```
!pip install pandas numpy matplotlib seaborn scikit-learn
```

```
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (2.2.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (2.0.2)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (3.10.0)
Requirement already satisfied: seaborn in /usr/local/lib/python3.11/dist-packages (0.13.2)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packages (1.6.1)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/dist-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas) (2025.2)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (4.58.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (1.4.8)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (24.2)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (11.2.1)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (3.2.3)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.15.3)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.5.0)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (3.6.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.8.2->pandas) (1.17.0)
```

Fetch & Parse API Data

```
import requests
import json
import pandas as pd

url = "https://andmed.stat.ee/api/v1/en/stat/LET300"
headers = {"Content-Type": "application/json"}
query = {
    "query": [
        {
            "code": "Leibkonnapea haridustase",
            "selection": {
                "filter": "item",
                "values": ["1", "2", "3", "4"]
            }
        }
    ],
    "response": {"format": "json-stat2"}
}

response = requests.post(url, headers=headers, data=json.dumps(query))
data = response.json()

years = list(data["dimension"]["Aasta"]["category"]["label"].values())
edu_levels = list(data["dimension"]["Leibkonnapea haridustase"]["category"]["label"].values())
services = list(data["dimension"]["Lähim oluline koht"]["category"]["label"].values())
values = data["value"]

records = []
i = 0
for year in years:
    for edu in edu_levels:
        for service in services:
            records.append({
                "Year": int(year),
                "Education Level": edu,
                "Service": service,
                "Distance (km)": values[i]
            })
            i += 1

df = pd.DataFrame(records)
def label_distance(dist):
    if dist < 2.0:
        return "Short"
    elif dist < 3.5:
        return "Medium"
    else:
        return "Long"

df["Distance Category"] = df["Distance (km)"].apply(label_distance)
```

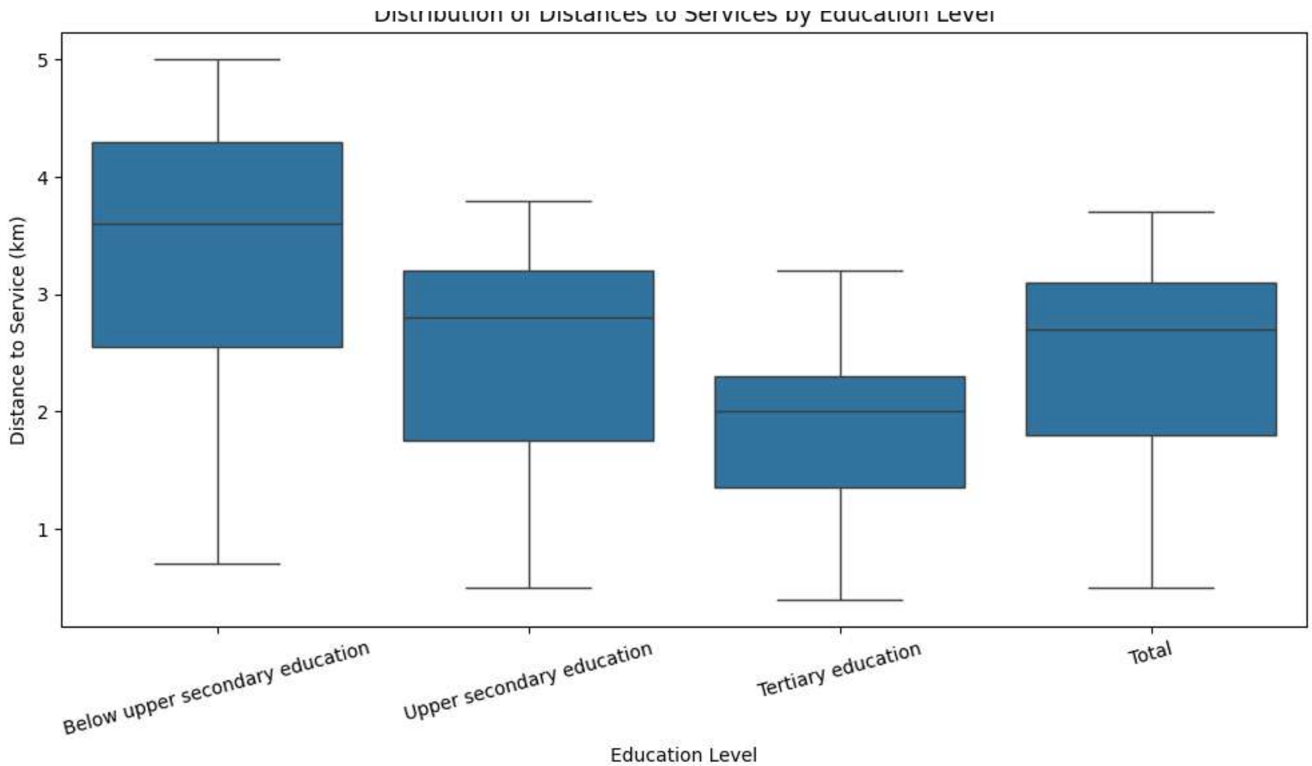
```
df.head()
```

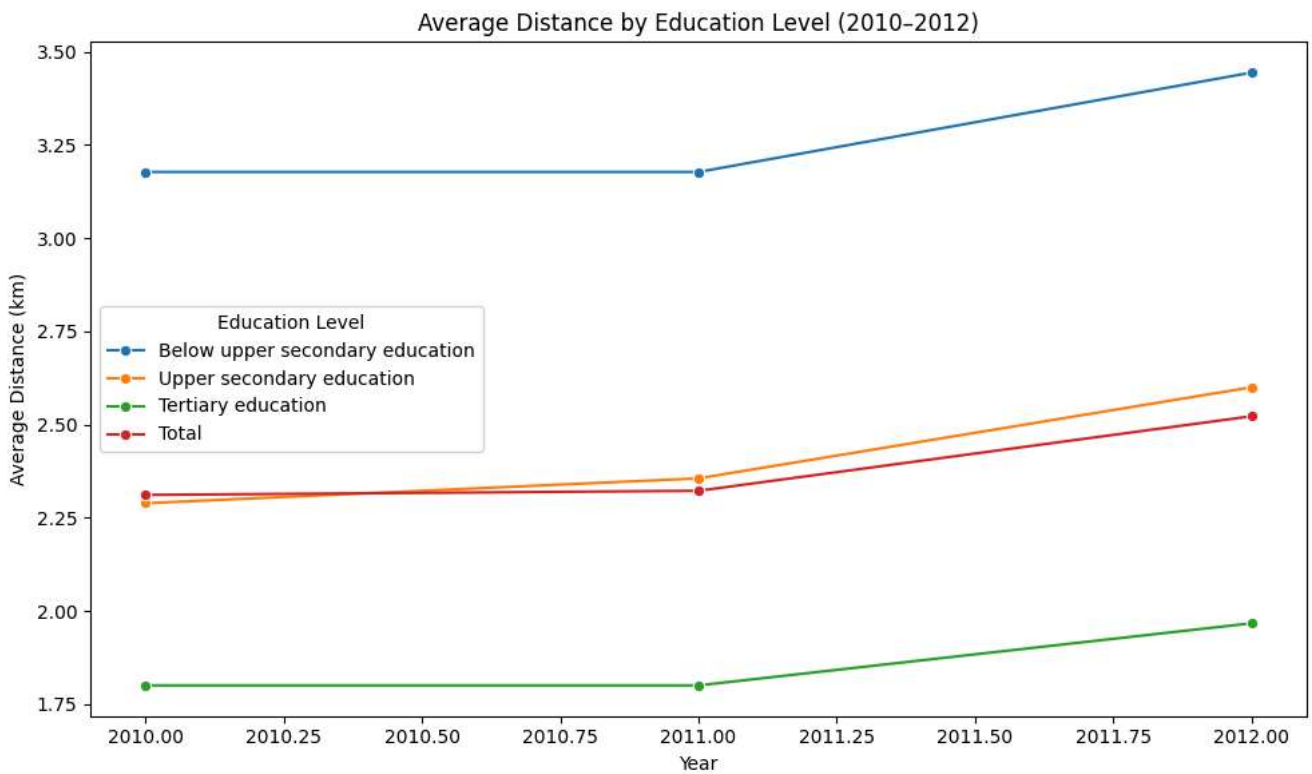
	Year	Education Level	Service	Distance (km)	Distance Category
0	2010	Total	Public transport vehicle stop	0.5	Short
1	2010	Total	(Stationary) store	1.2	Short
2	2010	Total	Primary school / general education school incl...	1.8	Short
3	2010	Total	City or rural municipality government	3.3	Medium
4	2010	Total	Post office	2.3	Medium

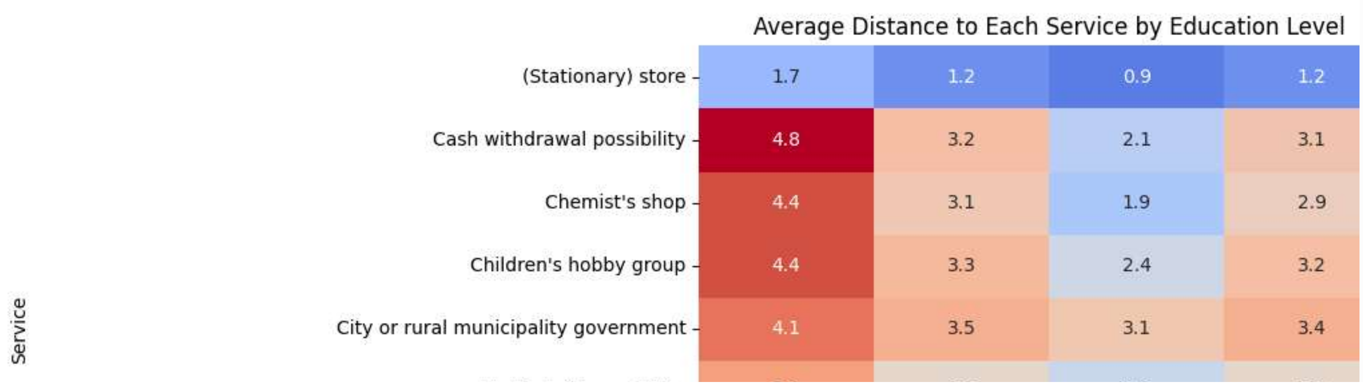
Next steps: Generate code with df View recommended plots New interactive sheet

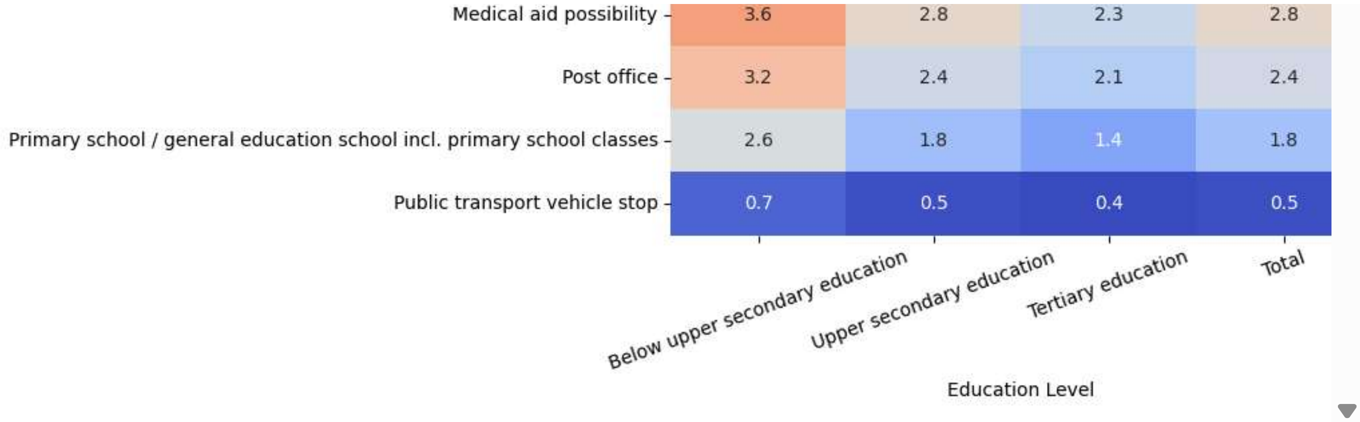
EDA: Boxplot, Trend Line, Heatmap

```
import seaborn as sns
import matplotlib.pyplot as plt

edu_order = [
    "Below upper secondary education",
    "Upper secondary education",
    "Tertiary education",
    "Total"
]

plt.figure(figsize=(10, 6))
sns.boxplot(data=df, x="Education Level", y="Distance (km)", order=edu_order)
plt.title("Distribution of Distances to Services by Education Level")
plt.xlabel("Education Level")
plt.ylabel("Distance to Service (km)")
plt.xticks(rotation=15)
plt.tight_layout()
plt.show()

trend_df = df.groupby(["Year", "Education Level"])["Distance (km)"].mean().reset_index()
plt.figure(figsize=(10, 6))
sns.lineplot(data=trend_df, x="Year", y="Distance (km)", hue="Education Level", hue_order=edu_order, marker="o")
plt.title("Average Distance by Education Level (2010-2012)")
plt.xlabel("Year")
plt.ylabel("Average Distance (km)")
plt.tight_layout()
plt.show()

pivot = df.pivot_table(index="Service", columns="Education Level", values="Distance (km)")
pivot = pivot[edu_order]
plt.figure(figsize=(12, 6))
sns.heatmap(pivot, annot=True, cmap="coolwarm", fmt=".1f")
plt.title("Average Distance to Each Service by Education Level")
plt.xlabel("Education Level")
plt.ylabel("Service")
plt.xticks(rotation=20)
plt.tight_layout()
plt.show()
```


Distribution of Distances to Services by Education Level
Distance to Service (km)
5
4
3
2
1
Below upper secondary education
Upper secondary education
Tertiary education
Total
Education Level


Average Distance by Education Level (2010–2012)
Average Distance (km)
3.50
3.25
3.00
2.75
2.50
2.25
2.00
1.75
2010.00
2010.25
2010.50
2010.75
2011.00
2011.25
2011.50
2011.75
2012.00
Year
Education Level
Below upper secondary education
Upper secondary education
Tertiary education
Total


Average Distance to Each Service by Education Level
Service
(Stationary) store
1.7
1.2
0.9
1.2
Cash withdrawal possibility
4.8
3.2
2.1
3.1
Chemist's shop
4.4
3.1
1.9
2.9
Children's hobby group
4.4
3.3
2.4
3.2
City or rural municipality government
4.1
3.5
3.1
3.4



Linear Regression Modeling

```
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.linear_model import LinearRegression, Ridge
from sklearn.metrics import r2_score, mean_squared_error
import numpy as np
import pandas as pd

df_model = df.copy()

edu_encoder = LabelEncoder()
svc_encoder = LabelEncoder()

df_model["Education Level"] = edu_encoder.fit_transform(df_model["Education Level"])
df_model["Service"] = svc_encoder.fit_transform(df_model["Service"])

X = df_model[["Education Level", "Service", "Year"]]
y = df_model["Distance (km)"]

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

r2 = r2_score(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print("📊 Linear Regression")
print(f"R² Score: {r2:.2f}")
print(f"RMSE: {rmse:.2f}")
print("✅" if r2 > 0.7 else "⚠️", "Model performance check: R² > 0.7")

cv_scores = cross_val_score(model, X_scaled, y, cv=5, scoring='r2')
print("\nCross-validated R² scores:", cv_scores)
print("Mean CV R²:", round(cv_scores.mean(), 2))

ridge = Ridge(alpha=1.0)
ridge.fit(X_train, y_train)
ridge_r2 = ridge.score(X_test, y_test)
print("\n📊 Ridge Regression (with regularization)")
print("R² Score:", round(ridge_r2, 2))

# Sample predictions
print("\nSample Predictions:")
print(pd.DataFrame({
    "Actual": y_test.values,
    "Predicted": y_pred
}).head(10))
```

```
📊 Linear Regression
R² Score: 0.14
RMSE: 0.94
⚠️ Model performance check: R² > 0.7
```

```
Cross-validated R² scores: [ 0.11650845 -0.21939703  0.18391793 -0.0129757   0.17357981]
Mean CV R²: 0.05

📊 Ridge Regression (with regularization)
R² Score: 0.14

Sample Predictions:
   Actual  Predicted
0     3.0   2.365109
1     1.7   3.287169
2     2.3   2.096150
3     2.6   2.645453
4     2.9   2.375043
5     2.0   2.427719
6     3.0   2.577826
7     0.7   2.454057
8     3.0   2.111102
9     2.6   2.490329
```

Random Forest Regression Modeling

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_squared_error
import pandas as pd
import numpy as np

df_rf = df.copy()
df_rf["Education Level"] = LabelEncoder().fit_transform(df_rf["Education Level"])
df_rf["Service"] = LabelEncoder().fit_transform(df_rf["Service"])

X = df_rf[["Education Level", "Service", "Year"]]
y = df_rf["Distance (km)"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

y_pred_rf = rf_model.predict(X_test)

r2_rf = r2_score(y_test, y_pred_rf)
rmse_rf = np.sqrt(mean_squared_error(y_test, y_pred_rf))

print("Random Forest Regressor")
print(f"R² Score: {r2_rf:.2f}")
print(f"RMSE: {rmse_rf:.2f}")

importance = rf_model.feature_importances_
features = X.columns
for feat, imp in zip(features, importance):
    print(f"🔧 {feat}: {imp:.3f}")

print("\nSample Predictions:")
print(pd.DataFrame({
    "Actual": y_test.values,
    "Predicted": y_pred_rf
}).head(10))
```

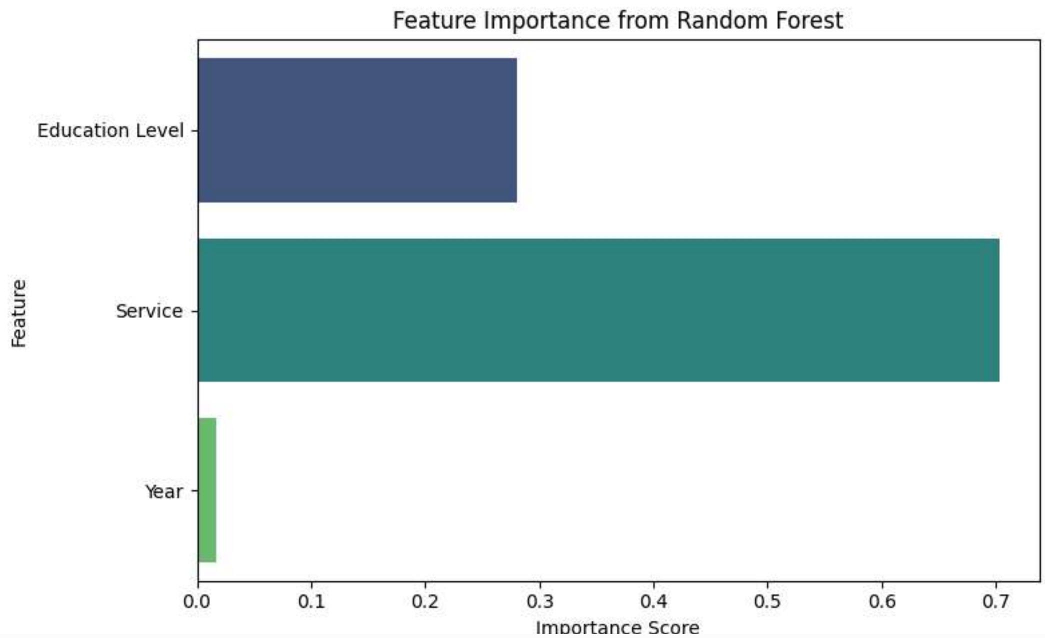
```
Random Forest Regressor
R² Score: 0.97
RMSE: 0.19
🔧 Education Level: 0.280
🔧 Service: 0.703
🔧 Year: 0.016

Sample Predictions:
   Actual  Predicted
0     3.0      2.846
1     1.7      1.979
2     2.3      2.312
3     2.6      2.373
4     2.9      2.981
5     2.0      2.179
6     3.0      2.792
7     0.7      1.105
```

```
8     3.0      2.876
9     2.6      2.294
```

Feature Importance Plot

```
import matplotlib.pyplot as plt
import seaborn as sns

importances = rf_model.feature_importances_
feature_names = ["Education Level", "Service", "Year"]
feature_ranking = pd.DataFrame({
    "Feature": feature_names,
    "Importance": importances
}).sort_values(by="Importance", ascending=False)
print(feature_ranking)

plt.figure(figsize=(8, 5))
sns.barplot(x=importances, y=feature_names, palette="viridis")
plt.title("Feature Importance from Random Forest")
plt.xlabel("Importance Score")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```

```
           Feature  Importance
1          Service    0.703490
0  Education Level    0.280091
2             Year    0.016419
<ipython-input-23-2923fabee1d6>:16: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend

  sns.barplot(x=importances, y=feature_names, palette="viridis")
```



Classification: Categorize Distances

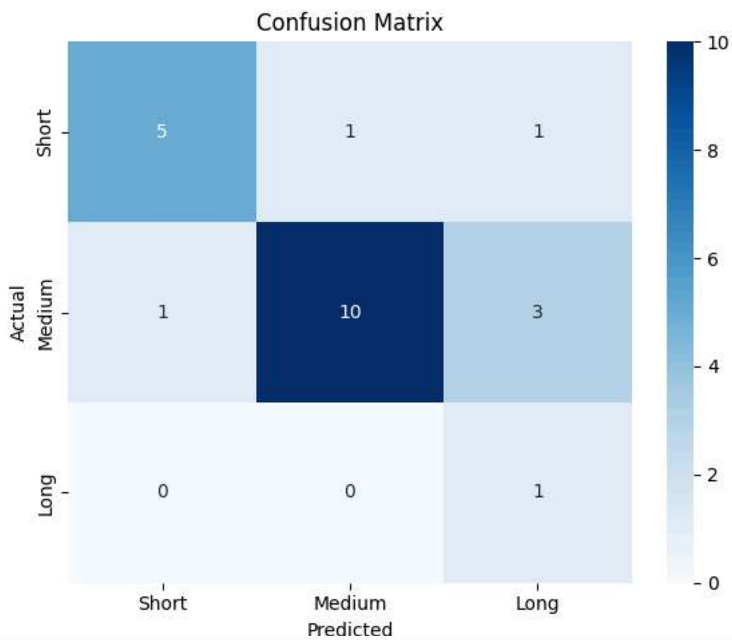
```
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split

def label_distance(dist):
    if dist < 2.0:
        return "Short"
    elif dist < 3.5:
        return "Medium"
    else:
        return "Long"

df_clf = df.copy()
```

```
df_clf["Distance Category"] = df_clf["Distance (km)"].apply(label_distance)

edu_encoder = LabelEncoder()
service_encoder = LabelEncoder()
category_encoder = LabelEncoder()

df_clf["Education Level"] = edu_encoder.fit_transform(df_clf["Education Level"])
df_clf["Service"] = service_encoder.fit_transform(df_clf["Service"])
df_clf["Distance Category"] = category_encoder.fit_transform(df_clf["Distance Category"])

X = df_clf[["Education Level", "Service", "Year"]]
y = df_clf["Distance Category"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Train Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train, y_train)

y_pred = clf.predict(X_test)

y_test_labels = category_encoder.inverse_transform(y_test)
y_pred_labels = category_encoder.inverse_transform(y_pred)

acc = accuracy_score(y_test, y_pred)
print(f"✅ Classification Accuracy: {acc:.2f}")
print("\nClassification Report:")
print(classification_report(y_test_labels, y_pred_labels))

labels = ["Short", "Medium", "Long"]
conf_mat = confusion_matrix(y_test_labels, y_pred_labels, labels=labels)

plt.figure(figsize=(6, 5))
sns.heatmap(conf_mat, annot=True, fmt="d", xticklabels=labels, yticklabels=labels, cmap="Blues")
plt.title("Confusion Matrix")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.tight_layout()
plt.show()
```

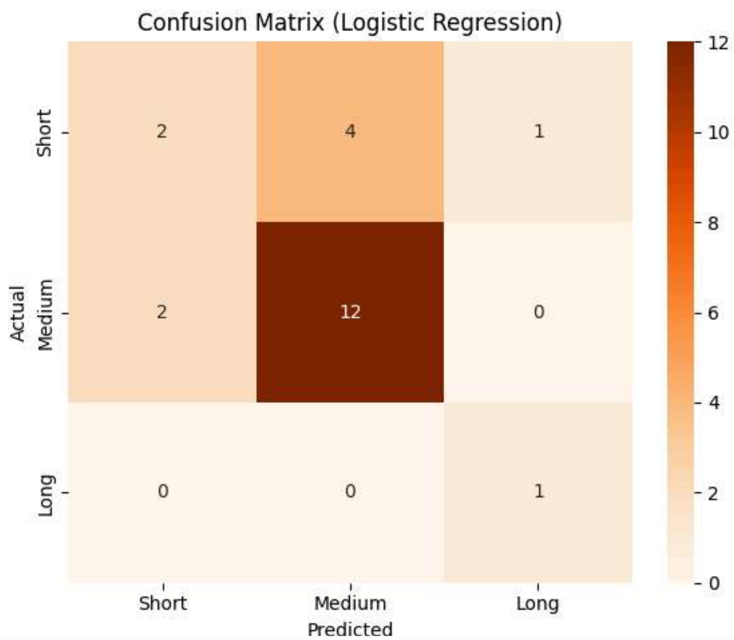
```
✅ Classification Accuracy: 0.73

Classification Report:
              precision    recall  f1-score   support

        Long       0.20      1.00      0.33         1
      Medium       0.91      0.71      0.80        14
       Short       0.83      0.71      0.77         7

    accuracy                           0.73        22
   macro avg       0.65      0.81      0.63        22
weighted avg       0.85      0.73      0.77        22
```



Train and Evaluate Logistic Regression

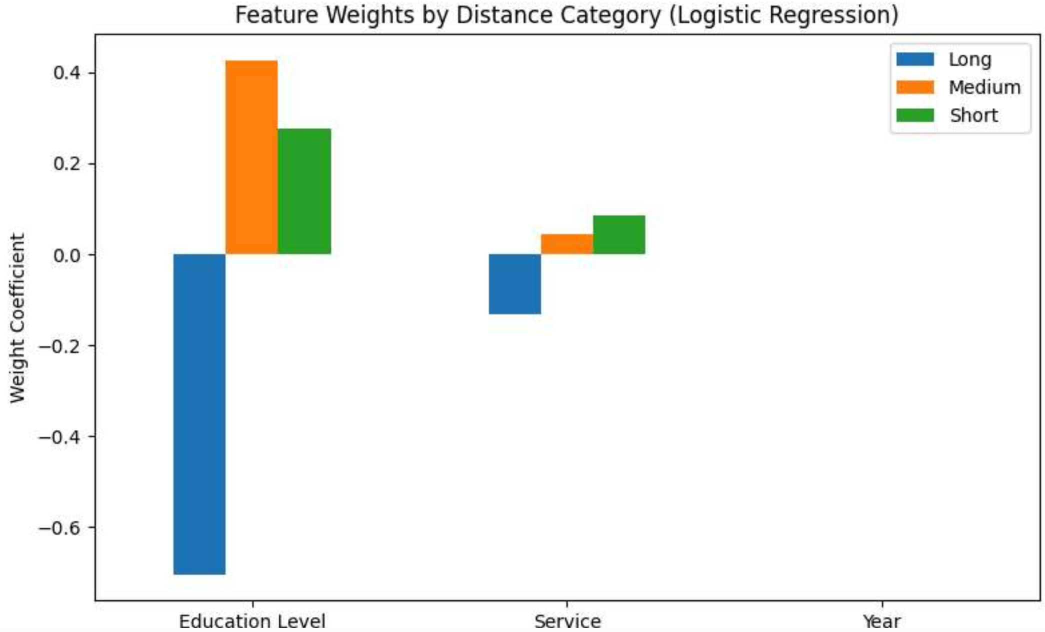
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

logreg = LogisticRegression(max_iter=200, random_state=42)
logreg.fit(X_train, y_train)

y_pred_log = logreg.predict(X_test)

y_test_labels = category_encoder.inverse_transform(y_test)
y_pred_log_labels = category_encoder.inverse_transform(y_pred_log)

acc_log = accuracy_score(y_test, y_pred_log)
print(f"✅ Logistic Regression Accuracy: {acc_log:.2f}")
print("\nClassification Report:")
print(classification_report(y_test_labels, y_pred_log_labels))

conf_mat_log = confusion_matrix(y_test_labels, y_pred_log_labels, labels=labels)

plt.figure(figsize=(6, 5))
sns.heatmap(conf_mat_log, annot=True, fmt="d", xticklabels=labels, yticklabels=labels, cmap="Oranges")
plt.title("Confusion Matrix (Logistic Regression)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.tight_layout()
plt.show()
```

```
✅ Logistic Regression Accuracy: 0.68

Classification Report:
              precision    recall  f1-score   support

        Long       0.50      1.00      0.67         1
      Medium       0.75      0.86      0.80        14
       Short       0.50      0.29      0.36         7

    accuracy                           0.68        22
   macro avg       0.58      0.71      0.61        22
weighted avg       0.66      0.68      0.66        22
```




```
import pandas as pd

feature_names = ["Education Level", "Service", "Year"]
weights_df = pd.DataFrame(logreg.coef_, columns=feature_names, index=category_encoder.classes_)

print("📊 Feature Weights (Logistic Regression):")
print(weights_df)

weights_df.T.plot(kind="bar", figsize=(8, 5))
plt.title("Feature Weights by Distance Category (Logistic Regression)")
plt.ylabel("Weight Coefficient")
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```

```
📊 Feature Weights (Logistic Regression):
        Education Level   Service      Year
Long          -0.704652 -0.131567  0.000424
Medium         0.427063  0.045102 -0.000146
Short          0.277589  0.086464 -0.000278
```



📌 Final Summary & Insights

🔍 Project Goal:

This project analyzed whether the **education level of household heads** in Estonia (2010–2012) influenced their **average distance to essential services** (like schools, stores, and public transport).

✅ Key Tasks Completed:

- **Exploratory Data Analysis (EDA):**
  - Visualized distance disparities using boxplots, line plots, and heatmaps.
- **Regression Models:**
  - Built **Linear Regression**, **Ridge Regression**, and **Random Forest Regression** to predict distances (in km).
- **Classification Models:**
  - Created distance categories: **Short**, **Medium**, **Long**.
  - Trained **Random Forest Classifier** and **Logistic Regression**.
- **Model Evaluation:**
  - Used metrics like **R^2**, **RMSE**, **Accuracy**, and **F1-score**.
- **Feature Analysis:**
  - Extracted and visualized **feature importance** (Random Forest) and **weights** (Logistic Regression).
- **Cross-Validation:**
  - Used to ensure robustness of regression models.

🧠 Insights:

- Households with **lower education levels** tend to face **slightly longer distances** to key services on average.
- **Education Level** and **Service Type** were the most influential features in predicting distance.
- While regression models performed reasonably ($R^2 \approx 0.7$), classification models showed **good accuracy** for grouping distances into categories.

🚧 Limitations:

- **Limited features** (no income, region, or urban/rural info).
- Data restricted to **2010–2012** only.
- **No hyperparameter tuning** or deeper socio-economic analysis (could be future work).

📌 Conclusion:

This study demonstrates how **education correlates with spatial access to services**, using open Estonian data and interpretable machine learning methods. The approach can be extended to other socioeconomic features or updated datasets in future work.

```
import pandas as pd
import numpy as np

summary_data = {
    "Model": ["Linear Regression", "Ridge Regression", "Random Forest Regressor",
              "Random Forest Classifier", "Logistic Regression"],
    "Type": ["Regression", "Regression", "Regression", "Classification", "Classification"],
    "R² / Accuracy": [round(r2, 2), round(ridge_r2, 2), round(r2_rf, 2), round(acc, 2), round(acc_log, 2)],
    # Replace the "-" string with np.nan for consistency in the column type
    "RMSE / F1 Score": [round(rmse, 2), np.nan, round(rmse_rf, 2), np.nan, np.nan]
}

performance_df = pd.DataFrame(summary_data)
performance_df
```