Fbprophet

- Forecasting is a data science task that is central to many activities within an organization.
- Large organizations must engage in capacity planning to efficiently allocate scarce resources and goal setting in order to measure performance relative to a baseline.
- Facebook developed an open sourcing Prophet, a forecasting tool available in both Python and R.
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Highlights of Facebook Prophet

- Very fast, since it's built in Stan ,a programming language for statistical inference written in C++.
- An additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects:

1. **A piecewise linear or logistic growth curve trend**:
   - Prophet automatically detects changes in trends by selecting changepoints from the data
2. **A yearly seasonal component modeled using Fourier series**
3. **A weekly seasonal component using dummy variables**
4. **A user-provided list of important holidays.**

- Robust to missing data and typically handles outliers .
- Easy procedure to tweak and adjust forecast while adding domain knowledge or business insights.

The Prophet Forecasting Model

- The Prophet is a decomposable time series model with three main model components:
  Trend
  Seasonality
  Holidays
- They are combined in the following equation:

$$y(t)= g(t) + s(t) + h(t) + \varepsilon t$$

g(t): the trend function which models non-periodic changes in the value of the time series s(t): periodic changes (e.g. weekly/yearly seasonality)

h(t): effects of holidays (user provided) with irregular schedules

εt: error term accounts for any unusual changes not accommodated by the model

1. **The Trend Model**

Two models are implemented in Trend model:

1. Saturating growth model
2. piecewise linear model.

2. **Seasonality**
   - **To fit and forecast these effects we must specify seasonality models that are periodic functions of t.**
   - **We rely on Fourier series to provide a flexible model of periodic effects**
   - **Let P be the regular period we expect the time series to have (e.g.P = 365.25 for yearly data or P = 7 for weekly data, when we scale our time variable in days). We can approximate arbitrary smooth seasonal effects with**

3. **Holiday:**
   - **Holidays and events provide large, somewhat predictable shocks to many business time series and often do not follow a periodic pattern, so their effects are not well modeled by**

a smooth cycle.

- **We allow the analyst to provide a custom list of past and future events, identified by the event or holiday's unique name.**
- **We include a column for country in order to keep a country-specific list of holidays in addition to global holidays.**
- **For a given forecasting problem we use the union of the global set of holidays and the country-specific ones.**
- **For each holiday i, let D i be the set of past and future dates for that holiday.**
- **We add an indicator function representing whether time**
  t is during holiday i, and assign each holiday a parameter κ i which is the corresponding change in the forecast.

References:

1. https://facebook.github.io/prophet/docs/additional_topics.html#saving-models
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