Improved Denoising Diffusion Probabilistic Models (Nichol et al., 2021):
Learning variances of the reverse diffusion process allows sampling with an order of magnitude fewer forward passes with a negligible difference in sample quality, which is important for the practical deployment of these models.
Similar outputs with far fewer computational steps (forward passes)
https://arxiv.org/abs/2102.09672

Cascaded Diffusion Models for High Fidelity Image Generation (Ho et al., 2021)
https://arxiv.org/abs/2106.15282

Diffusion Models Beat GANs on Image Synthesis (Dhariwal et al., 2021)
755 citations
Improve unconditional and conditional Image synthesis by a series of experiments. For conditional ones, they introduced a method called classifier guidance which allows for a trade-off between diversity and fidelity using gradients from a classifier. Seems efficient.
https://arxiv.org/abs/2105.05233

Classifier-Free Diffusion Guidance (Ho et al., 2021):
Introducing classifier-free guidance, allows for the adjustment of sample quality and diversity without using a separate classifier, but train both a conditional and an unconditional diffusion model. The score estimates from these models are then combined to control the trade-off between diversity and fidelity.
https://arxiv.org/abs/2207.12598

Hierarchical Text-Conditional Image Generation with CLIP Latents (DALL-E 2) (Ramesh et al., 2022)
Textual input -> CLIP embedding then decode it into images using diffusion model. More focusing on the text side.
https://arxiv.org/abs/2204.06125