COLX-531: Neural Machine Translation
Extra Slides on word2vec

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Table of Contents

Word2Vec

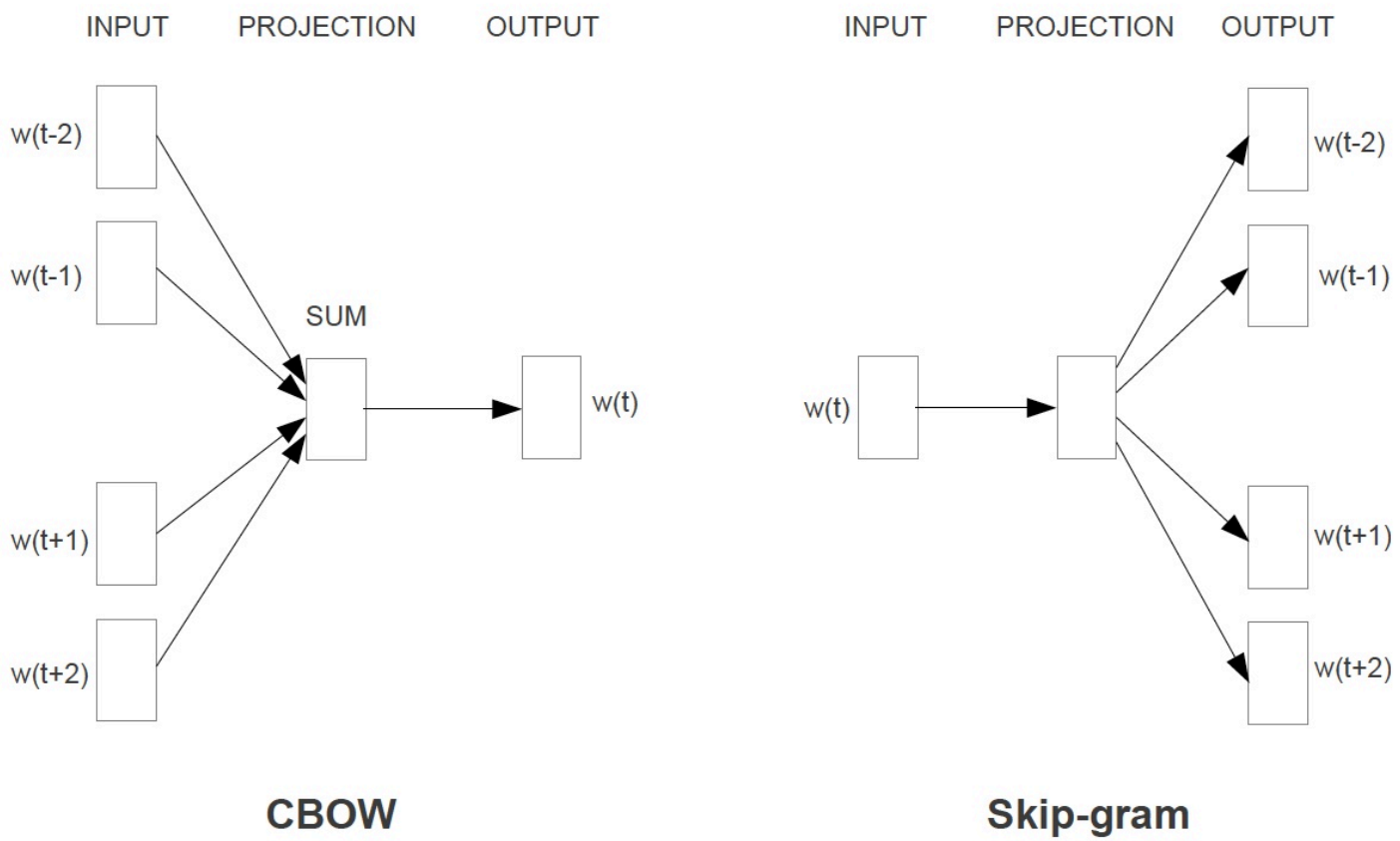


Figure 1: New model architectures. The CBOW architecture predicts the current word based on the context, and the Skip-gram predicts surrounding words given the current word.

Figure: Mikolov et al., 2013

Skip-Gram Net

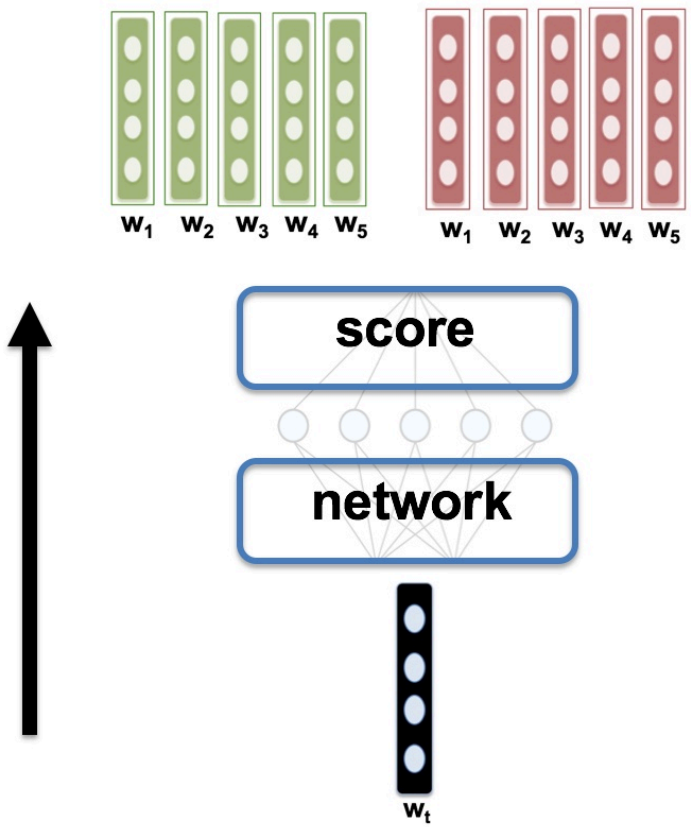


Figure: Skipgram

Vocabulary

```python
import re
from nltk.corpus import stopwords
data="""
Alex bought a bike.
Susan rides a bike to school.
Alex rides a car to work.
Susan goes to work by car.
Alex goes to meetings in a suite.
Susan goes to parties in a suite.
"""
data=re.sub("\.", "", data)
words=set(data.lower().split())
filtered_words = [word for word in words if word not in stopwords.words('english')]
vocab= {k: v for v, k in enumerate(filtered_words)}
vocab = sorted(vocab.items(), key=lambda (k,v): v)
for t in vocab:
    print(t)
```

```
('school', 0)
('alex', 1)
('susan', 2)
('car', 3)
('meetings', 4)
('work', 5)
('parties', 6)
('bike', 7)
('goes', 8)
('suite', 9)
('rides', 10)
('bought', 11)
```

One-Hot Encoding (in 4 Dimensions)

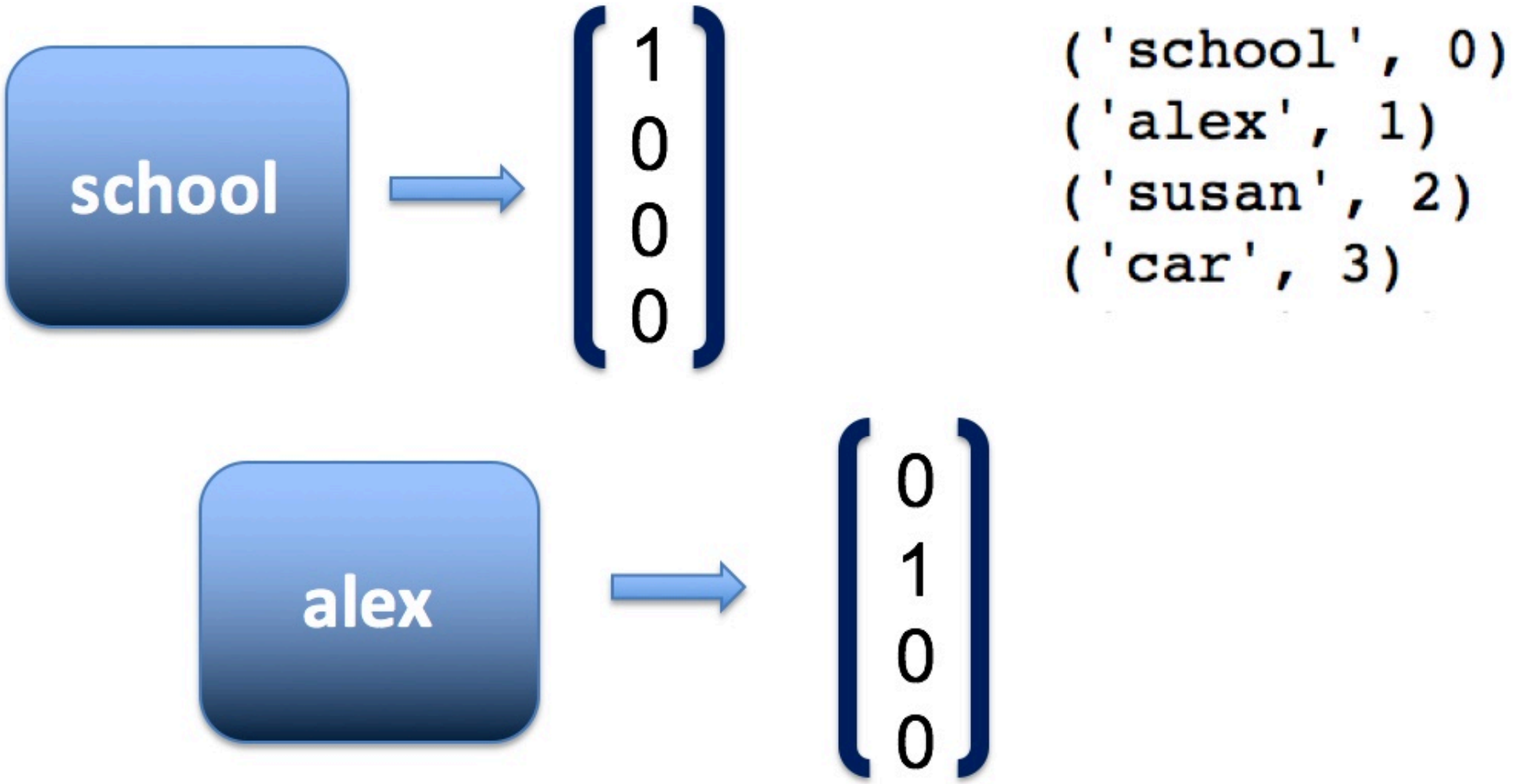


Figure: One-hot vectors **in 4 dimensions**

Embedding Matrix

	alex	bike	bought	car	goes	meetings	parties	...
school	0	1	0	0	0	0	0	...
alex	1	1	0	1	1	1	0	...
...	...	...	...	...	...	...	...	...

Figure: An Embedding Matrix **E** in $\mathbb{R}^{|\texttt{vocab}| x |\texttt{context}|}$.

Embedding Matrix (Raw Counts)

	alex	bike	bought	car	goes	meetings	parties	...
school	32	57	755	354	908	4262	977979	...
alex	1	6567	65674	154	7866	5576	456	...
...	...	...	...	...	...	...	...	...

Figure: Embedding matrix **E** with raw counts.

Varying Context Size

From Raw Counts to Continuous Space

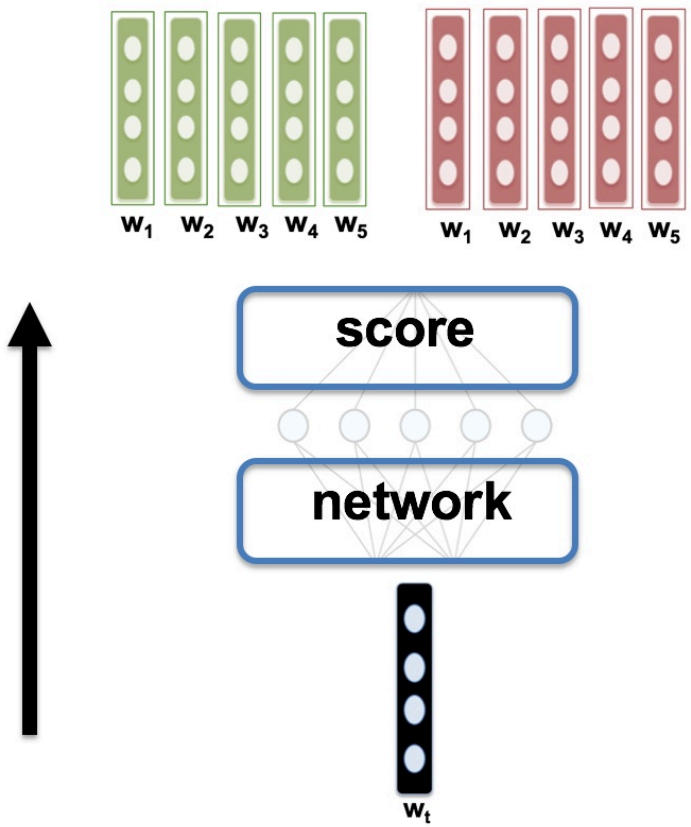


Figure: Skipgram

Skipgram Model Objective

- The **objective of the skipgram model** is to maximize the following log-likelihood:

1: Skipgram objective

$$\sum_{t=1}^{T} \sum_{c \in C_t} \log p(w_c | w_t)$$

- **Context** C_t: the set of indices of words surrounding word w_t.

Softmax as Probability of C?

- Consider that we are given a **scoring function** s which maps pairs of (word, context) to scores in $\mathbb{R}$.
- One possibility: Define the probability of a context word using **softmax** with word $w \in \{1, \ldots, W\}$ (as in Bengio et al., 2013):

2: Softmax scoring

$$p(w_c|w_t) = \frac{e^{s(w_t, w_c)}}{\sum_{j=1}^{W} e^{s(w_t, j)}}$$

- **Not adapted to our case** as it implies we only predict one context word.
- Predicting context words can instead be framed as a **set of independent binary classification tasks**.

Learning Via Binary Classification

- **Goal** is to **independently predict the presence (or absence) of context words**.
- For the word at position t we consider all context words as `positive examples` and sample `negative examples` at random from the dictionary (negative sampling).

Positive and negative sample of word "butter"

- Can programmable **butter** become intelligent? (**neg sample**)
- Can programmable **machines** become intelligent? (**pos sample**)

- **Negative sampling** is brilliant as it enables us to cast the whole task as supervised learning.

Skipgram Model V: Binary Logistic Regression

- For a chosen context position c, using the binary logistic loss, we obtain the following negative log-likelihood:

3: Binary Logistic Loss I

$$\log(1 + e^{-s(w_t, w_c)}) + \sum_{n \in \mathcal{N}_{t,c}} \log(1 + e^{s(w_t, n)})$$

- where $\mathcal{N}_{t,c}$ is a set of negative examples sampled from the vocabulary.

4: Binary Logistic Loss II

- By denoting the logistic loss function $\ell : x \longmapsto \log(1 + e^{-x})$, we can re-write the objective as:

$$\sum_{t=1}^{T} \Big[\sum_{c \in C_t} \ell(s(w_t, w_c)) + \sum_{n \in \mathcal{N}_{t,c}} \ell(-s(w_t, n)) \Big]$$

Some Details of Scoring Function s

Mechanics of Scoring Function

- To **parameterize the scoring function** s between a word w_t and a context word w_c, we **use word vectors**.
- We define **for each word** w **in the vocabulary two vectors** $\mathbf{u_w}$ (input) and $\mathbf{v_w}$ (output) in $\mathbb{R}^d$.
- Note: In literature, you will see vectors u_{wt} and v_{wt}, corresponding, respectively, to w_t and w_c.
- The score can be computed as the **scalar product between word and context vectors** as $s(w_t, w_c) = \mathbf{u_{w_t}^T v_{w_c}}$.
- Recall: The model described in this section is the **skipgram model with negative sampling**, introduced by Mikolov et al. (2013b).

But What Are Word Vectors Good For?

Linguistic Regularity

- Word representations can **capture both syntactic and semantic regularities** in language.
- Syntactic analogy questions of the form "a is to b as c is to --".
- **Example of syntactic analogy**: "good is to better as rough is to __"

Syntactic Analogy Tests

- base/comparative/superlative forms of adjectives
- singular/plural forms of common nouns
- possessive/non-possessive forms of common nouns
- base, past and 3rd person present tense forms of verbs

Mikolov 2013 Data Development Method

Benchmarking Word Embeddings (English)

- **POS-tagged 267M words of newspaper text** with Penn. Treebank POS tags (Marcus et al., 1993)
- **Selected top 100**: comparative adjectives (JJR), plural nouns (NNS), possessive nouns (NN POS), base form verbs (VB)
- Systematically **generated analogy questions** by randomly matching each of the 100 words with 5 other words from the same category, and creating variants (see table in next slide).
- **Total test set size is** 8000 **example pairs**, available at [link].

Syntactic Regularity (For Your Reference)

Category	Relation	Patterns Tested	# Questions	Example
Adjectives	Base/Comparative	JJ/JJR, JJR/JJ	1000	good:better rough:___
Adjectives	Base/Superlative	JJ/JJS, JJS/JJ	1000	good:best rough:___
Adjectives	Comparative/ Superlative	JJS/JJR, JJR/JJS	1000	better:best rougher:___
Nouns	Singular/Plural	NN/NNS, NNS/NN	1000	year:years law:___
Nouns	Non-possessive/ Possessive	NN/NN_POS, NN_POS/NN	1000	city:city's bank:___
Verbs	Base/Past	VB/VBD, VBD/VB	1000	see:saw return:___
Verbs	Base/3rd Person Singular Present	VB/VBZ, VBZ/VB	1000	see:sees return:___
Verbs	Past/3rd Person Singular Present	VBD/VBZ, VBZ/VBD	1000	saw:sees returned:___

Table 1: Test set patterns. For a given pattern and word-pair, both orderings occur in the test set. For example, if "see:saw return:___" occurs, so will "saw:see returned:___".

Figure: Mikolov et al., 2013: `Linguistic regularities in continuous space word representations.`

Semantic Test Set X

- Source: SemEval-2012 Task 2, **Measuring Relation Similarity** (Jurgens et al., 2012).
- **79 fine-grained word relations** (10 for training & 69 for testing)
- Each relation is exemplified by **3 or 4 gold word pairs**
- Task: Given a group of word pairs with same relation, **order the target pairs according to the *degree* to which this relation holds**.

Example relation

- Relation name: **OBJECT:TYPICAL ACTION**
- Relation schema: **an X will typically Y**
- Examples: glass:break; soldier:fight
- Analogy question: “glass" is to “break" as “soldier" is to “?" (answer: “fight")

Measuring Relation Similarity (For Your Reference)

Measuring Relation Similarity (Jurgens et al., 2012)

- SemEval-2012 Task 2: [link]
- Goal: **identifying the degree of prototypicality for instances within a given class.**

Subcategory	Relation name	Relation schema	Paradigms	Responses
8(e)	AGENT:GOAL	"Y is the goal of X"	pilgrim:shrine assassin:death climber:peak	patient:health runner:finish astronaut:space
5(e)	OBJECT:TYPICAL ACTION	"an X will typically Y"	glass:break soldier:fight juggernaut:crush	ice:melt lion:roar knife:stab
4(h)	DEFECTIVE	"an X is is a defect in Y"	fallacy:logic astigmatism:sight limp:walk	pimple:skin ignorance:learning tumor:body

Table 1: Examples of the three manually selected paradigms and the corresponding pairs generated by Turkers.

Figure: Jurgens et al., 2012

Sample Word Relationships

Table 1: *Examples of five types of semantic and nine types of syntactic questions in the Semantic-Syntactic Word Relationship test set.*

Type of relationship	Word Pair 1		Word Pair 2	
Common capital city	Athens	Greece	Oslo	Norway
All capital cities	Astana	Kazakhstan	Harare	Zimbabwe
Currency	Angola	kwanza	Iran	rial
City-in-state	Chicago	Illinois	Stockton	California
Man-Woman	brother	sister	grandson	granddaughter
Adjective to adverb	apparent	apparently	rapid	rapidly
Opposite	possibly	impossibly	ethical	unethical
Comparative	great	greater	tough	tougher
Superlative	easy	easiest	lucky	luckiest
Present Participle	think	thinking	read	reading
Nationality adjective	Switzerland	Swiss	Cambodia	Cambodian
Past tense	walking	walked	swimming	swam
Plural nouns	mouse	mice	dollar	dollars
Plural verbs	work	works	speak	speaks

Figure: Mikiolov et al., 2013: "Efficient Estimation. . . ". Example semantic and syntactic relationships.

Solving Analogy Via Vector Offsets

Vector Offset Method

- To recap, both **syntactic and semantic tasks are formulated as analogy questions**
- Finding: A simple vector offset method based on cosine distance is effective in solving these questions
- Assumption: **relationships are present as vector offsets**
- Thus, **in the embedding space, all pairs of words sharing a particular relation are related by the same constant offset**

Vector Offset Method: How it Works

- To answer the analogy question `a:b c:d` where **d is unknown**, find the embedding vectors:

$$x_a, x_b, x_c,$$

and compute:

$$y = x_b - x_a + x_c$$

- `y`: **the continuous space representation of the word expected to be the best answer**
- No word might exist at that exact position!
- **Search the space for the word whose embedding vector has the greatest cosine similarity to** `y`:

$$w^* = argmax_w \frac{x_w y}{||x_w||||y||}$$

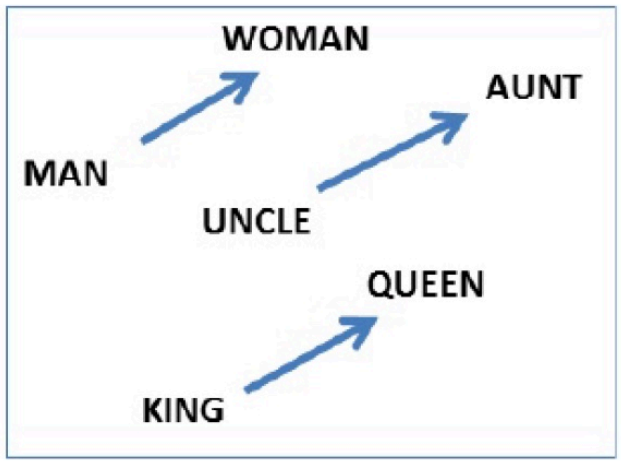
- For **benchmarking**, where `d` is given from the semantic test set, simply use:

$$cos(x_b - x_a + x_c, x_d)$$

Vector Offset Illustration

Vector Offset Example

- *vector("King") - vector("Man") + vector("Woman") = vector("Queen").*



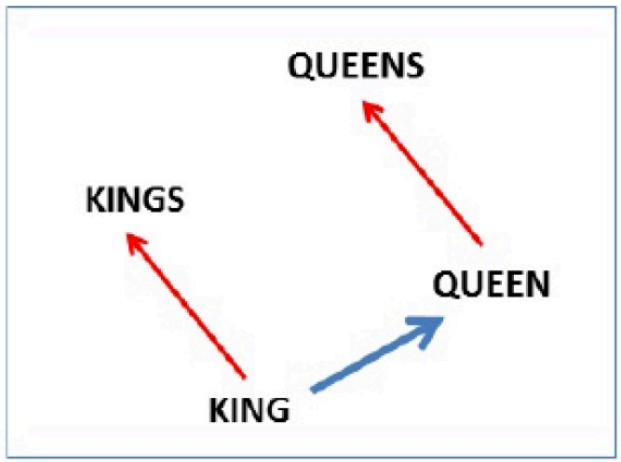


Figure: [Mikolov et al., 2013].

Sample Model Predictions

Table 8: *Examples of the word pair relationships, using the best word vectors from Table 4 (Skip-gram model trained on 783M words with 300 dimensionality).*

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

Figure: Mikiolov et al., 2013: "Efficient Estimation. . . ". Example model predictions.

Other Word Embedding Models

- GloVe: [lik]
- FastText: [lik]
- **Note:** Many models created for languages other than English
- If you know a language for which no models exist, a good things is to **create ones and share with community**