy 55.41196957199157
- Epoch 54 Accuracy 68.06892127211071
- Epoch 55 Accuracy 66.92328842452571
- Epoch 56 Accuracy 50.2520392264687
- Epoch 57 Accuracy 69.41618550087068 Epoch 58 Accuracy 60.59939510585648
- Epoch 59 Accuracy 72.09238383282926

```
Epoch 60 Accuracy 50.78361286774814
Epoch 61 Accuracy 74.3286591513152
Epoch 62 Accuracy 57.12583631197874
Epoch 63 Accuracy 59.04133443314087
Epoch 64 Accuracy 72.45898634405646
Epoch 65 Accuracy 49.39968838786546
Epoch 66 Accuracy 70.6443039134818
Epoch 67 Accuracy 63.183942810008254
Epoch 68 Accuracy 63.733846576849054
Epoch 69 Accuracy 74.01704701677207
Epoch 70 Accuracy 79.25946292732105
Epoch 71 Accuracy 77.72889744294748
Epoch 72 Accuracy 58.12482815507286
Epoch 73 Accuracy 62.20328109247548
Epoch 74 Accuracy 56.319310787278894
Epoch 75 Accuracy 72.20236458619742
Epoch 76 Accuracy 76.03336082852168
Epoch 77 Accuracy 70.66263403904317
Epoch 78 Accuracy 74.69526166254239
Epoch 79 Accuracy 75.87755476125011
Epoch 80 Accuracy 74.02621207955275
Epoch 81 Accuracy 50.18788378700394
Epoch 82 Accuracy 72.26652002566217
Epoch 83 Accuracy 75.45596187333882
Epoch 84 Accuracy 77.01402254605443
Epoch 85 Accuracy 76.16167170745119
Epoch 86 Accuracy 79.24113280175969
Epoch 87 Accuracy 78.94785079277793
Epoch 88 Accuracy 74.72275685088444
Epoch 89 Accuracy 70.58014847401705
Epoch 90 Accuracy 79.04866648336541
Epoch 91 Accuracy 74.87856291815599
Epoch 92 Accuracy 48.60232792594629
Epoch 93 Accuracy 71.7991018238475
Epoch 94 Accuracy 74.28283383741179
Epoch 95 Accuracy 59.28879112821923
Epoch 96 Accuracy 73.18302630373019
Epoch 97 Accuracy 73.9528915773073
Epoch 98 Accuracy 56.56676748235725
Epoch 99 Accuracy 63.596370635138854
Epoch 100 Accuracy 73.70543488222894
Epoch 101 Accuracy 78.09549995417468
Epoch 102 Accuracy 79.25029786454037
Epoch 103 Accuracy 67.26239574741088
Epoch 104 Accuracy 79.67189075245166
Epoch 105 Accuracy 77.11483823664193
Epoch 106 Accuracy 65.94262670699294
Epoch 107 Accuracy 75.29099074328659
Epoch 108 Accuracy 60.26028778297131
Epoch 109 Accuracy 61.79085326734488
Epoch 110 Accuracy 74.98854367152416
Epoch 111 Accuracy 61.77252314178352
Epoch 112 Accuracy 69.97525433049216
Epoch 113 Accuracy 78.28796627256897
Epoch 114 Accuracy 79.58024012464485
Epoch 115 Accuracy 75.43763174777747
Epoch 116 Accuracy 80.13930895426634
Epoch 117 Accuracy 78.76454953716433
Epoch 118 Accuracy 58.922188616992024
Epoch 119 Accuracy 71.45999450096234
```

```
Epoch 120 Accuracy 79.24113280175969
Epoch 121 Accuracy 58.75721748693978
Epoch 122 Accuracy 78.88369535331317
Epoch 123 Accuracy 79.48858949683806
Epoch 124 Accuracy 63.550545321235454
Epoch 125 Accuracy 78.58124828155073
Epoch 126 Accuracy 61.28677481440747
Epoch 127 Accuracy 68.1697369626982
Epoch 128 Accuracy 79.35111355512785
Epoch 129 Accuracy 80.8450187883787
Epoch 130 Accuracy 70.31436165337732
Epoch 131 Accuracy 67.41820181468243
Epoch 132 Accuracy 79.2869581156631
Epoch 133 Accuracy 76.4366235908716
Epoch 134 Accuracy 72.0190633305838
Epoch 135 Accuracy 61.66254238841537
Epoch 136 Accuracy 72.81642379250299
Epoch 137 Accuracy 67.83062963981304
Epoch 138 Accuracy 54.128860782696364
Epoch 139 Accuracy 80.95499954174686
Epoch 140 Accuracy 74.89689304371736
Epoch 141 Accuracy 71.73494638438274
Epoch 142 Accuracy 73.36632755934377
Epoch 143 Accuracy 76.64742003482723
Epoch 144 Accuracy 72.29401521400422
Epoch 145 Accuracy 72.58729722298598
Epoch 146 Accuracy 63.00064155439464
Epoch 147 Accuracy 69.84694345156265
Epoch 148 Accuracy 71.74411144716342
Epoch 149 Accuracy 72.3948309045917
Epoch 150 Accuracy 60.86518192649619
Epoch 151 Accuracy 77.27064430391349
Epoch 152 Accuracy 78.0405095774906
Epoch 153 Accuracy 76.88571166712492
Epoch 154 Accuracy 85.23508386032445
Epoch 155 Accuracy 84.91430666300064
Epoch 156 Accuracy 67.5190175052699
Epoch 157 Accuracy 56.56676748235725
Epoch 158 Accuracy 76.95903216937036
Epoch 159 Accuracy 88.2870497662909
Epoch 160 Accuracy 65.14526624507377
Epoch 161 Accuracy 85.14343323251764
Epoch 162 Accuracy 88.67198240307947
Epoch 163 Accuracy 77.59142150123728
Epoch 164 Accuracy 93.53863073962057
Epoch 165 Accuracy 83.6495279992668
Epoch 166 Accuracy 99.18430941251948
Epoch 167 Accuracy 99.84419393272844
Epoch 168 Accuracy 99.92667949775455
Epoch 169 Accuracy 99.78003849326367
Epoch 170 Accuracy 99.89918430941252
Epoch 171 Accuracy 99.53258179818532
Epoch 172 Accuracy 99.44093117037852
Epoch 173 Accuracy 99.79836861882504
Epoch 174 Accuracy 99.71588305379892
Epoch 175 Accuracy 99.85335899550913
Epoch 176 Accuracy 99.89001924663185
Epoch 177 Accuracy 99.83502886994776
Epoch 178 Accuracy 99.89001924663185
```

Epoch 179 Accuracy 99.84419393272844

```
Epoch 180 Accuracy 99.88085418385117
         Epoch 181 Accuracy 99.91751443497388
         Epoch 182 Accuracy 99.89918430941252
         Epoch 183 Accuracy 99.89918430941252
         Epoch 184 Accuracy 99.9083493721932
         Epoch 185 Accuracy 99.91751443497388
         Epoch 186 Accuracy 99.87168912107049
         Epoch 187 Accuracy 99.9083493721932
         Epoch 188 Accuracy 99.86252405828981
         Epoch 189 Accuracy 99.89918430941252
         Epoch 190 Accuracy 99.84419393272844
         Epoch 191 Accuracy 99.89918430941252
         Epoch 192 Accuracy 99.89001924663185
         Epoch 193 Accuracy 99.84419393272844
         Epoch 194 Accuracy 99.74337824214096
         Epoch 195 Accuracy 99.85335899550913
         Epoch 196 Accuracy 99.9083493721932
         Epoch 197 Accuracy 99.89918430941252
         Epoch 198 Accuracy 99.9083493721932
         Epoch 199 Accuracy 99.9083493721932
         pred_softmax = softmax_RICE.predict(X_train_RICE)
In [30]:
         print('The training accuracy is given by: %f' % (get_acc(pred_softmax, y_train_RICE)))
         The training accuracy is given by: 99.908349
```

#### Validate Softmax on Rice

```
In [31]: pred_softmax = softmax_RICE.predict(X_val_RICE)
    print('The validation accuracy is given by: %f' % (get_acc(pred_softmax, y_val_RICE)))
The validation accuracy is given by: 99.835029
```

### **Testing Softmax on Rice**

```
In [32]: pred_softmax = softmax_RICE.predict(X_test_RICE)
    print('The testing accuracy is given by: %f' % (get_acc(pred_softmax, y_test_RICE)))
The testing accuracy is given by: 99.862524
```

# **Logistic Classifier**

The Logistic Classifier has 2 hyperparameters that you can experiment with:

- Learning rate similar to as defined above in Perceptron, this parameter scales by how
  much the weights are changed according to the calculated gradient update.
- **Number of Epochs** As described for perceptron.
- Threshold The decision boundary of the classifier.

You will implement the Logistic Classifier in the **models/logistic.py** 

The following code:

Creates an instance of the Logistic classifier class

- The train function of the Logistic class is trained on the training data
- We use the predict function to find the training accuracy as well as the testing accuracy

## **Training Logistic Classifer**

```
In [33]:
         learning rate = 0.2
         n = 10
         threshold = 0
         y_train_RICE = np.where(y_train_RICE == 0, -1, y_train_RICE)
         lr = Logistic(learning_rate, n_epochs, threshold)
         lr.train(X_train_RICE, y_train_RICE)
         Epoch 0 Accuracy 54.779580240124645
         Epoch 1 Accuracy 69.36119512418661
         Epoch 2 Accuracy 71.91824763999634
         Epoch 3 Accuracy 68.49967922280268
         Epoch 4 Accuracy 91.74227843460727
         Epoch 5 Accuracy 78.38878196315645
         Epoch 6 Accuracy 94.84923471725781
         Epoch 7 Accuracy 97.35129685638346
         Epoch 8 Accuracy 95.8665566859133
         Epoch 9 Accuracy 98.47859957840711
In [34]: pred_lr = lr.predict(X_train_RICE)
         print('The training accuracy is given by: %f' % (get_acc(pred_lr, y_train_RICE)))
         The training accuracy is given by: 99.624232
```

### **Validate Logistic Classifer**

```
In [35]: y_val_RICE = np.where(y_val_RICE == 0, -1, y_val_RICE)
    pred_lr = lr.predict(X_val_RICE)
    print('The validation accuracy is given by: %f' % (get_acc(pred_lr, y_val_RICE)))
```

The validation accuracy is given by: 99.615067

## **Test Logistic Classifier**

```
In [36]: y_test_RICE = np.where(y_test_RICE == 0, -1, y_test_RICE)
    pred_lr = lr.predict(X_test_RICE)
    print('The testing accuracy is given by: %f' % (get_acc(pred_lr, y_test_RICE)))
The testing accuracy is given by: 99.642563
```