When labels are available

MONITORING MACHINE LEARNING IN PYTHON

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Estimated vs realized performance

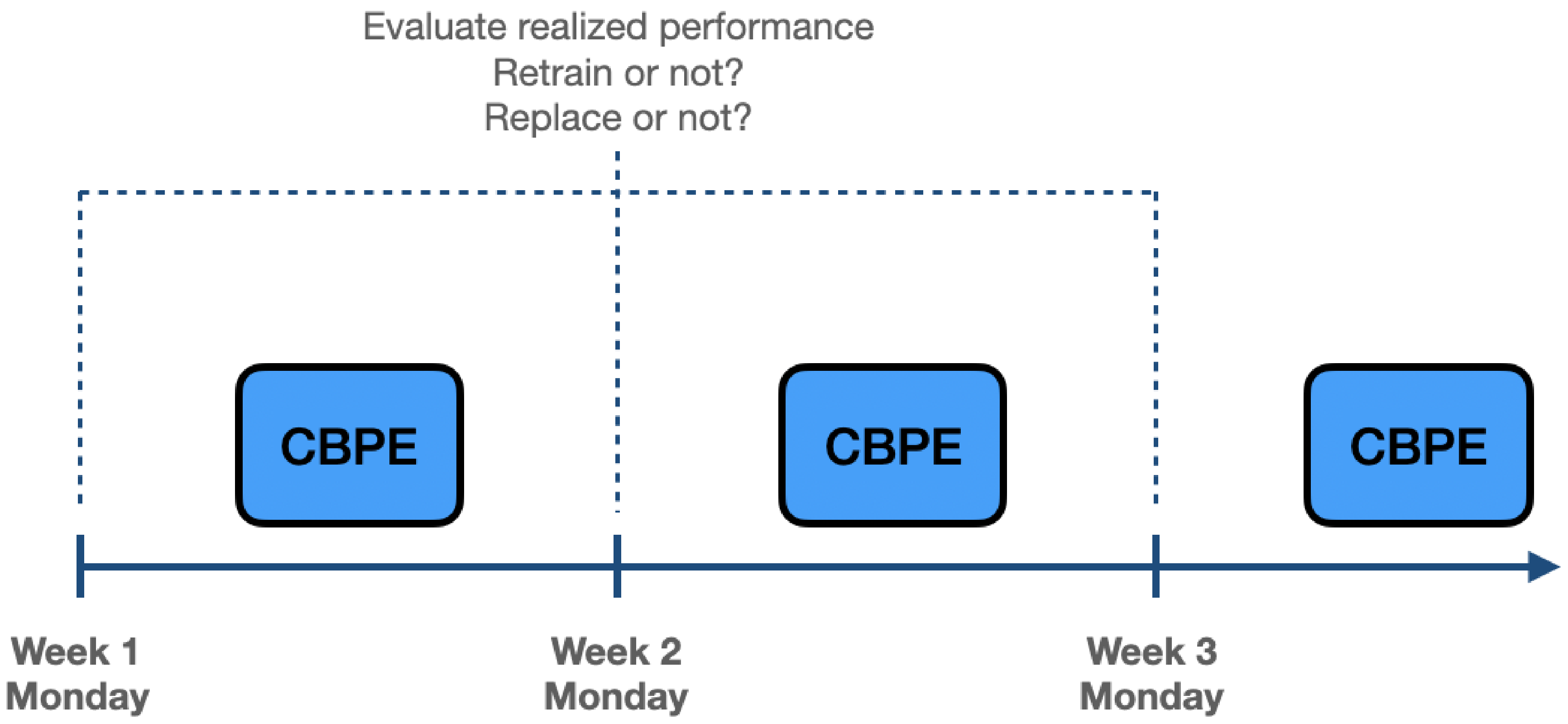
Estimated performance:

- measures how well model is expected to perform
- determined using **estimators** like CBPE, and DLE
- **estimated** when ground truth is not available

Realized performance:

- represents **measured** performance
- determined using performance **calculator**
- **calculated** when ground truth is available

Delayed ground truth



Performance calculator

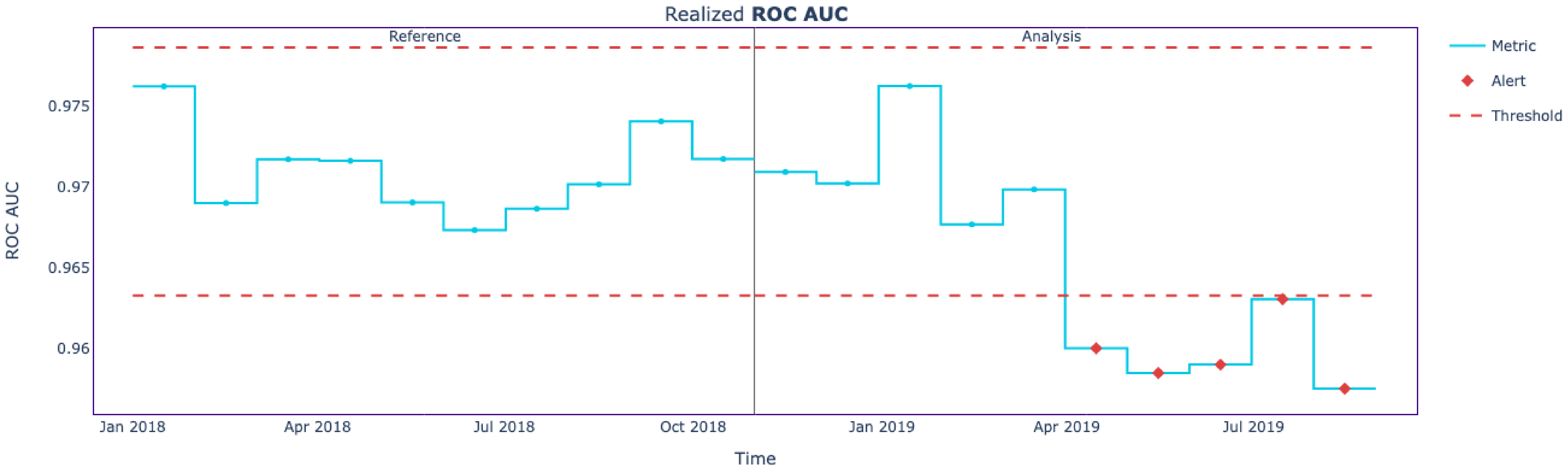
```python
# Intialize the calculator
calc = nannyml.PerformanceCalculator(
    y_pred_proba='y_pred_proba',
    y_pred='y_pred',
    y_true='arrived',
    timestamp_column_name='timestamp',
    problem_type='classification_binary',
    chunk_period='d',
    metrics=['roc_auc', 'accuracy'],
    )
```

```python
# Fit the calculator
calc.fit(reference)
realized_results = calc.calculate(analysis)
```

Plot the results

```
# Show realized performance plot
results.plot().show()
```

Realized performance

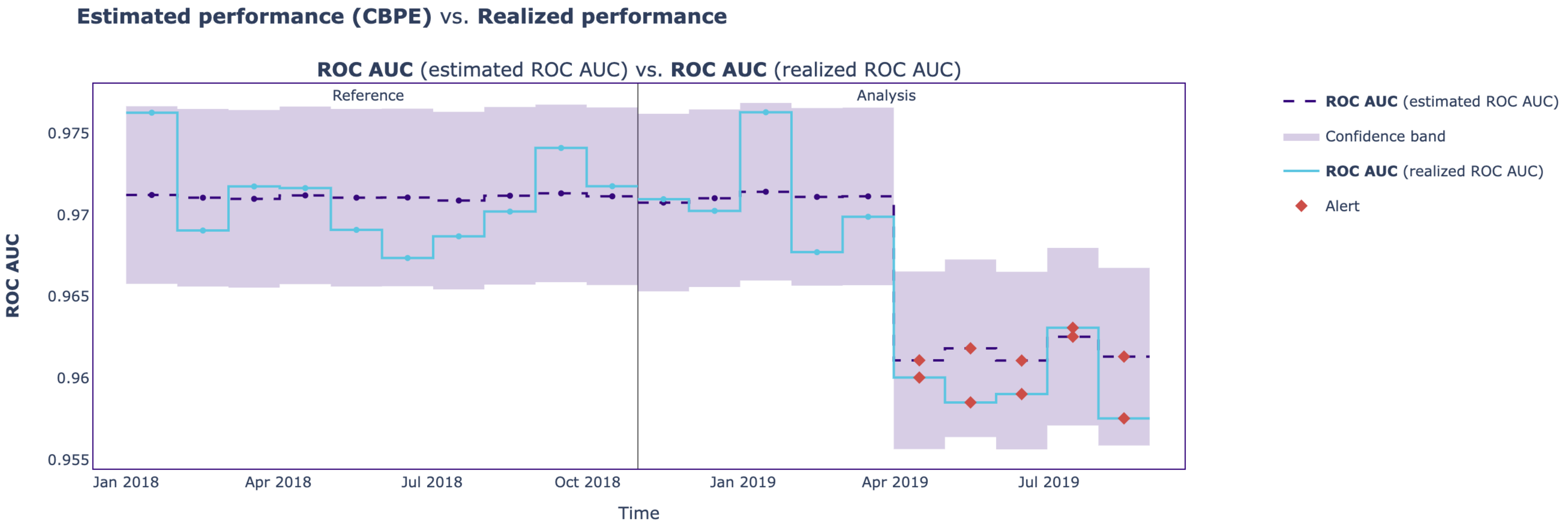


Realized and estimated performance

```
# Estimate and calculate results
estimated_results = estimator.estimate(analysis)
realized_results = calculator.calculate(analysis)

# Show comparison plot
realized_results.compare(estimated_results).plot().show()
```

Realized and estimated performance



Let's practice!

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datacamp

Working with calculated and estimated results

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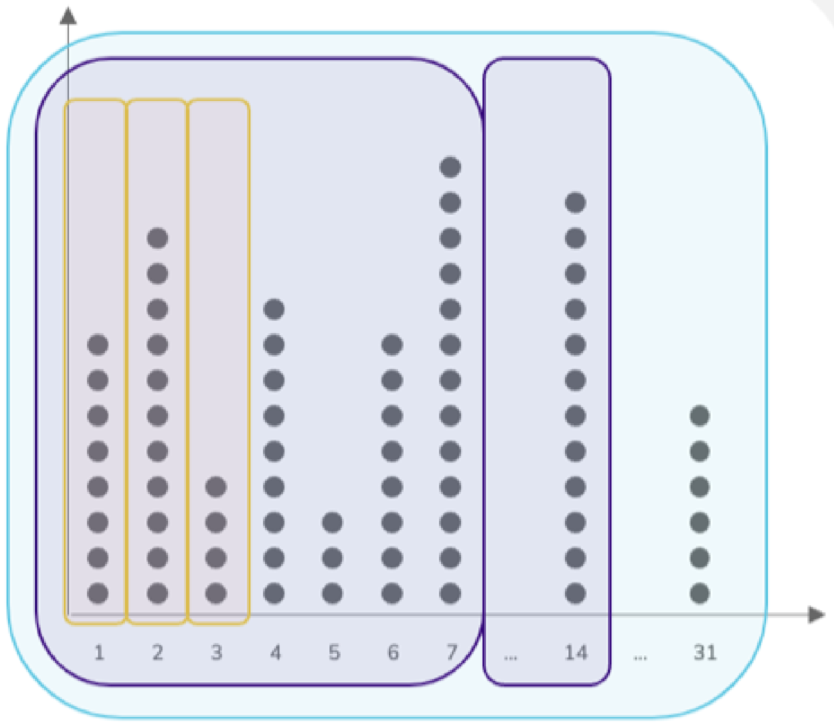
How to chunk the data?

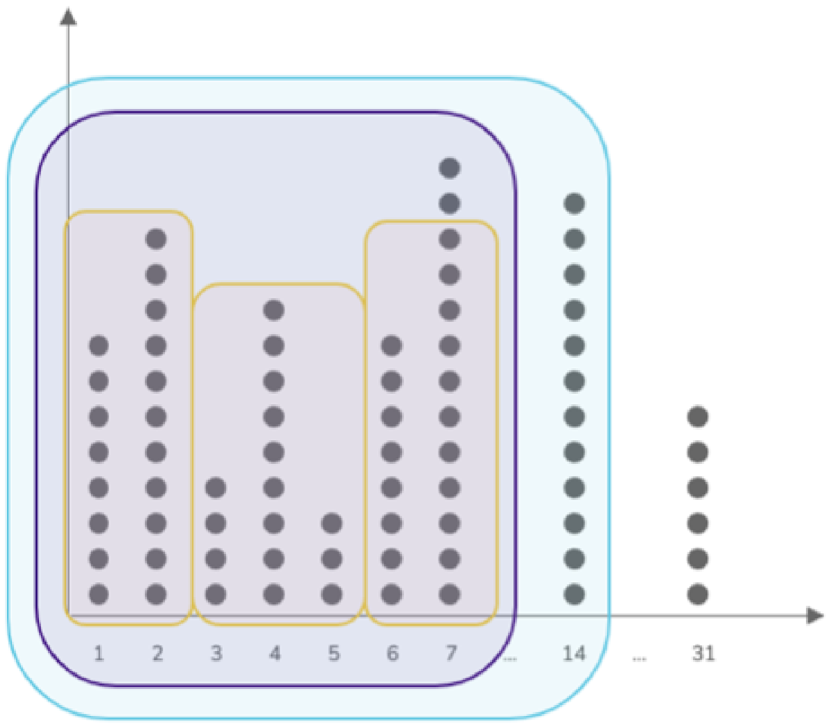
Time-based



Day

Daily – Weekly – Monthly

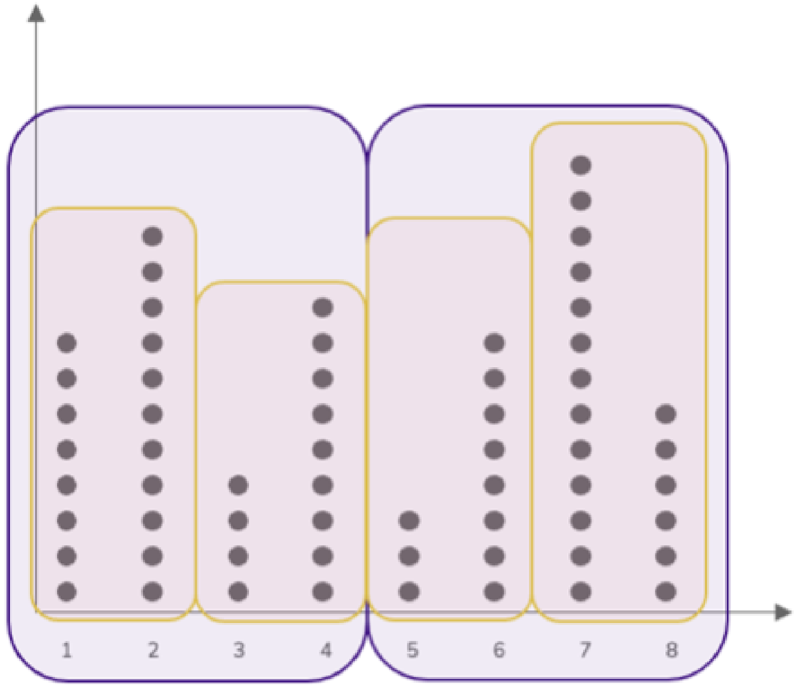
Size-based



Day

Every 15 – 45 – 90 points

Number-based



Total 4 – 2 number of chunks

Specifying different chunks

Chunking period arguments

Alias	Description
s	second
t	minute
h	hour
d	day
w	week
m	month
q	quarter
y	year

```
# Initialize the algorithm
cbpe = nannyml.CBPE(
    problem_type='classification_binary',
    y_pred_proba='predicted_probability',
    y_pred='prediction',
    y_true='employed',
    metrics=['roc_auc'],
    chunk_period='m',
    # chunk_size = 5000,
    # chunk_number = 10
)
```

Initializing custom thresholds

Standard deviation thresholds

- Manually set lower and upper standard deviation multiplier

```
# Standard deviation thresholds
stdt = StandardDeviationThreshold(
    std_lower_multiplier=3,
    std_upper_multiplier=3
    )
```

Constant thresholds

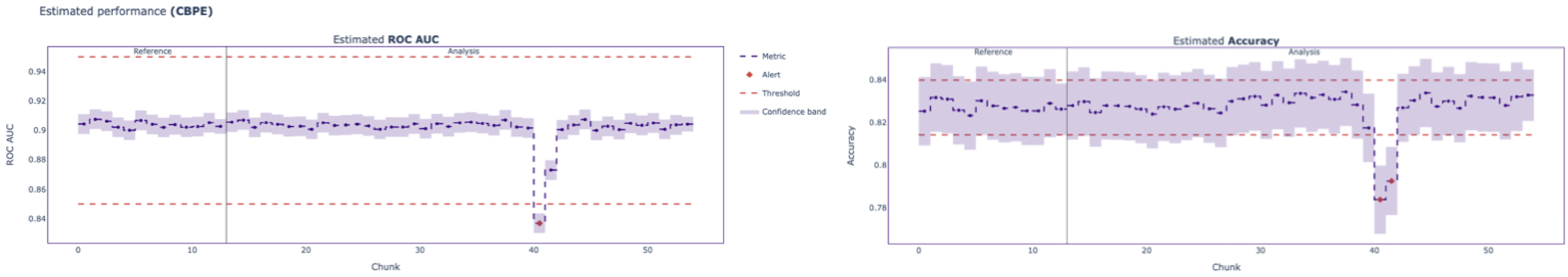
- Manually set the lower and upper threshold values

```
# Constant thresholds
ct = ConstantThreshold(
    lower=0.85,
    upper=0.95
    )
```

Specifying custom thresholds

```
# Import threshold methods(last slide)
from nannyml.thresholds import ConstantThreshold, StandardDeviationThreshold

# Passing thresholds to the CBPE algorithm
estimator = nannyml.CBPE(...
    metrics = ['roc_auc', 'accuracy'],
    thresholds={'roc_auc': ct, 'accuracy' : stdt}
)
```



Filtering results

- By period

```
filtered_results = results.filter(period='analysis')
```

- By metrics

```
filtered_results = results.filter(metrics=['mae'])
```

- Both

```
filtered_results = results.filter(period='analysis', metrics=['mae'])
```

Export results to dataframe

```
# Export results to dataframe format
results.filter(period='analysis').to_df()
```

	chunk							roc_auc							
	key	chunk_index	start_index	end_index	start_date	end_date	period	value	sampling_error	realized	upper_confidence_boundary	lower_confidence_boundary	upper_threshold	lower_threshold	alert
0	[0:4999]	0	0	4999	None	None	analysis	0.905547	0.002230	NaN	0.912236	0.898859	0.95	0.85	False
1	[5000:9999]	1	5000	9999	None	None	analysis	0.907030	0.002230	NaN	0.913719	0.900342	0.95	0.85	False
2	[10000:14999]	2	10000	14999	None	None	analysis	0.902044	0.002230	NaN	0.908733	0.895355	0.95	0.85	False
3	[15000:19999]	3	15000	19999	None	None	analysis	0.905250	0.002230	NaN	0.911939	0.898562	0.95	0.85	False
4	[20000:24999]	4	20000	24999	None	None	analysis	0.904054	0.002230	NaN	0.910742	0.897365	0.95	0.85	False

Let's practice!

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Business value calculation and estimation

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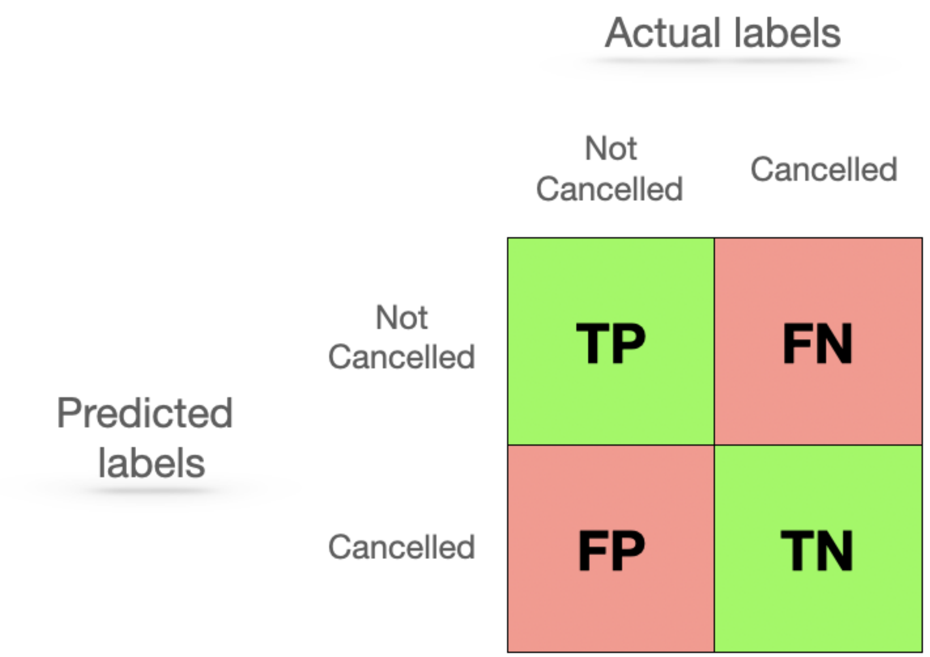
Model business value

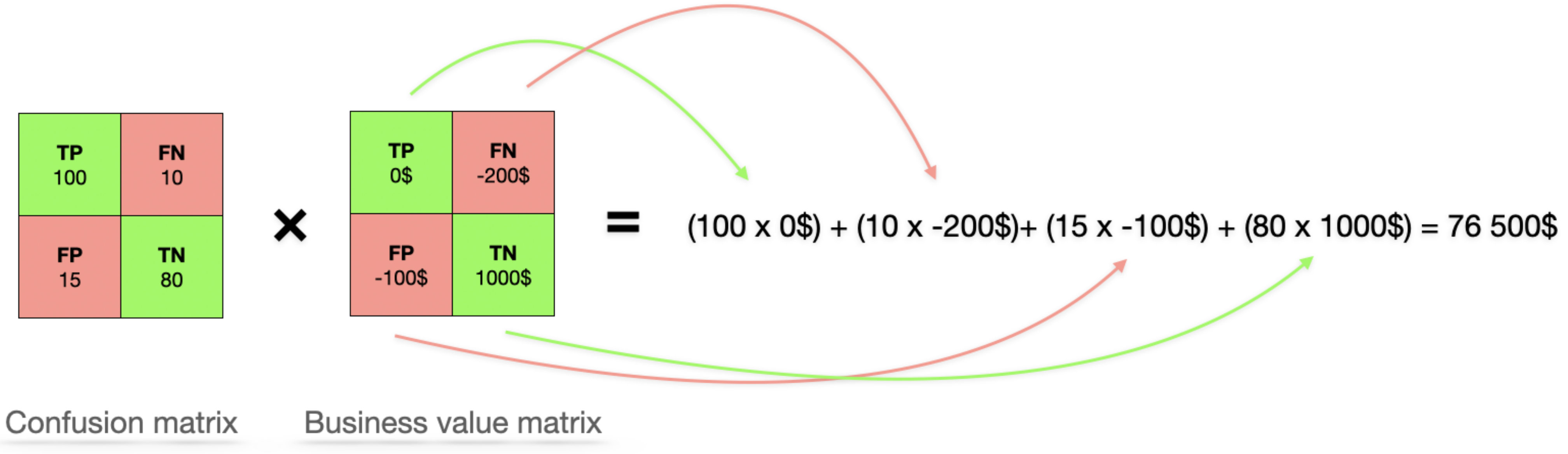
- The aim of machine learning model is to provide value to the business.
- The business value of the model can decrease due to:
  - Change in customer's habits
  - The model might not be useful anymore

Confusion matrix



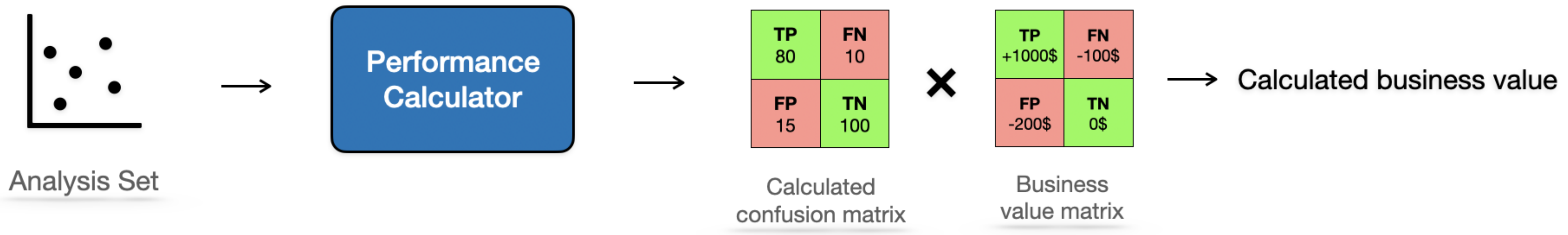
- True positive (TP) - the model correctly predicts that a booking will not be canceled
- False positive (FP) - the model incorrectly predicts a booking will not be canceled
- False negative (FN) - the model incorrectly predicts that a booking will be canceled
- True negative (TN) - the model correctly predicts that a booking will be canceled

Business value formula



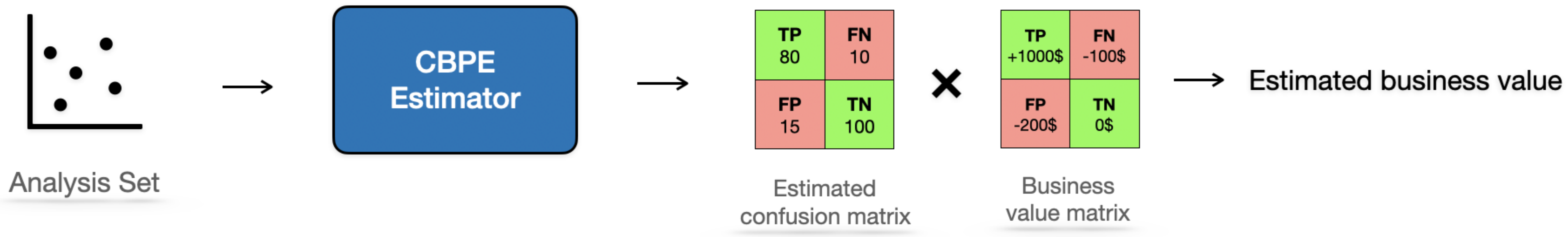
- True positive (TP) - doesn't add or subtract any value.
- False positive (FP) - leads to relocations and discounts, it costs hotel $200.
- False negative (FN) - costs hotel $100, a one-night stay until a replacement is found.
- True negative (TN) - worth $1000 because the hotel can rent the room to someone else.

When labels are available




```
# Initialize the calculator
calculator = nannyml.PerformanceCalculator(...
    problem_type='classification_binary',
    metrics=['business_value'],
    # [value_of_TN, value_of_FP], [value_of_FN, value_of_TP]]
    business_value_matrix = [[0, -200],[-100, 1000]],
    normalize_business_value='None')
```

When labels are not available




```python
# Initialize the estimator
estimator = nannyml.CBPE(...
    problem_type='classification_binary',
    metrics=['business_value'],
    # [value_of_TN, value_of_FP], [value_of_FN, value_of_TP]]
    business_value_matrix = [[0, -200],[-100, 1000]],
    normalize_business_value='per_prediction')
```

Let's practice!

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