Building the IMDb score prediction model

Sure, I can provide an outline for building an IMDb score prediction model by continuing with feature engineering, model training, and evaluation. This project assumes you're working with a dataset of movies, including various features, and you want to predict IMDb scores. Here's a step-by-step guide:

- Feature engineering
- Model training
- Evaluation.

Feature Engineering:

Data Preprocessing:

Handle missing data: Decide whether to impute or remove missing values in your dataset.

Data encoding: Convert categorical features to numerical using techniques like one-hot encoding or label encoding.

Feature scaling: Normalize or standardize numerical features to ensure they're on the same scale.

Feature Selection:

Analyze feature importance to select the most relevant features for prediction.

Consider using techniques like Recursive Feature Elimination (RFE), feature correlation analysis, or domain knowledge to choose the right features.

Feature Transformation:

Create new features that might be more informative.

For example,

you could calculate the director's average IMDb score or the movie's genre distribution.Use techniques like PCA for dimensionality reduction if you have many features.

Model Training:

Split Data:

Split your dataset into training, validation, and test sets. Common splits are 70% training, 15% validation, and 15% testing, but the ratio can vary depending on the dataset's size and characteristics.

Select a Model:

- Choose a machine learning model for regression. Common choices include linear regression, decision trees, random forests, gradient boosting, and neural networks.
- Consider trying different models to see which one performs the best.

Train the Model:

- Train the selected model using the training dataset.
- Tune hyperparameters using the validation dataset to improve the model's performance.

Evaluation:

- Model Evaluation
- Test the Model
- Interpret Results
- Fine-tuning and Deployment

Model Evaluation :

- Evaluate the model's performance on the validation dataset using appropriate regression metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R2).
- Adjust the model or hyperparameters as needed.

Test the Model:

Once satisfied with the model's performance on the validation dataset, test it on the test dataset to estimate its real-world performance.

Interpret Results

Interpret the model's predictions and assess the importance of each feature in the model.

Visualize the results, such as plotting actual IMDb scores against predicted scores.

Fine-tuning and Deployment

- If necessary, make final adjustments to the model based on test results and domain expertise.
- Once the model meets your requirements, prepare it for deployment in a production environment.

Sample code for prediction:

```
import pandas as pd

column_names = ['user_id', 'item_id', 'rating', 'timestamp']


path = 'https://media.geeksforgeeks.org/wp-content/uploads/file.tsv'


df = pd.read_csv(path, sep='\t', names=column_names)
```

```
df.head()
```

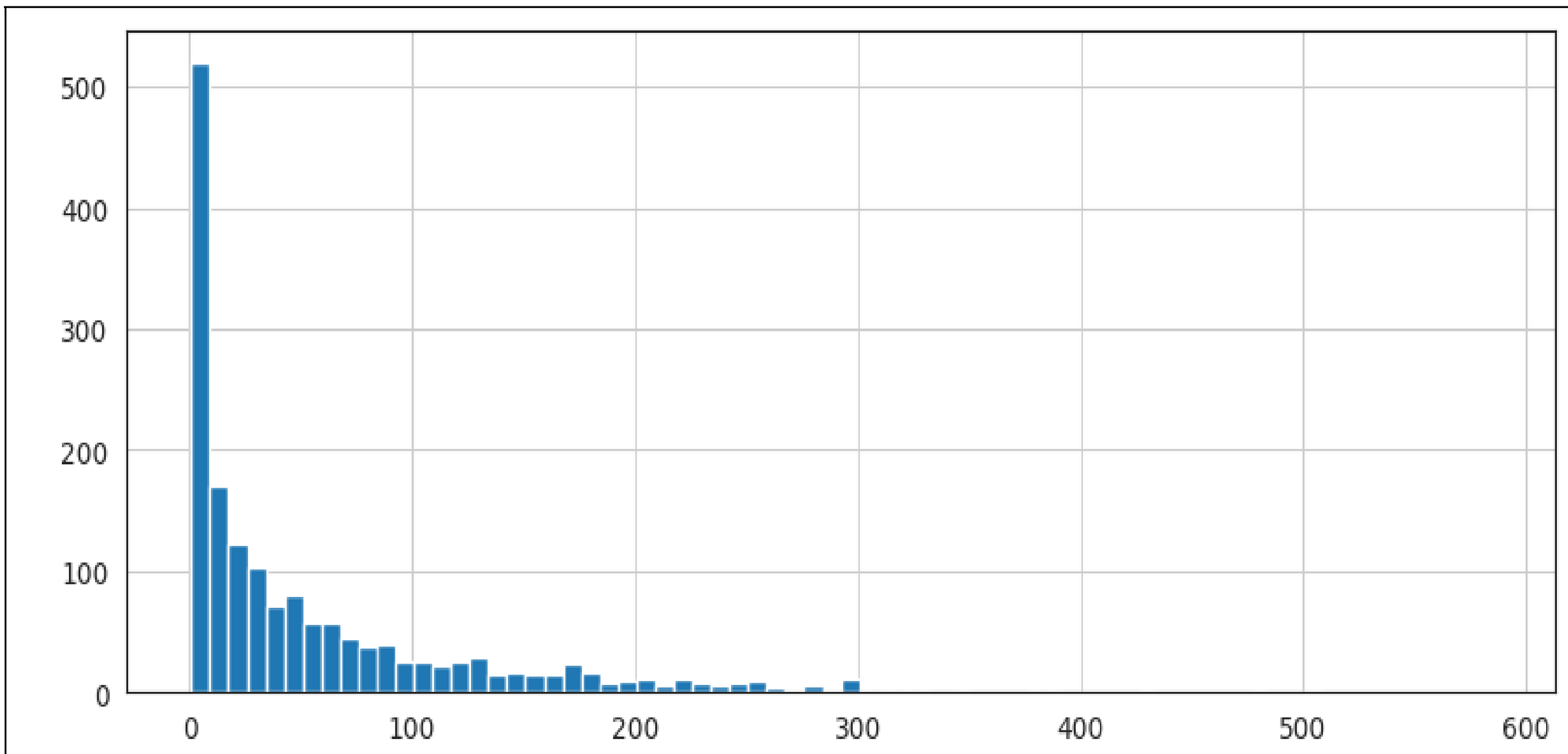
	user_id	item_id	rating	timestamp
0	0	50	5	881250949
1	0	172	5	881250949
2	0	133	1	881250949
3	196	242	3	881250949
4	186	302	3	891717742

```
data = pd.merge(df, movie_titles, on='item_id')
data.head()
```

	user_id	item_id	rating	timestamp	title
0	0	50	5	881250949	Star Wars (1977)
1	290	50	5	880473582	Star Wars (1977)
2	79	50	4	891271545	Star Wars (1977)
3	2	50	5	888552084	Star Wars (1977)
4	8	50	5	879362124	Star Wars (1977)

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


sns.set_style('white')
%matplotlib inline
plt.figure(figsize=(10, 4))
ratings['num of ratings'].hist(bins=70)
```




```
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ratings['rating'].hist(bins=70)
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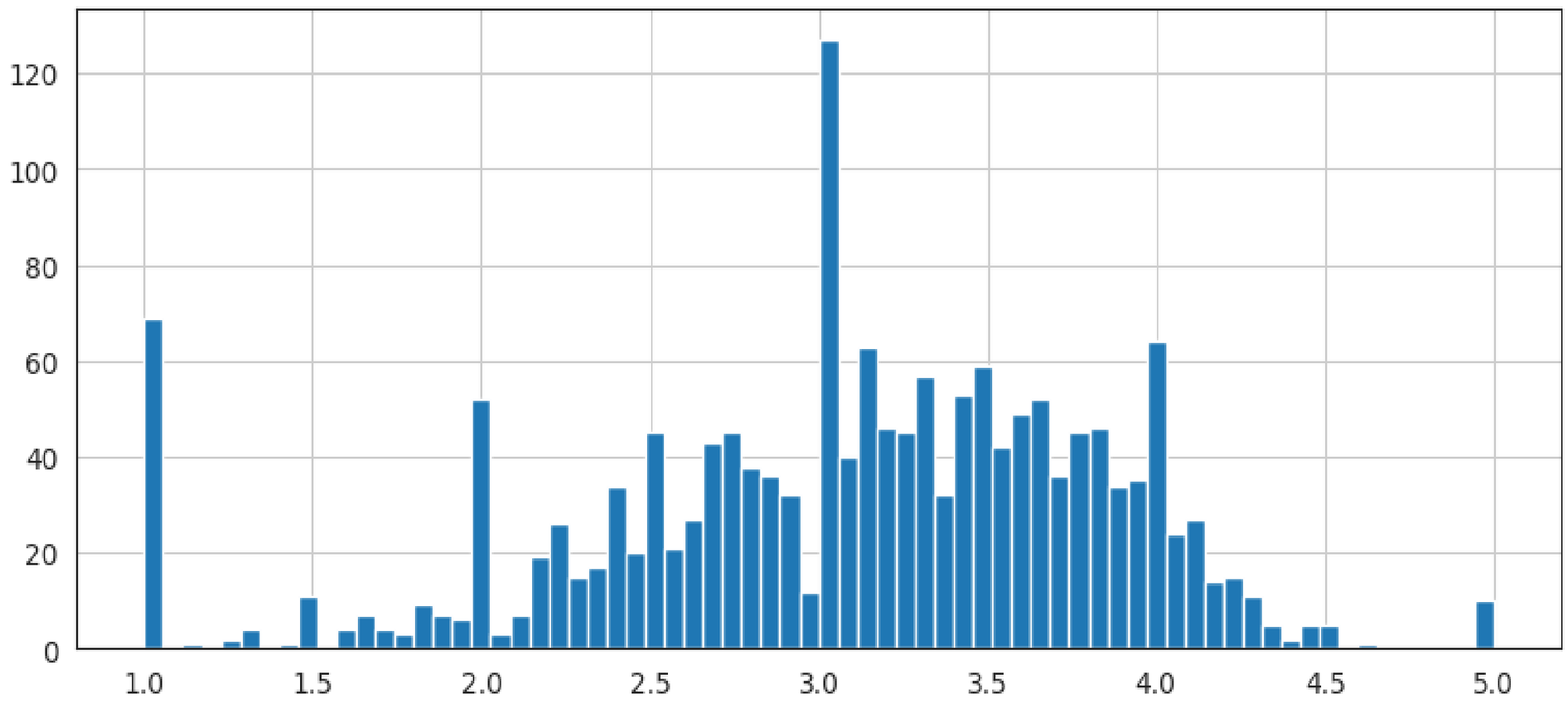


```
moviemat = data.pivot_table(index='user_id',
    columns='title', values='rating')
```

```
moviemat.head()
```

```
ratings.sort_values('num of ratings', ascending=False).head(10)
```

	rating	num of ratings
title		
Star Wars (1977)	4.359589	584

title	rating	num of ratings
Contact (1997)	3.803536	509
Fargo (1996)	4.155512	508
Return of the Jedi (1983)	4.007890	507
Liar Liar (1997)	3.156701	485
English Patient, The (1996)	3.656965	481
Scream (1996)	3.441423	478
Toy Story (1995)	3.878319	452
Air Force One (1997)	3.631090	431
Independence Day (ID4) (1996)	3.438228	429

Conclusion:

Remember to iterate through these steps, experimenting with different features, models, and hyperparameters as needed to achieve the best IMDb score prediction performance. Additionally, it's essential to keep track of the model's performance over time and update it as new data becomes available or the model's accuracy changes.