

Title: Hausdorff and spectral dimension of random graphs

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Abstract: We introduce a class of probability spaces whose objects are infinite graphs and whose probability distributions are obtained as limits of distributions for finite graphs. The notions of Hausdorff and spectral dimension for such ensembles are defined and some results on their value in concrete examples, such as random trees, will be described.

HAUSDORFF AND SPECTRAL DIMENSION
OF RANDOM GRAPHS

B. DURHUUS

"Random Matrix Techniques in Quantum Information Theory", Perimeter Institute, July 4, 2010.



(2)

Some motivation:

1) Random graphs in discretized gravity.

2 dimensions: Matrix models \leftrightarrow Topological gravity
Intrinsic geometry?

Ref: J. Ambjørn, B.D., T. Jonsson, *Quantum Geometry*, Cambridge Univ. Press, 1997.

2) Random media. Anomalous diffusion.

3) Percolation on a fixed graph, e.g. \mathbb{Z}^d
 \hookrightarrow Random percolation clusters.

4) Structure of networks.

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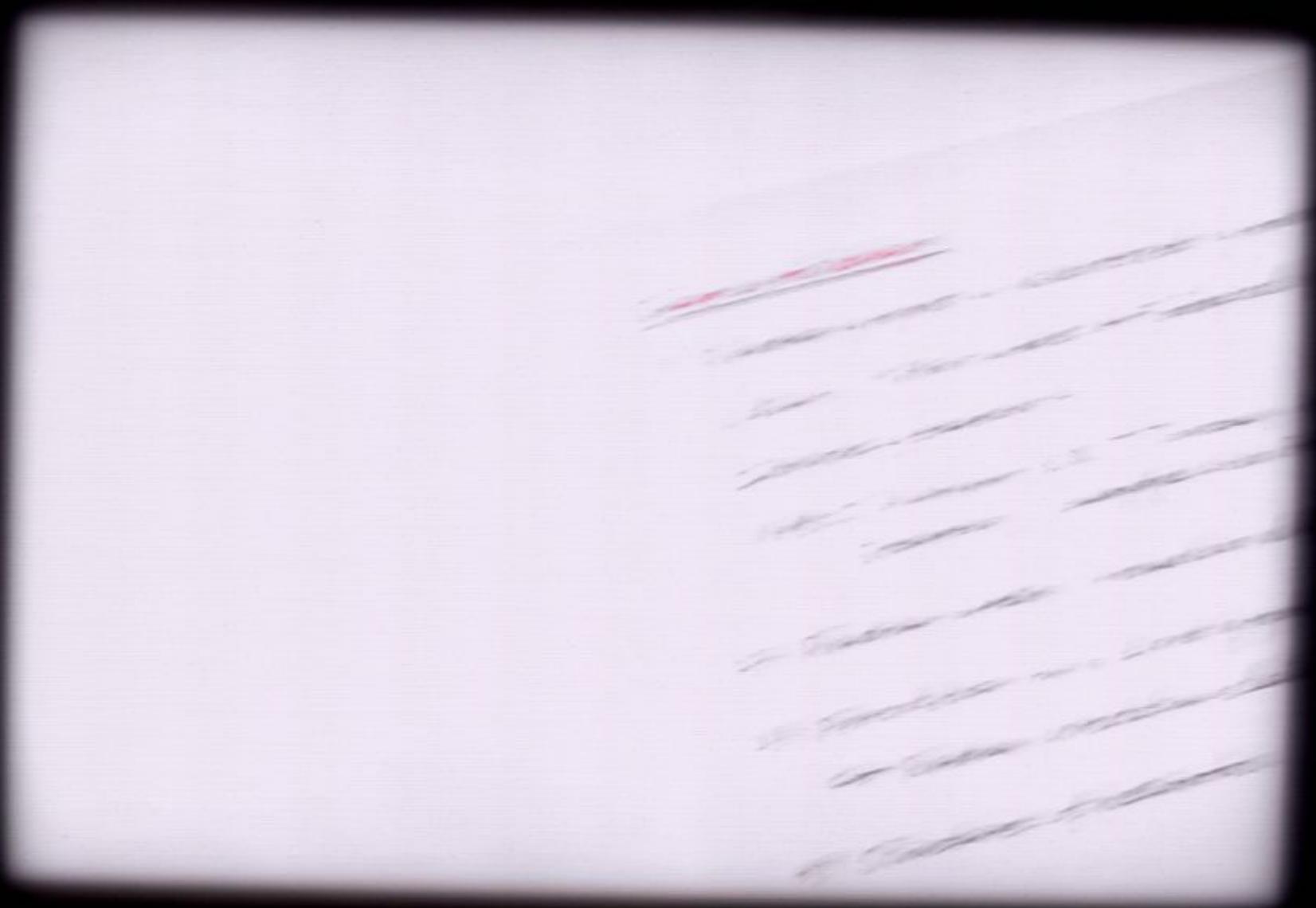
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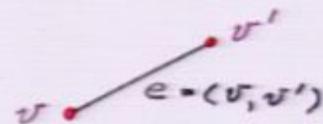
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- Graph G . $V(G)$ = vertex set
 $E(G)$ = edge set



$$\delta_v = \text{degree of } v < \infty$$

- Path in G : $(v_0, v_i), (v_i, v_2), \dots, (v_{k-1}, v_k)$
 all v_i different.

Circuit = closed path $(v_0 = v_k)$.

Graph distance: $d(v, v') = \# \text{edges in}$
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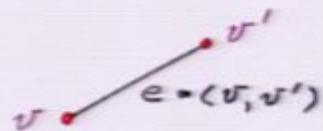
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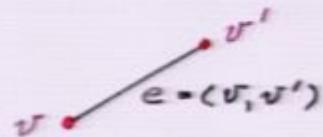
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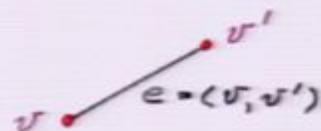
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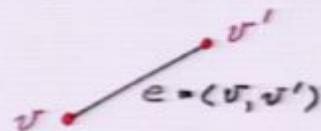
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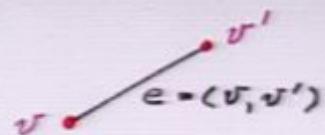
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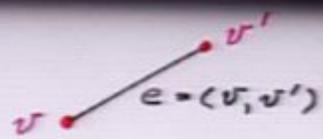
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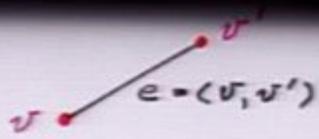
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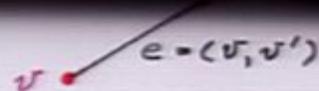
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It is often the case that the
path is the intermediate element
that is used to effect
change in the path function
and hence the path function
itself is often used as an
intermediate element.



(3)

- For $v_0 \in V(G)$, $R \geq 0$:

$B_R(G, v_0) =$ ball of radius R centered at v_0 , considered as subgraph of G .

$$|B_R(G, v_0)| = \# \text{ edges in } B_R(G, v_0)$$

Hausdorff dimension of G connected and infinite:

$$d_h = \lim_{R \rightarrow \infty} \frac{\ln |B_R(G, v_0)|}{\ln R}$$

Indep. of v_0 , but not well-defined for all G .

- A walk in G $\omega: v_0 \rightarrow v_k$ is a sequence of edges $(v_0, v_1), (v_1, v_2), \dots, (v_{k-1}, v_k)$ with v_i 's not necess. distinct.

$|\omega| = k =$ length of ω .

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$B_R(G, v_0)$ = ball of radius R centred
at v_0 , considered as sub-
graph of G .

$$|B_R(G, v_0)| = \# \text{ edges in } B_R(G, v_0)$$

Hausdorff dimension of G connected
and infinite:

$$d_h = \lim_{R \rightarrow \infty} \frac{\ln |B_R(G, v_0)|}{\ln R}$$

Indep. of v_0 , but not well-defined
for all G .

- A walk in G $\omega: v_0 \rightarrow v_k$ is a sequence
of edges $(v_0, v_1), (v_1, v_2), \dots, (v_{k-1}, v_k)$
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graph of α :

$$|B_R(\bar{v}_i, v_i)| = \# \text{ edges in } B_R(\bar{v}_i, v_i)$$

Hausdorff dimension of α connected and infinite:

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indep. of v_i , but not well defined for all α .

- * A walk in α w: $v_0 \rightarrow v_k$ is a sequence of edges $(v_0, v_1), (v_1, v_2), \dots, (v_{k-1}, v_k)$ with v_i 's not necessarily distinct,
 $l(w) = k = \text{length of } w.$

Set

$$\rho(w) = \prod_{i=0}^{k-1} \rho_{w(i)}^i$$

where $w(i)$ is i th vertex in w ,

ρ defines a probability distribution

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$$p(\omega) = \prod_{i=0}^{k-1} \sigma_{\omega(i)}$$

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$\pi_G(v_0)$

where $\Pi_n(v_0) =$ set of walks of length n emerging from v_0 . These probability distributions define the simple random walk on G .

For G connected: $p_0(G, v_0) =$ return probability to v_0 after time $t \geq 0$

$$p_0(G, v_0) = \sum_{\substack{\omega: v_0 \rightarrow v_0 \\ \text{wt } \omega = t}} p(\omega).$$

Spectral dimension for G connected and infinite:

$$d_s = -2 \lim_{t \rightarrow \infty} \frac{\ln p_0(G, v_0)}{\ln t}$$

Indep. of v_0 but not well-defined for all G .

Note:

$$d_h \geq 1, \quad d_s \geq 1 \quad \text{all } G.$$

$$d_h = d_s = d \text{ for } G = \mathbb{Z}^d.$$

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Schedule change Monday

Belinschi

Zeitoun

Zyczkowski

Nechita

Antunes

Pellegrini

(cyclic permutation)

$$2M_n \geq d_s \geq \frac{2d_n}{1+d_n}$$

PR





⑤

- Ensemble of graphs = random graph
= set of graphs \mathcal{G} with a probability measure μ .
 $\langle \cdot \rangle_\mu$ = expectation w.r.t. μ .

Assume graphs are rooted with root vertex r :

$$B_R(G) = B_R(G, r), \quad p_t(G) = p_t(G, r).$$

Hausdorff and spectral dimension of random graph:

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Almost sure existence of d_h or d_s :

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$\langle \cdot \rangle_\mu$ = expectation w.r.t. μ .

Assume graphs are rooted with root vertex r :

$$B_R(G) = B_R(G, r), \quad p_t(G) = p_t(G, r).$$

Hausdorff and spectral dimension of random graph:

$$d_h = \lim_{R \rightarrow \infty} \frac{\ln \langle |B_R| \rangle_\mu}{\ln R}$$

$$d_s = -2 \lim_{R \rightarrow \infty} \frac{\ln \langle p_R \rangle_\mu}{\ln t}$$

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- Generally obtain μ as a limit of probability distributions μ_N defined on finite sets of finite graphs $\mathcal{G}_N \subseteq \mathcal{G}$.

Consider \mathcal{G} as metric space:

$$d(G, G') = \inf \{(R+\epsilon)^{-1} \mid B_R(G) = B_R(G')\}$$

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for bounded continuous functions f .

Equivalent to

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S. D. Acta Phys. Pol. B 34 (2003) 4715

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$\mu(a, a') = \inf\{\mu_{n+1}(a, a') : n \in \mathbb{N}\}$

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S. D. Acta Phys. Pol. B 34 (2003) 4795

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(7)

3. The incipient infinite percolation cluster.

G infinite, connected, rooted graph.

$0 \leq p \leq 1$ fixed.

For $e \in E(G)$ set

$$\delta_e(\sigma) = \begin{cases} p & \text{if } \sigma = 1 \\ 1-p & \text{if } \sigma = 0 \end{cases}$$

Bond percolation on G is defined by the product measure

$$\rho_p = \prod_{e \in E(G)} \delta_e$$

on configurations $(\sigma_e)_{e \in E(G)}$ in $\{0,1\}^{E(G)}$.

Given a configuration c define the cluster C_r as the maximal connected subgraph of G containing r such that c assumes value 1 on all edges in C_r .

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The case $G = \mathbb{Z}^d$, $d \geq 2$: Choose $r = 0$.

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The case $G = \mathbb{Z}^d$, $d \geq 2$: Choose $r = 2$.

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Bond percolation on \mathcal{G} is defined by the product measure

$$\delta_{\mathcal{G}} = \prod_{e \in E(\mathcal{G})} \delta_e$$

on configurations $(\sigma_e)_{e \in E(\mathcal{G})}$ in $\{0,1\}^{E(\mathcal{G})}$.

Given a configuration σ define the cluster c_r as the maximal connected subgraph of \mathcal{G} containing r such that σ assumes value 1 on all edges in c_r .

The case $\mathcal{G} = \mathbb{Z}^d$, $d \geq 2$. Choose $r = 0$.

There exists a critical probability p_{crt} for $\sigma \in \{0,1\}^{\mathbb{Z}^d}$ such that

$$\delta(\{c_{r=0}\}) = \begin{cases} > 0 & \text{if } p < p_{crt} \\ < 0 & \text{if } p > p_{crt} \end{cases}$$

$$\delta_e(\sigma) = \begin{cases} 1 & \text{if } \sigma = 1 \\ 1-p & \text{if } \sigma = 0 \end{cases}$$

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The case $G = \mathbb{Z}^d$, $d \geq 2$: Choose $r = 0$.

There exists a critical probability $p_{cr} \in [0, 1]$ such that

$$\rho(|c_r| = \infty) \begin{cases} = 0 & \text{if } p < p_{cr} \\ > 0 & \text{if } p > p_{cr}. \end{cases}$$

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$$P(|c_r| = \infty) \begin{cases} = 0 & \text{if } p < p_{cr} \\ > 0 & \text{if } p > p_{cr}. \end{cases}$$

Bond percolation on G is defined by the product measure

$$\beta_p = \prod_{e \in E(G)} \delta_e$$

on configurations $(d_e)_{e \in E(G)}$ in $\{0, 1\}^{E(G)}$.

Given a configuration c define the cluster C_r as the maximal connected subgraph of G containing r such that c assumes value 1 on all edges in C_r .

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Bond percolation on G is defined by the product measure

$$\beta_p = \prod_{e \in E(G)} \delta_e$$

on configurations $(c_e)_{e \in E(G)}$ in $\{0, 1\}^{E(G)}$.

Given a configuration c define the cluster C_r as the maximal connected subgraph of G containing r such that c assumes value 1 on all edges in C_r .

The case $G = \mathbb{Z}^d$, $d \geq 2$: Choose $r = 0$.

There exists a critical probability $p_{cr} \in [0, 1]$ such that

$$\beta(p | C_r = \infty) \begin{cases} = 0 & \text{if } p < p_{cr} \\ > 0 & \text{if } p > p_{cr}. \end{cases}$$

⑧

For $d=2$ or $d \geq 19$ (but expected to hold for all $d \geq 2$):

$$g_{p_{cr}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{cr}$

$$g_p(|C_r|=n) \sim e^{-\alpha(p) \cdot n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\chi(p) = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{cr}$.

similar reasoning

(8)

For $d=2$ or $d \geq 19$ (but expected to hold for all $d \geq 2$):

$$g_{\text{per}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{\text{cr}}$

$$g_p(|C_r|=n) \sim e^{-\alpha(p) \cdot n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\chi(p) = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{\text{cr}}$.

Excluded scaling

(8)

For $d=2$ or $d \geq 19$ (but expected to hold for all $d \geq 2$):

$$g_{p_{cr}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{cr}$

$$g_p(|C_r|=n) \sim e^{-\alpha(p)n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\chi(p) = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{cr}$.

Expected scaling

(8)

For $d=2$ or $d \geq 19$ (but expected to hold for all $d \geq 2$) :

$$g_{p_{cr}}(|c_r| = \infty) = 0$$

i.e. percolation cluster c_r is almost surely finite at percolation threshold.

For $p < p_{cr}$

$$g_p(|c_r|=n) \sim e^{-\alpha(p)n}, n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\chi(p) = \langle |c_r| \rangle_{g_p}$$

is finite for $p < p_{cr}$.

Expected scaling

$$\chi(p) \sim \text{const.} \cdot (p_{cr}-p)^{-\gamma}, p > p_{cr}$$

(8)

For $d=2$ or $d \geq 19$ (but expected to hold for all $d \geq 2$):

$$g_{p_{cr}}(|C_r| = \infty) = 0$$

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Expected scaling

$$\chi(p) \sim \text{cst} \cdot (p_{cr} - p)^{-\gamma}, \quad p \nearrow p_{cr},$$

For $d=2$ or $d \geq 19$ (but expected to hold for all $d \geq 2$):

$$g_{\text{per}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{\text{cr}}$

$$g_p(|C_r|=n) \sim e^{-\alpha(p) \cdot n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\chi(p) = \langle |C_r| \rangle_{g_p}$$

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Expected scaling

$$\chi(p) \sim \text{const} \cdot (p_{\text{cr}} - p)^{-\gamma}, \quad p \nearrow p_{\text{cr}},$$

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Expected scaling

$$\chi(p) \sim \text{cst.} \cdot (p_{\text{cr}} - p)^{-\gamma}, \quad p \nearrow p_{\text{cr}},$$

for some $\gamma > 0$. I.e. clusters of arbi-

(8)

For $d=2$ or $d \geq 19$ (but expected to hold for all $d \geq 2$):

$$g_{p_c}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_c$

$$g_p(|C_r|=n) \sim e^{-\alpha(p) \cdot n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\chi(p) = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_c$.

Expected scaling

$$\chi(p) \sim \text{cst.} \cdot (p_c - p)^{-\gamma}, \quad p > p_c,$$

large size n , i.e. clusters of arbi-

$$g_{\text{per}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{\text{cr}}$

$$g_p(|C_r| = n) \sim e^{-\alpha(p) \cdot n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\chi(p) = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{\text{cr}}$.

Expected scaling

$$\chi(p) \sim \text{cst.} (p_{\text{cr}} - p)^{-\gamma}, \quad p \uparrow p_{\text{cr}},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define p_N to be g_{per} conditioned on cluster size N , i.e. for $|C| = N$

$$g_{p_{cr}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{cr}$

$$g_p(|C_r| = n) \sim e^{-\alpha(p) \cdot n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\langle C_r \rangle = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{cr}$.

Expected scaling

$$\langle C_r \rangle \sim \text{const.} (p_{cr} - p)^{-\gamma}, \quad p \nearrow p_{cr},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define p_N to be $g_{p_{cr}}$ conditioned on cluster size. Number for $|C_r| = N$

$$g_{p_{cr}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{cr}$

$$g_p(|C_r| = n) \sim e^{-\alpha(p) \cdot n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\chi(p) = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{cr}$.

Expected scaling

$$\chi(p) \sim \text{cst} \cdot (p_{cr} - p)^{-\gamma}, \quad p \nearrow p_{cr},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define μ_N to be $g_{p_{cr}}$ conditioned on cluster size N (say by MC/N)

$$g_{p_{cr}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{cr}$

$$g_p(|C_r| = n) \sim e^{-\alpha(p) \cdot n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\bar{x}(p) = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{cr}$.

Expected scaling

$$\bar{x}(p) \sim \text{cst} \cdot (p_{cr} - p)^{-\gamma}, \quad p \nearrow p_{cr},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define μ_N to be $g_{p_{cr}}$ conditioned on $|C_r| \leq N$.

$$g_{\text{per}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{\text{cr}}$

$$g_p(|C_r|=n) \sim e^{-\alpha(p)n}, n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\chi(p) = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{\text{cr}}$.

Expected scaling

$$\chi(p) \sim \text{cst} \cdot (p_{\text{cr}} - p)^{-\gamma}, p \uparrow p_{\text{cr}},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define p_N to be g_{per} conditioned on clusters of size N , i.e. for $|C|=N$

$$g_{\text{per}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{\text{cr}}$

$$g_p(|C_r| = n) \sim e^{-\alpha(p)n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\bar{\chi}(p) = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{\text{cr}}$.

Expected scaling

$$\bar{\chi}(p) \sim \text{cst} \cdot (p_{\text{cr}} - p)^{-\gamma}, \quad p > p_{\text{cr}},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define p_N to be g_{per} conditioned on clusters of size N , i.e. for $|C| = N$

$$g_{p_{\text{cr}}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{\text{cr}}$

$$g_p(|C_r| = n) \sim e^{-\alpha(p)n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\chi(p) = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{\text{cr}}$.

Expected scaling

$$\chi(p) \sim \text{cst} \cdot (p_{\text{cr}} - p)^{-\gamma}, \quad p \nearrow p_{\text{cr}},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define p_N to be $g_{p_{\text{cr}}}$ conditioned on clusters of size N , i.e. for $|C| = N$

$$S_{\text{per}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{\text{cr}}$

$$S_p(|C_r|=n) \sim e^{-\alpha(p)n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\bar{x}(p) = \langle |C_r| \rangle_{S_p}$$

is finite for $p < p_{\text{cr}}$.

Expected scaling

$$\bar{x}(p) \sim \text{const.} (p_{\text{cr}} - p)^{-\gamma}, \quad p \nearrow p_{\text{cr}},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define p_N to be S_{per} conditioned on clusters of size N , i.e. for $|C_r|=N$

$$g_{\text{per}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{\text{cr}}$

$$g_p(|C_r| = n) \sim e^{-\alpha(p)n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Here mean cluster size

$$\bar{\chi}(p) = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{\text{cr}}$.

Expected scaling

$$\bar{\chi}(p) \sim \text{const.} (p_{\text{cr}} - p)^{-\gamma}, \quad p \gg p_{\text{cr}}$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define p_N to be g_{per} conditioned on clusters of size N , i.e. for $|C_r| = N$

$$S_{\text{per}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{\text{cr}}$

$$S_p(|C_r|=n) \sim e^{-\alpha(p)n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\chi(p) = \langle |C_r| \rangle_{S_p}$$

is finite for $p < p_{\text{cr}}$.

Expected scaling

$$\chi(p) \sim \text{const.} (p_{\text{cr}} - p)^{-\gamma}, \quad p \nearrow p_{\text{cr}},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define p_N to be S_{per} conditioned on clusters of size N , i.e. for $|C_r|=N$

$$g_{p_{cr}}(|C_r| = \infty) = 0$$

i.e. percolation cluster C_r is almost surely finite at percolation threshold.

For $p < p_{cr}$

$$g_p(|C_r|=n) \sim e^{-\alpha(p) \cdot n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\chi(p) = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{cr}$.

Expected scaling

$$\chi(p) \sim \text{cst} \cdot (p_{cr} - p)^{-\gamma}, \quad p \nearrow p_{cr},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define μ_N to be $g_{p_{cr}}$ conditioned on clusters of size N , i.e. for $|C|=N$

i.e. percolation clusters are surely finite at percolation threshold.

For $p < p_{\text{cr}}$

$$g_p(|C_r|=n) \sim e^{-\alpha(p)n}, n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\langle C_r \rangle = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{\text{cr}}$.

Expected scaling

$$\langle C_r \rangle \sim \text{const.} (p_{\text{cr}} - p)^{-\gamma}, p \nearrow p_{\text{cr}},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define μ_N to be $g_{p_{\text{cr}}}$ conditioned on clusters of size N , i.e. for $|C_r|=N$

$$\mu_N(C) = \frac{g_{p_{\text{cr}}}(|C_r|=C)}{g_{p_{\text{cr}}}(|C_r|=N)}.$$

i.e. percolation clusters are surely finite at percolation threshold.

For $p < p_{\text{cr}}$

$$g_p(|C_r|=n) \sim e^{-\alpha(p)n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\langle C_r \rangle = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{\text{cr}}$.

Expected scaling

$$\langle C_r \rangle \sim \text{const.} (p_{\text{cr}} - p)^{-\gamma}, \quad p \uparrow p_{\text{cr}},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define μ_N to be $g_{p_{\text{cr}}}$ conditioned on clusters of size N , i.e. for $|C_r|=N$

$$\mu_N(C) = \frac{g_{p_{\text{cr}}}(|C_r|=C)}{g_{p_{\text{cr}}}(|C_r|=N)}.$$

For $p < p_{cr}$

$$g_p(|C_r|=n) \sim e^{-\alpha(p)n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\chi(p) = \langle |C_r| \rangle_{g_p}$$

is finite for $p < p_{cr}$.

Expected scaling

$$\chi(p) \sim \text{cst} \cdot (p_{cr} - p)^{-\gamma}, \quad p \nearrow p_{cr},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define μ_N to be $g_{p_{cr}}$ conditioned on clusters of size N , i.e. for $|C|=N$

$$\mu_N(C) = \frac{g_{p_{cr}}(C_r=C)}{g_{p_{cr}}(|C_r|=N)}.$$

For $p < p_{cr}$

$$g_p(|C_r|=n) \sim e^{-\alpha(p) \cdot n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

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Expected scaling

$$\chi(p) \sim \text{cst} \cdot (p_{cr} - p)^{-\gamma}, \quad p \nearrow p_{cr},$$

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Define μ_N to be $g_{p_{cr}}$ conditioned on clusters of size N , i.e. for $|C|=N$

$$\mu_N(C) = \frac{g_{p_{cr}}(C_r=C)}{g_{p_{cr}}(|C_r|=N)}.$$

$$g_p(|c_r|=n) \sim e^{-\alpha(p)n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\chi(p) = \langle |c_r| \rangle_{g_p}$$

is finite for $p < p_{cr}$.

Expected scaling

$$\chi(p) \sim \text{est.} (p_{cr}-p)^{-\gamma}, \quad p \nearrow p_{cr},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define μ_N to be $g_{p_{cr}}$ conditioned on clusters of size N , i.e. for $|c_r|=N$

$$\mu_N(c) = \frac{g_{p_{cr}}(c_r=c)}{g_{p_{cr}}(|c_r|=N)}.$$

$$g_p(|c_r|=n) \sim e^{-\alpha(p)n}, \quad n \rightarrow \infty,$$

where $\alpha(p) > 0$. Hence mean cluster size

$$\langle c_r \rangle = \langle |c_r| \rangle_{g_p}$$

is finite for $p < p_{cr}$.

Expected scaling

$$\langle c_r \rangle \sim \text{cst} \cdot (p_{cr} - p)^{-\gamma}, \quad p \nearrow p_{cr},$$

for some $\gamma > 0$. I.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

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$$g_p(|c_r|=n) \sim e^{-\alpha(p)n}, \quad n \rightarrow \infty,$$

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$$\chi(p) = \langle |c_r| \rangle_{g_p}$$

is finite for $p < p_{cr}$.

Expected scaling

$$\chi(p) \sim \text{cst.} (p_{cr} - p)^{-\gamma}, \quad p > p_{cr},$$

for some $\gamma > 0$. i.e. clusters of arbitrarily large size become increasingly frequent as p_{cr} is approached.

Define μ_N to be $g_{p_{cr}}$ conditioned on clusters of size N , i.e. for $|c_r| = N$

$$\mu_N(c) = \frac{g_{p_{cr}}(c_r = c)}{g_{p_{cr}}(|c_r| = N)}.$$



(9)

Let $\mathcal{C}\ell$ denote the set of clusters containing 0_+ considered as a set of graphs.

The incipient infinite cluster = $(\mathcal{C}\ell, \mu)$ where

$$\mu = \lim_{N \rightarrow \infty} \mu_N$$

provided the limit exists.

$d=2$: Existence shown by H.Kesten '86.

d large: Existence shown by R.van der Hofstad & A.A.Járai 2004.

Alexander & Orbach conjecture: $d_c = \frac{4}{3}$
for all $d \geq 2$.

Probably only valid for d large.

Proof for $d \geq 19$ by G.Kozma & A.Nachmias 2008.

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for all $d \geq 2$.

Probably only valid for d large.

Proof for $d \geq 19$ by G.Kozma & A.Nachmias 2008.

Not much known about d_h .

Let $\mathcal{C}\ell$ denote the set of clusters containing \varnothing , considered as a set of graphs.

The incipient infinite cluster = $(\mathcal{C}\ell, \mu)$
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Alexander & Orbach conjecture: $d_c = \frac{4}{3}$
for all $d \geq 2$.

Probably only valid for d large.

Proof for $d \geq 19$ by G. Kozma & A. Nachmias 2008.

Not much known about d_c .

Let \mathcal{C}_t denote the set of clusters containing \mathbb{G}_t considered as a set of graphs.
The largest infinite cluster = (\mathcal{C}_t, μ)
where

$$\mu_t = \lim_{n \rightarrow \infty} \mu_{t_n}$$

provided the limit exists.

$d=2$: Existence shown by Wierter '76

d large: Existence shown by van der Hofstad & A.A. Jaraai 2004.

Alexander & Orbach conjecture: $d_c = \frac{4}{3}$
for all $d \geq 2$.

Probably only valid for d large.

Proof for $d \geq 19$ by G. Kozma & A. Nachmias

Not much known about d_c .

Let $\mathcal{C}\ell$ denote the set of clusters containing 0 , considered as a set of graphs.

(9)

The incipient infinite cluster = $(\mathcal{C}\ell, \mu)$ where

$$\mu = \lim_{N \rightarrow \infty} \mu_N$$

provided the limit exists.

$d=2$: Existence shown by H. Kesten '86.

d large: Existence shown by R. van der Hofstad & A.A. Jánai 2004.

Alexander & Orbach conjecture: $d_h = \frac{4}{3}$
for all $d \geq 2$.

Probably only valid for d large.

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Alexander & Orbach conjecture: $d_c = \frac{4}{3}$
for all $d \geq 2$.

Probably only valid for d large.

Proof for $d \geq 19$ by G. Kozma & A. Nachmias 2008.

Not much known about d_c .

The incipient infinite cluster = (GIC, μ)
where

$$\mu = \lim_{N \rightarrow \infty} \mu_N$$

provided the limit exists.

$d=2$: Existence shown by H. Kesten '86.

d large: Existence shown by R. van der Hofstad & A.A. Järai 2004.

Alexander & Orbach conjecture: $d_c = \frac{4}{3}$
for all $d \geq 2$.

Probably only valid for d large.

Proof for $d \geq 19$ by G. Kozma & A. Nachmias 2008.

Not much known about d_c .

References:

G. Grimmett: Percolation, Springer 1999.

THE INCIPIENT INFINITE CLUSTER - CONJECTURE
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provided the limit exists.

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Proof for $d \geq 19$ by G. Kozma & A. Nachmias 2008.

Not much known about d_c .

References:

G. Grimmett: Percolation, Springer 1999.

M. Maes: The CCP in 2D percolation.

THE INCipient infinite cluster - $\text{IC}(\mu)$
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Proof for $d \geq 19$ by G. Kozma & A. Nachmias 2008.

Not much known about d_h .

References:

- G. Grimmett: Percolation, Springer 1999.
- M. Marstrand: The RVE in percolation.

THE INCISION IMPERFECT CONVERGENCE CONJECTURE
where

$$\mu_c = \lim_{N \rightarrow \infty} \mu_N$$

provided the limit exists.

$d=2$: Existence shown by H. Kesten '86.

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Probably only valid for d large.

Proof for $d \geq 19$ by G. Kozma & A. Nachmias 2008.

Not much known about d_c .

References:

- G. Grimmett: Percolation, Springer 1999.
- M. Marstrand: The SRB in percolation.

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Proof for $d \geq 19$ by G. Kozma & A. Nachmias 2008.

Not much known about d_h .

References:

G. Grimmett: Percolation, Springer 1999.
M. Maes: The SLE in 2D percolation.

The incipient infinite cluster = $(\mathcal{E}\ell, \mu)$
where

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$d=2$: Existence shown by H. Kesten '86.

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- G. Grimmett: Percolation, Springer 1999.
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Probab. Th. and Rel. Fields 73, 1986

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Proof for $d \geq 19$ by G. Kozma & A. Nachmias 2008.

Not much known about d_c .

References:

G. Grimmett: Percolation, Springer 1999.

H. Kesten: The IIP in 2D percolation,
Probab. Th. and Rel. Fields 73, 1986

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$d=2$: Existence shown by H. Kesten

d large: Existence shown by R. van der Hofstad & A.A. Järai 2004.

Alexander & Orbach conjecture: $d_1 = \frac{4}{3}$
for all $d \geq 2$.

Probably only valid for d large.

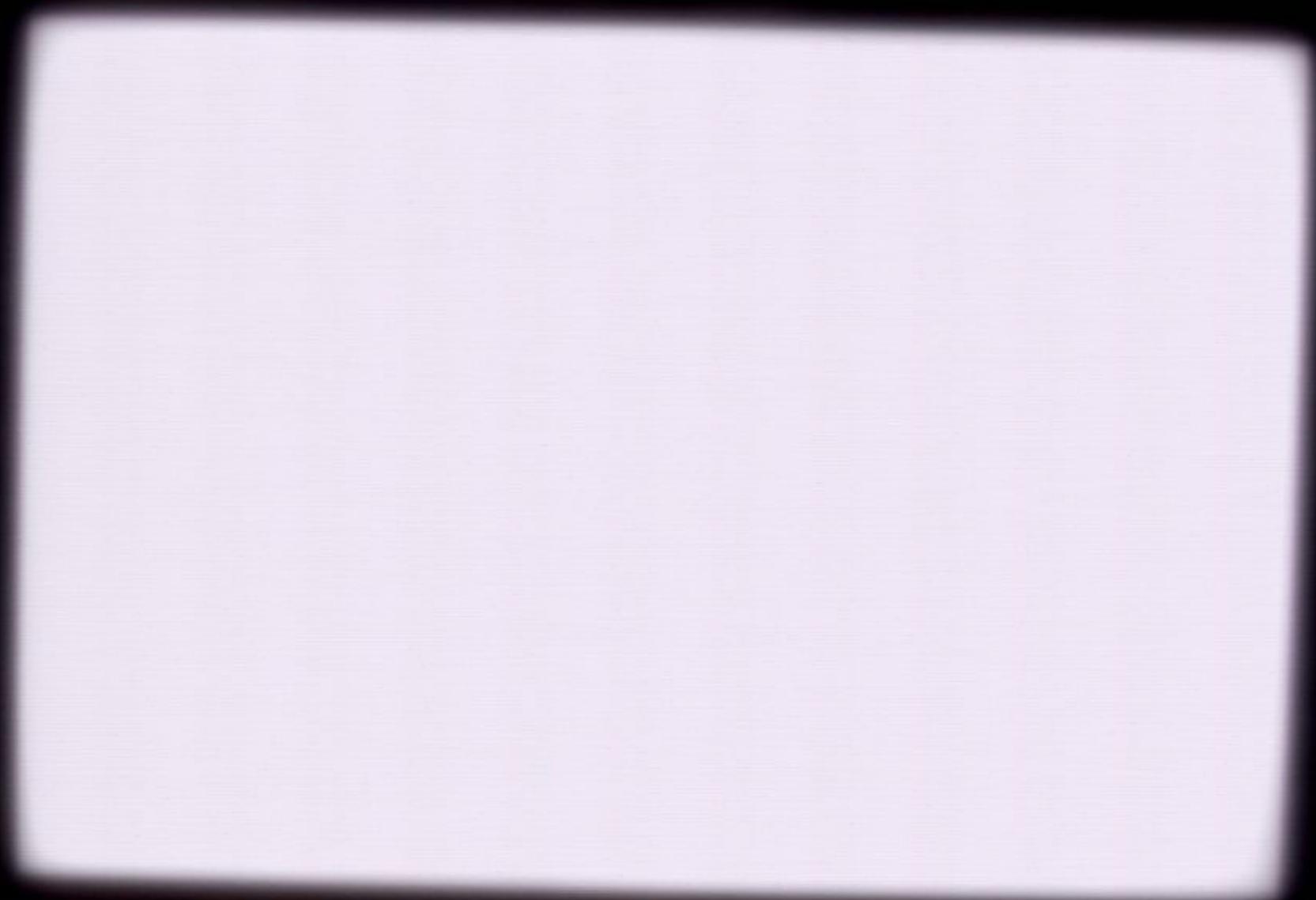
Proof for $d \geq 19$ by G. Kozma & A. Nachmias 2008.

Not much known about d_n .

References:

G. Grimmett: Percolation, Springer 1999.

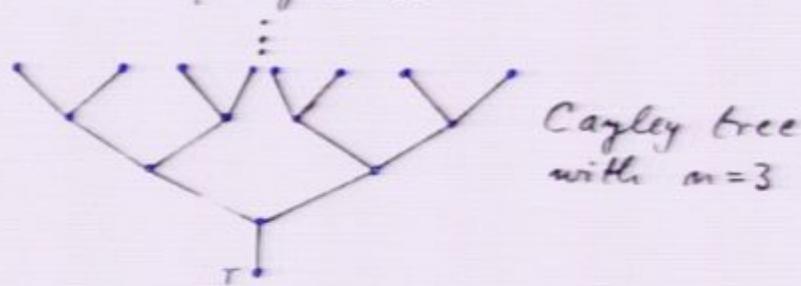
H. Kesten: The IIP in 2D percolation,
Probab. Th. and Rel. Fields 73, 1986
and Adv. Appl. Prob. 114, 2004



(10)

4. The case $G = \text{Cayley graph } \Gamma^c$ ($d = \infty$)

Assume vertices of Γ^c have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ^c with $1 \leq |T| < \infty$:

$$P_p(c_r = T) = p^{|T|} \prod_{v \in T \setminus r} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

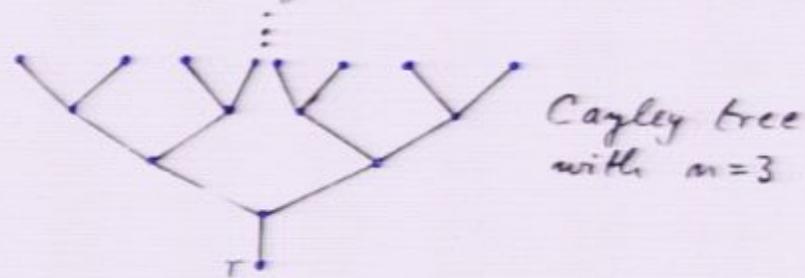
Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$\mathbb{P}(T) = \prod_{v \in T \setminus r} p_{vv-1},$$

(10)

4. The case $G = \text{Cayley graph } \Gamma^r$ ($d = \infty$)

Assume vertices of Γ^r have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ^r with $1 \leq |T| < \infty$:

$$P_p(C_r = T) = p^{|T|} \prod_{v \in T \setminus \{T\}} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

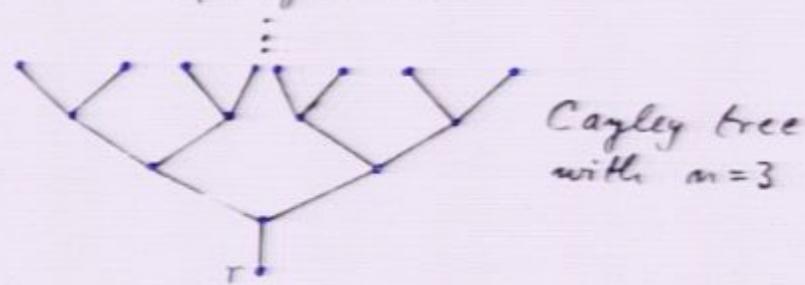
Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$g(T) = \prod_{v \in T \setminus \{T\}} P_{001},$$

(10)

4. The case $G = \text{Cayley graph } \Gamma^r$ ($d = \infty$)

Assume vertices of Γ^r have degree n
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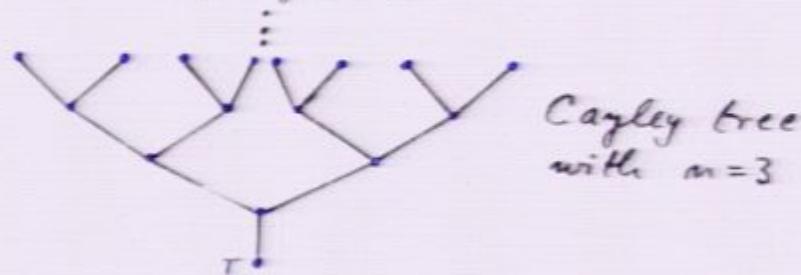
For a (non-trivial) rooted subtree T of Γ^r with $1 \leq |T| < \infty$:

$$P_p(C_r = T) = p^{|T|} \prod_{v \in T \setminus r} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$g(T) = \prod_{v \in T \setminus r} p_{v=1},$$

Assume vertices of P have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of P with $1 \leq |T| < \infty$:

$$P_p(C_T = T) = p \prod_{v \in T \setminus \{T\}} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

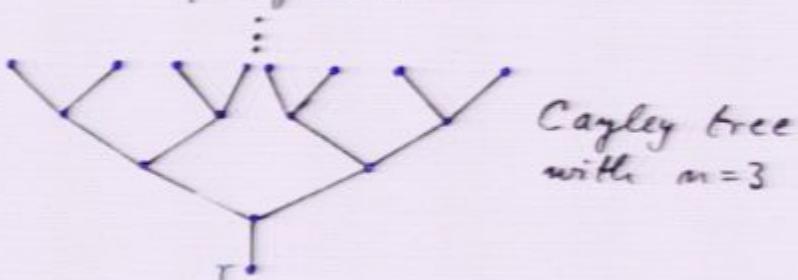
Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$g(T) = \prod_{v \in T \setminus \{T\}} p_{v-1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

Assume vertices of Γ have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(C_T = T) = p^{|T|} \prod_{v \in T \setminus r} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

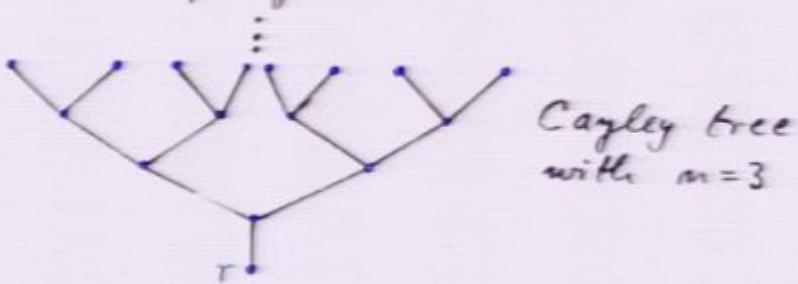
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$$g(T) = \prod_{v \in T \setminus r} p_{v-1},$$

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Assume vertices of Γ have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(C_T = T) = p^{|T|} \prod_{v \in T \setminus r} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

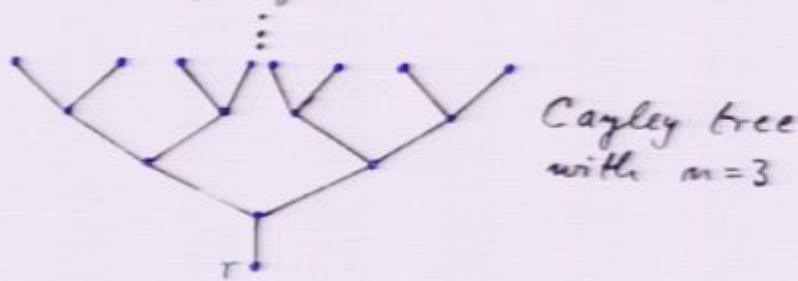
Hence, conditioning on configurations with root x_0 of value 1 we get the distribution of Galton-Watson type

$$P(T) = \prod_{v \in T \setminus r} P_k$$

where

$$P_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}$$

Assume vertices of Γ have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(c_T = T) = p^{|T|} \prod_{v \in T \setminus r} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

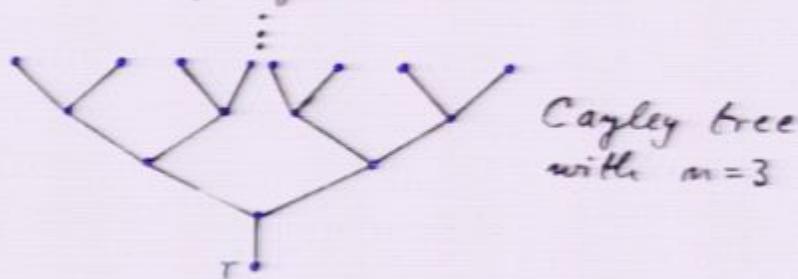
Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$g(T) = \prod_{v \in T \setminus r} p_{v-1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

Assume vertices of Γ have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(c_r = T) = p^{|T|} \prod_{v \in T \setminus r} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

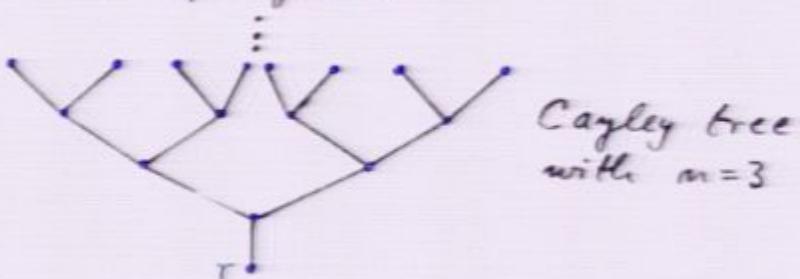
Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$g(T) = \prod_{v \in T \setminus r} p_{v-1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

Assume vertices of Γ have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(C_T = T) = p \prod_{v \in T \setminus r} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

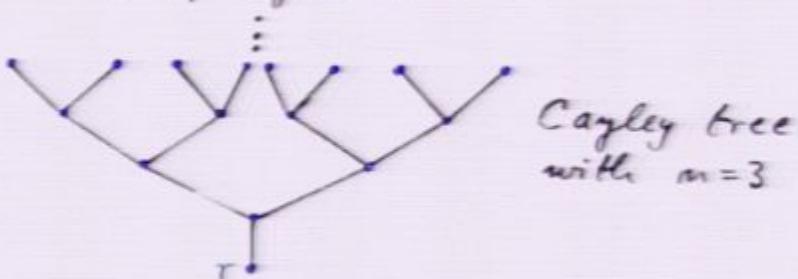
Hence, conditioning on configurations with root edge of type 1 we get the distribution of Galton-Watson type

$$P(T) = \prod_{v \in T \setminus r} p_{v-1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k = 0, 1, \dots, n-1.$$

Assume vertices of Γ have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(c_T = T) = p^{|T|} \prod_{v \in T \setminus r} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

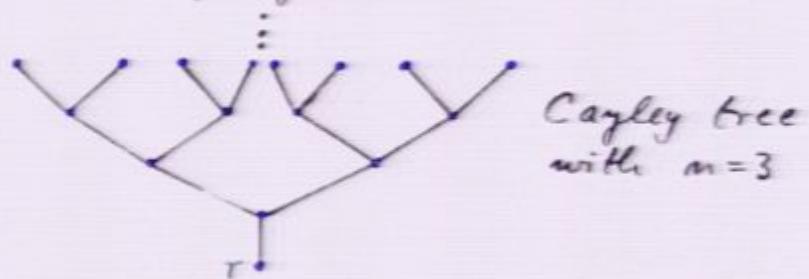
Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$g(T) = \prod_{v \in T \setminus r} p_{v-1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

Assume vertices of Γ have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(C_T = T) = p \prod_{v \in T \setminus r} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

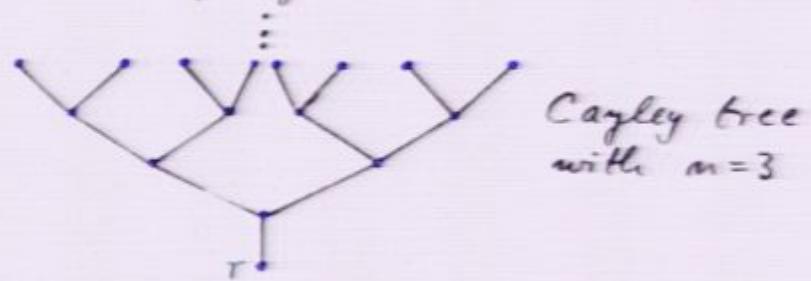
Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson tree

$$g(T) = \prod_{v \in T \setminus r} p_{v-1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}$$

Assume vertices of Γ have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(C_T = T) = p^{|T|} \prod_{v \in T \setminus \{r\}} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

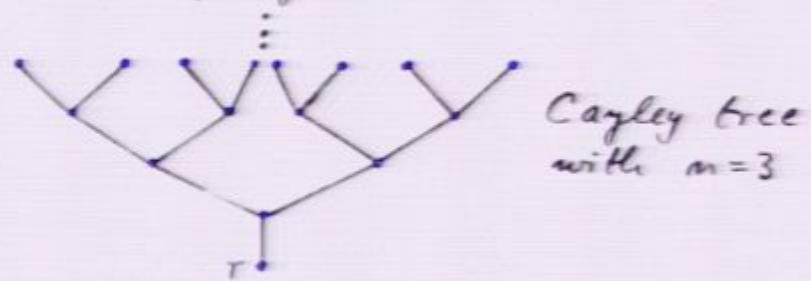
Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$g(T) = \prod_{v \in T \setminus \{r\}} p_{0,v-1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

Assume vertices of Γ have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(C_T = T) = p \prod_{v \in T \setminus r} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

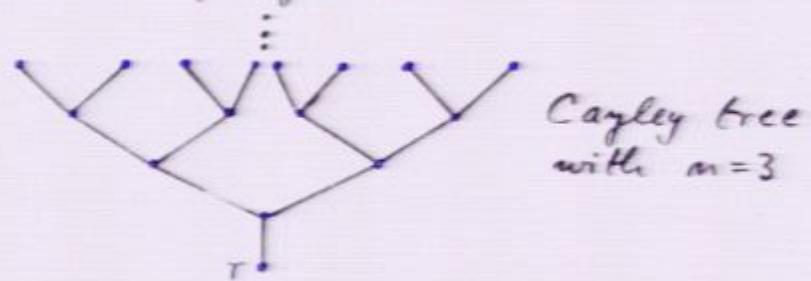
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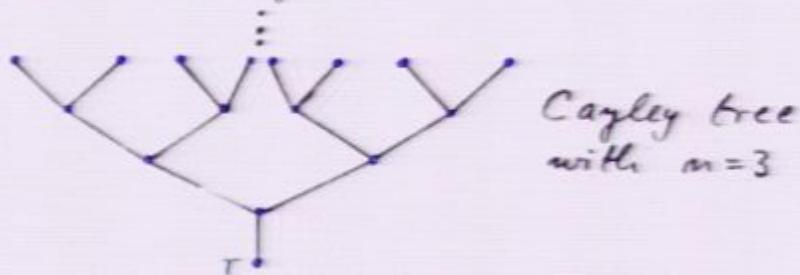
Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$g(T) = \prod_{v \in T \setminus r} p_{0v-1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, k=0, 1, 2, \dots, n-1.$$

Assume vertices of Γ have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(C_T = T) = p^{|T|} \prod_{v \in T \setminus \{T\}} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

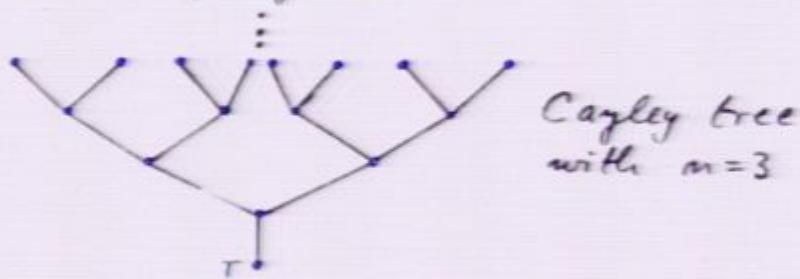
Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$g(T) = \prod_{v \in T \setminus \{T\}} p_{00-v},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

Assume vertices of Γ have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(C_T = T) = p^{|T|} \prod_{v \in T \setminus \{T\}} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

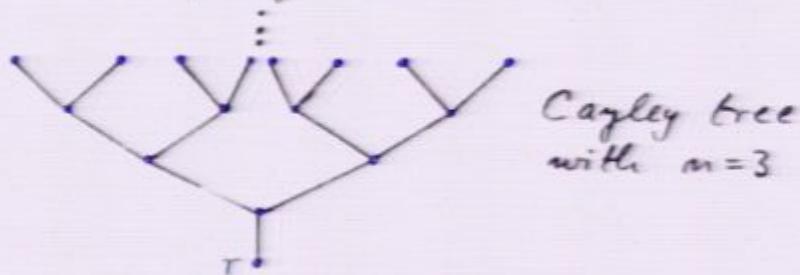
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except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(C_T = T) = p^{|T|} \prod_{v \in T \setminus r} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

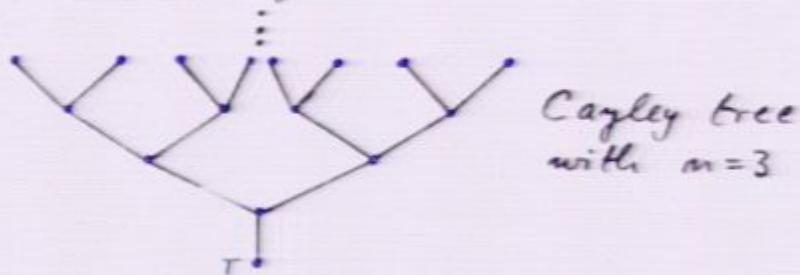
Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$P(T) = \prod_{v \in T \setminus r} p_{k(v)-1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

Assume vertices of Γ have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$p_p(c_r = T) = p_{root}^{|T|} \binom{n-1}{d_r-1} p^{d_r-1} (1-p)^{n-d_r}$$

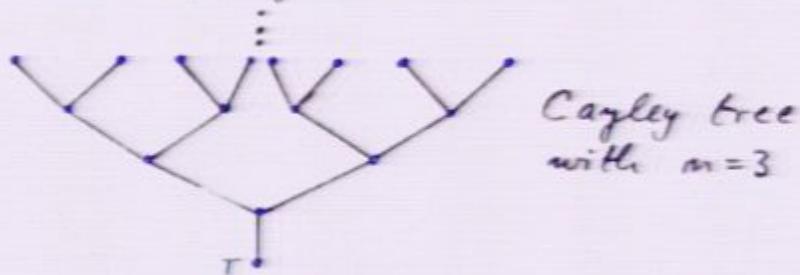
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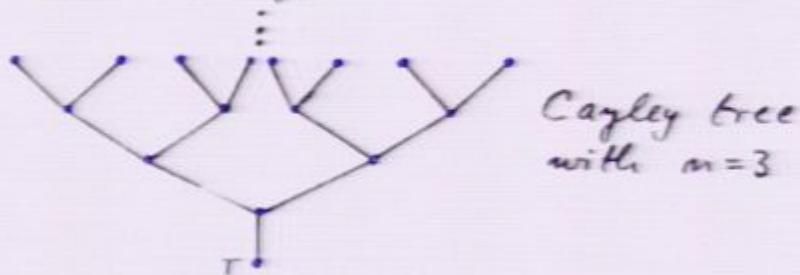
Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$g(T) = \prod_{v \in T \setminus \{T\}} p_{v \text{ root}},$$

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$$P_p(C_T = T) = p^{|T|} \prod_{v \in T \setminus \{T\}} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

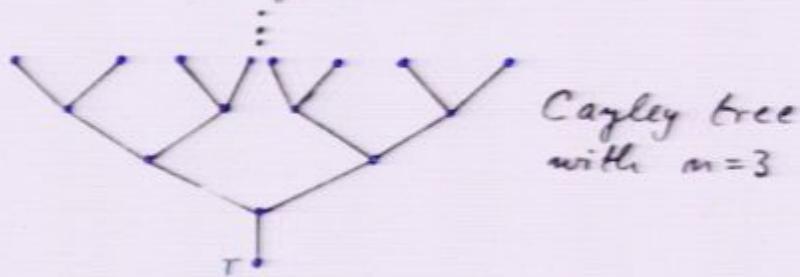
Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$P(T) = \prod_{v \in T \setminus \{T\}} P_{k+1},$$

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$$P_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

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For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$p_p(C_T = T) = p_{\text{root}}^{|T|} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

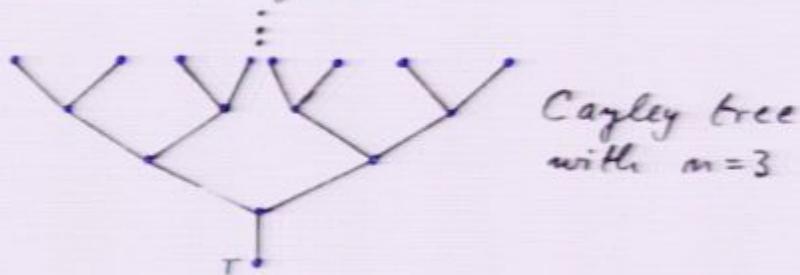
Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$g(T) = \prod_{v \in T \setminus \{r\}} p_{v,v-1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

Assume vertices of T have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(C_T = T) = p \prod_{v \in T \setminus \{T\}} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

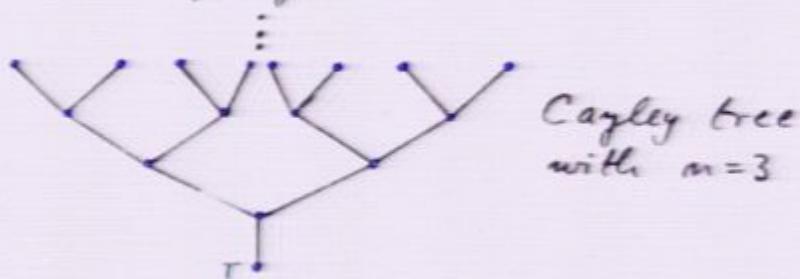
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$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

Assume vertices of Γ have degree n
except root of degree 1.



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

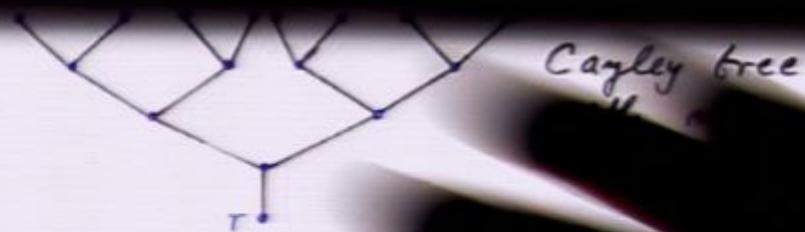
$$p_p(C_T = T) = p_{\text{root}}^{|T|} \binom{n-1}{d_T-1} p^{d_T-1} (1-p)^{n-d_T}$$

Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$q(T) = \prod_{v \in T \setminus r} p_{v \text{ root}},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$



For a (non-trivial) rooted set
 Γ with $1 \leq |\Gamma| < \infty$:

$$p_p(c_r=T) = p \prod_{v \in T} \binom{n-1}{\delta_v - 1} t$$

Hence, conditioning on configurations
 with root edge of value 1 we get
 the distribution of Galton-Watson type

$$\pi(T) = \prod_{v \in T} p_{\delta_v - 1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

Note:

$$\sum_{k=0}^{\infty} p_k = 1$$

(where $p_k = 0$ for $k \geq n$).



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(c_T = T) = p^{|T|} \prod_{v \in T} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$g(T) = \prod_{v \in T} p_{v+1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

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For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$p_p(c_r = T) = p_{\text{water}}^{\text{water}} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$q(T) = \prod_{v \in T \setminus \{r\}} p_{v-1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

Note:

$$\sum_{k=0}^{\infty} p_k = 1$$

(where $p_k \geq 0$ for $k \geq 0$)



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$p_p(c_r = T) = p_{\text{root}}^{\text{out}} \binom{n-1}{d_r-1} p^{d_r-1} (1-p)^{n-d_r}$$

Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$q(T) = \prod_{v \in T \setminus \{r\}} p_{v-1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

Note:

$$\sum_{k=0}^{\infty} p_k = 1$$

(where $p_k = 0$ for $k > n$).



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$g_p(c_r = T) = p^{\prod_{v \in T \setminus r} d_v} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

Hence, conditioning on configurations with root edge of value 1 we get the distribution of Walton-Wilson type

$$g(T) = \prod_{v \in T \setminus r} p_{d_v-1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

Note:

$$\sum_{k=0}^{\infty} p_k = 1$$

(where $p_k = 0$ for $k \geq n$).



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$g_p(c_r = T) = p^{\prod_{v \in T \setminus r} d_v} \binom{n-1}{d_r-1} p^{d_r-1} (1-p)^{n-d_r}$$

Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$g(T) = \prod_{v \in T \setminus r} p_{d_v-1},$$

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For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

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Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$q(T) = \prod_{v \in T \setminus \{r\}} p_{v-1},$$

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Note:

$$\sum_{k=0}^{\infty} p_k = 1$$

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For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$\rho_p(c_r = T) = p^{|T|} \prod_{v \in T \setminus r} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

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where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, \quad k=0, 1, 2, \dots, n-1.$$

Note:

$$\sum_{k=0}^{\infty} p_k = 1$$

(where $p_k = 0$ for $k \geq n$).



with $m=3$

For a (non-trivial) rooted subtree T of P with $1 \leq |T| < \infty$:

$$p_p(c_r=T) = p_{\text{root}}^{\infty} \binom{n-1}{s_{r-1}} p^{d_{r-1}} (1-p)^{n-d_r}$$

Hence, conditioning on configurations with root edge of value 1 we get the distribution of matton Wilson type

$$g(T) = \prod_{v \in T \setminus \{r\}} p_{v-1},$$

where

$$p_k = \binom{n-1}{k} p^k (1-p)^{n-1-k}, k=0,1,2,\dots$$

Note:

$$\sum_{k=0}^{\infty} p_k = 1$$

(where $p_k = 0$ for $k \geq n$).



For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$g_p(c_r = T) = p^{\prod_{v \in T} \binom{n-1}{d_v-1}} p^{d_r-1} (1-p)^{n-d_r}$$

Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

$$g(T) = \prod_{v \in T \setminus r} p_{v+1},$$

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(where $p_k = 0$ for $k \geq n$).

To a non-degenerate subset of
P with vertices

Given the set $\{x_1, x_2, \dots, x_n\}$

Draw a diagram in a plane
with one edge of the triangle
the distance of each side \leq

between the points

where

$\text{perimeter} \leq 2n$

Note -

$\frac{1}{2} P = t$

$t < P / 2$

T^*

For a (non-trivial) rooted subtree T of Γ with $1 \leq |T| < \infty$:

$$P_p(C_r = T) = p \prod_{v \in T \setminus r} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

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$$p_p(c_r=T) = p_{\text{root}}^{\text{II}} \binom{n-1}{d_v-1} p^{d_v-1} (1-p)^{n-d_v}$$

Hence, conditioning on configurations with root edge of value 1 we get the distribution of Galton-Watson type

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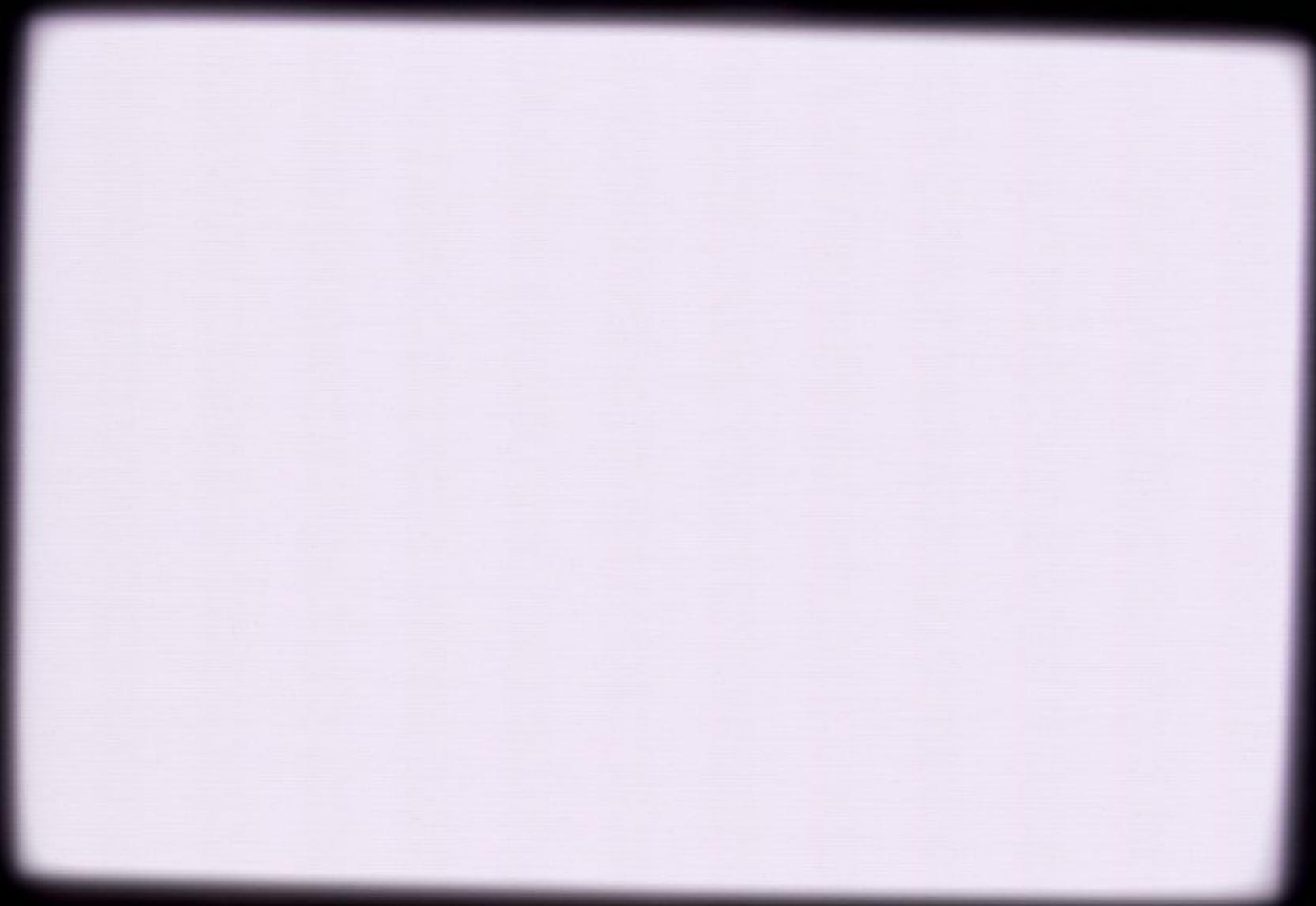
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Note:

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(II)

Determine for:

Set

$$Z_N = \sum_{T: |T| \geq N} p(T) = p(|T| \geq N).$$

generating functions

$$Z(t) = \sum_{n=0}^{\infty} Z_n t^n$$

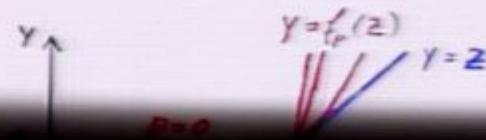
and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$Z(t) = t f(Z(t))$$

For Γ : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



(II)

Determine for:

Set

$$Z_N = \sum_{T: |T| \geq N} \ell(T) = \ell(|T| \geq N)$$

generating functions

$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

and

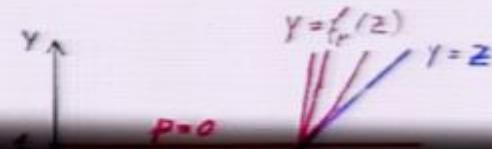
$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

For P :

$$f(t) = (1 - p + tp)^{n-1} = f_p(t)$$



(II)

Determine for:

Set

$$Z_N = \sum_{T: |T| \geq N} \rho(T) = \rho(|T| \geq N).$$

generating functions

$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

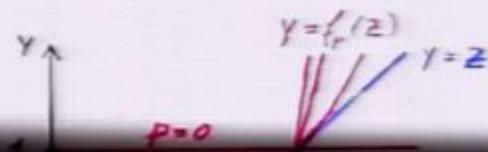
and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

For Γ : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



(II)

Determine for:

set

$$Z_N = \sum_{T: |T| \geq N} \rho(T) = \rho(|T| \geq N).$$

generating functions

$$Z(t) = \sum_{n=0}^{\infty} Z_n t^n$$

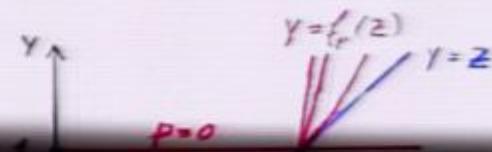
and

$$f(t) = \sum_{k=0}^{\infty} f_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

For Γ : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



(II)

Determine p_n :

Set

$$Z_N = \sum_{T: |T| \geq N} p(T) = p(|T| \geq N).$$

generating functions

$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

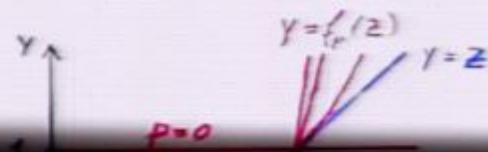
and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

For P : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



(II)

Determine for:

Set

$$Z_N = \sum_{T: |T| \geq N} p(T) = p(|T| \geq N).$$

generating functions

$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

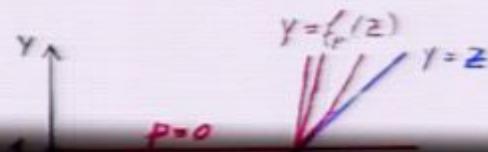
and

$$f(t) = \sum_{k=0}^{\infty} f_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

$$\text{For } P: \quad f(t) = (1 - p + tp)^{n-1} = f_p(t)$$



(II)

Determine for:

Set

$$Z_N = \sum_{T: |T| \geq N} \varrho(T) = \varrho(|T| \geq N).$$

generating functions

$$Z(t) = \sum_{n=0}^{\infty} Z_n t^n$$

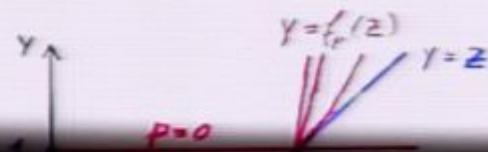
and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

For Γ : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



(II)

Determine for:

Set

$$Z_N = \sum_{T: |T|=N} \rho(T) = \rho(|T|>N).$$

generating functions

$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

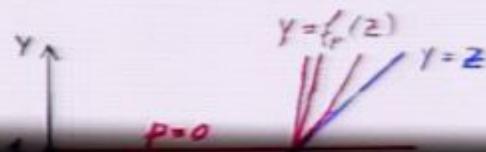
and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

$$\text{For } F: \quad f(t) = (1-p+tp)^{n-1} = f_p(t)$$



(II)

Determine for:

set

$$Z_N = \sum_{T: |T| \geq N} \rho(T) = \rho(|T| \geq N).$$

generating functions

$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

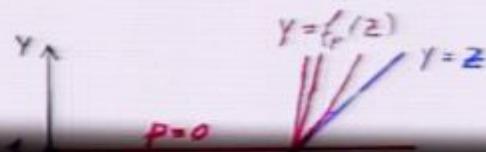
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$$f(t) = \sum_{k=0}^{\infty} f_k t^k$$

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$$\boxed{Z(t) = t f(Z(t))}$$

For Γ : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



(II)

Determine for:

set

$$Z_N = \sum_{T: |T| \geq N} \rho(T) = \rho(|T| \geq N).$$

generating functions

$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

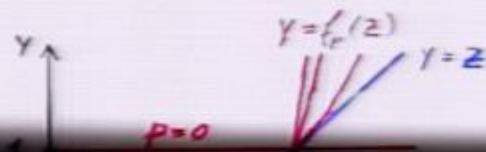
and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

For Γ : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



(II)

Determine p_{cr} :

Set

$$Z_N = \sum_{T: |T|=N} \ell(T) = \ell(|T|=N)$$

generating functions

$$Z(t) = \sum_{n=0}^{\infty} Z_n t^n$$

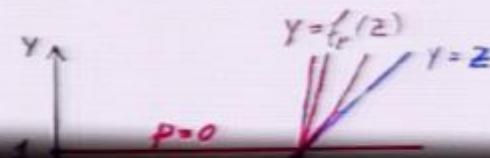
and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

For P : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



(ii)

Determine for:

set

$$Z_N = \sum_{T: |T| \geq N} f(T) = f(|T| \geq N).$$

generating functions

$$Z(t) = \sum_{n=0}^{\infty} Z_n t^n$$

and

$$f(t) = \sum_{k=0}^{\infty} f_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

For P : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$

$y \uparrow$

$$y = f_p(z)$$

$\parallel \quad \parallel \quad y = z$

(ii)

Determine for:

set

$$Z_N = \sum_{T: |T| \geq N} \ell(T) = \ell(|T| \geq N).$$

generating functions

$$Z(t) = \sum_{n=0}^{\infty} Z_n t^n$$

and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

For P : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$

 $\gamma \uparrow$

$$\begin{array}{c} Y = f_p(Z) \\ || \quad || \quad Y = Z \end{array}$$

(II)

Determine for:

Set

$$Z_N = \sum_{T: |T|=N} f(T) = f(|T|>N).$$

generating functions

$$Z(t) = \sum_{n=0}^{\infty} Z_n t^n$$

and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

For P :

$$f(t) = (t - p + tp)^{n-1} = f_p(t)$$

Y

$$Y = f_p(t) \\ \textcolor{red}{//} / \textcolor{blue}{//} Y = Z$$

(II)

Determine for:

Set

$$Z_N = \sum_{T: |T|=N} f(T) = f(\{T| |T|=N\}) .$$

generating functions

$$Z(t) = \sum_{n=0}^{\infty} Z_n t^n$$

and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

For P :

$$f(t) = (1 - p + tp)^{n-1} = f_p(t)$$

$y \uparrow$

$$y = f_p(t) \quad || \quad y = Z$$

(II)

Determine for:

Set

$$Z_N = \sum_{T: |T|=N} f(T) = f(\{T| |T|=N\}) .$$

generating functions

$$Z(t) = \sum_{n=0}^{\infty} Z_n t^n$$

and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

For P :

$$f(t) = (1 - p + tp)^{n-1} = f_p(t)$$

$y \uparrow$

$y = f_p(t)$
 $\parallel \quad \parallel \quad y = z$

(II)

Determine for:

Set

$$Z_N = \sum_{T: |T|=N} f(T) = f(\{T| |T|=N\}) .$$

generating functions

$$Z(t) = \sum_{n=0}^{\infty} Z_n t^n$$

and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

For $P:$ $f(t) = (1 - p + tp)^{n-1} = f_p(t)$

 $\gamma \uparrow$

$$\gamma = f_p(2)$$

$\parallel \quad \gamma = Z$

(II)

Determine for:

Set

$$Z_N = \sum_{T: |T|=N} f(T) = f(\{T| |T|=N\}) .$$

generating functions

$$Z(t) = \sum_{n=0}^{\infty} Z_n t^n$$

and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$\boxed{Z(t) = t f(Z(t))}$$

For $P:$ $f(t) = (1 - p + tp)^{n-1} = f_p(t)$

 $y \uparrow$

$$y = f_p(t) \\ || / / \quad y = z$$

(II)

Determine for:

Set

$$Z_N = \sum_{T: |T|=N} f(T) = f(\{T| |T|=N\}) .$$

generating functions

$$Z(t) = \sum_{n=0}^{\infty} Z_n t^n$$

and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

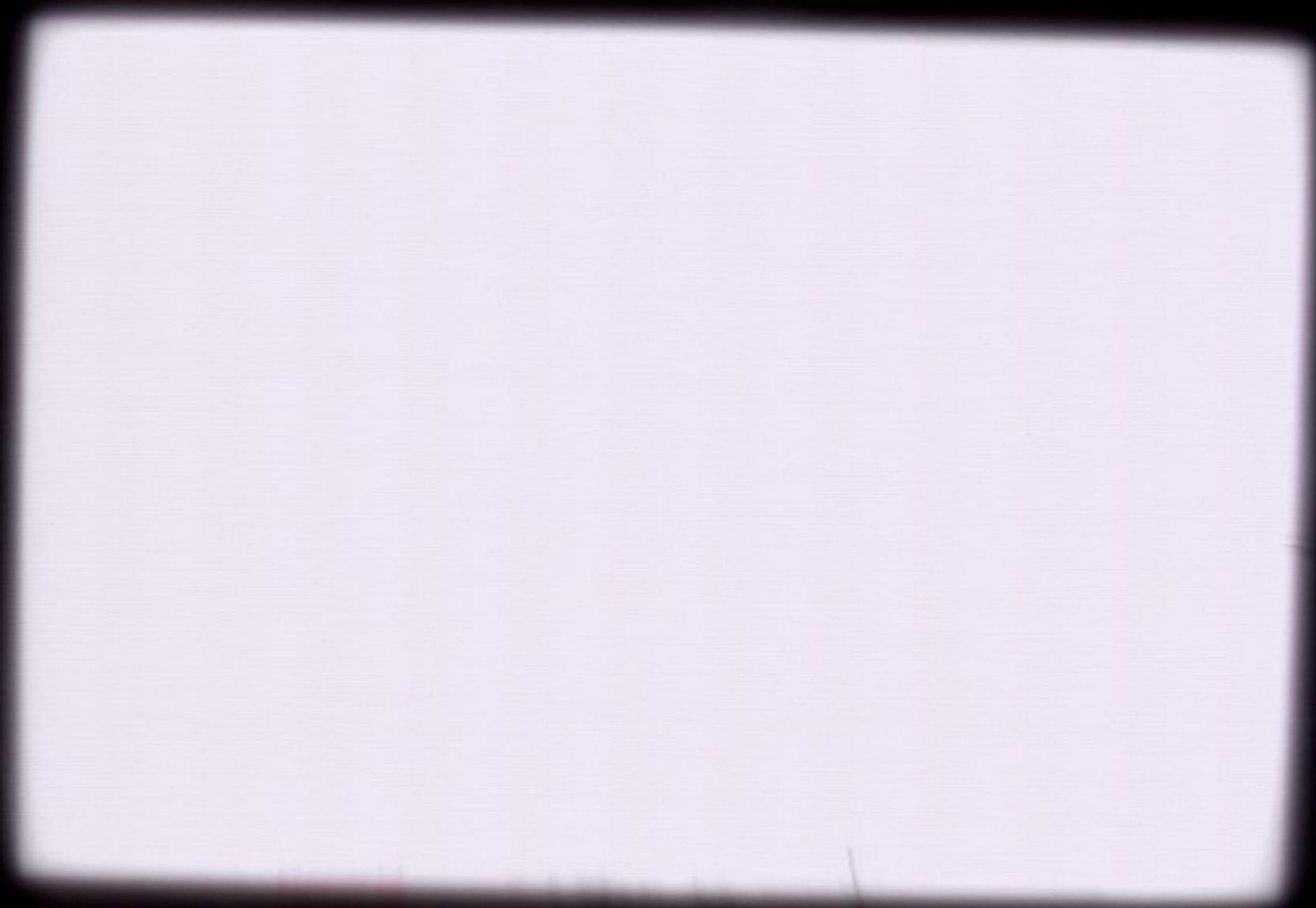
$$\boxed{Z(t) = t f(Z(t))}$$

For P :

$$f(t) = (1 - p + tp)^{n-1} = f_p(t)$$

$y \uparrow$

$$y = f_p(2) \\ // / y = z$$



(III)

$$\text{Diagram} = t \sum_{k=0}^{\infty} p_k \text{Diagram}$$

(W)

$$\text{Diagram} = t \sum_{k=0}^{\infty} p_k \text{Diagram}^{(k)}$$

(W)

$$\text{Diagram} = t \sum_{k=0}^{\infty} p_k \text{Diagram}$$

(W)

$$\text{Diagram} = t \sum_{k=0}^{\infty} p_k \text{Diagram}_k$$

The diagram consists of a circle with two internal lines. One line connects the top-left and bottom-right points, and the other connects the top-right and bottom-left points. This forms a cross-like shape inside the circle.

The sum is over $k=0$ to ∞ .

p_k is associated with the k -th term in the sum.

Diagram_k is shown as a tree with k levels. The root node has two children, which each have two children, and so on. The final level has two leaves.

(W)

$$\text{Diagram} = t \sum_{k=0}^{\infty} p_k \text{Diagram}$$



(W)

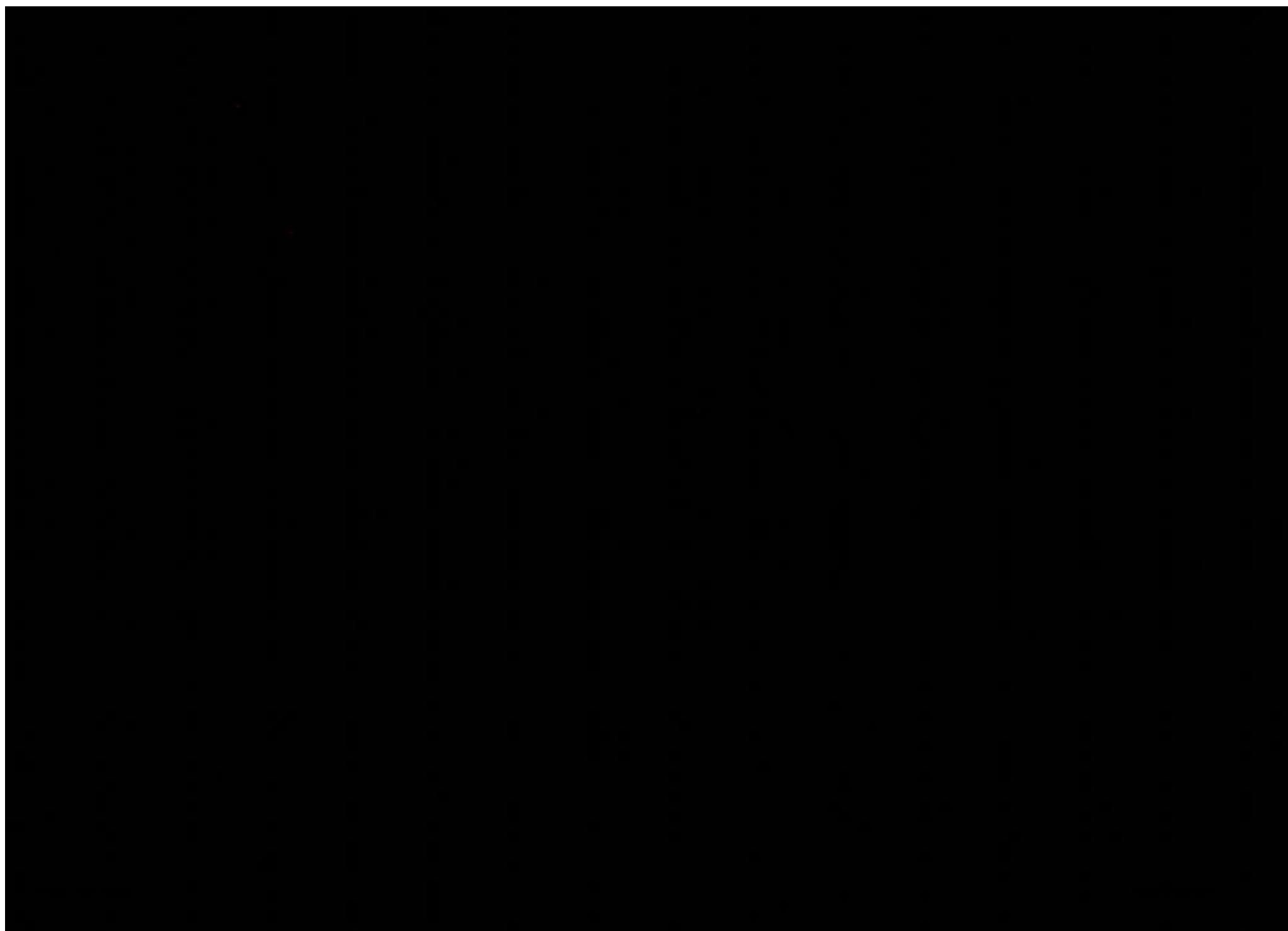
$$\text{Diagram} = t \sum_{k=0}^{\infty} p_k \text{Diagram}$$

(W)

$$\text{Diagram} = t \sum_{k=0}^{\infty} p_k \text{Diagram}$$

(W)

$$\text{Diagram} = t \sum_{k=0}^{\infty} p_k \text{Diagram}_k$$



HF

$$= t \sum_{k=0}^{\infty} \alpha_k \begin{array}{c} \nearrow \\ \searrow \end{array}$$

(II')

$$= t \sum_{k=0}^{\infty} p_k$$

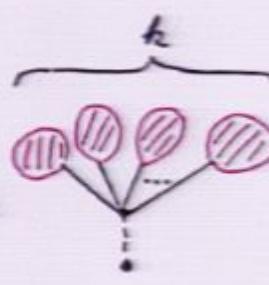
A diagram illustrating a binomial process. A single node at the top branches into two nodes, which then branch into four nodes, and so on. The nodes are represented by circles with diagonal hatching. A bracket above the first four nodes is labeled k , indicating the number of trials or successes.

(ii')

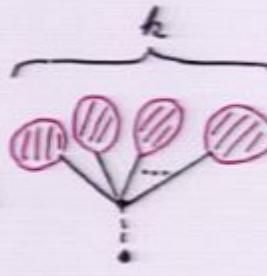
$$= t \sum_{k=0}^{\infty} p_k$$

k

(II')


$$= t \sum_{k=0}^{\infty} p_k$$


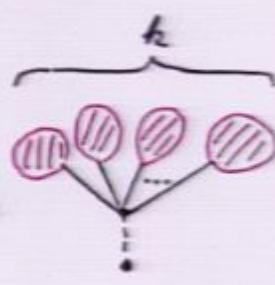
(II')


$$= t \sum_{k=0}^{\infty} p_k$$


(W)

$$= t \sum_{k=0}^{\infty} p_k$$

(W)


$$= t \sum_{k=0}^{\infty} p_k$$


(II')

A diagram illustrating a generating function. On the left, there is a circle containing several parallel diagonal lines from top-left to bottom-right, representing a combinatorial object. To its right is an equals sign followed by a sum symbol. The sum has a lower limit of $k=0$ and an upper limit of ∞ . Next to the sum symbol is the variable p_k . To the right of the sum is a term t^k , where k is indicated by a bracket above four circles. Each circle contains a smaller circle with diagonal hatching, representing a component of the object. Ellipses below the circles indicate the continuation of the sequence.

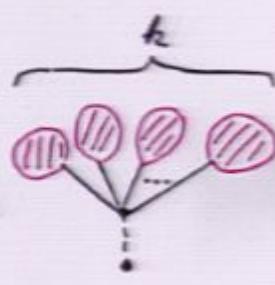
$$= t \sum_{k=0}^{\infty} p_k t^k$$

(W')


$$= t \sum_{k=0}^{\infty} p_k$$

A hand holding a black marker is pointing towards the diagram. A bracket above the series term p_k is labeled t_k .

(W)


$$= t \sum_{k=0}^{\infty} p_k$$


(II')

$$= t \sum_{k=0}^{\infty} p_k$$

The diagram illustrates a mathematical concept. On the left, there is a single circle filled with diagonal hatching. This is followed by an equals sign. To the right of the equals sign is a summation symbol (\sum) with the index $k=0$ below it and a infinity symbol (∞) above it. Next to the summation symbol is the variable p_k . To the right of the summation symbol is a series of circles connected by lines. A bracket above these circles is labeled t . The circles are arranged such that they branch out from a central point, with ellipses indicating continuation.

(W')

$$= t \sum_{k=0}^{\infty} p_k$$

The diagram consists of three parts: 1) A circle filled with diagonal hatching and a vertical line extending downwards from its center. 2) An equals sign followed by a summation symbol with the index $k=0$ and a superscript ∞ . 3) A tree diagram starting from a single point at the bottom, which branches upwards into two lines. These lines further branch into four lines, which then branch into eight lines, and so on. The total number of lines is 2^k , where k is the level of the tree. The entire tree is enclosed in a bracket above it labeled t^k .

intensity $\rho(t)$

generating function

$$g(t) = \sum_{k=0}^{\infty} p_k t^k$$

and

$$f(t) = \sum_{k=0}^{\infty} \rho_k t^k$$

are related by

$$g(t) = t f(g(t))$$

$$\text{and } f(t) = (1 - p + tp)^{-1} \cdot g(t)$$

Generating functions

$$\Xi(t) = \sum_{n=0}^{\infty} \Xi_n t^n$$

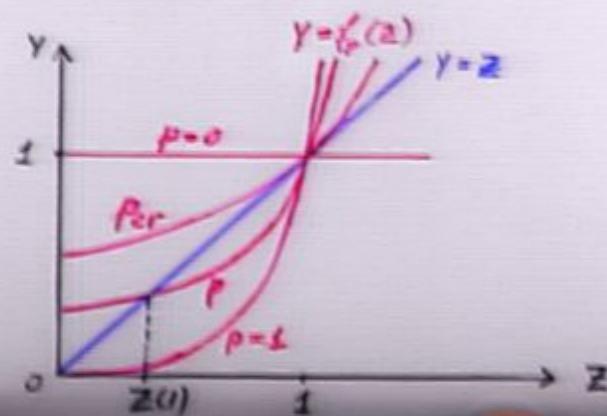
and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$\Xi(t) = t f(\Xi(t))$$

For Γ : $f(t) = (1 - p + tp)^{n-p} = f_p(t)$



Generating functions

$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

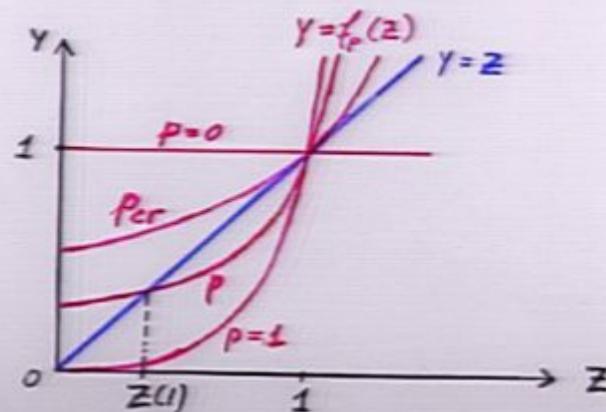
and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$Z(t) = t f(Z(t))$$

For P : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

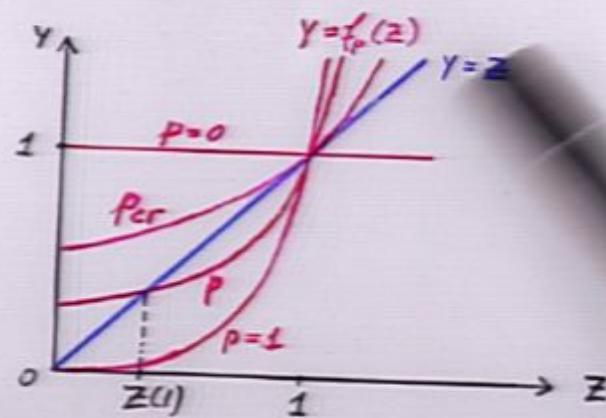
and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$Z(t) = t f(Z(t))$$

For P : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

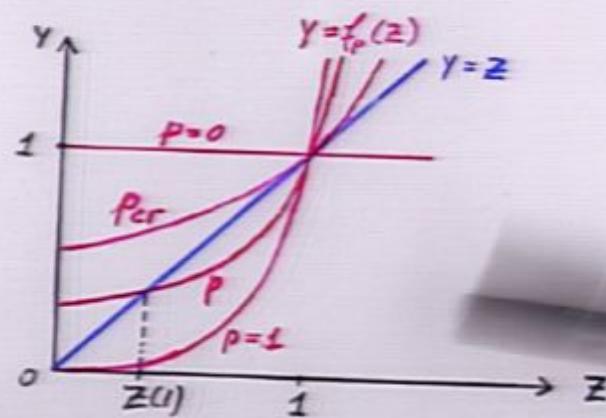
and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$Z(t) = t f(Z(t))$$

$$\text{For } P: \quad f(t) = (1 - p + tp)^{n-1} = f_p(t)$$



$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

and

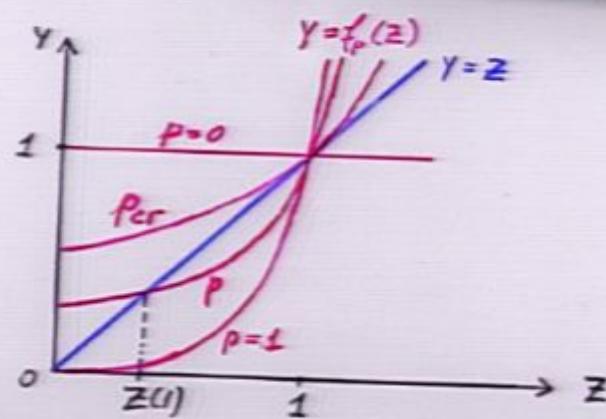
$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$Z(t) = t f(Z(t))$$

For n :

$$f(t) = (1 - p + tp)^{n-1} = f_n(t)$$



$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

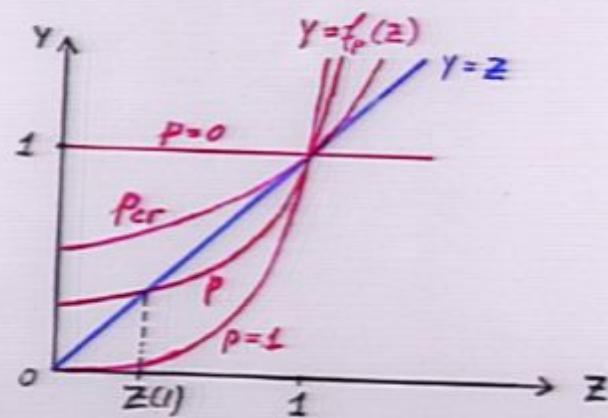
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$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

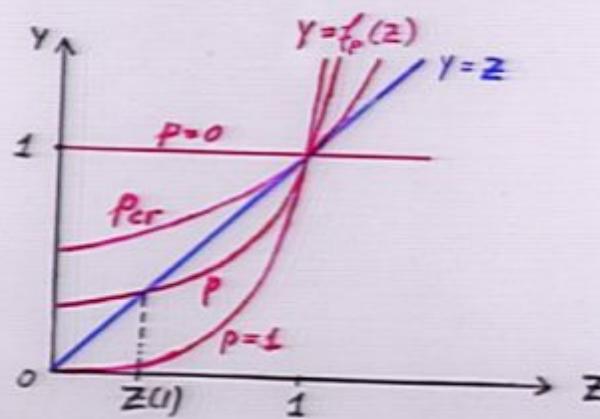
and

$$f(t) = \sum_{k=0}^{\infty} f_k t^k$$

are related by

$$Z(t) = t f(Z(t))$$

For Γ : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



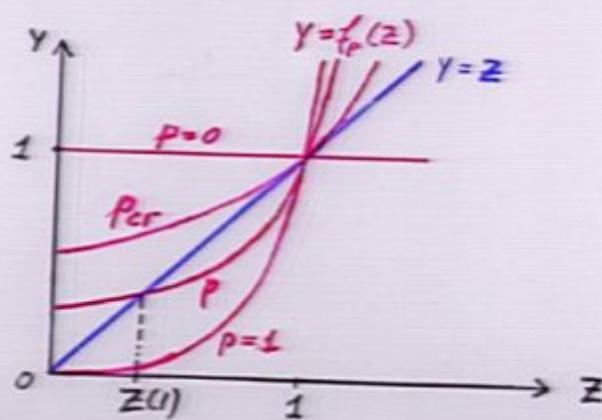
and $Z(t) = \sum_{n=1}^{\infty} Z_n t^n$

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$Z(t) = t f(Z(t))$$

For Γ : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

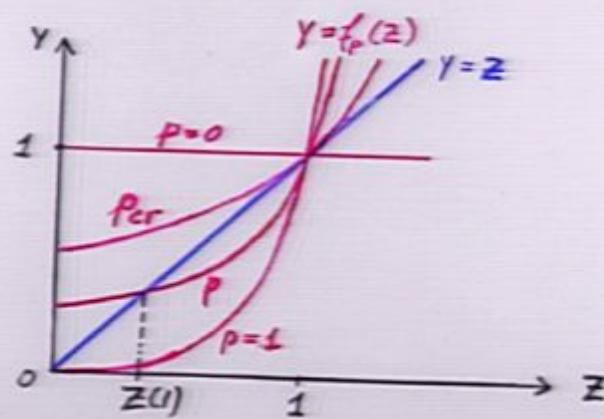
and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$Z(t) = t f(Z(t))$$

For Γ : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

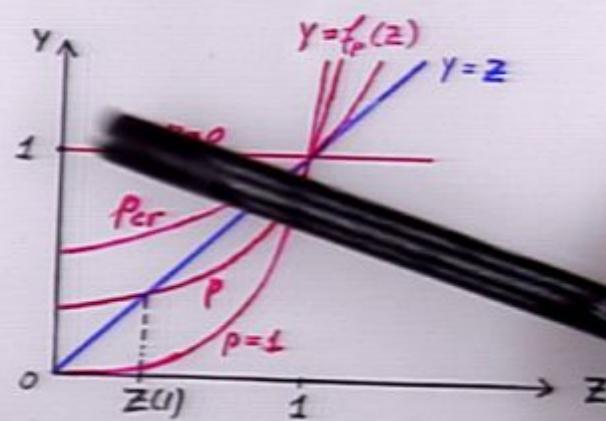
and

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$Z(t) = t f(Z(t))$$

For Γ : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



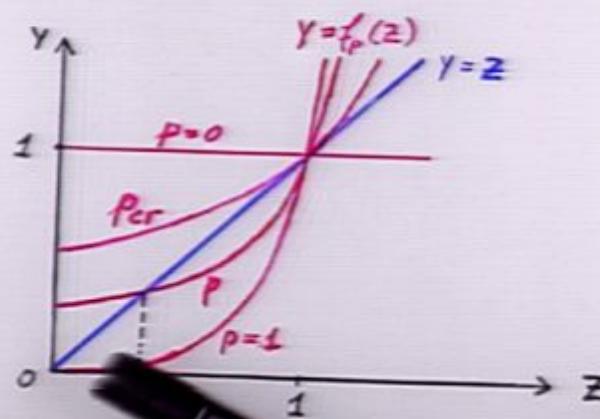
and $Z(t) = \sum_{n=1}^{\infty} Z_n t^n$

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

are related by

$$Z(t) = t f(Z(t))$$

For P : $f(t) = (1 - p + tp)^{n-1} = f_p(t)$



$$Z(t) = \sum_{n=1}^{\infty} Z_n t^n$$

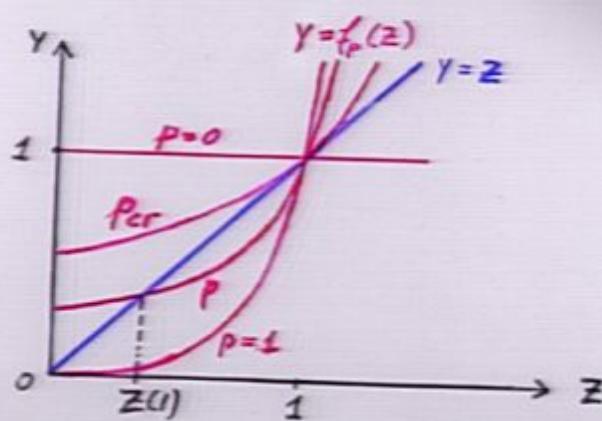
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$$Z(t) = t f(Z(t))$$

For Γ : $f(t) = (1 - p + tp)^{n-1} = \frac{1}{T_p}(t)$



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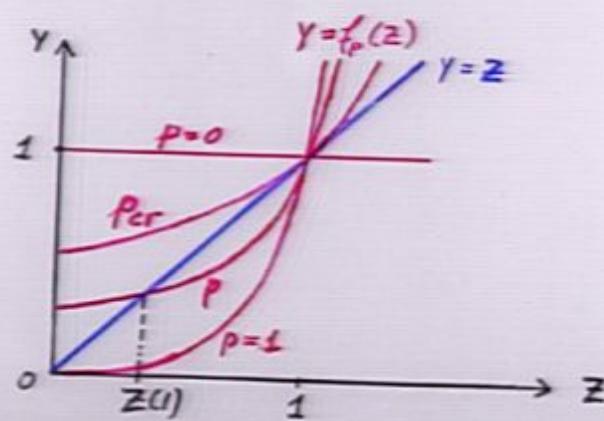
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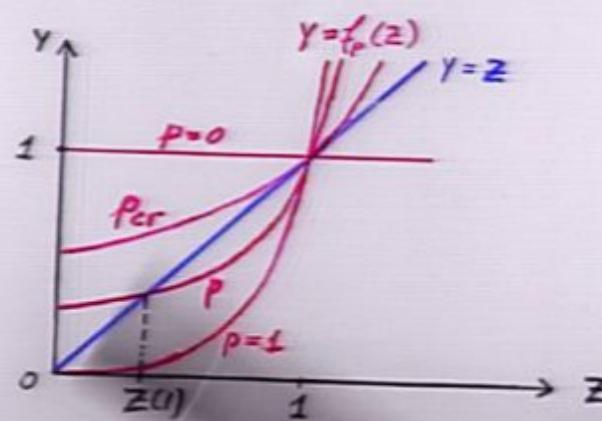
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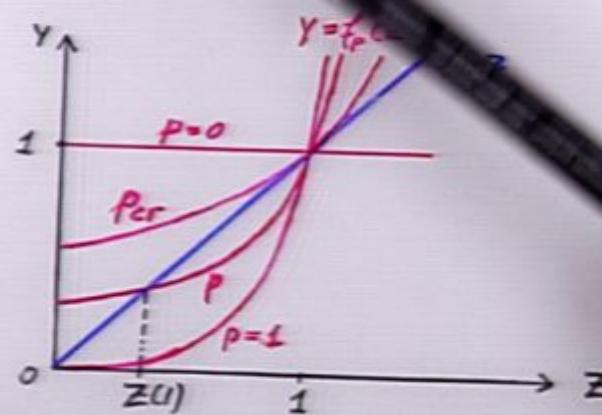
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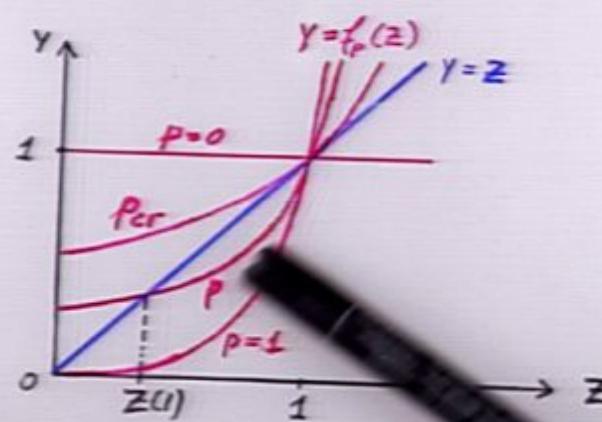
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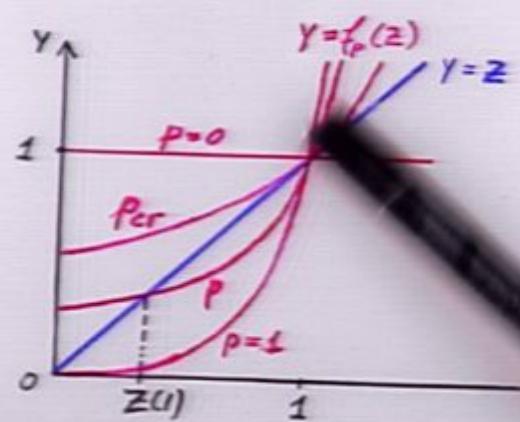
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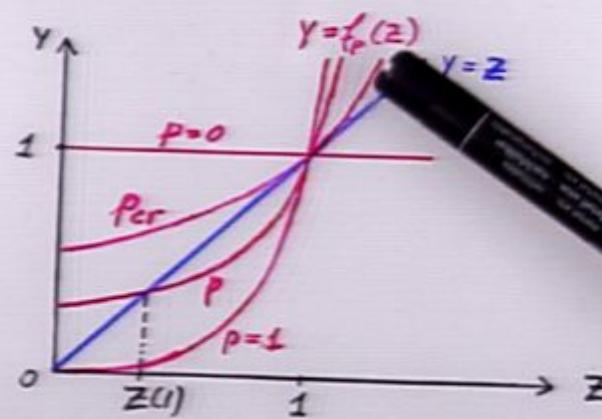
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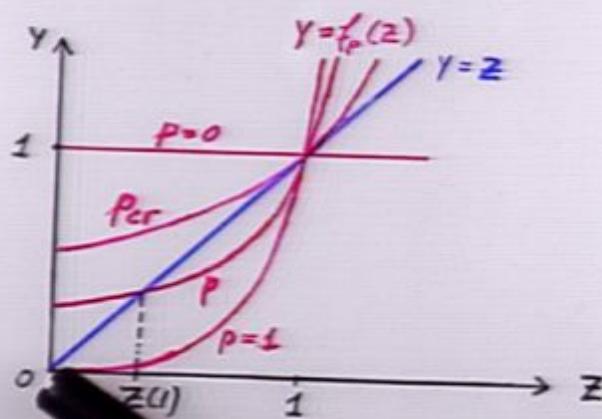
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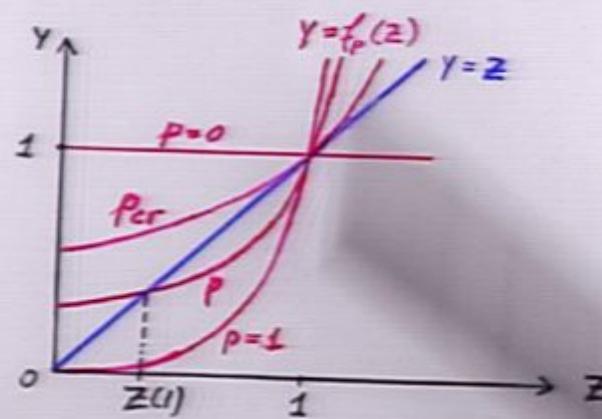
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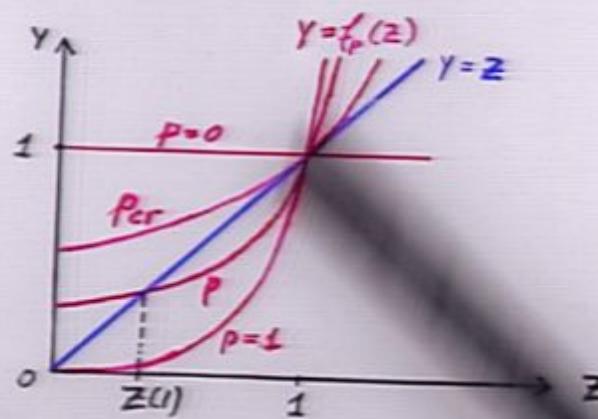
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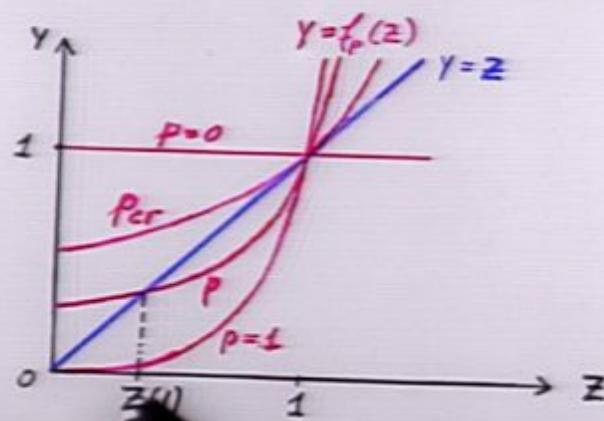
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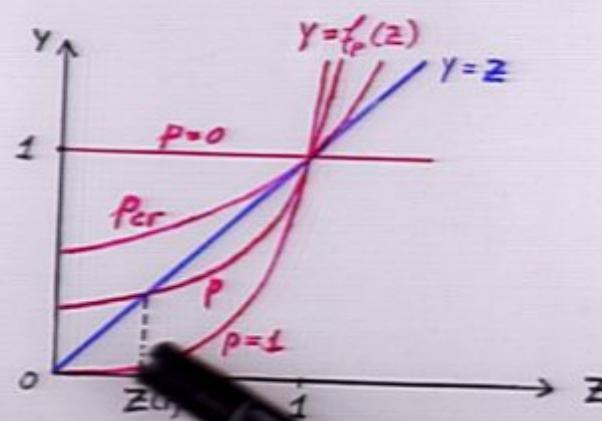
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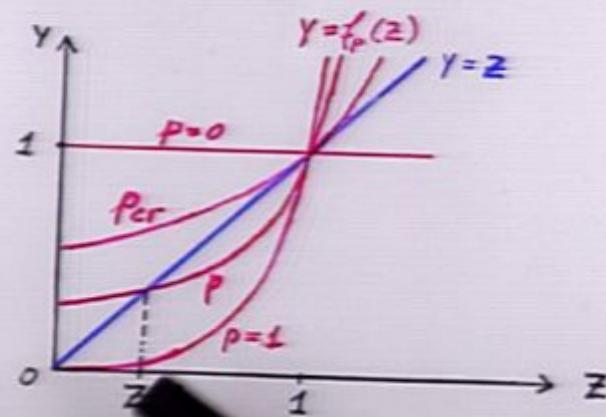
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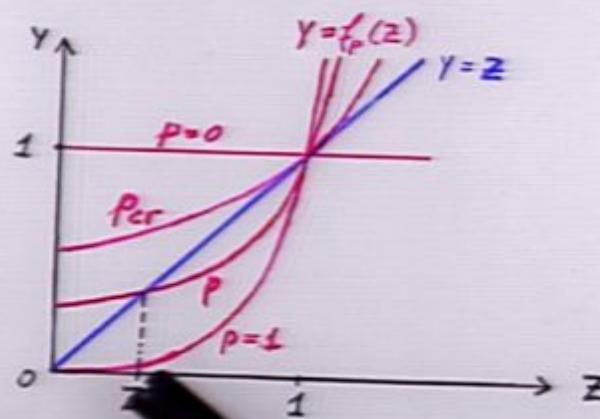
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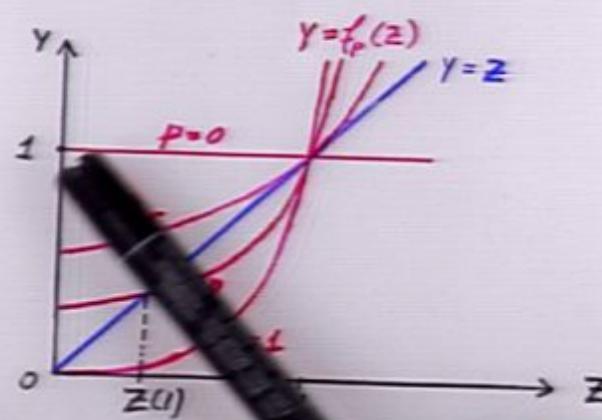
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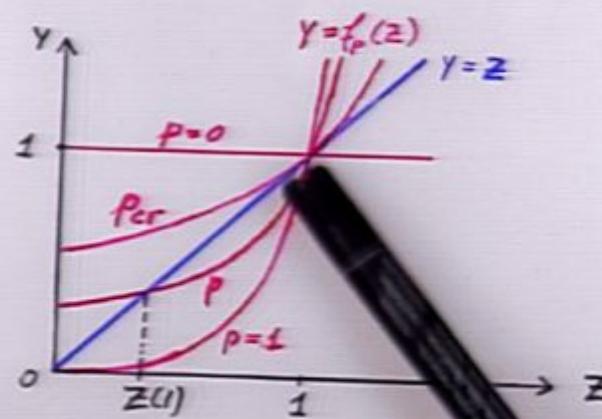
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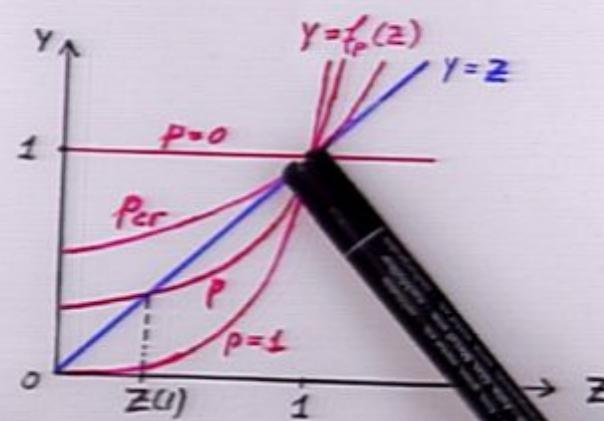
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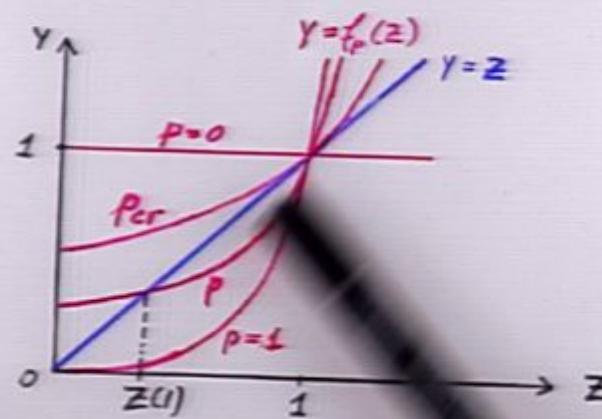
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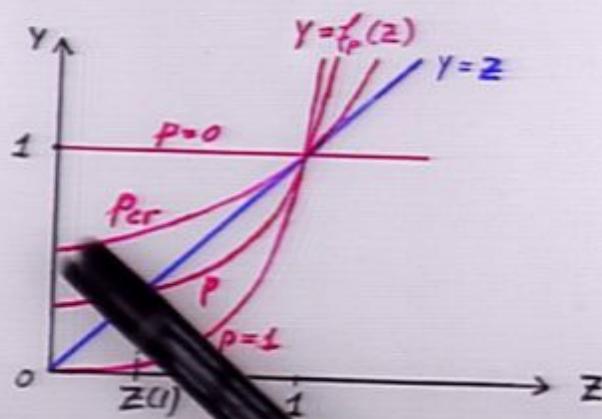
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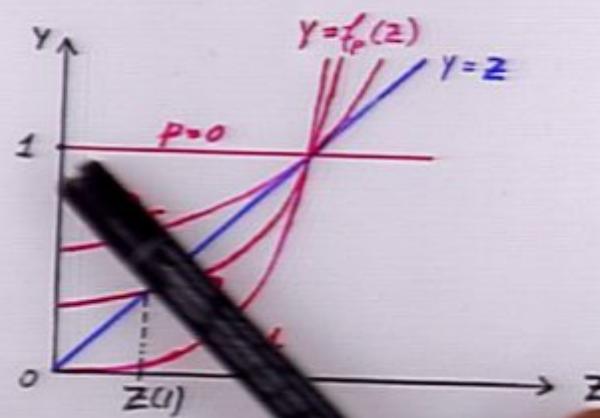
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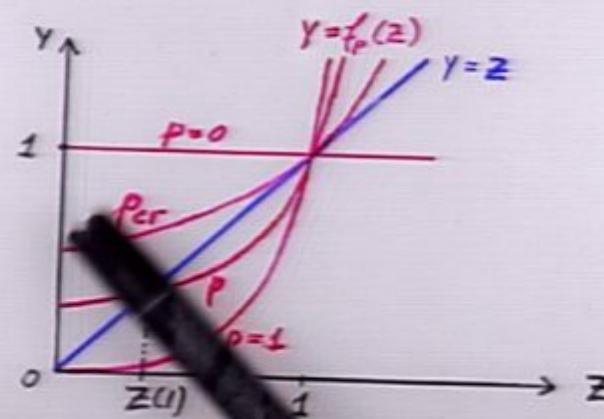
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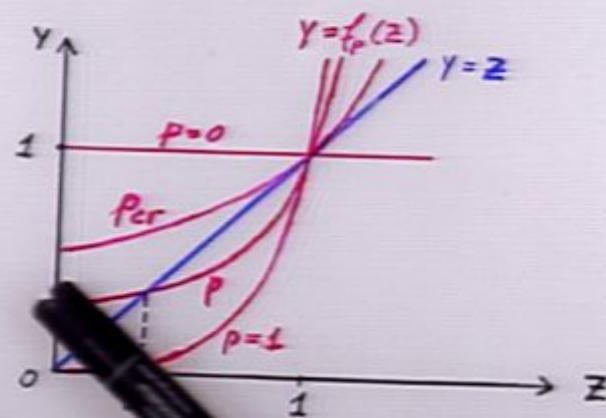
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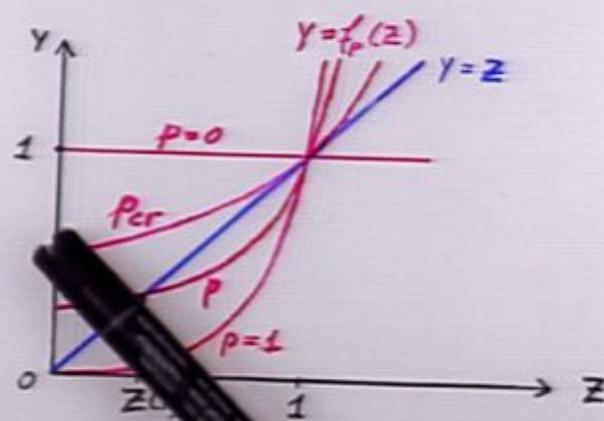
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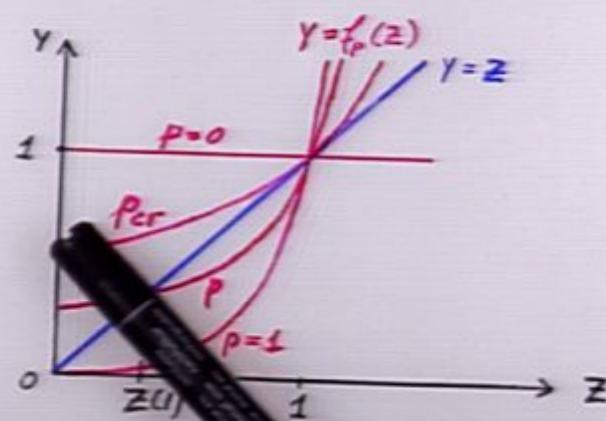
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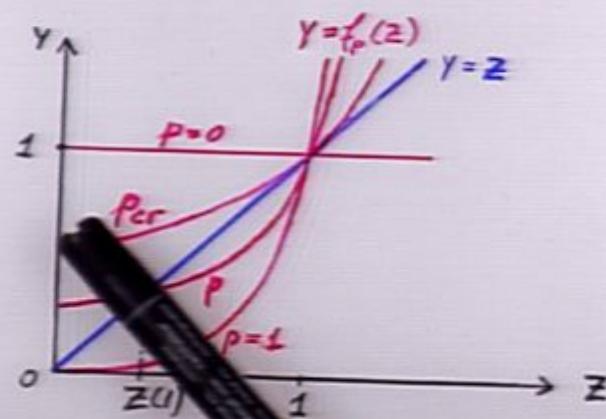
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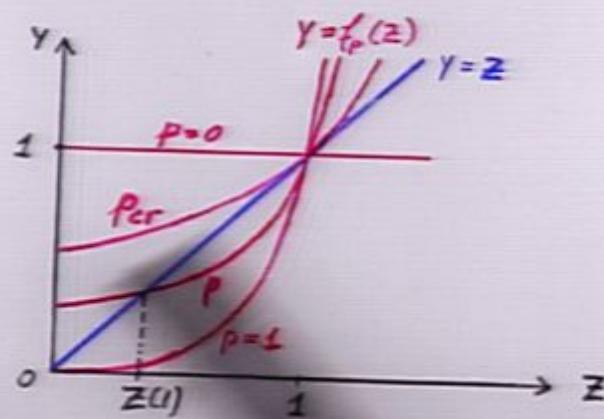
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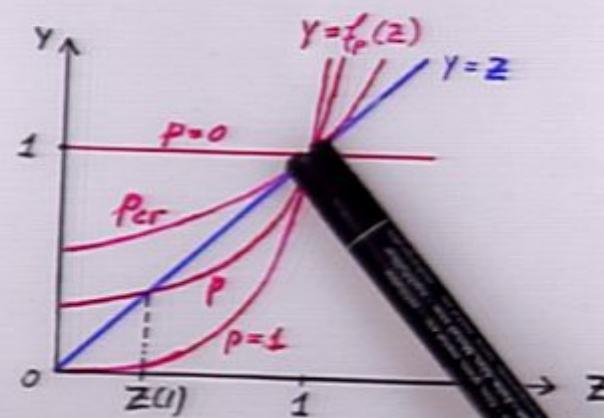
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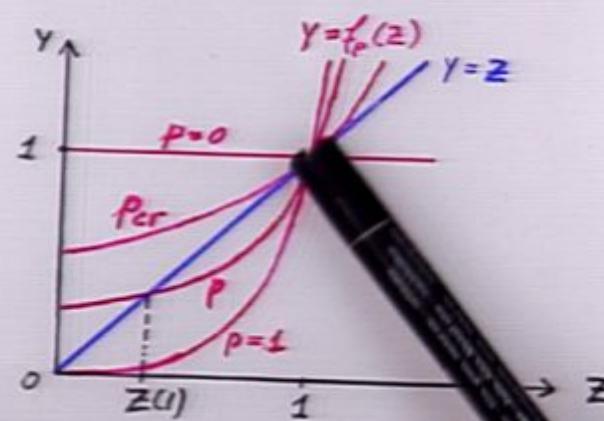
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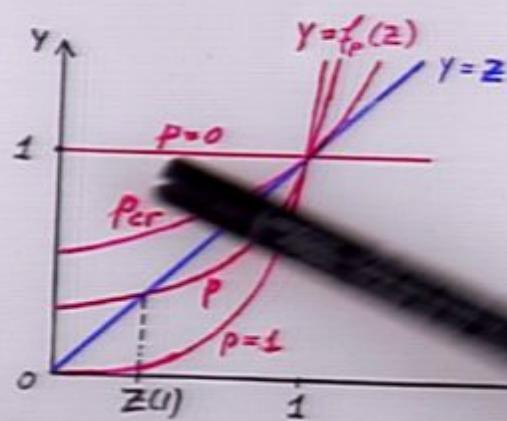
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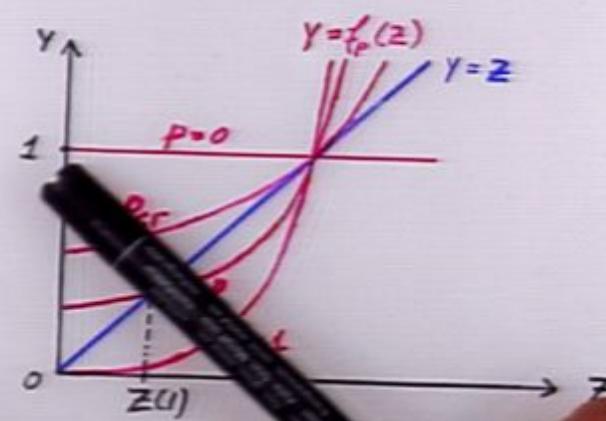
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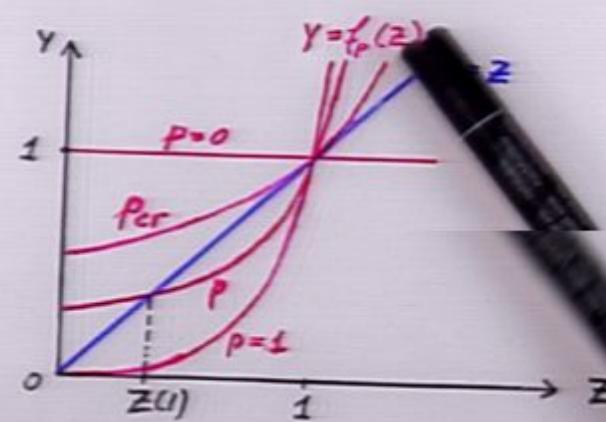
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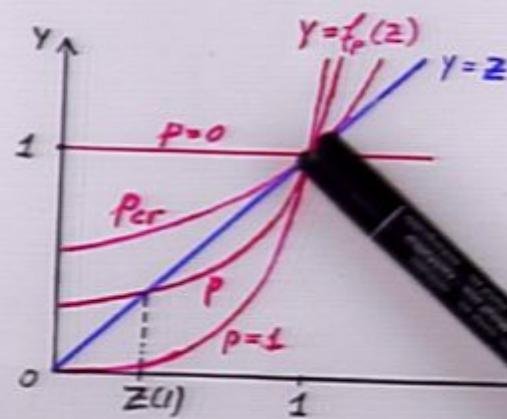
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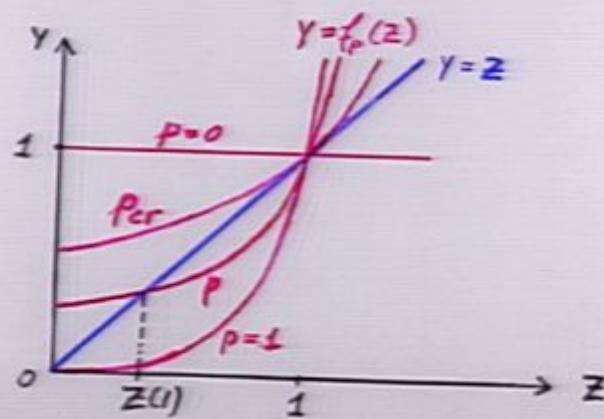
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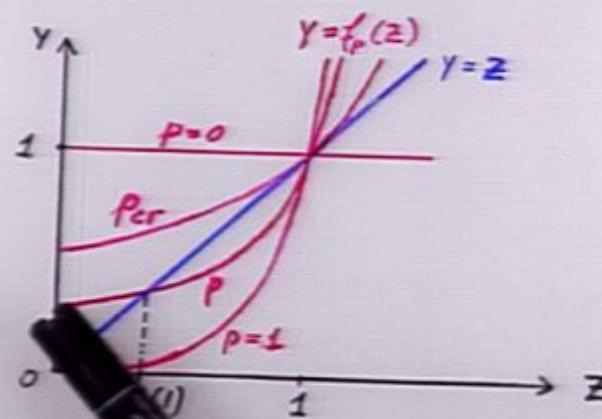
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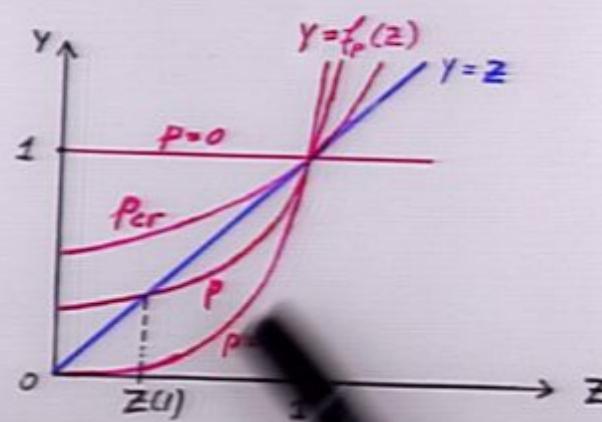
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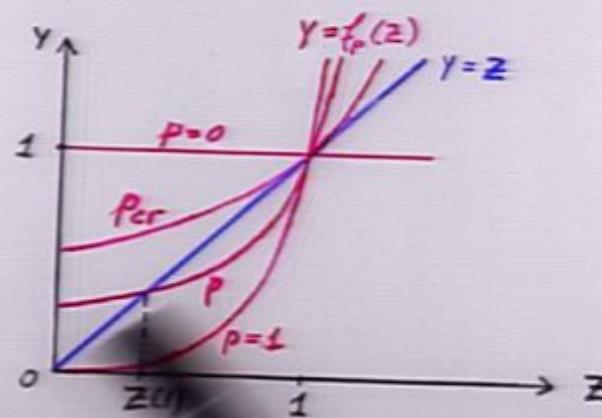
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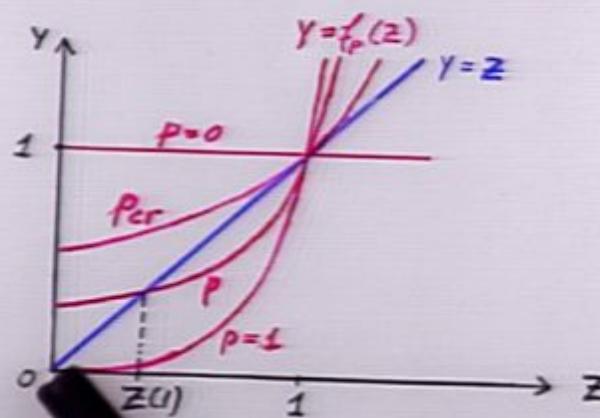
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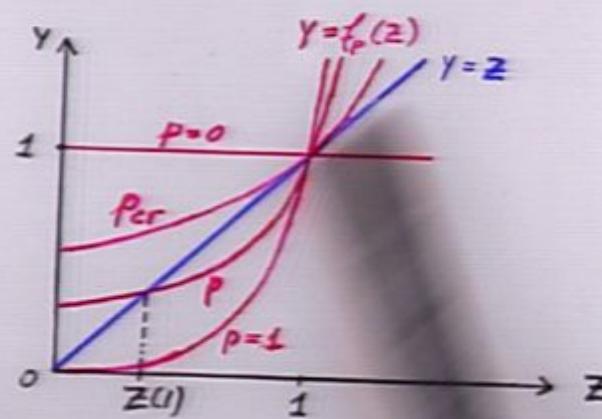
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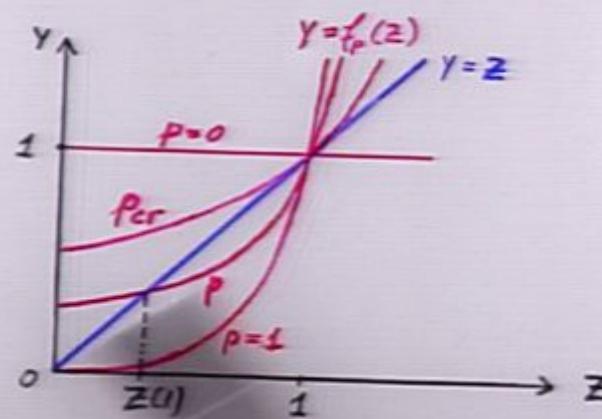
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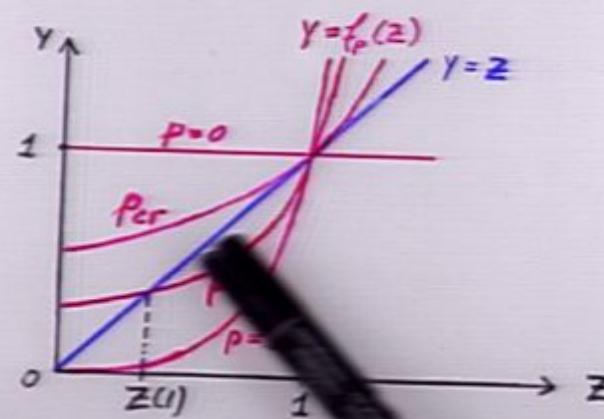
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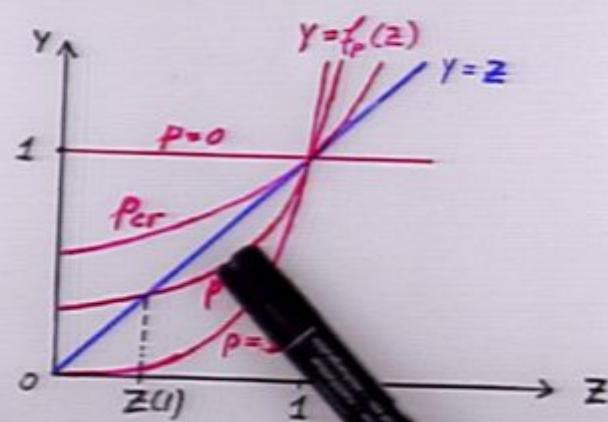
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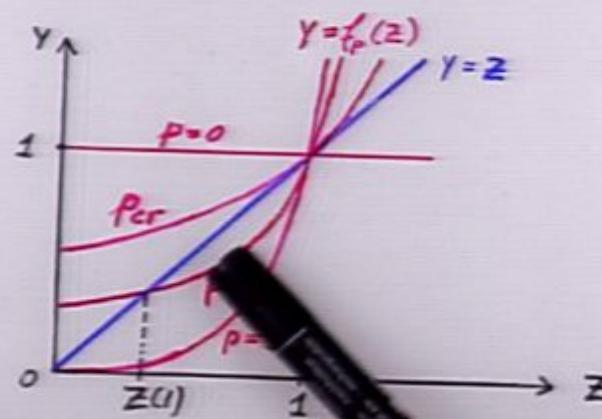
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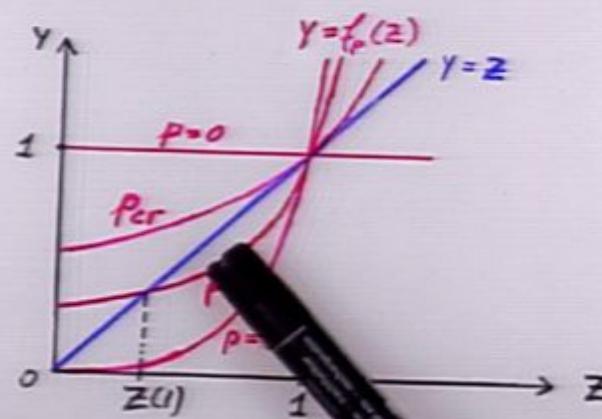
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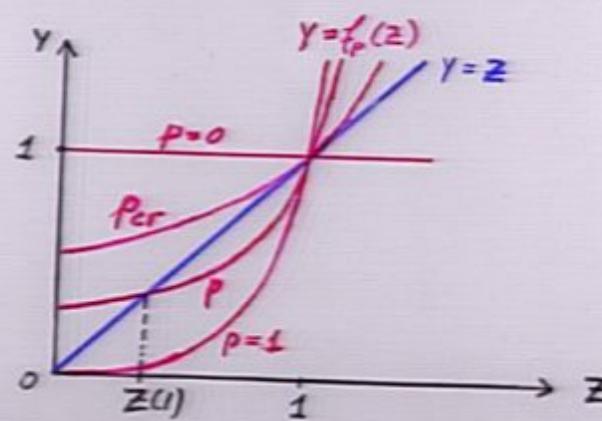
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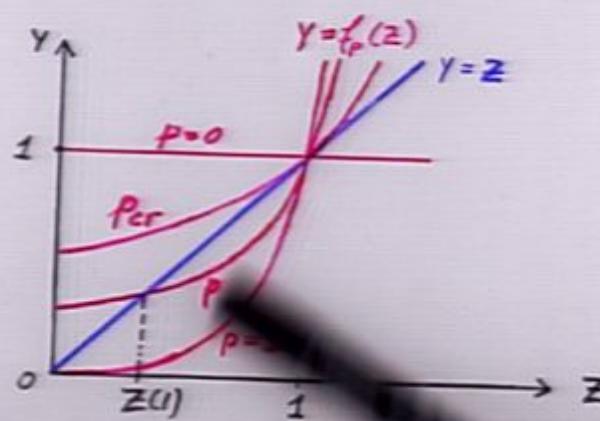
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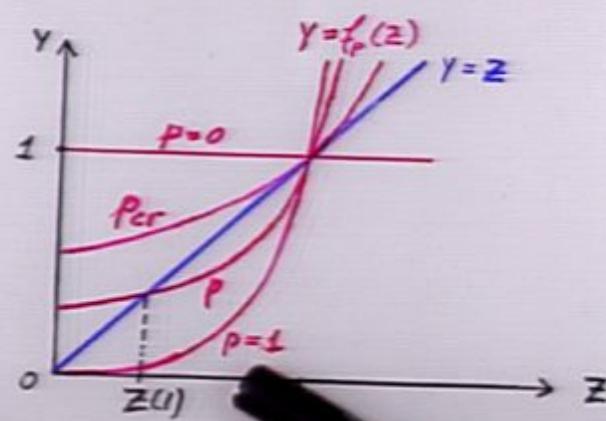
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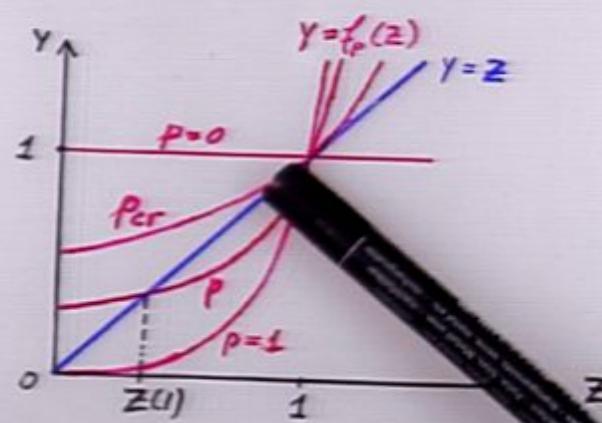
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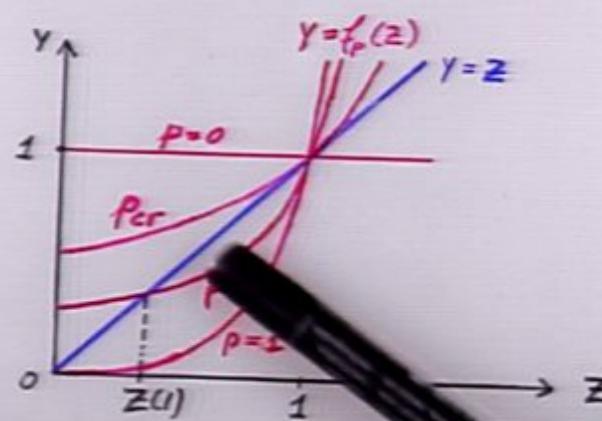
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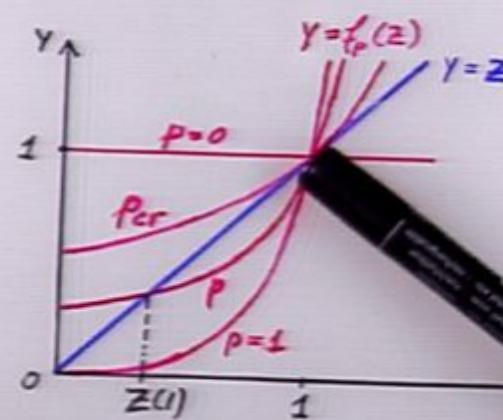
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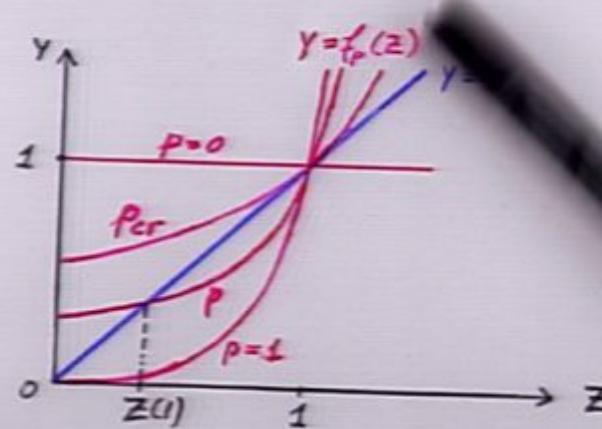
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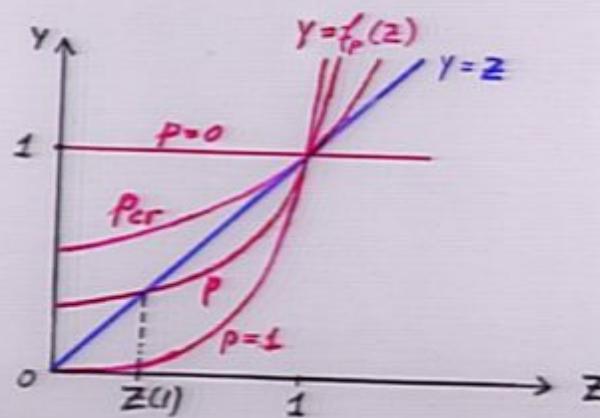
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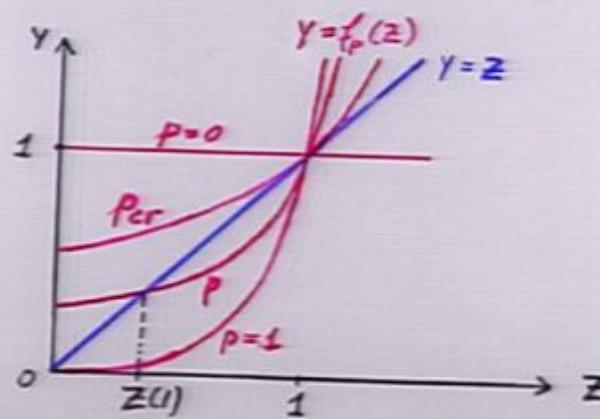
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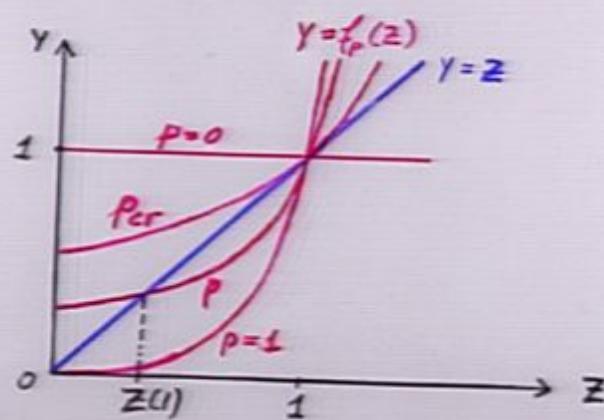
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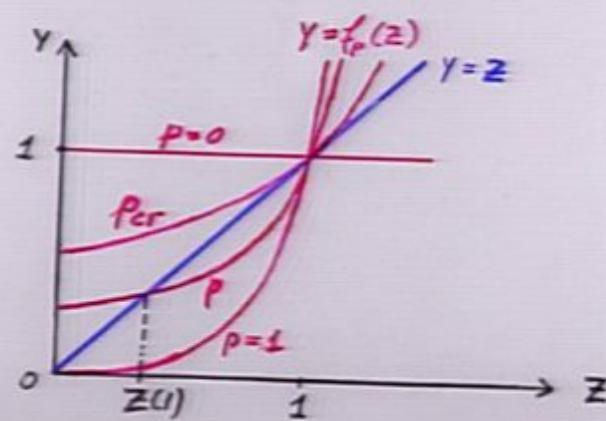
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$$P(\tau < \infty) = \sum_{n=1}^{\infty} P(\tau = n) = E(1).$$

From figure: $E(1) = 1$ if $p = p_c$, where
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 $\frac{f'_p}{f_p}(1) = 1$.

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$$\frac{f'_p}{f_p}(1) = (n-1)p \Rightarrow p_c = \frac{1}{n-1}.$$

Alternatively: For $p = p_c$

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Conditioning on trees of fixed size N
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5. Generic tree ensembles.

Assume off-spring probabilities $(p_k)_{k \geq 0}$ satisfy

$$\sum_{k=0}^{\infty} p_k = 1 \quad \text{and} \quad \sum_{k=1}^{\infty} k p_k = 1.$$

The corresponding critical Galton-Watson process is generic if generating func

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Note: f is a polynomial for percolation on a Cayley tree, hence generic

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Conditioning on trees of fixed size N
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is analytic in a neighborhood of the unit circle, i.e. has radius of convergence >

Note: f is a polynomial for percolation - a Cayley tree, hence generic.

Define probability distribution ϱ on finite rooted trees by

$$\varrho(T) = \prod_{v \in T \setminus \{r\}} p_{d(v)}$$

Conditioning on trees of fixed size gives probability distribution

$$\mu_N(T) = \frac{1}{Z_N} \varrho(T)$$

on T_N , where $Z_N = \varrho(T_N)$.

process is generic if generating function

$$f(t) = \sum_{k=0}^{\infty} p_k t^k$$

is analytic in a neighborhood of the unit circle, i.e. has radius of convergence > 1 .

Note: f is a polynomial for percolation on a Cayley tree, hence generic.

Define probability distribution β on finite rooted trees by

$$\beta(T) = \prod_{v \in T \setminus \{r\}} p_{d(v)-1}.$$

Conditioning on trees of fixed size gives probability distribution

$$\mu_N(T) = \frac{1}{Z_N} \beta(T)$$

on \mathcal{T}_N , where $Z_N = \beta(\mathcal{T}_N)$.

(14)

From functional relation

$$Z(t) = t f(Z(t))$$

follows

$$Z(t) \sim 1 - \text{cst} \cdot \sqrt{1-t}$$

for $t \rightarrow 1$. Hence by genericity

$$Z_N \sim \text{cst} \cdot N^{-\frac{3}{2}}, \quad N \rightarrow \infty.$$

Theorem 1 The sequence (μ_N) converges to a probability distribution μ on the set of all rooted planar trees T . It is concentrated on the subset \mathcal{G} of trees with a single spine s_0, s_1, s_2, \dots and is characterized by:

- i) The probability that $s_i, i \geq 1$, has degree $k+1$ is $k p_k$.
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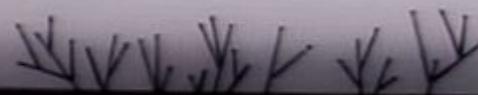
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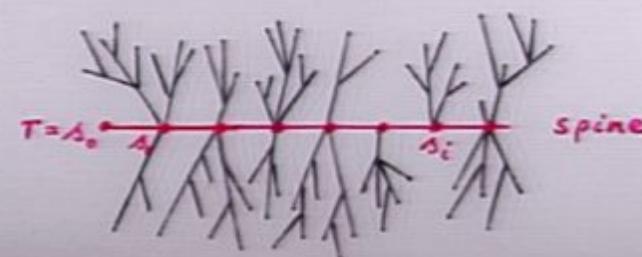


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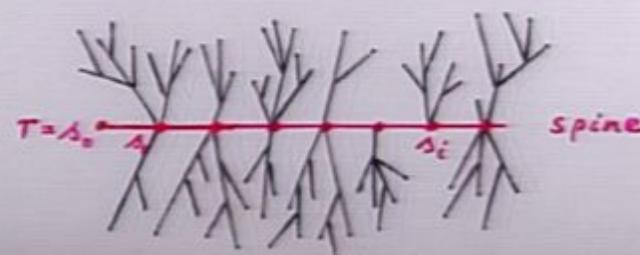


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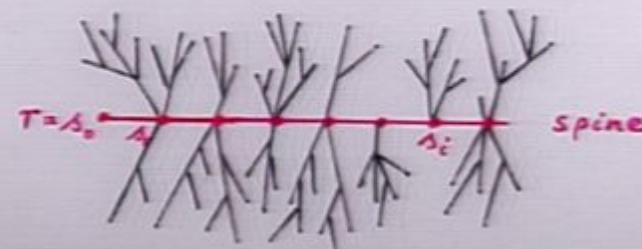


for $t \rightarrow 1$. Hence by generativity

$$Z_N \sim \text{cst} \cdot N^{-\frac{2}{\lambda}}, \quad N \rightarrow \infty.$$

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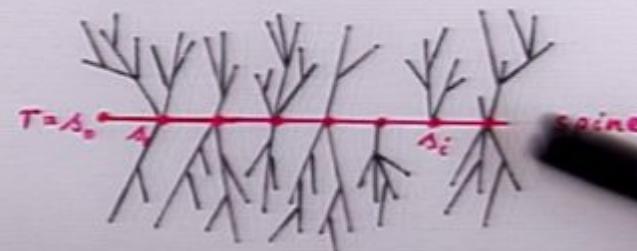


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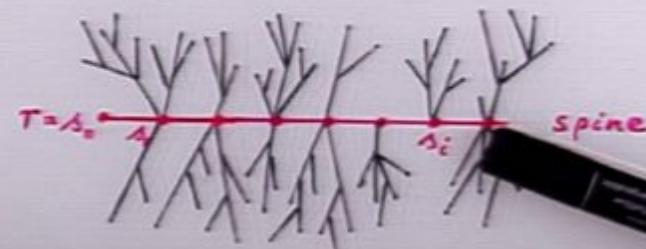


for $b \rightarrow 1$. Hence by generativity

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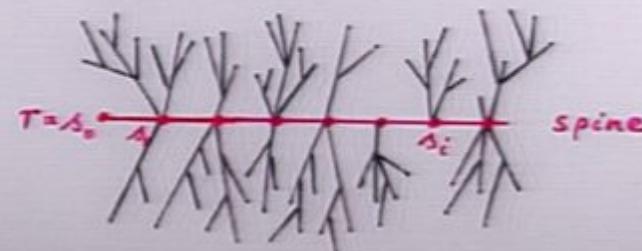


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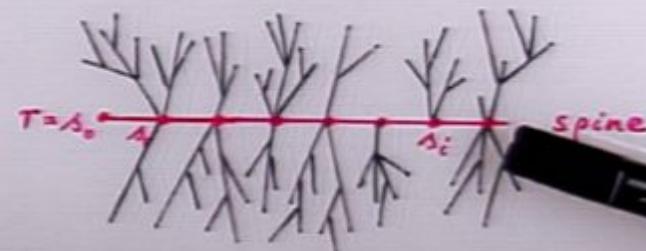


for $t \rightarrow 1$. Hence by generality

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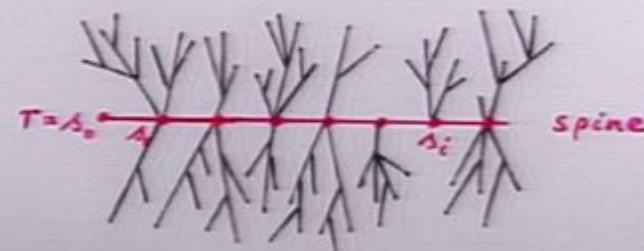


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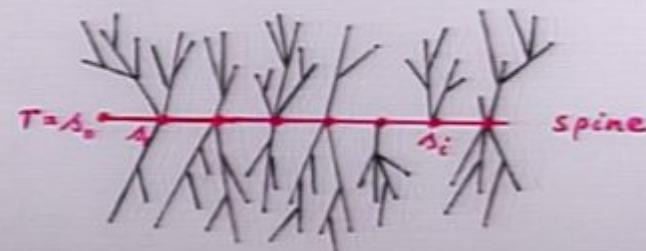


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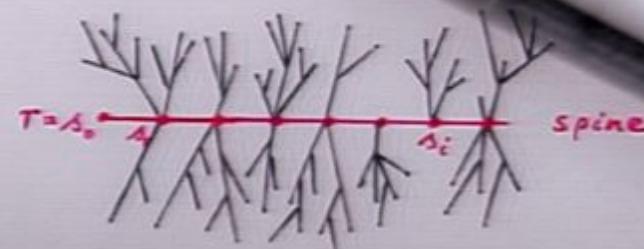


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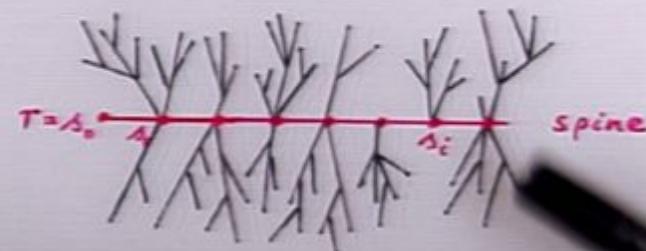


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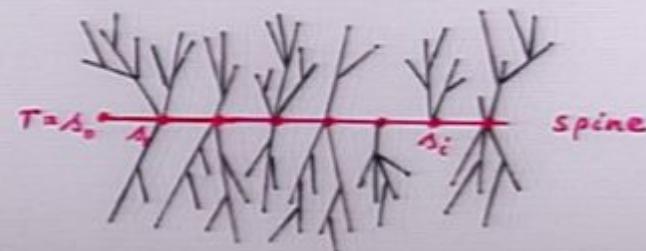


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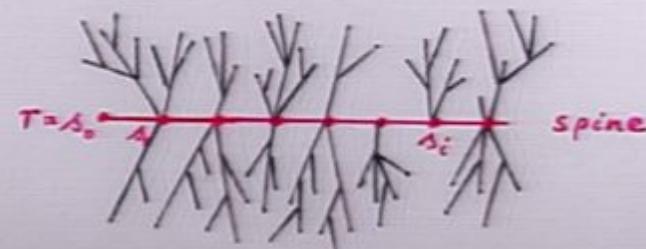


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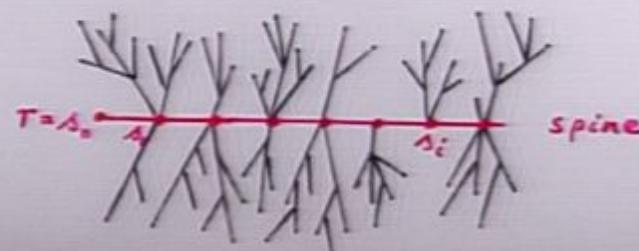


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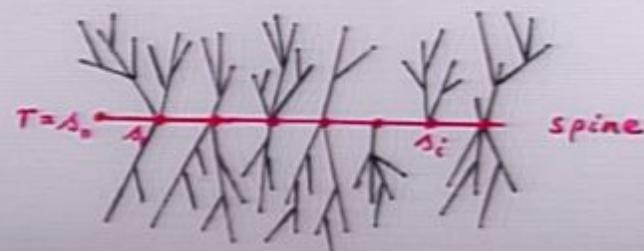


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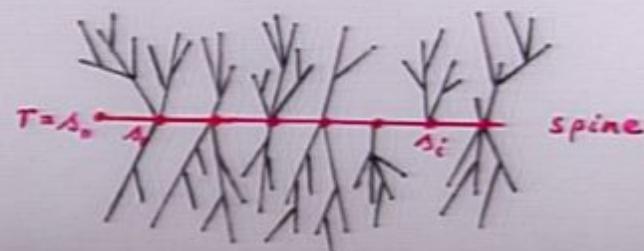


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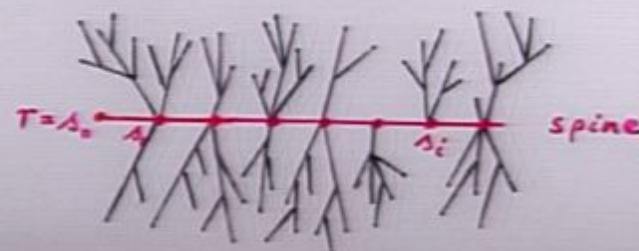


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From functional relation

$$Z(t) = t f(z(t))$$

follows $Z(t) \approx t - c t \sqrt{1-t}$

for $t < t_c$. Hence by genericity

$$Z_n \approx c t_c N^{-\frac{1}{2}}, \quad n \rightarrow \infty.$$

Theorem The sequence (μ_n) converges to a probability distribution μ on the set of all rooted planar trees T . It is concentrated on the subset S of trees with a single spine s_0, s_1, s_2, \dots and is characterized by:

- i) The probability that s_0, s_1, s_2, \dots degree set is $t^k \mu$.
- ii) The branches are independently distributed according to S .

(15)

Theorem 2 For a generic tree ensemble (\mathcal{S}, μ) we have

$$d_h = 2 \quad \text{and} \quad d_A = \frac{4}{3}.$$

Almost sure statements also hold, in particular

$$c'(\ln R)^2 R^2 \leq |B_R| \leq cR^2 \ln R$$

almost surely.

- $d_h = 2$ follows from previous theorem and

$$\langle |B_R| \rangle_3 \sim R$$

Average number of individuals in a Galton-Watson tree is constant.

For d_A one uses, among other results, Kolmogorov '32: Probability that more than R generations survive $\sim \frac{\text{const}}{R}$ for $R \rightarrow \infty$.

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almost surely.

- $d_h = 2$ follows from previous theorem and

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Average number of individuals in a Galton-Watson tree is constant.

For d_s one uses, among other results, Kolmogorov '32: Probability that more than R generations survive $\sim \frac{cst}{R}$ for $R \rightarrow \infty$.

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