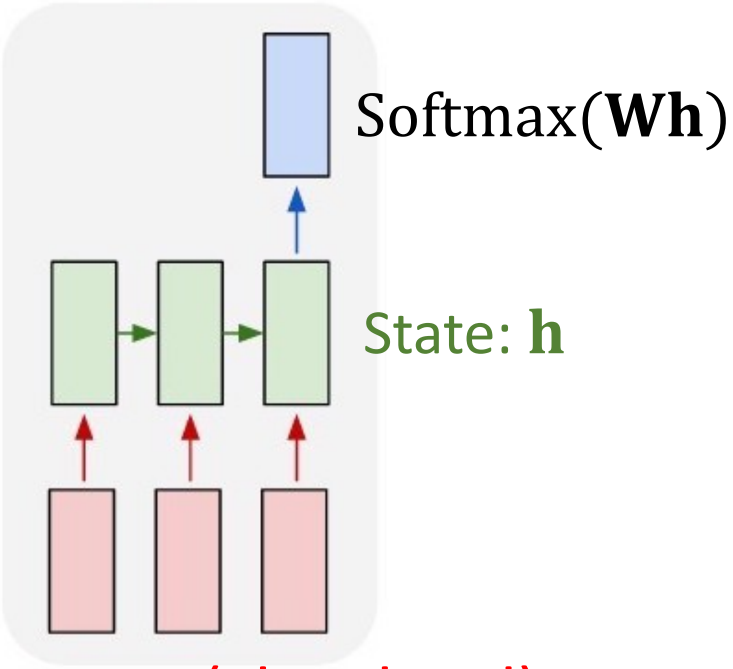
Main Idea

RNN for Text Prediction

Example

- Input text: “`the cat sat on the ma`”
- Question: what is the next char?

RNN for Text Prediction



sequence (char-level)

input text

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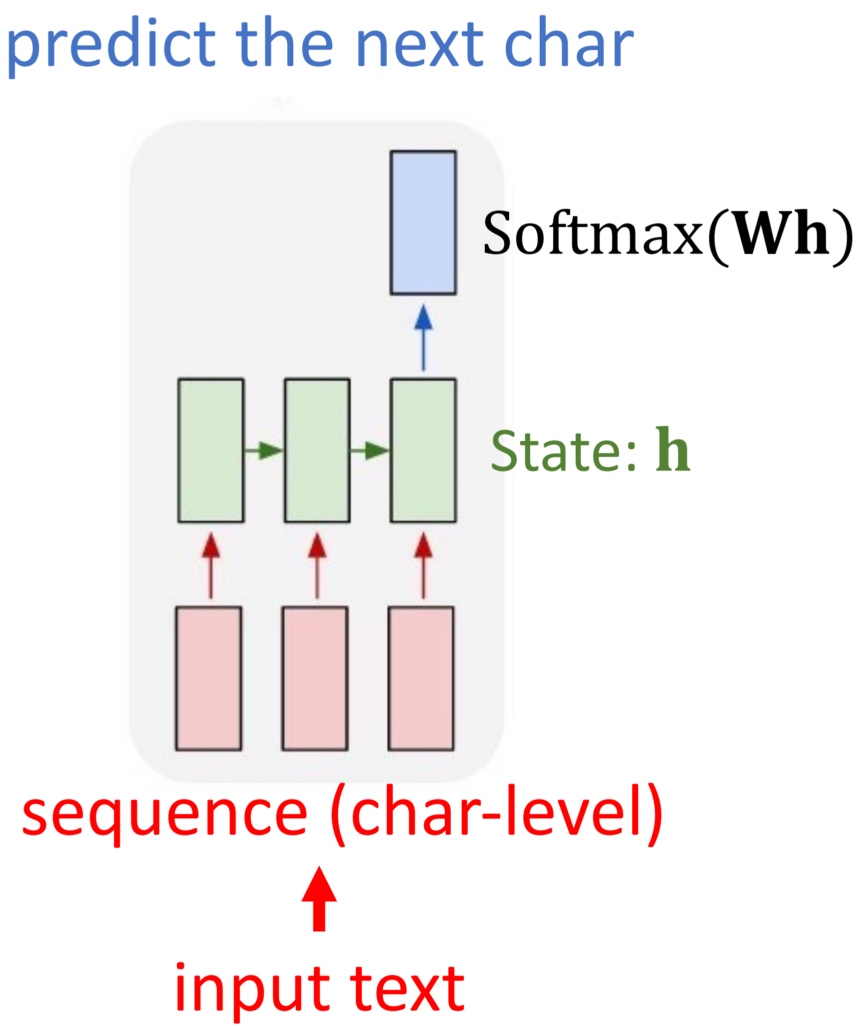
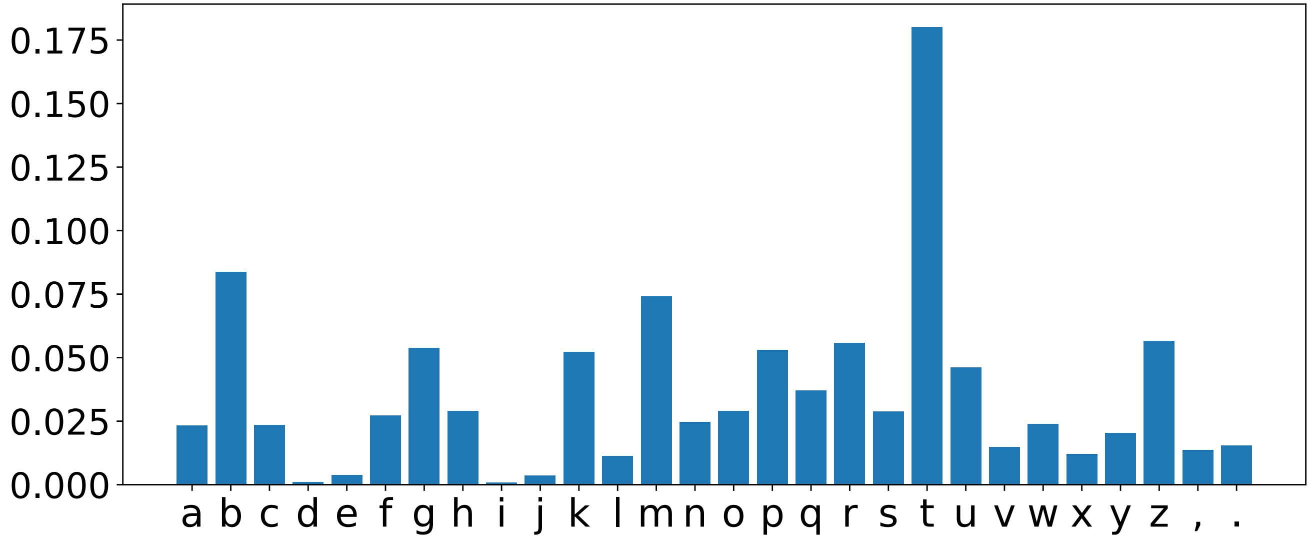
RNN for Text Prediction



Example

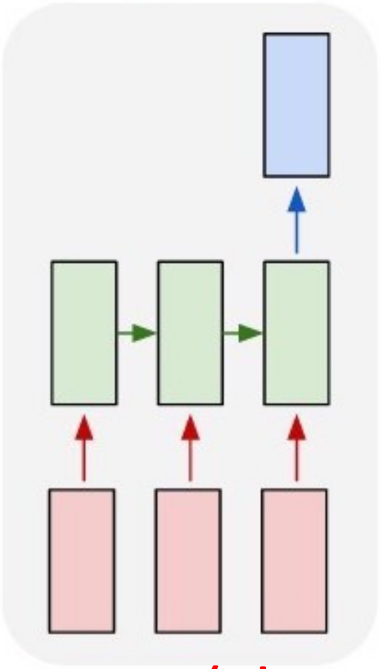
- Input text: "the cat sat on the ma"
- Question: what is the next char?

- RNN outputs a distribution over the chars.



RNN for Text Prediction

predict the next char



sequence (char-level)

input text

Example

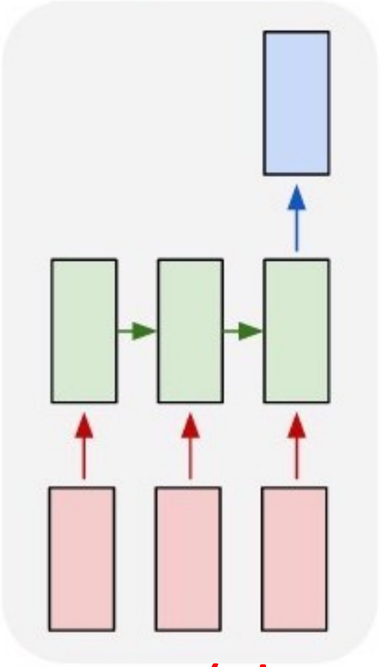
- Input text: "`the cat sat on the ma`"
- Question: what is the next char?

- RNN outputs a distribution over the chars.

- Sample a char from it; we may get '`t`'.
- Take "`the cat sat on the mat`" as input.
- Maybe the next char is period '`.`'.

Train an RNN for Text Prediction

predict the next char



sequence (char-level)

input text

How do we train such an RNN?

- Cut text to segments (with overlap).
  - E.g., `seg_len=40` and `stride=3`.

Machine learning is a subset of artificial intelligence in the field of computer science that often uses statistical techniques to give computers the ability to "learn" (i.e., progressively improve performance on a specific task) with data, without being explicitly programmed. The name machine learning was coined in 1959 by Arthur Samuel.

…

…

Train an RNN for Text Prediction

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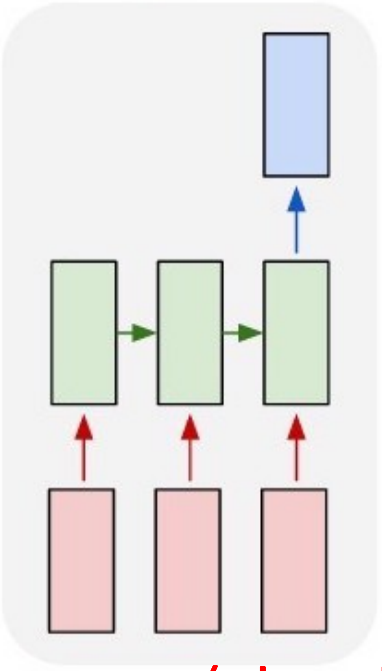

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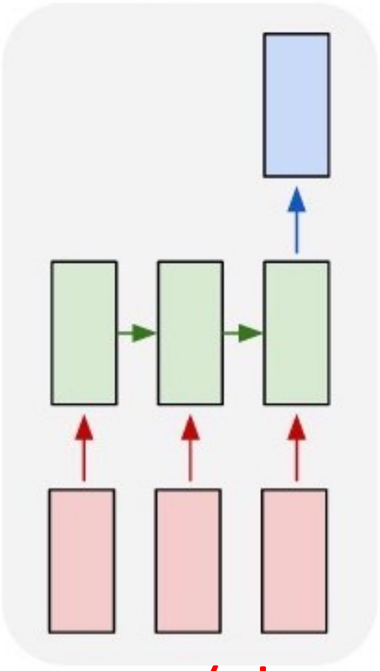

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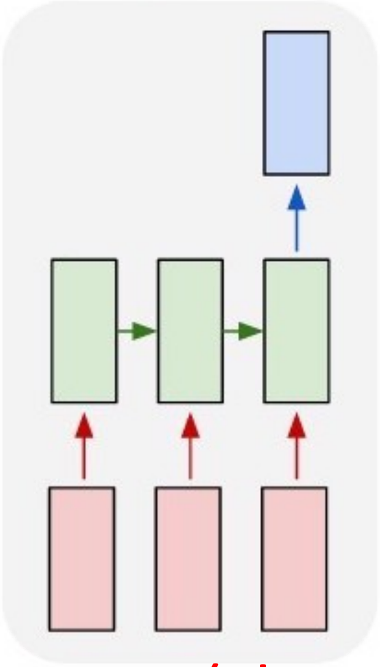

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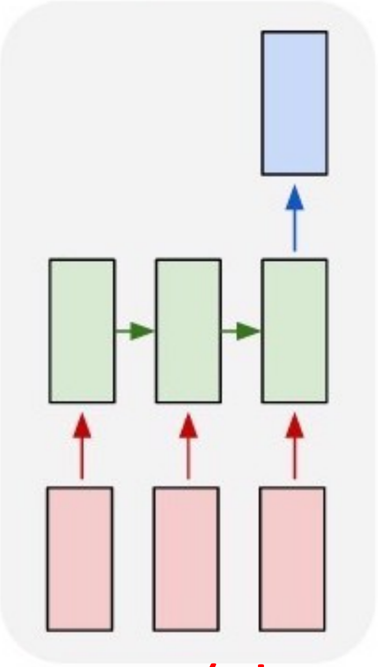

sequence (char-level)

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How do we train such an RNN?

- Cut text to segments (with overlap).
- A segment is used as input text.
- Its next char is used as label.
- Training data: `(segment, next_char)` pairs

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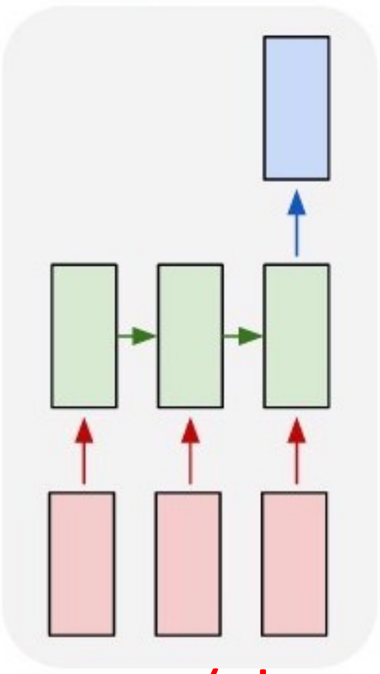

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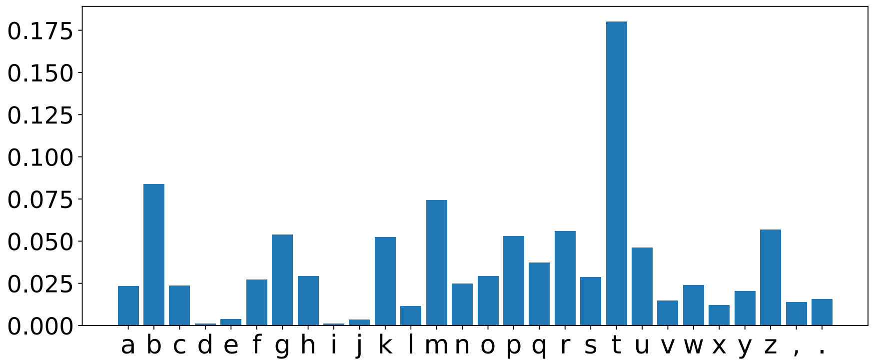
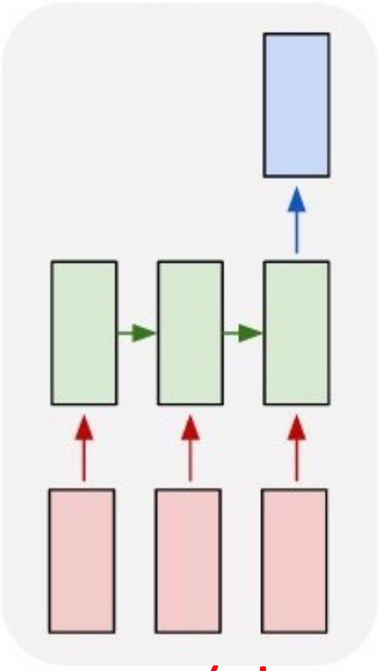
- It is a multi-class classification problem.
  - #class = #unique chars.



Train an RNN for Text Prediction

predict the next char



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If the RNN is trained on Shakespeare's books, then the generated text is Shakespeare's style.

Fun with Text Generation

Generate baby names (trained on 8000 baby names).

Rudi Levette Berice Lussa Hany Mareanne Chrestina Carissy Marylen Hammine Janye Marlise Jacacrie Hendred Romand Charienna Nenotto Ette Dorane Wallen Marly Darine Salina Elvyn Ersia Maralena Minoria Ellia Charmin Antley Nerille Chelon Walmor Evena Jeryly Stachon Charisa Allisa Anatha Cathanie Geetra Alexie Jerin Cassen Herbett Cossie Velen Daurenge Robester Shermond Terisa Licia Roselen Ferine Jayn Lusine Charyanne Sales Sanny Resa Wallon Martine Merus Jelen Candica Wallin Tel Rachene Tarine Ozila Ketia Shanne Arnande Karella Roselina Alessia Chasty Deland Berther Geamar Jackein Mellisand Sagdy Nenc Lessie Rasemy Guen Gavi Milea Anneda Margoris Janin Rodelin Zeanna Elyne Janah Ferzina Susta Pey Castina

Fun with Text Generation

Generate C code (trained on Linux source code).

```
/*
 * Increment the size file of the new incorrect UI_FILTER group information
 * of the size generatively.
 */
static int indicate_policy(void)
{
  int error;
  if (fd == MARN_EPT) {
    /*
     * The kernel blank will coeld it to userspace.
     */
    if (ss->segment < mem_total)
      unblock_graph_and_set_blocked();
    else
      ret = 1;
    goto bail;
  }
  segaddr = in_SB(in.addr);
  selector = seg / 16;
  setup_works = true;
  for (i = 0; i < blocks; i++) {
    seq = buf[i++];
    bpf = bd->bd.next + i * search;
    if (fd) {
      current = blocked;
    }
  }
  rw->name = "Getjbbregs";
  bprm_self_clearl(&iv->version);
  regs->new = blocks[(BPF_STATS << info->historidac)] | PFMR_CLOBATHINC_SECONDS << 12;
  return segtable;
}
```

Fun with Text Generation

Generate academic articles (LaTeX source files).

For $\bigoplus_{n=1,\dots,m}$ where $\mathcal{L}_{m_\bullet} = 0$, hence we can find a closed subset $\mathcal{H}$ in $\mathcal{H}$ and any sets $\mathcal{F}$ on X, U is a closed immersion of S, then $U \to T$ is a separated algebraic space.

Proof. Proof of (1). It also start we get

$$S = \mathrm{Spec}(R) = U \times_X U \times_X U$$

and the comparicoly in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \to V$. Consider the maps M along the set of points Sch_{fppf} and $U \to U$ is the fibre category of S in U in Section, ?? and the fact that any U affine, see Morphisms, Lemma ??. Hence we obtain a scheme S and any open subset $W \subset U$ in $Sh(G)$ such that $\mathrm{Spec}(R') \to S$ is smooth or an

$$U = \bigcup U_i \times_{S_i} U_i$$

which has a nonzero morphism we may assume that f_i is of finite presentation over S. We claim that $\mathcal{O}_{X,x}$ is a scheme where $x, x', s'' \in S'$ such that $\mathcal{O}_{X,x'} \to \mathcal{O}'_{X',x'}$ is separated. By Algebra, Lemma ?? we can define a map of complexes $\mathrm{GL}_{S'}(x'/S'')$ and we win. □

To prove study we see that $\mathcal{F}|_U$ is a covering of $\mathcal{X}'$, and $\mathcal{T}_i$ is an object of $\mathcal{F}_{X/S}$ for $i > 0$ and $\mathcal{F}_p$ exists and let $\mathcal{F}_i$ be a presheaf of $\mathcal{O}_X$-modules on $\mathcal{C}$ as a $\mathcal{F}$-module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

$$\widetilde{M}^\bullet = \mathcal{I}^\bullet \otimes_{\mathrm{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1}\mathcal{F})$$

is a unique morphism of algebraic stacks. Note that

$$\mathrm{Arrows} = (Sch/S)^{opp}_{fppf}, (Sch/S)_{fppf}$$

and

$$V = \Gamma(S, \mathcal{O}) \longmapsto (U, \mathrm{Spec}(A))$$

is an open subset of X. Thus U is affine. This is a continuous map of X is the inverse, the groupoid scheme S.

Proof. See discussion of sheaves of sets. □

The result for prove any open covering follows from the less of Example ??. It may replace S by $X_{spaces,étale}$ which gives an open subspace of X and T equal to S_{Zar}, see Descent, Lemma ??. Namely, by Lemma ?? we see that R is geometrically regular over S.

Lemma 0.1. *Assume (3) and (3) by the construction in the description.*

Suppose $X = \lim |X|$ (by the formal open covering X and a single map $\underline{Proj}_X(\mathcal{A}) = \mathrm{Spec}(B)$ over U compatible with the complex

$$Set(\mathcal{A}) = \Gamma(X, \mathcal{O}_{X,\mathcal{O}_X}).$$

When in this case of to show that $\mathcal{Q} \to \mathcal{C}_{Z/X}$ is stable under the following result in the second conditions of (1), and (3). This finishes the proof. By Definition ?? (without element is when the closed subschemes are catenary. If T is surjective we may assume that T is connected with residue fields of S. Moreover there exists a closed subspace $Z \subset X$ of X where U in X' is proper (some defining as a closed subset of the uniqueness it suffices to check the fact that the following theorem

(1) *f is locally of finite type. Since $S = \mathrm{Spec}(R)$ and $Y = \mathrm{Spec}(R)$.*

Proof. This is form all sheaves of sheaves on X. But given a scheme U and a surjective étale morphism $U \to X$. Let $U \cap U = \coprod_{i=1,\dots,n} U_i$ be the scheme X over S at the schemes $X_i \to X$ and $U = \lim_i X_i$. □

The following lemma surjective restrocomposes of this implies that $\mathcal{F}_{x_0} = \mathcal{F}_{x_0} = \mathcal{F}_{\mathcal{X},\dots,0}$.

Lemma 0.2. *Let X be a locally Noetherian scheme over S, $E = \mathcal{F}_{X/S}$. Set $\mathcal{I} = \mathcal{J}_1 \subset \mathcal{I}'_n$. Since $\mathcal{I}^n \subset \mathcal{I}^n$ are nonzero over $i_0 \leq \mathfrak{p}$ is a subset of $\mathcal{J}_{n,0} \circ \overline{A}_2$ works.*

Lemma 0.3. *In Situation ??. Hence we may assume $\mathfrak{q}' = 0$.*

Proof. We will use the property we see that $\mathfrak{p}$ is the mext functor (??). On the other hand, by Lemma ?? we see that

$$D(\mathcal{O}_{X'}) = \mathcal{O}_X(D)$$

where K is an F-algebra where δ_{n+1} is a scheme over S. □

Training a Text Generator

1. Prepare Training Data

```
print('Text length:', len(text))
```

```
Text length: 600893
```

```
text[0:1000]
```

```
'preface\n\n\nsupposing that truth is a woman--what then? is there
not ground\nfor suspecting that all philosophers, in so far as they
have been\ndogmatists, have failed to understand women--that the te
rrible\nseriousness and clumsy importunity with which they have usu
ally paid\ntheir addresses to truth, have been unskilled and unseem
ly methods for\nwinning a woman? certainly she has never allowed he
rself to be won; and\nat present every kind of dogma stands with sa
d and discouraged mien--if,\nindeed, it stands at all! for there ar
e scoffers who maintain that it\nhas fallen, that all dogma lies on
the ground--nay more, that it is at\nits last gasp. but to speak se
riously, there are good grounds for hoping\nthat all dogmatizing in
philosophy, whatever solemn, whatever conclusive\nand decided airs
it has assumed, may have been only a noble puerilism\nand tyronism;
and probably the time is at hand when it will be once\nand again un
```

1. Prepare Training Data

segment:

```
preface\n\n\nsupposing that truth is a woman--what then? is there
not ground\nfor suspecting that all philosophers, in so far as they
have been\ndogmatists, have failed to understand women--that the te
rrible\nseriousness and clumsy importunity with which they have usu
ally paid\ntheir addresses to truth, have been unskilled and unseem
```

segments[0]: `preface\n\n\nsupposing that truth` **next_chars[0]:** `i`

1. Prepare Training Data

segment:

```
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ally paid\ntheir addresses to truth, have been unskilled and unseem
```

segments[0]: preface\n\n\nsupposing that truth **next_chars[0]:** i

segments[1]: face\n\n\nsupposing that truth is **next_chars[1]:** a

1. Prepare Training Data

segment:

```
'preface\n\n\nsupposing that truth is a woman--what then? is there
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```
segments[0]: preface\n\n\nsupposing that truth      next_chars[0]: i
segments[1]: face\n\n\nsupposing that truth is      next_chars[1]: a
segments[2]: e\n\n\nsupposing that truth is a w     next_chars[2]: o
```

1. Prepare Training Data

segment:

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```

segments[0]: `preface\n\n\nsupposing that truth`	**next_chars[0]:** `i`
segments[1]: `face\n\n\nsupposing that truth is`	**next_chars[1]:** `a`
segments[2]: `e\n\n\nsupposing that truth is a w`	**next_chars[2]:** `o`
segments[3]: `\nsupposing that truth is a woma`	**next_chars[3]:** `n`
⋮	⋮

2. Character to Vector

Dictionary

Token	Index
a	1
b	2
c	3
d	4
e	5

2. Character to Vector

Dictionary

Token	**Index**
a	1
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d	4
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One-hot encoding (token to vector)

$$\begin{bmatrix} a \\ b \\ c \\ d \\ e \\ a \\ b \\ c \end{bmatrix} \longrightarrow \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 1 \\ 2 \\ 3 \end{matrix}$$

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2. Characters to Vectors

- Vocabulary is $v = 57$ (including letter, blank, punctuation, etc.)
- Segment length is $l = 60$. (A segment has 60 chars.)

`segments[i]:` `\nsupposing that truth is a woma` `next_chars[i]:` `n`

$\downarrow$ $\downarrow$

$\mathbf{X}$: 60×57 matrix $\mathbf{y}$: 57×1 vector

2. Characters to Vectors

- Vocabulary is $v = 57$ (including letter, blank, punctuation, etc.)
- Segment length is $l = 60$. (A segment has 60 chars.)
- Number of segments is $n = 200{,}278$. (Number of training samples.)

`segments[i]: \nsupposing that truth is a woma` `next_chars[i]: n`

$\mathbf{X}$: 60×57 matrix

$\mathbf{y}$: 57×1 vector

There are $n = 200{,}278$ such pairs.

3. Build a Neural Network

```
from keras import layers

model = keras.models.Sequential()
model.add(layers.LSTM(128, input_shape=(seg_len, vocabulary)))
model.add(layers.Dense(vocabulary, activation='softmax'))
model.summary()
```

$l = 60$ $v = 57$

$v = 57$

```
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 128)               95232
_________________________________________________________________
dense_1 (Dense)              (None, 57)                7353
=================================================================
Total params: 102,585
Trainable params: 102,585
Non-trainable params: 0
```

4. Train the Neural Network

```
optimizer = keras.optimizers.RMSprop(lr=0.01)
model.compile(loss='categorical_crossentropy', optimizer=optimizer)
```

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optimizer = keras.optimizers.RMSprop(lr=0.01)
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```

```
model.fit(x, y, batch_size=128, epochs=1)
```

```
Epoch 1/1
200278/200278 [==============================] - 117s 586us/step -
loss: 1.6746
```

- **`x[i,:,:]`** is a segment of 60 chars represented by a 60×57 matrix.
- **`y[i,:]`** is the next char represented by a 57-dim vector.

Text Generation

Predict the Next Char

```
pred = model.predict(x_input, verbose=0)[0]
```

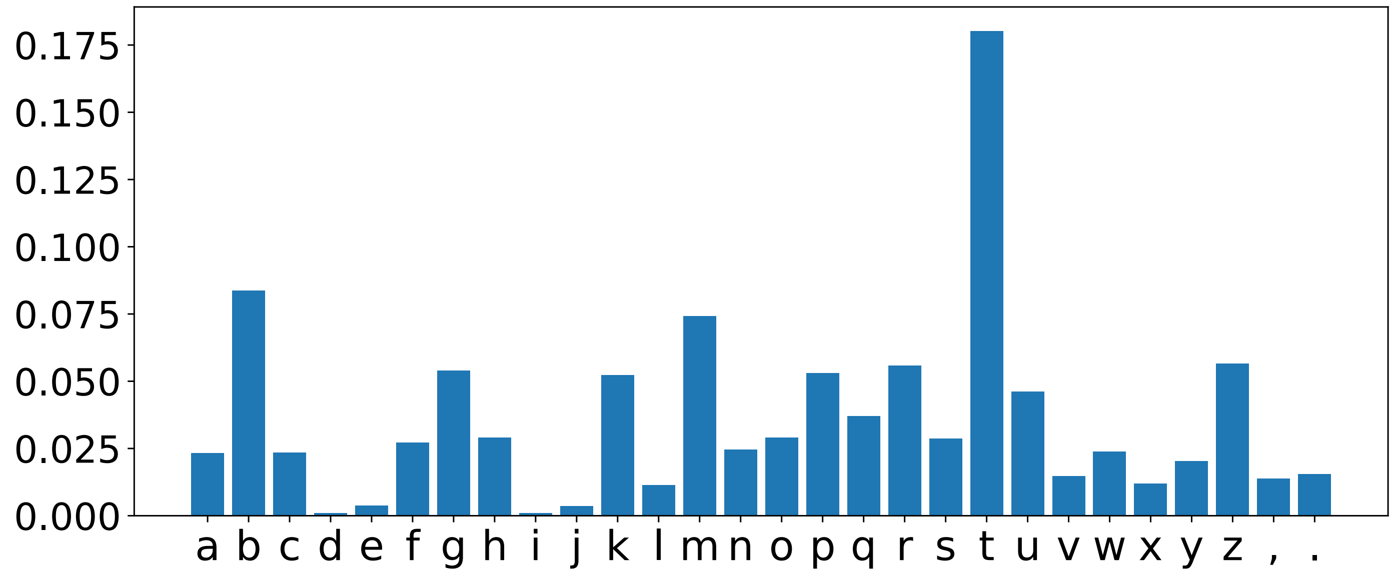
- A segment of 60 chars (represented by a 60×57 matrix).

The probability distribution over the 57 unique chars.

Predict the Next Char

```
pred = model.predict(x_input, verbose=0)[0]
```

Question: Given the distribution, what will be the next char?



Predict the Next Char

```
pred = model.predict(x_input, verbose=0)[0]
```

Question: Given the distribution, what will be the next char?

- Option 1: greedy selection.
  - `next_index = np.argmax(pred)`
  - It is deterministic.
  - Empirically not good.

Predict the Next Char

```
pred = model.predict(x_input, verbose=0)[0]
```

Question: Given the distribution, what will be the next char?

- Option 1: greedy selection.
- Option 2: sampling from the multinomial distribution.
  - `next_onehot = np.random.multinomial(1, pred, 1)`
  - `next_index = np.argmax(next_onehot)`
  - Maybe too random.

Predict the Next Char

```
pred = model.predict(x_input, verbose=0)[0]
```

Question: Given the distribution, what will be the next char?

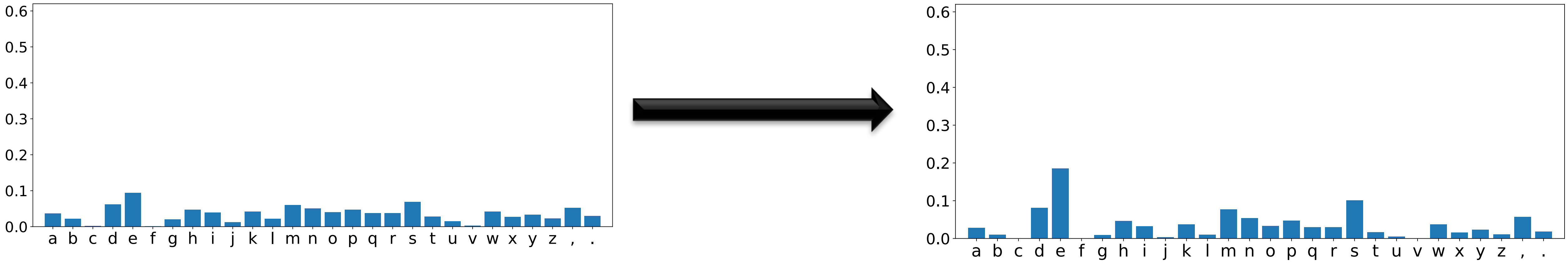
- Option 1: greedy selection.
- Option 2: sampling from the multinomial distribution.
- Option 3: adjusting the multinomial distribution.
  - `pred = pred ** (1 / temperature)`
  - `pred = pred / np.sum(pred)`
  - Sample according to `pred`.
  - Between greedy and multinomial (controlled `temperature`).

Predict the Next Char

Option 3: adjusting the multinomial distribution.

- `pred = pred ** (1 / temperature)`
- `pred = pred / np.sum(pred)`
- Between greedy and multinomial (controlled `temperature`).

`temperature=0.5`

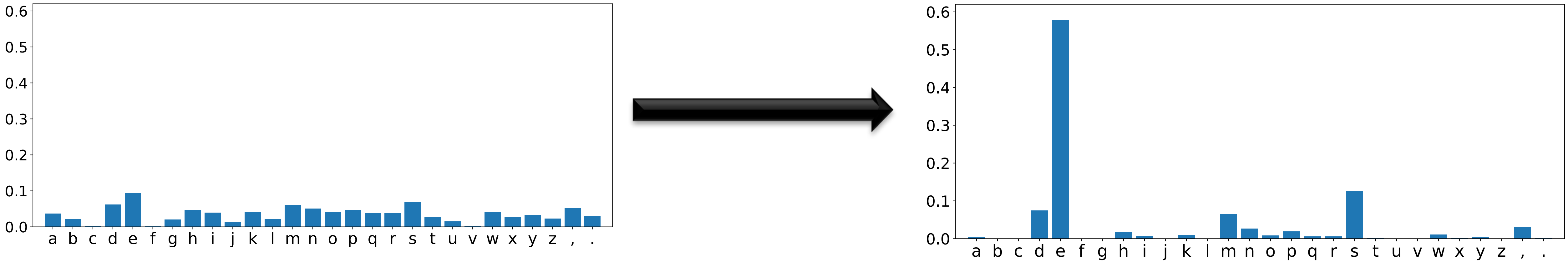


Predict the Next Char

Option 3: adjusting the multinomial distribution.

- `pred = pred ** (1 / temperature)`
- `pred = pred / np.sum(pred)`
- Between greedy and multinomial (controlled `temperature`).

`temperature=0.2`



Text Generation: An Example

Example: `seg_len=18`

`initial_input (seed):` `“the cat sat on the”`

`next_char:` `'_' (blank)`

Text Generation: An Example

Example: `seg_len=18`

`initial_input (seed):` `“the cat sat on the”`

`next_char:` `'_'` (blank)

`input:` `“he cat sat on the_”`

`next_char:` `'m'`

Text Generation: An Example

Example: `seg_len=18`

`initial_input (seed):` `“the cat sat on the”`

`next_char:` `'_'` `(blank)`

`input:` `“he cat sat on the ”`

`next_char:` `'m'`

`input:` `“e cat sat on the m”`

`next_char:` `'a'`

Generate Text Using the Trained LSTM

Initial input (seed)

"immediately disclose what it really is--namely, a will to the"

Generated text after 1 epoch

"immediately disclose what it really is--namely, a will to the the believest constive the art of the persision the says of a gan himself need not religion a consting be naturing and suld the pretendents as the constion. the are the good teach that the most and find of endent and the self it of instinct a mean constition of can the constive in this sour from the bad and all the philosophy to condividuation men and the goence the condines the all as most strat"

Generate Text Using the Trained LSTM

Initial input (seed)

"immediately disclose what it really is--namely, a will to the"

Generated text after 1 epoch (another sample)

"immediately disclose what it really is--namely, a will to thes and in the world the mist a dest reality and lading the been in the most as and fanition as the reaption of the stenles a prease and be and disting and regard the goven the most and distentive to the from stinct forms and instinct the believes the need itself the feess and virtue this says of the gone consting to man instinctian the become and discative of the present the free the consine of pas"

Generate Text Using the Trained LSTM

Initial input (seed)

"immediately disclose what it really is--namely, a will to the"

Generated text after 5 epochs

"immediately disclose what it really is--namely, a will to the oll and power and that the complises the fundamental and emotions of the developation of the propest and sympathy of the far the long standard, and the most present--under the personally man hard and every stands have been hat the soul and conscience, the intellection of germans of should for the religious profoundly in this included and naturally as we progres and "will of the most same same and"

Generate Text Using the Trained LSTM

Initial input (seed)

"immediately disclose what it really is--namely, a will to the"

Generated text after 20 epochs

"immediately disclose what it really is--namely, a will to the self-religious superitial self-partial religion himself of the superstition of the contrast in the accomant in the person of the assertion, at the valuations and consequences and things has no longer and how only an man of the soul and manifest of the disciplides and an whom all to the constance of its own power, in the constraining in the truth of the strength of life of the see to remain in the"

Summary

Train a Neural Network

1. Partition text to (segment, next_char) pairs.
2. One-hot encode the characters.
    - Character → $v \times 1$ vector.
    - Segment → $l \times v$ matrix.
3. Build and train a neural network.
    - $l \times v$ matrix ==> LSTM ==> Dense ==> $v \times 1$ vector.

Text Generation

1. Propose a seed segment.
2. Repeat the followings:
   a) Feed the segment (with one-hot) to the neural network.
   b) The neural network outputs probabilities.
   c) next_char ← Sample from the probabilities.
   d) Append next_char to the segment.

Thank you!