Monsters of D&D - Statistical Insights

June 23, 2025

1 Dungeons & Dragons 5e Monster Analysis & CR Estimator

1.1 Introduction

The Challenge Rating (CR) system in **Dungeons & Dragons 5th Edition (5e)** is designed to help Dungeon Masters gauge the power level of monsters relative to a party of adventurers. However, CR is ultimately a **qualitative and somewhat opaque metric**. Many official monsters seem over- or underpowered for their listed CR, and there's no transparent formula for how CR is derived.

This project takes a **data science approach** to demystify and quantify monster strength in D&D 5e. Using a dataset of over 300 official monsters and NPCs, we aim to:

- **Explore relationships** between CR and combat-relevant attributes
- **Engineer new metrics** like a composite "threat score" that combines HP, AC, and ability stats
- **Train a machine learning model** to predict CR from quantitative data
- **Build an interactive dashboard** where users can input custom monster stats and get:
  - A predicted CR
  - A visual comparison to similar monsters
  - Benchmark stats at each CR

This tool is designed for:

- **Game designers** seeking data-informed monster balance
- **Dungeon Masters** crafting homebrew creatures or encounters
- **Players and analysts** curious about the structure of 5e monster design

---

1.2 Project Structure

The notebook proceeds through several stages:

Data Cleaning & Preprocessing - Load and inspect the monster dataset - Handle missing values, normalize CR formats, and extract subtypes - One-hot encode binary fields (e.g., `is_legendary`)

Exploratory Data Analysis - Visualize distributions of CR, stats, and HP across monster types and legendary status - Analyze stat trends by CR and type - Identify outliers and patterns

Feature Engineering - Create an `avg_stat` field (average of STR, DEX, CON, INT, WIS, CHA) - Define a `threat_score` formula:
`threat_score = avg_stat * (hp + ac) * (1.25 if is_legendary else 1)`

Modeling - Fit a `RandomForestRegressor` to predict CR from core stats - Compare linear, quadratic, and exponential fits for threat score vs. CR - Evaluate model performance and interpret predictions

Interactive Dashboard - Use `ipywidgets` and `Voila` to allow users to enter custom monster stats - Display predicted CR, threat score, and comparison charts in real time

---

1.3 Why This Matters

The CR system is central to encounter balancing in D&D, but it often lacks precision — especially for homebrew content. By approaching monster balance as a **quantifiable problem**, this project provides a toolset for more consistent and scalable game design. It also offers an engaging example of applying **data analysis and machine learning** to a creative domain — combining storytelling with statistics.

Whether you're here for the math, the monsters, or the model-building, welcome aboard.

2 Setup & Initial Exploration

2.1 Load dataset

[1]:
```python
import pandas as pd

df = pd.read_csv('dnd_monsters.csv')
```

2.2 Preview Data

Out of the 762 entries, all have Challenge Rating (CR), Armor Class (AC), and Hit Points (HP). Only 709(93.0%) entries have stats and 65(8.53%) are legendary.

[2]:
```python
print(df.head(), end='\n\n\n\n')          # First five rows
print(df.info(), end='\n\n')             # Data types and non-null counts
print('SHAPE:\n', df.shape)              # (rows, columns)
```

```
         name                                               url   cr  \
0      boggle                                               NaN  1/8
1       camel   https://www.aidedd.org/dnd/monstres.php?vo=camel  1/8
2  giant-crab  https://www.aidedd.org/dnd/monstres.php?vo=gia…  1/8
3      bandit  https://www.aidedd.org/dnd/monstres.php?vo=bandit  1/8
4     dolphin  https://www.aidedd.org/dnd/monstres.php?vo=dol…  1/8

                 type    size  ac  hp speed                     align  \
0                 fey   Small  14  18   NaN           chaotic neutral
1               beast   Large   9  15   NaN                 unaligned
2               beast  Medium  15  13  swim                 unaligned
3  humanoid (any race)  Medium  12  11   NaN  any non-lawful alignment
4               beast  Medium  12  11  swim                 unaligned
```

```
  legendary                      source   str   dex   con   int   wis   cha
0       NaN  Volo's Guide to Monsters   8.0  18.0  13.0   6.0  12.0   7.0
1       NaN      Monster Manual (SRD)  16.0   8.0  14.0   2.0   8.0   5.0
2       NaN      Monster Manual (SRD)  13.0  15.0  11.0   1.0   9.0   3.0
3       NaN      Monster Manual (SRD)  11.0  12.0  12.0  10.0  10.0  10.0
4       NaN  Volo's Guide to Monsters  14.0  13.0  13.0   6.0  12.0   7.0
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 762 entries, 0 to 761
Data columns (total 17 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   name       762 non-null    object
 1   url        401 non-null    object
 2   cr         762 non-null    object
 3   type       762 non-null    object
 4   size       762 non-null    object
 5   ac         762 non-null    int64
 6   hp         762 non-null    int64
 7   speed      248 non-null    object
 8   align      762 non-null    object
 9   legendary  65 non-null     object
 10  source     762 non-null    object
 11  str        709 non-null    float64
 12  dex        709 non-null    float64
 13  con        709 non-null    float64
 14  int        709 non-null    float64
 15  wis        709 non-null    float64
 16  cha        709 non-null    float64
dtypes: float64(6), int64(2), object(9)
memory usage: 101.3+ KB
None

SHAPE:
 (762, 17)
```

2.3 Basic Stats for Numeric Fields

2.3.1 Analysis: Summary Statistics

This section provides descriptive statistics for all numeric fields. These values help identify the range, central tendency, and spread of variables like HP, AC, and CR.

[3]:
```
df.describe()      # Count, mean, std, min, max, quartiles
```

[3]:
```
               ac          hp         str         dex         con         int  \
count  762.000000  762.000000  709.000000  709.000000  709.000000  709.000000
```

```
mean     14.577428   88.129921   15.091678   13.235543   15.375176    9.383639
std       3.140581   94.822305    6.164991    3.381919    4.230005    5.812228
min       0.000000    0.000000    1.000000    1.000000    3.000000    1.000000
25%      12.000000   22.000000   11.000000   11.000000   12.000000    4.000000
50%      14.000000   58.000000   15.000000   14.000000   15.000000   10.000000
75%      17.000000  126.000000   19.000000   15.000000   18.000000   13.000000
max      25.000000  676.000000   30.000000   28.000000   30.000000   27.000000

              wis         cha
count  709.000000  709.000000
mean    12.176305   10.708039
std      3.395528    5.634910
min      1.000000    1.000000
25%     10.000000    6.000000
50%     12.000000   10.000000
75%     14.000000   15.000000
max     27.000000   30.000000
```

2.3.2 Analysis: Missing Values

This diagnostic shows how much data is missing in each column. It informs whether columns need to be dropped, filled, or imputed during preprocessing.

[4]:
```python
print(df.isnull().sum())        # Total missing per column
print(df.isnull().mean())       # Percentage of missing values
```

```
name           0
url          361
cr             0
type           0
size           0
ac             0
hp             0
speed        514
align          0
legendary    697
source         0
str           53
dex           53
con           53
int           53
wis           53
cha           53
dtype: int64
name         0.000000
url          0.473753
cr           0.000000
type         0.000000
```

```
size         0.000000
ac           0.000000
hp           0.000000
speed        0.674541
align        0.000000
legendary    0.914698
source       0.000000
str          0.069554
dex          0.069554
con          0.069554
int          0.069554
wis          0.069554
cha          0.069554
dtype: float64
```

2.4 Check for Unique Values (Categorical Insight)

2.4.1 Analysis: Unique Monster Types

Examining the diversity of monster types in the dataset. This helps us understand the categorical structure and plan comparisons across types.

[5]:
```python
print(df['type'].unique())          # Unique monster types
print(df['type'].value_counts())    # Frequency of types
```

```
['fey' 'beast' 'humanoid (any race)' 'humanoid (merfolk)' 'aberration'
 'fiend (demon)' 'monstrosity' 'humanoid (xvart)' 'humanoid (kobold)'
 'construct' 'plant' 'undead' 'humanoid (dwarf)' 'elemental'
 'swarm of Tiny beasts' 'humanoid (tabaxi)' 'humanoid (tortle)'
 'humanoid (kuo-toa)' 'ooze' 'humanoid (aarakocra)' 'humanoid (derro)'
 'humanoid (elf)' 'humanoid (kenku)' 'humanoid (troglodyte)'
 'humanoid (bullywug)' 'humanoid (grimlock)' 'humanoid (grung)'
 'humanoid (human)' 'humanoid (goblinoid)' 'dragon' 'humanoid (firenewt)'
 'humanoid (gnoll)' 'humanoid (lizardfolk)' 'humanoid (sahuagin)'
 'humanoid (shapechanger)' 'humanoid' 'humanoid (gnome)' 'humanoid (orc)'
 'fiend (devil)' 'monstrosity (titan)' 'fiend' 'construct (inevitable)'
 'fiend (demon, shapechanger)' 'celestial (titan)' 'celestial'
 'humanoid (nagpa)' 'giant (storm giant)' 'humanoid (gith)'
 'undead (shapechanger)' 'giant (fire giant)' 'giant' 'undead (titan)'
 'fiend (yugoloth)' 'giant (frost giant)'
 'monstrosity (shapechanger, yuan-ti)' 'giant (cloud giant)'
 'aberration (shapechanger)' 'giant (stone giant)' 'fey (elf)'
 'giant (hill giant)' 'humanoid (human, shapechanger)'
 'humanoid (saurial)' 'fiend (demon, orc)' 'fiend (shapechanger)'
 'fiend (gnoll)' 'monstrosity (shapechanger)' 'humanoid (quaggoth)'
 'humanoid (yuan-ti)' 'humanoid (meazel)' 'humanoid (thri-kreen)'
 'fiend (devil, shapechanger)']
beast                              106
monstrosity                         75
```

```
humanoid (any race)             68
dragon                          47
undead                          47
                              …
undead (titan)                   1
humanoid (aarakocra)             1
giant (fire giant)               1
humanoid (kenku)                 1
fiend (devil, shapechanger)      1
Name: type, Length: 71, dtype: int64
```

[6]:
```
print(df['cr'].value_counts().sort_index())
print(df['ac'].value_counts().sort_index())
```

```
0      56
1      65
1/2    50
1/4    63
1/8    29
10     22
11     18
12     15
13     20
14     11
15      9
16     12
17     10
18      6
19      4
2      85
20      8
21      8
22      4
23     11
24      4
25      1
26      3
3      54
30      2
4      37
5      57
6      25
7      27
8      22
9      24
Name: cr, dtype: int64
0       1
5       3
```

```
6        2
7        3
8        6
9        7
10      26
11      46
12     124
13     102
14      76
15      88
16      63
17      66
18      67
19      38
20      20
21       9
22      12
24       1
25       2
Name: ac, dtype: int64
```

Now to look at unique CR values. It's notable that some values are stored as fractions rather than floats. This will be rectified next.

[7]:
```
print(df['cr'].sort_values().unique())  # Unique challenge ratings sorted
```

```
['0' '1' '1/2' '1/4' '1/8' '10' '11' '12' '13' '14' '15' '16' '17' '18'
 '19' '2' '20' '21' '22' '23' '24' '25' '26' '3' '30' '4' '5' '6' '7' '8'
 '9']
```

3 Data Cleaning

3.1 Convert fractional ACs to decimal

The data stores some cr values as fractions (e.g., 1/2). These must be converted to float values for processing.

[8]:
```
from fractions import Fraction
```

[9]:
```
def convert_to_float(val):
    try:
        return float(val)
    except ValueError:
        try:
            return float(Fraction(val))
        except:
            return None  # or np.nan if using NumPy
```

[10]:
```
df['cr'] = df['cr'].apply(convert_to_float)
```

3.2 Splitting Subtypes From Types

The "types" column is split into "type_main" and "type_subtype".

[11]:
```
def split_types(val):
    if '(' in val:
        t, st = val.split('(')
        t = t.strip()
        st = st.strip(')')
    else:
        t = val
        st = 'none'
    return t, st

print(split_types('humanoid (any race)'))
print(split_types('beast'))
```

```
('humanoid', 'any race')
('beast', 'none')
```

[12]:
```
# Use regex to extract main type and optional subtype
df[['type_main', 'type_subtype']] = df['type'].str.extract(r'^([^\(]+)\s*(?:
↪\(([^)]+)\))?$')

# Strip whitespace
df['type_main'] = df['type_main'].str.strip()
df['type_subtype'] = df['type_subtype'].str.strip()
```

3.3 One-hot Encode the Legendary Column

Here, legendary status is encoded as a true/false value.

[13]:
```
df['is_legendary'] = df['legendary'].notnull().astype(int)
df['is_legendary']
```

[13]:
```
0      0
1      0
2      0
3      0
4      0
      ..
757    0
758    0
759    0
760    0
761    0
Name: is_legendary, Length: 762, dtype: int64
```

4 Exploratory Data Analysis

4.1 Summarizing the Key Variable

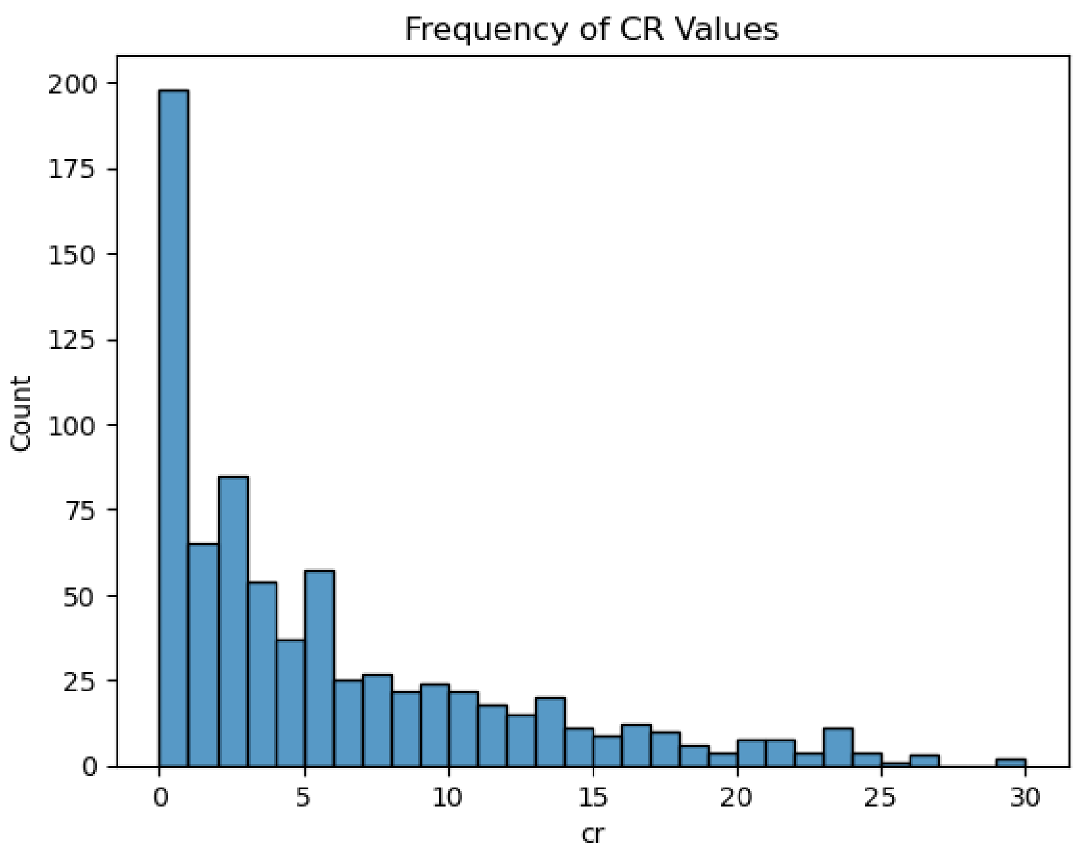
Challeng Rating (CR) is the key variable in question. In the D&D community, CR is considered a simple metric to gauge the threat a monster poses. However, it's also not considered perfectly reliable as a lone metric for estimating the threat of a monster, and many DMs opt to use experience budgets to balance encounters. Since CR correlates to the experience yielded by a foe upon defeat, I consider CR to be reliable with some variation in results.

[14]:
```python
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
```

[15]:
```python
def fit_model(df, x_col, y_col, model='linear'):
    """
    Fits a regression model (linear, quadratic, or exponential) and returns:
    - the model coefficients (tuple)
    - the equation string
    - the R² score (coefficient of determination)
    """
    # Drop missing values
    data = df[[x_col, y_col]].dropna()
    x = data[x_col].values
    y = data[y_col].values

    if model == 'linear':
        m, b = np.polyfit(x, y, 1)
        y_pred = m * x + b
        ss_res = np.sum((y - y_pred) ** 2)
        ss_tot = np.sum((y - np.mean(y)) ** 2)
        r2 = 1 - ss_res / ss_tot
        eq = f"y = {m:.3f}x + {b:.3f}"
        return (m, b), eq, r2

    elif model == 'quadratic':
        a, b, c = np.polyfit(x, y, 2)
        y_pred = a * x**2 + b * x + c
        ss_res = np.sum((y - y_pred) ** 2)
        ss_tot = np.sum((y - np.mean(y)) ** 2)
        r2 = 1 - ss_res / ss_tot
        eq = f"y = {a:.3f}x² + {b:.3f}x + {c:.3f}"
        return (a, b, c), eq, r2

    elif model == 'exponential':
        # Remove zero or negative y values
        mask = y > 0
        x = x[mask]
```

```
        y = y[mask]
        log_y = np.log(y)
        b, log_a = np.polyfit(x, log_y, 1)
        a = np.exp(log_a)
        y_pred = a * np.exp(b * x)
        ss_res = np.sum((y - y_pred) ** 2)
        ss_tot = np.sum((y - np.mean(y)) ** 2)
        r2 = 1 - ss_res / ss_tot
        eq = f"y = {a:.3f}e^({b:.3f}x)"
        return (a, b), eq, r2

    else:
        raise ValueError("Model must be 'linear', 'quadratic', or␣
↪'exponential'")
```

[16]:
```
plt.title('Frequency of CR Values')
sns.histplot(df['cr'], binwidth=1)
plt.show()
```



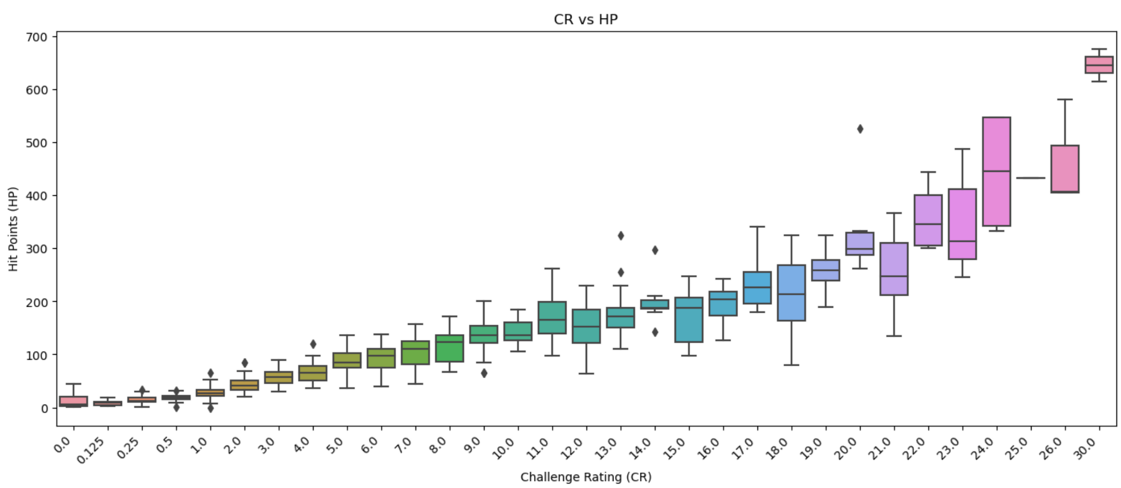
4.2 Visualization: Challenge Rating vs Attributes

These boxplots illustrate how various attributes are distributed across CRs. It highlights trends, variability, and outliers that could affect threat estimation.

4.2.1 Challenge Rating vs Hit Points

Here, we explore the correlation between challenge rating and hit points.

[17]:
```
plt.figure(figsize=(16, 6))  # wider figure
sns.boxplot(x='cr', y='hp', data=df)
plt.xticks(rotation=45, ha='right')  # rotate for readability
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Hit Points (HP)')
plt.title('CR vs HP')
plt.show()
```



[18]:
```
df.groupby('cr')['hp'].describe()
```

[18]:

cr	count	mean	std	min	25%	50%	75%	max
0.000	56.0	11.982143	12.103329	1.0	2.00	6.0	19.75	45.0
0.125	29.0	8.482759	3.670546	2.0	5.00	9.0	11.00	18.0
0.250	63.0	14.984127	6.287448	1.0	11.00	13.0	19.00	33.0
0.500	50.0	18.980000	5.593327	1.0	16.00	19.0	22.00	32.0
1.000	65.0	27.846154	11.200210	0.0	22.00	27.0	34.00	65.0
2.000	85.0	43.023529	13.553225	21.0	33.00	42.0	51.00	85.0
3.000	54.0	56.962963	14.989258	30.0	46.00	58.0	66.75	90.0
4.000	37.0	67.405405	19.619236	36.0	51.00	66.0	78.00	120.0
5.000	57.0	88.315789	23.736017	36.0	75.00	85.0	102.00	136.0
6.000	25.0	92.240000	28.120692	40.0	75.00	97.0	110.00	138.0
7.000	27.0	103.962963	27.378376	45.0	81.00	110.0	124.50	157.0

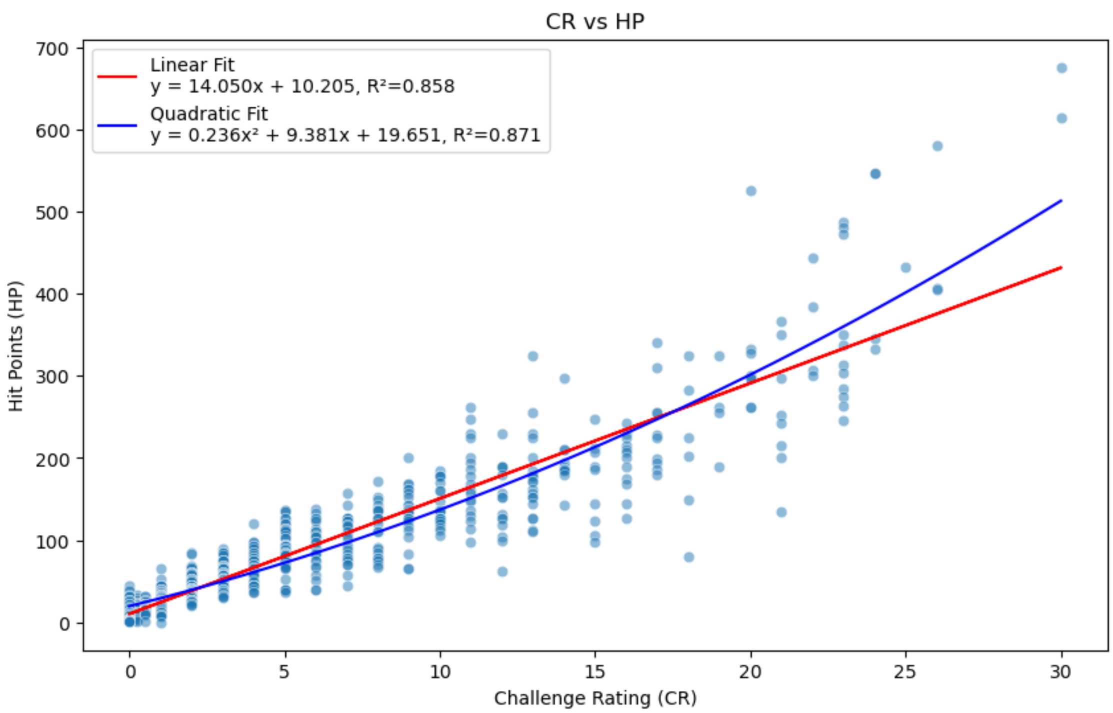
```
8.000     22.0  114.454545   30.557872   67.0   86.25  123.5  136.00  172.0
9.000     24.0  132.833333   31.576913   66.0  121.50  136.0  153.25  200.0
10.000    22.0  141.363636   24.200640  105.0  127.00  135.5  161.00  184.0
11.000    18.0  172.611111   46.918125   97.0  138.75  164.5  198.75  262.0
12.000    15.0  147.200000   43.362591   63.0  122.50  152.0  184.50  229.0
13.000    20.0  177.100000   51.565901  110.0  150.75  172.0  188.00  325.0
14.000    11.0  197.181818   37.522842  143.0  185.50  187.0  202.50  297.0
15.000     9.0  168.000000   52.623664   97.0  123.00  187.0  207.00  247.0
16.000    12.0  194.500000   35.227830  127.0  173.25  203.5  218.25  243.0
17.000    10.0  237.700000   53.793948  180.0  196.00  226.5  256.00  341.0
18.000     6.0  210.666667   88.443579   80.0  163.00  213.5  268.50  324.0
19.000     4.0  257.750000   55.602008  189.0  238.50  258.5  277.75  325.0
20.000     8.0  325.625000   85.022581  262.0  288.25  298.5  329.25  526.0
21.000     8.0  257.625000   77.801832  135.0  212.00  248.0  310.25  367.0
22.000     4.0  359.000000   68.522502  300.0  305.25  346.0  399.75  444.0
23.000    11.0  346.727273   90.781155  246.0  280.00  313.0  411.00  487.0
24.000     4.0  442.750000  119.340898  333.0  342.75  446.0  546.00  546.0
25.000     1.0  432.000000         NaN  432.0  432.00  432.0  432.00  432.0
26.000     3.0  463.666667  100.748863  405.0  405.50  406.0  493.00  580.0
30.000     2.0  645.500000   43.133514  615.0  630.25  645.5  660.75  676.0
```

[19]:

```python
x = df['cr']
y = df['hp']

print('Linear Model')
(slope, intercept), eq, r2 = fit_model(df, 'cr', 'hp')
print(eq)
print(f"R² = {r2:.3f}", end='\n\n')

print('Quadratic Model')
quad_params, quad_eq, quad_r2 = fit_model(df, 'cr', 'hp', model='quadratic')
print(quad_eq)
print(f"R² = {quad_r2:.3f}", end='\n\n')


# Filter and sort x values for smooth curves
x_vals = np.linspace(df['cr'].min(), df['cr'].max(), 500)

# Quadratic predictions
a, b, c = quad_params
y_quad = a * x_vals**2 + b * x_vals + c


plt.figure(figsize=(10, 6))
sns.scatterplot(x=x, y=y, alpha=0.5)
plt.plot(x, slope * x + intercept, color='red', label=f'Linear Fit\n{eq}, R²={r2:.3f}')
```

```
plt.plot(x_vals, y_quad, color='blue', label=f'Quadratic Fit\n{quad_eq},␣
↪R²={quad_r2:.3f}')
plt.legend()
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Hit Points (HP)')
plt.title('CR vs HP')
plt.show()
```

```
Linear Model
y = 14.050x + 10.205
R² = 0.858

Quadratic Model
y = 0.236x² + 9.381x + 19.651
R² = 0.871
```



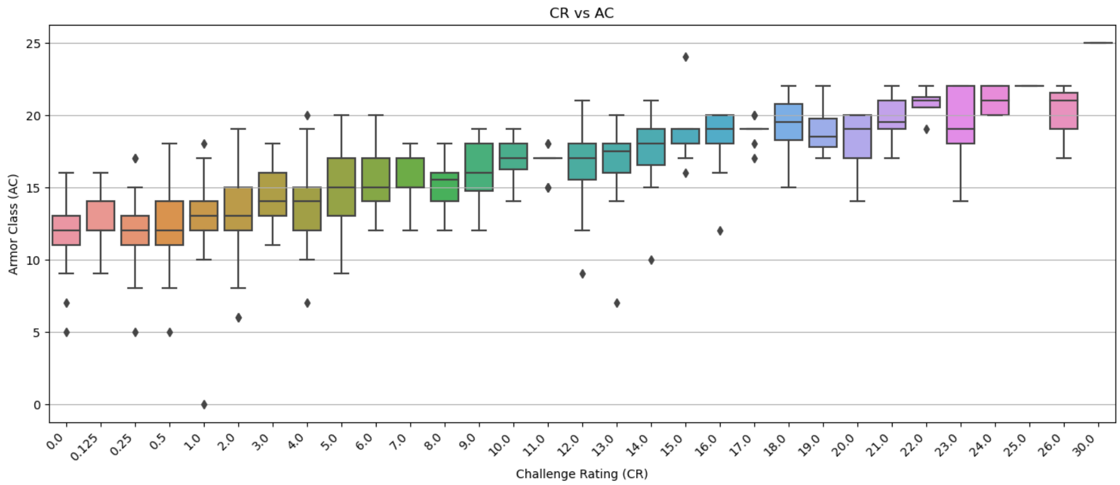
The above figure shows a fairly strong correlation between CR and HP with R^2 values above 0.85.

4.2.2 Challenge Rating vs Armor Class

Here, we explore the correlation between challenge rating and armor class.

[20]:
```
plt.figure(figsize=(16, 6))
sns.boxplot(x='cr', y='ac', data=df)
```

```
plt.grid(visible=True, axis='y')
plt.xticks(rotation=45, ha='right')
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Armor Class (AC)')
plt.title('CR vs AC')
plt.show()
```



[21]:
```
df.groupby('cr')['ac'].describe()
```

[21]:

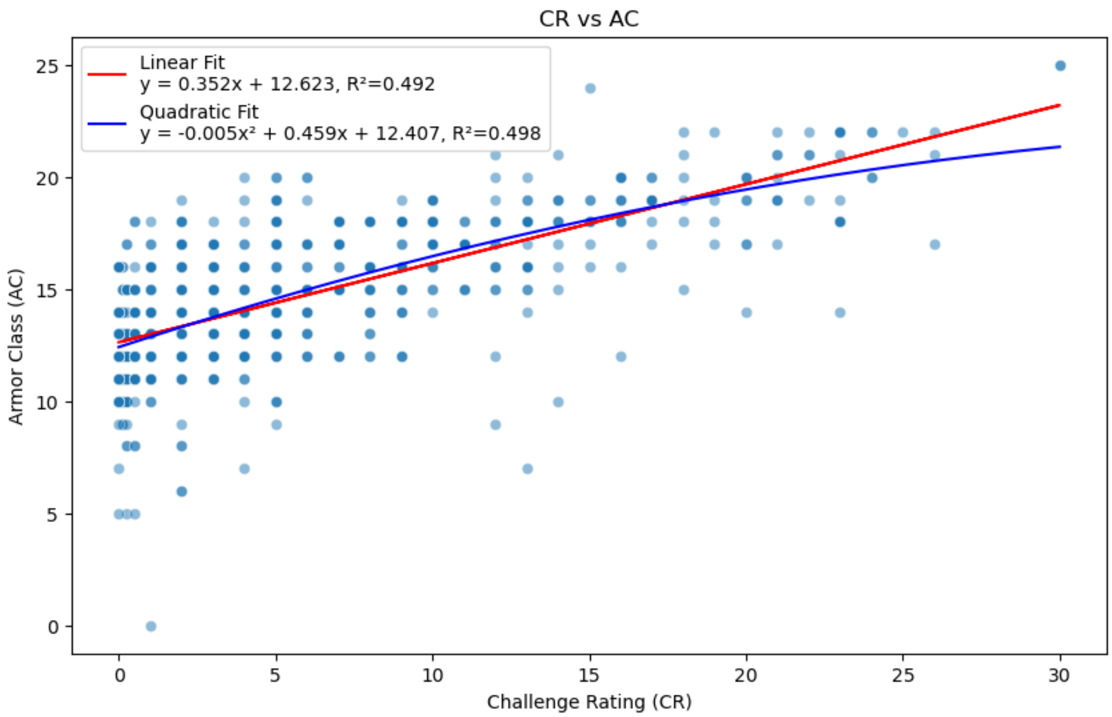
cr	count	mean	std	min	25%	50%	75%	max
0.000	56.0	12.125000	2.098159	5.0	11.00	12.0	13.00	16.0
0.125	29.0	12.517241	1.844310	9.0	12.00	12.0	14.00	16.0
0.250	63.0	12.079365	2.073656	5.0	11.00	12.0	13.00	17.0
0.500	50.0	12.540000	2.260666	5.0	11.00	12.0	14.00	18.0
1.000	65.0	12.938462	2.461433	0.0	12.00	13.0	14.00	18.0
2.000	85.0	13.482353	2.447602	6.0	12.00	13.0	15.00	19.0
3.000	54.0	14.203704	1.897164	11.0	13.00	14.0	16.00	18.0
4.000	37.0	13.891892	2.525248	7.0	12.00	14.0	15.00	20.0
5.000	57.0	14.947368	2.559444	9.0	13.00	15.0	17.00	20.0
6.000	25.0	15.200000	2.291288	12.0	14.00	15.0	17.00	20.0
7.000	27.0	15.777778	1.825742	12.0	15.00	15.0	17.00	18.0
8.000	22.0	15.363636	1.915984	12.0	14.00	15.5	16.00	18.0
9.000	24.0	15.916667	2.104171	12.0	14.75	16.0	18.00	19.0
10.000	22.0	17.181818	1.401916	14.0	16.25	17.0	18.00	19.0
11.000	18.0	16.777778	0.878204	15.0	17.00	17.0	17.00	18.0
12.000	15.0	16.466667	3.020564	9.0	15.50	17.0	18.00	21.0
13.000	20.0	16.600000	2.741494	7.0	16.00	17.5	18.00	20.0
14.000	11.0	17.272727	2.901410	10.0	16.50	18.0	19.00	21.0
15.000	9.0	18.555556	2.242271	16.0	18.00	18.0	19.00	24.0

16.000	12.0	18.250000	2.301185	12.0	18.00	19.0	20.00	20.0
17.000	10.0	18.900000	0.875595	17.0	19.00	19.0	19.00	20.0
18.000	6.0	19.166667	2.483277	15.0	18.25	19.5	20.75	22.0
19.000	4.0	19.000000	2.160247	17.0	17.75	18.5	19.75	22.0
20.000	8.0	18.250000	2.121320	14.0	17.00	19.0	20.00	20.0
21.000	8.0	19.750000	1.581139	17.0	19.00	19.5	21.00	22.0
22.000	4.0	20.750000	1.258306	19.0	20.50	21.0	21.25	22.0
23.000	11.0	19.454545	2.583162	14.0	18.00	19.0	22.00	22.0
24.000	4.0	21.000000	1.154701	20.0	20.00	21.0	22.00	22.0
25.000	1.0	22.000000	NaN	22.0	22.00	22.0	22.00	22.0
26.000	3.0	20.000000	2.645751	17.0	19.00	21.0	21.50	22.0
30.000	2.0	25.000000	0.000000	25.0	25.00	25.0	25.00	25.0

[22]:
```python
x = df['cr']
y = df['ac']

print('Linear Model')
(slope, intercept), eq, r2 = fit_model(df, 'cr', 'ac')
print(eq)
print(f"R² = {r2:.3f}", end='\n\n')

print('Quadratic Model')
quad_params, quad_eq, quad_r2 = fit_model(df, 'cr', 'ac', model='quadratic')
print(quad_eq)
print(f"R² = {quad_r2:.3f}", end='\n\n')

# Filter and sort x values for smooth curves
x_vals = np.linspace(df['cr'].min(), df['cr'].max(), 500)

# Quadratic predictions
a, b, c = quad_params
y_quad = a * x_vals**2 + b * x_vals + c


plt.figure(figsize=(10, 6))
sns.scatterplot(x=x, y=y, alpha=0.5)
plt.plot(x, slope * x + intercept, color='red', label=f'Linear Fit\n{eq},␣
↪R²={r2:.3f}')
plt.plot(x_vals, y_quad, color='blue', label=f'Quadratic Fit\n{quad_eq},␣
↪R²={quad_r2:.3f}')
plt.legend()
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Armor Class (AC)')
plt.title('CR vs AC')
plt.show()
```

```
Linear Model
y = 0.352x + 12.623
```

```
R² = 0.492

Quadratic Model
y = -0.005x² + 0.459x + 12.407
R² = 0.498
```



The above figure displays an upward trend, but with a weak correlation as both R^2 values are near 0.5.

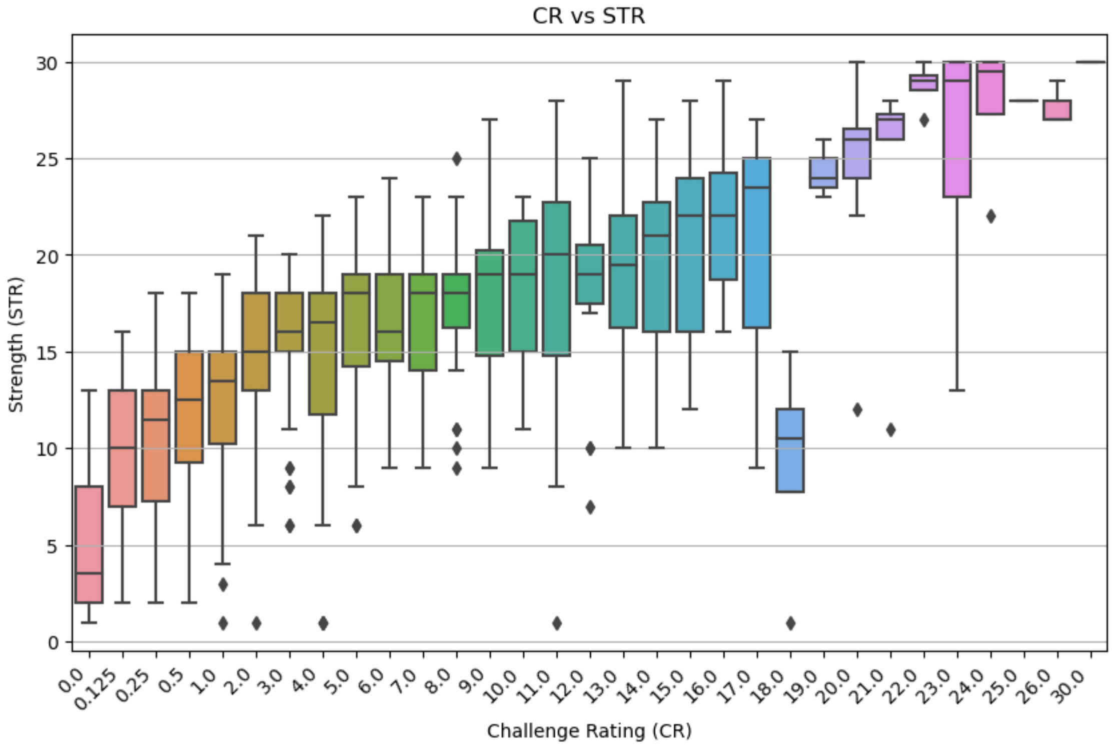
4.3 Visualization: Challenge Rating vs Abilities

The following six abilities show varying correlations to challenge rating. Constitution has a moderate correlation to CR, while dexterity has no correlation. The remaining four abilities (strength, intelligence, wisdom, and charisma) have weak correlations to CR.

4.3.1 Challenge Rating vs Strength

[23]:
```
plt.figure(figsize=(10,6))
sns.boxplot(x='cr', y='str', data=df)
plt.grid(visible=True, axis='y')
plt.xticks(rotation=45, ha='right')
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Strength (STR)')
plt.title('CR vs STR')
```

```
plt.show()
```



[24]:
```
df.groupby('cr')['str'].describe()
```

[24]:

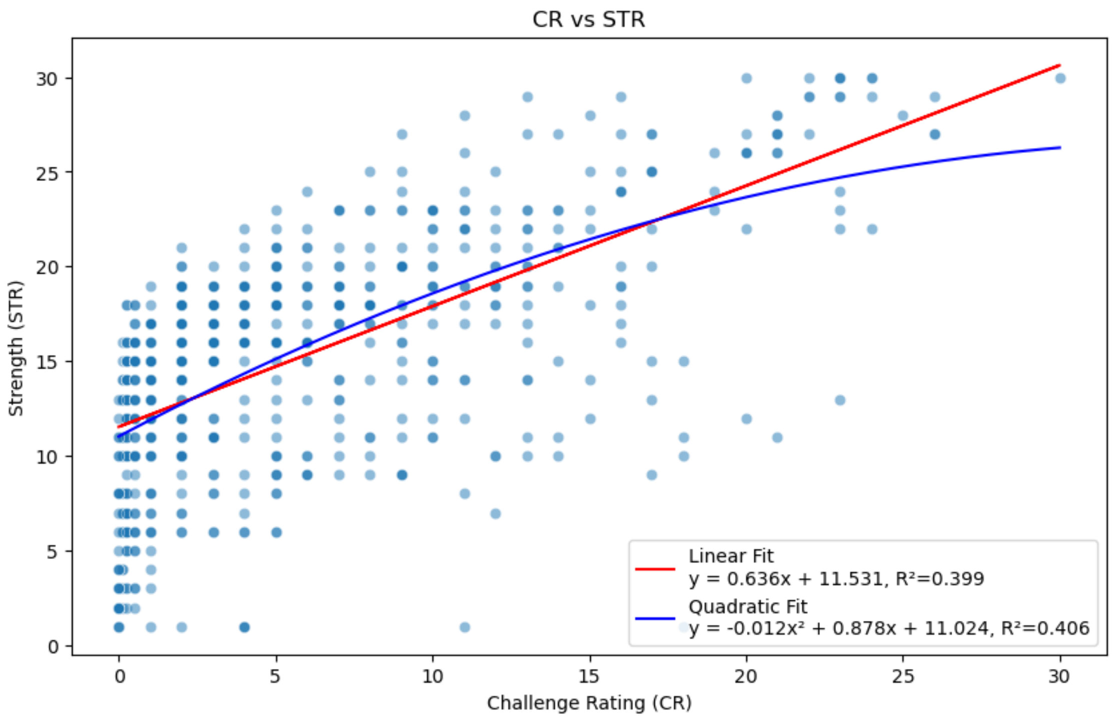
cr	count	mean	std	min	25%	50%	75%	max
0.000	32.0	5.062500	3.697754	1.0	2.00	3.5	8.00	13.0
0.125	29.0	9.620690	3.849061	2.0	7.00	10.0	13.00	16.0
0.250	62.0	10.693548	3.826520	2.0	7.25	11.5	13.00	18.0
0.500	46.0	11.652174	4.321612	2.0	9.25	12.5	15.00	18.0
1.000	62.0	12.516129	4.051885	1.0	10.25	13.5	15.00	19.0
2.000	81.0	14.740741	3.794001	1.0	13.00	15.0	18.00	21.0
3.000	54.0	15.222222	3.553721	6.0	15.00	16.0	18.00	20.0
4.000	36.0	14.416667	5.798399	1.0	11.75	16.5	18.00	22.0
5.000	54.0	16.055556	4.293113	6.0	14.25	18.0	19.00	23.0
6.000	24.0	16.166667	4.330545	9.0	14.50	16.0	19.00	24.0
7.000	27.0	17.074074	3.862302	9.0	14.00	18.0	19.00	23.0
8.000	22.0	17.318182	4.190538	9.0	16.25	18.0	19.00	25.0
9.000	24.0	17.791667	5.149750	9.0	14.75	19.0	20.25	27.0
10.000	22.0	18.136364	4.003516	11.0	15.00	19.0	21.75	23.0
11.000	18.0	18.500000	6.697234	1.0	14.75	20.0	22.75	28.0
12.000	15.0	17.866667	5.069047	7.0	17.50	19.0	20.50	25.0
13.000	18.0	19.166667	5.020546	10.0	16.25	19.5	22.00	29.0

14.000	10.0	19.200000	5.513620	10.0	16.00	21.0	22.75	27.0
15.000	7.0	20.285714	5.851333	12.0	16.00	22.0	24.00	28.0
16.000	12.0	21.833333	4.195958	16.0	18.75	22.0	24.25	29.0
17.000	10.0	20.800000	6.373556	9.0	16.25	23.5	25.00	27.0
18.000	4.0	9.250000	5.909033	1.0	7.75	10.5	12.00	15.0
19.000	3.0	24.333333	1.527525	23.0	23.50	24.0	25.00	26.0
20.000	7.0	24.142857	5.843189	12.0	24.00	26.0	26.50	30.0
21.000	8.0	25.000000	5.707138	11.0	26.00	27.0	27.25	28.0
22.000	4.0	28.750000	1.258306	27.0	28.50	29.0	29.25	30.0
23.000	9.0	25.555556	5.725188	13.0	23.00	29.0	30.00	30.0
24.000	4.0	27.750000	3.862210	22.0	27.25	29.5	30.00	30.0
25.000	1.0	28.000000	NaN	28.0	28.00	28.0	28.00	28.0
26.000	3.0	27.666667	1.154701	27.0	27.00	27.0	28.00	29.0
30.000	1.0	30.000000	NaN	30.0	30.00	30.0	30.00	30.0

[25]:

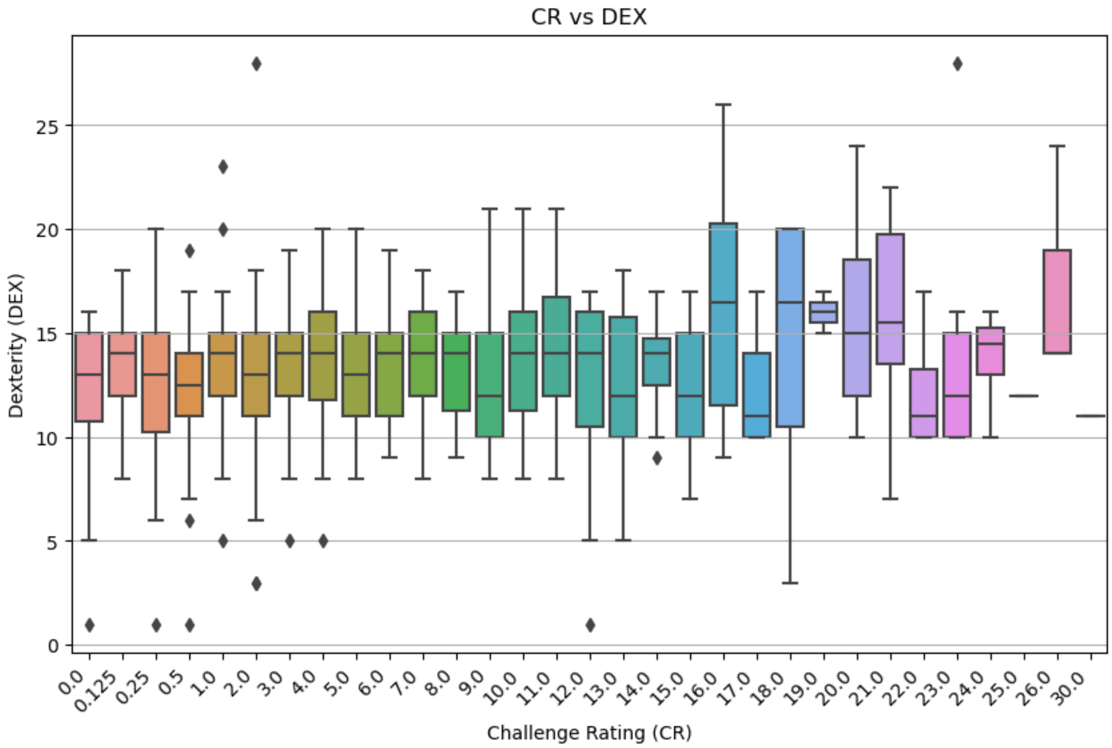
```python
x = df['cr']
y = df['str']

print('Linear Model')
(slope, intercept), eq, r2 = fit_model(df, 'cr', 'str')
print(eq)
print(f"R² = {r2:.3f}", end='\n\n')

print('Quadratic Model')
quad_params, quad_eq, quad_r2 = fit_model(df, 'cr', 'str', model='quadratic')
print(quad_eq)
print(f"R² = {quad_r2:.3f}", end='\n\n')

# Filter and sort x values for smooth curves
x_vals = np.linspace(df['cr'].min(), df['cr'].max(), 500)

# Quadratic predictions
a, b, c = quad_params
y_quad = a * x_vals**2 + b * x_vals + c


plt.figure(figsize=(10, 6))
sns.scatterplot(x=x, y=y, alpha=0.5)
plt.plot(x, slope * x + intercept, color='red', label=f'Linear Fit\n{eq}, R²={r2:.3f}')
plt.plot(x_vals, y_quad, color='blue', label=f'Quadratic Fit\n{quad_eq}, R²={quad_r2:.3f}')
plt.legend()
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Strength (STR)')
plt.title('CR vs STR')
plt.show()
```

```
Linear Model
y = 0.636x + 11.531
R² = 0.399

Quadratic Model
y = -0.012x² + 0.878x + 11.024
R² = 0.406
```



4.3.2 CR vs DEX

[26]:
```python
plt.figure(figsize=(10,6))
sns.boxplot(x='cr', y='dex', data=df)
plt.grid(visible=True, axis='y')
plt.xticks(rotation=45, ha='right')
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Dexterity (DEX)')
plt.title('CR vs DEX')
plt.show()
```



[27]:
```
df.groupby('cr')['dex'].describe()
```

[27]:

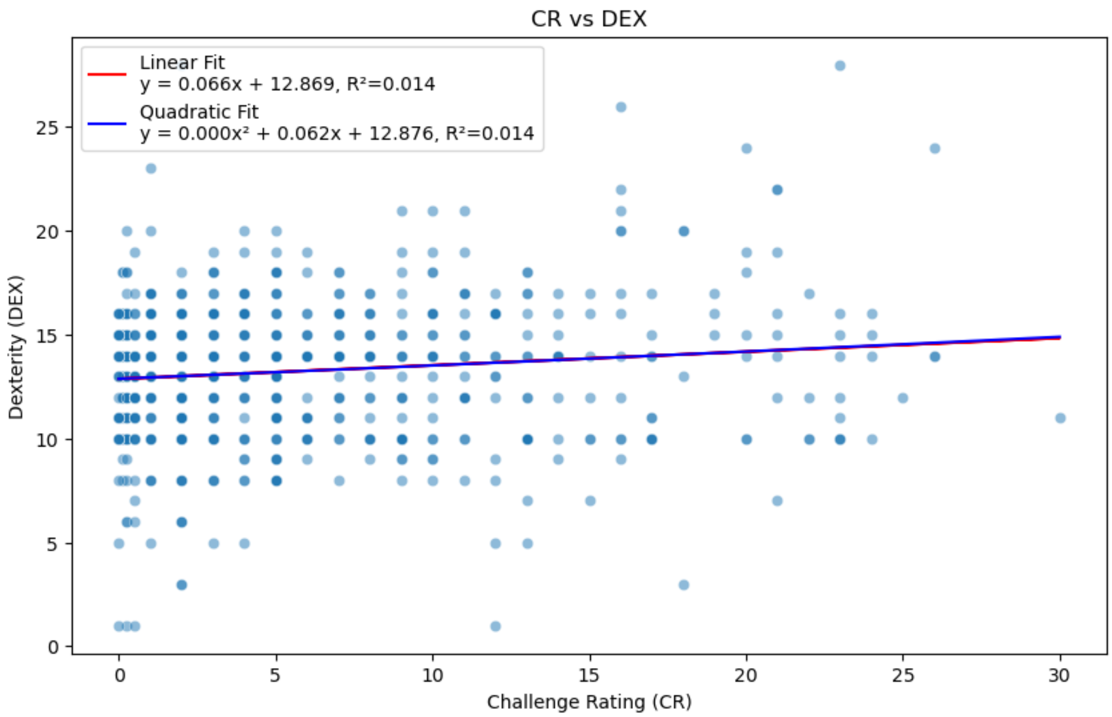
cr	count	mean	std	min	25%	50%	75%	max
0.000	32.0	12.312500	3.354703	1.0	10.75	13.0	15.00	16.0
0.125	29.0	13.517241	2.458523	8.0	12.00	14.0	15.00	18.0
0.250	62.0	12.709677	3.159099	1.0	10.25	13.0	15.00	20.0
0.500	46.0	12.326087	2.944331	1.0	11.00	12.5	14.00	19.0
1.000	62.0	13.709677	2.916247	5.0	12.00	14.0	15.00	23.0
2.000	81.0	12.604938	3.541465	3.0	11.00	13.0	15.00	28.0
3.000	54.0	13.388889	2.811141	5.0	12.00	14.0	15.00	19.0
4.000	36.0	13.527778	3.350788	5.0	11.75	14.0	16.00	20.0
5.000	54.0	13.092593	3.157910	8.0	11.00	13.0	15.00	20.0
6.000	24.0	13.208333	2.686183	9.0	11.00	14.0	15.00	19.0
7.000	27.0	13.925926	2.540835	8.0	12.00	14.0	16.00	18.0
8.000	22.0	13.363636	2.498484	9.0	11.25	14.0	15.00	17.0
9.000	24.0	12.875000	3.480536	8.0	10.00	12.0	15.00	21.0
10.000	22.0	14.000000	3.491486	8.0	11.25	14.0	16.00	21.0
11.000	18.0	14.111111	3.358727	8.0	12.00	14.0	16.75	21.0
12.000	15.0	12.400000	4.687369	1.0	10.50	14.0	16.00	17.0
13.000	18.0	12.500000	3.823303	5.0	10.00	12.0	15.75	18.0
14.000	10.0	13.500000	2.505549	9.0	12.50	14.0	14.75	17.0
15.000	7.0	12.285714	3.592320	7.0	10.00	12.0	15.00	17.0

```
16.000   12.0  16.416667  5.501377   9.0  11.50  16.5  20.25  26.0
17.000   10.0  12.200000  2.573368  10.0  10.00  11.0  14.00  17.0
18.000    4.0  14.000000  8.041559   3.0  10.50  16.5  20.00  20.0
19.000    3.0  16.000000  1.000000  15.0  15.50  16.0  16.50  17.0
20.000    7.0  15.714286  5.056820  10.0  12.00  15.0  18.50  24.0
21.000    8.0  15.875000  5.111262   7.0  13.50  15.5  19.75  22.0
22.000    4.0  12.250000  3.304038  10.0  10.00  11.0  13.25  17.0
23.000    9.0  14.000000  5.722762  10.0  10.00  12.0  15.00  28.0
24.000    4.0  13.750000  2.629956  10.0  13.00  14.5  15.25  16.0
25.000    1.0  12.000000       NaN  12.0  12.00  12.0  12.00  12.0
26.000    3.0  17.333333  5.773503  14.0  14.00  14.0  19.00  24.0
30.000    1.0  11.000000       NaN  11.0  11.00  11.0  11.00  11.0
```

[28]:
```python
x = df['cr']
y = df['dex']

print('Linear Model')
(slope, intercept), eq, r2 = fit_model(df, 'cr', 'dex')
print(eq)
print(f"R² = {r2:.3f}", end='\n\n')

print('Quadratic Model')
quad_params, quad_eq, quad_r2 = fit_model(df, 'cr', 'dex', model='quadratic')
print(quad_eq)
print(f"R² = {quad_r2:.3f}", end='\n\n')

# Filter and sort x values for smooth curves
x_vals = np.linspace(df['cr'].min(), df['cr'].max(), 500)

# Quadratic predictions
a, b, c = quad_params
y_quad = a * x_vals**2 + b * x_vals + c


plt.figure(figsize=(10, 6))
sns.scatterplot(x=x, y=y, alpha=0.5)
plt.plot(x, slope * x + intercept, color='red', label=f'Linear Fit\n{eq}, 
 ↪R²={r2:.3f}')
plt.plot(x_vals, y_quad, color='blue', label=f'Quadratic Fit\n{quad_eq}, 
 ↪R²={quad_r2:.3f}')
plt.legend()
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Dexterity (DEX)')
plt.title('CR vs DEX')
plt.show()
```

```
Linear Model
y = 0.066x + 12.869
```

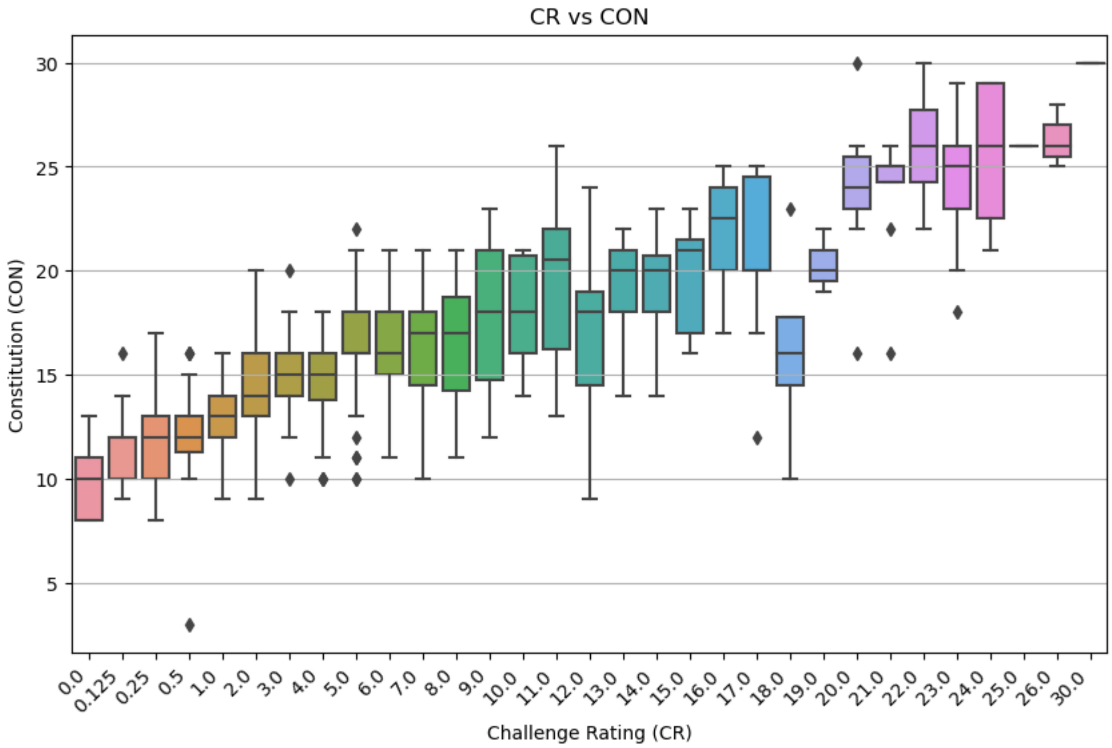
```
R² = 0.014

Quadratic Model
y = 0.000x² + 0.062x + 12.876
R² = 0.014
```



4.3.3 CR vs CON

[29]:

```python
plt.figure(figsize=(10,6))
sns.boxplot(x='cr', y='con', data=df)
plt.grid(visible=True, axis='y')
plt.xticks(rotation=45, ha='right')
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Constitution (CON)')
plt.title('CR vs CON')
plt.show()
```



[30]:
```
df.groupby('cr')['con'].describe()
```

[30]:

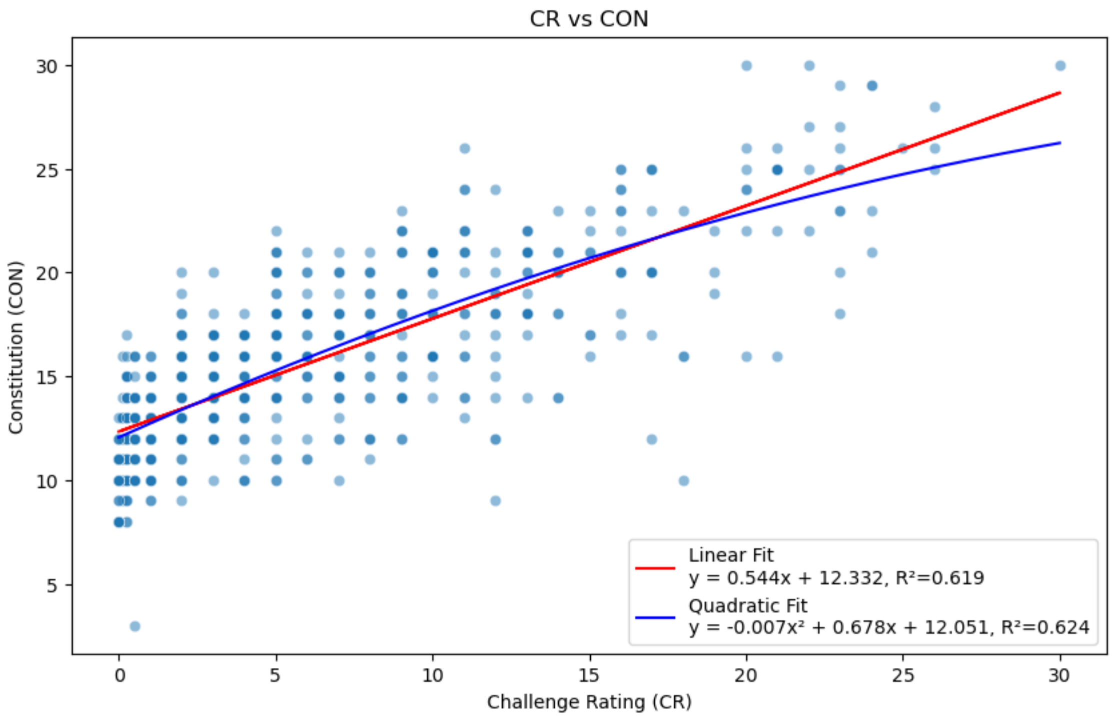
cr	count	mean	std	min	25%	50%	75%	max
0.000	32.0	9.937500	1.479701	8.0	8.00	10.0	11.00	13.0
0.125	29.0	11.586207	1.500410	9.0	10.00	12.0	12.00	16.0
0.250	62.0	11.870968	1.920416	8.0	10.00	12.0	13.00	17.0
0.500	46.0	12.217391	2.096696	3.0	11.25	12.0	13.00	16.0
1.000	62.0	12.661290	1.629075	9.0	12.00	13.0	14.00	16.0
2.000	81.0	14.222222	2.133073	9.0	13.00	14.0	16.00	20.0
3.000	54.0	14.833333	1.830043	10.0	14.00	15.0	16.00	20.0
4.000	36.0	14.694444	2.201551	10.0	13.75	15.0	16.00	18.0
5.000	54.0	16.407407	2.695339	10.0	16.00	16.0	18.00	22.0
6.000	24.0	16.291667	2.661794	11.0	15.00	16.0	18.00	21.0
7.000	27.0	16.185185	2.746145	10.0	14.50	17.0	18.00	21.0
8.000	22.0	16.409091	2.970636	11.0	14.25	17.0	18.75	21.0
9.000	24.0	17.583333	3.374027	12.0	14.75	18.0	21.00	23.0
10.000	22.0	18.181818	2.383202	14.0	16.00	18.0	20.75	21.0
11.000	18.0	19.388889	3.806170	13.0	16.25	20.5	22.00	26.0
12.000	15.0	16.800000	3.895052	9.0	14.50	18.0	19.00	24.0
13.000	18.0	19.500000	2.148871	14.0	18.00	20.0	21.00	22.0
14.000	10.0	18.900000	2.960856	14.0	18.00	20.0	20.75	23.0
15.000	7.0	19.571429	2.819997	16.0	17.00	21.0	21.50	23.0

```
16.000   12.0  21.750000  2.701010  17.0  20.00  22.5  24.00  25.0
17.000   10.0  20.700000  4.110961  12.0  20.00  20.0  24.50  25.0
18.000    4.0  16.250000  5.315073  10.0  14.50  16.0  17.75  23.0
19.000    3.0  20.333333  1.527525  19.0  19.50  20.0  21.00  22.0
20.000    7.0  23.857143  4.259443  16.0  23.00  24.0  25.50  30.0
21.000    8.0  23.625000  3.292307  16.0  24.25  25.0  25.00  26.0
22.000    4.0  26.000000  3.366502  22.0  24.25  26.0  27.75  30.0
23.000    9.0  24.000000  3.427827  18.0  23.00  25.0  26.00  29.0
24.000    4.0  25.500000  4.123106  21.0  22.50  26.0  29.00  29.0
25.000    1.0  26.000000       NaN  26.0  26.00  26.0  26.00  26.0
26.000    3.0  26.333333  1.527525  25.0  25.50  26.0  27.00  28.0
30.000    1.0  30.000000       NaN  30.0  30.00  30.0  30.00  30.0
```

[31]:
```
x = df['cr']
y = df['con']

print('Linear Model')
(slope, intercept), eq, r2 = fit_model(df, 'cr', 'con')
print(eq)
print(f"R² = {r2:.3f}", end='\n\n')

print('Quadratic Model')
quad_params, quad_eq, quad_r2 = fit_model(df, 'cr', 'con', model='quadratic')
print(quad_eq)
print(f"R² = {quad_r2:.3f}", end='\n\n')

# Filter and sort x values for smooth curves
x_vals = np.linspace(df['cr'].min(), df['cr'].max(), 500)

# Quadratic predictions
a, b, c = quad_params
y_quad = a * x_vals**2 + b * x_vals + c


plt.figure(figsize=(10, 6))
sns.scatterplot(x=x, y=y, alpha=0.5)
plt.plot(x, slope * x + intercept, color='red', label=f'Linear Fit\n{eq},␣
↪R²={r2:.3f}')
plt.plot(x_vals, y_quad, color='blue', label=f'Quadratic Fit\n{quad_eq},␣
↪R²={quad_r2:.3f}')
plt.legend()
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Constitution (CON)')
plt.title('CR vs CON')
plt.show()
```

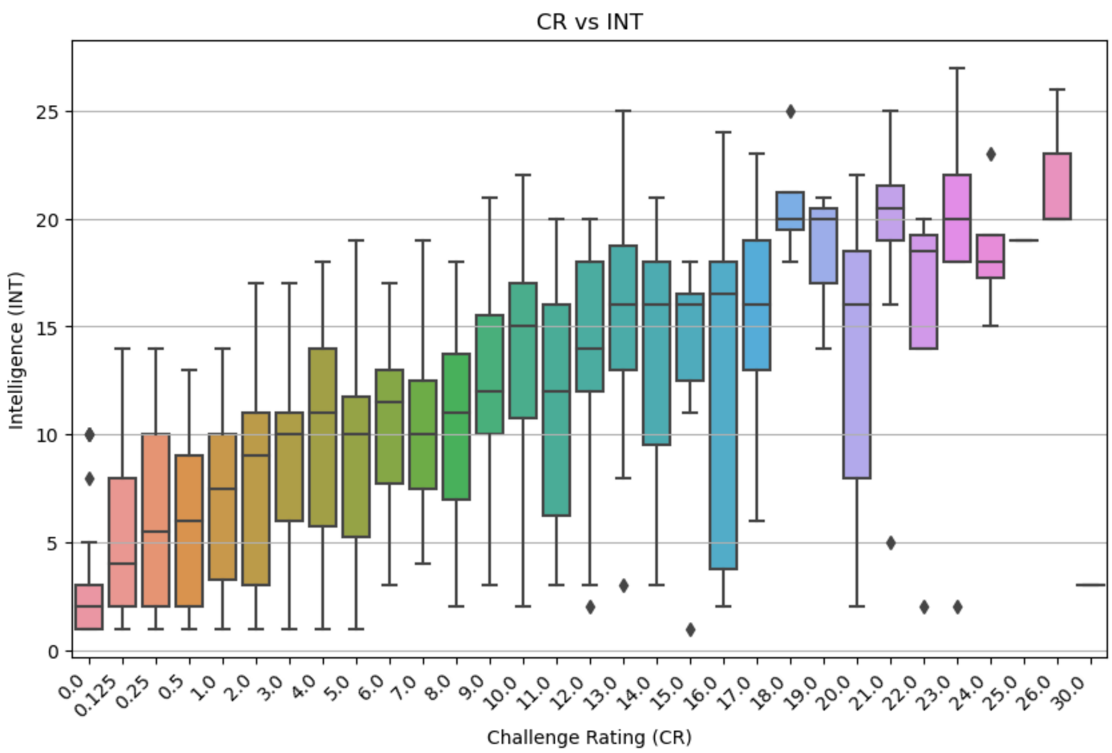
```
Linear Model
y = 0.544x + 12.332
```

```
R² = 0.619

Quadratic Model
y = -0.007x² + 0.678x + 12.051
R² = 0.624
```



4.3.4 CR vs INT

[32]:
```
plt.figure(figsize=(10,6))
sns.boxplot(x='cr', y='int', data=df)
plt.grid(visible=True, axis='y')
plt.xticks(rotation=45, ha='right')
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Intelligence (INT)')
plt.title('CR vs INT')
plt.show()
```



[33]:
```
df.groupby('cr')['int'].describe()
```

[33]:

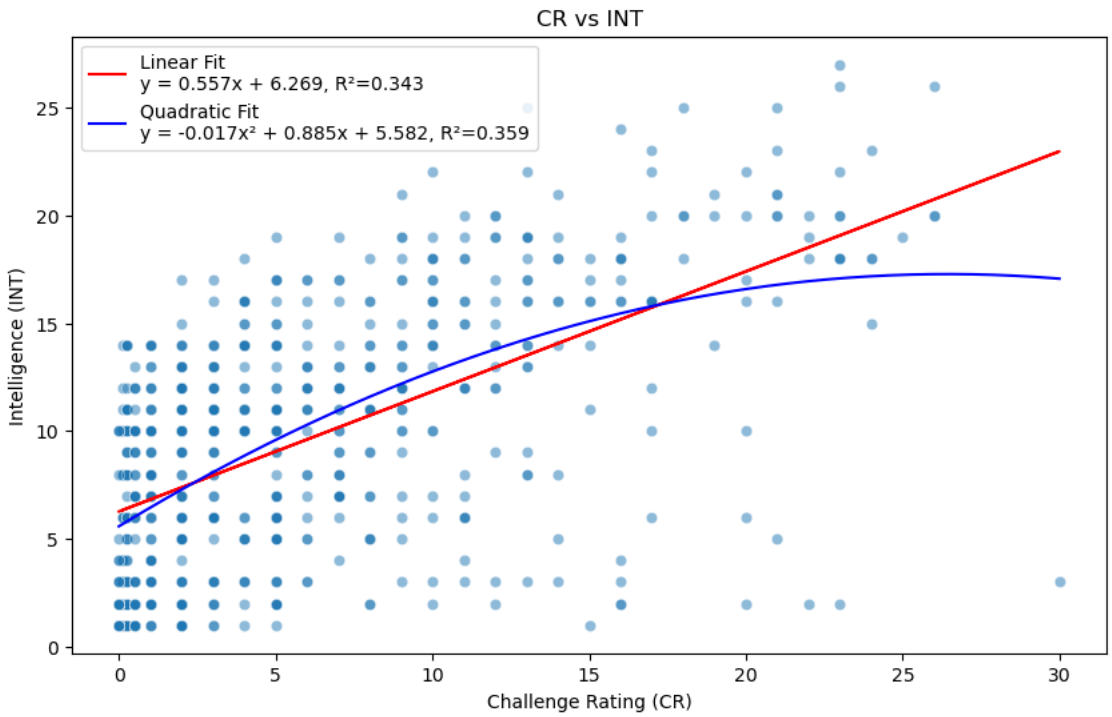
cr	count	mean	std	min	25%	50%	75%	max
0.000	32.0	2.937500	2.723109	1.0	1.00	2.0	3.00	10.0
0.125	29.0	5.310345	3.675240	1.0	2.00	4.0	8.00	14.0
0.250	62.0	6.129032	4.166549	1.0	2.00	5.5	10.00	14.0
0.500	46.0	5.630435	3.923483	1.0	2.00	6.0	9.00	13.0
1.000	62.0	7.145161	3.929071	1.0	3.25	7.5	10.00	14.0
2.000	81.0	7.666667	4.367494	1.0	3.00	9.0	11.00	17.0
3.000	54.0	8.777778	3.993706	1.0	6.00	10.0	11.00	17.0
4.000	36.0	10.194444	4.725732	1.0	5.75	11.0	14.00	18.0
5.000	54.0	9.018519	4.652006	1.0	5.25	10.0	11.75	19.0
6.000	24.0	10.583333	4.138017	3.0	7.75	11.5	13.00	17.0
7.000	27.0	10.592593	3.764809	4.0	7.50	10.0	12.50	19.0
8.000	22.0	10.318182	4.602136	2.0	7.00	11.0	13.75	18.0
9.000	24.0	12.500000	4.606234	3.0	10.00	12.0	15.50	21.0
10.000	22.0	13.636364	5.242187	2.0	10.75	15.0	17.00	22.0
11.000	18.0	11.833333	5.575682	3.0	6.25	12.0	16.00	20.0
12.000	15.0	13.666667	5.563486	2.0	12.00	14.0	18.00	20.0
13.000	18.0	15.000000	5.444911	3.0	13.00	16.0	18.75	25.0
14.000	10.0	13.800000	6.250333	3.0	9.50	16.0	18.00	21.0
15.000	7.0	13.285714	5.879747	1.0	12.50	16.0	16.50	18.0

16.000	12.0	13.083333	7.913835	2.0	3.75	16.5	18.00	24.0
17.000	10.0	15.700000	5.292552	6.0	13.00	16.0	19.00	23.0
18.000	4.0	20.750000	2.986079	18.0	19.50	20.0	21.25	25.0
19.000	3.0	18.333333	3.785939	14.0	17.00	20.0	20.50	21.0
20.000	7.0	13.285714	7.454625	2.0	8.00	16.0	18.50	22.0
21.000	8.0	18.875000	6.174545	5.0	19.00	20.5	21.50	25.0
22.000	4.0	14.750000	8.539126	2.0	14.00	18.5	19.25	20.0
23.000	9.0	19.000000	7.211103	2.0	18.00	20.0	22.00	27.0
24.000	4.0	18.500000	3.316625	15.0	17.25	18.0	19.25	23.0
25.000	1.0	19.000000	NaN	19.0	19.00	19.0	19.00	19.0
26.000	3.0	22.000000	3.464102	20.0	20.00	20.0	23.00	26.0
30.000	1.0	3.000000	NaN	3.0	3.00	3.0	3.00	3.0

[34]:
```
x = df['cr']
y = df['int']

print('Linear Model')
(slope, intercept), eq, r2 = fit_model(df, 'cr', 'int')
print(eq)
print(f"R² = {r2:.3f}", end='\n\n')

print('Quadratic Model')
quad_params, quad_eq, quad_r2 = fit_model(df, 'cr', 'int', model='quadratic')
print(quad_eq)
print(f"R² = {quad_r2:.3f}", end='\n\n')

# Filter and sort x values for smooth curves
x_vals = np.linspace(df['cr'].min(), df['cr'].max(), 500)

# Quadratic predictions
a, b, c = quad_params
y_quad = a * x_vals**2 + b * x_vals + c


plt.figure(figsize=(10, 6))
sns.scatterplot(x=x, y=y, alpha=0.5)
plt.plot(x, slope * x + intercept, color='red', label=f'Linear Fit\n{eq},␣
↪R²={r2:.3f}')
plt.plot(x_vals, y_quad, color='blue', label=f'Quadratic Fit\n{quad_eq},␣
↪R²={quad_r2:.3f}')
plt.legend()
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Intelligence (INT)')
plt.title('CR vs INT')
plt.show()
```

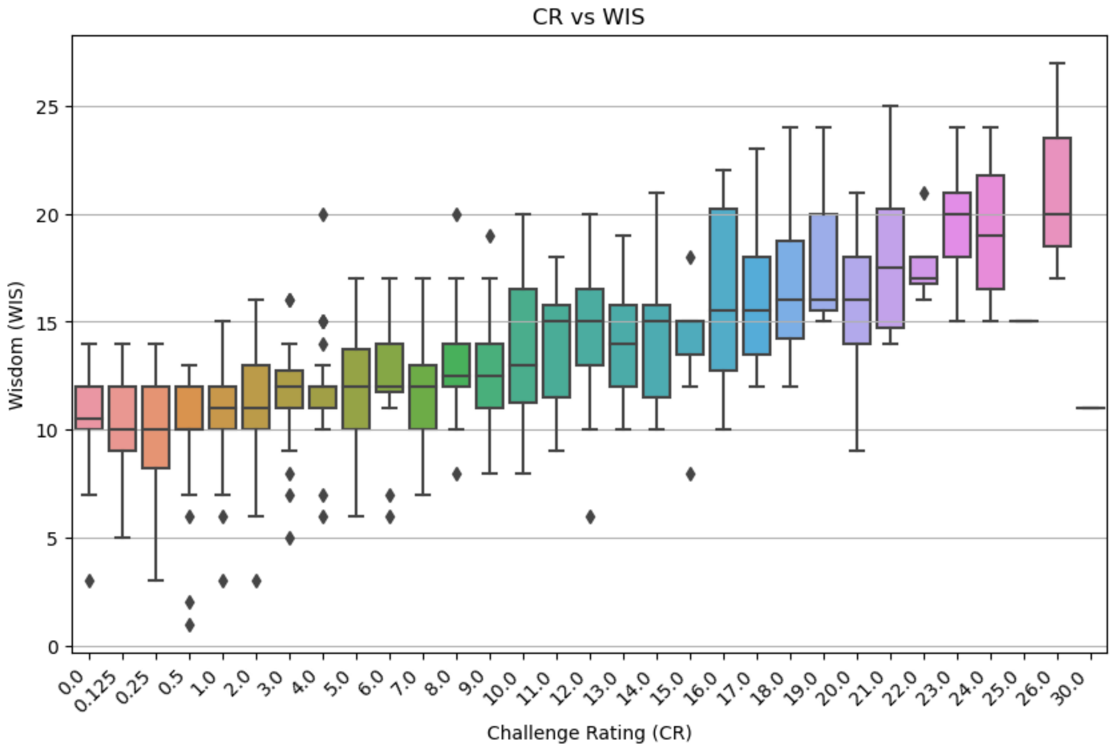
```
Linear Model
y = 0.557x + 6.269
```

```
R² = 0.343

Quadratic Model
y = -0.017x² + 0.885x + 5.582
R² = 0.359
```



4.3.5 CR vs WIS

[35]:
```
plt.figure(figsize=(10,6))
sns.boxplot(x='cr', y='wis', data=df)
plt.grid(visible=True, axis='y')
plt.xticks(rotation=45, ha='right')
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Wisdom (WIS)')
plt.title('CR vs WIS')
plt.show()
```



[36]:
```
df.groupby('cr')['wis'].describe()
```

[36]:

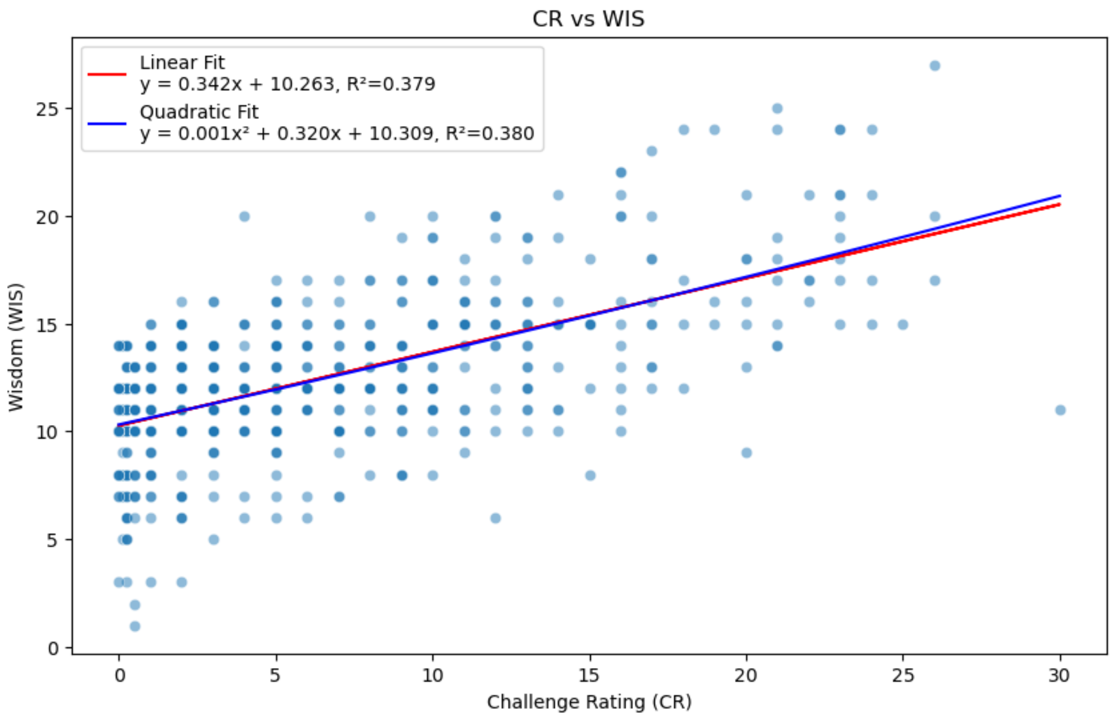
cr	count	mean	std	min	25%	50%	75%	max
0.000	32.0	10.437500	2.327085	3.0	10.00	10.5	12.00	14.0
0.125	29.0	10.310345	2.189316	5.0	9.00	10.0	12.00	14.0
0.250	62.0	9.951613	2.511791	3.0	8.25	10.0	12.00	14.0
0.500	46.0	10.130435	2.543914	1.0	10.00	10.0	12.00	13.0
1.000	62.0	10.870968	2.228606	3.0	10.00	11.0	12.00	15.0
2.000	81.0	11.358025	2.451064	3.0	10.00	11.0	13.00	16.0
3.000	54.0	11.574074	1.977247	5.0	11.00	12.0	12.75	16.0
4.000	36.0	11.833333	2.286607	6.0	11.00	12.0	12.00	20.0
5.000	54.0	11.703704	2.376216	6.0	10.00	12.0	13.75	17.0
6.000	24.0	12.416667	2.448010	6.0	11.75	12.0	14.00	17.0
7.000	27.0	11.814815	2.434322	7.0	10.00	12.0	13.00	17.0
8.000	22.0	13.136364	2.642067	8.0	12.00	12.5	14.00	20.0
9.000	24.0	12.708333	2.926330	8.0	11.00	12.5	14.00	19.0
10.000	22.0	13.863636	3.255698	8.0	11.25	13.0	16.50	20.0
11.000	18.0	13.888889	2.632129	9.0	11.50	15.0	15.75	18.0
12.000	15.0	14.666667	3.811012	6.0	13.00	15.0	16.50	20.0
13.000	18.0	14.166667	2.706202	10.0	12.00	14.0	15.75	19.0
14.000	10.0	14.600000	3.533962	10.0	11.50	15.0	15.75	21.0
15.000	7.0	14.000000	3.162278	8.0	13.50	15.0	15.00	18.0

16.000	12.0	16.333333	4.458563	10.0	12.75	15.5	20.25	22.0
17.000	10.0	16.300000	3.465705	12.0	13.50	15.5	18.00	23.0
18.000	4.0	17.000000	5.099020	12.0	14.25	16.0	18.75	24.0
19.000	3.0	18.333333	4.932883	15.0	15.50	16.0	20.00	24.0
20.000	7.0	15.714286	3.903600	9.0	14.00	16.0	18.00	21.0
21.000	8.0	18.250000	4.267820	14.0	14.75	17.5	20.25	25.0
22.000	4.0	17.750000	2.217356	16.0	16.75	17.0	18.00	21.0
23.000	9.0	19.888889	3.018462	15.0	18.00	20.0	21.00	24.0
24.000	4.0	19.250000	4.031129	15.0	16.50	19.0	21.75	24.0
25.000	1.0	15.000000	NaN	15.0	15.00	15.0	15.00	15.0
26.000	3.0	21.333333	5.131601	17.0	18.50	20.0	23.50	27.0
30.000	1.0	11.000000	NaN	11.0	11.00	11.0	11.00	11.0

[37]:
```
x = df['cr']
y = df['wis']

print('Linear Model')
(slope, intercept), eq, r2 = fit_model(df, 'cr', 'wis')
print(eq)
print(f"R² = {r2:.3f}", end='\n\n')

print('Quadratic Model')
quad_params, quad_eq, quad_r2 = fit_model(df, 'cr', 'wis', model='quadratic')
print(quad_eq)
print(f"R² = {quad_r2:.3f}", end='\n\n')

# Filter and sort x values for smooth curves
x_vals = np.linspace(df['cr'].min(), df['cr'].max(), 500)

# Quadratic predictions
a, b, c = quad_params
y_quad = a * x_vals**2 + b * x_vals + c


plt.figure(figsize=(10, 6))
sns.scatterplot(x=x, y=y, alpha=0.5)
plt.plot(x, slope * x + intercept, color='red', label=f'Linear Fit\n{eq},␣
↪R²={r2:.3f}')
plt.plot(x_vals, y_quad, color='blue', label=f'Quadratic Fit\n{quad_eq},␣
↪R²={quad_r2:.3f}')
plt.legend()
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Wisdom (WIS)')
plt.title('CR vs WIS')
plt.show()
```

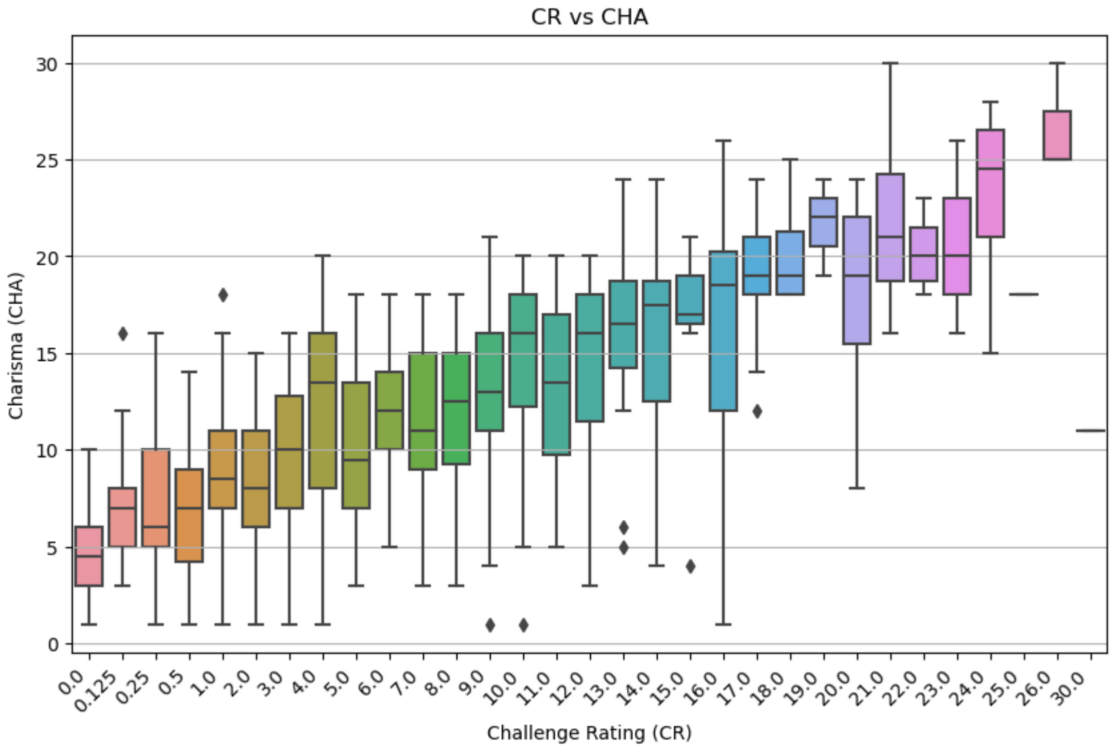
```
Linear Model
y = 0.342x + 10.263
```

```
R² = 0.379

Quadratic Model
y = 0.001x² + 0.320x + 10.309
R² = 0.380
```



4.3.6 CR vs CHA

[38]:
```
plt.figure(figsize=(10,6))
sns.boxplot(x='cr', y='cha', data=df)
plt.grid(visible=True, axis='y')
plt.xticks(rotation=45, ha='right')
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Charisma (CHA)')
plt.title('CR vs CHA')
plt.show()
```



[39]:
```
df.groupby('cr')['cha'].describe()
```

[39]:

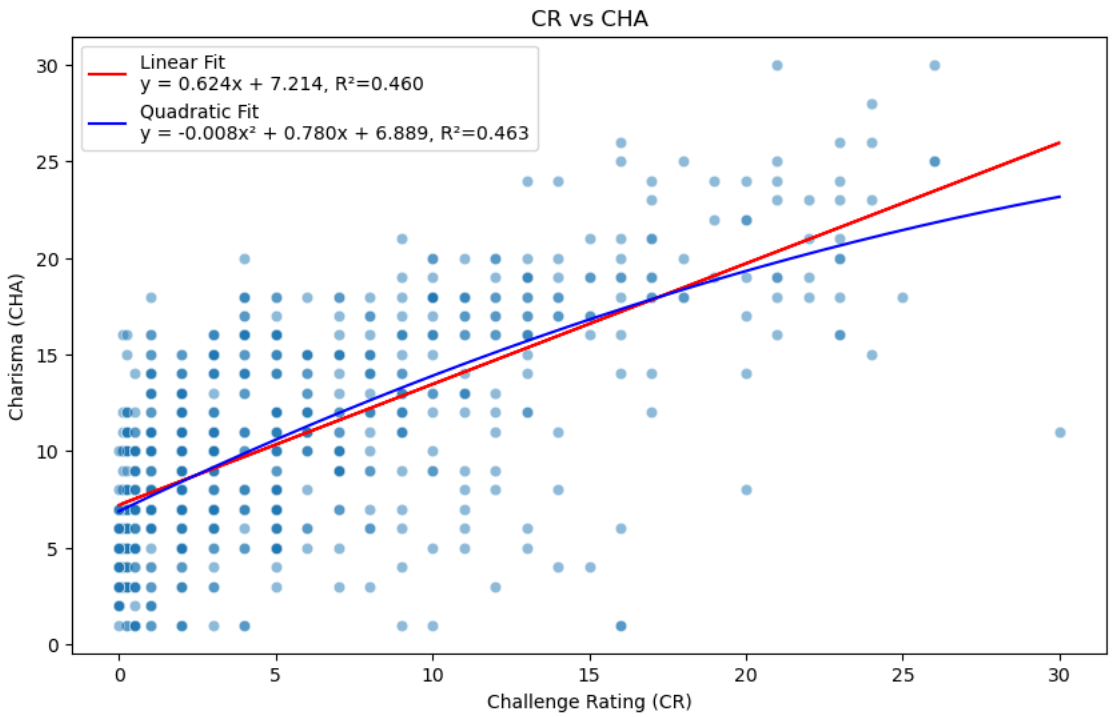
cr	count	mean	std	min	25%	50%	75%	max
0.000	32.0	4.593750	2.092373	1.0	3.00	4.5	6.00	10.0
0.125	29.0	6.827586	3.059750	3.0	5.00	7.0	8.00	16.0
0.250	62.0	6.951613	3.331063	1.0	5.00	6.0	10.00	16.0
0.500	46.0	6.565217	3.270421	1.0	4.25	7.0	9.00	14.0
1.000	62.0	8.903226	3.970009	1.0	7.00	8.5	11.00	18.0
2.000	81.0	8.543210	3.398711	1.0	6.00	8.0	11.00	15.0
3.000	54.0	9.851852	3.773829	1.0	7.00	10.0	12.75	16.0
4.000	36.0	12.000000	4.968472	1.0	8.00	13.5	16.00	20.0
5.000	54.0	9.944444	4.150093	3.0	7.00	9.5	13.50	18.0
6.000	24.0	11.625000	3.173429	5.0	10.00	12.0	14.00	18.0
7.000	27.0	11.444444	3.866357	3.0	9.00	11.0	15.00	18.0
8.000	22.0	12.045455	4.041184	3.0	9.25	12.5	15.00	18.0
9.000	24.0	12.541667	4.708726	1.0	11.00	13.0	16.00	21.0
10.000	22.0	14.500000	5.030857	1.0	12.25	16.0	18.00	20.0
11.000	18.0	13.333333	4.627285	5.0	9.75	13.5	17.00	20.0
12.000	15.0	14.466667	4.983783	3.0	11.50	16.0	18.00	20.0
13.000	18.0	15.722222	4.687977	5.0	14.25	16.5	18.75	24.0
14.000	10.0	15.600000	6.058969	4.0	12.50	17.5	18.75	24.0
15.000	7.0	16.142857	5.610365	4.0	16.50	17.0	19.00	21.0

16.000	12.0	15.500000	8.501337	1.0	12.00	18.5	20.25	26.0
17.000	10.0	18.900000	3.725289	12.0	18.00	19.0	21.00	24.0
18.000	4.0	20.250000	3.304038	18.0	18.00	19.0	21.25	25.0
19.000	3.0	21.666667	2.516611	19.0	20.50	22.0	23.00	24.0
20.000	7.0	18.000000	5.567764	8.0	15.50	19.0	22.00	24.0
21.000	8.0	21.750000	4.590363	16.0	18.75	21.0	24.25	30.0
22.000	4.0	20.250000	2.217356	18.0	18.75	20.0	21.50	23.0
23.000	9.0	20.444444	3.468109	16.0	18.00	20.0	23.00	26.0
24.000	4.0	23.000000	5.715476	15.0	21.00	24.5	26.50	28.0
25.000	1.0	18.000000	NaN	18.0	18.00	18.0	18.00	18.0
26.000	3.0	26.666667	2.886751	25.0	25.00	25.0	27.50	30.0
30.000	1.0	11.000000	NaN	11.0	11.00	11.0	11.00	11.0

[40]:
```python
x = df['cr']
y = df['cha']

print('Linear Model')
(slope, intercept), eq, r2 = fit_model(df, 'cr', 'cha')
print(eq)
print(f"R² = {r2:.3f}", end='\n\n')

print('Quadratic Model')
quad_params, quad_eq, quad_r2 = fit_model(df, 'cr', 'cha', model='quadratic')
print(quad_eq)
print(f"R² = {quad_r2:.3f}", end='\n\n')

# Filter and sort x values for smooth curves
x_vals = np.linspace(df['cr'].min(), df['cr'].max(), 500)

# Quadratic predictions
a, b, c = quad_params
y_quad = a * x_vals**2 + b * x_vals + c


plt.figure(figsize=(10, 6))
sns.scatterplot(x=x, y=y, alpha=0.5)
plt.plot(x, slope * x + intercept, color='red', label=f'Linear Fit\n{eq},␣
↪R²={r2:.3f}')
plt.plot(x_vals, y_quad, color='blue', label=f'Quadratic Fit\n{quad_eq},␣
↪R²={quad_r2:.3f}')
plt.legend()
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Charisma (CHA)')
plt.title('CR vs CHA')
plt.show()
```

```
Linear Model
y = 0.624x + 7.214
```

```
R² = 0.460

Quadratic Model
y = -0.008x² + 0.780x + 6.889
R² = 0.463
```

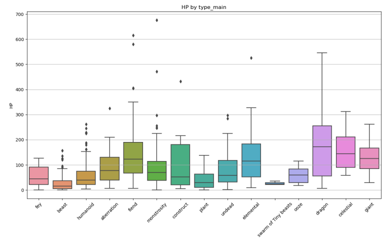


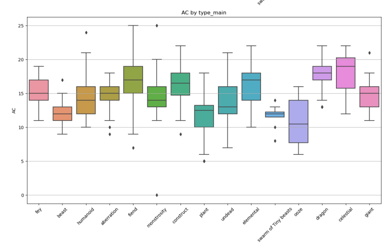
4.3.7 Stats By Monster Type

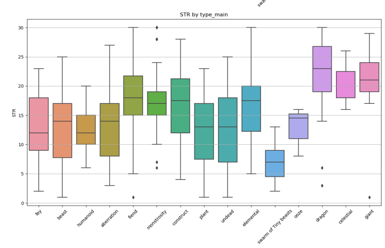
[41]:
```python
def plot_stats_by_type(df, group_col='type_main'):
    """
    Plots boxplots of ability scores grouped by a category (default: monster␣
    ↪type).
    Expects columns: str, dex, con, int, wis, cha
    """
    stats = ['hp', 'ac', 'str', 'dex', 'con', 'int', 'wis', 'cha']

    fig, axes = plt.subplots(8, 1, figsize=(12, 60))  # 8 rows, 1 column

    for i, stat in enumerate(stats):
        ax = axes[i]
        ax.grid()
        sns.boxplot(x=group_col, y=stat, data=df, ax=ax)
        ax.set_title(f'{stat.upper()} by {group_col}')
```

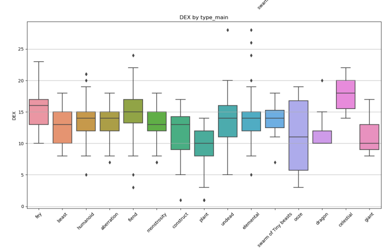
```
        ax.set_xlabel('')
        ax.set_ylabel(stat.upper())
        ax.tick_params(axis='x', rotation=45)

    plt.tight_layout()
    plt.show()
```

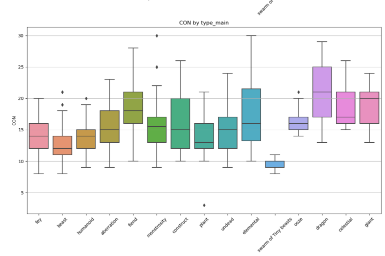
[42]:
```
plot_stats_by_type(df)
```

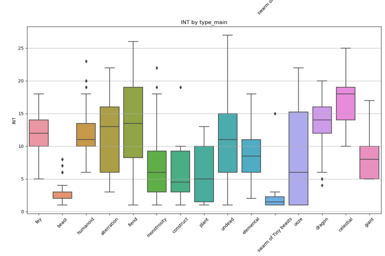

HP by type_main
HP
fey beast humanoid aberration fiend monstrosity construct plant undead elemental swarm of Tiny beasts ooze dragon celestial giant

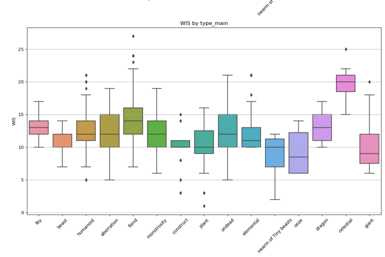

AC by type_main
AC
fey beast humanoid aberration fiend monstrosity construct plant undead elemental swarm of Tiny beasts ooze dragon celestial giant

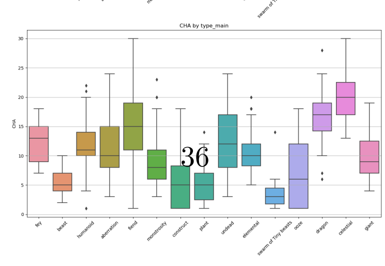

STR by type_main
STR
fey beast humanoid aberration fiend monstrosity construct plant undead elemental swarm of Tiny beasts ooze dragon celestial giant


DEX by type_main
DEX
fey beast humanoid aberration fiend monstrosity construct plant undead elemental swarm of Tiny beasts ooze dragon celestial giant


CON by type_main
CON
fey beast humanoid aberration fiend monstrosity construct plant undead elemental swarm of Tiny beasts ooze dragon celestial giant


INT by type_main
INT
fey beast humanoid aberration fiend monstrosity construct plant undead elemental swarm of Tiny beasts ooze dragon celestial giant


WIS by type_main
WIS
fey beast humanoid aberration fiend monstrosity construct plant undead elemental swarm of Tiny beasts ooze dragon celestial giant


CHA by type_main
CHA
fey beast humanoid aberration fiend monstrosity construct plant undead elemental swarm of Tiny beasts ooze dragon celestial giant

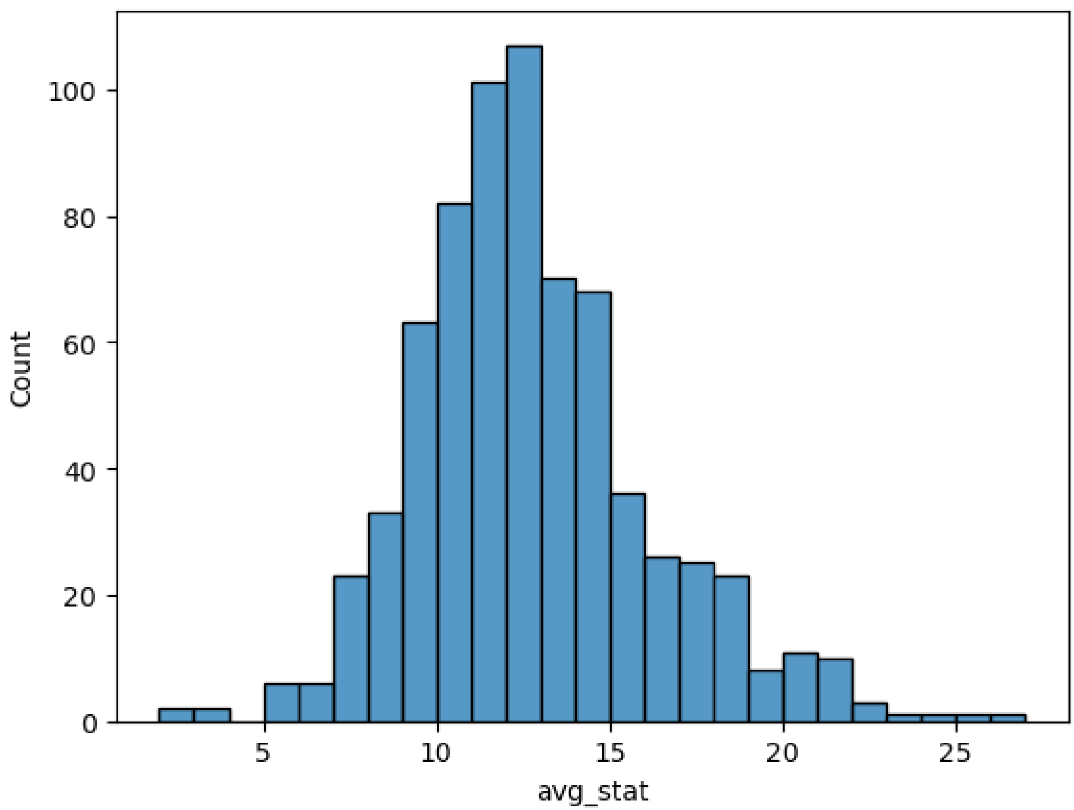
5 Feature Engineering

5.1 Average Stat

Since stats in each of the six abilities are directly tied to a monsters offensive and defensive capabilities, the average of all of them serves as a coarse measure of the threat a monster poses.

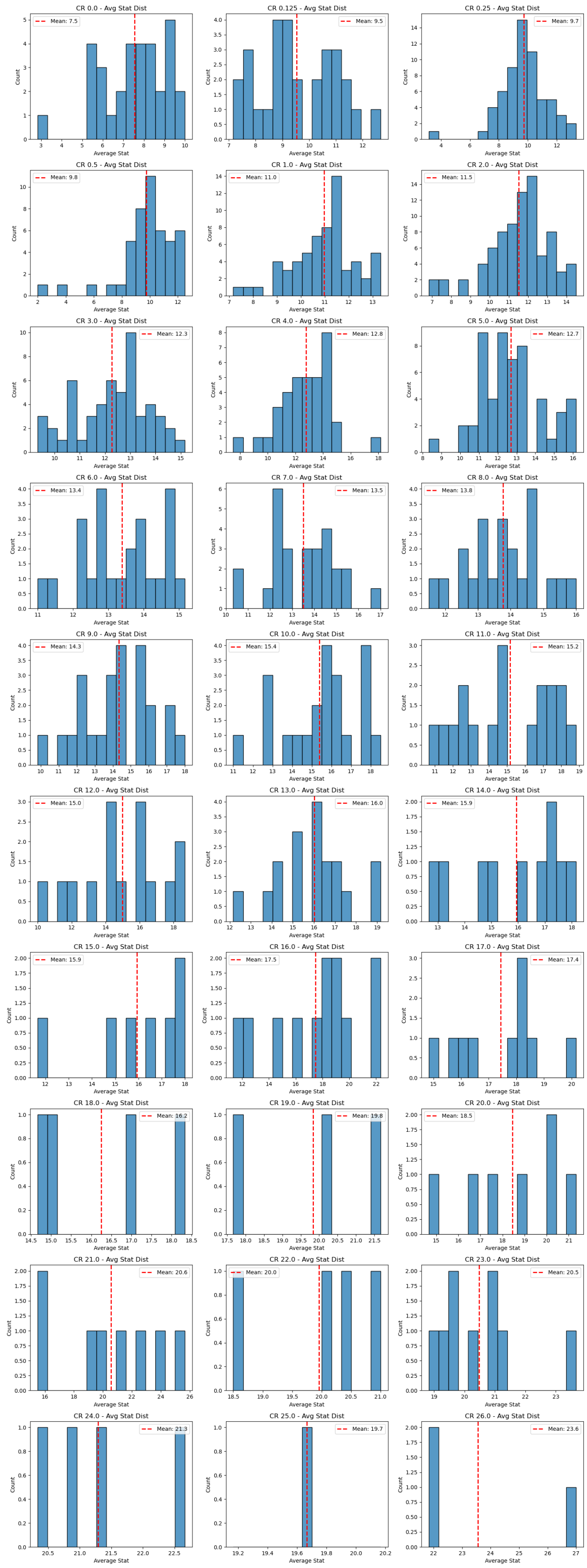
[43]:
```
df['avg_stat'] = df[['str', 'dex', 'con', 'int', 'wis', 'cha']].mean(axis=1)


sns.histplot(df['avg_stat'], binwidth=1)
```

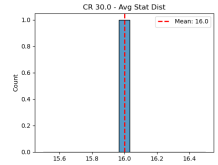
[43]: <AxesSubplot: xlabel='avg_stat', ylabel='Count'>



[44]:
```
def plot_avg_stat_histograms_by_cr(df, cr_values=None, bins=15):
    """
    Plots histograms of average stat scores for each specified CR.
```

```
    Parameters:
        df (DataFrame): The monster dataset with str, dex, con, int, wis, cha.
        cr_values (list or None): List of CRs to plot. If None, uses all unique␣
↪CRs sorted.
        bins (int): Number of bins in histogram.
    """
    # Calculate average stat if not already present
    if 'avg_stat' not in df.columns:
        df['avg_stat'] = df[['str', 'dex', 'con', 'int', 'wis', 'cha']].
↪mean(axis=1)

    # Define which CRs to plot
    if cr_values is None:
        cr_values = sorted(df['cr'].dropna().unique())

    # Create subplots grid
    n = len(cr_values)
    ncols = 3
    nrows = (n + ncols - 1) // ncols
    fig, axes = plt.subplots(nrows, ncols, figsize=(5 * ncols, 4 * nrows))
    axes = axes.flatten()

    for i, cr in enumerate(cr_values):
        subset = df[df['cr'] == cr]
        sns.histplot(subset['avg_stat'], bins=bins, kde=False, ax=axes[i])
        # Add average line
        mean_score = subset['avg_stat'].mean()
        axes[i].axvline(mean_score, color='red', linestyle='--', linewidth=2,␣
↪label=f'Mean: {mean_score:.1f}')
        axes[i].set_title(f'CR {cr} - Avg Stat Dist')
        axes[i].set_xlabel('Average Stat')
        axes[i].set_ylabel('Count')
        axes[i].legend()

    # Hide any unused subplots
    for j in range(i + 1, len(axes)):
        axes[j].axis('off')

    plt.tight_layout()
    plt.show()

plot_avg_stat_histograms_by_cr(df)
```


CR 0.0 - Avg Stat Dist
Mean: 7.5
CR 0.125 - Avg Stat Dist
Mean: 9.5
CR 0.25 - Avg Stat Dist
Mean: 9.7
CR 0.5 - Avg Stat Dist
Mean: 9.8
CR 1.0 - Avg Stat Dist
Mean: 11.0
CR 2.0 - Avg Stat Dist
Mean: 11.5
CR 3.0 - Avg Stat Dist
Mean: 12.3
CR 4.0 - Avg Stat Dist
Mean: 12.8
CR 5.0 - Avg Stat Dist
Mean: 12.7
CR 6.0 - Avg Stat Dist
Mean: 13.4
CR 7.0 - Avg Stat Dist
Mean: 13.5
CR 8.0 - Avg Stat Dist
Mean: 13.8
CR 9.0 - Avg Stat Dist
Mean: 14.3
CR 10.0 - Avg Stat Dist
Mean: 15.4
CR 11.0 - Avg Stat Dist
Mean: 15.2
CR 12.0 - Avg Stat Dist
Mean: 15.0
CR 13.0 - Avg Stat Dist
Mean: 16.0
CR 14.0 - Avg Stat Dist
Mean: 15.9
CR 15.0 - Avg Stat Dist
Mean: 15.9
CR 16.0 - Avg Stat Dist
Mean: 17.5
CR 17.0 - Avg Stat Dist
Mean: 17.4
CR 18.0 - Avg Stat Dist
Mean: 16.2
CR 19.0 - Avg Stat Dist
Mean: 19.8
CR 20.0 - Avg Stat Dist
Mean: 18.5
CR 21.0 - Avg Stat Dist
Mean: 20.6
CR 22.0 - Avg Stat Dist
Mean: 20.0
CR 23.0 - Avg Stat Dist
Mean: 20.5
CR 24.0 - Avg Stat Dist
Mean: 21.3
CR 25.0 - Avg Stat Dist
Mean: 19.7
CR 26.0 - Avg Stat Dist
Mean: 23.6
Count
Average Stat


CR 30.0 - Avg Stat Dist
Mean: 16.0
Count
Average Stat

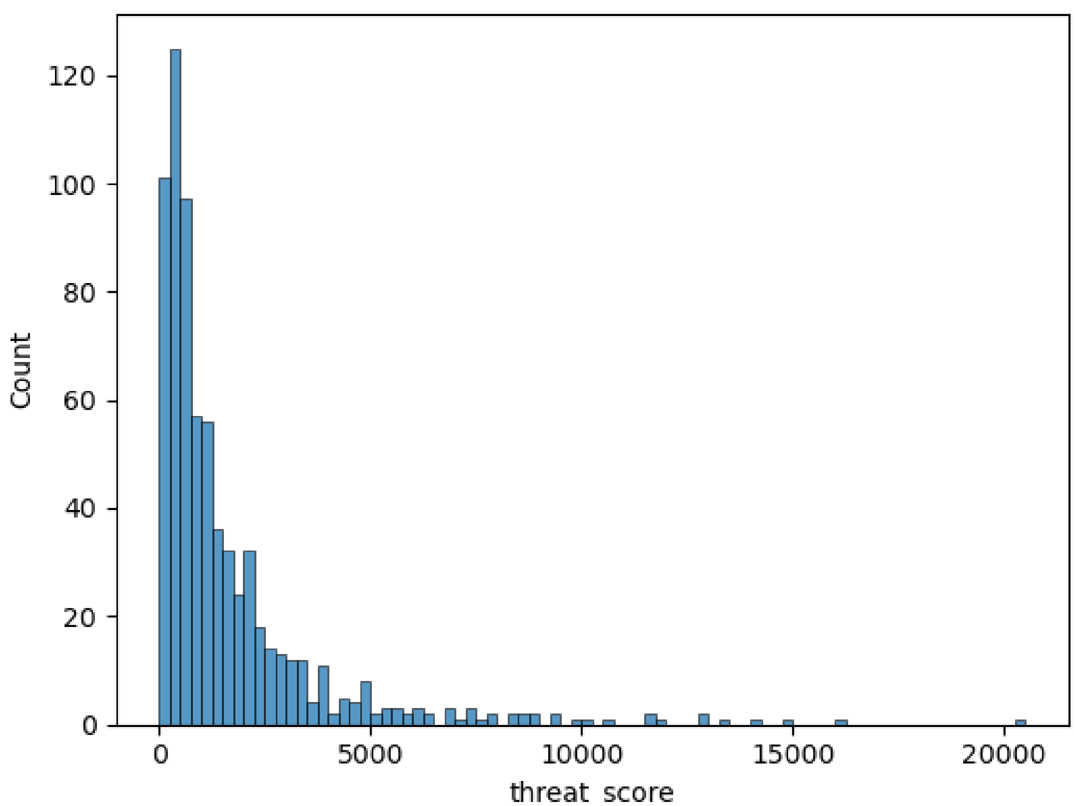
5.2 Threat Score

5.2.1 Feature Engineering: Threat Score

The threat score is engineered to represent a monster's effective combat capability. It combines durability (HP and AC) with statistical power (average ability scores) and factors in legendary status.

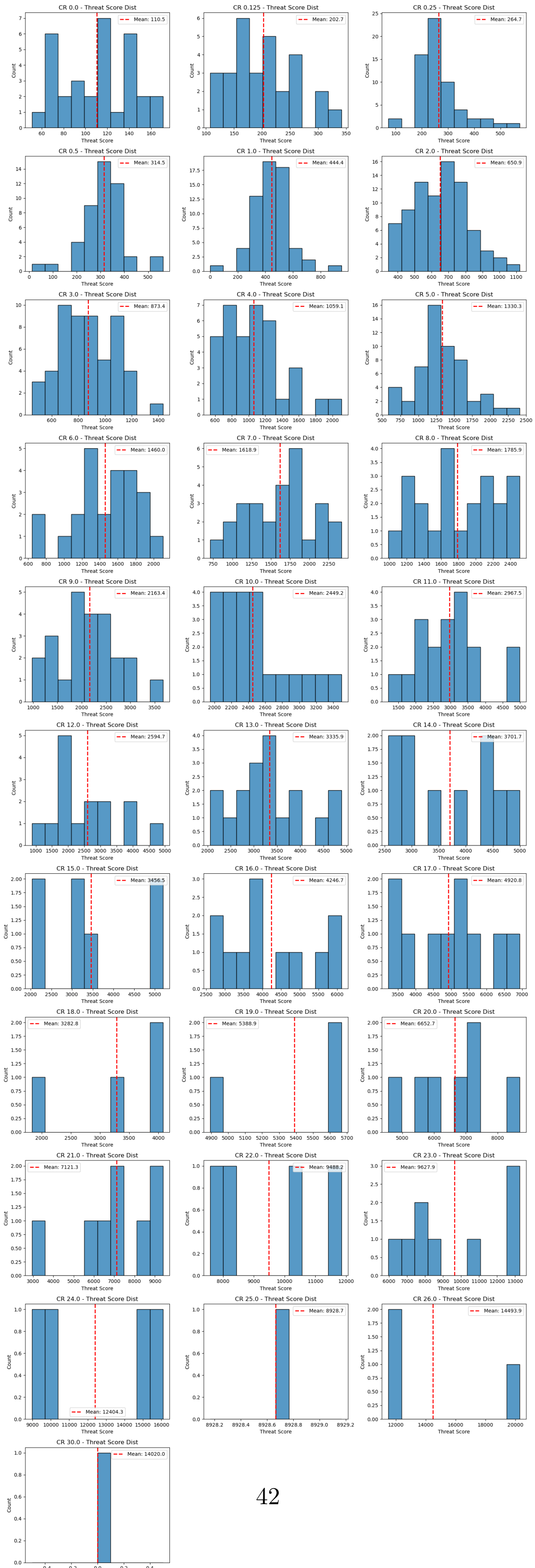
[45]:
```
df['threat_score'] = df['avg_stat'] * (df['hp'] + df['ac']) *␣
↪df['is_legendary'].apply(lambda x: 1.25 if x == 1 else 1)
sns.histplot(df['threat_score'], binwidth=250)
```

[45]: <AxesSubplot: xlabel='threat_score', ylabel='Count'>

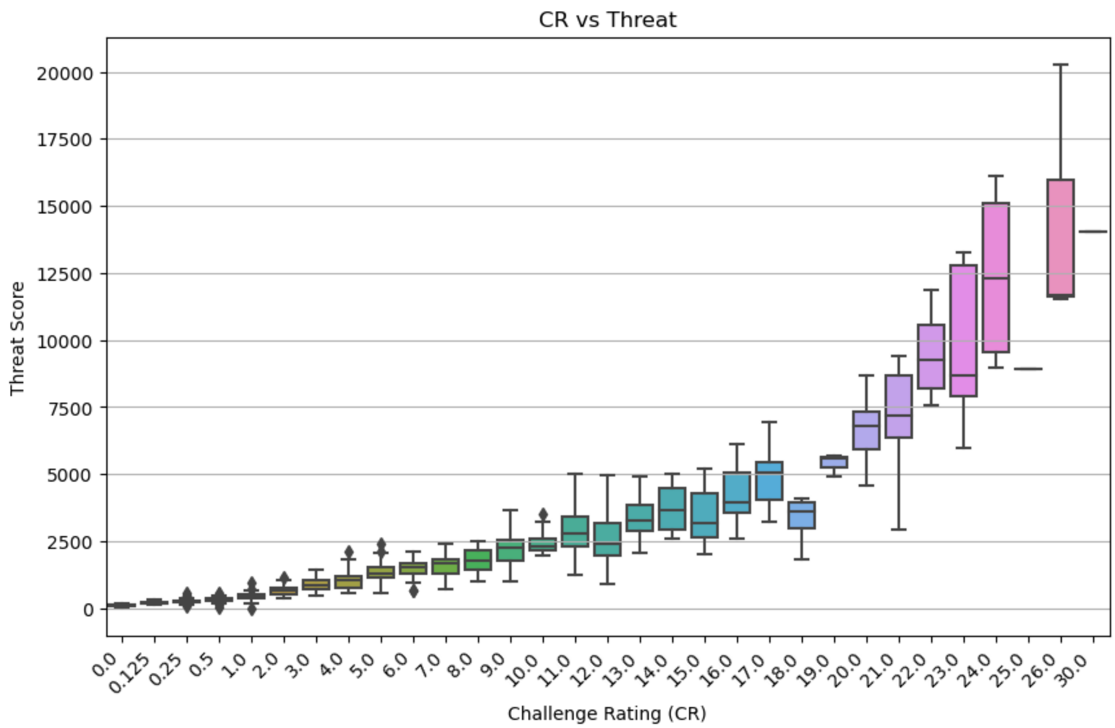


[46]:
```
def plot_threat_score_histograms_by_cr(df, cr_values=None, bins=10):
    """
    Plots histograms of threat scores grouped by CR,
    with a vertical line for each CR's average threat score.

```

```
    Parameters:
        df (DataFrame): Must include 'threat_score' and 'cr' columns.
        cr_values (list or None): List of CRs to plot. If None, uses all unique␣
↪CRs sorted.
        bins (int): Number of histogram bins.
    """
    if 'threat_score' not in df.columns:
        raise ValueError("DataFrame must contain 'threat_score' column.")

    if cr_values is None:
        cr_values = sorted(df['cr'].dropna().unique())

    n = len(cr_values)
    ncols = 3
    nrows = (n + ncols - 1) // ncols
    fig, axes = plt.subplots(nrows, ncols, figsize=(5 * ncols, 4 * nrows))
    axes = axes.flatten()

    for i, cr in enumerate(cr_values):
        subset = df[df['cr'] == cr]
        ax = axes[i]

        # Plot histogram
        sns.histplot(subset['threat_score'], bins=bins, ax=ax, kde=False)

        # Add average line
        mean_score = subset['threat_score'].mean()
        ax.axvline(mean_score, color='red', linestyle='--', linewidth=2,␣
↪label=f'Mean: {mean_score:.1f}')

        ax.set_title(f'CR {cr} - Threat Score Dist')
        ax.set_xlabel('Threat Score')
        ax.set_ylabel('Count')
        ax.legend()

    # Turn off unused subplots
    for j in range(i + 1, len(axes)):
        axes[j].axis('off')

    plt.tight_layout()
    plt.show()

plot_threat_score_histograms_by_cr(df)
```


CR 0.0 - Threat Score Dist
Mean: 110.5
CR 0.125 - Threat Score Dist
Mean: 202.7
CR 0.25 - Threat Score Dist
Mean: 264.7
CR 0.5 - Threat Score Dist
Mean: 314.5
CR 1.0 - Threat Score Dist
Mean: 444.4
CR 2.0 - Threat Score Dist
Mean: 650.9
CR 3.0 - Threat Score Dist
Mean: 873.4
CR 4.0 - Threat Score Dist
Mean: 1059.1
CR 5.0 - Threat Score Dist
Mean: 1330.3
CR 6.0 - Threat Score Dist
Mean: 1460.0
CR 7.0 - Threat Score Dist
Mean: 1618.9
CR 8.0 - Threat Score Dist
Mean: 1785.9
CR 9.0 - Threat Score Dist
Mean: 2163.4
CR 10.0 - Threat Score Dist
Mean: 2449.2
CR 11.0 - Threat Score Dist
Mean: 2967.5
CR 12.0 - Threat Score Dist
Mean: 2594.7
CR 13.0 - Threat Score Dist
Mean: 3335.9
CR 14.0 - Threat Score Dist
Mean: 3701.7
CR 15.0 - Threat Score Dist
Mean: 3456.5
CR 16.0 - Threat Score Dist
Mean: 4246.7
CR 17.0 - Threat Score Dist
Mean: 4920.8
CR 18.0 - Threat Score Dist
Mean: 3282.8
CR 19.0 - Threat Score Dist
Mean: 5388.9
CR 20.0 - Threat Score Dist
Mean: 6652.7
CR 21.0 - Threat Score Dist
Mean: 7121.3
CR 22.0 - Threat Score Dist
Mean: 9488.2
CR 23.0 - Threat Score Dist
Mean: 9627.9
CR 24.0 - Threat Score Dist
Mean: 12404.3
CR 25.0 - Threat Score Dist
Mean: 8928.7
CR 26.0 - Threat Score Dist
Mean: 14493.9
CR 30.0 - Threat Score Dist
Mean: 14020.0

[47]:
```
plt.figure(figsize=(10,6))
sns.boxplot(x='cr', y='threat_score', data=df)
plt.grid(visible=True, axis='y')
plt.xticks(rotation=45, ha='right')
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Threat Score')
plt.title('CR vs Threat')
plt.show()
```



[48]:
```
df.groupby('cr')['threat_score'].describe()
```

[48]:

cr	count	mean	std	min	25% \
0.000	32.0	110.494792	32.291528	51.000000	84.791667
0.125	29.0	202.689655	58.235934	107.500000	157.666667
0.250	62.0	264.680108	81.347919	72.833333	218.875000
0.500	46.0	314.452899	90.762529	12.000000	277.291667
1.000	62.0	444.424731	138.356317	0.000000	372.333333
2.000	81.0	650.907407	160.152735	345.000000	526.166667
3.000	54.0	873.373457	210.483869	451.500000	724.416667
4.000	36.0	1059.097222	356.743742	541.333333	761.458333

5.000	54.0	1330.349537	364.642528	584.000000	1133.375000
6.000	24.0	1459.951389	378.889770	641.333333	1299.375000
7.000	27.0	1618.938272	423.353798	712.500000	1302.833333
8.000	22.0	1785.863636	447.491221	987.500000	1450.333333
9.000	24.0	2163.416667	670.103228	975.000000	1780.166667
10.000	22.0	2449.151515	417.313105	1950.666667	2137.500000
11.000	18.0	2967.460648	936.171385	1216.000000	2301.000000
12.000	15.0	2594.700000	1063.320098	876.000000	1942.333333
13.000	18.0	3335.856481	806.778751	2058.000000	2877.250000
14.000	10.0	3701.741667	878.900197	2570.500000	2938.166667
15.000	7.0	3456.452381	1250.688354	2029.500000	2614.583333
16.000	12.0	4246.663194	1165.103689	2606.666667	3564.750000
17.000	10.0	4920.779167	1219.811427	3233.333333	4033.000000
18.000	4.0	3282.812500	1014.657245	1833.333333	2967.083333
19.000	3.0	5388.916667	429.967449	4893.666667	5249.958333
20.000	7.0	6652.702381	1337.721651	4561.333333	5914.041667
21.000	8.0	7121.328125	2092.934104	2945.000000	6332.968750
22.000	4.0	9488.229167	1901.992570	7585.000000	8176.562500
23.000	9.0	9627.861111	2798.188459	5967.000000	7915.833333
24.000	4.0	12404.270833	3562.813508	8972.083333	9563.020833
25.000	1.0	8928.666667	NaN	8928.666667	8928.666667
26.000	3.0	14493.888889	5014.835220	11517.083333	11598.958333
30.000	1.0	14020.000000	NaN	14020.000000	14020.000000

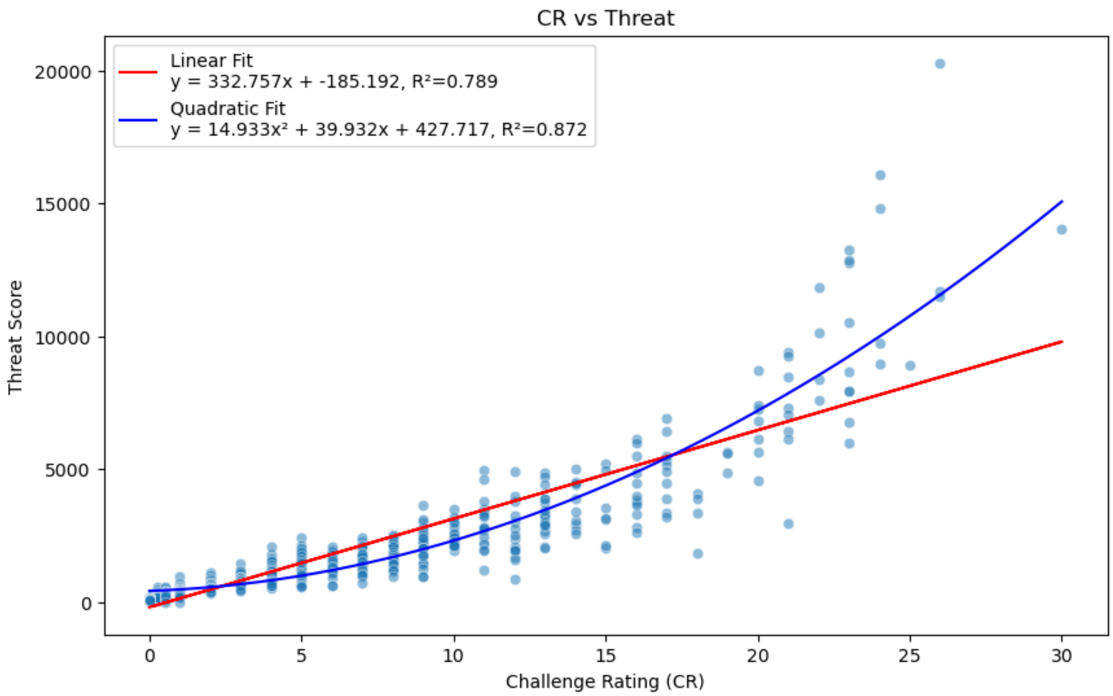
	50%	75%	max
cr			
0.000	116.416667	136.875000	171.000000
0.125	189.000000	242.666667	341.333333
0.250	247.000000	290.250000	573.333333
0.500	319.000000	354.083333	562.500000
1.000	441.666667	505.875000	950.000000
2.000	655.500000	746.666667	1120.000000
3.000	849.500000	1046.500000	1435.500000
4.000	1034.000000	1204.166667	2107.333333
5.000	1274.166667	1510.427083	2408.833333
6.000	1506.583333	1686.333333	2106.333333
7.000	1696.000000	1819.750000	2414.000000
8.000	1746.083333	2169.500000	2506.666667
9.000	2242.416667	2557.125000	3673.666667
10.000	2278.750000	2609.416667	3495.333333
11.000	2799.166667	3409.583333	4986.000000
12.000	2392.000000	3146.500000	4940.000000
13.000	3261.416667	3847.812500	4887.666667
14.000	3668.708333	4456.041667	4995.833333
15.000	3177.500000	4280.750000	5197.500000
16.000	3922.625000	5040.750000	6113.333333
17.000	5029.666667	5456.208333	6932.291667

```
18.000   3608.958333   3924.687500   4080.000000
19.000   5606.250000   5636.541667   5666.833333
20.000   6805.333333   7338.645833   8696.875000
21.000   7180.000000   8671.250000   9400.833333
22.000   9261.875000  10573.541667  11844.166667
23.000   8663.333333  12784.583333  13255.208333
24.000  12275.833333  15117.083333  16093.333333
25.000   8928.666667   8928.666667   8928.666667
26.000  11680.833333  15982.291667  20283.750000
30.000  14020.000000  14020.000000  14020.000000
```

[49]:
```python
x = df['cr']
y = df['threat_score']

print('Linear Model')
(slope, intercept), eq, r2 = fit_model(df, 'cr', 'threat_score')
print(eq)
print(f"R² = {r2:.3f}", end='\n\n')

print('Quadratic Model')
quad_params, quad_eq, quad_r2 = fit_model(df, 'cr', 'threat_score',␣
 ↪model='quadratic')
print(quad_eq)
print(f"R² = {quad_r2:.3f}", end='\n\n')

# Filter and sort x values for smooth curves
x_vals = np.linspace(df['cr'].min(), df['cr'].max(), 500)

# Quadratic predictions
a, b, c = quad_params
y_quad = a * x_vals**2 + b * x_vals + c


plt.figure(figsize=(10, 6))
sns.scatterplot(x=x, y=y, alpha=0.5)
plt.plot(x, slope * x + intercept, color='red', label=f'Linear Fit\n{eq},␣
 ↪R²={r2:.3f}')
plt.plot(x_vals, y_quad, color='blue', label=f'Quadratic Fit\n{quad_eq},␣
 ↪R²={quad_r2:.3f}')
plt.legend()
plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Threat Score')
plt.title('CR vs Threat')
plt.show()
```

```
Linear Model
y = 332.757x + -185.192
```

```
R² = 0.789

Quadratic Model
y = 14.933x² + 39.932x + 427.717
R² = 0.872
```



6 Deeper Insights

6.1 Correlation Analysis

[50]:
```python
df[['cr', 'hp', 'ac', 'avg_stat', 'threat_score', 'str', 'dex', 'con', 'int', 'wis', 'cha']].corr()
```

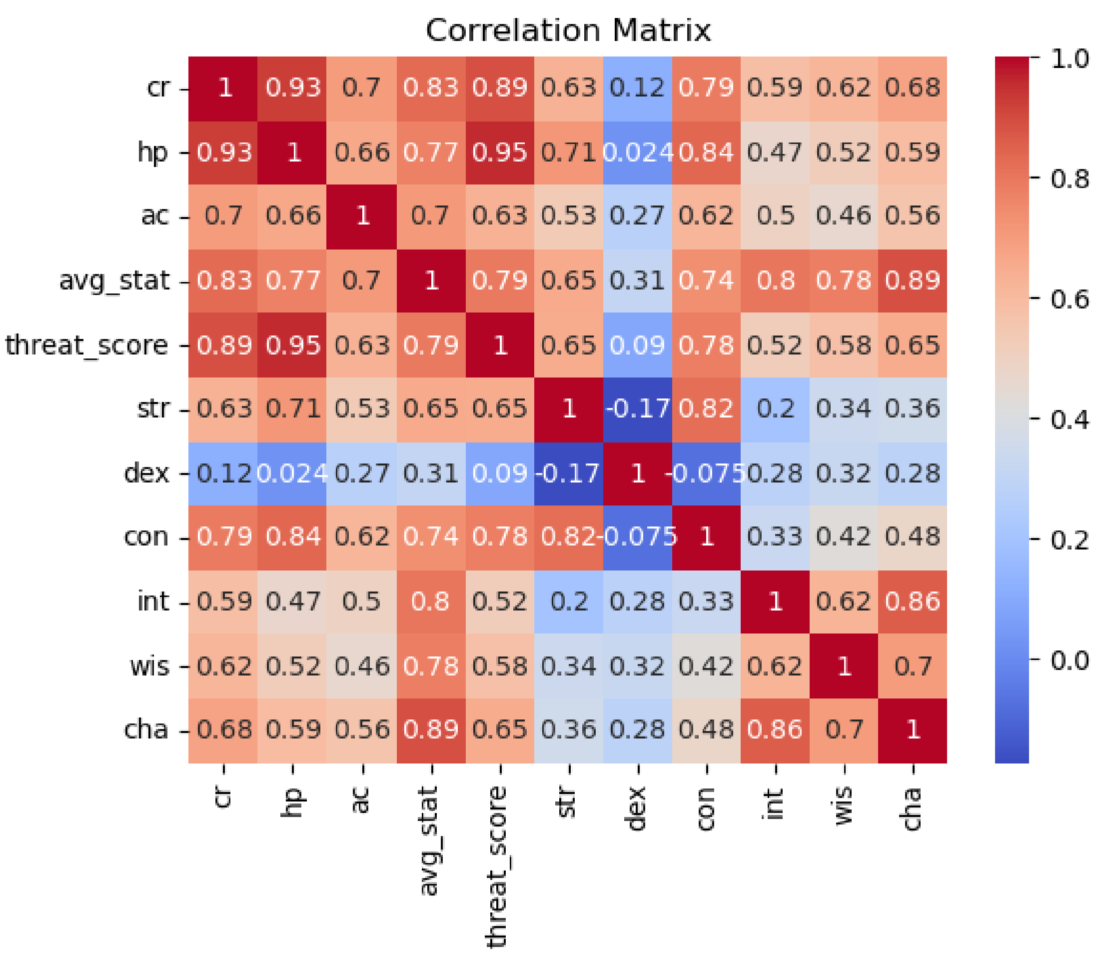
[50]:

	cr	hp	ac	avg_stat	threat_score	str \
cr	1.000000	0.926380	0.701578	0.827814	0.888536	0.631455
hp	0.926380	1.000000	0.664352	0.774670	0.954234	0.711987
ac	0.701578	0.664352	1.000000	0.704503	0.631692	0.530732
avg_stat	0.827814	0.774670	0.704503	1.000000	0.791992	0.653128
threat_score	0.888536	0.954234	0.631692	0.791992	1.000000	0.649389
str	0.631455	0.711987	0.530732	0.653128	0.649389	1.000000
dex	0.118485	0.023997	0.270235	0.307754	0.089949	-0.174191
con	0.786505	0.839105	0.618817	0.735757	0.776669	0.820693
int	0.585904	0.471107	0.495110	0.798263	0.516958	0.199732

```
wis            0.615923  0.515117  0.459228  0.777288      0.576891  0.337467
cha            0.677921  0.593221  0.563252  0.887636      0.647376  0.356530

                    dex       con       int       wis       cha
cr             0.118485  0.786505  0.585904  0.615923  0.677921
hp             0.023997  0.839105  0.471107  0.515117  0.593221
ac             0.270235  0.618817  0.495110  0.459228  0.563252
avg_stat       0.307754  0.735757  0.798263  0.777288  0.887636
threat_score   0.089949  0.776669  0.516958  0.576891  0.647376
str           -0.174191  0.820693  0.199732  0.337467  0.356530
dex            1.000000 -0.074904  0.279154  0.323429  0.281255
con           -0.074904  1.000000  0.327629  0.422467  0.475398
int            0.279154  0.327629  1.000000  0.622356  0.859989
wis            0.323429  0.422467  0.622356  1.000000  0.697338
cha            0.281255  0.475398  0.859989  0.697338  1.000000
```

[51]:

```python
sns.heatmap(df[['cr', 'hp', 'ac', 'avg_stat', 'threat_score', 'str', 'dex',
 'con', 'int', 'wis', 'cha']].corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```

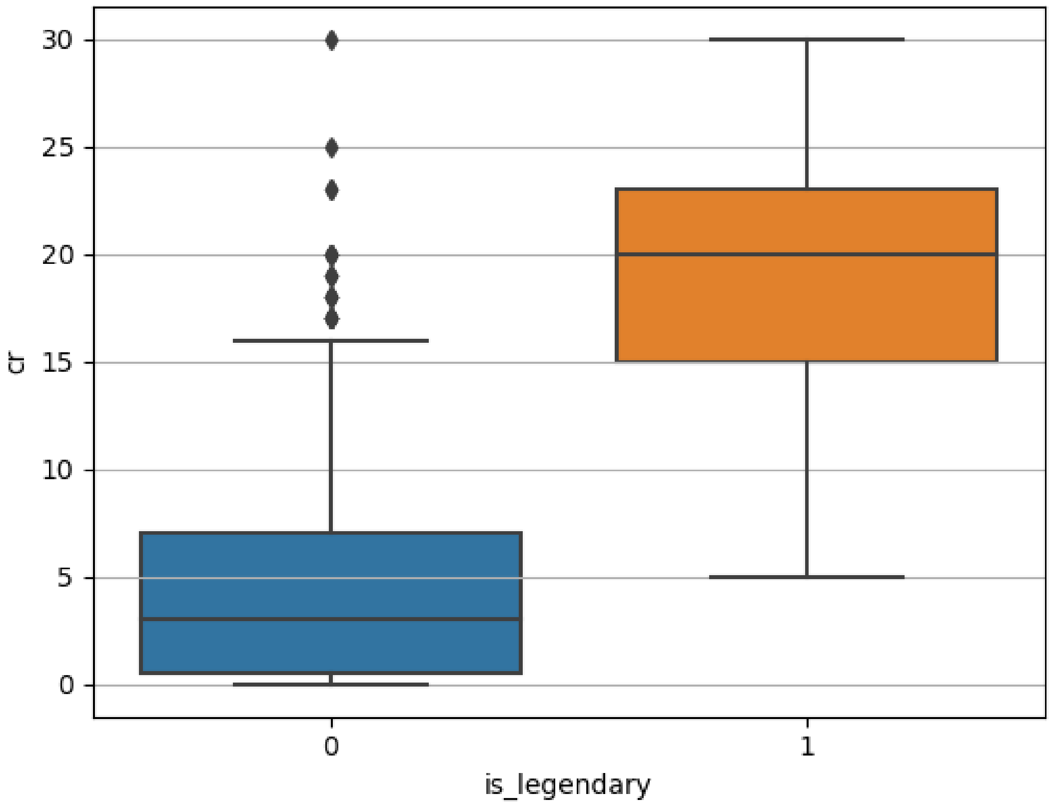


6.2 Legendary Monsters

How do legendary monsters compare to ordinary monsters?

6.2.1 Challenge Rating

[52]:
```
sns.boxplot(x='is_legendary', y='cr', data=df)
plt.grid(axis='y')
plt.show()
```



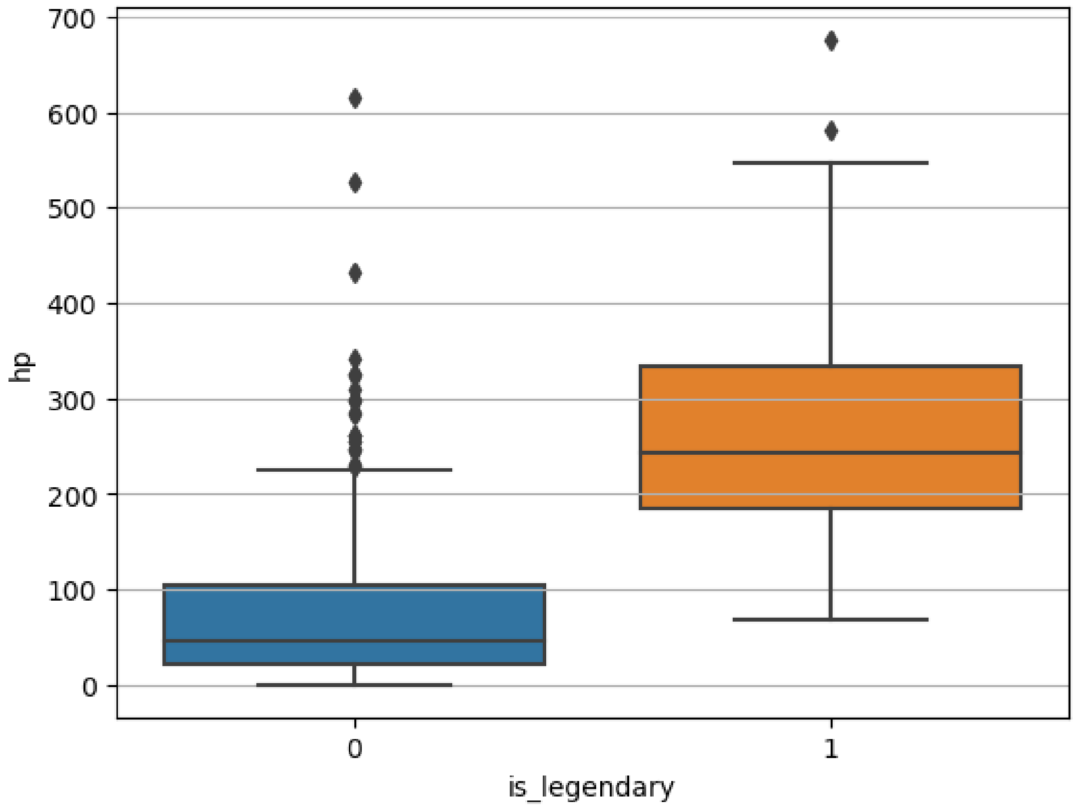
[53]:
```
df.groupby('is_legendary')['cr'].describe()
```

[53]:

is_legendary	count	mean	std	min	25%	50%	75%	max
0	697.0	4.327654	4.814827	0.0	0.5	3.0	7.0	30.0
1	65.0	18.615385	4.801342	5.0	15.0	20.0	23.0	30.0

6.2.2 Hit Points

[54]:
```
sns.boxplot(x='is_legendary', y='hp', data=df)
plt.grid(axis='y')
plt.show()
```



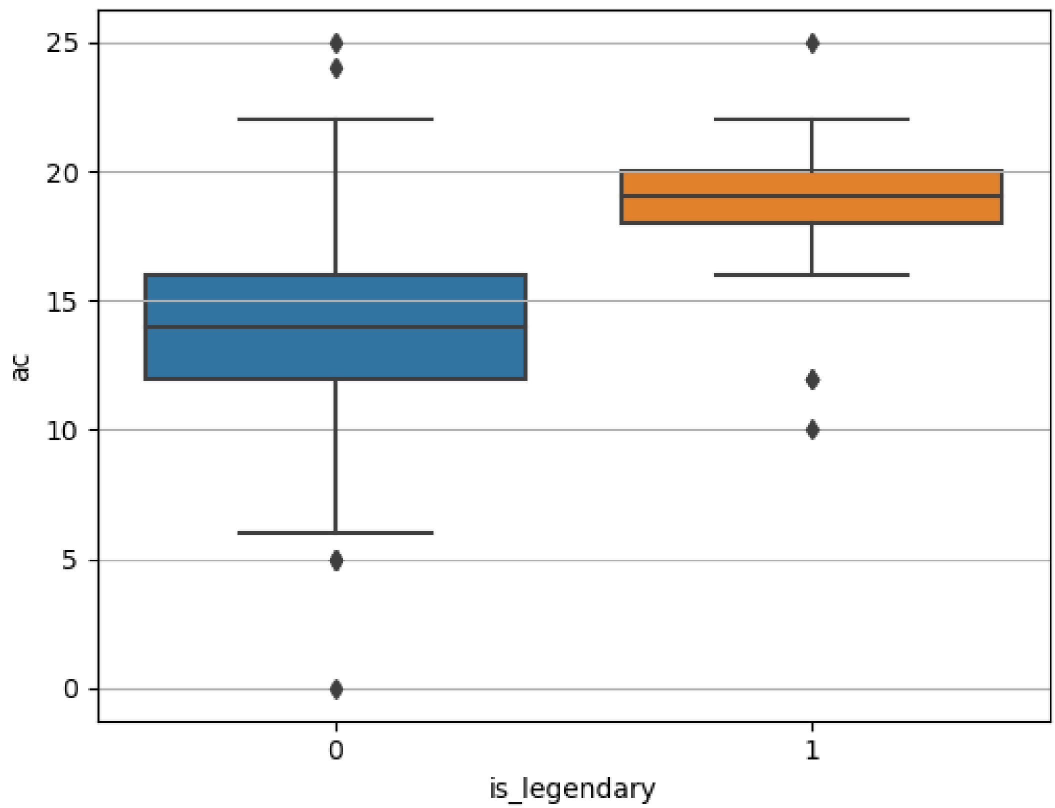
[55]:
```
df.groupby('is_legendary')['hp'].describe()
```

[55]:

is_legendary	count	mean	std	min	25%	50%	75%	max
0	697.0	71.222382	70.454850	0.0	22.0	45.0	104.0	615.0
1	65.0	269.430769	128.190163	67.0	184.0	243.0	333.0	676.0

6.2.3 Armor Class

[56]:
```
sns.boxplot(x='is_legendary', y='ac', data=df)
plt.grid(axis='y')
plt.show()
```



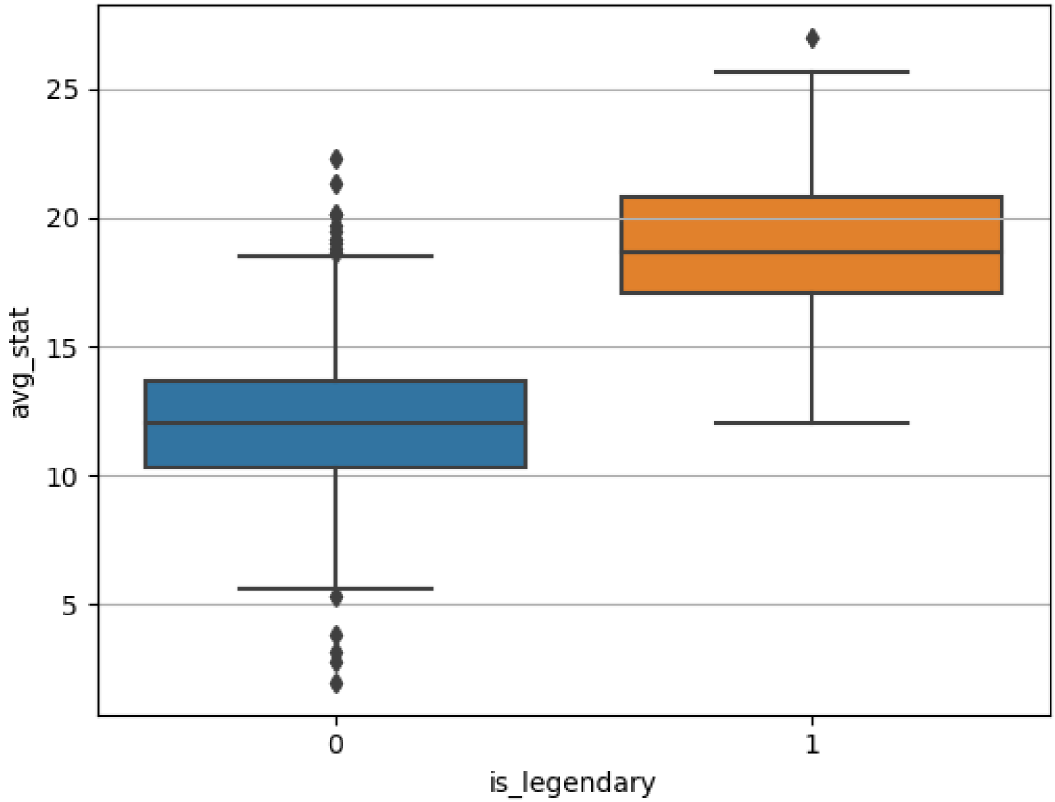
[57]:
```
df.groupby('is_legendary')['ac'].describe()
```

[57]:

	count	mean	std	min	25%	50%	75%	max
is_legendary								
0	697.0	14.175036	2.884921	0.0	12.0	14.0	16.0	25.0
1	65.0	18.892308	2.469331	10.0	18.0	19.0	20.0	25.0

6.2.4 Average Stat

[58]:
```
sns.boxplot(x='is_legendary', y='avg_stat', data=df)
plt.grid(axis='y')
plt.show()
```

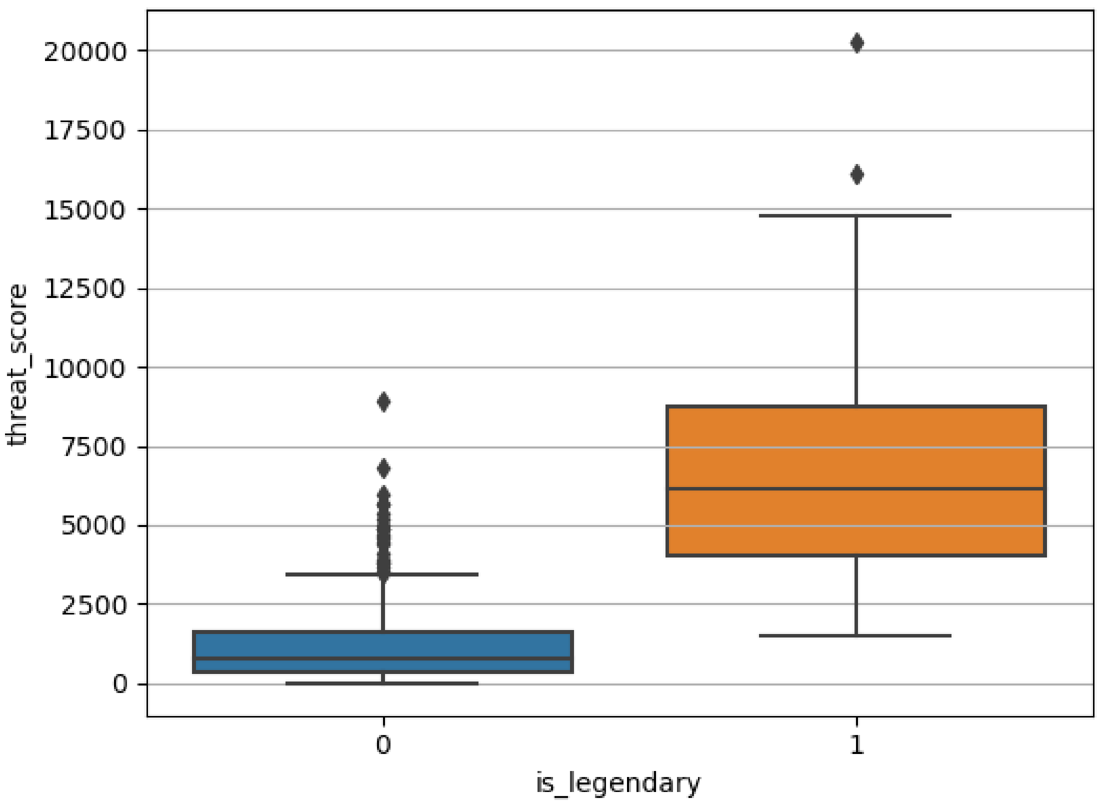


[59]:
```
df.groupby('is_legendary')['avg_stat'].describe()
```

[59]:
```
              count       mean       std   min        25%        50%  \
is_legendary
0             645.0  12.044186  2.789947   2.0  10.333333  12.000000
1              64.0  18.885417  2.803669  12.0  17.125000  18.666667

                    75%        max
is_legendary
0             13.666667  22.333333
1             20.833333  27.000000
```

6.2.5 Threat Score

[60]:
```
sns.boxplot(x='is_legendary', y='threat_score', data=df)
plt.grid(axis='y')
plt.show()
```



[61]:
```
df.groupby('is_legendary')['threat_score'].describe()
```

[61]:
```
              count         mean          std          min          25%  \
is_legendary
0             645.0  1146.647287  1114.769144     0.000000   351.333333
1              64.0  7018.740234  3795.938841  1497.708333  4005.312500

                      50%          75%           max
is_legendary
0              746.666667  1598.666667   8928.666667
1             6137.500000  8765.677083  20283.750000
```

6.2.6 Misc

[62]:
```
legendary = df[df['is_legendary'] == 1]
non_legendary = df[df['is_legendary'] == 0]

legendary_stats = legendary[['str', 'dex', 'con', 'int', 'wis', 'cha']].mean()
non_legendary_stats = non_legendary[['str', 'dex', 'con', 'int', 'wis', 'cha']].
 ↪mean()
```

```python
print('Legendary Average Stats')
print(legendary_stats, end='\n\n')
print('Non-legendary Average Stats')
print(non_legendary_stats)
```

```
Legendary Average Stats
str    23.171875
dex    13.968750
con    22.281250
int    16.500000
wis    17.515625
cha    19.875000
dtype: float64

Non-legendary Average Stats
str    14.289922
dex    13.162791
con    14.689922
int     8.677519
wis    11.646512
cha     9.798450
dtype: float64
```

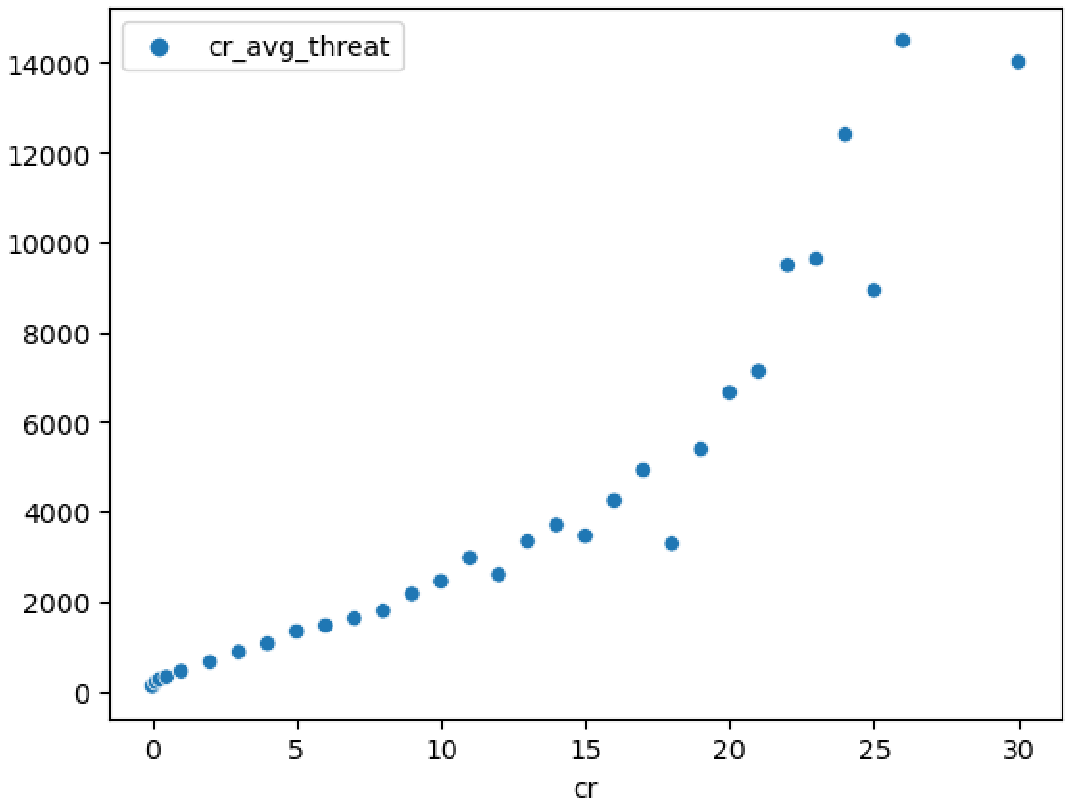
[63]:
```python
legendary['type_main'].value_counts()
```

[63]:
```
dragon          20
fiend           16
undead           6
monstrosity      5
aberration       5
celestial        4
elemental        4
humanoid         4
giant            1
Name: type_main, dtype: int64
```

7 Use-Case Scenarios

[64]:
```python
sns.scatterplot(df.groupby('cr')[['threat_score']].mean().
    ↪rename(columns={'threat_score': 'cr_avg_threat'}))
```

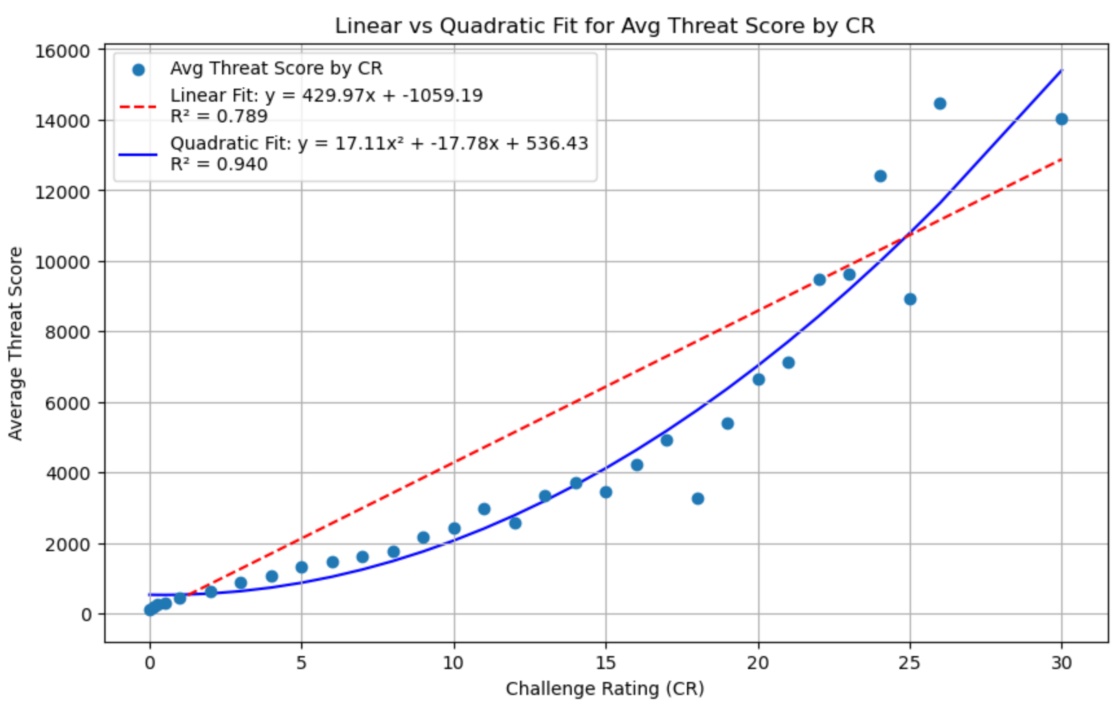
[64]:
```
<AxesSubplot: xlabel='cr'>
```



[65]:
```
grouped = df.groupby('cr')[['threat_score']].mean().
↪rename(columns={'threat_score': 'cr_avg_threat'}).reset_index()

x = grouped['cr'].values
y = grouped['cr_avg_threat'].values

# Fit a line
m, b_lin = np.polyfit(x, y, 1)
a, b, c = np.polyfit(x, y, 2)

# Predicted values for plotting
y_lin = m * x + b
y_quad = a * x**2 + b * x + c


# Total sum of squares
ss_tot = np.sum((y - np.mean(y)) ** 2)

# Linear R²
ss_res_lin = np.sum((y - y_lin) ** 2)
r2_lin = 1 - ss_res_lin / ss_tot
```

```python
# Quadratic R²
ss_res_quad = np.sum((y - y_quad) ** 2)
r2_quad = 1 - ss_res_quad / ss_tot

print(f"Linear Fit: R² = {r2_lin:.4f}")
print(f"Quadratic Fit: R² = {r2_quad:.4f}")


plt.figure(figsize=(10, 6))
plt.scatter(x, y, label='Avg Threat Score by CR', zorder=3)
plt.plot(x, y_lin, color='red', linestyle='--', label=f'Linear Fit: y = {m:.
↪2f}x + {b_lin:.2f}\nR² = {r2_lin:.3f}', zorder=2)
plt.plot(x, y_quad, color='blue', linestyle='-', label=f'Quadratic Fit: y = {a:.
↪2f}x² + {b:.2f}x + {c:.2f}\nR² = {r2_quad:.3f}', zorder=1)

plt.xlabel('Challenge Rating (CR)')
plt.ylabel('Average Threat Score')
plt.title('Linear vs Quadratic Fit for Avg Threat Score by CR')
plt.legend()
plt.grid(True)
plt.show()
```

```
Linear Fit: R² = 0.7895
Quadratic Fit: R² = 0.9405
```



[66]:
```
df['above_avg_threat'] = df['threat_score'] > df.groupby('cr')['threat_score'].
↪transform('mean')
```

[67]:
```
def suggest_monsters(df, party_level, top_n=5, include_legendary=False):
    # Estimate viable CR range
    min_cr = max(0, party_level - 1)
    max_cr = party_level + 1

    # Filter to CR range
    subset = df[(df['cr'] >= min_cr) & (df['cr'] <= max_cr)].copy()

    # Optionally filter legendary
    if not include_legendary:
        subset = subset[subset['is_legendary'] == 0]

    # Compare to average CR threat scores
    subset['cr_avg_threat'] = subset.groupby('cr')['threat_score'].
↪transform('mean')
    subset = subset[subset['threat_score'] > subset['cr_avg_threat']]

    # Return by threat score
    return subset.sort_values(by='threat_score', ascending=False)[
        ['name', 'cr', 'threat_score', 'avg_stat', 'type_main']
    ]
```

[68]:
```
suggested = suggest_monsters(df, party_level=1, top_n=5,␣
↪include_legendary=False)
print(suggested)
```

```
                  name   cr  threat_score   avg_stat  type_main
562     bandit-captain  2.0   1120.000000  14.000000   humanoid
571            pegasus  2.0   1029.500000  14.500000  celestial
559          berserker  2.0    986.666667  12.333333   humanoid
641       kuo-toa-whip  1.0    950.000000  12.500000   humanoid
558       plesiosaurus  2.0    918.000000  11.333333      beast
..                 …    …           …          …        …
745            octopus  0.0    117.500000   7.833333      beast
746                cat  0.0    116.666667   8.333333      beast
740               goat  0.0    116.666667   8.333333      beast
739  giant-fire-beetle  0.0    116.166667   6.833333      beast
748         cranium-rat  0.0    114.333333   8.166667      beast

[149 rows x 5 columns]
```

8 Summary

8.1 Save Summary

[69]:
```
df[['name', 'cr', 'hp', 'ac', 'avg_stat', 'threat_score']].
    ↪to_csv('monster_threat_summary.csv', index=False)
```

8.2 Monster Suggester

[70]:
```
import ipywidgets as widgets
from IPython.display import display, clear_output

# Create widgets
party_level_slider = widgets.IntSlider(value=5, min=1, max=20,␣
    ↪description='Party Level:')
legendary_toggle = widgets.Checkbox(value=False, description='Include␣
    ↪Legendary')

# Output area for results
output = widgets.Output()

# Callback function
def update_dashboard(change):
    with output:
        clear_output(wait=True)
        result = suggest_monsters(df, party_level=party_level_slider.value,␣
    ↪include_legendary=legendary_toggle.value)
        display(result)

# Trigger update when values change
party_level_slider.observe(update_dashboard, names='value')
legendary_toggle.observe(update_dashboard, names='value')

# Display widgets
display(party_level_slider, legendary_toggle, output)

# Run initial display
update_dashboard(None)
```

```
Widget Javascript not detected.  It may not be installed or enabled properly.
Reconnecting the current kernel may help.
```

```
Widget Javascript not detected.  It may not be installed or enabled properly.
Reconnecting the current kernel may help.
```

```
Widget Javascript not detected.  It may not be installed or enabled properly.
Reconnecting the current kernel may help.
```

8.3 Predict CR from Stats (Regression Model)

8.3.1 Predictive Modeling: CR Estimation

A random forest regressor is trained to predict Challenge Rating based on engineered features. This model is later used to estimate CR for custom monsters.

[71]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split

# Select features
features = ['hp', 'ac', 'avg_stat', 'threat_score', 'str', 'dex', 'con', 'int',␣
↪'wis', 'cha', 'is_legendary']
X = df[features]
y = df['cr']

# Drop rows with any NaNs in features or target
mask = X.notnull().all(axis=1) & y.notnull()
X = X[mask]
y = y[mask]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
model = RandomForestRegressor().fit(X_train, y_train)
```

[72]:
```
r2 = model.score(X_test, y_test)
print(f"R² on test set: {r2:.3f}")
```

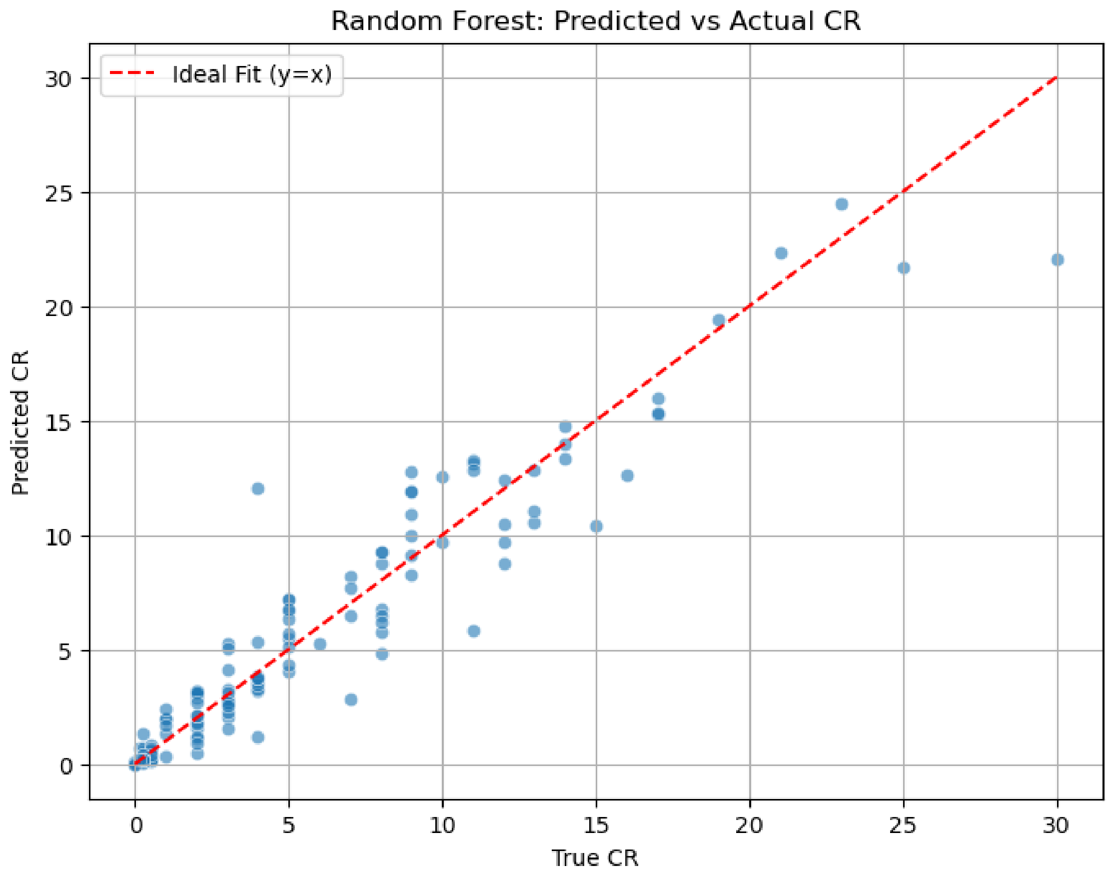
```
R² on test set: 0.914
```

[73]:
```
from sklearn.metrics import mean_absolute_error, mean_squared_error

y_pred = model.predict(X_test)

mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print(f"MAE: {mae:.2f}")
print(f"RMSE: {rmse:.2f}")
```

```
MAE: 1.06
RMSE: 1.69
```

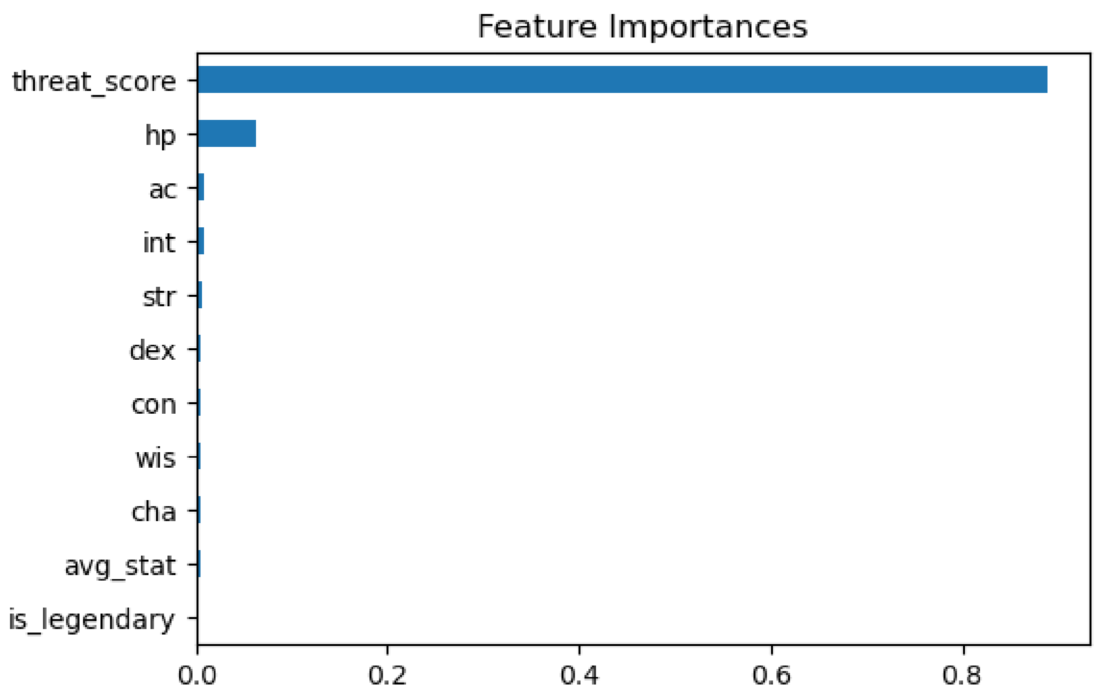
[74]:
```
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_test, y=y_pred, alpha=0.6)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--',␣
↪label='Ideal Fit (y=x)')
plt.xlabel('True CR')
plt.ylabel('Predicted CR')
plt.title('Random Forest: Predicted vs Actual CR')
```

```
plt.legend()
plt.grid(True)
plt.show()
```



[75]:
```
import pandas as pd

importances = pd.Series(model.feature_importances_, index=X.columns)
importances.sort_values(ascending=True).plot(kind='barh', figsize=(6, 4),␣
    ↪title='Feature Importances')
```

[75]: <AxesSubplot: title={'center': 'Feature Importances'}>



[76]:
```
custom = pd.DataFrame([{
    'hp': 100,
    'ac': 15,
    'avg_stat': 10,
    'threat_score': 1150,
    'str': 10,
    'dex': 10,
    'con': 10,
    'int': 10,
    'wis': 10,
    'cha': 10,
    'is_legendary': 0
}])
predicted_cr = model.predict(custom)
print(f"Estimated CR: {predicted_cr[0]:.1f}")
```

```
Estimated CR: 6.8
```

8.3.2 Advanced Monster CR Estimator

This tool uses the random forest regressor in a dashboard format.

[77]:
```
import ipywidgets as widgets
from IPython.display import display, clear_output
import pandas as pd
```

```python
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# Inputs
hp_input = widgets.IntText(value=100, description='HP:')
ac_input = widgets.IntText(value=15, description='AC:')
str_input = widgets.IntText(value=10, description='STR:')
dex_input = widgets.IntText(value=10, description='DEX:')
con_input = widgets.IntText(value=10, description='CON:')
int_input = widgets.IntText(value=10, description='INT:')
wis_input = widgets.IntText(value=10, description='WIS:')
cha_input = widgets.IntText(value=10, description='CHA:')
legendary_input = widgets.Checkbox(value=False, description='Legendary Monster?
 ↪')
estimate_button = widgets.Button(description='Estimate CR')
cr_output = widgets.Output()

# Logic
def estimate_cr(btn):
    with cr_output:
        clear_output()

        # Collect input
        abilities = {
            'str': str_input.value,
            'dex': dex_input.value,
            'con': con_input.value,
            'int': int_input.value,
            'wis': wis_input.value,
            'cha': cha_input.value
        }
        avg_stat = sum(abilities.values()) / 6
        hp = hp_input.value
        ac = ac_input.value
        is_legendary = 1.25 if legendary_input.value else 1
        threat_score = avg_stat * (hp + ac) * is_legendary

        # Predict CR
        input_data = pd.DataFrame([{
            'hp': hp,
            'ac': ac,
            'avg_stat': avg_stat,
            'threat_score': threat_score,
            'str': str_input.value,
            'dex': dex_input.value,
            'con': con_input.value,
```

```
            'int': int_input.value,
            'wis': wis_input.value,
            'cha': cha_input.value,
            'is_legendary': legendary_input.value
        }])
        predicted_cr = model.predict(input_data)[0]
        predicted_cr_rounded = round(predicted_cr)

        # Display numeric results
        print(f"Threat Score: {threat_score:.0f}")
        print(f"Estimated Challenge Rating (CR): {predicted_cr:.1f}")

        # --- Plot Threat Score vs CR ---
        plt.figure(figsize=(8, 5))
        grouped = df.groupby('cr')['threat_score'].mean().reset_index()
        sns.lineplot(data=grouped, x='cr', y='threat_score', label='Average Threat Score')
        plt.axhline(threat_score, color='red', linestyle='--', label='Your Monster')
        plt.axvline(predicted_cr, color='gray', linestyle=':', label='Predicted CR')
        plt.title('Threat Score vs CR')
        plt.xlabel('CR')
        plt.ylabel('Average Threat Score')
        plt.legend()
        plt.grid(True)
        plt.tight_layout()
        plt.show()

        # --- Compare with average monster at predicted CR ---
        if predicted_cr_rounded in df['cr'].values:
            cr_group = df[df['cr'] == predicted_cr_rounded]
            print("\nComparison to Average Monster at CR", predicted_cr_rounded)
            print(f" - Avg HP:         {cr_group['hp'].mean():.0f}")
            print(f" - Avg AC:         {cr_group['ac'].mean():.0f}")
            print(f" - Avg Stat:       {cr_group['avg_stat'].mean():.2f}")
            print(f" - Avg ThreatScore:{cr_group['threat_score'].mean():.0f}")
        else:
            print("\nNo monsters with CR =", predicted_cr_rounded, "in your dataset.")

# Bind to button
estimate_button.on_click(estimate_cr)

# Display widgets
display(widgets.VBox([
    widgets.HTML("<h3>Advanced Monster CR Estimator</h3>"),
```

```
    hp_input, ac_input,
    str_input, dex_input, con_input,
    int_input, wis_input, cha_input,
    legendary_input,
    estimate_button,
    cr_output
]))
```

```
Widget Javascript not detected.  It may not be installed or enabled properly.
Reconnecting the current kernel may help.
```

8.4 Conclusion

This project demonstrates a data-driven approach to evaluating and predicting the Challenge Rating (CR) of Dungeons & Dragons 5e monsters. By analyzing combat-relevant statistics across a large dataset of official creatures, we engineered a composite metric — the **Threat Score** — designed to quantify monster effectiveness through a combination of:

- **Hit Points (HP)** – reflecting durability
- **Armor Class (AC)** – capturing evasiveness
- **Average Ability Scores (STR–CHA)** – representing overall power
- **Legendary Status** – adjusting impact for action economy and encounter-shaping traits

We explored the relationship between these variables and the official CR values through both statistical visualizations and regression modeling. A **Random Forest Regressor** was trained to predict CR from the constructed features with reasonable fidelity, and further refined by incorporating legendary traits as a multiplicative modifier.

To make the model interactive and practically useful, an **interactive dashboard** was built using `ipywidgets` and deployed via `Voila`. This allows users to:

- Input custom monster stats (HP, AC, STR–CHA, Legendary)
- Instantly receive a predicted CR and calculated threat score
- Visually compare against the average threat score for each CR
- Benchmark against official monsters from the dataset

8.4.1 Key Insights:

- CR correlates strongly with HP and average stats, but not perfectly — special abilities and encounter design also matter.
- Legendary monsters consistently skew threat higher than their CR alone suggests.
- The threat score provides a more continuous and interpretable metric than CR alone, especially for fine-tuning homebrew balance.

8.4.2 Limitations:

- The model does not account for resistances, immunities, multiattack, magic, or terrain advantages.
- Some CRs are underrepresented in the dataset, which can reduce prediction accuracy.
- Threat score is a simplification and does not capture narrative or situational context.

8.4.3 Potential Next Steps:

- Incorporate **action economy**, resistances, and offensive traits into the model
- Extend the dashboard with **XP budgeting** and **party difficulty calibration**
- Train separate models for **legendary** and **non-legendary** monsters
- Create an interface for saving and exporting **homebrew monster stat blocks**

This project offers both an analytical foundation and a practical tool for game designers, DMs, and players seeking to better understand or balance monsters in combat scenarios. It bridges data science and storytelling, applying machine learning to a fantastical context with meaningful, game-enhancing results.

[ ]:

```

```