A major challenge in the practical use of reinforcement learning systems is the manual design of a reward function for large, high-dimensional state-action spaces. We show some results about how techniques like reward shaping can be useful in solving certain simple problems, then show that as the task becomes more complex, manual reward shaping becomes more unrealistic. In these complex scenarios, Inverse Reinforcement Learning (IRL) can be useful, the goal of which is the inference of a reward function given demonstrations of optimal behavior. We show that Maximum Entropy IRL can be reduced to a parameter estimation problem in a Fokker-Planck equation and give a novel approach for solving this inverse problem using optimal transport. We show that our scheme can also be extended to higher dimensional neural representations, allowing for the design of data-driven controllers of the brain. (Received September 03, 2019)