calories_burned_analysis

August 26, 2025

[ ]:
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'''
About the data:
"This dataset provides a detailed overview of gym members' exercise routines,␣
 ↪physical attributes, and fitness metrics. It contains 973
samples of gym data, including key performance indicators such as heart rate,␣
 ↪calories burned, and workout duration. Each entry also
includes demographic data and experience levels, allowing for comprehensive␣
 ↪analysis of fitness patterns, athlete progression, and
health trends."

From: https://www.kaggle.com/datasets/valakhorasani/gym-members-exercise-dataset

##############################################################################################

In this analysis we

    1. test the hypothesis that male and female gym members burn the same␣
 ↪amount of calories on average and conduct both
        an equal-tailed and one-sided hypothesis test
and
    2. use linear regression to select features within the pipeline and predict␣
 ↪the number of calories burned
        using the rest of the data

'''
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[41]:
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'''
1) Hypothesis testing
Question: Do male and female gym members burn the same number of calories on␣
 ↪average?

Conducting an Equal-tailed Test
H :   =   ie. Male and female gym members burn the same number of calories on␣
 ↪average.
H :       ie. Male and female gym members do not burn the same number of␣
 ↪calories on average.
```

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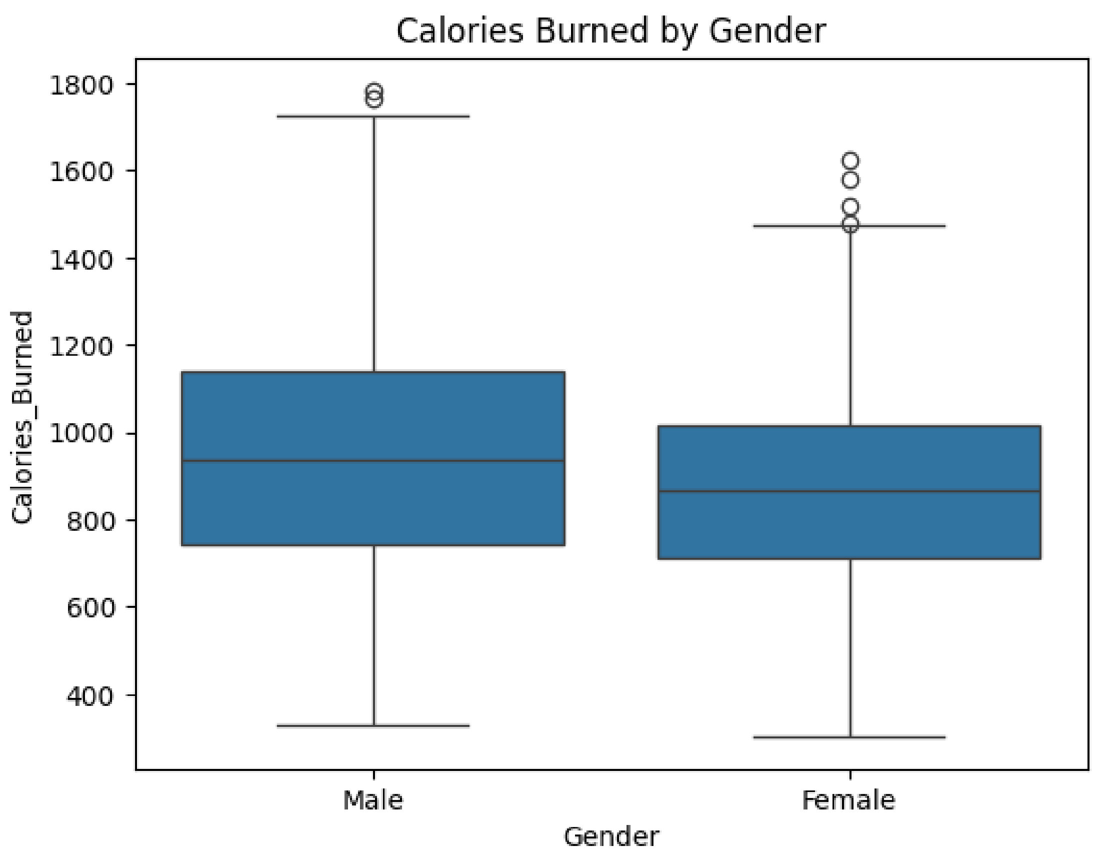
'''

import pandas as pd
df = pd.read_csv("gym_data.csv")
new = df[['Gender', 'Calories_Burned']].dropna()
male_calories = new[new['Gender'] == 'Male']['Calories_Burned']
female_calories = new[new['Gender'] == 'Female']['Calories_Burned']
```

[42]:
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.boxplot(x='Gender', y='Calories_Burned', data=df)
plt.title("Calories Burned by Gender")
plt.show()
```



[43]:
```
import scipy.stats as stats

t_stat, pvalue = stats.ttest_ind(male_calories, female_calories,␣
 ↪equal_var=False)
```

```
# pvalue=np.float64(2.0102943133909015e-06)

print('p-value = ', pvalue)
print('male mean cals burned: %.3f' % male_calories.mean())
print('female mean cals burned: %.3f' % female_calories.mean())

# p-value =  2.0102943133909015e-06
# male mean cals burned: 944.456
# female mean cals burned: 862.249
```

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male mean cals burned: 944.456
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```

[ ]:
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'''
Since the p-value is less than/equal to 0.001, we can conclude that there is␣
 ↪very strong evidence against the hypothesis that male and
female gym members burn the same amount of calories on average based on the␣
 ↪observed data. From the sample means, we can see that male
gym members burn more calories than female gym members on average.

'''
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[150]:
```
'''
Conducting a One-sided Test
H :    =    ie. Male and female gym members burn the same number of calories on␣
 ↪average.
H :    >    ie. Male gym members burn more calories than female gym members on␣
 ↪average.

'''

if t_stat > 0:
    pvalue_onesided = pvalue/2
else:
    pvalue_onesided = 1 - pvalue/2

print('one-sided test p-value = ', pvalue_onesided)
# one-sided test p-value =  1.0051471566954508e-06

'''
Since the one-sided test p-value is less than/equal to 0.001, we can conclude␣
 ↪that there is very strong evidence against the hypothesis that
on average, male and female gym members burn the same amount of calories based␣
 ↪on the observed data. Furthermore, it seems reasonable to
assume that male gym members burn more calories than female gym members on␣
 ↪average.
```

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'''
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```
one-sided test p-value =  1.0051471566954508e-06
```

[ ]:
```
'''
2) Predictive modeling
Question: Can we predict calories burned per session using member␣
↪characteristics and workout data?

Hypotheses:
- Male gym members burn more calories on average than female gym members
- Of the workout types, Cardio is correlated with burning the most calories
- A longer session duration is correlated with burning more calories
- A higher water intake may be correlated with burning more calories

Generally unsure about Age, BPM, and Workout Frequency as various factors could␣
↪cause competing trends amoung these features.

'''
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[44]:
```
categorical_features = ['Gender','Workout_Type']
numerical_features = ['Age','Weight (kg)','Height (m)','Max_BPM','Avg_BPM',␣
↪'Resting_BPM','Session_Duration (hours)','Fat_Percentage',
                      'Water_Intake (liters)','Workout_Frequency (days/
↪week)','Experience_Level','BMI']
target_name = 'Calories_Burned'

X = df[numerical_features + categorical_features]
y = df[target_name]
```

[45]:
```
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder, StandardScaler

from sklearn.feature_selection import SelectFromModel
from sklearn.svm import LinearSVR

preprocessor = ColumnTransformer(
    transformers=[
        ("num", StandardScaler(), numerical_features),
        ("cat", OneHotEncoder(drop='first'), categorical_features),
    ]
)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=0)

reg = Pipeline(
    steps=[("preprocessor", preprocessor),
           ('feature_selection', SelectFromModel(LinearSVR(epsilon=0.01,␣
 ↪max_iter=25000))), # lasso regression
           ("regression", LinearRegression())]
)

reg.fit(X_train, y_train)

scores = cross_val_score(reg, X, y, cv=5)
print("%0.2f accuracy with a standard deviation of %0.2f" % (scores.mean(),␣
 ↪scores.std()))
# 0.87 accuracy with a standard deviation of 0.05
# 5-fold cross-validated R² = 0.87 ± 0.05 means that the model generalizes well.

y_pred = reg.predict(X_test)
```

```
0.87 accuracy with a standard deviation of 0.05
```

[46]:
```
reg
```

[46]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('num', StandardScaler(),
                                                  ['Age', 'Weight (kg)',
                                                   'Height (m)', 'Max_BPM',
                                                   'Avg_BPM', 'Resting_BPM',
                                                   'Session_Duration (hours)',
                                                   'Fat_Percentage',
                                                   'Water_Intake (liters)',
                                                   'Workout_Frequency '
                                                   '(days/week)',
                                                   'Experience_Level', 'BMI']),
                                                 ('cat',
                                                  OneHotEncoder(drop='first'),
                                                  ['Gender',
                                                   'Workout_Type'])])),
                ('feature_selection',
                 SelectFromModel(estimator=LinearSVR(epsilon=0.01,
                                                     max_iter=25000))),
                ('regression', LinearRegression())])
```

[47]:
```
from sklearn.metrics import root_mean_squared_error
```

```
print("R² score: %.3f" % reg.score(X_test, y_test)) # score method returns R^2␣
↪for regressors by default
print("RMSE: %.3f" % root_mean_squared_error(y_test, y_pred))

# R² score: 0.868
# RMSE: 97.690
```

```
R² score: 0.868
RMSE: 97.690
```

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'''
From the output, the model explains 86.8% of the variance in y_test, the set of␣
↪true calories burned among gym members.
The average magnitude of the model's prediction errors is 97.7 calories from␣
↪the true value.

Thus, the model is moderately accurate in its predictive performance. Although␣
↪it captures most of the variability in calories burned, an
average error of around 98 calories makes it somewhat imprecise for reliably␣
↪estimating individual calorie expenditure among gym members.
'''
```

[48]:
```
# Regressed coefficients:
coefficients = reg.named_steps['regression'].coef_
feature_names = reg.named_steps['feature_selection'].get_feature_names_out()

coef_df = pd.DataFrame({"Feature": feature_names, "Coefficient": coefficients})
print(coef_df.sort_values(by="Coefficient", ascending=False))

#   Feature  Coefficient
# 0      x6   247.548701
# 1     x12    85.698388
# 3     x14    -4.135166
# 2     x13    -5.855987
# 4     x15   -13.960060

# Issue: does not show feature names!
```

```
  Feature  Coefficient
0      x6   247.548701
1     x12    85.698388
3     x14    -4.135166
2     x13    -5.855987
4     x15   -13.960060
```

[49]:
```
def get_pipeline_coefficients(fitted_pipeline):
    """
```

```
    Returns a DataFrame of selected features and their regression coefficients␣
↪from a fitted pipeline
    with ColumnTransformer, SelectFromModel, and LinearRegression.
    """
    preprocessor = fitted_pipeline.named_steps['preprocessor']
    selector = fitted_pipeline.named_steps['feature_selection']
    reg = fitted_pipeline.named_steps['regression']

    # Get transformed feature names
    feature_names = []
    for name, transformer, cols in preprocessor.transformers_:
        if name == 'num':
            feature_names.extend(cols)
        else:  # categorical
            feature_names.extend(transformer.get_feature_names_out(cols))

    # Map selected features to coefficients
    selected_features = [feature_names[i] for i in selector.
↪get_support(indices=True)]
    coef_df = pd.DataFrame({
        'Feature': selected_features,
        'Coefficient': reg.coef_
    }).sort_values(by='Coefficient', ascending=False).reset_index(drop=True)

    return coef_df

coef_df = get_pipeline_coefficients(reg)
print(coef_df)

#                      Feature  Coefficient
# 0  Session_Duration (hours)   247.548701
# 1               Gender_Male    85.698388
# 2      Workout_Type_Strength    -4.135166
# 3          Workout_Type_HIIT    -5.855987
# 4          Workout_Type_Yoga   -13.960060
```

```
                     Feature  Coefficient
0  Session_Duration (hours)   247.548701
1               Gender_Male    85.698388
2      Workout_Type_Strength    -4.135166
3          Workout_Type_HIIT    -5.855987
4          Workout_Type_Yoga   -13.960060
```

[ ]:
```
'''
The model's coefficients indicate that Session_Duration (hours) is the␣
↪strongest predictor of calories burned, with each additional
```

```
hour of exercise associated with an increase of approximately 248 calories.␣
 ↪Male participants are predicted to burn about 86 more
calories than female participants, holding other factors constant. Among␣
 ↪workout types, Yoga has the largest negative effect,
reducing predicted calories burned by around 14 calories relative to Cardio,␣
 ↪the baseline, while Strength and HIIT sessions have
smaller negative effects. Overall, the results align with expectations: longer␣
 ↪sessions and male participants are associated with
higher calorie expenditure, while all workout types burn fewer calories␣
 ↪compared to Cardio.

'''
```

[50]:

```
# Beyond evaluating predictive accuracy: statistical significance testing of␣
 ↪the selected features from the model

import statsmodels.api as sm

convert = reg.named_steps['preprocessor']
X_train_pre = convert.transform(X_train) # a NumPy array
X_train_pre_df = pd.DataFrame(X_train_pre, columns=convert.
 ↪get_feature_names_out())
X_train_pre_df = sm.add_constant(X_train_pre_df) # add col of 1s to fit to␣
 ↪intercept

y_train_reset = y_train.reset_index(drop=True)

ols_model = sm.OLS(y_train_reset, X_train_pre_df).fit()
print(ols_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:         Calories_Burned   R-squared:                       0.979
Model:                             OLS   Adj. R-squared:                  0.979
Method:                  Least Squares   F-statistic:                     2216.
Date:                 Mon, 25 Aug 2025   Prob (F-statistic):               0.00
Time:                         21:12:15   Log-Likelihood:                -3966.2
No. Observations:                  778   AIC:                             7966.
Df Residuals:                      761   BIC:                             8046.
Df Model:                           16
Covariance Type:             nonrobust
================================================================================
======================
                                         coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
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```

```
const                                866.8405      3.784    229.096      0.000
859.413     874.268
num__Age                             -41.6357      1.449    -28.733      0.000
-44.480     -38.791
num__Weight (kg)                     -21.8668     12.142     -1.801      0.072
-45.704       1.970
num__Height (m)                       14.8800      6.811      2.185      0.029
1.509      28.251
num__Max_BPM                          -0.1553      1.451     -0.107      0.915
-3.005       2.694
num__Avg_BPM                          90.2643      1.439     62.707      0.000
87.439      93.090
num__Resting_BPM                       2.4179      1.446      1.673      0.095
-0.420       5.256
num__Session_Duration (hours)        244.5269      2.302    106.209      0.000
240.007     249.047
num__Fat_Percentage                   -1.8420      2.378     -0.775      0.439
-6.510       2.826
num__Water_Intake (liters)            -1.5120      2.239     -0.675      0.500
-5.906       2.882
num__Workout_Frequency (days/week)    -0.1692      2.639     -0.064      0.949
-5.349       5.011
num__Experience_Level                  0.6357      3.342      0.190      0.849
-5.926       7.197
num__BMI                              24.1770     11.697      2.067      0.039
1.214      47.140
cat__Gender_Male                      82.9710      5.181     16.015      0.000
72.801      93.141
cat__Workout_Type_HIIT                -0.9409      4.136     -0.227      0.820
-9.061       7.179
cat__Workout_Type_Strength            -0.6168      3.947     -0.156      0.876
-8.366       7.132
cat__Workout_Type_Yoga                -6.2578      4.013     -1.559      0.119
-14.136       1.620
==============================================================================
Omnibus:                       29.446   Durbin-Watson:                   2.007
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               46.676
Skew:                           0.309   Prob(JB):                     7.32e-11
Kurtosis:                       4.029   Cond. No.                         23.2
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

[51]:
```
# Bonferroni correction
k = 5
```

```
alpha = 0.05
alpha_adj = alpha / k

def appendcatg(lst):
    L = []
    for col in lst:
        if col.startswith('Session'):
            L.append('num__' + col)
        else:
            L.append('cat__' + col)
    return L
model_features = appendcatg(coef_df['Feature'].tolist())

L_regular = []
L_bonferroni = []

for col in model_features:
    if ols_model.pvalues[col] < alpha:
        L_regular.append(col)
        if ols_model.pvalues[col] < alpha_adj:
            L_bonferroni.append(col)

print('alpha = 0.05 valid features: ', L_regular)
print('Bonferroni valid features: ', L_bonferroni)

# alpha = 0.05 valid features:  ['num__Session_Duration (hours)',␣
 ↪'cat__Gender_Male']
# Bonferroni valid features:  ['num__Session_Duration (hours)',␣
 ↪'cat__Gender_Male']
```

```
alpha = 0.05 valid features:  ['num__Session_Duration (hours)',
'cat__Gender_Male']
Bonferroni valid features:  ['num__Session_Duration (hours)',
'cat__Gender_Male']
```

[ ]:
```
'''
Although the predictive model selected five features, statistical testing␣
 ↪revealed that only two were individually significant predictors of
calorie expenditure (p < 0.05, and Bonferroni corrected). This suggests that␣
 ↪while the model performs adequately for prediction, not all
selected features show strong independent statistical evidence of association,␣
 ↪possibly due to multicollinearity or limited sample size.

'''
```