Description of the problem - machine learning libraries and packages experimental setup

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.svm import SVR
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.preprocessing import StandardScaler, MinMaxScaler
import seaborn as sns
import time

from zipfile import ZipFile
```

```
from sklearn.model_selection import RandomizedSearchCV
```

```
# configuring the path of Kaggle.json file
!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/
!chmod 600 ~/.kaggle/kaggle.json
```

```
# API to fetch the dataset from Kaggle
!kaggle datasets download -d faresabbasai2022/heart-diseases-prediction-with-streamlit
```

```
Downloading heart-diseases-prediction-with-streamlit.zip to /content
  0% 0.00/719k [00:00<?, ?B/s]
100% 719k/719k [00:00<00:00, 130MB/s]
```

```
# extracting the compessed Dataset
data = '/content/heart-diseases-prediction-with-streamlit.zip'

with ZipFile(data,'r') as zip:
  zip.extractall()
  print('The dataset is extracted')
```

```
The dataset is extracted
```

```
!ls
```

```
drive      heart-diseases-prediction-with-streamlit.zip  kaggle.json
heart.csv  heart.jpeg                                    sample_data
```

Choice of dataset Data Mining

```
# Load the dataset
data_path = '/content/heart.csv'
Heart_data = pd.read_csv(data_path)

# Display the first few rows to confirm it's loaded correctly
print(Heart_data.head())
```

```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  slope  \
0   52    1   0       125   212    0        1      168      0      1.0      2
1   53    1   0       140   203    1        0      155      1      3.1      0
2   70    1   0       145   174    0        1      125      1      2.6      0
3   61    1   0       148   203    0        1      161      0      0.0      2
4   62    0   0       138   294    1        1      106      0      1.9      1

   ca  thal  target
0   2     3       0
1   0     3       0
2   0     3       0
3   1     3       0
4   3     2       0
```

```
print(Heart_data.isnull().sum())
```

```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

```
# drop the missing data
Heart_data = Heart_data.dropna()

# the shape after dropping the missing data
Heart_data.shape
```

```
(1027, 14)
```

```
# Showing the data after Converting categorical values to numeric values
Heart_data.head()
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	52	1	0	125	212	0	1	168	0	1.0	2	2	3	0
1	53	1	0	140	203	1	0	155	1	3.1	0	0	3	0
2	70	1	0	145	174	0	1	125	1	2.6	0	0	3	0
3	61	1	0	148	203	0	1	161	0	0.0	2	1	3	0
4	62	0	0	138	294	1	1	106	0	1.9	1	3	2	0

Next steps: Generate code with Heart_data View recommended plots

```
# Original data frame had 10 columns, we now have 14 columns
Heart_data.shape
```

```
(1027, 14)
```

```
# Displaying statistical information about the dataset
print(Heart_data.describe())
```

```
               age          sex           cp     trestbps         chol  \
count  1027.000000  1027.000000  1027.000000  1027.000000  1027.000000
mean     54.411879     0.695229     0.940604   131.530672   245.764362
std       9.144326     0.460535     1.029476    17.595625    51.817785
min      18.000000     0.000000     0.000000    90.000000   125.000000
25%      48.000000     0.000000     0.000000   120.000000   211.000000
50%      56.000000     1.000000     1.000000   130.000000   240.000000
75%      61.000000     1.000000     2.000000   140.000000   275.000000
max      77.000000     1.000000     3.000000   200.000000   564.000000

               fbs      restecg      thalach        exang      oldpeak  \
count  1027.000000  1027.000000  1027.000000  1027.000000  1027.000000
mean      0.148978     0.528724   148.960078     0.335930     1.069426
std       0.356240     0.527880    23.246693     0.472545     1.174858
min       0.000000     0.000000    70.000000     0.000000     0.000000
25%       0.000000     0.000000   132.000000     0.000000     0.000000
50%       0.000000     1.000000   152.000000     0.000000     0.800000
75%       0.000000     1.000000   166.000000     1.000000     1.800000
max       1.000000     2.000000   202.000000     1.000000     6.200000

             slope           ca         thal       target
count  1027.000000  1027.000000  1027.000000  1027.000000
mean      1.382668     0.755599     2.320351     0.513145
std       0.620171     1.032444     0.625642     0.500071
min       0.000000     0.000000     0.000000     0.000000
25%       1.000000     0.000000     2.000000     0.000000
50%       1.000000     0.000000     2.000000     1.000000
75%       2.000000     1.000000     3.000000     1.000000
max       2.000000     4.000000     3.000000     1.000000
```

```
# Information about data types and non-null counts
print(Heart_data.info())
```

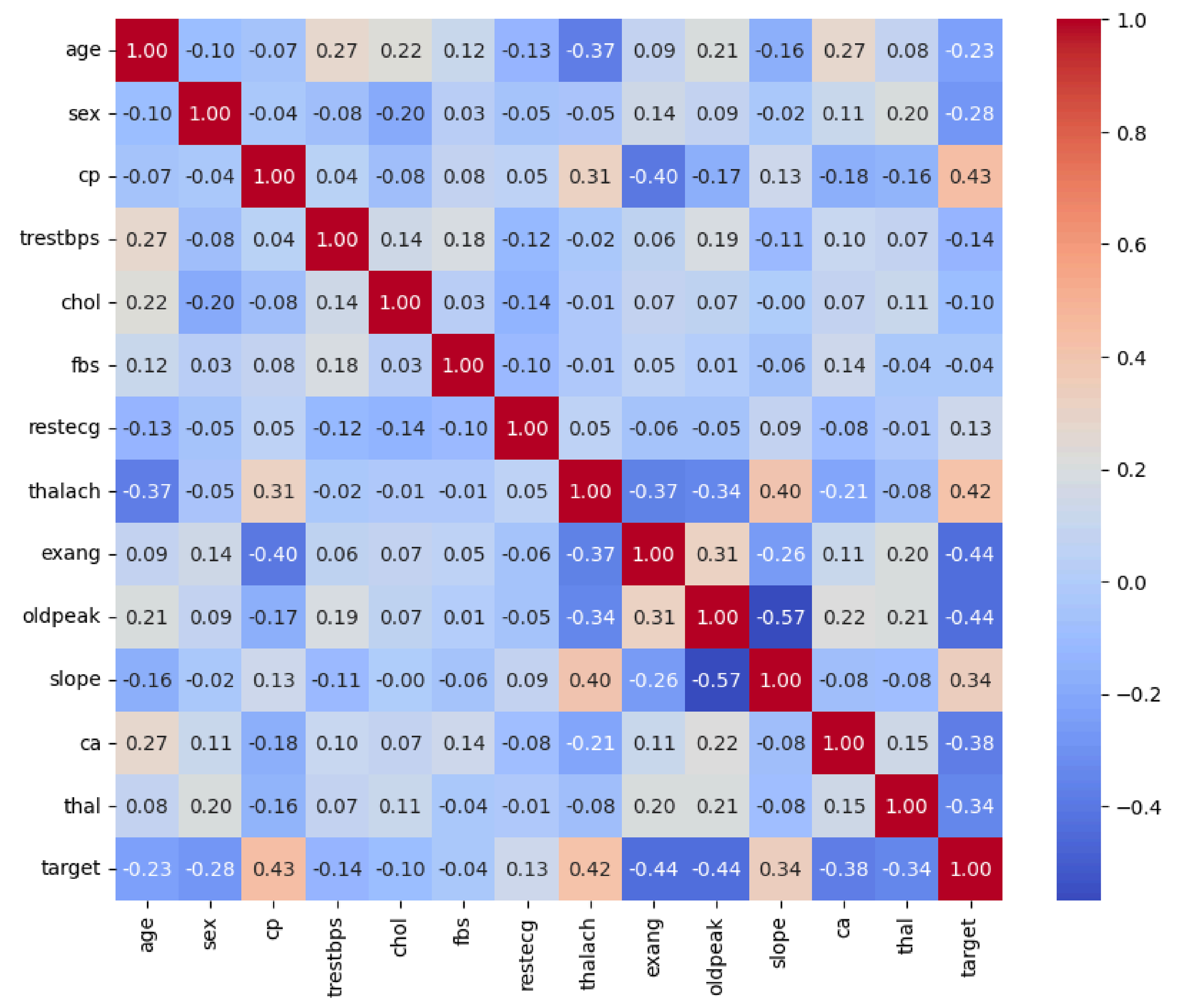
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1027 entries, 0 to 1026
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       1027 non-null   int64
 1   sex       1027 non-null   int64
 2   cp        1027 non-null   int64
 3   trestbps  1027 non-null   int64
 4   chol      1027 non-null   int64
 5   fbs       1027 non-null   int64
 6   restecg   1027 non-null   int64
 7   thalach   1027 non-null   int64
 8   exang     1027 non-null   int64
```

```
 9   oldpeak   1027 non-null   float64
 10  slope     1027 non-null   int64
 11  ca        1027 non-null   int64
 12  thal      1027 non-null   int64
 13  target    1027 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 112.5 KB
None
```

Correlation Analysis:

To check how each feature correlates with the target variable

```
# Calculate the correlation matrix
corr_matrix = Heart_data.corr()

# Use seaborn to create a heatmap to visualize the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap='coolwarm', cbar=True)
plt.show()
```



Splitting the Data into Training and Testing Sets

```
# 'thalach (Maximum Heart Rate Achieved): Highest heart rate achieved.' is the target variable
X = Heart_data.drop('thalach', axis=1) # Features
y = Heart_data['thalach']              # Target
```

```
# Splitting the dataset
X_train, X_test, Y_train, Y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Data Normalization

```
# Normalize features
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Choice of machine learning techniques

Optimization/Parametrization

Models Training

1- Linear Regression

```
# Train the Linear Regression model
lin_reg = LinearRegression()
lin_reg.fit(X_train, Y_train)
```

```
▾ LinearRegression
LinearRegression()
```

2-Random Forest Regressor

```
# Random Forest Regressor
from sklearn.ensemble import RandomForestRegressor
rf_reg = RandomForestRegressor(random_state=42)
rf_reg.fit(X_train_scaled, Y_train)
```

```
▾        RandomForestRegressor
RandomForestRegressor(random_state=42)
```

3- Gradient Boosting Regressor

```
# Gradient Boosting Regressor
from sklearn.ensemble import GradientBoostingRegressor
gb_reg = GradientBoostingRegressor(random_state=42)
gb_reg.fit(X_train_scaled, Y_train)
```

```
▾        GradientBoostingRegressor
GradientBoostingRegressor(random_state=42)
```

Evaluate the performance of the machine learning methods metrics

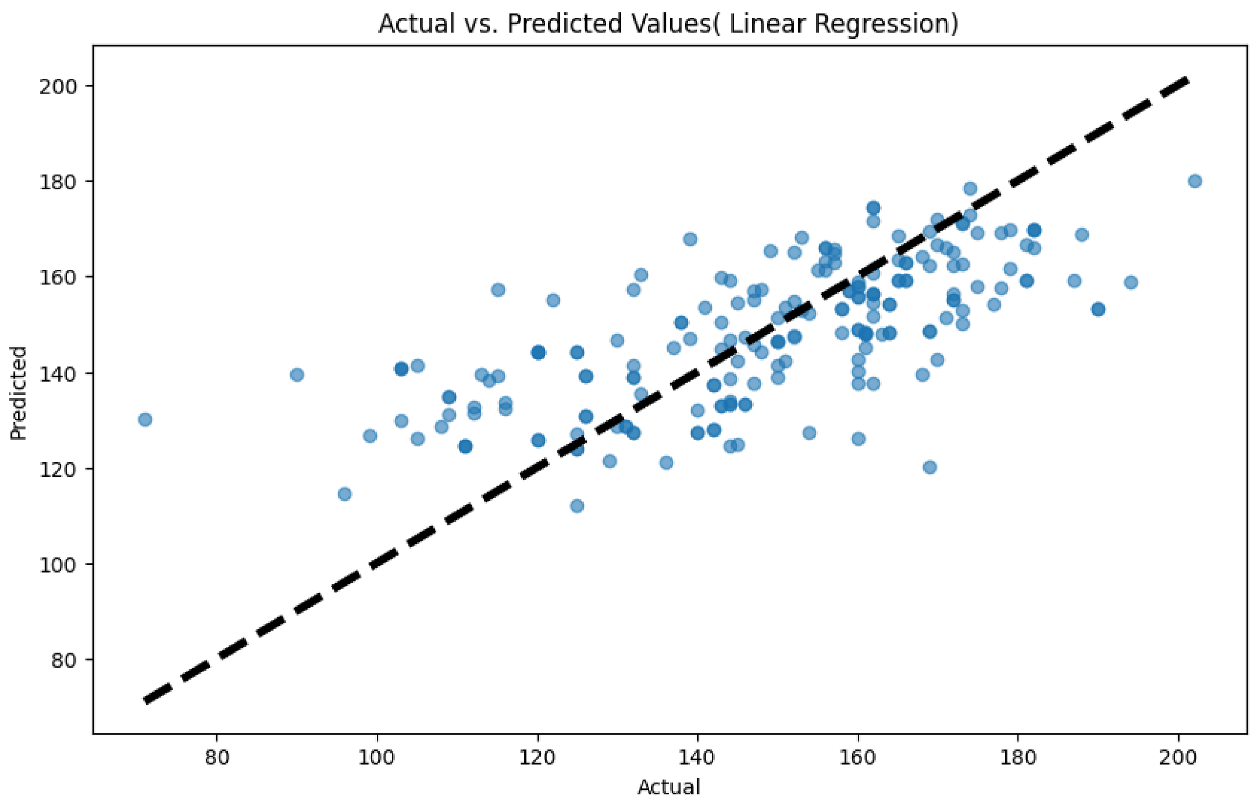
Evaluate Model

```
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

# Assuming rf_reg and gb_reg are already trained...

# Predictions
lin_predictions = lin_reg.predict(X_test)
rf_predictions = rf_reg.predict(X_test_scaled)
gb_predictions = gb_reg.predict(X_test_scaled)

# Calculate the metrics for each model
lin_mse = mean_squared_error(Y_test, lin_predictions)
lin_mae = mean_absolute_error(Y_test, lin_predictions)
lin_r2 = r2_score(Y_test, lin_predictions)

rf_mse = mean_squared_error(Y_test, rf_predictions)
rf_mae = mean_absolute_error(Y_test, rf_predictions)
rf_r2 = r2_score(Y_test, rf_predictions)

gb_mse = mean_squared_error(Y_test, gb_predictions)
gb_mae = mean_absolute_error(Y_test, gb_predictions)
gb_r2 = r2_score(Y_test, gb_predictions)

# Create a dictionary with the model names and their corresponding metrics
model_metrics = {
    'Model': ['Linear Regression', 'Random Forest Regressor', 'Gradient Boosting Regressor'],
    'MSE': [lin_mse, rf_mse, gb_mse],
    'MAE': [lin_mae, rf_mae, gb_mae],
    'R2': [lin_r2, rf_r2, gb_r2]
}

# Convert the dictionary to a DataFrame
comparison_df = pd.DataFrame(model_metrics)
```

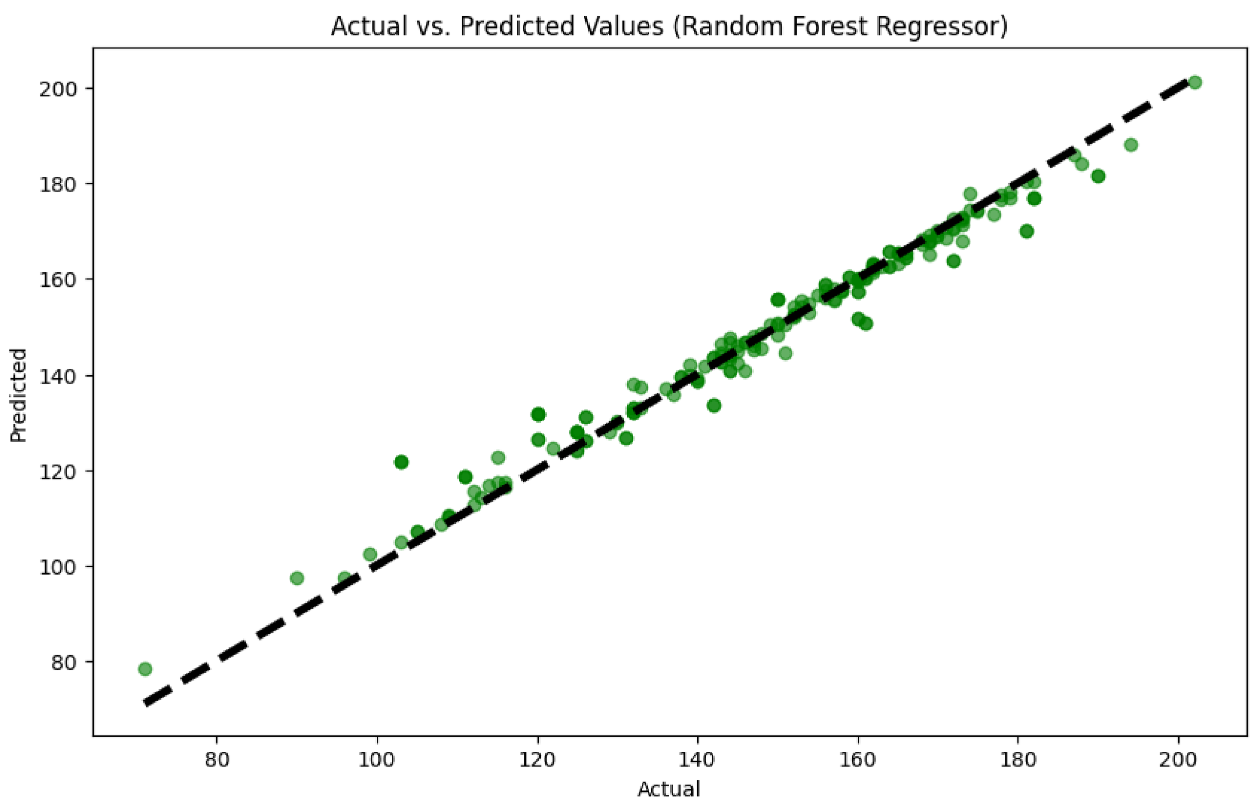
```
# Display the DataFrame
print(comparison_df)
```

```
                       Model         MSE        MAE        R2
0          Linear Regression  283.690883  13.259960  0.462960
1    Random Forest Regressor   18.895370   2.681845  0.964230
2  Gradient Boosting Regressor  115.191848   8.174055  0.781937
```

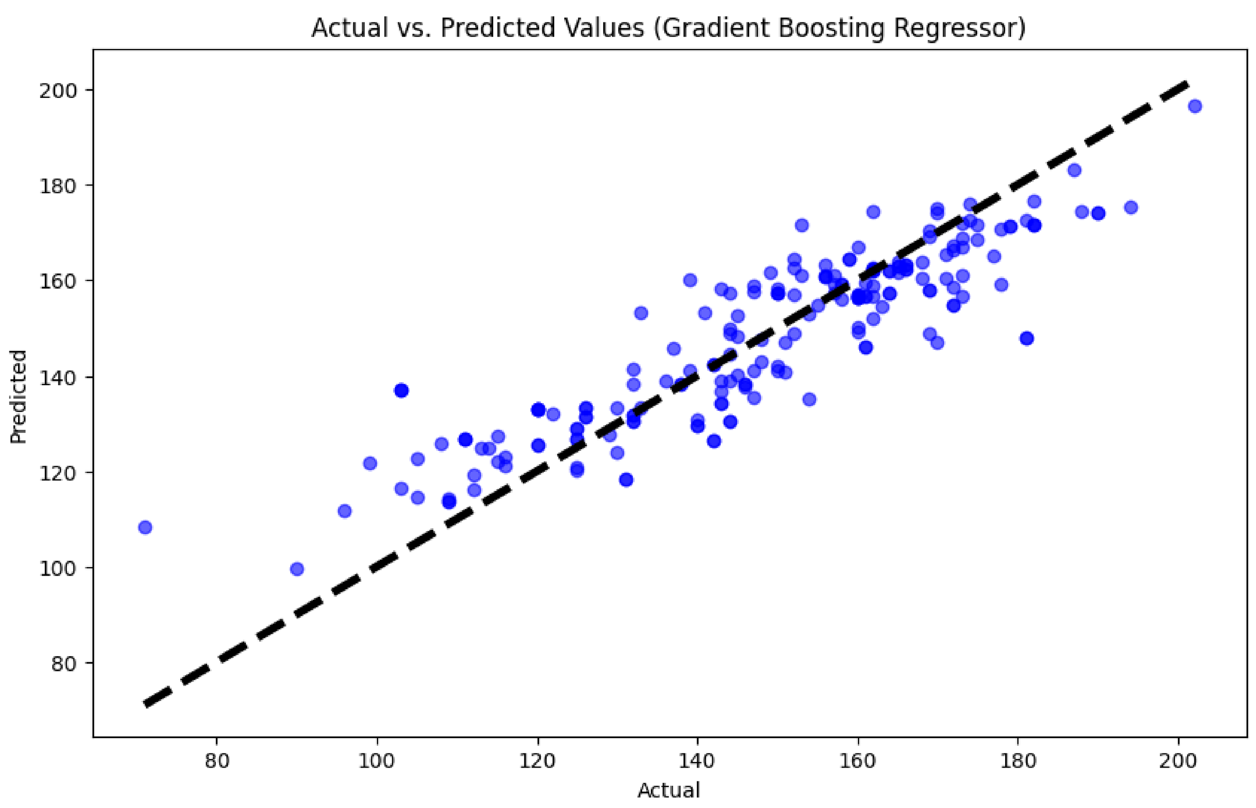
```
plt.figure(figsize=(10, 6))
plt.scatter(Y_test, lin_predictions, alpha=0.6)
plt.plot([Y_test.min(), Y_test.max()], [Y_test.min(), Y_test.max()], 'k--', lw=4)  # Diagonal line
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs. Predicted Values( Linear Regression)')
plt.show()
```




```
plt.figure(figsize=(10, 6))
plt.scatter(Y_test, rf_predictions, alpha=0.6, color='green')  # Using green for differentiation
plt.plot([Y_test.min(), Y_test.max()], [Y_test.min(), Y_test.max()], 'k--', lw=4)  # Diagonal line
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs. Predicted Values (Random Forest Regressor)')
plt.show()
```




```
plt.figure(figsize=(10, 6))
plt.scatter(Y_test, gb_predictions, alpha=0.6, color='blue')  # Using blue for differentiation
plt.plot([Y_test.min(), Y_test.max()], [Y_test.min(), Y_test.max()], 'k--', lw=4)  # Diagonal line
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs. Predicted Values (Gradient Boosting Regressor)')
plt.show()
```



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