TIDIO Assignment Report

1. Top 3 KPIs

What are the top 3 KPIs that we should track on a weekly/monthly/quarterly basis as the Customer Support? How do these metrics measure either performance efficiency, capacity utilization, or customer satisfaction? How should we interpret these metrics?

The top 3 KPIs to measure as Customer Support:

1. **Resolution time**

   Resolution time can be measured in a couple of ways – as an average for the whole team, across different Tiers, as a distribution across employees/teams, and with regard to first response time, to full resolution time, or the difference between them. This measure (or its components) can inform us about the teams' performance across time (lower response and resolution time means that employees are **performing better** at their tasks **as they learn**, their tasks are performed quicker, and the issue is solved quicker). This single metric (FullResolutionTime, to be exact) is the single variable correlating the most (0.15 correlation) with customer satisfaction score.

   To sum up, this metric informs us both about **teams' performance**, as well as gives us a good view of customer effort and satisfaction. One caveat is that the resolution time depends equally on the employee as it does on the customer (as they take time to respond too), so we have to treat customers' response time not changing, and assume the **only variable** is employee response time. This isn't a perfect assumption, but can give us some indication of teams' performance.

2. **Customer satisfaction**

   Customer satisfaction in that case is measured as a **binary score**, which gives us some (but not ideal) view over the overall experience. This approach leaves out graduality in satisfaction or dissatisfaction, which can give us better view at the quality of service. Moreover, around 80% of tickets don't have CustomerSatisfaction score, so they have to be taken with a grain of salt.

   Another indicator for customer satisfaction is **churn rate** which indicates how many customers stop using the service – high churn rate might indicate customers leaving the service because of **low satisfaction**. In this case the data is not conclusive, as there is **no indication of the actual number of unique customers** (using the service), just the number of unique tickets. Therefore, if there is decreasing number of CS tickets, it might either mean decreasing number of overall customers, or on the contrary, increasing quality of overall service that requires less customer support effort.

3. **# tickets per employee**

   Number of tickets per employee indicates **available capacity utilisation**. This also can be measured both as an average, or as a distribution across employees. This measure has to assume all employees working the same # of hours (only a small fraction is contingent workers, so it's negligible). If across time more tickets are handled by an average employee, it might indicate better capacity utilization.

Moreover, one other indicator – **FirstResponseTime** – can give us some insight into capacity utilisation. If the first response time goes down across time, it might indicate the resources being handled more efficiently, i.e. cases being assigned more quickly or to less busy agents.

* FOR ALL KPIs – they can all be measured weekly/monthly/quarterly

2. KPIs Trends

For these top 3 KPIs, how do the trends look like during a given period? Are there any positive signs or things to be concerned about? What is causing positive/negative trends? Are there any areas in which it would be worth digging deeper into data?

Overview of the dataset

A handful of statistics and info about the dataset:

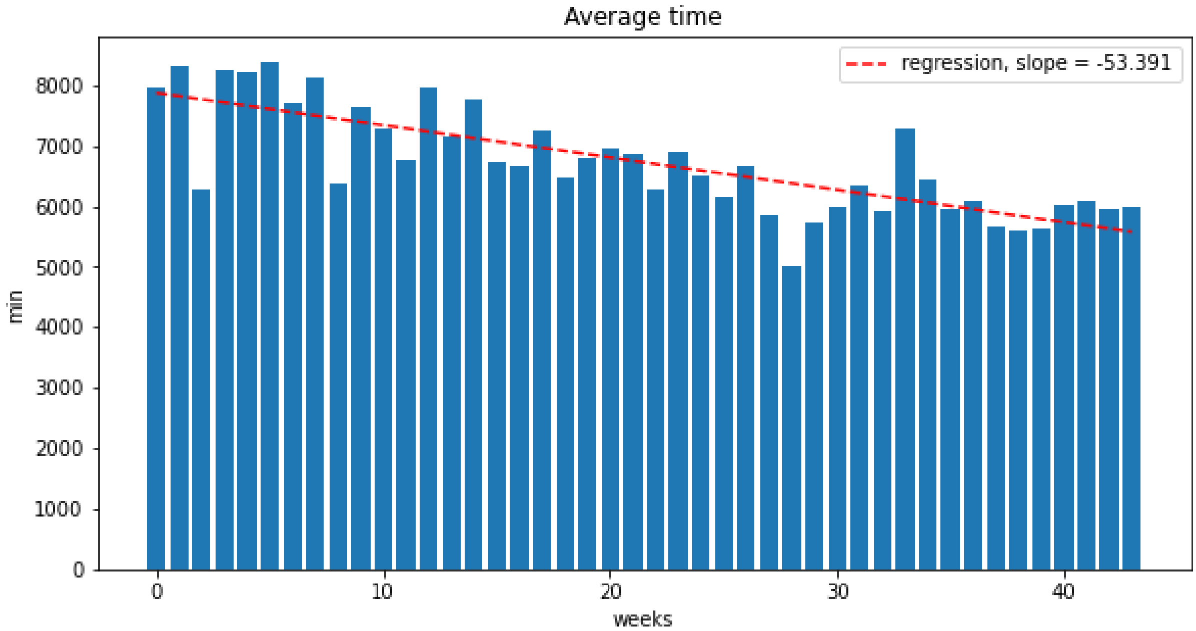
- Data encompasses daily activities of customer service employees
- 210k rows (and unique Ticket IDs)
- 10 months period of data collection
- 190 unique employees
- 11 employee locations
- 14 different plans
- 9 ticket channels
- 26 ticket groups

Caveats

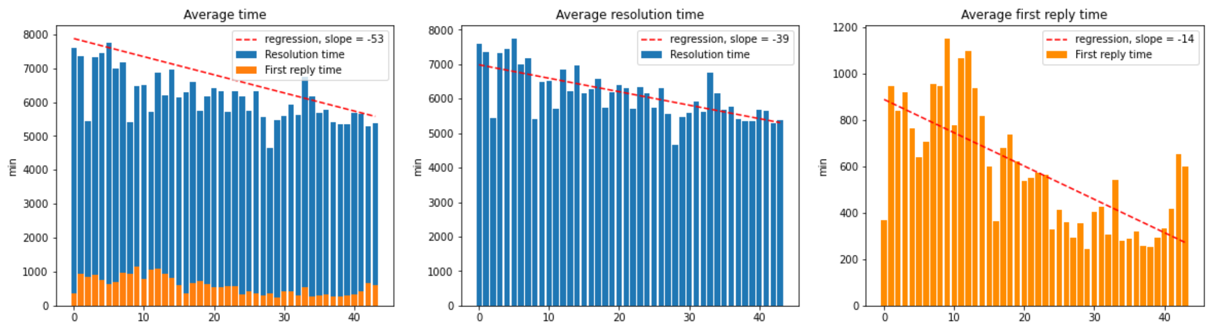
In this report graphs' x axis are labelled starting from 0 (weeks, months, quarters), and don't have names of months due to ease of analysis. 0 means January (or beginning of the year), 10 months' worth of data has been analysed. (Of course, in the polished up version I would include all the correct labels.)

2.1 Resolution time

First average full resolution time was measured. From the graph below we can clearly infer that the average resolution time decreased significantly over the period of 10 months. This can mean either better performance of employees once they get more experience, as well as better allocation of resources.



Below one can see the breakdown of average time into first response time and full resolution time.

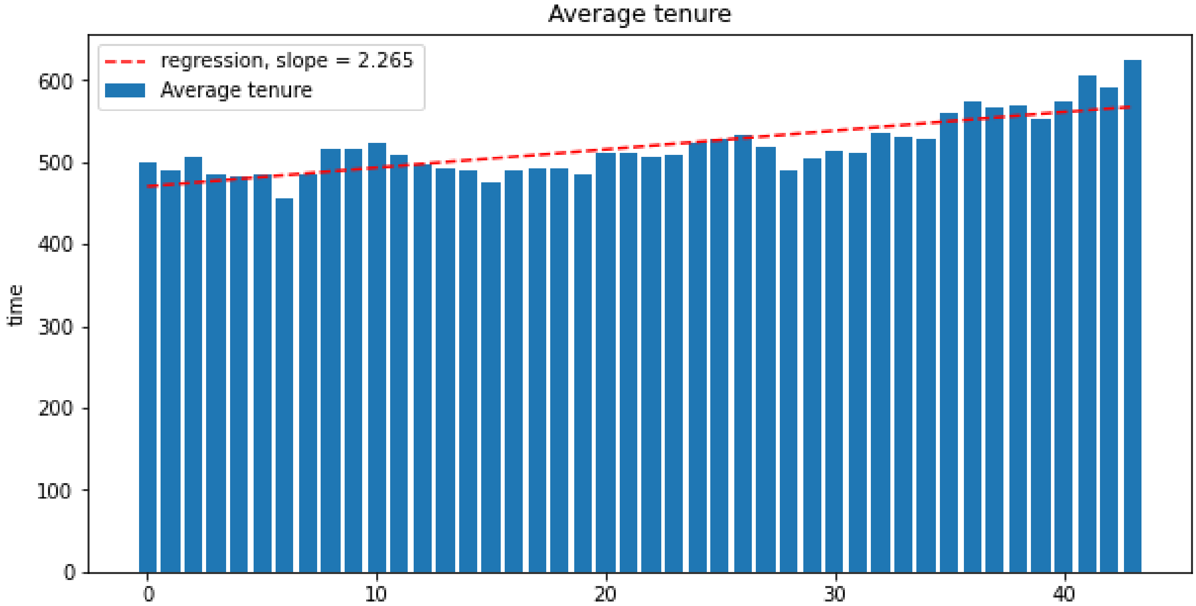


It turns out that both the average resolution time as well as average first reply time dropped significantly, with average first response time most dramatically, by means of regression dropping by more than a half.

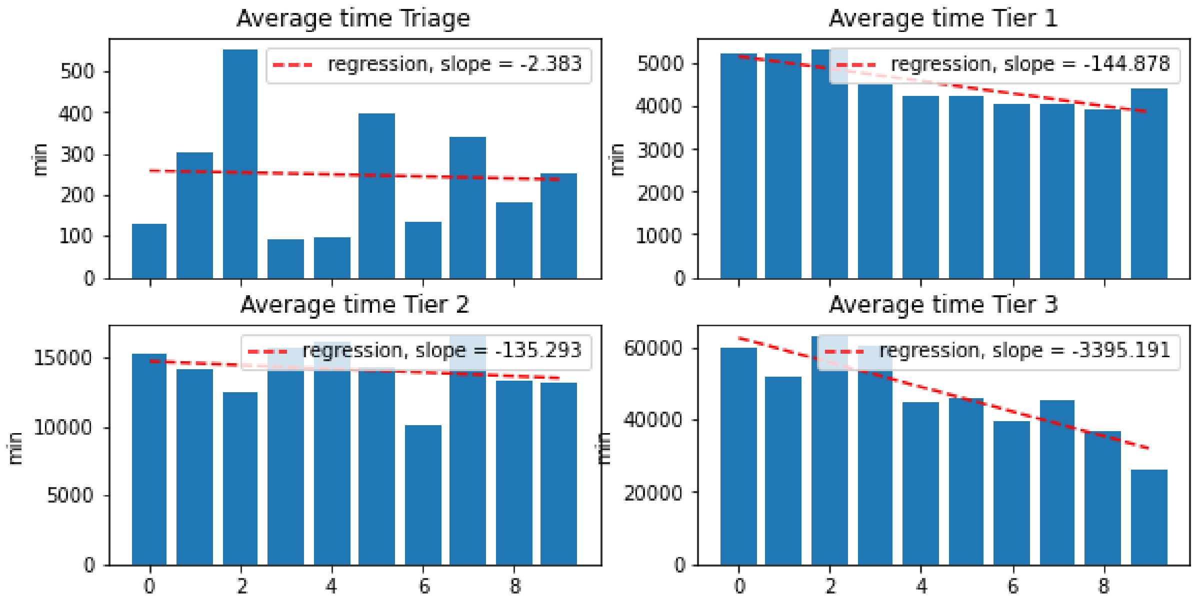
As one can infer, the average resolution time had a more significant effect on the overall drop, but in essence we can assume both the **efficiency of the employees** possibly due to their improved experience, and **resource allocation improved** over the course of 10 months.

One area that might be of concern and that is worth investigating is the **increase in first response time** over the last few weeks in October, and the manager should ensure it does not increase further as this is an resource allocation issue, as well as an indicator of customer satisfaction.

To support the hypothesis of increasing employee performance with experience, **average tenure** was looked into, and it shows that it increased by roughly 100 days on average. This, assuming rising performance with experience, supports the aforementioned hypothesis.

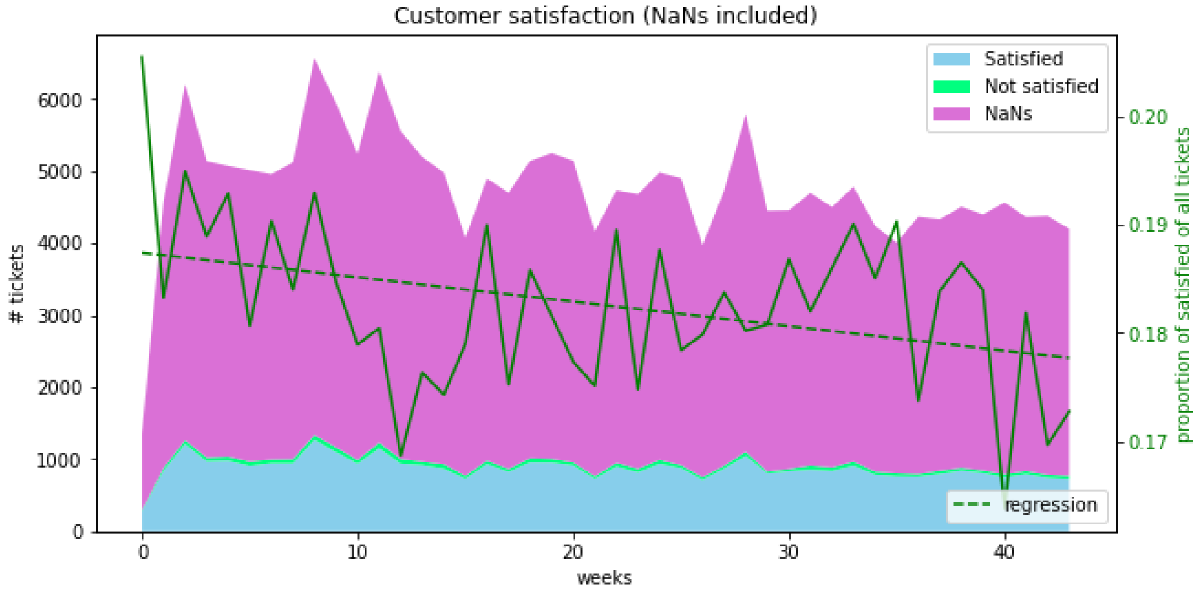


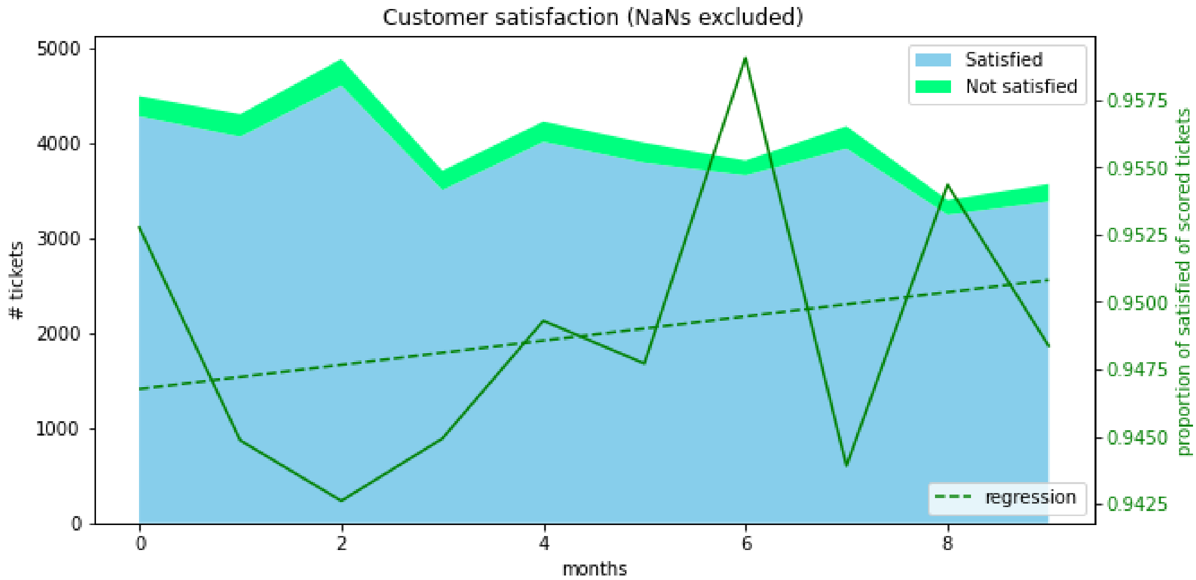
The analysis of full response time broken down into Tiers showed that biggest of performance improvements were achieved in Tier 3, and further in Tier 1, as we can see below.



2.2. Customer satisfaction

Customer satisfaction was measured two ways, one including non-responders, the other one excluding.





(These graphs also showcase different timescales, just to show that timescale can be changed easily within my Python analysis – the trends are all visible nevertheless)

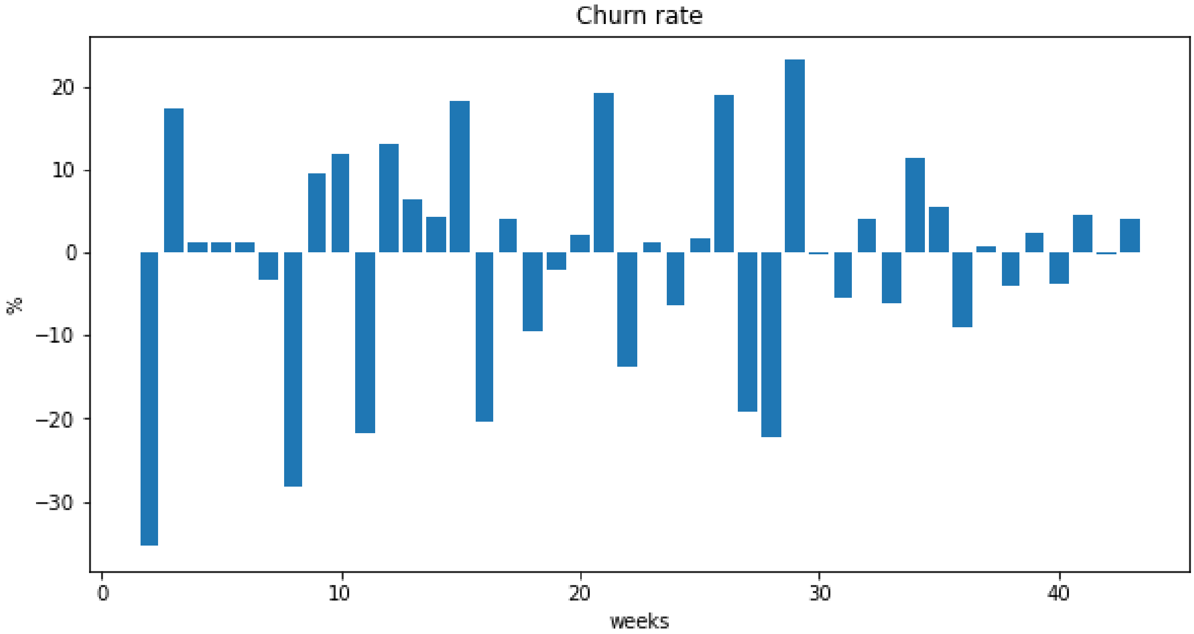
From the first graph we can infer that all of the scores (Satisfied -21%, Not Satisfied -26%, NaNs -17%) **decreased**.

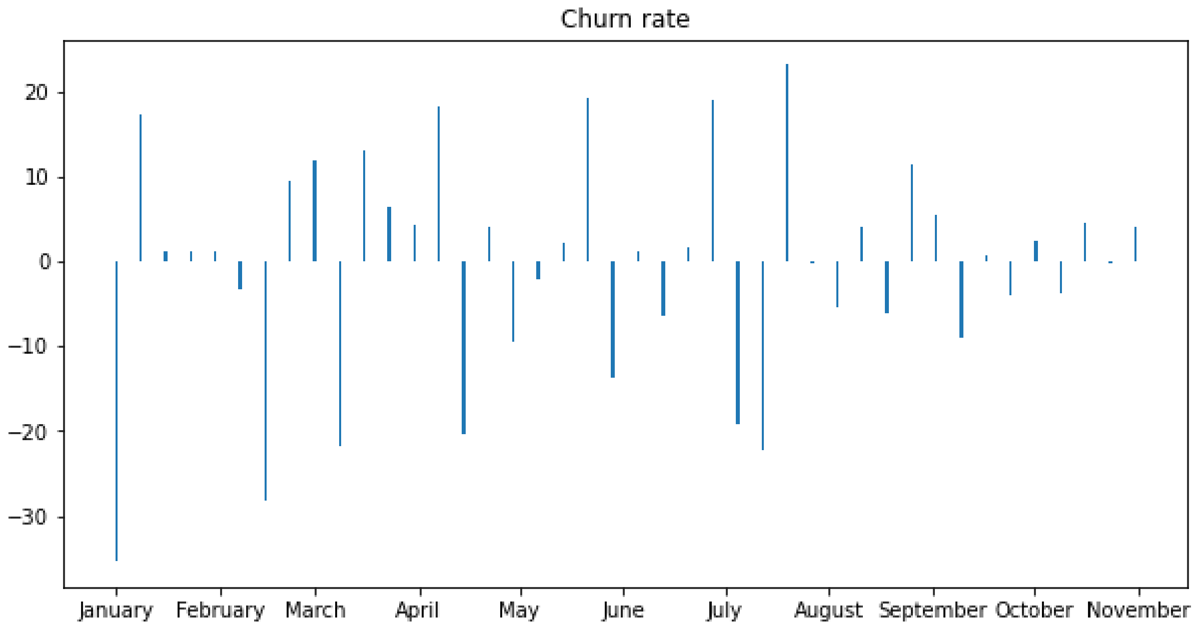
The overall proportion of positive satisfaction points to overall ticket count decreased from 19% to 18% - this means that customers are less likely to rate their experience, and that is a decrease in absolute terms of about 5% of satisfied score as a proportion to entire ticket count.

On the other hand, those customers who rated their experience declared **a very slight increase** in customer satisfaction (as a proportion of positive to positive+negative).

Overall the scoring is pretty stable, and decrease in count for all variables is proportional to overall decrease in ticket numbers (17%). One could argue that the slightly larger decrease in satisfied customers is concerning, but in order to make sure that is the case, one would have to look at whether the customers needing less customer service, or just leaving the service altogether. Moreover, as the best numerical indicators of customer satisfaction are improving one would have to dive deeper into data (i.e. different tiers of customers, or plans they are on) or look at other business circumstances.

Another metric is **churn rate**



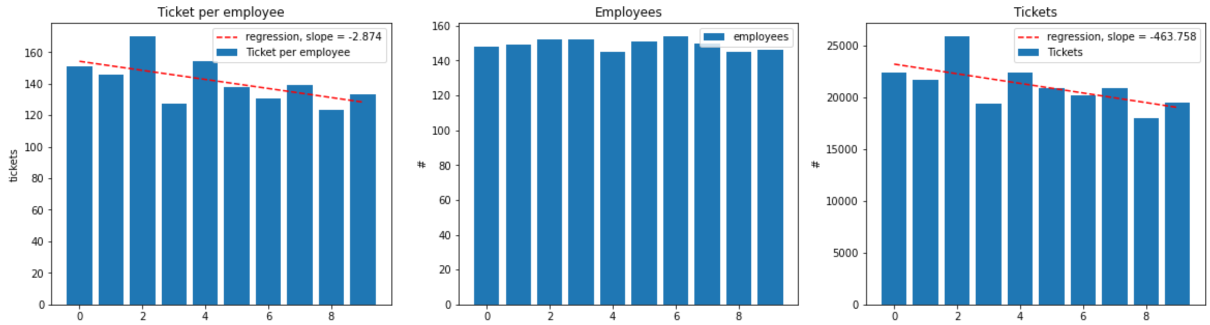


Churn rate was pretty **fluctuating** during the first half of the year with churn as much as 20% either way, and after August it has smoothed out. That could mean that the customers were trying out the service, or there were influxes of new customers (we cannot confirm that without delving into more accurate data on **customer base** itself).

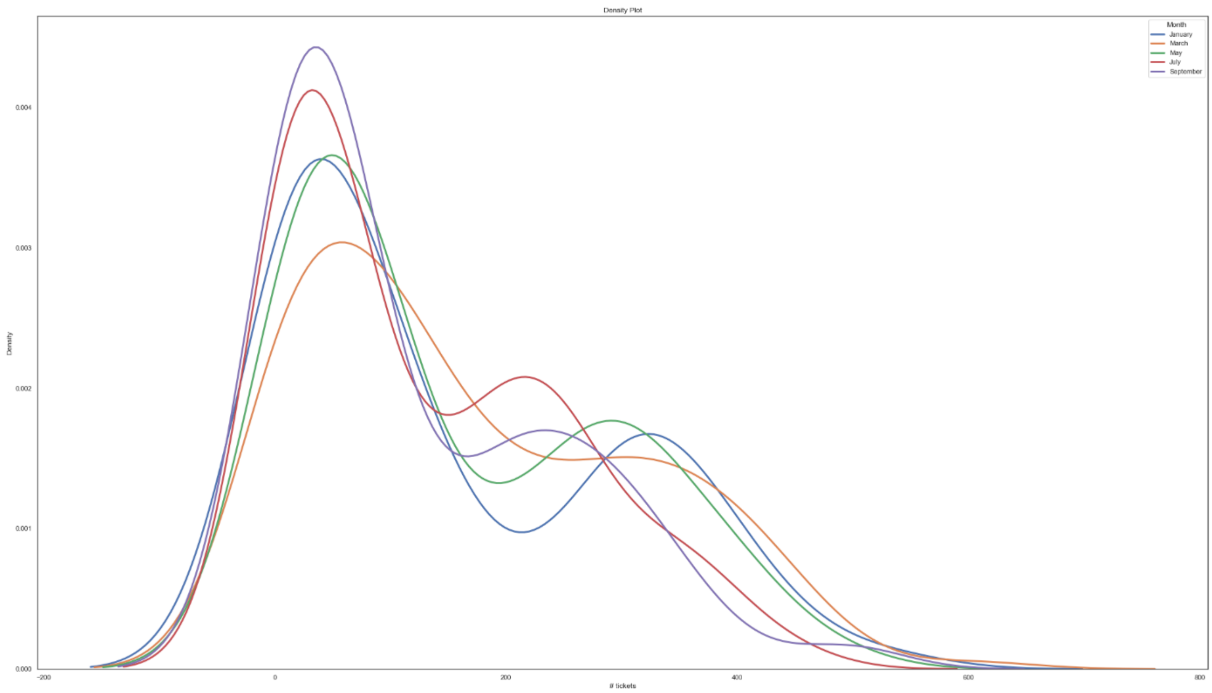
Overall, January to October, the ticket count decreased by about 17% (regression from point 2.3) which can, repeating after the point 1.2 can mean either improvement in service, or customers leaving. With regards to the satisfaction score, it was **pretty consistent**, with evening out **fluctuations in churn** towards the end of the year.

2.3 # tickets per employee

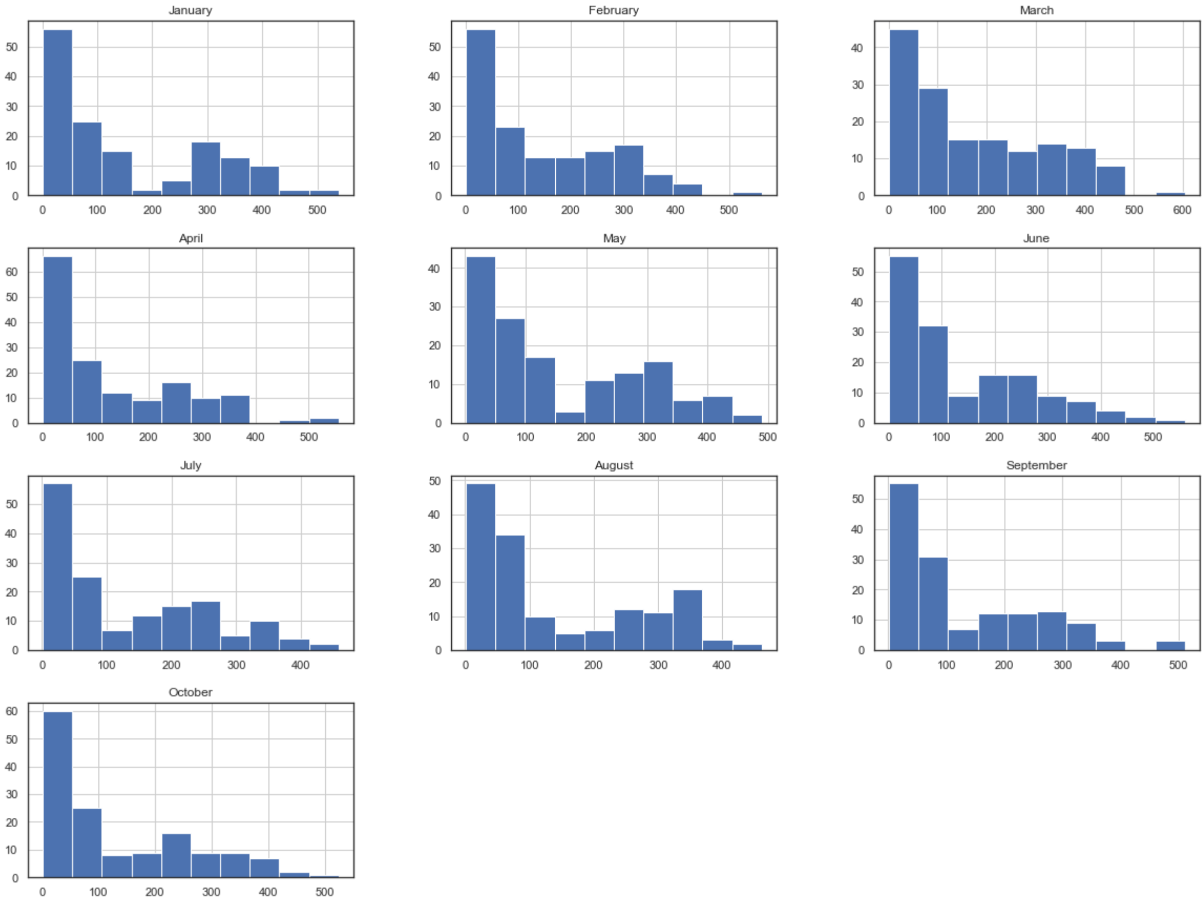
The average number of tickets per employee did drop by means of regression (by around 11%), with roughly the same number of employees across time, so the drop in tickets per employee can be assumed to be caused by the drop in overall tickets count (17%).



Looking at the density plots for each month there are small discrepancies between workloads in every second month (for readability), and there is a tendency to concentrate the largest amount of workers on 0-150 range in terms of number of tickets, and the further down the timeline, the greater the concentration, which might indicate on focusing on less quantity per most employees.



Histogram for every month can be found down below.



In conclusion, this metric did not show any changes in capacity utilization apart from assigning more and more employees at the 0-150 range, the number of overall tickets **dropped** which in turn influenced the number of tickets per employee.

Areas which would be interesting to research more would be checking how the ticket (and what type of ticket) is assigned to a particular employee, whether some employees handle certain tasks more quickly /efficiently than the other ones and in turn assign them this particular set of tasks.

Comments

To every part of the aforementioned analysis, certain points and data gathered from stakeholders would help make the analysis quicker, more focused and accurate:

- Getting to know the **specifics of the business** that the customer service is working for – as for this one, we *don't know* whether, e.g. average resolution time is good, or can potentially be dramatically improved,
- **Business circumstances** specific to this company, i.e. what changed before or within the period analysed (e.g. change in company policy, marketing, new product, etc.) , as this might point towards the reasons for certain trends occurring
- Which parts of the customer service process are already automated, or which tasks do the customer service perform in order to see what can be sped up/automated/improved (or taken into account as a constant)

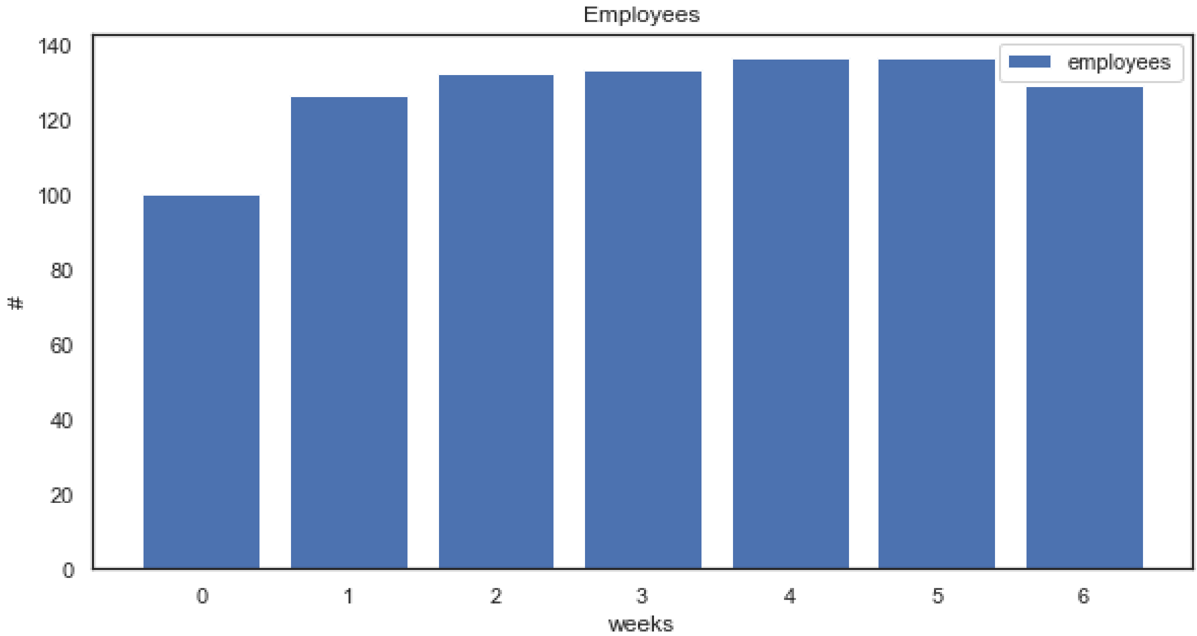
- Data about the **customers** themselves – specifically it would help in customer churn, so we can actually assess whether the service is that good that customers need it less, or they just leave it.

3. Customer satisfaction decreased

From Jan to Feb. Why? Should we be concerned about this? Are there any recommendations that you would share with the Customer Support team?

Jan to Feb saw a decrease in positive customer service score by 5%, an increase in negative scores by 12% and a decrease of 3% of customers using customer service. However, the proportion of those to each other (graphs in 2.2) has not changed as dramatically. Moreover, later on this proportion fluctuated, and the absolute numbers of subsequent scores (satisfied, not satisfied, NaNs) fell quite proportionately (point 2.2) to overall number of tickets decreasing. Hence it is not very concerning.

Increasing employment in January (workforce grew from 100 in 1st week to 136) – more than 1/3 growth of team, which in turn could cause possibly less experienced employees to work in customer service.



The average WorkerTenure has also dropped a little (as you can see below on statistical information – 2nd row (blue) is mean). All the other indicators either stayed the same or improved over the course of 2 months. Also, by inspection, non-numerical indicators (i.e. TicketChanel, TicketGroup, Plan, WorkerLocation) were checked for discrepancies and there haven't been significant differences between two months.

```
cs_months[0].describe() ## January
```

EmployeeID	TicketID	FirstReplyTime	FullResolutionTime	NumAgentComments	NumPublicComments	TicketEscalated	CustomerSatisfaction	WorkerTenure
22354.000000	2.235400e+04	16936.000000	22298.000000	20717.000000	20480.000000	22354.000000	4489.000000	22354.000000
1627.392055	2.164873e+06	1101.401866	7706.918558	3.059420	3.806689	0.199025	0.952773	492.856044
582.085607	2.857283e+04	7845.921136	27486.965551	4.045407	4.524284	0.399276	0.212147	343.709755
1.000000	2.116910e+06	0.000000	0.000000	1.000000	1.000000	0.000000	0.000000	-223.000000
1246.000000	2.141978e+06	13.000000	29.000000	1.000000	2.000000	0.000000	1.000000	303.000000
1708.000000	2.161524e+06	61.000000	203.500000	2.000000	2.000000	0.000000	1.000000	441.000000
2031.000000	2.188261e+06	725.000000	9888.500000	4.000000	4.000000	0.000000	1.000000	640.750000
3307.000000	2.221240e+06	498116.000000	548814.000000	370.000000	245.000000	1.000000	1.000000	2093.000000

```
cs_months[1].describe() ## February
```

EmployeeID	TicketID	FirstReplyTime	FullResolutionTime	NumAgentComments	NumPublicComments	TicketEscalated	CustomerSatisfaction	WorkerTenure
21670.000000	2.167000e+04	16173.000000	21621.000000	19846.000000	19811.000000	21670.000000	4298.000000	21670.000000
1693.626304	2.266516e+06	1102.509429	7570.518940	2.987907	3.710666	0.205168	0.944858	487.520904
592.005189	2.564859e+04	5265.338108	24930.968519	3.066830	4.175066	0.403834	0.228284	333.609459
1.000000	2.221243e+06	0.000000	0.000000	1.000000	1.000000	0.000000	0.000000	-138.000000
1385.000000	2.244884e+06	15.000000	27.000000	1.000000	2.000000	0.000000	1.000000	237.000000
1729.000000	2.266931e+06	60.000000	253.000000	2.000000	2.000000	0.000000	1.000000	445.000000
2244.000000	2.289165e+06	704.000000	10119.000000	3.000000	4.000000	0.000000	1.000000	647.750000
3051.000000	2.323787e+06	324420.000000	508260.000000	66.000000	90.000000	1.000000	1.000000	2121.000000

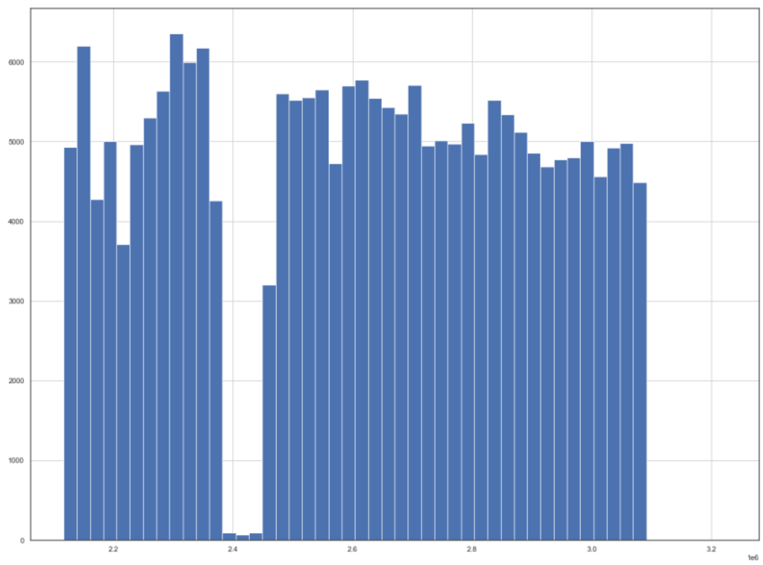
The recommendation for Customer Support team is either to grow slower, or invest more into training before putting new employees to work quickly, as this might impact customer satisfaction.

4. Bonus!

Are there any other insights that you would like to share? Any issues or challenges with analyzing the dataset?

I had a couple of insights while analysing the dataset:

- TicketID part was missing values around 2.4k mark – as all the other metrics seemed continuous and consistent, I did not investigate further



- A couple of interesting correlations, namely the main correlating factors of customer satisfaction were, in order of significance, FullResolutionTime, NumPublicComments and NumAgentComments, as we can see below:

```
CustomerSatisfaction    1.000000
EmployeeID              0.008382
TicketID                0.005555
WorkerTenure           -0.007264
TicketEscalated        -0.018300
FirstReplyTime         -0.050813
NumAgentComments       -0.069062
NumPublicComments      -0.070080
FullResolutionTime     -0.151891
```

- FullResolutionTime correlates quite well with number of comments (self-explanatory), but also whether the ticket has escalated (0.2), and quite predictably, with WorkerTenure

```
FullResolutionTime      1.000000
NumAgentComments        0.367931
NumPublicComments       0.326019
FirstReplyTime          0.312951
TicketEscalated         0.211951
WorkerTenure            0.081439
TicketID               -0.031055
EmployeeID             -0.088032
CustomerSatisfaction   -0.151891
Name: FullResolutionTime, dtype: float64
```

- There were 26 different ticket groups, mostly T1,T2 and their language counterparts. It would be interesting to measure them separately with the metrics from point 1,2 and look for differences (in cases where the data is conclusive enough)

```
Support (T1)                  112207
Support (T2)                   34780
Support (T1 English Phones)    24721
Support (Triage)               12913
Support (T1 - French)           5163
Support (T1 - Portuguese)       3661
Support (T1 - German)           3544
Support (T3)                    2962
Support (Analytics)             2325
Support (T1 - Japanese)         1693
Support (T1 - Spanish)          1535
Support (T1 - Italian)          1071
Support (T1 - Russian)           908
Support (T1 - Dutch)             878
Support (T2 - French)            700
Support (ARM)                    358
Support (Outbound)               357
Support (T2 - German)            339
Support (T2 - Spanish)           225
Support (T2 - Russian)           132
Support (T2 - Japanese)          125
Support (T2 - Italian)            93
Support (Managers)                55
Support (T1 - Chinese)            55
Security (Projects)                1
Support (T2 - Portuguese)          1
```

- Moreover, it would be interesting to see the breakdown Tiers and Plans to see whether those customer groups differ and require different approach, e.g. for assigning to specific agents or they require different time or are of different satisfaction, and hence, expectation, levels.