NIHR | Applied Research Collaboration South West Peninsula

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Module 9 : Forecasting
Session 9A : Intro to Forecasting
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"A Great Way to Fly"

HSMA 5

#hsma5isalive

What we'll learn this morning...

- What can be forecast?
- The process of forecasting
- Time series data in health
- The importance of benchmark forecasts (Simple approaches that should always be tried first)
- Evaluating forecasts (Essential step in any forecasting study!)

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 (May require pre-processing to get into a time series format)
3) Exploratory analysis (including visualisations)
4) Fitting & trialling candidate forecasting models
5) Forecast evaluation and selection of the best model
6) Generating the forecasts (what does the forecast actually look like?)

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* (v. complex!)

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 is 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 if we hadn’t amended practice as a result of the forecast produced i.e. NHS being overwhelmed by Covid patients.

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, or resource planning over the long term?
- *Do you need to forecast one, or multiple things?*
  - Example: Total Emergency Dept. demand, or demand per condition, age group, etc.
  - Important that need of organisation 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? (A.k.a. horizon)*
- *What is the frequency of your data? (e.g. weekly, monthly, or hourly → preprocess to daily)*
  - We can’t provide daily forecasts if only monthly data 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

We’ll focus on quantitative 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.

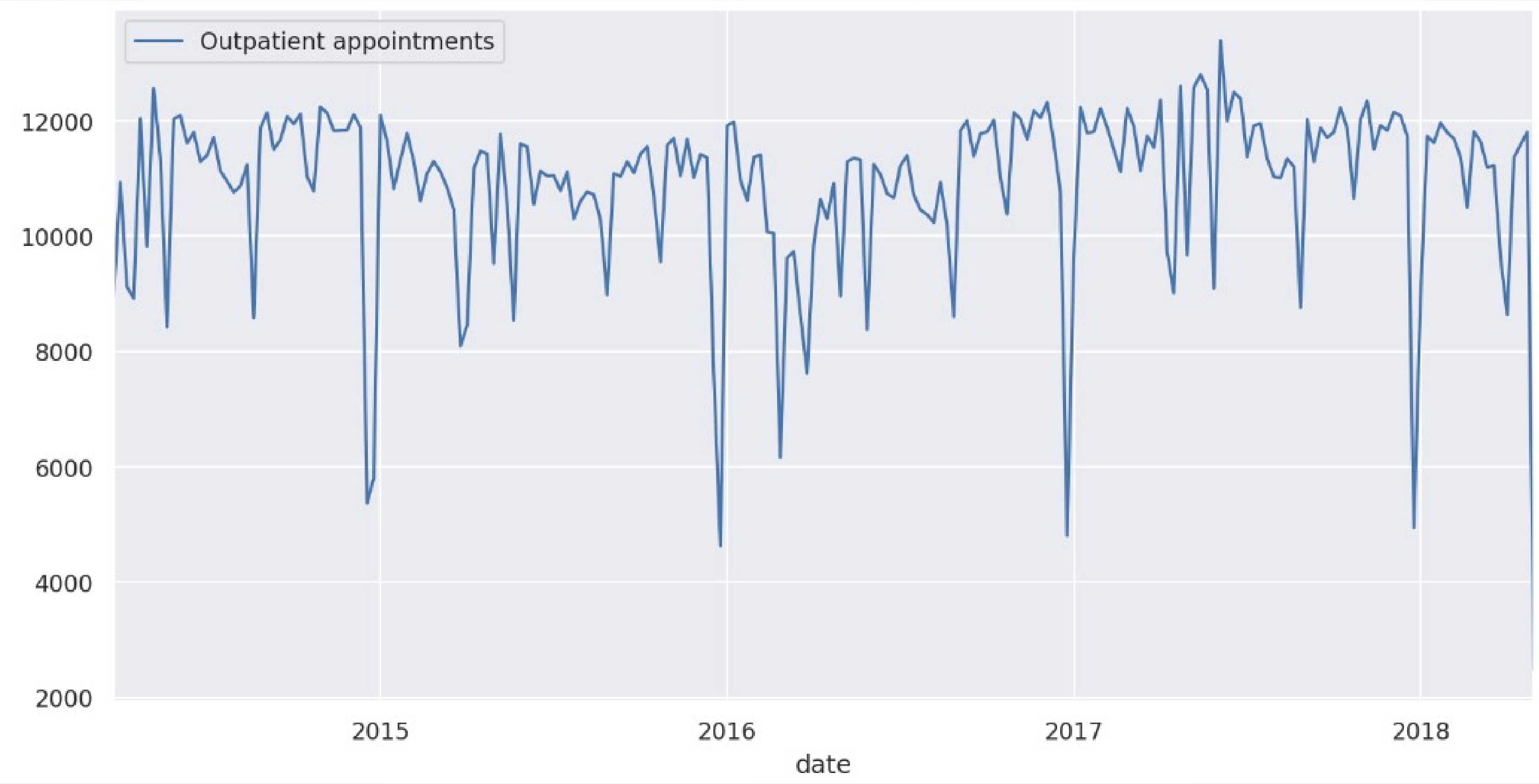
Extreme events break this assumption. Unfortunately that’s a problem at the moment!

An introduction to...

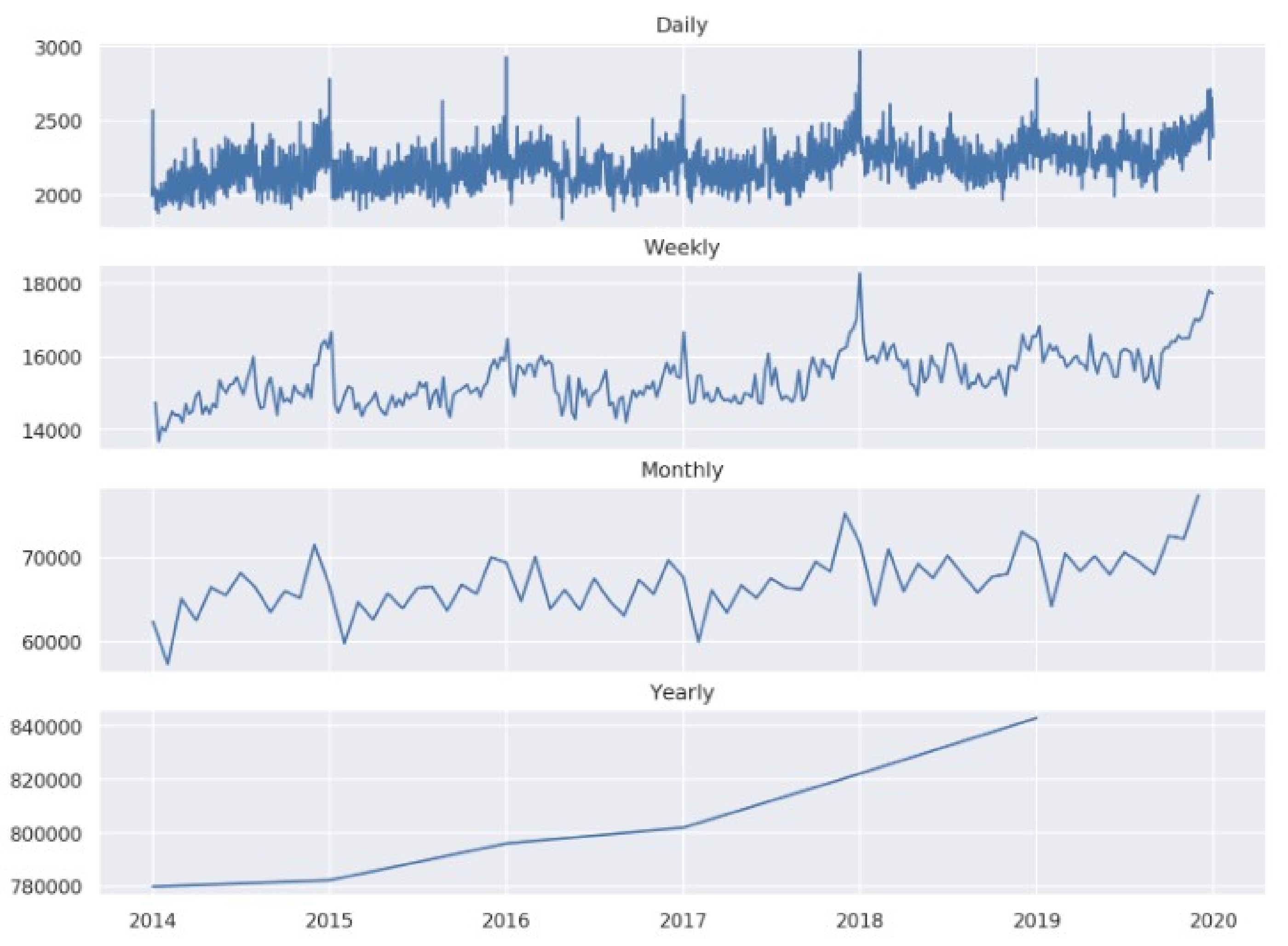
Time Series

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 (or signals) may not be visually identifiable



Frequency: Ambulance dispatches



Statistical characteristics of time series data

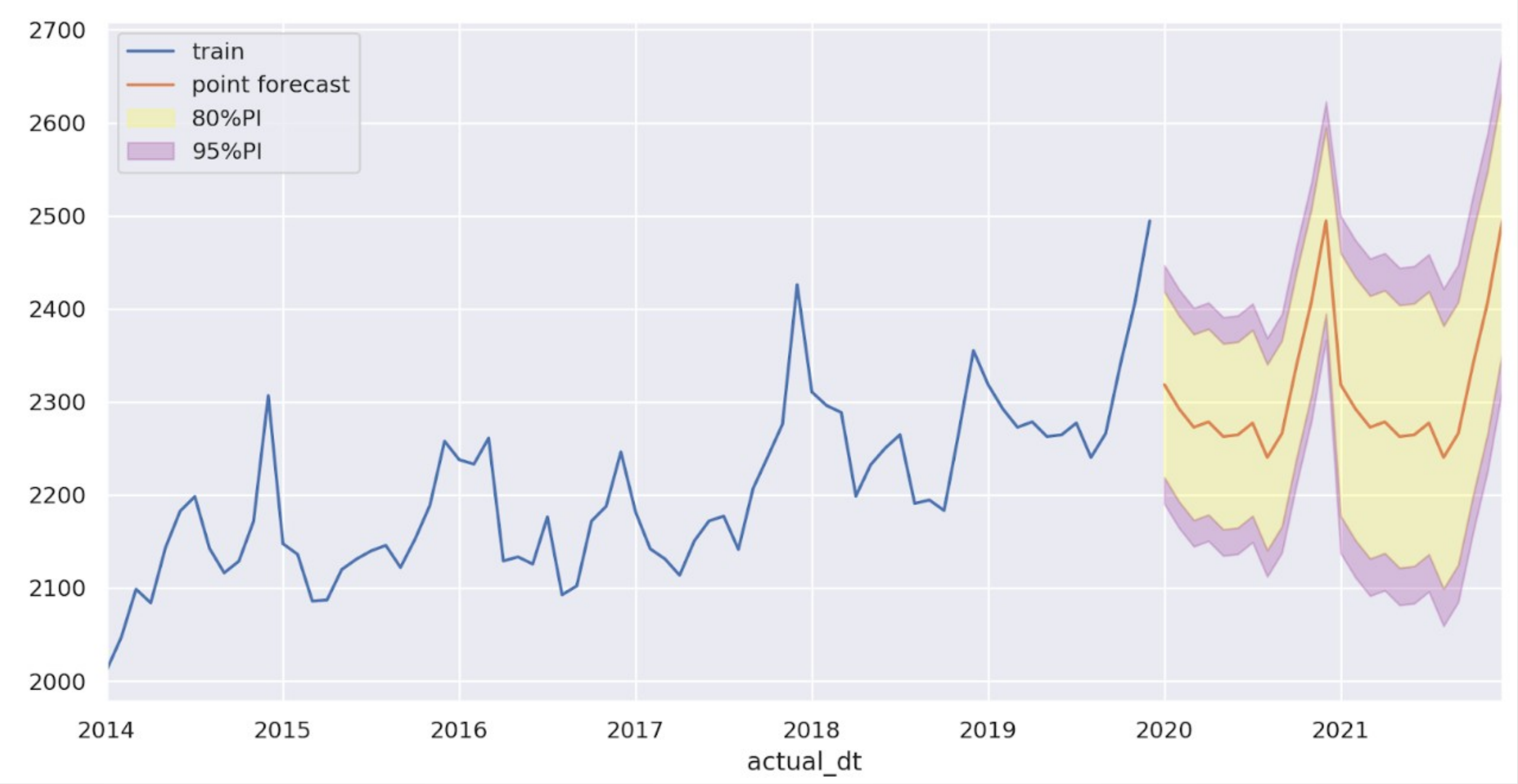
- Trend
- Seasonality *– How does the series rise and fall periodically over time?*
- Mean *– Also called ‘level’ in literature*
- Variance
- ***Stationarity***
- ***Autocorrelation*** *– i.e., number of sales on a Thursday is related to sales on a Wednesday, which is related to sales on a Tuesday...*

Introducing...

Naive benchmarks

Seasonal Naive

Trend
Seasonality



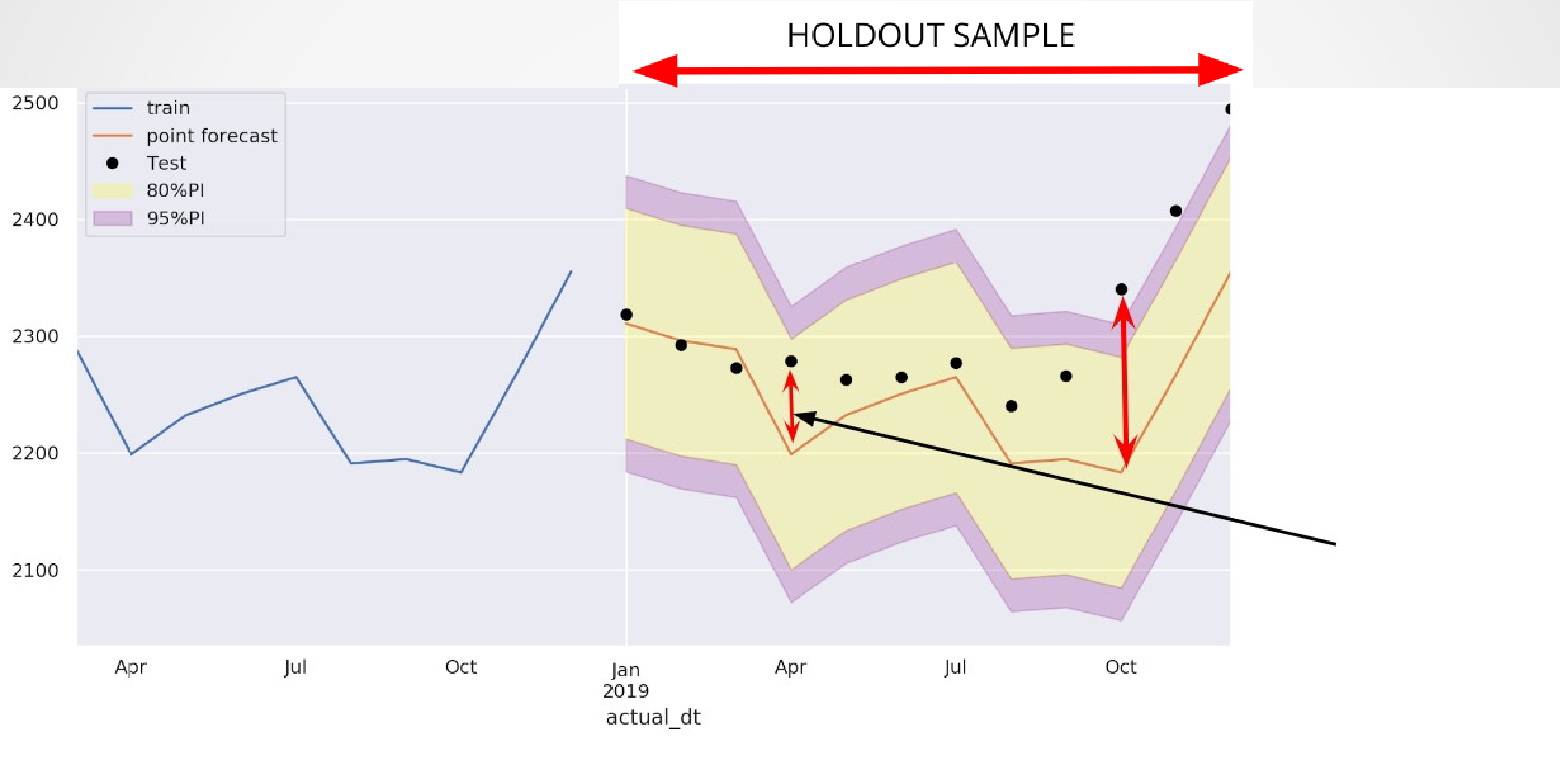
Naive benchmarks

- 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

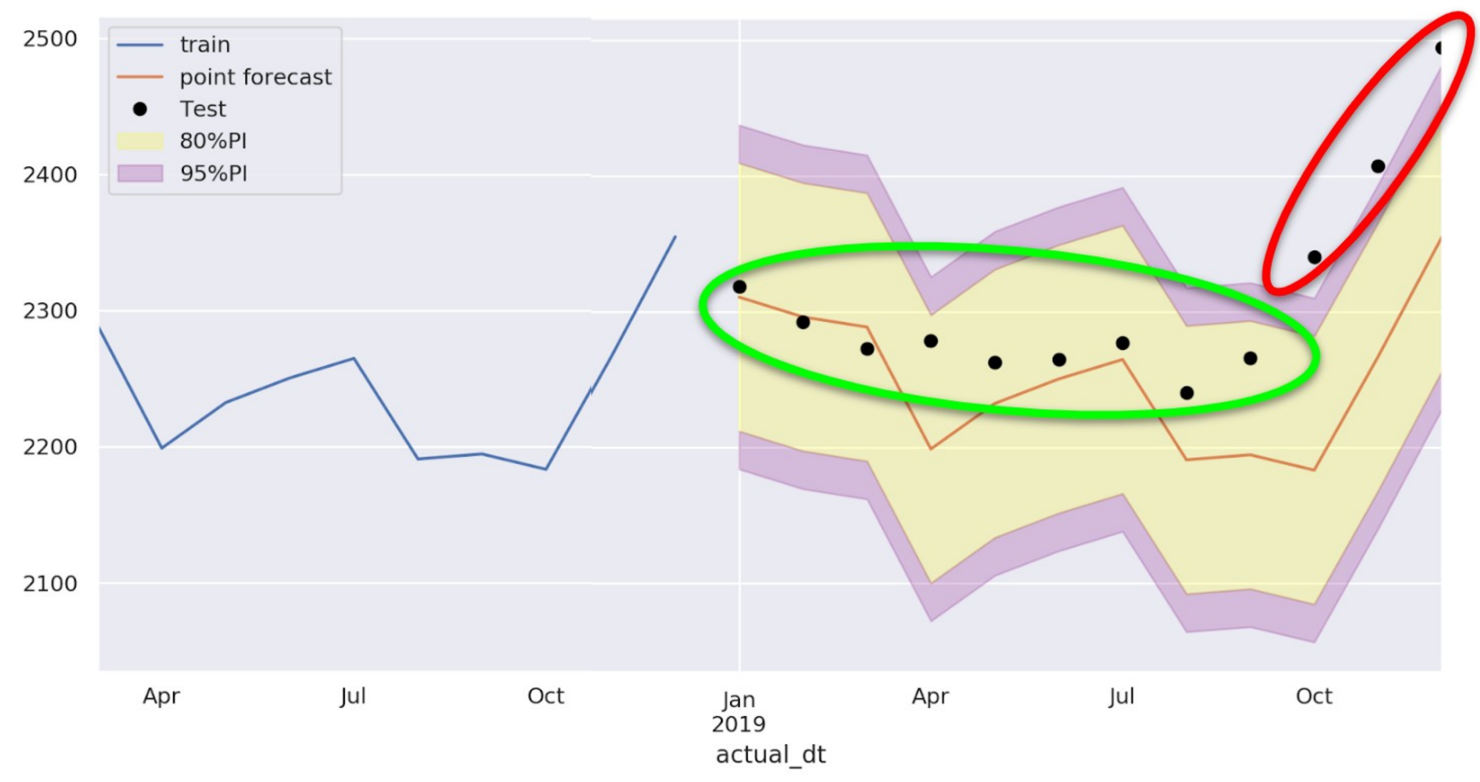
Point Forecast Error



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