# Forecasting at Scale using FBProphet in Python

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What does it mean “at scale” ?

Forecasting “at scale” is
**25% a technology problem**
and **75% a people problem**

# What’s FBProphet ?

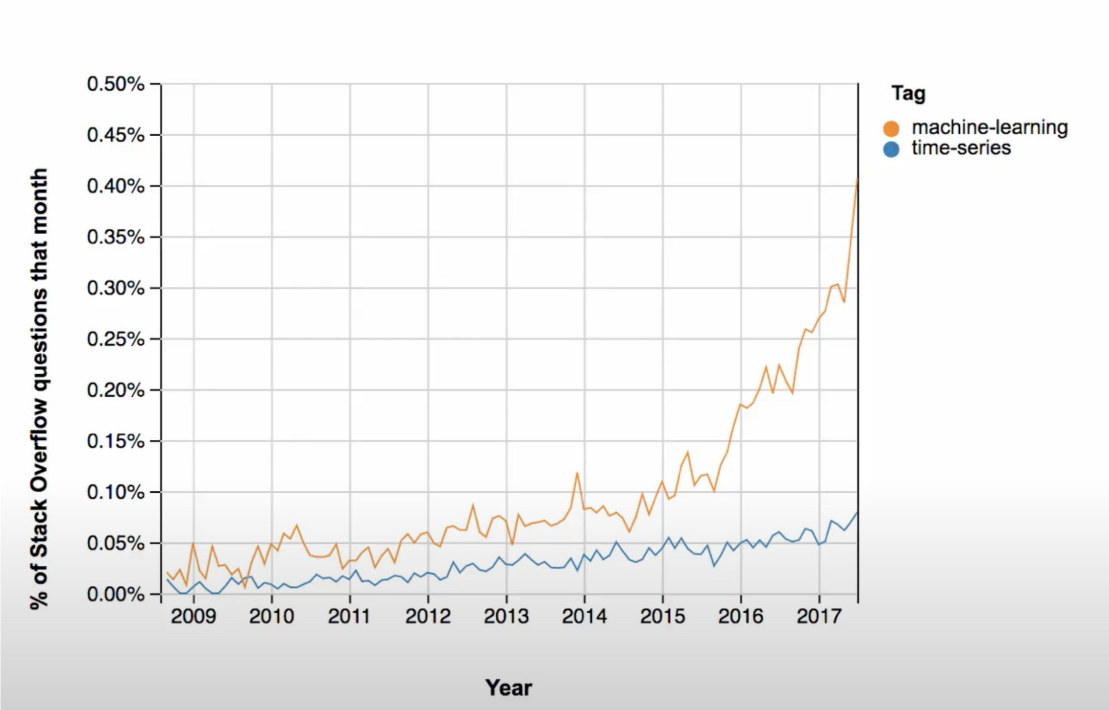
- Prophet is based on an additive model where non-linear trends are fit with **yearly, weekly, and daily seasonality, plus holiday effects**.

- It **works best** with time series that have **strong seasonal effects and several seasons of historical data**. Facebook claims that Prophet is **robust to missing data** and shifts in the trend, and typically **handles outliers** well

# Problems

- Many applications that require forecast
- Single metric can be forecasted numerous times (eg. each country, ..)
- Not many people have forecasting training
- Not many existing tool

# Machine Learning vs Time Series Trend




Source : http://insights.stackoverflow.com/trends

# Why was FBProphet developed at the first place ?

(semi) automated forecasting :

- Find similarities across of forecasting problem
- Build a tool that can solve most of the forecasting problem
- Make it **easy to** use and **teach** everyone to use it
- Offer advanced features when necessary

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# FBProphet is decomposed time series model

y(t) : piecewise_trend(t) + seasonality(t) + holiday_effect(t) + noise

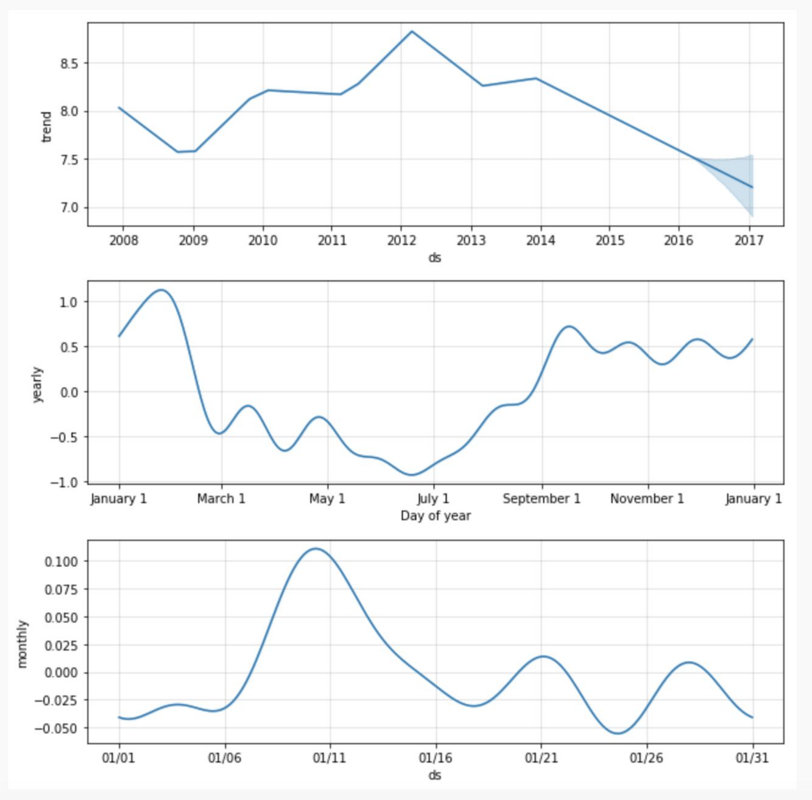
- Saturating growth model
- Piecewise linear model
- Automatic Changepoints Selection
- Trend forecast uncertainty

provides a adaptability to the model by allowing periodic changes based on sub-daily, daily, weekly and yearly seasonality

| Holiday | Country | Year | Date |
|---|---|---|---|
| Thanksgiving | US | 2015 | 26 Nov 2015 |
| Thanksgiving | US | 2016 | 24 Nov 2016 |
| Thanksgiving | US | 2017 | 23 Nov 2017 |
| Thanksgiving | US | 2018 | 22 Nov 2018 |
| Christmas | * | 2015 | 25 Dec 2015 |
| Christmas | * | 2016 | 25 Dec 2016 |
| Christmas | * | 2017 | 25 Dec 2017 |
| Christmas | * | 2018 | 25 Dec 2018 |

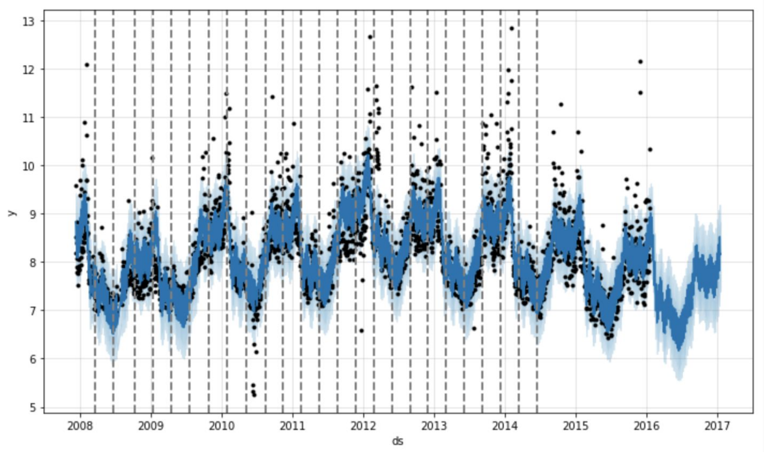
Reference : [The Math of Prophet - Future Vision]

# Forecast Component

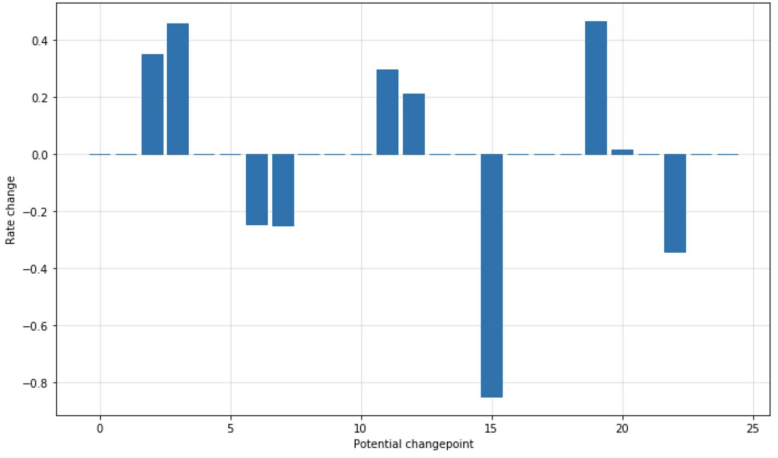



Split single model of forecast to tell us the trend on yearly, monthly, day or even in hour unit level in descriptive way

# Trend changepoints




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)



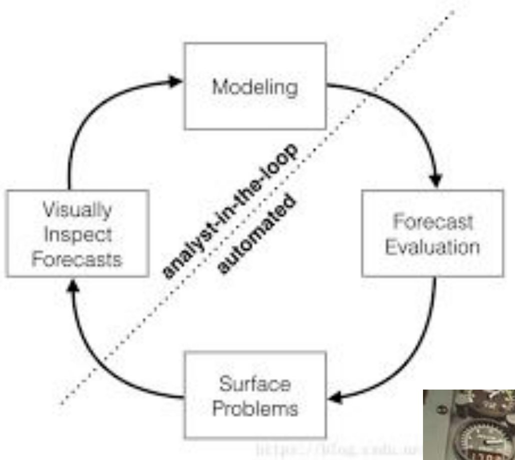

~ Laplace

Fit : Estimate trend change distribution

Estimate : Sample future trend change from distribution

Reference : [The Math of Prophet - Future Vision]

# Knobs and Lever




- Priors and seasonality parameter
- Priors on how often we expect changepoints
- Functional form of growth (piecewise linear and logistics)
- Covariates and holiday
- Custom seasonalities
- MAP and full posterior

# Conclusion

Prophet was developed to close the skill gap and help analysts with a variety of backgrounds produce more forecasts with less time invested towards doing so. This was achieved by sticking to a relatively plain mode

If you have some of free time, please watch this video, it will gives you some insights regarding Prophet : Forecasting at Scale: How and Why We Developed Prophet for Forecasting at Facebook

# Let’s practice together ! ;)

Google Colab