Scaling—a Plenitude of Power Laws
Principles of Complex Systems
Course 300, Fall, 2008

Prof. Peter Dodds
Department of Mathematics & Statistics
University of Vermont

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Definitions

General observation:

Systems (complex or not) that cross many spatial and temporal scales often exhibit some form of scaling.
All about scaling:

- Definitions.
- Examples.
- How to measure your power-law relationship.
- Mechanisms giving rise to your power-laws.
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Definitions

A power law relates two variables $x$ and $y$ as follows:

$$y = cx^\alpha$$

- $\alpha$ is the **scaling exponent** (or just exponent)
- $(\alpha$ can be any number in principle but we will find various restrictions.)
- $c$ is the **prefactor** (which can be important!)
Definitions

► The prefactor $c$ must balance dimensions.

► eg., length $\ell$ and volume $v$ of common nails are related as:

$$\ell = cv^{1/4}$$

► Using $[\cdot]$ to indicate dimension, then

$$[c] = [\ell]/[v^{1/4}] = L/L^{3/4} = L^{1/4}.$$
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Power-law relationships are linear in log-log space:

\[ y = cx^\alpha \]

\[ \Rightarrow \log_b y = \alpha \log_b x + \log_b c \]

with slope equal to \( \alpha \), the scaling exponent.

- Much searching for straight lines on log-log or double-logarithmic plots.
- Good practice: Always, always, always use base 10.
- Talk only about orders of magnitude (powers of 10).
Looking at data

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A beautiful, heart-warming example:

\[ \alpha \approx 1.23 \]

gray matter: ‘computing elements’

white matter: ‘wiring’

from Zhang & Sejnowski, PNAS (2000) [?]
Why is $\alpha \simeq 1.23$?

Quantities (following Zhang and Sejnowski):

- $G = \text{Volume of gray matter (cortex/processors)}$
- $W = \text{Volume of white matter (wiring)}$
- $T = \text{Cortical thickness (wiring)}$
- $S = \text{Cortical surface area}$
- $L = \text{Average length of white matter fibers}$
- $p = \text{density of axons on white matter/cortex interface}$

A rough understanding:

- $G \sim ST$ (convolutions are okay)
- $W \sim \frac{1}{2}pSL$
- $G \sim L^3$
- Eliminate $S$ and $L$ to find $W \propto \frac{G^{4/3}}{T}$
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- $G \sim L^3 \leftarrow$ this is a little sketchy...
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A rough understanding:

- We are here: $W \propto G^{4/3}/T$
- Observe weak scaling $T \propto G^{0.10\pm0.02}$.
- (Implies $S \propto G^{0.9} \rightarrow$ convolutions fill space.)
- $\Rightarrow W \propto G^{4/3}/T \propto G^{1.23\pm0.02}$
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Trickiness:

- With $V = G + W$, some power laws must be approximations.
- Measuring exponents is a hairy business...
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**Trickiness:**

- With $V = G + W$, some power laws must be approximations.
- Measuring exponents is a hairy business...
Good scaling:

General rules of thumb:

- **High quality**: scaling persists over three or more orders of magnitude for each variable.

- **Medium quality**: scaling persists over three or more orders of magnitude for only one variable and at least one for the other.

- **Very dubious**: scaling ‘persists’ over less than an order of magnitude for both variables.
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Unconvincing scaling:

Average walking speed as a function of city population:

Two problems:
1. use of natural log, and
2. minute variation in dependent variable.

from Bettencourt et al. (2007) [?]; otherwise very interesting!
Definitions

Power laws are the signature of scale invariance:

Scale invariant ‘objects’ look the ‘same’ when they are appropriately rescaled.

- Objects = geometric shapes, time series, functions, relationships, distributions,
- ‘Same’ might be ‘statistically the same’
- To rescale means to change the units of measurement for the relevant variables
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Our friend $y = cx^\alpha$:

- If we rescale $x$ as $x = rx'$ and $y$ as $y = r^\alpha y'$,
- then

$$r^\alpha y' = c(rx')^\alpha$$

$$\Rightarrow y' = cr^\alpha x'^\alpha r^{-\alpha}$$

$$\Rightarrow y' = c x'^\alpha$$
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Compare with $y = ce^{-\lambda x}$:

- If we rescale $x$ as $x = rx'$, then
  \[ y = ce^{-\lambda rx'} \]

- Original form cannot be recovered.
- $\Rightarrow$ scale matters for the exponential.
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More on $y = ce^{-\lambda x}$:

- Say $x_0 = 1/\lambda$ is the characteristic scale.
- For $x \gg x_0$, $y$ is small, while for $x \ll x_0$, $y$ is large.
- $\Rightarrow$ More on this later with size distributions.
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Outline

Scaling-at-large

Allometry
  Definitions
  Examples
  History: Metabolism
  Measuring exponents
  History: River networks
  Earlier theories
  Geometric argument
  Blood networks
  River networks
  Conclusion

References
Definitions

Allometry (畳):

[refers to] differential growth rates of the parts of a living organism’s body part or process.
Definitions:

**Isometry:**
dimensions scale linearly with each other.

**Allometry:**
dimensions scale non-linearly.
Definitions

Isometry versus Allometry:

- Isometry = ‘same measure’
- Allometry = ‘other measure’

Confusingly, we use allometric scaling to refer to both:

1. nonlinear scaling (e.g., $x \propto y^{1/3}$)
2. and the relative scaling of different measures (e.g., resting heart rate as a function of body size)
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A wonderful treatise on scaling:

McMahon and Bonner, 1983
The biggest living things (left). All the organisms are drawn to the same scale. 1, the largest flying bird (albatross); 2, the largest known animal (the blue whale); 3, the largest extinct land mammal (Baluchitherium) with a human figure shown for scale; 4, the tallest living land animal (giraffe); 5, Ty rannosaurus; 6, Diplodocus; 7, one of the largest flying reptiles (Pteranodon); 8, the largest extinct snake; 9, the length of the largest tapeworm found in man; 10, the largest living reptile (West African crocodile); 11, the largest extinct lizard; 12, the largest extinct bird (Aepyornis); 13, the largest jellyfish (Cyanea); 14, the largest living lizard (Komodo dragon); 15, sheep; 16, the largest bivalve mollusc (Tridacna); 17, the largest fish (whale shark); 18, horse; 19, the largest crustacean (Japanese spider crab); 20, the largest sea scorpion (Eurypterus); 21, large tarpon; 22, the largest lobster; 23, the largest mollusc (deep-water squid, Architeuthis); 24, ostrich; 25, the lower 105 feet of the largest organism (giant sequoia), with a 100-foot larch superposed.

p. 2, McMahon and Bonner[?]
The many scales of life:

p. 2, McMahon and Bonner [?]
Medium-sized creatures (above). 1, Dog; 2, common herring; 3, the largest egg (Aepyornis); 4, song thrush with egg; 5, the smallest bird (hummingbird) with egg; 6, queen bee; 7, common cockroach; 8, the largest stick insect; 9, the largest polyp (Branchiocerianthus); 10, the smallest mammal (flying shrew); 11, the smallest vertebrate (a tropical frog); 12, the largest frog (goliath frog); 13, common grass frog; 14, house mouse; 15, the largest land snail (Achatina) with egg; 16, common snail; 17, the largest beetle (goliath beetle); 18, human hand; 19, the largest starfish (Luidia); 20, the largest free-moving protozoan (an extinct nummulite).
The many scales of life:

p. 3, McMahon and Bonner [?]
For the following slide:

Small, “naked-eye” creatures (lower left). 1, One of the smallest fishes (Trimmatom nanus); 2, common brown hydra, expanded; 3, housefly; 4, medium-sized ant; 5, the smallest vertebrate (a tropical frog, the same as the one numbered 11 in the figure above); 6, flea (Xenopsylla cheopsis); 7, the smallest land snail; 8, common water flea (Daphnia).

The smallest “naked-eye” creatures and some large microscopic animals and cells (below right). 1, Vorticella, a ciliate; 2, the largest ciliate protozoan (Bursaria); 3, the smallest many-celled animal (a rotifer); 4, smallest flying insect (Elaphis); 5, another ciliate (Paramecium); 6, cheese mite; 7, human sperm; 8, human ovum; 9, dysentery amoeba; 10, human liver cell; 11, the foreleg of the flea (numbered 6 in the figure to the left).

p. 2, McMahon and Bonner [?]
The many scales of life:

p. 3, McMahon and Bonner [?]
Size range and cell differentiation:

- Blue whale: $>10^8$
- Human: $10^7$
- Hamster: $10^5$
- Bee: $10^3$
- Large amoeba: $10^4$
- *Tetrahymena*: $10^2$
- Malaria parasite: $10^1$
- Mycoplasma (PPLO): $10^{-3}$
Non-uniform growth:

p. 32, McMahon and Bonner [?]
Non-uniform growth—arm length versus height:

Good example of a **break in scaling**:

A **crossover** in scaling occurs around a height of 1 metre.

p. 32, McMahon and Bonner[?]
Weightlifting: $M_{\text{worldrecord}} \propto M_{\text{lifter}}^{2/3}$

Idea: Power $\sim$ cross-sectional area of isometric lifters.

p. 53, McMahon and Bonner[?]
Titanotheres horns: $L_{\text{horn}} \sim L_{\text{skull}}^4$
The allometry of nails:

- Diameter $\propto$ Mass$^{3/8}$
- Length $\propto$ Mass$^{1/4}$
- Diameter $\propto$ Length$^{2/3}$

p. 58–59, McMahon and Bonner[?]
The allometry of nails:

A buckling instability?:

- Physics/Engineering result: Columns buckle under a load which depends on $d^4/\ell^2$.
- To drive nails in, resistive force $\propto$ nail circumference $= \pi d$.
- Match forces independent of nail size: $d^4/\ell^2 \propto d$.
- Leads to $d \propto \ell^{2/3}$. 
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Rowing: Speed $\propto (\text{number of rowers})^{1/9}$

<table>
<thead>
<tr>
<th>No. of oarsmen</th>
<th>Modifying description</th>
<th>Length, $l$ (m)</th>
<th>Beam, $b$ (m)</th>
<th>$l/b$</th>
<th>Boat mass per oarsman (kg)</th>
<th>Time for 2000 m (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>Heavyweight</td>
<td>18.28</td>
<td>0.610</td>
<td>30.0</td>
<td>14.7</td>
<td>5.87 5.92 5.82 5.73</td>
</tr>
<tr>
<td>8</td>
<td>Lightweight</td>
<td>18.28</td>
<td>0.598</td>
<td>30.6</td>
<td>14.7</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>With coxswain</td>
<td>12.80</td>
<td>0.574</td>
<td>22.3</td>
<td>18.1</td>
<td>6.33 6.42 6.48 6.13</td>
</tr>
<tr>
<td>4</td>
<td>Without coxswain</td>
<td>11.75</td>
<td>0.574</td>
<td>21.0</td>
<td>18.1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Double scull</td>
<td>9.76</td>
<td>0.381</td>
<td>25.6</td>
<td>13.6</td>
<td>6.87 6.92 6.95 6.77</td>
</tr>
<tr>
<td>2</td>
<td>Pair-oared shell</td>
<td>9.76</td>
<td>0.356</td>
<td>27.4</td>
<td>13.6</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>Single scull</td>
<td>7.93</td>
<td>0.293</td>
<td>27.0</td>
<td>16.3</td>
<td>7.16 7.25 7.28 7.17</td>
</tr>
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![Graph showing speed (km/hr) vs. number of oarsmen](image-url)
Scaling in Cities:

▶ “Growth, innovation, scaling, and the pace of life in cities”
Bettencourt et al., PNAS, 2007. [?]

▶ Quantified levels of
  ▶ Infrastructure
  ▶ Wealth
  ▶ Crime levels
  ▶ Disease
  ▶ Energy consumption

as a function of city size $N$ (population).
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as a function of city size $N$ (population).
Scaling in Cities:

Table 1. Scaling exponents for urban indicators vs. city size

<table>
<thead>
<tr>
<th>Y</th>
<th>$\beta$</th>
<th>95% CI</th>
<th>Adj-$R^2$</th>
<th>Observations</th>
<th>Country–year</th>
</tr>
</thead>
<tbody>
<tr>
<td>New patents</td>
<td>1.27</td>
<td>[1.25,1.29]</td>
<td>0.72</td>
<td>331</td>
<td>U.S. 2001</td>
</tr>
<tr>
<td>Inventors</td>
<td>1.25</td>
<td>[1.22,1.27]</td>
<td>0.76</td>
<td>331</td>
<td>U.S. 2001</td>
</tr>
<tr>
<td>Private R&amp;D employment</td>
<td>1.34</td>
<td>[1.29,1.39]</td>
<td>0.92</td>
<td>266</td>
<td>U.S. 2002</td>
</tr>
<tr>
<td>“Supercreative” employment</td>
<td>1.15</td>
<td>[1.11,1.18]</td>
<td>0.89</td>
<td>287</td>
<td>U.S. 2003</td>
</tr>
<tr>
<td>R&amp;D establishments</td>
<td>1.19</td>
<td>[1.14,1.22]</td>
<td>0.77</td>
<td>287</td>
<td>U.S. 1997</td>
</tr>
<tr>
<td>R&amp;D employment</td>
<td>1.26</td>
<td>[1.18,1.43]</td>
<td>0.93</td>
<td>295</td>
<td>China 2002</td>
</tr>
<tr>
<td>Total wages</td>
<td>1.12</td>
<td>[1.09,1.13]</td>
<td>0.96</td>
<td>361</td>
<td>U.S. 2002</td>
</tr>
<tr>
<td>Total bank deposits</td>
<td>1.08</td>
<td>[1.03,1.11]</td>
<td>0.91</td>
<td>267</td>
<td>U.S. 1996</td>
</tr>
<tr>
<td>GDP</td>
<td>1.15</td>
<td>[1.06,1.23]</td>
<td>0.96</td>
<td>295</td>
<td>China 2002</td>
</tr>
<tr>
<td>GDP</td>
<td>1.26</td>
<td>[1.09,1.46]</td>
<td>0.64</td>
<td>196</td>
<td>EU 1999–2003</td>
</tr>
<tr>
<td>GDP</td>
<td>1.13</td>
<td>[1.03,1.23]</td>
<td>0.94</td>
<td>37</td>
<td>Germany 2003</td>
</tr>
<tr>
<td>Total electrical consumption</td>
<td>1.07</td>
<td>[1.03,1.11]</td>
<td>0.88</td>
<td>392</td>
<td>Germany 2002</td>
</tr>
<tr>
<td>New AIDS cases</td>
<td>1.23</td>
<td>[1.18,1.29]</td>
<td>0.76</td>
<td>93</td>
<td>U.S. 2002–2003</td>
</tr>
<tr>
<td>Serious crimes</td>
<td>1.16</td>
<td>[1.11,1.18]</td>
<td>0.89</td>
<td>287</td>
<td>U.S. 2003</td>
</tr>
<tr>
<td>Total housing</td>
<td>1.00</td>
<td>[0.99,1.01]</td>
<td>0.99</td>
<td>316</td>
<td>U.S. 1990</td>
</tr>
<tr>
<td>Total employment</td>
<td>1.01</td>
<td>[0.99,1.02]</td>
<td>0.98</td>
<td>331</td>
<td>U.S. 2001</td>
</tr>
<tr>
<td>Household electrical consumption</td>
<td>1.00</td>
<td>[0.94,1.06]</td>
<td>0.88</td>
<td>377</td>
<td>Germany 2002</td>
</tr>
<tr>
<td>Household electrical consumption</td>
<td>1.05</td>
<td>[0.89,1.22]</td>
<td>0.91</td>
<td>295</td>
<td>China 2002</td>
</tr>
<tr>
<td>Household water consumption</td>
<td>1.01</td>
<td>[0.89,1.11]</td>
<td>0.96</td>
<td>295</td>
<td>China 2002</td>
</tr>
<tr>
<td>Gasoline stations</td>
<td>0.77</td>
<td>[0.74,0.81]</td>
<td>0.93</td>
<td>318</td>
<td>U.S. 2001</td>
</tr>
<tr>
<td>Gasoline sales</td>
<td>0.79</td>
<td>[0.73,0.80]</td>
<td>0.94</td>
<td>318</td>
<td>U.S. 2001</td>
</tr>
<tr>
<td>Length of electrical cables</td>
<td>0.87</td>
<td>[0.82,0.92]</td>
<td>0.75</td>
<td>380</td>
<td>Germany 2002</td>
</tr>
<tr>
<td>Road surface</td>
<td>0.83</td>
<td>[0.74,0.92]</td>
<td>0.87</td>
<td>29</td>
<td>Germany 2002</td>
</tr>
</tbody>
</table>

Data sources are shown in SI Text. CI, confidence interval; Adj-$R^2$, adjusted $R^2$; GDP, gross domestic product.
Scaling in Cities:

Intriguing findings:

- Global supply costs scale sublinearly with $N$ ($\beta < 1$).
  - Returns to scale for infrastructure.
- Total individual costs scale linearly with $N$ ($\beta = 1$).
  - Individuals consume similar amounts independent of city size.
- Social quantities scale superlinearly with $N$ ($\beta > 1$).
  - Creativity (# patents), wealth, disease, crime, ...

Density doesn’t seem to matter...

- Surprising given that across the world, we observe two orders of magnitude variation in area covered by agglomerations of fixed populations.
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Ecology—Species-area law: $N_{\text{species}} \propto A^\beta$

Allegedly (data is messy):

- On islands: $\beta \approx 1/4$.
- On continuous land: $\beta \approx 1/8$. 
A focus:

- How much energy do organisms need to live?
- And how does this scale with organismal size?
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- And how does this scale with organismal size?
Animal power

Fundamental biological and ecological constraint:

\[ P = c M^\alpha \]

\[ P = \text{basal metabolic rate} \]
\[ M = \text{organismal body mass} \]
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- \( P = \) basal metabolic rate
- \( M = \) organismal body mass
\[ P = c M^\alpha \]

Prefactor \( c \) depends on body plan and body temperature:
\[ P = c M^{\alpha} \]

Prefactor \( c \) depends on **body plan** and **body temperature**:

- **Birds**: 39–41°C
- **Eutherian Mammals**: 36–38°C
- **Marsupials**: 34–36°C
- **Monotremes**: 30–31°C
What one might expect:

\[ \alpha = \frac{2}{3} \]

- Dimensional analysis suggests an energy balance surface law:
  \[ P \propto S \propto V^{2/3} \propto M^{2/3} \]

- Lognormal fluctuations:
  Gaussian fluctuations in log \( P \) around log \( cM^\alpha \).

- Stefan-Boltzmann relation for radiated energy:
  \[ \frac{dE}{dt} = \sigma \varepsilon ST^4 \]
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The prevailing belief of the church of quarterology

\[ \alpha = \frac{3}{4} \]

\[ P \propto M^{3/4} \]
The prevailing belief of the church of quarterology

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\[ P \propto M^{3/4} \]

Huh?
Related putative scalings:

- number of capillaries $\propto M^{3/4}$
- time to reproductive maturity $\propto M^{1/4}$
- heart rate $\propto M^{-1/4}$
- cross-sectional area of aorta $\propto M^{3/4}$
- population density $\propto M^{-3/4}$
The great ‘law’ of heartbeats:

Assuming:

- Average lifespan \( \propto M^\beta \)
- Average heart rate \( \propto M^{-\beta} \)
- Irrelevant but perhaps \( \beta = 1/4 \).

Then:

- Average number of heart beats in a lifespan \( \propto M^0 \)

\[ \approx 1.5 \text{ billion} \ldots \]
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- Irrelevant but perhaps $\beta = 1/4$.

Then:

- Average number of heart beats in a lifespan
  $\simeq (\text{Average lifespan}) \times (\text{Average heart rate})$
  $\propto M^{\beta-\beta}$
  $\propto M^0$

Number of heartbeats per life time is independent of organism size!

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- Average heart rate $\propto M^{-\beta}$
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  $\propto M^0$

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- Number of heartbeats per life time is independent of organism size!
- $\approx 1.5$ billion....
1840’s: Sarrus and Rameaux first suggested $\alpha = 2/3$. 
1883: Rubner$^\text{[?]}$ found $\alpha \simeq 2/3$. 
1930’s: Brody, Benedict study mammals. [?] Found $\alpha \simeq 0.73$ (standard).
1932: Kleiber analyzed 13 mammals. Found $\alpha = 0.76$ and suggested $\alpha = 3/4$. 
1950/1960: Hemmingsen [? , ?]
Extension to unicellular organisms.
\( \alpha = 3/4 \) assumed true.
History

1964: Troon, Scotland: [?]
3rd symposium on energy metabolism.
\( \alpha = 3/4 \) made official . . .
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\[ \alpha = \frac{3}{4} \text{ made official . . .} \quad \ldots \text{29 to zip.} \]
Today

- 3/4 is held by many to be the one true exponent.

*In the Beat of a Heart: Life, Energy, and the Unity of Nature*—by John Whitfield
Today

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- But—much controversy...
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- But—much controversy...
- See ‘Re-examination of the “3/4-law” of metabolism’ Dodds, Rothman, and Weitz [?]
Some data on metabolic rates

Heusner’s data (1991) [?]

391 Mammals

blue line: 2/3

red line: 3/4.

(B = P)
Some data on metabolic rates

B = 0.041 M^{0.664}

- Bennett and Harvey’s data (1987) [?]
- 398 birds
- blue line: 2/3
- red line: 3/4.
- (B = P)

Passerine vs. non-passerine...
Important:

- Ordinary Least Squares (OLS) Linear regression is only appropriate for analyzing a dataset \( \{(x_i, y_i)\} \) when we know the \( x_i \) are measured without error.
- Here we assume that measurements of mass \( M \) have less error than measurements of metabolic rate \( B \).
- Linear regression assumes Gaussian errors.
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Measuring exponents

More on regression:

If (a) we don’t know what the errors of either variable are,
Measuring exponents

More on regression:
If (a) we don’t know what the errors of either variable are, or (b) no variable can be considered independent,
Measuring exponents

More on regression:
If (a) we don’t know what the errors of either variable are, or (b) no variable can be considered independent, then we need to use Standardized Major Axis Linear Regression. aka Reduced Major Axis = RMA.
Measuring exponents

For Standardized Major Axis Linear Regression:

\[ \text{slope}_{\text{SMA}} = \frac{\text{standard deviation of } y \text{ data}}{\text{standard deviation of } x \text{ data}} \]

Very simple!
Measuring exponents

Relationship to ordinary least squares regression is simple:

\[
\text{slope}_{\text{SMA}} = r^{-1} \times \text{slope}_{\text{OLS } y \text{ on } x} \\
= r \times \text{slope}_{\text{OLS } x \text{ on } y}
\]

where \( r \) = standard correlation coefficient:

\[
r = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}}
\]
### Heusner’s data, 1991 (391 Mammals)

<table>
<thead>
<tr>
<th>range of $M$</th>
<th>$N$</th>
<th>$\hat{\alpha}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\leq 0.1$ kg</td>
<td>167</td>
<td>$0.678 \pm 0.038$</td>
</tr>
<tr>
<td>$\leq 1$ kg</td>
<td>276</td>
<td>$0.662 \pm 0.032$</td>
</tr>
<tr>
<td>$\leq 10$ kg</td>
<td>357</td>
<td>$0.668 \pm 0.019$</td>
</tr>
<tr>
<td>$\leq 25$ kg</td>
<td>366</td>
<td>$0.669 \pm 0.018$</td>
</tr>
<tr>
<td>$\leq 35$ kg</td>
<td>371</td>
<td>$0.675 \pm 0.018$</td>
</tr>
<tr>
<td>$\leq 350$ kg</td>
<td>389</td>
<td>$0.706 \pm 0.016$</td>
</tr>
<tr>
<td>$\leq 3670$ kg</td>
<td>391</td>
<td>$0.710 \pm 0.021$</td>
</tr>
</tbody>
</table>
### Bennett and Harvey, 1987 (398 birds)

<table>
<thead>
<tr>
<th>$M_{\text{max}}$</th>
<th>$N$</th>
<th>$\hat{\alpha}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\leq 0.032$</td>
<td>162</td>
<td>$0.636 \pm 0.103$</td>
</tr>
<tr>
<td>$\leq 0.1$</td>
<td>236</td>
<td>$0.602 \pm 0.060$</td>
</tr>
<tr>
<td>$\leq 0.32$</td>
<td>290</td>
<td>$0.607 \pm 0.039$</td>
</tr>
<tr>
<td>$\leq 1$</td>
<td>334</td>
<td>$0.652 \pm 0.030$</td>
</tr>
<tr>
<td>$\leq 3.2$</td>
<td>371</td>
<td>$0.655 \pm 0.023$</td>
</tr>
<tr>
<td>$\leq 10$</td>
<td>391</td>
<td>$0.664 \pm 0.020$</td>
</tr>
<tr>
<td>$\leq 32$</td>
<td>396</td>
<td>$0.665 \pm 0.019$</td>
</tr>
<tr>
<td>$\leq 100$</td>
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</tr>
</tbody>
</table>
Hypothesis testing

Test to see if $\alpha'$ is consistent with our data $\{(M_i, B_i)\}$:

$H_0 : \alpha = \alpha'$ and $H_1 : \alpha \neq \alpha'$.

- Assume each $B_i$ (now a random variable) is normally distributed about $\alpha' \log_{10} M_i + \log_{10} c$.
- Follows that the measured $\alpha$ for one realization obeys a $t$ distribution with $N - 2$ degrees of freedom.
- Calculate a $p$-value: probability that the measured $\alpha$ is as least as different to our hypothesized $\alpha'$ as we observe.

(see, for example, DeGroot and Scherish, “Probability and Statistics”[?])
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Revisiting the past—mammals

Full mass range:

<table>
<thead>
<tr>
<th></th>
<th>$N$</th>
<th>$\hat{\alpha}$</th>
<th>$p_{2/3}$</th>
<th>$p_{3/4}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kleiber</td>
<td>13</td>
<td>0.738</td>
<td>$&lt; 10^{-6}$</td>
<td>0.11</td>
</tr>
<tr>
<td>Brody</td>
<td>35</td>
<td>0.718</td>
<td>$&lt; 10^{-4}$</td>
<td>$&lt; 10^{-2}$</td>
</tr>
<tr>
<td>Heusner</td>
<td>391</td>
<td>0.710</td>
<td>$&lt; 10^{-6}$</td>
<td>$&lt; 10^{-5}$</td>
</tr>
<tr>
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<td>398</td>
<td>0.664</td>
<td>0.69</td>
<td>$&lt; 10^{-15}$</td>
</tr>
<tr>
<td>and Harvey</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Revisiting the past—mammals

\[
\begin{array}{cccc}
M \leq 10 \text{ kg}: & N & \hat{\alpha} & \rho_{2/3} & \rho_{3/4} \\
\hline
\text{Kleiber} & 5 & 0.667 & 0.99 & 0.088 \\
\text{Brody} & 26 & 0.709 & < 10^{-3} & < 10^{-3} \\
\text{Heusner} & 357 & 0.668 & 0.91 & < 10^{-15} \\
\hline
M \geq 10 \text{ kg}: & N & \hat{\alpha} & \rho_{2/3} & \rho_{3/4} \\
\hline
\text{Kleiber} & 8 & 0.754 & < 10^{-4} & 0.66 \\
\text{Brody} & 9 & 0.760 & < 10^{-3} & 0.56 \\
\text{Heusner} & 34 & 0.877 & < 10^{-12} & < 10^{-7} \\
\end{array}
\]
Fluctuations—Kolmogorov-Smirnov test

\[ P(B | M) = \frac{1}{M^{2/3}} f(B/M^{2/3}) \]
Analysis of residuals

1. Presume an exponent of your choice: 2/3 or 3/4.

2. Fit the prefactor ($\log_{10} c$) and then examine the residuals:

   $$ r_i = \log_{10} B_i - (\alpha' \log_{10} M_i - \log_{10} c). $$

3. $H_0$: residuals are uncorrelated
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We use the spiffing **Spearman Rank-Order Correlation Coefficient**.

Basic idea:

- Given \((x_i, y_i)\), rank the \(\{x_i\}\) and \(\{y_i\}\) separately from smallest to largest. Call these ranks \(R_i\) and \(S_i\).
- Now calculate correlation coefficient for ranks, \(r_s\):

\[
 r_s = \frac{\sum_{i=1}^{n} (R_i - \bar{R})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n} (R_i - \bar{R})^2} \sqrt{\sum_{i=1}^{n} (S_i - \bar{S})^2}}
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- Perfect correlation: \(x_i\)'s and \(y_i\)'s both increase monotonically.
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Analysis of residuals

We assume all rank orderings are equally likely:

- $r_S$ is distributed according to a Student’s distribution with $N – 2$ degrees of freedom.
- Excellent feature: Non-parametric—real distribution of $x$’s and $y$’s doesn’t matter.
- Bonus: works for non-linear monotonic relationships as well.
- See “Numerical Recipes in C/Fortran” which contains many good things. [?]
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Analysis of residuals—mammals

(a) $M < 3.2$ kg, (b) $M < 10$ kg, (c) $M < 32$ kg, (d) all mammals.
Analysis of residuals—birds

(a) $M < .1$ kg, (b) $M < 1$ kg, (c) $M < 10$ kg, (d) all birds.
Basic basin quantities: \(a, l, L_{||}, L_{\perp} \):

- \(a\) = drainage basin area
- \(l\) = length of longest (main) stream
- \(L_{||} = L\) = longitudinal length of basin
River networks

- 1957: J. T. Hack\[1\]
  “Studies of Longitudinal Stream Profiles in Virginia and Maryland”
  \[ \ell \sim a^h \]
  \[ h \sim 0.6 \]

- Anomalous scaling: we would expect \( h = 1/2 \)...
- Subsequent studies: \( 0.5 \lesssim h \lesssim 0.6 \)
- Another quest to find universality/god...
- A catch: studies done on small scales.
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Large-scale networks

(1992) Montgomery and Dietrich: 

- **Composite data set**: includes everything from unchanneled valleys up to world’s largest rivers.
- **Estimated fit**: 
  
  \[ L \approx 1.78a^{0.49} \]
- **Mixture of basin and main stream lengths.**
World’s largest rivers only:

- Data from Leopold (1994) \[?, ?\]
- Estimate of Hack exponent: \( h = 0.50 \pm 0.06 \)
Outline

Scaling-at-large

Allometry
  Definitions
  Examples
  History: Metabolism
  Measuring exponents
  History: River networks
  Earlier theories
  Geometric argument
  Blood networks
  River networks
  Conclusion

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Earlier theories

Building on the surface area idea...

- Blum (1977) speculates on four-dimensional biology:

  \[ P \propto M^{(d-1)/d} \]

  - \( d = 3 \) gives \( \alpha = 2/3 \)
  
  - \( d = 4 \) gives \( \alpha = 3/4 \)
  
  - So we need another dimension...
  
  - Obviously, a bit silly.
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- McMahon (70’s, 80’s): Elastic Similarity
- Idea is that organismal shapes scale allometrically with 1/4 powers (like nails and trees...)
- Appears to be true for ungulate legs.
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- 1960’s: Rashevsky considers blood networks and finds a $2/3$ scaling.
- 1997: West et al. use a network story to find $3/4$ scaling.
Nutrient delivering networks:

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![Diagram of nutrient delivering networks](image-url)
Nutrient delivering networks:

West et al.’s assumptions:

- hierarchical network
- capillaries (delivery units) invariant
- network impedance is minimized via evolution

Claims:

- $P \propto M^{3/4}$
- networks are fractal
- quarter powers everywhere
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Claims:

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- quarter powers everywhere
Impedance measures:

Poiseuille flow (outer branches):

\[ Z = \frac{8 \mu}{\pi} \sum_{k=0}^{N} \frac{\ell_k}{r_k^4 N_k} \]

Pulsatile flow (main branches):

\[ Z \propto \sum_{k=0}^{N} \frac{h_k^{1/2}}{r_k^{5/2} N_k} \]
Not so fast . . .

Actually, model shows:

- $P \propto M^{3/4}$ does not follow for pulsatile flow
- networks are not necessarily fractal.

Do find:

- Murray’s cube law (1927) for outer branches:
  \[ r_0^3 = r_1^3 + r_2^3 \]
- Impedance is distributed evenly.
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Connecting network structure to $\alpha$

1. Ratios of network parameters:

\[
R_n = \frac{n_{k+1}}{n_k}, \quad R_\ell = \frac{\ell_{k+1}}{\ell_k}, \quad R_r = \frac{r_{k+1}}{r_k}
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2. Number of capillaries $\propto P \propto M^\alpha$.

Soldiering on, assert:

- area-preservingness: $R_r = R_n^{-1/2}$
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# Data from real networks

<table>
<thead>
<tr>
<th>Network</th>
<th>$R_n$</th>
<th>$R_r^{-1}$</th>
<th>$R_{\ell}^{-1}$</th>
<th>$-\frac{\ln R_r}{\ln R_n}$</th>
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<th>$\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>West <em>et al.</em></td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>1/2</td>
<td>1/3</td>
<td>3/4</td>
</tr>
<tr>
<td>rat (PAT)</td>
<td>2.76</td>
<td>1.58</td>
<td>1.60</td>
<td>0.45</td>
<td>0.46</td>
<td>0.73</td>
</tr>
<tr>
<td>cat (PAT)</td>
<td>3.67</td>
<td>1.71</td>
<td>1.78</td>
<td>0.41</td>
<td>0.44</td>
<td>0.79</td>
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<td>(Turcotte <em>et al.</em> [?])</td>
<td></td>
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<td></td>
<td></td>
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<tr>
<td>dog (PAT)</td>
<td>3.69</td>
<td>1.67</td>
<td>1.52</td>
<td>0.39</td>
<td>0.32</td>
<td>0.90</td>
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<tr>
<td>pig (LCX)</td>
<td>3.57</td>
<td>1.89</td>
<td>2.20</td>
<td>0.50</td>
<td>0.62</td>
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<tr>
<td>pig (RCA)</td>
<td>3.50</td>
<td>1.81</td>
<td>2.12</td>
<td>0.47</td>
<td>0.60</td>
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<tr>
<td>pig (LAD)</td>
<td>3.51</td>
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<td>2.02</td>
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<td>0.65</td>
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<td>human (PAT)</td>
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Simple supply networks


► Flow rate argument

► Ignore impedance

► Very general attempt to find most efficient transportation networks
Simple supply networks

- Banavar *et al.* find ‘most efficient’ networks with
  \[ P \propto M^{d/(d+1)} \]

- ... but also find
  \[ V_{\text{network}} \propto M^{(d+1)/d} \]

- \( d = 3 \):
  \[ V_{\text{blood}} \propto M^{4/3} \]

- Consider a 3 g shrew with \( V_{\text{blood}} = 0.1 V_{\text{body}} \)
- \( \Rightarrow \) 3000 kg elephant with \( V_{\text{blood}} = 10V_{\text{body}} \)
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- Such a pachyderm would be rather miserable.
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Scaling-at-large

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Geometric argument

- Consider one source supplying many sinks in a $d$-dim. volume in a $D$-dim. ambient space.
- Assume sinks are invariant.
- Assume $\rho = \rho(V)$.
- Assume some cap on flow speed of material.
- See network as a bundle of virtual vessels:

- Q: how does the number of sustainable sinks $N_{sinks}$ scale with volume $V$ for the most efficient network design?
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- Allometrically growing regions:

- Have $d$ length scales which scale as

  $$L_i \propto V^\gamma_i \text{ where } \gamma_1 + \gamma_2 + \ldots + \gamma_d = 1.$$  

- For isometric growth, $\gamma_i = 1/d$.

- For allometric growth, we must have at least two of the $\{\gamma_i\}$ being different
Geometric argument

- Best and worst configurations (Banavar et al.)

\[ \min V_{\text{net}} \propto \sum \text{distances from source to sinks.} \]
Geometric argument

- Best and worst configurations (Banavar et al.)

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Minimal network volume:

Real supply networks are close to optimal:

Figure 1. (a) Commuter rail network in the Boston area. The arrow marks the assumed root of the network. (b) Star graph. (c) Minimum spanning tree. (d) The model of equation (3) applied to the same set of stations.

Minimal network volume:

Approximate network volume by integral over region:

\[ \min V_{\text{net}} \propto \int_{\Omega_{d,D}(V)} \rho \| \vec{x} \| \, d\vec{x} \]
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\[ \to \rho V^{1+\gamma_{\text{max}}} \int_{\Omega_{d,D}(c)} (c_1^2 u_1^2 + \ldots + c_k^2 u_k^2)^{1/2} \, d\vec{u} \]
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\[\propto \rho V^{1+\gamma_{\text{max}}} \]
Geometric argument

- General result:

\[ \min V_{\text{net}} \propto \rho V^{1+\gamma_{\text{max}}} \]

- If scaling is isometric, we have \( \gamma_{\text{max}} = 1/d \):

\[ \min V_{\text{net/iso}} \propto \rho V^{1+1/d} = \rho V^{(d+1)/d} \]

- If scaling is allometric, we have \( \gamma_{\text{max}} = \gamma_{\text{allo}} > 1/d \):

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- Isometrically growing volumes require less network volume than allometrically growing volumes:

\[ \frac{\min V_{\text{net/iso}}}{\min V_{\text{net/allo}}} \rightarrow 0 \text{ as } V \rightarrow \infty \]
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Scaling-at-large

Allometry

Definitions
Examples
History: Metabolism
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Blood networks

- **Material costly** ⇒ expect lower optimal bound of $V_{\text{net}} \propto \rho V^{(d+1)/d}$ to be followed closely.
- For cardiovascular networks, $d = D = 3$.
- Blood volume scales linearly with blood volume \[?\], $V_{\text{net}} \propto V$.
- Sink density must decrease as volume increases: $ho \propto V^{-1/d}$.
- Density of suppliable sinks decreases with organism size.
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Then $P$, the rate of overall energy use in $\Omega$, can at most scale with volume as

$$P \propto \rho V$$

For $d = 3$ dimensional organisms, we have

$$P \propto M^{2/3}$$
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Recap:

- The exponent \( \alpha = \frac{2}{3} \) works for all birds and mammals up to 10–30 kg
- For mammals > 10–30 kg, maybe we have a new scaling regime
- Economos: limb length break in scaling around 20 kg
- White and Seymour, 2005: unhappy with large herbivore measurements. Find \( \alpha \approx 0.686 \pm 0.014 \)
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Prefactor:

Stefan-Boltzmann law:

\[
\frac{dE}{dt} = \sigma ST^4
\]

where \( S \) is surface and \( T \) is temperature.

Very rough estimate of prefactor based on scaling of normal mammalian body temperature and surface area \( S \):

\[ B \approx 10^5 M^{2/3} \text{erg/sec}. \]

Measured for \( M \leq 10 \text{ kg} \):

\[ B = 2.57 \times 10^5 M^{2/3} \text{erg/sec}. \]
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River networks

- View river networks as collection networks.
- Many sources and one sink.
- Assume $\rho$ is constant over time:

$$V_{\text{net}} \propto \rho V^{(d+1)/d} = \text{constant} \times V^{3/2}$$

- Network volume grows faster than basin ‘volume’ (really area).
- It’s all okay:
  Landscapes are $d=2$ surfaces living in $D=3$ dimension.
- Streams can grow not just in width but in depth...
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Hack’s law

- Volume of water in river network can be calculated by adding up basin areas
- Flows sum in such a way that

\[ V_{net} = \sum_{\text{all pixels}} a_{\text{pixel } i} \]

- Hack’s law again:

\[ \ell \sim a^h \]

- Can argue

\[ V_{net} \propto V_{basin}^{1+h} = a_{\text{basin}}^{1+h} \]

where \( h \) is Hack’s exponent.
- \( \therefore \) minimal volume calculations gives

\[ h = 1/2 \]
Real data:

- Banavar et al.'s approach \([\rho]\) is okay because \(\rho\) really is constant.
- The irony: shows optimal basins are isometric
- Optimal Hack's law: \(\ell \sim a^h\) with \(h = 1/2\)
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- (Zzzzz)

From Banavar et al. (1999)
Even better—prefactors match up:

- Amazon
- Mississippi
- Congo
- Nile

\[ \log_{10} \text{area } a \ [m^2] \]
\[ \log_{10} \text{water volume } V \ [m^3] \]
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- Supply network story consistent with dimensional analysis.
  - Isometrically growing regions can be more efficiently supplied than allometrically growing ones.
  - Ambient and region dimensions matter ($D = d$ versus $D > d$).
  - Deviations from optimal scaling suggest inefficiency (e.g., gravity for organisms, geological boundaries).
  - Actual details of branching networks not that important.
  - Exact nature of self-similarity varies.
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