Neural networks

Architectures and training tips

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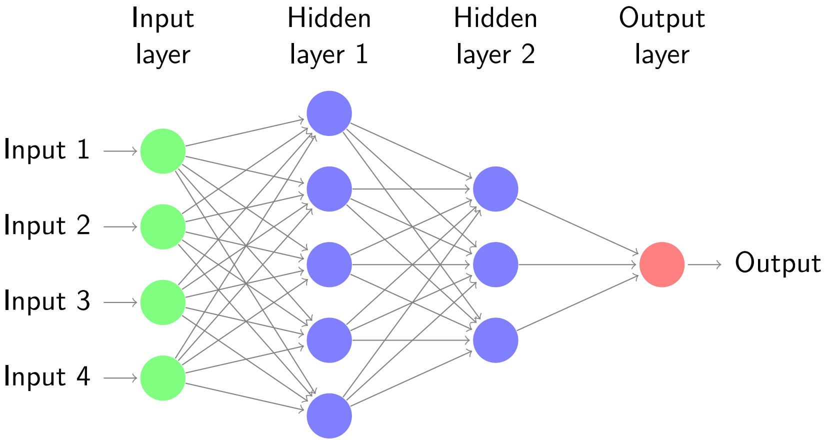
What is a neural network?



Modified from `http://www.texample.net/tikz/examples/neural-network/`

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The function σ is called the activation function. It must be non-linear to allow the network to learn non-linear dependencies.

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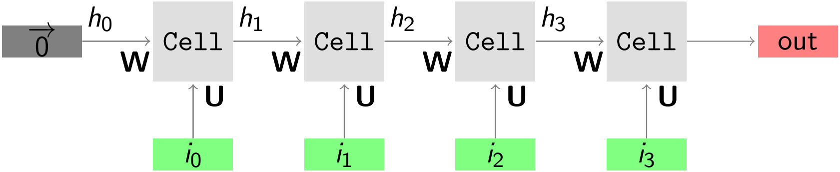
- Useful especially when the amount of data is large
- Less need for feature engineering compared to traditional ML methods

Recurrent neural network (RNN)



Processes each element of the input sequence in order, and keeps information about the past elements in a hidden state vector.

Recurrent neural network (RNN)

At each timestep t the new hidden state is calculated using the new input at this timestep and the existing hidden state. The most basic version is the following:

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Other RNN architectures (for instance LSTM or GRU) use more complicated ways of updating the hidden state to control the flow of information to and from the hidden state.

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– Training may be slow when sequence length is large

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3. A prior art search for a new patent can then be done by searching for the nearest neighbors of the vector created from the new invention

RNN real life use case: Patent search

- table
  - worktop
  - legs
    - telescope pipe
    - motor

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US patent no. 7 908 981

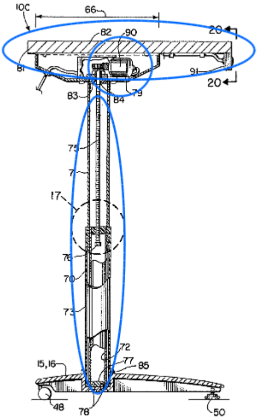

FIG. 16.

Convolutional neural network (CNN)

TODO: Picture here

Extracts features of two-dimensional input (usually an image) using convolutional and pooling layers.

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− Does not take into account position or orientation of the object

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- The model may be sensitive to changes in hyperparameters
- A model may take several hours or even days to train
  - This makes hyperparameter searches very expensive

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- Start by using small batch size
  - Usually makes model less sensitive to other hyperparameters
- Use normalization (batch, layer, group, weight...)
  - Speeds up convergence significantly
  - Start by trying batch normalization for CNN and feed-forward nets and layer normalization for RNN

The curious case of the batch size

References

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