Online Learning

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Introduction, overview and examples

Structure

- Introduction
- Use cases
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Introduction

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    - At the beginning of each round the algorithm is presented with an input sample, and must perform a prediction
    - The algorithm verifies whether its prediction was correct or incorrect, and feeds this information back into the model, for subsequent rounds

Introduction

Whereas in **batch (or offline) learning** you have access to the whole dataset to train on

D features

N samples

x_1	x_2	x_3	...	x_d	y
x_1	x_2	x_3	...	x_d	y
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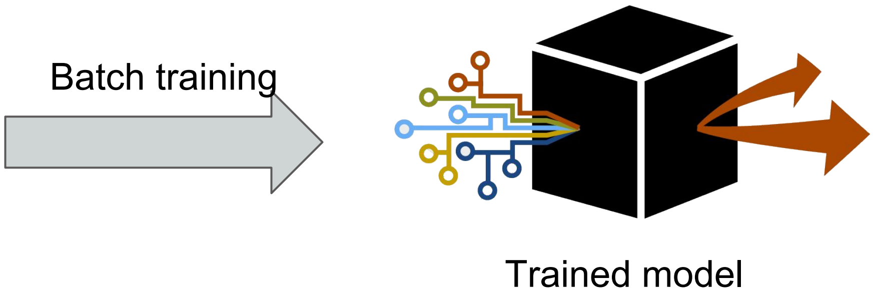
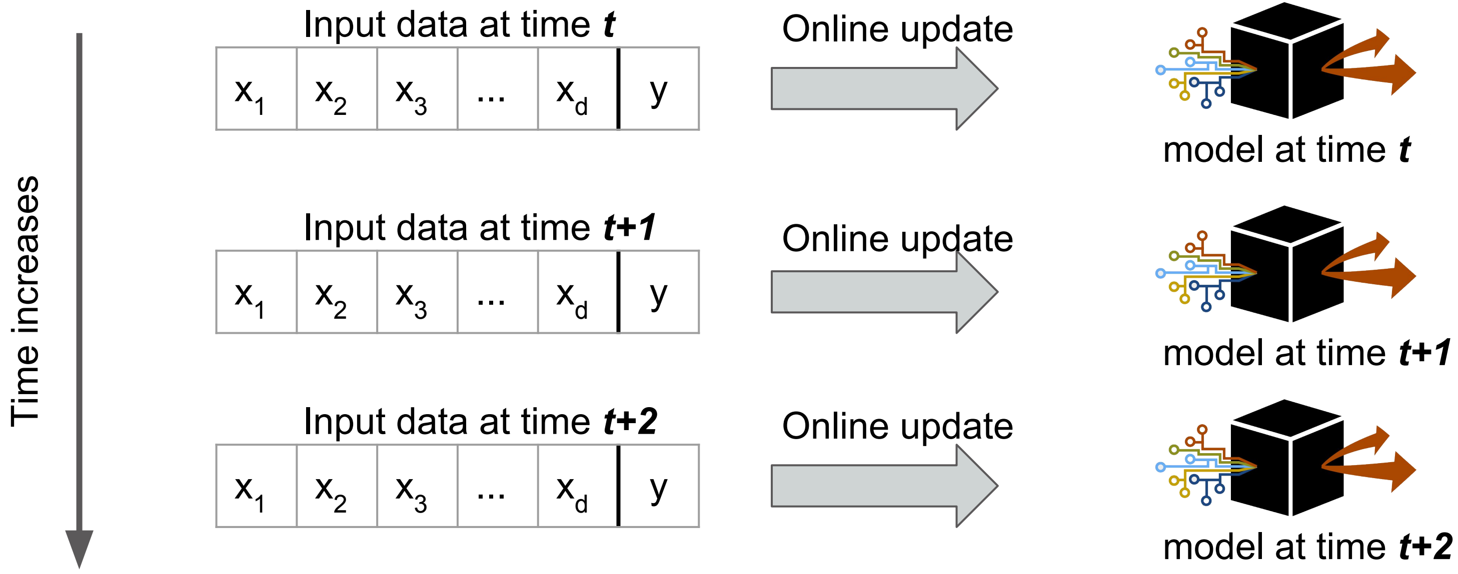


Introduction

In **online learning** your model evolves as you see new data, one example at a time



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  receive question $\mathbf{x}_t \in \mathcal{X}$

  predict $p_t \in D$

  receive true answer $y_t \in \mathcal{Y}$

  suffer loss $l(p_t, y_t)$

Adapted from Shalev-Shwartz 2012

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After computing the loss, the algorithm will use this information to update the model generating the predictions for the next trials

Introduction: Main Concepts

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The **regret** is the difference between the performance of:

- the online algorithm
- an ideal algorithm that has been able to train on the whole data seen so far, in batch fashion

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This is measured by the **regret**.

Use cases

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  - When new data is constantly being generated, and/or is dependent upon time

Use cases

Some cases where data is constantly being generated and you need quick predictions:

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Some cases where data is constantly being generated and you need quick predictions:

- Real-time Recommendation
- Fraud Detection
- Spam detection
- Portfolio Selection
- Online ad placement

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Types of Targets

There are **two** main ways to think about an online learning problem, as far as the target functions (that we are trying to learn) are concerned:

- **Stationary Targets**
  - The target function you are trying to learn does **not** change over time (but may be stochastic)
- **Dynamic Targets**
  - The process that is generating input sample data is assumed to be non-stationary (i.e. may change over time)
  - The process may even be adapting to your model (i.e. in an **adversarial** manner)

Example I: Stationary Targets

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- Ex.: Some process generates, at each time step *t*, inputs of the form (x_1, x_2, x_3) where each attribute is a *bit*, and the label **y** is the result of $(x_1 \vee (x_2 \wedge x_3))$:

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	x_1	x_2	x_3	**y**
Input at time ***t***	1	0	1	1
Input at time ***t+1***	0	1	1	1
Input at time ***t+2***	0	0	0	0
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From the point of view of the online learning algorithm, obviously!

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Spam filtering

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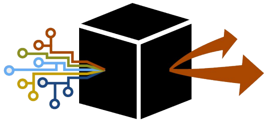

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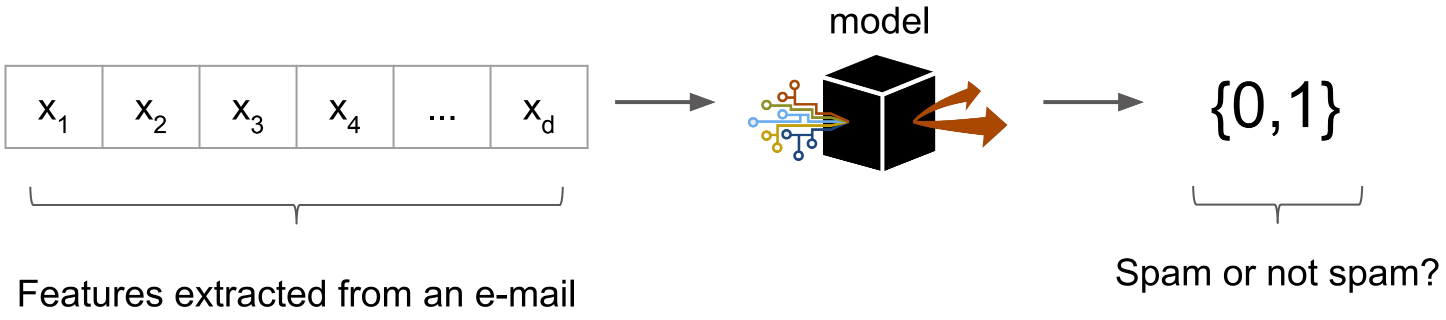

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Spam filtering

- So suppose you have learned that the presence of the word `“Dollars”` implies that an e-mail is likely spam.

- Spammers have noticed that their scammy e-mails are falling prey to spam filters so they change tactics:
  - So instead of using the word `“Dollars”` they start using the word `“Euro”`, which fools your filter but also accomplishes their goal (have people read the e-mail)

Approaches

A couple of approaches have been proposed in the literature:

- Online Learning from Expert Advice

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- Online Learning from Expert Advice
- Online Learning from Examples
- General algorithms that may also be used in the online setting

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In this approach, it is assumed that the algorithm has multiple *oracles* (or experts at its disposal), which its can use to produce its output, in each trial.

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The simplest algorithm in this realm is the **Randomized Weighted Majority Algorithm**

Approaches: Expert Advice

Randomized Weighted Majority Algorithm

- Every expert has a *weight* (starting at 1)

- For every trial:
  - Randomly select an expert (larger weight => more likely)
  - Use that expert's output as your prediction
  - Verify the correct answer
  - For each expert:
    - If it was mistaken, decrease its weight by a constant factor

Approaches: Learning from Examples

Learning from examples is different from using Expert Advice inasmuch as we don’t need to previously define prebuild experts we will derive our predictions from.

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We need, however, to know what **Concept Class** we want to search over.

Approaches: Learning from Examples

A **Concept Class** is a set of of functions (concepts) that subscribe to a particular model.

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Some examples of concept classes are:

- The set of all monotone disjunctions of N variables
- The set of non-monotone disjunctions of N variables
- Decision lists with N variables
- Linear threshold formulas
- DNF (disjunctive normal form) formulas

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In other words, it learns any concept (function), provided the concept belongs to the **Concept Class** of monotone disjunctions.

It also uses weights, as in the previous example.

Approaches: Learning from Examples

Winnow algorithm

- Initialize all weights (w_1, w_2,... w_n) to 1
- Given a new example:
  - Predict 1 if $w^T x > n$
  - Predict 0 otherwise
- Check the true answer
- For each input attribute:
  - If algorithm predicted 1 but true answer was 0, double the value of every weight corresponding to an attribute = 1
  - If algorithm predicted 0 but true answer was 1, halve the value of each weight corresponding to an attribute = 0

Approaches: Learning from Examples

Winnow algorithm

We aimed too low, let's try to make our guess higher

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We aimed too high, let's try to make our guess lower

Approaches: Other Approaches

More general algorithms can also be used in an online setting, such as:

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- Stochastic Gradient Descent

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- Stochastic Gradient Descent
- Perceptron Learning Algorithm

Current Trends / Related Areas

Adversarial Machine Learning

- Refers to scenarios where your input-generating process is an adaptive adversary
- Applications in:
  - Information Security
  - Games

Current Trends / Related Areas

One-shot Learning

- Refers to scenarios where your must perform predictions after seeing just a few, or even a single input sample
- Applications in:
  - Computer Vision

Links

- http://ttic.uchicago.edu/~shai/papers/ShalevThesis07.pdf
- Blum 1998 Survey Paper
- UofW CSE599S Online Learning
- Machine Learning From Streaming data
- Twitter Fighting Spam with BotMaker
- CS229 - Online Learning Lecture
- Building a real time Recommendation Engine with Data Science
- Online Optimization for Large Scale Machine Learning by prof A. Banerjee
- Learning, Regret, Minimization and Equilibria

Links

- https://github.com/JohnLangford/vowpal_wabbit
- Shai Shalev-Shwartz 2011 Survey Paper
- Hoi et al 2014 - LIBOL
- MIT 6.883 Online Methods in Machine Learning