CMSC 510
Regularization Methods for Machine Learning

Course Summary

Take-home message

- Modern view of machine learning:
  - objective function
  - model with parameters
    - structure of the model will constrain the space of possible predictors
  - optimizer that find parameters that minimize the objective function
    - Typically, some variant of gradient descent
- Often, models have statistical interpretation
  - E.g. maximal likelihood estimation

Take-home message

- Objective functions:
  - Mean squared error
  - Logistic loss / cross-entropy loss
  - Hinge loss (SVM loss)
- Models:
  - Linear
  - Kernel machines
    - linear in high-dimensional “feature space”, but non-linear in input space
  - Neural networks
    - nonlinear thanks to an activation function like ReLU

Take-home message

- Regularization:
  - Improving ability of models to generalize
    - So that they work better
      on previously unseen data (aka “test data”)

- Two main approaches in classical machine learning:
  - Reducing the complexity of the model
  - Adding more data / information during training

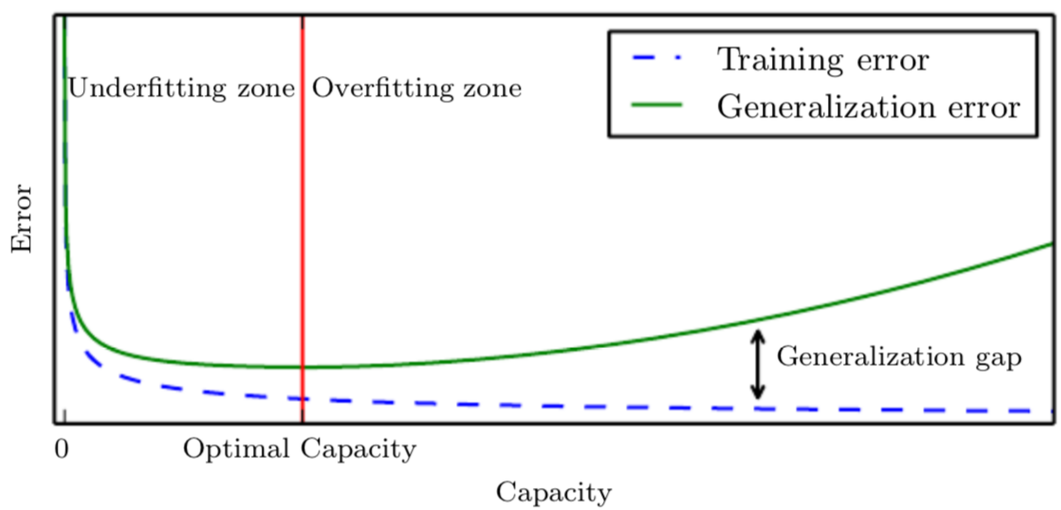
Take-home message

- Regularization:

- Reducing complexity of the model:

  Occam's razor: "Simpler solutions are more likely to be correct than complex ones."

  - by preferring simpler models e.g. through complexity penalty,
    - L2 / L1 regularization
  - by enforcing simplicity through
    eliminating some of the freedom in choosing model parameters



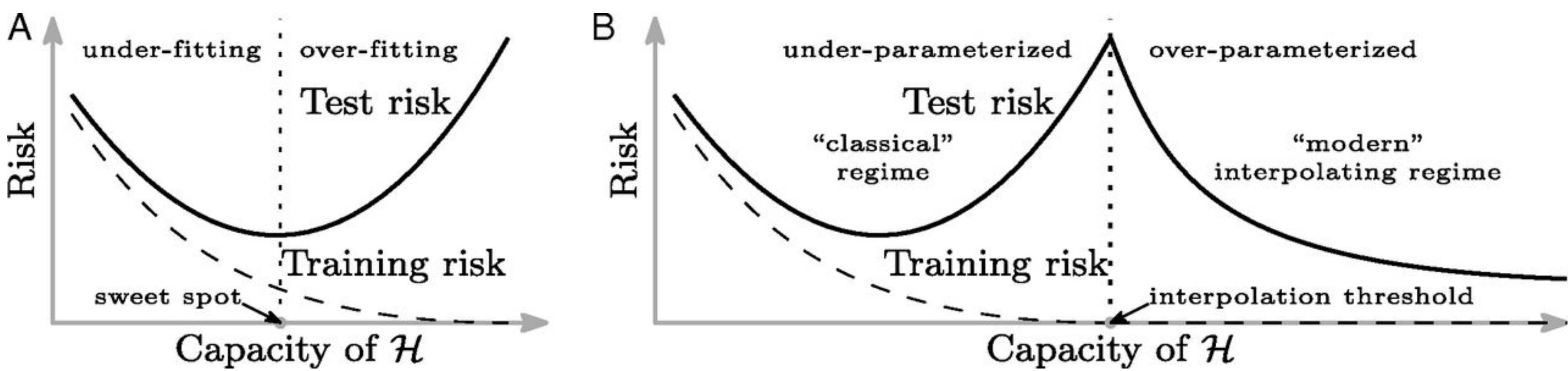
Take-home message

- Regularization:

- Adding more data / information during training
  - semi-supervised learning
    (use unlabeled examples and graph of their similarities)
  - graph / group submodular penalties
    (add knowledge about relationships among features)

Take-home message

- Regularization in deep models:
  - We need new techniques beyond what works for “classical” models
    - pre-training
    - weights sharing
    - normalization layers
  - We need better understanding how can networks with so many parameters learn at all
    - Instead of just memorizing training data



Belkin et al. 2019. Reconciling modern machine-learning practice and the classical bias–variance trade-off