# U.S. Meat Production Analysis – anomalies and Transformers

**Target Audience:**
Highly Technical, but unaware of my project

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STAT443 Statistical Machine Learning II – Prof. Joseph Reid

# Intro

- This report examines U.S. meat production statistics and attempts to forecast meat production for the year.
- The sanitized dataset includes variables such as beef, veal, pork, lamb and mutton, broilers, turkey, total poultry production, and total meat production.
- Dataset for the transformer forecasting looks a little different this time

# Source

- USDA
- Meat statistics table, historical
- Cropped the data to the period of January 2025 – January 1977 as this was the period that lacked any missing values for federally inspected meat.
- I additional removed all columns for non-federally inspected meat as I wanted to look at the longest historical trends.
- Variables casted to float32 and commas removed (excel moment).

# Quick Look(uncleaned)

Red meat and poultry production (million pounds)

| Type 1/ | Commercial 2/ | | | | | Federally inspected | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Beef 3/ | Veal 3/ | Pork 3/ | Lamb and mutton 3/ | Total red meat 3/ 4/ | Beef 3/ | Veal 3/ | Pork 3/ | Lamb and mutton 3/ | Total red meat 3/ 4/ | Broilers 5/ | Other chicken 5/ | Turkey 5/ | Total poultry 4/ 5/ 6/ | Total red meat and poultry 4/ |
| Jan 2025 | 2,370.1 | 2.5 | 2,501.9 | 10.9 | 4,885.3 | 2,335.6 | 2.3 | 2,492.6 | 9.7 | 4,840.2 | 4,137.7 | 48.0 | 415.2 | 4,612.7 | 9,452.9 |
| Jan 2024 | 2,280.8 | 3.9 | 2,472.7 | 10.6 | 4,768.0 | 2,246.1 | 3.8 | 2,462.4 | 9.6 | 4,721.9 | 4,051.4 | 47.4 | 435.2 | 4,547.6 | 9,269.5 |
| Jan-2025 | 2,370.1 | 2.5 | 2,501.9 | 10.9 | 4,885.3 | 2,335.6 | 2.3 | 2,492.6 | 9.7 | 4,840.2 | 4,137.7 | 48.0 | 415.2 | 4,612.7 | 9,452.9 |
| Dec-2024 | 2,200.7 | 3.1 | 2,328.7 | 12.0 | 4,544.4 | 2,168.6 | 2.9 | 2,319.9 | 10.8 | 4,502.1 | 3,882.4 | 42.0 | 376.3 | 4,311.2 | 8,813.3 |
| Nov-2024 | 2,216.6 | 3.1 | 2,334.4 | 10.4 | 4,564.5 | 2,185.0 | 3.0 | 2,325.7 | 9.2 | 4,522.9 | 3,651.4 | 36.9 | 394.1 | 4,093.1 | 8,616.0 |
| Oct-2024 | 2,465.5 | 3.3 | 2,543.5 | 11.7 | 5,024.0 | 2,425.8 | 3.1 | 2,532.2 | 10.3 | 4,971.4 | 4,370.9 | 52.6 | 493.9 | 4,929.6 | 9,901.0 |
| Sep-2024 | 2,204.9 | 3.1 | 2,232.6 | 10.6 | 4,451.2 | 2,170.7 | 2.9 | 2,221.8 | 9.4 | 4,404.8 | 3,892.6 | 49.2 | 413.4 | 4,366.2 | 8,771.0 |
| Aug-2024 | 2,288.1 | 3.1 | 2,289.9 | 10.5 | 4,591.7 | 2,256.1 | 3.0 | 2,278.5 | 9.2 | 4,546.8 | 4,038.7 | 49.6 | 435.0 | 4,533.2 | 9,080.0 |
| Jul-2024 | 2,286.8 | 3.3 | 2,252.8 | 11.3 | 4,554.3 | 2,255.9 | 3.2 | 2,242.5 | 10.0 | 4,511.7 | 4,072.1 | 50.5 | 433.5 | 4,566.2 | 9,077.9 |
| Jun-2024 | 2,135.8 | 3.1 | 2,117.7 | 10.4 | 4,267.0 | 2,103.6 | 3.0 | 2,109.2 | 9.1 | 4,225.0 | 3,724.9 | 47.7 | 408.9 | 4,190.7 | 8,415.7 |
| May-2024 | 2,326.4 | 3.5 | 2,278.6 | 11.5 | 4,619.9 | 2,292.3 | 3.4 | 2,269.5 | 10.2 | 4,575.4 | 4,011.0 | 50.3 | 446.8 | 4,518.9 | 9,094.3 |
| Apr-2024 | 2,303.4 | 3.5 | 2,317.4 | 11.4 | 4,635.6 | 2,269.3 | 3.3 | 2,308.2 | 10.1 | 4,590.9 | 3,917.7 | 47.2 | 450.7 | 4,427.5 | 9,018.4 |
| Mar-2024 | 2,110.4 | 3.6 | 2,250.1 | 12.3 | 4,376.4 | 2,076.5 | 3.4 | 2,240.7 | 11.1 | 4,331.7 | 3,636.8 | 42.9 | 409.5 | 4,100.3 | 8,432.0 |
| Feb-2024 | 2,168.6 | 3.6 | 2,371.2 | 10.9 | 4,554.3 | 2,135.0 | 3.4 | 2,361.4 | 9.8 | 4,509.7 | 3,741.9 | 45.0 | 423.9 | 4,221.4 | 8,731.1 |
| Jan-2024 | 2,280.8 | 3.9 | 2,472.7 | 10.6 | 4,768.0 | 2,246.1 | 3.8 | 2,462.4 | 9.6 | 4,721.9 | 4,051.4 | 47.4 | 435.2 | 4,547.6 | 9,269.5 |

# Yesterday's Data

[7]:
```
print(df.sample(n=10))
```

| | Date | Beef | Veal | Pork | Lamb and mutton | Total red meat | Broilers |
|---|---|---|---|---|---|---|---|
| 4 | 24-Sep | 2204.9 | 3.1 | 2232.6 | 10.6 | 4451.2 | 3892.6 |
| 268 | 2-Sep | 2201.0 | 16.3 | 1638.0 | 17.6 | 3873.2 | 2596.4 |
| 217 | 6-Dec | 2049.6 | 13.1 | 1796.4 | 15.4 | 3874.5 | 2737.8 |
| 105 | 16-Apr | 1964.0 | 6.0 | 2000.2 | 12.9 | 3983.0 | 3302.1 |
| 0 | 25-Jan | 2370.1 | 2.5 | 2501.9 | 10.9 | 4885.3 | 4137.7 |
| 122 | 14-Nov | 1849.5 | 6.5 | 1890.2 | 11.5 | 3757.7 | 2939.9 |
| 277 | 1-Dec | 2110.0 | 16.0 | 1668.0 | 19.0 | 3813.6 | 2464.8 |
| 139 | 13-Jun | 2157.0 | 8.4 | 1676.3 | 12.7 | 3854.5 | 3002.0 |
| 210 | 7-Jul | 2256.7 | 10.7 | 1659.5 | 13.5 | 3940.4 | 3055.0 |
| 285 | 1-Apr | 1939.0 | 15.0 | 1533.0 | 20.0 | 3507.5 | 2515.7 |

| | Other chicken | Turkey | Total poultry | Total red meat and poultry |
|---|---|---|---|---|
| 4 | 49.2 | 413.4 | 4366.2 | 8771.0 |
| 268 | 46.4 | 444.6 | 3098.3 | 6918.3 |
| 217 | 36.9 | 429.1 | 3215.5 | 7043.0 |
| 105 | 43.8 | 484.8 | 3842.1 | 7787.9 |
| 0 | 48.0 | 415.2 | 4612.7 | 9452.9 |
| 122 | 36.1 | 480.8 | 3467.3 | 7190.1 |
| 277 | 40.9 | 419.8 | 2935.4 | 6694.4 |
| 139 | 42.9 | 473.4 | 3527.6 | 7345.1 |
| 210 | 44.6 | 505.2 | 3616.0 | 7512.8 |
| 285 | 42.2 | 428.8 | 2997.9 | 6455.9 |

# Anomaly Detection

| | Z_Score_Anomaly | IsolationForest_Anomaly | DBSCAN_Anomaly |
|---|---|---|---|
| 2 | False | True | True |
| 16 | True | True | True |
| 28 | False | True | True |
| 50 | False | True | False |
| 62 | False | True | True |
| 74 | False | False | True |
| 193 | False | False | True |
| 194 | False | False | True |
| 206 | True | True | True |
| 213 | False | False | True |
| 238 | False | True | True |
| 249 | True | True | True |
| 250 | False | True | True |
| 253 | False | True | True |
| 266 | False | True | True |
| 273 | True | True | True |
| 278 | False | True | True |
| 285 | True | True | True |
| 286 | False | True | True |

| | Beef | Veal | Pork | Lamb and mutton | Total red meat | Broilers | \ |
|---|---|---|---|---|---|---|---|
| 2 | 1.763860 | -1.506932 | 2.097974 | -0.794782 | 2.335388 | 2.662100 | |
| 16 | 1.133685 | -1.283683 | 1.172164 | -1.240029 | 1.360655 | 2.154742 | |
| 28 | 2.016554 | -1.159655 | 1.202427 | -0.794782 | 1.782946 | 2.283181 | |
| 50 | 1.818142 | -1.010823 | 2.303833 | -1.240029 | 2.516370 | 1.425102 | |
| 62 | 1.600389 | -0.564324 | 2.332975 | -0.349536 | 2.451574 | 2.020378 | |
| 74 | 1.546106 | -0.539519 | 1.750515 | -0.228105 | 1.992975 | 1.567523 | |
| 193 | -1.394503 | 0.477505 | -0.358148 | -0.349536 | -0.889050 | -1.385869 | |
| 194 | 0.986436 | 1.023225 | 0.664800 | 0.540958 | 0.953725 | 0.054689 | |
| 206 | 1.623474 | 0.427894 | 0.609506 | 1.107636 | 1.194755 | 0.322942 | |
| 213 | -0.403069 | 1.023225 | -0.451925 | 2.402899 | -0.489940 | -0.757654 | |
| 238 | -2.591835 | 0.651143 | -1.317956 | 0.581435 | -2.133859 | -1.373546 | |
| 249 | -0.466710 | 1.172058 | -0.676091 | 3.455301 | -0.678184 | -0.815949 | |
| 250 | -2.363475 | 1.271280 | -1.535398 | 0.460004 | -2.186924 | -1.847729 | |
| 253 | -2.494501 | 1.444918 | -0.986189 | 1.067159 | -1.829709 | -1.951760 | |
| 266 | 2.053990 | 2.313109 | -0.564008 | 2.443376 | 0.542606 | -0.697226 | |
| 273 | -0.772439 | 1.395307 | -1.498037 | 3.455301 | -1.424734 | -1.569760 | |
| 278 | 1.286549 | 2.139471 | -0.537855 | 2.564807 | 0.215833 | -0.830167 | |
| 285 | -0.541583 | 1.643362 | -1.329911 | 3.779117 | -1.188452 | -1.561465 | |
| 286 | -1.883044 | 1.643362 | -1.852967 | 1.350498 | -2.200610 | -2.192761 | |

| | Other chicken | Turkey | Total poultry | Total red meat and poultry | \ |
|---|---|---|---|---|---|
| 2 | 2.059533 | 0.525361 | 2.675792 | 2.601590 | |
| 16 | 3.522404 | 0.417453 | 2.183877 | 1.868369 | |
| 28 | 2.717825 | -0.711434 | 2.206174 | 2.075121 | |
| 50 | 1.181810 | 1.324989 | 1.515216 | 2.024943 | |
| 62 | 0.572281 | 2.113550 | 2.169013 | 2.373033 | |
| 74 | 1.645053 | 2.711196 | 1.786722 | 1.941008 | |
| 193 | -1.353833 | 0.929326 | -1.297850 | -1.145038 | |
| 194 | 1.571909 | 2.957448 | 0.316319 | 0.617610 | |
| 206 | 0.840474 | 3.048755 | 0.582714 | 0.879268 | |
| 213 | -1.134402 | 0.193336 | -0.736027 | -0.646941 | |
| 238 | -1.305071 | -1.818185 | -1.513615 | -1.856323 | |
| 249 | 0.230944 | -0.111021 | -0.804774 | -0.780792 | |
| 250 | -2.889848 | -2.128076 | -2.018536 | -2.169998 | |
| 253 | -2.499749 | -0.537120 | -1.983001 | -1.981767 | |
| 266 | 1.596290 | 1.410762 | -0.548133 | -0.076074 | |
| 273 | -0.329823 | -0.766771 | -1.606284 | -1.586127 | |
| 278 | 0.694187 | 1.836862 | -0.650093 | -0.284796 | |
| 285 | 0.060276 | -0.357273 | -1.560066 | -1.450963 | |
| 286 | -1.085640 | -1.815419 | -2.314196 | -2.349035 | |

# Anomalies Continued

```
Proportion of anomalies detected by Isolation Forest: 5.21%
Proportion of anomalies detected by DBSCAN: 6.25%
Proportion of anomalies detected by Z-Score: 1.74%
```

```python
### METHOD 1: Z-Score ###
z_scores = np.abs(stats.zscore(df_scaled))
threshold = 3
df_scaled['Z_Score_Anomaly'] = (z_scores > threshold).any(axis=1)

### METHOD 2: Isolation Forest ###
iso_forest = IsolationForest(contamination=0.05, random_state=42)
df_scaled['IsolationForest_Anomaly'] = iso_forest.fit_predict(df_scaled) == -1  # Convert to True/False

### METHOD 3: DBSCAN ###
dbscan = DBSCAN(eps=1.5, min_samples=5)
df_scaled['DBSCAN_Anomaly'] = dbscan.fit_predict(df_scaled) == -1  # Convert to True/False
```

# New Clean

```
df = pd.read_csv(r'T:\Users\caleb.hart\DSAI443\Meats1977.csv')

# Apply conversion by removing commas and turning to numeric
for col in df:
    if df[col].dtype == 'object':  # Check if the column contains string values
        df[col] = df[col].replace({',': ''}, regex=True)  # Remove commas
        df[col] = pd.to_numeric(df[col], errors='raise')  # Convert to numeric
df.head()
```

| | Beef 3/ | Veal 3/ | Pork 3/ | Lamb and mutton 3/ | Total red meat 3/ 4/ | Broilers 5/ | Turkey 5/ | Total poultry 4/ 5/ 6/ | Total red meat and poultry 4/ |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 2335.6 | 2.3 | 2492.6 | 9.7 | 4840.2 | 4137.7 | 415.2 | 4612.7 | 9452.9 |
| **1** | 2246.1 | 3.8 | 2462.4 | 9.6 | 4721.9 | 4051.4 | 435.2 | 4547.6 | 9269.5 |
| **2** | 2335.6 | 2.3 | 2492.6 | 9.7 | 4840.2 | 4137.7 | 415.2 | 4612.7 | 9452.9 |
| **3** | 2168.6 | 2.9 | 2319.9 | 10.8 | 4502.1 | 3882.4 | 376.3 | 4311.2 | 8813.3 |
| **4** | 2185.0 | 3.0 | 2325.7 | 9.2 | 4522.9 | 3651.4 | 394.1 | 4093.1 | 8616.0 |

Units: Millions of pounds

# Data Description

- Variables: Beef, Veal, Pork, Lamb and Mutton, Total Red Meat, Broilers, Turkey, Total Poultry, Total Red Meat and Poultry, and Date.

- Variable Types: Continuous Numeric (e.g., production volume)

# Transformer-based supervised forecasting

```python
class TransformerForecastingModel(torch.nn.Module):
    def __init__(self, input_dim, embed_dim, num_heads, ff_dim, num_layers, dropout=0.1):
        super().__init__()
        self.embedding = torch.nn.Linear(input_dim, embed_dim)
        self.relu1 = torch.nn.ReLU()
        self.dropout1 = torch.nn.Dropout(dropout)

        encoder_layer = torch.nn.TransformerEncoderLayer(
            d_model=embed_dim, nhead=num_heads, dim_feedforward=ff_dim, dropout=dropout
        )
        self.transformer_encoder = torch.nn.TransformerEncoder(encoder_layer, num_layers=num_layers)

        self.relu2 = torch.nn.ReLU()
        self.dropout2 = torch.nn.Dropout(dropout)
        self.fc_out = torch.nn.Linear(embed_dim, input_dim)
        self.relu3 = torch.nn.ReLU()

    def forward(self, x):
        x = self.embedding(x)
        x = self.relu1(x)
        x = self.dropout1(x)
        x = self.transformer_encoder(x)
        x = self.relu2(x)
        x = self.dropout2(x)
        x = self.fc_out(x[:, -1, :])  # Take the last time step output
        x = self.relu3(x)
        return x
```

# Model Parameters

```python
# Model parameters
input_dim = X.shape[2]  # Number of features
embed_dim = 64  # Embedding dimension
num_heads = 4  # Number of attention heads
ff_dim = 128  # Feedforward network dimension
num_layers = 3  # Number of transformer layers
dropout = 0.1  # Dropout rate
```

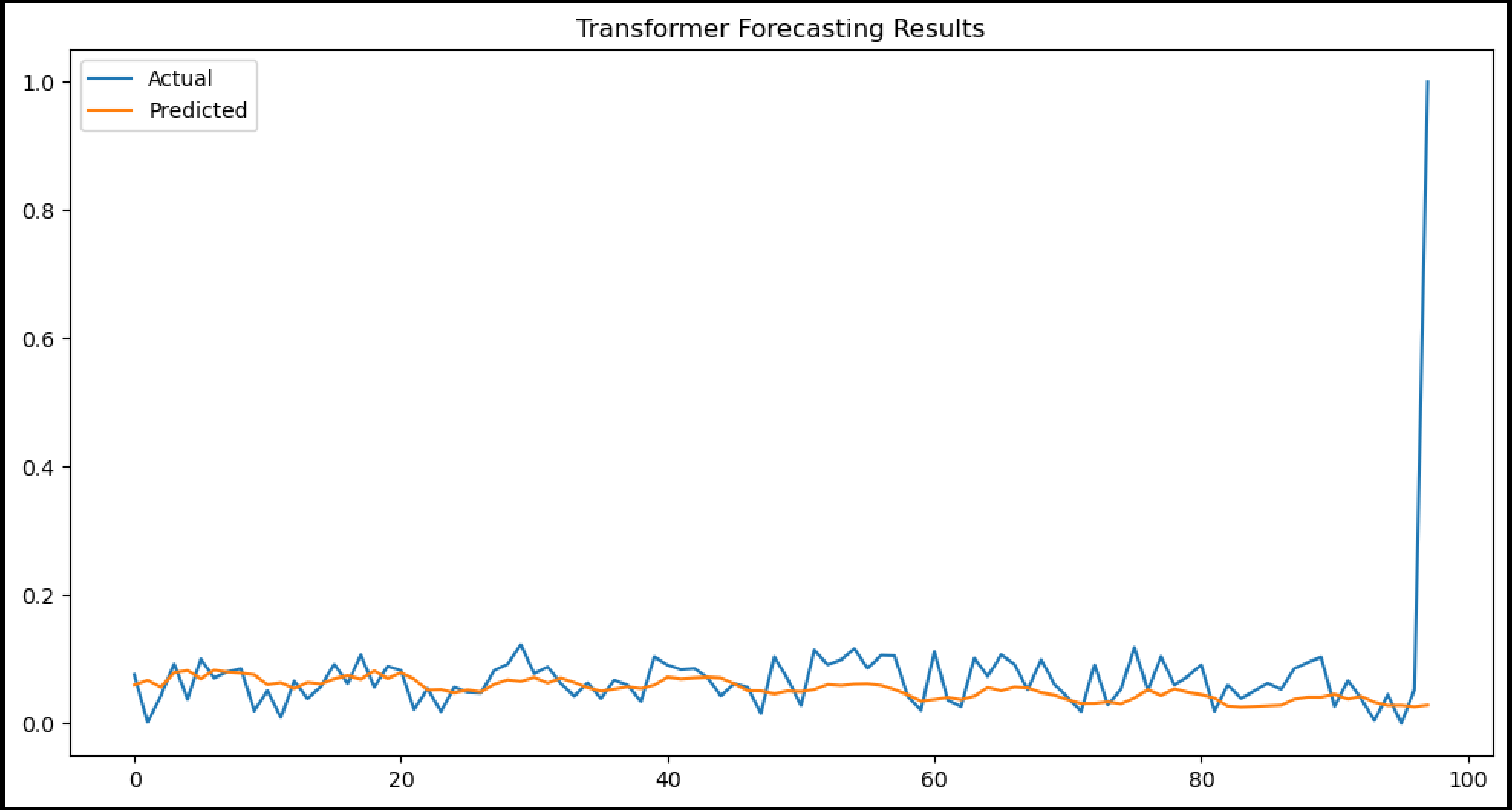
# Optimizer and Loss Function

- criterion = torch.nn.MSELoss()

- optimizer = optim.Adam(tmodel.parameters(), lr=0.001)

```
Epoch 5/50, Loss: 0.0200
Epoch 6/50, Loss: 0.0175
Epoch 7/50, Loss: 0.0158
Epoch 8/50, Loss: 0.0138
Epoch 9/50, Loss: 0.0127
Epoch 10/50, Loss: 0.0116
Epoch 11/50, Loss: 0.0104
Epoch 12/50, Loss: 0.0095
Epoch 13/50, Loss: 0.0104
Epoch 14/50, Loss: 0.0083
Epoch 15/50, Loss: 0.0078
Epoch 16/50, Loss: 0.0084
Epoch 17/50, Loss: 0.0077
Epoch 18/50, Loss: 0.0074
Epoch 19/50, Loss: 0.0076
Epoch 20/50, Loss: 0.0070
Epoch 21/50, Loss: 0.0068
Epoch 22/50, Loss: 0.0065
Epoch 23/50, Loss: 0.0063
Epoch 24/50, Loss: 0.0060
Epoch 25/50, Loss: 0.0058
Epoch 26/50, Loss: 0.0057
Epoch 27/50, Loss: 0.0062
Epoch 28/50, Loss: 0.0058
Epoch 29/50, Loss: 0.0060
Epoch 30/50, Loss: 0.0059
Epoch 31/50, Loss: 0.0056
Epoch 32/50, Loss: 0.0054
Epoch 33/50, Loss: 0.0050
Epoch 34/50, Loss: 0.0053
Epoch 35/50, Loss: 0.0050
Epoch 36/50, Loss: 0.0050
Epoch 37/50, Loss: 0.0044
Epoch 38/50, Loss: 0.0047
Epoch 39/50, Loss: 0.0046
Epoch 40/50, Loss: 0.0049
Epoch 41/50, Loss: 0.0049
Epoch 42/50, Loss: 0.0047
Epoch 43/50, Loss: 0.0044
Epoch 44/50, Loss: 0.0044
Epoch 45/50, Loss: 0.0043
Epoch 46/50, Loss: 0.0041
Epoch 47/50, Loss: 0.0039
Epoch 48/50, Loss: 0.0046
Epoch 49/50, Loss: 0.0045
Epoch 50/50, Loss: 0.0043
```

# Training



Transformer Forecasting Results
Actual
Predicted
1.0
0.8
0.6
0.4
0.2
0.0
0
20
40
60
80
100

# Predictions

Unscaled Future Predictions:

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 1741.0094 | 32.8152 | 1309.6686 | 31.1271 | 2822.1050 | 1405.9308 | 380.1586 | 1956.3875 | 5425.0786 |
| 1 | 1886.8129 | 26.1994 | 1275.5325 | 24.3964 | 3365.1445 | 1713.3722 | 391.3523 | 2178.2158 | 5530.1543 |
| 2 | 1960.1750 | 21.9284 | 1373.6909 | 21.6222 | 3632.3477 | 1988.3779 | 406.1049 | 2433.3838 | 5942.7886 |
| 3 | 2003.7330 | 18.0578 | 1505.2623 | 18.4523 | 3837.4453 | 2326.9846 | 429.4685 | 2763.1968 | 6459.6069 |
| 4 | 2068.4082 | 14.1441 | 1656.1318 | 16.3812 | 3932.5452 | 2686.8577 | 449.2589 | 3133.7710 | 7017.6904 |
| 5 | 2093.5562 | 10.8822 | 1793.6283 | 14.9633 | 3918.9602 | 2940.5046 | 460.7080 | 3417.1995 | 7406.4473 |
| 6 | 2113.3562 | 8.9785 | 1896.0061 | 13.3408 | 3949.0161 | 3109.6438 | 468.7467 | 3625.2012 | 7693.3213 |
| 7 | 2117.9890 | 8.1316 | 1961.2762 | 12.0100 | 4004.7803 | 3216.7402 | 474.0439 | 3765.1921 | 7864.8477 |
| 8 | 2123.5330 | 7.9407 | 1994.4252 | 11.6604 | 4055.2300 | 3270.8459 | 475.9704 | 3838.4641 | 7981.8794 |
| 9 | 2125.2400 | 7.8247 | 2006.6818 | 11.5188 | 4073.0515 | 3291.5183 | 475.9724 | 3863.3645 | 8027.1855 |
| 10 | 2125.9209 | 7.7744 | 2012.1145 | 11.4549 | 4081.2314 | 3300.5908 | 475.9526 | 3874.3167 | 8047.4150 |
| 11 | 2126.2141 | 7.7519 | 2014.5176 | 11.4265 | 4084.8560 | 3304.6008 | 475.9412 | 3879.1487 | 8056.3550 |

First 12 rows of the original dataset:

| | Beef 3/ | Veal 3/ | Pork 3/ | Lamb and mutton 3/ | Total red meat 3/ 4/ |
|---|---|---|---|---|---|
| 0 | 2335.6000 | 2.3000 | 2492.6000 | 9.7000 | 4840.2000 |
| 1 | 2246.1000 | 3.8000 | 2462.4000 | 9.6000 | 4721.9000 |
| 2 | 2335.6000 | 2.3000 | 2492.6000 | 9.7000 | 4840.2000 |
| 3 | 2168.6000 | 2.9000 | 2319.9000 | 10.8000 | 4502.1000 |
| 4 | 2185.0000 | 3.0000 | 2325.7000 | 9.2000 | 4522.9000 |
| 5 | 2425.8000 | 3.1000 | 2532.2000 | 10.3000 | 4971.4000 |
| 6 | 2170.7000 | 2.9000 | 2221.8000 | 9.4000 | 4404.8000 |
| 7 | 2256.1000 | 3.0000 | 2278.5000 | 9.2000 | 4546.8000 |
| 8 | 2255.9000 | 3.2000 | 2242.5000 | 10.0000 | 4511.7000 |
| 9 | 2103.6000 | 3.0000 | 2109.2000 | 9.1000 | 4225.0000 |
| 10 | 2292.3000 | 3.4000 | 2269.5000 | 10.2000 | 4575.4000 |
| 11 | 2269.3000 | 3.3000 | 2308.2000 | 10.1000 | 4590.9000 |

| | Broilers 5/ | Turkey 5/ | Total poultry 4/ 5/ 6/ |
|---|---|---|---|
| 0 | 4137.7000 | 415.2000 | 4612.7000 |
| 1 | 4051.4000 | 435.2000 | 4547.6000 |
| 2 | 4137.7000 | 415.2000 | 4612.7000 |
| 3 | 3882.4000 | 376.3000 | 4311.2000 |
| 4 | 3651.4000 | 394.1000 | 4093.1000 |
| 5 | 4370.9000 | 493.9000 | 4929.6000 |
| 6 | 3892.6000 | 413.4000 | 4366.2000 |
| 7 | 4038.7000 | 435.0000 | 4533.2000 |
| 8 | 4072.1000 | 433.5000 | 4566.2000 |
| 9 | 3724.9000 | 408.9000 | 4190.7000 |
| 10 | 4011.0000 | 446.8000 | 4518.9000 |
| 11 | 3917.7000 | 450.7000 | 4427.5000 |

| | Total red meat and poultry 4/ |
|---|---|
| 0 | 9452.9000 |
| 1 | 9269.5000 |
| 2 | 9452.9000 |
| 3 | 8813.3000 |
| 4 | 8616.0000 |
| 5 | 9901.0000 |
| 6 | 8771.0000 |
| 7 | 9080.0000 |
| 8 | 9077.9000 |
| 9 | 8415.7000 |
| 10 | 9094.3000 |
| 11 | 9018.4000 |

# Discussion

- Strengths: Transformer based predictions are much easier to get working than VAE predictions.

- Limitations: It still sucks :(

- Hyperparameter Tuning
  - latent dimensionality, learning rate, sequence length, network architecture , and loss function parameters

# Conclusions

- Successfully applied time-series forecasting techniques using a transformer-based model.
- A transformer could likely be effective for strategic decision making.
- Further testing and research are needed to more fully understand my model's lack of improvement.
- Food production statistics are effective for time-series analysis.

# References

- Some understanding and techniques have been gained from Hunter Heidenreich's tutorial on VAE's which is available on their personal blog though none of their original code has been used for this project.


- Heidenreich, H. (2024, March 3). Modern Pytorch techniques for Vaes: A comprehensive tutorial. Hunter Heidenreich, Machine Learning Engineer. https://hunterheidenreich.com/posts/modern-variational-autoencoder-in-pytorch/