# Words and Morphology

Philipp Koehn

20 October 2020

# 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*)

# 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



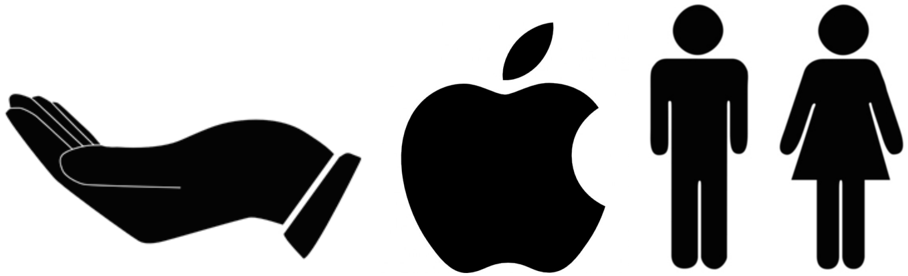
- From Catullus, First Book, first verse (Latin):
- Gender (and case) agreement links adjectives to nouns

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

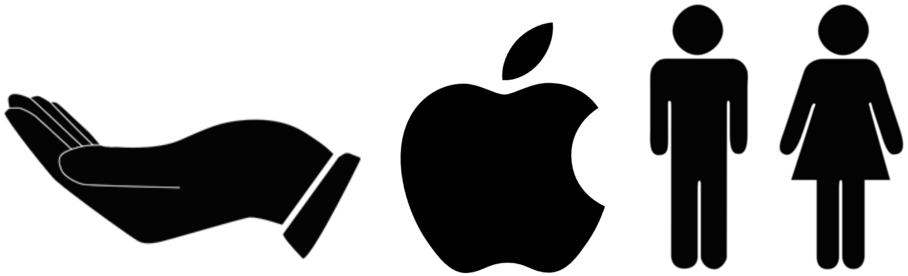
*(To whom do I present this lovely new little book now polished with a dry pumice?)*

# Marking of Relationships to Verb: Case





# 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

# 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

# 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

# Changing Part-of-Speech



- Derivational morphology allows changing part of speech of words

- Example:
  - base: *nation*, noun

  $\rightarrow$ *national*, adjective
  $\rightarrow$ *nationally*, adverb
  $\rightarrow$ *nationalist*, noun
  $\rightarrow$ *nationalism*, noun
  $\rightarrow$ *nationalize*, verb

# Changing Part-of-Speech



- Derivational morphology allows changing part of speech of words

- Example:
  - base: *nation*, noun

  $\rightarrow$ *national*, adjective
  $\rightarrow$ *nationally*, adverb
  $\rightarrow$ *nationalist*, noun
  $\rightarrow$ *nationalism*, noun
  $\rightarrow$ *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*

# Meaning Altering Affixes



- English

*undo*

*redo*

*hypergraph*

- German: *zer-* implies action causes destruction

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

# 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 +$\epsilon$* |
| *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

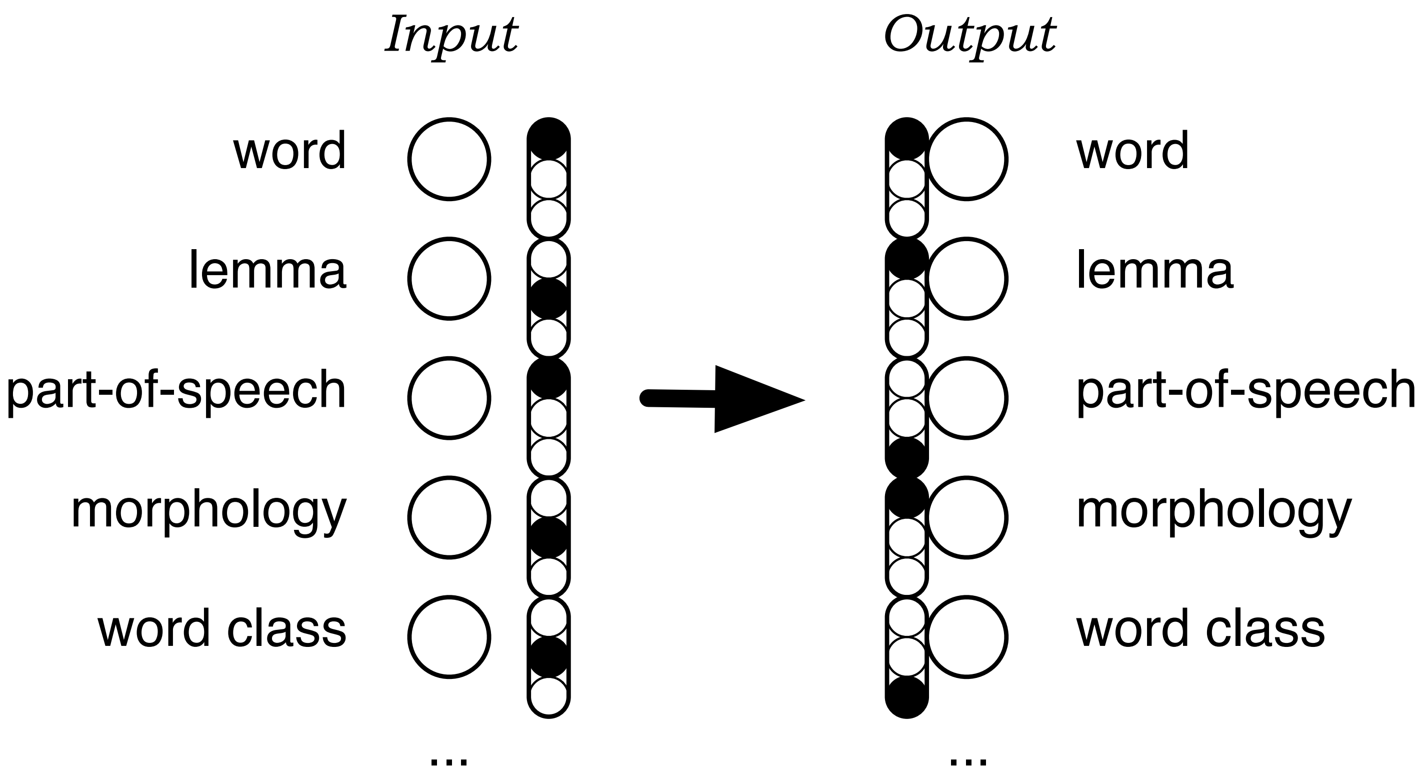
*w+ s+ y+ nhy Al+ r}ys jwl +p +h b+ zyAr +p <lY trkyA .*

**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

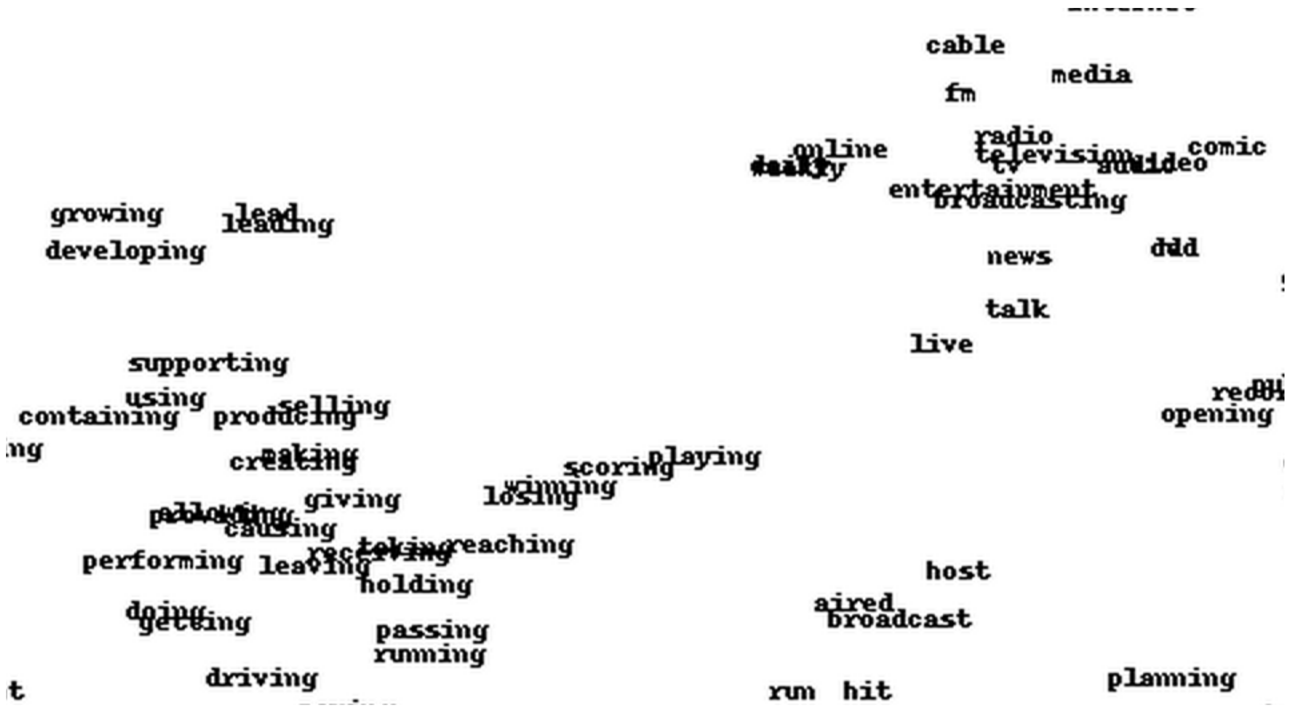



- Encode each factor with a one-hot vector

# 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

# 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 matrix very sparse

$\Rightarrow$ Reduce into lower dimensional matrix

# Singular Value Decomposition



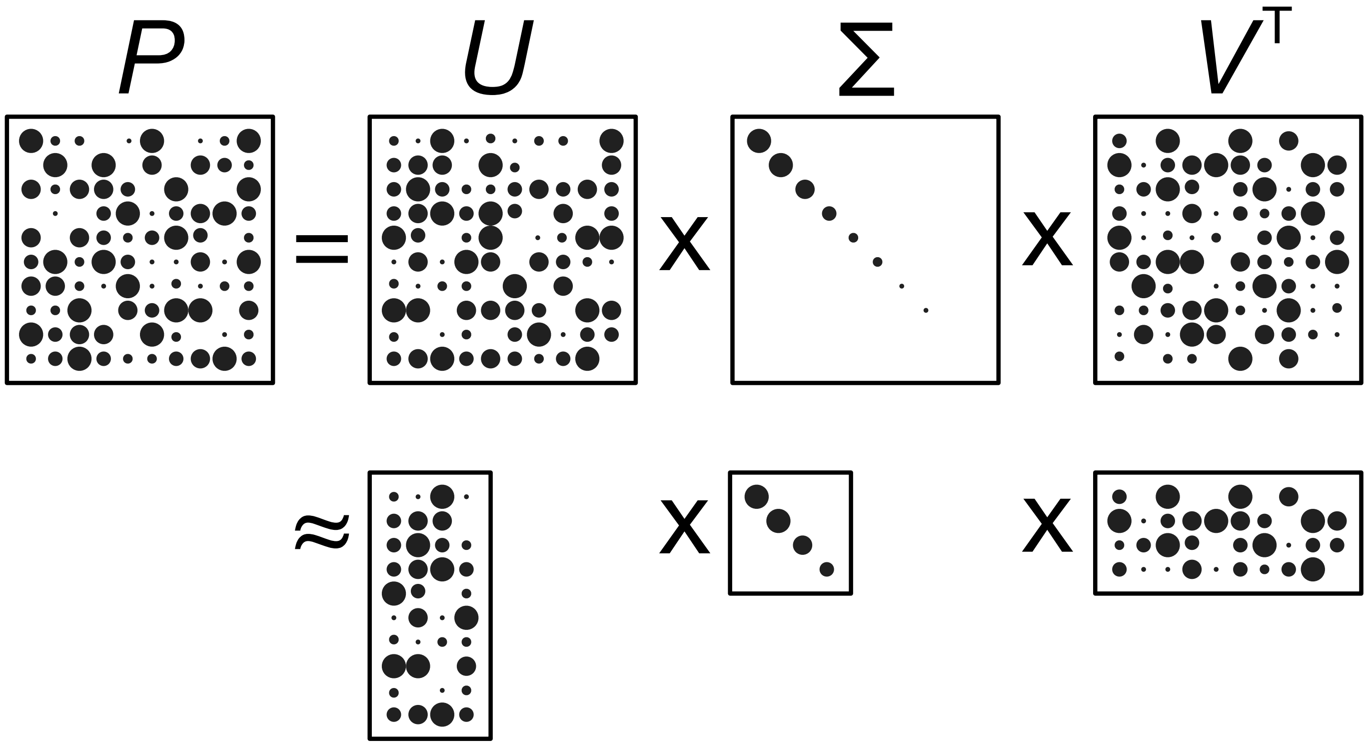
- Raw co-occurence statistics matrix very sparse

⇒ 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 $\Sigma$
    (i.e., it only has non-zero values on the diagonal)

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

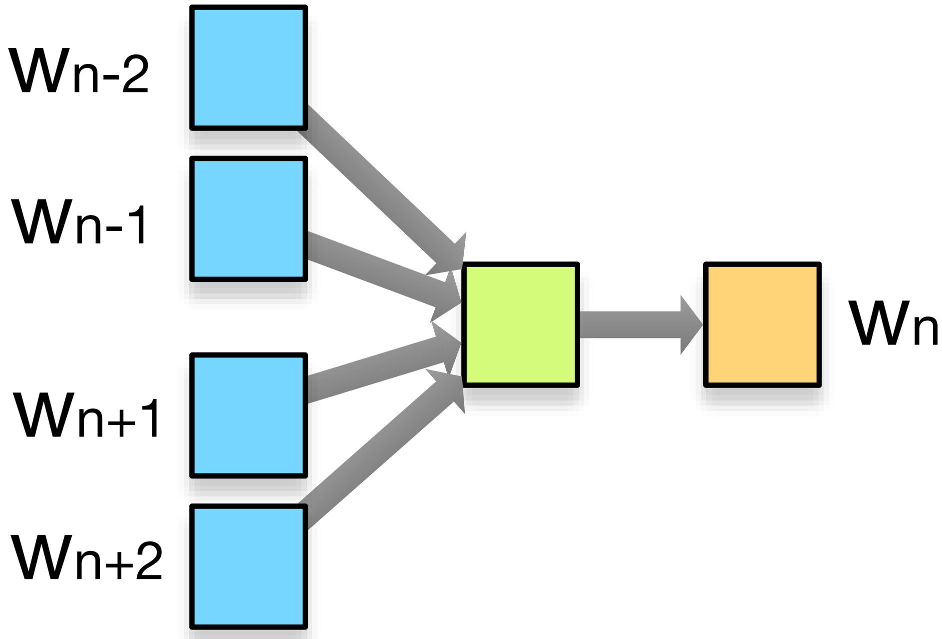
# Singular Value Decomposition




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

# Continuous Bag of Words (CBOW)





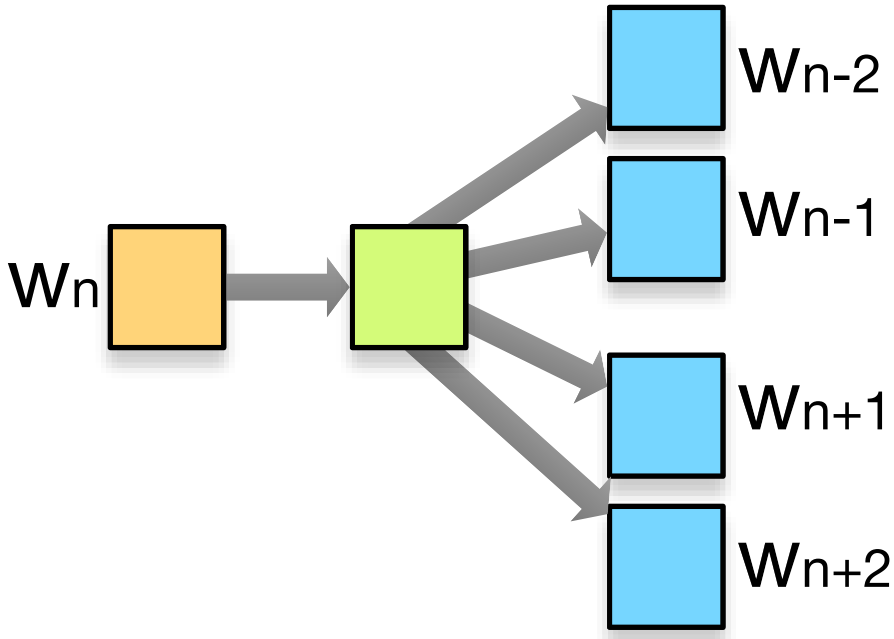

- Predict word from context

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

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

- 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 $\tilde{b}$

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

# 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

# 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

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

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

# 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

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

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

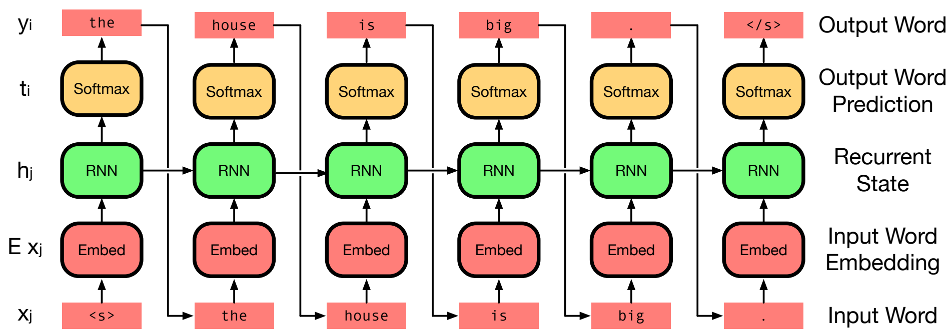
- Complete refined cost function

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

# 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

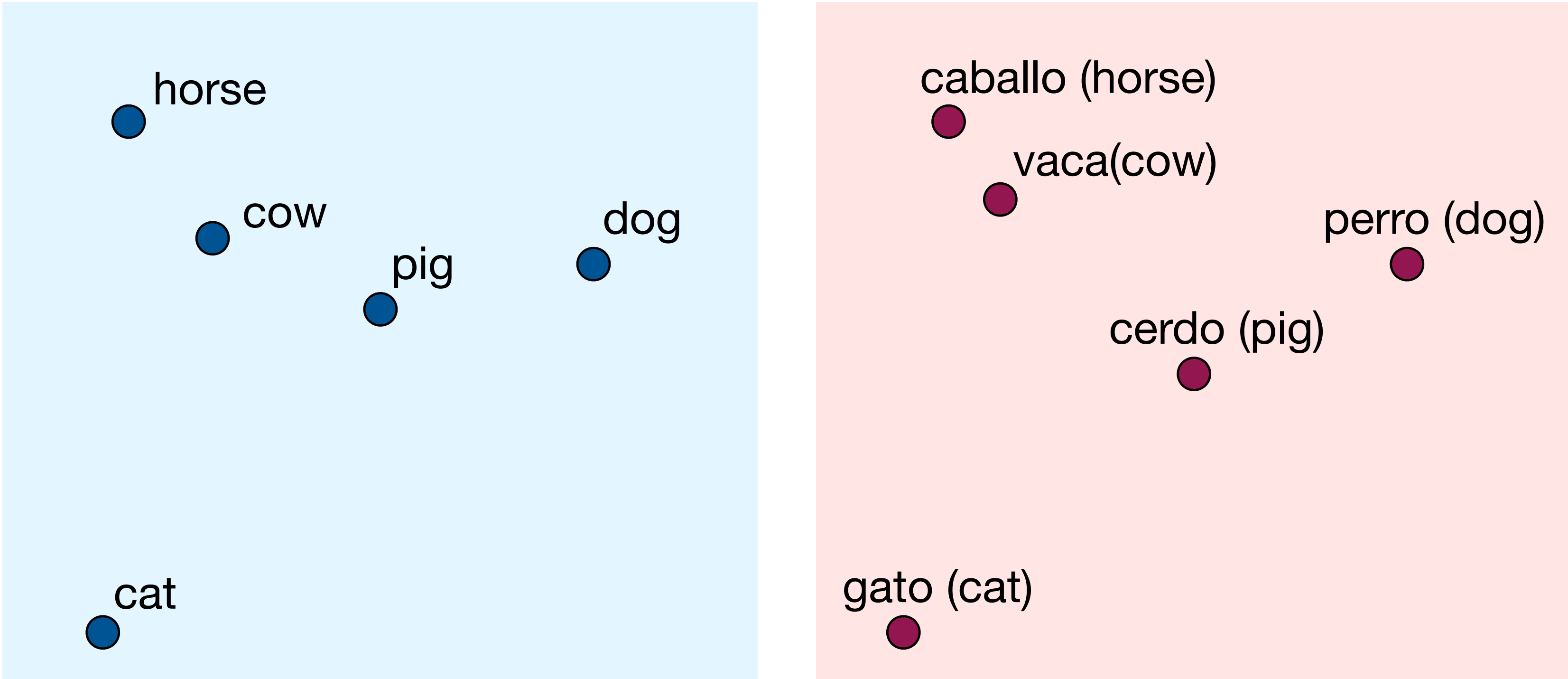
# Multi-Lingual Word Embeddings



- 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

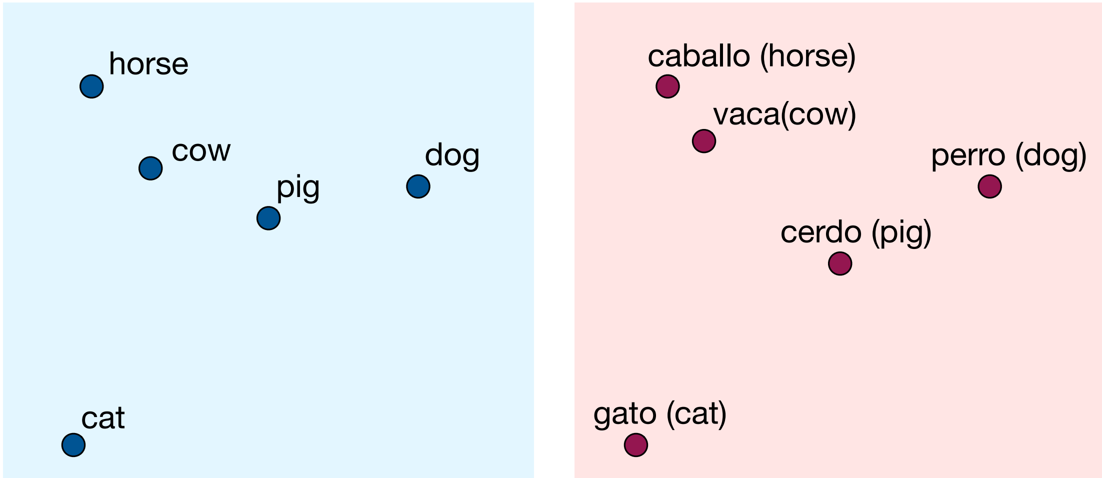





- Train English word embeddings $C_E$ and Spanish word embeddings $C_S$

# Mapping Word Embedding Spaces






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

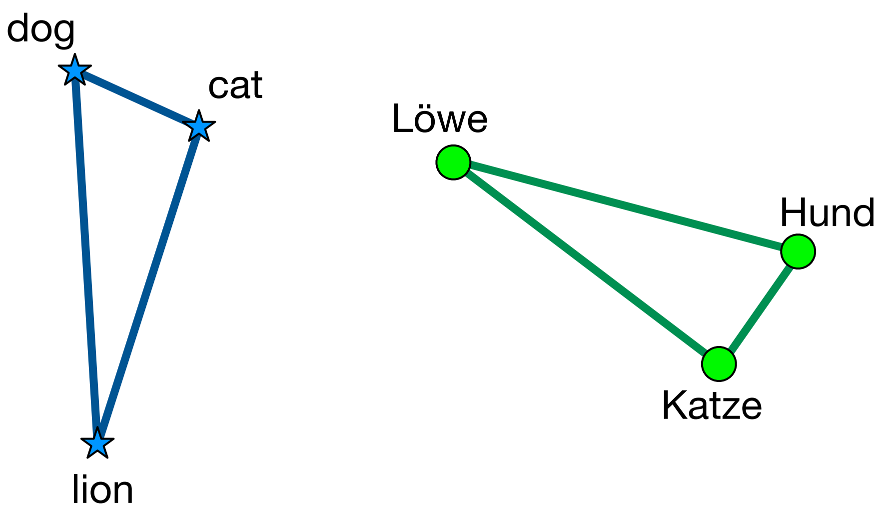
$$\text{cost} = \sum_i ||W_{S \to E}\ c_i^S - c_i^E||$$

- Needed: Seed lexicon of word translations (may be based on cognates)

- Hubness problem: some words being the nearest neighbor of many words

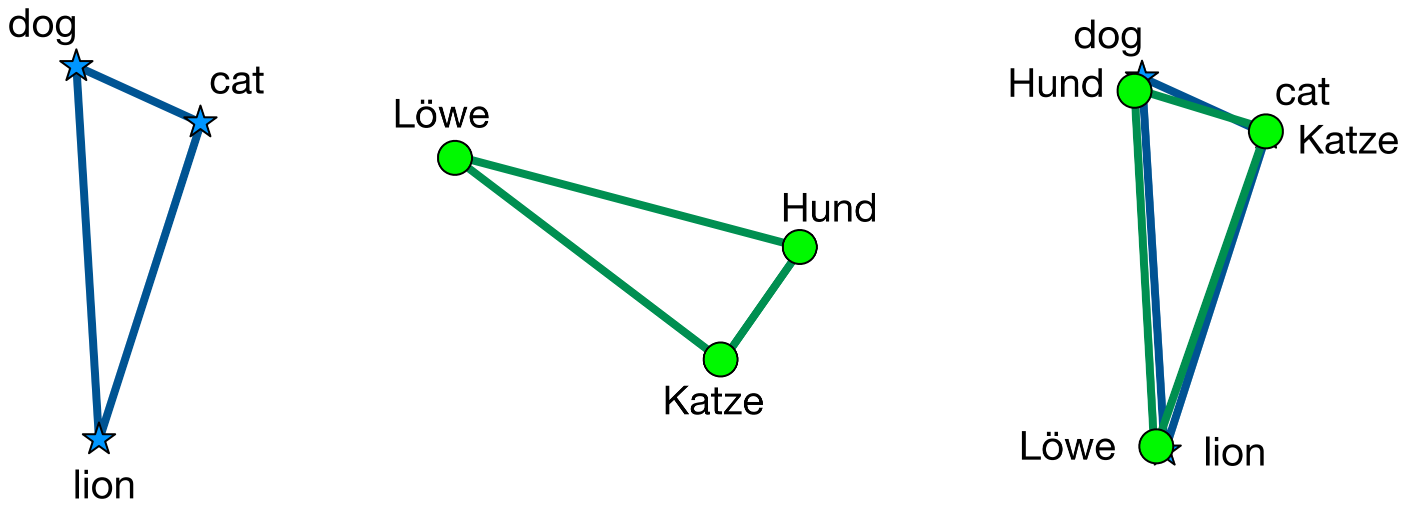
# Using only Monolingual Data






- Learn transformation matrix $W_{S \to E}$ 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

# 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

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

# 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*

# 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 $\rightarrow$ word embeddings)

# 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?

# Some Causes for Large Vocabularies



- Morphology

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

  $\rightarrow$ morphological analysis?

- Compounding

  *homework*, *website*, ...

  $\rightarrow$ compound splitting?

# Some Causes for Large Vocabularies



- Morphology

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

  $\rightarrow$ morphological analysis?

- Compounding

  *homework*, *website*, ...

  $\rightarrow$ compound splitting?

- Names

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

  $\rightarrow$ transliteration?

# Some Causes for Large Vocabularies



- Morphology

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

  $\rightarrow$ morphological analysis?

- Compounding

  *homework*, *website*, ...

  $\rightarrow$ compound splitting?

- Names

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

  $\rightarrow$ transliteration?

$\Rightarrow$ 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
  - $\rightarrow$ 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`
  - $\rightarrow$ embedding for `beautifully`

- Hope that this learns morphological principles

# Character Sequence Models

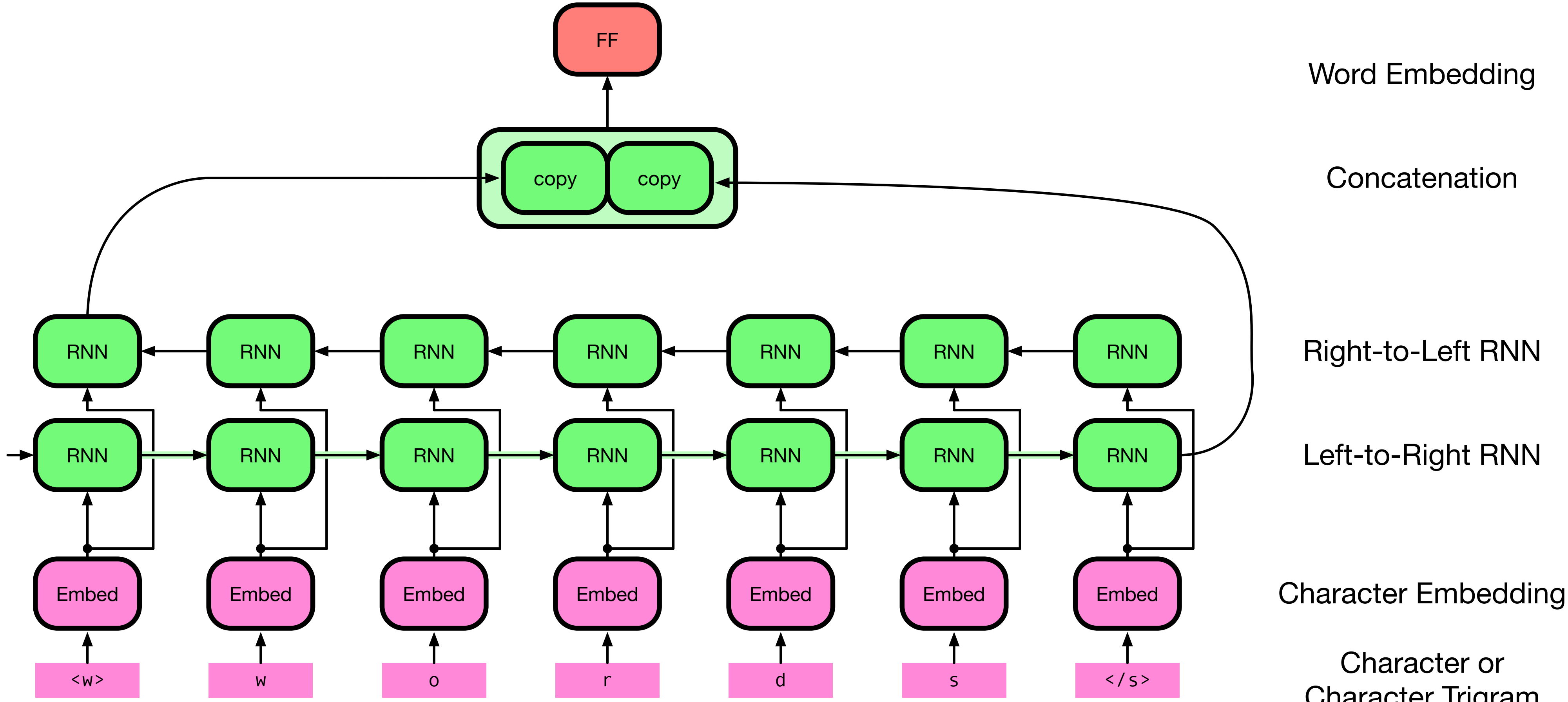
- Same model as for words
- Tokens = single characters, incl. special space symbol
- But: generally poor performance
- With some refinements, use in output shown competitive

# Character Based Word Models

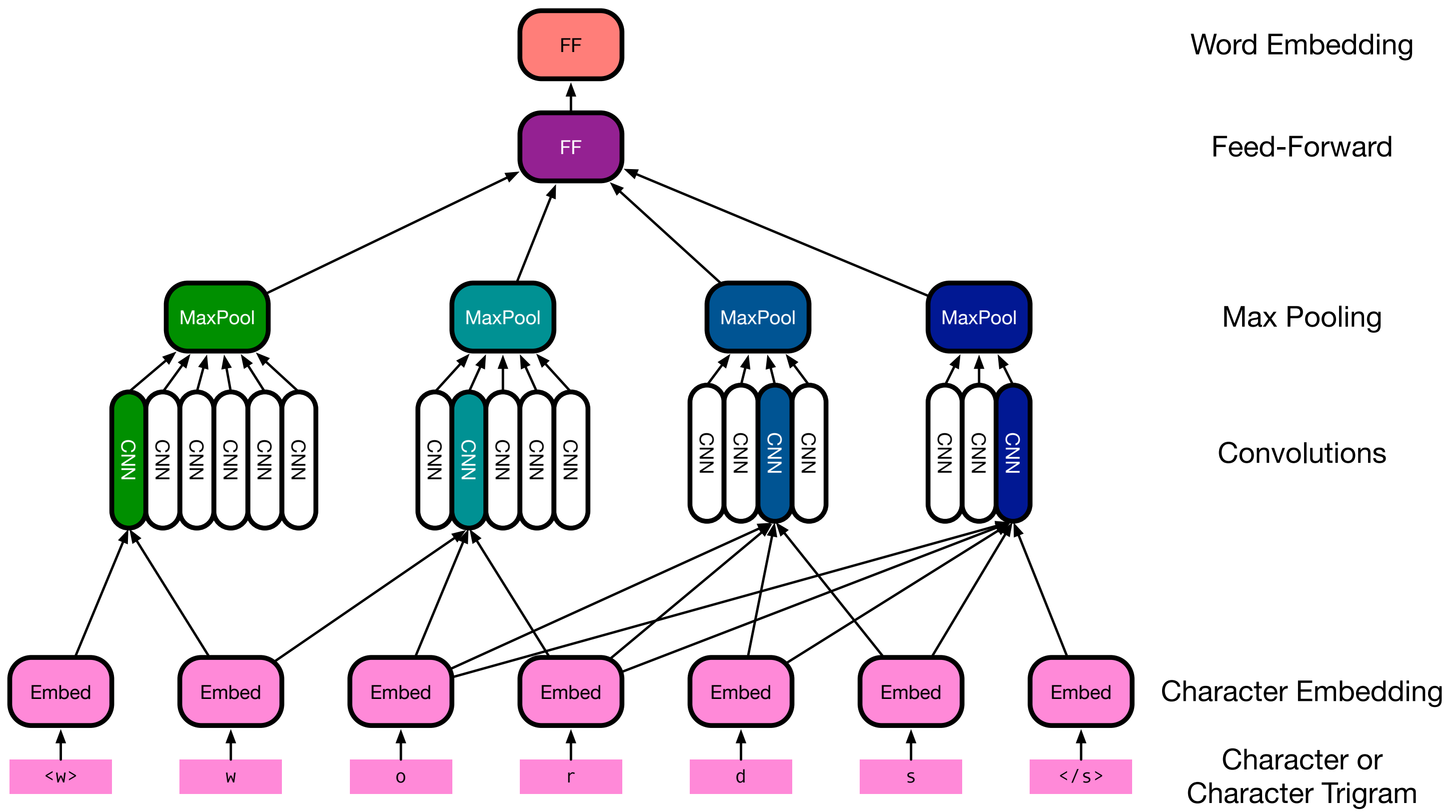


- Word embeddings as before
- Compute word embeddings based on character sequence
- Typically, interpolated with traditional word embeddings

# 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)