IIT Jodhpur

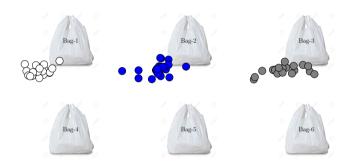
Biological Vision and Applications

Module 03-07: Hierarchical Bayesian Model

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#### An example

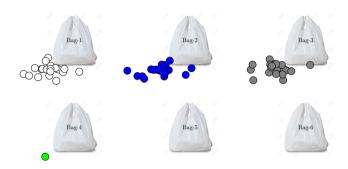
Prior belief: The bags can have marbles of any color or mix



- What do we learn from these observations?
- Can we predict something about bags 4 6 that are yet to be sampled?

### An example

... Contd.

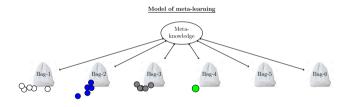


• What do we infer about bag 4 from this new observation?

This is the very basis of transfer learning

# Specific knowledge and Generic knowledge

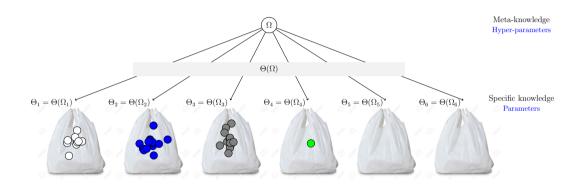
- Specific Knowledge: When we sample marbles from a particular bag, we gain knowledge about the content of that bag
- Generic (Meta) Knowledge: When we sample marbles from several bags, we gain knowledge about all bags ... even for those which are not sampled



This is an instance of inductive reasoning or inductive generalization

### Modeling the problem

#### Hierarchical Bayesian Model



# Modeling the problem

contd ...

- Let  $\Theta_i$  represent the model parameters for bag i
  - $\Theta_i = (\theta_{i1}, \theta_{i2}, \dots), \theta_{ii}$ : probability of a marble to be of color i  $ightharpoonup 0 \le \theta_{ij} \le 1$ ,  $\sum_i \theta_{ij} = 1$
  - Parameters  $\theta_{ii}$ 's can be individually learned using Bayesian inferencing
- $\Theta_i$ s are modeled as probabilistic functions of some hyper-parameters  $\Omega$  in HBM
- A common approach is to use Dirichlet distribution

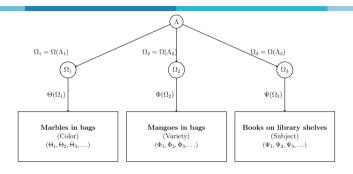
Dirichlet distribution: 
$$P_{\alpha}(x) = \frac{1}{B(\alpha)} \prod_{i=1}^k x_i^{(\alpha_i+1)}$$
, where  $B(\alpha) = \frac{\prod_{i=1}^k \Gamma(\alpha_i)}{\Gamma(\sum_{i=1}^k \alpha_i)}$ 

Example of Dirichlet Distribution

### What is really happening?

- ullet When we have no observations, we have some priors on  $\Omega$ 
  - ▶ This determines priors (constraints) for  $\Theta_i$ 's
- As we observe *i*-th bag, we learn (update)  $\Theta_i$ 
  - As we "observe"  $\Theta_i$ , we learn (update)  $\Omega$
- As we update  $\Omega$ , values of all  $\Theta_i$  are updated
  - Hyper-parameters  $\Omega$  are learned together with the model parameters  $\Theta_i$ 's
  - Hyper-parameters  $\Omega$  links the model parameters  $\Theta_i$ 's
  - An observation for one bag serves as an observation for the other bags too

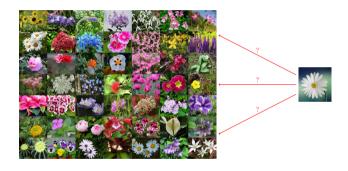
### Progressive generalization of knowledge



- It is possible to model generic knowlege with even higher abstraction (level) of knowledge, and so on ...
- The entire knowledge-base gets linked
  - Generalization from one problem to another will be efficient for similar problems

# Feature Learning

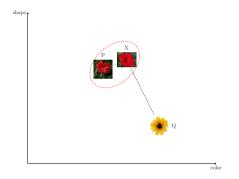
Which feature do you choose ?



BioVision 03-07

### Which category X belongs to?

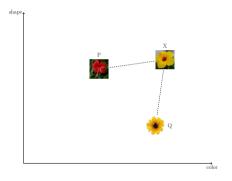
P and Q are rare flowers, you have one sample for each



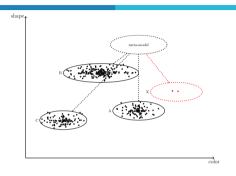
Pretty simple!

### Which category X belongs to?

P and Q are rare flowers, you have one sample for each



### Meta-learning from abundant classes

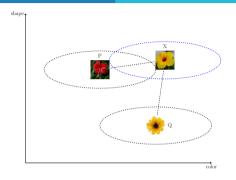


Meta-learn visual model for objects from abundant classes:

Object features have more spread in color than shape

Use the meta-model to create models for new (and rare) classes

#### Create models for rare classes from meta-model



X belongs to class P

We put more emphasis on shape than color

### Shape bias

#### That is exactly how a child learns to distinguish objects by their shapes



Source: Shape Bias

## Quiz

Quiz 03-07

End of Module 03-07