Eesti Energy

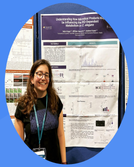
Building a Scalable Data & Modeling Architecture for Prosumer Energy Forecasting

Group 1

Group Leader /
Data Architect

Data Engineer

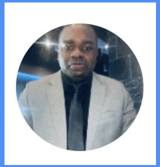
Kenichi
Data Engineer



Selin
Data Scientist

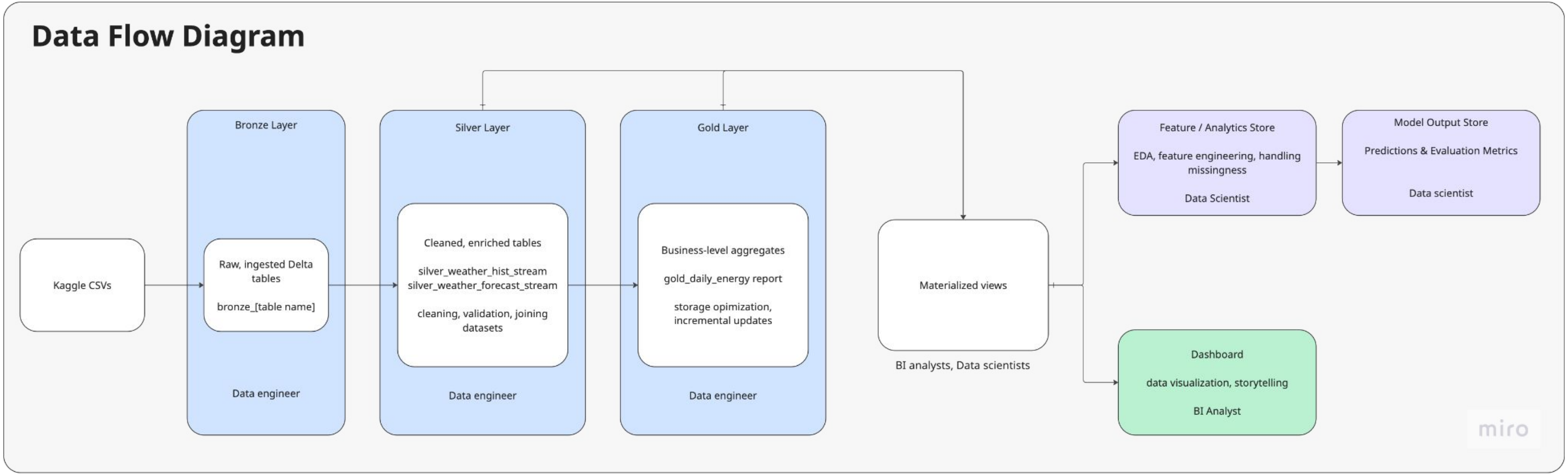
Liwei
Data Scientist /
BI Analyst

Peiran
BI Analyst



Chijioke
Data Architect

Data Architecture | Process Overview



Data Flow Diagram

Kaggle CSVs

Bronze Layer

Raw, ingested Delta tables

bronze_[table name]

Data engineer

Silver Layer

Cleaned, enriched tables

silver_weather_hist_stream
silver_weather_forecast_stream

cleaning, validation, joining datasets

Data engineer

Gold Layer

Business-level aggregates

gold_daily_energy report

storage opimization, incremental updates

Data engineer

Materialized views

BI analysts, Data scientists

Feature / Analytics Store

EDA, feature engineering, handling missingness

Data Scientist

Model Output Store

Predictions & Evaluation Metrics

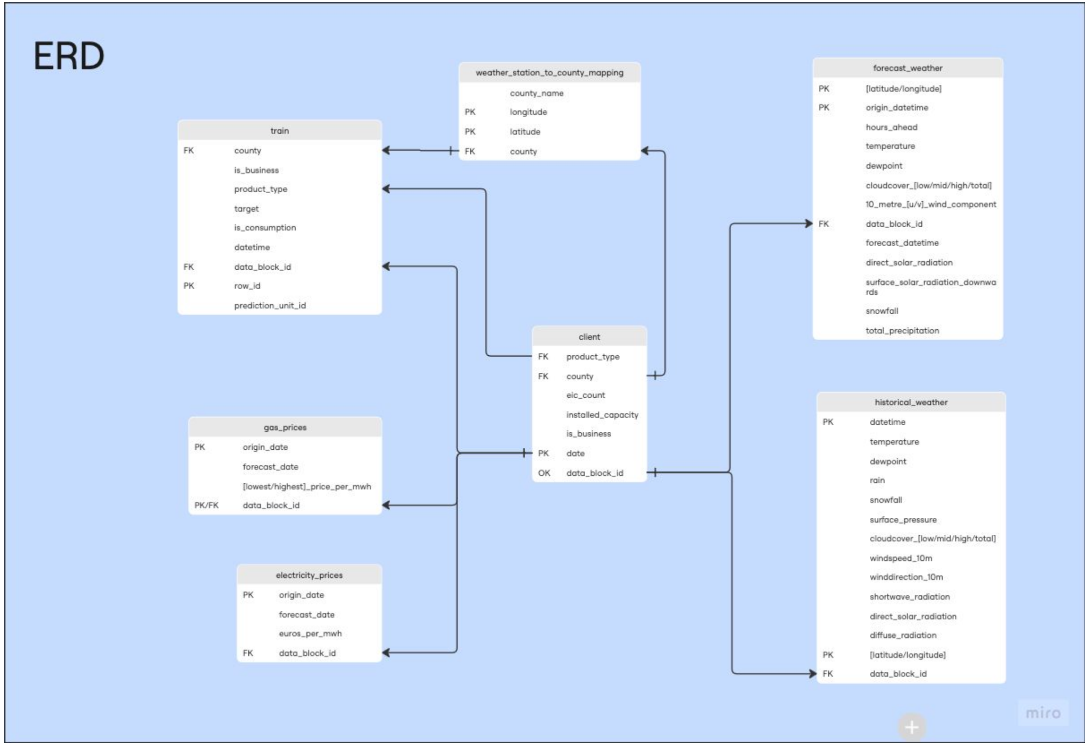
Data scientist

Dashboard

data visualization, storytelling

BI Analyst

Data Architecture | Data Overview



ERD

	train
FK	county
	is_business
	product_type
	target
	is_consumption
	datetime
FK	data_block_id
PK	row_id
	prediction_unit_id

	weather_station_to_county_mapping
	county_name
PK	longitude
PK	latitude
FK	county

	forecast_weather
PK	[latitude/longitude]
PK	origin_datetime
	hours_ahead
	temperature
	dewpoint
	cloudcover_[low/mid/high/total]
	10_metre_[u/v]_wind_component
FK	data_block_id
	forecast_datetime
	direct_solar_radiation
	surface_solar_radiation_downwards
	snowfall
	total_precipitation

	client
FK	product_type
FK	county
	eic_count
	installed_capacity
	is_business
PK	date
OK	data_block_id

	gas_prices
PK	origin_date
	forecast_date
	[lowest/highest]_price_per_mwh
PK/FK	data_block_id

	historical_weather
PK	datetime
	temperature
	dewpoint
	rain
	snowfall
	surface_pressure
	cloudcover_[low/mid/high/total]
	windspeed_10m
	winddirection_10m
	shortwave_radiation
	direct_solar_radiation
	diffuse_radiation
PK	[latitude/longitude]
FK	data_block_id

	electricity_prices
PK	origin_date
	forecast_date
	euros_per_mwh
FK	data_block_id

Data Engineering | Key Data Challenges

Fragmented Data Sources

Kaggle data was distributed across multiple raw CSVs with varying schemas and update patterns, requiring standardization before it could support reliable analytics.

Geospatial Data Incompatibility

Weather data indexed by latitude and longitude conflicted with grid operations organized by county boundaries, preventing seamless integration of datasets.

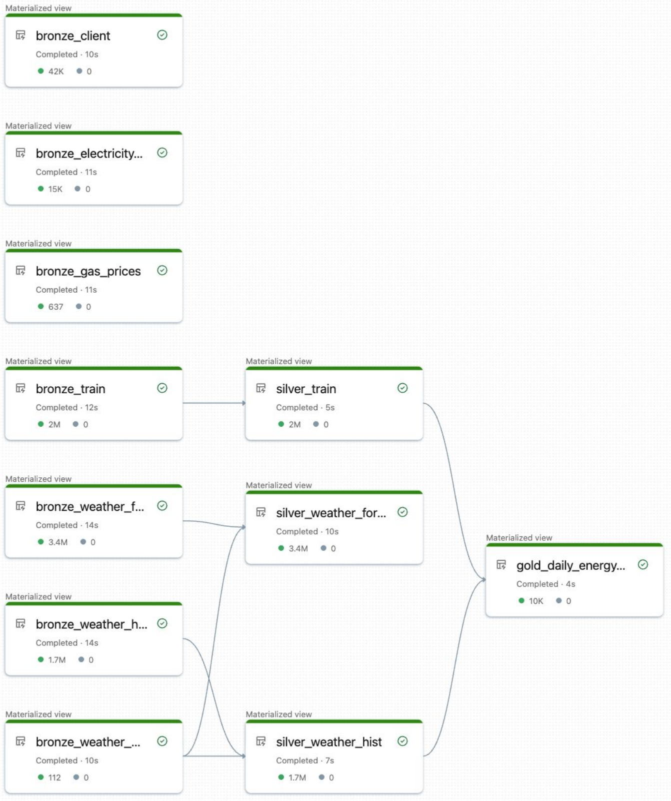
Diverging Analytical Needs

Machine-learning models demanded high-granularity historical data, while BI teams required stable KPI reporting, creating conflicting data requirements.

Need for Scalable Engineering

These challenges required a scalable engineering approach to support real-time operational reporting alongside advanced forecasting models.

Data Engineering | Solving Data Challenges with Medallion Pipeline



Key Engineering Decisions

Bronze: Foundation & Ingestion

- Developed reusable ingestion module to convert Kaggle CSVs into managed Delta Tables
- Using Delta Tables the system inherently manages idempotency and Schema Evolution

Silver: Compute Optimization

- Mapped massive weather history (Lat/Long) to county grid (IDs) using Broadcast Join
- Eliminates network shuffles, significantly reducing processing time for downstream models

Gold: Reporting

- Aggregated daily energy vs. temperature metrics to provide atomic, pre-calculated data for reporting/dashboards.
- Eliminates heavy run-time calculations, ensuring the reporting layer is consistent and loads quickly.

Data Engineering | Key Contributions

Silver Structured Streaming Pipeline

Implemented a robust Structured Streaming pipeline to incrementally process and join data from Bronze tables, writing the results to Silver streaming tables.

Data Quality/Configuration

Added table existence and schema validation checks, centralized catalog/schema/volume configuration, and improved error surfacing to enhance pipeline robustness and daily execution readiness.

Gold Layer Optimization (ZORDER)

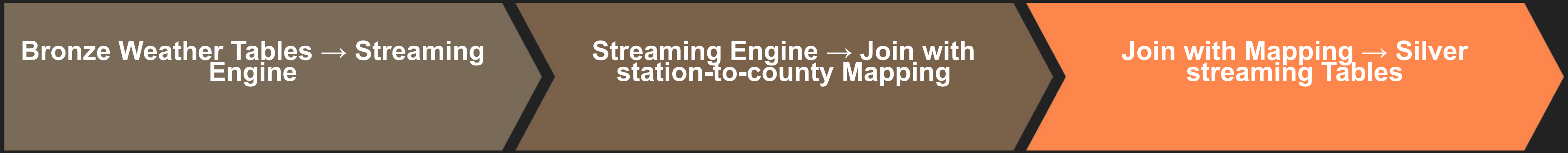
Optimized the Gold layer by applying ZORDER partitioning on the 'gold_daily_energy_report' table, improving BI query performance and data skipping.

End-to-End Data Lineage Diagram

Created a comprehensive data lineage diagram showcasing the end-to-end flow from Bronze to Silver (Batch and Streaming) to Gold, providing visual clarity and an anchor for the final presentation.

Helper Utilities & Documentation

Developed a suite of helper utilities, including table_info(), compare_schemas(), preview(), and validate_columns(), to enhance team productivity and support the data science and BI teams.



Bronze Weather Tables → Streaming Engine

Streaming Engine → Join with station-to-county Mapping

Join with Mapping → Silver streaming Tables

The data flow starts with the Bronze Weather Tables, which are then processed by the Streaming Engine.

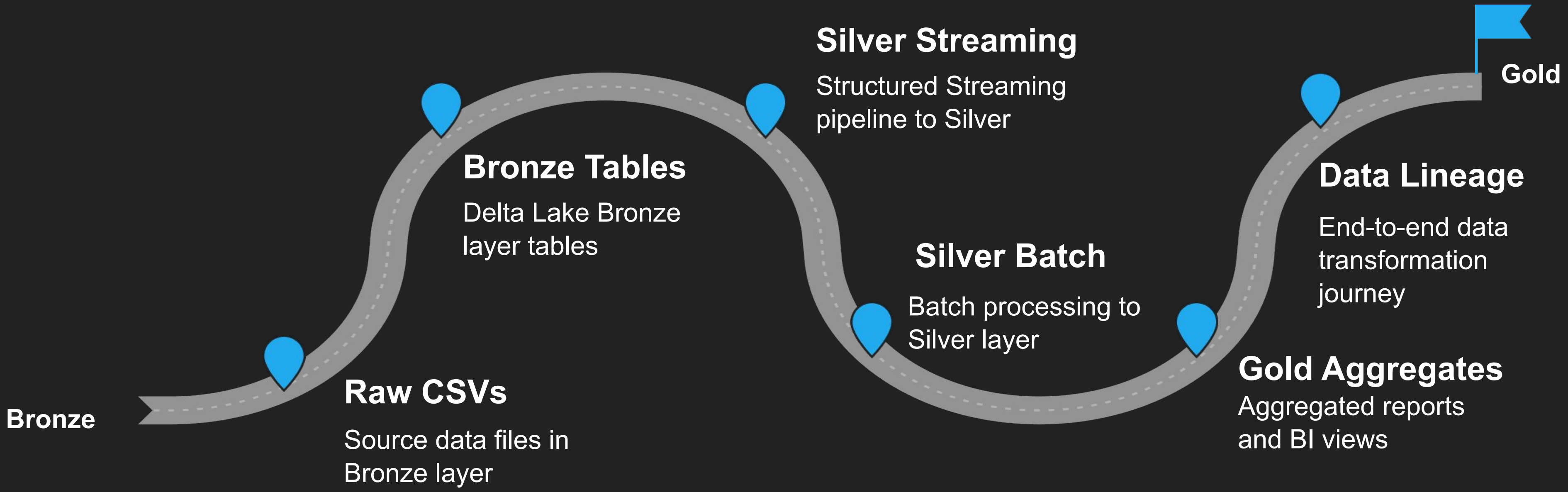
NOTE: spark.readStream.table()

The data from the Streaming Engine is then joined with the Mapping data to enrich the information.

NOTE: trigger(once=True)

The enriched data is then written to the Silver Streaming Tables, which are the final output of this pipeline.

NOTE: Checkpointing stored in UC Volume



Raw CSVs

Source data files in Bronze layer

Bronze Tables

Delta Lake Bronze layer tables

Silver Streaming

Structured Streaming pipeline to Silver

Silver Batch

Batch processing to Silver layer

Gold Aggregates

Aggregated reports and BI views

Data Lineage

End-to-end data transformation journey

Data Science | EDA

Questions to ask: What are the key factors that determine energy consumption?

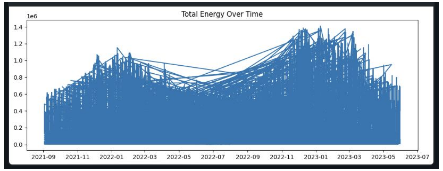
Need to perform exploratory data analysis on the gold layer data first!

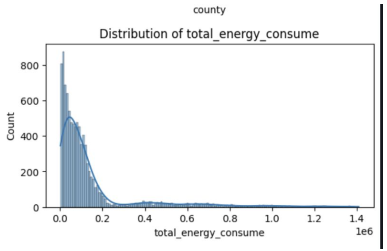
Things to look for

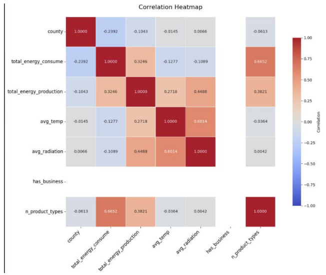
- Skewness/Distribution
- Missing values
- Duplicated rows
- Outliers
- Correlation Matrix (Multicollinearity)
- Visualisations between variables to understand relationships

Actions taken

- Log transformed heavily right skewed variables
- No missing or duplicated values
- There is some minor multicollinearity (ex: temp and radiation) but xgboost can handle it,so chose to leave variables







Data Science | Model Selection & Performance

- AutoML wasn't available in the Databricks free edition environment, used xgboost for both models.
- Split data into train and test
- Used MLFlow for lifecycle management, every run is recorded as an experiment.

Performance metrics to look for:

- Plot Actual vs Prediction values
- RMSE, R2, MAE, MAPE
- Residual plot
- Error distribution
- Feature importance values from the model

Important Considerations

- The Date column had to be split into day, month and year to make data more meaningful/
- The County column (ID) has to be categorical instead of an integer, otherwise the model would interpret the ID numbers as numbers instead of categories.
- Need to convert metrics after running the model, since target variable was initially log transformed

Data Science | Key takeaways and improvement

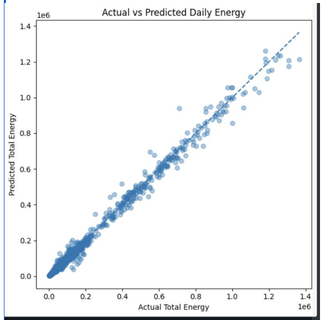
Findings:

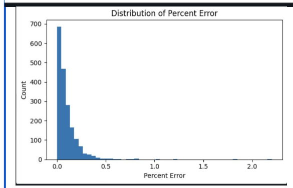
- Simple vs Complex model aren't that different in prediction power (R2: 0.9831 vs 0.9863). Models explain at least 98% of variability in both cases.
- County is the most important variable, followed by n_product_types and year.
  - This makes sense since geographical location and how industrial or rural the area is deterministic in energy consumption
  - Product type reflects economic activity
  - Year tells us there are also trends over time

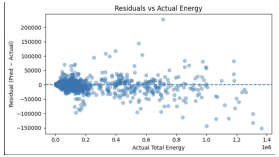
How to improve?

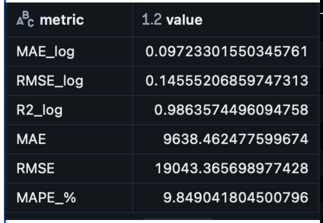
- Didn't optimize for the best model possible. Could use autoML and try many more
- Geographical location has a distinct effect, could remove that and focus on other variables to see what else impacts energy consumption (eg: more focus on weather radiation etc)

Performance Metrics:

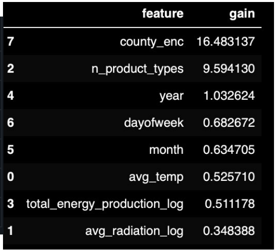






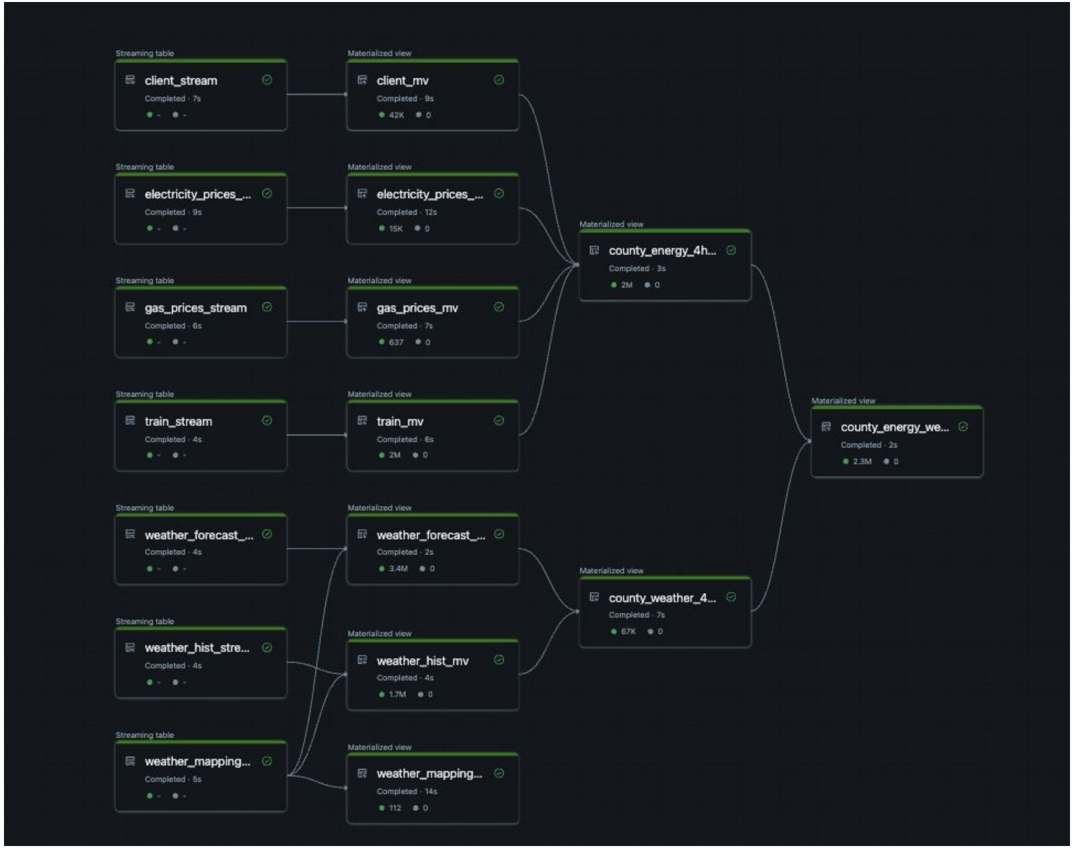


metric	value
MAE_log	0.09723301550345761
RMSE_log	0.14555206859747313
R2_log	0.9863574496094758
MAE	9638.462477599674
RMSE	19043.365698977428
MAPE_%	9.849041804500796



	feature	gain
7	county_enc	16.483137
2	n_product_types	9.594130
4	year	1.032624
6	dayofweek	0.682672
5	month	0.634705
0	avg_temp	0.525710
3	total_energy_production_log	0.511178
1	avg_radiation_log	0.348388

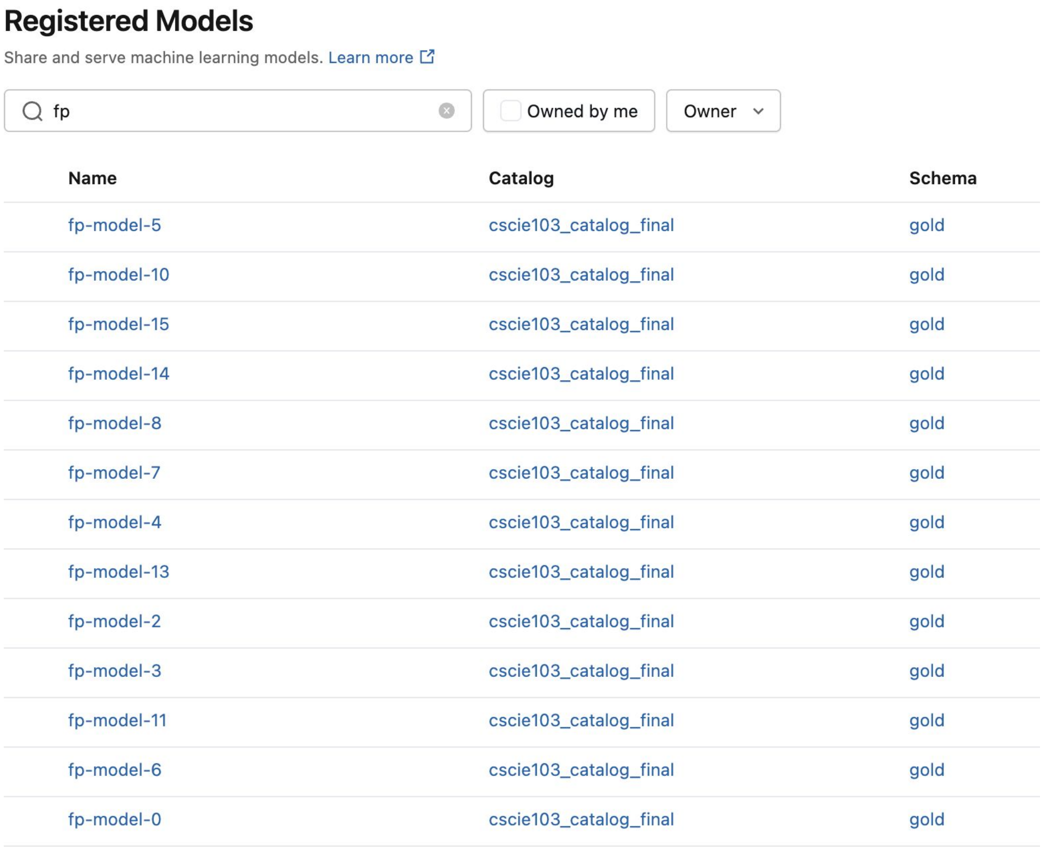
Data Science | MLOps Feature Pipelines



Key Improvements:

1. **Create Streaming at the Bronze layer for incremental ingestions**
2. **Added Materialized View at Silver layer for cleansed data**
3. **Created County level Weather and Energy aggregated view for data analysis and feature engineering**

Data Science | MLOps Model Pipeline



Registered Models

Share and serve machine learning models. Learn more

Name	Catalog	Schema
fp-model-5	cscie103_catalog_final	gold
fp-model-10	cscie103_catalog_final	gold
fp-model-15	cscie103_catalog_final	gold
fp-model-14	cscie103_catalog_final	gold
fp-model-8	cscie103_catalog_final	gold
fp-model-7	cscie103_catalog_final	gold
fp-model-4	cscie103_catalog_final	gold
fp-model-13	cscie103_catalog_final	gold
fp-model-2	cscie103_catalog_final	gold
fp-model-3	cscie103_catalog_final	gold
fp-model-11	cscie103_catalog_final	gold
fp-model-6	cscie103_catalog_final	gold
fp-model-0	cscie103_catalog_final	gold

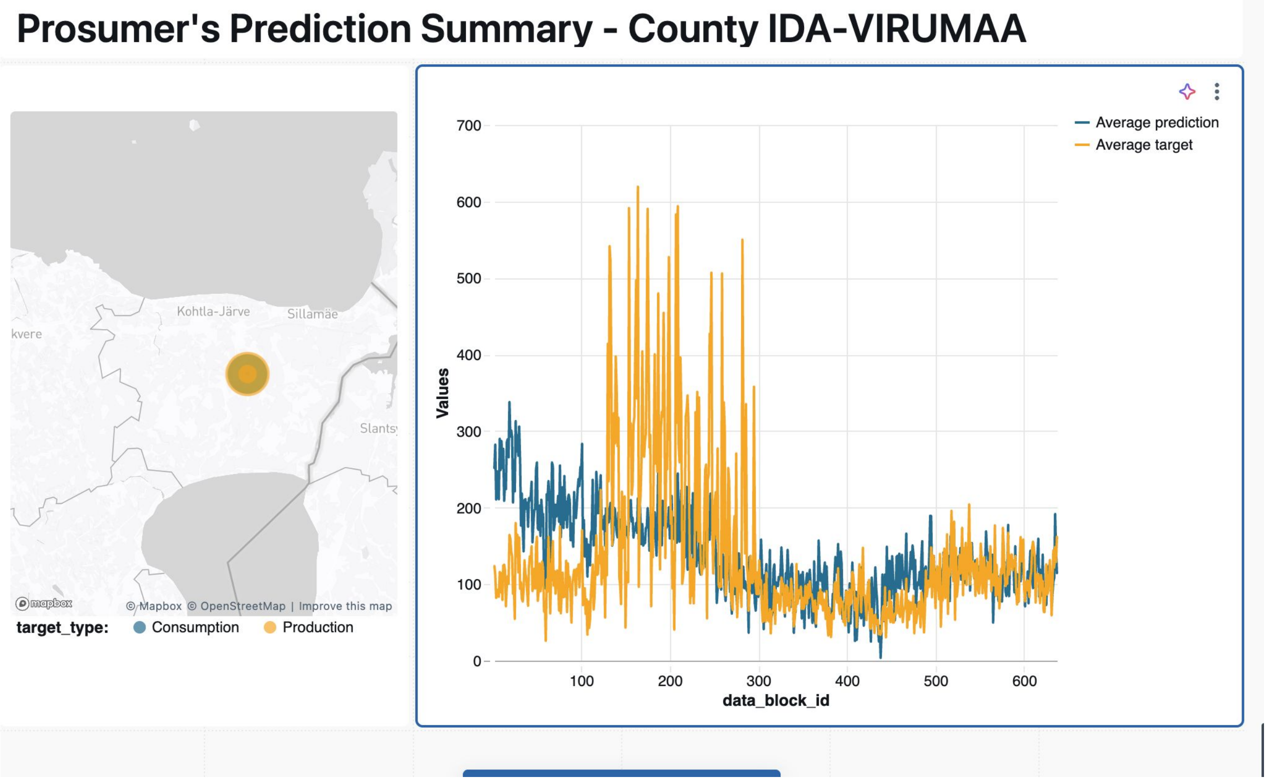
Key Streamlines:

1. Model training by County based on findings
2. Feature Reduction and Selection
3. Use mlflow log model training input and output and save model in UC model registry
4. Retrieve model from registry for prosumer energy prediction

Data Science | Model Evaluations

Model	County	Train	Test	RMSE	Rank
fp-model-1	HIIUMAA	85264	21548	50.792517	1
fp-model-6	LÄÄNEMAA	28392	7212	82.672502	2
fp-model-8	PÕLVAMAA	85264	21548	136.156688	3
fp-model-4	JÕGEVAMAA	136879	34311	198.750356	4
fp-model-7	LÄÄNEMAA	160629	40007	262.997524	5
fp-model-2	IDA-VIRUMAA	106998	26908	299.840072	6
fp-model-11	TARTUMAA	183526	45772	1042.838145	7
fp-model-0	HARJUMAA	198229	49319	1733.095094	8

Data Science | Model Prediction Application

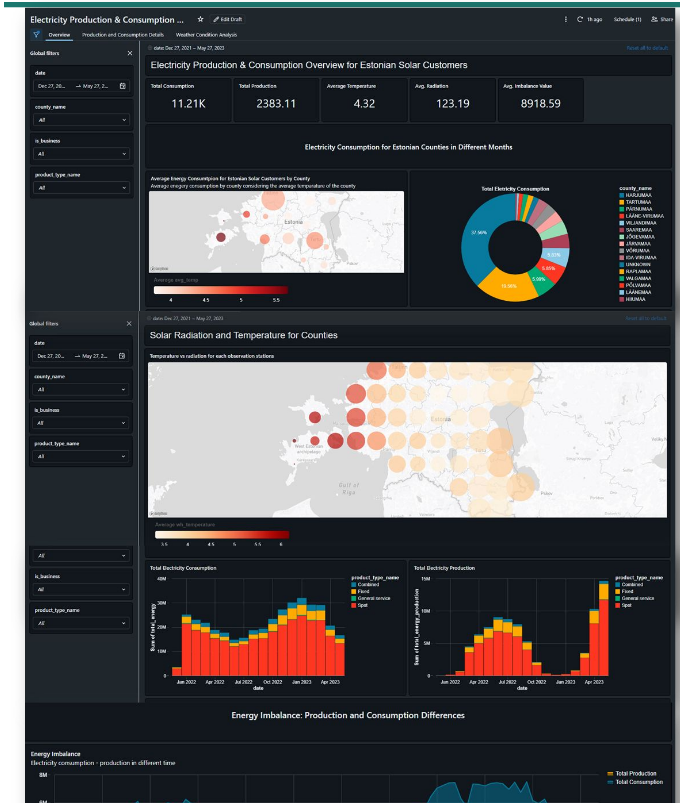


Prosumer's Prediction Summary - County IDA-VIRUMAA

Key Observations:

1. Data block id is equivalent to datetime
2. The linear regression model is missing seasonality
3. Need to enhance leverage time series models
4. Setup Prediction pipeline. With mlflow we can load model and get predictions

BI Dashboard | Objectives



Electricity Production & Consumption ...

Overview | Production and Consumption Details | Weather Condition Analysis

Global filters

date: Dec 27, 2021 ~ May 27, 2023

date: Dec 27, 20... → May 27, 2...

county_name: All

is_business: All

product_type_name: All

Electricity Production & Consumption Overview for Estonian Solar Customers

Total Consumption	Total Production	Average Temperature	Avg. Radiation	Avg. Imbalance Value
11.21K	2383.11	4.32	123.19	8918.59

Electricity Consumption for Estonian Counties in Different Months

Average Energy Consumtpion for Estonian Solar Customers by County

Average enegery consumption by county considering the average temparature of the county

Total Eletricity Consumption

Solar Radiation and Temperature for Counties

Temperature vs radiation for each observation stations

Total Electricity Consumption

Total Electricity Production

Energy Imbalance: Production and Consumption Differences

Energy Imbalance

Electricity consumption - production in different time

01. Identify key drivers of energy demand & supply.

Highlight the main factors influencing energy production and consumption, such as time (month/season), geographic conditions, county-level characteristics, product type, and residential vs. business usage.

02. Detect energy imbalances & actionable root causes.

Expose where and when gaps between production and consumption occur, analyze likely root causes, and indicate the specific counties and time periods where energy providers should prioritize corrective actions.

03. Geographic focus for targeted optimization

Visualize county-level conditions and performance to pinpoint high-risk or high-impact areas, helping stakeholders decide where to focus resources to reduce energy imbalance most effectively.

BI Dashboard | Key Functions

Data Ingestion and Integration

Queries curated data from the Gold layer of the data model.

Enriches core metrics with supporting datasets (e.g., customer attributes, environmental factors)

Why it matters

- Ensures analytics are built on clean, consistent, and business-ready data

Automated Data Refresh

Daily automatic refresh at 0:30

Consistent updates for all user groups

Why it matters

- User always access latest data
- Eliminate manual refresh and reduce operational risk

Data Governance & Security

Role Level Access Control
Off_shore county users: access data for county 1 and 10

Mainland_conty users: Access to all others

Why it matters

- Enforce data privacy and compliance
- Delivers relevant views

Business Insights & Decision Support

Analyze the electricity production, consumption and imbalance
Correlate trends

Why it matters

- Identify drivers of imbalance
- Support data-driven actions

Data Architecture | Governance, Security, Disaster Recovery

- Governance & Security
  - GDPR-compliance
  - Data validation and quality checks embedded throughout
  - Implement role-based access and least-privilege controls across layers
- Disaster recovery
  - Store all code in version control environment
  - For data
    - Durable & replayable storage
    - Cross-region replication for critical datasets
    - Checkpointing for streaming jobs

Data Architecture | Future Considerations

- If business comes back with streaming requirement
  - Kafka streams continuous meter, weather, and market price events
  - Spark Structured Streaming with Databricks/MLflow models for near–real-time predictions
  - Forecasts feed grid operations and alerts
    - all data persisted in Delta Lake for retraining and trends
- Future automation
  - Deploy infrastructure with Terraform
  - Later CI/CD set up via DABs with github actions