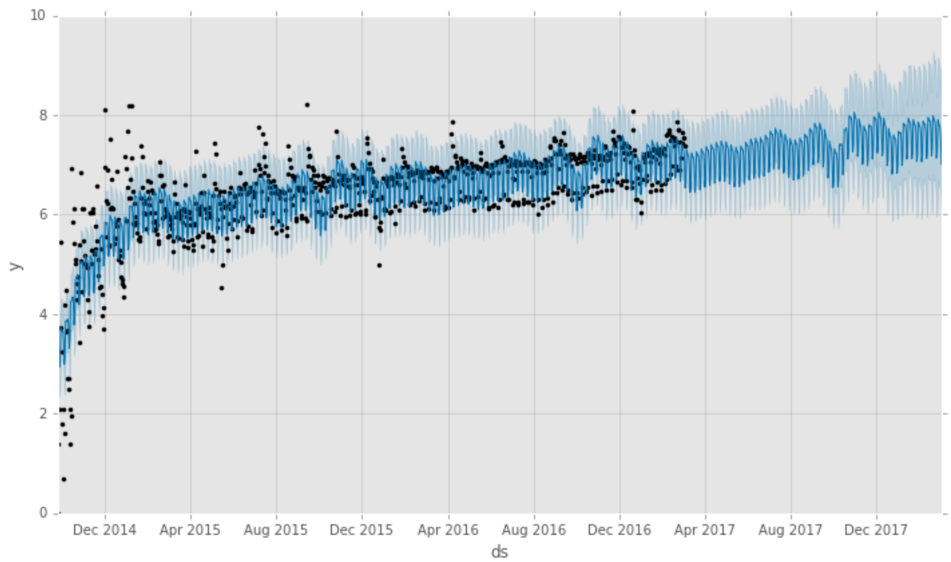
Practical Business Python (http://pbpython.com/)

Taking care of business, one python script at a time

Mon 06 March 2017

Forecasting Website Traffic Using Facebook's Prophet Library (http://pbpython.com/prophet-overview.html)

Posted by Chris Moffitt (http://pbpython.com/author/chris-moffitt.html) in articles (http://pbpython.com/category/articles.html)



Introduction

A common business analytics task is trying to forecast the future based on known historical data. Forecasting is a complicated topic and relies on an analyst knowing the ins and outs of the domain as well as knowledge of relatively complex mathematical theories. Because the mathematical concepts can be complex, a lot of business forecasting approaches are "solved" with a little linear regression and "intuition." More complex models would yield better results but are too difficult to implement.

Given that background, I was very interested to see that Facebook recently open sourced a python and R library called prophet (https://facebookincubator.github.io/prophet/) which seeks to automate the forecasting process in a more sophisticated but easily tune-able model. In this article, I'll introduce prophet and show how to use it to predict the volume of traffic in the next year for Practical Business Python. To make this a little more interesting, I will post the prediction through the end of March so we can take a look at how accurate the forecast is.

Overview of Prophet

For those interested in learning more about prophet, I recommend reading Facebook's white paper (https://facebookincubator.github.io/prophet/static/prophet_paper_20170113.pdf) on the topic. The paper is relatively light on math and heavy on the background of forecasting and some of the business challenges associated with building and using forecasting models at scale.

The paper's introduction contains a good overview of the challenges with current forecasting approaches:

> Producing high quality forecasts is not an easy problem for either machines or for most analysts. We have observed two main themes in the practice of creating business forecasts:
>
> 1. Completely automatic forecasting techniques can be brittle and they are often too inflexible to incorporate useful assumptions or heuristics.
>
> 2. Analysts who can produce high quality forecasts are quite rare because forecasting is a specialized data science skill requiring substantial experience. The result of these themes is that the demand for high quality forecasts often far outstrips the pace at which the organization can produce them.

Prophet seeks to provide a simple to use model that is sophisticated enough to provide useful results - even when run by someone without deep knowledge of the mathematical theories of forecasting. However, the modeling solution does provide several tuneable parameters so that analysts can easily make changes to the model based on their unique business needs.

Installation

Before going any further, make sure to install prophet. The complex statistical modeling is handled by the Stan (http://mc-stan.org/) library and is a prerequisite for prophet. As long as you are using anaconda, the installation process is pretty simple:

```
conda install pystan
pip install fbprophet
```

Starting the Analysis

For this analysis, I will be using a spreadsheet of the actual web traffic volume from pbpython starting in Sept 2014 and going through early March 2017. The data is downloaded from Google analytics and looks like this:

	A	B
1	Day Index	Sessions
2	9/25/2014	1
3	9/26/2014	4
4	9/27/2014	8
5	9/28/2014	42
6	9/29/2014	233
7	9/30/2014	26
8	10/1/2014	6
9	10/2/2014	8
10	10/3/2014	2
11	10/4/2014	5
12	10/5/2014	65

```
import pandas as pd
import numpy as np
from fbprophet import Prophet

data_file = "All Web Site Data Audience Overview.xlsx"
df = pd.read_excel(data_file)
df.head()
```

	Day Index	Sessions
0	2014-09-25	1
1	2014-09-26	4
2	2014-09-27	8
3	2014-09-28	42
4	2014-09-29	233

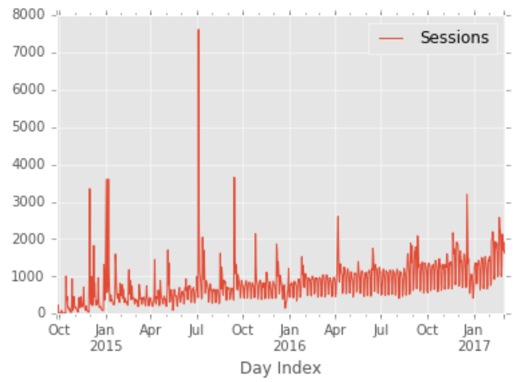
The first thing we need to check is to make sure the Day Index column came through as a datetime type:

```
df.dtypes
```

```
Day Index    datetime64[ns]
Sessions              int64
dtype: object
```

Since that looks good, let's see what kind of insight we can get with just simple pandas plots:

```
df.set_index('Day Index').plot();
```

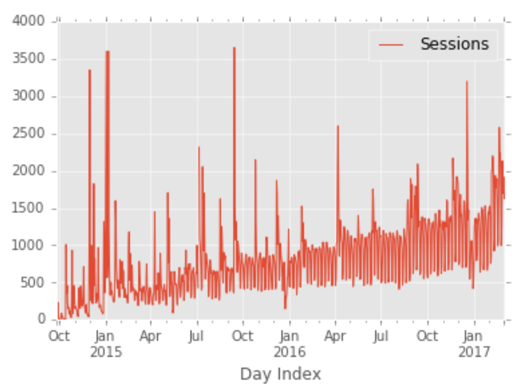


The basic plot is interesting but, like most time series data, it is difficult to get much out of this without doing further analysis. Additionally, if you wanted to add a predicted trend-line, it is a non-trivial task with stock pandas.

Before going further, I do want to address the outlier in the July 2015 timeframe. My most popular article is Pandas Pivot Table Explained (http://pbpython.com/pandas-pivot-table-explained.html) which saw the biggest traffic spike on this blog. Since that article represents an outlier in volume, I am going to change those values to `nan` so that it does not unduly influence the projection.

This change is not strictly required but it will be useful to show that prophet can handle this missing data without further manipulation. This process also highlights the need for the analyst to still be involved in the process of making the forecast.

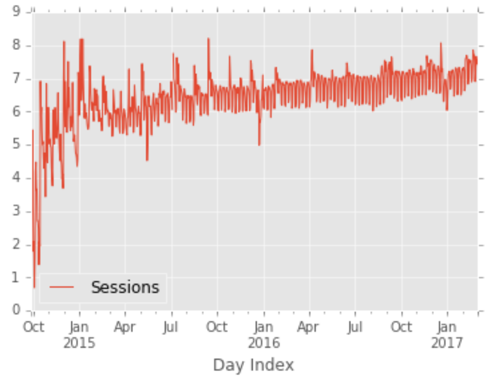
```
df.loc[(df['Sessions'] > 5000), 'Sessions'] = np.nan
df.set_index('Day Index').plot();
```



This is pretty good but I am going to do one other data transformation before continuing. I will convert the `Sessions` column to be a log value. This article (https://people.duke.edu/~rnau/411log.htm) has more information on why a log transform is useful for these types of data sets. From the article:

> … logging converts multiplicative relationships to additive relationships, and by the same token it converts exponential (compound growth) trends to linear trends. By taking logarithms of variables which are multiplicatively related and/or growing exponentially over time, we can often explain their behavior with linear models.

```
df['Sessions'] = np.log(df['Sessions'])
df.set_index('Day Index').plot();
```



The data set is almost ready to make a prediction. The final step is to rename the columns to `ds` and `y` in order to comply with the prophet API.

```
df.columns = ["ds", "y"]
df.head()
```

	ds	y
0	2014-09-25	0.000000
1	2014-09-26	1.386294
2	2014-09-27	2.079442
3	2014-09-28	3.737670
4	2014-09-29	5.451038

Now that the data is cleaned and labeled correctly, let's see what prophet can do with it.

Making a Prediction

The prophet API is similar to scikit-learn. The general flow is to `fit` the data then `predict` the future time series. In addition, prophet supports some nice plotting features using `plot` and `plot_components` .

Create the first model (m1) and fit the data to our dataframe:

```
m1 = Prophet()
m1.fit(df)
```

In order to tell prophet how far to predict in the future, use `make_future_dataframe.` In this example, we will predict out 1 year (365 days).

```
future1 = m1.make_future_dataframe(periods=365)
```

Then make the forecast:

```
forecast1 = m1.predict(future1)
```

The `forecast1` is just a pandas dataframe with a several columns of data. The predicted value is called `yhat` and the range is defined by `yhat_lower` and `yhat_upper` . To see the last 5 predicted values:

```
forecast1[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].tail()
```

	ds	yhat	yhat_lower	yhat_upper
1250	2018-02-27	7.848040	6.625887	9.081303
1251	2018-02-28	7.787314	6.565903	9.008327
1252	2018-03-01	7.755146	6.517481	8.948139
1253	2018-03-02	7.552382	6.309191	8.785648
1254	2018-03-03	7.011651	5.795778	8.259777

	ds	yhat	yhat_lower	yhat_upper

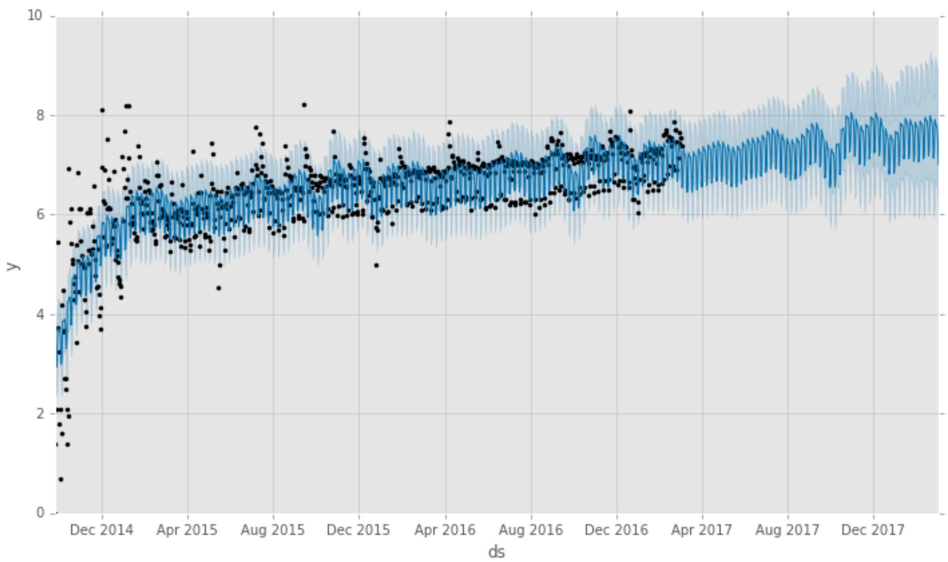
To convert back to the numerical values representing sessions, use `np.exp`

```
np.exp(forecast1[['yhat', 'yhat_lower', 'yhat_upper']].tail())
```

	yhat	yhat_lower	yhat_upper
1250	2560.709477	754.373407	8789.412841
1251	2409.836175	710.452848	8170.840734
1252	2333.549138	676.871358	7693.563414
1253	1905.275686	549.600404	6539.712030
1254	1109.484324	328.907843	3865.233952

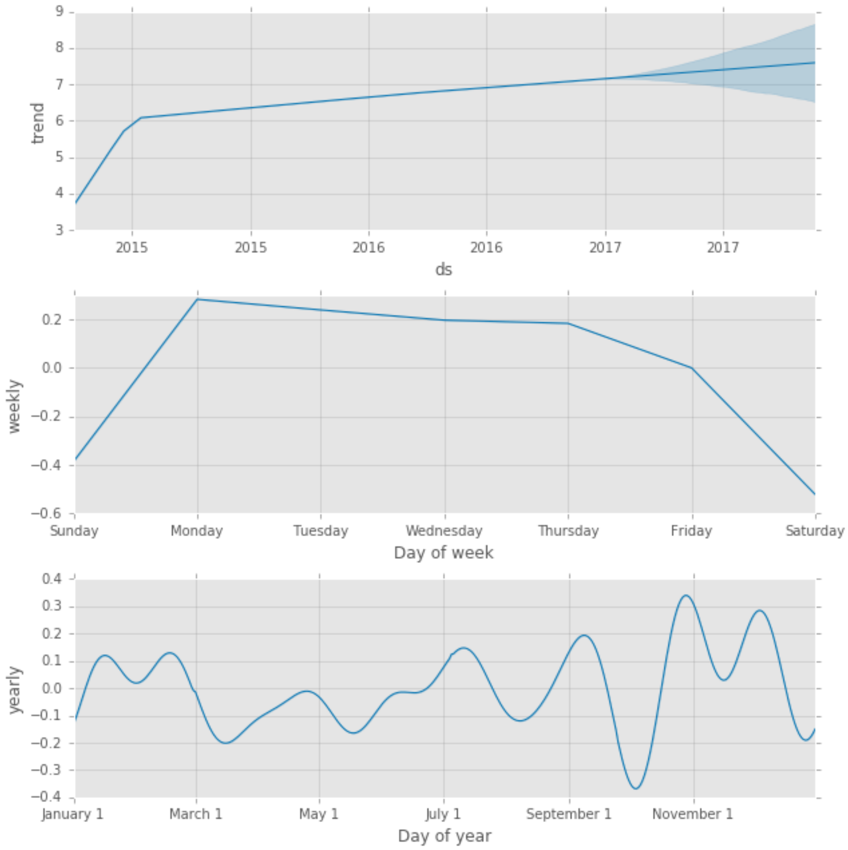
To make this look nice and impress management, plot the data:

```
m1.plot(forecast1);
```



Very cool. The other useful feature is the ability to plot the various components:

```
m1.plot_components(forecast1);
```



I really like this view because it is a very simple way to pull out the daily and weekly trends. For instance, the charts make it easy to see that Monday-Thursday are peak times with big fall offs on the weekend. Additionally, I appear to have bigger jumps in traffic towards the end of the year.

Refining the Model

I hope you'll agree that the basic process to create a model is relatively straightforward and you can see that the results include more rigor than a simple linear trend line. Where prophet really shines is the ability to iterate the models with different assumptions and inputs.

One of the features that prophet supports is the concept of a "holiday." The simplest way to think about this idea is the typical up-tick in store sales seen around the Thanksgiving and Christmas holidays. If we have certain known events that have major impacts on our time series, we can define them and the model will use these data points to try to make better future predictions.

For this blog, any time a new article is published, there is an uptick in traffic for about 1 week, then there is a slow decay back to steady state. Therefore for this analysis, we can define a holiday as a blog post. Since I know that the post drives increased traffic for about 5-7 days, I can define an `upper_window` to encapsulate those 5 days in that holiday window. There is also a corresponding `lower_window` for days leading up to the holiday. For this analysis, I will only look at the upper_window.

To capture the holidays, define a holiday dataframe with a datestamp and the description of the holiday:

```
articles = pd.DataFrame({
  'holiday': 'publish',
  'ds': pd.to_datetime(['2014-09-27', '2014-10-05', '2014-10-14', '2014-10-26', '2014-11-9',
                        '2014-11-18', '2014-11-30', '2014-12-17', '2014-12-29', '2015-01-06',
                        '2015-01-20', '2015-02-02', '2015-02-16', '2015-03-23', '2015-04-08',
                        '2015-05-04', '2015-05-17', '2015-06-09', '2015-07-02', '2015-07-13',
                        '2015-08-17', '2015-09-14', '2015-10-26', '2015-12-07', '2015-12-30',
                        '2016-01-26', '2016-04-06', '2016-05-16', '2016-06-15', '2016-08-23',
                        '2016-08-29', '2016-09-06', '2016-11-21', '2016-12-19', '2017-01-17',
                        '2017-02-06', '2017-02-21', '2017-03-06']),
  'lower_window': 0,
  'upper_window': 5,
})
articles.head()
```

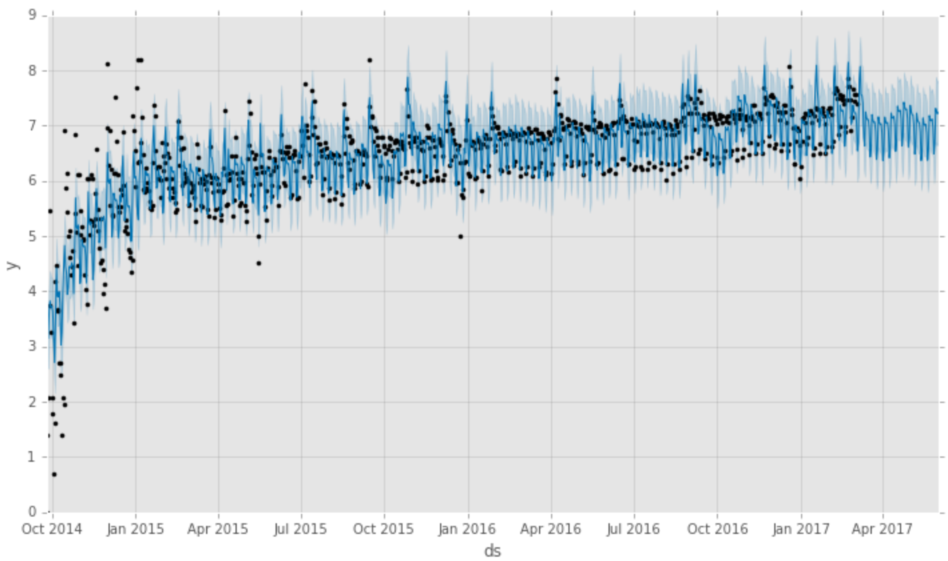
	ds	holiday	lower_window	upper_window

0	2014-09-27	publish	0	5
1	2014-10-05	publish	0	5
2	2014-10-14	publish	0	5
3	2014-10-26	publish	0	5
4	2014-11-09	publish	0	5

Astute readers may have noticed that you can include dates in the future. In this instance, I am including today's blog post in the holiday dataframe.

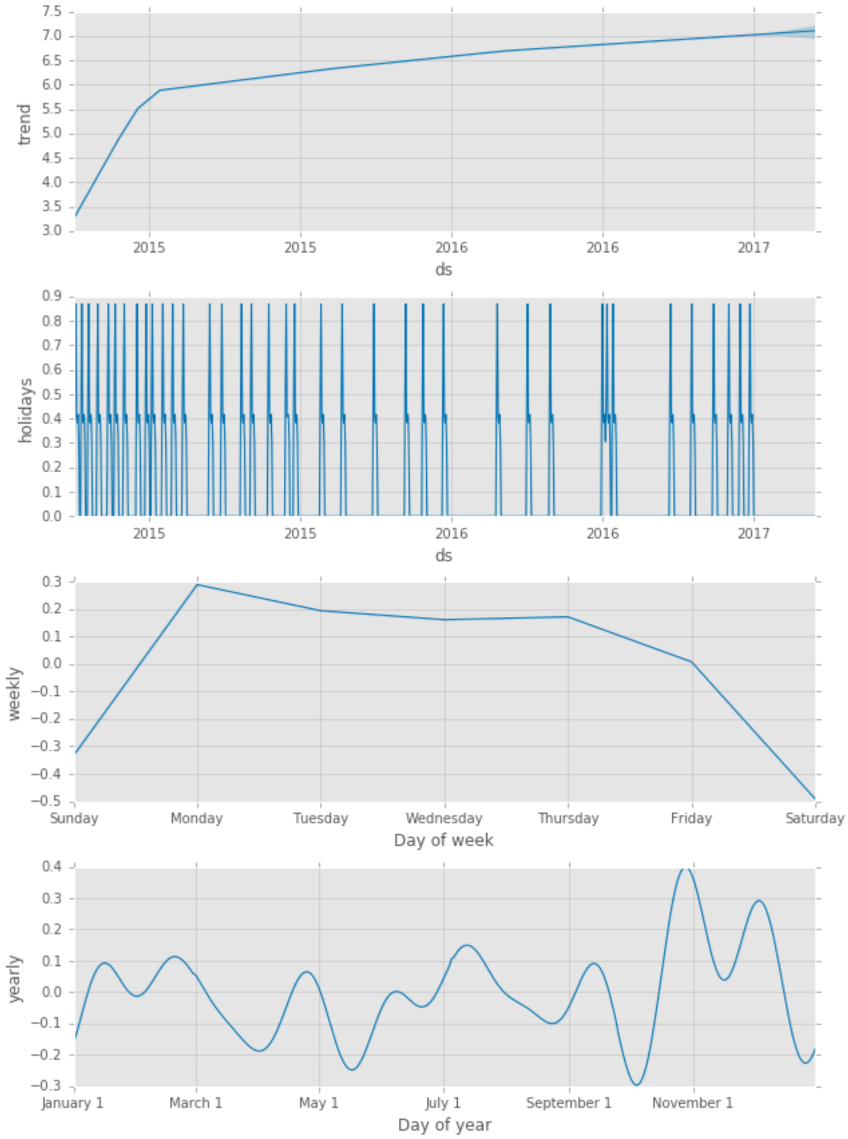
To use the publish dates in the model, pass it to the model via the `holidays` keyword. Perform the normal `fit` , `make_future` (this time we'll try 90 days), `predict and plot` :

```
m2 = Prophet(holidays=articles).fit(df)
future2 = m2.make_future_dataframe(periods=90)
forecast2 = m2.predict(future2)
m2.plot(forecast2);
```



Because we have defined holidays, we get a little more information when we plot components:

```
m2.plot_components(forecast2);
```



Predictions

Prophet offers a couple of other options for continuing to tweak the model. I encourage you to play around with them to get a feel for how they work and what and can be used for your models. I have included one new option `mcmc_samples` in the final example below.

As promised, here is my forecast for website traffic between today and the end of March:

```
m3 = Prophet(holidays=articles, mcmc_samples=500).fit(df)
future3 = m3.make_future_dataframe(periods=90)
forecast3 = m3.predict(future3)
forecast3["Sessions"] = np.exp(forecast3.yhat).round()
forecast3["Sessions_lower"] = np.exp(forecast3.yhat_lower).round()
forecast3["Sessions_upper"] = np.exp(forecast3.yhat_upper).round()
forecast3[(forecast3.ds > "3-5-2017") &
          (forecast3.ds < "4-1-2017")][["ds", "yhat", "Sessions_lower",
                                        "Sessions", "Sessions_upper"]]
```

	ds	yhat	Sessions_lower	Sessions	Sessions_upper
892	2017-03-06	7.845280	1432.0	2554.0	4449.0
893	2017-03-07	8.087120	1795.0	3252.0	5714.0
894	2017-03-08	7.578796	1142.0	1956.0	3402.0
895	2017-03-09	7.556725	1079.0	1914.0	3367.0
896	2017-03-10	7.415903	917.0	1662.0	2843.0

	ds	yhat	Sessions_lower	Sessions	Sessions_upper
897	2017-03-11	6.796987	483.0	895.0	1587.0
898	2017-03-12	6.627355	417.0	755.0	1267.0
899	2017-03-13	7.240586	811.0	1395.0	2341.0

The model passes the intuitive test in that there is a big spike anticipated with the publishing of this article. The upper and lower bounds represent a fairly large range but for the purposes of this forecast, that is likely acceptable.

To keep me honest, you can see all of the values in the github notebook (https://github.com/chris1610/pbpython/blob/master/notebooks/Forecasting-with-prophet.ipynb).

Final Thoughts

It is always interesting to get insights into the ways big companies use various open source tools in the their business. I am impressed with the functionality that Facebook has given us with prophet. The API is relatively simple and since it uses the standard panda's dataframe and matplotlib for displaying the data, it fits very easily into the python datascience workflow. There is a lot if recent github activity for this library so I suspect it to get more useful and powerful over the months ahead.

As Yogi Berra said, "It's tough to make predictions, especially about the future." I think this library is going to be very useful for people trying to improve their forecasting approaches. I will be interested to see how well this particular forecast works on this site's data. Stay tuned for an update where I will compare the prediction against the actuals and we will see what insight can be gained.

Updates

- May 23, 2017: Published an update (http://pbpython.com/prophet-accuracy.html) on the predictions.

← Populating MS Word Templates with Python (http://pbpython.com/python-word-template.html)

Understanding the Transform Function in Pandas → (http://pbpython.com/pandas_transform.html)

Comments

Donna Alcott • 3 months ago

Hello!
Will you please share the actual result with us? I want to try this for my own website.

Reply • Share ›

Chris Moffitt Mod → Donna Alcott • 3 months ago

Sorry. I haven't looked at it yet to see how well it matches up. I will try to pull that together. Thanks for reminding me.

Reply • Share ›

Brian Torretta • 3 months ago

Apologies off the bat as I don't work in statistics but with large server farms. I executed the python script as instructed here: https://facebookincubator.g... for Payton Manning and I was hoping for graphical output. I am on a mac running python 2.7. Here is my output, if someone can help me make sense of it, or pipe it into something that will show graphical information, that would be helpful.

$ python prophet.py
Initial log joint probability = -19.4685
Iter log prob ||dx|| ||grad|| alpha alpha0 # evals Notes
99 7977.57 0.000941357 431.339 0.3404 0.3404 134
Iter log prob ||dx|| ||grad|| alpha alpha0 # evals Notes
199 7988.7 0.000894011 356.862 0.739 0.739 241
Iter log prob ||dx|| ||grad|| alpha alpha0 # evals Notes
299 7996.29 0.00359033 180.856 1 1 358
Iter log prob ||dx|| ||grad|| alpha alpha0 # evals Notes
399 8000.11 0.000546236 205.358 0.09131 0.7253 481
Iter log prob ||dx|| ||grad|| alpha alpha0 # evals Notes
499 8002.89 0.00024026 99.613 1 1 608
Iter log prob ||dx|| ||grad|| alpha alpha0 # evals Notes
514 8003.11 5.25911e-05 135.817 7.646e-07 0.001 671 LS failed, Hessian reset

see more

^ | v • Reply • Share ›

Chris Moffitt Mod → Brian Torretta • 3 months ago

Did you execute the code within a jupyter notebook? If you execute this in a notebook and include the %matplotlib inline directive, the images will automatically show.

If you want to run from a script, make sure you have this at the top of your script:

import matplotlib.pyplot as plt

then at the bottom try plt.show() to display the image.

^ | v • Reply • Share ›

pretoriadeux • 4 months ago

I don't understand what the statistical reasoning is behind this model. Is that explained in the documentation?

^ | v • Reply • Share ›

Chris Moffitt Mod → pretoriadeux • 4 months ago

The documentation and the associate white paper explain it in more detail. I would recommend checking them out to see if that helps.

^ | v • Reply • Share ›

Isaak Lin • 4 months ago

Hi,

I am using anaconda too but can't install pystan &
pip install fbprophet.

Thanks

^ | v • Reply • Share ›

Chris Moffitt Mod → Isaak Lin • 4 months ago

What OS are you on and what errors are you getting?

^ | v • Reply • Share ›

Isaak Lin → Chris Moffitt • 4 months ago

I'm using window 8.1, open anaconda prompt enter "conda install pystan" error pop up "PackageNot Found Error: Package missing in current win-32 channels: - pystan Close matches found; did you mean one of these pystan:pysal" That's the error I got. thanks

^ | v • Reply • Share ›

Chris Moffitt Mod → Isaak Lin • 4 months ago

Are you using Python 3? I think you need to have 3.5+ on Windows for it to work.

^ | v • Reply • Share ›

Isaak Lin → Chris Moffitt • 4 months ago

I'm using python 3.6. Maybe I will google it for another solution.

^ | v • Reply • Share ›

Paula → Isaak Lin • 3 months ago

Try pip install for pystan and fbprophet. Check the documentation because there are special instructions to install on Windows.

^ | v • Reply • Share ›

Craig Bing • 4 months ago

Thanks a ton! I was trying to understand how's prophet different from ARIMA / ARMA models and when would you choose to use one over the other? For ex: I am trying to create counterfactual predictions and was wondering if I should use ARMA / ARIMA or prophet?

^ | v • Reply • Share ›

Chris Moffitt Mod ➦ Craig Bing • 4 months ago

To be honest, I do not have extensive experience with ARIMA models. I get the sense that you need a more indepth understanding of this modes in order to make them work. Prophet on the other hand, abstracts away many portions of the complexity to quickly provide a projection. I assume this comes at the loss of some flexibility/power.

My recommendation would be to spend a few minutes trying out prophet and see how it works for your use case. If you're not satisfied then you could try ARIMA.

Hope that helps.

1 ^ | v • Reply • Share ›

Craig Bing ➦ Chris Moffitt • a month ago

Thanks Chris! I recently used ARIMA and facebook's prophet to come up with counterfactual predictions for measing causal impact of marketing event. ARIMA performed horribly on validation set. However, prophet was far superior. And, that made me wonder why?

^ | v • Reply • Share ›

Chris Moffitt Mod ➦ Craig Bing • a month ago

Hmm. I'm not really sure. I don't have a lot of experience with ARIMA models so I'm not sure why they are not performing as well as prophet. Sorry I couldn't help you more.

^ | v • Reply • Share ›

Hans Rogério Zimermann • 5 months ago

Nice

^ | v • Reply • Share ›

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