Replay-Driven
Continual Learning for
the Industrial Internet
of Things

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Replay-Driven Continual Learning for the Industrial Internet of Things

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Industrial Internet of Things (IIoT)

- Interconnection of sensors, devices, and industrial machines
- Streaming access to data from sensors for ML applications
- Challenges of evolving data in dynamic IIoT environments
Continual learning – background and challenges

- Humans can continually learn without forgetting the past
- Artificial neural networks can catastrophically forget if trained only on new data
- Replay as a mechanism to consolidate short-term memory to long-term memory
Contributions: Replay-Driven Continual Learning Pipeline

- Novel Replay-Driven Continual Learning Pipeline
- New Tool Support (open-source ML pipeline)
- Evaluation on Industrial Case Studies
Continual Learning Pipeline Overview

- Inspired by human learning experiences: learning, replaying, and inferring
- Six stages in the pipeline:
  1. Experience configuration
  2. Data pre-processing
  3. Experience fusion
  4. Training ML model
  5. Evaluating model performance
  6. Inference service (optional)
Experience Configuration

• ML experience engineer configures experiences:
  • Baseline learning, inference, and replay-driven learning
  • Experience parameters: type, features, train/test split, replay data, ML model, and evaluation
Data Pre-processing

- Data pre-processing:
  - Raw data queue (MQTT, Apache Kafka)
  - Data profiling, cleaning, feature engineering, splitting, scaling, and sequentializing
Experience Fusion, Model Training, and Evaluation

• Experience fusion: Combine new data with past experiences
  • Store and recall replay experience data to prevent catastrophic forgetting

• Training ML model:
  • DNNs/FCNNs, CNNs, and LSTM for training
  • Validation dataset to prevent overfitting
  • Model saved in Model DB

• Evaluating model performance:
  • Metrics: MSE, R2 score, MAPE, accuracy, and F1-score
  • Test dataset for unbiased evaluation
Baseline Learning Experience

- First step in the pipeline
- Train ML model with static dataset
- Leverage correlations between input and target variables
- Fine-tune control parameters for acceptable performance
- Store trained model in Model DB
Inference Experience

• Utilize existing ML model for predictions
• Runs model against a batch of new data
• Pre-processes data for inference
• Inference occurs when learning experiences are not happening
• Model remains stable under current circumstances
Replay-Driven Learning Experience

- Improve past ML models using new incoming data
- Monitor inference process for data drift and poor performance
- Combine new and past data for training
- Evaluate performance of new ML model
- Invoke inference experience with new model if satisfactory
Evaluation: Subjects of the Evaluation

Three industrial case studies:

1. Bosch CNC Machining Dataset
   • Real-world industrial vibration data from milling CNC machines
   • Task: classify signals as normal or anomalous

2. Broaching of Airplane Turbine Discs
   • Data from broaching tools cutting slots on jet engine turbine discs
   • Task: predict tool wear in millimeters

3. Piston Rod Manufacturing Dataset
   • Data from the machining process of piston rods at CiP learning factory
   • Task: predict the remaining useful lifetime of the tool

Example setup from the broaching case study
Evaluation: RQ1 - Baseline Model Performance

RQ1: How does a baseline model based on static legacy data perform on new IIoT data for predictive inference?

Performance measures: F1-score (classification) and $R^2$ score (regression)

The data from all use cases were split into five datasets in chronological order.

Bosch CNC Machining:
- F1-score of 0.891 (1st dataset), significantly lower on other datasets (0.489 to 0.025)
- Performance deteriorates over time

Broaching of Airplane Turbine Discs:
- $R^2$ score lower than 0 on test data from the same dataset
- Performance degrades quickly in each subsequent dataset

Piston Rod Manufacturing:
- $R^2$ score of 0.539 (1st dataset), becomes negative on the 2nd dataset
- Performance quickly deteriorates

Conclusion: Results indicate the need for updating the models through continual learning.
RQ2: How does replay-driven continual learning perform on new and old IIoT data for predictive inference?

- **Replay**: Fusion of a certain percentage of past data with new IIoT data to train existing ML models
- Evaluated on Bosch CNC dataset, Broaching dataset, and Piston Rod dataset
- Tested replay percentages: 0%, 20%, 60%, and 100% (100% is equivalent to traditional ML)
Evaluation: Performance of Replay-driven Continual Learning on Use Cases

Bosch CNC Machining:
- All degrees of replay work well in predicting anomalies in new data
- 0% replay: Model performance declines significantly with fewer anomalies
- 20%-100% replay: Prevents catastrophic forgetting and maintains model performance

Broaching of Airplane Turbine Discs:
- 0% replay: Steady deterioration in model performance
- 20%-100% replay: Improved performance on past data, but poor performance on new data
- Tool wear process understanding needed for better performance

Piston Rod Manufacturing:
- 0% replay: Poor performance on past data, better on new data
- 20%+ replay: Significant improvement on past data, high performance on new data (except for Piston Rod Set 5)
- Data imbalance affects performance
Evaluation: Conclusion for RQ2

• 20% replay is adequate to maintain good performance on continual learning, minimizing catastrophic forgetting

• Both continual learning and traditional ML with 100% replay perform poorly on new unforeseen data that is likely out-of-distribution

• Careful selection of data for 20% replay is important to maintain the balance between performance on new and old data
RQ3: How can our approach be run in industrial production environments?
Lessons learned in two different industrial settings

Key Challenges & Solutions:
1. Data versioning and dependency management
   • Custom data and model management
2. Deployment infrastructure
   • Virtualized Docker container, shared model repository
3. Quality attributes
   • Data profiling, domain-specific assertions
4. Monitoring and logging
   • Purge policies, Bayesian neural networks for uncertainty estimation
5. Integration of models and components
   • Standalone continual learning pipeline, coupling learning and inference
Discussion: Actionable Guidelines and Selection of Replay Data

**Actionable Guidelines for Engineers:**
- Configure pipeline to create a baseline model
- Monitor performance metrics on new and unforeseen data
- Assess training on new data and pros/cons of forgetting past knowledge

**Selection of Replay Data:**
- Realistic scenario: random selection of 20% of old training data
- Alternative data selection techniques: maintaining class balance and value range
Conclusion and Future Work

- Presented a replay-driven continual learning pipeline
- Assessed pipeline with three IIoT case studies
- Performance maintenance by replaying 20% of past data
- Discussed AI engineering dimensions

Future Work:
- New continual learning metrics
- Continual balancing techniques
- Uncertainty estimation
- Green AI and Continual Learning
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