COMPSCI 689
Lecture 25: Course Wrap-Up

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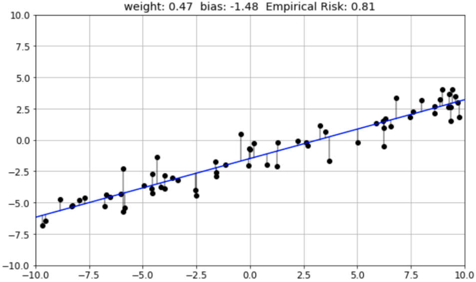
OLS Linear Regression (1800's)



Adrien-Marie Legendre

1805: Linear least squares method

Carl Friedrich Gauss

1822: Linear least squares optimality

Text to Images and Video (2022)

Learning Outcomes

1. To be able to correctly define core supervised and unsupervised machine learning tasks.
2. To gain familiarity with optimization-based frameworks for developing machine learning algorithms including exact and iterative non-linear numerical optimization methods.
3. To gain familiarity with select classical machine learning models and algorithms including what task they solve, how they are derived, and what their computational scalability properties are.
4. To be able to develop customized machine learning models and prediction and/or inference methods for solving a specified task within multiple generalized modeling frameworks including neural networks and generalized probabilistic models

Learning Outcomes

5. To be able to explain concepts including generalization, capacity control, overfitting, training error, validation error, test error and to understand when to apply different metrics for evaluating the performance of machine learning methods.
6. To be able to design valid machine learning experiments for assessing model performance including while optimizing model hyper-parameters.
7. To be able to clearly communicate the results of machine learning experiments using appropriately selected and correctly formatted tables and plots and to be able to correctly interpret such output.
8. To gain practical experience developing efficient and numerically stable implementations of learning and inference methods for both classical and customized models.

Learning Outcomes

9. To gain practical experience using current machine learning software and tools based on Python including Numpy, SciPy, and PyTorch and to understand key facilities of these tools such as automatic differentiation.
10. To understand the limitations of optimization-based machine learning.

What have we covered?

- **Foundations:** Numerical optimization, multivariate probability
- **Learning Frameworks:** ERM, RRM, MLE, Variational Learning, Adversarial Learning (GANs)
- **Tasks:** Regression, Classification, Clustering, Dimensionality Reduction, Density Estimation, Reconstruction, Denoising, Generation
- **Supervised Models:** OLS, SVM/SVR, MLPs, CNNs, RNNs, Logistic Regression, Probabilistic Supervised Models.
- **Unsupervised Models:** Mixture Models, Factor Analysis, Autoencoders, VAEs, GANs, Transformers, Diffusion

What have we covered?

- **Implementing custom models:** Periodic regression, kernel logistic regression, heteroskedastic regression, symbolic regression, autoencoders.
- **Meta-Issues:** Generalization assessment, hyper-parameter selection, experiment design.
- **Tools:** NumPy, SciPy, PyTorch, optimization, autodiff
- **Skills:** Visualizing and communicating results of experiments

NOT COVERED:
BAYESIAN ML, LAGRANGE DUALS

Course Metrics

- **Piazza:** 414 posts. 368 instructor responses. 1200+ student contributions. 2h average response time.
- **Grading:** 6000+ homework question parts graded. 7-10 day turn-around.
- **Material:** 3 new lectures (PyTorch Crash Course, Transformers, Multi-Modal Transcoders)

Final Exam Rules

- No electronic devices may be used during the exam.
- You may consult your paper notes and/or a print copy of texts during the exam.
- Sharing of notes/texts during the exam is strictly prohibited.
- Show your work for all derivation questions.
- A suitable explanation must be provided for all questions that ask for one to earn full credit.

Final Exam Procedures

- The exam will run for exactly 2 hours.
- Course staff will arrive to set up 20 minutes prior to the start time.
- The only items allowed at your seat are writing materials, notes/books, and drinks/snacks.
- Bags and coats need to be left at the front or back of the room.
- Phones and smartwatches must be turned off and left in your bag.
- Bring your UMass ID to sign in to the exam.

Possible Final Exam Topics

- **Learning Frameworks:** MLE (including NLML)
- **Supervised Models:** MLPs, RNNs, classical and generalized probabilistic supervised models (regression, classification, linear, non-linear, etc.)
- **Unsupervised Models:** Multivariate normals, product of marginals, mixtures, factor analysis, non-linear factor analysis, autoencoders
- **Probabilistic Inference:** Marginalization, conditioning, making predictions, handling missing data

Possible Final Exam Topics

- **Properties:** Computational complexity, numerical stability, optimization convergence
- **Meta Issues:** Generalization assessment, hyper-parameter selection, experiment design for unsupervised learning
- **Skills and Tools:** Matrix/Tensor-based programming, recognizing problems with implementations, interpreting results and graphs

More Machine Learning

- **What if I have a small amount of training data?** Data augmentation. Bayesian machine learning.
- **What if I have a small amount of labeled data and a large amount of un-labeled data?** Semi-supervised learning. Active learning.
- **What if I have a small amount of data for the task I care about and a large amount of data for somewhat related tasks?** Domain adaptation, transfer learning.
- **What if I have data for several different, but related tasks?** Multi-task learning.

More Machine Learning

- **What if the data distribution I am trying to model is changing over time?** Lifelong learning, continual learning.
- **What if I'm concerned about robustness to arbitrary outliers during deployment?** Robust models, out-of-distribution detection.
- **What if I need to be robust to the possibility of direct attack against a deployed model?** Adversarial training.
- **What if my classification problem has severely imbalanced classes?** Instance weighted learning.

More Machine Learning

- **What if I have missing data in the inputs of my model?** Imputation, probabilistic modeling.
- **What if I need to predict outputs over a structure like a graph or a tree?** Structured prediction.
- **What if I need to predict a ranking over objects?** Learning to rank.
- **What if I need to understand what data variables are impacting model performance?** Feature selection.

More Machine Learning

- **What if I need to understand what training data cases are most impacting impacting model performance?** Influence functions.
- **What if I need to understand why my model makes the predictions it does?** Model explainability.
- **What if I want to make sure my model isn't prejudiced or racist?** Algorithmic bias detection and mitigation.
- **What if I need to reduce the deployment resource use of my model?** Model compression, pruning and distillation.
- **How do I keep up with advances in machine learning?**

Where to go from here? - ML Courses

- COMPSCI 682: Deep Learning
- COMPSCI 687: Reinforcement Learning
- COMPSCI 688: Probabilistic Graphical Models
- COMPSCI 651: Optimization

Where to go from here? - Applications Courses

- COMPSCI 685: Advanced Natural Language Processing
- COMPSCI 603: Robotics
- COMPSCI 646: Information Retrieval
- COMPSCI 670: Computer Vision
- COMPSCI 574/674: Intelligent Visual Computing

Where to go from here? - Ethics

- COMPSCI 508 - Ethical Considerations in Computing

The End

Thank You!

(Don't forget to complete your SRTI)