

Bakery Sales Prediction

Group presentation: Introduction to Datascience and Machine Learning

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Data imputation

Missing Values

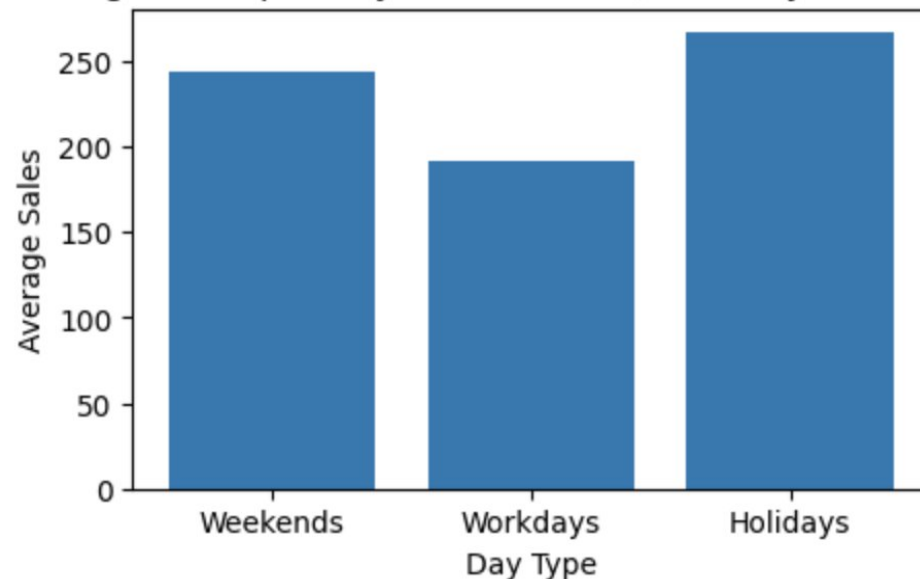
- KiWo
- Weather Data
 - Temperatur
 - Windgeschwindigkeit
 - Bewölkung
 - Wettercode
- Methods
 - Binary categories
 - Average
 - Copy from Day/Week/Month before

```
Missing values in train data:
  id          0
Datum         0
Warengruppe   0
Umsatz        0
KielerWoche   9111
Bewoelkung    70
Temperatur    16
Windgeschwindigkeit 16
Wettercode    2325
dtype: int64
Missing values in test data:
  id          0
Datum         0
Warengruppe   0
KielerWoche   1785
Bewoelkung    65
Temperatur    65
Windgeschwindigkeit 65
Wettercode    337
dtype: int64
```

Data exploration

- Impact of
 - Weekdays
 - Weekends
 - Public Holidays

Average Sales per Day on Weekends, Workdays and Holidays



```
1  ## create german holidays
2  from datetime import datetime
3  import holidays
4
5  ger_holidays = holidays.Germany()
6  print(ger_holidays.items())
7  # print dictionary of german holidays
8  print("German holidays: \n",ger_holidays.items())
9
10 for key, value in holidays.Germany(2013).items():
11     print(key, value)
```

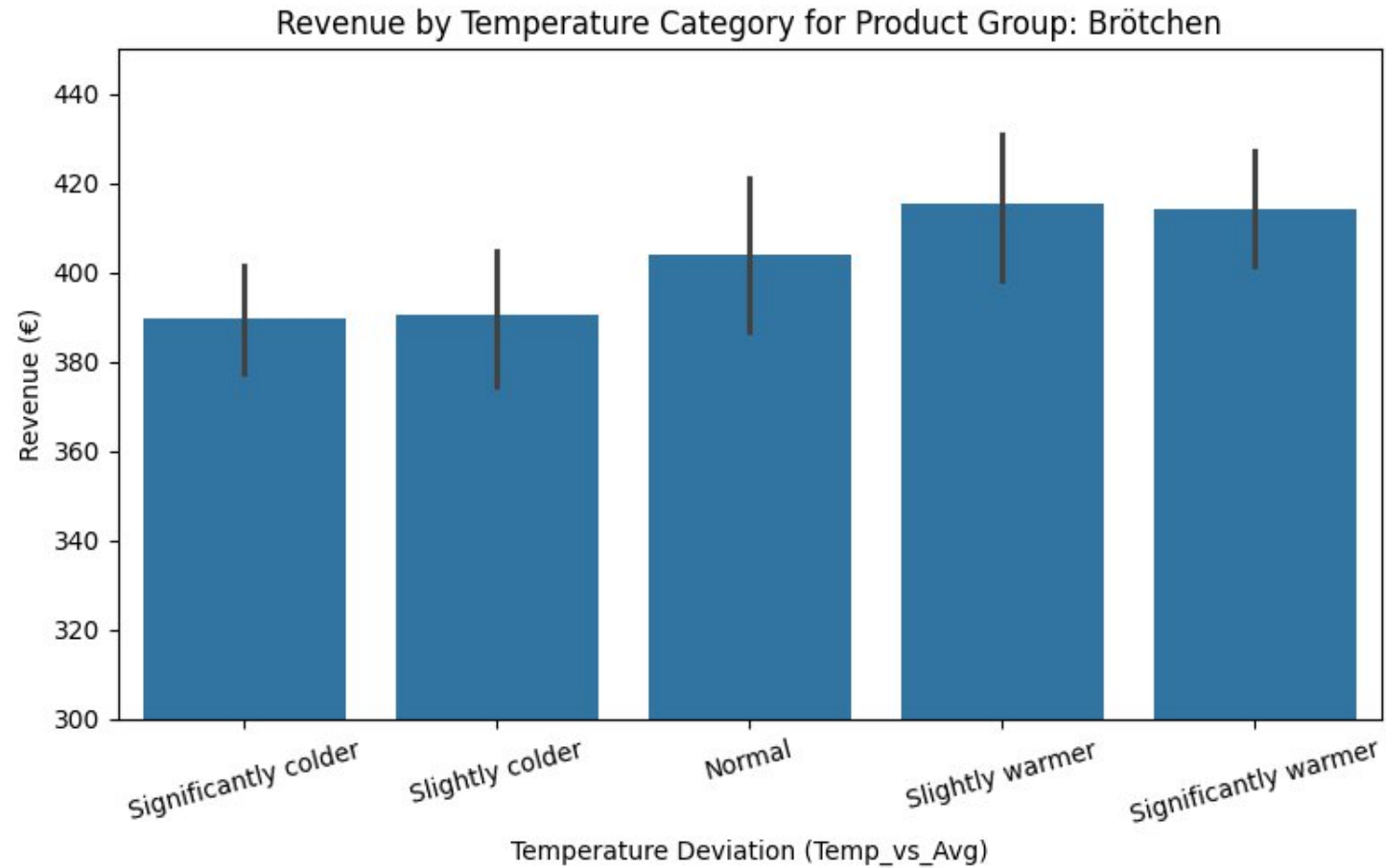
✓ 0.1s

```
dict_items([])
German holidays:
dict_items([])
2013-01-01 Neujahr
2013-03-29 Karfreitag
2013-04-01 Ostermontag
2013-05-01 Erster Mai
2013-05-09 Christi Himmelfahrt
2013-05-20 Pfingstmontag
2013-10-03 Tag der Deutschen Einheit
2013-12-25 Erster Weihnachtstag
2013-12-26 Zweiter Weihnachtstag
```

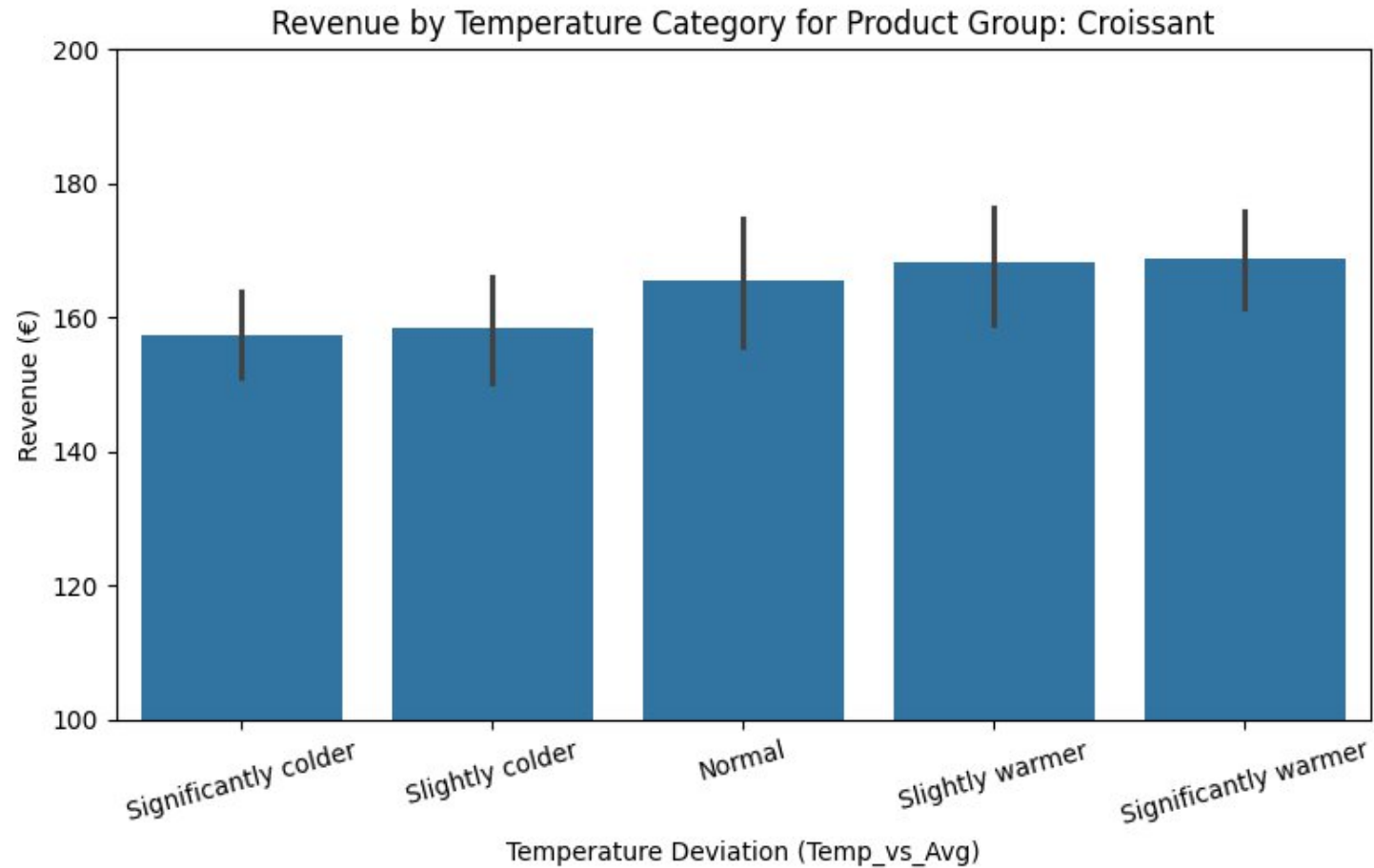
Self created variables

- Weekday
- Is_holiday
 - added all the holidays
- Temp_vs_Avg
 - weekly temperature compared to daily temperature
- Weather_Impression
 - used weathercode to classify weather into categories

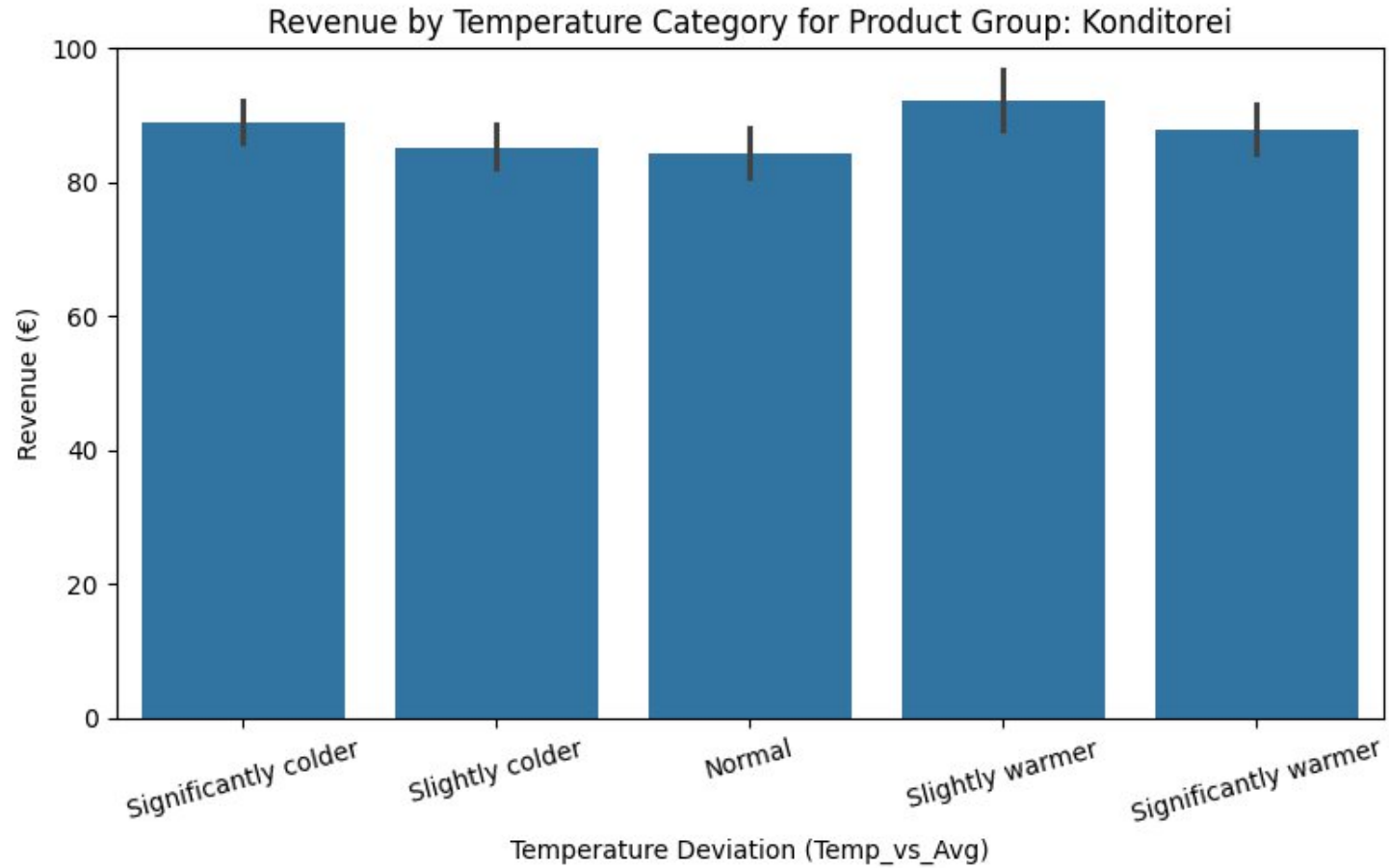
Categorized temperature



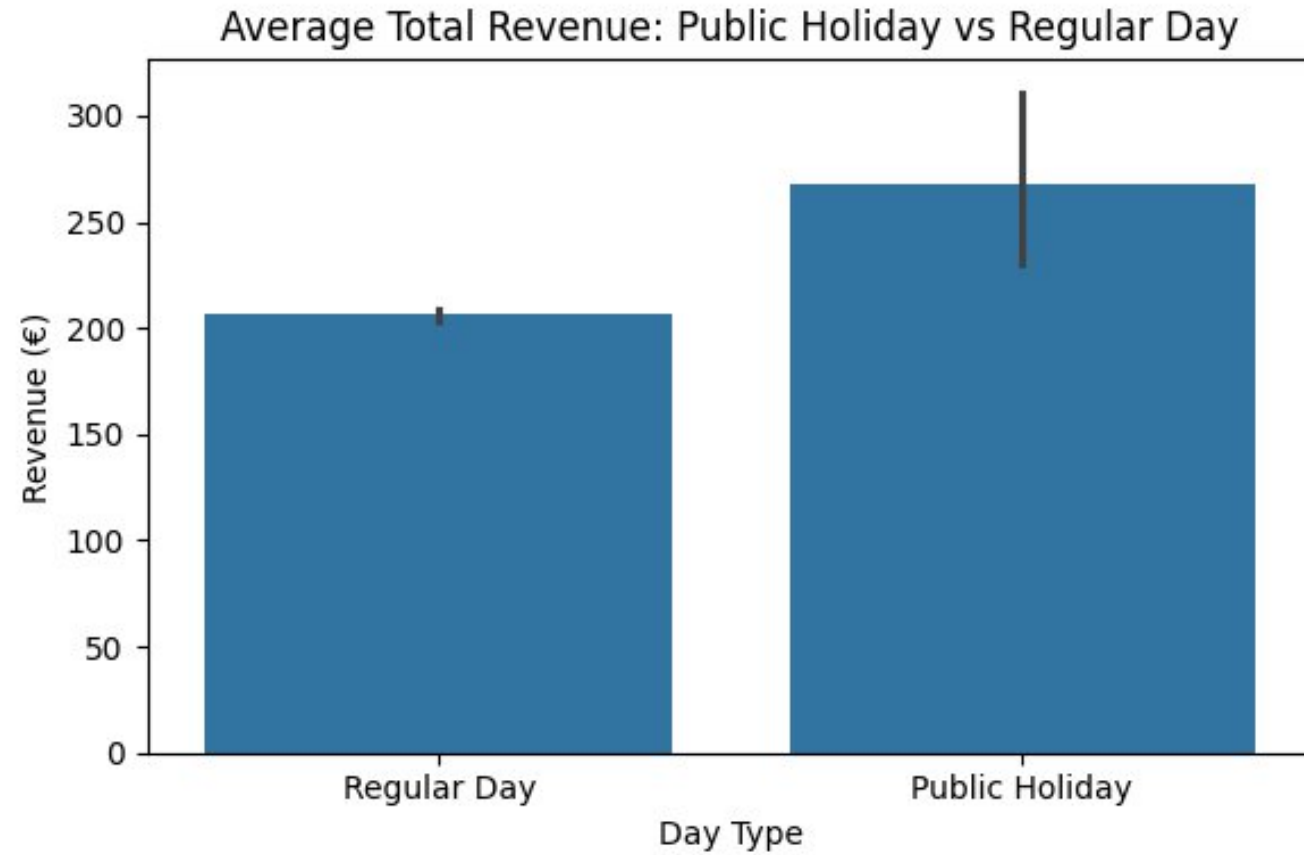
Categorized temperature



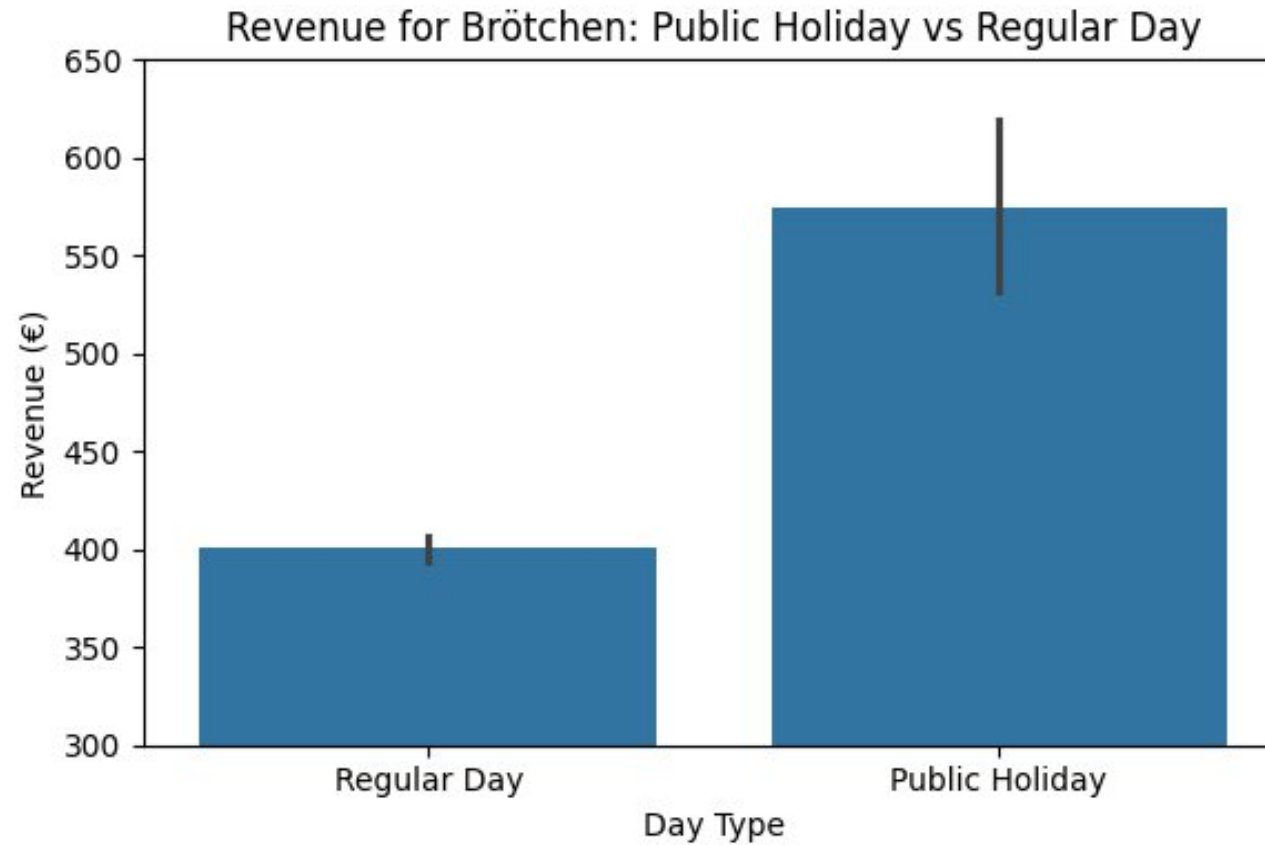
Categorized temperature



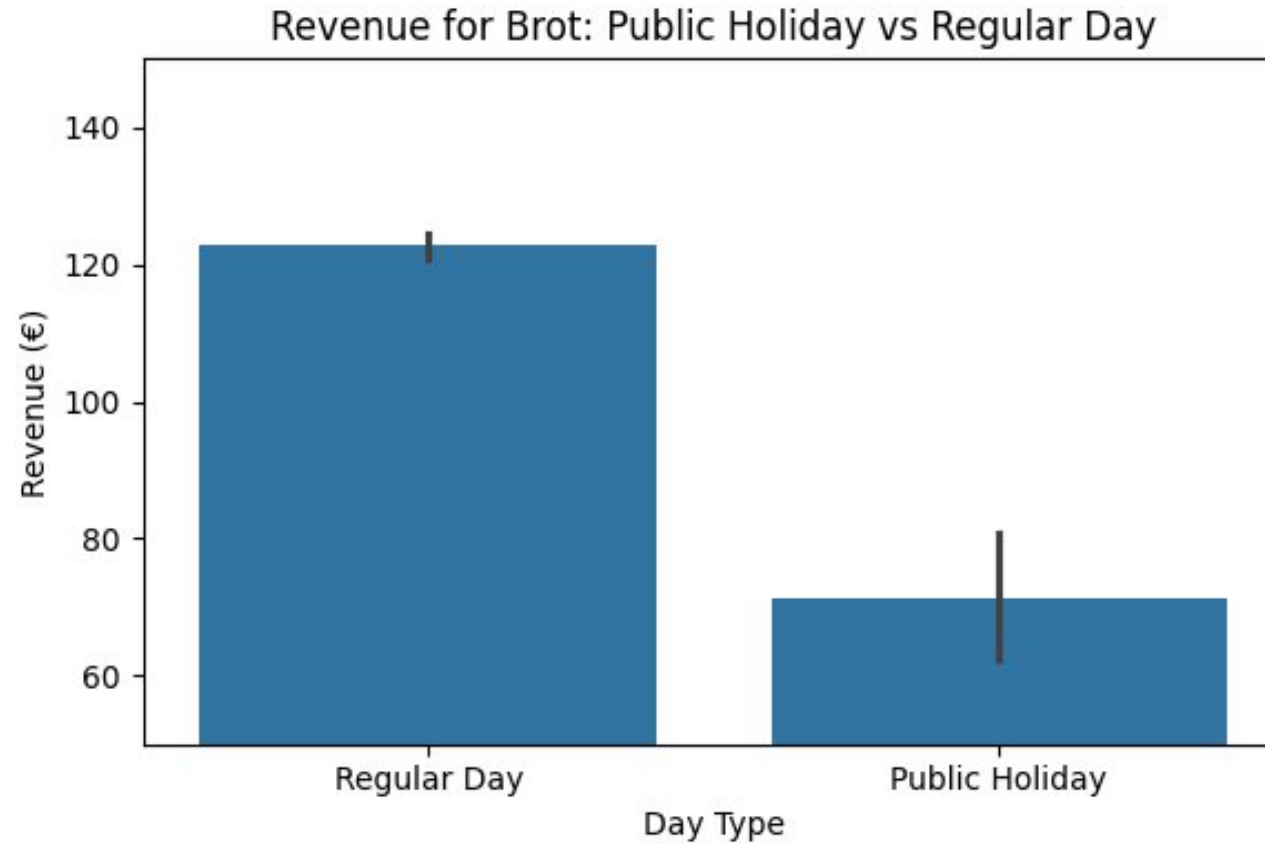
Public Holiday vs Regular Day



Public Holiday vs Regular Day



Public Holiday vs Regular Day

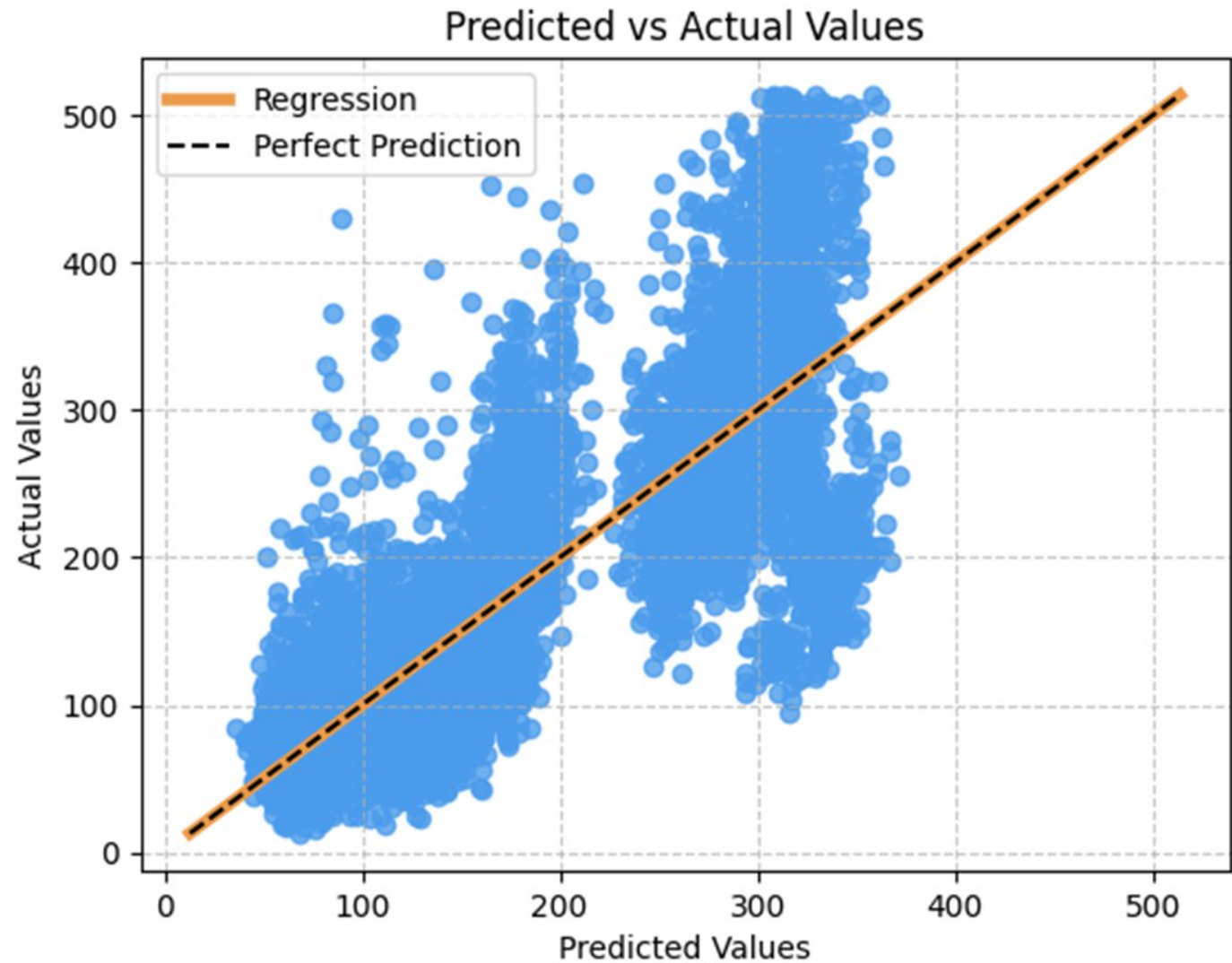


Linear Model - Preparation

- Missing values replaced with the average of the previous and following value
- IQR method: statistical technique for detecting outliers
- $IQR = Q3 - Q1$
- Q1 (first quartile): 25% of the data is below this value
- Q3 (third quartile): 75% of the data is below this value
- IQR: The range between Q1 and Q3, containing the middle 50% of the data

Linear Model

- $R^2 = 0.672$
- Kaggle Submission Score: 0.26734



Neural network optimization

- Source code

```
# Neural net architecture
model = Sequential([
    InputLayer(shape=(training_features.shape[1], )),
    Dense(64, activation='relu'),
    BatchNormalization(),
    Dropout(0.3),
    Dense(32, activation='relu'),
    BatchNormalization(),
    Dropout(0.3),
    Dense(16, activation='relu'),
    BatchNormalization(),
    Dense(1)
])
```

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 64)	2,752
batch_normalization (BatchNormalization)	(None, 64)	256
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 32)	2,080
batch_normalization_1 (BatchNormalization)	(None, 32)	128
dropout_1 (Dropout)	(None, 32)	0
dense_2 (Dense)	(None, 16)	528
batch_normalization_2 (BatchNormalization)	(None, 16)	64
dense_3 (Dense)	(None, 1)	17

Neural network optimization

- Source code

Total params: 5,825 (22.75 KB)

Trainable params: 5,601 (21.88 KB)

Non-trainable params: 224 (896.00 B)

```
# Compile & train with EarlyStopping
model.compile(loss="mse", optimizer=Adam(learning_rate=0.001))

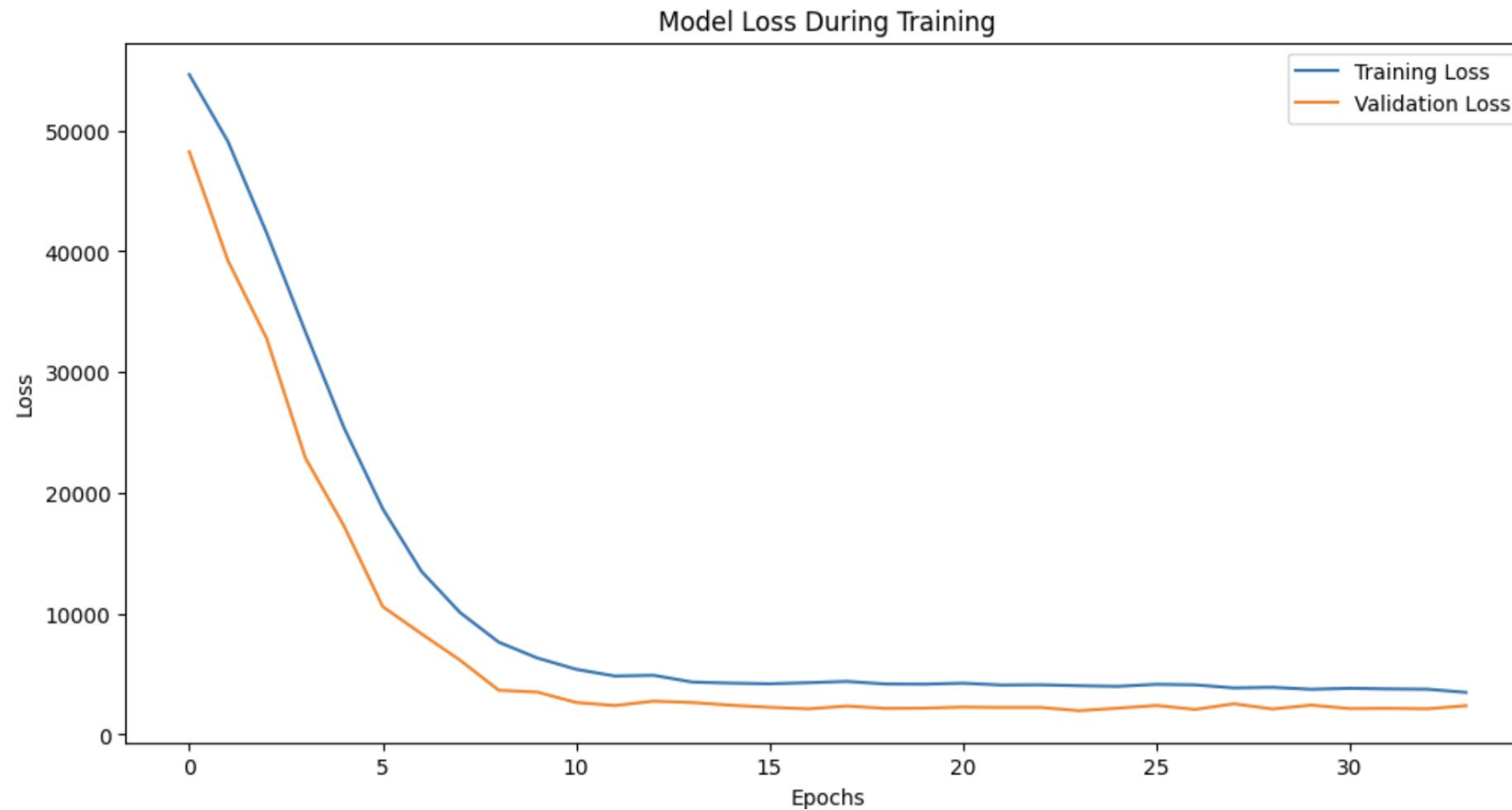
early_stop = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)

history = model.fit(
    training_features, training_labels,
    epochs=200,
    validation_data=(validation_features, validation_labels),
    callbacks=[early_stop]
)

# Save the improved model
model.save("improved_python_model1.h5")
```



Neural network optimization

- Loss function plot



Neural network optimization

- MAPE

276/276  0s 445us/step
66/66  0s 420us/step
Training MAPE: 18.00%
Validation MAPE: 18.80%

Warengruppe_Brötchen Validation MAPE: 14.81%
Warengruppe_Croissant Validation MAPE: 18.90%
Warengruppe_Konditorei Validation MAPE: 21.99%
Warengruppe_Kuchen Validation MAPE: 13.34%
Warengruppe_Saisonbrot Validation MAPE: 43.34%

Highlights & Lowlights

Worst Fail

- Weather data imputation
 - Getting weather data from weather station
- Adding time-series features
 - Took a lot of times, didn't improve the model

Best Improvement

- Keeping it simple
 - Resulted in best MAPE and R^2