3 Idiots' Approach for Display Advertising Challenge

YuChin Juan, Yong Zhuang, and Wei-Sheng Chin

NTU CSIE MLGroup

What This Competition Challenges Us?

Predict the click probabilities of impressions.

Dataset

Label	I1	I2	$\cdots$	I13	C1	C2	$\cdots$	C26
1	3	20	$\cdots$	2741	68fd1e64	80e26c9b	$\cdots$	4cf72387
0	7	91	$\cdots$	1157	3516f6e6	cfc86806	$\cdots$	796a1a2e
0	12	73	$\cdots$	1844	05db9164	38a947a1	$\cdots$	5d93f8ab
					$\vdots$			
?	9	62	$\cdots$	1457	68fd1e64	cfc86806	$\cdots$	cf59444f

#Train: $\approx$ 45M
#Test: $\approx$ 6M
#Features after one-hot encoding: $\approx$ 33M

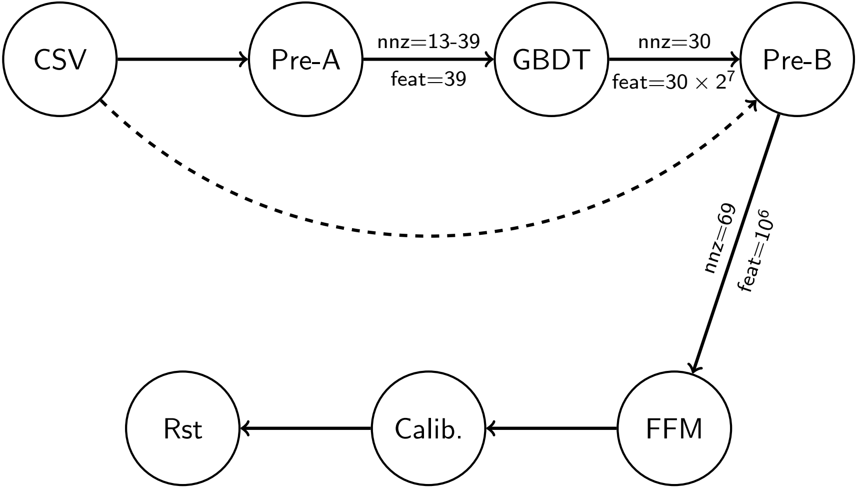
Evaluation

$$\text{logloss} = -\frac{1}{L}\sum_{i=1}^{L} y_i \log \bar{y}_i + (1-y_i)\log(1-\bar{y}_i),$$

where L is the number of instances, y_i is the true label (0 or 1), and $\bar{y}_i$ is the predicted probability.

This slide introduces our approach to achieve 0.44488 and 0.44479 on the public and private leaderboards, respectively.

Flowchart



"nnz" means the number of non-zero elements of each impression; "feat" represents the size of feature space.

Preprocessing-A

Purpose: generate features for GBDT.

- All numerical data are included. (13 features)
- Categorical features (after one-hot encoding) appear more than 4 million times are also included. (26 features)

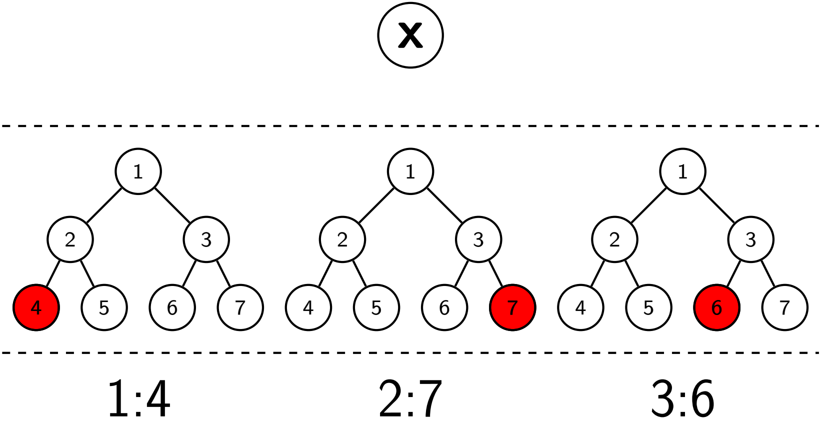
Gradient Boosting Decision Tree (GBDT)

Purpose: generate GBDT features.

- We use trees in GBDT to generate features.
- 30 trees with depth 7 are used.
- 30 features are generated for each impression.
- This approach is proposed by Xinran He et al. at Facebook.
- The imlementation of GBDT is base on Algorithm 5 in the following slides:
  `http://statweb.stanford.edu/~jhf/ftp/trebst.pdf`

Gradient Boosting Decision Tree (GBDT)

Example: Assuming that we have already trained GBDT with 3 trees with depth 2. We feed an impression **x** *into these trees. The first tree thinks* **x** *belong to node 4, the second node 7, and the third node 6. Then we generate the feature "1:4 2:7 3:6" for this impression.*



Preprocessing-B

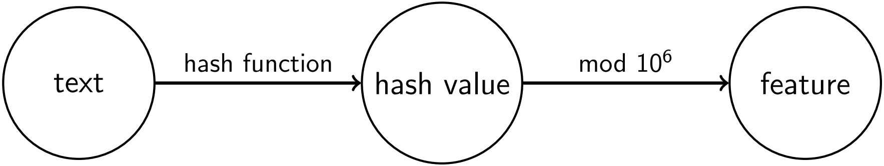
Purpose: generate features for FFM.

- Numerical features (I1-I13) greater than 2 are transformed by

$$v \leftarrow \lfloor \log(v)^2 \rfloor.$$

- Categorical features (C1-C26) appear less than 10 times are transformed into a sepcial value.
- GBDT features are directly included.
- These three groups of features are hashed into 1M-dimension by hashing trick.
- Each impression has 13 (numerical) + 26 (categorical) + 30 (GBDT) = 69 features.

Hashing Trick



I1:3	739920192382357839297	839297
C1-68fd1e64	839193251324345167129	167129
GBDT1:173	923490878437598392813	392813

Field-aware Factorization Machine (FFM)

For the details of FFM, please check the following slides:

`http://www.csie.ntu.edu.tw/~r01922136/slides/ffm.pdf`

Calibration

Purpose: calibrate the final result.

- The average CTRs on the public / private leaderboards are 0.2632 and 0.2627, respectively.
- The average CTR of our submission is 0.2663.
- There is a gap. So we minus every prediction by 0.003, and the logloss is reduced by around 0.0001.

Running Time

Environment: A workstation with two 6-core CPUs

All processes are parallelized.

Process	Time (min.)	Memory (GB)
Pre-A	8	0
GBDT	29	15
Pre-B	38	0
FFM	100	16
Calibration	1	0
Total	176	

Comparison Among Different Methods

Method	Public	Private
LR-Poly2	0.44984	0.44954
FFM	0.44613	0.44598
FFM + GBDT	0.44497	0.44483
FFM + GBDT (v2)	0.44474	0.44462
FFM + GBDT + calib.	0.44488	0.44479
FFM + GBDT + calib. (v2)	0.44461	0.44449

v2: 50 trees and 8 latent factors