dm24s1

Topic 05 : Exploratory Data Analysis2

Part 01 : EDA Pass2 3

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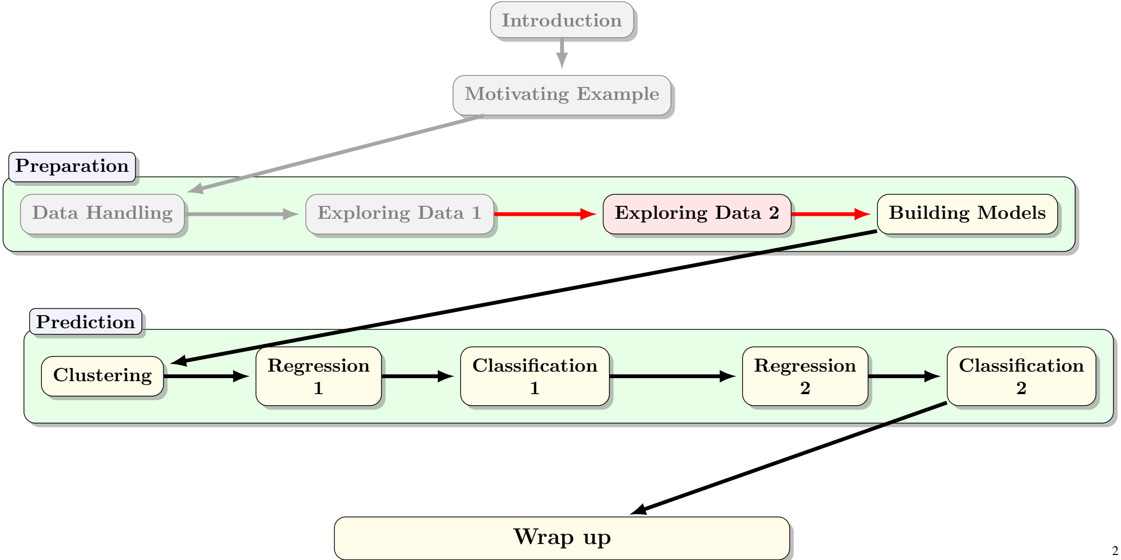
Outline

- EDA Process
- Datasets = Tips, Titanic and Algae Blooms
- Identifying and resolving issues (missing value, outliers)
- Generating ToDo list for Feature Engineering/Transformation/Selection

Data Mining (Week 5)



EDA Pass2 3 — Summary

Acknowledgment

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

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  - Leave blank, impute value, drop row/column?

Categorical vs Numerical Variables

Recall statistical *Levels of Measurement*

Categorical vs Numerical Variables

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Type	Drawn from	Examples	Used to
Nominal	Finite Set, Unrelated	Manufacturers, Countries, Gender	Categorise with descriptive label
Ordinal	Finite Set, Ordered	Size (S,M,L), Army Ranks, Satisfaction	Categorise with descriptive label
Interval	Ordered, Differences matter	Exam Scores, Temperatures (Celsius)	Assign numeric score to
Ratio	Ordered, Differences and ratios matter	Distance (m), Cost ($), Temperatures (Kelvin)	Assign numeric score to

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Generally, *Nominal* and *Ordinal* are considered categorical, *Interval* and *Ratio* are considered Numerical

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Generally, *Nominal* and *Ordinal* are considered categorical, *Interval* and *Ratio* are considered Numerical

But what about a variable which contains *Months of the year*?

Categorical and Numerical variables

A Selection of Statistical Visualisations and Metrics

	Feature
Categorical	`nunique`, `unique`, `describe`, `value_counts`, ...
	`countplot`, ...

Categorical and Numerical variables

A Selection of Statistical Visualisations and Metrics

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Categorical	`nunique`, `unique`, `describe`, `value_counts`, …
	`countplot`, …
Numerical	`describe`, …
	`histplot`, `boxplot`, `displot`, `qqplot`, …

Categorical and Numerical variables

A Selection of Statistical Visualisations and Metrics

	Feature	Relationship to Target: Categorical	Relationship to Target: Numerical
Categorical	`nunique`, `unique`, `describe`, `value_counts`, ... `countplot`, ...		
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Categorical	`nunique`, `unique`, `describe`, `value_counts`, …	`crosstab`, …	
	`countplot`, …	`countplot`, …	
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	`histplot`, `boxplot`, `displot`, `qqplot`, …		

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Numerical	`describe`, ... `histplot`, `boxplot`, `displot`, `qqplot`, ...	`groupby`+`describe`, ... `catplot`, `boxplot`, ...	

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Categorical	`nunique`, `unique`, `describe`, `value_counts`, … `countplot`, …	`crosstab`, … `countplot`, …	`boxplot`, … `catplot`, `boxplot`, …
Numerical	`describe`, … `histplot`, `boxplot`, `displot`, `qqplot`, …	`groupby+describe`, … `catplot`, `boxplot`, …	

Categorical and Numerical variables

A Selection of Statistical Visualisations and Metrics

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

Second Pass — Individual Features and Target

- Categorical vs numerical target

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- Identify (and possibly address) issues

Is it usable?

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Is it usable?

- Relationship to target.

Is it useful?

Dataset: `Titanic`, Target: `Survived`

```
df.Survived.describe()
```

```
count     891
unique      2
top         0
freq      549
Name: Survived, dtype: int64
```

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Categories (2, int64): [0, 1]
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df.Survived.value_counts(normalize=True, dropna=False)
```

```
0    0.616162
1    0.383838
Name: Survived, dtype: float64
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sns.countplot(x="Survived", data=df);
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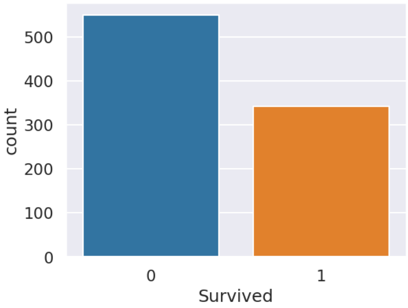


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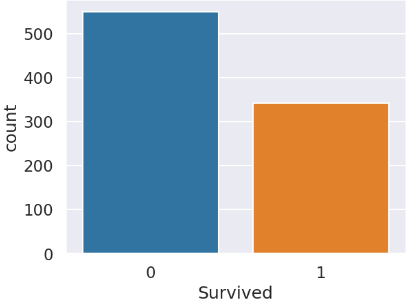


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- Simplest classification problem (two classes) with both classes nearly equal frequency.
- In a unbalanced classification problem where the minority class occurs about 20% or lower, models can focus on the majority class.

Dataset: `Algae Blooms`, Target: `a1`, . . . , `a7`

```
targets = [c for c in df.columns if c[0]=="a"]
targets
```

```
['a1', 'a2', 'a3', 'a4', 'a5', 'a6', 'a7']
```

Dataset: Algae Blooms, Target: a1,. . . , a7

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```
df[targets].describe()
```

	a1	a2	a3	a4	a5	a6	a7
count	198.000000	198.000000	198.000000	198.000000	198.000000	198.000000	198.000000
mean	16.996465	7.470707	4.334343	1.997475	5.115657	6.004545	2.487374
std	21.421713	11.065461	6.976788	4.439205	7.511846	11.711053	5.181536
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.525000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	6.950000	3.000000	1.550000	0.000000	2.000000	0.000000	1.000000
75%	24.800000	11.275000	4.975000	2.400000	7.500000	6.975000	2.400000
max	89.800000	72.600000	42.800000	44.600000	44.400000	77.600000	31.600000

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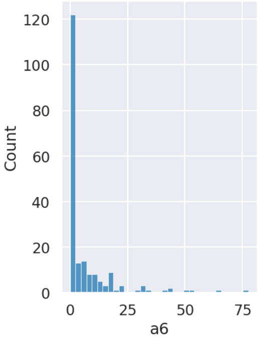
```
plt.figure(figsize=(4,6))
sns.histplot(x="a6", data=df);
```



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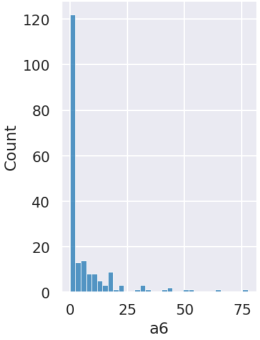
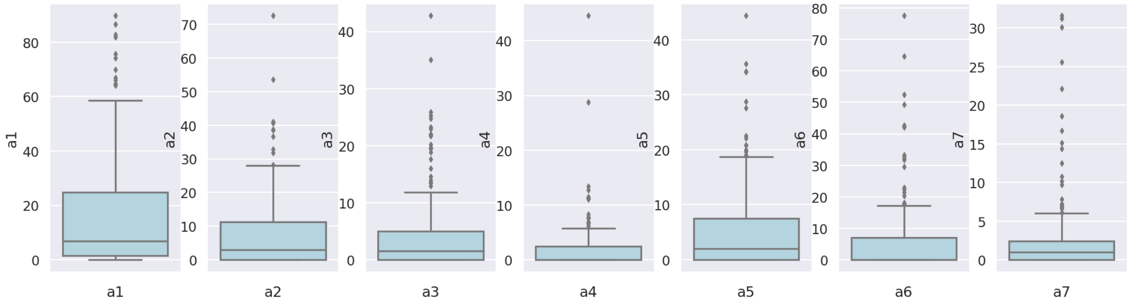


All distributions are heavily skewed to the right, many with outliers (see next slide). All of the zero measurements are probably due to population levels too low to be measured.

Dataset: `Algae Blooms`, Target: `a1`, . . . , `a7`

```
fig, axs = plt.subplots(1, 7, figsize=(24,6))
for k, c in enumerate(targets):
    sns.boxplot(data=df, y=c, color="lightblue", ax=axs[k])
    axs[k].set_xlabel(c)
```



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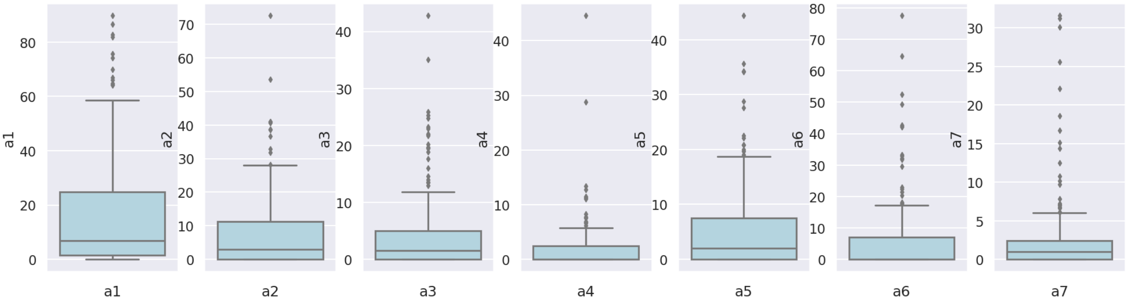

The outliers are likely to be true measurements, but their presence can heavily influence the model training — common strategy is to fit two models (one with the case with target outliers and one without) to assess impact of outliers.

Individual Features

To keep this more manageable we will focus more on the `Algae Blooms` data set . . .

	Season	Size	Speed	max_pH	min_O2	mean_Cl	mean_NO3	mean_NH4	mean_oPO4	mean_PO4	mean_Chlor	a1	a2	a3	a4	a5
0	winter	small	medium	8.00	9.8	60.800	6.238	578.00000	105.00000	170.00000	50.000	0.0	0.0	0.0	0.0	34.2
1	spring	small	medium	8.35	8.0	57.750	1.288	370.00000	428.75000	558.75000	1.300	1.4	7.6	4.8	1.9	6.7
2	autumn	small	medium	8.10	11.4	40.020	5.330	346.66699	125.66700	187.05701	15.600	3.3	53.6	1.9	0.0	0.0
3	spring	small	medium	8.07	4.8	77.364	2.302	98.18200	61.18200	138.70000	1.400	3.1	41.0	18.9	0.0	1.4

Sneak perview

- Three categorical variables `Season`, `Size`, and `Speed`.

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  - No missing values

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    - No missing values
    - No high cardinality, and reasonable balanced.

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Sneak perview

- Three categorical variables `Season`, `Size`, and `Speed`.
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- Eight numerical variables `max_pH`, . . . , `mean_Chlor`

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- Eight numerical variables `max_pH`, . . . , `mean_Chlor`
- Missing values present

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  - No missing values
  - No high cardinality, and reasonable balanced.
- Eight numerical variables `max_pH`, ..., `mean_Chlor`
- Missing values present
- Some variables heavily skewed — might need to transform.

Individual Features

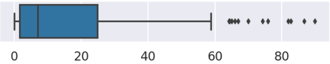
To keep this more manageable we will focus more on the `Algae Blooms` data set . . .

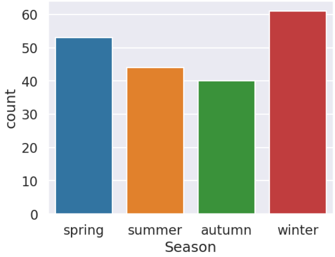
	Season	Size	Speed	max_pH	min_O2	mean_Cl	mean_NO3	mean_NH4	mean_oPO4	mean_PO4	mean_Chlor	a1	a2	a3	a4	a5
0	winter	small	medium	8.00	9.8	60.800	6.238	578.00000	105.00000	170.00000	50.000	0.0	0.0	0.0	0.0	34.2
1	spring	small	medium	8.35	8.0	57.750	1.288	370.00000	428.75000	558.75000	1.300	1.4	7.6	4.8	1.9	6.7
2	autumn	small	medium	8.10	11.4	40.020	5.330	346.66699	125.66700	187.05701	15.600	3.3	53.6	1.9	0.0	0.0
3	spring	small	medium	8.07	4.8	77.364	2.302	98.18200	61.18200	138.70000	1.400	3.1	41.0	18.9	0.0	1.4

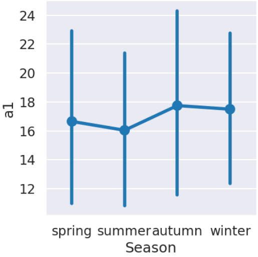
Sneak perview

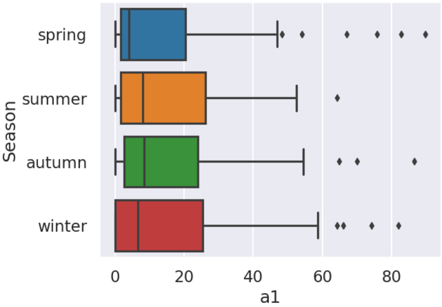
- Three categorical variables `Season`, `Size`, and `Speed`.
  - No missing values
  - No high cardinality, and reasonable balanced.
- Eight numerical variables `max_pH`, . . . , `mean_Chlor`
- Missing values present
- Some variables heavily skewed — might need to transform.
- Possibility of features being interrelated — multicollinearity — try principal component analysis.

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

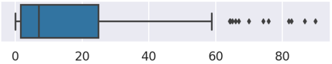


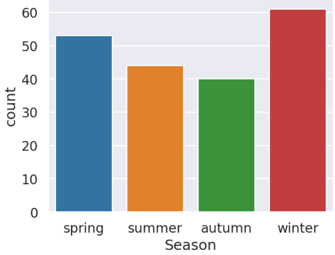


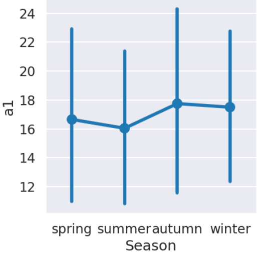


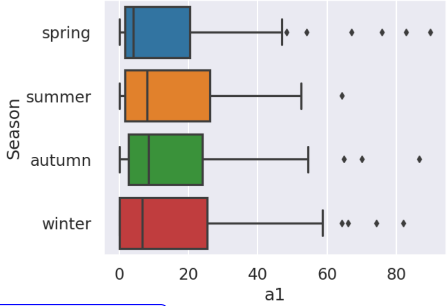


Dataset: `Algae Blooms`, Feature: `Season`, Target: `a1`





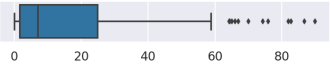


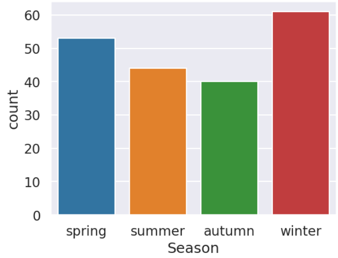


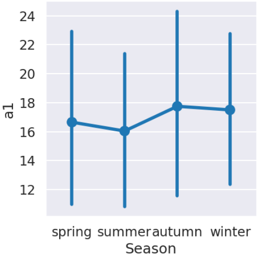

```
df.groupby("Season")["a1"].agg(["min","max","mean","count","std"])
```

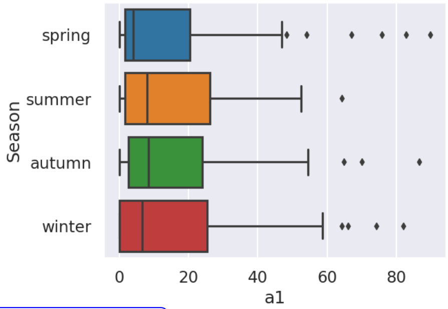
	min	max	mean	count	std
Season			$\bar{x}$	n	σ
spring	0.0	89.8	16.649057	53	23.093786
summer	0.0	64.2	16.038636	44	17.920798
autumn	0.0	86.6	17.745000	40	21.611203
winter	0.0	81.9	17.498361	61	22.568256

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







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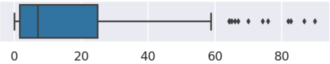
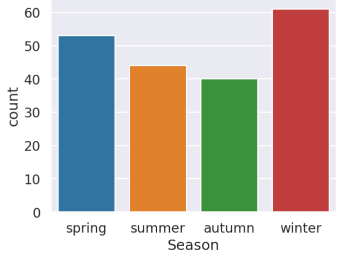
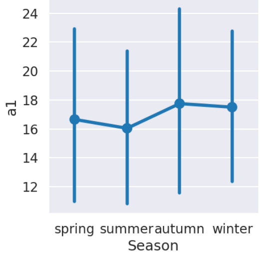
winter	0.0	81.9	17.498361	61	22.568256

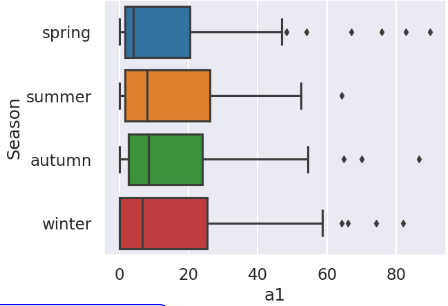
- Countplot shows no issues with feature `Season` — all levels approximately equally represented.

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










```
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```

	min	**max**	**mean**	**count**	**std**
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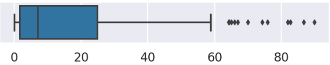
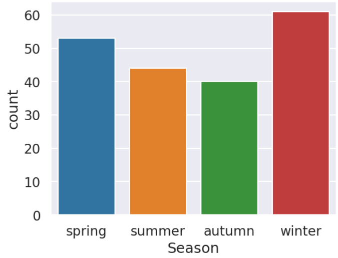
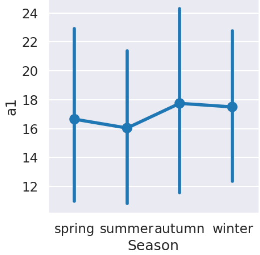
winter	0.0	81.9	17.498361	61	22.568256

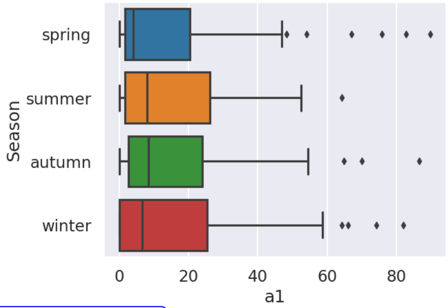
- Countplot shows no issues with feature `Season` — all levels approximately equally represented.
- Countplots show slightly less spread in `a1` for `Season="summer"` observations.

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










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

	min	**max**	**mean**	**count**	**std**
Season			$\bar{x}$	n	σ
spring	0.0	89.8	16.649057	53	23.093786
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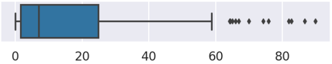
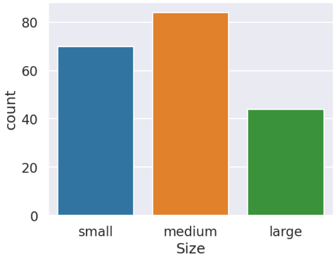
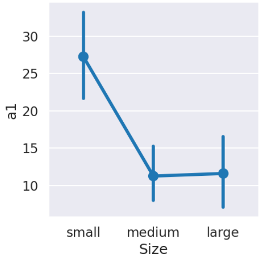
winter	0.0	81.9	17.498361	61	22.568256

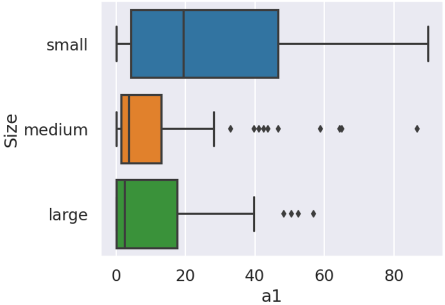
- Countplot shows no issues with feature `Season` — all levels approximately equally represented.
- Countplots show slightly less spread in `a1` for `Season="summer"` observations.
- No/weak relationship between `Season` feature and `a1` target.

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



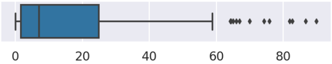




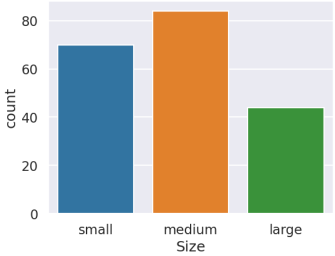


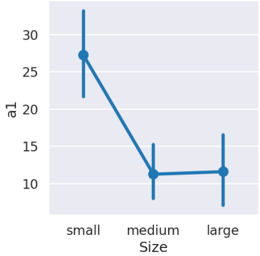

```
df.groupby("Size")["a1"].agg(["min","max","mean","count","std"])
```

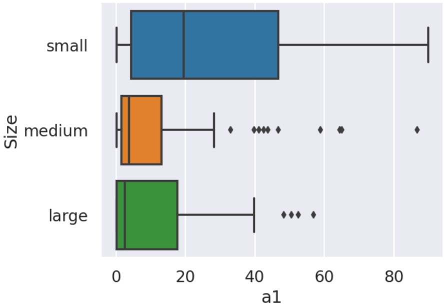
	min	max	mean	count	std
Size					
small	0.0	89.8	27.255714	70	24.895426
medium	0.0	86.6	11.267857	84	17.163124
large	0.0	56.8	11.611364	44	16.556123



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





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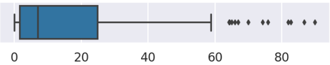
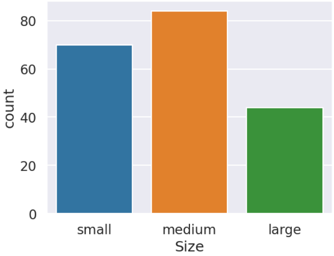
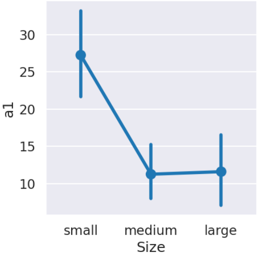
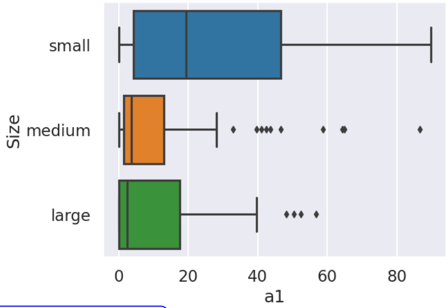
- Countplot shows no issues with feature `Size`.

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







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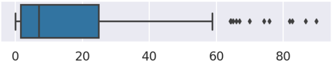
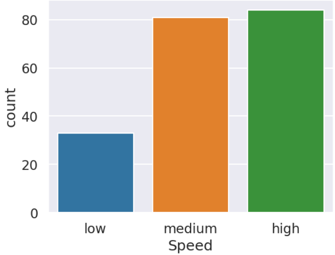
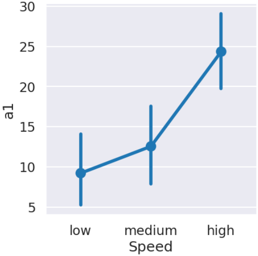
medium	0.0	86.6	11.267857	84	17.163124
large	0.0	56.8	11.611364	44	16.556123

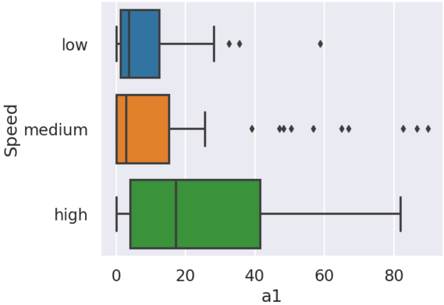
- Countplot shows no issues with feature `Size`.
- `Size="small"` rivers have higher frequencies of `a1` alga ((point) catplot), and observed frequencies for small rivers is much more widespread across the domain of frequencies than for other types of rivers (boxplot).

Dataset: `Algae Blooms`, Feature: `Speed`, Target: `a1`





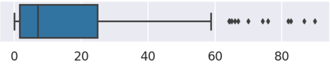


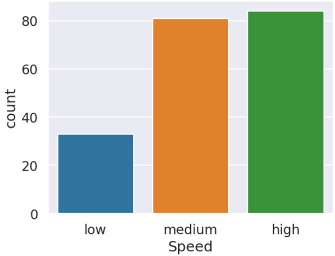


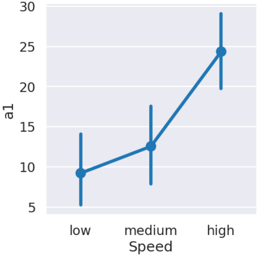

```
df.groupby("Speed")["a1"].agg(["min","max","mean","count","std"])
```

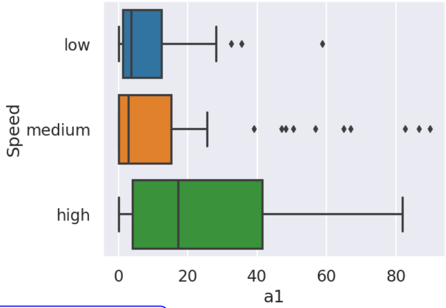
	min	max	mean	count	std
Speed					
low	0.0	58.7	9.209091	33	13.164758
medium	0.0	89.8	12.548148	81	21.146986
high	0.0	81.9	24.345238	84	22.209123

Dataset: `Algae Blooms`, Feature: `Speed`, Target: `a1`







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medium	0.0	89.8	12.548148	81	21.146986
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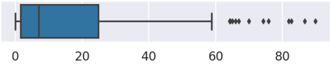
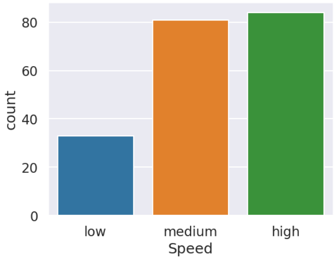
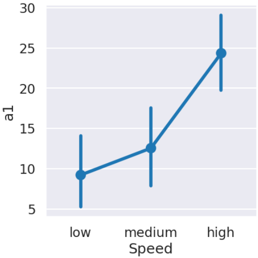
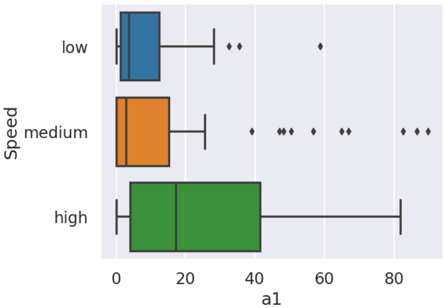
- Countplot shows no issues with feature `Speed`.

Dataset: `Algae Blooms`, Feature: `Speed`, Target: `a1`







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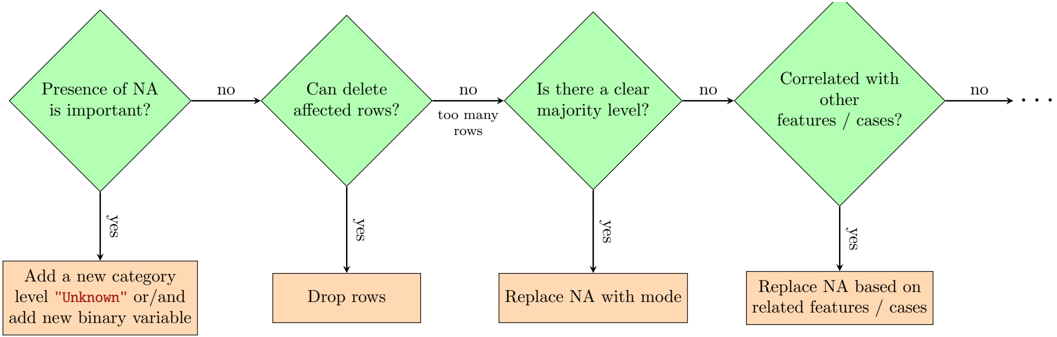
medium	0.0	89.8	12.548148	81	21.146986
high	0.0	81.9	24.345238	84	22.209123

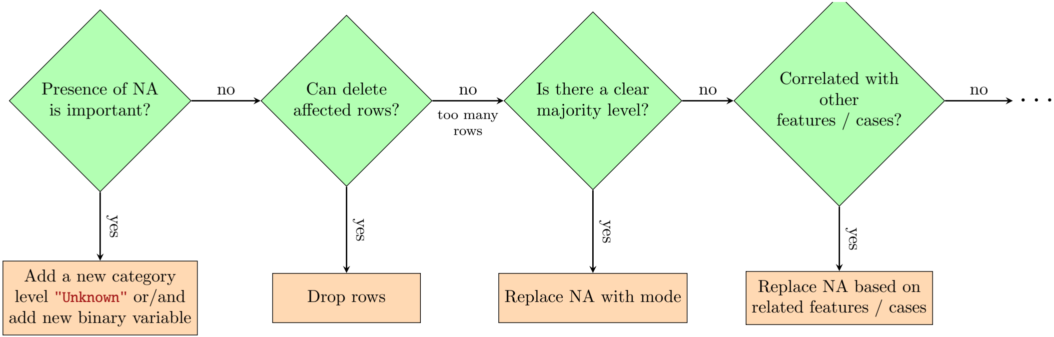
- Countplot shows no issues with feature `Speed`.
- `Speed="high"` rivers have average population of `a1` alga ((point) catplot), and observed frequencies is much more widespread across the domain of frequencies than for other types of rivers (boxplot).

Categorical Variables — Dealing with Missing Values



In terms of our three datasets, only `Titanic` has missing values in categorical features:

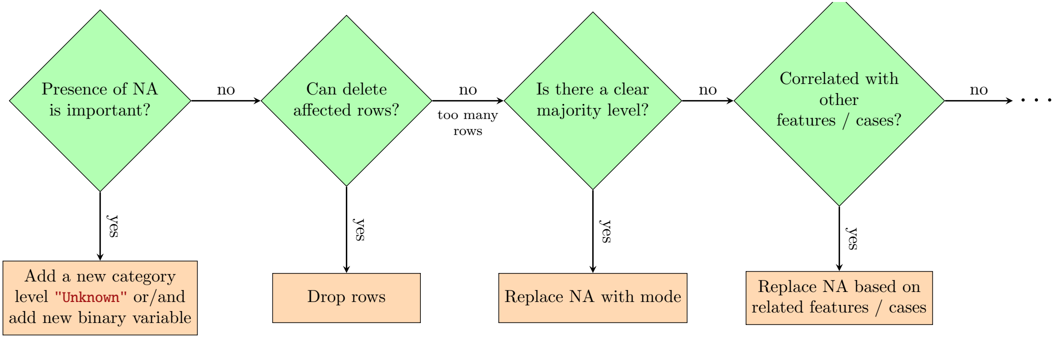
Categorical Variables — Dealing with Missing Values



In terms of our three datasets, only `Titanic` has missing values in categorical features:

- Location of `cabin`'s missing values are important (1st class passengers were most likely to have a cabin) so add new category level `"Unknown"`.

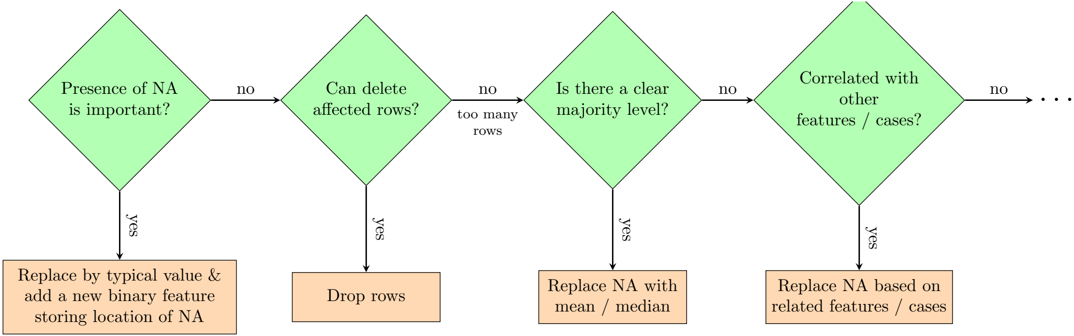
Categorical Variables — Dealing with Missing Values



In terms of our three datasets, only `Titanic` has missing values in categorical features:

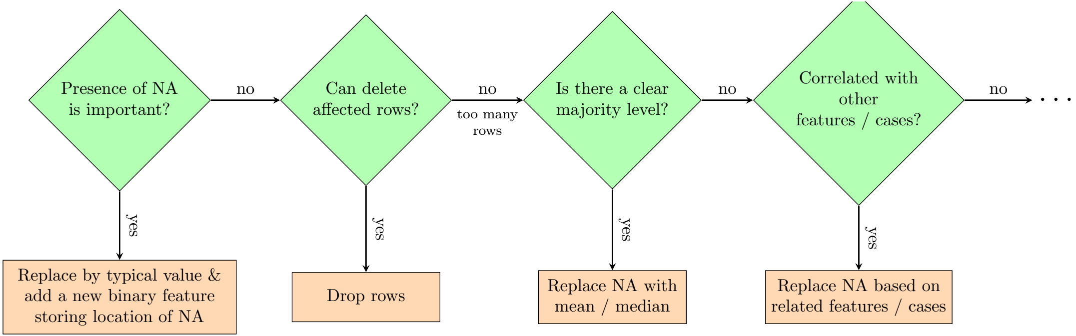
- Location of `cabin`'s missing values are important (1st class passengers were most likely to have a cabin) so add new category level `"Unknown"`.
- Replace `Embarked`'s 2 missing values with mode (`"S"`, 644/891=72%).
  Note: Use `df.Embarked.value_counts(dropna=False)` to include missing values in count tables.

Numerical Variables — Dealing with Missing Values



In terms of our three datasets:

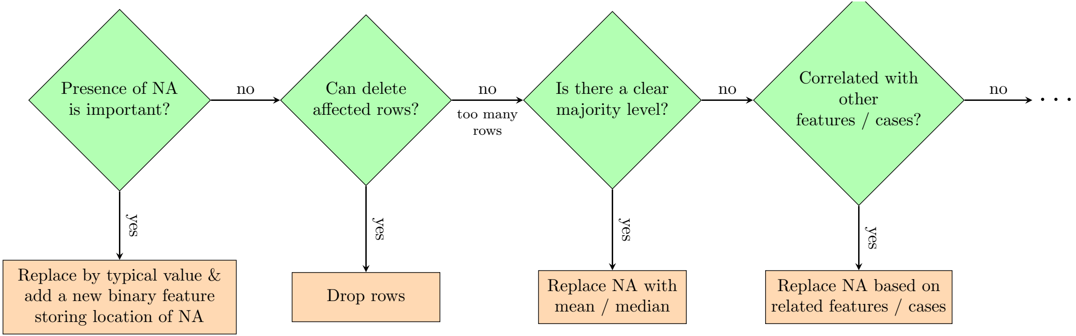
Numerical Variables — Dealing with Missing Values



In terms of our three datasets:

- In `Titanic`, feature `Fare` appears to have no missing values, but has 15 zero entries. Are these missing values? or free tickets due to age? . . .

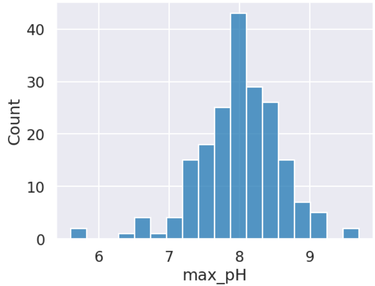
Numerical Variables — Dealing with Missing Values

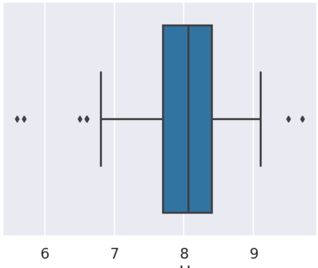


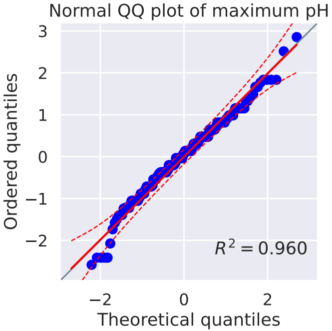
In terms of our three datasets:

- In `Titanic`, feature `Fare` appears to have no missing values, but has 15 zero entries. Are these missing values? or free tickets due to age? . . .
- In `Algae Blooms`, some of the 8 numeric features have NAs . . . next few slides.

Dataset: `Algae Blooms`, Feature: `max_pH`








```
count    197.000000
mean       8.019975
std        0.590169
min        5.600000
25%        7.700000
50%        8.060000
75%        8.400000
max        9.700000
Name: max_pH, dtype: float64
```

- Data is relatively normal — minor issue with (left) outliers.

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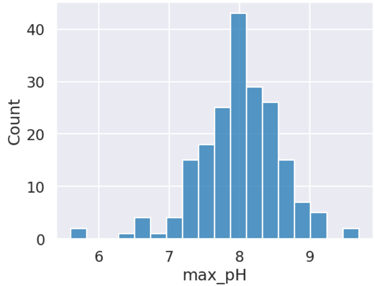

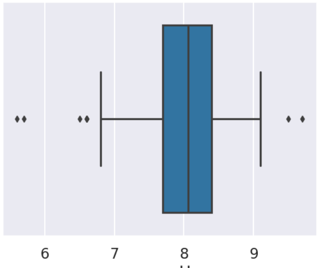

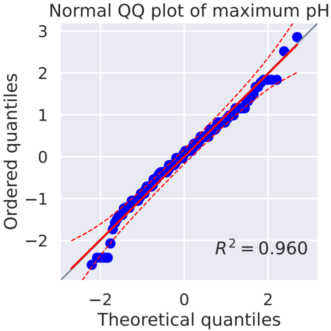


```
df.max_pH.isna().sum()
```

```
1
```

```
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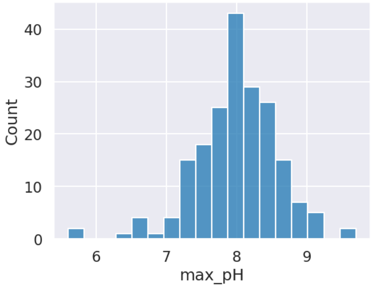

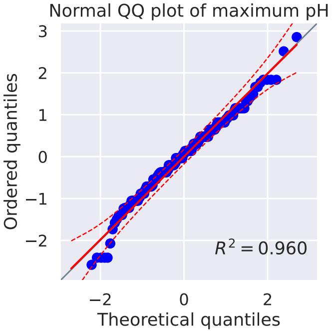


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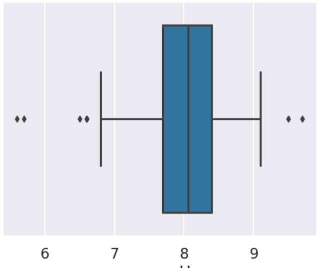

- Data is relatively normal — minor issue with (left) outliers.

⇒ Will replace (single) NA by mean

```
df.max_pH.fillna(df.max_pH.mean(), inplace=True)
```

Dataset: `Algae Blooms`, Feature: `max_pH`, Target: `a1`

Is there a relationship between feature `max_pH` and target `a1`?

Dataset: Algae Blooms, Feature: max_pH, Target: a1

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```
df[["max_pH", "a1"]].corr()
```

	max_pH	a1
max_pH	1.000000	-0.268539
a1	-0.268539	1.000000

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sns.lmplot(x="max_pH", y="a1", data=df);
```

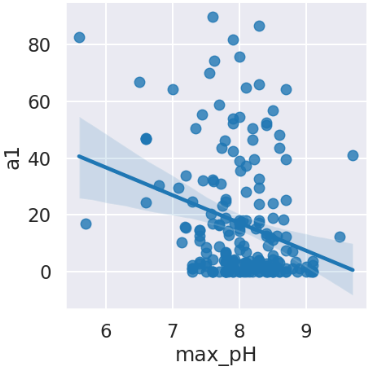

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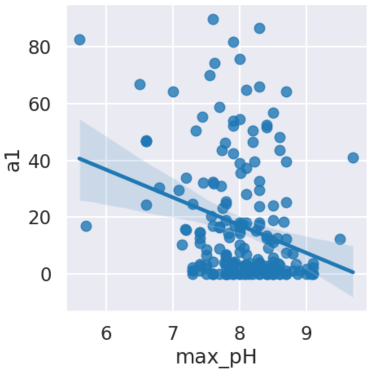
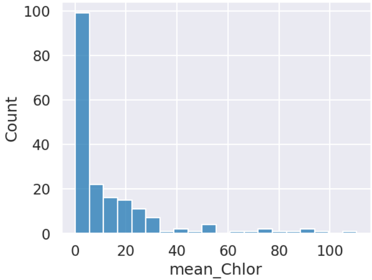
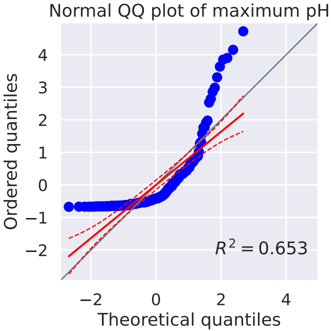


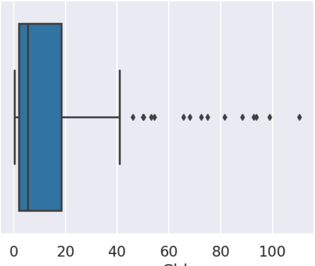
- Correlation coefficient, $r = -0.27$, shows (at most) a weak negative linear relationship.
- No obvious relationship visible in scatter plot.

Dataset: `Algae Blooms`, Feature: `mean_Chlor`





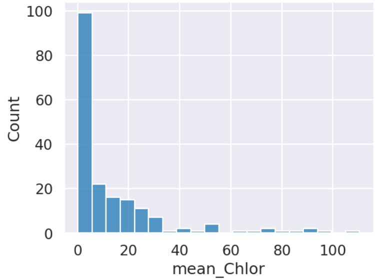

```
count    188.000000
mean      13.971197
std       20.495920
min        0.200000
25%        2.000000
50%        5.475000
75%       18.307500
max      110.456000
Name: mean_Chlor, dtype: float
```

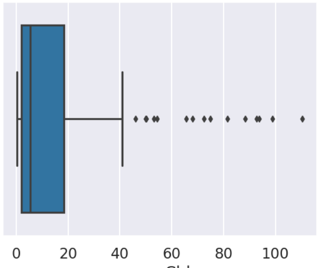


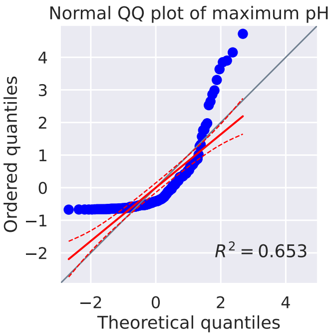
- Data is not normal, heavily skewed to the right
- So will replace (single) NA by median, not the mean

```
df.mean_Chlor.fillna(df.mean_Chlor.median(), inplace=True)
```

Dataset: `Algae Blooms`, Feature: `mean_Chlor`








```
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```
10
```

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- skew $\Rightarrow$ mean is a poor representative of the central location.
- So will replace (single) NA by median, not the mean

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df.mean_Chlor.fillna(df.mean_Chlor.median(), inplace=True)
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After Target and Individual Feature Pass — Where are we? I

Tips

- Reviewed each feature — location, spread, shape, issues.
- No missing values
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- Generated ToDo list for cleaning, feature extraction
  - Identified features that appear to be related to the target.
  - Feature `age` has missing values.
  - Feature `Fare`
    - has 15 measurements with value 0 — decide missing value or not.
    - distribution has large outliers and is skewed — remove/fix outliers and transform.
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Algae Blooms

- Reviewed each feature — location, spread, shape, issues.
- Imputed missing values using feature distributions (mean/median).
- Identified features that appear to be related to the target.

Aside: Steps needed to create new feature `Title` from feature `Name`

```
df = pd.read_csv('assets/train.csv')
df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.28		
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.925		
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
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1 Have a (text) feature representing the passenger's name.

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Title	Count
Capt	1
Col	4
Don	1
Dona	1
Dr	8
Jonkheer	1
Lady	1
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Master	61
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Mlle	2
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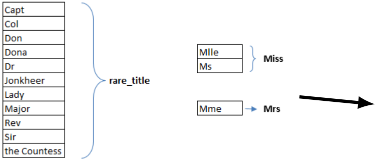
2 Rare categories can be merged under a single label – 'Dona', 'Lady', 'the Countess', 'Capt', 'Col', etc. .
Duplicate/redundant categories can be merged – the titles 'Mlle', and 'Ms' and can be merged under 'Miss'. 'Mme' can be merged with 'Mrs'.



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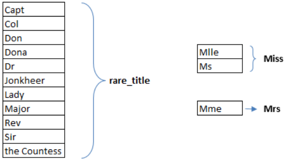

3 New categorical feature with 5 unique values

Master	Miss	Mr	Mrs	rare_title
61	264	757	198	29

Third Pass — Relationships Between Features (and Target)

- Correlations

We distinguish later between feature-feature and feature-target correlations

Correlations — Relationship Between two Variables

Pearson's correlation coefficient, r

is a measure of linear correlation between two variables. Its value lies between -1 and +1, -1 indicating total negative linear correlation, 0 indicating no linear correlation and 1 indicating total positive linear correlation.

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Phi-k, ϕk

is a new and practical correlation coefficient that works consistently between categorical, ordinal and interval variables, captures non-linear dependency and reverts to the Pearson correlation coefficient in case of a bivariate normal input distribution. Its value also lies between 0 and +1, with values near zero indicating no relation.

Pearson's Correlation Coefficient — Dataset: `Algae Blooms`

```
columns = df.columns[:12]
corr = df[columns].corr()
corr
```

	max_pH	min_O2	mean_Cl	mean_NO3	mean_NH4	mean_oPO4	mean_PO4	mean_Chlor	a1
max_pH	1.000000	-0.167981	0.136369	-0.130762	-0.093521	0.158769	0.179885	0.445864	-0.268539
min_O2	-0.167981	1.000000	-0.278333	0.099444	-0.087478	-0.416163	-0.487486	-0.153265	0.285564
mean_Cl	0.136369	-0.278333	1.000000	0.225041	0.071913	0.391054	0.457449	0.149856	-0.371171
mean_NO3	-0.130762	0.099444	0.225041	1.000000	0.721444	0.144588	0.168601	0.139679	-0.241211
mean_NH4	-0.093521	-0.087478	0.071913	0.721444	1.000000	0.227237	0.208180	0.088947	-0.132656
mean_oPO4	0.158769	-0.416163	0.391054	0.144588	0.227237	1.000000	0.914365	0.115621	-0.417358
mean_PO4	0.179885	-0.487486	0.457449	0.168601	0.208180	0.914365	1.000000	0.253621	-0.487023
mean_Chlor	0.445864	-0.153265	0.149856	0.139679	0.088947	0.115621	0.253621	1.000000	-0.277987
a1	-0.268539	0.285564	-0.371171	-0.241211	-0.132656	-0.417358	-0.487023	-0.277987	1.000000

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```
cmap = sns.diverging_palette(230, 20, as_cmap=True)
sns.heatmap(corr, square=True, vmin=-1, vmax=1, cmap=cmap);
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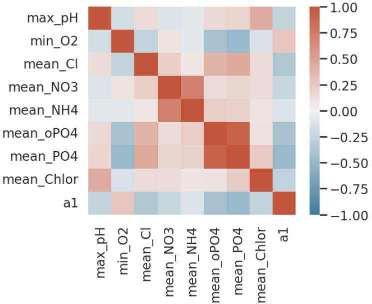

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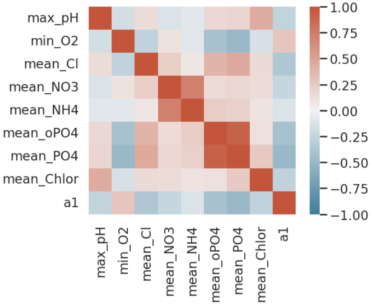
mean_NO3	-0.130762	0.099444	0.225041	1.000000	0.721444	0.144588	0.168601	0.139679	-0.241211
mean_NH4	-0.093521	-0.087478	0.071913	0.721444	1.000000	0.227237	0.208180	0.088947	-0.132656
mean_oPO4	0.158769	-0.416163	0.391054	0.144588	0.227237	1.000000	0.914365	0.115621	-0.417358
mean_PO4	0.179885	-0.487486	0.457449	0.168601	0.208180	0.914365	1.000000	0.253621	-0.487023
mean_Chlor	0.445864	-0.153265	0.149856	0.139679	0.088947	0.115621	0.253621	1.000000	-0.277987
a1	-0.268539	0.285564	-0.371171	-0.241211	-0.132656	-0.417358	-0.487023	-0.277987	1.000000



- Categorical variables are not included.
- Suggests best predictors for `a1` are `mean_PO4`, `mean_oPO4`, and `meanCl`.
- `mean_PO4` and `mean_oPO4` are highly correlated (0.91) — could use values of one to estimate missing values of the other.

Spearman's Rank Correlation Coefficient — Dataset: `Algae Blooms`

```python
columns = df.columns[:12]
corr = df[columns].corr(method='spearman')
corr
```

	max_pH	min_O2	mean_Cl	mean_NO3	mean_NH4	mean_oPO4	mean_PO4	mean_Chlor	a1
max_pH	1.000000	-0.148676	0.159079	-0.145182	0.026160	0.290245	0.214569	0.394813	-0.247787
min_O2	-0.148676	1.000000	-0.405142	0.057610	-0.348226	-0.457805	-0.519786	-0.217714	0.283418
mean_Cl	0.159079	-0.405142	1.000000	0.530374	0.592052	0.670399	0.713479	0.564915	-0.546845
mean_NO3	-0.145182	0.057610	0.530374	1.000000	0.425010	0.432303	0.451272	0.346805	-0.382403
mean_NH4	0.026160	-0.348226	0.592052	0.425010	1.000000	0.603157	0.646690	0.406656	-0.449194
mean_oPO4	0.290245	-0.457805	0.670399	0.432303	0.603157	1.000000	0.914921	0.510930	-0.671019
mean_PO4	0.214569	-0.519786	0.713479	0.451272	0.646690	0.914921	1.000000	0.554167	-0.656670
mean_Chlor	0.394813	-0.217714	0.564915	0.346805	0.406656	0.510930	0.554167	1.000000	-0.537823
a1	-0.247787	0.283418	-0.546845	-0.382403	-0.449194	-0.671019	-0.656670	-0.537823	1.000000

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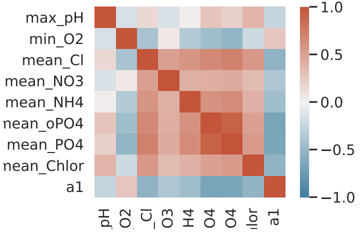

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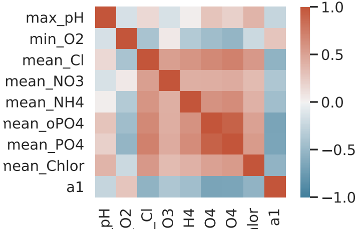

- Now best predictors for `a1` also include `mean_Chlor` and `mean_NH4`.

Phik Correlation Coefficient — Dataset: `Algae Blooms`

```python
import phik
columns = df.columns[:12]
corr = df[columns].phik_matrix()
corr
```

	Season	Size	Speed	max_pH	min_O2	mean_Cl	mean_NO3	mean_NH4	mean_oPO4	mean_PO4	mean_Chlor	a1
Season	1.000000	0.000000	0.000000	0.000000	0.343496	0.000000	0.000000	0.034202	0.000000	0.093199	0.045361	0.000000
Size	0.000000	1.000000	0.620101	0.655207	0.270013	0.268198	0.182410	0.000000	0.000000	0.531635	0.173516	0.353390
Speed	0.000000	0.620101	1.000000	0.445096	0.437356	0.339237	0.000000	0.101348	0.483298	0.594480	0.479735	0.369374
max_pH	0.000000	0.655207	0.445096	1.000000	0.125231	0.000000	0.000000	0.000000	0.000000	0.175105	0.528134	0.372031
min_O2	0.343496	0.270013	0.437356	0.125231	1.000000	0.353196	0.000000	0.416999	0.492457	0.535996	0.296376	0.000000
mean_Cl	0.000000	0.268198	0.339237	0.000000	0.353196	1.000000	0.243887	0.073692	0.443047	0.472824	0.225583	0.000000
mean_NO3	0.000000	0.182410	0.000000	0.000000	0.000000	0.243887	1.000000	0.642789	0.158463	0.259915	0.368142	0.000000
mean_NH4	0.034202	0.000000	0.101348	0.000000	0.416999	0.073692	0.642789	1.000000	0.734681	0.776197	0.167533	0.000000
mean_oPO4	0.000000	0.000000	0.483298	0.000000	0.492457	0.443047	0.158463	0.734681	1.000000	0.954601	0.000000	0.000000
mean_PO4	0.093199	0.531635	0.594480	0.175105	0.535996	0.472824	0.259915	0.776197	0.954601	1.000000	0.192920	0.221308
mean_Chlor	0.045361	0.173516	0.479735	0.528134	0.296376	0.225583	0.368142	0.167533	0.000000	0.192920	1.000000	0.000000
a1	0.000000	0.353390	0.369374	0.372031	0.000000	0.000000	0.000000	0.000000	0.000000	0.221308	0.000000	1.000000

Phik Correlation Coefficient — Dataset: `Algae Blooms`

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corr = df[columns].phik_matrix()
corr
```

```python
cmap = sns.diverging_palette(230, 20, as_cmap=Tr
sns.heatmap(corr, square=True, vmin=-1, vmax=1,
```

	Season	Size	Speed	max_pH	min_O2	mean_Cl	mean_NO3	mean_NH4	mean_oPO4	mean_PO4	mean_Chlor	a1
Season	1.000000	0.000000	0.000000	0.000000	0.343496	0.000000	0.000000	0.034202	0.000000	0.093199	0.045361	0.000000
Size	0.000000	1.000000	0.620101	0.655207	0.270013	0.268198	0.182410	0.000000	0.000000	0.531635	0.173516	0.353390
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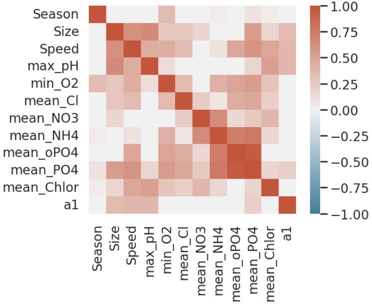

Phik Correlation Coefficient — Dataset: `Algae Blooms`

```python
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columns = df.columns[:12]
corr = df[columns].phik_matrix()
corr
```

```python
cmap = sns.diverging_palette(230, 20, as_cmap=Tr
sns.heatmap(corr, square=True, vmin=-1, vmax=1,
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	Season	Size	Speed	max_pH	min_O2	mean_Cl	mean_NO3	mean_NH4	mean_oPO4	mean_PO4	mean_Chlor	a1
Season	1.000000	0.000000	0.000000	0.000000	0.343496	0.000000	0.000000	0.034202	0.000000	0.093199	0.045361	0.000000
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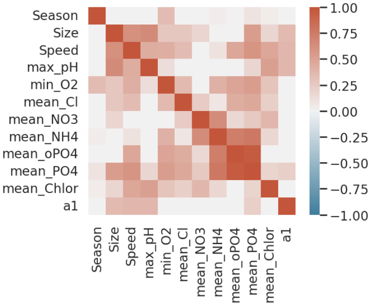
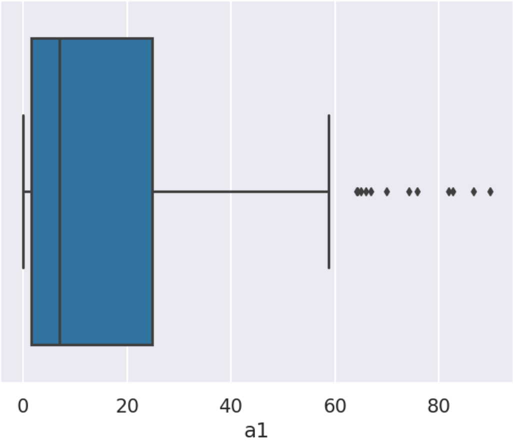


- Now include categorical variables — `Season` is not related, but `Size` and `Speed` are.

Multi-Relation Plots

```
sns.boxplot(x="a1", data=df);
```

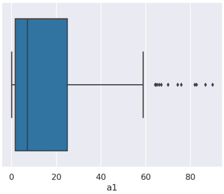
•

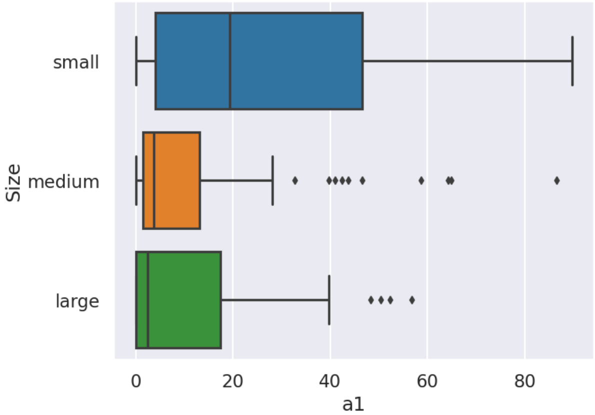


Multi-Relation Plots

```
sns.boxplot(x="a1", data=df);
```

```
sns.boxplot(x="a1", y="Size", data=df);
```





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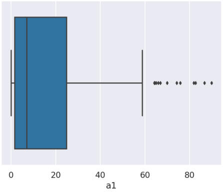


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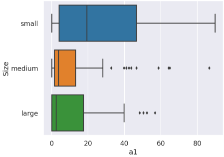
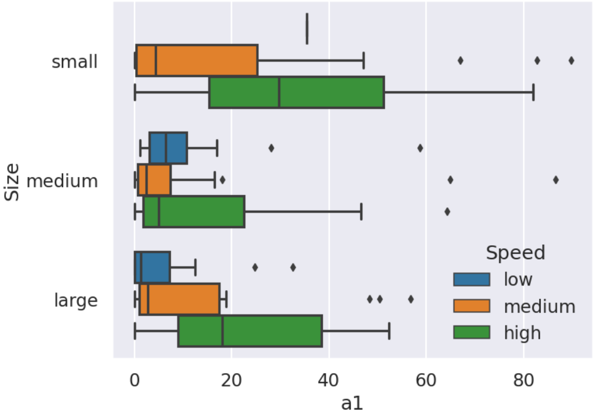



```
sns.boxplot(x="a1", y="Size", hue="Speed", data=df);
```



- If have n features, then have $n(n-1)$ possible visualisations — gets a bit crazy.

After Third Pass — Where are we?

- Reviewed each feature — location, spread, shape, issues.

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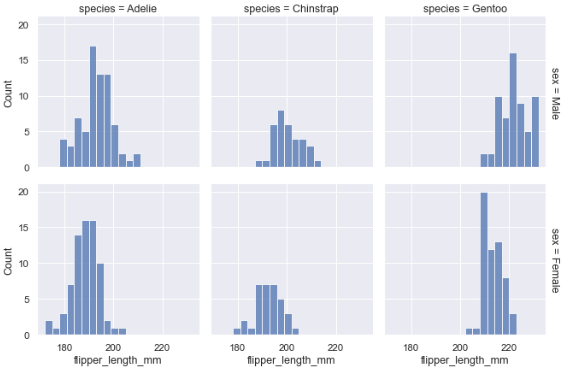
- Reviewed each feature — location, spread, shape, issues.
- Identified any correlation among features and with target.
- Located and resolved missing values.
- Generated list of possible feature engineering tasks.

Selected seaborn-based visualisations

- We could easily spend several weeks on EDA visualisation
- There is a long history of visualisation, from infographics to bubble plots
- Seaborn provides a gallery of data science-related visualisation examples
- We consider a selection today that are useful in practice

Histograms with facets

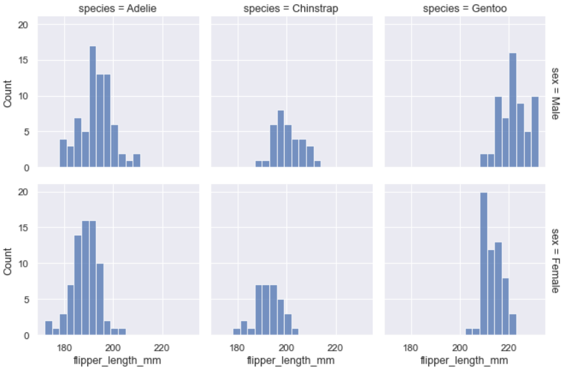


Source: `https://seaborn.pydata.org/examples/faceted_histogram.html`

What it does

- Facets: show a grid of related plots
- Conditioned by 1 or 2 categorical variables
- Here: flipper length of penguins, by sex $\times$ species.

Histograms with facets



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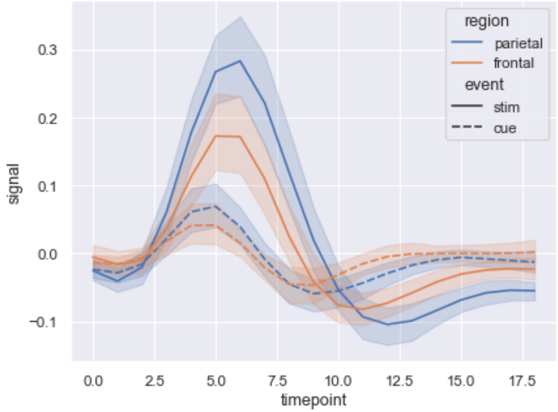
- Conditioned by 1 or 2 categorical variables
- Here: flipper length of penguins, by sex × species.

When to use it

- Have a key variable, represented by a suitable plot
- Wish to view dependence on 1 or 2 categorical variables in same plot group

Line plots with error bands

Source: `https://seaborn.pydata.org/examples/errorband_lineplots.html`



What it does

- Multiple numeric variables as lineplots
- Use of colour and linetype
- Overlaid on error bands

Line plots with error bands

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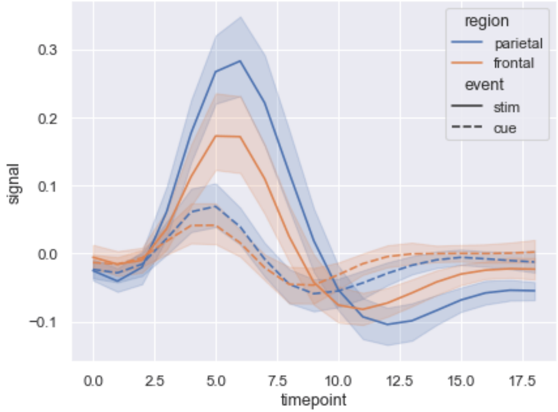


What it does

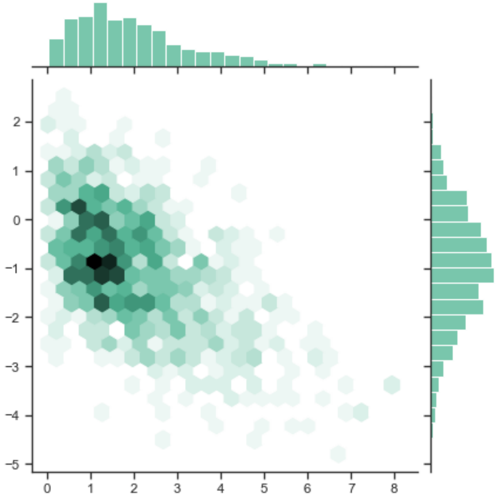
- Multiple numeric variables as lineplots
- Use of colour and linetype
- Overlaid on error bands

When to use it

- Multiple numeric variables on same scale
- Highlight uncertainties

Binning with distribution plots

Source: `https://seaborn.pydata.org/examples/hexbin_marginals.html`



What it does

- Numeric target with 2 attributes
- Binning provides a heatmap

Binning with distribution plots

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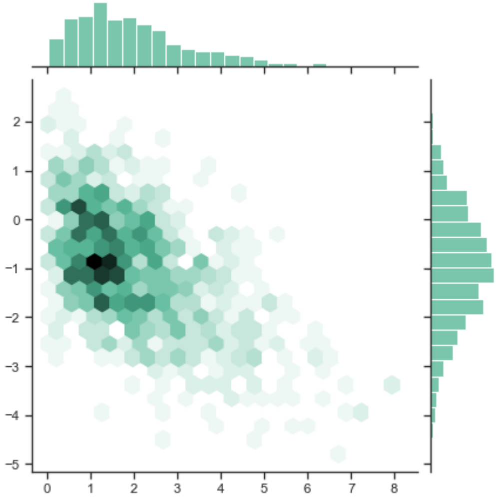


What it does

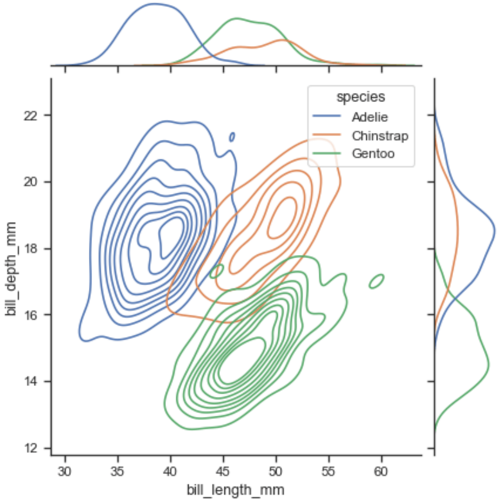
- Numeric target with 2 attributes
- Binning provides a heatmap

When to use it

- Numeric target with 2 numeric attributes
- Attributes may be correlated

Contour plots of distributions

Source: `https://seaborn.pydata.org/examples/joint_kde.html`

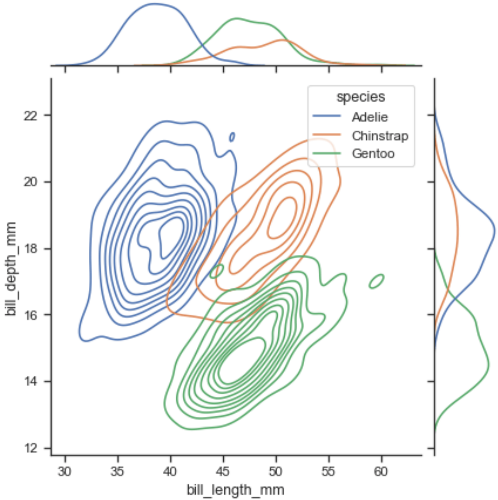


What it does

- Penguin bill length × bill width per species
- Two ways of showing distributions

Contour plots of distributions

Source: `https://seaborn.pydata.org/examples/joint_kde.html`



What it does

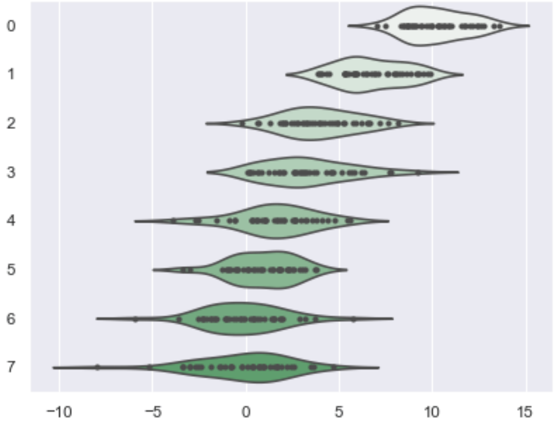
- Penguin bill length × bill width per species
- Two ways of showing distributions

When to use it

- 2 numeric attributes, split by 1 categorical attribute

Violin plots

Source: `https://seaborn.pydata.org/examples/simple_violinplots.html`

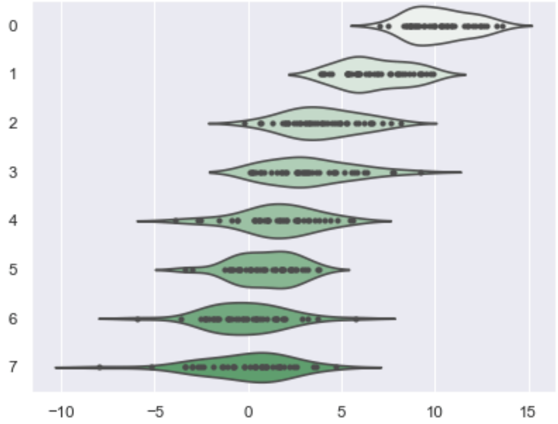


What it does

- Numeric variable, split by category
- Alternative to boxplot
- data points shown here

Violin plots

Source: `https://seaborn.pydata.org/examples/simple_violinplots.html`



What it does

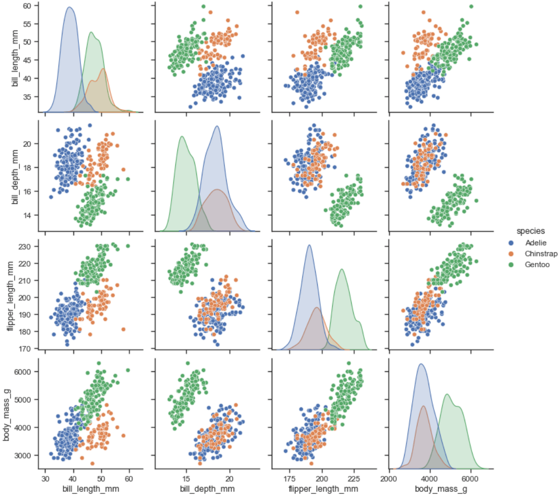
- Numeric variable, split by category
- Alternative to boxplot
- data points shown here

When to use it

- Numeric attibute by categorical attribute
- Interested in the shape of the distribution

Scatterplot matrix

Source: `https://seaborn.pydata.org/examples/scatterplot_matrix.html`

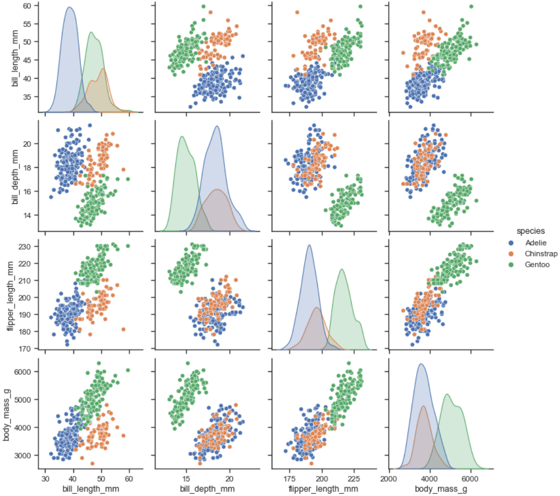


What it does

- Penguin data - 4 numeric attributes (bill length, bill depth, flipper length, body mass), 1 categorical attribute (species) with 3 levels
- All combinations shown

Scatterplot matrix

Source: `https://seaborn.pydata.org/examples/scatterplot_matrix.html`



What it does

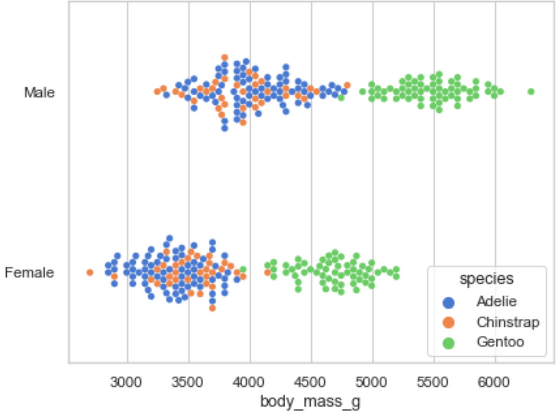
- Penguin data - 4 numeric attributes (bill length, bill depth, flipper length, body mass), 1 categorical attribute (species) with 3 levels
- All combinations shown

When to use it

- Look at many numeric variables together
- Can use colour or other indicator to show categorical variable

Scatterplot with categorical variables

Source: `https://seaborn.pydata.org/examples/scatterplot_categorical.html`

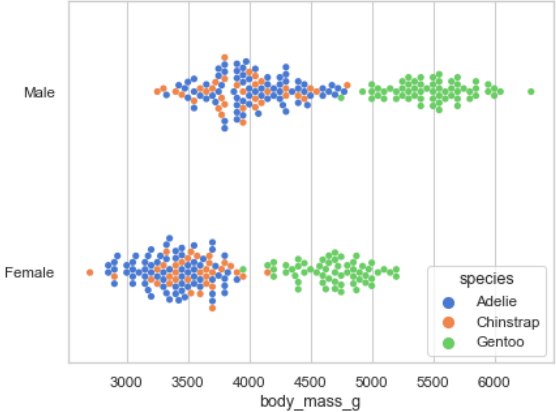


What it does

- Show numerical variable in terms of 1 or more categorical variables

Scatterplot with categorical variables

Source: `https://seaborn.pydata.org/examples/scatterplot_categorical.html`



What it does

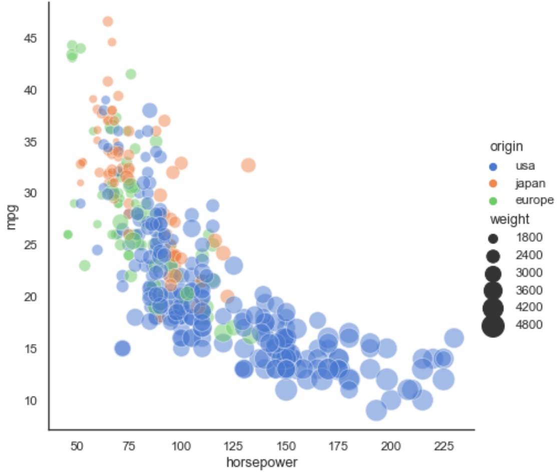
- Show numerical variable in terms of 1 or more categorical variables

When to use it

- More detailed alternative to violinplot

Scatterplot with bubbles

Source: `https://seaborn.pydata.org/examples/scatter_bubbles.html`

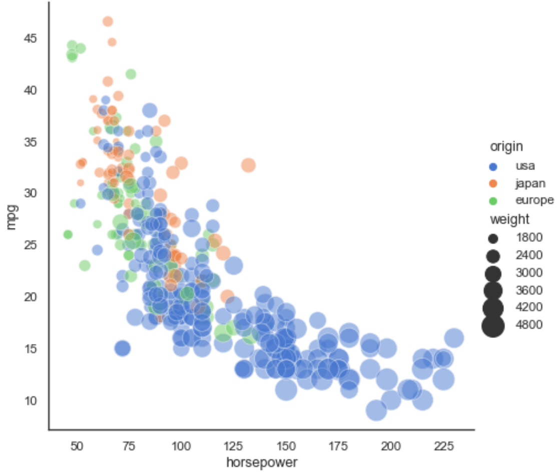


What it does

- Auto mpg data, mpg $\times$ horsepower
- Plot attributes represent categorical attributes
- Note grouping of numeric variable to create categories

Scatterplot with bubbles

Source: `https://seaborn.pydata.org/examples/scatter_bubbles.html`



What it does

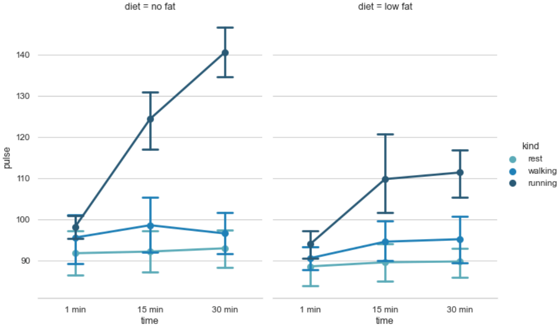
- Auto mpg data, mpg $\times$ horsepower
- Plot attributes represent categorical attributes
- Note grouping of numeric variable to create categories

When to use it

- Represent multiple categorical variables in terms of 2 numerical variables

Pointplot for Analysis of Variance

Source: `https://seaborn.pydata.org/examples/pointplot_anova.html`

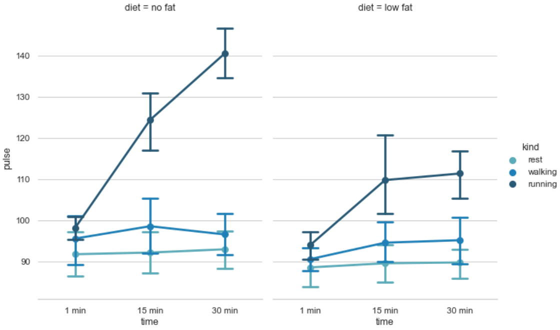


What it does

- Trend in pulse rates, by time $\times$ activity (ordered categories)
- Rich plot, with drill down capability

Pointplot for Analysis of Variance

Source: `https://seaborn.pydata.org/examples/pointplot_anova.html`



What it does

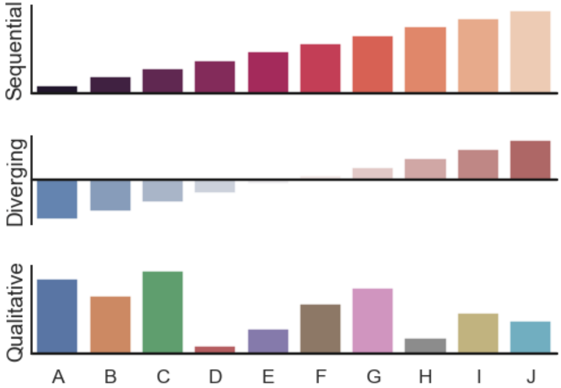
- Trend in pulse rates, by time × activity (ordered categories)
- Rich plot, with drill down capability

When to use it

- Numeric target as function of multiple categorical attributes

Colour palettes

Source: `https://seaborn.pydata.org/examples/palette_choices.html`

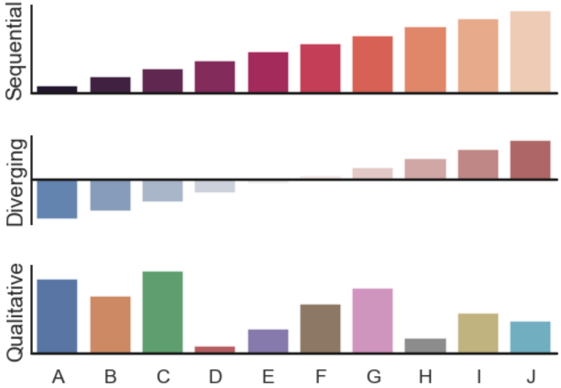


What it does

- Options for choosing palettes
- Qualitative, Sequential, Diverging

Colour palettes

Source: `https://seaborn.pydata.org/examples/palette_choices.html`



What it does

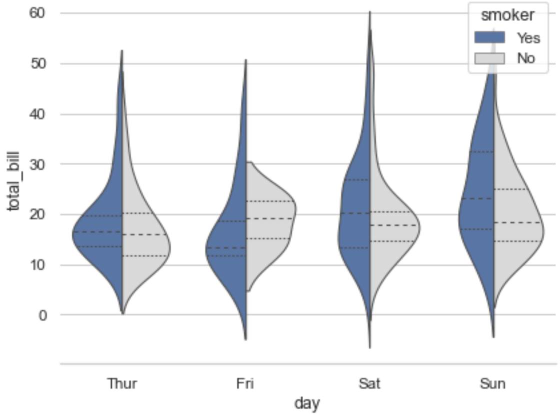
- Options for choosing palettes
- Qualitative, Sequential, Diverging

When to use it

- Qualitative: unordered categorical variable
- Sequential: ordered categorical variable
- Diverging: ordered sequential variable

Grouped Violinplots

Source: `https://seaborn.pydata.org/examples/grouped_violinplots.html`

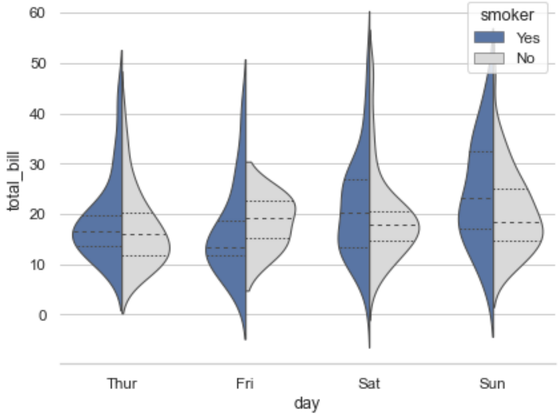


What it does

- Tips data: total_bill by day $\times$ smoker
- Note splits in “violins” to accomodate a category

Grouped Violinplots

Source: `https://seaborn.pydata.org/examples/grouped_violinplots.html`



What it does

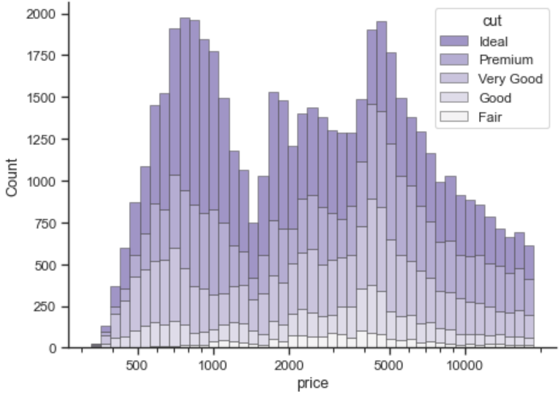
- Tips data: total_bill by day × smoker
- Note splits in "violins" to accomodate a category

When to use it

- Adding a second categorical variable to violinplot
- Alternative to faceting

Stacked histograms

Source: `https://seaborn.pydata.org/examples/histogram_stacked.html`

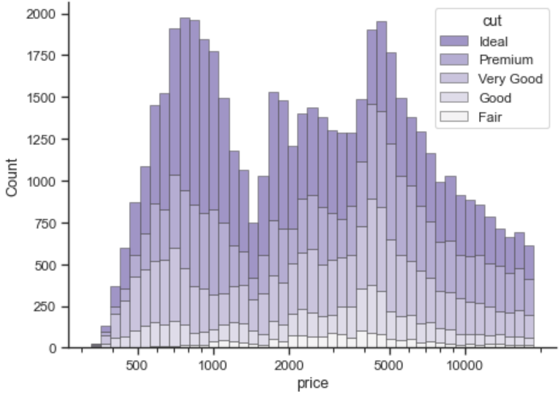


What it does

- Diamond valuation data
- Show distribution of price by cut
- Be careful: stacked not overlaid!

Stacked histograms

Source: `https://seaborn.pydata.org/examples/histogram_stacked.html`



What it does

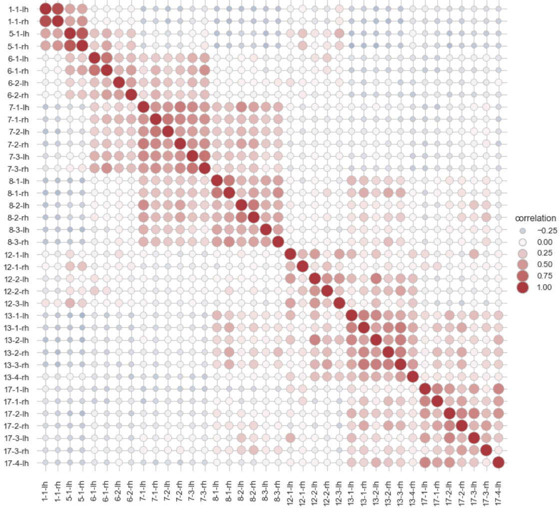
- Diamond valuation data
- Show distribution of price by cut
- Be careful: stacked not overlaid!

When to use it

- Can compare histograms by category variable
- Alternative to faceting

Heatmap with scatterplot

Source: `https://seaborn.pydata.org/examples/heat_scatter.html`

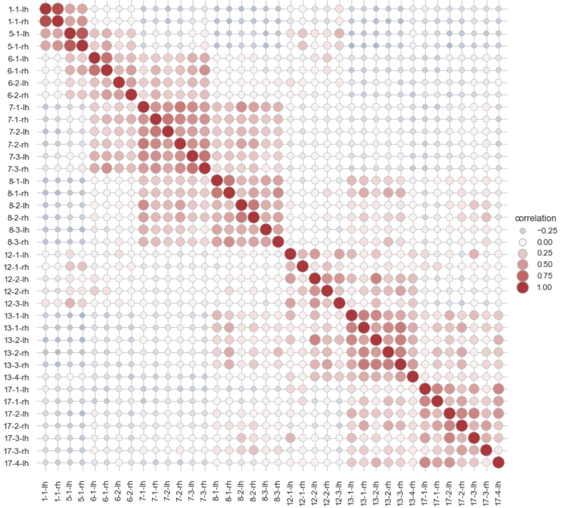


What it does

- Network data
- Highlighting correlated flows
- Use of colour and size of bubbles

Heatmap with scatterplot

Source: `https://seaborn.pydata.org/examples/heat_scatter.html`



What it does

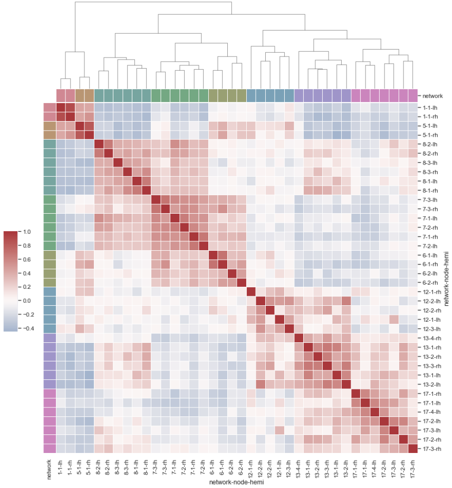
- Network data
- Highlighting correlated flows
- Use of colour and size of bubbles

When to use it

- Emphasise sign and magnitude of correlations

Heatmap with dendrogram

Source: `https://seaborn.pydata.org/examples/structured_heatmap.html`

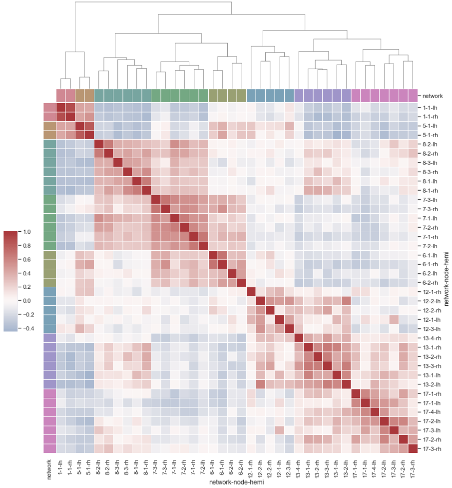


What it does

- Heatmap of correlations
- Dendrogram clusters them to highlight similar values

Heatmap with dendrogram

Source: `https://seaborn.pydata.org/examples/structured_heatmap.html`



What it does

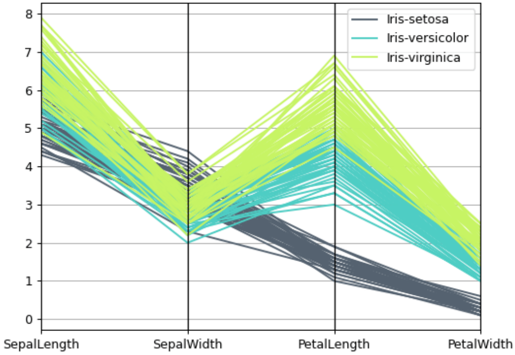
- Heatmap of correlations
- Dendrogram clusters them to highlight similar values

When to use it

- Need to identify groups of correlated numerical variables

Parallel coordinate plots

Source: https://pandas.pydata.org/docs/reference/api/pandas.plotting.parallel_coordinates.html

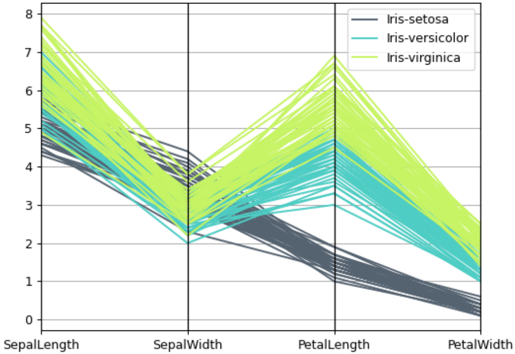


What it does

- Each piecewise linear "line" represesents an instance
- Each vertical split (context) line represents a numerical variable (feature or target)
- Instance lines pass through values they take on the context variables

Parallel coordinate plots

Source: `https://pandas.pydata.org/docs/reference/api/pandas.plotting.parallel_coordinates.html`



What it does

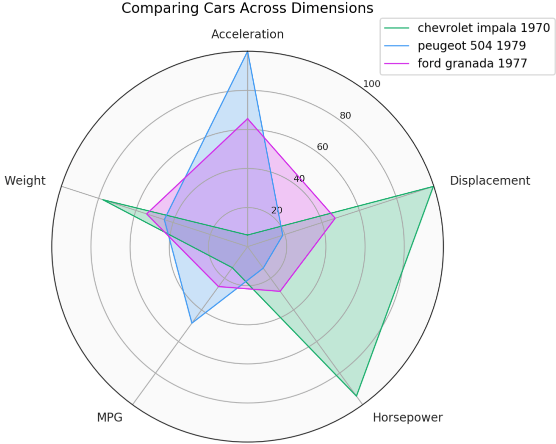
- Each piecewise linear "line" represesents an instance
- Each vertical split (context) line represents a numerical variable (feature or target)
- Instance lines pass through values they take on the context variables

When to use it

- Need to compare subsets of instances (note use of colour to distinguish)
- Compare instances based on a (subset) of their numerical values

Radar charts

Source: `https://www.pythoncharts.com/matplotlib/radar-charts/`

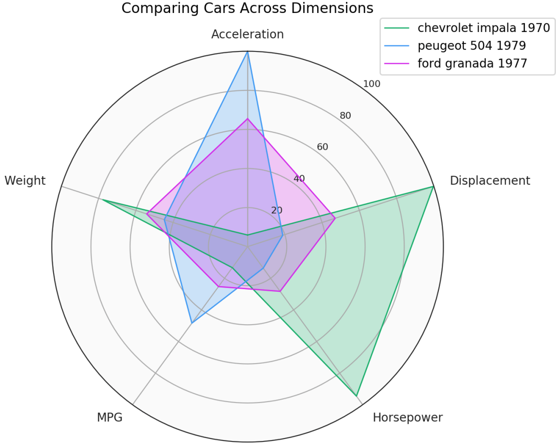


What it does

- Each polygon represents an instance, colour legend identifies the instance
- Each radial line represents a numerical variable
- Vertices of the polygon indicate the value an instance takes on that variable

Radar charts

Source: `https://www.pythoncharts.com/matplotlib/radar-charts/`



What it does

- Each polygon represents an instance, colour legend identifies the instance
- Each radial line represents a numerical variable
- Vertices of the polygon indicate the value an instance takes on that variable

When to use it

- Have a small number of instances to compare over selected numerical variables
- Visualise correlations between numerical variables, for selected instances

Resources

Resources

Guides

- 1 hour, Youtube on generating seaborn plots — excellent (but wrong on interpretation of box plot)
  `www.youtube.com/watch?v=6GUZXDef2U0&t=1363s`

Articles on Exploratory Data Analysis

- Exploratory Data Analysis (EDA) and Data Visualization with Python
  `www.kite.com/blog/python/data-analysis-visualization-python/`
- When Should You Delete Outliers from a Data Set?
  `humansofdata.atlan.com/2018/03/when-delete-outliers-dataset`

Visualisation

- (Seaborn) Example Gallery
  `https://seaborn.pydata.org/examples/index.html`