3 Idiots' Approach for Display Advertising Challenge

Yu-Chin 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

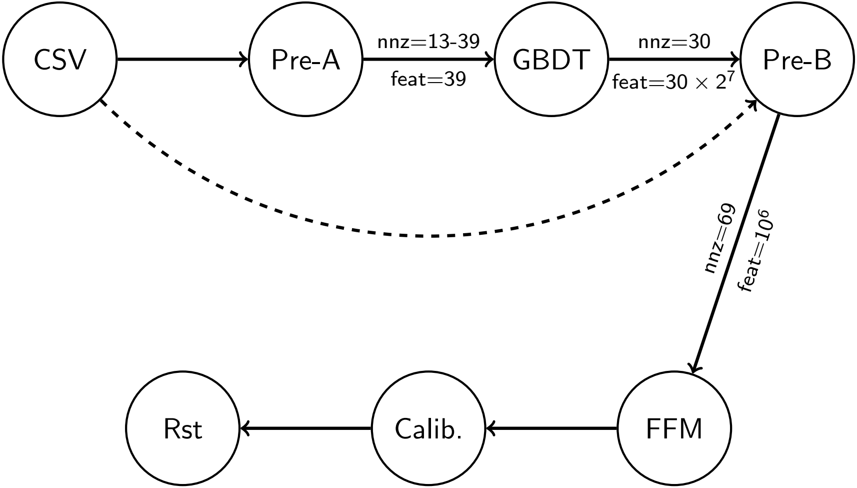
Evaluation

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

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)

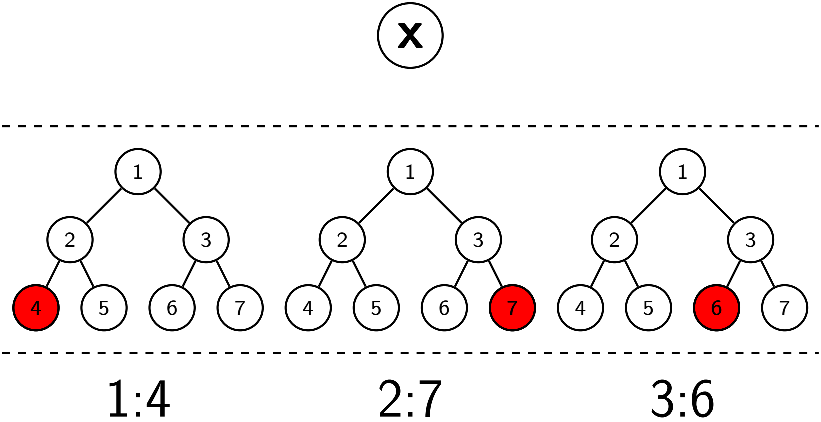
Gradient Boosting Decision Tree (GBDT)

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.

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 FM.

- 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

$$\text{text} \xrightarrow{\text{hash function}} \text{hash value} \xrightarrow{\text{mod } 10^6} \text{feature}$$

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

Concept of Field

The concept of field is important for the FM model.

Each impression has 69 features, and each feature corresponds to a particular field, which corresponds to a particular source. For example, field 1 comes from I1, 14 from C1, and 40 from the first tree of GBDT.

feature	361	$\cdots$	571	557	$\cdots$	131	172	$\cdots$	398
source	I1	$\cdots$	I13	C1	$\cdots$	C26	GBDT1	$\cdots$	GBDT30
field	1	$\cdots$	13	14	$\cdots$	39	40	$\cdots$	69

Logistic Regression (LR)

Before introducing FM, let us review the basic logistic regression first.

$$\min_{\mathbf{w}} \quad \frac{\lambda}{2}\|\mathbf{w}\|_2^2 + \sum_i \log(1 + e^{-y_i \phi(\mathbf{w}, \mathbf{x}_i)})$$

- For linear model,
$$\phi(\mathbf{w}, \mathbf{x}) = \mathbf{w}^T \mathbf{x}$$
- For degree 2 polynomial model (Poly2),
$$\phi(\mathbf{w}, \mathbf{x}) = \sum_{j_1, j_2 \in C} \mathbf{w}_{\text{hash}(j_1, j_2)} \mathbf{x}_{j_1} \mathbf{x}_{j_2},$$

  where C is all combinations of selecting two non-zero features out of $\mathbf{x}$.

Factorization Machine (FM)

Our major model.

- For FM,
$$\phi(\mathbf{w}, \mathbf{x}) = \sum_{j_1, j_2 \in C} \langle \mathbf{w}_{j_1, f_2}, \mathbf{w}_{j_2, f_1} \rangle \mathbf{x}_{j_1} \mathbf{x}_{j_2},$$
where f_1 and f_2 are the corresponding fields of j_1 and j_2, respectively.
- The number of latent factors (i.e., the length of the vectors $\mathbf{w}_{j_1, f_2}$ and $\mathbf{w}_{j_2, f_1}$) is 4.
- This approach was proposed by Michael Jahrer et al. in KDD Cup 2012 Track 2.

Factorization Machine (FM)

Example: an impression $\mathbf{x}$ *has four features: 376 (field 1), 248 (field 2), 571 (field 3), and 942 (field 4). The corresponding* $\phi(\mathbf{w}, \mathbf{x})$ *is:*

$$
\begin{aligned}
\langle \mathbf{w}_{376,2}, \mathbf{w}_{248,1} \rangle \mathbf{x}_{376} \mathbf{x}_{248} + \langle \mathbf{w}_{376,3}, \mathbf{w}_{571,1} \rangle \mathbf{x}_{376} \mathbf{x}_{571} + \langle \mathbf{w}_{376,4}, \mathbf{w}_{942,1} \rangle \mathbf{x}_{376} \mathbf{x}_{942} \\
+ \langle \mathbf{w}_{248,3}, \mathbf{w}_{571,2} \rangle \mathbf{x}_{248} \mathbf{x}_{571} + \langle \mathbf{w}_{248,4}, \mathbf{w}_{942,2} \rangle \mathbf{x}_{248} \mathbf{x}_{942} \\
+ \langle \mathbf{w}_{571,4}, \mathbf{w}_{942,3} \rangle \mathbf{x}_{571} \mathbf{x}_{942}
\end{aligned}
$$

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
FM	100	16
Calibration	1	0
Total	176	

Comparison Among Different Methods

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

v2: 50 trees and 8 latent factors