Time Series Analysis & Forecasting

Class 10

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Polynomial and Non-linear Regression

Polynomial regression

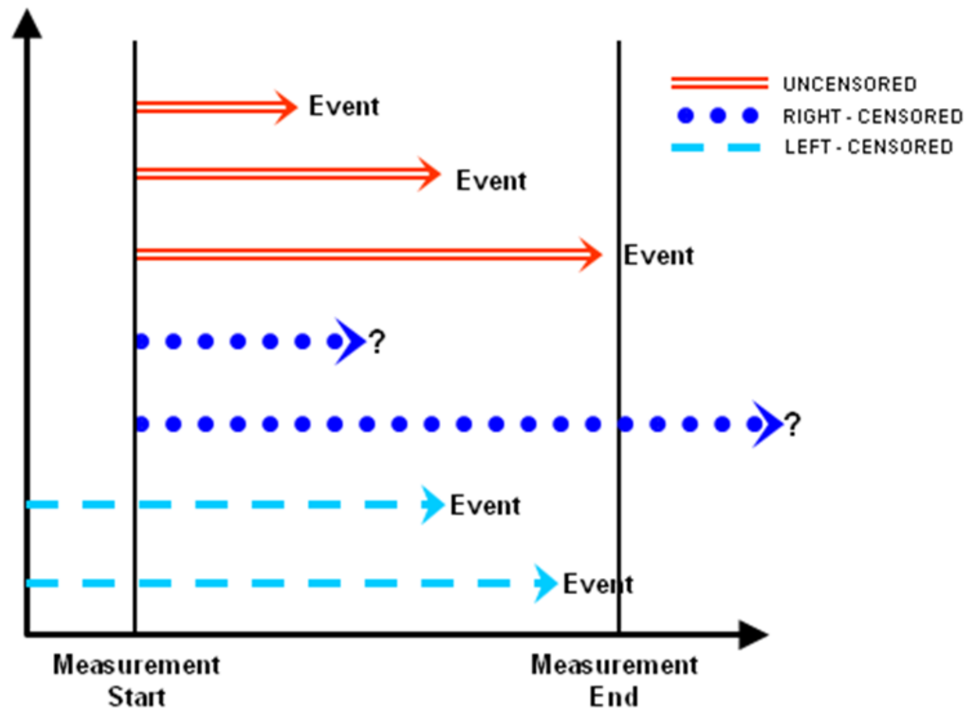
$$Y_t = \beta_0 + \beta_1 X_t + \beta_2 X_t^2 + u_t$$

The squared is represented directly in R using *I*(.)

Non-linear regression

$$Y_t = a - be^{-cX_t}$$

Survival Regression – Data censoring for time-to-event



Survival Regression – Cox Regression

The Cox model is expressed by the hazard function denoted by h(t) that can be interpreted as the risk of dying at time t and estimated as follows:

$$h(t) = h_0(t) * \exp(b_1 x_1 + b_2 x_2 + \cdots + b_p x_p)$$

where,

t represents the survival time

$h(t)$ is the hazard function determined by a set of p covariates

coefficients $(x_1, x_2, \dots, x_p)$ measure the impact (i.e., the effect size) of covariates

$h_0(t)$ is the baseline hazard. It corresponds to the value of the hazard if all the covariates are equal to zero (the quantity exp(0) equals 1).

The ‘t’ in $h(t)$ reminds us that the hazard may vary over time.

exp(b_i*)* is called hazard ratio (HR).

HR = 1 (no effect), HR < 1 (reduction in hazard), HR > 1 (increase in hazard)

http://www.sthda.com/english/wiki/cox-proportional-hazards-model

R code – Survival Regression

```
library("survival")

library("survminer")

data("lung")

res.cox <- coxph(Surv(time, status) ~ sex, data = lung)

summary(res.cox)

res.cox.mult <- coxph(Surv(time, status) ~ age + sex + ph.ecog, data
=  lung)

summary(res.cox.mult)

ggsurvplot(survfit(res.cox.mult, data=lung), color = "#2E9FDF",ggtheme =
theme_minimal())
```

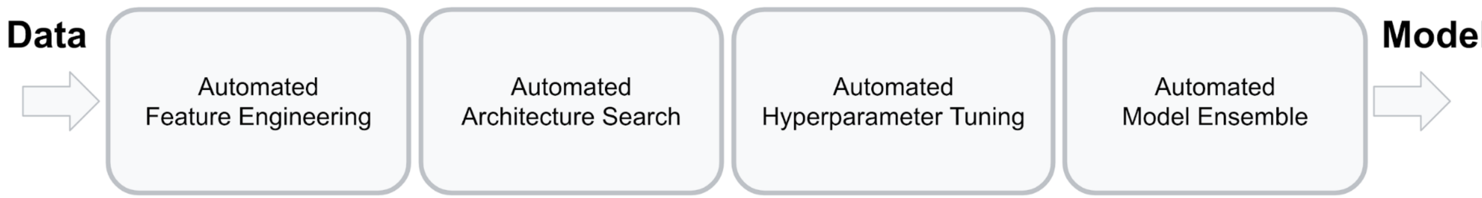
AutoML in the Clouds

3 criteria for scalable end-to-end time series forecasting AutoML:

1. **Fully automated:** The solution takes in data as input, and produces a servable [TensorFlow] model as output with no human intervention.

2. **Generic:** Use an ensemble of top models to make final predictions to make the solution robust and less likely to overfit.

3. **High-quality:** The produced models predict also the probability that a future value is 0, to address intermittency.



https://ai.googleblog.com/2020/12/using-automl-for-time-series-forecasting.html

https://docs.microsoft.com/en-us/azure/machine-learning/how-to-auto-train-forecast

https://docs.aws.amazon.com/forecast/latest/dg/what-is-forecast.html

https://github.com/crawles/automl_service

What we Learnt this quarter ?

TS EDA

- ACF = SERIAL_CORRELATION + RANDOMNESS
- PACF
- STATIONARITY = ADF + KPSS
- NORMALITY = SHAPIRO_WILK
- HETEROSCEDASTICITY = QQ-PLOT + McLEOD_LI
- CYCLICAL = FIXED_PERIODICITY (SEASONALITY) + APERIODIC
- TRENDING = DETERMINISTIC + STOCHASTIC (DRIFT)
- INTERMITTENT = COEF_OF_VARIATION + AVG_DEMAND_INTERVAL
- TRANSFORMATION = BOX-COX + INTEGRATED_ORDER
- SIMILARITY = DTW
- CCF

What we Learnt this quarter ?

DETERMINATION

- SMOOTHING = ETS + HOLT-WINTERS
- REGRESSION = LINEAR + COINTEGRATION + SURVIVAL
- BOX JENKINS = ARIMA Models + SEASONAL + DYNAMIC REGRESSION + ARFIMA
- CURVE FITTING = PROPHET + ORBIT + STL + BSTS
- ML = RF + XGBOOST
- HETEROSCHEDASTICITY = ARCH/GARCH
- INTERVENTION / OUTLIER = TRANSFER FUNCTION MODELS + OUTLIER DETECTION
- HIERARCHICAL = HTS + MIXED-EFFECTS + VECTOR MODELS
- SPECTRAL MODELS = TBATS
- PANEL = RNN + DeepAR
- AUTOML

SPECIFICATION

- ACF + PACF
- YULE WALKER
- NONSTATIONARITY
- AICc + BIC

What we Learnt this quarter ?

ESTIMATION

- ORDINARY LEAST SQUARES
- MAXIMUM LIKELIHOOD
- YULE WALKER
- CROSS-VALIDATION
- BOOTSTRAPPING

EVALUATION

- RESIDUAL ANALYSIS = (TREND) STATIONARITY + WHITE NOISE + AUTOCORRELATION (ORIGINAL + SQUARED SERIES)
- RMSE + sMAPE + MASE
- PREDICTION INTERVAL
- CAUSALITY

Enterprise Adoption of TS Forecasting

Enterprise adoption of forecasting has many challenges:

1. You will spend (more than) 50% of your time explaining your forecast to business.
2. Point forecasts as useless and more often than not, harmful to business strategies.
3. Does not matter if you are using statistical or machine learning models.
4. Holt-Winters and Box Cox methods still are the gold standards.
5. Domain knowledge is key and common-sense is the silver lining.
6. Operational challenges never go away and increase with age of your forecasting workflow.

Use Case – IoT Anomaly Detection

ANOMALY DETECTION

Major manufacturing company based in Chicago

Objective

1. Anomaly detection from IoT sensors of jet-pump components
2. Predict leak or failure of a component in High-pressure Jet pumps before machine breakdown by providing early maintenance

Solution

1. Baseline-Challenger approach to detect anomalies
2. ARIMA as baseline model and LSTM, RNN and SVM as challenger models
3. IoT time-series data for developing the models like temperature, pressure, stroke rate, etc.
4. Visualization of time-series data to identify patterns and define anomaly

Benefits

1. Identification of components leading to anomalous behaviour
2. Pre-emptive action based on anomalous behaviour to avoid breakdowns
3. Savings in terms of both cost and effort
4. Reduced downtime and increased efficiency

IoT Anomaly Detection – Solution Overview

1. Time series forecast of the components and prediction of jet-pump status to develop the baseline model using ARIMA and Local Outlier Factor (LOF) algorithm

2. Develop challenger model to benchmark accuracy:
   i. Long Short-Term Model (LSTM) - Sequence prediction from past time-series IoT data
   ii. Recurrent Neural Network (RNN) – Anomaly scores on a single time-series dataset
   iii. Support Vector Machine (SVM) – One class SVM for anomaly detection using labelled training dataset

3. Sliding time window for forecasting data points dynamically

4. Calculate false-positive rate to obtain fraction of normal points from outliers and recall value

IoT Anomaly Detection – Background and TS Data

High-Pressure Jet is used to compress raw food materials in their machine by providing high-pressure water

2 intensifiers (left and right) provide stroke to the Jets to create pressure

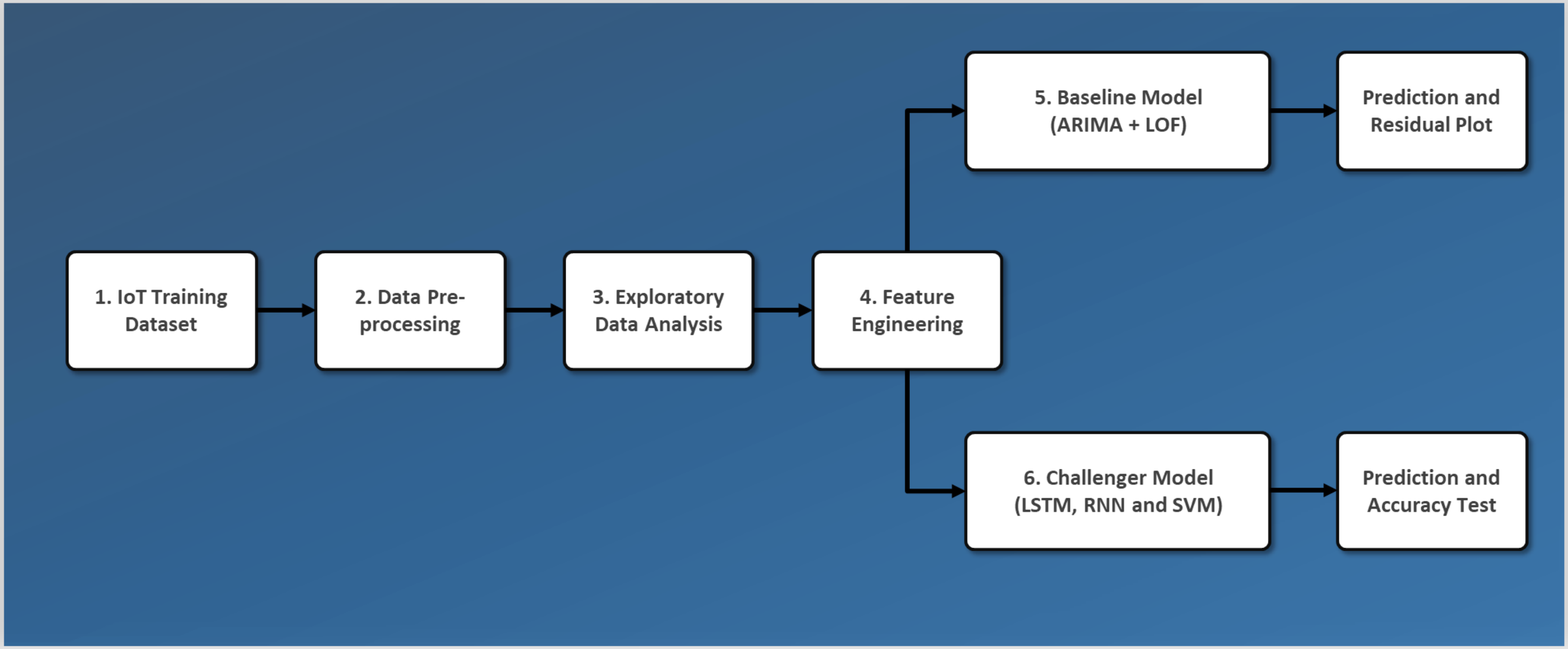
Data is sent out by probes placed on pumps to measure factors, such as temperature of valves, water pressure, etc.

Timestamp	Temp on left valve in intensifier 1	Temp on right valve in intensifier 2	Hyperjet Low pressure command	Hyperjet High pressure command	Hyperjet oil temp	Hyperjet water temp	Final_Status
18-12-2018 02:56:53	98	86	20000	85000	92	66	Normal
24-12-2018 19:46:39	182	81	20000	78000		69	Warning
27-12-2018 17:39:16	36	39			69	45	Pump Stopped
28-12-2018 02:56:53	98	86	20000	86000	92	66	Normal
28-12-2018 19:46:15	92	131	20000	78000	99	70	Warning
30-12-2018 17:39:41	38	39			67	44	Pump Stopped

Leaks are increasing due to high valve temp

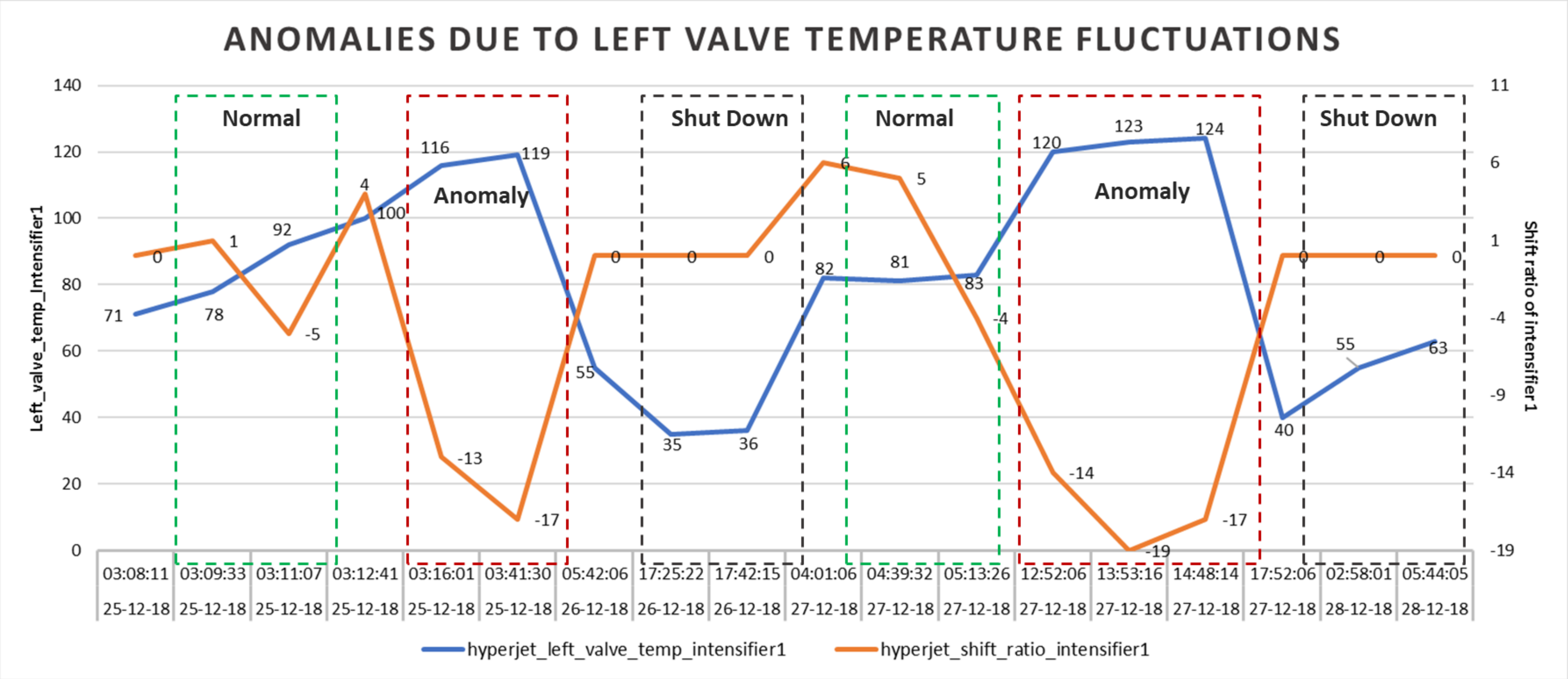
1. **Normal** State – Balanced stroke rates for both intensifiers (left and right) indicating a normal system to create the expected pressure by the jet pumps
2. **Warning** State– Leaks in the system created due to factors like disruption in balance, over-temperature of any of the valves of the intensifiers or high oil temp etc.
3. **Pump Stopped** State - As the leaks size increases, there comes a point where the system indicates to shut down and the maintenance team is sent for repair

IoT Anomaly Detection – Solution Workflow



IoT Anomaly Detection – TS Plot

Anomaly detection indicates the increase in leaks so that the machine failure can be prevented beforehand by providing early maintenance



Shift ratio variable indicates the uneven stroking for the intensifiers caused due to unbalanced system as the temperature rises abruptly

Use Case – Demand Forecasting

1. Our DL-based solution applies complex mathematical algorithms to automatically recognize time dependent patterns, capture demand signals and spot complicated relationships in large datasets, across multiple individual item/store sales data.

2. Two pronged approach: The solution is equipped with pre-built prediction models to forecast product demand with experimentation and feedback:

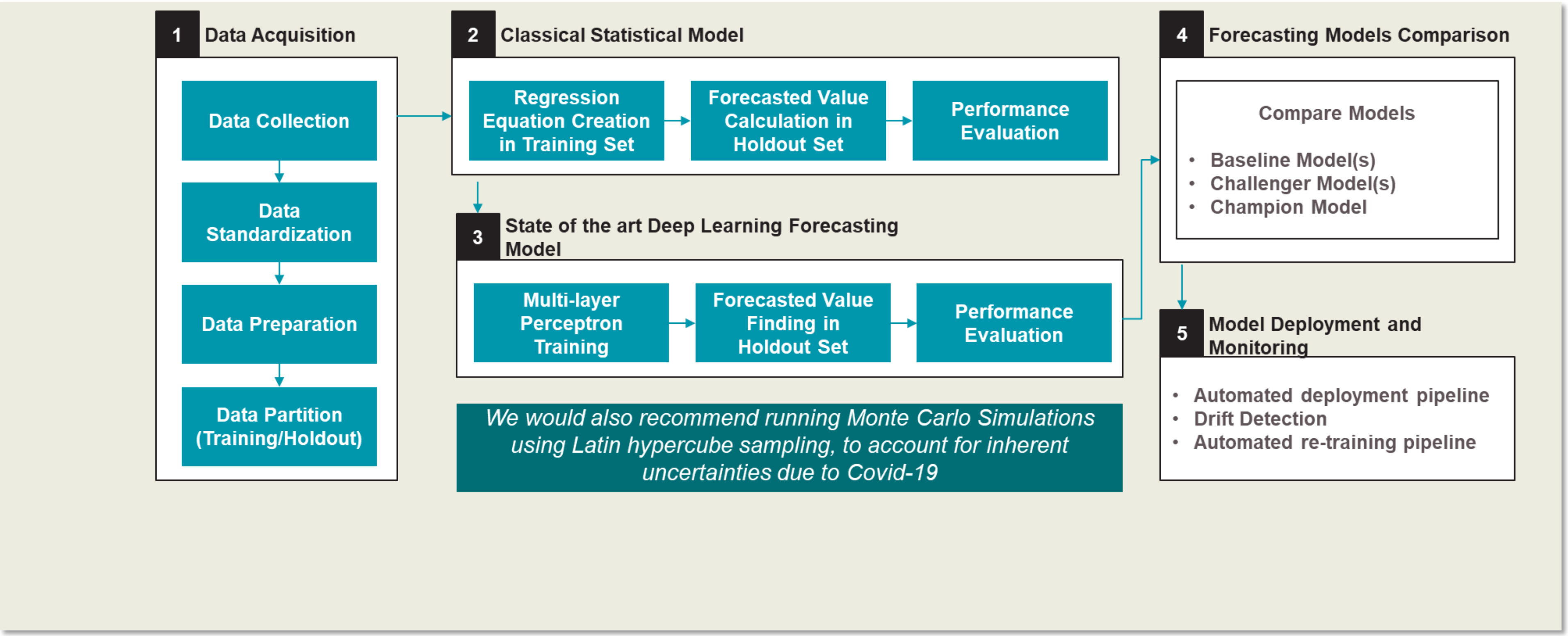
- Classical statistical modeling focused on data generation mathematical models
- State of the art Deep Learning modelling focused on pattern recognition

3. The solution determines which forecasting algorithm or an ensemble of algorithms fits your individual item/store best

4. It provides the capability to track and predict AI enabled forecast accuracy with the following features:

- Incorporating experimentation, heuristics, and user feedback loop in the model
- Track and evaluate forecast accuracy, using robust expanding & sliding window strategy

Demand Forecasting – Solution Architecture



Textbook Chapters

Materials covered available in book chapters:

PTS: 13 – 15

Questions ?


A child can ask questions
that a wise man cannot
answer.
- Anonymous Author
Wishafriend.com

Thank You