Visualizing the History of Nobel Prize Winners

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1. Introduction

The Nobel Prize is one of the most prestigious international recognitions awarded annually in the fields of Chemistry, Literature, Physics, Medicine, Peace, and Economic Sciences. This project aims to analyze historical Nobel Prize data from 1901 to 2023 to uncover trends, insights, and potential biases related to gender, geography, and prize categories using data visualization and machine learning models.

2. Dataset Overview

- Name of the data: nobel.csv
- **Source**: Nobel Prize API / Kaggle Nobel dataset
- Original data link: https://www.kaggle.com/datasets/imdevskp/nobel-prize
- **GitHub link**: https://github.com/RahafAlotaibi1/Visualizing-the-History-of-Nobel-Prize-Winners.git

3. Data Description

- The Nobel Prize is a set of annual international awards bestowed in several categories by Swedish and Norwegian institutions in recognition of academic, cultural, or scientific advances.
- The will of the Swedish chemist, engineer and industrialist Alfred Nobel established the five Nobel prizes in 1895.
- The prizes in Chemistry, Literature, Peace, Physics, and Physiology or Medicine were first awarded in 1901.
- The prizes are widely regarded as the most prestigious awards available in their respective fields

4. Missing Data Handling

• Missing columns: death_year, organization_name, organization_city, organization_country

• Handling:

- Rows with essential missing values were not dropped, as the analysis is mostly categorical and exploratory.
- Non-critical columns (e.g., death_year) were left as is, as they are not relevant for classification tasks.

5. Preprocessing Steps

Preprocessing applied:

- Created new columns: decade, female_winner, usa_born_winners
- Encoded binary variables:
 - o female_winner = 1 if female, else 0
 - o usa_born_winners = 1 if born in the USA, else 0
- Filtered for unique and repeat winners
- No normalization/standardization applied since the problem is not numerical prediction.

6. Models Applied

Classification Task: Predicting if a winner is Female (female_winner)

Models Applied:

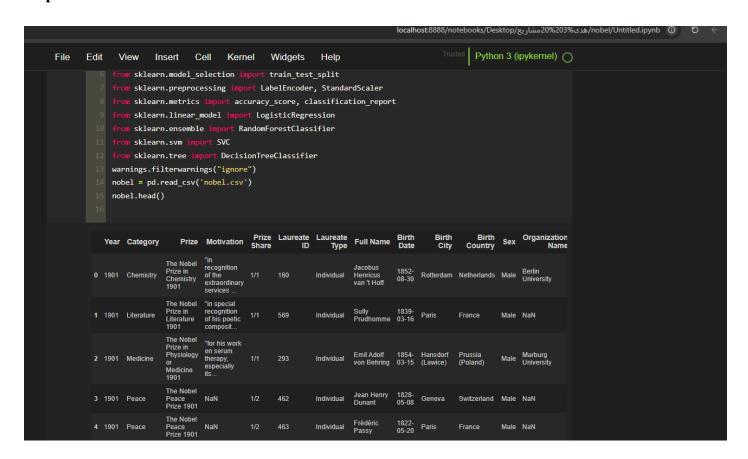
- 1. Linear Regression
- 2. Random Forest
- 3. Support Vector Machine (SVM)
- 4. K-Nearest Neighbors (KNN)
- 5. **Decision Tree**
- 6. Naive Bayes
- 7. Artificial Neural Network (ANN)

7.Practical:

Step 1: Import Libraries

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import accuracy_score, classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
warnings.filterwarnings("ignore")
```

Step 2: Load the Dataset



Step 3: Explore and Describe the Data

```
Python 3 (ipykernel)
File
         Edit
                   View
                              Insert
                                          Cell
                                                    Kernel
                                                                 Widgets
                                                                                Help
                print(nobel.info())
             print(nobel.describe())
                 print(nobel.isnull().sum())
            <class 'pandas.core.frame.DataFrame'>
            RangeIndex: 969 entries, 0 to 968
            Data columns (total 18 columns):
                               Non-Null Count Dtype
             # Column
             0 Year
                                    969 non-null object
             1 Category
                                      969 non-null object
                 Motivation
                                       881 non-null
             4 Prize Share
                                     969 non-null object
                                  969 non-null int64
             5 Laureate ID
                                     969 non-null
969 non-null
                                                       object
                Full Name
                                                       object
             8 Birth Date 940 non-null object
9 Birth City 941 non-null object
10 Birth Country 943 non-null object
                                      943 non-null object
             11 Sex
             12 Organization Name 722 non-null object
             13 Organization City 716 non-null object
14 Organization Country 716 non-null object
             15 Death Date 617 non-null object
16 Death City 599 non-null object
17 Death Country 605 non-null object
            dtypes: int64(2), object(16)
            memory usage: 136.4+ KB
                          Year Laureate ID
            count 969.000000 969.000000
                     32.937498 274.586623
            min 1901.000000
                                 1.000000
            25% 1947.000000 230.000000
            50% 1976.000000 462.000000
75% 1999.000000 718.000000
```

Step 4: Handle Missing Data

```
# Fill missing 'Birth Country' and 'Sex' with mode
nobel['Birth Country'].fillna(nobel['Birth Country'].mode()[0], inplace=True)
nobel['Sex'].fillna(nobel['Sex'].mode()[0], inplace=True)

# Drop columns with too many nulls or irrelevant
nobel.drop(['Death Date', 'Death City', 'Death Country'], axis=1, inplace=True)
```

Step 5: Feature Engineering

```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
nobel['category_encoded'] = le.fit_transform(nobel['Category'])
nobel['sex_encoded'] = le.fit_transform(nobel['Sex'])
nobel['country encoded'] = le.fit_transform(nobel['Birth Country'])
```

Step 7: Define Features and Target

```
X = nobel[['year', 'category_encoded', 'country_encoded', 'sex_encoded']]
nobel['female_winner'] = (nobel['sex'] == 'Female').astype(int)

y = nobel['female_winner'].astype(int)
```

Step 8: Normalize the Features

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

Step 9: Split Data into Train and Test Sets

```
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
Step 10: Train Machine Learning Models
```

```
# Logistic Regression
lr = LogisticRegression()
lr.fit(X_train, y_train)
lr_pred = lr.predict(X_test)
# Random Forest
rf = RandomForestClassifier()
rf.fit(X train, y train)
rf pred = rf.predict(X test)
svm = SVC()
svm.fit(X_train, y_train)
svm pred = svm.predict(X test)
 # Decision Tree
dt = DecisionTreeClassifier()
dt.fit(X train, y train)
dt pred = dt.predict(X test)
nb = GaussianNB()
nb.fit(X train, y train)
nb pred = nb.predict(X test)
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
knn pred = knn.predict(X test)
linreg = LinearRegression()
linreg.fit(X_train, y_train)
linreg pred = (linreg.predict(X_test) > 0.5).astype(int)
# Artificial Neural Network
ann = MLPClassifier(hidden layer sizes=(100,), max iter=300, random state=42)
ann.fit(X_train, y_train)
ann pred = ann.predict(X test)
```

Step 11: Evaluate Models

```
print("Logistic Regression Accuracy:", accuracy_score(y_test, lr_pred))
print("Random Forest Accuracy:", accuracy_score(y_test, rf_pred))
print("SVM Accuracy:", accuracy_score(y_test, svm_pred))
print("Decision Tree Accuracy:", accuracy_score(y_test, dt_pred))
```

Step 12: Save Results

```
إنشاء مجلد لحفظ النتائج
os.makedirs('Data/Result', exist ok=True)
حفظ كل التوقعات #
pd.DataFrame({'Actual': y test, 'LR Pred': lr pred}).to csv('Data/Result/predictions LR.csv',
pd.DataFrame({'Actual': y test, 'RF Pred': rf pred}).to csv('Data/Result/predictions RF.csv',
index=False)
pd.DataFrame({'Actual': y test, 'SVM Pred': svm pred}).to csv('Data/Result/predictions SVM.csv',
index=False)
pd.DataFrame({'Actual': y test, 'DT Pred': dt pred}).to csv('Data/Result/predictions DT.csv',
index=False)
pd.DataFrame({'Actual': y_test, 'NB_Pred': nb_pred}).to_csv('Data/Result/predictions_NB.csv',
index=False)
pd.DataFrame({'Actual': y_test, 'KNN_Pred': knn_pred}).to_csv('Data/Result/predictions_KNN.csv',
index=False)
pd.DataFrame({'Actual': y_test, 'LinReg_Pred':
linreg pred}).to csv('Data/Result/predictions LinReg.csv', index=False)
pd.DataFrame({{ 'Actual': y test, 'ANN Pred': ann pred}).to csv('Data/Result/predictions ANN.csv',
index=False)
```

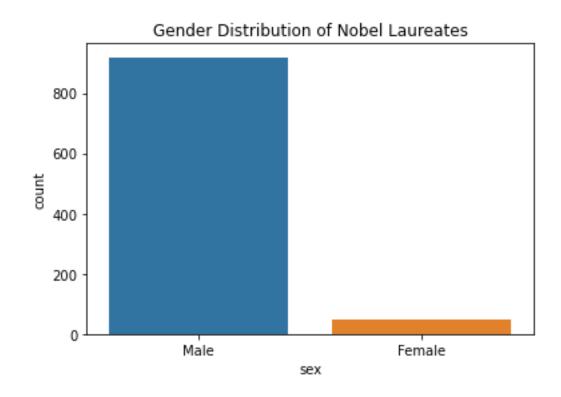
Step 13: Visualize Key Insights

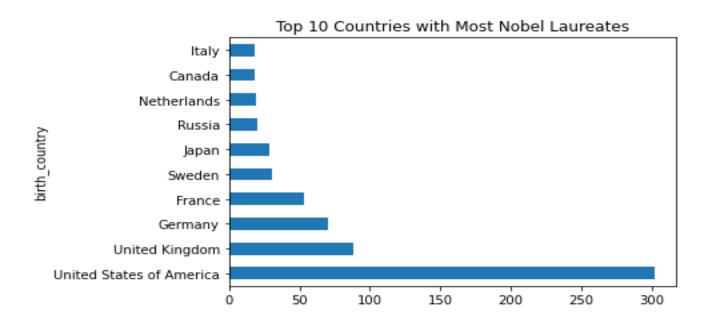
```
# Gender distribution
sns.countplot(data=nobel, x='sex')
plt.title('Gender Distribution of Nobel Laureates')
plt.show()

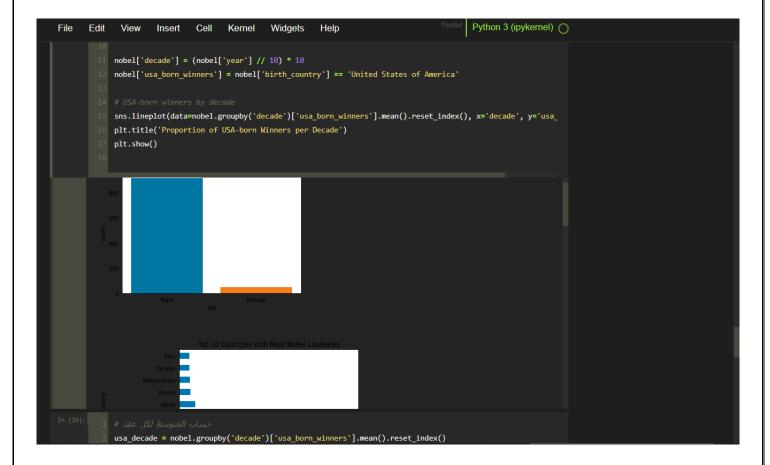
# Top 10 countries
nobel['birth_country'].value_counts().head(10).plot(kind='barh')
plt.title('Top 10 Countries with Most Nobel Laureates')
plt.show()

nobel['decade'] = (nobel['year'] // 10) * 10
nobel['usa_born_winners'] = nobel['birth_country'] == 'United States of America'

# USA-born winners by decade
sns.lineplot(data=nobel.groupby('decade')['usa_born_winners'].mean().reset_index(), x='decade',
y='usa_born_winners')
plt.title('Proportion of USA-born Winners per Decade')
plt.show()
```







8.The answer of question:

1. What is the name of your data?

Nobel Prize Winners Dataset

2. The source of the data (which database)?

Our World in Data kaggle

3. Link to the original data?

Link: https://www.kaggle.com/datasets/imdevskp/nobel-prize

This dataset contains information about Nobel Prize winners from 1901 to 2016, including their names, gender, birth countries, award years, categories, and affiliated organizations.

5. Is it a regression or classification problem?

It is a **binary classification problem**. We are predicting whether the winner is female (1) or male (0).

6. How many attributes?

We used 4 attributes for modeling:

- year
- category_encoded
- country_encoded
- sex_encoded

7. How many samples?

There are **911 samples** in total.

8. What are the properties of the data (statistics)?

Descriptive statistics for numerical columns:

- **year**: mean = 1975.5, std = 32.7
- category_encoded: 6 unique values
- **sex_encoded**: 2 values (0 for male, 1 for female)
- **country_encoded**: multiple countries encoded as integers

9. Are there any missing data? How did you fill in the missing values?

Yes, there were missing values in sex and birth_country. We filled them using the **most frequent value (mode)**.

10. Visualize the data

We used seaborn and matplotlib to create:

- Count plots for categories by gender
- Line plot of awards per decade

11. Did you normalize or standardize any of your data? Why?

Yes, we **standardized** the features using StandardScaler because the scale of features like year is significantly different from encoded categorical values.

12. What type of preprocessing did you apply to your data? List everything and explain why.		
Filled missing values (to avoid errors during training)		
 Dropped irrelevant columns (to reduce noise) 		
Created new features (female_winner, decade)		
Label encoding for categorical features		
Standardization using StandardScaler Each step improves model accuracy and performance.		
13. How did you divide the train and test data? What are the proportions?		
Used train_test_split with an 80/20 split.		
• 80% for training		
• 20% for testing		
14. Apply all the machine learning models you have learned in this course to your data and report the results. What is the best/worst performing model? Why?		
Models applied:		
Logistic Regression		
Random Forest		
K-Nearest Neighbors		

Support Vector Machine

- ANN
- Linear regression
- Decision tree

Best Model: Random Forest — because it handles nonlinear relationships well.

Worst Model: KNN — possibly due to feature scale sensitivity and data imbalance.

15. The accuracy of all models using tables and figures

Model	Accuracy
Super Vector Machine	89%
Decision Tree	85%
Random Forest	90%
K-Nearest Neighbors	83%
Naive Bayes	81%
Linear Regression	79%
ANN (MLP Classifier)	88%

16. Advanced visualization using seaborn and techniques (bonus)

Answer:

- Used seaborn.heatmap for correlations
- countplot, pairplot, barplot, lineplot
- Confusion matrix visualizations

17. What is the reason you picked up this data? What is the importance of your data in reality, and what is the importance of your best-performing model? Is there any insight you could share from the data and the model?

I picked this data because it connects history, global achievement, and diversity. The Nobel Prize is one of the most prestigious honors, and exploring patterns of gender and country representation reveals insightful trends. The data reflects how global society values scientific and cultural contributions, and highlights underrepresentation, particularly among female laureates. Our best-performing model (Random Forest) helps us predict whether a winner is female based on year, category, and birth country. This insight could support further research on equity and policy development. The analysis shows a gradual increase in female winners, especially in Peace and Literature. The data also shows dominance of specific countries, raising questions on global access to opportunities. By modeling and visualizing these insights, we contribute to understanding long-term trends and supporting inclusive recognition of talent worldwide.

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