

Setting up ML Projects:
forecasting customers
lifetime value

Yandex

Outline

- Intro to unit economics
- Discussing parts of ML project
 - Setting the goal
 - Getting data
 - Modelling
 - Deployment

Yandex

Intro to unit economics

Background

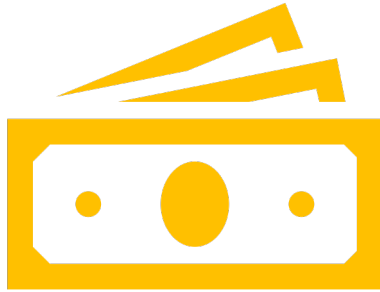
- Yandex has a lot of customers both private person and businesses.
- LTV pipeline is implemented for both types of customers.

| **Unit economics** – a calculation of profit and loss for a particular business model on a per-unit basis. Basically, it tells you how much value each item or unit creates for the business.

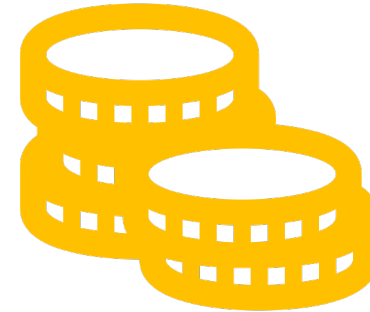
| Unit = 1 client / user

The goal

- Estimate the effectiveness of sales and distribution channels.



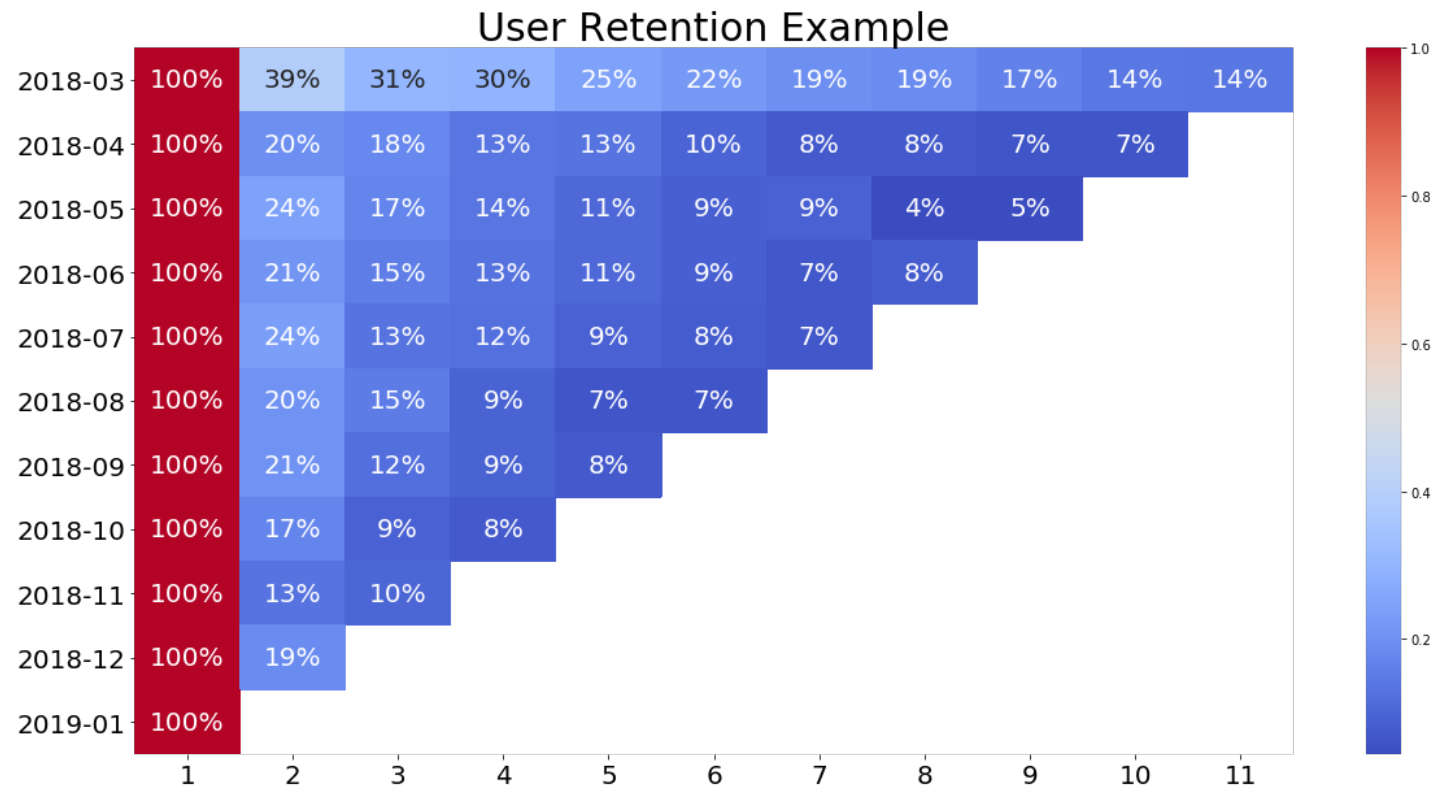
Assess the financial value of each customer.



In other words: How much do we earn from 1 customer

Definitions

- **Cohort** – a group of users, who made target action at the same time.



Definitions

- **LTV** (Life Time Value) – all the value that customer bring to the company for the whole period of his/her life
- When we talk about customer acquisition we keep in mind costs and payback time of invested money. Usually this period is 1 year.
- **CAC** (Customer Acquisition Costs) – total money spent on the customer acquisition divided by number of customers
- **ROI** = LTV / CAC – return on invested capital

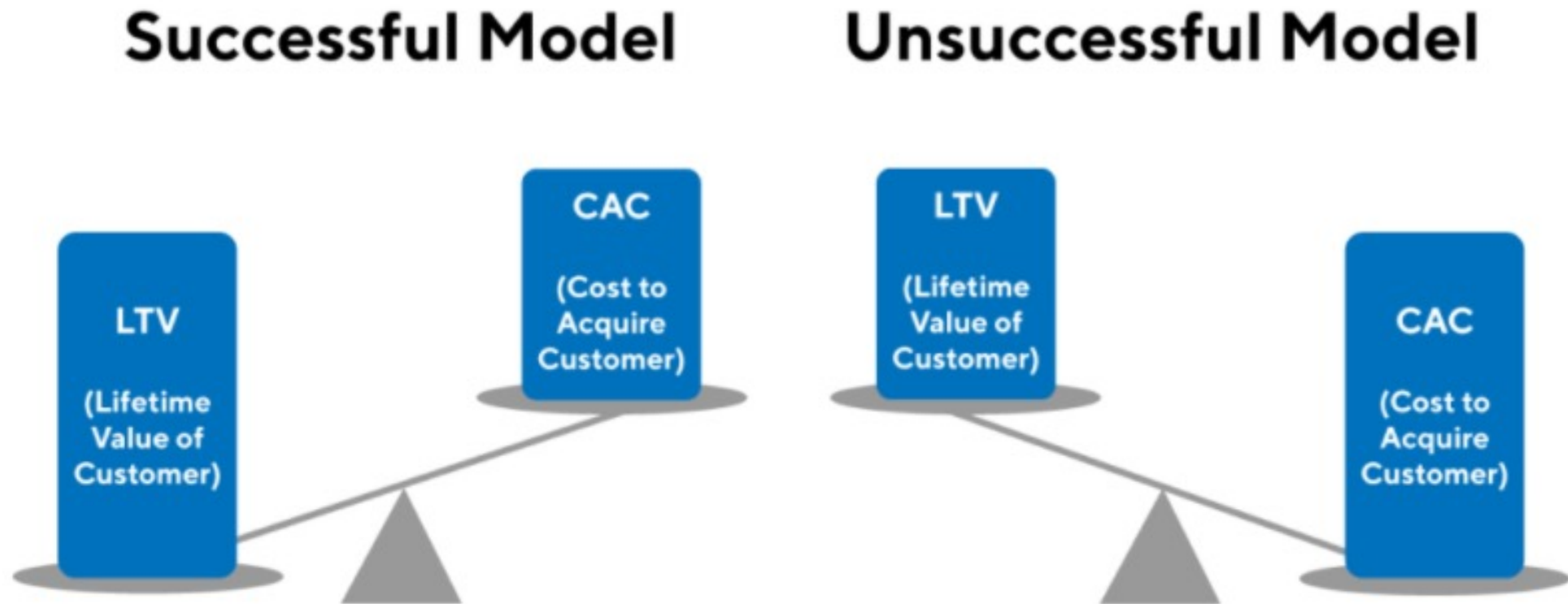
- **ROI** = LTV / CAC – return on invested capital
- CAC – is visible at the moment of acquisition
- LTV – longer indicator (have to wait some time or forecast)

Why

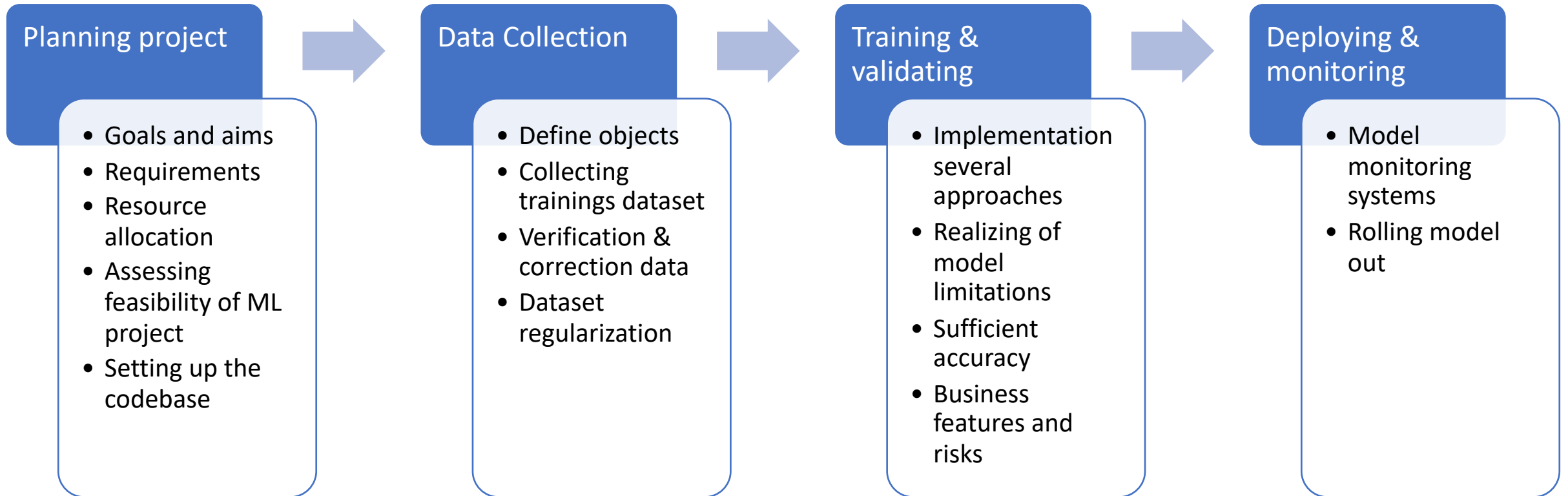
- Transparent argumentation for investments we do: explainable to CFO & CMO
- Comparison of customer acquisition channels
- Comparison of different products
- Comparison user cohorts in time (old vs new)

channel	activations	costs	CAC	LTV 365	ROI 365	LTV 60	ROI 60
cold sales	934	100000	107.06638	110000	1.1	15000	0.15
emails	459	45781	99.740741	38748	0.84637732	4649.76	0.10156528
pre-installs	781	8543	10.93854	7549	0.88364743	1509.8	0.17672949
total	2174	154324	70.986201	156297	1.01278479	21159.56	0.13711127

Importance of business model



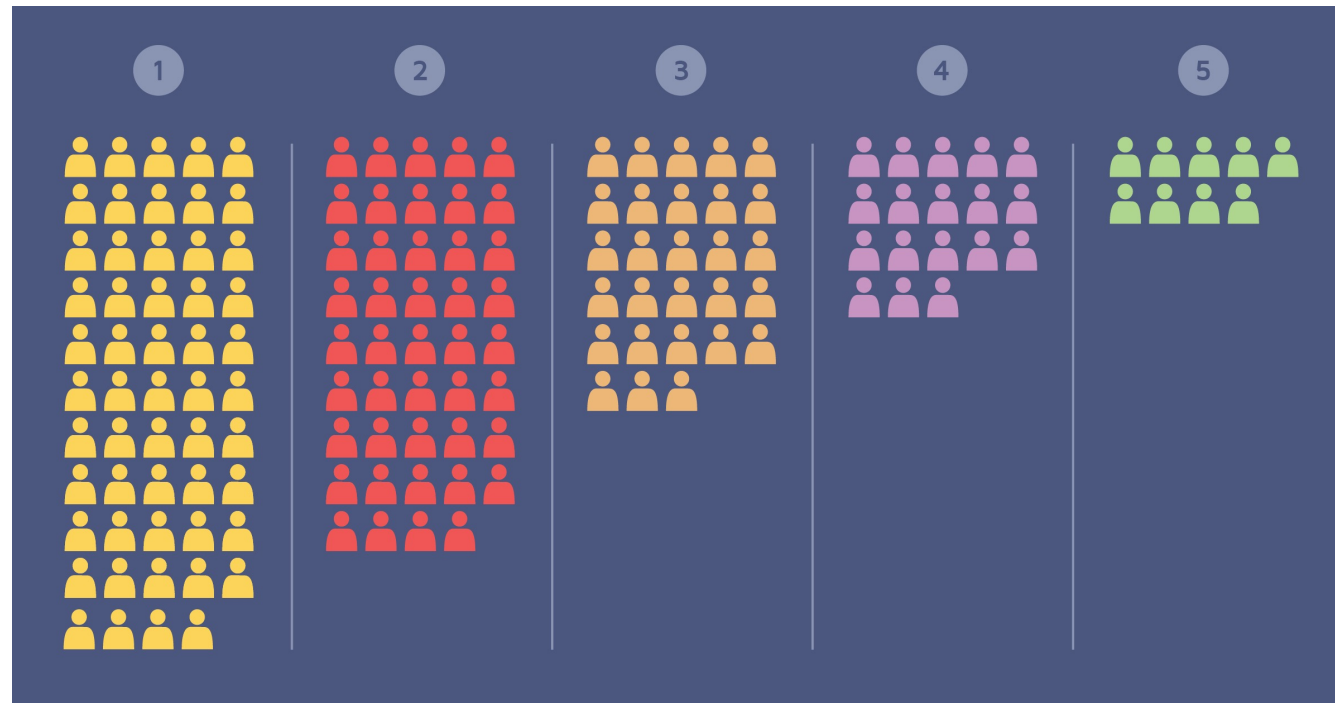
Machine learning project: life cycle



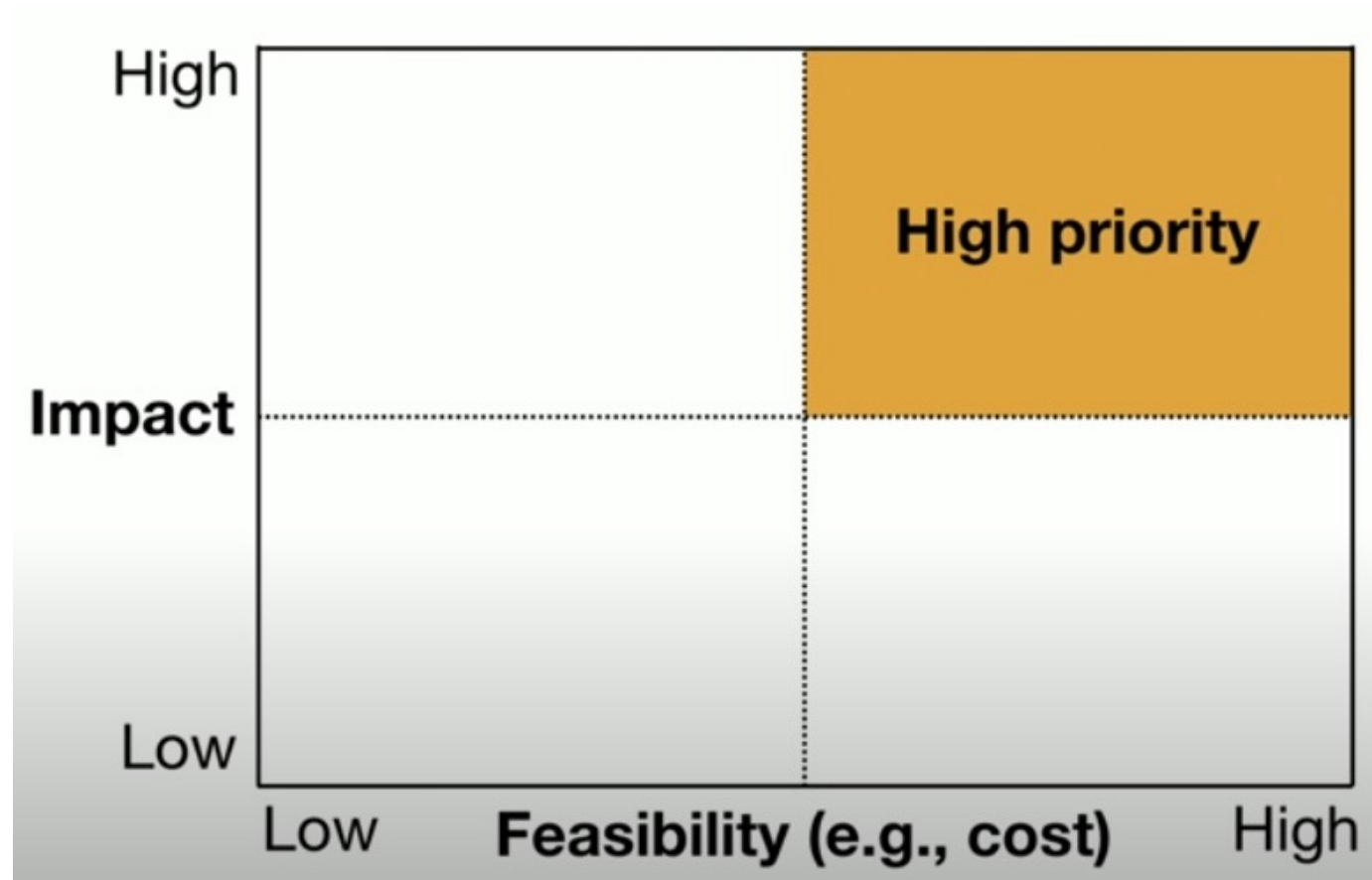
Planning project

Requirements

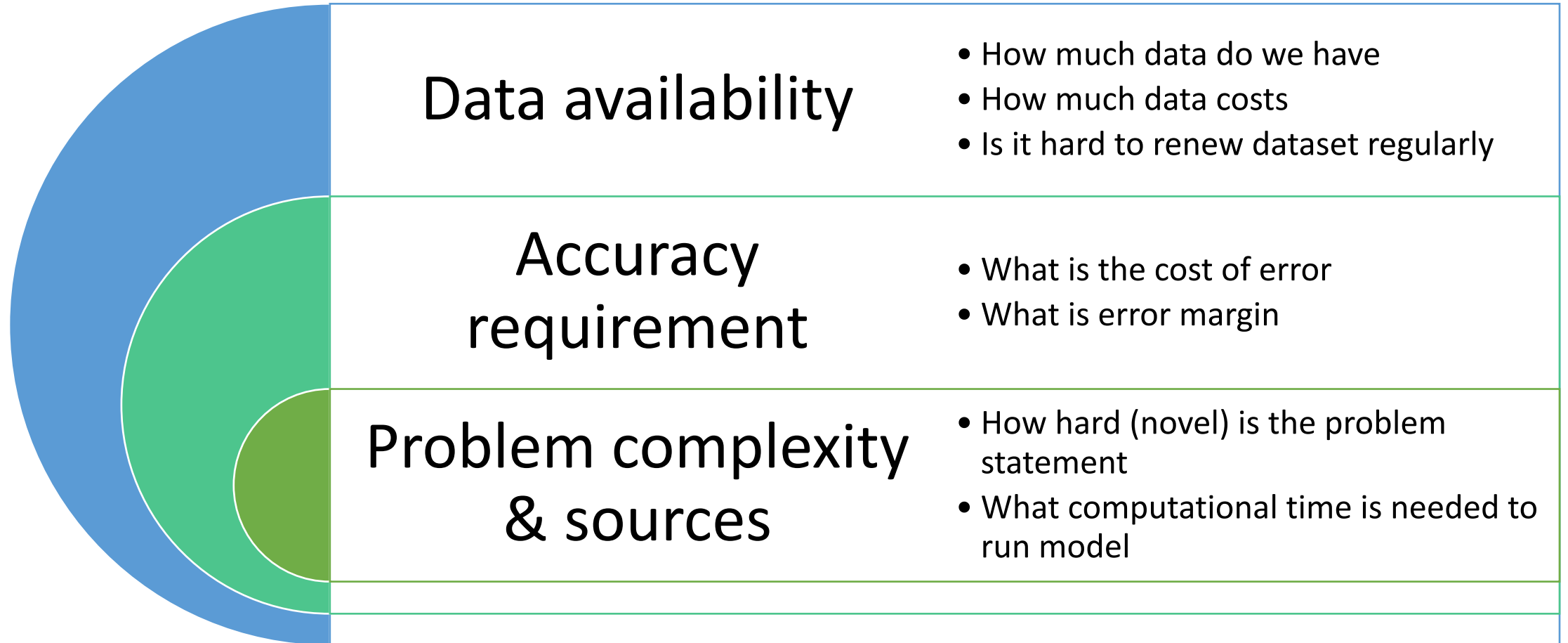
- Forecast of LTV at 365 and 60 days from event (may be activation or current date)
- Interested in cohort forecast (average of user-forecasts)
- Accuracy requirements (better than baseline)
- SLA: daily calculations, delays are critical



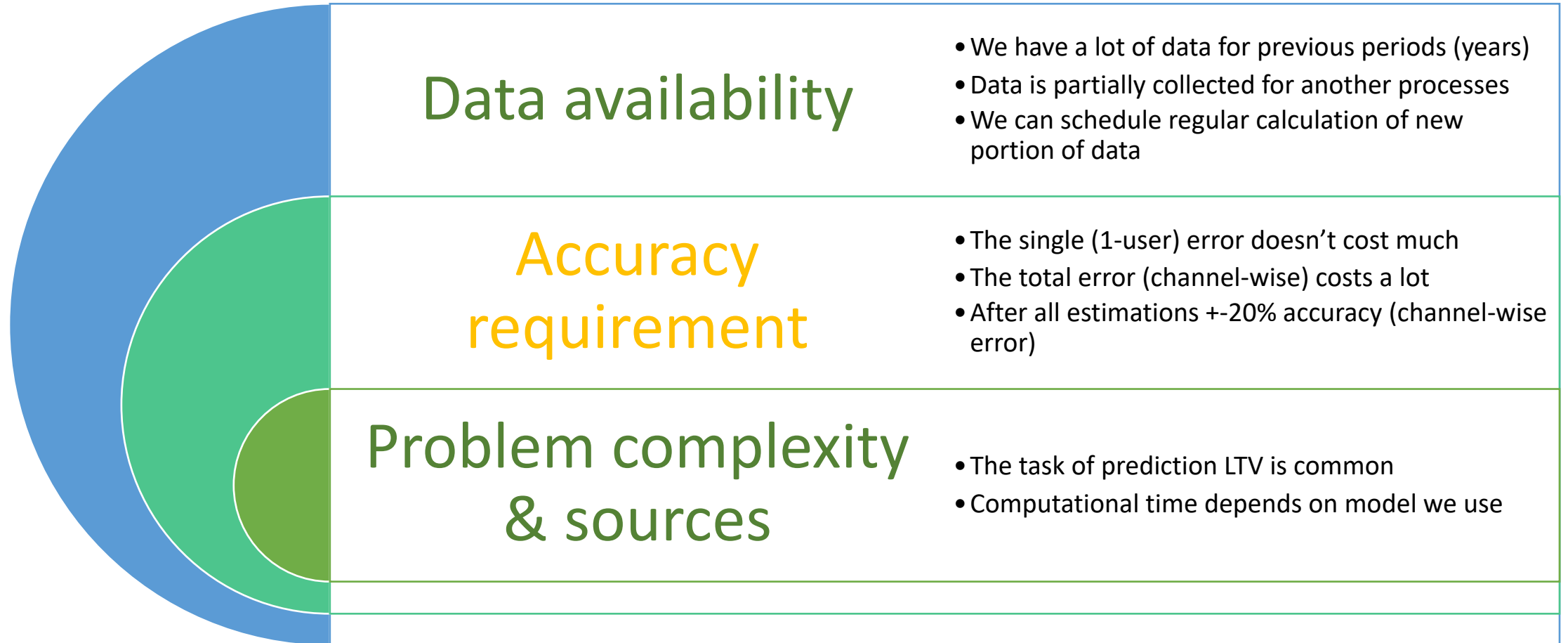
Prioritizing projects



Feasibility of ML project



Feasibility of ML project: LTV prediction



Why do we need accuracy

- **ROI** = LTV / CAC

New service
Low CAC

Mature service
High CAC



low accuracy
requirement

high accuracy
requirement

it may be enough
if we guess only
magnitude of LTV

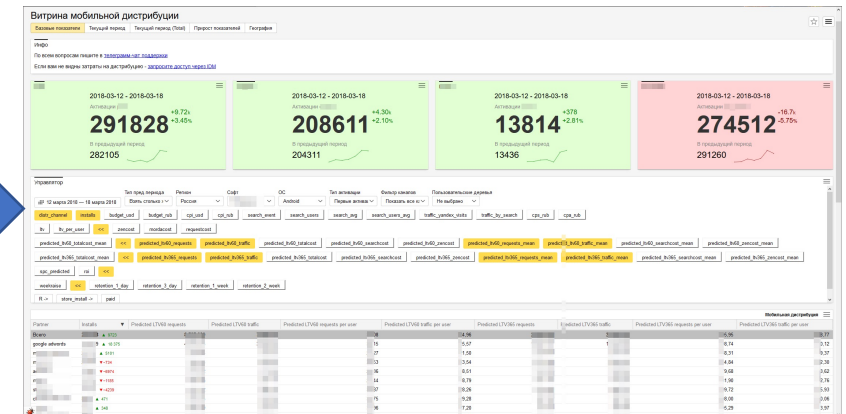
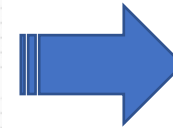
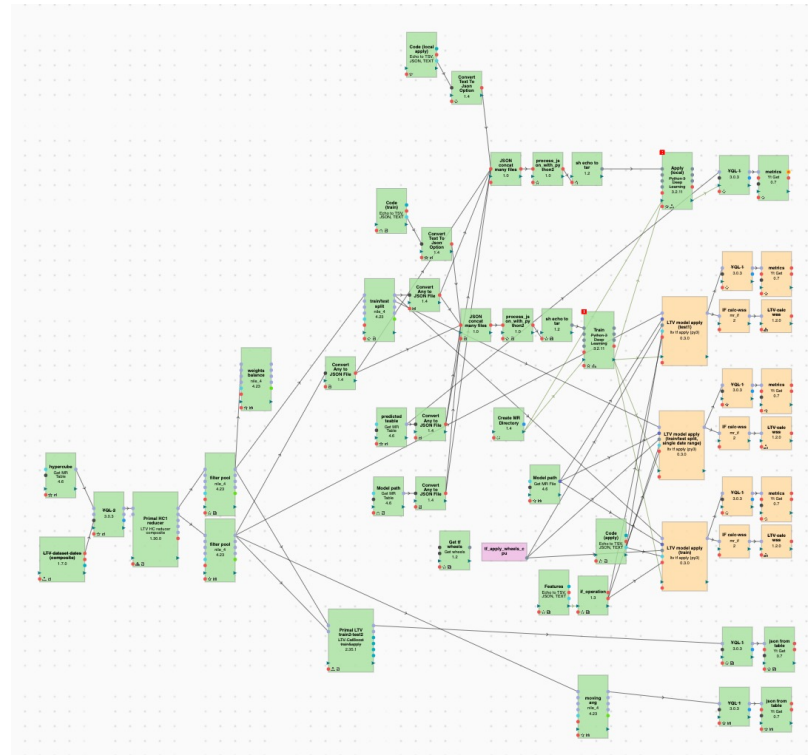
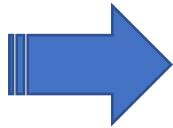
We compete for every
percent of ROI -> need
precise LTV forecast

Setting up the codebase

- MapReduce (Yandex cluster, inhouse solution)
- Python (libraries: CatBoost, TensorFlow)
- Cloud workflow platform (inhouse solution)
- Scheduler (inhouse solution)

Workflow

New dataset arrives



Scheduler

Data preparation and model

Dashboards

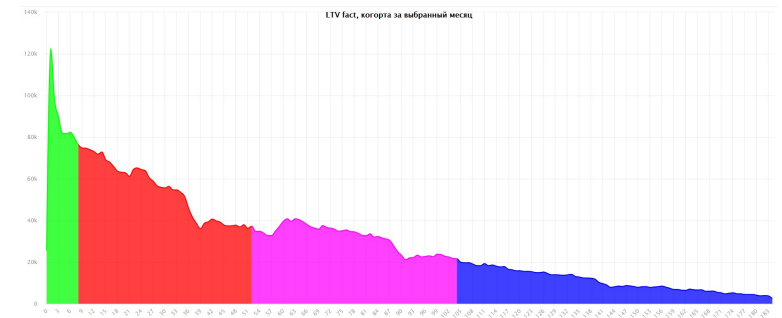
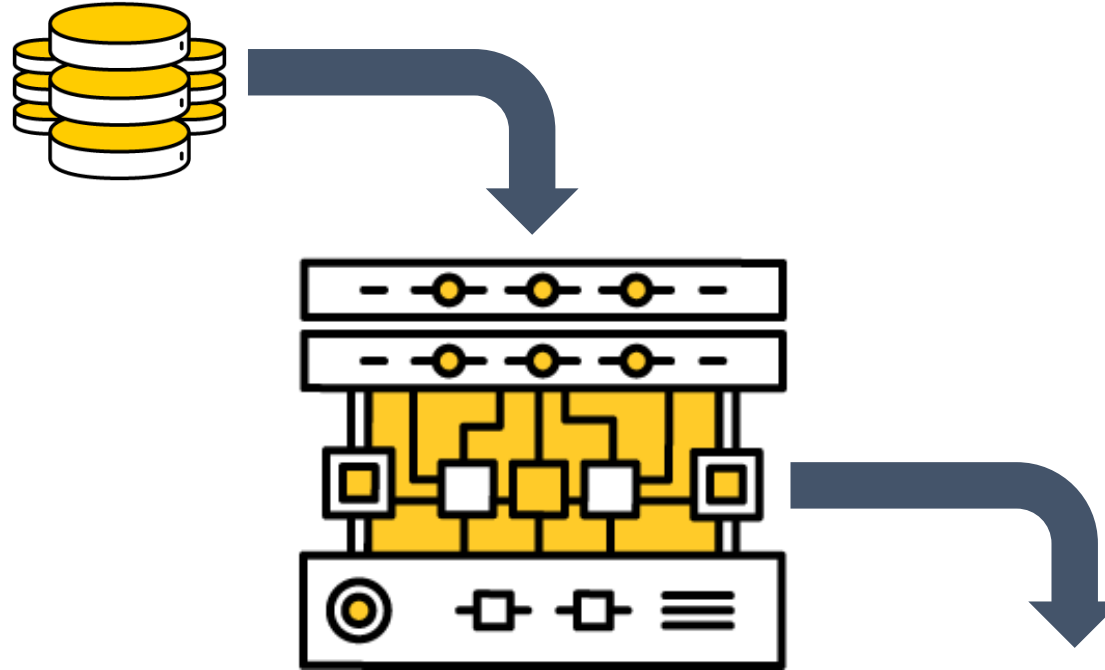
Planning summary:

- We are interested in cohort LTV forecast
- Project seems to be feasible:
 - We have necessary data
 - We have existing baseline
 - LTV is clear metrics to predict

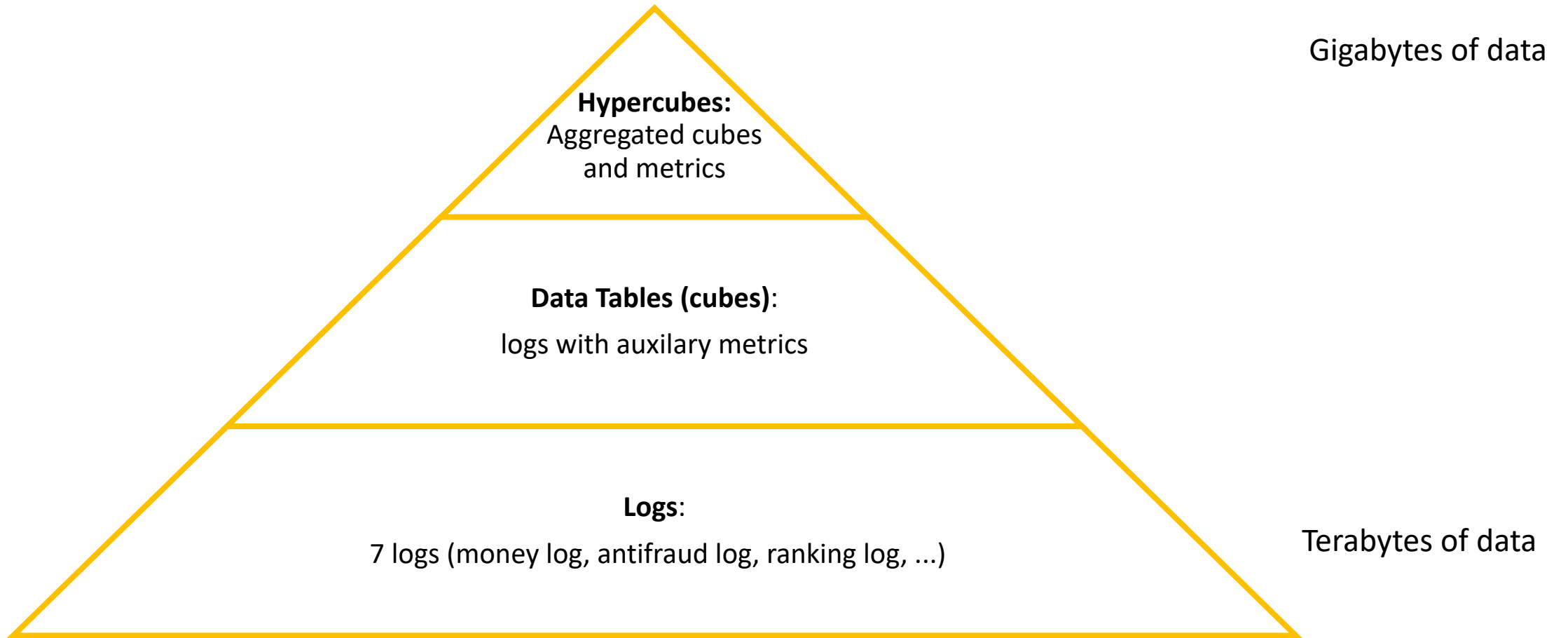
Data collection

Technical architecture

- In:
 - Aggregated data tables
- Out:
 - LTV forecasts (by user)
 - Logs (errors, metrics, ...)
- After:
 - Dashboards
 - Tables with predictions



Raw model data



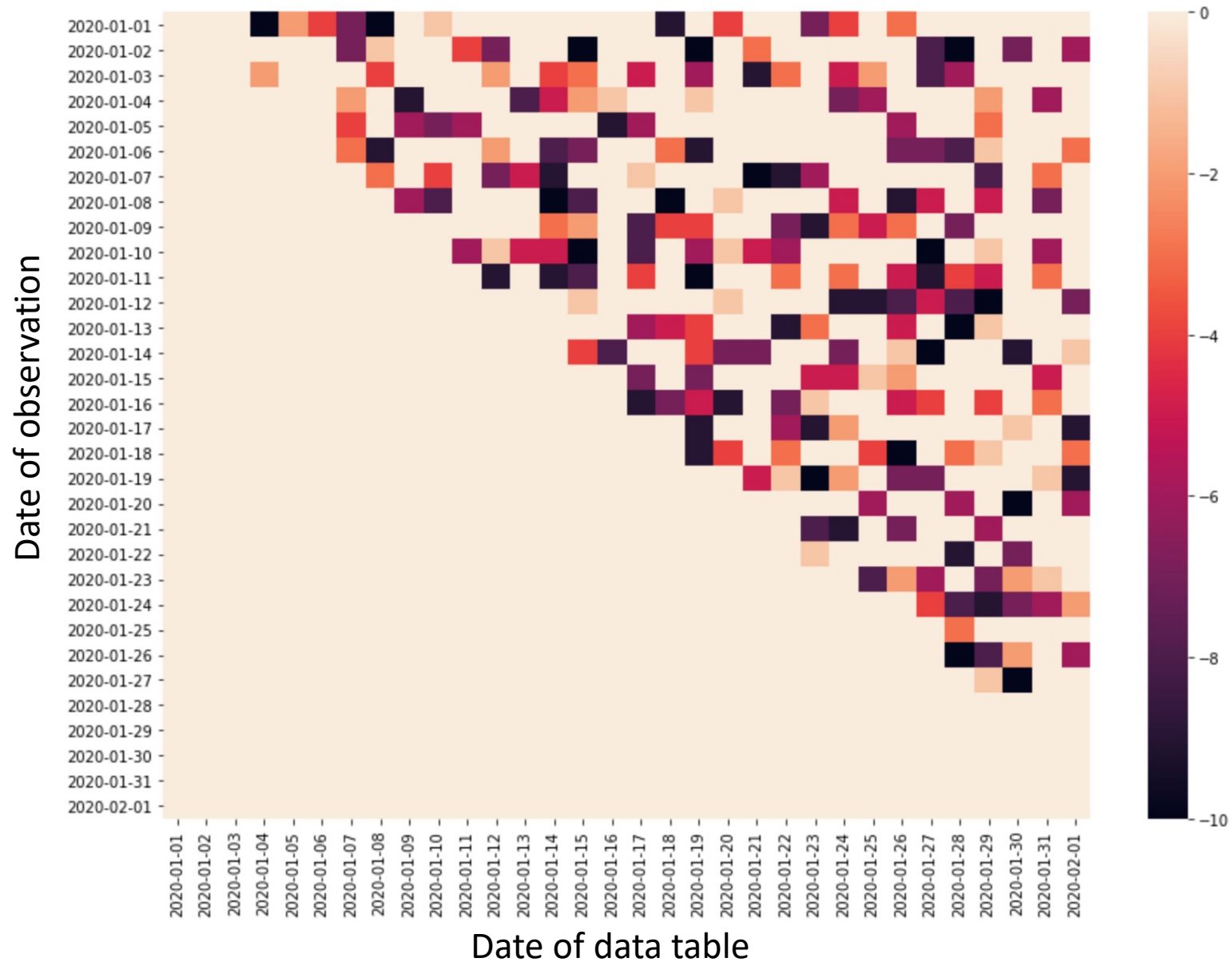
Raw data is subject to change

- ~90 days to arrive new data:
 - Fraud
 - Errors in collection pipeline
 - Logical errors

Monitoring of differences in data: 2-dimensional representation of time

- 1st Dimension: date of event
 - E.g., activation cohort
- 2nd Dimension: calculation date
 - Forecast logging
 - Calculation and storing differences in fact data
 - “2D” monitorings (index data with tuple
 <date of observation, date of data table>
)

Monitoring of differences in data: 2-dimensional representation of time



Общие наблюдения за качеством ЛТВ

- 1. DWH имеет значение
- 2. Учитывайте все САС вашего бизнеса, включая неявные (альтернативные)
- 3. Автоматически обновляйте прогнозы
- 4. Следите за показателями в динамике
- 5. Иногда больше фичей – хуже

Data collection summary

- Data pipeline matters!
- New portion of data can correct the old one -> need to live with this
- Collect as much features as it is possible -> extra features can be easily removed

Training and validation

Training and validation: baseline

Baseline – simple approach that gives lower bound for expected model performance.

Good practice: set existing approach as baseline.

First baseline is moving average for N previous periods:

$$Money_i = \frac{\sum_{prev} Money}{N}$$

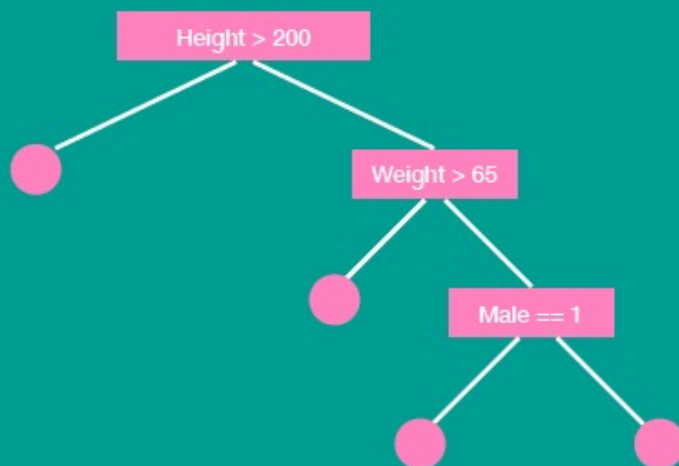
RMSE (baseline) = 3795

Training and validation: Model v.1



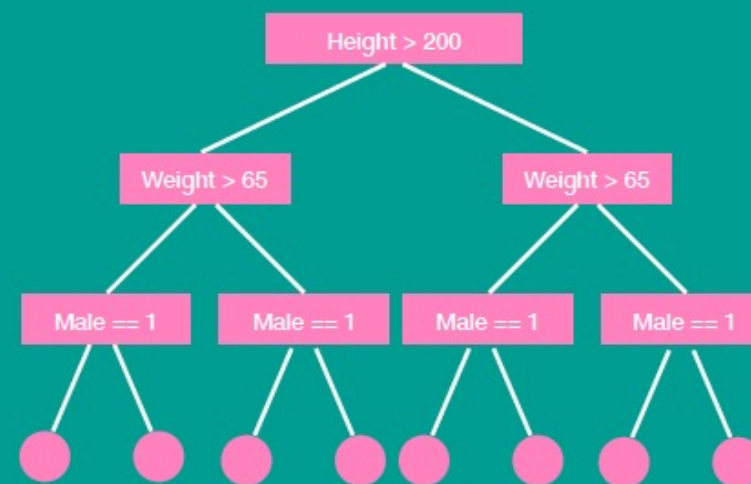
Yandex
CatBoost

Asymmetric trees



**XGBoost
LightGBM**

Oblivious trees



CatBoost

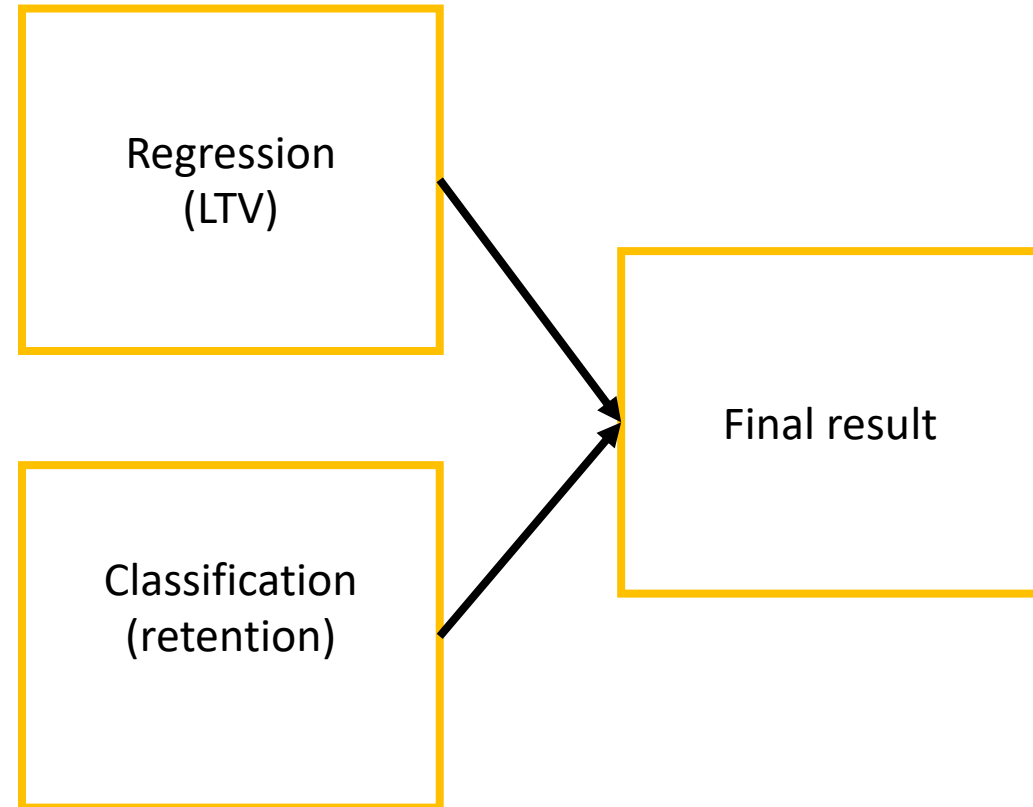
Model v.1 structure



1st step: solve regression problem to estimate LTV

2nd step: solve classification problem to estimate if customer is going to pay or not

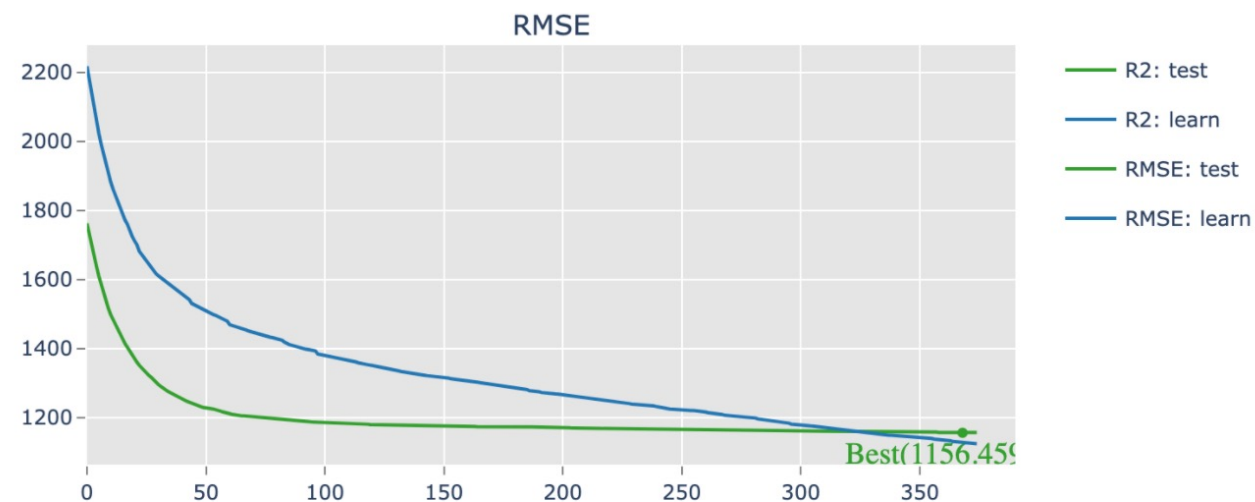
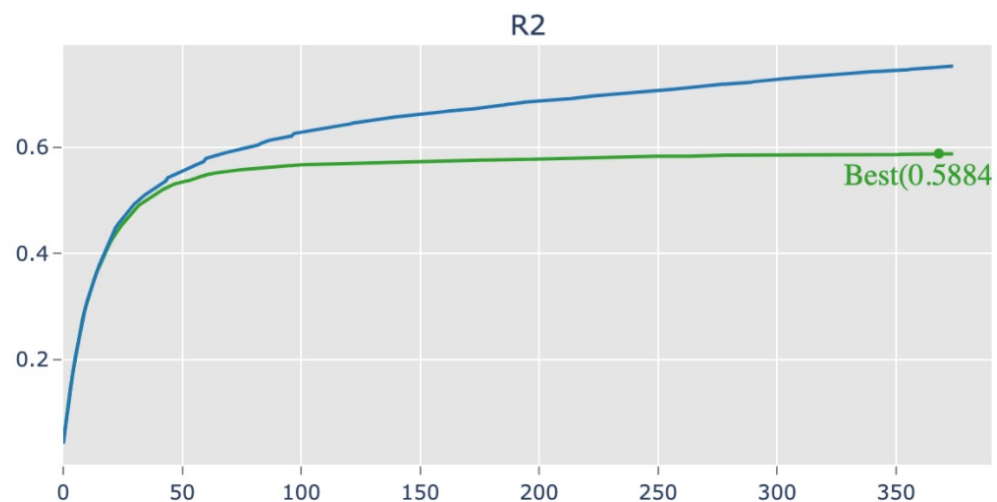
3rd step: combine these prediction in Final result



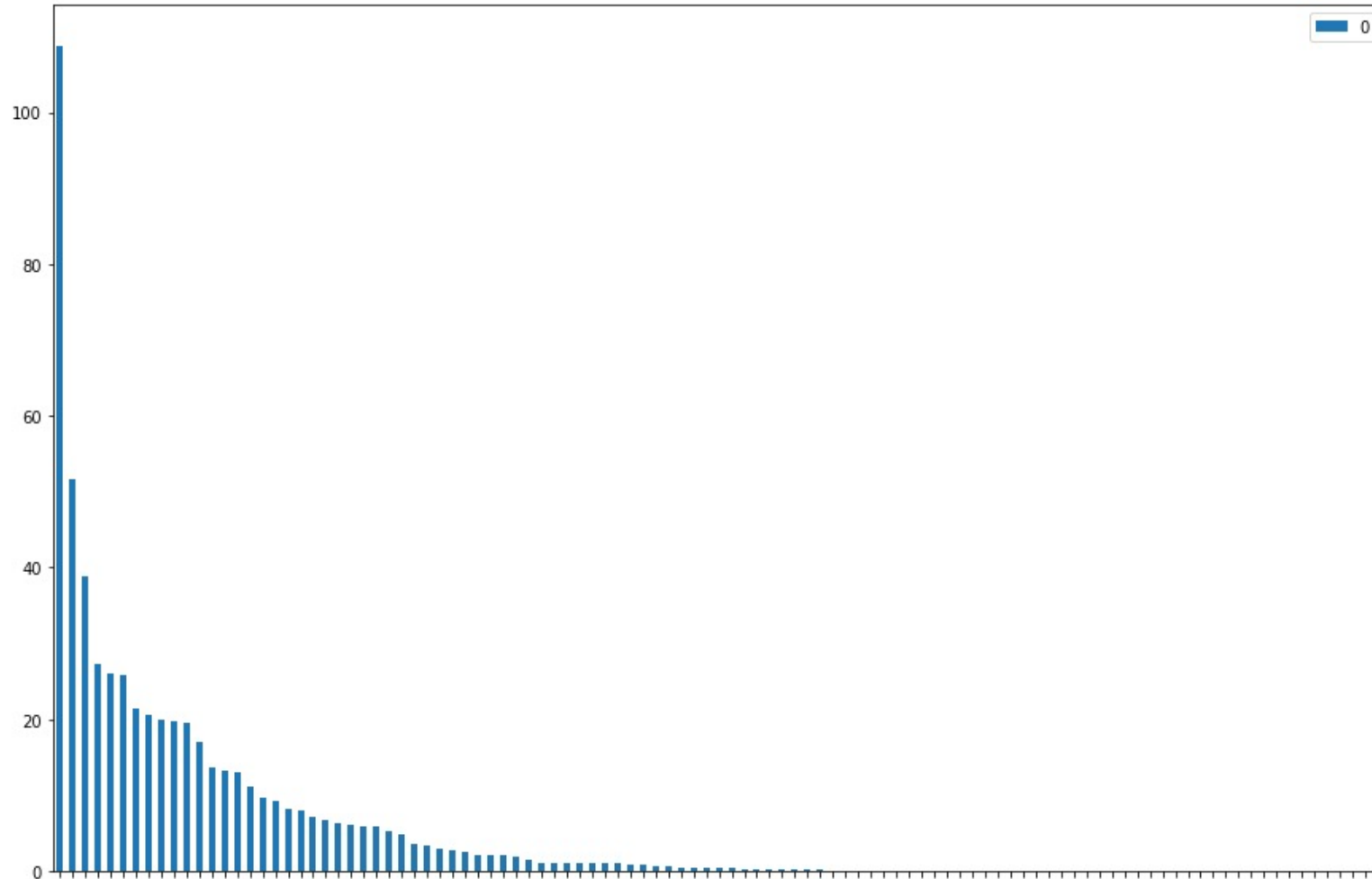
Metrics

For training we use RMSE. For reporting MAPE.

Best Values
R2: test(0.588482)
RMSE: test(1156.459549)



Feature importance regression



Heavily relies on features that correspond volume of previous activities

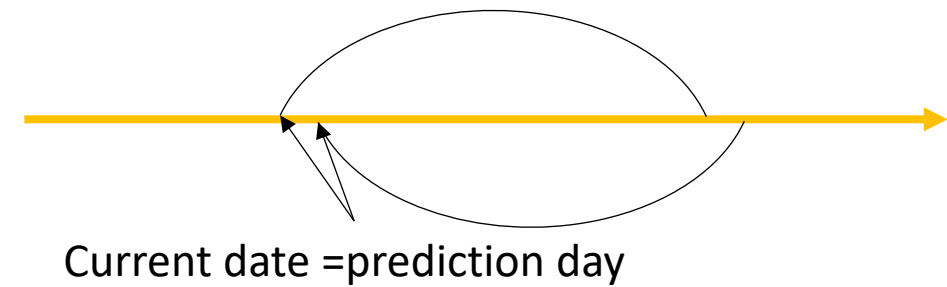
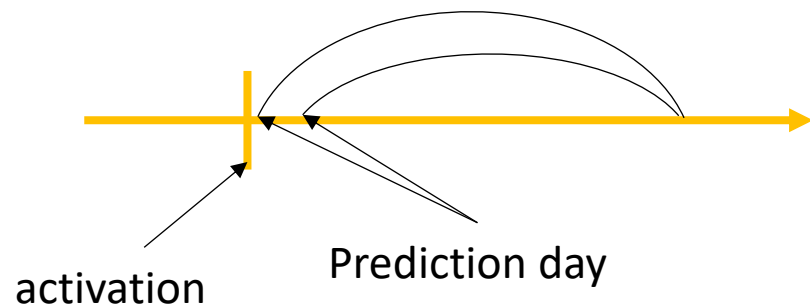
Feature importance classification



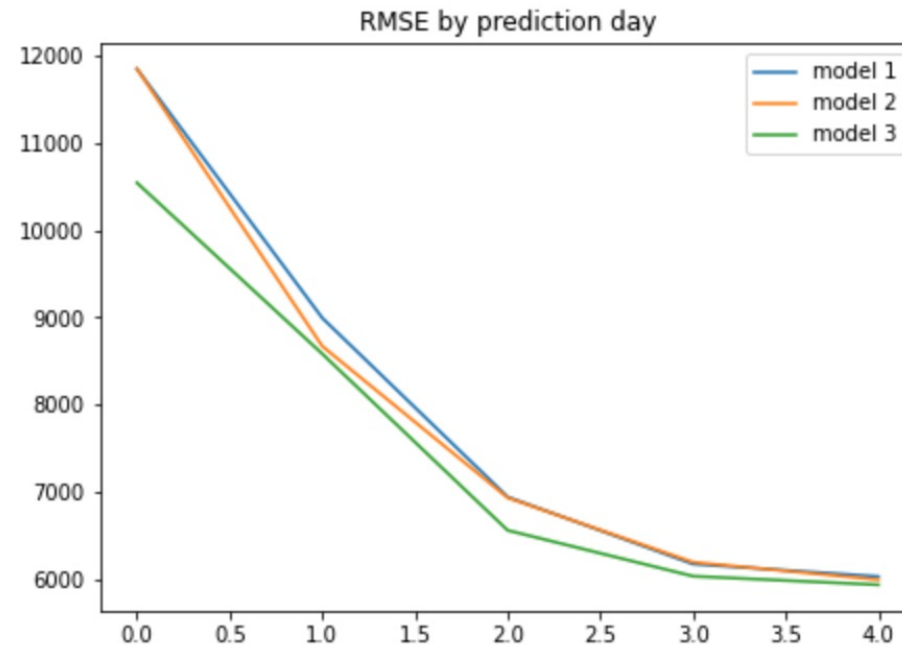
Heavily relies on features that correspond fact of previous activity

Parameter optimization

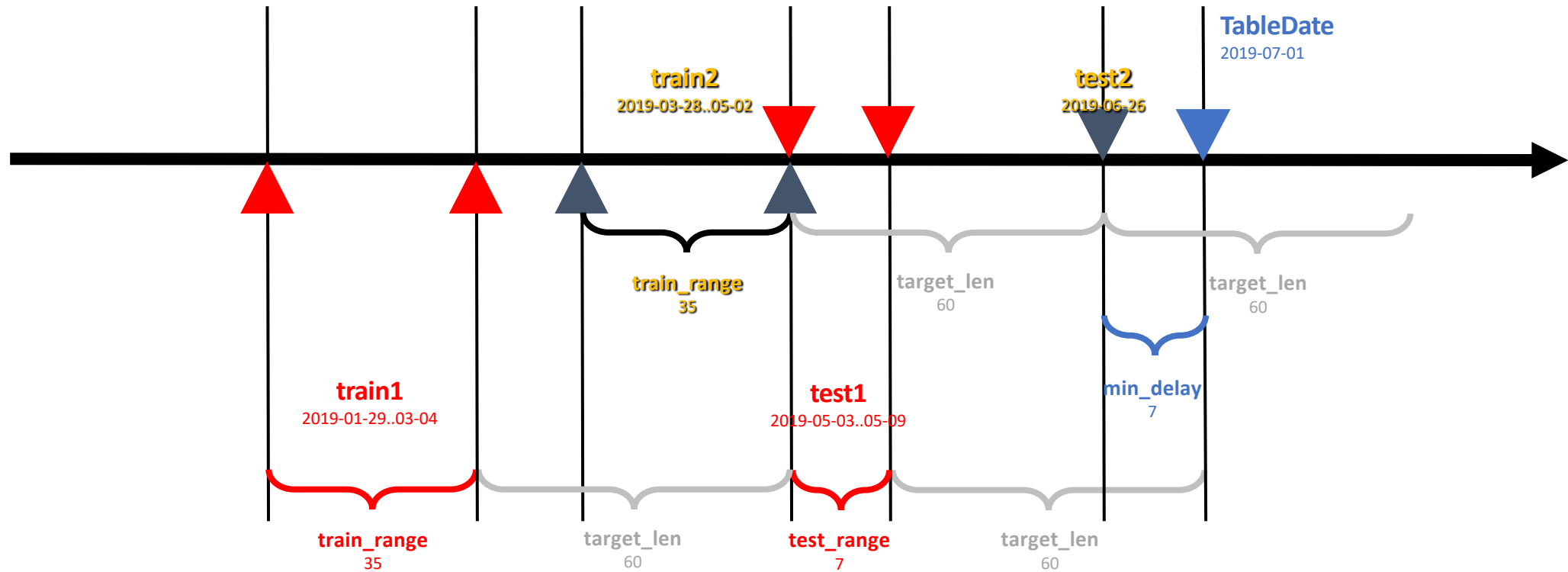
2 scenarios:



- Predict only the rest of window
- We get more accurate predictions for latest dates
- The value of predictions in first days is greater than in last days



Training and validation



Quality improvement retrospective

- Good quality at large channels (many samples)
- Poor quality at tiny channels (few samples)
- Solutions:
 - Add more features (geo, channel-attributes, social features) – FAILED
 - Smart sampling procedure (pick diverse samples – from different channels) – SUCCESS
- Reduce number of features: from 320+ to 80

Training and validation: Model v.2



- Baseline: CatBoost model
- RMSE improved: 30% less than CatBoost

These are metrics for old clients:

RMSE CatBoost	RMSE TF model
3795	2651

Quality of forecast in time

- The data can be modified (due to various things) -> we have to recalculate forecasts
- Log previous forecasts “for the record”



Training and validation summary

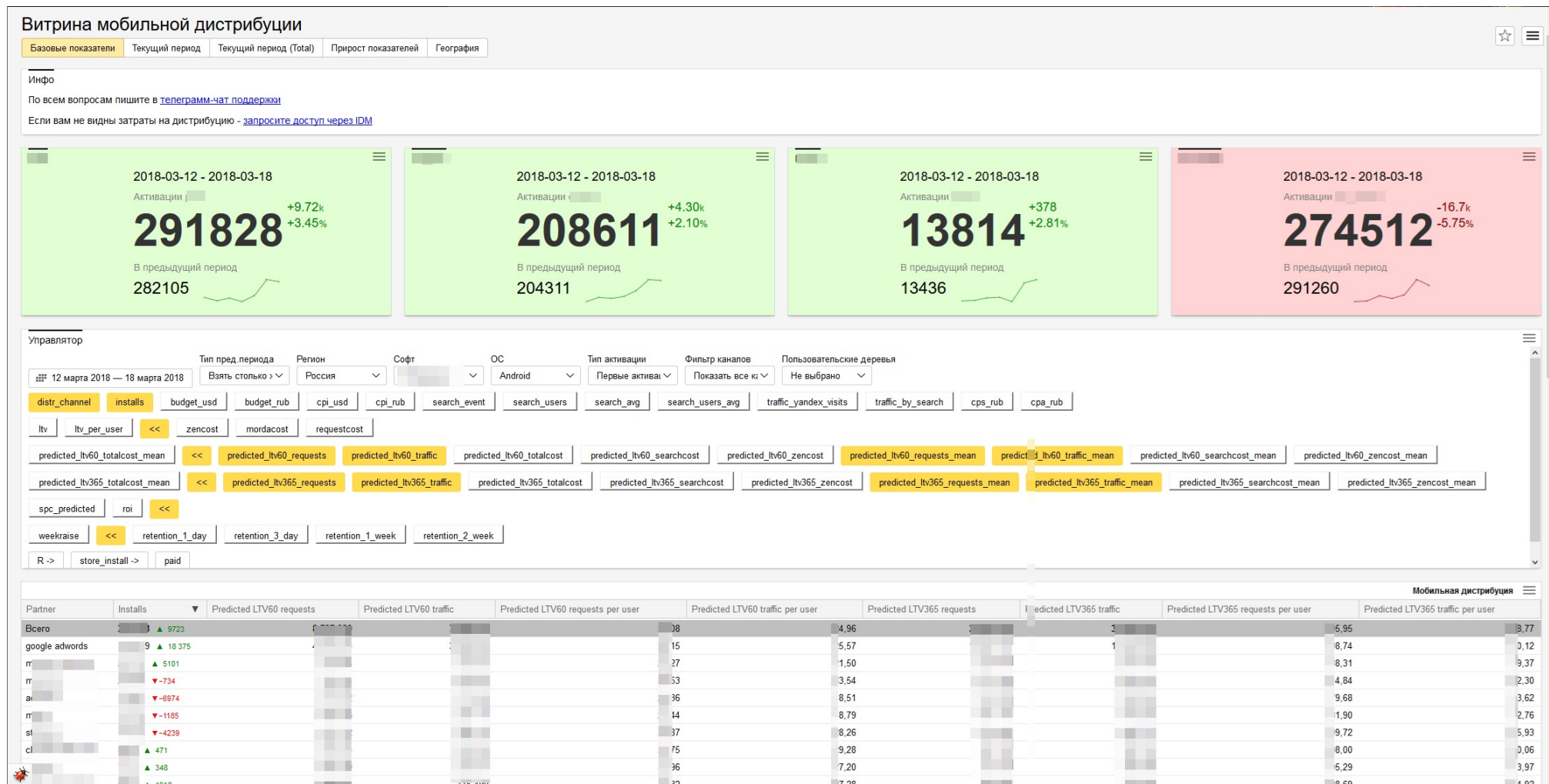
- Baseline matters!
- Not only train and validate model but go through scenarios of pipeline (data modifications in history, SLA, ...)

Deploying and monitoring

Monitoring

- Cases:
 - Anomalies in data
 - Create metrics linked to data (e.g. number of rows in dataset, average value in columns, ...)
 - Monitor this metrics behavior (deviation from usual values, length of this deviation, ...)
 - Data structure changes
 - Changes are significant and model calculation fails – good scenario, we immediately check this problem;
 - Changes don't lead to computational failure -> we don't see this
 - Not enough computing power
 - restart

Dashboards



Other scenarios

- We provide our user based forecasts for a lot of purposes:
 - Validating hypothesis (A/B without control)
 - Planning headcount
 - Calculating dynamics

Deploying model

- Monitor your solution!
- Provide results in people-friendly format :)