Introduction to RES production forecasting

Prof. Nikos Hatziargyriou,
Thodoris Konstantinou,
Smart Grids Research Unit - Smart RUE
School of Electrical and Computer Engineering National Technical University of Athens

Overview

- Introduction
- Mathematical Formulation of forecasting
- Artificial Neural Networks
- Evaluation

Introduction

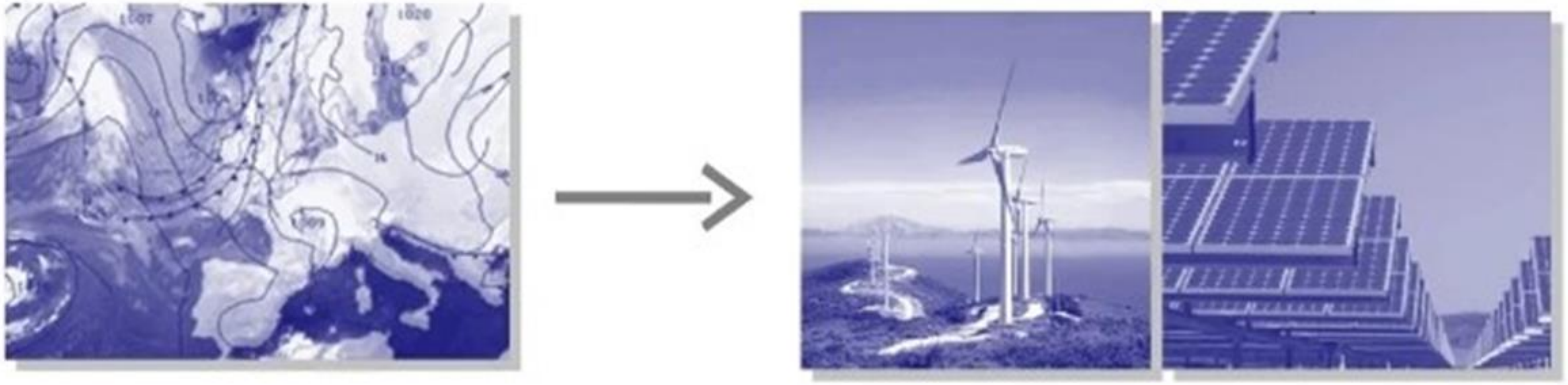
- What is power generation prediction?
  - Estimate the power generation of RES in the future
  - Horizons from minutes to years ahead
- Why are power predictions necessary?
  - RES generation is highly dependent on meteorological conditions
  - Meteorological conditions are uncertain and meteorological variables are random variables
  - RES generation must be considered as a random variable conditional to meteorological random variables (e.g wind speed, wind direction, cloud coverage, temperature, solar radiation)
  - Contribution of RES generation in the production mix must be known in advance for safe and stable power system scheduling

Who needs wind and solar power predictions?

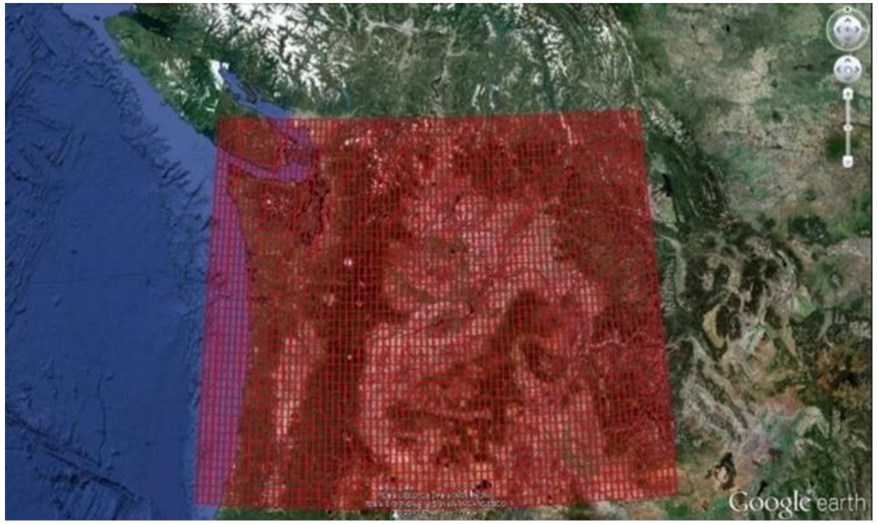
Time scale of forecast	User	Area of application
Shortest-term (0 - 6h)	Energy traders	Trading on intraday energy market Control of curtailment due to negative market prices
	System operators	Balancing Unit re-dispatch Curtailment of power plants
Short-term (6 - 48h)	Energy traders	Trading on day-ahed energy market Participation in reserve market Influence of RES production on market price
	System operators	Unit dispatch Load flow calculations Day-ahead congestion forecast
	RES Plant operators	Day-ahead planning of maintenance
Medium-term (48h - 2 weeks)	System operators	Week-ahead congestion forecast Week-ahead planning
	RES Plant operators	Medium-term planning of maintenance

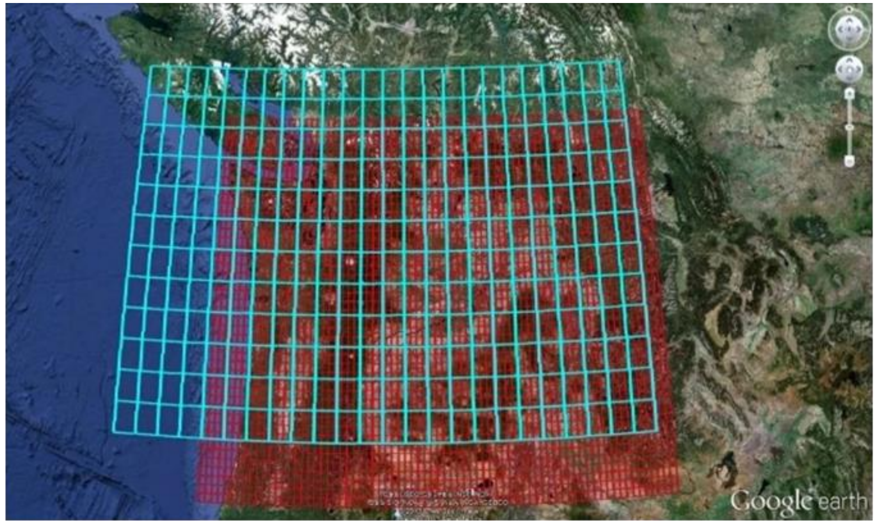
How do power predictions work?

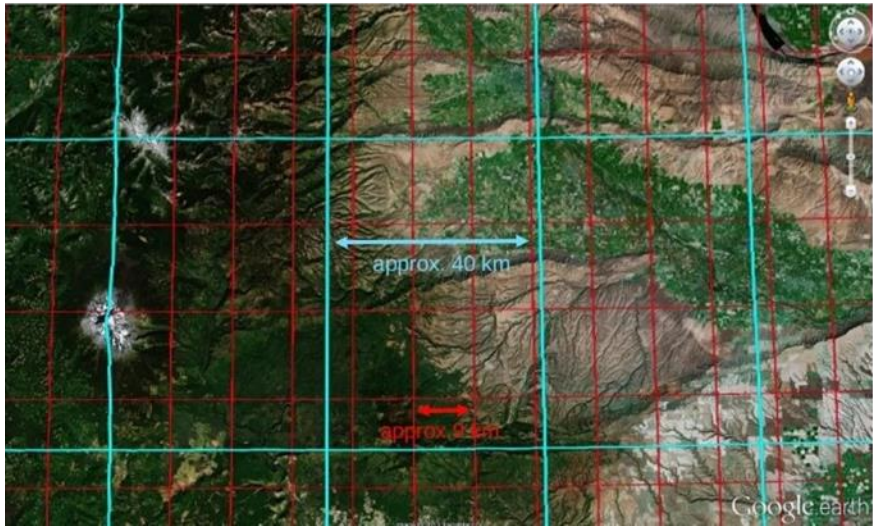
- The main goal is to convert meteorological variables into power generation of RES plants
- Main input source: Numerical Weather Predictions (NWP)

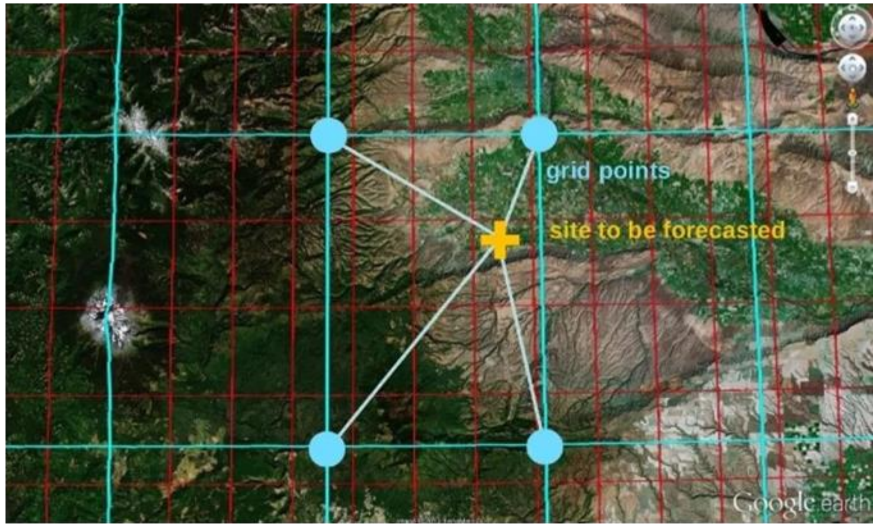


Numerical Weather Predictions







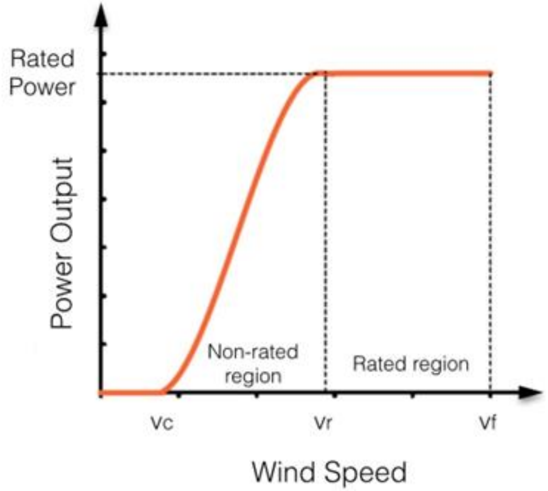


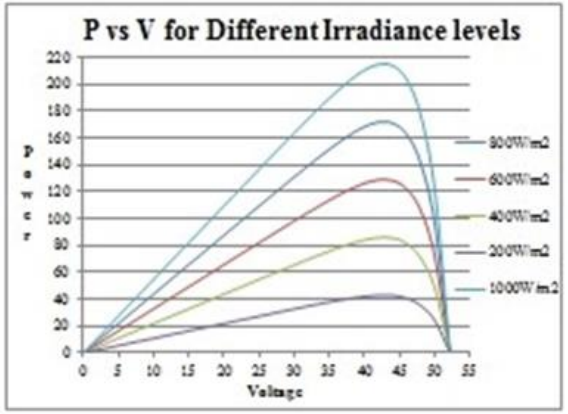
Power conversion functions

Physical models

- Analytical expression of conversion functions

- Advantages:
    - Fairly simple solution
    - No historical data required
    - Site-irrelevant
- Disadvantages:
    - Limitation in input variables
    - Sensitive to noisy input data



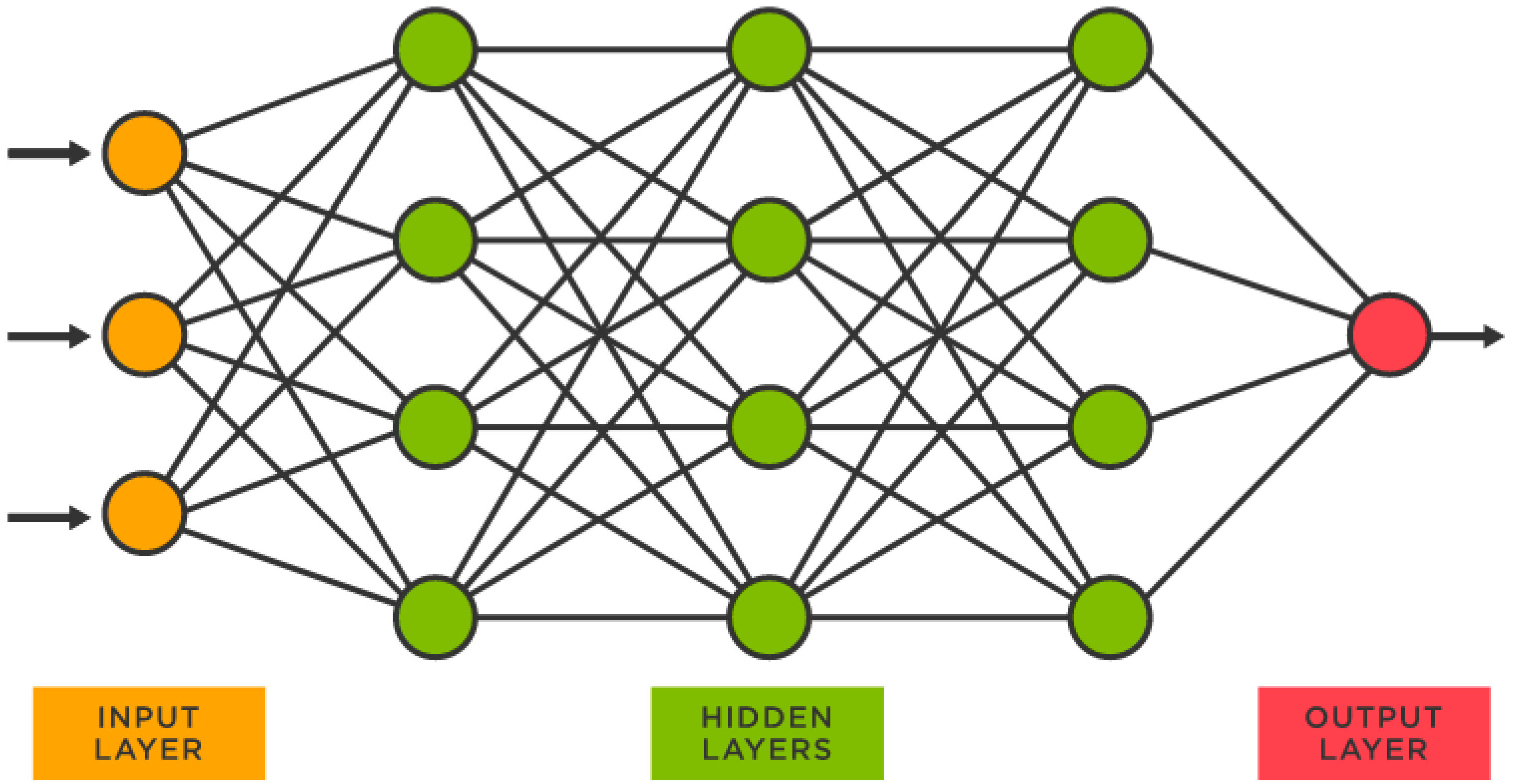


Statistical models

- Approximation of through an optimization process

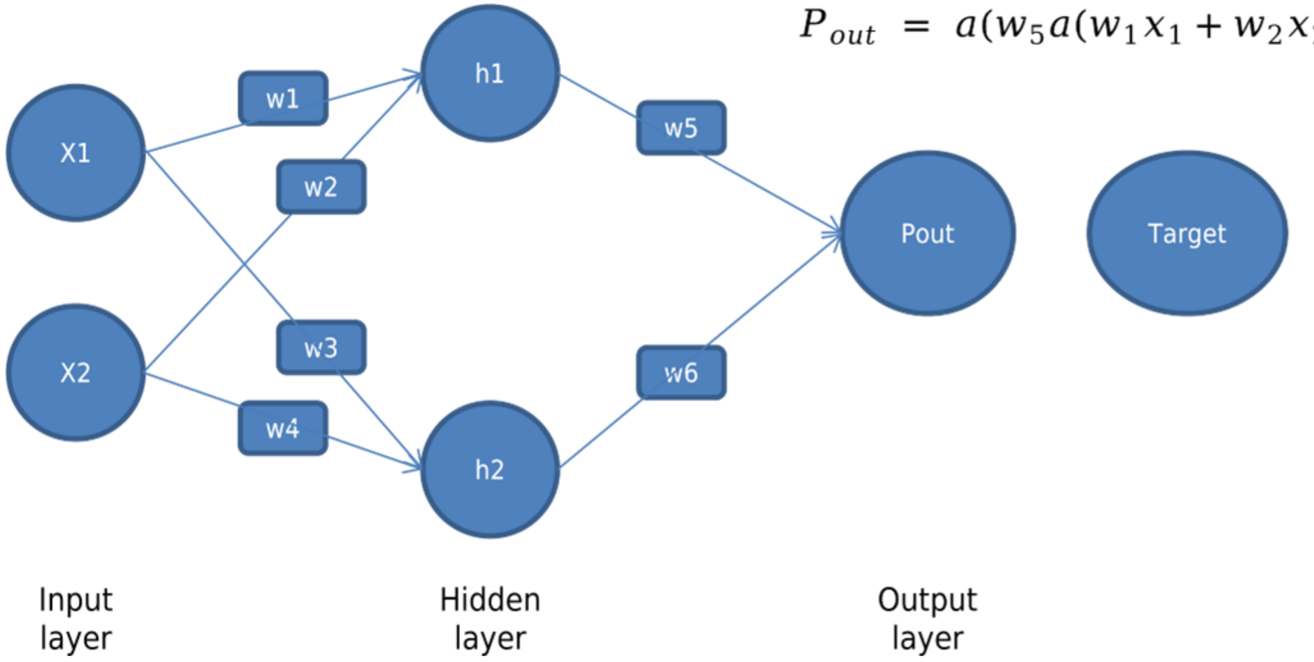
- Advantages:
    - No limitations in input features
    - Less sensitive to noisy input
- Disadvantages:
    - Historical data are required
    - Site-specific

Artificial Neural Networks



Training Artificial Neural Networks

$$P_{out} = a(w_5 a(w_1 x_1 + w_2 x_2) + w_6 a(w_3 x_1 + w_4 x_2))$$

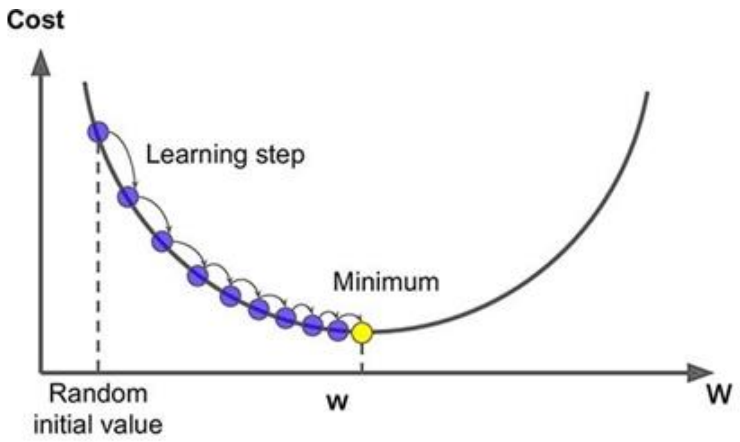


Back-Propagation of error

- Minimize $$L = \frac{1}{N}\sum_{i=1}^{N}\frac{(Target^{i} - P_{out}{}^{i})^2}{2}$$

- Mechanism used to update the weights using gradient descent. It calculates the gradient of the error function with respect to the neural network's weights. The calculation proceeds backwards through the network
- Gradient descent:
  - An iterative optimization algorithm for finding the minimum of a function; in our case we want to minimize the error function. To find a local minimum of a function using gradient descent, one takes steps proportional to the negative of the gradient of the function at the current point

$$w_i{}^{t+1} = w_i{}^{t} - \lambda\left(\frac{\partial L^t}{\partial w^t}\right) : \forall\, i \in W, \forall\, t \in [1, Epochs]$$



Wind power forecasting example

- Input:
  - Wind speed (100 meter)
  - Wind direction (100 meter)
- Target:
  - Wind power generation

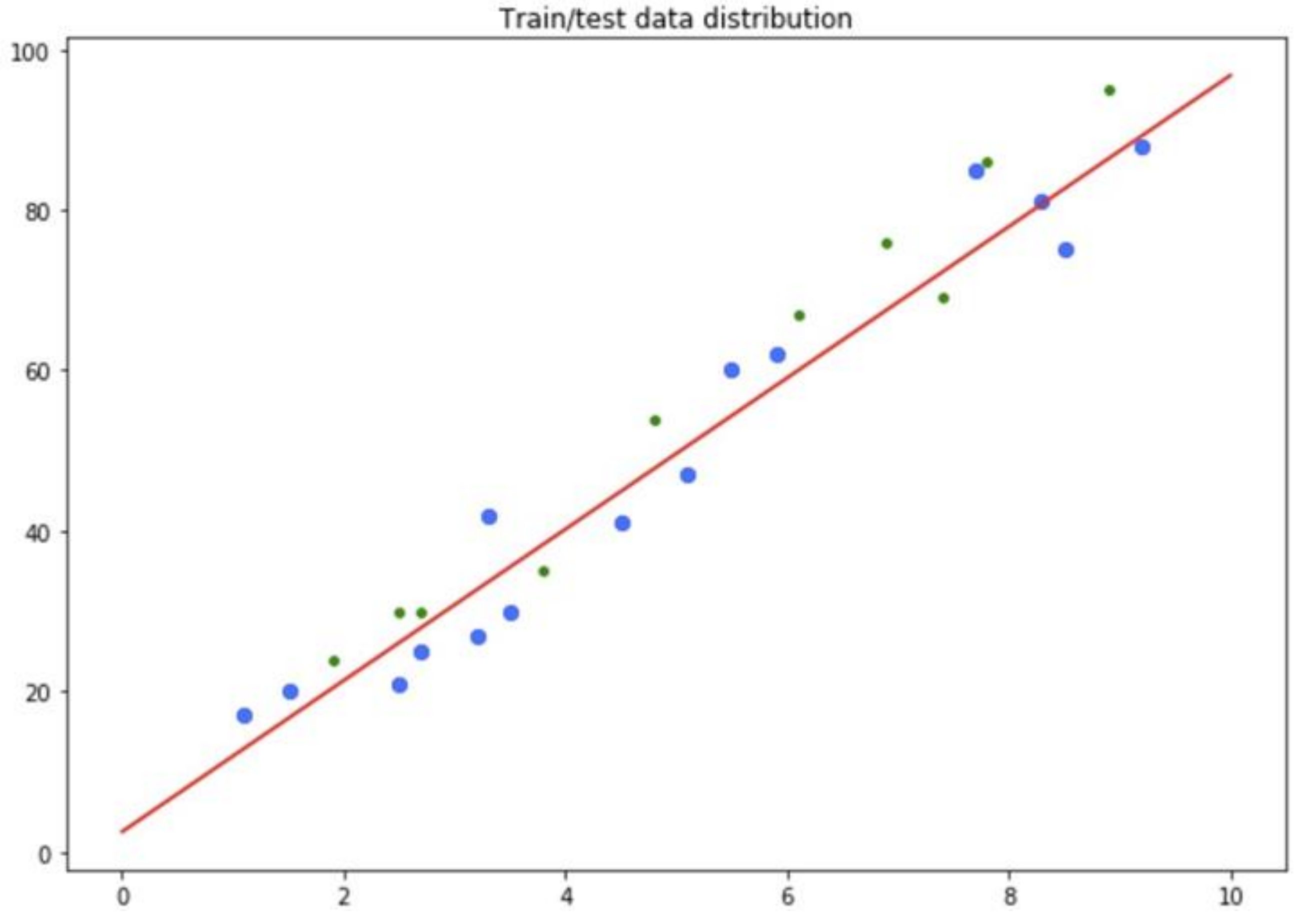
- $w_i{}^{t+1} = w_i{}^{t} - a\left(\frac{\partial L^t}{\partial w^t}\right)$
- $\Delta = \frac{1}{N}\sum_{i=1}^{N}(Target^i - P_{out}{}^i)$

$$^*w_6 = w_6 - a\,(h_2\,.\,\Delta)$$
$$^*w_5 = w_5 - a\,(h_1\,.\,\Delta)$$
$$^*w_4 = w_4 - a\,(i_2\,.\,\Delta w_6)$$
$$^*w_3 = w_3 - a\,(i_1\,.\,\Delta w_6)$$
$$^*w_2 = w_2 - a\,(i_2\,.\,\Delta w_5)$$
$$^*w_1 = w_1 - a\,(i_1\,.\,\Delta w_5)$$

Iteration	WS	WD	w1	w2	w3	w4	h1	h2	w5	w6	Pout	Target	Error
0	0.5	0.6	0.1	0.3	0.27	0.5	0.23	0.435	0.4	0.8	0.44	0.8	0.0648
1	0.5	0.6	0.104	0.304	0.277	0.509	0.23	0.44	0.404	0.808	0.453	0.8	0.06
15	0.5	0.6	0.143	0.352	0.357	0.603	0.28	0.54	0.452	0.899	0.613	0.8	0.01748
30	0.5	0.6	0.166	0.379	0.402	0.658	0.31	0.59	0.481	0.955	0.718	0.8	0.00336
50	0.5	0.6	0.178	0.394	0.429	0.691	0.32	0.62	0.497	0.989	0.784	0.8	0.00012

Why do we evaluate?

- After a model is trained, we would like to assess the performance of the model by comparing model predictions to actual data
- It is important to evaluate a model on data that had not been used in the training process (Evaluate the generalization)
- Generalization : This essentially means how good our model is at learning from the given data and applying the learnt information elsewhere



Evaluation Metrics

- We evaluate our forecasts based on a variety of metrics:
  - **Bias:**

$$\text{Bias} = \frac{1}{N}\sum_{i=1}^{N}({P_{out}}^{i} - Target^{i})$$

  - **Mean Absolute Error:**

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|Target^{i} - {P_{out}}^{i}|$$

  - **Mean Square Error:**

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}\frac{(Target^{i} - {P_{out}}^{i})^2}{2}$$

Bias

- Bias is obtained by calculating the average value of all residuals as follows:

$$\text{Bias} = \frac{1}{N}\sum_{i=1}^{N}({P_{out}}^{i} - Target^{i})$$

- Positive Bias indicated that the model has a tendency on overestimating the predictions
- Negative Bias indicated that the model has a tendency on underestimating the predictions
- Zero or close to zero Bias indicates that the model has trained well

Mean Absolute Error

- Mean Absolute Error (MAE) is obtained by calculating the absolute difference between the model predictions and the true (actual) values
- MAE is a measure of the average magnitude of error generated by the model
- The MAE is calculated as follows:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} |Target^{i} - {P_{out}}^{i}|$$

Mean Square Error

- Mean Square Error (MSE) is very similar to MAE but instead of using absolute values, we square the difference between the model's predictions and true values
- MSE values are generally larger compared to the MAE since the residuals are being squared
- In MSE, error increases in a quadratic fashion while the error increases in proportional fashion in MAE

- The MSE is calculated as follows:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}\frac{(Target^{i} - {P_{out}}^{i})^2}{2}$$

Thank you!
Questions?

E-mail: tkonstantinou@mail.ntua.gr