PINNS (physics informed neural networks) have recently become popular as a means of solving ODEs and PDES by using the tools of deep learning. They have both shown promise for solving some differential equations, and have struggled to solve others. Whilst advertised as being 'mesh free methods' they do rely on the use of collocation points. The accuracy of the numerical solution of PDEs using Finite Element methods depends crucially on the choice of an appropriate mesh. This can be obtained an r-adaptive strategy, which equidistributes the error over the mesh elements based on a-priori/posteriori knowledge of the solution. The core of this talk will describe how r-adaptivity can be useful in the context of Deep Learning. First, we will show that a one-dimensional mesh can be equidistributed by training a feed forward Neural Network. This approach yields better results than other standard numerical methods. We will then explain the training process of PINNs for solving boundary value problems (BVPs) and show numerical results for a reaction-diffusion and convection-dominated equation. It appears that PINNs fail to be trained in the latter case unless the homotropy method is employed. Finally, we will introduce the deep-Ritz network (DRN) for solving the Poisson's equation on a non-convex 2-dimensional domain. If the collocation points are uniformly random sampled and fixed for the entire training process, we obtain a solution with poor accuracy. On the contrary, the adoption of an Optimal Transport strategy, which determines the 'optimal' collocation points, results in a more stable training process and a much more accurate solution.