COMS30035, Machine learning: Combining Models 4, Conditional Mixture Models

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Agenda

- Model Selection
- Model Averaging
- Ensembles: Bagging
- Ensembles: Boosting and Stacking
- Tree-based Models
- Conditional Mixture Models
- Ensembles of Humans

Recap

- Model selection: choose the right model for the whole dataset -> hard selection
- Bayesian model averaging (BMA): probabilistically select the right model for the whole dataset -> soft selection
- Decision trees: split the feature space and model each region by one leaf node -> hard selection depending on features

Recap

- Model selection: choose the right model for the whole dataset -> hard selection
- Bayesian model averaging (BMA): probabilistically select the right model for the whole dataset -> soft selection
- Decision trees: split the feature space and model each region by one leaf node -> hard selection depending on features
- Conditional mixture models: perform a soft, probabilistic split of the feature space -> soft selection depending on features

- Each data point is processed by a weighted combination of specialised 'expert' models
- Weights: probabilities that depend on the features \boldsymbol{x}_n of the data point

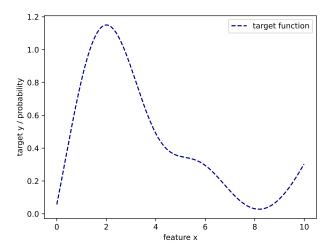
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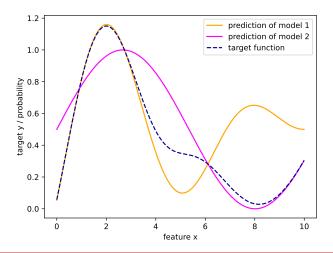
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- Similarly, some inputs \boldsymbol{x}_n may require a combination of expert models
- Contrast with decision trees, which assign each data point to a single leaf node

Imagine we would like to learn a model of this function:



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We have two expert models: model 1 is close to our target on the left, model 2 is close to our target on the right.

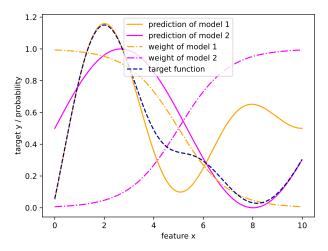


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Mixture of Experts (MoE)

MoE reproduces the target function by learning weights for each model and taking a weighted sum of their predictions.



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- Goal: predict target variable t_n given features x_n
- Component distribution depends on input feature vector x_n.

$$p(t_n | \boldsymbol{x}_n, \phi, \pi) = \sum_{k=1}^{K} \pi_k(\boldsymbol{x}_n) p(t_n | \boldsymbol{x}_n, \phi_k)$$
(1)

- ▶ $\pi_k(\mathbf{x}_n)$ is the weight for model *k* in a combination of models.
- The weights can be learned as part of EM (see Bishop 14.5.3 for more)

Now do the quiz!

Please do the quiz for this lecture on Blackboard.