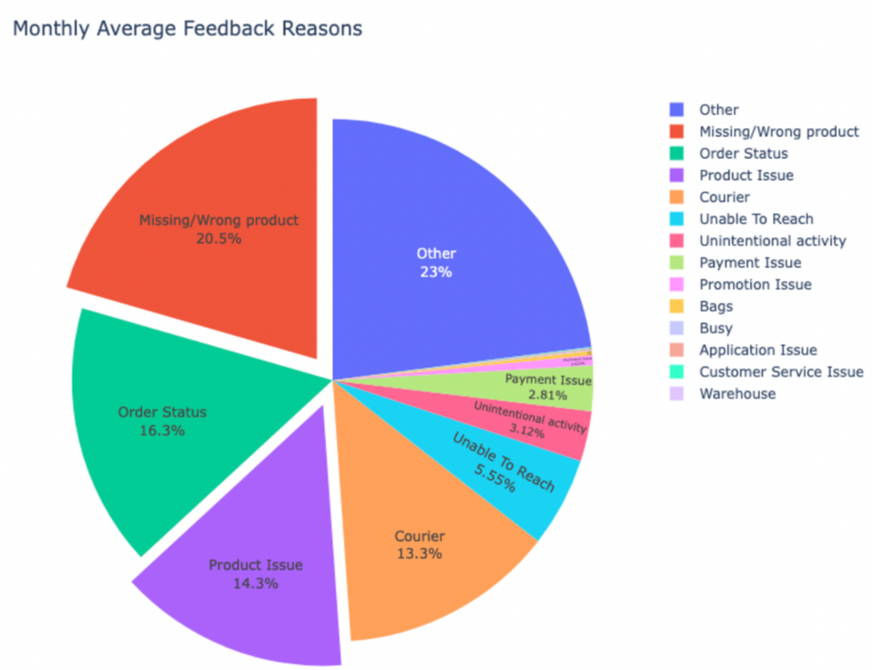
Customer Trust Score

Authors: @Dorukhan Afacan @Hasan Can Karapınar

❓Scope

Unsatisfied customers contact Customer Services through various feedback channels for order cancellation, product issues, service issues, payment issues etc. The median monthly workload of CS through GSM and Live Support channels is 260.000 approx.



For various feedback reasons CS agents follow instructions that pop-up on the live chat screen. Those pop-ups are called “assistflows“. Agents are obligated to apply these assistflows to inbound customers during conversation.

Reasons that require refund and discount are prone to monetary loss for the company side and thus requires attention for abusive behavior. Risk of such cases would push any CS to be more vigilant via **refund with statement** where a statement of the issue that deems refund is taken from the customer. However, even if rightfully applied, such processes can create a huge pain point to valuable customers and increase churn rates. Sadly in most cases, due to traffic and noise (human factor) such processes are not applied to full extent and **valuable customers are upset** sometimes with rejection. Or due to high throughput, abusive behavior might be overlooked for fast resolution.

Needs

The need is a **ranked segmentation** of customers in terms of **value and trustworthiness** to:

- reduce pain points for high-end customers by lowering their friction via special CS processes.
- work lower levels through controlled processes for structured vigilance.

🏹 Objectives

- Business aims:
  - **alleviate load of CS** by designing processes for certain feedback reasons that provide fast and/or auto resolving to certain customers.
  - shake hands with necessary stakeholders that the processes touch.
- Data aims:

- Data aims:
    - **build a data product that segments customers** for specialized processes.
    - shake hands with necessary stakeholders over the nature of the segments(trust groups) who will use them.
    - provide analysis over the segments/groups for business decisions.

Solution Idea

The objective of Trust Score project is here to:

- surface out a high-end customer profile (**happy paths**, fast/auto-acceptance).
- create **buffer levels** between Premium and Lowest segments for special processes.
- Analyze post-order behavior in terms of fraudulent activity and share insights with **Fraud Analytics**.

Important note: The final objective is a calculated score/group for a customer. There is no ground truth label for fraudulent feedbacks, the solution is to come up with a **favorability index** for a customer. When there is no label for supervised ML modeling there are two approaches for segmenting.

- Rule based / expert system.
- Unsupervised ML methods (Clustering, Anomaly detection)

Rules for calculating the groups are decided upon exploration of data and discussion with relevant business stakeholders.

💪 Challenges

There is **no clear label for a trustworthy post-order cancel/refund/exchange experience**. There are recorded notes for the customer during inbound conversation from CS agents about:

- potential promo abuse relying on **insights from fraud analytics**.
- **warehouse testimony** whether a product was really missing.
- **agent's experience** with customer behavior. (rude, relentless calling etc.)

Pre-order transactional and post-order feedback channel behavior is taken into account for insight since there is no actual proof of whether a customer lies or not via in-home observation. Information from business logic is used to decide segments and rule to separate customers into those segments.

👥 Customer Groups

After discussing with various business domains and analysis of customer data it was decided to segment customers into 5 profiles (A, B, C, D and E).

- A : Premium level for happy paths.
- B : Friendly buffer before premium level.
- C : Neutral
- D : Low trust buffer before danger level.
- E : Caution level.

V1

👀 Constraints

These are main segmenting rules and remarks from Fraud analytics and customer services no matter what.

- Customers with all_total_order_count above **X** are not to be upset despite recent impulsive behaviors.
- Customers with frequent feedbacks, refund and below zero contribution to profit.
- Customers with B, C and D Neptune segment and moderate order count should not have highest trust score.
- Customers whose refund and cs discount amount exceeds quarter of total charged amount should be segmented below neutral.

Approach

The first way was to approach segmentation of customers via a rule engine/rule based/expert system.

- Incorporate business logic via rules since there is no ground truth for a supervised learning scheme.
- On the fly explanations for decisions.
- Select features to further rule based system with an unsupervised model.

In order to decide rules for segmenting customers into 5 groups, what is at hand was examined. It included.

- Persona segments (transactional profiling for marketing)
- Value models (predicting a customer's future at Getir)
- Post-order feedback behavior.
- Features of past value (CP, order count)
- Churn (both prediction and history)

Methodology:

- Review agent notes on feedbacks table for customers that seem potentially abusive. (Do not use them as definitive flags as they are biased to agent/warehouse/courier).
- Order normalized persona occurrence within `P(persona=p|text_flag=pos)` to rank persona classes into buckets from A to D.

Trust Group	Persona Groups
A	Getir Core
B	Reliable, Getir Promo Core
C	Budget Promo Browser, Premium Low Habit.
D	Impulsive

- Migrate customers between buckets via fine grained set of rules such as:
  - min LTV of customer above the average of its respective trust group.
  - order count of customer lies on an outlier margin of its respective trust group.
  - feedback ratio of customer lies on an outlier margin of its respective trust group.

🗺 Explorations + Decisions

Coarse Level

For each persona, default trust score is assigned before fine tuning by labelling abusive behavior in accordance with the occurrence of "suistimal" word declared by the corresponding CS agent in feedback note. The conditional probability enabled arranging the order of personas in terms of trustworthiness.

> i.e $P(pers=\text{"}PLH\text{"}|abuse=True) \rightarrow$ Probability of Customer Persona is Premium Low Habit given there is a reported abuse.

> Getir Core, Reliable, Getir Promo Core, Premium Low Habit, Impulsive and Budget Promo Browser personas are assigned to default trust score A, B, C, D and E respectively.

Fine Level

Expert system consists of 3 layers. First layer called as "**PS-LTV Layer**", determines the trust groups in accordance with persona and the rules that are associated with persona. Second layer is called "**Dynamic Rules Layer**". Dynamic layer takes trust groups assigned by "" as input to dynamically demote or promote. Third layer is called as "**Red Line Layer**". Red Line Layer only expresses the trust group that a customer should not be in.

1. **PS-LTV Layer**

- Getir Core
  - If ***maximum CP*** observed in order is smaller than the ***median CP*** of corresponding persona cluster → B
  - If ***maximum LTV*** observed last month is smaller than ***median LTV*** of corresponding persona cluster → B (LTV scores are calculated on daily basis)

  - If ***feedback ratio*** is greater than 1 → B
  - If none of the terms above apply → A
- Reliable
  - If ***minimum CP*** observed in order is greater than the ***median CP*** of corresponding persona cluster → A
  - If ***minimum LTV*** observed last month is greater than ***median LTV*** of corresponding persona cluster → A (LTV scores are calculated on daily basis)
  - If none of the terms above apply → B
- Getir Promo Core
  - If ***minimum CP*** observed in order is greater than the ***median CP*** of corresponding persona cluster → A
  - If ***minimum LTV*** observed last month is greater than ***median LTV*** of corresponding persona cluster → A (LTV scores are calculated on daily basis)
  - If ***order count all time*** is greater than 100 and ***feedback ratio*** is equal to 0 → A
  - If none of the terms above apply → B
- Premium Low Habit
  - If ***minimum CP*** observed in order is greater than the ***median CP*** of corresponding persona cluster → B
  - If ***minimum LTV*** observed last month is greater than ***median LTV*** of corresponding persona cluster → B (LTV scores are calculated on daily basis)
  - If ***Average CP*** in last 6 months is greater than 50₺ and ***logarithm of average LTV*** last month is greater than or equal to 6 and ***warehouse weighted feedback ratio*** is smaller than 0.5 → A
  - If none of the terms above apply → C
- Impulsive
  - If ***minimum CP*** observed in order is greater than the ***median CP*** of corresponding persona cluster → C
  - If ***minimum LTV*** observed last month is greater than ***median LTV*** of corresponding persona cluster → C (LTV scores are calculated on daily basis)
  - If ***maximum CP*** observed in order is smaller than the ***median CP*** of corresponding persona cluster → E
  - If ***feedback ratio*** is greater than 0.7 → E
  - If ***refund ratio*** is greater than 0.5 → E
  - If none of the terms above apply → D
- Budget Promo Browser
  - If ***maximum CP*** observed in order is smaller than the ***median CP*** of corresponding persona cluster → E
  - If ***feedback ratio*** is equal to 0 → C
  - If ***feedback ratio*** is greater than 0.7 → E
  - ***warehouse weighted feedback ratio*** is greater than 0.5 → E
  - If ***refund ratio*** is greater than 0.5 → E
  - If none of the terms above apply → D

2. Dynamic Rule Layer

- If Neptune Segment is B → Demote 1 rank
- If Neptune Segment is C or D → Demote 2 ranks
- If ***order count all time*** is smaller than 41 and ***feedback count*** in last 15 days is greater than 3 → demote 1 rank

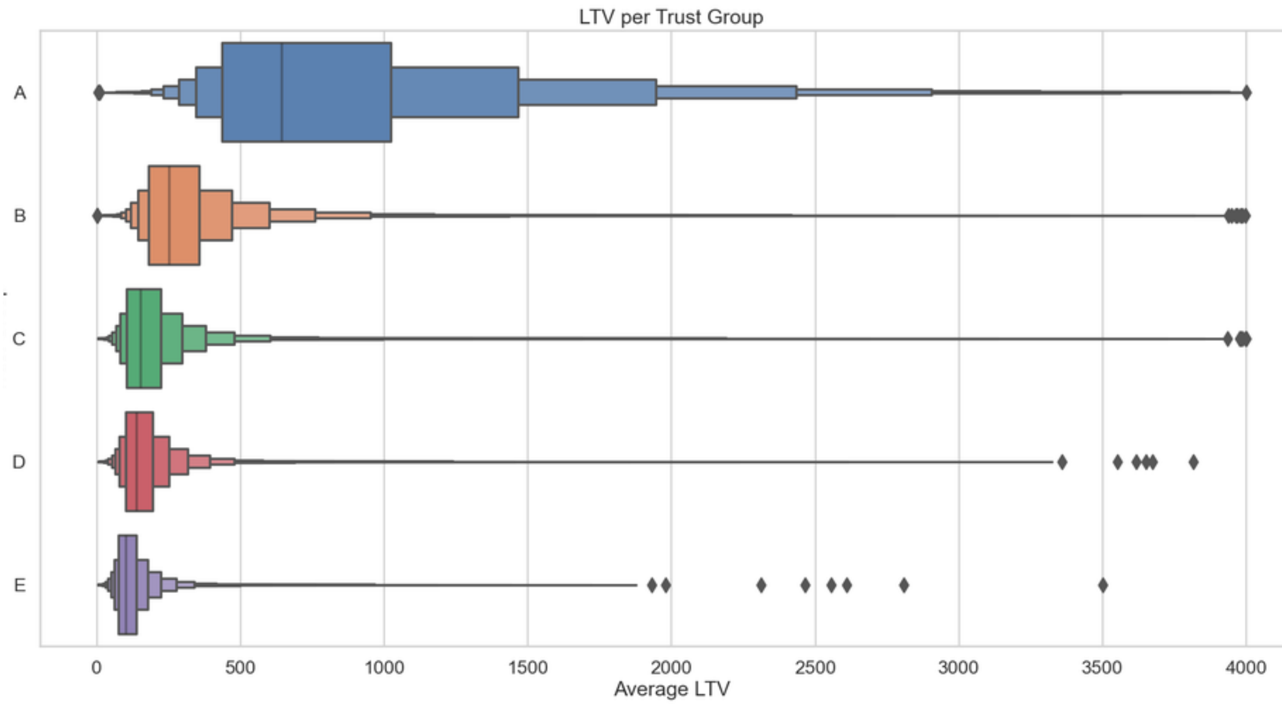
3. Redline Layer

- If ***order count all time*** is greater than 49 and ***feedback ratio*** is smaller than 2%, trust group should not be C ,D or E
- If ***order count all time*** is greater than 99 and ***feedback ratio*** is smaller than 2%, trust group should not be B, C, D or E
- If ***order count all time*** is greater than 49 and ***average CP*** is greater than 50%, trust group should not be C, D or E
- If ***order count all time*** is greater than 99 and ***average CP*** is greater than 50%, trust group should not be B, C, D or E

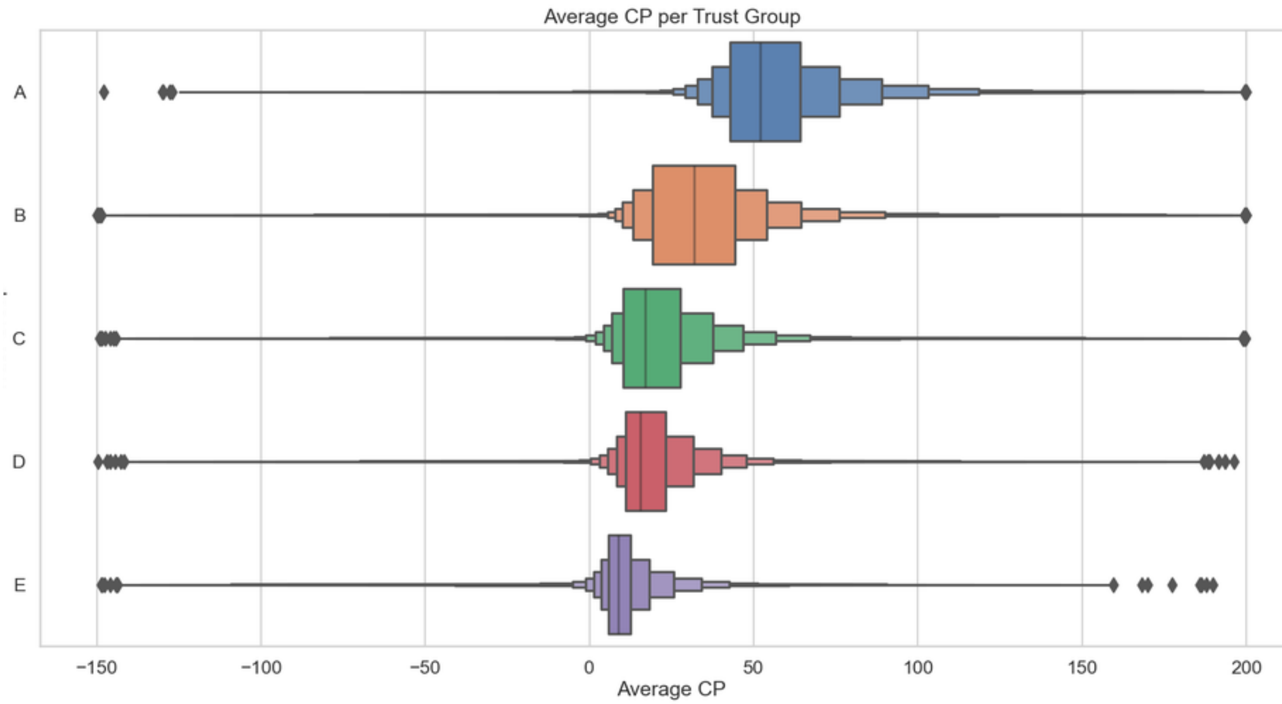
- If ***feedback ratio*** is greater than 10%, trust group should not be A or B
- If ***feedback ratio*** is greater than 50%, trust group should not be A, B or C
- If ***order count all time*** is smaller than 10, trust group should not be A
- If sum of ***total MH discount amount*** and ***total refund amount***, divided by ***total basket amount*** is greater than 25%, trust group should not be A, B or C

Group Stats

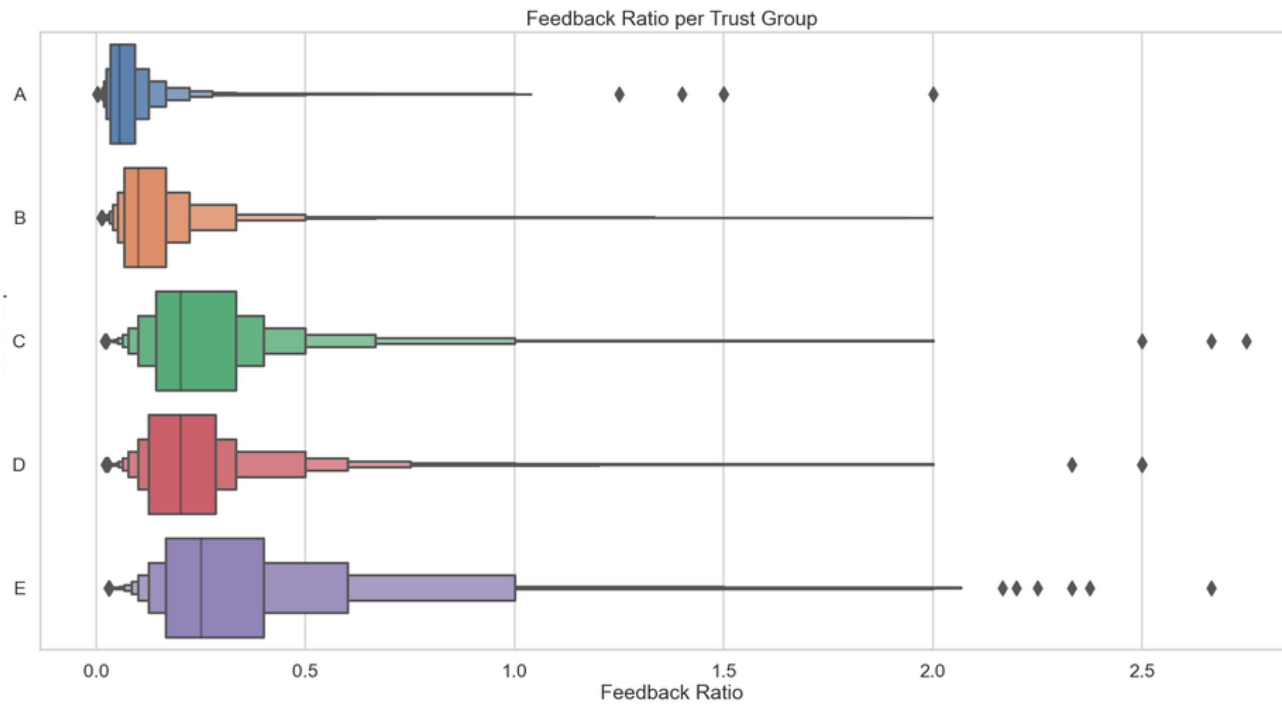
- **LTV**



- **Contribution Profit**

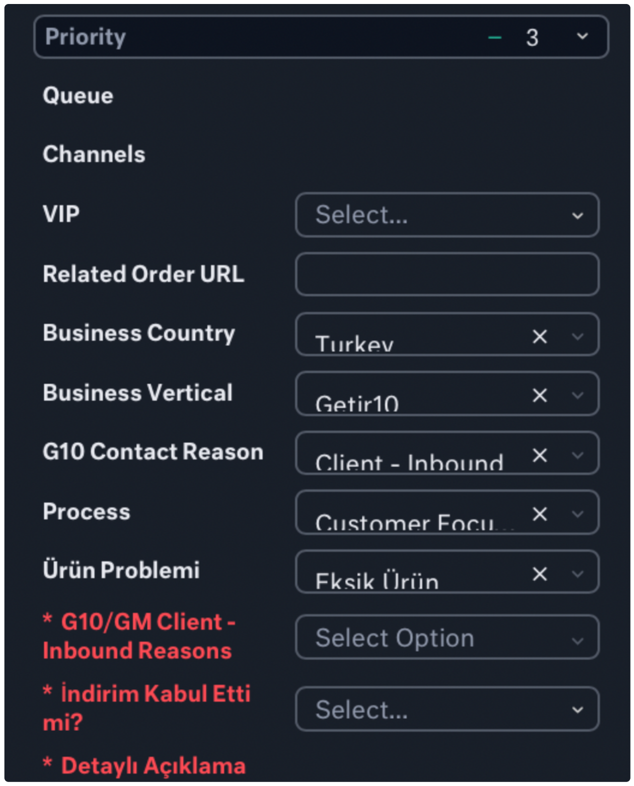


- **Feedback Ratio**



☎ CS Application

Customer services have designed special processes for the application of TS on A,B and E levels separate from the existing ones. Agents do not see a Trust Score in order not to share confidential information about the customers. The processes guide agents for fast resolution or hard monitoring based on the Trust Group. Live chat screens implemented on Kustomer can be viewed from the docs.



“Customer Focused” process based on Market Trust Group A.

Drawbacks

Due to direct influence from business logic during setting segments and rules, there are risks of biases. Below are potential biases and how they are addressed.

- Using persona group as the first and foremost discriminative rule induces bias from marketing objectives.
- High feedback ratio does not necessarily mean abusive behavior. The customer might have had a frequent experience with a low score warehouse.
- LTV prediction for some customers might be misleading. Future valuable customer may not be granted with smooth experience due to low score.
- Repetitive connection to agent might be due to application error or connection failure rather than abusive behavior.

V2

IN PROGRESS…

📅 Releases

Release Name	Value it adds	Scope	Status	Complete date
Rule Based v1	Explainable segmentation.	Calculate a value index through pre-defined rules.	DONE	Oct 10, 2022

👣 Next steps

- Segmentation via unsupervised algorithms. Fine tuning via anomaly detection.
- Merge Domain based scores for a Cross-Domain Trust Score.
- Auto resolution from Bot will be available for discount/refund.

📈 Impact

Key Metrics:

- CSAT scores post agent interaction.
- Refund amount in target groups.
- Feedback frequency in target groups.
- Churn rate in target groups.
- Conversion of the premium group.