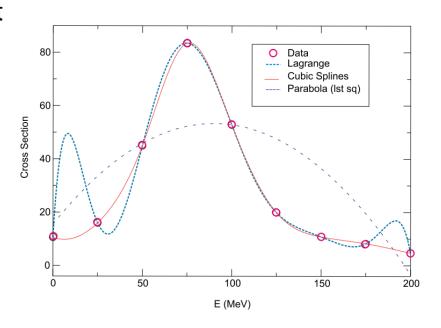
Interpolation vs regression

- Interpolation: find a continuous function that passes through all the data points ("join the dots")
 - Typical use: change sampling, resolution
 - Formula of the fitting function is not interesting
- Fitting, regression: find the best parameters of a known model function, that is closest to data points
 - Typical use: find parameters of a physical model
 - Sometimes the model is just approximation



Interpolation

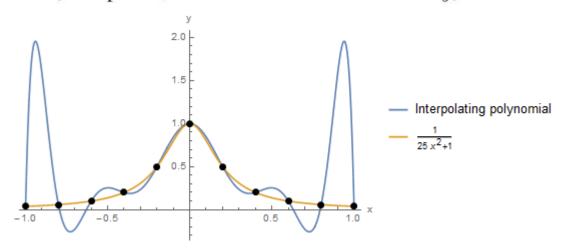
Lagrange's formula

Polynomial goes through all points

Through any two points there is a unique line. Through any three points, a unique quadratic. Et cetera. The interpolating polynomial of degree N-1 through the N points $y_1 = f(x_1), y_2 = f(x_2), \ldots, y_N = f(x_N)$ is given explicitly by Lagrange's classical formula,

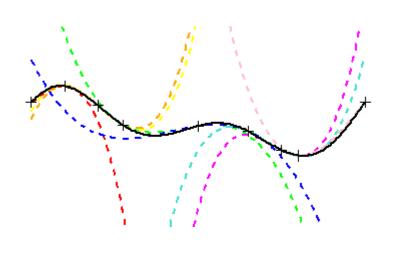
$$P(x) = \frac{(x - x_2)(x - x_3)...(x - x_N)}{(x_1 - x_2)(x_1 - x_3)...(x_1 - x_N)} y_1 + \frac{(x - x_1)(x - x_3)...(x - x_N)}{(x_2 - x_1)(x_2 - x_3)...(x_2 - x_N)} y_2 + \dots + \frac{(x - x_1)(x - x_2)...(x - x_{N-1})}{(x_N - x_1)(x_N - x_2)...(x_N - x_{N-1})} y_N$$
(3.1.1)

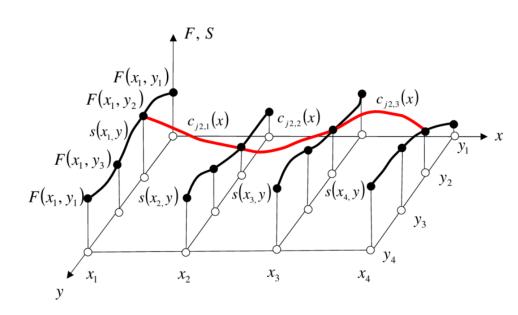
There are N terms, each a polynomial of degree N-1 and each constructed to be zero at all of the x_i except one, at which it is constructed to be y_i .



Interpolation

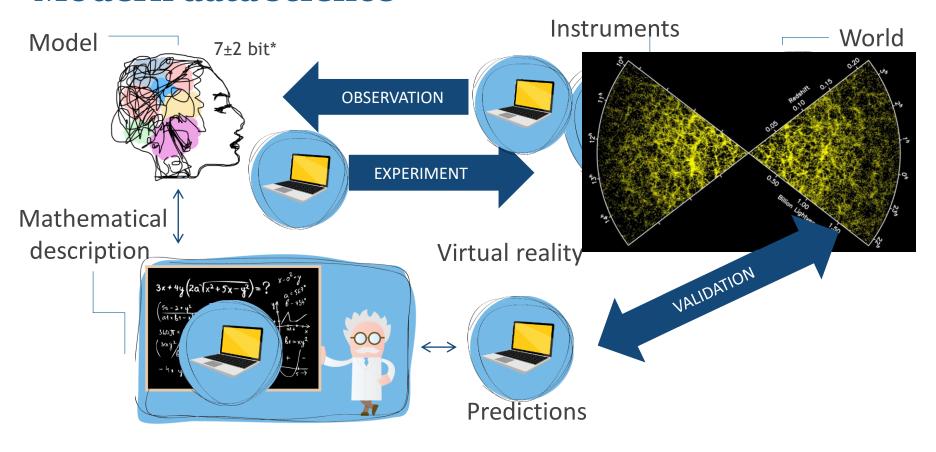
- Cubic spline:
 - Local: low order polynomial through neighboring points
 - Local interpolators join smoothly to each other
 - Bi-cubic spline for 2D





Least Squares and Maximum Likelihood

Modern data science



Initial values

$$\wedge$$
=0.7 $\Omega_{\rm m}$ =0.3

"laws", equations

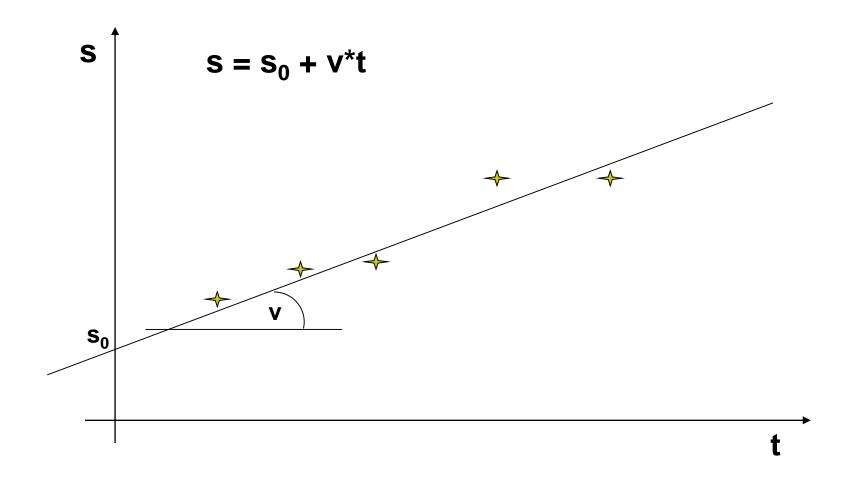
$$oldsymbol{F} = oldsymbol{G} rac{oldsymbol{m_1 m_2}}{oldsymbol{r^2}} \ egin{aligned} R_{\mu
u} - rac{1}{2} R\, g_{\mu
u} + \Lambda g_{\mu
u} = rac{8\pi G}{c^4} T_{\mu
u} \end{aligned}$$

Simulated reality

Goal

- Find a MODEL for measurement/simulation data, that:
 - Fits some theory
 - Reproduce measurement data
 - Can be parametrized
- Parameters may have "physical" meaning
 - Displacement/time diagram linear fit slope: speed

Example: linear motion: speed



Errors

- Measurements contain errors (in each variables!)
 - noise, inaccuracy
 - Systematic errors
 - outliers
- Hence: the calculated parameters will have errors, too

Least square fit

Given: (x_i, y_i) ; i=1..N measurement points. Fit some function :

$$y(x) = y(x; a_1, a_2, ..., a_M)$$

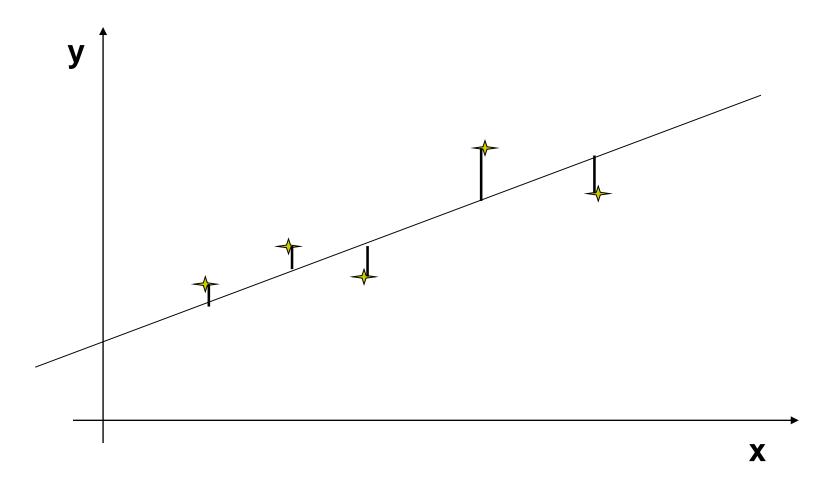
 a_j parameters, $j=1..M$

Least square fit:

$$\min_{a_1...a_M} \left(\sum_{i=1}^N \left[y_i - y(x_i; a_1...a_M) \right]^2 \right)$$

Take derivatives by $a_1, a_2, ..., a_M$ -> set of linear equations (!! Also for some nonlin func.)

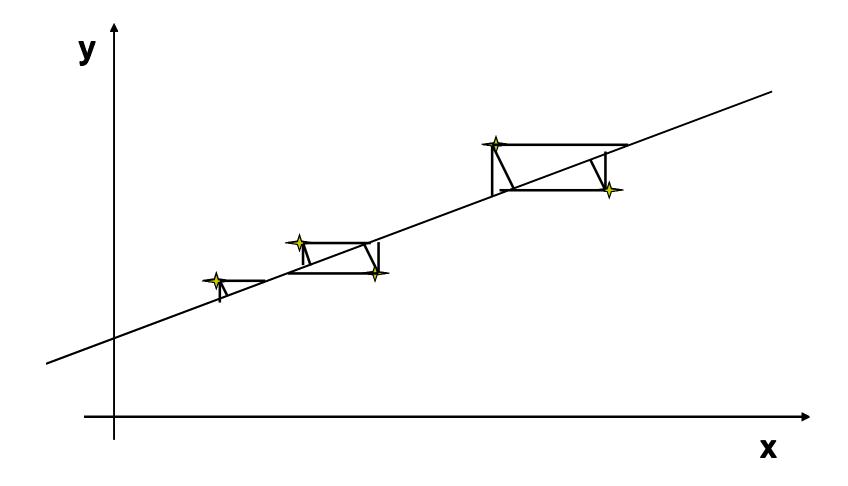
Least squares



Why not least absolute values, fourth powers, etc?

$$\min_{a_{1}...a_{M}} \left(\sum_{i=1}^{N} \left[y_{i} - y(x_{i}; a_{1}...a_{M}) \right]^{2} \right) \\
\min_{a_{1}...a_{M}} \left(\sum_{i=1}^{N} \left| y_{i} - y(x_{i}; a_{1}...a_{M}) \right| \right) \\
\min_{a_{1}...a_{M}} \left(\sum_{i=1}^{N} \left[y_{i} - y(x_{i}; a_{1}...a_{M}) \right]^{4} \right) \\
\min_{a_{1}...a_{M}} \left(\sum_{i=1}^{N} \left| y_{i} - y(x_{i}; a_{1}...a_{M}) \right| \right) \\
a_{1}...a_{M} \right) = 0$$

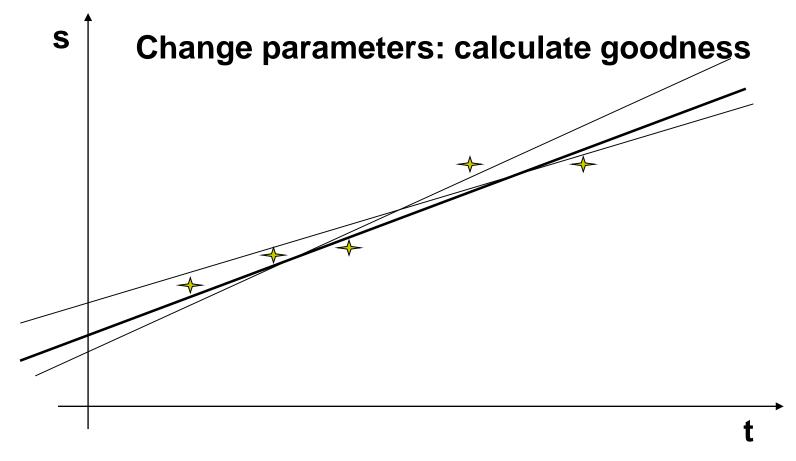
Least distances?



Why least squares?

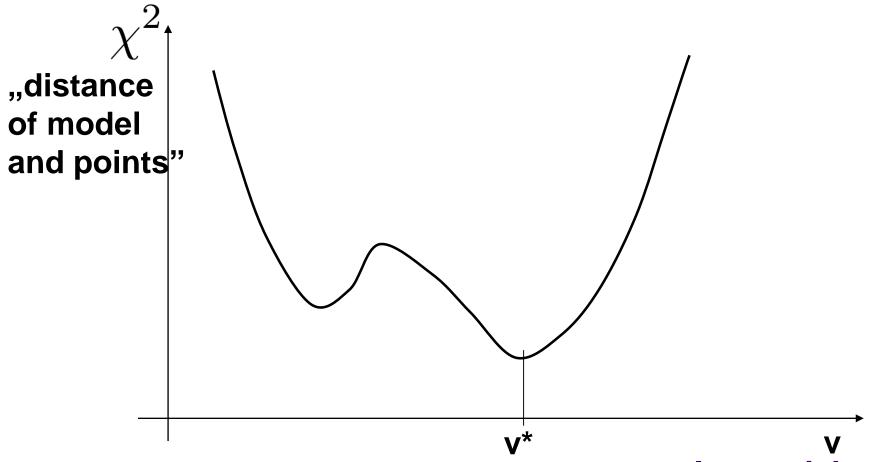
- Maximum likelihood estimation
- Least quare gives best parameters, if:
 - Errors only in y_i
 - Errors are normal (Gauss) distributed
 - Errors are independent

Cost function



Find optimal parameters, with largest goodness / smallest "cost/energy"

Cost function



Finding minimum: in general leads to a nonlinear optimization problem

In special case: linear set of equations

Maximum likelihood

$$P \propto \prod_{i=1}^{N} \left\{ \exp \left[-\frac{1}{2} \left(\frac{y_i - y(x_i)}{\sigma} \right)^2 \right] \Delta y \right\}$$

Find parameters where P is maximal.

The log() func. is monotonuous, so find maximum of log(P), or minimum of –log(P)

-log(P) =
$$\left[\sum_{i=1}^{N} \frac{[y_i - y(x_i)]^2}{2\sigma^2}\right] - N\log \Delta y$$

This is Least Squares!

