# Optimization

## Assignment 2

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### Q1

In the above figure we wish find d, the minimal distance between point and line .

We do so by projecting onto , using the principal of orthogonality:

QED

### Q2

What makes this problem convex is the minimization of L2 norm in

In fact this is equivalent to the quadratic programming problem as learned in class:

Prove: is convex

Proof:

Due to triangle inequality of the L2 Norm

QED

Prove: is convex

Proof:

Ask Alex how a linear expression can be defined as convex

### Q3

Condition (4a) is constraint given in the Primal form.

To prove the rest we use KKT conditions. The Lagrangian for this problem is:

Differentiating (\*) by and will give us

We of course have from the Lagrangian

Proof of (4c)

Say we have the following Lagrangian of a general convex problem ()

Then the first order optimality condition is

If the constraint is inactive then

If the constraint is active then

Either way the equality holds true.

Using this we get:

The active constraints correspond to the case of

Where as the inactive constraints correspond to the case of

So we conclude that only the vectors corresponding to the active constrains play a role in defining . These are *the* support vectors that give SVM it's name.

### Q4

The Dual form is derived by taking the results from the previous question (4d), (4e) and substituting them into the Lagrangian:

Using strong duality we derive the dual form from the above equation:

QED

### Q5

Equation (4d) can be expressed in matrix form as:

So in order get ***w*** all we need to do, is to solve the above linear equation. We know how to do this using Least Squares either directly or iteratively as done in the last assignment using GD/CG.

In order to extract we make use of the inequality constraints when they are active.

We can also average over the entire active set to get a better estimate