Statistical Algorithm: using fbprophet for Crypto Data Time Series Forecast

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fbprophet package can be found on [https://github.com/facebook/prophet/tree/master/notebooks (https://github.com/facebook/prophet/tree/master/notebooks)](https://github.com/facebook/prophet/tree/master/notebooks)

Data Explanation and Drawbacks of the package

Drawback of this package: fbprophet assumes the type of time series is one data point per day. This causes incompatibility of the model package, and the issue of timestamp remains to be optimized in future in our time series analysis.

The input to Prophet is always a dataframe with two columns: ds and y. The ds (datestamp) column should be of a format expected by Pandas, ideally `YYYY-MM-DD` for a date or `YYYY-MM-DD HH:MM:SS` for a timestamp. The y column must be numeric, and represents the measurement we wish to forecast.

However, I have problem in changing the timestamp format, there is timezone information in the timestamp. It turns out error like this:

ValueError: Column ds has timezone specified, which is not supported. Remove timezone.

I used 'spread.csv' data, only chosing 2 columns: 'spread' and the timestamp, each has 1000 rows of data.

---

timestamp	closeH20	closeM20	close	spread	spread_rate
2020-02-12 10:00:00+00:00	10665.0	10879.5	10291.5	214.5	0.020842442792595800
2020-02-12 11:00:00+00:00	10730.5	10949.5	10335.0	219.0	0.02119013062409290
2020-02-12 12:00:00+00:00	10792.5	11005.0	10373.5	212.5	0.02048488938159730
2020-02-12 13:00:00+00:00	10770.0	10989.0	10368.5	219.0	0.021121666586295000
2020-02-12 14:00:00+00:00	10815.5	11027.5	10401.5	212.0	0.0203816757198481
2020-02-12 15:00:00+00:00	10765.0	10970.5	10375.5	205.5	0.01980627439641460
2020-02-12 16:00:00+00:00	10714.5	10926.0	10347.5	211.5	0.020439719739067400

But I found that fbprophet isn't accustomed to **one day dozens of data** style, as this model only assumes **one data in one day**. For analysis purpose, I changed each timestamp to an increasing list of virtual days.

ds	y
2020/2/12	214.5
2020/2/13	219
2020/2/14	212.5
2020/2/15	219
2020/2/16	212
2020/2/17	205.5
2020/2/18	211.5
2020/2/19	219.5

Although the real meaning of 'date' is false, as I changed from an hourly-basis to a daily-basis, but somehow we can view this as a new time series and conduct analysis on the data of 'spread' only. We can also map the 'false date' in the model to the real timestamp in our original data, using the spread column.

In [1]:

```
!pip install fbprophet
from fbprophet import Prophet
import pandas as pd
%matplotlib inline
from fbprophet import Prophet
import pandas as pd
from matplotlib import pyplot as plt
import numpy as np
import logging
logging.getLogger('fbprophet').setLevel(logging.ERROR)
import warnings
warnings.filterwarnings("ignore")
```

```
Requirement already satisfied: fbprophet in /Users/junfanzhu/opt/anaco
nda3/lib/python3.7/site-packages (0.6)
Requirement already satisfied: Cython>=0.22 in /Users/junfanzhu/opt/an
aconda3/lib/python3.7/site-packages (from fbprophet) (0.29.13)
Requirement already satisfied: cmdstanpy==0.4 in /Users/junfanzhu/opt/
anaconda3/lib/python3.7/site-packages (from fbprophet) (0.4.0)
Requirement already satisfied: pystan>=2.14 in /Users/junfanzhu/opt/an
aconda3/lib/python3.7/site-packages (from fbprophet) (2.19.1.1)
Requirement already satisfied: numpy>=1.10.0 in /Users/junfanzhu/opt/a
naconda3/lib/python3.7/site-packages (from fbprophet) (1.17.2)
Requirement already satisfied: pandas>=0.23.4 in /Users/junfanzhu/opt/
anaconda3/lib/python3.7/site-packages (from fbprophet) (0.25.1)
Requirement already satisfied: matplotlib>=2.0.0 in /Users/junfanzhu/o
pt/anaconda3/lib/python3.7/site-packages (from fbprophet) (3.1.1)
Requirement already satisfied: LunarCalendar>=0.0.9 in /Users/junfanzh
u/opt/anaconda3/lib/python3.7/site-packages (from fbprophet) (0.0.9)
Requirement already satisfied: convertdate>=2.1.2 in /Users/junfanzhu/
opt/anaconda3/lib/python3.7/site-packages (from fbprophet) (2.2.0)
Requirement already satisfied: holidays>=0.9.5 in /Users/junfanzhu/op
t/anaconda3/lib/python3.7/site-packages (from fbprophet) (0.10.2)
Requirement already satisfied: setuptools-git>=1.2 in /Users/junfanzh
u/opt/anaconda3/lib/python3.7/site-packages (from fbprophet) (1.2)
Requirement already satisfied: python-dateutil>=2.8.0 in /Users/junfan
zhu/opt/anaconda3/lib/python3.7/site-packages (from fbprophet) (2.8.0)
Requirement already satisfied: pytz>=2017.2 in /Users/junfanzhu/opt/an
aconda3/lib/python3.7/site-packages (from pandas>=0.23.4->fbprophet)
(2019.3)
Requirement already satisfied: cycler>=0.10 in /Users/junfanzhu/opt/an
aconda3/lib/python3.7/site-packages (from matplotlib>=2.0.0->fbprophe
t) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /Users/junfanzhu/o
pt/anaconda3/lib/python3.7/site-packages (from matplotlib>=2.0.0->fbpr
ophet) (1.1.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.
1 in /Users/junfanzhu/opt/anaconda3/lib/python3.7/site-packages (from
matplotlib>=2.0.0->fbprophet) (2.4.2)
Requirement already satisfied: ephem>=3.7.5.3 in /Users/junfanzhu/opt/
anaconda3/lib/python3.7/site-packages (from LunarCalendar>=0.0.9->fbpr
ophet) (3.7.7.1)
Requirement already satisfied: pymeeus<=1,>=0.3.6 in /Users/junfanzhu/
opt/anaconda3/lib/python3.7/site-packages (from convertdate>=2.1.2->fb
prophet) (0.3.7)
Requirement already satisfied: six in /Users/junfanzhu/opt/anaconda3/l
ib/python3.7/site-packages (from holidays>=0.9.5->fbprophet) (1.12.0)
Requirement already satisfied: korean-lunar-calendar in /Users/junfanz
hu/opt/anaconda3/lib/python3.7/site-packages (from holidays>=0.9.5->fb
```

```
prophet) (0.2.1)
Requirement already satisfied: setuptools in /Users/junfanzhu/opt/anac
onda3/lib/python3.7/site-packages (from kiwisolver>=1.0.1->matplotlib>
=2.0.0->fbprophet) (41.4.0)
```

In [2]:

```
df = pd.read_csv('/Users/junfanzhu/Desktop/spreadscopy.csv')
df
```

Out[2]:

	ds	y
0	2020/2/12	214.5
1	2020/2/13	219.0
2	2020/2/14	212.5
3	2020/2/15	219.0
4	2020/2/16	212.0
...	...	...
995	2022/11/3	-20.0
996	2022/11/4	-33.5
997	2022/11/5	-17.0
998	2022/11/6	-19.0
999	2022/11/7	-30.5

1000 rows × 2 columns

Fit the model

In [3]:

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

```
INFO:numexpr.utils:NumExpr defaulting to 8 threads.
```

Out[3]:

```
<fbprophet.forecaster.Prophet at 0x10bae6150>
```

Make Predictions. Dataframe extends into the future

In [4]:

```
future = m.make_future_dataframe(periods=365)
future
```

Out[4]:

	ds
0	2020-02-12
1	2020-02-13
2	2020-02-14
3	2020-02-15
4	2020-02-16
...	...
1360	2023-11-03
1361	2023-11-04
1362	2023-11-05
1363	2023-11-06
1364	2023-11-07

1365 rows × 1 columns

Forecast. Forecast will include an uncertainty interval

In [5]:

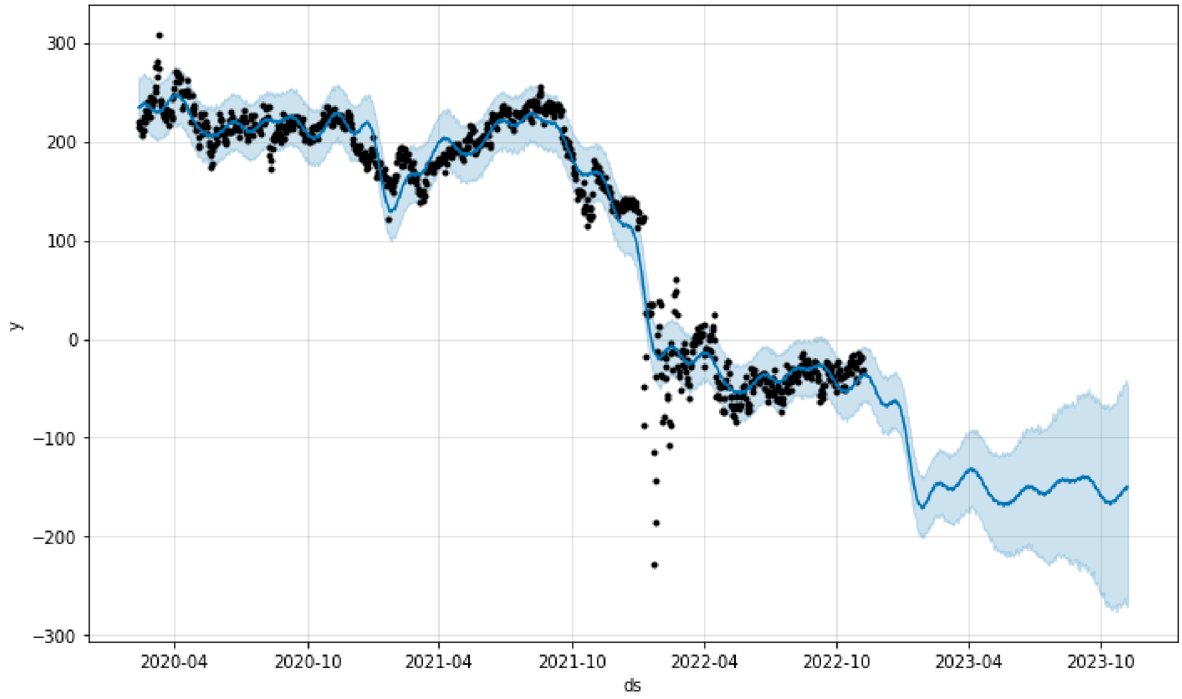
```
forecast = m.predict(future)
forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].tail()
```

Out[5]:

	ds	yhat	yhat_lower	yhat_upper
1360	2023-11-03	-152.248368	-261.369097	-46.483839
1361	2023-11-04	-153.222283	-267.121835	-45.951069
1362	2023-11-05	-150.554875	-267.310703	-41.745024
1363	2023-11-06	-151.482359	-271.121427	-44.923339
1364	2023-11-07	-149.725717	-265.523044	-46.936435

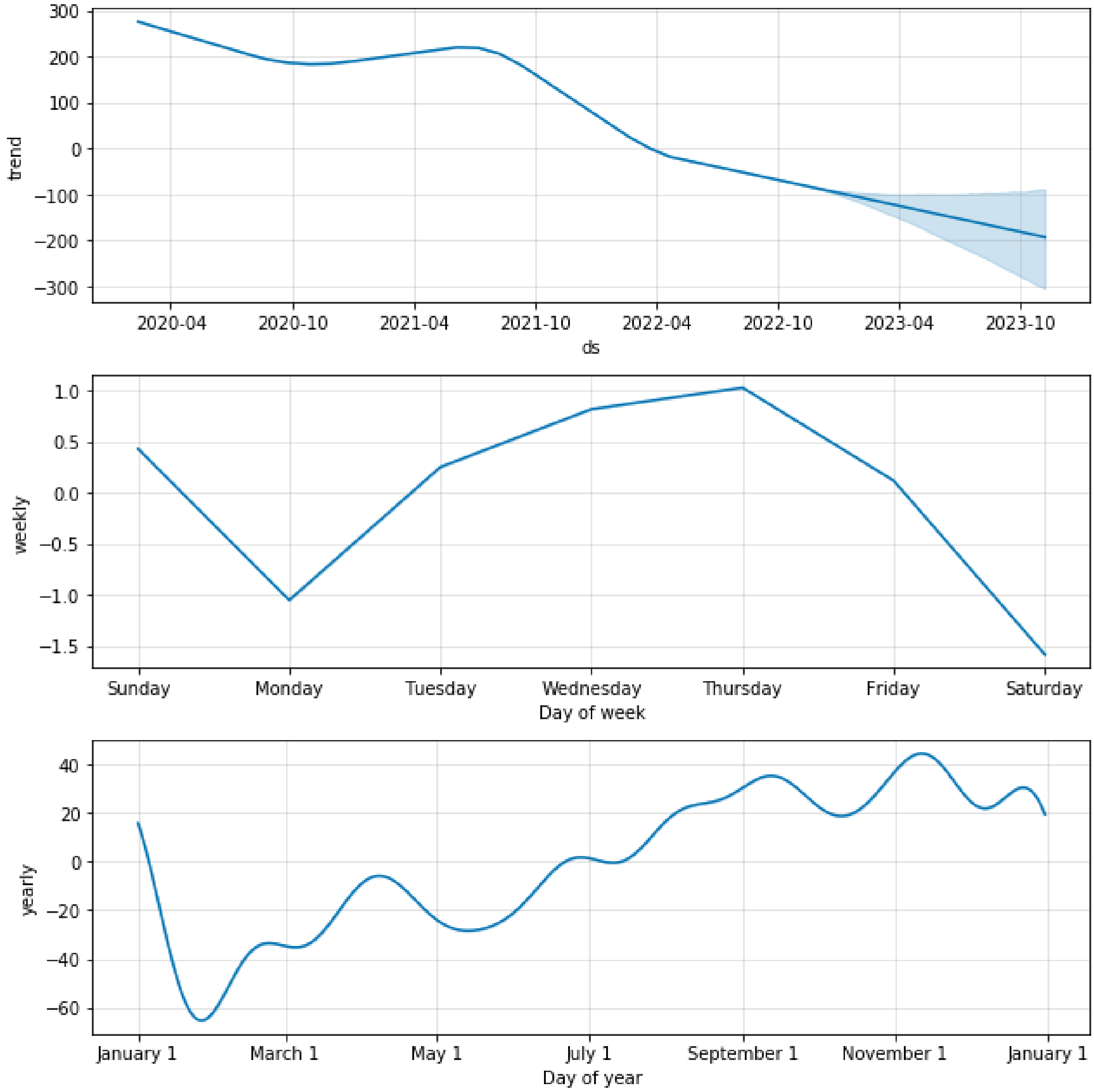
In [6]:

```
fig1 = m.plot(forecast)
```



In [7]:

```
fig2 = m.plot_components(forecast)
```



In [8]:

```
!pip install plotly
```

```
Requirement already satisfied: plotly in /Users/junfanzhu/opt/anaconda
3/lib/python3.7/site-packages (4.7.1)
Requirement already satisfied: six in /Users/junfanzhu/opt/anaconda3/l
ib/python3.7/site-packages (from plotly) (1.12.0)
Requirement already satisfied: retrying>=1.3.3 in /Users/junfanzhu/op
t/anaconda3/lib/python3.7/site-packages (from plotly) (1.3.3)
```

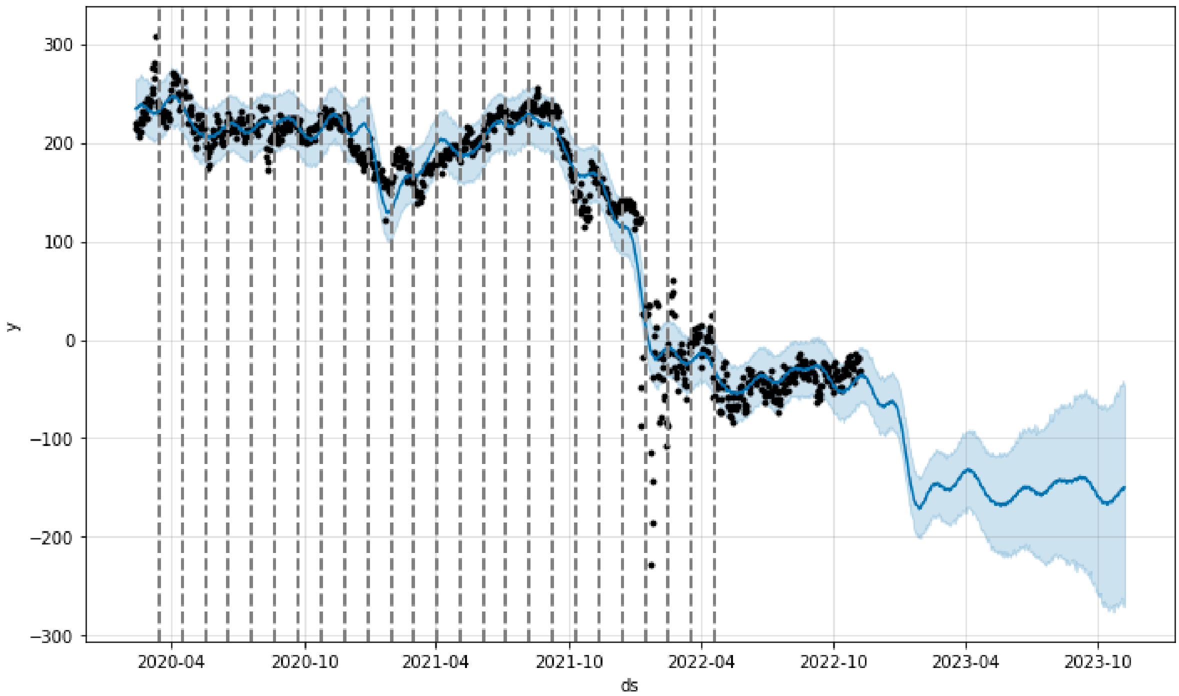
Automatic Change Point Detection

Real time series frequently have abrupt changes in their trajectories. By default, Prophet automatically detects these changepoints and will allow the trend to adapt appropriately.

Prophet detects changepoints by first specifying a large number of potential changepoints at which the rate is allowed to change. It then puts a sparse prior on the magnitudes of the rate changes (equivalent to L1 regularization). By default, Prophet specifies 25 potential changepoints which are uniformly placed in the first 80% of the time series. The vertical lines in this figure indicate where the potential changepoints were placed:

In [9]:

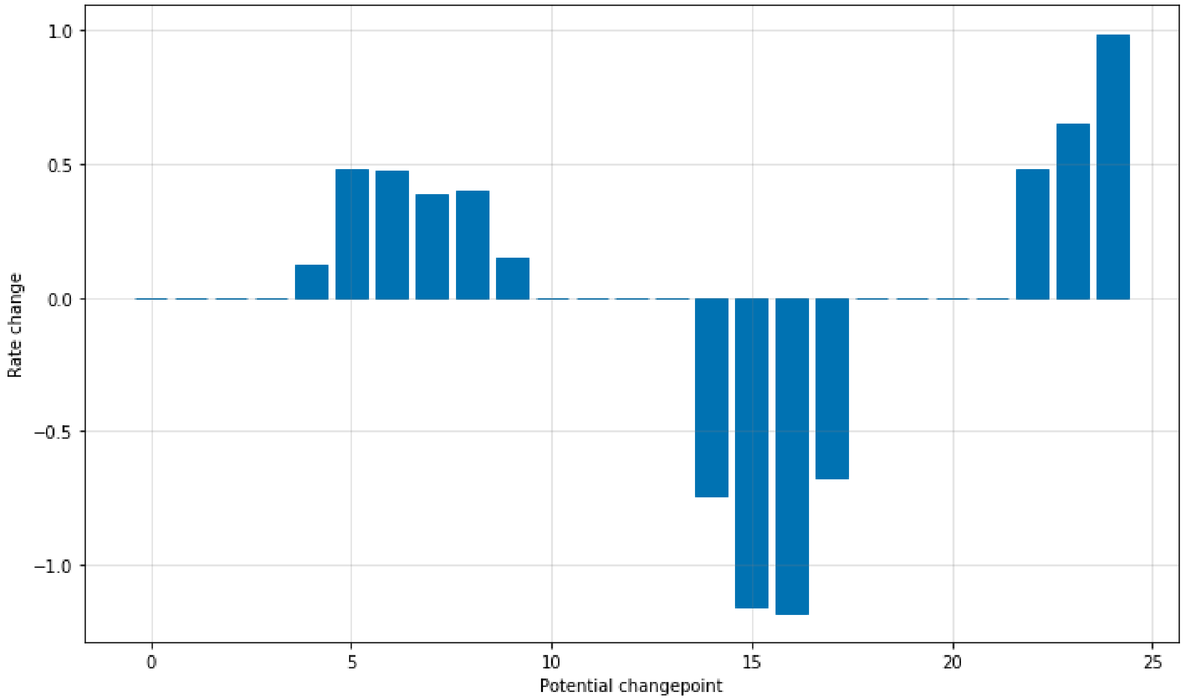
```
fig = m.plot(forecast)
for cp in m.changepoints:
    plt.axvline(cp, c='gray', ls='--', lw=2)
```



Even though we have a lot of places where the rate can possibly change, because of the sparse prior, most of these changepoints go unused. We can see this by plotting the magnitude of the rate change at each changepoint:

In [10]:

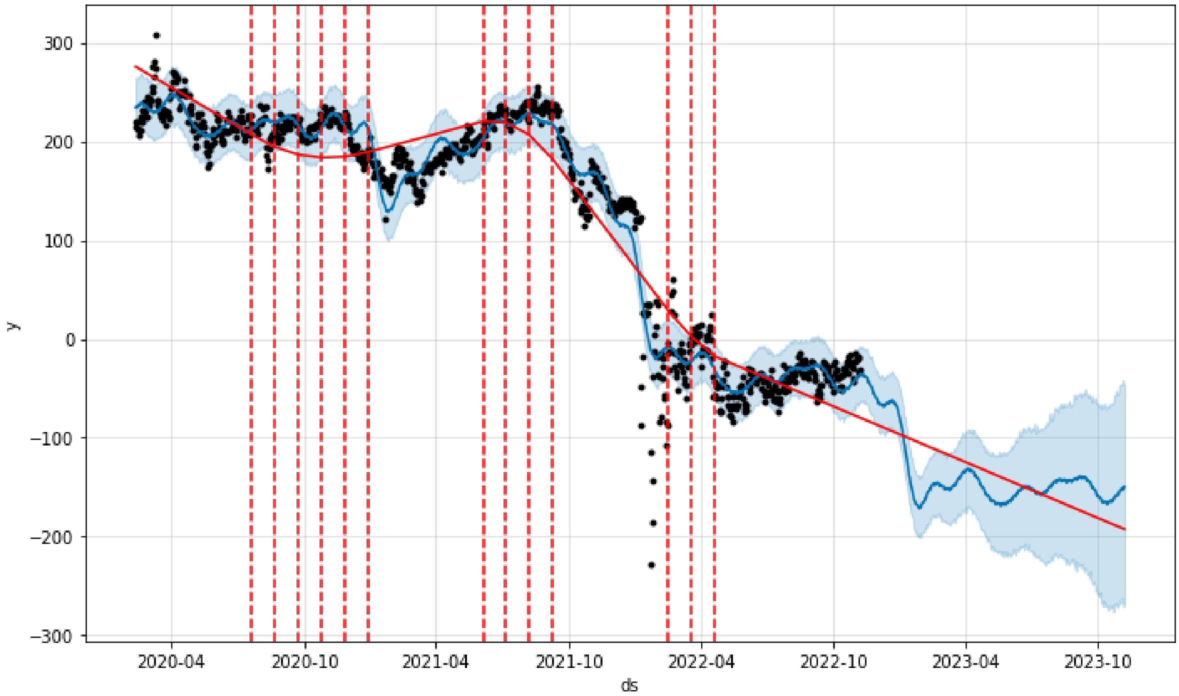
```
deltas = m.params['delta'].mean(0)
fig = plt.figure(facecolor='w', figsize=(10, 6))
ax = fig.add_subplot(111)
ax.bar(range(len(deltas)), deltas, facecolor='#0072B2', edgecolor='#0072B2')
ax.grid(True, which='major', c='gray', ls='-', lw=1, alpha=0.2)
ax.set_ylabel('Rate change')
ax.set_xlabel('Potential changepoint')
fig.tight_layout()
```



The number of potential changepoints can be set using the argument n_changepoints, but this is better tuned by adjusting the regularization. The locations of the signification changepoints can be visualized with:

In [11]:

```
from fbprophet.plot import add_changepoints_to_plot
fig = m.plot(forecast)
a = add_changepoints_to_plot(fig.gca(), m, forecast)
```



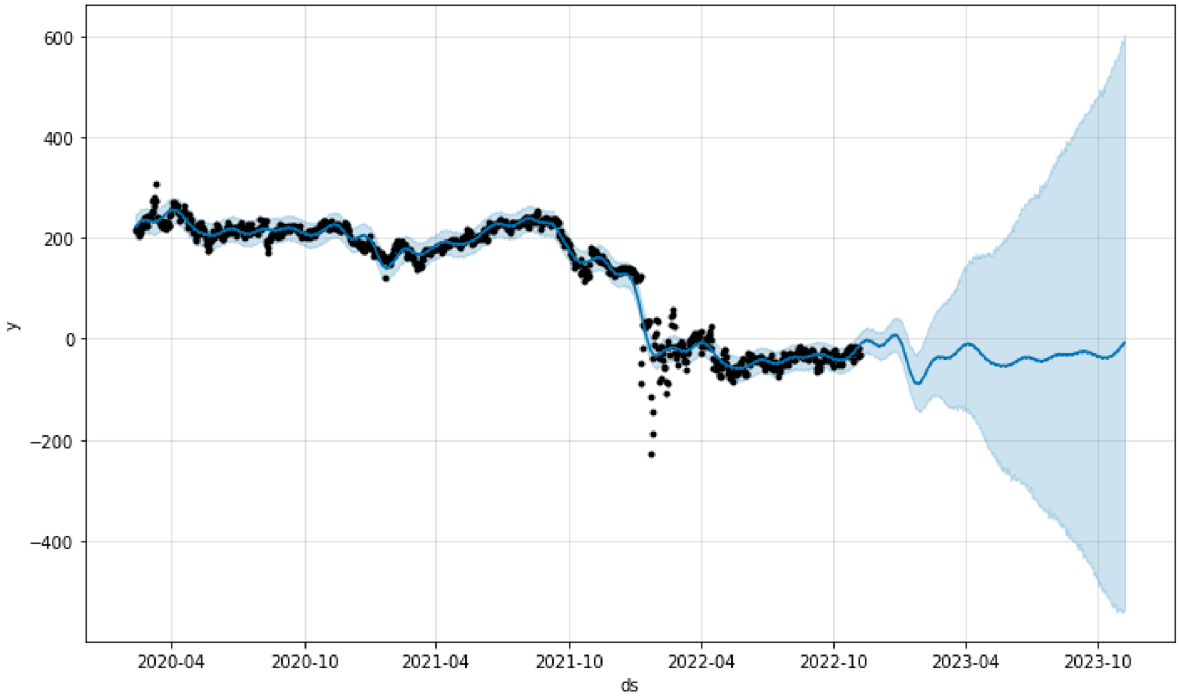
By default changepoints are only inferred for the first 80% of the time series in order to have plenty of runway for projecting the trend forward and to avoid overfitting fluctuations at the end of the time series. This default works in many situations but not all, and can be change using the changepoint_range argument. For example, `m = Prophet(changepoint_range=0.9)` will place potential changepoints in the first 90% of the time series.

Adjusting trend flexibility

If the trend changes are being overfit (too much flexibility) or underfit (not enough flexibility), you can adjust the strength of the sparse prior using the input argument `changepoint_prior_scale`. By default, this parameter is set to 0.05. Increasing it will make the trend ***more*** flexible:

In [12]:

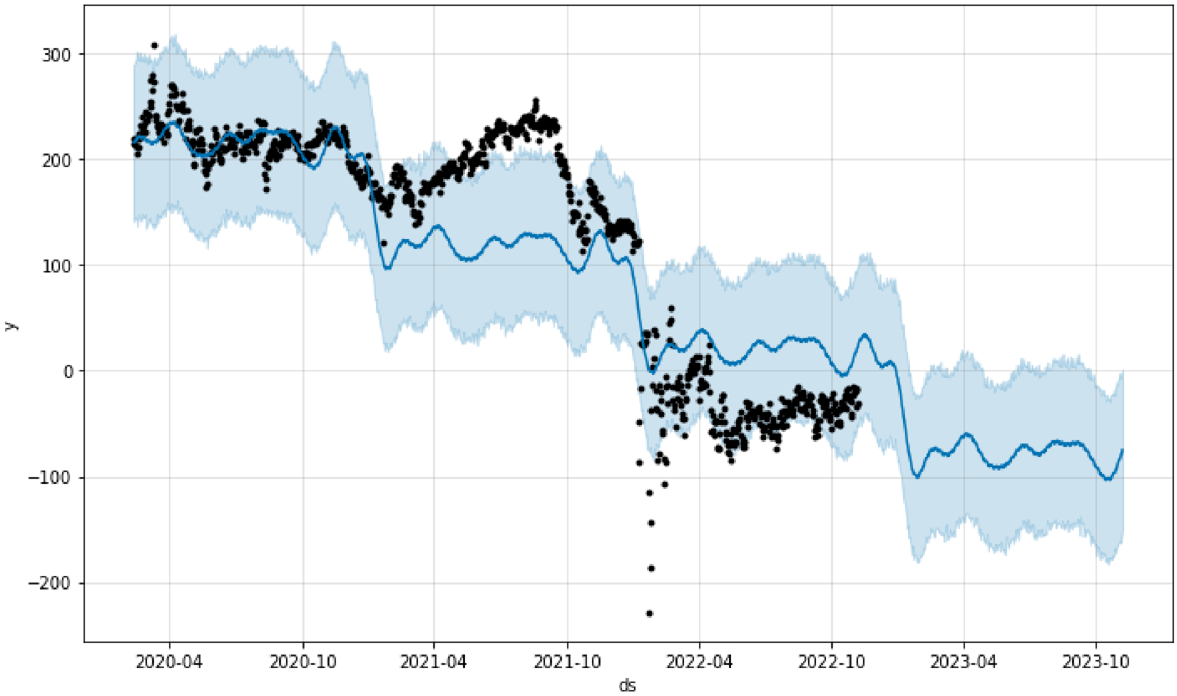
```
m = Prophet(changepoint_prior_scale=0.5)
forecast = m.fit(df).predict(future)
fig = m.plot(forecast)
```



Decreasing it will make the trend ***less*** flexible:

In [13]:

```
m = Prophet(changepoint_prior_scale=0.001)
forecast = m.fit(df).predict(future)
fig = m.plot(forecast)
```



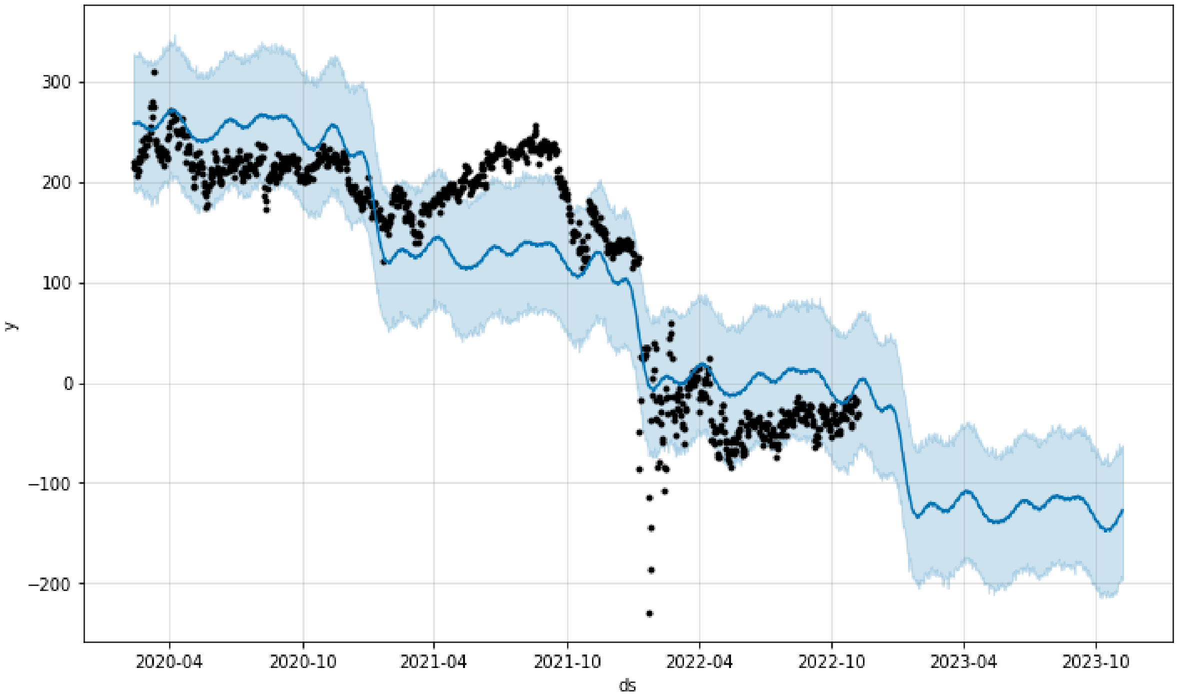
Specifying the locations of the changepoints

Manually specify the locations of potential changepoints with the changepoints argument.

Slope changes will then be allowed only at these points, with the same sparse regularization as before. We can create a grid of points as is done automatically, but then augment that grid with some specific dates that are known to be likely to have changes. The changepoints could be entirely limited to a small set of dates, as is done here:

In [14]:

```
m = Prophet(changepoints=['2020-03-01'])
forecast = m.fit(df).predict(future)
fig = m.plot(forecast)
```



Modeling the Trend effect

The biggest source of uncertainty in the forecast is the potential for future trend changes. The time series we have seen already in this documentation show clear trend changes in the history. We assume that the average frequency and magnitude of trend changes in the future will be the same as that which we observe in the history. We project these trend changes forward and by computing their distribution we obtain uncertainty intervals.

One property of this way of measuring uncertainty is that allowing higher flexibility in the rate, by increasing changepoint_prior_scale, will increase the forecast uncertainty. This is because if we model more rate changes in the history then we will expect more in the future, and makes the uncertainty intervals a useful indicator of overfitting.

The width of the uncertainty intervals (by default 80%) can be set using the parameter interval_width:

In [15]:

```
forecast_new = Prophet(interval_width=0.95).fit(df).predict(future)
forecast_new
```

Out[15]:

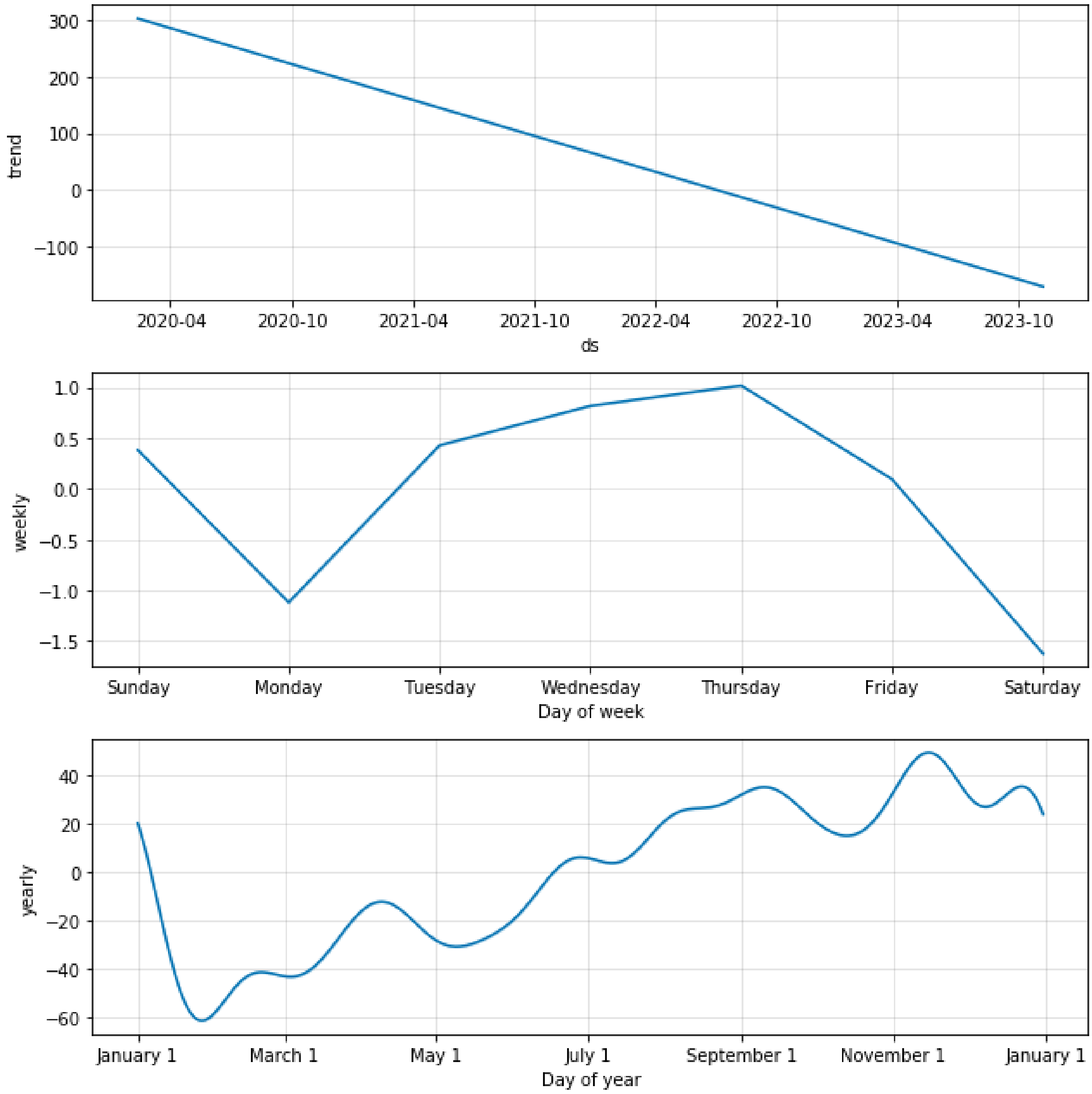
	ds	trend	yhat_lower	yhat_upper	trend_lower	trend_upper	additive_terms	ad
0	2020-02-12	275.553034	191.359940	275.331806	275.553034	275.553034	-41.466301	
1	2020-02-13	275.123610	193.378789	281.502099	275.123610	275.123610	-39.712894	
2	2020-02-14	274.694186	193.547349	281.925635	274.694186	274.694186	-39.219182	
3	2020-02-15	274.264762	190.901446	276.546890	274.264762	274.264762	-39.666151	
4	2020-02-16	273.835338	193.173303	281.656251	273.835338	273.835338	-36.547152	
...	...	...	...	...	...	...	...	
1360	2023-11-03	-191.329210	-337.889387	18.957850	-370.271935	-31.618297	39.080842	
1361	2023-11-04	-191.638879	-335.652507	11.763975	-371.403671	-31.152095	38.416596	
1362	2023-11-05	-191.948548	-335.439230	15.547051	-372.535407	-30.829139	41.393674	
1363	2023-11-06	-192.258218	-334.335050	18.575366	-373.667143	-30.526224	40.775859	
1364	2023-11-07	-192.567887	-333.463895	20.346998	-374.798879	-30.223310	42.842170	

1365 rows × 19 columns

Modeling the Seasonality Effect

In [16]:

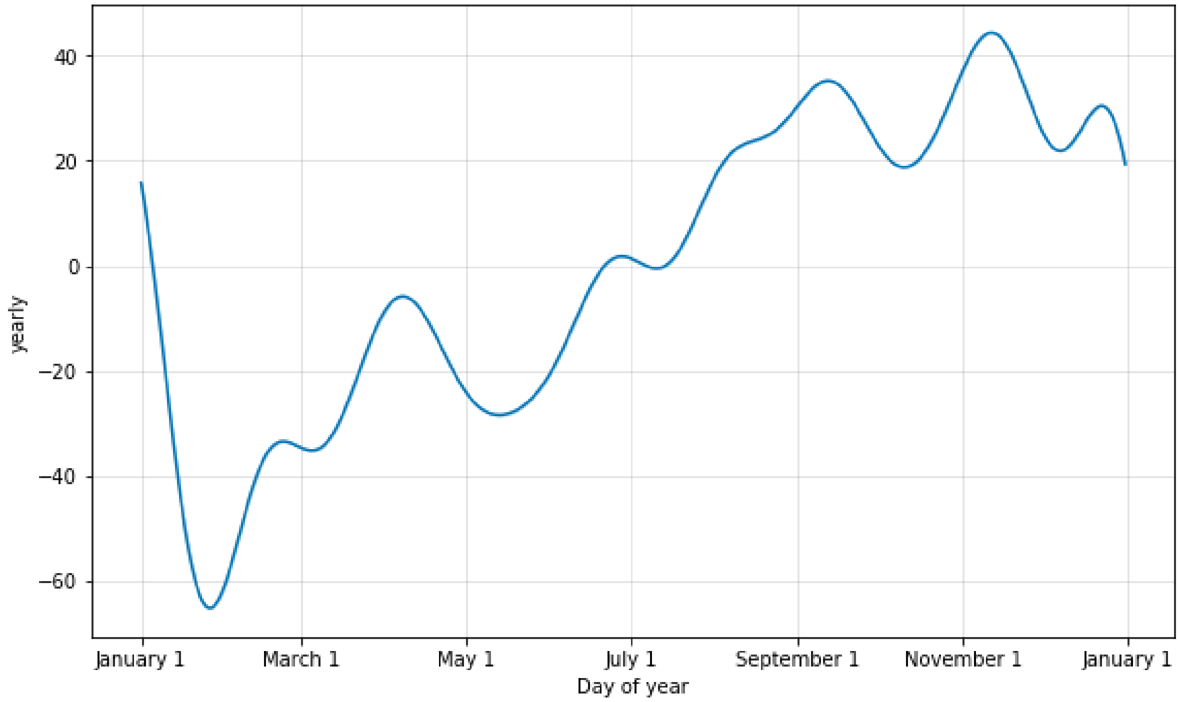
```
fig = m.plot_components(forecast)
```



Fourier Order for Seasonalities¶

In [17]:

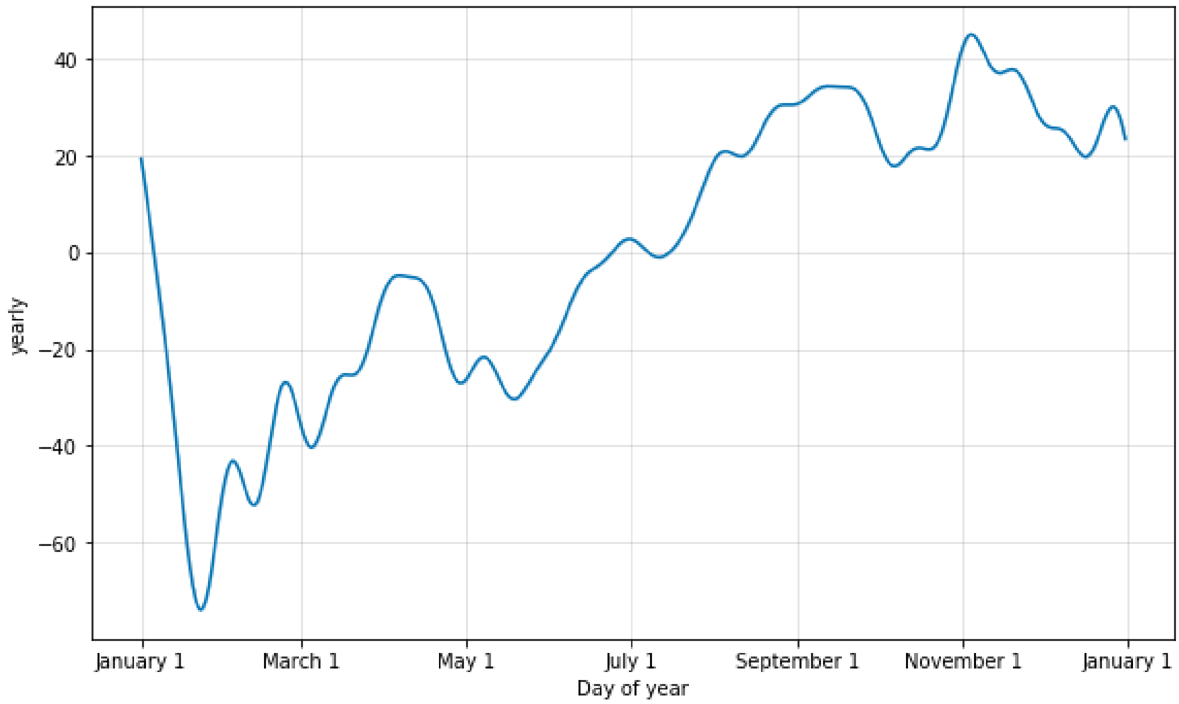
```
from fbprophet.plot import plot_yearly
m = Prophet().fit(df)
a = plot_yearly(m)
```



The default values are often appropriate, but they can be increased when the seasonality needs to fit higher-frequency changes, and generally be less smooth. The Fourier order can be specified for each built-in seasonality when instantiating the model, here it is increased to 20:

In [18]:

```
from fbprophet.plot import plot_yearly
m = Prophet(yearly_seasonality=20).fit(df)
a = plot_yearly(m)
```



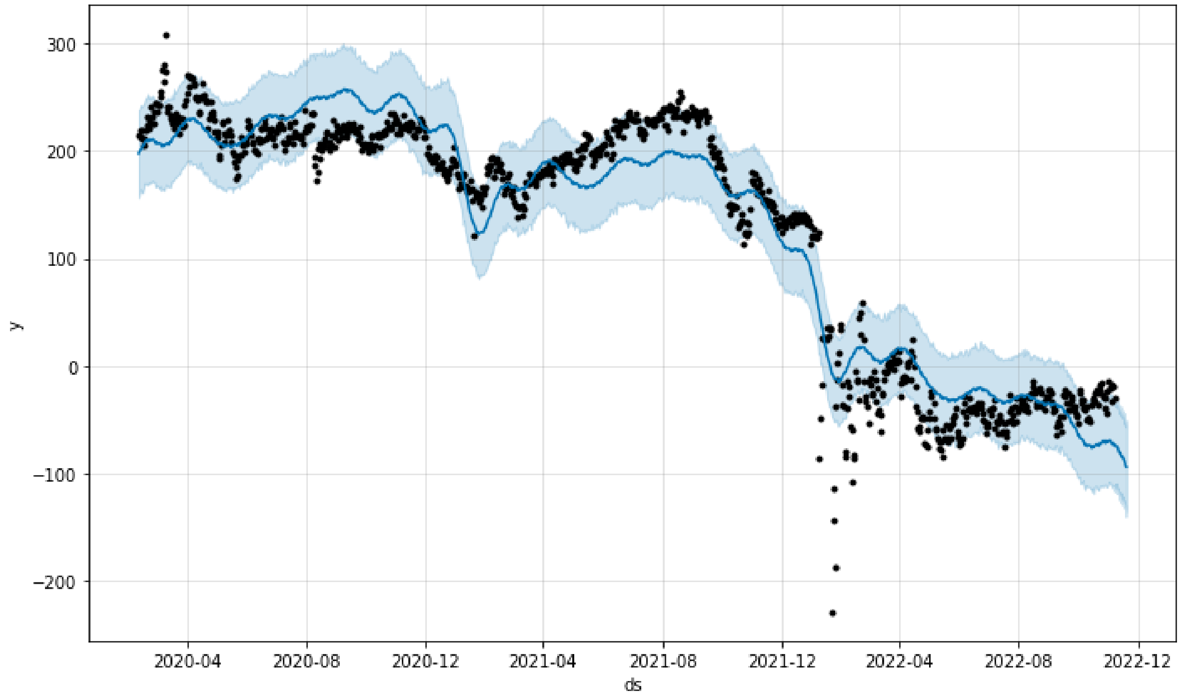
Increasing the number of Fourier terms allows the seasonality to fit faster changing cycles, but can also lead to overfitting: N Fourier terms corresponds to 2N variables used for modeling the cycle

Sub-daily data¶

Prophet can make forecasts for time series with sub-daily observations by passing in a dataframe with timestamps in the `ds` column. The format of the timestamps should be `YYYY-MM-DD HH:MM:SS`. When sub-daily data are used, daily seasonality will automatically be fit.

In [19]:

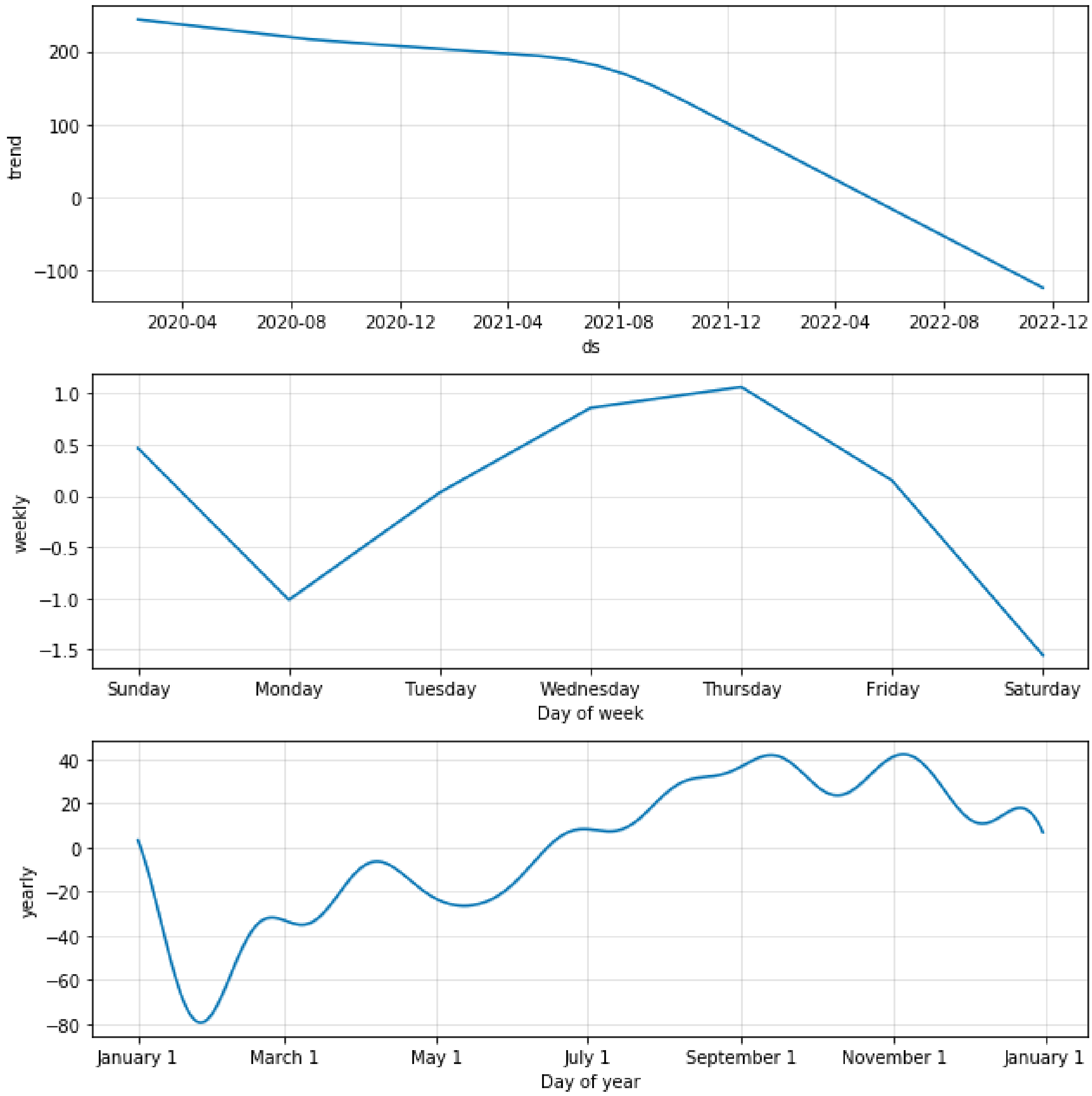
```
df_new = pd.read_csv('/Users/junfanzhu/Desktop/spreadscopy.csv')
m = Prophet(changepoint_prior_scale=0.01).fit(df_new)
future = m.make_future_dataframe(periods=300, freq='H')
fcst = m.predict(future)
fig = m.plot(fcst)
```



Daily seasonality

In [20]:

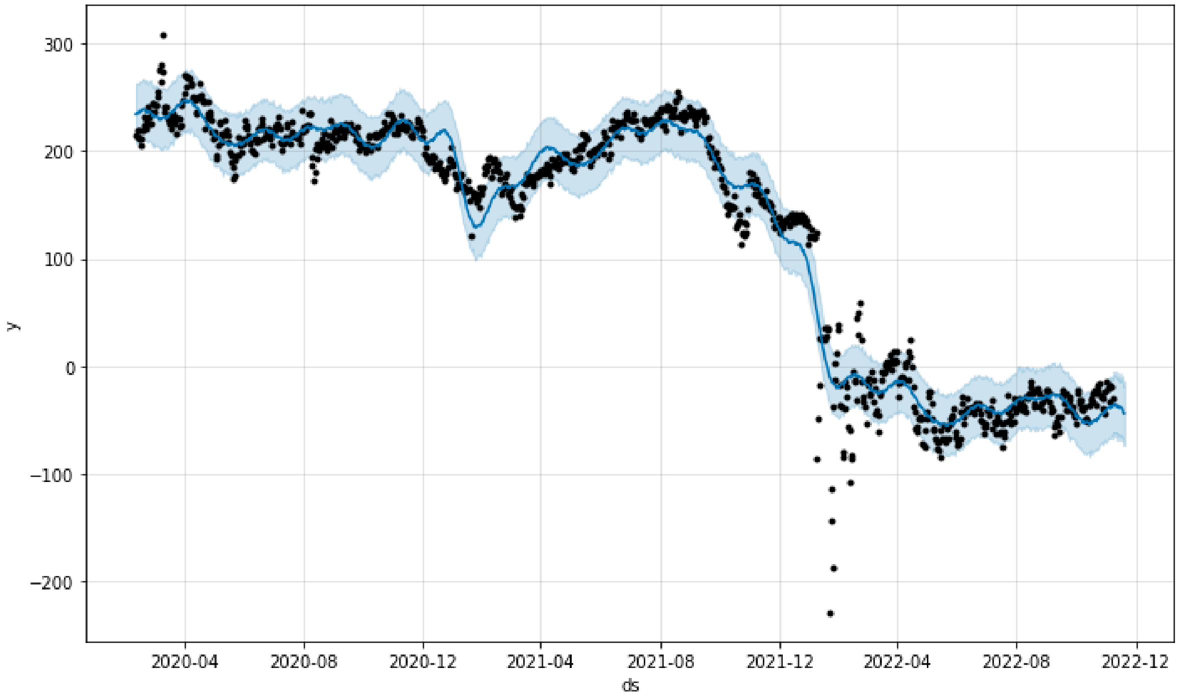
```
fig = m.plot_components(fcst)
```



Data with regular gaps

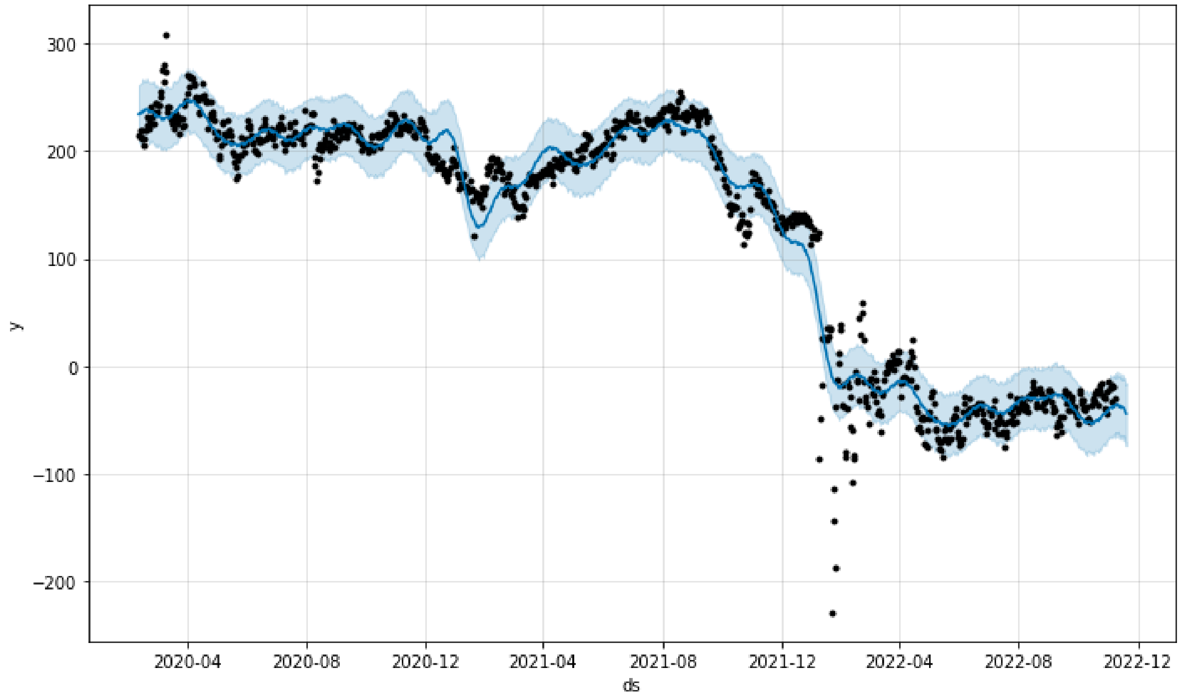
In [21]:

```
df2 = df.copy()
df2['ds'] = pd.to_datetime(df2['ds'])
df2 = df2[df2['ds'].dt.hour < 6]
m = Prophet().fit(df2)
future = m.make_future_dataframe(periods=300, freq='H')
fcst = m.predict(future)
fig = m.plot(fcst)
```



In [22]:

```
future2 = future.copy()
future2 = future2[future2['ds'].dt.hour < 6]
fcst = m.predict(future2)
fig = m.plot(fcst)
```

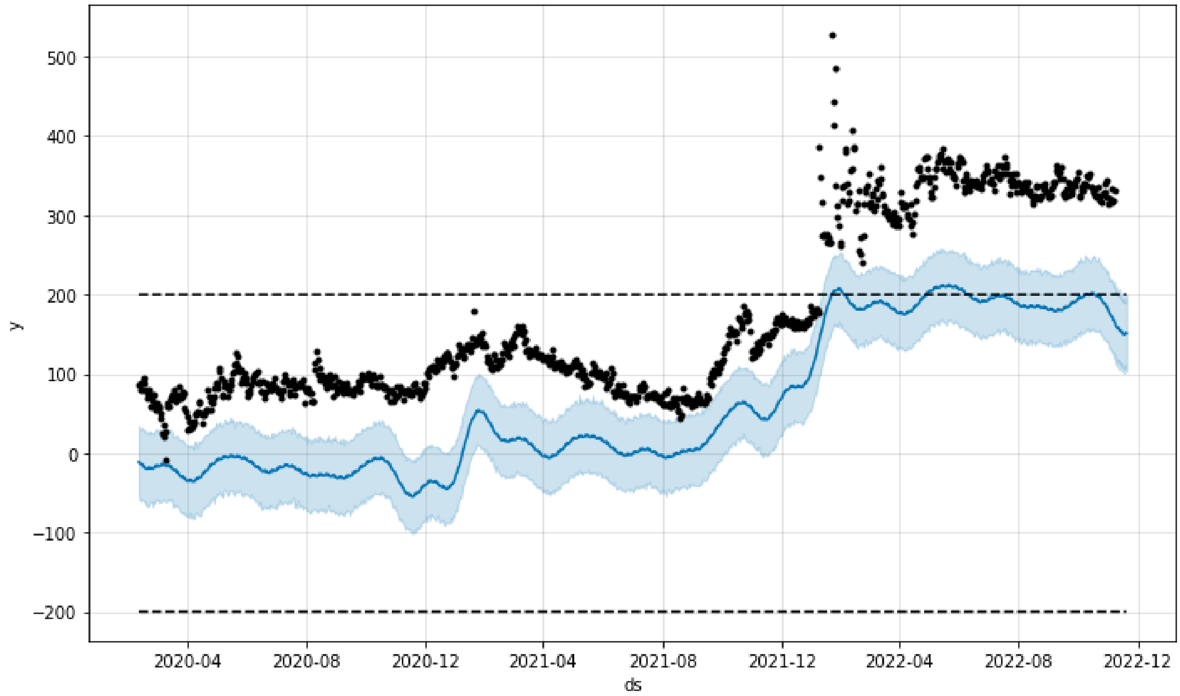


Saturating Forecasts

The logistic growth model can also handle a saturating minimum, which is specified with a column floor in the same way as the cap column specifies the maximum:

In [23]:

```
df['y'] = 300 - df['y']
df['cap'] = 300
df['floor'] = -100
future['cap'] = 200
future['floor'] = -200
m = Prophet(growth='logistic')
m.fit(df)
fcst = m.predict(future)
fig = m.plot(fcst)
```



To use a logistic growth trend with a saturating minimum, a maximum capacity must also be specified.