TEAM CELONIS

TUM Data Innovation Lab

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AGENDA

STRATEGIC GOAL

PHASE I: DATA ANALYSIS

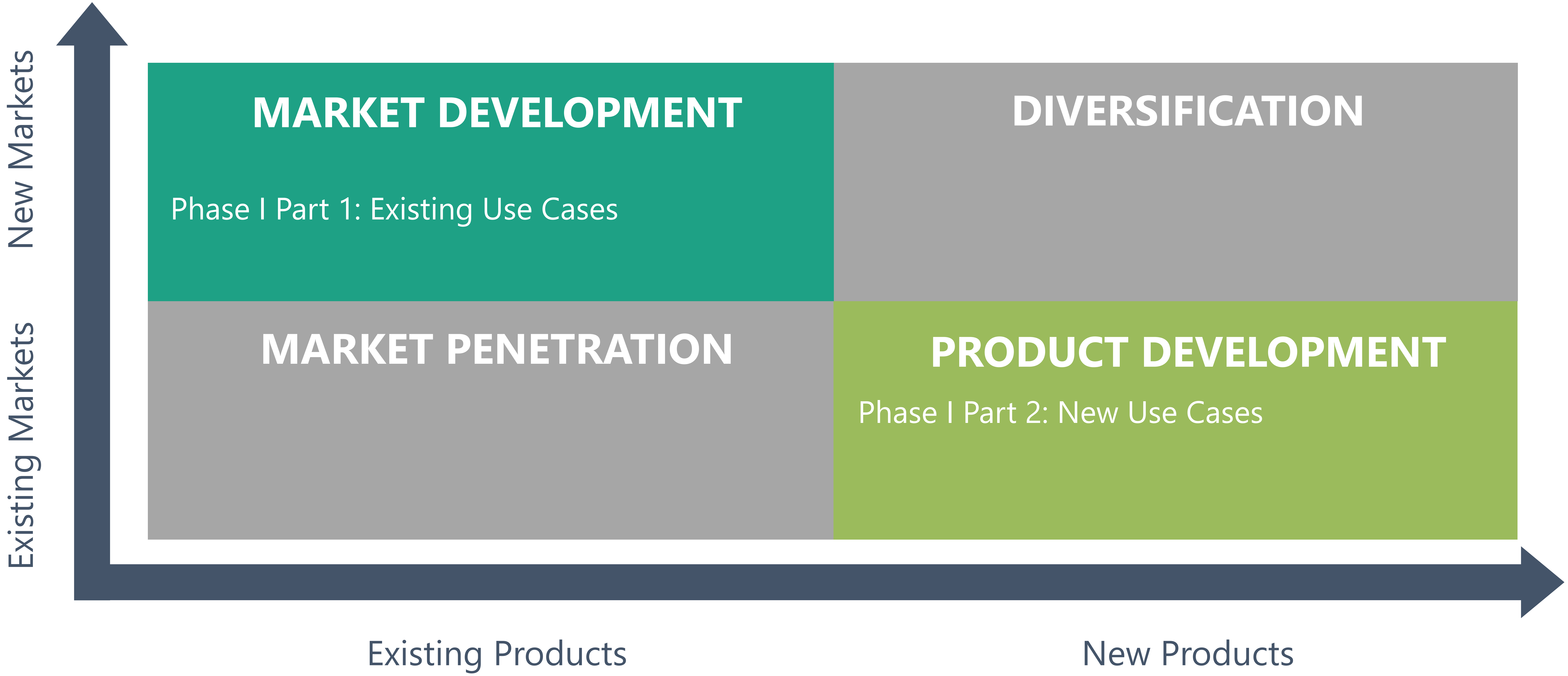
PART 1: EXISTING USE CASES

PART 2: NEW USE CASES

PHASE II: MACHINE LEARNING

STRATEGIC GOAL

Strategic positioning of the project within the Ansoff Matrix



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- STRATEGIC GOAL
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PHASE I: DATA ANALYSIS

PART I: EXISTING USE CASES

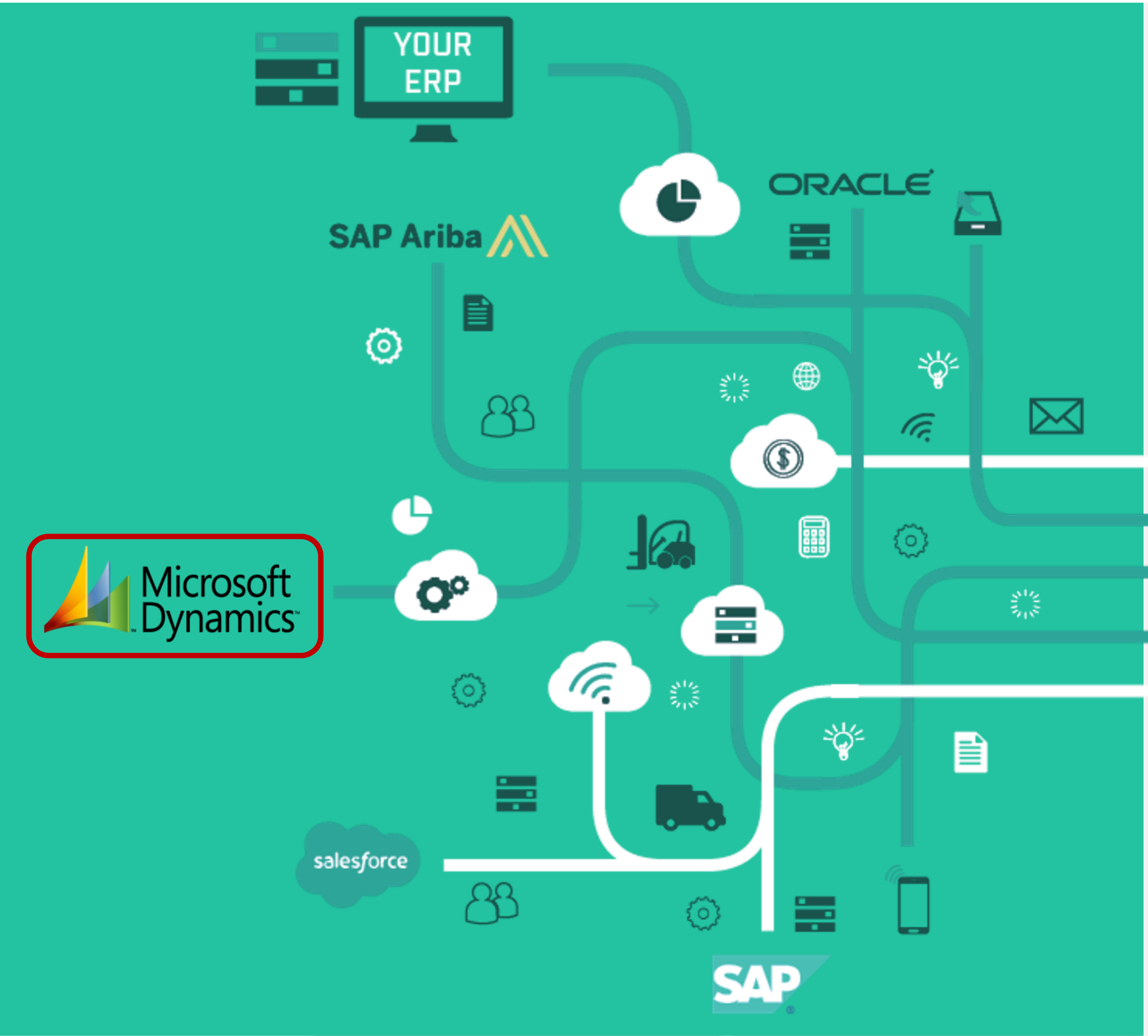
PART II: NEW USE CASES

PHASE I: DATA ANALYSIS

PART I: EXISTING USE CASES

EXISTING USE CASES

11 new Analyses in the Content Store



VISUALIZATION OF THE ACTUAL PROCESSES

AI-POWERED ROOT CAUSE ANALYSIS & IMPROVEMENT

EVENT LOG

2016-12-01 CREATE PURCHASE ORDER #1234
2016-06-23 START PRODUCTION #5678
2016-07-14 RECEIVE PAYMENT #1234
2016-07-14 SEND EMAIL #9012

PHASE I: DATA ANALYSIS

PART I: EXISTING USE CASES

PART II: NEW USE CASES

PHASE I: DATA ANALYSIS

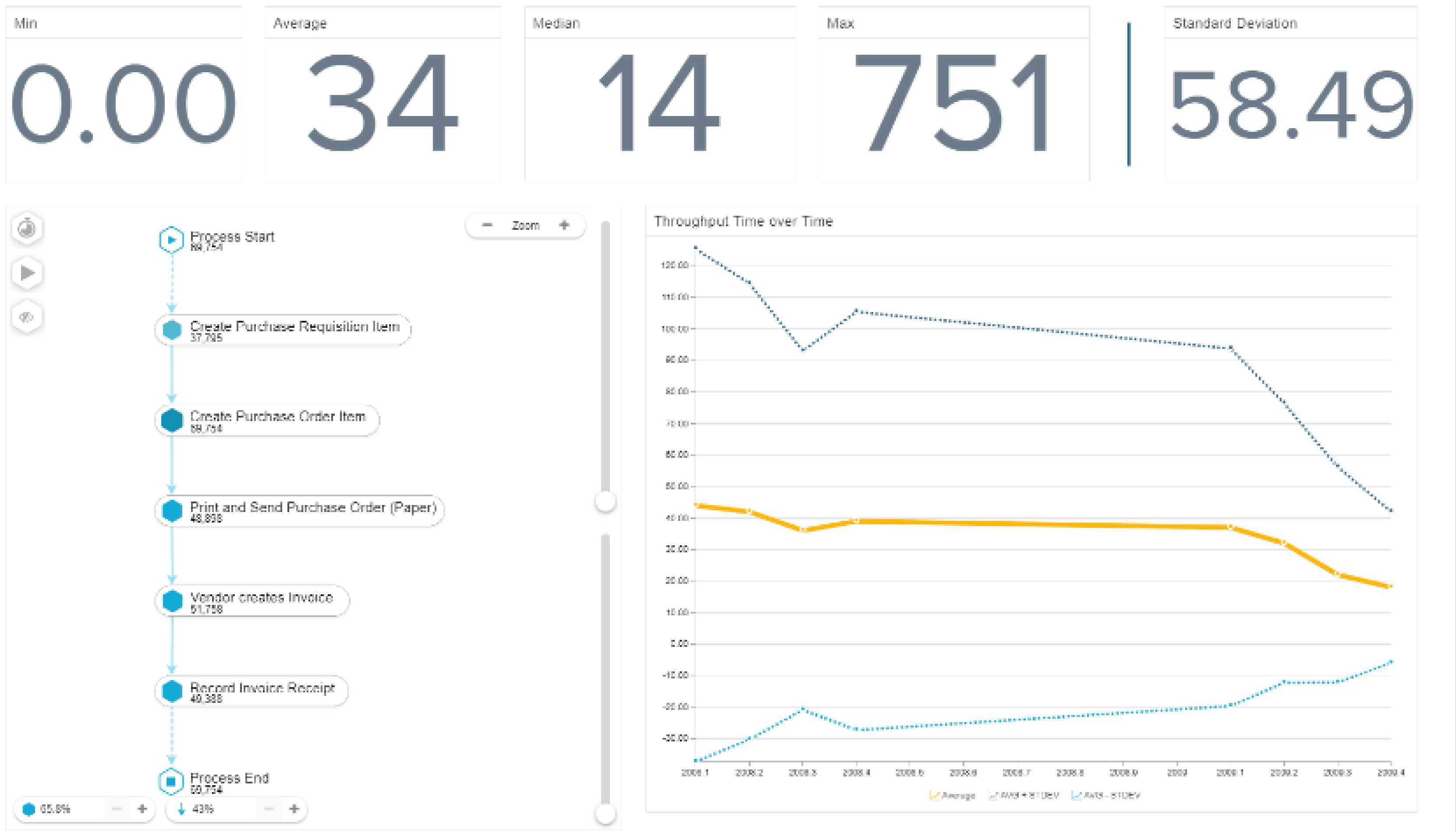
PART II: NEW USE CASES

THREE NEW USE CASES

for any process, for any ERP platform

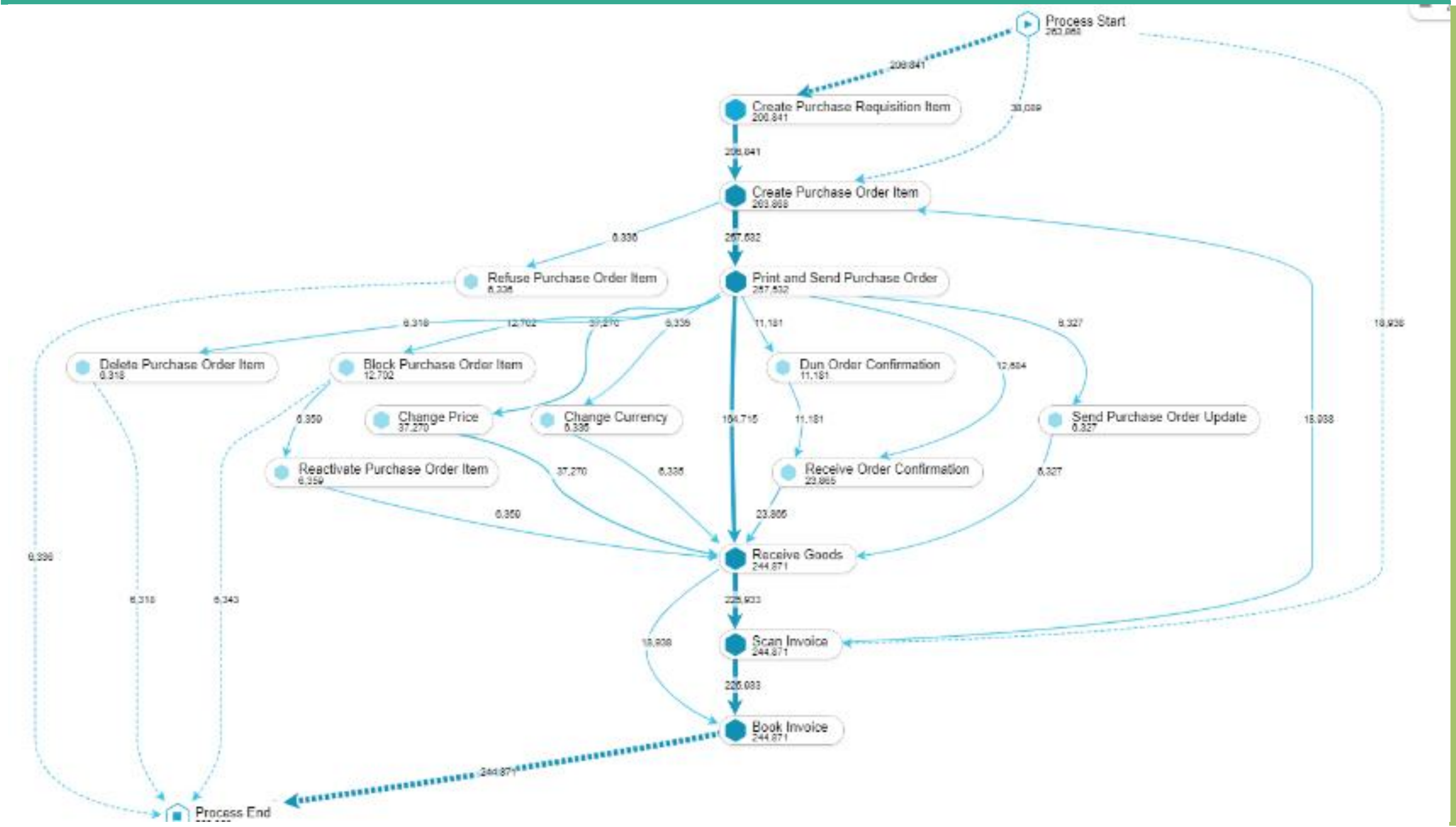
COMPLEXITY ANALYSIS

Get a feeling for the complexity for your processes – *quantified*.



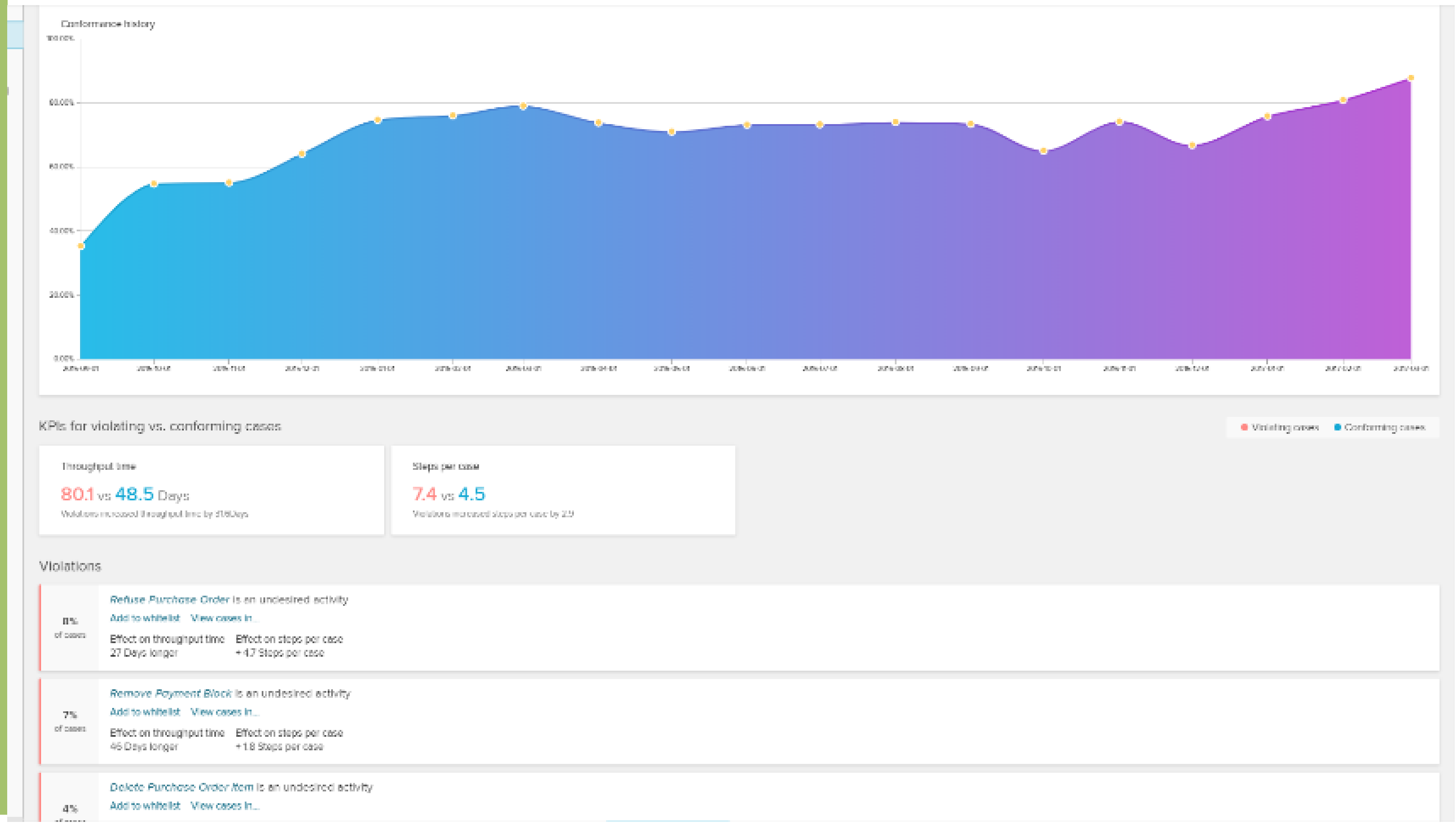
UNDESIRED ACTIVITIES

Analyze where undesired activities happen – *and why*.



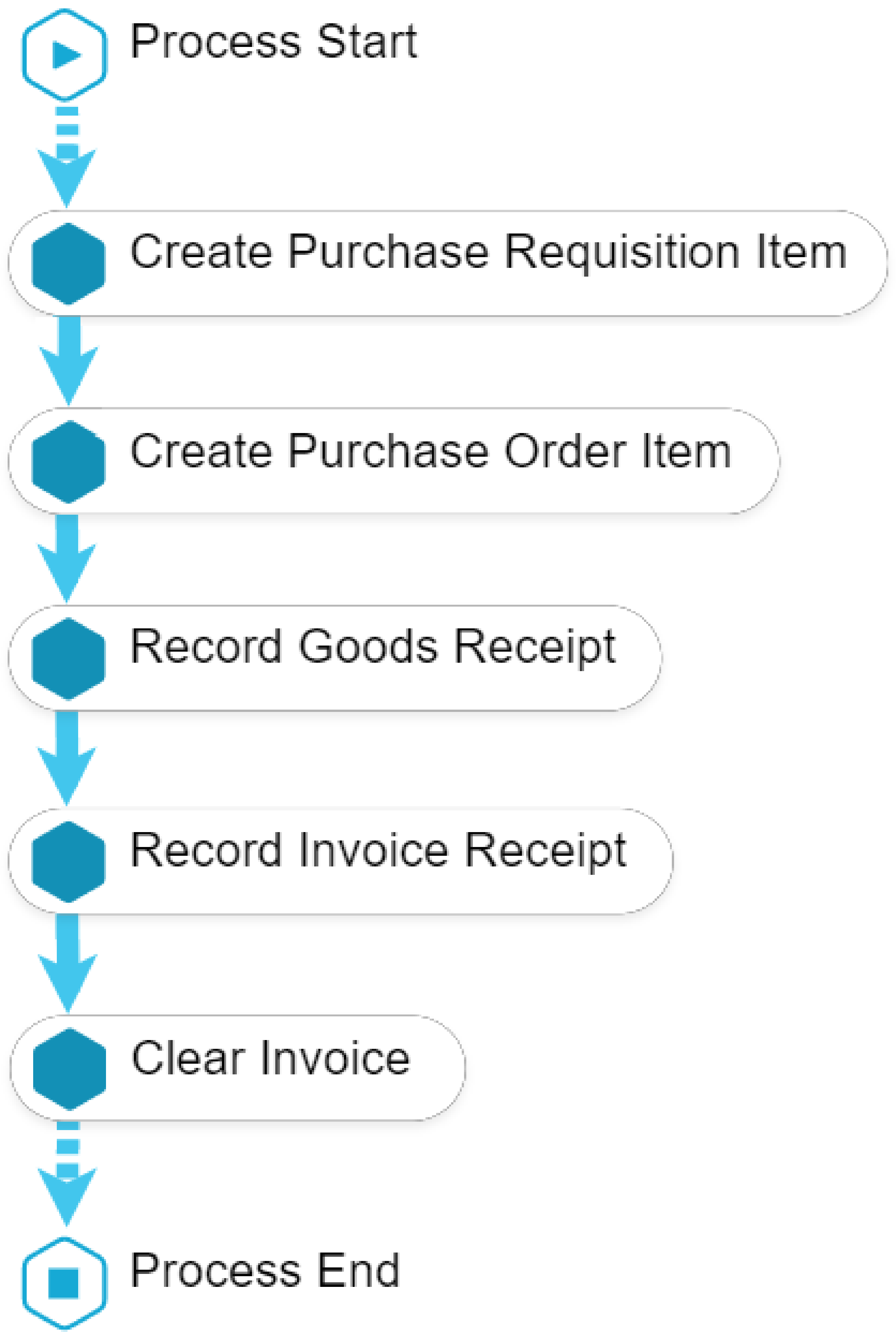
EFFICIENCY ANALYSIS

See exactly which process steps can be improved – *for sure*.



COMPLEXITY ANALYSIS

Get a feeling for the complexity of your processes – quantified.



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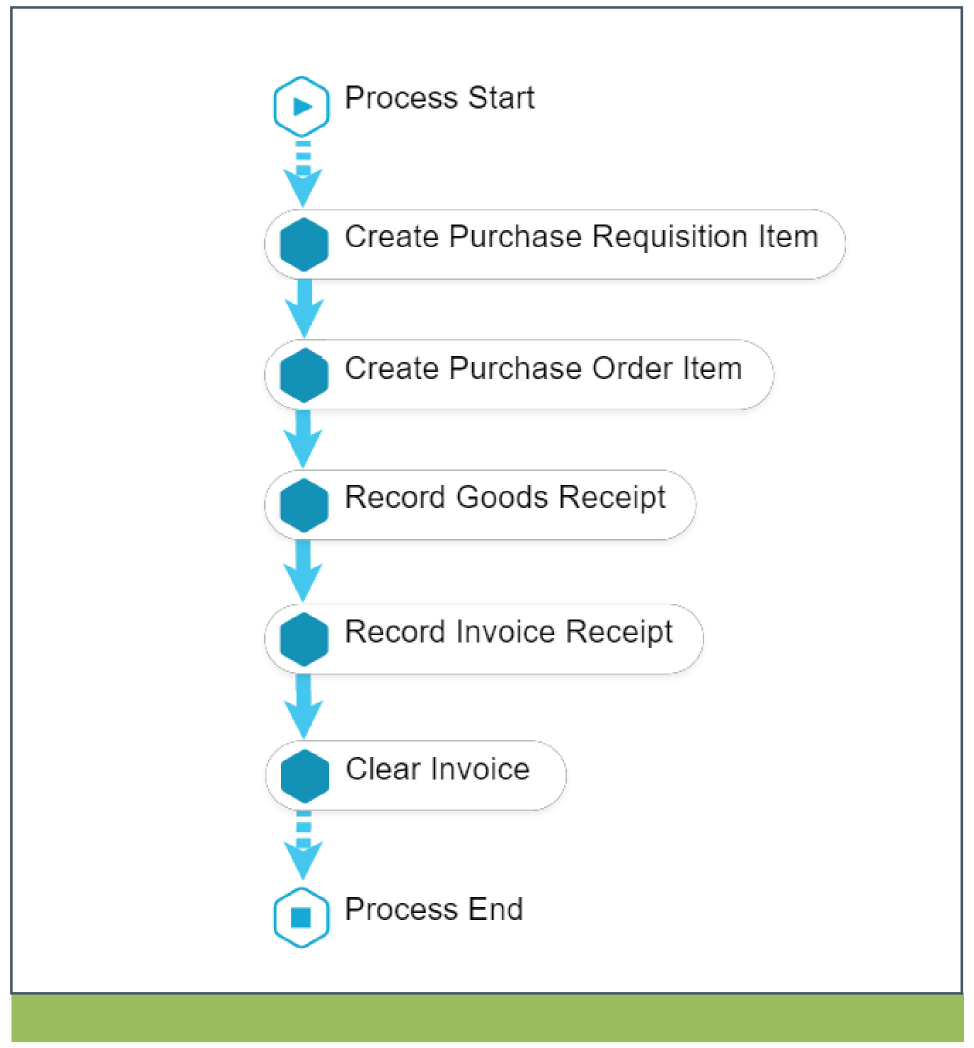

Perfect world

COMPLEXITY ANALYSIS

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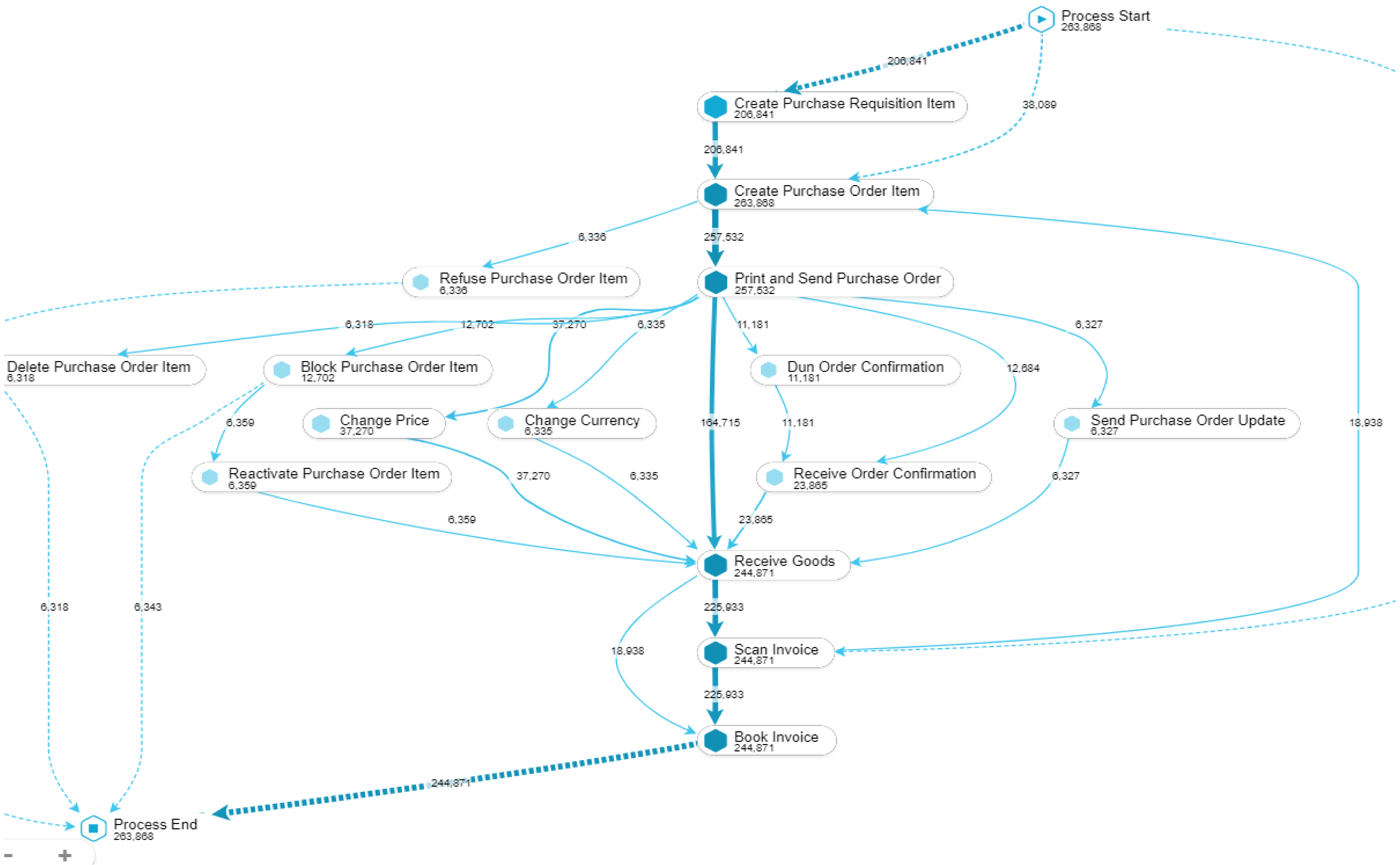

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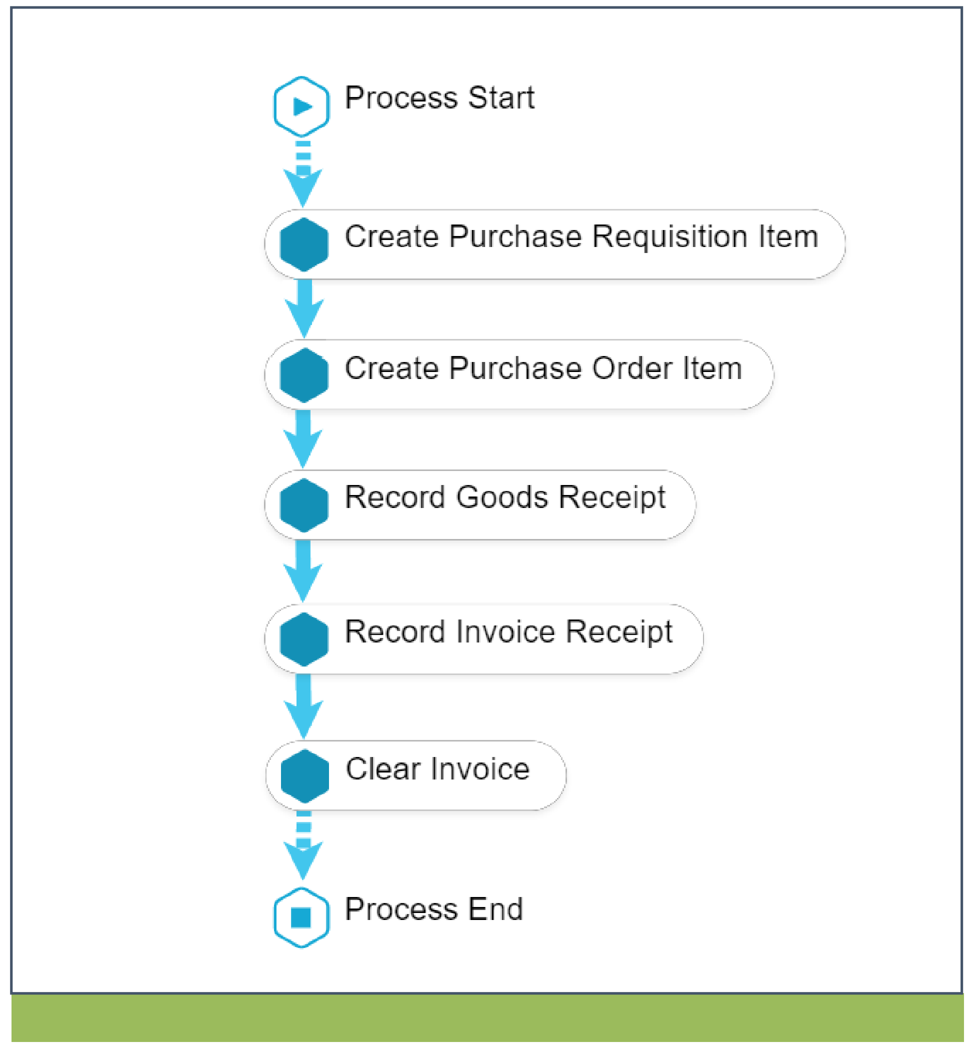
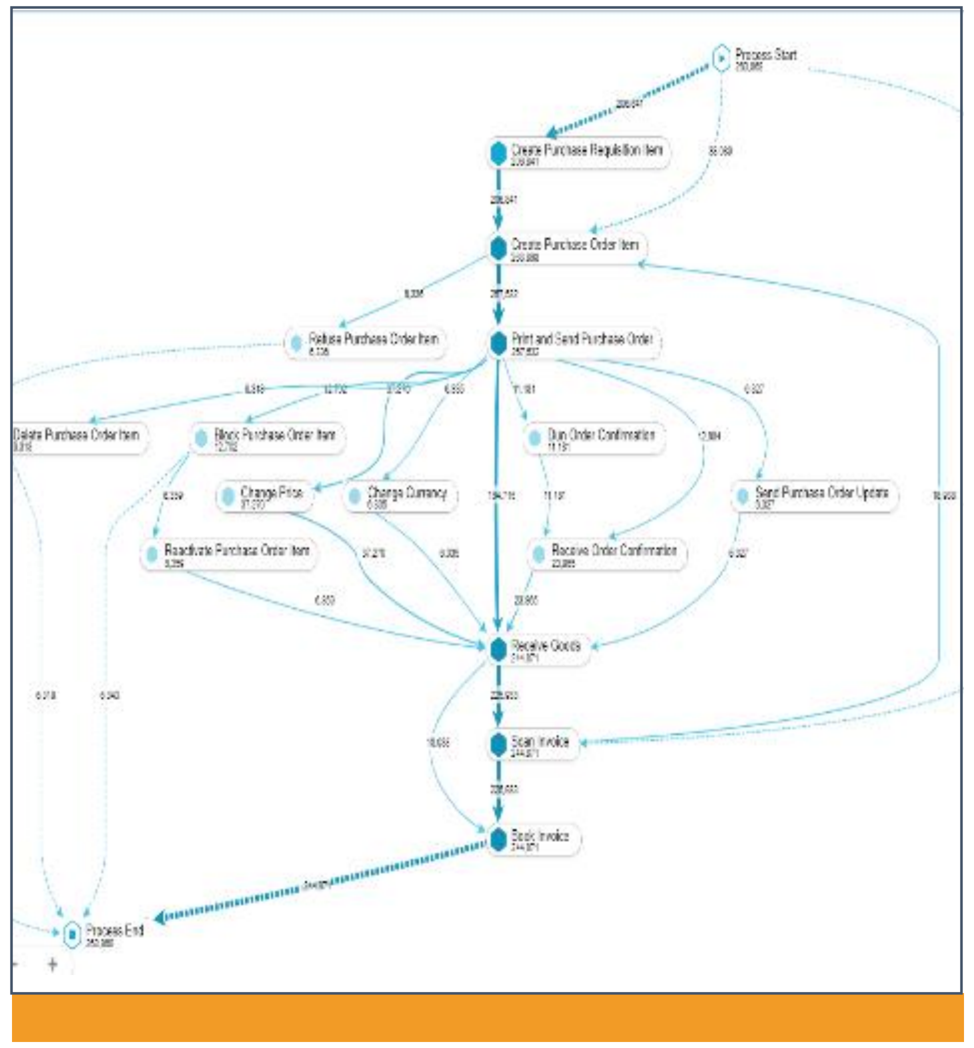


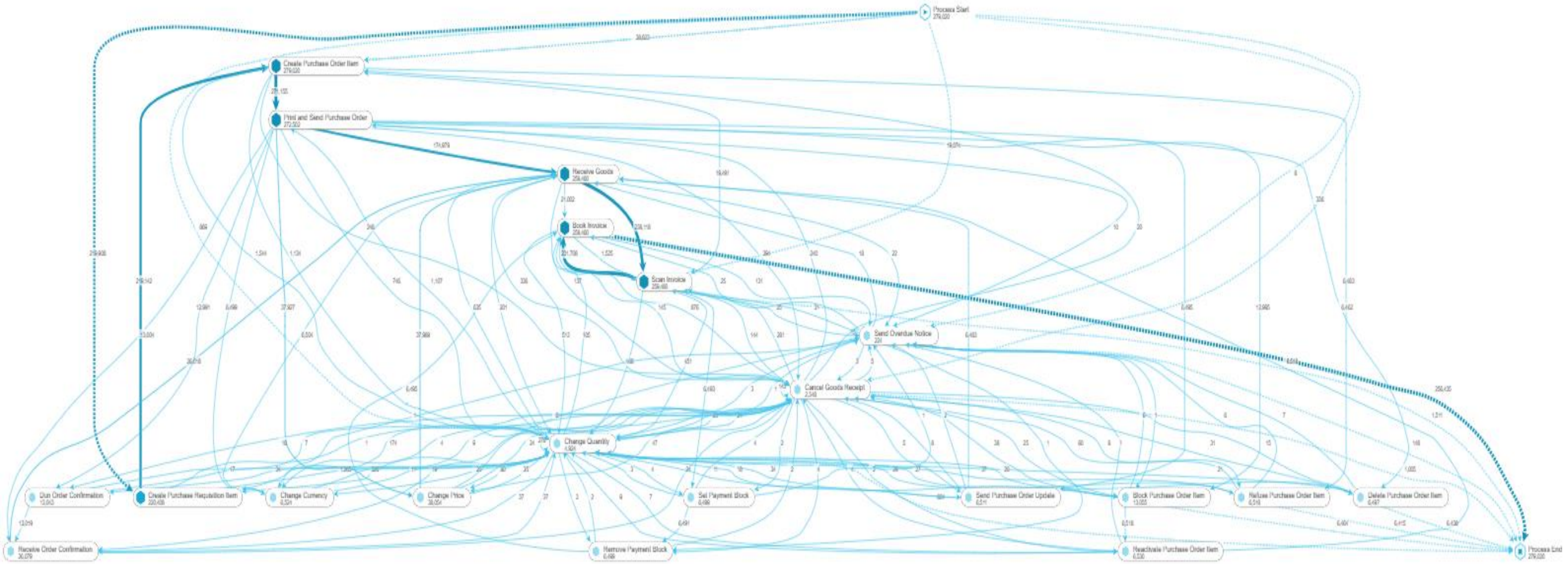
Perfect world



Expectation

COMPLEXITY ANALYSIS

Get a feeling for the complexity of your processes – quantified.



COMPLEXITY ANALYSIS

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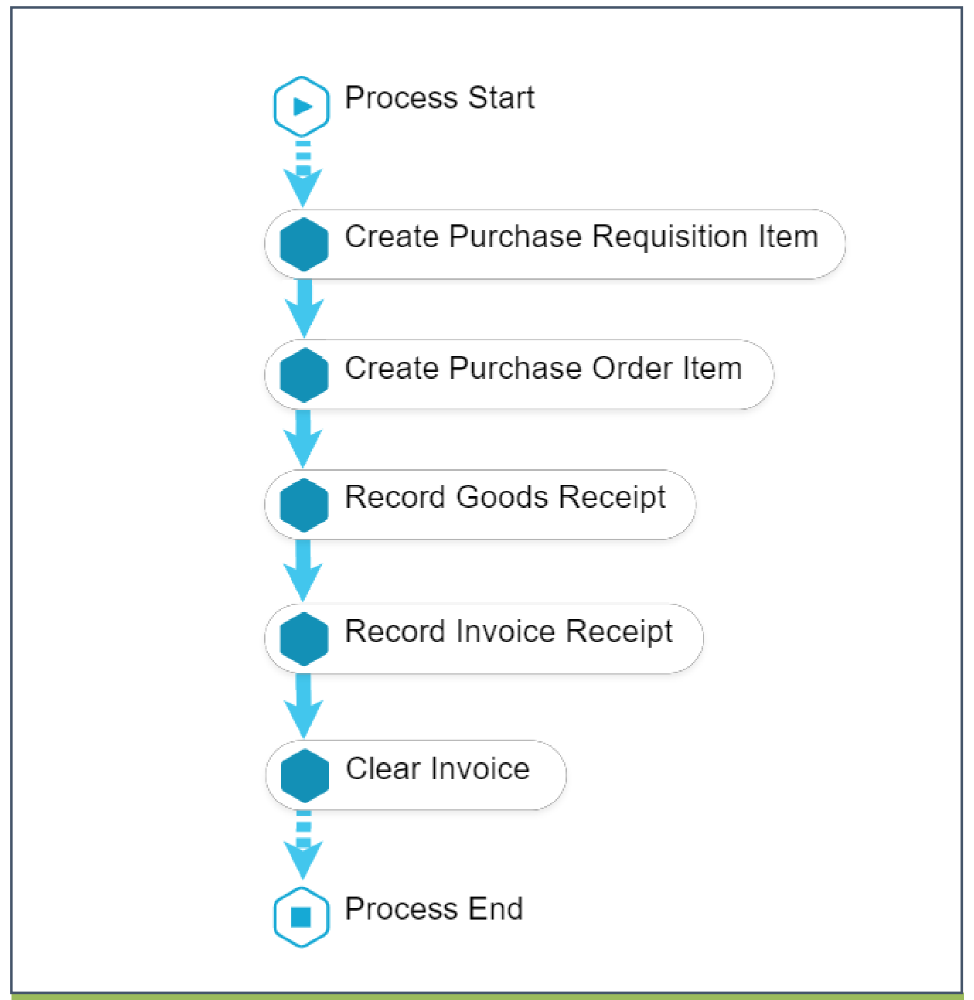

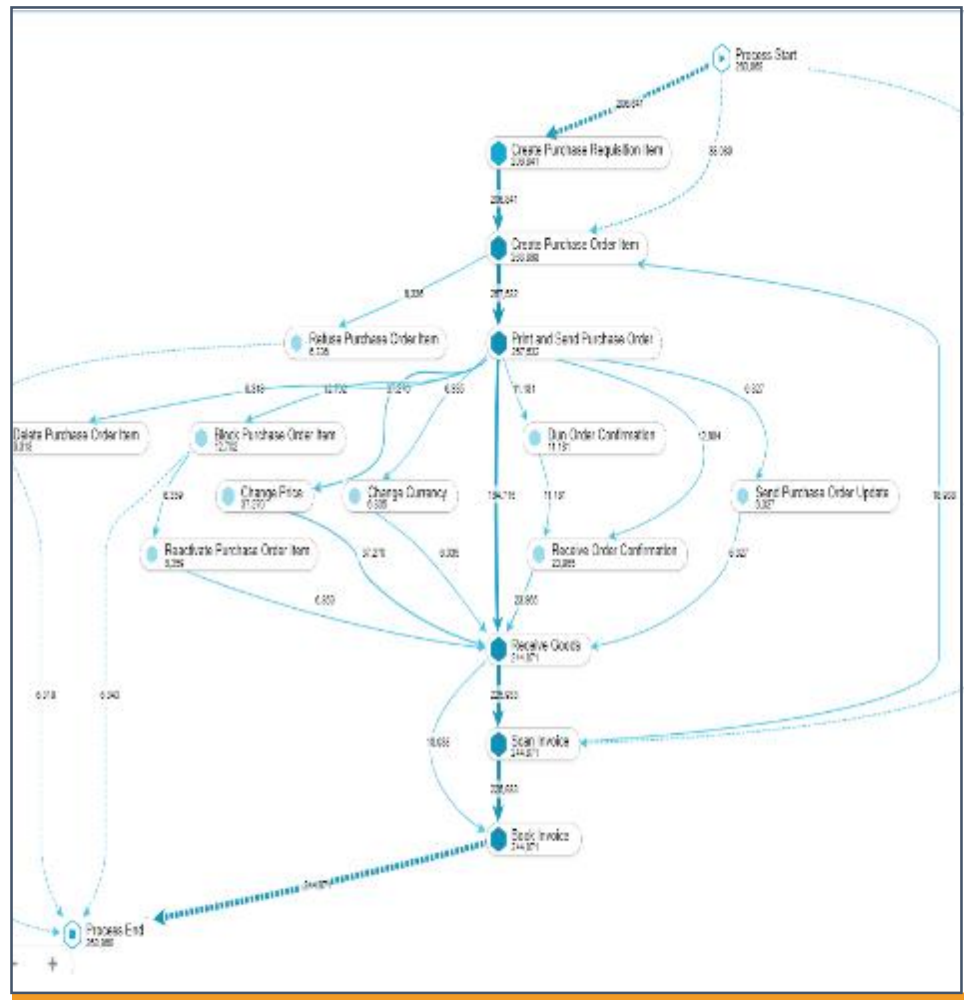

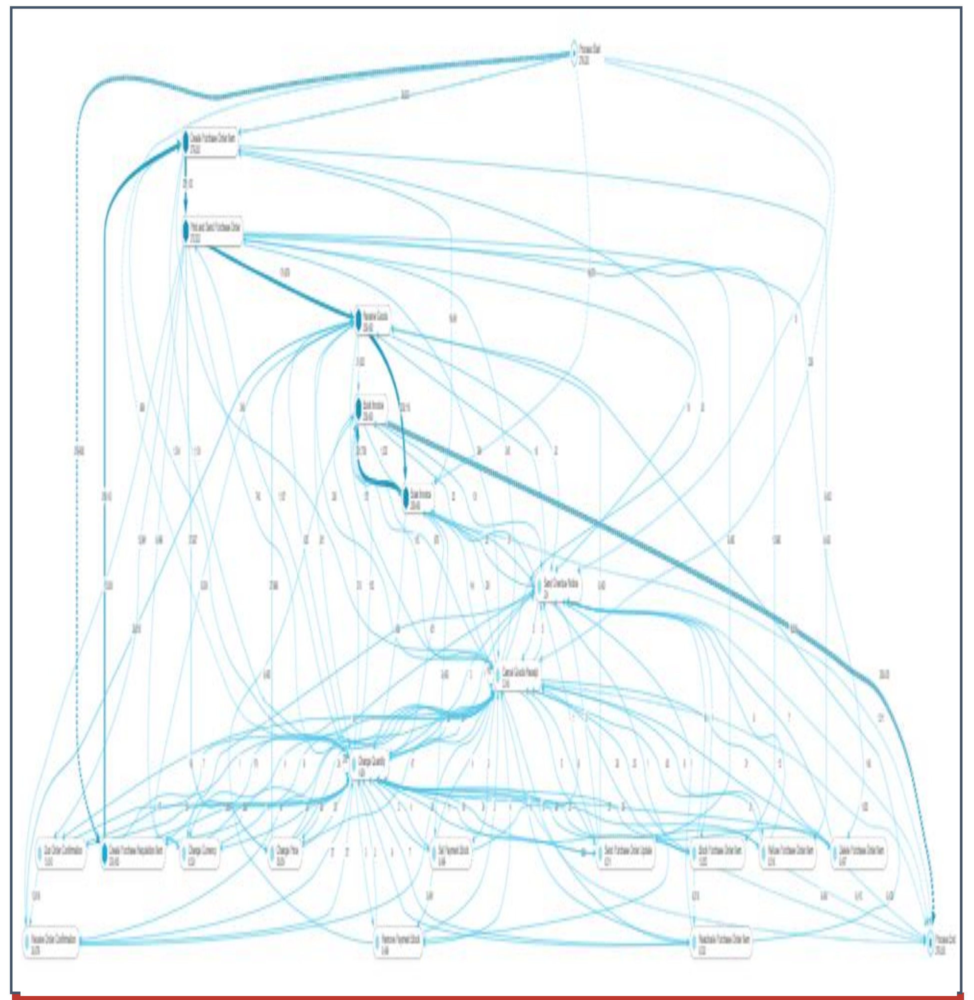

Perfect world **Expectation** **Reality**

COMPLEXITY ANALYSIS

Get a feeling for the complexity of your processes – quantified.

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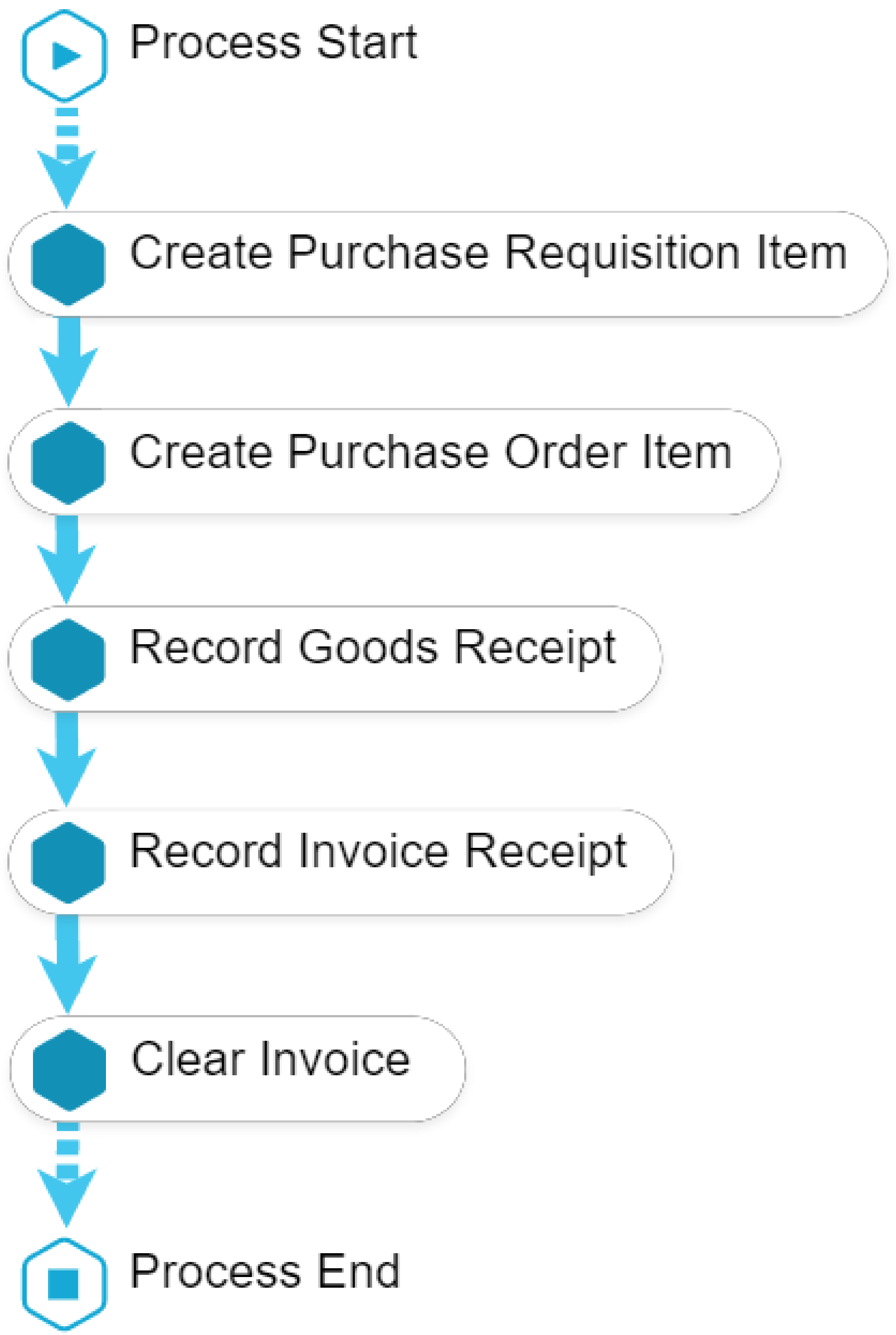
ROBLEM

where machine learning empowers process mining



ARIMA

Classical Statistics

ARD Regression

Bayesian Trade-off

LSTM

Advanced Machine Learning

ARIMA

Auto**R**egressive **I**ntegrated **M**oving **A**verage

$$(1-\sum_{i=1}^{p} L^{i})(1-L^{d})y_t = (1+\sum_{i=1}^{q} \theta_i L^{i})\varepsilon_t$$

Advantages

- Time series specific
- Removes polynomial trend
- Easy to implement
- Computationally fast

Limitations

- Works with stationary time series only
- Cannot deal with trend other then polynomial

ARD

Automatic Relevance Determination regression

$$\mathbf{y} = \mathbf{w}^{\mathrm{T}}\mathbf{X} + \varepsilon$$

$$p(\mathbf{w}|\lambda) \sim N(\mathbf{0}, \Lambda^{-1}), \Lambda = diag(\lambda_1, \ldots, \lambda_N)$$

$$p(\varepsilon_i|\alpha) \sim N(0, \alpha^{-1}), \{\varepsilon_i\}_{i \in \overline{1,N}} - i.i.d.$$

Advantages

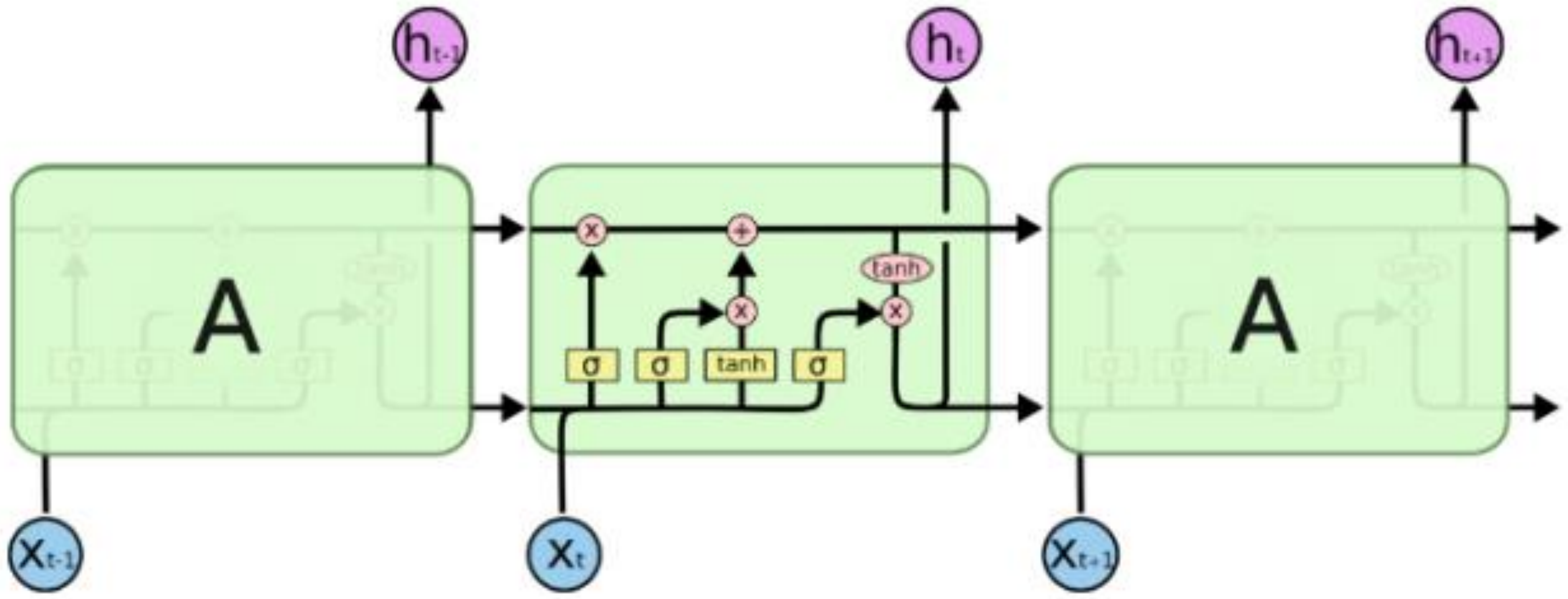
- Automatic feature selection
- Confidence intervals
- Easy to implement
- Computationally fast

Limitations

- ~~Not times series specific~~
- ~~Not robust to distributional changes~~

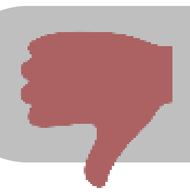
LSTM

Long **S**hort-**T**erm **M**emory recurrent neural network



Advantages

- Sequential data specific
- Captures long and short-term dependencies
- Can handle complex data structures

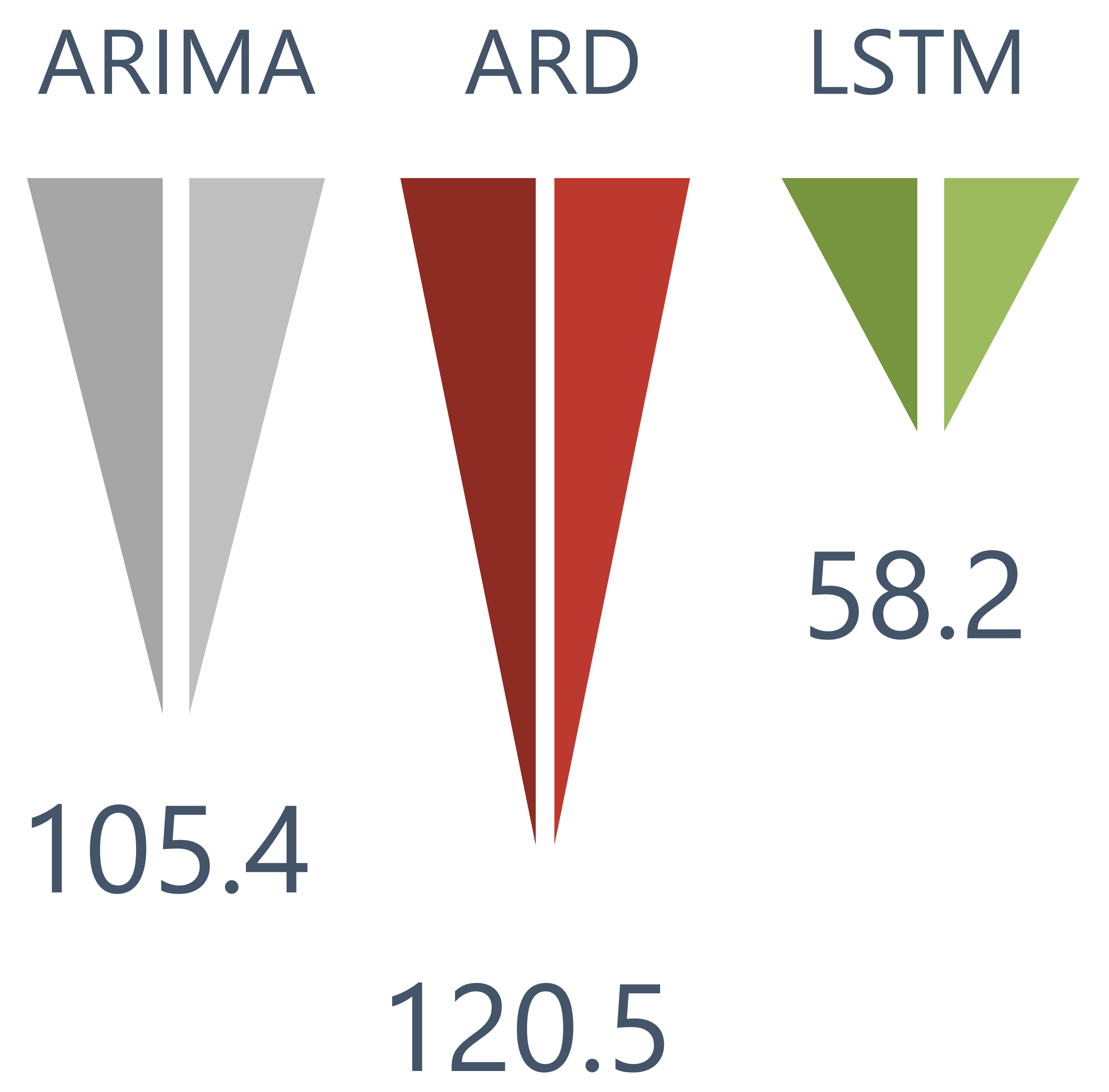


Limitations

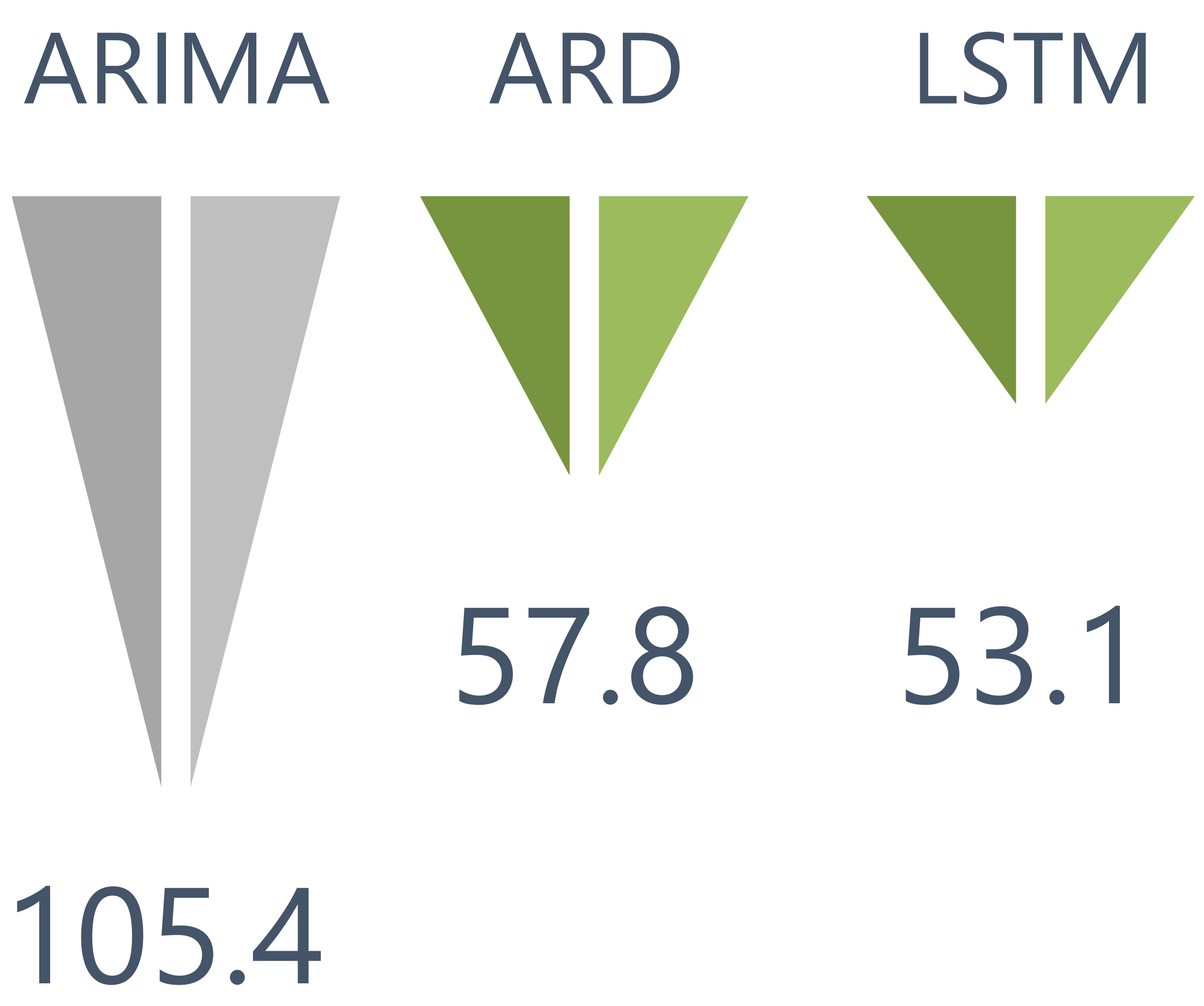
- Gives point estimates
- Requires large datasets
- Computationally expensive

RESULTS

in terms of Mean Absolute Error



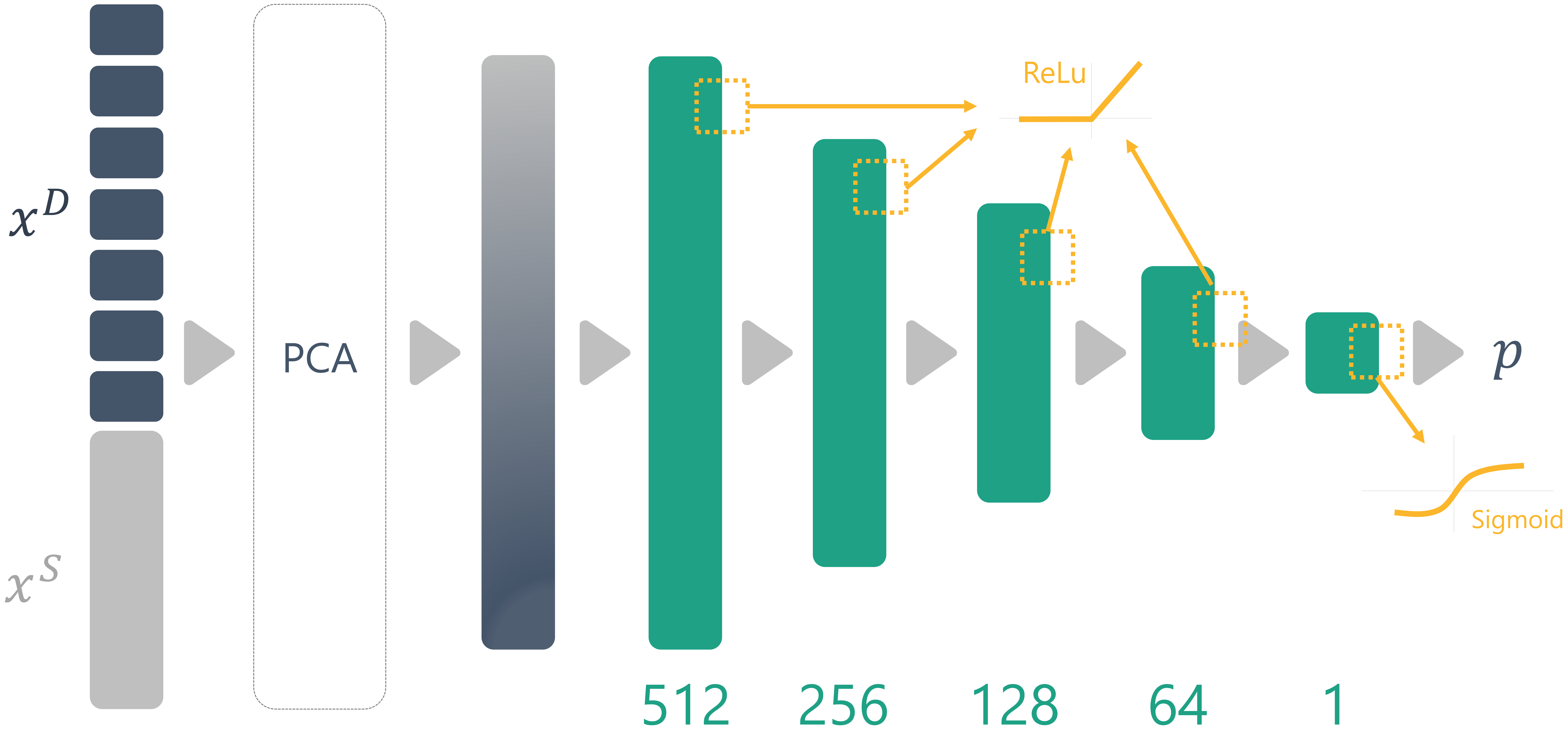
Before Truncation



After Truncation

MACHINE LEARNING

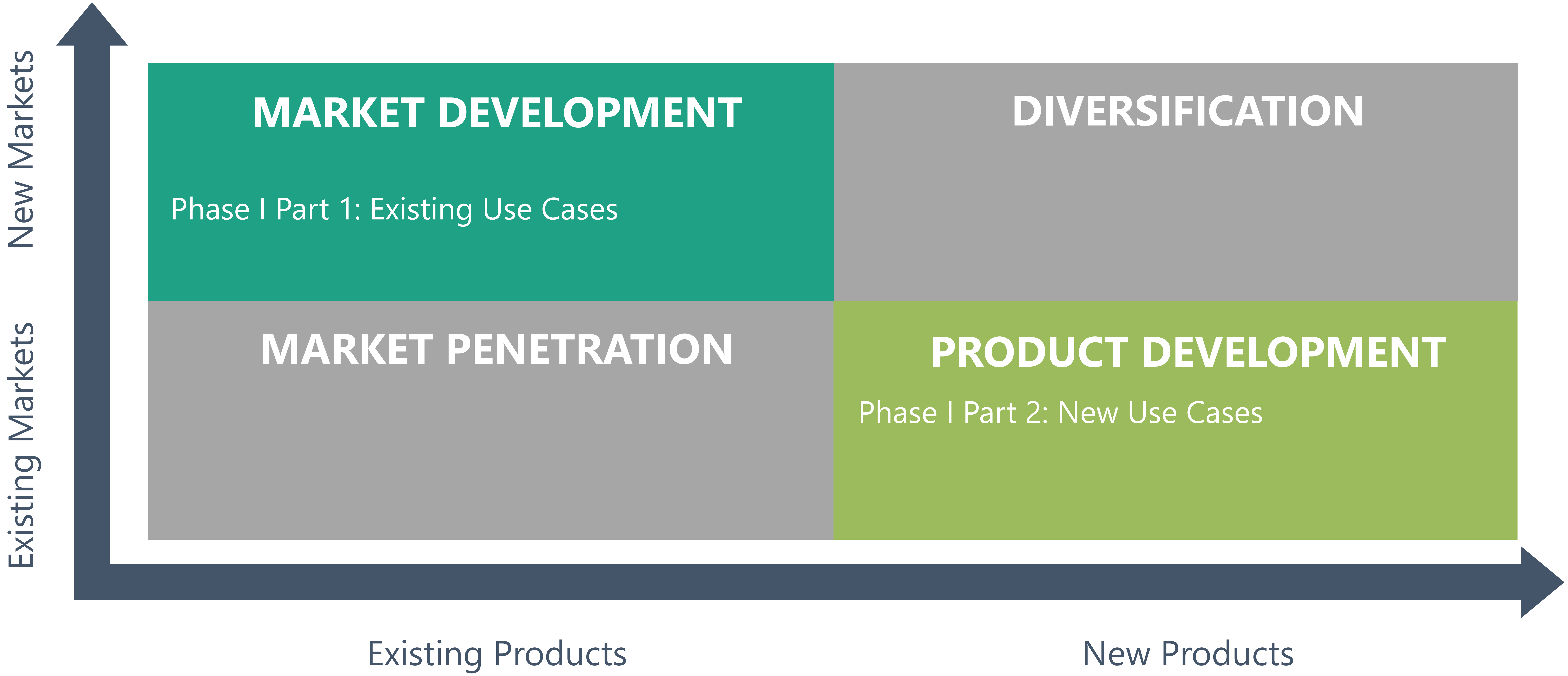
1. Naïve Bayes
2. Logistic Regression
3. K-Nearest Neighbors
4. Decision Trees
5. Random Forests
6. Feedforward Neural Networks


x^D
x^S
PCA
ReLu
p
Sigmoid
512
256
128
64
1

	Naïve Bayes	Logistic Regression	KNN	Decision Trees	Random Forests	Neural Networks
1	38	14	59	60	63	85
2	40	37	64	70	74	88
3	42	41	69	75	79	89
4	46	50	75	81	85	85
5	46	63	83	85	89	92
6	47	60	77	79	86	93
7	55	68	81	79	84	90
8	52	72	80	80	86	89
9	50	66	78	79	81	84
10	59	74	78	81	85	83
Overall	43	45	65	74	78	88

	Naïve Bayes	Logistic Regression	KNN	Decision Trees	Random Forests	Neural Networks
1	38	14	59	60	63	**85**
2	40	37	64	70	74	**88**
3	42	41	69	75	79	**89**
4	46	50	75	81	**85**	**85**
5	46	63	83	85	89	**92**
6	47	60	77	79	86	**93**
7	55	68	81	79	84	**90**
8	52	72	80	80	86	**89**
9	50	66	78	79	81	**84**
10	59	74	78	81	**85**	83
Overall	43	45	65	74	78	**88**

CONCLUSION


New Markets
Existing Markets
MARKET DEVELOPMENT
Phase I Part 1: Existing Use Cases
DIVERSIFICATION
MARKET PENETRATION
PRODUCT DEVELOPMENT
Phase I Part 2: New Use Cases
Existing Products
New Products


thank you