

# Why Deep Learning rocks

A philosophical note

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No free lunch

# No free lunch theorem

No free lunch theorem states that **in average** all learning algorithms are equally bad at learning.

Examples:

- › crazy algorithm:

$$f(x) = \left\lfloor \left( \left[ \sum_i x_i \right] \mod 17 + 1027 \right)^\pi \right\rfloor \mod 2$$

- › SVM

perform equally well **in average**.

# No free lunch

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

# No free lunch

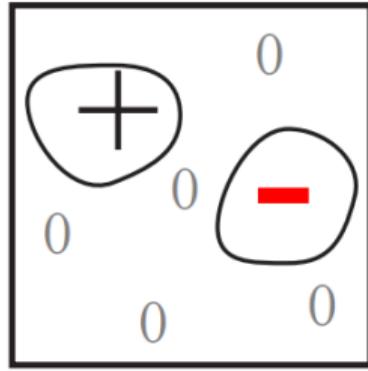
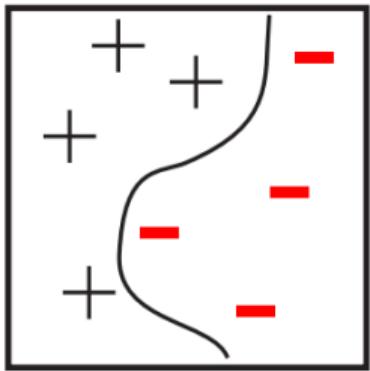
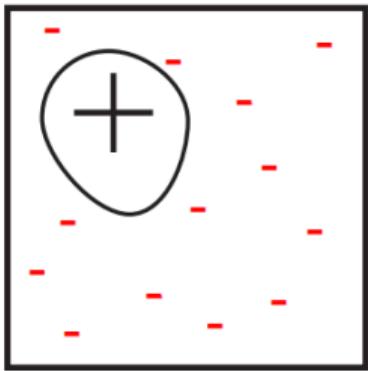
$$X = \begin{pmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} 2 \\ 3 \\ 3 \\ 4 \\ 0 \\ 1 \\ 1 \\ ? \end{pmatrix} = y \quad X = \begin{pmatrix} 2 \\ 7 \\ 1 \\ 0 \\ 4 \\ 3 \\ 5 \\ 6 \end{pmatrix} \begin{pmatrix}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

# No free lunch

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

$$y = \left| \sum_{i=0}^2 2^i x_i - 4 \right| = |x - 4|$$

# No free lunch theorem



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

- › **+** - better than the average;
- › **-** - worse than the average.

# Are Machine Learning algorithms useless?

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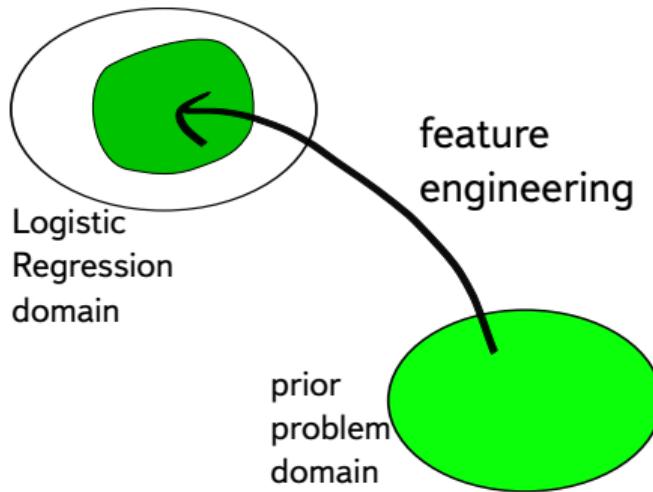
No.

# Are Machine Learning algorithms useless?

- › Machine Learning algorithms have data scientists;
- › data scientists are 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	...
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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]

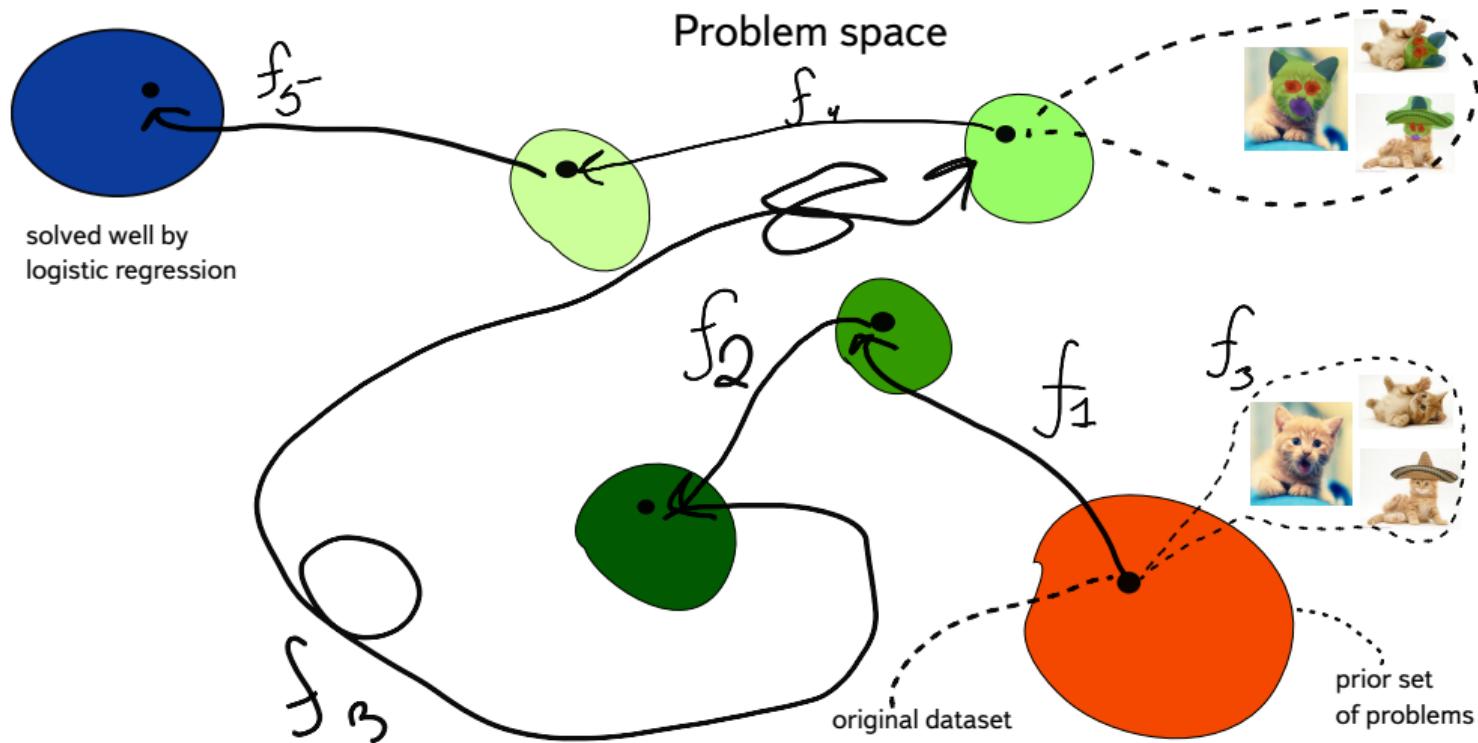
...,

[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

# Solution?



# Solution?

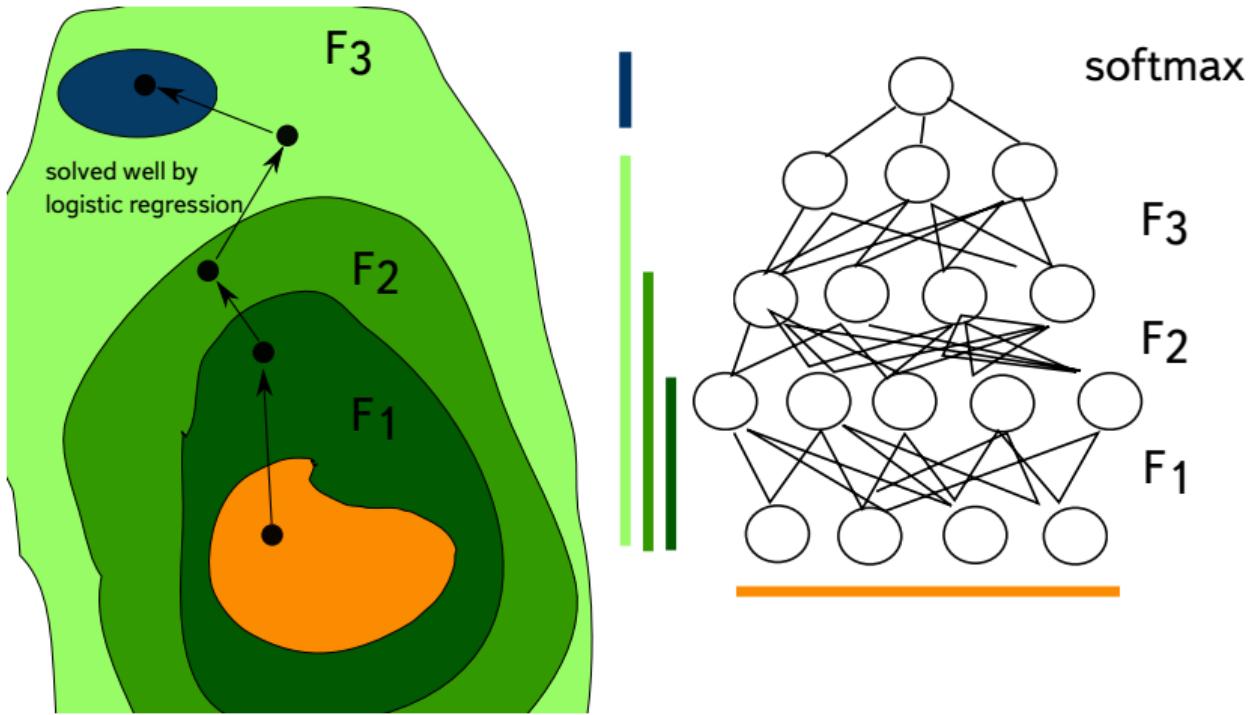
Perhaps, more Machine Learning and less Human Engineering?

# Deep Learning

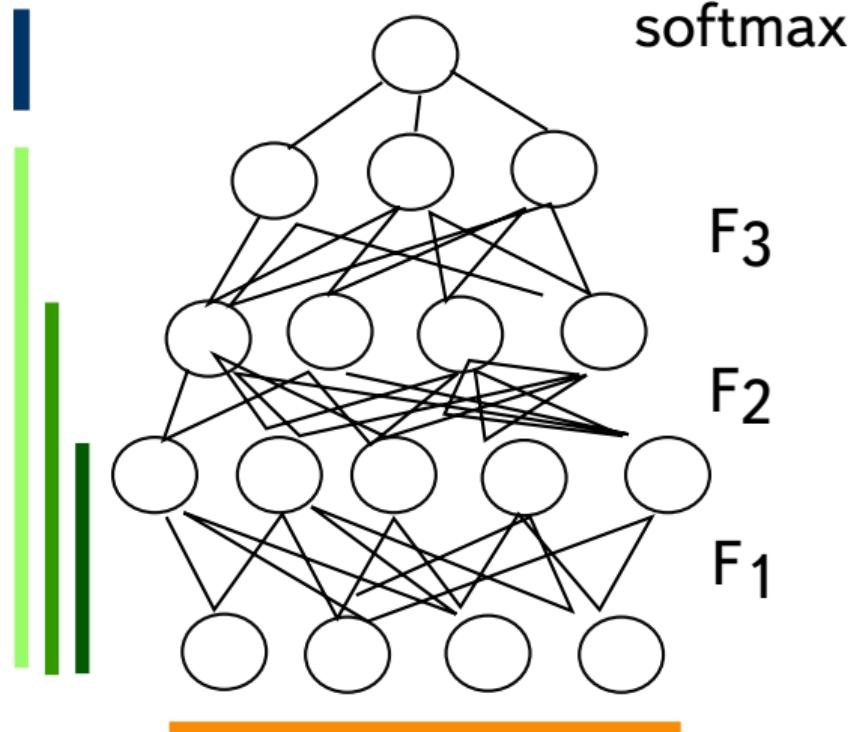
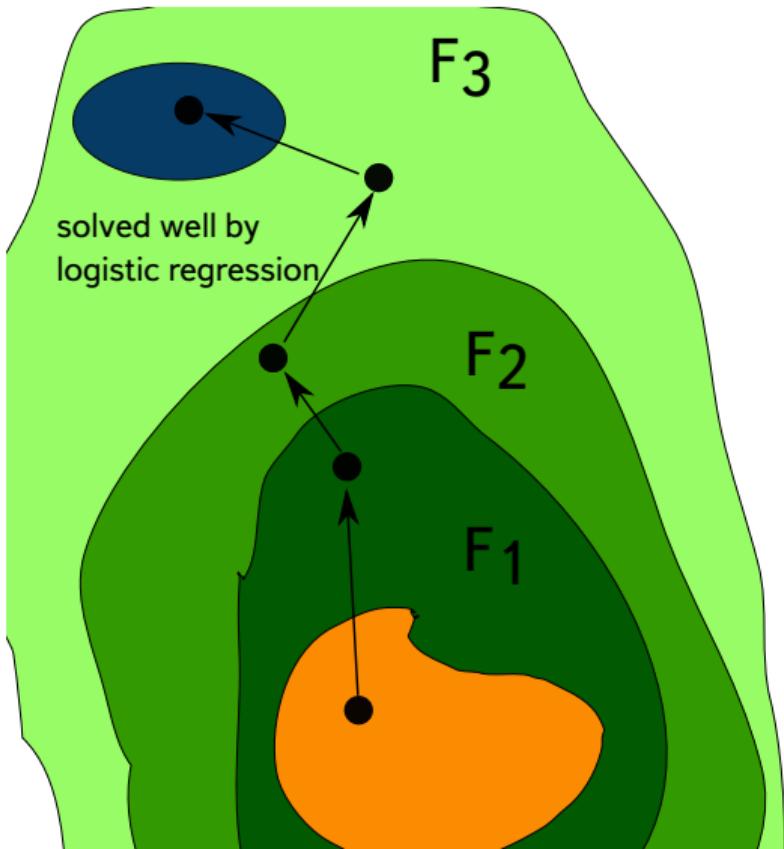
# Deep Learning

Let's learn features!

# Original picture



# Deep Learning

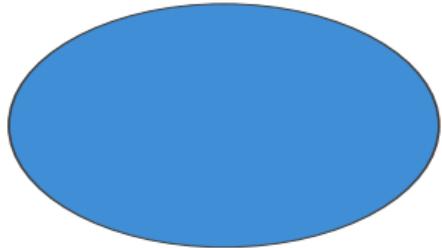


# How

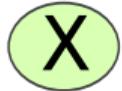
- › apply some abstract simple transformation to the original input:

$$X \rightarrow f(X) \cdots y$$

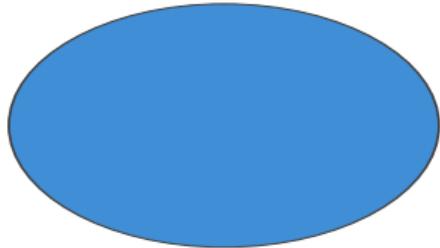
# Original picture



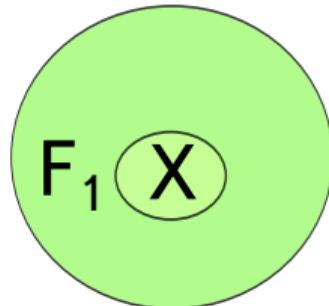
Logistic  
Regression  
domain



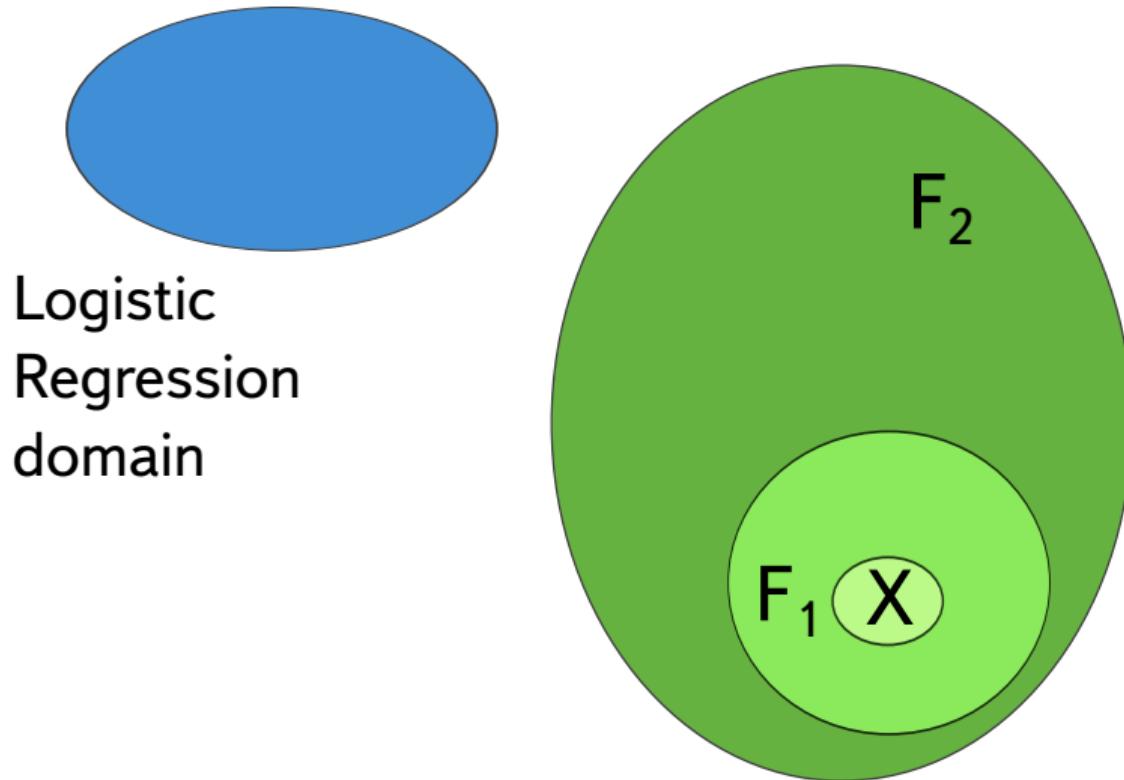
# Some transformation applied



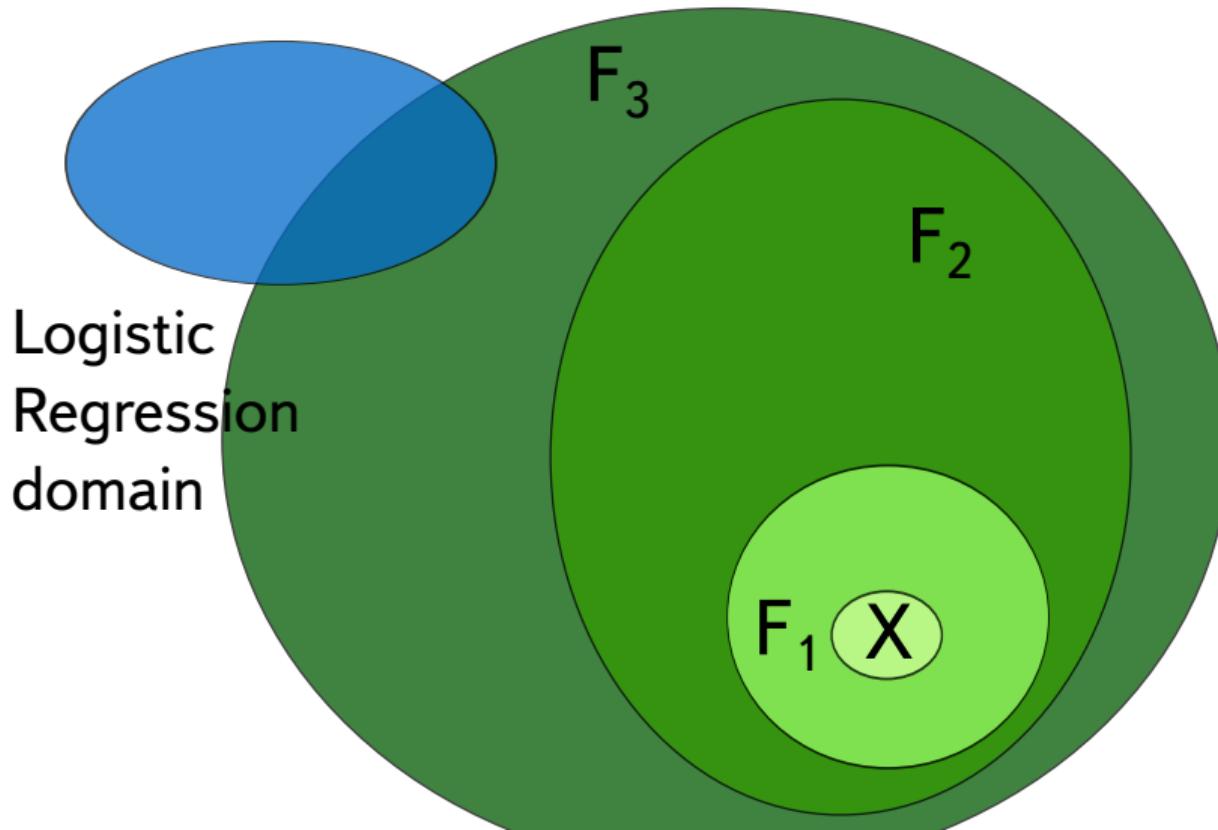
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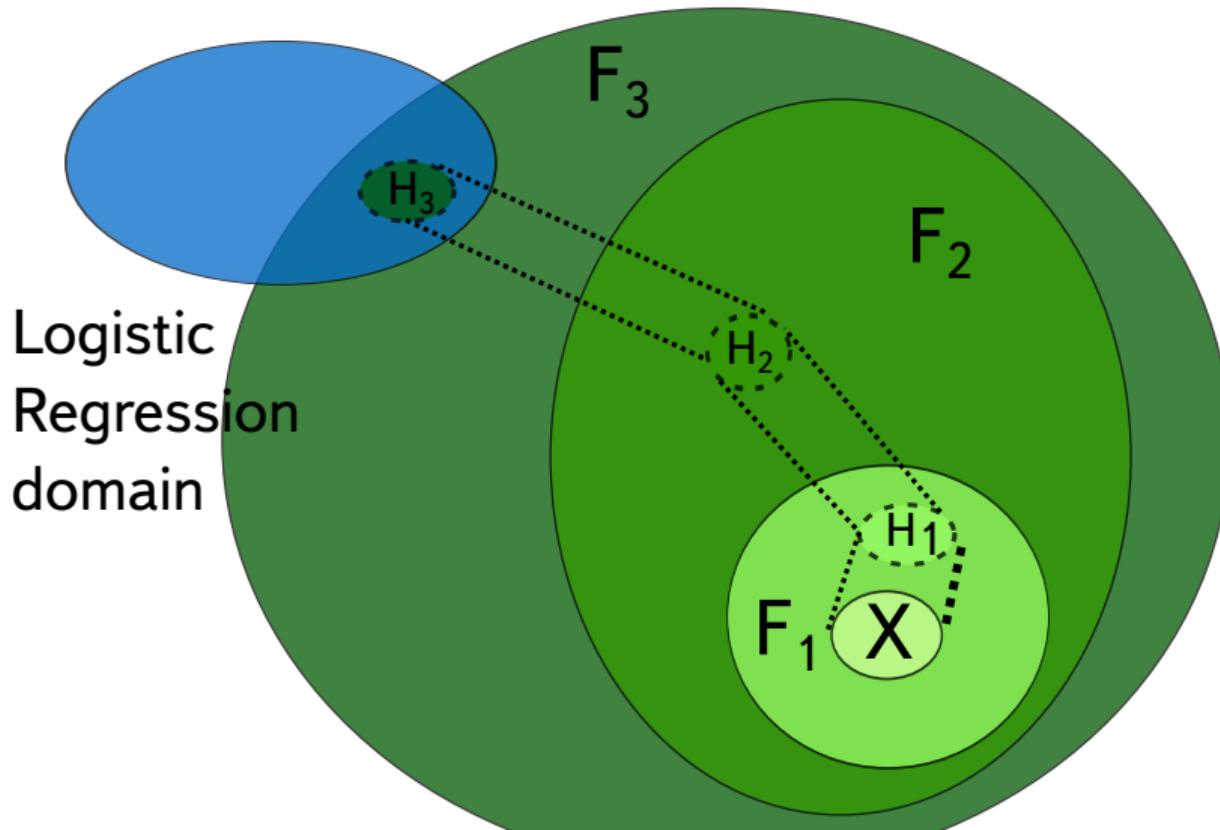
# How



# How



# How



# Kitten



- › use convolutions;
- › use convolutions again;
- › and again;
- › and again;
- › ...
- › logistic regression.

# Why deep?

- › new set of features is generated from previous one by a simple learnable 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 a single algorithm;
- › is a framework;
- › very flexible framework;
- › allows to express our assumptions in much more general way.

# Why DL rocks

Solves much harder problems:

- › purely a human factor:
  - › research time;
  - › limits of our intuition and understanding of the world; A framework;
  - › algorithms are like constructor;
  - › possible to solve almost every possible problem:
    - › classification;
    - › regression;
    - › clasterisation;
    - › sample generation...

# 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 your knowledge easier;
- › solves much harder problems.