

# Intro to ML and Language models

Radoslav Neychev

Spring 2021

### Outline

- 1. Introduction to Machine Learning, motivation
- 2. ML thesaurus and notation
- 3. RNN intuitions
- 4. Language models
- 5. Q&A

Motivation, historical overview and

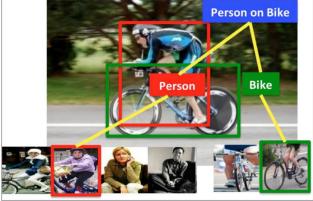
current state of ML and Al

# Machine Learning applications



- Object detection
- Action classification
- Image captioning
- ...





# Machine Learning applications

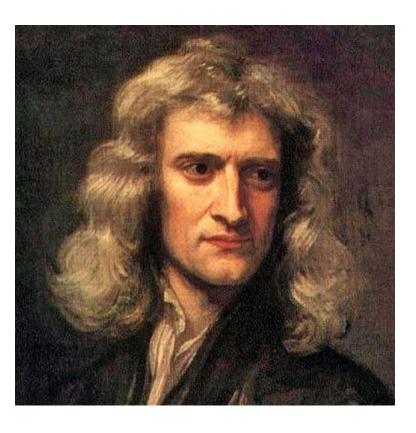


# Machine Learning applications



# Data — Knowledge

# Long before the ML

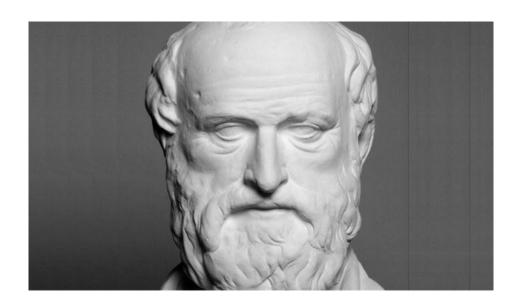


Isaac Newton



Johannes Kepler

# Long before the ML



Eratosthenes

**FALSE** 

### Denote the dataset.

23

Some

student

Dellote	Denote the <b>dataset.</b>										
		Statistics	Python		Native		Target				
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(passed)				
John	22	2 5	4	Brown	English	5	TRUE				
Aahna	17	4	5	Brown	Hindi	4	TRUE				
Emily	25	5	5	Blue	Chinese	5	TRUE				
Michael	27	3	4	Green	French	5	TRUE				

3 NA

Esperanto

**FALSE** 

Observation (or datum, or data point) is one piece of information.

		Statistics	Python		Native		larget
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
Some							

student 23 3 NA Esperanto 2 In many cases the observations are supposed to be *i.i.d.* 

- independent
- identically distributed

4

5

5

**TRUE** 

**TRUE** 

TRUE

**TRUE** 

**FALSE** 

Fostura (or predictor) represents some special property

reature	or bi	redictor) r	epreser	its some	e speciai p	property.	
		Statistics	Python		Native		T
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(r
John	22	5	4	Brown	English	5	

4

5

3

3

Aahna

**Emily** 

Some

Michael

student

17

25

27

23

	1 - 1 -				[ ]	<u> </u>	
		Statistics	Python		Native		Target
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(passed)

5 Brown

4 Green

5 Blue

3 NA

Hindi

Chinese

French

Esperanto

These all are features

		Statistics	Python		Native		larget
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
Some							
student	23	3	3	NA	Esperanto	2	FALSE

**FALSE** 

### These all are features

23

Some

student

illese a	These all are realures										
		Statistics	Python		Native		Target				
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(passed)				
John	22	5	. 4	Brown	English	5	TRUE				
Aahna	17	4	5	Brown	Hindi	4	TRUE				
Emily	25	5	5	Blue	Chinese	5	TRUE				
N 4 1 1	0.7					_	TDUE				

ivame	Age	(mark)	(mark)	Eye color	language	rarget (mark)	(passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE

3 NA

3

Esperanto

**FALSE** 

23

3

Some

student

These all are features										
		Statistics	Python		Native		Target			
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(passed)			
John	22	2 5	4	Brown	English	5	TRUE			
Aahna	17	4	5	Brown	Hindi	4	TRUE			
Emily	25	5	5	Blue	Chinese	5	TRUE			
Michael	27	3	4	Green	French	5	TRUE			

3 NA

Esperanto

**FALSE** 

These all are features									
		Statistics	Python		Native		Target		
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(passed)		
John	22	5	4	Brown	English	5	TRUE		
Aahna	17	4	5	Brown	Hindi	4	TRUE		
Emily	25	5	5	Blue	Chinese	5	TRUE		
Michael	27	3	4	Green	French	5	TRUE		

3 NA

Esperanto

Name	Age	(mark)
John	22	
Achno	17	

23

3

Some

student

### And even the name is a *feature*

		Statistics	Python		Native		Target
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
Some							
student	23	3	3	NA	Esperanto	2	FALSE

(despite it might be not informative)

**FALSE** 

The *design matrix* contains all the features and observations. Statistics Dython Mativa Taract

		Statistics	r yulon		INALIVE		iaiyet
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE

Esperanto

3 NA

Some

student

23

3

Features can even be multidimensional, we will discuss it later in this course.

**FALSE** 

Target represents the information we are interested in.

		Statistics	Python		inative		rarget
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
Some							

3 NA

Esperanto

Target can be either a **number** (real, integer, etc.) – for **regression** problem

23

*Target* represents the information we are interested in.

		Statistics	Python		Native		Target
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(passed)
John	22	5	4	Brown	English	5	TRUE
Aahna	17	4	5	Brown	Hindi	4	TRUE
Emily	25	5	5	Blue	Chinese	5	TRUE
Michael	27	3	4	Green	French	5	TRUE
Some							
student	23	3	3	NA	Esperanto	2	FALSE

# Or a label – for classification problem

**Target** represents the information we are interested in.

	-						
		Statistics	Python		Native		T
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(
John	22	5	4	Brown	English	5	

5 Blue

3 NA

4 Green

Mark can be treated as a label too (due to finite number of labels:

17 Aahna 5 Brown

5

3

3

25

27

23

1 to 5). We will discuss it later.

**Emily** 

Some

Michael

student

Esperanto

Hindi

Chinese

French

Target (passed)

5

5

TRUE

TRUE

**TRUE** 

**TRUE** 

**FALSE** 

Further we will work with the numerical target (mark)

		Statistics	Python		Native	
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)
John	22	5	4	Brown	English	5
Aahna	17	4	5	Brown	Hindi	4
Emily	25	5	5	Blue	Chinese	5
Michael	27	3	4	Green	French	5
Some student	23	3	3	NA	Esperanto	2

The *prediction* contains values we predicted using some *model*.

Statistics Bython Native Predicted

		Statistics	Python		inative		riedicted
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(mark)
John	22	5	4	Brown	English	5	4.5
Aahna	17	4	5	Brown	Hindi	4	4.5

 Aahna
 17
 4
 5 Brown
 Hindi
 4
 4.5

 Emily
 25
 5
 5 Blue
 Chinese
 5
 5

 Michael
 27
 3
 4 Green
 French
 5
 3.5

Some student 23 3 NA Esperanto 2 3

One could notice that prediction just averages of Statistics and Python marks. So our **model** can be represented as follows:

The *prediction* contains values we predicted using some *model*. Predicted Statistics Python **Native** 

Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(mark)
John	22	5	4	Brown	English	5	4.5

Aanna	17	4	5	Brown	Hindi	4	4.5
Emily	25	5	5	Blue	Chinese	5	5
Michael	27	3	4	Green	French	5	3.5

Emily	25	5	5	Blue	Chinese	5	5
Michael	27	3	4	Green	French	5	3.5
Some							
student	23	3	3	NA	Esperanto	2	3

 $\operatorname{mark}_{ML} = \frac{1}{2} \operatorname{mark}_{Statistics} + \frac{1}{2} \operatorname{mark}_{Python}$ 

Different models can provide different predictions:

5

5

3

The *prediction* contains values we predicted using some *model*. Pradictad Mativo Ctatiation Dython

		Statistics	Python		ivalive		i icalcica
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(mark)
John	22		4	Brown	English	5	1
Aahna	17	4	5	Brown	Hindi	4	5

5 Blue

 $\operatorname{mark}_{ML} = \operatorname{random}(\operatorname{integer from} [1; 5])$ 

Michael 27 4 Green French Some 23 student 3 NA **Esperanto** 

Different models can provide different predictions:

5

25

**Emily** 

Chinese

5

4

3

The *prediction* contains values we predicted using some *model*.

		Statistics	Python		Native		Predicted
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(mark)
John	22	5	4	Brown	English	5	1
Aahna	17	4	5	Brown	Hindi	4	5
Emily	25	5	5	Blue	Chinese	5	2
							_

4 Green

French

23 3 NA **Esperanto** Different models can provide different predictions.

3

3

Michael

student

Some

27

Usually some hypothesis lies beneath the model choice.

### Loss function measures the error rate of our model.

Square		Predicted
Square deviation	Target (mark)	(mark)
16	5	1
1	4	5
9	5	2
1	5	4
4	0	2
1	2	3

• **Mean Squared Error** (where y is vector of targets):

$$MSE(\mathbf{y}, \mathbf{\hat{y}}) = \frac{1}{N} ||\mathbf{y} - \mathbf{\hat{y}}||_2^2 = \frac{1}{N} \sum_i (y_i - \hat{y}_i)^2$$

### Loss function measures the error rate of our model.

Absolute		Predicted
deviation	Target (mark)	(mark)
4	5	1
1	4	5
3	5	2
1	5	4
1	2	3

• *Mean Absolute Error* (where y is vector of targets):

$$MAE(\mathbf{y}, \hat{\mathbf{y}}) = \frac{1}{N} ||\mathbf{y} - \hat{\mathbf{y}}||_1 = \frac{1}{N} \sum_{i} |y_i - \hat{y}_i|$$

5

5

5

3.5

3

To learn something, our *model* needs some degrees of freedom:

		Statistics	Python		Native		Predicted
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(mark)
John	22	5	4	Brown	English	5	4.5

5 Brown

5 Blue

27 Michael 4 Green French Some 23 3 student

 $\operatorname{mark}_{ML} = w_1 \cdot \operatorname{mark}_{Statistics} + w_2 \cdot \operatorname{mark}_{Python}$ 

5

Aahna

**Emily** 

17

25

Esperanto 3 NA

Chinese

4.5 Hindi 4

4

5

5

2

4.734

5.101

3.714

3.060

To learn something, our *model* needs some degrees of freedom:

				<del>_</del>			
		Statistics	Python		Native		Predicted
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(mark)
John	22	5	4	Brown	English	5	4.447

5 Brown

5 Blue

Hindi

Chinese

Michael 27 3 4 Green French
Some
student 23 3 NA Esperanto

 $\operatorname{mark}_{ML} = w_1 \cdot \operatorname{mark}_{Statistics} + w_2 \cdot \operatorname{mark}_{Python}$ 

5

Aahna

**Emily** 

17

25

4

5

5

5

4

3

To learn something, our *model* needs some degrees of freedom:

		Statistics	Python		Native		Predicted
Name	Age	(mark)	(mark)	Eye color	language	Target (mark)	(mark)
John	22	5	4	Brown	English	5	1

5 Brown

**Emily** 25 5 5 Blue Chinese 27 Michael 4 Green French Some

3

17

23

Aahna

student

$$25$$
  $3$   $4$  Green French
 $23$   $3$  NA Esperanto
 $23\hat{k}_{ML} = \mathrm{random}(\mathrm{integer\ from\ [1;\ 5]})$ 

Hindi

Last term we should learn for now is hyperparameter.

*Hyperparameter* should be fixed before our model starts to work with the data.

We will discuss it later with kNN as an example.

# ML thesaurus Recap: Dataset Observation (datum) Feature Design matrix Target Prediction Model Loss function Parameter Hyperparameter

Language generation

### RNNs generating...

#### Shakespeare

#### PANDARUS:

Alas, I think he shall be come approached and the day When little srain would be attain'd into being never fed, And who is but a chain and subjects of his death, I should not sleep.

#### Second Senator:

They are away this miseries, produced upon my soul, Breaking and strongly should be buried, when I perish The earth and thoughts of many states.

#### DUKE VINCENTIO:

Well, your wit is in the care of side and that.

#### Second Lord:

They would be ruled after this chamber, and my fair nues begun out of the fact, to be conveyed, Whose noble souls I'll have the heart of the wars.

#### Clown:

Come, sir, I will make did behold your worship.

#### VIOLA:

I'll drink it.

# Algebraic Geometry (Latex)

```
Proof. Omitted.
Lemma 0.1. Let C be a set of the construction.
   Let C be a gerber covering. Let F be a quasi-coherent sheaves of O-modules. We
have to show that
                                   \mathcal{O}_{\mathcal{O}_{x}} = \mathcal{O}_{X}(\mathcal{L})
Proof. This is an algebraic space with the composition of sheaves \mathcal{F} on X_{Oute} we
have
                          O_X(F) = \{morph_1 \times_{O_X} (G, F)\}
where G defines an isomorphism F \to F of O-modules.
Lemma 0.2. This is an integer Z is injective.
Proof. See Spaces, Lemma ??.
Lemma 0.3. Let S be a scheme. Let X be a scheme and X is an affine open
covering. Let U \subset X be a canonical and locally of finite type. Let X be a scheme.
Let X be a scheme which is equal to the formal complex.
The following to the construction of the lemma follows.
Let X be a scheme. Let X be a scheme covering. Let
                      b: X \rightarrow Y' \rightarrow Y \rightarrow Y \rightarrow Y' \times_X Y \rightarrow X.
be a morphism of algebraic spaces over S and Y.
Proof. Let X be a nonzero scheme of X. Let X be an algebraic space. Let F be a
quasi-coherent sheaf of O_X-modules. The following are equivalent

 F is an algebraic space over S.

   (2) If X is an affine open covering.
Consider a common structure on X and X the functor O_X(U) which is locally of
finite type.
```

# Linux kernel (source code)

```
* If this error is set, we will need anything right after that BSD.
static void action new function(struct s stat info *wb)
 unsigned long flags;
 int lel idx bit = e->edd, *sys & -((unsigned long) *FIRST COMPAT);
 buf[0] = 0xFFFFFFFF & (bit << 4);
 min(inc, slist->bytes);
 printk(KERN WARNING "Memory allocated %02x/%02x, "
   "original MLL instead\n"),
   min(min(multi run - s->len, max) * num data in),
   frame pos, sz + first seg);
 div u64 w(val, inb p);
 spin unlock(&disk->queue lock);
 mutex unlock(&s->sock->mutex);
 mutex unlock(&func->mutex);
 return disassemble(info->pending bh);
```

Proof. Omitted.

**Lemma 0.1.** Let C be a set of the construction.

Let C be a gerber covering. Let F be a quasi-coherent sheaves of O-modules. We have to show that

$$\mathcal{O}_{\mathcal{O}_X} = \mathcal{O}_X(\mathcal{L})$$

Proof. This is an algebraic space with the composition of sheaves F on  $X_{\acute{e}tale}$  we have

$$\mathcal{O}_X(\mathcal{F}) = \{morph_1 \times_{\mathcal{O}_X} (\mathcal{G}, \mathcal{F})\}$$

where G defines an isomorphism  $F \to F$  of O-modules.

**Lemma 0.2.** This is an integer Z is injective.

Proof. See Spaces, Lemma ??.

**Lemma 0.3.** Let S be a scheme. Let X be a scheme and X is an affine open covering. Let  $U \subset X$  be a canonical and locally of finite type. Let X be a scheme. Let X be a scheme which is equal to the formal complex.

The following to the construction of the lemma follows.

Let X be a scheme. Let X be a scheme covering. Let

$$b: X \to Y' \to Y \to Y \to Y' \times_X Y \to X$$
.

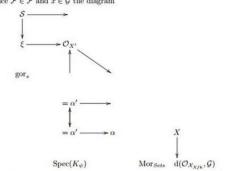
be a morphism of algebraic spaces over S and Y.

*Proof.* Let X be a nonzero scheme of X. Let X be an algebraic space. Let  $\mathcal{F}$  be a quasi-coherent sheaf of  $\mathcal{O}_X$ -modules. The following are equivalent

- F is an algebraic space over S.
- (2) If X is an affine open covering.

Consider a common structure on X and X the functor  $\mathcal{O}_X(U)$  which is locally of finite type.

This since  $F \in F$  and  $x \in G$  the diagram



is a limit. Then  $\mathcal G$  is a finite type and assume S is a flat and  $\mathcal F$  and  $\mathcal G$  is a finite type  $f_*$ . This is of finite type diagrams, and

- the composition of G is a regular sequence,
- O<sub>X'</sub> is a sheaf of rings.

Proof. We have see that  $X = \operatorname{Spec}(R)$  and  $\mathcal{F}$  is a finite type representable by algebraic space. The property  $\mathcal{F}$  is a finite morphism of algebraic stacks. Then the cohomology of X is an open neighbourhood of U.

Proof. This is clear that G is a finite presentation, see Lemmas ??. A reduced above we conclude that U is an open covering of C. The functor F is a "field

$$\mathcal{O}_{X,x} \longrightarrow \mathcal{F}_{\overline{x}} -1(\mathcal{O}_{X_{\ell tate}}) \longrightarrow \mathcal{O}_{X_{\ell}}^{-1}\mathcal{O}_{X_{\lambda}}(\mathcal{O}_{X_{\eta}}^{\overline{v}})$$

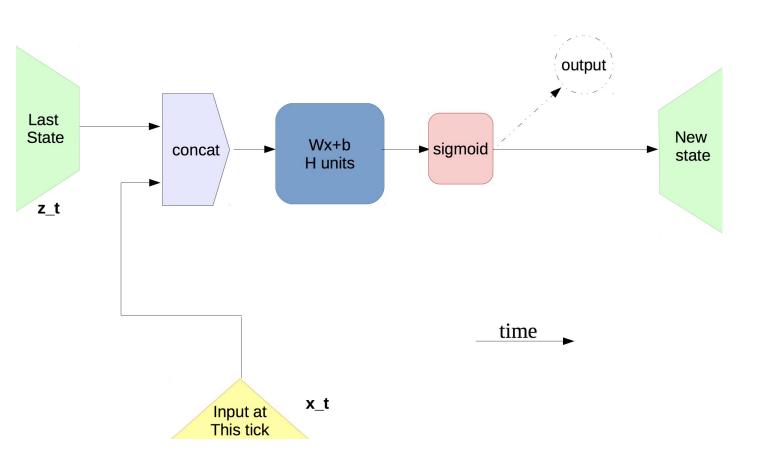
is an isomorphism of covering of  $\mathcal{O}_{X_i}$ . If  $\mathcal{F}$  is the unique element of  $\mathcal{F}$  such that X is an isomorphism.

The property  $\mathcal{F}$  is a disjoint union of Proposition ?? and we can filtered set of presentations of a scheme  $\mathcal{O}_{X}$ -algebra with  $\mathcal{F}$  are opens of finite type over S. If  $\mathcal{F}$  is a scheme theoretic image points.

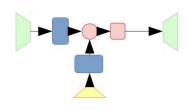
If  $\mathcal{F}$  is a finite direct sum  $\mathcal{O}_{X_{\lambda}}$  is a closed immersion, see Lemma ??. This is a sequence of  $\mathcal{F}$  is a similar morphism.

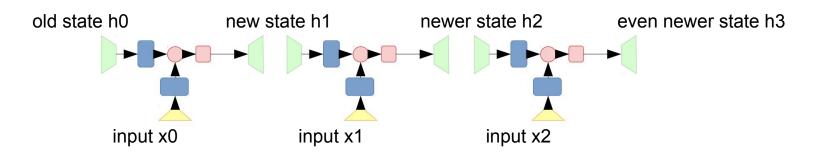
```
#include <asm/io.h>
#include <asm/prom.h>
#include <asm/e820.h>
#include <asm/system info.h>
#include <asm/setew.h>
#include <asm/pgproto.h>
#define REG_PG vesa slot addr pack
#define PFM NOCOMP AFSR(0, load)
#define STACK DDR(type)
                           (func)
#define SWAP_ALLOCATE(nr)
                             (e)
#define emulate sigs() arch get unaligned child()
#define access rw(TST) asm volatile("movd %%esp, %0, %3" :: "r" (0)); \
 if ( type & DO READ)
static void stat PC SEC read mostly offsetof(struct seq argsqueue, \
          pC>[1]);
static void
os prefix(unsigned long sys)
#ifdef CONFIG_PREEMPT
  PUT PARAM RAID(2, sel) = get state state();
  set pid sum((unsigned long)state, current state str(),
           (unsigned long)-1->lr full; low;
```

38

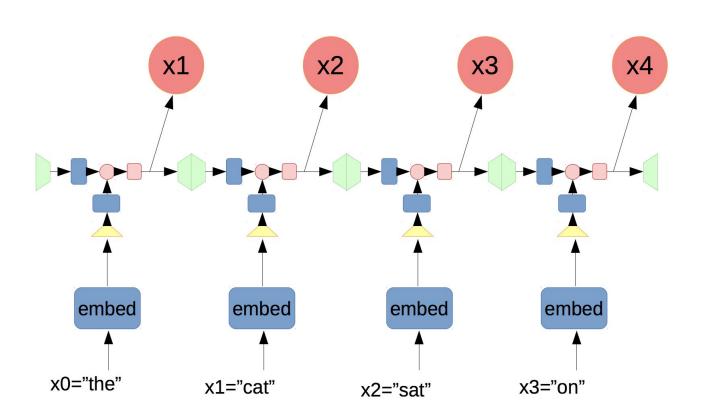


Recurrent Neural Networks intuition





We use same weight matrices for all steps



# Recurrent neural network: with formulas

$$h_{0} = \bar{0}$$

$$h_{1} = \sigma(\langle W_{\text{hid}}[h_{0}, x_{0}] \rangle + b)$$

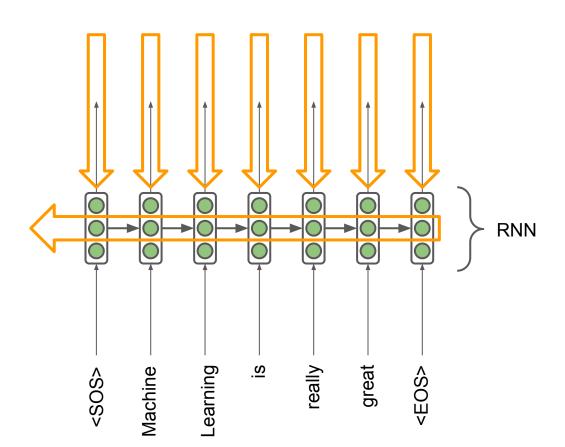
$$h_{2} = \sigma(\langle W_{\text{hid}}[h_{1}, x_{1}] \rangle + b) = \sigma(\langle W_{\text{hid}}[\sigma(\langle W_{\text{hid}}[h_{0}, x_{0}] \rangle + b, x_{1}] \rangle + b)$$

$$h_{i+1} = \sigma(\langle W_{\text{hid}}[h_{i}, x_{i}] \rangle + b)$$

$$P(x_{i+1}) = \operatorname{softmax}(\langle W_{\text{out}}, h_{i} \rangle + b_{\text{out}})$$

#### How to train it?

Loss (e.g. Negative log-likelihood)



### RNNs generating...

#### Shakespeare

#### PANDARUS:

Alas, I think he shall be come approached and the day When little srain would be attain'd into being never fed, And who is but a chain and subjects of his death, I should not sleep.

#### Second Senator:

They are away this miseries, produced upon my soul, Breaking and strongly should be buried, when I perish The earth and thoughts of many states.

#### DUKE VINCENTIO:

Well, your wit is in the care of side and that.

#### Second Lord:

They would be ruled after this chamber, and my fair nues begun out of the fact, to be conveyed, Whose noble souls I'll have the heart of the wars.

#### Clown:

Come, sir, I will make did behold your worship.

#### VIOLA:

I'll drink it.

# Algebraic Geometry (Latex)

```
Proof. Omitted.
Lemma 0.1. Let C be a set of the construction.
   Let C be a gerber covering. Let F be a quasi-coherent sheaves of O-modules. We
have to show that
                                   \mathcal{O}_{\mathcal{O}_{x}} = \mathcal{O}_{X}(\mathcal{L})
Proof. This is an algebraic space with the composition of sheaves \mathcal{F} on X_{Oute} we
have
                          O_X(F) = \{morph_1 \times_{O_X} (G, F)\}
where G defines an isomorphism F \to F of O-modules.
Lemma 0.2. This is an integer Z is injective.
Proof. See Spaces, Lemma ??.
Lemma 0.3. Let S be a scheme. Let X be a scheme and X is an affine open
covering. Let U \subset X be a canonical and locally of finite type. Let X be a scheme.
Let X be a scheme which is equal to the formal complex.
The following to the construction of the lemma follows.
Let X be a scheme. Let X be a scheme covering. Let
                      b: X \rightarrow Y' \rightarrow Y \rightarrow Y \rightarrow Y' \times_X Y \rightarrow X.
be a morphism of algebraic spaces over S and Y.
Proof. Let X be a nonzero scheme of X. Let X be an algebraic space. Let F be a
quasi-coherent sheaf of O_X-modules. The following are equivalent

 F is an algebraic space over S.

   (2) If X is an affine open covering.
Consider a common structure on X and X the functor O_X(U) which is locally of
finite type.
```

# Linux kernel (source code)

```
* If this error is set, we will need anything right after that BSD.
static void action new function(struct s stat info *wb)
 unsigned long flags;
 int lel idx bit = e->edd, *sys & -((unsigned long) *FIRST COMPAT);
 buf[0] = 0xFFFFFFFF & (bit << 4);
 min(inc, slist->bytes);
 printk(KERN WARNING "Memory allocated %02x/%02x, "
   "original MLL instead\n"),
   min(min(multi run - s->len, max) * num data in),
   frame pos, sz + first seg);
 div u64 w(val, inb p);
 spin unlock(&disk->queue lock);
 mutex unlock(&s->sock->mutex);
 mutex unlock(&func->mutex);
 return disassemble(info->pending bh);
```