Import Library

In [37]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt

from sklearn.feature_selection import mutual_info_regression
from sklearn.preprocessing import PolynomialFeatures
```

Import Dataset

In [38]:
```
df = pd.read_csv('./feature_store/merged.csv', index_col=0)
```

In [39]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1906 entries, 0 to 1909
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   cycle_id              1906 non-null   float64
 1   start_weight          1906 non-null   float64
 2   last_weight           1906 non-null   float64
 3   average_weight        1906 non-null   float64
 4   average_adg           1906 non-null   float64
 5   fasting               1906 non-null   bool   
 6   pond_id               1906 non-null   float64
 7   measured_date         1906 non-null   object 
 8   morning_temperature   1906 non-null   float64
 9   evening_temperature   1906 non-null   float64
 10  morning_do            1906 non-null   float64
 11  evening_do            1906 non-null   float64
 12  morning_salinity      1906 non-null   float64
 13  morning_pH            1906 non-null   float64
 14  transparency          1906 non-null   float64
 15  long_cycle            1906 non-null   int64  
 16  total_seed            1906 non-null   float64
 17  area                  1906 non-null   float64
 18  size                  1906 non-null   float64
 19  weight                1906 non-null   float64
 20  num_of_harvest        1906 non-null   float64
dtypes: bool(1), float64(18), int64(1), object(1)
memory usage: 314.6+ KB
```

In [40]:
```
df.head()
```

Out[40]:

	cycle_id	start_weight	last_weight	average_weight	average_adg	fasting	pond_id
0	3458.0	5.23	25.18	14.428	0.270	True	12969.0
1	3459.0	4.95	26.59	15.167	0.267	True	12996.0
2	4038.0	5.25	16.25	10.725	0.281	True	14334.0
3	4039.0	5.40	15.70	11.035	0.273	True	14335.0
4	4044.0	2.77	24.76	13.033	0.256	True	14348.0

5 rows × 21 columns

Preprocessing

In [41]:
```
df = df.drop(columns=["cycle_id", "pond_id", "measured_date"], axis=1)
```

In [42]:
```
df['fasting'] = df['fasting'].replace({True: 1, False: 0})
```

```
/var/folders/zz/htmnld_148b1dbm4wj_hyrq80000gn/T/ipykernel_64560/232860989.p
y:1: FutureWarning: Downcasting behavior in `replace` is deprecated and will
be removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set `p
d.set_option('future.no_silent_downcasting', True)`
  df['fasting'] = df['fasting'].replace({True: 1, False: 0})
```

In [43]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1906 entries, 0 to 1909
Data columns (total 18 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   start_weight         1906 non-null   float64
 1   last_weight          1906 non-null   float64
 2   average_weight       1906 non-null   float64
 3   average_adg          1906 non-null   float64
 4   fasting              1906 non-null   int64  
 5   morning_temperature  1906 non-null   float64
 6   evening_temperature  1906 non-null   float64
 7   morning_do           1906 non-null   float64
 8   evening_do           1906 non-null   float64
 9   morning_salinity     1906 non-null   float64
 10  morning_pH           1906 non-null   float64
 11  transparency         1906 non-null   float64
 12  long_cycle           1906 non-null   int64  
 13  total_seed           1906 non-null   float64
 14  area                 1906 non-null   float64
 15  size                 1906 non-null   float64
 16  weight               1906 non-null   float64
 17  num_of_harvest       1906 non-null   float64
dtypes: float64(16), int64(2)
memory usage: 282.9 KB
```

Feature Selection

Mutual Information

In [44]:
```
target_column = 'average_adg'
```

In [45]:
```
# Mendefinisikan fitur dan variabel target
X = df.drop(target_column, axis=1)  # Fitur
y = df[target_column]  # Variabel target
```

In [46]:
```
# Menghitung informasi mutual
mi = mutual_info_regression(X, y, random_state=69)
```

In [47]:
```
mi_score = pd.Series(mi, index=X.columns).sort_values(ascending=False)

print(mi_score)
```

```
average_weight         0.286023
last_weight            0.283015
size                   0.269980
start_weight           0.150300
long_cycle             0.093424
morning_salinity       0.074241
num_of_harvest         0.072455
morning_temperature    0.061878
total_seed             0.052857
weight                 0.051184
evening_do             0.045641
morning_pH             0.042245
morning_do             0.036917
area                   0.036127
evening_temperature    0.015473
transparency           0.002977
fasting                0.000000
dtype: float64
```

Table Mutual Infomation

In [48]:
```
mi_score_style = pd.DataFrame({'Feature': X.columns, 'Mutual Information': m
mi_score_style = mi_score_style.sort_values(by='Mutual Information', ascendi

mi_score_style.style.background_gradient(low=0.7, high=1.0,cmap='YlOrRd')
```

Out[48]:

	Feature	Mutual Information
2	average_weight	0.286023
1	last_weight	0.283015
14	size	0.269980
0	start_weight	0.150300
11	long_cycle	0.093424
8	morning_salinity	0.074241
16	num_of_harvest	0.072455
4	morning_temperature	0.061878
12	total_seed	0.052857
15	weight	0.051184
7	evening_do	0.045641
9	morning_pH	0.042245
6	morning_do	0.036917
13	area	0.036127
5	evening_temperature	0.015473
10	transparency	0.002977
3	fasting	0.000000

Feature Engineering

Mathematical Transformations

In [49]:

```
top_features = mi_score.index[:5]
```

In [50]:

```
# MEMBUAT POLYNOMIAL FEATURES

poly = PolynomialFeatures(degree=2, include_bias=False)
poly_features = poly.fit_transform(X[top_features])
poly_feature_names = poly.get_feature_names_out(top_features)
```

In [59]:

```
poly_feature_names
```

Out[59]:
```
array(['average_weight', 'last_weight', 'size', 'start_weight',
       'long_cycle', 'average_weight^2', 'average_weight last_weight',
       'average_weight size', 'average_weight start_weight',
       'average_weight long_cycle', 'last_weight^2', 'last_weight size',
       'last_weight start_weight', 'last_weight long_cycle', 'size^2',
       'size start_weight', 'size long_cycle', 'start_weight^2',
       'start_weight long_cycle', 'long_cycle^2'], dtype=object)
```

In [51]:
```
# MEMBUAT DF DENGAN POLYNOMIAL FEATURES

poly_df = pd.DataFrame(poly_features, columns=poly_feature_names)
```

In [52]:
```
# TAMBAH FEATURES POLY KE DF UTAMA

data_with_poly_features = pd.concat([df, poly_df], axis=1)
```

In [53]:
```
data_with_poly_features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1910 entries, 0 to 713
Data columns (total 38 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   start_weight                 1906 non-null   float64
 1   last_weight                  1906 non-null   float64
 2   average_weight               1906 non-null   float64
 3   average_adg                  1906 non-null   float64
 4   fasting                      1906 non-null   float64
 5   morning_temperature          1906 non-null   float64
 6   evening_temperature          1906 non-null   float64
 7   morning_do                   1906 non-null   float64
 8   evening_do                   1906 non-null   float64
 9   morning_salinity             1906 non-null   float64
 10  morning_pH                   1906 non-null   float64
 11  transparency                 1906 non-null   float64
 12  long_cycle                   1906 non-null   float64
 13  total_seed                   1906 non-null   float64
 14  area                         1906 non-null   float64
 15  size                         1906 non-null   float64
 16  weight                       1906 non-null   float64
 17  num_of_harvest               1906 non-null   float64
 18  average_weight               1906 non-null   float64
 19  last_weight                  1906 non-null   float64
 20  size                         1906 non-null   float64
 21  start_weight                 1906 non-null   float64
 22  long_cycle                   1906 non-null   float64
 23  average_weight^2             1906 non-null   float64
 24  average_weight last_weight   1906 non-null   float64
 25  average_weight size          1906 non-null   float64
 26  average_weight start_weight  1906 non-null   float64
 27  average_weight long_cycle    1906 non-null   float64
 28  last_weight^2                1906 non-null   float64
 29  last_weight size             1906 non-null   float64
 30  last_weight start_weight     1906 non-null   float64
 31  last_weight long_cycle       1906 non-null   float64
 32  size^2                       1906 non-null   float64
 33  size start_weight            1906 non-null   float64
 34  size long_cycle              1906 non-null   float64
 35  start_weight^2               1906 non-null   float64
 36  start_weight long_cycle      1906 non-null   float64
 37  long_cycle^2                 1906 non-null   float64
dtypes: float64(38)
memory usage: 582.0 KB
```

In [54]:

```
data_with_poly_features.head()
```

Out[54]:

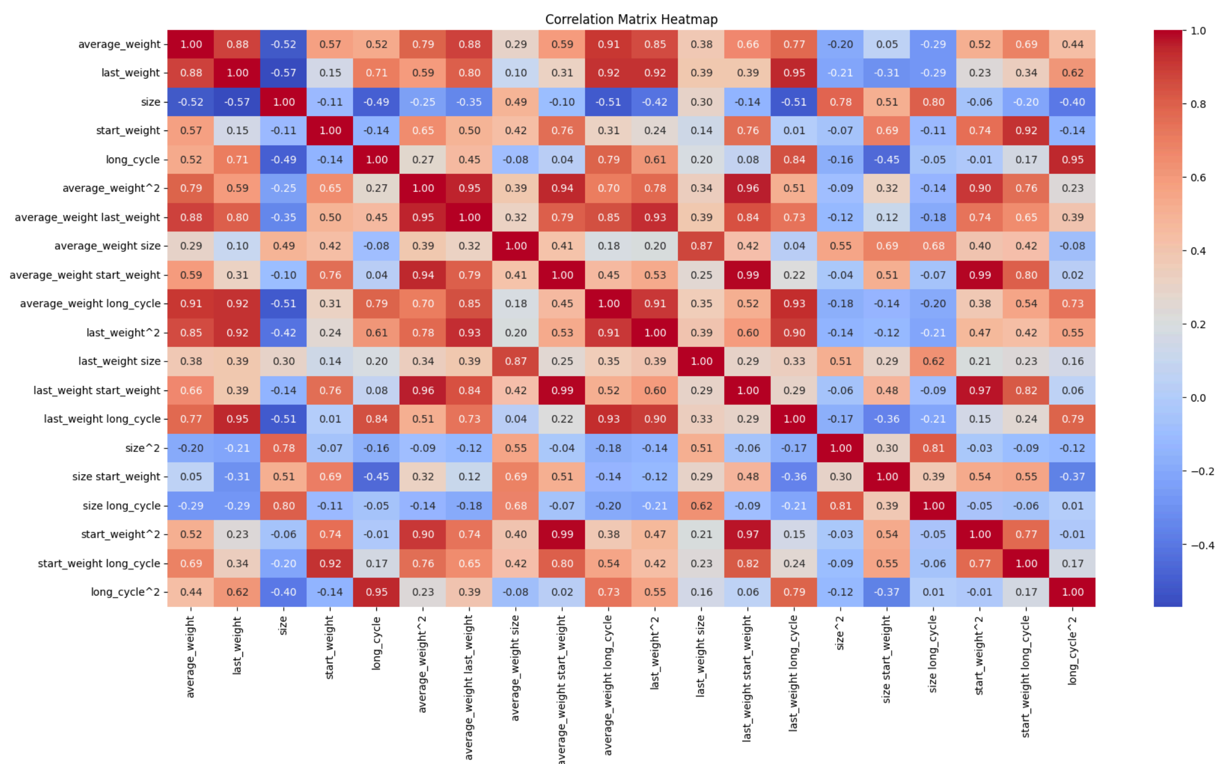
	start_weight	last_weight	average_weight	average_adg	fasting	morning_tempera
0	5.23	25.18	14.428	0.270	1.0	
1	4.95	26.59	15.167	0.267	1.0	
2	5.25	16.25	10.725	0.281	1.0	
3	5.40	15.70	11.035	0.273	1.0	
4	2.77	24.76	13.033	0.256	1.0	

5 rows × 38 columns

In [60]:
```
data_with_poly_features.to_csv("./feature_store/polynomial-features.csv")
```

In [61]:
```
plt.figure(figsize=(20, 10))
correlation_matrix = poly_df.corr()

sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap='coolwarm', cbar
plt.title('Correlation Matrix Heatmap')
plt.show()
```



Conclusion

---

1. Fitur yang didapatkan

- Mutual information menghasilkan nilai `mi` table mutual information

- Angka Mutual Information (MI) dalam tabel tersebut mewakili seberapa banyak informasi yang dimiliki oleh setiap fitur tentang target variabel
- Target variable menggunakan fitur `average_adg`
- Fitur-fitur yang paling informatif: `[average_weight, last_weight, start_weight, size, long_cycle]`. Fitur-fitur ini mungkin sangat penting untuk model prediksi Anda dan sebaiknya diprioritaskan dalam pemilihan fitur.
- Fitur dengan kontribusi informasi rendah: Fitur-fitur seperti fasting yang memiliki nilai Mutual Information sangat rendah atau nol mungkin tidak relevan dan bisa dipertimbangkan untuk diabaikan dalam model prediksi.
- Kami menggunakan 5 fitur terbaik.

3. Identifikasi fitur baru dari 5 fitur terbaik

- Pada proses mutual information menggunakan `transformasi matematika`
- Proses transform menggunakan proses perkalian antar fitur terpilih dan fitur itu sendiri.
- kemudian akan menghasilkan fitur baru seperti pada chart

github : https://github.com/sugengdcahyo/shrimp-prediction/blob/main/02-Filter%20Based%20Feature%20Selection.ipynb