

Beyond summary performance metrics for forecast selection and combination

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Marketing Analytics
and Forecasting



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A couple of moments for model selection and combination

Code Editor Visual Editor Normal text

```
1 \documentclass[preprint,review]{article}
2 % use the option review to obtain double line spacing
3 \usepackage{preprint,review}{article}
4
5 \usepackage{amsmath,multicol,amsthm,array,siunitx,rotating,booktabs}
6 \usepackage{graphics,upstart}
7
8 \usepackage{color} % Used for revisions
9 \usepackage{normaln}[t] % Used for revisions
10 % For additions use \color{red}...
11 % For deletions use \textcolor{blue}...
12
13 % \usepackage{nowinners}{endfloat} % Move all figures and tables at the end for JMR submission
14
15 % \usepackage{refcheck} % Used to list uncond references
16
17 \begin{document}
18 \begin{frontmatter}
19
20 \title{Beyond summary performance metrics for forecast selection and combination}
21
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```

Abstract

Model selection (or forecast combination) is a key tool in forecasting. In this paper, we propose a modification in the use of the Akaike Information Criterion (AIC) and an associated procedure for selecting a single forecast or constructing combination weights that aim to go beyond the use of summary statistics to characterise each forecast. We demonstrate that our approach does not require an arbitrary dichotomy between forecast selection, combination or pooling, and switches appropriately depending on the time series on hand and the pool of forecasts considered. The performance of the approach is evaluated empirically on a large number of real time series from various sources. We argue that the proposed approach is useful for model selection and combination more generally, beyond the forecasting domain.

Keywords

Model selection, forecast combination, Akaike Information Criterion, Uncertainty, Cross-validation

1

The Plan

Introduction

How many of you have used combinations for forecasting?

How do you combine forecasts?

There's lots of papers on different combination methods:

- Means, trimmed and winsorised (Jose and Winkler, 2008);
- Median (Agnew, 1985; Stock and Watson, 2004);
- Weighted combinations (Elliott, 2011; Elliott and Timmermann, 2016; Kolassa, 2011);
- Claeskens et al. (2016) explains why simple combinations are more robust than the weighted ones.

Introduction

How many models do you have in your pool? Do you need all of them?

Geweke and Amisano (2011) shows that using a subset of models helps.

In your pool of models:

- some will perform consistently poorly, and need to be removed;
- some will do consistently well. Keep them!

But how can we decide?

Kourentzes et al. (2018) develop a heuristic to reduce the pool of models.

Introduction

Are you sure that your combination is adequate?

Will it change tomorrow?

Yes! Everything is random! You cannot be sure of anything...

Yet all the combination approaches rely on some summary statistics from a sample.

Vehtari et al. (2017) use the leave-one-out CV errors to get the standard errors for forecasts.

This way we can compare model performance...

Point likelihood



how likely is it to rain at maspalomas



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Forums

Web

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Tools ▾

Results for **Maspalomas** · [Choose area](#) ⋮



29 °C | °F

Precipitation: 0%

Humidity: 61%

Wind: 6 km/h

Weather

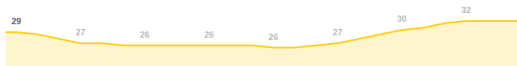
Wednesday 18:00

Sunny

Temperature

Precipitation

Wind



19:00

22:00

01:00

04:00

07:00

10:00

13:00

16:00

Wed



29° 26°

Thu



32° 27°

Fri



31° 23°

Sat



27° 21°

Sun



26° 21°

Mon



26° 21°

Tue



26° 21°

Wed



27° 22°

[Weather data](#) • [Feedback](#)

Point likelihood

Take a look at AIC:

$$\text{AIC}_m = 2k_m - 2\ell_m, \quad (1)$$

ℓ_m is the log-likelihood value, k_m is the number of estimated parameters of a model m in the pool.

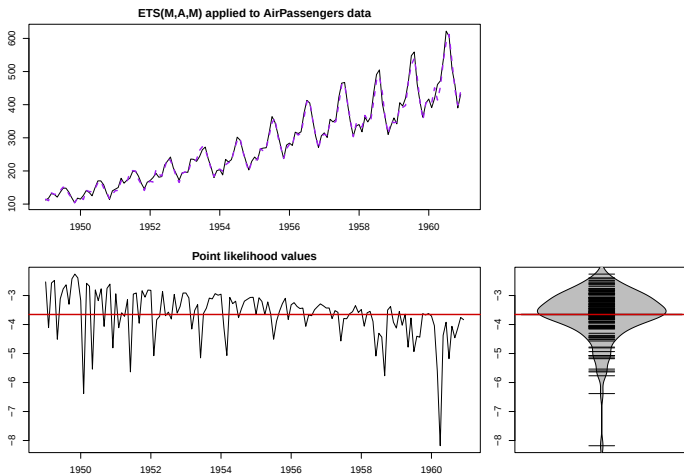
This relies on the summary statistics, log-likelihood ℓ_m

It shows how likely it is to have such a model given the data.

This is a sum of point log-likelihoods:

$$\ell_m = \sum_{t=1}^T \ell_{m,t} \quad (2)$$

Point likelihood



Point IC

So, we can use point log-likelihoods to compare models.

The only issue is the bias in the likelihood estimate (Akaike, 1974).

We propose a point AIC:

$$\text{pAIC}_{m,t} = 2k_m - 2T\ell_{m,t}. \quad (3)$$

T is needed to bring the point likelihood value to the overall level.

Other criteria can be modified like that as well.

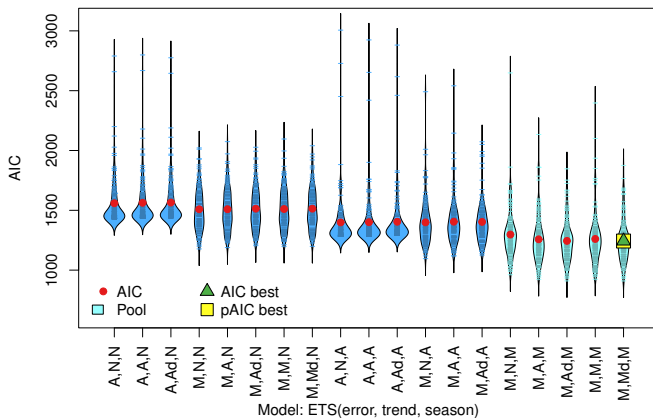
Pooling with point IC

How can we use that?

1. Apply models to the data;
2. Extract pAIC values for each of them;
3. Use Nemenyi test ([Demšar, 2006](#)) to group models;
4. Combine their forecasts.

Pooling with point IC

ETS on air passengers data!



Pooling with point IC

You can do that with CV errors as well (e.g. rolling origin).

Nemenyi can be substituted by other tests.

Real data experiment

The screenshot shows the RStudio interface with a script editor, environment pane, and documentation pane.

Script Editor:

```
1 # remotes::install_github("config-l1/ggcybos", upgrade="never")
2 # remotes::install_github("config-l1/smooth", upgrade="never")
3 remotes::install_github("config-l1/smooth", upgrade="never", ref="ADAM-ARIMA")
4
5 source("~/R/Projects/smooth/R/arimaCompact.R")
6
7 library(Rcomp)
8 library(Rcomp)
9
10 library(forecast)
11 library(smooth)
12 library(rzo)
13
14 library(dplyr)
15 registerS3Method(detectores())
16
17 # Create a small but neat function that will return a vector of error measures
18 errorMeasuresFunction = function(object, holdout, usample){
19   return(c(measures(holdout, object$mean, usample),
20     mean(holdout ~ object$upper ~ holdout ~ object$lower),
21     mean(object$upper ~ holdout)/mean(usample),
22     pinball(holdout, object$upper, 0.95)/mean(usample),
23     pinball(holdout, object$lower, 0.05)/mean(usample),
24     shts(holdout, object$lower, object$upper, mean(usample), 0.95),
25     object$timeLapsed))
26 }
27
28 datasets <- c(M1, M3, tourist)
29 datasetLength <- length(datasets)
30 methodNames <- c("ADAM ETS", "ES", "ETS", "ADAM ARIMA", "ADAM ARIMA B", "ARIMA", "CompactARIMA B", "CompactARIMA")
31 methodNumber <- length(methodNames)
32 test <- adam(datasets[[1]])
33 # testAccuracy = measure(test$holdout, forecast(test$holdout[[1:100]]$mean, actuals(test))
34 testResults[20240730] = array(NA, c(methodNumber, datasetLength, length(test$accuracy)),
35   dnames=list(methodNames, NA,
36     c(name=test$accuracy),
37     "Coverage", "Range",
38     "pinballUpper", "pinballLower", "shts",
39     "time"))
40
41 ##### ADAM ETS #####
42 } ~ 1)
43 result <- foreach(i=1:datasetLength, combine="cbind", .packages="smooth") %doPar% {
44   testTime <- Sys.time()
45   test <- adam(datasets[[i]], "D2")
46   testForecast <- forecast(test, h=datasetLength, interval="pred")
47   testForecast$timeLapsed <- Sys.time() - startTime
48   return(errorMeasuresFunction(testForecast, datasets[[i]][50x, datasets[[i]][1:100])
49 }
50 testResults[20240730][M1, 1:100, 1:100] = result[1:100]
14:13 Compact ARIMA 2
```

Environment Pane:

Name	Type	Length	Size	Value
parameterSample	Integer	1	56 B	131
parameterNumber	Integer	1	56 B	46
statisticsLength	Integer	1	56 B	1011
modelSample	list	4	86.3 KB	List of 4
understand	list	3	632 B	List of 3
datasets	list	5315	N/A	Large List (5315 elements, 19.3 MB)
nonseasonalData	logical	5315	28.8 KB	logi [1:5315] TRUE TRUE TRUE TRUE TRUE T...
nonrendata	logical	5315	28.8 KB	logi [1:5315] FALSE FALSE FALSE FALSE FA...
seasonalData	logical	5315	28.8 KB	logi [1:5315] FALSE FALSE FALSE FALSE FA...
selectedData	logical	5315	28.8 KB	logi [1:5315] TRUE TRUE TRUE TRUE TRUE T...
rendata	logical	5315	28.8 KB	logi [1:5315] TRUE TRUE TRUE TRUE TRUE T...
constant	logical	1	208 B	Named logi FALSE
dampedETS	logical	6	88 B	logi [1:6] FALSE FALSE TRUE FALSE FALSE ...
multiplicativeError	logical	8	48 B	logical (empty)

Documentation Pane:

Multiple steps ahead forecast errors

Description

The function extracts 1 to h steps ahead forecast errors from the model.

Usage

```
resultStep(object, h = 10, ...)
```

Arguments

- object: Model estimated using one of the forecasting functions.
- h: The forecasting horizon to use
- ...: Currently nothing is accepted via ellipsis.

Details

The errors correspond to the error term ϵ_t in the ETS models. Don't forget that different models make different assumptions about ϵ_t and / or $1-\epsilon_t$.

Value

The matrix with observations in rows and h steps ahead values in columns. So, the first row corresponds to the forecast produced from the 0th observation from 1 to h steps ahead.

Real data experiment

We used M1 (Makridakis et al., 1982), M3 (Makridakis and Hibon, 2000), and Tourism competition data (Athanasopoulos et al., 2011).

A mixture of monthly, quarterly, annual data.

Horizons of 18, 8, and 6.

We measure RMSSE (Athanasopoulos and Kourentzes, 2023), sCE, and Computational Time.

greybox (Svetunkov, 2025a) and smooth (Svetunkov, 2025b) packages from R (R Core Team, 2024).

Real data experiment

We use ETS to select/combine forecasts (`adam()` function from `smooth`):

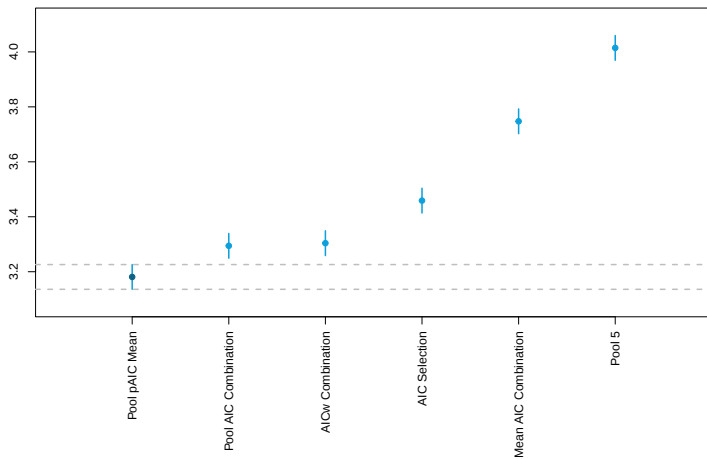
1. **AIC Selection** – apply all models, select the best based on AIC;
2. **AICw Combination** – weighted combination from [Kolassa \(2011\)](#);
3. **Mean Combination** – simple mean of the combination;
4. **Pool pAIC Mean** – form a pool based on Nemenyi (`rmcb()` from the `greybox` package), take the mean;
5. **Pool AIC Combination** - same as (4), but with AIC weights;
6. **Pool 5** - mean of the pool of the best 5 models.

Real data experiment

Method	min	Q1	median	Q3	max	mean	sCE	Time
AIC Selection	0.015	0.667	1.171	2.278	51.616	1.922	0.452	0.382
AICw Combination	0.021	0.658	1.167	2.286	51.255	1.904	0.458	0.738
Mean AIC Combination	0.034	0.741	1.258	2.428	372.899	2.116	0.338	0.990
Pool pAIC Mean	0.027	0.653	1.169	2.238	50.598	1.877	0.450	0.766
Pool AIC Combination	0.021	0.658	1.168	2.283	51.242	1.903	0.455	0.700
Pool 5	0.082	0.786	1.289	2.408	50.973	2.003	0.532	0.397

Real data experiment

The p-value from the significance test is 0.000.
95% confidence intervals constructed.



Conclusions



Your PC can't even

Conclusions

- All modern combination approaches rely on summary statistics;
- We consider a distribution of point likelihoods;
- This allows forming pools of models, kicking out the bad ones (superforecasters?);
- Their combination is more robust.

Thank you for your attention!

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