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

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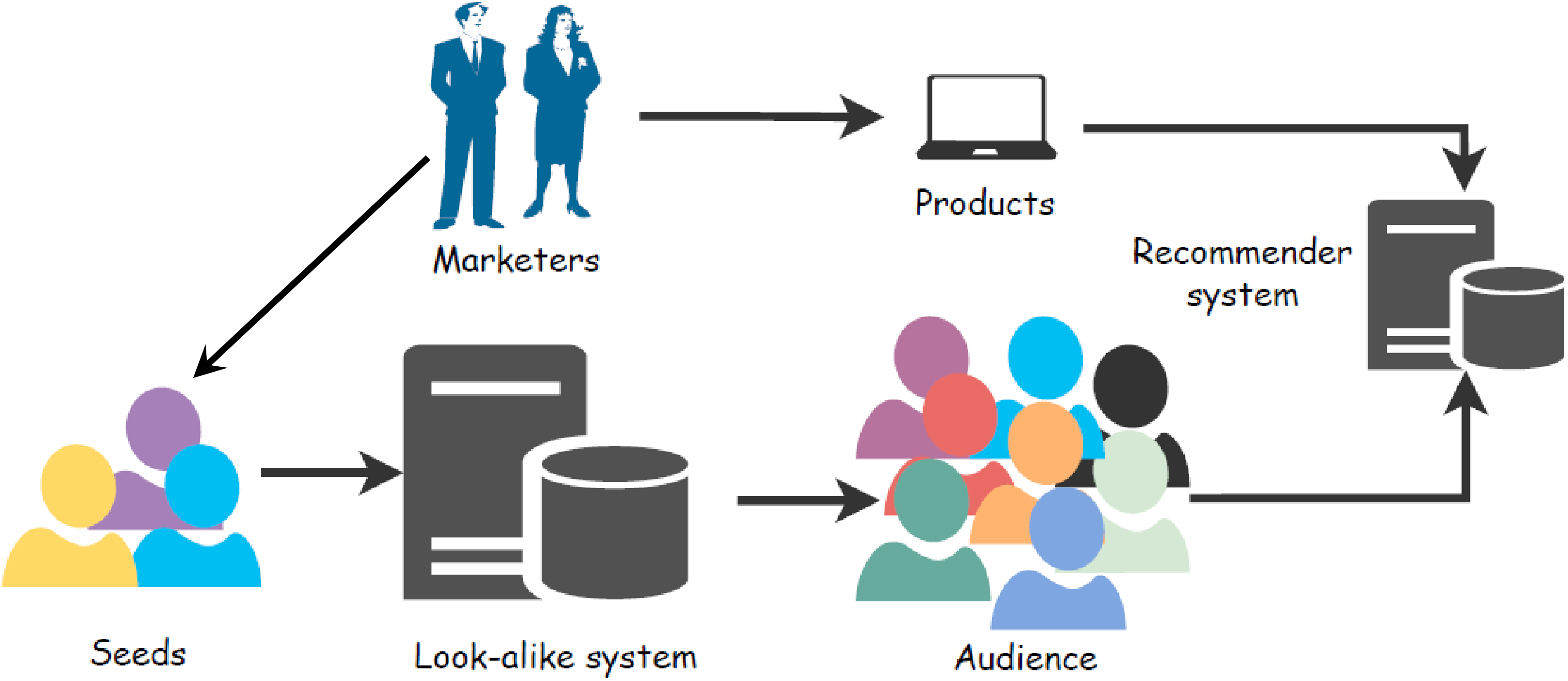
Motivation

Audience expansion (Look-alike modeling)



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Motivation

- 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.

Motivation

Challenges

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

Existing methods

- Rule-based methods: **specific demographic tags**
- Similarity-based methods: **artificially pre-defined similarity**
- One-stage model-based methods: **overfitting**
- Two-stage model-based methods: **unsatisfying generalization ability and ignore the task relationships**

Motivation

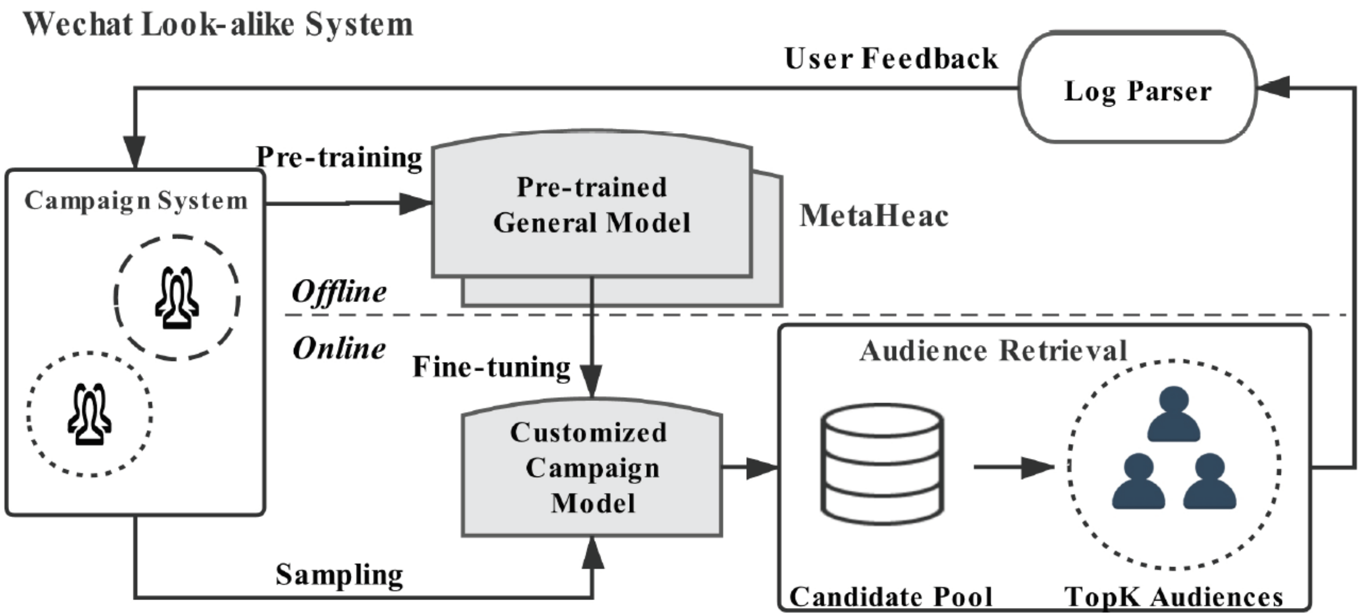
Two stages

- Offline stage: train a **general model** with various existing marketing campaigns.
- Online stage: a **customized model** is learned by **fine-tuning** the pre-trained general model for the certain campaign.

Two key ideas for the general model

- The general model is expected to **learn the ability to expand audiences**.
- The general model should learn **transferable knowledge** from various marketing campaigns.

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.

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Meta Hybrid Experts and Critics

Definitions

Campaign c: $c = \{x_1^c, \ldots, x_N^c\}$

A user: $u = \{x_1^u, \ldots, x_M^u\}$

Seed users: $\mathcal{S}_{[c]}$

Samples of certain campaign: $\mathcal{D}_{[c]}$

User candidate pool: $\mathcal{U}$

Expanded audience: $\mathcal{U}_{[c]}$

Meta Hybrid Experts and Critics

Learn to expand audience

The general model: $f(\cdot;\theta)$

A customized model: $f_{[c]}(\cdot;\theta_{[c]})$

Binary prediction: $\hat{p} = f_{[c]}(\boldsymbol{c}, \boldsymbol{u}; \theta_{[c]})$

Two-phases simulation

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**

Meta Hybrid Experts and Critics

Hybrid Experts and Critics

Task-driven gate:

$$\boldsymbol{w}^{expert} = \text{softmax}(g(\boldsymbol{c}, \mathcal{G}(\boldsymbol{u})))$$

Hybrid experts:

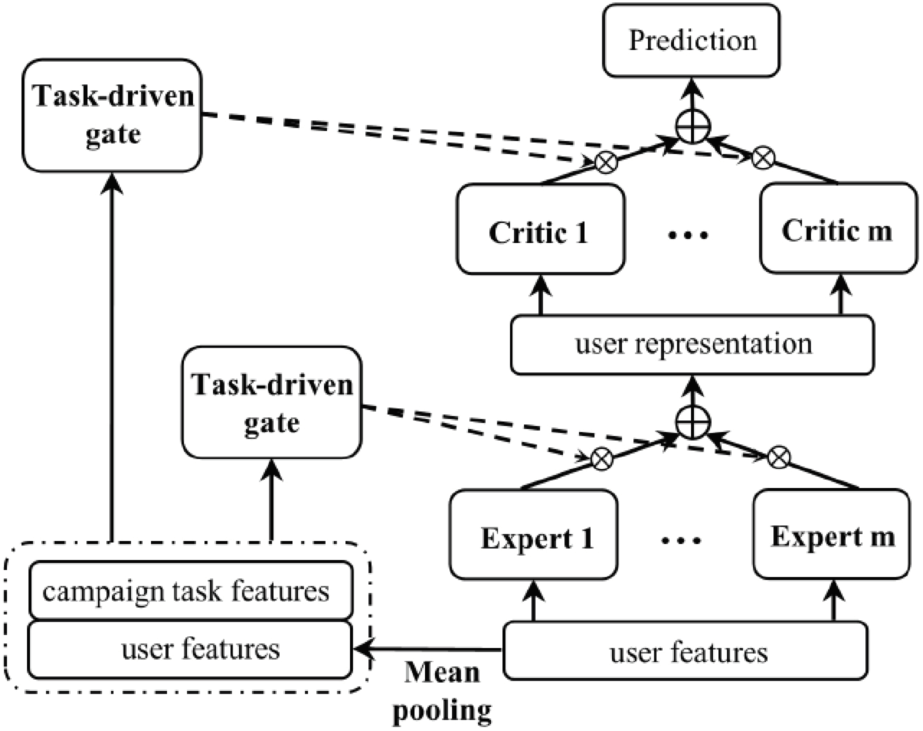
$$\boldsymbol{r} = \frac{1}{n}\sum_{i=1}^{n} w_i^{expert} h_i(\boldsymbol{u}),$$

Hybrid critics:

$$\hat{p} = \frac{1}{m}\sum_{i=1}^{m} w_i^{critic} \sigma(t_i(\boldsymbol{r}))$$

Overall:

$$f(\boldsymbol{c}, \boldsymbol{u}) = \frac{1}{m}\sum_{i=1}^{m} w_i^{critic} \sigma(t_i(\frac{1}{n}\sum_{i=1}^{n} w_i^{expert} h_i(\boldsymbol{u})))$$



Meta Hybrid Experts and Critics

Overall procedure:

Overall structure: $$f(c, \boldsymbol{u}) = \frac{1}{m}\sum_{i=1}^{m} w_i^{critic}\sigma(t_i(\frac{1}{n}\sum_{i=1}^{n} w_i^{expert}h_i(\boldsymbol{u})))$$

Offline stage: In this stage, we learn the general look-alike model with the meta-learning framework of the **two-phases simulation** on all existing marketing campaigns.

Online stage: For a new marketing campaign *c*, given the dataset $D_{[c]}$ of the new campaign, we **fine-tune** the general look-alike model. And we can obtain a **customized look-alike model**. Then, the customized model can be directly exploited to find the potential audiences

Experiments

Research questions

- RQ1 Does our proposed MetaHeac outperform other look-alike approaches in different tasks?
- RQ2 Does this MetaHeac framework get improvement on the performance of WeChat Look-alike system?
- RQ3 What are the effects of meta-learning, hybrid experts, and hybrid critics in our proposed MetaHeac?

Datasets

- Tencent Look-alike Dataset
- WeChat Look-alike Dataset

Two test groups

- Limited seeds $S_{[c]} \leq T$
- Sufficient seeds $S_{[c]} > T$

Experiments

Baselines

- One-stage methods: LR, MLP_one-stage
- Two-stage methods (pre-train emb): MLP+emb, Pinterest, Hubble
- Two-stage methods (pre-train all): : MLP+pre-training, Shared-Bottom+pre-training, MMoE+pre-training

Metrics: AUC, P@K%, R@K%

$$\mathrm{P@K\%} = \frac{|\mathcal{U}_{at} \cap \mathcal{U}_{cdd,K}|}{|\mathcal{U}_{cdd,K}|}, \quad \mathrm{R@K\%} = \frac{|\mathcal{U}_{at} \cap \mathcal{U}_{cdd,K}|}{|\mathcal{U}_{at}|}$$

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Experiments

Offline Results (RQ1)

- The effectiveness of pre-training embedding.
- The effectiveness of pre-training networks.
- The effectiveness of MetaHeac.

Dataset	Method	Pre-trained		$\mathcal{S}_{[c]} \leq T$			$\mathcal{S}_{[c]} > T$		
		Emb	Network	AUC	P@5%	R@5%	AUC	P@5%	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%

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Experiments

Table 3: 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%

Online Results (RQ2)

- The effectiveness of MetaHeac on **video** promotion.
- The effectiveness of MetaHeac on **advertisement** promotion.
- The effectiveness of MetaHeac on **article** promotion.

Experiments

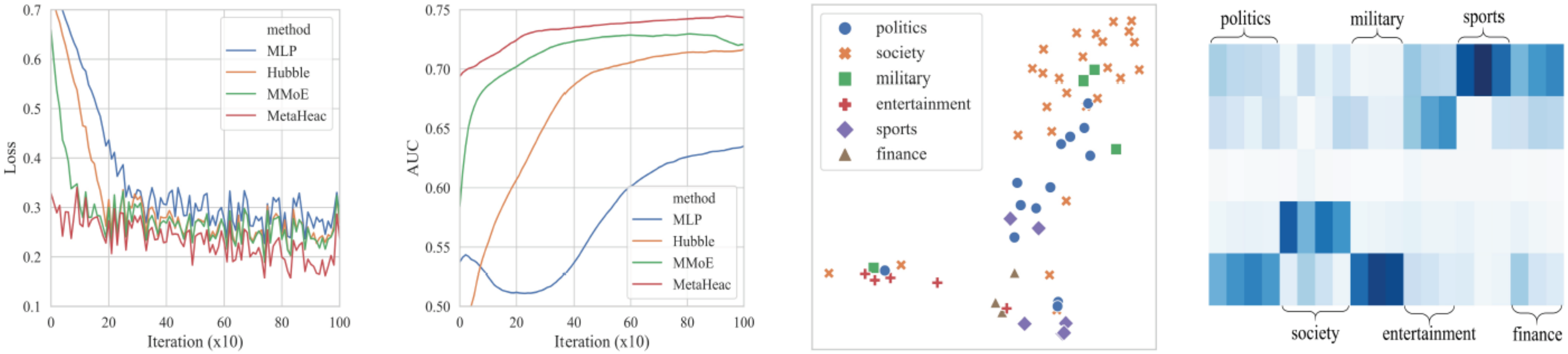
Table 4: Ablation Study on Tencent Look-alike Dataset. HC denotes Hybrid Critics, and HE denotes Hybrid Experts.

Method	$S_{[c]} \leq T$		$S_{[c]} > T$	
	AUC	P@5%	AUC	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**

Ablation Study (RQ3)

- The effectiveness of Hybrid Critics.
- The effectiveness of Hybrid Experts.
- The effectiveness of two-phases meta-learning framework.

Experiments



(a) Training Loss (b) AUC (c) Average Representations of Seeds (d) Gate of Hybrid Critics

Other Analysis (RQ3)

- Better Convergence.
- The ability to capture the relationships among tasks.

Thanks Q & A

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