A Heuristic Approach To Compute Service Request Resolution Time

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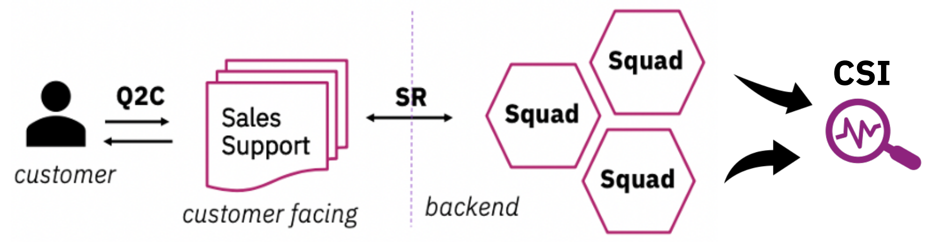
Abstract

In companies with thousands of product portfolios, sales personnel may not be aware of all details related to the contract they are working on with the clients. To get assistance, they might open a **ticket** to help them better navigate the deal. For example, at IBM, the sales support staff often requests **Quote To Cash** (Q2C) support and opens a new ticket called ***Service Request*** (SR) with the Q2C team, which routes the SR to the appropriate **squad**. Stakeholders at different stages in the business process would benefit from **forecasts** around SR **resolution times**, to make wiser **business decisions**. Hence, predicting time required by squads to resolve future SRs becomes an important and challenging problem.

Project Overview

Introduction



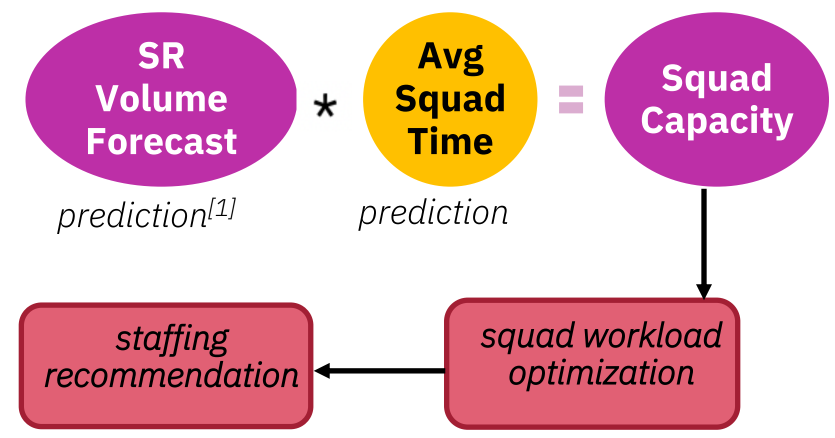
- Cognitive Squad Insight (CSI) : An application tool that provides insight into the sales support process, staffing utilization, and recommendation for support organization to efficiently manage the workload. SR resolution time prediction, part of CSI.
- SR resolution time varies because of SR complexity, employee skills and availability, SR volume (workload) and various SR features, such as the market (tribe), sub-brand (business subdivision) and engage-option (pre/post sales)

Goal : Given the complexity and volume of SRs and the several features that characterize these SRs, predict the average resolution time for a given SR type.

Challenges

- *"At what level should we predict the SR resolution time? Squad level, market level or tribe level?"*
- *"Which features would be the most useful for the task?"*
- *"Would a monthly prediction be more accurate than a weekly?"*
- *"Should we predict for the long term or for the short term?"*

Overall Picture : CSI Project



Interoperability

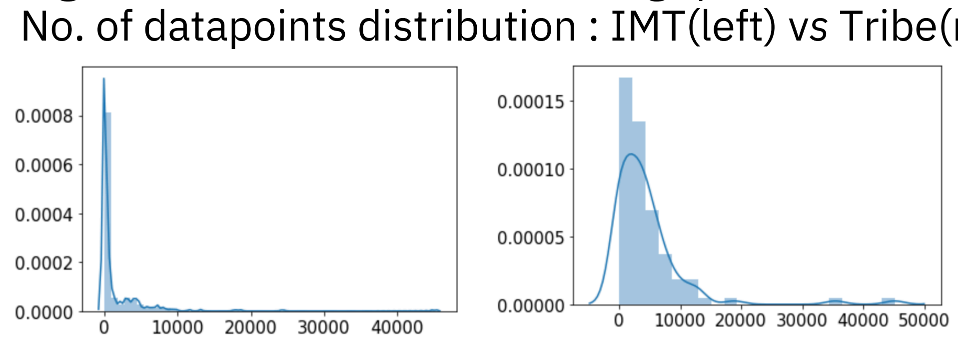
This work can be used in other scenarios where future resources need to be managed based on forecasts, such as supply chain management or warehouse capacity computing

Methodology

Step 1 : Feature Engineering

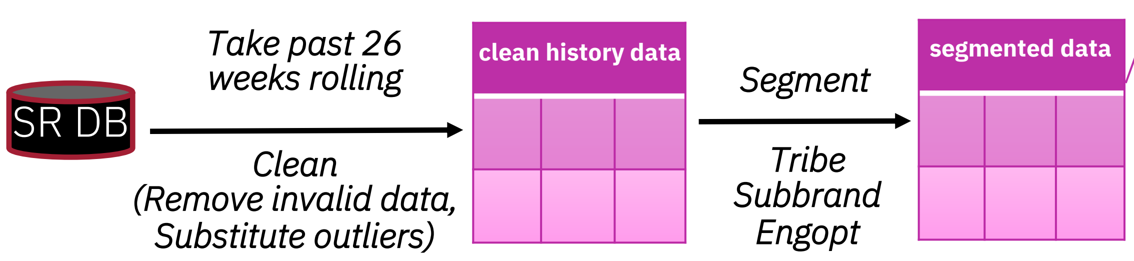
Challenge: Many features determine SR resolution times. Also, hierarchy within features. More features more information, but also more data sparsity after segmentation.

E.g. Decision : *IMT-Subbrand-EngOpt* or *Tribe-Subbrand-EngOpt?*
No. of datapoints distribution : IMT(left) vs Tribe(right)



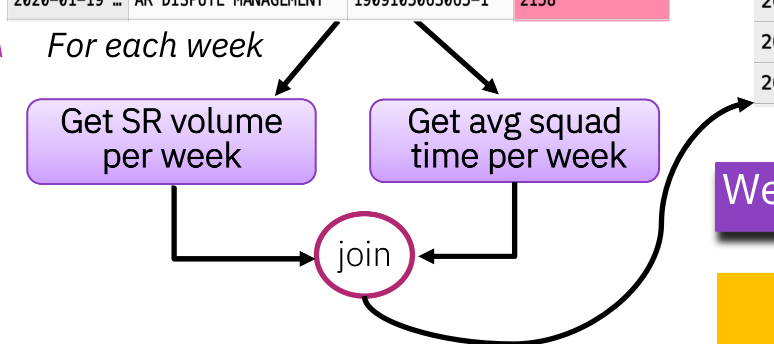
As there is less data sparsity for Tribe → Tribe chosen as segmentation feature

Step 2 : Data Preprocessing



Step 3 : Analytics

WEEK	REQTYPE	SR_NO	SQUAD_TIME_TOTAL
2020-01-19 …	AR DISPUTE MANAGEMENT	1909105063065-1	2366
2020-01-19 …	AR DISPUTE MANAGEMENT	1909105063065-1	2213
2020-01-19 …	AR DISPUTE MANAGEMENT	1909105063065-1	2238
2020-01-19 …	AR DISPUTE MANAGEMENT	1909105063065-1	2057
2020-01-19 …	AR DISPUTE MANAGEMENT	1909105063065-1	2158

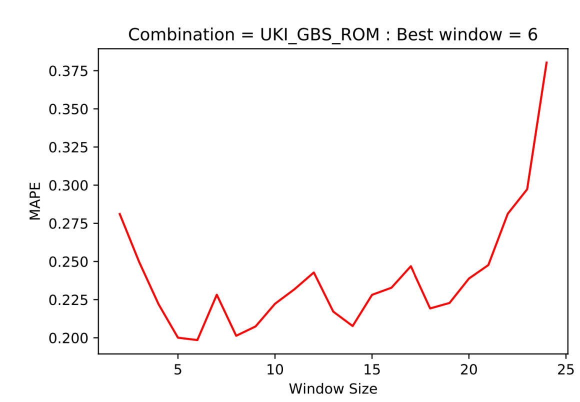


WEEK	VOLUME	AVG_ST_PER_SR
2020-01-19 00:00:00	249	6193.76
2020-01-26 00:00:00	252	5970.54
2020-02-02 00:00:00	221	5445.86
2020-02-09 00:00:00	173	8104.52
2020-02-16 00:00:00	157	8173.61
2020-02-23 00:00:00	136	8932.01
2020-03-01 00:00:00	208	5885.24
2020-03-08 00:00:00	113	6710.44
2020-03-15 00:00:00	112	5936.76

Weighted Moving Averages

M = AVG_ST * VOL
WAVG = M / sum (VOL)

1. *Do for range of rolling windows*
2. *Select best rolling window*



Deal with Insufficient Data

- *Interpolate missing volumes*
- *Replace missing week avg squad time with quarter avg squad time*

Evaluation Metric

MAPE (mean absolute percentage error), to compute model accuracy

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

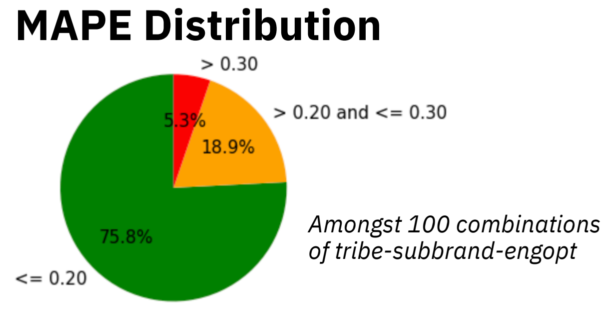
A_t = actual value and F_t = forecast

Step 4 : Prediction

1. Choose best rolling window to predict for 1st forecast week.
2. Use Simple Moving Averages on all predicted values recursively for the upcoming weeks in horizon.

Results and Future Vision

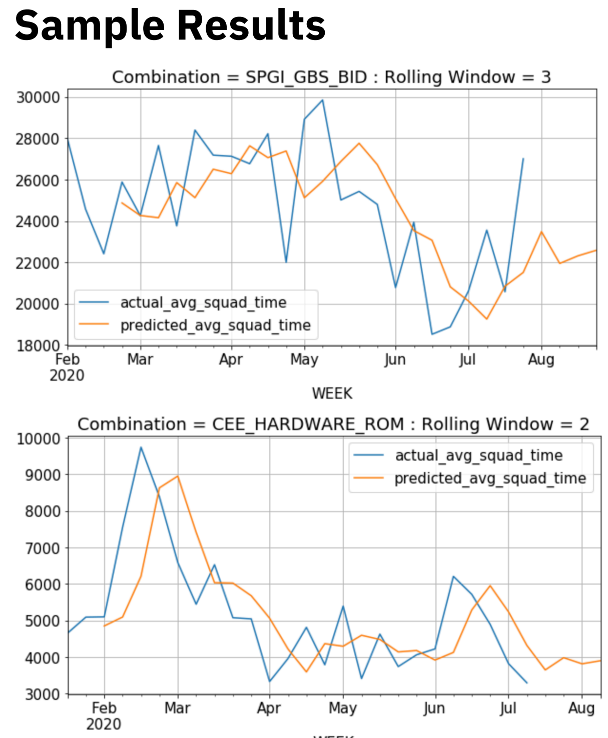
MAPE Distribution



Conclusion and Business Impact

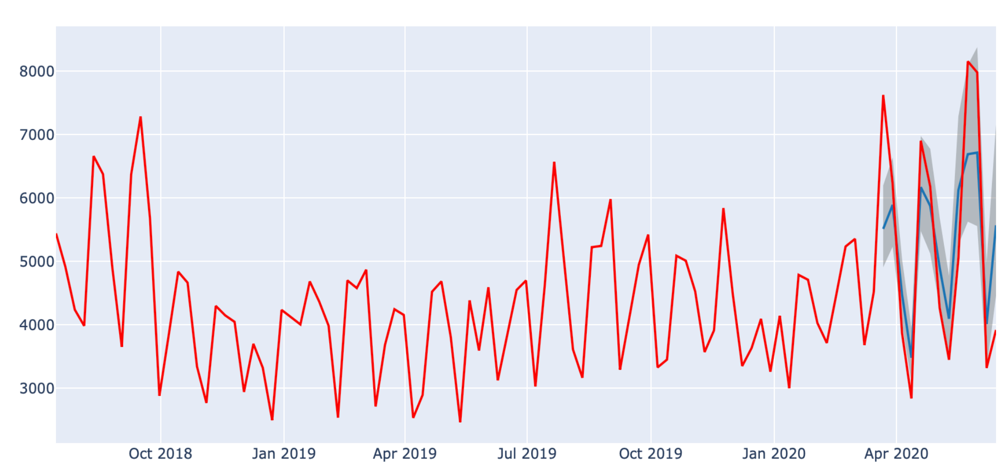
- Model succeeds in predicting for >228000 SRs with less than 20% error
- Dynamic window, outlier substitution insufficient data dealing techniques improve results
- Formulated model incorporated in CSI project and being accessed by Q2C team

Sample Results



Future Vision

- Regression methods, Experimenting with Prophet
- Volume as a regressor, *Boxcox* transformation
- Holiday and seasonality adjustment
- Using categorical features as embedding regressors



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