NIHR | Applied Research Collaboration South West Peninsula

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Module 9 : Forecasting
Session 9A : Intro to Forecasting
Elliott Coyne

“A Great Way to Fly”

SINGAPORE AIRLINES

HSMA 5

#hsma5isalive

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What we’ll learn this morning...

- What can be forecast?
- The process of forecasting
- Time series data in health
- The importance of benchmark forecasts
- Evaluating forecasts

Disclaimer...

Forecasting is difficult!

1. The future is uncertain – even for advanced mathematical tools
2. Approach and tools are statistically complex

Steps for forecasting projects

1) Problem definition (***what*** to forecast and ***how*** will they be used)
2) Data collection
3) Exploratory analysis
4) Fitting & trialling candidate forecasting models
5) Forecast evaluation and selection of the best model
6) Generating the forecasts

What is “forecastable”?

Examples

- Call volumes to a call centre to help determine staffing levels
- Stock requirements for inventory management
- Outpatient appointments
- Elective operation demand
- The spread of disease*

Forecast Horizons

- minutes, hours, weeks, months or years

* Not covered here

Some things are easier to forecast than others!

How accurately we can forecast something is determined by:

- how well we understand the factors that contribute to it (i.e., weather);
- how much data are available (some methods are very ‘data hungry’);
- whether the forecasts can affect the thing we are trying to forecast
  - i.e., if a change in practice occurs, won’t know what *would* have happened.

Things to consider when asked for forecast something

- *What are the decisions that forecasting will support?*
  - Short term operational;
  - determining future resource requirements;
  - or strategic planning?
- *Do you need to forecast one, or multiple things?*
  - Example: Total ED demand, or demand per condition
  - Important that need matches what can be (well) forecast
- *What level of forecast accuracy is needed to support decisions? (Will the mean suffice? Requester may not have considered)*
- *How far ahead do you need to forecast?*
- *What is the frequency of your data? (e.g. weekly, monthly)*
  - We cant provide daily data if only monthly available.
- *How frequently are forecasts needed?*

Advice...

Make sure you spend time talking to the people who need the forecasts to understand their needs before doing any analysis and modelling!

Time series forecasting

Most quantitative forecasting uses time series data. Examples include...

- *The monthly number of patients that are carried by ambulance to an ED*
- *The daily number of patients admitted to hospital with respiratory diseases*
- *Quarterly sales of toilet rolls in the UK*

Quantitative forecasting can be applied when it is safe to assume that historical patterns will continue into the future.

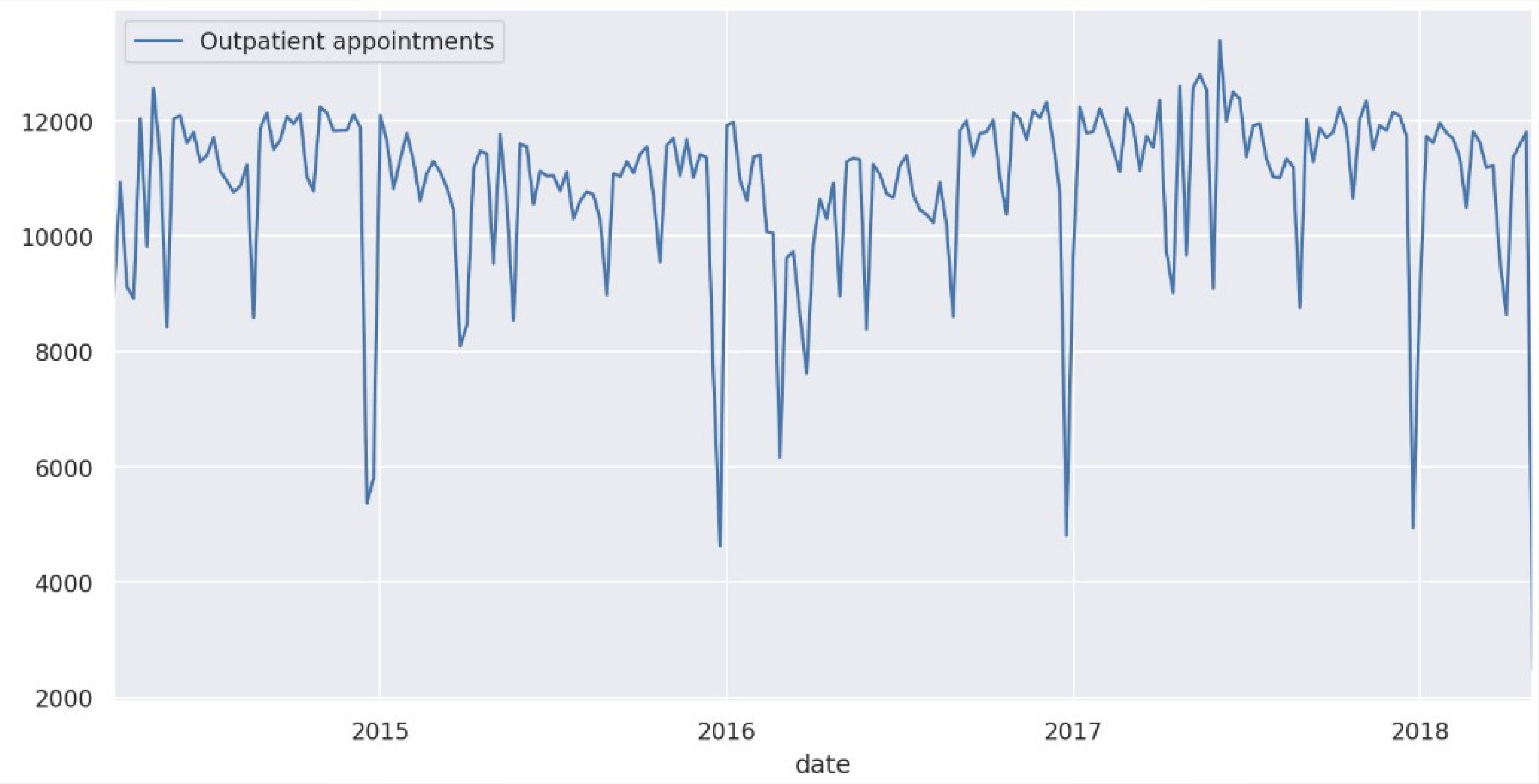
Extreme events break this assumption. Unfortunately that's a problem at the moment!

An introduction to...

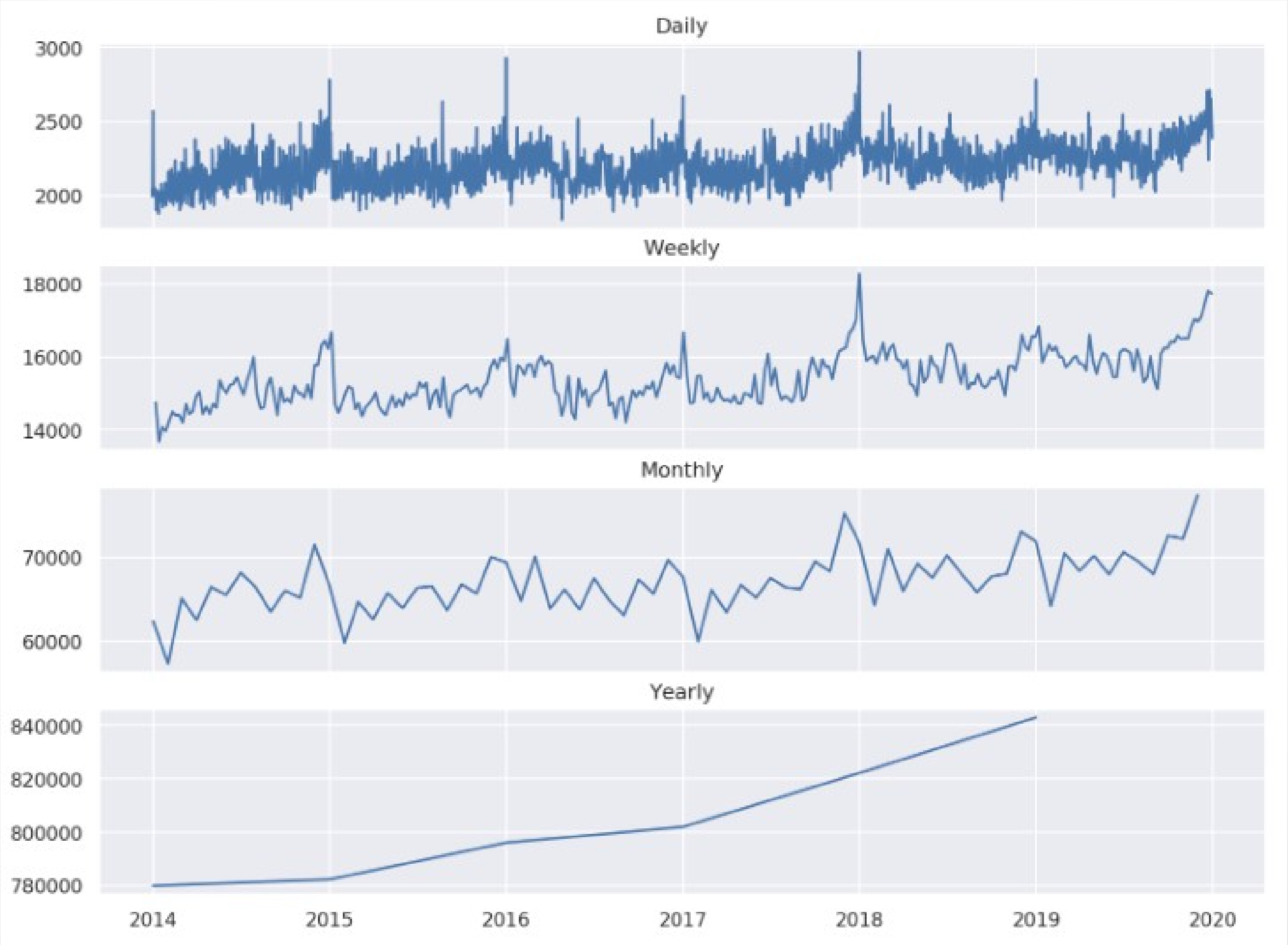
Time Series

Weekly outpatient appointments

Chart that plots quantity over time…
Weekly total observations recorded: 2014 – c2018
Patterns visually present within data…
… Useful for some form of quantitative method can use to predict into the future
Other properties may not be visually identifiable



Frequency: Ambulance dispatches



Statistical characteristics of time series data

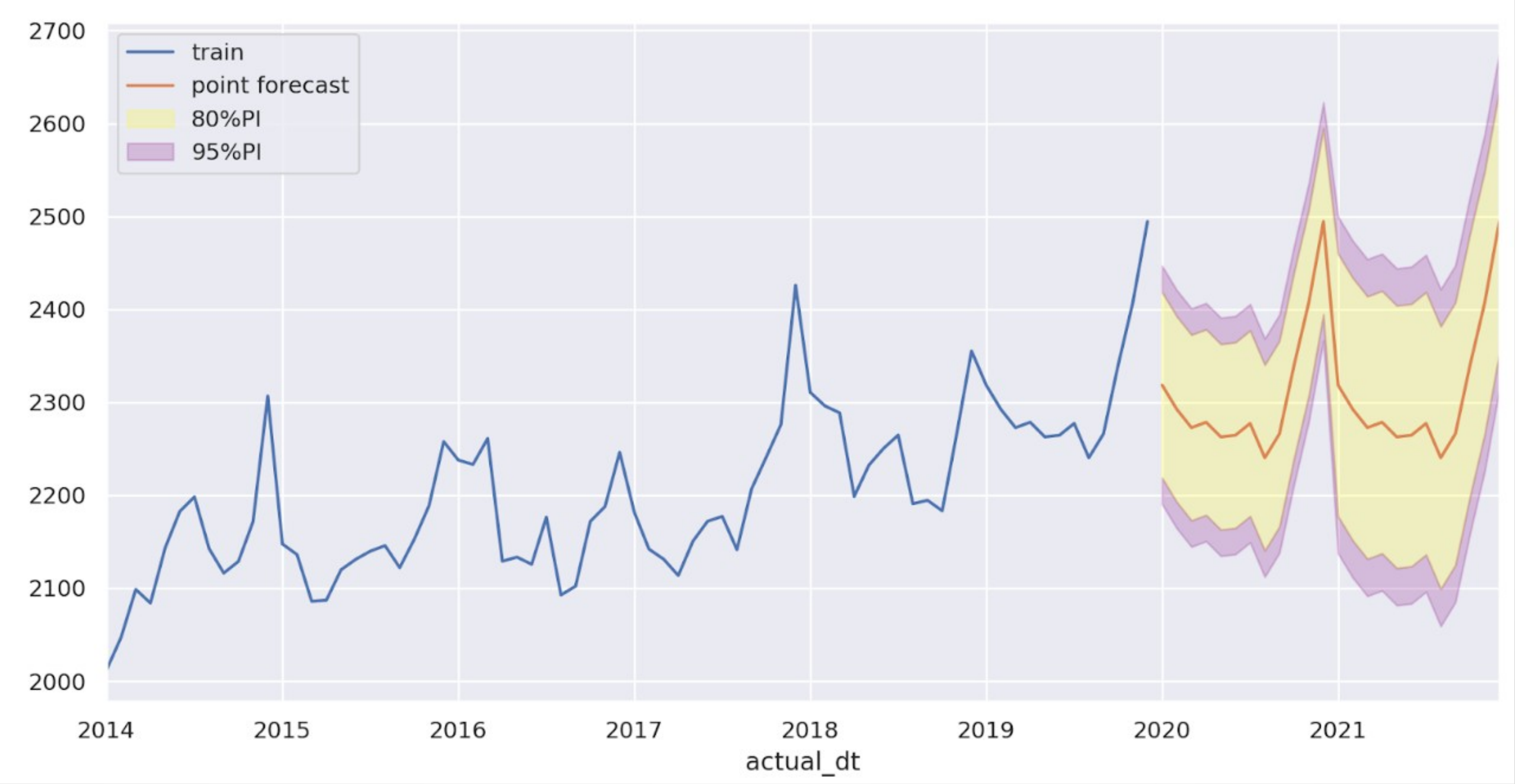
- Trend
- Seasonality *– How does the series rise and fall periodically over time?*
- Mean *– Also called ‘level’ in literature*
- Variance
- ***Stationarity***
- ***Autocorrelation*** *– i.e., number of sales on a Thursday is related to sales on a Wednesday, which is related to sales on a Tuesday...*

Introducing...

Naive benchmarks

Seasonal Naive

Trend
Seasonality



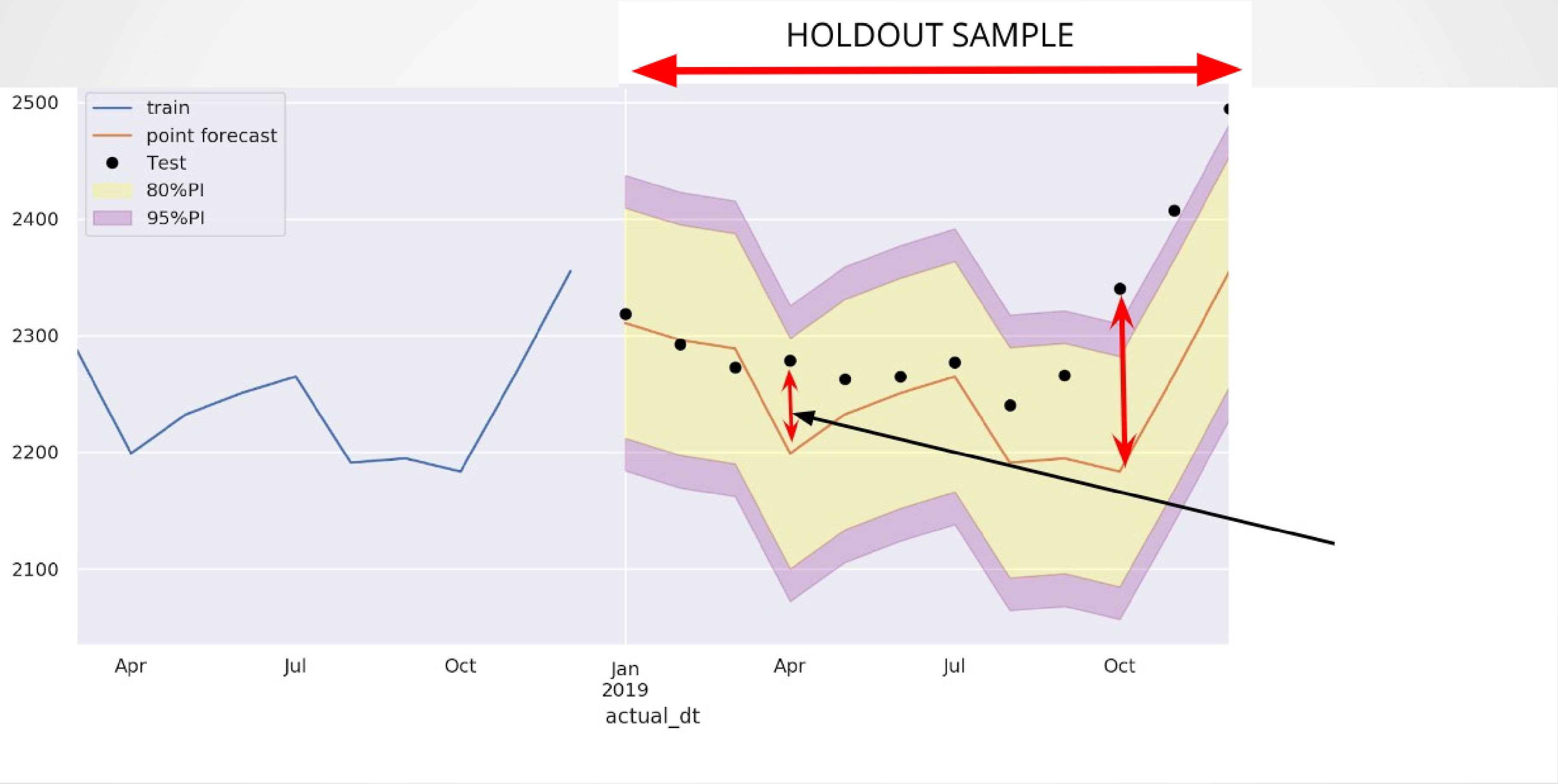
Naive benchmarks

- Naive methods should always be used before getting sophisticated.
  - A ‘clever’ model may not be as good as you think!
  - It may even be worse than a naive model.
  - The burden is on you as a forecaster to PROVE your method is better.
- Classic naive models:
  - **Naive 1**: Carry the last observation forward
  - **Seasonal Naive**: Carry the last observation from same period forward
  - **Drift**: Introduce a simple trend into Naive 1
  - **Average**: The mean of the time series
- The models produce point forecasts and prediction intervals

Introducing...

Evaluating Forecasts

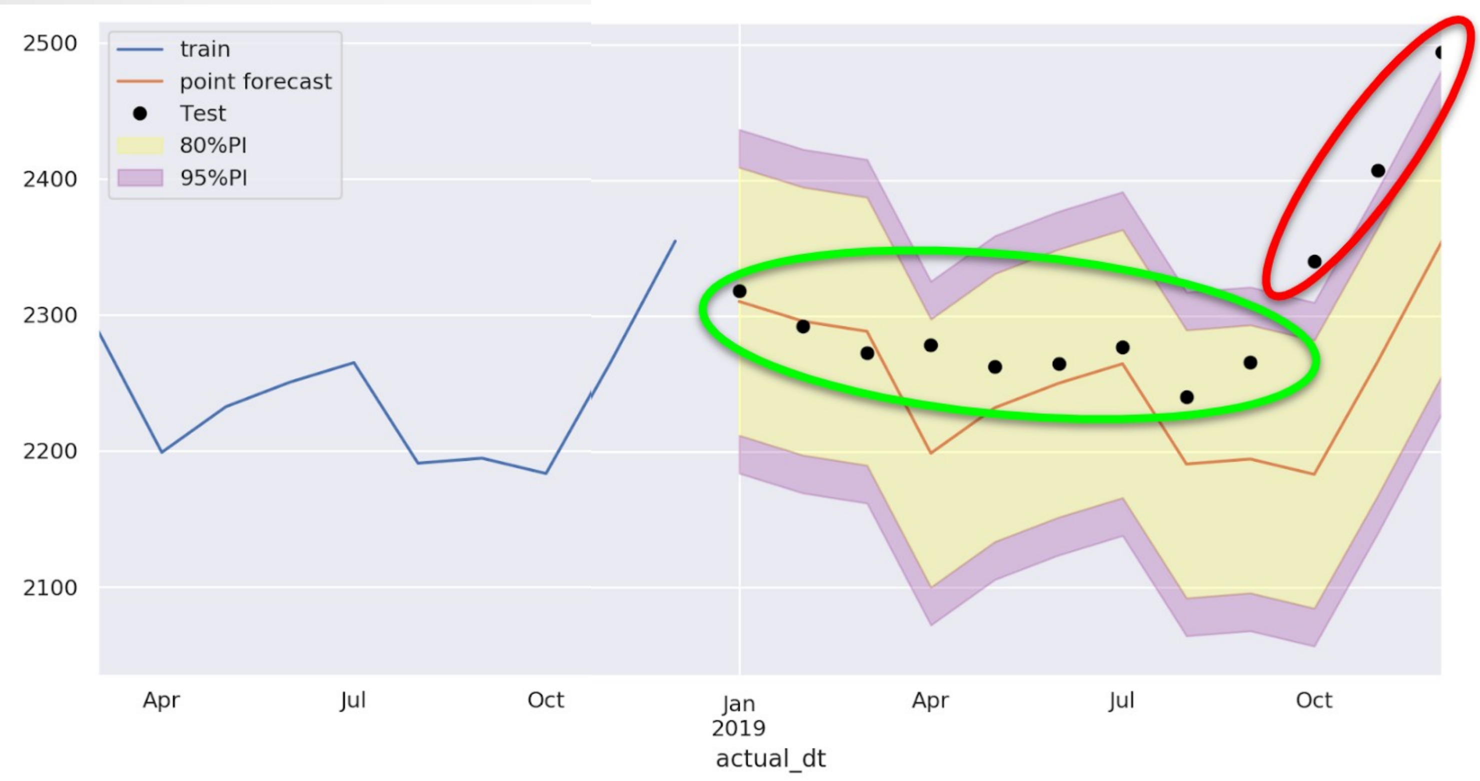
Point Forecast Error



Measurement of point forecast accuracy

- Mean Error
  - Suffers from some errors being negative and some positive
- Better scale dependent measures
  - Mean Absolute Error (**MAE**)
  - Mean Squared Error (**MSE**)
    - Root Mean Squared Error (**RMSE**)
- Relative measures
    - Mean Absolute Percentage Error (**MAPE**)
      - symmetric **MAPE** (sMAPE)
- Scaled Errors
    - Mean Absolute Scaled Error (**MASE**)

PI Coverage



Intervals that give the correct coverage are difficult to get in practice! But it is good to know the limitations of the method in use.

Lets see some code...

After a 15 min comfort break.

Then we'll look at two code along notebooks:
- Pandas time series
- Exploring Time Series (ts) data

...Before attempting Practical 1 in your PSGs

Lets see some more code...

After a 10 min comfort break.

Then we’ll look at one final code along notebook:

- Benchmark forecasts

...Before attempting Practical 2 in your PSGs

Lecture Summary

- Forecasting of demand can happen at multiple levels in health
- The importance of a naive forecasting benchmark
- Forecast evaluation
  - Point forecast error
  - Prediction interval coverage