Introduction to NLP

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MIPT

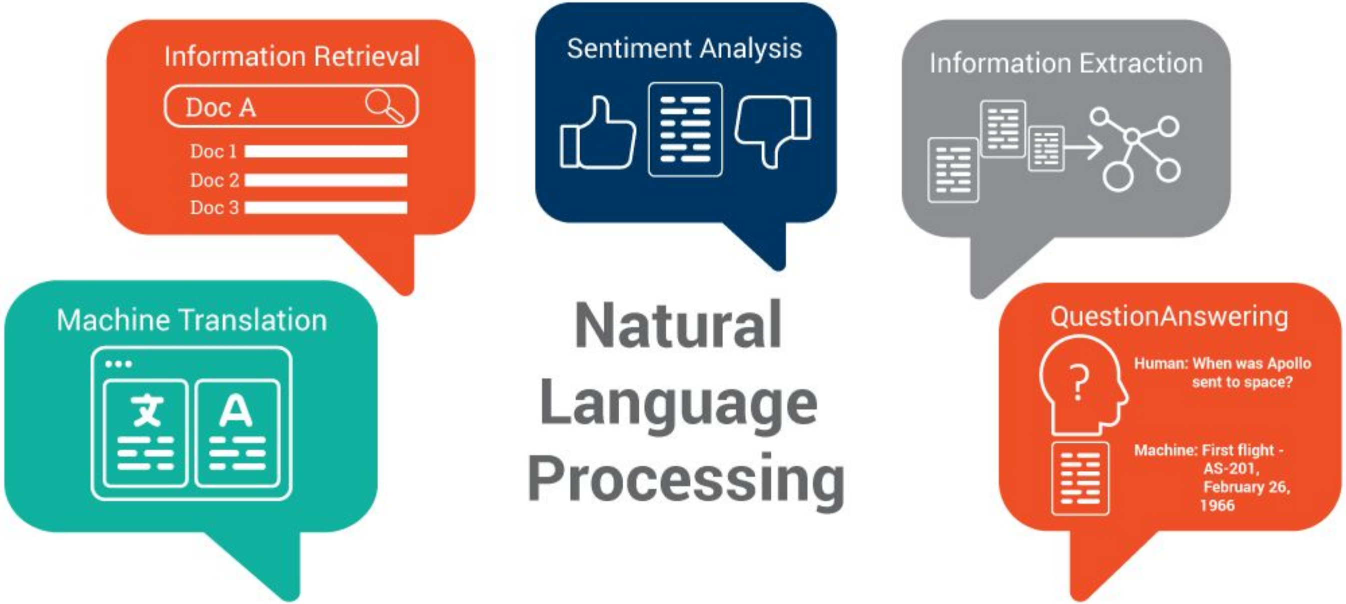
Today

01 What is NLP

02 Text representation

03 Text processing

What is
Natural Language Processing?


Information Retrieval
Doc A
Doc 1
Doc 2
Doc 3
Sentiment Analysis
Information Extraction
Machine Translation
文
A
Natural Language Processing
QuestionAnswering
?
Human: When was Apollo sent to space?
Machine: First flight - AS-201, February 26, 1966

ML tasks in NLP

- Text classification
  - Sentiment, emotion, opinion analysis
  - Word sense disambiguation
- Sequence labelling
  - P-O-S tagging, named entity recognition, dialogue acts
- Parsing dependencies
- Coreference resolution
- Text generation
  - QA, summarization
  - data-to-text generation
  - dialogue systems
- Learning without supervision
  - clustering
  - matrix factorization
  - latent semantic indexing
- Semi-supervised learning
  - graph-based
  - clustering + classification

Word representations

Vector word representations

■ dog	[0.033, -0.009, 0.037, 0.068, ..., 0.053]
■ cat	[0.067, 0.069, -0.015, -0.0249, ... , 0.0317]
■ home	[-0.0004, 0.0199, 0.03, -0.04, ... , -0.031]
■ computer	[-0.0016 , 0.0872, -0.0314, -0.0523, ... , 0.0228]
■ love	[-0.169, 0.0382, 0.0084, -0.0182, ... , -0.0209]

Vector word representations

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- Wikipedia
- Twitter
- НКРЯ - Национальный корпус русского языка (собрание русских текстов в электронной форме)
- Тайга - корпус русского языка (в основе, художественная литература)

Vector word representations

Why not just use one-hot encoding?

- dog: [1, 0, 0, 0, ..., 0]
- cat: [0, 1, 0, 0, ... , 0]
- home: [0, 0, 1, 0, ... , 0]
- computer: [0, 0, 0, 1, ... , 0]
- love: [0, 0, 0, 0, ... , 1]

Vector word representations

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■ love:	[0, 0, 0, 0, ... , 1]

These vectors know nothing about the word!

Vector word representations

What properties should a representation share with its word?

Vector word representations

What properties should a representation share with its word?

- run ~ running
- walk ~ walked
- to describe ~ descriptor

Vector word representations

What properties should a representation share with its word?

- run ~ running
- walk ~ walked
- to describe ~ descriptor

- big ~ huge
- to buy ~ to purchase
- pineapple ~ coconut

Distributional semantics

You shall know a word by the company it keeps

Firth, 1957

Oculist and eye-doctor . . . occur in almost the same *environments*.

If A and B have almost identical *environments* we say that they are *synonyms*

Zellig Harris (1954)

Distributional semantics

Do you know what the word "*tezgüino*" means?

The example is from Jacob Eisenstein's NLP notes; the tezgüino example originally appeared in Lin, 1998.

Distributional semantics

Do you know what the word “*tezgüino*” means?

But what if we know the following contexts:

1. a bottle of *tezgüino* is on the table,
2. everybody likes *tezgüino*,
3. *tezgüino* makes you drunk,
4. we make *tezgüino* out of corn.

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Now we know!

Tezgüino is a kind of alcoholic beverage made from corn!

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context

	1.	2.	3.	4.
tezgüino	1	1	1	1
loud	0	0	0	0
motor oil	1	0	0	1
tortillas	0	1	0	1
wine	1	1	1	0

Now we know!

Tezgüino is a kind of alcoholic beverage made from corn!

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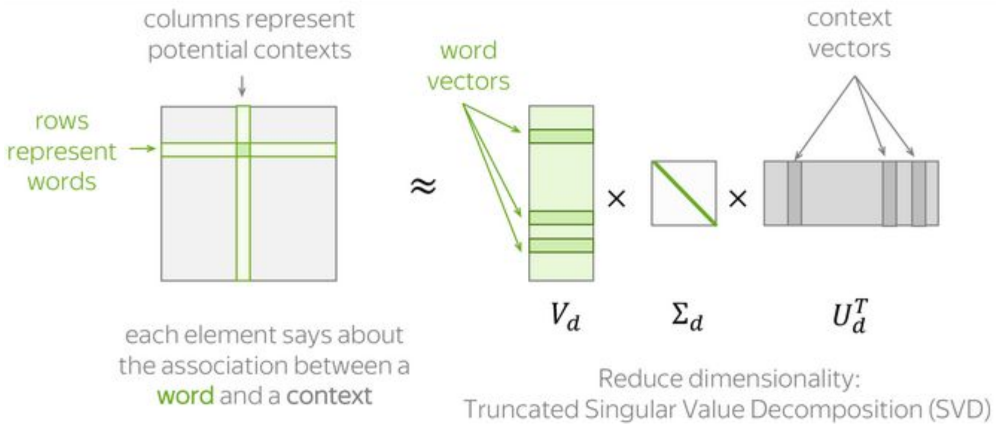
Count-based methods

Main idea: We have to put information about contexts into word vectors.



Count-based methods

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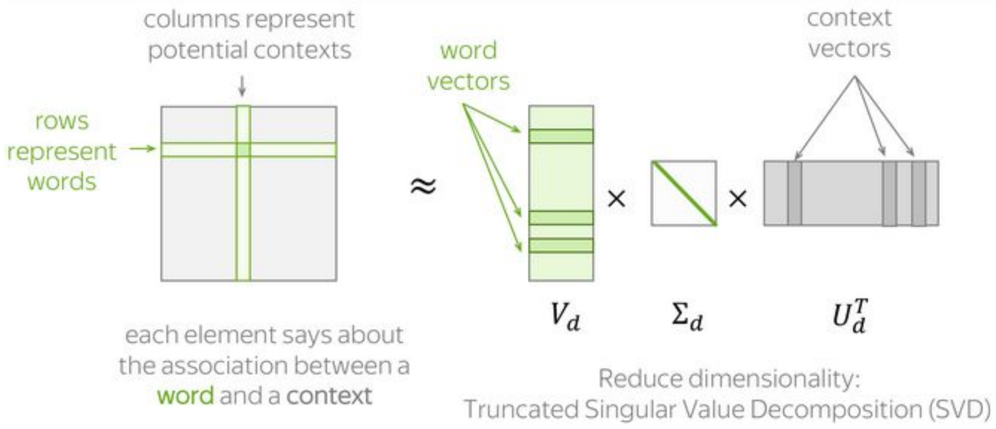


Ok but how do we represent context information?

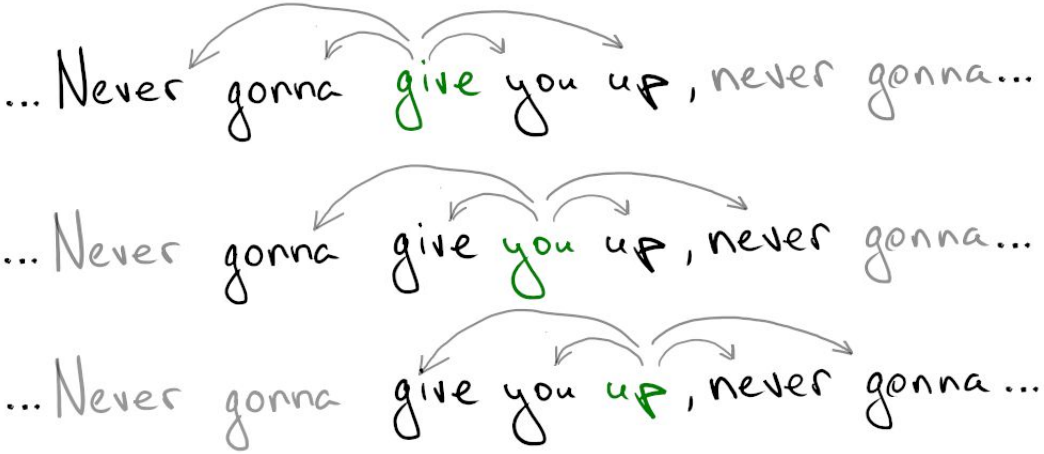
images from Lena Voita NLP course

AIRI × Университет Сириус

Count-based methods

...Never gonna give you up, never gonna...

Count-based methods



Count-based methods

$$\dots \text{Never } \underbrace{\text{gonna } \textbf{give} \text{ you up}}_{\text{context}}, \text{ never gonna}\dots$$

1. Co-Occurrence counts

   $N(w, c)$ = number of times w appears in c

2. Tf-Idf

$$\text{tf-idf}(w, d, D) = \text{tf}(w, d) \cdot \text{idf}(w, D) = N(w, d) \cdot \log\left(\frac{|D|}{|\{d \in D : w \in D\}|}\right)$$

3. Positive PMI

   ppmi(w, c) = max(0, PMI(w, c))

$$\text{pmi}(w, c) = \log\left(\frac{P(w, c)}{P(w)\,P(c)}\right) = \log\left(\frac{N(w, c) \cdot |(w, c)|}{N(w)\,N(c)}\right)$$

Word2Vec

<u>Idea:</u> teach embeddings to predict their contexts.

Algorithm

1) use a large text corpus
2) for each word start with 2 vectors: central **u** + context **v**
3) go over the text with a sliding window (*use negative sampling*)
4) compute probabilities for words from c based on w
5) adjust the vectors to increase probabilities

$$P(o|c) = SM(u_o^T \cdot v_c) = \frac{e^{u_o^T v_c}}{\sum_{w \in V} e^{u_w^T v_c}}$$

Efficient Estimation of Word Representations in Vector Space (2013)

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Objective function:

$$\text{Likelihood} = L(\theta) = \prod_{t=1}^{T} \prod_{-m \le j \le m, j \ne 0} P(w_{t+j} | w_t, \theta),$$

$$\text{Loss} = J(\theta) = -\frac{1}{T} \log L(\theta) = -\frac{1}{T} \sum_{t=1} \sum_{\substack{-m \le j \le m, \\ j \ne 0}} \log P(w_{t+j} | w_t, \theta)$$

agrees with our plan above $\mapsto$ go over text

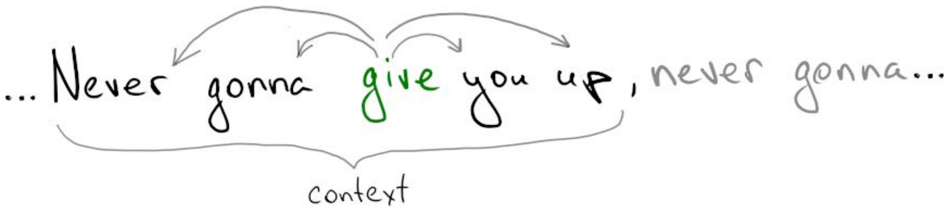
with a sliding window

compute probability of the context word given the central

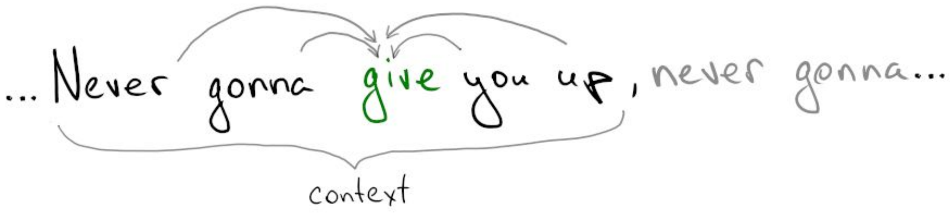
Efficient Estimation of Word Representations in Vector Space (2013)

Word2Vec

1. Skip-Gram
   from central word predict context



2. CBOW
   from sum of context predict word



Word2Vec

King
Queen
Woman
Princess
...
Royalty
Masculinity
Femininity
Age
...
0.99
0.99
0.05
0.7
0.99
0.05
0.93
0.6
0.02
0.01
0.999
0.5
0.98
0.02
0.94
0.1

GloVe

<u>Idea:</u> use **glo**bal corpus statistics to learn embedding **ve**ctors

W2V:

$$J_{t,j}(\theta) = -\log P(cute|cat) = -\log \frac{\exp u_{cute}^T v_{cat}}{\sum_{w \in Voc} \exp u_w^T v_{cat}} = -u_{cute}^T v_{cat} + \log \sum_{w \in Voc} \exp u_w^T v_{cat}.$$

GloVe

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context vector

word vector

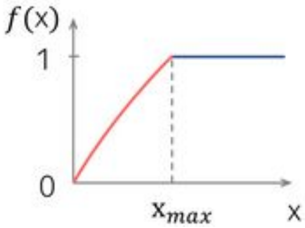
bias terms (also learned)

GloVe:

$$J(\theta) = \sum_{w,c \in V} f(\mathrm{N}(w,c)) \cdot (u_c^T v_w + b_c + \overline{b_w} - \log \mathrm{N}(w,c))^2$$

Weighting function to:

- penalize rare events
- not to over-weight frequent events



$$\begin{cases} (x/x_{max})^{\alpha} & \text{if } x < x_{max}, \\ 1 & \text{otherwise.} \end{cases}$$

$\alpha = 0.75,\ x_{max} = 100$

Processing language

Problems

- OOV: what does “wher” mean?
- word ordering

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FastText (2016, Facebook)

where = <wh, whe, her, ere, re> and <where>

wher = <wh, er>

Problems

- OOV: what does “wher” mean?
- word ordering

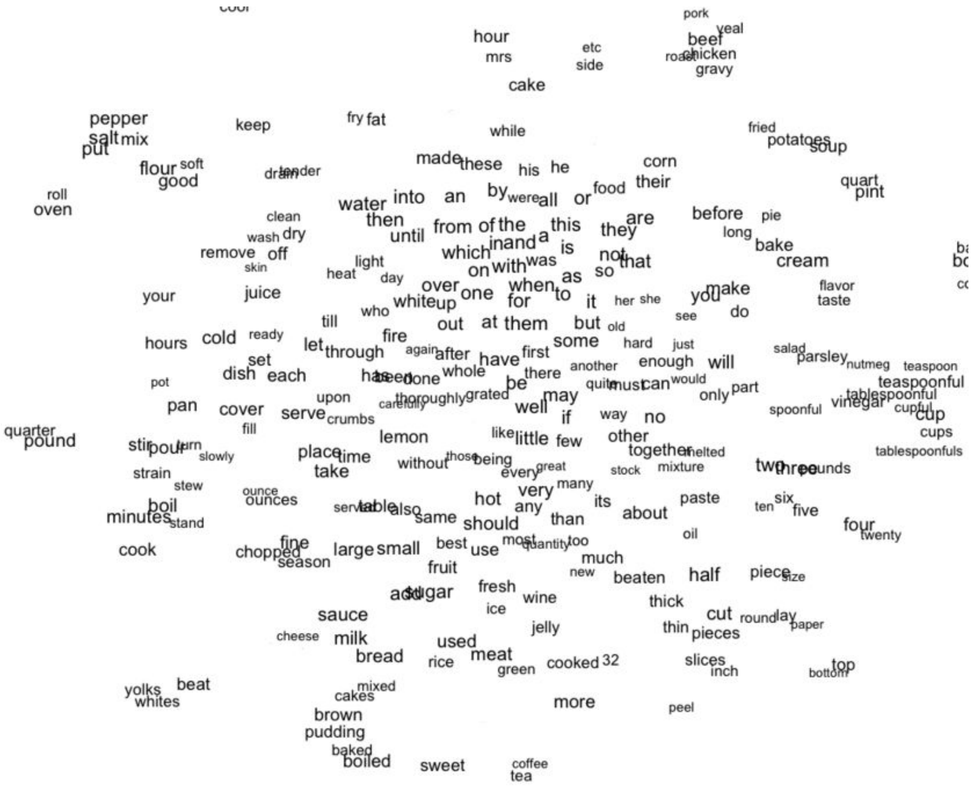
FastText (2016, Facebook)

where = <wh, whe, her, ere, re> and <where>

wher = <wh, er>

- ambiguity (context-dependency): what does “plant” mean?
- Los Angeles, Barack Obama, Doctor House

What now?


pork
beef
veal
chicken
gravy
hour
mrs
etc
side
cake
pepper
salt
mix
put
keep
fry
fat
while
fried
potatoes
soup
flour
soft
good
made
these
his
he
corn
their
food
roll
oven
water
into
an
by
were
all
or
quart
pint
before
pie
then
from
of
the
this
they
are
long
bake
cream
clean
wash
dry
remove
off
skin
until
which
in
and
a
is
not
that
so
light
heat
day
on
with
was
as
your
juice
over
one
when
to
for
it
her
she
you
make
do
flavor
taste
white
up
who
out
at
them
but
old
see
till
hours
cold
ready
let
through
fire
again
after
have
first
some
hard
just
salad
parsley
nutmeg
teaspoon
teaspoonful
tablespoonful
set
dish
each
whole
there
another
enough
will
pot
be
must
can
would
only
part
spoonful
vinegar
cupful
cup
cups
tablespoonfuls
pan
cover
serve
upon
crumbs
thoroughly
grated
may
well
if
way
no
quarter
pound
fill
lemon
like
little
few
other
together
melted
stir
pour
turn
slowly
place
time
take
without
those
being
every
great
stock
mixture
two
three
pounds
strain
stew
many
ounce
ounces
hot
very
its
paste
six
ten
five
boil
minutes
stand
table
also
same
should
any
than
about
four
twenty
cook
chopped
fine
season
large
small
best
use
most
quantity
too
much
oil
fruit
new
beaten
half
piece
size
add
sugar
fresh
wine
thick
sauce
ice
cut
round
lay
paper
cheese
milk
jelly
thin
pieces
used
bread
rice
meat
green
cooked
32
slices
inch
bottom
top
yolks
whites
beat
mixed
cakes
more
peel
brown
pudding
baked
boiled
sweet
coffee
tea

Operations with embeddings

$$p = (p_1, p_2, \dots, p_n)$$

$$q = (q_1, q_2, \dots, q_n)$$

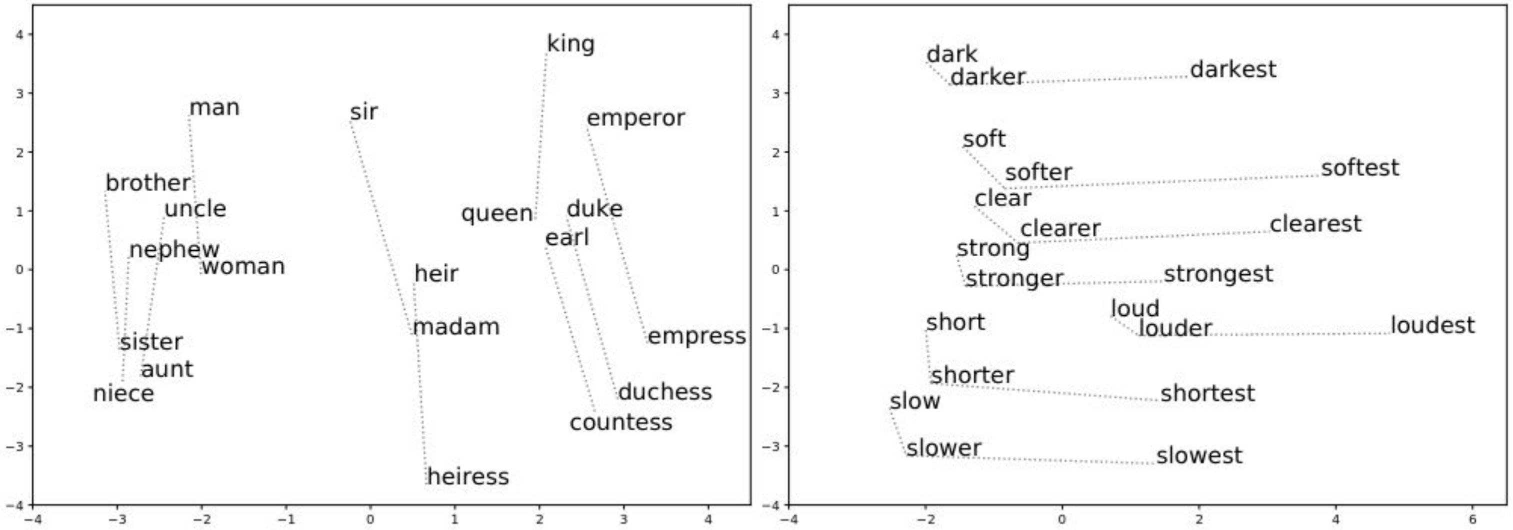
Euclidean distance

$$d(p, q) = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2}$$

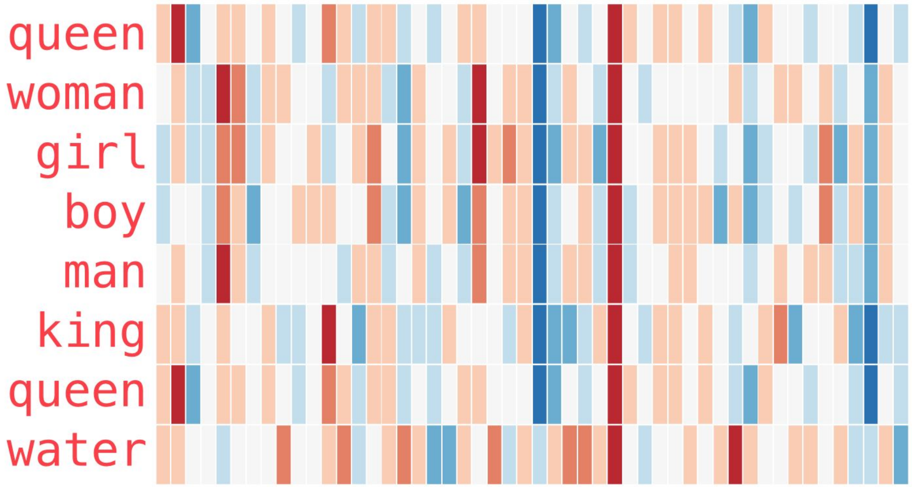
Cosine distance

$$cos(p, q) = 1 - \frac{P \times Q}{\| P \|_2 \| Q \|_2} = 1 - \frac{\sum_{i=1}^{n} p_i \times q_i}{\sqrt{\sum_{i=1}^{n} p_i^2} \times \sqrt{\sum_{i=1}^{n} q_i^2}}$$

Operations with embeddings



Operations with embeddings



king – queen ≈ man – woman

man – boy ≈? – girl
japan – sushi ≈? – pasta
euro – france ≈? – russia

Centroid(january, february, march) ≈?
Centroid(moscow, siberia, caucasus ≈?
Centroid(sunday, monday, tuesday) ≈?

How to process sequences?

...Never gonna give you up, never gonna...

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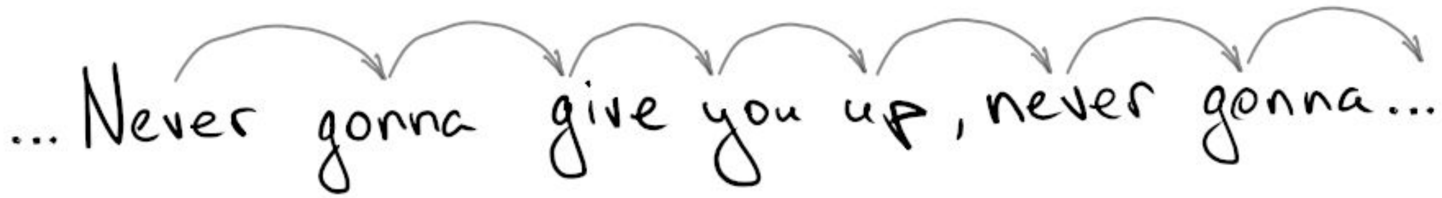

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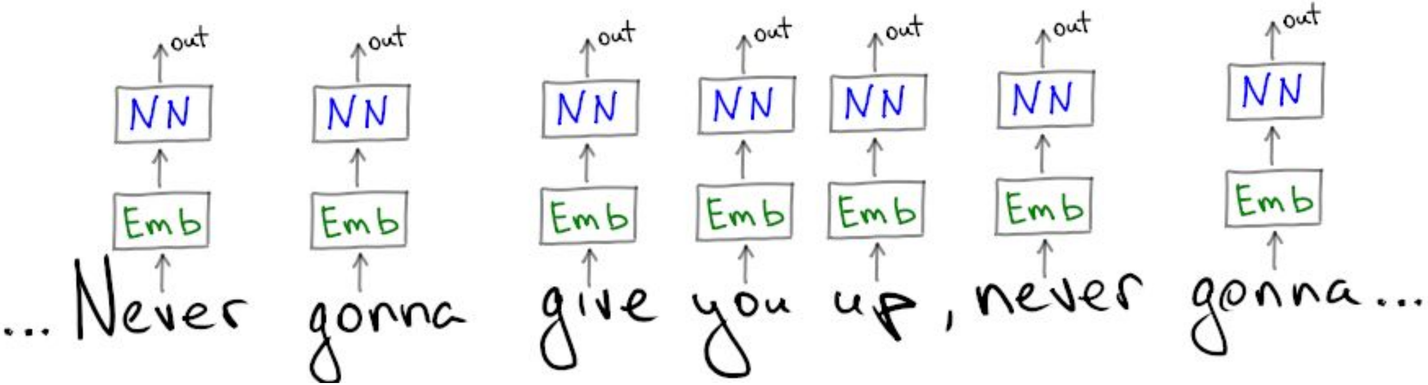

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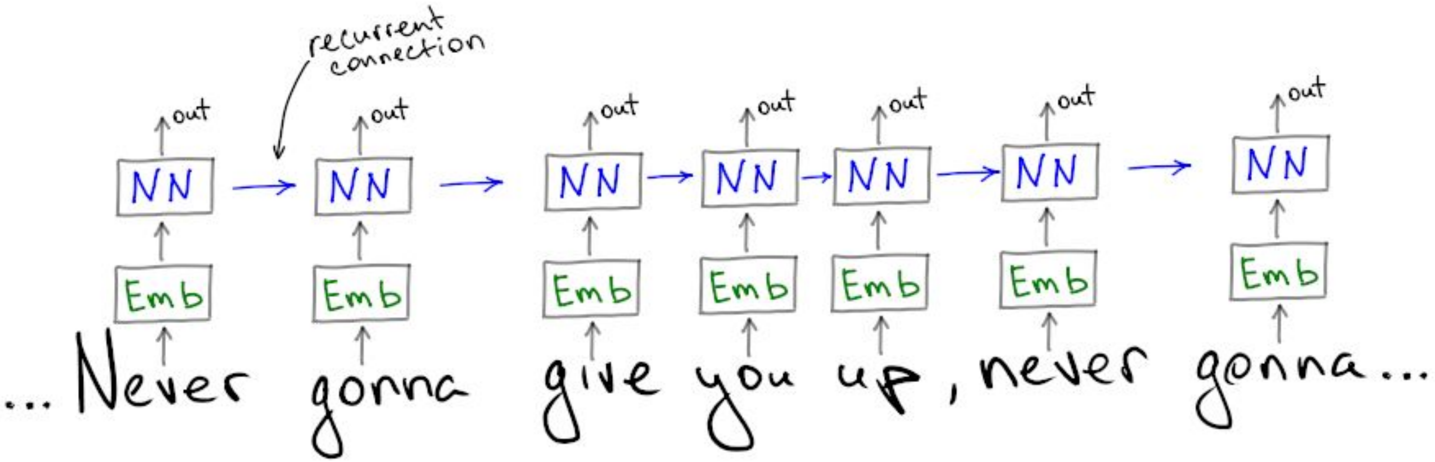

Next: RNN, LSTM

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