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using LinearAlgebra
    gradient_descent(f, \nabla f, x0; \alpha, tol, LIMIT)
Gradient descent algorithm for a function f, gradient 
abla f, initial guess x0, learning rate lpha,
and tolerance tol. LIMIT is max iterations.
function gradient descent(f, \nabla f, \times 0; \alpha = 1.e-3, tol = 1.e-7, LIMIT = 5.e6)
    global counter = 0
    x = x0
    while norm(\nabla f(x)) > tol \&\& counter < LIMIT
        x = x \cdot - \alpha \cdot * \nabla f(x)
        global counter += 1
    end
    println("Number of iterations: $counter.")
    if counter == LIMIT
         println("Max iterations reached.")
    end
    return x
end
    newton_method(f, \nablaf, \nabla2f, x0; tol, LIMIT)
Newton method for a function f, gradient \nabla f, Hessian \nabla 2f, initial guess x0, and tolerance
tol. LIMIT is max iterations.
function newton_method(f, \nablaf, \nabla2f, x0; tol = 1.e-7, LIMIT = 500000)
    global counter = 0
    x = x0
    while norm(\nabla f(x)) > tol \&\& counter < LIMIT
        x = x \cdot - \nabla 2f(x) \setminus \nabla f(x)
        global counter += 1
    end
    println("Number of iterations: $counter.")
    if counter == LIMIT
         println("Max iterations reached.")
    end
    return x
end
    nonnegative_matrix_factorization(X, k; tol, LIMIT)
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Performs nonnegative matrix factorization X = W * H where X is n x p, W is n x k, and H is k
x p. The inner dimension k is a hyperparameter.
function nonnegative_matrix_factorization(X, k; tol = 1.e-7, LIMIT = 1000)
    n, p = size(X)
    W = ones(n, k)
    H = ones(k, p)
    global counter = 0
    oldWH = X
    newWH = W * H
    while norm(newWH - oldWH) > tol && counter < LIMIT</pre>
        oldWH = W * H
        H num = W' * X
        H_{denom} = W' * W * H
        H = H .* (H_num ./ H_denom)
        W_num = X * H'
        W_denom = W * H * H'
        W = W .* (W_num ./ W_denom)
        global counter +=1
        newWH = W * H
    end
    return W, H
end
    adaboost(X, y)
Performs the AdaBoost algorithm on a data set with entries consisting of -1's and 1's.
The columns of X are weak classifiers, and the entries of y are the labels for the rows of X.
function adaboost(X, y; tol = 1.e-5, LIMIT = 5)
    n, p = size(X)
    coeffs = zeros(p)
    f(R) = dot(coeffs, R)
    global counter = 1
    \epsilon = 1
    while counter < LIMIT && norm(\epsilon) > tol
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current_min = Inf
        current_min_index = 1
        total error = 0
        polarity = 1
        for c = 1:p
            class_error = 0
            total error = 0
            for r = 1:n
                if X[r, c] != y[r]
                     class_error += exp(-y[r] * f(X[r, :]))
                end
                total_error += exp(-y[r] * f(X[r, :]))
            end
            this_polarity = 1
            if class_error > total_error / 2
                class_error = total_error - class_error
                this_polarity = -1
            end
            if class_error < current_min</pre>
                current_min = class_error
                current_min_index = c
                polarity = this_polarity
            end
        end
        ε = current_min / total_error
        \alpha = 1/2 * \log((1-\epsilon)/\epsilon + 1e-10)
        coeffs[current_min_index] += polarity * α
        global counter += 1
    end
    println("Number of iterations: $counter.")
    return R -> dot(R, coeffs)
    k_means(X, k; LIMIT)
Performs k-means clustering on the matrix X with k clusters.
function k_means(X, k; LIMIT = 500)
```

end

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n, p = size(X)
centroids = zeros(k, p)
used = []
nearest = zeros(n)
# generate initial centroids randomly
for i = 1:k
    rand idx = rand(1:n)
    while rand_idx ∈ used
        rand_idx = rand(1:n)
    end
    centroids[i, :] = X[rand_idx, :]
    append!(used, [rand_idx])
end
#identify nearest centroids for each observation given initial centroids
for row = 1:n
    current_min = Inf
    current_min_idx = 1
    for ctrd in 1:k
        dist = norm(X[row, :] .- centroids[ctrd, :])
        if dist < current_min</pre>
            current_min = dist
            current_min_idx = ctrd
        end
    end
    nearest[row] = current_min_idx
end
global counter = 0
centroids_changed = true
while counter < LIMIT && centroids_changed
    centroids_changed = false
    # update centroids
    for ctrd in 1:k
        idxs = []
        for row = 1:n
            if nearest[row] == ctrd
                append!(idxs, [row])
            end
        end
        this_cluster = X[idxs, :]
        numrows, _ = size(this_cluster)
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cluster_mean = zeros(p)
        for col in 1:p
            for row in 1:numrows
                cluster_mean[col] += 1/numrows * this_cluster[row, col]
            end
        end
        if centroids[ctrd, :] != cluster_mean[:]
            centroids_changed = true
        end
        centroids[ctrd, :] = cluster_mean[:]
    end
    #identify new nearest centroids for each observation
    for row = 1:n
        current_min = Inf
        current min idx = 1
        for ctrd in 1:k
            dist = norm(X[row, :] .- centroids[ctrd, :])
            if dist < current_min</pre>
                current_min = dist
                current_min_idx = ctrd
            end
        end
        nearest[row] = current_min_idx
    end
    counter += 1
end
#final nearest centroids
for row = 1:n
    current_min = Inf
    current_min_idx = 1
    for ctrd in 1:k
        dist = norm(X[row, :] .- centroids[ctrd, :])
        if dist < current_min</pre>
            current_min = dist
            current_min_idx = ctrd
        end
    end
    nearest[row] = current_min_idx
end
return centroids, nearest
```