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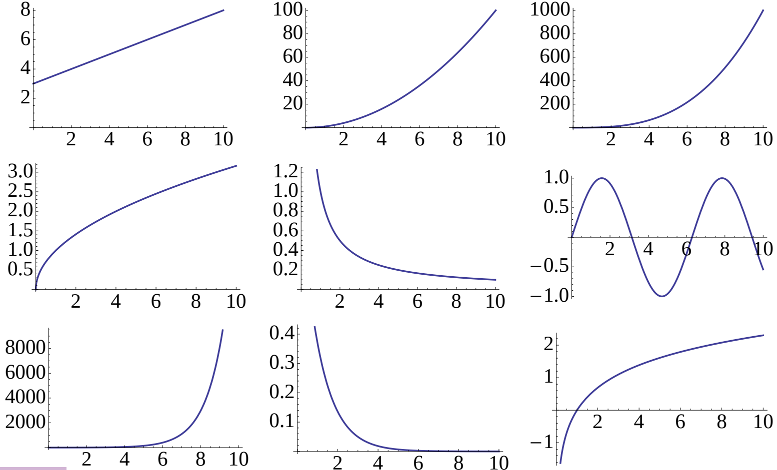
- More evaluation: Determine errors, evaluation criteria...

Functions you should recognize on sight



Think Pair Share

What are these functions?

What is the most general equation of each type?

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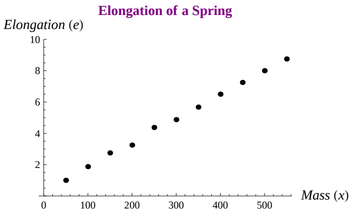
When we plot the data, we get the following **scatterplot**.



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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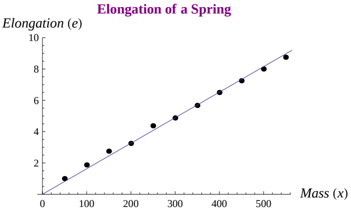

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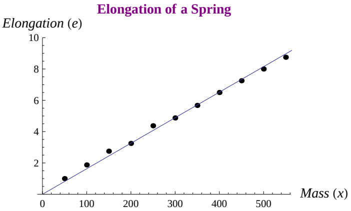
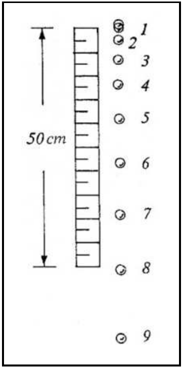


2. Mathematically: **Linear Regression / Least Squares**
   (For another day)

Fitting Gravity Data

Example. Modeling the dropping of a golf ball



Source:
practicalphysics.org

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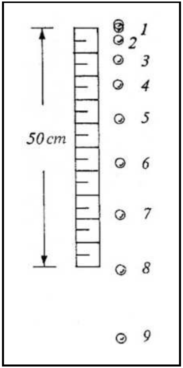

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Let's use an experiment to test the gravity model from last time.

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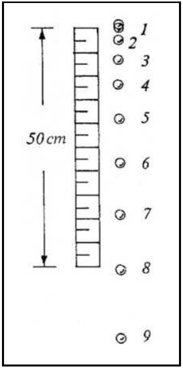

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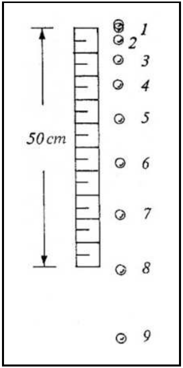

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Let's use an experiment to test the gravity model from last time.

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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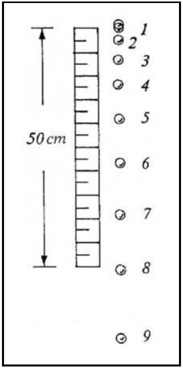

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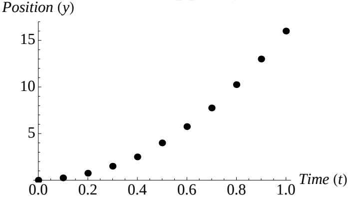
Data would be similar to the table→
It's plotted in the scatterplot below.

Position of a dropped golf ball



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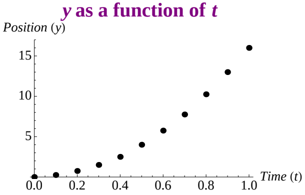

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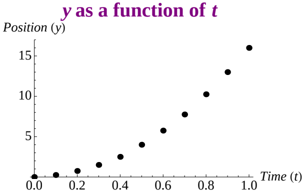

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These data seem to fit a $\underline{\hspace{4cm}}$ (type of function). How can we be sure?

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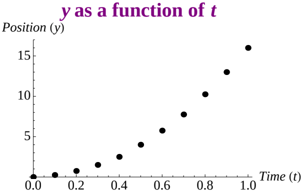

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These data seem to fit a $\underset{\text{(type of function)}}{\underline{\hspace{3cm}}}$. How can we be sure?

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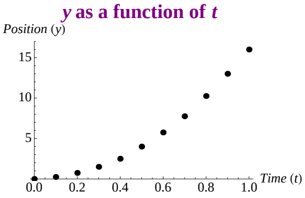

t	t^2	y
0.0		0.00
0.1		0.25
0.2		0.75
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Fitting Gravity Data

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

1. Plot distance as a function of t^2.
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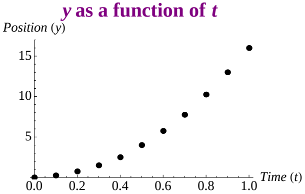

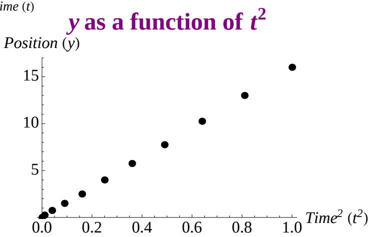

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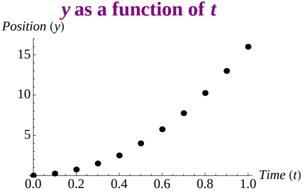
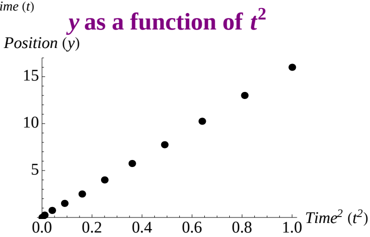


transform



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This implies
$y \approx \underline{\quad} t^2$.

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Key Concept: When fitting data to a function $y = Ct^k$,
An alternate method is:

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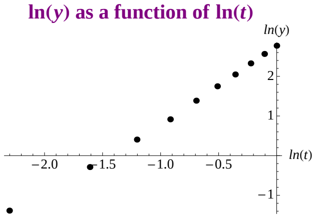

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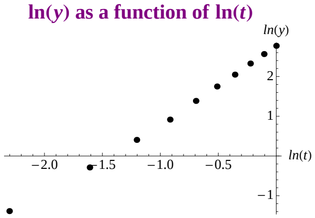
  - The y-intercept approximates $\ln C$.



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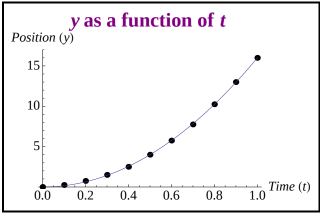
$$y(t) = 16t^2$$

appears to model the dropping of a golf ball.



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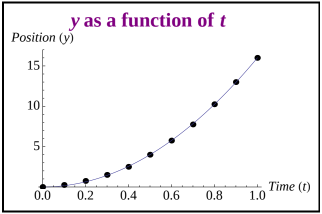

Example. Raindrops

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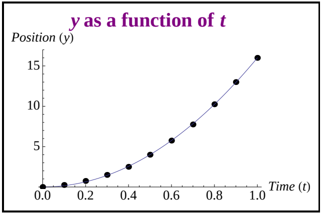

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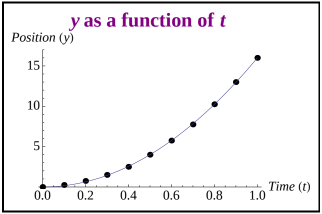

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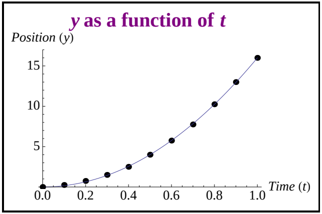

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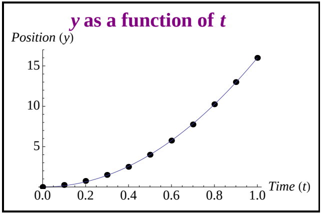

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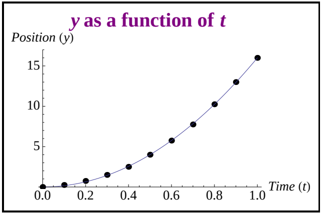

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Even if we have a good model for one situation doesn't mean it will apply everywhere. **We always need to question our assumptions.**

—Extensive gravity discussion in Section 1.3.—

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

Population Growth

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

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A model for the size of a population is

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where $P(0)$ and r are constants.

Applying the Malthusian Model

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

Example 1. Suppose that the current US population is 323,090,000. 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://www.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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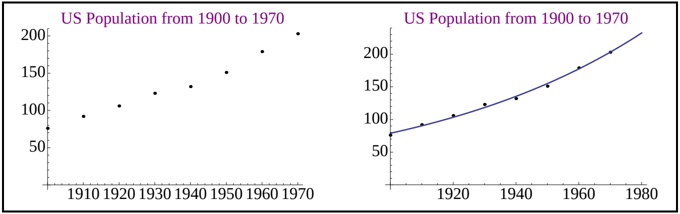
Determining constants of exponential growth

Goal: Given population data, determine model constants.



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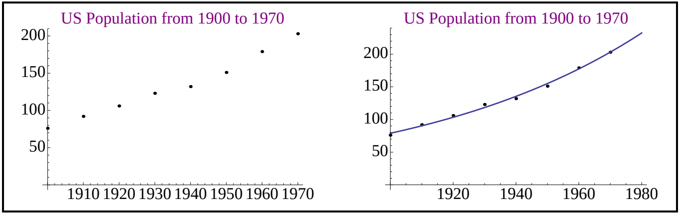

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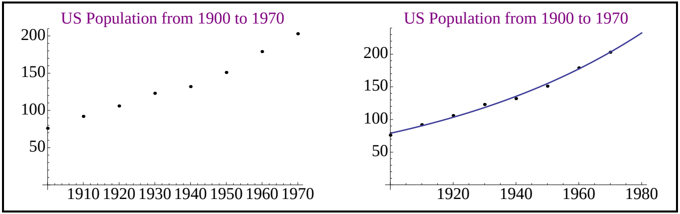

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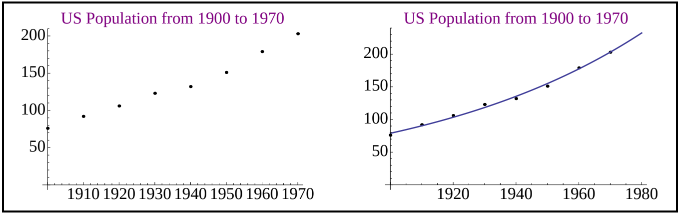

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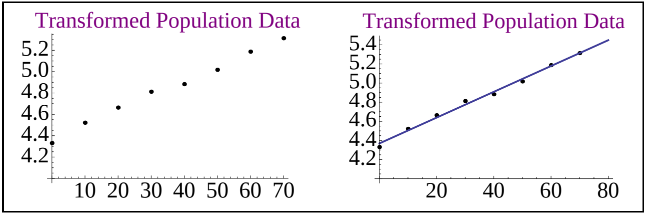

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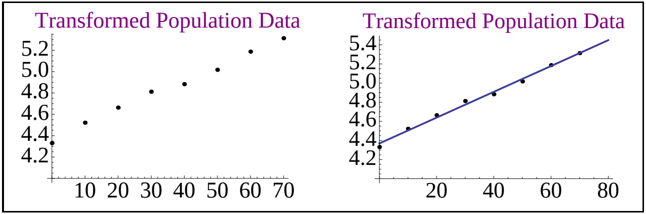

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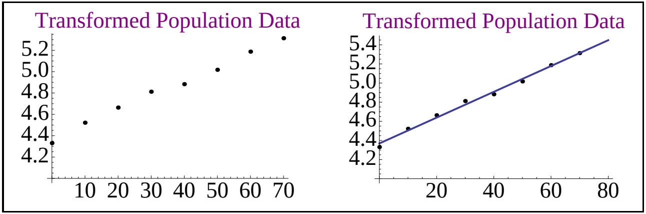

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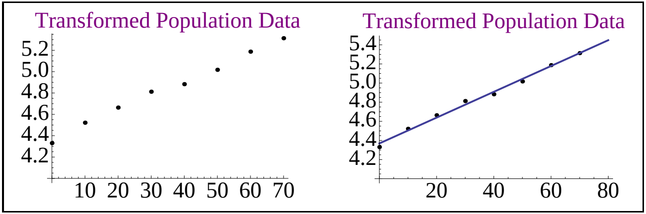

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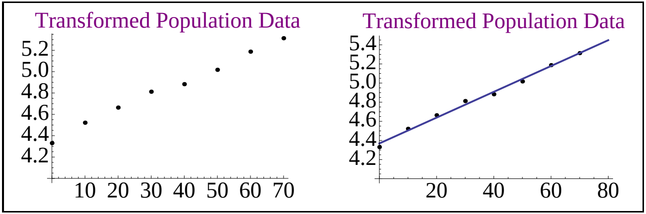

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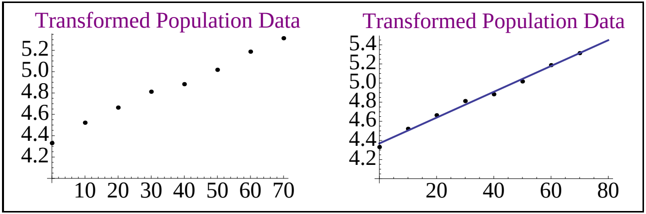

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⋆ Important: Transformations distort distances between points, so verification of a fit should always take place on y versus x axes. ⋆

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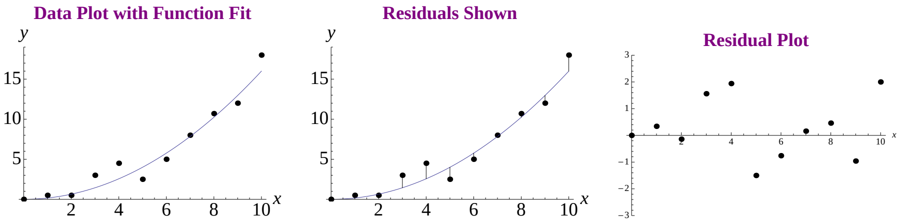

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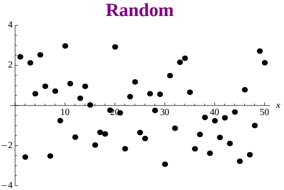

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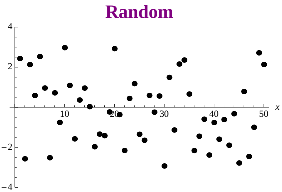

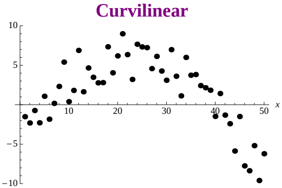

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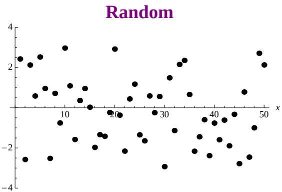
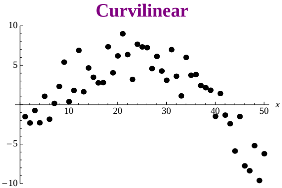
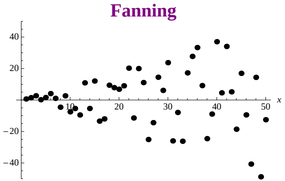
3. **Fanning**: Residuals small at first and get larger (or vice versa). Indicates non-constant variability (model better for small x?).







Interpolation vs. Extrapolation

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The name for such an estimation depends on the placement of the x-value relative to the *known* x-values.

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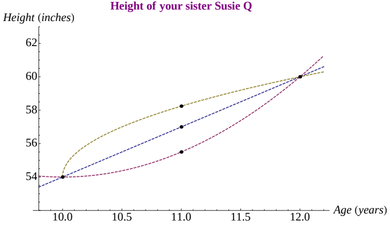
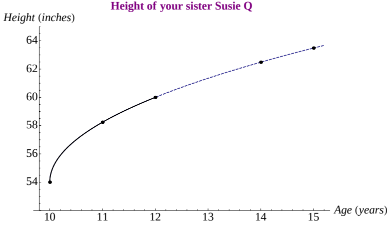
Interpolation

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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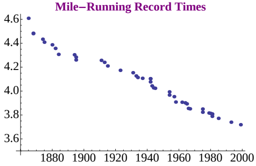
Extrapolation: Running the Mile (p. 162)

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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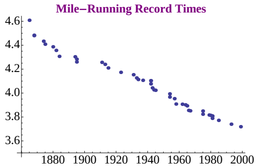

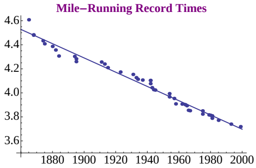

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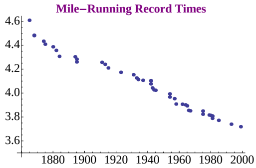

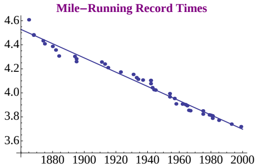

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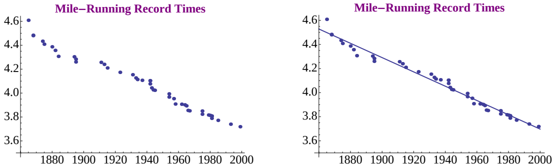

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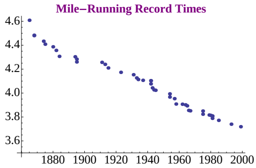

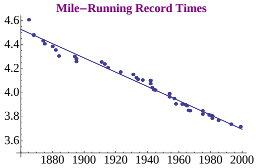

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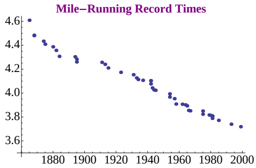

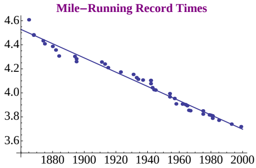

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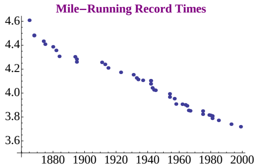

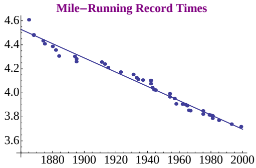

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