

# Energy Behaviour Prediction of Prosumers

**PURPLE - TEAM 4**

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# I. INTRODUCTION

## Business Problem

The primary business problem is addressing energy imbalance in the power grid caused by the increasing number of prosumers — consumers who both consume and generate energy. The goal is to create an energy prediction model for prosumers to reduce energy imbalance costs.

### STAKEHOLDERS

- Energy Companies
- Prosumers
- Renewable Energy Advocates

### OPPORTUNITIES

- Reduced Imbalance Costs
- Grid Stability
- Promoting Renewable Energy

### CHALLENGES

- Unpredictable Behaviour
- Increasing Operational Costs
- Grid Instability

### ETHICAL CONSIDERATIONS

- Privacy
- Transparency
- Equity

# I. WHY THIS DATASET

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- Novelty of Prosumer Behavior
  - eic\_count
  - installed\_capacity
  - is\_business
  - is\_consumption
- Sustainable Energy Practices
- Renewable Energy Integration

# II. DATA SOURCES & PREPROCESSING

## Overview of Data Sources

- Energy Production and Consumption Data
- Weather Data
- Energy Prices (Gas & Electricity)
- Installed Photovoltaic Capacity Records

Data Collection Period: September 1, 2021, to May 29, 2023 (636 days, approx. 1.74 years)

**5** datasets, **51** variables, **138** columns, **2,018,352** rows

## DATA PREPROCESSING STEPS



## II. DATA SOURCES & PREPROCESSING

### train.csv

county  
is\_business  
product\_type  
target  
is\_consumption  
datetime  
data\_block\_id  
row\_id  
prediction\_unit\_id

### gas\_prices.csv

origin\_date  
forecast\_date  
[lowest/highest]  
\_price\_per\_mwh  
data\_block\_id

### electricity\_prices.csv

origin\_date  
forecast\_date  
euros\_per\_mwh  
data\_block\_id

### client.csv

product\_type  
county  
eic\_count  
installed\_capacity  
is\_business  
date  
data\_block\_id

### historical\_weather.csv

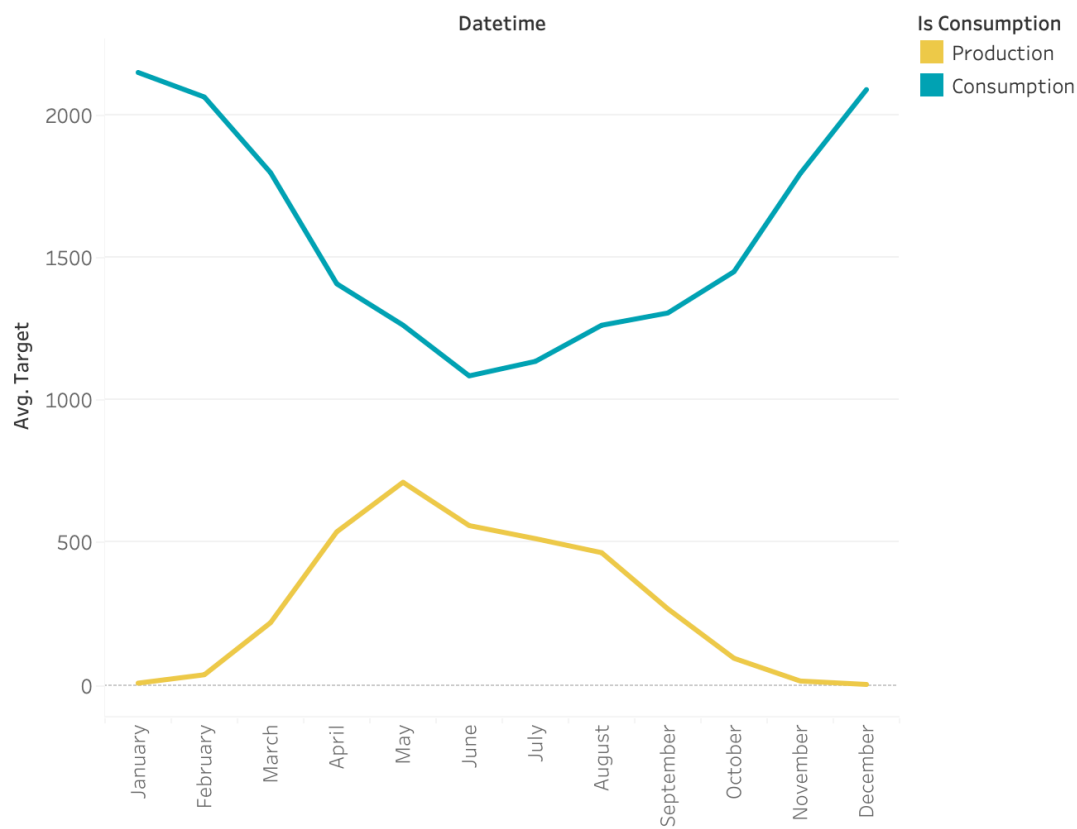
datetime  
temperature  
dewpoint  
rain  
snowfall  
surface\_pressure  
cloudcover\_[low/mid/high/total]  
windspeed\_10m  
winddirection\_10m  
shortwave\_radiation  
direct\_solar\_radiation  
diffuse\_radiation  
[latitude/longitude]  
data\_block\_id

- \*target - The consumption or production amount for the relevant segment for the hour. The segments are defined by the county, is\_business, and product\_type
- is\_consumption - Boolean for whether or not this row's target is consumption or production.
- is\_business - Boolean for whether or not the prosumer is a business.
- installed\_capacity: Installed photovoltaic solar panel capacity in kilowatts

# III. EXPLORATORY DATA ANALYSIS (EDA)

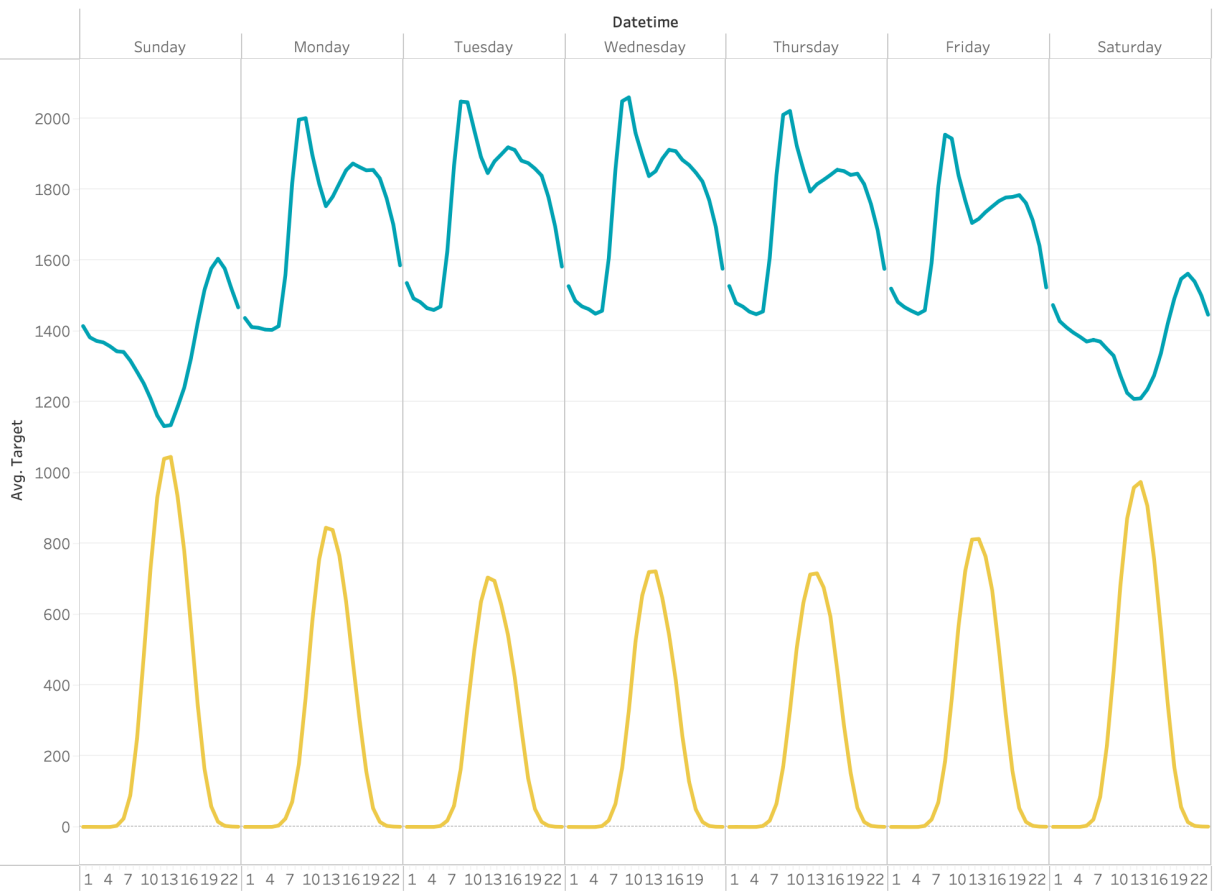
## Temporal Features

Variation in consumption/production patterns based on the month of the year.



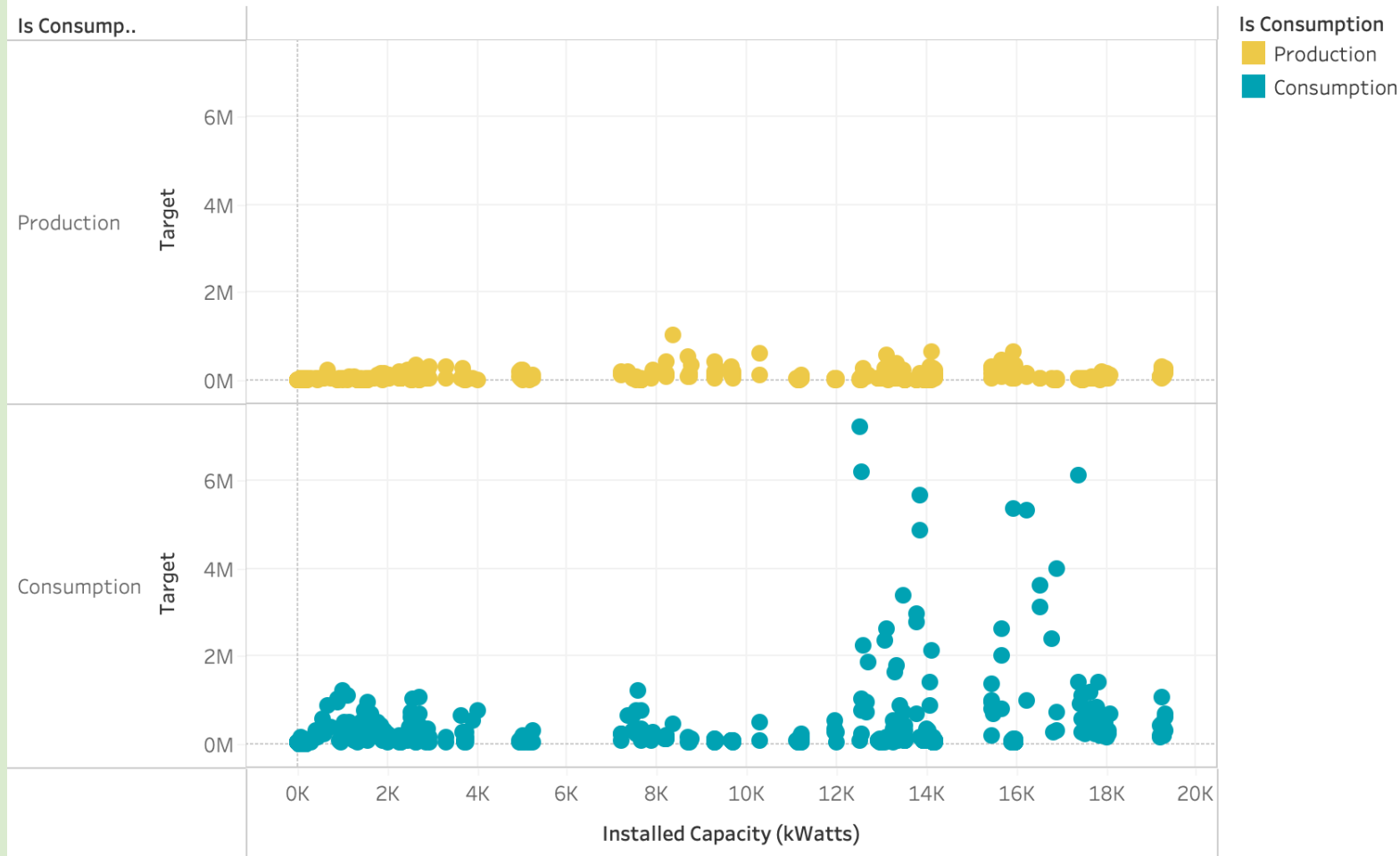
## Temporal Features

Variation in consumption/production patterns based on the time of the day over a week

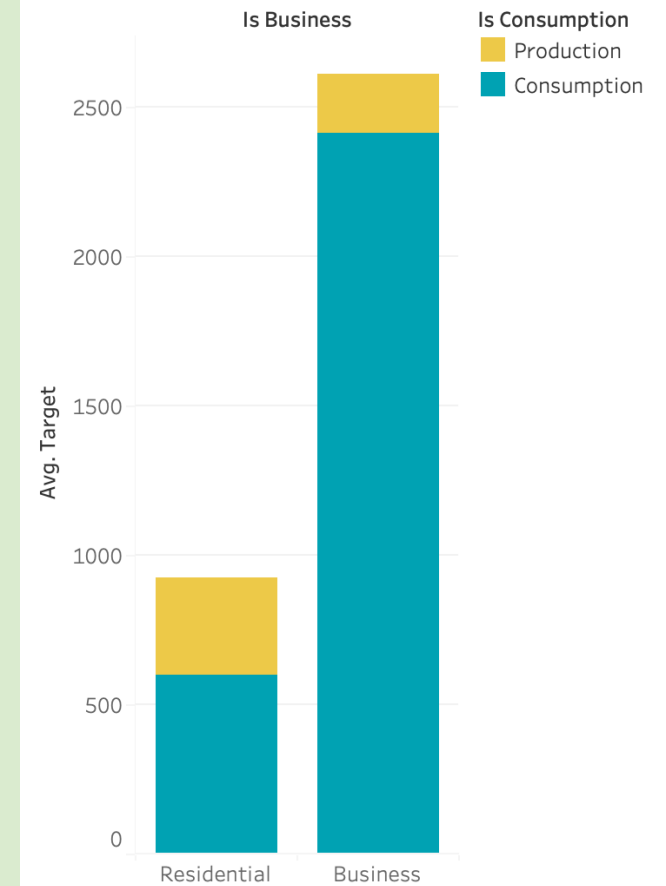


# III. EXPLORATORY DATA ANALYSIS (EDA)

## Energy Production and Consumption Correlation with Installed Solar Panel Capacity



## Business vs. Residential Energy Profile: Average Production and Consumption



# III. EXPLORATORY DATA ANALYSIS (EDA)

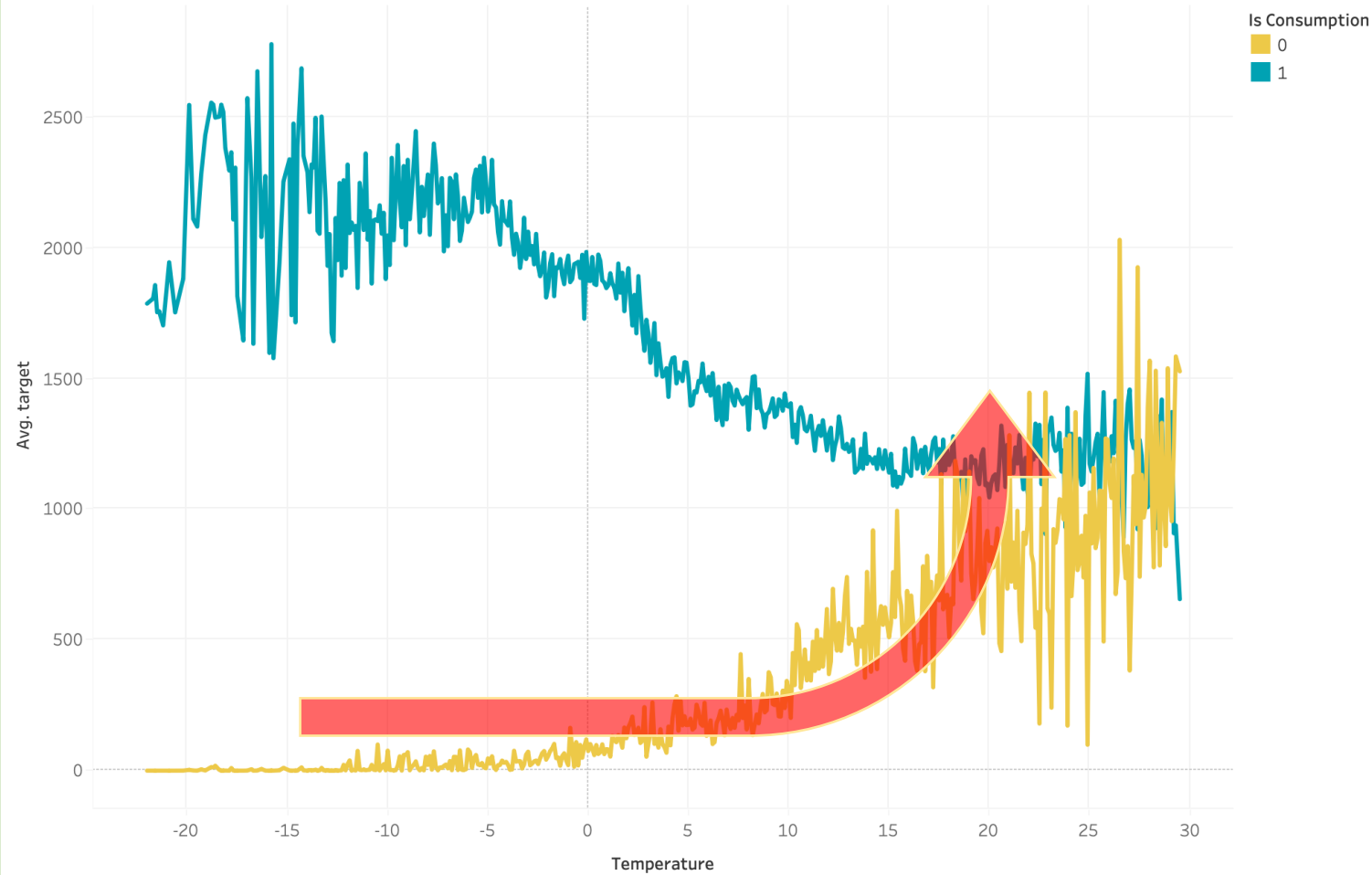
Energy Production and Consumption Dynamics in Response to Gas Prices





# III. EXPLORATORY DATA ANALYSIS (EDA)


Avg. Target & Temperature



The trend of average of target for Temperature. Color shows details about Is Consumption.

### III. EDA FINDINGS



- No linear relationship found between independent variables and the target variable.
  - **Temperature-Related Insights:**
    - Identify temperature ranges with significant energy changes.
    - Adjust energy production based on weather forecasts, optimizing renewables during extreme temperatures.
  - **Time-Related Insights (Hour of the Day):**
    - Identify peak hours for energy consumption, aiding utility planning.
    - Explore pricing structures to balance energy demand throughout the day.
- 

# IV. FEATURE SELECTION

```
'county, is_business, product_type, target, is_consumption, datetime, row_id, prediction_unit_id, date, installed_capacity, euros_per_mwh, lowest_price_per_mwh, highest_price_per_mwh, temperature, dewpoint, rain, snowfall, surface_pressure, cloudcover_total, cloudcover_low, cloudcover_mid, cloudcover_high, windspeed_10m, winddirection_10m, shortwave_radiation, direct_solar_radiation, diffuse_radiation, latitude, longitude'
```

## TOTAL FEATURES (23)

- Numerical features (20)
- Categorical Features (3): is\_business, product\_type, is\_consumption

## FEATURE ENGINEERING

- Categorical features: one-hot encoding
- Numerical features: normalization, convert datetime

# V. MODEL SELECTION

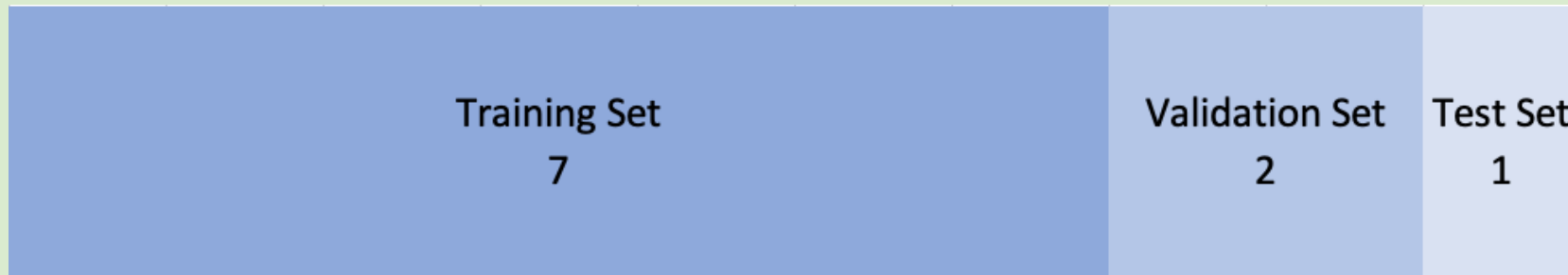
## REGRESSION MODELS

Model	Linear	Lasso/Ridge	Polynomial	MLP
	$y = ax + b$		$y = a_1x + a_2x^2 + \dots + a_kx^k + b$	
Pros	<ul style="list-style-type: none"><li>• Simple</li><li>• Interpretable</li></ul>	<ul style="list-style-type: none"><li>• Avoid overfitting</li></ul>	<ul style="list-style-type: none"><li>• Able to capture non-linear relationship</li></ul>	<ul style="list-style-type: none"><li>• Able to capture complex nonlinear relationships</li><li>• Automatic feature learning</li></ul>
Cons	<ul style="list-style-type: none"><li>• Limited capability</li></ul>	<ul style="list-style-type: none"><li>• Limited capability</li></ul>	<ul style="list-style-type: none"><li>• Higher computational complexity</li></ul>	<ul style="list-style-type: none"><li>• Overfit</li></ul>

# V. MODEL TRAINING

## CV & HYPERPARAMETER TUNING

- Cross-validation



- Parameters to tune

- Polynomial Regression: the degree of X
- MLP: hidden units

# VI. EVALUATION

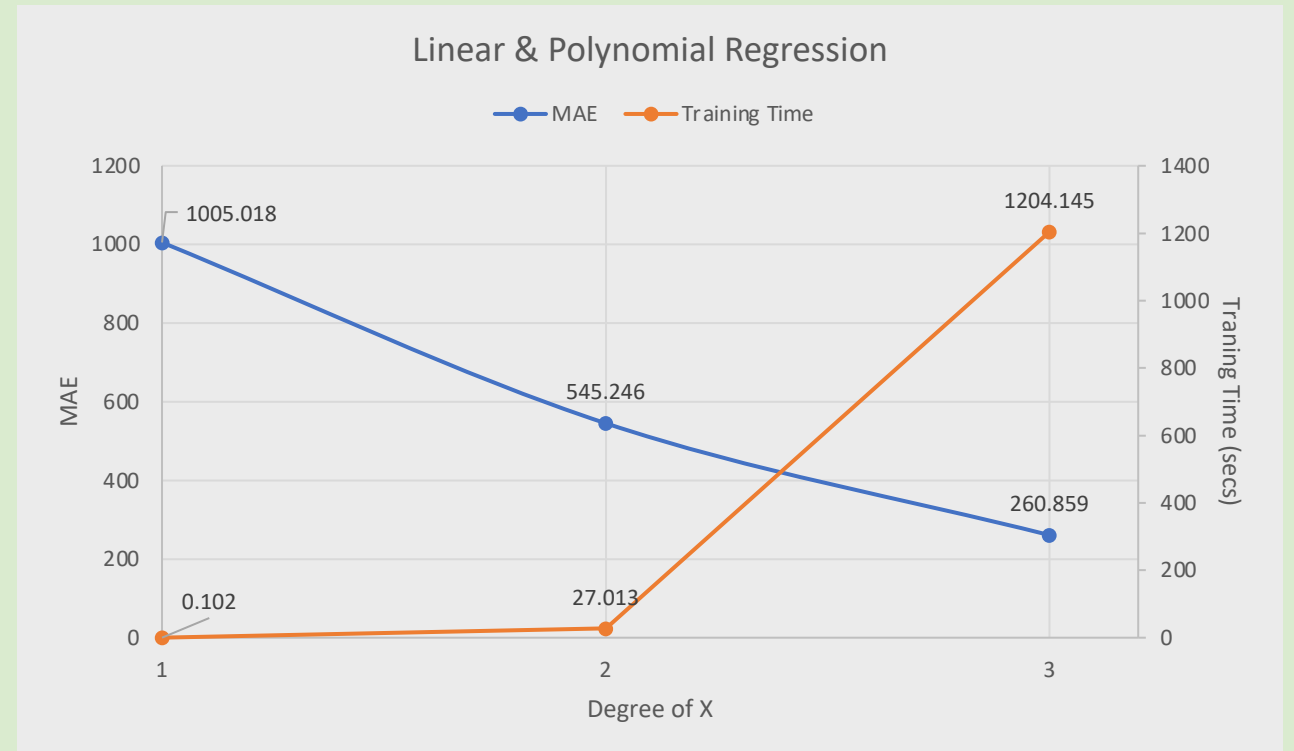
## Polynomial Regression vs MLP

### Polynomial Regression

- Degree of X increases
  - **MAE** decreases
  - Training time increases
- Performance vs Cost

### MLP

- Loss decreases rapidly in first few iterations



# VI. EVALUATION

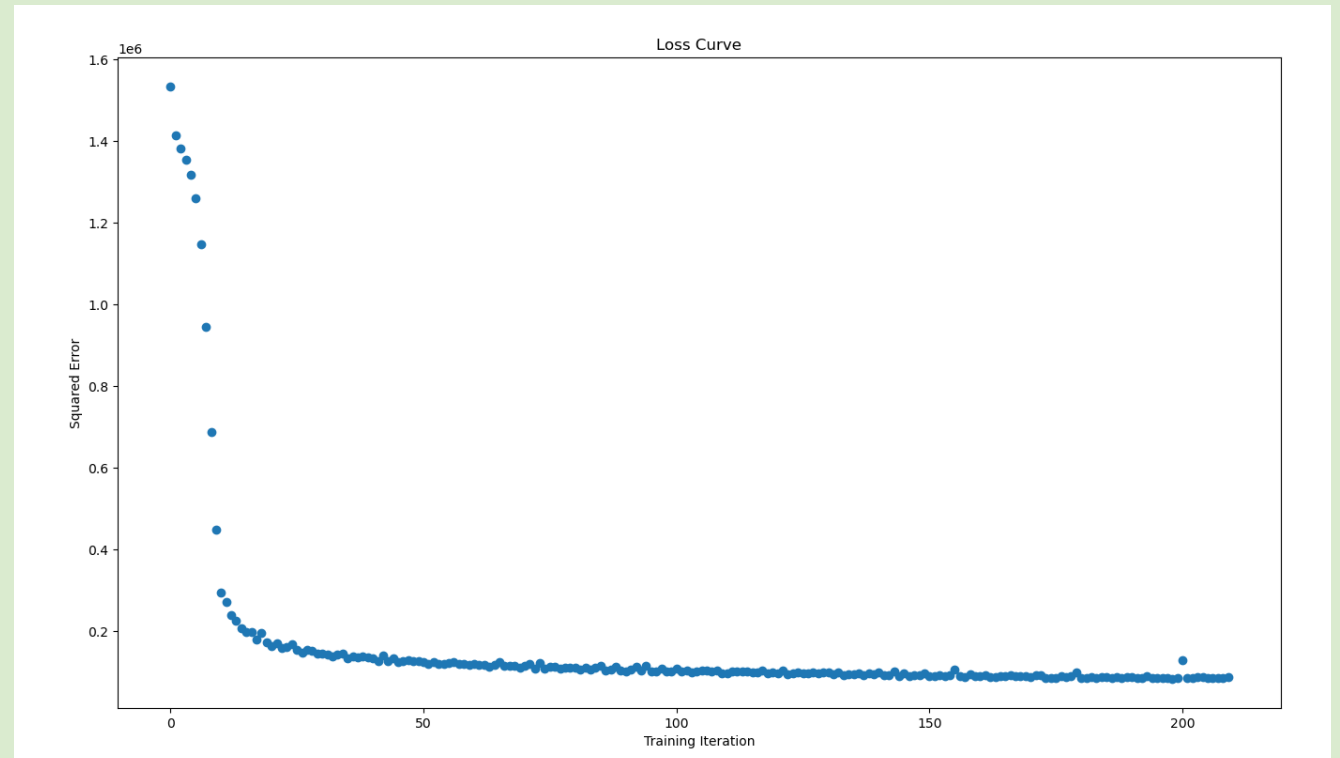
## Polynomial Regression vs MLP

### Polynomial Regression

- Degree of X increases
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### MLP

- Loss decreases rapidly in first few iterations



# VII. RESULT AND CONCLUSION



- Our analysis indicates that the Multilayer Perceptron (MLP) model provides the most accurate predictions for the target variable.
  - While the MLP model excels in predictive accuracy, it inherently lacks interpretability. This poses a challenge in directly extracting insights from the model structure.
  - Although the model's intricacies may not be directly interpretable, our intuition suggests that factors such as weather conditions, fuel prices, and electricity prices likely play pivotal roles in influencing energy demand. Further interpretative analysis could shed light on these aspects.
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# VIII. BUSINESS CONCLUSIONS & RECOMMENDATIONS

- Knowing how much energy prosumers use is crucial to avoid problems with power grid and to save money on logistics and operations.
- The Multilayer Perceptron model helps predict exactly how much energy prosumers will use.

## IMPACT OF ACCURATE PREDICTION

- Reduction in Energy Imbalance Costs
- Enhanced Grid Stability
- Efficient Prosumer Integration
- Encouraging Prosumer Transition

## STRATEGIC IMPLICATIONS:

- Cost savings and Efficiency
- Customer Friendly Systems

## **RECOMMENDATIONS –**

- **Continuous Model Improvement:** Ongoing refinement of the predictive model as more data becomes available.
- **Collaboration with Experts:** to identify and prioritize the most influential factors affecting energy consumption.

# IX. ACKNOWLEDGMENTS AND REFERENCES

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- The data for this project was provided by Enefit – an energy company in Baltic region.
- Citation: Kristjn Eljand, Martin Laid, Jean-Baptiste Scellier, Sohier Dane, Maggie Demkin, Addison Howard. (2023). Enefit - Predict Energy Behavior of Prosumers. Kaggle. <https://kaggle.com/competitions/predict-energy-behavior-of-prosumers>

**THANKYOU**