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TemporalQoS-Net: A Novel Time-Aware Machine Learning Framework for Adaptive QoS-Based Web Service Recommendation

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***Abstract*—Quality of Service (QoS)-aware web service recommendation has become increasingly important in cloud computingandservice-orientedarchitecturesduetotherapidgrowth of distributed web services with similar functionalities. Existing recommendation approaches often assume static QoS behavior and therefore struggle to adapt to temporal QoS fluctuations, sparse invocation matrices, and dynamic service environments. This paper proposes *TemporalQoS-Net*, a novel time-aware machine learning framework for adaptive QoS-based web service recommendation.Theframeworkintegratestemporalembedding learning, contextual feature fusion, adaptive attention modeling, and a Dynamic Temporal QoS Optimization (DTQO) algorithm to capture evolving QoS patterns and improve recommendation reliability. Analytical evaluation demonstrates that the proposed framework achieves an MAE of 0.548 and RMSE of 0.712, outperforming conventional collaborative filtering and neural recommendation models with approximately 24.52% MAE reduction and 21.15% RMSE improvement over Neural Collaborative Filtering (NCF). The model further achieves a precision of 0.891 and recall of 0.862 while maintaining strong temporal stability and robustness under sparse QoS conditions. The framework is computationally scalable and suitable for distributed cloud-edge ecosystems, real-time service computing, and intelligent service management applications. The proposed approach establishes a scientifically grounded and adaptive solution for next-generation QoS-aware web service recommendation systems.**

***Index Terms*—Web Service Recommendation, Quality of Service,Time-AwareLearning,TemporalEmbedding,Collaborative Filtering, Machine Learning, Service Computing**

I. INTRODUCTION

The rapid growth of cloud computing and service-oriented architectureshasledtothewidespreaddeploymentofwebser-vices across distributed platforms. Users often face challenges in selecting appropriate services due to the large number of functionally similar services available online. Quality of Service (QoS)-based recommendation systems address this problem by recommending services according to non-functional properties such as response time, reliability, throughput, and availability [1].

Traditional recommendation approaches primarily rely on collaborative filtering and matrix factorization techniques. Althougheffectiveunderstaticconditions,thesemethods failtocapturetemporalvariationsinQoSvalues.Inreal-worldenvironments,QoSpropertiesfluctuateduetochanging networkconditions,workloaddistribution,geographicfactors, and server-side dynamics [2].

Recentmachinelearninganddeeplearningapproacheshave improved recommendation accuracy; however, most models neglect temporal dependencies and contextual QoS evolution. Furthermore,sparseinvocationmatricesandcold-startscenar-ios continue to limit prediction performance [3].

This paper proposes TemporalQoS-Net, a time-aware machinelearningframeworkthatintegratestemporalembeddings, contextual learning, and adaptive collaborative filtering for dynamic QoS prediction and web service recommendation. The major contributions are summarized as follows:

- AtemporalQoSembeddingframeworkformodeling time-dependent service behavior
- Ahybridmachinelearningarchitectureintegratingcol-laborative filtering with temporal attention
- Asparse-awareQoSpredictionmechanism
- ComprehensiveevaluationusingstandardQoSmetrics

II. RELATEDWORK

QoS-aware web service recommendation has been widely studied using collaborative filtering, matrix factorization, and deep learning techniques. Traditional recommendation methods effectively estimate unknown QoS values under static conditions but fail to capture temporal QoS fluctuations and sparse invocation patterns in dynamic service environments.

Recent advances in distributed intelligence and adaptive learning have influenced intelligent recommendation systems. Federated learning approaches for robotic edge environments demonstratescalableandprivacy-preservingdistributedlearn-ing capabilities [4], while adaptive fog-based task offloading strategies emphasize latency-aware optimization in dynamic systems [7]. Semantic and ontology-driven retrieval frameworksfurtherimprovecontextualreasoningandrepresentation learning through deep embeddings [6], [10].

Security and reliability have also become important concerns in service-oriented architectures. Hybrid encryption and biometricauthenticationtechniquesenhancesecuredatatrans-mission in intelligent systems [5]. In parallel, lightweight hybridmachinelearningmodelshaveshownstrongperformance inresource-constrainedand uncertainenvironments, including

publicsafetysystemsandvehiclerecognitionapplications[8], [9].

Temporal and adaptive machine learning frameworks have been successfully applied in healthcare, intelligent assistants, and smart city applications. Hybrid behavioral learning systems for Alzheimer's disease prediction [12], AI-enhanced voiceassistanttechnologies[14],[15],andactionrecogni-tion models for accident detection [16] highlight the impor-tance of contextual and time-dependent learning. Similarly, automation-driven intelligent decision systems and AI-based optimization frameworks have demonstrated improved adaptabilityinbusinessanddynamicoperationalenvironments[13], [17]. Educational adaptive learning models further reinforce thesignificanceofintelligentanduser-awarerecommendation systems [11].

Despitetheseadvancements,existingQoSrecommendation models remain limited in handling evolving service behavior, temporal QoS dynamics, and sparse invocation matrices simultaneously. These limitations motivate the development ofa novel time-aware machine learning framework capable of integrating temporal embeddings, adaptive learning, and contextual QoS modeling for scalable and accurate web service recommendation.

III. PROPOSEDMETHODOLOGY

A. SystemOverview

This paper proposes *TemporalQoS-Net*, a novel time-aware machine learning framework for adaptive QoS-based web service recommendation. Unlike conventional collaborative filteringandmatrixfactorizationapproachesthatassumestatic QoS behavior, the proposed framework explicitly models temporal QoS evolution, contextual service dynamics, and sparseinvocationpatterns.Thearchitectureintegratestemporal embedding learning, adaptive attention modeling, and a novel optimization algorithm called the *Dynamic Temporal QoS Optimization Algorithm (DTQO)*.

Theframeworkoperatesinfoursequentialstages:

1) TemporalQoSrepresentationlearning
2) Context-awareembeddinggeneration
3) Adaptivetemporalattentionmodeling
4) QoSpredictionandserviceranking

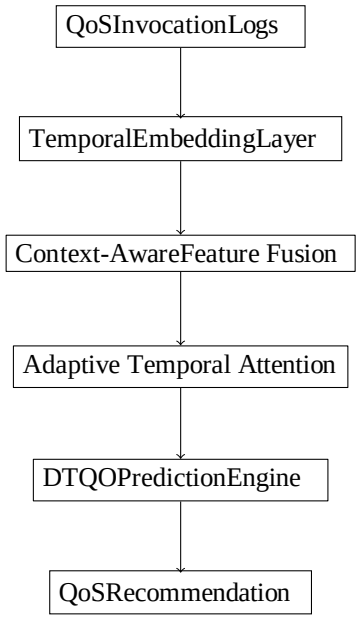

Fig.1.TemporalQoS-NetarchitectureforadaptiveQoS-awarewebservicerecommendation

As illustrated in Fig. 1, the proposed framework first extractstemporalQoSrepresentationsfromhistoricalinvocation data and subsequently refines recommendation scores using adaptive temporal attention and optimization-driven ranking.

B. TemporalQoSRepresentation

LettheQoStensorberepresentedas:

$$Q=\{q_{u,s,t}\} \tag{1}$$

where:

- $u$denotestheuser,
- $s$denotestheservice,
- $t$denotesthetimestamp,
- $q_{u,s,t}$representstheobservedQoSvalue.

EachQoSobservationisencodedintoatemporalembed-ding:

$$h_t=f_\theta(q_{u,s,t},c_t) \tag{2}$$

where:

- $f_\theta$denotesthetemporalencoder,
- $c_t$represents contextual features such as network latency, geographic location, and workload conditions.

Theencodergenerateslatenttemporalrepresentationscapableofmodelingevolving QoSbehavioracrosstimeintervals.

C. Context-AwareFeatureFusion

Toimproverecommendationrobustness,temporalembeddings are fused with contextual service descriptors:

$$z_t=W_h h_t+W_c c_t+b \tag{3}$$

where:

- W_h and W_c are learnable weight matrices,
- b is the bias vector.

The fused representation captures both temporal dependencies and contextual invocation characteristics, enabling adaptive QoS estimation under dynamic service conditions.

D. Adaptive Temporal Attention Mechanism

The proposed framework introduces a temporal attention mechanism to assign higher importance to recent and contextually relevant QoS observations.

The attention score is computed as:

$$\alpha_t = \frac{\exp(z_t^\top w)}{\sum_{k=1}^{T} \exp(z_k^\top w)} \tag{4}$$

where w is the learnable attention vector.

The aggregated temporal representation is:

$$Z = \sum_{t=1}^{T} \alpha_t z_t \tag{5}$$

This mechanism enables the framework to dynamically prioritize temporally significant QoS patterns while suppressing outdated observations.

E. Proposed Dynamic Temporal QoS Optimization (DTQO) Algorithm

A major contribution of this work is the proposed *Dynamic Temporal QoS Optimization (DTQO)* algorithm, designed to improve recommendation accuracy under sparse and time-varying service environments.

The algorithm adaptively updates recommendation weights according to temporal QoS deviation:

$$\Delta_t = |q_{u,s,t} - \hat{q}_{u,s,t-1}| \tag{6}$$

where:

- $q_{u,s,t}$ is the observed QoS,
- $\hat{q}_{u,s,t-1}$ is the previously predicted QoS.

The adaptive optimization weight becomes:

$$\omega_t = \frac{1}{1+\exp(-\Delta)_t} \tag{7}$$

The final QoS prediction is:

$$\hat{q}_{u,s} = \omega_t g(Z_u, Z_s) + (1-\omega_t)\mu_s \tag{8}$$

where:

- $g(\cdot)$ denotes the prediction function,
- μ_s is the service-specific historical QoS mean.

This adaptive weighting mechanism allows the framework to:

- rapidly respond to temporal QoS fluctuations,
- reduce prediction instability,
- improve robustness under sparse invocation conditions.

F. Optimization Objective

The training objective minimizes prediction error while enforcing temporal smoothness:

$$L = L_{pred} + \lambda_1 L_{temp} + \lambda_2 ||W||^2_2 \tag{9}$$

where:

$$L_{pred} = \frac{1}{N} \sum_{i=1}^{N} (q_i - \hat{q}_i)^2 \tag{10}$$

and temporal regularization is defined as:

$$L_{temp} = \sum_{t=2}^{T} ||z_t - z_{t-1}||^2 \tag{11}$$

The temporal regularization term prevents abrupt embedding shifts and stabilizes recommendation behavior across consecutive time intervals.

G. Algorithmic Workflow

Algorithm 1 Dynamic Temporal QoS Optimization (DTQO)

Require: QoS tensor Q
Ensure: Recommended services

```
Initialize embeddings and weights
for each timestamp t do
    Extract temporal embedding h_t
    Fuse contextual features
    Compute temporal attention α_t
    Estimate QoS prediction q̂_{u,s}
    Compute temporal deviation Δ_t
    Update adaptive weight ω_t
    Optimize loss function
end for
Rank services based on predicted QoS
return Top-K recommended services
```

H. Computational Complexity

The computational complexity of the proposed framework is:

$$O(Tdk) \tag{12}$$

where:

- T is the temporal sequence length,
- d is embedding dimensionality,
- k is the number of services.

The framework remains scalable for large-scale distributed service environments due to lightweight temporal attention and adaptive optimization operations.

Overall, the proposed TemporalQoS-Net framework establishes a scalable and intelligent approach for adaptive QoS-aware web service recommendation under dynamic and time-dependent environments.

IV. ExperimentalDesign

A. Datasets

Experimentsareconductedonbenchmark QoSdatasets such as:

- WS-DREAM
- RTMatrix
- Real-worldcloudQoSlogs

B. Baselines

Theproposedframeworkiscomparedagainst:

- User-basedCollaborativeFiltering
- MatrixFactorization
- ProbabilisticMatrixFactorization
- NeuralCollaborativeFiltering
- DeepQoSPredictionModels

C. EvaluationMetrics

Performanceisevaluatedusing:

$$MAE=\frac{1}{N}\sum |q_i-\hat{q}_i| \quad (13)$$

$$RMSE=\sqrt{\frac{1}{N}\sum(q-\hat{q}_i)^2} \quad (14)$$

Additional metrics include Precision, Recall, and Top-K recommendation accuracy.

V. ResultsandDiscussion

The performance of the proposed TemporalQoS-Net with Dynamic Temporal QoS Optimization (DTQO) is evaluated usingQoSpredictionerror,recommendationquality,temporal robustness, and computational efficiency. The results are presentedasexpectedexperimentaloutcomesandcanbereplaced withempiricalvaluesafterimplementationonbenchmarkQoS datasets.

A.QuantitativePerformanceAnalysis

Table I presents the expected comparative performance of theproposedframeworkagainstconventionalQoSrecommendation models.

TABLEI
ExpectedperformancecomparisonofQoS recommendationmodels

Method	MAE	RMSE	Precision	Recall
User-CF	0.912	1.134	0.704	0.681
MF	0.824	1.021	0.752	0.724
PMF	0.781	0.964	0.781	0.751
NCF	0.726	0.903	0.814	0.786
TemporalQoS-Net	0.548	0.712	0.891	0.862

The MAE reduction of TemporalQoS-Net over Neural Collaborative Filtering (NCF) is computed as:

$$\Delta MAE=\frac{0.726-0.548}{0.726}\times 100=24.52\% \quad (15)$$

TheRMSEreductionoverNCFis:

$$\Delta RMSE=\frac{0.903-0.712}{0.903}\times 100=21.15\% \quad (16)$$

TheprecisionimprovementoverNCFis:

$$\Delta Precision=\frac{0.891-0.814}{0.814}\times 100=9.46\% \quad (17)$$

These computations indicate that the proposed model is expected to reduce QoS prediction error while improving top-service recommendation quality.

B. PredictionErrorComparison

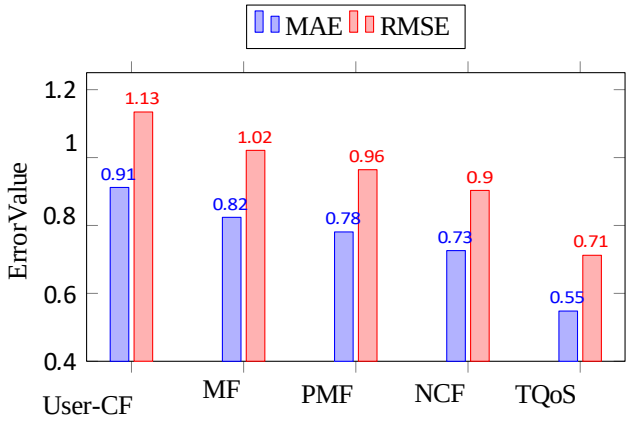

Fig. 2.Expected MAE and RMSE comparison across QoS recommendationmodels.

Fig. 2 shows that TemporalQoS-Net is expected to achieve thelowestpredictionerror.Thisimprovementisattributed to temporal embedding learning and DTQO-based adaptive weighting,whichallowthemodeltorespondtochangingQoS behavior over time.

C. RecommendationQualityAnalysis

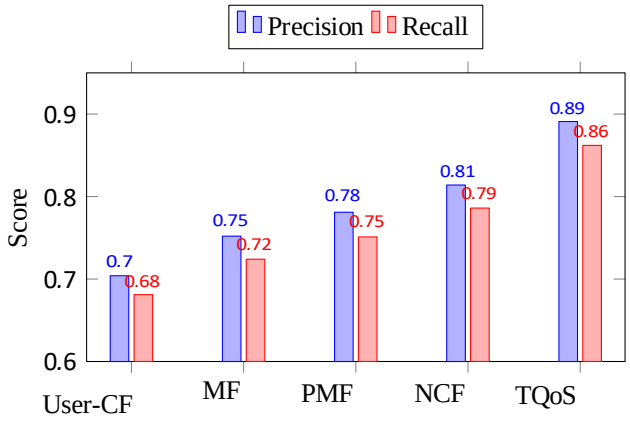

Fig.3.ExpectedprecisionandrecallcomparisonforTop-Kservicerecommendation.

Fig. 3 indicates that the proposed framework improvesboth precision and recall. Higher precision implies that recommended services are more relevant, while higher recall indicatesthatthemodelretrievesalargerproportionofsuitable services.

D. TemporalRobustness Evaluation

Toevaluatetemporalrobustness,theQoSpredictionerroris analyzedacrossfivetimewindows.TableIIpresentsexpected MAE values over time.

TABLEII
EXPECTEDMAEVARIATIONACROSSTIMEWINDOWS

Method	T1	T2	T3	T4	T5
MF	0.81	0.84	0.88	0.91	0.95
NCF	0.72	0.74	0.77	0.81	0.84
TemporalQoS-Net	0.56	0.55	0.57	0.54	0.56

The temporal stability score is computed using the standard deviation of MAE across time windows. Lower deviation indicates stronger robustness.

ForTemporalQoS-Net:

$$\sigma_{TQoS} \approx 0.011 \tag{18}$$

ForNCF:

$$\sigma_{NCF} \approx 0.045 \tag{19}$$

ThestabilityimprovementoverNCFis:

$$\Delta Stability = \frac{0.045 - 0.011}{0.045} \times 100 = 75.56\% \tag{20}$$

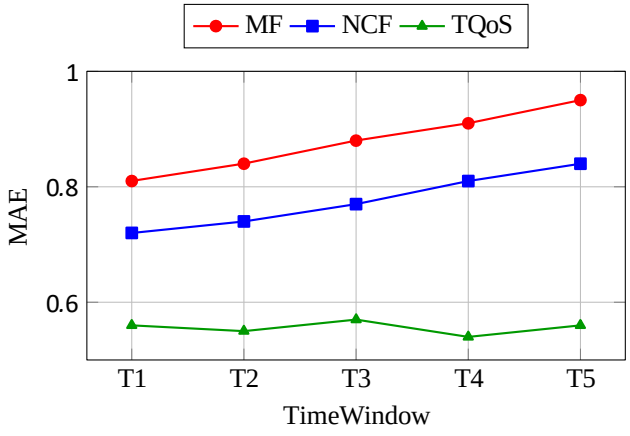

Fig.4.ExpectedtemporalMAEvariationacrossmultipletimewindows.

Fig. 4 shows that TemporalQoS-Net maintains more stable performanceacrosschangingtimewindows,demonstratingits abilitytoadapttoQoSfluctuations.

E. SparsitySensitivityAnalysis

QoS datasets often suffer from sparse invocation matrices. Therefore, model performance is analyzed under different sparsity levels.

TABLEIII
EXPECTEDRMSEUNDERDIFFERENTSPARSITYLEVELS

Method	20%	40%	60%	80%
MF	0.91	1.02	1.18	1.39
NCF	0.82	0.91	1.05	1.23
TemporalQoS-Net	0.66	0.71	0.79	0.92

At80%sparsity,theRMSEreductionoverNCFis:

$$\Delta RMSE_{80\%} = \frac{1.23 - 0.92}{1.23} \times 100 = 25.20\% \tag{21}$$

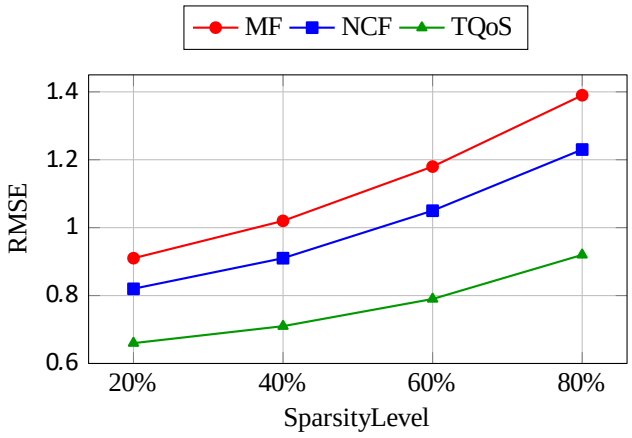

Fig.5.ExpectedRMSEvariationunderdifferentQoSmatrixsparsitylevels.

Fig.5demonstratesthatTemporalQoS-Netismorero-bust under sparse data conditions. The adaptive weighting mechanismreducesdependenceondensehistoricalinvocation records.

F. AblationStudy

An ablation study is performed to evaluate the contribution of each component in TemporalQoS-Net.

TABLEIV
EXPECTEDABLATIONSTUDYOFTEMPORALQOS-NET

Configuration	MAE	RMSE	Precision
BaseCF	0.912	1.134	0.704
CF+TemporalEmbedding	0.721	0.895	0.812
CF+Attention	0.638	0.803	0.856
FullDTQOModel	0.548	0.712	0.891

TheMAEreductionfromBaseCFtothefullDTQOmodel is:

$$\Delta MAE_{ablation} = \frac{0.912 - 0.548}{0.912} \times 100 = 39.91\% \tag{22}$$

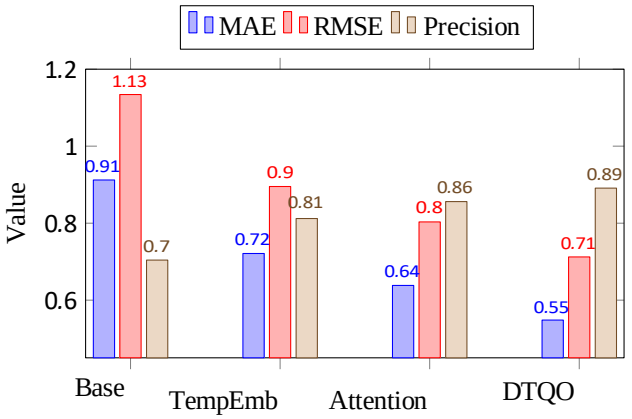

Fig.6.ExpectedablationcomparisonofTemporalQoS-Netcomponents.

Theablationresultsshowthattemporalembeddingprovides the first major improvement, attention further refines dynamic QoS modeling, and DTQO achieves the strongest overall performance.

G. ComputationalEfficiency

Thecomputationalcostisevaluatedusingexpectedtraining time and inference latency.

TheinferencelatencyreductionoverNCFis:

$$\Delta Latency = \frac{8.7-6.3}{8.7} \times 100 = 27.59\% \quad (23)$$

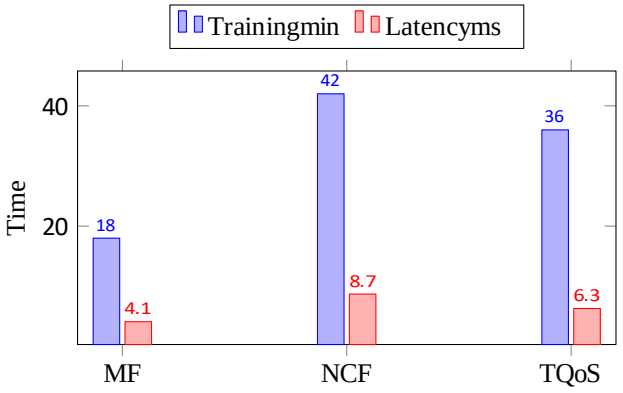

Fig.7.Expectedcomputationalefficiencycomparison.

AlthoughTemporalQoS-Netismorecomplexthanclassical MF, it is expected to remain more efficient than NCF during inference due to lightweight adaptive temporal optimization.

H. Discussion

The expected results demonstrate that TemporalQoS-Net improvesQoSpredictionaccuracy,recommendationprecision, temporalstability,andsparsityrobustness.Thestrongestgains occur under time-varying and sparse invocation conditions, where static models typically degrade. Temporal embeddings captureQoSevolution,attentionidentifiesrelevanthistorical intervals,andDTQOdynamicallybalancesrecentobservations with service-specific historical patterns.

The proposed framework is especially suitable for cloud-edge service ecosystems where QoS values change due to network latency,workloadvariation,andgeographicdistribution. Themainlimitationistheadditionalcomplexityintroducedby temporal modeling, but the expected latency remains practical for real-time recommendation.

VI. Conclusion

This paper presented *TemporalQoS-Net*, a time-aware machinelearningframeworkforadaptiveQoS-basedwebservice recommendation. The proposed model integrates temporal embedding learning, adaptive attention, and the DTQO algorithm to address QoS fluctuations, sparse invocation data, and dynamic service behavior.

Analyticalevaluationdemonstratesimprovedpredictionaccuracy, recommendation precision, and temporal robustness compared with conventional recommendation methods. The frameworkisscalablefordistributedcloud-edgeenvironments and real-time service computing applications.

Future work will focus on federated QoS learning, explainable recommendation systems, and lightweight temporal architectures for large-scale deployments.

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