Logistic_discrimination(X, Y, eta, max_iter): given data from two linearly seperable classes ω_1 and ω_2 , trains a linear logistic discriminator to distinguish the two classes.

This function uses gradient descent with the update rule described as follows, as per presented in the slides:

$$\begin{split} w_i &= w_i + \Delta w_i, \, \Delta w_i = -\eta \, \frac{\partial E}{\partial w_i} \text{ where } E \text{ is the crossentropy loss} \\ \Delta w_j &= \eta \sum_i \, (y_i - z_i) x_{\text{ij}}, \, j = 1, 2, \cdots, l \\ \Delta w_0 &= \eta \sum_i \, (y_i - z_i) \\ z_i &= \sigma \big(w^T x + w_0 \big) \end{split}$$

Args:

- *X*: the input data.
- *Y*: the labels corresponding to *X*. Must be 0 and 1 encoded.
- η: desired learning rate.
- max_iter: maximum number of allowed iterations.

Returns:

• w: the trained weights that can perform as a logistic discriminator for X according to Y.

```
function w = logistic discrimination(X, Y, eta, max iter)
    if nargin<4</pre>
        if nargin < 3</pre>
            % learning rate
            eta = 0.01;
        end
        % maximum number of allowed iterations, if it takes longer than
        % this, assume the algorithm cannot converge
        max iter = 5000;
    end
    % augment the training data with a vector of "1"s
    X \text{ aug} = [X, \text{ ones}([\text{size}(X,1), 1])];
    % set initial weights to a standard normal value
    w = normrnd(0, 1, [3,1]);
    % convergence tolerance
    % if the updates are smaller than a certain amount, assume convergence
    convergence_tol = 1e-8;
    % the perceptron algorithm main loop
    iteration = 1;
    while iteration < max_iter</pre>
        delta w = zeros([3, 1]);
        % note that because we augmented X, we don't need to separate the
        % special case for the bias term as the update rule will
        % automatically account for it.
        for j=1:3
            sum = 0;
            for i=1:size(X_aug,1)
```

```
sum = sum + (Y(i) - logsig(w'*X_aug(i,:)'))*X_aug(i,j);
end
    delta_w(j) = eta*sum;
end
    if max(abs(delta_w), [], 'all') < convergence_tol
        % assume convergence
        break;
end
    w = w + delta_w;
    iteration = iteration + 1;
end
fprintf('Stopped in %d steps.\n', iteration);
disp('Final weights:');
w
end</pre>
```