Feature Store: The Heart of Your Operational ML Pipeline



Yaron Haviv CTO and Co-Founder Iguazio

Most AI Projects Never Make it to Production

Research Environment









Operationalizing Machine Learning is Challenging









Siloed Work

Re-implementation and lack of collaboration due to silos

Lengthy Process

Resource and time-consuming route from lab to production

Access to Features

Accessing and preparing real-world features at scale

Model Accuracy

Tracking, maintaining and explaining model accuracy

<mark>?</mark>• iguazio





ML/AI Research Projects



Interactive / Iterative model development

ML/AI Projects start with focus on building models With a small data science team



But Productizing ML Is Exponentially Harder



Productizing AI/ML takes ages and requires an army of engineers



Accelerate Data Science to Production By Adopting Automation and a Production-first Mindset



Operationalize ML/AI 12X Faster

<mark>2</mark>• iguazio

Before: Siloed, Complex and Manual Process



With 🎖 iguazio : Automated, Fast, and Continuous



MLRun's Key Components For MLOps Acceleration

#3



Feature Store

Automated offline & online feature engineering for real-time and batch data



#2

CI/CD for ML

End to end MLOps automation. Integrated with mainstream ML, Git & CI/CD Frameworks



Real-Time Serving Pipeline

Rapid deployment of scalable data and ML pipelines using real-time serverless technology



#4



Codeless data & model monitoring, drift detection & automated remediation/re-training



#1

Feature Store - Automated Offline & Online Feature Engineering at Scale



Operational Pipeline

Benefits:

- Fast, simple and scalable way to build features from production data
- Implement once, use in training, real-time serving and monitoring
- Share and re-use features across teams and projects
- Glue-less integration with data and model monitoring
- Enable re-training directly from production data



Implementing A <u>SINGLE</u> Feature Using SQL

REATE TABLE recency_feature_group_1 AS CASE WHEN std_interval_between_group_1_in_days IS NULL OR std_interval_between_group_1_in_days = 0 THEN NULL. ELSE mean_interval_between_group_1_in_days/std_interval_between_group_1_in_days END as cv_interval_group_1 SELECT user_id. AVG(time_interval)/(3600*24) as mean_interval_between_group_1_in_days, stddev_pop(time_interval)/(3600*24) as std_interval_between_group_1_in_days SELECT user_id. event_timestamp, extract(epoch from event_timestamp) - lag(extract(epoch from event_timestamp)) over (PARTITION BY user_id order by event_timestamp) as time_interval FROM "My_big_transactional_table" WHERE event_timestamp::timestamp <=

(cast(' "2014-09-01 00:00:00" ' as date) - INTERVAL '7' DAY)

AND

event_timestamp::timestamp >=

ast(' "2014-09-01 00:00:00" ' as date) - INTERVAL '7' DAY - INTERVAL '6' MONTH)

) as table_layer_2 GROUP BY user id

) as table_layer_3



Slow and Resource Intensive



Won't work in real-time



MLRun Feature Store - How Does It Work?





Key Challenges for Online Feature Engineering

• Data scientists are not data engineers

- Re-written code is needed to deploy it in production
- Working with streaming sources as opposed to parquet files
- **Performance** Calculate features in real time on live data at scale
- **Robust transformation –** e.g. aggregations on sliding windows
- Enrichment Enrich real time events with historical / operational data
- **Consistency** between training and serving
- Data drift based on feature drift
- **Feature reuse –** use features for many projects



Feature versioning – aligning feature and model version in production





Simple SDK for Creating a Real-Time Transformation

Quickly develop ML/DL features for offline and online/real-time use

transaction_set.graph\

.to(DateExtractor(parts = ['hour', 'day_of_week'], timestamp_col = 'timestamp'))\
.to(MapValues(mapping={'age': {'U': '0'}}, with_original_features=True))\
.to(OneHotEncoder(mapping=one_hot_encoder_mapping))

Projects







Assemble online & offline features from catalog

Pr	rojects > Runway >	Feature store					
	Datasets Feature sets	Features Feature	vectors				
	Q Search features by n	ame Labels:	All 👻 Er	ntity: All 🔻 Featu	ure set: All 👻		transactions_f_vector
	Feature Name	Feature set	Туре	Entity	Description	Labels	Name Version
	user	Customers	Int	User			transactions_t_vector 1.2
	name	Customers	String	User			this feature vector is used for the scoring model. It has the customer transactions data along with real time aggregations and zscore
	score	Customers	Float	User			
	last_balance	Customers	Float	User		balance	product_id : Products
	product_id	Products	Int	Product_name			volume : Customer_transactions
	Product_name	Products	Int	Product_name			Vol_last_hr : Customer_transactions
	Catalog_id	Products	Int	Product_name			Vol_last_day : Customer_transactions
	Price	Products	Int	Product_name			avg_purchase_1w : Purchases_history
	Trans_id	Customer_transactions	Int	User			rank : Financial_institutions
	volume	Customer_transactions	Float	User			
	Vol_last_hr	Customer_transactions	Float	User		agg	
	Vol_last_day	Customer_transactions	Float	User		agg	
	Vol_last_week	Customer_transactions	Float	User		agg	
	Vol zecore 1d	Customer transactions	Int	llear	Calculating zecore for the last day	algulated	



Trivial Access APIs

Offline (Training & Exploration)

resp = client.get_offline_features(vector)
df = resp.to_dataframe()

Real-time (Serving & monitoring)

service = client.get_online_feature_service(vector)
service.get([{"patient_id": "838-21-8151"}])



Integration with Model Monitoring Drift Detection & Auto-Retraining

	Models Model endpoints											
٢	Q. Search model by name		Status: All 👻	Labels: All 👻 Group by: Models 👻							C	0
Hope of S	Name	Version	Class	Labels	Uptime	Last prediction	Prediction/s	Arg. latency (ms)	Error ratio	Drift	Accuracy	
iervices	> K-Nearest Neighbors	1.2	Logistic	excepteur: eu Culpa: Lorem	3 Days	2 Days	26 10	1	0.3%	0	81%	
_	> • DeOldify	1.0	Regression	Culpa: Lorem (mollit: minim) (+2)	2 Hrs	2 Hrs	40 ~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	2	0.9%	0	92%	
Data	> • StyleGAN2	1.1	Regression	ad: dolore (incididunt: magna)	40 Mins	38 Mins	32 2000	10	0.2%	0	90%	
D	Vector Quantization											
Logs	Server 1	1.3	Logistic	Culpa: Lorem (moliit: minim) (+2)	3 Weeks	3 Weeks	42 000	1	0.5%	0	89%	
Sec.	Server 2	1.4	Logistic	ad: defore (incididunt: magna)	1 Month	1 Month	23 ~~~~	з	0.1%	0	97%	
_	> = Random Forest	1.1	Logistic	labore: magna cupidatat: esse +5	4 Days	3 Days	62 m	8	0.8%	•	92%	
Storage	> Deep Learning	1.3	Regression	eu: est aute: nisi (+1)	20 Hrs	19 Hirs	41 ~~~~	5	0.9%	0	88%	
n	> • AlphaGo	2.1	Logistic	ad: dolore (incididunt: magna	5 Mins	3 Mins	29 MM	4	0.3%	0	89%	
dentity	• GPT-3	1.5	Regression	esse: voluptate velit: irure	9 Hirs	4 Hrs	34 ~~~~	6	0.2%	•	95%	
A	🛩 🔹 Deep Blue											
	Server 34	2.3	Logistic	(labore: magna) (cupidatat: esse) (+5)	12 Hrs	3 Hrs	12 MM	3	0.1%	0	91%	
teports .	Server 35	2.3	Logistic	excepteur: eu Culpa: Lorem	11 Hrs	10 Hrs	32 ~~~~	2	0.3%	0	92%	

Detect **model drift** based on **feature drift** via the integrated feature store and start retraining **Monitor** your models in production, identify and mitigate **drift** on the fly





<mark>२</mark> iguazio

Live Demo: ML Production Pipeline - Real-Time Fraud Predictions





Demo



17

Serverless Stream Processing For Real-Time & Batch



Simplicity, Performance, and Scale

<mark>२</mark> iguazio

Thank you!

Do you have any questions?

Yaron Haviv yaronh@iguazio.com



www.linkedin.com/in/yaronh/

) @y

@yaronhaviv