Ensemble Learning

7주차 담당:14기 박상준



1. Boosting Models Cathoost

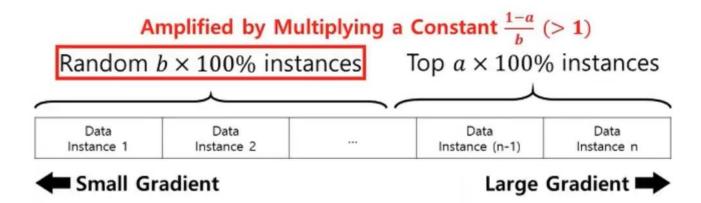
2. Coding Session



Gradient based One-Side Sampling (GOSS)



Gradient based One-Side Sampling (GOSS)

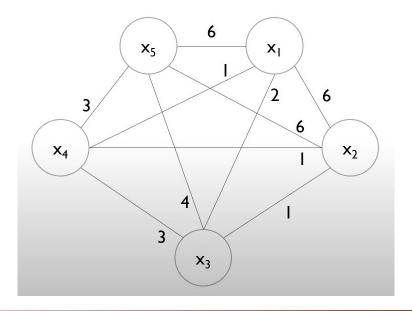




	Χı	x ₂	X ₃	X ₄	X ₅
I_1	I	I	0	0	I
l ₂	0	0	ı	I	ı
I ₃	I	2	0	0	2
I ₄	0	0	2	3	I
I ₅	2	I	0	0	3
I ₆	3	3	0	0	I
I ₇	0	0	3	0	2
I ₈	ı	2	3	4	3
l ₉	ı	0	1	0	0
I ₁₀	2	3	0	0	2

	x _I	x_2	X ₃	x ₄	X ₅
x_1	-	6	2	I	6
x_2	6	-	I	I	6
X ₃	2	I	-	3	4
X ₄	ı	I	3	-	3
X ₅	6	6	4	3	_

	X ₅	ΧI	X ₂	X ₃	X ₄
d	19	15	14	10	8





	ΧI	x ₂	X ₃	X ₄	X ₅
I_1	- 1	1	0	0	- 1
l ₂	0	0	1	1	- 1
l ₃	- 1	2	0	0	2
I ₄	0	0	2	3	ı
l ₅	2	ı	0	0	3
l ₆	3	3	0	0	- 1
l ₇	0	0	3	0	2
l ₈	- 1	2	3	4	3
l ₉	- 1	0	- 1	0	0
I ₁₀	2	3	0	0	2

	× ₅	x_1	X ₄	x_2	X ₃
-1_1	1	- 1	0	- 1	0
I ₂	1	0	1	0	1
l ₃	2	- 1	0	2	0
I ₄	ı	0	3	0	2
I ₅	3	2	0	1	0
16	1	3	0	3	0
I ₇	2	0	0	0	3
I ₈	3	- 1	4	2	3
l ₉	0	- 1	0	0	1
110	2	2	0	3	0



		9		1.	
	X ₅	ΧĮ	X ₄	× ₂	×3
I_1	1	I.	0	1	0
I ₂	1	0	1	0	-1
I ₃	2	1	0	2	0
I ₄	1	0	3	0	2
I ₅	3	2	0	1	0
16	1	3	0	3	0
I ₇	2	0	0	0	3
I ₈	3	1	4	2	3
l ₉	0	1	0	0	- 1
I ₁₀	2	2	0	3	0

	X ₅	X ₁₄	X ₂₃
$I_{1} =$	-1	1	-1
l ₂	-1	4	4
l ₃	2	1	2
l ₄	- 1	6	5
l ₅	3	2	1
l ₆	1	3	3
I ₇	2	0	6
l ₈	3	1	2
19	0	1	4
I ₁₀	2	2	3



Coding Session

- ▶ boosting_type(gbdt, rf, dart, goss): 기본 설정은 gbdt(GBM), goss 로 바꾸면 GOSS 적용 가능
- top_rate(default = 0.2): retain ratio of large gradient data
- low_rate(default = 0.1): retain ratio of small gradient data
- enable_bundle(default = True): EFB 실행 여부

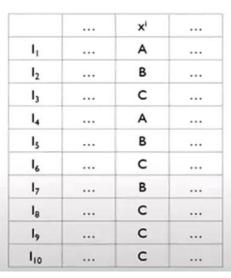


Target Leakage

→ Ordered TS(Target Statistics)

Prediction Shift







		xi(A)	xi(B)	x'(C)	
I _t		1	0	0	
l ₂		0	L	0	
13		0	0	1	
14		1	0	0	
I ₅		0	- 1	0	
16		0	0	1	
17		0	1	0	
I ₈		0	0	1	
وا	***	0	0	1	
110		0	0	1	



Index		X1		Υ
L1	***	Α		1
L2		В		1
L3	***	С	***	1
L4		Α		0
L5		В		1
L6		С		1
L7		В	***	0
L8		С		1
L9		С		0



Index	 X1(TS)		Υ
L1	 0.5		1
L2	 0.67	***	1
L3	 0.75		1
L4	 0.5		0
L5	 0.67		1
L6	 0.75		1
L7	0.67		0
L8	0.75		1
L9	0.75		0



Cathoost

- ✓ Another popular method: to group categories by target statistics (TS)
 - Greedy TS with smoothing

$$\hat{x}_k^i = \frac{\sum_{j=1}^n \mathbb{1}_{\{x_j^i = x_k^i\}} \cdot y_j + ap}{\sum_{j=1}^n \mathbb{1}_{\{x_j^i = x_k^i\}} + a}$$

- a > 0 is a parameter
- A common setting for p is the average target value in the dataset
- Used to remove the negative effect of low-frequency noisy categories



$$\hat{x}_k^i = \frac{\sum_{j=1}^n \mathbb{1}_{\{x_j^i = x_k^i\}} \cdot y_j + ap}{\sum_{j=1}^n \mathbb{1}_{\{x_j^i = x_k^i\}} + a}$$

	Y=1	Y=0	TS
А	10	10	0.5
В	40	10	0.8
С	10	40	0.2
D	25	25	0.5
E	1.	0	1



Index		Х		TS	Υ
L1	•••	Α		0.000	1
L2		В	(***)	1.000	1
L3		С			1
L4	***	Α			0
L5		В			1
L6		С			1
L7		В			0
L8		С			1
L9		С			0
L10		С			1

$$\hat{x}_{k}^{i} = \frac{\sum_{\mathbf{x}_{j} \in \mathcal{D}_{k}} \mathbb{1}_{\{x_{j}^{i} = x_{k}^{i}\}} \cdot y_{j} + ap}{\sum_{\mathbf{x}_{j} \in \mathcal{D}_{k}} \mathbb{1}_{\{x_{j}^{i} = x_{k}^{i}\}} + a}$$
$$= \frac{0 + 0.1 \times 0}{0 + 0.1} = 0$$

$$= \frac{0 + 0.1 \times 1.0}{0 + 0.1} = 1.0$$



Index		Х		TS	Υ
L1	•••	Α		0.000	1
L2		В		1.000	
L3		С		1.000	1
L4	***	Α	•••	1.000	0
L5	•••	В		0.977	1
L6		С			1
L7		В			0
L8		С			1
L9		С			0
L10		С			1

$$=\frac{1 + 0.1 \times 0.75}{1 + 0.1} = 0.977$$



Index	 Х		TS	Υ
L1	 Α		0.000	1
L2	 В	1.000		1
L3	 С	1.000		1
L4	 Α		1.000	0
L5	 В	0.977		1
L6	 С		0.982	1
L7	 В		0.922	0
L8	 С			1
L9	 С			0
L10	 С			1

$$=\frac{2 \ + \ 0.1 \times 0.833}{2 \ + \ 0.1} \ = \ 0.992$$

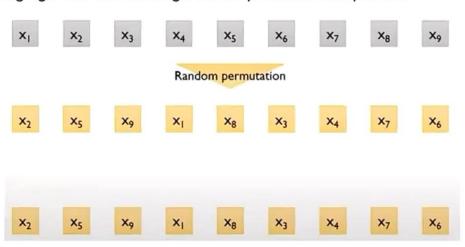


3. Cat Boost의 직관적 이해

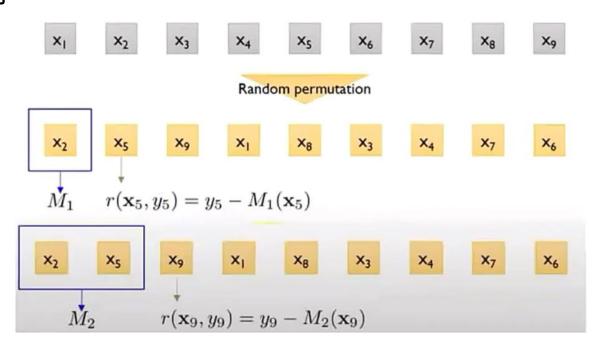
	F1	F2	F3	F4	F5	F6	F7	Y
X1								
X2								
Х3								
X4								
X5								
X6								
X7								
X8								



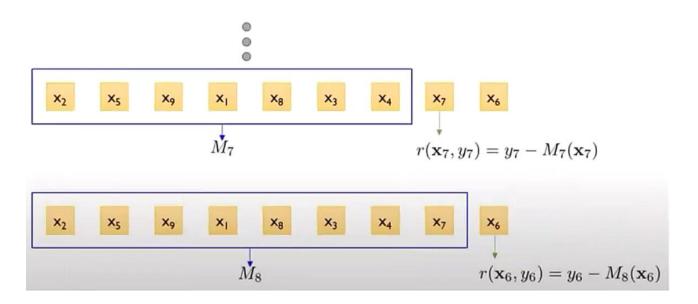
- Ordered Boosting
 - ✓ A boosting algorithm not suffering from the prediction shift problem













Coding Session

- cat_features: 범주형 feature 입력
- boosting_type(ordered, plain): "ordered" 설정 시 ordered boosting
- has_time: 시간에 따라 변화하는 데이터 유무
- sum_models: 범주 특성 별 모델을 각자 생성하고
 후에 결합

