Predictors for Trickling in WSN INE5424 Operating Systems II

Douglas Martins Lucas May Petry Maike de Paula Santos

Department of Informatics and Statistics Federal University of Santa Catarina

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Predictors for Trickling in WSN

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Objective

Project Planning

Project Plan Changes & Issues Design

Develo

Linear Regression Predictor with Gradient Descent MLP Predictor Comparison

> Conclusion & Future Work

Demo

mplementation

Outline

Motivation & Objective

Project Planning

Project Plan Changes & Issues Design

Development

Linear Regression Predictor with Gradient Descent MLP Predictor Comparison

Conclusion & Future Work

Demo

Implementation

Predictive Smart Data Predictors

Predictors for Trickling in WSN

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Project Plan Changes & Issues Design

Linear Regression Predictor with Gradient Descent MI P Predictor Comparison

Motivation & Objective

Motivation

- IoT environment with numerous devices
- Power consumption is an issue (devices' batteries)
- Communication between sensors consumes a lot of power

Objective

- Improvement of energy efficiency by reducing communication
- Development of SmartData predictors

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Motivation & Objective

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Project Plan Changes & Issues Design

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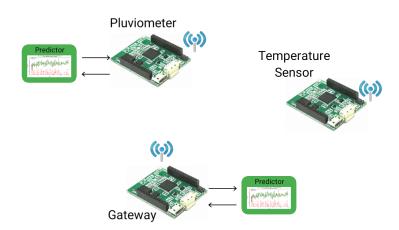
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Motivation & Objective



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Demo



Project Plan

 Study system restrictions and limitations of EPOSMote III and elaborate implementation strategies, such as design patterns √

- 2. Code and test the chosen prediction algorithms in C++ for a general purpose operating system ✓
- 3. Code and test the linear regression with gradient descent predictor on EPOS \checkmark
- 4. Code and test the Elman neural network on EPOS¹
- 5. Deploy the final product using the UFSC IoT $Gateway^1$

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Linear Regression Predictor with Gradient Descent

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Implementation
Predictive Smart

¹See project changes

Changes & Issues

Changes

- ► Elman Neural Network to Multilayer Perceptron Network
- Deploy the final product using the UFSC IoT Gateway to test with data from UFSC IoT

Issues

- Synchronization of predictors
- Implementation of exponential function

Predictors for Trickling in WSN

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Objective 2

Project Planning
Project Plan

Changes & Issues
Design

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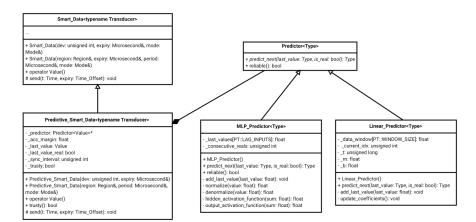
Linear Regression Predictor with Gradient Descent MLP Predictor Comparison

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Implementation

Project Design Class Diagram





Project Design Design Patterns

Design Patterns

- Bridge
- Composition

Programming Techniques

- ► Generic programming
- Static metaprogramming

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Linear Regression Predictor with Gradient Descent MLP Predictor Comparison

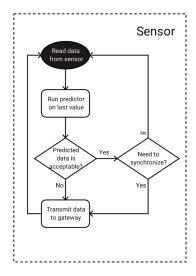
Conclusion & Future Work

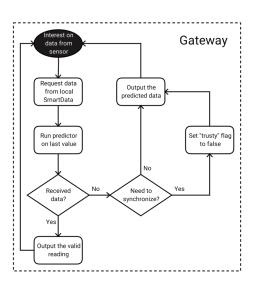
Demo

Implementation

Project Design

Sensor and Gateway Operation







Linear Regression Predictor with Gradient Descent

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Linear Regression Predictor with Gradient Descent MLP Predictor Comparison

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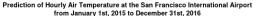
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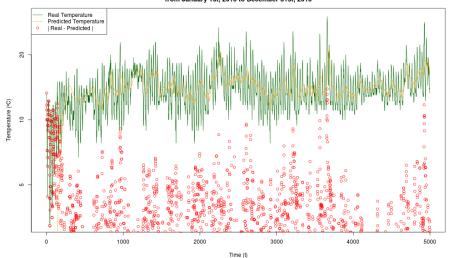
mnlementation

- ▶ Performance tests and simulation in C++
- Static parameterization via Traits.h on EPOS
- Generic type prediction

Linear Regression Predictor

Performance Tests





MLP Predictor

- ▶ Prediction of time series x(t) based on n last values of x(t).
- ▶ Requires historical data of the series to be predicted.
- ▶ Neural network training on a third-party software².

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Linear Regression Predictor with Gradient Descent

MLP Predictor

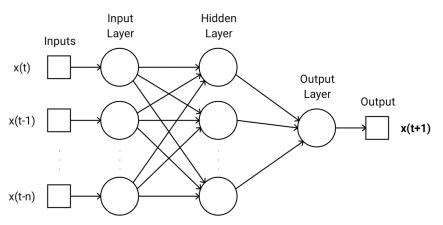
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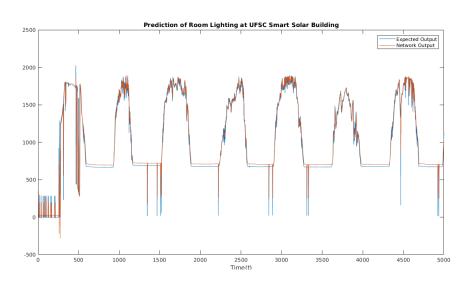
²MATLAB - MathWorks

Multilayer Perceptron Network



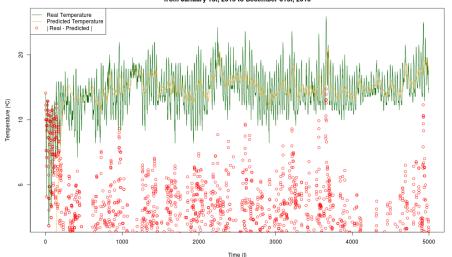


MLP Predictor Performance Tests



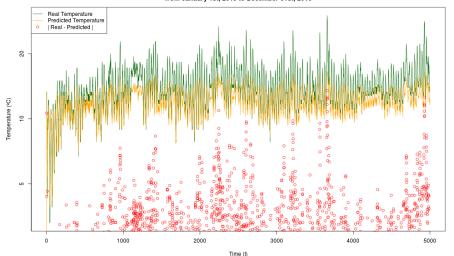
Linear Regression vs. MLP Predictor Linear Regression Predictor

Prediction of Hourly Air Temperature at the San Francisco International Airport from January 1st, 2015 to December 31st, 2016



Linear Regression vs. MLP Predictor MLP Predictor

Prediction of Hourly Air Temperature at the San Francisco International Airport from January 1st, 2015 to December 31st, 2016



Linear Regression vs. MLP Predictor Overall Comparison

| Feature | Linear Predictor | MLP Predictor |
|-------------------|------------------|---------------|
| Туре | Dynamic | Static |
| Online learning | ✓ | |
| Needs series | | |
| historical data | | V |
| Resilient to | | |
| desynchronization | | V |
| No preprocessing | / | |
| needed | V | |

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Comparison

Lonclusion & Future Work

Demo

mplementation

Conclusion & Future Work

- Project planning requirements fulfilled
- Achieved satisfying results
- ► Future Work
 - Develop other types of predictors
 - Expand neural network implementation

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Project Demo

Project demonstration

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Implementation

Predictive_Smart_Data

```
template <> template <typename S> struct Traits <
    Predictive_Smart_Data <S>>: public Traits <
    Smart_Data <S>> {
    enum {LINEAR, MLP};

    static const bool debugged = true;
    static const unsigned int ACC_MARGIN = 8;
    static const unsigned int PREDICTOR = LINEAR;
    static const unsigned int SYNC_INTERVAL = 2;
};
```

${\sf Predictive_Smart_Data}$

Predictor Selection

Predictive_Smart_Data send()

```
void send(const Time t, Time_Offset expiry) {
    Value predicted = _predictor->predict_next(
        last value. last value real):
    Value real = Smart_Data<Transducer>::_value;
    bool acceptable_margins, check_sync = ...
    if(acceptable_margins && check_sync) {
        _last_value = predicted;
        _last_value_real = false;
        _sync_interval --;
    } else {
        _last_value = real;
        _last_value_real = true;
        Smart_Data < Transducer > :: send(t, expiry);
        _sync_interval = PT::SYNC_INTERVAL;
```

Predictive_Smart_Data operator Value()

```
operator Value() {
  Value predicted;
  bool device_remote, sensor_side = ...
  if (device_remote)
    predicted = _predictor->predict_next(
      last value. last value real):
  if(Smart_Data<Transducer>::expired()) {
    if (sensor side) {
      Transducer::sense(
        Smart_Data < Transducer > :: _device , this);
      Smart_Data < Transducer > :: _time = TSTP :: now();
    } else {
      _last_value = predicted;
      last value real = false:
      if(PT::SYNC_INTERVAL && !_sync_interval)
        _trusty = false;
      if(_sync_interval > 0)
        _sync_interval --;
```

Predictive_Smart_Data operator Value()

```
else {
    _last_value = Smart_Data<Transducer>::_value;
    _last_value_real = true;
    if(device_remote)
        _sync_interval = PT::SYNC_INTERVAL;
    }

if(!_trusty)
    _trusty = _predictor->reliable();
    return _last_value;
}
```

Predictor

Predictor Interface

```
template < typename Type >
class Predictor
public:
    virtual Type predict_next(
        Type last_value, bool is_real = false) = 0;
    virtual bool reliable() { return false; };
};
template < typename Type >
class Linear_Predictor: public Predictor<Type>
  . . .
};
template < typename Type >
class MLP_Predictor: public Predictor<Type>
  . . .
};
```

Linear_Predictor

```
template <typename S> struct Traits<Linear_Predictor<S
    >>: public Traits<void>
{
    static const bool debugged = true;
    static const unsigned int WINDOW_SIZE = 30;
    static const float LRATE;
    static const unsigned short GD_ITERATIONS = 200;
    static const unsigned short M = 0;
    static const unsigned short B = 10;
};
template <typename S> const float Traits<
    Linear_Predictor<S>>::LRATE = 0.0000000001f;
```

MLP_Predictor

```
template <typename S> struct Traits<MLP_Predictor<S>>:
     public Traits < void >
{
    static const bool debugged = true;
    static const unsigned int HIDDEN_UNITS = 5;
    static const unsigned int LAG_INPUTS = 3;
    static const float HIDDEN_WEIGHTS[HIDDEN_UNITS*
        LAG INPUTS1:
    static const float HIDDEN BIASES[HIDDEN UNITS]:
    static const float OUTPUT_WEIGHTS[HIDDEN_UNITS];
    static const float OUTPUT_BIAS;
    static const bool NORMALIZATION = true:
    static const float NORMALIZATION_MIN;
    static const float NORMALIZATION MAX:
};
```