

# Machine learning mistakes

MACHINE LEARNING FOR BUSINESS



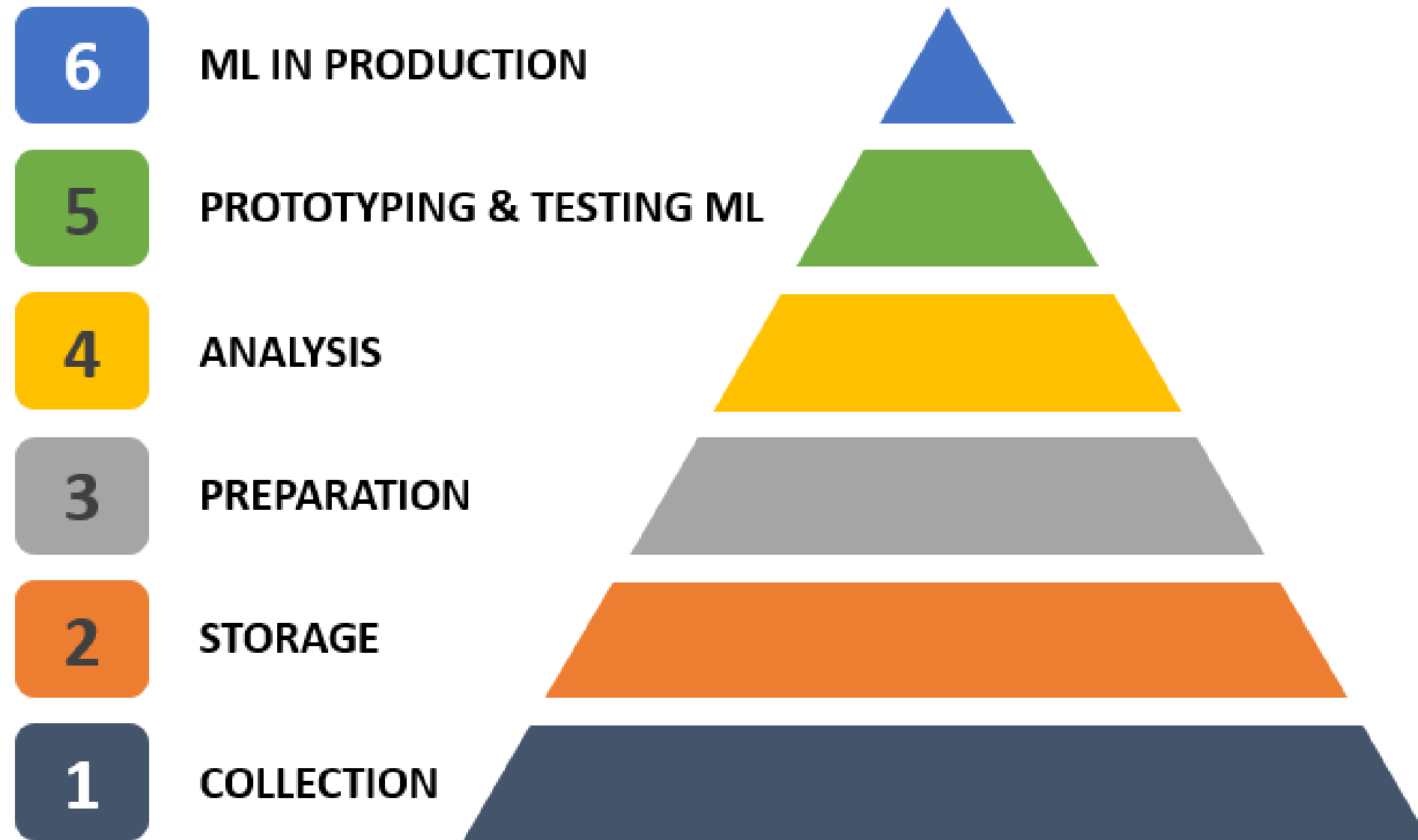
**Karolis Urbonas**

Head of Machine Learning & Science,  
Amazon

# Mistakes

- Machine learning first
- Not enough data
- Target variable definition
- Late testing, no impact
- Feature selection

# Machine learning first



# Not enough data



# Target variable definition

- What are we predicting?
- Can we observe it?
  - Contractual churn - customer terminated the premium credit card
  - Non-contractual churn - customer started using another grocery store
- In-depth analysis
- Business field expertise

# Feature selection

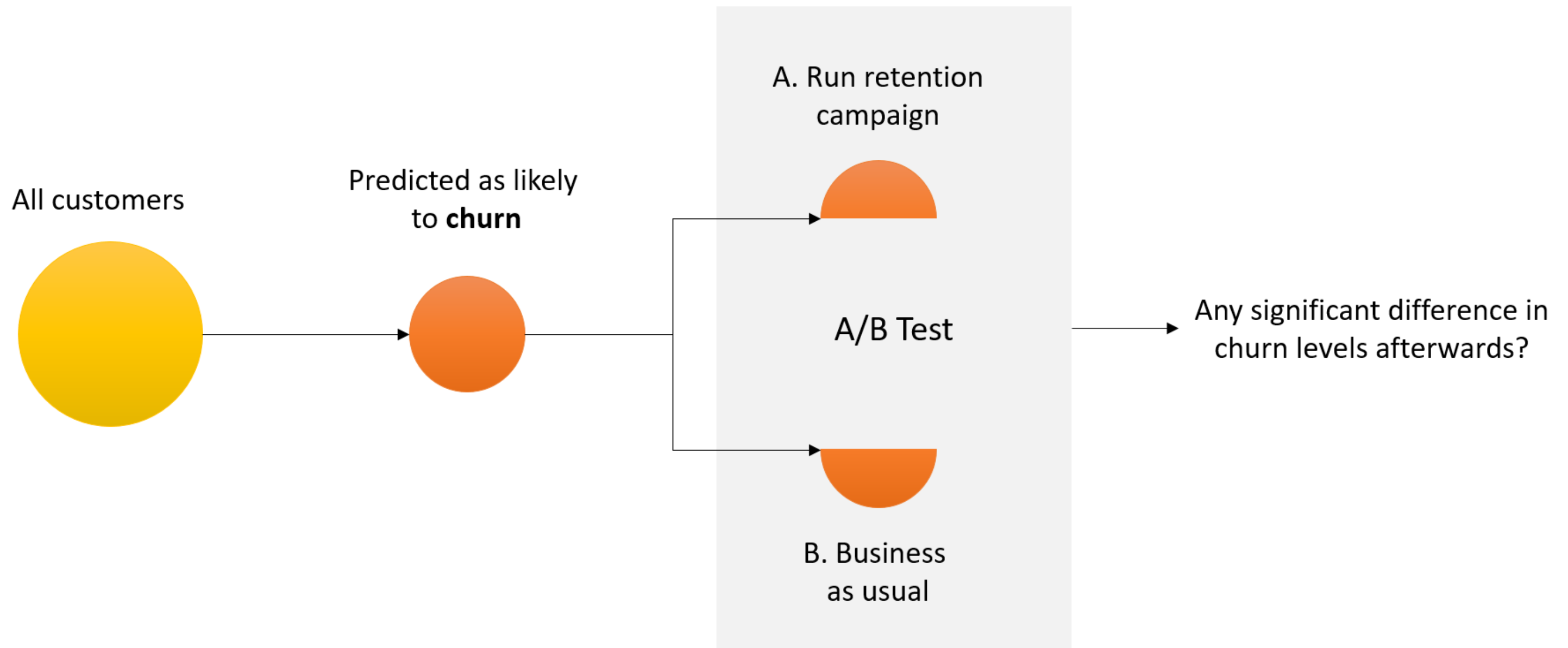
Inference (what affects the target variable?)

- Choose variables that you can control (website latency, price, delivery, customer service etc.)
- Business has to be involved in feature selection

Prediction (can we **estimate** the target variable value in the future?)

- Start with readily available data
- If model performance is OK, test it
- Introduce new features iteratively

# Late testing, no impact



# Let's practice!

MACHINE LEARNING FOR BUSINESS



# Communication management

MACHINE LEARNING FOR BUSINESS



**Karolis Urbonas**

Head of Machine Learning & Science,  
Amazon

# Working groups

Schedule recurring meetings to track progress and define the following:

- Define the business requirements
- Review machine learning model **and** business products
- Inference vs. prediction
- Baseline model results & outline model updates
- Market testing
- Production

# Business requirements

1. What is the business **situation**?
  - *Churn rate has started increasing*
2. What is the business **opportunity** and how big is it?
  - *Reduce churn from X% to Y%*
3. What are the business **actions** we will take?
  - *Run retention campaigns targeting customers at risk*

# Machine learning products

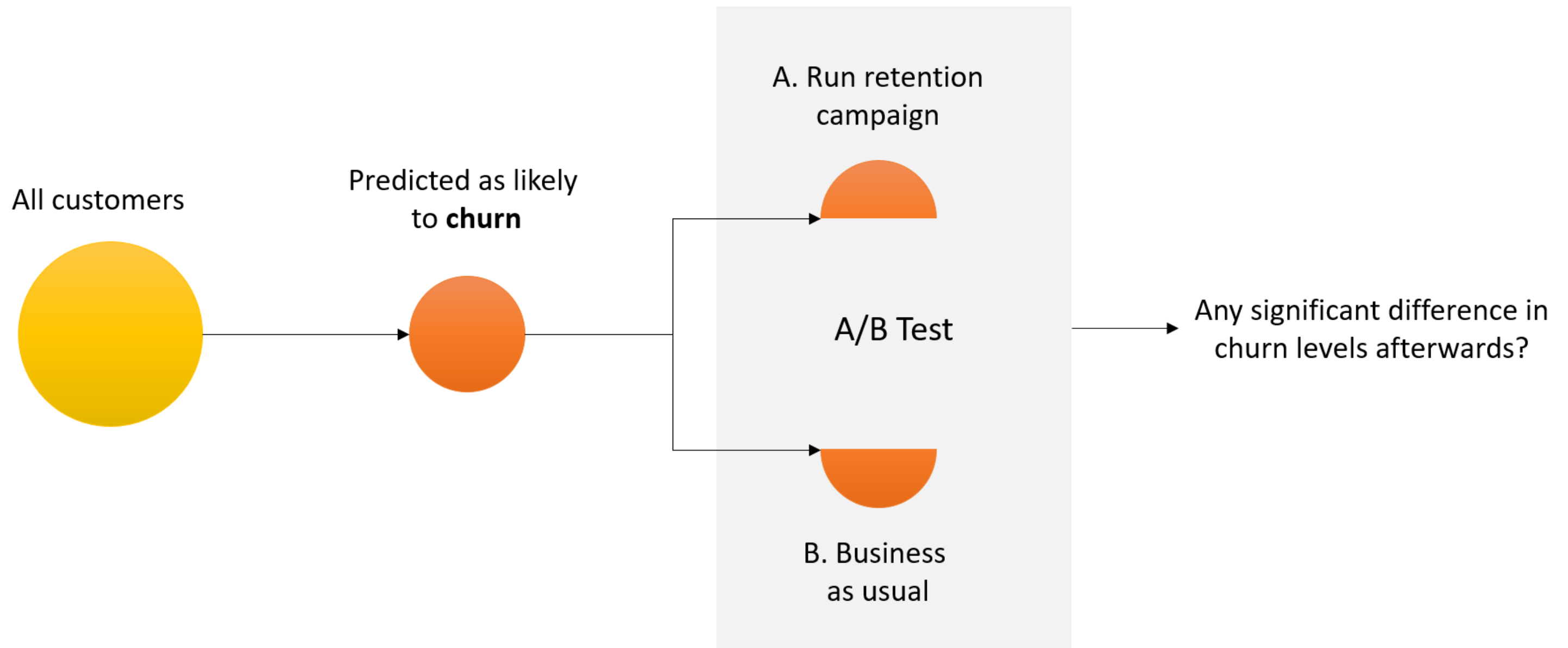
- What ML products does the business needs?
- **Example 1** - Predict churn. Business wants 1) inference into drivers of the churn updated quarterly, and 2) daily customer classification into: lost customers, customers at risk, no risk
- **Example 2** - Fraud prediction. Business wants 1) inference into strong indicators of churn, and 2) real-time list of very risky transactions for manual review and medium risk ones for additional data request

# Model performance and improvements

Identify what is the tolerance for model mistakes (remember - all models are wrong):

- **Classification**
  - Which class is more expensive to mis-classify?
  - Example - it's likely more expensive to mis-classify fraud as non-fraud than vice versa
- **Regression**
  - What is the error tolerance for prediction?
  - Example - in demand prediction the company will have to buy more inventory than needed if the model error is very high

# Market testing



# Machine learning in production

- Are test results delivering consistent positive improvements?
- Is the model stable enough?
- Do we have systems and tools where the model be integrated to?

# Let's practice!

MACHINE LEARNING FOR BUSINESS



# Machine learning in production

MACHINE LEARNING FOR BUSINESS



**Karolis Urbonas**

Head of Machine Learning & Science,  
Amazon

# Production systems

Production system is live, customer facing and business critical.

- Customer Relationship Management (CRM)
- Fraud detection system
- Online banking platform
- Autonomous cars

# CRM

Production system - Customer Relationship Management (CRM)

**Example** - predicted churn triggers automatic emails



# Fraud detection system

Production system - fraud detection system

**Example** - predicted fraud probability automatically triggers transaction block and requests a manual review

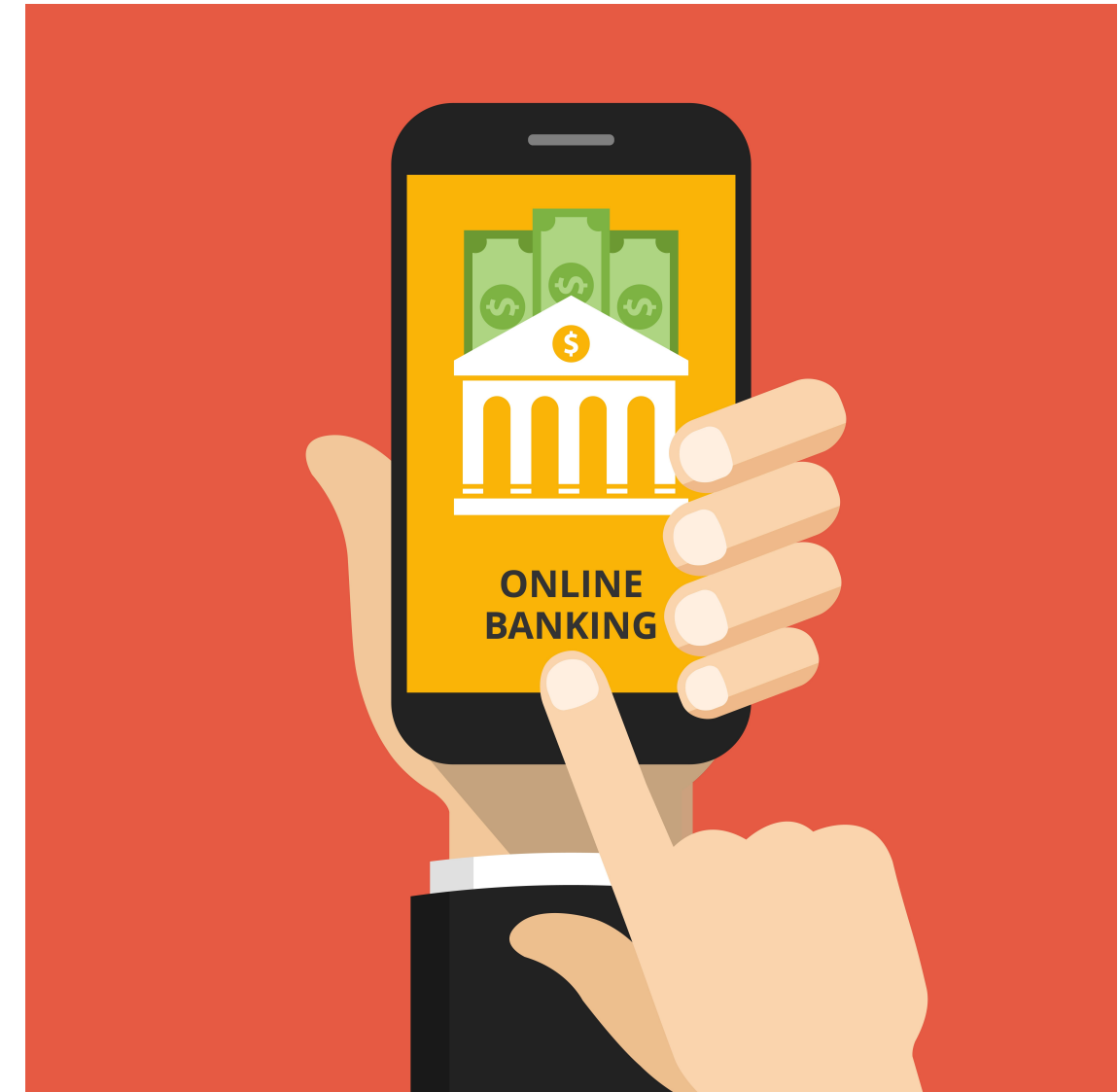


**FRAUD  
DETECTION**

# Online banking system

Production system - online banking platform

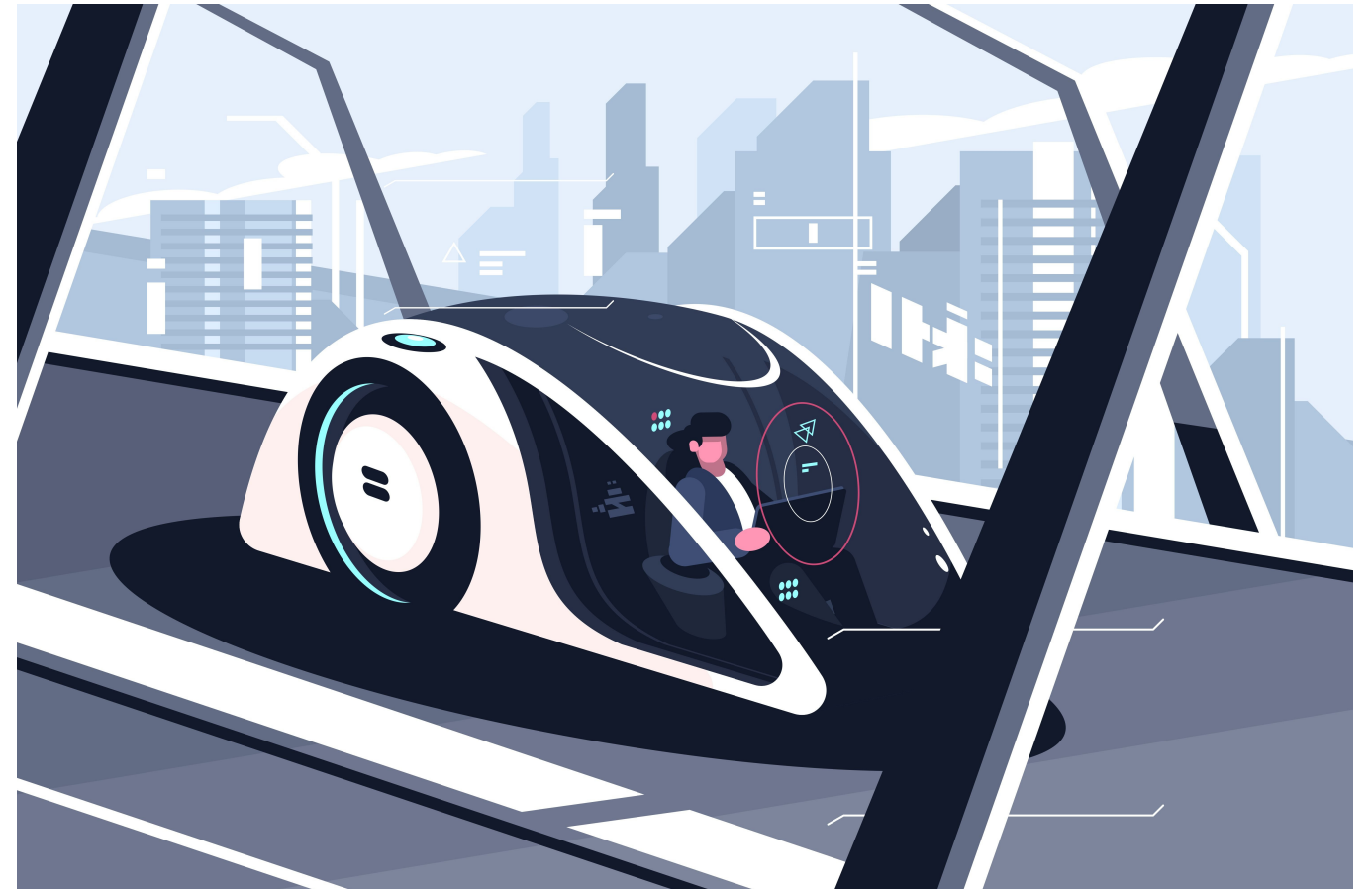
**Example** - recommended products shown on the customer's online banking profile



# Autonomous cars

Production system - autonomous cars

**Example** - predicted collision kicks off automatic initiation of brakes and collision avoidance steps



# Staffing

## Prototype ML

- Data Scientists
- ML Engineers

## ML in production

- Software engineers
- Data Engineers
- Infrastructure owners

# Launch, tracking and feedback

1. Murphy's law
2. Launch to a small subset of customers
3. Track results and if they're consistent
4. Track performance, stability, customer feedback
5. Scale up
6. Repeat 3, 4, 5



# Let's practice!

MACHINE LEARNING FOR BUSINESS

# Wrap-up

MACHINE LEARNING FOR BUSINESS



**Karolis Urbonas**

Head of Machine Learning & Science,  
Amazon

# Thank you!

MACHINE LEARNING FOR BUSINESS