Accelerating ML at Uber with Michelangelo Palette

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Michelangelo Palette

Evolution into a Feature Engineering Platform

Shared repository				Feature Quality & Monitoring	Feature APIs
Offline Store	Batch feature	Near real-time	Scalability	Automatic	Provenance
Online Store	computation	feature computation	Reliability	Feature Selection	Embeddings

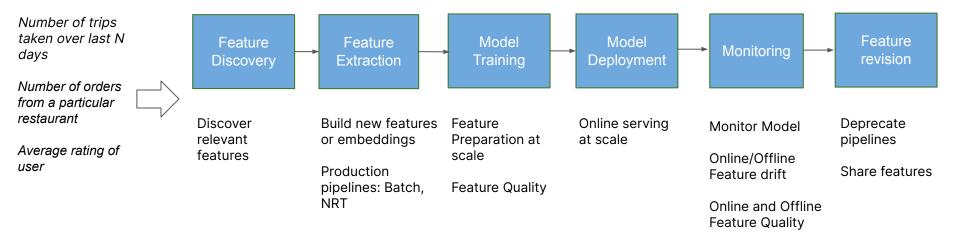
2016

2022





Feature Engineering: User journey







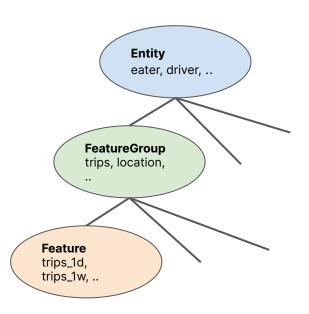
Browsing through Git repo

Entity: Primary entity associated with a Feature Group (table)

Feature Group: A logical table of individual features

Feature: A logical column within a Feature Group

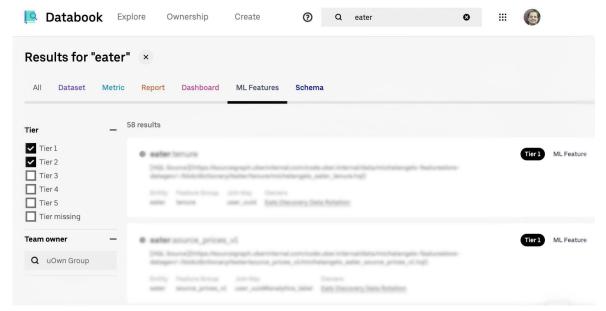
Metadata: Type information, Join/Lookup Key, Feature extraction ETL, Online dispersal info







Keyword Search





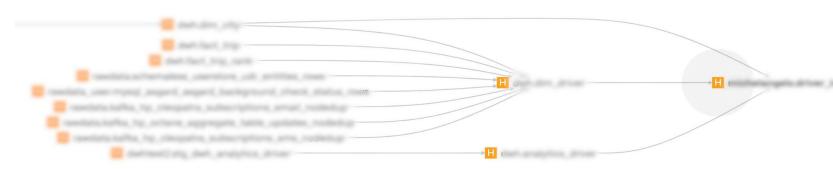


Data Lineage

Warehouse: dim, fact, business tables, event logs

Staging tables: joins, aggregations

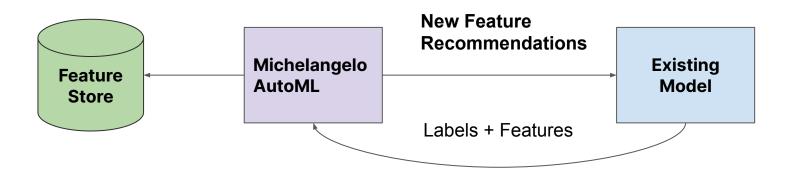
Feature Store tables (Point-in-time snapshots)







Advanced: Michelangelo AutoML tool



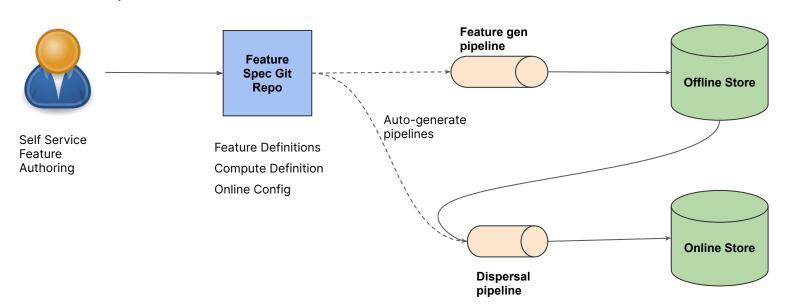
Boost Model Performance through Feature Discovery





Feature Extraction

Batch computed features

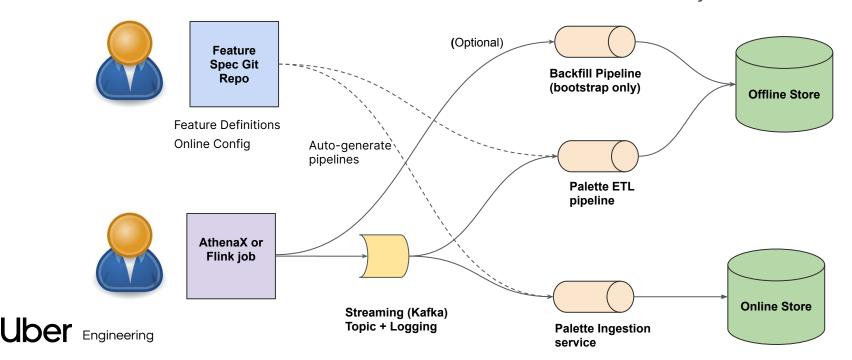






Feature Extraction

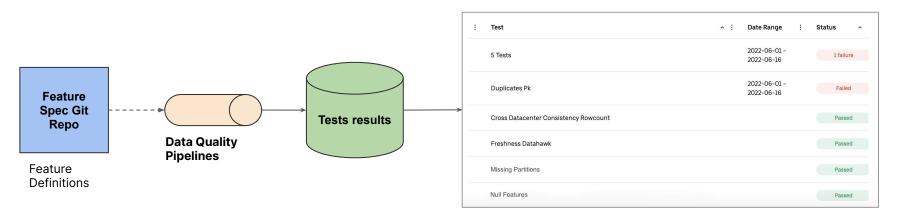
Near real-time features: automation critical for iteration velocity!





Model Training

Feature Quality: avoid debugging training time failures



At Training kickoff..





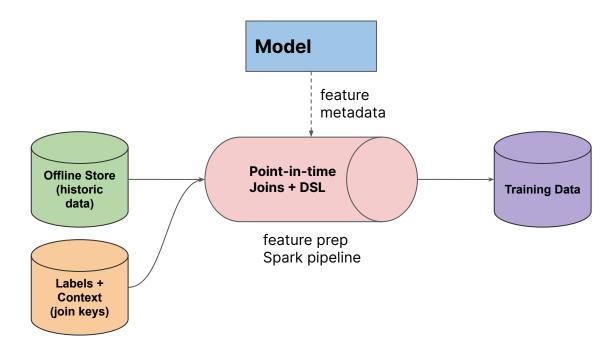
Model Training

Feature Preparation at Scale

Materialize at use: DSL for lightweight or model-specific xforms

Reducing shuffle overhead of joins is key

Incremental feature computation (Delta Store)







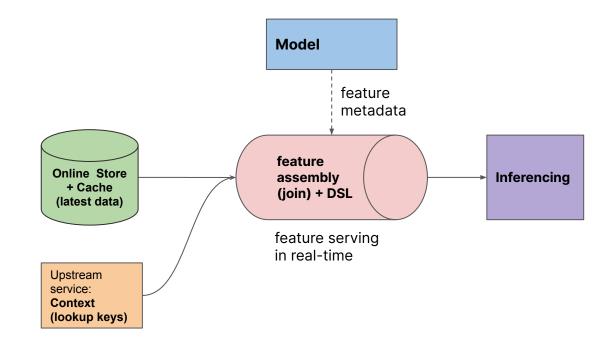
Online Model Deployment

Provisioning for Scale

Materialize at use: DSL + feature join has semantic parity to offline

Process to estimate Redis + Cassandra capacity from access patterns and feature payload

Shadow Testing through cloning Production traffic



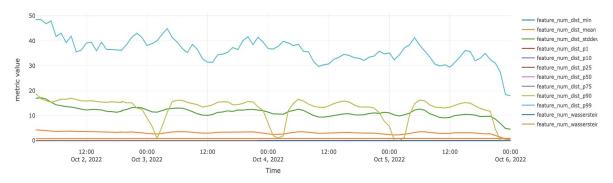




Model Monitoring

Near real-time monitoring: use prediction logs to detect feature distribution shifts wrt to training/historic baseline

Feature Store monitoring: offline only (pre-training, pre-dispersal)



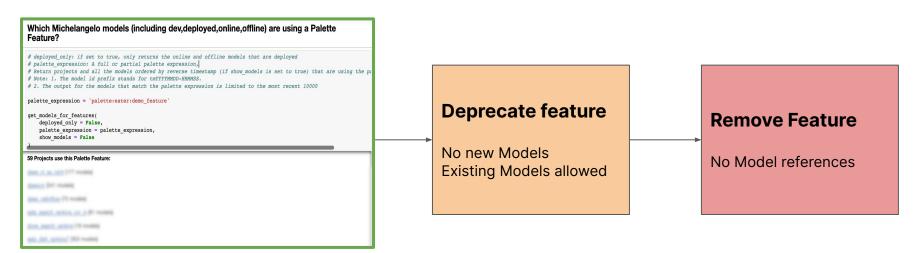
metric_name	† min	≑ max	† avg	<pre>training_baseline</pre>	feature_importance
filter data					
feature_num_dist_min	0	0	0	0	0.766606
feature_num_dist_mean	0.530115	4.285806	3.078492	25.7552	0.766606
feature_num_dist_stddev	4.556955	17.183177	11.366911	33.591095	0.766606
feature_num_dist_p1	0	0	0	0	0.766606
feature_num_dist_p10	0	0	0	0	0.766606
feature_num_dist_p25	0	0	0	19.375021	0.766606
feature_num_dist_p50	0	0	0	37.451324	0.766606





Feature Revision

Feature Sharing, Deprecation



Feature → Model Lineage via metadata





Accelerating end-to-end ML

Summing it up

- Feature Discovery through search and automatic feature selection
- Feature Extraction via automated pipeline generation from spec
- Feature Preparation through data validation and scalable point-in-time joins
- Feature Serving in real-time through a process for capacity estimation, and scalable online store
- Near real-time feature monitoring via prediction logs, daily monitoring of features
- Feature sharing and deprecation via Model-Feature lineage tracking



Thank you!





