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Leveraging Label Distributions as Anchors to Enhance Video Recommendation

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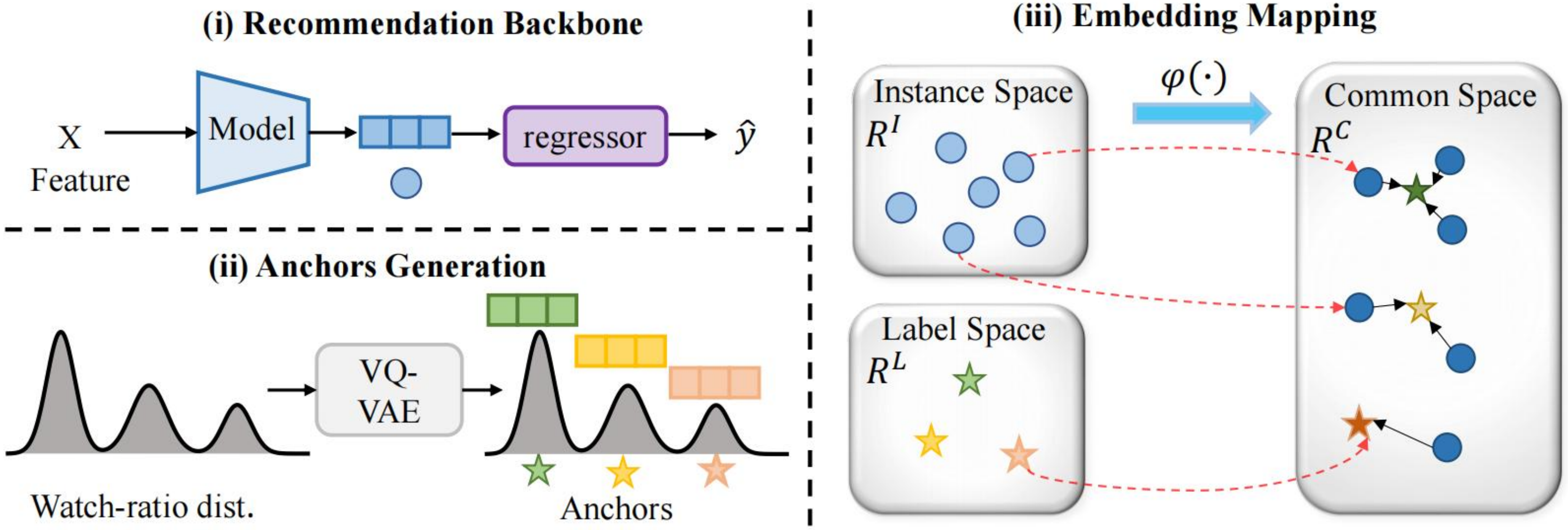
Motivation

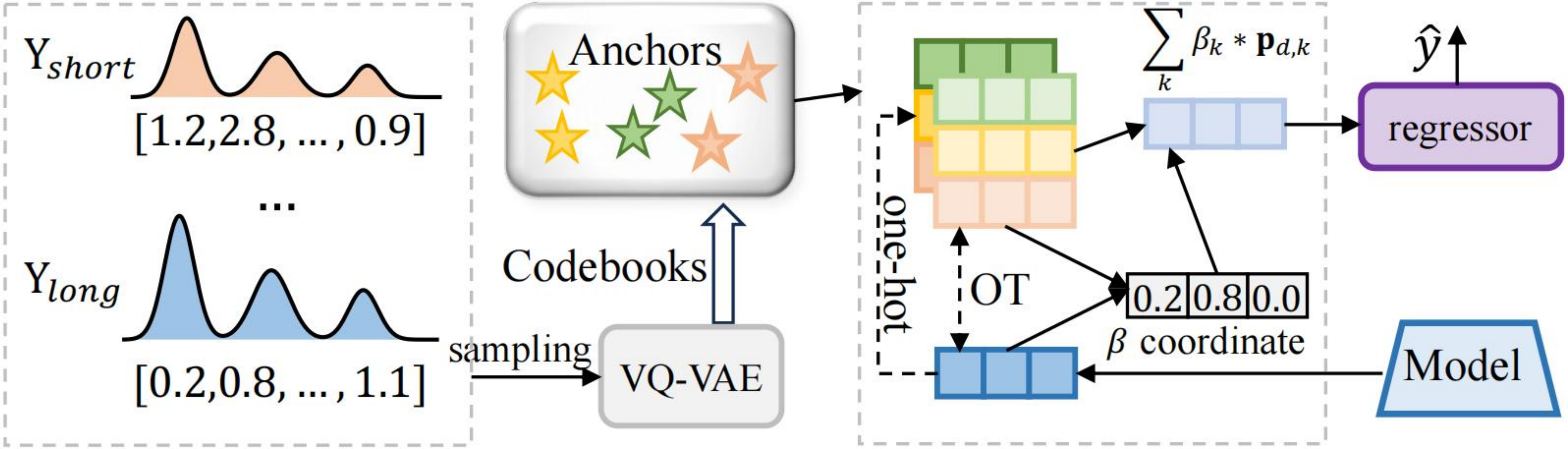
- ***Watch Time > CTR(Click-Through Rate)***
  - *In short-video platforms, watch time is a more meaningful signal than CTR, as videos auto-play and users don’t need to click.*
- ***Existing methods focus on label transformation or debiasing***
  - *Prior work improves watch time prediction by transforming labels (e.g., quantiles) or removing duration bias, but these approaches ignore representation quality.*
- ***Core Issue: Poor instance representations***
  - *The main cause of prediction error is inaccurate instance representations—not label bias alone.*
- ***Our Proposal: Label distributions as anchors***
  - *We propose to leverage label distributions as anchors to guide the learning of better instance representations.*

LDA Overview



- ***Step 1: Learn discrete anchors via VQ-VAE***
  - *Capture multi-peak label distributions across video duration groups.*
- ***Step 2: Align instance features with anchors using Optimal Transport***
  - *Project both into a shared space and generate pseudo-labels for alignment.*
- ***Step 3: Predict watch time by aggregating anchor vectors***
  - *Final prediction is a weighted combination of aligned anchors.*

Framework



Y_{short}
[1.2,2.8, … , 0.9]
…
Y_{long}
[0.2,0.8, … , 1.1]
Anchors
Codebooks
sampling
VQ-VAE
$\sum_k \beta_k * \mathbf{p}_{d,k}$
one-hot
OT
0.2 0.8 0.0
β coordinate
$\hat{y}$
regressor
Model

Method - Anchor Generation (VQ-VAE)

- ***Bucket the watch ratio by video duration***
  - The label distribution Y is divided into D duration-specific subsets $\{Y_d\}_{d=1}^{D}$ to preserve multi-modal structure.
- ***Train a VQ-VAE for each duration bucket***
  - Each sampled sequence s is encoded into latent space $z_e = E(s)$, then discretized by selecting the nearest anchor from a codebook $A = \{a_k\}_{k=1}^{K}$:

$$z = arg\min_{a_k \in A} \|z_e - a_k\|_2$$

- ***VQ-VAE captures the multi-peak nature of the distribution***
  - The loss function used to train VQ-VAE is:

$$\mathcal{L}_{VQ-VAE} = \|s - D(z)\|^2 + \|sg[z_e] - z\|^2 + \beta\|z_e - sg[z]\|^2$$

where s is the input watch-ratio sequence, z is the discrete anchor vector, $sg[\cdot]$denotes the stop-gradient operator, and β is the commitment loss weight.

Method - Representation Alignment (OT)

- ***Map instances and anchors into a common latent space***
  - For each instance x_i, compute: $h_i = \phi(f(x_i))$, $p_k = \phi(a_k)$, where $f(x_i)$ is the instance feature and a_k is is an anchor from the codebook.
- ***Use Optimal Transport to generate soft pseudo-labels***
  - Compute the cost matrix using cosine similarity: $C_{i,k} = 1 - \cos(h_i, p_k)$
  - Apply entropy-regularized OT to obtain the transport plan:

$$Q^* = UOT_\kappa(C, \mu_1, \mu_2)$$

  where Q^* serves as soft pseudo-labels between instance h_i and anchors $\{p_k\}$.
- ***Aggregate anchors for final prediction***
  - Compute anchor weights: $\beta_{i,k} = \frac{exp(h_i^\top p_k)}{\sum_{j=1}^{K} exp(h_i^\top p_j)}$
  - Predict watch time using the weighted sum and a regressor: $y_i = g(\sum_k \beta_{i,k} \cdot p_k)$

Experimental Results

Method	KuaiRec		Wechat		Indust	
	MAE	XAUC	MAE	XAUC	MAE	XAUC
VR	6.25	0.523	20.89	0.601	10.64	0.558
WLR	5.83	0.532	20.17	0.626	10.25	0.572
D2Q	5.21	0.563	19.05	0.633	9.88	0.589
OR	5.11	0.548	19.88	0.631	9.81	0.577
CWM	4.83	0.579	19.21	0.639	9.57	0.599
TPM	4.35	0.603	18.97	0.642	9.26	0.611
LDA	**3.22**	**0.611**	**18.42**	**0.655**	**8.72**	**0.628**

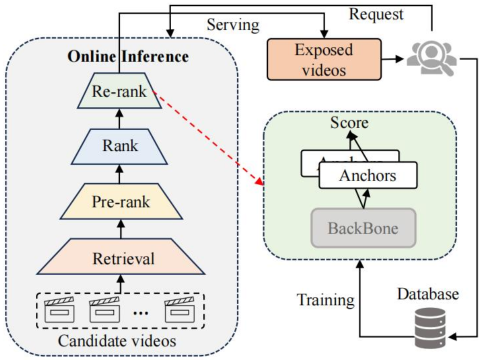
- ***Matrics***
- ***Datasets: KuaiRec, WeChat, Indust***
- ***Baselines: VR, WLR, D2Q, TPM, CWM***

LDA outperforms all baselines across all datasets

– Lowest MAE and highest XAUC on every benchmark

– Consistent gains on both small-scale and industrial-scale datasets

Online A/B Testing



- ***Deployment***
  - LDA is deployed in the re-ranking stage of KuaiShou's recommendation system, serving over 300 million daily active users
- ***Setup***
  - 15-day online A/B testing is conducted on both the main app and the lightweight version
- ***Results***
  - Compared to the D2Q baseline, LDA consistently improves user engagement metrics:

APP	watch time	app usage	like	follow
Main	+0.039%	+0.021%	+0.401%	+0.108%
Light	+0.122%	+0.098%	+0.379%	+0.147%

- ***Conclusion***
  - LDA improves watch-time prediction and enhances user engagement in real-world environments.

Thank you