Scaling—a Plenitude of Power Laws

Principles of Complex Systems
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References
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.**
- **Examples.**

  - How to measure your power-law relationship.
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Outline

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▶ How to measure your power-law relationship.
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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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- Using $[\cdot]$ to indicate dimension, then
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Power-law relationships are linear in log-log space:

\[ y = c x^\alpha \]

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

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:

\[ \alpha \simeq 1.23 \]

gray matter: ‘computing elements’

white matter: ‘wiring’

from Zhang & Sejnowski, PNAS (2000) [41]
Why is $\alpha \sim 1.23$?

Quantities (following Zhang and Sejnowski):

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

A rough understanding:

- $G \sim ST$ (convolutions are okay)
- $W \sim \rho SL$
- $G \sim L^4$
- Eliminate $S$ and $L$ to find $W \sim G^{4/3}/T$
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- $G \sim ST$ (convolutions are okay)
- $W \sim \frac{1}{2} \rho SL$
- $G \sim L^3$
- Eliminate $S$ and $L$ to find $W \propto G^{4/3} / T$
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- $G \sim ST$ (convolutions are okay)
- $W \sim \frac{1}{2} pSL$
- $G \sim L^3$ $\leftarrow$ this is a little sketchy...
- Eliminate $S$ and $L$ to find $W \propto \frac{G^{4/3}}{T}$
Why is $\alpha \sim 1.23$?

A rough understanding:

- We are here: $W \propto G^{4/3}/T$
- Observe weak scaling $T \propto G^{0.10 \pm 0.02}$.
- (Implies $S \propto G^{0.9} \rightarrow$ convolutions fill space.)
- $\Rightarrow W \propto G^{4/3}/T \propto G^{1.23 \pm 0.02}$
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**Trickiness:**

- With $V = G + W$, some power laws must be approximations.
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Trickiness:

Scaling

Scaling-at-large

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

References
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) [4]; 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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Scale invariance

Our friend $y = cx^\alpha$:

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

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

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

$$\Rightarrow y' = cx'^\alpha$$
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Scale invariance

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.
- More on this later with size distributions.
Scale invariance

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Definitions:

Isometry: dimensions scale linearly with each other.

Allometry: dimensions scale nonlinearly.
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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Scaling-at-large

Allometry

Definitions

Examples

History: Metabolism

Measuring exponents

History: River networks

Earlier theories

Geometric argument

Blood networks

River networks

Conclusion

References
McMahon and Bonner, 1983 [26]
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, Tyrannosaurus; 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 (Eurypterid); 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 [26]
The many scales of life:
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 (*Branchiocierianthus*); 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).
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- Scaling
- Scaling-at-large
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  - Definitions
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p. 3, McMahon and Bonner [26]
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 cheopis*); 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).
The many scales of life:

1. Fish
2. Spider
3. Ant
4. Fly
5. Frog
6. Flea
7. Snail
8. Plant
9. Egg
10. Tree
11. Earth

p. 3, McMahon and Bonner [26]
Non-uniform growth:

p. 32, McMahon and Bonner[26]
Non-uniform growth—arm length versus height:

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

p. 32, McMahon and Bonner [26]
Weightlifting: $M_{\text{worldrecord}} \propto M_{\text{lifter}}^{2/3}$

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

p. 53, McMahon and Bonner[26]
Titanotheres horns: \( L_{\text{horn}} \sim L_{\text{skull}}^4 \)
The allometry of nails:

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

p. 58–59, McMahon and Bonner [26]
The allometry of nails:

A buckling instability?:

- Physics/Engineering result: Columns buckle under a load which depends on $d^4/ℓ^2$.
- To drive nails in, resistive force $\propto$ nail circumference = $\pi d$.
- Match forces independent of nail size: $d^4/ℓ^2 \propto d$.
- Leads to $d \propto ℓ^{2/3}$.
- Argument made by Galileo \cite{13} in 1638 in “Discourses on Two New Sciences.” (⊞) [pdf] Also, see here (⊞).
- Also see McMahon, “Size and Shape in Biology,” Science, 1973. \cite{24}
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Rowing: Speed $\propto (\text{number of rowers})^{1/9}$

Shell dimensions and performances.

<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></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>6.33  6.42  6.48  6.13</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>
</tbody>
</table>

![Graph showing the relationship between speed (km/hr) and number of oarsmen]
Scaling in Cities:

- “Growth, innovation, scaling, and the pace of life in cities”
- Quantified levels of
  - Infrastructure
  - Wealth
  - Crime levels
  - Disease
  - Energy consumption as a function of city size $N$ (population).
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  - Disease
  - Energy consumption

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Scaling in Cities:

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

<table>
<thead>
<tr>
<th>Indicator</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...

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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:

\[ P = c M^\alpha \]

- \( P \) = basal metabolic rate
- \( M \) = 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 law** for radiated energy:

  \[ \frac{dE}{dt} = \sigma c S T^4 \propto S \]
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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

\[ \alpha = 3/4 \]

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

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

$\propto (\text{Average lifespan}) \times (\text{Average heart rate}) \propto M^\beta - (\beta) \propto M^0$

Number of heartbeats per lifetime is independent of organism size! $\approx 1.5$ billion...
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- Number of heartbeats per lifetime is independent of organism size!
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  \( \sim (\text{Average lifespan}) \times (\text{Average heart rate}) \)
  \( \propto M^{\beta-\beta} \)
  \( \propto M^{0} \)
▶ Number of heartbeats per life time is independent of organism size!
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  $\propto M^0$

- 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\footnote{31} found $\alpha \sim \frac{2}{3}$.
History

1930’s: Brody, Benedict study mammals. \[\alpha \simeq 0.73\] (standard).

Found $\alpha \simeq 0.73$ (standard).
1932: Kleiber analyzed 13 mammals.[^22]

Found $\alpha = 0.76$ and suggested $\alpha = \frac{3}{4}$.
1950/1960: Hemmingsen\textsuperscript{[18, 19]}
Extension to unicellular organisms.
$\alpha = 3/4$ assumed true.
History

1964: Troon, Scotland: \[^{[5]}\]
3rd symposium on energy metabolism.

\(\alpha = 3/4\) made official . . .
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3rd symposium on energy metabolism.
\[ \alpha = 3/4 \] made official . . .
\[ \ldots 29 \text{ to zip.} \]
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

and ensuing madness...
Today

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► But—much controversy...
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- See ‘Re-examination of the “3/4-law” of metabolism’ Dodds, Rothman, and Weitz[^11] and ensuing madness...
Some data on metabolic rates

Heusner's data (1991) [20]

- 391 Mammals
- blue line: 2/3
- red line: 3/4.

\[ B = 0.026 M^{0.668} \]
Some data on metabolic rates

\[ \log_{10} B = 0.041 M^{0.664} \]

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

Passerine vs. non-passerine...
Linear regression

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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More on regression:

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

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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. [32, 30] (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!
- Scale invariant.
Measuring exponents

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\]

- Very simple!
- Scale invariant.
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)

| range of $M$ (kg) | $N$ | $\hat{\alpha}$  
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\leq 0.1$</td>
<td>167</td>
<td>$0.678 \pm 0.038$</td>
</tr>
<tr>
<td>$\leq 1$</td>
<td>276</td>
<td>$0.662 \pm 0.032$</td>
</tr>
<tr>
<td>$\leq 10$</td>
<td>357</td>
<td>$0.668 \pm 0.019$</td>
</tr>
<tr>
<td>$\leq 25$</td>
<td>366</td>
<td>$0.669 \pm 0.018$</td>
</tr>
<tr>
<td>$\leq 35$</td>
<td>371</td>
<td>$0.675 \pm 0.018$</td>
</tr>
<tr>
<td>$\leq 350$</td>
<td>389</td>
<td>$0.706 \pm 0.016$</td>
</tr>
<tr>
<td>$\leq 3670$</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>
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<td>371</td>
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</tr>
</tbody>
</table>
Hypothesis testing

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

$$H_0 : \alpha = \alpha' \text{ and } H_1 : \alpha \neq \alpha'.$$

- 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." [8]
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- 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.”[8]
Hypothesis testing

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

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Revisiting the past—mammals

Full mass range:

<table>
<thead>
<tr>
<th></th>
<th>$N$</th>
<th>$\alpha$</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>
<td>Bennett and Harvey</td>
<td>398</td>
<td>0.664</td>
<td>0.69</td>
<td>$&lt; 10^{-15}$</td>
</tr>
</tbody>
</table>
Revisiting the past—mammals

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

<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>5</td>
<td>0.667</td>
<td>0.99</td>
<td>0.088</td>
</tr>
<tr>
<td>Brody</td>
<td>26</td>
<td>0.709</td>
<td>(&lt; 10^{-3})</td>
<td>(&lt; 10^{-3})</td>
</tr>
<tr>
<td>Heusner</td>
<td>357</td>
<td>0.668</td>
<td>0.91</td>
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\( M \geq 10 \text{ kg}: \)

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<th>( p_{3/4} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kleiber</td>
<td>8</td>
<td>0.754</td>
<td>(&lt; 10^{-4})</td>
<td>0.66</td>
</tr>
<tr>
<td>Brody</td>
<td>9</td>
<td>0.760</td>
<td>(&lt; 10^{-3})</td>
<td>0.56</td>
</tr>
<tr>
<td>Heusner</td>
<td>34</td>
<td>0.877</td>
<td>(&lt; 10^{-12})</td>
<td>(&lt; 10^{-7})</td>
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Scaling

Fluctuations—Things look normal...

\[ P(B \mid M) = \frac{1}{M^{2/3}} f\left(\frac{B}{M^{2/3}}\right) \]

Use a Kolmogorov-Smirnov test.
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
   
   \(H_1\): residuals are correlated.

4. Measure the correlations in the residuals and compute a \(p\)-value.
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Analysis of residuals

We use the spiffing Spearman Rank-Order Correlation Coefficient (ようです)

Basic idea:

- Given \( (x_i, y_i) \), rank the \( x_i \) and \( y_i \) separately from smallest to largest. Call these ranks \( R \) and \( S \).
- Now calculate correlation coefficient for ranks \( R \) and \( S \):

\[
\rho_s = \frac{\sum_{i=1}^{n}(R_i - \bar{R})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n}(R_i - \bar{R})^2} \sqrt{\sum_{i=1}^{n}(S_i - \bar{S})^2}}
\]

Perfect correlation: \( x_i \)'s and \( y_i \)'s both increase monotonically.
Analysis of residuals

We use the spiffing Spearman Rank-Order Correlation Coefficient (-olds)

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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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Analysis of residuals

We assume all rank orderings are equally likely:

- $r_s$ is distributed according to a Student's $t$-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.\textsuperscript{[29]}
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Analysis of residuals—mammals

(a) $M < 3.2 \text{ kg}$,

(b) $M < 10 \text{ kg}$,

(c) $M < 32 \text{ kg}$,

(d) all mammals.
Analysis of residuals—birds

(a) $M < 0.1$ kg,
(b) $M < 1$ kg,
(c) $M < 10$ kg,
(d) all birds.
Other approaches to measuring exponents:

For distributions with power law tails:

- Clauset et al..
Recap:

- So: The exponent $\alpha = 2/3$ works for all birds and mammals up to 10–30 kg
- For mammals $> 10–30$ kg, maybe we have a new scaling regime
- Possible connection?: Economos (1983)—limb length break in scaling around 20 kg $^{[12]}$
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Now we’re really confused (empirically):

- White and Seymour, 2005: unhappy with large herbivore measurements. Pro 2/3: Find $\alpha \simeq 0.686 \pm 0.014$.
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Basic basin quantities: \( a, l, L_{\parallel}, L_{\perp} \):

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

\[ L_{\perp} \]

\[ L_{\parallel} = L \]
River networks

1957: J. T. Hack\cite{17}
“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: \( 0.5 \lesssim h \lesssim 0.6 \)
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Large-scale networks:
(1992) Montgomery and Dietrich[27]:

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

- Data from Leopold (1994) \(^{[23, 10]}\)
- 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

References
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Building on the surface area idea...

- Blum (1977)\(^6\) speculates on four-dimensional biology:
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P \propto M^{(d-1)/d}
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- 1960’s: Rashevsky considers blood networks and finds a 2/3 scaling.
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Nutrient delivering networks:

West et al.’s assumptions:

1. hierarchical network
2. capillaries (delivery units) invariant
3. network impedance is minimized via evolution

Claims:

- $P \propto W^{3/4}$
- networks are fractal
- quarter powers everywhere
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\[ P \propto \frac{M^{3/4}}{1} \]

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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.
- Can still assume networks are fractal.
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Connecting network structure to $\alpha$

1. Ratios of network parameters:

$$R_n = \frac{n_{k+1}}{n_k}, \quad R_\ell = \frac{\ell_{k+1}}{\ell_k}, \quad R_r = \frac{r_{k+1}}{r_k}$$

2. Number of capillaries $\propto P \propto M^\alpha$.

Soldiering on, assert:

- **area-preservingness:** $R_r = R_r^{1/2}$
- **space-fillingness:** $R_\ell = R_\ell^{1/3}$

$\Rightarrow \alpha = 3/4$
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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### 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>
<th>$-\frac{\ln R_\ell}{\ln R_n}$</th>
<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>
</tr>
<tr>
<td>(Turcotte <em>et al.</em>[37])</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<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>
</tr>
<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>
<td>0.62</td>
</tr>
<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>
<td>0.65</td>
</tr>
<tr>
<td>pig (LAD)</td>
<td>3.51</td>
<td>1.84</td>
<td>2.02</td>
<td>0.49</td>
<td>0.56</td>
<td>0.65</td>
</tr>
<tr>
<td>human (PAT)</td>
<td>3.03</td>
<td>1.60</td>
<td>1.49</td>
<td>0.42</td>
<td>0.36</td>
<td>0.83</td>
</tr>
<tr>
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<td>0.37</td>
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<td>0.94</td>
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Simple supply networks

- Banavar et al., Nature, (1999) \(^1\)
- 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 \( V_{\text{blood}} = 10 V_{\text{body}} \)
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Simple supply networks

Such a pachyderm would be rather miserable:
Geometric argument


▶ Consider one source supplying many sinks in a $d$-dim. volume in a $D$-dim. ambient space.

▶ Assume sinks are invariant.

▶ Assume sink density $\rho = \rho(V)$.

▶ Assume some cap on flow speed of material.

▶ See network as a bundle of virtual vessels:
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➢ “Optimal Form of Branching Supply and Collection Networks.” Dodds, Phys. Rev. Lett., 2010.\cite{9}

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Q: how does the number of sustainable sinks $N_{\text{sinks}}$ scale with volume $V$ for the most efficient network design?

Q: or: what is the highest $\alpha$ for $N_{\text{sinks}} \propto V^\alpha$?
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Or: what is the highest $\alpha$ for $N_{\text{sinks}} \propto V^\alpha$?
**Geometric argument**

- Allometrically growing regions:

  ![Diagram](image)

  - 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

---

References
Geometric argument

- Best and worst configurations (Banavar et al.)

Rather obviously:
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\min V_{\text{net}} \propto \sum \text{distances from source to sinks.}
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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 \left\| \vec{x} \right\| \, d\vec{x}
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\[ \rightarrow \rho V^{1+\gamma_{\text{max}}} \int_{\Omega_{d,D}(c)} \left( c_1^2 u_1^2 + \ldots + c_k^2 u_k^2 \right)^{1/2} d\vec{u} \]
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- General result:

\[
\min V_{\text{net}} \propto \rho V^{1 + \gamma_{\text{max}}}
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- If scaling is isometric, we have \( \gamma_{\text{max}} = 1/d' \):

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

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\min V_{\text{net/iso}} \to 0 \text{ as } V \to \infty
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- **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 body volume \[^{[36]}\], $V_{\text{net}} \propto V$.
- Sink density must decrease as volume increases: $\rho \propto V^{-1/d}$.
- Density of suppliable sinks decreases with organism size.
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Stefan-Boltzmann law: \( \boxed{\frac{dE}{dt} = \sigma ST^4} \)

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

- Very rough estimate of prefactor based on scaling of normal mammalian body temperature and surface area \( S \):
  \[ B \sim 10^5 M^{2/3} \text{erg/sec}. \]

- 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).
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    Landscapes are $d=2$ surfaces living in $D=3$ dimension.
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Scaling

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Allometry
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History: Metabolism
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Conclusion

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- Volume of water in river network can be calculated by adding up basin areas

  - Flows sum in such a way that

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  - Hack’s law again:

    \[ \ell \sim a^h \]

  - Can argue

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Even better—prefactors match up:
Yet more theoretical madness from the Quarterologists:

- Banavar et al., 2010, PNAS: “A general basis for quarter-power scaling in animals.”[2]

- “It has been known for decades that the metabolic rate of animals scales with body mass with an exponent that is almost always < 1, > 2/3, and often very close to 3/4.”

- Cough, cough, cough, hack, wheeze, cough.
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Conclusion

- 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.
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Scaling

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Allometry
Definitions
Examples
History: Metabolism
Measuring exponents
History: River networks
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Geometric argument
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River networks
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