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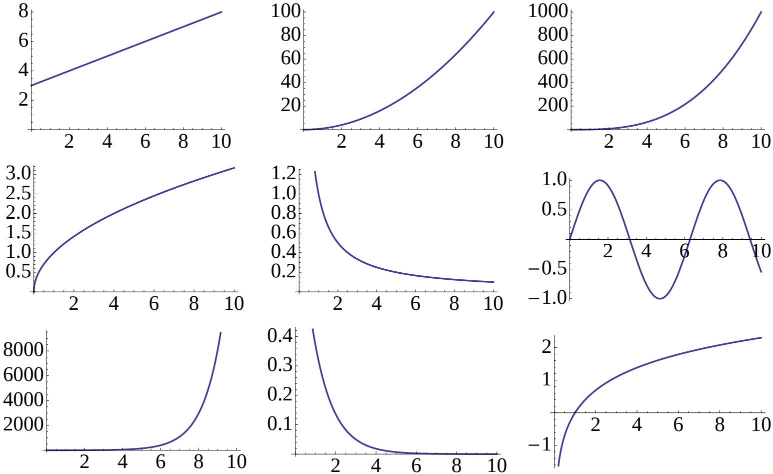
Functions you should recognize on sight



TWPS: What are these functions? What is the most general equation?

Springs and Elongations

Example: Modeling Spring Elongation

Take your favorite spring. Attach different masses.
How much does it stretch from rest? [Its **elongation**.]

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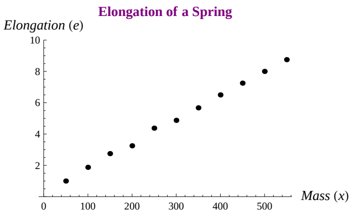
When we plot the data, we get the following **scatterplot**.



What do you notice? ____________________

mass x	elong y
50	1.000
100	1.875
150	2.750
200	3.250
250	4.375
300	4.875
350	5.675
400	6.500
450	7.250
500	8.000
550	8.750

Proportionality

When data seems to lie on a line through the origin, we expect the two variables to be **proportional**; in this case, $y = kx$ for some constant k.

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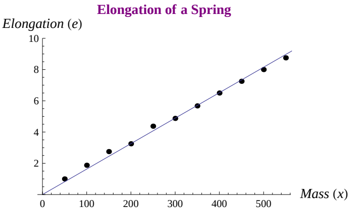
So: Estimate the slope of the line. **How?**

1. Guesstimating



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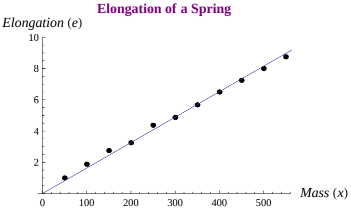
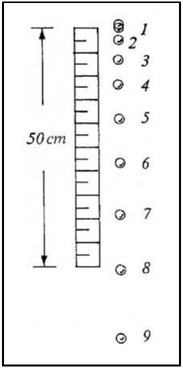


2. Mathematically: **Linear Regression / Least Squares**
   (For another day)

Fitting Gravity Data

Example. Modeling the dropping of a golf ball



Source:
practicalphysics.org

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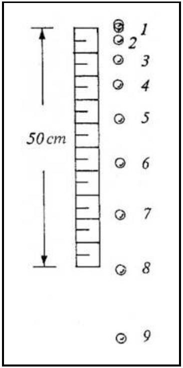

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Let's use an experiment to test the gravity model from last time.

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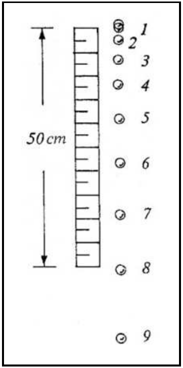

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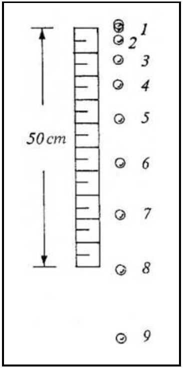

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Use a camera to record the position every tenth of a second.

Data would be similar to the table→

t	y
0.0	0.00
0.1	0.25
0.2	0.75
0.3	1.50
0.4	2.50
0.5	4.00
0.6	5.75
0.7	7.75
0.8	10.25
0.9	13.00
1.0	16.00

[Ignore data on p. 25.]
[It's BAD data.]

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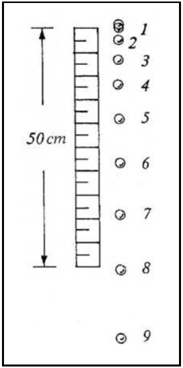

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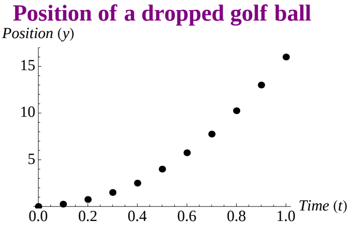
It's plotted in the scatterplot below.



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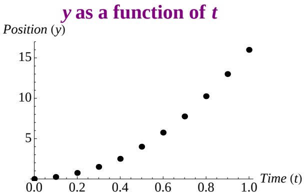
These data seem to fit a $\overline{\text{(type of function)}}$.



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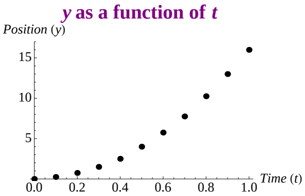

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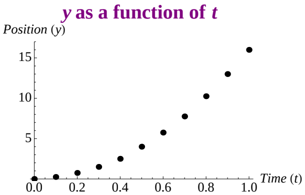

Fitting Gravity Data

These data seem to fit a $\underline{\hspace{3cm}}$ (type of function). How can we be sure?

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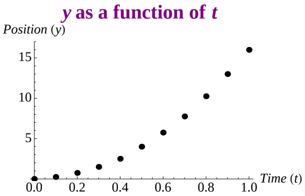

t	t^2	y
0.0		0.00
0.1		0.25
0.2		0.75
0.3		1.50
0.4		2.50
0.5		4.00
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0.7		7.75
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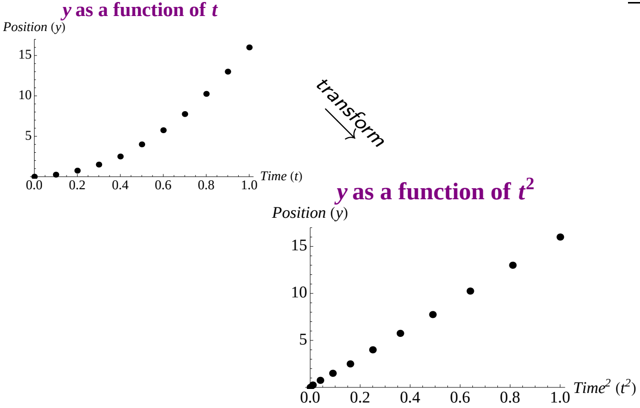
0.9		13.00
1.0		16.00

Fitting Gravity Data

These data seem to fit a $\underline{\qquad\qquad}$ (type of function). How can we be sure?

1. Plot distance as a function of t^2.
   Next, estimate the constant of proportionality.



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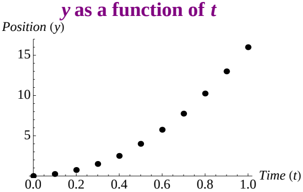

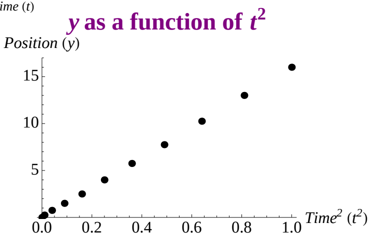

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This implies
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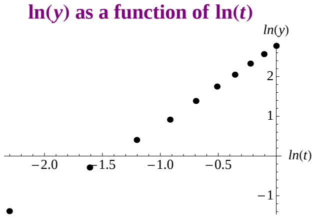

$\ln y \approx 2 \ln t + 2.8$

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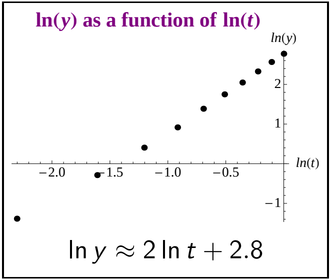
  - The slope is an approximation for k.
  - The y-intercept approximates $\ln C$.



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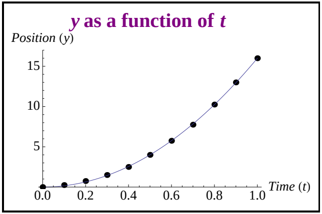
We have determined that our gravity model

$$y(t) = 16t^2$$

appears to model the dropping of a golf ball.



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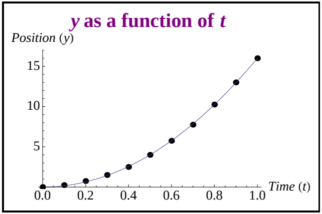

Example. Raindrops

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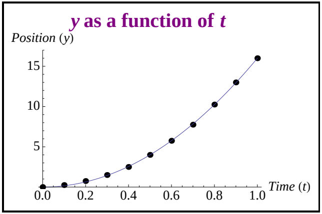

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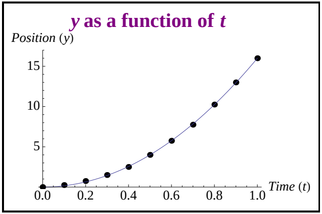

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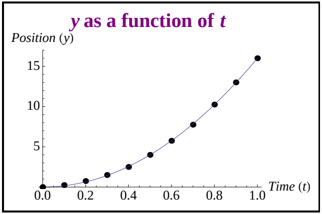

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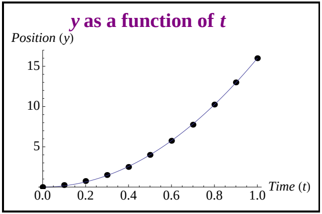

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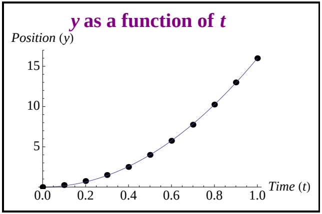

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However, an experiment shows that the fastest drop takes 40 seconds, and that drops fall at different rates depending on their size.

Even if we have a good model for one situation doesn't mean it will apply everywhere. **We always need to question our assumptions.**

—Extensive gravity discussion in Section 1.3.—

Modeling Population Growth

Example. Modeling the size of a population.

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$P(t)$ = size of population at time t.
$B(t)$ = number of births between times t and $t + 1$.
$D(t)$ = number of deaths between times t and $t + 1$.

Therefore, $P(t + 1) =$ ________________.

Definitions imply
$P(4) =$
$B(\frac{1}{2}) =$
$B(5) - D(5) =$

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Assumption: The birth rate and death rate stay constant.

That is, the birth rate $b = \frac{B(t)}{P(t)}$ and death rate $d = \frac{D(t)}{P(t)}$ are constants.

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Assumption: No migration.

Population Growth

Therefore, $$P(t+1) = P(t)\left[\frac{P(t)}{P(t)} + \frac{B(t)}{P(t)} - \frac{D(t)}{P(t)}\right].$$

Under our assumptions, $$P(t+1) = P(t)[1 + b - d].$$

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This implies:
$$\begin{aligned} P(1) &= \underline{\hspace{4cm}}, \\ P(2) &= \underline{\hspace{4cm}}, \ldots \end{aligned}$$

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This implies: $P(1) = $ ____________,

$P(2) = $ ____________, ...

In general, $P(n) = $ ____________.

Population Growth

Therefore, $$P(t+1) = P(t)\left[\frac{P(t)}{P(t)} + \frac{B(t)}{P(t)} - \frac{D(t)}{P(t)}\right].$$

Under our assumptions, $$P(t+1) = P(t)[1+b-d].$$

This implies: $P(1) = $ ____________,

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> A model for the size of a population is
> $$P(t) = P(0)r^t,$$
> where $P(0)$ and r are constants.

Applying the Malthusian Model

Approximate US Population at: http://www.census.gov/main/www/popclock.html

Example 1. Suppose that the current US population is 315,400,000. Assume that the birth rate is 0.02 and the death rate is 0.01. What will the population be in 10 years?

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Refinement. Approx. US Growth Rate at http://www63.wolframalpha.com/input/?i=US+birth+rate

Resource: Wolfram Alpha, integrable directly into *Mathematica*.

Example 2. How long will it take the population to double?

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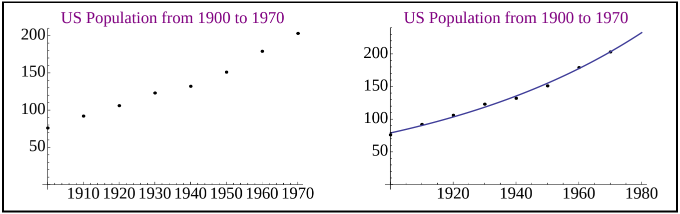
Determining constants of exponential growth

Goal: Given population data, determine model constants.



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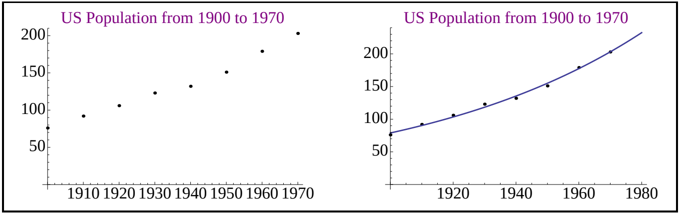

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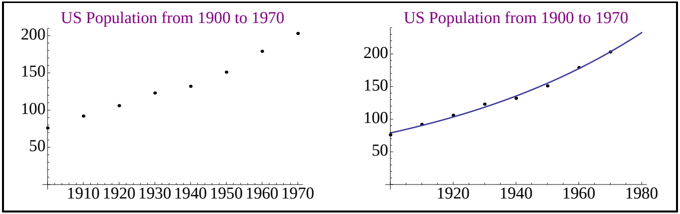

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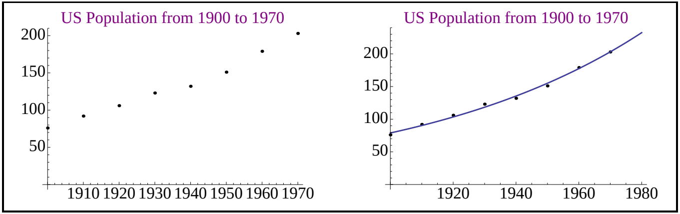

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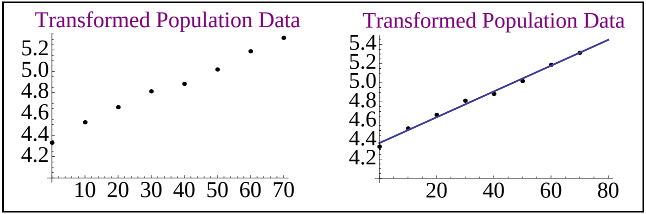

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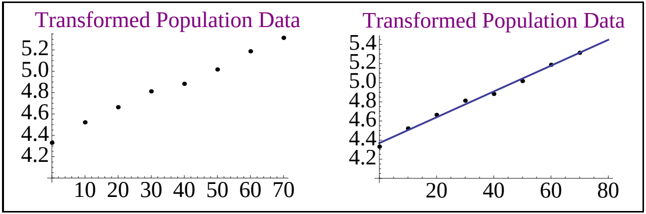

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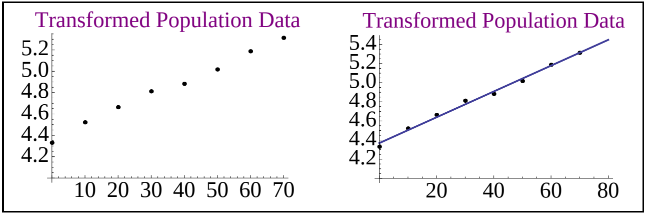

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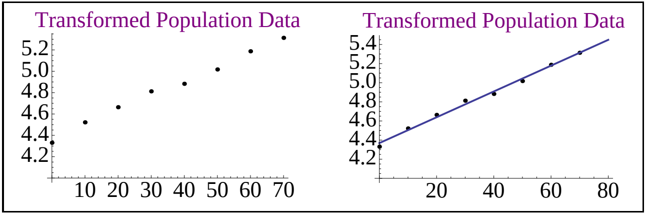

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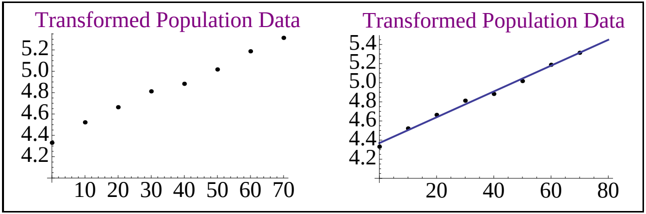

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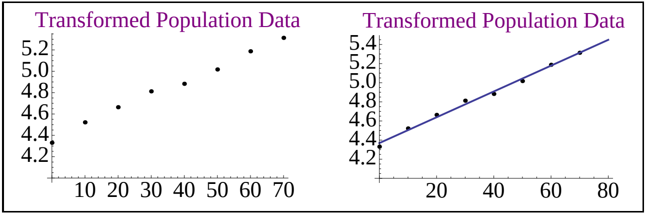

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⋆ Important: Transformations distort distances between points, so verification of a fit should always take place on y versus x axes. ⋆

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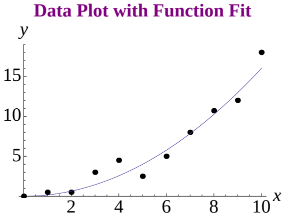

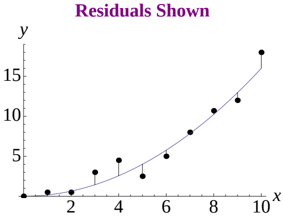

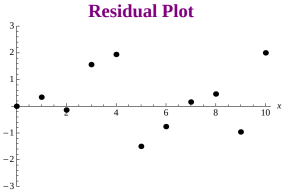

Residuals

The structure of the points in the residual plot give clues about whether the function fits the data well. Three common appearances:

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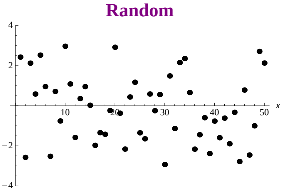

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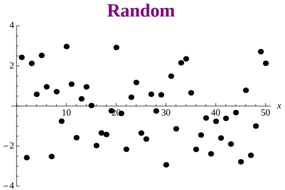

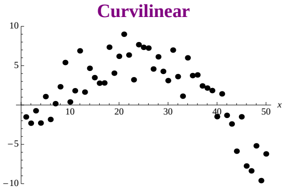

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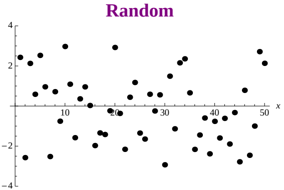
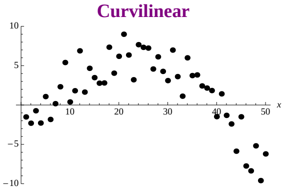
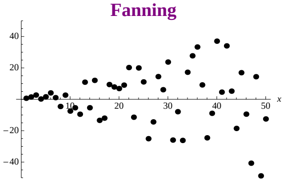
3. **Fanning**: Residuals small at first and get larger (or vice versa). Indicates non-constant variability (model better for small x?).







Interpolation vs. Extrapolation

Suppose you have collected a set of *known* data points (x_i, y_i), and you would like to estimate the y-value for an *unknown* x-value.

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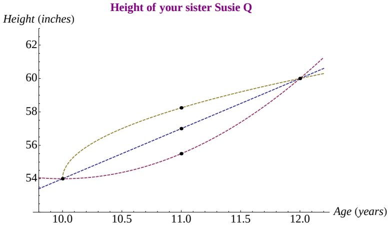
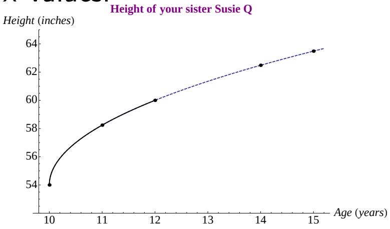
Interpolation

Inserting one or more x-values between known x-values.



Extrapolation

Inserting one or more x-values outside of the range of known x-values.



Interpolation vs. Extrapolation

- The most common method for interpolation is taking a weighted average of the two nearest data points; suppose $x_1 < x < x_2$, then,
$$f(x) \approx y_1 + \frac{y_2 - y_1}{x_2 - x_2}(x - x_1).$$

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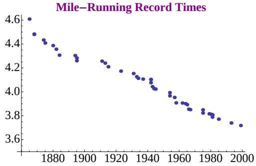
Extrapolation: Running the Mile (p. 162)

Below is a plot of the years in which a record was broken for running a mile and the record-breaking time.



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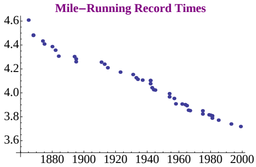

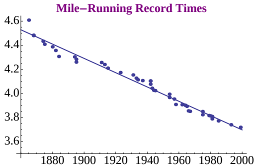

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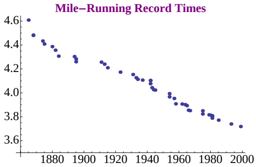

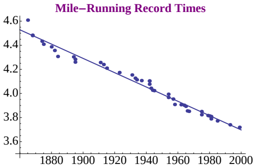

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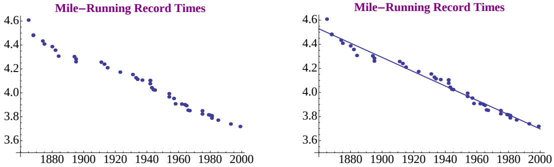

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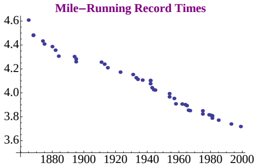

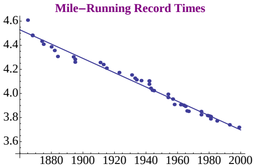

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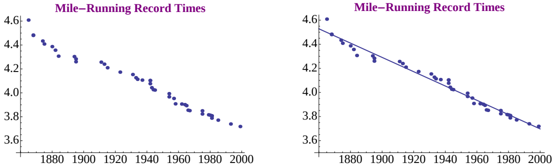

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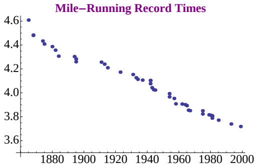

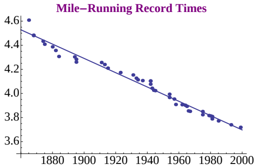

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