

Extreme Statistics in Real-space Condensation

Satya N. Majumdar

Laboratoire de Physique Théorique et Modèles Statistiques, CNRS,
Université Paris-Sud, France

June 5, 2009

Collaborators:

M.R. Evans (Edinburgh, UK)

R.K.P. Zia (Virginia Tech, USA)

Plan:

- A brief review on **Extreme Value Statistics** of **i.i.d** random variables
⇒ three limiting distributions: **GUMBEL, FRÉCHET & WEIBULL**

Plan:

- A brief review on **Extreme Value Statistics** of **i.i.d** random variables
 - ⇒ three limiting distributions: **GUMBEL**, **FRÉCHET** & **WEIBULL**
- **Extreme** statistics for **Correlated** variables

Plan:

- A brief review on **Extreme Value Statistics** of **i.i.d** random variables
⇒ three limiting distributions: **GUMBEL, FRÉCHET & WEIBULL**
- **Extreme** statistics for **Correlated** variables
- Condensation transition in mass transport models
→ **Correlation** imposed by a **global** constraint.

Plan:

- A brief review on **Extreme Value Statistics** of **i.i.d** random variables
⇒ three limiting distributions: **GUMBEL, FRÉCHET & WEIBULL**
- **Extreme** statistics for **Correlated** variables
- Condensation transition in mass transport models
→ **Correlation** imposed by a **global** constraint.
- **Exact** distribution of the **Maximal** mass
⇒ **New universal** extreme value distributions

Plan:

- A brief review on **Extreme Value Statistics** of **i.i.d** random variables
 - ⇒ three limiting distributions: **GUMBEL, FRÉCHET & WEIBULL**
- **Extreme** statistics for **Correlated** variables
- Condensation transition in mass transport models
 - **Correlation** imposed by a **global** constraint.
- **Exact** distribution of the **Maximal** mass
 - ⇒ **New universal** extreme value distributions
- Summary and Conclusions

Law of Averages: Central Limit Theorem

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables

—each drawn from $p(x) \rightarrow$ parent distribution

Key property: $P(x_1, x_2, \dots, x_N) = p(x_1)p(x_2) \dots p(x_N)$

Law of Averages: Central Limit Theorem

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables

—each drawn from $p(x) \rightarrow$ parent distribution

Key property: $P(x_1, x_2, \dots, x_N) = p(x_1)p(x_2) \dots p(x_N)$

- Average: $\bar{x} = (x_1 + x_2 + \dots + x_N)/N$

Law of Averages: Central Limit Theorem

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables

—each drawn from $p(x) \rightarrow$ parent distribution

Key property: $P(x_1, x_2, \dots, x_N) = p(x_1)p(x_2) \dots p(x_N)$

- Average: $\bar{x} = (x_1 + x_2 + \dots + x_N)/N$
- Probability distribution of \bar{x} ?

Law of Averages: Central Limit Theorem

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables

—each drawn from $p(x) \rightarrow$ parent distribution

Key property: $P(x_1, x_2, \dots, x_N) = p(x_1)p(x_2) \dots p(x_N)$

- Average: $\bar{x} = (x_1 + x_2 + \dots + x_N)/N$
- Probability distribution of \bar{x} ?
- Central Limit Theorem \implies for large N :
if $\mu = \int xp(x)dx$ and $\sigma^2 = \int x^2p(x)dx - \mu^2 \rightarrow$ finite

Law of Averages: Central Limit Theorem

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables

—each drawn from $p(x) \rightarrow$ parent distribution

Key property: $P(x_1, x_2, \dots, x_N) = p(x_1)p(x_2) \dots p(x_N)$

- Average: $\bar{x} = (x_1 + x_2 + \dots + x_N)/N$

- Probability distribution of \bar{x} ?

- Central Limit Theorem \implies for large N :

if $\mu = \int xp(x)dx$ and $\sigma^2 = \int x^2p(x)dx - \mu^2 \rightarrow$ finite

$\text{Prob}[\bar{x} \leq x] \rightarrow G \left[\frac{(x-\mu)}{\sigma/\sqrt{N}} \right]$ where $G[z] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-u^2/2} du$

Law of Averages: Central Limit Theorem

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables

—each drawn from $p(x) \rightarrow$ parent distribution

Key property: $P(x_1, x_2, \dots, x_N) = p(x_1)p(x_2) \dots p(x_N)$

- Average: $\bar{x} = (x_1 + x_2 + \dots + x_N)/N$

- Probability distribution of \bar{x} ?

- Central Limit Theorem \implies for large N :

if $\mu = \int xp(x)dx$ and $\sigma^2 = \int x^2p(x)dx - \mu^2 \rightarrow$ finite

$\text{Prob}[\bar{x} \leq x] \rightarrow G \left[\frac{(x-\mu)}{\sigma/\sqrt{N}} \right]$ where $G[z] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-u^2/2} du$

Prob. density: $G'(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2} \implies$ GAUSSIAN

Law of Averages: Central Limit Theorem

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables

—each drawn from $p(x) \rightarrow$ parent distribution

Key property: $P(x_1, x_2, \dots, x_N) = p(x_1)p(x_2) \dots p(x_N)$

- Average: $\bar{x} = (x_1 + x_2 + \dots + x_N)/N$

- Probability distribution of \bar{x} ?

- Central Limit Theorem \implies for large N :

if $\mu = \int xp(x)dx$ and $\sigma^2 = \int x^2p(x)dx - \mu^2 \rightarrow$ finite

$\text{Prob}[\bar{x} \leq x] \rightarrow G \left[\frac{(x-\mu)}{\sigma/\sqrt{N}} \right]$ where $G[z] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-u^2/2} du$

Prob. density: $G'(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2} \implies$ GAUSSIAN

\implies LAW OF AVERAGES

Law of Averages: Central Limit Theorem

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables

—each drawn from $p(x) \rightarrow$ parent distribution

Key property: $P(x_1, x_2, \dots, x_N) = p(x_1)p(x_2) \dots p(x_N)$

- Average: $\bar{x} = (x_1 + x_2 + \dots + x_N)/N$

- Probability distribution of \bar{x} ?

- Central Limit Theorem \implies for large N :

if $\mu = \int xp(x)dx$ and $\sigma^2 = \int x^2p(x)dx - \mu^2 \rightarrow$ finite

$\text{Prob}[\bar{x} \leq x] \rightarrow G \left[\frac{(x-\mu)}{\sigma/\sqrt{N}} \right]$ where $G[z] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-u^2/2} du$

Prob. density: $G'(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2} \implies$ GAUSSIAN

\implies LAW OF AVERAGES

- If $p(x) \sim x^{-\gamma}$ ($0 < \gamma < 3$): $\bar{x} \implies$ LÉVY laws

Extreme Value Statistics of i.i.d Random Variables

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables
- each drawn from $p(x) \rightarrow P(x_1, x_2, \dots, x_N) = \prod_{i=1}^N p(x_i)$

Extreme Value Statistics of i.i.d Random Variables

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables
- each drawn from $p(x) \rightarrow P(x_1, x_2, \dots, x_N) = \prod_{i=1}^N p(x_i)$
- Maximum: $x_{\max} = \max(x_1, x_2, \dots, x_N)$

Extreme Value Statistics of i.i.d Random Variables

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables
- each drawn from $p(x) \rightarrow P(x_1, x_2, \dots, x_N) = \prod_{i=1}^N p(x_i)$
- Maximum: $x_{\max} = \max(x_1, x_2, \dots, x_N)$
- $Q_N(x) = \text{Prob}[x_{\max} \leq x] = \text{Prob}[x_1 \leq x, x_2 \leq x, \dots, x_N \leq x]$

Extreme Value Statistics of i.i.d Random Variables

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables
—each drawn from $p(x) \rightarrow P(x_1, x_2, \dots, x_N) = \prod_{i=1}^N p(x_i)$
- Maximum: $x_{\max} = \max(x_1, x_2, \dots, x_N)$
- $Q_N(x) = \text{Prob}[x_{\max} \leq x] = \text{Prob}[x_1 \leq x, x_2 \leq x, \dots, x_N \leq x]$
- Independence $\implies Q_N(x) = \left[\int_{-\infty}^x p(x') dx' \right]^N = \left[1 - \int_x^{\infty} p(x') dx' \right]^N$

Extreme Value Statistics of i.i.d Random Variables

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables
—each drawn from $p(x) \rightarrow P(x_1, x_2, \dots, x_N) = \prod_{i=1}^N p(x_i)$
- Maximum: $x_{\max} = \max(x_1, x_2, \dots, x_N)$
- $Q_N(x) = \text{Prob}[x_{\max} \leq x] = \text{Prob}[x_1 \leq x, x_2 \leq x, \dots, x_N \leq x]$
- Independence $\implies Q_N(x) = \left[\int_{-\infty}^x p(x') dx' \right]^N = \left[1 - \int_x^{\infty} p(x') dx' \right]^N$
- Scaling Limit: N large, x large: $Q_N(x) \rightarrow F[(x - a_N)/b_N]$

Extreme Value Statistics of i.i.d Random Variables

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables
- each drawn from $p(x) \rightarrow P(x_1, x_2, \dots, x_N) = \prod_{i=1}^N p(x_i)$
- Maximum: $x_{\max} = \max(x_1, x_2, \dots, x_N)$
- $Q_N(x) = \text{Prob}[x_{\max} \leq x] = \text{Prob}[x_1 \leq x, x_2 \leq x, \dots, x_N \leq x]$
- Independence $\implies Q_N(x) = \left[\int_{-\infty}^x p(x') dx' \right]^N = \left[1 - \int_x^{\infty} p(x') dx' \right]^N$
- Scaling Limit: N large, x large: $Q_N(x) \rightarrow F[(x - a_N)/b_N]$
 $a_N, b_N \rightarrow$ Scale factors dependent on $p(x)$; $F(z) \rightarrow$ Scaling function

Extreme Value Statistics of i.i.d Random Variables

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables
- each drawn from $p(x) \rightarrow P(x_1, x_2, \dots, x_N) = \prod_{i=1}^N p(x_i)$
- Maximum: $x_{\max} = \max(x_1, x_2, \dots, x_N)$
- $Q_N(x) = \text{Prob}[x_{\max} \leq x] = \text{Prob}[x_1 \leq x, x_2 \leq x, \dots, x_N \leq x]$
- Independence $\implies Q_N(x) = \left[\int_{-\infty}^x p(x') dx' \right]^N = \left[1 - \int_x^{\infty} p(x') dx' \right]^N$
- Scaling Limit: N large, x large: $Q_N(x) \rightarrow F[(x - a_N)/b_N]$
 $a_N, b_N \rightarrow$ Scale factors dependent on $p(x)$; $F(z) \rightarrow$ Scaling function
- Example: $p(x) = e^{-x}$ for $(x \geq 0)$

Extreme Value Statistics of i.i.d Random Variables

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables
- each drawn from $p(x) \rightarrow P(x_1, x_2, \dots, x_N) = \prod_{i=1}^N p(x_i)$
- Maximum: $x_{\max} = \max(x_1, x_2, \dots, x_N)$
- $Q_N(x) = \text{Prob}[x_{\max} \leq x] = \text{Prob}[x_1 \leq x, x_2 \leq x, \dots, x_N \leq x]$
- Independence $\implies Q_N(x) = \left[\int_{-\infty}^x p(x') dx' \right]^N = \left[1 - \int_x^{\infty} p(x') dx' \right]^N$
- Scaling Limit: N large, x large: $Q_N(x) \rightarrow F[(x - a_N)/b_N]$
 $a_N, b_N \rightarrow$ Scale factors dependent on $p(x)$; $F(z) \rightarrow$ Scaling function
- Example: $p(x) = e^{-x}$ for $(x \geq 0)$
 $Q_N(x) = [1 - e^{-x}]^N$

Extreme Value Statistics of i.i.d Random Variables

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables
- each drawn from $p(x) \rightarrow P(x_1, x_2, \dots, x_N) = \prod_{i=1}^N p(x_i)$
- Maximum: $x_{\max} = \max(x_1, x_2, \dots, x_N)$
- $Q_N(x) = \text{Prob}[x_{\max} \leq x] = \text{Prob}[x_1 \leq x, x_2 \leq x, \dots, x_N \leq x]$
- Independence $\implies Q_N(x) = \left[\int_{-\infty}^x p(x') dx' \right]^N = \left[1 - \int_x^{\infty} p(x') dx' \right]^N$
- Scaling Limit: N large, x large: $Q_N(x) \rightarrow F[(x - a_N)/b_N]$
 $a_N, b_N \rightarrow$ Scale factors dependent on $p(x)$; $F(z) \rightarrow$ Scaling function
- Example: $p(x) = e^{-x}$ for $(x \geq 0)$
 $Q_N(x) = [1 - e^{-x}]^N \simeq e^{-N e^{-x}}$

Extreme Value Statistics of i.i.d Random Variables

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables
- each drawn from $p(x) \rightarrow P(x_1, x_2, \dots, x_N) = \prod_{i=1}^N p(x_i)$
- Maximum: $x_{\max} = \max(x_1, x_2, \dots, x_N)$
- $Q_N(x) = \text{Prob}[x_{\max} \leq x] = \text{Prob}[x_1 \leq x, x_2 \leq x, \dots, x_N \leq x]$
- Independence $\implies Q_N(x) = \left[\int_{-\infty}^x p(x') dx' \right]^N = \left[1 - \int_x^{\infty} p(x') dx' \right]^N$
- Scaling Limit: N large, x large: $Q_N(x) \rightarrow F[(x - a_N)/b_N]$
 $a_N, b_N \rightarrow$ Scale factors dependent on $p(x)$; $F(z) \rightarrow$ Scaling function
- Example: $p(x) = e^{-x}$ for $(x \geq 0)$

$$Q_N(x) = [1 - e^{-x}]^N \simeq e^{-N e^{-x}} = e^{-e^{-(x - \ln N)}}$$

Extreme Value Statistics of i.i.d Random Variables

- $\{x_1, x_2, \dots, x_N\} \implies$ set of N i.i.d random variables
- each drawn from $p(x) \rightarrow P(x_1, x_2, \dots, x_N) = \prod_{i=1}^N p(x_i)$
- Maximum: $x_{\max} = \max(x_1, x_2, \dots, x_N)$
- $Q_N(x) = \text{Prob}[x_{\max} \leq x] = \text{Prob}[x_1 \leq x, x_2 \leq x, \dots, x_N \leq x]$
- Independence $\implies Q_N(x) = \left[\int_{-\infty}^x p(x') dx' \right]^N = \left[1 - \int_x^{\infty} p(x') dx' \right]^N$
- Scaling Limit: N large, x large: $Q_N(x) \rightarrow F[(x - a_N)/b_N]$
 $a_N, b_N \rightarrow$ Scale factors dependent on $p(x)$; $F(z) \rightarrow$ Scaling function
- Example: $p(x) = e^{-x}$ for $(x \geq 0)$
 $Q_N(x) = [1 - e^{-x}]^N \simeq e^{-N e^{-x}} = e^{-e^{-(x - \ln N)}}$
 $\implies a_N = \ln N, b_N = 1$ and $F(z) = e^{-e^{-z}} \rightarrow$ GUMBEL

Three Universal Extreme Value Distributions

Scale factors a_N and $b_N \implies$ **Non-universal** (depends on full $p(x)$)

Three Universal Extreme Value Distributions

Scale factors a_N and $b_N \implies$ **Non-universal** (depends on full $p(x)$)

But only **3** possible varieties of scaling functions $F(z)$ (depending **only** on the **tails** of $p(x)$)

\implies **LAW OF EXTREMES**

Three Universal Extreme Value Distributions

Scale factors a_N and $b_N \implies$ **Non-universal** (depends on full $p(x)$)

But only **3** possible varieties of scaling functions $F(z)$ (depending **only** on the **tails** of $p(x)$)

\implies **LAW OF EXTREMES**

[Fréchet (1927), Fisher and Tippett (1928), Gnedenko (1943), Gumbel (1958)...]

Three Universal Extreme Value Distributions

Scale factors a_N and $b_N \implies$ **Non-universal** (depends on full $p(x)$)

But only **3** possible varieties of scaling functions $F(z)$ (depending **only** on the **tails** of $p(x)$)

\implies **LAW OF EXTREMES**

[Fréchet (1927), Fisher and Tippett (1928), Gnedenko (1943), Gumbel (1958)...]

Several applications \implies Climate, Finance, Oceanography, Disordered Systems (Random Energy Model of Derrida),.....

Three types of Scaling Functions:

Type I (GUMBEL): If $p(x)$ is unbounded with faster than power law tail (e.g., exponential)

$$F_I(z) = \exp[-e^{-z}]$$

Three types of Scaling Functions:

Type I (GUMBEL): If $p(x)$ is unbounded with faster than power law tail (e.g., exponential)

$$F_I(z) = \exp[-e^{-z}]$$

Type II (FRÉCHET): If $p(x)$ has power law tails: $p(x) \sim x^{-(\gamma+1)}$

$$F_{II}(z) = \begin{cases} 0 & z \leq 0 \\ \exp[-z^{-\gamma}] & z \geq 0 \end{cases}$$

Three types of Scaling Functions:

Type I (GUMBEL): If $p(x)$ is unbounded with faster than power law tail (e.g., exponential)

$$F_I(z) = \exp[-e^{-z}]$$

Type II (FRÉCHET): If $p(x)$ has power law tails: $p(x) \sim x^{-(\gamma+1)}$

$$F_{II}(z) = \begin{cases} 0 & z \leq 0 \\ \exp[-z^{-\gamma}] & z \geq 0 \end{cases}$$

Type III (WEIBULL): If $p(x)$ is bounded: $p(x) \sim (1-x)^{(\gamma-1)}$

$$F_{III}(z) = \begin{cases} \exp[-|z|^\gamma] & z \leq 0 \\ 1 & z \geq 0 \end{cases}$$

Three types of Scaling Functions:

Type I (GUMBEL): If $p(x)$ is unbounded with faster than power law tail (e.g., exponential)

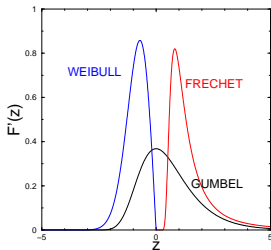
$$F_I(z) = \exp[-e^{-z}]$$

Type II (FRÉCHET): If $p(x)$ has power law tails: $p(x) \sim x^{-(\gamma+1)}$

$$F_{II}(z) = \begin{cases} 0 & z \leq 0 \\ \exp[-z^{-\gamma}] & z \geq 0 \end{cases}$$

Type III (WEIBULL): If $p(x)$ is bounded: $p(x) \sim (1-x)^{(\gamma-1)}$

$$F_{III}(z) = \begin{cases} \exp[-|z|^\gamma] & z \leq 0 \\ 1 & z \geq 0 \end{cases}$$



Maximal Statistics in Weakly Correlated Systems:

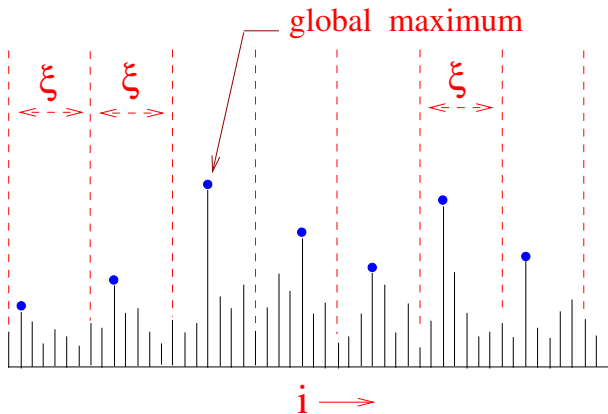
Weakly correlated variables $\{x_1, x_2, \dots, x_N\}$

Maximal Statistics in Weakly Correlated Systems:

Weakly correlated variables $\{x_1, x_2, \dots, x_N\} \rightarrow$ finite correlation length ξ

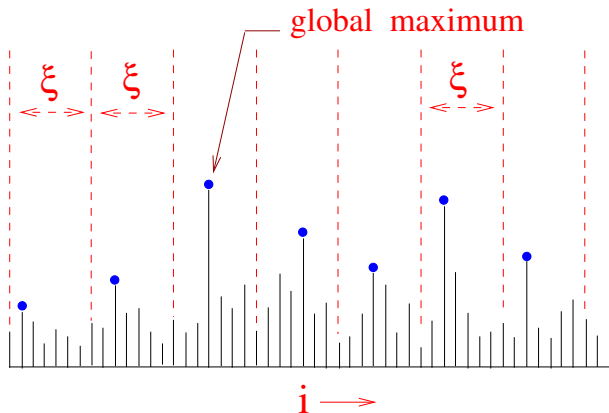
Maximal Statistics in Weakly Correlated Systems:

Weakly correlated variables $\{x_1, x_2, \dots, x_N\} \rightarrow$ finite correlation length ξ



Maximal Statistics in Weakly Correlated Systems:

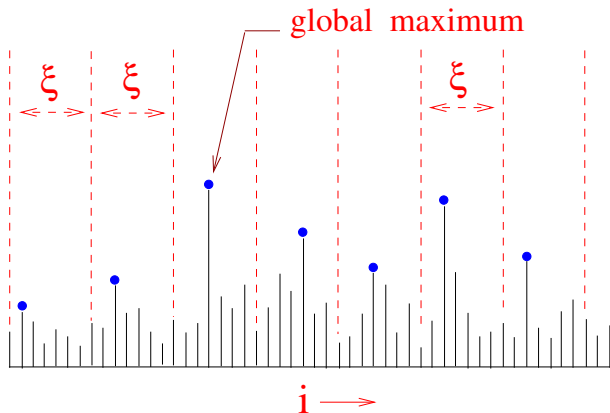
Weakly correlated variables $\{x_1, x_2, \dots, x_N\} \rightarrow$ finite correlation length ξ



- $z_i \rightarrow$ maximum in the i -th block \rightarrow uncorrelated

Maximal Statistics in Weakly Correlated Systems:

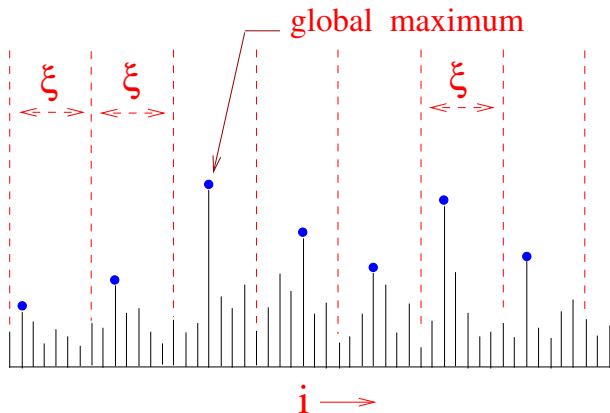
Weakly correlated variables $\{x_1, x_2, \dots, x_N\} \rightarrow$ finite correlation length ξ



- $z_i \rightarrow$ maximum in the i -th block \rightarrow uncorrelated
- Global maximum: $x_{\max} = \max(z_1, z_2, \dots)$

Maximal Statistics in Weakly Correlated Systems:

Weakly correlated variables $\{x_1, x_2, \dots, x_N\} \rightarrow$ finite correlation length ξ



- $z_i \rightarrow$ maximum in the i -th block \rightarrow uncorrelated
- Global maximum: $x_{\max} = \max(z_1, z_2, \dots)$
 \implies Gumbel, Fréchet, or Weibull

Maximal Statistics in Strongly Correlated Systems:

For **strongly** correlated $\{x_1, x_2, \dots, x_N\}$: maximal statistics \rightarrow **nontrivial**
 \implies **few** exact results

Maximal Statistics in Strongly Correlated Systems:

For **strongly** correlated $\{x_1, x_2, \dots, x_N\}$: maximal statistics \rightarrow **nontrivial**

\implies **few** exact results

- **Random walk:** $x_n = x_{n-1} + \eta_n$ where η_n 's are i.i.d $\rightarrow f(\eta)$

exact distribution of maximum x_{\max} \rightarrow **Pollaczek-Spitzer** formula
(1952)

Maximal Statistics in Strongly Correlated Systems:

For **strongly** correlated $\{x_1, x_2, \dots, x_N\}$: maximal statistics \rightarrow **nontrivial**

\implies **few** exact results

- **Random walk**: $x_n = x_{n-1} + \eta_n$ where η_n 's are i.i.d $\rightarrow f(\eta)$

exact distribution of maximum x_{\max} \rightarrow Pollaczek-Spitzer formula (1952)

- **Random matrix**: largest eigenvalue \rightarrow Tracy-Widom (1994).

applications: **directed polymer**, **growth models**, **sequence matching**...

Maximal Statistics in Strongly Correlated Systems:

For **strongly** correlated $\{x_1, x_2, \dots, x_N\}$: maximal statistics \rightarrow **nontrivial**
 \implies **few** exact results

- **Random walk:** $x_n = x_{n-1} + \eta_n$ where η_n 's are i.i.d $\rightarrow f(\eta)$
exact distribution of maximum x_{\max} \rightarrow Pollaczek-Spitzer formula (1952)
- **Random matrix:** largest eigenvalue \rightarrow Tracy-Widom (1994).
applications: directed polymer, growth models, sequence matching...
- **Airy-distribution function:** maximal relative height in fluctuating interfaces (S.M. & Comtet, 2004, Gyorgi et. al., 2006).

Maximal Statistics in Strongly Correlated Systems:

For **strongly** correlated $\{x_1, x_2, \dots, x_N\}$: maximal statistics \rightarrow **nontrivial**
 \implies **few** exact results

- **Random walk:** $x_n = x_{n-1} + \eta_n$ where η_n 's are i.i.d $\rightarrow f(\eta)$
exact distribution of maximum x_{\max} \rightarrow Pollaczek-Spitzer formula (1952)
- **Random matrix:** largest eigenvalue \rightarrow Tracy-Widom (1994).
applications: directed polymer, growth models, sequence matching...
- **Airy-distribution function:** maximal relative height in fluctuating interfaces (S.M. & Comtet, 2004, Gyorgi et. al., 2006).
- **logarithmically correlated Gaussian variables:** (Carpentier & Le Doussal 2001, Fyodorov-Bouchaud 2008)

Maximal Statistics in Strongly Correlated Systems:

For **strongly** correlated $\{x_1, x_2, \dots, x_N\}$: maximal statistics \rightarrow **nontrivial**
 \implies **few** exact results

- **Random walk**: $x_n = x_{n-1} + \eta_n$ where η_n 's are i.i.d $\rightarrow f(\eta)$
exact distribution of maximum x_{\max} \rightarrow Pollaczek-Spitzer formula (1952)
- **Random matrix**: largest eigenvalue \rightarrow Tracy-Widom (1994).
applications: directed polymer, growth models, sequence matching...
- **Airy-distribution function**: maximal relative height in fluctuating interfaces (S.M. & Comtet, 2004, Gyorgi et. al., 2006).
- **logarithmically correlated Gaussian variables**: (Carpentier & Le Doussal 2001, Fyodorov-Bouchaud 2008)
- **hierarchically correlated variables**: directed polymer on a tree (Derrida & Spohn, 87)
 \rightarrow distribution of the minimal energy (Dean & S.M, 2001).

Globally Constrained System: Condensation

Variables $\{x_1, x_2, \dots, x_N\}$ \rightarrow are i.i.d but only upto a **global constraint**

$$P(x_1, x_2, \dots, x_N) = \frac{1}{Z_N(M)} f(x_1)f(x_2)\dots f(x_N) \delta\left(\sum x_i - M\right)$$

Globally Constrained System: Condensation

Variables $\{x_1, x_2, \dots, x_N\}$ \rightarrow are i.i.d but only upto a **global constraint**

$$P(x_1, x_2, \dots, x_N) = \frac{1}{Z_N(M)} f(x_1)f(x_2)\dots f(x_N) \delta\left(\sum x_i - M\right)$$

\Rightarrow **Correlations** imposed only via the **global constraint**

Globally Constrained System: Condensation

Variables $\{x_1, x_2, \dots, x_N\}$ \rightarrow are i.i.d but only upto a **global constraint**

$$P(x_1, x_2, \dots, x_N) = \frac{1}{Z_N(M)} f(x_1)f(x_2)\dots f(x_N) \delta\left(\sum x_i - M\right)$$

\Rightarrow **Correlations** imposed only via the **global constraint**

- **Question:** How is the maximum $x_{\max} = \max(x_1, x_2, \dots, x_N)$ distributed for a given M ?

Globally Constrained System: Condensation

Variables $\{x_1, x_2, \dots, x_N\}$ \rightarrow are i.i.d but only upto a **global constraint**

$$P(x_1, x_2, \dots, x_N) = \frac{1}{Z_N(M)} f(x_1)f(x_2)\dots f(x_N) \delta\left(\sum x_i - M\right)$$

\Rightarrow **Correlations** imposed only via the **global constraint**

- **Question:** How is the maximum $x_{\max} = \max(x_1, x_2, \dots, x_N)$ distributed for a given M ?
- The conserved quantity $M \rightarrow$ controls the degree of correlations

Globally Constrained System: Condensation

Variables $\{x_1, x_2, \dots, x_N\}$ \rightarrow are i.i.d but only upto a **global constraint**

$$P(x_1, x_2, \dots, x_N) = \frac{1}{Z_N(M)} f(x_1)f(x_2)\dots f(x_N) \delta\left(\sum x_i - M\right)$$

\Rightarrow **Correlations** imposed only via the **global constraint**

- **Question:** How is the maximum $x_{\max} = \max(x_1, x_2, \dots, x_N)$ distributed for a given M ?
- The conserved quantity $M \rightarrow$ controls the degree of correlations
- For a class of $f(x)$: there is a **critical** value M_c

$$M < M_c \Rightarrow \text{Gumbel}$$

$$M > M_c \Rightarrow \text{new universal distributions}$$

Real-space Condensation in Mass Transport Processes

- Transport of a scalar from site to site \rightarrow mass/particles/energy

Real-space Condensation in Mass Transport Processes

- Transport of a scalar from site to site \rightarrow mass/particles/energy
- Local transport rules \rightarrow (i) homogeneous (translational invariance)
(ii) violate detailed balance
(ii) conserve total scalar M (mass)

Real-space Condensation in Mass Transport Processes

- Transport of a scalar from site to site \rightarrow mass/particles/energy
 - Local transport rules \rightarrow (i) homogeneous (translational invariance)
 - (ii) violate detailed balance
 - (ii) conserve total scalar M (mass)
- \Rightarrow Nonequilibrium Steady State at long times

Real-space Condensation in Mass Transport Processes

- Transport of a scalar from site to site \rightarrow mass/particles/energy
- Local transport rules \rightarrow (i) homogeneous (translational invariance)
(ii) violate detailed balance
(ii) conserve total scalar M (mass)
 \implies Nonequilibrium Steady State at long times
- Steady-state Joint distribution of masses $\{m_1, m_2, \dots, m_N\}$ at N different sites

Given M :

$$P(m_1, m_2, \dots, m_N) = ?$$

Real-space Condensation in Mass Transport Processes

- Transport of a scalar from site to site \rightarrow mass/particles/energy
- Local transport rules \rightarrow (i) homogeneous (translational invariance)
(ii) violate detailed balance
(ii) conserve total scalar M (mass)

\implies Nonequilibrium Steady State at long times

- Steady-state Joint distribution of masses $\{m_1, m_2, \dots, m_N\}$ at N different sites

Given M :

$$P(m_1, m_2, \dots, m_N) = ?$$

- Under certain conditions the dynamics \implies Condensation in real space

Real-space Condensation in Mass Transport Processes

- Transport of a scalar from site to site \rightarrow mass/particles/energy
- Local transport rules \rightarrow (i) homogeneous (translational invariance)
(ii) violate detailed balance
(ii) conserve total scalar M (mass)

\implies Nonequilibrium Steady State at long times

- Steady-state Joint distribution of masses $\{m_1, m_2, \dots, m_N\}$ at N different sites

Given M :

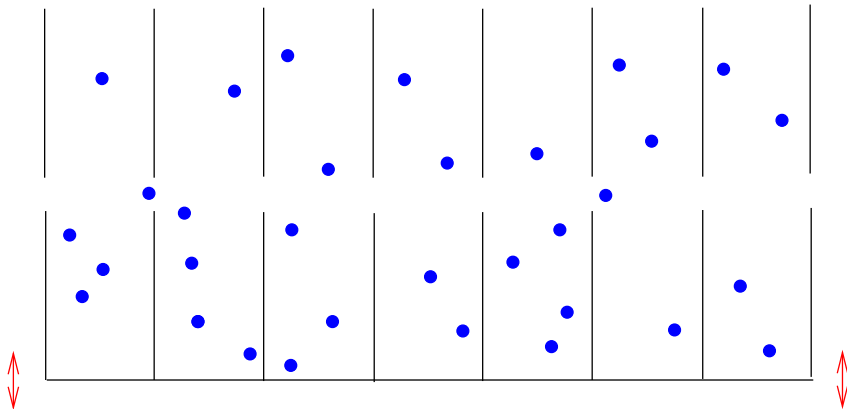
$$P(m_1, m_2, \dots, m_N) = ?$$

- Under certain conditions the dynamics \implies Condensation in real space
Macroscopic amount of the scalar (mass) condenses onto a single site in space

\implies Spontaneous Symmetry Breaking

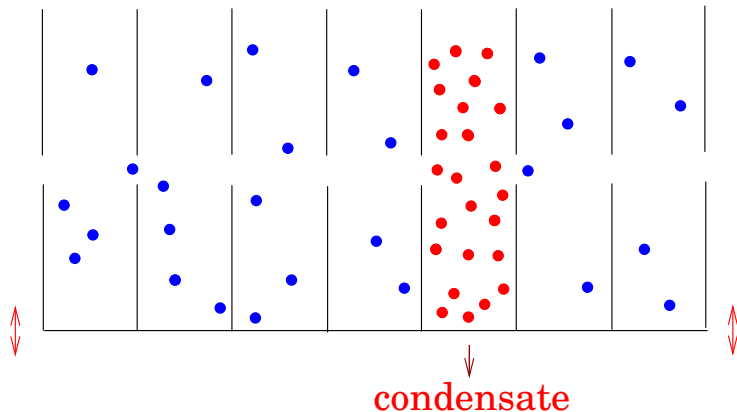
Shaken Granular System

Shaken granular system: (van der Meer et. al., 2007)



Condensation in Shaken Granular System

Shaken granular system: (van der Meer et. al., 2007)



Physical Systems with Real-space Condensation:

- Traffic and Granular flow (O'Loan, Evans, Cates, '98)
- Cluster Aggregation and Fragmentation (S.M, Krishnamurthy, Barma, '98)
- Granular clustering (van der Meer et. al., 2000)
- Phase separation in driven systems (Kafri et. al., 2002).
- Socio-economic contexts: company formation, city formation, wealth condensation etc. (Burda et. al., 2002)
- Networks (Dorogovstev & Mendes, 2003,....)
- ...

A Prototype Model: Zero Range Process

Zero Range Process (Spitzer, '70)

A Prototype Model: Zero Range Process

Zero Range Process (Spitzer, '70)

Recent reviews: (Evans & Hanney, 2004, Godrèche, 2006)

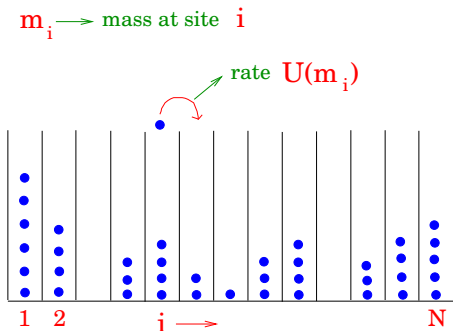
(Barma, Groskinsky, Gupta, Harris, Kafri, Levine, Luck, Mukamel, Schütz, Spohn,...)

A Prototype Model: Zero Range Process

Zero Range Process (Spitzer, '70)

Recent reviews: (Evans & Hanney, 2004, Godrèche, 2006)

(Barma, Groskinsky, Gupta, Harris, Kafri, Levine, Luck, Mukamel, Schütz, Spohn,...)

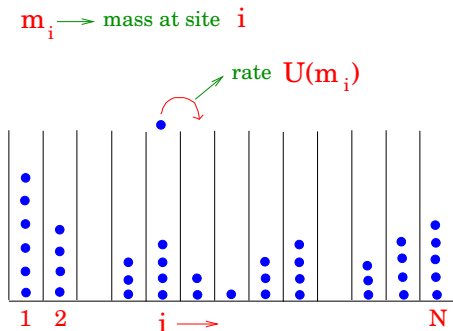


A Prototype Model: Zero Range Process

Zero Range Process (Spitzer, '70)

Recent reviews: (Evans & Hanney, 2004, Godrèche, 2006)

(Barma, Groskinsky, Gupta, Harris, Kafri, Levine, Luck, Mukamel, Schütz, Spohn,...)



Dynamics: in time dt , each site i with mass $m_i > 0$

(i) transfers a single unit of mass to $i + 1$ with prob. $U(m_i) dt$

(ii) does nothing with prob. $1 - U(m_i) dt$

Nonequilibrium Steady State

- At long times \implies nonequilibrium steady state

Nonequilibrium Steady State

- At long times \implies nonequilibrium steady state
- Joint distribution of masses at N sites become time-independent

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

Nonequilibrium Steady State

- At long times \implies nonequilibrium steady state
- Joint distribution of masses at N sites become time-independent

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

\implies Product Measure

Nonequilibrium Steady State

- At long times \implies nonequilibrium steady state
- Joint distribution of masses at N sites become time-independent

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

\implies Product Measure

where

$$f(m) = \prod_{k=1}^N \frac{1}{U(k)} \quad \text{if } m > 1$$
$$= 1 \quad \text{if } m = 0$$

Nonequilibrium Steady State

- At long times \implies nonequilibrium steady state
- Joint distribution of masses at N sites become time-independent

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

\implies Product Measure

where

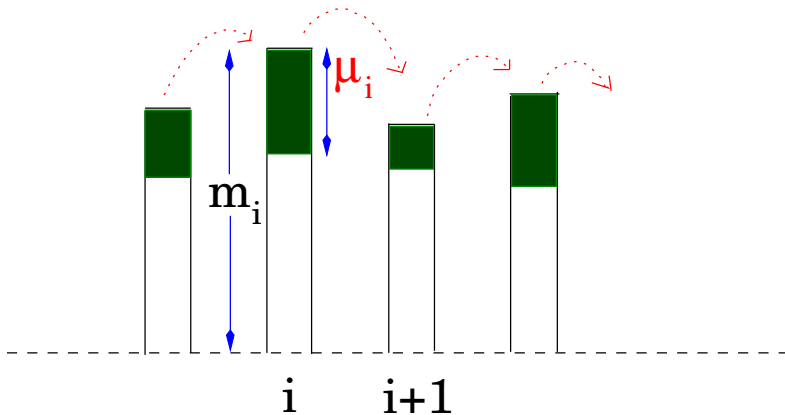
$$f(m) = \prod_{k=1}^N \frac{1}{U(k)} \quad \text{if } m > 1$$
$$= 1 \quad \text{if } m = 0$$

By choosing the transfer rate $U(m)$

\implies a class of $f(m)$

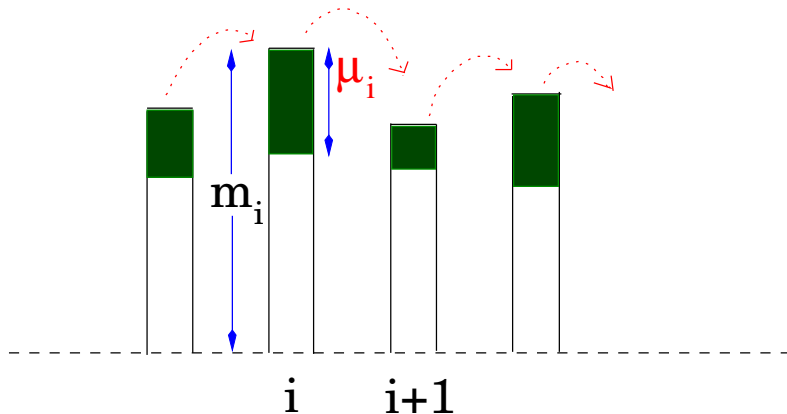
Generalized Mass Transport Model

Generalized mass transport model (Evans, S.M. & Zia, 2004)



Generalized Mass Transport Model

Generalized mass transport model (Evans, S.M. & Zia, 2004)



Dynamics: in time dt , each site i with mass $m_i > 0$

(i) transfers mass $0 \leq \mu_i \leq m_i$ to $i+1$ with prob. $\alpha(\mu_i|m_i) dt$

(ii) does nothing with prob. $1 - dt \int_0^{m_i} \alpha(\mu|m_i) d\mu$

Special Cases:

Different choices of the kernel $\alpha(\mu|m) \implies$ various models

$m \rightarrow$ current mass and $\mu \rightarrow$ mass to be transferred to right neighbour

Special Cases:

Different choices of the kernel $\alpha(\mu|m) \implies$ various models

$m \rightarrow$ current mass and $\mu \rightarrow$ mass to be transferred to right neighbour

- If $\alpha(\mu|m) = \delta(\mu - 1) U(m) \implies$ Zero Range process

Special Cases:

Different choices of the kernel $\alpha(\mu|m) \implies$ various models

$m \rightarrow$ current mass and $\mu \rightarrow$ mass to be transferred to right neighbour

• If $\alpha(\mu|m) = \delta(\mu - 1) U(m) \implies$ Zero Range process

• If $\alpha(\mu|m) = w \delta(\mu - 1) + \delta(\mu - m) \implies$ Chipping Model

(S.M, Krishnamurthy, Barma, 1998)

Special Cases:

Different choices of the kernel $\alpha(\mu|m) \implies$ various models

$m \rightarrow$ current mass and $\mu \rightarrow$ mass to be transferred to right neighbour

- If $\alpha(\mu|m) = \delta(\mu - 1) U(m) \implies$ Zero Range process
- If $\alpha(\mu|m) = w \delta(\mu - 1) + \delta(\mu - m) \implies$ Chipping Model
(S.M, Krishnamurthy, Barma, 1998)
- If $\alpha(\mu|m) = \frac{1}{m} \implies$ Asymmetric Random Average process
(Krug & Garcia, Rajesh & S.M, 2000)

Special Cases:

Different choices of the kernel $\alpha(\mu|m) \implies$ various models

$m \rightarrow$ current mass and $\mu \rightarrow$ mass to be transferred to right neighbour

- If $\alpha(\mu|m) = \delta(\mu - 1) U(m) \implies$ Zero Range process
- If $\alpha(\mu|m) = w \delta(\mu - 1) + \delta(\mu - m) \implies$ Chipping Model
(S.M, Krishnamurthy, Barma, 1998)
- If $\alpha(\mu|m) = \frac{1}{m} \implies$ Asymmetric Random Average process
(Krug & Garcia, Rajesh & S.M, 2000)

Question: Given $\alpha(\mu|m)$: what is the steady state?

Special Cases:

Different choices of the kernel $\alpha(\mu|m) \implies$ various models

$m \rightarrow$ current mass and $\mu \rightarrow$ mass to be transferred to right neighbour

- If $\alpha(\mu|m) = \delta(\mu - 1) U(m) \implies$ Zero Range process
- If $\alpha(\mu|m) = w \delta(\mu - 1) + \delta(\mu - m) \implies$ Chipping Model
(S.M, Krishnamurthy, Barma, 1998)
- If $\alpha(\mu|m) = \frac{1}{m} \implies$ Asymmetric Random Average process
(Krug & Garcia, Rajesh & S.M, 2000)

Question: Given $\alpha(\mu|m)$: what is the steady state?

\implies In general, hard to answer !

\rightarrow brief review on mass transport model (S.M., Les Houches 2008, arXiv:0904.4097)

Product Measure: Necessary and Sufficient Condition

If (and only if) the kernel

$$\alpha(\mu|m) = y(\mu) \frac{f(m - \mu)}{f(m)}$$

where $y(x)$ and $f(x)$ are arbitrary positive functions

Product Measure: Necessary and Sufficient Condition

If (and only if) the kernel $\alpha(\mu|m) = y(\mu) \frac{f(m-\mu)}{f(m)}$

where $y(x)$ and $f(x)$ are arbitrary positive functions

\implies Product Measure steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

Product Measure: Necessary and Sufficient Condition

If (and only if) the kernel $\alpha(\mu|m) = y(\mu) \frac{f(m-\mu)}{f(m)}$

where $y(x)$ and $f(x)$ are arbitrary positive functions

\implies Product Measure steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

where the partition function

$$Z_N(M) = \int f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right) \prod_{i=1}^N dm_i$$

Product Measure: Necessary and Sufficient Condition

If (and only if) the kernel $\alpha(\mu|m) = y(\mu) \frac{f(m-\mu)}{f(m)}$

where $y(x)$ and $f(x)$ are arbitrary positive functions

\implies Product Measure steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

where the partition function

$$Z_N(M) = \int f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right) \prod_{i=1}^N dm_i$$

Generalization to parallel dynamics, arbitrary graphs ...

(Evans, S.M., Zia, 2004-2007)

Steady State Properties: Condensation Transition

- **Product Measure** steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1)f(m_2)\dots f(m_N) \delta\left(\sum m_i - M\right)$$

Steady State Properties: Condensation Transition

- **Product Measure** steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta \left(\sum m_i - M \right)$$

- Given $f(m)$, tune the parameter $M = \rho N$: $\rho \rightarrow$ mass density and monitor: $\rho(m) \rightarrow$ single site mass distribution

Steady State Properties: Condensation Transition

- **Product Measure** steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1)f(m_2)\dots f(m_N) \delta\left(\sum m_i - M\right)$$

- Given $f(m)$, tune the parameter $M = \rho N$: $\rho \rightarrow$ mass density and monitor: $p(m) \rightarrow$ single site mass distribution

$p(m) dm \rightarrow$ fraction of sites with mass $[m, m + dm]$

Steady State Properties: Condensation Transition

- **Product Measure** steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

- Given $f(m)$, tune the parameter $M = \rho N$: $\rho \rightarrow$ mass density and monitor: $p(m) \rightarrow$ single site mass distribution

$p(m) dm \rightarrow$ fraction of sites with mass $[m, m + dm]$

$$\int p(m) dm = 1 \quad \text{and} \quad \int m p(m) dm = \rho$$

Steady State Properties: Condensation Transition

- **Product Measure** steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1)f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

- Given $f(m)$, tune the parameter $M = \rho N$: $\rho \rightarrow$ mass density and monitor: $p(m) \rightarrow$ single site mass distribution

$p(m) dm \rightarrow$ fraction of sites with mass $[m, m + dm]$

$$\int p(m) dm = 1 \quad \text{and} \quad \int m p(m) dm = \rho$$

- Criterion for **Condensation**: If $e^{-c m} < f(m) < 1/m^2$ for large m

Example: $f(m) \simeq \frac{A}{m^\gamma}$ with $\gamma > 2$

Steady State Properties: Condensation Transition

- **Product Measure** steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

- Given $f(m)$, tune the parameter $M = \rho N$: $\rho \rightarrow$ mass density and monitor: $p(m) \rightarrow$ single site mass distribution

$p(m) dm \rightarrow$ fraction of sites with mass $[m, m + dm]$

$$\int p(m) dm = 1 \quad \text{and} \quad \int m p(m) dm = \rho$$

- Criterion for **Condensation**: If $e^{-cm} < f(m) < 1/m^2$ for large m

Example: $f(m) \simeq \frac{A}{m^\gamma}$ with $\gamma > 2$

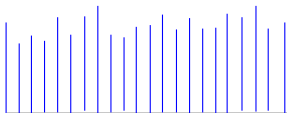
There is a **critical** density $\rho_c = 1/(\gamma - 2)$ such that

$$\begin{aligned} p(m) &\simeq e^{-m/m^*} && \text{for } \rho < \rho_c \\ &\simeq m^{-\gamma} && \text{for } \rho = \rho_c \\ &\simeq m^{-\gamma} + \text{"condensate"}, && \text{for } \rho > \rho_c \end{aligned}$$

Typical Configurations: Subcritical, Critical and Supercritical

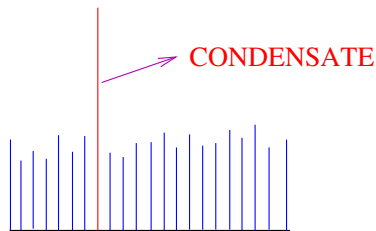


$$\rho < \rho_c$$



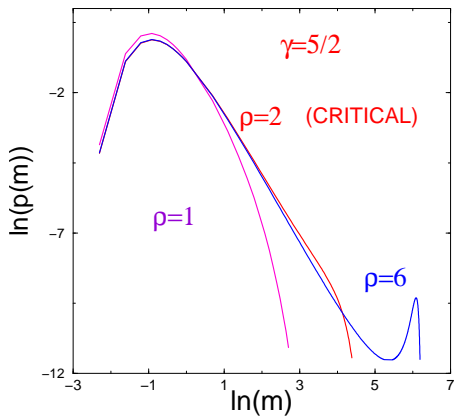
$$\rho = \rho_c$$

(CRITICAL)

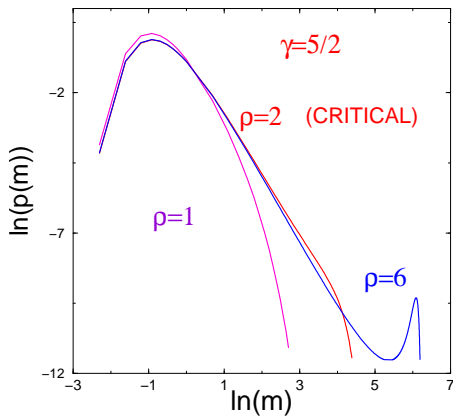


$$\rho > \rho_c$$

Single Site Mass Distribution



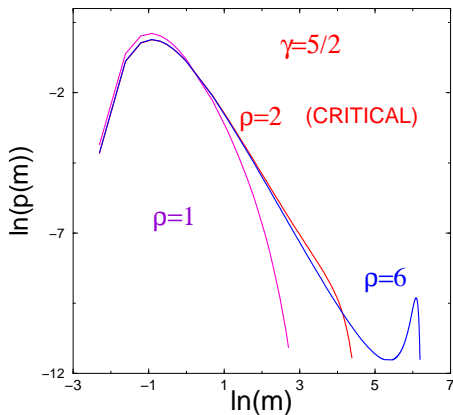
Single Site Mass Distribution



For $\rho > \rho_c$:

$$\int_{\text{bump}} p(m) dm \simeq 1/N \rightarrow \text{single condensate}$$

Single Site Mass Distribution



For $\rho > \rho_c$:

$$\int_{\text{bump}} p(m) dm \simeq 1/N \rightarrow \text{single condensate}$$

$$\int_{\text{bump}} m p(m) dm \simeq (\rho - \rho_c) \rightarrow \text{extra density}$$

Analysis of the Maximal Mass: Sub-critical Phase

$$\rho < \rho_c$$

- **Product Measure** steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta \left(\sum m_i - M \right)$$

Analysis of the Maximal Mass: Sub-critical Phase

$$\rho < \rho_c$$

- **Product Measure** steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta \left(\sum m_i - M \right)$$

- distribution of **maximal** mass: $m_{\max} = \max(m_1, m_2, \dots, m_N)$

Analysis of the Maximal Mass: Sub-critical Phase

$$\rho < \rho_c$$

- **Product Measure** steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1)f(m_2)\dots f(m_N) \delta\left(\sum m_i - M\right)$$

- distribution of **maximal** mass: $m_{\max} = \max(m_1, m_2, \dots, m_N)$
- Grand Canonical Analysis ($\rho < \rho_c$)

$$\delta\left(\sum m_i - M\right) \rightarrow e^{-s(m_1+m_2+\dots+m_N)}$$

Analysis of the Maximal Mass: Sub-critical Phase

$$\rho < \rho_c$$

- **Product Measure** steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

- distribution of **maximal** mass: $m_{\max} = \max(m_1, m_2, \dots, m_N)$
- Grand Canonical Analysis ($\rho < \rho_c$)

$$\delta\left(\sum m_i - M\right) \rightarrow e^{-s(m_1+m_2+\dots+m_N)}$$

$$P(m_1, m_2, \dots, m_N) = \prod_{i=1}^N p(m_i) \text{ where } p(m) \propto f(m) e^{-s m}$$

Analysis of the Maximal Mass: Sub-critical Phase

$$\rho < \rho_c$$

- **Product Measure** steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

- distribution of **maximal** mass: $m_{\max} = \max(m_1, m_2, \dots, m_N)$
- Grand Canonical Analysis ($\rho < \rho_c$)

$$\delta\left(\sum m_i - M\right) \rightarrow e^{-s(m_1+m_2+\dots+m_N)}$$

$$P(m_1, m_2, \dots, m_N) = \prod_{i=1}^N p(m_i) \text{ where } p(m) \propto f(m) e^{-s m}$$

Fix s via:
$$\rho = \frac{\int_0^\infty dm m f(m) e^{-s m}}{\int_0^\infty dm f(m) e^{-s m}} = g(s)$$

Analysis of the Maximal Mass: Sub-critical Phase

$$\rho < \rho_c$$

- **Product Measure** steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

- distribution of **maximal** mass: $m_{\max} = \max(m_1, m_2, \dots, m_N)$
- Grand Canonical Analysis ($\rho < \rho_c$)

$$\delta\left(\sum m_i - M\right) \rightarrow e^{-s(m_1+m_2+\dots+m_N)}$$

$$P(m_1, m_2, \dots, m_N) = \prod_{i=1}^N p(m_i) \text{ where } p(m) \propto f(m) e^{-s m}$$

Fix s via:
$$\rho = \frac{\int_0^\infty dm m f(m) e^{-s m}}{\int_0^\infty dm f(m) e^{-s m}} = g(s)$$

- Let $f(m) \simeq \frac{A}{m^\gamma}$ with $\gamma > 2 \implies g(0)$ finite

Analysis of the Maximal Mass: Sub-critical Phase

$$\rho < \rho_c$$

- **Product Measure** steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

- distribution of **maximal** mass: $m_{\max} = \max(m_1, m_2, \dots, m_N)$
- Grand Canonical Analysis ($\rho < \rho_c$)

$$\delta\left(\sum m_i - M\right) \rightarrow e^{-s(m_1+m_2+\dots+m_N)}$$

$$P(m_1, m_2, \dots, m_N) = \prod_{i=1}^N p(m_i) \text{ where } p(m) \propto f(m) e^{-s m}$$

Fix s via:
$$\rho = \frac{\int_0^\infty dm m f(m) e^{-s m}}{\int_0^\infty dm f(m) e^{-s m}} = g(s)$$

- Let $f(m) \simeq \frac{A}{m^\gamma}$ with $\gamma > 2 \implies g(0)$ finite

As ρ increases, a solution $s > 0$ exists as long as $\rho < g(0) = \rho_c$

Analysis of the Maximal Mass: Sub-critical Phase

$$\rho < \rho_c$$

- **Product Measure** steady state

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(M)} f(m_1) f(m_2) \dots f(m_N) \delta\left(\sum m_i - M\right)$$

- distribution of **maximal** mass: $m_{\max} = \max(m_1, m_2, \dots, m_N)$
- Grand Canonical Analysis ($\rho < \rho_c$)

$$\delta\left(\sum m_i - M\right) \rightarrow e^{-s(m_1 + m_2 + \dots + m_N)}$$

$$P(m_1, m_2, \dots, m_N) = \prod_{i=1}^N p(m_i) \text{ where } p(m) \propto f(m) e^{-s m}$$

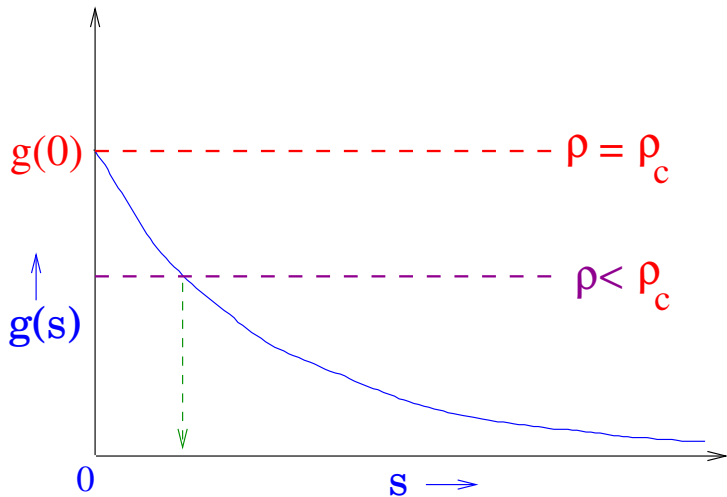
Fix s via:
$$\rho = \frac{\int_0^\infty dm m f(m) e^{-s m}}{\int_0^\infty dm f(m) e^{-s m}} = g(s)$$

- Let $f(m) \simeq \frac{A}{m^\gamma}$ with $\gamma > 2 \implies g(0)$ finite

As ρ increases, a solution $s > 0$ exists as long as $\rho < g(0) = \rho_c$

- In the **sub-critical** phase $\rho < \rho_c$ maximal mass distribution

Critical Density



Maximal Mass at the Critical Point $\rho = \rho_c$

- As $\rho \rightarrow \rho_c$: $s \rightarrow 0$
- Exactly at $\rho = \rho_c$, $s = 0$

Maximal Mass at the Critical Point $\rho = \rho_c$

- As $\rho \rightarrow \rho_c$: $s \rightarrow 0$
- Exactly at $\rho = \rho_c$, $s = 0$

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(\rho_c N)} \prod_{i=1}^N f(m_i)$$

where $f(m) \simeq \frac{A}{m^\gamma}$ with $\gamma > 2$

Maximal Mass at the Critical Point $\rho = \rho_c$

- As $\rho \rightarrow \rho_c$: $s \rightarrow 0$
- Exactly at $\rho = \rho_c$, $s = 0$

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(\rho_c N)} \prod_{i=1}^N f(m_i)$$

where $f(m) \simeq \frac{A}{m^\gamma}$ with $\gamma > 2$

- Effect of the global constraint **disappears** at the **critical** point !

Maximal Mass at the Critical Point $\rho = \rho_c$

- As $\rho \rightarrow \rho_c$: $s \rightarrow 0$
- Exactly at $\rho = \rho_c$, $s = 0$

$$P(m_1, m_2, \dots, m_N) = \frac{1}{Z_N(\rho_c N)} \prod_{i=1}^N f(m_i)$$

where $f(m) \simeq \frac{A}{m^\gamma}$ with $\gamma > 2$

- Effect of the global constraint **disappears** at the **critical** point !
- Distribution of **maximal** mass: $m_{\max} = \max(m_1, m_2, \dots, m_N)$

$$Q_N(x) = \text{Prob}(m_{\max} \leq x) \rightarrow \text{FRÉCHET}$$

Maximal Mass in the Condensed Phase: $\rho > \rho_c$

- For $\rho > \rho_c$: Grand canonical analysis breaks down !

Maximal Mass in the Condensed Phase: $\rho > \rho_c$

- For $\rho > \rho_c$: Grand canonical analysis breaks down !

- The system is “strongly” correlated: $P(m_i, m_j) \neq p(m_i)p(m_j)$

global constraint plays an important role

Maximal Mass in the Condensed Phase: $\rho > \rho_c$

- For $\rho > \rho_c$: Grand canonical analysis breaks down !
- The system is “strongly” correlated: $P(m_i, m_j) \neq p(m_i)p(m_j)$
global constraint plays an important role
- Physical picture: maximal mass carried by a single condensate which coexists with a background critical fluid on $(N - 1)$ sites

Maximal Mass in the Condensed Phase: $\rho > \rho_c$

- For $\rho > \rho_c$: Grand canonical analysis breaks down !
- The system is “strongly” correlated: $P(m_i, m_j) \neq p(m_i)p(m_j)$
global constraint plays an important role
- Physical picture: maximal mass carried by a single condensate which coexists with a background critical fluid on $(N - 1)$ sites

$$m_{\max} = m_{\text{cond}} =$$

Maximal Mass in the Condensed Phase: $\rho > \rho_c$

- For $\rho > \rho_c$: Grand canonical analysis breaks down !
- The system is “strongly” correlated: $P(m_i, m_j) \neq p(m_i)p(m_j)$
global constraint plays an important role
- Physical picture: maximal mass carried by a single condensate which coexists with a background critical fluid on $(N - 1)$ sites

- $$m_{\max} = m_{\text{cond}} = M - M_{\text{fluid}} = M - \sum_{i \in \text{fluid}} m_i$$

Maximal Mass in the Condensed Phase: $\rho > \rho_c$

- For $\rho > \rho_c$: Grand canonical analysis breaks down !

- The system is “strongly” correlated: $P(m_i, m_j) \neq p(m_i)p(m_j)$

global constraint plays an important role

- Physical picture: maximal mass carried by a single condensate which coexists with a background critical fluid on $(N - 1)$ sites

- $$m_{\max} = m_{\text{cond}} = M - M_{\text{fluid}} = M - \sum_{i \in \text{fluid}} m_i$$

- masses at $(N - 1)$ sites of the critical fluid \implies uncorrelated i.i.d variables \implies each distributed via $f(m)$

Maximal Mass in the Condensed Phase: $\rho > \rho_c$

- For $\rho > \rho_c$: Grand canonical analysis breaks down !
- The system is “strongly” correlated: $P(m_i, m_j) \neq p(m_i)p(m_j)$
global constraint plays an important role
- Physical picture: maximal mass carried by a single condensate which coexists with a background critical fluid on $(N - 1)$ sites

- $$m_{\max} = m_{\text{cond}} = M - M_{\text{fluid}} = M - \sum_{i \in \text{fluid}} m_i$$

- masses at $(N - 1)$ sites of the critical fluid \implies uncorrelated i.i.d variables \implies each distributed via $f(m)$

$$M_{\text{fluid}} = \sum_{i \in \text{fluid}} m_i \rightarrow \text{sum of } (N - 1) \text{ i.i.d variables}$$

Maximal Mass in the Condensed Phase: $\rho > \rho_c$

- For $\rho > \rho_c$: Grand canonical analysis breaks down !

- The system is “strongly” correlated: $P(m_i, m_j) \neq p(m_i)p(m_j)$

global constraint plays an important role

- Physical picture: maximal mass carried by a single condensate which coexists with a background critical fluid on $(N - 1)$ sites

- $$m_{\max} = m_{\text{cond}} = M - M_{\text{fluid}} = M - \sum_{i \in \text{fluid}} m_i$$

- masses at $(N - 1)$ sites of the critical fluid \implies uncorrelated i.i.d variables \implies each distributed via $f(m)$

$$M_{\text{fluid}} = \sum_{i \in \text{fluid}} m_i \rightarrow \text{sum of } (N - 1) \text{ i.i.d variables}$$

- distribution of extreme \implies distribution of sum of i.i.d variables

Maximal Mass in the Condensed Phase: $\rho > \rho_c$

- For $\rho > \rho_c$: Grand canonical analysis breaks down !

- The system is “strongly” correlated: $P(m_i, m_j) \neq p(m_i)p(m_j)$

global constraint plays an important role

- Physical picture: maximal mass carried by a single condensate which coexists with a background critical fluid on $(N - 1)$ sites

- $$m_{\max} = m_{\text{cond}} = M - M_{\text{fluid}} = M - \sum_{i \in \text{fluid}} m_i$$

- masses at $(N - 1)$ sites of the critical fluid \implies uncorrelated i.i.d variables \implies each distributed via $f(m)$

$$M_{\text{fluid}} = \sum_{i \in \text{fluid}} m_i \rightarrow \text{sum of } (N - 1) \text{ i.i.d variables}$$

- distribution of extreme \implies distribution of sum of i.i.d variables

- $$P(M_{\text{fluid}}) = \int \prod_i^{N-1} f(m_i) dm_i \delta \left(M_{\text{fluid}} - \sum m_i \right)$$

Maximal Mass for $\rho > \rho_c$

- $$P(M_{\text{fluid}}) = \int \prod_i^{N-1} f(m_i) dm_i \delta \left(M_{\text{fluid}} - \sum m_i \right)$$

where $f(m) \simeq \frac{A}{m^\gamma}$ with $\gamma > 2$

Maximal Mass for $\rho > \rho_c$

- $$P(M_{\text{fluid}}) = \int \prod_i^{N-1} f(m_i) dm_i \delta \left(M_{\text{fluid}} - \sum m_i \right)$$

where $f(m) \simeq \frac{A}{m^\gamma}$ with $\gamma > 2$

- For $\gamma > 3$: Central limit theorem holds $\implies M_{\text{fluid}} \rightarrow \text{Gaussian}$

Maximal Mass for $\rho > \rho_c$

- $$P(M_{\text{fluid}}) = \int \prod_i^{N-1} f(m_i) dm_i \delta \left(M_{\text{fluid}} - \sum m_i \right)$$

where $f(m) \simeq \frac{A}{m^\gamma}$ with $\gamma > 2$

- For $\gamma > 3$: Central limit theorem holds $\implies M_{\text{fluid}} \rightarrow \text{Gaussian}$

$$P(m_{\text{max}}) \simeq \frac{1}{\sqrt{2\pi N}} \exp \left[-\frac{(m_{\text{max}} - (\rho - \rho_c)N)^2}{2N} \right]$$

Maximal Mass for $\rho > \rho_c$

- $$P(M_{\text{fluid}}) = \int \prod_i^{N-1} f(m_i) dm_i \delta \left(M_{\text{fluid}} - \sum m_i \right)$$

where $f(m) \simeq \frac{A}{m^\gamma}$ with $\gamma > 2$

- For $\gamma > 3$: Central limit theorem holds $\implies M_{\text{fluid}} \rightarrow$ Gaussian

$$P(m_{\text{max}}) \simeq \frac{1}{\sqrt{2\pi N}} \exp \left[-\frac{(m_{\text{max}} - (\rho - \rho_c)N)^2}{2N} \right]$$

- For $2 < \gamma < 3$: $M_{\text{fluid}} \rightarrow$ anomalous \rightarrow Lévy laws ('+'ve variables)

Maximal Mass for $\rho > \rho_c$

- $$P(M_{\text{fluid}}) = \int \prod_i^{N-1} f(m_i) dm_i \delta \left(M_{\text{fluid}} - \sum m_i \right)$$

where $f(m) \simeq \frac{A}{m^\gamma}$ with $\gamma > 2$

- For $\gamma > 3$: Central limit theorem holds $\implies M_{\text{fluid}} \rightarrow$ Gaussian

$$P(m_{\text{max}}) \simeq \frac{1}{\sqrt{2\pi N}} \exp \left[-\frac{(m_{\text{max}} - (\rho - \rho_c)N)^2}{2N} \right]$$

- For $2 < \gamma < 3$: $M_{\text{fluid}} \rightarrow$ anomalous \rightarrow Lévy laws ('+'ve variables)

$$P(m_{\text{max}}) \simeq \frac{1}{N^{1/(\gamma-1)}} V_\gamma \left[\frac{m_{\text{max}} - (\rho - \rho_c)N}{N^{1/(\gamma-1)}} \right]$$

Maximal Mass for $\rho > \rho_c$

- $$P(M_{\text{fluid}}) = \int \prod_i^{N-1} f(m_i) dm_i \delta \left(M_{\text{fluid}} - \sum m_i \right)$$

where $f(m) \simeq \frac{A}{m^\gamma}$ with $\gamma > 2$

- For $\gamma > 3$: Central limit theorem holds $\implies M_{\text{fluid}} \rightarrow$ Gaussian

$$P(m_{\text{max}}) \simeq \frac{1}{\sqrt{2\pi N}} \exp \left[-\frac{(m_{\text{max}} - (\rho - \rho_c)N)^2}{2N} \right]$$

- For $2 < \gamma < 3$: $M_{\text{fluid}} \rightarrow$ anomalous \rightarrow Lévy laws ('+'ve variables)

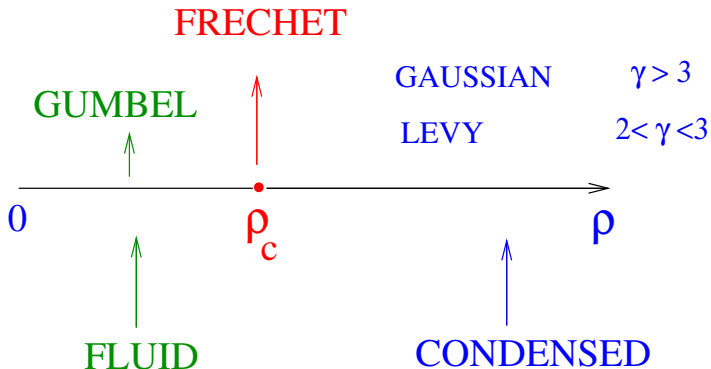
$$P(m_{\text{max}}) \simeq \frac{1}{N^{1/(\gamma-1)}} V_\gamma \left[\frac{m_{\text{max}} - (\rho - \rho_c)N}{N^{1/(\gamma-1)}} \right]$$

where $V_\gamma(z) \simeq A|z|^{-\gamma}$ as $z \rightarrow -\infty$

$\simeq c_1 z^{(3-\gamma)/(\gamma-2)} \exp \left[-c_2 z^{(\gamma-1)/(\gamma-2)} \right]$ as $z \rightarrow \infty$

Summary of Maximal Mass Distribution

EXTREME VALUE DISTRIBUTION



(Evans & S.M, 2008)

Summary and Conclusions

- Mass transport models with a globally conserved M
 - ⇒ Nonequilibrium Steady State
 - Real-space condensation via spontaneous symmetry breaking

Summary and Conclusions

- Mass transport models with a globally conserved M
 - ⇒ Nonequilibrium Steady State
 - Real-space condensation via spontaneous symmetry breaking
- Tuning $M = \rho N$ one can tune correlations
maximal mass distribution:
 - Fluid ($\rho < \rho_c$): Uncorrelated i.i.d (Gumbel)

Summary and Conclusions

- Mass transport models with a globally conserved M
 - ⇒ Nonequilibrium Steady State
 - Real-space condensation via spontaneous symmetry breaking
- Tuning $M = \rho N$ one can tune correlations
 - maximal mass distribution:
 - Fluid ($\rho < \rho_c$): Uncorrelated i.i.d (Gumbel)
 - Condensed ($\rho > \rho_c$): Strongly correlated (Gaussian, Lévy)
 - ⇒ New Extreme value distributions

Summary and Conclusions

- Mass transport models with a globally conserved M
 - ⇒ Nonequilibrium Steady State
 - Real-space condensation via spontaneous symmetry breaking
- Tuning $M = \rho N$ one can tune correlations
maximal mass distribution:
 - Fluid ($\rho < \rho_c$): Uncorrelated i.i.d (Gumbel)
 - Condensed ($\rho > \rho_c$): Strongly correlated (Gaussian, Lévy)
 - ⇒ New Extreme value distributions
- Extreme Value Statistics in Strongly correlated system
 - ⇒ interesting open problems

References

Jointly with [M.R. Evans](#) and [R.K.P. Zia](#):

- J. Phys. A: Math. Gen. **37**, L275 (2004)
- JSTAT, **L10001** (2005)
- Phys. Rev. Lett. **94**, 180601 (2005)
- J. Stat. Phys. **123**, 357 (2006)
- J. Phys. A: Math. Gen. **39**, 4859 (2006)
- Phys. Rev. Lett. **97**, 010602 (2006)
- JSTAT, P05004 (2008)

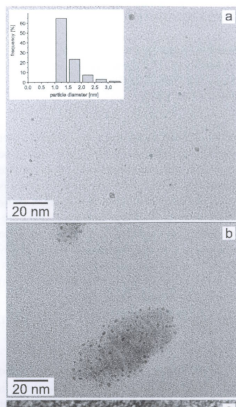
A recent brief review on real-space condensation:

[S.M.](#), Les Houches Lecture Notes (2008), [arXiv: 0904.4097](#)

Island formation: Au clusters on Carbon films

WERNER *et al.*

PHYSICAL REVIEW B 72, 045426 (2005)



and their stability tested in a heating experiment (Sec. IV D).

In Sec. V the formation of the islands and the shape of the Au clusters on their surface is modeled with MC simulations, followed by the conclusion in Sec. VI.

II. METHODS

A. Experiment: Substrate and sample preparation

The commercial aC substrate films were produced by evaporation in a carbon arc by Arizona Carbon Foils and distributed by Plano GmbH as type S160. The films are mounted on a 200 nm mesh Cu grid for support. The film thickness is given by the manufacturer as $d_{\text{subs}} = 10\text{--}12.5$ nm with a density of $\rho_{\text{subs}} \approx 2.0$ g/cm³, corresponding to a mass of $2\text{--}2.5$ $\mu\text{g}/\text{cm}^2$. The density of the substrate is closer to that of graphite ($\rho_{\text{graph}} = 2.267$ g/cm³) than to that of diamond ($\rho_{\text{dia}} = 3.515$ g/cm³), suggesting a structure that contains regions with trivalent coordination.²³ The similarities in the electronic structure between aC and graphite are supported by electron energy loss spectroscopy (EELS) measurements,²⁴ which show spectra that differ significantly from those of diamond. Amorphous-carbon films produced with similar methods and of similar density have been found to be semiconducting.^{23,25}