Words and Morphology

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A Naive View of Language

- Language needs to name
  - nouns: objects in the world (*dog*)
  - verbs: actions (*jump*)
  - adjectives and adverbs: properties of objects and actions (*brown*, *quickly*)

- Relationship between these have to specified
  - word order
  - morphology
  - function words

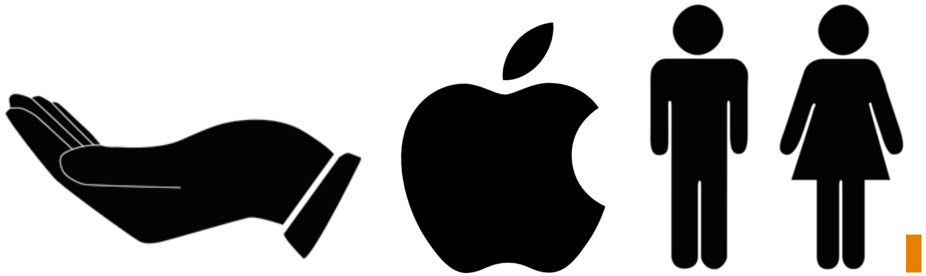
Marking of Relationships: Agreement

- From Catullus, First Book, first verse (Latin):
- Gender (and case) agreement links adjectives to nouns

Cui	*dono*	*lepidum*	*novum*	*libellum*	*arida*	*modo*	*pumice*	*expolitum*	*?*
Whom	*I-present*	*lovely*	*new*	*little-book*	*dry*	*manner*	*pumice*	*polished*	*?*

(To whom do I present this lovely new little book now polished with a dry pumice?)

Marking of Relationships to Verb: Case



- German:

Die Frau	*gibt*	*dem Mann*	*den Apfel*
The woman	*gives*	*the man*	*the apple*
subject		indirect object	object

- Case inflection indicates role of noun phrases

Writingwordstogether

- Definition of word boundaries purely an artifact of writing system
- Differences between languages
  - Agglutinative compounding
    Informatikseminar vs. *computer science seminar*
  - Function word vs. affix
- Border cases
  - *Joe's* — one token or two?
  - Morphology of affixes often depends on phonetics / spelling conventions
    dog+s → *dogs* vs. *pony* → *ponies*

    ... but note the English function word *a*:
    a donkey vs. *an aardvark*

Changing Part-of-Speech

- Derivational morphology allows changing part of speech of words

- Example:
  - base: *nation*, noun

  → *national*, adjective
  → *nationally*, adverb
  → *nationalist*, noun
  → *nationalism*, noun
  → *nationalize*, verb

- Sometimes distinctions between POS quite fluid (enabled by morphology)
  - *I want to integrate morphology*
  - *I want the integration of morphology*

Meaning Altering Affixes

- English

undo

redo

hypergraph

- German: *zer-* implies action causes destruction

Er **zer***redet das Thema* → *He talks the topic* **to death**

- Spanish: *-ito* means object is small

burro → *burrito*

Adding Subtle Meaning

- Morphology allows adding subtle meaning
  - verb tenses: time action is occurring, if still ongoing, etc.
  - count (singular, plural): how many instances of an object are involved
  - definiteness (*the cat* vs. *a cat*): relation to previously mentioned objects
  - grammatical gender: helps with co-reference and other disambiguation

- Sometimes redundant: same information repeated many times

how does morphology impact machine translation?

Unknown Words

- Ratio of unknown words in WMT 2013 test set:

Source language	Ratio unknown
Russian	2.0%
Czech	1.5%
German	1.2%
French	0.5%
English (to French)	0.5%

- Caveats:
  - corpus sizes differ
  - not clear which unknown words have known morphological variants

Differently Encoded Information

- Languages with different sentence structure

das	*behaupten*	*sie*	*wenigstens*
this	*claim*	*they*	*at least*
the		*she*	

- Convert from inflected language into configuration language
  (and vice versa)

- Ambiguities can be resolved through syntactic analysis
  - the meaning *the* of *das* not possible (not a noun phrase)
  - the meaning *she* of *sie* not possible (subject-verb agreement)

Non-Local Information

- Pronominal anaphora

I saw the movie and it is good.

- How to translate *it* into German (or French)?
  - *it* refers to *movie*
  - *movie* translates to *Film*
  - *Film* has masculine gender
  - ergo: *it* must be translated into masculine pronoun *er*

- We are not handling pronouns very well

Complex Semantic Inference

- Example

Whenever I visit my uncle and his daughters,
I can't decide who is my favorite cousin.

- How to translate *cousin* into German? Male or female?

morphological pre-precessing schemes

German

- German sentence with morphological analysis

Er	*wohnt*	*in*	*einem*	*großen*	*Haus*
Er	*wohnen -en+t*	*in*	*ein +em*	*groß +en*	*Haus +ϵ*
He	*lives*	*in*	*a*	*big*	*house*

- Four inflected words in German, but English...

also inflected both English verb *live* and German verb *wohnen*
inflected for tense, person, count

not inflected corresponding English words not inflected (*a* and *big*)
→ easier to translate if inflection is stripped

less inflected English word *house* inflected for count
German word *Haus* inflected for count and case
→ reduce morphology to singular/plural indicator

- Reduce German morphology to match English

Er	*wohnen+*3P-SGL	*in*	*ein*	*groß*	*Haus+*SGL

Turkish

- Example
  - Turkish: Sonuçlarına$_1$ dayanılarak$_2$ bir$_3$ ortakliği$_4$ oluşturulacaktır$_5$.
  - English: **a**$_3$ **partnership**$_4$ *will be* **drawn-up**$_5$ *on the* **basis**$_2$ *of* **conclusions**$_1$.
- Turkish morphology $\rightarrow$ English function words (*will*, *be*, *on*, *the*, *of*)
- Morphological analysis

Sonuç +lar +sh +na daya +hnhl +yarak bir ortaklık +sh oluş +dhr +hl +yacak +dhr

- Alignment with morphemes

sonuç	*+lar*	*+sh*	*+na*		*daya+hnhl*	*+yarak*	*bir*	*ortaklık*	*+sh*	*oluş*	*+dhr*	*+hl*	*+yacak*	*+dhr*
conclusion	*+s*		*of*	*the*	*basis*	*on*	*a*	*partnership*		*draw up*	*+ed*		*will*	*be*

$\Rightarrow$ Split Turkish into morphemes, drop some

Arabic

- Basic structure of Arabic morphology

*[*CONJ+ *[*PART+ *[*al+ BASE +PRON*]]]*

- Examples for clitics (prefixes or suffixes)
  - definite determiner *al+* (English *the*)
  - pronominal morpheme *+hm* (English *their/them*)
  - particle *l+* (English *to/for*)
  - conjunctive pro-clitic *w+* (English *and*)

- Same basic strategies as for German and Turkish
  - morphemes akin to English words → separated out as tokens
  - properties (e.g., tense) also expressed in English → keep attached to word
  - morphemes without equivalence in English → drop

Arabic Preprocessing Schemes

ST Simple tokenization (punctuations, numbers, remove diacritics)

wsynhY Alr}ys jwlth bzyArp AlY trkyA .

D1 Decliticization: split off conjunction clitics

w+ synhy Alr}ys jwlth bzyArp <lY trkyA .

D2 Decliticization: split off the class of particles

w+ s+ ynhy Alr}ys jwlth b+ zyArp <lY trkyA .

D3 Decliticization: split off definite article (Al+) and pronominal clitics

w+ s+ ynhy Al+ r}ys jwlp +P$_{3MS}$ *b+ zyArp <lY trkyA .*

MR Morphemes: split off any remaining morphemes

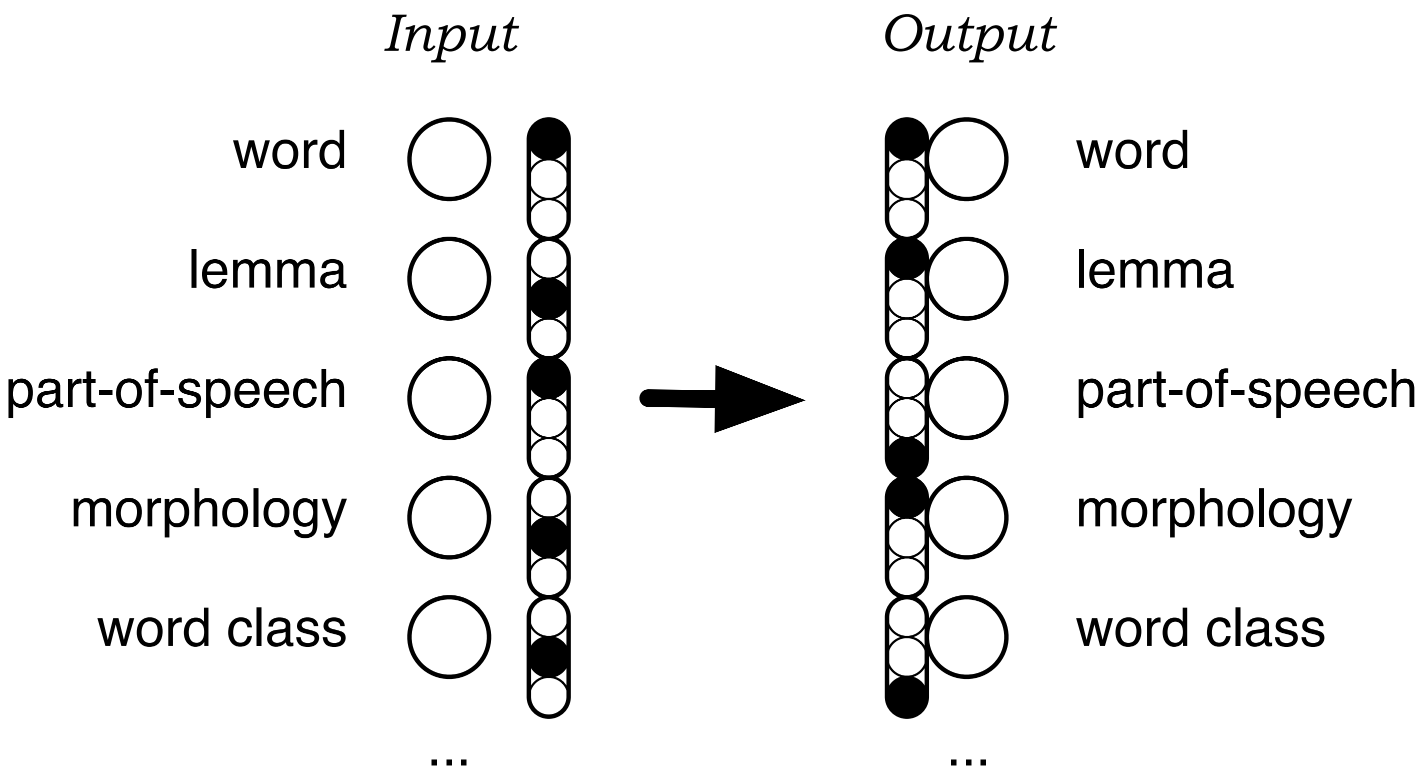
w+ s+ y+ nhy Al+ r}ys jwl +p +h b+ zyAr +p <lY trkyA .

EN English-like: use lexeme and English-like POS tags, indicates pro-dropped verb subject as a separate token

w+ s+ >nhY$_{VBP}$ *+S*$_{3MS}$ *Al+ r}ys*$_{NN}$ *jwlp*$_{NN}$ *+P*$_{3MS}$ *b+ zyArp*$_{NN}$ *<lY trky*$_{NNP}$

Factored Models

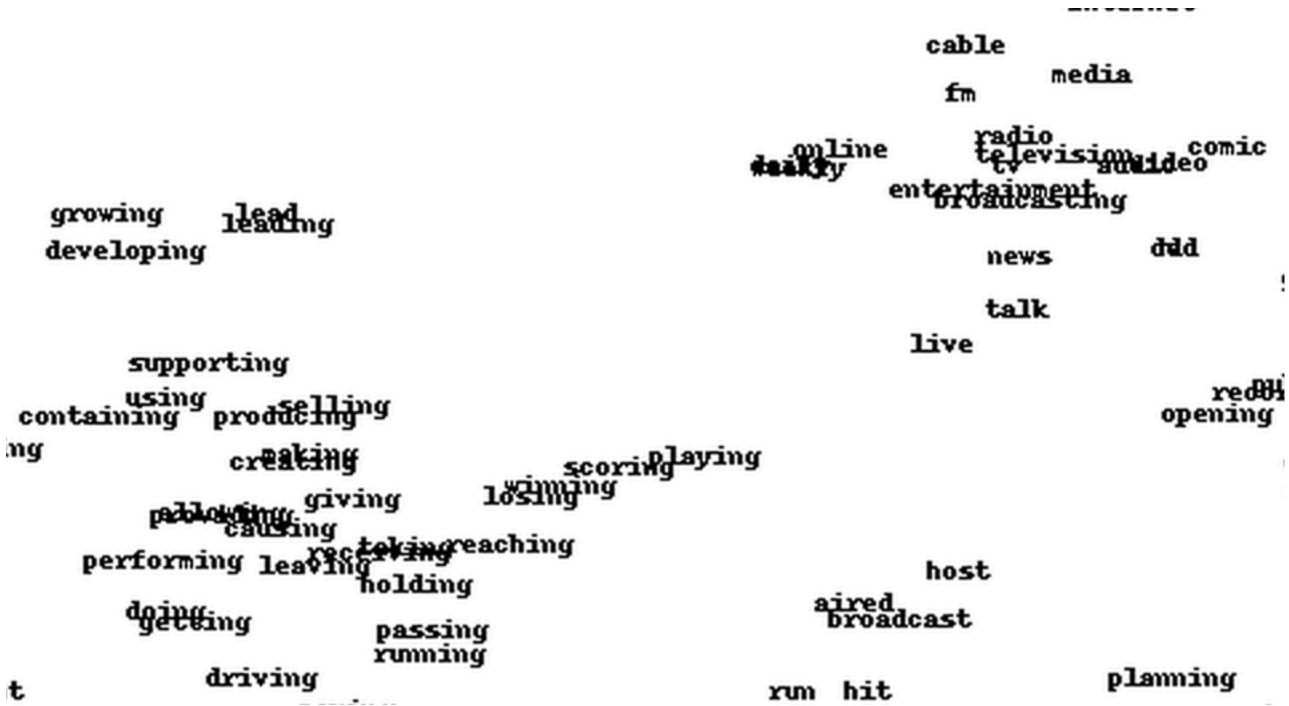
- Factored representation of words



- Encode each factor with a one-hot vector

word embeddings

Word Embeddings



- In neural translation models words are mapped into, say, 500-dimensional continuous space
- Contextualized in encoder layers

Latent Semantic Analysis

- Word embeddings not a new idea
- Representing words based on their context has long tradition in natural language processing
- Co-occurence statistics

word	**context**			
	cute	*fluffy*	*dangerous*	*of*
dog	231	76	15	5767
cat	191	21	3	2463
lion	5	1	79	796

- But: large counts of function words misleading

Pointwise Mutual Information

- Pointwise mutual information

$$\text{PMI}(x;y) = \log \frac{p(x,y)}{p(x)p(y)}$$

- Intuition: measures how much more frequent than chance

word	**context**			
	cute	*fluffy*	*dangerous*	*of*
dog	9.4	6.3	0.2	1.1
cat	8.3	3.1	0.1	1.0
lion	0.1	0.0	12.1	1.0

- Similar words have similar vectors

Singular Value Decomposition

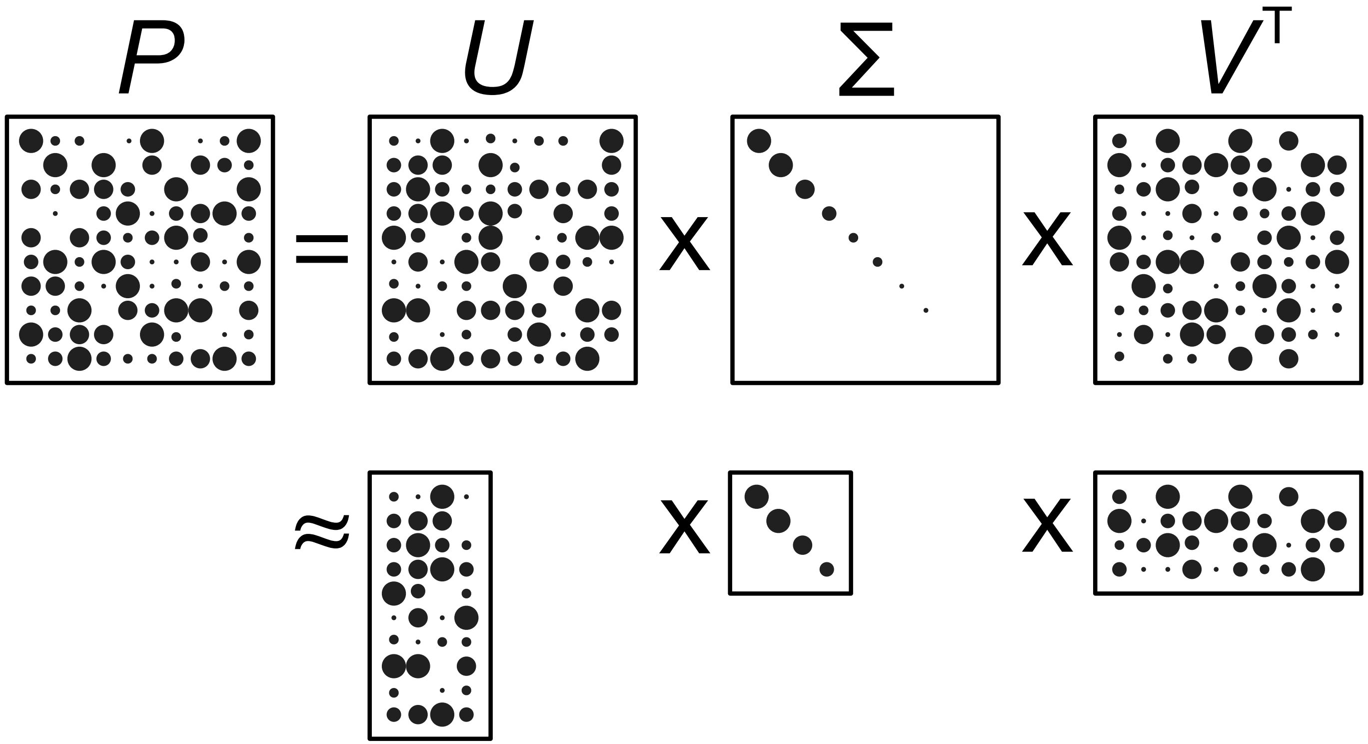
- Raw co-occurence statistics matrxi very sparse

⇒ Reduce into lower dimensional matrix

- Factorize the PMI matrix P into
  - two orthogonal matrices U and V
    (i.e. UU^T and VV^T are an identity matrix)
  - diagonal matrix Σ
    (i.e., it only has non-zero values on the diagonal)

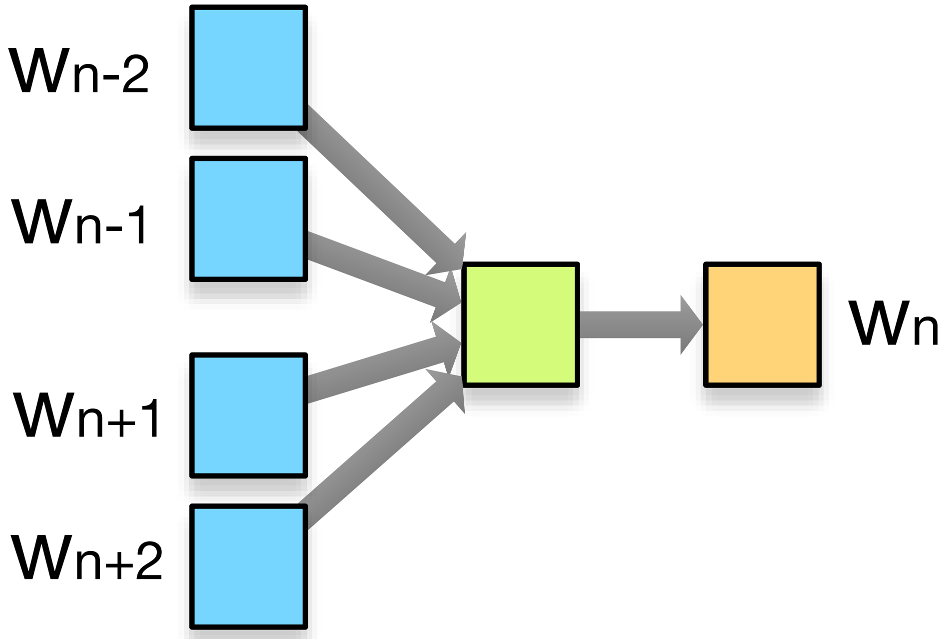
$$P = U\Sigma V^T$$

Singular Value Decomposition



- Not going into details how to compute this
- Geometric interpretation: rotation U, a stretching Σ, and another rotation V^T
- Matrices U and V^T play similar role as embedding matrices

Continuous Bag of Words (CBOW)



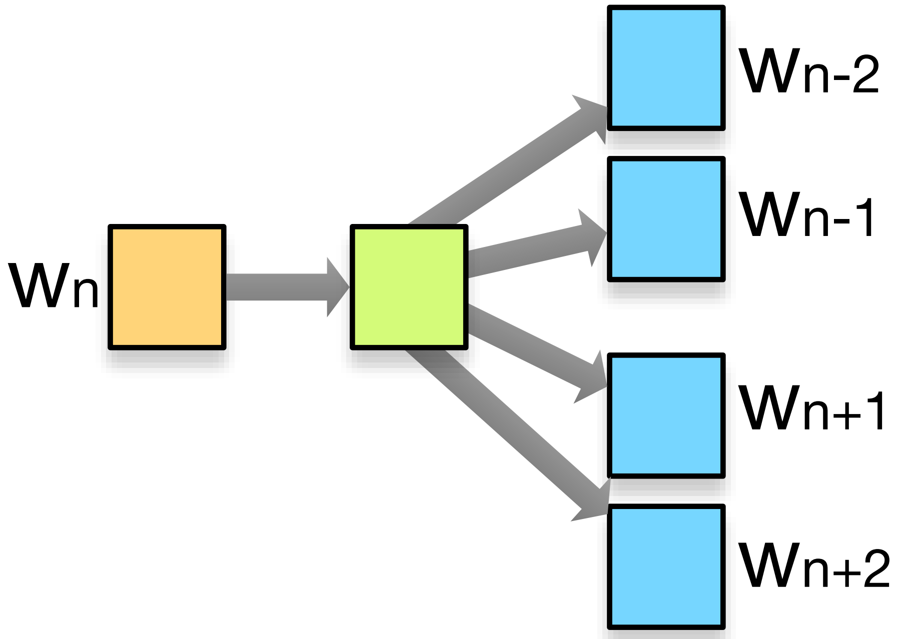
- Predict word from context

$$h_t = \frac{1}{2n} \sum_{j \in \{-n,...,-1,1,...,n\}} C w_{t+j}$$

$$y_t = \text{softmax}(U h_t)$$

- Similar to n-gram language model

Skip Gram



- Predict context from word

$$y_t = \text{softmax}(UCw_t)$$

- C input word embedding matrix, U output word embedding matrix

GloVe

- Global Vectors: use co-occurrence statistics

word	**context**			
	cute	*fluffy*	*dangerous*	*of*
dog	231	76	15	5767
cat	191	21	3	2463
lion	5	1	79	796

- Predict the values in this matrix X, using target word embeddings v_i and context word embeddings $\tilde{v}_j$

$$\text{cost} = \sum_i \sum_j \tilde{v}_j^T |v_i - \log X_{ij}|$$

- Training: loop over all words, and their context words

Refinements

- Bias terms b and $\tilde{b}$

$$\text{cost} = \sum_i \sum_j |b_i + \tilde{b}_j + \tilde{v}_j^T v_i - \log X_{ij}|$$

- Most word pairs (i, j) meaningless, especially for rare words

- Discount them with a scaling function

$$f(x) = \min(1, (x/x_{\max})^\alpha)$$

hyper parameter values, e.g., $\alpha = \frac{3}{4}$ and $x_{\max} = 200$

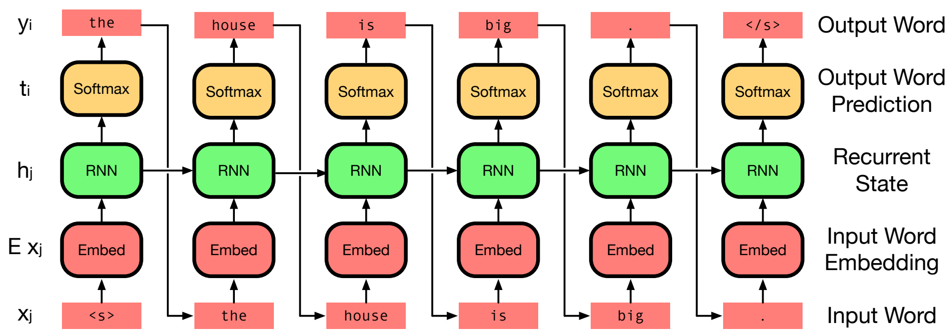
- Complete refined cost function

$$\text{cost} = \sum_i \sum_j f(X_{ij})(b_i + \tilde{b}_j + \tilde{v}_j^T v_i - \log X_{ij})^2$$

ELMo

- Word embeddings widely used in natural language processing
- But: better refine them in the sentence context

⇒ *Embeddings from language models* (ELMo)
(we have always done this in the encoder of our neural translation models)



- Several layers, use weighted sum of representations at different layers
  - syntactic information is better represented in early layers
  - semantic information is better represented in deeper layers.

BERT

- Contextualized word embeddings with Transformer model
- Masked training

```
The quick brown fox jumps over the lazy dog.
                    ⇑
  The quick MASK fox MASK over the lazy dog.
```

- Next sentence prediction

```
Each unhappy family is unhappy in its own way.
                    ⇑
        All happy families are alike.
```

GPT-3 (2020)

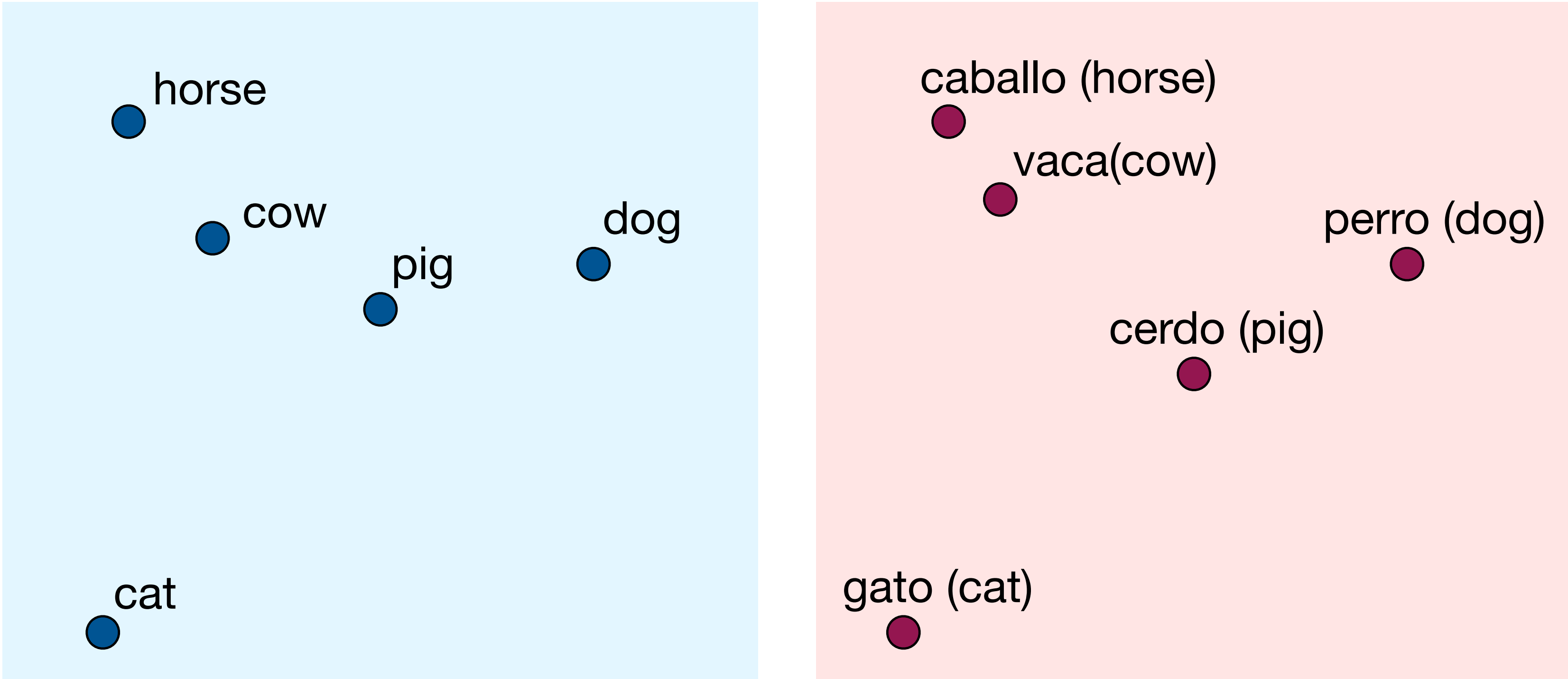
- Essentially BERT, but bigger
- Model: Transformer
  - 175 billion parameters
  - 96 layers
  - 12288 dimensional representations
  - 96 attention heads
- Training
  - trained on about 500 billion word data set, less than 1 epoch
  - 3640 petaflop/s-days on NVIDIA V100 (each can do 0.1 petaflops)
- There currently seems to be not plateau: bigger is better

multi-lingual word embeddings

Multi-Lingual Word Embeddings

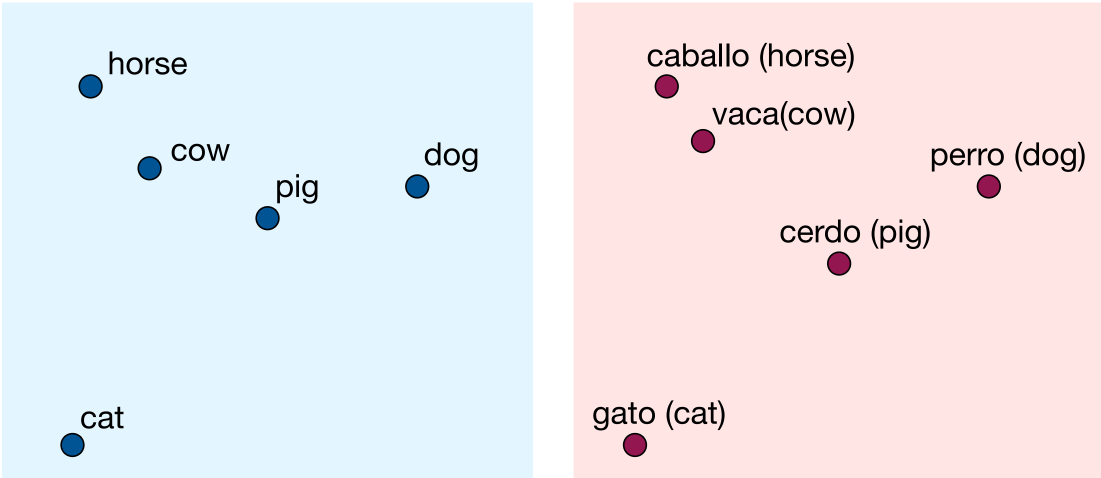
- Word embeddings often viewed as semantic representations of words
- Tempting to view embedding spaces as language-independent
  cat (English), *gato* (Spanish) and *Katze* (German) are mapped to same vector
- Common semantic space for words in all languages?

Language-Specific Word Embeddings



- Train English word embeddings C_E and Spanish word embeddings C_S

Mapping Word Embedding Spaces

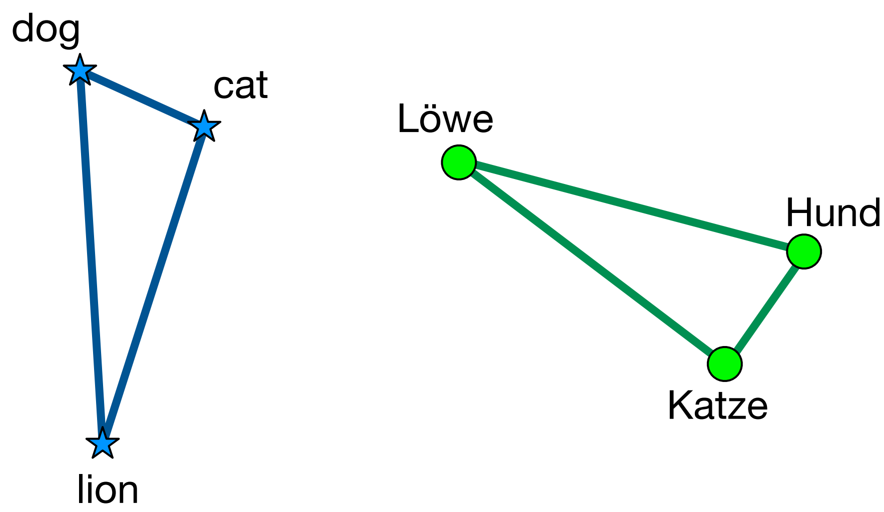


- Learn mapping matrix $W_{S \to E}$ to minimize Euclidean distance between each word and its translation

$$\text{cost} = \sum_i ||W_{S \to E}\, c_i^S - c_i^E||$$

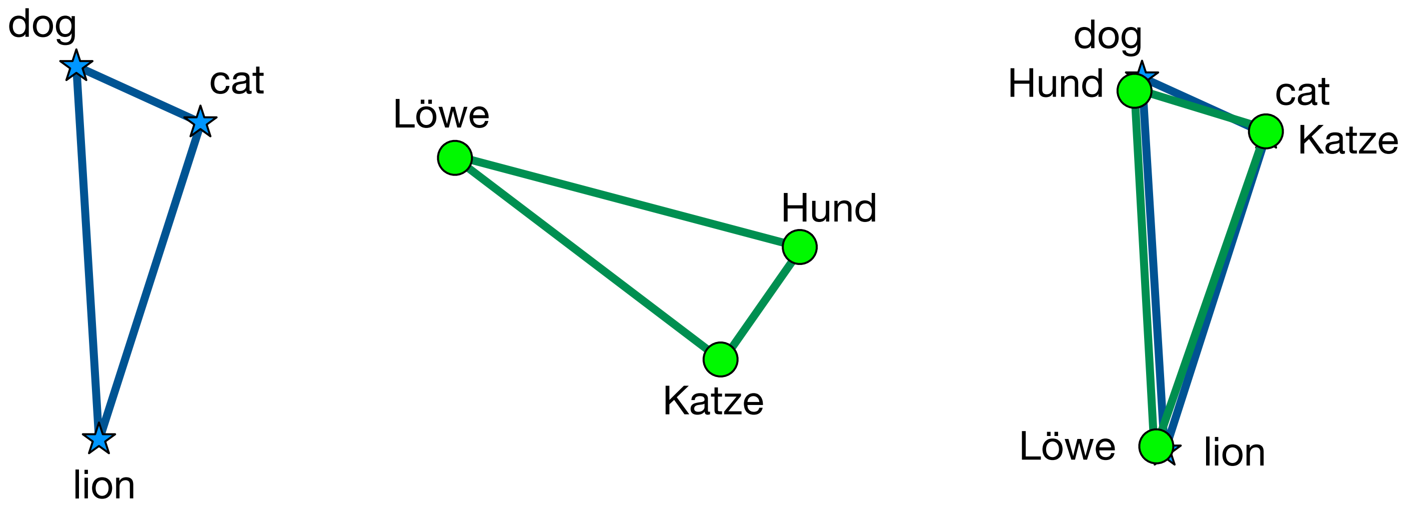
- Needed: Seed lexicon of word translations (may be based on cognates)
- Hubness problem: some words being the nearest neighbor of many words

Using only Monolingual Data



- Learn transformation matrix $W_{S \rightarrow E}$ without seed lexicon?
- Intuition: relationship between *dog*, *cat*, and *lion*, independent of language
- How can we rotate the triangle to match up?

Using only Monolingual Data



- One idea: learn transformation matrix $W_{\text{German}\rightarrow\text{English}}$ so that words match up

Adversarial Training

- Another idea: adversarial training
  - points in the German and English space do not match up

  $\rightarrow$ adversary can classify them as either German and English

- Training objective of adversary to learn classifier P

$$\text{cost}_D(P|W) = -\frac{1}{n}\sum_{i=1}^{n} \log P(\text{German}|Wg_i) - \frac{1}{m}\sum_{j=1}^{m} \log P(\text{English}|e_j)$$

- Training objective of unsupervised learner

$$\text{cost}_D(W|P) = -\frac{1}{n}\sum_{i=1}^{n} \log P(\text{English}|Wg_i) - \frac{1}{m}\sum_{j=1}^{m} \log P(\text{German}|eji)$$

large vocabularies

Large Vocabularies

- Zipf's law tells us that words in a language are very unevenly distributed.
  - large tail of rare words
    (e.g., new words *retweeting, website, woke, lit*)
  - large inventory of names, e.g., *eBay, Yahoo, Microsoft*

- Neural methods not well equipped to deal with such large vocabularies
  (ideal representations are continuous space vectors → word embeddings)

- Large vocabulary
  - large embedding matrices for input and output words
  - prediction and softmax over large number of words

- Computationally expensive, both in terms of memory and speed

Special Treatment for Rare Words

- Limit vocabulary to 20,000 to 80,000 words
- First idea
  - map other words to unknown word token (UNK)
  - model learns to map input UNK to output UNK
  - replace with translation from backup dictionary
- Not used anymore, except for numbers and units
  - numbers: English *540,000*, Chinese *54* TENTHOUSAND, Indian *5.4 lakh*
  - units: map *25cm* to *10 inches*

Some Causes for Large Vocabularies

- Morphology

  tweet, *tweets*, *tweeted*, *tweeting*, *retweet*, ...

  → morphological analysis?

- Compounding

  homework, *website*, ...

  → compound splitting?

- Names

  Netanyahu, *Jones*, *Macron*, *Hoboken*, ...

  → transliteration?

⇒ Breaking up words into **subwords** may be a good idea

Byte Pair Encoding

- Start by breaking up words into characters

```
t h e ␣ f a t ␣ c a t ␣ i s ␣ i n ␣ t h e ␣ t h i n ␣ b a g
```

- Merge frequent pairs

```
t h→th    th e ␣ f a t ␣ c a t ␣ i s ␣ i n ␣ th e ␣ th i n ␣ b a g
a t→at    th e ␣ f at ␣ c at ␣ i s ␣ i n ␣ th e ␣ th i n ␣ b a g
i n→in    th e ␣ f at ␣ c at ␣ i s ␣ in ␣ th e ␣ th in ␣ b a g
th e→the  the ␣ f at ␣ c at ␣ i s ␣ in ␣ the ␣ th in ␣ b a g
```

- Each merge operation increases the vocabulary size
  - starting with the size of the character set (maybe 100 for Latin script)
  - stopping after, say, 50,000 operations

Byte Pair Encoding

Obama receives Net@@ any@@ ahu

the relationship between Obama and Net@@ any@@ ahu is not exactly friendly . the two wanted to talk about the implementation of the international agreement and about Teheran 's destabil@@ ising activities in the Middle East . the meeting was also planned to cover the conflict with the Palestinians and the disputed two state solution . relations between Obama and Net@@ any@@ ahu have been stra@@ ined for years . Washington critic@@ ises the continuous building of settlements in Israel and acc@@ uses Net@@ any@@ ahu of a lack of initiative in the peace process . the relationship between the two has further deteriorated because of the deal that Obama negotiated on Iran 's atomic programme . in March , at the invitation of the Republic@@ ans , Net@@ any@@ ahu made a controversial speech to the US Congress , which was partly seen as an aff@@ ront to Obama . the speech had not been agreed with Obama , who had rejected a meeting with reference to the election that was at that time im@@ pending in Israel .

Subwords

- Byte pair encoding induces subwords

- But: only accidentally along linguistic concepts of morphology
  - morphological: `critic@@ ises`, `im@@ pending`
  - not morphological: `aff@@ ront`, `Net@@ any@@ ahu`

- Still: Similar to unsupervised morphology (frequent suffixes, etc.)

Sentence Piece

_Obama _receives _Net any ahu

_the _relationship _between _Obama _and _Net any ahu _is _not _exactly _friendly _. _the _two _wanted _to _talk _about _the _implementation _of _the _international _agreement _and _about _Teheran _'s _destabil ising _activities _in _the _Middle _East _. _the _meeting _was _also _planned _to _cover _the _conflict _with _the _Palestinians _and _the _disputed _two _state _solution _. _relations _between _Obama _and Net _any _ahu _have _been _stra ined _for _years _. _Washington _critic ises _the _continuous _building _of _settlements _in _Israel _and _acc uses _Net any ahu _of _a _lack _of _initiative _in _the _peace _process _. _the _relationship _between _the _two _has _further _deteriorated _because _of _the _deal _that _Obama _negotiated _on _Iran _'s _atomic _programme _. _in _March _, _at _the _invitation _of _the _Republic ans _, _Net any ahu _made _a _controversial _speech _to _the _US _Congress _, _which _was _partly _seen _as _an _aff ront _to _Obama _. _the _speech _had _not _been _agreed _with _Obama _, _who _had _rejected _a _meeting _with _reference _to _the _election _that _was _at _that _time _im pending _in _Israel .

character-based models

Character-Based Models

- Explicit word models that yield word embeddings
- Standard methods for frequent words
  - distribution of `beautiful` in the data

  → embedding for `beautiful`
- Character-based models
  - create sequence embedding for character string `b e a u t i f u l`
  - training objective: match word embedding for `beautiful`
- Induce embeddings for unseen morphological variants
  - character string `b e a u t i f u l l y`

  → embedding for `beautifully`
- Hope that this learns morphological principles

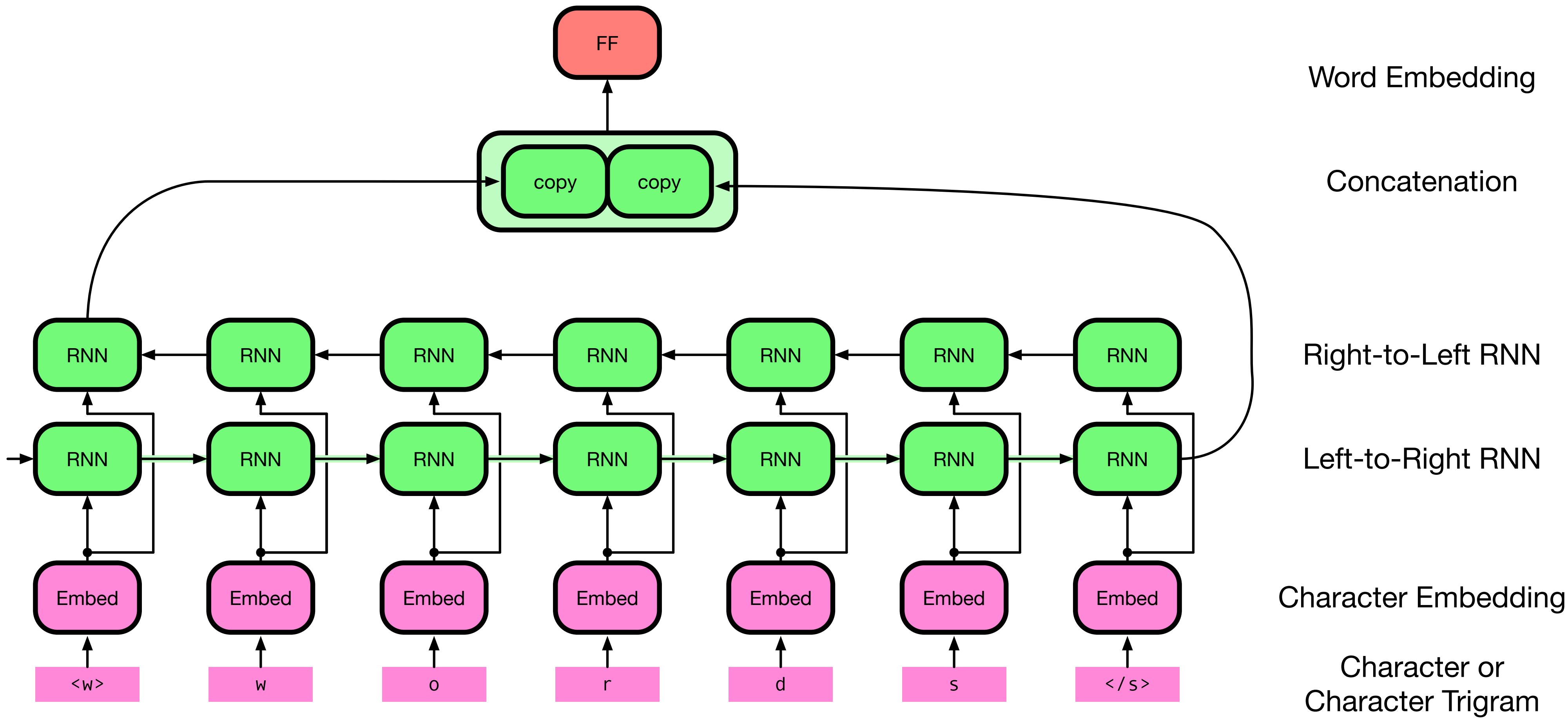
Character Sequence Models

- Same model as for words
- Tokens = single characters, incl. special space symbol
- But: generally poor performance
- With some refinements, use in output shown competitive

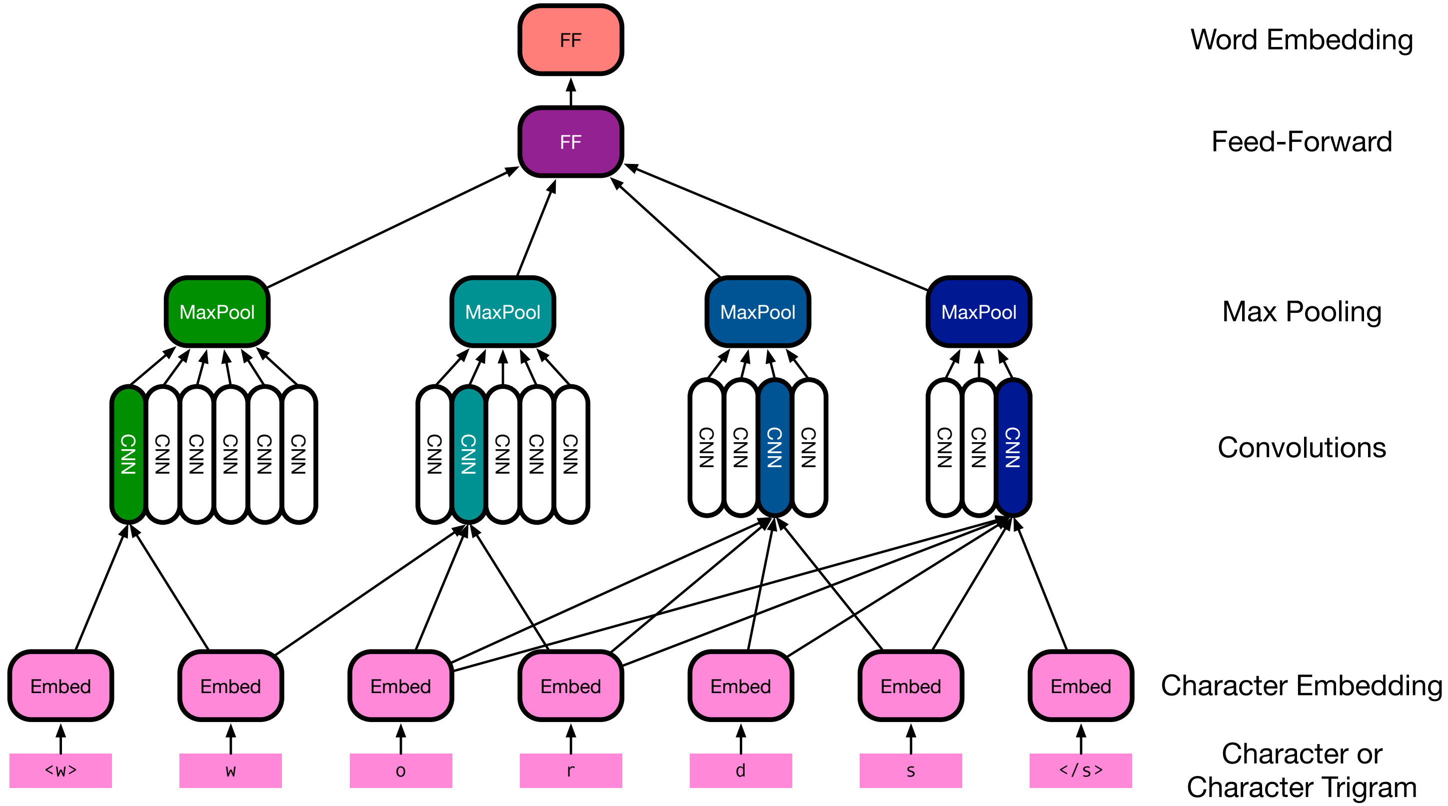
Character Based Word Models

- Word embeddings as before
- Compute word embeddings based on character sequence
- Typically, interpolated with traditional word embeddings

Recurrent Neural Networks



Convolutional Neural Networks



- Convolutions of diferent size: 2 characters, 3 characters, ..., 7 characters
- May be based on letter n-grams (trigrams shown)