# Towards deeper understandings of deep learning

Yuanzhi Li

Stanford University

date: Today

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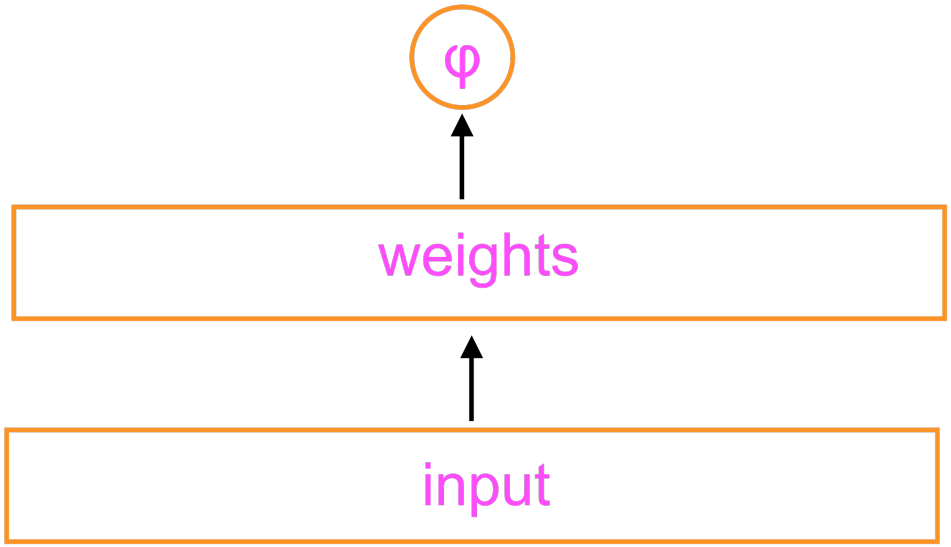

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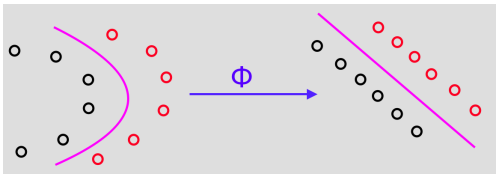

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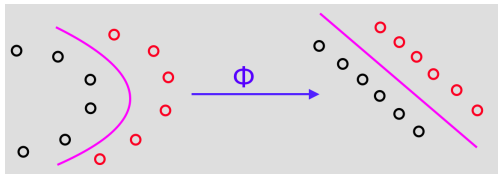


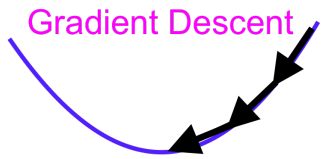

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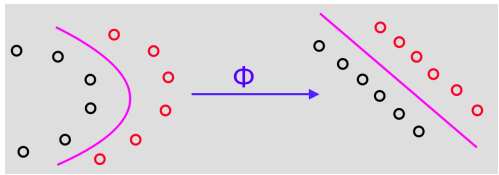
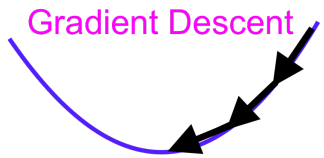
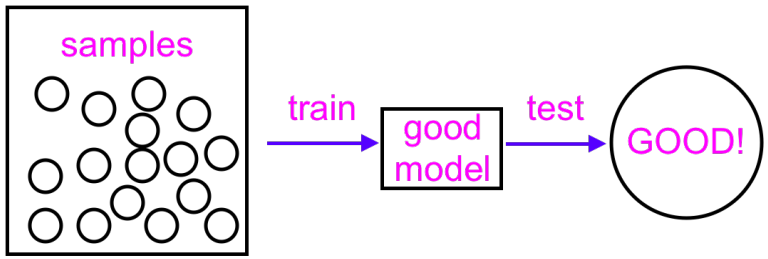



  - Convex optimization (training time bounds).
  - VC theory (sample complexity and generalization).



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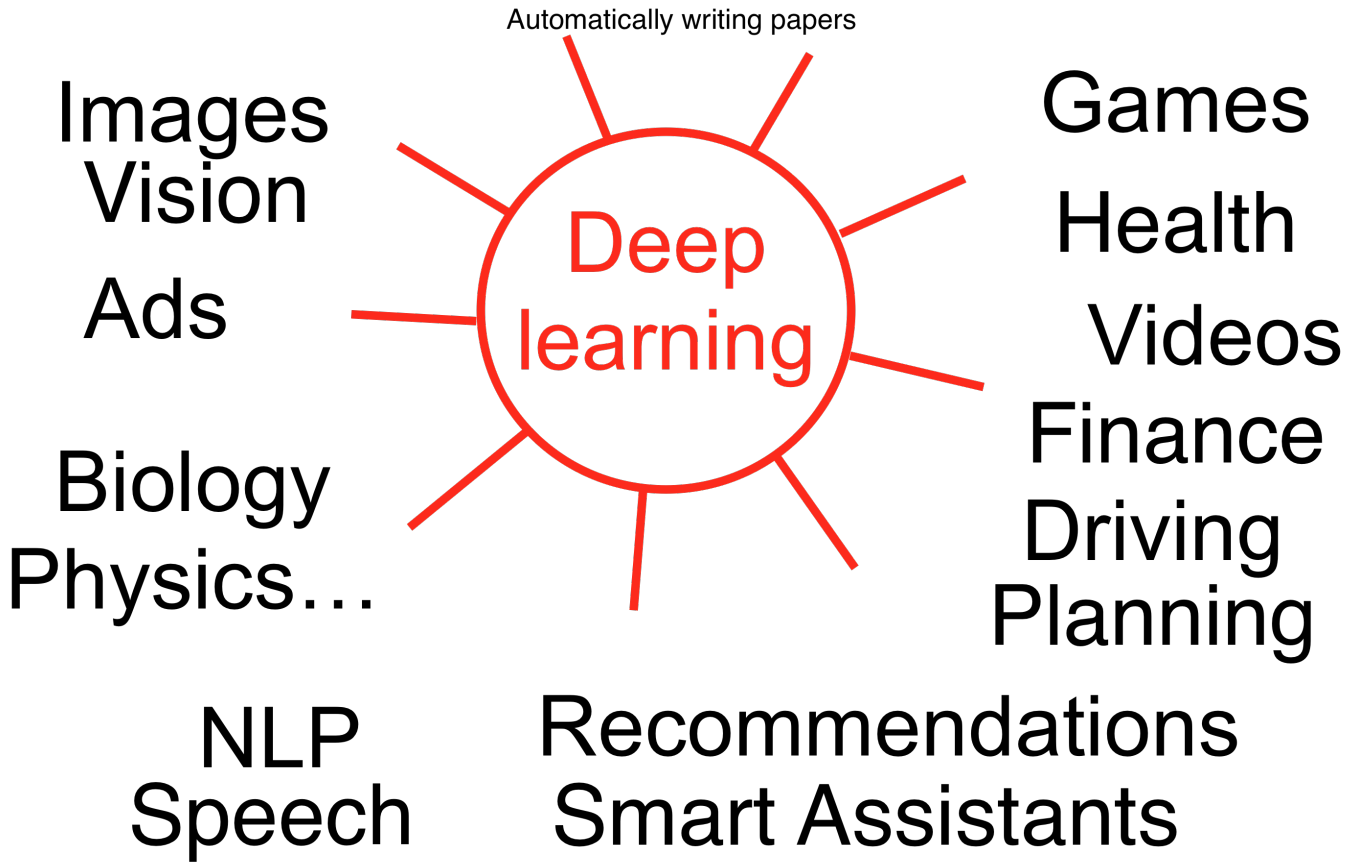

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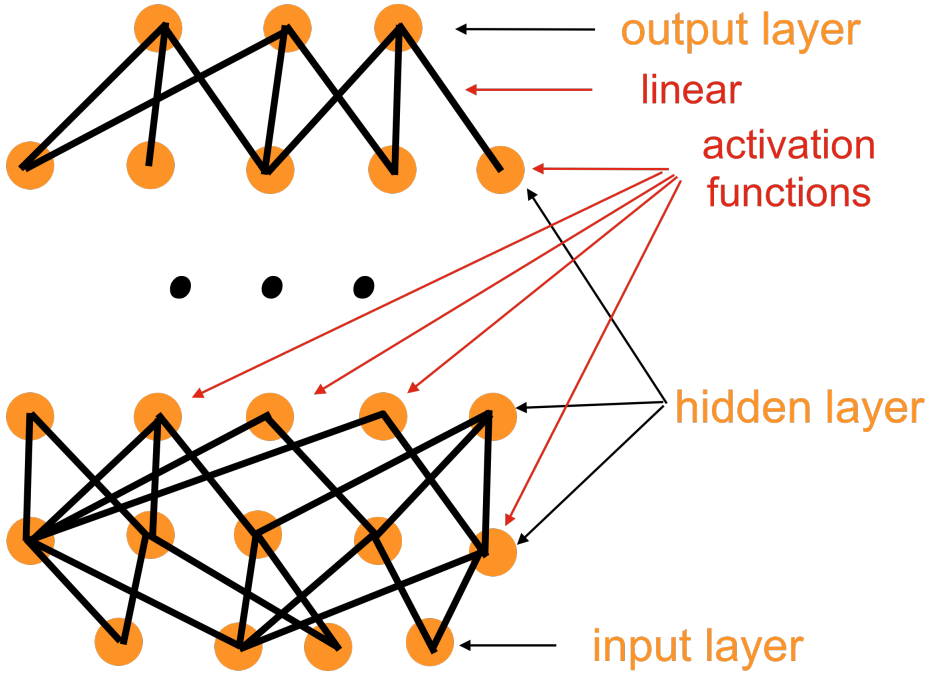

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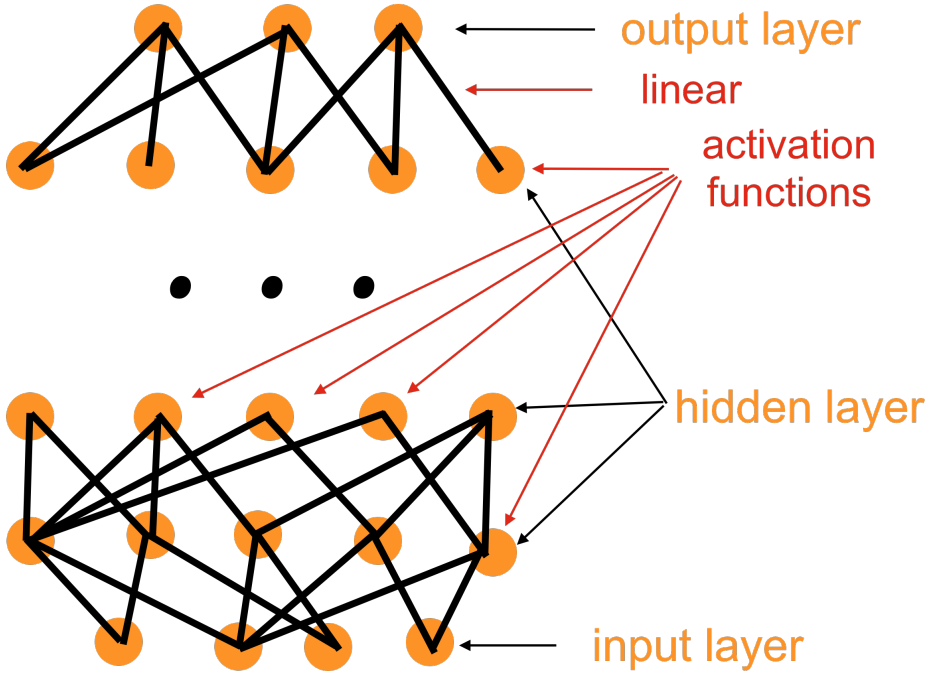


- In this talk, I will particularly focus on neural networks with ReLU activations. ReLU

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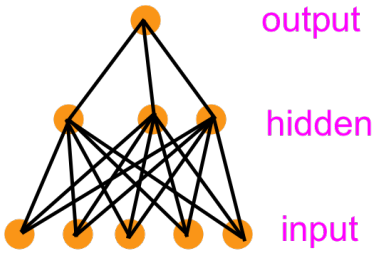


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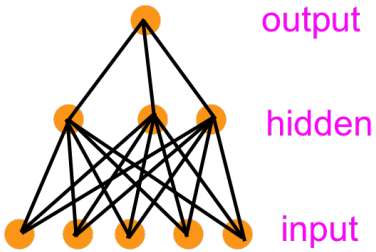
  - 

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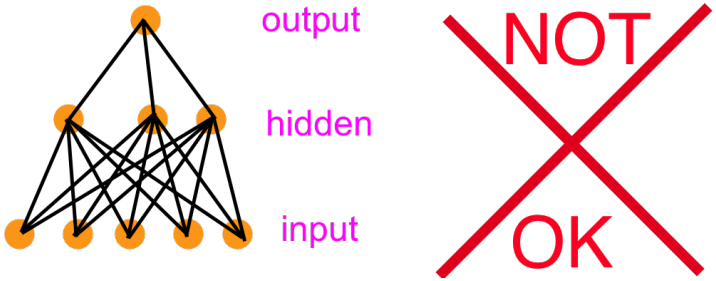
  - 
    
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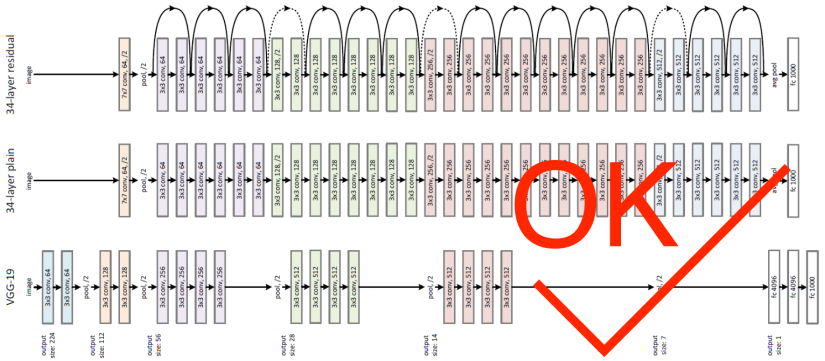
  - 
    

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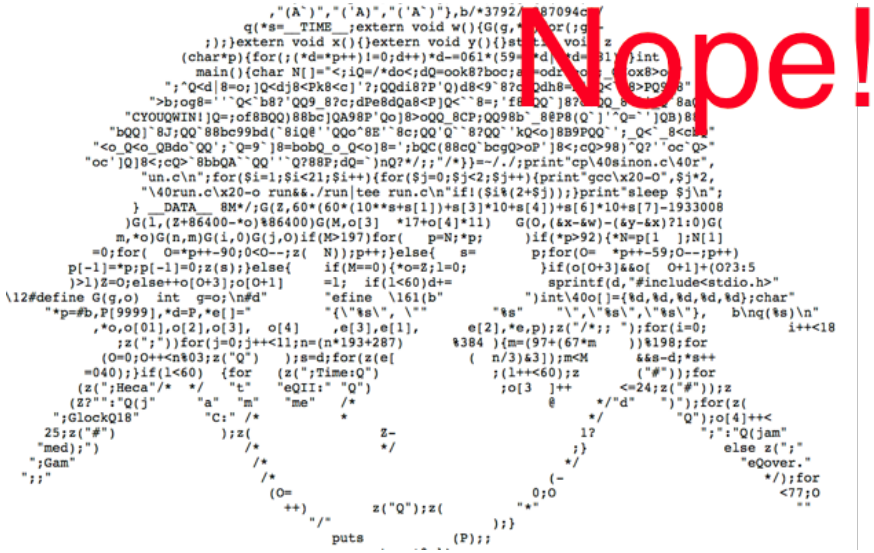
- 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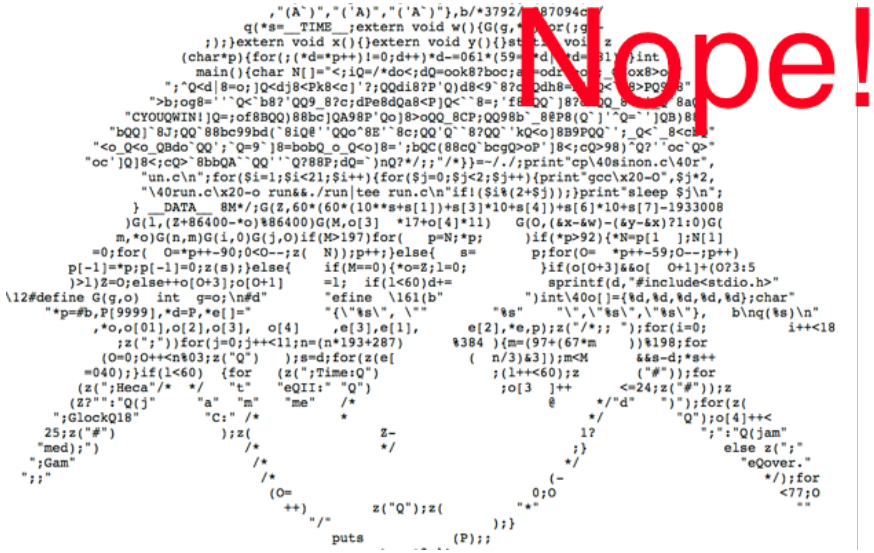
- 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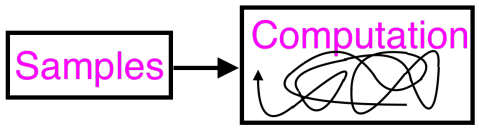

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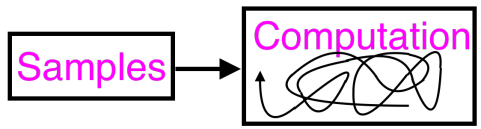


- And how can they help in learning neural networks, provably.

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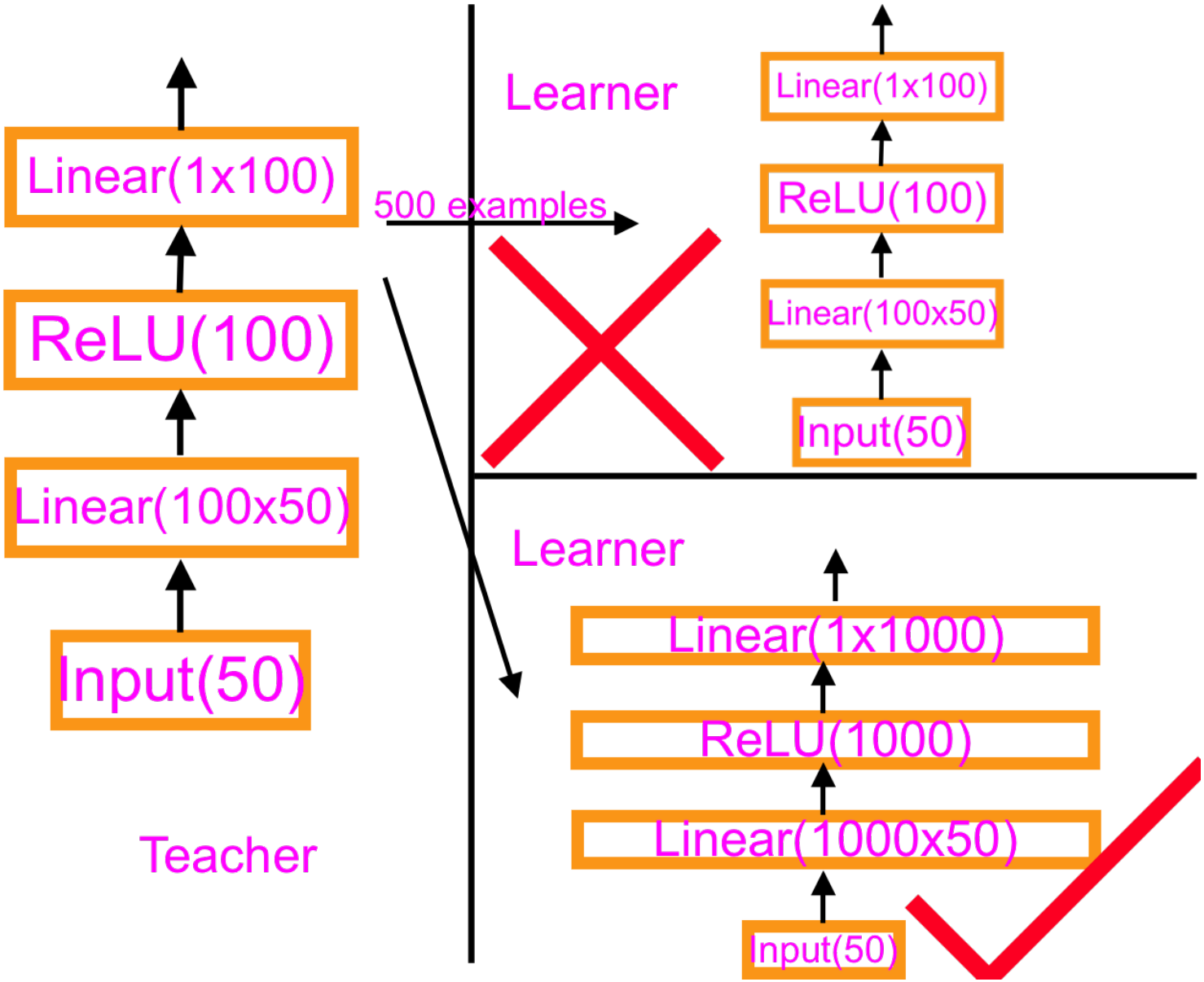
- Improves both the training and generalization.
- And it improves the theory.

# Folklore example for training.



# Example for generalization

| Widen factor | Number of parameters | Test error |
|---|---|---|
| 1 | 0.6M | 6.85 |
| 2 | 2.2M | 5.33 |
| 4 | 8.9M | 4.97 |
| 8 | 36.5M | 4.66 |

Table: Depth 40 WideResNet on CIFAR-10 (0.05M training examples), training errors are all 0.

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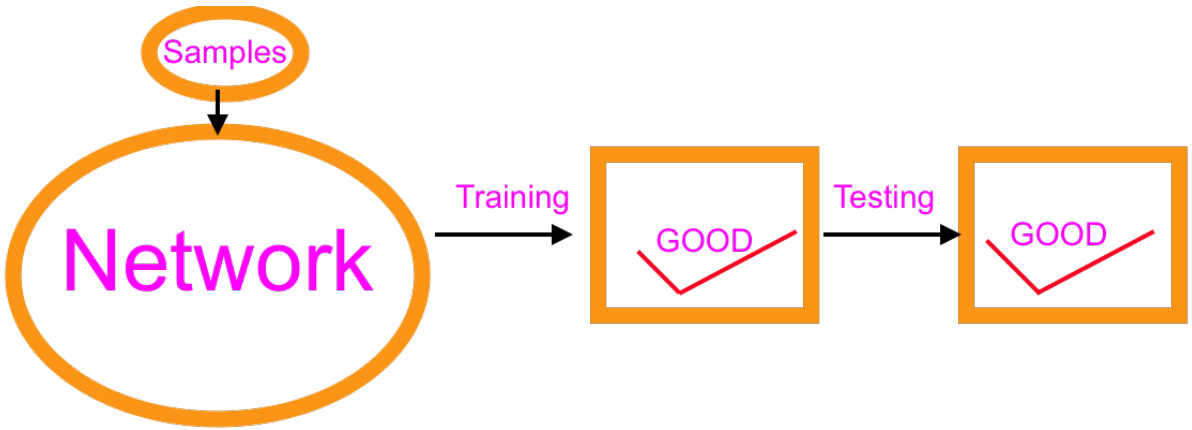

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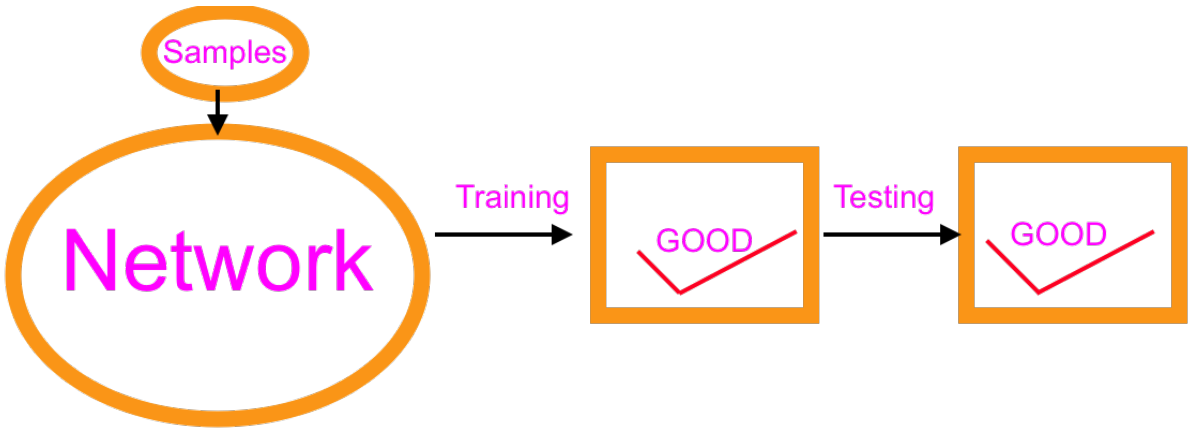
- 

- We begin with our theorem for (1), then we will see (2) as well.

# Our Theorem

**Theorem (Sketched, (LL'18, ALS'18a,b))**

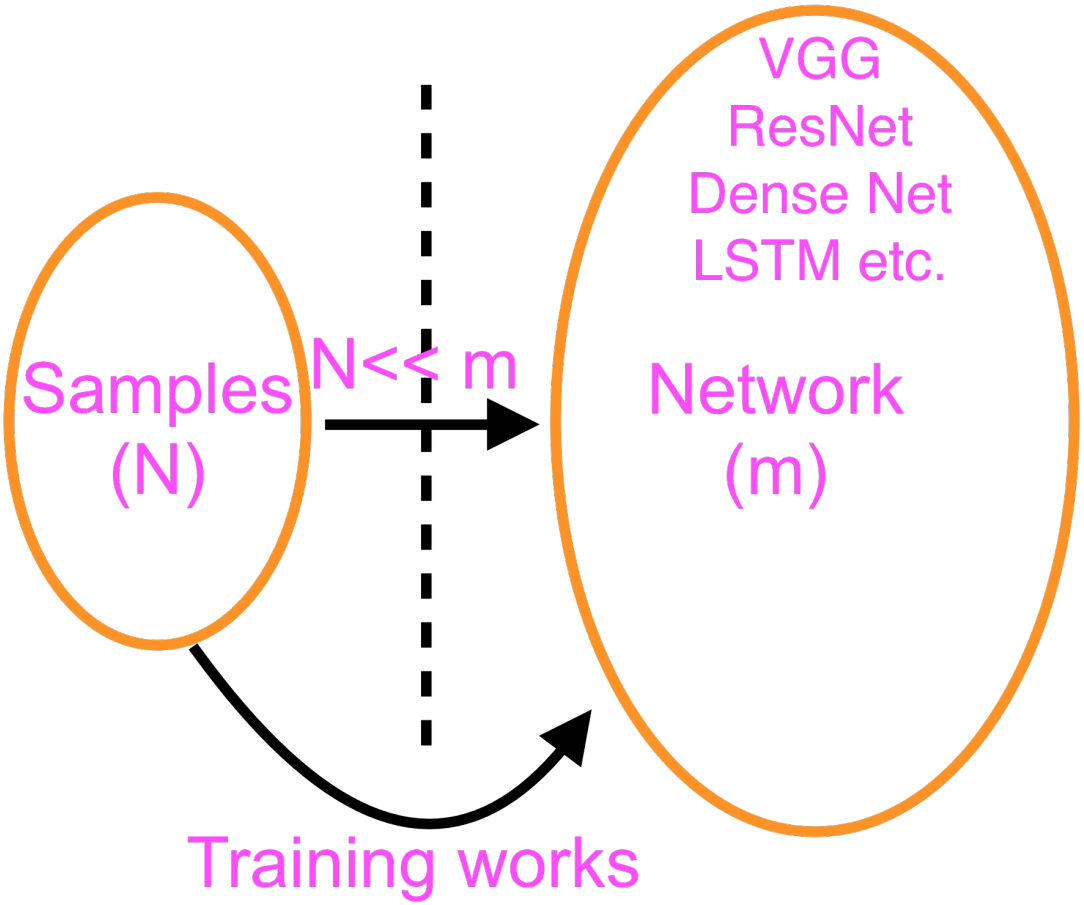
*Given $N$ different training examples $x_1, ..., x_N$ with labels $y_1, ..., y_N$, then for every $\varepsilon > 0$, as long as the number of neurons ($m$) in the network satisfies*

$$m \geq poly(N \log(1/\varepsilon))$$

*then SGD starting from gaussian random initialization finds an $\varepsilon$-approximate global optimal of the training objective in time $poly(m/\varepsilon)$.*

The theorem holds for multi-layer DNNs, CNNs, ResNet and Recurrent Neural Networks (all with ReLU activation functions), the training loss can be given by $\ell_2$ loss, cross entropy etc.

# Our theorem by picture



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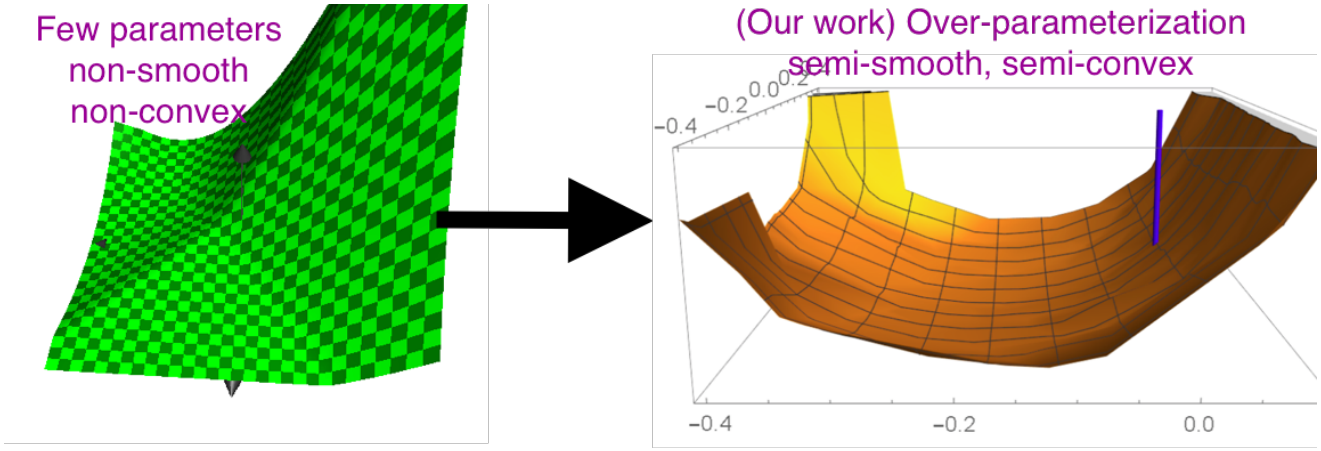

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  - So why does the solution found by SGD still generalize?

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  - We start with two layer networks, and then multi-layer ones.

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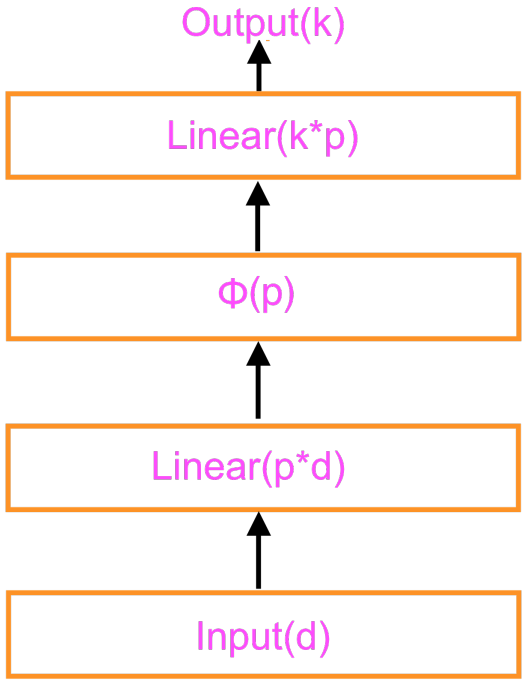


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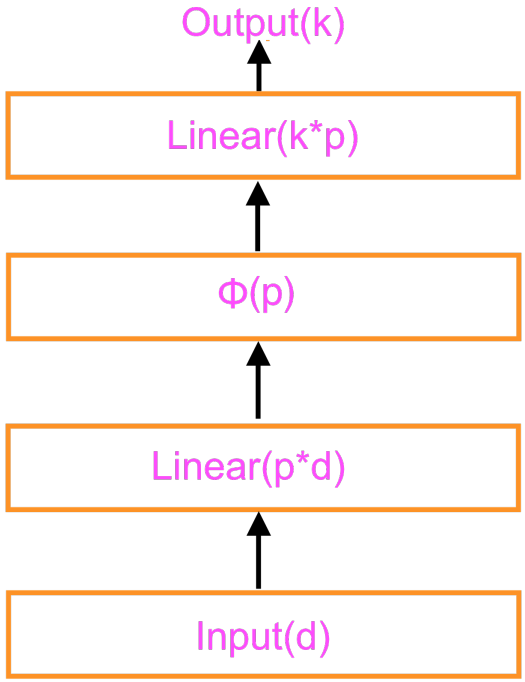


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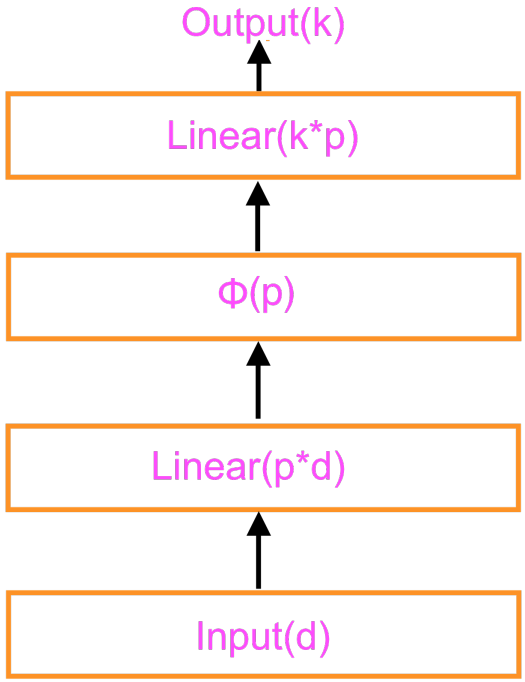


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- Such that the average loss of this network on the training data set is $\leq \varepsilon$.

# Our Theorem

**Theorem (Sketched (LL'18, ALL'18))**

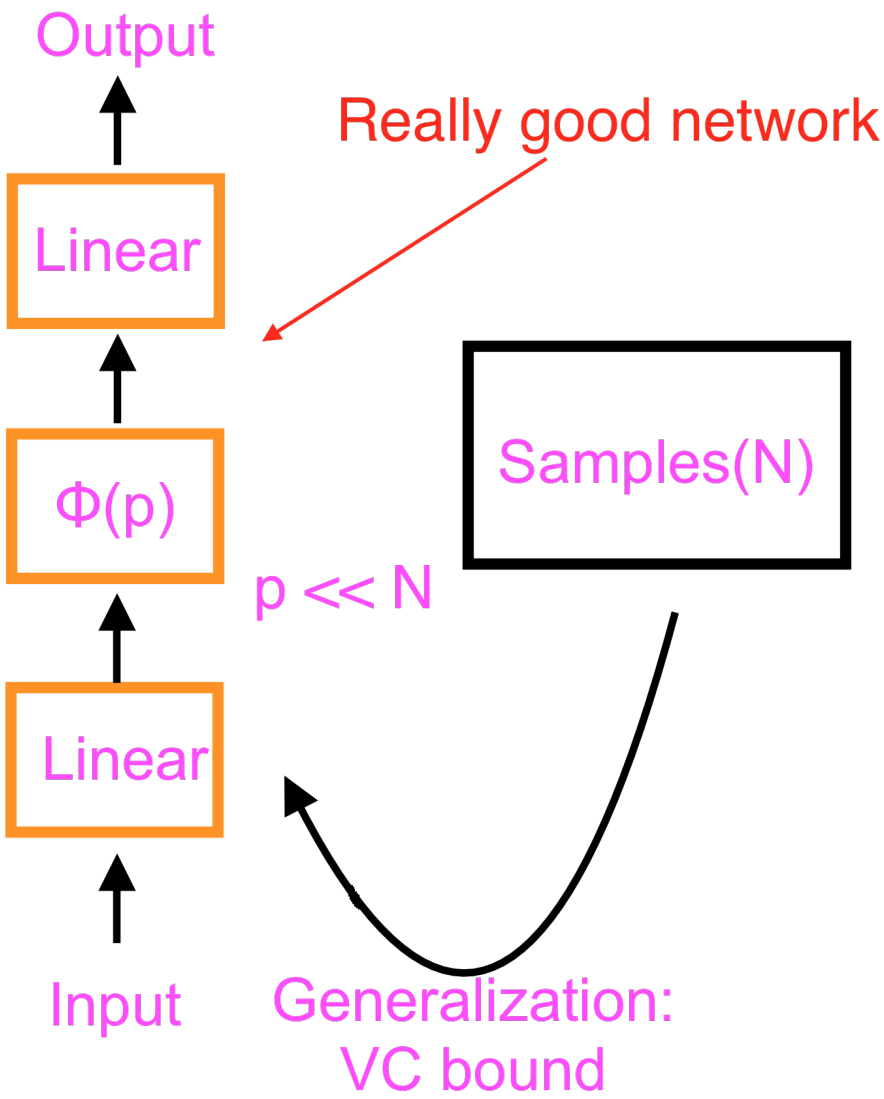
*Suppose the labels of the data can be realized as in the previous slides, then as long as the number of training examples $N$ satisfies:*

$$N \geq poly(kp/\varepsilon) \times poly(log(m))$$

*Then SGD on a two layer neural network (with $m$ neurons and ReLU activation functions) finds a solution with generalization gap $\leq \varepsilon$ in time $poly(m/\varepsilon)$.*

Generalization gap = average error on test data - average error on training data.

# Picture of the Theorem



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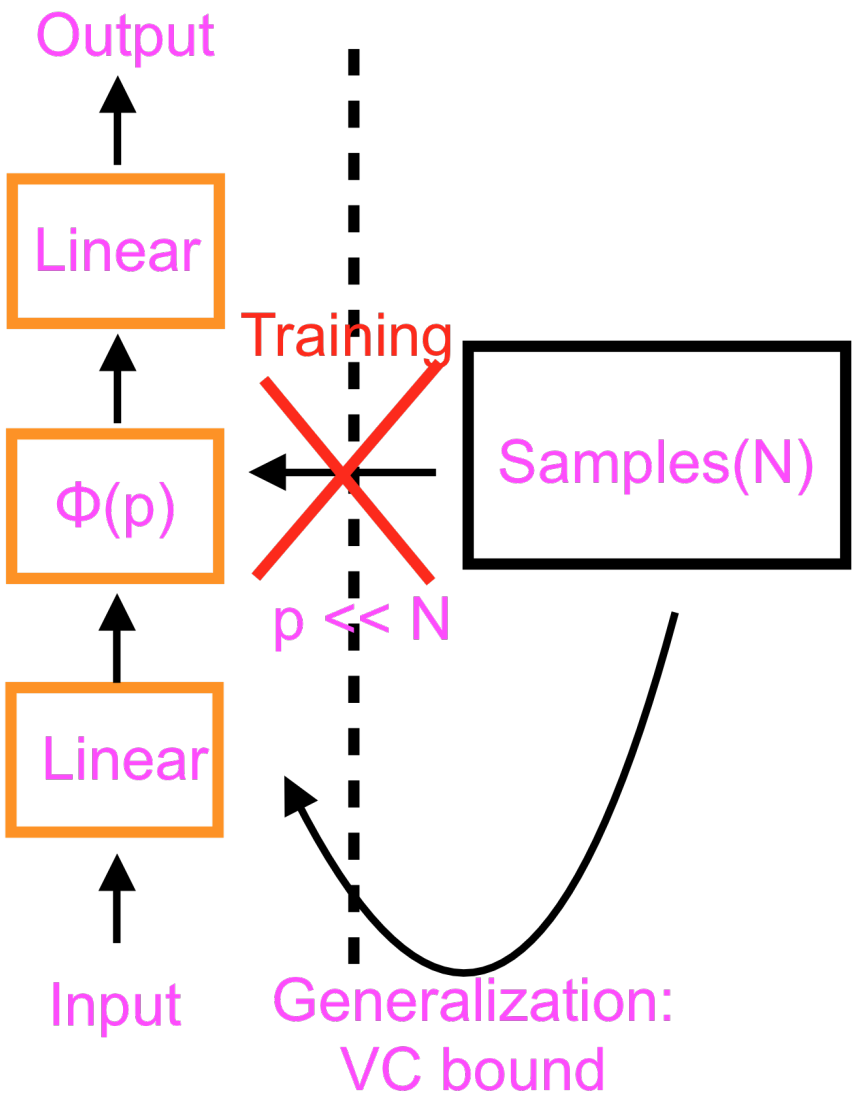

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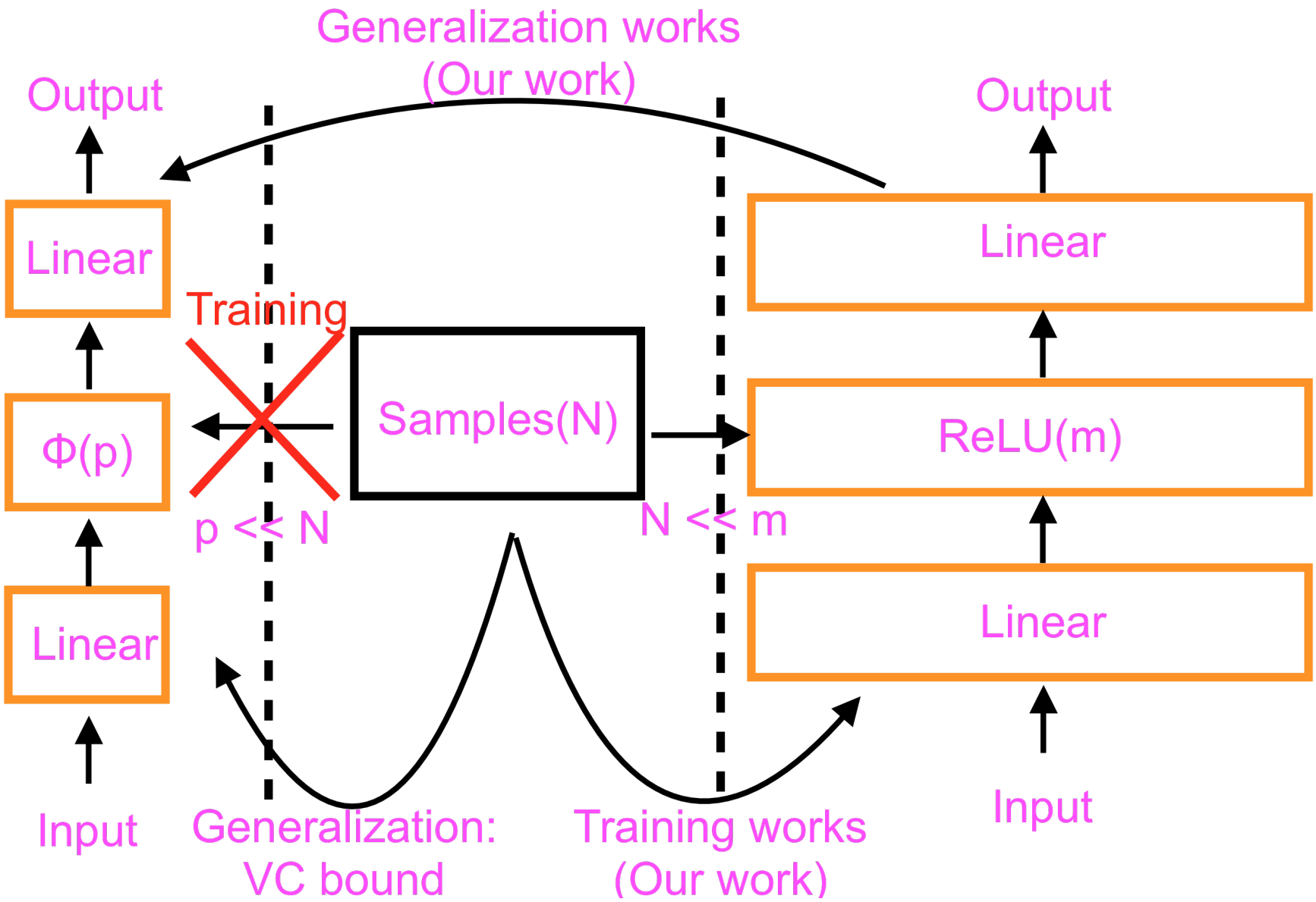

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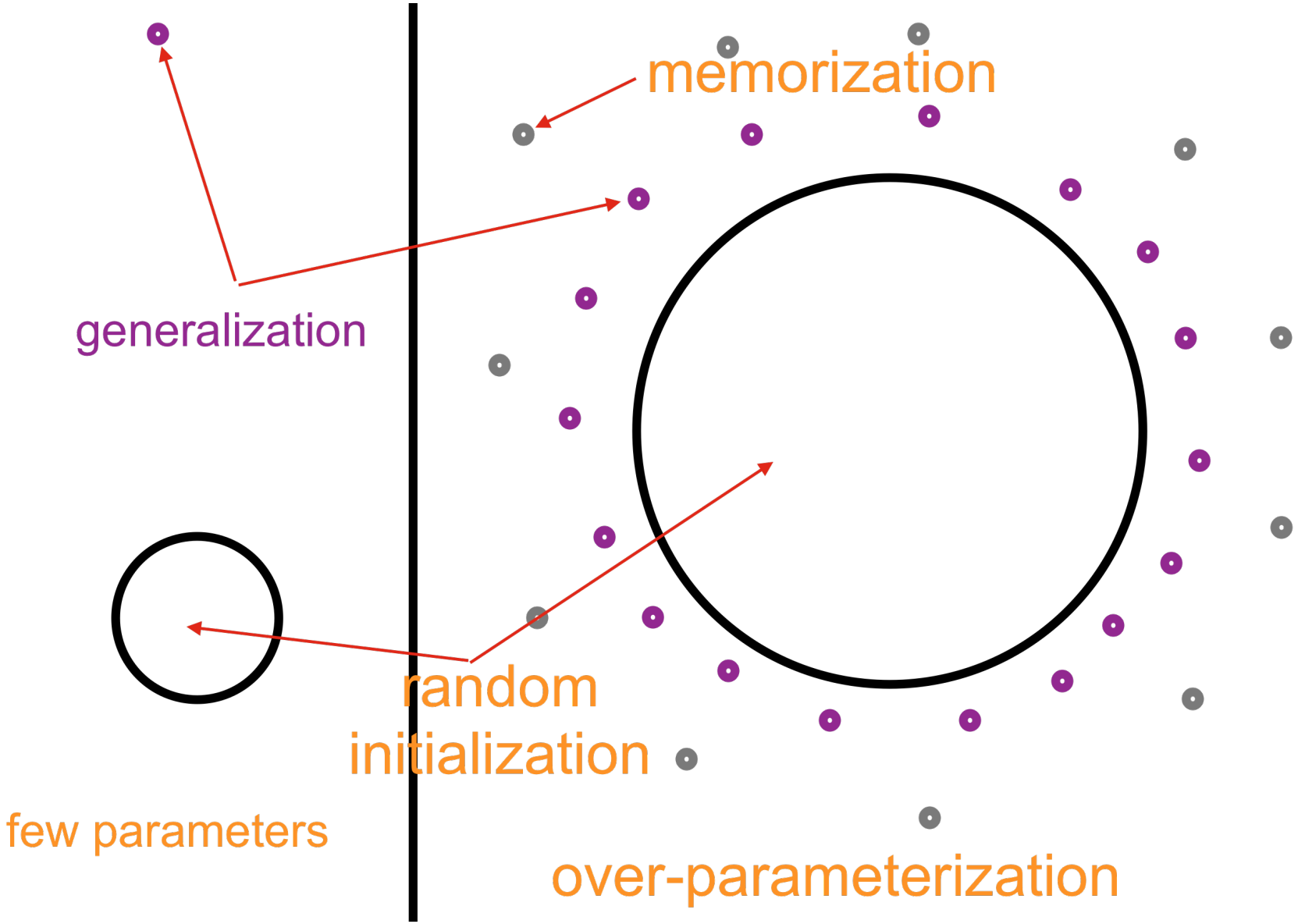
- This is what behind the principle of over-parameterization.

# Intuition


memorization
generalization
random
initialization
few parameters
over-parameterization

# Intuition

## Generalization

$y = \cos(x)$

Simple!

## Memorization

if x = 1, y = 0.54
if x = 2, y = -0.42
if x = 3, y = -0.99
if x = 4, y = -0.65
if x = 5, y = 0.28
if x = 6, y = 0.96
if x = 7, y = 0.75
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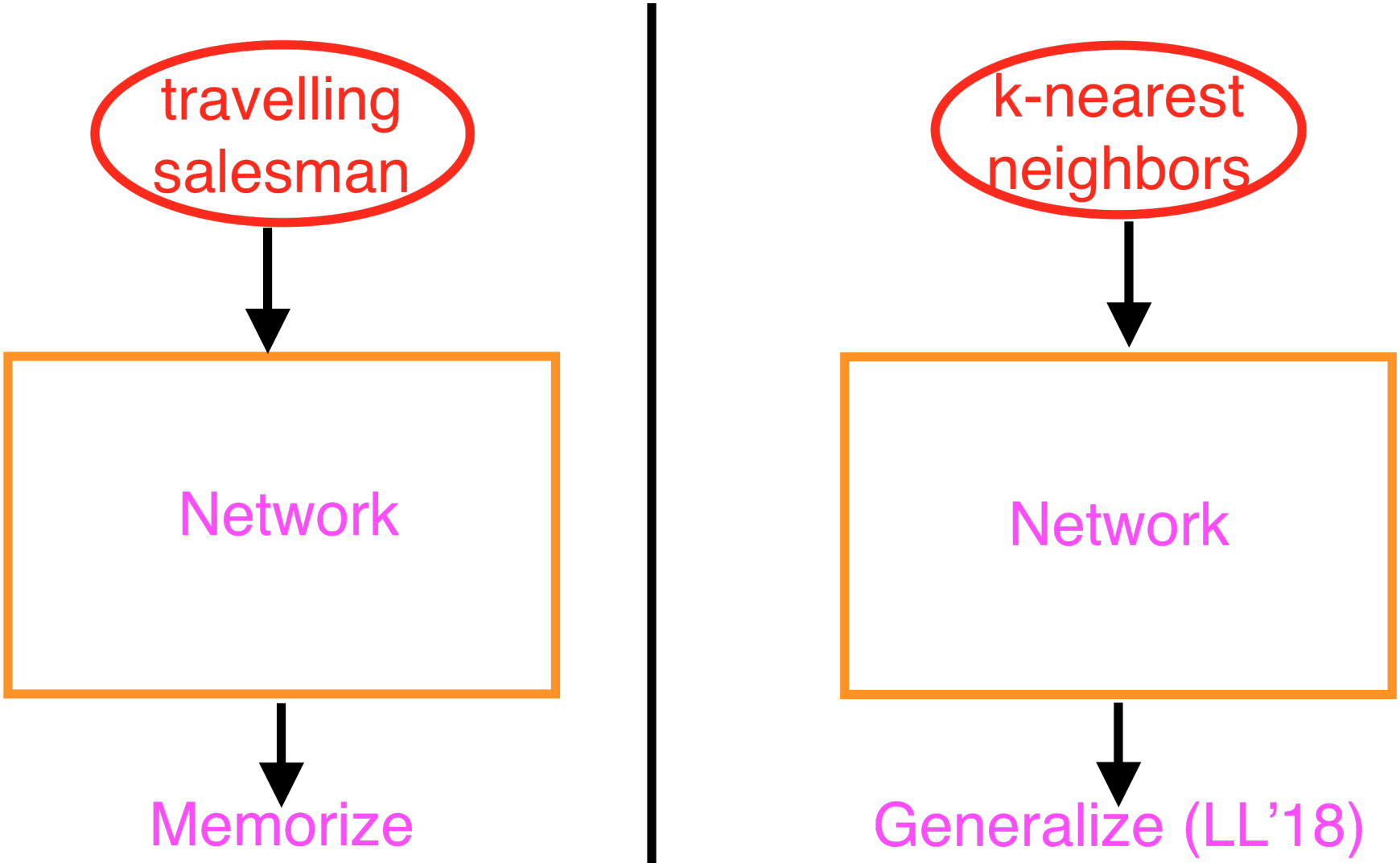


Existence of small networks is somewhat necessary

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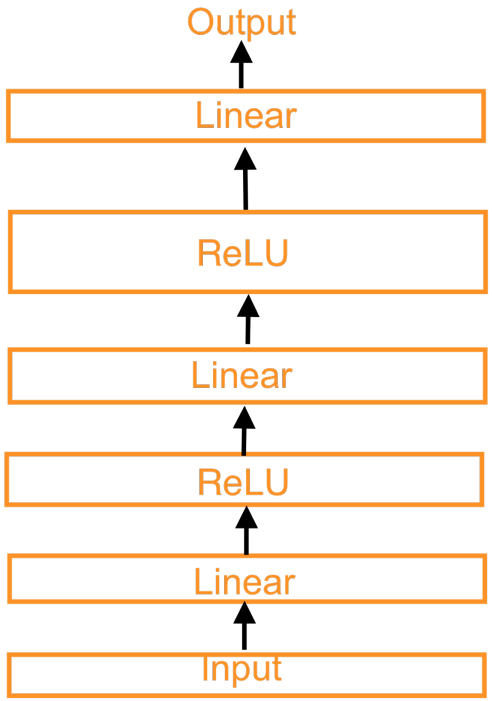


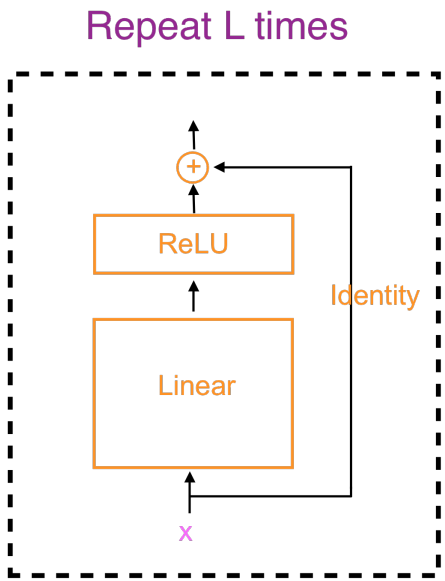

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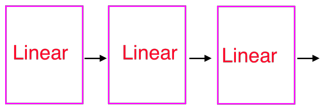
  - Linear networks. 

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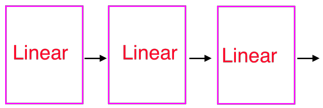
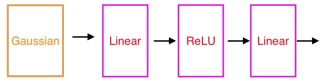
  - Linear networks. 

  - Networks on Gaussian inputs (tensor decomposition). 

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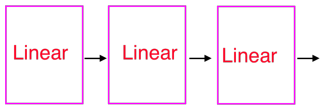
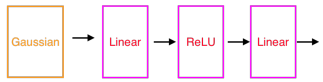
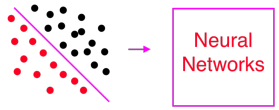
  - Linear networks. 

  - Networks on Gaussian inputs (tensor decomposition). 

  - Networks to learn linear separable data. 

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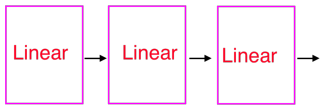
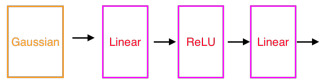
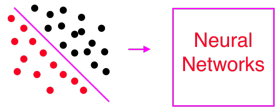
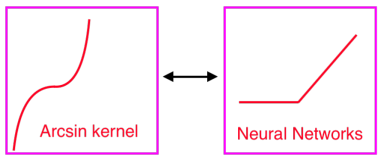
  - Linear networks. 

  - Networks on Gaussian inputs (tensor decomposition). 

  - Networks to learn linear separable data. 

  - Networks to learn functions that are learnable by arcsin kernel. 

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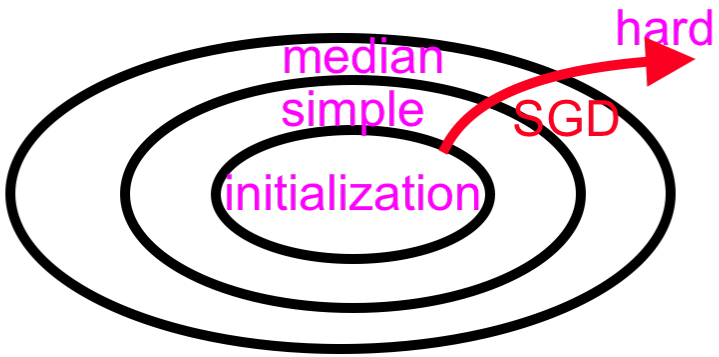

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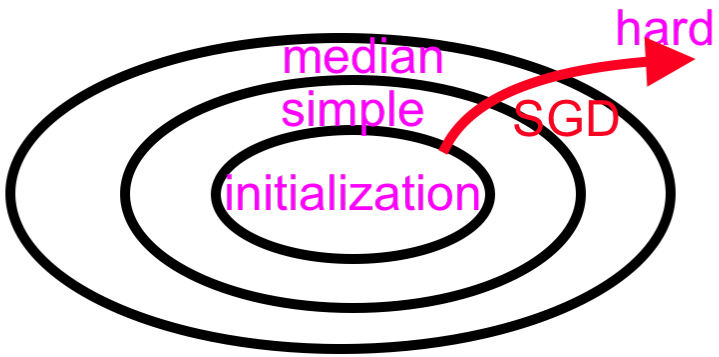


- Question: Does this bias always lead to best generalization? Can we do better?

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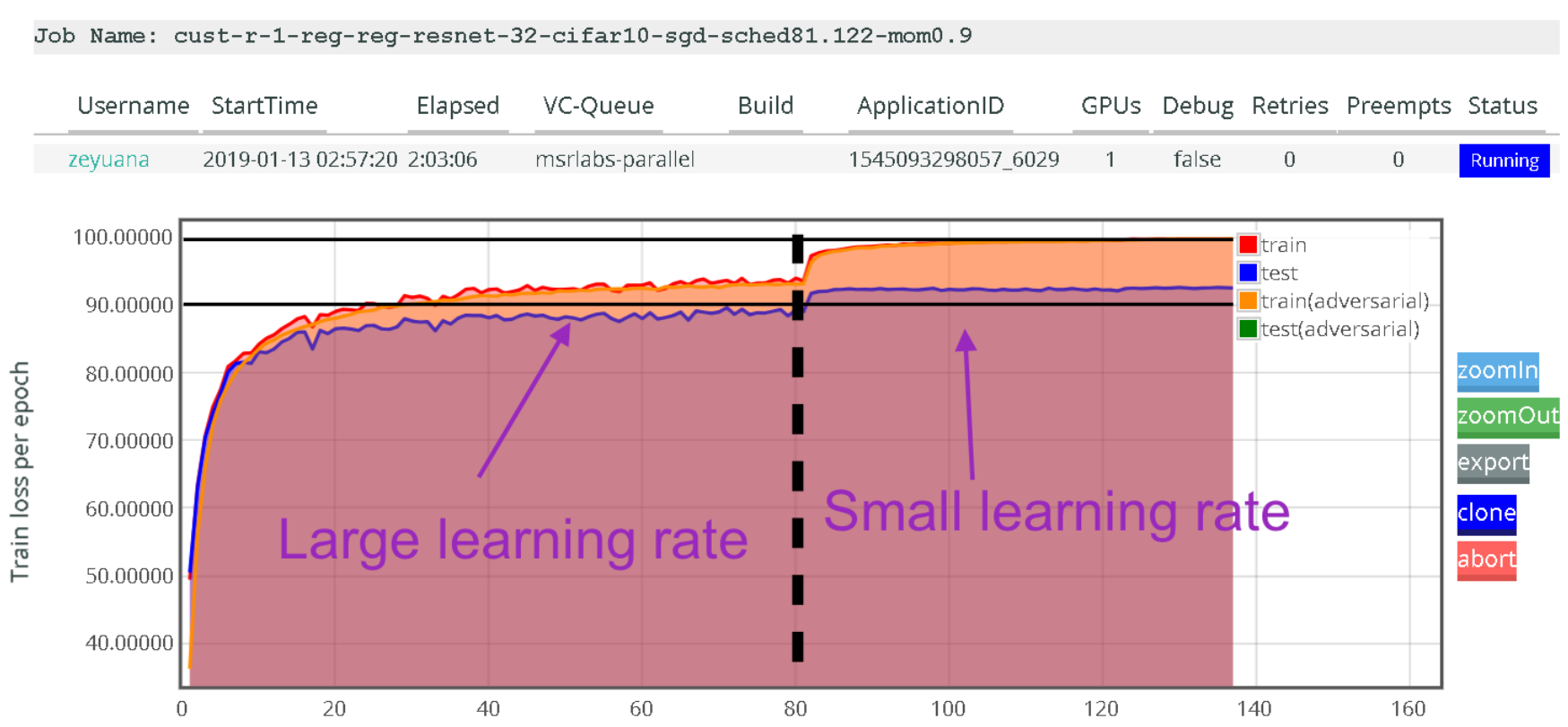

# SGD with different learning rates

Job Name: cust-r-1-reg-reg-resnet-32-cifar10-sgd-sched81.122-mom0.9

| Username | StartTime | Elapsed | VC-Queue | Build | ApplicationID | GPUs | Debug | Retries | Preempts | Status |
|---|---|---|---|---|---|---|---|---|---|---|
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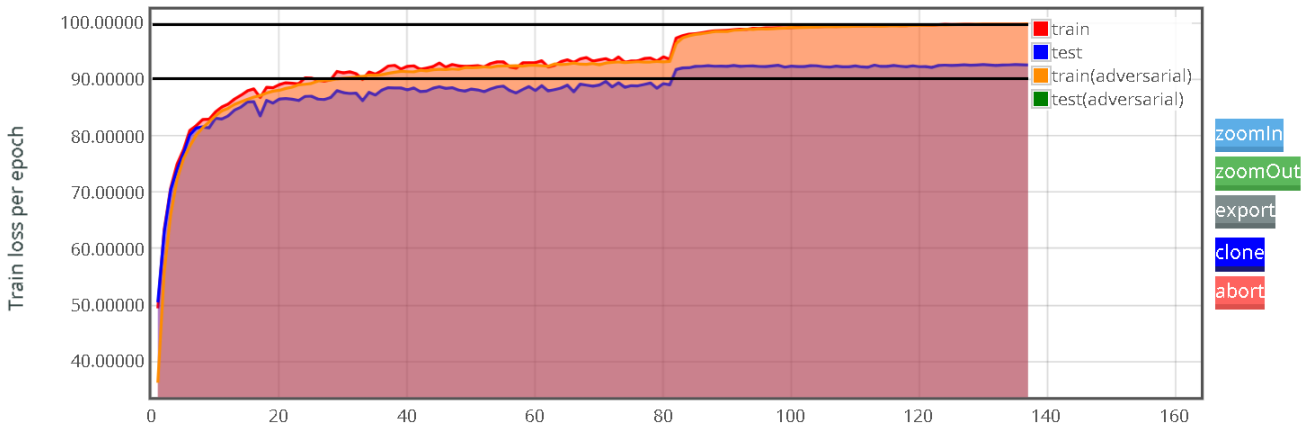


Name: cust-r-1-reg-reg-resnet-32-cifar10-sgd-lr0.001-epo5000-sched5000.5001-mom0.9

| Username | StartTime | Elapsed | VC-Queue | Build | ApplicationID | GPUs | Debug | Ret |
|---|---|---|---|---|---|---|---|---|
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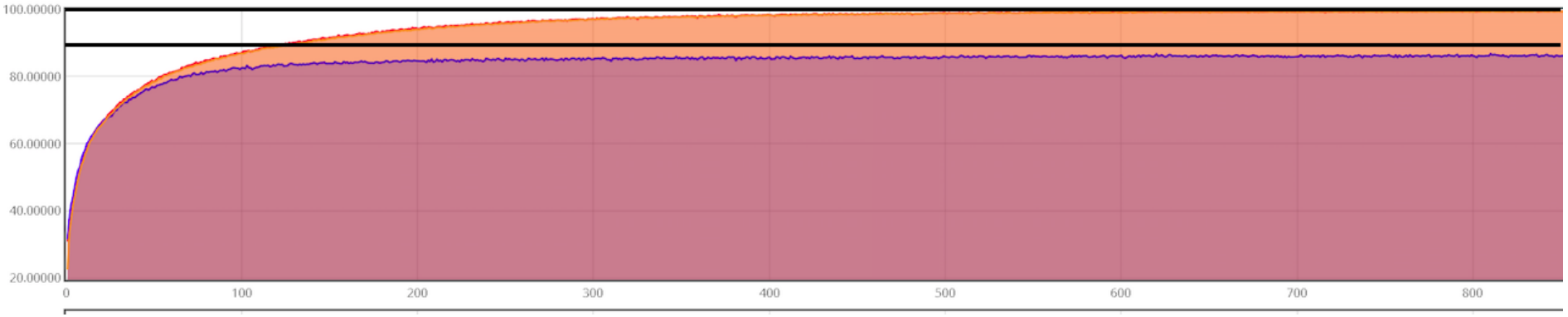

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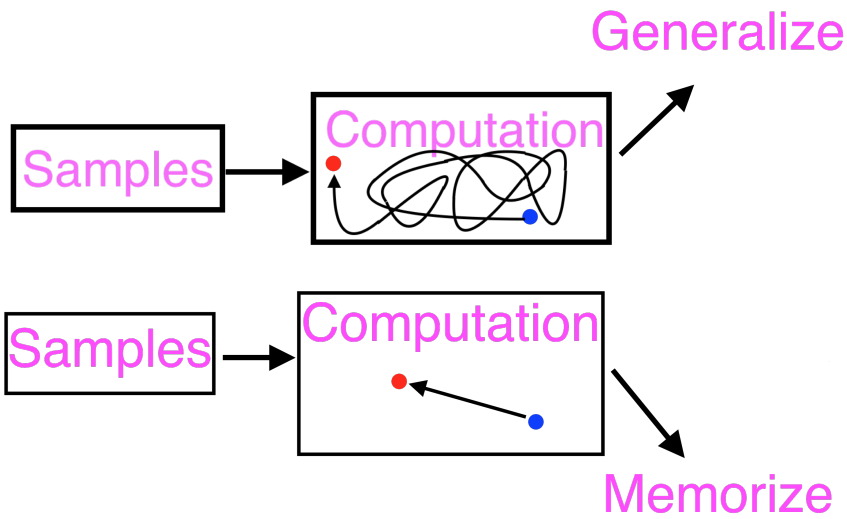

# Principle of "Noisy computation"

- Training loss of using large learning rate + learning rate decay and using small learning rate are all close to zero.
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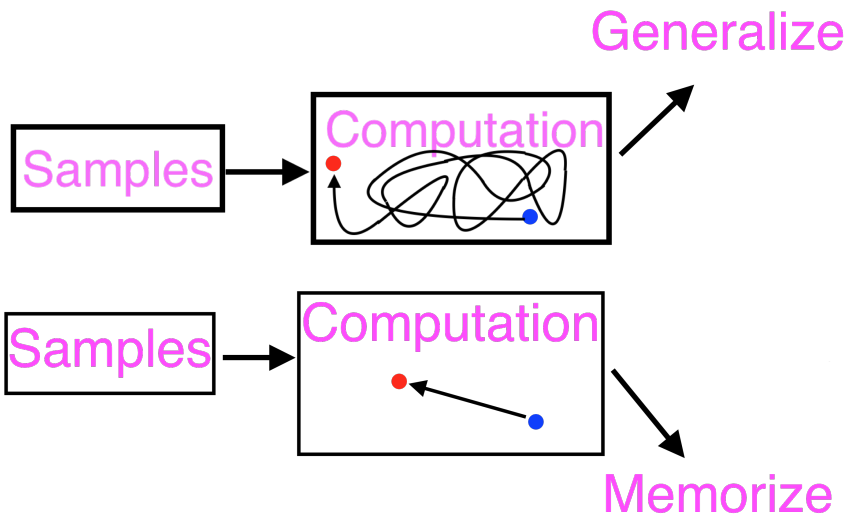


- 
- But why?

# Our current work

- The principle of "noisy computation":

# Our current work

- The principle of "noisy computation":
- On certain data sets, when training a neural network using SGD, large learning rate + learning rate decay provably generalizes better than small learning rate.

# Example of the data set

- Texts labeled as happy:

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- Texts labeled as happy:
  - I am so happy ☺

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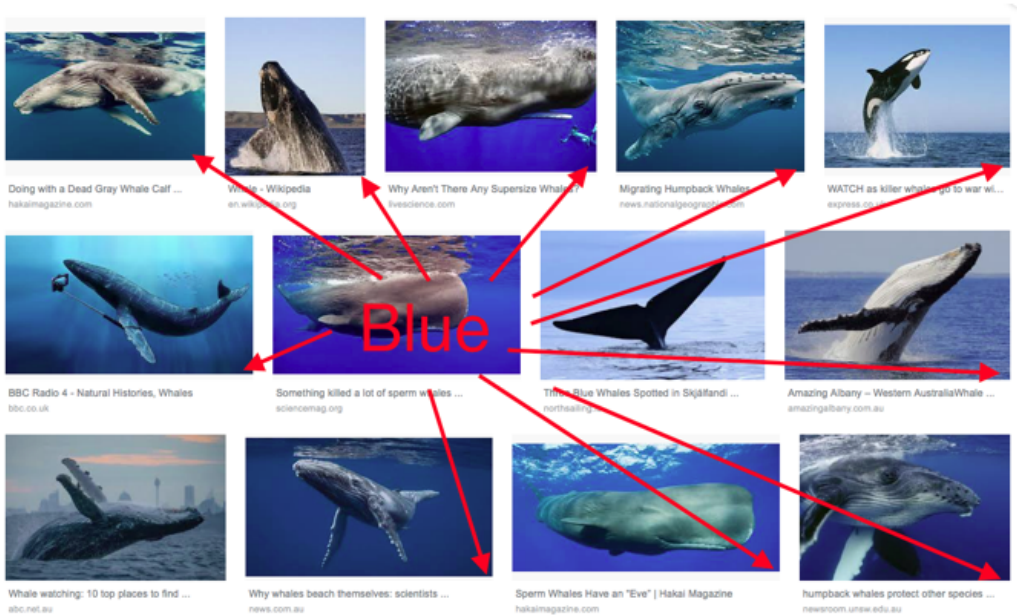

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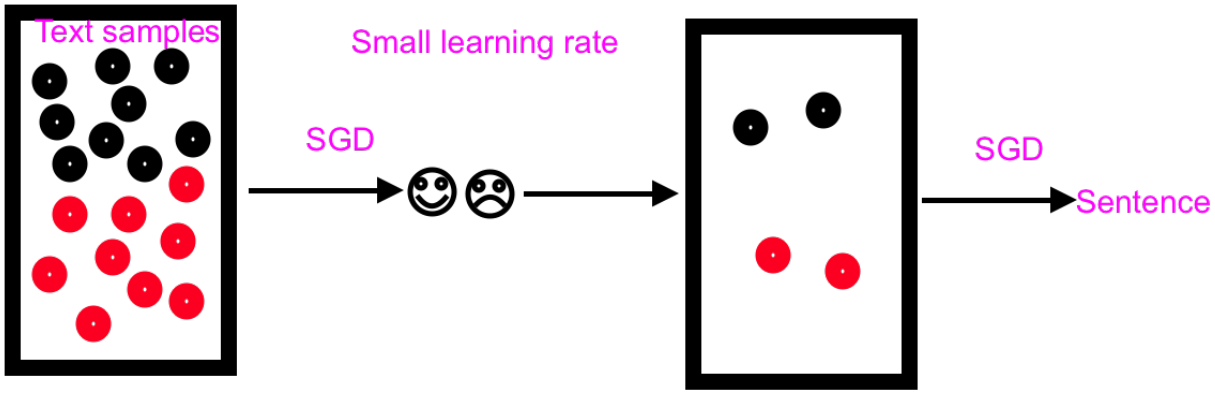

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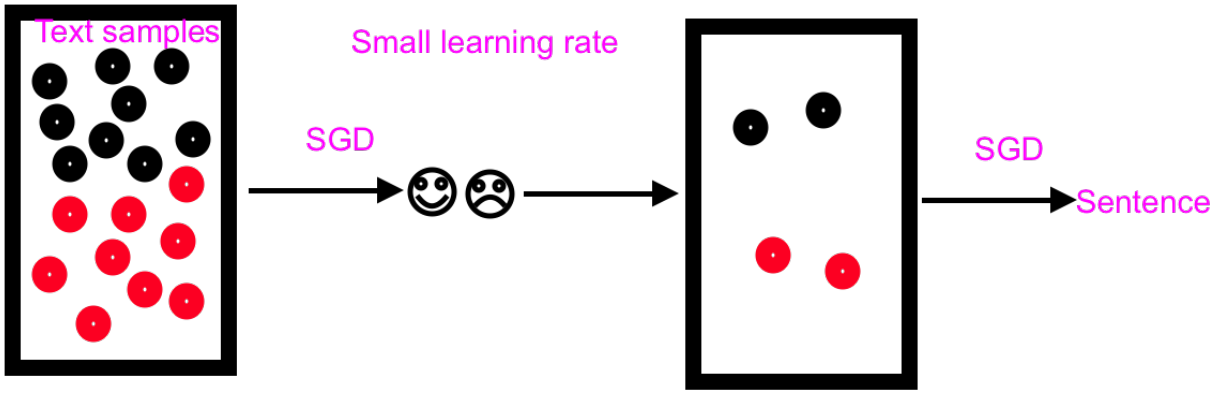


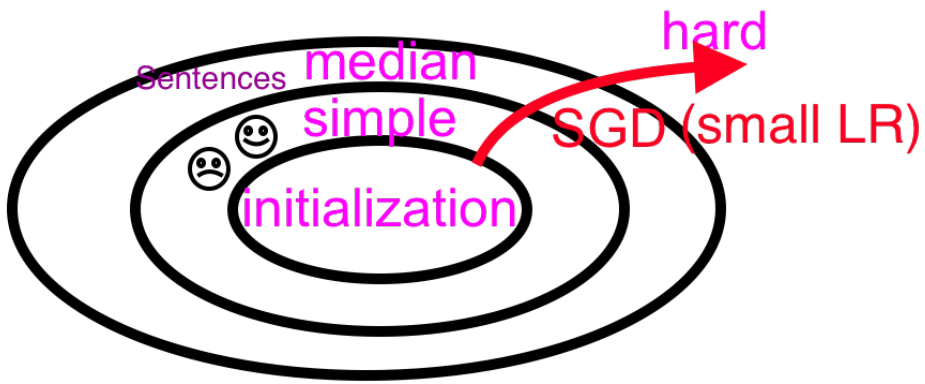

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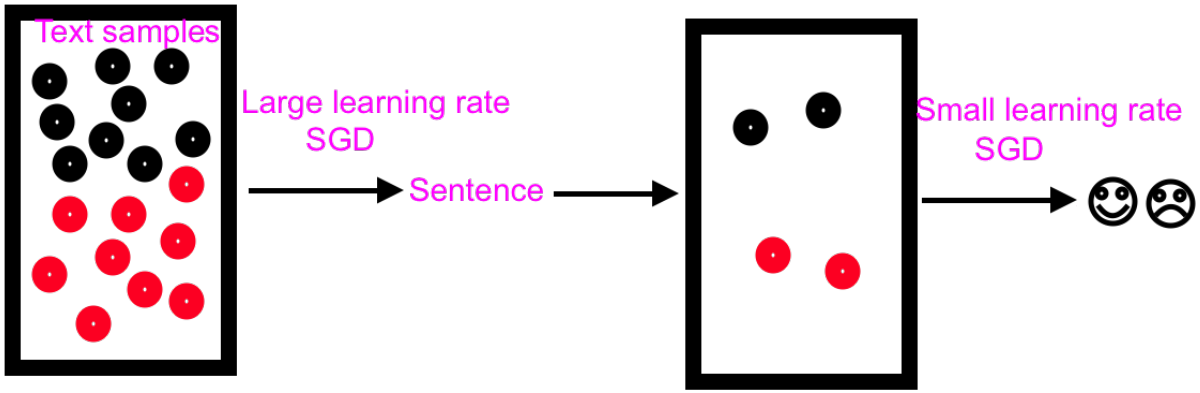

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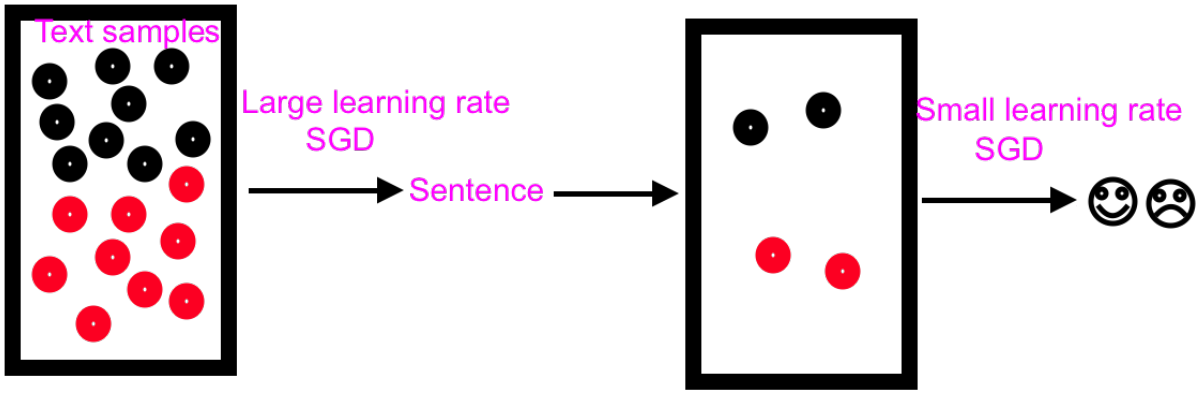


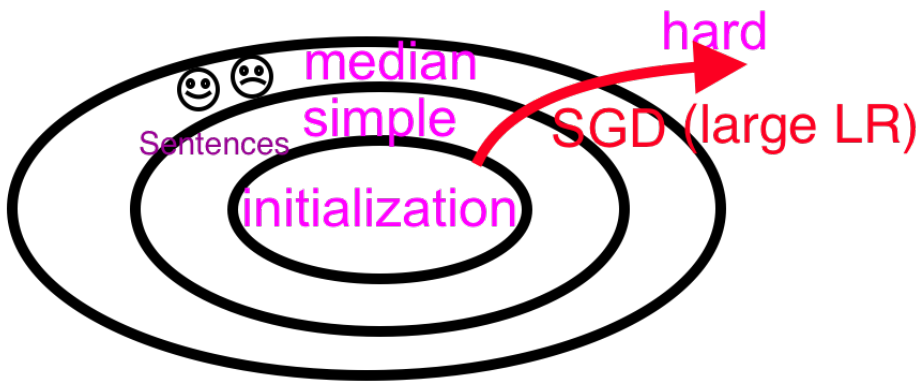

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- The order matters: memorization after generalization.

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- Remark: $\langle w, x \rangle$ can be replaced by two layer networks.

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*Given $N \approx p/\tau$ ($\tau \ll 1$) training examples, at training error (two layer over-parameterized neural network with ReLU activation) $\tau^2$ for the cross entropy loss:*

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- When $N \gg p$, they both generalize (as shown in the principle of over-parameterization), but SGD with large learning rate + learning rate decay generalizes even better.

# Intuition

Generalization:

```
def @@_talk_example(x):
    x = x^2
    x = x + 10
    x = x*3
    x = x^(1/3)
    x = x - 3
    return x
```

Memorization:

```
def @@_talk_example(x):
    if x = 1, return 0.2
    if x = 2, return 0.48
    if x = 3, return 0.84
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SGD with
small learning rate:
I like this one!

# Intuition

Generalization:

```
def @@_talk_example(x):
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    x = x + 10.04
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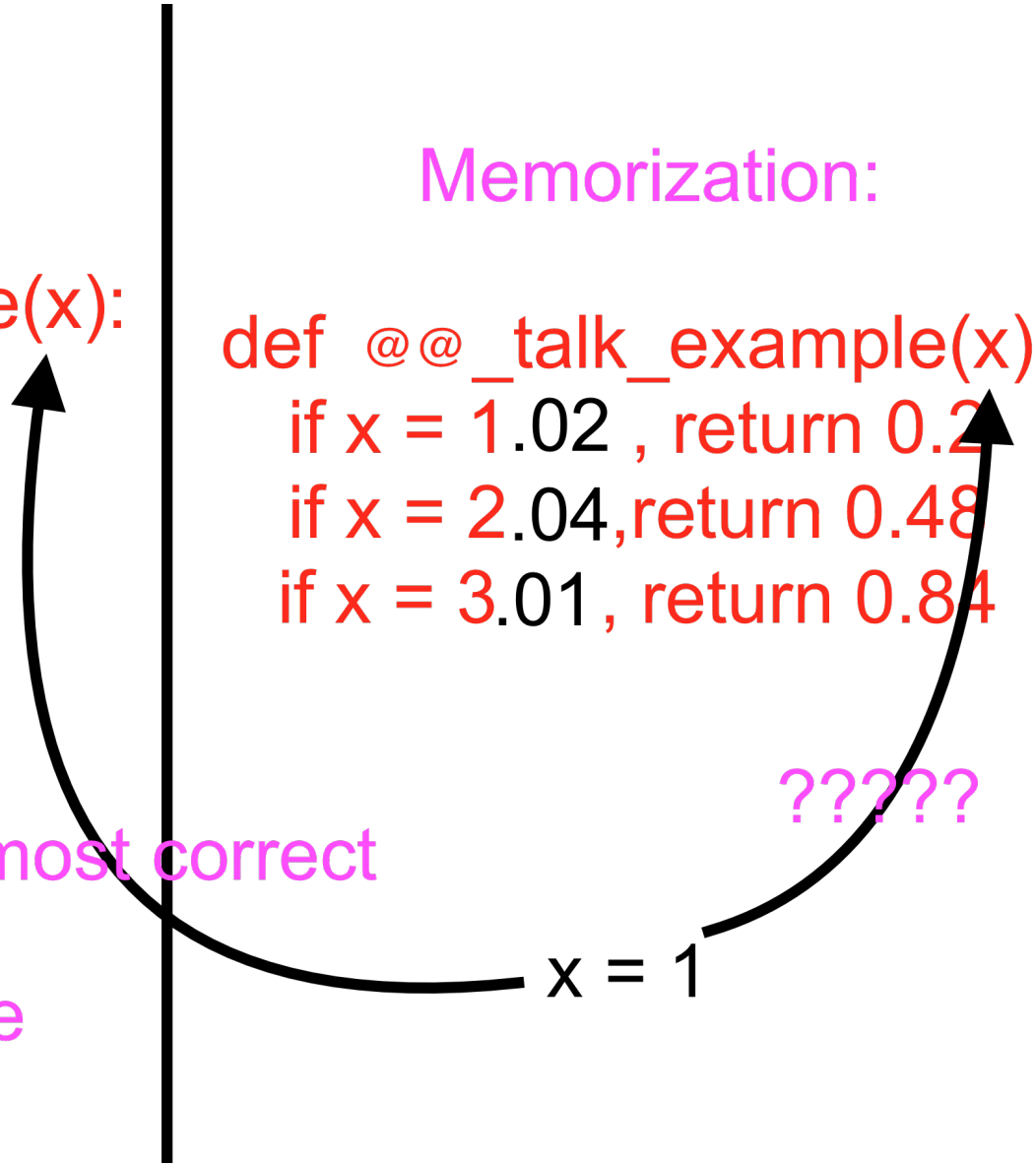
    x = x^(1/3.01)
    x = x - 3.05
    return x
```

SGD with
large learning rate
(noisy)

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# Principle of "noisy computation"

- Memorization in neural network: when $m \gg N$, by chance there will be $N$-neurons in the network that maps all data to linear independent positions. (Geometry of ReLU Lemma in [LL'18, ALS'18(a,b)])

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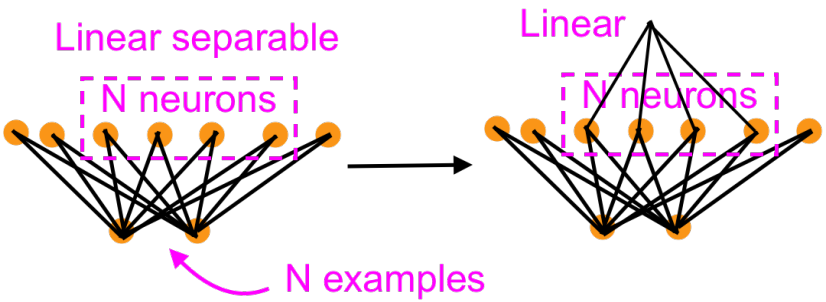

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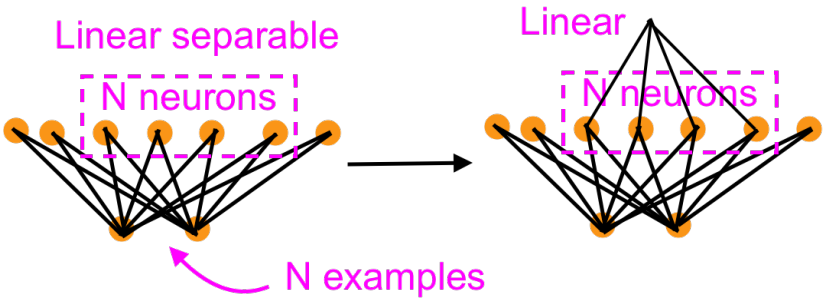


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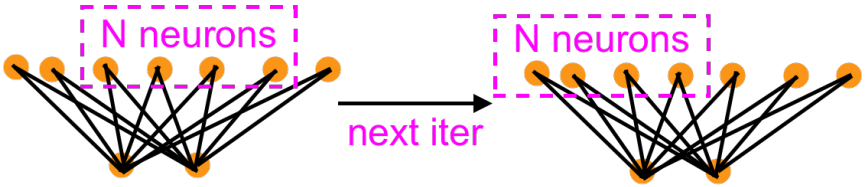

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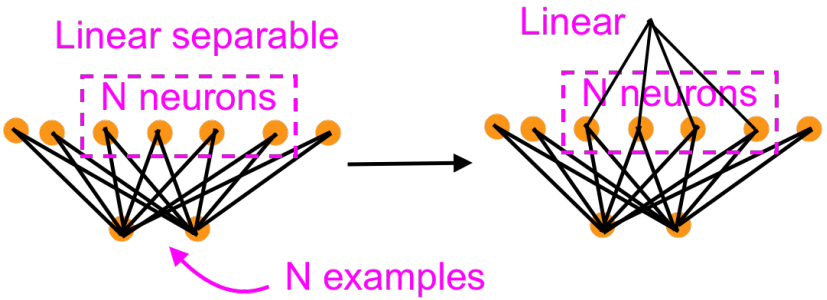


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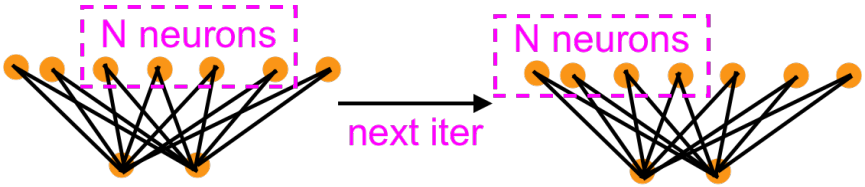


- This is what behind the principle of "noisy computation".

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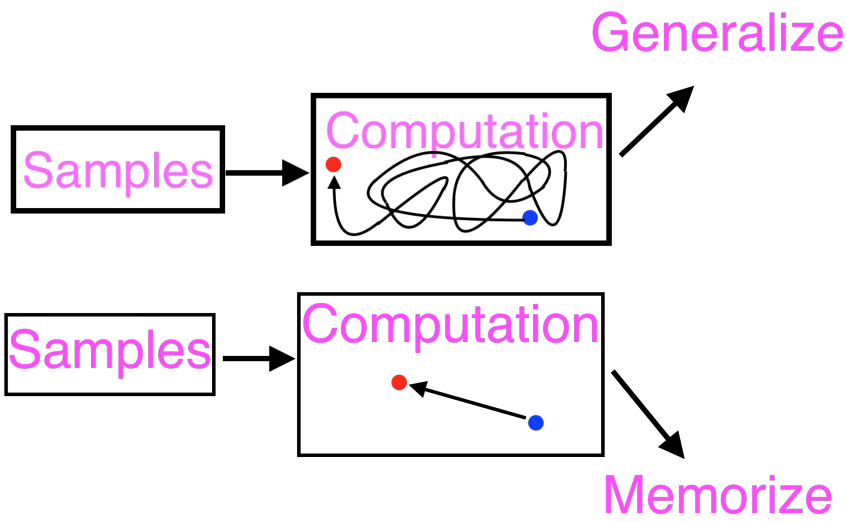

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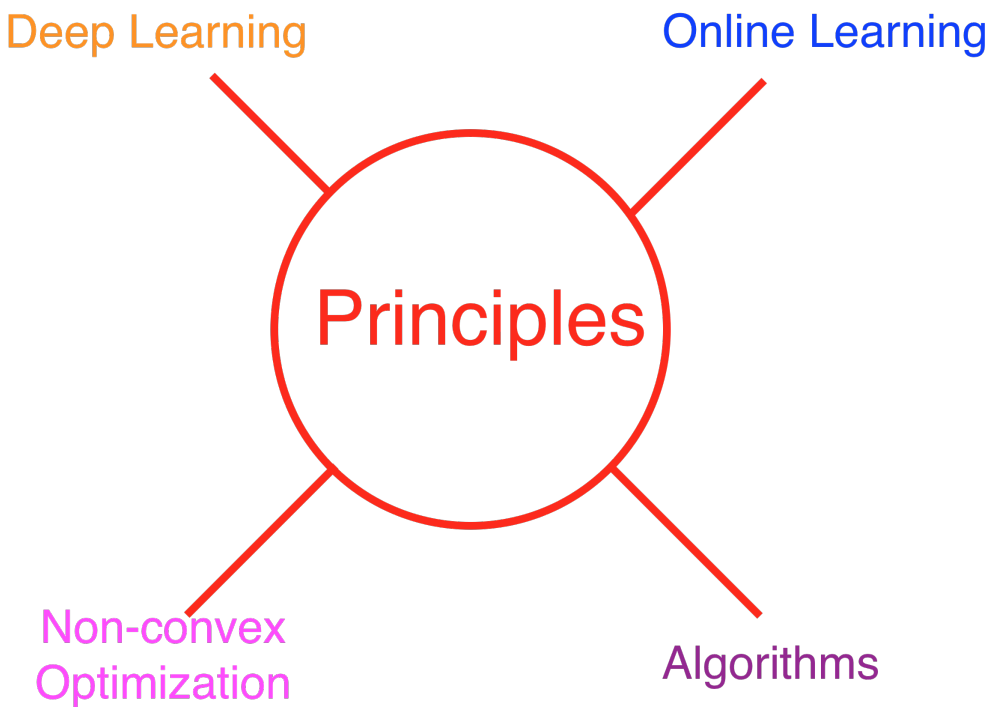

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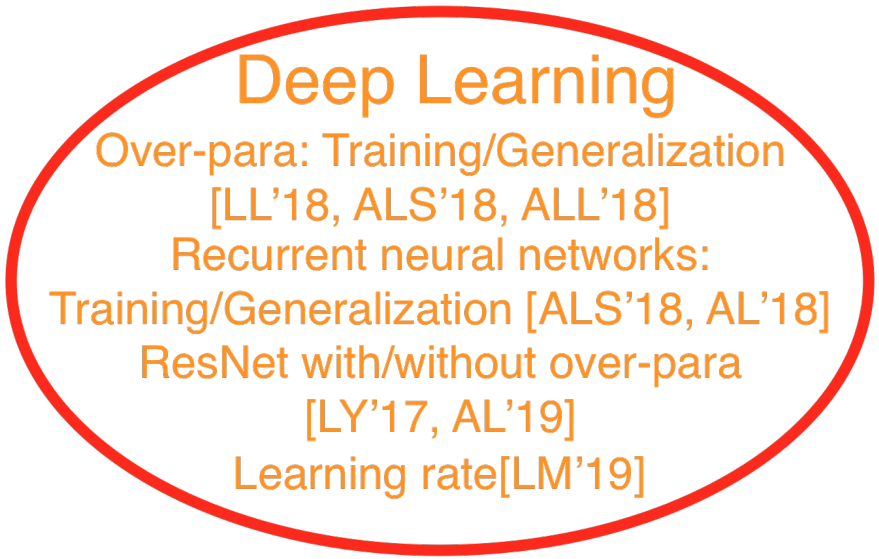
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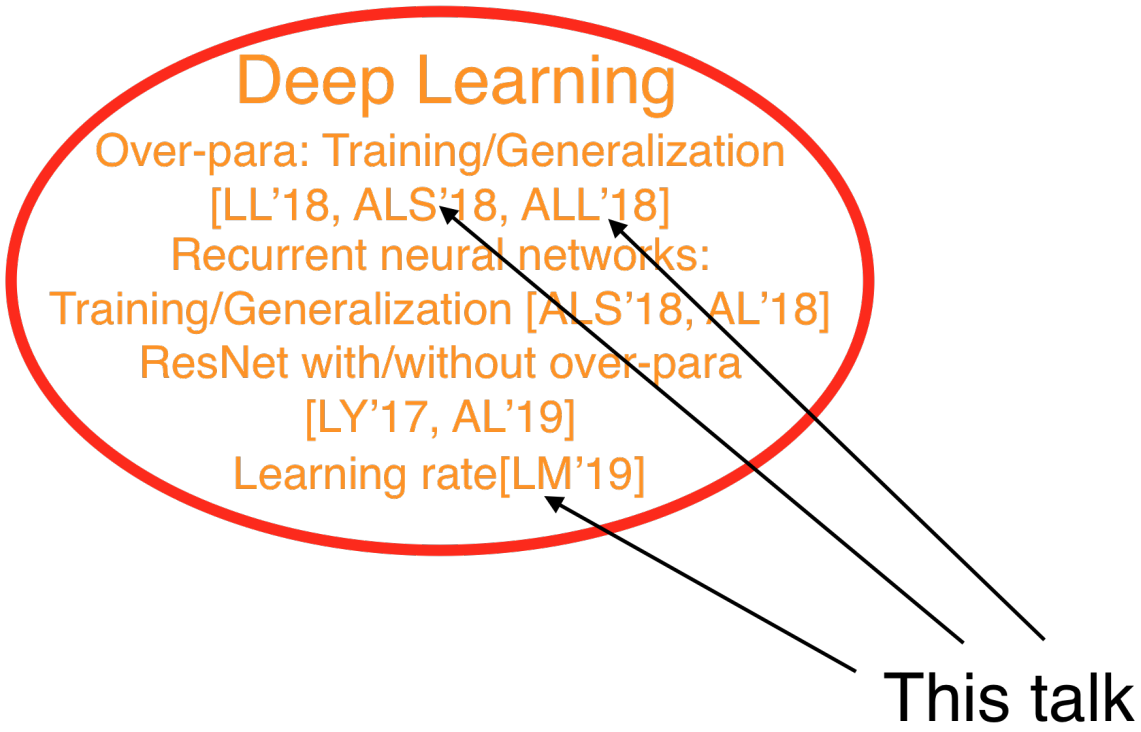
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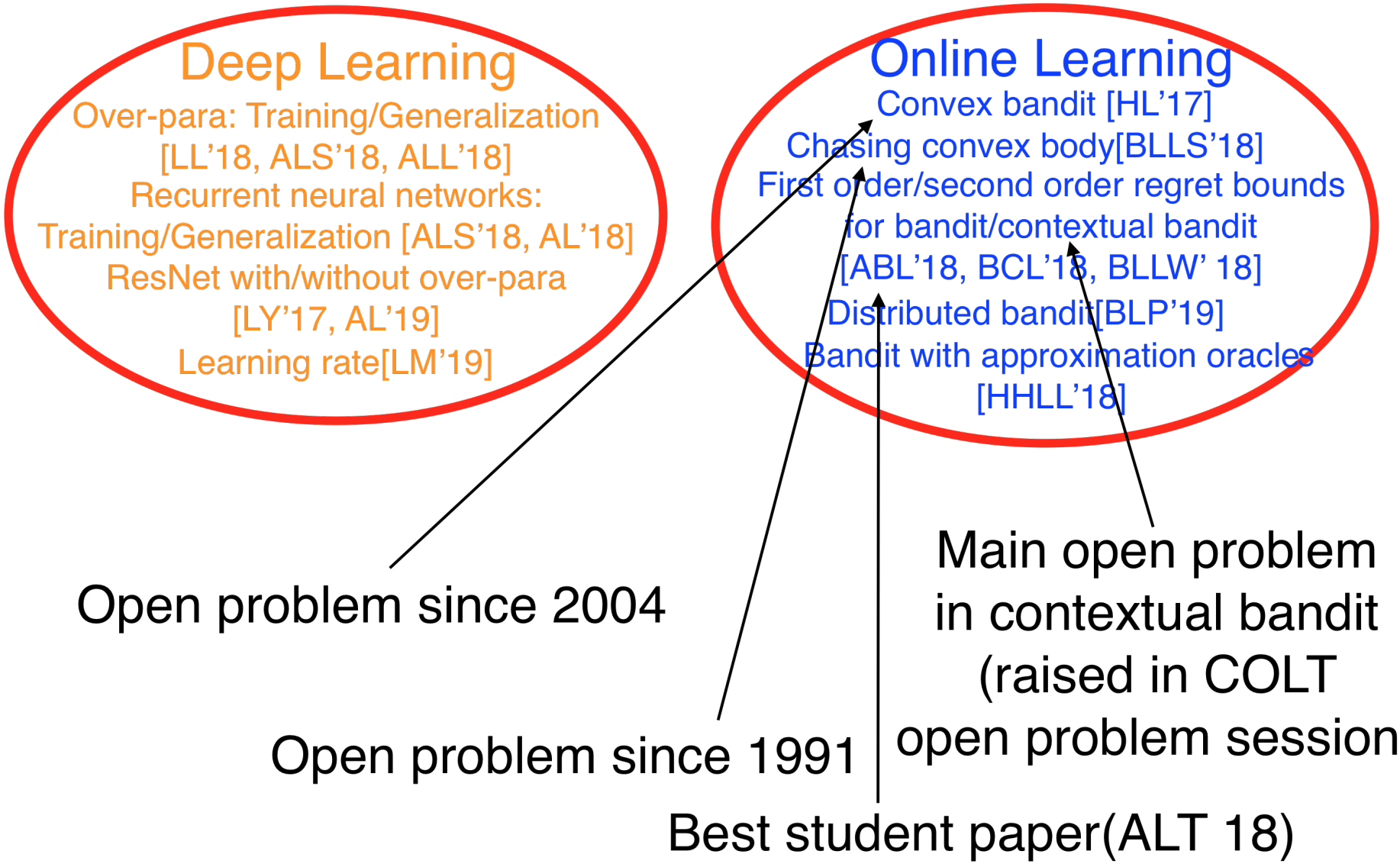
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Chasing convex body[BLLS'18]

First order/second order regret bounds for bandit/contextual bandit [ABL'18, BCL'18, BLLW' 18]

Distributed bandit[BLP'19]

Bandit with approximation oracles [HHLL'18]

## Non-convex opt.

Topic model/Matrix completion

Matrix sensing/Tensor decomposition [LL'17, LLR'16, LLR'16, LMZ'18, LZ'19]

Mixture of regressions [LL'18]

Graphical Models [LR'17]

Escaping saddle points/approximate convex optimization[AL'18, LR'16]

Experiments design[ALW'17]

With practical improvements

Best paper(COLT 18)

# In each area

## Deep Learning

Over-para: Training/Generalization [LL'18, ALS'18, ALL'18]

Recurrent neural networks: Training/Generalization [ALS'18, AL'18]

ResNet with/without over-para [LY'17, AL'19]

Learning rate[LM'19]

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## Algorithms

SVD(PCA), CCA, PCR, Online PCA [AL'17(abcd)]

Smoothed analysis[LS'18(ab)]

Higher order acceleration/Distributed Convex optimization[BJLLS'19(ab)]

Matrix/Operator Scaling/Orbit Closure Testing[ALOW'17, AGLOW'18]

Lp regression[BCLL'18]

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One step towards derandomizing PIT (complexity)

## Non-convex opt.

Topic model/Matrix completion

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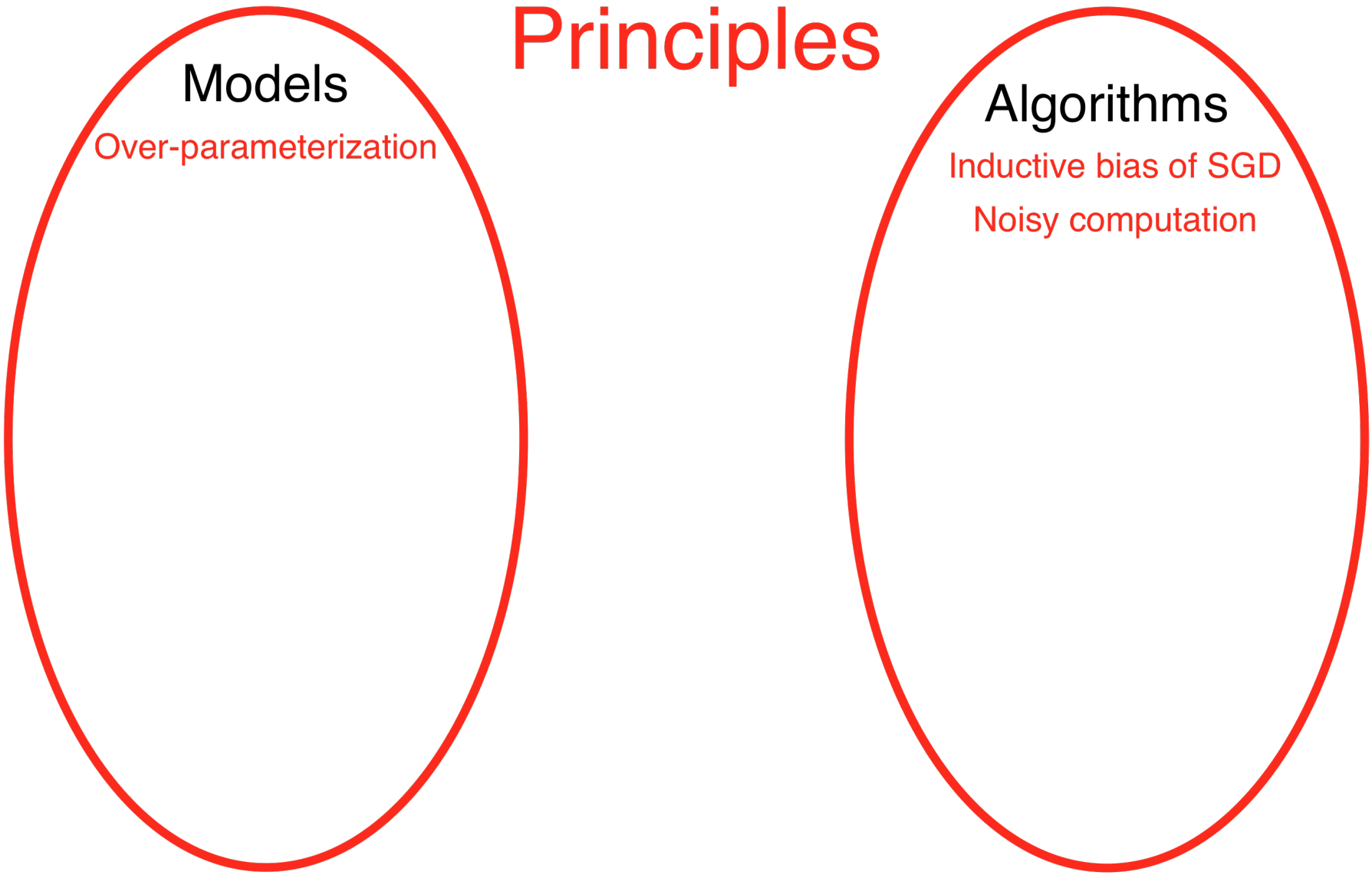
# Connected by principles



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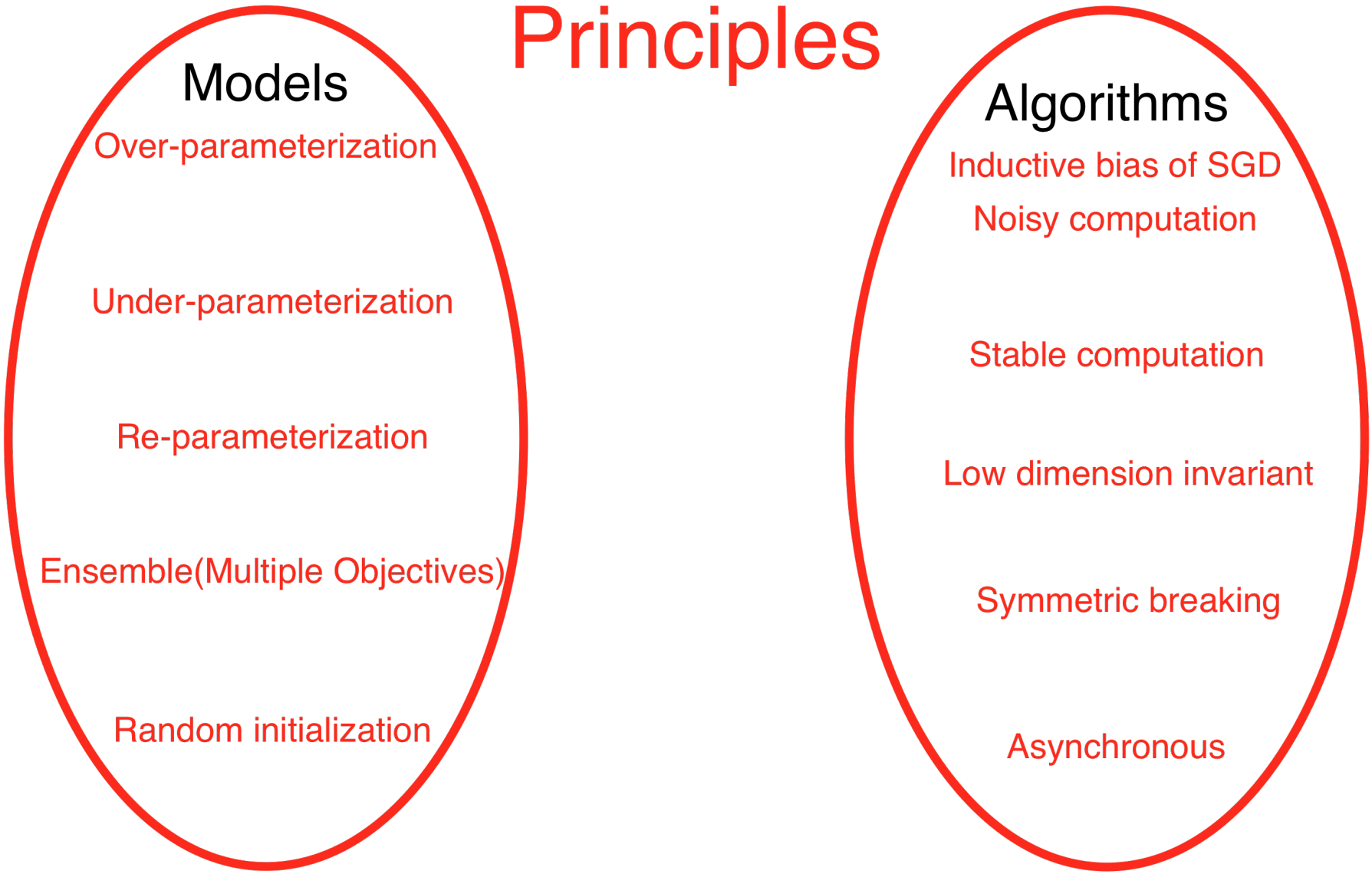

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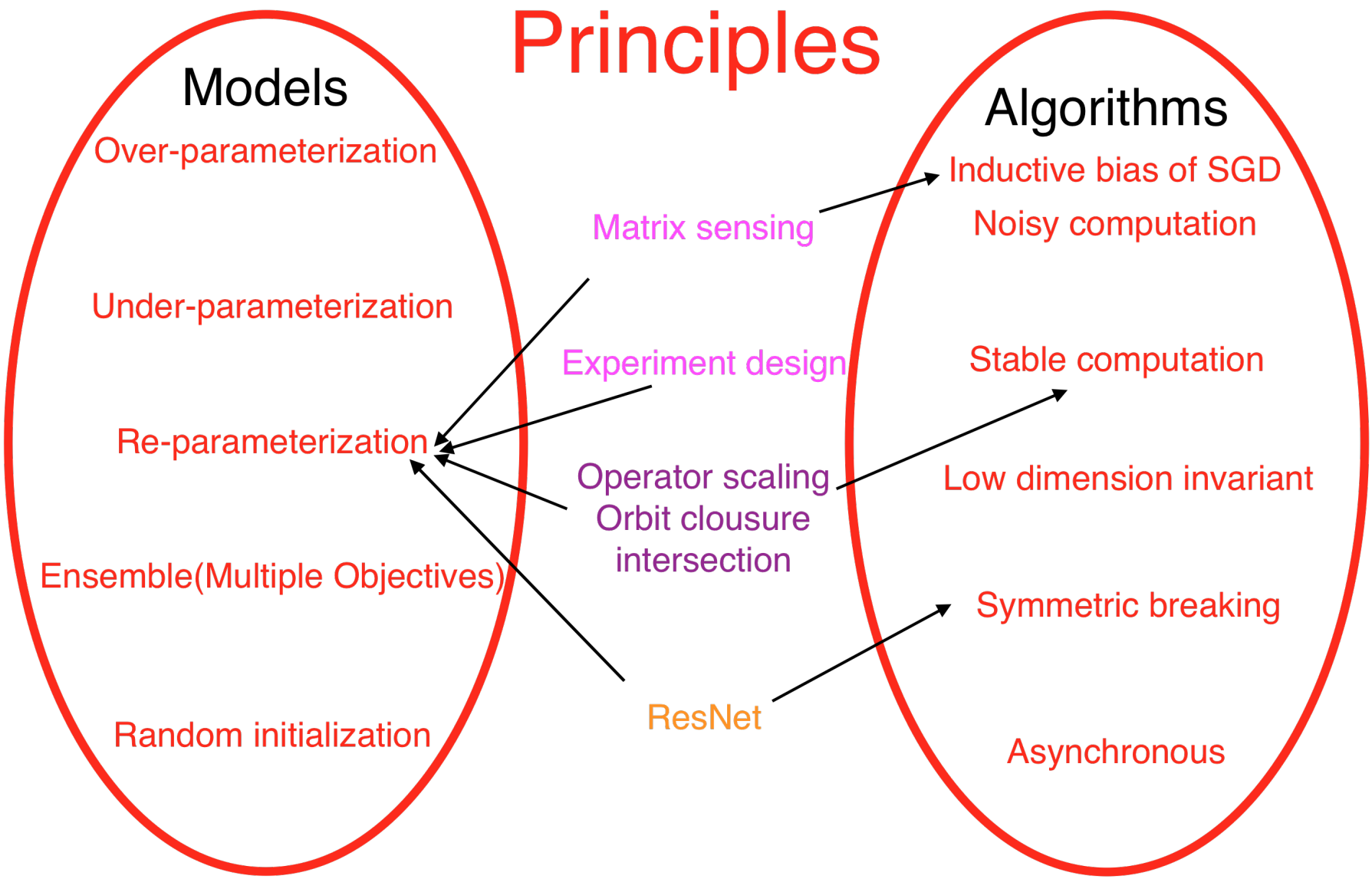

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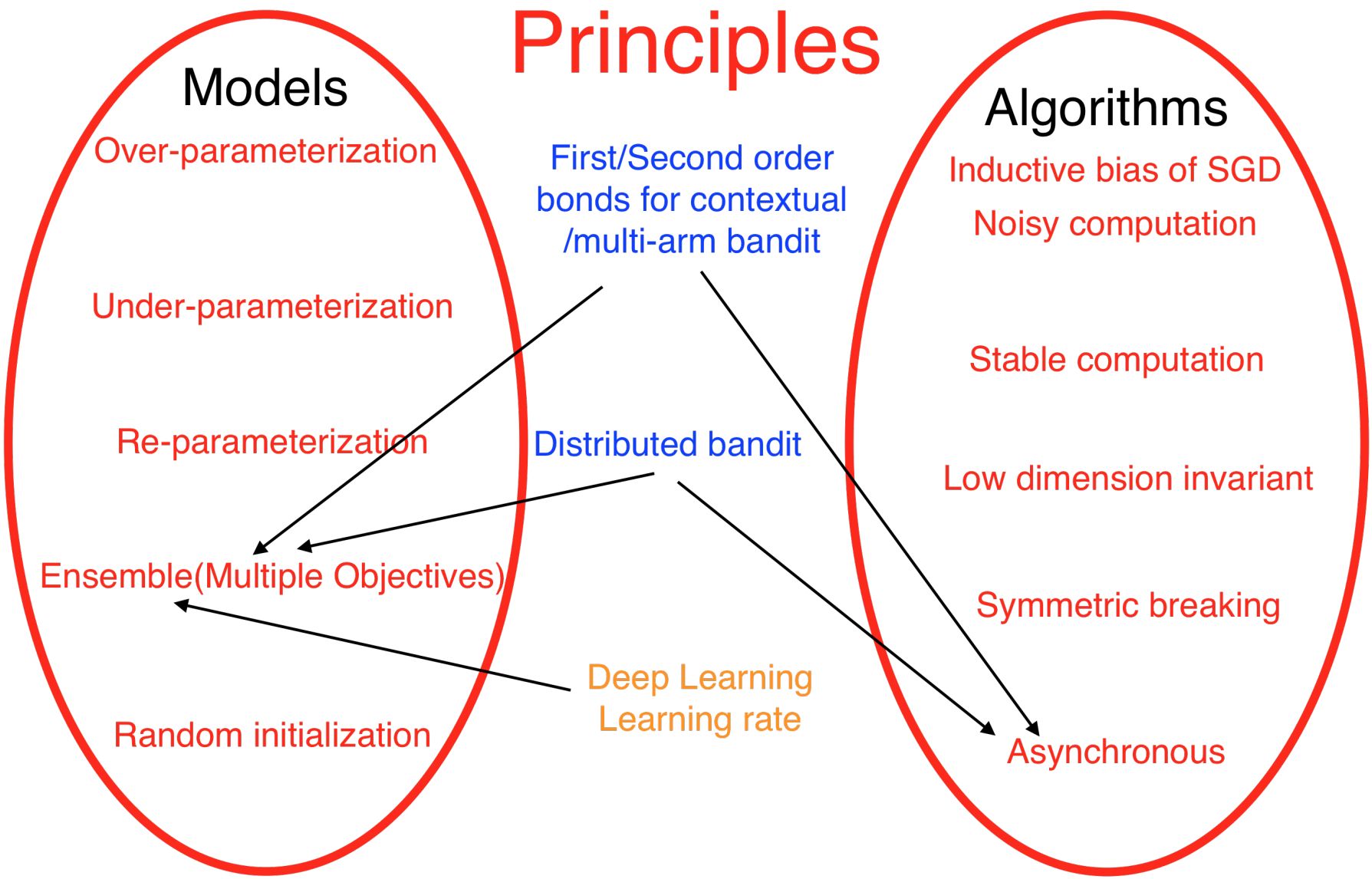

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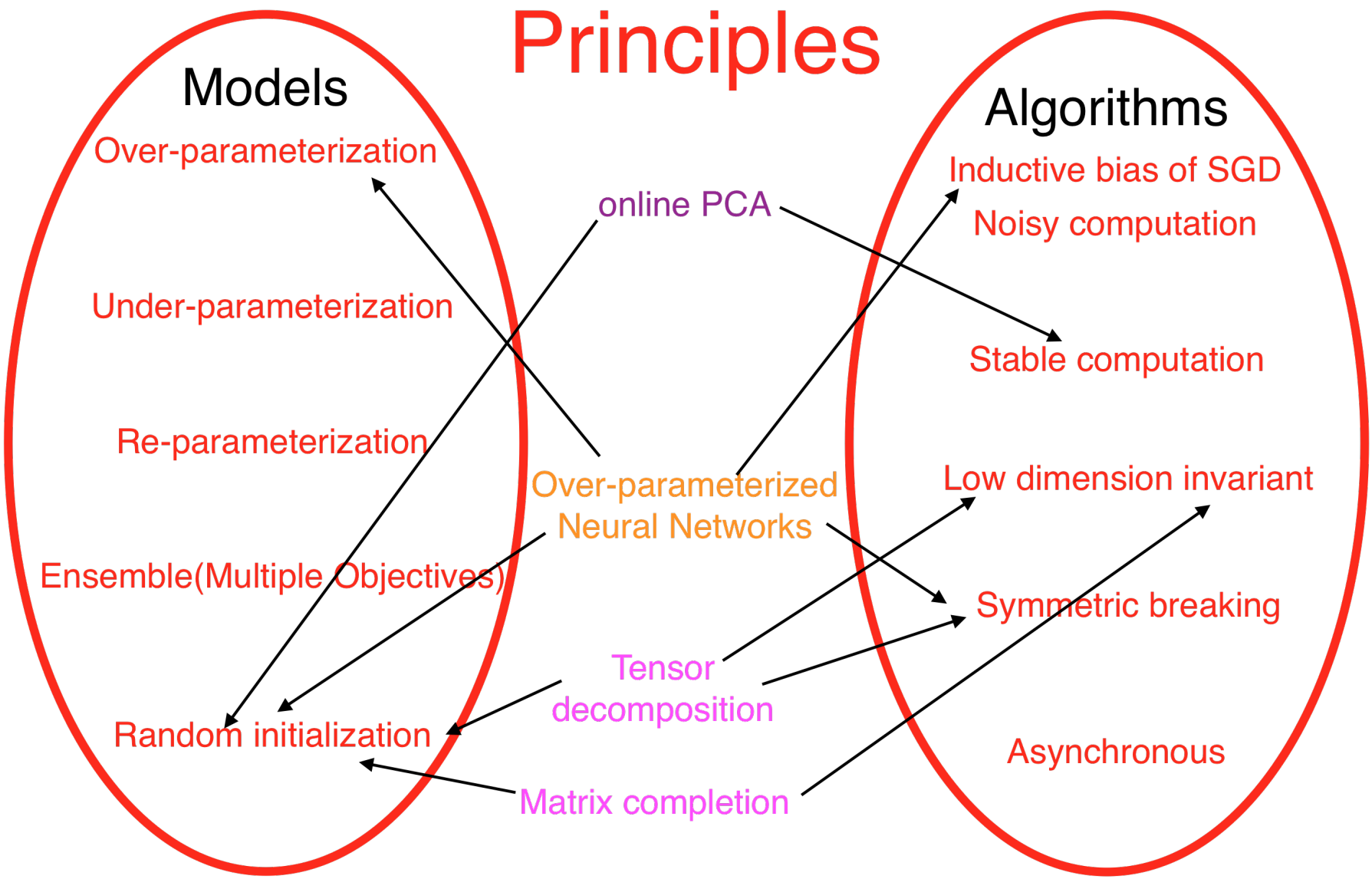

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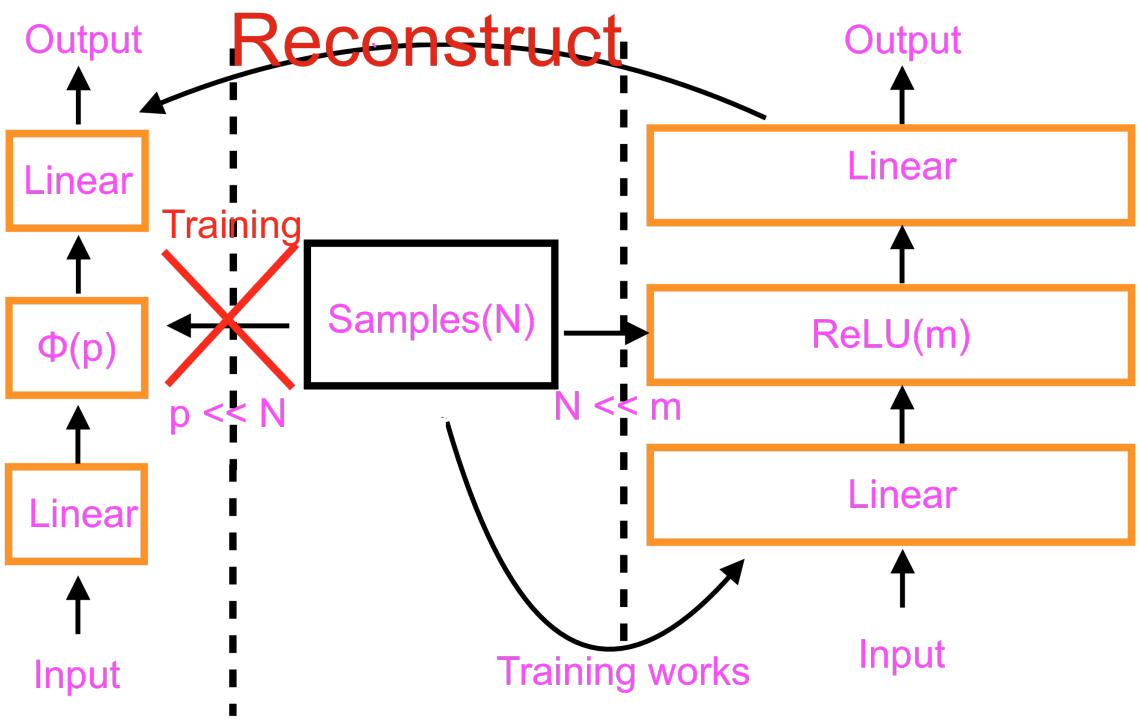

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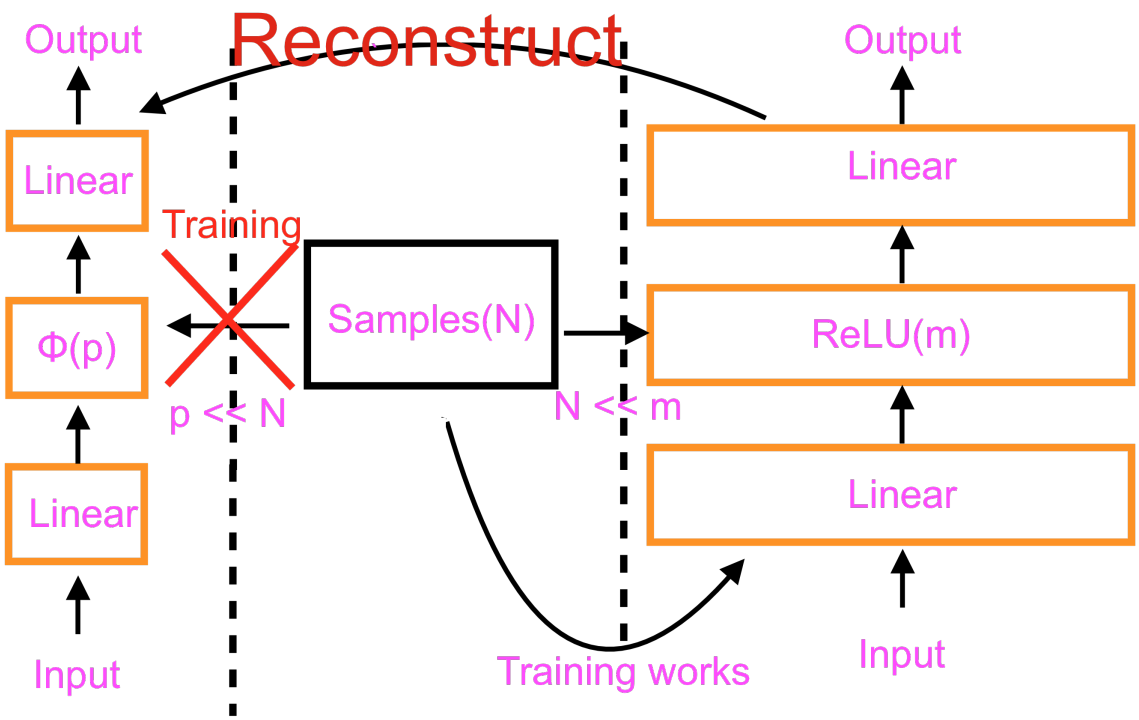


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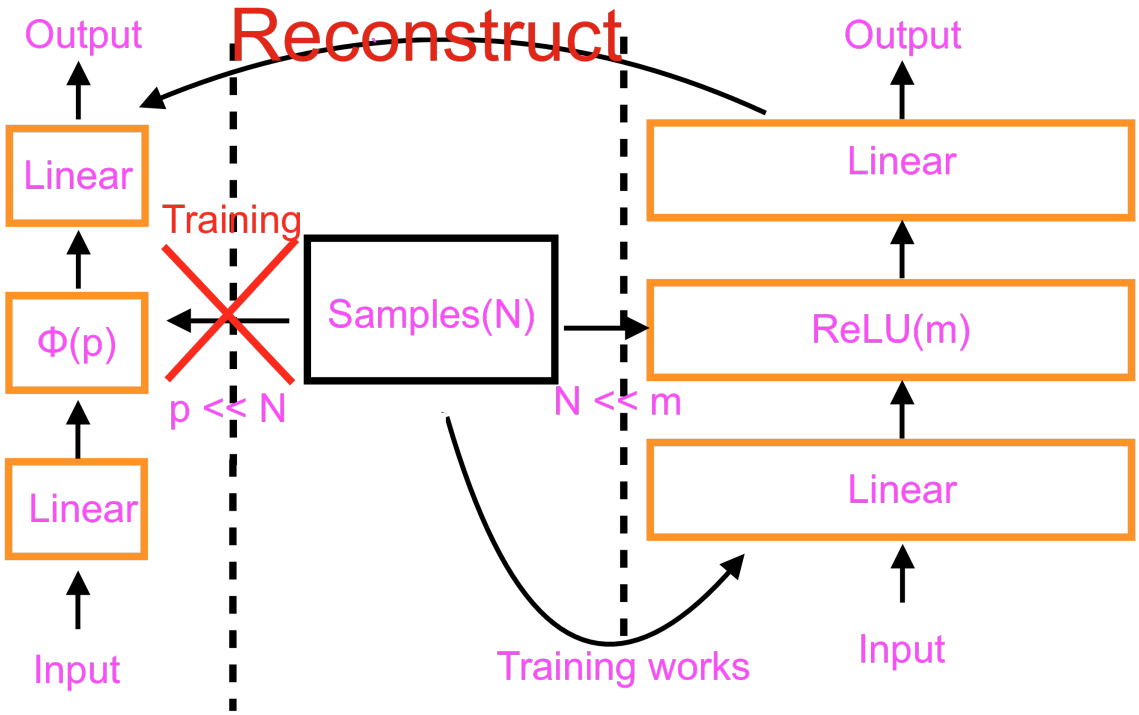


- Deep learning: incorporate noise in a more controllable way. (SVRG + noise?)
- Much more exciting directions.

# Yelp: Local Food & Services

Restaurant & Delivery Finder

4.1 ★★★★☆
4.42K Ratings

#10
Travel

12+
Age

## What's New

Version History

Version 12.27.0 — 2d ago

We apologize to anyone who had problems with the app this week. We trained a neural net to eliminate all the bugs in the app and it deleted everything. We had to roll everything back. To be fair, we were 100% bug-free... briefly.