Neural Vector Representations beyond Words: Sentence and Document Embeddings

Gerard de Melo

http://gerard.demelo.org

Rutgers University

Outline

- Word Representations
- Phrase Representations
- Sentence Representations
- Document Representations
- Applications and Outlook

Cross-Lingual Retrieval

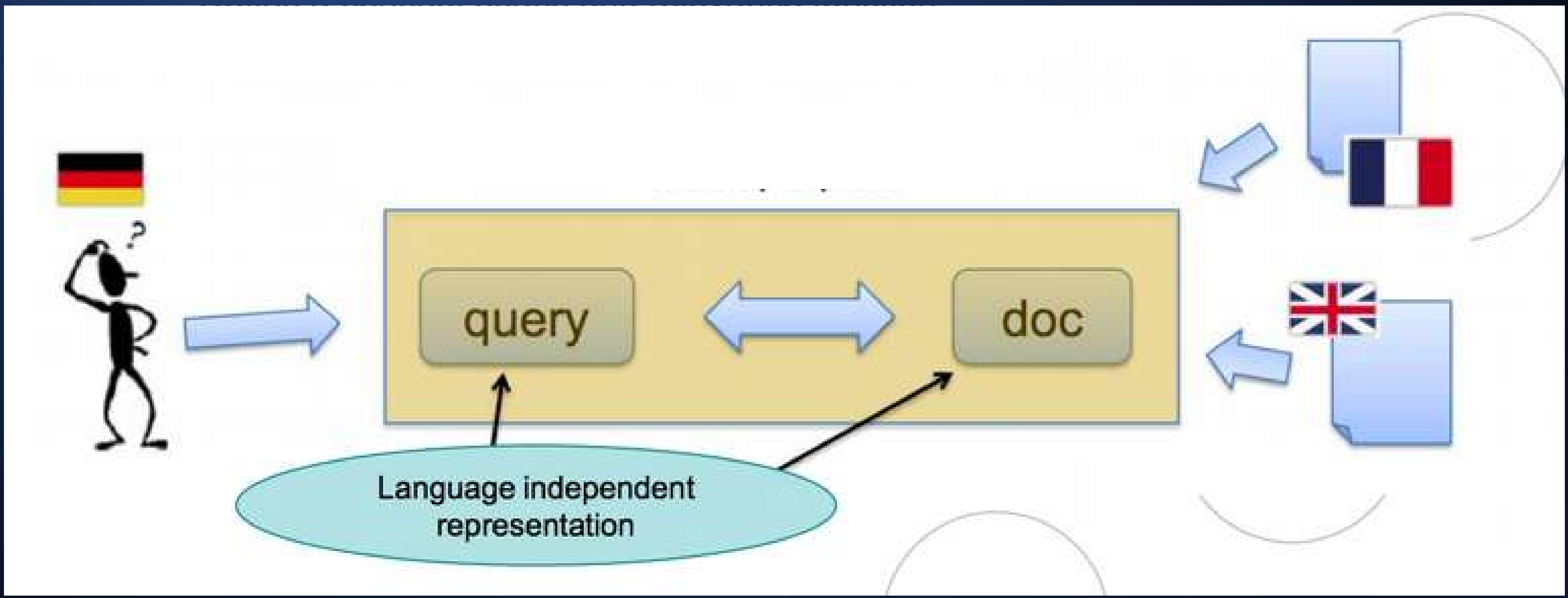


Image: Nitish Aggarwal

Plagiarism Detection (incl. Cross-Lingual)

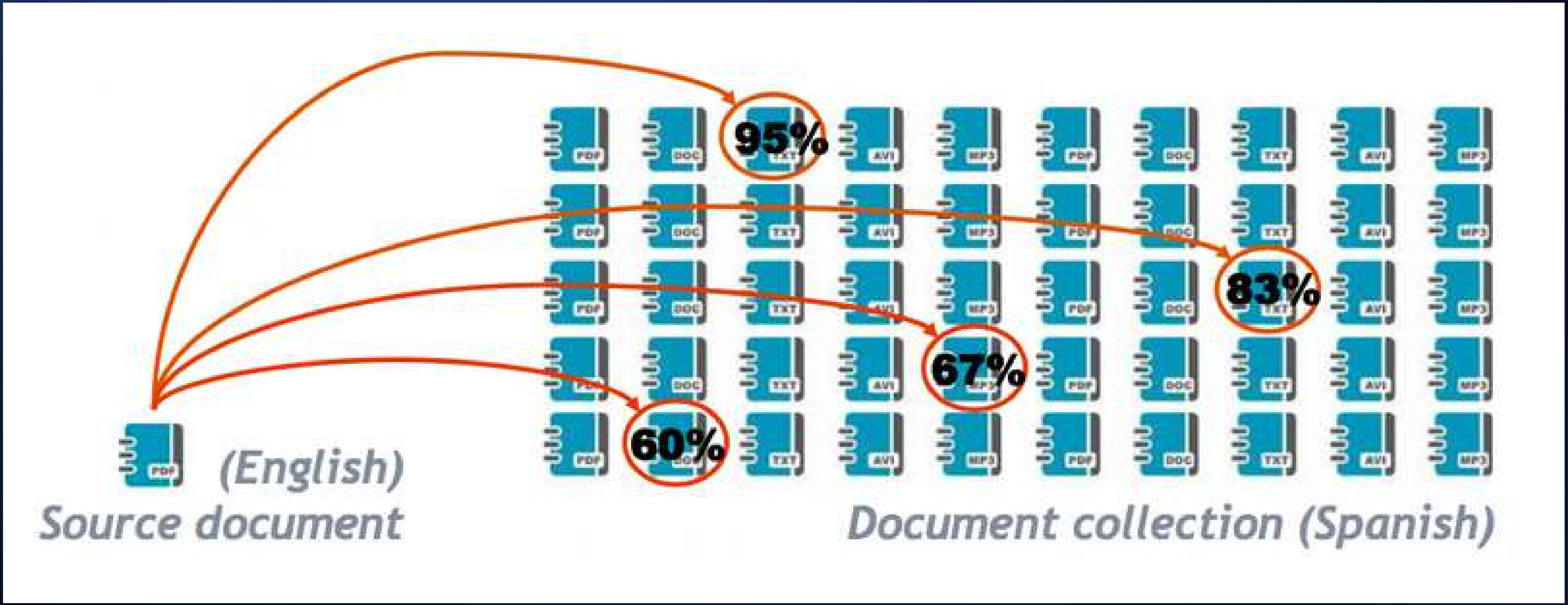
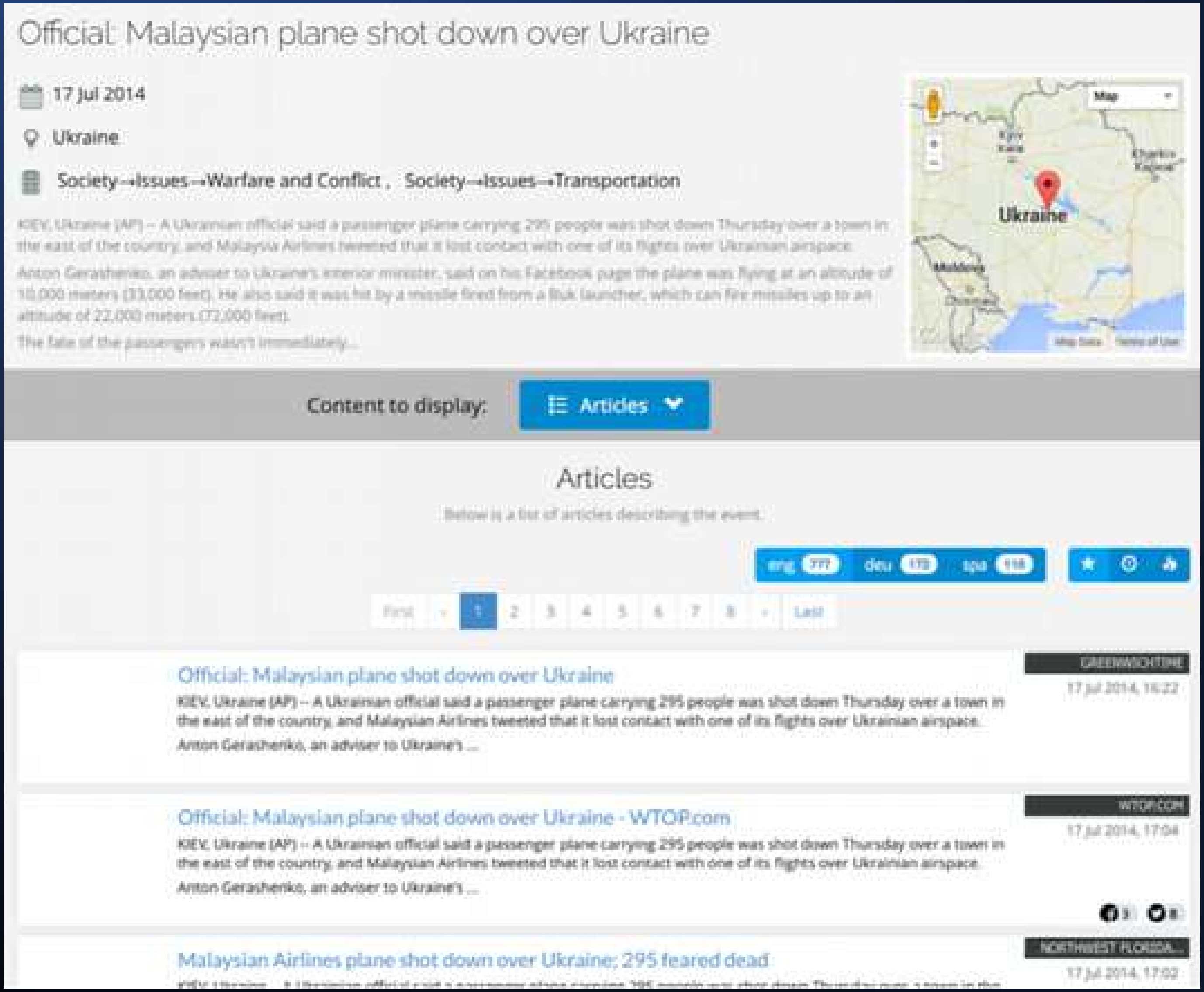


Image: Rafael Banchs

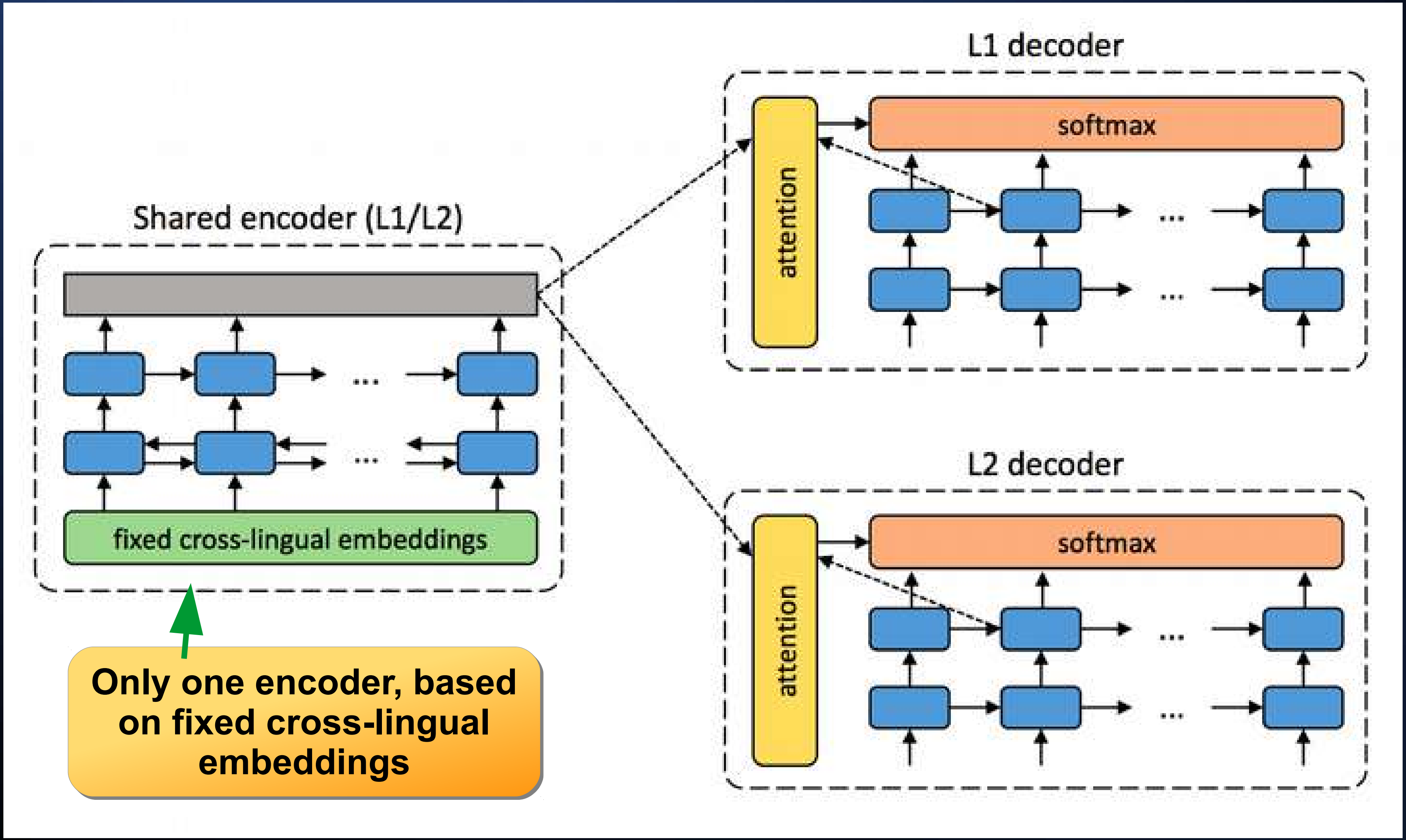
e.g. M. Potthast, B. Stein, A. Eiselt, A. Barrón, and P. Rosso (2009). Overview of the 1st international competition on plagiarism detection

News Tracking (incl. Cross-Lingual)



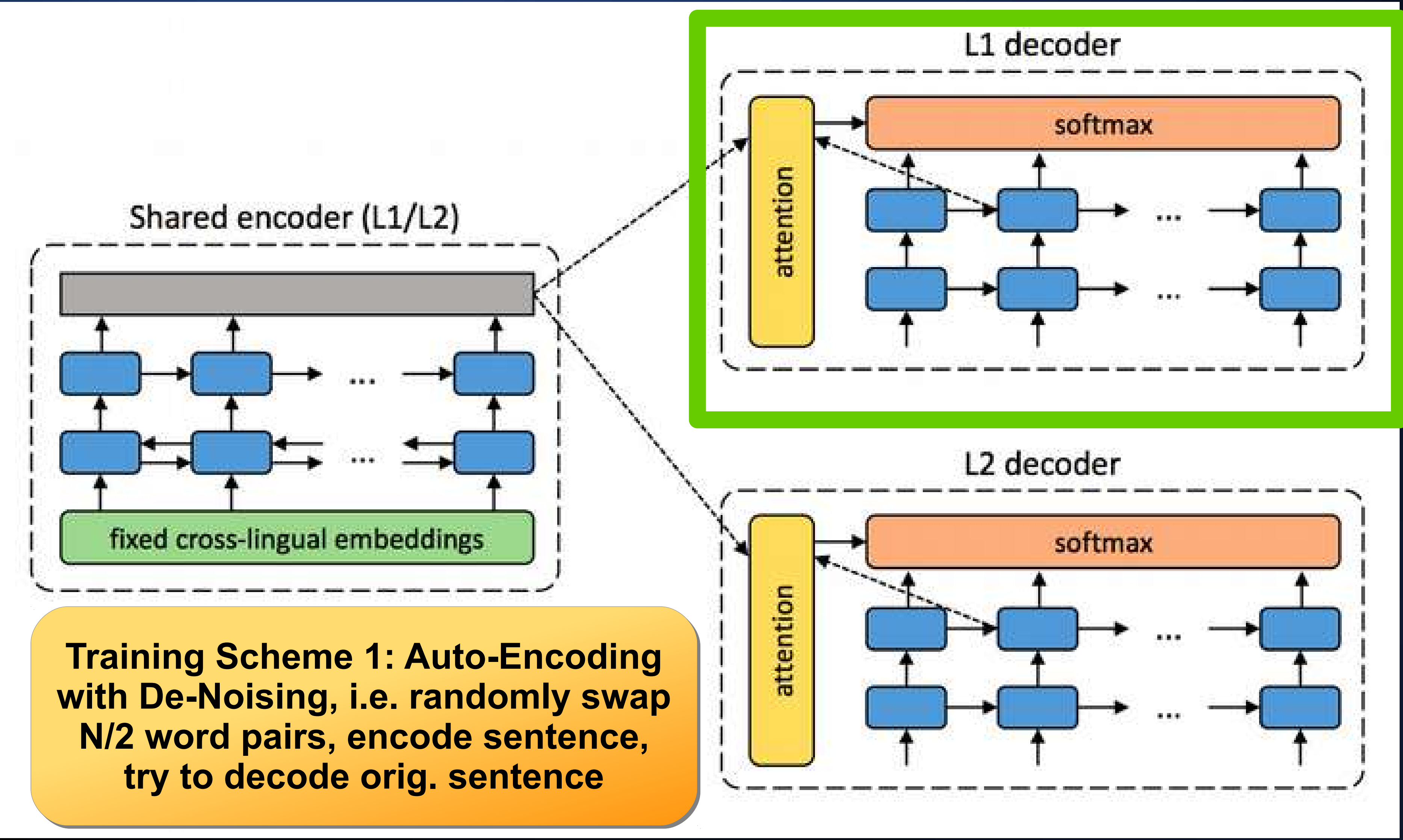
Rupnik et al. 2016. News Across Languages - Cross-Lingual Document Similarity and Event Tracking

Unsupervised Neural MT



Mikel Artetxe, Gorka Labaka, Eneko Agirre, Kyunghyun Cho. Unsupervised Neural Machine Translation. ArXiv 2017

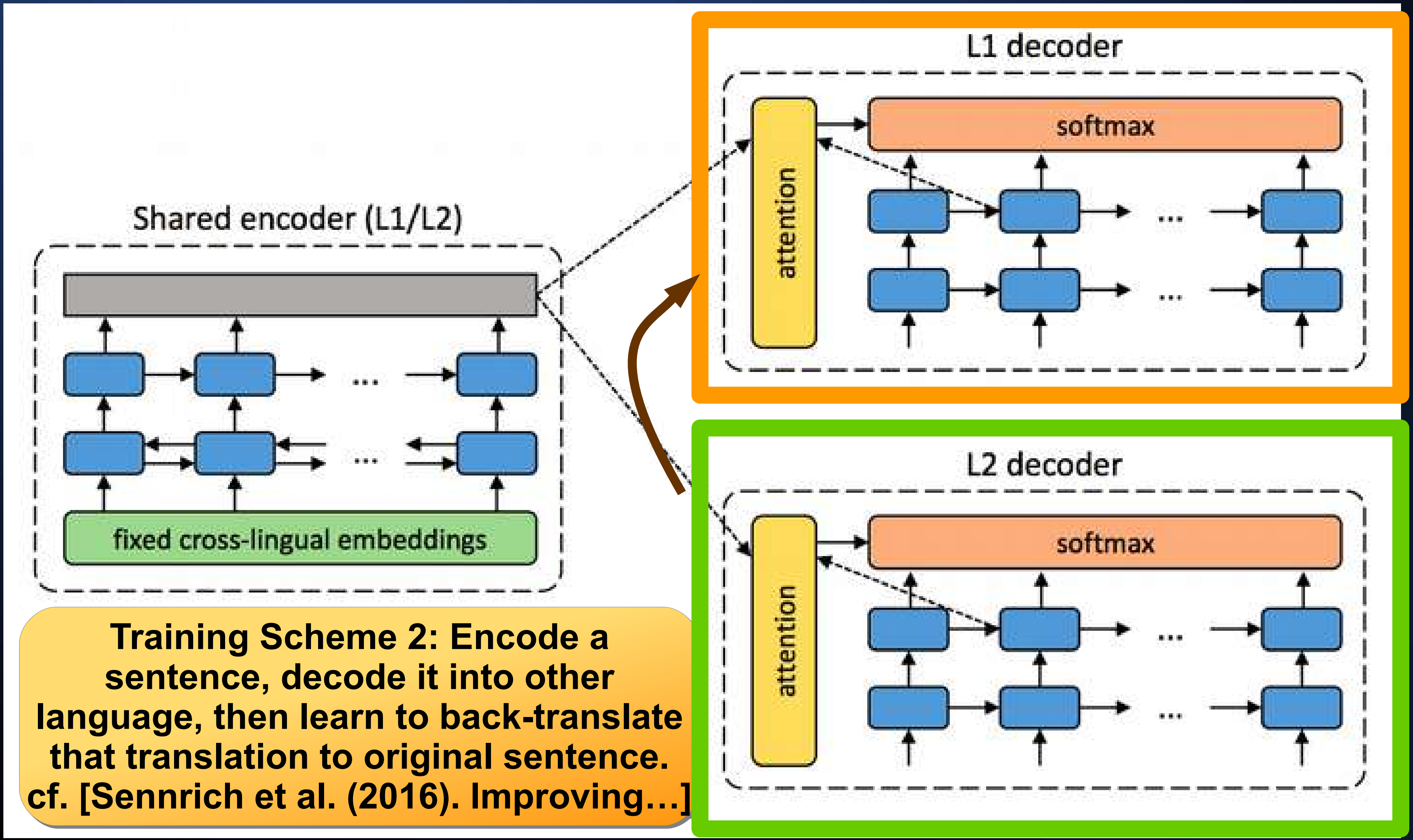
Unsupervised Neural MT



Training Scheme 1: Auto-Encoding with De-Noising, i.e. randomly swap N/2 word pairs, encode sentence, try to decode orig. sentence

Mikel Artetxe, Gorka Labaka, Eneko Agirre, Kyunghyun Cho. Unsupervised Neural Machine Translation. ArXiv 2017

Unsupervised Neural MT



Training Scheme 2: Encode a sentence, decode it into other language, then learn to back-translate that translation to original sentence. cf. [Sennrich et al. (2016). Improving…]

Mikel Artetxe, Gorka Labaka, Eneko Agirre, Kyunghyun Cho. Unsupervised Neural Machine Translation. ArXiv 2017

Unsupervised Neural MT

		FR-EN	EN-FR	DE-EN	EN-DE
Unsupervised	1. Baseline (emb. nearest neighbor)	9.98	6.25	7.07	4.39
	2. Proposed (denoising)	7.28	5.33	3.64	2.40
	3. Proposed (+ backtranslation)	15.56	15.13	10.21	6.55
	4. Proposed (+ BPE)	15.56	14.36	10.16	6.89
Semi-supervised	5. Proposed (full) + 100k parallel	21.81	21.74	15.24	10.95
Supervised	6. Comparable NMT	20.48	19.89	15.04	11.05
	7. GNMT (Wu et al., 2016)	-	38.95	-	24.61

BLEU scores on newstest2014

Mikel Artetxe, Gorka Labaka, Eneko Agirre, Kyunghyun Cho. Unsupervised Neural Machine Translation. ArXiv 2017

Unsupervised Neural MT

Source	Reference	Proposed system (full)
Une fusillade a eu lieu à l'aéroport international de Los Angeles.	There was a shooting in Los Angeles International Airport.	A shooting occurred at Los Angeles International Airport.
Cette controverse croissante autour de l'agence a provoqué beaucoup de spéculations selon lesquelles l'incident de ce soir était le résultat d'une cyber-opération ciblée.	Such growing controversy surrounding the agency prompted early speculation that tonight's incident was the result of a targeted cyber operation.	This growing scandal around the agency has caused much speculation about how this incident was the outcome of a targeted cyber operation.
Le nombre total de morts en octobre est le plus élevé depuis avril 2008, quand 1 073 personnes avaient été tuées.	The total number of deaths in October is the highest since April 2008, when 1,073 people were killed.	The total number of deaths in May is the highest since April 2008, when 1 064 people had been killed.
À l'exception de l'opéra, la province reste le parent pauvre de la culture en France.	With the exception of opera, the provinces remain the poor relative of culture in France.	At an exception, opera remains of the state remains the poorest parent culture.

Mikel Artetxe, Gorka Labaka, Eneko Agirre, Kyunghyun Cho. Unsupervised Neural Machine Translation. ArXiv 2017

Sentiment Embeddings

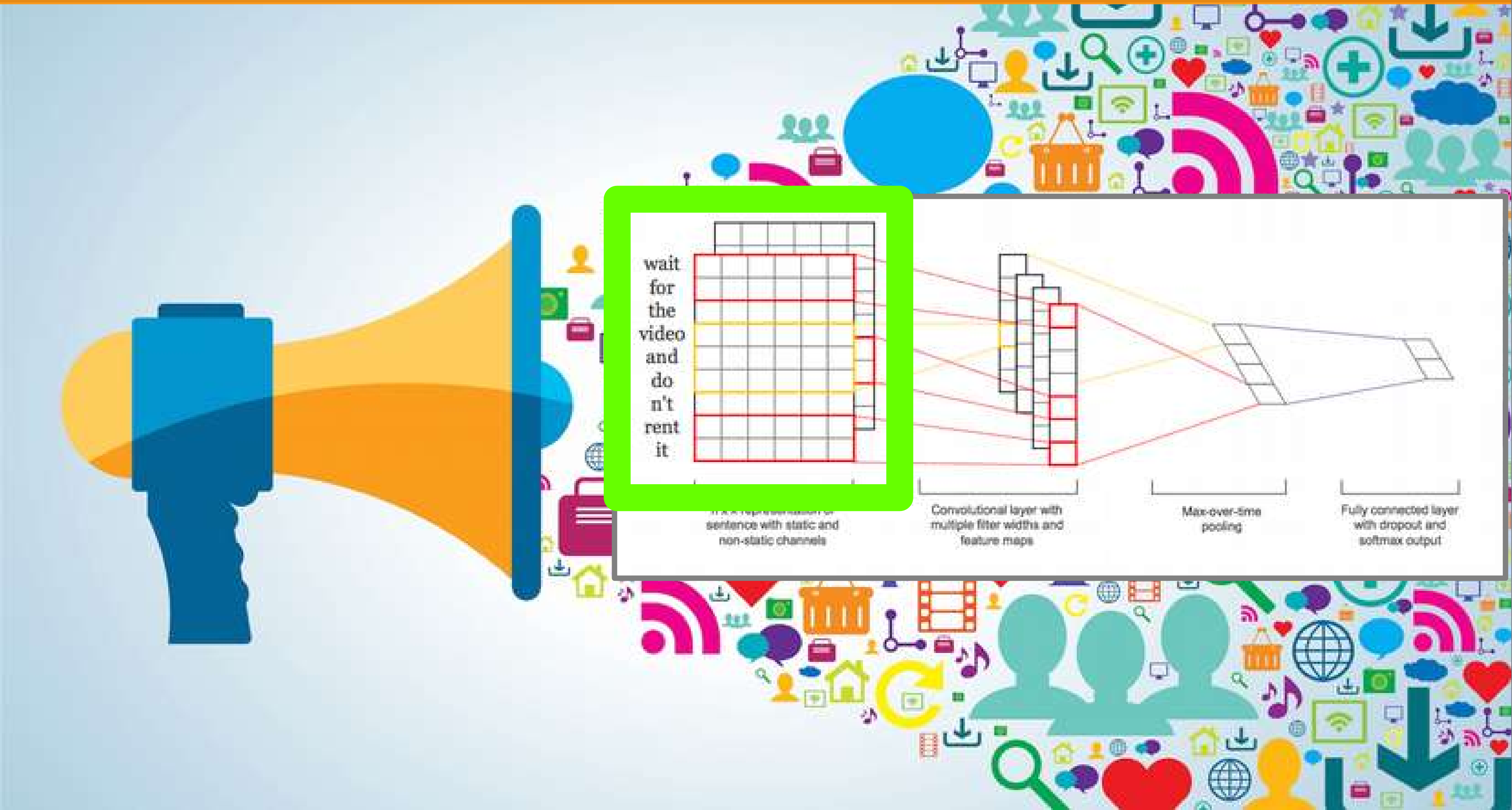
Sentiment Analysis

Across the globe, people are expressing their opinion in social media, reviews, etc.

If you don't **pay attention**, you may be **losing millions of dollars!**

Image: https://www.synthesio.com/blog/social-sentiment-and-your-business/

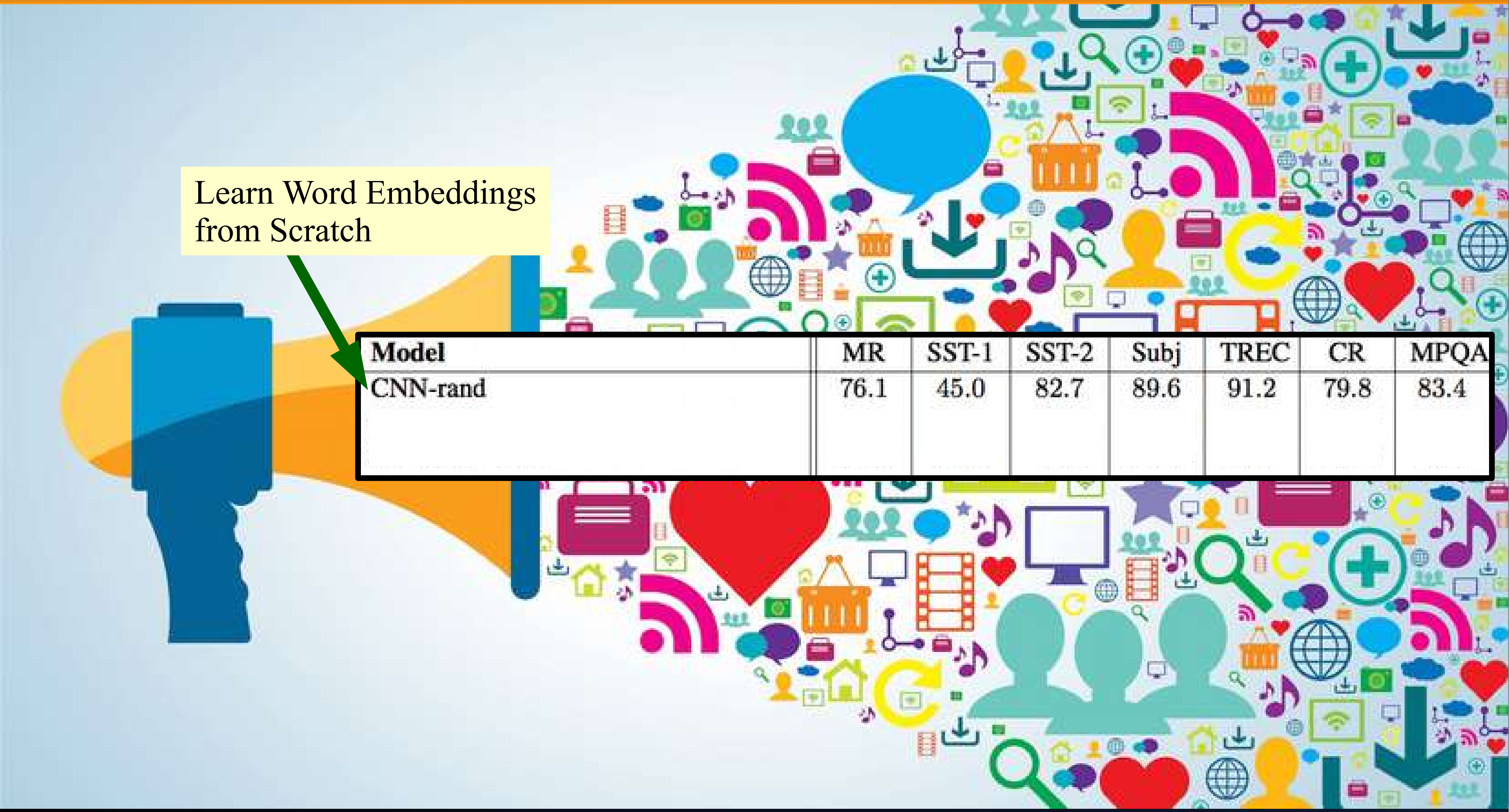
Word Representations for Deep Sentiment Analysis



ConvNet image by Yoon Kim (2014). Convolutional Neural Networks for Sentence Classification

Background Image: https://www.synthesio.com/blog/social-sentiment-and-your-business/

Word Representations for Deep Sentiment Analysis



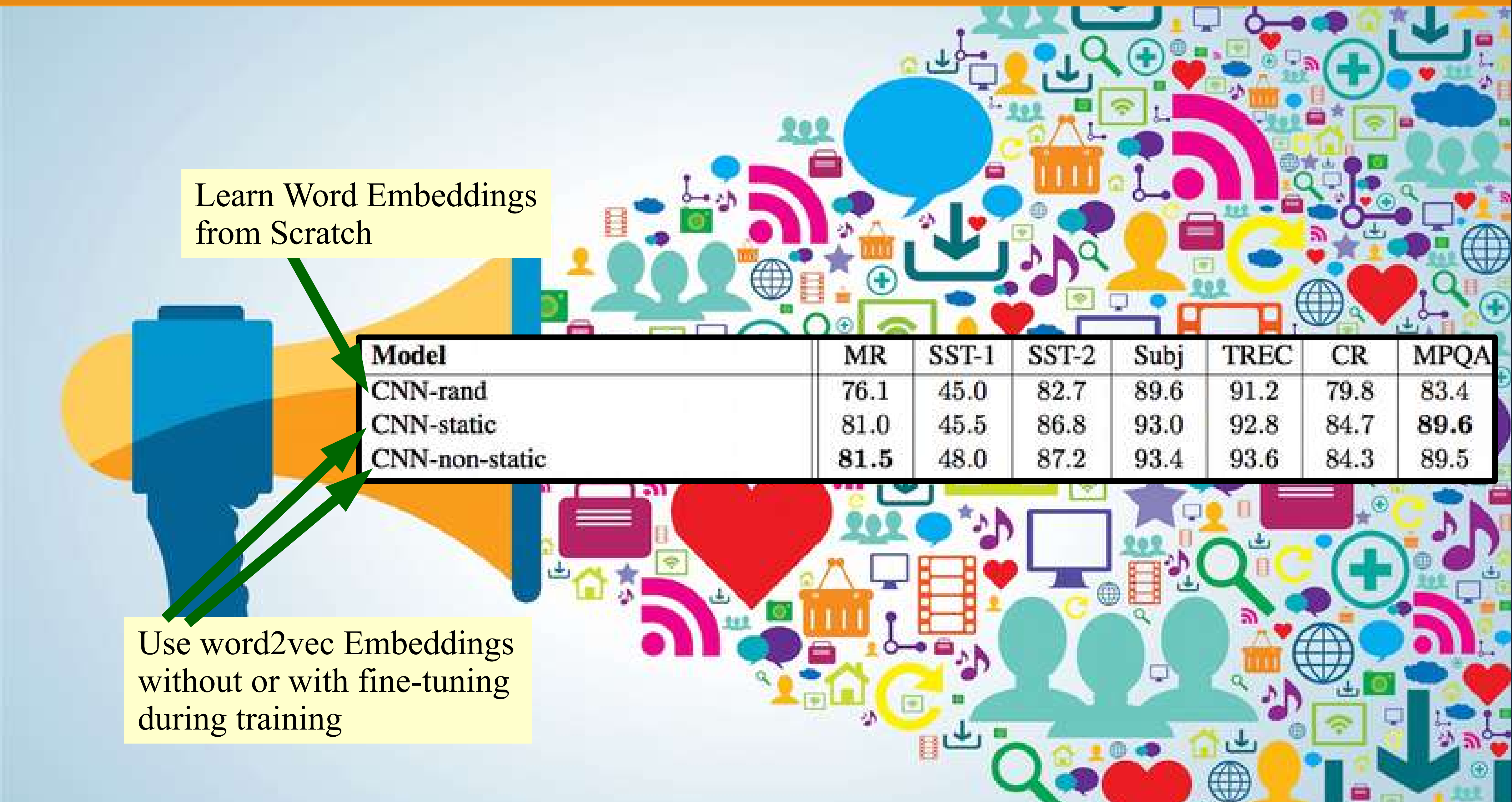
Learn Word Embeddings from Scratch

Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-rand	76.1	45.0	82.7	89.6	91.2	79.8	83.4

Results by Yoon Kim (2014). Convolutional Neural Networks for Sentence Classification

Image: https://www.synthesio.com/blog/social-sentiment-and-your-business/

Word Representations for Deep Sentiment Analysis



Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-rand	76.1	45.0	82.7	89.6	91.2	79.8	83.4
CNN-static	81.0	45.5	86.8	93.0	92.8	84.7	**89.6**
CNN-non-static	**81.5**	48.0	87.2	93.4	93.6	84.3	89.5

Results by Yoon Kim (2014). Convolutional Neural Networks for Sentence Classification

Image: https://www.synthesio.com/blog/social-sentiment-and-your-business/

Why Sentiment Embeddings?

Regular word embeddings don't aim to capture sentiment specifically.

Can we learn "Sentiment Embeddings"?

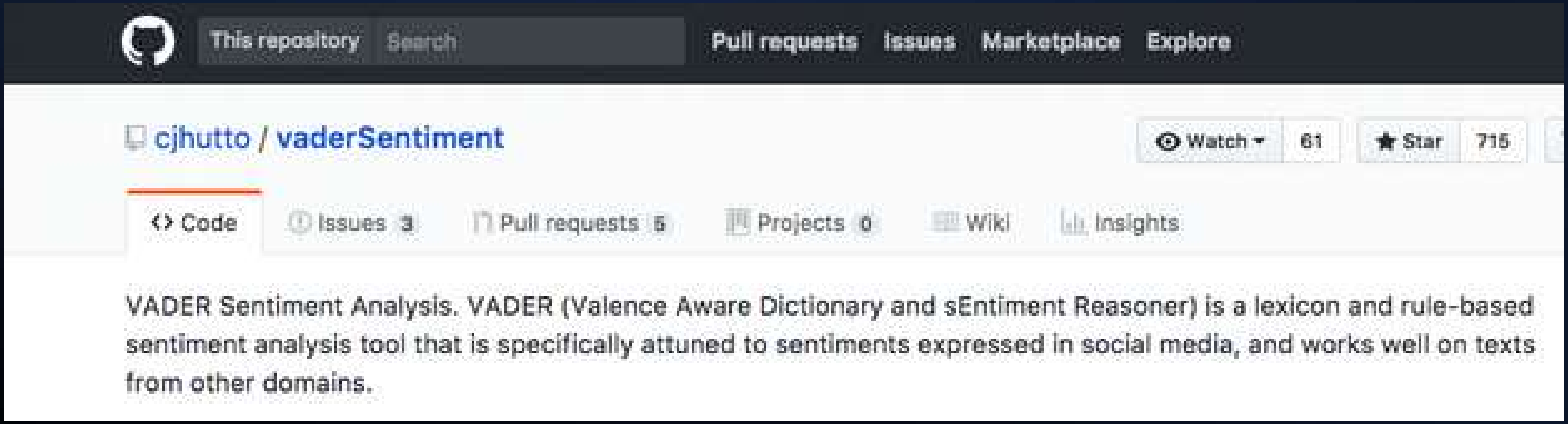
Image: https://www.synthesio.com/blog/social-sentiment-and-your-business/

Option 1: Sentiment Lexicons

Option 1:

Sentiment Lexicons as 1-dimensional embeddings in [-1,1]

Image: Hassan Saif, Miriam Fernandez, Yulan He, Harith Alani



Xin Dong, Gerard de Melo. Cross-Lingual Propagation for Deep Sentiment Analysis. AAAI 2018

Option 2: Multiple Sentiment Lexicons

Option 2:

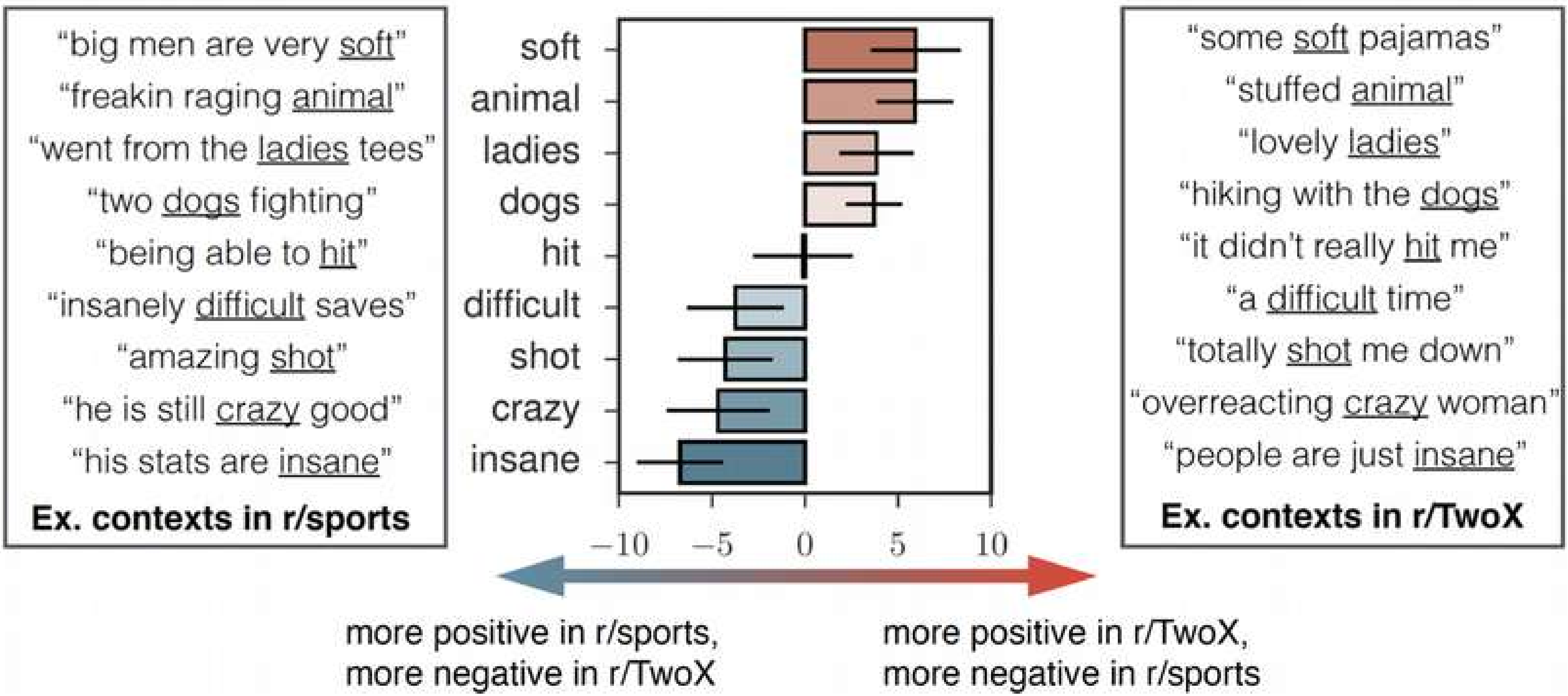
250 sentiment Lexicons
as 250-dimensional
embeddings

Mined 250
Reddit topics

SocialSent: Domain-Specific Sentiment Lexicons for Computational Social Science
William L. Hamilton, Kevin Clark, Jure Leskovec, Dan Jurafsky

Xin Dong, Gerard de Melo. Cross-Lingual Propagation for Deep Sentiment Analysis. AAAI 2018

Option 2: Multiple Sentiment Lexicons



Mined 250 Reddit topics

SocialSent: Domain-Specific Sentiment Lexicons for Computational Social Science

William L. Hamilton, Kevin Clark, Jure Leskovec, Dan Jurafsky

Xin Dong, Gerard de Melo. Cross-Lingual Propagation for Deep Sentiment Analysis. AAAI 2018

Option 3: Data-Driven Sentiment Embeddings

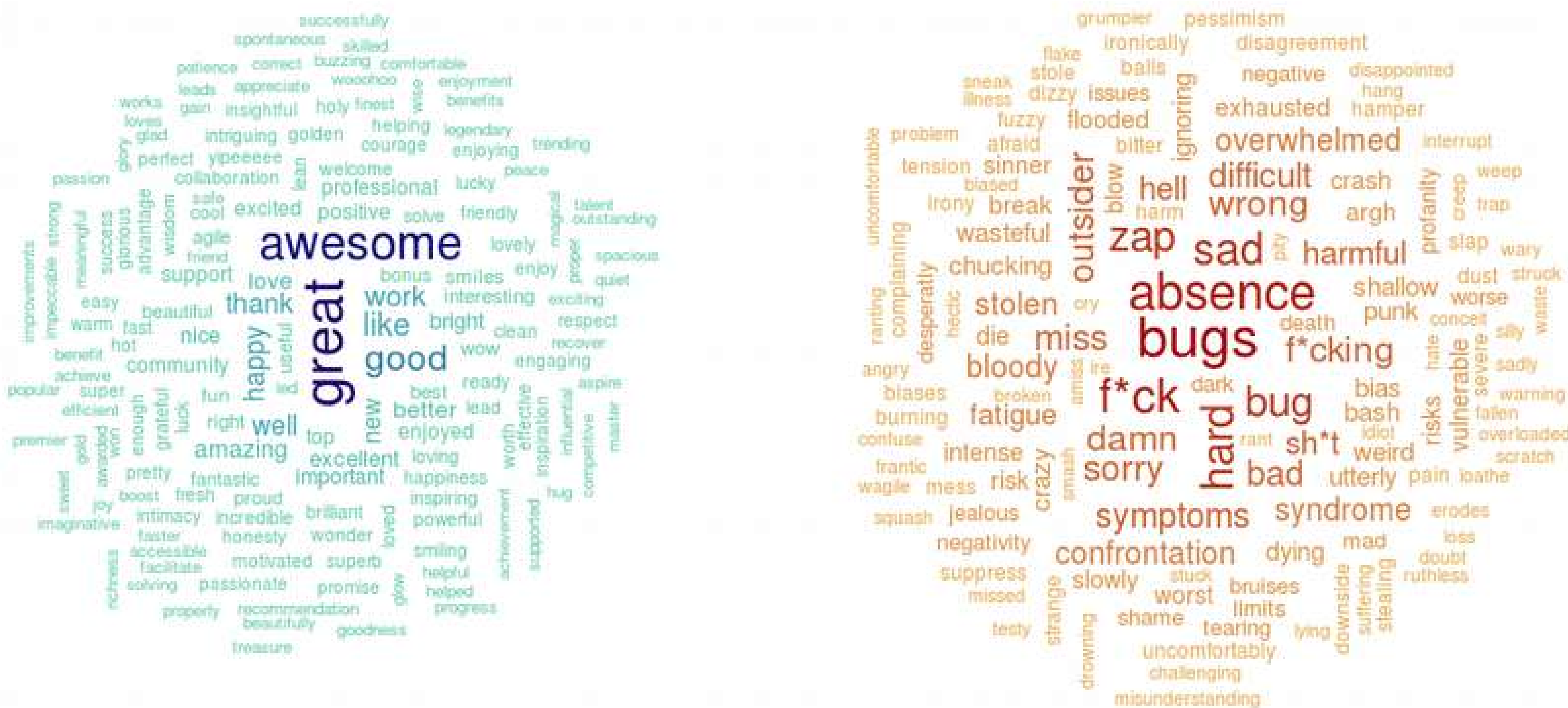


Image: http://blog.scottlogic.com/2016/11/09/r-twitter-mining-and-sentiment-analysis.html

Option 3: Data-Driven Sentiment Embeddings

Option 3:

Transfer Learning using Supervised Linear Models

Train n linear models

$$f_i(\mathbf{x}) = \mathbf{w}_\mathbf{i}^\top \mathbf{x} + \mathbf{b}_\mathbf{i}$$

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Option 3: Data-Driven Sentiment Embeddings

Train n linear models

$$f_i(\mathbf{x}) = \mathbf{w}_\mathbf{i}^\intercal \mathbf{x} + \mathbf{b}_\mathbf{i}$$

Used 25 different domains from Amazon

Books, Electronics, Movies, Kitchen, etc.

Xin Dong, Gerard de Melo. Cross-Lingual Propagation for Deep Sentiment Analysis. AAAI 2018

Option 3: Data-Driven Sentiment Embeddings

Train n linear models

$$f_i(\mathbf{x}) = \mathbf{w}_\mathbf{i}^\intercal \mathbf{x} + \mathbf{b}_\mathbf{i}$$

For a given word, turn its linear coefficients across different models into a single vector

$$[w_{1,j}, \cdots, w_{n,j}]$$

	0.0
	0.8
hot	0.2
	...
	–0.8
	0.1

25+1 dimensions

Xin Dong, Gerard de Melo. Cross-Lingual Propagation for Deep Sentiment Analysis. AAAI 2018

Sentiment Embeddings

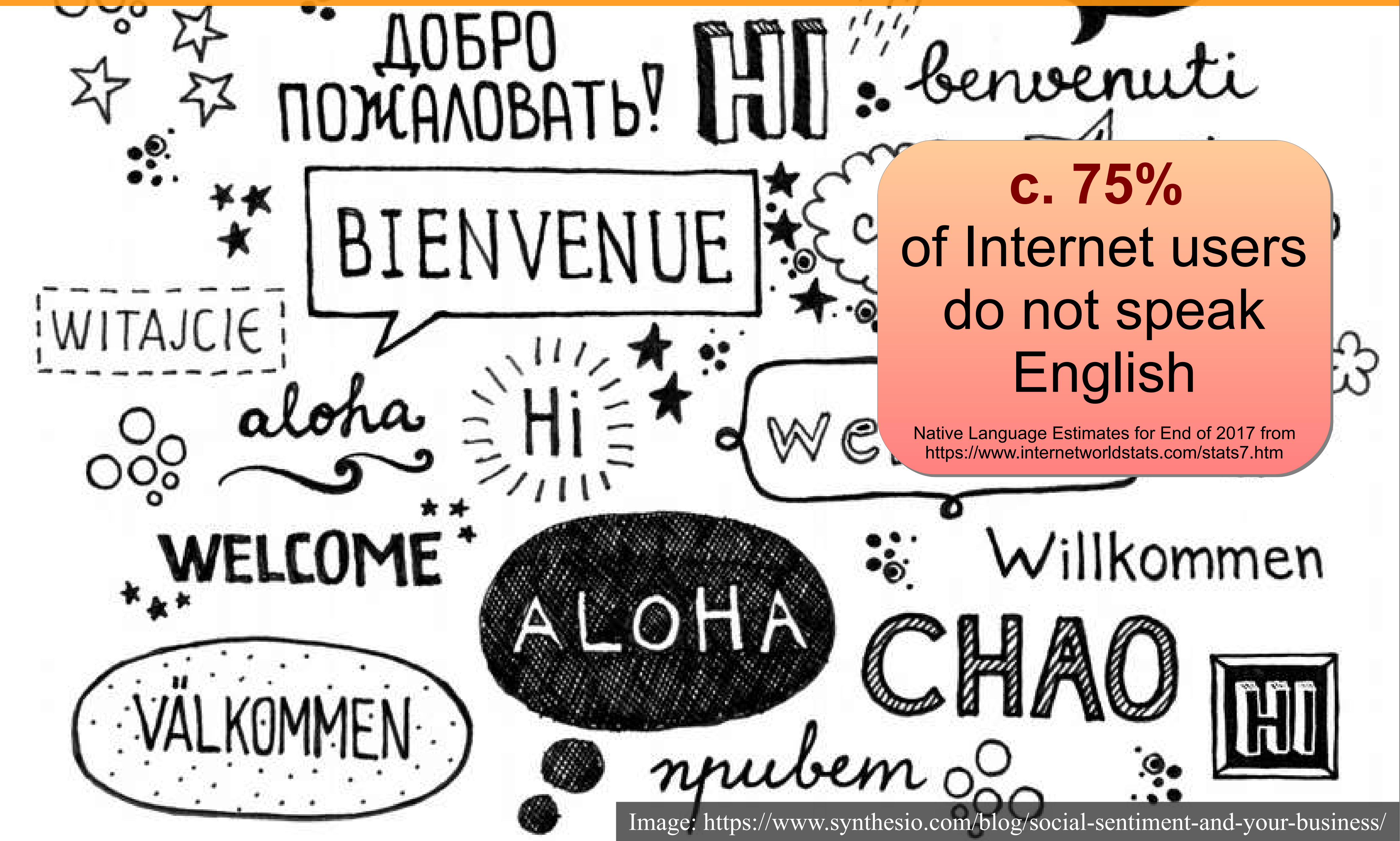
Image: http://www.thewilliamnyc.com/william-gallery/

	0.0
	0.8
hot	0.2
	...
	–0.8
	0.1

25+1 dimensions

Xin Dong, Gerard de Melo. Cross-Lingual Propagation for Deep Sentiment Analysis. AAAI 2018

Multilingual World



c. 75%
of Internet users do not speak English

Native Language Estimates for End of 2017 from https://www.internetworldstats.com/stats7.htm

Image: https://www.synthesio.com/blog/social-sentiment-and-your-business/

Multilingual World

People across the globe are using the Internet

Image: http://www.techarena.co.ke/2016/09/22/samsung-smart-school-solution/

Sentiment Analysis in Local Markets

Need to pay attention to the public opinion in different local markets

Image: https://twitter.com/lingholic/status/658780794584985600

Cross-Lingual Extension

Image: http://maxpixel.freegreatpicture.com/Foreign-Dictionary-Learning-Languages-Translation-2317654

Cross-Lingual Extension

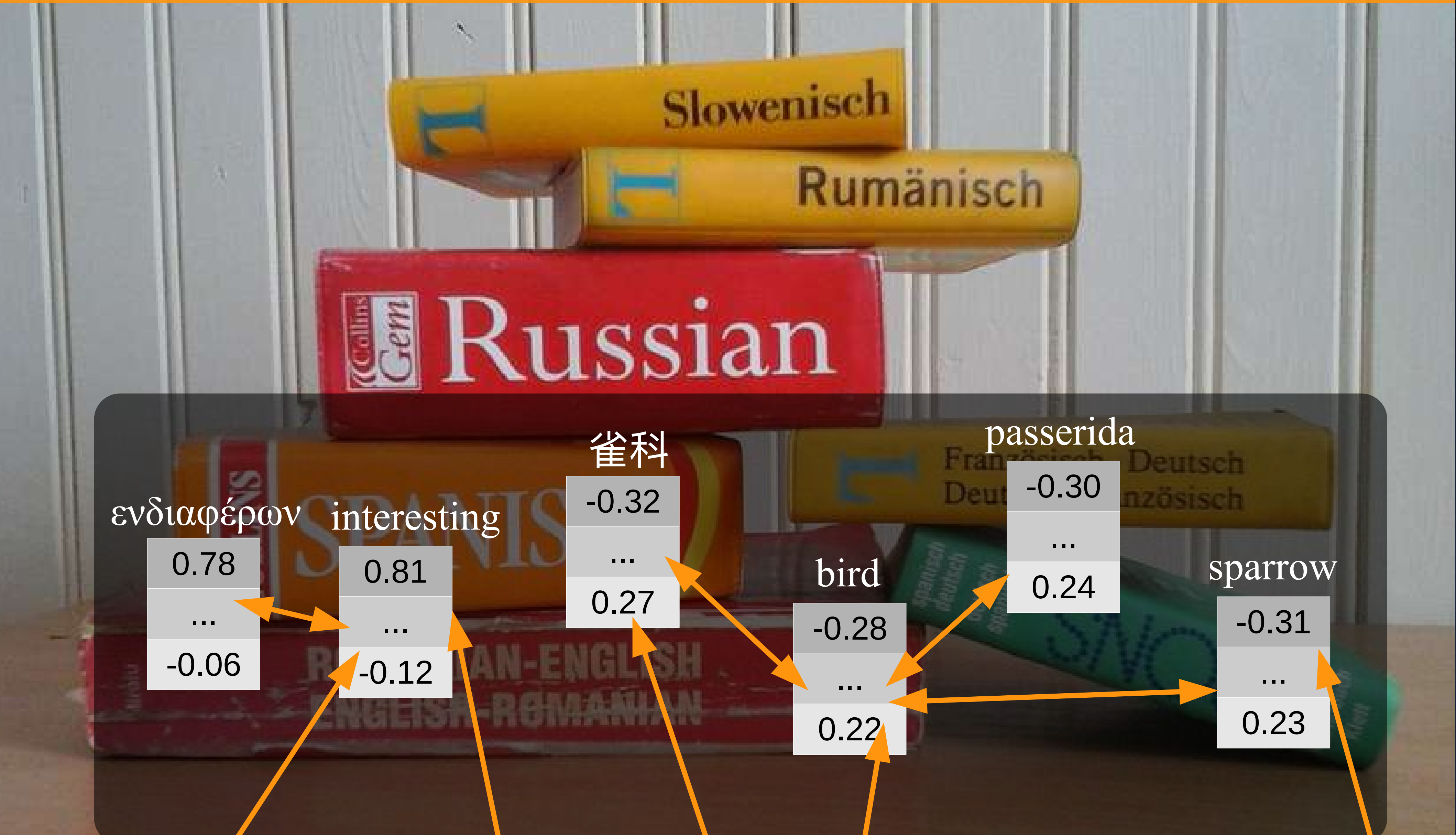
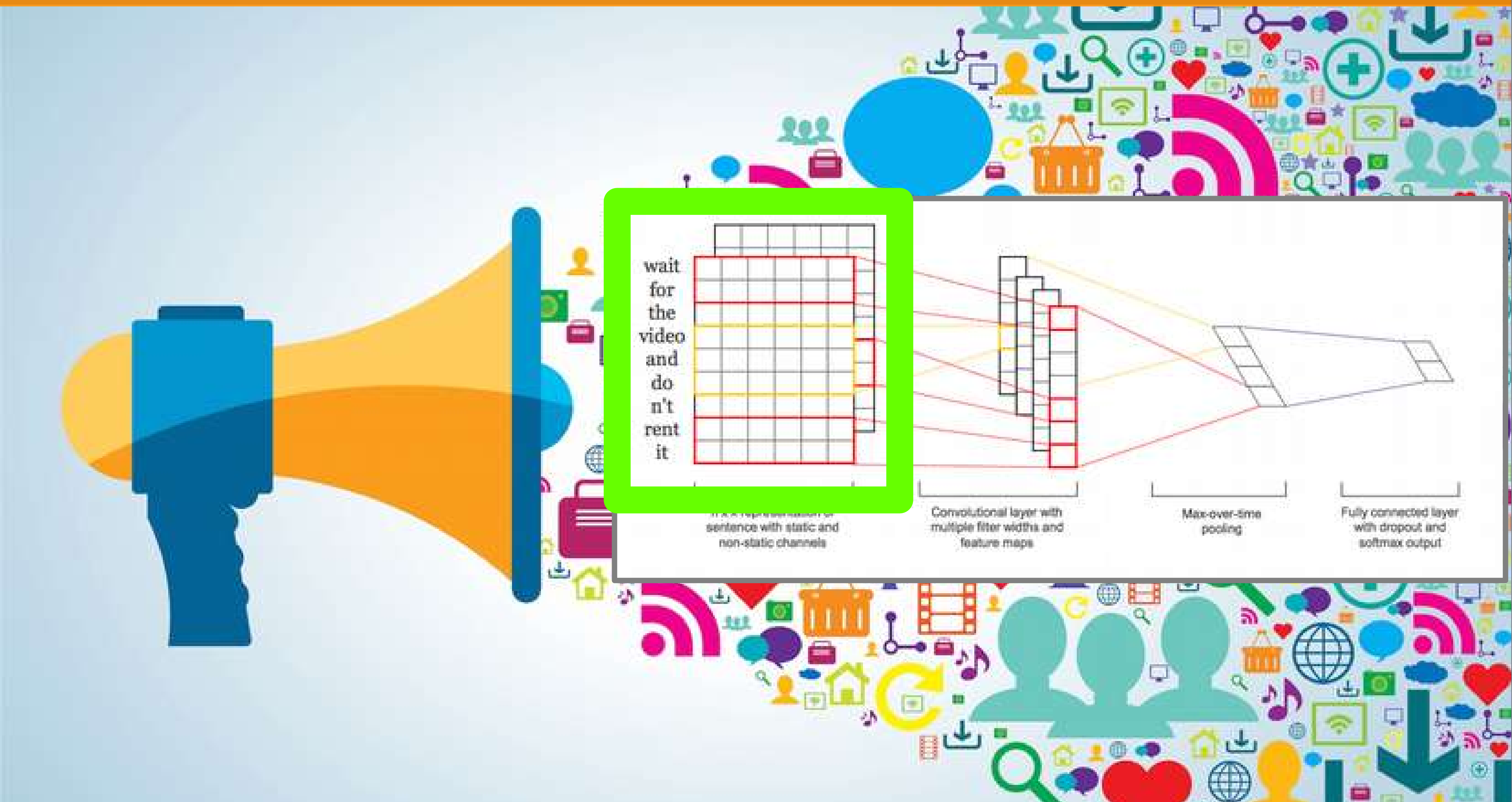


Image: http://max[illegible]el.freegreatpicture.com/Foreign-Dictionary-Learning-Languages-Translation-2317654

Sentiment Embeddings in Deep Neural Networks



ConvNet image by Yoon Kim (2014). Convolutional Neural Networks for Sentence Classification

Background Image: https://www.synthesio.com/blog/social-sentiment-and-your-business/

Sentiment Embeddings in Deep Neural Networks

Language	Source	Domain	train	test
en	Stanford Sentiment Treebank	movie	6,920	1,821
	Amazon food reviews	food	5,945	1,189
es	SemEval-2016 Task 5	restaurant	2,070	881
nl	SemEval-2016 Task 5	restaurant	1,317	575
de	TripAdvisor	restaurant	1,687	481
ru	TripAdvisor	hotel	2,387	682
it	TripAdvisor	hotel	3,437	982
ja	TripAdvisor	restaurant	1,435	411
cs	TripAdvisor	restaurant	1722	491
fr	Allocine	Television series	2,737	782

Xin Dong, Gerard de Melo. Cross-Lingual Propagation for Deep Sentiment Analysis. AAAI 2018

Sentiment Embeddings

	Embedding	d	en		es	nl	ru	de	cs	it	fr	ja
			MR	FR	RR	RR	HR	RR	RR	HR	TR	RR
Baselines	R	300	80.78	86.54	81.50	75.30	90.18	88.09	90.00	93.18	87.21	78.59
	G/F	300	85.99	88.73	85.13	77.57	93.84	92.10	92.46	95.92	91.82	76.89

Across languages, results tend to improve when using regular word vectors.

Xin Dong, Gerard de Melo. Cross-Lingual Propagation for Deep Sentiment Analysis. AAAI 2018

Sentiment Embeddings in Deep Neural Networks

	Embedding	d	en		es	nl	ru	de	cs	it	fr	ja
			MR	FR	RR	RR	HR	RR	RR	HR	TR	RR
Baselines	R	300	80.78	86.54	81.50	75.30	90.18	88.09	90.00	93.18	87.21	78.59
	G/F	300	85.99	88.73	85.13	77.57	93.84	92.10	92.46	95.92	91.82	76.89
	G/F + PG	301	86.11	88.90	85.02	77.91	93.84	92.10	93.28	95.36	91.43	75.18

Chen & Skiena. Building Sentiment Lexicons for All Major Languages. ACL 2014

Xin Dong, Gerard de Melo. Cross-Lingual Propagation for Deep Sentiment Analysis. AAAI 2018

Sentiment Embeddings in Deep Neural Networks

	Embedding	d	en		es	nl	ru	de	cs	it	fr	ja
			MR	FR	RR	RR	HR	RR	RR	HR	TR	RR
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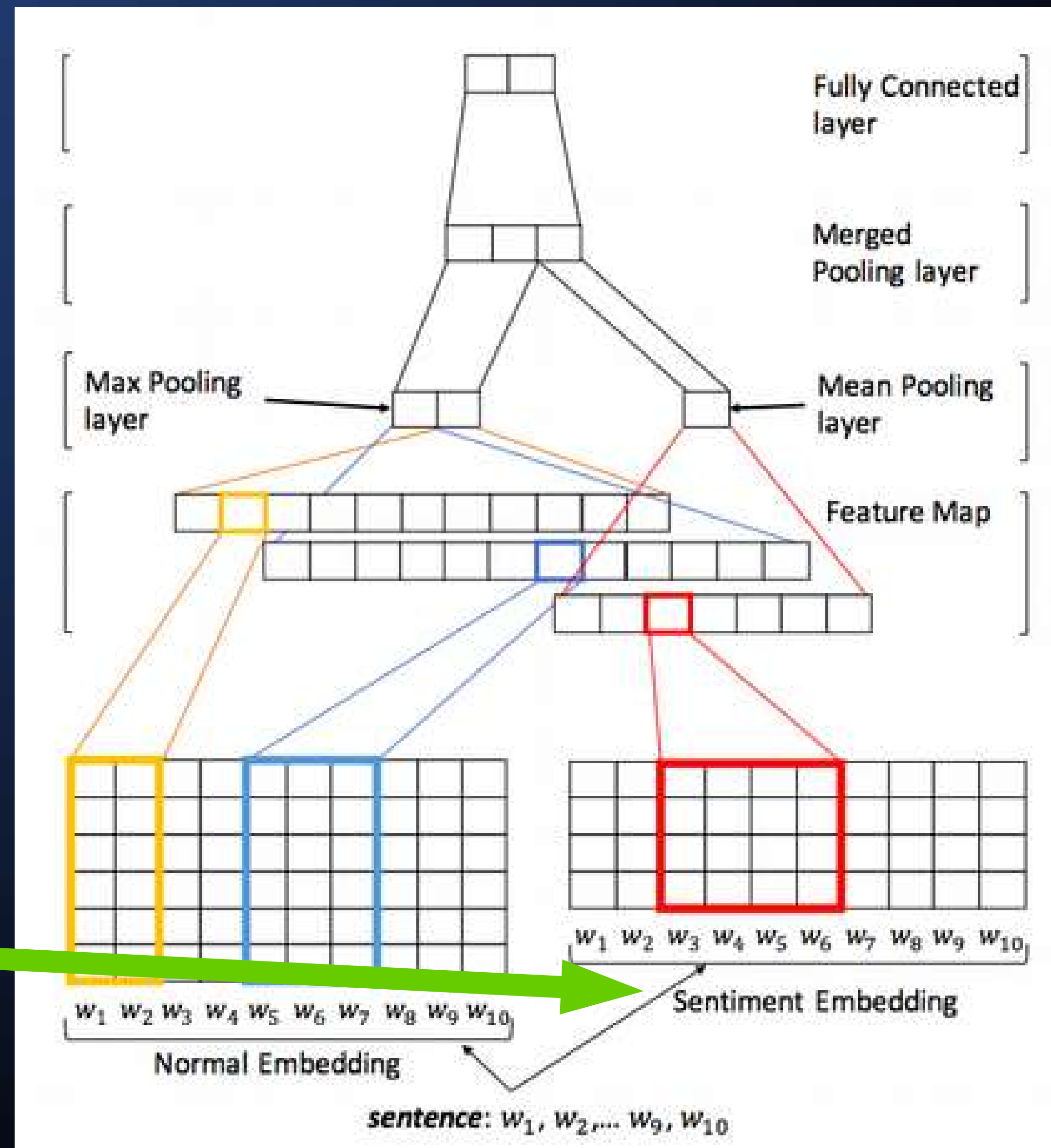
	G/F + PG	301	86.11	88.90	85.02	77.91	93.84	92.10	93.28	95.36	91.43	75.18
Concatenation (Our Embeddings)	G/F + V	301	86.33	88.81	84.45	78.26	**94.28**	92.93	92.87	**96.91**	91.56	75.18
	G/F + SS	550	85.45	88.14	83.31	76.87	91.50	91.48	91.85	94.80	90.41	75.67
	G/F + A	326	86.55	89.23	84.56	78.96	93.40	**93.56**	93.28	96.34	92.33	75.91

Concatenating our cross-lingual Amazon embedings seems to work reasonably well, but improvements are not that consistent.

Xin Dong, Gerard de Melo. Cross-Lingual Propagation for Deep Sentiment Analysis. AAAI 2018

Sentiment Embeddings in Deep Neural Networks



	0.0
	0.8
hot	0.2
	...
	–0.8
	0.1

25+1 dimensions

Xin Dong, Gerard de Melo. Cross-Lingual Propagation for Deep Sentiment Analysis. AAAI 2018

Sentiment Embeddings in Deep Neural Networks

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			MR	FR	RR	RR	HR	RR	RR	HR	TR	RR
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	G/F + A	326	86.55	89.23	84.56	78.96	93.40	**93.56**	93.28	96.34	92.33	75.91
Our Full Approach	G/F ‖ A	300/26	86.60	**89.49**	**85.93**	**79.30**	93.26	92.31	**93.69**	96.48	**92.97**	**88.08**

Xin Dong, Gerard de Melo. Cross-Lingual Propagation for Deep Sentiment Analysis. AAAI 2018

Sentiment Embeddings in Deep Neural Networks

	Embedding	d	en		es	nl	ru	de	cs	it	fr	ja
			MR	FR	RR	RR	HR	RR	RR	HR	TR	RR
Baselines	R	300	80.78	86.54	81.50	75.30	90.18	88.09	90.00	93.18	87.21	78.59
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	G/F + A	326	86.55	89.23	84.56	78.96	93.40	**93.56**	93.28	96.34	92.33	75.91
Dual Channel Baselines	G/F ‖ R	300/26	85.78	89.07	84.79	78.09	93.40	92.31	93.08	95.78	91.82	76.64
	G/F ‖ PG	300/1	85.72	88.73	85.13	77.39	93.11	91.68	93.08	95.78	91.30	76.64
Our Full Approach	G/F ‖ V	300/1	85.78	88.98	84.45	77.39	93.11	92.31	93.28	95.64	91.82	77.13
	G/F ‖ SS	300/250	86.11	88.73	84.56	77.91	**94.28**	92.10	**93.69**	96.77	91.94	85.40
	G/F ‖ A	300/26	86.60	**89.49**	**85.93**	**79.30**	93.26	92.31	**93.69**	96.48	**92.97**	**88.08**
Analysis	G/F ‖ SA	300/26	**86.82**	88.81	84.45	78.43	93.84	91.89	93.08	95.92	92.07	77.62

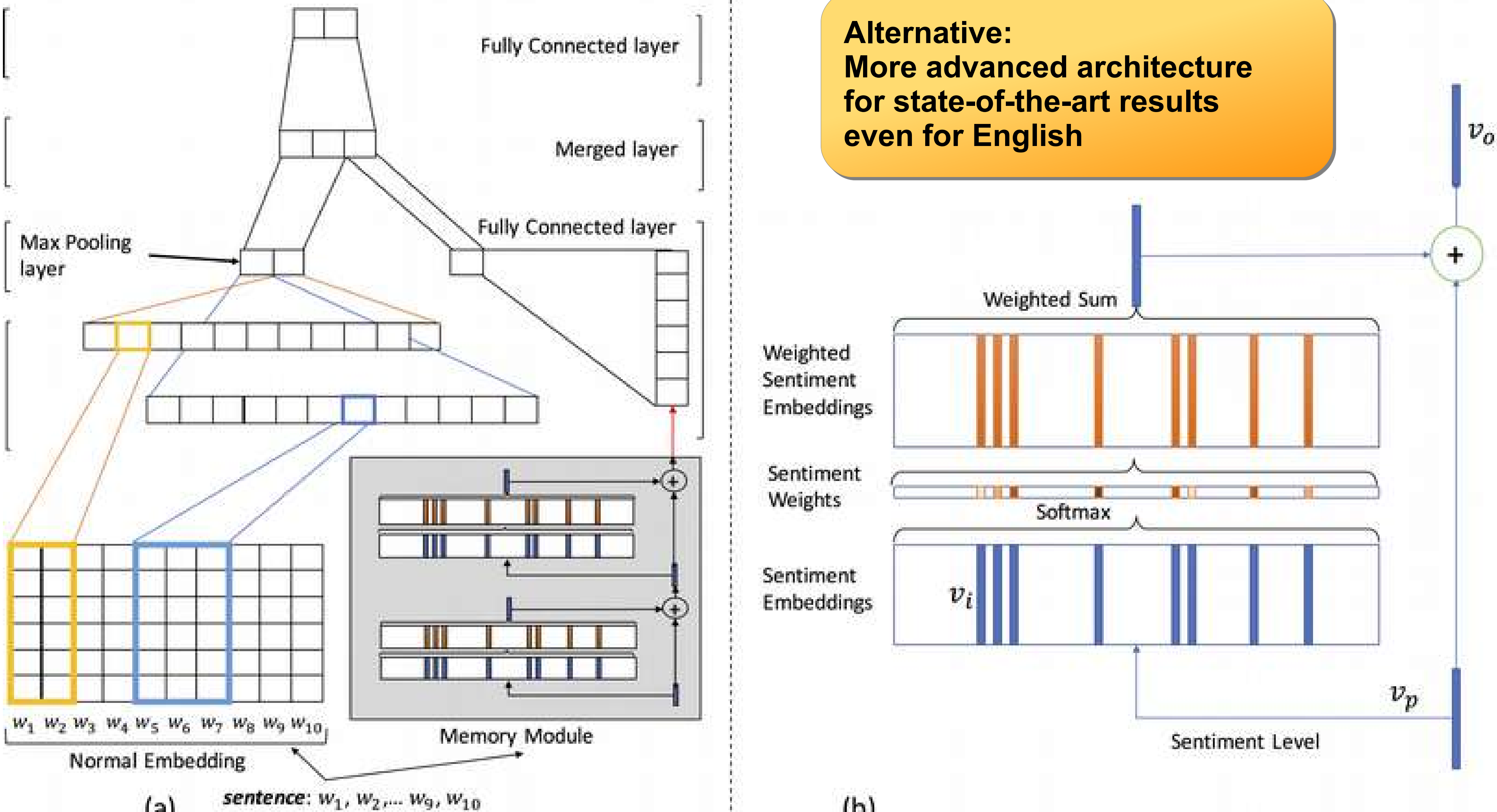
Available for download:

http://gerard.demelo.org/sentiment/

Xin Dong, Gerard de Melo. Cross-Lingual Propagation for Deep Sentiment Analysis. AAAI 2018

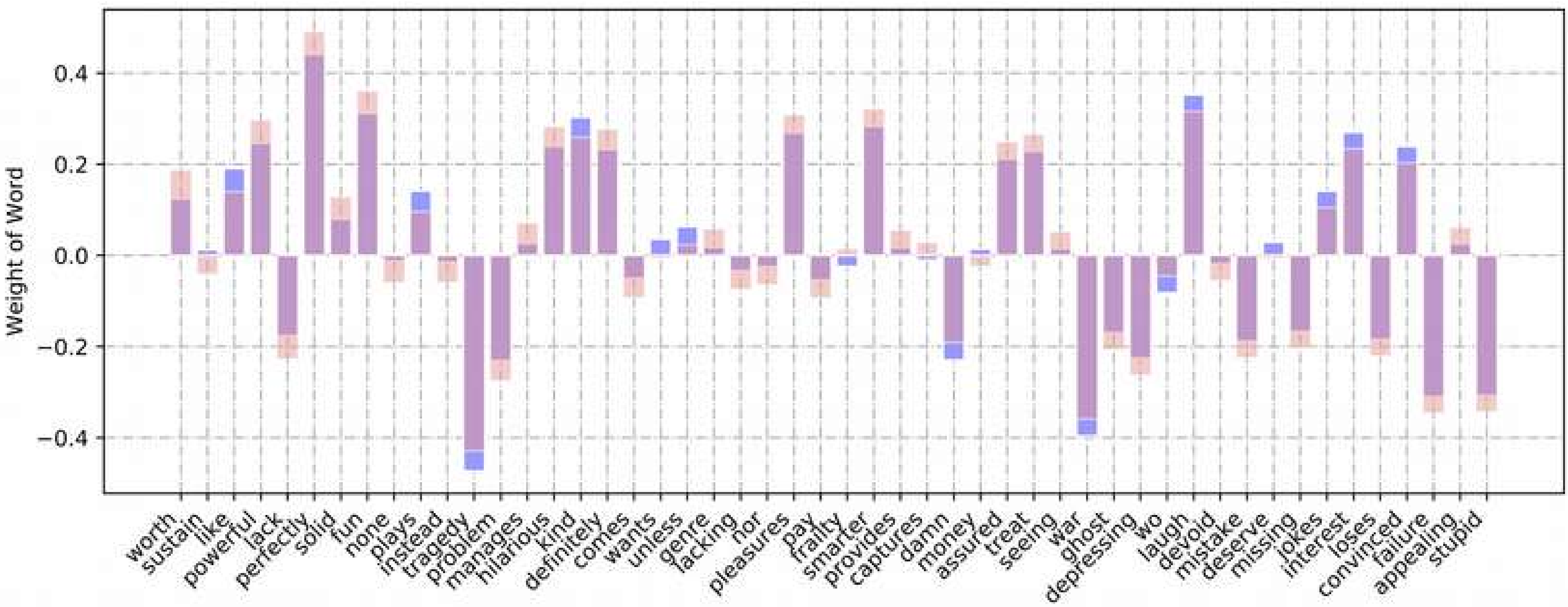
Sentiment Embeddings in Deep Neural Networks

Alternative:
More advanced architecture for state-of-the-art results even for English



Xin Dong, Gerard de Melo. A Helping Hand: Transfer Learning for Deep Sentiment Analysis. ACL 2018

Sentiment Embeddings in Deep Neural Networks



Blue: original weights (VADER)
Red: weights after fine-tuning

Xin Dong, Gerard de Melo. A Helping Hand: Transfer Learning for Deep Sentiment Analysis. ACL 2018

Font Perception Embeddings

Sentiment vs. Appearance

exciting	positive	negative	playful	serious	disturbing
EXCITING	positive	negative	playful	serious	DISTURBING
exciting	positive	negative	playful	serious	disturbing
exciting	positive	NEGATIVE	playful	serious	disturbing
exciting	positive	negative	playful	serious	DISTURBING

Different fonts should be chosen depending on the sentiment, emotion, and values one wishes to convey.

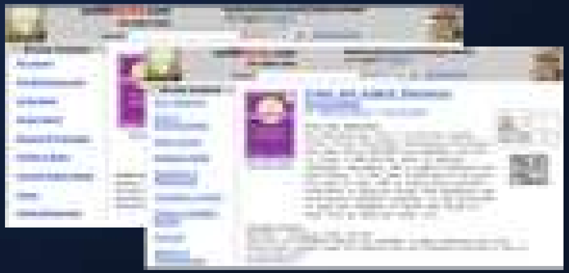
Tugba Kulahcioglu, Gerard de Melo. FontLex: A Typographical Lexicon based on Affective Associations

Sentiment vs. Appearance

Rompay and Pruyn, 2011

Fonts affect perceived brand credibility, price expectations, aesthetics

Fonts affect perceived professionalism, trustworthiness, intent to act



Shaikh, 2007

Sentiment vs. Appearance

Product Sans

Based on geometric shapes in Google logo

Gmail
Search
Calendar
Drive

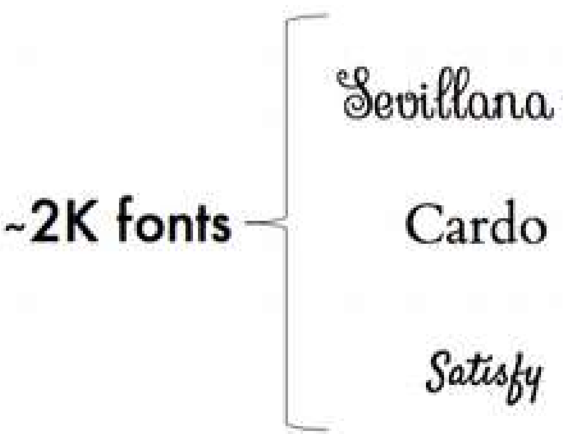
Corporate fonts such as Google's Product Sans, Intel Clear, IBM Plex, etc.

Sentiment vs. Appearance

Gillette

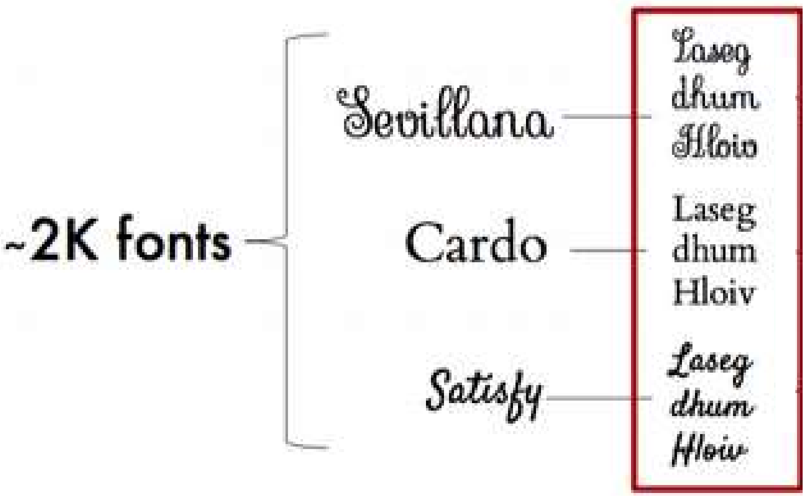
Source: http://www.downwithdesign.com/logo-design/hidden-razor-sharp-brilliance-gillette-logo/

Learning Representations of Fonts



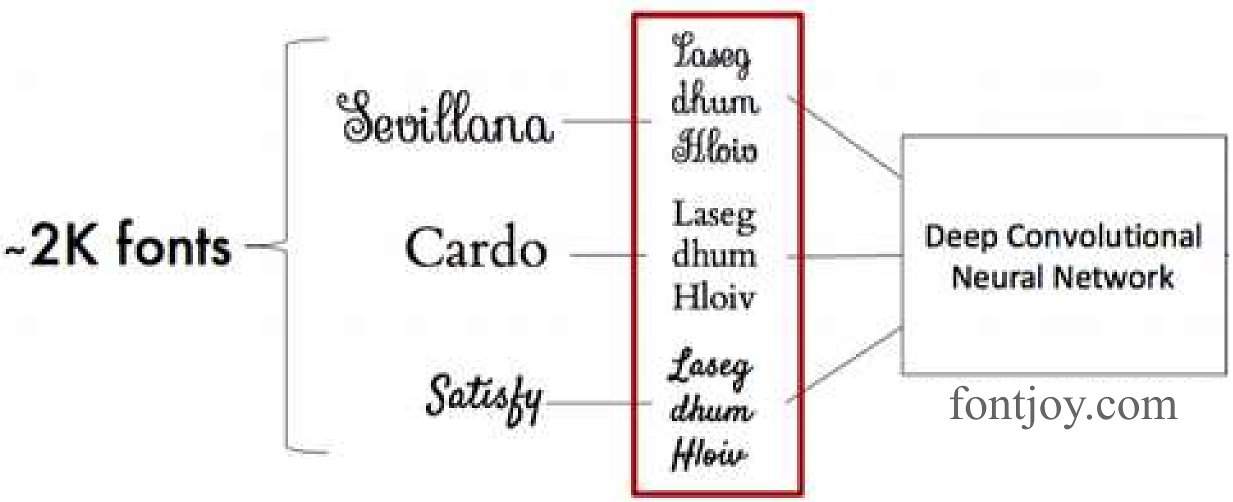
Tugba Kulahcioglu, Gerard de Melo. Predicting Semantic Signatures of Fonts

Learning Representations of Fonts



Tugba Kulahcioglu, Gerard de Melo. Predicting Semantic Signatures of Fonts

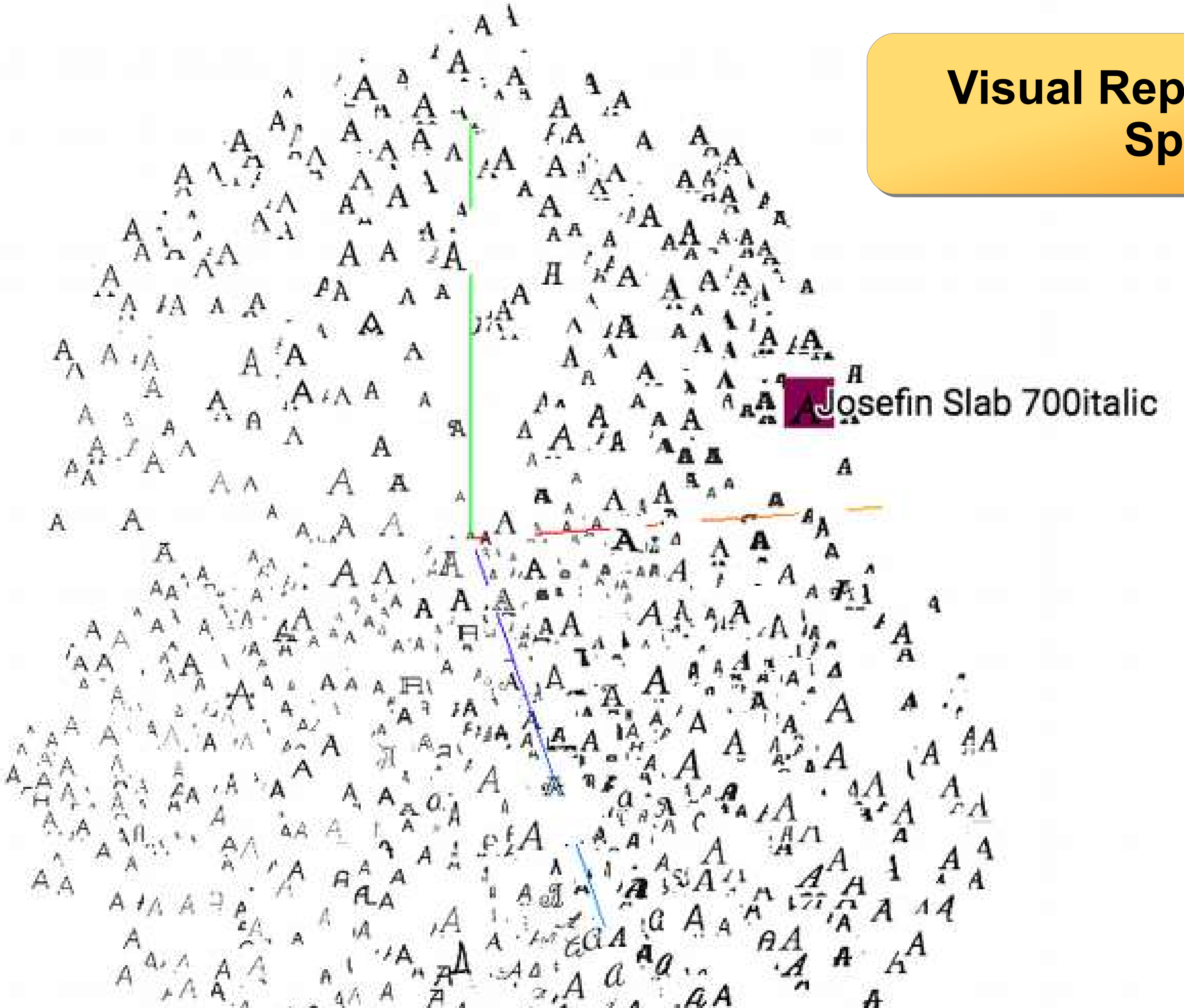
Learning Representations of Fonts



Tugba Kulahcioglu, Gerard de Melo. Predicting Semantic Signatures of Fonts

Learning Representations of Fonts

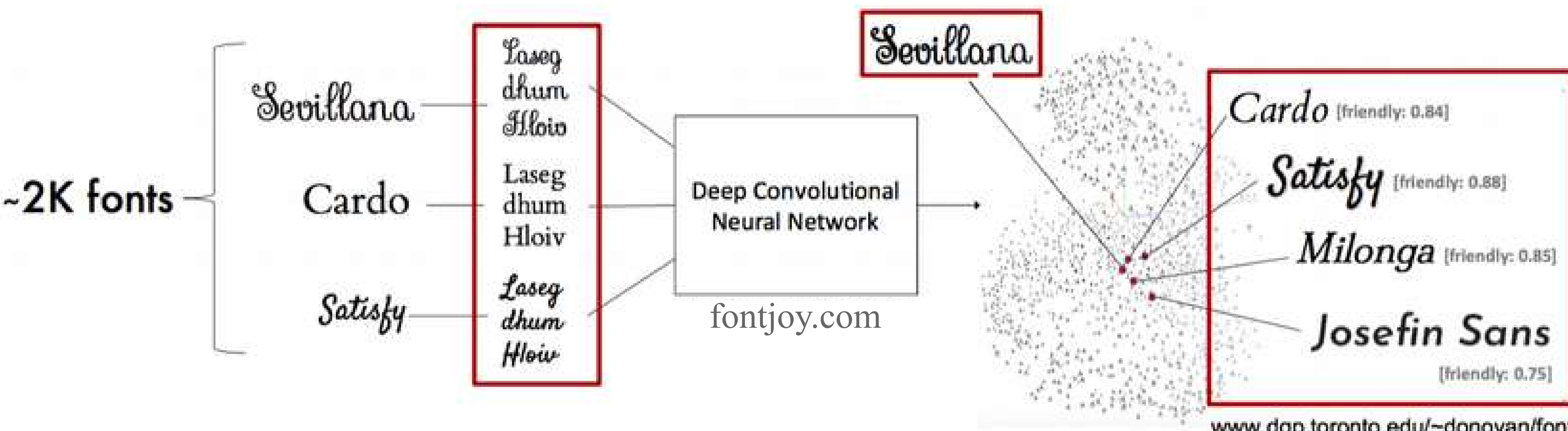
Visual Representation Space



http://fontjoy.com/projector/

Learning Representations of Fonts

Weighted 4–NN Using CNN Embeddings



Infer Attribute-Based Representations

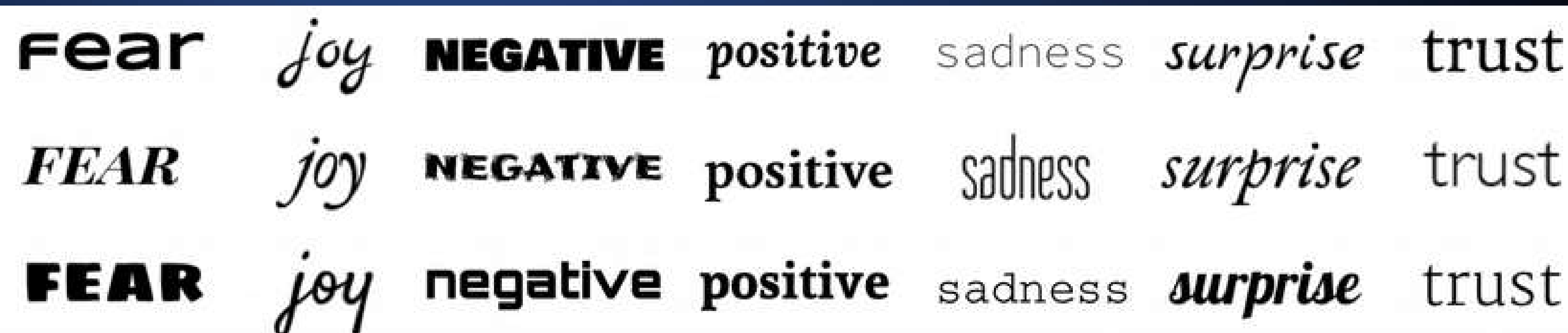
font	clumsy	formal	happy	strong
Margarine	**0.75**	0.27	0.55	0.42
Cormorant Medium	0.05	**0.94**	0.51	0.48
Oleo Script Swash Caps	0.54	0.52	**0.84**	0.38
HOLTWOOD ONE SC	0.41	0.56	0.32	**0.90**

Tugba Kulahcioglu, Gerard de Melo. Predicting Semantic Signatures of Fonts

Learning Representations of Fonts

Tugba Kulahcioglu, Gerard de Melo. Predicting Semantic Signatures of Fonts

FontLex



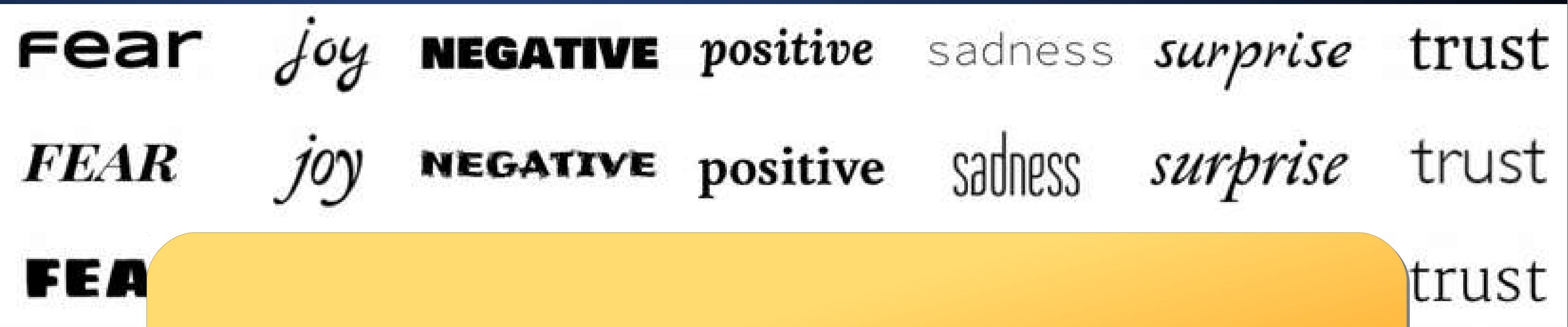
Infer additional attributes, especially sentiment/emotions

Tugba Kulahcioglu, Gerard de Melo. FontLex: A Typographical Lexicon based on Affective Associations

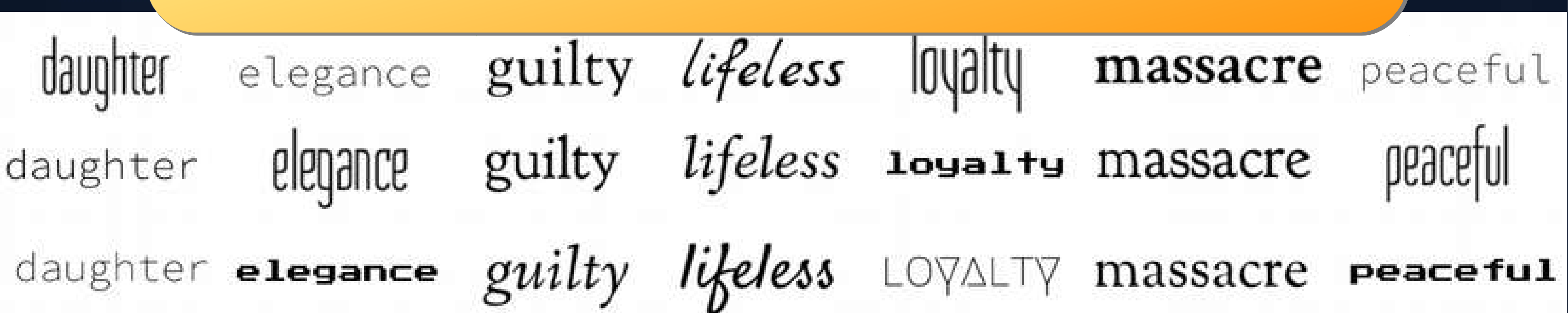
FontLex

Tugba Kulahcioglu, Gerard de Melo. FontLex: A Typographical Lexicon based on Affective Associations

FontLex



For any desired sentiment/emotion/association,
we can automatically choose suitable fonts.



Color + Fonts

The Smurfs: The Lost Village (2017)

Scream (1996)

Tugba Kulahcioglu, Gerard de Melo. Paralinguistic Recommendations for Affective Word Clouds. Proc. IUI

Color + Fonts

Yelp reviews

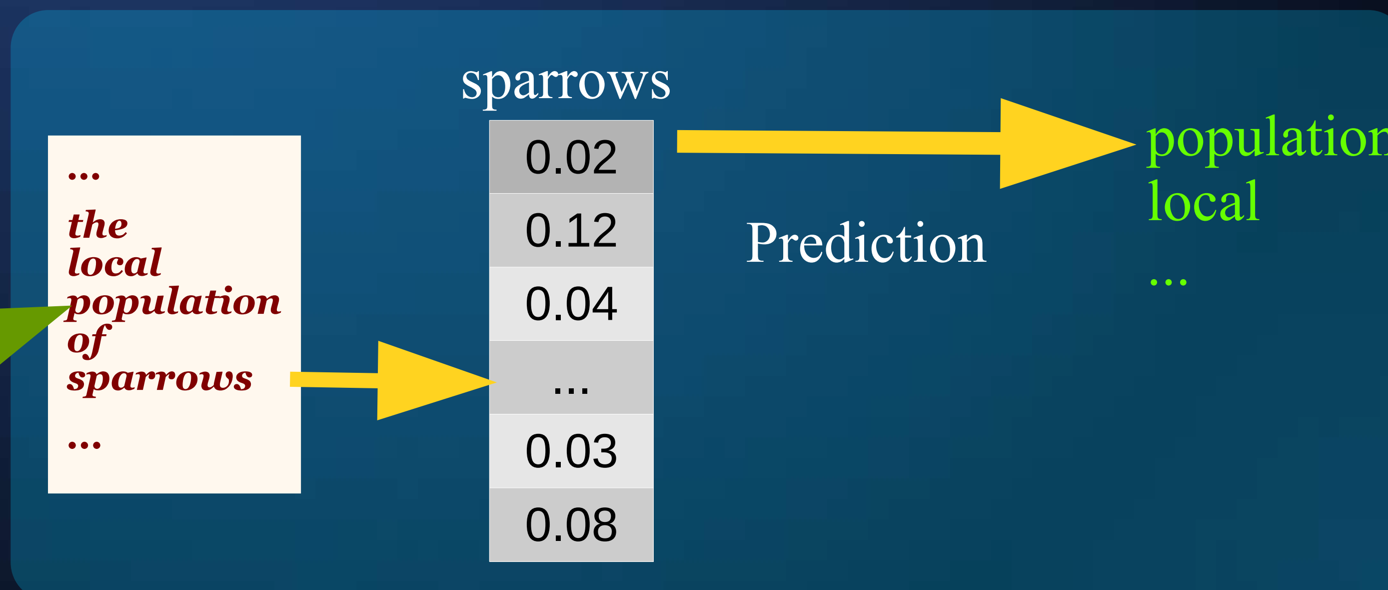
Tugba Kulahcioglu, Gerard de Melo. Paralinguistic Recommendations for Affective Word Clouds. Proc. IUI

Graphs

Word Vector Representations: word2vec

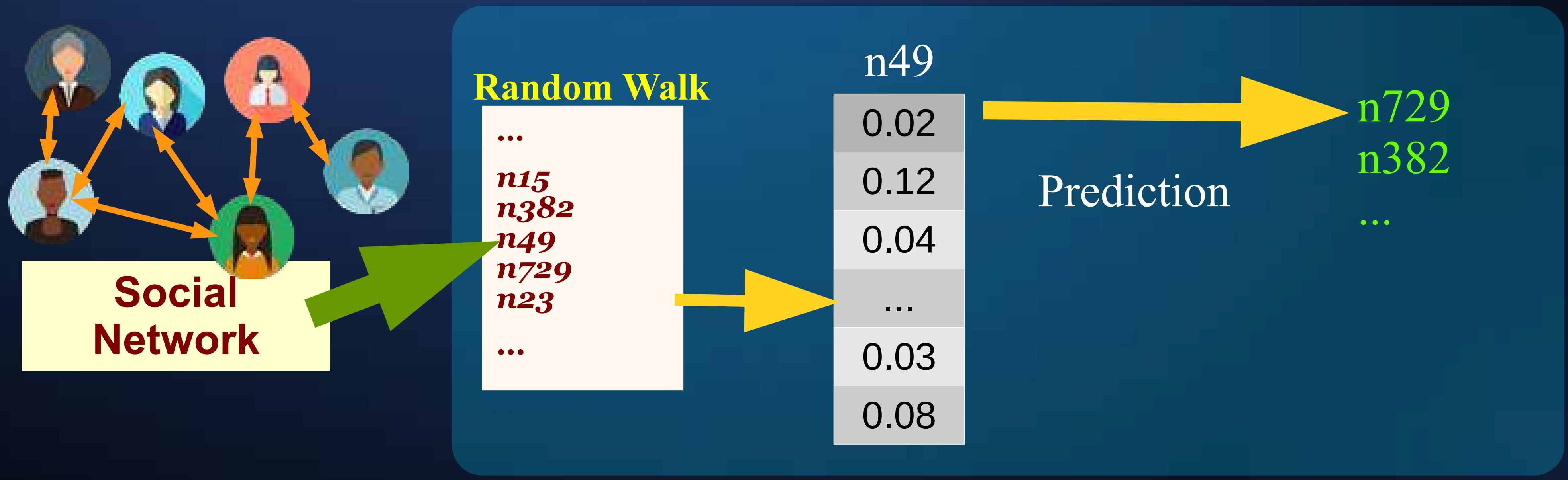
word2vec

Tool for computing continuous distributed representations of words.



word2vec Skip-Gram Model

Graph Node Representations: DeepWalk



word2vec Skip-Gram Model

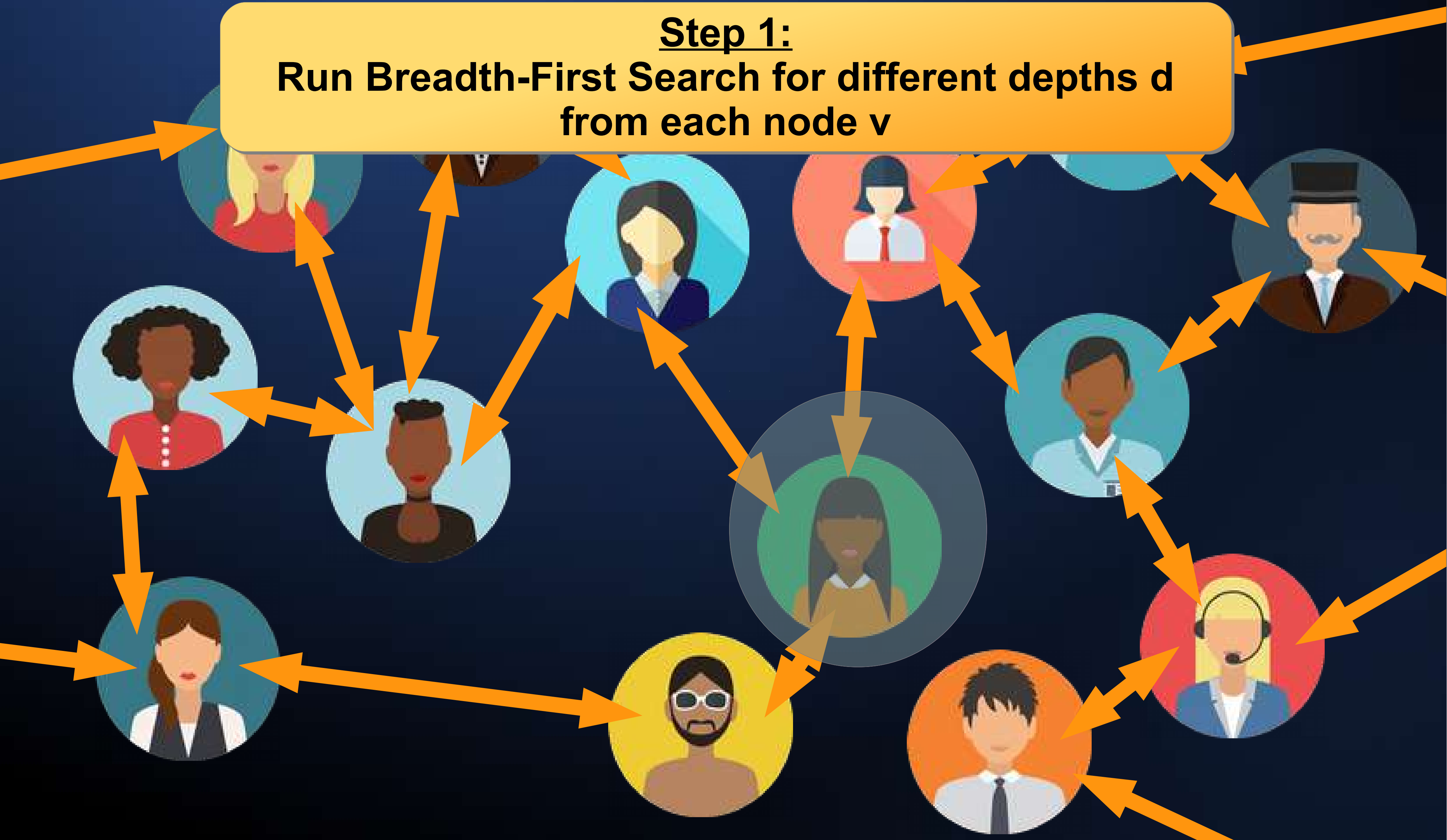
Perozzi et al. 2014. DeepWalk: Online Learning of Social Representations

Graph Node Representations: SEMAC

Graph Node Representations: SEMAC

Step 1:

Run Breadth-First Search for different depths d from each node v



Graph Node Representations: SEMAC

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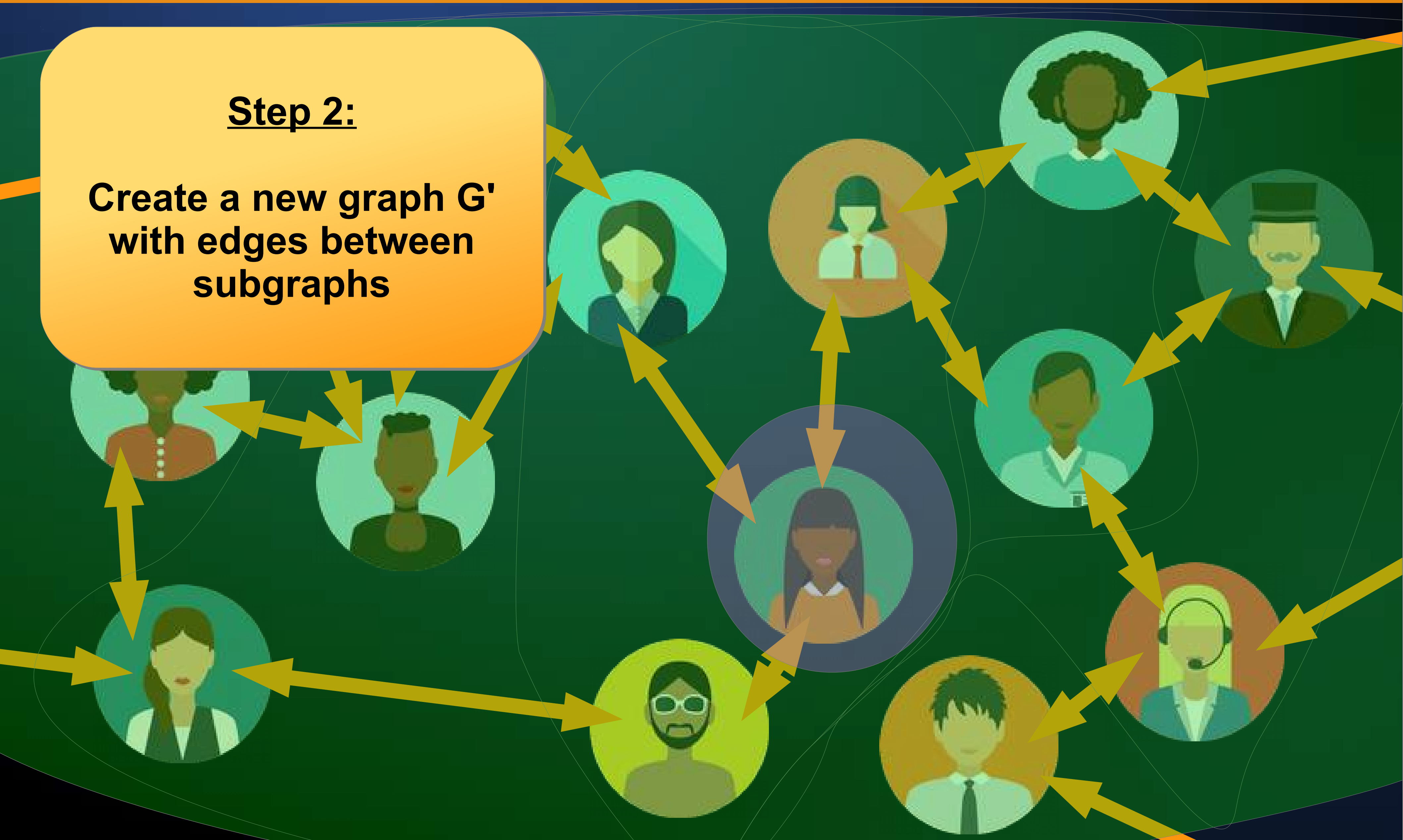
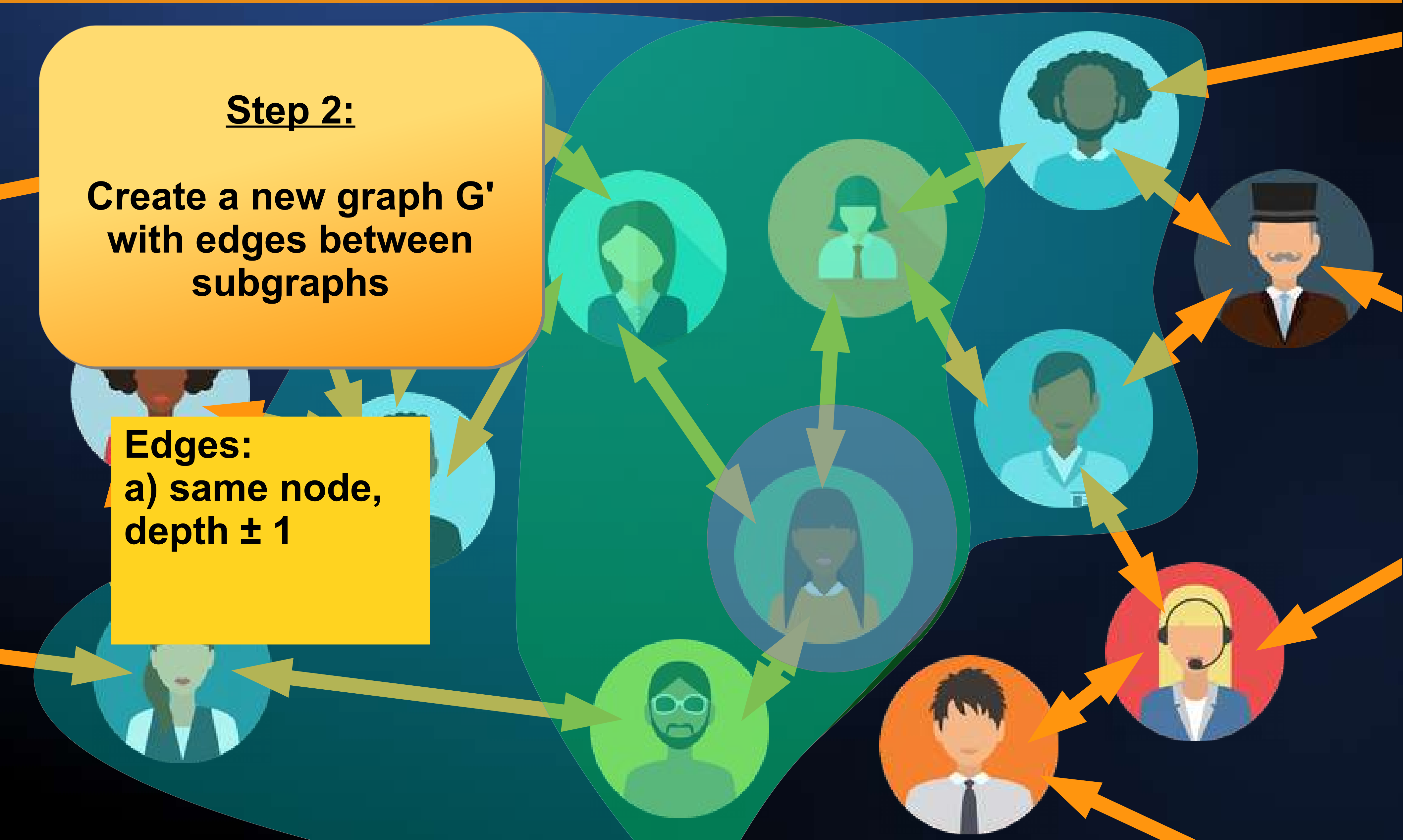


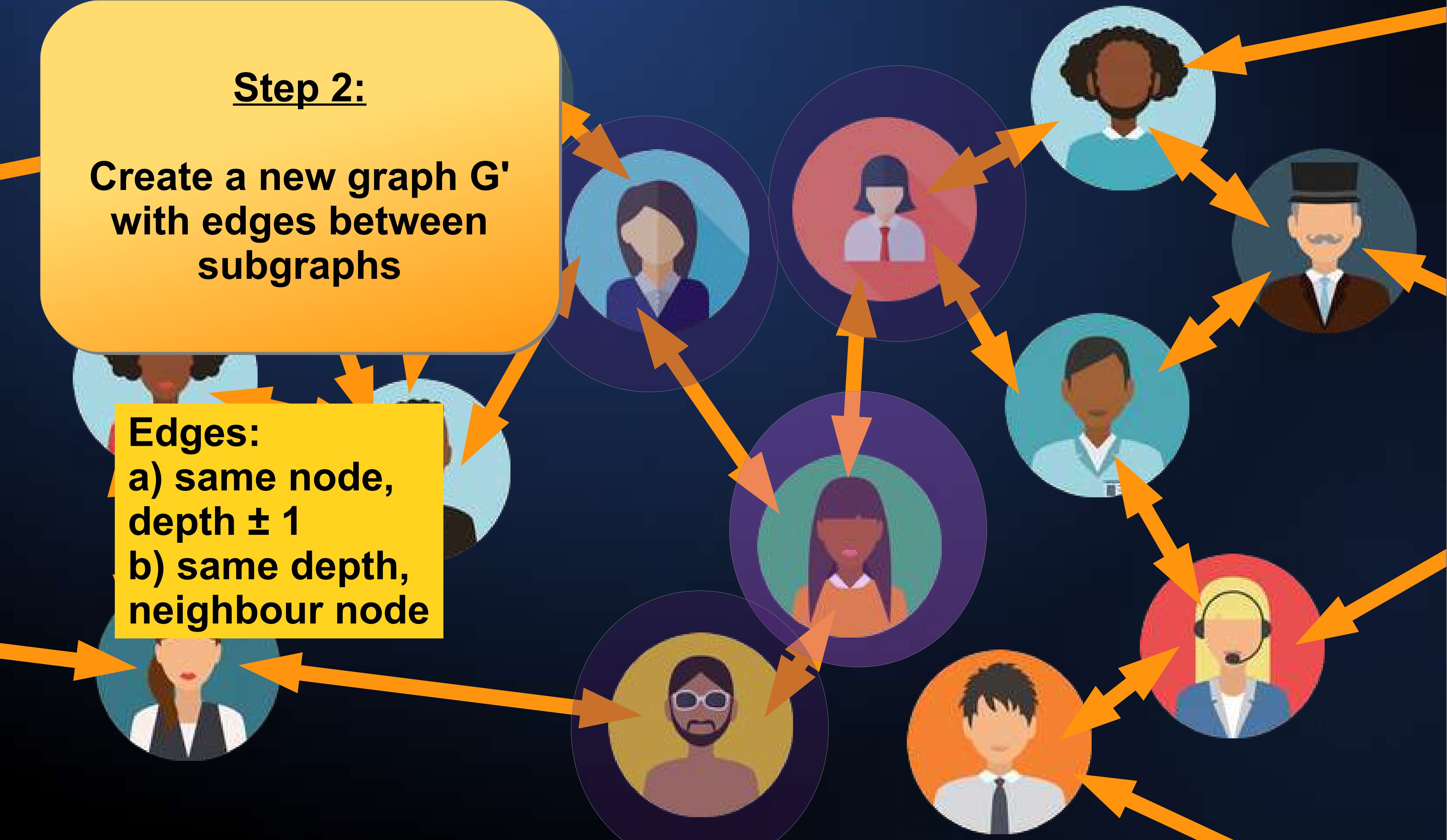
<u>Step 2:</u>

Create a new graph G' with edges between subgraphs

Graph Node Representations: SEMAC



Graph Node Representations: SEMAC

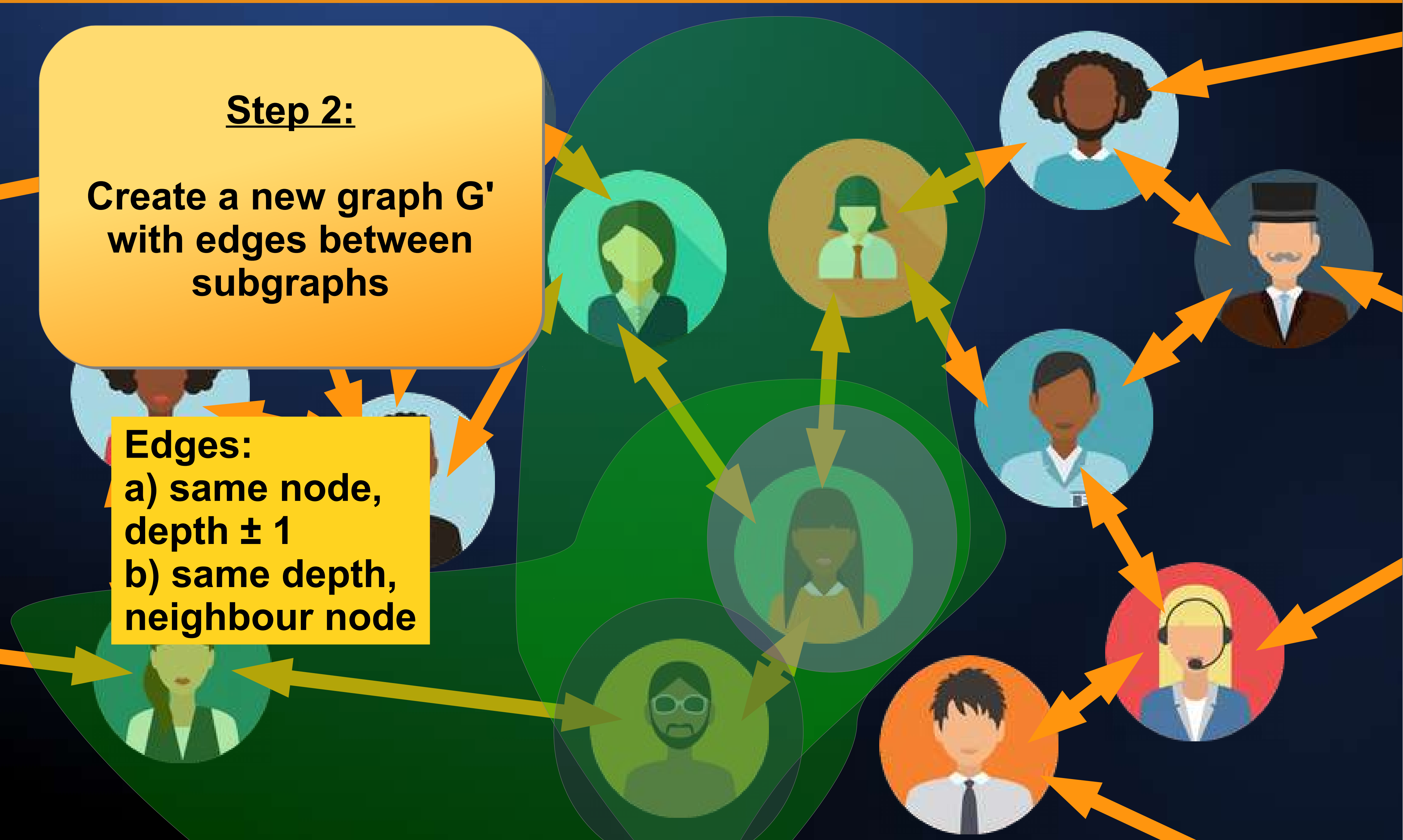


Step 2:

Create a new graph G' with edges between subgraphs

Edges:
a) same node, depth ± 1
b) same depth, neighbour node

Graph Node Representations: SEMAC



Graph Node Representations: SEMAC

Step 3:

Learn subgraph embeddings using G'

$$A_{ij} = \begin{cases} 0 & (v_i, v_j) \notin E' \\ 1/d_{v_i} & (v_i, v_j) \in E' \end{cases}$$

$$M = (A + A^2)/2$$

Graph Node Representations: SEMAC

Step 3:

Learn subgraph embeddings using G'

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Nuclear Norm Minimization

Find W that minimizes

$$\frac{1}{2}||P_\Omega(M) - P_\Omega(W)||_F^2 + \lambda||W||_*$$

Nuclear Norm

$$\|W\|_* = \sum_{i=1}^{\min\{m,n\}} \sigma_i(W)$$

Graph Node Representations: SEMAC

Step 3:

Learn subgraph embeddings using G'

$$A_{ij} = \begin{cases} 0 & (v_i, v_j) \notin E' \\ 1/d_{v_i} & (v_i, v_j) \in E' \end{cases}$$

$$M = (A + A^2)/2$$

Nuclear Norm Minimization

Find W that minimizes

$$\frac{1}{2}||P_\Omega(M) - P_\Omega(W)||_F^2 + \lambda||W||_*$$

Compare only non-zero (observed) entries (unlike SVD)

Frobenius Norm

Nuclear Norm

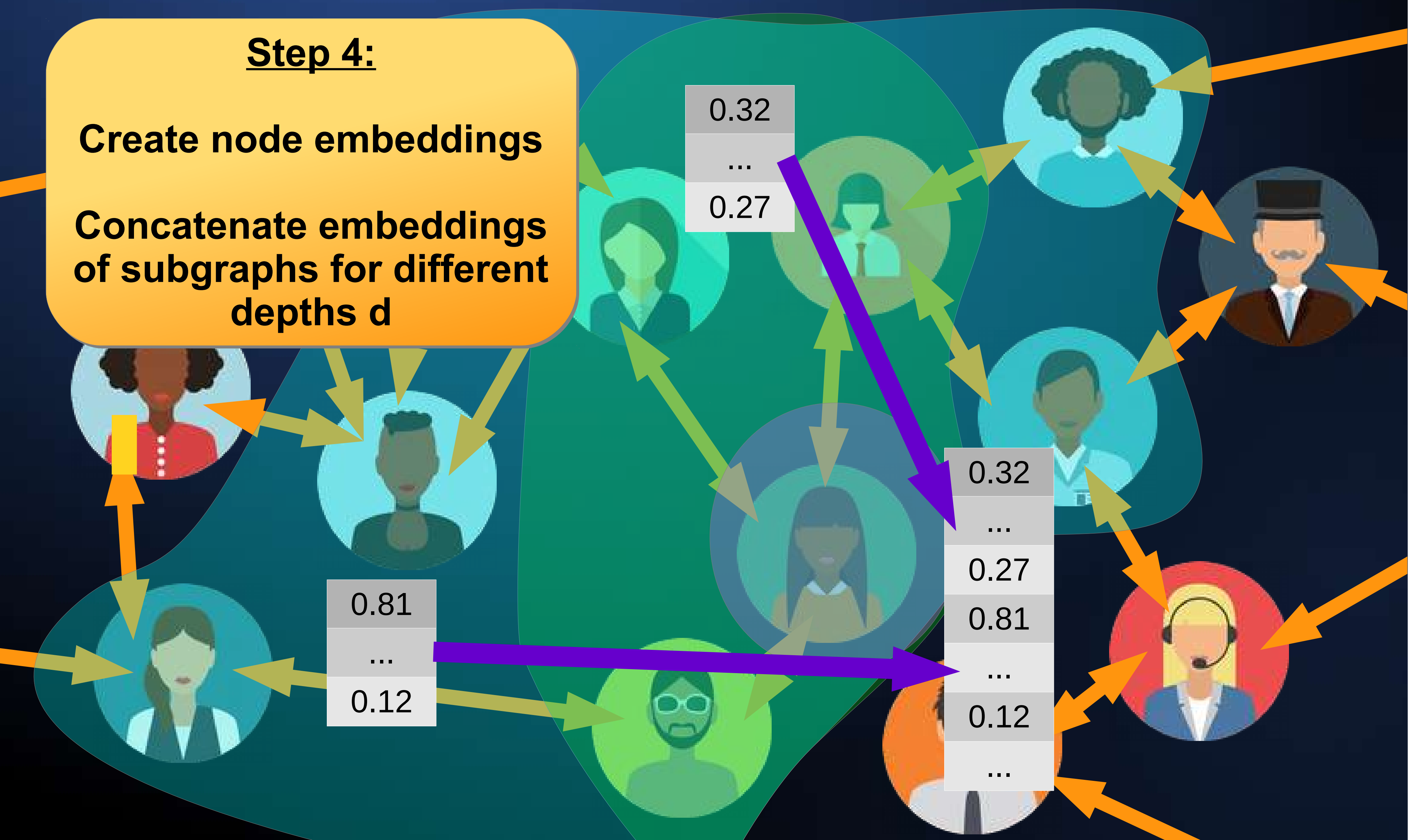
$$||W||_* = \sum_{i=1}^{\min\{m,n\}} \sigma_i(W)$$

Graph Node Representations: SEMAC

Result of Step 3:

Embedding for every subgraph

Graph Node Representations: SEMAC



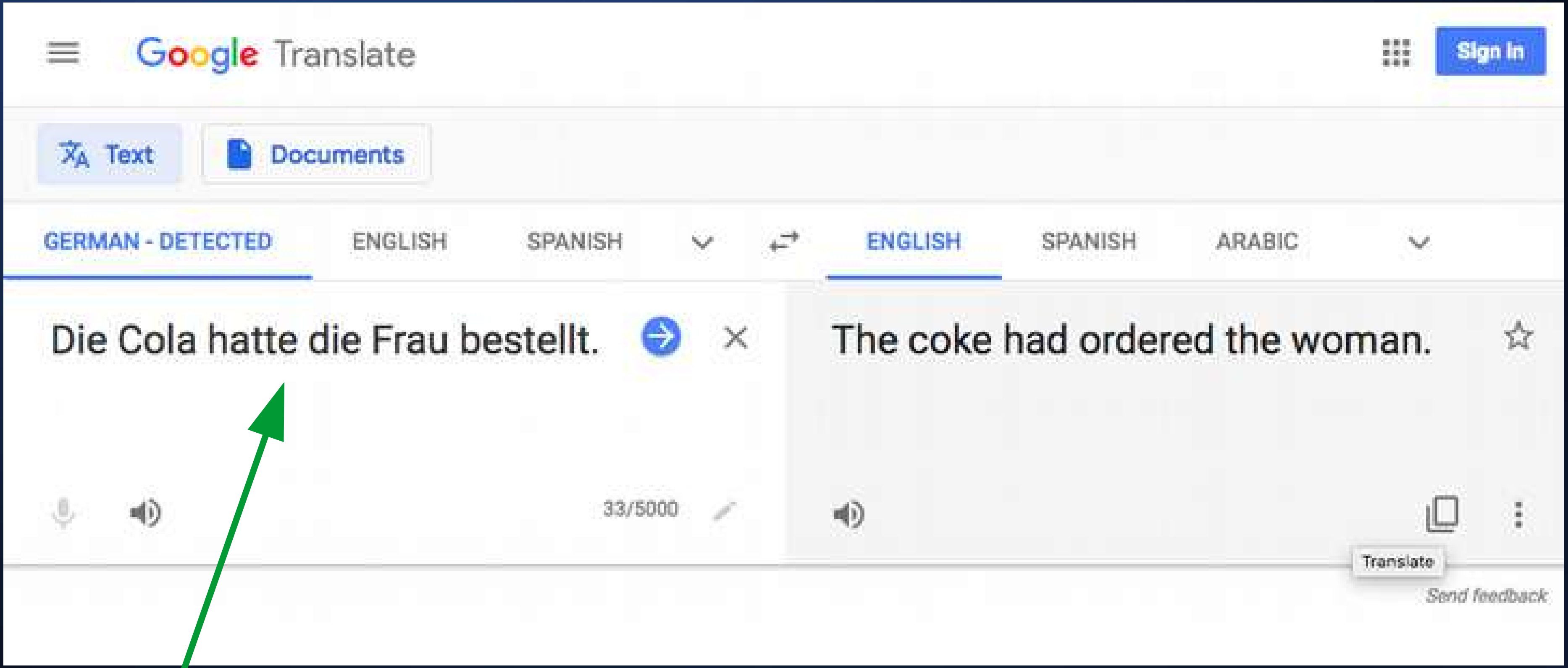
Future Perspectives

What is missing

Is a coke capable of ordering?

J. Chen, N. Tandon, C. Hariman, G. de Melo (2016).
WebBrain: Joint Neural Learning of Large-Scale Commonsense Knowledge

Missing World Knowledge



Syntax not sufficient for interpretation

J. Chen, N. Tandon, C. Hariman, G. de Melo.
WebBrain: Joint Neural Learning of Large-Scale Commonsense Knowledge

Missing World Knowledge

Do finches have feathers?

Are mugs used for drinking?

J. Chen, N. Tandon, C. Hariman, G. de Melo (2016).
WebBrain: Joint Neural Learning of Large-Scale Commonsense Knowledge

Prototype Theory

Features for the concept of bird:

- having feathers (strong),
- being able to fly (quite strong),
- having a liver (very weak, although all birds have a liver)
- ...

Difference between prototypical members and less prototypical ones
(Eleanore Rosch)

Lots of psychological evidence

<u>Simplified</u> version of prototype theory: #features

Prototype image: Image: http://web.csulb.edu/~cwallis/482/concepts2/concepts2.html
Penguin Image: http://commons.wikimedia.org/wiki/File:Penguins_walking_-Moltke_Harbour,_South_Georgia,_British_overseas_territory,_UK-8.jpg

Mining from Text

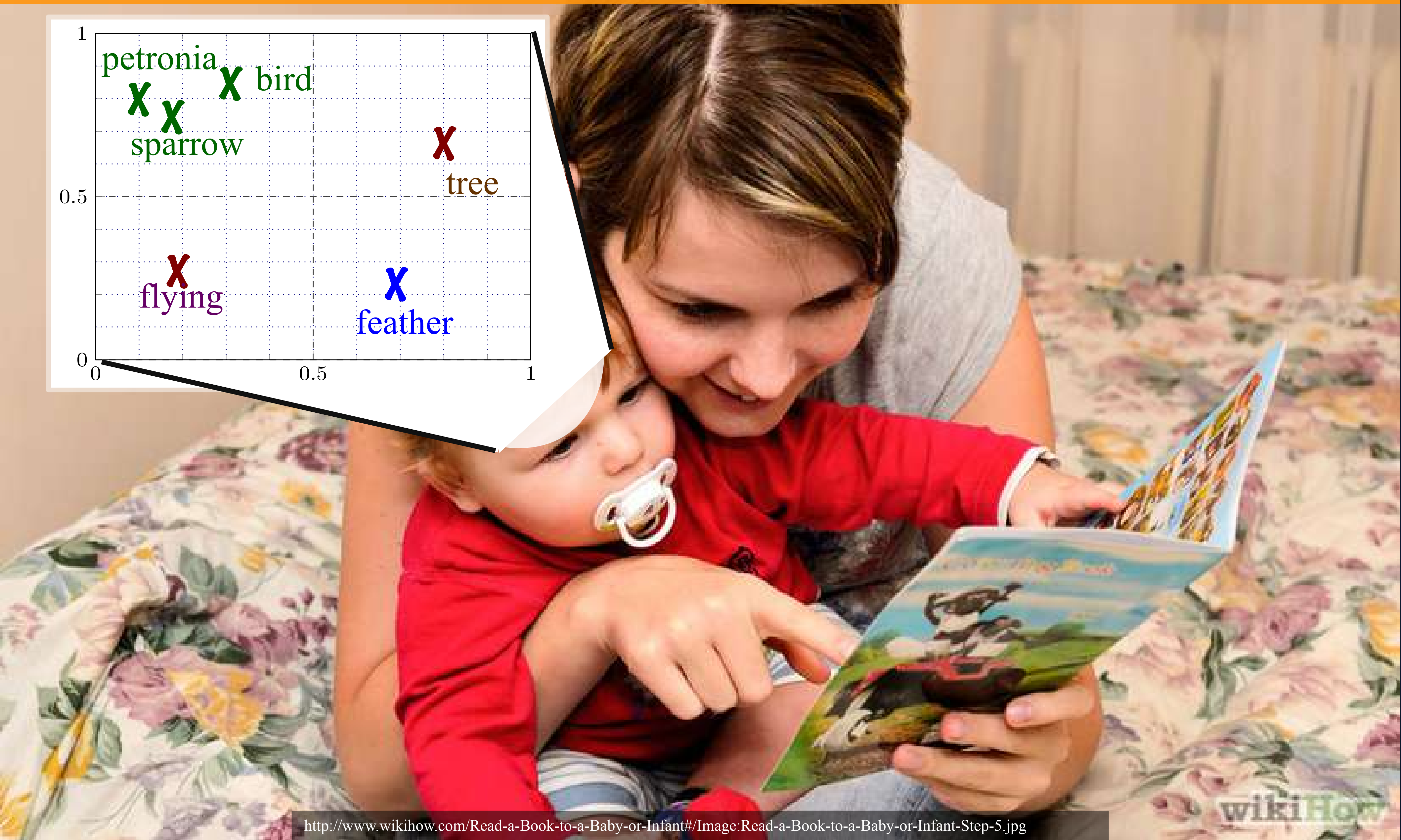
Mining from Text

Seed-based pattern extraction for 24 relations

c. 1.1 million triples

sparrow	*hasPart*	*feather*
concept	*definedAs*	*theory*
grass	*hasProperty*	*green*
predator	*desires*	*food*

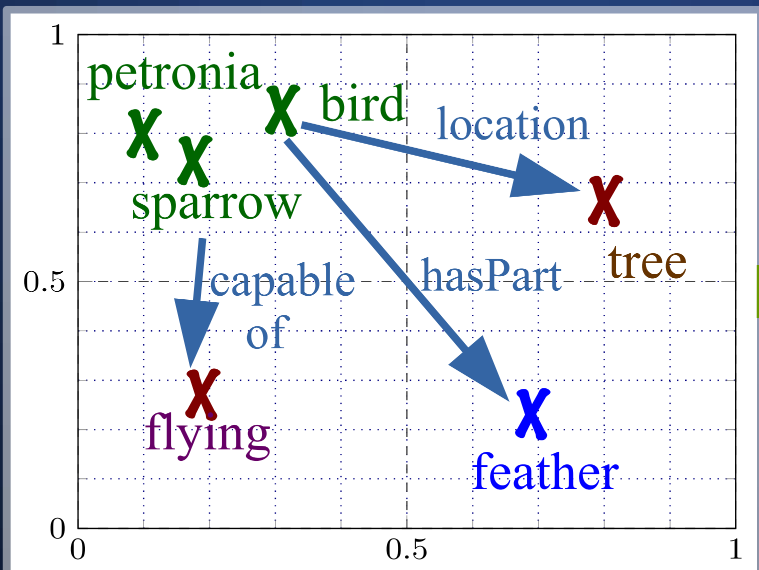
Neural Representations of Concepts



Neural Representations of Concepts and Commonsense Relations

http://www.wikihow.com/Read-a-Book-to-a-Baby-or-Infant#/Image:Read-a-Book-to-a-Baby-or-Infant-Step-5.jpg

Neural Representations of Concepts and Commonsense Relations



Do finches have feathers?

Yes

Can chipmunks fly?

No

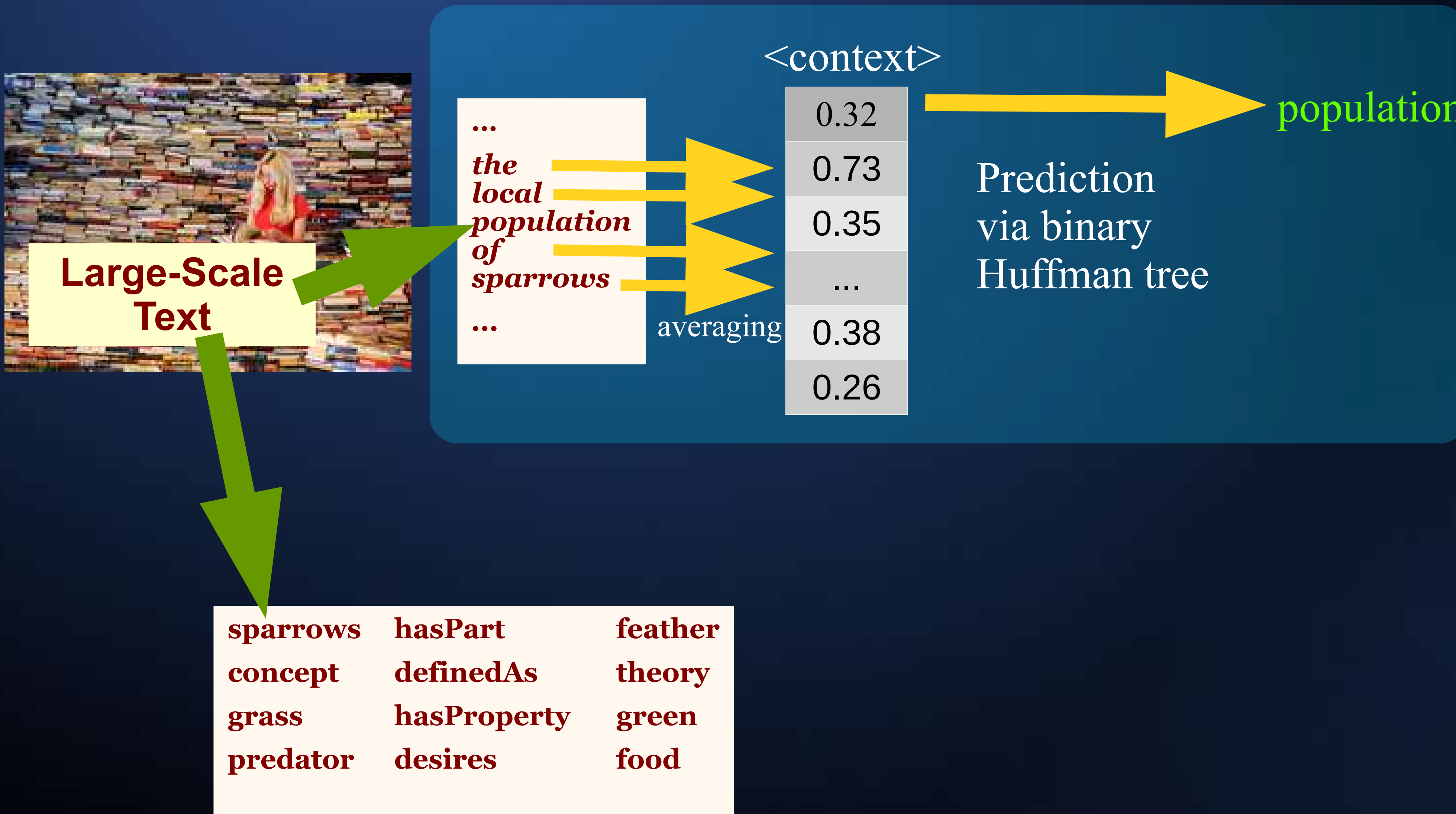
Chen et al. WebBrain: Joint Neural Learning of Large-Scale Commonsense Knowledge. ISWC 2016

Approach

word2vec CBOW Model

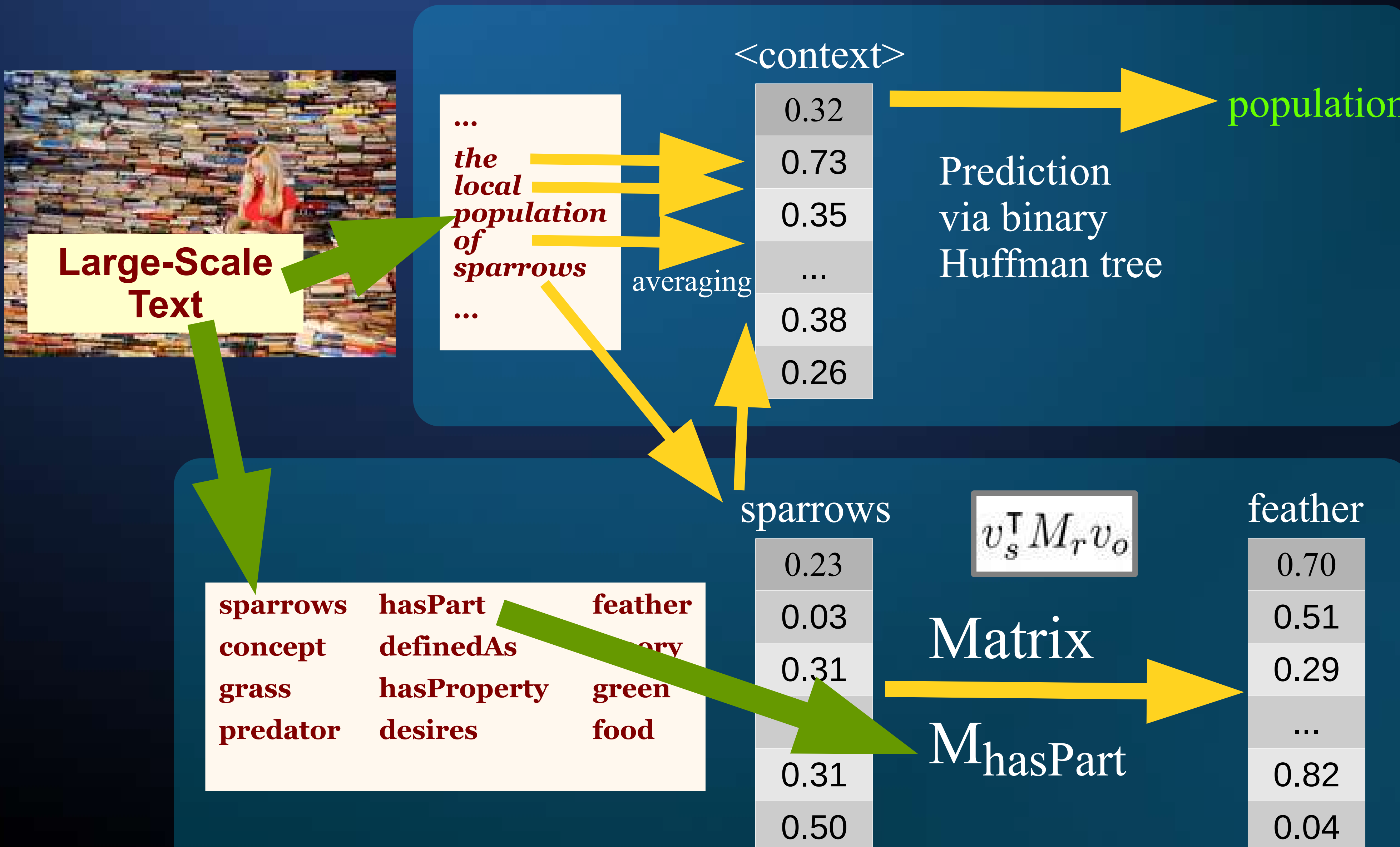
J. Chen, N. Tandon, C. Hariman, G. de Melo (2016).
WebBrain: Joint Neural Learning of Large-Scale Commonsense Knowledge

Approach



J. Chen, N. Tandon, C. Hariman, G. de Melo (2016).
WebBrain: Joint Neural Learning of Large-Scale Commonsense Knowledge

Approach



Chen et al. WebBrain: Joint Neural Learning of Large-Scale Commonsense Knowledge. ISWC 2016

WebBrain

Is a coke capable of ordering?

No.

J. Chen, N. Tandon, C. Hariman, G. de Melo (2016).
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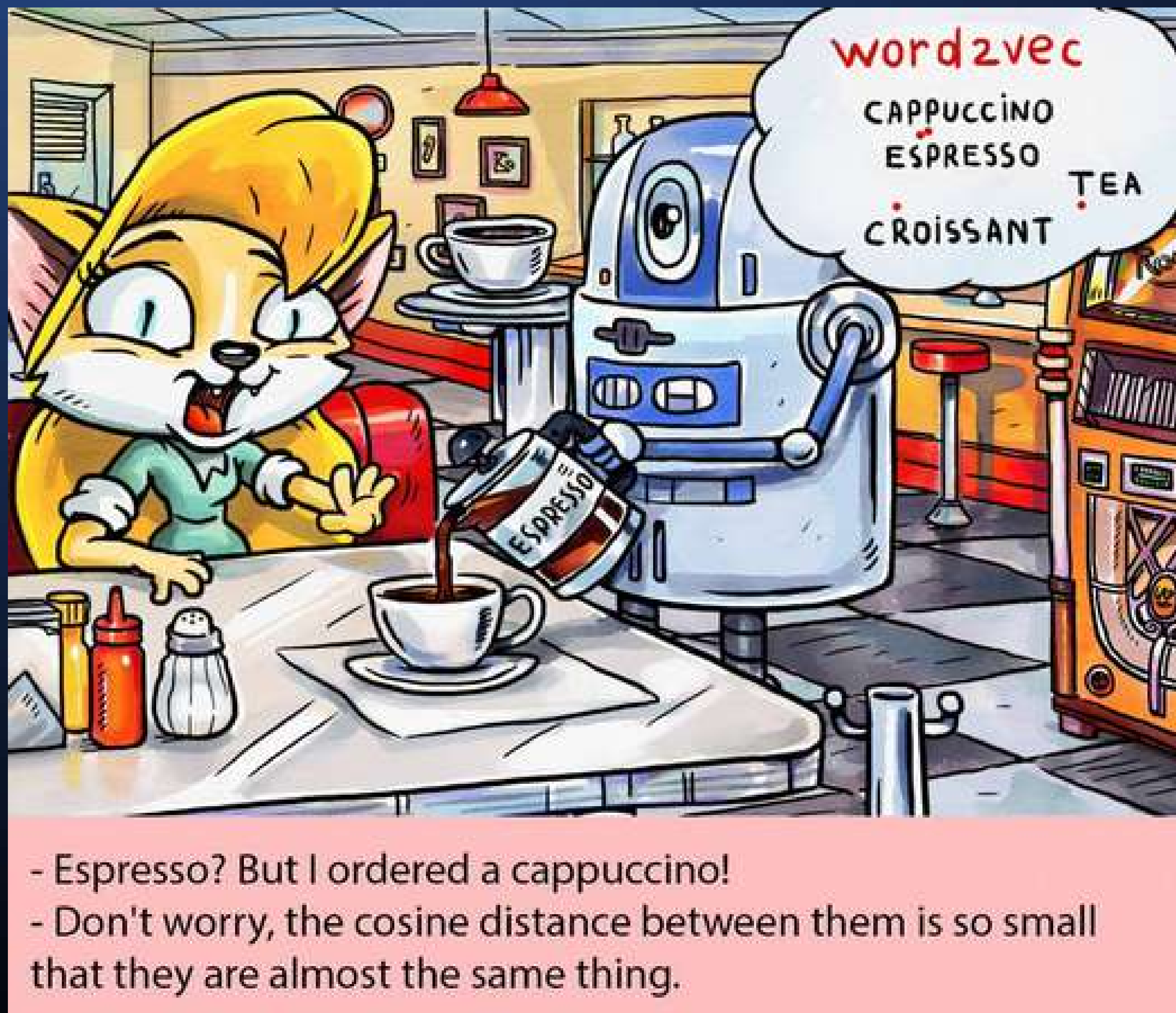
Common-Sense Knowledge



Source: https://twitter.com/DanilBaibak/status/844647217885581312

Summary

- **Word Representations**
  - ▶ Projection Approach
  - ▶ Parallel Corpora Approaches
  - ▶ External Supervision
- **Sentence Representations**
  - ▶ Word Vector-Inspired
  - ▶ External Supervision
- **Document Representations**
  - ▶ Word Vector-Based
  - ▶ Semantic Relevance-Based

Get in Touch!

http://gerard.demelo.org
gdm@demelo.org