

Constructive Incremental Learning From Only Local Information

Receptive Field Weighted Regression

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Agenda

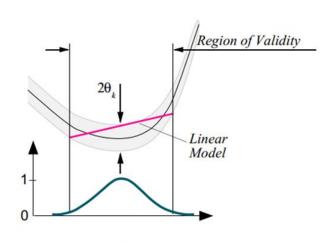
- Algorithms
 - Receptive Fields Weighted Regression (RFWR)
 - Locally Weighted Projection Regression (LWPR)
- Implementation
- Live Demo

Algorithm

Receptive Fields Weighted Regression (RFWR)

- Constructive Incremental Learning From Only Local Information by Stefan Schaal & Christopher Atkeson - University of Southern California, Los Angeles, 1998
- Models data by means of spatially localized linear models
- Learning Scenario:
 - Limited memory
- Two major challenges:
 - Amount of receptive fields (Over and Underfitting)
 - Negative interference (Forgetting of useful knowledge)

Receptive Fields



Weighted Regression

$$\beta = (X^T W X)^{-1} X^T W Y$$

```
Initialize the RFWR with no receptive field (RF);
For every new training sample (x,y):
             For k=1 to #RF:
      a)
                           calculate the activation from (5)
                           update the receptive field parameters according to (13), and (18)
             end:
      b)
             If no subnet was activated by more than w_{gen};
                           create a new RF with c=x, M=M_{def}
             end:
             If two RFs are activated more than w_{prune}:
      c)
                           erase the RF with the larger det(D)
             end;
             calculate the m=E\{wMSE\} and std=E\{(wMSE-m)^2\}^{0.5} of all RFs;
      d)
      e)
             For k=1 to #RF:
                    If |wMSE-m| > \varphi std,
                                  reinitialize receptive field with \mathbf{M} = \varepsilon \mathbf{M}_{def}
                    end:
             end:
```

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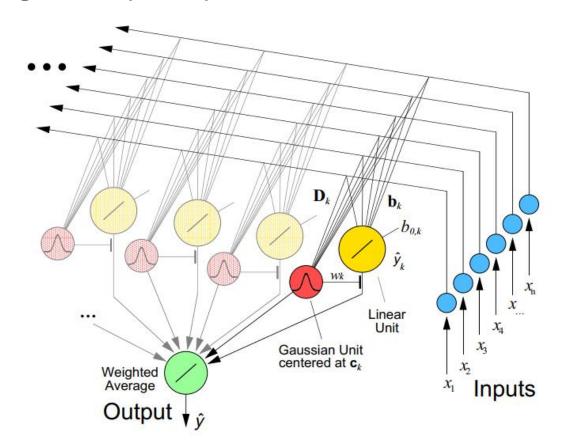
Receptive Fields

• Input: x_n

• Output: \hat{y}

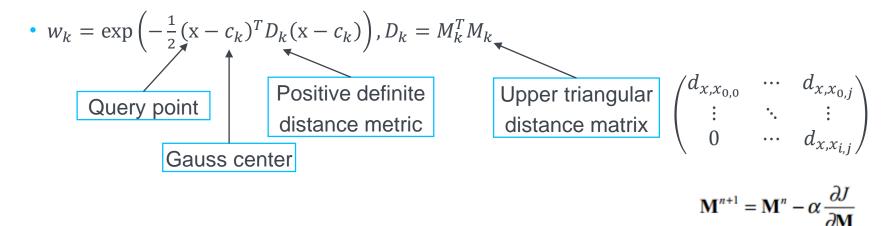
• Gaussian Unit centered: c_k

• Gaussian Kernel: w_k



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Gaussian Kernel: w_k



Gaussian Kernel: w_k

•
$$w_k = \exp\left(-\frac{1}{2}(x - c_k)^T D_k(x - c_k)\right), D_k = M_k^T M_k$$

•
$$W = \begin{pmatrix} w_{0,0} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_{i,i} \end{pmatrix}$$
 Diagonal weights matrix

Gaussian Kernel: w_k

•
$$w_k = \exp\left(-\frac{1}{2}(x - c_k)^T D_k(x - c_k)\right), D_k = M_k^T M_k$$

$$W = \begin{pmatrix} w_{0,0} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_{i,i} \end{pmatrix}$$

• $\beta = (X^T X)^{-1} X^T Y \leftarrow$

Linear

Regression

Gaussian Kernel: w_k

•
$$w_k = \exp\left(-\frac{1}{2}(x - c_k)^T D_k(x - c_k)\right), D_k = M_k^T M_k$$

$$W = \begin{pmatrix} w_{0,0} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_{i,i} \end{pmatrix}$$

$$\beta = (X^T X)^{-1} X^T Y$$

•
$$\beta = (X^T W X)^{-1} X^T W Y \leftarrow$$
 Weighted Regression

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Gaussian Kernel: w_k

•
$$w_k = \exp\left(-\frac{1}{2}(\mathbf{x} - c_k)^T D_k(\mathbf{x} - c_k)\right), D_k = M_k^T M_k$$

$$\bullet \ W = \begin{pmatrix} w_{0,0} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & w_{i,i} \end{pmatrix}$$

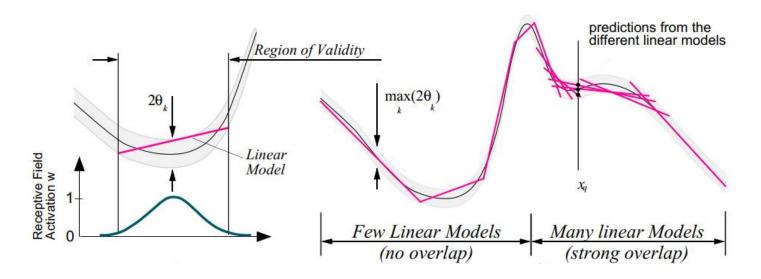
$$\beta = (X^T X)^{-1} X^T Y$$

•
$$\beta = (X^T W X)^{-1} X^T W Y$$

For each receptive field *independently*, without any information about the other receptive fields

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- Receptive Fields
- Weighted Regression



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Adjusting Receptive Fields

• Shape, Size, Amount

•
$$J = \frac{1}{W} \sum_{i=1}^{p} w_i ||y_i - \hat{y}_i||^2 \text{ where } W = \sum_{i=1}^{p} w_i$$

Minimizing J → overfitting

•
$$J = \frac{1}{W} \sum_{i=1}^{p} w_i ||y_i - \hat{y}_{i,-i}||^2$$

Minimizing J → leave-one-out cross validation (is expensive)

•
$$J = \frac{1}{W} \sum_{i=1}^{p} w_i ||y_i - \hat{y}_{i,-i}||^2 = \frac{1}{W} \sum_{i=1}^{p} \frac{w_i ||y_i - \hat{y}_{i,-i}||^2}{(1 - w_i \tilde{x}_i^T P \tilde{x}_i)^2}$$

Minimizing J → receptive fields will shrink to a very small size

•
$$J = \frac{1}{W} \sum_{i=1}^{p} \frac{w_i \|y_i - \hat{y}_{i,-i}\|^2}{(1 - w_i \tilde{x}_i^T P \tilde{x}_i)^2} + \gamma \sum_{i,j=1}^{n} D_{ij}^2$$

Adjusting Receptive Fields

- Shape, Size, Amount
- Increase
 - A new receptive field is created if a training sample (x,y) does not activate any of the
 existing receptive field by more than a threshold
- Decrease
 - Overlaping fields, do not degrade approximation quality
 - Computational cost

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- RFWR vs. Locally Weighted Projection Regression (LWPR)
- LWPR downsizes actively the dimension in the receptive fields
 - Partial Least Squares
 - Principal Component Regression
 - Covariant Projection Regression

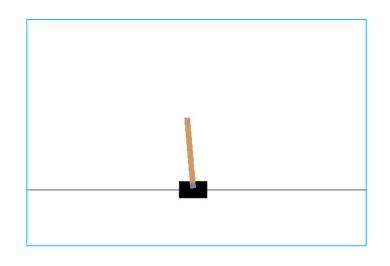
- Open Gym Cartpole (python3)
- LWPR Module (python2)

Observation

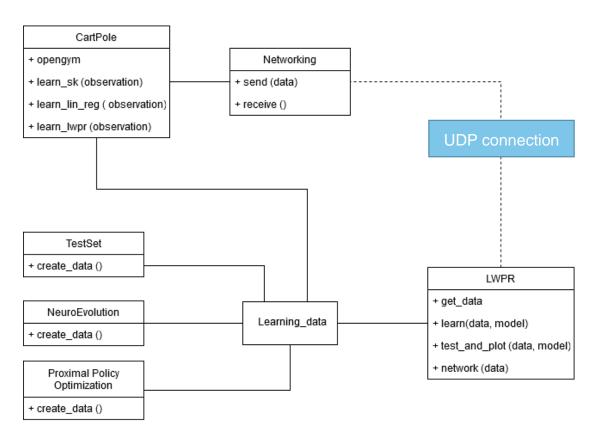
Num	Observation	Min	Max
0	Cart Position	-4.8	4.8
1	Cart Velocity	-Inf	Inf
2	Pole Angle	-24 deg	24 deg
3	Pole Velocity At Tip	-Inf	Inf



Num	Action
0	Push cart to the left
1	Push cart to the right



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Jupyter notebook demo



Thank you!



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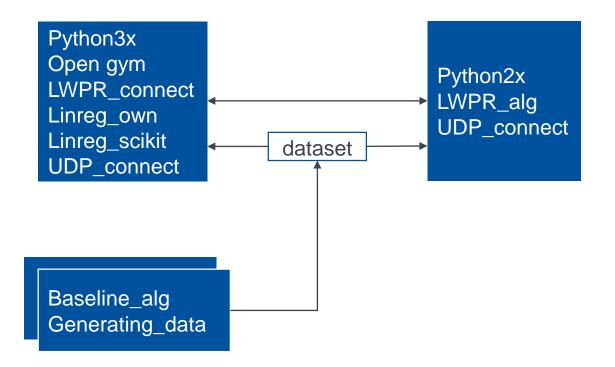
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Outlock

Comparision

- Open Gym Cartpole (python3)
- LWPR Module (python2)
 - Client-Server application via UDP
 - Generating Training data

- Open Gym Cartpole (python3)
 - Started implementation
 - Unclear parts
 - Found matlab file
 - Very complex
 - Found module for the algorithm
 - Python2
 - Couldn't execute it
 - Specific version of python, gcc and packages
- LWPR Module (python2)



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