

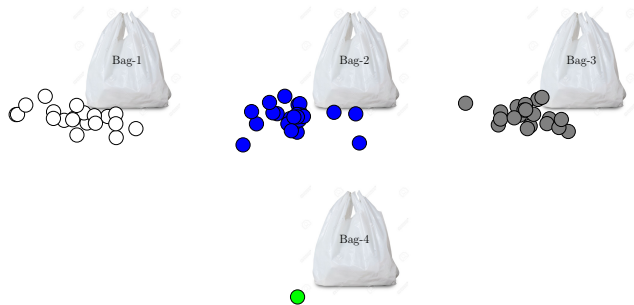
Biological Vision and Applications

Module 03-09: Hierarchical Bayesian Model

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An example

The bags can have marbles



Specific knowledge and Generic knowledge

- Specific Knowledge
 - ▶ When we sample marbles from a particular bag, we gain knowledge about that bag
 - ▶ e.g. uniformity of colors and color of marbles in that bag
- Generic Knowledge
 - ▶ When we sample marbles from several bags, we gain knowledge about all bags
 - ▶ ... even those are not sampled
 - ▶ e.g. uniform color of marbles in each bag
- Specific knowledge about several bags lead to generic knowledge
 - ▶ This is an instance of **inductive reasoning** or **inductive generalization**
 - ▶ The process of gaining generic knowledge is also known as **meta-learning**

Modeling the problem

- Let $\vec{\theta}_i$ represent the model parameters for bag i
 - ▶ $\vec{\theta}_i = (\theta_{ij}, j = 1 \dots n)$
 - ▶ j represents the different colors. $\sum_j \theta_{ij} = 1$
- In HBM
 - ▶ $\vec{\theta}_i$ s are modeled as probabilistic functions of some hyper-parameters
 - ▶ The hyper-parameters represent a higher (more abstract) level of knowledge
- A common approach is to use Dirichlet distribution
 - ▶ In this example, parameters can be $\alpha, \vec{\beta}$
 - ▶ α represents the heterogeneity of colors of the marbles in the individual bags
 - ▶ $\vec{\beta}$ representing the average color distribution across all the bags

On Dirichlet distribution

- Beta Distribution

- ▶ A probability distribution function with two parameters (α, β)
- ▶ $p(\theta)_{\alpha, \beta} = \frac{1}{k} \cdot \theta^{\alpha-1} \cdot (1 - \theta)^{\beta-1}$
- ▶ where $k = \frac{\Gamma(\alpha) \cdot \Gamma(\beta)}{\Gamma(\alpha + \beta)}$
- ▶ where $\Gamma(x) = \int_{t=0}^{\infty} t^{x-1} e^{-t} dt$

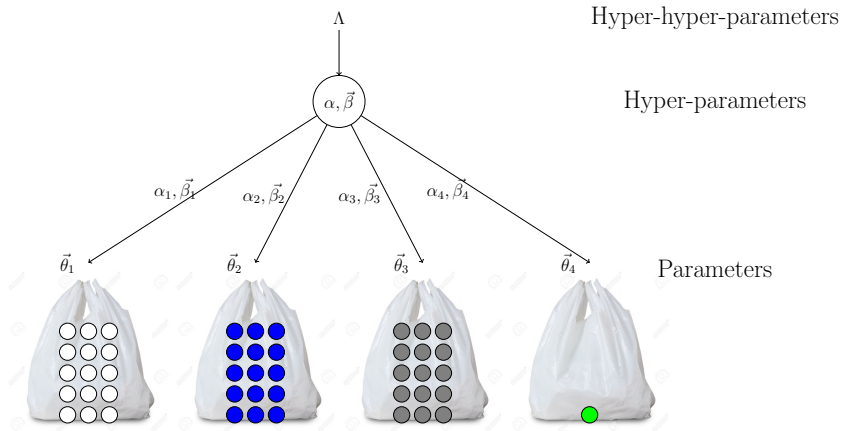
- Dirichlet Distribution (a generalization of Beta distribution)

- ▶ $\vec{\theta} = (\theta_1, \theta_2 \dots \theta_n)$
- ▶ $\vec{\alpha} = (\alpha_1, \alpha_2 \dots \alpha_n)$
- ▶ $p(\vec{\theta})_{\vec{\alpha}} = \frac{1}{k} \cdot \prod_{i=1}^n \theta_i^{\alpha_i-1}$
- ▶ where $k = \frac{\prod_{i=1}^n \Gamma(\alpha_i)}{\Gamma(\sum_{i=1}^n \alpha_i)}$

<https://leimao.github.io/blog/Introduction-to-Dirichlet-Distribution/>

Hierarchical Bayesian Model

A graphical depiction



Discussions

- The models for the bags are linked with hyper-parameters $\alpha, \vec{\beta}$
 - ▶ Are learned together with θ s
 - ▶ An observation for one bag serves as an observation for the other bags too
 - ▶ Hyper-parameters $\alpha, \vec{\beta}$ are learned together with the parameters θ_i s
- $\vec{\theta}_i$ is a probabilistic function of $\alpha, \vec{\beta}$
 - ▶ $\alpha, \vec{\beta}$ impose constraints on values of $\vec{\theta}_i$ s
 - ▶ Priors for $\vec{\theta}_i$ s (no observations) are closer to actual values
 - ▶ $\vec{\theta}_i$ can be learned (reliably estimated) from less number of observations
- Hyper-parameters represent more abstract knowledge
- It is possible to model $\alpha, \vec{\beta}$ with even higher level of knowledge ...
 - ▶ Further inductive generalization is possible
 - ▶ Generalization from one problem to another will be efficient for similar problems

Quiz 03-09

End of Module 03-09