Hands-On Tutorial SAP Predictive Analytics, Automated Mode: Time Series Forecasting

This guide gives a practical introduction to time series forecasting with SAP Predictive Analytics, Automated Mode. Based on past numbers of bicycle rentals in London, you will create a forecast of future rental numbers.
An initial forecast uses only the actual rental numbers. A second forecast uses additional predictors such as weather data to produce an even more accurate forecast.

The data used in this guide is publicly available so that the reader can follow hands-on and practice by carrying out the same forecasts.

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INTRODUCTION

You may know, or guess, that the “Automated Analytics” in SAP Predictive Analytics is all about automating the process of creating predictive models. This tutorial gives some hands-on introduction and practice with time series forecasting, which is part of the “Automated Analytics” functionality. We start with a simple example and built on this with a more complex scenario.

The time series we are using are the daily numbers from the London bicycle hire scheme. We use historic rental numbers to forecast future rental numbers. Think of it as a demand forecast.

In this tutorial we will be looking at only one time series, the total numbers of bikes rented per day. SAP Predictive Analytics can also automatically forecast multiple time series, ie rentals by location. That concept is described in another tutorial[1], which you may want to read after having gone through this document.

“Thank you”s go to Ben Lee-Rodgers for sharing detailed recordings from his weather station in London and Antoine Carme for his expertise on time series forecasting.

[1] Hands-On Tutorial SAP Predictive Analytics, Automated Mode: Multiple Time Series
https://scn.sap.com/docs/DOC-68223

HANDS-ON IMPLEMENTATION

Background

The city of London, United Kingdom, provides a bicycle hire scheme. There are over 700 locations spread around town where bikes can be rented out and returned. More than 10.000 bicycles are available. The Greater London Authority is sharing daily statics on the number of bikes rented out. We will use this data ranging from January 2011 to September 2011 to forecast future rental numbers. Then in a second step we enrich this data with additional information, such as weather data, to produce a more accurate forecast.

Please see the separate chapter “DATA DESCRIPTION” for more information on the data.

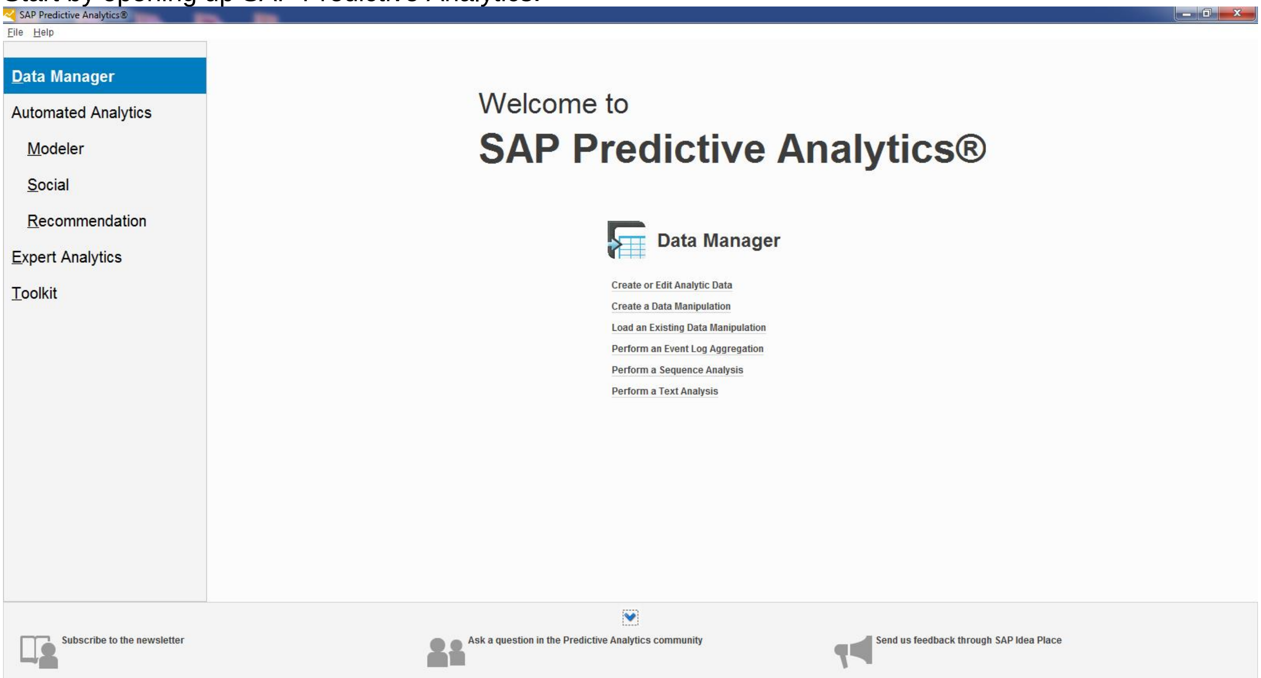
Pre-Requisites

You need to have an installation of SAP Predictive Analytics, which includes the time series forecasting used in this tutorial. This guide has been written with SAP Predictive Analytics 2.3. Evaluation copies are currently available on the SAP Community Network.[2]

The data used in this guide is available as download on the SAP Community Network (SCN).[3]

Initial Forecast

Start by opening up SAP Predictive Analytics.



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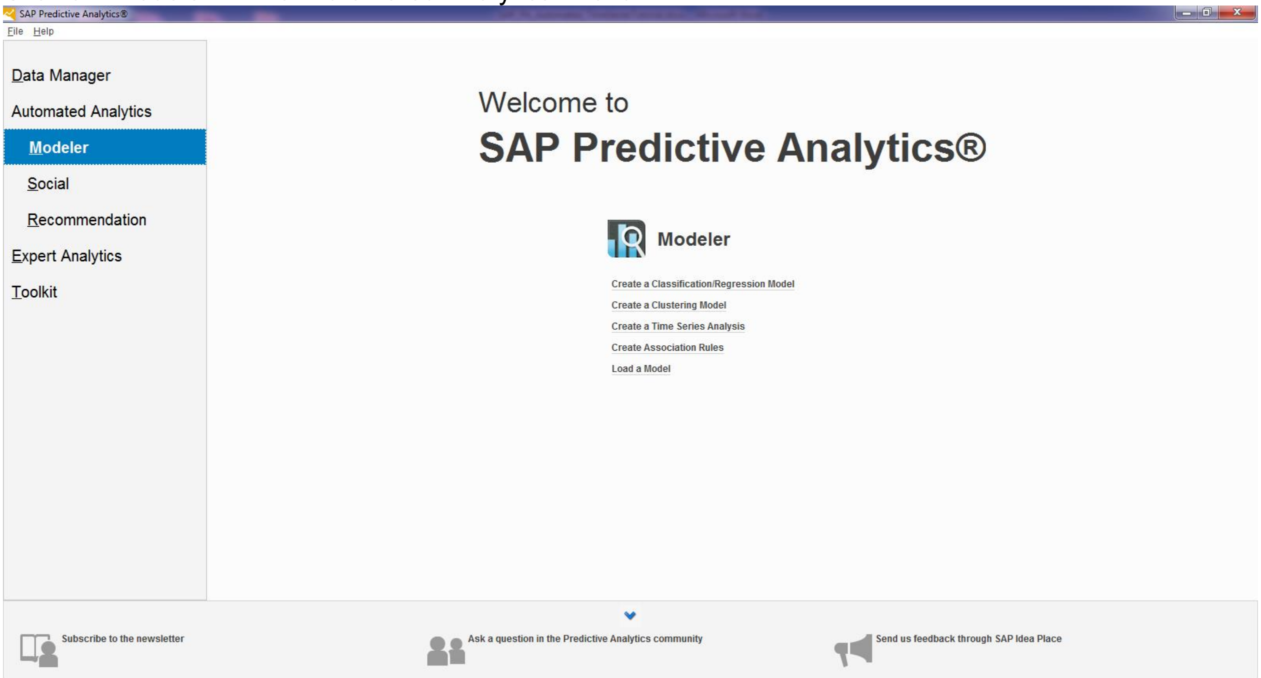
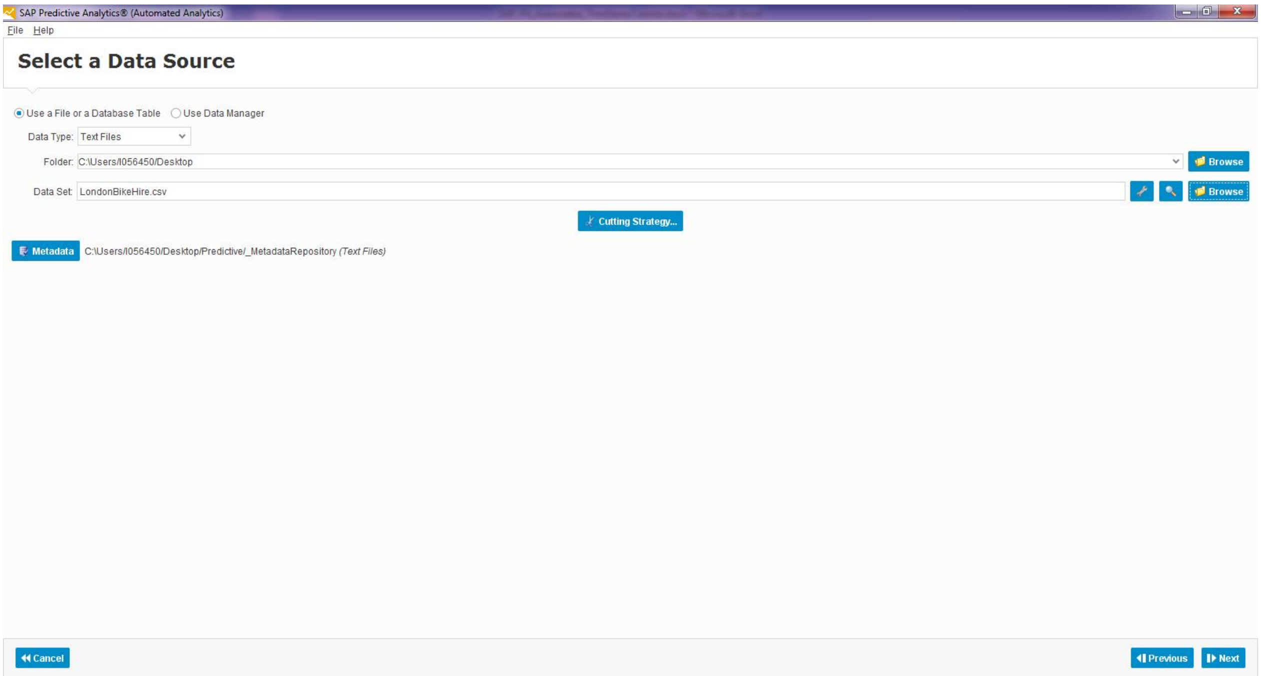
[2] SCN, http://scn.sap.com/community/predictive-analytics
[3] Hands-On Tutorial SAP Predictive Analytics, Automated Mode: Time Series Analysis, http://scn.sap.com/docs/DOC-69324

Click on “Modeler” in the “Automated Analytics” menu.



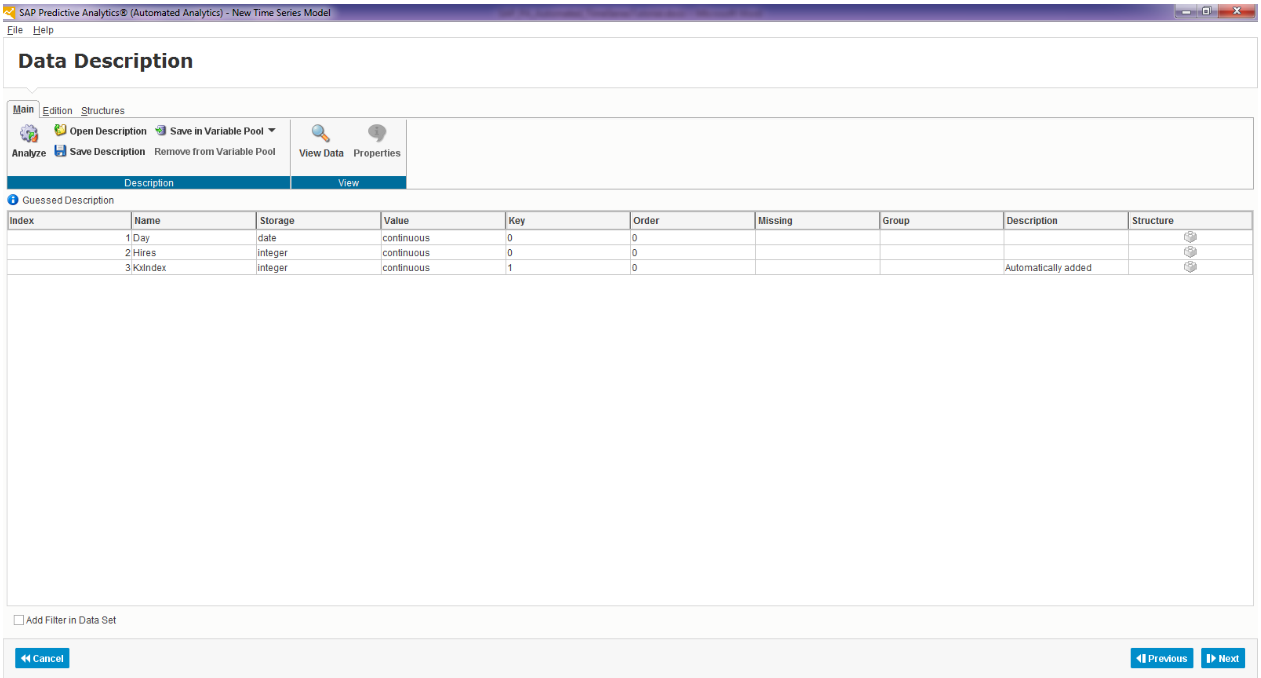
Go into “Create a Time Series Analysis”. First you need to specify the data source. In our example we work with a flat file.

Ensure the “Data Type” drop down is set to “Text Files”. Then click the first “Browse” button on the right hand side select the folder you saved the files into. Finally, click the second “Browse” button and point the “Data Set” to the file LondonBikeHire.csv.



No further changes are needed. Click “Next”.

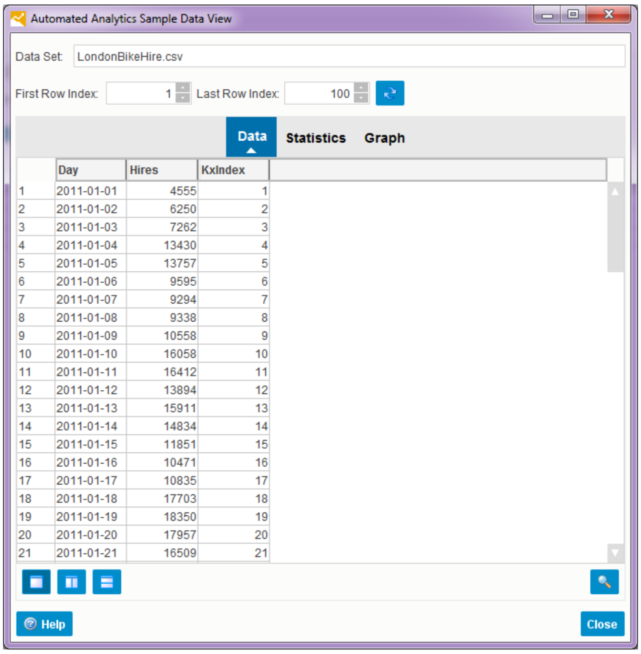
In the “Data Description” windows click “Analyze” so that SAP Predictive Analytics analyses the file’s data structure.



You see the columns “Day” and “Hires” from the file. A third column “KxIndex” has been added by the tool for internal processing.

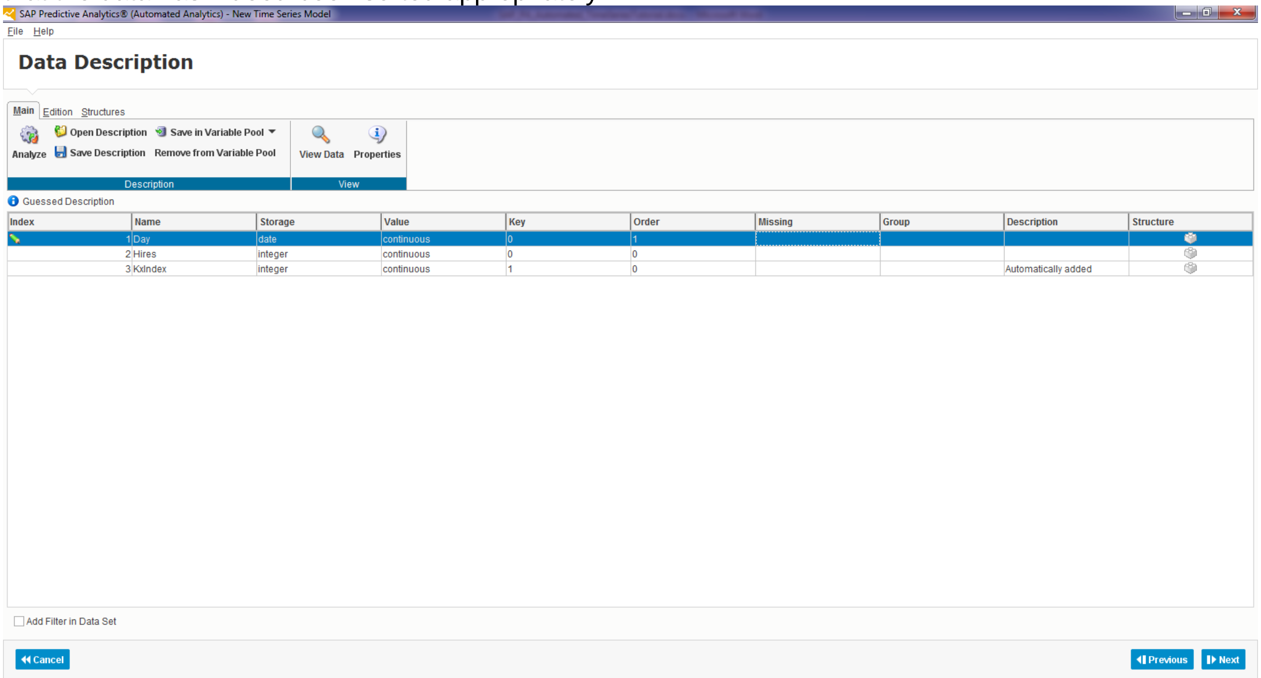
It is crucial that the Storage type for the “Day” variable has been identified as “date”. This is the case for our dataset, so all is fine. Should you want to try out other datasets and the variable has not been identified as “date”, then see the chapter “HINTS AND TIPPS” to specify your data’s date format.

To see the historic data click the “View Data” icon. The first 100 rows are displayed. Each row shows a day with the number of rentals.



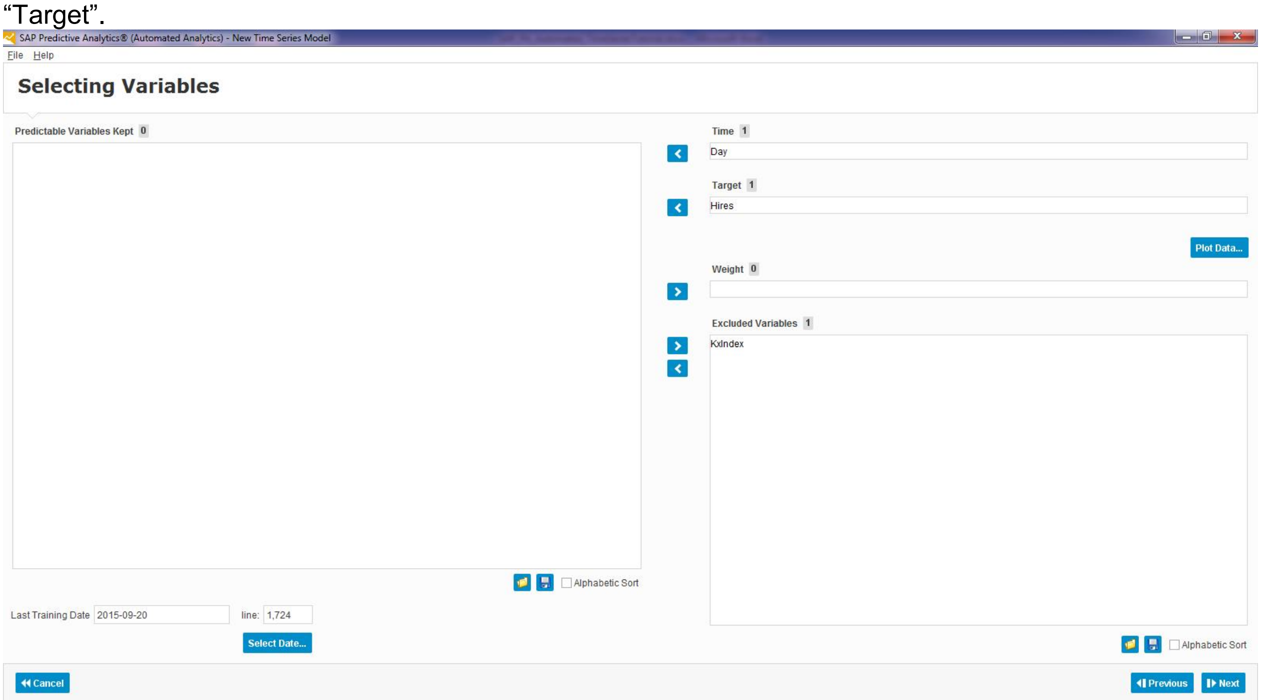
Close this window.

Back in the “Data Description” window you have to change the “Order” of the “Day” column to 1. The data has to be ordered by date in descending order (so most recent dates are at the bottom). This flag indicates that the data has indeed been sorted appropriately.



Click “Next”.

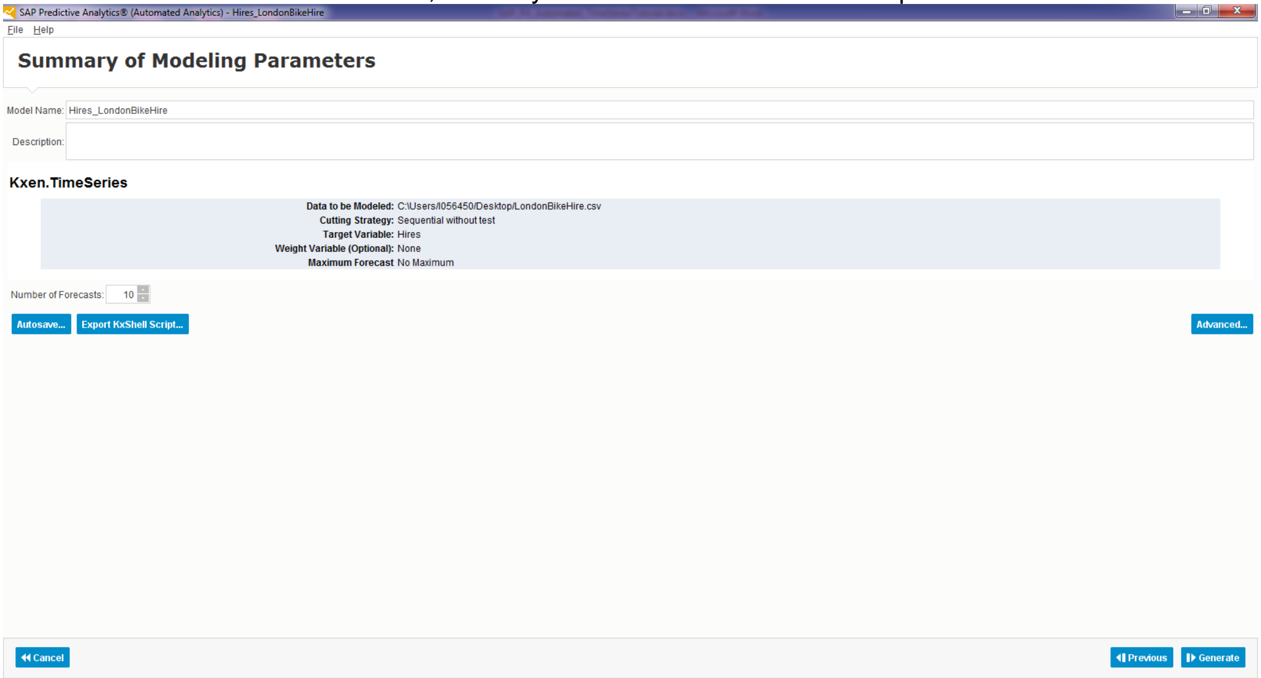
No changes should be needed in the “Selecting Variables” screen. The “Day” variable has been automatically entered as “Time” indicator and the “Hires” variable has been selected automatically as “Target”.



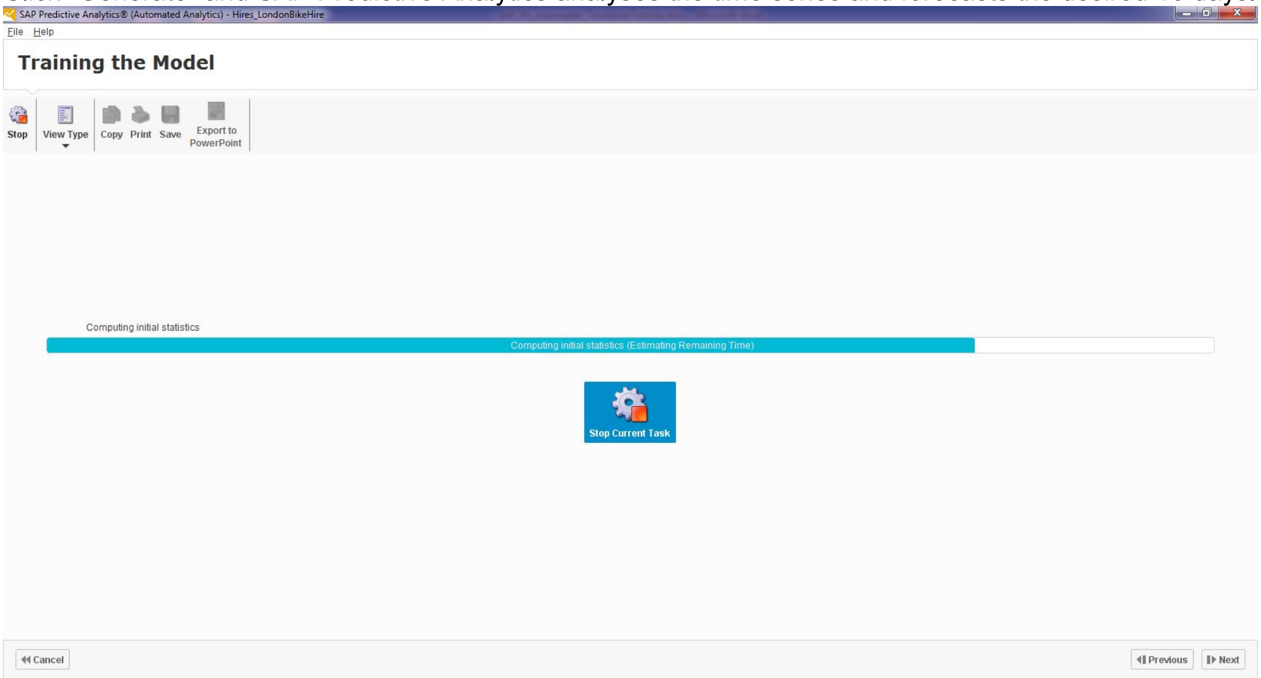
You can see on the bottom left that the last training date is September 20 2015. This is the last date in our dataset.

Click “Next”.

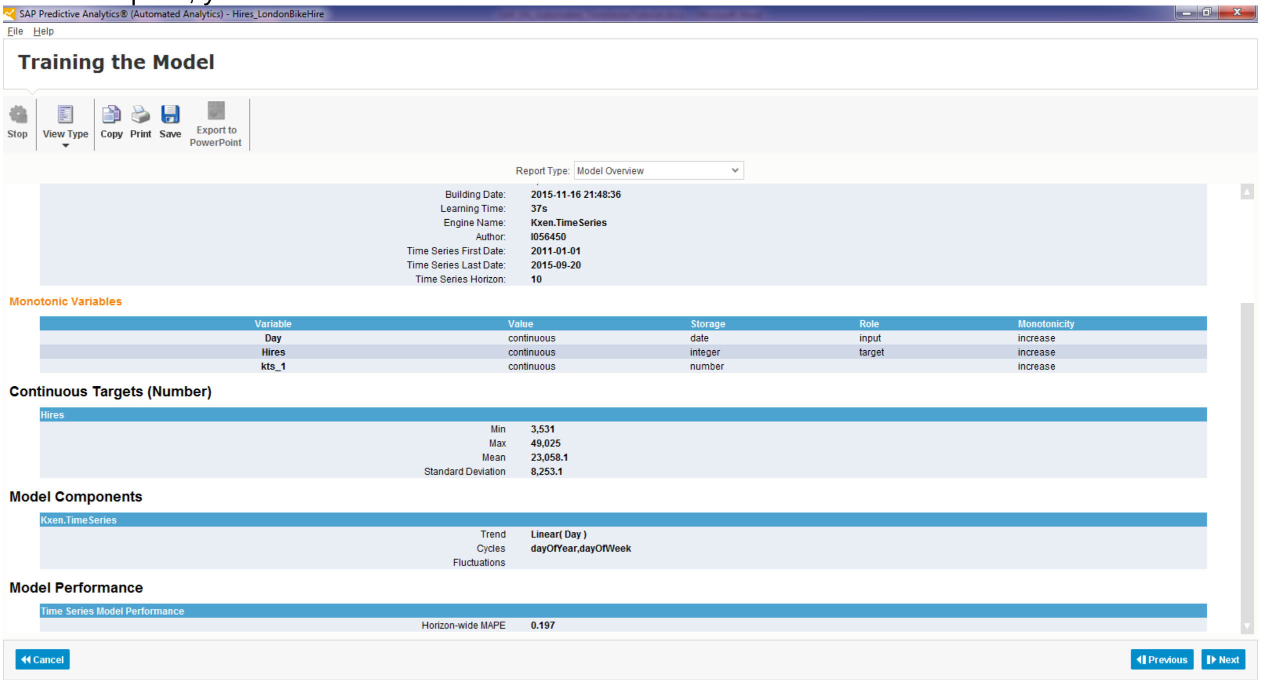
Set the “Number of Forecasts” to 10, so that you forecast until the end of September 2015.



Click “Generate” and SAP Predictive Analytics analyses the time series and forecasts the desired 10 days.



When complete, you see an overview of the model.



Scroll down and you see the “Horizon-wide MAPE” of 0.197. MAPE is a common term in time series forecasting and stands for Mean Absolute Percentage Error. The MAPE is calculated as follows:

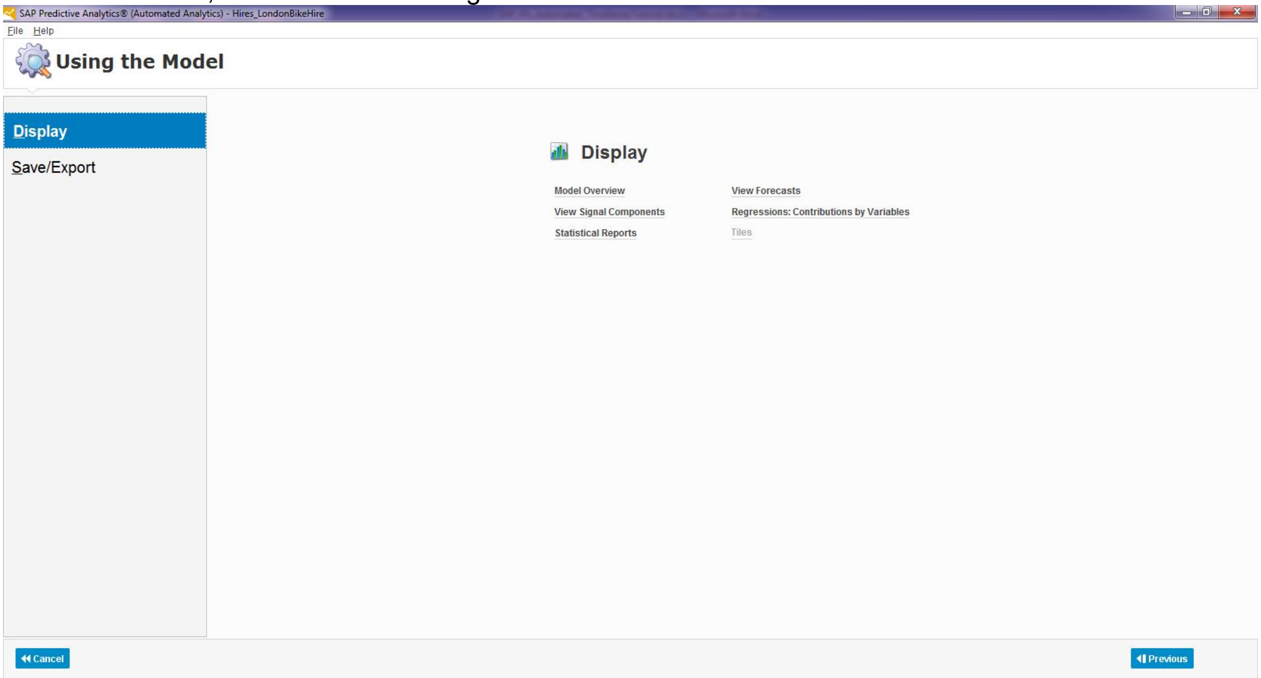
Beginning from the first date in our dataset:

- The following days were forecasted with the model.
- Each forecast was compared with the actual value
- For each date the error was calculated in percent.
- The absolute value is taken of the error percentage (so negatives become positives)
- Out of all these absolute percentage errors, the mean value is calculated

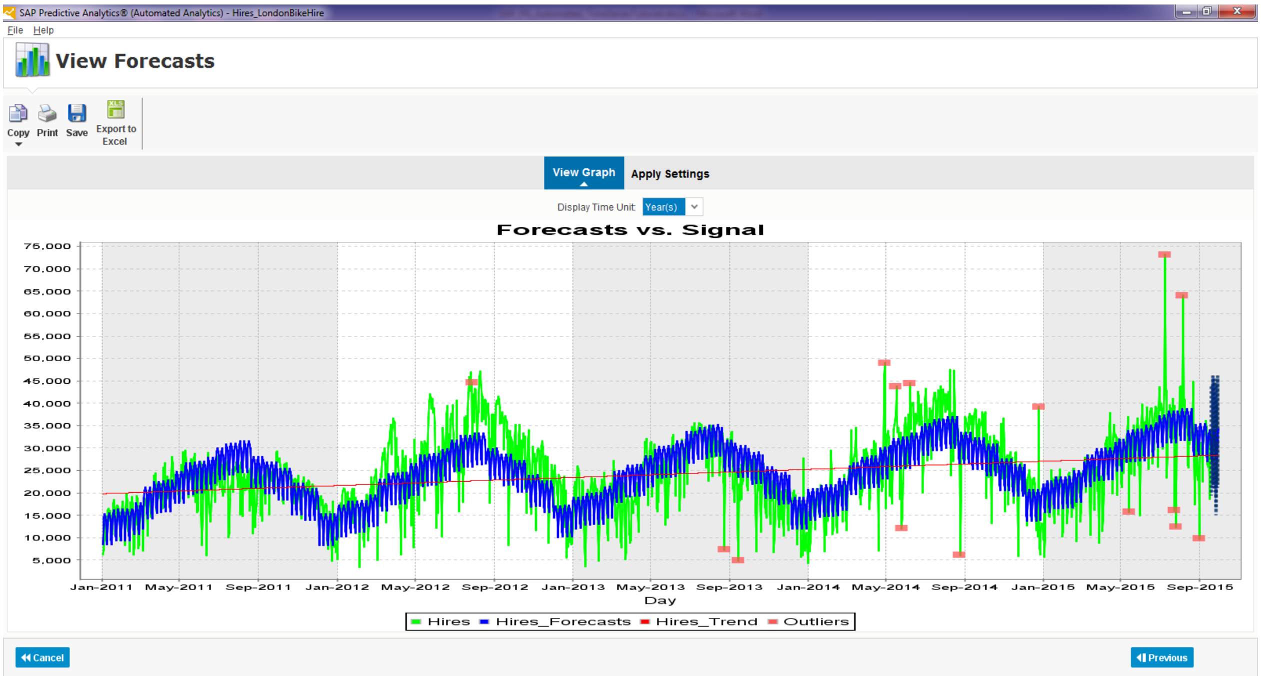
Obviously we want to reduce this error as much as possible. We will address this in the next chapter “Extended Forecast with Additional Predictors”.

Also note the “Model Components”. The model found a linear trend in the data, we will see this trend later also in chart. Similarly, the model found two cycles in the data. These are patterns that repeat over time. The cycles “dayOfYear” and “dayOfWeek” specify that both yearly and weekly cycles were found. We will also see these later on in more detail.

For now however, click “Next” to investigate the model.



Select “View Forecasts”.

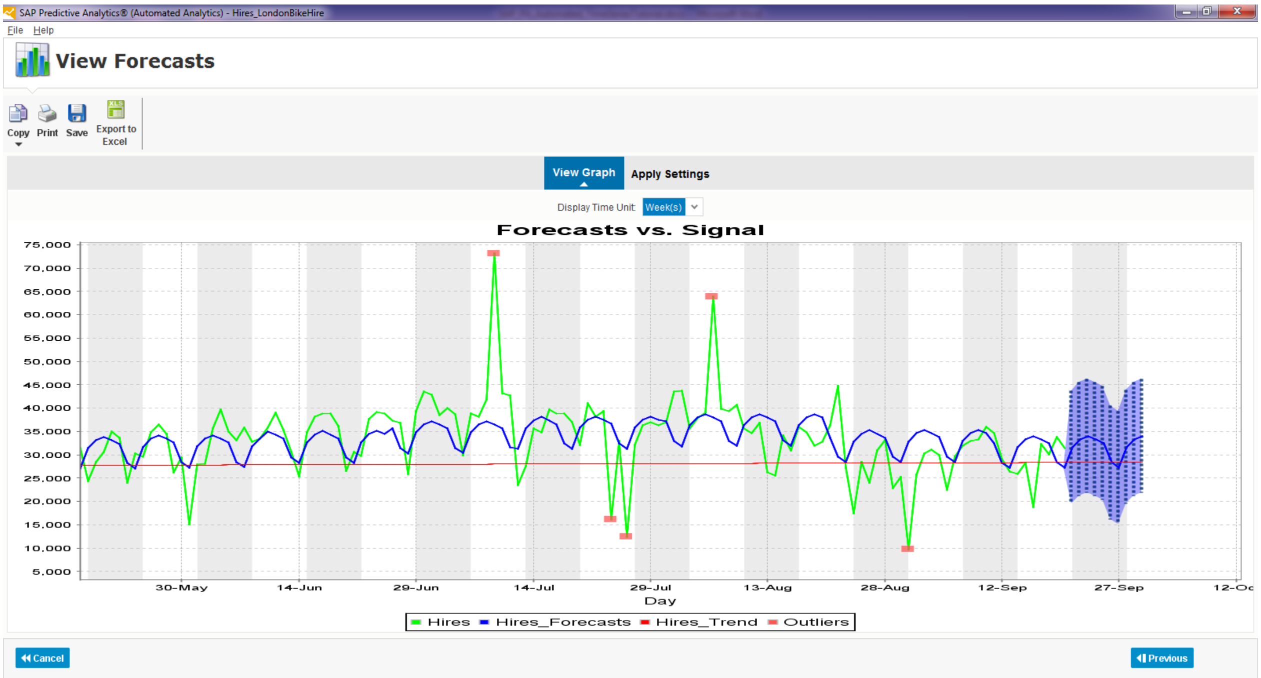


The green line shows the actual values as provided by the city of London. The blue line shows the forecast produced by SAP Predictive Analytics. Overall there is a strong yearly pattern. Not surprisingly, rental numbers are much higher in summer than in winter. The red line rising from left to right indicates a rising trend over time. Rental numbers are clearly rising over time.

Values marked with a red rectangle indicate dates, in which the forecast was significantly different to the actual value. Accordingly, these outliers increase the model’s MAPE. With a richer dataset, ie additional predictor columns that describe the weather for instance, we can hope to better catch the data’s pattern. We will see this in the next chapter.

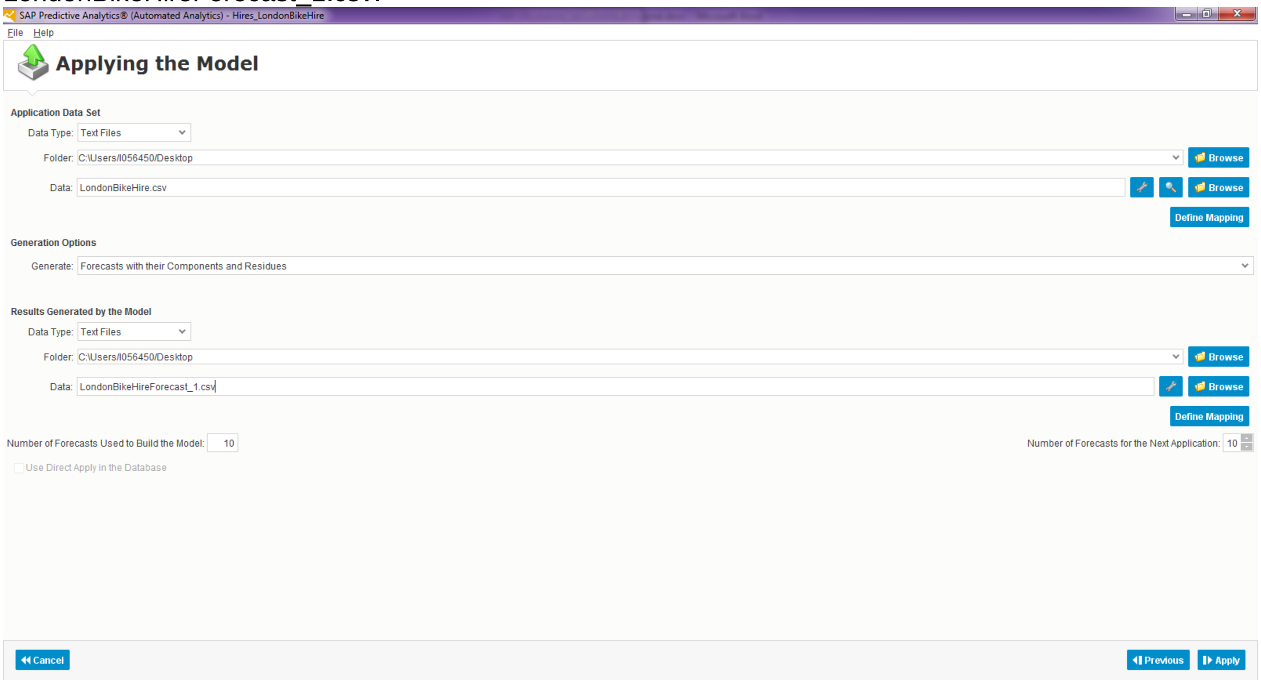
To get a closer look at the forecast you can zoom into the data by drawing a rectangle with the mouse over the area of interest. The following screenshot shows the most recent data with the forecasted values. Just change the “Display Time Unit” to “Week(s)”. You can clearly see the weekly pattern that was identified earlier. Rental numbers are highest during the middle of the working week and lowest on the weekend.

The area shaded in blue on the right hand side around the forecasts of future values specifies the confidence interval of the prediction (twice the standard-deviation either side). Simply put, the more narrow this range, the more confident we are in the forecast.

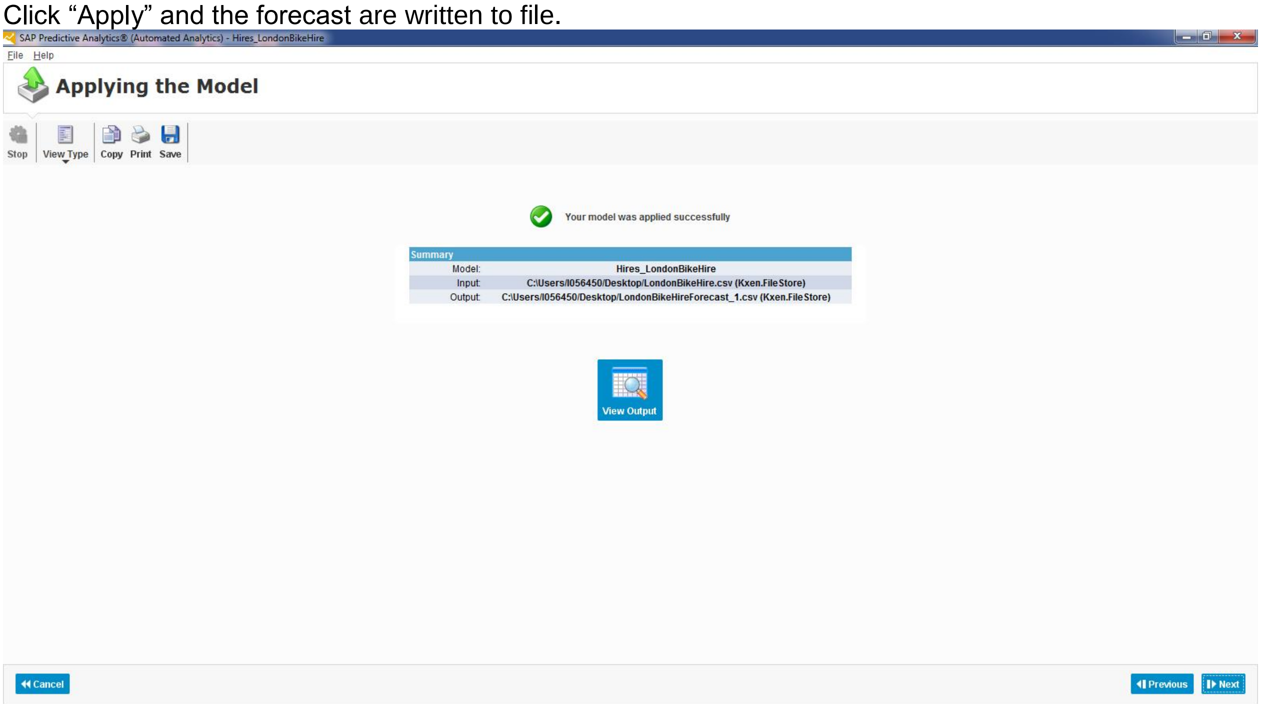


To save the forecast, click “Previous”, then “Save/Export” and “Apply Model”.

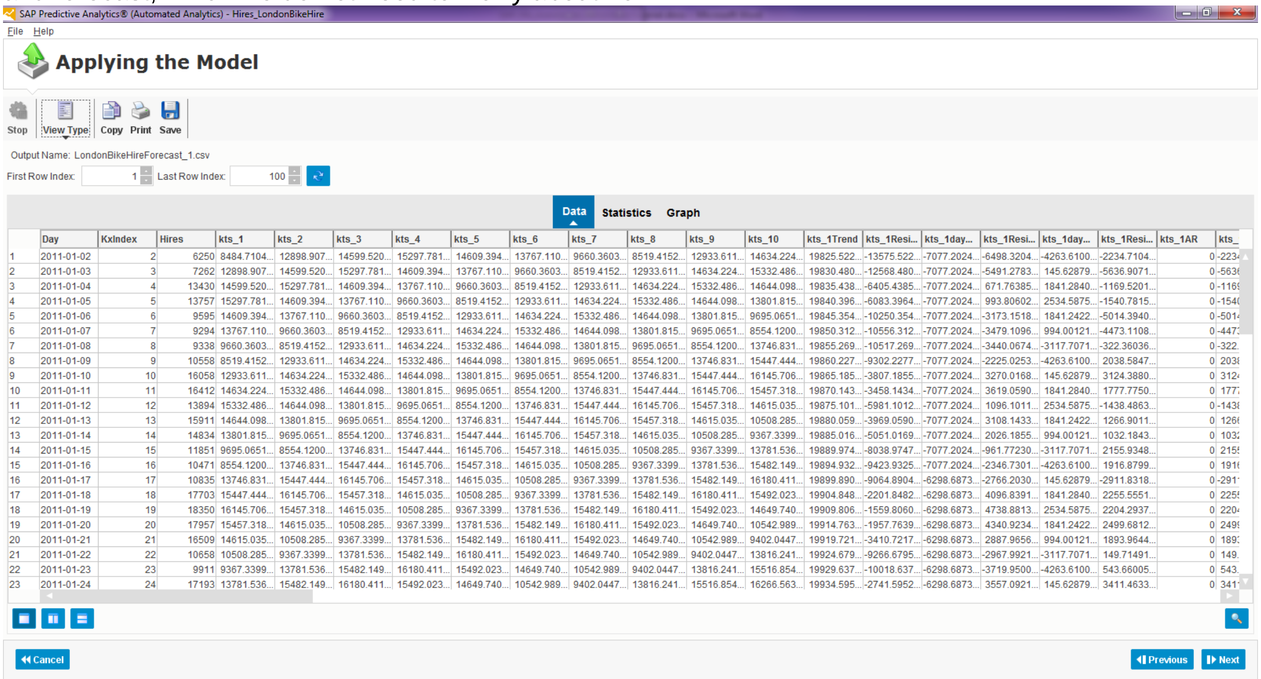
You can keep most of the default settings. Just specify the file name to write the forecasts into: LondonBikeHireForecast_1.csv.



Click “Apply” and the forecast are written to file.



By clicking on the familiar “View Output” icon you see a preview of the forecasts. The most important column is “kts_1”, which contains the day’s forecast. The remaining columns describe various details of the model and forecast, which we do not need to worry about now.



	Day	KxIndex	Hires	kts_1	kts_2	kts_3	kts_4	kts_5	kts_6	kts_7	kts_8	kts_9	kts_10	kts_1Trend	kts_1Resi...	kts_1day...	kts_1Resi...	kts_1day...	kts_1Resi...	kts_1AR	kts_
1	2011-01-02	2	6250	8484.7104...	12898.907...	14599.520...	15297.781...	14609.394...	13767.110...	9660.3603...	8519.4152...	12933.611...	14634.224...	19825.522...	-13575.522...	-7077.2024...	-6498.3204...	-4263.6100...	-2234.7104...	0	-2234
2	2011-01-03	3	7262	12898.907...	14599.520...	15297.781...	14609.394...	13767.110...	9660.3603...	8519.4152...	12933.611...	14634.224...	15332.486...	19830.480...	-12568.480...	-7077.2024...	-5491.2783...	145.62879...	-5636.9071...	0	-5636
3	2011-01-04	4	13430	14599.520...	15297.781...	14609.394...	13767.110...	9660.3603...	8519.4152...	12933.611...	14634.224...	15332.486...	14644.098...	19835.438...	-6405.4385...	-7077.2024...	671.76385...	1841.2840...	-1169.5201...	0	-1169
4	2011-01-05	5	13757	15297.781...	14609.394...	13767.110...	9660.3603...	8519.4152...	12933.611...	14634.224...	15332.486...	14644.098...	13801.815...	19840.396...	-6083.3964...	-7077.2024...	993.80602...	2534.5875...	-1540.7815...	0	-1540
5	2011-01-06	6	9595	14609.394...	13767.110...	9660.3603...	8519.4152...	12933.611...	14634.224...	15332.486...	14644.098...	13801.815...	9695.0651...	19845.354...	-10250.354...	-7077.2024...	-3173.1518...	1841.2422...	-5014.3940...	0	-5014
6	2011-01-07	7	9294	13767.110...	9660.3603...	8519.4152...	12933.611...	14634.224...	15332.486...	14644.098...	13801.815...	9695.0651...	8554.1200...	19850.312...	-10556.312...	-7077.2024...	-3479.1096...	994.00121...	-4473.1108...	0	-4473
7	2011-01-08	8	9338	9660.3603...	8519.4152...	12933.611...	14634.224...	15332.486...	14644.098...	13801.815...	9695.0651...	8554.1200...	13746.831...	19855.269...	-10517.269...	-7077.2024...	-3440.0674...	-3117.7071...	-322.36036...	0	-322.
8	2011-01-09	9	10558	8519.4152...	12933.611...	14634.224...	15332.486...	14644.098...	13801.815...	9695.0651...	8554.1200...	13746.831...	15447.444...	19860.227...	-9302.2277...	-7077.2024...	-2225.0253...	-4263.6100...	2038.5847...	0	2038
9	2011-01-10	10	16058	12933.611...	14634.224...	15332.486...	14644.098...	13801.815...	9695.0651...	8554.1200...	13746.831...	15447.444...	16145.706...	19865.185...	-3807.1855...	-7077.2024...	3270.0168...	145.62879...	3124.3880...	0	3124
10	2011-01-11	11	16412	14634.224...	15332.486...	14644.098...	13801.815...	9695.0651...	8554.1200...	13746.831...	15447.444...	16145.706...	15457.318...	19870.143...	-3458.1434...	-7077.2024...	3619.0590...	1841.2840...	1777.7750...	0	1777
11	2011-01-12	12	13894	15332.486...	14644.098...	13801.815...	9695.0651...	8554.1200...	13746.831...	15447.444...	16145.706...	15457.318...	14615.035...	19875.101...	-5981.1012...	-7077.2024...	1096.1011...	2534.5875...	-1438.4863...	0	-1438
12	2011-01-13	13	15911	14644.098...	13801.815...	9695.0651...	8554.1200...	13746.831...	15447.444...	16145.706...	15457.318...	14615.035...	10508.285...	19880.059...	-3969.0590...	-7077.2024...	3108.1433...	1841.2422...	1266.9011...	0	1266
13	2011-01-14	14	14834	13801.815...	9695.0651...	8554.1200...	13746.831...	15447.444...	16145.706...	15457.318...	14615.035...	10508.285...	9367.3399...	19885.016...	-5051.0169...	-7077.2024...	2026.1855...	994.00121...	1032.1843...	0	1032
14	2011-01-15	15	11851	9695.0651...	8554.1200...	13746.831...	15447.444...	16145.706...	15457.318...	14615.035...	10508.285...	9367.3399...	13781.536...	19889.974...	-8038.9747...	-7077.2024...	-961.77230...	-3117.7071...	2155.9348...	0	2155
15	2011-01-16	16	10471	8554.1200...	13746.831...	15447.444...	16145.706...	15457.318...	14615.035...	10508.285...	9367.3399...	13781.536...	15482.149...	19894.932...	-9423.9325...	-7077.2024...	-2346.7301...	-4263.6100...	1916.8799...	0	1916
16	2011-01-17	17	10835	13746.831...	15447.444...	16145.706...	15457.318...	14615.035...	10508.285...	9367.3399...	13781.536...	15482.149...	16180.411...	19899.890...	-9064.8904...	-6298.6873...	-2766.2030...	145.62879...	-2911.8318...	0	-2911
17	2011-01-18	18	17703	15447.444...	16145.706...	15457.318...	14615.035...	10508.285...	9367.3399...	13781.536...	15482.149...	16180.411...	15492.023...	19904.848...	-2201.8482...	-6298.6873...	4096.8391...	1841.2840...	2255.5551...	0	2255
18	2011-01-19	19	18350	16145.706...	15457.318...	14615.035...	10508.285...	9367.3399...	13781.536...	15482.149...	16180.411...	15492.023...	14649.740...	19909.806...	-1559.8060...	-6298.6873...	4738.8813...	2534.5875...	2204.2937...	0	2204
19	2011-01-20	20	17957	15457.318...	14615.035...	10508.285...	9367.3399...	13781.536...	15482.149...	16180.411...	15492.023...	14649.740...	10542.989...	19914.763...	-1957.7639...	-6298.6873...	4340.9234...	1841.2422...	2499.6812...	0	2499
20	2011-01-21	21	16509	14615.035...	10508.285...	9367.3399...	13781.536...	15482.149...	16180.411...	15492.023...	14649.740...	10542.989...	9402.0447...	19919.721...	-3410.7217...	-6298.6873...	2887.9656...	994.00121...	1893.9644...	0	1893
21	2011-01-22	22	10658	10508.285...	9367.3399...	13781.536...	15482.149...	16180.411...	15492.023...	14649.740...	10542.989...	9402.0447...	13816.241...	19924.679...	-9266.6795...	-6298.6873...	-2967.9921...	-3117.7071...	149.71491...	0	149.
22	2011-01-23	23	9911	9367.3399...	13781.536...	15482.149...	16180.411...	15492.023...	14649.740...	10542.989...	9402.0447...	13816.241...	15516.854...	19929.637...	-10018.637...	-6298.6873...	-3719.9500...	-4263.6100...	543.66005...	0	543.
23	2011-01-24	24	17193	13781.536...	15482.149...	16180.411...	15492.023...	14649.740...	10542.989...	9402.0447...	13816.241...	15516.854...	16266.563...	19934.595...	-2741.5952...	-6298.6873...	3557.0921...	145.62879...	3411.4633...	0	341

We have successfully carried out our first time series forecast!

The dataset was rather basic though in that it consisted only of the day and the date’s value. In the next chapter we improve the forecast by enriching the dataset with additional variables. Any information about the individual day that can influence the rental numbers can be helpful, such as temperature or an indicator for bank holidays.

CONCEPTS BEHIND THE SCENE

SAP Predictive Analytics is going through various iterations looking for many different patterns to find the best forecasting model. It is trying to describe the target variable (also called “signal”) with

- a trend
- through repeating periods
- and fluctuations

The model might include some or all of the above elements. Any delta that is not explained by the model is called a residual. The aim is obviously to explain as much as possible of the signal. So the smaller the remaining residual the better the model.

Mathematically, this leads to the following formula
Signal = Trend + Periodic + Fluctuation + Residual

The elements trend, periodic and fluctuations are further explained below.

Trend
A trend describes the long-term evolution of the data. All together 7 different trend models, both deterministic and stochastic (using probability distributions), are estimated.

Periodic
Next periodic components are investigated. These represent either cycles or seasons.

- Cycles describe a fixed periods, ie a week or year. Cycles are also evaluated for extra-predictable variables, of type ordinal or continuous (not for nominal).
- Seasonal functions describe calendar events, such as “day of month”, “week of month”, “month of year”, “day of week”, ….

When investigating these periods, the previously calculated trends are also taken into account. Subtracting an individual trend from the signal results in a time series that does not have a long-term evolution anymore. Hence periodic elements become apparent.

Fluctuation
Deducting trend and periodic elements from the signal might still leave a certain pattern in the data. Such fluctuations are caught with autoregressive elements.

Residual
Deducting trend, periodic elements and fluctuations from the signal leave the remaining inexplicable element called the residual.

Once the final model has been selected, it is applied on the historic data to calculate its accuracy, which is measured as Mean Absolute Percentage Error (MAPE).

The MAPE is calculated with the following steps:

- Each historic value is compared with the forecasted value.
- The difference, so the error, is calculated.
- This error is calculated in percent of the actual value.
- The absolute value of that percentage is taken, so negatives become positives.
- This absolute percentage error is calculated for each historic signal.
- The mean value of the above absolute percentage error is calculated and the MAPE has been found.

A MAPE of 0.12 for instance indicates that the mean absolute percentage error is 12%. So on average, 88% of the signal was explained by the model.

EXTENDED FORECAST WITH ADDITIONAL PREDICTORS

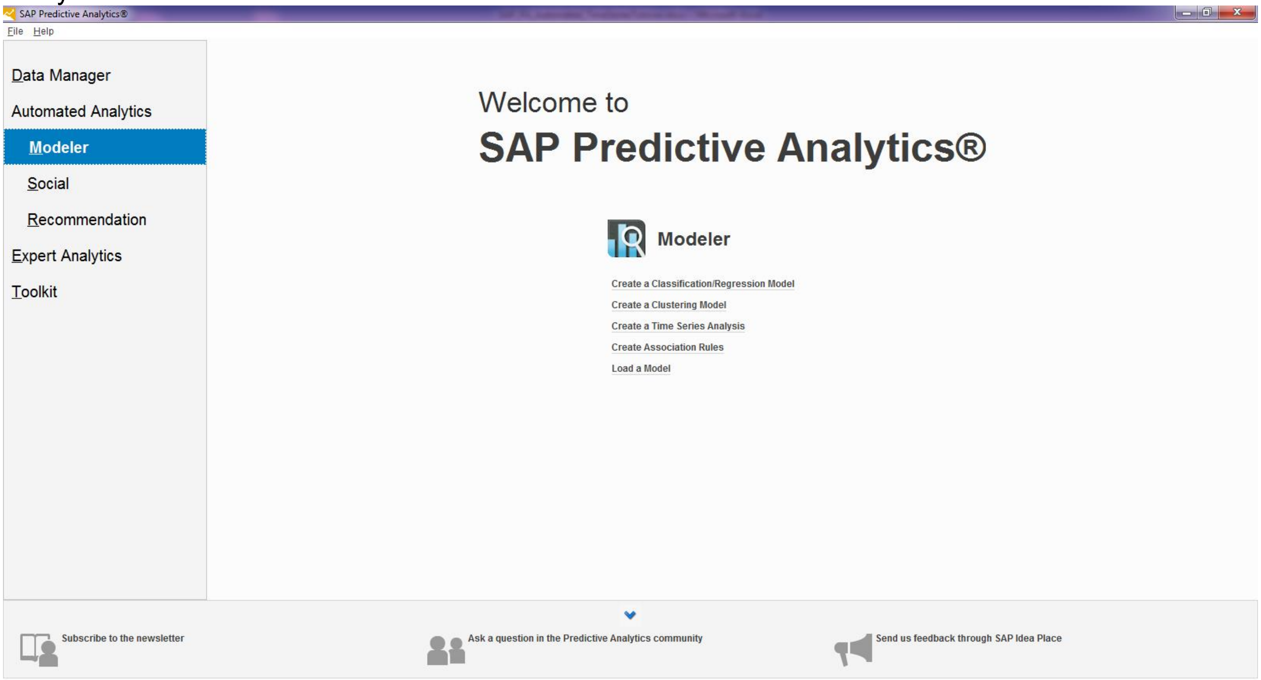
We now aim to improve the forecasting accuracy through additional predictor variables. These are described in more detail in the chapter “DATA DESCRIPTION”.

In short, we have 66 additional variables

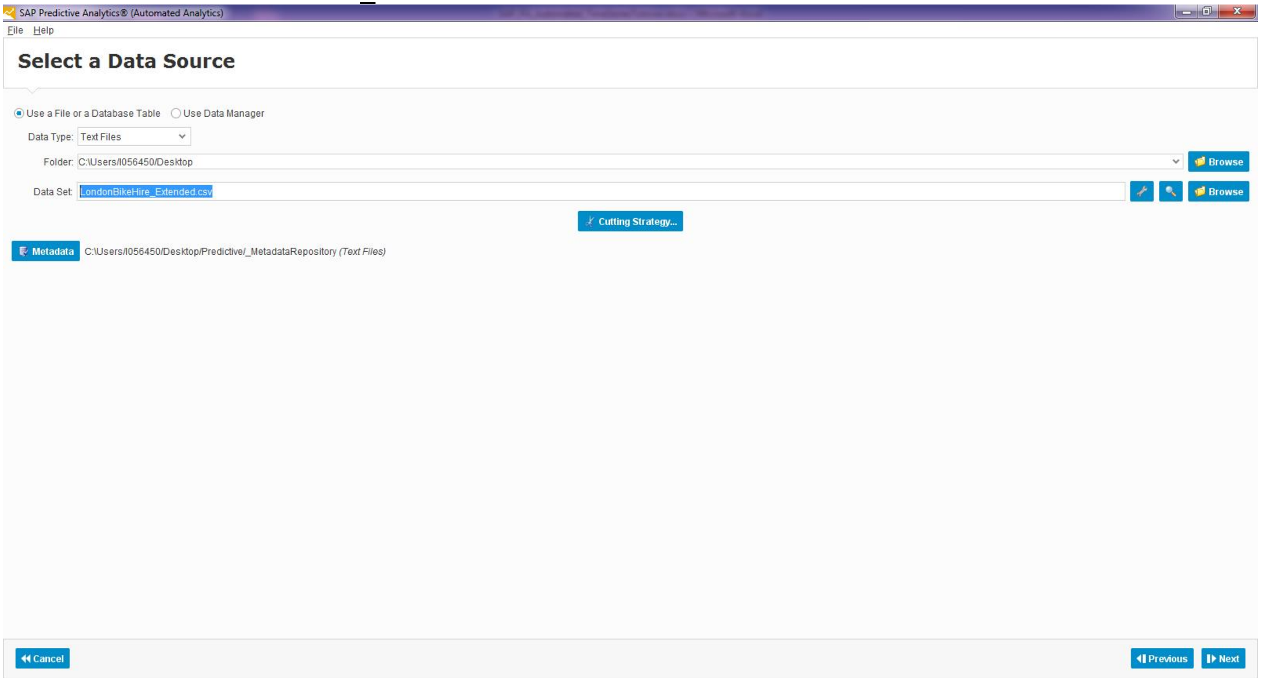
- 32 variables provide calendar information such as holiday flags
- 30 variables describe the weather in London
- 4 variables are related to special events in London, such as the Olympic games or underground strikes

It is very important, that the values of these additional variables must be in the dataset for the dates we want to forecast. We will see this in a few clicks.

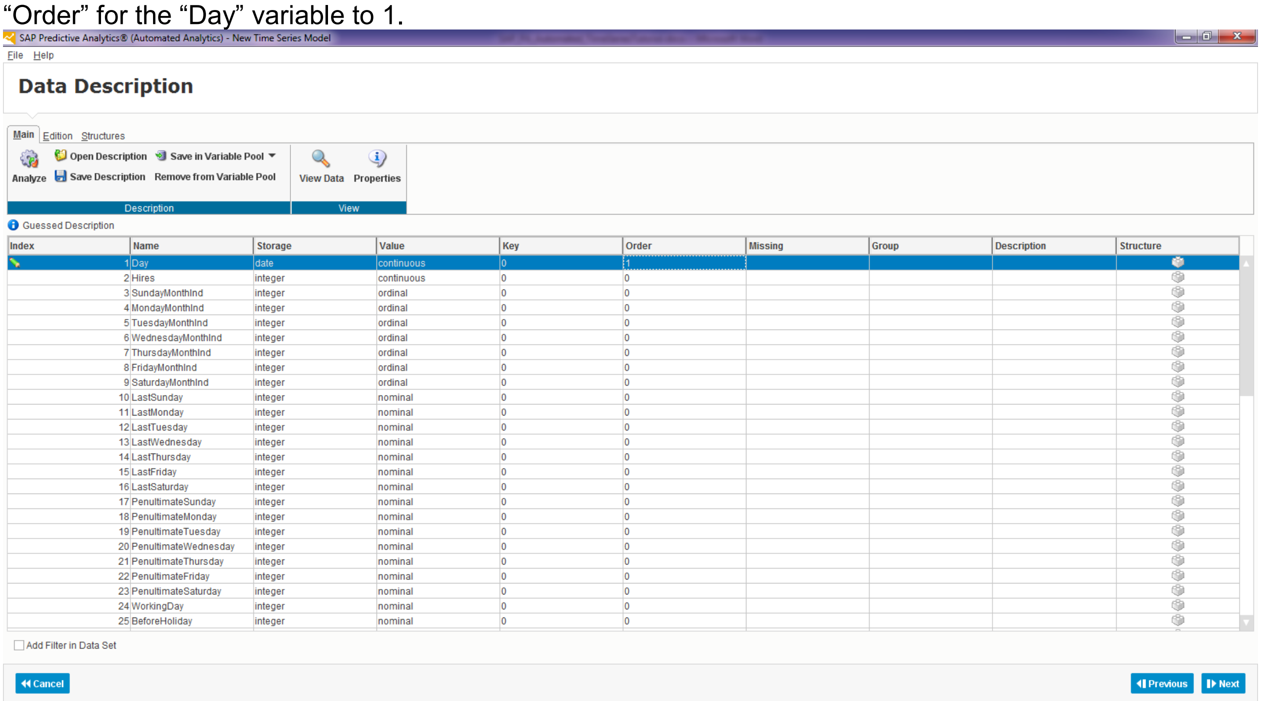
Most steps forecasting the richer dataset are identical to the forecast using the simpler dataset. Go back to the main screen of SAP Predictive Analytics, in the Modeler section click into “Create a Time Series Analysis”.



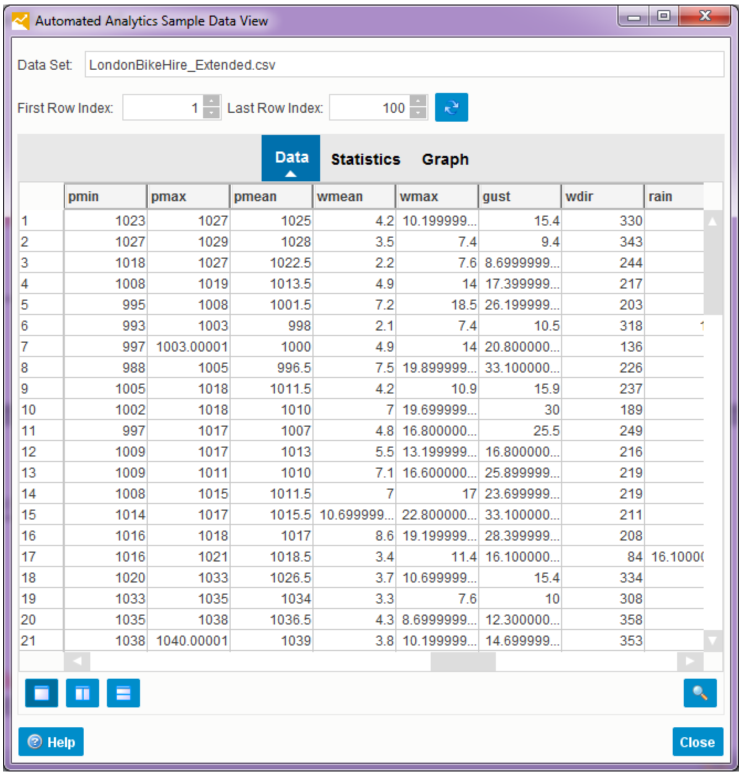
Select the file LondonBikeHire_Extended.csv.



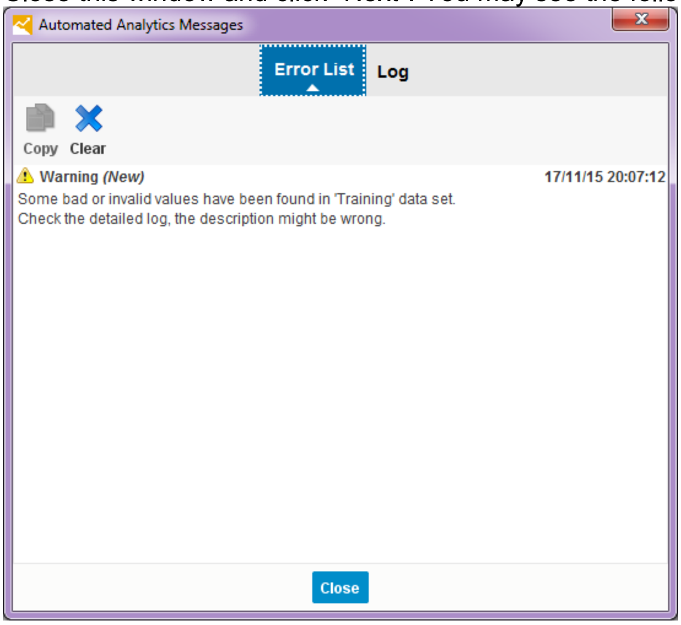
Click “Next”. Then click on “Analyze”. You see all columns of the richer dataset. It is good practice to get in the habit of checking that the time variable has been identified with storage “date”. Also remember to set the “Order” for the “Day” variable to 1.



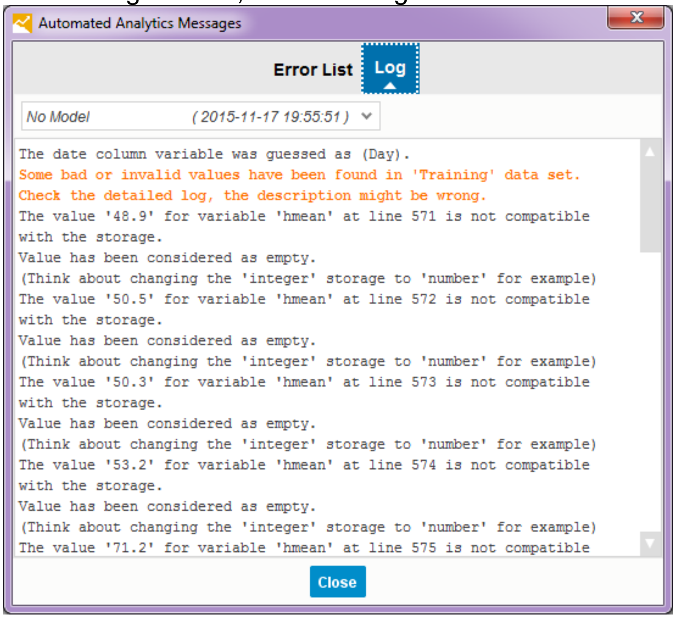
Click on “View Data” to see the file’s content.



Close this window and click “Next”. You may see the following warning.

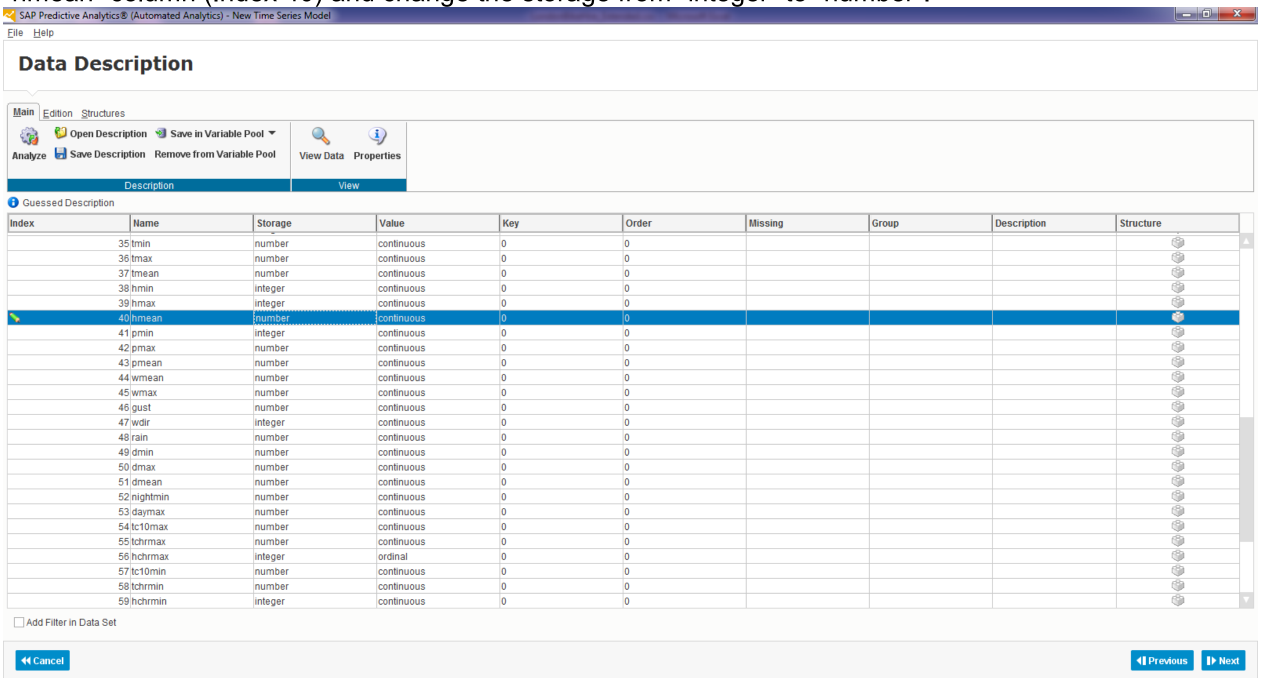


This messages means that you need to fine-tune the “Data Description” that was analyzed automatically. On the warning window, click the “Log” tab and scroll to the top of the log.



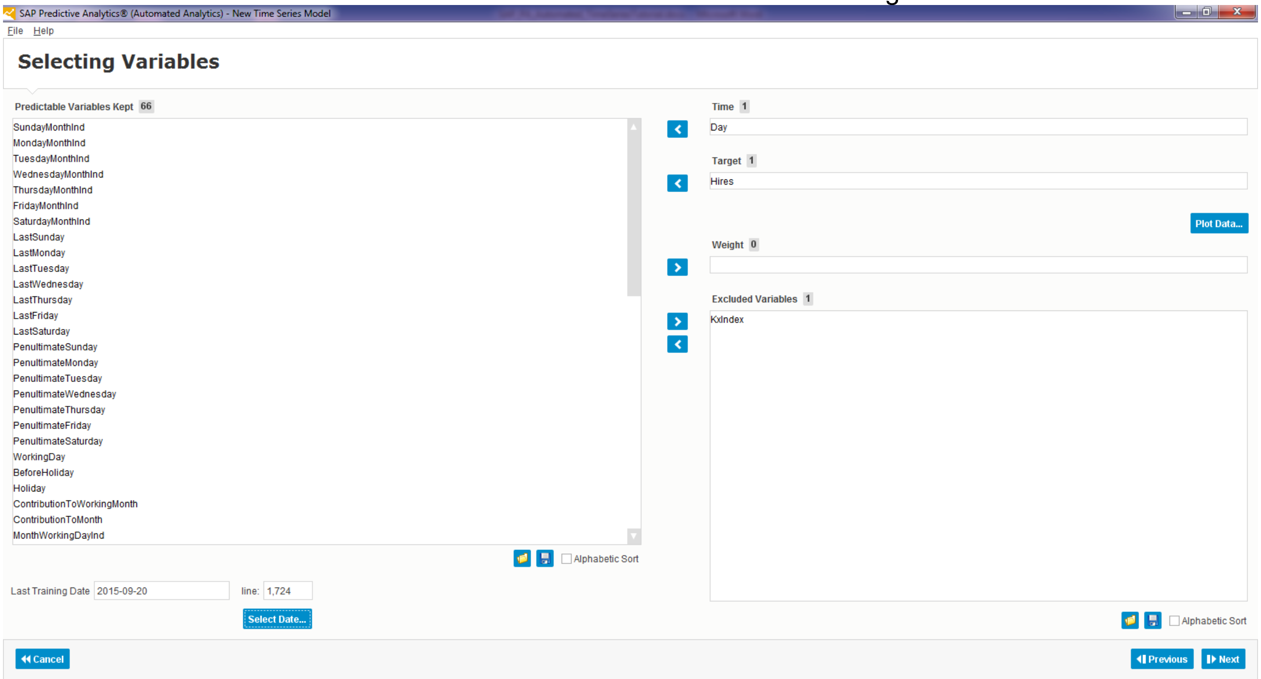
Here you see details about what caused the warning.
The value '48.9' for variable 'hmean' at line 571 is not compatible with the storage.
Value has been considered as empty.
(Think about changing the 'integer' storage to 'number' for example)

We will do exactly this. Close that window and click “Previous” to get back to the “Data Description”. Find the “hmean” column (Index 40) and change the storage from “integer” to “number”.

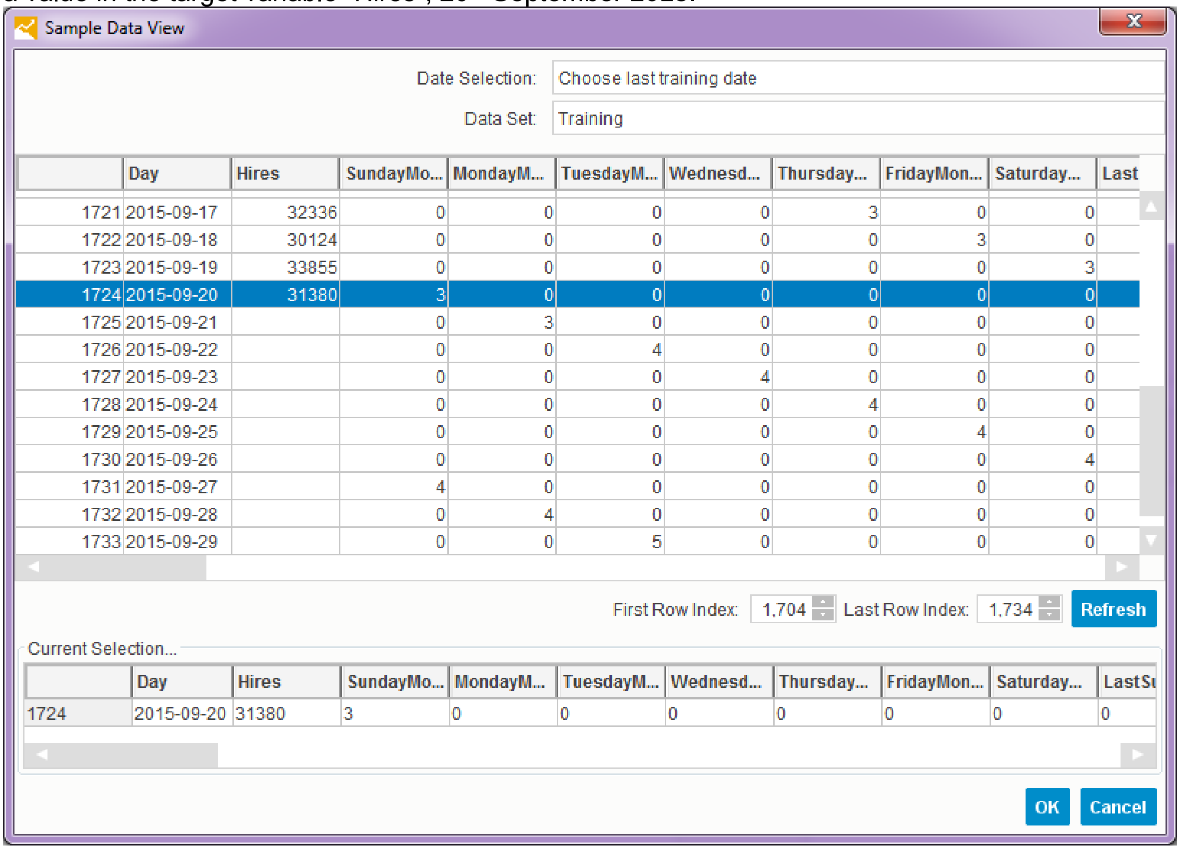


If you like you can save this modified description as a file for later reuse. When done, click “Next” to continue. This time no warning should appear. The modification of the data description was successful.

You should just need to change the “Target” variable. Remove the existing variable by clicking on the icon to the left of it. Then select the “Hires” variable on the left and select it as “Target”.

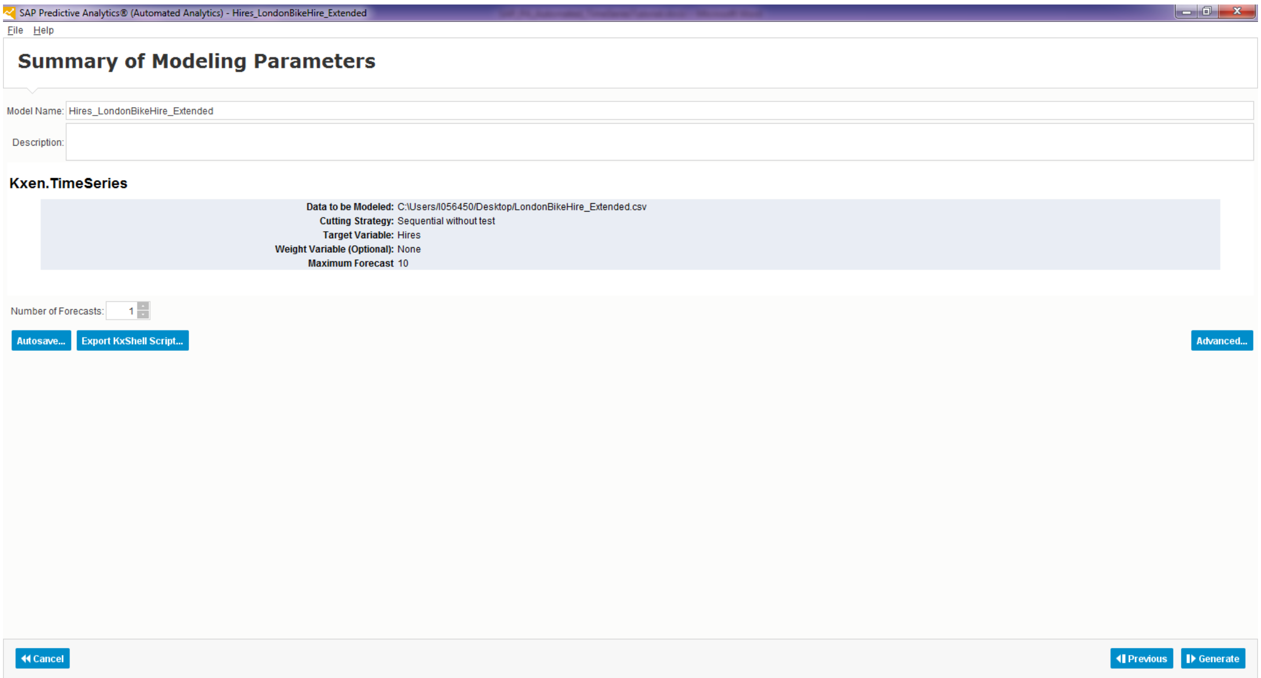


At the bottom left you see a new option, that is only available when you have additional predictor variables. Click on “Select Date…” and you see the last record used for training the model. This is the last row that has a value in the target variable “Hires”, 20th September 2015.

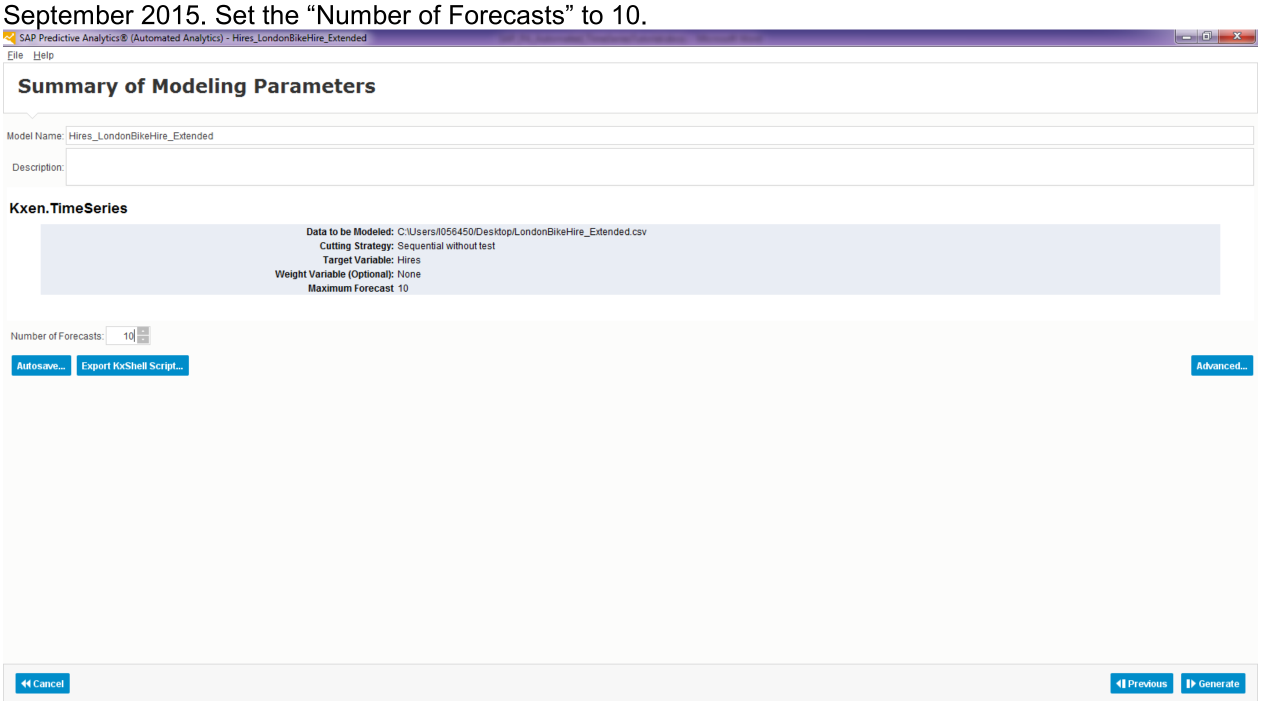


You also see additional rows for future dates beyond the last training date are in the dataset. This is very important when using additional predictor variables. Each date you want to forecast must be added to the dataset with values entered for these predictor variables.

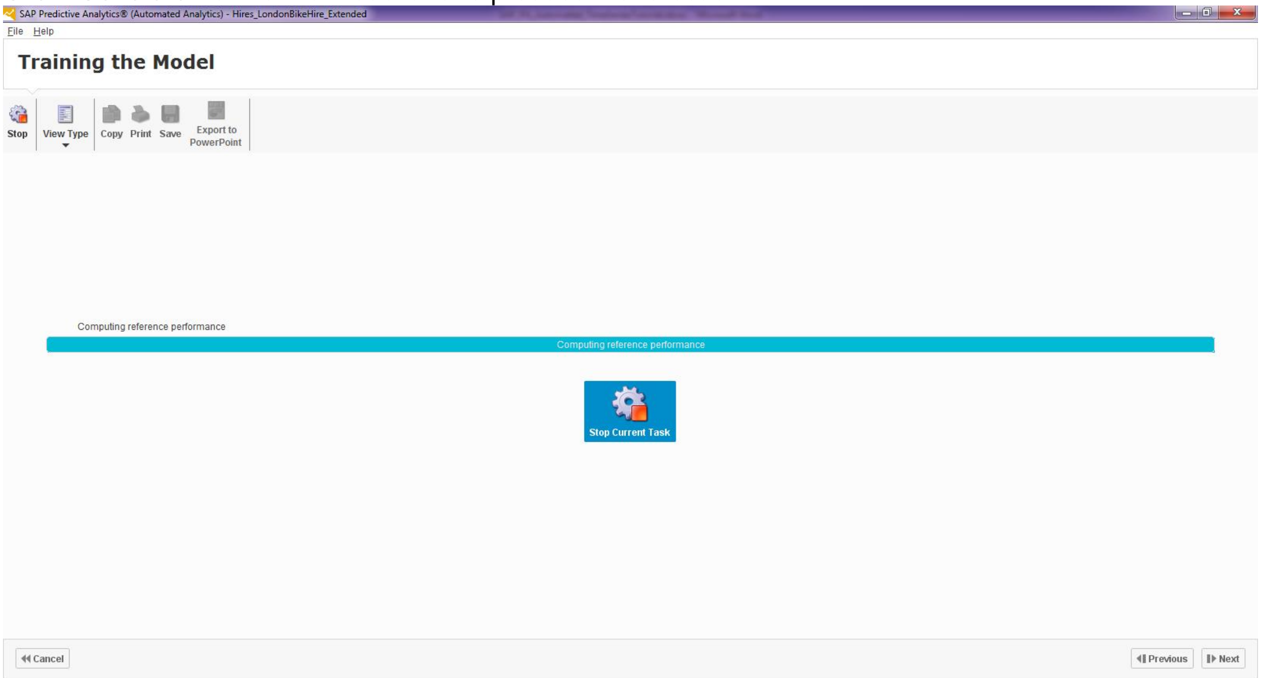
Close this window with “OK” and continue with “Next”.



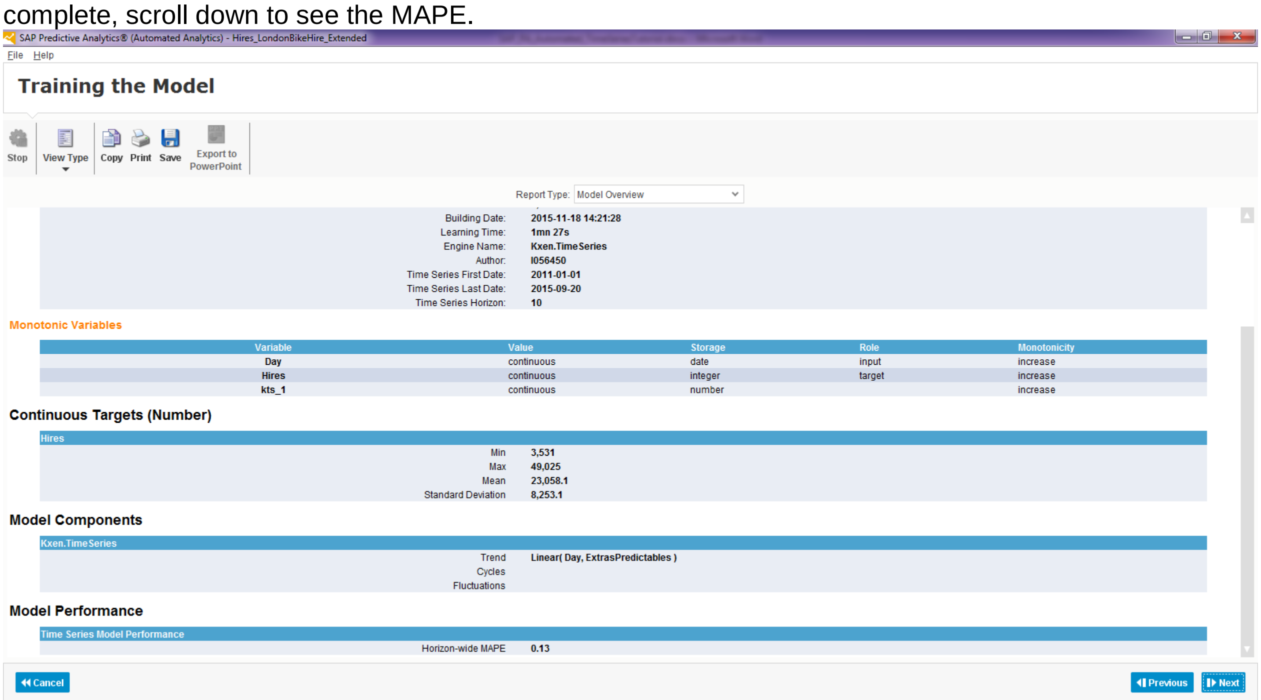
You also see that the “Maximum Forecast” is 10. This means you can forecast 10 days into the future. With our dataset 10 is the maximum, as we have 10 future dates in the dataset, from 21st September to 30th September 2015. Set the “Number of Forecasts” to 10.



Click “Generate” to find the model and to produce the forecast.



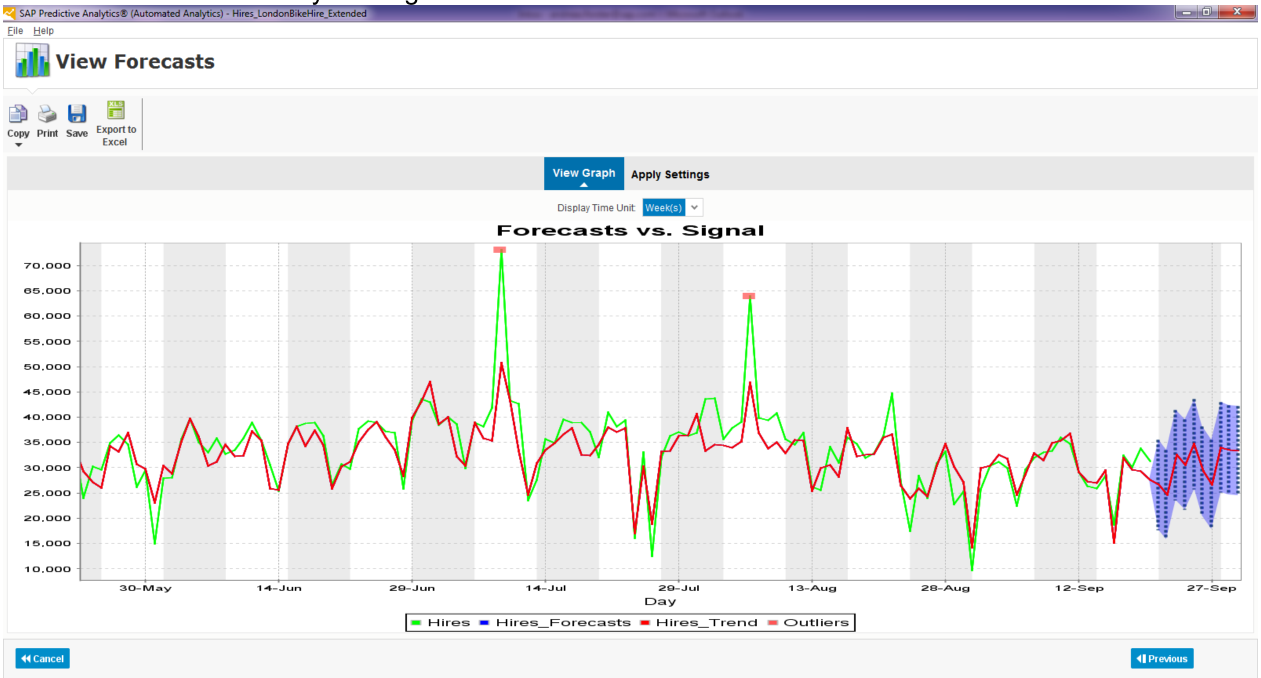
The model generation will take longer because more complex models are taken into account. When complete, scroll down to see the MAPE.



The additional predictor variables have pushed the MAPE down from 0.197 to 0.13. So the model is considerably more accurate than before.

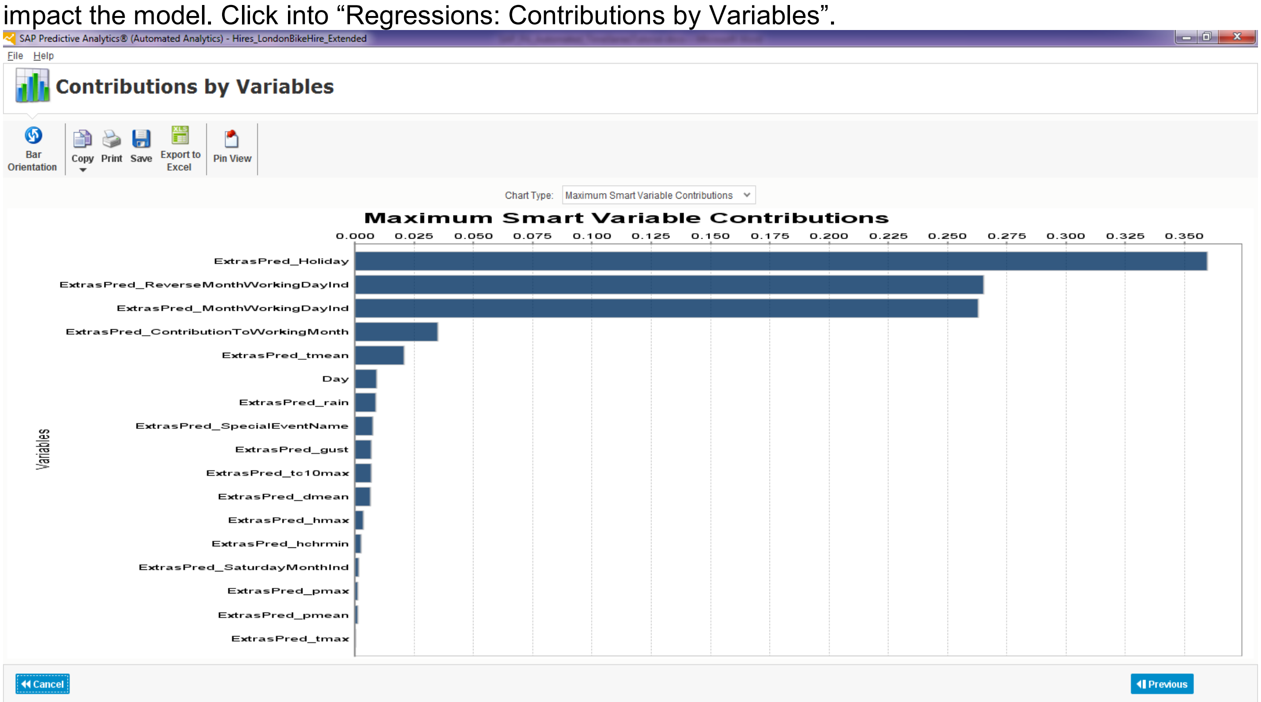
Interestingly, no cycles are used. The new variables describe the data’s pattern than the weekly or yearly cycles that were used in the earlier model!

Now look at the forecast by clicking “Next” and “View Forecasts”. Zoom into the most recent data.



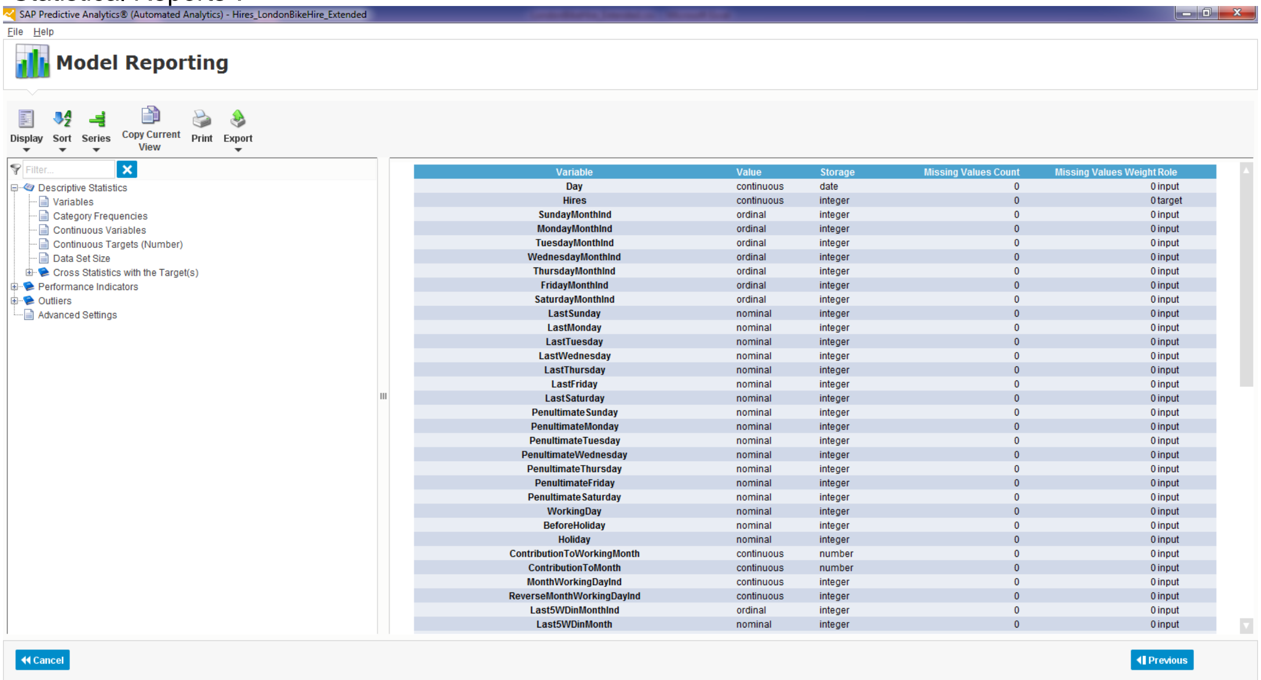
You can compare this display with the earlier forecast. This forecast using the additional predictors clearly describes the data even better. Overall the forecast is very close to the actual values. Fewer outliers than before remain. It turns out that the two outliers with larger rental numbers are dates on which the London Underground was on strike.

Click “Previous” to get back to the main screen. Now we want to understand how the additional predictors impact the model. Click into “Regressions: Contributions by Variables”.

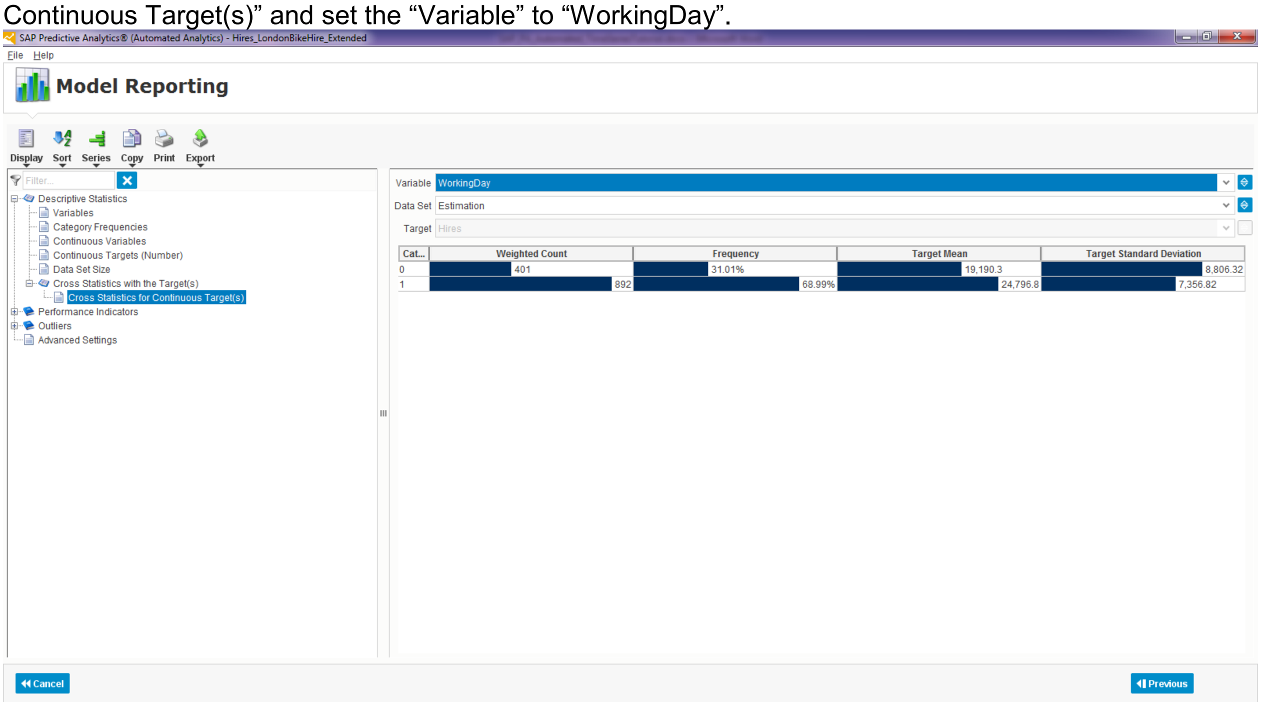


The predictors that were selected for the model are displayed in descending importance. The most important variable “Holiday” is separating working days (Monday to Friday) from non-working days (Saturday, Sunday, bank holiday). The most important weather variable is “tmean”, the mean temperature.

In order to understand how these variables relate to the rental numbers click on “Previous” and go into “Statistical Reports”.

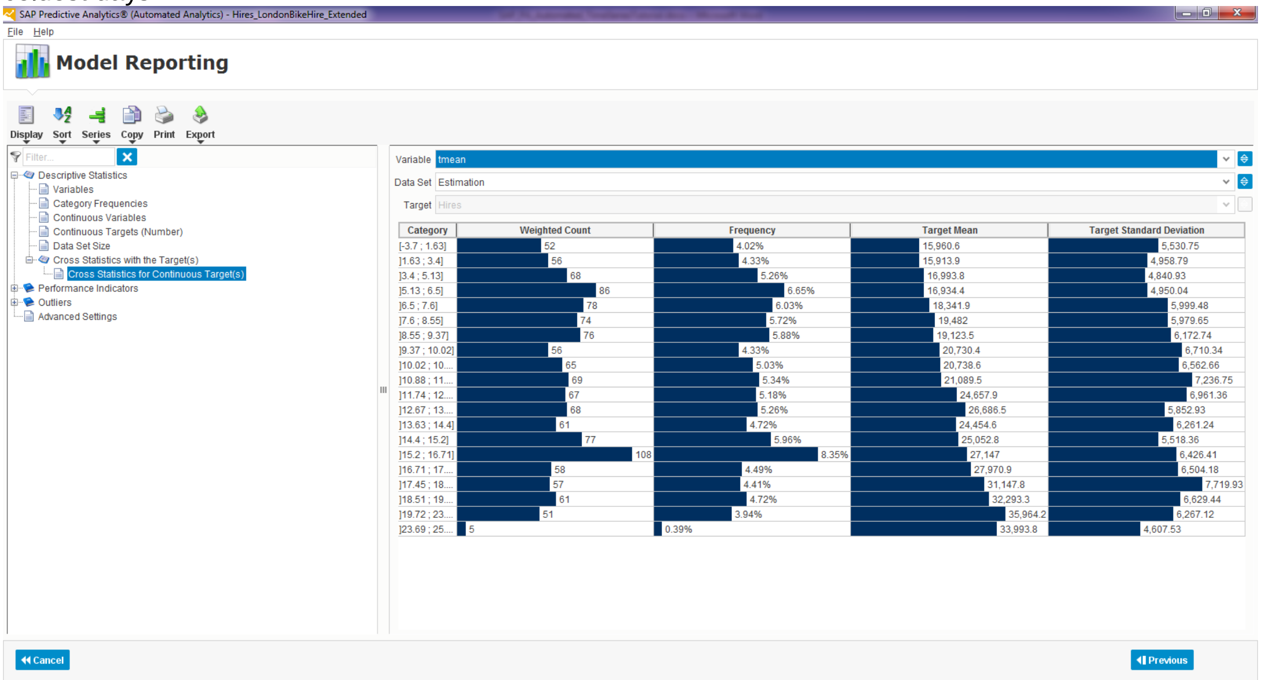


Here you find very detailed information on the data and the model. Go into the “Cross Statistics for Continuous Target(s)” and set the “Variable” to “WorkingDay”.

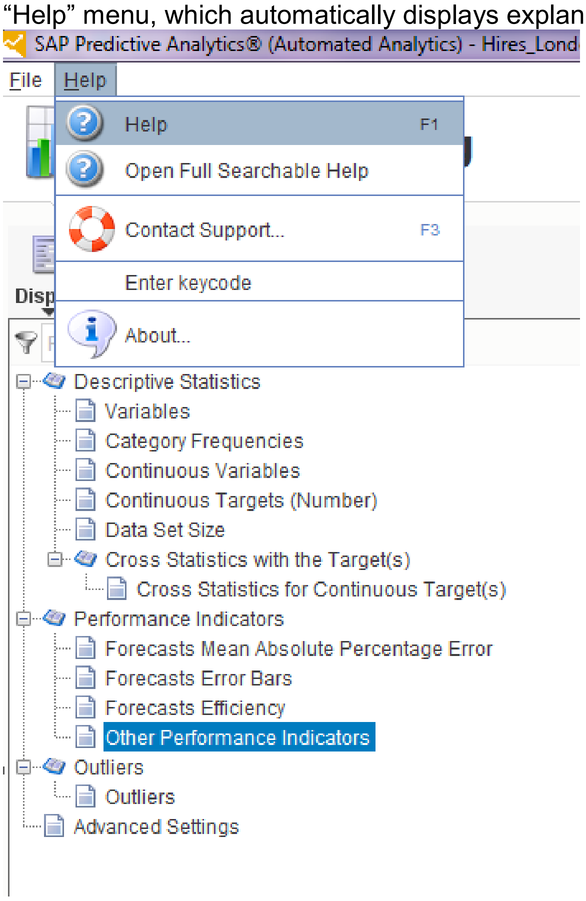


This shows for instance the large difference between mean rental numbers on a working day (24,796.8) and a non-working day (19,190.3).

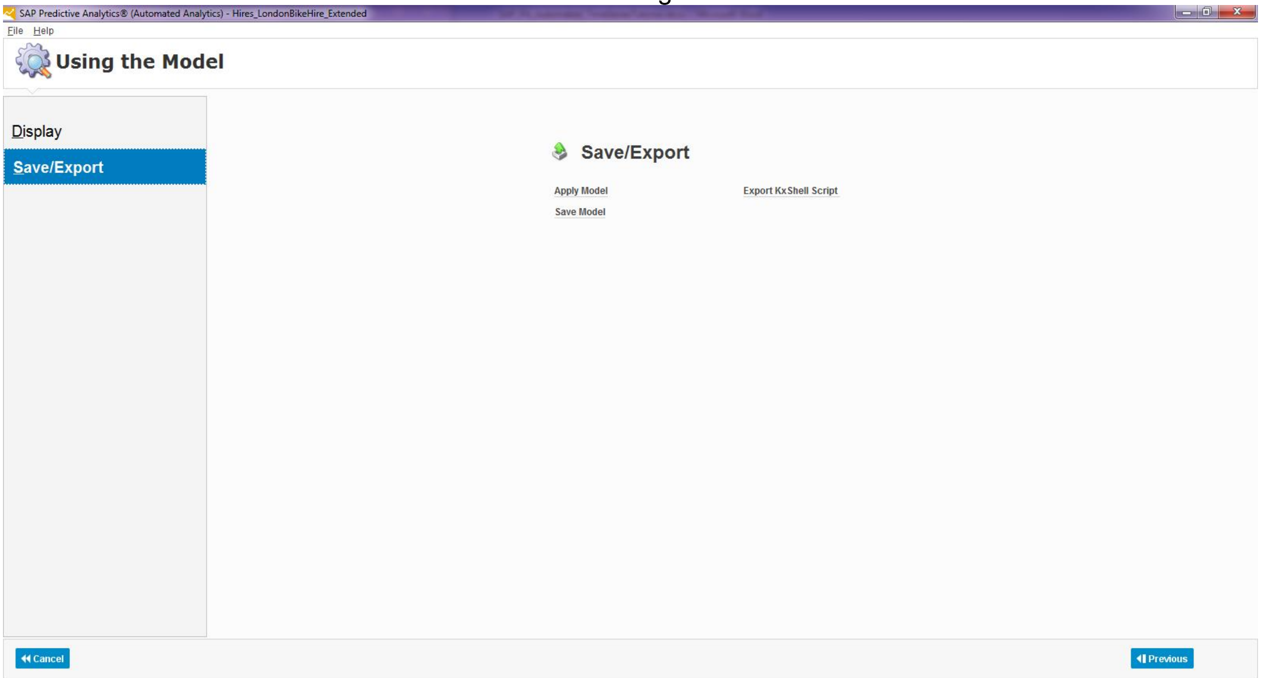
Similarly you can look at different variables, ie “tmean”, the mean temperature. SAP Predictive Analytics has split the temperature in 20 ranges. Such ranges help producing more robust models. By comparing the “Target Mean” of these ranges you see that on the warmest day twice as many bikes are rented as on the coldest days.



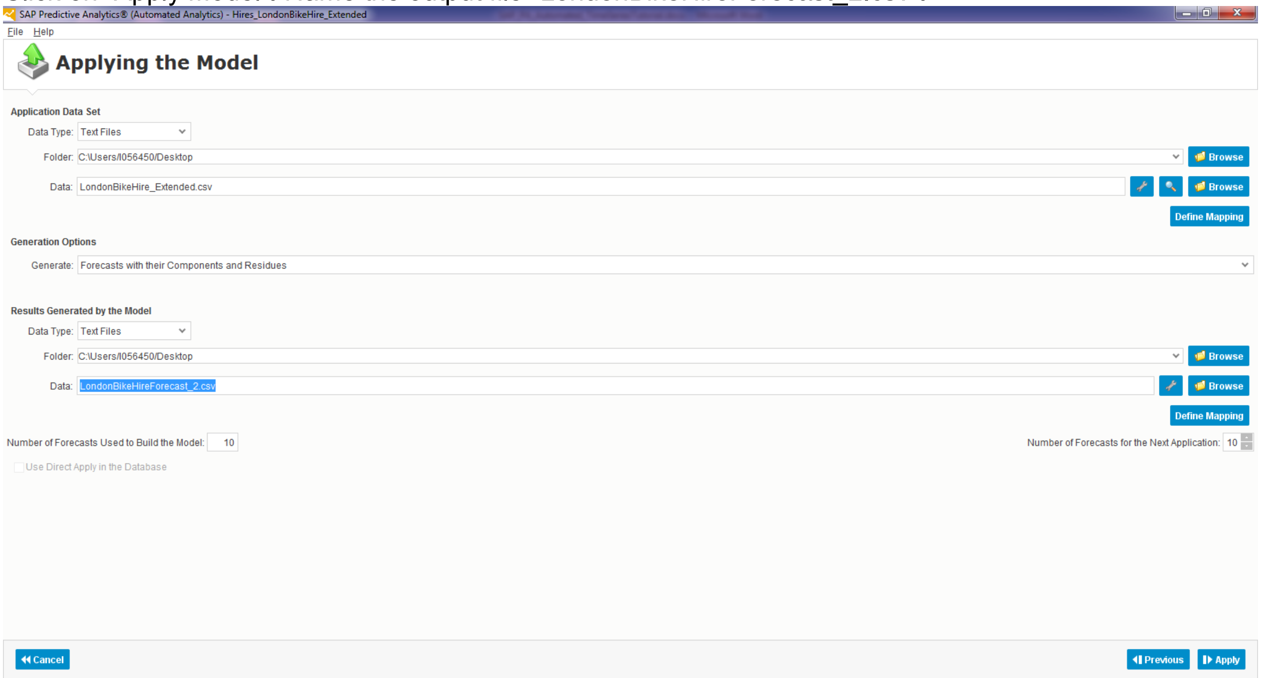
Feel free to look at further details on this screen. To help understand the information you can click into the “Help” menu, which automatically displays explanation the screen that is currently open.



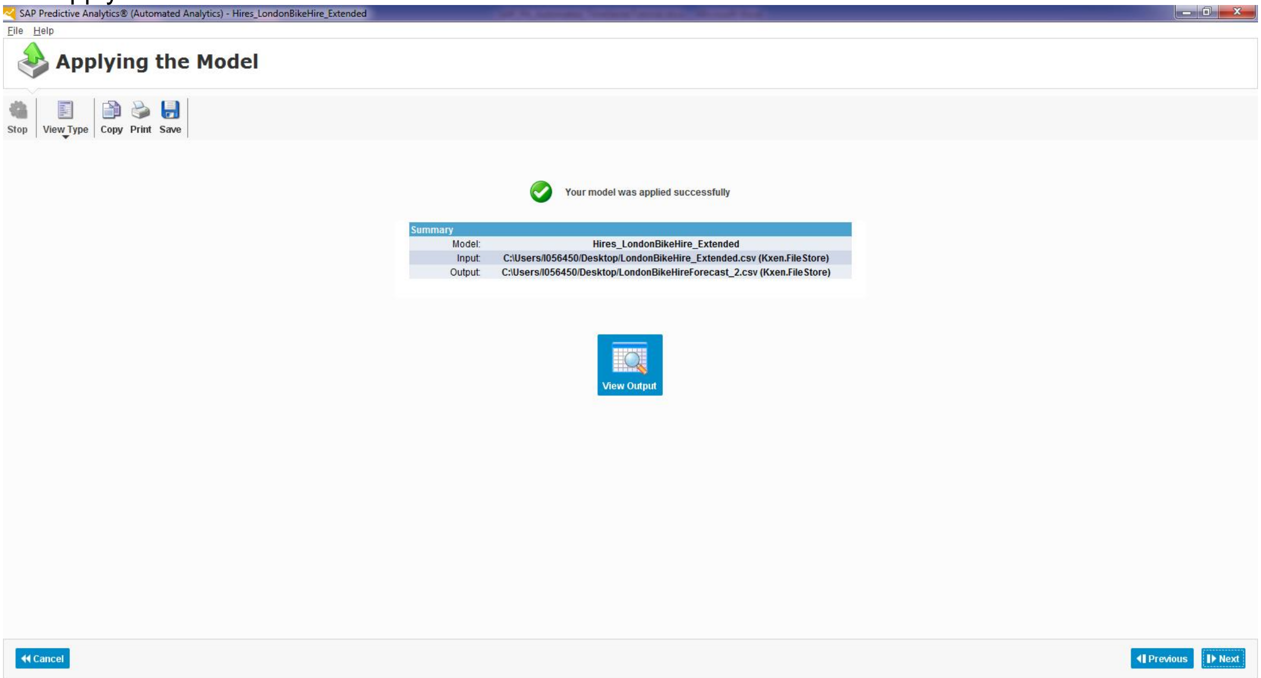
Save the forecasted values as before. Go into the "Using the Model" screen.



Click on "Apply Model". Name the output file "LondonBikeHireForecast_2.csv".



Hit “Apply” and the forecasted values are saved to file.



You have completed a comprehensive time series forecast! With that background you can now experiment with your own data. Just see the next chapter for some further hints and tips.

You can also try to enhance the bike rental forecast with additional columns. Some ideas to improve the forecast are

- Derive new variables from the given datasets. Maybe a day’s change in temperature has an impact (tmax – tmin)
- Combining multiple columns through composite variables might help. Maybe the temperature for instance has a different impact on working days. This tutorial briefly touches on composite variables.[4]
- Try to find completely new columns that have an impact.

Please let me know in case you manage to improve the MAPE below 0.12!

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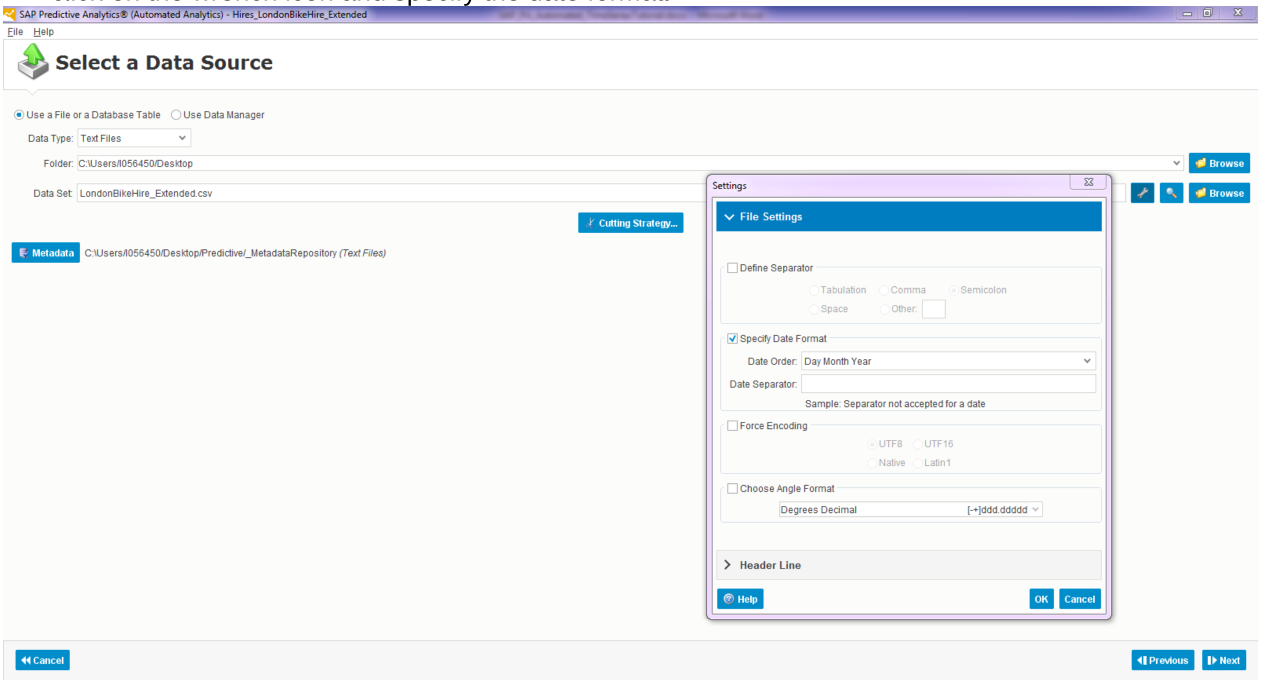
SAP Switzerland
andreas.forster@sap.com

[4] Hands-On Tutorial SAP Predictive Analytics, Automated Mode: Classification, http://scn.sap.com/docs/DOC-68110

HINTS AND TIPS / MORE INFORMATION

If you would like to forecast your own time series, please consider the following.

- The graphical interface used in this tutorial can forecast a single time series. If you would like to forecast multiple time series at once, you might find a separate tutorial helpful.[5]
- The individual time series, that will be forecasted, needs to be sorted by date in descending order.
- In the “Data Description” the Order of the date columns has to be flagged with the value 1.
- In the “Data Description” the Storage type of the date columns has to be “date”. In case the type has not been identified correctly, you can set your own data format. In the screen “Select a Data Source” click on the wrench icon and specify the date format.



- When using additional predictor variables, you must have the dates you want to forecast in the training dataset with the corresponding values of the various predictors. Only the target variable must be empty for these future dates.

For further information see the help file “Time Series Scenarios” on http://help.sap.com/pa

[5] Hands-On Tutorial SAP Predictive Analytics, Automated Mode: Multiple Time Series https://scn.sap.com/docs/DOC-68223

DATA DESCRIPTION

The historic rental numbers are shared by "Transport for London"[6] under an "Open Government Licence".[7]

Ben Lee-Rodgers, who is operating a private weather station in London, kindly contributed the weather statistics.[8]

Date-related variables (ie "Workinday") were produced with a Custom R Component in SAP Predictive Analytics, Expert Mode.[9]

LondonBikeHire.csv

	Column	Description
1	Day	The date.
2	Hires	Number of bicycle hires.

LondonBikeHire_Extended.csv

	Column	Description
1	Day	The date.
2	Hires	Number of bicycle hires.
3	SundayMonthInd	Indicates if the date is a Sunday with the weekday's occurrence count in the month so far. 0 otherwise.
4	MondayMonthInd	Indicates if the date is a Monday with the weekday's occurrence count in the month so far. 0 otherwise.
5	TuesdayMonthInd	Indicates if the date is a Tuesday with the weekday's occurrence count in the month so far. 0 otherwise.
6	WednesdayMonthInd	Indicates if the date is a Wednesday with the weekday's occurrence count in the month so far. 0 otherwise.
7	ThursdayMonthInd	Indicates if the date is a Thursday with the weekday's occurrence count in the month so far. 0 otherwise.
8	FridayMonthInd	Indicates if the date is a Friday with the weekday's occurrence count in the month so far. 0 otherwise.
9	SaturdayMonthInd	Indicates if the date is a Saturday with the weekday's occurrence count in the month so far. 0 otherwise.
10	LastSunday	1 if last Sunday of the month. 0 otherwise.
11	LastMonday	1 if last Monday of the month. 0 otherwise.

[6] Transport for London, Number of Bicycle Hires, http://data.london.gov.uk/dataset/number-bicycle-hires
[7] Open Government Licence, http://www.nationalarchives.gov.uk/doc/open-government-licence/version/2/
[8] Ben Lee-Rodgers, http://nw3weather.co.uk/
[9] Custom R Component - Add Date Attributes, http://scn.sap.com/docs/DOC-69323

12	LastTuesday	1 if last Tuesday of the month. 0 otherwise.
13	LastWednesday	1 if last Wednesday of the month. 0 otherwise.
14	LastThursday	1 if last Thursday of the month. 0 otherwise.
15	LastFriday	1 if last Friday of the month. 0 otherwise.
16	LastSaturday	1 if last Saturday of the month. 0 otherwise.
17	PenultimateSunday	1 if penultimate Sunday of the month. 0 otherwise.
18	PenultimateMonday	1 if penultimate Monday of the month. 0 otherwise.
19	PenultimateTuesday	1 if penultimate Tuesday of the month. 0 otherwise.
20	PenultimateWednesday	1 if penultimate Wednesday of the month. 0 otherwise.
21	PenultimateThursday	1 if penultimate Thursday of the month. 0 otherwise.
22	PenultimateFriday	1 if penultimate Friday of the month. 0 otherwise.
23	PenultimateSaturday	1 if penultimate Saturday of the month. 0 otherwise.
24	Workingday	1 if working day (Saturday, Sunday, Bank Holiday). 0 otherwise.
25	BeforeHoliday	1 if before holiday. 0 otherwise.
26	Holiday	1 if holiday (Saturday, Sunday, Bank Holiday). 0 otherwise.
27	ContributionToWorkingMonth	If working day: 1 divided by number of month's working days. 0 otherwise.
28	ContributionToMonth	1 divided by number of month's days.
29	MonthWorkingDayInd	Indicates if working day with the work day's occurrence count in the month so far. 0 otherwise.
30	ReverseMonthWorkingDayInd	Indicates if working day by counting down the work day's occurrence count in the month. 0 otherwise.
31	Last5WDinMonthInd	Indicates the month's last 5 working days by counting them up from 1 to 5. 0 otherwise.
32	Last5WDinMonth	1 if one the month's last 5 working days. 0 otherwise.
33	Last4WDinMonthInd	Indicates the month's last 4 working days by counting them up from 1 to 4. 0 otherwise.
34	Last4WDinMonth	1 if one the month's last 5 working days. 0 otherwise.
35	tmin	Minimum temperature.
36	tmax	Maximum temperature.
37	tmean	Mean temperature.
38	hmin	Minimum humidity

39	hmax	Maximum humidity
40	hmean	Mean humidity.
41	pmin	Minimum pressure.
42	pmax	Maximum pressure.
43	pmean	Mean pressure.
44	wmean	Mean wind speed.
45	wmax	Maximum wind speed.
46	gust	Maximum gust.
47	wdir	Mean wind direction.
48	rain	Rainfall.
49	dmin	Minimum dew point.
50	dmax	Maximum dew point.
51	dmean	Mean dew point.
52	nightmin	Minimum temperature during night (21h – 9h).
53	daymax	Maximum temperature during the day (9h – 21h).
54	tc10max	Maximum 10 minute temperature rise.
55	tchrmax	Maximum 1 hour temperature rise.
56	hcrmax	Maximum 1 hour humidity rise.
57	tc10min	Minimum 10 minute temperature rise.
58	tchrmin	Minimum 1 hour temperature rise.
59	hchrmin	Minimum 1 hour humidity rise.
60	w10max	Maximum 10 minute wind speed
61	fmin	Minimum feels-like temperature.
62	fmax	Maximum feels-like temperature.
63	fmean	Mean feels-like temperature.
64	afhrs	Air-frost hours.
65	TubeStrike	1 strike on the underground. 0 otherwise.
66	Olympics	1 if the Olympic Games were happening in London. 0 otherwise.
67	SpecialEvent	1 if a special event happened (underground strike or Olympic Games). 0 otherwise.

68	SpecialEventName	Name of the special event. “none” otherwise.