

- Assignment #5 is on course website this weekend
- Start working on your formal report
 - due April 7 @ 14:00 in SC1 241

Last Time: given a linear set of data $(x_i, y_i \pm \sigma_i)$, the best intercept & slope for the line passing through the data are given by:

$$a = \frac{1}{\Delta} \left(\sum \frac{x_i^2}{\sigma_i^2} \sum \frac{y_i}{\sigma_i^2} - \sum \frac{x_i}{\sigma_i^2} \sum \frac{x_i y_i}{\sigma_i^2} \right) \quad \text{intercept}$$

$$\Delta = \sum \frac{1}{\sigma_i^2} \sum \frac{x_i^2}{\sigma_i^2} - \left(\sum \frac{x_i}{\sigma_i^2} \right)^2$$

$$\sigma_a^2 = \frac{1}{\Delta} \sum \frac{x_i^2}{\sigma_i^2}$$

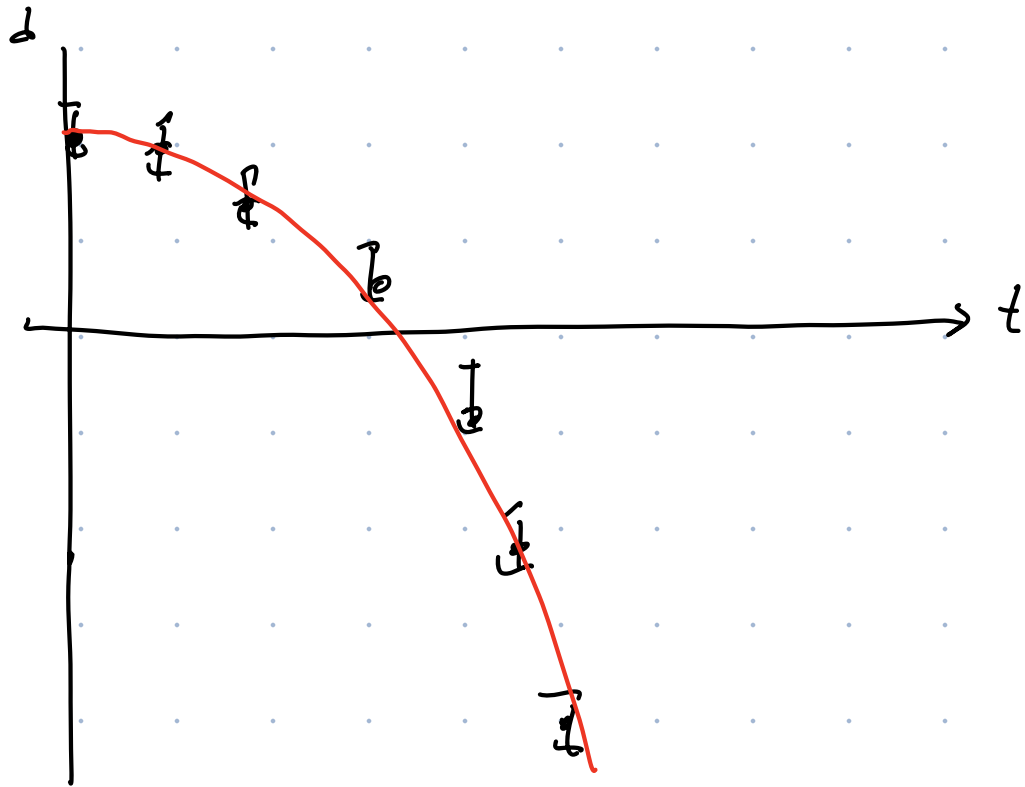
$$b = \frac{1}{\Delta} \left(\sum \frac{1}{\sigma_i^2} \sum \frac{x_i y_i}{\sigma_i^2} - \sum \frac{x_i}{\sigma_i^2} \sum \frac{y_i}{\sigma_i^2} \right) \quad \text{slope}$$

$$\sigma_b^2 = \frac{1}{\Delta} \sum \frac{1}{\sigma_i^2}$$

Today: Linearizing data

Eg. Object in free starting rest

$$d = d_0 - \frac{1}{2} g t^2$$



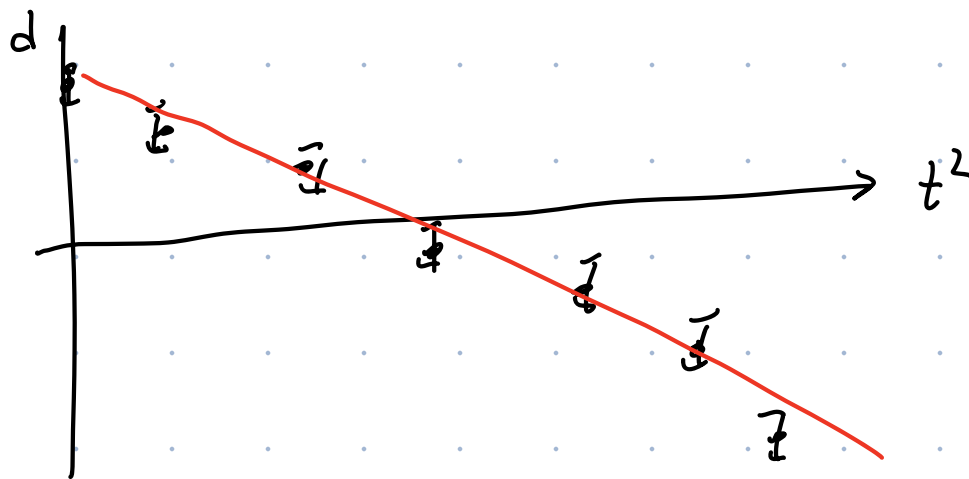
Instead of plotting d vs t consider

d vs t^2

$$d = d_0 - \frac{1}{2} g (t^2)$$

Annotations below the equation:

- Red arrow pointing to d with label y
- Red arrow pointing to d_0 with label a
- Red bracket under $\frac{1}{2} g$ with red arrow pointing to b
- Red bracket under (t^2) with red arrow pointing to x



Another example: In thermal waves, the amplitude of the fundamental fourier component is

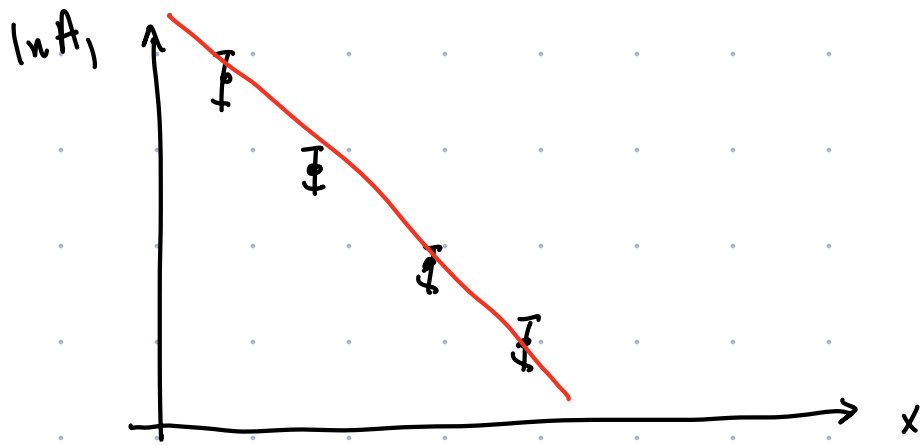
$$A_1 = \left(\frac{4T_0}{\pi} \right) \exp \left(-\sqrt{\frac{\omega}{2\alpha}} x \right)$$

To linearize, take the $\ln$ of both sides

$$\underbrace{\ln A_1}_{\substack{\uparrow \\ y}} = \underbrace{\ln \left(\frac{4T_0}{\pi} \right)}_{\substack{\uparrow \\ a}} + \underbrace{\left(-\sqrt{\frac{\omega}{2\alpha}} \right)}_{\substack{\uparrow \\ b}} \underbrace{x}_{\substack{\uparrow \\ x}}$$

slope b is related to the thermal diffusivity α .

$$b^2 = \frac{\omega}{2\alpha} \Rightarrow \boxed{\alpha = \frac{\omega}{2b^2}}$$



Another example (used in current research)

Low-temperature thermal conductivity of a conductor is typically of the form:

$$K = \underbrace{C_1 T}_{\text{electron contribution}} + \underbrace{C_3 T^3}_{\text{lattice/phonon contribution}}$$

Meas. K as a fun of T . Does not appear to be easily linearized at first glance.

Consider

$$\underbrace{\frac{K}{T}}_y = C_1 + C_3 \underbrace{T^2}_x$$

$\downarrow$ $\downarrow$ $\downarrow$
 a b x

Plot $\frac{K}{T}$ vs T^2 , get intercept
slope

$$\begin{aligned} a &= C_1 \\ b &= C_3 \end{aligned}$$

Another example: Sometimes a pair of variables cannot be strictly linearized.

In Blackbody radiation

$$I = \frac{2c^2h}{\lambda^5} \left[\frac{1}{e^{hc/\lambda k_B T} - 1} \right]$$

meas I vs T , its not linear.

However, under certain conditions, can make valid approx. that allow the data to be linearized.

In this case, if $\frac{hc}{\lambda k_B T} \gg 1$

then $e^{hc/\lambda k_B T} - 1 \approx e^{hc/\lambda k_B T}$

$$\therefore I \approx \frac{2c^2 h}{\lambda^5} e^{-hc/\lambda k_B T}$$

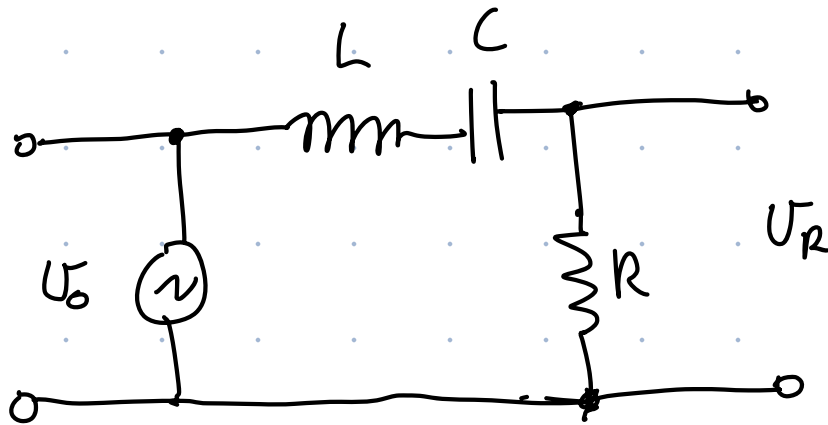
Now, we can take the $\ln$ of both sides:

$$\underbrace{\ln I}_{\downarrow y} = \underbrace{\ln \left(\frac{2c^2 h}{\lambda^5} \right)}_{\downarrow a} + \underbrace{\left(\frac{-hc}{\lambda k_B} \right)}_{\downarrow b} \underbrace{\frac{1}{T}}_{\downarrow x}$$

$$\Rightarrow b = -\frac{hc}{\lambda k_B} \quad ; \quad \boxed{h = -\frac{\lambda k_B b}{c}}$$

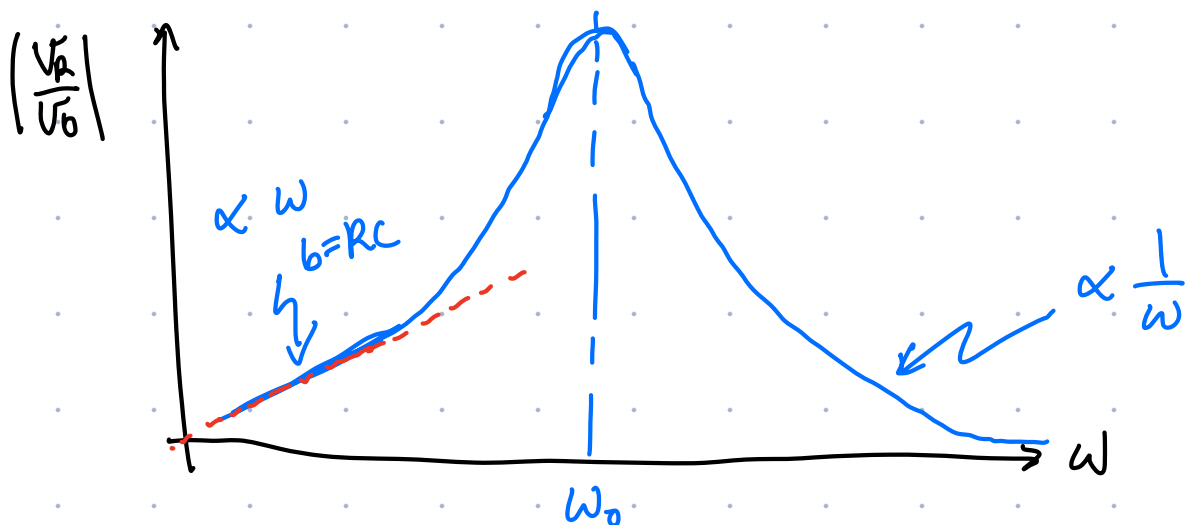
Sometimes it's just not possible to linearize a data set.

Eg. LRC resonance



meas. $\left| \frac{U_R}{U_0} \right|$ vs ω

$$\left| \frac{U_R}{U_0} \right| = \frac{1}{\sqrt{1 + \left(\omega \frac{L}{R} - \frac{1}{\omega RC} \right)^2}}$$



$\left| \frac{V_R}{V_0} \right|$ is clearly not linear.

Check behaviour at low freq ($\omega \rightarrow 0$)

$$\left| \frac{V_R}{V_0} \right| \approx \frac{1}{\sqrt{1 + \left(-\frac{1}{\omega RC}\right)^2}} \approx \frac{1}{\frac{1}{\omega RC}} = \omega RC$$

At low freq, $\left| \frac{V_R}{V_0} \right|$ vs ω is linear w/
slope $b = RC$

Check behaviour at high freq ($\omega \rightarrow \infty$)

$$\left| \frac{V_R}{V_0} \right| \approx \frac{1}{\sqrt{1 + \left(\omega \frac{L}{R}\right)^2}} \approx \frac{1}{\omega \frac{L}{R}} = \left(\frac{R}{L}\right) \frac{1}{\omega}$$

At high freq, can plot $\left| \frac{V_R}{V_0} \right|$ vs $\frac{1}{\omega}$ to find a
slope $b = \frac{R}{L}$

Can we fit the entire freq. dependence?

start w/

$$\left| \frac{V_R}{V_0} \right| = \frac{1}{\sqrt{1 + \left(\omega \frac{L}{R} - \frac{1}{\omega RC} \right)^2}}$$

square both sides...

$$\left| \frac{V_R}{V_0} \right|^2 = \frac{1}{1 + \left(\omega \frac{L}{R} - \frac{1}{\omega RC} \right)^2}$$

invert

$$\left| \frac{V_0}{V_R} \right|^2 = 1 + \left(\omega \frac{L}{R} - \frac{1}{\omega RC} \right)^2$$

expand the square

$$\left| \frac{V_0}{V_R} \right|^2 = \left(1 - \frac{2L}{R^2 C} \right) + \omega^2 \left(\frac{L}{R} \right)^2 + \frac{1}{\omega^2} \left(\frac{1}{RC} \right)^2$$

Not linearizable

Need some new fitting techniques for fns that cannot be linearized.

Eg. Calibration of a thermocouple over a large span of temperatures follows a polynomial dependence.

Fitting T vs V to a polynomial

$$T = a_0 + a_1 V + a_2 V^2 \leftarrow \text{not linearizable.}$$

In general, we want to be able to fit data to a fn of the form:

$$y(x) = a_0 + a_1 x + a_2 x^2 + \dots + a_m x^m$$

In fact, the technique that we'll develop can be further generalized to fit data to a fn of the form:

$$y(x) = a_1 f_1(x) + a_2 f_2(x) + \dots + a_m f_m(x)$$

Here, $f_k(x)$ are fns of x that do not involve the unknown parameters $a_1, a_2, \dots, a_m$ that we're trying to determine.

For example, for a polynomial up to x^2

$$f_1 = 1, \quad f_2 = x, \quad f_3 = x^2$$

s.t. $y = a_1 + a_2 x + a_3 x^2 \rightarrow$ thermocouple example.

or, for the LRC example, we can take

$$f_1 = 1, \quad f_2 = \omega^2, \quad f_3 = \frac{1}{\omega^2}$$

st. $y = a_1 + a_2 \omega^2 + a_3 \frac{1}{\omega^2}$

$\uparrow \qquad \qquad \downarrow \qquad \qquad \downarrow$

$\left(1 - \frac{2L}{R^2 C}\right) \qquad \left(\frac{L}{R}\right)^2 \qquad \frac{1}{(RC)^2}$

Next time, apply method of maximum likelihood to determine the best-fit parameters for fits to functions of the form:

$$y = a_1 f_1(x) + a_2 f_2(x) + \dots + a_m f_m(x)$$