GP regression: Bayesian method, predicts unknown function values

We understand how well we can learn on continuous spaces – what about discrete ones?

Consider functions on graphs, with random walk kernel

The Random Walk Kernel weights the inference it makes about a node from its neighbours using the chance a random walk will finish there

It is tunable by two parameters,

- Total # of attempts at taking a step, $p$
- Probability of taking a step, $a^{-1}$

$p$ controls the length of the tail of the kernel

$p/a$ controls the typical correlation length
- We look at 3 different random graph ensembles
- We study the learning curves (mean square error) as we increase the number of examples
- We find that learning consists of two regimes and that the known good approximation in the Euclidean case fails in the crossover between these regimes
- Structures of the different ensembles affect the learning rates greatly
- The approximation is better for some ensembles than others