models, including many of the ideas described above. They highlight the fact that there are many different uses of generative models and that the choice of metric must match the intended use of the model. For example, some generative models are better at assigning high probability to most realistic points while other generative models are better at rarely assigning high probability to unrealistic points. These differences can result from whether a generative model is designed to minimize $D_{\mathrm{KL}}(p_{\mathrm{data}} \| p_{\mathrm{model}})$ or $D_{\mathrm{KL}}(p_{\mathrm{model}} \| p_{\mathrm{data}})$, as illustrated in figure 3.6. Unfortunately, even when we restrict the use of each metric to the task it is most suited for, all of the metrics currently in use continue to have serious weaknesses. One of the most important research topics in generative modeling is therefore not just how to improve generative models, but in fact, designing new techniques to measure our progress.

20.15 Conclusion

Training generative models with hidden units is a powerful way to make models understand the world represented in the given training data. By learning a model $p_{\mathrm{model}}(\boldsymbol{x})$ and a representation $p_{\mathrm{model}}(\boldsymbol{h} \mid \boldsymbol{x})$, a generative model can provide answers to many inference problems about the relationships between input variables in $\boldsymbol{x}$ and can provide many different ways of representing $\boldsymbol{x}$ by taking expectations of $\boldsymbol{h}$ at different layers of the hierarchy. Generative models hold the promise to provide AI systems with a framework for all of the many different intuitive concepts they need to understand, and the ability to reason about these concepts in the face of uncertainty. We hope that our readers will find new ways to make these approaches more powerful and continue the journey to understanding the principles that underlie learning and intelligence.