General vs. personalized modeling: When and how to get specific

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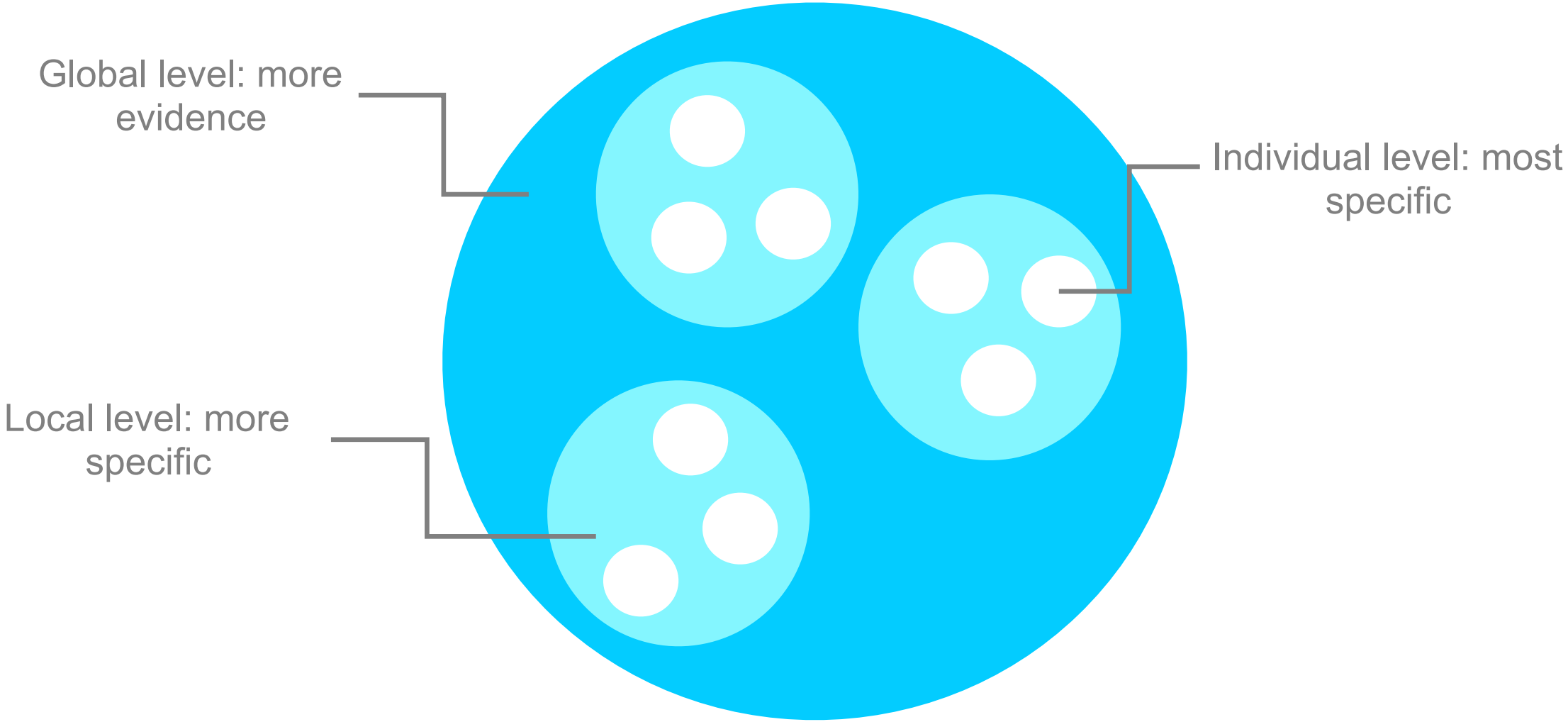
An AI service enabling any app or device to boost user engagement by adapting to each user’s persona & lifestyle and reacting to key moments throughout their day.

Outline

- Global vs Personalized modeling different considerations
- Local Level Models subpopulation segmentation
- Hierarchical Models personalized models with shared parameters

Global vs Personalized modeling general considerations



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Global vs Personalized modeling data considerations

Global model - Risk of bias

Does the population represent the individuals well?

- Is it reasonable to assume all individuals share one distribution?
- Are certain subpopulations missing certain features?
- Do individuals' data change more rapidly than the population average?

Individual models - Risk of overfitting

Is there enough data to train a model at the individual level?

- How many data points per individual?
- How much noise in the data – can you trust individual measurements?

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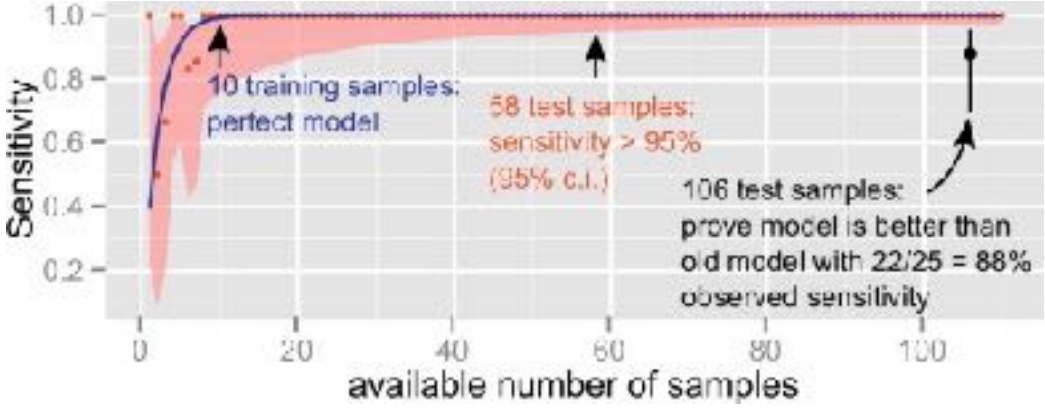
Global vs Personalized modeling data considerations

In most cases the answer is not straightforward

- Many “rules of thumb” for different types of models – e.g. the number of data points should be at least 10 times the number of parameters for regression models.
- You can gain a lot of insight by doing some empirical analysis:
  - Look at the feature distribution over the population
  - For time series data – look at dynamics of population average vs individuals
  - Construct a learning curve:



Sample Size Planning for Classification Models, http://www.sciencedirect.com/science/article/pii/S0003267012016479?via%3Dihub (https://arxiv.org/abs/1211.1323)

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Global vs Personalized modeling domain considerations

What is the right population for your particular problem?

- Is the average relevant at the individual level?
  - Prediction based on behavioral patterns – e.g. most people grocery shop on weekends, but a particular individual may shop at a different time.
- How important is individual accuracy? **Is it ok to consider variation between individuals as "noise"?**
  - Medical studies intentionally look for average effects over population.
  - Insurance/credit risk models – Main concern is with overall loss, although to optimize overall loss, individual accuracy is important.
  - Personalized recommendation models – only have value if they have high accuracy at the individual level.
- Will the model have to be applied to new individuals?
- Does the model need to be evaluated/trained online? Does the global population scale support that?

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Local Level Models subpopulation segmentation

Individuals are best represented by a similar subset

Each subset is independent and trained separately.

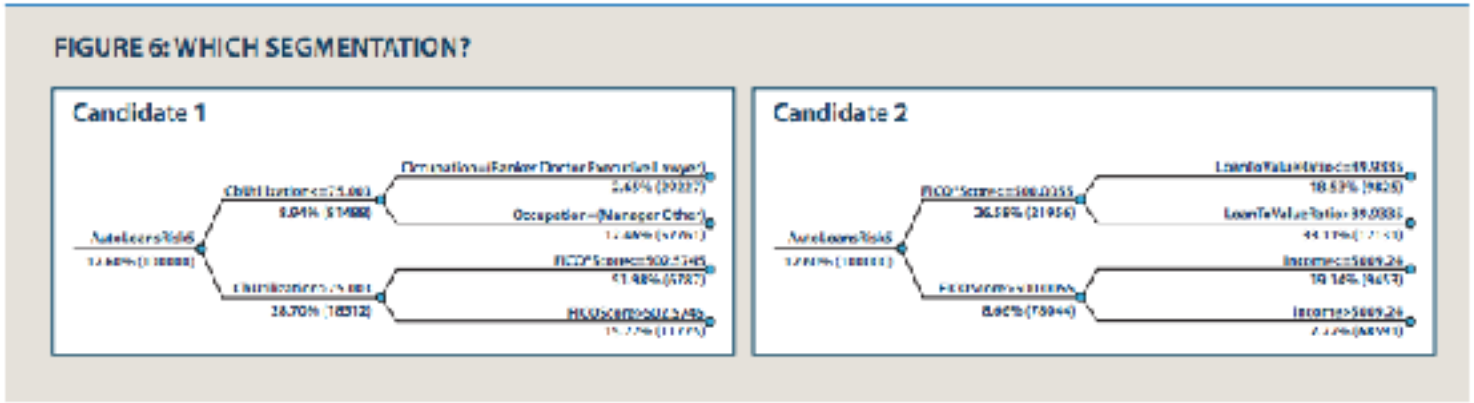
Most effective when:

- Natural segmentation or clustering
- Different features may be more relevant for different subsets

Local Level Models some examples

Segmented Scorecard module of FICO® Model Builder

- Automated module for choosing best population segmentation for credit risk scorecards.
- The system builds multiple decision trees:



- Chooses best tree based on performance of scorecards at each leaf.

http://www.fico.com/en/node/8140?file=9737

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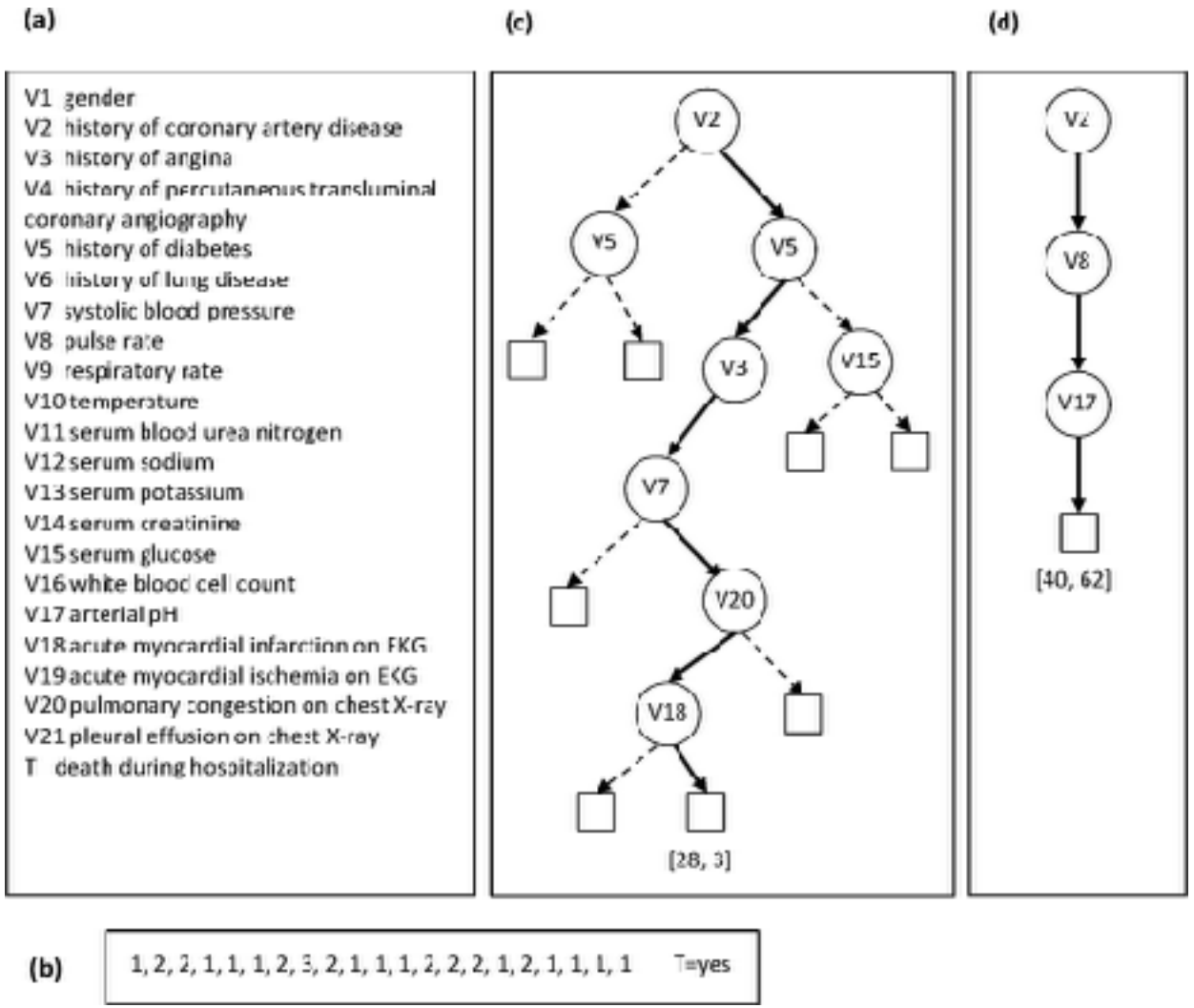
Local Level Models some examples

Decision-Path Model

- Instance-based model
- Binary outcome T
- The goal is to construct a “personalized” decision tree that is most suited to predict outcome T for a particular patient (LazyDT).
- At each node choose the feature that optimizes a score (e.g. information gain) out of the particular patient’s features.
- At the end, each path is pruned to the node with the highest score.



Personalized Modeling for Prediction with Decision-Path Models
http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0131022

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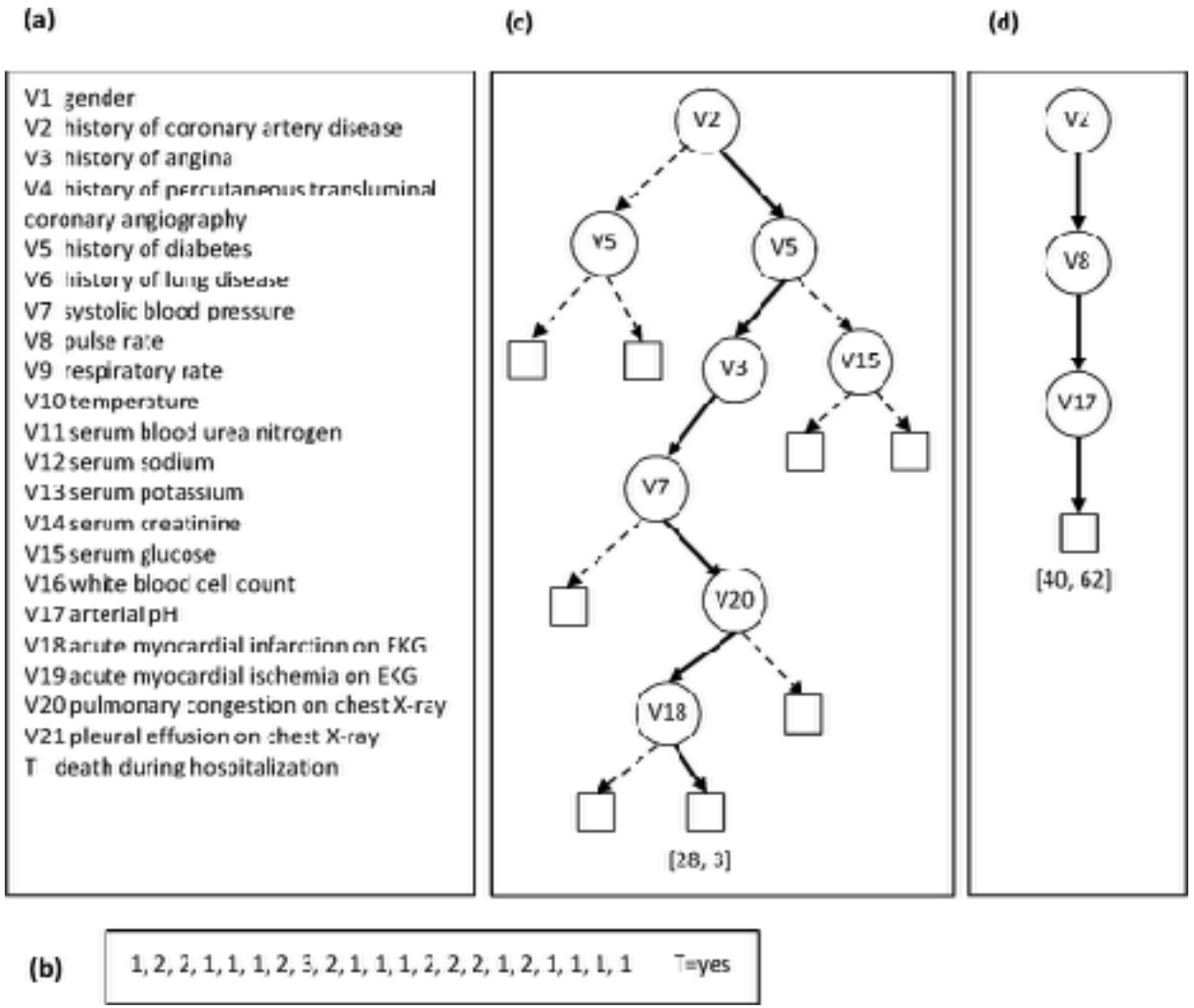
Local Level Models some examples

Decision-Path Model

- Personalization comes from:
  - Only test patient's features are considered – good for sparse data sets.
  - If the score is not averaged over all sides of the split, it gives a chance to features that are rare but significant for a small population. (the authors of this paper chose to average over both sides of the split)
  - Pruning each path separately



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Hierarchical Models personalized models with shared parameters

Individuals are diverse but not independent

Use information from more than one level simultaneously, population and individual are modeled together.

Most effective when:

- Models reflect hierarchy in the population
- Some features are shared by many individuals

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Hierarchical Models hierarchical Bayes method

Hierarchical Bayes Method

- The distribution of individual parameters within a group is modeled by a higher level distribution with its own parameters (or many levels).
- Individual and group-level parameters are evaluated simultaneously. That way each individual's parameters are informed by the group.

Hierarchical Models hierarchical Bayes method

Classic example

Heads of a coin depends on bias ($p(heads) = \theta$), which in turn depends on coin manufacturing process. Say we have J coins from the same manufacturing line, each tossed n_j times resulting in k_j heads.

$$P(k_j|\theta_j, n_j) = \binom{n_j}{k_j} \theta_j^{k_j} (1-\theta_j)^{n_j - k_j} \qquad j = 1, \dots, J$$

Model assumption: Each coin's bias θ_j is drawn from a prior distribution over all coins manufactured on the same line.

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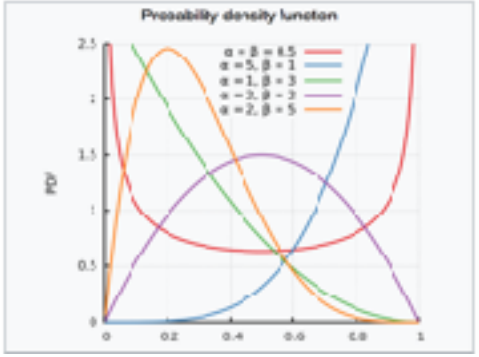
Hierarchical Models hierarchical Bayes method

Choose a Beta distribution prior for θ_j, where α and β are shared by all coins in the manufacturing line.

$$\pi(\theta|\,\alpha,\beta) = \frac{\theta^{\alpha-1}(1-\theta)^{\beta-1}}{\underbrace{\int_0^1 d\theta\,\theta^{\alpha-1}(1-\theta)^{\beta-1}}_{B(\alpha,\beta)}} = Beta(\alpha,\beta)$$



mean

$$\mu = \frac{\alpha}{\alpha+\beta}$$

α and β can be estimated by maximizing the likelihood for the overall sample:

$$L(\boldsymbol{k}|\alpha,\beta,\boldsymbol{n}) = \prod_j \int_0^1 d\theta\, P(k_j|\theta,n_j)\pi(\theta|\,\alpha,\beta)$$

$$= \prod_j \binom{n_j}{k_j} \frac{B(k_j+\alpha, n_j-k_j+\beta)}{B(\alpha,\beta)}$$

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Hierarchical Models hierarchical Bayes method

Given α and β we can estimate the posterior distribution for θ_j:

$$g(\theta_j|\,\alpha,\beta,k_j,n_j) = \frac{P(k_j|\theta,n_j)\pi(\theta|\,\alpha,\beta)}{\int_0^1 d\theta\, P(k_j|\theta,n_j)\pi(\theta|\,\alpha,\beta)} = Beta(k_j+\alpha, n_j-k_j+\beta)$$

And so for coin *j*:

$$E_g[\theta_j] = \frac{k_j+\alpha}{n_j+\alpha+\beta} = \underbrace{\left(\frac{k_j}{n_j}\right)}_{\text{Sample average for coin } j}\underbrace{\left(\frac{n_j}{n_j+\alpha+\beta}\right)}_{\text{“Weight” of sample}} + \underbrace{\left(\frac{\alpha}{\alpha+\beta}\right)}_{\text{Prior mean}}\underbrace{\left(\frac{\alpha+\beta}{n_j+\alpha+\beta}\right)}_{\text{“Weight” of prior}}$$

$\nu = \alpha + \beta$ represents an effective sample size for the prior distribution

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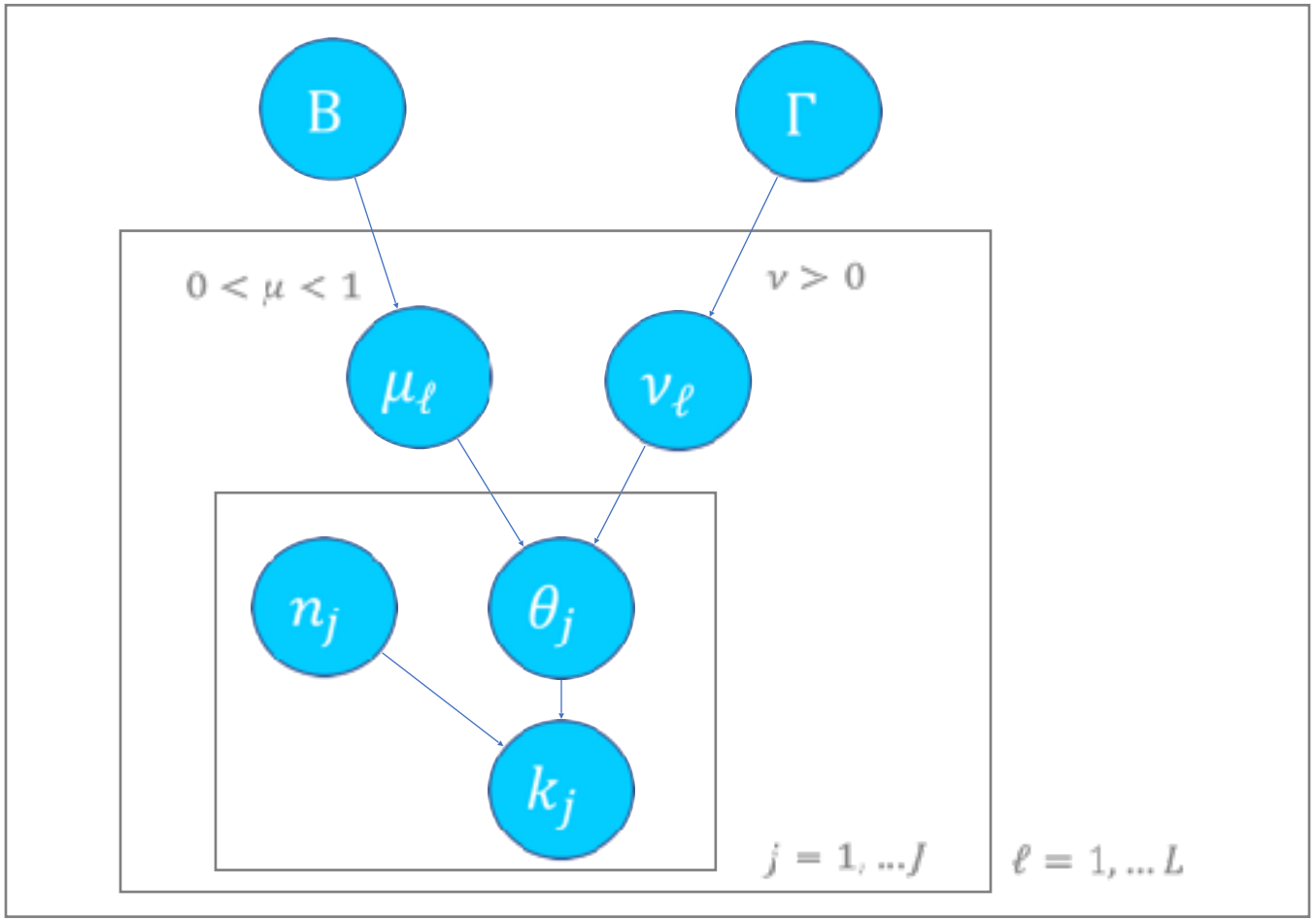
Hierarchical Models hierarchical Bayes method

If there is more than one manufacturing line, we add another layer to the hierarchy:



All parameters are evaluated simultaneously from samples of all coins from all lines.

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Hierarchical Models multilevel features

Classic example: home radon levels

Model of home radon levels based on one individual home level feature, x_{ij} (whether the measurement of house *i* in county *j* was taken in the basement), and one county level feature, u_j (county-level uranium level).

$$y_{ij} \sim N(\alpha_j + \beta x_{ij}, \sigma_y^2) \quad i = 1, \dots, n_j, j = 1, \dots, J$$
$$\alpha_j \sim N(\gamma_0 + \gamma_1 u_j, \sigma_\alpha^2) \quad j = 1, \dots, J$$

- σ_y^2 - variation within county not explained by basement indicator, shared by all individuals
- σ_α^2 - variation between counties not explained by uranium, shared by all counties
- α_j, β - also shared

Multilevel (Hierarchical) Modeling: What It Can and Cannot Do, http://www.stat.columbia.edu/~gelman/research/published/multi2.pdf

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Hierarchical Models multitask regression

Age estimation

- Problem of trying to estimate person's age from photograph. Model based on two available databases of tagged photos, several per user.
- Previous studies show that personalized models perform better than global models.
- The authors propose a multi-level expansion of a Warped Gaussian Process

Figure 4. Sample images of one person in the FG-NET database.

Figure 5. Sample images of two persons in the MORPH database.

Multi-Task Warped Gaussian Process for Personalized Age Estimation, http://repository.ust.hk/ir/bitstream/1783.1-6695/1/multi_taskw.pdf

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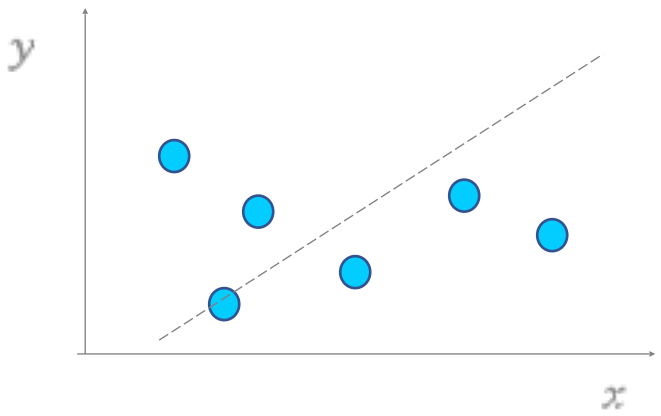
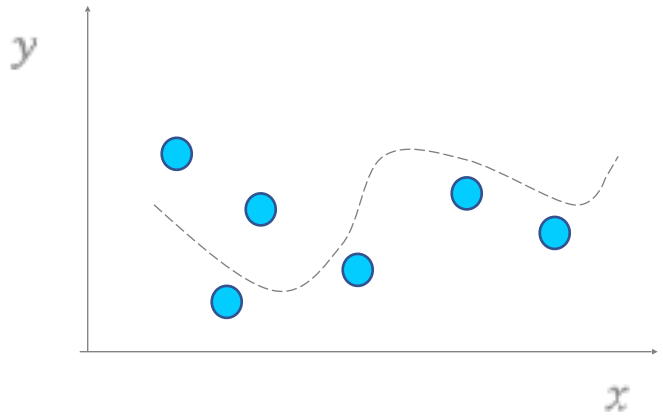
Hierarchical Models multitask regression

Gaussian Process (GP)



$$y = \theta_0 + \theta_1 x + \epsilon$$

Bayesian method estimates the distribution of parameters that best fits the observed data.



$$y = f(x) + \epsilon$$

Gaussian process estimates the distribution of all possible functions $f(x)$.

Multi-Task Warped Gaussian Process for Personalized Age Estimation, http://repository.ust.hk/ir/bitstream/1783.1-6695/1/multi_taskw.pdf

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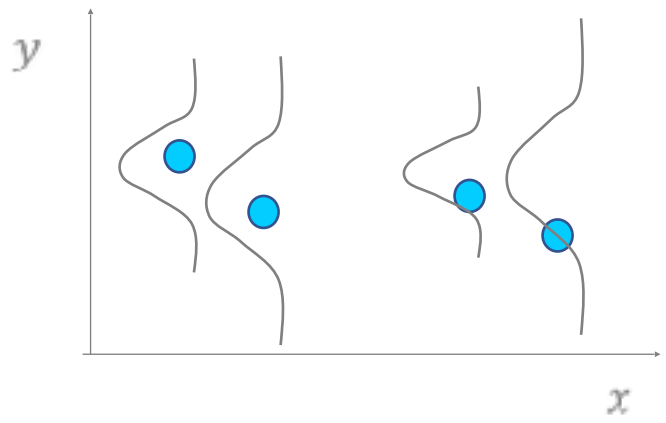
Hierarchical Models multitask regression

Gaussian Process (GP)

GP represents the function $f(x)$ as a series of values f_i which are jointly Gaussian with correlated errors



f is modeled as a series of Gaussian variables at each x

$$p(\boldsymbol{f}|\boldsymbol{x}) \sim N(\mathbf{0}_n, \mathbf{K})$$

$$p(y_i|f_i) \sim N(f_i, \sigma^2)$$

Parameters θ, σ are estimated from the likelihood

$$p(\boldsymbol{y}|\boldsymbol{x}) \sim N(\mathbf{0}_n, \mathbf{K} + \sigma^2 \mathbf{I}_n)$$

And then f can be evaluated on new x_*

fs are correlated through the covariance matrix $\mathbf{K}$:

$$K_{ij} = k_\theta(x_i, x_j)$$

k_θ is the kernel function defining similarity between xs.

-> If x's are similar then corresponding f's are also similar.

$\mathbf{K}$ and σ^2 contain all the information of how y depends on x and are learned automatically from the data

Multi-Task Warped Gaussian Process for Personalized Age Estimation, http://repository.ust.hk/ir/bitstream/1783.1-6695/1/multi_taskw.pdf

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Hierarchical Models multitask regression

Warped Gaussian Process (WGP)

A generalization of a GP where the outputs $\{y_i\}$ do not satisfy the GP assumptions, but their transformations $z_i = g_\phi(y_i)$ do.

$$p(f|\boldsymbol{x}) \sim N(\mathbf{0}_n, \mathbf{K})$$

$$p(z_i = g_\phi(y_i)|f_i) \sim N(f_i, \sigma^2)$$

Multi-Task Warped Gaussian Process for Personalized Age Estimation, http://repository.ust.hk/ir/bitstream/1783.1-6695/1/multi_taskw.pdf

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Hierarchical Models multitask regression

Multi-Task WGP

- Multi-task learning is a method of learning several models ("tasks") at once. Sharing information (e.g. structure) between tasks helps improve their accuracy.
- Hierarchical models can be treated as multi-task models where each individual is a "task".
- Each individual i has n_i data points (photos) $\{(\boldsymbol{x}_j^i, y_j^i)\}_{j=1}^{n_i}$

  $\boldsymbol{x}_j^i$ - feature vector from photo j of individual i

  y_j^i - age of individual i in photo j

Multi-Task Warped Gaussian Process for Personalized Age Estimation, http://repository.ust.hk/ir/bitstream/1783.1-6695/1/multi_taskw.pdf

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Hierarchical Models multitask regression

Multi-Task WGP

- The data is modeled as a WGP

$$p(\boldsymbol{f}|\boldsymbol{X}) \sim N(\mathbf{0}_n, \mathbf{K})$$

[illegible]

- The likelihood of each data point is defined on a latent variable $z_j^i = g_\phi(y_j^i)$

$$p(z_j^i|y_j^i) \sim N(y_j^i, \sigma_i^2)$$

- $\mathbf{K}$, parameterized by θ and ϕ are shared by all tasks and capture the dependence of y on global features.
- σ_i^2 captures the dependence of y on "task" (individual) level features.

Multi-Task Warped Gaussian Process for Personalized Age Estimation, http://repository.ust.hk/ir/bitstream/1783.1-6695/1/multi_taskw.pdf

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Questions? Thank you

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