Sampler Method	ON LDA	Maybe on DMM
SparseLDA-Gibbs优化	利用n_m^k & n_k^t的稀疏性质 将Gibbs采样式子拆解为 $p(z_{di}=k \mid rest) \propto s+r+q$ $s=\frac{\alpha_k\beta_w}{n_k^{-di}+\vec{\beta}}\ \ r=\frac{n_{kd}^{-di}\beta_w}{n_k^{-di}+\vec{\beta}}\ \ q=\frac{n_{kw}^{-di}(n_{kd}^{-di}+\alpha_k)}{n_k^{-di}+\vec{\beta}}$ $sampleX \sim \mu(0,s+r+q)$ $if\ \ x<s\ \ hit\ \ the\ \ smoothing\ \ only\ \ bucket$ $if\ \ s<x<s+r\ \ hit\ \ the\ \ document\ \ topic\ \ bucket$ $if\ \ x>s+r\ \ hit\ \ the\ \ topic\ \ word\ \ bucket$	
Alias-Method-LDA	将Gibbs采样式子分解为$u\ \ v$ u项为稀疏项v近似项 建立一个Alias Table采样复杂度$O(1)$ $p(z_{di}=k \mid rest) \propto u+v$ $u=\frac{n_{kd}^{-di}(n_{kw}^{-di}+\beta_w)}{n_k^{-di}+\vec{\beta}}\ \ v=\frac{\alpha_k(n_{kw}^{-di}+\beta_w)}{n_k^{-di}+\vec{\beta}}$	
F+LDA	用FenwickTree数据结构采样 $p_t=\frac{(n_{td}+\alpha)(n_{tw}+\beta)}{n_t+\vec{\beta}}$ $doc-by-doc: p_t=\beta(\frac{n_{td}+\alpha}{n_t+\vec{\beta}})+n_{tw}(\frac{n_{td}+\alpha}{n_t+\vec{\beta}})$ $word-by-word: p_t=\alpha(\frac{n_{tw}+\beta}{n_t+\vec{\beta}})+n_{td}(\frac{n_{tw}+\beta}{n_t+\vec{\beta}})$	
WarpLDA	设置$D*V$矩阵 MCEM Algorithm(MC+EM) E-step:Sample $z_{dn} \sim q(z_{dn}=k)$,where $q(z_{dn}=k) \propto (C_{dk}+\alpha_k)\frac{C_{wk}+\beta_w}{C_k+\vec{\beta}}$ M-step:Compute C_d & C_w by Z $q^{doc}(z_{dn}=k) \propto C_{dk}+\alpha_k$ $q^{word}(z_{dn}=k) \propto C_{wk}+\beta$ 用上面两个作为proposal distributions用MH算法交替采样	
LightLDA	MH+Alias Table(doc-proposal+word proposal)构建一系列 $proposal\ \ function$轮流使用 $q(z_{di}=k \mid rest) \propto (n_{kd}+\alpha_k) \times \frac{n_{kw}+\beta_w}{n_k+\vec{\beta}}$ $n_{kd}+\alpha_k$为$doc-proposal$ $\frac{n_{kw}+\beta_w}{n_k+\vec{\beta}}$为$word-proposal$	
LDA*	$long-documents: WarpLDA$ $short-documents: F+LDA$	

Basic Sampler	
Importance Sampling	
Elliptical Slice Sampling	
Variational Inference	
Metropolis-Hasting	
Gibbs	$p(z_i = k \mid \vec{Z}_{\neg i}, \vec{W})$