Reading summaries:

"Hidden Markov Model for Stock Trading"
A Hidden Markov Model was trained for predicting S&P 500 stock prices. The optimal number of latent states was determined by the minimization of several parsimony heuristics (information content criteria). First, the Baum-Welch algorithm was used to 'calibrate' the HMM's parameters given observations; then, the likelihood of the sequence of predictions was calculated using the forward/backward algorithm. Last, the likelihood was used to determine the model's informativeness, as a function of number of parameters and likelihood. A metric was developed for evaluating the performance on unseen training data. The model predicted prices well and was even able to earn money on trades.

"Gene finding and the Hidden Markov models"
Prokaryotic open reading frame DNA sequences can be described using codon-alphabet string sequences. The Viterbi algorithm can be used to determine the most likely sequence of hidden states, given observations, transmission/emission probability matrices, and initial state probability vectors. Often a combination of supervised learning (estimating initial/transition/emission probabilities from annotations) and unsupervised learning (iterative improvements of initial parameter estimates and predicted maximum likelihood hidden sequences) are used together to improve the model given a few annotated examples.

"Modelling Spatial Patterns Using Graph Convolutional Networks"
https://drops.dagstuhl.de/opus/volltexte/2018/9401/pdf/LIPIcs-GISCIENCE-2018-73.pdf
Traditional convolutional neural networks work well on images but do not work well on geographical data. Features in geographical data structured as a graph can still be used with graph convolution. With graph convolution, even long-distance non-Euclidean relationships can be learned. In this paper, there is an example where a model learns to place a facility in an optimal location according to a complex spatial decision function. The data features are extracted using convolution on graph Laplacians. The loss function is mean square error from the true optimal site placement.