Step 1: Dataset analysis

Before I start analyzing I would like to get a first look at the data and to make sure that the dataset has no critical problems.

In [1]:

```
# importing libs that I need
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
df = pd.read_csv('/Users/mac/Downloads/Test.csv - test.csv')
pd.set_option('display.max_columns', None)
```

In [67]:

```
# base check dataset structure
df.head()
```

Out[67]:

	order_id_new	order_try_id_new	calc_created	metered_price	upfront_price	distance	duration	gps_c
0	22	22	2020-02-02 3:37:31	4.04	10.0	2839	700	
1	618	618	2020-02-08 2:26:19	6.09	3.6	5698	493	
2	657	657	2020-02-08 11:50:35	4.32	3.5	4426	695	
3	313	313	2020-02-05 6:34:54	72871.72	NaN	49748	1400	
4	1176	1176	2020-02-13 17:31:24	20032.50	19500.0	10273	5067	

In [65]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4943 entries, 0 to 4942
Data columns (total 26 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   order_id_new           4943 non-null   int64  
 1   order_try_id_new       4943 non-null   int64  
 2   calc_created           4943 non-null   object 
 3   metered_price          4923 non-null   float64
 4   upfront_price          3409 non-null   float64
 5   distance               4943 non-null   int64  
 6   duration               4943 non-null   int64  
 7   gps_confidence         4943 non-null   int64  
 8   entered_by             4943 non-null   object 
 9   b_state                4943 non-null   object 
 10  dest_change_number     4943 non-null   int64  
 11  prediction_price_type  4923 non-null   object 
 12  predicted_distance     4923 non-null   float64
 13  predicted_duration     4923 non-null   float64
 14  change_reason_pricing  298 non-null    object 
 15  ticket_id_new          4943 non-null   int64  
 16  device_token           0 non-null      float64
 17  rider_app_version      4927 non-null   object 
 18  order_state            4943 non-null   object 
 19  order_try_state        4943 non-null   object 
 20  driver_app_version     4943 non-null   object 
 21  driver_device_uid_new  4943 non-null   int64  
 22  device_name            4943 non-null   object 
 23  eu_indicator           4943 non-null   int64  
 24  overpaid_ride_ticket   4943 non-null   int64  
 25  fraud_score            2184 non-null   float64
dtypes: float64(6), int64(10), object(10)
memory usage: 1004.2+ KB
```

In [5]:

```
#checking missing data
df.isna().sum()
```

Out[5]:

```
order_id_new                0
order_try_id_new            0
calc_created                0
metered_price              20
upfront_price            1534
distance                    0
duration                    0
gps_confidence              0
entered_by                  0
b_state                     0
dest_change_number          0
prediction_price_type      20
predicted_distance         20
predicted_duration         20
change_reason_pricing    4645
ticket_id_new               0
device_token             4943
rider_app_version          16
order_state                 0
order_try_state             0
driver_app_version          0
driver_device_uid_new       0
device_name                 0
eu_indicator                0
overpaid_ride_ticket        0
fraud_score              2759
dtype: int64
```

In [63]:

```
#checking duplicates
df[(df.duplicated() == True)]
```

Out[63]:

order_id_new	order_try_id_new	calc_created	metered_price	upfront_price	distance	duration	gps_co

In [66]:

```
#checking general statistics of the dataset
df.describe()
```

Out[66]:

	order_id_new	order_try_id_new	metered_price	upfront_price	distance	duration	gp
count	4943.000000	4943.000000	4923.000000	3409.000000	4943.000000	4943.000000	
mean	2061.074449	2061.074044	7998.471296	4160.095747	9769.223144	1566.230629	
std	1199.298429	1199.299081	15815.850352	17015.711912	10912.426401	1650.329858	
min	0.000000	0.000000	2.000000	2.000000	0.000000	0.000000	
25%	1020.500000	1020.500000	5.380000	4.200000	3785.500000	604.000000	
50%	2065.000000	2065.000000	13.350000	6.600000	7140.000000	1054.000000	
75%	3090.500000	3090.500000	10991.670000	4000.000000	11953.000000	1929.500000	
max	4165.000000	4165.000000	194483.520000	595000.000000	233190.000000	22402.000000	

Step 2: Exploratory data analysis

Generally, I did not see any critical problems with the quality of the dataset. We have a missing data within a few columns - it should be researched. Also, we have no duplicates or sharp changes for most entities in general statistics, it's a good sign.

But I have seen that the median of upfront_price and metered_price have almost twice the difference. Predicted and actual distance and duration have different mean and median as well. It's a reason to dive deeper in these metrics later in this analysis.

One more thing that looks strange for me is max for upfront/metred price. It may be related to different currencies (since we have not only the EU region), but in real life I would check it in documentation or colleagues (the ride with a cost of a half million euros looks scary).

Next, I would like to validate the issue I got in this task.

In [4]:

```
df2 = df[(df['overpaid_ride_ticket'] == 1)]
print(f"{df2.overpaid_ride_ticket.count() / df.shape[0] * 100: .2f}% rides have overpric
df2.head()
```

```
6.82% rides have overpriced problems.
```

Out[4]:

	order_id_new	order_try_id_new	calc_created	metered_price	upfront_price	distance	duration	gps_
3	313	313	2020-02-05 6:34:54	72871.72	NaN	49748	1400	
20	201	201	2020-02-03 21:46:30	18929.92	6500.0	14560	1421	
23	1477	1477	2020-02-15 19:41:47	6000.00	10000.0	2478	372	
24	1825	1825	2020-02-19 19:05:31	12329.22	NaN	8063	1950	
51	1867	1867	2020-02-20 7:26:49	55192.74	NaN	38311	1819	

Observations

We have almost 7% of overpaid rides, which means that almost one of ten riders reported about the problem (especially if we consider that not every rider reports). Definitely not good.

After I got a first look at the data I decided to check distributions of problem rides by gps confidence and geo (EU/not EU).

In [585…

```
df2.groupby(['eu_indicator', 'gps_confidence']).count().order_id_new
print(f"{df2[(df2['eu_indicator'] == 0)].eu_indicator.count() / df2.shape[0] * 100: .2f
print(f"{df2[(df2['gps_confidence'] == 0)].gps_confidence.count() / df2.shape[0] * 100:
print(f"{df[(df['eu_indicator'] == 0)].eu_indicator.count() / df.shape[0] * 100: .2f}% o
print(f"{df[(df['gps_confidence'] == 0)].gps_confidence.count() / df.shape[0] * 100: .2f
```

```
96.14% of overprices rides happened not in EU
59.64% of overprices rides have problem with gps
43.96% of all rides happened not in EU
19.93% of all rides have problem with gps
```

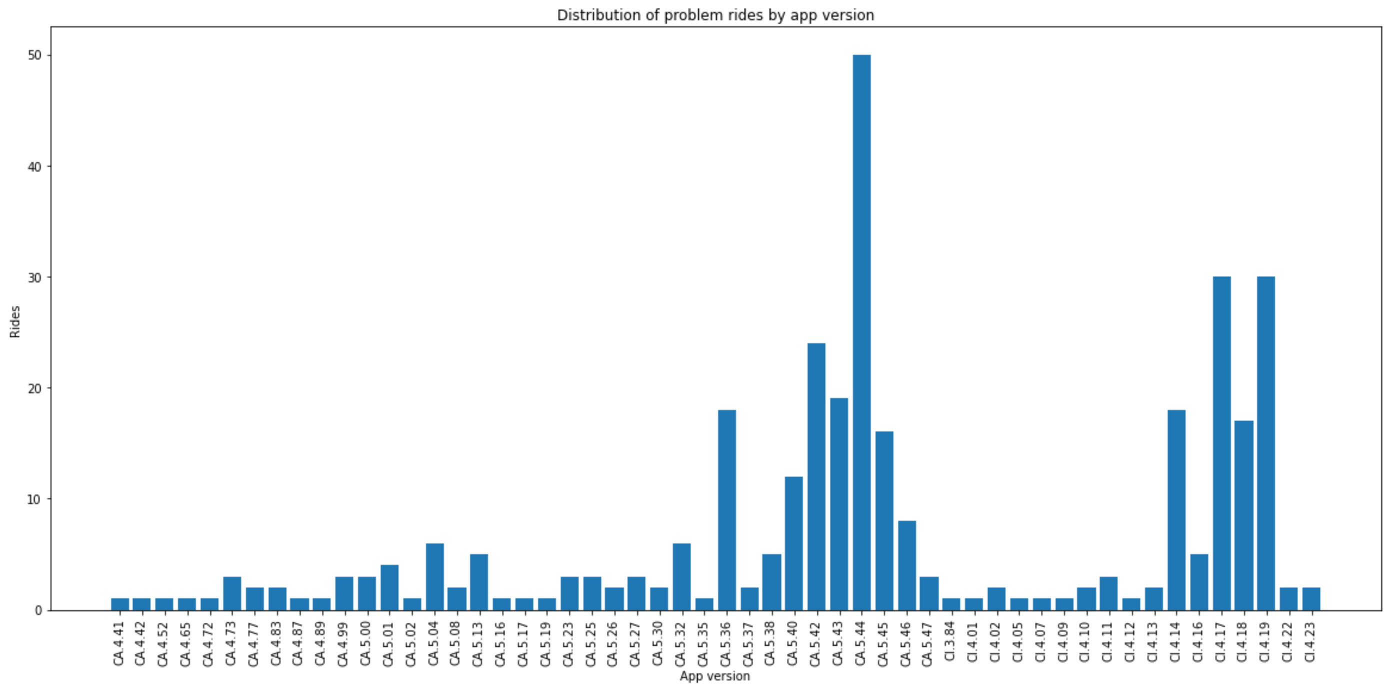
Observations

As the result, I found out that more than 95% of the problem rides happened not in the EU and around 60% have problems with gps.

Also, I would like to check how the problem is distributed by devices and app_version (maybe we released something with a critical bug).

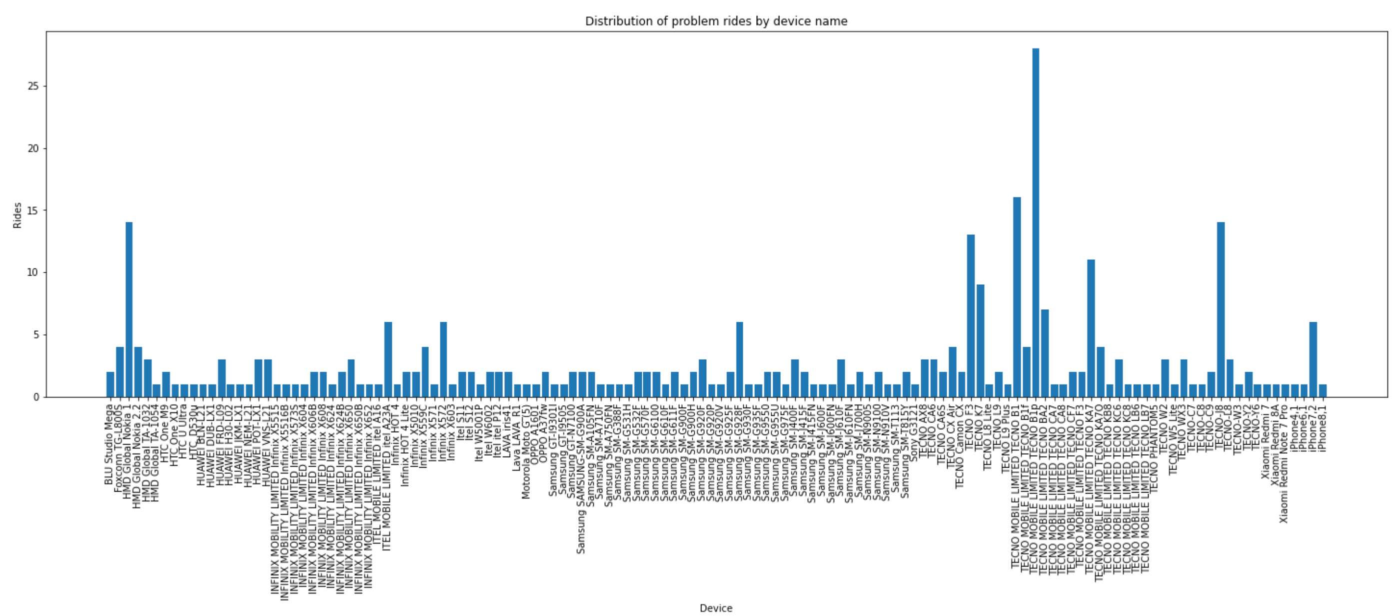
In [524…

```
df7 = df2.groupby(['rider_app_version'], as_index=False).count()
x = np.array(df7['rider_app_version'])
y = np.array(df7['order_id_new'])

plt.figure(figsize=(20,9))
plt.xticks(rotation=90)
plt.xlabel("App version")
plt.ylabel("Rides")
plt.title("Distribution of problem rides by app version")
plt.bar(x, y)
plt.show()
```



In [526…

```python
df7 = df2.groupby(['device_name'], as_index=False).count()
x = np.array(df7['device_name'])
y = np.array(df7['order_id_new'])

plt.figure(figsize=(25,7))
plt.xticks(rotation=90)
plt.xlabel("Device")
plt.ylabel("Rides")
plt.title("Distribution of problem rides by device name")
plt.bar(x, y)
plt.show()
```



Observations

There is some splashes on the graph for named "TECHNO" devices and for a few group of app versions (CA.5.37 - CA.5.47 and CI.4.16 - CI.4.19) and probably we should to look at this case in more details, but generally we see that it is a smooth distribution of the problem.

During the initial check of the dataset I also found out problems with upfront price and I want to dive deeper in this value.

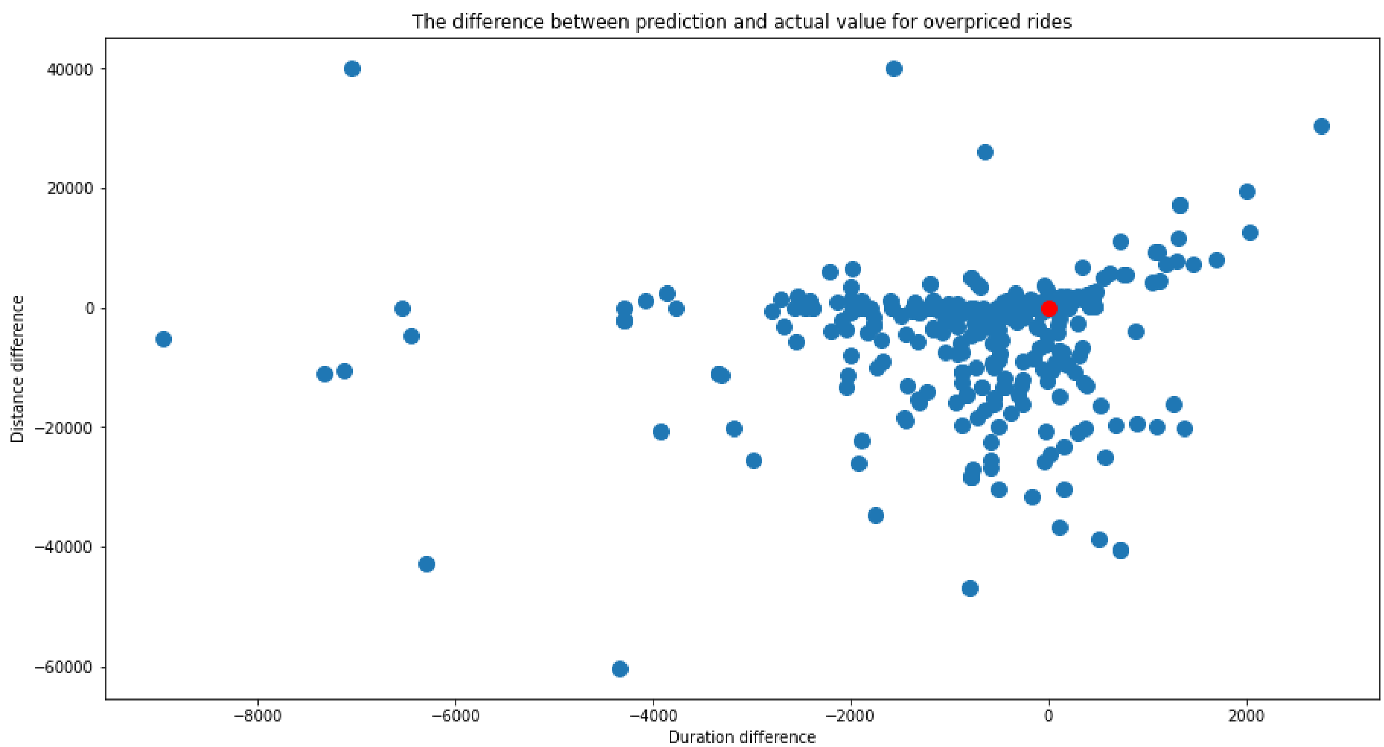
In [550…

```
print(str(round((df2["upfront_price"].isnull().sum() / df2.shape[0] * 100), 2)) + '% of
```

67.95% of overpriced rides have a problem with upfront price

In [552…

```
df3 = df2[['metered_price', 'upfront_price', 'distance', 'duration', 'predicted_distance
df3.loc[:, 'change_duration'] = df3['predicted_duration'] - df3['duration']
df3.loc[:, 'change_distance'] = df3['predicted_distance'] - df3['distance']
x = np.array(df3['change_duration'])
y = np.array(df3['change_distance'])
plt.figure(figsize=(15,8))
plt.scatter(x, y, s=100)
plt.scatter(0, 0, s=100, color="red")
plt.xlabel("Duration difference")
plt.ylabel("Distance difference")
plt.title("The difference between prediction and actual value for overpriced rides")
plt.show()
print(f"{df3[(df3['change_duration'] != 0)].change_duration.count() / df2.shape[0] * 10(
print(f"{df3[(df3['change_distance'] != 0)].change_distance.count() / df2.shape[0] * 10(
print(f"{df3[(df3['change_duration'] < 0)].change_duration.count() / df2.shape[0] * 100:
print(f"{df3[(df3['change_distance'] < 0)].change_distance.count() / df2.shape[0] * 100:
```

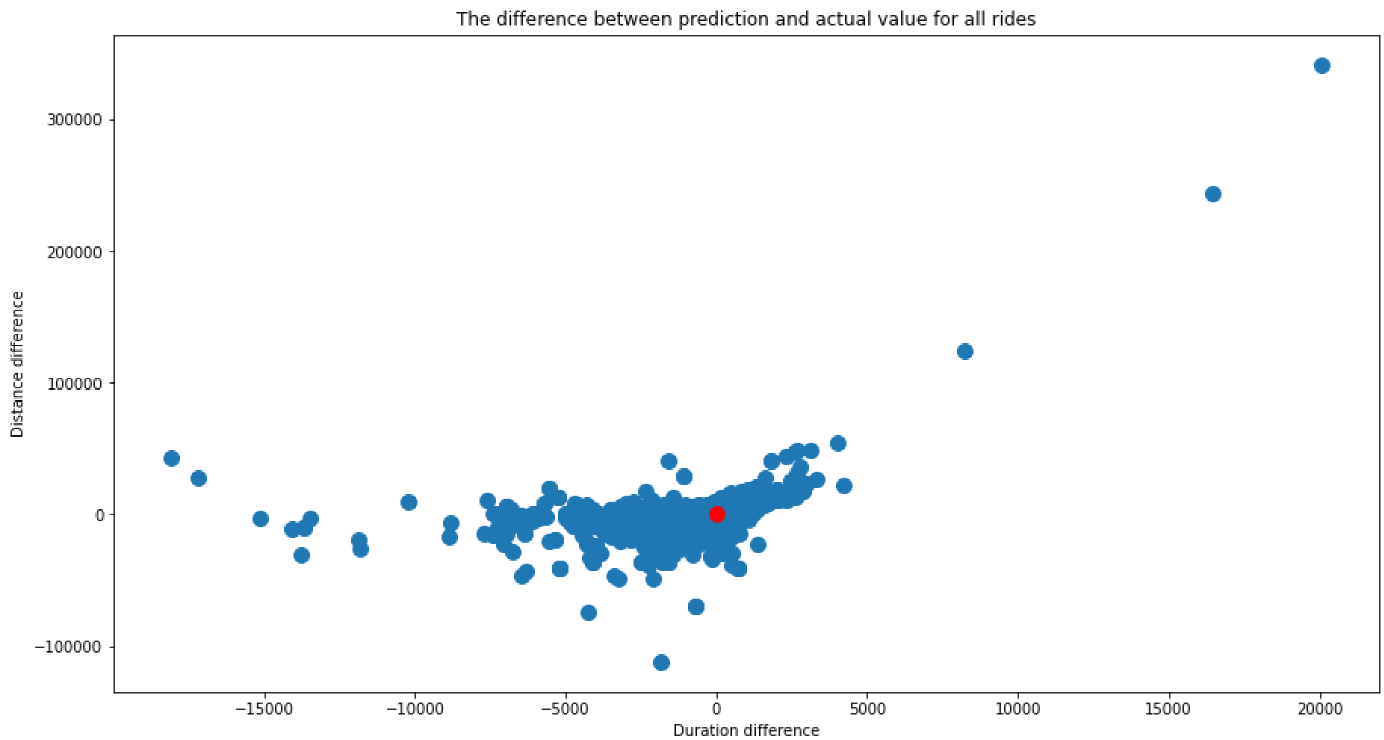



```
100.00% of overpriced rides have problems with duration prediction
89.32% of overpriced rides have problems with distance prediction
72.11% of overpriced rides obtained final duration more than promised
59.35% of overpriced rides obtained final distance more than promised
```

In [554…

```
df4 = df[(df['overpaid_ride_ticket'] == 0)]
df5 = df4[['metered_price', 'upfront_price', 'distance', 'duration', 'predicted_distance
df5.loc[:, 'change_duration'] = df5['predicted_duration'] - df5['duration']
df5.loc[:, 'change_distance'] = df5['predicted_distance'] - df5['distance']
x = np.array(df5['change_duration'])
y = np.array(df5['change_distance'])
plt.figure(figsize=(15,8))
plt.scatter(x, y, s=100)
plt.scatter(0, 0, s=100, color="red")
plt.xlabel("Duration difference")
plt.ylabel("Distance difference")
plt.title("The difference between prediction and actual value for all rides")
plt.show()
print(f"{df5[(df5['change_duration'] != 0)].change_duration.count() / df4.shape[0] * 10(
```

```
print(f"{df5[(df5['change_distance'] != 0)].change_distance.count() / df4.shape[0] * 10(
print(f"{df5[(df5['change_duration'] < 0)].change_duration.count() / df4.shape[0] * 100:
print(f"{df5[(df5['change_distance'] < 0)].change_distance.count() / df4.shape[0] * 100:
```




```
99.37% of rides have problems with duration prediction
96.22% of rides have problems with distance prediction
63.59% of rides obtained final duration more than promised
59.29% of rides obtained final distance more than promised
```

Observation

I checked and compared the difference between predicted distance and duration for all rides as for overpriced rides. It looks like our prediction model works not very well and could be improved. The model has a big scatter for duration in overpriced rides and smaller but still essential scatter for distance of overpriced rides.

The picture looks better for all rides, but has notable problems with duration prediction anyway.

Also, I saw that almost 70% of problem rides have no upfront price. It means that in this case the user does not get the promised price and may report just because he has no price to compare.

This pushed me to the idea to check how many reports without troubles with gps/upfront price we have in not the EU.

In [580…

```
print(str(df2[(df2['eu_indicator'] == 0) & (df2['gps_confidence'] == 0) & (df2["upfront_
```

```
8 rides have been reported but have no visible problems
```

Definitely, we have 8 rides that had been reported as overpriced but had not the reason for this. I suppose that there are just mistakes or misclicks, but just in case it makes sense to check whether we have a problem with price policy in not EU countries.

Insights and hypothesys

- **96% of the problem rides happened in non EU regions** and it would be useful to get more specific details. Even though most overcharged rides have problems, **at least 8 of them have no obvious**

reasons to be reported and I think we should validate the hypothesis about price policy in non EU region.

- **Almost 60% overpriced rides have problems with gps** and this value is twice bigger than for all rides. Considering the previous point and **68% of raids that have problems with upfront price (most likely that means users do not get upfront price)** we can say that it relates things. Also, I detected splashes of the problem on some types of devices and app's versions. **I suggest conducting technical research** of these problems together with the engineering team.

- Also, **I may suppose the prediction model is very noisy** as it has problems with distance prediction and even bigger problems with duration prediction. On graphs we can see that most cases have a negative difference between predicted and actual value. That means users get promised duration/distance less than actual after the ride. That may affect the user experience too. Probably, we should communicate with the ML team and discuss this theme.