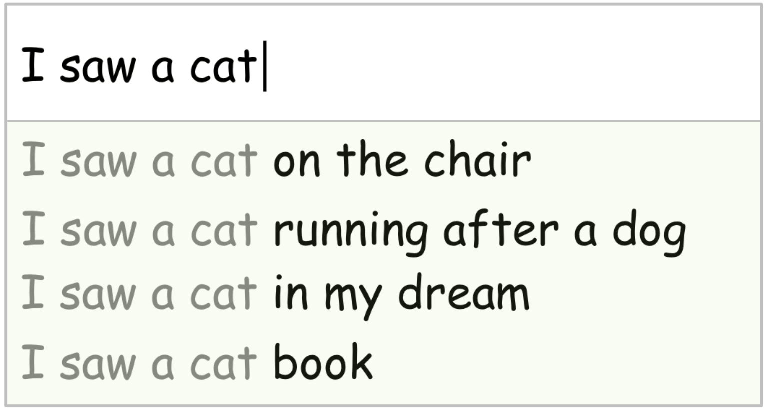
Intro to Neural Networks

BA865 – Mohannad Elhamod

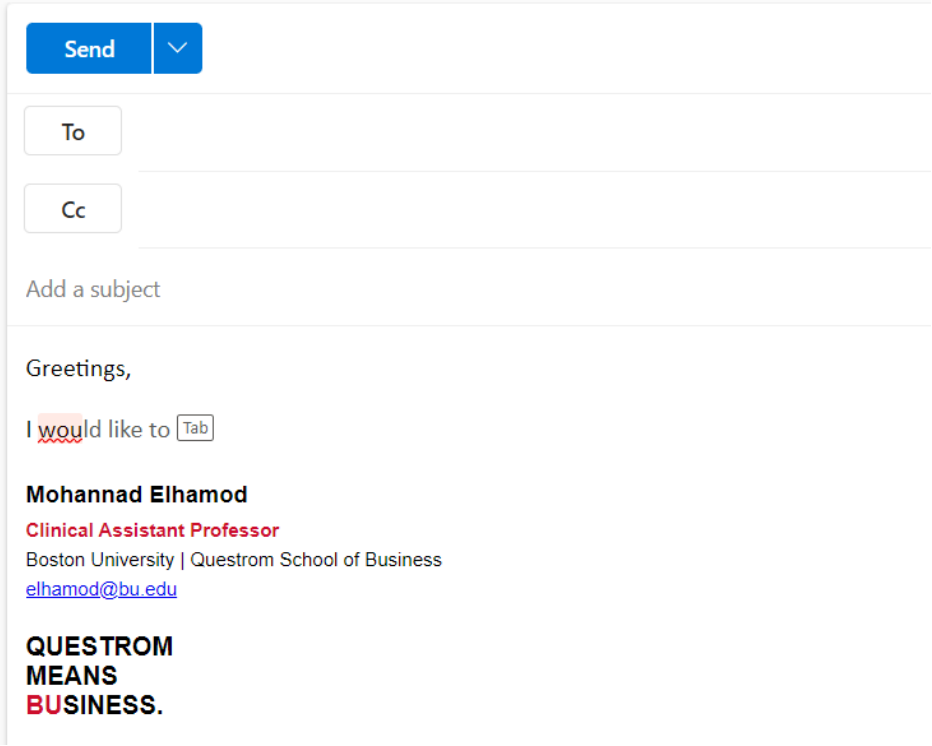
Language Modeling

What is language modeling anyway?...

Web search engine / ...



Lena-voita



What is language modeling anyway?...

I grabbed the branch and broke it.

I went to the branch and deposited some money.

Context matters!

What is language modeling anyway?...

- I went to ____.
- I woke up at 7 am and went to ___.
- I woke up at 7 am, packed my book and notebook, and went to ____.

The more context, the more certain

What is language modeling anyway?...

I went to the branch and deposited some money.

I went to the bank and deposited some money.

I went to the ATM and deposited some money.

> Words which frequently appear in **similar contexts** have **similar meaning**.

[Lena-voita]

Formalizing our thoughts

- It seems we process language sequentially**.
- So, language modeling is the chaining of word probabilities.

$$P(\text{I saw a cat on} \ldots) =$$

$$\underbrace{P(\text{I}) \cdot P(\text{saw}|\text{I}) \cdot P(\text{a}|\text{I saw}) \cdot P(\text{cat}|\text{I saw a}) \cdot P(\text{on}|\text{I saw a cat})}_{\text{Probability of I saw a cat on}} \cdot \underbrace{\ldots}$$

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- How do we calculate these probabilities?

counting…

$$P(\text{cat}) = \frac{N(\text{"cat" in corpus})}{N(\text{all words in corpus})}$$

$$P(\text{cat} \mid \text{my}) = \frac{N(\text{"my cat" in corpus})}{N(\text{"my" in corpus})}$$

Can you foresee any problem with this calculation?...

N-grams

Instead, let’s just use a context of ***fixed-length.***

P(I saw a cat on a mat) =

P(I)
· P(saw | I)
· P(a | I saw)
· P(cat | I saw a)
· P(on | I saw a cat)
· P(a | I saw a cat on)
· P(mat | I saw a cat on a)

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- n=3 (trigram model): $P(y_t|y_1, \ldots, y_{t-1}) = P(y_t|y_{t-2}, y_{t-1})$,
- n=2 (bigram model): $P(y_t|y_1, \ldots, y_{t-1}) = P(y_t|y_{t-1})$,
- n=1 (unigram model): $P(y_t|y_1, \ldots, y_{t-1}) = P(y_t)$.

N-grams

Context is like a sliding window into the past.

Hugging Face is a startup based in New York City and Paris

p(word)

[Huggingface]

Context size

- I went to the beach. My wife sat next to me. She was replying to some emails, and the bird stole our sandwich. Then it started raining suddenly and ___.

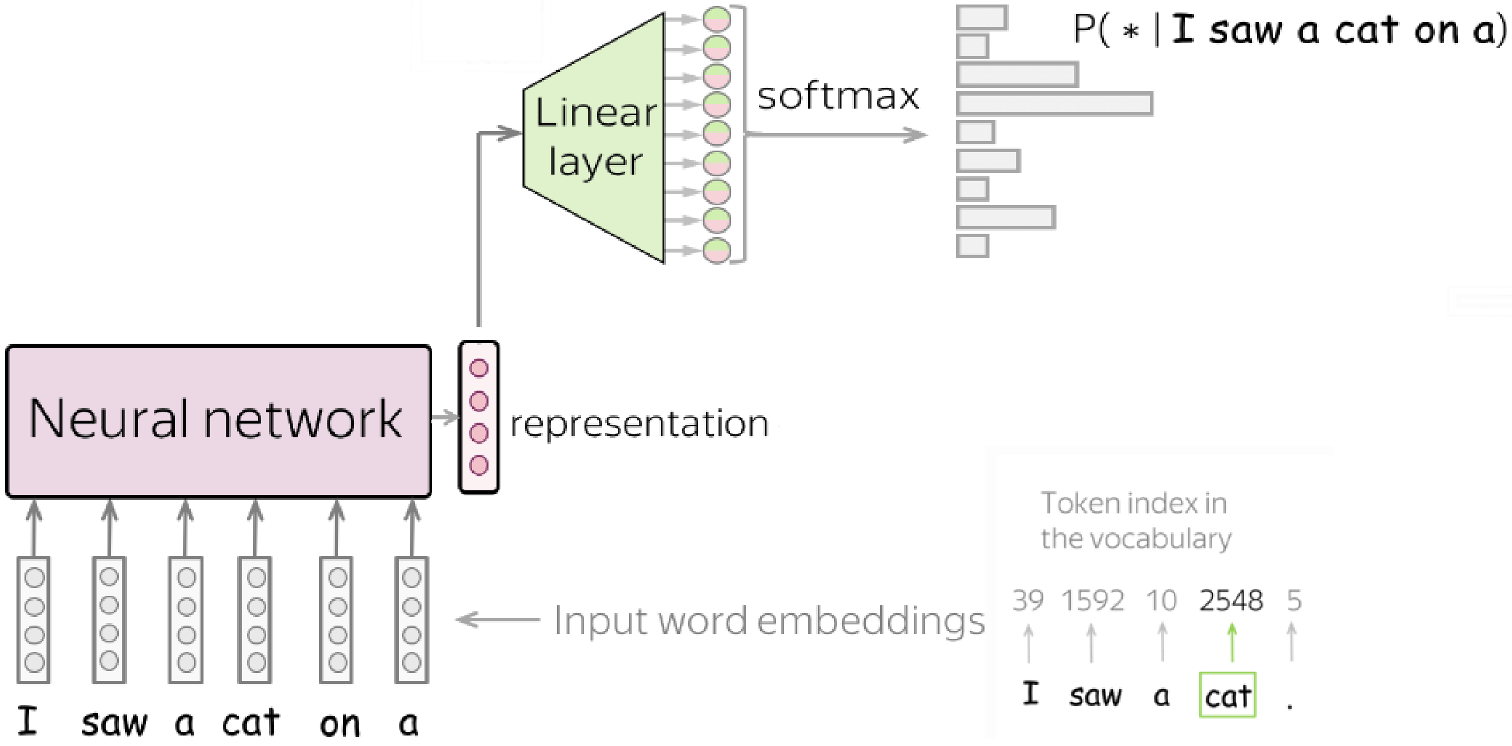
- Longer context: predictable outcome.
- Shorter context: Too unpredictable.

Neural Networks for Language Modeling

BOSTON UNIVERSITY

Boston University Questrom School of Business

General Model Architecture



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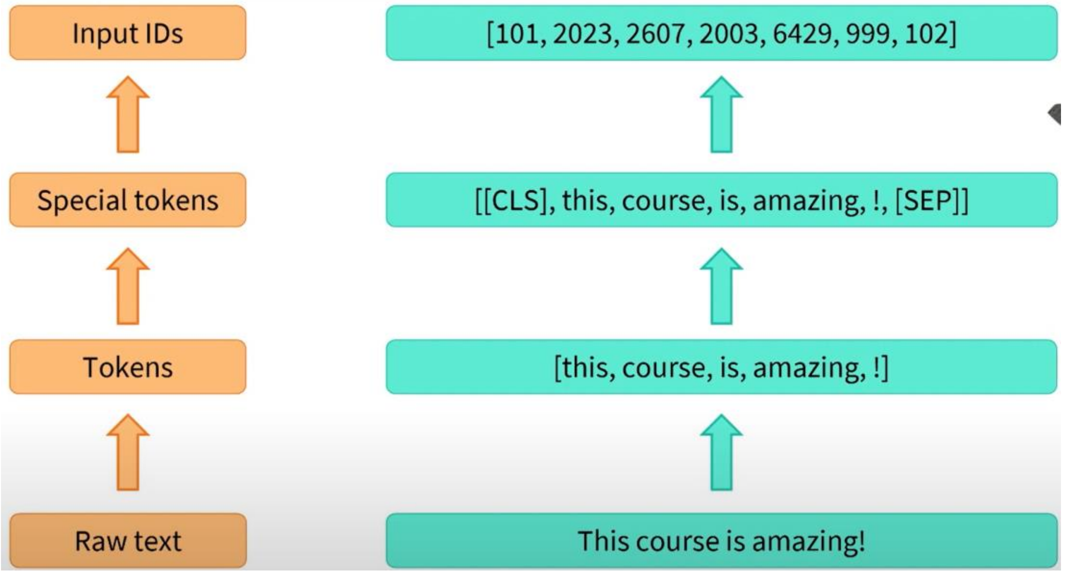
Can you see any issue with inputting words into an NN?

Tokenization

- Computers only understand numbers.
- We need to convert the text into tokens (e.g., words).
- Can we use the Input IDs as representation?
- Is it a good representation?

Huggingface

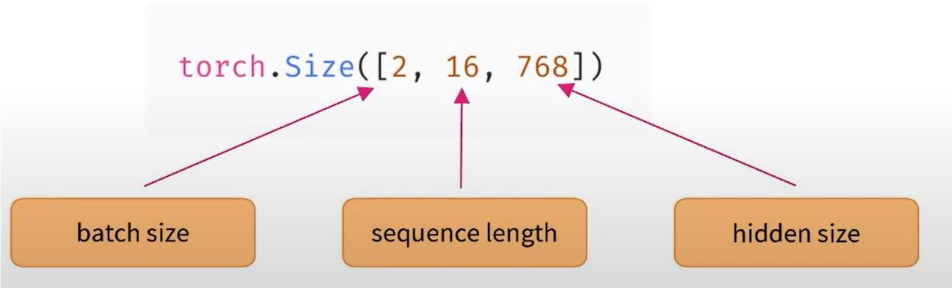


Syntax vs. Semantics

- Notice that:
  - Different tokens might have the same meaning (e.g., like, enjoy)
  - The same token might have different meanings (is *like* something, to *like* something)
- **So, while tokens represent syntax, we really care about meaning/semantics.**
- In many cases, you can only get the meaning through **context** (i.e., the token's place with respect to other tokens.)

Vectorization

- Once tokenized, we convert the tokens into vectors.
- So, if we have a dataset of sentences, we represent them as:
  - A batch of sentences (i.e., batches)
  - Each sentence is represented as a sequence of tokens (sequence length)
  - Each token is represented as a vector (hidden size)



Word Embeddings

- We ideally want words that have similar meanings to have smaller distances.
- Demo
- Examples:
  1. Word2Vec (Google)
  2. GloVe (Stanford)
  3. Train your own!

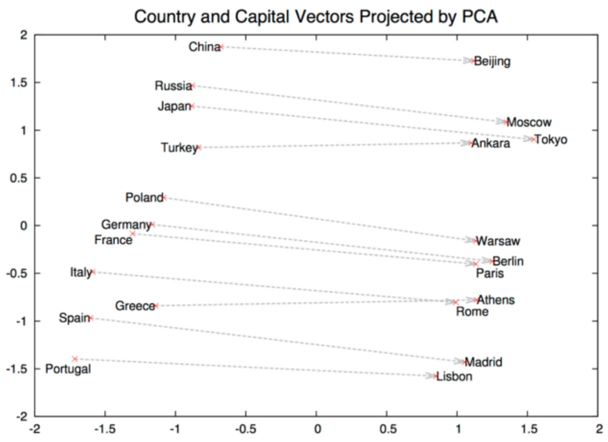
Word embeddings

Word embeddings can also be used find directionality in the corpus:

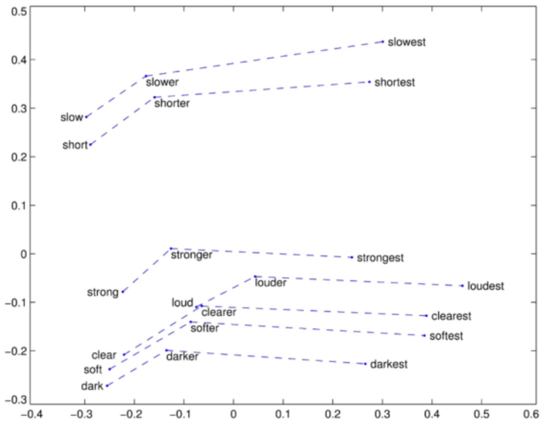
- Demo 1 (semantics)
- Demo 2 (vector view)
- Demo 3 (dimensionality)

Word embeddings

Word embeddings can also be used find directionality in the corpus.



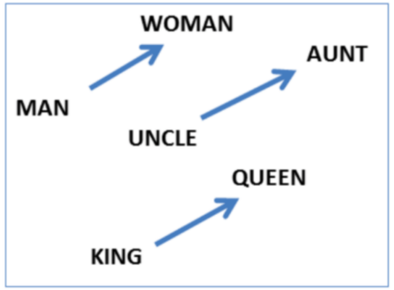
Word2Vec

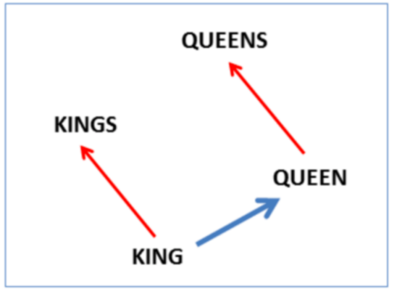


GloVe

semantic: v(king) – v(man) + v(woman) ≈ v(queen)

syntactic: v(kings) – v(king) + v(queen) ≈ v(queens)





Recurrent Neural Nets (RNNs)

- Combines the embeddings of previous context and current word → gives next word.

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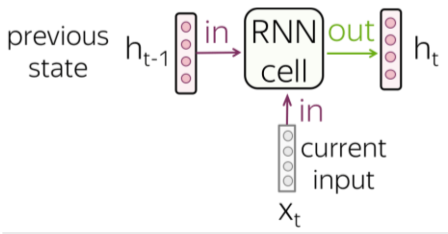

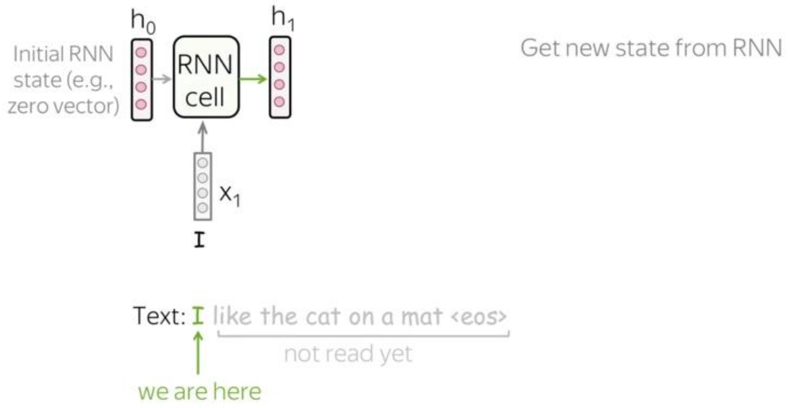

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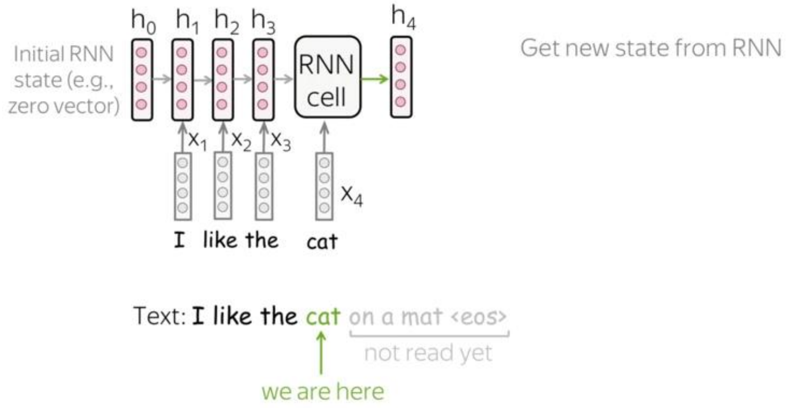
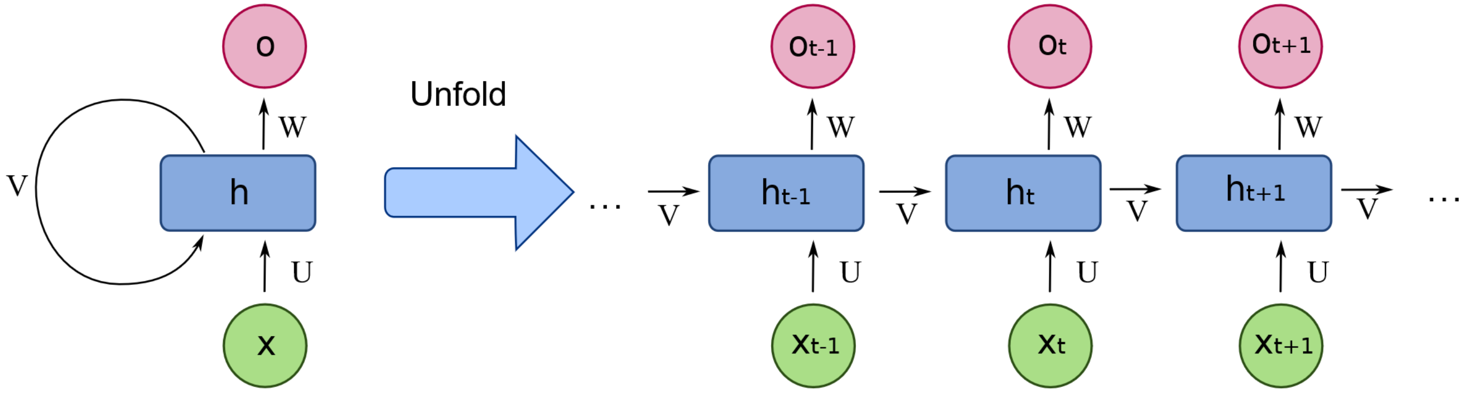


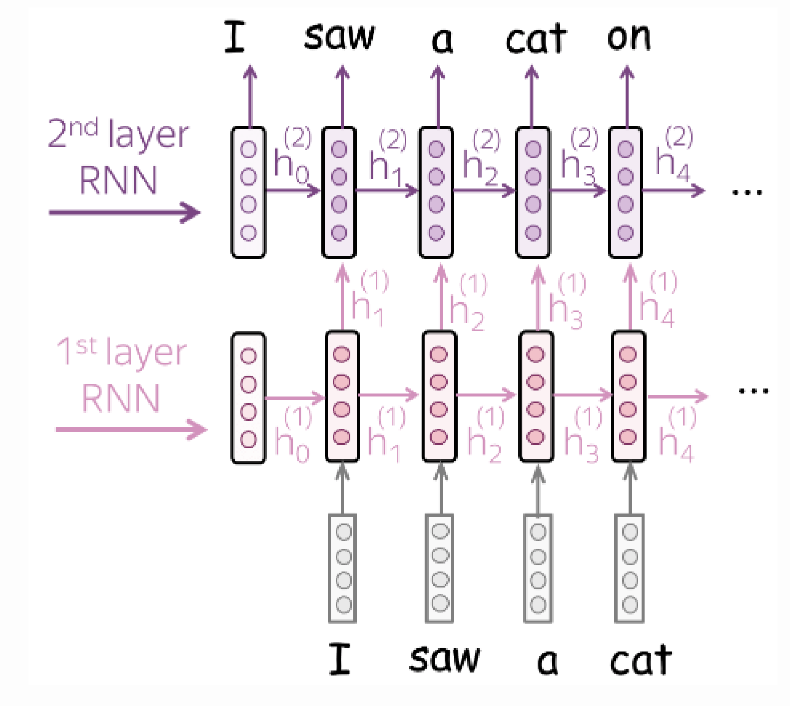
What is an RNN cell?

The same W, U, and V are being reused for all tokens.



Recurrent Neural Nets (RNNs)

- We can add more layers and units per layer to increase complexity.
- Demo



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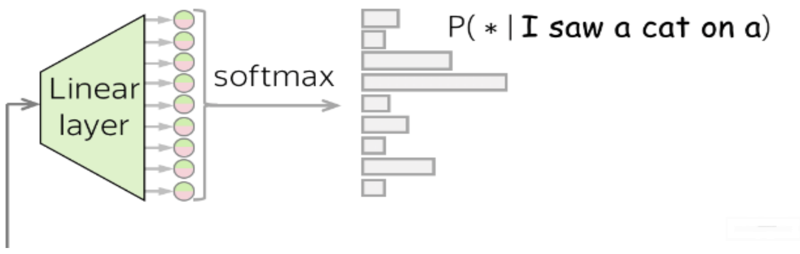
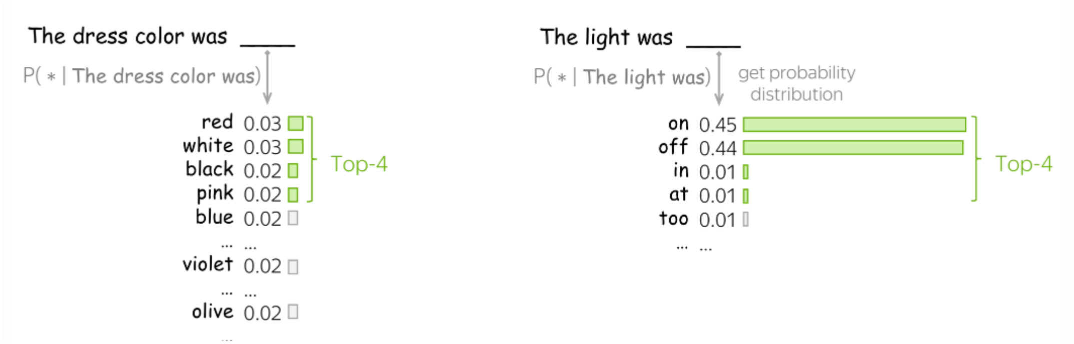
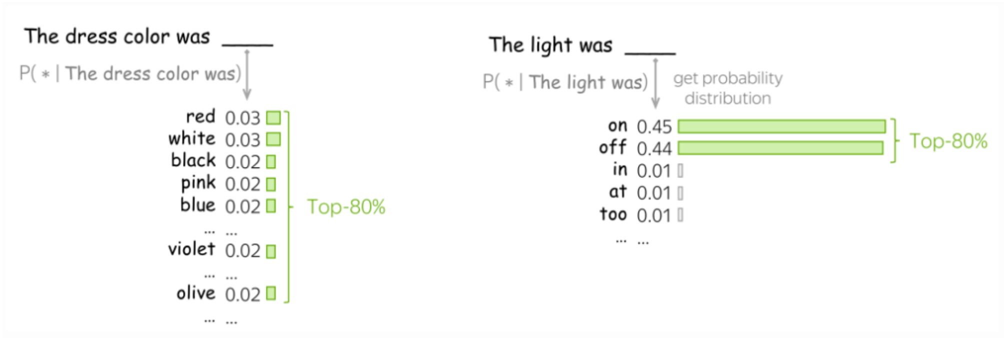
Sampling The Distribution

- Always take top probability?
  - That makes the model deterministic (no creativity).
- Alternative?
  - Sampling, Top-k, or top-p.







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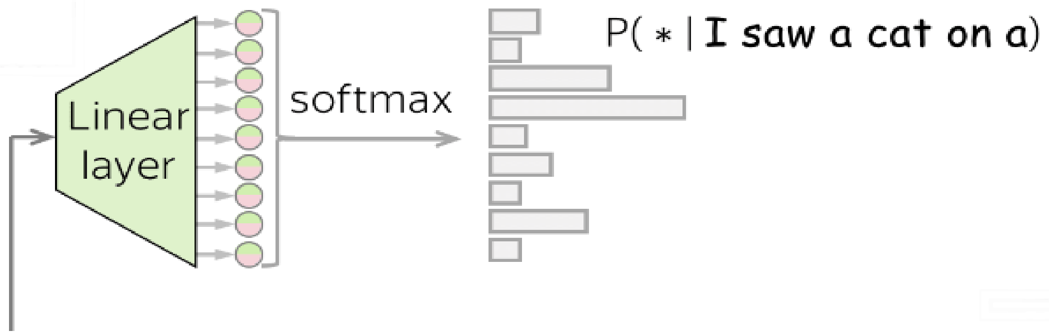
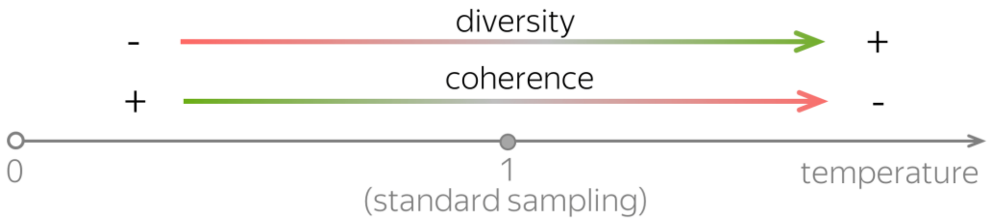
Sampling The Distribution

- Some words have way higher probability than others.
- This can be manually tuned through temperature.
- [Demo]





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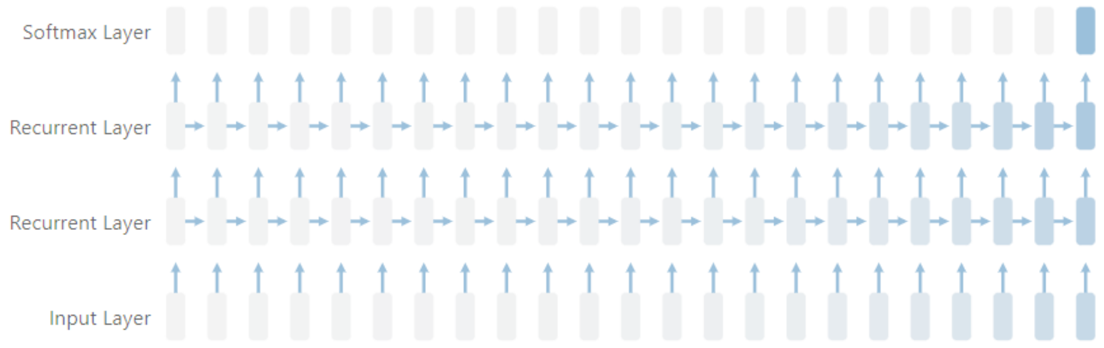
Measuring The Metric

- What are we looking for?
  - A model that is not surprised by the new text it seen.
- We use perplexity.
  - Takes values between 1 and number of possible tokens.
  - Smaller is better.
  - Demo

RNNs (issues)

- Gradient becomes insignificant for long contexts
  - The network forgets early words…
  - It is called the “vanishing gradient” or “memorization” problem.
  - RNNs have an issue memorizing long contexts.

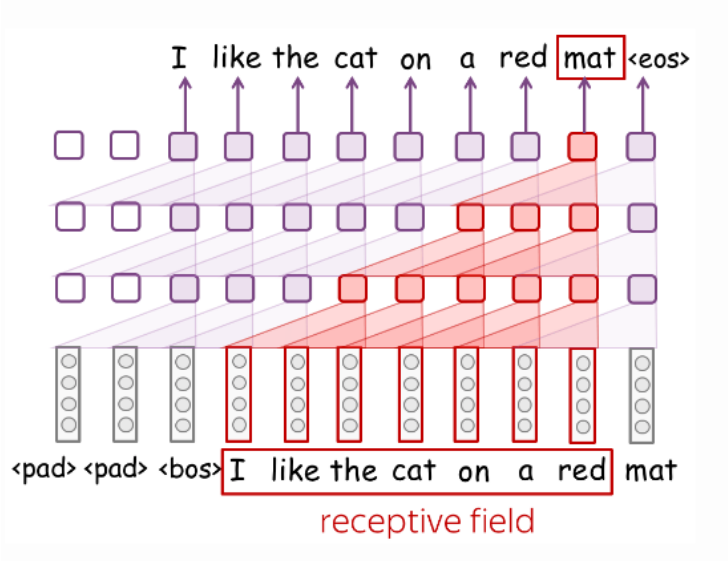


Vanishing Gradient: where the contribution from the earlier steps becomes insignificant in the gradient for the vanilla RNN unit.

distill.pub

Other ways to think about this.

- You can even use convolution!
- We will explore more sophisticated networks later…



CNN