A Bayesian Approach to Judgmental Forecasting

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1 Introduction

Human judgment is involved in most of the forecasts made by companies. Surveying 173 companies from different sectors, Weller and Crone (2012) found that 44% of their forecasts were created using human judgment aided by a statistical baseline. The rest of the forecasts were almost equally divided between pure statistics (29%) and pure human judgment (26%).[1]

Utilizing a Bayesian approach, Tenenbaum & Griffiths (2012) showed that people's judgments of common phenomena –such as predicted lifespan or cake-baking times– used prior probabilities that are seemingly close to optimal. Research in judgmental forecasting has shown that humans display effects of trend damping (Harvey & Reimers, 2013), framing (Harvey & Bolger, 1996), noise-adding (Harvey, 1995), and exaggeration of sequential dependence (Reimers & Harvey, 2011). Could these effects be associated to the prior hypotheses about structural compositions that subjects might utilize to arrive at their predictions?

2 Goal

The goal of this study is to understand how individuals update the compositional structure of their forecasts of time-series when presented with new data. Initially, we will study how subjects produce forecasts when provided with minimal information (i.e. one single data-point). Then, we will analyse how subjects forecast the same variables, but now providing them with a larger dataset. With this information, we will uncover how the compositional structure of the forecasts was updated between the minimal information and the larger dataset scenarios.

To achieve the aforementioned goal, the study will be divided into three stages, where the first two include experiments.

2.1 Stage I: Uncover the kernel structure in minimal data scenario

The first stage of our study has the goal of uncovering the underlying kernel structure that each individual subject uses to predict different variables, when provided with a minimal dataset of one observation. This will be done by computing where the posterior peaks, assuming different additive components for the kernel structure (Schaechtle, Zinberg, Radul, Stathis, & Mansinghka, 2015).

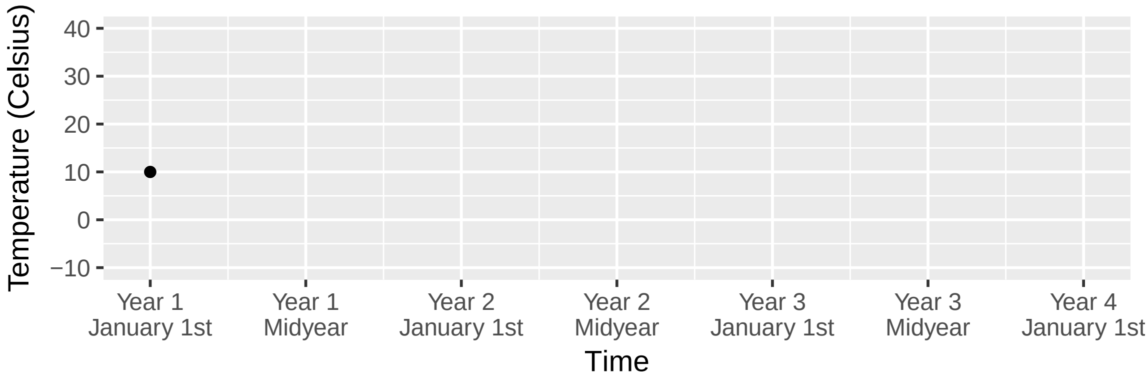
- **Experiment**: Give subjects one data-point and a corresponding data-label. Ask them to predict the other values of the variable.
  - **Independent variable**: The value-label pair.
  - **Dependent variable**: A plot of predictions starting from a single point.
- **Result**: Intuitive compositional structure for each individual and for each prediction dataset.

[1] The percentages in the original source do not add up to 100%.

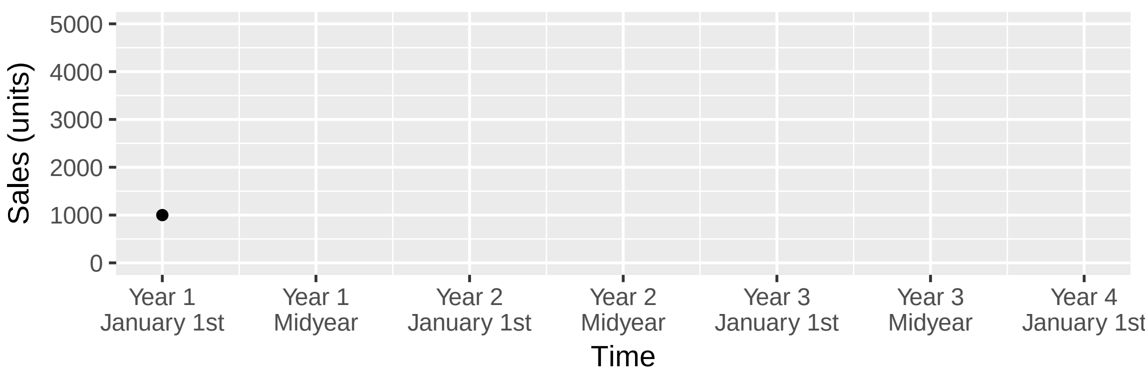
2.1.1 Questions to be asked

Each subject will be shown the following questions in random order. The value of the single data-point will be the same for every subject.

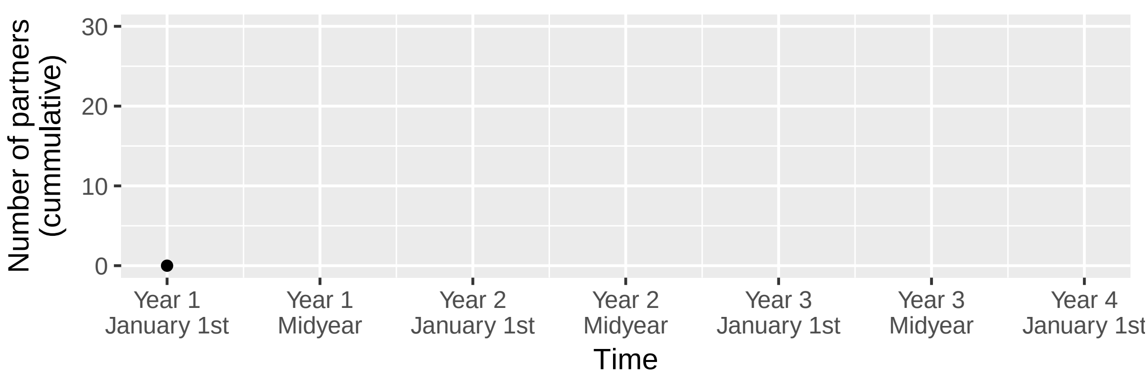
1- Please draw the **weather forecast** *for a large city:*
NOTE: change the initial temperature to 15 degrees.



2- Please draw the **sales forecast** *for a large company:*



3- Please draw a graph showing the **number of cummulative sexual partners** *that a 21 year old male will have in the future:*



2.2 Stage II: Understand the Bayesian learning function

At this point, we will have the kernel structure for each individual subject, for each variable. However, whether and how subjects will integrate new information is uncertain. Hence, in this part of the research project, participants are given data for part of the predictions they made, and are asked to predict again.

- **Experiment**: give subjects a dataset and ask them to predict a few values into the future.
  - **Independent variable**: the variable to be predicted (e.g. sales, temperature) and the data given.
  - **Dependent variable**: a plot of predictions starting from a dataset
- **Result**: analysis of whether the individuals are using the same prediction function when there is only one data-point presented or a dataset. How do the subjects incorporate the new data?

2.2.1 Questions to be asked

Each subject will be shown the following questions in random order. There will be three different conditions for each question; each participant will be shown only one of the conditions.

*1- Please draw the **weather forecast** for a certain city, considering that the first year presented the shown behaviour*:
Three conditions: downward-facing cycle, upward-facing cycle, halved downward-facing cycle (see Appendix I).

*2- Please draw the **sales forecast** for a certain company, considering that the first year presented the shown behaviour:*
Three conditions: stable, growth, or decline (see Appendix II).

*3- Please draw a graph showing the **number of cumulative sexual partners** that a 21 year old male will have in the future:*
Three conditions: slow growth, mid growth, rapid growth (see Appendix III).

As it can be seen in the Appendix, the subjects will be given information of the first year and will be asked to predict the values for the following years. In each condition, the curves of the first year will be produced using the same Gaussian process. Hence, subjects on the same condition will not observe exactly the same curve, but a curve generated from the same Gaussian process.

2.3 Stage III: Analysis

At this point, there will be data about how each individual predicts each value starting from a minimal dataset, and then how the subject predicts given a larger dataset. Using the procedure described by Schaechtle et al. (2015), the components of the kernel structure of (i) the prediction with minimal information, (ii) the data shown in Stage II, and (iii) the predictions on Stage III will be calculated. Given this information, we will derive how participants are integrating the newly-received information into their predictions of each of the case-variables.

Moreover, although this could be part of a future study, these results could give insights into how the effects of trend damping, framing, noise-adding, and exaggeration of sequential dependence could be explained from a Bayesian perspective.

References

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Reimers, S., & Harvey, N. (2011). Sensitivity to autocorrelation in judgmental time series forecasting. *International Journal of Forecasting*, 27(4), 1196-1214.

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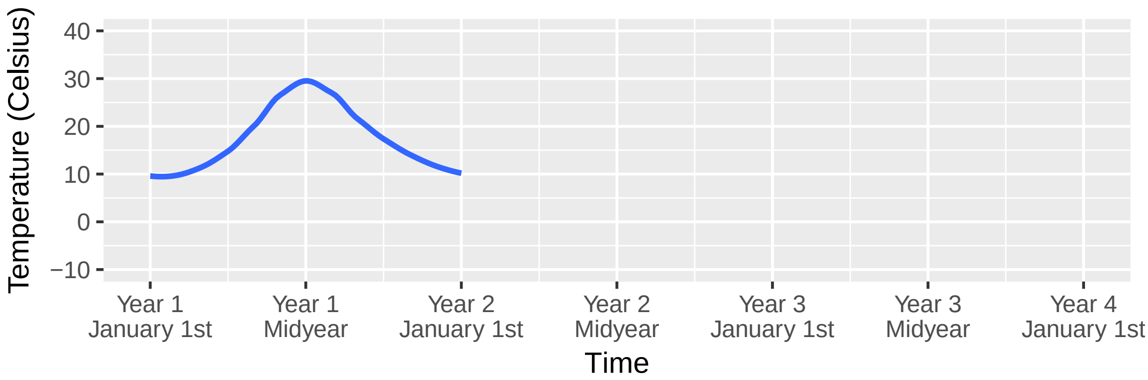
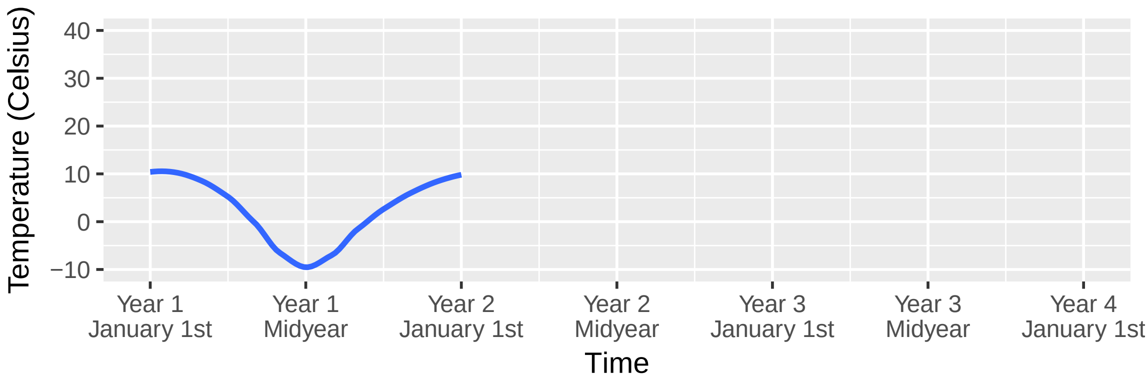
Appendix I: Weather forecast

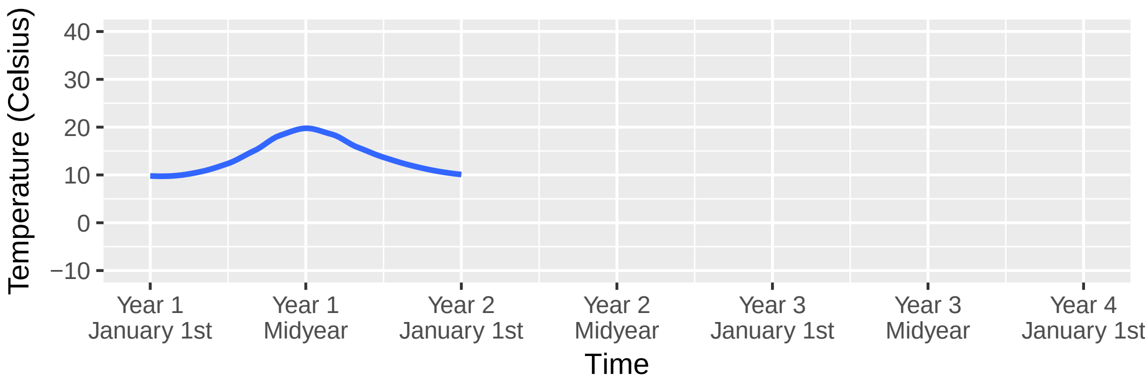
Condition 1: downward-facing cycle



Condition 2: upward-facing cycle

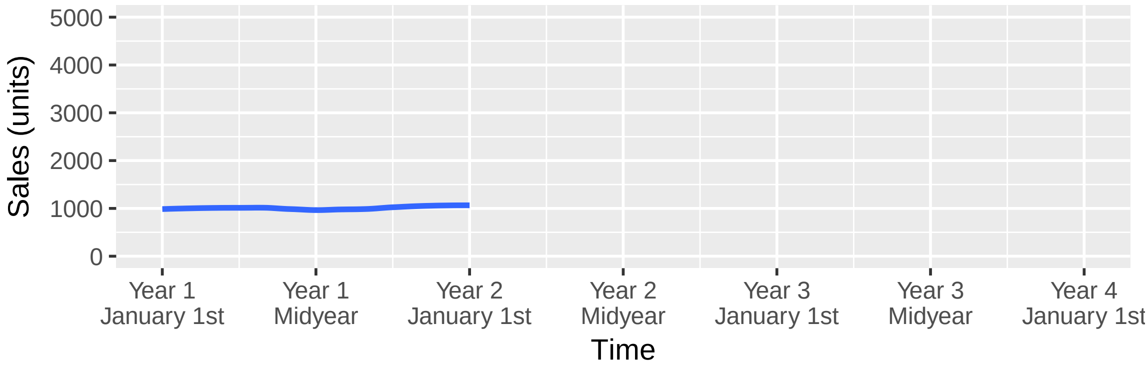


Condition 3: halved downward-facing cycle

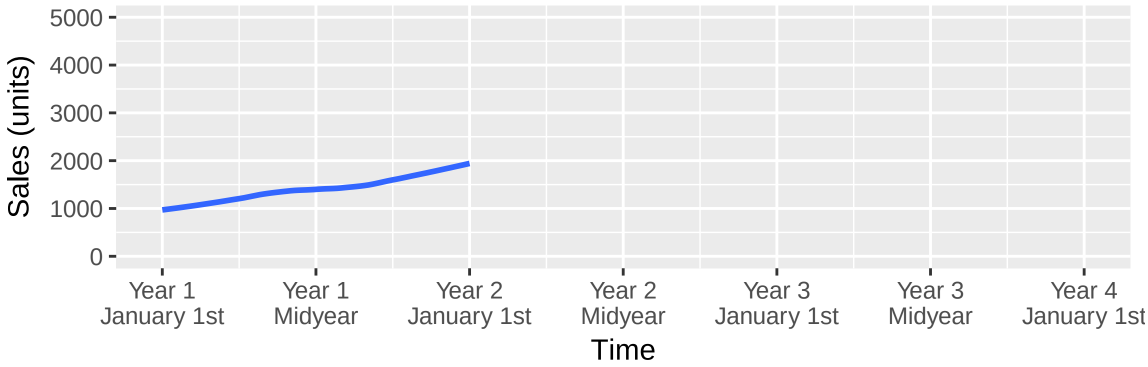


Appendix II: Sales forecast

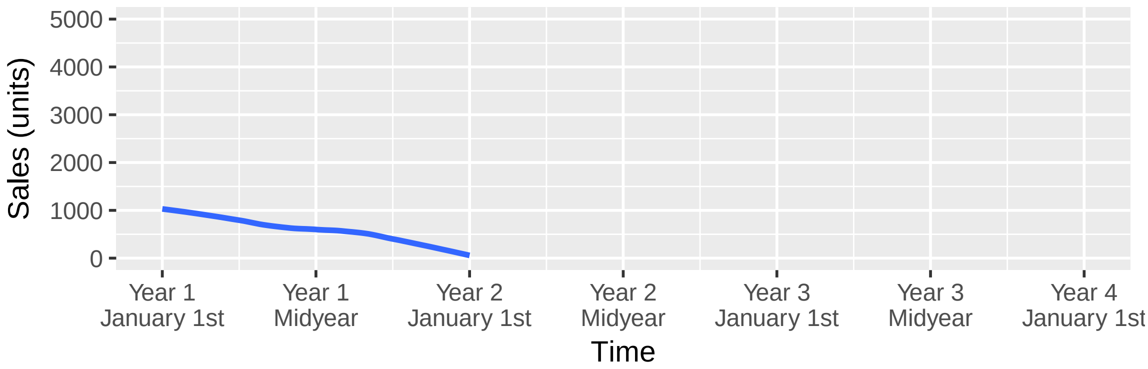
Condition 1: stable



Condition 2: growth

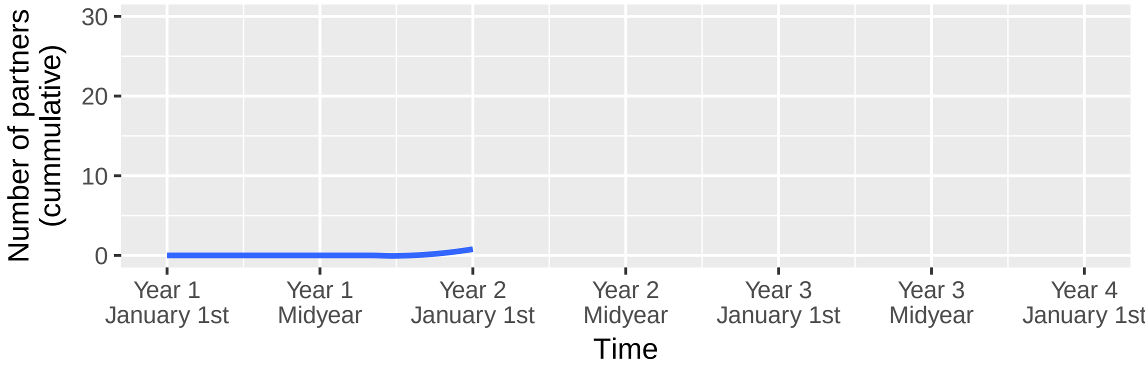


Condition 3: decline

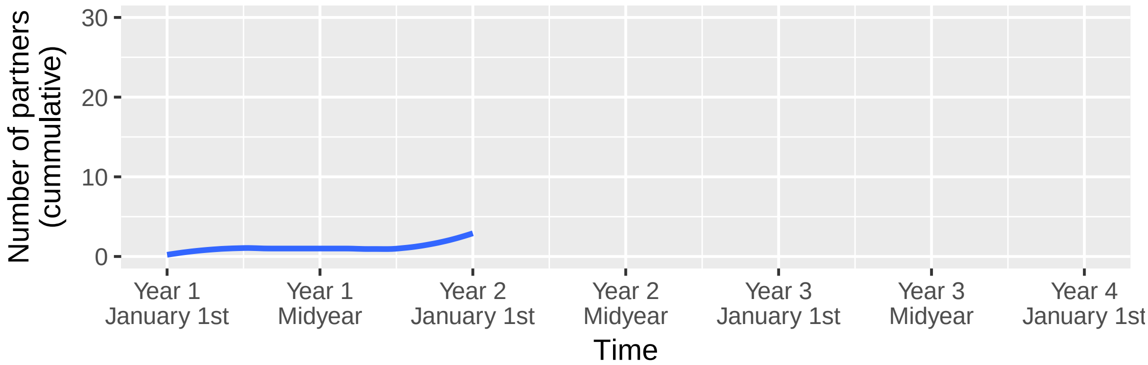


Appendix III: Partners forecast

Condition 1: slow growth



Condition 2: mid growth



Condition 3: rapid growth