NEXT-BEST-ACTION: ML-LEL A JÖVŐ EGYEDI DÖNTÉSEINEK NYOMÁBAN

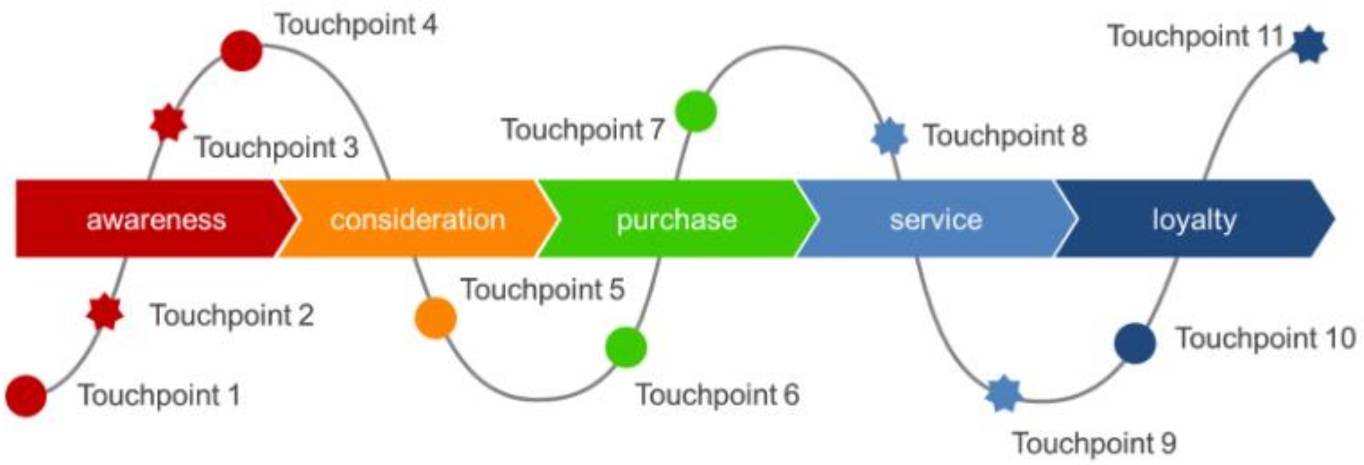
ALL THE SAME?

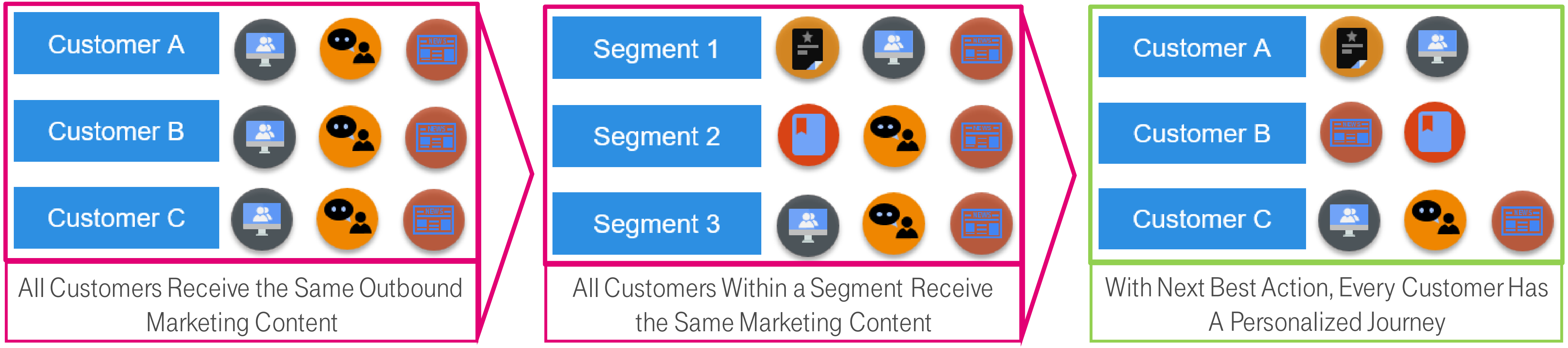
	Data - Based	Data - Driven
Decision	Human Intelligence	Learning from Data
Learning	Manual	Learning from Data
#Decision Capacity	Low	Scalable

	Data - Based	Data - Driven
Preference	No Idea	It is Understood
Decision Making	No Idea	It is Known
Channel	No Idea	It is Recognized

Customer Journey & Optimization with NBA

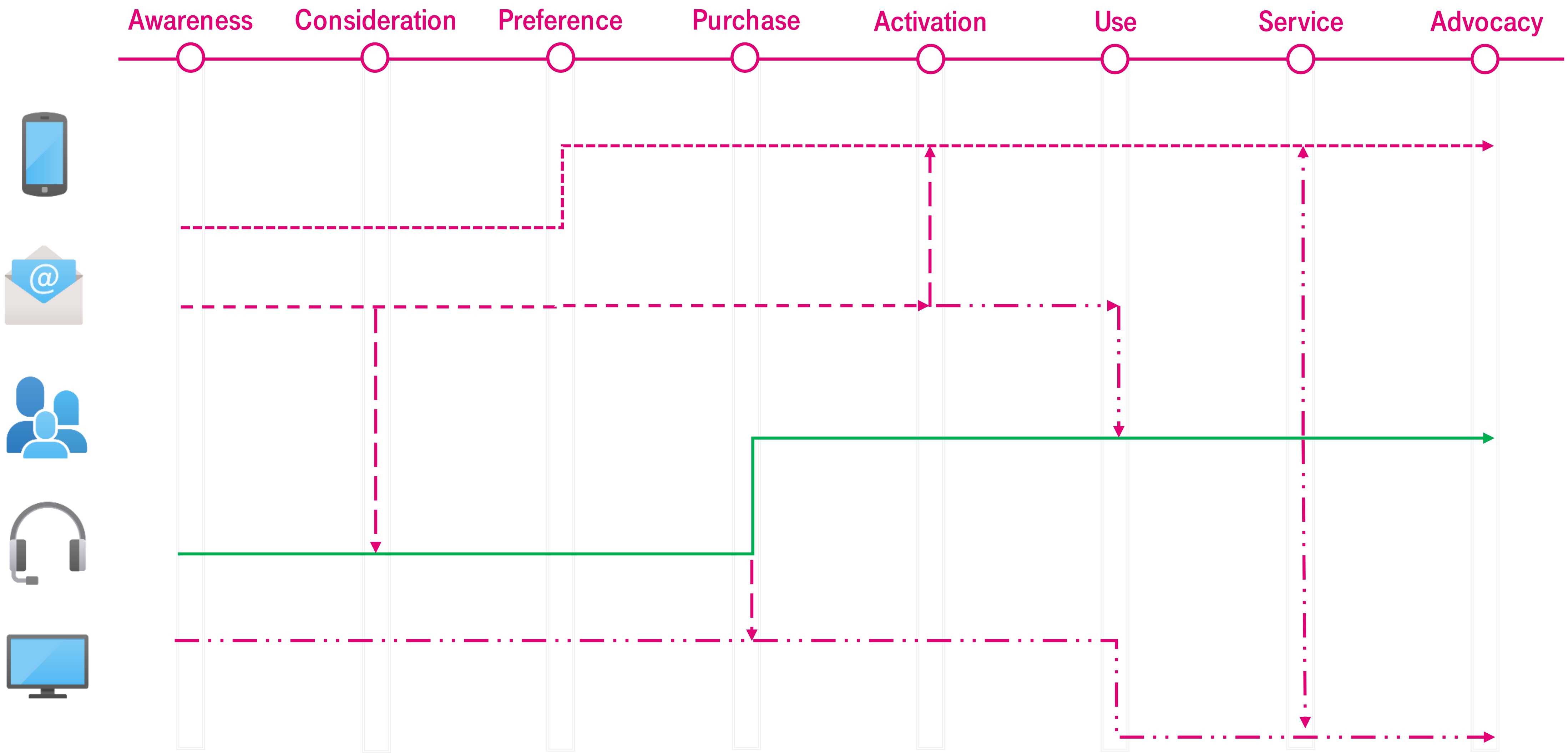
It recommends next actions that help users progress towards business goals as quickly and smoothly as possible





https://blog.datarobot.com/delivering-next-best-action-with-artificial-intelligence

Customer Lifecycle



Next Best Action Engine – ML based approach

Key Challenges

- Optimization objective is typically complex
- Historical feedback is typically incomplete – feedback for other prediction are not available
- Historical feedback is skewed towards a small set of actions
- Actions are typically dynamic (seasonal changes or business strategies)

Standard classification or regression models

- Only bandit feedback is available
- Sampling bias presented in historical data can not be handled properly

Regular contextual multi-armed bandit model

- It lacks the ability to model multiple objectives

→ Stage-advancement policy (e.g. from login to complete profile)

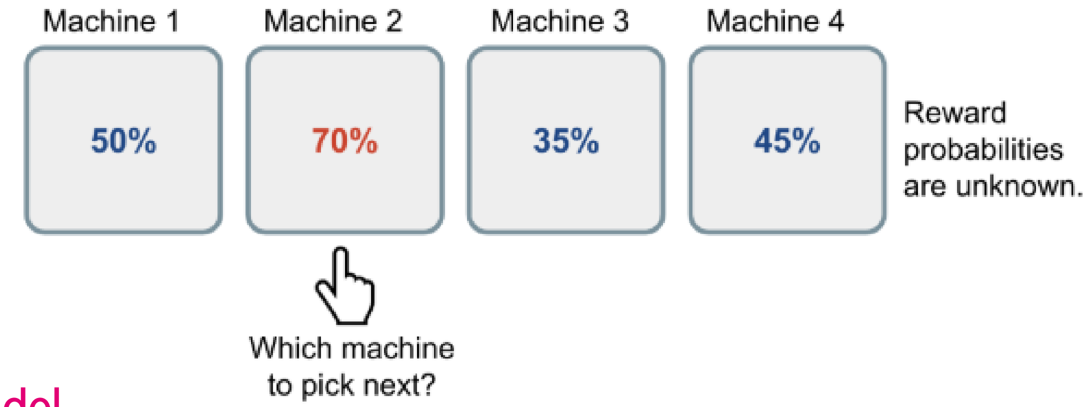
→ Goal-oriented policy (e.g. different purchase, becoming superfan)

Hybrid model

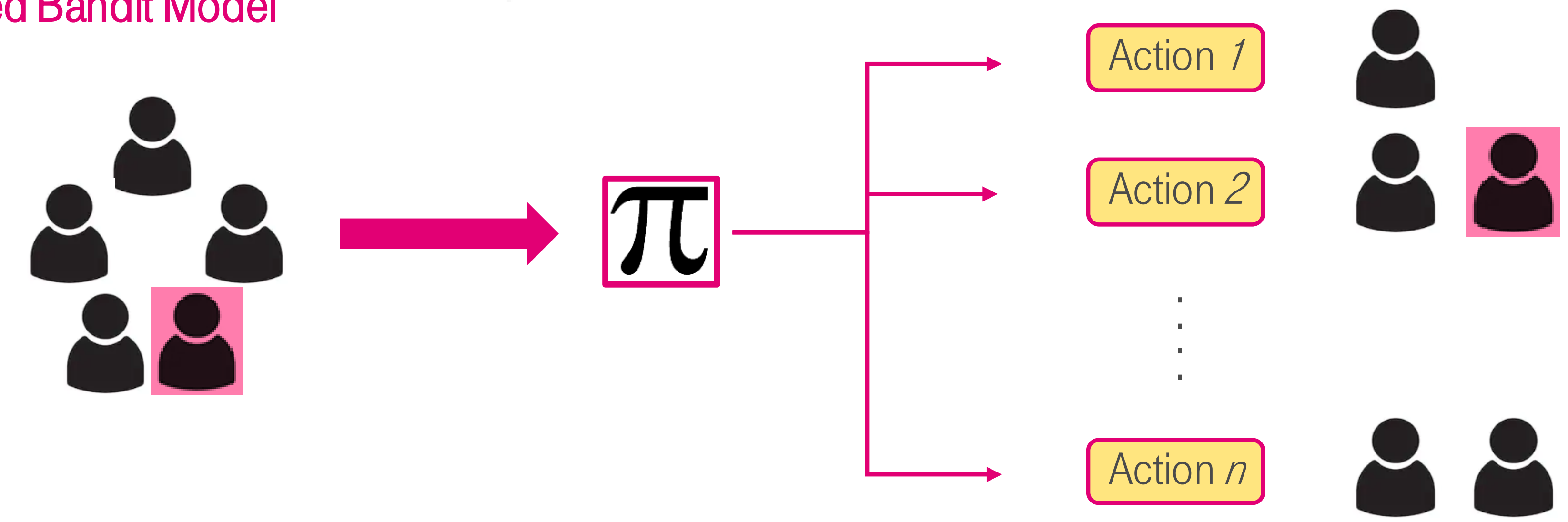
Offline Learning		Online Learning
Propensity Scorer	+	Multi-armed bandit model
Intent Predictor Policy Selector		Contextual Action Engine

Problem Setting

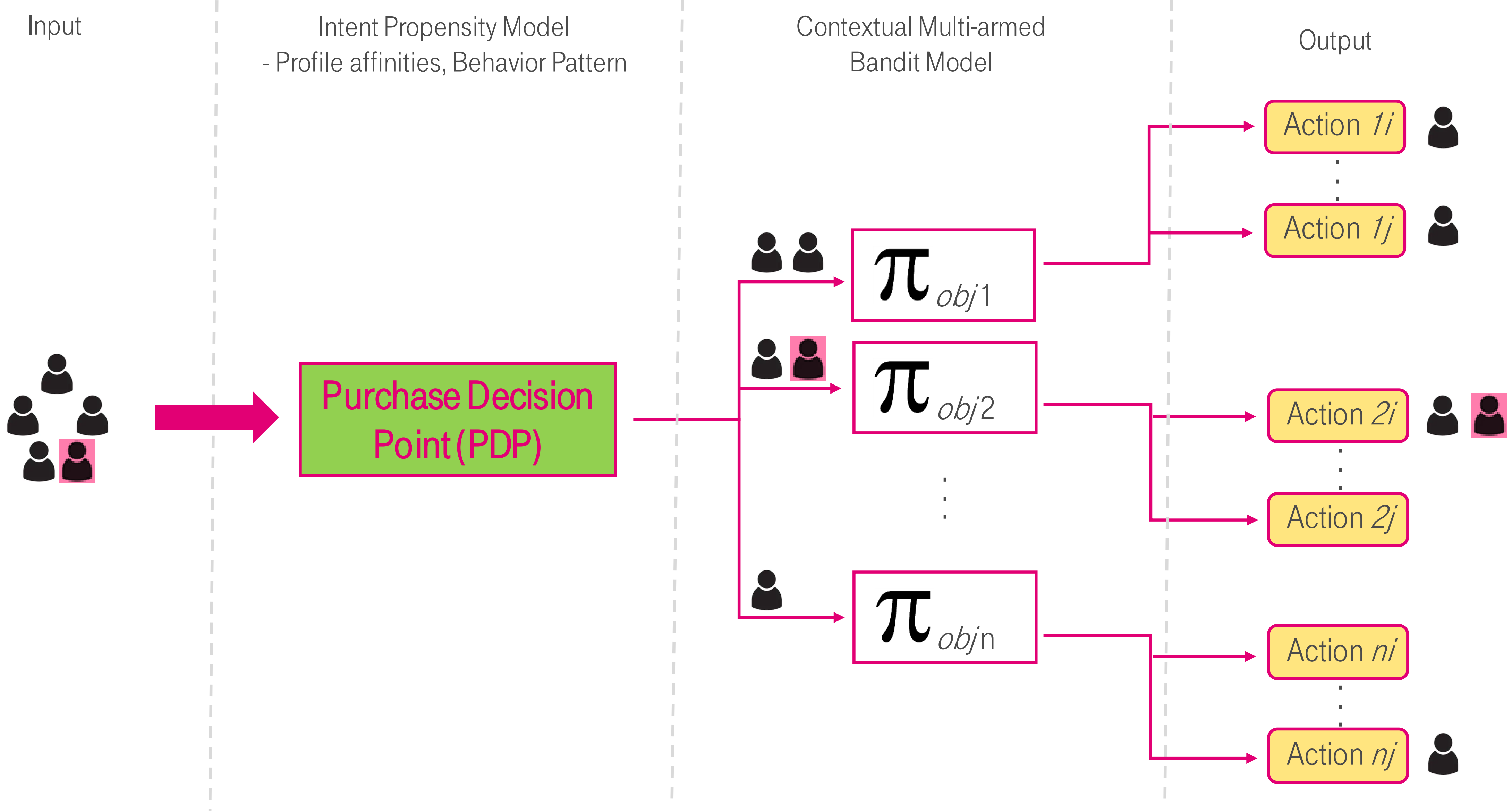
π : User + Current Context → Action | Reward Maximized



Multi-armed Bandit Model

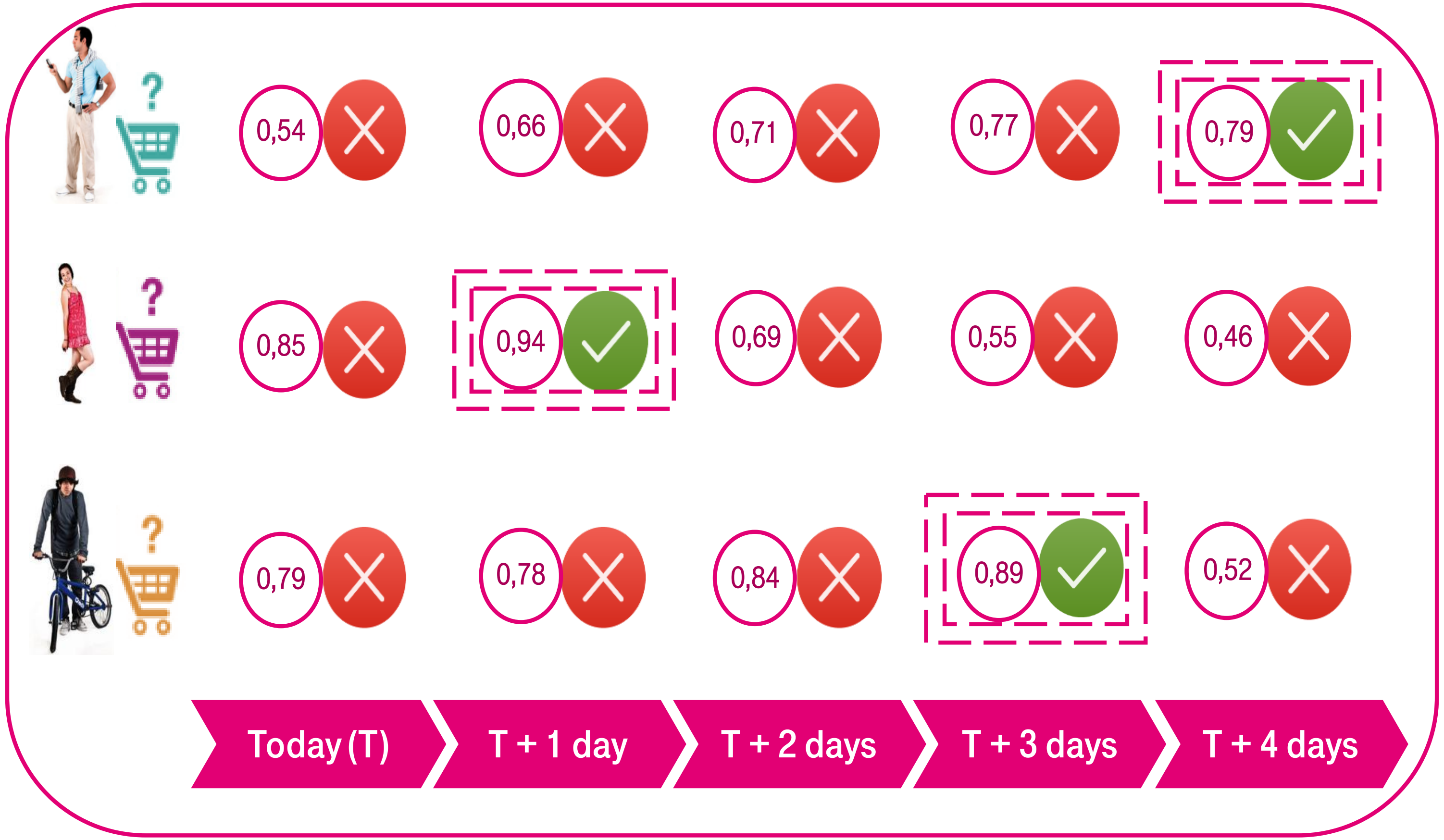


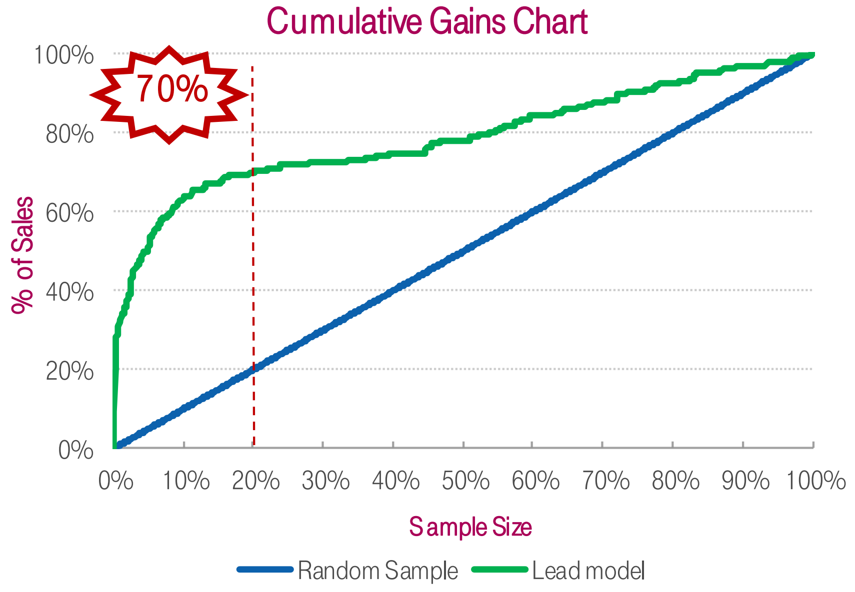
Advanced Approach



Point of purchase – algorithmic analytical approach to the scoring model

Sales probability   Purchase decision - No   Purchase decision - Yes

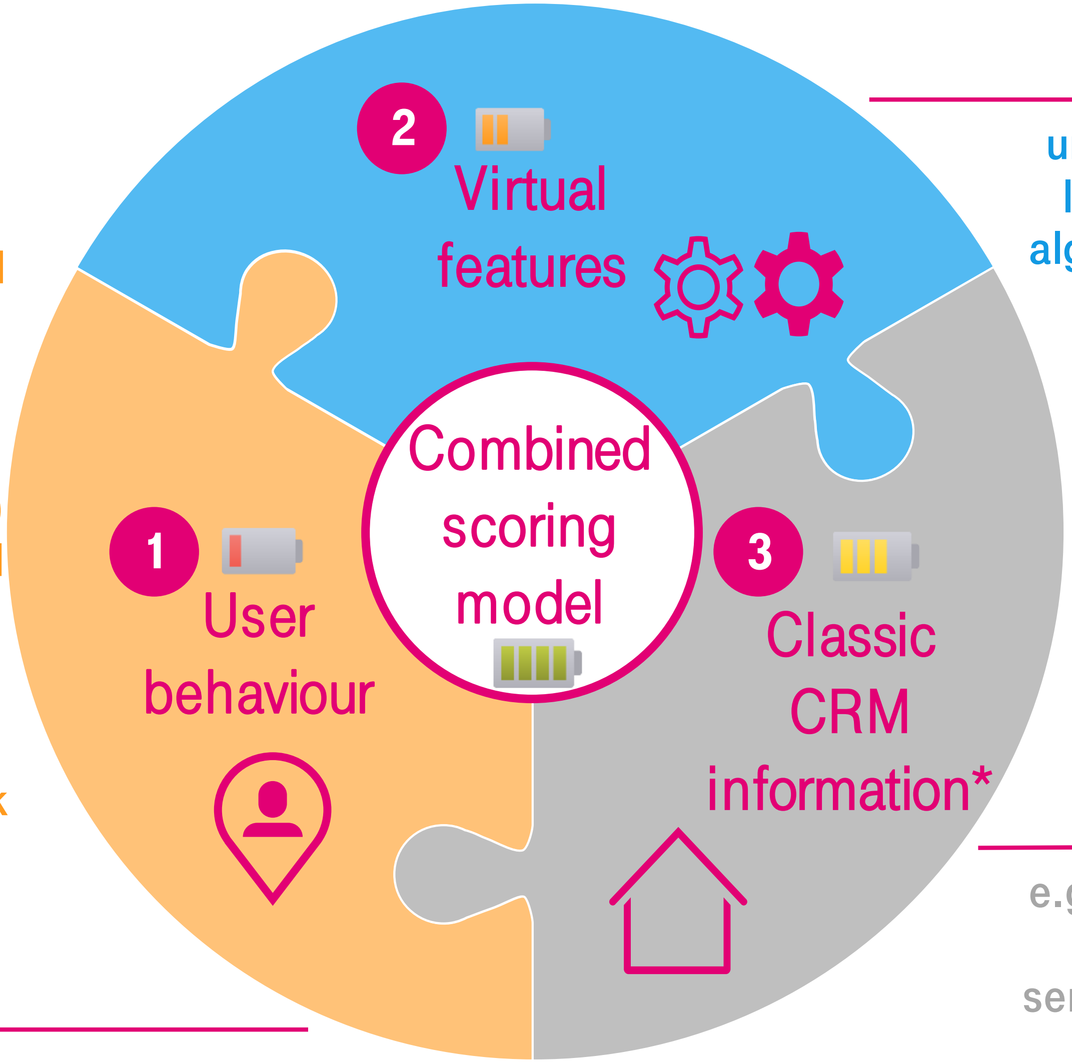




3 mathematical rules and 0,8 the goodness of probability

Point of purchase – fundamental elements of the scoring model

- **Different visited pages**
  e.g. product, comparison, Check-out stages
- **User activity** – user selection on pages
  e.g. colour selector, tariff plan calculation, add to compare, summary details
- **Cardinality and density** - with dynamic parameters
  e.g. Total sum of visited product pages $(x1, x2)$ between now and $t1, t2$ (e.g. $t1 := 24$ hours and $t2 := 36$ hours). There is a calculation in every 10 minutes : if $x2/(x2-x1) >= p1$ (e.g. $p1 := 2$) is true then visitor gets higher score.
- **Events** e.g. add to cart, personalized item click
- **Solvency test / Willingness to pay** - Customer and order check - Information from BE
  e.g. high risk personal data, backlist, debt



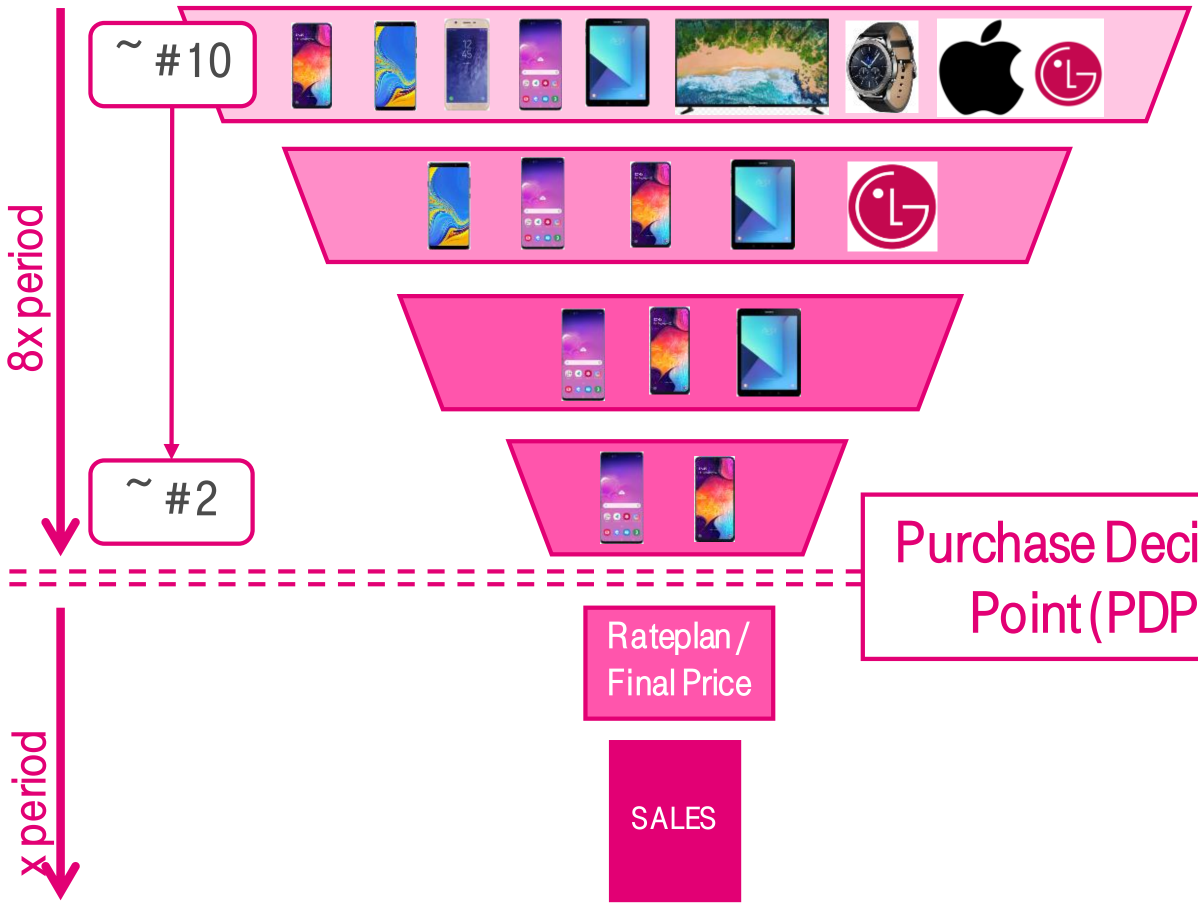
unsupervised learning ML algorithms e.g. SVD

* if possible

e.g. actual tariff plans and services, TF, HH

Visitor Decision Process

Sales funnel – boosted by physical product



Purchase Decision Point (PDP)

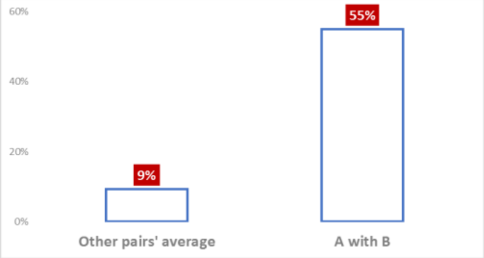
The faster the more focused guidance
Win-win situation
ML Recommendation

NEW

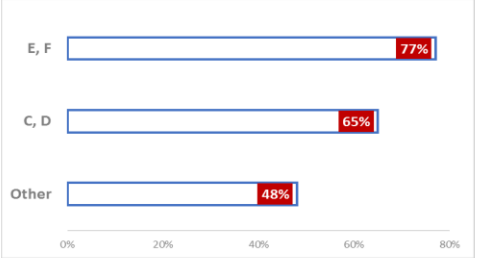
+ Retargeting Recommendation
+ Lead (in- and outbound)

Findings

Brand pairs – alternative brand sales potential

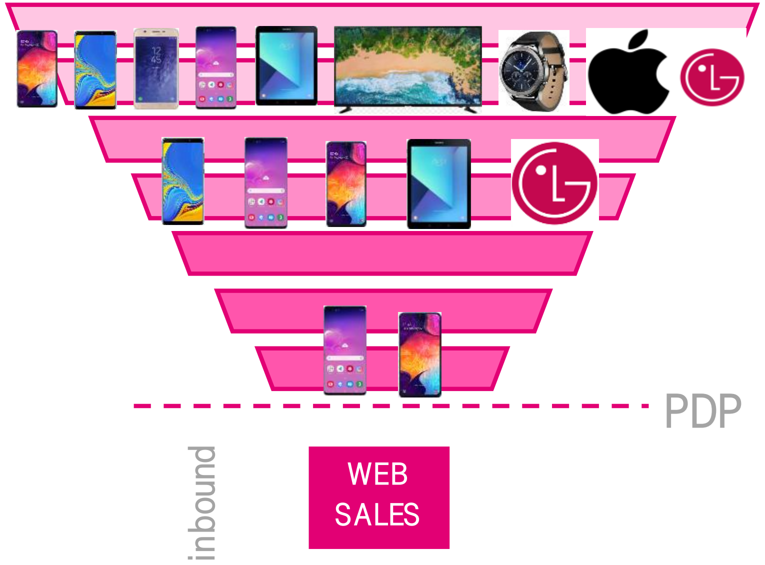


3 buckets of brand loyalty – the rate of the same brand's views 15 days before purchase

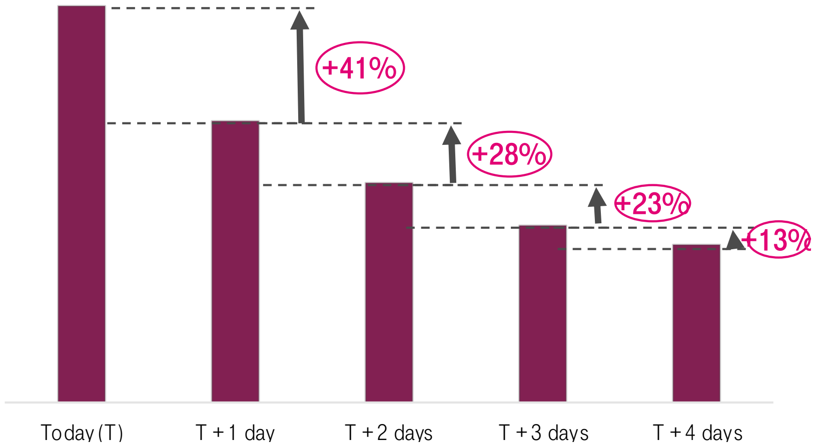


Analytical lead generating process

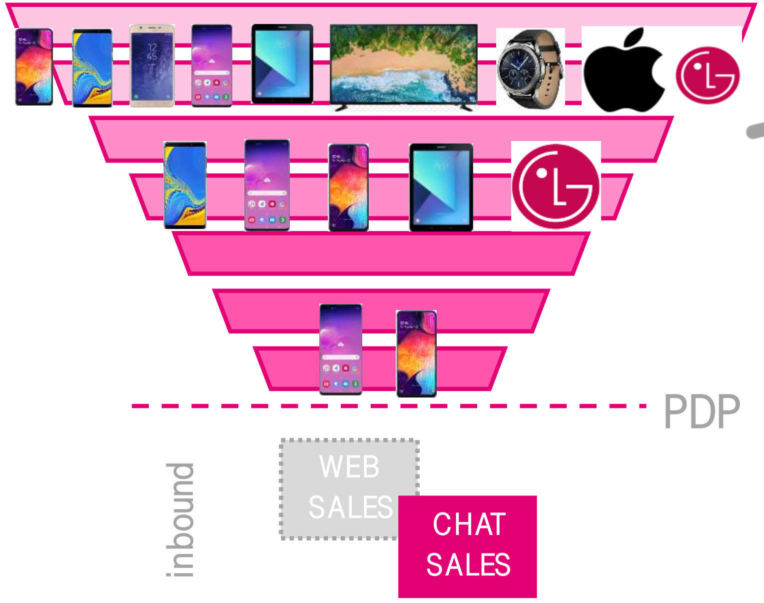
Online session w/ sales decision



Lead efficiency - Conversion Rates by time

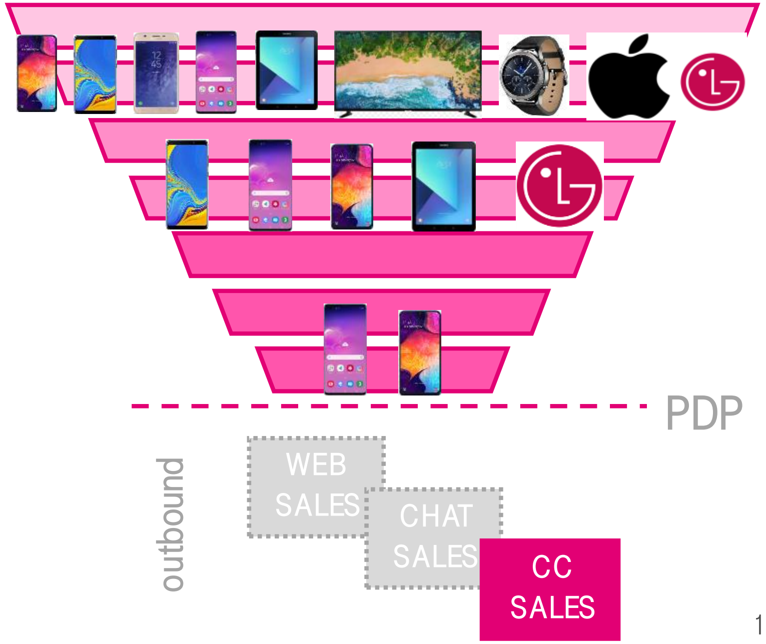


Online session w/o sales decision



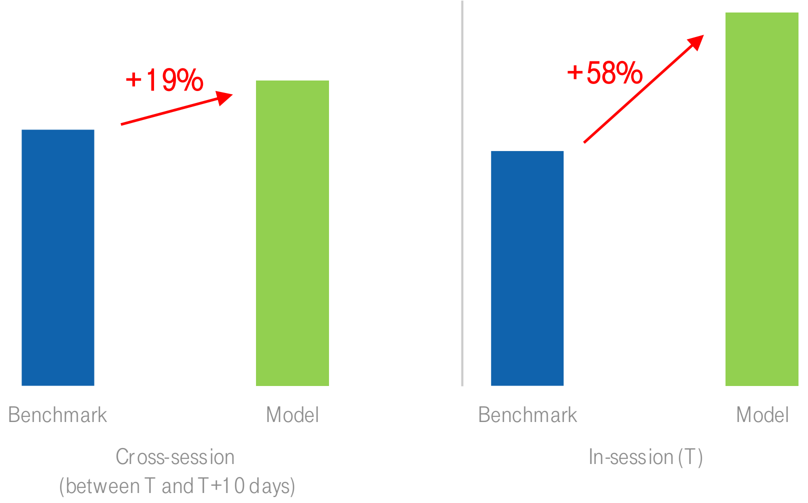
Rates of return
The scoring model's painted profiles on the web

Without online session

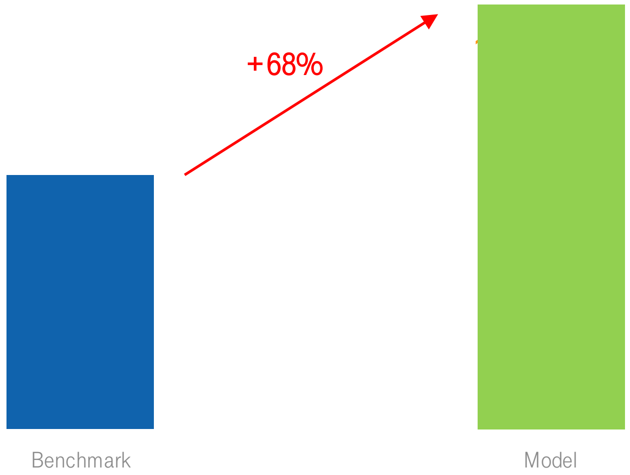


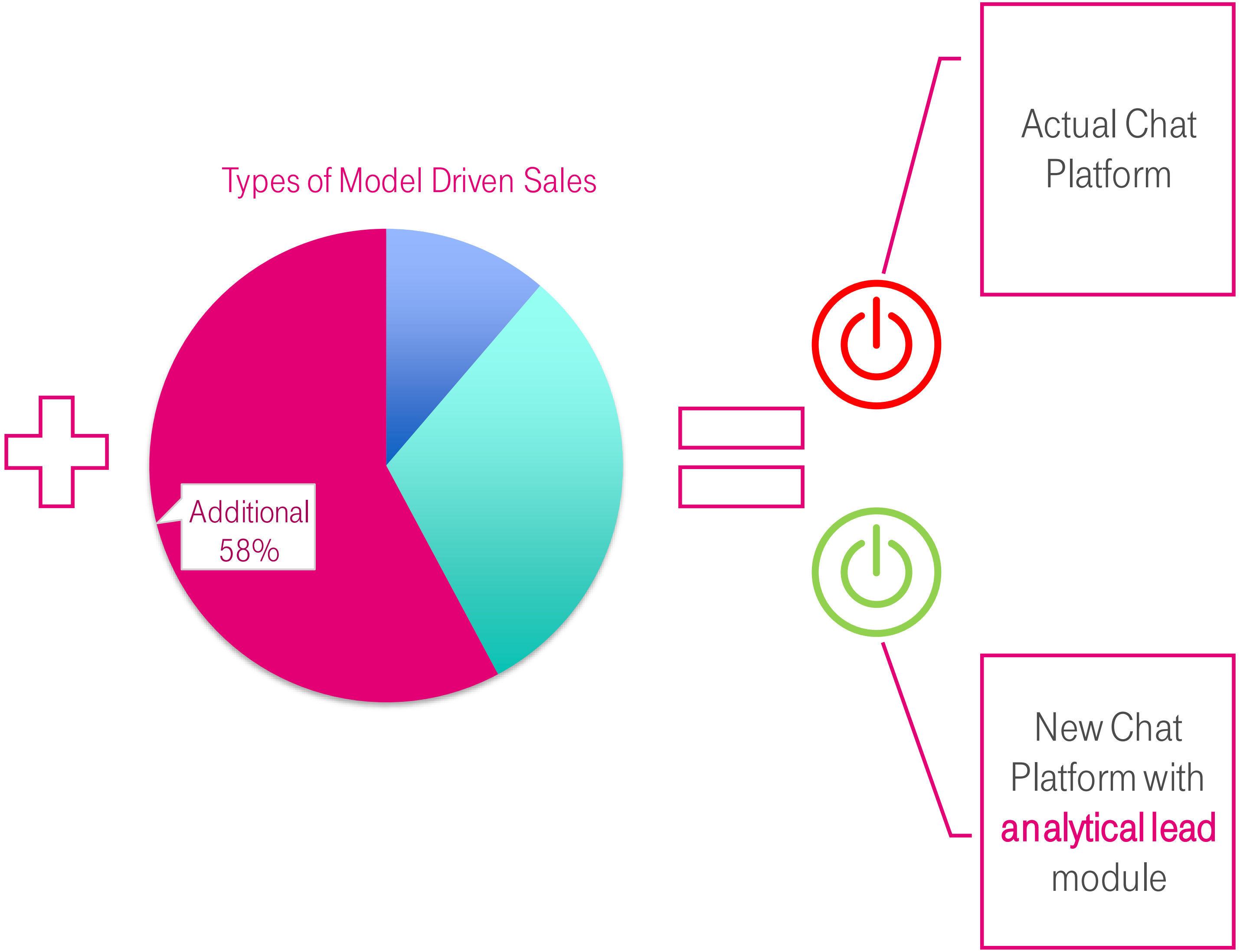
Results of the analytical lead model

Online Chat – Conversion Rate



CC (In-session) – Conversion Rate





Hybrid model - realization

Hybrid model

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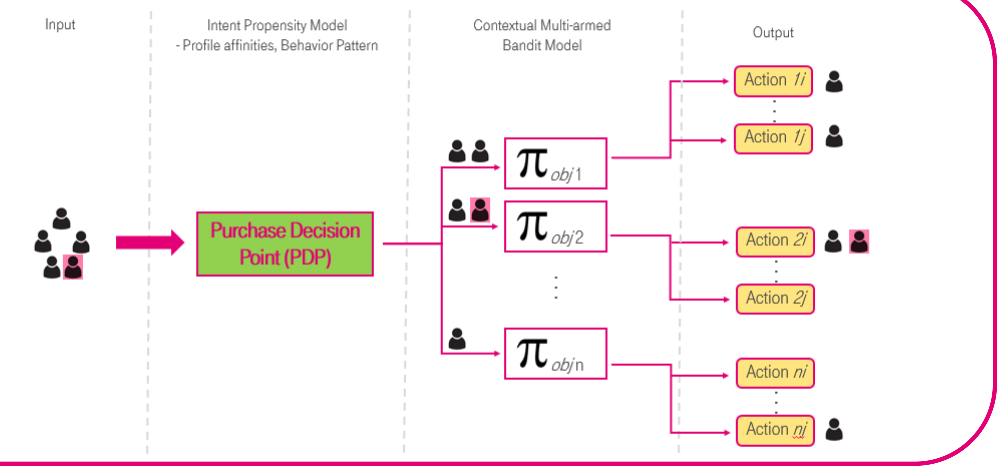

Hybrid contextual multi-armed bandit model

1. More than regular: purchase decision points are in the model – plus special features (user intent & interest) → different actions are recommended to users that show different interests e.g. different purchase, skipping a few stages for fast shoppers
2. Reward strategy – we don't reward zero or negative stage progression
3. Both policies incorporate Thompson Sampling with Gaussian kernel for better exploration

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Q&A

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