# Beta processes, stick-breaking, and power laws 

T. Broderick, M. Jordan, J. Pitman

Presented by Jixiong Wang \& J. Li

November 17, 2011

- Dirichlet Process
- Beta Process
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- $G \sim D P\left(\alpha B_{0}\right)$ :
- Beta Process
- $G \sim B P\left(\theta, \gamma B_{0}\right)$ :

$$
G=\sum_{i=1}^{\infty} \pi_{i} \delta_{\psi_{i}}, \quad \sum_{i=1}^{\infty} \pi_{i}=1
$$

$$
G=\sum_{i=1}^{\infty} q_{i} \delta_{\psi_{i}}, \quad q_{i} \in(0,1)
$$

## DP vs. $B P$

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- CRP - marginalize out $\pi_{i}$
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- IBP - marginalize out $q_{i}$


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- CRP - marginalize out $\pi_{i}$
- Clustering framework
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- Featural framework


## Poisson Point Process (PPP)

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Figure: PPP realizations with different rate measure $\mu$

## Poisson Point Process (PPP)

- PPP: A counting measure $N$ such that $\forall A \in \mathcal{S}, N(A) \sim \operatorname{Pois}(\mu(A))$


Figure: PPP realizations with different rate measure $\mu$

- PPP is a completely random measure because for all disjoint subsets $A_{1}, \ldots, A_{n} \in \mathcal{S}, N\left(A_{1}\right), \ldots, N\left(A_{n}\right)$ are independent.
- Note: DP is not a c.r.m..


## Beta Process: $B \sim B P\left(\theta, \gamma B_{0}\right)$

BP is defined by a PPP that lives on $\Psi \times[0,1]$

- Rate measure: $\nu(d \psi, d u)=\theta(\psi) u^{-1}(1-u)^{\theta(\psi)-1} d u \gamma B_{0}(d \psi)$


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- To draw $B \sim B P\left(\theta, \gamma B_{0}\right)$

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\begin{aligned}
& \bullet \Longrightarrow \Pi=\left\{\left(\psi_{i}, U_{i}\right)\right\}_{i} \\
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$\Theta$

## Bernoulli process \& Binary feature matrix

- $Y \sim \operatorname{Be} P(B): Y=\sum_{i=1}^{\infty} b_{i} \delta_{\psi_{i}}$, where $b_{i} \sim \operatorname{Bern}\left(U_{i}\right)$
- Draw $Y_{1}, \ldots, Y_{N} \sim \operatorname{Be} P(B)$



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K

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- Draw $Y_{1}, \ldots, Y_{N} \sim B e P(B)$

$\Psi$

$\Psi$


K

- Form binary feature matrix $Z \sim \operatorname{BP}-\operatorname{BeP}(N, \gamma, \theta)$

[Ghahramani et al '06]


## Stick-breaking construction of BP

$$
\begin{aligned}
B & =\sum_{i=1}^{\infty} \sum_{j=1}^{C_{i}} V_{i, j}^{(i)} \prod_{l=1}^{i-1}\left(1-V_{i, j}^{(l)}\right) \delta_{\psi_{i, j}} \\
C_{i} & \stackrel{i i d}{\sim} \operatorname{Pois}(\gamma) \\
V_{i, j}^{(l)} & \stackrel{i i d}{\sim} \\
\psi_{i, j} & \stackrel{i i d}{\sim} \\
& \frac{1}{\gamma} B_{0}
\end{aligned}
$$

## Stick-breaking construction of BP

(Paisley et al 2010):

$$
\begin{array}{rlr}
B=\sum_{i=1}^{\infty} \sum_{j=1}^{C_{i}} V_{i, j}^{(i)} \prod_{l=1}^{i-1}\left(1-V_{i, j}^{(l)}\right) \delta_{\psi_{i, j}} & B= & \sum_{j=1}^{C_{1}} V_{1, j}^{(1)} \delta_{\psi_{1, j}}+ \\
C_{i} \stackrel{i i d}{\sim} \operatorname{Pois}(\gamma) & & \sum_{j=1}^{C_{2}} V_{2, j}^{(2)}\left(1-V_{i j}^{(1)}\right) \delta_{\psi_{2, j}}+ \\
V_{i, j}^{(l)} \stackrel{i i d}{\sim} \operatorname{Beta}(1, \theta) & & \sum_{j=1}^{C_{3}} V_{3, j}^{(3)}\left(1-V_{3, j}^{(2,)}\right)\left(1-V_{3, j}^{(1)}\right) \delta_{\psi_{3, j}}+\ldots \\
\psi_{i, j} \stackrel{i i d}{\sim} \frac{1}{\gamma} B_{0} . &
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V_{i, j}^{(l)} \stackrel{i i d}{\sim} \operatorname{Beta}(1, \theta) & & \sum_{j=1}^{C_{3}} V_{3, j}^{(3)}\left(1-V_{3, j}^{(2,)}\right)\left(1-V_{3, j}^{(1)}\right) \delta_{\psi_{3, j}}+\ldots \\
\psi_{i, j} \stackrel{i i d}{\sim} \frac{1}{\gamma} B_{0} . &
\end{array}
$$

- Think of each $i$ as a "round"
- It is "a multiple of stick-breaking DP"
- 3 parameter stick-breaking ("a multiple of Pitman-Yor")

$$
\begin{aligned}
B & =\sum_{i=1}^{\infty} \sum_{j=1}^{C_{i}} V_{i, j}^{(i)} \prod_{l=1}^{i-1}\left(1-V_{i, j}^{(l)}\right) \delta_{\psi_{i, j}} \\
C_{i} & \stackrel{i i d}{\sim} \\
V_{i, j}^{(l)} & \stackrel{i n d e i s}{ }(\gamma) \\
\psi_{i, j} & \stackrel{i i d}{\sim} \\
\sim & \operatorname{Beta}(1-\alpha, \theta+i \alpha) \\
& \frac{1}{\gamma} B_{0} .
\end{aligned}
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- 3 parameter stick-breaking ("a multiple of Pitman-Yor")

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\sim & \operatorname{Beta}(1-\alpha, \theta+i \alpha) \\
& \frac{1}{\gamma} B_{0} .
\end{aligned}
$$

- 3 parameter $B P\left(\theta, \alpha, B_{0}\right)$. Rate measure:

$$
\begin{aligned}
\nu_{B P}(d \psi, d u) & =B_{o}(d \psi) \times \mu_{B P}(d u) \\
& =B_{o}(d \psi) \times \frac{\Gamma(1+\theta)}{\Gamma(1-\alpha) \Gamma(\theta+\alpha)} u^{-1-\alpha}(1-u)^{\theta+\alpha-1} d u
\end{aligned}
$$

## Equivalence - An elegant proof

## Proposition 1

$B$ presented in the stick-breaking construction is equivalent to $B \sim B P\left(\theta, \alpha, B_{0}\right)$

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Idea of proof:

- The stick-breaking representation is also a PPP, and induces rate measure $\nu$


## Equivalence - An elegant proof

## Proposition 1

$B$ presented in the stick-breaking construction is equivalent to $B \sim B P\left(\theta, \alpha, B_{0}\right)$

Idea of proof:

- The stick-breaking representation is also a PPP, and induces rate measure $\nu$
- Therefore only need to show that $\nu=\nu_{B P}$


## Power law behavior:

Power laws in clustering models:

- $K_{N, j}=\sum_{i=1}^{\infty} I\left(N_{i}=j\right)$
- $K_{N}=\sum_{i=1}^{\infty} I\left(N_{i}>0\right)$
- Type 1: $K_{N} \sim c N^{a}, N \rightarrow \infty$
- Type 2: $K_{N, j} \sim \frac{a \Gamma(j-a)}{j!\Gamma(1-a)} c N^{a}, N \rightarrow \infty$

Power laws in featural models:

- Type 3: $P\left(k_{n}>M\right) \sim c M^{-a}$


## Power law derivations: Type 1 and 2

Poissonization

## Mean feature counts

## Proposition 3

$$
\begin{array}{cc}
K(t), K_{j}(t) & \Phi(t)=E[K(t)], \Phi_{j}(t)=E\left[K_{j}(t)\right] \\
K(N), K_{j}(N) & \Phi(N), \Phi_{j}(N) \\
K_{N}, \underbrace{K_{N, j}}_{\text {Lemma 4 }} & \Phi_{N}=E\left[K_{N}\right], \Phi_{N, j}=E\left[K_{N, j}\right] \\
\text { Proposition } 6 &
\end{array}
$$

## Power law derivations: Poissonization

$K(t)$ will be the number of such Poisson processes with points in the interval $[0, t]$

- $K(t)=\sum_{i} I\left|\Pi_{i} \cap[0, t]\right|>0$
$K_{j}(t)$ will be the number of such Poisson processes with $j$ points in the interval $[0, t]$
- $K_{j}(t)=\sum_{i} I\left|\Pi_{i} \cap[0, t]\right|=j$


Figure 4: The first five sets of points, starting from the top of the figure, illustrate Poisson processes on the positive half-line in the range $t \in(0,5)$ with respective rates $q_{1}, \ldots, q_{5}$. The bottom set of points illustrates the union of all points from the preceding Poisson point processes and is, therefore, itself a Poisson process with rate $\sum_{i} q_{i}$. In this example, we have for instance that $K(1)=2, K(4)=5$, and $K_{2}(4)=1$.

## Power law derivations

Theorem 2 (Part of Campbell's Theorem). Let $\Pi$ be a Poisson process on $S$ with rate measure $\mu$, and let $f: S \rightarrow \mathbb{R}$ be measurable. If $\int_{S} \min (|f(x)|, 1) \mu(d x)<$ $\infty$, then

$$
\begin{gather*}
\mathbb{E}\left[\sum_{X \in \Pi} f(X)\right]=\int_{S} f(x) \mu(d x)  \tag{21}\\
\Phi(t)=\mathbb{E}\left[\sum_{i}\left(1-e^{-t q_{i}}\right)\right]=\int_{0}\left(1-e^{-t x}\right) \nu(d x) \\
\Phi_{N}=\mathbb{E}\left[\sum_{i}\left(1-\left(1-q_{i}\right)^{N}\right)\right]=\int_{0}^{1}\left(1-(1-x)^{N}\right) \nu(d x) \\
\Phi_{j}(t)=\mathbb{E}\left[\sum_{i} \frac{\left(t q_{i}\right)^{j}}{j!} e^{-t q_{i}}\right]=\frac{t^{j}}{j!} \int_{0}^{1} x^{j} e^{-t x} \nu(d x) \\
\Phi_{N, j}=\binom{N}{j} \mathbb{E}\left[\sum_{i} q_{i}^{j}\left(1-q_{i}\right)^{N-j}\right]=\binom{N}{j} \int_{0}^{1} x^{j}(1-x)^{N-j} \nu(d x) .
\end{gather*}
$$

Proposition 3. Asymptotic behavior of the integral of $\nu$ of the following form

$$
\begin{equation*}
\nu_{1}[0, x]:=\int_{0}^{x} u \nu(d u) \sim \frac{\alpha}{1-\alpha} x^{1-\alpha} l(1 / x), \quad x \rightarrow 0 \tag{27}
\end{equation*}
$$

where $l$ is a regularly varying function and $\alpha \in(0,1)$ implies

$$
\begin{aligned}
\Phi(t) & \sim \Gamma(1-\alpha) t^{\alpha} l(t), \quad t \rightarrow \infty \\
\Phi_{j}(t) & \sim \frac{\alpha \Gamma(j-\alpha)}{j!} t^{\alpha} l(t), \quad t \rightarrow \infty \quad(j>1)
\end{aligned}
$$

## Power law derivations

Lemma 4. Let $\nu$ be $\sigma$-finite with $\int_{0}^{\infty} \nu(d u)=\infty$ and $\int_{0}^{\infty} u \nu(d u)<\infty$. Then the number of represented features has unbounded growth almost surely. The expected number of represented features has unbounded growth, and the expected number of features has sublinear growth. That is,

$$
K(t) \uparrow \infty \text { a.s., } \quad \Phi(t) \uparrow \infty, \quad \Phi(t) \ll t
$$

Lemma 5. Suppose the $\left\{q_{i}\right\}$ are generated according to a Poisson process with rate measure as in Lemma 4. Then, for $N \rightarrow \infty$,

$$
\begin{gathered}
\left|\Phi_{N}-\Phi(N)\right|<\frac{2}{N} \Phi_{2}(N) \rightarrow 0 \\
\left|\Phi_{N, j}-\Phi_{j}(N)\right|<\frac{c_{j}}{N} \max \left\{\Phi_{j}(N), \Phi_{j+2}(N)\right\} \rightarrow 0
\end{gathered}
$$

for some constants $c_{j}$.

Proposition 6. Suppose the $\left\{q_{i}\right\}$ are generated from a Poisson process with rate measure as in Lemma 4. For $N \rightarrow \infty$,

$$
K_{N} \stackrel{a . s .}{\sim} \Phi_{N}, \quad \sum_{k<j} K_{N, k} \stackrel{a . s .}{\sim} \sum_{k<j} \Phi_{N, k} .
$$

## Power law derivations: Type 1 and 2

Poissonization

## Mean feature counts

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\begin{array}{cc}
K(t), K_{j}(t) & \Phi(t)=E[K(t)], \Phi_{j}(t)=E\left[K_{j}(t)\right] \\
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\end{array}
$$

## Power law derivations: Type 3

Let $Z_{i}$ be a Bernoulli random variable with success probability $q_{i}$ and such that all the $Z_{i}$ are independent. Then $\mathbb{E}\left[\sum_{i} Z_{i}\right]=\sum_{i} q_{i}=: Q$. In this case, a Chernoff bound [Chernoff, 1952, Hagerup and Rub, 1990] tells us that, for any $\delta>0$, we have

$$
\mathbb{P}\left[\sum_{i} Z_{i} \geq(1+\delta) Q\right] \leq e^{\delta Q}(1+\delta)^{-(1+\delta) Q}
$$

When $M$ is large enough such that $M>Q$, we can choose $\delta$ such that $(1+\delta) Q=$ $M$. Then this inequality becomes

$$
\begin{equation*}
\mathbb{P}\left[\sum_{i} Z_{i} \geq M\right] \leq e^{M-Q} Q^{M} M^{-M} \quad \text { for } M>Q \tag{31}
\end{equation*}
$$

We see from Eq. (31) that the number of features $\sum_{i} Z_{i}$ that are expressed for a data point exhibits super-exponential tail decay and therefore cannot have a power law probability distribution when the sum of feature probabilities $\sum_{i} q_{i}$ is finite. For comparison, let $Z \sim \operatorname{Pois}(Q)$. Then [Franceschetti et al., 2007]

$$
\mathbb{P}[Z \geq M] \leq e^{M-Q} Q^{M} M^{-M} \quad \text { for } M>Q
$$

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- $\alpha=0$ (classic), $\alpha=0.3$ and $\alpha=0.6 ; \gamma=3, \theta=1$.
- Generate 2000 random variables $C_{i}$ and $\sum_{i=1}^{2000} C_{i}$ feature probabilities.
- With these probabilities, we generated $N=1000$ data points, i.e., 1000 vectors of (2000) independent Bernoulli random variables.


## Simulation: Type 1 \& 2




$$
\phi_{N}=\mathbb{E}\left[K_{N}\right]=\mathbb{E}\left[\sum_{n=1}^{N} \operatorname{Pois}\left(\gamma \frac{\theta}{n+\theta}\right)\right]=\sum_{n=1}^{N} \gamma \frac{\theta}{n+\theta} \sim \gamma \theta \log (N)
$$

$$
\Phi_{N, 1}=\mathbb{E}\left[K_{N, 1}\right]=\binom{N}{1} \int_{0}^{1} x^{1}(1-x)^{N-1} \cdot \theta x^{-1}(1-x)^{\theta-1} d x
$$

$$
=N \theta \cdot \frac{\Gamma(1) \Gamma(N-1+\theta)}{\Gamma(N+\theta)}=\theta \frac{N}{N-1+\theta} \sim \theta
$$

## Simulation: Type 3



## Experimental results

- Beta process coupled with a discrete factor analysis model.
- Handwritten digit: $28 \times 28$ pixels projected into 50 dimensions with PCA.


# Two-parameter model <br>  <br> Three-parameter model <br> <div class="inline-tabular"><table id="tabular" data-type="subtable">
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## Conclusions

- (BP, stick-breaking, IBP) - (DP, stick-breaking, CRP)
- Three-parameter generalization of BP - Pitman-Yor generalization of DP
- Type $1 \& 2$ power laws follow from the three-parameter model.
- Type 3: an open problem to discover new class of stochastic process.

