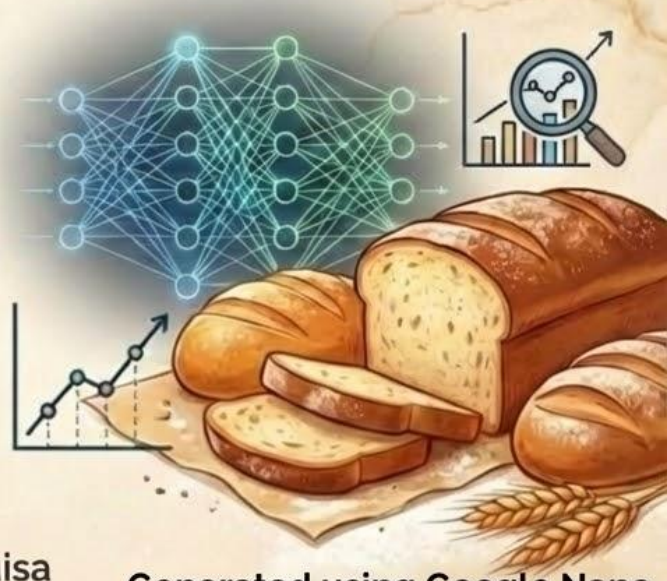
Bakery Sales Prediction Project: From Linear Regression to Neural Networks

Course name: Introduction to Data Science & Machine Learning



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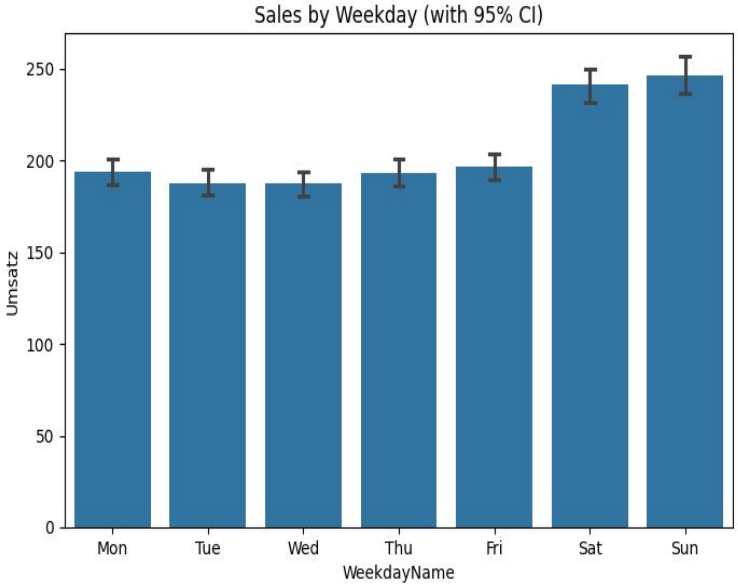
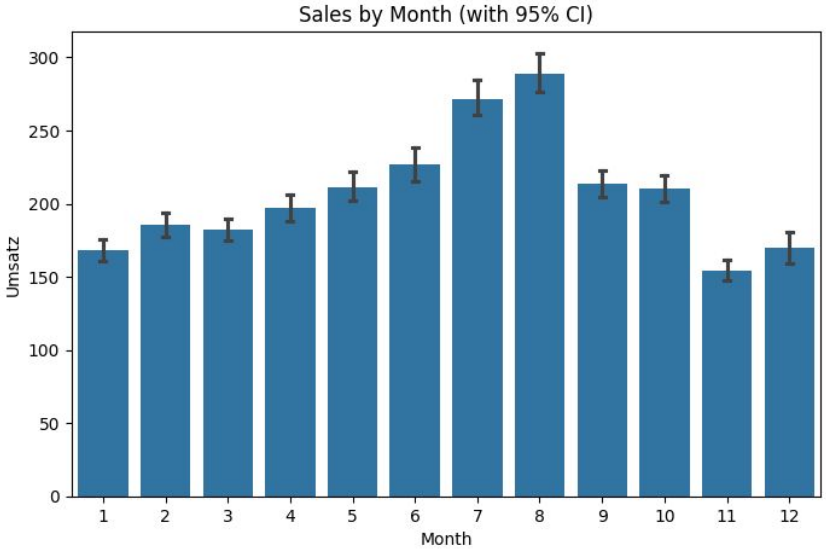
Generated using Google Nano Banana Model (6th Jan, 2026)

List and brief description of self-created variables

- **Overview:** To improve our model's ability to capture seasonality and trends, we engineered several features from the raw Datum column.
- **Variables:**
  - **Year**, **Month**, **Day**: Extracted to capture annual growth and monthly seasonality.
  - **Weekday**: Integer values were assigned (0=Monday, 6=Sunday) to capture weekly cycles.
  - **IsWeekend**: Boolean flag (True for Saturday/Sunday) to capture the high traffic on weekends.
  - **KielerWoche**: Binary flag (1 during the event, 0 otherwise). Accounts for the massive influx of visitors during the festival.

Bar charts with confidence intervals for two self-created variables





Baseline Model - Linear Regression

Model Equation:

Sales = β0 - 70.68 (Warengruppe_1) + 218.58 (Warengruppe_2) - 27.87 (Warengruppe_3) - 103.27 (Warengruppe_4) + 88.88 (Warengruppe_5) - 105.64 (Warengruppe_6) + 47.88 (IsWeekend) + 1.13 (Weekday) + 14.84 (KielerWoche) + 3.92 (Temperature) + 0.15 (WindSpeed) - 0.08 (CloudCover) + 0.01 (WeatherCode) - 11.48 (Year) - 1.06 (Month) + 0.35 (Day)

Key Drivers:

- **Product Type:** The strongest predictor (Group 2 sells +218€ vs baseline).
- **Seasonality:** Weekends (+48€) and Events (+15€) are significant positive drivers.

Model Performance:

- **Validation Adjusted R^2: 0.6859** (Strong Baseline).
- **Validation MAPE: 32.12%**.
- **Conclusion:** The model explains **~69%** of the variance in sales, proving that basic features (Product + Time) work well. However, a **32% average error** is still too high for precise inventory planning.

Type of missing value imputation used

Challenge: The **weather** dataset and **Kieler Woche** contained missing entries.

Imputation Strategy:

1. **KielerWoche & Wettercode Dataset:** Filled `NaN` with `0` (Assumed "No Event" / "No significant weather" if missing). **Reasoning:** This is a structural decision, not a guess. Since the original files only listed dates when the festival or a weather event *actually occurred*, any date that didn't match during our merge is logically a 'non-event' day. Therefore, treating `NaN` as `0` correctly represents 'No Festival' or 'Normal Weather'.
2. **Weather Imputation (Temp, Wind, Clouds):** Used **Forward Fill** followed by **Backward Fill**. **Reasoning:** Weather conditions (like temperature or cloud cover) typically persist over short periods. Using the last known value is a safe, logical baseline (Persistence Model).

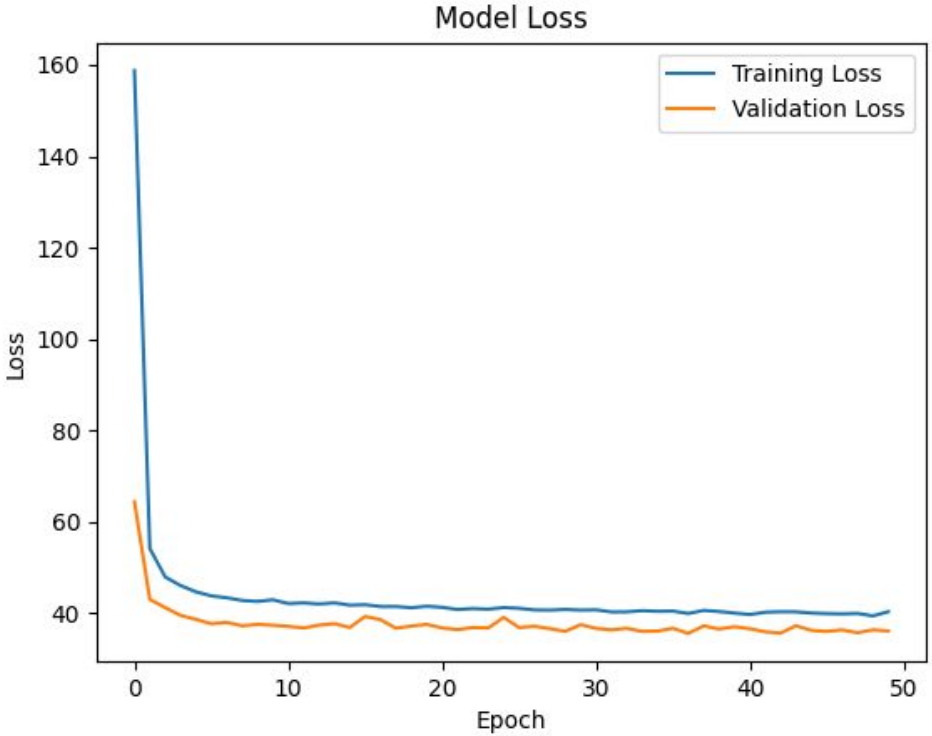
Neural network model

```
# Define Model
model = keras.Sequential([
    layers.Dense(64, activation='relu', input_shape=[X_train.shape[1]]), # Input
Layer matching feature dimensions
    layers.Dropout(0.2), # Dropout layer to prevent Overfitting
    layers.Dense(32, activation='relu'), # Hidden Layer
    layers.Dense(1) # Output Layer ( Single value for Regression)
])


model.compile(
        optimizer='adam',
        loss='mae', # Mean Absolute Error is often good for regression
    )

# Train
history = model.fit(
    X_train_scaled, y_train,
    validation_data=(X_val_scaled, y_val),
    batch_size=32,
    epochs=50,
    verbose=1
)
```

Neural Network Training



Observations:

- The training loss decreases steadily, indicating the model is learning.
- The validation loss stabilizes around 50 epochs, suggesting the model has converged without significant overfitting (thanks to the Dropout layer).

Neural Network Results (MAPE)

Overall Validation Performance:

- **Neural Net Validation MAPE: 0.2018** (20.18%). On average, our predictions are off by ~20.18%)

Performance by Product Group:

- **Warengruppe 1:** 0.2342 (23.4%)
- **Warengruppe 2:** 0.1380 (13.8%) (Best performing group)
- **Warengruppe 3:** 0.2042 (20.4%)
- **Warengruppe 4:** 0.2394 (23.9%)
- **Warengruppe 5:** 0.1451 (14.5%)
- **Warengruppe 6:** 0.5812 (58.1%) (Hardest to predict)

"Worst Fail" vs. "Best Improvement"

- **Worst Fail (The Model's Blind Spot)**
  - **Date:** 2017-12-31 (New Year's Eve)
  - **Actual Sales:** 1,432.42 €
  - **Predicted:** 262.21 €
  - **Error: 1,170.21 € (Underestimated by ~82%)**
  - **Diagnosis:** The model treated this as a regular Sunday. It failed to capture the massive, irregular demand spike specific to New Year's Eve.
- **Best Improvement (Model Strength)**
  - **Date:** 2017-08-13 (Summer Sunday)
  - **Actual Sales:** 537.19 €
  - **Predicted:** 515.50 €
  - **Error: 21.69 € (Only ~4% Error)**
  - **Success Factor:** Unlike the linear baseline, the Neural Network correctly identified the non-linear interaction between "Sunday" and "Summer Weather," predicting the high volume almost perfectly.

Conclusion

Summary:

- Transitioning from Linear Regression to Neural Networks improved prediction accuracy by **~37%** (MAPE dropped from **32.1%** to **20.2%**).

Key Learnings:

- **Feature Engineering:** Simple flags (Weekends/Holidays) were more impactful than complex raw data.
- **Non-Linear Patterns:** Neural Networks successfully captured complex interactions (e.g., Summer + Weekend) that linear models missed.

Next Steps:

- Incorporate **"School Holidays"** and specific **"Public Holidays"** (like New Year's Eve) as explicit features to fix the "Worst Fail" cases.