Short Forecasting

Electrical Load Forecasting 101

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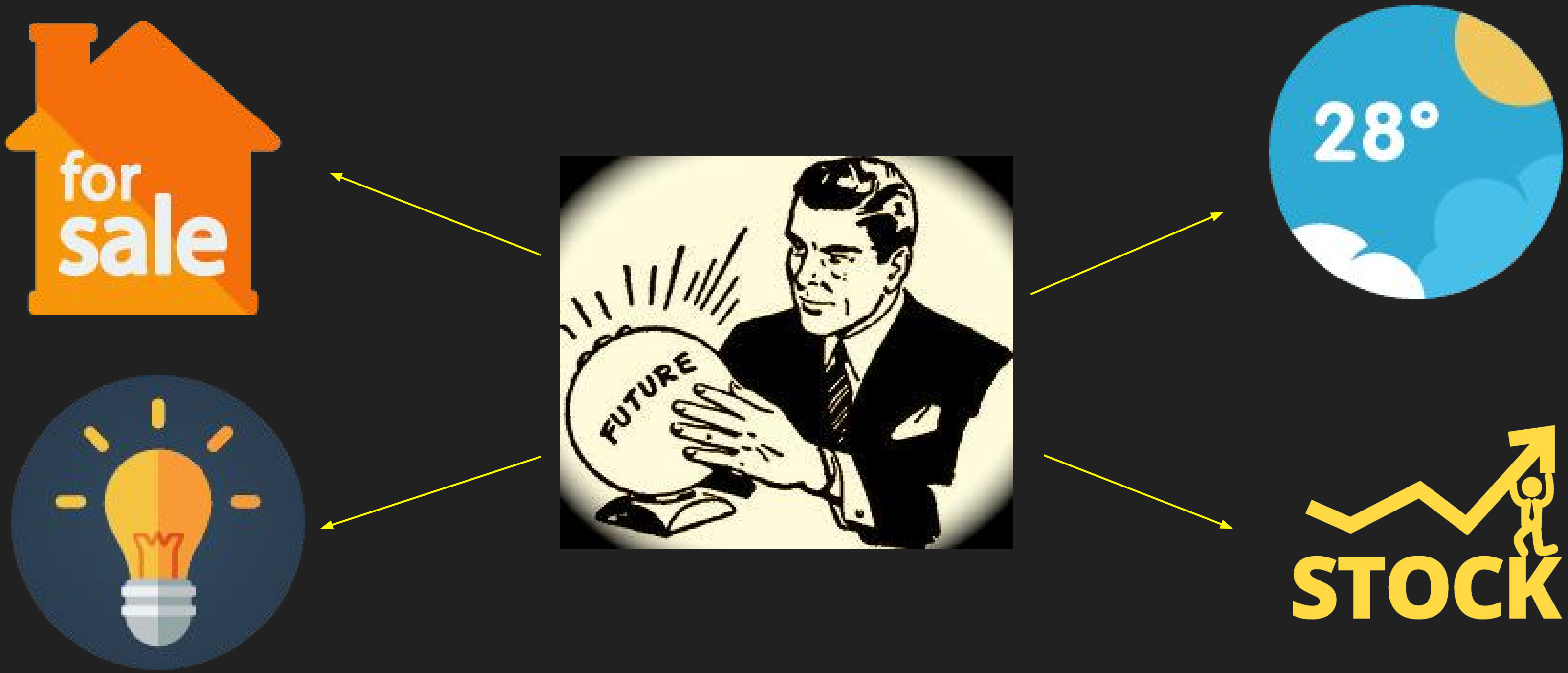
Outline

- What is forecasting?
- Electrical Load Forecasting Motivation and Types
- Short-term load forecasting
- Input Parameters and Modeling
- Methods and Algorithms
  - How to..
  - Strength/Weaknesses
- General Problems with load forecasting
- Evaluation of Performance
  - Examples

- Conclusion

What is forecasting?



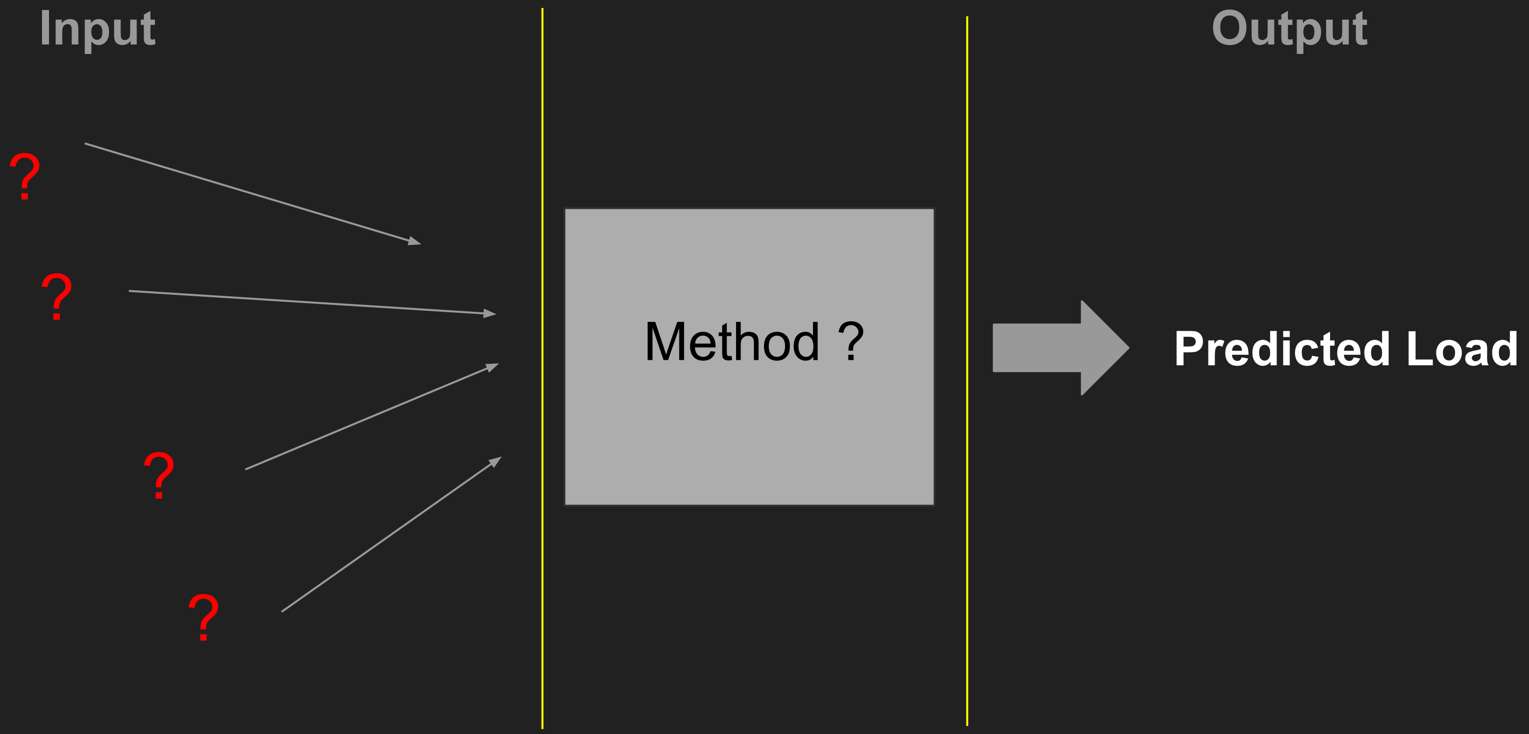
Motivation behind electrical load forecasting

We need to have a look into the future

Types of load forecasting

Type
Short Term forecasting (STLF)
Medium term forecasting
Long term forecasting

Basic model of electrical load forecasting



Regarding the input

Garbage in, Garbage out!

Influencing Factors for Forecasts

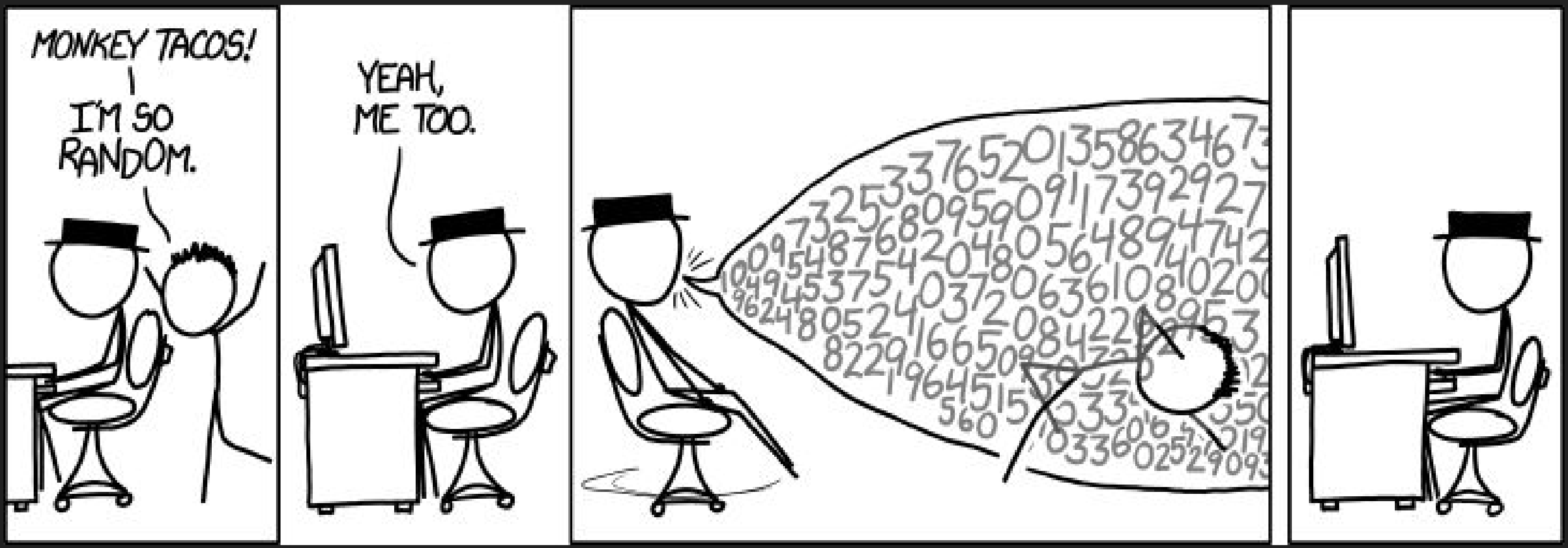
!

Influencing factor: Weather

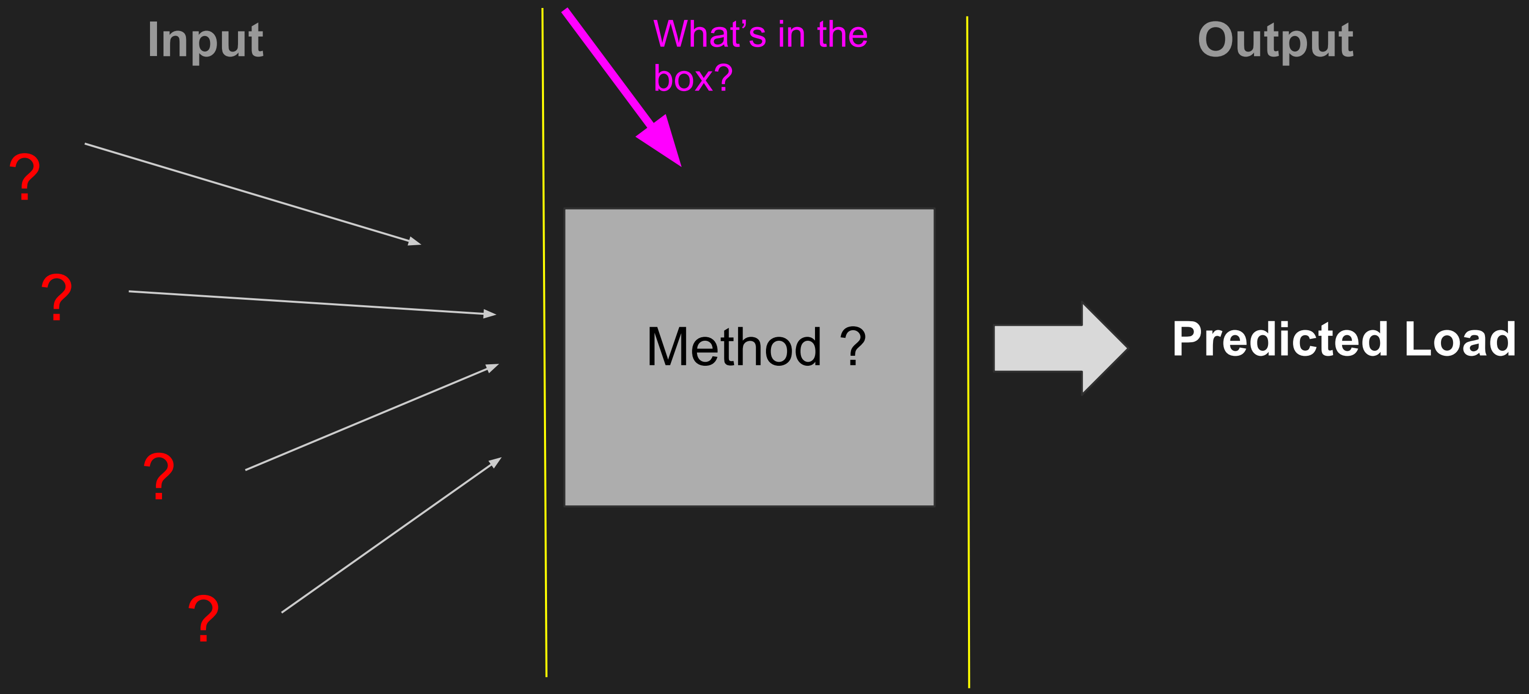
Influencing factor: Historical Data

Influencing factor: Social Factors

Influencing factor: Randomness



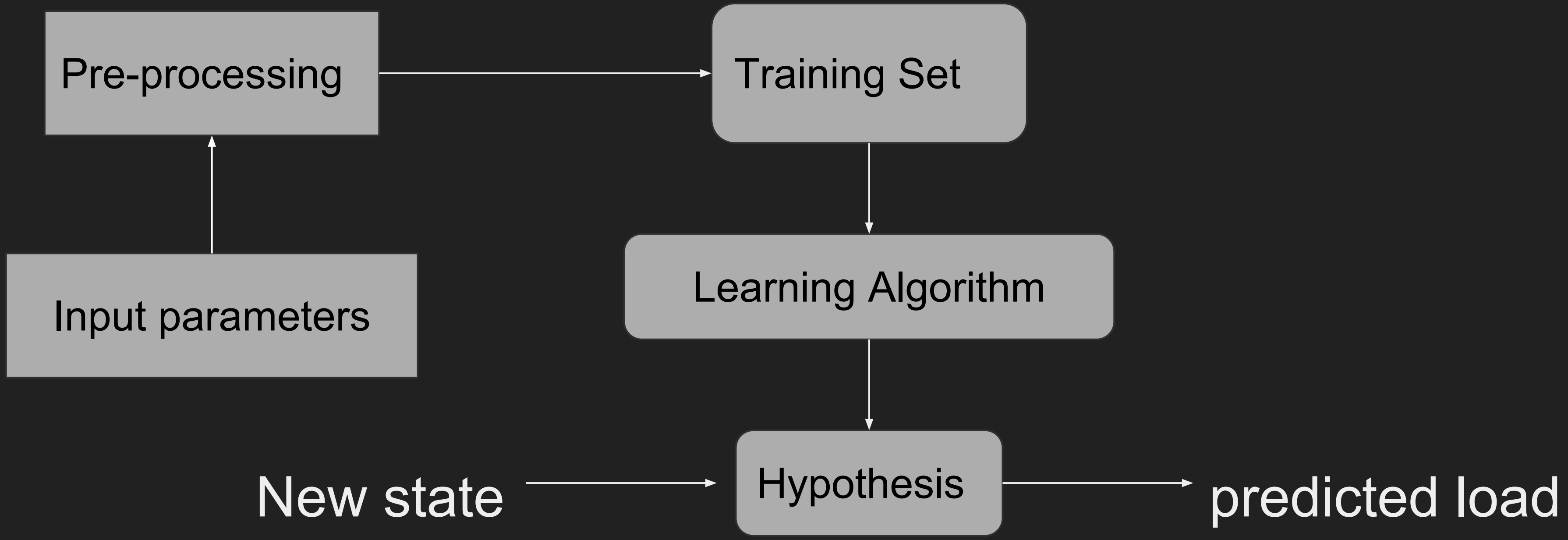
Basic model of electrical load forecasting



Load Forecasting Methods [Classical and AI]

Classical or Conventional	**Computational Intelligence**
Time series	Neural Networks
Kalman Filtering	Expert Systems
Regression	Fuzzy inference and fuzzy neural models
	Evolutionary programming and genetic algorithms

Before looking in depth..



Can we identify the best algorithm?

Classical 1 : Basic idea of time series

$$z(t) = y_p(t) + y(t)$$

Classical 1: Time series

[Kyriakides et.al] "Short term load forecasting : A tutorial"

Random behaviour

$$y(t) = \sum_{i=1}^{n} a_i y(t-i) + \sum_{k=1}^{n_u} \sum_{j_k=0}^{m_k} b_{j_k} u_k(t-j_k) + \sum_{h=1}^{H} c_h w(t-h),$$

Weather

GOAL: Identify the parameters a_i,b_{jk},ch n,n_u,m_k,and H

Time series

Advantages:

Very useful, if no new changes appear to the variables that affect the load (environmental or social variables)

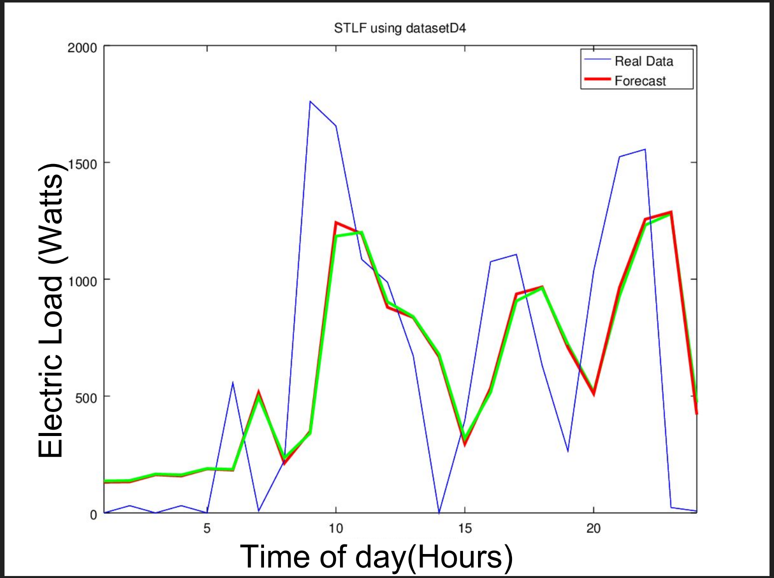
Disadvantages:

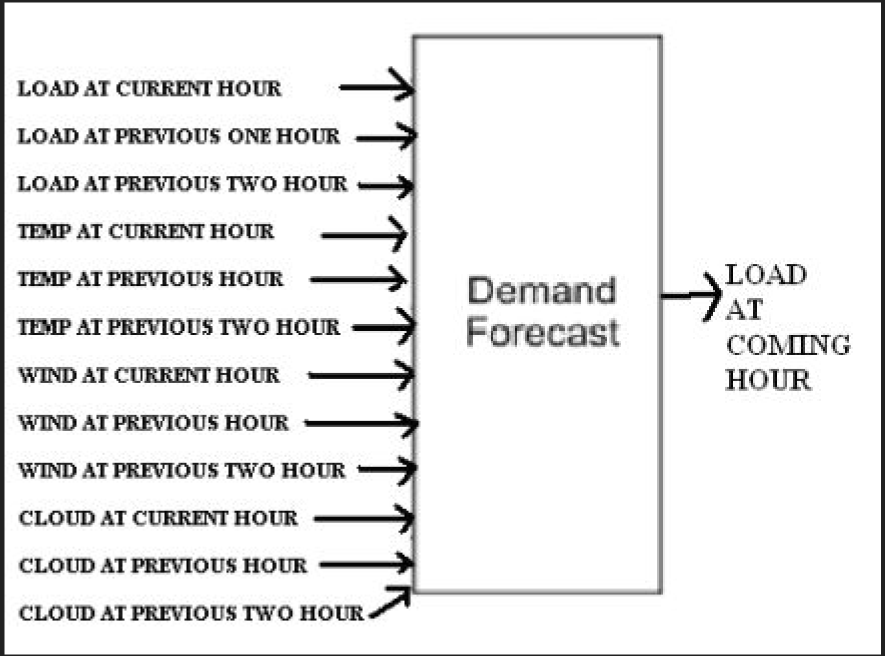
Assumes that the load has normal distribution characteristics

Requires significant computational time.

May result in a numerical instability (Over-fit & under-fit).

Classical 2- Linear Regression





[Rothe et. al] Short Term Load Forecasting Using Multi Parameter Regression

Regression

Hypothesis:

$$Y = h\theta(x) = \theta_0 + \theta_1 . x_1 + \theta_2 . x_2 + \ldots + \theta_n . x_n$$

Least square cost function (for optimization):

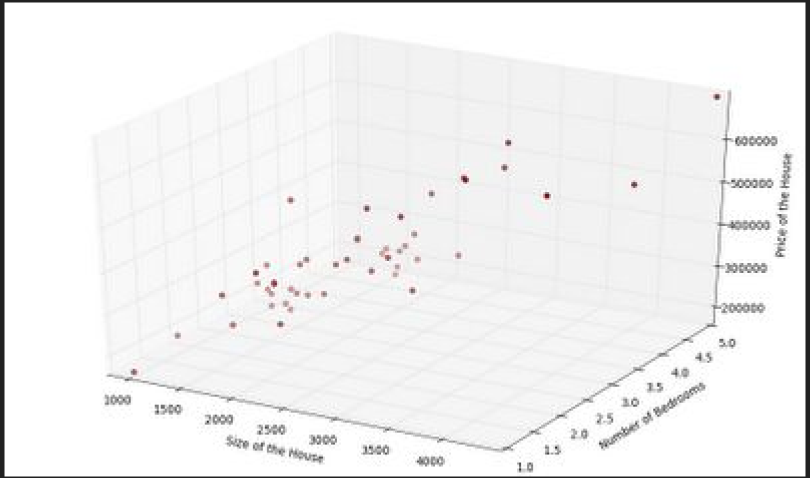
$$J(\theta) = \frac{1}{2} \sum_{i=1}^{m} (h_\theta(x^{(i)}) - y^{(i)})^2$$

When to stop?

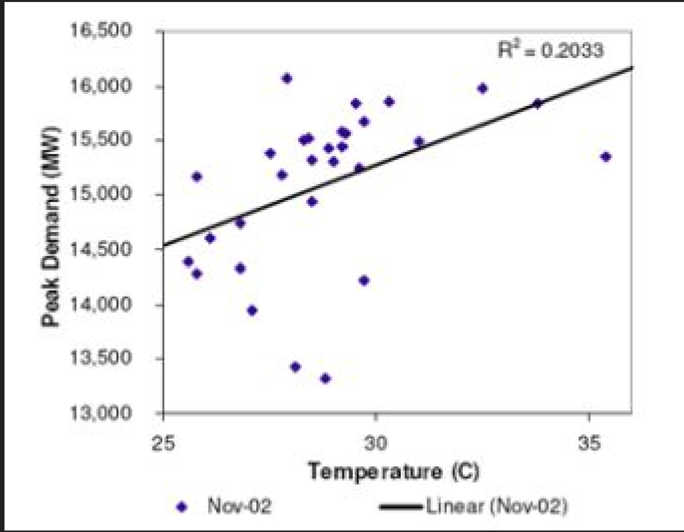
$$\text{Repeat until convergence } \{$$
$$\forall\ j \in \mathbb{N}\ ;\ \theta_j := \theta_j + \alpha \sum_{i=1}^{m} \left(y^{(i)} - h_\theta(x^{(i)})\right) x_j^{(i)}$$
$$\}$$

Feature Scaling

$$x' = \frac{x_i - \mu}{\sigma} = \frac{x_i - mean(x_i)}{max(x_i) - min(x_i)}$$



Regression (con.)



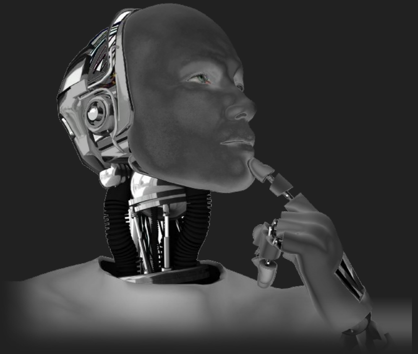
Advantages:

- Does not require much data for training.
- Can be used for online prediction.
- Very fast compared to other algorithms.

Disadvantages:

- Requires extensive study to find linear relationships between the features and the predicted values.
- Has a big error space compared to other algorithms.

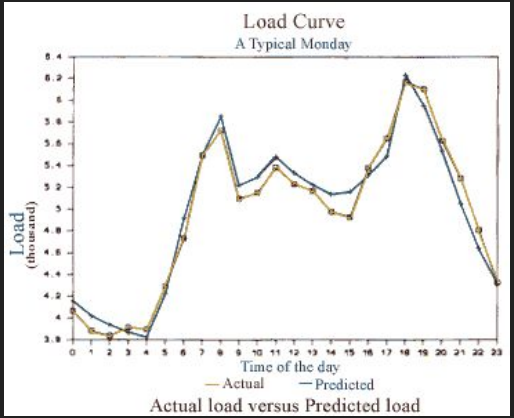
Artificial intelligence



General goal is the same.

The modeling is different and the way they deal with the data is different.

AI more complex and usually gives **nonlinear** result.



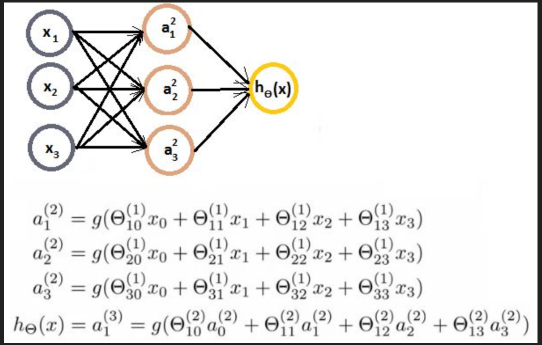
Efficiency?

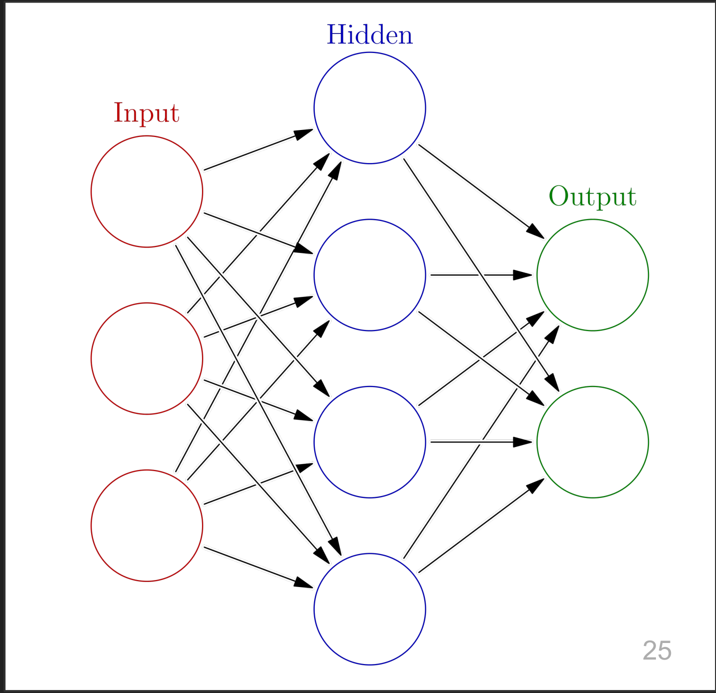
- Some proved to be promising (with optimization).
- Some still "research in progress" until we can deploy it.

Neural Networks

Constructing a model is done in three steps:

1. Preprocessing and choosing the input/output **parameters**, **layers** and **weights**.
2. Training.
3. Testing on a new data with unknown output.





Neural Networks

Advantages

- Good black-box.
- Generic-algorithm is ready to use
  - We need to pick the number of neurons, layers,weights.
- Can apply/hide inputs to guess important variables.
- Nonlinear

Disadvantages

- Long training time ⇒ can not be use online (real time).
- Not stable (no adaptiveness for sudden changes).
- Hard to use known periodical information (should be continuous).
- Need more that one net (winter/ summer) or (weekend/ weekday).

More intelligent solutions

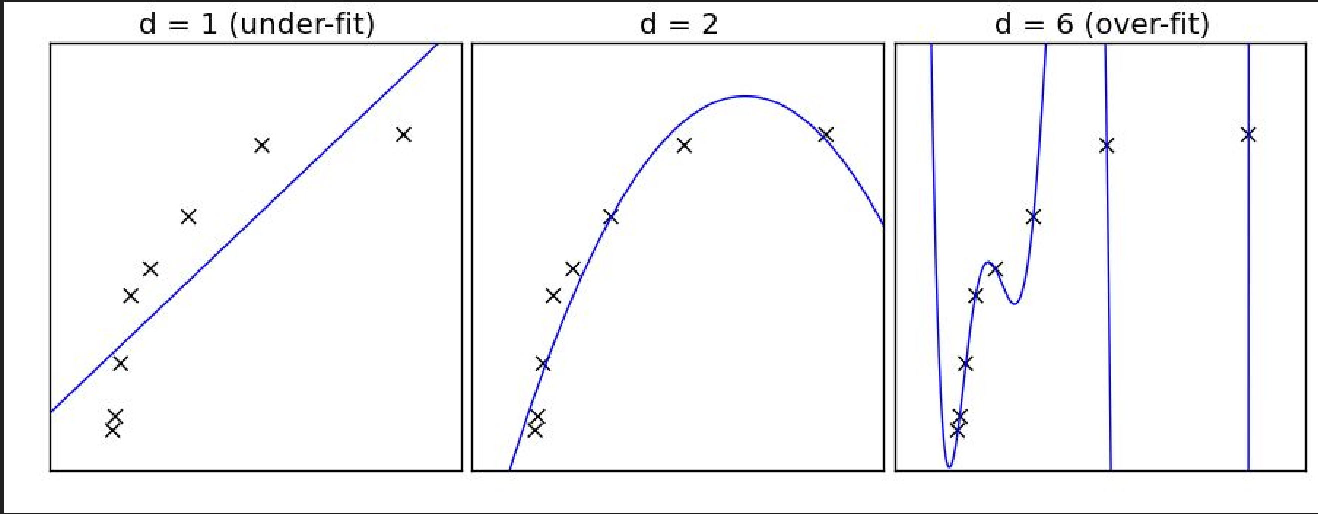
- Expert systems
- Fuzzy logic
- Support vector machines(SVM)
- Genetic algorithms

Problems in STLF [Fernandez et. al]

- Non obvious selection of variables(especially in NN).
- Requires much data to lean for the (intelligent algorithms).
- Over fitting (for a specific problem).
- Adaptiveness to other similar systems that has small differences.
- Adaptiveness to new changes and trends or sudden changes.

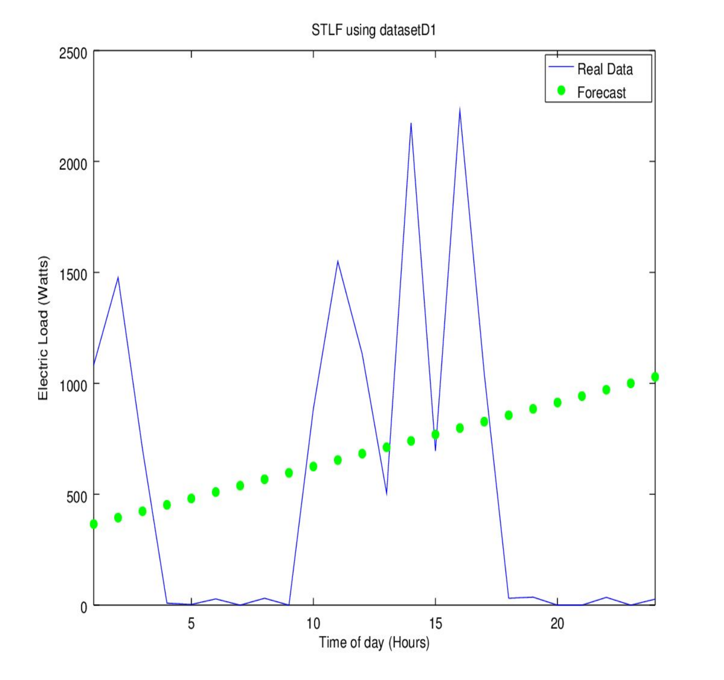
Over-fitting

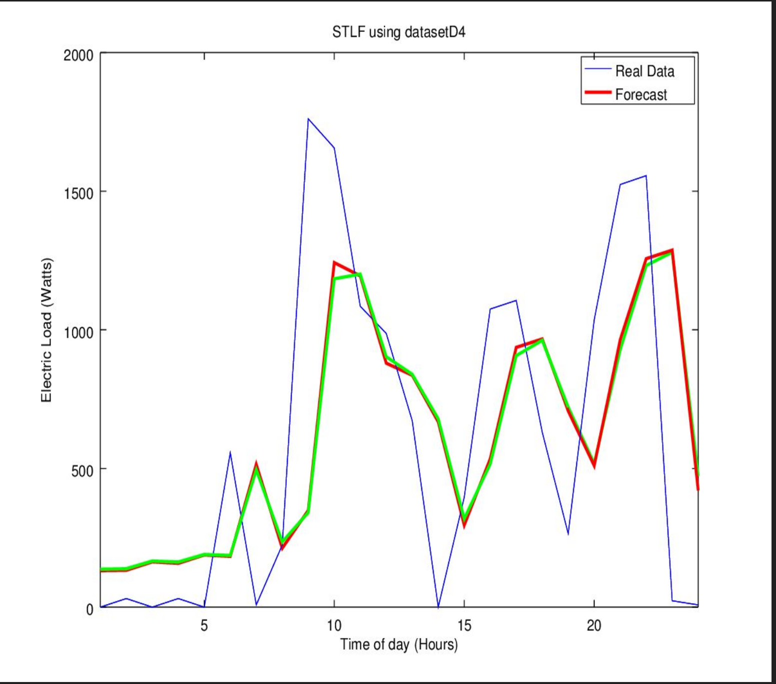
- All the algorithms have historical data that is fed as an input
- When training the model, sometimes it gets too good an learn every single value in the dataset.



Over-fitting: https://en.wikipedia.org/wiki/Overfitting

Regression Problem (Example)





From our project

Can this be improved?

- **If using one algorithm:**
  - New error reduction formulas/layer/weights.
  - Try different parameters and carefully study the relation to the output if possible.
  - **[Tuaimah et]** one algorithms several models

- **Use several algorithms**
  - **[Kyriakides et. al]** Hybrid systems.
  - **[Fernandez et.al]**
    - Use sliding window (work calendar).
    - One model several algorithms

Question still not answered………..

Which algorithm is the best?

None!

Evaluation of Performance

Mean Absolute Percentage Error (MAPE) : is a way to evaluate the performance of forecast models.

$$MAPE := \frac{1}{N_h} \sum_{i=1}^{N_h} \left(\frac{|\, actualload - forecastedload \,|}{actualload} \right) X100$$

Where N_h is the number of hours the forecast contain.

[Fernandez et.al] “Efficient Building load forecasting“

[Fernandez et al.]'s Experiment

Poly : Polynomial Model
AR : Auto Regressive
NN : Neural Networks
SVM : Support vector machine

Models	*Poly*	*AR*	*NN*	*SVM*
1-day	11.91	7.35	13.46	7.92
2-days	12.66	8.29	14.38	8.95
3-days	13.41	8.99	15.12	9.70
4-days	14.18	9.59	15.74	10.17
5-days	14.89	10.25	16.42	10.80
6-days	15.75	10.97	17.11	11.58

TABLE V
MAPE RESULTS *donosti*$_1$ FORECASTING (%).

Models	*Poly*	*AR*	*NN*	*SVM*
1-day	6.94	5.73	6.63	5.88
2-days	7.65	6.50	7.32	6.52
3-days	8.49	7.24	8.01	7.21
4-days	9.29	7.88	8.80	7.99
5-days	10.12	8.62	9.55	8.75
6-days	11.02	9.37	10.18	9.41

TABLE VII
MAPE RESULTS *ashrae* FORECASTING (%).

Models	*Poly*	*AR*	*NN*	*SVM*
1-day	19.73	13.87	17.64	14.25
2-days	20.38	14.74	18.69	15.35
3-days	20.92	15.34	19.46	16.02
4-days	21.53	15.95	20.11	16.64
5-days	22.23	16.51	20.32	17.14
6-days	23.01	17.31	20.78	17.78

TABLE VI
MAPE RESULTS *donosti*$_2$ FORECASTING (%).

Models	*Poly*	*AR*	*NN*	*SVM*
1-day	7.42	6.69	7.78	7.34
2-days	7.69	6.92	8.48	8.08
3-days	7.77	7.04	8.70	8.34
4-days	7.72	7.07	8.49	8.15
5-days	7.87	7.15	7.61	7.25
6-days	8.32	7.6	6.85	6.45

TABLE VIII
MAPE RESULTS *eunite* FORECASTING (%).

[Fernandez et.al] "Efficient Building load forecasting"

Conclusion

- There is a wide **variety of algorithms** that could be used for short-term load forecasting.
- Each algorithm has its **advantages and drawbacks**.
- **Non-linearizability** → load changes and randomness is hard to predict.

When constructing a model:

- Picking the right input parameters can be tricky.
- Picking the algorithm **depends** on the problem being solved.
- You might need more than one model or algorithm to be accurate.
- Dataset's size matters.

Recap

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