

# Predictive Process Monitoring

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# 1. Introduction of Data and Tasks

## Data

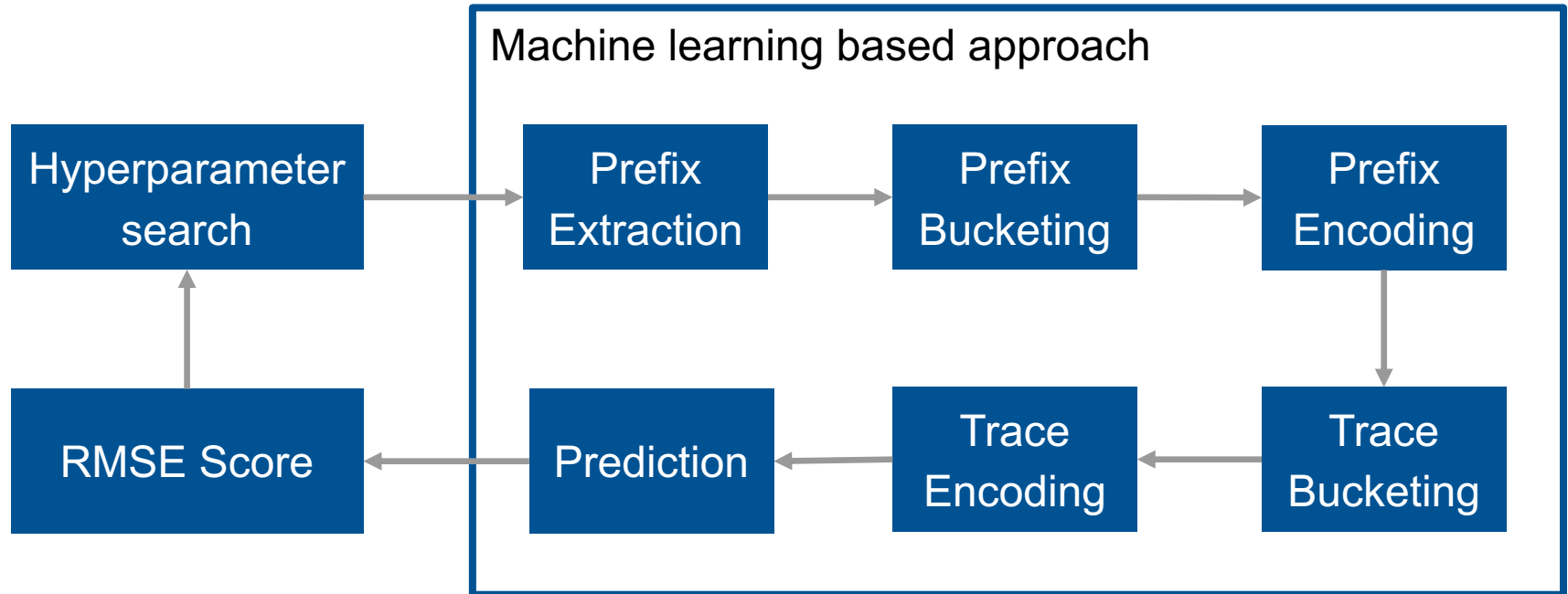
- Sepsis\_Cases\_1
- Event log with treatments of patients with sepsis symptoms in hospital
- Number of cases: 782
- Number of activities: 15
- Trace duration between 3 hours and 114 days with an average of 7.5 days

## Tasks

- Analyse data
- Machine learning based remaining time prediction
- Improve explainability
- Deep learning based remaining time prediction



## 2. Hyperparameter Search with Ray Tune



## 2. Hyperparameter Search with Ray Tune

Table representation of search space

Parameter	Distribution	Values
<b>temporal_split_sort_by</b>	Choice	$x \in$ ["timesincecasestart", "time:timestamp"]
<b>bucketing_technique</b>	Grid	$x \in$ ["SingleBucket", "PrefixLength", "Clustering"]
<b>bucketing_upper_bound</b>	Uniform integer	$x \in [2, 20]$
...	...	...

Code representation of search space

```
{
  "temporal_split_sort_by": tune.choice(
    ["timesincecasestart", "time:timestamp"]),

  "bucketing_technique": tune.grid_search(
    ["SingleBucket", "PrefixLength", "Clustering"]),

  "bucketing_lower_bound": tune.randint(2, 20),
  ...
}
```

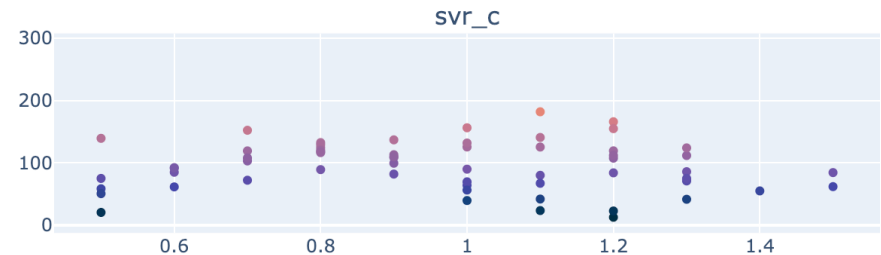
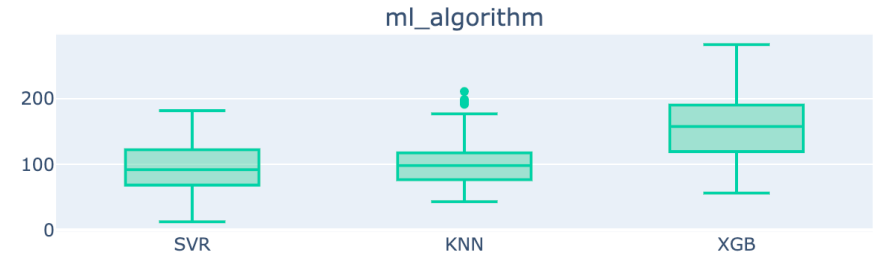
### 3. Visualizations with Plotly for Explainability

Plotly is an:

- Free
- Interactive
- Well documented

Graphing library with publication-quality graphs

Examples



## 4. Deep learning with Pytorch Lightning

Pytorch Lightning is a

- Relatively simple
- Flexible
- Well documented

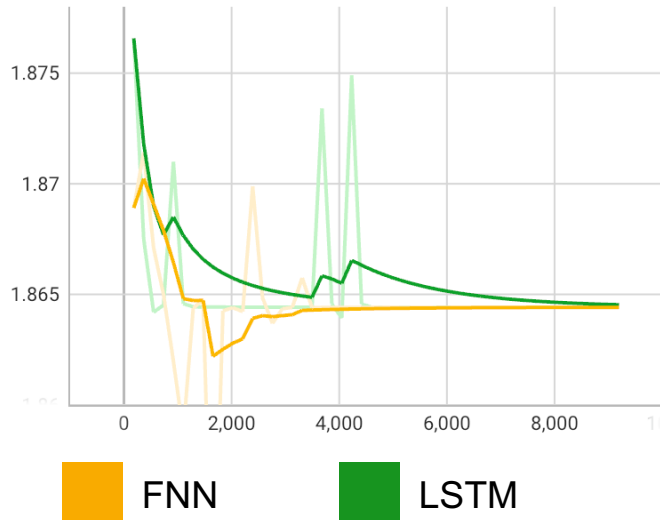
Deep learning framework

Easy implementation of neural networks

```
self.dfn = nn.Sequential(  
    nn.Linear(self.input_dim, self.hidden_dim1),  
    nn.BatchNorm1d(self.hidden_dim1),  
    nn.ReLU(),  
    nn.Dropout(self.dropout),  
  
    nn.Linear(self.hidden_dim, self.hidden_dim2),  
    nn.BatchNorm1d(self.hidden_dim2),  
    nn.ReLU(),  
    nn.Dropout(self.dropout),  
    ...
```

## 5. Challenges: Develop Neural Networks that learn

### Problem



### Solution

- Keep it simple at first
- Stick to best practices instead to papers at first
- Revisit slides of Introduction to Deep Learning
- Visualize predictions with Tensorboard



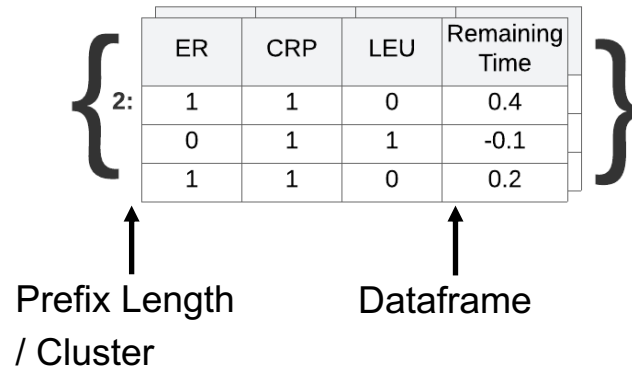
## 5. Challenges: Common data structure for prefixes

### Problem

- Machine learning and deep learning based approach follow similar structure
- Different techniques can be used for same steps in approaches
- Code should be clear, maintainable and reusable
- Data structure for storing prefixes should be the same for all settings

### Solution

- Reordering of steps in approaches
- Idea testing with pen and paper



## 5. Challenges: Understanding key concepts

### Problem

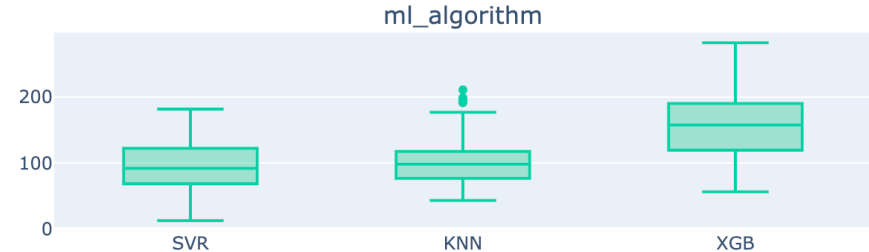
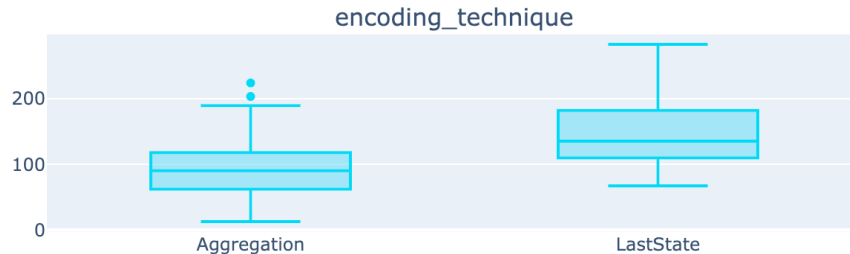
- What is prefix extraction?
- What is prefix bucketing?
- What is last state encoding?
- What is aggregation encoding?
- ...

### Solution

- Reading multiple sources about concepts
- Finding explanations with helpful visualizations
- Asking the same questions multiple times during consultations 😊

## 6. Results: Best Machine Learning Approaches

RMSE	MAE	Prefix length	Bucketing technique	Encoding technique	ML algorithm
0.008	761.00	14	Single Bucket	Aggregation	SVM
0.009	1366.20	10	Prefix Length	Aggregation	SVM
0.018	1227.12	17	Prefix Length	Aggregation	SVM



## 6. Results: Deep learning architectures

### Feedforward Neural Network architecture

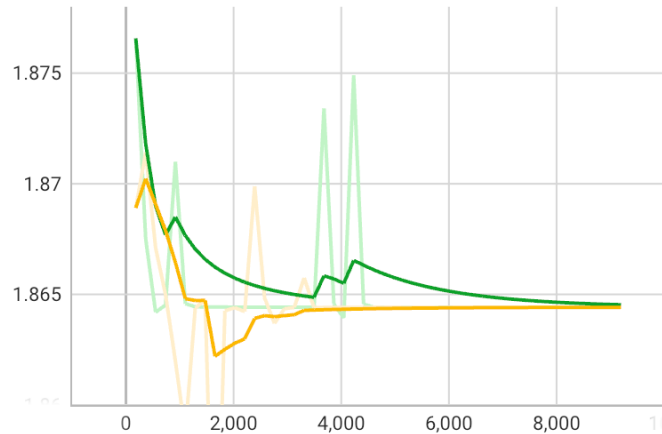
Parameter	Value
# layers	5
# neurons per layer	[input_dim, hidden_dim, hidden_dim * 1.2, hidden_dim * 0.6, hidden_dim * 0.3, output_dim]
# dropout layer	5
Activation functions	[relu, relu, relu, relu, tanh]

### Long Short Term Memory architecture

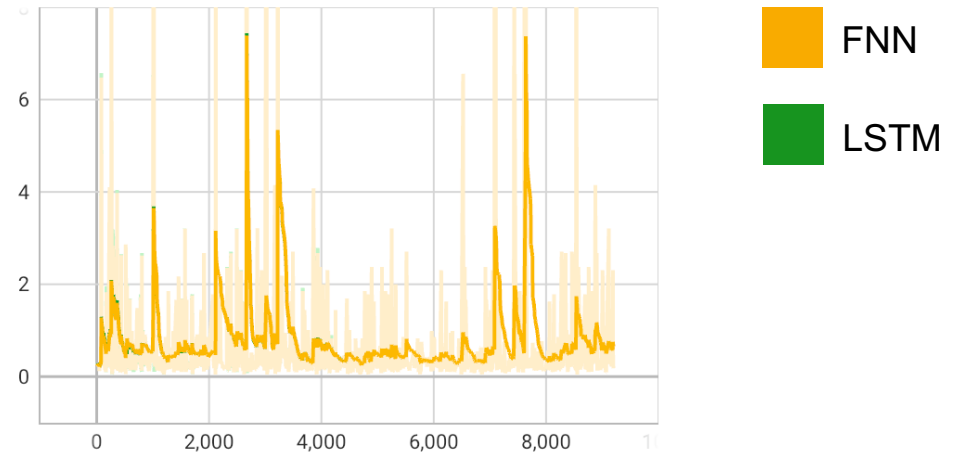
Parameter	Value
# layers	[2 lstm, 2 fully connected]
# neurons per layer	[input_dim, hidden_dim, hidden_dim, hidden_dim * 0.3, output_dim]
# dropout layer	2
Activation functions	[relu, tanh]

## 6. Results: Deep learning with frequency encoding

Validation loss



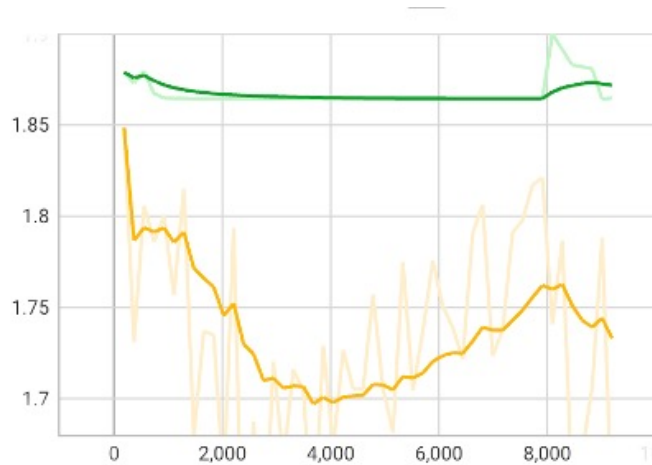
Test loss



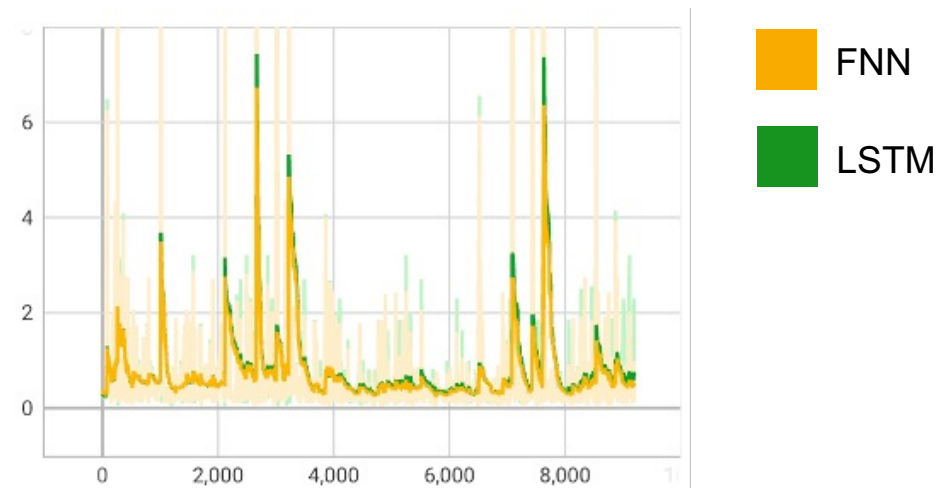
→ No learning of remaining time prediction evident, bad RMSE and MAE scores

## 6. Results: Deep learning with Batch Normalization

Validation loss



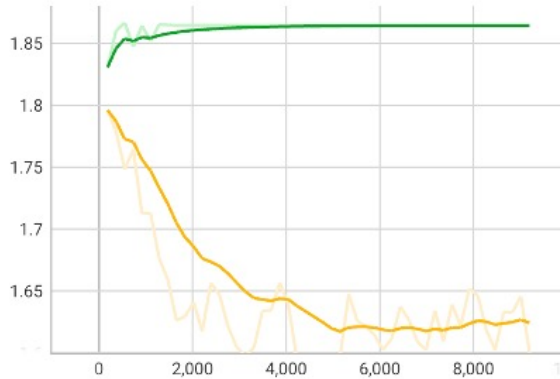
Test loss



→ Improved results for Feedforward neural network

## 6. Results: Further experiments with deep learning

### Decrease in number of layers



→ Improved results for Feed-forward neural network

### Experiments without improvements

- Decrease in batch size (50 → 20)
- Increase in batch size (50 → 70)
- Decrease in size of „hidden\_dim“ (100 → 50)
- Increase in size of „hidden\_dim“ (100 → 150)
- One-Hot encoding for event encoding



## 6. Results: Summary

### Best results per approach

Approach	RMSE	MAE
Machine Learning	0.02	762.94
Feedforward Neural Network	5.64	16677.14
Long Short Term Memory	7.14	19190.72

### Key takeaways

- Machine learning based approach outperformed deep learning based approach
- Single bucketing, aggregation encoding and Support Vector Machines were main contributors to success of machine learning
- Results of Feedforward Neural Network were improved, but still not useful
- Long Short Term Memories tended to not learn anything