dm25s1

Topic 04 : Exploratory Data Analysis

Part 02 : EDA Pass2

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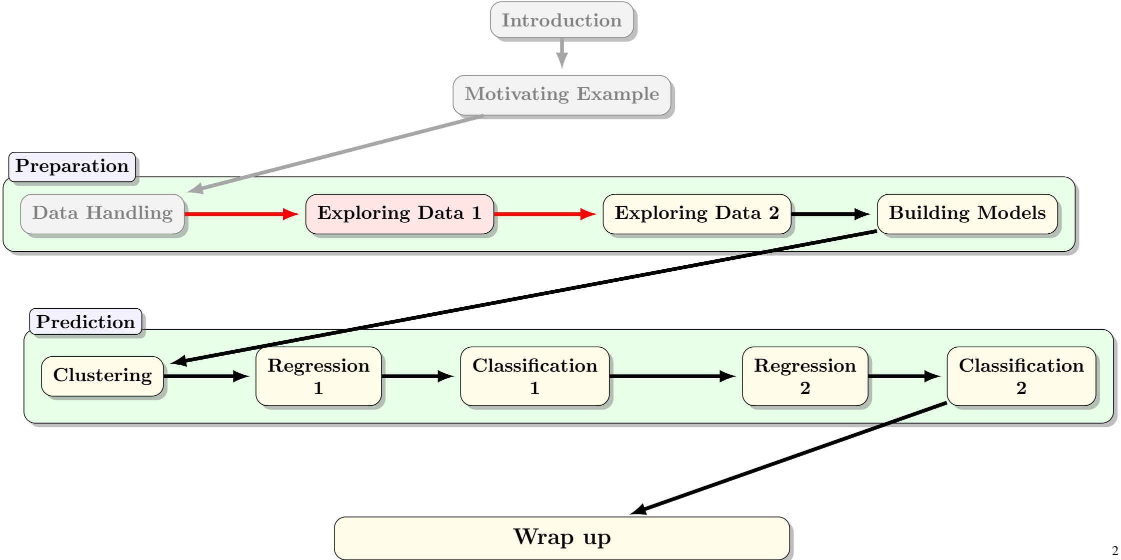
Autumn Semester, 2025

Outline

- Feature and target distributions
- Plotting
- After EDA Pass 2

Data Mining (Week 4)



EDA Pass2 — Summary

Acknowledgment

A big thanks to Dr Kieran Murphy, who provided many of the slides for today's lecture.

Introducing EDA Pass2

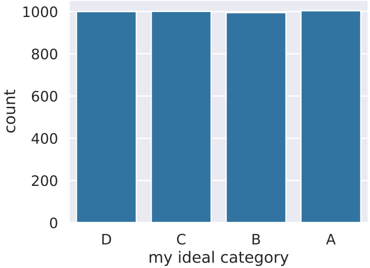
A Selection of Statistical Visualisations and Metrics

		Relationship to Target	
	Feature	Categorical	Numerical
Categorical	`nunique`, `unique`, `describe`, `value_counts`, … `countplot`, …	`crosstab`, … `countplot`, …	`boxplot`, … `catplot`, `boxplot`, …
Numerical	`describe`, … `histplot`, `boxplot`, `displot`, `qqplot`, …	`groupby`+`describe`, … `catplot`, `boxplot`, …	correlations, … `lmplot`, …

Categorical Variables

The Ideal

- Each level equally likely.
- Not too many levels: 2–12(ish).



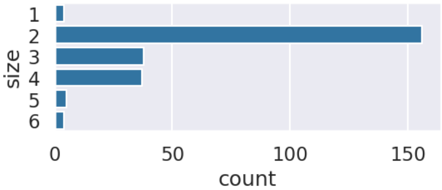
Tools

- `nunique`, `unique`, `value_counts`.
- `sns.countplot` — shows the counts of observations in each categorical level using bars.

Reality

Tips

```
sns.countplot(y="size", data=df);
```

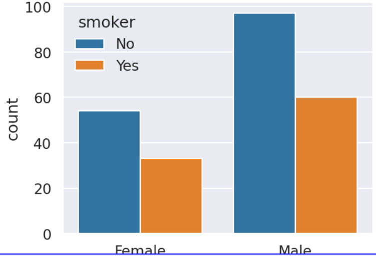


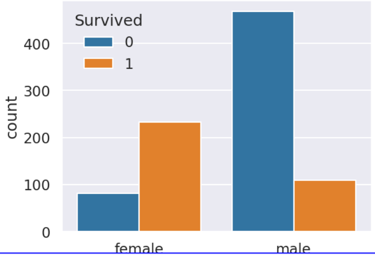
- If `size` was the target, then most models will train towards the majority class (`size=2`).
- If `size` was a feature, then quality of predictor could vary greatly depending on the feature categorical level.
- Consider merge/drop rare category levels.

Categorical Variables — Relationship with (Categorical) Target

feature   target   Titanic

```
sns.countplot(x="Sex", hue="Survived", data=df);
```






```
pd.crosstab(columns=df.Sex, index=df.Survived, margins=True, normalize='columns') \
    .style.format("{:.2%}").background_gradient(cmap='summer_r')
```

sex	Female	Male	All
smoker			
No	62.07%	61.78%	61.89%
Yes	37.93%	38.22%	38.11%

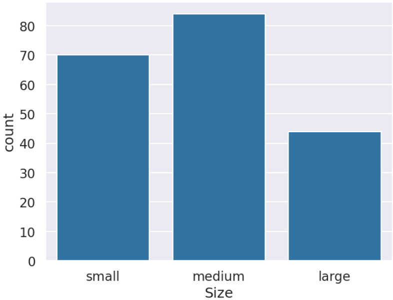
No relationship between `sex` and `smoker`

Sex	female	male	All
Survived			
0	25.80%	81.11%	61.62%
1	74.20%	18.89%	38.38%

Strong relationship between `Sex` and `Survived`

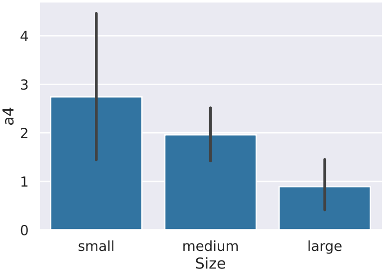
Categorical Variables — Relationship with (Numerical) Target I

```
sns.countplot(x="Size", data=df);
```



- Shows the counts of observations in each categorical level using bar (height/width).

```
sns.catplot(x="Size", y="a4", data=df, kind='bar');
```



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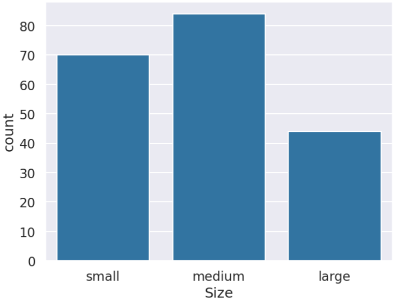

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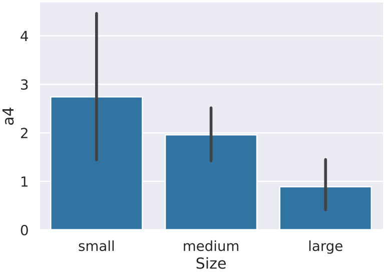

- Shows the average level (mean) and uncertainty (std) of the numerical target (`a4`) in each categorical level of the categorical variable.
- Vertical bar shows 95% confidence interval.

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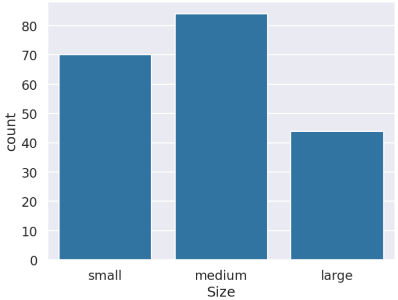

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Is it usable?

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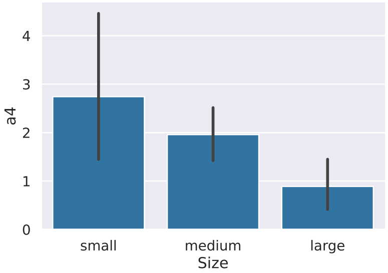

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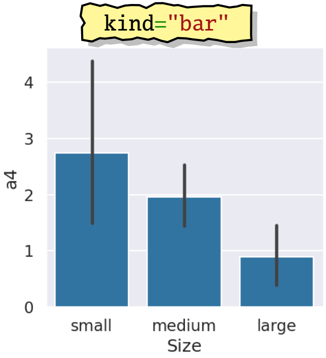
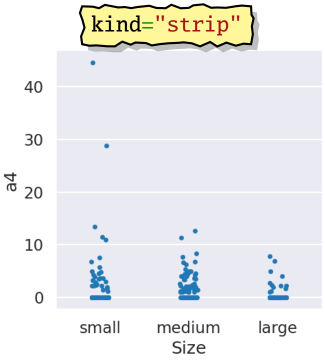
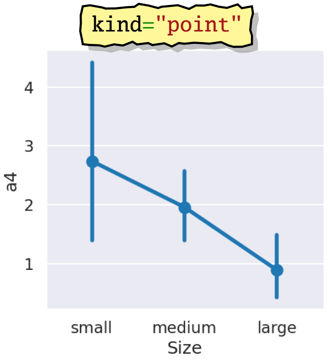
Categorical Variables — Relationship with (Numerical) Target II

The option `kind` in `catplot` can be:







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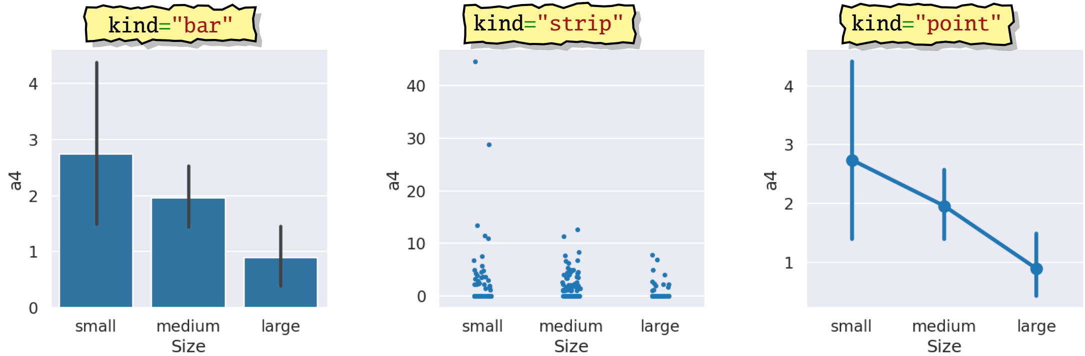
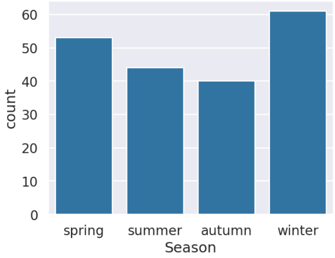
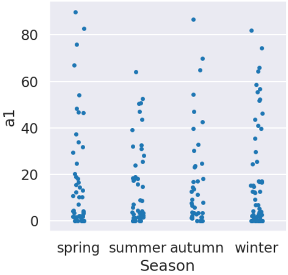
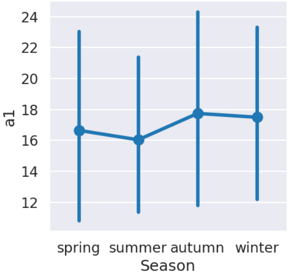


- `bar` and `point` show essentially the same information, but `point` is more compact when comparing multiple categorical features to a continuous target on the same plot.
- `strip` shows individual observations — useful (as in this case) to show that the larger uncertainty in `Size="small"` observations is mainly due to two outliers.

Example — Dataset: `Algae Blooms`, Feature: `Season`, Target: `a1`







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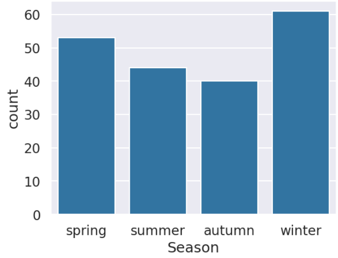

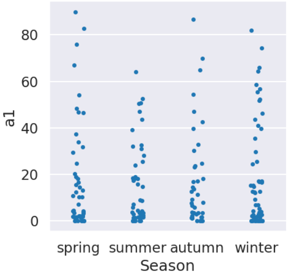

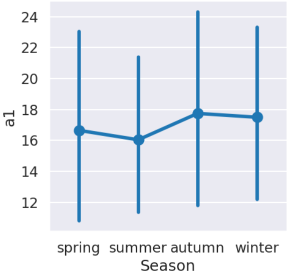


```
df.groupby("Season")["a1"].agg(["mean","count","std"])
```

	mean	count	std
Season	$\bar{x}$	n	σ
spring	16.649057	53	23.093786
summer	16.038636	44	17.920798
autumn	17.745000	40	21.611203
winter	17.498361	61	22.568256

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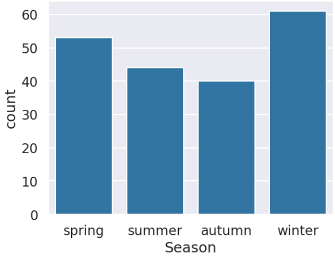

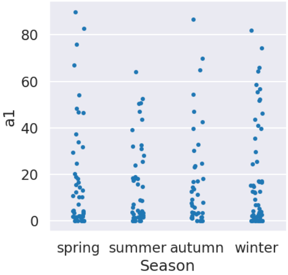

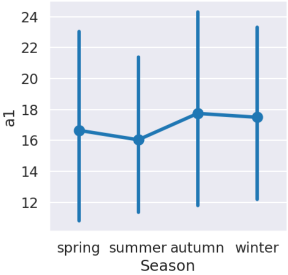


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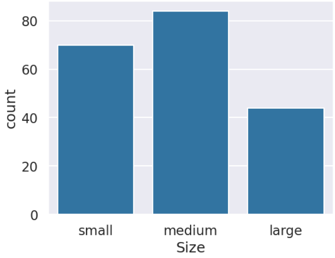
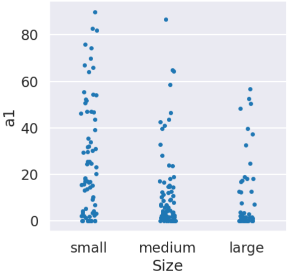
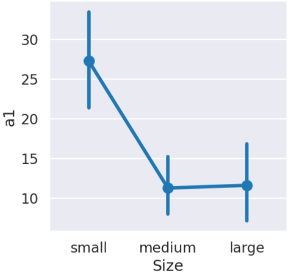
- Countplot shows no issues with feature `Season` — all levels approximately equally represented.
- Catplots show slightly less spread in `a1` for `Season="summer"` observations. (`strip` shows smaller range, `point` shows smaller standard deviation).

$\Rightarrow$ Mean levels of `a1` for different levels of `Season` are well within the 95% confidence intervals ($\bar{x} \pm \sigma 1.96/\sqrt{n}$), so no/weak relationship between categorical feature and numerical target.

Example — Dataset: `Algae Blooms`, Feature: `Size`, Target: `a1`







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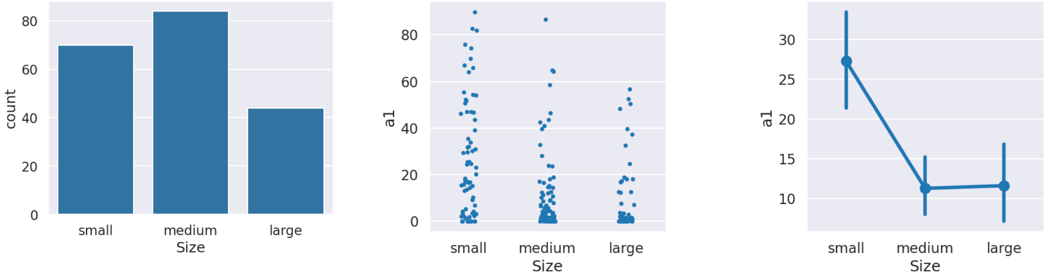


```
df.groupby("Size")["a1"].agg(["min","max","mean","count","std"])
```

	min	max	mean	count	std
Size			$\bar{x}$	n	σ
small	0.0	89.8	27.255714	70	24.895426
medium	0.0	86.6	11.267857	84	17.163124
large	0.0	56.8	11.611364	44	16.556123

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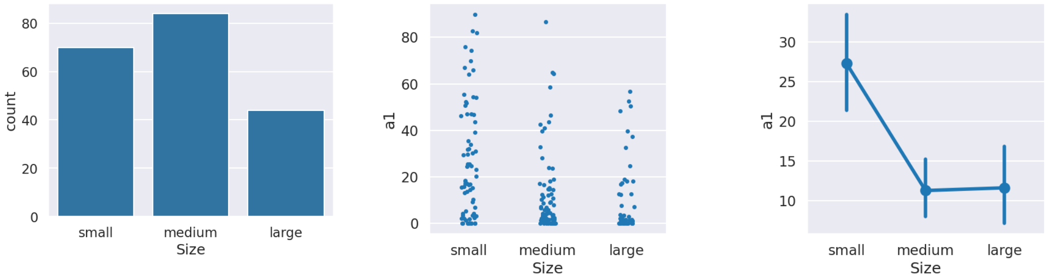


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- Countplot shows no issues with feature `Size`.
- Catplot (`point`) shows that levels of `a1` are higher for `Size="small"` observations.

$\Rightarrow$ Confidence interval for `Size="small"` observations do not overlap with CI for other levels, so significant relationship between categorical feature and numerical target.

Numerical Variables

Things here are more complicated as a numerical variable could follow many different distributions. Here we look at data following the standard normal distribution. To start we generate 10,000 values and put in to new DataFrame, `df2`.

```
rv = stats.norm()
data = rv.rvs(size=10_000)
df2 = pd.DataFrame(data, columns=["x"])
df2.head(5)
```

	x
0	-1.915795
1	0.641175
2	0.040114
3	0.725531
4	0.252675

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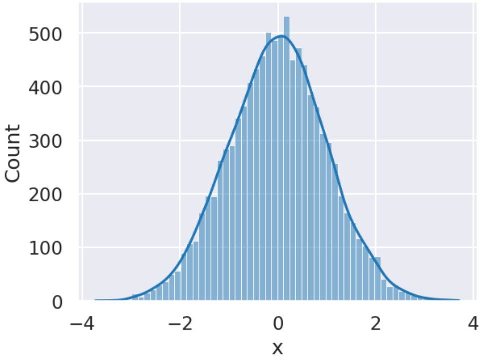
```
sns.histplot(x="x", data=df2, kde=True);
```



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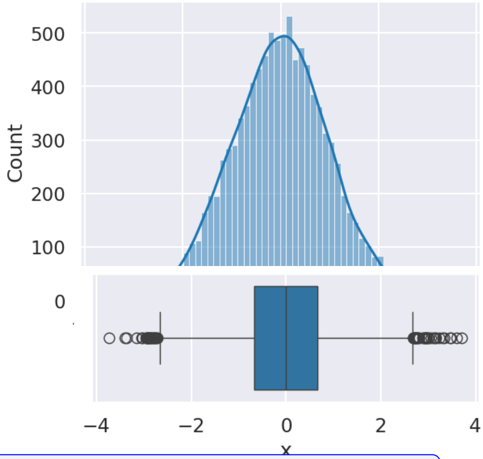
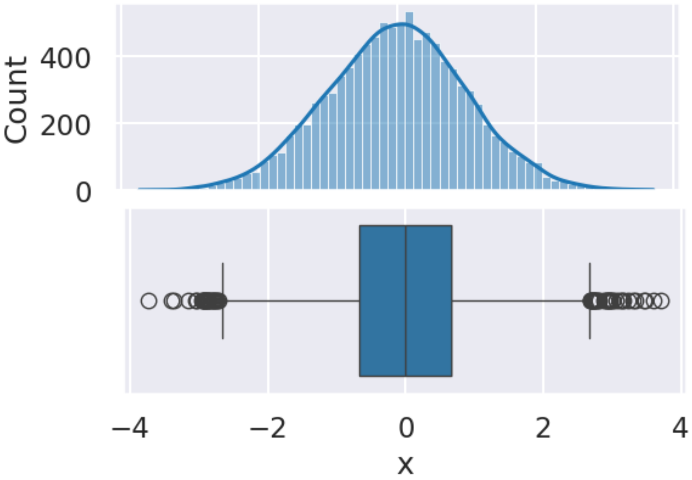



```
sns.boxplot(x="x", data=df2);
```

Histplot (Histogram) and Boxplot



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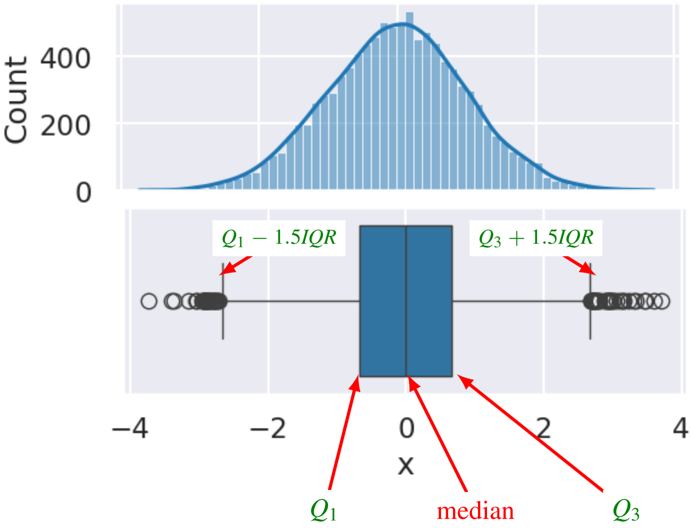

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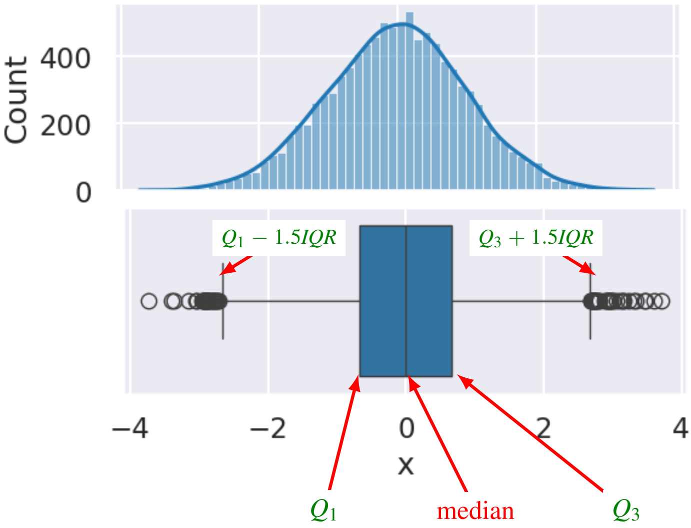
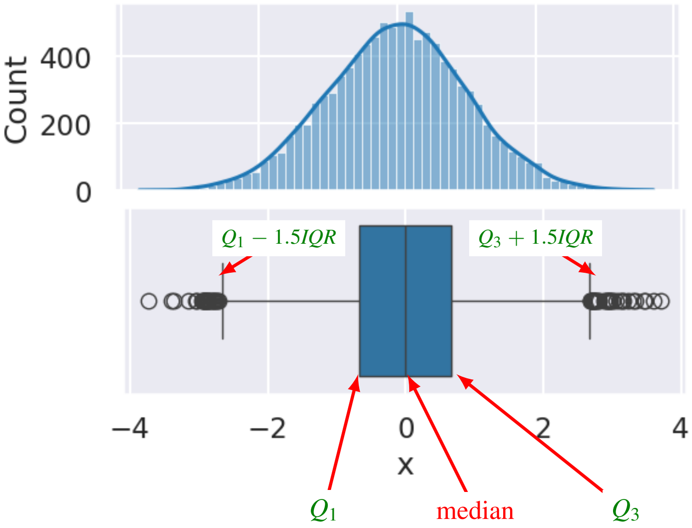


- Histogram is useful in depicting location, spread and shape.
- Curve, is estimate of shape given infinite data and infinite number of bins.
- Boxplots also depicts location, spread and shape, but uses median for estimate of centre, and quartiles for spread.

Histplot (Histogram) and Boxplot



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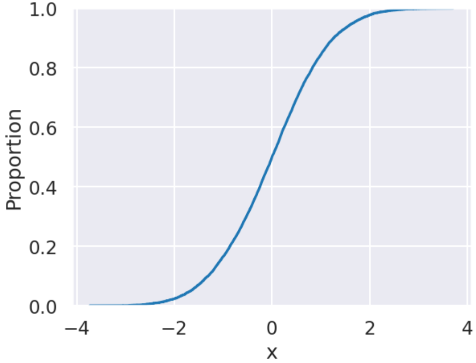
- Boxplots also depicts location, spread and shape, but uses median for estimate of centre, and quartiles for spread.
- Half the data is within the box, data points outside the whiskers (lines) are possible outliers, denoted by circles.

Cumulative Plot and QQ-Plot

```
sns.ecdfplot(data=df2, x="x");
```



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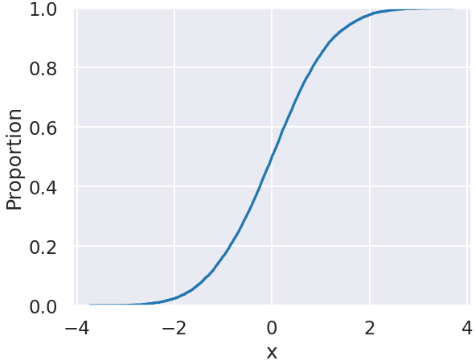

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Cumulative Plot and QQ-Plot

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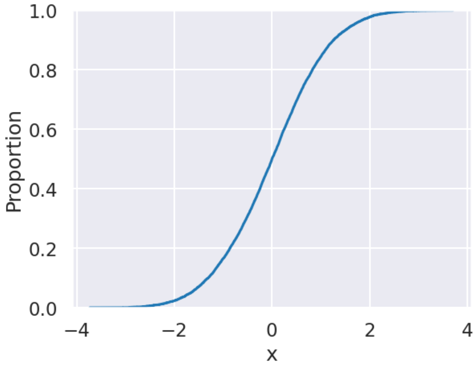

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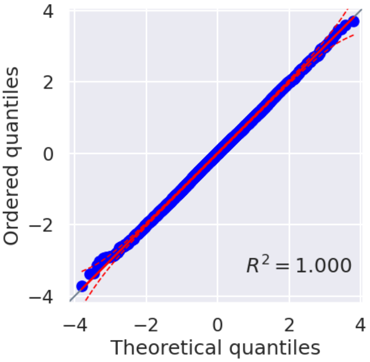
```
import pingouin as pg
pg.qqplot(df2.x);
```



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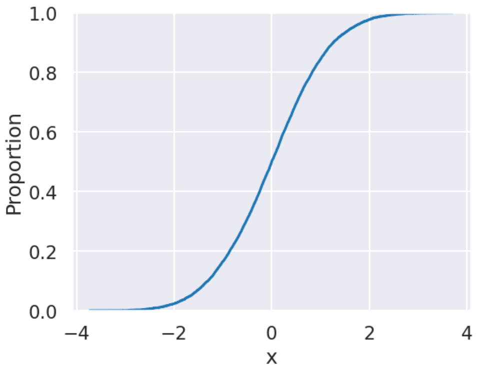

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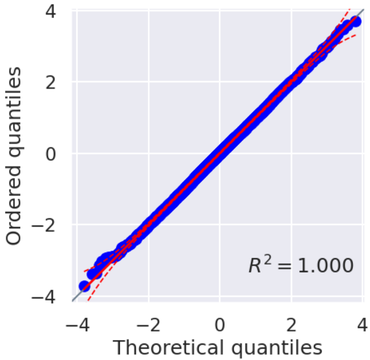
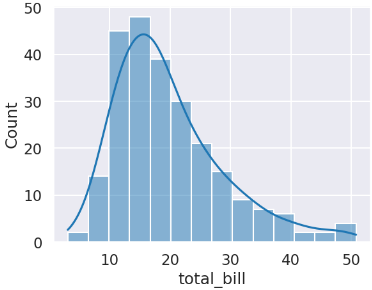
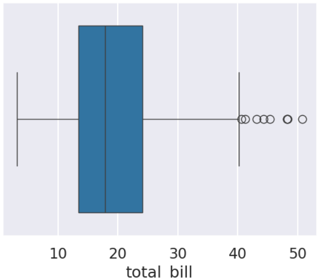
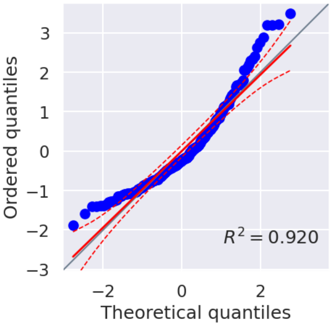


- Plot of observed quantiles against theoretical (assumed normal) quantiles. If both sets of quantiles came from the same distribution, the points lie on a line (approx.).

Example — Dataset: `Tips`, Feature: `total_bill`








```
df.total_bill.describe()
```

```
count    244.000000
mean      19.785943
std        8.902412
min        3.070000
25%       13.347500
50%       17.795000
75%       24.127500
max       50.810000
Name: total_bill, dtype: float
```

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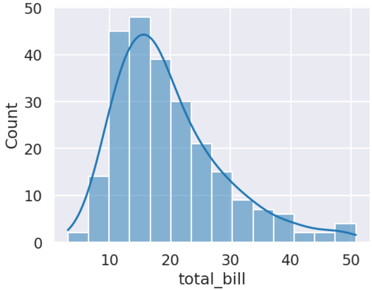

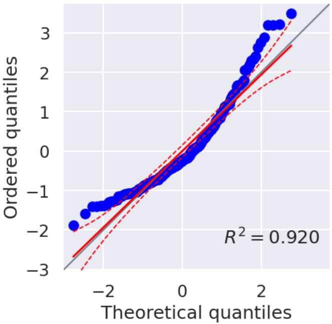


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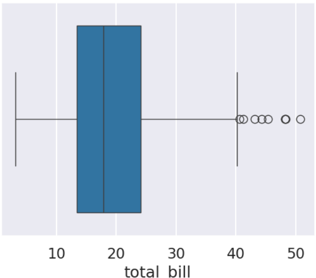
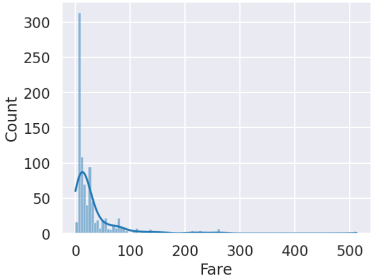
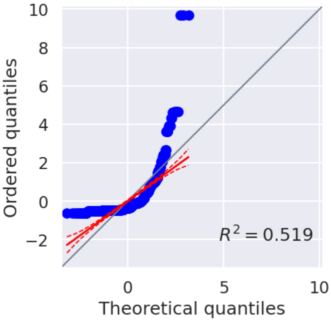
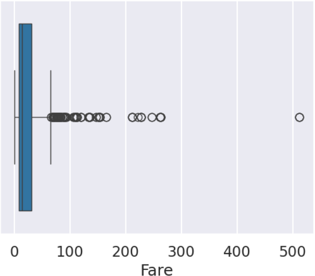


- Data is bell curve shaped, but right skewed (data is more spread out to the right).
- Outliers to the right.
- QQ-Plot indicate that data is not normal, but we could transform it to be more closer to normal.

Example — Dataset: `Titanic`, Feature: `Fare`








```
df.Fare.describe()
```

```
count    891.000000
mean      32.204208
std       49.693429
min        0.000000
25%        7.910400
50%       14.454200
75%       31.000000
max      512.329200
Name: Fare, dtype: float64
```

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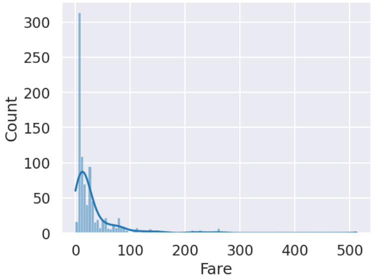

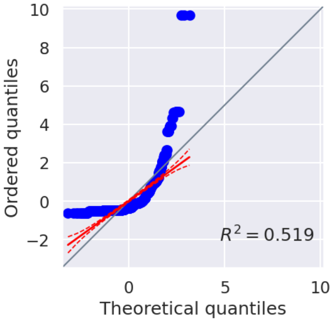

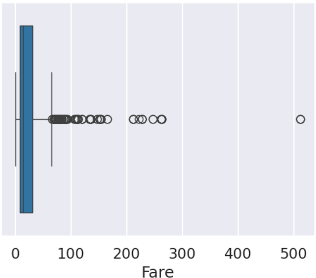


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- This variable is more skewed and dominated by its outliers which need to be resolved.

Warning —- Plot Output Depends on Data Assumptions

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df = pd.read_csv("data/train.csv")
sns.catplot(data=df, x="Fare", y="Survived");
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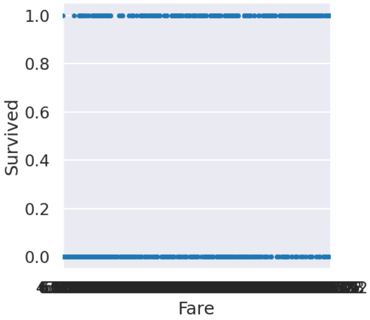

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sns.catplot(data=df, x="Fare", y="Survived");
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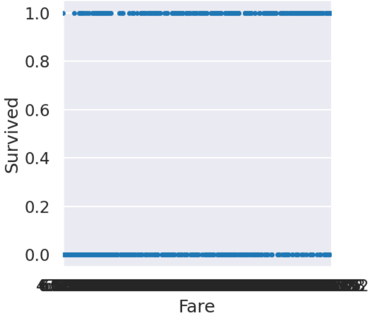

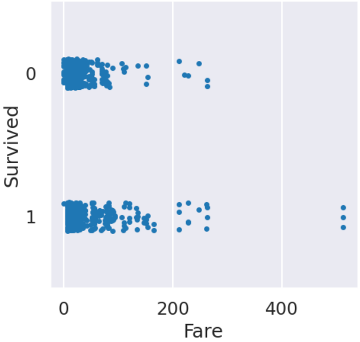

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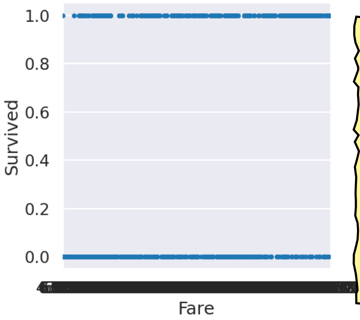
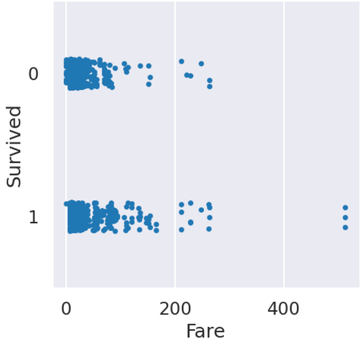


- `seaborn` tries to infer the correct graph based on the data values/type, but it does not always get it correct.
- `Survived` stores 0 and 1 and has dtype `int`.
- Converting to a `Categorical` with numeric levels is not enough.
- `astype(str)` converts `0` and `1` to `"0"` and `"1"`.



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