

Quadratic Optimization

This is an important application of the spectral theorem and positive-definiteness.

It is the simplest case of **quadratic programming**, which is a big subfield of optimization. (So is **least squares**.)

For an example application, see the Wikipedia page for **support-vector machine**, an important tool in machine learning that reduces to a quadratic optimization problem. (There are tons of other applications.)

Def: An **optimization problem** means finding extremal values (minimum & maximum) of a function $f(x_1, \dots, x_n)$ subject to some constraint on (x_1, \dots, x_n) .

In quadratic optimization, we consider quadratic functions.

Def: A **quadratic form** in n variables is a function $q(x_1, \dots, x_n) = \text{sum of terms of the form } a_{ij} x_i x_j$

Eg: $q(x_1, x_2) = \frac{5}{2}x_1^2 + \frac{5}{2}x_2^2 - x_1x_2$

Non-eg: $q(x_1, x_2) = x_1^2 + x_2^2 + x_1 + x_2$ is **not** a quadratic form: x_1, x_2 are linear terms.

NB: Thinking of $x = (x_1, \dots, x_n)$ as a vector,
 $q(cx) = q(cx_1, \dots, cx_n) = \sum a_{ij} (cx_i)(cx_j)$
 $= \sum c^2 a_{ij} x_i x_j = c^2 q(x)$

$$q(cx) = c^2 q(x)$$

In quadratic optimization, the **constraint** on $x = (x_1, \dots, x_n)$ is usually $\|x\| = 1$, i.e. $x_1^2 + \dots + x_n^2 = 1$.

Quadratic Optimization Problem:

Given a quadratic form $q(x)$, find the minimum & maximum values of $q(x)$ subject to $\|x\| = 1$.

Eg: $q(x_1, x_2) = 2x_1^2 + 3x_2^2$

Maximum:

$$\begin{aligned} q(x_1, x_2) &= 2x_1^2 + 3x_2^2 \leq 3x_1^2 + 3x_2^2 \\ &= 3(x_1^2 + x_2^2) = 3\|x\|^2 = 3 \end{aligned}$$

So the maximum value is **3**; it is achieved at $(x_1, x_2) = \pm(0, 1)$: $q(0, \pm 1) = 3$.

Minimum:

$$\begin{aligned} q(x_1, x_2) &= 2x_1^2 + 3x_2^2 \geq 2x_1^2 + 2x_2^2 \\ &= 2(x_1^2 + x_2^2) = 2\|x\|^2 = 2 \end{aligned}$$

So the minimum value is 2; it is achieved at $(x_1, x_2) = \pm(1, 0)$: $q(\pm 1, 0) = 2$.

This example is easy because $q(x_1, x_2) = 2x_1^2 + 3x_2^2$ involves only squares of the coordinates: there is no cross-term $x_1 x_2$.

Def: A quadratic form is diagonal if it has the form $q(x_1, \dots, x_n) = \text{sum of terms of the form } \lambda_i x_i^2$.

Terms of the form $a_{ij} x_i x_j$ ($i \neq j$) are cross-terms.

Quadratic Optimization of Diagonal Forms:

Let $q(x) = \sum_i \lambda_i x_i^2$. Order the x_i so that

$\lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$. Then

- The maximum value of $q(x)$ is λ_n .
- The minimum value of $q(x)$ is λ_1 .

(subject to $\|x\|=1$).

NB: the λ_i could be negative.

Strategy: To solve a quadratic optimization problem, we want to **diagonalize** it to get rid of the **cross terms**.

To do this, we use symmetric matrices!

Fact: Every quadratic form can be written

$$q(x) = x^T S x$$

for a symmetric matrix S .

Eg: $S = \begin{pmatrix} 1 & 2 & 3 \\ 2 & 4 & 5 \\ 3 & 5 & 6 \end{pmatrix}$

$$\hookrightarrow x^T S x = (x_1 \ x_2 \ x_3) \begin{pmatrix} 1 & 2 & 3 \\ 2 & 4 & 5 \\ 3 & 5 & 6 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

$$= (x_1 \ x_2 \ x_3) \begin{pmatrix} x_1 + 2x_2 + 3x_3 \\ 2x_1 + 4x_2 + 5x_3 \\ 3x_1 + 5x_2 + 6x_3 \end{pmatrix}$$

$$= x_1^2 + 2x_1x_2 + 3x_1x_3$$

$$+ 2x_2x_1 + 4x_2^2 + 5x_2x_3$$

$$+ 3x_3x_1 + 5x_3x_2 + 6x_3^2$$

$$= x_1^2 + 4x_2^2 + 6x_3^2 + 4x_1x_2 + 6x_1x_3 + 10x_2x_3$$

NB: The (1,2) and (2,1) entries contribute to the x_1x_2 coefficient.

Given q , how to get S ?

The x_i^2 coefficients go on the diagonal, and half of the $x_i x_j$ coefficient goes in the (i,j) and (j,i) entries.

$$q(x_1, x_2, x_3) = a_{11}x_1^2 + a_{22}x_2^2 + a_{33}x_3^2 \\ + a_{12}x_1x_2 + a_{13}x_1x_3 + a_{23}x_2x_3$$

$$\leadsto S = \begin{pmatrix} a_{11} & a_{12}/2 & a_{13}/2 \\ a_{12}/2 & a_{22} & a_{23}/2 \\ a_{13}/2 & a_{23}/2 & a_{33} \end{pmatrix}$$

NB: q is diagonal $\iff S$ is diagonal: the a_{ij} are the coefficients of the cross-terms.

$$x^T \begin{pmatrix} \lambda_1 & \dots & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{pmatrix} x = \lambda_1 x_1^2 + \lambda_2 x_2^2 + \dots + \lambda_n x_n^2$$

How does this help quadratic optimization?

Orthogonally diagonalize!

$$q(x) = x^T S x$$

Find a diagonal matrix D and orthogonal matrix Q such that $S = Q D Q^T \leadsto$

$$q(x) = x^T Q D Q^T x$$

Let $x = Qy$: this is a change of variables

$$q(x) = q(Qy) = (Qy)^T Q D Q^T (Qy) \\ = y^T \cancel{Q^T Q}^I \cancel{D Q^T Q}^I y = y^T D y$$

This is now diagonal!

NB: Q is orthogonal $\Rightarrow \|x\| = \|Qy\| = \|y\|$

$$\text{So } \|x\|=1 \Leftrightarrow \|y\|=1$$

Eg: Find the minimum & maximum of

$$q(x_1, x_2) = \frac{5}{2}x_1^2 + \frac{5}{2}x_2^2 - x_1x_2 \quad \leftarrow \text{cross term} \quad \text{☹️}$$

subject to $\|x\|=1$.

$$q(x) = x^T \begin{pmatrix} 5/2 & -1/2 \\ -1/2 & 5/2 \end{pmatrix} x \rightsquigarrow S = \frac{1}{2} \begin{pmatrix} 5 & -1 \\ -1 & 5 \end{pmatrix}$$

Orthogonally diagonalize: $S = Q D Q^T$ for

$$Q = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & -1 \\ 1 & 1 \end{pmatrix} \quad D = \begin{pmatrix} 2 & 0 \\ 0 & 3 \end{pmatrix}$$

Set $x = Qy$:

$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & -1 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \frac{1}{\sqrt{2}} \begin{pmatrix} y_1 - y_2 \\ y_1 + y_2 \end{pmatrix}$$

$$\begin{cases} x_1 = \frac{1}{\sqrt{2}}(y_1 - y_2) \\ x_2 = \frac{1}{\sqrt{2}}(y_1 + y_2) \end{cases} \quad \text{is a linear change of variables}$$

$$\text{Then } q(x) = y^T \begin{pmatrix} 2 & 0 \\ 0 & 3 \end{pmatrix} y = 2y_1^2 + 3y_2^2.$$

Check:

$$\begin{aligned} q(x) &= q\left(\frac{1}{\sqrt{2}}(y_1 - y_2), \frac{1}{\sqrt{2}}(y_1 + y_2)\right) \\ &= \frac{5}{2} \cdot \frac{1}{2}(y_1 - y_2)^2 + \frac{5}{2} \cdot \frac{1}{2}(y_1 + y_2)^2 - \frac{1}{2}(y_1 - y_2)(y_1 + y_2) \\ &= \frac{5}{4}y_1^2 + \frac{5}{4}y_2^2 - \cancel{\frac{5}{2}y_1y_2} + \frac{5}{4}y_1^2 + \frac{5}{4}y_2^2 + \cancel{\frac{5}{2}y_1y_2} \\ &\quad - \frac{1}{2}y_1^2 + \frac{1}{2}y_2^2 \\ &= \frac{5}{2}y_1^2 - \frac{1}{2}y_1^2 + \frac{5}{2}y_2^2 + \frac{1}{2}y_2^2 = 2y_1^2 + 3y_2^2 \quad \checkmark \end{aligned}$$

The **maximum value** of q subject to $\|x\| = \|y\| = 1$ is **3**, achieved at

$$y = (0, \pm 1) \rightsquigarrow x = Qy = \pm \frac{1}{\sqrt{2}} \begin{pmatrix} -1 \\ 1 \end{pmatrix}$$

The **minimum value** of q subject to $\|x\| = \|y\| = 1$ is **2**, achieved at

$$y = (\pm 1, 0) \rightsquigarrow x = Qy = \pm \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

NB: The minimum value is the smallest diagonal entry of $D \rightsquigarrow$ **smallest eigenvalue**.

$Q \begin{pmatrix} \pm 1 \\ 0 \end{pmatrix}$ is \pm the first column of Q

\rightsquigarrow is a **unit eigenvector** for that eigenvalue.

Likewise for the largest eigenvalue.

Quadratic Optimization:

To find the minimum/maximum of a quadratic form $q(x)$ subject to $\|x\|=1$:

(1) Write $q(x) = x^T S x$ for a symmetric matrix S

(2) Orthogonally diagonalize $S = Q D Q^T$ for

$$Q = \left(\underbrace{\begin{pmatrix} | & & | \\ u_1 & \dots & u_n \\ | & & | \end{pmatrix}}_{\text{eigenvectors}} \right) \quad D = \left(\underbrace{\begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{pmatrix}}_{\text{eigenvalues}} \right)$$

Order the eigenvalues so $\lambda_1 \leq \dots \leq \lambda_n$

(3) The minimum value of $q(x)$ is the smallest eigenvalue λ_1 .

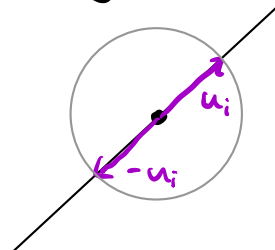
It is achieved for $x = \text{any unit } \lambda_1\text{-eigenvector}$.

The maximum value of $q(x)$ is the largest eigenvalue λ_n .

It is achieved for $x = \text{any unit } \lambda_n\text{-eigenvector}$.

NB: If $\dim(\lambda_i) = 1$ then the only unit λ_i -eigenvectors are $\pm u_i$. (only 2 unit vectors are on any line)

NB: $x = Qy$ diagonalizes q :
 $q(x) = \lambda_1 y_1^2 + \dots + \lambda_n y_n^2$



Quadratic Optimization Problem, Variant:

Given a quadratic form $q(x)$, find the minimum & maximum values of $\|x\|^2$ subject to $q(x)=1$.

In general this will not work well:

- $q(x_1, x_2) = -x_1^2 - 2x_2^2$:

there is **no** x such that $q(x)=1$!

- $q(x_1, x_2) = x_1^2 - x_2^2$:

there is **no maximum** $\|x\|^2$ subject to $q(x)=1$:

$$q(C, \sqrt{C^2-1}) = 1 \quad \text{for any (huge) } C.$$

Problem: $q(x)$ may be 0 or negative!

Def: A quadratic form is **positive-definite** if $q(x) > 0$ for all $x \neq 0$.

NB: If $q(x) = x^T S x$ then q is positive-definite $\iff S$ is positive-definite: this is the positive-energy criterion.

In this case, the problem is equivalent to the previous one.

NB: For q positive-definite,

$$q(x)=1 \Leftrightarrow q\left(\frac{x}{\|x\|}\right) = \frac{1}{\|x\|^2} q(x) = \frac{1}{\|x\|^2}$$

So $\|x\|^2$ **minimized/maximized** subject to $q(x)=1$

$$\Leftrightarrow q\left(\frac{x}{\|x\|}\right) \text{ is } \text{maximized/minimized}$$

Then $\frac{1}{\|x\|^2} = \text{maximum/maximum value of } q(u)$
subject to $\|u\|^2=1$. ($u = \frac{x}{\|x\|}$)

Eg: Extremize $\|x\|^2$ subject to

$$q(x_1, x_2) = \frac{5}{2}x_1^2 + \frac{5}{2}x_2^2 - x_1x_2 = 1$$

We know q is maximized at $u_1 = \pm \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ 1 \end{pmatrix}$ with maximum value 3.

$$q(u_1) = 3 \Rightarrow q\left(\frac{u_1}{\sqrt{3}}\right) = 1$$

The **minimum value** of $\|x\|^2$ subject to $q(x)=1$ is **$1/3$** . It is achieved at $\frac{1}{\sqrt{3}} u_1$.

And q is minimized at $u_2 = \pm \frac{1}{\sqrt{2}} \begin{pmatrix} 1 \\ -1 \end{pmatrix}$ with minimum value 2.

The **maximum value** of $\|x\|^2$ subject to $q(x)=1$ is **$1/2$** . It is achieved at $\frac{1}{\sqrt{2}} u_2$.

Quadratic Optimization, Variant:

Given a **positive-definite** quadratic form q ,
to find the minimum/maximum values of $\|x\|^2$
subject to $q(x)=1$:

(1) Write $q(x)=x^T S x$ for a symmetric matrix S

(2) Orthogonally diagonalize $S=QDQ^T$ for

$$Q = \underbrace{\begin{pmatrix} | & & | \\ u_1 & \dots & u_n \\ | & & | \end{pmatrix}}_{\text{eigenvectors}} \quad D = \underbrace{\begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{pmatrix}}_{\text{eigenvalues}}$$

Order the eigenvalues so $\lambda_1 \leq \dots \leq \lambda_n$

(3) The **minimum value** of $\|x\|^2$ is

$1/(\text{the largest eigenvalue } \lambda_n.)$

It is achieved for

$$x = \frac{\text{any unit } \lambda_n\text{-eigenvector}}{\sqrt{\lambda_n}}$$

The **maximum value** of $\|x\|^2$ is

$1/(\text{the smallest eigenvalue } \lambda_1.)$

It is achieved for

$$x = \frac{\text{any unit } \lambda_1\text{-eigenvector}}{\sqrt{\lambda_1}}$$