# PCANet: Price Change Aware Framework for Mitigating Inconsistencies in Large-Scale Ranking Systems.

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## 1. Background

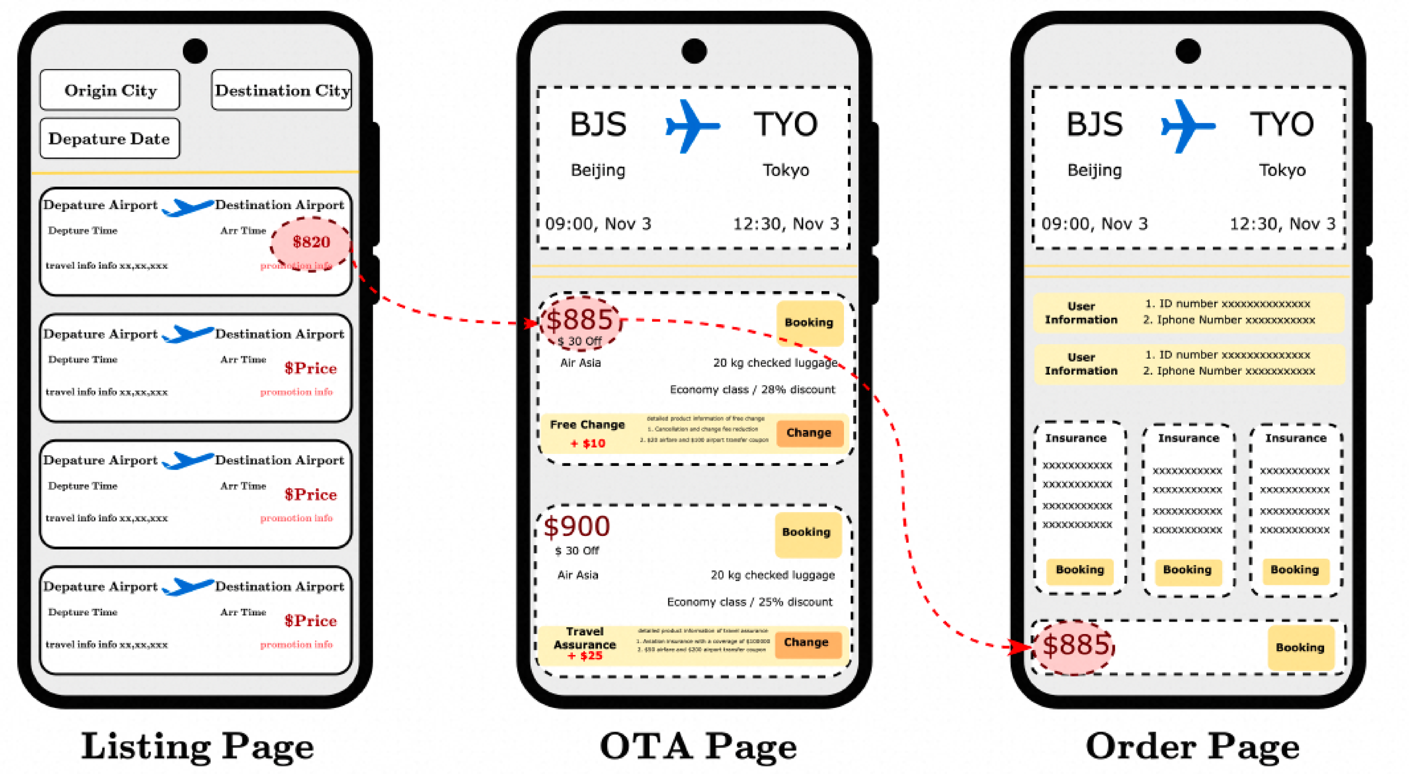



**Figure 1: Listing Page: Flight Selection Interface; OTA Page: Cabin and Service Selection Interface; Order Page: Flight Booking Interface.**

I. **Industrial Necessity:** On large-scale Online Travel Platforms (OTPs) like Fliggy, system responsiveness relies on cached fare data to handle massive search traffic. This creates a technical ***trade-off*** between millisecond-level latency and real-time inventory accuracy.

II. **The "Price Jump" Phenomenon:** Due to distributed system synchronization latency, a temporal gap emerges between the fare displayed on the listing page and the actual price at the booking stage. This staleness frequently manifests as sudden "***price jumps***" that disrupt the user's booking journey.

III. **The Core Conflict:** While traditional ranking models excel at relevance and conversion prediction, they operate under the assumption of static pricing, largely ignoring the volatility inherent in real-time airline inventory dynamics.

## 2. Challenge

I. **Cognitive Friction & Trust Erosion:** Price fluctuations during the booking funnel represent a significant source of user frustration. These discrepancies act as "***cognitive friction***," eroding platform credibility and directly leading to higher user churn and lost conversions.

II. **Dynamic Inventory Volatility:** Price volatility is driven by two complex, stochastic mechanisms:

  I. **Inventory-driven shifts:** Exhaustion of lower-priced cabin buckets triggers an automatic price hike.

  II. **Dynamic revenue management:** Real-time airline market adjustments that are both frequent and non-deterministic.

III. **The Modeling Gap:** Existing ranking frameworks lack a mechanism to explicitly model or calibrate against this staleness. Bridging the gap between the cached representations (used for ranking) and real-time price reality is a major, yet previously underexplored, challenge for industrial-scale recommendation systems.

## 3. Architecture Design(PCANet)

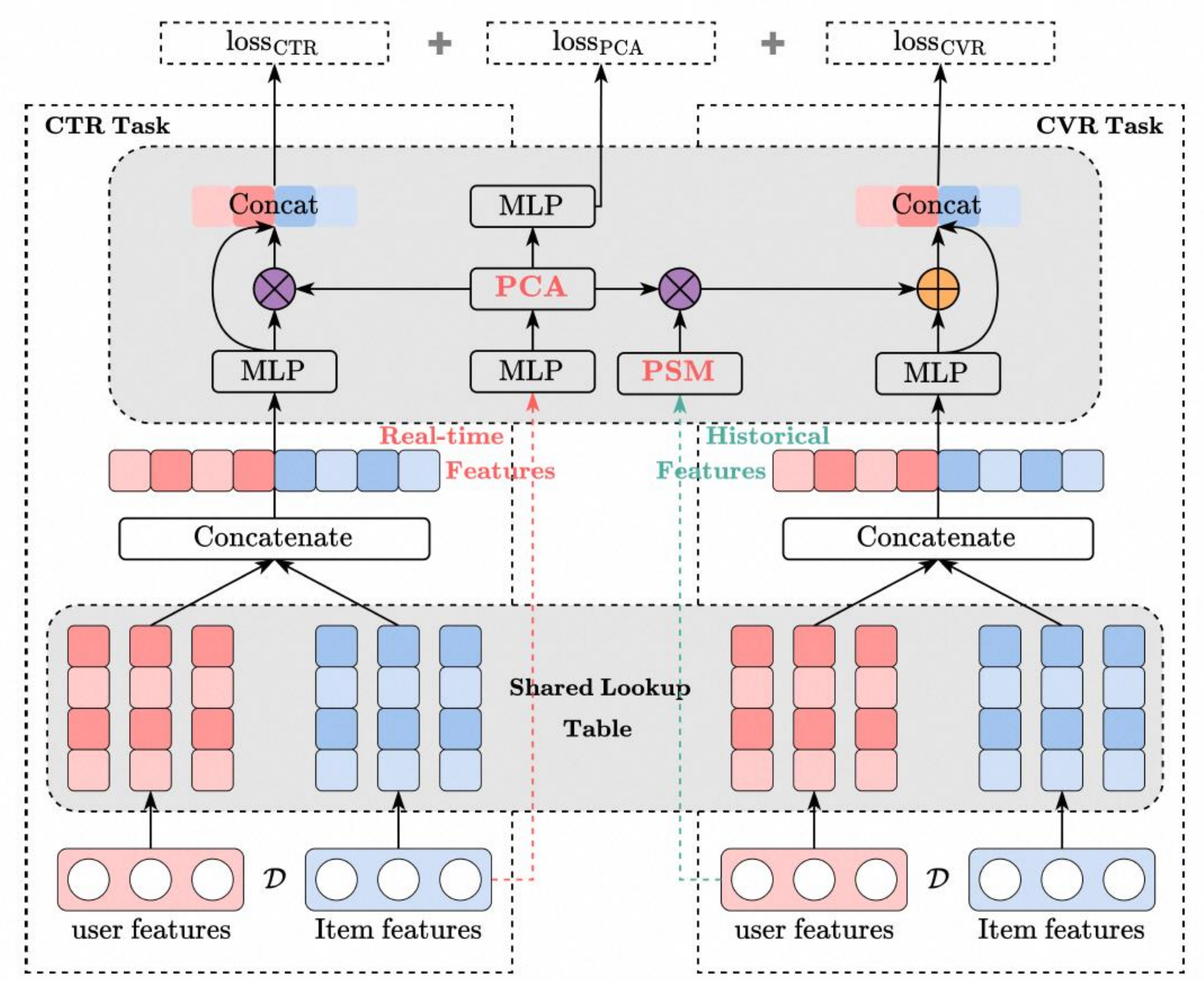



**Figure 2: Architecture overview of the proposed framework (PCANet).**

### Price Consistency Aligning (PCA)

The PCA module treats price inconsistency as a constrained learning problem. By employing a ***Monotonic Neural Network***, we encode the industrial heuristic that inventory scarcity and cache staleness are non-decreasing functions of price risk. This yields a calibrated volatility embedding $\mathcal{E}_{pca}$ that quantifies the "**jump**" probability.

$$\boldsymbol{\mathcal{E}_{pca} = \sigma\left(W^{(1)} \ldots W^{(l)} x_{rt} + b^{(l)}\right), \quad \text{s.t.}\, W^{(l)} \geq 0}$$

$$\mathcal{L}_{\mathcal{PCA}} = \frac{1}{|\mathcal{D}|} \sum_{f \in \mathcal{D}} |\widehat{\Delta_p}(f) - \max\left(0, p_f^{order} - p_f^{list}\right)|^2$$

$$\frac{\partial \mathcal{E}_{pca}}{\partial c} \geq 0, \quad \frac{\partial \mathcal{E}_{pca}}{\partial q} \geq 0, \quad \frac{\partial \mathcal{E}_{pca}}{\partial i} \leq 0$$

### Price Sensitive Matching (PSM)

The PSM module models heterogeneous price sensitivity. Using a ***Price Attention Network (PAN)***, it dynamically aligns the current candidate's volatility signal $\mathcal{E}_{pca}$ with the user's historical price-related actions $S_u$. This generates a personalized sensitivity vector $h_u^{sens}$ that reflects the user's unique tolerance threshold.

$$\alpha_t = \text{softmax}_t\left(\text{score}(\mathcal{E}_{pca}, e_{st})\right), \quad h_u^{sens} = \sum_{t=1}^{T} \alpha_t \cdot e_{st}$$

### Residual Feature Fusion & Calibration

PCANet integrates the volatility risk and user sensitivity via a ***residual matching structure***. This mechanism "**calibrates**" the ranking scores, allowing the system to adaptively down-weight volatile itineraries for sensitive users while preserving options for those with higher price elasticity.

$$\mathbf{x}_{\text{match}} = \left(h_u^{sens} \otimes \mathcal{E}'_{pca}\right) \oplus \text{MLP}_{main}(e_u, e_f)$$

## 4. Offline Evaluation

We conduct comprehensive evaluations on a massive industrial dataset of 2 billion samples, validating PCANet's superior ability to optimize ranking relevance while maintaining price consistency through systematic ablation studies and multi-metric benchmarking against state-of-the-art frameworks.

Offline evaluations on production datasets demonstrate that PCANet consistently achieves state-of-the-art performance, significantly surpassing competitive baselines (e.g., DIN, PLE, ATIM) across all ranking and recommendation metrics (**AUC, GAUC, HR**). Ablation studies further validate the necessity of the PCA and PSM modules, confirming their pivotal role in enhancing ranking accuracy and resolving price-consistency challenges.

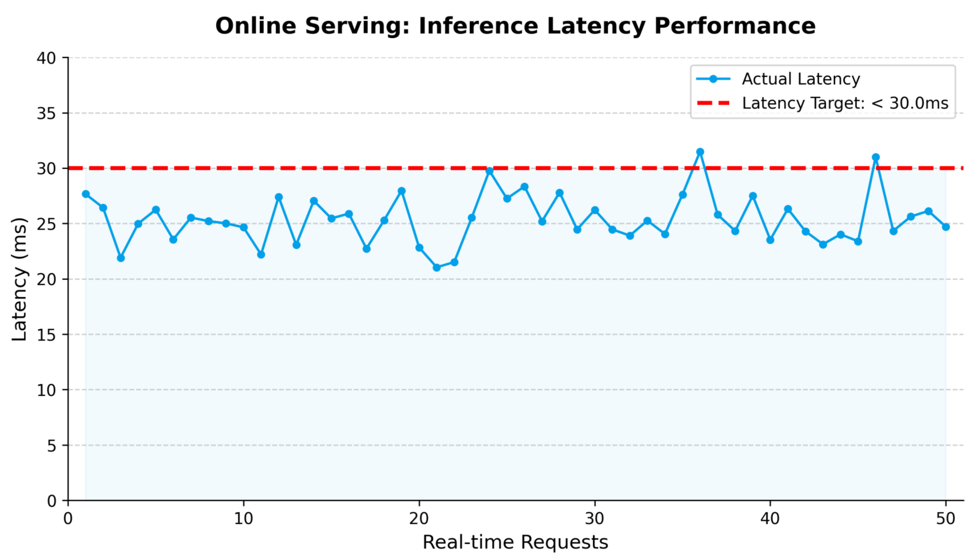
**Table 1: Performance comparison on production datasets.**

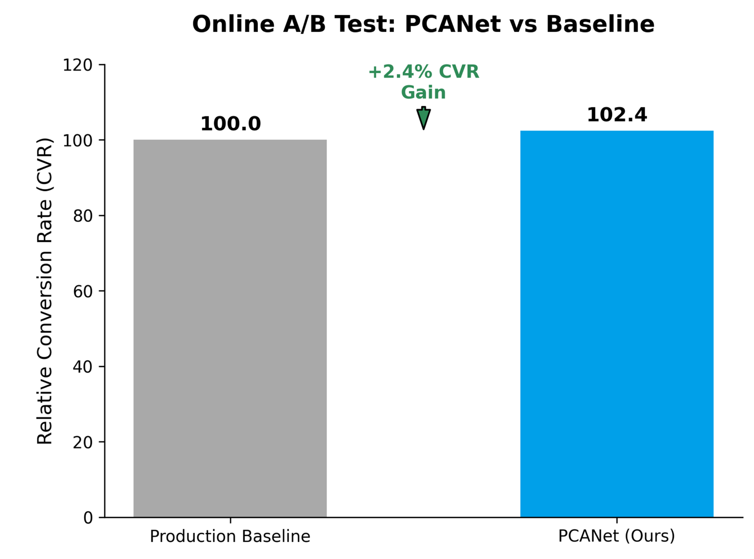
| Methods | $TOP_5$ | $TOP_{10}$ | GAUC | AUC |
|---|---|---|---|---|
| DIN | 0.5573 | 0.5721 | 0.5690 | 0.7516 |
| CPNet | 0.5912 | 0.6013 | 0.6112 | 0.7861 |
| DCRNet | 0.5886 | 0.6002 | 0.5936 | 0.7802 |
| PlanRanker | 0.5891 | 0.6121 | 0.6102 | 0.7688 |
| ESMM | 0.5895 | 0.6099 | 0.6109 | 0.7712 |
| PLE | 0.5901 | 0.6126 | 0.6116 | 0.7884 |
| ATIM | 0.6013 | 0.6201 | 0.6219 | 0.7916 |
| **PCANet(ours)** | **0.6175** | **0.6320** | **0.6317** | **0.8314** |

**Table 2: Ablation Study of PCANet.**

| Methods | $TOP_5$ | $TOP_{10}$ | GAUC | AUC |
|---|---|---|---|---|
| w/o Sec. 3.2 | 0.5992 | 0.6187 | 0.6210 | 0.8124 |
| w/o Sec. 3.3 | 0.6012 | 0.6206 | 0.6214 | 0.8203 |

## 5. System Deployment Design & Online A/B Test




### Deployment & Efficiency

- **High Efficiency:** Online inference latency is consistently maintained below 30 ms, meeting stringent real-time responsiveness requirements.
- **Scalable Architecture:** Deployed on a distributed TensorFlow framework, ensuring efficient scalability for large-scale industrial use without sacrificing training efficiency.

### Online A/B Test

- **+2.4% CVR Lift :** Achieved a significant ***+2.4%*** increase in Conversion Rate (CVR) compared to the production baseline in a two-week live A/B test.
- **Proven Robustness:** Demonstrated superior performance in handling rapid data shifts and sparsity, especially during high-traffic holiday periods.