**Structure:**

* Different chapters for every algorithm
* Theoretical examples for each algorithm in respective chapters to show how the algorithms work
* A separate chapter for case study on EnergyPlus to compare all algos
* A separate chapter for case study on L’Aquila to compare best models (GPs and NNs)

**Title: Methods for data-driven model predictive control**

**With application to intelligent building control**

**Chapter 1: Introduction**

* Physics-based modeling not suitable in applications like building control
* Need for cost reduction in order to deploy MPC at scale
* This work explores the use of machine learning based models
* How is machine learning used in a traditional sense?
* What are the requirements for predictive control?
* predictive dynamical model,
* performance guarantees for control
* Inversion of machine learning models for control
* Challenges with constrained optimization using ML models
* hard because of non-convexities, non-differentiabilities, non-closed form solution, give examples with trees, forests, Gaussian processes, neural networks
* cannot use RL, we want model-based
* traditionally optimization in ML unconstrained
* for control we need constrained optimization
* Examples of different applications – building will be main focus
* Outline of the work
* Economic MPC
* What we don’t do

**Chapter 2: Application — Building Control and Demand Response**

* intro to building control and demand response
* Need for model predictive control
* energy efficiency, energy flexibility —> energy savings, cost savings
* So we need models, why is traditional way of modeling hard
* model capture using historical data
* change in material properties
* model heterogeneity
* Practical challenges
* quality of historical data, need for new experiments, sensor failure
* computational complexity of control/optimization algorithms, real-time control
* performance guarantees and robustness
* model adaptability
* indicator for deterioration, when to update, use statistics of error in prediction
* A concrete example that describes the modeling and control problem
* description of building: different types of buildings like RTU, central heating/cooling, impact of thermal inertia
* goals for modeling — types of models to be identified
* goals for control — cost minimization, energy minimization, thermal comfort bounds

**Chapter 3: Regression trees**

* Theory on training regression trees [Hastie]
* Approach 1: Multi-output regression trees [BuildSys, TCPS]
* Approach 2: Multiple single-output regression trees [ACC, CDC, AE]
* From static models to dynamical models in the leaves [ADHS]
* uses ideas from system identification
* Benchmark with MPC on bilinear building model [CDC, ADHS]
* Best example — find example where this approach would stand out [Missing]
* Merits and demerits of using regression trees
* interpretability vs accuracy argument [example]
* strong assumption of separation of variables
* overfitting problem
* no performance guarantees
* Summary of the chapter

**Chapter 4: Random Forests**

* Theory on training random forests — reduce variance [Hastie]
* Algorithm — extension of single-output regression trees [ACC, CDC, AE]
* From static models to dynamical models in the leaves [ADHS]
* Benchmark with MPC on bilinear building model [CDC]
* Results with another highly non-linear example [Missing]
* Compare with the best tree model
* Best example — find example where this approach would stand out, construct theoretical example [Missing]
* Merits and demerits of using random forests
* again strong assumption of separation of variables
* no interpretability
* fast to train
* optimization problem convex
* require lots of data
* no performance guarantees
* Summary of the chapter

**Chapter 5: Gaussian Processes**

* Theory on training Gaussian processes [Rasmussen]
* Gaussian processes for dynamical systems [ICCPS]
* Bayesian optimization, experiment design, active learning
* Algorithm, problem formulation [ICCPS, AE2]
* Benchmark with MPC on bilinear building model [Missing]
* Results with another highly non-linear example [Missing]
* Compare with random forests [Missing]
* Results with faster linearized GP [Truong’s updated version] [Missing]
* can we make GPs scalable, on-going discussion with Weijie, Edgar [Missing]
* Merits and demerits of using GPs
* slower to train O(n^3)
* optimization problem non-convex
* works with small datasets
* can provide probabilistic performance guarantees
* can account for prior model knowledge
* unscalable for data >10K, memory limitations
* Summary of the chapter

**Chapter 6: Deep Neural Networks**

* Theory on training deep learning [Goodfellow]
* Deep learning for dynamical systems
* Benchmark with MPC on bilinear building model [Missing]
* Results with another highly non-linear example [Missing]
* Compare with GPs [Missing]
* Scalability issues, comparison with GPs
* Merits and demerits
* faster to train, use SGD
* but require much more samples for same performance
* Summary of the chapter

**Chapter 7: Experiments on a simulated building in EnergyPlus**

* Building setup
* Data collection, functional tests
* Prediction models — learning and validation
* Problem formulation
* Control with RFs
* Control with GPs
* Control with neural networks
* Results and comparison with all algorithms

**Chapter 8: Experiments on a real building**

* Building setup
* Interface with BMS, real-time monitoring
* Data collection, functional tests
* Prediction models — learning and validation
* Do we need different models for each zone or can one model suffice?
* Problem formulation
* Control with GPs
* Control with neural networks
* Combine neural networks for energy with GPs for temperature
* Benefits, challenges and limitations

**Conclusions**

* compare merits/demerits of all different methods in a table
* compare results of all different methods in a table

**Limitations, Future work**

* availability of “good” data, often marred with sensor failures
* hardware/sensors must be fixed before you can trust the data
* error in long-term forecast can cause error to blow up exponentially, so challenges with long horizon for MPC

**Appendix A: Constrained optimization in Tensorflow [Missing]**

**Appendix B: DPC toolbox for Python**

**Appendix C: Examples of problems that can be solved using DPC toolbox**