Distributional Semantics

João Sedoc
IntroHLT class
November 4, 2019

Intuition of distributional word similarity

Nida example:

```
A bottle of tesgüino is on the table
Everybody likes tesgüino
Tesgüino makes you drunk
We make tesgüino out of corn.
```

From context words humans can guess ***tesgüino*** means

- an alcoholic beverage like **beer**

Intuition for algorithm:

- Two words are similar if they have similar word contexts.

Distributional Hypothesis

If we consider **optometrist** and **eye-doctor** we find that, as our corpus of utterances grows, these two occur in almost the same environments. In contrast, there are many sentence environments in which **optometrist** occurs but **lawyer** does not...

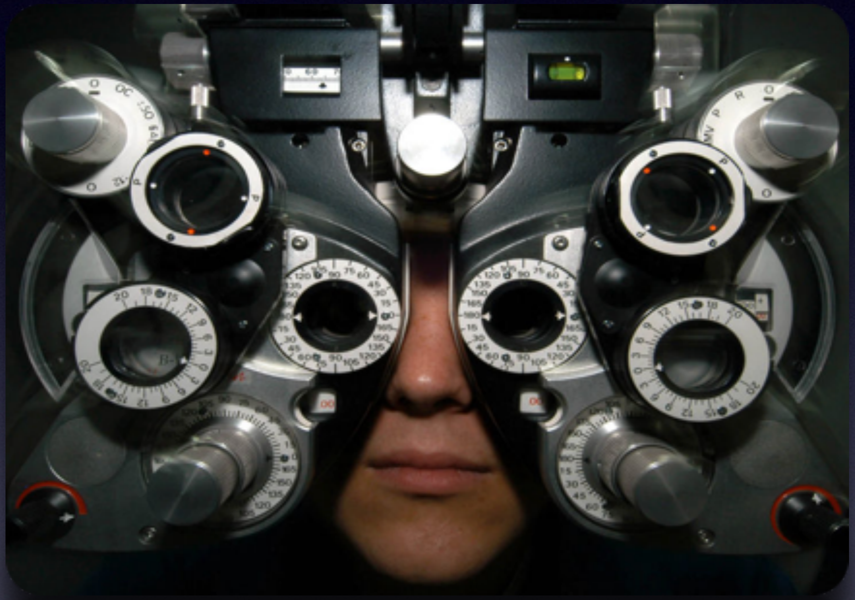
It is a question of the relative frequency of such environments, and of what we will obtain if we ask an informant to substitute any word he wishes for **optometrist** (not asking what words have the same meaning).

These and similar tests all measure the probability of particular environments occurring with particular elements... If A and B have almost identical environments we say that they are synonyms.

–Zellig Harris (1954)

"You shall know a word by the company it keeps!"

–John Firth (1957)



Distributional models of meaning
= vector-space models of meaning
= vector semantics

Intuitions: Zellig Harris (1954):

- “oculist and eye-doctor … occur in almost the same environments”
- “If A and B have almost identical environments we say that they are synonyms.”

Firth (1957):

- “You shall know a word by the company it keeps!”

Intuition

Model the meaning of a word by “embedding” in a vector space.

The meaning of a word is a vector of numbers

- Vector models are also called “**embeddings**”.

Contrast: word meaning is represented in many computational linguistic applications by a vocabulary index (“word number 545”)

vec(“dog”) = (0.2, -0.3, 1.5,…)

vec(“bites”) = (0.5, 1.0, -0.4,…)

vec(“man”) = (-0.1, 2.3, -1.5,…)

Term-document matrix

Term-document matrix

Each cell: count of term *t* in a document *d*: $\text{tf}_{t,d}$:

- Each document is a count vector in $\mathbb{N}^{v}$: a column below

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	1	8	15
soldier	2	2	12	36
fool	37	58	1	5
clown	6	117	0	0

Term-document matrix

Two documents are similar if their vectors are similar

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The words in a term-document matrix

Each word is a count vector in $\mathbb{N}^D$: a row below

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Brilliant insight: Use running text as implicitly supervised training data!

- A word *s* near *fine*
  - Acts as gold ‘correct answer’ to the question
  - “Is word *w* likely to show up near *fine*?”
- No need for hand-labeled supervision
- The idea comes from **neural language modeling**
  - Bengio et al. (2003)
  - Collobert et al. (2011)

Word2vec

Popular embedding method

Very fast to train

Code available on the web

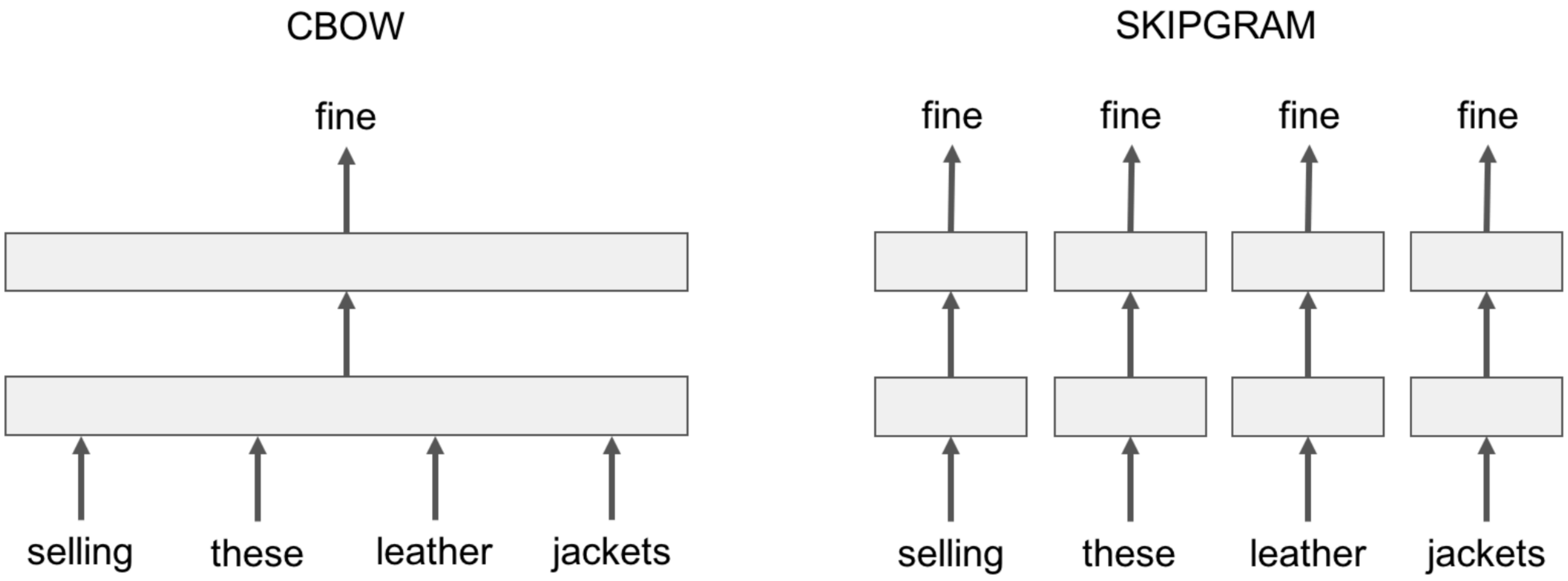
Idea: **predict** rather than **count**

Word2vec

- Instead of **counting** how often each word *w* occurs near *"fine"*
- Train a classifier on a binary **prediction** task:
  - Is *w* likely to show up near *"fine"*?

- We don't actually care about this task
  - But we'll take the learned classifier weights as the word embeddings

Word2vec

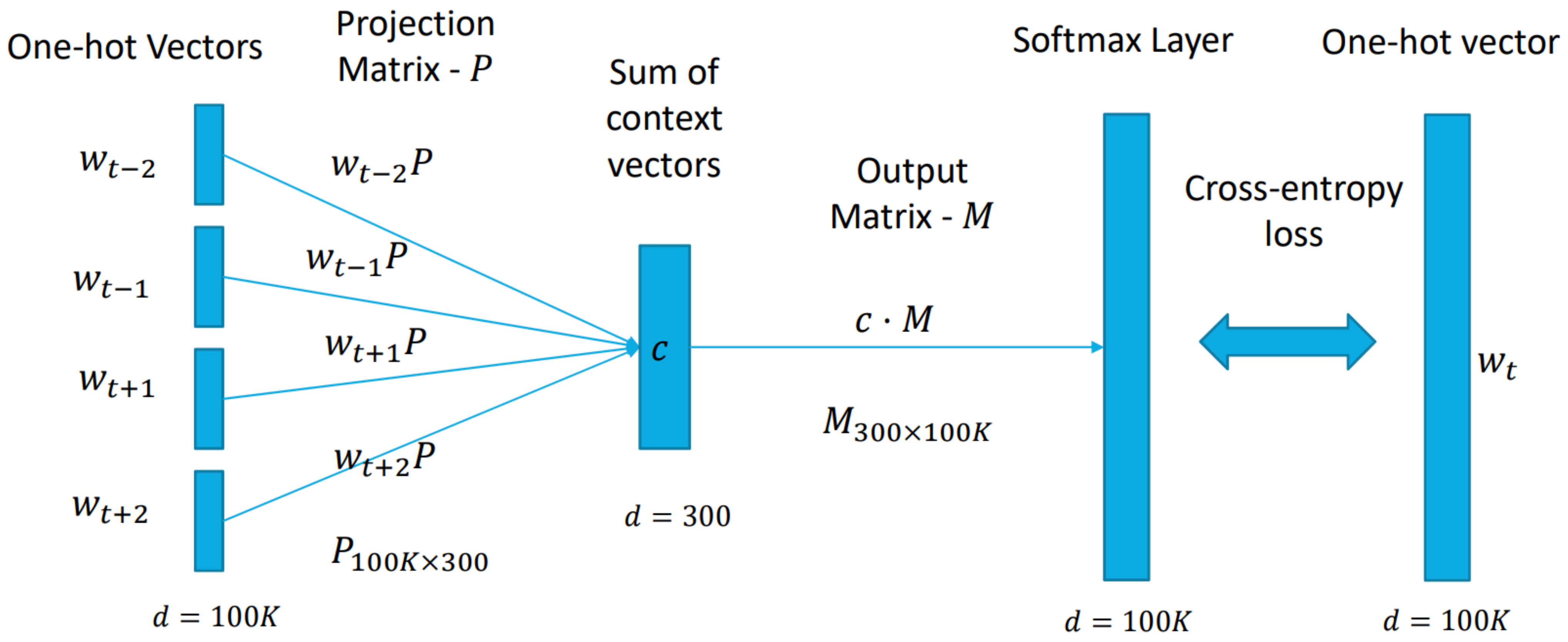


I am selling these fine leather jackets

CBOW – high level

The resulting projection matrix P is the embedding matrix

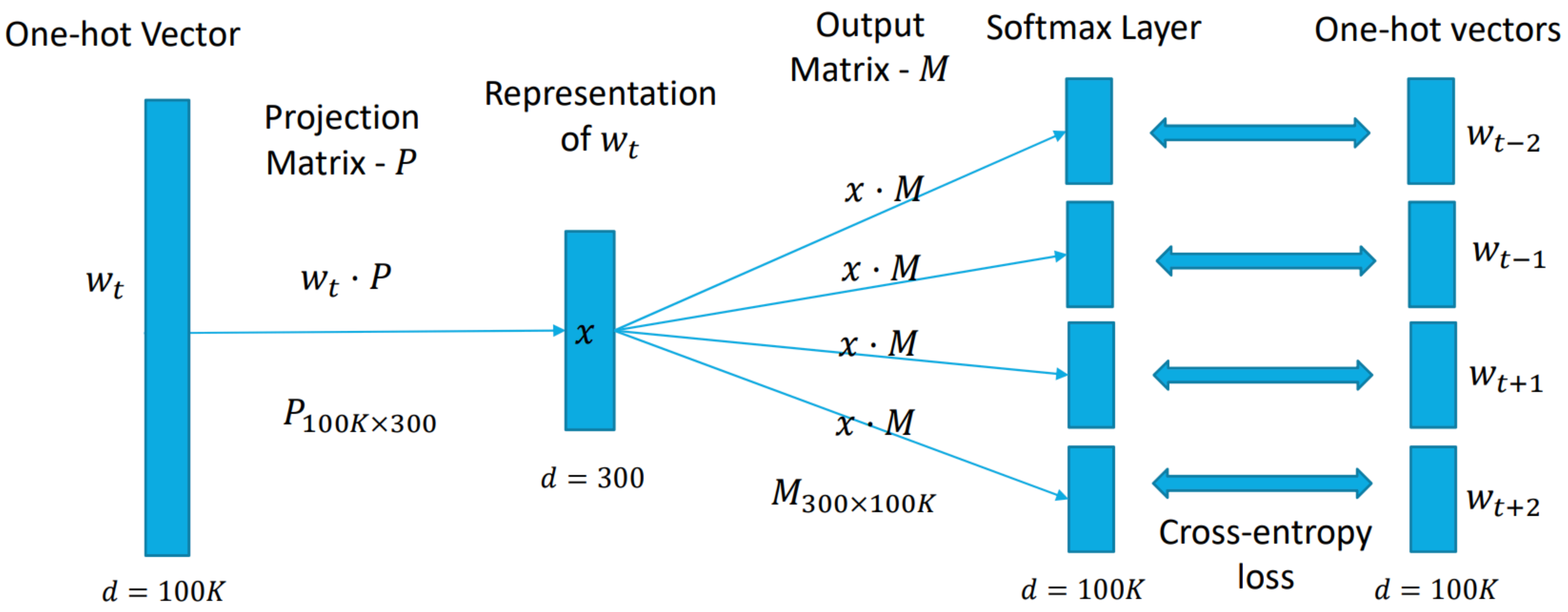
Goal: Predict the middle word given the words of the context



Skip-gram – high level

The resulting projection matrix P is the embedding matrix

Goal: Predict the context words given the middle word



Dense embeddings you can download!

Word2vec (Mikolov et al.)
https://code.google.com/archive/p/word2vec/

Fasttext http://www.fasttext.cc/

Glove (Pennington, Socher, Manning)
http://nlp.stanford.edu/projects/glove/

Why vector models of meaning? Computing the similarity between words

"**fast**" is similar to "**rapid**"

"**tall**" is similar to "**height**"

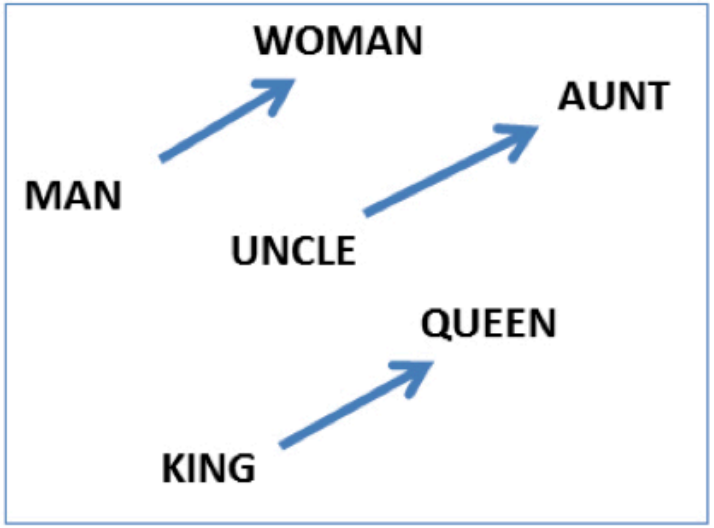
Question answering:

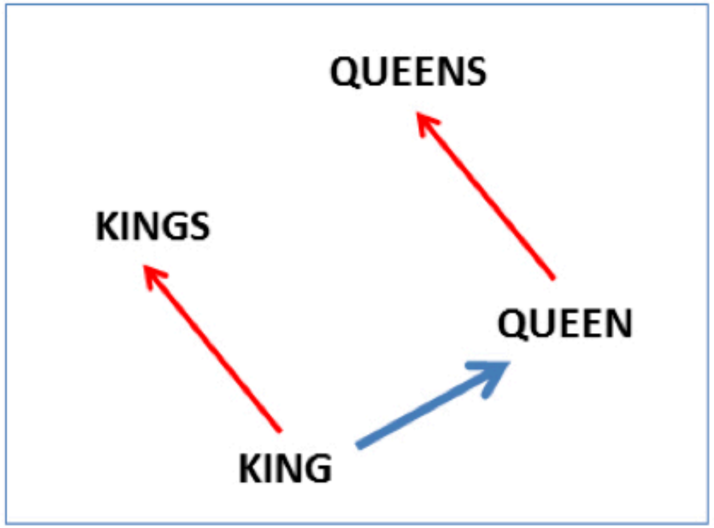
*Q: "How **tall** is Mt. Everest?"*
*Candidate A: "The official **height** of Mount Everest is 29029 feet"*

Analogy: Embeddings capture relational meaning!

vector(*'king'*) - vector(*'man'*) + vector(*'woman'*) ≈ vector('queen')

vector(*'Paris'*) - vector(*'France'*) + vector(*'Italy'*) ≈ vector('Rome')





Evaluating similarity

Extrinsic (task-based, end-to-end) Evaluation:

- Question Answering
- Spell Checking
- Essay grading

Intrinsic Evaluation:

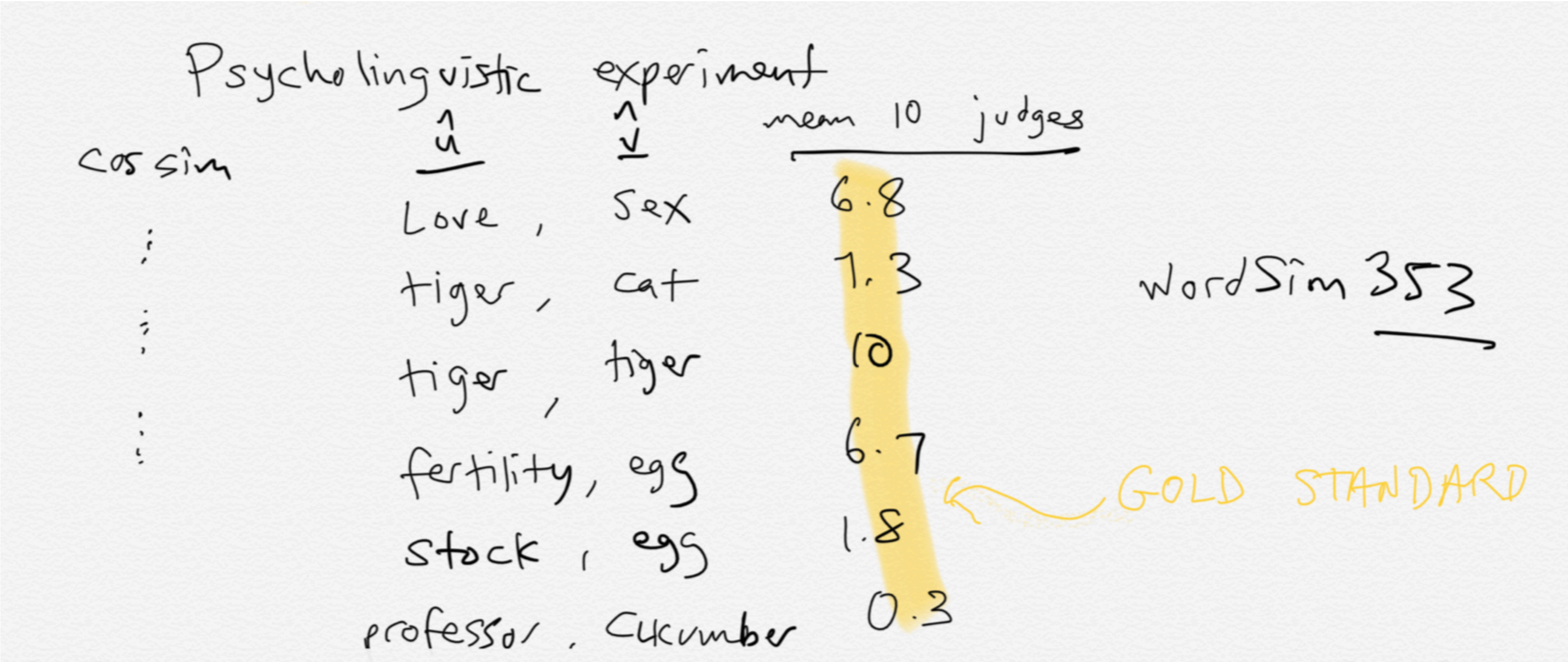
- Correlation between algorithm and human word similarity ratings
  - Wordsim353: 353 noun pairs rated 0-10. *sim(plane,car)=5.77*
- Taking TOEFL multiple-choice vocabulary tests
  - `Levied is closest in meaning to:`
    `imposed, believed, requested, correlated`

Evaluating embeddings

Compare to human scores on word similarity-type tasks:

- WordSim-353 (Finkelstein et al., 2002)
- SimLex-999 (Hill et al., 2015)
- Stanford Contextual Word Similarity (SCWS) dataset (Huang et al., 2012)
- TOEFL dataset: *Levied is closest in meaning to: imposed, believed, requested, correlated*

Intrinsic evaluation



Intrinsic evaluation

Measuring similarity

Given 2 target words *v* and *w*

We'll need a way to measure their similarity.

Most measure of vectors similarity are based on the:

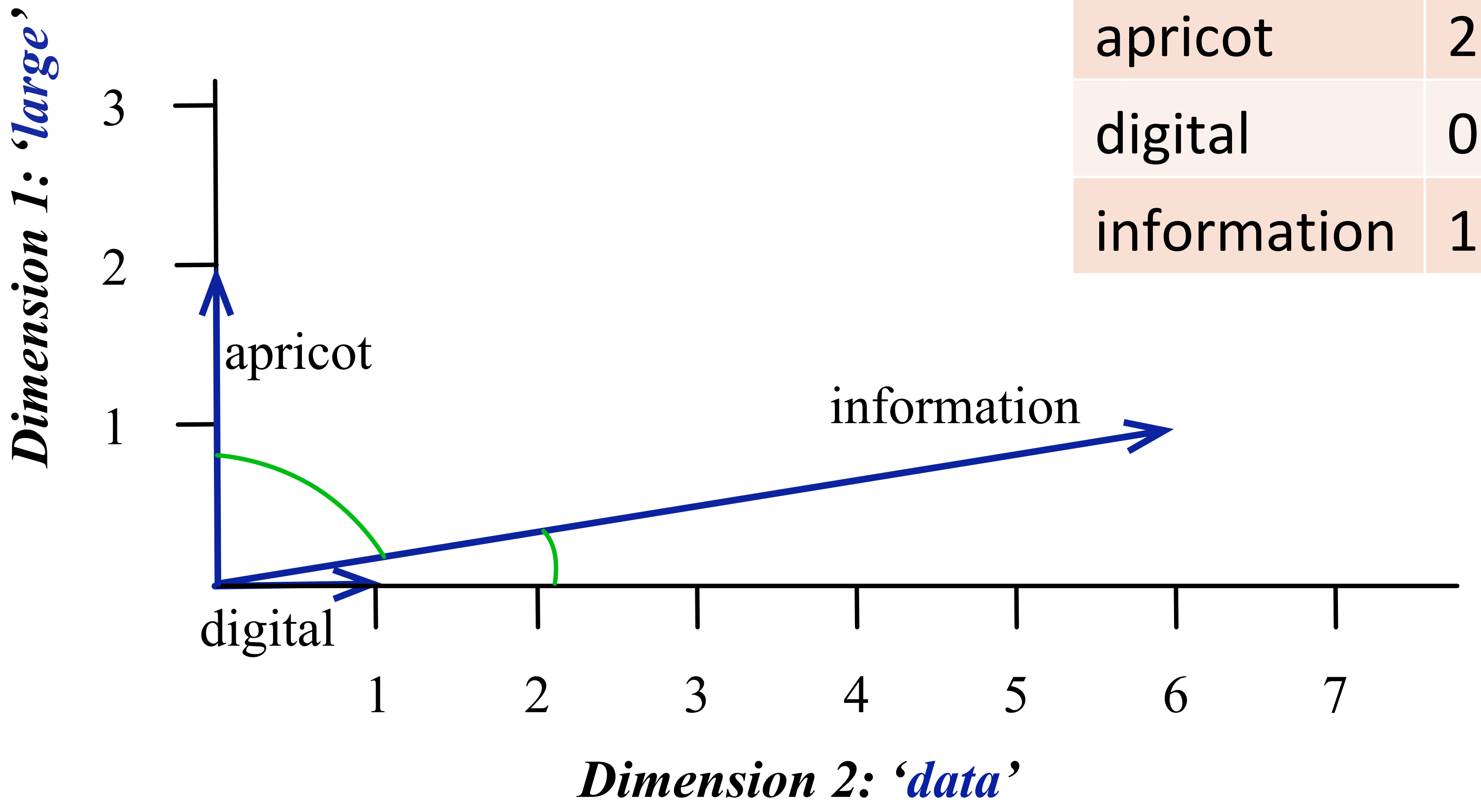
Cosine between embeddings!

The similarity between two vectors v and w is: $$\frac{v \cdot w}{||v||||w||}$$

- High when two vectors have large values in same dimensions.
- Low (in fact 0) for **orthogonal vectors** with zeros in complementary distribution

Visualizing vectors and angles

	large	data
apricot	2	0
digital	0	1
information	1	6



Bias in Word Embeddings

Extreme *she* occupations

1. homemaker	2. nurse	3. receptionist
4. librarian	5. socialite	6. hairdresser
7. nanny	8. bookkeeper	9. stylist
10. housekeeper	11. interior designer	12. guidance counselor

Extreme *he* occupations

1. maestro	2. skipper	3. protege
4. philosopher	5. captain	6. architect
7. financier	8. warrior	9. broadcaster
10. magician	11. figher pilot	12. boss

More to come on bias later …

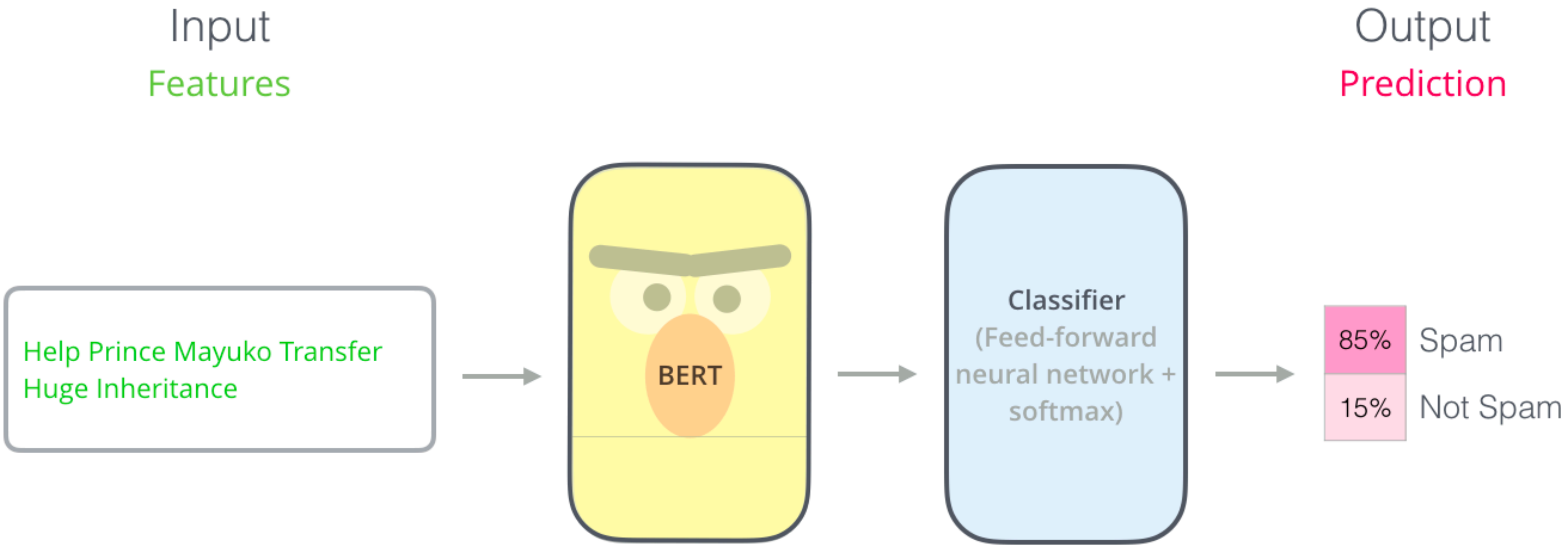
Embeddings are the workhorse of NLP

- Used as pre-initialization for language models, neural MT, classification, NER systems…
- Downloaded and easily trainable
- Available in ~100s of languages

- And … **contextualized word embeddings** are built on top of them

Contextualized Word Embeddings

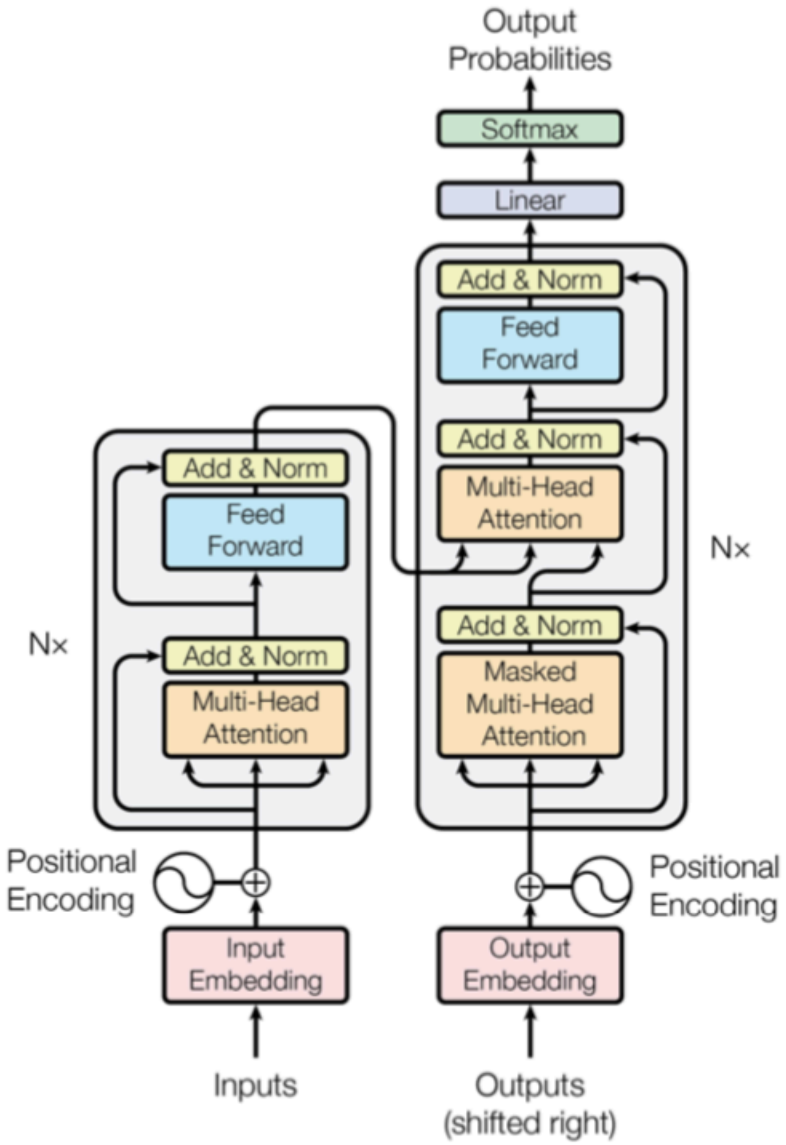
BERT - Deep Bidirectional Transformers



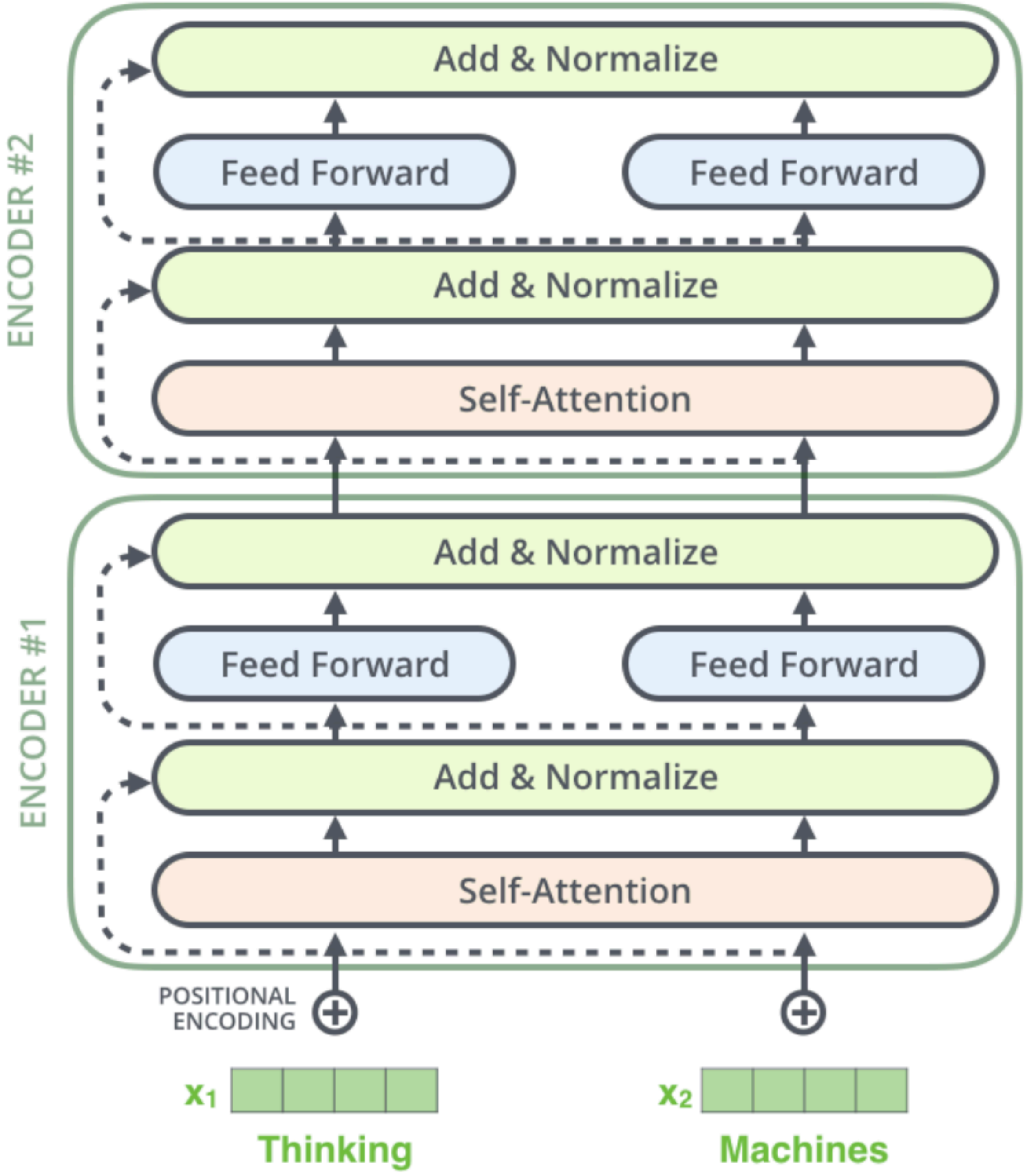
From last time…

Putting it together

- Multiple (N) layers
- For encoder-decoder attention, Q: previous decoder layer, K and V: output of encoder
- For encoder self-attention, Q/K/V all come from previous encoder layer
- For decoder self-attention, allow each position to attend to all positions up to that position
- Positional encoding for word order



Transformer

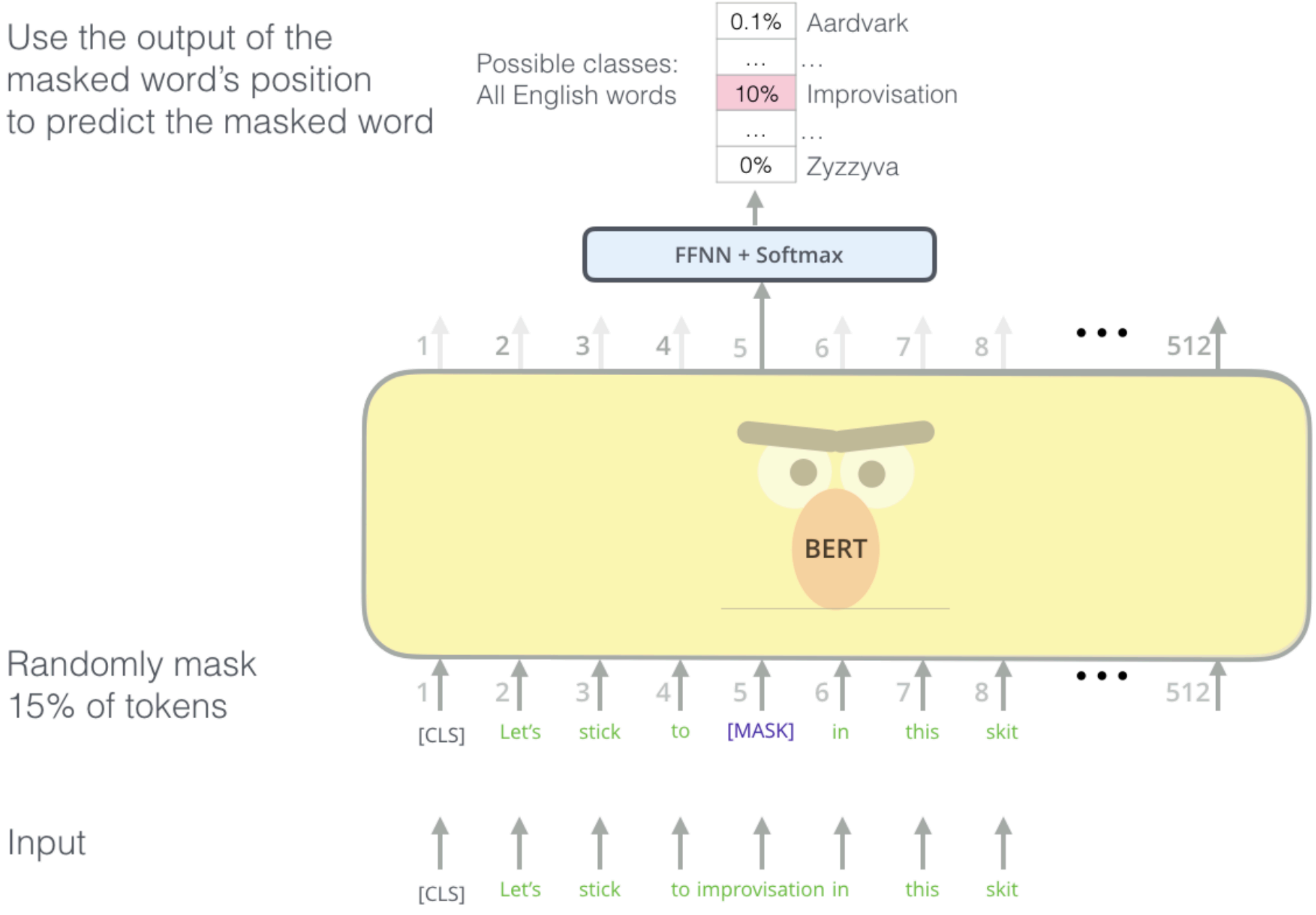


Training BERT

- BERT has two training objectives:

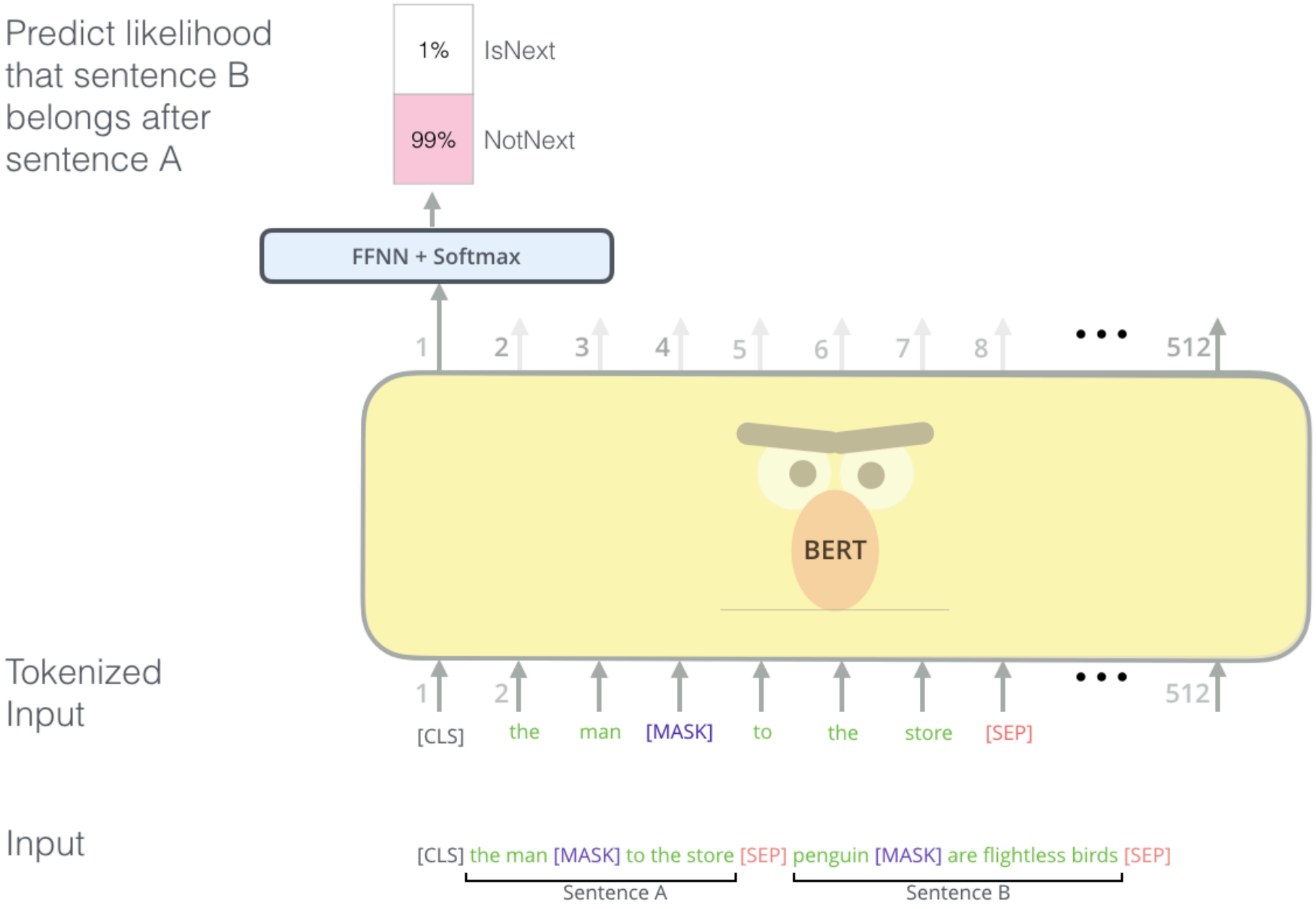
1. Predict missing (masked) words
2. Predict if a sentence is the next sentence

BERT- predict missing words

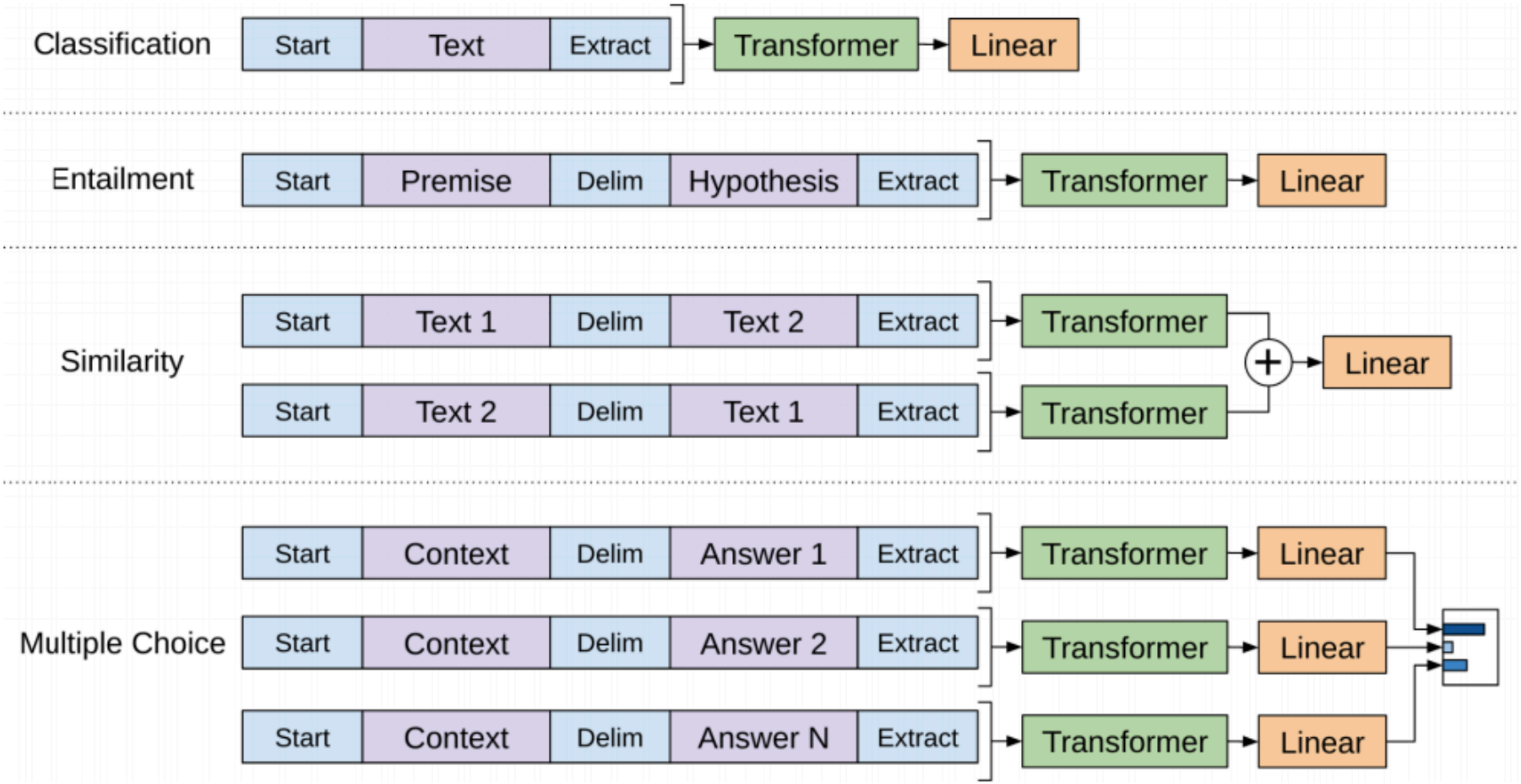


BERT's clever language modeling task masks 15% of words in the input and asks the model to predict the missing word.

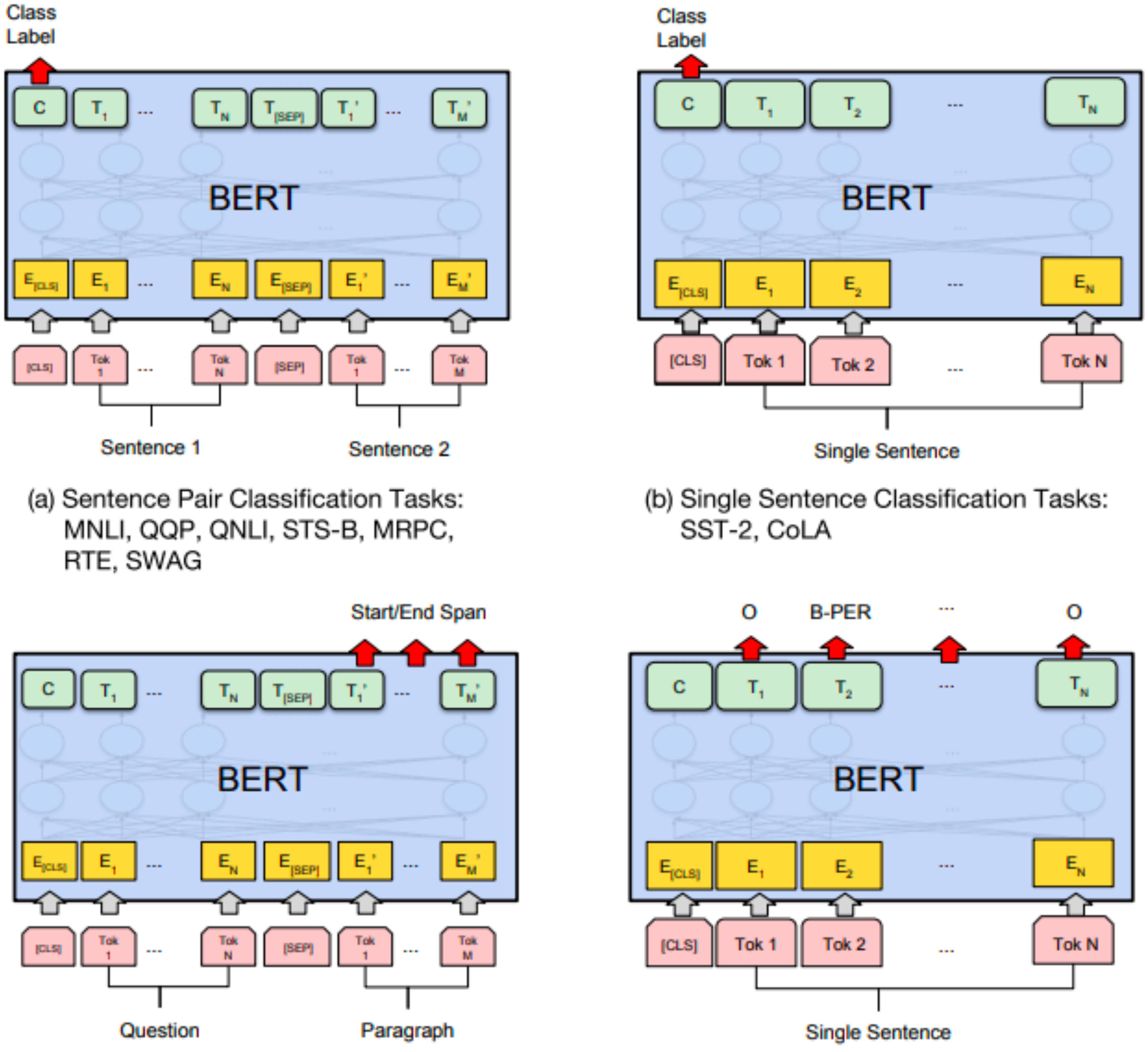
BERT- predict is next sentence?



The second task BERT is pre-trained on is a two-sentence classification task. The tokenization is oversimplified in this graphic as BERT actually uses WordPieces as tokens rather than words --- so some words are broken down into smaller chunks.


Classification
Start
Text
Extract
Transformer
Linear
Entailment
Start
Premise
Delim
Hypothesis
Extract
Transformer
Linear
Similarity
Start
Text 1
Delim
Text 2
Extract
Transformer
Start
Text 2
Delim
Text 1
Extract
Transformer
Linear
Multiple Choice
Start
Context
Delim
Answer 1
Extract
Transformer
Linear
Start
Context
Delim
Answer 2
Extract
Transformer
Linear
Start
Context
Delim
Answer N
Extract
Transformer
Linear

BERT on tasks



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

(b) Single Sentence Classification Tasks: SST-2, CoLA

(c) Question Answering Tasks: SQuAD v1.1

(d) Single Sentence Tagging Tasks: CoNLL-2003 NER

Take-Aways

- Distributional semantics – learn a word's "meaning" by its context
- Simplest representation is frequency in documents
- Word embeddings (Word2Vec, GloVe, FastText) predict rather than use co-occurrence
- Similarity measured often using cosine
- Intrinsic evaluation uses correlation with human judgements of word similarity
- Contextualized embeddings are the new stars of NLP