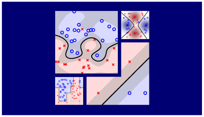
Machine Learning Techniques
(機器學習技法)



Lecture 16: Finale

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Roadmap

1. Embedding Numerous Features: Kernel Models
2. Combining Predictive Features: Aggregation Models
3. Distilling Implicit Features: Extraction Models

Lecture 15: Matrix Factorization

linear models of movies on **extracted user features** (or **vice versa**) jointly optimized with **stochastic gradient descent**

Lecture 16: Finale

- Feature Exploitation Techniques
- Error Optimization Techniques
- Overfitting Elimination Techniques
- Machine Learning in Practice

Exploiting Numerous Features via Kernel

numerous features within some $\mathbf{\Phi}$:
embedded in kernel $K_{\mathbf{\Phi}}$ with inner product operation

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Polynomial Kernel

'scaled' polynomial transforms

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Gaussian Kernel

infinite-dimensional transforms

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Stump Kernel

decision-stumps as transforms

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transform union

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Polynomial Kernel	Gaussian Kernel	Stump Kernel
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Sum of Kernels	Product of Kernels	Mercer Kernels
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possibly **Kernel PCA**, **Kernel k-Means**, ...

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$$\phi_t(\mathbf{x}) = g_t(\mathbf{x})$$

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Decision Stump

simplest perceptron;
simplest DecTree

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branching (divide) +
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prototype (center) +
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Uniform	Non-Uniform	Conditional

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possibly **Infinite Ensemble Learning**, **Decision Tree SVM**, . . .

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hidden features within some $\mathbf{\Phi}$:

as hidden variables to be 'jointly' optimized with usual weights

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Neural Network; Deep Learning	RBF Network
neuron weights	RBF centers

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possibly **GradientBoosted Neurons**, **NNet on Factorized Features**, ...

Exploiting Low-Dim. Features via Compression

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compressed from original features

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projection from abstract to concrete

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projection from abstract to concrete

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possibly **other 'dimension reduction' models**

Fun Time

Consider running AdaBoost-Stump on a PCA-preprocessed data set. Then, in terms of the original features $\mathbf{x}$, what does the final hypothesis $G(\mathbf{x})$ look like?

1. a neural network with $\tanh(\cdot)$ in the hidden neurons
2. a neural network with $\text{sign}(\cdot)$ in the hidden neurons
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Reference Answer: 2

PCA results in a linear transformation of $\mathbf{x}$. Then, when applying a decision stump on the transformed data, it is *as if* a perceptron is applied on the original data. So the resulting G is simply a linear aggregation of perceptrons.

Numerical Optimization via Gradient Descent

when ∇E 'approximately' defined, use it for **1st order approximation**:

$$\text{new variables} = \text{old variables} - \eta \nabla E$$

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SGD/Minibatch/GD

(Kernel) LogReg;

Neural Network [backprop];

Matrix Factorization;

Linear SVM (maybe)

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Functional GD

AdaBoost;

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possibly **2nd order techniques**, **GD under constraints**, . . .

Indirect Optimization via Equivalent Solution

when difficult to solve original problem,
seek for **equivalent solution**

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equivalence via
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Kernel RidgeReg

equivalence via
representer

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Dual SVM	Kernel LogReg Kernel RidgeReg	PCA
equivalence via convex QP	equivalence via representer	equivalence to eigenproblem

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some **other boosting models** and **modern solvers of kernel models** rely on such a technique heavily

Complicated Optimization via Multiple Steps

when difficult to solve original problem,
seek for **'easier' sub-problems**

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Multi-Stage

probabilistic SVM;

linear blending;

stacking;

RBF Network;

DeepNet pre-training

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Alternating Optim.

k-Means;

alternating LeastSqr;

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Multi-Stage	Alternating Optim.	Divide & Conquer
probabilistic SVM;	k-Means;	decision tree;
linear blending;	alternating LeastSqr;	
stacking;	(steepest descent)	
RBF Network;		
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Alternating Optim.

k-Means;

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(steepest descent)

Divide & Conquer

decision tree;

useful for **complicated models**

Fun Time

When running the DeepNet algorithm introduced in Lecture 213 on a PCA-preprocessed data set, which optimization technique is used?

1. variants of gradient-descent
2. locating equivalent solutions
3. multi-stage optimization
4. all of the above

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Reference Answer: 4

minibatch GD for training; equivalent eigenproblem solution for PCA; multi-stage for pre-training

Overfitting Elimination via Regularization

when model too 'powerful':

add brakes somewhere

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when model too 'powerful':

add brakes somewhere

large-margin

SVM;

AdaBoost (indirectly)

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L2

SVR;

kernel models;

NNet [weight-decay]

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SVR;

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NNet [weight-decay]

voting/averaging

uniform blending;

Bagging;

Random Forest

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early stopping

NNet (any GD-like)

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weight-elimination

NNet

constraining

autoenc. [weights];

RBF [# centers];

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arguably **most important techniques**

Overfitting Elimination via Validation

when model too 'powerful':

check performance carefully and honestly

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OOB

Random Forest

Overfitting Elimination via Validation

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 # SV

SVM/SVR

OOB

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Overfitting Elimination via Validation

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# SV	OOB	Internal Validation
SVM/SVR	Random Forest	blending; DecTree pruning

Overfitting Elimination via Validation

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 # SV

SVM/SVR

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Internal Validation

blending;

DecTree pruning

simple but **necessary**

Fun Time

What is the major technique for eliminating overfitting in Random Forest?

1. voting/averaging
2. pruning
3. early stopping
4. weight-elimination

Fun Time

What is the major technique for eliminating overfitting in Random Forest?

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Reference Answer: 1

Random Forest, based on uniform blending, relies on voting/averaging for regularization.

NTU KDDCup 2010 World Champion Model

Feature engineering and classifier ensemble for KDD Cup 2010,
Yu et al., KDDCup 2010

linear blending of

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Random Forest +
human-designed features

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yes, you've learned everything! :-)

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A linear ensemble of individual and blended models for music rating prediction, Chen et al., KDDCup 2011

NNet, DecTree-like, and then linear blending of

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yes, you can 'easily' understand everything! :-)

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A two-stage ensemble of diverse models for advertisement ranking in KDD Cup 2012, Wu et al., KDDCup 2012

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- Logistic Regression variants

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- Matrix Factorization variants
- . . .

'key' is to **blend properly without overfitting**

NTU KDDCup 2013 Track 1 World Champion Model

Combination of feature engineering and ranking models for paper-author identification in KDD Cup 2013, Li et al., KDDCup 2013

linear blending of

NTU KDDCup 2013 Track 1 World Champion Model

Combination of feature engineering and ranking models for paper-author identification in KDD Cup 2013, Li et al., KDDCup 2013

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'another key' is to **construct features with domain knowledge**

ICDM 2006 Top 10 Data Mining Algorithms

1. C4.5: another **decision tree**

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2. *k*-Means

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personal view of five missing ML competitors:
LinReg, LogReg,
Random Forest, GBDT, NNet

Machine Learning Jungle

bagging decision tree support vector machine **neural network** *kernel*
AdaBoost aggregation *sparsity* autoencoder **functional gradient**
dual uniform blending deep learning nearest neighbor decision stump
kernel LogReg large-margin *prototype* quadratic programming **SVR**
GBDT **PCA** `random forest` *matrix factorization* **Gaussian kernel**
soft-margin *k-means* OOB error **RBF network** probabilistic SVM

welcome to the **jungle**!

Fun Time

Which of the following is the official lucky number of this class?

1. 9876
2. 1234
3. 1126
4. 6211

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Reference Answer: 3

May the luckiness always be with you!

Summary

1. Embedding Numerous Features: Kernel Models
2. Combining Predictive Features: Aggregation Models
3. Distilling Implicit Features: Extraction Models

Lecture 16: Finale

- Feature Exploitation Techniques
  kernel, aggregation, extraction, low-dimensional
- Error Optimization Techniques
  gradient, equivalence, stages
- Overfitting Elimination Techniques
  (lots of) regularization, validation
- Machine Learning in Practice
  welcome to the jungle

- **next: happy learning!**