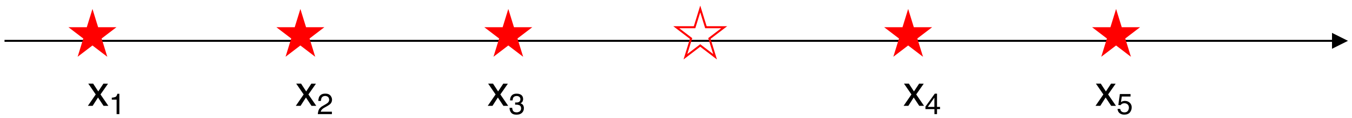
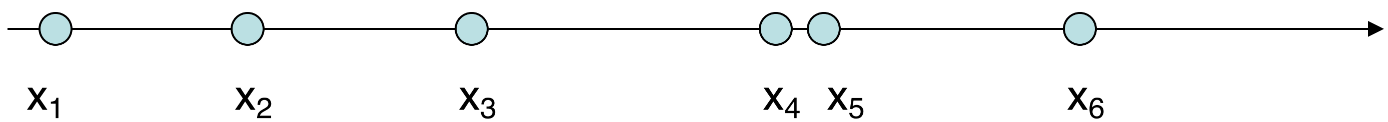
Week 10: Interpolating Data

Common problems in data analysis are

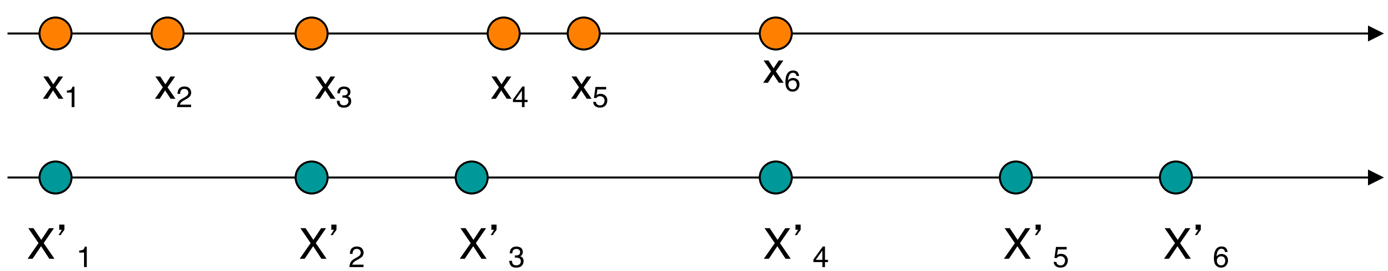
1. Missing data: want to fill in gaps



2. Unevenly-spaced data: would like evenly spaced data



3. Differently spaced data in two data sets: want to compare data from same time, place



This requires ***estimating*** data at locations or times where we ***don't*** have a measurement

Week 11: Interpolating Data

Same underlying issue: want to fill in the gaps or re-grid onto an even sampling interval!

One way to handle this is BINNING your data and then taking the mean / median / mode in each bin – we have indirectly used this approach in Assignment 2 (annual averages)

This is not always practical since don't always have many repeat or nearby measurements

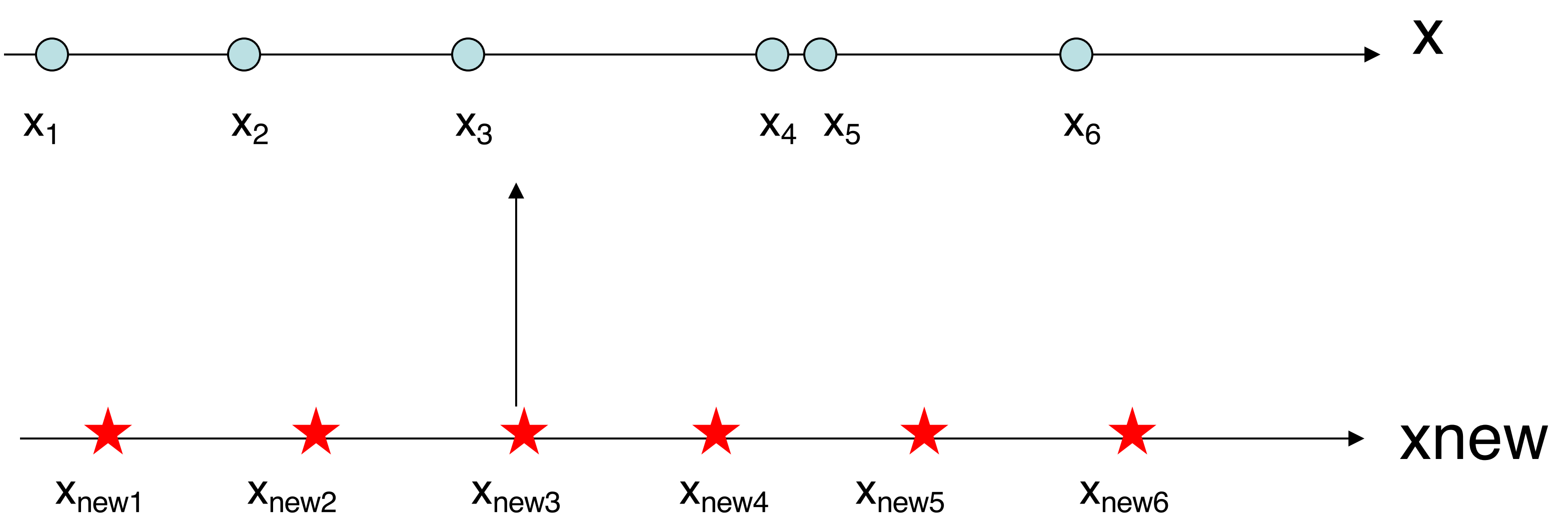
INTERPOLATION:	Estimating data between some known measurement points Done all the time, care needed
EXTRAPOLATION:	Estimating data beyond the end of your measurement set This is VERY dangerous, and should be avoided

Why interpolate or re-grid data?

1. Comparing / overlaying multiple data sets (maps especially)
2. Create evenly spaced data so we can use our running-mean code for example
3. If we have lots of observations in one time interval and few in another any statistics will be biased toward the time period w/ more observations - want evenly gridded data
4. Doing spectral analysis (fourier transforms etc)

How to do this? The first thing is to define a new, evenly spaced x-axis:

Our original x-axis has a uneven spacing of data points

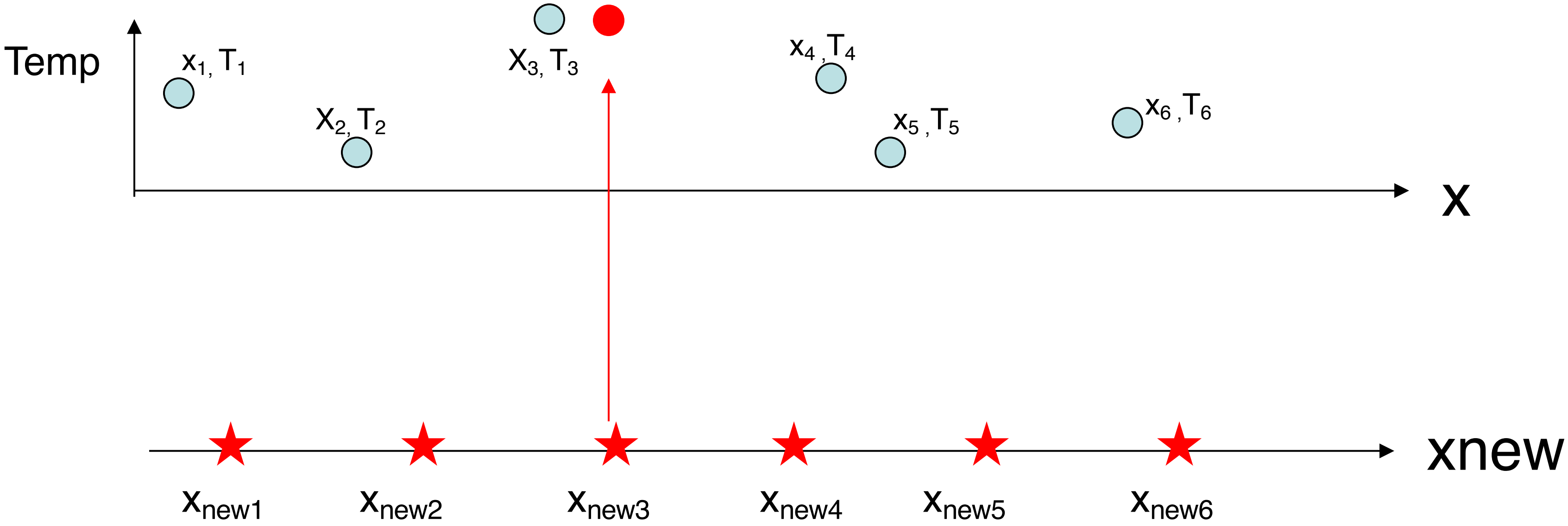


Our new x-axis has an even spacing: $\Delta = x_{new(j+1)} - x_{new(j)}$

Next, we want to estimate our quantity of interest, y, (e.g. temperature) at our new points, x_{new}.

There are many ways to do this……….

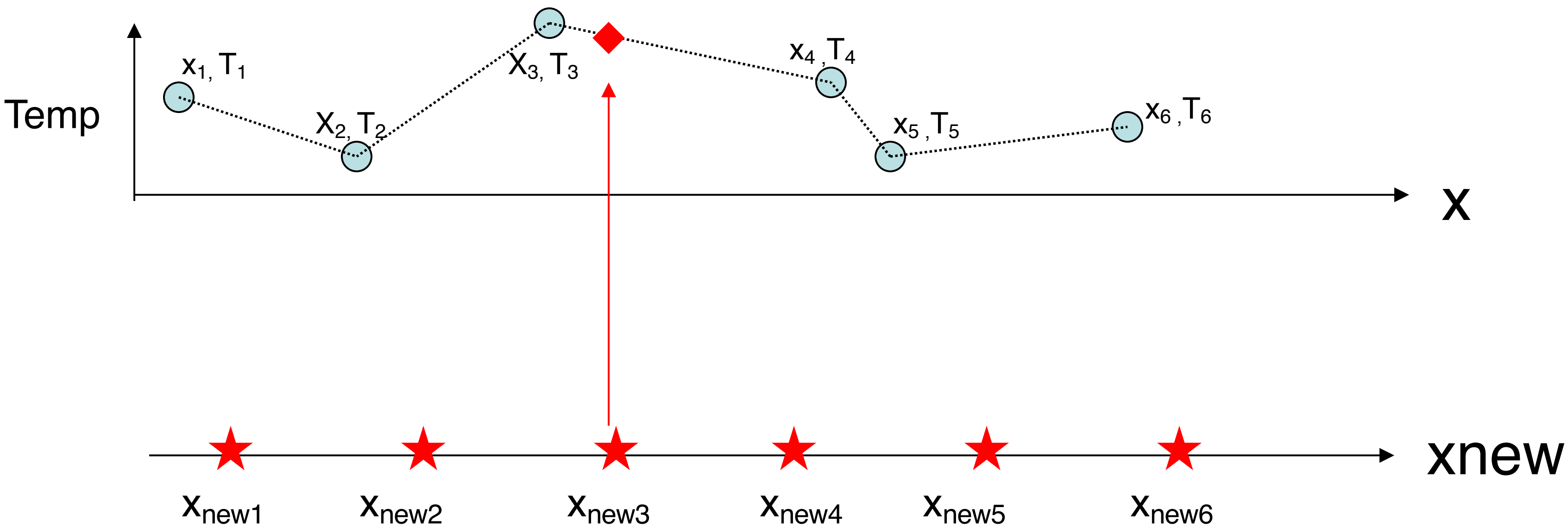
Let's say our original measurements are temperature, T, versus distance, x



We could estimate the temperature at each of our new points, $x_{new(j)}$ by assigning

1. The value of temp at the nearest point $x_{(i)}$ in the original time series,
   e.g., x_3 is closest to x_{new3}, so we could put Temperature(x_{new3}) = T_3

   Name: nearest neighbor interpolation
   Advantage: fast
   Disadvantage: produces a "step-like" function, *i.e.*, discontinuous



2. We could average the values of temperature at the two points x_3 and x_4

   Not so great, but …..

3. We could add a percentage of the difference T_4-T_3 to the value T_3, and the % would be based on the fractional distance $xnew_3$ is toward x_4 from x_3

   Name: linear interpolation
   Advantage: (1) still pretty fast, (2) produces continuous function
   Disadvantage: "corners" at data points, discontinuous first derivative

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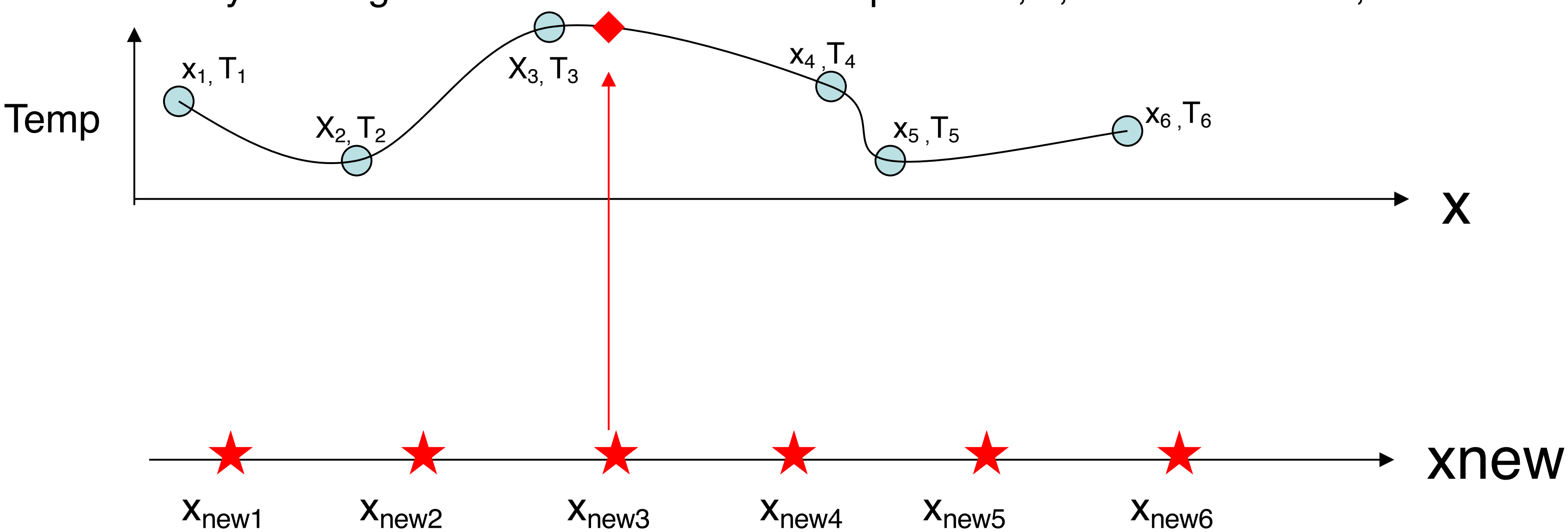

4. We might want our estimates to be more smoothly varying and fit a polynomial. A better version of this approach involves the use of functions called **splines**.

Name: cubic splines
Advantage: smooth function, continuous second derivative
Disadvantage: slower (not big deal), can produce "overshoots" in large data gaps