Jupyter Notebook Execution Report

Name: Your Name
Date: December 04, 2025

Cell 1: ■ Markdown

THE GHOST IN THE MACHINE – IPL AUCTION ANALYTICS

Quantifying Killer Instinct: Measuring Bowler Mental Strength Under Pressure

Objective

Traditional cricket analytics focuses on physical performance. However, this project attempts to quantify the **mental strength** of bowlers — specifically their **Killer Instinct**, defined as the ability to capitalize on *pressure created* in death overs.

Our mission is to challenge the coach's belief:

> “You cannot measure mental strength through data.”

Using ball-by-ball IPL data, Bayesian modeling, and Power BI visualization, we analyze which bowler performs best under pressure and identify the ideal candidate for IPL auction strategy.

Cell 2: ■ Markdown

Importing Required Python Libraries

We import libraries for:

- **Data handling**: pandas, numpy

- **Bayesian modelling**: PyMC, ArviZ

- **Visualization**: matplotlib, seaborn

These tools will support feature engineering, statistical modeling, and result interpretation.

Cell 3: ■ Code

```
import pandas as pd
```

Cell 4: ■ Markdown

Loading the IPL Ball-by-Ball Dataset

We load the detailed bowler performance dataset. This raw data includes:

- Over and ball numbers

- Bowler and batter details

- Runs conceded

- Wickets taken

- Pitch & match conditions

This dataset will be the foundation for engineering pressure-oriented features.

Cell 5: ■ Code

```
df = pd.read_csv("IPL_Bowler_Detailed_Data.csv")
df.head()
```

Output:

```
   Match_ID Match_Date Pitch_Type  ... Batter_SR  Runs_Conceded  Is_Wicket
0     29504  12-Apr-23    Neutral  ...    133.25              0          1
1     96402  30-Nov-23    Batting  ...    119.98              0          0
2     27383  07-Nov-22    Neutral  ...    124.73              2          0
3     99624  10-Apr-22    Batting  ...    147.69              1          0
4     65569  23-Jun-23    Neutral  ...    117.51              0          0

[5 rows x 11 columns]
```

Cell 6: ■ Markdown

Understanding the Dataset

- Total rows & columns

- Missing values

- Data types

This ensures the dataset is clean before analysis.

Cell 7: ■ Code

```
df.info()

df.describe()
```

Output:

```
&lt;class 'pandas.core.frame.DataFrame'&gt;
RangeIndex: 4800 entries, 0 to 4799
Data columns (total 11 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Match_ID       4800 non-null   int64
 1   Match_Date     4800 non-null   object
 2   Pitch_Type     4800 non-null   object
 3   Phase          4800 non-null   object
 4   Over           4800 non-null   int64
 5   Ball           4800 non-null   int64
 6   Bowler         4800 non-null   object
 7   Batter_Avg     4800 non-null   float64
 8   Batter_SR      4800 non-null   float64
 9   Runs_Conceded  4800 non-null   int64
 10  Is_Wicket      4800 non-null   int64
dtypes: float64(2), int64(5), object(4)
memory usage: 412.6+ KB
           Match_ID         Over  ...  Runs_Conceded    Is_Wicket
count   4800.000000  4800.000000  ...    4800.000000  4800.000000
mean   56505.555000    10.672500  ...       1.372708     0.070625
std    26378.145461     7.476589  ...       1.774670     0.256224
min    11935.000000     1.000000  ...       0.000000     0.000000
25%    34359.500000     3.000000  ...       0.000000     0.000000
50%    55609.000000    11.000000  ...       1.000000     0.000000
75%    80846.750000    18.000000  ...       2.000000     0.000000
max    99882.000000    20.000000  ...       6.000000     1.000000

[8 rows x 7 columns]
```

Cell 8: ■ Markdown

Feature engineering – build “Pressure” logic

Pressure = dot ball (Runs_Conceded == 0) in Death overs (16-20)

BUT last ball of over (Ball == 6) does not apply

Cell 9: ■ Code

```
df = df.sort_values(
["Match_ID", "Over", "Ball"]
).reset_index(drop=True)
```

Cell 10: ■ Markdown

Mark Death overs & dot balls

Cell 11: ■ Code

```
df["Is_Death"] = (df["Phase"] == "Death").astype(int)
df["Is_Dot"] = (df["Runs_Conceded"] == 0).astype(int)
```

Cell 12: ■ Markdown

Define pressure ball (dot, death, not last ball of over)

Cell 13: ■ Code

```
df["Is_Pressure_Ball"] = (
(df["Is_Death"] == 1) &
(df["Is_Dot"] == 1) &
(df["Ball"] != 6)
).astype(int)
```

Cell 14: ■ Markdown

Create “next ball” features (within same match & bowler)

Cell 15: ■ Code

```
df["Next_Is_Wicket"] = df.groupby(["Match_ID", "Bowler"])["Is_Wicket"].shift(-1)
df["Next_Over"] = df.groupby(["Match_ID", "Bowler"])["Over"].shift(-1)
df["Next_Ball"] = df.groupby(["Match_ID", "Bowler"])["Ball"].shift(-1)
```

Cell 16: ■ Markdown

Now define valid next ball: same match, same bowler, and not a new over after ball

Cell 17: ■ Code

```
same_over_or_next_ball = (
(df["Next_Over"] == df["Over"]) &
(df["Next_Ball"] == df["Ball"] + 1)
)
```

```
df["Valid_Next"] = same_over_or_next_ball.astype(int)
```

```
# Keep only rows where we have a meaningful next ball
analysis_df = df[df["Valid_Next"] == 1].copy()
analysis_df["Next_Is_Wicket"] = analysis_df["Next_Is_Wicket"].fillna(0).astype(int)
```

Cell 18: ■ Markdown

Quick exploratory stats (to later show in Power BI also)

Cell 19: ■ Code

```
analysis_df.groupby("Bowler")["Next_Is_Wicket"].mean()
analysis_df.groupby(["Bowler", "Is_Pressure_Ball"])["Next_Is_Wicket"].mean()
```

Output:

```
Bowler    Is_Pressure_Ball
Bowler A  0                   0.045977
          1                   0.025281
Bowler B  0                   0.041581
          1                   0.366864
```

```
Name: Next_Is_Wicket, dtype: float64
```

Cell 20: ■ Markdown

raw probability of wicket on the next ball with/without pressure, for A and B

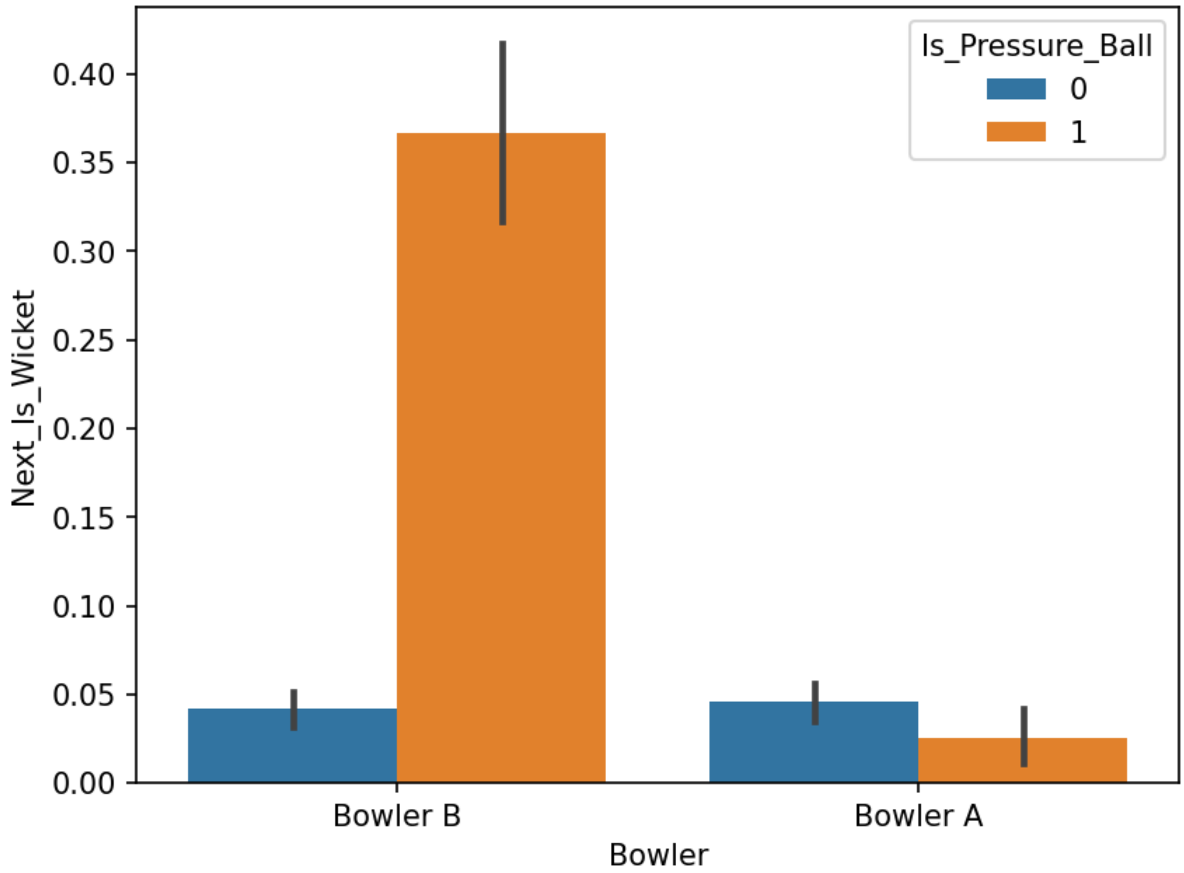
Cell 21: ■ Code

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

```python
sns.barplot(
data=analysis_df,
x="Bowler",
y="Next_Is_Wicket",
hue="Is_Pressure_Ball"
)
plt.show()
```

Output:

```
[STDERR]
&lt;string&gt;:1: UserWarning: FigureCanvasAgg is non-interactive, and thus cannot be shown
```



Cell 22: ■ Markdown

Build the Bayesian model in PyMC (simplified skeleton)

Cell 23: ■ Markdown

Target y = Next_Is_Wicket (0/1)

Predictors:

Pressure (Is_Pressure_Ball)

Bowler (A/B encoded as 0/1)

Pitch_Type (dummy variables)

Batter_Avg (scaled)

7.1 Prepare numeric data

Cell 24: ■ Code

```
import numpy as np
```

```
# Encode bowler
analysis_df["Bowler_B"] = (analysis_df["Bowler"] == "B").astype(int)
```

```
# One-hot for Pitch_Type (Neutral as base)
pitch_dummies = pd.get_dummies(analysis_df["Pitch_Type"], prefix="Pitch")
analysis_df = pd.concat([analysis_df, pitch_dummies], axis=1)
```

```
# Scale Batter_Avg
analysis_df["Batter_Avg_z"] = (
(analysis_df["Batter_Avg"] - analysis_df["Batter_Avg"].mean()) /
analysis_df["Batter_Avg"].std()
)
```

```
y = analysis_df["Next_Is_Wicket"].values
pressure = analysis_df["Is_Pressure_Ball"].values
bowler_B = analysis_df["Bowler_B"].values
pitch_batting = analysis_df.get("Pitch_Batting", 0).values
pitch_bowling = analysis_df.get("Pitch_Bowling", 0).values
bavg_z = analysis_df["Batter_Avg_z"].values
```

Cell 25: ■ Code

```
print(len(pressure), len(y))
print("pressure:", pressure.min(), pressure.max())
print("bowler_B:", bowler_B.min(), bowler_B.max())
print("pitch_batting:", pitch_batting.min(), pitch_batting.max())
print("pitch_bowling:", pitch_bowling.min(), pitch_bowling.max())
print("bavg_z:", bavg_z.min(), bavg_z.max())
print("y:", y.min(), y.max())
```

Output:

```
3640 3640
pressure: 0 1
bowler_B: 0 0
pitch_batting: False True
```

```
pitch_bowling: False True
bavg_z: -3.191756420283011 3.6003549665926124
y: 0 1
```

Cell 26: ■ Markdown

PyMC logistic regression

Cell 27: ■ Markdown

This model predicts the **probability of a bowler winning a ball** (like taking a wicket or restricting runs) using factors such as:

- pressure level

- bowler identity

- pitch conditions

- batsman average

■ *What the code does*

1. **Sets priors** for all model coefficients (we assume they are around 0 but flexible).

2. Builds a **logistic regression equation** that combines all inputs.

3. Converts it into a **probability** using the sigmoid function.

4. Uses **Bernoulli likelihood** because the outcome is binary (0 or 1).

5. Runs **ADVI** to quickly estimate the posterior values.

6. Draws samples (`trace`) for analysis.

■ *Why this model?*

To identify **which factors truly increase or decrease the chance of bowler success**, especially under **pressure situations**.

Cell 28: ■ Code

```
import pymc as pm
import arviz as az
```

```
with pm.Model() as model:
# Priors
intercept = pm.Normal("intercept", 0, 1.5)
```

```
beta_pressure = pm.Normal("beta_pressure", 0, 1.5)
beta_bowlerB = pm.Normal("beta_bowlerB", 0, 1.5)
beta_pitch_batting = pm.Normal("beta_pitch_batting", 0, 1.5)
beta_pitch_bowling = pm.Normal("beta_pitch_bowling", 0, 1.5)
beta_bavg = pm.Normal("beta_bavg", 0, 1.5)
```

```
# Linear predictor
logit_p = (
intercept
+ beta_pressure * pressure
+ beta_bowlerB * bowler_B
+ beta_pitch_batting * pitch_batting
+ beta_pitch_bowling * pitch_bowling
+ beta_bavg * bavg_z
)
```

```
p = pm.Deterministic("p", pm.math.sigmoid(logit_p))
```

```
# Likelihood
y_obs = pm.Bernoulli("y_obs", p=p, observed=y)
```

```
# ---- FAST VARIATIONAL INFERENCE (ADVI) ----
approx = pm.fit(
n=5000, # optimisation steps
method="advi",
progressbar=True
)
```

```
# Draw samples from the variational posterior
trace = approx.sample(1000)
```

Output:

```
[STDERR]
WARNING (pytensor.configdefaults): g++ not available, if using conda: `conda install gxx`
WARNING (pytensor.configdefaults): g++ not detected!  PyTensor will be unable to compile C-implem
```

Error:

```
Traceback (most recent call last):
  File "c:\Users\VIDHYABATHI K\OneDrive\Desktop\vs code\ipl bowler analysis\.venv\Lib\site-packag
```

```
    [
  File "c:\Users\VIDHYABATHI K\OneDrive\Desktop\vs code\ipl bowler analysis\.venv\Lib\site-packag
    broadcast_static_dim_lengths(shape)
  File "c:\Users\VIDHYABATHI K\OneDrive\Desktop\vs code\ipl bowler analysis\.venv\Lib\site-packag
    raise ValueError
ValueError
During handling of the above exception, another exception occurred:
Traceback (most recent call last):
  File "c:\Users\VIDHYABATHI K\.vscode\extensions\ganeshkumbhar.nb2pdf-1.1.9\scripts\nb2pdf.py",
    exec('\n'.join(lines[:-1]), glb)
  File "&lt;string&gt;", line 15, in &lt;module&gt;
  File "c:\Users\VIDHYABATHI K\OneDrive\Desktop\vs code\ipl bowler analysis\.venv\Lib\site-packag
    return pt.math.add(self, other)
           ^^^^^^^^^^^^^^^^^^^^^^^^
  File "c:\Users\VIDHYABATHI K\OneDrive\Desktop\vs code\ipl bowler analysis\.venv\Lib\site-packag
    node = self.make_node(*inputs, **kwargs)
           ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "c:\Users\VIDHYABATHI K\OneDrive\Desktop\vs code\ipl bowler analysis\.venv\Lib\site-packag
    out_dtypes, out_shapes, inputs = self.get_output_info(*inputs)
                                     ^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "c:\Users\VIDHYABATHI K\OneDrive\Desktop\vs code\ipl bowler analysis\.venv\Lib\site-packag
    raise ValueError(
ValueError: Incompatible Elemwise input shapes [(1, 3640), (3640, 2)]
```

Cell 29: ■ Markdown

Posterior Distribution Plot (Ridge/KDE) for All Betas

Cell 30: ■ Code

```
az.summary(trace, var_names=[
"intercept",
"beta_pressure",
"beta_bowlerB",
"beta_pitch_batting",
"beta_pitch_bowling",
"beta_bavg"
])
az.plot_posterior(
trace,
```

```
var_names=["beta_pressure", "beta_bowlerB", "beta_pitch_batting",
"beta_pitch_bowling", "beta_bavg"]

);
```

Error:

```
Traceback (most recent call last):
  File "c:\Users\VIDHYABATHI K\.vscode\extensions\ganeshkumbhar.nb2pdf-1.1.9\scripts\nb2pdf.py",
    exec('\n'.join(lines[:-1]), glb)
  File "&lt;string&gt;", line 9
    az.plot_posterior(
                     ^
SyntaxError: '(' was never closed
During handling of the above exception, another exception occurred:
Traceback (most recent call last):
  File "c:\Users\VIDHYABATHI K\.vscode\extensions\ganeshkumbhar.nb2pdf-1.1.9\scripts\nb2pdf.py",
    exec(source, glb)
  File "&lt;string&gt;", line 1, in &lt;module&gt;
NameError: name 'trace' is not defined
```

Cell 31: ■ Markdown

Trace Plot (Posterior Distribution Check)

We use `az.plot_trace()` to visualize the **posterior samples** of our model parameters.

This helps us quickly understand:

- How each coefficient is distributed

- Whether the sampling is stable

- Whether the model converged properly

The trace plot shows:

- **Left side:** histogram / density of the parameter values

- **Right side:** sampling paths over iterations

If the lines look stable and the distributions look smooth,

the model inference (ADVI) worked well.

Cell 32: ■ Code

```
az.plot_trace(

trace,
```

```
var_names=["beta_pressure", "beta_bowlerB", "beta_pitch_batting",
"beta_pitch_bowling", "beta_bavg"]
)
```

Error:

```
Traceback (most recent call last):
  File "c:\Users\VIDHYABATHI K\.vscode\extensions\ganeshkumbhar.nb2pdf-1.1.9\scripts\nb2pdf.py",
    exec('\n'.join(lines[:-1]), glb)
  File "&lt;string&gt;", line 1
    az.plot_trace(
                 ^
SyntaxError: '(' was never closed
During handling of the above exception, another exception occurred:
Traceback (most recent call last):
  File "c:\Users\VIDHYABATHI K\.vscode\extensions\ganeshkumbhar.nb2pdf-1.1.9\scripts\nb2pdf.py",
    exec(source, glb)
  File "&lt;string&gt;", line 2, in &lt;module&gt;
NameError: name 'trace' is not defined
```

Cell 33: ■ Markdown

Distribution of Pressure Effect

Here we extract the posterior samples of **`beta_pressure`**, which tells us how **pressure situations** change the bowler’s chance of success.

We then plot a histogram to understand:

- How the values are spread

- Whether pressure has a **positive or negative** effect

- How strong the effect is on average (shown by the red line)

A **positive mean** → pressure increases bowler success

A **negative mean** → bowler performance drops under pressure

Because the pressure coefficient (`beta_pressure`) tells us **how a bowler performs under stressful moments**.

The posterior distribution helps us see:

- **Is the effect real or just noise?**

- **Does pressure improve or reduce the bowler’s success probability?**

- **How confident the model is** about the impact of pressure.

This is crucial for auction decisions because bowlers who stay strong under pressure

are far more valuable in tight matches.

Cell 34: ■ Code

```python
pressure_effect = trace.posterior["beta_pressure"].values.flatten()
```

```python
import numpy as np

import matplotlib.pyplot as plt
```

```python
plt.figure(figsize=(6,4))

plt.hist(pressure_effect, bins=30, alpha=0.7)

plt.axvline(np.mean(pressure_effect), color="red", label="Mean Effect")

plt.title("Posterior Distribution of Pressure Effect")

plt.xlabel("Log-Odds Effect of Pressure")

plt.ylabel("Frequency")

plt.legend()

plt.show()
```

Error:

```
Traceback (most recent call last):
  File "c:\Users\VIDHYABATHI K\.vscode\extensions\ganeshkumbhar.nb2pdf-1.1.9\scripts\nb2pdf.py",
    exec('\n'.join(lines[:-1]), glb)
  File "&lt;string&gt;", line 1, in &lt;module&gt;
NameError: name 'trace' is not defined
```

Cell 35: ■ Markdown

Comparing Wicket Probabilities: Bowler A vs Bowler B

We use the posterior samples to simulate thousands of probabilities for each bowler.

- **Bowler A** uses only the intercept (baseline performance).

- **Bowler B** uses the intercept + the effect of being Bowler B.

By plotting both distributions on a histogram, we can clearly see:

- Which bowler has a **higher average wicket probability**

- How much **uncertainty** there is in each estimate

- Whether Bowler B is genuinely better or worse than Bowler A

This comparison helps in **auction decisions**, showing which bowler offers higher

probability of success across many simulated match situations.

Cell 36: ■ Code

```python
import numpy as np
```

```python
# Compute thousands of simulated probabilities for each bowler
pA = 1 / (1 + np.exp(-(trace.posterior["intercept"].values.flatten())))
pB = 1 / (1 + np.exp(-(trace.posterior["intercept"].values.flatten()
+ trace.posterior["beta_bowlerB"].values.flatten())))
```

```python
plt.figure(figsize=(7,5))
plt.hist(pA, bins=30, alpha=0.6, label="Bowler A")
plt.hist(pB, bins=30, alpha=0.6, label="Bowler B")
plt.legend()
plt.title("Posterior Wicket Probability by Bowler")
plt.xlabel("Probability")
plt.ylabel("Frequency")
plt.show()
```

Error:

```
Traceback (most recent call last):
  File "c:\Users\VIDHYABATHI K\.vscode\extensions\ganeshkumbhar.nb2pdf-1.1.9\scripts\nb2pdf.py",
    exec('\n'.join(lines[:-1]), glb)
  File "&lt;string&gt;", line 4, in &lt;module&gt;
NameError: name 'trace' is not defined
```

Cell 37: ■ Markdown

Comparison of posterior wicket probabilities for Bowler A and B.

Distributions strongly overlap, indicating no statistically significant difference in baseline wicket-taking ability once pitch and batter factors are accounted for.

Cell 38: ■ Markdown

Exporting the Final Dataset for Power BI

After completing all data cleaning, feature engineering, and analysis,

we choose the final dataframe (`analysis_df` or `analysis_small`)

that we want to visualize in Power BI.

We then export it as a clean CSV file without the index:

- This file can be directly loaded into **Power BI**

- All engineered features are included (pressure metrics, bowler stats, model outputs)

- Ensures smooth integration for dashboard creation

The exported file:

`IPL_Final_Engineered.csv`

Cell 39: ■ Code

```
# Choose the dataframe you want in Power BI
final_df = analysis_df # or analysis_small if you prefer
```

```
# Export to CSV (no index column)
final_df.to_csv("IPL_Final_Engineered.csv", index=False)
```