SCHOOL OF DATA ANALYSIS

LAMBDA

Why Deep Learning rocks

A deep philosophical note

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No free lunch

IQ test: try to learn yourself!

First question from MENSA website:
Following the pattern shown in the number sequence below, what is the missing number?

$$1, 8, 27, ?, 125, 216$$

Possible answers:

- 36
- 45
- 46
- 64
- 99

IQ test: try to learn yourself!

First question from MENSA website:

Following the pattern shown in the number sequence below, what is the missing number?

X_{train}	1	2	3	5	6
y_{train}	1	8	27	125	216

$$X_{\text{test}} = (4,)$$

IQ test: try to learn yourself!

My solution:

$$y = \frac{1}{12}(91x^5 - 1519x^4 + 9449x^3 - 26705x^2 + 33588x - 14940)$$

- fits perfectly!

My answer:

- 99

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:

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

By this definition, e.g. XGBoost is a **family** of algorithms.

No free lunch theorem

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

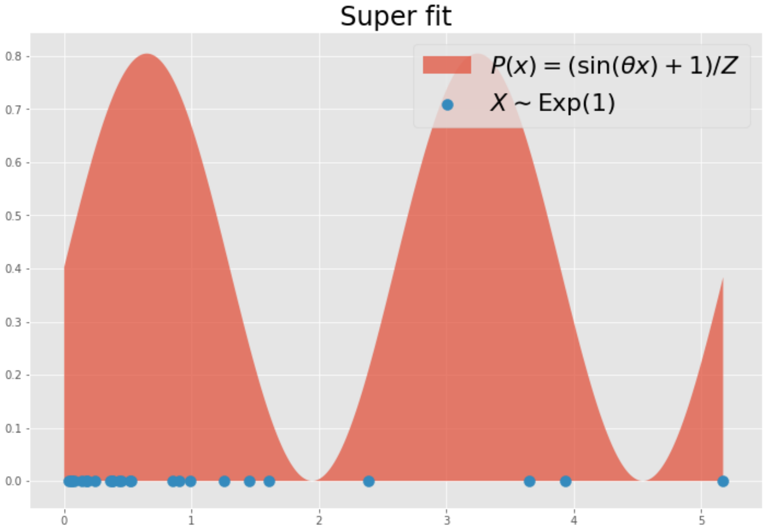
- crazy algorithm:

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

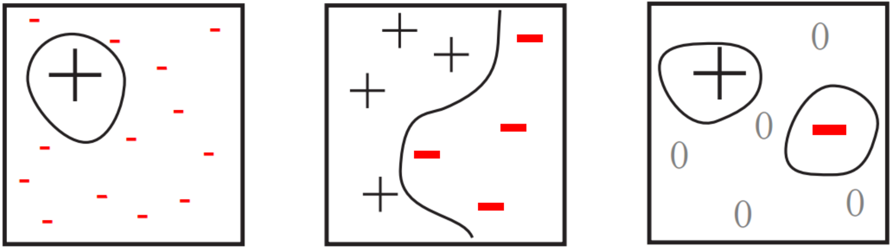
- any configuration of SVM

perform equally well **on average**.

No free lunch theorem, stat. edition



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?

- No Free Lunch theorem applies to:
  - one learning algorithm;
  - against all possible problems.
- in real world we have:
  - **data scientist** with prior knowledge of the world;
  - problem description;
  - data description;
  - a set of standard algorithms.

Corollary

A good machine learning family of algorithms/framework:

- has clear relation between hyperparameters and set of problems each algorithm covers;
- i.e. a data scientist can easily map their prior knowledge on hyperparameters.

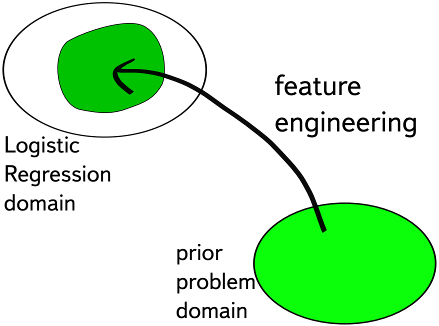
A great machine learning family/frameworks:

- covers a wide range of problems;
- but each algorithm covers a small set of problems;
- i.e. a lot of sensitive and well-defined hyperparameters.

Here feature engineering/selection/generation is a part of the algorithm.

Traditional Machine Learning (simplified)

- 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	gender	age	fare	...

Essentially, performance of the algorithm depends on:

- knowledge of the domain;
- feature engineering skills;
- understanding of assumptions behind standard algorithms.

Kitten

Let's try to detect kittens!

Kitten seen by a machine

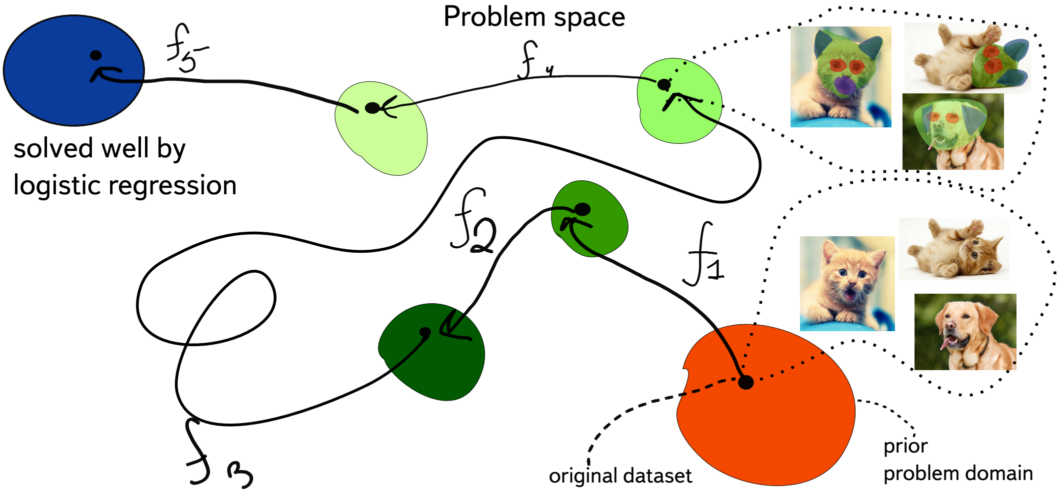
```
[[ 22  25  28  32  29 ...,  58  36  35  34  34]
 [ 26  29  30  31  36 ...,  65  38  42  41  42]
 [ 27  28  31  30  40 ...,  84  58  51  52  44]
 [ 27  26  27  29  43 ...,  90  70  60  57  43]
 [ 20  26  28  28  31 ...,  83  73  62  52  45]
 ...,
 [173 187 180 183 184 ..., 170 227 244 219 199]
 [193 199 194 188 185 ..., 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;
- logistic regression.

* not an practical solution

Solution?


Problem space
solved well by
logistic regression
f_5
f_4
f_2
f_1
f_3
original dataset
prior
problem domain

Solution?

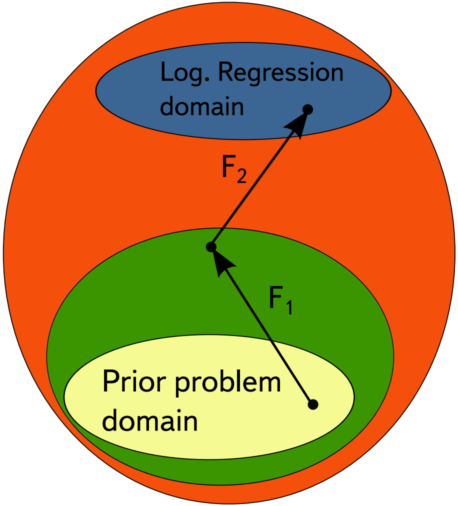
Perhaps, more Machine Learning and less Human Engineering?

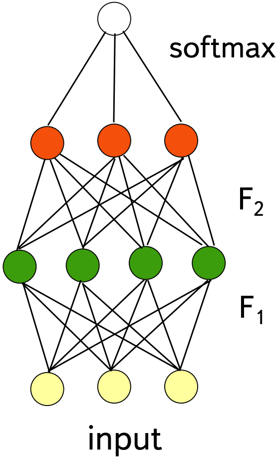
Deep Learning

Deep Learning

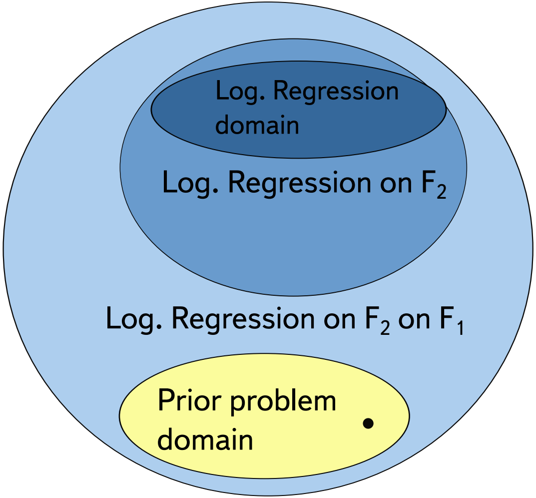
Let's learn features!

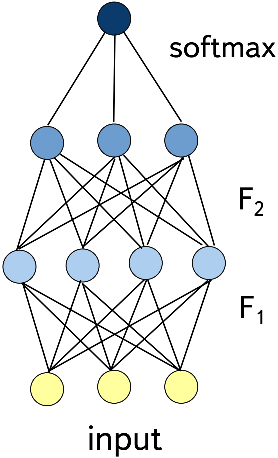
Deep Learning





Deep Learning





Kitten

Traditional approach:

- edge detection;
- image segmentation;
- fit nose, ears, eyes;
- average, standard deviation of segment color;
- fluffiness model;
- kitten's face model;
- logistic regression.

Deep Learning:

- non-linear transformation;
- another non-linear transformation;
- non-linear transformation, again;
- non-linear transformation, and again;
- non-linear transformation (why not?);
- logistic regression.

Deep Learning

- is not a superior algorithm;
- is not even a single algorithm;
- is a <u>framework</u>;
- <u>allows to express our assumptions in much more general way</u>.

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*.

* Non-differentiable also, but with a special care.

Example

A problem contains groups of features:

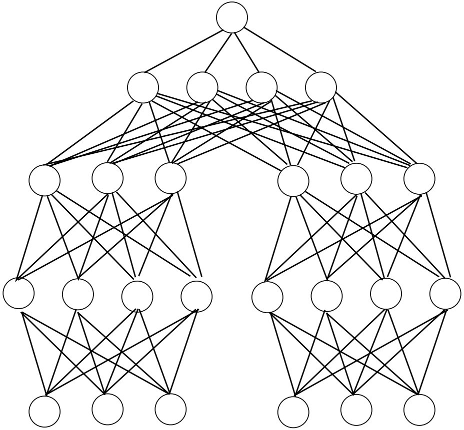
- image;
- sound features;

Prior knowledge:

- features from different group should not interact directly;

Example of a solution:

- build a subnetwork upon each group of features;
- merge them together.



Almost Free Lunch

Disclaimer

This is not a comprehensive overview of Deep Learning, just some examples.

Hacking layers

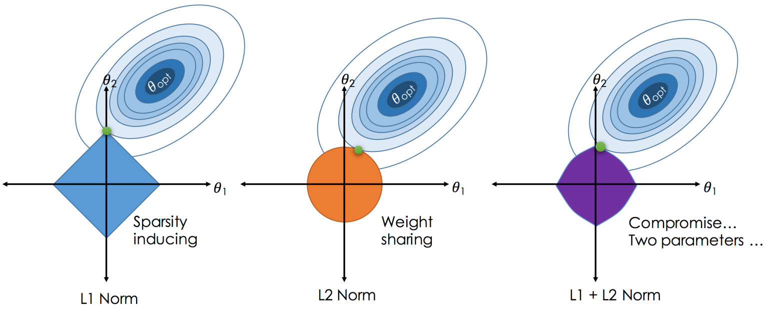
- restrictions on weights: convolutions, weight matrix decomposition, ...;
- activation: ReLU, ELU, SELU, ...;
- new operations: pooling, maxout, ...;
- specific unit behaviour: GRU, LSTM units, ...

Hacking model

Restrictions on search space:

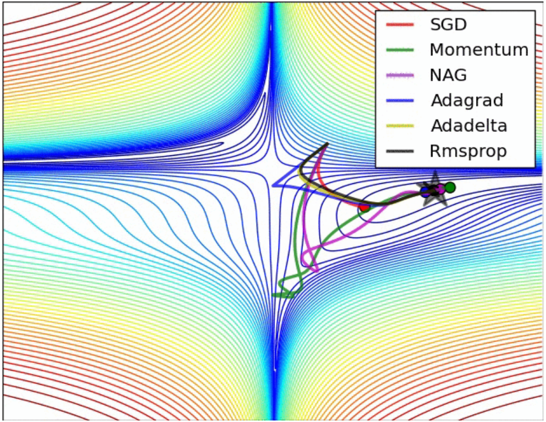
- regularization, e.g.:

$$\mathcal{L} = \mathcal{L}_{\text{cross-entropy}} + \alpha \|W\|_2^2$$



Hacking search procedure

- SGD-like methods:
  - adam, adadelta, adamax, rmsprop;
  - nesterov momentum;
- quasi-Newton methods;
- batch normalization, weight normalization;
- weight matrix decomposition.



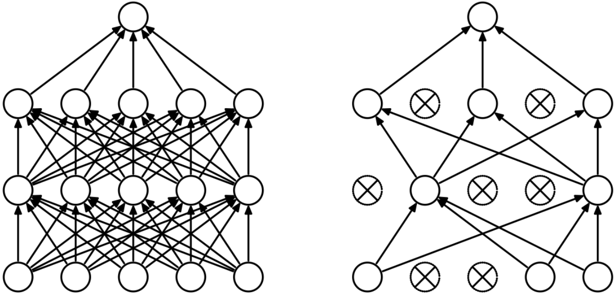
Data augmentation

- symmetries: shifts, rotations, ...:
  - searching for a network that produces the same response for shifted/rotated samples;
  - eliminating symmetries;
- random noise:
  - pushing separation surface farther from samples - robust output;

Hacking model

Interference with network (change of objective):

- drop-out, drop-connect:
  - searching for a robust network.



(a) Standard Neural Net (b) After applying dropout.

Hacking loss

Hacking objectives:

- introducing loss for each layer:

$$\mathcal{L} = \mathcal{L}_n + \sum_{i=1}^{n-1} C_i \mathcal{L}_i$$

  where:

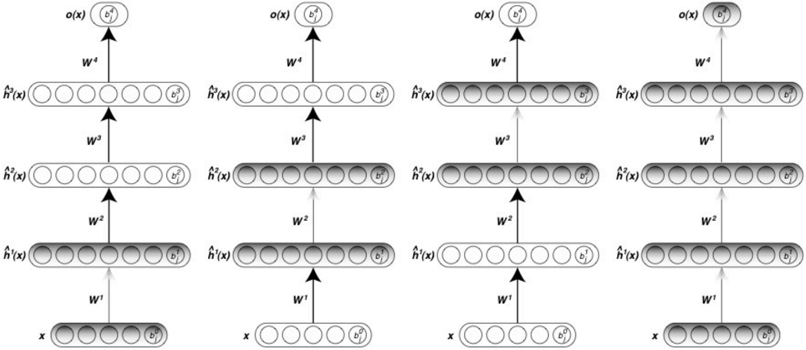
  - $\mathcal{L}_i$ - loss on i-th layer.

- Deeply Supervised Networks:
  - searches for network that obtains good intermediate results.

Hacking initial guess

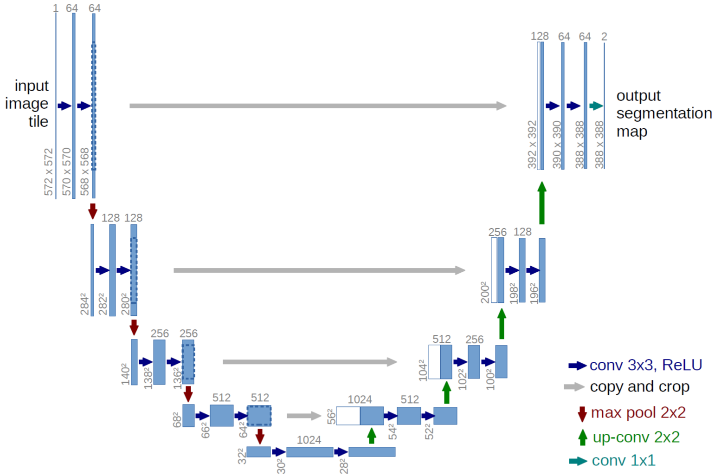
Pretraining:

- unsupervised pretraining;
- greedy layer-wise pretraining with e.g. AutoEncoders.



Hacking architecture: U-net

› skip connections allow to combine context with low-level representation.



Hacking architecture: ResNet

- residual connections produce boosting-like behaviour;
- no vanishing gradients;
- brute-force: up to 1000+ layers.

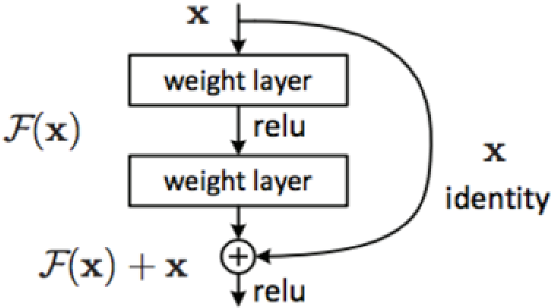
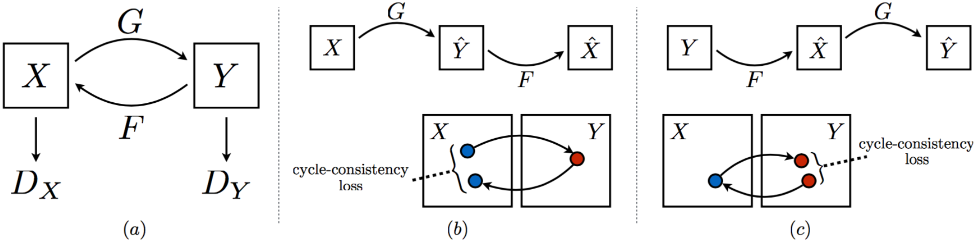


Figure 2. Residual learning: a building block.

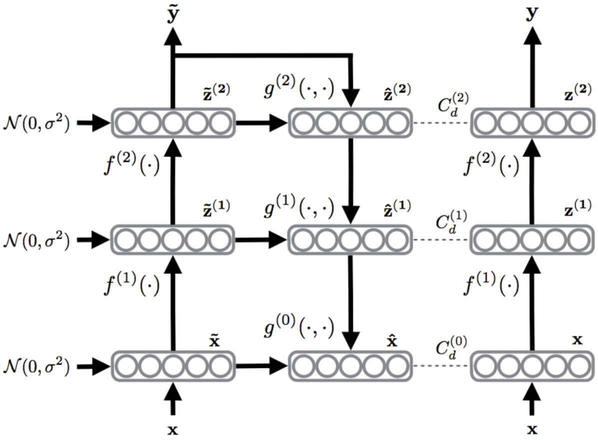
Hacking architecture: Cycle-GAN

- reverse transformation;
- symmetric discrimination.



Hacking architecture: Ladder Network

- introduces auxiliary task: denoising;



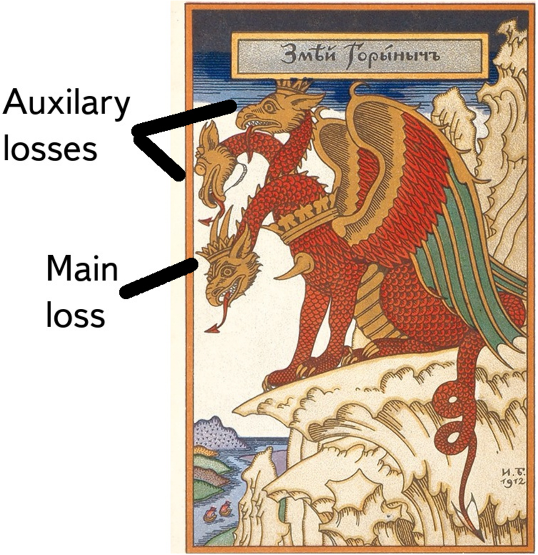
Breaking No Free Lunch

Auxilary task

- introducing additional task for a network might considerably improve generalization:

$$\mathcal{L} = \mathcal{L}_{\text{main}} + \alpha \mathcal{L}_{\text{auxilary}}$$

- e.g. along with particle identification restore momentum;
- brings additional information.



Pretraining

- pretraining on a similar dataset;
  - as initial guess;
  - regularization relative to another model $\{W_i^0\}_{i=1}^n$:

$$\mathcal{L} = \mathcal{L}_{\text{main}} + \lambda \sum_{i=1}^{n} \|W_i - W_i^0\|_2^2$$

- using weights from the zoo;
- unsupervised pretraining (semi-supervised learning).

Summary

Summary

No Free Lunch theorem:

- Machine Learning is about using prior knowledge about the problem wisely.

Deep Learning:

- a framework that covers a large range of problems;
- allows to express prior knowledge freely;
- makes it easier to solve hard problems.

References

No-Free-Lunch theorem:

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- Rasmus, Antti, et al. "Semi-supervised learning with ladder networks." Advances in Neural Information Processing Systems. 2015.

More resources

A lot of useful links can be found in:

- Schmidhuber, Jürgen. "Deep learning in neural networks: An overview." Neural networks 61 (2015): 85-117.
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