CV Prep

Here's how you can **structure your storyline** and prepare for **real-world interview questions** based on your **Food Recommendation System using SVD, collaborative & content-based filtering**, and your deployment pipeline using **TensorFlow Lite, Firebase, GCP, etc.**

✅ Your Best Storyline (Interview-Ready Pitch)

> "I built a real-time personalized food recommendation system that integrates both collaborative filtering and content-based techniques. For collaborative filtering, I implemented SVD to learn latent user-item preferences. For content-based filtering, I utilized food metadata, ingredients, and user-tag interactions.
>
> I deployed the model using TensorFlow Lite for edge inference, allowing faster, on-device recommendations with a 20% improvement in latency. To enhance personalization, I integrated Firebase Analytics to collect real-time feedback. This data was piped through Google Cloud Scheduler and retraining pipelines to periodically fine-tune the model—resulting in a 15% improvement in precision.
>
> The entire pipeline was deployed on GCP using Cloud Run for scalable inference, GA4 for user analytics, and BigQuery for efficient querying of user behavior and food data. Overall, I achieved 90% accuracy and created a robust feedback loop that keeps the model dynamic and responsive."

💬 Common Interview Questions and Best Answers

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1. ❓Why did you choose SVD for collaborative filtering?

Answer:
SVD (Singular Value Decomposition) is a powerful matrix factorization technique that captures latent relationships between users and items. I chose SVD because it works well with sparse data and allows us to uncover hidden patterns, even when we have limited user-food interactions. It provided better generalization and lower RMSE compared to basic neighborhood methods in my experiments.

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2. ❓How did you combine collaborative and content-based recommendations?

Answer:
I used a hybrid approach. First, I generated scores using SVD (collaborative filtering) based on user-item interactions. Then, I calculated content similarity using cosine similarity on food metadata (ingredients, cuisine type, etc.). I weighted both scores—collaborative and content—based on user history and used a blending strategy to recommend top items. This approach helped balance cold-start issues and increased diversity in suggestions.

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3. ❓How does your system handle new users or new food items?

Answer:
For new users (cold start), the system initially relies more on content-based filtering, using tag preferences or demographics if available. For new food items, we match based on content features (ingredients, cuisine, tags) with existing items. As interaction data accumulates, the collaborative part (SVD) becomes more influential.

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4. ❓Why TensorFlow Lite?

Answer:
TensorFlow Lite was used for on-device inference to reduce latency and allow offline functionality. This was important for real-time responsiveness in the app. It led to a 20% faster recommendation delivery compared to server-side models, improving the user experience significantly.

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5. ❓How did you implement real-time feedback?

Answer:
User interactions and feedback (likes, skips, views) were captured using Firebase Analytics and Google Analytics 4 (GA4). These events were logged to BigQuery, and a scheduled job (using Google Cloud Scheduler) would periodically extract recent data and retrain the model. This closed feedback loop helped refine recommendations based on evolving user preferences.

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6. ❓How often is the model retrained?

Answer:
Retraining was scheduled weekly using Google Cloud Scheduler. Depending on the volume of new interactions, the frequency could be adjusted. I used Dataflow for scalable preprocessing and retraining on GCP with the latest data.

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7. ❓What challenges did you face with deployment and how did you solve them?

Answer:
One challenge was handling scaling during peak usage. To address this, I deployed the inference service using **Cloud Run**, which auto-scales based on incoming traffic. Also, ensuring low latency required optimizing the TFLite model and reducing its size using quantization.

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8. ❓How did you evaluate model performance?

Answer:
I used metrics like Precision@K, Recall@K, and NDCG to evaluate recommendation quality. For collaborative filtering (SVD), RMSE was used during training. I also ran A/B tests in the production app using Firebase Remote Config to compare different recommendation strategies and measure engagement uplift.

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9. ❓How does BigQuery fit into your pipeline?

Answer:
BigQuery was used for logging, aggregating, and querying user interaction data at scale. It enabled fast retrieval of clickstream data, which powered model retraining and user analytics dashboards for the product team.

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10. ❓Can you sketch the architecture or data flow of your system?

Answer (you can sketch this if allowed or say verbally):

- **User interaction** (app) → **Firebase Analytics + GA4**
- → logs into **BigQuery**

- → **Cloud Scheduler** triggers pipeline daily
- → **Data Preprocessing** using Dataflow
- → **Model retraining** (SVD + content features) using Vertex AI / GCP
- → Export to **TFLite** and redeploy to app
- → Served via **Cloud Run** or on-device inference

🔥 Bonus: How to End Your Answer

> "This project helped me deeply understand not just the ML part, but also how to make a system production-ready—handling data pipelines, user feedback loops, model deployment, and monitoring. I'm excited to bring this end-to-end thinking to your team."

🔍 Evaluation Metrics and Tools Explained

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1. 🧠 Precision@K

What it is:
Precision at K measures **how many of the top K recommended items are actually relevant** to the user.

Formula:

$$\text{Precision@K} = \frac{\text{Number of relevant items in top K}}{K}$$

In your case:
If the system recommends 5 food items ($K=5$), and the user liked 3 of them, then:

$$\text{Precision@5} = \frac{3}{5} = 0.6 \text{ or } 60\%$$

Why it's used:
To check if the top recommendations are actually **useful** to the user.

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2. 🧲 Recall@K

What it is:
Recall@K measures how well the system captures **all relevant items** in the top K suggestions.

Formula:

Recall@K=Number of relevant items in top KTotal number of relevant items\text{Recall@K} = \frac{\text{Number of relevant items in top K}}{\text{Total number of relevant items}}

In your case:
If a user likes 4 food items and 3 of them are in top 5, then:

Recall@5=34=0.75 or 75%\text{Recall@5} = \frac{3}{4} = 0.75 \text{ or } 75\%

Why it's used:
To ensure that the system is **not missing too many good options** for the user.

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3. 📈 NDCG (Normalized Discounted Cumulative Gain)

What it is:
NDCG considers **not just relevance but also position** in the recommendation list. It rewards systems that show more relevant items **higher up**.

In simple terms:
If a very relevant food is ranked at position 1, it gives more value than if it were ranked at position 5.

Why it's used:
Because **order matters** in recommendations—users are more likely to click the top few options.

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4. 🧮 RMSE (Root Mean Squared Error)

What it is:
RMSE measures the difference between **predicted ratings** and **actual user ratings**.

RMSE=1n∑i=1n(r^i−ri)2\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{r}_i - r_i)^2}

Where:

- r^i\hat{r}_i: Predicted rating by SVD model
- rir_i: Actual rating or interaction (e.g., like/dislike)

Why it's used in training:
To evaluate how well your collaborative filtering (SVD) model is learning from known user-food ratings.

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5. 🧪 A/B Testing

What it is:
A/B testing compares **two versions** of your recommendation system (e.g., SVD-only vs. hybrid model).

How you used it:
You randomly split users into two groups:

- **Group A**: Gets recommendations from Model A (e.g., baseline)
- **Group B**: Gets recommendations from Model B (e.g., improved model with feedback loop)

You then compare performance (click-through rate, dwell time, conversion, etc.)

Why it's used:
To test if the **new model actually performs better** in the real world before rolling it out to everyone.

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6. 🧩 Firebase Remote Config

What it is:
A tool that lets you **dynamically change the app's behavior or UI** without releasing a new version.

How you used it:
You used Remote Config to:

- Switch between recommendation models in A/B testing.

- Roll out new models gradually.
- Personalize logic for different user segments.

Why it's used:
To **safely test or update** your recommendation logic in production without affecting all users at once.

🔄 Summary (Interview-friendly)

Term	Purpose in Recommendation System
Precision@K	Measures how many top K items are relevant (accuracy of top picks)
Recall@K	Measures how much of all relevant items were captured in top K
NDCG	Considers both **relevance** and **ranking position**
RMSE	Evaluates how close your predicted user preferences are to actual ones
A/B Testing	Validates model performance in live environment
Firebase Remote Config	Safely switch between models or settings without code changes

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