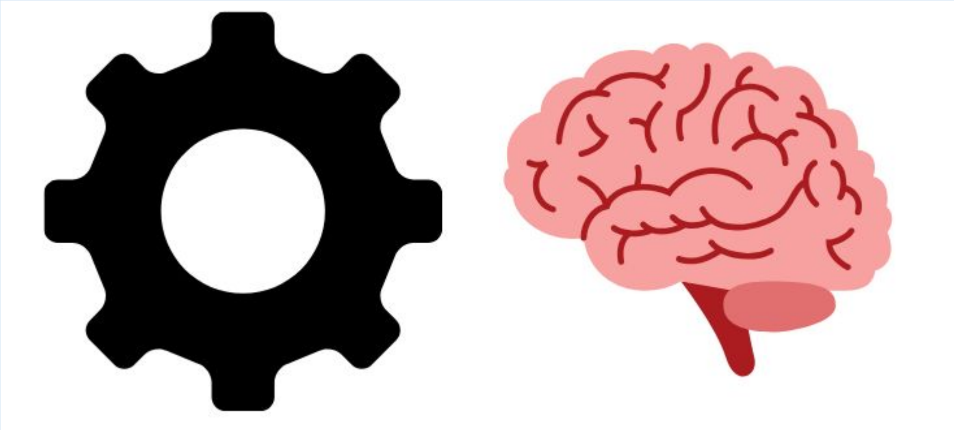
Approaching Applied ML Interviews



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Agenda

- My Journey
- Anatomy of ML Interviews
- How to Prepare
- Sample Case
- Lessons Learned
- Q&A

Introduction

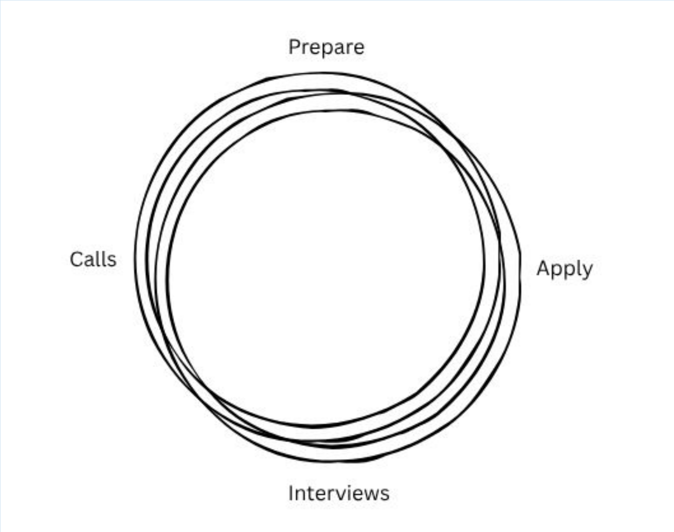
- Applied Researcher @eBay (Current)
- Jefferies (Quant/ML Intern) (Summer 2019)
- PhD, Applied Mathematics and Statistics @Stony Brook
- Quant Researcher @Versor Investments
- BS & MS - Mathematics, Statistics and Computing @ IIT Kharagpur

My Interview Journey

Hedge Funds & Banks

Consulting

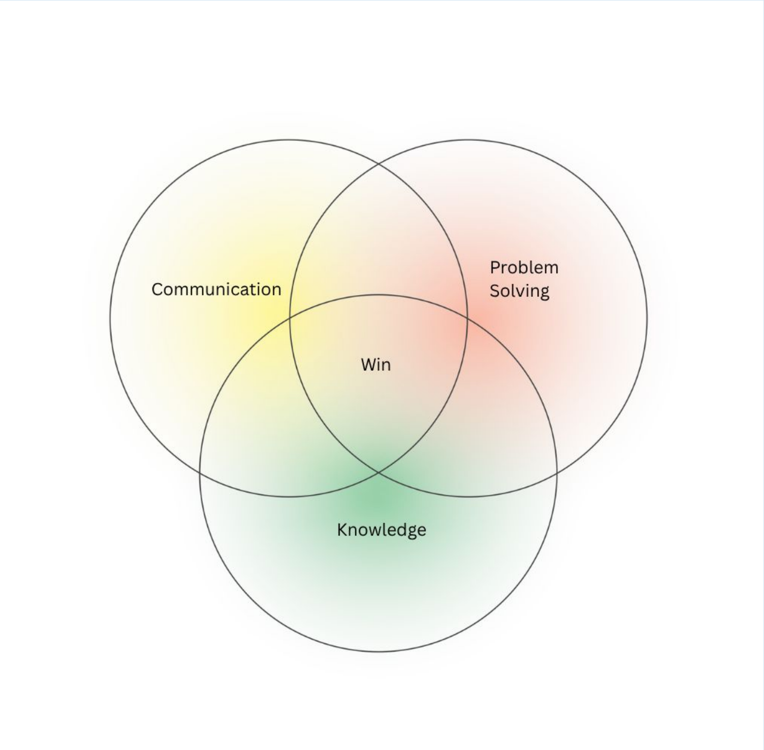
Tech



What Interviews Really Test?

Typical Rounds

- Coding / Leetcode-style problem
- ML fundamentals
- Applied ML / case studies
- System design for ML
- Behavioral and research rounds



Anatomy of Interviews

Round	Focus	Examples
Coding	Algorithms & Data Structures	Leetcode style, Debugging
ML Fundamentals	Bias-Variance Trade Offs, Metrics	F1 score vs accuracy?
Applied ML	Case Study	Design a ETA model
ML System Design	Data flow, Scale etc.	Production?
Behavioral	Team fit, Communication	Tell me about a failed project?

Preparation Framework

Core Knowledge

- Math foundations (linear algebra, probability, optimization)
- ML algorithms (trees, ensembles, neural nets, metrics)
- Practical intuition (what happens if data is skewed, noisy, or unbalanced)

Application Layer

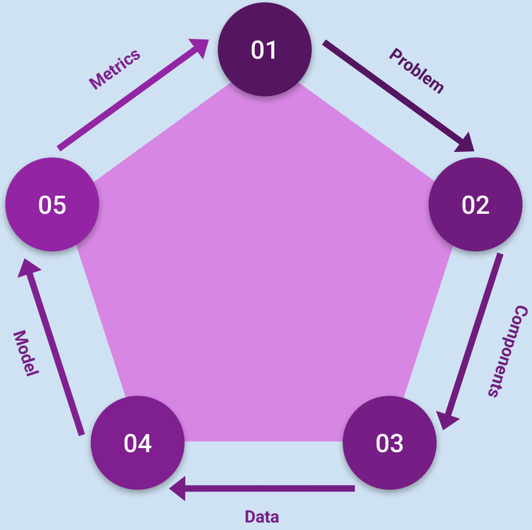
- Case studies: walk through end-to-end pipelines
- Debugging ML systems (data leakage, drift)
- Reading papers efficiently

Practice Layer

- Mock interviews, GitHub projects
- Build small, explain deeply
- Communication: how to narrate your thought process

Sample ML Design - ETA Prediction

- Understand the Objective/Requirements
- Define the Scope
- Identify Key Components
- Define Metrics
- Iterate between System and ML



Goal: Demonstrate Thinking

Understand the Objective

- What exactly are we predicting or optimizing?
  - ETA for a given route and time.
- Who are the users, and what does “good” mean?
  - Drivers need accurate, real-time, trustworthy ETAs.

Define the System Scope

- Inputs: GPS traces, map data, live traffic, weather.
- Outputs: ETA (and confidence) per route.
- Constraints: Latency, scale, freshness, privacy.

Identify Key Components

- Data pipeline
- Feature engineering
- Model
- Serving
- Feedback loop

Define Metrics Early

- Model Metrics - Accuracy, Early or Late
- System Metrics - Latency, Reliability
- Product Metrics - User Satisfaction, Coverage

Goal & Data

Goal / Problem:

- Predict arrival time for a route given origin, destination, route path, and context (traffic, time of day, etc.).
- Output must be accurate, adaptive, and fast.

Key Data Sources:

- Historical trip data: GPS traces, start/end times, distance, route segments.
- Real-time signals: live traffic speeds, incidents, weather, construction.
- Map graph data: road network topology, segment lengths, speed limits.
- Contextual data: time of day, day of week, holidays, events.

Processing:

- Map-match raw GPS data to road segments.
- Aggregate speed/time distributions per segment × time window.
- Filter out anomalies (e.g., driver stops, GPS jumps).

System Components & ML Roles

Component	Function	ML / Data Role
Data Ingestion & Cleaning	Collect GPS and traffic data	Noise filtering, map-matching (HMM / sequence models)
Speed Estimation per Segment	Estimate travel speed for each road	Time-series regression, Bayesian smoothing
Route ETA Prediction	Aggregate segment times along route	Gradient boosting / GNN / Seq2Seq
Real-Time Adjustment	Adjust ETA as conditions change	Online learning / Kalman filter
Personalization Layer	Adapt to driver or vehicle type	Contextual modeling (meta-features)

Metrics and Evaluation

Metric Type	Example	Purpose
Accuracy	MAE / MAPE between predicted and actual arrival time	Core performance
Calibration	% trips arriving within ±5% of predicted	Reliability
Freshness	Latency of traffic updates	Real-time responsiveness
Coverage	% of routes with ETA prediction available	System completeness
User Impact	Trip satisfaction, navigation corrections	Product validation

Common Pitfalls & Lessons learned

- Over Focusing on Jargons
- Ignoring basics like evaluation or data
- Not explaining trade-offs clearly
- Burning out before interview day

- Consistency beats intensity
- Learn to explain ideas simply
- Rejection = redirection
- Build what you love — it shows

"You don't rise to the level of your expectations — you fall to the level of your preparation."

"ML interviews aren't about proving perfection — they're about showing curiosity, clarity, and growth"

My Interview Journey - Stories

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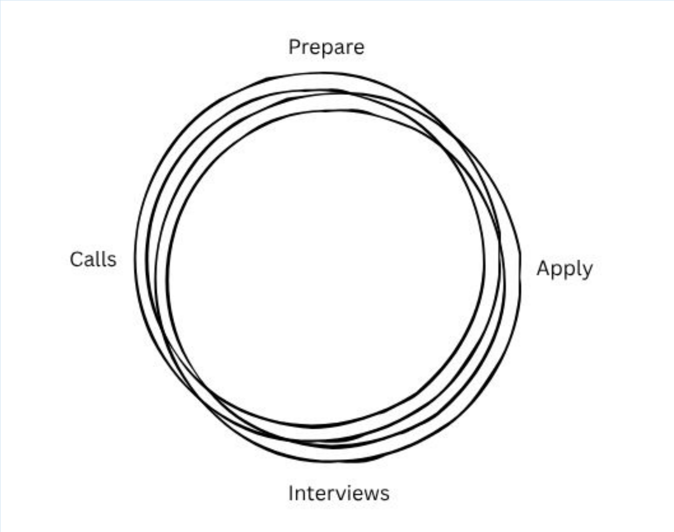

Questions?