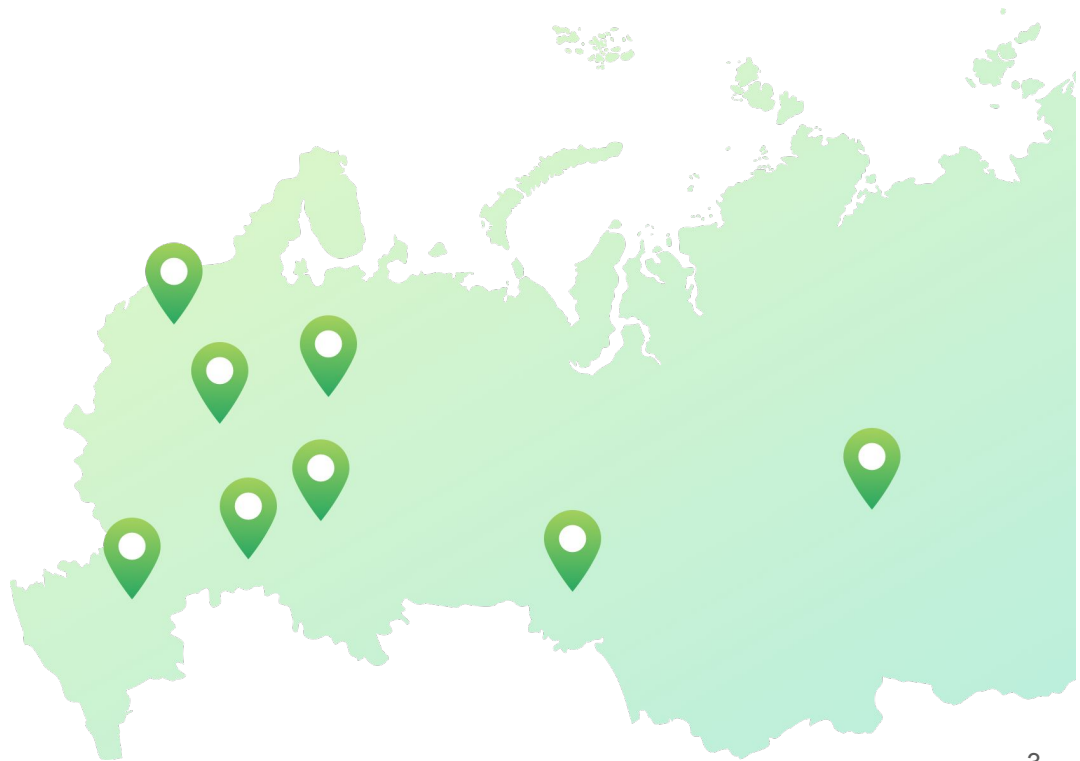


Predicting customers' next purchases





About us



Sbermarket operates in 157 cities across the country

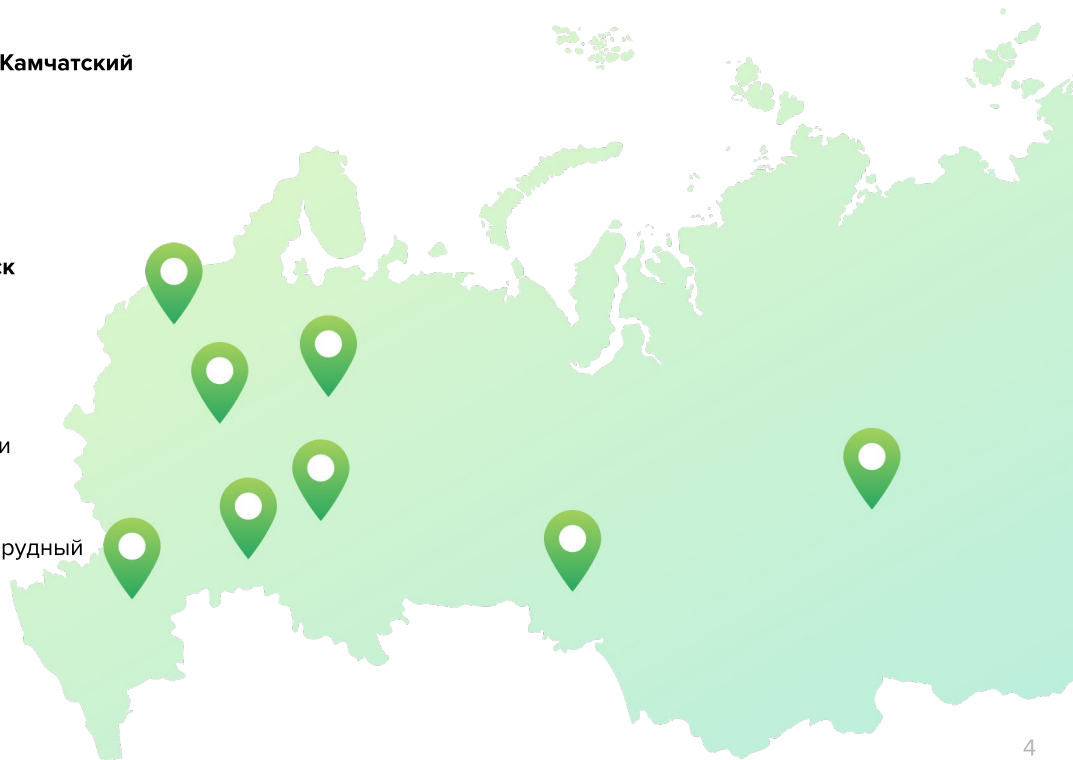
Москва
Санкт-Петербург
Волгоград
Воронеж
Екатеринбург
Казань
Краснодар
Красноярск
Нижний Новгород
Новосибирск
Омск
Ростов-на-Дону
Самара
Уфа

Челябинск
Пермь
Тюмень
Калининград
Рязань
Иркутск
Сургут
Владимир
Тверь
Ярославль
Тула
Калуга
Благовещенск
Псков

Петрозаводск
Чита
Улан-Удэ
Чита
Владивосток
Петропавловск-Камчатский
Анадырь
Горно-Алтайск
Хабаровск
Магадан
Элиста
Южно-Сахалинск
Якутск
Биробиджан

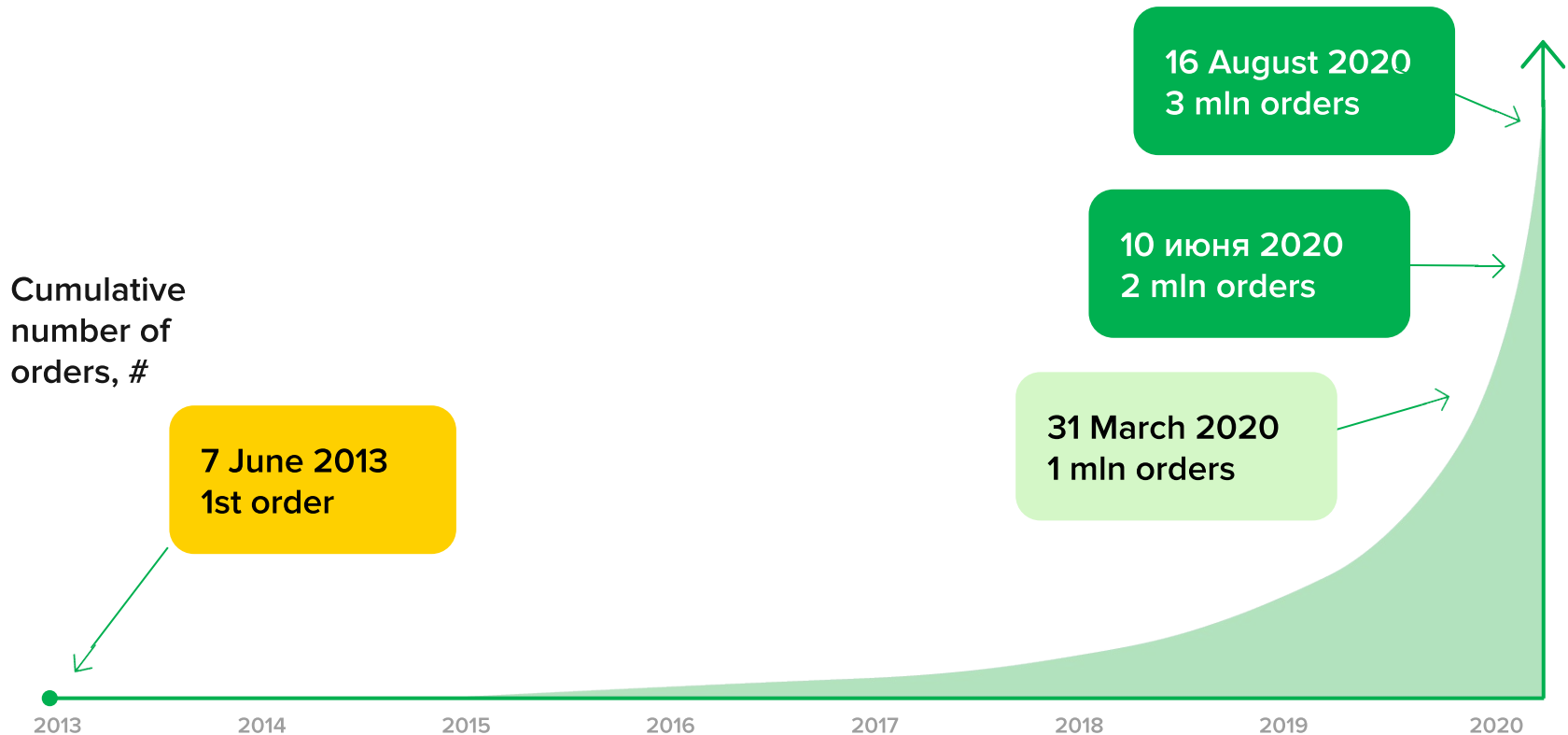
Железнодорожный	Дзержинский	Электросталь	Мытищи
Балашиха	Зеленоград	Подольск	Химки
Одинцово	Лобня	Щербинка	Реутов
Город МО	Ногинск	Видное	Долгопрудный
Картмазово			

Sbermarket is represented in every region of Russia



* Кроме Крыма и Севастополя

It took Sbermarket 7 years to deliver first million of orders
and **71 day to deliver second million**



Our goals

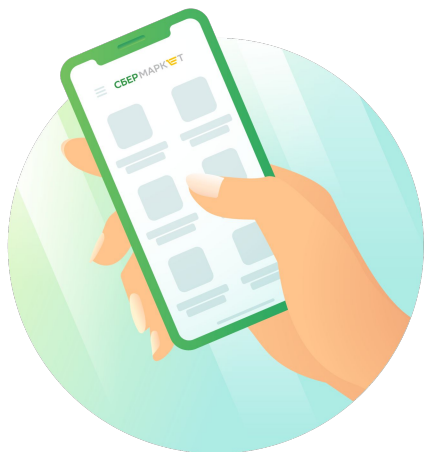


Our mission:

Save time, energy and money of our customers for something more important

Our vision:

Become an e-grocery market leader in Russia



Lowest prices







Widest assortment



Best quality

The service is focused on meeting the daily needs of a mass audience

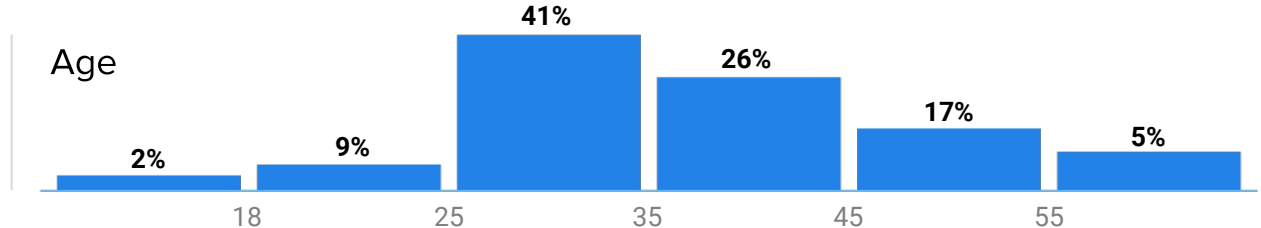
...

 Moms / Housewives	 Office staff	 Other types of consumers	 Corporate Clients / B2B
32%	19%	28%	21%
<ul style="list-style-type: none">• Active Internet users• No time to shop in brick-and-mortar stores• Shopping for the family	<ul style="list-style-type: none">• Accustomed to on-demand• Little free time• Wide range of purchases	<ul style="list-style-type: none">• Mobility impaired and / or elderly• Customers who order products for loved ones• No time to visit hypermarkets	<ul style="list-style-type: none">• Big and heavy shopping• Shopping for office and staff

Current client profile

22% male

78% female



... and covers 100% of the grocery basket and convenience goods

Average basket breakdown of by category

Fresh **49%**



Fruits and
vegetables

19%



Beverages

8%



Canned goods

5%



Dairy

15%



Sweet and Snacks

8%



Cheeses

4%



Grocery

9%



Personal Care

7%



Bakery

4%



Household
products

8%



Meat and
Seafood

9%



Frozen

4%

COVID accelerated not only GMV growth...



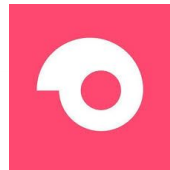
COVID accelerated not only GMV growth...



igoods



ВкусВилл
экспресс



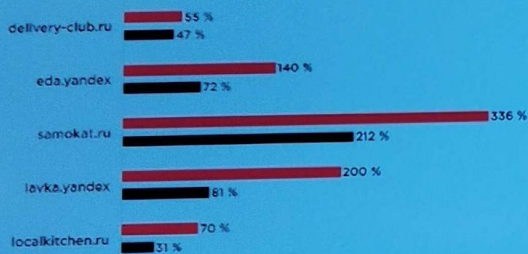
... but also a rapid spike in number of competitors

“Blue ocean turned extremely red”

ЭКСПРЕСС ДОСТАВКА: ГОЛУБОЙ ОКЕАН КОТОРЫЙ СТАЛ ЯРКО АЛЫМ!

Сохраняется высокая динамика роста категории и высокая рекламная активность (в 2 раза больше медиа инвестиций чем продуктовый ритейл)

ПРИРОСТ ТРАФИКА

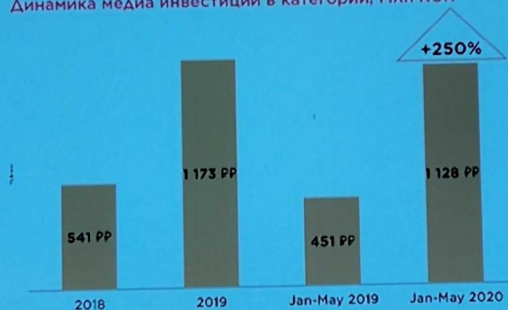


■ Изоляция vs ДО ■ ПОСТ vs ДО

Источник: Similarweb: Десктоп и Мобильный трафик сайтов. Период - 60 дней каждый. ПРЕКРАТЕНИЕ: 1 Jan 20 - 29 Feb 20. Карентин: 1 Apr 20 - 30 May 20. ПОСТ-карантин: 26 Jun 20 - 24 Aug 20

После снятия изоляции наблюдался отток (17%) аудитории 18-29 в Москве у всех кроме Самоката

Динамика медиа инвестиций в категории, млн RUR



Источник: Mediascope, Russia 2018-Jan-May 2020. Costs est. by publicis media



Яндекс Еда и Лавка показали самый высокий прирост аудитории до 17 лет. DC — рост аудитории 50+ в Москве (+121%) и регионах (+233%)

Динамика мобильных обращений к хостам, %

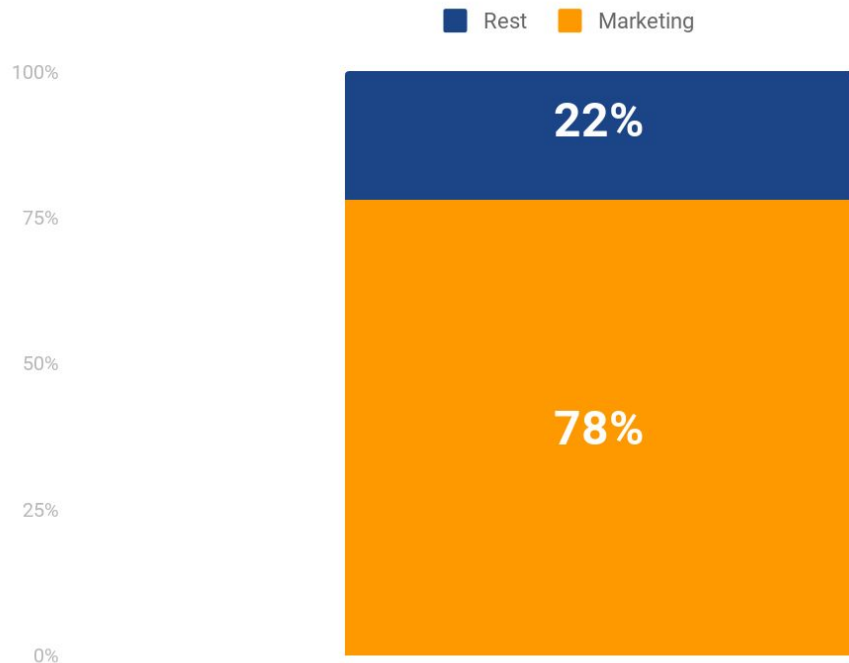


	Изоляция vs ДО		ПОСЛЕ vs Изоляция	
	Москва	Россия	Москва	Россия
delivery-club.ru	-3,8%	-3,6%	24,8%	168,4%
eda.yandex	-11,8%	22,2%	13,0%	82,1%
lavka.yandex	300,8%	255,3%	-67,3%	-36,9%
localkitchen.ru	20,0%	76,8%	1594,2%	8539,4%
samokat.ru	233,7%	97,3%	42,7%	123,9%

Источник: Beeline Big Data, mobile internet only

Such competition causes **huge burn of marketing budgets** across industry

Sbermarket budget shares



- Budget is allocated on acquisition and reactivation
- **Each percentage gain in conversion from launch to order leads to drastic optimization of marketing budget (tens of millions \$ per month)**

One way to increase conversion is to **predict customers future basket** and to offer it somehow



Customer **doesn't struggle with service interface/** catalogue while collecting products one-after-another

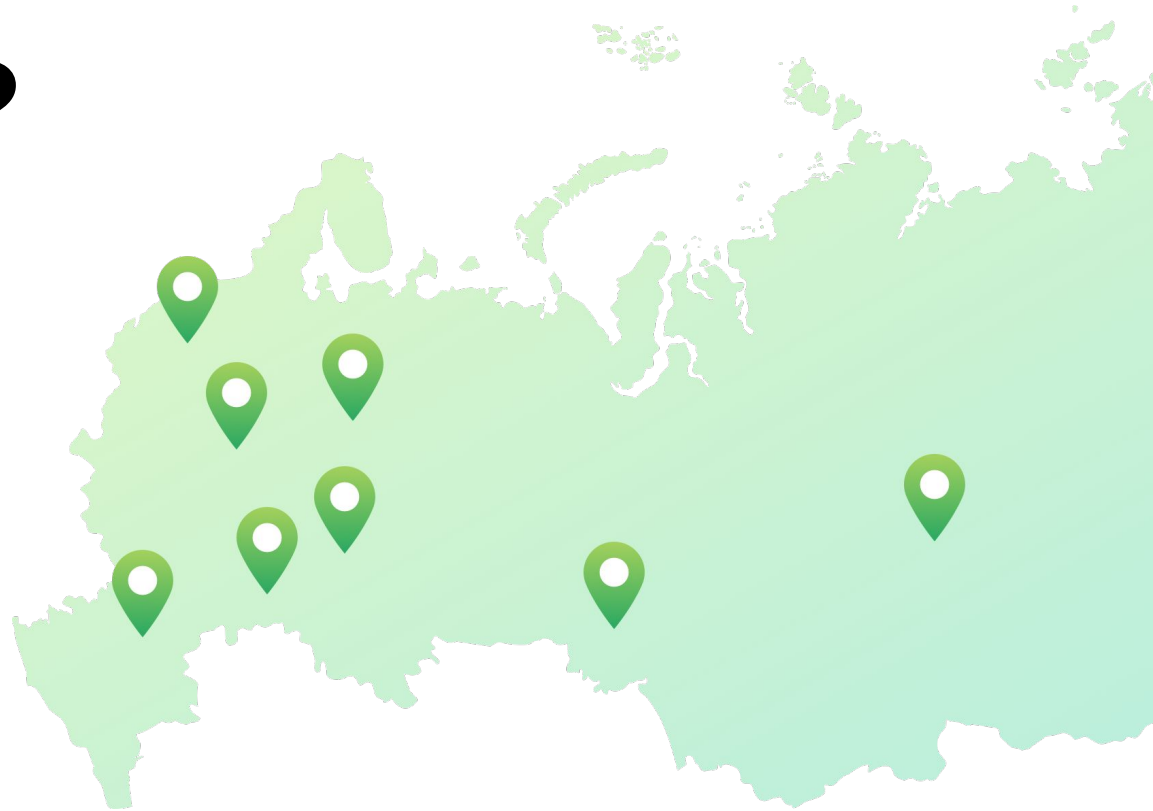


Customers loyalty (and retention) increases as they **feel that we know their taste and care about them**



We are able to **communicate with customer in advance of his purchase**, delivering WOW-effect

What do we offer?



Problem:

- Using our dataset help us predict which products will customers order next time sorted by relevance

Tasks:

- Propose a solution (predictive model) that would allow you to **predict customers next purchase products sorted by relevance**
- What **business tasks** are being solved with the help of recommendations? Suggest **ways to change the MAP@k metric or supplement it with new metrics** in order to measure the performance of the model on historical data in relation to various business tasks
- While crunching data, prepare some ExploratoryDA and **share at least 5 your most interesting insights regarding clients/orders patterns**

How your solution will be evaluated?

Part of your solution	Metrics of evaluation	# of points
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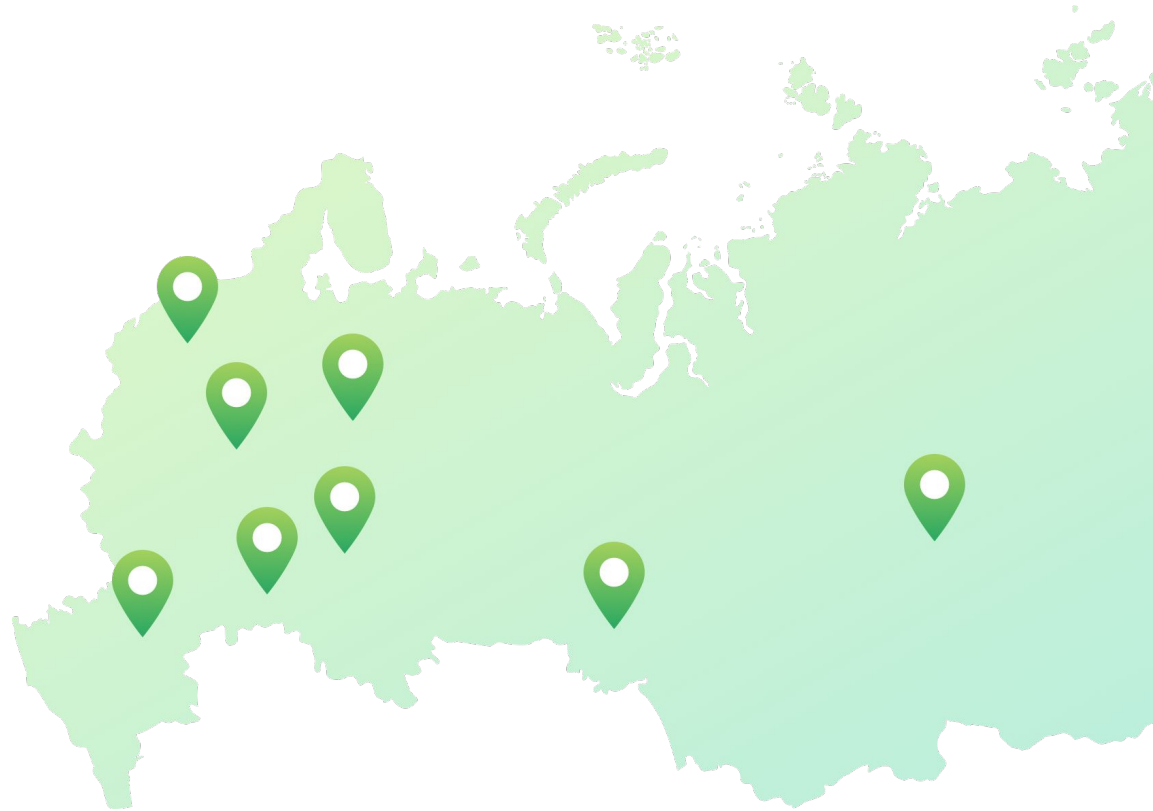
Quality of the model	MAP@k	10
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Data insights	Jury decision	5
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Any crazy business ideas on task/metric	Jury decision	5
---	---------------	---

Pitch & QA session	Jury decision	5
--------------------	---------------	---

Data & Metrics



p@k

$$p@K(target, prediction) = \frac{1}{K} \sum_{k=1}^K r^{true}(\pi^{-1}(k)) = \frac{\text{number of relevant}}{K}$$

$r^{true}(e)$ can take values of 1 or 0 for relevant or irrelevant item e

$\pi^{-1}(k)$ represents the element with position k

p@k example

milk
bread
bananas

k = 6

algorithm 1

1	ice cream
2	tomatos
3	water
4	milk
5	bread
6	bananas

p@k = 3/6

algorithm 2

1	milk
2	bread
3	bananas
4	cookies
5	coffee
6	ice cream

p@k = 3/6

p@k example

milk
bread
bananas

k = 6

algorithm 1

1	ice cream
2	tomatos
3	water
4	milk
5	bread
6	bananas

p@k = 3/6

algorithm 2

1	milk
2	bread
3	bananas
4	cookies
5	coffee
6	ice cream

p@k = 3/6

AP@k

$$p@K(target, prediction) = \frac{1}{K} \sum_{k=1}^K r^{true}(\pi^{-1}(k)) = \frac{\text{number of relevant}}{K}$$

$$AP@K(target, prediction) = \frac{1}{\min(K, M)} \sum_{k=1}^K r^{true}(\pi^{-1}(k)) \cdot p@k(target, prediction)$$

M - number of elements in real order

AP@k example

algorithm 1

milk
bread
bananas

k = 6

1	ice cream
2	tomatos
3	water
4	milk
5	bread
6	bananas

AP@k = 1/3 * (

0 * 0 +

0 * 0 +

0 * 0 +

1 * 1/4 +

1 * 2/5 +

1 * 3/6) = 0.383

$$AP@K(target, prediction) = \frac{1}{\min(K, M)} \sum_{k=1}^K r^{true}(\pi^{-1}(k)) \cdot p@k(target, prediction)$$

AP@k example

algorithm 2

milk
bread
bananas

k = 6

1	milk
2	bread
3	bananas
4	cookies
5	coffee
6	ice cream

AP@k = 1/3 * (

1 * 1/1 +
1 * 2/2 +
1 * 3/3 +
0 * 3/4 +
0 * 3/5 +
0 * 3/6) = 1

$$AP@K(target, prediction) = \frac{1}{\min(K, M)} \sum_{k=1}^K r^{true}(\pi^{-1}(k)) \cdot p@k(target, prediction)$$

AP@k example

milk
bread
bananas

k = 6

algorithm 1

1	ice cream
2	tomatos
3	water
4	milk
5	bread
6	bananas

AP@k = 0.383

algorithm 2

1	milk
2	bread
3	bananas
4	cookies
5	coffee
6	ice cream

AP@k = 1

MAP@k

$$p@K(target, prediction) = \frac{1}{K} \sum_{k=1}^K r^{true}(\pi^{-1}(k)) = \frac{\text{number of relevant}}{K}$$

$$AP@K(target, prediction) = \frac{1}{\min(K, M)} \sum_{k=1}^K r^{true}(\pi^{-1}(k)) \cdot p@k(target, prediction)$$

$$MAP@K(solution, submission) = \frac{1}{N} \sum_{n=1}^N AP@K_n(target_n, prediction_n)$$

Table 1 - orders

	user_id	order_id	order_created_time	retailer	store_id	platform
0	72	17431000	2020-09-26 10:48:57	METRO	21	app
1	83	9718154	2020-05-08 09:46:18	METRO	87	web
2	142	10056850	2020-05-14 15:06:03	METRO	320	app
3	187	15952443	2020-09-01 17:34:00	ВкусВилл	533	app
4	224	10409918	2020-05-20 06:32:50	Ашан	183	web

Table 2 - products

	user_id	order_id	line_item_id	price	quantity	discount	product_name	product_id	brand_name	master_category_id	parent_category_id
0	51	10717803	99293130	65.720001	1	0.0	Морковь мытая свежая	94333	Без бренда	85.0	84
1	51	10717803	99293227	127.330002	1	20.9	Помидоры	55133	Без бренда	85.0	84
2	51	10717803	99293243	99.900002	2	0.0	Помидоры черри Новиков 250 г	22035	Новиков	85.0	84
3	51	10717803	99293334	229.899994	1	0.0	Кукуруза сладкая в вакууме 230 г	6005183	Без бренда	85.0	84
4	51	10717803	99293366	69.900002	1	10.0	Бананы	709	Без бренда	91.0	90

Table 3 - categories

	id	name	parent_id
0	1	Продукты питания	0
1	2	Замороженные продукты	1
2	3	Замороженные овощи и фрукты	2
3	4	Замороженные полуфабрикаты	2
4	5	Рыба замороженная	2

Table 4 - user profiles

	user_id	gender	bdate
0	2224890	NaN	NaN
1	1683001	male	1987-10-11
2	2102480	NaN	NaN
3	2224895	NaN	NaN
4	930197	NaN	NaN

Table 5 - product properties

product_id	proterty_name	property_value	
0	1	Вес	100 г
1	2	Вид	Молочный напиток
2	2	Вес	100 г
3	2	Вкус	Черника
4	2	Сырье	Натуральное молоко

