This algorithm is based off the Sequential Minimal Optimization algorithm described in:

http://research.microsoft.com/pubs/69644/tr-98-14.pdf

We only need to use vectors that have a Lagrange multiplier > 0 as support vectors, so this algorithm will return the array of multipliers α . An outside algorithm will check if they are > 0 and if so, use those in calculating the weight of the vectors, ignoring the others.

Algorithm 1 Sequential Minimal Optimization SVM

```
procedure smo\ svm(input[][], output[], tolerance, c, <math>\epsilon)
INPUTS: input - SET OF N INPUT IMAGE VECTORS
         output - SET OF N OUTPUT DECISIONS (-1 OR 1)
         tolerance - CONVERGENCE TOLERANCE
         c - SOFT MARGIN PARAMETER
         \epsilon - EPSILON INSENSITIVITY ZONE
    \alpha \leftarrow \emptyset, bias \leftarrow 0, error \leftarrow 0
    num changed \leftarrow 0, examine \leftarrow 1
    while (num changed > 0 || examine) do
        num changed \leftarrow 0
       if (examine) then
           for (i = 0 \rightarrow input.size) do
               num changed+ = examine example(i)
           end for
        else
           for (i = 0 \rightarrow input.size) do
               if (\alpha[i] \neq 0 \&\& \alpha[i] \neq c) then
                   num changed+ = examine_example(i)
               end if
           end for
        end if
       if (examine == 1) then
           examine \leftarrow 0
        else if (num \ changed == 0) then
           num changed \leftarrow 1
        end if
    end while
    return α
end procedure
```

```
Algorithm 2 examine example()
  procedure examine example(i_2)
  INPUTS: i_2 - INDEX TO EXAMPLE IN TRAINING SET
      p_2 \leftarrow input[i_2], y_2 \leftarrow output[i_2], \alpha_2 \leftarrow \alpha[i_2]
      if (\alpha_2 > 0 \&\& \alpha_2 < c) then
          compute\_error_2 \leftarrow error[i_2]
      else
          compute error_2 \leftarrow compute\_svm(p_2) - y_2
      end if
      r_2 \leftarrow compute\_error_2 * y_2
      #Check Lagrangian multiplier outside of allowable bounds.
      #This tests KKT conditions for 1st choice lagrangian
      if ((r_2 < -tolerance \&\& \alpha_2 < c) \&\& (r_2 > tolerance \&\& \alpha_2 > 0)) then
          #Choose 2nd Lagrangian multiplier to maximize size of step taken during joint optimization.
          #Approximate step size by: |E_1 - E_2|
          i_1 \leftarrow 0, max \leftarrow 0
          for (i = 0 \rightarrow input.size) do
              if (\alpha[i] > 0 \&\& \alpha[i] < c) then
                  aux \ error \leftarrow error[i]
                  step\_size \leftarrow |error[i] - compute\_error_2|
                  if (step\_size > max) then
                      max \leftarrow step size
                      i_1 \leftarrow i
                  end if
               end if
          end for
          if (i_1 \ge 0 \&\& (take\_step(i_1, i_2)) == true) then
               return 1
          end if
          #Sometimes SMO cannot make positive progress with heuristic above. So, iterate through
          #non-bound examples, searching for second example that makes positive progress
          rnd \leftarrow random(input.size)
          for (i_1 = rnd \rightarrow input.size) do
              if (\alpha[i_1] > 0 \&\& \alpha[i_1] < c) then
                  if (take\ step(i_1,i_2)) == true) then
                      return 1
                  end if
               end if
          end for
          for (i_1 = 0 \rightarrow rnd) do
              if (\alpha[i_1] > 0 \&\& \alpha[i_1] < c) then
                  if (take\_step(i_1, i_2)) == true) then
```

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return 1

end if

end if end for

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#If none of the non-bound examples lead to positive progress, SMO iterates through entire #training set until positive progress. If this still doesn't work, abandon this example and move #to next iteration for a better one $rnd \leftarrow random(input.size)$ for $(i_1 = rnd \rightarrow input.size)$ do if $(take_step(i_1, i_2)) == true)$ then $return\ 1$ end if end for for $(i_1 = 0 \rightarrow rnd)$ do if $(take_step(i_1, i_2)) == true)$ then $return\ 1$ end if

end if

end for

return 0

end procedure

else

```
Algorithm 3 take step()
```

```
procedure take step(i_1, i_2)
INPUTS: i_1 - 1ST INDEX TO EXAMPLE IN TRAINING SET
             i_2 - 2ND INDEX TO EXAMPLE IN TRAINING SET
     if (i_1 == i_2) then
          return false
     end if
     p_1 \leftarrow input[i_1], y_1 \leftarrow output[i_1], \alpha_1 \leftarrow \alpha[i_1]
     if (\alpha_1 > 0 \&\& \alpha_1 < c) then
          compute error<sub>1</sub> \leftarrow error[i_1]
     else
          compute error_1 \leftarrow compute\_svm(p_1) - y_1
     end if
     p_2 \leftarrow input[i_2], y_2 \leftarrow output[i_2], \alpha_2 \leftarrow \alpha[i_2]
     if (\alpha_2 > 0 \&\& \alpha_2 < c) then
          compute error_2 \leftarrow error[i_2]
     else
          compute error<sub>2</sub> \leftarrow compute svm(p<sub>2</sub>) - y<sub>2</sub>
     end if
     s \leftarrow y_1 * y_2
     if (y_1 \neq y_2) then
          L \leftarrow max(0, \alpha_2 - \alpha_1)
          H \leftarrow min(c, c + \alpha_2 - \alpha_1)
     else
          L \leftarrow max(0, \alpha_2 + \alpha_1 - c)
          H \leftarrow min(c, \alpha_2 + \alpha_1)
     end if
     if (L == H) then
          return false
     end if
     k_{11} \leftarrow gaussian \ kernel(p_1, p_1)
     k_{12} \leftarrow \mathbf{gaussian}_{\mathbf{kernel}}(p_1, p_2)
     k_{22} \leftarrow \mathbf{gaussian}_{\mathbf{kernel}}(p_2, p_2)
     \eta \leftarrow k_{11} + k_{22} - 2 * k_{12}
     if (\eta > 0) then
          a_2 \leftarrow \alpha_2 + y_2 * \frac{\textit{compute\_error}_1 - \textit{compute\_error}_2}{\cdots}
          if (a_2 < L) then
                a_2 \leftarrow L
          end if
          if (a_2 > H) then
               a_2 \leftarrow H
          end if
     else
          f_1 \leftarrow y_1 * (compute \ error_1 + bias) - \alpha_1 * k_{11} - s * \alpha_2 * k_{12}
          f_2 \leftarrow y_2 * (compute\_error_2 + bias) - s * \alpha_1 * k_{12} - \alpha_2 * k_{22}
          L_1 \leftarrow \alpha_1 + s * (\alpha_2 - L)
          H_1 \leftarrow \alpha_1 + s * (\alpha_2 - H)
          \Psi_L \leftarrow L_1 * f_1 + L * f_2 + \frac{1}{2} * L_1^2 * k_{11} + \frac{1}{2} * L^2 * k_{22} + s * L * L_1 * k_{12}
          \Psi_H \leftarrow H_1 * f_1 + H * f_2 + \frac{1}{2} * H_1^2 * k_{11} + \frac{1}{2} * H^2 * k_{22} + s * H * H_1 * k_{12}
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         if (\Psi_L < \Psi_H - \epsilon) then
             a_2 \leftarrow L
         else if (\Psi_L > \Psi_H + \epsilon) then
             a_2 \leftarrow H
         else
              a_2 \leftarrow \alpha_2
         end if
    end if
    if (|a_2 - \alpha_2| < \epsilon * (a_2 + \alpha_2 + \epsilon)) then
         return false
    end if
    a_1 \leftarrow \alpha_1 + s * (\alpha_2 - a_2)
    if (a_1 < 0) then
         a_2 + = s * a_1
         a_1 \leftarrow 0
    else if (a_1 > c) then
         a_2 + = s * (a_1 - c)
         a_1 \leftarrow c
    end if
    #Update bias
    new bias \leftarrow 0, delta bias \leftarrow 0
    if (a_1 > 0 \&\& a_1 < c) then
         new bias \leftarrow compute error<sub>1</sub> + y_1 * (a_1 - \alpha_1) * k_{12} + y_2 * (a_2 - \alpha_2) *
k_{22} + bias
    else
         #Both new Lagrangians at bound, choose threshold halfway between them
         b_1 \leftarrow compute\ error_1 + y_1 * (a_1 - \alpha_1) * k_{11} + y_2 * (a_2 - \alpha_2) * k_{12} + bias
         b_2 \leftarrow compute\_error_2 + y_1 * (a_1 - \alpha_1) * k_{12} + y_2 * (a_2 - \alpha_2) * k_{22} + bias
         new bias \leftarrow \frac{b_1+b_2}{2}
    end if
    delta\_bias \leftarrow new\_bias - bias
    bias ← new bias
    #Update error cache
    for (i = 0 \rightarrow input.size) do
         if (0 < \alpha[i] \&\& \alpha[i] < c) then
              error[i] += y_1 * (a_1 - a_1) * gaussian_kernel(p_1, input[i])
                             +y_2*(a_2-a_2)* gaussian_kernel(p_2, input[i])
                             -delta bias
         end if
    end for
    error[i_1] \leftarrow 0
    error[i_2] \leftarrow 0
    #Update Lagrangians
    \alpha[i_1] \leftarrow a_1
    \alpha[i_2] \leftarrow a_2
    return true
end procedure
```

Algorithm 4 compute_svm()

```
procedure compute\_svm(p_1)

INPUTS: p_1 - POINT TO COMPUTE DISTANCE AGAINST

sum \leftarrow -bias

for (i = 0 \rightarrow input.size) do

if (\alpha[i] > 0) then

sum + = \alpha[i] * output[i] * gaussian\_kernel(input[i], p_1)

end if
end for

return sum
end procedure
```

Algorithm 5 guassian_kernel()

```
procedure gaussian\_kernel(input[i], p_1)
INPUTS: input[i] - 1ST POINT
i_1 - 2ND POINT
guassian \leftarrow exp(-\frac{(|p_1-p_2|)^2}{2*\sigma^2})
return \ guassian
end procedure
```