# Essentials of Deep Learning 

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## Agenda

- Many machine learning models cannot make "insights" on data.
- Neural networks.
- How neural networks are built.
- Convolutional neural networks for images.
- Recurrent neural networks for text.



## Many ML algorithms cannot make

 insights

- Logistic model:

49\%


Many ML algorithms cannot make insights


| Rank 1 | Suit 1 | $\ldots$ | Rank 5 | Suit 5 | \# A | \#2 | $\ldots$ | \# | \# | Type |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 2 |  | $\ldots$ | 8 |  | 0 | 3 |  | 1 | 2 | FH |
| 10 |  | $\ldots$ | A |  | 1 | 0 |  | 0 | 5 | RF |

## Many ML algorithms cannot make

 insights

- Neural network:

99\%


| Rank 1 | Suit 1 | $\ldots$ | Rank 5 | Suit 5 | Type |
| :--- | :--- | :--- | :--- | :--- | :--- |
| 2 | - | $\ldots$ | 8 |  | FH |
| 10 |  | $\ldots$ | A |  | RF |

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## Neural networks are assemblies of logistic models



Sports

## Neural networks are assemblies of

 logistic models

Sp orts

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$$
R=\sigma(0 \times 26-1.5 \times 4+3)
$$

Sp orts

Neural networks are assemblies of logistic models


Sp orts

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$$
R=0.12
$$

Sp orts

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Sports

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Sp orts

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Sp orts


$$
\begin{gathered}
R=\sigma(0 \times B M I+1.5 \times \text { Sports }-3) \\
B=\sigma(-2.5 \times B M I+0 \times \text { Sports }-27)
\end{gathered}
$$

$$
y=\sigma(\mathbb{1} \times R+\mathbb{1} \times B)
$$

## Neural networks are assemblies of

 logistic models

Sp orts


$$
\begin{aligned}
R & =\sigma(? \times B M I+? \times \text { Sports }+?) \\
B & =\sigma(? \times B M I+? \times \text { Sports }+?) \\
y & =\sigma(? \times R+? \times B)
\end{aligned}
$$



# Predicting poker hands 

| 2 |  | ${ }^{2}$ | 8 |  | 8 |
| :---: | :---: | :---: | :---: | :---: | :---: |

Are there more than 2 aces in the hand?


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## Gradient descent:

## How neural networks are built



Sports

## 1) Make a guess for the lines



## 2) Compute gradients for all lines


3) Slightly move lines as indicated by the gradients


## 4) Go to step 2



## 2) Compute gradients for all lines


3) Slightly move lines as indicated by the gradients


Spurts

## Algorithm for training a neural network

1. Make a guess for the lines.
2. Compute gradients.
3. Slightly move lines.
4. Go to (2).

Algorithm for training a neural network

1. Make a guess for the lines.
2. For $\mathrm{i}=1$... NumEpochs
a) Compute gradients.
b) Slightly move lines.

Each iteration in step (2) is called an epoch.

You must indicate (ahem! guess) the number of epochs before calling this algorithm.

## Flower classification



Iris setosa


Iris tectorum


Iris latifolia

## Data representation

| Sepal <br> length | Sepal <br> width | Petal <br> length | Petal <br> width |  | Is <br> setosa? |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 5.1 | 3.5 | 1.4 | 0.2 |  | 1 |
| 2.1 | 1.2 | 3.3 | 3.2 |  | 0 |
| 3.1 | 1.6 | 2.2 | 4.1 |  | 1 |
| 2.2 | 4.1 | 1.3 | 1.4 |  | 1 |

## Data representation

- $X[i, j]$ : Value of column $j$ for flower $i$.
- $y[i]$ : 1 if flower i is an iris setosa and 0 otherwise.

Flower
examples Labels


## Script organization

1. Input parsing: Read $X$ and $y$.
2. Network architecture: Define neural network layers.

3. Compilation and training: Compile and train neural network.

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## Image recognition



## Image recognition



## Image recognition

## ©

| 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 |  | $\ldots$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |



Millions!


## Convolutional neural networks

## ®



## Convolutional neural networks



filter


## Convolutional neural networks


filter


## Convolutional neural networks



filter


## Convolutional neural networks



filter


## Convolutional neural notworks



## Convolutional neural networks



## Convolutional neural networks



MAX


## Convolutional neural networks



## Convolutional neural networks



## Convolutional neural networks



## Convolutional neural networks



## Convolutional neural networks



## Convolutional neural networks



## Convolutional

## etworks

## Convolutional neural networks




## Convolutional neural networks



## Author guessing

## Text

- O Romeo, Romeo, wherefore art thou Romeo? Deny thy father and refuse thy name; Or if thou wilt not, be but sworn my love.
- It is better to be feared, than to be loved, if you cannot have both.
- When I was young I
thought that money was the most important thing in life; now that I am old I know that it is.


## Author

- Shakespeare
- Machiavelli
- Oscar Wilde


## Why not...

- Standard neural networks? Text has variable size and with very long texts, we would need very complex neural networks.
- Convolutional neural networks? A filter may miss important information! See Oscar Wilde's quote.


## Recurrent neural networks

| Review | Positive review? |
| :---: | :---: |
| "Nice film" | 1 |
| "OK film" | 1 |
| "Bad movie" | 0 |
| "Terrible!" | 0 |

## Bag-of-words vectorization

| Review | Positive review? |
| :---: | :---: |
| "Nice film" | 1 |
| "OK film" | 1 |
| "Bad movie" | 0 |
| "Terrible!" | 0 |


| bad | film | movie | nice | ok | terrible | Positive? |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | 1 | 0 | 1 | 0 | 0 | 1 |
| 0 | 1 | 0 | 0 | 1 | 0 | 1 |
| 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 1 | 0 |

## Analogously, words are vectors

|  | bad | film | movie | nice | ok | terrible |
| ---: | :---: | :---: | :---: | :---: | :---: | :---: |
| bad | 1 | 0 | 0 | 0 | 0 | 0 |
| film | 0 | 1 | 0 | 0 | 0 | 0 |
| movie | 0 | 0 | 1 | 0 | 0 | 0 |
| nice | 0 | 0 | 0 | 1 | 0 | 0 |

## Recurrent neural networks



* Recall that words can be represented as vectors



## Recurrent neural networks



* Recall that words can be represented as vectors


## Author guessing

## Text

- O Romeo, Romeo, wherefore art thou Romeo? Deny thy father and refuse thy name; Or if thou wilt not, be but sworn my love.
- Mr. and Mrs. Dursley, of number four Privet Drive, were proud to say that they were perfectly normal, thank you very much.
- It is better to be feared, than to be loved, if you cannot have both.
- When I was young I thought that money was the most important thing in life; now that I am old I know that it is.


## Author

- Shakespeare
- J.K. Rowling (Harry Potter)
- Machiavelli
- Oscar Wilde


## What we learned

- Many machine learning models cannot make "insights" on data.
- What are neural networks?
-What are convolutional neural networks?
- What are recurrent neural networks?

