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Applications of QR

(1) Solve square linear systems. How?

$$Ax = b \rightsquigarrow QRx = b \quad O(n^3)$$

$$Qy = b \Leftrightarrow Q^T b = y \quad O(n^2)$$

$$Rx = y \text{ solvable using backsubstitution } O(n^2)$$

This works, but it is practically a little slower than LU.

(2) Solve tall and skinny linear systems. How?

Tall and skinny: $m > n$

More equations than unknowns

A square linear system often only has a single solution.

So applying *more* conditions to the solution will mean...

we have no exact solution. \rightarrow Get as close as we can.

~~$A\vec{x} = \vec{b}$~~
 nope

Find \vec{x} so that $\|A\vec{x} - \vec{b}\|_2^2$ is as small as possible.

$\vec{r} = A\vec{x} - \vec{b}$ is called the residual (not zero, but ideally small)

$$\|A\vec{x} - \vec{b}\|_2^2 = r_1^2 + \dots + r_m^2 \quad \leftarrow \text{squares}$$

This is called a (linear) least-squares problem.

Is there other notation for least-squares problems?

All these are equivalent:

- Find \vec{x} so that $\|A\vec{x} - \vec{b}\|_2^2$ is as small as possible.
- $\vec{x} = \underset{\vec{x}}{\operatorname{arg\,min}} \|A\vec{x} - \vec{b}\|_2^2$
- $A\vec{x} \approx \vec{b}$

And how does QR help with least-squares problems?

$$A = QR$$

$$\|A\vec{x} - \vec{b}\|_2^2 = \|QR\vec{x} - \vec{b}\|_2^2$$

$$= \|Q^T(QR\vec{x} - \vec{b})\|_2^2$$

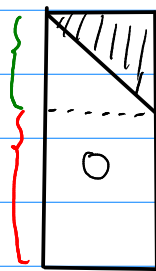
$$= \|R\vec{x} - Q^T\vec{b}\|_2^2$$

← Since this is *exactly equal* to the expression we wanted to minimize originally, we might as well minimize this.

Is this any easier to minimize?

upper triangular square invertible

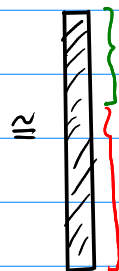
zero



R



\vec{x}



$Q^T\vec{b}$

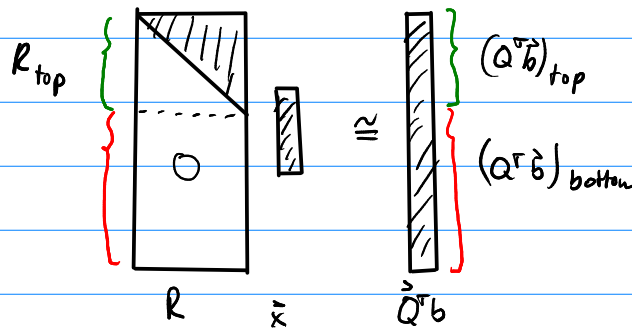
can make $R\vec{x} = Q^T\vec{b}$ exactly in this part

This part of the residual cannot be changed by varying \vec{x} .

So how do I solve a least-squares problem with QR?

(1) Compute a QR factorization $A = QR$

(2) Introduce notation:



(3) Solve $R_{top} \hat{x} = (Q^T b)_{top}$ (using backsubst)

(4) The norm of the residual will be

$$\|A\hat{x} - b\|_2 = \|(Q^T b)_{bottom}\|_2.$$

What about the "normal equations"?

$$A^T A x = A^T b$$

solves the same problem

produces the same x

is not well-behaved numerically

$$\kappa(A^T A) \approx \kappa(A)^2$$

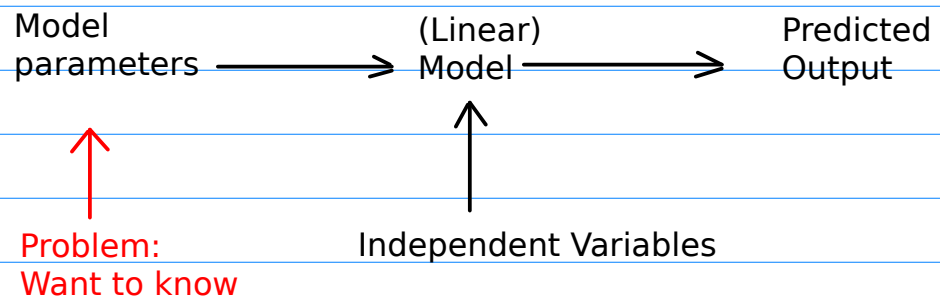
↑
bigger

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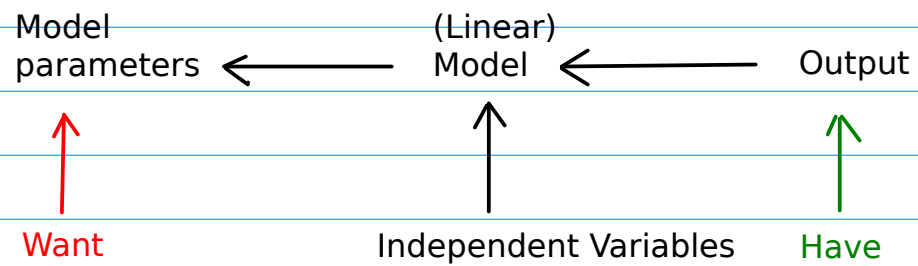
↑
bad

Demo: Solving Least-Squares Problems

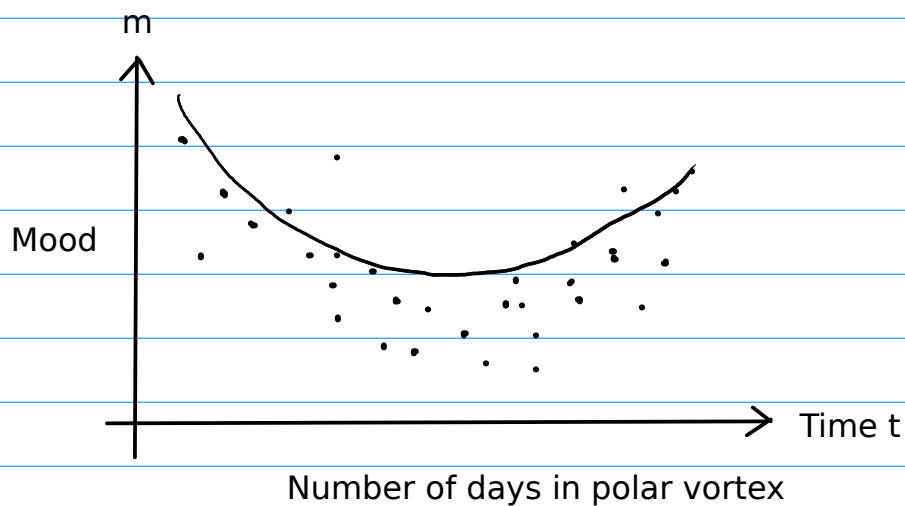
How can I use least-squares problems for fitting a linear model to data?



Data fitting:



Can you give an example?



$$\text{Model: } \hat{m}(t) = \alpha t^2 + \beta t + \gamma$$

ers

by 2 will result in the predicted output being multiplied by 2.

How do we find the parameters then?

Have: 300 data points $(t_1, m_1), (t_2, m_2), \dots, (t_{300}, m_{300})$

Want: 3 unknowns (α, β, γ)

Write down equations:

$$m_1 \stackrel{!}{=} \hat{m}(t_1) = \alpha t_1^2 + \beta t_1 + \gamma \cdot 1$$

$$m_2 \stackrel{!}{=} \hat{m}(t_2) = \alpha t_2^2 + \beta t_2 + \gamma \cdot 1$$

\vdots

$$m_{300} \stackrel{!}{=} \hat{m}(t_{300}) = \alpha t_{300}^2 + \beta t_{300} + \gamma \cdot 1$$

$$\begin{matrix} \nearrow y \\ \uparrow \end{matrix} \begin{pmatrix} t_1^2 & t_1 & 1 \\ t_2^2 & t_2 & 1 \\ \vdots & \vdots & \vdots \\ t_{300}^2 & t_{300} & 1 \end{pmatrix} \begin{pmatrix} \alpha \\ \beta \\ \gamma \end{pmatrix} \approx \begin{pmatrix} m_1 \\ m_2 \\ \vdots \\ m_{300} \end{pmatrix}$$

Go to matrix form
Write as least squares problem

Now solvable using QR.

Demo: Data Fitting