Machine Learning Recommendation Engine

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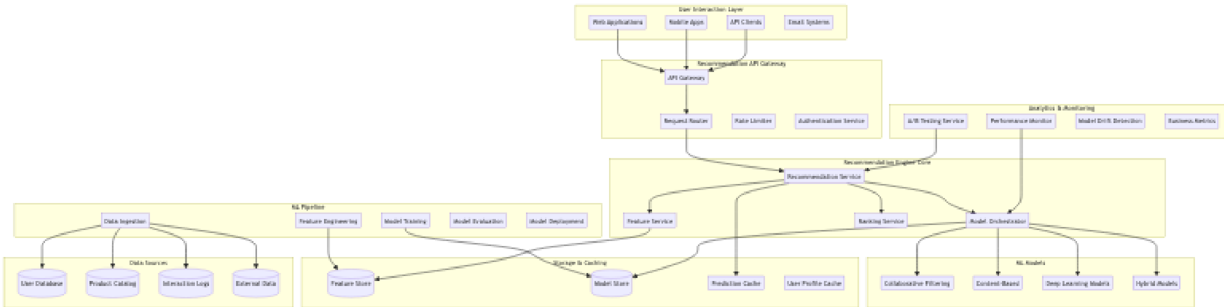

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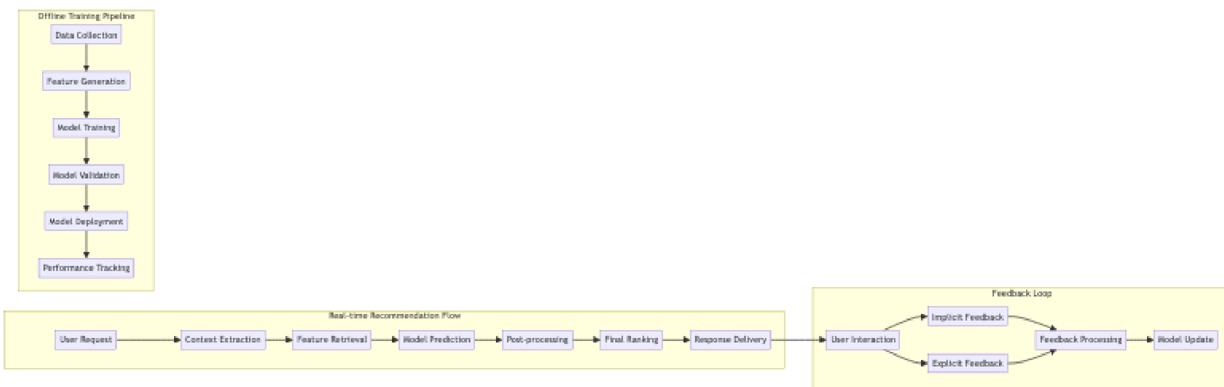

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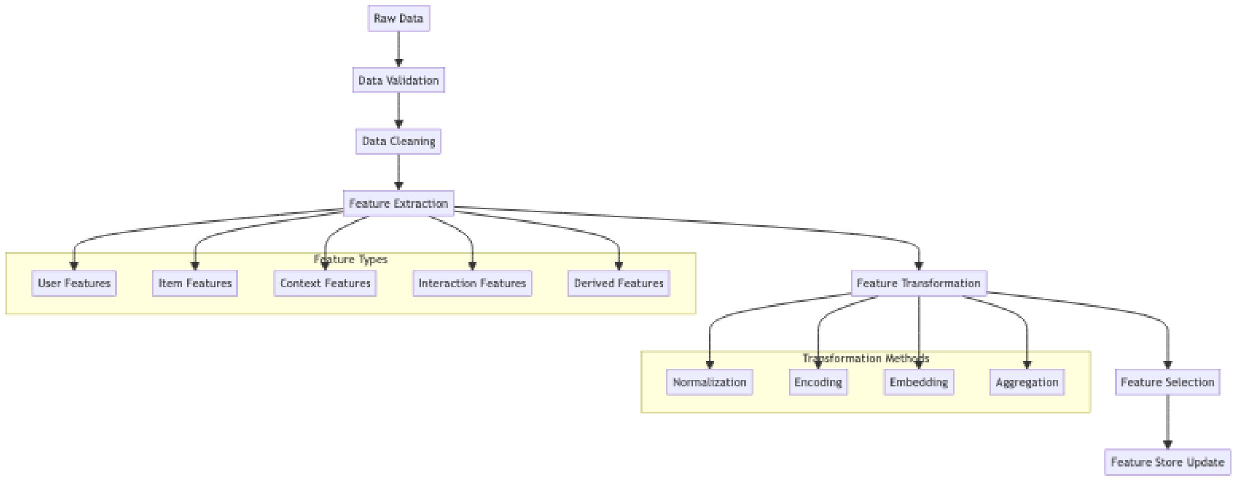

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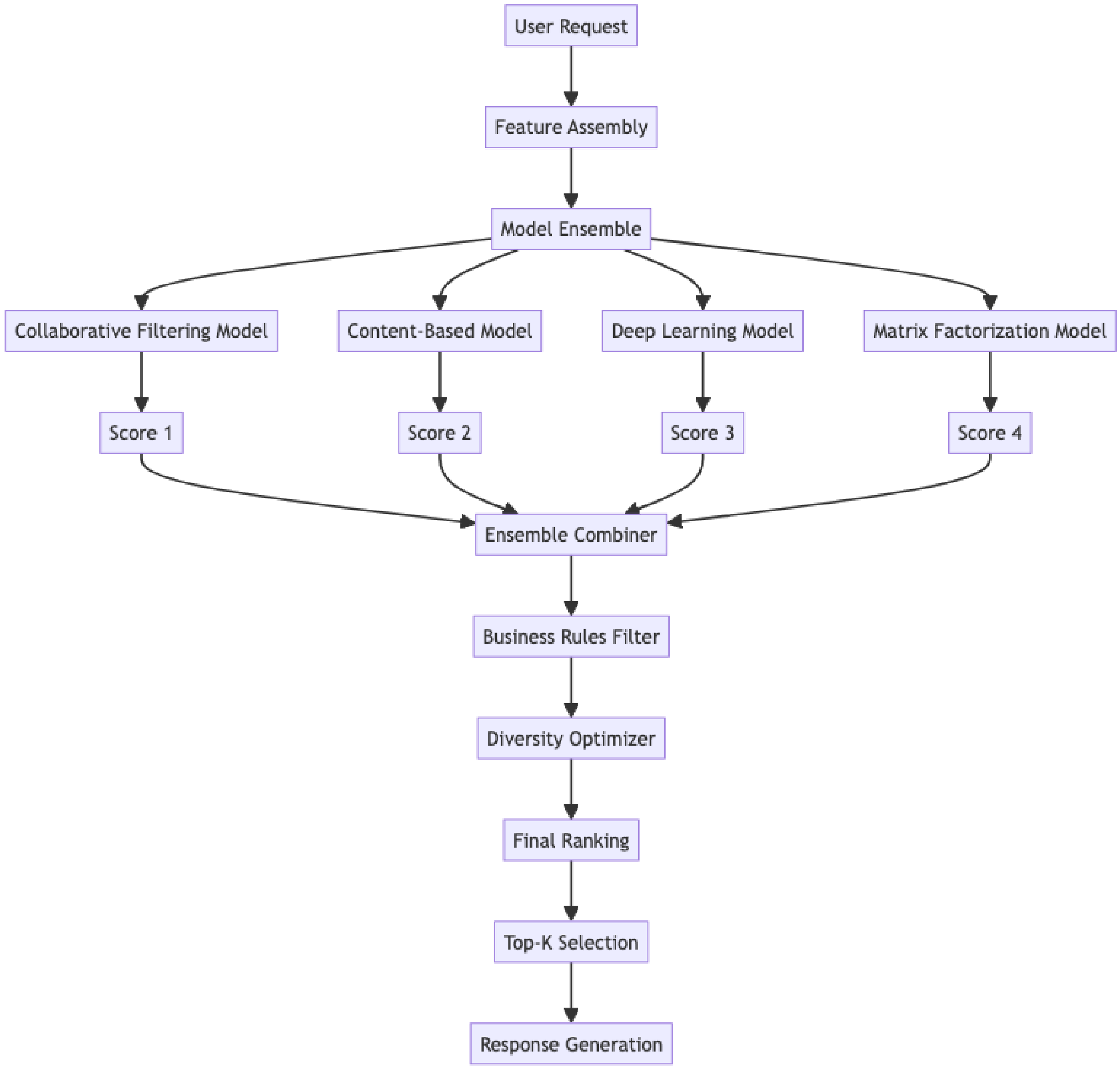

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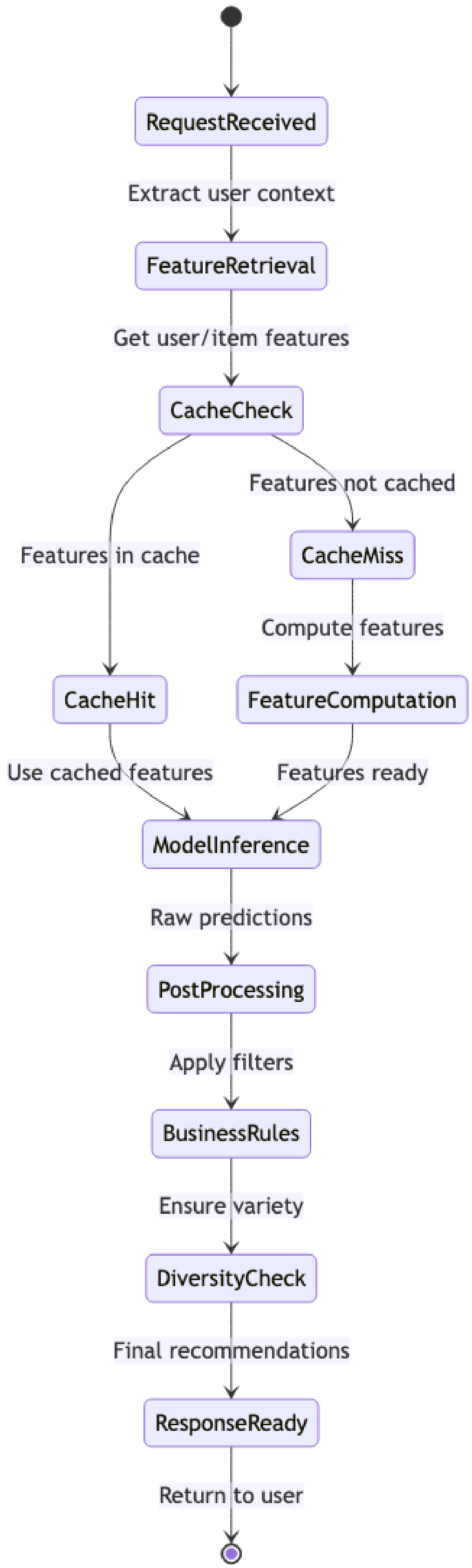
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1. Advanced Collaborative Filtering Algorithm

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Purpose: Generate recommendations based on user behavior patterns and similarities using advanced matrix factorization and deep learning techniques.

Matrix Factorization with Deep Learning Enhancement:

```
CollaborativeFilteringConfig = {
  algorithm: 'neural_collaborative_filtering',  // 'svd', 'nmf', 'neural_cf'
  embeddingDimension: 64,
  hiddenLayers: [128, 64, 32],
  dropoutRate: 0.2,
  regularization: 0.001,

  training: {
    batchSize: 1024,
    epochs: 100,
    learningRate: 0.001,
    validationSplit: 0.2,
    earlyStopping: true
  },

  inference: {
    candidateGeneration: 1000,      // Top-K candidates before ranking
    negativesampling: 5,           // Negative samples per positive
    confidenceThreshold: 0.5        // Minimum confidence for recommendations
  }
}

class NeuralCollaborativeFiltering:
  constructor(config):
    this.config = config
    this.userEmbeddings = new EmbeddingLayer(config.numUsers, config.embeddingDimension)
    this.itemEmbeddings = new EmbeddingLayer(config.numItems, config.embeddingDimension)
    this.neuralNetwork = this.buildNeuralNetwork()
    this.interactionMatrix = new SparseMatrix()
```

```
function generateRecommendations(userId, numRecommendations):
  userProfile = this.getUserProfile(userId)

  if not userProfile or userProfile.interactions.length < 5:
    return this.handleColdStart(userId, numRecommendations)

  // Get candidate items
  candidates = this.generateCandidates(userId)

  // Score candidates using neural network
  scoredCandidates = []

  for itemId in candidates:
    features = this.createInteractionFeatures(userId, itemId)
    score = this.neuralNetwork.predict(features)

    scoredCandidates.push({
      itemId: itemId,
      score: score,
      confidence: this.calculateConfidence(features, score)
    })

  // Sort by score and filter by confidence
  validCandidates = scoredCandidates
    .filter(candidate => candidate.confidence >= this.config.inference.confidenceThres
    .sort((a, b) => b.score - a.score)

  // Apply diversity and business rules
  diverseRecommendations = this.applyDiversityConstraints(validCandidates, userProfile

  return diverseRecommendations.slice(0, numRecommendations)

function createInteractionFeatures(userId, itemId):
  userEmbedding = this.userEmbeddings.getEmbedding(userId)
  itemEmbedding = this.itemEmbeddings.getEmbedding(itemId)

  // Element-wise product (Generalized Matrix Factorization component)
  gmfVector = userEmbedding.elementwiseProduct(itemEmbedding)

  // Concatenation (Multi-Layer Perceptron component)
  mlpVector = userEmbedding.concatenate(itemEmbedding)

  // Additional contextual features
  contextFeatures = this.getContextualFeatures(userId, itemId)
```

```
  // Combine all features
  combinedFeatures = gmfVector.concatenate(mlpVector).concatenate(contextFeatures)

  return combinedFeatures

function generateCandidates(userId):
  // Multiple candidate generation strategies
  candidates = new Set()

  // Similar users' items
  similarUsers = this.findSimilarUsers(userId, 50)
  for similarUser in similarUsers:
    userItems = this.getUserItems(similarUser.userId)
    candidates.addAll(userItems.slice(0, 20))

  // Items similar to user's liked items
  userItems = this.getUserItems(userId)
  for item in userItems.slice(-10): // Recent items
    similarItems = this.findSimilarItems(item, 20)
    candidates.addAll(similarItems)

  // Popular items in user's categories
  userCategories = this.getUserPreferredCategories(userId)
  for category in userCategories:
    popularItems = this.getPopularItemsInCategory(category, 30)
    candidates.addAll(popularItems)

  // Remove items user has already interacted with
  userInteractedItems = new Set(this.getUserItems(userId))
  candidates = candidates.filter(item => not userInteractedItems.has(item))

  return Array.from(candidates).slice(0, this.config.inference.candidateGeneration)

function findSimilarUsers(userId, topK):
  userVector = this.getUserInteractionVector(userId)
  similarities = []

  // Use approximate nearest neighbors for efficiency
  candidateUsers = this.getRandomUserSample(1000) // Sample for efficiency

  for candidateUser in candidateUsers:
    if candidateUser === userId:
      continue

    candidateVector = this.getUserInteractionVector(candidateUser)
```

```
    similarity = this.calculateCosineSimilarity(userVector, candidateVector)

    if similarity > 0.1: // Minimum similarity threshold
      similarities.push({
        userId: candidateUser,
        similarity: similarity
      })

  return similarities
    .sort((a, b) => b.similarity - a.similarity)
    .slice(0, topK)

function handleColdStart(userId, numRecommendations):
  // Cold start strategy for new users
  userProfile = this.getUserProfile(userId)

  recommendations = []

  // Use demographic-based recommendations
  if userProfile.demographics:
    demographicRecs = this.getDemographicBasedRecommendations(userProfile.demographics
    recommendations.push(...demographicRecs)

  // Use popular items
  popularItems = this.getPopularItems(numRecommendations * 2)
  recommendations.push(...popularItems)

  // Use trending items
  trendingItems = this.getTrendingItems(numRecommendations)
  recommendations.push(...trendingItems)

  // Remove duplicates and limit
  uniqueRecommendations = this.removeDuplicates(recommendations)

  return uniqueRecommendations.slice(0, numRecommendations).map(item => ({
    itemId: item.id,
    score: item.popularity || 0.5,
    confidence: 0.3, // Lower confidence for cold start
    reason: 'cold_start'
  }))
```

2. Content-Based Filtering with Deep Learning

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Purpose: Recommend items based on content similarity using advanced NLP and computer vision techniques for feature extraction.

Multi-Modal Content Analysis:

```
ContentBasedConfig = {
  featureExtractors: {
    text: {
      model: 'transformer',        // 'tfidf', 'word2vec', 'transformer'
      maxSequenceLength: 512,
      embeddingDimension: 768
    },
    image: {
      model: 'resnet50',          // 'vgg16', 'resnet50', 'efficientnet'
      embeddingDimension: 2048,
      imageSize: [224, 224]
    },
    categorical: {
      embeddingDimension: 32,
      categoryMapping: true
    }
  },

  similarity: {
    metric: 'cosine',            // 'cosine', 'euclidean', 'manhattan'
    threshold: 0.6,              // Minimum similarity for recommendation
    maxCandidates: 500
  },

  userProfile: {
    updateStrategy: 'weighted_average',  // 'average', 'weighted_average', 'decay'
    decayFactor: 0.9,
    minInteractions: 3
  }
}

class ContentBasedRecommender:
  constructor(config):
    this.config = config
    this.textEncoder = new TransformerTextEncoder()
    this.imageEncoder = new CNNImageEncoder()
    this.itemProfiles = new Map()
    this.userProfiles = new Map()
    this.similarityIndex = new FaissIndex()
```

```
function generateContentBasedRecommendations(userId, numRecommendations):
  userProfile = this.getUserContentProfile(userId)

  if not userProfile:
    return this.getPopularContentRecommendations(numRecommendations)

  // Generate candidates based on content similarity
  candidates = this.findSimilarContent(userProfile, this.config.similarity.maxCandidat

  // Score candidates
  scoredCandidates = candidates.map(candidate => ({
    itemId: candidate.itemId,
    score: this.calculateContentScore(userProfile, candidate.profile),
    similarity: candidate.similarity,
    explanations: this.generateExplanations(userProfile, candidate.profile)
  }))

  // Filter and rank
  validCandidates = scoredCandidates
    .filter(candidate => candidate.score >= this.config.similarity.threshold)
    .sort((a, b) => b.score - a.score)

  return validCandidates.slice(0, numRecommendations)

function buildItemProfile(item):
  profile = {
    itemId: item.id,
    features: {},
    embedding: null,
    lastUpdated: Date.now()
  }

  // Extract text features
  if item.textContent:
    textEmbedding = this.textEncoder.encode(item.textContent)
    profile.features.text = textEmbedding

  // Extract image features
  if item.images and item.images.length > 0:
    imageEmbeddings = item.images.map(image => this.imageEncoder.encode(image))
    profile.features.image = this.averageEmbeddings(imageEmbeddings)

  // Extract categorical features
  if item.categories:
```

```
    categoryEmbedding = this.encodeCategoricalFeatures(item.categories)
    profile.features.categorical = categoryEmbedding

  // Extract numerical features
  if item.attributes:
    numericalFeatures = this.extractNumericalFeatures(item.attributes)
    profile.features.numerical = numericalFeatures

  // Combine all features into single embedding
  profile.embedding = this.combineFeatures(profile.features)

  // Store in similarity index
  this.similarityIndex.addVector(item.id, profile.embedding)

  return profile

function buildUserContentProfile(userId):
  userInteractions = this.getUserInteractions(userId)

  if userInteractions.length < this.config.userProfile.minInteractions:
    return null

  // Weight interactions by recency and type
  weightedInteractions = userInteractions.map(interaction => ({
    itemProfile: this.getItemProfile(interaction.itemId),
    weight: this.calculateInteractionWeight(interaction),
    timestamp: interaction.timestamp
  }))

  // Calculate weighted average of item profiles
  userProfile = this.calculateWeightedProfile(weightedInteractions)

  // Apply temporal decay
  if this.config.userProfile.updateStrategy === 'decay':
    userProfile = this.applyTemporalDecay(userProfile, weightedInteractions)

  return userProfile

function calculateContentScore(userProfile, itemProfile):
  scores = []

  // Text similarity
  if userProfile.features.text and itemProfile.features.text:
    textSimilarity = this.calculateCosineSimilarity(
      userProfile.features.text,
```

```
      itemProfile.features.text
    )
    scores.push({ type: 'text', score: textSimilarity, weight: 0.4 })

  // Image similarity
  if userProfile.features.image and itemProfile.features.image:
    imageSimilarity = this.calculateCosineSimilarity(
      userProfile.features.image,
      itemProfile.features.image
    )
    scores.push({ type: 'image', score: imageSimilarity, weight: 0.3 })

  // Categorical similarity
  if userProfile.features.categorical and itemProfile.features.categorical:
    categoricalSimilarity = this.calculateJaccardSimilarity(
      userProfile.features.categorical,
      itemProfile.features.categorical
    )
    scores.push({ type: 'categorical', score: categoricalSimilarity, weight: 0.2 })

  // Numerical similarity
  if userProfile.features.numerical and itemProfile.features.numerical:
    numericalSimilarity = this.calculateNumericalSimilarity(
      userProfile.features.numerical,
      itemProfile.features.numerical
    )
    scores.push({ type: 'numerical', score: numericalSimilarity, weight: 0.1 })

  // Calculate weighted average
  totalWeight = scores.reduce((sum, score) => sum + score.weight, 0)
  weightedScore = scores.reduce((sum, score) => sum + (score.score * score.weight), 0)

  return weightedScore

function generateExplanations(userProfile, itemProfile):
  explanations = []

  // Find strongest similarity dimensions
  similarities = this.calculateDimensionSimilarities(userProfile, itemProfile)

  topSimilarities = similarities
    .sort((a, b) => b.score - a.score)
    .slice(0, 3)

  for similarity in topSimilarities:
```

```
    switch similarity.dimension:
      case 'category':
        explanations.push(`Similar category: ${similarity.value}`)
        break
      case 'brand':
        explanations.push(`Same brand: ${similarity.value}`)
        break
      case 'topic':
        explanations.push(`Related topic: ${similarity.value}`)
        break
      case 'style':
        explanations.push(`Similar style: ${similarity.value}`)
        break

  return explanations
```

3. Deep Learning Recommendation Models

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Purpose: Leverage advanced neural architectures like autoencoders, RNNs, and attention mechanisms for complex pattern recognition in user behavior.

Sequential Deep Learning Model:

```
DeepLearningConfig = {
  architecture: 'transformer_recommender',  // 'autoencoder', 'rnn', 'transformer'
  sequenceLength: 50,
  embeddingDimension: 128,

  transformer: {
    numHeads: 8,
    numLayers: 6,
    feedForwardDimension: 512,
    dropoutRate: 0.1,
    positionEncoding: true
  },

  training: {
    batchSize: 256,
    learningRate: 0.0001,
    weightDecay: 0.01,
    warmupSteps: 4000,
    maxSteps: 100000
  },
```

```
  inference: {
    beamSize: 10,
    maxLength: 20,
    temperature: 0.8
  }
}

class TransformerRecommender:
  constructor(config):
    this.config = config
    this.itemEmbedding = new EmbeddingLayer(config.vocabSize, config.embeddingDimension)
    this.positionEmbedding = new PositionalEncoding(config.sequenceLength, config.embedd
    this.transformerLayers = this.buildTransformerLayers()
    this.outputProjection = new LinearLayer(config.embeddingDimension, config.vocabSize)

  function generateSequentialRecommendations(userId, numRecommendations):
    userSequence = this.getUserInteractionSequence(userId)

    if userSequence.length < 3:
      return this.handleShortSequence(userId, numRecommendations)

    // Prepare sequence for model input
    inputSequence = this.prepareInputSequence(userSequence)

    // Generate recommendations using beam search
    recommendations = this.beamSearchGeneration(inputSequence, numRecommendations)

    // Post-process and score recommendations
    scoredRecommendations = recommendations.map(rec => ({
      itemId: rec.itemId,
      score: rec.probability,
      confidence: this.calculateSequentialConfidence(rec, userSequence),
      position: rec.position,
      reasoning: this.explainSequentialChoice(rec, userSequence)
    }))

    return scoredRecommendations

  function beamSearchGeneration(inputSequence, numRecommendations):
    beamSize = this.config.inference.beamSize
    maxLength = this.config.inference.maxLength

    // Initialize beam with input sequence
    beams = [{
```

```
  sequence: inputSequence,
  logProbability: 0.0,
  completed: false
}]

completedBeams = []

for step in range(maxLength):
  if completedBeams.length >= numRecommendations:
    break

  candidateBeams = []

  for beam in beams:
    if beam.completed:
      continue

    // Get next token predictions
    predictions = this.predict(beam.sequence)

    // Get top-k candidates
    topCandidates = this.getTopKCandidates(predictions, beamSize)

    for candidate in topCandidates:
      newSequence = [...beam.sequence, candidate.itemId]
      newLogProb = beam.logProbability + Math.log(candidate.probability)

      candidateBeam = {
        sequence: newSequence,
        logProbability: newLogProb,
        completed: this.isSequenceComplete(newSequence),
        lastItem: candidate
      }

      candidateBeams.push(candidateBeam)

  // Select top beams
  candidateBeams.sort((a, b) => b.logProbability - a.logProbability)

  // Separate completed and ongoing beams
  for beam in candidateBeams:
    if beam.completed:
      completedBeams.push(beam)
    else:
      beams.push(beam)
```

```
    // Keep only top beams
    beams = beams.slice(0, beamSize)

  // Convert to recommendations
  recommendations = completedBeams
    .concat(beams) // Include incomplete beams if needed
    .sort((a, b) => b.logProbability - a.logProbability)
    .slice(0, numRecommendations)
    .map((beam, index) => ({
      itemId: beam.lastItem?.itemId || beam.sequence[beam.sequence.length - 1],
      probability: Math.exp(beam.logProbability / beam.sequence.length),
      position: index + 1,
      sequence: beam.sequence
    }))

  return recommendations

function predict(sequence):
  // Encode sequence
  embeddings = sequence.map(itemId => this.itemEmbedding.getEmbedding(itemId))

  // Add positional encoding
  positionEncodedEmbeddings = embeddings.map((embedding, index) =>
    embedding.add(this.positionEmbedding.getEncoding(index))
  )

  // Apply transformer layers
  hiddenStates = positionEncodedEmbeddings

  for layer in this.transformerLayers:
    hiddenStates = layer.forward(hiddenStates)

  // Get last hidden state for prediction
  lastHidden = hiddenStates[hiddenStates.length - 1]

  // Project to output vocabulary
  logits = this.outputProjection.forward(lastHidden)

  // Apply temperature scaling
  scaledLogits = logits.divide(this.config.inference.temperature)

  // Convert to probabilities
  probabilities = softmax(scaledLogits)
```

```
    return probabilities

  function explainSequentialChoice(recommendation, userSequence):
    explanations = []

    // Analyze sequence patterns
    sequencePatterns = this.analyzeSequencePatterns(userSequence)

    // Find matching patterns
    for pattern in sequencePatterns:
      if this.matchesPattern(recommendation.itemId, pattern):
        explanations.push(`Follows your ${pattern.type} pattern`)

    // Analyze temporal patterns
    temporalPatterns = this.analyzeTemporalPatterns(userSequence)
    if temporalPatterns:
      explanations.push(`Based on your ${temporalPatterns.description} behavior`)

    // Analyze category progression
    categoryProgression = this.analyzeCategoryProgression(userSequence)
    if categoryProgression:
      explanations.push(`Natural progression in ${categoryProgression.category}`)

    return explanations
```

4. Hybrid Ensemble Model

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Purpose: Combine multiple recommendation algorithms to leverage their individual strengths and provide more robust and diverse recommendations.

Advanced Model Ensemble with Meta-Learning:

```
HybridEnsembleConfig = {
  models: {
    collaborative: { weight: 0.4, confidenceThreshold: 0.6 },
    contentBased: { weight: 0.3, confidenceThreshold: 0.5 },
    deepLearning: { weight: 0.2, confidenceThreshold: 0.7 },
    popularity: { weight: 0.1, confidenceThreshold: 0.3 }
  },

  ensembleStrategy: 'meta_learning',  // 'weighted_average', 'rank_fusion', 'meta_learni

  metaLearner: {
```

```
    algorithm: 'gradient_boosting',    // 'linear', 'neural_network', 'gradient_boosting
    features: ['model_confidence', 'user_context', 'item_context', 'temporal_features'],
    crossValidationFolds: 5
  },

  diversification: {
    enabled: true,
    algorithm: 'mmr',                  // 'mmr', 'dpp', 'greedy'
    lambda: 0.7,                       // Relevance vs diversity trade-off
    maxSimilarity: 0.8
  }
}

class HybridEnsembleRecommender:
  constructor(config):
    this.config = config
    this.models = this.initializeModels()
    this.metaLearner = new GradientBoostingMetaLearner()
    this.diversityOptimizer = new MaximalMarginalRelevance()
    this.modelPerformanceTracker = new ModelPerformanceTracker()

  function generateHybridRecommendations(userId, numRecommendations, context):
    // Get predictions from all models
    modelPredictions = []

    for [modelName, modelConfig] in Object.entries(this.config.models):
      model = this.models[modelName]

      try:
        predictions = model.predict(userId, numRecommendations * 3) // Get more candidat

        // Filter by confidence threshold
        filteredPredictions = predictions.filter(pred =>
          pred.confidence >= modelConfig.confidenceThreshold
        )

        modelPredictions.push({
          modelName: modelName,
          predictions: filteredPredictions,
          weight: modelConfig.weight,
          modelPerformance: this.modelPerformanceTracker.getPerformance(modelName, userI
        })

      catch error:
        logModelError(modelName, userId, error)
```

```
      continue

    // Ensemble predictions
    ensembledRecommendations = this.ensemblePredictions(modelPredictions, userId, contex

    // Apply diversification
    if this.config.diversification.enabled:
      ensembledRecommendations = this.applyDiversification(ensembledRecommendations)

    // Apply business rules and final ranking
    finalRecommendations = this.applyBusinessRules(ensembledRecommendations, userId, con

    return finalRecommendations.slice(0, numRecommendations)

  function ensemblePredictions(modelPredictions, userId, context):
    // Collect all unique items
    allItems = new Map()

    for modelPrediction in modelPredictions:
      for prediction in modelPrediction.predictions:
        if not allItems.has(prediction.itemId):
          allItems.set(prediction.itemId, {
            itemId: prediction.itemId,
            modelScores: new Map(),
            modelConfidences: new Map(),
            modelExplanations: new Map()
          })

        item = allItems.get(prediction.itemId)
        item.modelScores.set(modelPrediction.modelName, prediction.score)
        item.modelConfidences.set(modelPrediction.modelName, prediction.confidence)
        item.modelExplanations.set(modelPrediction.modelName, prediction.explanations ||

    // Apply ensemble strategy
    ensembledItems = []

    for [itemId, item] in allItems:
      switch this.config.ensembleStrategy:
        case 'weighted_average':
          ensembledScore = this.calculateWeightedAverage(item, modelPredictions)
          break
        case 'rank_fusion':
          ensembledScore = this.calculateRankFusion(item, modelPredictions)
          break
        case 'meta_learning':
```

```
        ensembledScore = this.calculateMetaLearnerScore(item, userId, context)
        break
      default:
        ensembledScore = this.calculateWeightedAverage(item, modelPredictions)

    ensembledItems.push({
      itemId: itemId,
      score: ensembledScore.score,
      confidence: ensembledScore.confidence,
      modelContributions: this.calculateModelContributions(item, modelPredictions),
      explanations: this.combineExplanations(item)
    })

  return ensembledItems.sort((a, b) => b.score - a.score)

function calculateMetaLearnerScore(item, userId, context):
  // Prepare features for meta-learner
  features = []

  // Model confidence features
  for [modelName, confidence] in item.modelConfidences:
    features.push(confidence)

  // Model score features
  for [modelName, score] in item.modelScores:
    features.push(score)

  // User context features
  userFeatures = this.extractUserContextFeatures(userId, context)
  features.push(...userFeatures)

  // Item context features
  itemFeatures = this.extractItemContextFeatures(item.itemId, context)
  features.push(...itemFeatures)

  // Temporal features
  temporalFeatures = this.extractTemporalFeatures(context)
  features.push(...temporalFeatures)

  // Predict final score using meta-learner
  prediction = this.metaLearner.predict(features)

  return {
    score: prediction.score,
    confidence: prediction.confidence
```

```
  }

function applyDiversification(recommendations):
  if this.config.diversification.algorithm === 'mmr':
    return this.applyMMR(recommendations)
  else if this.config.diversification.algorithm === 'dpp':
    return this.applyDPP(recommendations)
  else:
    return this.applyGreedyDiversification(recommendations)

function applyMMR(recommendations):
  // Maximal Marginal Relevance for diversification
  selectedItems = []
  remainingItems = [...recommendations]
  lambda = this.config.diversification.lambda

  // Select first item (highest relevance)
  if remainingItems.length > 0:
    selectedItems.push(remainingItems.shift())

  while selectedItems.length < recommendations.length and remainingItems.length > 0:
    maxMMRScore = -Infinity
    bestItemIndex = -1

    for i in range(remainingItems.length):
      item = remainingItems[i]

      // Calculate MMR score
      relevanceScore = item.score

      // Calculate max similarity to already selected items
      maxSimilarity = 0
      for selectedItem in selectedItems:
        similarity = this.calculateItemSimilarity(item.itemId, selectedItem.itemId)
        maxSimilarity = Math.max(maxSimilarity, similarity)

      // MMR formula:   * relevance - (1- ) * max_similarity
      mmrScore = lambda * relevanceScore - (1 - lambda) * maxSimilarity

      if mmrScore > maxMMRScore:
        maxMMRScore = mmrScore
        bestItemIndex = i

    if bestItemIndex >= 0:
      selectedItems.push(remainingItems.splice(bestItemIndex, 1)[0])
```

```
    return selectedItems

  function calculateModelContributions(item, modelPredictions):
    contributions = new Map()
    totalWeight = 0

    for modelPrediction in modelPredictions:
      if item.modelScores.has(modelPrediction.modelName):
        score = item.modelScores.get(modelPrediction.modelName)
        weight = modelPrediction.weight

        contributions.set(modelPrediction.modelName, {
          score: score,
          weight: weight,
          normalizedContribution: score * weight
        })

        totalWeight += weight

    // Normalize contributions
    for [modelName, contribution] in contributions:
      contribution.normalizedContribution /= totalWeight

    return contributions
```

5. Real-time Personalization Engine

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Purpose: Provide real-time recommendation updates based on immediate user interactions and contextual changes.

Contextual Bandits for Real-time Learning:

```
RealTimePersonalizationConfig = {
  algorithm: 'contextual_bandits',     // 'contextual_bandits', 'online_learning'

  bandits: {
    algorithm: 'linear_ucb',           // 'epsilon_greedy', 'ucb', 'linear_ucb', 'thomps
    alpha: 0.2,                        // Confidence parameter
    dimension: 100,                    // Feature dimension
    lambda: 1.0                        // Regularization parameter
  },
```

```
  contextFeatures: {
    user: ['demographics', 'behavior_history', 'current_session'],
    item: ['content_features', 'popularity', 'freshness'],
    temporal: ['time_of_day', 'day_of_week', 'season'],
    environmental: ['device', 'location', 'weather']
  },

  updateStrategy: {
    frequency: 'immediate',            // 'immediate', 'batch', 'periodic'
    rewardDelay: 300000,              // 5 minutes max delay for reward
    explorationRate: 0.1              // 10% exploration
  }
}

class RealTimePersonalizationEngine:
  constructor(config):
    this.config = config
    this.contextualBandits = new LinearContextualBandits(config.bandits)
    this.featureExtractor = new ContextualFeatureExtractor()
    this.rewardTracker = new RewardTracker()
    this.sessionManager = new UserSessionManager()

  function getPersonalizedRecommendations(userId, context, numRecommendations):
    # Extract current context features
    contextFeatures = this.featureExtractor.extract(userId, context)

    # Get candidate items
    candidates = this.getCandidateItems(userId, context)

    # Score candidates using contextual bandits
    scoredCandidates = []

    for candidate in candidates:
      candidateFeatures = this.featureExtractor.extractItemFeatures(candidate, context)
      combinedFeatures = this.combineFeatures(contextFeatures, candidateFeatures)

      # Get bandit prediction with confidence bounds
      prediction = this.contextualBandits.predict(combinedFeatures)

      scoredCandidates.push({
        itemId: candidate.id,
        score: prediction.expectedReward,
        confidence: prediction.confidenceBound,
        features: combinedFeatures,
        explorationBonus: prediction.explorationBonus
```

```
    })

  # Balance exploration and exploitation
  finalCandidates = this.balanceExplorationExploitation(scoredCandidates)

  # Track recommendations for reward learning
  recommendationIds = finalCandidates.slice(0, numRecommendations).map(c => c.itemId)
  this.trackRecommendations(userId, recommendationIds, contextFeatures)

  return finalCandidates.slice(0, numRecommendations)

function updateWithFeedback(userId, itemId, feedbackType, context):
  # Convert feedback to reward signal
  reward = this.convertFeedbackToReward(feedbackType, context)

  # Get the features used for this recommendation
  recommendationFeatures = this.getRecommendationFeatures(userId, itemId)

  if recommendationFeatures:
    # Update contextual bandit with reward
    this.contextualBandits.update(recommendationFeatures, reward)

    # Update user session state
    this.sessionManager.updateSession(userId, {
      itemId: itemId,
      feedback: feedbackType,
      reward: reward,
      timestamp: Date.now()
    })

    # Trigger real-time model updates if needed
    if this.shouldTriggerModelUpdate(userId, reward):
      this.triggerModelUpdate(userId)

function balanceExplorationExploitation(candidates):
  explorationRate = this.config.updateStrategy.explorationRate

  # Sort by expected reward + exploration bonus
  candidates.sort((a, b) =>
    (b.score + b.explorationBonus) - (a.score + a.explorationBonus)
  )

  # Implement epsilon-greedy exploration
  finalCandidates = []
```

```
  for i in range(candidates.length):
    if Math.random() < explorationRate:
      # Exploration: select based on confidence/uncertainty
      explorationCandidate = this.selectExplorationCandidate(candidates)
      finalCandidates.push(explorationCandidate)
    else:
      # Exploitation: select best predicted candidate
      finalCandidates.push(candidates[i])

  return finalCandidates

function convertFeedbackToReward(feedbackType, context):
  rewardMapping = {
    'click': 1.0,
    'view': 0.5,
    'like': 2.0,
    'share': 3.0,
    'purchase': 10.0,
    'ignore': 0.0,
    'dislike': -1.0,
    'block': -5.0
  }

  baseReward = rewardMapping[feedbackType] || 0.0

  # Apply contextual modifiers
  if context.timeToFeedback < 10000: # Quick feedback (< 10 seconds)
    baseReward *= 1.2

  if context.sessionPosition === 1: # First recommendation clicked
    baseReward *= 1.1

  return baseReward

function extractContextualFeatures(userId, context):
  features = []

  # User features
  userProfile = this.getUserProfile(userId)
  features.push(...this.encodeUserFeatures(userProfile))

  # Temporal features
  temporalFeatures = this.encodeTemporalFeatures(context.timestamp)
  features.push(...temporalFeatures)
```

```
    # Session features
    sessionFeatures = this.encodeSessionFeatures(userId, context)
    features.push(...sessionFeatures)

    # Device and environment features
    environmentFeatures = this.encodeEnvironmentFeatures(context)
    features.push(...environmentFeatures)

    return features

  function encodeSessionFeatures(userId, context):
    session = this.sessionManager.getSession(userId)

    return [
      session.duration / 3600000,          # Session duration in hours
      session.pageViews,                   # Number of page views
      session.interactions,                # Number of interactions
      session.conversionEvents,            # Number of conversions
      session.bounceRate,                  # Session bounce rate
      context.positionInSession || 0       # Position in current session
    ]
```

Performance Optimizations

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Real-time Serving Optimization

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Caching and Precomputation Strategy:

```
ServingOptimization = {
  precomputation: {
    userEmbeddings: true,
    itemEmbeddings: true,
    popularityScores: true,
    categoryTrends: true
  },

  caching: {
    userProfiles: { ttl: 3600000, size: 100000 },    # 1 hour, 100K users
```

```
    recommendations: { ttl: 1800000, size: 50000 },   # 30 minutes, 50K sets
    modelPredictions: { ttl: 600000, size: 200000 }   # 10 minutes, 200K predictions
  },

  approximation: {
    nearestNeighbors: 'faiss',
    dimensionalityReduction: 'pca',
    quantization: 'product_quantization'
  }
}
```

Model Training Optimization

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Distributed Training Pipeline: - Parallel feature extraction - Distributed model training - Incremental learning updates - A/B testing infrastructure

Security Considerations

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Recommendation Security Framework

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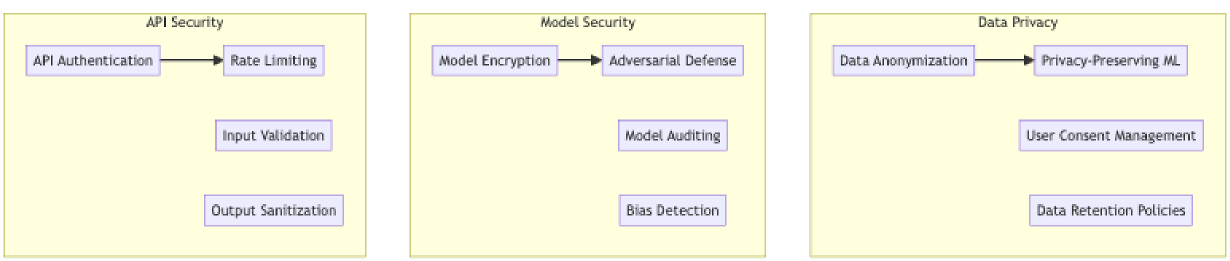

Testing Strategy

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A/B Testing Framework

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Experimentation Platform: - Multi-armed bandit testing - Statistical significance testing - Business metric tracking - Model performance comparison

Model Evaluation

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Evaluation Metrics: - Precision, Recall, F1-Score - NDCG (Normalized Discounted Cumulative Gain) - Diversity metrics - Novelty and serendipity measures

Trade-offs and Considerations

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Accuracy vs Explainability

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- **Complex models**: Higher accuracy vs interpretability
- **Feature engineering**: Performance vs transparency
- **Ensemble methods**: Robustness vs complexity
- **Deep learning**: Pattern recognition vs explainability

Personalization vs Privacy

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- **Data collection**: Personalization quality vs privacy concerns
- **Model complexity**: Individual targeting vs data minimization
- **Cross-platform tracking**: Consistency vs privacy
- **Real-time updates**: Responsiveness vs data protection

Exploration vs Exploitation

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- **Recommendation diversity**: Discovery vs relevance
- **New item promotion**: Novelty vs proven preferences
- **Long-tail coverage**: Comprehensive catalog vs popular items
- **User engagement**: Immediate satisfaction vs long-term value

This machine learning recommendation engine provides a comprehensive foundation for personalized recommendations with features like advanced collaborative filtering, content-based analysis, deep learning models, hybrid ensembles, and real-time personalization while maintaining high accuracy, scalability, and user privacy standards.