Learning to Expand Audience via Meta Hybrid Experts and Critics for Recommendation and Advertising

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WeChat

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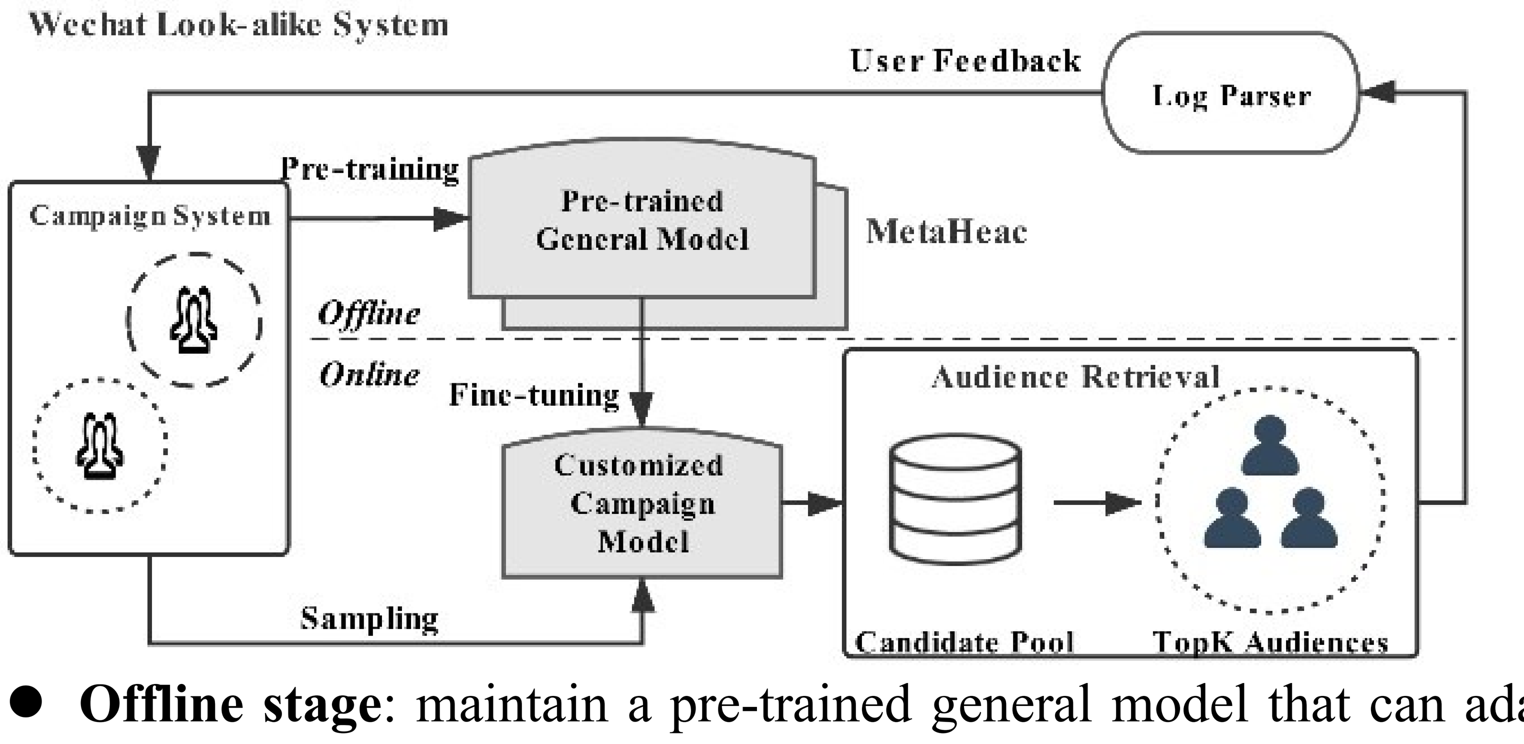
Introduction

Internet companies conduct hundreds of marketing campaigns to promote products, contents, and advertisements every day. The audience expansion technique (look-alike modeling) is the key which has been deployed in many online systems. A good look-alike technique can result in a great economic benefit, but it suffers from two significant challenges.

- The tasks of various campaigns can cover diverse contents.
- A certain campaign gives a seed set that can only cover limited users.

However, existing methods cannot solve the two challenges. We propose a novel two-stage framework named MetaHeac for the audience expansion problem.

WeChat Look-alike System



- **Offline stage**: maintain a pre-trained general model that can adapt fast to new campaigns.
- **Online stage**: find potential audiences for a certain campaign with a customized model.

MetaHeac Framework

Learn to expand audience

To learn a general pre-trained model that knows how to expand audiences, we propose a training procedure to simulate the Look-alike modeling process.

- Understanding phase: $\theta_{[c]} = \theta - \alpha \frac{\partial \mathcal{L}_a}{\partial \theta}$

$$\mathcal{L}_a(\theta) = \sum_{\mathcal{D}^a_{[c]}} [-y \log \hat{p} - (1-y)\log(1-\hat{p})]$$

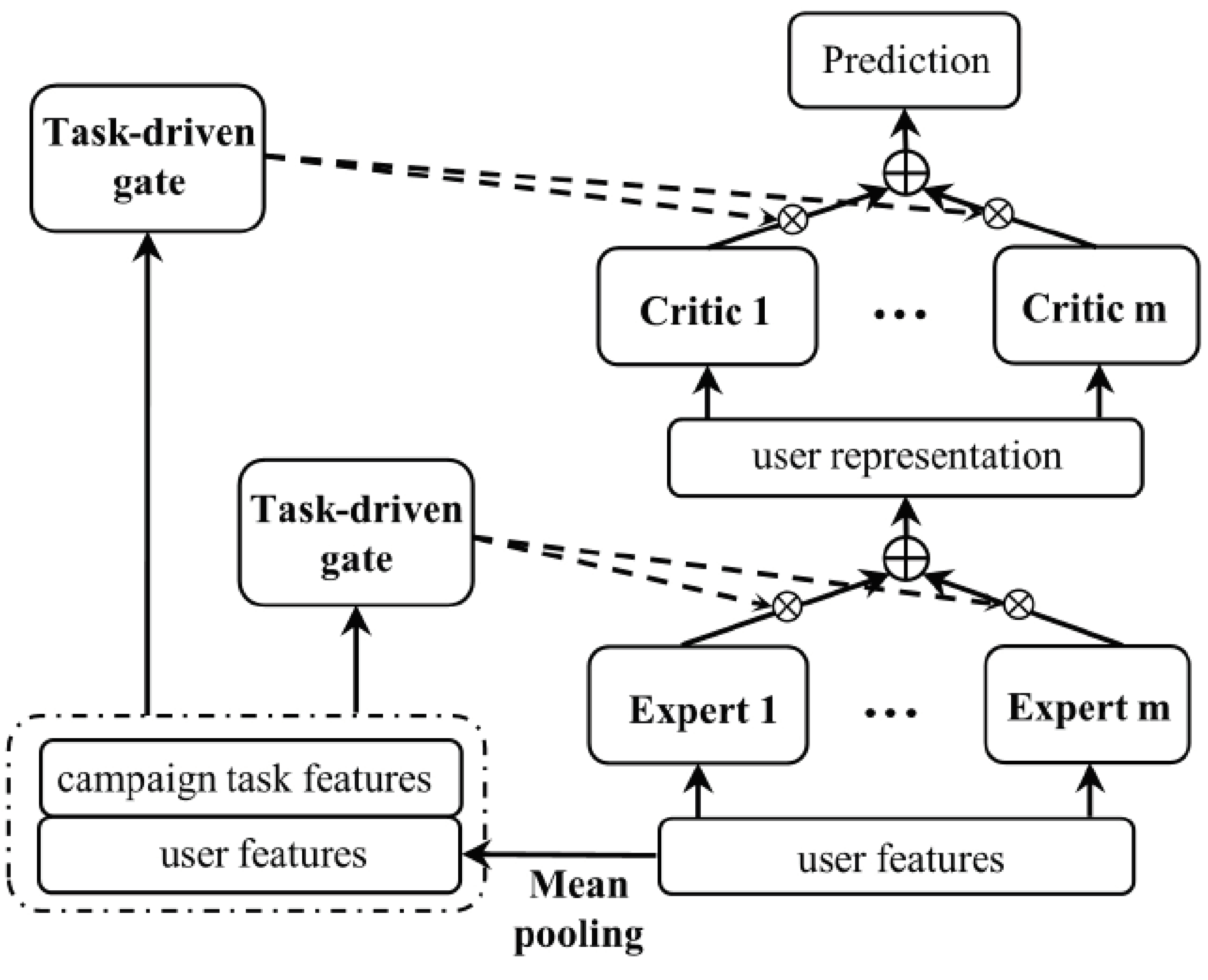
- Finding phase: $\theta = \theta - \beta \frac{\partial \mathcal{L}_b(\theta_{[c]})}{\partial \theta} = \theta - \beta \frac{\partial \mathcal{L}_b(\theta_{[c]})}{\partial \theta_{[c]}} \frac{\partial \theta_{[c]}}{\partial \theta}$

Algorithm 1 Training MetaHeac from a meta-learning perspective.

Input: Given hundreds of marketing campaign dataset $\mathcal{D}_{[c]}$.
Input: The general model f_θ.
Input: The learning rate α, β.

1. randomly initialize θ.
2. **while** not converge **do**:
3. sample batch of training tasks $\{\mathcal{T}_1, ..., \mathcal{T}_n\}$.
4. **for** $\mathcal{T}_i \in \{\mathcal{T}_1, ..., \mathcal{T}_n\}$ do:
5. $\mathcal{T}_i$ contains two disjoint sets $\mathcal{D}^a_{[c]}, \mathcal{D}^b_{[c]}$
6. evaluate loss $\mathcal{L}_a(\theta)$ with $\mathcal{D}^a_{[c]}$
7. compute updated parameter $\theta_{[c]} = \theta - \alpha \frac{\partial \mathcal{L}_a(\theta)}{\partial \theta}$
8. evaluate loss $\mathcal{L}_b(\theta_{[c]})$ with $\mathcal{D}^b_{[c]}$
9. **end**
10. update $\theta = \theta - \beta \sum_{\mathcal{T}_i \in \{\mathcal{T}_1,...,\mathcal{T}_n\}} \frac{\partial \mathcal{L}_b(\theta_{[c]})}{\partial \theta}$
11. **end**

Hybrid Experts and Critics



- Task-driven gate: $w^{expert} = \mathrm{softmax}(g(\mathbf{c}, \mathcal{G}(\mathbf{u})))$
- Hybrid experts: $r = \frac{1}{n}\sum_{i=1}^{n} w_i^{expert} h_i(\mathbf{u})$
- Hybrid critics: $\hat{p} = \frac{1}{m}\sum_{i=1}^{m} w_i^{critic} \sigma(t_i(r))$
- Overall: $f(\mathbf{c}, \mathbf{u}) = \frac{1}{m}\sum_{i=1}^{m} w_i^{critic} \sigma(t_i(\frac{1}{n}\sum_{i=1}^{n} w_i^{expert} h_i(\mathbf{u})))$

Experiments

Offline experiments

Dataset	Method	Pre-trained Emb	Pre-trained Network	$\mathcal{S}_{[c]} \leq T$ AUC	$\mathcal{S}_{[c]} \leq T$ P@5%	$\mathcal{S}_{[c]} \leq T$ R@5%	$\mathcal{S}_{[c]} > T$ AUC	$\mathcal{S}_{[c]} > T$ P@5%	$\mathcal{S}_{[c]} > T$ R@5%
Tencent Look-alike Dataset	LR	-	-	0.5942	0.1015	0.1044	0.6824	0.1910	0.2006
	MLP_one-stage	-	-	0.5928	0.1048	0.1081	0.6910	0.1797	0.1888
	MLP+emb	✓	-	0.6624	0.1881	0.1930	0.7060	0.2118	0.2224
	Pinterest	✓	-	0.6245	0.1635	0.1665	0.6802	0.1687	0.1770
	Hubble	✓	-	0.6797	0.2056	0.2110	0.7085	0.2171	0.2279
	MLP+pre-training	✓	✓	0.7117	0.2325	0.2384	0.7082	0.2136	0.2242
	Shared-Bottom+pre-training	✓	✓	0.6936	0.2198	0.2258	0.7089	0.2144	0.2250
	MMoE+pre-training	✓	✓	0.6977	0.2224	0.2280	0.7088	0.2150	0.2257
	MetaHeac	✓	✓	**0.7239****	**0.2489****	**0.2554****	**0.7142****	**0.2244****	**0.2356****
	Improve			1.7%	7.0%	7.1%	0.8%	4.7%	4.7%
WeChat Look-alike Dataset	LR	-	-	0.5654	0.1351	0.0742	0.6711	0.2166	0.1182
	MLP_one-stage	-	-	0.6663	0.2477	0.1363	0.6970	0.2605	0.1419
	MLP+emb	✓	-	0.7143	0.3058	0.1684	0.7217	0.2988	0.1628
	Pinterest	✓	-	0.6289	0.1947	0.1066	0.7044	0.2639	0.1439
	Hubble	✓	-	0.7391	0.3524	0.1936	0.7243	0.3062	0.1668
	MLP+pre-training	✓	✓	0.7440	0.3473	0.1908	0.7272	0.3030	0.1673
	Shared-Bottom+pre-training	✓	✓	0.7271	0.3093	0.1700	0.7275	0.3052	0.1663
	MMoE+pre-training	✓	✓	0.7368	0.3265	0.1797	0.7292	0.3051	0.1675
	MetaHeac	✓	✓	**0.7607****	**0.3839****	**0.2110****	**0.7323***	**0.3133***	**0.1707***
	Improve			2.3%	8.9%	9.0%	0.4%	2.3%	1.9%

Online A/B testing results

Scenarios	Exposure	Conversion	CVR
video	+3.07%	+10.18%	+7.90%
advertisements	+0.65%	+15.50%	+15.40%
article	+3.18%	+9.23%	+4.64%

Ablation study

Method	$\mathcal{S}_{[c]} \leq T$ AUC	$\mathcal{S}_{[c]} \leq T$ P@5%	$\mathcal{S}_{[c]} > T$ AUC	$\mathcal{S}_{[c]} > T$ P@5%
MetaHeac w/o HC	0.7199	0.2472	0.7115	0.2220
MetaHeac w/o HE	0.7181	0.2419	0.7112	0.2193
MetaHeac w/o Meta	0.7173	0.2431	0.7107	0.2180
MetaHeac	**0.7239**	**0.2489**	**0.7142**	**0.2244**