PROJECT PERSONAL NOTE

**Question: why don't i just retrain the model, recalibrate and find a new threshold to ensure FPR < 0.2? why does the paper does not want to find a new threshold?**

**1. Decoupling Principle**

**Core Idea**: The paper’s main goal is to **decouple** the ML model from the business logic (i.e., the decision threshold). In many real-world applications (like fraud detection), changing the threshold frequently can be:

1. **Time-Consuming**
   * Business teams often need to document or approve threshold changes.
   * Repeatedly re-tuning a threshold after each model update adds overhead.
2. **Risky for Consistency**
   * Frequent threshold shifts can lead to unpredictable behaviors from the business perspective (e.g., one month you flag many frauds, another month you miss too many).
3. **Compliance & Regulations**
   * In regulated industries (finance, healthcare), your thresholds may need to remain consistent or require extensive auditing when changed.

By **calibrating** the model, the paper shows how you can keep **one fixed threshold** that reliably corresponds to a specific operational target (e.g., FPR ≤ 0.2) **across multiple retrains**, thus **reducing** the need for repeated threshold fine-tuning.

**2. Stability Over Time**

The paper likely demonstrates experimentally that if the **data distribution** or model’s output distribution has **small** to **moderate** changes:

* **Calibrated Probabilities** remain aligned with the same real-world meaning.
* **Old Threshold** (the numeric probability cutoff) still yields near the same FPR and recall as before.
* **Hence**, recalculating a threshold for every retrain doesn’t significantly improve performance and could create operational friction.

**3. When You Would Recompute the Threshold**

The paper **doesn’t forbid** ever recalculating a threshold—rather, it shows that you **don’t need** to do it **every** time:

1. **Major Distribution Shifts**
   * If new data drastically differ (e.g., new fraud tactics, changed user behavior), the old threshold may no longer yield your desired 0.2 FPR.
   * In that case, you’d **re-run** threshold selection on fresh validation data.
2. **New Business Criteria**
   * If risk tolerance changes (e.g., you now want FPR ≤ 0.1 instead of 0.2), you’d obviously pick a new threshold.

**4. Practical Advantages of Not Recomputing a Threshold**

1. **Reduced Overhead**
   * Many organizations prefer to avoid constantly adjusting thresholds because each adjustment typically requires sign-off from multiple stakeholders, extensive testing, etc.
2. **Predictable Decision Rules**
   * Keeping the threshold the same fosters predictability in business operations or regulatory environments.
3. **Empirical Support in the Paper**
   * The research likely includes experiments indicating that after calibration, reusing the old threshold (under moderate data shifts) yields **comparable** performance to re-finding a new threshold—showing recalibration can handle small shifts without re-tuning the threshold.