# Bayesian model validation metrics in retail datasets

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Bachelor's thesis
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**Abstract**

Your abstract in English. Keep the abstract short. The abstract explains your research topic, the methods you have used, and the results you obtained.

**Keywords** Bayesian models, model validation, information criterion, Facebook Prophet

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**Tekniikan kandidaatintyön tiivistelmä**

| | |
|---|---|
| **Tekijä** Leevi Rönty | |
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| **Koulutusohjelma** Teknillinen fysiikka ja matematiikka | |
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**Tiivistelmä**

Tiivistelmässä on lyhyt selvitys kirjoituksen tärkeimmästä sisällöstä: mitä ja miten on tutkittu, sekä mitä tuloksia on saatu.

Tämän opinnäytteen tiivistelmäteksti kirjoitetaan opinnäytteen luettavan osan lomakkeen lisäksi myös pdf-tiedoston metadataan \thesisabstract-makron avulla (kasto yllä). Kirjoita tähän luettavaan tiivistelmälomakkeeseen menevä teksti. Tässä saa olla erikoismerkkejä kuten kreikkalaiset kirjaimet ja rivinvaiho- ja kappaleenjakomerkit. Tämän tekstin on muuten oltava sama kuin metedatatiivistelmän teksti.

Jos tiivistelmäsi ei sisällä erikoimerkkejä eikä kaipaa kappaleenjakoa, voit hyödynttää makroa \abstracttext luodessasi lomakkeen tiivistelmää (katso kommentti alla).

**Avainsanat** Bayeslaiset mallit, mallin validointi, informaatiokriteeri, Facebook Prophet

# Contents

# 1 Introduction

Businesses need to forecast a multitude of things to succeed. As companies collect more and more data the possibilities of forecastable subjects and possible features increase dramatically. However, one can't just thow more features at a model and except it to perform well. Also not all models are suitable for all forecasting tasks. The amount of possible models is endless, but most of them are bad. To find the usefull ones we must be able to measure the goodness of a model.

Model validation is an integral part of a robust modelling framework. Bayesian models are a relatively novel model type which has gained a lot of populatiry in recent years as computational power of modern computers has kept rising. As a relatively new method not too many validation metrics have been proposed with these kinds of models in mind.

The current state of model validation for bayesian models can be described as "unsatisfactory". Information criterions which try to predict out of sample fit can have strong biases and some may not take into consideration the nature of bayesian models and distributions of parameters. Cross validation can be computationally extremely intensive. Also most information criterions are based on a loss function proportional to the root mean square of errors, but that may not always be the most usefull function to optimize for. In some businesses the consecuences of errors in forecasts can be described better with the mean absotule percentage error. All in all there does not exist a clearly better method for solving all bayesian model validation problems.

In this paper we will model sales timeseries of some Wallmart stores in the United States. We will be using the Facebook's Prophet modelling framework. It consists of a flexible bayesian model which can be customized to fit a wide range of possible time series modelling tasks. We will implement some information criterions for the model and compare it to more ad-hoc methods for model validation.

# 2 Background

In retail business many things can be a subject for optimizing. Predictions of sales can be used to minimize waste and ensure sufficient supply of goods. Advertising products can yield greater sales but not all ads are equally effective. Shifting marketing investments to more impactfull marketing channels can increase sales while keeping costs the same. Both of these examples demonstrate scenarios where statistical models can be used to avoid making unoptimal decisions my manual guesswork.

Models can be viewed as simplifications of reality. This means that no model never really mathces the true data generating processes, but if we can formulate a model that works well enough we can try to draw some conclusions from them. Most of the models we are concerned with link together some explanatory variables to the measured data. The parameters of the function are learned by fitting the data to the model. The fitted model can then be used to predict future observations if we can know the explanatory variables beforehand. The fitted model parameters can also give insight on the behaviour of the physical world, assuming that said parameters have a sensible interpretation.

Bayesian models differ from frequentist models in two major ways. In bayesian thinking parameters are not expressed as point values but distibutions. Uncertainty can be expressed with wider distributions. New data is not the sole source of the newly fitted parameters as it is merely used to update prior beliefs about parameter distribution.

## 2.1 Rakenne

# 3 Tutkimusaineisto ja -menetelmät

# 4 Tulokset

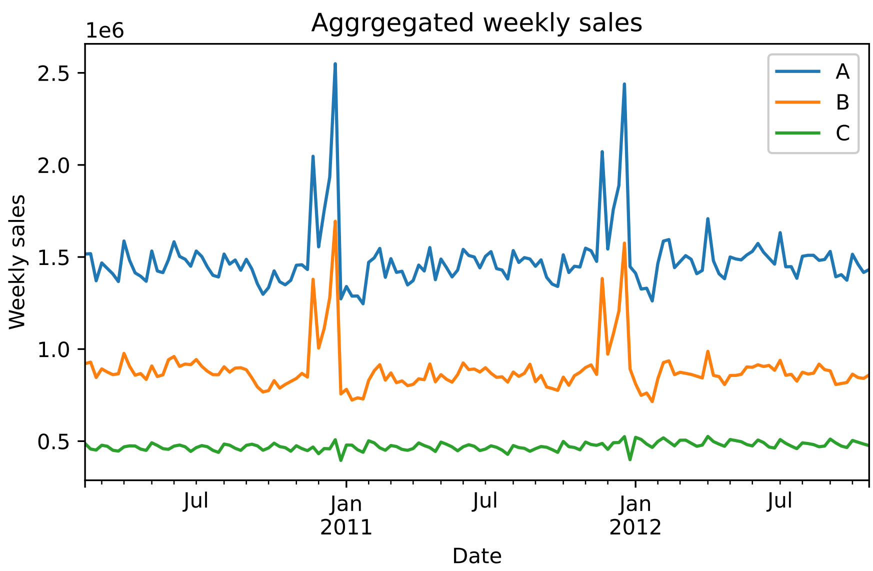
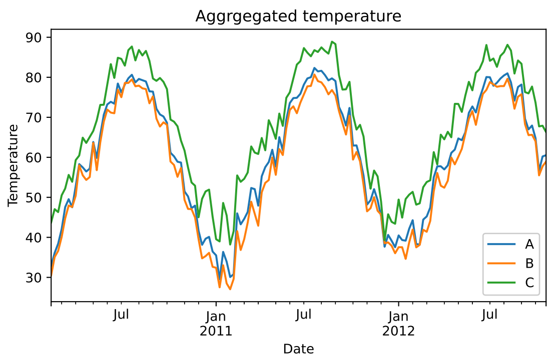


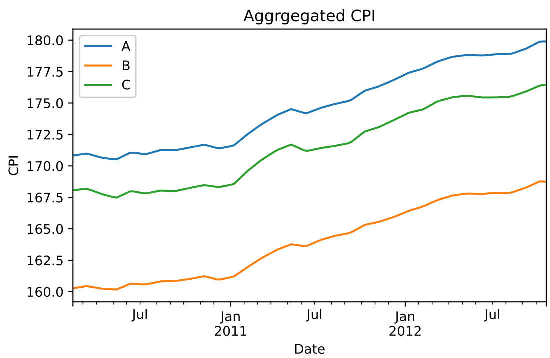

Figure 1: Aggregated weekly sales by store group. Groups A and B demonstrate holiday effects while group C remains relatively stable through each year.

Table 1: Results of validation metrics applied on store group A

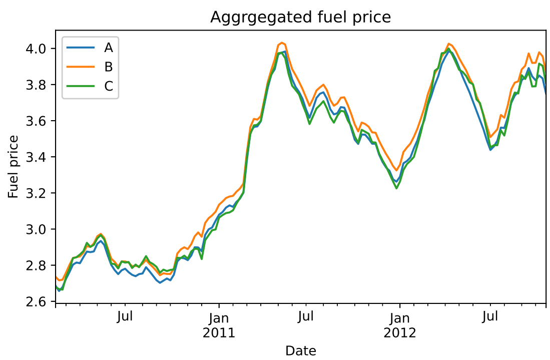
| **Model** | **AIC** | **DIC** | **WAIC** | **MAPE** | **10-fold CV** |
|---|---|---|---|---|---|
| m1 | -394.4 | -438.8 | -15.9 | 0.0336 | 205.4 |
| m2 | -384.6 | -431.5 | 136.5 | 0.0445 | 208.2 |
| m3 | -654.5 | -702.1 | -669.3 | 0.0219 | 349.6 |
| m4 | -457.4 | -512.4 | -41.6 | 0.0275 | 164.1 |
| m5 | -703.9 | -703.2 | -707.8 | 0.0253 | 351.3 |



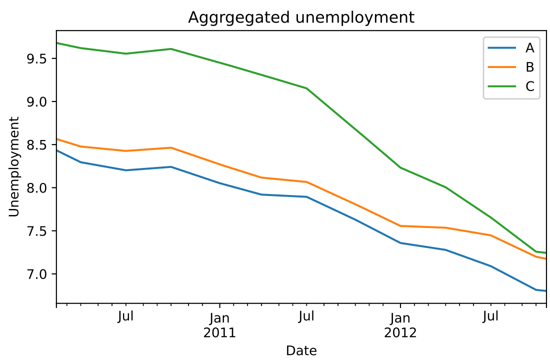

(a) Temperature by store group




(b) Consumer price index by store group




(c) Fuel price by store group




(d) Interpolated unemployment rate by store group

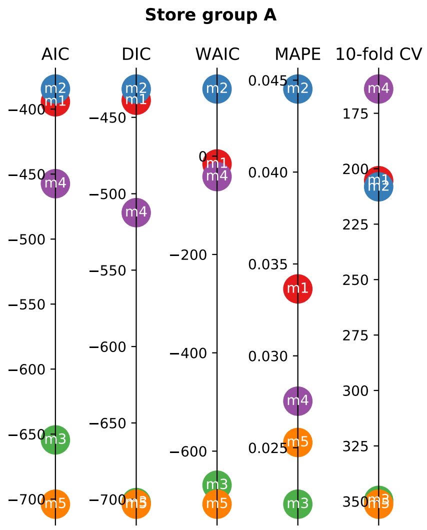



Figure 3: Visualisation of model validation metric results applied on store group A. Agganged such that visually lower is better. Each axis is scales so that extreme values are at the ends. Please note the inverted axis of 10-fold cross validation metric. For precise values please refer to table 1.

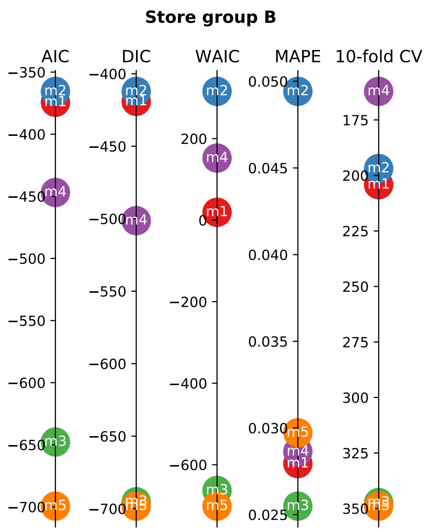



Figure 4: Caption this

# 5 Summary

# References

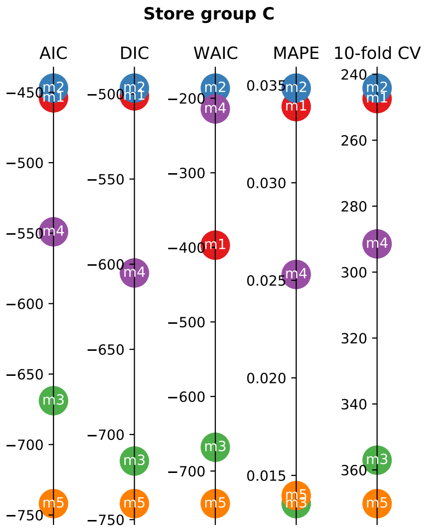



Figure 5: Caption this

Table 2: Results of validation metrics applied on store group B

| **Model** | **AIC** | **DIC** | **WAIC** | **MAPE** | **10-fold CV** |
|---|---|---|---|---|---|
| m1 | -374.3 | -419.1 | 19.3 | 0.0279 | 204.2 |
| m2 | -365.5 | -412.2 | 315.9 | 0.0494 | 196.9 |
| m3 | -647.8 | -695.3 | -663.2 | 0.0255 | 347.3 |
| m4 | -446.9 | -501.4 | 152.2 | 0.0286 | 162.1 |
| m5 | -699.4 | -698.3 | -701.5 | 0.0297 | 348.9 |

Table 3: Results of validation metrics applied on store group C

| **Model** | **AIC** | **DIC** | **WAIC** | **MAPE** | **10-fold CV** |
|---|---|---|---|---|---|
| m1 | -454.0 | -501.2 | -397.1 | 0.0339 | 247.4 |
| m2 | -447.1 | -496.6 | -186.4 | 0.0349 | 244.2 |
| m3 | -668.9 | -715.6 | -668.1 | 0.0136 | 357.0 |
| m4 | -549.1 | -605.1 | -214.3 | 0.0253 | 291.4 |
| m5 | -741.9 | -740.6 | -743.7 | 0.014 | 370.2 |

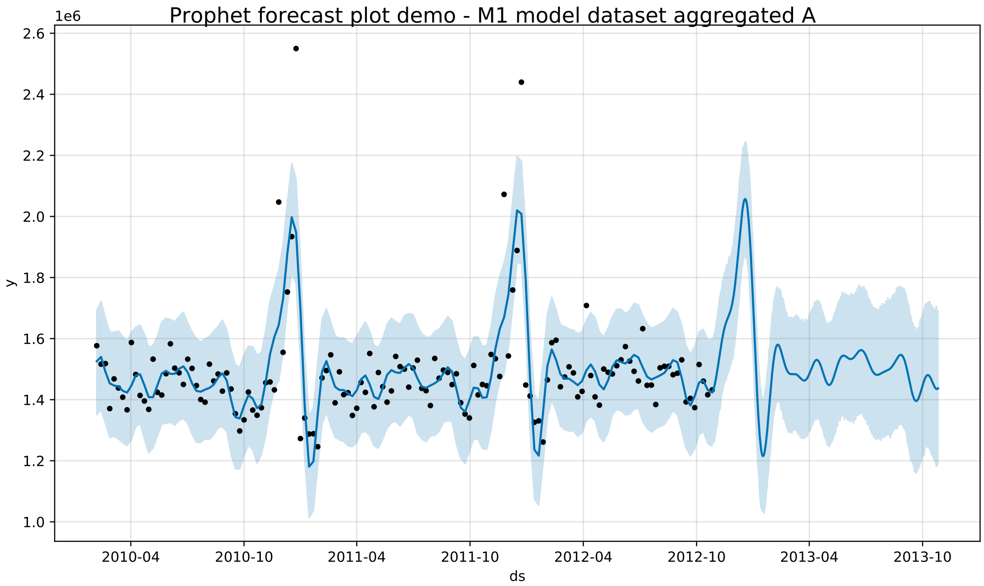



Figure 6: Demo of what kind of precidtion plots the Propchet package can produce by default. These may be helpful (?)

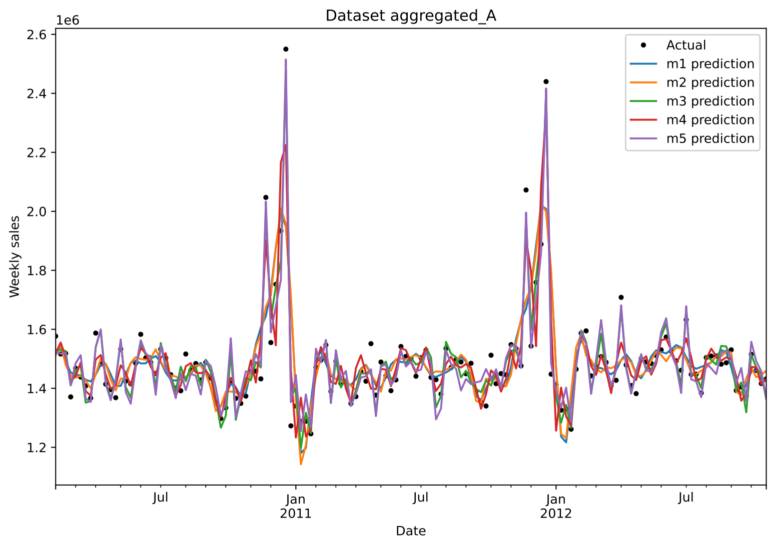



Figure 7: A concept of what another kind of prediction plot could look like. This plot shows in-sample predictions from each of the models in one dataset.

# A Esimerkki liitteestä

# B Toinen esimerkki liitteestä