Exploring Anomalies in Authentication Logs with Autoencoders

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Introduction

Can we use ML to detect cyber security events at Scale?

Problem Statement

- Cyber security events difficult to detect at scale with non-restrictive lookback windows.
- Too much data!
    - ~30k Adobe Actors.
    - ~1.5 million logins per day.
- How to extract the most probable events of interest.
- How to understand Adobe Employee’s Login behavior.

The Plan

- Use ML to detect and understand anomalies.
- Apply rules to anomalies for specific use cases.
- Return prioritized list of anomalies for human review.
- Explore blending data sources.

What Happens Today

How Most Authentication Software Monitors for Anomalies

~1.5 million Logins

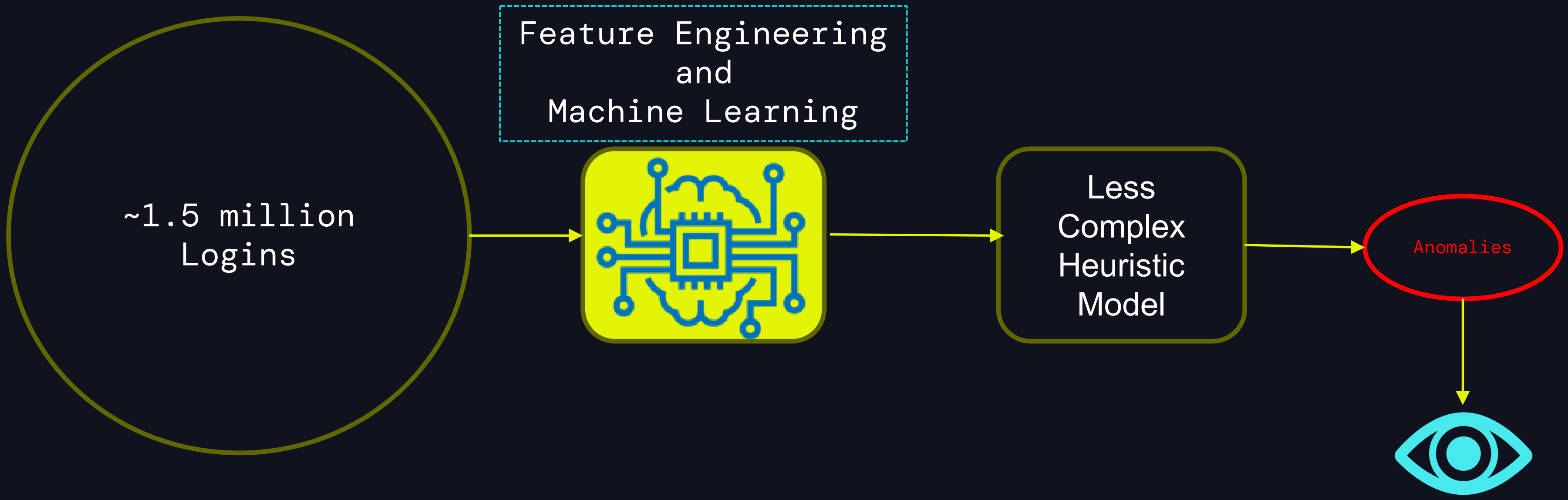
Heuristic Model

- Last 20-50 logins
- Can be increased at cost of compute time
- Hard to capture complex behavior
- Lots of rules, hard to maintain
- Limited to a single data source

Anomalies

Can Machine Learning Help?

Use a model as a filter to eliminate most of the rules.



Machine Learning Challenges

Feature Engineering

Establish User Baselines

- Where do they live?
- What do they use?
- What devices do they have?
- What IP Addresses do they login to?

Encode Violations

- Latitude / Longitude encoding
- How to establish accurate baselines?
- Pyspark / MLFlow to create encodings.

Send them to the model

- Training / Validation Workflow.
- Inference Workflow.
- Model Store.

Feature Engineering

Encoding Multi-dimensional data

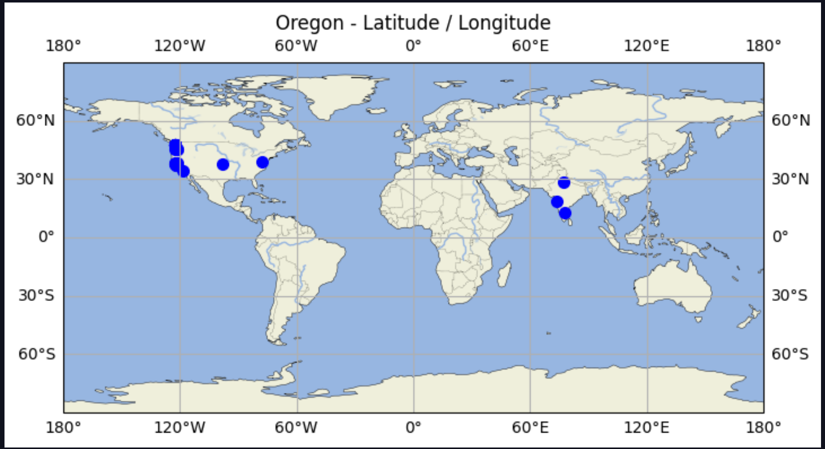
- Break down multi-dimensional features to one dimension
- Need to clean up noise
- Embedding layer may occur too far downstream
- Z-order curve, hashing are good options

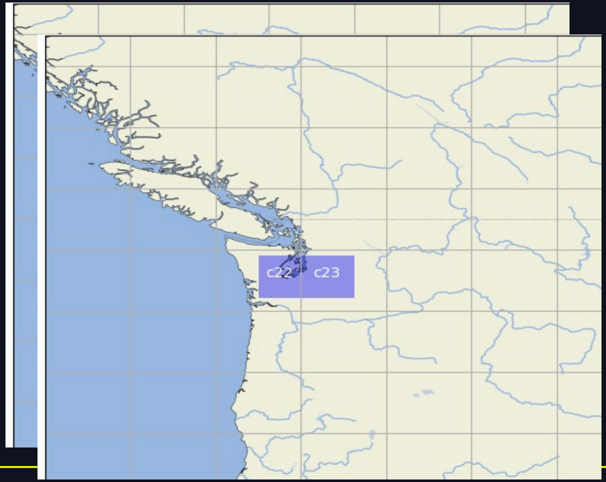
```
import zCurve
Import pyspark.sql.functions as fn

@fn.udf(returnType=DoubleType())
def process_zcurve(input_arr):
    int_process = [int(x) for x in input_arr]
    curve = zCurve.interlace(*int_process, dims=2,
    bits_per_dim=8)
    return float(curve)

df = spark.sql(f"SELECT * FROM {input_table}")
vec_assembler =
    VectorAssembler(inputCols=['device_os_encode',
    'device_browser_encode'], outputCol="features")

silver_df = vec_assembler.transform(df)
# Apply Zcurve to device features
silver_df = silver_df.withColumn(“zcurve_device”,
    process_zcurve(fn.col(“features”))
```

Feature Engineering - Geohash

Encoding Features – Reducing Noise

Features are High Dimensional	Need to widen a range and assign an area to a user
Latitude / Longitude - Too noisy	Geohashing - 3bit precision





Wilson Score Interval

Creating User Baselines

Logins – Samples of Truth

- We want to estimate the ground truth from the sample.
- Retrieve probabilities of successful logins.
- Use Wilson Score Interval to estimate population confidence intervals.

Applying Wilson Score – 80% CI

- Number of Successful Logins from Y.
  - Where Y is a location, application or device.
- $p(x|Y) = \frac{n_s}{s}$
- $z_a = 1.28\ (or\ 1.96\ etc)$
  - Determines CI window (1.28 is 80% CI)
- $w^-, w^+ = \frac{1}{1+\frac{z_a^2}{n}}\left(p + \frac{z_a^2}{2n} \pm \frac{z_a}{n}\sqrt{4np(1-p)} + z_a^2\right)$

Wilson Score Interval

Code – Implement Baselines

Wilson Scoring	Apply Wilson Score Threshold

Wilson Scoring

```
from pyspark.sql.types import ArrayType, DoubleType

@fn.udf(returnType=ArrayType(DoubleType()))
def wilson_score_interval(login_counts, n):
    if n == 0:
        return [0.0, 0.0]
    else:
        p = login_counts / n
        z = 1.28155156554

    upper_left = p + (math.pow(z, 2) / (2 * n))
    upper_right = z * math.sqrt(((p* (1-p))/n) + (math.pow(z, 2)
    / (4 * math.pow(n, 2))))
    lower = 1 + (math.pow(z, 2) / n)

    w_lower_estimate = (upper_left - upper_right) / lower
    w_upper_estimate = (upper_left + upper_right) / lower

    return [w_lower_estimate, w_upper_estimate]
```

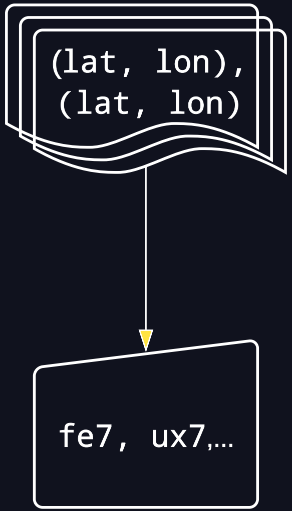
Apply Wilson Score Threshold

```
@fn.udf(returnType=DoubleType())
def wilson_mean(login_counts):
    return sum(login_counts) / len(login_counts)

gold_df =
    df_agg_zcurve_counts.withColumn("wilcox_90%_conf_interval",
    wilson_score_interval(fn.col("device_counts"),
    fn.col("zcurve_count_total")))

gold_df = gold_df.withColumn("mean_frequency",
    wilson_mean(fn.col("wilcox_90%_conf_interval")))

THRESHOLD = .1
final_df = gold_df.filter(f"mean_frequency > {THRESHOLD}")
final_df =
    final_df.groupBy("actor_id").agg(fn.collect_set(fn.col("zcurv
    e_device")).alias("device_set"),
    fn.collect_set(fn.col("device_arr")).alias("device_set_full")
    )
final_df = final_df.withColumn("threshold", fn.lit(THRESHOLD))
```

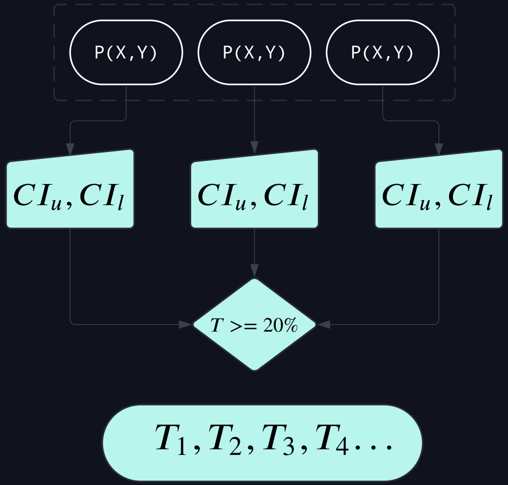
Bringing it together

What it looks like

Apply Hashing

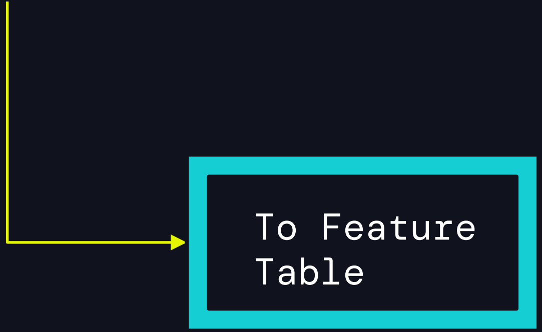


Wilson Score



Baselines

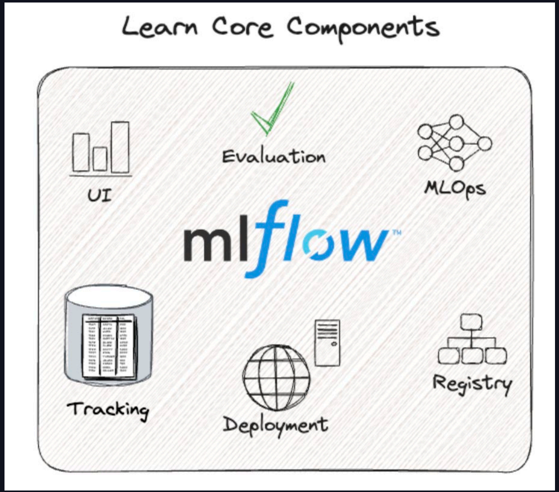
actor_id	geohash_set	threshold
...@adobe.com	["9q9"]	.3
...@adobe.com	["sxf"]	.3
...@adobe.com	["u1x", "dp4"]	.3



ML Challenge - Changing Encodings

How to track Encoding State? When to update?

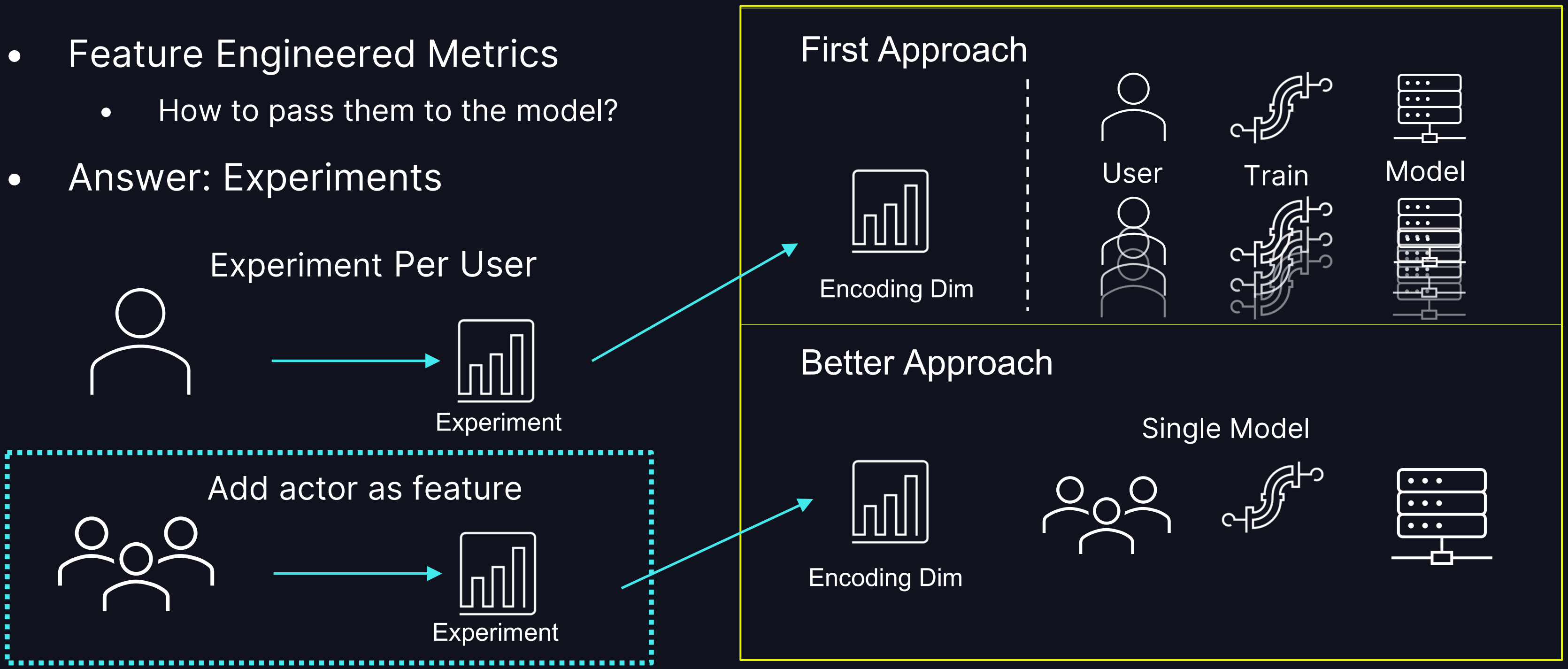
- How do we update encodings for different features?
- Model needs to be trained frequently
- Answer – MLFlow!
    - Pass info via Experiments
    - Metrics



MLFlow - Approaches

Encoding Dimension, testing ideas

- Feature Engineered Metrics
  - How to pass them to the model?
- Answer: Experiments



MLFlow - Code Snippets

Generating Parameters, using them in training

Scala - Generating Parameters	Python - Training

`import org.mlflow.tracking.MlflowContext`
 	
`// Create function to create or replace mlflow run`
`def upsert_run(context: MlflowContext, run_name: String) ={`
`  … // Create or replace mlflow run…`
`}`
`//Create Run, save metrics as json string,`
`val active_run = upsert_run(mlflowContext, cur_date_string)`
`val active_run_id = active_run.getId`
`// Log Encoding Map`
`client.logParam(active_run_id, "encoding_json_map", agg_json_str)`
`client.logParam(active_run_id, "job_new_type", "daily_alpha_job")`
`//Terminate run`
`client.logArtifact(active_run_id, file)`
`client.setTerminated(active_run_id)`
	`client = MlflowClient()`
	`# Retrieve experiment`
	
	`experiment = client.get_experiment_by_name(input_mlflow_path)`
	`experiment_id = experiment.experiment_id`
	`# Pull down run`
	`lookup_run = client.search_runs([experiment_id],`
	`    filter_string=f"attributes.run_name = '{2024-01-22}'")[0]`
	`lookup_run_id = lookup_run.info.run_id`
	`# Download json artifact`
	
	`local_dir = "/tmp/artifact_downloads"`
	`if not os.path.exists(local_dir):`
	`os.mkdir(local_dir)`
	`encoding_map = client.download_artifacts(lookup_run_id,`
	`    "encodings.json", local_dir)`

Databricks - Training Workflow

Journey so far

Hashing | Score Interval | Baselines | MLFlow | Training

Feature Engineering – Key Pre-step

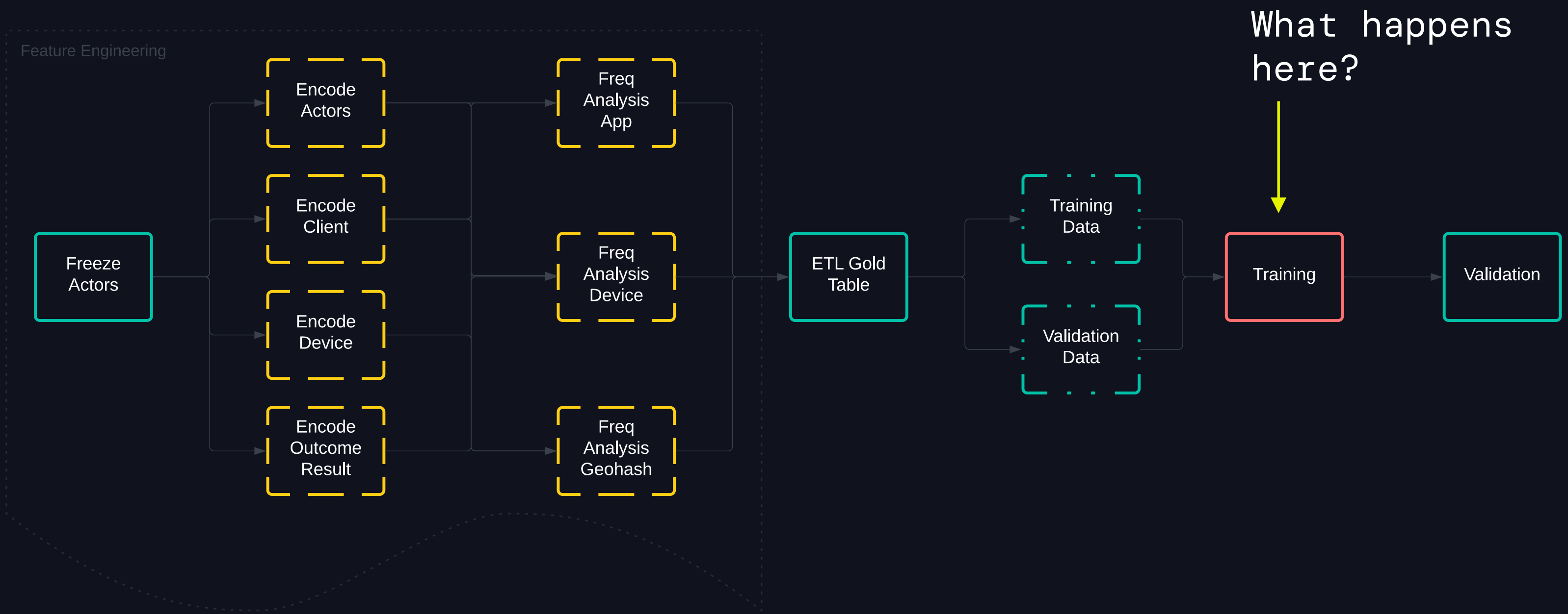
- Baselines help determine AutoEncoder output.
- Allow us to build validation data.
- Store encodings and **version** it.
    - Encodings change if the vocab changes.

Training Param Considerations

- Encoder / Decoder layer sizes?
- Batch Size / Epochs?
- Final Features?
    - actor_id, baseline fields, event date, event hour, login event.

Databricks - Training

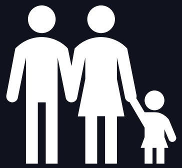
Workflow



Model Considerations

Heuristic Models

- Difficult to maintain for all use cases.
- Lookback restrictions.
- Difficult to scale.
- Difficult to blend with new data sources.
- Difficult to discover new edge cases and anomaly types.



Supervised Models

- Requires Labels.
    - Introduce bias.
- No lookback restrictions.
- Easily blend with new data sources.
- Easy to maintain.

Unsupervised Models

- Does not require labels.
- No lookback restrictions.
- Easily blend with new data sources.
- Easy to maintain.
- Can reveal unexpected patterns.
- Flexible.

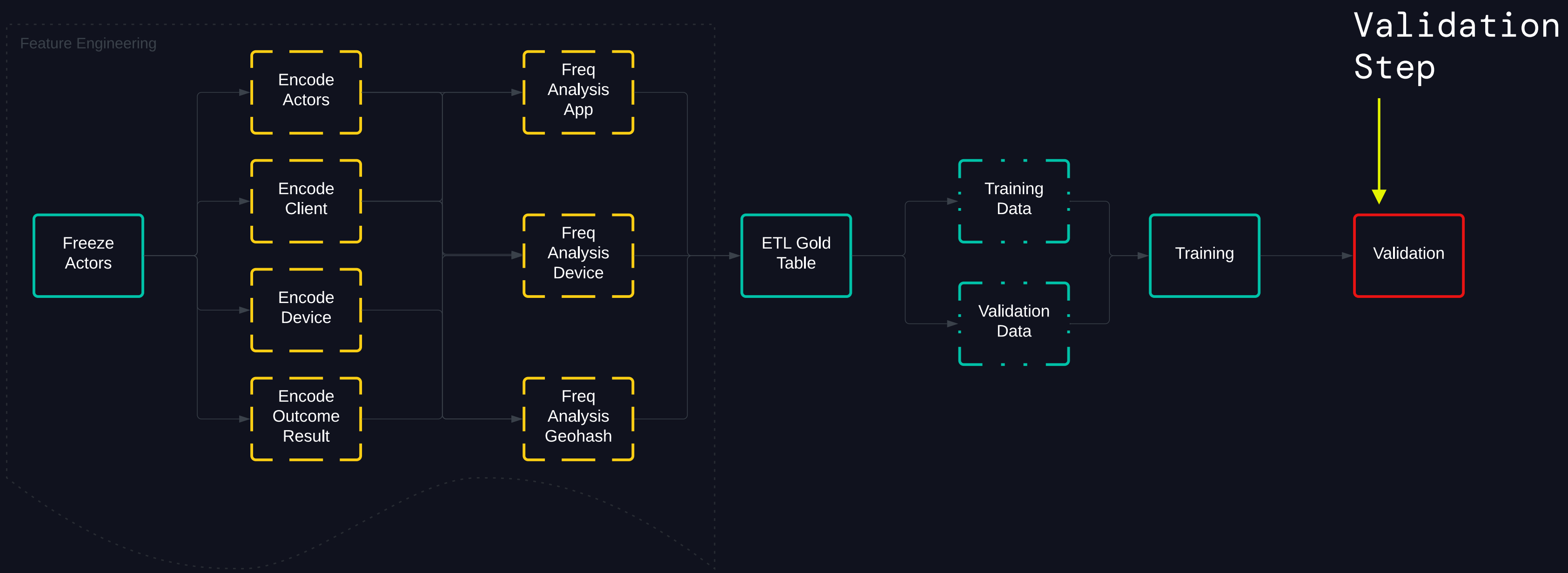
Deep Learning

Autoencoder

- Autoencoder: reconstruct input from latent space representation.
- Feature engineering minimizes historically missed anomalies in training set → small loss.
- Compute average standard deviation across all samples: $\boldsymbol{\sigma}_{train}$.
- Store model and $\boldsymbol{\sigma}_{train}$ in MLFLOW.

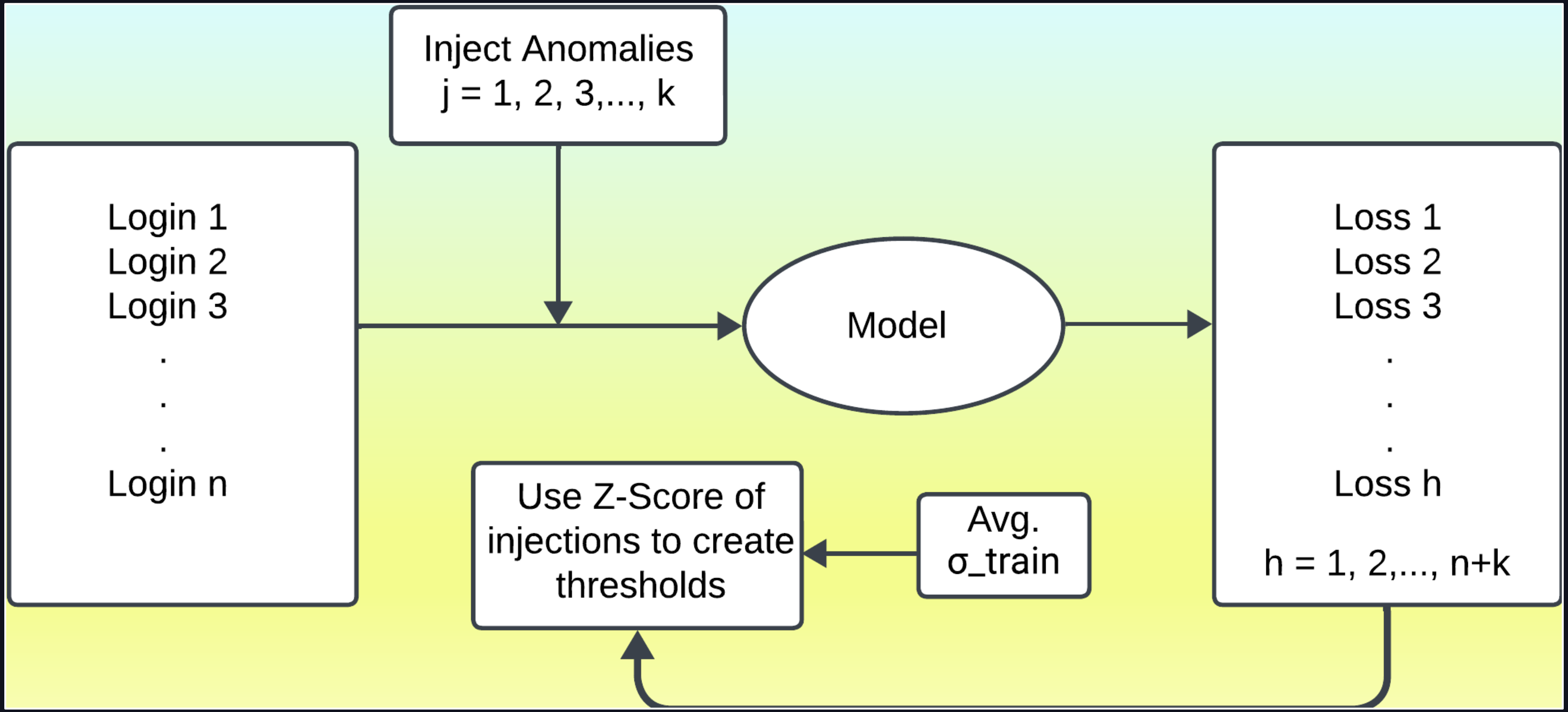
Databricks - Validation

Workflow



Anomaly Detection

Validation Workflow for a Single User



Validation: Use Case of Interest

Impossible Travel

- Injected Anomalies
  - Geohash change, reasonable time of travel.
    - Normal event times.
    - Abnormal event times.
  - Geohash change, unreasonable time of travel.
    - Normal event times.
    - Abnormal event times.
  - No Geohash change.
    - Abnormal event times.
  - Reasonable time of travel?
    - Compute effective travel velocity.
    - Does it exceed speed of commercial passenger jet?

Validation: Use Case of Interest

Impossible Travel

- Considered 100 users
- Test Set
  - 18 injected anomalies
- Recovered 17/18 anomalies
  - All geohash change anomalies recovered
    - high to low loss, highest when event time also abnormal
  - All but 1 non–geohash change anomalies recovered
    - User has broad spectrum of login times

	True Positive	True Negative
Predicted Positive	17	0
Predicted Negative	1	2115

Validation - Scale It Up

Inject anomalies for all 30k users

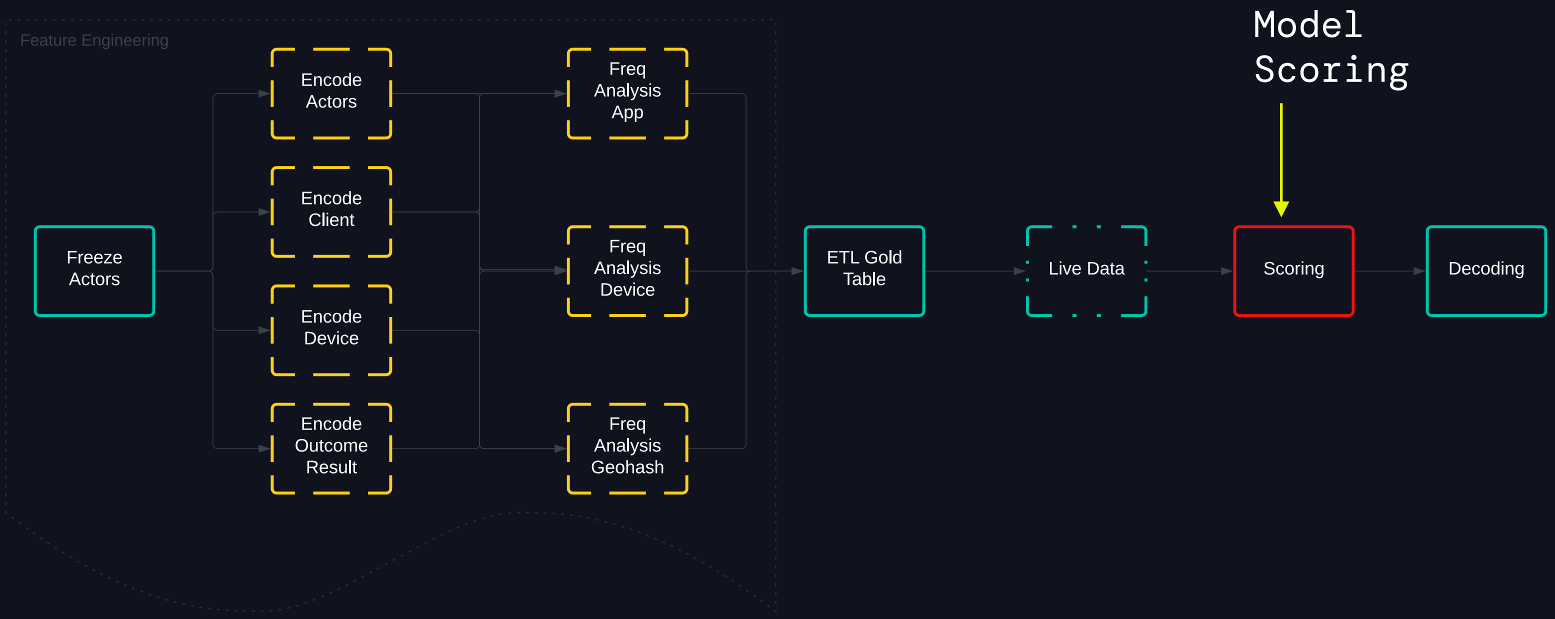
- Compute average standard deviation from training.
- Create validation set for each user.
- User specific mean loss wide distribution – single z-score won't do.
- A z-score exists for each user that captures all injected anomalies.
- This z-score serves as threshold when scoring new incoming data.
- F1 average across all users 98%

User	Data Size	F1	Z-Score	TN	TP
A	613	1	7.1	527	86
B	718	1	6.6	600	118
C	1198	1	7.7	1029	169
D	659	1	7.9	576	83
E	881	1	7.9	746	135
F	1978	1	6.9	1688	290
G	815	1	8	691	124

Table 1: A sample of 7 out of 30k users. Each user data set leads to user specific z-scores to create thresholds capturing each injected anomaly.

Inference

Workflow



PyTorch Modeling

Insights

Training Model

- Test on CPU before CUDA
  - To avoid any CUDA related errors
- Use Parquet tables to store vectors, rather than Delta
- Petastorm Library helps with larger data sets

Testing

- Multiprocessing can be used alongside the GPU
- Be aware of IO bounds when using multiple GPUs
- Use P3 Ec2 instances

Anomalies Found

Types of Anomalies Caught

Session Hijacking

- User uses session on one device in new location.
- Model caught travel over locations in an impossible window.

Impossible Travel

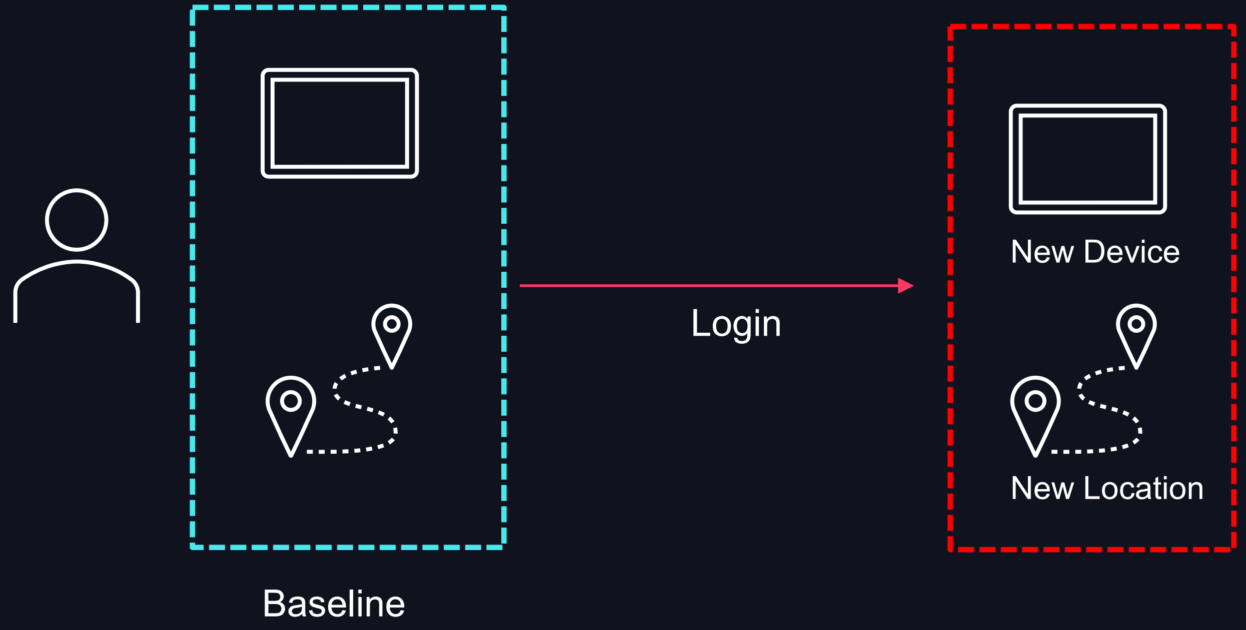
- Someone logs in from X device, location, application in an impossible window of time.
- Can be due to other factors.
  - Third-party VPNs.
  - Registering new device.

Interesting Edge Cases

- Unexplainable things happening at the edge.
  - Odd VPN behaviors.
  - Device registry behaviors.

Edge Cases Found

Anomalies that drive policy change



Explanation: User enrolled a new device. Cloudflare assigned a login ip to the new device when registering, that logged it in a separate location

Edge Cases Found

Anomalies that drive policy change

<u>Explanation:</u> Multiple users registered anomalies to the same external ip or area. Turns out a proxy was being used

Next?

Future Work

- Review raw anomalies prior to use case rules with high loss.
  - Are these malicious?
  - Create anomaly type and edge case type classifications.
    - Could malicious activity look like edge cases – if not can we safely ignore?
  - Can we automatically classify anomaly type without a heuristic?
  - Explore loss associated with other use cases.
- Explore other unsupervised anomaly detection approaches.
- Blend multiple data sources.
  - View user behavior holistically
    - OKTA
    - Entra ID (Azure AD Formerly)

Q/A

Anomalies in Authentication Logs