price_analysis

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1 USD AAI 500 final project - Group 3

Group members

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[1]:
```
# Load necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from scipy import stats
import seaborn as sns
from matplotlib import gridspec
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import LabelEncoder
import math

sns.set()
```

2 Data Cleaning and Organization

[2]:
```
dataset = 'primary'
data = pd.read_csv(f'../dataset/mapped_{dataset}.csv', sep=",")
data = data.drop(columns='uuid')
```

3 Artists affect prices?

Assuming USD only for analysis

- Null hypothesis H_0: artists have no impact on prices
- Alt hypothesis H_A: artists do have an impact

3.1 Intepretation

The F-statistic of 2.101 suggests that there is a significant amount of variance between the average prices of cards from different artists compared to the variance within each artist's prices.

Since the P-value is significantly less than 0.05, you can reject the null hypothesis (H0), which states that artists have no impact on prices.

3.1.1 Implications

Artist Impact: The results suggest that the artist associated with a card does influence its price, meaning that some artists may produce cards that are valued more highly in the market than others.

Market Insights: For collectors and sellers, understanding these differences can inform buying and pricing strategies.

[3]:
```
# Hypothesis H0: Artists have no impact on prices

# groups mean prices by artists
artists = data['artist'].unique()

# Create a group of prices for each unique artist to performing a ANOVA test
artist_price_groups = [ data[data['artist'] == artist]['price'].to_numpy()
    for artist in artists if len(data[data['artist'] == artist]['price']) > 1 ]

# Removing Zero Variance artist prices
filtered_prices = [row for row in artist_price_groups if np.var(row) > 0]
```

[4]:
```
# Conduct the one-way ANOVA
# Paper cards, no outliers, Q1_Q3, only in USD
t_stat, p_value = stats.f_oneway(*filtered_prices)

print("Can artist impact prices: \n Data: Paper cards, no outliers, Q1_Q3, only␣
 ↪in USD")
print("T-statistic ANOVA: %.4f" % t_stat)
print("P-value: %.6f" % p_value);

if p_value < 0.05:
    print("Reject the null hypothesis. There is a statistically significant␣
 ↪difference.")
else:
    print("Fail to reject the null hypothesis. There is no statistically␣
 ↪significant difference.")
```

```
Can artist impact prices:
 Data: Paper cards, no outliers, Q1_Q3, only in USD
T-statistic ANOVA: 5.0445
P-value: 0.000000
Reject the null hypothesis. There is a statistically significant difference.
```

4 Prediction Exercises

Trying to understand what affects the price the most

[5]:
```
# Create linear regression model and use it based on selected feature and target
def prediction(features, target):
    X_train, X_test, y_train, y_test = train_test_split(features, target,␣
 ↪test_size=0.2, random_state=42)

    poly = PolynomialFeatures(degree=2)
    X_train_poly = poly.fit_transform(X_train)
    X_test_poly = poly.transform(X_test)

    model = LinearRegression().fit(X_train_poly, y_train)

    y_pred = model.predict(X_test_poly)

    # Calculate metrics
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    return y_test, y_pred, mse, r2
```

5 Price Prediction model - using categorical data

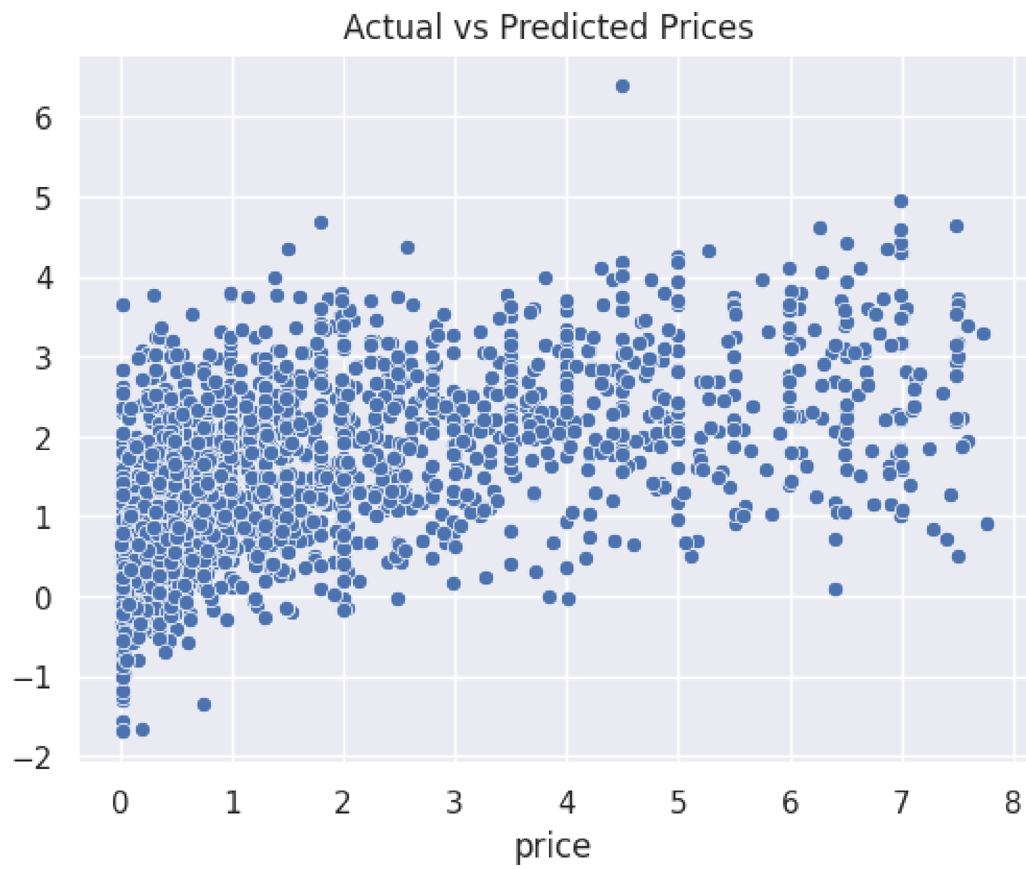
- Mean Squared Error: 1.970043342975583
- R-squared: 0.2172273808523122

Not the best model result

[6]:
```
import statsmodels.api as sm
# Price Prediction based on Rank

target = data['price']
features = data.copy()
features = features.drop(columns='price')

# Polinomial Linear Regression
y_test, y_pred, mse, r2 = prediction(features, target)

print(f'Mean Squared Error: {mse}')
print(f'R-squared: {r2}')

# Ploting results
sns.scatterplot(x=y_test, y=y_pred)
plt.title(f'Actual vs Predicted Prices ')
```

```
plt.show()
```

```
Mean Squared Error: 1.91355490272543
R-squared: 0.35104788760622274
```



6 OLS data interpretation

6.1 Key Metrics Interpretation

6.1.1 R-squared and Adjusted R-squared

- **R-squared (0.418)**: Approximately **41.8%** of the variability in card prices can be explained by the independent variables included in the model.
- **Adjusted R-squared (0.417)**: indicates that the model's explanatory power remains consistent even after accounting for additional variables.

6.1.2 F-statistic and Prob (F-statistic)

- **F-statistic (550.1)**: Sugests that at least one predictor variable significantly contributes to explaining the variability in price.

- **Prob (F-statistic) (0.00)**: Model is statistically significant, where independent variables collectively have a significant effect on card prices.

6.2 Conclusions

Highest Contributors to price increse

- **Finishes Encoded**: Coefficient: **0.1251** suggests that cards with different finishes (like foil) tend to be priced higher by about $0.13 on average.
- **Price Provider Encoded**: - Coefficient: **0.3187** indicates that different price providers contribute to higher prices on average, which is statistically significant.

The OLS regression results suggest that several factors significantly influence card prices, including rarity, power, artist identity, finish type, EDHREC rank, price provider, and set code.

1) The negative impact of rarity on price may indicate market dynamics where rarer cards are less frequently sold or valued differently.
2) The positive relationship between power and price suggests that more powerful cards are valued higher by collectors and players.
3) Collectors and sellers can leverage these insights to inform pricing strategies based on card attributes.

[7]:
```
# Checking statsmodel OLS
model = sm.OLS(target,features)
fit = model.fit()
fit.summary()
```

[7]:

Dep. Variable:	price	**R-squared (uncentered):**	0.498
Model:	OLS	**Adj. R-squared (uncentered):**	0.497
Method:	Least Squares	**F-statistic:**	654.9
Date:	Sat, 12 Oct 2024	**Prob (F-statistic):**	0.00
Time:	06:18:59	**Log-Likelihood:**	-27745.
No. Observations:	15214	**AIC:**	5.554e+04
Df Residuals:	15191	**BIC:**	5.571e+04
Df Model:	23		
Covariance Type:	nonrobust		

	coef	std err	t	P> |t|	[0.025	0.975]
artist	-0.0001	9.52e-05	-1.390	0.164	-0.000	5.43e-05
cardFinish	-0.3984	0.022	-17.710	0.000	-0.443	-0.354
colorIdentity	0.0150	0.006	2.652	0.008	0.004	0.026
colors	-0.0137	0.006	-2.406	0.016	-0.025	-0.003
edhrecRank	-4.789e-05	2.71e-06	-17.658	0.000	-5.32e-05	-4.26e-05
edhrecSaltiness	0.8681	0.043	20.391	0.000	0.785	0.952
gameAvailability	1.3893	0.049	28.612	0.000	1.294	1.485
isReprint	-0.1448	0.027	-5.333	0.000	-0.198	-0.092
layout	0.2547	0.029	8.863	0.000	0.198	0.311
manaCost	0.0003	0.000	1.657	0.098	-4.67e-05	0.001
manaValue	0.0621	0.010	6.258	0.000	0.043	0.082
name	-1.338e-05	3.18e-05	-0.420	0.674	-7.58e-05	4.9e-05
number	8.447e-05	6.24e-05	1.354	0.176	-3.78e-05	0.000
originalType	-0.0010	0.000	-6.922	0.000	-0.001	-0.001
power	-0.0038	0.007	-0.553	0.580	-0.017	0.010
priceProvider	-0.1241	0.017	-7.138	0.000	-0.158	-0.090
providerListing	-0.4133	0.038	-10.768	0.000	-0.489	-0.338
rarity	-0.4203	0.013	-31.138	0.000	-0.447	-0.394
setCode	0.0012	0.000	4.969	0.000	0.001	0.002
supertypes	0.2266	0.055	4.153	0.000	0.120	0.334
toughness	-0.0193	0.009	-2.244	0.025	-0.036	-0.002
type	0.0006	0.000	3.581	0.000	0.000	0.001
types	0.4023	0.056	7.231	0.000	0.293	0.511

Omnibus:	4828.653	**Durbin-Watson:**	1.191
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	13067.893
Skew:	1.723	**Prob(JB):**	0.00
Kurtosis:	5.957	**Cond. No.**	3.99e+04

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The condition number is large, 3.99e+04. This might indicate that there are
strong multicollinearity or other numerical problems.