# Workshop 1: Apply System Design Framework to Netflix || ~~Facebook~~

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## Step 1. Understand the problem and establish design scope:

**Functional Requirements:**

- Support For Play / Pause, Fast Forward, Rewind
- Creation / Login User Profiles, Curated Recommendations, Search
- Account State Management
- Subscription Management

**Non-Functional Requirements**

- Low Latency
- High Availability
- Fault Tolerance
- Cost Efficiency
- Scalability {}

**Workloads & Constraints**:

- Mainly read-heavy
- Large Media Files
- Heavy Network Bandwidth Consumption
- Global Distribution Needed

## Assumptions & Estimations:

> Tip
>
> # High Level Assumptions
>
> **Average Movie Size:**
>
> - Average Movie Length[1]: $\approx 131 \text{minutes}$

- Uses Adaptive Bitrate Streaming via DASH[2], so no clear way to determine, but, they[3] state the following:
  - (The following are adjusted estimates because of the shorter average runtime)
    - Standard Definition (SD): Approximately 1.2 GB.
    - High Definition (HD): Approximately 3.5 GB.
    - Ultra High Definition (4K): Approximately 7 GB.

**Estimate % based on quality**

- All titles are probably in SD (100%)
- HD for say 80%
- 4K for say 30%

**Weighted Average:**

- (1.0 * 1.2GB) + (0.8 * 3.5GB) + (0.3 * 7GB) = ~ 6GB approx

**Number Of Titles:**

- Total Titles: Depends on the region, US had ≈ 6,621 movies[4]; AUS had ≈ 4,462 movies[5], so globally ≈ 7000 titles total.

Therefore Sum Total: $\approx 6\text{GB} \times 7000\text{titles} = \approx 42\text{TB}$

- DAU[6]: $\approx 302\text{M} \times 0.5 \approx 151\text{M}$
- Each user watches $\approx 5$ titles per day, that's $\approx 775$ Million titles Watched Per Day.
- Assuming a 200:1 read to write ration, that's $\approx 3.875$ Million titles written per day.
  - thats, $3.875M \times 6\text{GB} \approx 23\text{TB}$
- Total File Size: $\approx 98\text{TB}$

Tip

## QPS Estimation

**Read QPS:**

- Reads Per Day = $3.875M \times 200 = 775M$
- Per Second = $\frac{775M}{24 \times 60 \times 60} \approx 9000 rps$

**Write QPS:**

- Writes Per Second = $\frac{3.875M}{86400} \approx 45wps$

Note

## QPS SUMMARY

- Reads: ~9k/s
- Writes: ~45/s
- Peak Traffic:
  - Reads: 18k/s
  - Writes: 90/s

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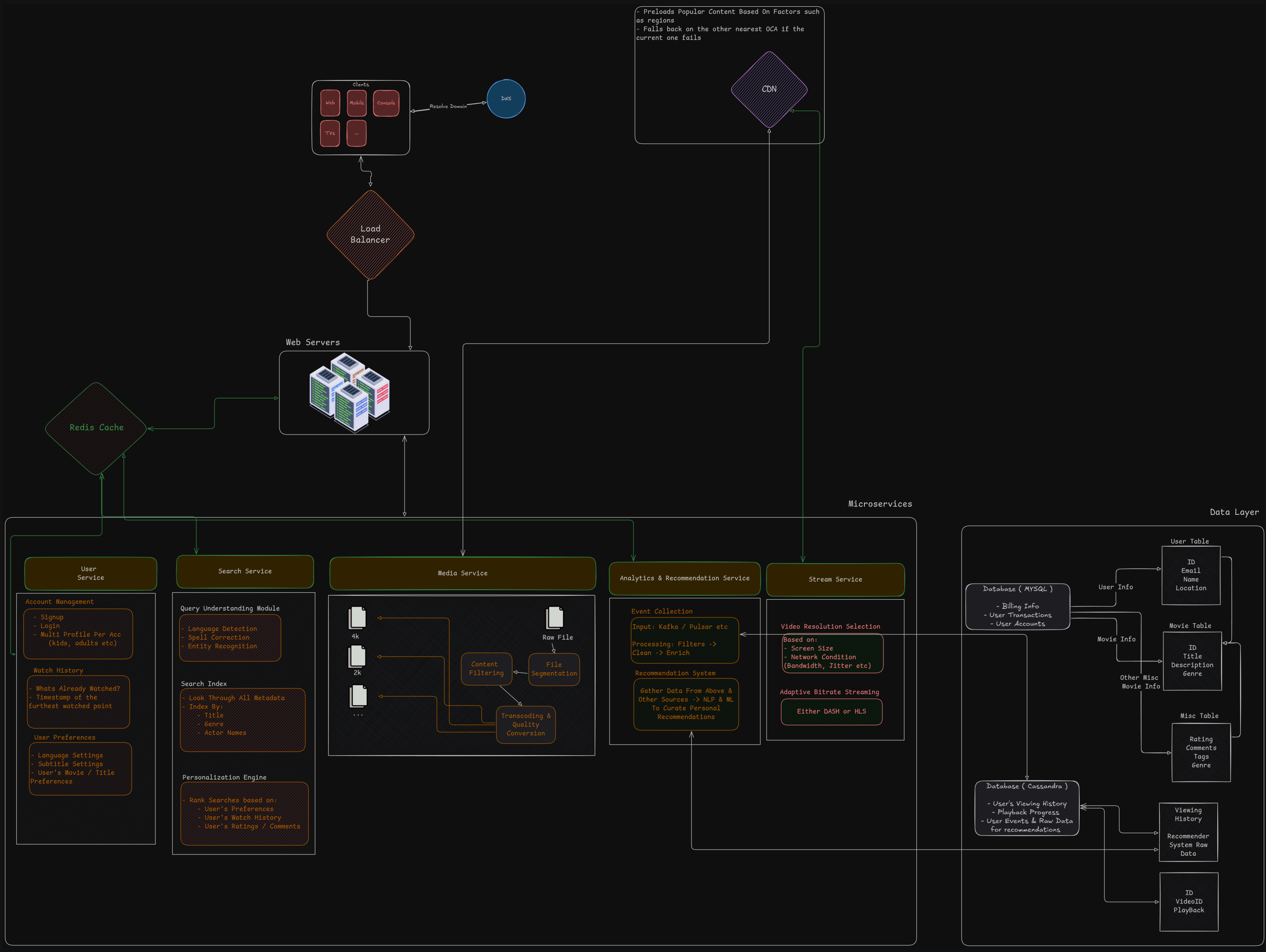
## Step 2. Propose a High-Level Design and Get Buy-In:




## Step 3: Dive into the details

### Identify Bottlenecks & Mitigation:

| Component | Potential Bottleneck | Mitigation Strategy |
|---|---|---|
| CDN | Sudden traffic spikes during premieres | Use regional CDNs, cache popular content aggressively |
| Auth Service | Mass Login(e.g., new movie drop) | Introduce rate limiting, cache auth tokens, async session validation |
| Recommendation Engine | Heavy ML model computation | Use pre-computed recommendations with nightly batch jobs, cache results |
| Video Transcoding | CPU-intensive and slow | Do it asynchronously, use specialized GPU clusters, queue |

| Component | Potential Bottleneck | Mitigation Strategy |
|---|---|---|
| | | using priority system |

**Replication & Scaling Plan**

| Layer | Strategy |
|---|---|
| **Video Storage** | Globally replicated via object stores |
| **Databases** | Partition by region + entity (user_id, movie_id); strong consistency only where needed |
| **User Profiles** | Eventually consistent replicas, cache-first design |
| **Recommendations** | Pre-generated |

**Resilience Methods**

| Component | Resilience Strategy |
|---|---|
| All Services | Circuit Breakers |
| Microservices Comm. | Timeout fallback responses, dead-letter queues for failed jobs,latency monkey |
| Data Loss | Daily backups, versioned storage buckets |
| Chaos Monkey | Randomly kills instances to test auto-healing; Netflix uses it in prod |
| UI | Graceful fallback ("Try Again", offline support, loading states, degraded mode) |

**Tradeoff Vitals**

| Trade-off | Netflix Approach |
|---|---|
| **Latency vs Cost** | Pay premium for low-latency CDNs, cache content close to users |
| **Consistency vs Availability** | Prioritize availability, use eventual consistency for user-generated data |
| **Durability vs Speed** | Use write-ahead logs + background replication to balance |
| **Batch vs Real-time Processing** | Batch for ML workloads, real-time for metrics and playback data |

### Step 4: Wrap Up with Bottlenecks, Improvements, and Scaling Paths

**Fallback & Recovery**:

- Auth Faliure -> Serve Cached Session Tokens
- Recommendation Engine Faliure -> Default Popular Titles or user's past favourites
- Search Timeout -> Show default category

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## Comparison: This vs Real-World Netflix System

This architecture aims to capture a solid high-level overview of how a streaming service like Netflix could function. It includes key components such as client devices (TV, web, mobile), DNS resolution, media services (filtering, segmentation, transcoding), and a search system with language detection and metadata indexing.

However, in reality, Netflix's architecture is far more complex and optimized for massive scale. Some of the more obvious differences include:

- DNS Resolution: While DNS resolution does happen, Netflix uses AWS Route53 along with their proprietary global traffic controller to route users to the closest Open Connect CDN edge server, not just a simple domain resolution.
- Media Service: The media pipeline involves studio-level ingestion, automated quality checks, and multiple encoding passes tailored for device and network conditions—handled by their internal tools like Cosmos and Titus.

- Search & Recommendation: For search and recommendations, Netflix goes beyond metadata indexing. Their system uses a knowledge graph, deep learning-based query understanding, and reinforcement learning models to personalize rankings in real time. Playback is handled via adaptive bitrate streaming (DASH), with manifests generated dynamically per device.
- Faliure & Recovery: The real Netflix architecture emphasizes resilience through heavy chaos engineering. They use tools like Chaos Monkey, Janitor Monkey, Latency Monkey etc. They have multi-level fallback strategies and have predictive scaling.
- Data Storage: Netflix uses a mix of Cassandra, DynamoDB, EVCache , and multi-layered object storage (S3) with tunable consistency per data type. They replicate data globally with region-aware routing and carefully balance consistency and availability depending on the service needs.
- Tradeoffs: Cost vs Latency is heavily optimized in the real Netflix, they own their own CDNs to cut costs, while keeping the latency low. Recommendations are updated near real-time using multiple ML models running simultaniously

While a high-level architecture can capture the essential components of a streaming platform—such as media processing, user authentication, content delivery, and recommendation systems—the real-world implementation at Netflix demonstrates the immense complexity required to operate at global scale. Netflix's system is deeply optimized for reliability, performance, and cost-efficiency through advanced tools, automated pipelines, and intelligent traffic management. Their use of chaos engineering, real-time personalization, and globally distributed infrastructure illustrates how engineering is critical to delivering seamless streaming experiences to hundreds of millions of users worldwide.

**Scaling Path: 1M -> 100M**

| Phase | Action |
| --- | --- |
| 1M → 10M | Horizontal scaling, CDN expansion, DB sharding by region/entity |
| 10M → 100M | Multi-region data centers, async pipelines for all writes, stronger cache hierarchy |

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1. https://thedailyaztec.com/117837/opinion/despite-growing-criticism-the-length-of-movies-arent-getting-too-long/ ↩
2. https://www.quora.com/Does-Netflix-use-Dash ↩
3. https://www.quora.com/What-is-the-average-size-of-a-3-hour-movie-file-on-Netflix ↩

4. https://www.whats-on-netflix.com/news/netflix-originals-now-make-up-55-of-us-library/ ↩

5. https://www.tomsguide.com/reference/netflix-price-australia ↩

6. https://evoca.tv/netflix-user-statistics/#:~:text=How Many Subscribers Does Netflix,subscribers in the last year.&text=The United States And Canada,Region as of Q3 2024. ↩