## Data Science PROJECT

Client: ABC Tech | Category: ITSM - ML Project

### **Business Case:**

ABC Tech is a mid-size organization operation in IT-enabled business segment over a decade. On an average ABC Tech receives 22-25k IT incidents/tickets, which were handled to best practice ITIL framework with incident management, problem management, change management and configuration management processes. These ITIL practices attained matured process level and a recent audit confirmed that further improvement initiatives may not yield return of investment.

ABC Tech management is looking for ways to improve the incident management process as recent customer survey results shows that incident management is rated as poor.

## Machine Learning as way to improve ITSM processes:

ABC Tech management recently attended Machine Learning conference on ML for ITSM. Machine learning looks prospective to improve ITSM processes through prediction and automation. They came up with 4 key areas, where ML can help ITSM process in ABC Tech.

- 1. Predicting High Priority Tickets: To predict priority 1 & 2 tickets, so that they can take preventive measures or fix the problem before it surfaces.
- 2. Forecast the incident volume in different fields, quarterly and annual. So that they can be better prepared with resources and technology planning.

# 1. Predicting High Priority Tickets: To predict priority 1 & 2 tickets, so that they can take preventive measures or fix the problem before it surfaces.

## > Assumptions:

Identify the dataset as supervised categorical and numerical dataset.

#### **Existing dataset:**

The following data is the original dataset, having **46606** rows (records) with some missing values and **25** columns (feature variables).

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 46606 entries, 0 to 46605
Data columns (total 25 columns):
CI Name
                              46606 non-null object
CI Cat
                             46606 non-null object
                             46606 non-null object
CI Subcat
WBS
                             46606 non-null object
Incident ID
                              46606 non-null object
                             46606 non-null object
Status
                             46606 non-null object
Impact
                             46606 non-null object
Urgency
Priority
                              46606 non-null object
number cnt
                             46606 non-null object
                             46606 non-null object
Category
                             46606 non-null object
KB number
Alert Status
                             46606 non-null object
No of Reassignments
                             46606 non-null object
Open Time
                              46606 non-null object
                              46606 non-null object
Reopen Time
Resolved Time
                              46606 non-null object
Close Time
                              46606 non-null object
Handle Time hrs
                             46606 non-null object
                              46606 non-null object
Closure Code
No of Related Interactions 46606 non-null object
Related Interaction
                             46606 non-null object
No of Related Incidents
                            46606 non-null object
No of Related Changes
                            46606 non-null object
Related Change
                             46606 non-null object
dtypes: object(25)
memory usage: 8.9+ MB
```

#### **Refined dataset:**

 As some of the columns are not useful for Analysis and Modelling, we will remove them.

Dropped columns are -

'Status', 'number\_cnt', 'Alert\_Status', 'Open\_Time', 'Resolved\_Time', 'Close\_Time', 'Handle\_Time\_hrs', 'Related\_Interaction', 'Related\_Change'.

- As 'No\_of\_Related\_Changes' and 'No\_of\_Related\_Incidents' columns has more number of missing values and also not useful for prediction, we can drop the column.
- Adding a new column based on 'Reopen\_Time' as 'ReOpen\_flag' for the incidents which has been Re-Opened → (1) or Not Re-Opened → (0).
- As per the business problem, we need to predict High priority tickets i.e., Priority 1 and Priority 2.

So we filter the feature variable '**Priority**' based on condition and add a new feature as '**New\_Priority**' → Target variable (y)

'New\_Priority' will contain 'High Priority' and 'Low Priority'.

The Priority which is 1 and 2 are High\_Priority.

The Priority which is 3, 4 and 5 are Low\_Priority.

## > Top Features influencing the prediction of High priority tickets:

After Data cleaning, Exploration data analysis, Correlation and based on some domain knowledge, we came up with some features which will impact the High priority prediction.

Features	Description	
CI_Name	Name of CI. CI is basically a service being used	
	by the organizational user, it could be an	
	application, infrastructure service etc.	
WBS	WBSE Could be the department or equivalently a	
	charge code for using the CI service.	
No_of_Reassignments	It's the no. of Hands offs between Resolution	
	Agents before the issue gets resolved. Generally	
	High priority tickets should have less hand-offs	
	to other agent. Re-assignments happen in	
	following scenarios:	
	1) When the Agent at the time of creation assigns	
	to wrong resolution team	
	2) When the issue require resolutions from	
	multiple teams (like software, infra teams) and	
	there is no one single owner that could be	
	established.	

	3) Sometimes issue is reassigned due to cursory		
	or inadequate investigation.		
Closure_Code	It could be a code to capture the cause of		
	incident. This information is updated by the		
	ticket resolution agent. Since at the time of		
	capture, the ticket creation agent will not know		
	about the information, it cannot be a predictor.		
	However if we assume that the Ticket Creation		
	agent can see the list of related incidents at the		
	time of creating a new ticket, the closure code		
	can be of some value to assess the priority.		
No_of_Related_Interactions	Count of number of interactions with customer		
	before the ticket was resolved. In general sense,		
	if the priority of the tickets is higher, the SLA		
	will be stringent and the Resolution agent may		
	try to have many calls to get as much information		
	required for reproduction of issue etc. to resolve		
	it. Hence this could predict the priority		
ReOpen_flag	Time Stamp when the ticket was reopened.		
	Typically if the resolution agent closes/resolves		
	the tickets without satisfaction of the user or the		
	issue resurfaces, then the user re-opens the ticket		
	and this time may be by increasing the priority,		
	(ITIL doesn't recommend such behaviors).		
	Reopen Time may not help but can be converted		
	into binary yes/no to have the impact of		
	Reopening on Priority		

## > Machine Learning algorithms:

Algorithm	Accuracy	Recall	Precision
Logistic Regression	76	73	76
K-Nearest Neighbor	83	79	86
SVM	83	80	84
MLP Classifier (ANN)	79	60	93
Decision Tree	83	67	96
Random Forest	86	79	91
XG Boost	87	84	<mark>89</mark>

## > Tools used:

Jupyter - Python 3.7, MySQL, Excel, Machine learning algorithms.

## > Results:

Algorithm XG boost classifier has given a good Accuracy with 87% and Recall rate with 84%, which is more efficient for Model prediction.

## > Summary:

Our goal is to predict High priority tickets i.e., Priority 1 and 2 tickets. But the data here is more skewed towards low priority tickets and more number of data entries are among low priority tickets. There is an imbalance nature in the dataset. So here we used under-sampling technique to equalize the dataset among high priority and low priority tickets.

## Before Under-sampling:

New priority	<b>Total count</b>	
Low Priority	35634	
High Priority	685	

## After Under-sampling:

New priority	<b>Total count</b>		
Low Priority	685		
High Priority	685		