SCHOOL OF DATA ANALYSIS

LAMBDA

Yandex
Data Factory

Why Deep Learning rocks

A philosophical note

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No free lunch

Terminology

Machine Learning is about learning algorithms A that:

- defined on sample set $\mathcal{X}$ (e.g. $\mathbb{R}^n$) and targets $\mathcal{Y}$ (e.g. $\{0, 1\}$);
- take a problem (dataset) $D = (X, y) \subseteq \mathcal{X} \times \mathcal{Y}$;
- learn relation between $\mathcal{X}$ and $\mathcal{Y}$;
- and return prediction function:

$$\begin{aligned} A(D) &= f \\ f : \mathcal{X} &\to \mathcal{Y} \end{aligned}$$

No free lunch theorem

No free lunch theorem states that **on average by all datasets** all learning algorithms are equally bad at learning.
Examples:

- crazy algorithm:

$$f(x) = \left\lfloor \left(\left\lceil \sum_i x_i + \theta \right\rceil \mod 17 + 1027 \right)^{\pi} \right\rfloor \mod 2$$

- SVM

perform equally well **on average**.

No free lunch

Try to learn yourself! Predict missing y.

$$X = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix} y = \begin{pmatrix} 0 \\ 2 \\ 3 \\ 1 \\ 1 \\ 4 \\ 3 \\ ? \end{pmatrix}$$

No free lunch

It is binary... obviously...

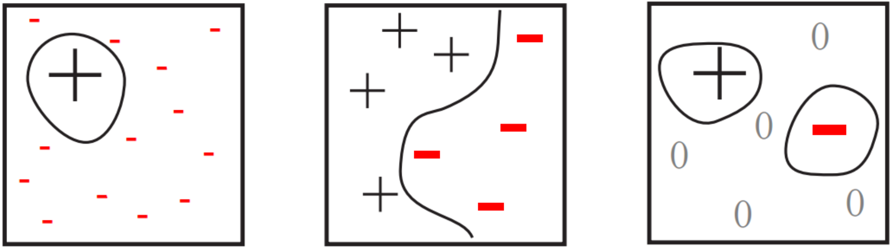
$$X = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix} y = \begin{pmatrix} 0 \\ 2 \\ 3 \\ 1 \\ 1 \\ 4 \\ 3 \\ ? \end{pmatrix} \qquad X = \begin{pmatrix} 4 \\ 6 \\ 7 \\ 3 \\ 5 \\ 0 \\ 1 \\ 2 \end{pmatrix} y = \begin{pmatrix} 0 \\ 2 \\ 3 \\ 1 \\ 1 \\ 4 \\ 3 \\ ? \end{pmatrix} \qquad X = \begin{pmatrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \end{pmatrix} y = \begin{pmatrix} 4 \\ 3 \\ ? \\ 1 \\ 0 \\ 1 \\ 2 \\ 3 \end{pmatrix}$$

No free lunch

And dependency was: $y = |x - 4|$.

$$X = \begin{pmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{pmatrix} y = \begin{pmatrix} 0 \\ 2 \\ 3 \\ 1 \\ 1 \\ 4 \\ 3 \\ 2 \end{pmatrix} \quad X = \begin{pmatrix} 4 \\ 6 \\ 7 \\ 3 \\ 5 \\ 0 \\ 1 \\ 2 \end{pmatrix} y = \begin{pmatrix} 0 \\ 2 \\ 3 \\ 1 \\ 1 \\ 4 \\ 3 \\ 2 \end{pmatrix} \quad X = \begin{pmatrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \end{pmatrix} y = \begin{pmatrix} 4 \\ 3 \\ 2 \\ 1 \\ 0 \\ 1 \\ 2 \\ 3 \end{pmatrix}$$

No free lunch theorem



Possible learning algorithm behaviours in **problem space:**

- + - better than the average;
- — - worse than the average.

Are Machine Learning algorithms useless?

Are Machine Learning algorithms useless?

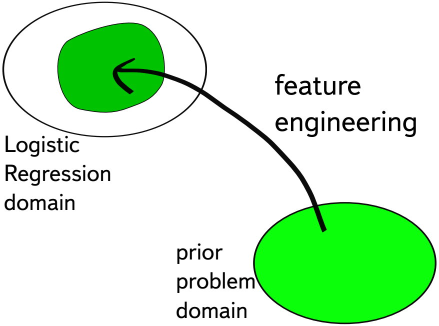
No.

Are Machine Learning algorithms useless?

- Machine Learning algorithms have data scientists;
- data scientists are an additional source of prior information;
- prior information helps to bypass No Free Lunch Theorem.

Traditional Machine Learning

- analyse the problem and make assumptions;
- pick an algorithm from a toolkit (e.g. logistic regression);
- provide assumptions suitable for the algorithm **(feature engineering)**.



Discussion

- this approach works well for traditional datasets with a small number of features:
- e.g. Titanic dataset:

passenger class	name	sex	age	fare	...

> **Essentially, performance of the algorithm depends data scientist's ability to generate features.**

- but our abilities are limited.

Kitten

Kitten seen by a machine

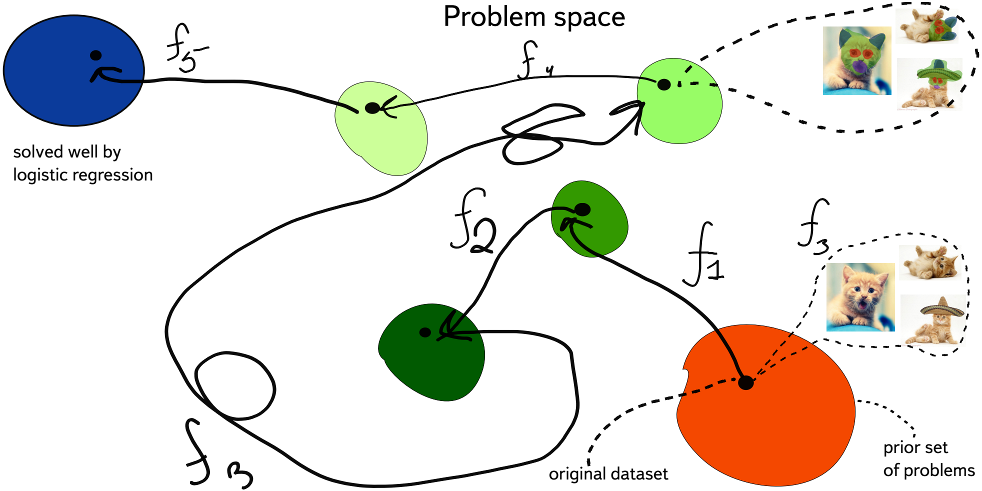
```
[[ 22  25  28  32  29 ...,  58  36  35  34  34]
 [ 26  29  30  31  36 ...,  65  38  42  41  42]
 [ 27  28  31  30  40 ...,  84  58  51  52  44]
 [ 27  26  27  29  43 ...,  90  70  60  57  43]
 [ 20  26  28  28  31 ...,  83  73  62  52  45]
 ...,
 [173 187 180 183 184 ..., 170 227 244 219 199]
 [193 199 194 188 185 ..., 181 197 201 209 187]
 [175 177 156 166 171 ..., 226 215 194 185 182]
 [161 159 160 187 178 ..., 216 193 220 211 200]
 [178 180 177 185 164 ..., 190 184 212 216 189]]
```

Solution?

- edge detection;
- image segmentation;
- eyes, ears, nose models;
- fit nose, ears, eyes;
- average color of segments;
- standard deviation of color segments;
- goodness of fit for segments;
- kitten's face model;
- feed it to Logistic Regression

* not an practical solution

Solution?


Problem space
f_5
f_4
solved well by
logistic regression
f_2
f_1
f_3
f_3
original dataset
prior set
of problems

Solution?

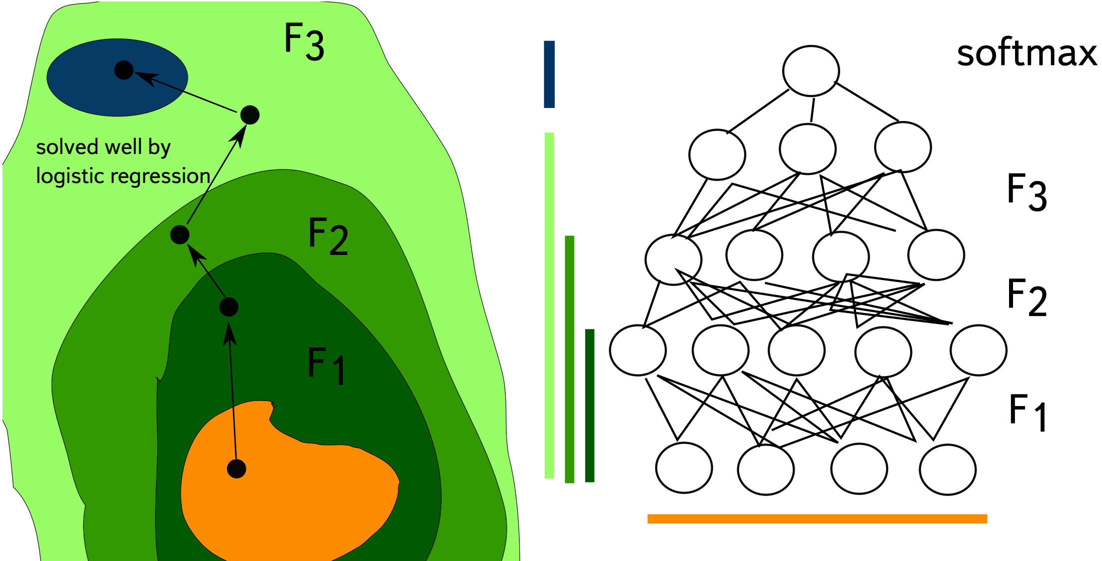
Perhaps, more Machine Learning and less Human Engineering?

Deep Learning

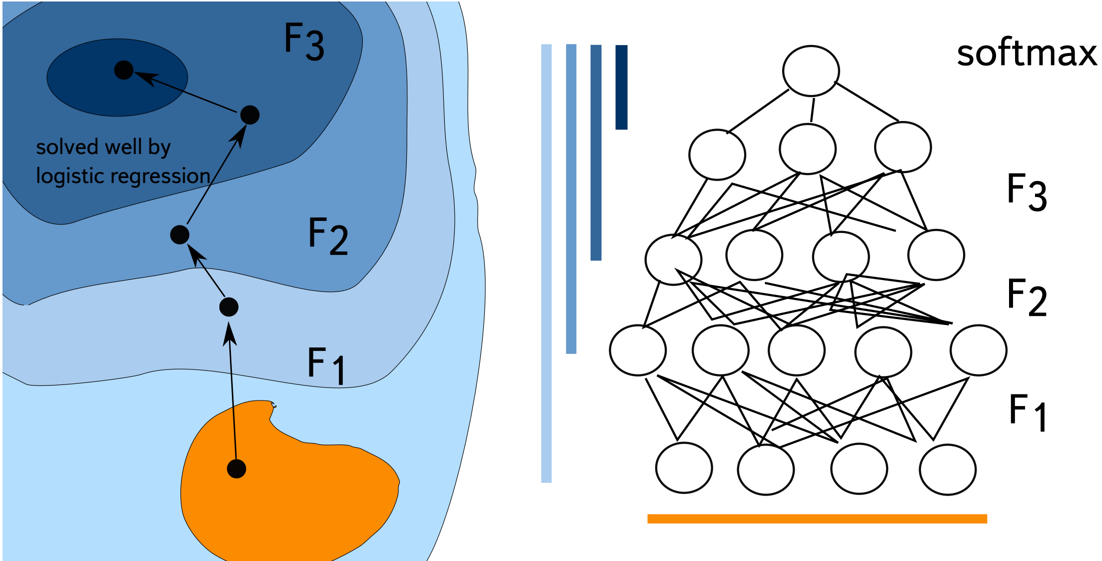
Deep Learning

Let's learn features!

Deep Learning



Deep Learning



Kitten

Traditional approach:

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Deep Learning:

- convolutions;
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- convolutions;
- convolutions;
- logistic regression.

Why deep?

- new set of features is generated from previous one by a simple <u>learnable</u> transformation;
- each step increases complexity of feature generation;
- high-level features (kitten or puppy) are complex ones thus requires a lot of steps;
- therefore, deep.

Deep Learning

- is not a superior algorithm;
- is not even a single algorithm;
- is a framework;
- very flexible framework;
- allows to express our assumptions in much more general way.

Why DL rocks

- can crack much harder problems;
  - it is easier to formulate models for features than features itself;
- easy to construct networks:
  - merge together;
  - bring new objectives;
  - inject something inside network;
  - build networks inside networks;
  - any differentiable magic is allowed.

Example

A problem contains groups of features:

- velocity features, m/s;
- distance features, m;
- time features, s;
- acceleration features, m/s^2.

Prior knowledge: different groups of features can not be summed.

Downsides

- learning features requires data;
  - big datasets;
  - big computational resources (GPUs);
- there is almost always a better algorithm:
  - with hand-made features;
  - probably constructed by a super-intelligent alien.

Summary

Summary

Deep Learning:

- a flexible framework;
- allows to express you knowledge easier;
- solves much harder problems.