

Identifying Stable vs Unstable Relationships Using Classical Machine Learning Techniques

Importing Libraries

```
In [12]: # SECTION 1: Import Required Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# To split dataset and build ML model
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
import warnings
warnings.filterwarnings('ignore')

In [13]: # Loading Dataset
data=pd.read_csv("relationship_stability_dataset.csv")
data
```

| | communication_frequency | average_reply_time_minutes | initiates_conversation_percent | conflict_frequency | apology_sincerity_score | support_in_stress_score | respect_boundaries_score | makes_future_plans_score | jealousy_level_score | relationship_stability |
|-----|-------------------------|----------------------------|--------------------------------|--------------------|-------------------------|-------------------------|--------------------------|--------------------------|----------------------|------------------------|
| 0 | 7 | 70 | 41 | 0 | 7 | 8 | 8 | 9 | 1 | 1 |
| 1 | 15 | 252 | 59 | 8 | 10 | 7 | 3 | 5 | 1 | 0 |
| 2 | 11 | 275 | 16 | 7 | 9 | 5 | 4 | 10 | 5 | 0 |
| 3 | 8 | 182 | 17 | 1 | 7 | 10 | 10 | 4 | 9 | 0 |
| 4 | 7 | 167 | 74 | 7 | 1 | 10 | 6 | 5 | 6 | 0 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 495 | 17 | 288 | 24 | 5 | 7 | 4 | 4 | 10 | 10 | 0 |
| 496 | 7 | 266 | 43 | 9 | 6 | 1 | 8 | 1 | 2 | 0 |
| 497 | 13 | 162 | 70 | 3 | 2 | 2 | 2 | 10 | 1 | 0 |
| 498 | 4 | 87 | 44 | 4 | 8 | 5 | 6 | 10 | 4 | 0 |
| 499 | 4 | 55 | 73 | 8 | 4 | 8 | 6 | 7 | 4 | 0 |

500 rows × 10 columns

```
In [14]: data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   communication_frequency    500 non-null   int64  
 1   average_reply_time_minutes  500 non-null   int64  
 2   initiates_conversation_percent 500 non-null   int64  
 3   conflict_frequency        500 non-null   int64  
 4   apology_sincerity_score   500 non-null   int64  
 5   support_in_stress_score   500 non-null   int64  
 6   respect_boundaries_score  500 non-null   int64  
 7   makes_future_plans_score  500 non-null   int64  
 8   jealousy_level_score      500 non-null   int64  
 9   relationship_stability    500 non-null   int64  
dtypes: int64(10)
memory usage: 39.2 KB
```

```
In [15]: data.describe()
```

| | communication_frequency | average_reply_time_minutes | initiates_conversation_percent | conflict_frequency | apology_sincerity_score | support_in_stress_score | respect_boundaries_score | makes_future_plans_score | jealousy_level_score | relationship_stability |
|-------|-------------------------|----------------------------|--------------------------------|--------------------|-------------------------|-------------------------|--------------------------|--------------------------|----------------------|------------------------|
| count | 500.000000 | 500.000000 | 500.000000 | 500.000000 | 500.000000 | 500.000000 | 500.000000 | 500.000000 | 500.000000 | 500.000000 |
| mean | 9.616000 | 146.712000 | 54.086000 | 4.514000 | 5.454000 | 5.420000 | 5.404000 | 5.466000 | 5.588000 | 0.04200 |
| std | 5.663922 | 86.944632 | 25.83609 | 2.986034 | 2.763411 | 2.847423 | 2.84411 | 2.908644 | 2.838021 | 0.20079 |
| min | 1.000000 | 1.000000 | 10.000000 | 0.000000 | 0.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 | 0.00000 |
| 25% | 4.750000 | 71.500000 | 32.000000 | 2.000000 | 3.000000 | 3.000000 | 3.000000 | 3.000000 | 3.000000 | 0.00000 |
| 50% | 9.000000 | 145.000000 | 63.500000 | 5.000000 | 5.000000 | 5.000000 | 5.000000 | 5.000000 | 5.000000 | 0.00000 |
| 75% | 15.000000 | 222.250000 | 76.000000 | 7.000000 | 8.000000 | 8.000000 | 8.000000 | 8.000000 | 8.000000 | 0.00000 |
| max | 19.000000 | 299.000000 | 99.000000 | 9.000000 | 10.000000 | 10.000000 | 10.000000 | 10.000000 | 10.000000 | 1.00000 |

```
In [16]: data.head(10)
```

| | communication_frequency | average_reply_time_minutes | initiates_conversation_percent | conflict_frequency | apology_sincerity_score | support_in_stress_score | respect_boundaries_score | makes_future_plans_score | jealousy_level_score | relationship_stability |
|---|-------------------------|----------------------------|--------------------------------|--------------------|-------------------------|-------------------------|--------------------------|--------------------------|----------------------|------------------------|
| 0 | 7 | 70 | 41 | 0 | 7 | 8 | 8 | 9 | 1 | 1 |
| 1 | 15 | 252 | 59 | 8 | 10 | 7 | 3 | 5 | 1 | 0 |
| 2 | 11 | 275 | 16 | 7 | 9 | 5 | 4 | 10 | 5 | 0 |
| 3 | 8 | 182 | 17 | 1 | 7 | 10 | 10 | 4 | 9 | 0 |
| 4 | 7 | 167 | 74 | 7 | 1 | 10 | 6 | 5 | 6 | 0 |
| 5 | 19 | 91 | 66 | 8 | 8 | 8 | 10 | 10 | 3 | 0 |
| 6 | 11 | 202 | 76 | 0 | 4 | 9 | 3 | 5 | 3 | 0 |
| 7 | 11 | 19 | 97 | 4 | 3 | 5 | 2 | 8 | 7 | 0 |
| 8 | 4 | 39 | 96 | 7 | 7 | 10 | 6 | 10 | 6 | 0 |
| 9 | 8 | 126 | 68 | 1 | 3 | 5 | 5 | 5 | 8 | 0 |

Check Distribution of Target Variable

```
In [19]: # SECTION 4: Target Variable Distribution
sns.countplot(x="relationship_stability", data=data, palette='coolwarm')
plt.title("Relationship Stability Distribution")
plt.show()

data["relationship_stability"].value_counts(normalize=True)
```

Out[19]: relationship_stability

0 0.958
1 0.042
Name: proportion, dtype: float64

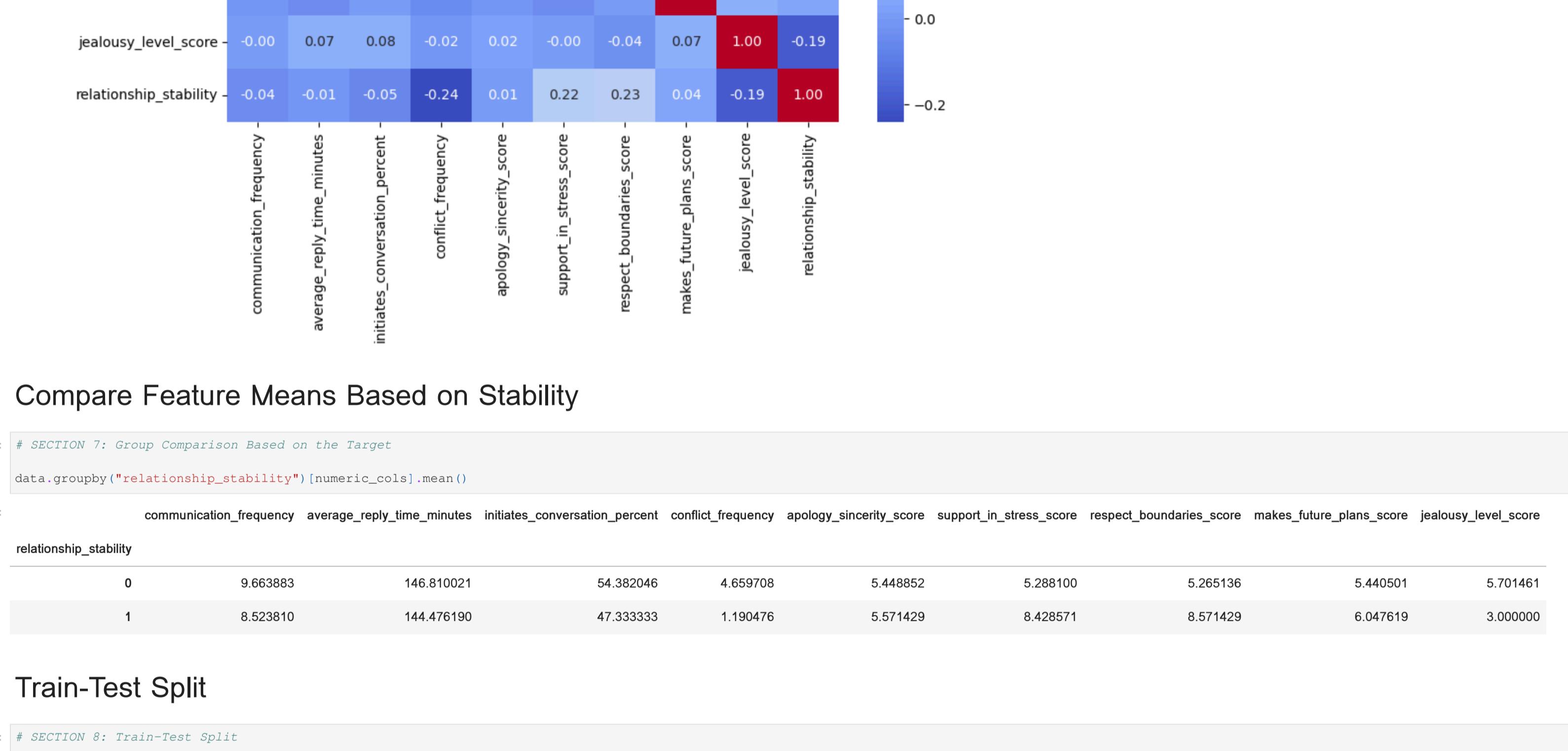
Check Feature Distributions

```
In [23]: # Distribution Plots for Key Numerical Features
numeric_cols = [
    "communication_frequency",
    "average_reply_time_minutes",
    "initiates_conversation_percent",
    "conflict_frequency",
    "apology_sincerity_score",
    "support_in_stress_score",
    "respect_boundaries_score",
    "makes_future_plans_score",
    "jealousy_level_score"
]

plt.figure(figsize=(14, 10))

for i, col in enumerate(numeric_cols, 1):
    plt.subplot(3, 3, i)
    sns.histplot(data[col], kde=True, palette='Greens')
    plt.title(col)

plt.tight_layout()
plt.show()
```



Check Correlation Between Features

```
In [25]: # SECTION 6: Correlation Heatmap
plt.figure(figsize=(10, 7))
sns.heatmap(data.corr(), annot=True, fmt=".2f", cmap='coolwarm')
plt.title("Correlation Heatmap of Features")
plt.show()
```



Compare Feature Means Based on Stability

```
In [27]: # SECTION 7: Group Comparison Based on the Target
data.groupby("relationship_stability")[numeric_cols].mean()
```

| relationship_stability | communication_frequency | average_reply_time_minutes | initiates_conversation_percent | conflict_frequency | apology_sincerity_score | support_in_stress_score | respect_boundaries_score | makes_future_plans_score | jealousy_level_score |
|------------------------|-------------------------|----------------------------|--------------------------------|--------------------|-------------------------|-------------------------|--------------------------|--------------------------|----------------------|
| 0 | 9.603883 | 146.810021 | 54.362046 | 4.659708 | 5.448852 | 5.288100 | 5.265136 | 5.440501 | 5.701461 |
| 1 | 8.523810 | 144.476190 | 47.333333 | 1.190476 | 5.571429 | 8.428571 | 8.571429 | 6.047619 | 3.000000 |

Train-Test Split

```
In [28]: # SECTION 8: Train-Test Split
X = data.drop(["relationship_stability"], axis=1)
y = data["relationship_stability"]

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)

X_train.shape, X_test.shape
```

(400, 9), (100, 9)

Baseline Model – Logistic Regression

```
In [29]: # Logistic Regression Model
log_model = LogisticRegression(max_iter=1000)
log_model.fit(X_train, y_train)

y_pred_log = log_model.predict(X_test)

print("Accuracy (Logistic Regression):", accuracy_score(y_test, y_pred_log))
print("Classification Report:\n", classification_report(y_test, y_pred_log))

Accuracy (Logistic Regression): 0.96
```

Classification Report:

precision recall f1-score support

0 0.98 0.98 0.98 96

1 0.50 0.50 0.50 4

accuracy 0.74 0.74 0.74 100

macro avg 0.96 0.96 0.96 100

weighted avg 0.92 0.92 0.92 100

Confusion Matrix for Logistic Regression

```
In [32]: # SECTION 10: Confusion Matrix for Logistic Regression
cm = confusion_matrix(y_test, y_pred_log)
sns.heatmap(cm, annot=True, fmt="d", cmap='Greens')
plt.title("Logistic Regression - Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```


Random Forest Model (Main Model)

```
In [33]: # SECTION 11: Random Forest Classifier
rf_model = RandomForestClassifier(
    n_estimators=500,
    max_depth=None,
    random_state=42,
    n_jobs=-1
)

rf_model.fit(X_train, y_train)

y_pred_rf = rf_model.predict(X_test)

print("Accuracy (Random Forest):", accuracy_score(y_test, y_pred_rf))
print("Classification Report:\n", classification_report(y_test, y_pred_rf))

Accuracy (Random Forest): 0.96
```

Classification Report:

precision recall f1-score support

0 0.98 0.98 0.98 96

1 0.50 0.50 0.50 4

accuracy 0.74 0.74 0.74 100

macro avg 0.96 0.96 0.96 100

weighted avg 0.92 0.92 0.92 100

Feature Importance (Interpretation)

```
In [34]: # Feature Importance
importances = rf_model.feature_importances_
importances.sort_values(ascending=True).plot(kind='barh', figsize=(8, 6))
plt.title("Feature Importance (Random Forest)")
plt.show()
```