Mechanisms for Generating Power-Law Distributions
Principles of Complex Systems
Course CSYS/MATH 300, Fall, 2009

Prof. Peter Dodds

Dept. of Mathematics & Statistics
Center for Complex Systems :: Vermont Advanced Computing Center
University of Vermont
Outline

Random Walks
  The First Return Problem
  Examples

Variable transformation
  Basics
  Holtsmark’s Distribution
  PLIPLO

Growth Mechanisms
  Random Copying
  Words, Cities, and the Web

References
Mechanisms

A powerful theme in complex systems:

- structure arises out of randomness.
Mechanisms

A powerful theme in complex systems:

- structure arises out of randomness.
A powerful theme in complex systems:

- structure arises out of randomness.
- Exhibit A: Random walks... ( соседнее окно )
Random walks

The essential random walk:

- One spatial dimension.
- Time and space are discrete
- Random walker (e.g., a drunk) starts at origin $x = 0$.
- Step at time $t$ is $\epsilon_t$:

\[ \epsilon_t = \begin{cases} 
+1 & \text{with probability } 1/2 \\
-1 & \text{with probability } 1/2 
\end{cases} \]
Random walks

The essential random walk:

- One spatial dimension.
- Time and space are discrete
- Random walker (e.g., a drunk) starts at origin $x = 0$.
- Step at time $t$ is $\epsilon_t$:

$$\epsilon_t = \begin{cases} 
+1 & \text{with probability } 1/2 \\
-1 & \text{with probability } 1/2 
\end{cases}$$
Random walks

The essential random walk:

- One spatial dimension.
- Time and space are discrete.
- Random walker (e.g., a drunk) starts at origin $x = 0$.
- Step at time $t$ is $\epsilon_t$:

\[ \epsilon_t = \begin{cases} 
+1 & \text{with probability } 1/2 \\
-1 & \text{with probability } 1/2 
\end{cases} \]
Random walks

The essential random walk:

- One spatial dimension.
- Time and space are discrete.
- Random walker (e.g., a drunk) starts at origin $x = 0$.
- Step at time $t$ is $\epsilon_t$:

$$\epsilon_t = \begin{cases} +1 & \text{with probability } 1/2 \\ -1 & \text{with probability } 1/2 \end{cases}$$
Random walks

Displacement after $t$ steps:

$$x_t = \sum_{i=1}^{t} \epsilon_i$$

Expected displacement:

$$\langle x_t \rangle = \left\langle \sum_{i=1}^{t} \epsilon_i \right\rangle = \sum_{i=1}^{t} \langle \epsilon_i \rangle = 0$$
Random walks

Displacement after $t$ steps:

$$x_t = \sum_{i=1}^{t} \epsilon_i$$

Expected displacement:

$$\langle x_t \rangle = \left\langle \sum_{i=1}^{t} \epsilon_i \right\rangle = \sum_{i=1}^{t} \langle \epsilon_i \rangle = 0$$
Random walks

Displacement after $t$ steps:

$$x_t = \sum_{i=1}^{t} \epsilon_i$$

Expected displacement:

$$\langle x_t \rangle = \left\langle \sum_{i=1}^{t} \epsilon_i \right\rangle = \sum_{i=1}^{t} \langle \epsilon_i \rangle = 0$$
Random walks

Displacement after $t$ steps:

$$x_t = \sum_{i=1}^{t} \epsilon_i$$

Expected displacement:

$$\langle x_t \rangle = \left\langle \sum_{i=1}^{t} \epsilon_i \right\rangle = \sum_{i=1}^{t} \langle \epsilon_i \rangle = 0$$
Random walks

Variances sum: (田)*

\[ \text{Var}(x_t) = \text{Var} \left( \sum_{i=1}^{t} \epsilon_i \right) \]

\[ = \sum_{i=1}^{t} \text{Var}(\epsilon_i) = \sum_{i=1}^{t} 1 = t \]

* Sum rule = a good reason for using the variance to measure spread
Random walks

Variance sum: \(\sum\)\(*

\text{Var}(x_t) = \text{Var} \left( \sum_{i=1}^{t} \epsilon_i \right) = \sum_{i=1}^{t} \text{Var}(\epsilon_i) = \sum_{i=1}^{t} 1 = t

\(*\) Sum rule = a good reason for using the variance to measure spread
Random walks

Variances sum: (田)*

\[
\text{Var}(x_t) = \text{Var} \left( \sum_{i=1}^{t} \epsilon_i \right) \\
= \sum_{i=1}^{t} \text{Var} (\epsilon_i) = \sum_{i=1}^{t} 1 = t
\]

* Sum rule = a good reason for using the variance to measure spread
Random walks

So typical displacement from the origin scales as

$$\sigma = t^{1/2}$$

⇒ A non-trivial power-law arises out of additive aggregation or accumulation.
Random walks

So typical displacement from the origin scales as

\[ \sigma = t^{1/2} \]

⇒ A non-trivial power-law arises out of additive aggregation or accumulation.
Random walks

Random walks are weirder than you might think...

For example:

- $\xi_{r,t} =$ the probability that by time step $t$, a random walk has crossed the origin $r$ times.
- Think of a coin flip game with ten thousand tosses.
- If you are behind early on, what are the chances you will make a comeback?
- The most likely number of lead changes is...
Random walks

Random walks are weirder than you might think...

For example:

- $\xi_{r,t} = \text{the probability that by time step } t, \text{ a random walk has crossed the origin } r \text{ times.}$
- Think of a coin flip game with ten thousand tosses.
- If you are behind early on, what are the chances you will make a comeback?
- The most likely number of lead changes is...
Random walks are weirder than you might think...

For example:

- $\xi_{r,t} = \text{the probability that by time step } t, \text{ a random walk has crossed the origin } r \text{ times.}$
- Think of a coin flip game with ten thousand tosses.
- If you are behind early on, what are the chances you will make a comeback?
- The most likely number of lead changes is...
Random walks

Random walks are weirder than you might think...

For example:

- $\xi_{r,t} = \text{the probability that by time step } t, \text{ a random walk has crossed the origin } r \text{ times.}$
- Think of a coin flip game with ten thousand tosses.
- If you are behind early on, what are the chances you will make a comeback?
- The most likely number of lead changes is...
Random walks are weirder than you might think...

For example:

- $\xi_{r,t} = \text{the probability that by time step } t, \text{ a random walk has crossed the origin } r \text{ times.}$
- Think of a coin flip game with ten thousand tosses.
- If you are behind early on, what are the chances you will make a comeback?
- The most likely number of lead changes is...
Random walks

Random walks are weirder than you might think...

For example:

- $\xi_{r,t} = \text{the probability that by time step } t, \text{ a random walk has crossed the origin } r \text{ times.}$
- Think of a coin flip game with ten thousand tosses.
- If you are behind early on, what are the chances you will make a comeback?
- The most likely number of lead changes is... 0.
Random walks are weirder than you might think...

For example:

- $\xi_{r,t} = $ the probability that by time step $t$, a random walk has crossed the origin $r$ times.
- Think of a coin flip game with ten thousand tosses.
- If you are behind early on, what are the chances you will make a comeback?
- The most likely number of lead changes is... $0$.

See Feller, [3] Intro to Probability Theory, Volume I
Random walks

In fact:

\[ \xi_{0,t} > \xi_{1,t} > \xi_{2,t} > \cdots \]

Even crazier:
Random walks

In fact:

\[ \xi_0, t > \xi_1, t > \xi_2, t > \cdots \]

Even crazier:
The expected time between tied scores = \( \infty \)!
Random walks—some examples

![Graphs of random walks](image-url)
Random walks—some examples
Random walks

The problem of first return:

- What is the probability that a random walker in one dimension returns to the origin for the first time after $t$ steps?
- Will our drunkard always return to the origin?
- What about higher dimensions?
Random walks

The problem of first return:

- What is the probability that a random walker in one dimension returns to the origin for the first time after $t$ steps?
- Will our drunkard always return to the origin?
- What about higher dimensions?
Random walks

The problem of first return:

► What is the probability that a random walker in one dimension returns to the origin for the first time after $t$ steps?
► Will our drunkard always return to the origin?
► What about higher dimensions?
Random walks

The problem of first return:

- What is the probability that a random walker in one dimension returns to the origin for the first time after \( t \) steps?
- Will our drunkard always return to the origin?
- What about higher dimensions?
First returns

Reasons for caring:

1. We will find a power-law size distribution with an interesting exponent
2. Some physical structures may result from random walks
3. We’ll start to see how different scalings relate to each other
First returns

Reasons for caring:

1. We will find a power-law size distribution with an interesting exponent
2. Some physical structures may result from random walks
3. We’ll start to see how different scalings relate to each other
First returns

Reasons for caring:

1. We will find a power-law size distribution with an interesting exponent

2. Some physical structures may result from random walks

3. We’ll start to see how different scalings relate to each other
First returns

Reasons for caring:

1. We will find a power-law size distribution with an interesting exponent
2. Some physical structures may result from random walks
3. We’ll start to see how different scalings relate to each other
Random Walks

Again: expected time between ties = \( \infty \)

Let’s find out why...
Random Walks

Again: expected time between ties = $\infty$…
Let’s find out why… [3]
First Returns
First Returns

For random walks in 1-d:

- Return can only happen when $t = 2n$. 
First Returns

For random walks in 1-d:

- Return can only happen when \( t = 2n \).
- Call \( P_{\text{first return}}(2n) = P_{\text{fr}}(2n) \) probability of first return at \( t = 2n \).
First Returns

For random walks in 1-d:

- Return can only happen when $t = 2n$.
- Call $P_{\text{first return}}(2n) = P_{\text{fr}}(2n)$ probability of first return at $t = 2n$.
- Assume drunkard first lurches to $x = 1$. 
First Returns

For random walks in 1-d:

- Return can only happen when $t = 2n$.
- Call $P_{\text{first return}}(2n) = P_{fr}(2n)$ probability of first return at $t = 2n$.
- Assume drunkard first lurches to $x = 1$.
- The problem

$$P_{fr}(2n) = 2Pr(x_t \geq 1, t = 1, \ldots, 2n - 1, \text{ and } x_{2n} = 0)$$
A useful restatement: 
\[ P_{fr}(2n) = 2 \cdot \frac{1}{2} Pr(x_t \geq 1, t = 1, \ldots, 2n - 1, \text{ and } x_1 = x_{2n-1} = 1) \]

Want walks that can return many times to \( x = 1 \).

(The \( \frac{1}{2} \) accounts for stepping to 2 instead of 0 at \( t = 2n \).)
A useful restatement: \( P_{fr}(2n) = 2 \cdot \frac{1}{2} \Pr(x_t \geq 1, t = 1, \ldots, 2n - 1, \text{ and } x_1 = x_{2n-1} = 1) \)

Want walks that can return many times to \( x = 1 \).

(The \( \frac{1}{2} \) accounts for stepping to 2 instead of 0 at \( t = 2n \).)
A useful restatement: $P_{fr}(2n) = 2 \cdot \frac{1}{2} Pr(x_t \geq 1, t = 1, \ldots, 2n - 1, \text{ and } x_1 = x_{2n-1} = 1)$

Want walks that can return many times to $x = 1$.

(The $\frac{1}{2}$ accounts for stepping to 2 instead of 0 at $t = 2n$.)
First Returns

A useful restatement: $P_{fr}(2n) = 2 \cdot \frac{1}{2} \Pr(x_t \geq 1, t = 1, \ldots, 2n - 1, \text{ and } x_1 = x_{2n-1} = 1)$

Want walks that can return many times to $x = 1$.

(The $\frac{1}{2}$ accounts for stepping to 2 instead of 0 at $t = 2n$.)
A useful restatement: $P_{fr}(2n) = 2 \cdot \frac{1}{2} Pr(x_t \geq 1, t = 1, \ldots, 2n - 1, \text{ and } x_1 = x_{2n-1} = 1)$

Want walks that can return many times to $x = 1$.

(The $\frac{1}{2}$ accounts for stepping to 2 instead of 0 at $t = 2n$.)
First Returns

- Counting problem (combinatorics/statistical mechanics)
  - Use a method of images
  - Define $N(i, j, t)$ as the # of possible walks between $x = i$ and $x = j$ taking $t$ steps.
  - Consider all paths starting at $x = 1$ and ending at $x = 1$ after $t = 2n - 2$ steps.
  - Subtract how many hit $x = 0$. 
First Returns

- Counting problem (combinatorics/statistical mechanics)
- Use a method of images
  - Define $N(i, j, t)$ as the # of possible walks between $x = i$ and $x = j$ taking $t$ steps.
  - Consider all paths starting at $x = 1$ and ending at $x = 1$ after $t = 2n - 2$ steps.
  - Subtract how many hit $x = 0$. 
First Returns

- Counting problem (combinatorics/statistical mechanics)
- Use a method of images
- Define $N(i, j, t)$ as the # of possible walks between $x = i$ and $x = j$ taking $t$ steps.
- Consider all paths starting at $x = 1$ and ending at $x = 1$ after $t = 2n - 2$ steps.
- Subtract how many hit $x = 0$. 

Power-Law
Mechanisms

Random Walks
The First Return Problem
Examples

Variable
transformation
Basics
Holtsmark’s Distribution
PLIPLO

Growth
Mechanisms
Random Copying
Words, Cities, and the Web

References
First Returns

- Counting problem (combinatorics/statistical mechanics)
- Use a method of images
- Define $N(i, j, t)$ as the # of possible walks between $x = i$ and $x = j$ taking $t$ steps.
- Consider all paths starting at $x = 1$ and ending at $x = 1$ after $t = 2n - 2$ steps.
- Subtract how many hit $x = 0$. 
First Returns

- Counting problem (combinatorics/statistical mechanics)
- Use a method of images
- Define $N(i, j, t)$ as the # of possible walks between $x = i$ and $x = j$ taking $t$ steps.
- Consider all paths starting at $x = 1$ and ending at $x = 1$ after $t = 2n - 2$ steps.
- Subtract how many hit $x = 0$. 
First Returns

Key observation:

# of \( t \)-step paths starting and ending at \( x = 1 \)
and hitting \( x = 0 \) at least once
First Returns

Key observation:

# of \( t \)-step paths starting and ending at \( x = 1 \)
and hitting \( x = 0 \) at least once

= # of \( t \)-step paths starting at \( x = -1 \) and ending at \( x = 1 \)
First Returns

Key observation:

\# of \( t \)-step paths starting and ending at \( x = 1 \)
and hitting \( x = 0 \) at least once
= \# of \( t \)-step paths starting at \( x = -1 \) and ending at \( x = 1 \)
= \( N(-1, 1, t) \)
First Returns

Key observation:

# of $t$-step paths starting and ending at $x = 1$
and hitting $x = 0$ at least once
= # of $t$-step paths starting at $x = -1$ and ending at $x = 1$
= $N(-1, 1, t)$

So $N_{\text{first return}}(2n) = N(1, 1, 2n - 2) - N(-1, 1, 2n - 2)$
First Returns

Key observation:

# of \( t \)-step paths starting and ending at \( x = 1 \)
and hitting \( x = 0 \) at least once
= # of \( t \)-step paths starting at \( x = -1 \) and ending at \( x = 1 \)
= \( N(-1, 1, t) \)

So \( N_{\text{first return}}(2n) = N(1, 1, 2n - 2) - N(-1, 1, 2n - 2) \)

See this 1-1 correspondence visually...
First Returns

The graph shows a random walk with first returns. The x-axis represents time (t), and the y-axis represents the position (x). The walk starts at the origin and moves randomly, with possible first returns indicated by the red dashed line at x=0.
First Returns

- For any path starting at $x = 1$ that hits 0, there is a unique matching path starting at $x = -1$.
- Matching path first mirrors and then tracks.
First Returns

- For any path starting at \( x = 1 \) that hits 0, there is a unique matching path starting at \( x = -1 \).
- Matching path first mirrors and then tracks.
First Returns
Next problem: what is $N(i, j, t)$?

- # positive steps + # negative steps = $t$.
- Random walk must displace by $j - i$ after $t$ steps.
- # positive steps - # negative steps = $j - i$.
- # positive steps = $(t + j - i)/2$.

$$N(i, j, t) = \binom{t}{\text{# positive steps}} = \binom{t}{(t + j - i)/2}$$
First Returns

▶ Next problem: what is $N(i, j, t)$?
▶ # positive steps + # negative steps = $t$.
▶ Random walk must displace by $j - i$ after $t$ steps.
▶ # positive steps - # negative steps = $j - i$.
▶ # positive steps = $(t + j - i)/2$.

$$N(i, j, t) = \binom{t}{\text{# positive steps}} = \binom{t}{(t + j - i)/2}$$
First Returns

- Next problem: what is $N(i, j, t)$?
- $\#$ positive steps + $\#$ negative steps = $t$.
- Random walk must displace by $j - i$ after $t$ steps.
- $\#$ positive steps - $\#$ negative steps = $j - i$.
- $\#$ positive steps = $(t + j - i)/2$.

$$N(i, j, t) = \binom{t}{\# \text{ positive steps}} = \binom{t}{(t + j - i)/2}$$
First Returns

 ► Next problem: what is $N(i, j, t)$?
 ► $\# \text{ positive steps} + \# \text{ negative steps} = t$.
 ► Random walk must displace by $j - i$ after $t$ steps.
 ► $\# \text{ positive steps} - \# \text{ negative steps} = j - i$.
 ► $\# \text{ positive steps} = (t + j - i)/2$.

\[ N(i, j, t) = \left( \begin{array}{c} t \\ \# \text{ positive steps} \end{array} \right) = \left( \begin{array}{c} t \\ (t + j - i)/2 \end{array} \right) \]
First Returns

- Next problem: what is \( N(i, j, t) \)?
- \# positive steps + \# negative steps = \( t \).
- Random walk must displace by \( j - i \) after \( t \) steps.
- \# positive steps - \# negative steps = \( j - i \).
- \# positive steps = \( (t + j - i)/2 \).

\[
N(i, j, t) = \binom{t}{\# \text{ positive steps}} = \binom{t}{(t + j - i)/2}
\]
First Returns

- Next problem: what is $N(i, j, t)$?
- $\#$ positive steps + $\#$ negative steps = $t$.
- Random walk must displace by $j - i$ after $t$ steps.
- $\#$ positive steps - $\#$ negative steps = $j - i$.
- $\#$ positive steps = $(t + j - i)/2$.

\[
N(i, j, t) = \binom{t}{\# \text{ positive steps}} = \binom{t}{(t + j - i)/2}
\]
First Returns

We now have

\[ N_{\text{first return}}(2n) = N(1, 1, 2n - 2) - N(-1, 1, 2n - 2) \]

where

\[ N(i, j, t) = \binom{t}{(t + j - i)/2} \]
First Returns

Insert question 1, assignment 2 ()

Find \( N_{\text{first return}}(2n) \sim \frac{2^{2n-3/2}}{\sqrt{2\pi n^{3/2}}} \).

- Normalized Number of Paths gives Probability
- Total number of possible paths = \( 2^{2n} \)

\[
P_{\text{first return}}(2n) = \frac{1}{2^{2n}} N_{\text{first return}}(2n)
\]

\[
\sim \frac{1}{2^{2n}} \frac{2^{2n-3/2}}{\sqrt{2\pi n^{3/2}}}
\]

\[
= \frac{1}{\sqrt{2\pi}} (2n)^{-3/2}
\]
First Returns

Insert question 1, assignment 2 ( Ipsum)

Find $N_{\text{first return}}(2n) \sim \frac{2^{2n-3/2}}{\sqrt{2\pi n^{3/2}}}$.

- Normalized Number of Paths gives Probability
- Total number of possible paths = $2^{2n}$

\[
P_{\text{first return}}(2n) = \frac{1}{2^{2n}} N_{\text{first return}}(2n)
\]

\[
\sim \frac{1}{2^{2n}} \frac{2^{2n-3/2}}{\sqrt{2\pi n^{3/2}}}
\]

\[
= \frac{1}{\sqrt{2\pi}} (2n)^{-3/2}
\]
First Returns

Insert question 1, assignment 2 (تان)

Find $N_{\text{first return}}(2n) \sim \frac{2^{2n-3/2}}{\sqrt{2\pi n^{3/2}}}$.

- Normalized Number of Paths gives Probability
- Total number of possible paths = $2^{2n}$

\[
P_{\text{first return}}(2n) = \frac{1}{2^{2n} N_{\text{first return}}(2n)}
\]

\[
\approx \frac{1}{2^{2n} \sqrt{2\pi n^{3/2}}}
\]

\[
= \frac{1}{\sqrt{2\pi} (2n)^{-3/2}}
\]
First Returns

Insert question 1, assignment 2 (답)

Find $N_{\text{first return}}(2n) \sim \frac{2^{2n-3/2}}{\sqrt{2\pi n^{3/2}}}$.

- Normalized Number of Paths gives Probability
- Total number of possible paths = $2^{2n}$

\[ P_{\text{first return}}(2n) = \frac{1}{2^{2n}} N_{\text{first return}}(2n) \]
\[ \sim \frac{1}{2^{2n}} \frac{2^{2n-3/2}}{\sqrt{2\pi n^{3/2}}} \]
\[ = \frac{1}{\sqrt{2\pi}} (2n)^{-3/2} \]
First Returns

Insert question 1, assignment 2 (➕)

Find $N_{\text{first return}}(2n) \sim \frac{2^{2n-3/2}}{\sqrt{2\pi n^{3/2}}}$.

- Normalized Number of Paths gives Probability
- Total number of possible paths = $2^{2n}$

$$P_{\text{first return}}(2n) = \frac{1}{2^{2n}} N_{\text{first return}}(2n)$$

$$\sim \frac{1}{2^{2n}} \frac{2^{2n-3/2}}{\sqrt{2\pi n^{3/2}}}$$

$$= \frac{1}{\sqrt{2\pi}} (2n)^{-3/2}$$
First Returns

- Same scaling holds for continuous space/time walks.
  \[ P(t) \propto t^{-3/2}, \quad \gamma = 3/2 \]

- \( P(t) \) is normalizable
- **Recurrence**: Random walker always returns to origin
- **Moral**: Repeated gambling against an infinitely wealthy opponent must lead to ruin.
First Returns

- Same scaling holds for continuous space/time walks.

\[ P(t) \propto t^{-3/2}, \quad \gamma = 3/2 \]

- \( P(t) \) is normalizable
- **Recurrence:** Random walker always returns to origin
- **Moral:** Repeated gambling against an infinitely wealthy opponent must lead to ruin.
First Returns

- Same scaling holds for continuous space/time walks.

\[ P(t) \propto t^{-3/2}, \quad \gamma = 3/2 \]

- \( P(t) \) is normalizable

- Recurrence: Random walker always returns to origin

- Moral: Repeated gambling against an infinitely wealthy opponent must lead to ruin.
First Returns

- Same scaling holds for continuous space/time walks.
  \[ P(t) \propto t^{-3/2}, \gamma = 3/2 \]
- \( P(t) \) is normalizable
- **Recurrence**: Random walker always returns to origin
  - **Moral**: Repeated gambling against an infinitely wealthy opponent must lead to ruin.
First Returns

- Same scaling holds for continuous space/time walks.
  \[ P(t) \propto t^{-3/2}, \gamma = 3/2 \]
- \( P(t) \) is normalizable
- **Recurrence:** Random walker always returns to origin
- **Moral:** Repeated gambling against an infinitely wealthy opponent must lead to ruin.
First Returns

Higher dimensions:

- Walker in $d = 2$ dimensions must also return
- Walker may not return in $d \geq 3$ dimensions
- For $d = 1$, $\gamma = 3/2 \rightarrow \langle t \rangle = \infty$
- Even though walker must return, expect a long wait...
First Returns

Higher dimensions:

- Walker in $d = 2$ dimensions must also return
- Walker may not return in $d \geq 3$ dimensions
- For $d = 1$, $\gamma = 3/2 \rightarrow \langle t \rangle = \infty$
- Even though walker must return, expect a long wait...
First Returns

Higher dimensions:

- Walker in $d = 2$ dimensions must also return
- Walker may not return in $d \geq 3$ dimensions
- For $d = 1$, $\gamma = 3/2 \rightarrow \langle t \rangle = \infty$
- Even though walker must return, expect a long wait...
First Returns

Higher dimensions:

- Walker in $d = 2$ dimensions must also return
- Walker may not return in $d \geq 3$ dimensions
- For $d = 1$, $\gamma = 3/2 \rightarrow \langle t \rangle = \infty$
- Even though walker must return, expect a long wait...
Random walks

On finite spaces:

- In any finite volume, a random walker will visit every site with equal probability
- Random walking $\equiv$ Diffusion
- Call this probability the Invariant Density of a dynamical system
- Non-trivial Invariant Densities arise in chaotic systems.
Random walks

On finite spaces:

- In any finite volume, a random walker will visit every site with equal probability
- Random walking ≡ Diffusion
- Call this probability the Invariant Density of a dynamical system
- Non-trivial Invariant Densities arise in chaotic systems.
Random walks

On finite spaces:

- In any finite volume, a random walker will visit every site with equal probability
- Random walking $\equiv$ Diffusion
- Call this probability the Invariant Density of a dynamical system
- Non-trivial Invariant Densities arise in chaotic systems.
Random walks

On finite spaces:

- In any finite volume, a random walker will visit every site with equal probability
- Random walking $\equiv$ Diffusion
- Call this probability the Invariant Density of a dynamical system
- Non-trivial Invariant Densities arise in chaotic systems.
Random walks on networks:

- On networks, a random walker visits each node with frequency $\propto$ node degree.
- Equal probability still present: walkers traverse edges with equal frequency.
Random walks on networks:

- On networks, a random walker visits each node with frequency \( \propto \) node degree.
- Equal probability still present: walkers traverse edges with equal frequency.
Outline

Random Walks
  The First Return Problem
  Examples

Variable transformation
  Basics
  Holtsmark’s Distribution
  PLIPLO

Growth Mechanisms
  Random Copying
  Words, Cities, and the Web

References
Scheidegger Networks \cite{10, 2}

- Triangular lattice
- ‘Flow’ is southeast or southwest with equal probability.
Scheidegger Networks

- Creates basins with random walk boundaries

- Observe Subtracting one random walk from another gives random walk with increments

\[ \epsilon_t = \begin{cases} 
+1 & \text{with probability } 1/4 \\
0 & \text{with probability } 1/2 \\
-1 & \text{with probability } 1/4 
\end{cases} \]

- Basin length \( \ell \) distribution: \( P(\ell) \propto \ell^{-3/2} \)
Scheidegger Networks

- Creates basins with random walk boundaries
- **Observe** Subtracting one random walk from another gives random walk with increments

\[ \epsilon_t = \begin{cases} 
+1 & \text{with probability } 1/4 \\
0 & \text{with probability } 1/2 \\
-1 & \text{with probability } 1/4 
\end{cases} \]

- Basin length \( \ell \) distribution: \( P(\ell) \propto \ell^{-3/2} \)
Creates basins with random walk boundaries

Observe: Subtracting one random walk from another gives random walk with increments

\[ \epsilon_t = \begin{cases} 
+1 & \text{with probability } 1/4 \\
0 & \text{with probability } 1/2 \\
-1 & \text{with probability } 1/4 
\end{cases} \]

Basin length \( \ell \) distribution: \( P(\ell) \propto \ell^{-3/2} \)
Connections between Exponents

- For a basin of length $\ell$, width $\propto \ell^{1/2}$
- Basin area $a \propto \ell \cdot \ell^{1/2} = \ell^{3/2}$
- Invert: $\ell \propto a^{2/3}$
- $d\ell \propto d(a^{2/3}) = 2/3a^{-1/3}da$
- $Pr(\text{basin area} = a)da$
  $= Pr(\text{basin length} = \ell)dl$
  $\propto \ell^{-3/2}dl$
  $\propto (a^{2/3})^{-3/2}a^{-1/3}da$
  $= a^{-4/3}da$
  $= a^{-4/3}da$
Connections between Exponents

- For a basin of length $\ell$, width $\propto \ell^{1/2}$
- Basin area $a \propto \ell \cdot \ell^{1/2} = \ell^{3/2}$
- Invert: $\ell \propto a^{2/3}$
- $d\ell \propto d(a^{2/3}) = 2/3a^{-1/3}da$
- $Pr(\text{basin area} = a)da$
  $= Pr(\text{basin length} = \ell)dl$
  $\propto \ell^{-3/2}dl$
  $\propto (a^{2/3})^{-3/2}a^{-1/3}da$
  $= a^{-4/3}da$
  $= a^{-\tau}da$
Connections between Exponents

- For a basin of length $\ell$, width $\propto \ell^{1/2}$
- Basin area $a \propto \ell \cdot \ell^{1/2} = \ell^{3/2}$
- Invert: $\ell \propto a^{2/3}$
- $d\ell \propto d\left(a^{2/3}\right) = \frac{2}{3}a^{-1/3} da$
- $Pr($basin area $= a)da$
  $= Pr($basin length $= \ell)d\ell$
  $\propto \ell^{-3/2} d\ell$
  $\propto \left(a^{2/3}\right)^{-3/2} a^{-1/3} da$
  $= a^{-4/3} da$
  $= a^{-\tau} da$
Connections between Exponents

- For a basin of length $\ell$, width $\propto \ell^{1/2}$
- Basin area $a \propto \ell \cdot \ell^{1/2} = \ell^{3/2}$
- Invert: $\ell \propto a^{2/3}$
- $d\ell \propto d(a^{2/3}) = 2/3a^{-1/3}da$
- $Pr(\text{basin area} = a)da$
  
  $= Pr(\text{basin length} = \ell)d\ell$
  $\propto \ell^{-3/2}d\ell$
  $\propto (a^{2/3})^{-3/2}a^{-1/3}da$
  $= a^{-4/3}da$
  $= a^{-\tau}da$
Connections between Exponents

- For a basin of length $\ell$, width $\propto \ell^{1/2}$
- Basin area $a \propto \ell \cdot \ell^{1/2} = \ell^{3/2}$
- Invert: $\ell \propto a^{2/3}$
- $d\ell \propto d(a^{2/3}) = 2/3 a^{-1/3} da$
- $Pr(\text{basin area} = a) da$
  $= Pr(\text{basin length} = \ell) d\ell$
  $\propto \ell^{-3/2} d\ell$
  $\propto (a^{2/3})^{-3/2} a^{-1/3} da$
  $= a^{-4/3} da$
  $= a^{-\tau} da$
Connections between Exponents

- For a basin of length \( l \), width \( \propto l^{1/2} \)
- Basin area \( a \propto l \cdot l^{1/2} = l^{3/2} \)
- Invert: \( l \propto a^{2/3} \)
- \( dl \propto d(a^{2/3}) = 2/3 a^{-1/3} da \)
- \( Pr(\text{basin area} = a) da = Pr(\text{basin length} = l) dl \)
  \( \propto l^{-3/2} dl \)
  \( \propto (a^{2/3})^{-3/2} a^{-1/3} da \)
  \( = a^{-4/3} da \)
  \( = a^{-\tau} da \)
Connections between Exponents

- For a basin of length $\ell$, width $\propto \ell^{1/2}$
- Basin area $a \propto \ell \cdot \ell^{1/2} = \ell^{3/2}$
- Invert: $\ell \propto a^{2/3}$
- $d\ell \propto d(a^{2/3}) = 2/3a^{-1/3}da$
- $Pr(\text{basin area} = a)da = Pr(\text{basin length} = \ell)d\ell$
  $\propto \ell^{-3/2}d\ell$
  $\propto (a^{2/3})^{-3/2}a^{-1/3}da$
  $= a^{-4/3}da$
  $= a^{-\tau}da$
Connections between Exponents

- For a basin of length $\ell$, width $\propto \ell^{1/2}$
- Basin area $a \propto \ell \cdot \ell^{1/2} = \ell^{3/2}$
- Invert: $\ell \propto a^{2/3}$
- $d\ell \propto d(a^{2/3}) = 2/3a^{-1/3}da$
- $Pr($basin area $= a)da = Pr($basin length $= \ell)d\ell \propto \ell^{-3/2}d\ell$
  $\propto (a^{2/3})^{-3/2}a^{-1/3}da$
  $= a^{-4/3}da$
  $= a^{-\tau}da$
Connections between Exponents

- For a basin of length $\ell$, width $\propto \ell^{1/2}$
- Basin area $a \propto \ell \cdot \ell^{1/2} = \ell^{3/2}$
- Invert: $\ell \propto a^{2/3}$
- $d\ell \propto d(a^{2/3}) = 2/3a^{-1/3}da$
- $Pr(\text{basin area} = a)da$
  - $= Pr(\text{basin length} = \ell)d\ell$
  - $\propto \ell^{-3/2}d\ell$
  - $\propto (a^{2/3})^{-3/2}a^{-1/3}da$
  - $= a^{-4/3}da$
  - $= a^{-\tau}da$
Connections between Exponents

- Both basin area and length obey power law distributions
- Observed for real river networks
- Typically: $1.3 < \beta < 1.5$ and $1.5 < \gamma < 2$
- Smaller basins more allometric ($h > 1/2$)
- Larger basins more isometric ($h = 1/2$)
Connections between Exponents

- Both basin area and length obey power law distributions
- Observed for real river networks
  - Typically: $1.3 < \beta < 1.5$ and $1.5 < \gamma < 2$
  - Smaller basins more allometric ($h > 1/2$)
  - Larger basins more isometric ($h = 1/2$)
Connections between Exponents

- Both basin area and length obey power law distributions
- Observed for real river networks
- Typically: $1.3 < \beta < 1.5$ and $1.5 < \gamma < 2$
  - Smaller basins more allometric ($h > 1/2$)
  - Larger basins more isometric ($h = 1/2$)
Connections between Exponents

- Both basin area and length obey power law distributions
- Observed for real river networks
- Typically: $1.3 < \beta < 1.5$ and $1.5 < \gamma < 2$
- Smaller basins more allometric ($h > 1/2$)
- Larger basins more isometric ($h = 1/2$)
Connections between Exponents

- Generalize relationship between area and length
  - Hack’s law $^{[4]}$:
    \[ \ell \propto a^h \]
    where $0.5 \lesssim h \lesssim 0.7$
  - Redo calc with $\gamma$, $\tau$, and $h$. 

References
Connections between Exponents

- Generalize relationship between area and length
- Hack’s law\(^4\):
  \[ \ell \propto a^h \]
  where \(0.5 \lesssim h \lesssim 0.7\)
- Redo calc with \(\gamma\), \(\tau\), and \(h\).
Connections between Exponents

- Generalize relationship between area and length
- Hack’s law \[^{[4]}\]:
  \[ \ell \propto a^h \]
  where \(0.5 \lesssim h \lesssim 0.7\)
- Redo calc with \(\gamma\), \(\tau\), and \(h\).
Connections between Exponents

Given

\[ \ell \propto a^h, \quad P(a) \propto a^{-\tau}, \quad \text{and} \quad P(\ell) \propto \ell^{-\gamma} \]

- \[ d\ell \propto d(a^h) = ha^{h-1}da \]
- \[ Pr(\text{basin area} = a)da \]
  \[ = Pr(\text{basin length} = \ell)d\ell \]
  \[ \propto \ell^{-\gamma}d\ell \]
  \[ \propto (a^h)^{-\gamma}a^{h-1}da \]
  \[ = a^{-(1+h(\gamma-1))}da \]

\[ \tau = 1 + h(\gamma - 1) \]
Connections between Exponents

- Given

\[ \ell \propto a^h, \ P(a) \propto a^{-\tau}, \text{ and } P(\ell) \propto \ell^{-\gamma} \]

- \[ d\ell \propto d(a^h) = ha^{h-1}da \]

- \[ Pr(\text{basin area} = a)da = Pr(\text{basin length} = \ell)d\ell \]
  \[ \propto \ell^{-\gamma}d\ell \]
  \[ \propto (a^h)^{-\gamma}a^{h-1}da \]
  \[ = a^{-(1+h(\gamma-1))}da \]

- \[ \tau = 1 + h(\gamma - 1) \]
Connections between Exponents

- Given

\[ \ell \propto a^h, \quad P(a) \propto a^{-\tau}, \text{ and } P(\ell) \propto \ell^{-\gamma} \]

- \[ d\ell \propto d(a^h) = ha^{h-1}da \]

- \[ Pr(\text{basin area} = a)da = Pr(\text{basin length} = \ell)d\ell \]
  \[ \propto \ell^{-\gamma}d\ell \]
  \[ \propto (a^h)^{-\gamma}a^{h-1}da \]
  \[ = a^{-(1+h(\gamma-1))}da \]

- \[ \tau = 1 + h(\gamma - 1) \]
Connections between Exponents

- **Given**
  \[ \ell \propto a^h, \quad P(a) \propto a^{-\tau}, \quad \text{and} \quad P(\ell) \propto \ell^{-\gamma} \]

- \[ d\ell \propto d(a^h) = ha^{h-1}da \]

- \[ Pr(\text{basin area} = a)da = Pr(\text{basin length} = \ell)d\ell \]
  \[ \propto \ell^{-\gamma}d\ell \]
  \[ \propto (a^h)^{-\gamma}a^{h-1}da \]
  \[ = a^{-(1+h(\gamma-1))}da \]

- \[ \tau = 1 + h(\gamma - 1) \]
Connections between Exponents

Given

\[ l \propto a^h, \quad P(a) \propto a^{-\tau}, \quad \text{and} \quad P(\ell) \propto \ell^{-\gamma} \]

\[ d\ell \propto d(a^h) = ha^{h-1}da \]

\[ Pr(\text{basin area} = a)da \]

\[ = Pr(\text{basin length} = \ell) d\ell \]

\[ \propto \ell^{-\gamma}d\ell \]

\[ \propto (a^h)^{-\gamma} a^{h-1}da \]

\[ = a^{-(1+h(\gamma-1))}da \]

\[ \tau = 1 + h(\gamma - 1) \]
Connections between Exponents

Given

\[ \ell \propto a^h, \quad P(a) \propto a^{-\tau}, \quad \text{and} \quad P(\ell) \propto \ell^{-\gamma} \]

\[ d\ell \propto d(a^h) = ha^{h-1}da \]

\[ Pr(\text{basin area} = a)da = Pr(\text{basin length} = \ell) d\ell \]
\[ \propto \ell^{-\gamma} d\ell \]
\[ \propto (a^h)^{-\gamma} a^{h-1}da \]
\[ = a^{-(1+h(\gamma-1))}da \]

\[ \tau = 1 + h(\gamma - 1) \]
Connections between Exponents

> Given

\[ \ell \propto a^h, \ P(a) \propto a^{-\tau}, \ \text{and} \ P(\ell) \propto \ell^{-\gamma} \]

> \[d\ell \propto d(a^h) = ha^{h-1}da\]

> \[Pr(\text{basin area} = a)da = Pr(\text{basin length} = \ell)d\ell \]

> \[= \ell^{-\gamma}d\ell \]

> \[\propto (a^h)^{-\gamma}a^{h-1}da \]

> \[= a^{-(1+h(\gamma-1))}da \]

> \[\tau = 1 + h(\gamma - 1)\]
Connections between Exponents

With more detailed description of network structure, 

\[ \tau = 1 + h(\gamma - 1) \]

simplifies:

\[ \tau = 2 - h \]

\[ \gamma = 1/h \]
Connections between Exponents

With more detailed description of network structure, 
\[ \tau = 1 + h(\gamma - 1) \] simplifies:

\[ \tau = 2 - h \]

\[ \gamma = \frac{1}{h} \]

- Only one exponent is independent
Connections between Exponents

With more detailed description of network structure, \( \tau = 1 + h(\gamma - 1) \) simplifies:

\[ \tau = 2 - h \]

\[ \gamma = 1 / h \]

- Only one exponent is independent
- Simplify system description
Connections between Exponents

With more detailed description of network structure, $\tau = 1 + h(\gamma - 1)$ simplifies:

$\tau = 2 - h$

$\gamma = 1/h$

- Only one exponent is independent
- Simplify system description
- Expect scaling relations where power laws are found
Connections between Exponents

With more detailed description of network structure, 
\[ \tau = 1 + h(\gamma - 1) \] simplifies:

\[ \tau = 2 - h \]

\[ \gamma = 1/h \]

- Only one exponent is independent
- Simplify system description
- Expect scaling relations where power laws are found
- Characterize universality class with independent exponents
Other First Returns

Failure

- A very simple model of failure/death:
- \( x_t \) = entity’s ‘health’ at time \( t \)
- \( x_0 \) could be \( > 0 \).
- Entity fails when \( x \) hits 0.

Streams

- Dispersion of suspended sediments in streams.
- Long times for clearing.
Other First Returns

Failure

- A very simple model of failure/death:
  - $x_t = \text{entity’s ‘health’ at time } t$
  - $x_0$ could be $> 0$.
  - Entity fails when $x$ hits 0.

Streams

- Dispersion of suspended sediments in streams.
- Long times for clearing.
More than randomness

- Can generalize to Fractional Random Walks
  - Levy flights, Fractional Brownian Motion
  - In 1-d,
    \[ \sigma \sim t^\alpha \]

- Extensive memory of path now matters...
More than randomness

- Can generalize to Fractional Random Walks
- Levy flights, Fractional Brownian Motion

In 1-d,

\[ \sigma \sim t^{\alpha} \]

- Extensive memory of path now matters...
More than randomness

- Can generalize to Fractional Random Walks
- Levy flights, Fractional Brownian Motion
- In 1-d,
  \[ \sigma \sim t^{\alpha} \]

- Extensive memory of path now matters...
More than randomness

- Can generalize to Fractional Random Walks
- Levy flights, Fractional Brownian Motion
- In 1-d,

\[ \sigma \sim t^\alpha \]

\[ \alpha > 1/2 \rightleftharpoons \text{superdiffusive} \]
\[ \alpha < 1/2 \rightleftharpoons \text{subdiffusive} \]

- Extensive memory of path now matters...
More than randomness

- Can generalize to Fractional Random Walks
- Levy flights, Fractional Brownian Motion
- In 1-d,
  \[ \sigma \sim t^\alpha \]
  \[ \alpha > 1/2 \text{ — superdiffusive} \]
  \[ \alpha < 1/2 \text{ — subdiffusive} \]
- Extensive memory of path now matters...
Outline

Random Walks
The First Return Problem
Examples

Variable transformation
Basics
Holtsmark’s Distribution
PLIPL0

Growth Mechanisms
Random Copying
Words, Cities, and the Web

References
Variable Transformation

Understand power laws as arising from

1. elementary distributions (e.g., exponentials)
Variable Transformation

Understand power laws as arising from

1. elementary distributions (e.g., exponentials)
2. variables connected by power relationships
Variable Transformation

- Random variable $X$ with known distribution $P_X$
- Second random variable $Y$ with $y = f(x)$.

\[
P_Y(y)dy = P_X(x)dx
\]

\[
= \sum_{y|f(x)=y} P_X(f^{-1}(y)) \frac{dy}{|f'(f^{-1}(y))|}
\]

- Easier to do by hand...
Variable Transformation

- Random variable $X$ with known distribution $P_x$
- Second random variable $Y$ with $y = f(x)$.

\[
P_y(y)dy = P_x(x)dx
\]
\[
= \sum_{y | f(x) = y} P_x(f^{-1}(y)) \frac{dy}{|f'(f^{-1}(y))|}
\]

- Easier to do by hand...
Variable Transformation

- Random variable $X$ with known distribution $P_x$
- Second random variable $Y$ with $y = f(x)$.

$$P_y(y)dy = P_x(x)dx$$

$$= \sum_{y \mid f(x) = y} P_x(f^{-1}(y)) \frac{dy}{|f'(f^{-1}(y))|}$$

- Easier to do by hand...
Variable Transformation

- Random variable $X$ with known distribution $P_X$
- Second random variable $Y$ with $y = f(x)$.

\[
P_y(y)dy = P_x(x)dx
\]

\[
= \sum_{y|f(x)=y} P_x(f^{-1}(y)) \frac{dy}{|f'(f^{-1}(y))|}
\]

- Easier to do by hand...
General Example

Assume relationship between $x$ and $y$ is 1-1.

- Power-law relationship between variables:
  \[ y = cx^{-\alpha}, \alpha > 0 \]

- Look at $y$ large and $x$ small

\[ dy = d\left(cx^{-\alpha}\right) \]
General Example

Assume relationship between $x$ and $y$ is 1-1.

- Power-law relationship between variables: $y = cx^{-\alpha}$, $\alpha > 0$
- Look at $y$ large and $x$ small

\[
\frac{dy}{dx} = d\left(cx^{-\alpha}\right)
\]
**General Example**

Assume relationship between $x$ and $y$ is 1-1.

- Power-law relationship between variables:
  $$y = cx^{-\alpha}, \alpha > 0$$
- Look at $y$ large and $x$ small

$$dy = d\left(cx^{-\alpha}\right)$$
General Example
Assume relationship between $x$ and $y$ is 1-1.

- Power-law relationship between variables:
  \[ y = cx^{-\alpha}, \; \alpha > 0 \]
- Look at $y$ large and $x$ small

\[
\begin{align*}
  \mathrm{d}y &= \mathrm{d}\left(cx^{-\alpha}\right) \\
  &= c(-\alpha)x^{-\alpha - 1}\mathrm{d}x
\end{align*}
\]
General Example

Assume relationship between $x$ and $y$ is 1-1.

- Power-law relationship between variables:
  \[ y = cx^{-\alpha}, \quad \alpha > 0 \]
- Look at $y$ large and $x$ small

\[
\begin{align*}
\text{invert: } \ dx &= \frac{-1}{c\alpha} x^{\alpha+1} \ dy
\end{align*}
\]
General Example
Assume relationship between $x$ and $y$ is 1-1.

- Power-law relationship between variables:
  \[ y = cx^{-\alpha}, \quad \alpha > 0 \]
- Look at $y$ large and $x$ small

\[
\begin{align*}
  dy &= d\left(cx^{-\alpha}\right) \\
  &= c(-\alpha)x^{-\alpha-1}dx \\
  \text{invert: } dx &= \frac{-1}{c\alpha}x^{\alpha+1}dy \\
  &= \frac{-1}{c\alpha} \left(\frac{y}{c}\right)^{-\alpha+1/\alpha} dy
\end{align*}
\]
General Example

Assume relationship between $x$ and $y$ is 1-1.

- Power-law relationship between variables:
  \[ y = cx^{-\alpha}, \quad \alpha > 0 \]
- Look at $y$ large and $x$ small

\[
\begin{align*}
\frac{dy}{dx} &= d \left( cx^{-\alpha} \right) \\
&= c(-\alpha)x^{-\alpha-1}dx \\
\text{invert: } dx &= \frac{-1}{c\alpha} x^{\alpha+1}dy \\
&= \frac{-1}{c\alpha} \left( \frac{y}{c} \right)^{-(\alpha+1)/\alpha} dy \\
dx &= \frac{-c^{1/\alpha}}{\alpha} y^{-1-1/\alpha} dy
\end{align*}
\]
General Example

Now make transformation:

\[ P_Y(y)dy = P_X(x)dx \]

\[ P_Y(y) \propto y^{-1-1/\alpha} \text{ as } y \to \infty \]

providing

\[ P_X(x) \to \text{constant as } x \to 0. \]
General Example

Now make transformation:

\[ P_y(y)dy = P_x(x)dx \]

\[ P_y(y)dy = P_x \left( \left( \frac{y}{c} \right)^{-1/\alpha} \right) \frac{c^{1/\alpha}}{\alpha} y^{-1-1/\alpha} dy \]

So \( P_y(y) \propto y^{-1-1/\alpha} \) as \( y \to \infty \)

providing

\( P_x(x) \to \text{constant as } x \to 0. \)
General Example

Now make transformation:

\[ P_y(y)dy = P_x(x)dx \]

\[ P_y(y)dy = P_x \left( \left( \frac{y}{c} \right)^{-1/\alpha} \right)^{\frac{c^{1/\alpha}}{\alpha}} y^{-1-1/\alpha} dy \]

\[ \text{So } P_y(y) \propto y^{-1-1/\alpha} \text{ as } y \to \infty \]

providing

\[ P_x(x) \to \text{constant as } x \to 0. \]
General Example

\[ P_y(y)dy = P_x \left( \left( \frac{y}{c} \right)^{-1/\alpha} \right) \frac{c^{1/\alpha}}{\alpha} y^{-1-1/\alpha} dy \]

- If \( P_x(x) \to x^\beta \) as \( x \to 0 \) then
  \[ P_y(y) \propto y^{-1-1/\alpha-\beta/\alpha} \text{ as } y \to \infty \]
General Example

\[ P_y(y)dy = P_x \left( \left( \frac{y}{c} \right)^{-1/\alpha} \right) \frac{c^{1/\alpha}}{\alpha} y^{-1-1/\alpha} dy \]

If \( P_x(x) \rightarrow x^\beta \) as \( x \rightarrow 0 \) then

\[ P_y(y) \propto y^{-1-1/\alpha-\beta/\alpha} \text{ as } y \rightarrow \infty \]
Example

Exponential distribution

Given $P_x(x) = \frac{1}{\lambda} e^{-x/\lambda}$ and $y = cx^{-\alpha}$, then

$$P(y) \propto y^{-1-1/\alpha} + O\left(y^{-1-2/\alpha}\right)$$
Example

Exponential distribution

Given $P_x(x) = \frac{1}{\lambda} e^{-x/\lambda}$ and $y = cx^{-\alpha}$, then

$$P(y) \propto y^{-1-1/\alpha} + O(y^{-1-2/\alpha})$$

- Exponentials arise from randomness...
Example

Exponential distribution

Given $P_x(x) = \frac{1}{\lambda} e^{-x/\lambda}$ and $y = cx^{-\alpha}$, then

$$P(y) \propto y^{-1-1/\alpha} + O(y^{-1-2/\alpha})$$

- Exponentials arise from randomness...
- More later when we cover robustness.
Outline

Random Walks
  The First Return Problem
  Examples

Variable transformation
  Basics
  Holtsmark’s Distribution
  PLIPLO

Growth Mechanisms
  Random Copying
  Words, Cities, and the Web

References
Gravity

- Select a random point in space $\vec{x}$
- Measure the force of gravity $F(\vec{x})$
- Observe that $P_F(F) \sim F^{-5/2}$. 
Gravity

- Select a random point in space $\vec{x}$
- Measure the force of gravity $F(\vec{x})$
- Observe that $P_F(F) \sim F^{-5/2}$. 
Gravity

- Select a random point in space $\vec{x}$
- Measure the force of gravity $F(\vec{x})$
- Observe that $P_F(F) \sim F^{-5/2}$. 
**Ingredients** [12]

Matter is concentrated in stars:

- $F$ is distributed unevenly
  - Probability of being a distance $r$ from a single star at $\vec{x} = \vec{0}$:
    
    $$P_r(r)dr \propto r^2 dr$$

  - Assume stars are distributed randomly in space
  - Assume only one star has significant effect at $\vec{x}$.
  - Law of gravity:
    
    $$F \propto r^{-2}$$

- invert:
    
    $$r \propto F^{-1/2}$$
Ingredients\cite{12}

Matter is concentrated in stars:

- $F$ is distributed unevenly
- Probability of being a distance $r$ from a single star at $\vec{x} = \vec{0}$:
  \[ P_r(r)dr \propto r^2dr \]
- Assume stars are distributed randomly in space
- Assume only one star has significant effect at $\vec{x}$.
- Law of gravity:
  \[ F \propto r^{-2} \]
- invert:
  \[ r \propto F^{-1/2} \]
Ingredients \textsuperscript{[12]}

Matter is concentrated in stars:

- $F$ is distributed unevenly
- Probability of being a distance $r$ from a single star at $\vec{x} = \vec{0}$:
  \[ P_r(r)dr \propto r^2dr \]
- Assume stars are distributed randomly in space
- Assume only one star has significant effect at $\vec{x}$.
- Law of gravity:
  \[ F \propto r^{-2} \]
- invert:
  \[ r \propto F^{-1/2} \]
Matter is concentrated in stars:

- $F$ is distributed unevenly
- Probability of being a distance $r$ from a single star at $\vec{x} = \vec{0}$:
  \[ P_r(r)dr \propto r^2dr \]
- Assume stars are distributed randomly in space
- Assume only one star has significant effect at $\vec{x}$.
- Law of gravity:
  \[ F \propto r^{-2} \]
- invert:
  \[ r \propto F^{-1/2} \]
Ingredients [12]

Matter is concentrated in stars:

- $F$ is distributed unevenly
- Probability of being a distance $r$ from a single star at $\vec{x} = \vec{0}$:
  \[ P_r(r)dr \propto r^2dr \]
- Assume stars are distributed randomly in space
- Assume only one star has significant effect at $\vec{x}$.
- Law of gravity:
  \[ F \propto r^{-2} \]
- invert:
  \[ r \propto F^{-1/2} \]
Transformation

\[\begin{align*}
dF & \propto d(r^{-2}) \\
& \propto r^{-3} dr \\
& \propto F^{-3/2} dF
\end{align*}\]
Transformation

\[ dF \propto d(r^{-2}) \]

\[ \propto r^{-3} dr \]

\[ \propto F^{-3/2} dF \]

invert:

\[ dr \propto r^3 dF \]
Transformation

\[ dF \propto d(r^{-2}) \]

\[ \propto r^{-3} dr \]

invert:

\[ dr \propto r^3 dF \]

\[ \propto F^{-3/2} dF \]
Transformation

\[ dF \propto d(r^{-2}) \]

\[ \propto r^{-3} dr \]

\[ dr \propto r^3 dF \]

\[ \propto F^{-3/2} dF \]
Transformation

Using $r \propto F^{-1/2}$, $dr \propto F^{-3/2}dF$ and $P_r(r) \propto r^2$

\[ P_F(F)dF = P_r(r)dr \]

\[ \propto P_r(F^{-1/2})F^{-3/2}dF \]

\[ \propto (F^{-1/2})^2 F^{-3/2}dF \]

\[ = F^{-1-3/2}dF \]

\[ = F^{-5/2}dF \]
Transformation

Using $r \propto F^{-1/2}$, $dr \propto F^{-3/2}dF$ and $P_r(r) \propto r^2$

\[ P_F(F)dF = P_r(r)dr \]

$\propto P_r(F^{-1/2})F^{-3/2}dF$

$\propto \left(F^{-1/2}\right)^2 F^{-3/2}dF$

$= F^{-1-3/2}dF$

$= F^{-5/2}dF$
Transformation

Using \( r \propto F^{-1/2} \), \( dr \propto F^{-3/2}dF \) and \( P_r(r) \propto r^2 \)

\[
P_F(F)dF = P_r(r)dr
\]

\[
\propto P_r(F^{-1/2})F^{-3/2}dF
\]

\[
\propto \left(F^{-1/2}\right)^2 F^{-3/2}dF
\]

\[
= F^{-1-3/2}dF
\]

\[
= F^{-5/2}dF
\]
Transformation

Using \( r \propto F^{-1/2} \), \( dr \propto F^{-3/2}dF \) and \( P_r(r) \propto r^2 \)

\[
\begin{align*}
P_F(F)dF &= P_r(r)dr \\
&\propto P_r(F^{-1/2})F^{-3/2}dF \\
&\propto \left(F^{-1/2}\right)^2 F^{-3/2}dF \\
&= F^{-1-3/2}dF \\
&= F^{-5/2}dF
\end{align*}
\]
Transformation

Using \( r \propto F^{-1/2} \), \( dr \propto F^{-3/2}dF \) and \( P_r(r) \propto r^2 \),

\[
\begin{align*}
P_F(F)dF &= P_r(r)dr \\
&\propto P_r(F^{-1/2})F^{-3/2}dF \\
&\propto \left(F^{-1/2}\right)^2 F^{-3/2}dF \\
&= F^{-1-3/2}dF \\
&= F^{-5/2}dF
\end{align*}
\]
Gravity

\[ P_F(F) = F^{-5/2} \, dF \]

\[ \gamma = 5/2 \]

- Mean is finite
- Variance = \( \infty \)
- A wild distribution
- Random sampling of space usually safe but can end badly...
Gravity

\[ P_F(F) = F^{-5/2} \, dF \]

\[ \gamma = 5/2 \]

- Mean is finite
- Variance = \( \infty \)
- A wild distribution
- Random sampling of space usually safe but can end badly...
Gravity

\[ P_F(F) = F^{-5/2} \, dF \]

\[ \gamma = 5/2 \]

- Mean is finite
- Variance = \( \infty \)
  - A wild distribution
  - Random sampling of space usually safe but can end badly...
Gravity

\[ P_F(F) = F^{-5/2} \, dF \]

\[ \gamma = 5/2 \]

- Mean is finite
- Variance = \( \infty \)
- A wild distribution
  - Random sampling of space usually safe but can end badly...
Gravity

\[ P_F(F) = F^{-5/2} \, dF \]

\[ \gamma = 5/2 \]

- Mean is finite
- Variance = $\infty$
- A wild distribution
- Random sampling of space usually safe but can end badly...
Outline

Random Walks
  The First Return Problem
  Examples

Variable transformation
  Basics
  Holtsmark’s Distribution
  PLIPLO

Growth Mechanisms
  Random Copying
  Words, Cities, and the Web

References
Caution!

PLIPLO = Power law in, power law out
Caution!

PLIPLO = Power law in, power law out

Explain a power law as resulting from another unexplained power law.
Caution!

PLIPLO = Power law in, power law out

Explain a power law as resulting from another unexplained power law.

Don’t do this!!! (slap, slap)
Caution!

PLIPLO = Power law in, power law out

Explain a power law as resulting from another unexplained power law.

Don’t do this!!! (slap, slap)

We need mechanisms!
Outline

Random Walks
- The First Return Problem
- Examples

Variable transformation
- Basics
- Holtsmark’s Distribution
- PLIPLO

Growth Mechanisms
- Random Copying
- Words, Cities, and the Web

References
Aggregation

- Random walks represent **additive aggregation**
  - Mechanism: Random addition and subtraction
  - Compare across realizations, no competition.
  - Next: Random Additive/Copying Processes involving Competition.
- **Widespread**: Words, Cities, the Web, Wealth, Productivity (Lotka), Popularity (Books, People, ...)
- Competing mechanisms (trickiness)
Aggregation

- Random walks represent **additive aggregation**
- **Mechanism**: Random addition and subtraction
  - Compare across realizations, no competition.
  - Next: **Random Additive/Copying Processes involving Competition**.
- **Widespread**: Words, Cities, the Web, Wealth, Productivity (Lotka), Popularity (Books, People, ...)
- Competing mechanisms (trickiness)
Random walks represent additive aggregation

Mechanism: Random addition and subtraction

Compare across realizations, no competition.

Next: Random Additive/Copying Processes involving Competition.

Widespread: Words, Cities, the Web, Wealth, Productivity (Lotka), Popularity (Books, People, ...)

Competing mechanisms (trickiness)
Aggregation

- Random walks represent **additive aggregation**
- Mechanism: Random addition and subtraction
- Compare across realizations, no competition.
- Next: **Random Additive/Copying Processes** involving Competition.
  - Widespread: Words, Cities, the Web, Wealth, Productivity (Lotka), Popularity (Books, People, ...)
  - Competing mechanisms (trickiness)
Aggregation

- Random walks represent **additive aggregation**
- Mechanism: Random addition and subtraction
- Compare across realizations, no competition.
- Next: **Random Additive/Copying Processes involving Competition.**
- **Widespread**: Words, Cities, the Web, Wealth, Productivity (Lotka), Popularity (Books, People, ...)
- Competing mechanisms (trickiness)
Aggregation

- Random walks represent **additive aggregation**
- Mechanism: Random addition and subtraction
- Compare across realizations, no competition.
- Next: **Random Additive/Copying Processes involving Competition.**
- **Widespread:** Words, Cities, the Web, Wealth, Productivity (Lotka), Popularity (Books, People, ...)
- Competing mechanisms (trickiness)
Work of Yore

1924: G. Udny Yule\textsuperscript{13}: 
# Species per Genus

1926: Lotka\textsuperscript{6}: 
# Scientific papers per author (Lotka’s law)

1953: Mandelbrot\textsuperscript{7}: 
Optimality argument for Zipf’s law; focus on language.

1955: Herbert Simon\textsuperscript{11, 14}: 
Zipf’s law for word frequency, city size, income, publications, and species per genus.

1965/1976: Derek de Solla Price\textsuperscript{8, 9}: 
Network of Scientific Citations.

1999: Barabasi and Albert\textsuperscript{1}: 
Work of Yore

- 1924: G. Udny Yule\textsuperscript{[13]}: 
  # Species per Genus
- 1926: Lotka\textsuperscript{[6]}: 
  # Scientific papers per author (Lotka’s law)
- 1953: Mandelbrot\textsuperscript{[7]}: 
  Optimality argument for Zipf’s law; focus on language.
- 1955: Herbert Simon\textsuperscript{[11, 14]}: 
  Zipf’s law for word frequency, city size, income, publications, and species per genus.
- 1965/1976: Derek de Solla Price\textsuperscript{[8, 9]}: 
  Network of Scientific Citations.
- 1999: Barabasi and Albert\textsuperscript{[1]}: 
Work of Yore

- 1924: G. Udny Yule[^13]:
  # Species per Genus
- 1926: Lotka[^6]:
  # Scientific papers per author (Lotka’s law)
- 1953: Mandelbrot[^7]:
  Optimality argument for Zipf’s law; focus on language.
- 1955: Herbert Simon[^11, 14]:
  Zipf’s law for word frequency, city size, income, publications, and species per genus.
- 1965/1976: Derek de Solla Price[^8, 9]:
  Network of Scientific Citations.
- 1999: Barabasi and Albert[^1]:

[^1]: Barabasi and Albert (1999)
[^2]: Lotka (1926)
[^3]: Mandelbrot (1953)
[^4]: Herbert Simon (1955)
[^5]: Derek de Solla Price (1965/1976)
Work of Yore

- 1924: G. Udny Yule\textsuperscript{[13]}: 
  # Species per Genus

- 1926: Lotka\textsuperscript{[6]}: 
  # Scientific papers per author (Lotka’s law)

- 1953: Mandelbrot\textsuperscript{[7]}: 
  Optimality argument for Zipf’s law; focus on language.

- 1955: Herbert Simon\textsuperscript{[11, 14]}: 
  Zipf’s law for word frequency, city size, income, publications, and species per genus.

- 1965/1976: Derek de Solla Price\textsuperscript{[8, 9]}: 
  Network of Scientific Citations.

- 1999: Barabasi and Albert\textsuperscript{[1]}: 
Work of Yore

- 1924: G. Udny Yule\textsuperscript{[13]}:  
  # Species per Genus

- 1926: Lotka\textsuperscript{[6]}:  
  # Scientific papers per author (Lotka’s law)

- 1953: Mandelbrot\textsuperscript{[7]}:  
  Optimality argument for Zipf’s law; focus on language.

- 1955: Herbert Simon\textsuperscript{[11, 14]}:  
  Zipf’s law for word frequency, city size, income, publications, and species per genus.

- 1965/1976: Derek de Solla Price\textsuperscript{[8, 9]}:  
  Network of Scientific Citations.

- 1999: Barabasi and Albert\textsuperscript{[1]}:  
Work of Yore

► 1924: **G. Udny Yule**[^13]:
  # Species per Genus
► 1926: **Lotka**[^6]:
  # Scientific papers per author (Lotka’s law)
► 1953: **Mandelbrot**[^7]:
  Optimality argument for Zipf’s law; focus on language.
► 1955: **Herbert Simon**[^11, 14]:
  Zipf’s law for word frequency, city size, income, publications, and species per genus.
► 1965/1976: **Derek de Solla Price**[^8, 9]:
  Network of Scientific Citations.
► 1999: **Barabasi and Albert**[^1]:

[^1]: Barabasi and Albert, 1999
[^2]: G. Udny Yule, 1924
[^3]: Lotka, 1926
[^4]: Mandelbrot, 1953
[^5]: Herbert Simon, 1955
[^6]: Derek de Solla Price, 1965/1976
Essential Extract of a Growth Model

Random Competitive Replication (RCR):

1. Start with 1 element of a particular flavor at $t = 1$
2. At time $t = 2, 3, 4, \ldots$, add a new element in one of two ways:
   - With probability $\rho$, create a new element with a new flavor
   - With probability $1 - \rho$, randomly choose from all existing elements, and make a copy.
   - Elements of the same flavor form a group
Random Competitive Replication (RCR):

1. Start with 1 element of a particular flavor at $t = 1$
2. At time $t = 2, 3, 4, \ldots$, add a new element in one of two ways:
   - With probability $\rho$, create a new element with a new flavor
   - With probability $1 - \rho$, randomly choose from all existing elements, and make a copy.

   Elements of the same flavor form a group
Essential Extract of a Growth Model

Random Competitive Replication (RCR):

1. Start with 1 element of a particular flavor at \( t = 1 \)
2. At time \( t = 2, 3, 4, \ldots \), add a new element in one of two ways:
   - With probability \( \rho \), create a new element with a new flavor
   - With probability \( 1 - \rho \), randomly choose from all existing elements, and make a copy.

   Elements of the same flavor form a group
Random Competitive Replication (RCR):

1. Start with 1 element of a particular flavor at $t = 1$
2. At time $t = 2, 3, 4, \ldots$, add a new element in one of two ways:
   - With probability $\rho$, create a new element with a new flavor
   - With probability $1 - \rho$, randomly choose from all existing elements, and make a copy.
   - Elements of the same flavor form a group
Essential Extract of a Growth Model

Random Competitive Replication (RCR):

1. Start with 1 element of a particular flavor at $t = 1$
2. At time $t = 2, 3, 4, \ldots$, add a new element in one of two ways:
   - With probability $\rho$, create a new element with a new flavor
     - **Mutation/Innovation**
   - With probability $1 - \rho$, randomly choose from all existing elements, and make a copy.
   - Elements of the same flavor form a group
Essential Extract of a Growth Model

Random Competitive Replication (RCR):

1. Start with 1 element of a particular flavor at $t = 1$
2. At time $t = 2, 3, 4, \ldots$, add a new element in one of two ways:
   - With probability $\rho$, create a new element with a new flavor
     ➤ Mutation/Innovation
   - With probability $1 - \rho$, randomly choose from all existing elements, and make a copy.
     ➤ Replication/Imitation
   - Elements of the same flavor form a group
Random Competitive Replication

Example: Words in a text
- Consider words as they appear sequentially.
- With probability $\rho$, the next word has not previously appeared.
- With probability $1 - \rho$, randomly choose one word from all words that have come before, and reuse this word.
Random Competitive Replication

Example: Words in a text

- Consider words as they appear sequentially.
  - With probability $\rho$, the next word has not previously appeared.
  - With probability $1 - \rho$, randomly choose one word from all words that have come before, and reuse this word.
Random Competitive Replication

Example: Words in a text

- Consider words as they appear sequentially.
- With probability $\rho$, the next word has not previously appeared.

- With probability $1 - \rho$, randomly choose one word from all words that have come before, and reuse this word.
Random Competitive Replication

Example: Words in a text

- Consider words as they appear sequentially.
- With probability $\rho$, the next word has not previously appeared

- With probability $1 - \rho$, randomly choose one word from all words that have come before, and reuse this word
Example: Words in a text

- Consider words as they appear sequentially.
- With probability $\rho$, the next word has not previously appeared
  - **Mutation/Innovation**
- With probability $1 - \rho$, randomly choose one word from all words that have come before, and reuse this word
Example: Words in a text

- Consider words as they appear sequentially.
- With probability $\rho$, the next word has not previously appeared
  - Mutation/Innovation
  - With probability $1 - \rho$, randomly choose one word from all words that have come before, and reuse this word
  - Replication/Imitation
Random Competitive Replication

- Competition for replication between elements is random
- Competition for growth between groups is not random
- Selection on groups is biased by size
- Rich-gets-richer story
- Random selection is easy
- No great knowledge of system needed
Random Competitive Replication

- Competition for replication between elements is random
- Competition for growth between groups is not random
  - Selection on groups is biased by size
  - Rich-gets-richer story
  - Random selection is easy
  - No great knowledge of system needed
Random Competitive Replication

- Competition for replication between elements is random
- Competition for growth between groups is not random
- Selection on groups is biased by size
  - Rich-gets-richer story
  - Random selection is easy
  - No great knowledge of system needed
Random Competitive Replication

- Competition for replication between elements is random
- Competition for growth between groups is not random
- Selection on groups is biased by size
- Rich-gets-richer story
  - Random selection is easy
  - No great knowledge of system needed
Random Competitive Replication

- Competition for replication between elements is random
- Competition for growth between groups is not random
- Selection on groups is biased by size
- Rich-gets-richer story
- Random selection is easy
- No great knowledge of system needed
Random Competitive Replication

- Competition for replication between elements is random
- Competition for growth between groups is not random
- Selection on groups is biased by size
- Rich-gets-richer story
- Random selection is easy
- No great knowledge of system needed
Random Competitive Replication

- Steady growth of system: +1 element per unit time.
- Steady growth of distinct flavors at rate $\rho$.
- We can incorporate:
  1. Element elimination
  2. Elements moving between groups
  3. Variable innovation rate $\rho$
  4. Different selection based on group size
Random Competitive Replication

- Steady growth of system: +1 element per unit time.
- Steady growth of distinct flavors at rate $\rho$
- We can incorporate
  1. Element elimination
  2. Elements moving between groups
  3. Variable innovation rate $\rho$
  4. Different selection based on group size
Random Competitive Replication

- Steady growth of system: +1 element per unit time.
- Steady growth of distinct flavors at rate $\rho$
- We can incorporate
  1. Element elimination
  2. Elements moving between groups
  3. Variable innovation rate $\rho$
  4. Different selection based on group size
Random Competitive Replication

- Steady growth of system: +1 element per unit time.
- Steady growth of distinct flavors at rate $\rho$.
- We can incorporate
  1. Element elimination
  2. Elements moving between groups
  3. Variable innovation rate $\rho$
  4. Different selection based on group size
Random Competitive Replication

- Steady growth of system: +1 element per unit time.
- Steady growth of distinct flavors at rate $\rho$
- We can incorporate
  1. Element elimination
  2. Elements moving between groups
  3. Variable innovation rate $\rho$
  4. Different selection based on group size
Random Competitive Replication

- Steady growth of system: +1 element per unit time.
- Steady growth of distinct flavors at rate $\rho$.
- We can incorporate:
  1. Element elimination
  2. Elements moving between groups
  3. Variable innovation rate $\rho$
  4. Different selection based on group size.
Random Competitive Replication

- Steady growth of system: +1 element per unit time.
- Steady growth of distinct flavors at rate $\rho$.
- We can incorporate:
  1. Element elimination
  2. Elements moving between groups
  3. Variable innovation rate $\rho$
  4. Different selection based on group size
Random Competitive Replication

- Steady growth of system: +1 element per unit time.
- Steady growth of distinct flavors at rate $\rho$
- We can incorporate
  1. Element elimination
  2. Elements moving between groups
  3. Variable innovation rate $\rho$
  4. Different selection based on group size
     (But mechanism for selection is not as simple...)
Random Competitive Replication

Definitions:

- $k_i$ = size of a group $i$
- $N_k(t)$ = # groups containing $k$ elements at time $t$. 

Basic question: How does $N_k(t)$ evolve with time?

First: 

$$
\sum k_i N_{k_i}(t) = t = \text{number of elements at time } t
$$
Random Competitive Replication

Definitions:

- $k_i = \text{size of a group } i$
- $N_k(t) = \# \text{ groups containing } k \text{ elements at time } t.$
Random Competitive Replication

Definitions:

- $k_i =$ size of a group $i$
- $N_k(t) =$ # groups containing $k$ elements at time $t$.

Basic question: How does $N_k(t)$ evolve with time?
Random Competitive Replication

Definitions:
- $k_i =$ size of a group $i$
- $N_k(t) =$ number of groups containing $k$ elements at time $t$.

Basic question: How does $N_k(t)$ evolve with time?

First: $\sum_k kN_k(t) = t =$ number of elements at time $t$
Random Competitive Replication

\[ P_k(t) = \text{Probability of choosing an element that belongs to a group of size } k: \]

- \( N_k(t) \) size \( k \) groups
- \( \Rightarrow kN_k(t) \) elements in size \( k \) groups
- \( t \) elements overall
Random Competitive Replication

\[ P_k(t) = \text{Probability of choosing an element that belongs to a group of size } k: \]

- \( N_k(t) \) size \( k \) groups
- \( \Rightarrow kN_k(t) \) elements in size \( k \) groups
- \( t \) elements overall
Random Competitive Replication

\[ P_k(t) = \text{Probability of choosing an element that belongs to a group of size } k: \]

- \( N_k(t) \) size \( k \) groups
- \( \Rightarrow kN_k(t) \) elements in size \( k \) groups
- \( t \) elements overall
Random Competitive Replication

\[ P_k(t) = \text{Probability of choosing an element that belongs to a group of size } k: \]

\[ \begin{align*}
&\quad N_k(t) \text{ size } k \text{ groups} \\
&\quad \Rightarrow kN_k(t) \text{ elements in size } k \text{ groups} \\
&\quad t \text{ elements overall}
\end{align*} \]
Random Competitive Replication

\[ P_k(t) = \text{Probability of choosing an element that belongs to a group of size } k: \]

- \( N_k(t) \) size \( k \) groups
- \( \Rightarrow kN_k(t) \) elements in size \( k \) groups
- \( t \) elements overall

\[ P_k(t) = \frac{kN_k(t)}{t} \]
Random Competitive Replication

\(N_k(t)\), the number of groups with \(k\) elements, changes at time \(t\) if

1. An element belonging to a group with \(k\) elements is replicated

2. An element belonging to a group with \(k - 1\) elements is replicated
Random Competitive Replication

$N_k(t)$, the number of groups with $k$ elements, changes at time $t$ if

1. An element belonging to a group with $k$ elements is replicated

2. An element belonging to a group with $k - 1$ elements is replicated
Random Competitive Replication

\( N_k(t) \), the number of groups with \( k \) elements, changes at time \( t \) if

1. An element belonging to a group with \( k \) elements is replicated

2. An element belonging to a group with \( k - 1 \) elements is replicated
Random Competitive Replication

\( N_k(t) \), the number of groups with \( k \) elements, changes at time \( t \) if

1. An element belonging to a group with \( k \) elements is replicated
   \[ N_k(t + 1) = N_k(t) - 1 \]

2. An element belonging to a group with \( k - 1 \) elements is replicated
Random Competitive Replication

\( N_k(t) \), the number of groups with \( k \) elements, changes at time \( t \) if

1. An element belonging to a group with \( k \) elements is replicated
   \( N_k(t + 1) = N_k(t) - 1 \)
   Happens with probability \((1 - \rho)kN_k(t)/t\)

2. An element belonging to a group with \( k - 1 \) elements is replicated
Random Competitive Replication

\( N_k(t) \), the number of groups with \( k \) elements, changes at time \( t \) if

1. An element belonging to a group with \( k \) elements is replicated
   \( N_k(t + 1) = N_k(t) - 1 \)
   Happens with probability \( (1 - \rho)kN_k(t)/t \)

2. An element belonging to a group with \( k - 1 \) elements is replicated
   \( N_k(t + 1) = N_k(t) + 1 \)
Random Competitive Replication

\( N_k(t) \), the number of groups with \( k \) elements, changes at time \( t \) if

1. An element belonging to a group with \( k \) elements is replicated
   \[ N_k(t + 1) = N_k(t) - 1 \]
   Happens with probability \( (1 - \rho)kN_k(t)/t \)

2. An element belonging to a group with \( k - 1 \) elements is replicated
   \[ N_k(t + 1) = N_k(t) + 1 \]
   Happens with probability \( (1 - \rho)(k - 1)N_{k-1}(t)/t \)
Random Competitive Replication

Special case for $N_1(t)$:

1. The new element is a new flavor:

   $$N_1(t + 1) = N_1(t) + 1$$
   Happens with probability $\rho$

2. A unique element is replicated.

   $$N_1(t + 1) = N_1(t) - 1$$
   Happens with probability $\left(1 - \frac{1}{N_1(t)}\right)$
Random Competitive Replication

Special case for $N_1(t)$:

1. The new element is a new flavor:

   \[ N_1(t+1) = N_1(t) + 1 \]
   Happens with probability $\rho$

2. A unique element is replicated.

   \[ N_1(t+1) = N_1(t) - 1 \]
   Happens with probability $(1 - \rho)N_1/t$
Random Competitive Replication

Special case for $N_1(t)$:

1. The new element is a new flavor:

2. A unique element is replicated.
Random Competitive Replication

Special case for $N_1(t)$:

1. The new element is a new flavor:
   $$N_1(t + 1) = N_1(t) + 1$$

2. A unique element is replicated.

$$N_1(t + 1) = N_1(t) - 1$$

Happens with probability $\frac{N_1}{t}$
Random Competitive Replication

Special case for $N_1(t)$:

1. The new element is a new flavor:
   $$N_1(t + 1) = N_1(t) + 1$$
   Happens with probability $\rho$

2. A unique element is replicated.
Random Competitive Replication

Special case for $N_1(t)$:

1. The new element is a new flavor:
   $N_1(t + 1) = N_1(t) + 1$
   Happens with probability $\rho$

2. A unique element is replicated.
   $N_1(t + 1) = N_1(t) - 1$
Random Competitive Replication

Special case for $N_1(t)$:

1. The new element is a new flavor:
   \[ N_1(t + 1) = N_1(t) + 1 \]
   Happens with probability $\rho$

2. A unique element is replicated.
   \[ N_1(t + 1) = N_1(t) - 1 \]
   Happens with probability $(1 - \rho)N_1/t$
Random Competitive Replication

Put everything together:

For $k > 1$:

$$\langle N_k(t+1) - N_k(t) \rangle = (1 - \rho) \left( (k - 1) \frac{N_{k-1}(t)}{t} - k \frac{N_k(t)}{t} \right)$$
Put everything together:

For $k > 1$:

$$\langle N_k(t + 1) - N_k(t) \rangle = (1 - \rho) \left( (k - 1) \frac{N_{k-1}(t)}{t} - k \frac{N_k(t)}{t} \right)$$

For $k = 1$:

$$\langle N_1(t + 1) - N_1(t) \rangle = \rho - (1 - \rho) \cdot \frac{N_1(t)}{t}$$
Random Competitive Replication

Assume distribution stabilizes: $N_k(t) = n_k t$

(Reasonable for $t$ large)

- Drop expectations
- Numbers of elements now fractional
- Okay over large time scales
- $n_k/\rho = \text{the fraction of groups that have size } k$. 

Random Competitive Replication

Assume distribution stabilizes: \( N_k(t) = n_k t \)

(Reasonable for \( t \) large)

- Drop expectations
  - Numbers of elements now fractional
  - Okay over large time scales
  - \( n_k/\rho \) = the fraction of groups that have size \( k \).
Random Competitive Replication

Assume distribution stabilizes: \( N_k(t) = n_k t \)

(Reasonable for \( t \) large)

- Drop expectations
- Numbers of elements now fractional
  - Okay over large time scales
  - \( n_k / \rho \) = the fraction of groups that have size \( k \).
Random Competitive Replication

Assume distribution stabilizes: \( N_k(t) = n_k t \)

(Reasonable for \( t \) large)

- Drop expectations
- Numbers of elements now fractional
- Okay over large time scales
  - \( n_k/\rho = \) the fraction of groups that have size \( k \).
Random Competitive Replication

Assume distribution stabilizes: \( N_k(t) = n_k t \)

(Reasonable for \( t \) large)

- Drop expectations
- Numbers of elements now fractional
- Okay over large time scales
- \( n_k / \rho \) = the fraction of groups that have size \( k \).
Random Competitive Replication

Stochastic difference equation:

\[
\langle N_k(t+1) - N_k(t) \rangle = (1 - \rho) \left( (k - 1) \frac{N_{k-1}(t)}{t} - k \frac{N_k(t)}{t} \right)
\]

becomes

\[
n_k(t+1) - n_k t = (1 - \rho) \left( (k - 1) \frac{n_{k-1} t}{t} - k \frac{n_k t}{t} \right)
\]
Random Competitive Replication

Stochastic difference equation:

\[ \langle N_k(t + 1) - N_k(t) \rangle = (1 - \rho) \left( (k - 1) \frac{N_{k-1}(t)}{t} - k \frac{N_k(t)}{t} \right) \]

becomes

\[ n_k(t + 1) - n_k t = (1 - \rho) \left( (k - 1) \frac{n_{k-1} t}{t} - k \frac{n_k t}{t} \right) \]

\[ n_k(t + 1 - t) = (1 - \rho) \left( (k - 1) \frac{n_{k-1} t}{t} - k \frac{n_k t}{t} \right) \]
Random Competitive Replication

Stochastic difference equation:

\[
\langle N_k(t + 1) - N_k(t) \rangle = (1 - \rho) \left( (k - 1) \frac{N_{k-1}(t)}{t} - k \frac{N_k(t)}{t} \right)
\]

becomes

\[
n_k(t + 1) - n_k t = (1 - \rho) \left( (k - 1) \frac{n_{k-1}t}{t} - k \frac{n_k t}{t} \right)
\]

\[
n_k(t + 1 - t) = (1 - \rho) \left( (k - 1) \frac{n_{k-1}t'}{t'} - k \frac{n_k t'}{t'} \right)
\]

\[\Rightarrow n_k = (1 - \rho) ((k - 1)n_{k-1} - kn_k)\]
Random Competitive Replication

Stochastic difference equation:

\[
\langle N_k(t+1) - N_k(t) \rangle = (1 - \rho) \left( (k - 1) \frac{N_{k-1}(t)}{t} - k \frac{N_k(t)}{t} \right)
\]

becomes

\[
n_k(t+1) - n_k t = (1 - \rho) \left( (k - 1) \frac{n_{k-1} t}{t} - k \frac{n_k t}{t} \right)
\]

\[
n_k(t+1 - t) = (1 - \rho) \left( (k - 1) \frac{n_{k-1} t}{t} - k \frac{n_k t}{t} \right)
\]

\[
\Rightarrow n_k = (1 - \rho) \left( (k - 1) n_{k-1} - k n_k \right)
\]

\[
\Rightarrow n_k \left( 1 + (1 - \rho)k \right) = (1 - \rho)(k - 1) n_{k-1}
\]
Random Competitive Replication

We have a simple recursion:

\[
\frac{n_k}{n_{k-1}} = \frac{(k - 1)(1 - \rho)}{1 + (1 - \rho)k}
\]

- Interested in \( k \) large (the tail of the distribution)
- Expand as a series of powers of \( 1/k \)
Random Competitive Replication

We have a simple recursion:

\[
\frac{n_k}{n_{k-1}} = \frac{(k - 1)(1 - \rho)}{1 + (1 - \rho)k}
\]

- Interested in \(k\) large (the tail of the distribution)
- Expand as a series of powers of \(1/k\)
Random Competitive Replication

We have a simple recursion:

\[
\frac{n_k}{n_{k-1}} = \frac{(k - 1)(1 - \rho)}{1 + (1 - \rho)k}
\]

- Interested in \( k \) large (the tail of the distribution)
- Expand as a series of powers of \( 1/k \)
We have a simple recursion:

\[
\frac{n_k}{n_{k-1}} = \frac{(k - 1)(1 - \rho)}{1 + (1 - \rho)k}
\]

- Interested in \(k\) large (the tail of the distribution)
- Expand as a series of powers of \(1/k\)
- Insert question 3, assignment 2 (VOID)
Random Competitive Replication

- We (okay, you) find

\[
\frac{n_k}{n_{k-1}} \approx \left(1 - \frac{1}{k}\right)^{(2-\rho)\left(1-\rho\right)}
\]

- \[
\frac{n_k}{n_{k-1}} \approx \left(\frac{k-1}{k}\right)^{\left(2-\rho\right)\left(1-\rho\right)}
\]

- \[
n_k \propto k^{-\left(2-\rho\right)\left(1-\rho\right)} = k^{-\gamma}
\]
Random Competitive Replication

- We (okay, you) find

\[ \frac{n_k}{n_{k-1}} \sim (1 - \frac{1}{k})^{(2-\rho)/(1-\rho)} \]

- \[ \frac{n_k}{n_{k-1}} \sim \left( \frac{k - 1}{k} \right)^{(2-\rho)/(1-\rho)} \]

- \[ n_k \propto k^{-(2-\rho)/(1-\rho)} = k^{-\gamma} \]
We (okay, you) find

\[
\frac{n_k}{n_{k-1}} \approx \left(1 - \frac{1}{k}\right)^{(2-\rho)/(1-\rho)}
\]

\[
\frac{n_k}{n_{k-1}} \approx \left(\frac{k-1}{k}\right)^{(2-\rho)/(1-\rho)}
\]

\[
n_k \propto k^{-(2-\rho)/(1-\rho)} = k^{-\gamma}
\]
Random Competitive Replication

We (okay, you) find

\[
\frac{n_k}{n_{k-1}} \sim \left(1 - \frac{1}{k}\right)^{(2-\rho)/(1-\rho)}
\]

\[
\frac{n_k}{n_{k-1}} \sim \left(\frac{k-1}{k}\right)^{(2-\rho)/(1-\rho)}
\]

\[
n_k \propto k^{-(2-\rho)/(1-\rho)} = k^{-\gamma}
\]

\[
\gamma = \frac{(2-\rho)}{(1-\rho)} = 1 + \frac{1}{(1-\rho)}
\]
Random Competitive Replication

\[ \gamma = \frac{(2 - \rho)}{(1 - \rho)} = 1 + \frac{1}{(1 - \rho)} \]

- Observe \(2 < \gamma < \infty\) as \(\rho\) varies.
- For \(\rho \approx 0\) (low innovation rate):
  \[ \gamma \approx 2 \]
- Recalls Zipf’s law: \(s_r \sim r^{-\alpha}\)  
  \((s_r = \text{size of the } r\text{th largest element})\)
- We found \(\alpha = 1/(\gamma - 1)\)
- \(\gamma = 2\) corresponds to \(\alpha = 1\)
Random Competitive Replication

\[ \gamma = \frac{(2 - \rho)}{(1 - \rho)} = 1 + \frac{1}{(1 - \rho)} \]

- Observe \( 2 < \gamma < \infty \) as \( \rho \) varies.
- For \( \rho \approx 0 \) (low innovation rate):
  \[ \gamma \approx 2 \]
- Recalls Zipf's law: \( s_r \sim r^{-\alpha} \)
  \((s_r = \text{size of the } r\text{th largest element})\)
- We found \( \alpha = 1/(\gamma - 1) \)
- \( \gamma = 2 \) corresponds to \( \alpha = 1 \)
Random Competitive Replication

\[ \gamma = \frac{(2 - \rho)}{(1 - \rho)} = 1 + \frac{1}{(1 - \rho)} \]

- Observe \( 2 < \gamma < \infty \) as \( \rho \) varies.
- For \( \rho \approx 0 \) (low innovation rate):
  \[ \gamma \approx 2 \]
  - Recalls Zipf’s law: \( s_r \sim r^{-\alpha} \)
    \( (s_r = \text{size of the } r\text{th largest element}) \)
  - We found \( \alpha = 1/(\gamma - 1) \)
  - \( \gamma = 2 \) corresponds to \( \alpha = 1 \)
Random Competitive Replication

\[
\gamma = \frac{(2 - \rho)}{(1 - \rho)} = 1 + \frac{1}{(1 - \rho)}
\]

- Observe \(2 < \gamma < \infty\) as \(\rho\) varies.
- For \(\rho \simeq 0\) (low innovation rate):
  \[\gamma \simeq 2\]
- Recalls Zipf’s law: \(s_r \sim r^{-\alpha}\)
  \((s_r = \text{size of the } r\text{th largest element})\)
  - We found \(\alpha = 1/(\gamma - 1)\)
  - \(\gamma = 2\) corresponds to \(\alpha = 1\)
Random Competitive Replication

\[ \gamma = \frac{2 - \rho}{1 - \rho} = 1 + \frac{1}{1 - \rho} \]

- Observe $2 < \gamma < \infty$ as $\rho$ varies.
- For $\rho \approx 0$ (low innovation rate):
  \[ \gamma \approx 2 \]
- Recalls Zipf’s law: $s_r \sim r^{-\alpha}$
  \[(s_r = \text{size of the } r\text{th largest element})\]
- We found $\alpha = 1/(\gamma - 1)$
  \[ \gamma = 2 \text{ corresponds to } \alpha = 1 \]
Random Competitive Replication

\[ \gamma = \frac{(2 - \rho)}{(1 - \rho)} = 1 + \frac{1}{(1 - \rho)} \]

- Observe \( 2 < \gamma < \infty \) as \( \rho \) varies.
- For \( \rho \approx 0 \) (low innovation rate):
  \[ \gamma \approx 2 \]
- Recalls Zipf’s law: \( s_r \sim r^{-\alpha} \)
  \( (s_r = \text{size of the } r\text{th largest element}) \)
- We found \( \alpha = 1/(\gamma - 1) \)
- \( \gamma = 2 \) corresponds to \( \alpha = 1 \)
Random Competitive Replication

- We (roughly) see Zipfian exponent $[14]$ of $\alpha = 1$ for many real systems: city sizes, word distributions, ...
- Corresponds to $\rho \rightarrow 0$ (Krugman doesn’t like it) $[5]$
- But still other mechanisms are possible...
- Must look at the details to see if mechanism makes sense...
Random Competitive Replication

- We (roughly) see Zipfian exponent \(\alpha = 1\) for many real systems: city sizes, word distributions, ...
- Corresponds to \(\rho \rightarrow 0\) (Krugman doesn’t like it) \([5]\)
- But still other mechanisms are possible...
- Must look at the details to see if mechanism makes sense...
Random Competitive Replication

- We (roughly) see Zipfian exponent \( \alpha = 1 \) for many real systems: city sizes, word distributions, ...
- Corresponds to \( \rho \to 0 \) (Krugman doesn’t like it) \([5]\)
- But still other mechanisms are possible...
- Must look at the details to see if mechanism makes sense...
Random Competitive Replication

We had one other equation:

\[
\langle N_1(t + 1) - N_1(t) \rangle = \rho - (1 - \rho)1 \cdot \frac{N_1(t)}{t}
\]

- As before, set \( N_1(t) = n_1 t \) and drop expectations

\[
n_1(t + 1) - n_1 t = \rho - (1 - \rho)1 \cdot \frac{n_1 t}{t}
\]

- Rearrange:

\[
n_1 = \rho - (1 - \rho)n_1
\]

\[
n_1 + (1 - \rho)n_1 = \rho
\]

\[
n_1 = \frac{\rho}{2 - \rho}
\]
Random Competitive Replication

We had one other equation:

\[
\langle N_1(t + 1) - N_1(t) \rangle = \rho - (1 - \rho) t \cdot \frac{N_1(t)}{t}
\]

As before, set \( N_1(t) = n_1 t \) and drop expectations

\[
n_1(t + 1) - n_1 t = \rho - (1 - \rho) t \cdot \frac{n_1 t}{t}
\]

\[
n_1 = \rho - (1 - \rho)n_1
\]

Rearrange:

\[
n_1 + (1 - \rho)n_1 = \rho
\]

\[
n_1 = \frac{\rho}{2 - \rho}
\]
Random Competitive Replication

We had one other equation:

\[
\langle N_1(t+1) - N_1(t) \rangle = \rho - (1 - \rho) \frac{N_1(t)}{t}
\]

As before, set \( N_1(t) = n_1 t \) and drop expectations

\[
n_1(t+1) - n_1 t = \rho - (1 - \rho) \frac{n_1 t}{t}
\]

Rearrange:

\[
n_1 + (1 - \rho)n_1 = \rho
\]

\[
n_1 = \frac{\rho}{2 - \rho}
\]
Random Competitive Replication

We had one other equation:

\[
\langle N_1(t + 1) - N_1(t) \rangle = \rho - (1 - \rho) \frac{N_1(t)}{t}
\]

As before, set \( N_1(t) = n_1 t \) and drop expectations

\[
n_1(t + 1) - n_1 t = \rho - (1 - \rho) \frac{n_1 t}{t}
\]

Rearrange:

\[
n_1 = \rho - (1 - \rho) n_1
\]

\[
n_1 + (1 - \rho) n_1 = \rho
\]

\[
n_1 = \frac{\rho}{2 - \rho}
\]
Random Competitive Replication

We had one other equation:

\[
\langle N_1(t+1) - N_1(t) \rangle = \rho - (1 - \rho)1 \cdot \frac{N_1(t)}{t}
\]

As before, set \( N_1(t) = n_1 t \) and drop expectations

\[
n_1(t+1) - n_1 t = \rho - (1 - \rho)1 \cdot \frac{n_1 t}{t}
\]

Rearrange:

\[
n_1 = \rho - (1 - \rho)n_1
\]

\[
n_1 + (1 - \rho)n_1 = \rho
\]

\[
n_1 = \frac{\rho}{2 - \rho}
\]
Random Competitive Replication

So...

\[ N_1(t) = n_1 t = \frac{\rho t}{2 - \rho} \]

- Recall number of distinct elements = \( \rho t \).
- Fraction of distinct elements that are unique (belong to groups of size 1):

\[ \frac{N_1(t)}{\rho t} = \frac{1}{2 - \rho} \]

(also = fraction of groups of size 1)
- For \( \rho \) small, fraction of unique elements \( \sim 1/2 \)
- Roughly observed for real distributions
- \( \rho \) increases, fraction increases
- Can show fraction of groups with two elements \( \sim 1/6 \)
- Model does well at both ends of the distribution
Random Competitive Replication

So...  \[ N_1(t) = n_1 t = \frac{\rho t}{2 - \rho} \]

- Recall number of distinct elements = \( \rho t \).
- Fraction of distinct elements that are unique (belong to groups of size 1):
  \[ \frac{N_1(t)}{\rho t} = \frac{1}{2 - \rho} \]
  (also = fraction of groups of size 1)
- For \( \rho \) small, fraction of unique elements \( \sim 1/2 \)
- Roughly observed for real distributions
- \( \rho \) increases, fraction increases
- Can show fraction of groups with two elements \( \sim 1/6 \)
- Model does well at both ends of the distribution
Random Competitive Replication

So...

\[ N_1(t) = n_1 t = \frac{\rho t}{2 - \rho} \]

- Recall number of distinct elements = \( \rho t \).
- Fraction of distinct elements that are unique (belong to groups of size 1):

\[ \frac{N_1(t)}{\rho t} = \frac{1}{2 - \rho} \]

(also = fraction of groups of size 1)

- For \( \rho \) small, fraction of unique elements \( \sim 1/2 \)
- Roughly observed for real distributions
- \( \rho \) increases, fraction increases
- Can show fraction of groups with two elements \( \sim 1/6 \)
- Model does well at both ends of the distribution
Random Competitive Replication

\[ N_1(t) = n_1 t = \frac{\rho t}{2 - \rho} \]

- Recall number of distinct elements = \( \rho t \).
- Fraction of distinct elements that are unique (belong to groups of size 1):
  \[
  \frac{N_1(t)}{\rho t} = \frac{1}{2 - \rho}
  \]
  (also = fraction of groups of size 1)
- For \( \rho \) small, fraction of unique elements \( \sim \frac{1}{2} \)
- Roughly observed for real distributions
- \( \rho \) increases, fraction increases
- Can show fraction of groups with two elements \( \sim \frac{1}{6} \)
- Model does well at both ends of the distribution
Random Competitive Replication

So... \[ N_1(t) = n_1 t = \frac{\rho t}{2 - \rho} \]

- Recall number of distinct elements = \( \rho t \).
- Fraction of distinct elements that are unique (belong to groups of size 1):
  \[ \frac{N_1(t)}{\rho t} = \frac{1}{2 - \rho} \]
  (also = fraction of groups of size 1)
- For \( \rho \) small, fraction of unique elements \( \sim 1/2 \)
- Roughly observed for real distributions
  - \( \rho \) increases, fraction increases
  - Can show fraction of groups with two elements \( \sim 1/6 \)
  - Model does well at both ends of the distribution
Random Competitive Replication

So... \[ N_1(t) = n_1 t = \frac{\rho t}{2 - \rho} \]

- Recall number of distinct elements = \( \rho t \).
- Fraction of distinct elements that are unique (belong to groups of size 1):
  \[ \frac{N_1(t)}{\rho t} = \frac{1}{2 - \rho} \]
  (also = fraction of groups of size 1)
- For \( \rho \) small, fraction of unique elements \( \sim 1/2 \)
- Roughly observed for real distributions
- \( \rho \) increases, fraction increases
- Can show fraction of groups with two elements \( \sim 1/6 \)
- Model does well at both ends of the distribution
Random Competitive Replication

So... \[ N_1(t) = n_1 t = \frac{\rho t}{2 - \rho} \]

- Recall number of distinct elements = \( \rho t \).
- Fraction of distinct elements that are unique (belong to groups of size 1):
  \[ \frac{N_1(t)}{\rho t} = \frac{1}{2 - \rho} \]
  (also = fraction of groups of size 1)
- For \( \rho \) small, fraction of unique elements \( \sim 1/2 \)
- Roughly observed for real distributions
- \( \rho \) increases, fraction increases
- Can show fraction of groups with two elements \( \sim 1/6 \)
- Model does well at both ends of the distribution
Random Competitive Replication

So...

\[ N_1(t) = n_1 t = \frac{\rho t}{2 - \rho} \]

- Recall number of distinct elements \( = \rho t \).
- Fraction of distinct elements that are unique (belong to groups of size 1):

\[ \frac{N_1(t)}{\rho t} = \frac{1}{2 - \rho} \]

(also = fraction of groups of size 1)

- For \( \rho \) small, fraction of unique elements \( \sim 1/2 \)
- Roughly observed for real distributions
- \( \rho \) increases, fraction increases
- Can show fraction of groups with two elements \( \sim 1/6 \)
- Model does well at both ends of the distribution
Outline

Random Walks
  The First Return Problem
  Examples

Variable transformation
  Basics
  Holtsmark’s Distribution
  PLIPLO

Growth Mechanisms
  Random Copying
  Words, Cities, and the Web

References
Words

From Simon\cite{11}:

Estimate $\rho_{est} = \# \text{unique words}/\# \text{all words}$
Words

From Simon\cite{11}:

Estimate $\rho_{est} = \# \text{unique words}/\# \text{all words}$

For Joyce’s *Ulysses*: $\rho_{est} \approx 0.115$
Words

From Simon\cite{11}:

Estimate $\rho_{est} = \# \text{unique words}/\# \text{all words}$

For Joyce’s Ulysses: $\rho_{est} \simeq 0.115$

<table>
<thead>
<tr>
<th>$N_1$ (real)</th>
<th>$N_1$ (est)</th>
<th>$N_2$ (real)</th>
<th>$N_2$ (est)</th>
</tr>
</thead>
<tbody>
<tr>
<td>16,432</td>
<td>15,850</td>
<td>4,776</td>
<td>4,870</td>
</tr>
</tbody>
</table>
Evolution of catch phrases

- Yule’s paper (1924)\(^{[13]}\):
  “A mathematical theory of evolution, based on the conclusions of Dr J. C. Willis, F.R.S.”
- Simon’s paper (1955)\(^{[11]}\):
  “On a class of skew distribution functions” (snore)

From Simon’s introduction:
It is the purpose of this paper to analyse a class of distribution functions that appear in a wide range of empirical data—particularly data describing sociological, biological and economic phenomena.

Its appearance is so frequent, and the phenomena so diverse, that one is led to conjecture that if these phenomena have any property in common it can only be a similarity in the structure of the underlying probability mechanisms.
Evolution of catch phrases

- Yule’s paper (1924)\textsuperscript{[13]}: “A mathematical theory of evolution, based on the conclusions of Dr J. C. Willis, F.R.S.”

- Simon’s paper (1955)\textsuperscript{[11]}: “On a class of skew distribution functions” (snore)

From Simon’s introduction:
It is the purpose of this paper to analyse a class of distribution functions that appear in a wide range of empirical data—particularly data describing sociological, biological and economic phenomena.

Its appearance is so frequent, and the phenomena so diverse, that one is led to conjecture that if these phenomena have any property in common it can only be a similarity in the structure of the underlying probability mechanisms.
Evolution of catch phrases

- Yule’s paper (1924)\(^{[13]}\):
  “A mathematical theory of evolution, based on the conclusions of Dr J. C. Willis, F.R.S.”
- Simon’s paper (1955)\(^{[11]}\):
  “On a class of skew distribution functions” (snore)

From Simon’s introduction:

It is the purpose of this paper to analyse a class of distribution functions that appear in a wide range of empirical data—particularly data describing sociological, biological and economic phenomena.

Its appearance is so frequent, and the phenomena so diverse, that one is led to conjecture that if these phenomena have any property in common it can only be a similarity in the structure of the underlying probability mechanisms.
Evolution of catch phrases

- Yule’s paper (1924) \[^{[13]}\]:
  “A mathematical theory of evolution, based on the conclusions of Dr J. C. Willis, F.R.S.”
- Simon’s paper (1955) \[^{[11]}\]:
  “On a class of skew distribution functions” (snore)

From Simon’s introduction:
It is the purpose of this paper to analyse a class of distribution functions that appear in a wide range of empirical data—particularly data describing sociological, biological and economic phenomena.

Its appearance is so frequent, and the phenomena so diverse, that one is led to conjecture that if these phenomena have any property in common it can only be a similarity in the structure of the underlying probability mechanisms.
Evolution of catch phrases

- Yule’s paper (1924)\textsuperscript{[13]}: “A mathematical theory of evolution, based on the conclusions of Dr J. C. Willis, F.R.S.”
- Simon’s paper (1955)\textsuperscript{[11]}: “On a class of skew distribution functions” (snore)

From Simon’s introduction:
It is the purpose of this paper to analyse a class of distribution functions that appear in a wide range of empirical data—particularly data describing sociological, biological and economic phenomena.

Its appearance is so frequent, and the phenomena so diverse, that one is led to conjecture that if these phenomena have any property in common it can only be a similarity in the structure of the underlying probability mechanisms.
Evolution of catch phrases

- Yule’s paper (1924)\(^{[13]}\):
  “A mathematical theory of evolution, based on the conclusions of Dr J. C. Willis, F.R.S.”
- Simon’s paper (1955)\(^{[11]}\):
  “On a class of skew distribution functions” (snore)

From Simon’s introduction:
It is the purpose of this paper to analyse a class of distribution functions that appear in a wide range of empirical data—particularly data describing sociological, biological and economic phenomena.

Its appearance is so frequent, and the phenomena so diverse, that one is led to conjecture that if these phenomena have any property in common it can only be a similarity in the structure of the underlying probability mechanisms.
Evolution of catch phrases

- Yule’s paper (1924)\textsuperscript{[13]}: “A mathematical theory of evolution, based on the conclusions of Dr J. C. Willis, F.R.S.”
- Simon’s paper (1955)\textsuperscript{[11]}: “On a class of skew distribution functions” (snore)

From Simon’s introduction:

It is the purpose of this paper to analyse a class of distribution functions that appear in a wide range of empirical data—particularly data describing sociological, biological and economic phenomena.

Its appearance is so frequent, and the phenomena so diverse, that one is led to conjecture that if these phenomena have any property in common it can only be a similarity in the structure of the underlying probability mechanisms.
Evolution of catch phrases

- Yule’s paper (1924)\(^{[13]}\):
  “A mathematical theory of evolution, based on the conclusions of Dr J. C. Willis, F.R.S.”

- Simon’s paper (1955)\(^{[11]}\):
  “On a class of skew distribution functions” (snore)

From Simon’s introduction:
It is the purpose of this paper to analyse a class of distribution functions that appear in a wide range of empirical data—particularly data describing sociological, biological and economic phenomena.

Its appearance is so frequent, and the phenomena so diverse, that one is led to conjecture that if these phenomena have any property in common it can only be a similarity in the structure of the underlying probability mechanisms.
Evolution of catch phrases

More on Herbert Simon (1916–2001):

- Political scientist
  - Involved in Cognitive Psychology, Computer Science, Public Administration, Economics, Management, Sociology
  - Coined ‘bounded rationality’ and ‘satisficing’
  - Nearly 1000 publications
  - Nobel Laureate in Economics
Evolution of catch phrases

More on Herbert Simon (1916–2001):

- Political scientist
- Involved in Cognitive Psychology, Computer Science, Public Administration, Economics, Management, Sociology
- Coined ‘bounded rationality’ and ‘satisficing’
- Nearly 1000 publications
- Nobel Laureate in Economics
Evolution of catch phrases

More on Herbert Simon (1916–2001):

► Political scientist
► Involved in Cognitive Psychology, Computer Science, Public Administration, Economics, Management, Sociology
► Coined ‘bounded rationality’ and ‘satisficing’
► Nearly 1000 publications
► Nobel Laureate in Economics
Evolution of catch phrases

More on Herbert Simon (1916–2001):

- Political scientist
- Involved in Cognitive Psychology, Computer Science, Public Administration, Economics, Management, Sociology
- Coined ‘bounded rationality’ and ‘satisficing’
- Nearly 1000 publications
  - Nobel Laureate in Economics
Evolution of catch phrases

More on Herbert Simon (1916–2001):

- Political scientist
- Involved in Cognitive Psychology, Computer Science, Public Administration, Economics, Management, Sociology
- Coined ‘bounded rationality’ and ‘satisficing’
- Nearly 1000 publications
- Nobel Laureate in Economics

More on Herbert Simon (1916–2001):

- Political scientist
- Involved in Cognitive Psychology, Computer Science, Public Administration, Economics, Management, Sociology
- Coined ‘bounded rationality’ and ‘satisficing’
- Nearly 1000 publications
- Nobel Laureate in Economics
Evolution of catch phrases

More on Herbert Simon (1916–2001):

- Political scientist
- Involved in Cognitive Psychology, Computer Science, Public Administration, Economics, Management, Sociology
- Coined ‘bounded rationality’ and ‘satisficing’
- Nearly 1000 publications
- Nobel Laureate in Economics
Derek de Solla Price was the first to study network evolution with these kinds of models. Citation network of scientific papers. Price’s term: Cumulative Advantage. Idea: papers receive new citations with probability proportional to their existing # of citations. Directed network. Two (surmountable) problems: 1. New papers have no citations 2. Selection mechanism is more complicated.
Evolution of catch phrases

- Derek de Solla Price was the first to study network evolution with these kinds of models.
- Citation network of scientific papers
  - Price’s term: Cumulative Advantage
  - Idea: papers receive new citations with probability proportional to their existing # of citations
  - Directed network
  - Two (surmountable) problems:
    1. New papers have no citations
    2. Selection mechanism is more complicated
Evolution of catch phrases

- Derek de Solla Price was the first to study network evolution with these kinds of models.
- Citation network of scientific papers
- Price’s term: **Cumulative Advantage**
  - Idea: papers receive new citations with probability proportional to their existing # of citations
  - Directed network
  - Two (surmountable) problems:
    1. New papers have no citations
    2. Selection mechanism is more complicated
Evolution of catch phrases

- Derek de Solla Price was the first to study network evolution with these kinds of models.
- Citation network of scientific papers
- Price’s term: *Cumulative Advantage*
- Idea: papers receive new citations with probability proportional to their existing # of citations
  - Directed network
  - Two (surmountable) problems:
    1. New papers have no citations
    2. Selection mechanism is more complicated
Evolution of catch phrases

- Derek de Solla Price was the first to study network evolution with these kinds of models.
- Citation network of scientific papers
- Price’s term: *Cumulative Advantage*
- Idea: papers receive new citations with probability proportional to their existing # of citations
- Directed network
  - Two (surmountable) problems:
    1. New papers have no citations
    2. Selection mechanism is more complicated
Derek de Solla Price was the first to study network evolution with these kinds of models.

Citation network of scientific papers

Price’s term: **Cumulative Advantage**

Idea: papers receive new citations with probability proportional to their existing # of citations

Directed network

Two (surmountable) problems:

1. New papers have no citations
2. Selection mechanism is more complicated
Evolution of catch phrases

- Robert K. Merton: the Matthew Effect
  - Studied careers of scientists and found credit flowed disproportionately to the already famous

- Matilda effect: women’s scientific achievements are often overlooked

Robert K. Merton: the Matthew Effect

- Studied careers of scientists and found credit flowed disproportionately to the already famous

Matilda effect: women’s scientific achievements are often overlooked
Evolution of catch phrases

- Robert K. Merton: the Matthew Effect
- Studied careers of scientists and found credit flowed disproportionately to the already famous

- Matilda effect: women’s scientific achievements are often overlooked
Evolution of catch phrases

- Robert K. Merton: the Matthew Effect
  Studied careers of scientists and found credit flowed disproportionately to the already famous
  From the Gospel of Matthew: “For to every one that hath shall be given...

- Matilda effect: women’s scientific achievements are often overlooked
Evolution of catch phrases

- Robert K. Merton: the Matthew Effect
- Studied careers of scientists and found credit flowed disproportionately to the already famous

From the Gospel of Matthew:
“For to every one that hath shall be given... (Wait! There’s more....)

- Matilda effect: women’s scientific achievements are often overlooked
Evolution of catch phrases

- Robert K. Merton: the Matthew Effect
- Studied careers of scientists and found credit flowed disproportionately to the already famous

From the Gospel of Matthew:
“For to every one that hath shall be given...
(Wait! There’s more....)
but from him that hath not, that also which he seemeth to have shall be taken away.

- Matilda effect: women’s scientific achievements are often overlooked
Evolution of catch phrases

- Robert K. Merton: the Matthew Effect
- Studied careers of scientists and found credit flowed disproportionately to the already famous

From the Gospel of Matthew:
“For to every one that hath shall be given...
(Wait! There’s more....)
but from him that hath not, that also which he seemeth to have shall be taken away.
And cast the worthless servant into the outer darkness; there men will weep and gnash their teeth.”

- Matilda effect: women’s scientific achievements are often overlooked
Evolution of catch phrases

- Robert K. Merton: **the Matthew Effect**
- Studied careers of scientists and found credit flowed disproportionately to the already famous

From the Gospel of Matthew:
“For to every one that hath shall be given... (Wait! There’s more....)
but from him that hath not, that also which he seemeth to have shall be taken away. And cast the worthless servant into the outer darkness; there men will weep and gnash their teeth.”

- Matilda effect: women’s scientific achievements are often overlooked
Evolution of catch phrases

Merton was a catchphrase machine:

1. self-fulfilling prophecy
2. role model
3. unintended (or unanticipated) consequences
4. focused interview $\rightarrow$ focus group
Evolution of catch phrases

Merton was a catchphrase machine:

1. self-fulfilling prophecy
2. role model
3. unintended (or unanticipated) consequences
4. focused interview → focus group
Evolution of catch phrases

Merton was a catchphrase machine:

1. self-fulfilling prophecy
2. role model
3. unintended (or unanticipated) consequences
4. focused interview → focus group
Merton was a catchphrase machine:
1. self-fulfilling prophecy
2. role model
3. unintended (or unanticipated) consequences
4. focused interview → focus group
Evolution of catch phrases

Merton was a catchphrase machine:

1. self-fulfilling prophecy
2. role model
3. unintended (or unanticipated) consequences
4. focused interview → focus group

And just to rub it in...

Merton's son, Robert C. Merton, won the Nobel Prize for Economics in 1997.
Evolution of catch phrases

Merton was a catchphrase machine:
1. self-fulfilling prophecy
2. role model
3. unintended (or unanticipated) consequences
4. focused interview → focus group

And just to rub it in...

Merton’s son, Robert C. Merton, won the Nobel Prize for Economics in 1997.
Evolution of catch phrases

- Barabasi and Albert\textsuperscript{[1]}—thinking about the Web
- Independent reinvention of a version of Simon and Price’s theory for networks
- Another term: “Preferential Attachment”
- Considered undirected networks (not realistic but avoids 0 citation problem)
- Still have selection problem based on size (non-random)
- Solution: Randomly connect to a node (easy)
- + Randomly connect to the node’s friends (also easy)
- Scale-free networks = food on the table for physicists
Evolution of catch phrases

- Barabasi and Albert\textsuperscript{[1]}—thinking about the Web
- Independent reinvention of a version of Simon and Price’s theory for networks
  - Another term: “Preferential Attachment”
- Considered undirected networks (not realistic but avoids 0 citation problem)
- Still have selection problem based on size (non-random)
- Solution: Randomly connect to a node (easy)
  - + Randomly connect to the node’s friends (also easy)
- Scale-free networks = food on the table for physicists
Evolution of catch phrases

- Barabasi and Albert\textsuperscript{[1]}—thinking about the Web
- Independent reinvention of a version of Simon and Price’s theory for networks
- Another term: “\textit{Preferential Attachment}”
- Considered undirected networks (not realistic but avoids 0 citation problem)
- Still have selection problem based on size (non-random)
- Solution: Randomly connect to a node (\textit{easy})
- + Randomly connect to the node’s friends (\textit{also easy})
- Scale-free networks = food on the table for physicists
Evolution of catch phrases

- Barabasi and Albert\textsuperscript{[1]}—thinking about the Web
- Independent reinvention of a version of Simon and Price’s theory for networks
- Another term: “Preferential Attachment”
- Considered undirected networks (not realistic but avoids 0 citation problem)
- Still have selection problem based on size (non-random)
- Solution: Randomly connect to a node (easy)
- + Randomly connect to the node’s friends (also easy)
- Scale-free networks = food on the table for physicists

\textsuperscript{[1]} Barabasi and Albert—thinking about the Web

Independent reinvention of a version of Simon and Price’s theory for networks

Another term: “Preferential Attachment”

Considered undirected networks (not realistic but avoids 0 citation problem)

Still have selection problem based on size (non-random)

Solution: Randomly connect to a node (easy)

+ Randomly connect to the node’s friends (also easy)

Scale-free networks = food on the table for physicists
Evolution of catch phrases

- Barabasi and Albert\textsuperscript{[1]}—thinking about the Web
- Independent reinvention of a version of Simon and Price’s theory for networks
- Another term: “Preferential Attachment”
- Considered undirected networks (not realistic but avoids 0 citation problem)
- Still have selection problem based on size (non-random)
  - Solution: Randomly connect to a node (easy)
  - + Randomly connect to the node’s friends (also easy)
  - Scale-free networks = food on the table for physicists

\textsuperscript{[1]} Barabasi and Albert—thinking about the Web
Evolution of catch phrases

- Barabasi and Albert\textsuperscript{[1]}—thinking about the Web
- Independent reinvention of a version of Simon and Price’s theory for networks
- Another term: “Preferential Attachment”
- Considered undirected networks (not realistic but avoids 0 citation problem)
- Still have selection problem based on size (non-random)
- Solution: Randomly connect to a node (easy)
  - + Randomly connect to the node’s friends (also easy)
- Scale-free networks = food on the table for physicists
Evolution of catch phrases

- Barabasi and Albert\textsuperscript{[1]}—thinking about the Web
- Independent reinvention of a version of Simon and Price’s theory for networks
- Another term: “Preferential Attachment”
- Considered undirected networks (not realistic but avoids 0 citation problem)
- Still have selection problem based on size (non-random)
- Solution: Randomly connect to a node (easy)
  + Randomly connect to the node’s friends (also easy)
- Scale-free networks = food on the table for physicists
Evolution of catch phrases

- Barabasi and Albert\textsuperscript{[1]}—thinking about the Web
- Independent reinvention of a version of Simon and Price’s theory for networks
- Another term: “Preferential Attachment”
- Considered undirected networks (not realistic but avoids 0 citation problem)
- Still have selection problem based on size (non-random)
- Solution: Randomly connect to a node (easy)
  + Randomly connect to the node’s friends (also easy)
- Scale-free networks = food on the table for physicists

\textsuperscript{[1]}Barabasi and Albert—thinking about the Web
A.-L. Barabási and R. Albert. 
Emergence of scaling in random networks. 

P. S. Dodds and D. H. Rothman. 
Scaling, universality, and geomorphology. 

W. Feller. 
*An Introduction to Probability Theory and Its Applications*, volume I. 
J. T. Hack.
Studies of longitudinal stream profiles in Virginia and Maryland.

P. Krugman.
*The self-organizing economy.*

A. J. Lotka.
The frequency distribution of scientific productivity.
References III

B. B. Mandelbrot. 
An informational theory of the statistical structure of languages. 

D. J. d. S. Price. 
Networks of scientific papers. 

D. J. d. S. Price. 
A general theory of bibliometric and other cumulative advantage processes. 
A. E. Scheidegger.
The algebra of stream-order numbers.  

H. A. Simon.
On a class of skew distribution functions.  
pdf (日本語)

D. Sornette.
*Critical Phenomena in Natural Sciences*.  

G. U. Yule.
A mathematical theory of evolution, based on the conclusions of Dr J. C. Willis, F.R.S.  
G. K. Zipf.

*Human Behaviour and the Principle of Least-Effort.*
Addison-Wesley, Cambridge, MA, 1949.