

# E2E forecasting flow overview

Input data  
preprocessing

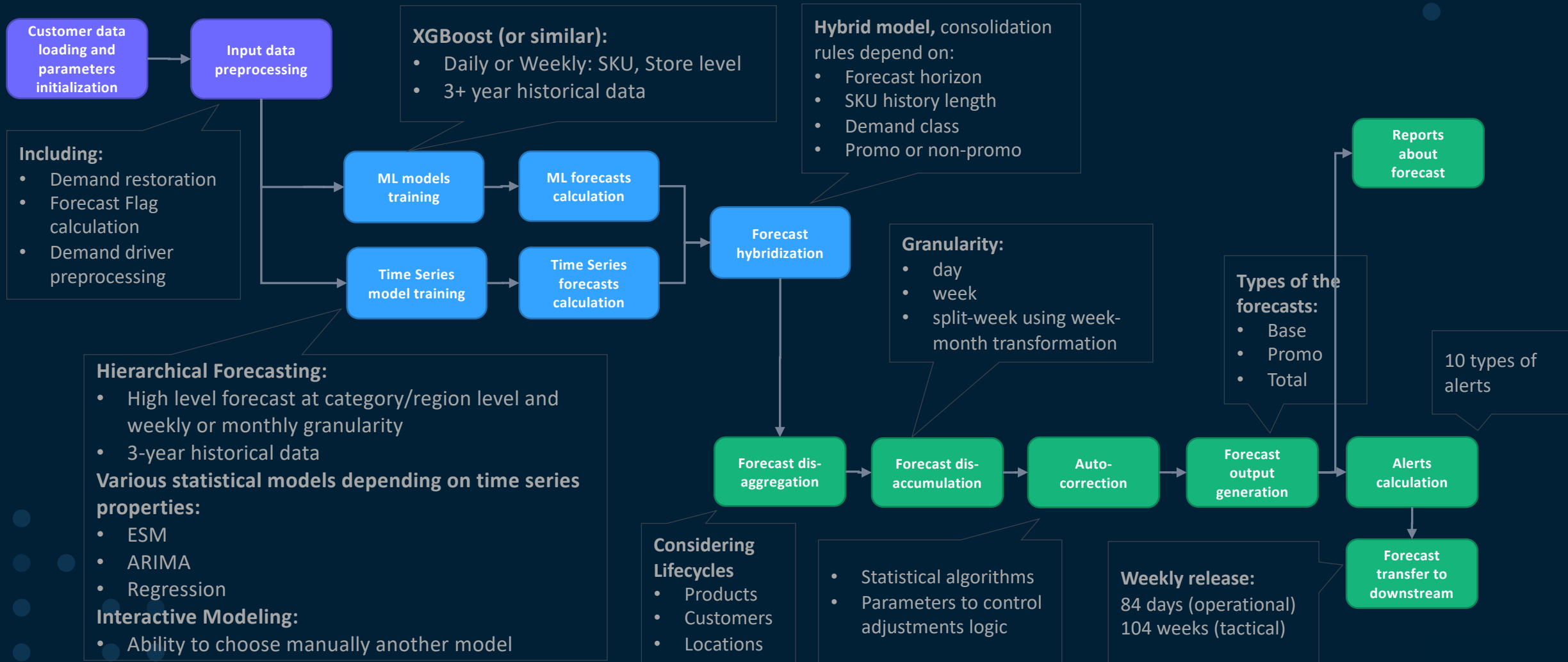
Data pre-processing

ML model  
training

Core analytical tasks

Forecast  
disaggregation

Post-processing



# Definition of data entities

IA Table name	Description	Type
PRODUCT	Stores basic information about products, including product hierarchy.	Mandatory
LOCATION	Stores information about locations (location hierarchy).	Mandatory
CUSTOMER	Stores basic information about customers (distributors, retailers etc.), including customer hierarchy.	Mandatory
DISTR_CHANNEL	Stores basic information about distribution channel, including distribution channels hierarchy.	Mandatory
SELL_IN	Stores information about historical sales (e.g. shipment data).	Mandatory
SELL_OUT	Stores information about historical sales of the customers (POS data).	Mandatory
ASSORT_MATRIX	Stores information about product matrix, to define assortments that should be forecasted by the solution.	Critical
PRODUCT_LIFE	Stores information about products lifecycle. Aimed at covering the situations when the history of sales should be inherited by one product from the other.	Critical
LOCATION_LIFE	Stores information about locations lifecycle. Aimed at covering the situations when the history of sales should be inherited by one location from the other.	Critical
CUSTOMER_LIFE	Stores information about customers lifecycle. Aimed at covering the situations when the history of sales should be inherited by one customer from the other.	Critical
EVENTS	Stores information about calendar events.	Optional
PRODUCT_ATTR	Stores information about product attributes.	Optional
LOCATION_ATTR	Stores information about location attributes.	Optional
CUSTOMER_ATTR	Stores information about customer attributes.	Optional
DISTR_CHANNEL_ATTR	Stores information about distribution channel attributes.	Optional
STOCK	Stores historical information about inventories.	Optional
PROMO_TYPE	Stores information about types of promo events.	Optional
PROMO	Stores information about planned and historical promotions events.	Optional
PROMO_ATTR	Stores information about promo attributes.	Optional
PRICE	Stores information about planned and historical prices.	Optional
CROSS_ATTRIBUTES	Stores information about cross attributes. Aimed at covering the cases when the same product can have country or region or location specific attributes.	Optional

# DQ examples

## Check values range

```
def check_val_range(data_quality_output, table, target_col, th=0):  
    result = table[table[target_col] < th]  
    if not result.empty:  
        data_quality_output = pd.concat([data_quality_output, result])  
  
    return data_quality_output
```

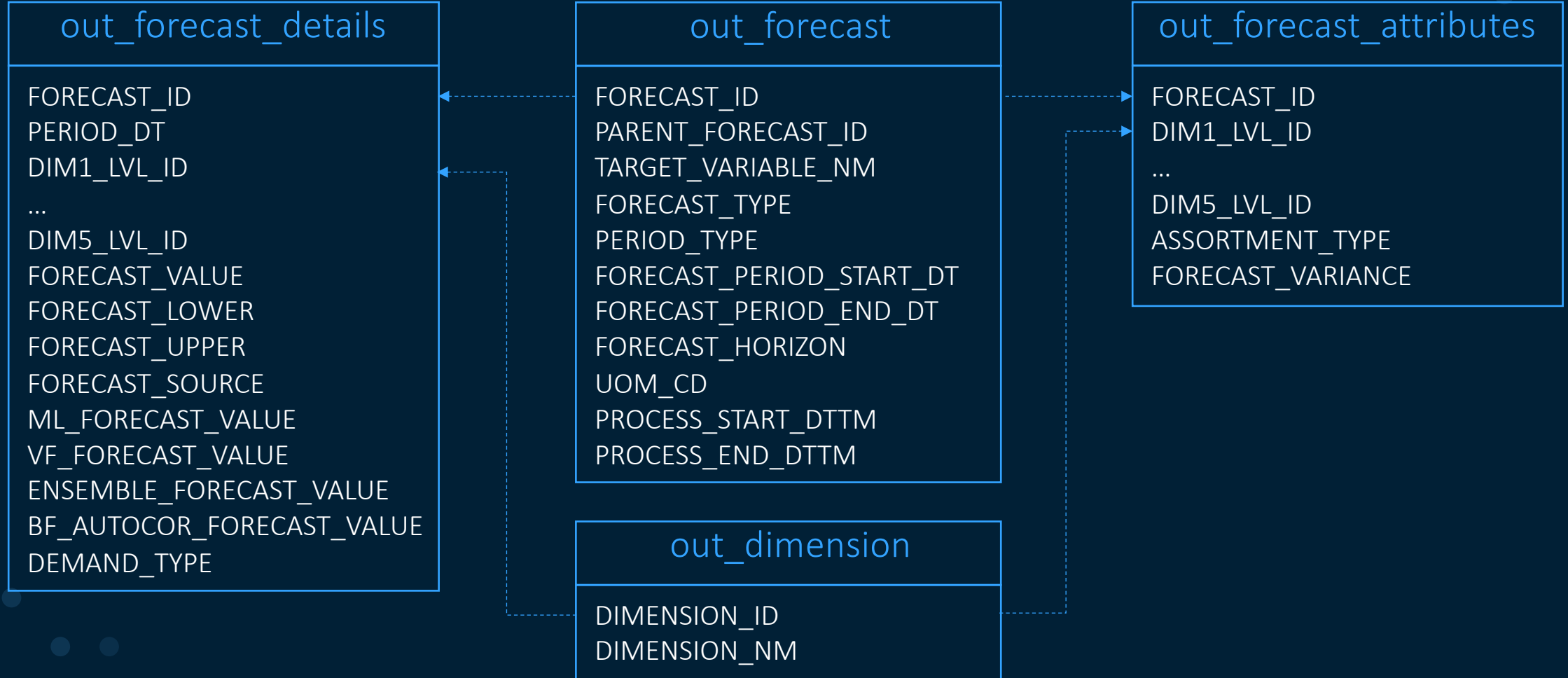
```
data_quality_output = check_val_range(data_quality_output, promo, 'PROMO_PRICE')
```

PRODUCT_ID	LOCATION_ID	CUSTOMER_ID	DISTR_CHANNEL_ID	PERIOD_START_DT	PERIOD_END_DT	PRICE	PRICE_TYPE	M
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## Check cross consistency

```
def check_cross_consistency(data_quality_output, df1, df2):  
    common_cols = df1.columns.intersection(df2.columns)  
    common_cols = list(common_cols[common_cols.str.contains('ID')])  
  
    if common_cols == []:  
        return data_quality_output  
  
    df_merged = df1.drop_duplicates(common_cols).merge(df2.drop_duplicates(common_cols), on=common_cols,  
                                                       how='left', indicator=True)  
  
    result = df_merged[df_merged['_merge'] == 'left_only']  
  
    if not result.empty:  
        data_quality_output = pd.concat([data_quality_output, result])  
  
    return data_quality_output
```

# Forecast output structure (real case)



# Demand Restoration



The image shows a hand pointing at a large, semi-transparent digital screen. The screen displays a variety of financial and data-related icons and charts, including bar graphs, line graphs, pie charts, and candlestick charts. Some icons are enclosed in rounded rectangular frames. The background is a blurred image of a crowd of people, suggesting a public or professional setting. The overall theme is data analysis and demand management.

# Sales VS Demand

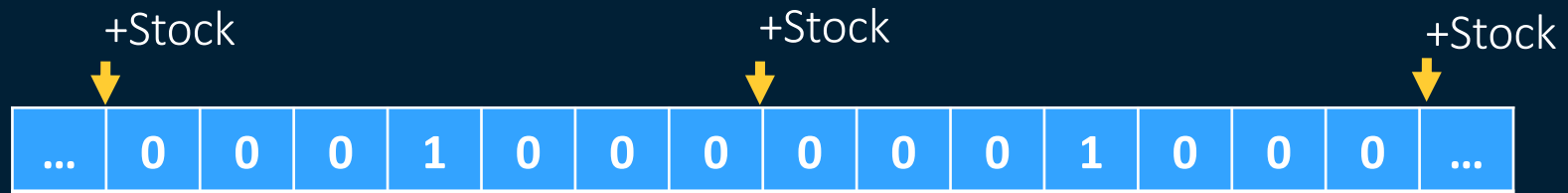
## Item 1

Daily Sales



## Item 2

Daily Sales



# Sales VS Demand

## Item 1

		+Stock						+Stock								+Stock	
Daily Sales	...	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	...
Daily Stock	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0

## Item 2

		+Stock						+Stock								+Stock	
Daily Sales	...	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	...
Daily Stock	0	1	1	1	1	0	0	0	1	1	1	1	0	0	0	0	0

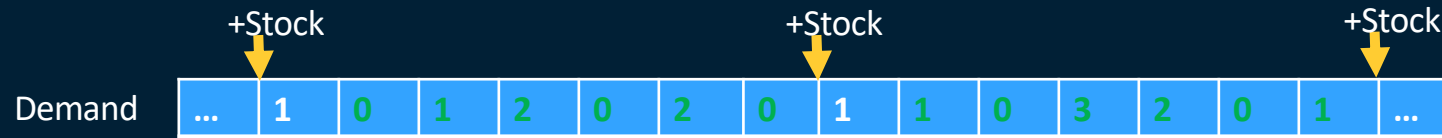
# Poisson Model

## Key Assumptions

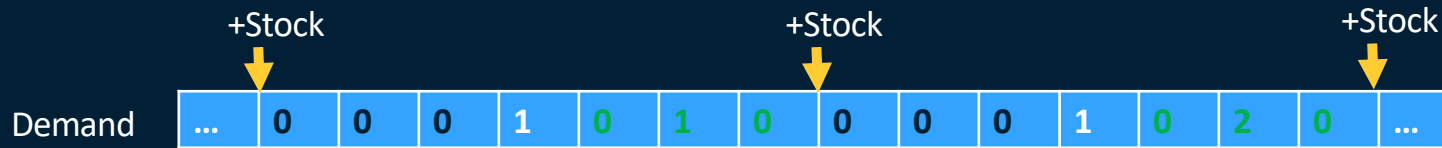
- The number of sales in different periods of time is a random variable
- Probability to sell  $k$  pieces in  $t$  days (in case of infinite stock) is Poisson distribution

$$P_{\infty}(x = k) = \frac{\lambda^k}{k!} e^{-\lambda}$$

Item 1:  $\lambda = 1$



Item 2:  $\lambda = 0.4231$





# Poisson model for Demand restoration

Model of birth and death

- $m$  – number of pieces in stock
- $k$  – sales amount
- $P_m(x = k)$  - probability to sell  $k$  pieces having  $m$  pieces in stock

$$P_m(x = k) = \begin{cases} 1, & k = m = 0, \\ 0, & k > m \text{ or } k < 0 \end{cases}$$

# Poisson model for Demand restoration

Model of birth and death

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$$P_m(x = k) = \begin{cases} 1, & k = m = 0, \\ 0, & k > m \text{ or } k < 0 \\ \frac{(\lambda)^k}{k!} e^{-\lambda}, & 0 \leq k < m, \end{cases}$$

# Poisson model for Demand restoration

Model of birth and death

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- $k$  – sales amount
- $P_m(x = k)$  - probability to sell  $k$  pieces having  $m$  pieces in stock

$$P_m(x = k) = \begin{cases} 1, & k = m = 0, \\ 0, & k > m \text{ or } k < 0 \\ \frac{(\lambda)^k}{k!} e^{-\lambda}, & 0 \leq k < m, \\ 1 - \sum_{l=0}^{m-1} \frac{(\lambda)^l}{l!} e^{-\lambda}, & k = m > 0 \end{cases}$$

How to estimate  $\lambda$  for each item:

- Long history of data
- Find proper estimation method

# Poisson model for Demand restoration

Estimation of  $\lambda$

- There is a sample realization of a random variable for a two parameters

$$(k_1, m_1), (k_2, m_2), \dots, (k_T, m_T)$$

- Likelihood

$$\begin{aligned} L &= P_{m_1}(x = k_1) \cdot P_{m_2}(x = k_2) \cdot \dots \cdot P_{m_T}(x = k_{m_T}) = \\ &= \prod_{i: 0 \leq k_i < m_i} \frac{(\lambda)^{k_i}}{k_i!} e^{-\lambda} \cdot \prod_{i: k_i = m_i > 0} \left( 1 - \sum_{l=0}^{m_i-1} \frac{(\lambda)^l}{l!} e^{-\lambda} \right) \cdot \prod_{i: k_i = m_i = 0} 1 \end{aligned}$$

# Poisson model for Demand restoration

Estimation of  $\lambda$

- Log likelihood

$$\begin{aligned}\ln L &= \ln \left( \prod_{i: 0 \leq k_i < m_i} \frac{(\lambda)^{k_i}}{k_i!} e^{-\lambda} \cdot \prod_{i: k_i = m_i > 0} \left( 1 - \sum_{l=0}^{m_i-1} \frac{(\lambda)^l}{l!} e^{-\lambda} \right) \cdot \prod_{i: k_i = m_i = 0} 1 \right) = \\ &= \sum_{i: 0 \leq k_i < m_i} \ln \left( \frac{(\lambda)^{k_i}}{k_i!} e^{-\lambda} \right) + \sum_{i: k_i = m_i > 0} \ln \left( 1 - \sum_{l=0}^{m_i-1} \frac{(\lambda)^l}{l!} e^{-\lambda} \right) = \\ &= \ln \lambda \cdot \sum_{i: 0 \leq k_i < m_i} k_i - \lambda \cdot \underbrace{\sum_{i: 0 \leq k_i < m_i} 1}_{n_{0 \leq k < m}} + \sum_{i: k_i = m_i > 0} \ln \left( 1 - \sum_{l=1}^{m_i} \frac{(\lambda)^l}{l!} e^{-\lambda} \right)\end{aligned}$$

# Poisson model for Demand restoration

Estimation of  $\lambda$

- $m_i$  - stock in a day  $i$
- $\sum_{i:k_i>0} k_i$  - sum of sales within observed days
- $n_{0 \leq k < m}$  - number of days, when sales less than stock
- $n_{k=m>0}$  - number of days, when sales are equal to stock

$$\ln L = \ln \lambda \cdot \sum_{i: 0 \leq k_i < m_i} k_i - \lambda \cdot n_{0 \leq k < m} + \sum_{i: k_i = m_i > 0} \ln \left( 1 - \sum_{l=1}^{m_i} \frac{(\lambda)^l}{l!} e^{-\lambda} \right) \rightarrow \max_{\lambda > 0}$$

# Poisson model for Demand restoration

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# Poisson model for Demand restoration

## MLE for $\lambda$ estimation

- Taylor series for exponent

$$1 - \sum_{l=0}^{m_i-1} \frac{(\lambda)^l}{l!} e^{-\lambda} = e^{-\lambda} \left( e^{\lambda} - \sum_{l=0}^{m_i-1} \frac{(\lambda)^l}{l!} \right) = e^{-\lambda} \left( \sum_{l=0}^{\infty} \frac{(\lambda)^l}{l!} - \sum_{l=0}^{m_i-1} \frac{(\lambda)^l}{l!} \right) = e^{-\lambda} \sum_{l=m_i}^{\infty} \frac{(\lambda)^l}{l!} = \frac{(\lambda)^{m_i}}{m_i!} e^{\theta_{m_i,\lambda} \cdot \lambda} e^{-\lambda}$$

- Log likelihood

$$\ln L = \ln \lambda \cdot \sum_{i: 0 \leq k_i < m_i} k_i - \lambda \cdot n_{0 \leq k < m} + \sum_{i: k_i = m_i > 0} \ln \left( \frac{(\lambda)^{m_i}}{m_i!} e^{\theta_{m_i,\lambda} \cdot \lambda} e^{-\lambda} \right) =$$

$$= \ln \lambda \cdot \sum_{i: 0 \leq k_i < m_i} k_i - \lambda \cdot n_{0 \leq k_i < m_i} + \sum_{i: k_i = m_i > 0} (k_i \cdot \ln \lambda + (\theta_{m_i,\lambda} - 1) \cdot \lambda) + C =$$

$$= \ln \lambda \cdot \sum_{i: 0 \leq k_i \leq m_i} k_i - \lambda \cdot \left( n_{0 \leq k < m} + \sum_{i: k_i = m_i > 0} (1 - \theta_{m_i,\lambda}) \right) + C$$



# Poisson model for Demand restoration

MLE for  $\lambda$  estimation

- Necessary condition:

$$\frac{\partial \ln L}{\partial \lambda} = \frac{\sum_{i: 0 \leq k_i \leq m_i} k_i}{\lambda} - \left( n_{0 \leq k < m} + \sum_{i: k_i = m_i > 0} (1 - \theta_{m_i, \lambda}) \right) = 0$$

$$\lambda = \frac{\sum_{i: 0 \leq k_i \leq m_i} k_i}{n_{0 \leq k < m} + \sum_{i: k_i = m_i > 0} (1 - \theta_{m_i, \lambda})} = \frac{\sum k_i}{n_{0 \leq k < m} + \alpha \cdot n_{k=m > 0}},$$

где  $\alpha \in [0, 1]$

# Poisson model for Demand restoration

MLE for  $\lambda$  estimation

$m_i$  - stock in a day  $i$

$\sum_{i:k_i>0} k_i$  - sum of sales within observed days

$n_{0 \leq k < m}$  - number of days, when sales less than stock

$n_{k=m>0}$  - number of days, when sales are equal to stock

$$\ln L = \ln \lambda \cdot \sum_{i: 0 \leq k_i < m_i} k_i - \lambda \cdot n_{0 \leq k < m} + \sum_{i: k_i = m_i > 0} \ln \left( 1 - \sum_{l=1}^{m_i} \frac{(\lambda)^l}{l!} e^{-\lambda} \right) \rightarrow \max_{\lambda > 0}$$

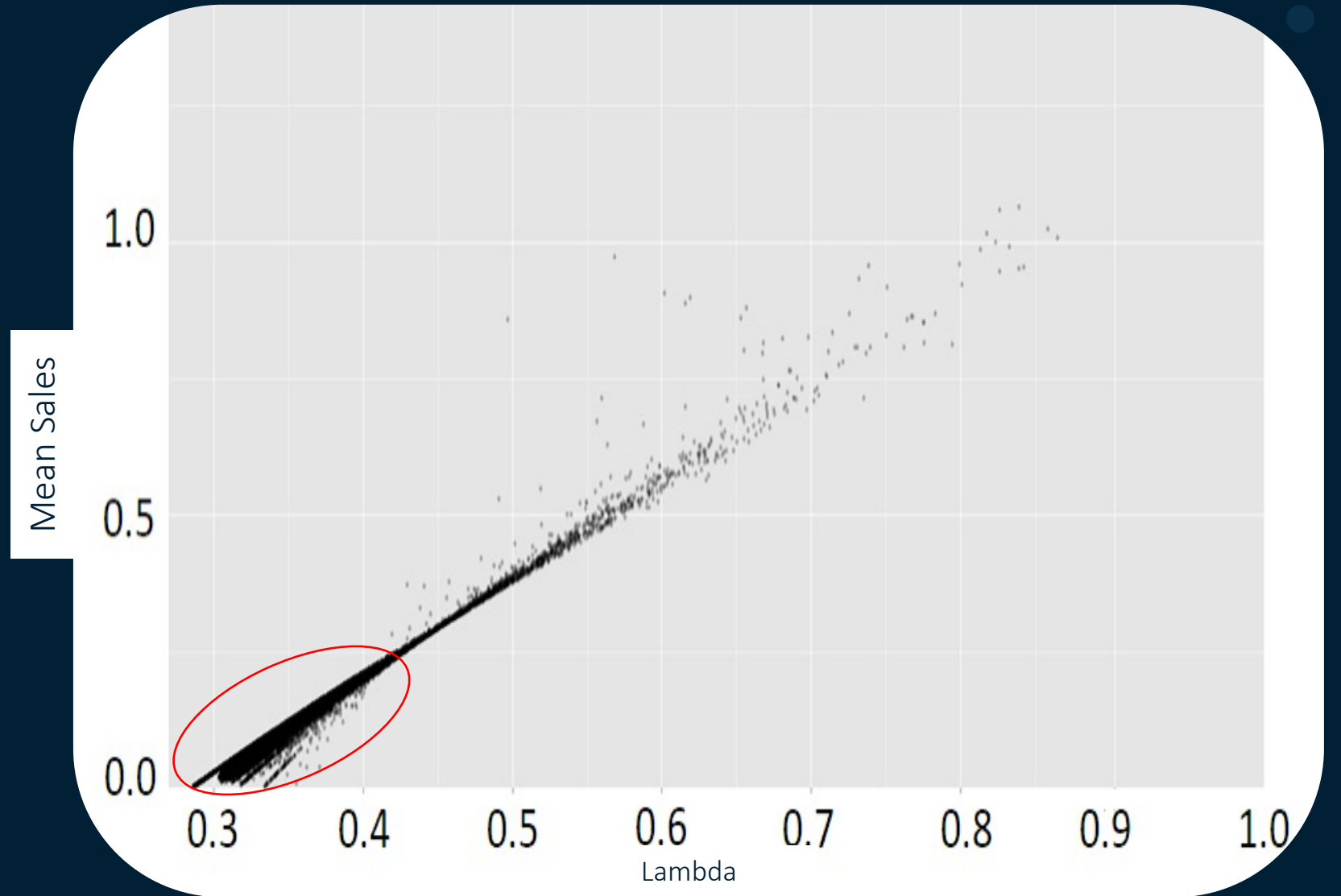
Solution:

$$\lambda = \frac{\sum k_i}{n_{0 \leq k < m} + \alpha \cdot n_{k=m>0}},$$

where  $\alpha \in [0,1]$

# Lambda vs Mean Sales

Lambda is significantly higher than Mean Sales for low-demand items



# Demand Restoration results

Several approaches to restore demand

# 10%-20%

## Realistic Uplift

- Sales
- Optimistic demand
- Conservative demand
- Pessimistic demand

