Are Right, A Lot

Question: Tell me about a time when you were wrong and had to change your approach.

Response: Situation: At Intuit, I was leading the development of a churn prediction model for TurboTax to identify and retain users who might abandon the tax filing process. Initially, I designed a single, comprehensive model to be used throughout the entire tax season.

Task: I needed to design and build an effective churn prediction system that would accurately identify at-risk users and enable targeted retention actions.

Action: I spent several weeks developing a sophisticated XGBoost model trained on historical data from previous tax seasons. I was confident in my approach of using a single unified model, believing it would be more efficient and easier to maintain than multiple models.

During a review meeting, one of my team members challenged this fundamental assumption. He presented compelling evidence that different user segments exhibited distinct abandonment patterns throughout the tax season: early filers (typically expecting refunds) behaved differently from mid-season filers (often with investment income) and late filers (typically with balances due).

Initially, I defended my unified model approach, citing advantages in maintenance and consistency. However, as I listened to his reasoning and examined the data he presented, I recognized he was right and I was wrong. The seasonal patterns were clear, and a one-size-fits-all approach was suboptimal.

I changed course and worked with the team to:

1. Segment our users based on filing timeline and tax situation
2. Build separate specialized models for each major season segment
3. Incorporate unique feature sets relevant to each user segment
4. Develop a framework to smoothly transition between models

Result: This pivot to a segmented modeling approach improved our prediction accuracy by 27% and led to more effective, targeted interventions. The improved churn prediction system reduced abandonment rate by 0.25%, resulting in $10 M in additional revenue. This experience reinforced the importance of remaining open to different perspectives and valuing team input, even when it contradicts your initial direction. By acknowledging I was wrong and embracing my team member's insight, we achieved a far better outcome than would have been possible with my original approach. I now actively seek contradictory viewpoints on all my projects, recognizing that being right often comes from being willing to admit when you're wrong.

Learn and Be Curious

Question: Tell me about something that you learned recently in your role.

Response: Situation: When leading Intuit's Tax Assistant/Copilot project, I realized we needed to optimize our LLM fine-tuning approach to improve response accuracy.

Task: I needed to investigate and implement more advanced fine-tuning methodologies beyond traditional supervised learning to achieve better alignment with user expectations.

Action: I immersed myself in learning about Direct Preference Optimization (DPO), a newer technique that serves as a more efficient alternative to Reinforcement Learning from Human Feedback (RLHF). I:

1. Dedicated personal time to studying research papers on preference optimization, particularly the original DPO paper from Stanford/Berkeley researchers
2. Set up a Sagemaker instance leveraging A100 GPUs to accommodate the computational requirements of fine-tuning LLMs
3. Focused specifically on implementing DPO for the Mistral 7B model using Hugging Face's DPO Trainer class
4. Developed a systematic approach to collect high-quality preference pairs from tax experts, creating a curated dataset of preferred vs. non-preferred responses
5. Setup an evaluation framework to measure improvements in response quality

Result: This learning journey resulted in implementing a DPO-based fine-tuning pipeline for Mistral 7B that improved response accuracy by 24% compared to our previous methods. The optimized model required significantly less training time and computational resources than traditional RLHF approaches while delivering superior results. I also shared this knowledge across teams through documentation and workshops, establishing it as a best practice for future GenAI projects at Intuit. This experience exemplifies my commitment to continuous learning - I wasn't satisfied with using standard approaches and pushed myself to master cutting-edge techniques that delivered significantly better results.

Earn Trust

Question: Tell me about a time when you had to earn the trust of a skeptical stakeholder or team.

Response: Situation: When kickstarting the LLM-based Tax Assistant initiative at Intuit, I faced significant skepticism from the legal and compliance teams. They expressed serious concerns about AI potentially providing incorrect tax advice, misinterpreting regulations, or creating substantial liability issues for the company.

Task: I needed to earn the trust of these stakeholders to gain their support for this innovative but potentially risky initiative, as their approval was essential for the project to proceed and would ultimately determine whether millions of customers would benefit from this technology.

Action: I took a systematic approach to build trust with these skeptical teams:

1. Acknowledged their concerns openly and treated them as legitimate rather than dismissing them as obstacles to innovation
2. Organized educational sessions on LLM capabilities and limitations, translating complex AI concepts into business and legal terminology they could relate to
3. Collaborated with them to develop specific guardrails and safety measures, including:
    - Implementing robust toxicity and bias detection mechanisms
    - Creating clear boundaries for out-of-scope questions the system shouldn't answer
    - Designing systems to prevent prompt leakage and protect sensitive information
4. Built a small proof-of-concept that demonstrated these safety measures in action
5. Created a transparent evaluation framework that illustrated AI reasoning for a set of test cases specifically designed to measure hallucination rates in tax-related scenarios
6. Invited legal and compliance teams to participate in regular review sessions where they could test the system themselves and identify potential issues
7. Incorporated their feedback into the core design process rather than treating it as an afterthought or compliance checkbox

Result: Over a three-month period, I transformed the legal and compliance teams from blockers into active collaborators and champions of the initiative. What began as skepticism evolved into genuine excitement about creating an innovative solution that could safely help customers navigate tax complexity. The trust-building process resulted in a significantly stronger product with robust safeguards. The framework we developed has since become the standard for responsible AI deployment across Intuit, with legal and compliance teams now proactively engaging with new AI initiatives. This experience reinforced my conviction that earning trust doesn't come from persuasion tactics but from demonstrating genuine respect for others' perspectives, maintaining complete transparency, and willingly adapting plans to address legitimate concerns.

Dive Deep

Question: Tell me about a time when you dove deep to understand an issue.

Response: Situation: At Ticketmaster, we faced a critical issue with our Verified Fan program where sophisticated scalpers were bypassing our detection systems to secure large blocks of tickets for high-demand concerts, preventing genuine fans from attending shows. Despite our standard measures, these scalpers were successfully acquiring approximately 20% of available inventory for major events.

Task: As the Lead for this initiative, I needed to understand how these scalpers were evading our detection systems and develop effective countermeasures to protect ticket inventory for real fans.

Action: I dove deep into this problem through a methodical investigation:

1. Personally analyzed registration and purchase patterns from the last 10 major concert tours and documented scalper behaviors involving identity data (email, phone, ip, device fingerprint)
2. Extracted and analyzed raw network data including IP information, device fingerprints, browser signatures, and timing patterns
3. Wrote specialized SQL queries that revealed subtle connections between seemingly unrelated user accounts
4. Discovered that scalpers were operating in coordinated rings, with each individual account staying below detection thresholds
5. Built custom visualization tools to map the complex networks of connected accounts, devices, and behaviors

Result: My deep dive revealed that scalpers were operating in sophisticated fraud rings using distributed networks of accounts with carefully managed behavior to appear legitimate when viewed individually. I realized our traditional ML algorithms were fundamentally limited by their assumption that data points are independent and identically distributed (i.i.d.), which prevented them from capturing the relational nature of scalper networks. This insight led me to implement a GraphSAGE-based graph neural network approach that specifically does not assume i.i.d. data, but instead models dependencies between entities. The GraphSAGE model identified subtle connection patterns by representing users, devices, and behaviors as nodes in a graph and analyzing message-passing between them, enabling us to detect coordinated activity that was invisible when analyzing accounts in isolation. This solution reduced scalper ticket acquisitions by 73% for subsequent high-demand events and decreased false positives by 35%, ensuring genuine fans weren't incorrectly flagged.

Deliver Results

Question: Tell me about a time when you overcame a significant obstacle to deliver results.

Response: Situation: At Intuit, our existing system for recommending tax deductions and credits to TurboTax users relied on a cumbersome combination of rule-based logic and multi-label classification. This approach created significant friction with users by requiring them to answer numerous questions, resulting in a low engagement rate of only 4%, far below our target of 10%. With tax season approaching rapidly, we had just eight weeks to implement a solution.

Task: As the Technical Lead, I needed to dramatically improve the recommendation system's performance before the upcoming tax season to meet our 10% engagement target while overcoming both technical limitations and severe time constraints.

Action: I identified that our biggest obstacle was the model's inability to capture sequential user behaviors effectively, requiring too many explicit questions from users. I approached this challenge by:

1. Redesigning our approach to use Transformers4Rec with a BERT4Rec architecture and multi-head self-attention to predict relevant deductions based on user behavior rather than direct questioning
2. Leveraging Nvidia's open-source Transformers4Rec library to accelerate development rather than building from scratch
3. Utilizing our already existing clickstream data pipeline for both training and inference, avoiding the need to build new data infrastructure
4. Establishing daily model evaluation meetings to track improvements and quickly address issues
5. Creating a fallback system to ensure we could seamlessly revert if needed
6. Working with product teams to improve recommendation presentation within tight engineering constraints

Result: We successfully delivered an improved recommendation system that achieved an 11% engagement rate (against our 10% target), contributing $18M in incremental revenue. The system processed over 5 million tax returns during peak season without performance issues. What made this particularly satisfying was overcoming both technical and time constraints to deliver a solution that directly improved customer outcomes by helping them claim deductions they might have otherwise missed. By leveraging existing infrastructure and open-source components strategically, we transformed a high-friction experience into one that felt personalized and intuitive. The architecture we developed became a reference implementation for other recommendation systems at Intuit, demonstrating how to deliver sophisticated ML solutions even under tight deadlines.

Think Big

Question: Tell me about a time when you thought big or innovated in your role.

Response: Situation: In my early days at Intuit, most teams were using traditional ML approaches for targeted use cases with limited scope—recommendation systems operated independently from customer support, which was separate from form preparation assistance.

Task: While my initial mandate was focused on developing point solutions for taxes, I saw an opportunity to fundamentally transform how customers interact with our tax products through a more comprehensive AI-driven approach that would integrate these disparate experiences.

Action: I developed and championed a vision for an AI-first tax experience:

1. Collaborated with product to build a multi-year roadmap for transitioning from isolated ML models to an integrated AI assistant that would combine the strengths of both predictive and generative AI
2. Built a proof-of-concept that demonstrated conversational tax guidance powered by a hybrid system integrating:
   - Our existing predictive models (deduction recommendations, churn prediction, user intent classification)
   - New generative AI capabilities
   - A unified architecture that allowed GenAI systems to trigger predictive AI models
3. Advocated across organization levels, from engineers to C-suite executives, showing how this integrated approach would create exponential rather than incremental value
4. Formed alliances with product, core engg, security, legal, and finance teams to address non-technical challenges
5. Established partnerships with leading AI companies (Anthropic, AWS) to access cutting-edge LLM capabilities
6. Created a feedback loop where customer interactions with the conversational assistant would improve our predictive models, creating a virtuous cycle of enhancement

Result: My big-picture thinking led to the upleveling of Intuit's Tax Assistant/Copilot, which has become a flagship initiative frequently cited in earnings calls and media coverage. What began as a theoretical concept is now generating $50M in incremental revenue and has changed how Intuit approaches AI integration across its product suite. The integration of predictive models with generative AI created a system greater than the sum of its parts—predictive models provide personalized, data-driven insights while the conversational interface makes these insights accessible and actionable. This has transformed the customer experience from form-filling to conversation, dramatically reducing the complexity of tax filing. This initiative has led to multiple patents where I'm listed as first inventor. The integrated approach has become a blueprint for other Intuit products, creating a foundation for AI-first experiences across the company's portfolio.

Customer Obsession

Situation: At Intuit, our research revealed a critical pain point: 78% of TurboTax users experienced significant anxiety during tax preparation, with 42% temporarily abandoning the process due to confusion about tax concepts and eligibility requirements. Traditional solutions (UI improvements, simplified language) were addressing symptoms rather than the core problem: customers needed expert guidance within a self-service product.

Task: As Staff Applied ML Scientist leading TurboTax AI initiatives, I needed to transform the tax preparation experience from form-filling to conversation, reducing anxiety while improving accuracy and completion rates.

Action: I led the development of Tax Assistant/Copilot through a comprehensive approach:

1. **Customer-centered research:**
   - Analyzed 1,000+ support transcripts and conducted 50+ customer interviews to identify tax confusion patterns
   - Created journey maps with emotional tracking to pinpoint key anxiety moments
   - Built a taxonomy of 450+ common tax questions and misconceptions
2. **Technical innovation:**
   - Architected a hybrid LLM system combining retrieval-augmented generation with domain-specific tax models
   - Implemented fine-tuned LLMs (Claude and Mistral) trained on expert tax responses
   - Developed an automated LLM-as-a-judge evaluation framework (patent filed: 18/767,899) to ensure accuracy
3. **Cross-functional leadership:**
   - Led a team of 6 applied scientists and 3 ML engineers while collaborating with product, legal, and UX
   - Established continuous improvement mechanisms using real-time customer feedback

Result: This solution delivered significant impact:

- **Business metrics:** 0.25% conversion increase ($10M revenue), 40% improved response accuracy, 28% reduced support calls
- **Customer experience:** 82% reported improved tax concept understanding, anxiety scores decreased by 47%
- **Strategic impact:** Became Intuit's flagship AI initiative highlighted in earnings calls; multiple patents filed
- **Personal growth:** Established as technical authority on conversational AI systems at Intuit

Customer Obsession

Question: Tell me about a time when you put customers at the center of your work.

Response: Situation: At Ticketmaster, we faced a significant challenge with our high-demand concert events where genuine fans were consistently being shut out of ticket purchases by scalpers who would acquire large blocks of tickets and resell them at 5-10x face value. This created tremendous frustration for fans, artists, and event organizers.

Task: As Lead ML Scientist for the Verified Fan program, I needed to develop a solution that would prioritize genuine fans' access to tickets while effectively identifying and blocking professional scalpers. This required balancing sophisticated fraud detection with a seamless experience for legitimate customers.

Action: I approached this challenge by:

1. Personally analyzing thousands of customer complaints and feedback to understand the emotional impact of being unable to purchase tickets to see favorite artists
2. Conducting direct interviews with fans who had both positive and negative experiences with previous ticket sales to understand their pain points
3. Working directly with artist management teams to understand their vision for who their target audience should be
4. Creating detailed personas of genuine fans versus scalpers based on behavioral patterns
5. Designing our fraud detection algorithms to prioritize fan experience by minimizing false positives
6. Implementing tiered verification levels that applied appropriate friction based on risk, with minimal barriers for clearly legitimate fans (rule based and ML based)
7. Establishing clear communication channels explaining the verification process and why it benefited genuine fans (social media, press releases)

Result: The enhanced Verified Fan system successfully transformed the ticket-buying experience for genuine fans. For major tours using our system, we saw a 73% reduction in tickets appearing on secondary markets at inflated prices, while fan satisfaction ratings increased by 42%. Most importantly, artists reported seeing more genuine fans at their shows rather than just those who could afford secondary market prices. The fan-first approach even garnered public praise from several high-profile artists who appreciated that their true fans were now able to attend shows. By obsessing over the fan experience rather than just building another security system, we created a solution that delivered meaningful value to our primary customers—the fans—while still meeting the business objective of reducing scalper activity.

Invent and Simplify

Question: Tell me about a time you created a simple solution to a complex problem.

Response: Situation: At Ticketmaster, our Verified Fan program faced a critical challenge when several high-profile concert campaigns experienced unexpectedly high scalper success rates, with bad actors acquiring up to 35% of available tickets despite our sophisticated detection systems. This created significant disappointment for genuine fans and damaged trust with artists and promoters.

Task: As an AI Lead, I needed to identify why our otherwise successful scalper detection models were failing for these specific campaigns and develop an efficient solution that could be implemented quickly before upcoming high-value events.

Action: Rather than adding more complexity to our already sophisticated detection systems, I invented a simpler, elegant approach:

1. First, I conducted a thorough root cause analysis, comparing the problematic campaigns to our historical successes
2. Discovered that these campaigns had fundamentally different characteristics from our training data—they were highly localized events with unique fan demographics and behavior patterns
3. Instead of building separate models for different campaign types (which would have been complex to maintain), I designed a simple distribution drift detection system using:
    - A one-class SVM model to establish the "normal" boundary of our training data
    - Autoencoders to measure reconstruction error between new campaign data and historical patterns
    - A threshold-based alert system that would flag when new campaigns diverged too much from training data
4. When significant drift was detected, we implemented an automated re-sampling process that would select training examples more closely matching the current campaign's characteristics
5. Created a streamlined re-training pipeline that could rapidly deploy updated models before ticket sales began

Result: This simple yet effective approach reduced scalper success rates from 35% back down to under 8% for all subsequent campaigns, including several that had characteristics very different from our historical data. What made this particularly effective was that rather than building increasingly complex models to handle every edge case, we invented a simple mechanism to detect when our models needed adjustment and automated the adaptation process. The solution demonstrated that simplicity and adaptability often outperform raw complexity, especially in adversarial settings where patterns constantly evolve.

Invent and Simplify

Question: Tell me about a time you created a simple solution to a complex problem.

Response: Situation: At Intuit, we faced a significant challenge with evaluating the accuracy and quality of responses from our Tax Copilot for TurboTax, which used Large Language Models to provide tax guidance to customers. Traditional evaluation methods were proving inadequate for our needs.

Task: As the AI lead, I needed to develop an efficient and reliable evaluation approach that would ensure tax accuracy while also allowing us to iterate quickly on improvements to the system.

Action: I identified the limitations of our existing evaluation approaches:

1. Tax/Human expert evaluation was extremely thorough but prohibitively time-consuming, requiring 5-7 business days for comprehensive review cycles, which severely hindered our ability to iterate rapidly
2. Standard NLP metrics (BLEU, ROUGE, etc) were quick but showed almost no correlation with what we actually cared about—tax accuracy and compliance with regulations

Rather than accepting this trade-off between speed and quality, I invented a simpler, more elegant solution:

1. Developed an "LLM-as-a-Judge" approach specifically for tax domain evaluation
2. Created a systematic process to encode tax domain knowledge into the judge LLM through carefully crafted prompts and fine-tuning
3. Designed a comprehensive rubric that broke down "tax accuracy" into measurable components
4. Built an evaluation framework that allowed side-by-side assessment of different model versions

Result: This simplified approach transformed our evaluation process, reducing assessment time from 5-7 days to just 2-3 hours while maintaining a 92% correlation with expert human evaluation on tax accuracy. This dramatic improvement in evaluation speed enabled us to increase our iteration velocity by 10x, directly contributing to the 40% improvement in response accuracy we ultimately achieved. The approach was so effective that we filed a patent for the methodology (with me as first inventor), and it has since been adopted across multiple AI projects at Intuit. This exemplifies how sometimes the best way to simplify a complex problem isn't to reduce its scope but to find an elegant approach that addresses the core challenges in a fundamentally new way.

Ownership

Question: Tell me about a time you took on something significant outside your area of responsibility.

Response: Situation: At Intuit, I noticed that our ML models were occasionally experiencing unexpected performance degradation. Upon investigation, I discovered the root cause was data quality issues in upstream data pipelines—an area outside my direct responsibility as the Staff Applied ML Scientist focused on model development.

Task: While not technically my responsibility, I recognized that these data quality issues were fundamentally undermining the effectiveness of our ML systems and would continue to cause problems if left unaddressed. Rather than treating this as "someone else's problem," I decided to take ownership of finding a comprehensive solution.

Action: I took initiative well beyond my defined role:

- Researched tools that could systematically address data quality monitoring and identified PyDeequ (an open-source tool developed by AWS) as an ideal solution for our environment
- Created a detailed proposal outlining how PyDeequ could be implemented to monitor data quality across our data stores, particularly the base tables that fed our ML training pipelines
- Proactively reached out to data engineering and infrastructure teams who owned these pipelines, presenting both the problem and my proposed solution
- Collaborated cross-functionally with:

  - Data engineers to understand their pipeline constraints
  - DevOps teams to establish deployment processes
  - Platform architects to ensure system compatibility
  - Legal teams to address any compliance considerations

- Built a working prototype on a subset of our data to demonstrate effectiveness
- Developed a phased implementation plan that minimized disruption to existing processes
- Created documentation and training materials to ensure the solution would be sustainable long-term

Result: The PyDeequ implementation was successfully deployed across our core data stores, creating an automated monitoring system that proactively identified data quality issues before they affected model performance. This reduced unexpected model degradation incidents by 85% and improved overall data reliability across the organization. What began as an initiative outside my scope became a significant infrastructure improvement that benefited multiple teams long term. This experience reinforced my belief that ownership means caring about the broader mission and long-term success of the company, not just completing assigned tasks within defined boundaries.

Bias for Action

Question: Describe a time when you needed to act quickly to address an urgent situation.

Response: Situation: At Intuit, we faced a critical challenge with our TurboTax churn prediction models (abandonment, FUD, and price sensitivity) just weeks before tax season. The models were showing disappointing offline metrics, significantly below our targets, which threatened our ability to effectively retain users and optimize revenue during the upcoming tax season.

Task: As the AI lead responsible for these models, I needed to dramatically improve performance with extremely limited time—just a few weeks before the tax season commenced. I had to work within significant constraints: no access to additional data sources, no time for extensive experimentation, and the requirement that models remain interpretable (ruling out complex deep learning approaches).

Action: Rather than getting caught in analysis paralysis or requesting timeline extensions, I immediately took decisive action:

1. Recognized that with limited time, we needed to extract more value from our existing data rather than seeking new sources
2. Within 48 hours, designed and implemented an aggressive feature engineering approach focusing on the untapped potential of clickstream data
3. Transformed the last 50 screens visited by users and their timestamps into rich time-series and graph-based features:
    - Created behavioral metrics like screen revisit frequency (how often users returned to the same screen)
    - Calculated session velocity measures (time difference between 1st and 50th screen)
    - Engineered graph-based features (number of incoming/outgoing edges between screens)
    - Extracted statistical properties of time between screens (variance, skewness, kurtosis)
    - Built session complexity metrics (unique screens vs. total screens viewed)
4. Prioritized the evaluation of feature importance to ensure interpretability was maintained
5. Made decisive implementation decisions without waiting for perfect information or consensus

Result: This bias for action resulted in a 35% improvement in offline metrics for our churn prediction models within just one week of work. When deployed, the enhanced models increased conversion rates by 0.25%, translating to approximately $10M in incremental revenue during tax season. This experience reinforced my belief that in time-constrained situations, imperfect action is vastly superior to perfect planning.

Have Backbone; Disagree and Commit

Question: Tell me about a time when you disagreed with a decision but committed to it anyway.

Response: Situation: At Intuit, I developed a price-sensitive churn prediction model for TurboTax that identified users likely to abandon the product due to pricing concerns. The model was part of a retention strategy where users predicted to churn would receive a discount offer to encourage completion of their tax returns.

Task: Initially, we had implemented a 25% discount for at-risk users, which showed strong conversion metrics. However, due to budget constraints, leadership proposed changing the discount to a flat $10 offer regardless of product tier or user price sensitivity score.

Action: Based on my data analysis and understanding of user behavior, I strongly disagreed with this change. I presented a data-driven case against the flat $10 discount:

- Showed historical data demonstrating that users who abandoned due to price typically had a minimum discount threshold of 15-20% to change their decision
- Provided segment analysis revealing that a $10 discount represented less than 5% of the cost for our higher-tier products, making it psychologically insignificant for those users
- Proposed a tiered approach that would maintain budget goals while providing more meaningful discounts to high-value customers

I presented these arguments clearly and respectfully in multiple meetings with leadership, advocating for what I believed would better serve both customers and long-term business interests. However, after thorough discussion, the leadership team made the final decision to proceed with the $10 flat discount due to strict budget constraints and broader revenue strategy considerations.

Once the decision was made, I fully committed to making it as successful as possible:

1. Collaborated with content design team for the offer messaging to maximize the psychological impact of the $10 discount
2. Implemented enhanced targeting to focus on user segments most likely to respond to the smaller discount
3. Created detailed monitoring dashboards to track performance across different user segments

Result: While the $10 discount did result in lower conversion rates than the previous 25% offer (as I had predicted), my commitment to its successful implementation helped minimize the negative impact. The enhanced targeting approach I developed improved response rates by 15% compared to initial projections for the $10 offer. More importantly, the detailed performance tracking I established provided valuable data that later informed a revised discount strategy for the following tax season, where leadership approved a more nuanced approach incorporating elements of my original proposal.

Insist on the Highest Standards

Question: Tell me about a time when you refused to compromise on quality despite pressure to do so.

Response: Situation: At Ticketmaster, we were preparing to deploy a new version of our fraud detection system for the Verified Fan program ahead of several high-profile concert tours. The system used machine learning to distinguish between genuine fans and scalpers, determining who could access ticket inventory. Just two weeks before deployment, our testing revealed that while the system showed overall improved detection rates, it had concerning false positive rates (30%) for a certain customer segments - international fans, using VPNs and shared networks.

Task: As the AI Lead, I needed to determine whether the system met our quality standards for deployment. Business stakeholders were pushing to launch on schedule, arguing that the improved overall detection rate justified accepting higher false positives for minority segments, especially since we were under pressure to protect these high-demand events from scalpers.

Action: I insisted on higher standards by:

1. Refusing to accept that a 30% false positive rate for legitimate international fans was acceptable, even if they represented a smaller segment of our user base
2. Quantifying the negative impact this would have on fan experience and artist relations, showing it would affect approximately 45,000 genuine fans across the upcoming tours
3. Assembling a focused task force to address the specific issue without delaying the entire release
4. Implementing a more sophisticated modeling approach (stacking) that could better distinguish between legitimate VPN usage and suspicious patterns (trusted vs non trusted VPN, IP address associated with known VPN providers, etc – maxmind APIs)
5. Creating a specialized verification path for users flagged in these edge cases, allowing them additional ways to prove legitimacy (e.g. phone call)
6. Personally working extended hours to ensure we could meet both quality standards and timelines

Result: We successfully improved the system to reduce false positives to under 5% for international fan segments while maintaining the enhanced fraud detection capabilities. The system launched on schedule and successfully protected ticket inventory for the tours while ensuring legitimate fans weren't wrongfully excluded. Post-event analysis showed we incorrectly blocked fewer than 800 legitimate fans (who were subsequently assisted through customer service). By insisting on the highest standards for all user segments, not just the majority, we delivered a solution that fulfilled our responsibility to both the business and our customers.

Hire and Develop the Best

Question: Tell me about a time when you helped someone grow and develop in their career.

Response: Situation: At Intuit, I identified that a newly promoted tech lead on my team was struggling with task management and prioritization. Despite strong technical skills, these challenges were affecting both their personal effectiveness and the team's ability to meet project deadlines for our Tax Assistant initiative. The tech lead was becoming increasingly stressed as deadlines approached, and team morale was beginning to suffer.

Task: As AI lead for the group, I needed to help this tech lead overcome these challenges without undermining their authority or confidence. My goal was to transform their performance while providing the support and resources needed for long-term professional growth.

Action: I implemented a comprehensive development approach:

1. Arranged a private one-on-one meeting to understand the specific challenges they were facing, creating a safe space for honest discussion about their difficulties
2. Collaborated with them to conduct a thorough review of their current workload, helping categorize tasks based on urgency and importance using an Eisenhower Matrix approach
3. Identified opportunities for delegation to distribute workload more effectively across the team while empowering other team members
4. Connected them with specialized training resources focused on organizational and time management skills, including workshops on task prioritization and project management methodologies
5. Conducted coaching sessions on effective delegation techniques, helping them become comfortable with distributing responsibility
6. Established regular check-in meetings to monitor progress, provide feedback, and address emerging challenges
7. Created a supportive environment where discussing difficulties was encouraged, allowing for real-time adjustments to the development plan

Result: Within three months, the tech lead demonstrated remarkable improvement in their ability to manage competing priorities. Project deadlines were consistently met, and team productivity improved. Beyond the immediate performance improvements, they gained valuable leadership skills that positioned them for career advancement. This experience reinforced my belief that effective leadership involves recognizing both technical and non-technical growth opportunities for team members and providing the right combination of challenge, support, and resources to help them succeed.

Frugality

Question: Describe a time when you found a way to deliver results with fewer resources.

Response: Situation: At Ticketmaster, we discovered a significant problem with ticket reservation abuse, where bad actors were systematically holding premium seats without purchasing them—artificially restricting inventory for genuine fans. Initial proposals to address this issue involved a complete rearchitecture of our reservation system with an estimated cost of >$1 million and a 6-month implementation timeline. With the upcoming high-demand concert season just 10 weeks away, this expensive, time-intensive solution wasn't feasible.

Task: As the AI lead, I needed to find a cost-effective way to combat this reservation abuse pattern quickly, using minimal resources while still delivering substantial protection for our ticketing inventory and improving the fan experience.

Action: I embraced frugality as a catalyst for creative problem-solving:

1. Utilized available log data we were already collecting rather than implementing new data capture mechanisms, reducing both storage costs and development time
2. Implemented a tiered approach that applied more resource-intensive monitoring only to high-demand events, focusing our limited computational resources where they would have the greatest impact
3. Developed a rules-based filtering system that could identify 80% of the abusive patterns using just 20% of the computational resources a full machine learning solution would require (association rule mining, velocity/email/num of seats pattern)
4. Assembled a small, cross-functional task force of volunteers from different fraud and abuse prevention teams who contributed part-time hours instead of hiring dedicated resources
5. Used existing infrastructure to deploy this lightweight solution

Result: Our frugal approach enabled us to implement an effective reservation abuse detection and prevention system for less than $70,000—just 7% of the originally proposed budget. The solution was fully deployed in 8 weeks, in time for the high-demand concert season. Despite its modest cost, the system reduced reservation abuse by 65% for high-demand events, directly improving fan satisfaction ratings by 40% and increasing legitimate sales conversion rates. Additionally, this rule-based system became the foundation of ML based solution that we developed later. This experience reinforced my belief that resource constraints can drive innovation, and that often the most elegant and efficient solutions emerge when we challenge ourselves to do more with less.