Learning for Web Rankings

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Machine Learning for Web Rankings

- **What are Web Rankings ?**
- What is Machine Learning ?
- Classical Learning Algorithms
- Learning Approaches to Web Rankings

Web Rankings

Rankings are everywhere

- Google, Bing **search** results
  text query $\rightarrow$ url ranking
- Yelp, Yellowpages listings
  business category, location $\rightarrow$ business ranking
- Yahoo! related news articles
  current article, user history $\rightarrow$ article ranking
- Netflix, Amazon **recommendations**
  purchasing history, submitted reviews $\rightarrow$ item ranking

Web Rankings

Primary Goal:

Given the **query** (text query, user profile, location, purchase history, etc.), the ranker orders the **corpus items**, such that the ordering shows the **most relevant first.**

(Optional) Secondary Goals: diversity, advertising revenue...

Web Rankings

How?

- a **scoring** function f assigns a real value to each **(query, item) pair**,
- given a query, the items are scored and sorted by **decreasing scores**.

Example

- query: fast food
- corpus:

  Wallgreen

  McDonald's

  Century 21

  Chipotle Mexican

  Home Depot

Web Rankings

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- given a query, the items are scored and sorted by **decreasing scores**.

Example

- query: fast food
- scoring:

Wallgreen	f(fast food, Wallgreen)	=	0.2
McDonald's	f(fast food, McDonald's)	=	4.1
Century 21	f(fast food, Century 21)	=	0.1
Chipotle Mexican	f(fast food, Chipotle Mexican)	=	2.1
Home Depot	f(fast food, Home Depot)	=	-0.1

Web Rankings

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- a **scoring** function f assigns a real value to each **(query, item) pair**,
- given a query, the items are scored and sorted by **decreasing scores**.

Example

- query: fast food
- sorting:

McDonald's	(4.2)
Chipotle Mexican	(2.1)
Wallgreen	(0.2)
Century 21	(0.1)
Home Depot	(-0.1)

More formally...

- Each (query, item) pair is represented by a vector of features

$$\Phi(\text{query, item}) \in \mathbb{R}^n.$$

- The scoring function

$$f : \mathbb{R}^n \to \mathbb{R}$$

Features

- Each (query, item) pair is represented by $\Phi(\mathrm{query}, \mathrm{item}) \in \mathbb{R}^n$.
- Examples of features from web search

  # of common words between the query and the webpage text
  # of common words between the query and the webpage title
  # of common words between the query and the webpage url
  webpage length
  webpage readability
  likelihood to be spam
  webpage popularity (page rank), etc...
- Feature engineering is a big effort in this industry

Scoring Function

- f is the main factor in the quality of the ranking
  (other factors: corpus size & accuracy, feature quality, result presentation...)
- 1960s–90s, hand design f optimizing quality on a small query set.
- 2000s–now, **automatic selection** relying on **massive datasets**:
  - editors evaluate massive (query, document) sets for quality,
  - implicit feedback from users (click or non-click on results),
  - traffic statistics from toolbars (e.g. Yahoo, Google, Bing toolbars).

Scoring Function

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- 1960s–90s, hand design f optimizing quality on a small query set.
- 2000s–now, **learning from data**:
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Scoring Function Learning

Examples of **data sources** for web-search

- explicit supervision

  editors grades the relevance of document *d* for query *q*,
  editors manually re-order the results for a query,
  users reports a link as spam, inappropriate...
- implicit feedback from users

  click on a low ranked results (positive feedback)
  no click on a highly ranked result (negative)
  click on a link and come back soon to result page (negative)
  reformulating the query (negative)...
- other sources

  toolbar traces, query misspellings...

Scoring Function Learning

Goal of the learning process

- on a new query, relevant documents should appear above the others.
- this is assessed by evaluating a **quality metric** on a set of **labeled test queries**

Quality Metrics

A quality metric induces preferences over output configurations

e.g. which one is the best ranking?

	-	2–relevant	-	-	5–relevant	-
or	1–relevant	-	-	-	-	6–relevant
or	-	-	3–relevant	4–relevant	-	-

Quality metrics for web-search

- Precision at 10
- Discounted Cumulative Gain at 10
- etc...

Quality Metrics

Precision at 10

For each test query, documents are labeled as {relevant, non-relevant}

$$P@10 = \frac{\text{number of relevant doc. in top 10}}{10}$$

Quality Metrics

Discounted Cumulative Gain at 10

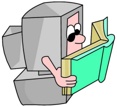
For any test query, doc. labels $\in \{0 \text{ (non-relevant)}, \dots, 5 \text{ (very relevant)}\}$

$$DCG@10 = \sum_{i=1}^{10} p_i \; l(d_i)$$

where
- $p_i \searrow$ when $i \nearrow$ (more weight to top positions)
- $l(d) \nearrow$ with relevance of d (more to weight to rel. docs)

Web Rankings: Conclusions

- web rankings are ubiquitous
- ranking function quality is core
- lots of data to drive ranking function selection
- **select the ranking function from these training data**



This is a machine learning problem!
BTW What is Machine Learning ?

Machine Learning for Web Rankings

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Introduction to Machine Learning

- We are concerned with **predictive modeling**.
- given a **labeled training set** of n (input, output) examples

$$(x_1, y_1), \ldots, (x_n, y_n)$$

- we want to **predict** the output for any **new** example x,

$$x \to y?$$

Examples of learning problems

Examples of learning problems

	input (x)	output (y)
regression	mon.–sat. temperature	sun. temperature
	house features	selling price
classification	digital image	human face or not
	email features	spam or non-spam
ranking	query and documents	document ranking
	user's watching history	movie ranking

Learning Process

Learning Algorithm

- it takes the training set $(x_1, y_1), \ldots, (x_n, y_n)$
- it selects f in a family of functions F

After Learning

- f is used for prediction, i.e. given a new x, we predict $f(x)$

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What objective drives the selection of f ?

Generalization Performance

Learning Objective:

- Generalization Performance We want f to perform well on the unlabeled examples we receive after learning, the **test examples**.
- Training Performance This is different from performing well on the points for which the algorithm was given the label, **the training examples**.

How to reach high generalization performance ?

Occam's Razor (14th-century logician)

The simplest explanation is most likely the correct one.

Learning Theory

- when selecting f in F, prefer simple functions to complex ones

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Learning Theory

- when selecting f in F, prefer simple functions to complex ones
- the complexity of f is called its capacity.

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Occam's Razor (14th-century logician)

The simplest explanation is most likely the correct one.

Learning Theory

- when selecting f in F, prefer simple functions to complex ones
- the complexity of f is called its capacity.
- the learning process achieves a trade-off between
  - f is simple, i.e. low capacity.
  - f explains the training data well, i.e. low training error.

How to reach high generalization performance ?

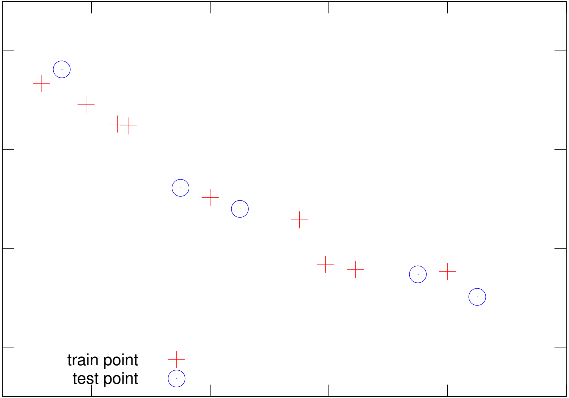
Example of the trade-off low capacity, low training error.

- function family: polynomials
- capacity: measured by the polynomial degree,

  e.g. $$\begin{aligned} \text{degree}(2x+1) &= 1 \\ \text{degree}(3x^3+5x^2+x) &= 3 \end{aligned}$$
- error: $(f(x)-y)^2$

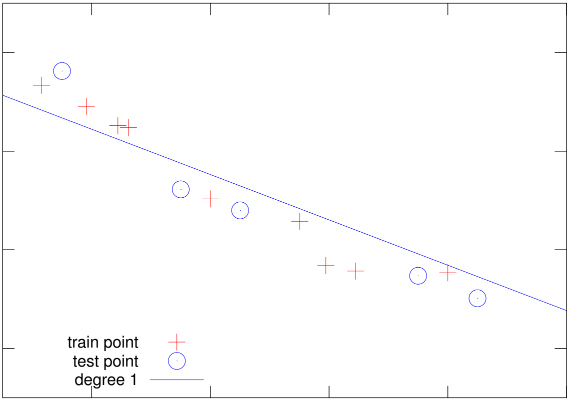
How to reach high generalization performance ?

Data



How to reach high generalization performance ?

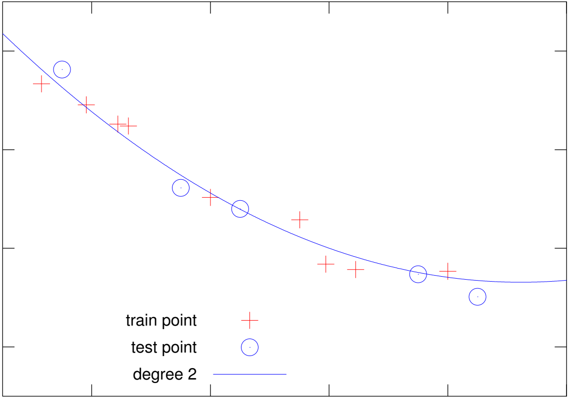
Degree 1 Polynomial



training error: 39.1 – test error: 36.4

How to reach high generalization performance ?

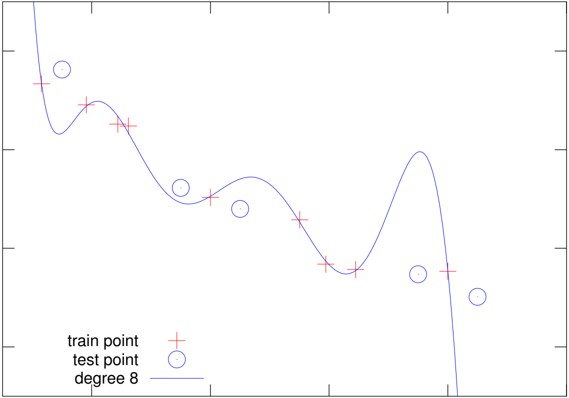
Degree 2 Polynomial



training error: 5.2 – test error: 6.1

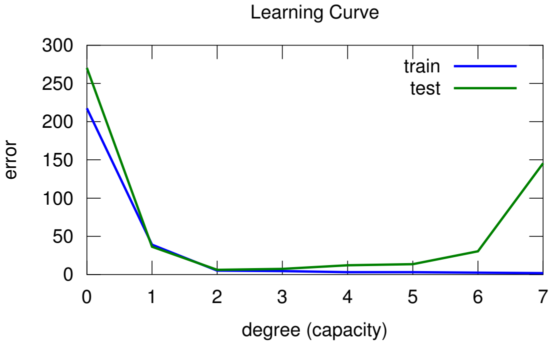
How to reach high generalization performance ?

Degree 8 Polynomial



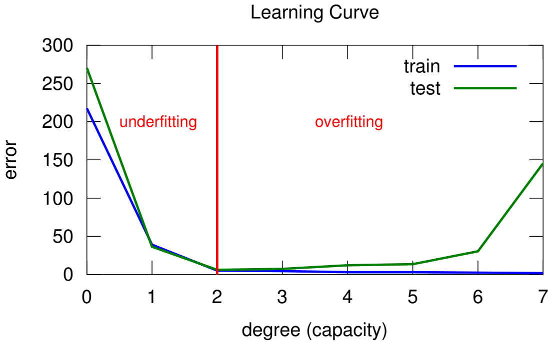
training error: 0.5 – test error: 2,735.9

How to reach high generalization performance ?



	train err.	test err.	capacity
under-fitting	high	high	too low
over-fitting	low	high	too high

How to reach high generalization performance ?



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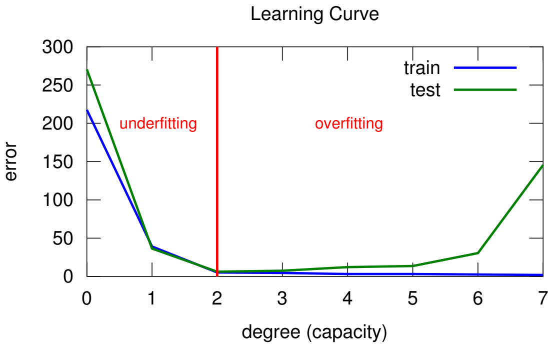

Validation

- How to set capacity?
- exclude data from the train set, the validation data (simulate test).
- vary capacity, estimate test err using validation data.
- select model which performs best on the validation set.

What is Machine Learning?

- Learning: selecting a predictor $f \in F$ from training data
- Goal: low test error
- How: training data error/capacity tradeoff

What is a Learning Algorithm?

Given

- family of function F
  e.g. linear functions $f_w(x) = w \cdot x = \sum_i w_i x_i$
- measure of capacity, also referred as regularizer
  e.g. weight L1 norm $\mathrm{Reg}(f_w) = \|w\|_1 = \sum_i |w_i|$
- measure of error
  e.g. squared error $(f_w(x) - y)^2$

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Then learning is cast as an optimization problem

- $f^\star = \mathrm{argmin}_f \ \mathrm{Error}(f, \mathrm{train}) + \lambda \ \mathrm{Reg}(f)$
  where λ sets the trade-off between train error and capacity
  e.g. $w^\star = \mathrm{argmin}_w \ \sum_{(x,y) \in \mathrm{train}} (f_w(x) - y)^2 + \lambda \|w\|_1$

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- validation is used to select λ.

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- specific optimizer often proposed for scalability

Machine Learning for Web Rankings

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- **Classical Learning Algorithms**
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Classical Learning Algorithms

- **Linear learning algorithms**
  - regression algorithms (LASSO, Ridge reg.)
  - classification algorithms (logistic reg., linear SVM, adaboost)
- Non-linear learning algorithms
  - neural networks
  - decision trees
  - gradient boosted trees

Linear Learning Algorithms

F is the set of linear functions,

$$f_w(x) = w \cdot x \text{ where } x \in \mathbb{R}^d, w \in \mathbb{R}^d$$

- x is a feature vector of dimension D describing an example.
- w is a weight vector defining the function f_w.
- $f_w(x)$ is the prediction of f_w for example x.

Linear Learning Algorithms

F is the set of linear functions,

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Regularization is (mostly) either

- L2 regularization, $|w|_2^2 = \sum_i w_i^2$
  $\rightarrow$ prefer "flat" weights (all weights are the same).
  $\rightarrow$ the output is not too dependent on a single component of x
- L1 regularization, $|w|_1 = \sum_i |w_i|$
  $\rightarrow$ prefer "sparse" weights (i.e. most weights are zero)
  $\rightarrow$ only few components in x explains the outputs

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Linear Learning for Regression

Task: predict a real value.
e.g. a temperature, a stock price, an aircraft speed...

The most common error measure is the Mean Squared Error (MSE)

$$\mathrm{MSE}(f_w, \mathrm{set}) = \frac{1}{|\mathrm{set}|} \sum_{(x,y) \in \mathrm{set}} (f_w(x) - y)^2$$

Popular linear regression techniques

Ridge regression	MSE with L2 regularization $w^\star = \mathrm{argmin}_w \; \mathrm{MSE}(f_w, \mathrm{set}) + \lambda \|w\|_2^2$
LASSO	MSE with L1 regularization $w^\star = \mathrm{argmin}_w \; \mathrm{MSE}(f_w, \mathrm{set}) + \lambda \|w\|_1$

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Linear Learning for Classification

Task: discriminate between two classes, $\left|\begin{array}{l}\text{positive class, } y = +1 \\ \text{negative class, } y = -1.\end{array}\right.$

e.g. is a face present in the image? spam or non-spam e-mail? etc.

Linear Learning for Classification

Task: discriminate between two classes, | positive class, $y = +1$ | negative class, $y = -1$.

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Prediction

$$f_w(x) = w \cdot x \quad \begin{array}{llr} > 0 & \text{predicts} & +1\text{, positive class} \\ < 0 & & \text{-1, negative class} \end{array}$$

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Classification error: counts the number of errors, i.e. when $y \; f_w(x) < 0$

$$\mathrm{Err}(f_w, \mathrm{set}) = \frac{1}{|\mathrm{set}|} \sum_{(x,y) \in \mathrm{set}} I\{y \; f_w(x) < 0\}$$

where $I\{c\} = 1$ if c is true, 0 otherwise.

Linear Learning for Classification

Classification error: counts the number of errors, i.e. when $y \ f_w(x) < 0$

$$E = \mathrm{Err}(f_w, \mathrm{set}) = \frac{1}{|\mathrm{set}|} \sum_{(x,y) \in \mathrm{set}} I\{y \ f_w(x) < 0\}$$

Optimization problem: for learning, we solve

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- optimizers like differentiable, convex functions
- Err is not!

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$\rightarrow$ replace Err with a differentiable, convex upper bound.

Linear Learning for Classification

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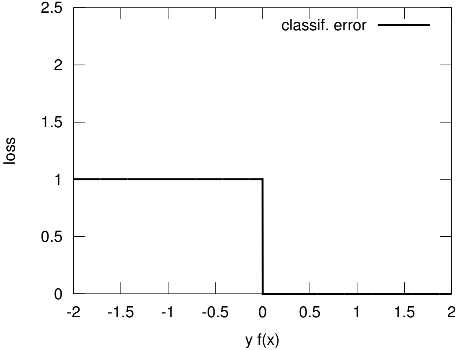
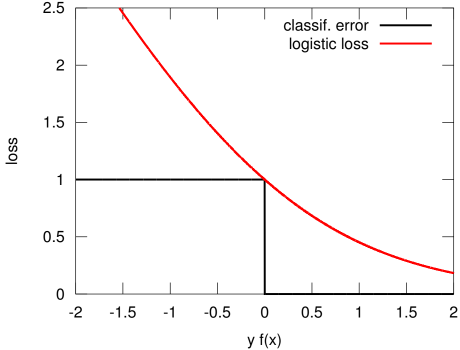


$I\{y \ f_w(x) < 0\}$ classification error

Linear Learning for Classification

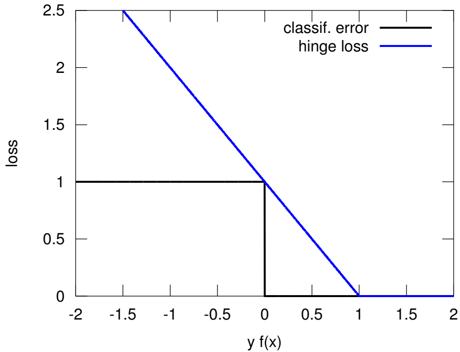
$\rightarrow$ replace Err with a differentiable, convex upper bound.



$$\log(1 + \exp(-y \ f_w(x))) \qquad \text{logistic loss}$$

Linear Learning for Classification

→ replace Err with a differentiable, convex upper bound.



$\max(0, 1 - y\ f_w(x))$ hinge loss

Linear Learning for Classification

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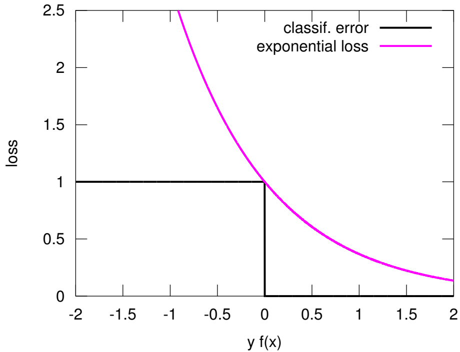

$\exp(-y\ f_w(x))$ exponential loss

Linear Learning for Classification

Common algorithms

	loss	regularizer
Logistic Regression	logistic loss	L1 or L2
(Linear) Support Vector Machines (SVM)	hinge loss	L2
Adaboost	exponential loss	kind of L1

Classical Learning Algorithms

- Linear learning algorithms
  - regression algorithms (LASSO, Ridge reg.)
  - classification algorithms (logistic reg., linear SVM, adaboost)
- **Non-linear learning algorithms**
  - neural networks
  - decision trees
  - gradient boosted trees

Non-linear Algorithms

Why?

- some complex input/output relation requires a non-linear model

But...

- difficult, costly optimization problem for learning

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Non-linear Algorithms: Neural Networks

Artificial Neural Networks

- inspired by biological neural networks (e.g. your brain).
- compose several layers
- each layer performs a linear operation or a non-linear activation.

Non-linear Algorithms: Neural Networks

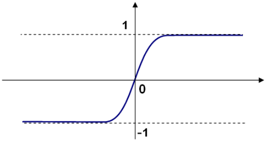
3 layer neural networks

$$f_{A,B}(x) = B \ \mathrm{sigmoid}(A \ x)$$

linear:	$z_1 = A \ x$, where $x \in \mathbb{R}^d, A \in \mathbb{R}^{d \times h}$	(input layer)
activation:	$z_2 = \mathrm{sigmoid}(z_1)$	(hidden layer)
linear:	$z_3 = B \ z_2$, where $B \in \mathbb{R}^h$	(output layer)

Note:

- h is referred as the number of hidden units.
- Sigmoid applies $t \to \frac{1-\exp(-t)}{1+\exp(t)}$ to each component of the vector.



Non-linear Algorithms: Neural Networks

3 layer neural networks are Universal Approximators

- any function can be approximated by a neural network
- for any function g and $\epsilon > 0$, there exists a neural network f, s.t.

$$\forall x, |f(x) - g(x)| < \epsilon$$

Non-linear Algorithms: Neural Networks

Learning Algorithm

- Learning parameters through gradient descent optimization
  - find A, B which minimize $\mathrm{Loss}(f_{A,B}, \mathrm{train}) + \lambda \mathrm{Regularizer}$
  - works with any differentiable loss.
- NNs can be applied to classification (logistic loss) or regression (MSE)
- regularization by controlling
  - h, the number of hidden units
  - L2 regularization on A, B...

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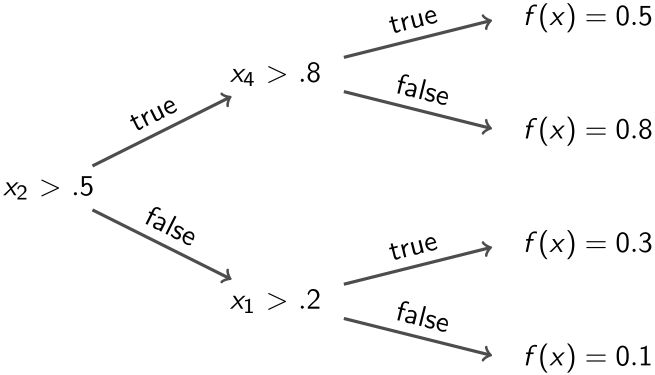
Decision Trees



- examples travel the tree from the root to the leaf
- each node performs a test on the input x
- each leaf corresponds to a prediction

Decision Trees

Advantages

- low computation cost for prediction
- easy to interpret

Disadvantages

- regression tree only models piecewise constant function
- learning deep trees req. a lot of training examples
- greedy learning yields a sub-optimal test sequence

Decision Trees: Greedy Learning for Regression

Greedy Learning Algorithm

1. starts with a tree containing only the root
2. splitting: for each node with depth $< \mathrm{max\_depth}$,
    - find best test & create two leaves from the node
    - find best prediction for these two leaves
3. repeat 2 until no more nodes with depth $< \mathrm{max\_depth}$.

Greedy Learning Algorithm

$$f(x) = 0.5$$

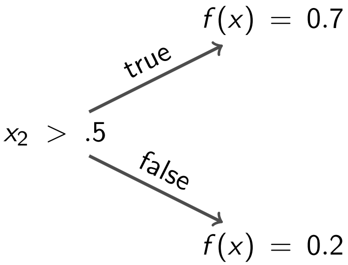
Greedy Learning Algorithm

$$f(x) = 0.5$$

Best split: $x_2 > .5$,

Best predictions: $\left| \begin{array}{lll} f(x) = 0.7 & \text{if} & x_2 > .5 \\ f(x) = 0.2 & \text{if} & x_2 \leq .5 \end{array} \right.$

Greedy Learning Algorithm



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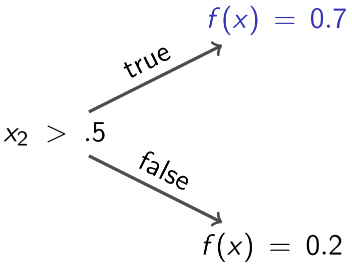
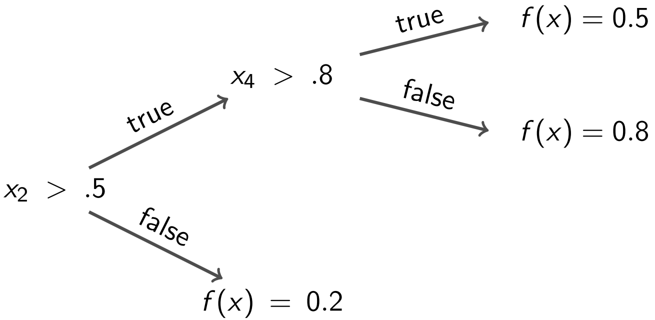


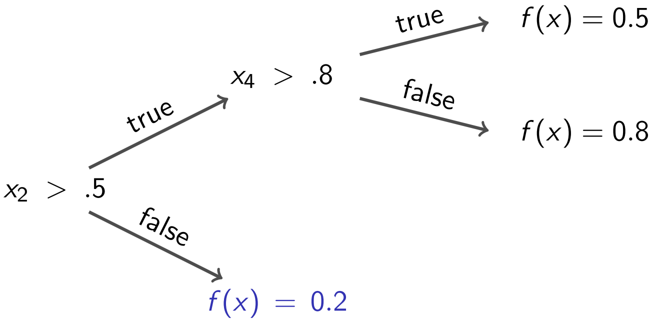
Best split: $x_4 > .8$,

Best predictions: $\left| \begin{array}{lll} f(x) = 0.5 & \text{if} & x_4 > .8 \\ f(x) = 0.8 & \text{if} & x_4 \leq .8 \end{array} \right.$

Greedy Learning Algorithm



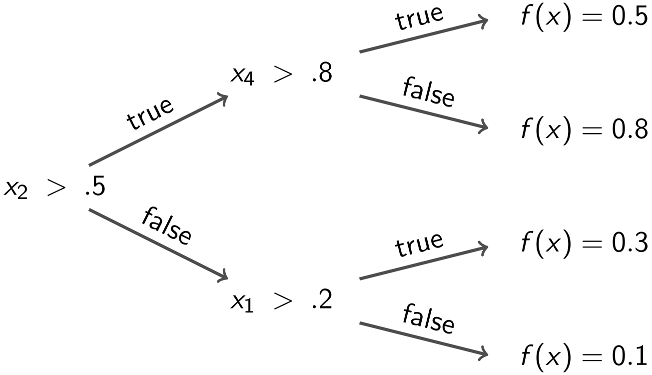
Greedy Learning Algorithm



Best split: $x_1 > .2$,

Best predictions: $\left| \begin{array}{lll} f(x) = 0.3 & \text{if} & x_1 > .2 \\ f(x) = 0.1 & \text{if} & x_2 \leq .2 \end{array} \right.$

Greedy Learning Algorithm



Learning Decision Trees

- Decision trees can be applied for classification & regression.
- Regularization by controlling
    - depth
    - number of training examples to estimate a split

Decision Trees: Greedy Learning for Regression

Greedy Learning Algorithm

1. starts with a tree containing only the root
2. splitting: for each node with depth $< \mathrm{max\_depth}$,
   - find best test & create two leaves from the node
   - find best prediction for these two leaves
3. repeat 2 until no more nodes with depth $< \mathrm{max\_depth}$.

Decision Trees: Greedy Learning for Regression

Splitting Node N (Step 2)

- Given S_N all training examples reaching N,
- we find

i, t	defining the test $x_i < t$
a, b	the prediction when $x_i < t$ is true or false

  to minimize MSE

$$\sum_{(x,y)\in S_N : x_i \leq t} (a - y)^2 + \sum_{(x,y)\in S_N : x_i > t} (b - y)^2$$

- efficient algorithm, complexity $D \times \|S_N\|$

Classical Learning Algorithms

- Linear learning algorithms
  - regression algorithms (LASSO, Ridge reg.)
  - classification algorithms (logistic reg., linear SVM, adaboost)
- Non-linear learning algorithms
  - neural networks
  - decision trees
  - **gradient boosted decision trees**

Gradient Boosted Decision Trees

A GBDT is a mixture of decision trees

$$f(x) = \sum_{t=1}^{T} h_t(x) \text{ where } \forall t, \quad h_t \text{ is a tree.}$$

Advantages

- model more complex functions than a single tree.
- learning many shallow trees req. less training data than one deep tree.

Regularization

- like trees, depth and minimum number of training examples in a leaf
- T, number of trees

Gradient Boosted Decision Trees

Iterative Learning called Gradient Boosting

- Goal: find f to minimize

$$\mathrm{Loss}(f, \mathrm{train}) = \sum_{(x,y) \in \mathrm{train}} \mathrm{Loss}(f(x), y)$$

- add a new tree at each step:

Gradient Boosted Decision Trees

Iterative Learning called Gradient Boosting

For $t = 1, \ldots T$

- current model: $f_t = \sum_{i=1}^{t-1} h_t$

Gradient Boosted Decision Trees

Iterative Learning called Gradient Boosting

For $t = 1, \ldots T$

- current model: $f_t = \sum_{i=1}^{t-1} h_t$
- for each training example (x, y),
  - predict $\hat{y} = f_t(x)$ and derive $g_x = \frac{\partial \mathrm{Loss}}{\partial \hat{y}}(\hat{y}, y)$

Gradient Boosted Decision Trees

Iterative Learning called Gradient Boosting

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- current model: $f_t = \sum_{i=1}^{t-1} h_t$
- for each training example (x, y),
  - predict $\hat{y} = f_t(x)$ and derive $g_x = \frac{\partial \mathrm{Loss}}{\partial \hat{y}}(\hat{y}, y)$
- learn next tree h_t

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  - the gradient indicates how to decrease the loss

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  - i.e. $f_t(x) - \alpha g_x$ yields a lower loss (for small $\alpha > 0$)

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    - we want a tree s.t. $h_t(x) \simeq -\alpha g_x$

Gradient Boosted Decision Trees

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- learn next tree h_t
  - the gradient indicates how to decrease the loss
  - i.e. $f_t(x) - \alpha g_x$ yields a lower loss (for small $\alpha > 0$)
  - we want a tree s.t. $h_t(x) \simeq -\alpha g_x$
  - decision tree for regression to minimize $\sum_{(x,y)\in \mathrm{train}} (h_t(x) - (-\alpha g_x))^2$

Classical Learning Algorithms

- Linear learning algorithms
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  - classification algorithms (logistic reg., linear SVM, adaboost)
- Non-linear learning algorithms
  - neural networks
  - decision trees
  - gradient boosted decision trees

Machine Learning for Web Rankings

- What are Web Rankings ?
- What is Machine Learning ?
- Classical Learning Algorithms
- **Learning Approaches to Web Rankings**

Learning Approaches to Web Rankings

Learning the scoring function: $q, d \rightarrow f(\phi(q, d))$

- various family of functions
  e.g. linear, neural networks, trees...
- but the core effort has been about loss functions.

Loss Functions for Web Rankings

A loss function

- measures performance on the training data
- should be optimizable during learning:
  - $\rightarrow$ continuous, differentiable, possibly convex in the model parameters.
- common quality metrics like $P@10$ or $DCG@10$ are not
  - $\rightarrow$ depends only on score ordering
    depends only on whether $f(q, d') < f(q, d)$ for all pairs d, d'
    $P@10$, $DCG@10$ are piecewise constant functions

Loss Functions for Web Rankings

3 types of approaches

- regression
- pairwise
- listwise

Loss Functions for Web Rankings: Regression

Training data: query, document pairs labeled with a relevance level.

e.g.

query (q)	document (d)	relevance (r)
listen to music	pandora radio	+5
listen to music	san francisco giants	0
car repairs	car talk	+3
car repairs	jiffy lube oil change	+2

...

Regression Learning: predict relevance levels.

$$f = \operatorname{argmin} \sum_{(q,d,r) \in \text{train}} (f(q,d) - r)^2 + \lambda \text{Reg}(f)$$

Loss Functions for Web Rankings: Regression

Drawback

- does not reflect ranking quality closely.
  e.g. 3 documents (a,b,c) with relevance $+2, +1, 0$

	score(a)	score(b)	score(c)	ranking	
case 1	4	3	0	(a,b,c)	MSE $= 2.66$
case 2	0	1	2	(c,b,a)	MSE $= 1.66$

- only relative scores matter for ranking

Loss Functions for Web Rankings: Pairwise Loss

Only relative scores matter for ranking

- given two items d, d' labeled r, r' for query q, we want

$$f(q,d) \quad > \quad f(q,d') \quad \text{if and only if} \qquad r \quad > \quad r'$$

Loss Functions for Web Rankings: Pairwise Loss

Only relative scores matter for ranking

- given two items d, d' labeled r, r' for query q, we want

$$
\begin{aligned}
f(q,d) &> f(q,d') \quad \text{if and only if} \quad & r &> r' \\
f(q,d) - f(q,d') &> 0 & r - r' &> 0
\end{aligned}
$$

Loss Functions for Web Rankings: Pairwise Loss

Only relative scores matter for ranking

- given two items d, d' labeled r, r' for query q, we want

$$
\begin{array}{rclcrcl}
f(q,d) & > & f(q,d') & \text{if and only if} & r & > & r' \\
f(q,d) - f(q,d') & > & 0 & & r - r' & > & 0 \\
f(q,d) - f(q,d') & > & 0 & & y_{r,r'} & > & 0
\end{array}
$$

where $y_{r,r'} = \mathrm{sign}\{r - r'\}$.

Loss Functions for Web Rankings: Pairwise Loss

Only relative scores matter for ranking

- given two items d, d' labeled r, r' for query q, we want

$$\begin{array}{rclcrcl} f(q,d) & > & f(q,d') & \text{if and only if} & r & > & r' \\ f(q,d) - f(q,d') & > & 0 & & r - r' & > & 0 \\ f(q,d) - f(q,d') & > & 0 & & y_{r,r'} & > & 0 \end{array}$$

where $y_{r,r'} = \mathrm{sign}\{r - r'\}$.

Pairwise Loss leverages binary classification

- In classification, we want $f(x) > 0$ if and only if $y > 0$

Loss Functions for Web Rankings: Pairwise Loss

- In binary classification,

$$\mathrm{Loss}(f(x), y)$$

where Loss is
- logistic loss (logistic regression)
- hinge loss (SVM)
- exponential loss (Adaboost)

- For ranking, pairwise loss works with pair of examples (d, d')

$$\mathrm{Loss}(f(q,d) - f(q,d'), y_{r,r'})$$

where Loss is
- logistic loss (RankNet)
- hinge loss (Ranking SVM)
- exponential loss (RankBoost)

Loss Functions for Web Rankings: Pairwise Loss

Example with Hinge Loss (SVM):

- binary classification, we minimize

$$\sum_{(\mathbf{x},\mathbf{y})\in \text{train}} \max(0, 1 - \mathbf{y}\ \mathbf{f}(\mathbf{x})) + \lambda \mathrm{Reg}(f)$$

- pairwise rankings, we minimize

$$\sum_{(\mathbf{q},\mathbf{d},\mathbf{d}',\mathbf{y}_{\mathbf{r},\mathbf{r}'})\in \text{train}} \max(0, 1 - \mathbf{y}_{\mathbf{r},\mathbf{r}'}(\mathbf{f}(\mathbf{q},\mathbf{d}) - \mathbf{f}(\mathbf{q},\mathbf{d}'))) + \lambda \mathrm{Reg}(f)$$

Loss Functions for Web Rankings: Pairwise Loss

Drawback

- all pairs are considered equals.
- does not emphasize the top of the ranking.

Loss Functions for Web Rankings: Listwise Loss

Ideal Loss for Ranking

- Given the vector y^q with the labels of all documents for query q,
  the vector z^q with the scores of all documents for query q,
- $L(z^q, y^q)$ should be such that
  - it is continuous, differentiable
  - its gradient indicates the direction which improves the metric of interest, like $P@10$ or $DCG@10$.
- that is not easy!

Loss Functions for Web Rankings: Listwise Loss

$L(z^q, y^q)$ should be such that

- it is continuous, differentiable
- its gradient indicates the direction which improves the metric of interest, like $P@10$ or $DCG@10$.

Different Approaches

- probabilistic (ListNet, SoftRank),
- gradient-driven (LambdaRank, LambdaMART),
- structured prediction (Structured SVM, Graph Transformer Networks...)

Loss Functions for Web Rankings: Listwise Loss

$L(z^q, y^q)$ should be such that

- it is continuous, differentiable
- its gradient indicates the direction which improves the metric of interest, like P@10 or DCG@10.

Probabilistic Approaches

- define $P(\sigma|z^q)$ probability of an ordering given scores
  $L(z^q, y^q) = \sum_\sigma P(\sigma|z^q)\ \mathrm{DCG@10}(\sigma, y^q)$
- such that $L(z^q, y^q)$ is differentiable and cheap to compute.
- e.g. ListNet, SoftRank

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That's it!
Thank you for your attention.