What can Airlines Learn from Retailers About Demand Forecasting

Ross Winegar
Michael Wu

2021.05.04

AGIFORS
Airline Group of the International Federation of Operational Research Societies

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Speaker Bios

Ross Winegar PhD

- 7 yrs @ PROS as manager of the forecast science team
- economics PhD @ Purdue Univ.
- Ross Winegar received his Ph.D. in Economics from Purdue University and has worked at PROS for 7 years in the Science and Research department developing data science models for airline revenue management.

Michael Wu PhD

- 2.5 yrs @ PROS as chief AI strategist
- senior research fellow @ Ecole des Ponts B-School
- advisor for UC Berkeley AI program
- biophysics PhD @ UC Berkeley
  - triple major in applied math, physics, + molecular cell biology/neurobiology
- 10 yrs @ Lithium Tech as chief scientist
- US DOE fellow @ Los Alamos National Lab

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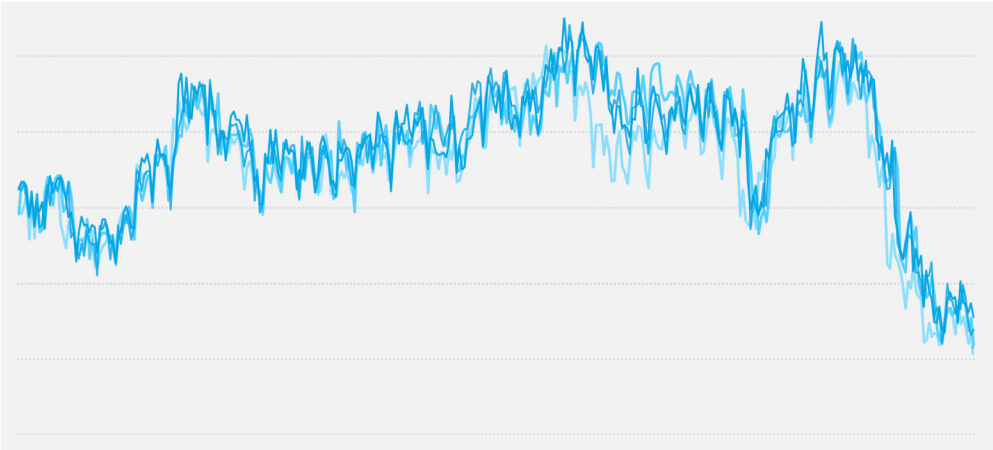
History is Very Predictive Until COVID19



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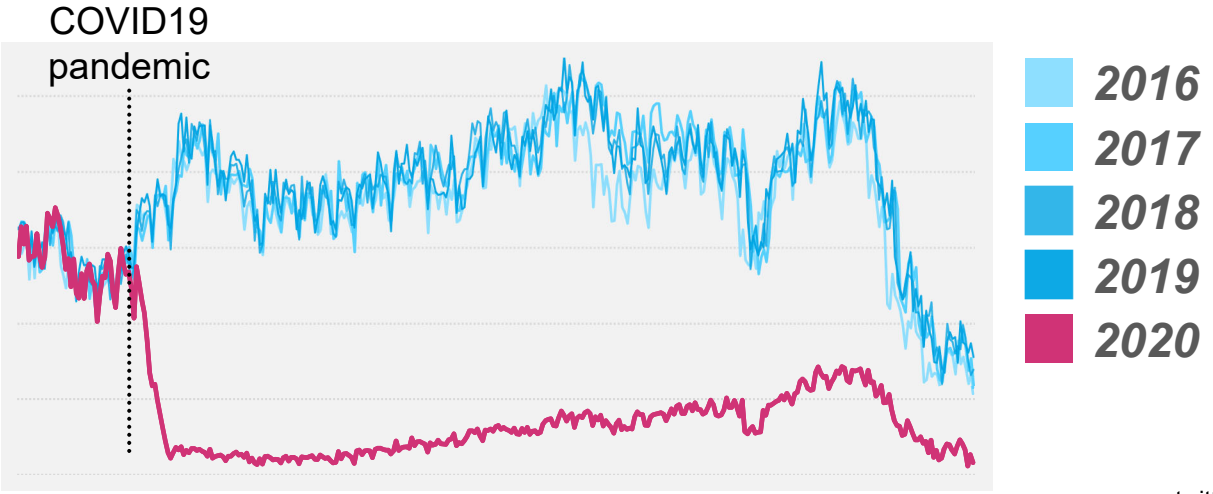
But History is Still Relevant

does that really mean history is useless?



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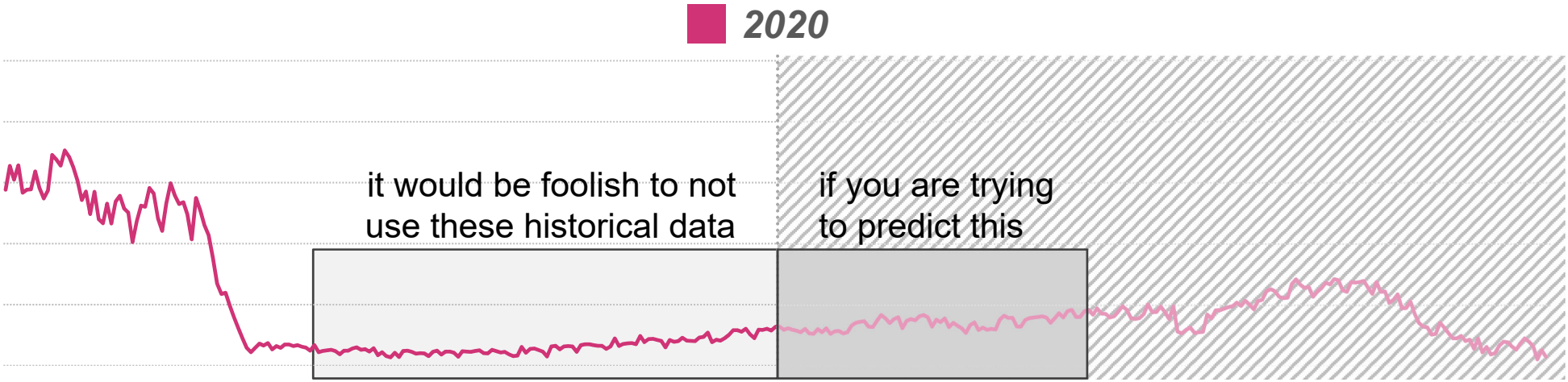
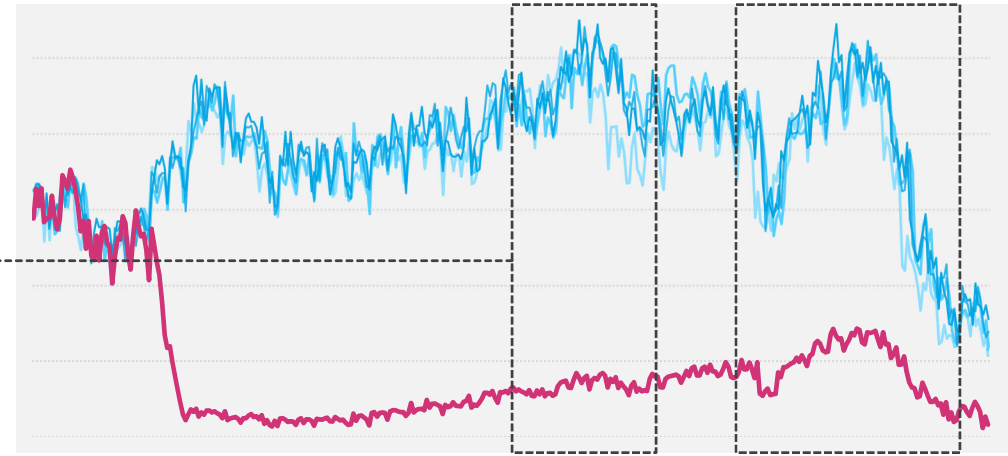


some seasonality may still be very relevant



2016
2017
2018
2019

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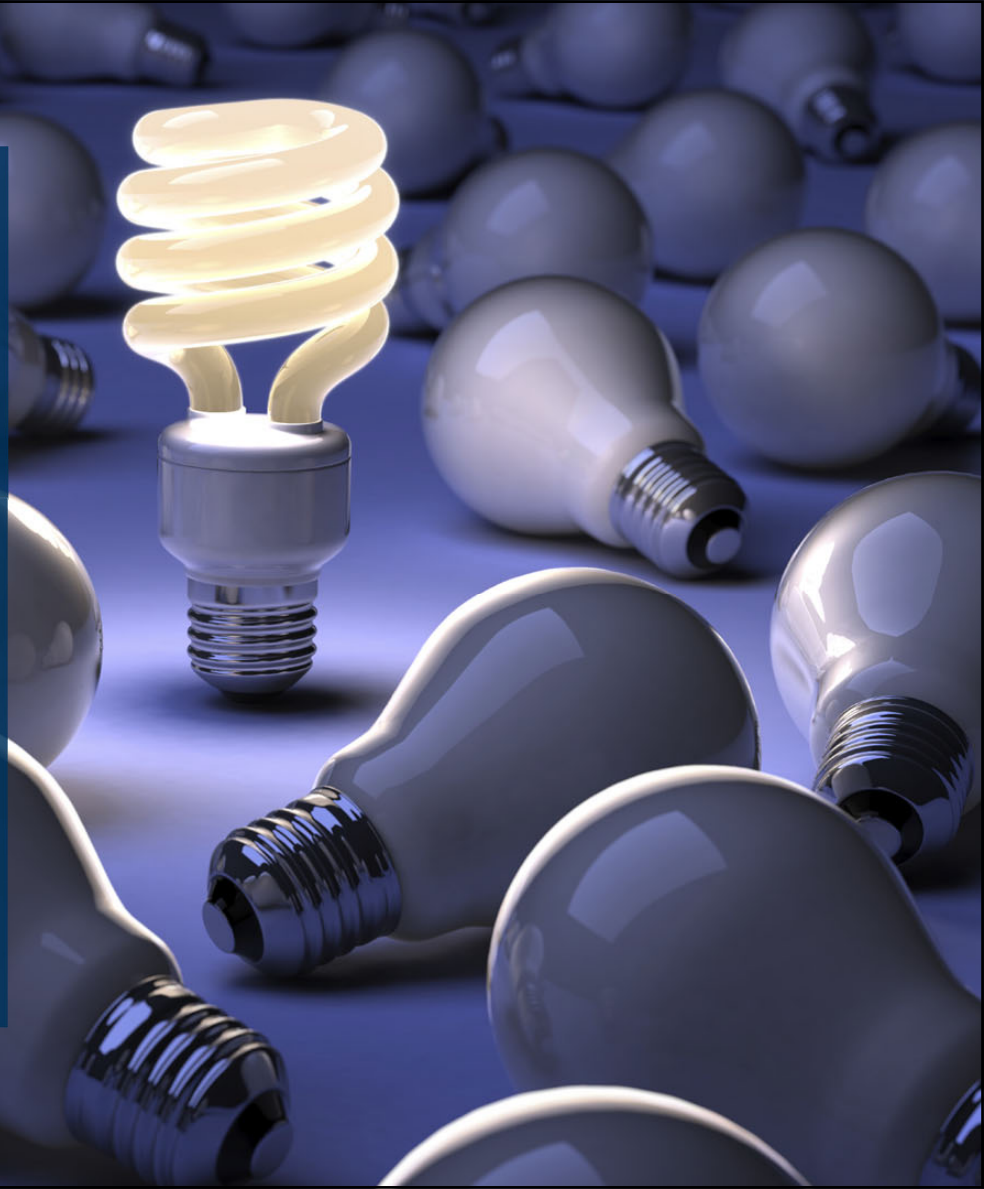
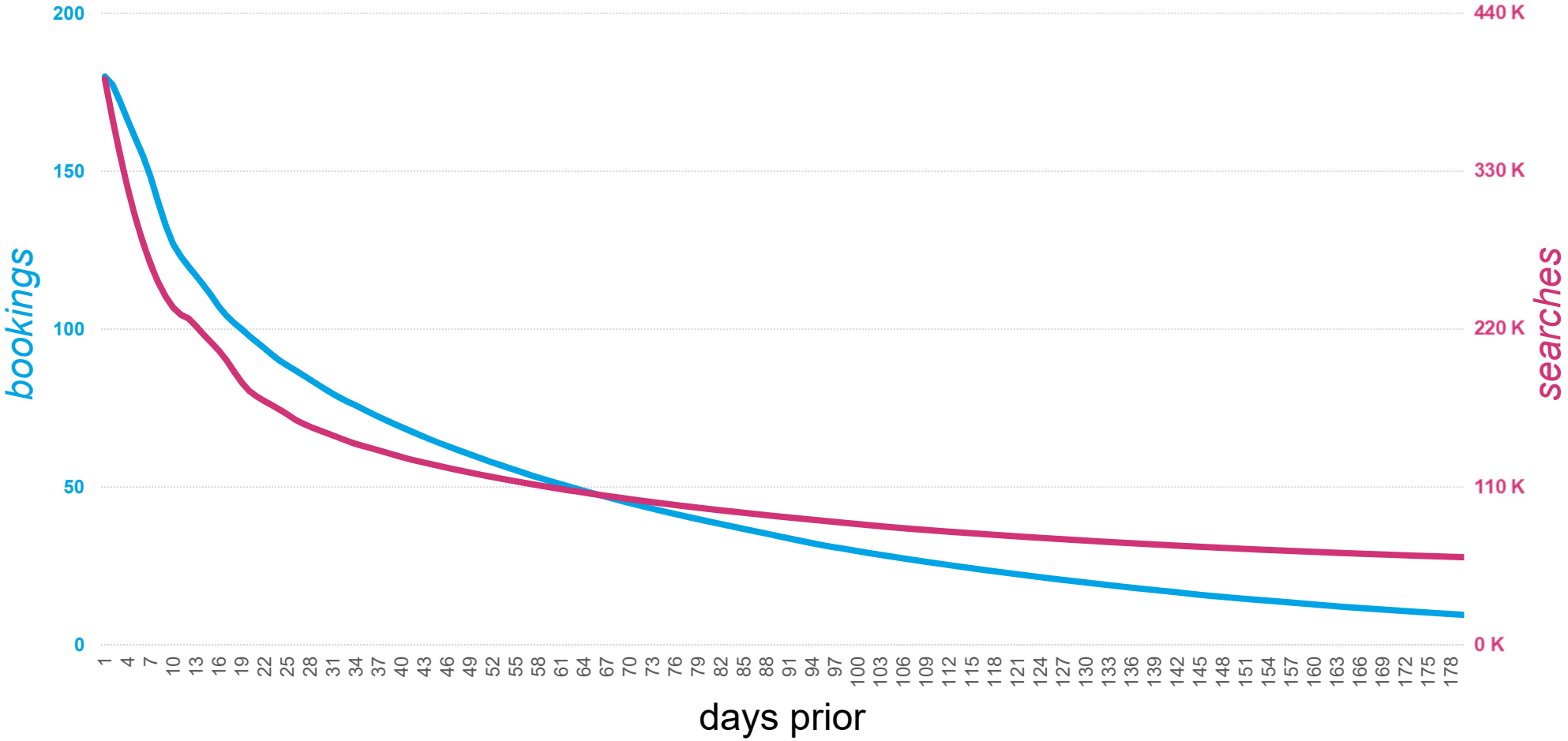
we can’t use history the same way, but that doesn’t mean history is useless

- we can’t use long histories to forecast far future, but we can still use shorter history to forecast the near future
- this reduces the forecasting data volume, and forecast confidence
- learn from the retailers and augment the shorter history creatively using more variety of data sources



learning from retailers, and leverage shopping data

Booking Curve vs. Looking Curve



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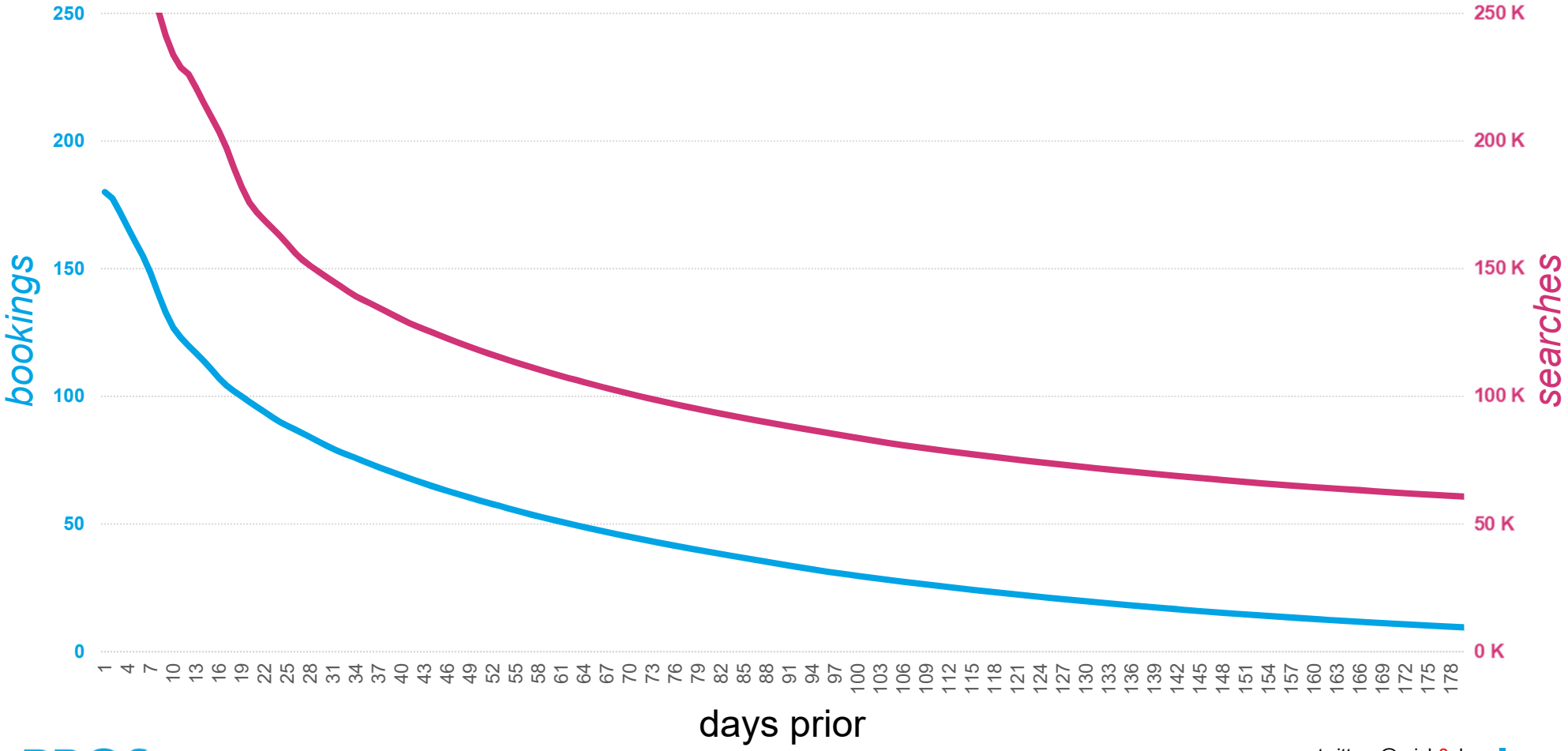
Proportionalized Looks



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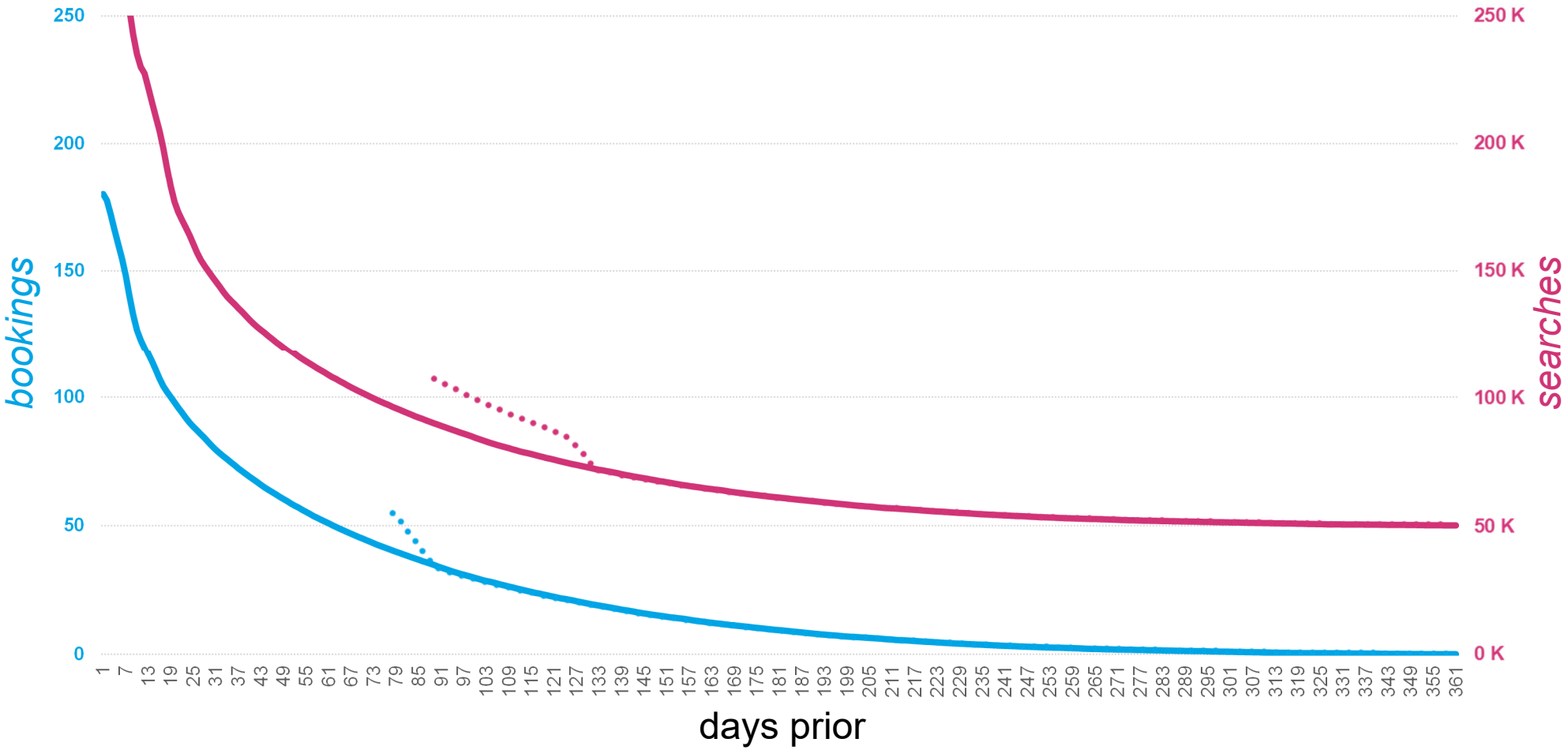
Uptick in Looks is Followed by Uptick in Books



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most people look before they book

models
deep
dive

Structured Model Spec

shopping
$s_{od}(t, T)$
booking
$b_{od}(t, T)$

t = time when the shopping and booking is done (e.g. booking date)

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Structured Model Spec

shopping

$s_{od}(t, T)$

booking

$b_{od}(t, T)$

T = time when the travel will happen (departure date)

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Structured Model Spec

since $t \leq T$, define:

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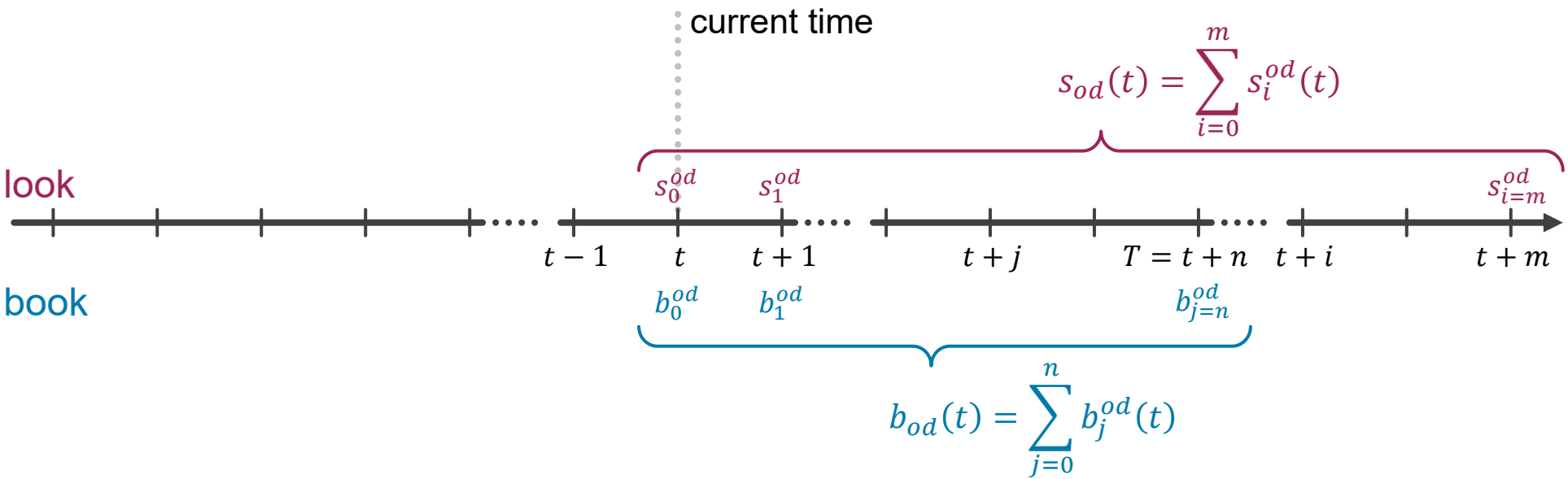
$$m > n$$



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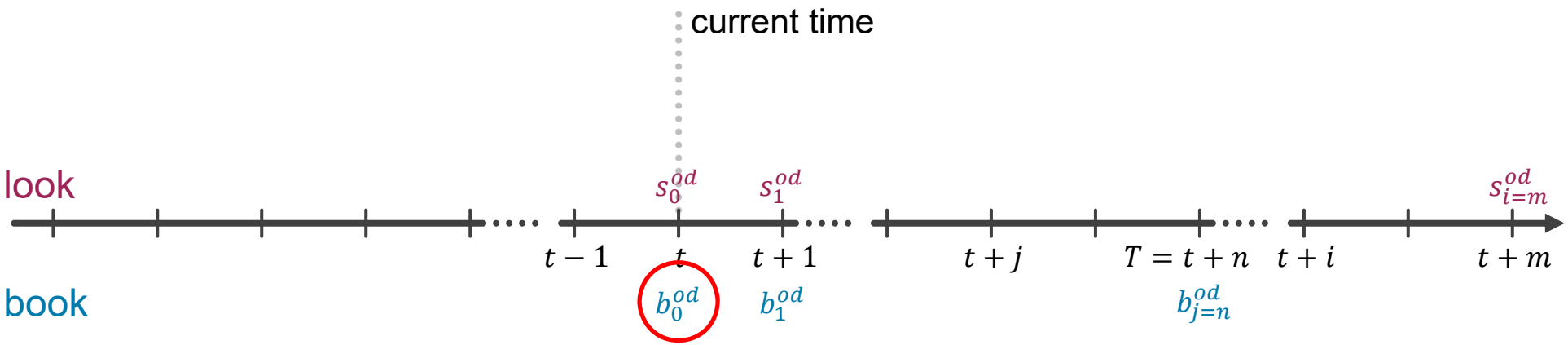

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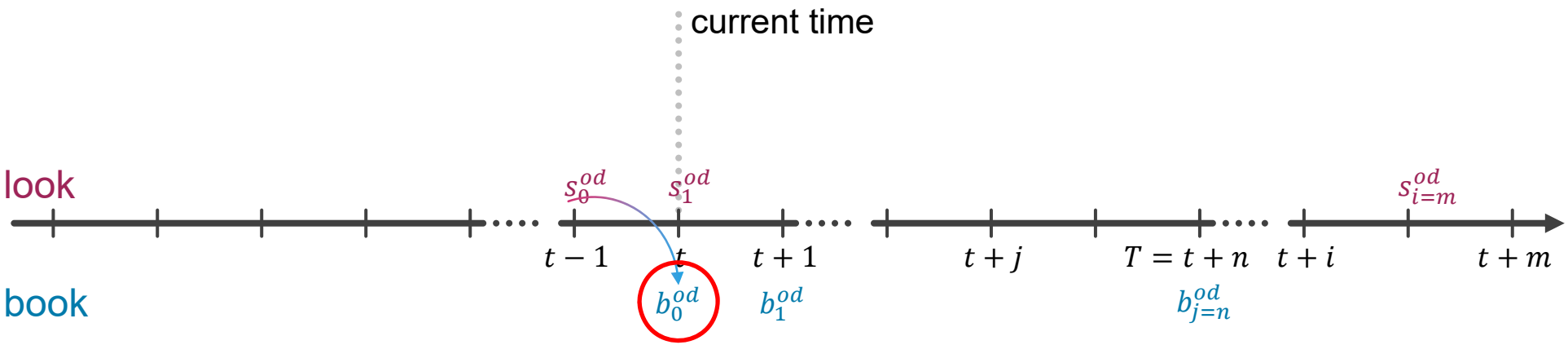

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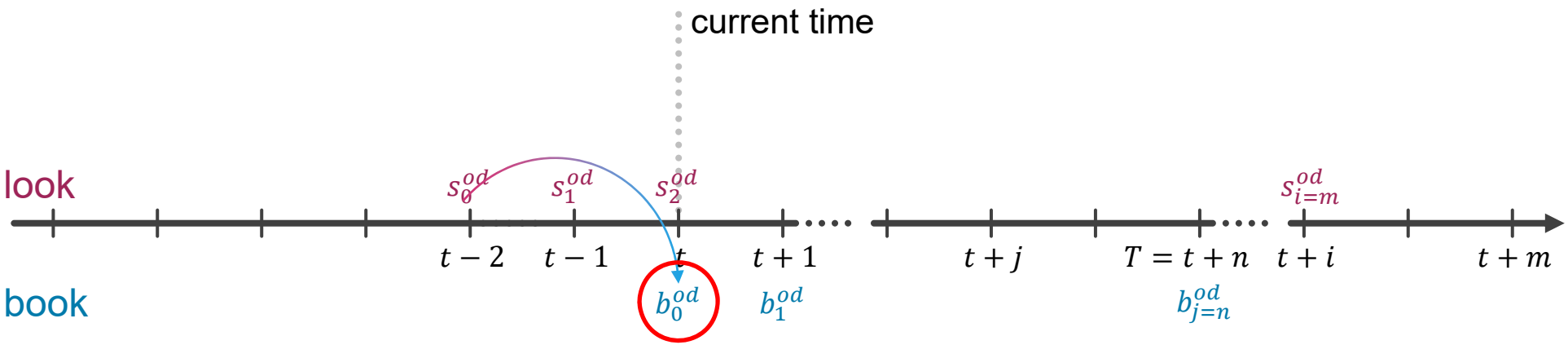

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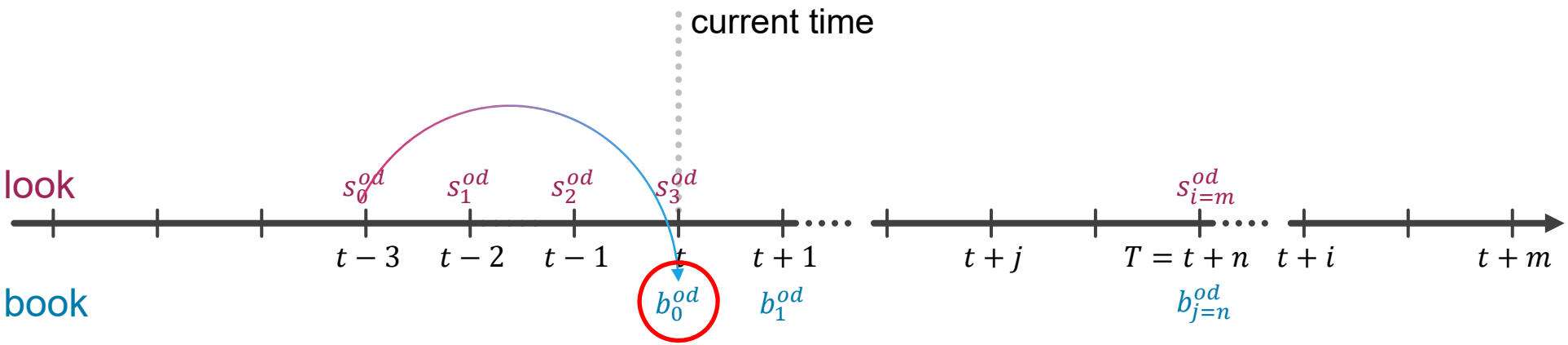

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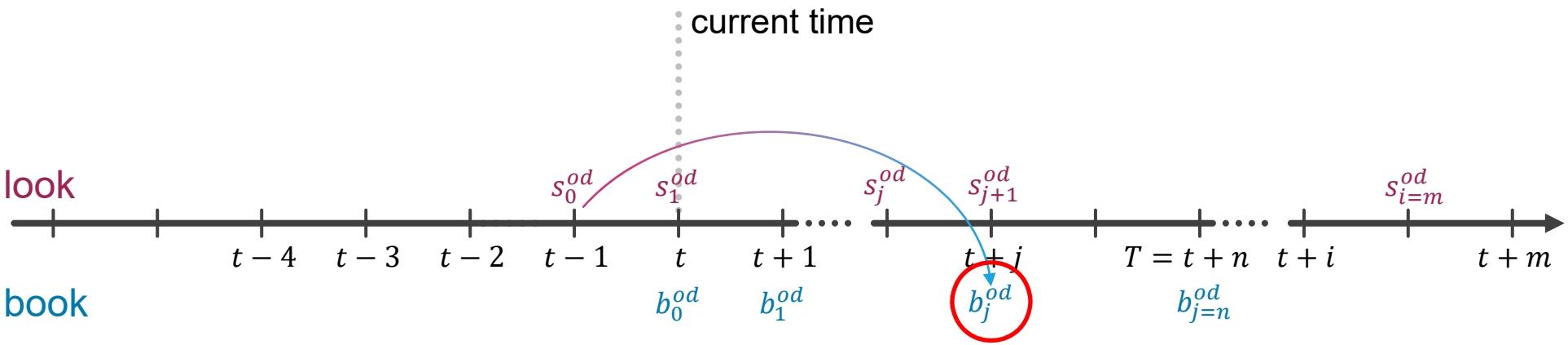

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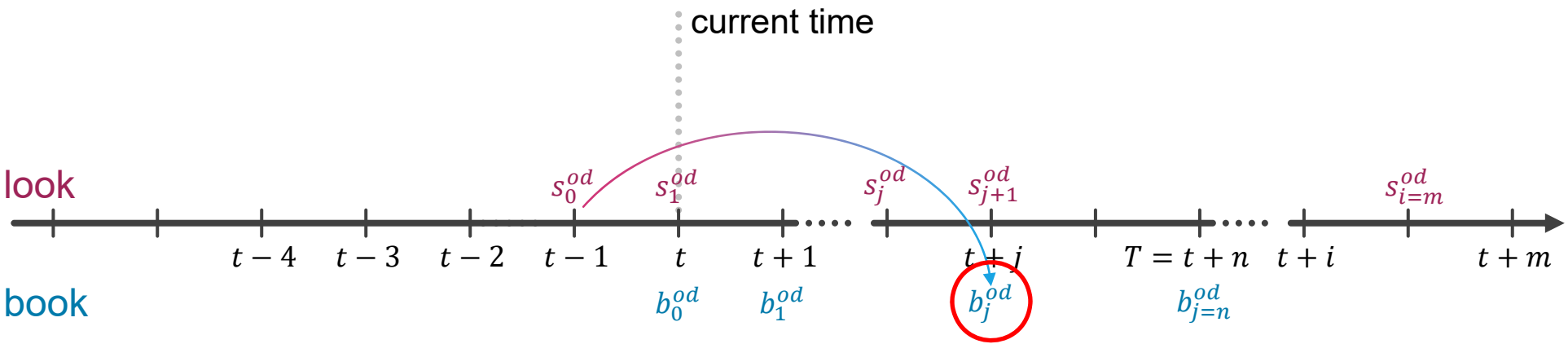

$$b_j^{od}(t) = \sum_{i=1}^{m-j} \beta_{ji} \underline{s_{j+i}^{od}}(\underline{t-i}) \qquad b_{od}(t) = \sum_{j=0}^{n} b_j^{od}(t)$$

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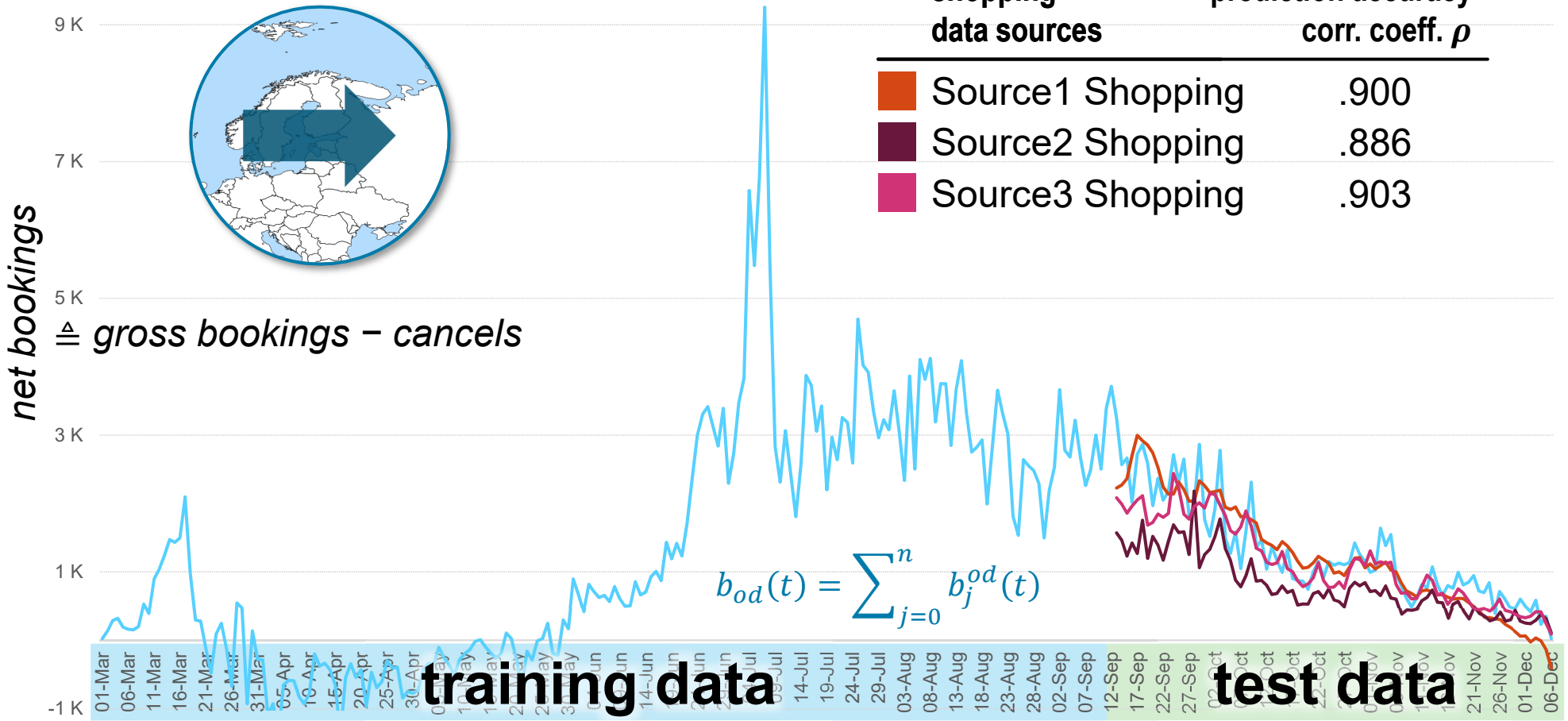
Domestic O&D: Northern Europe

≙ *gross bookings − cancels*

shopping data sources	prediction accuracy corr. coeff. ρ
Source1 Shopping	.900
Source2 Shopping	.886
Source3 Shopping	.903



$$b_{od}(t) = \sum_{j=0}^{n} b_j^{od}(t)$$

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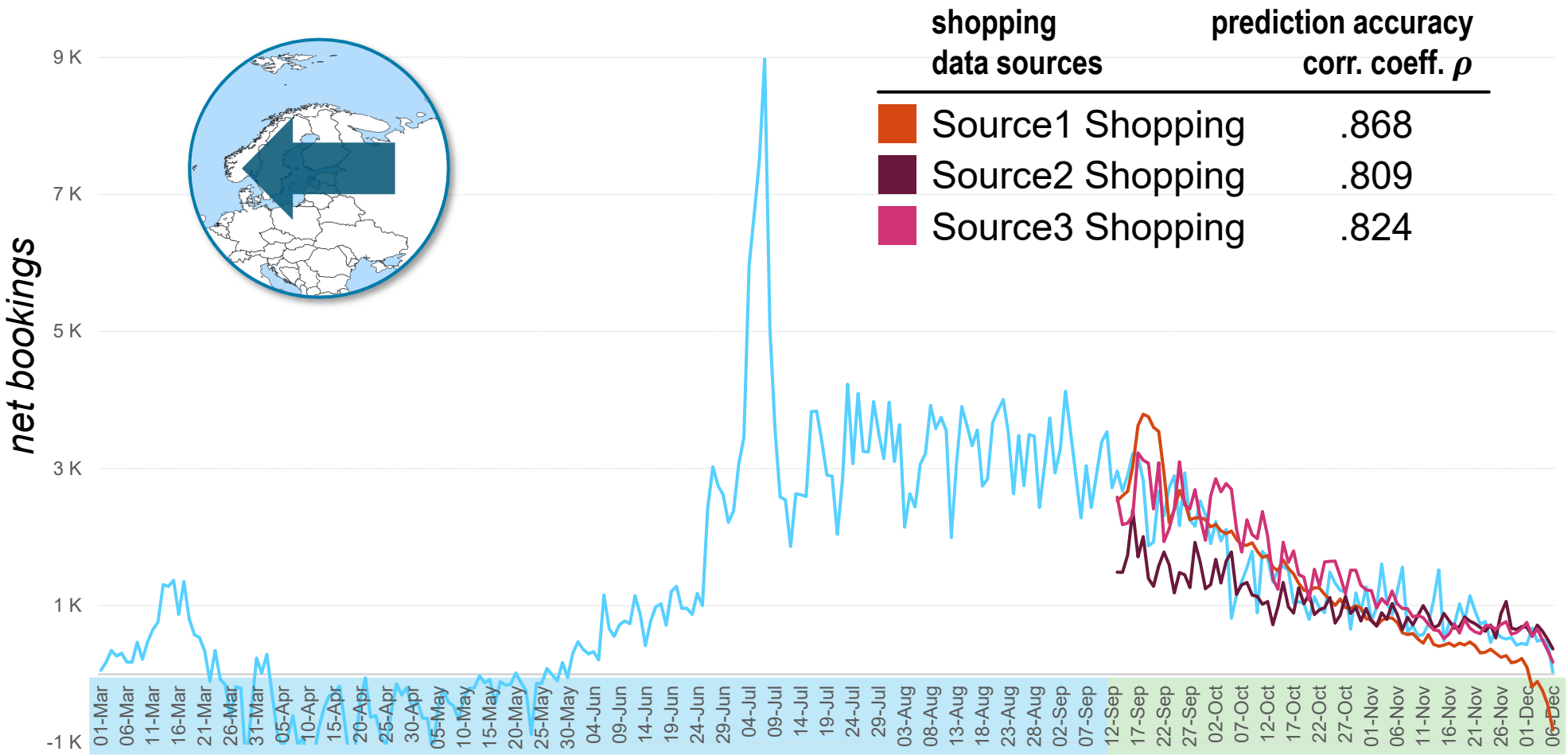
Domestic O&D: Northern Europe Returning Flight



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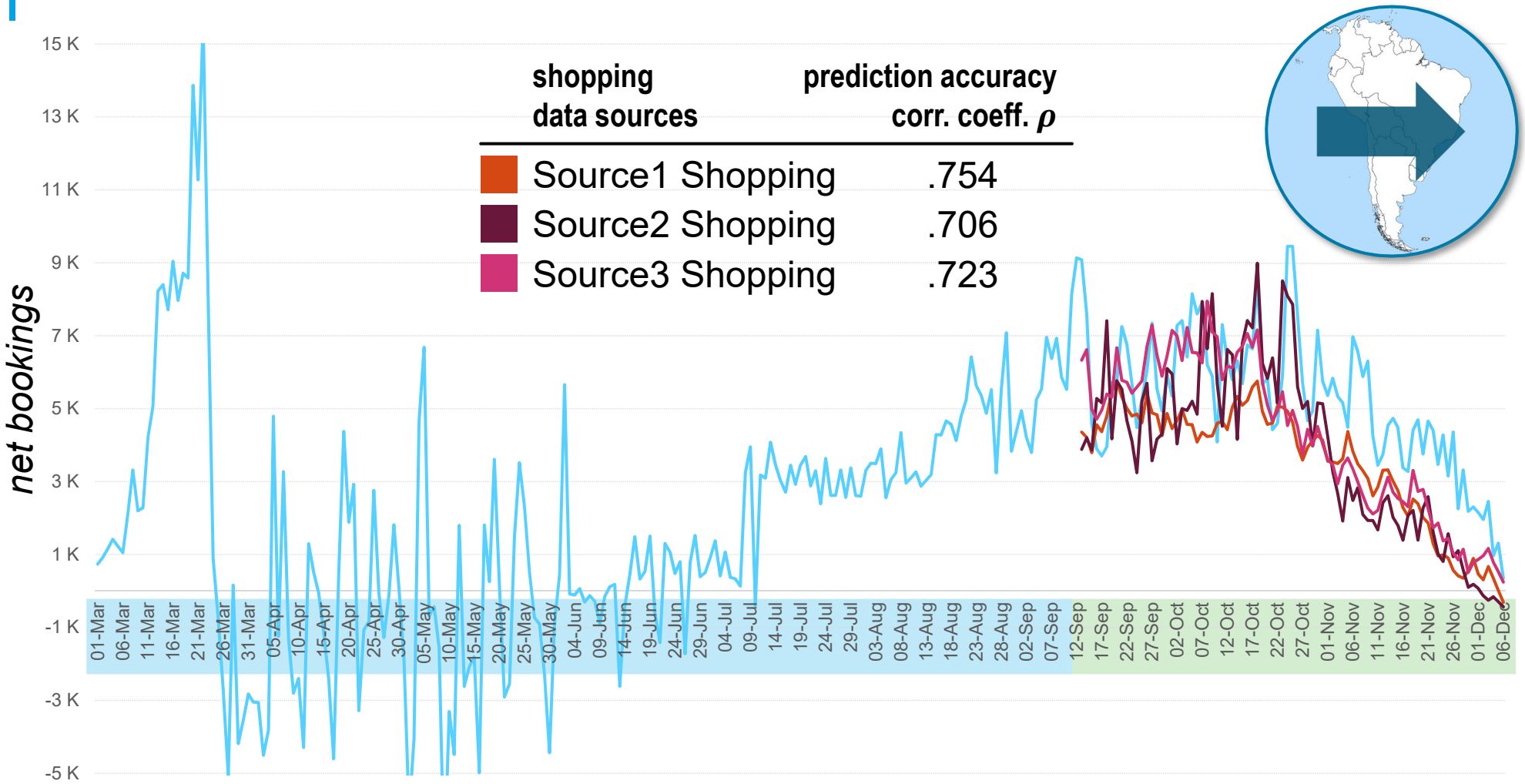
Domestic O&D: South America



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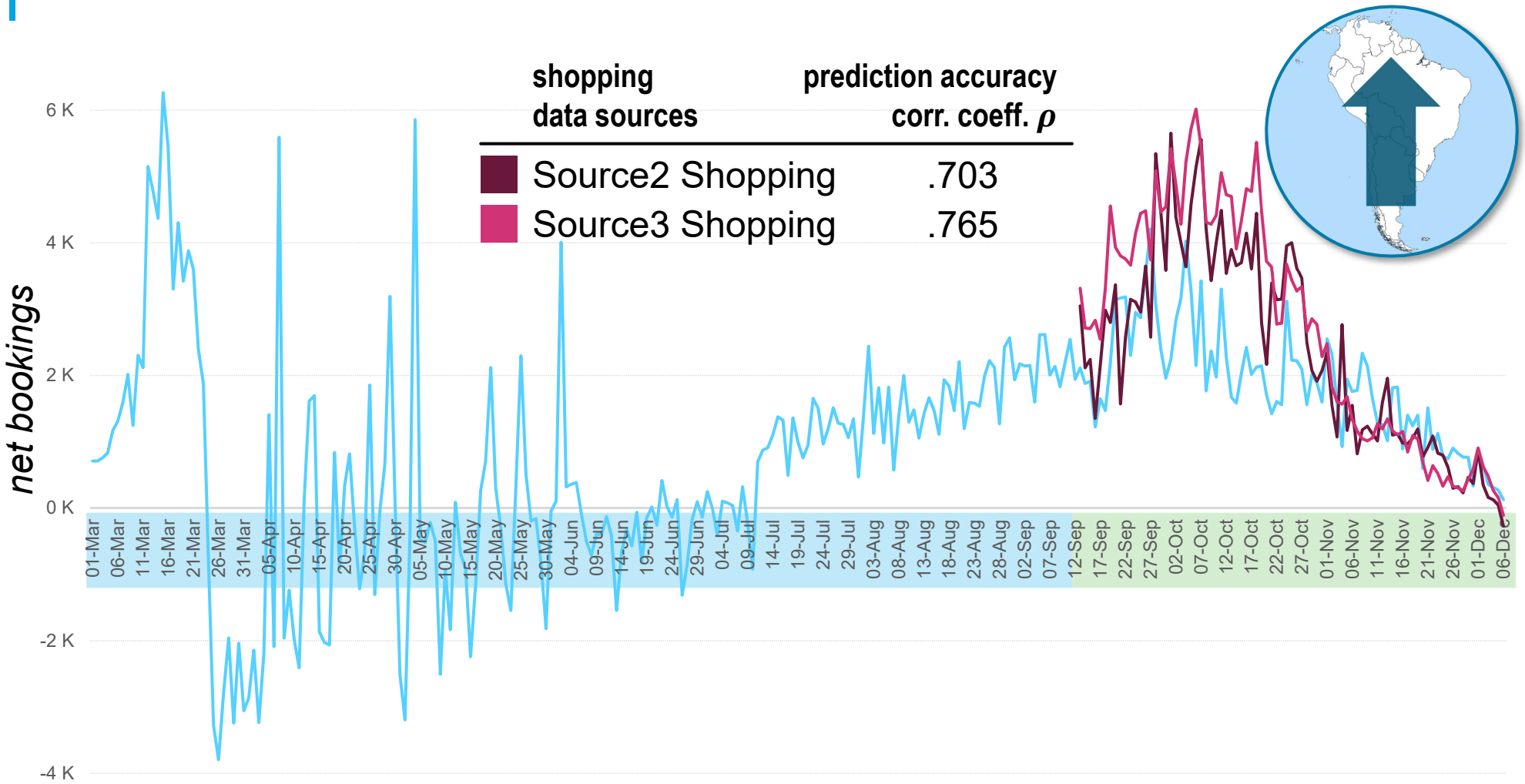

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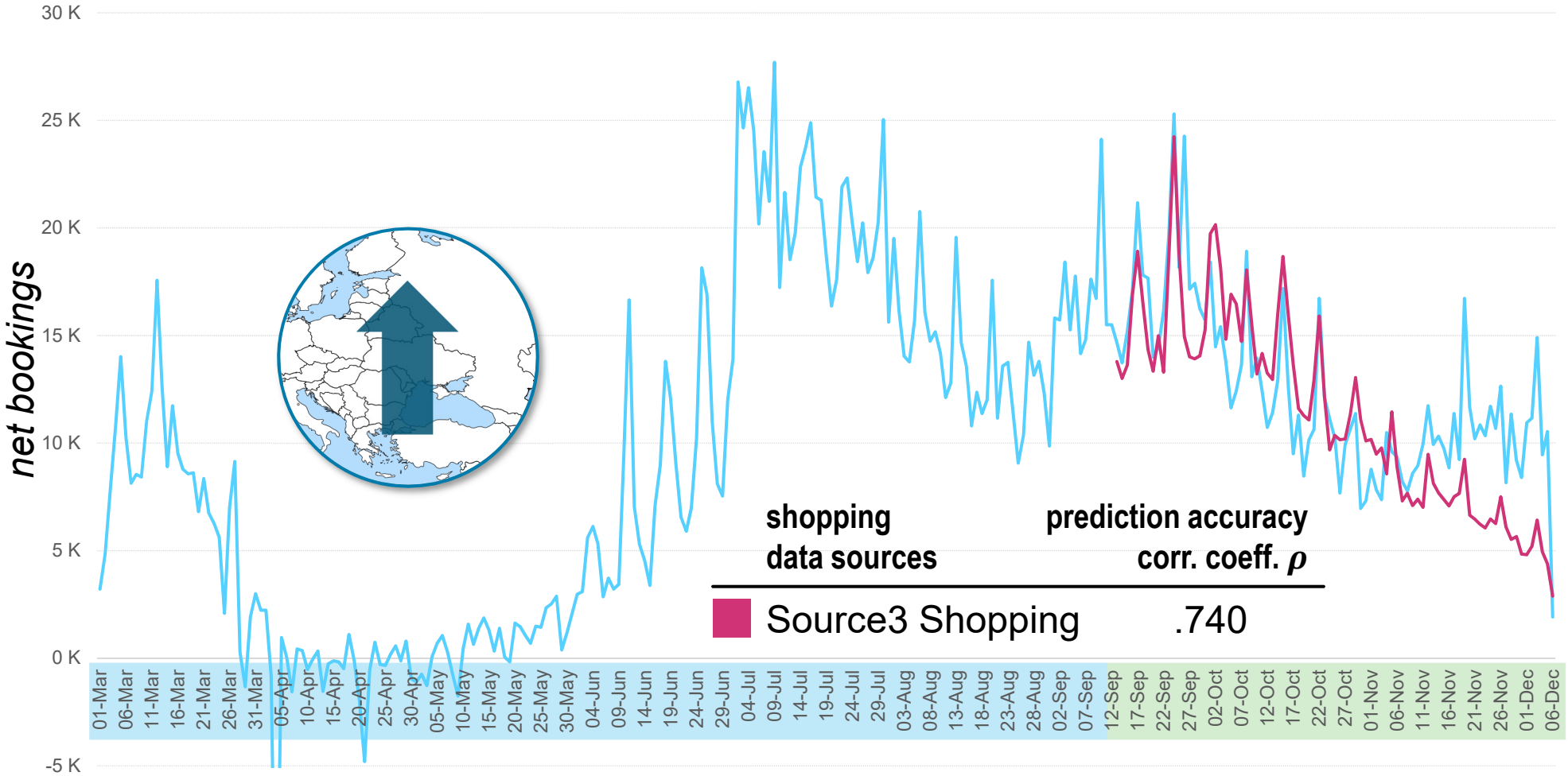
Domestic O&D: Eastern Europe



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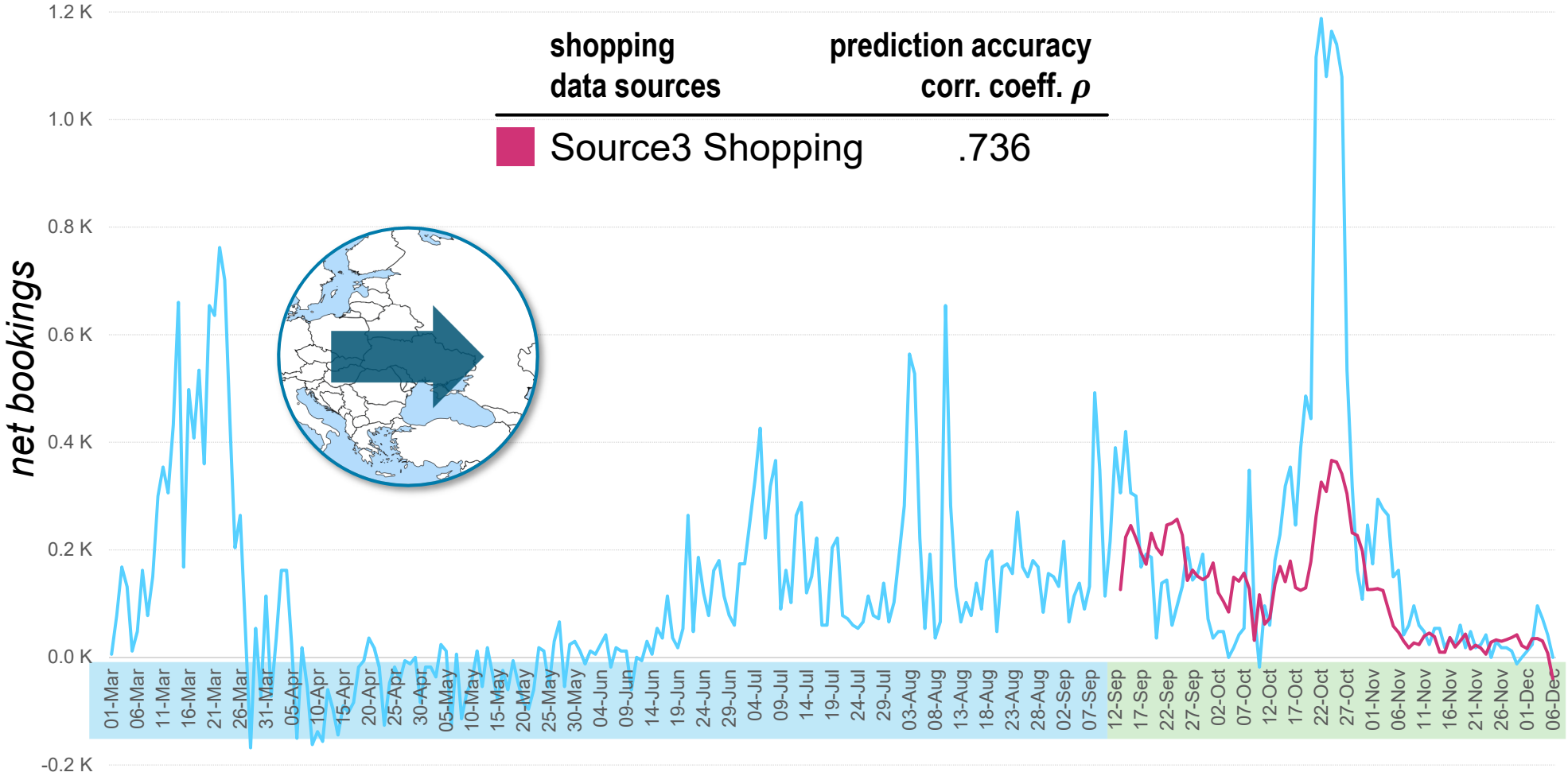
Domestic O&D: Eastern Europe



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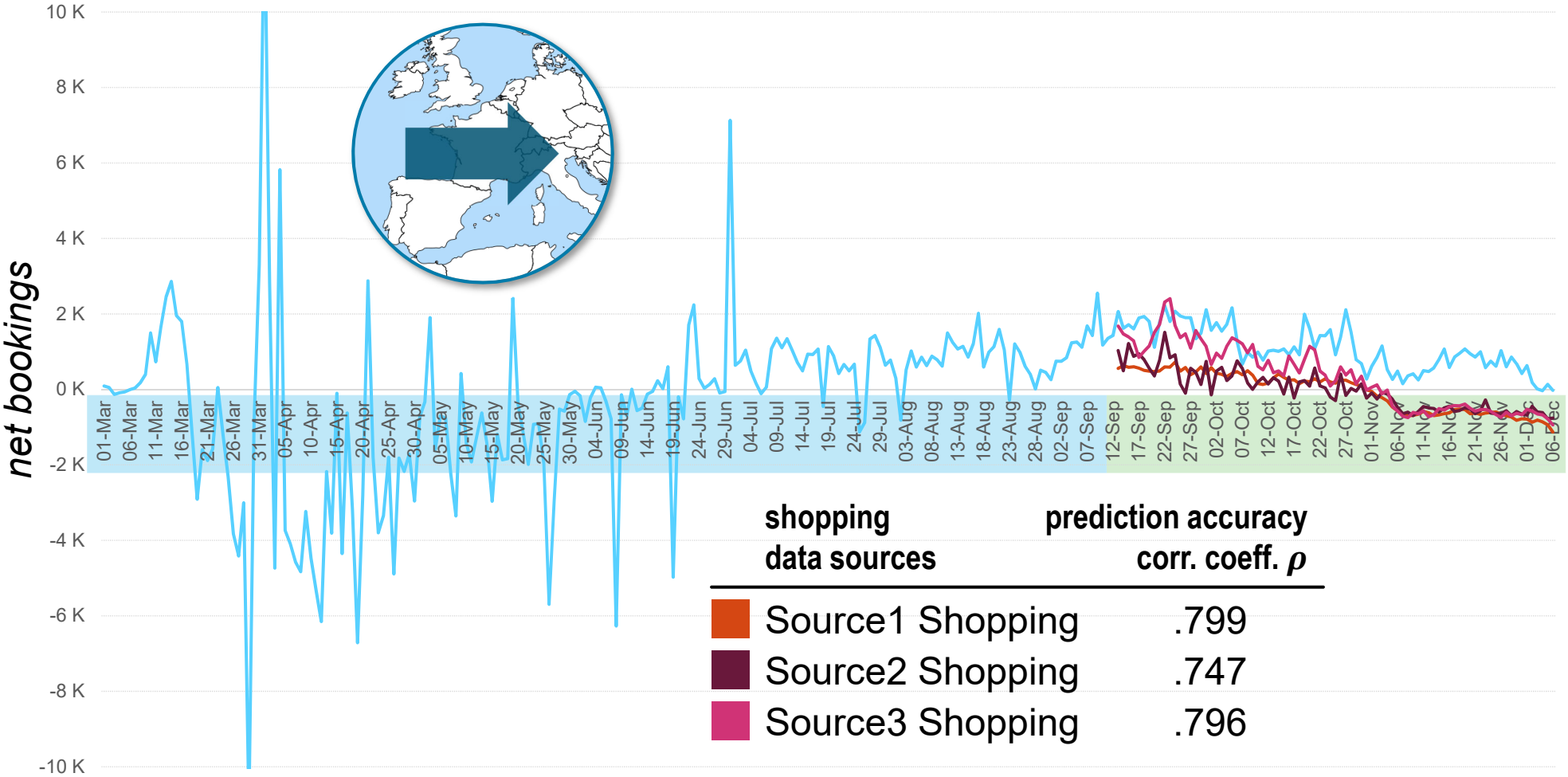
International O&D: Western Europe



shopping data sources	prediction accuracy corr. coeff. ρ
Source1 Shopping	.799
Source2 Shopping	.747
Source3 Shopping	.796

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conclusion + current progress

1. shopping data is highly predictive of people's intent to travel
2. predict gross bookings instead of net-bookings
3. feature engineering (shopping rate change, ratio, etc.)
4. use nonlinear model (e.g. XGboost, neural network etc.)
5. quantify performance lift from the use of shopping data

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the future:

1. **augmenting the PROS Bayesian forecaster**

2. **potentially replacing holiday-special events model**

3. **other ways to use shopping data**
   - total market demand
   - demand for non-scheduled flights
   - price sensitivity analysis base on win/loss (look-to-book ratio)

4. **shopping data is just the first; we will be leveraging other data sources (e.g. competitor fares, events data, weather, economics indicators, etc.)**

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