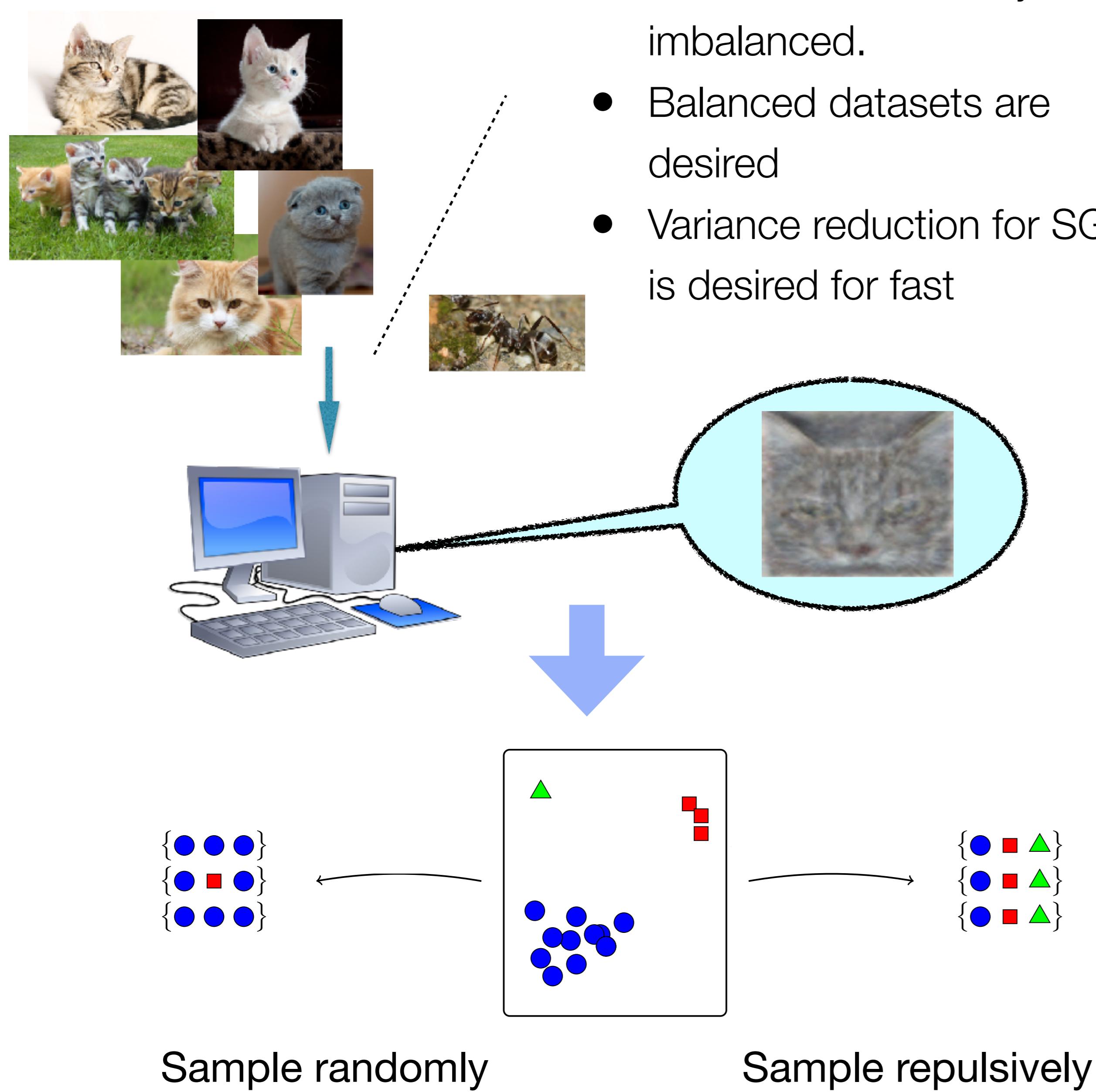


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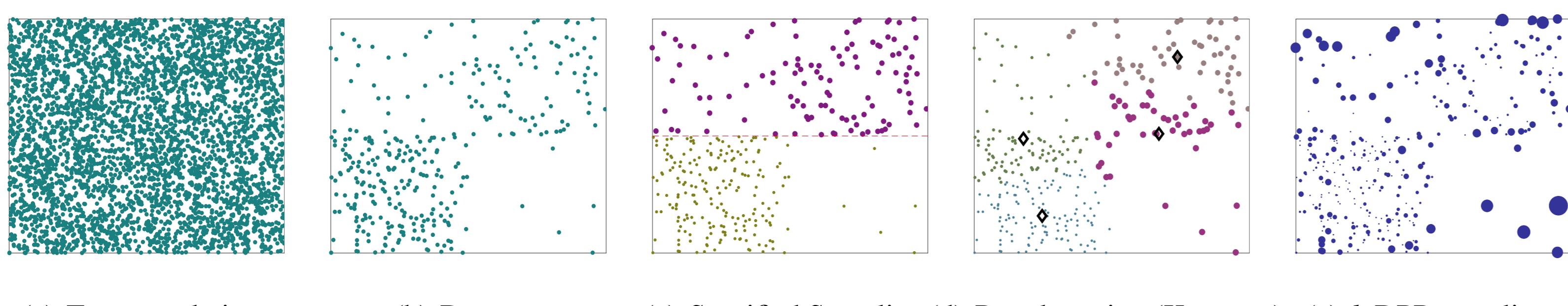
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Introduction



Related Work



(a) True population (b) Dataset (c) Stratified Sampling (d) Pre-clustering (K-means) (e) k -DPP sampling

Goal: Point wise data re-balancing.

(c) P.L. Zhao and T. Zhang. Accelerating minibatch stochastic gradient descent using stratified sampling. *arXiv preprint arXiv:1405.3080*, 2014.

(d) T.F. Fu and Z.H. Zhang. CPSG-MCMC: Clustering-based preprocessing method for stochastic gradient MCMC. In *AISTATS*, 2017.

(e) C. Zhang, H. Kjellström, and S. Mandt. Determinantal Point Processes for Mini-Batch Diversification. *UAI*, 2017.

- Determinantal Point Processes (DPP):

$$\mathcal{P}(Y) = \frac{\det(L_Y)}{\det(L+I)} \propto \det(L_Y)$$

$$\begin{vmatrix} L_{ii} & L_{ij} \\ L_{ji} & L_{jj} \end{vmatrix} = L_{ii}L_{jj} - L_{ij}L_{ji}$$

- k-DPP: $\mathcal{P}_L^k(Y) = \frac{\det(L_Y)}{\sum_{|Y'|=k} \det(L_{Y'})}$

Diversified risk: $J^*(\theta) = \frac{1}{k} \mathbb{E}_{\vec{x} \sim k\text{-DPP}} [\ell(\vec{x}; \theta)] \quad J^*(\theta) = \frac{1}{k} \sum_{i=1}^N b_i \ell(x_i, \theta)$

Main contribution

- Generalization of our previous working using DPP (d). We generalize the proof of variance reduction and show that all we need is a point process with repulsive correlations.
- Accelerate the sampling using Poisson Disk Sampling with dart throwing.

$$\mathcal{O}(Nk^3) \longrightarrow \mathcal{O}(k^2)$$

Mini-Batch Sampling with Stochastic Point Processes

Define stochastic point processes with product densities [1,2]:

$$\begin{aligned} \text{1st order product densities} \quad \lambda(\mathbf{x}) &:= \varrho^{(1)}(\mathbf{x}) = \lambda && \text{pair correlation function} \\ \text{2nd order product densities} \quad \varrho(\mathbf{x}, \mathbf{y}) &:= \varrho^{(2)}(\mathbf{x}, \mathbf{y}) = \lambda^2 g(\mathbf{x} - \mathbf{y}) \end{aligned}$$

Diversified risk: $\hat{J}_{\text{data'}}(\theta) = \sum w_i l(\mathbf{x}_i, \theta)$ Gradient: $\mathbf{k}(\mathbf{x}_i, \theta) := \nabla l(\mathbf{x}_i, \theta)$

$$\text{var}_{\mathcal{P}}(\hat{\mathbf{K}}) = \int_{\mathcal{V} \times \mathcal{V}} w(\mathbf{x}) \lambda(\mathbf{x}) w(\mathbf{y}) \lambda(\mathbf{y}) \mathbf{k}(\mathbf{x}, \theta)^T \mathbf{k}(\mathbf{y}, \theta) \left[\frac{\varrho(\mathbf{x}, \mathbf{y})}{\lambda(\mathbf{x}) \lambda(\mathbf{y})} - 1 \right] d\mathbf{x} d\mathbf{y}$$

$$+ \int_{\mathcal{V}} w^2(\mathbf{x}) \|\mathbf{k}(\mathbf{x}, \theta)\|^2 \lambda(\mathbf{x}) d\mathbf{x},$$

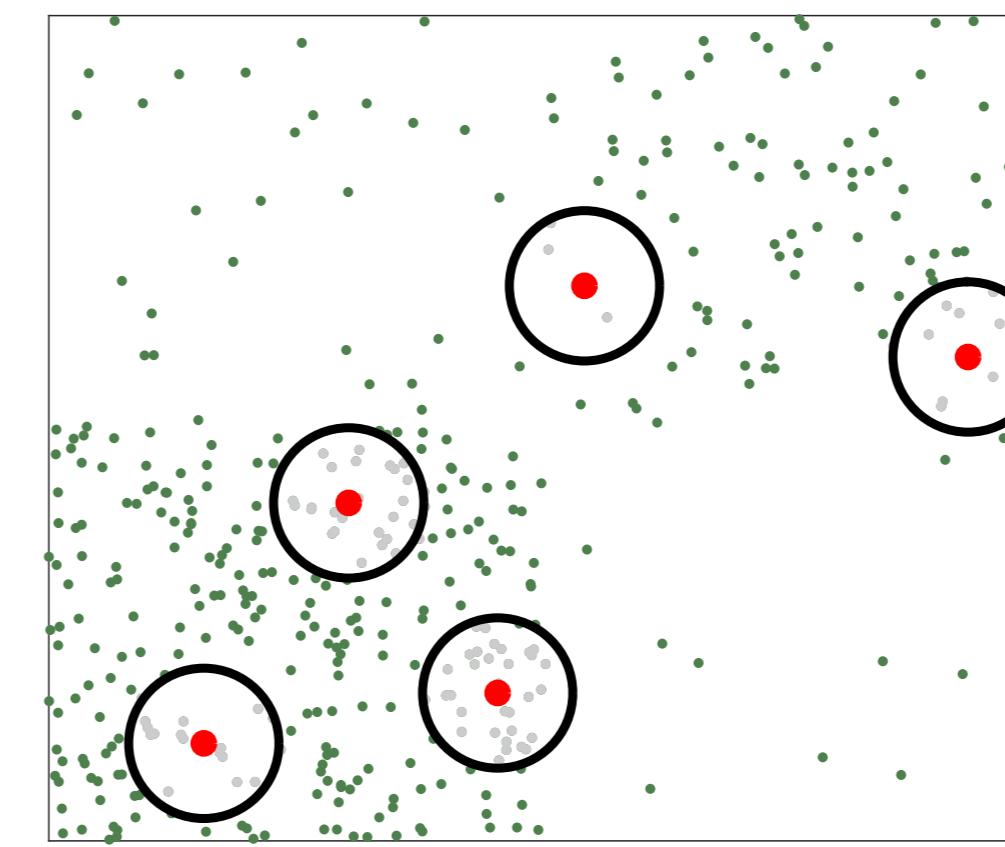
Variance for standard SGD

$$\mathbf{k}(\mathbf{x}, \theta)^T \mathbf{k}(\mathbf{y}, \theta) \left[\frac{\varrho(\mathbf{x}, \mathbf{y})}{\lambda(\mathbf{x}) \lambda(\mathbf{y})} - 1 \right] < 0 \longrightarrow \text{Variance reduction}$$

Any repulsive point processes

Poisson Disk Sampling with Dart Throwing

We can simulate all stochastic point processes with generalized dart throwing and statistics fitting as in [1].



The smallest distance between each pair of sample points should be at least r :

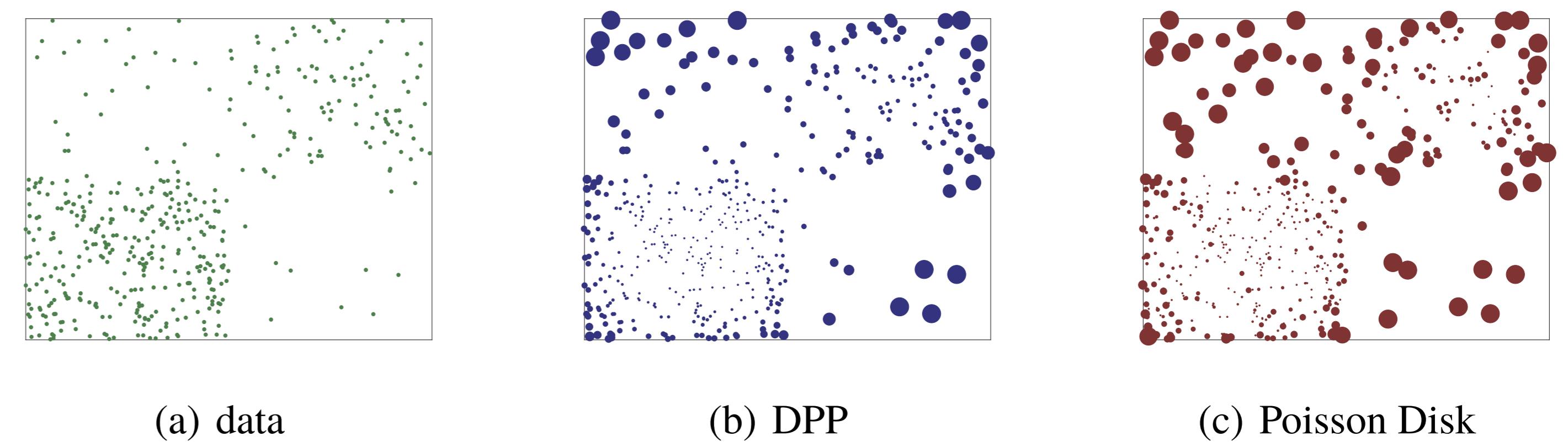
- 1.) randomly sample a data point;
- 2) if it is within a distance r of any already accepted data point, reject; otherwise, accept the new point.

$$\mathcal{O}(Nk^3) \longrightarrow \mathcal{O}(k^2)$$

Experiments

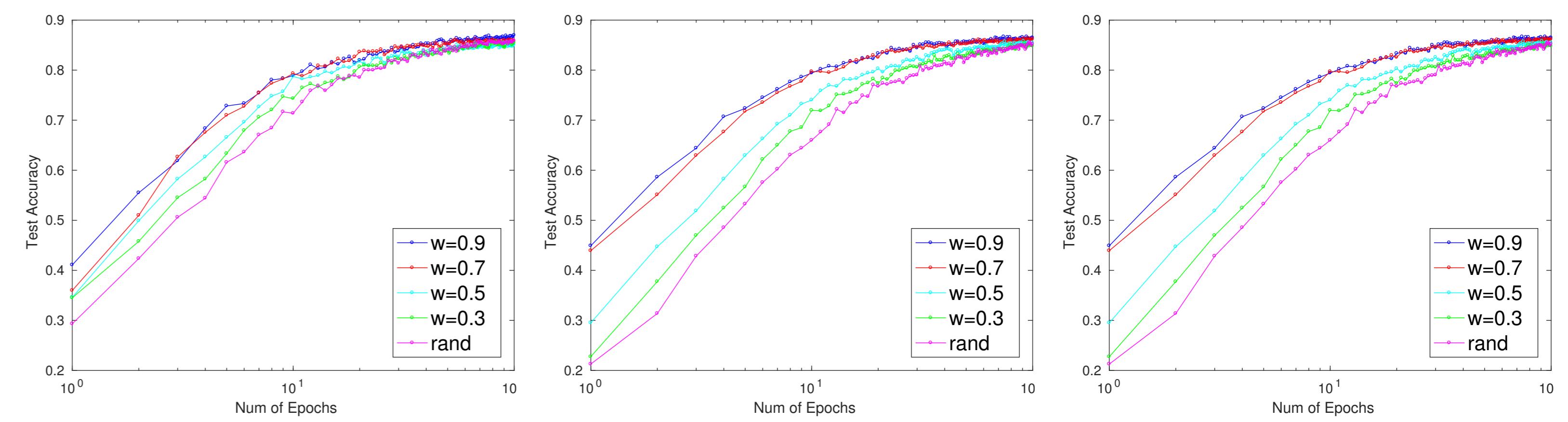
Toy example:

the marker size is positive provisional to the marginal probability



Oxford Flower Classification:

Test Accuracy:



Sampling time:

k	50	80	102	150	200
k-DPP time	7.1680	29.687	58.4086	189.0303	436.4746
Fast k-DPP	0.1032	0.3312	0.6512	1.8745	4.1964
Poisson Disk	0.0461	0.0795	0.1048	0.1657	0.2391

References

- [1] J. Illian, A. Penttinen, H. Stoyan, and D. Stoyan, editors. *Statistical Analysis and Modelling of Spatial Point Patterns*. John Wiley and Sons, Ltd., 2008
[2] C.A. Öztireli and M. Gross. Analysis and synthesis of point distributions based on pair correlation. *ACM Trans. Graph.*, 2012.