Scenarios requiring humans to choose from multiple seemingly optimal actions are commonplace, however standard imitation learning often fails to capture this behavior. Instead, an over-reliance on replicating expert actions induces inflexible and unstable policies, leading to poor generalizability in an application. To address the problem, this thesis presents the first imitation learning framework that incorporates Bayesian variational inference for learning flexible non-parametric multi-action policies, while simultaneously robustifying the policies against sources of error, by introducing and optimizing disturbances to create a richer demonstration dataset. This combinatorial approach forces the policy to adapt to challenging situations, enabling stable multi-action policies to be learned efficiently. The effectiveness of the proposed method is evaluated through simulations and real-robot experiments for a table-sweep task and an assembly task using the UR3 6-DOF robotic arm. Results show that, through improved flexibility and robustness, the learning performance and control safety are better than comparison methods.