DATA MANIPULATION & PUBLICATION-GRADE PLOTS

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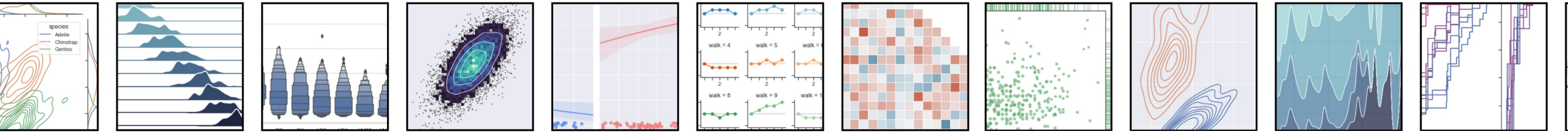
Feb 20, 2023



Publication-grade Plots?

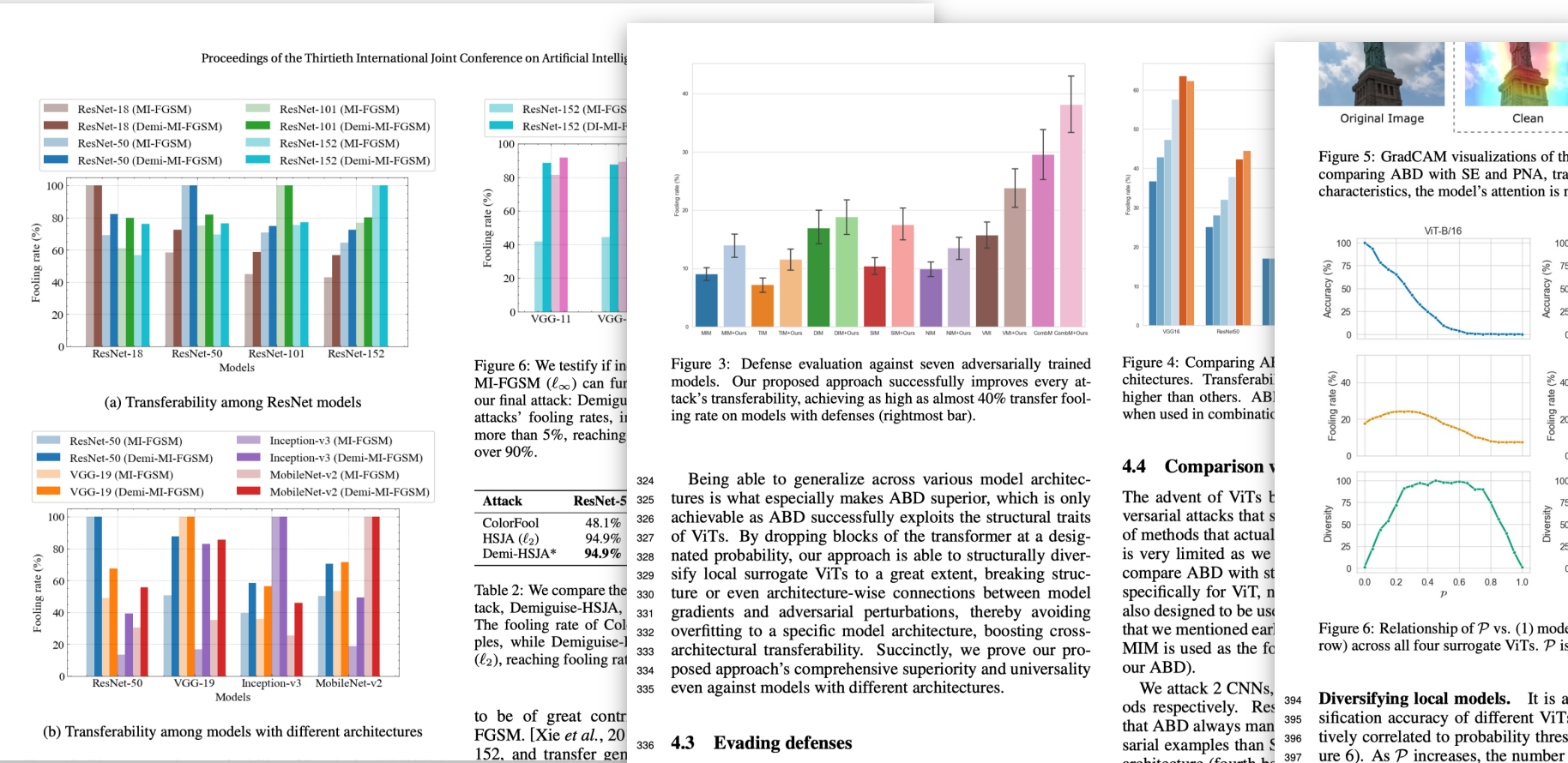


Figure 3: Defense evaluation against seven adversarially trained models. Our proposed approach successfully improves every attack's transferability, achieving as high as almost 40% transfer fooling rate on models with defenses (rightmost bar).

Being able to generalize across various model architectures is what especially makes ABD superior, which is only achievable as ABD successfully exploits the structural traits of ViTs. By dropping blocks of the transformer at a designated probability, our approach is able to structurally diversify local surrogate ViTs to a great extent, breaking structure or even architecture-wise connections between model gradients and adversarial perturbations, thereby avoiding overfitting to a specific model architecture, boosting cross-architectural transferability. Succinctly, we prove our proposed approach's comprehensive superiority and universality even against models with different architectures.

4.3 Evading defenses

Figure 4: Comparing AB
chitectures. Transferabi
higher than others. AB
when used in combinatio

4.4 Comparison

The advent of ViTs b
versarial attacks that s
of methods that actual
is very limited as we
compare ABD with st
specifically for ViT, n
also designed to be us
that we mentioned ear
MIM is used as the fo
our ABD).

We attack 2 CNNs,
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that ABD always man
sarial examples than S
architecture (fourth ba

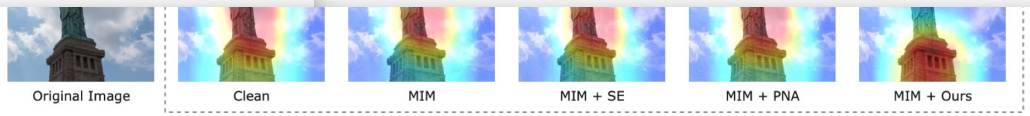


Figure 5: GradCAM visualizations of the model's attention on adversarial examples generated by compared methods (baseline attack MIM, comparing ABD with SE and PNA, transferring from T2T-ViT-24 to black-box ResNet50). Without exploiting ViT-specific architectural characteristics, the model's attention is not diverted, resulting in a failed transfer attack.

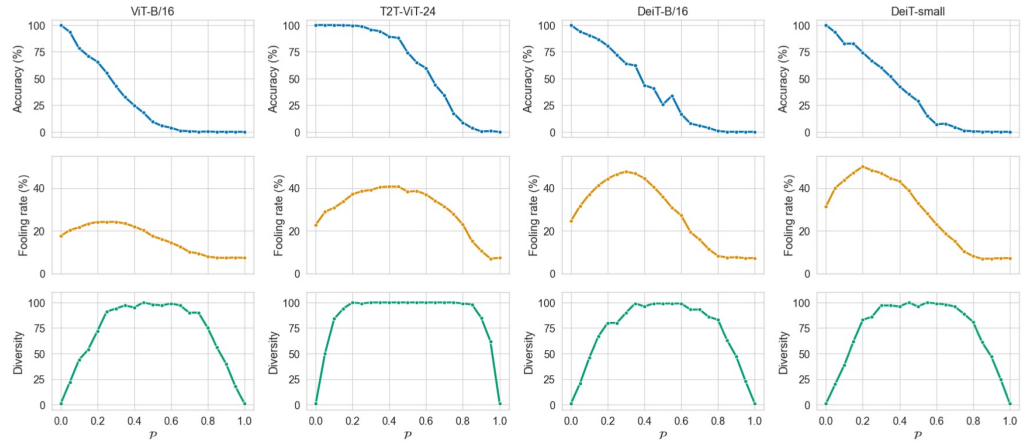


Figure 6: Relationship of $\mathcal{P}$ vs. (1) model accuracy (top row), (2) transfer fooling rate (middle row), and (3) model structure diversity (bottom row) across all four surrogate ViTs. $\mathcal{P}$ is grid searched within range $[0, 1]$ with a step size of 0.05.

Diversifying local models. It is as expected that the classification accuracy of different ViTs is almost always negatively correlated to probability threshold $\mathcal{P}$ (first row in Figure 6). As $\mathcal{P}$ increases, the number of dropped blocks in the transformer also increases, reducing the stability and accuracy of the ViT. However, this is the very act that enriches that exploit these architectural features. Our proposed approach involving dropping partial blocks is novel and flexible, achieving significant performance gains. Specifically, we find that ignoring the attention gradient generated by partial blocks at each iteration prevents overfitting from interfering with the self-attention mechanism, thereby improving

Data Manipulation

- Logging data: CSV, Excel, even plain text files.

Model	Attack	MIM	MIM+Ours	TIM	TIM+Ours	DIM	DIM+Ours
T2T-ViT-24	Inc-V3	10.50%	13.50%	8.10%	12.50%	17.70%	18.10%
T2T-ViT-24	Inc-V4	12.50%	18.20%	9.00%	16.60%	28.40%	30.20%
T2T-ViT-24	IncRes-v2	4.70%	6.40%	4.20%	5.50%	8.50%	8.80%
T2T-ViT-24	Res-v2	6.70%	11.50%	3.30%	7.20%	17.20%	20.00%
T2T-ViT-24	Inc-V3ens3	10.90%	13.80%	9.60%	11.30%	16.90%	17.60%
T2T-ViT-24	Inc-V3ens4	10.90%	14.20%	10.90%	12.70%	17.50%	18.10%
T2T-ViT-24	IncRes-v2ens	4.70%	6.40%	4.20%	5.50%	8.50%	8.80%
ViT-B/16	Inc-V3	9.50%	11.30%	7.50%	9.40%	12.50%	13.40%
ViT-B/16	Inc-V4	7.80%	11.90%	4.60%	7.10%	10.10%	12.90%
ViT-B/16	IncRes-v2	5.20%	7.10%	3.60%	4.80%	7.00%	8.20%
ViT-B/16	Res-v2	3.10%	4.40%	0.60%	1.60%	4.00%	5.00%
ViT-B/16	Inc-V3ens3	8.80%	10.00%	8.50%	10.00%	12.10%	13.50%
ViT-B/16	Inc-V3ens4	9.70%	12.00%	10.10%	11.80%	14.00%	15.00%
ViT-B/16	IncRes-v2ens	5.20%	7.10%	3.60%	4.80%	7.00%	8.20%
DeiT-B/16	Inc-V3	13.10%	20.00%	9.70%	15.90%	18.30%	22.00%
DeiT-B/16	Inc-V4	11.50%	24.10%	6.60%	16.70%	20.10%	23.00%
DeiT-B/16	IncRes-v2	6.20%	11.60%	5.00%	9.20%	10.90%	14.10%
DeiT-B/16	Res-v2	6.00%	16.30%	1.00%	8.40%	12.00%	14.40%
DeiT-B/16	Inc-V3ens3	10.10%	19.00%	9.10%	15.50%	17.20%	22.70%

defense.xlsx

```
outputs/True_DIM_MI_ResNet50_20_8_100_False
model_name succ_rate misclass_rate lpips
MyImageNetFastAT 0 314 0.2501748852990568
MyImageNetFreeAT 1 247 0.2501748852990568
Densenet121 90 406 0.2501748852990568
Densenet161 89 331 0.2501748852990568
Densenet169 101 351 0.2501748852990568
Densenet201 84 345 0.2501748852990568
InceptionV3 16 417 0.2501748852990568
VGG13 38 476 0.2501748852990568
VGG16 39 461 0.2501748852990568
VGG19 29 421 0.2501748852990568
Resnet18 67 484 0.2501748852990568
Resnet34 92 473 0.2501748852990568
Resnet50 998 999 0.2501748852990568
Resnet101 124 451 0.2501748852990568
Resnet152 94 374 0.2501748852990568
WideResnet50 105 403 0.2501748852990568
MyAdvEfficientnetb0 1 169 0.2501748852990568
MyAdvEfficientnetb1 2 140 0.2501748852990568
MyAdvEfficientnetb2 5 170 0.2501748852990568
```

outputs.txt

Data Manipulation

Recommended:

- File format: **CSV**.
- Use type-friendly: `csv.DictWriter`

Relevant Documentation

- Writing CSV File From a Dictionary With csv
- Python 3 - csv.DictReader/DictWriter

```python
import csv

header_fields = ["attack", "model", "eps", "fooling_rate"]
with open("results.csv", "w+") as f:
    writer = csv.DictWriter(f, fieldnames=header_fields)
    writer.writeheader()

    # Iterate over all experiments
    for some_exp in enum_experiments:
        writer.writerow(
            {
                "attack": attack,
                "model": model,
                "eps": eps,
                "fooling_rate": fooling_rate,
            }
        )
```

Transforming Data

Data Manipulation

pandas – Python Data Analysis Library

- `import pandas as pd`
- Provide high-performance data structures and analysis tools.
- **`pd.DataFrame`**: for representing tabular data.
- Why? Most plotting libraries build on pandas' data structures.

📒 **Note:** Looking for optimized speed? Try polars (rust-based).

Transforming Data

Data Manipulation

Reading raw data:

- `df = pd.read_csv()`
- `df = pd.read_excel()` (`pip install openpyxl`)

Initial read-out of the data:

- `df.head()`

Access index and columns:

- `df.columns`
- `df.index`

```
import pandas as pd

df = pd.read_excel("../plot_ijcai23_abd/defense.xlsx")
df.head()
```

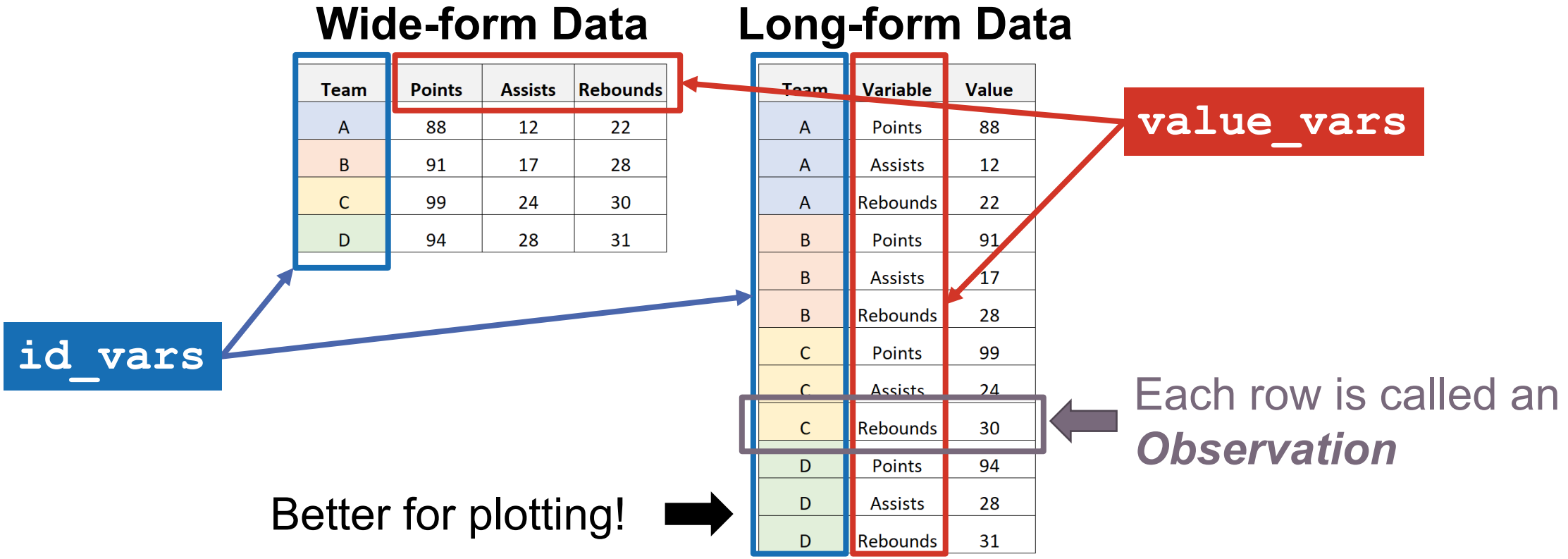
✓ 0.4s

	Model	Attack	MIM	MIM+Ours	TIM	TIM+Ours	DIM	DIM+Ours	SIM	SIM+Ours	NIM
0	T2T-ViT-24	Inc-V3	0.105	0.135	0.081	0.125	0.177	0.181	0.115	0.152	0.106
1	T2T-ViT-24	Inc-V4	0.125	0.182	0.090	0.166	0.284	0.302	0.135	0.226	0.148
2	T2T-ViT-24	IncRes-v2	0.047	0.064	0.042	0.055	0.085	0.088	0.044	0.066	0.044
3	T2T-ViT-24	Res-v2	0.067	0.115	0.033	0.072	0.172	0.200	0.081	0.160	0.079
4	T2T-ViT-24	Inc-V3ens3	0.109	0.138	0.096	0.113	0.169	0.176	0.102	0.144	0.105

Wide-form vs. Long-form Data

Data Manipulation

- Data: *long* (or tidy) form, or *wide* form.



Wide-form vs. Long-form Data

Data Manipulation

Wide to long:

- `df.melt(id_vars=.., var_name=.., value_name=..)`

Team	Points	Assists	Rebounds
A	88	12	22
B	91	17	28
C	99	24	30
D	94	28	31

```
df = df.melt(id_vars="Team", var_name="Stats", value_name="Value")
df
```

✓ 0.0s

	Team	Stats	Value
0	A	Points	88
1	B	Points	91
2	C	Points	99
3	D	Points	94
4	A	Assists	12
5	B	Assists	17
6	C	Assists	24

https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.melt.html

Long to wide: `df.pivot().reset_index()`

Aggregate?

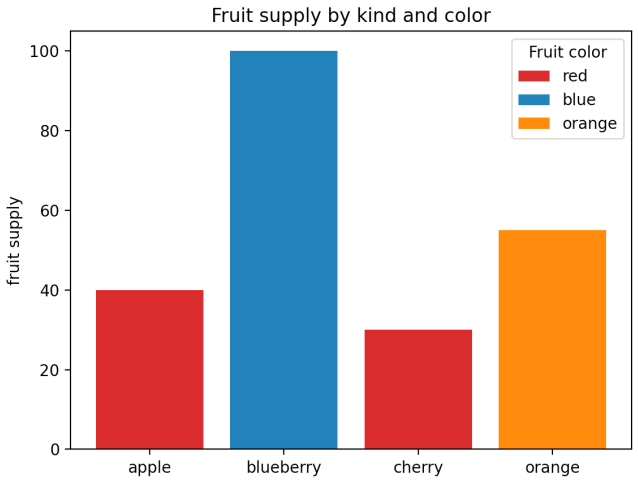
Data Manipulation

- Drop NaN: `df.dropna()` (pandas.DataFrame.dropna)
- Replace: `df.replace()` (pandas.DataFrame.replace)
- Sort: `df.sort_values()` (pandas.DataFrame.sort_values)
- Rename: `df.rename()` (pandas.DataFrame.rename)
- Apply lambda function: `df.apply()` (pandas.DataFrame.apply)

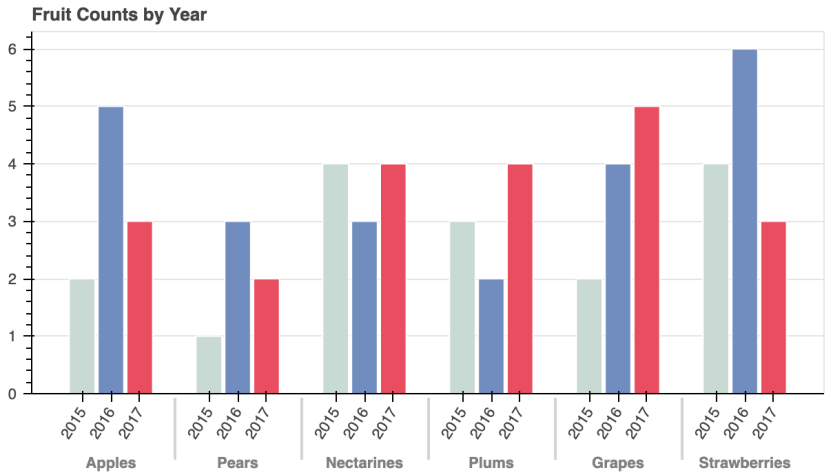
📒 **More on this:** pandas user guide - 10 minutes to pandas.

Plot

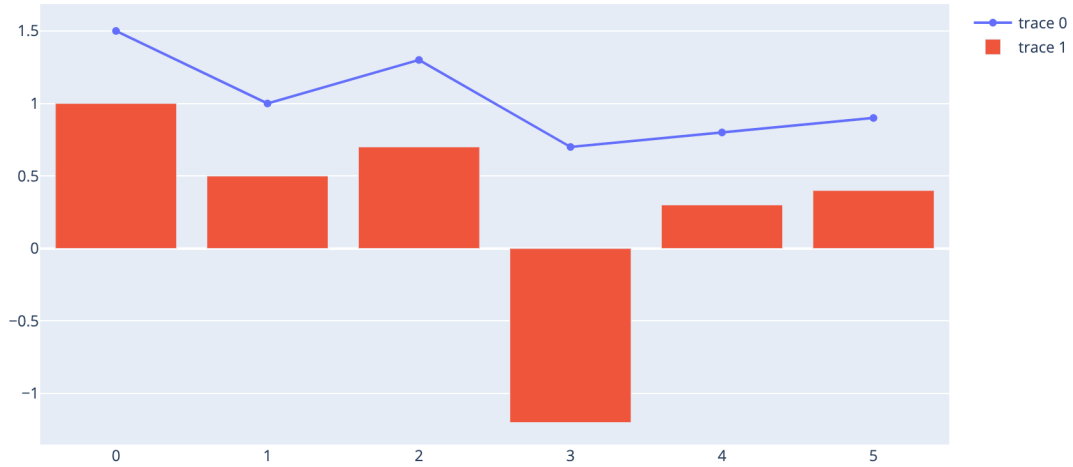
Matplotlib



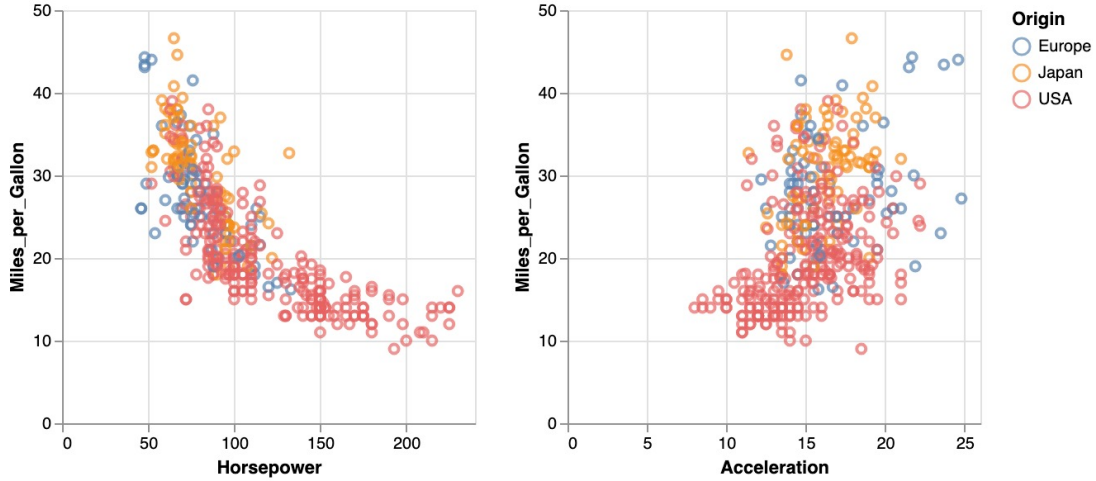
bokeh



plotly.py



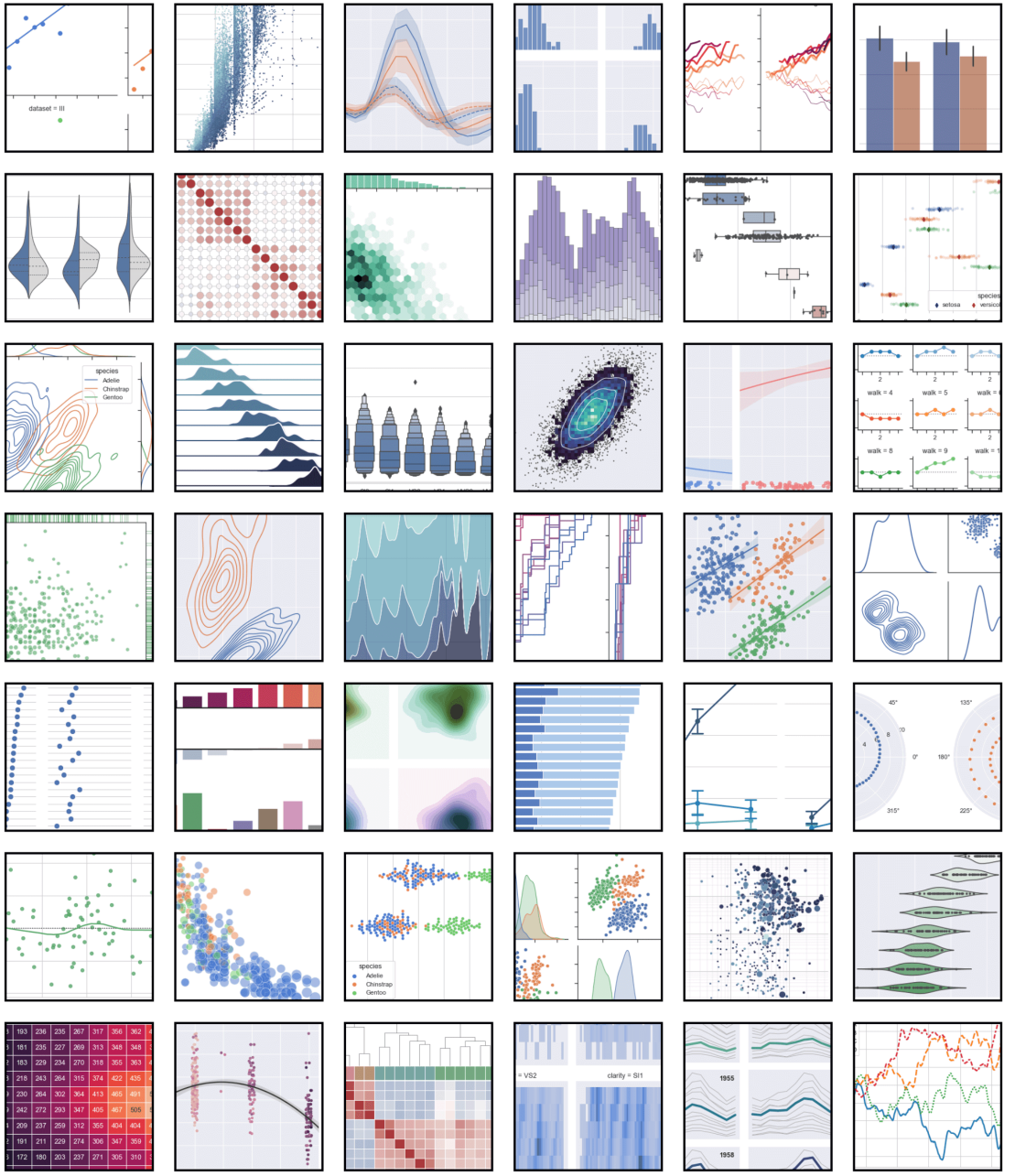
Altair (Vega / Vega-Lite)



Plot

Use seaborn!

- Seaborn, statistical data visualization:
  - https://seaborn.pydata.org
- `import seaborn as sns`
- Good amount of abstraction over `matplotlib`.
- Great color/style defaults.



Seaborn Styles

Plots

```
sns.set_theme(context=.., style=.., palette=..,
font=.., font_scale=..)
```

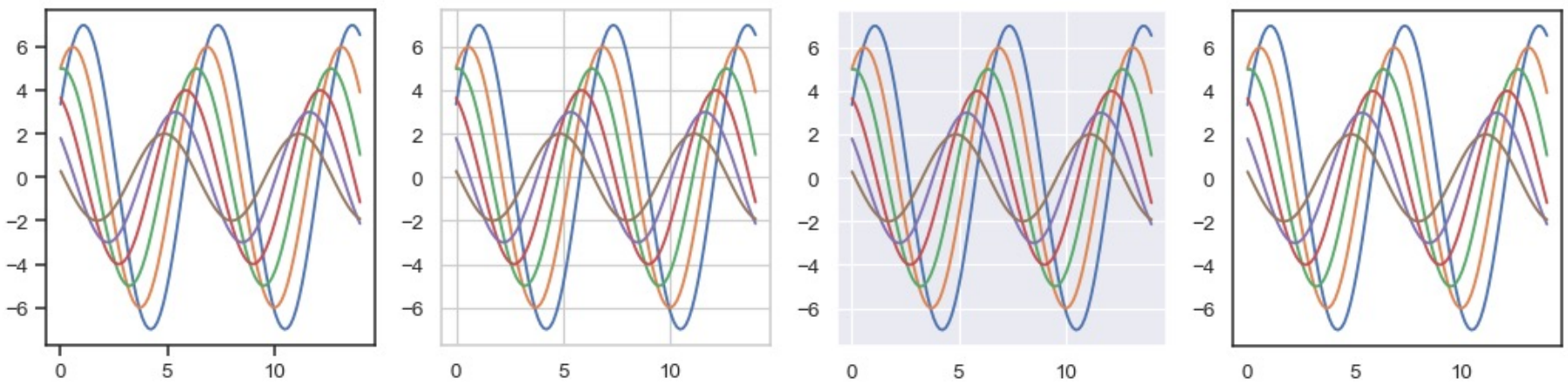
context	Plotting context.	`notebook|paper|talk|poster`
style	Axes style.	`darkgrid|whitegrid|dark|white|ticks`
palette	Color palette.	`sns.color_palette()`
font & font_scale	Controls font style and size.	

Seaborn Styles

Plots

For plots in publications, use:

```
import seaborn as sns
sns.set_theme(context="paper", style="whitegrid", font_scale=1.5)
```



Data Types

Plots

Attribute Type

- **Categorical:**

- **Ordered:**
  - Ordinal

  - Quantitative

Ordering Direction

- Sequential:

- Diverging:

- Cyclic:

Data Encoding

Plots – Data Marks

Data Marks:

- Points: scatter plots, `sns.scatterplot(data, *)`
- Line: line plots, `sns.lineplot(data, *)`
- Bar: bar plots, `sns.barplot(data, *)`
- *Area: heatmaps, `sns.heatmap(data, *)`

Data Encoding

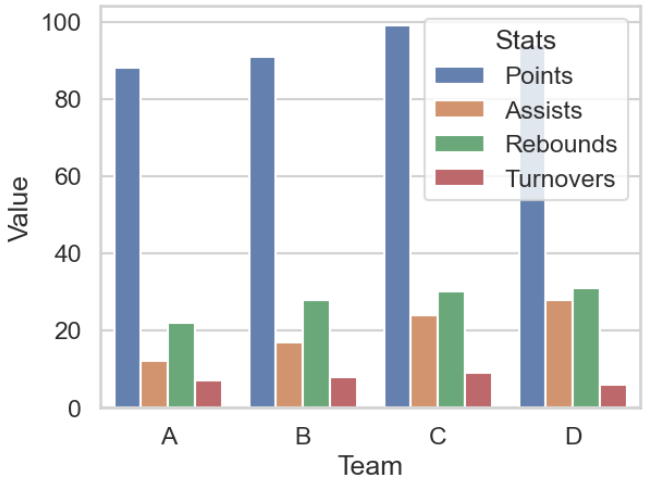
Plots – Data Marks

`sns.barplot(data, x, y, hue, palette, …, ax, …)`

- `x, y, hue`: Some column name in the DataFrame.
- `palette`: Color palette name.
  - `deep, muted, bright, pastel, dark, colorblind`

	Team	Stats	Value
0	A	Points	88
1	B	Points	91
2	C	Points	99
3	D	Points	94
4	A	Assists	12
5	B	Assists	17
6	C	Assists	24

```
import seaborn as sns
sns.set_theme(context="talk", style="whitegrid")
sns.barplot(df, x="Team", y="Value", hue="Stats")
```



Data Encoding

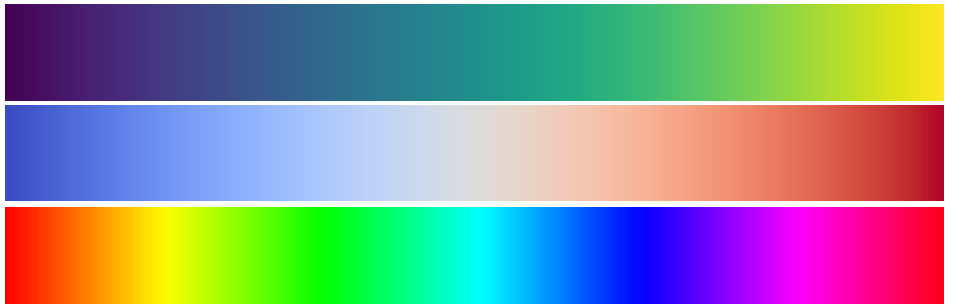
Plots – Color Palettes

Color Palettes – Chosen based on ***data type***.

- **Categorical:**

`sns.color_palette(“deep”)`

- **Ordinal:**
  - Sequential
  - Diverging
  - Cyclic



`sns.color_palette("viridis”)`

`sns.color_palette(”coolwarm”)`

`sns.color_palette(”hsv”)`

Tutorial: Choosing seaborn color palettes

Tutorial: Choosing Colormaps in Matplotlib

Data Encoding

Plots – Color Palettes

Categorical

- What if there are more categories than the default color cycle?

```
sns.color_palette("husl", 12)
```

✓ 0.0s

```
palette = sns.color_palette("husl", 4)
sns.barplot(df, x="Team", y="Value", hue="Stats", palette=palette)
```

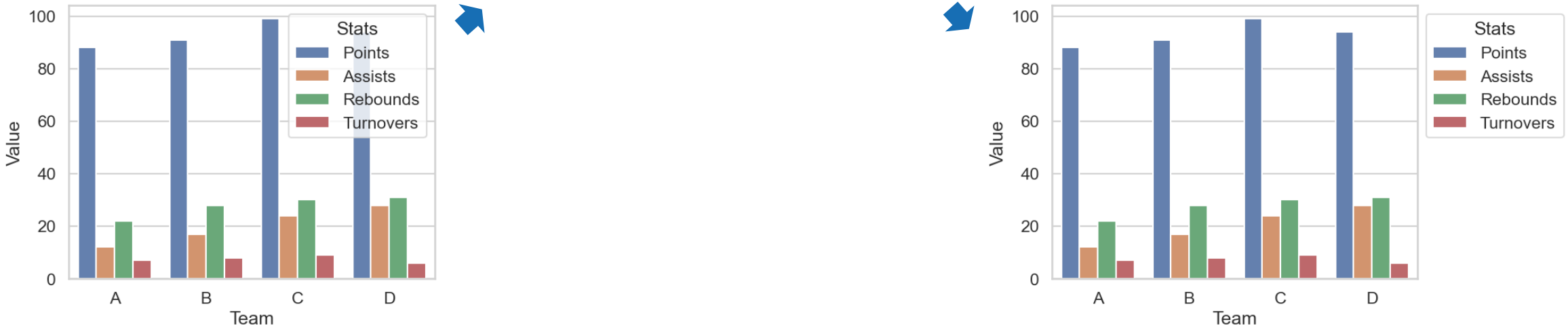
Legend

Plots – Legend

`sns.move_legend(ax, …)`

- Example:

```
ax = sns.barplot(df, x="Team", y="Value", hue="Stats")
sns.move_legend(ax, "upper left", bbox_to_anchor=(1, 1))
```



- https://seaborn.pydata.org/generated/seaborn.move_legend.html

Extend Seaborn with Matplotlib

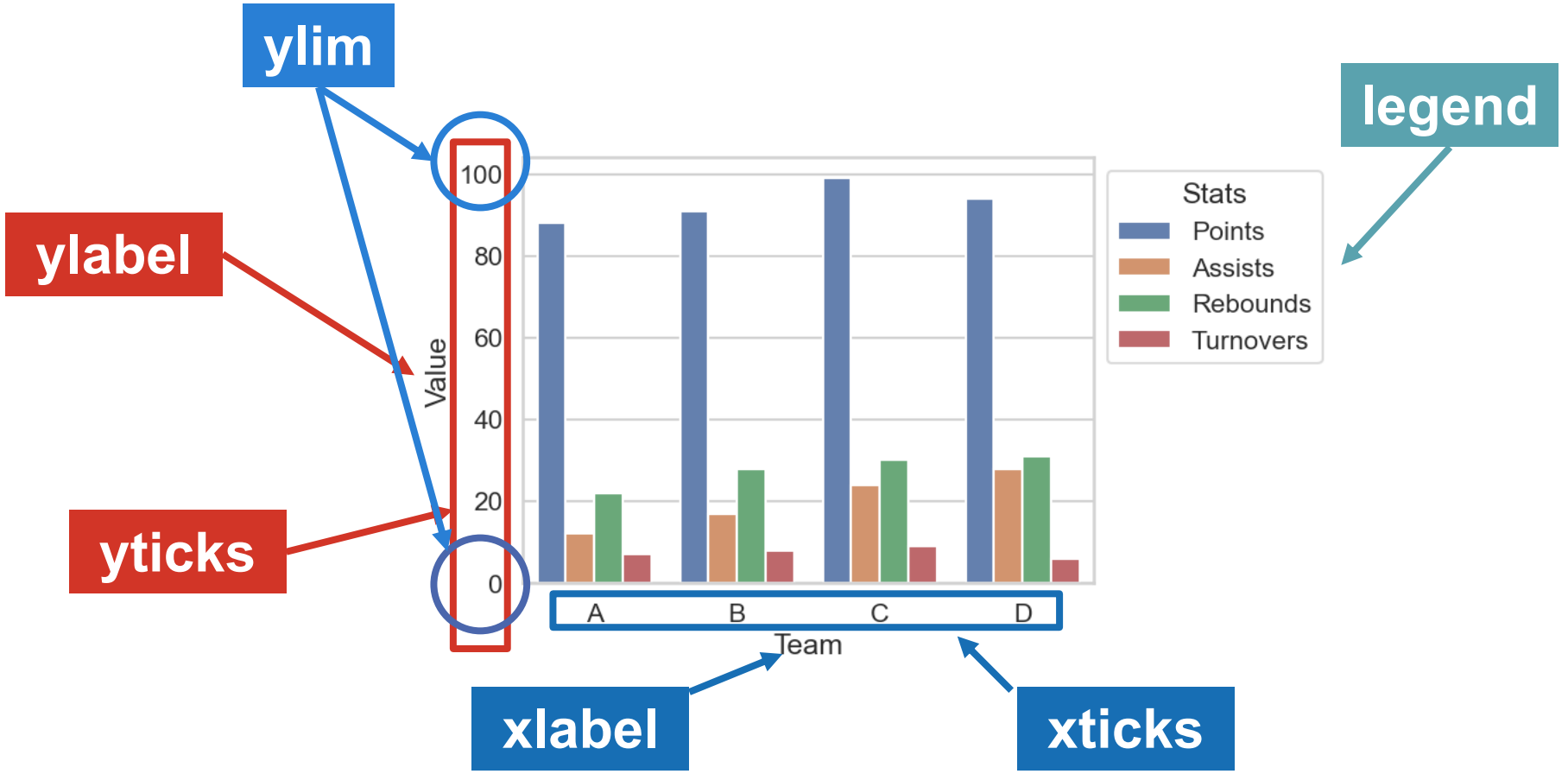
```
import matplotlib.pyplot as plt
```

Used for:

- Defining figure size: `plt.figure(figsize=(10, 6))`
- Setting axis attribute:
  - `set_xlabel, set_ylabel, set_xticks, set_yticks, set_xlim, set_ylim`
- Subplots and more general control over the plot.

Extend Seaborn with Matplotlib

Matplotlib Figure

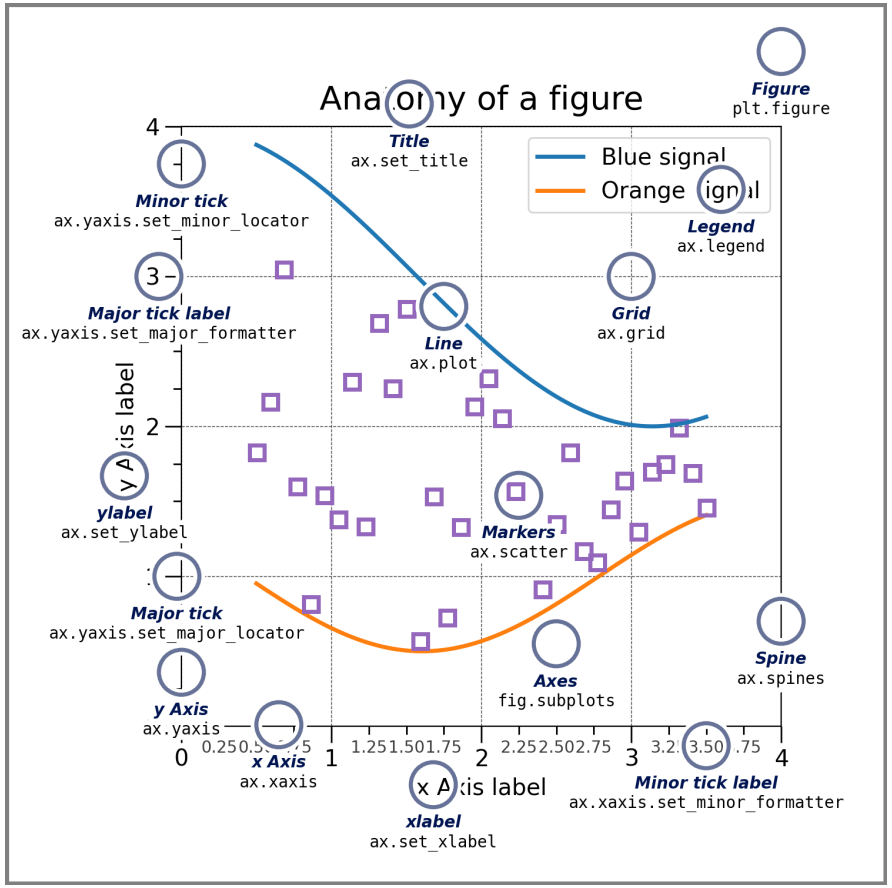


Extend Seaborn with Matplotlib

Matplotlib Figure

Anatomy of a Matplotlib Figure

- https://matplotlib.org/stable/tutorials/introductory/quick_start.html#parts-of-a-figure



Extend Seaborn with Matplotlib

Subplots and layout

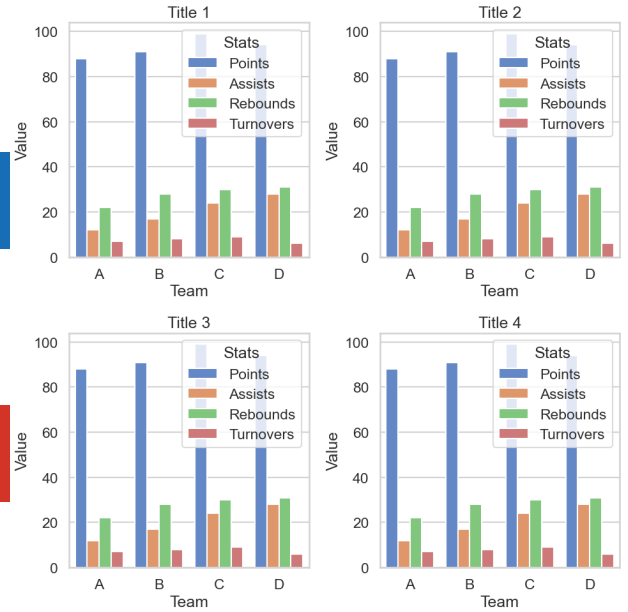
General workflow:

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

fig, axs = plt.subplots(2, 2, figsize=(10, 10))

for i, axi in enumerate(axs.flat):
    sns.barplot(df, x="Team", y="Value", hue="Stats", palette="muted", ax=axi)
    axi.set_title(f"Title {i + 1}")

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

Two rows, two cols

Seaborn plot on `axi`

Set `axi` attribute (label, ticks, title…)



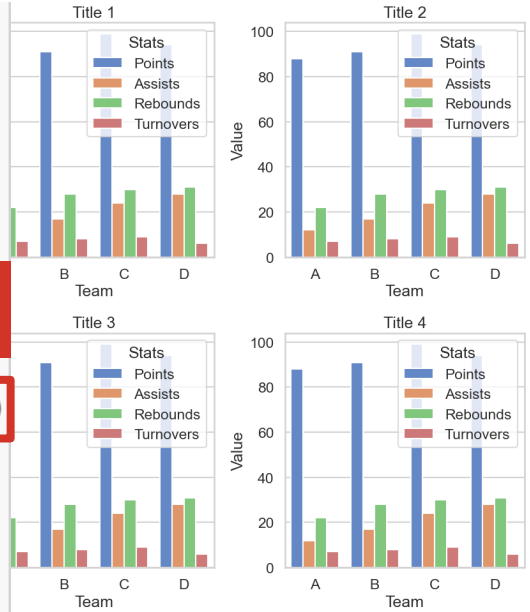
Extend Seaborn with Matplotlib

Subplots and layout

General workflow:

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

fig, axs = plt.subplots(2, 2, figsize=(10, 10))

for i in range(2):
    for j in range(2):
        sns.barplot(df, x="Team", y="Value", hue="Stats", palette="muted", ax=axs[i, j])
        axs[i, j].set_title(f"Title {i + 1}")

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

Access axes by index

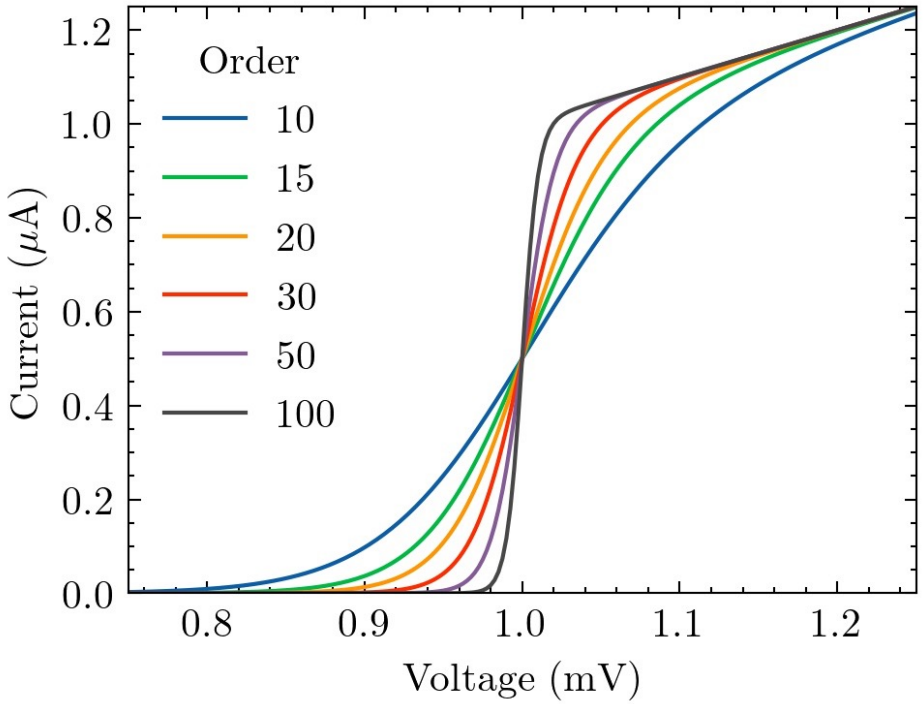


Additionally

Library – SciencePlots

garrettj403/SciencePlots

- 👍 Render fonts with LaTeX.
- 👍 Professional colors and fonts.
- 😓 Can only be used with **`matplotlib`**!



Thanks for listening

https://github.com/spencerwooo

https://scholar.google.com/citations?user=Mf-JoyQAAAAJ

https://spencerwoo.com