that examples from the same class have similar representations. Unsupervised learning can provide useful cues for how to group examples in representation space. Examples that cluster tightly in the input space should be mapped to similar representations. A linear classifier in the new space may achieve better generalization in many cases (Belkin and Niyogi, 2002; Chapelle *et al.*, 2003). A long-standing variant of this approach is the application of principal components analysis as a pre-processing step before applying a classifier (on the projected data).

Instead of having separate unsupervised and supervised components in the model, one can construct models in which a generative model of either $P(\mathbf{x})$ or $P(\mathbf{x}, \mathbf{y})$ shares parameters with a discriminative model of $P(\mathbf{y} \mid \mathbf{x})$. One can then trade-off the supervised criterion $-\log P(\mathbf{y} \mid \mathbf{x})$ with the unsupervised or generative one (such as $-\log P(\mathbf{x})$ or $-\log P(\mathbf{x}, \mathbf{y})$). The generative criterion then expresses a particular form of prior belief about the solution to the supervised learning problem (Lasserre *et al.*, 2006), namely that the structure of $P(\mathbf{x})$ is connected to the structure of $P(\mathbf{y} \mid \mathbf{x})$ in a way that is captured by the shared parametrization. By controlling how much of the generative criterion is included in the total criterion, one can find a better trade-off than with a purely generative or a purely discriminative training criterion (Lasserre *et al.*, 2006; Larochelle and Bengio, 2008).

Salakhutdinov and Hinton (2008) describe a method for learning the kernel function of a kernel machine used for regression, in which the usage of unlabeled examples for modeling $P(\mathbf{x})$ improves $P(\mathbf{y} \mid \mathbf{x})$ quite significantly.

See Chapelle *et al.* (2006) for more information about semi-supervised learning.

7.7 Multi-Task Learning

Multi-task learning (Caruana, 1993) is a way to improve generalization by pooling the examples (which can be seen as soft constraints imposed on the parameters) arising out of several tasks. In the same way that additional training examples put more pressure on the parameters of the model towards values that generalize well, when part of a model is shared across tasks, that part of the model is more constrained towards good values (assuming the sharing is justified), often yielding better generalization.

Figure 7.2 illustrates a very common form of multi-task learning, in which different supervised tasks (predicting $\mathbf{y}^{(i)}$ given $\mathbf{x}$) share the same input $\mathbf{x}$, as well as some intermediate-level representation $\boldsymbol{h}^{(\text{shared})}$ capturing a common pool of