

CLOSED DOMAIN QUESTION ANSWERING, EMBEDDING SPACES

AN INTELLIGENT SYSTEM FOR ENTERPRISE-WIDE OPEN DOMAIN
QUESTION ANSWERING

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DARBA VADĪTĀJS: DR. DAT., PROF. GUNTIS BĀRZDIŅŠ

VIRTUAL ASSISTANT

- AMAZON ECHO / ALEXA
- SIRI
- GOOGLE ASSISTANT
- MESSENGER / CHAT BOTS
- IMAGE / AR BOTS
- PROGRAMMABLE API / HOOKS TO DEVICES



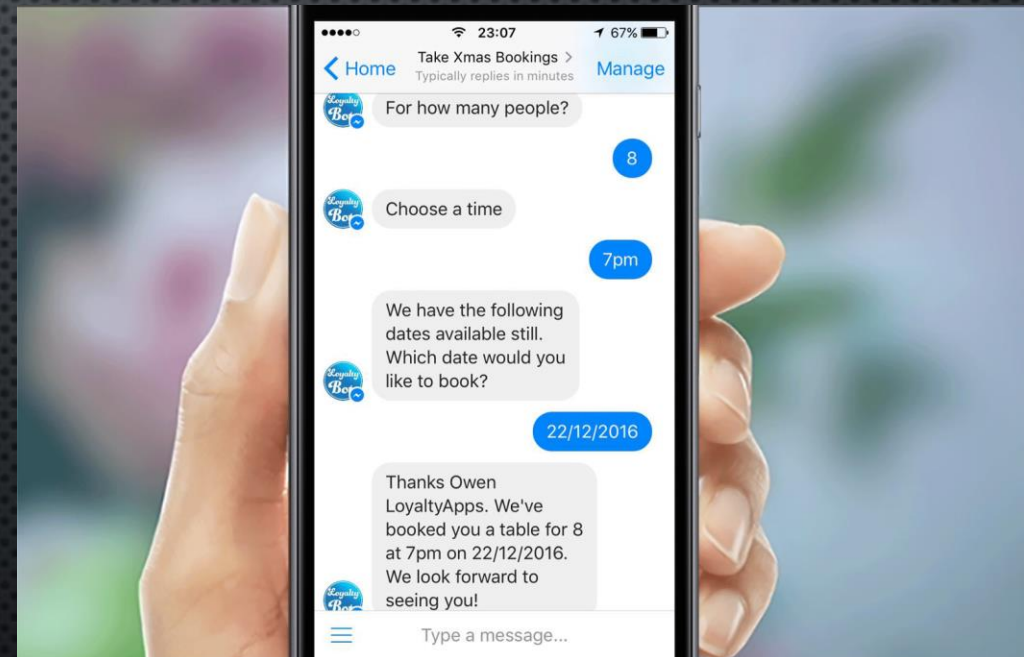
amazon echo



Bixby

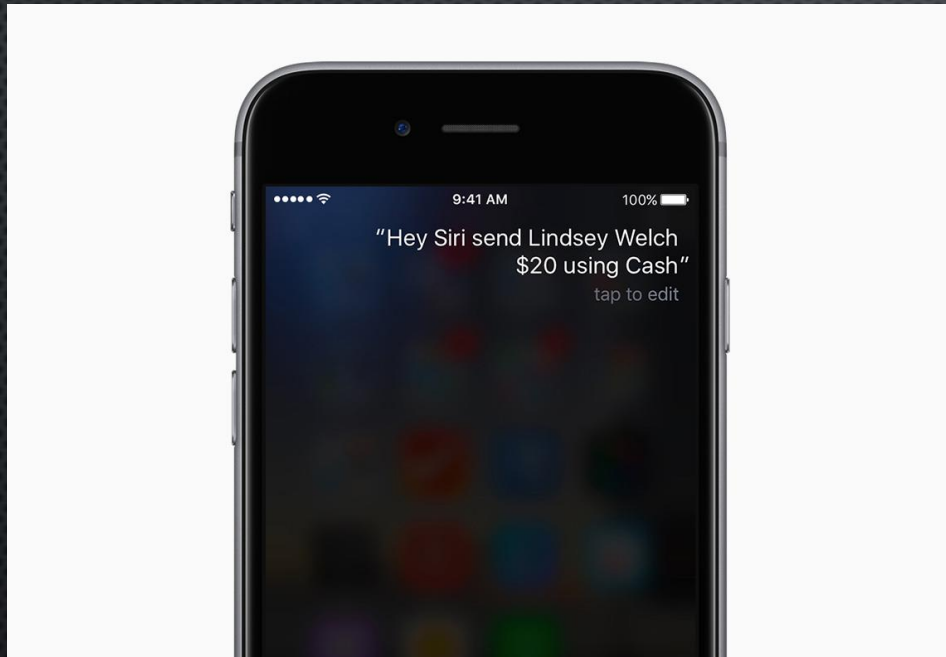
ASSISTANTS & CHATBOTS

- TEXT / VOICE INTERFACE
- SIMPLE QUESTIONS
- INTEGRATED IN DEVICE (PHONE) OR WHOLE PLATFORM (GOOGLE)
- INTENT RECOGNITION
- NOT CONTEXT AWARE (USUALLY)

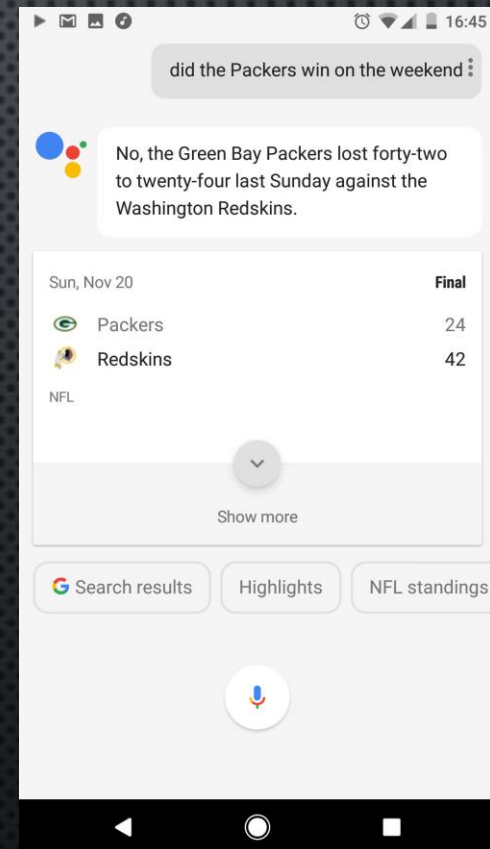


<https://chatbotlife.com/5-benefits-of-using-a-chatbot-937b8b793826>

USE CASES



<https://media.idownloadblog.com/wp-content/uploads/2016/09/iOS-10-Siri-Cash-payment-teaser-001.jpg>

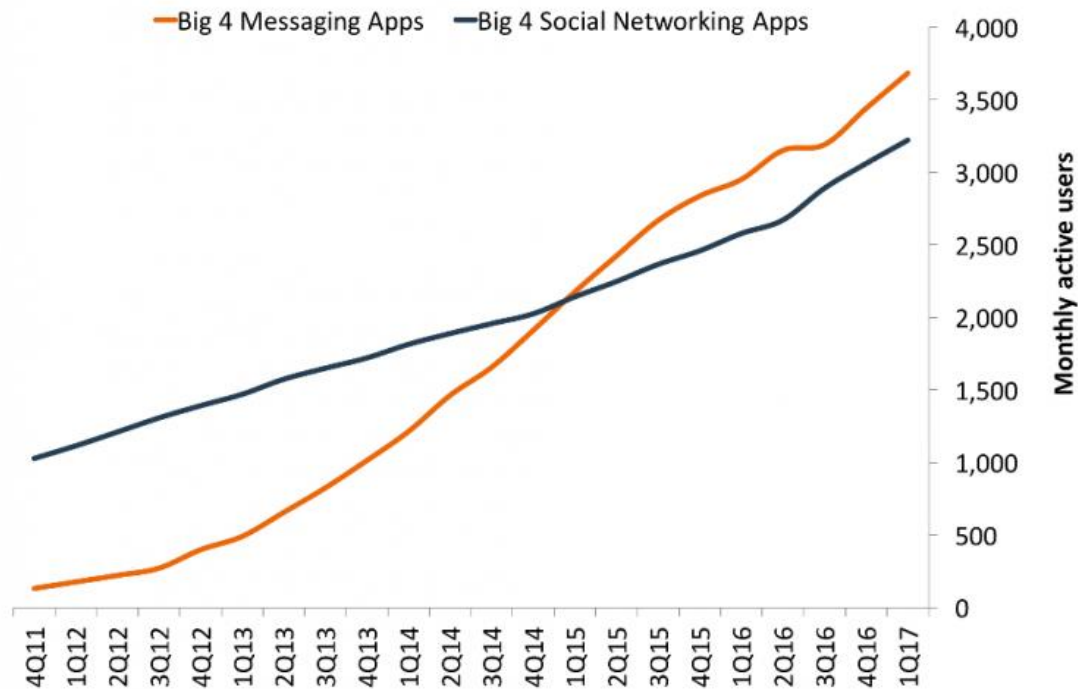


<https://www.androidcentral.com/heres-what-google-assistant-can-do-your-pixel>

CHATBOTS & CHATBOT PLATFORMS

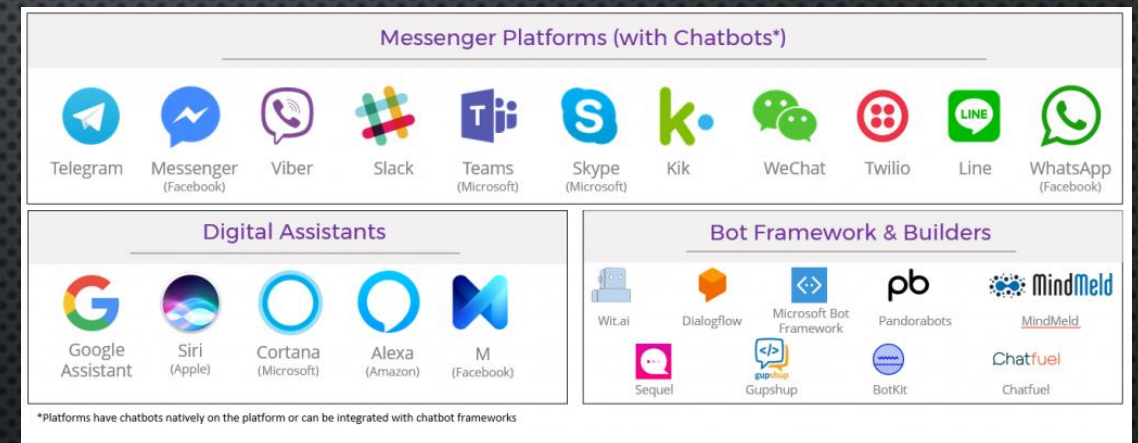
Messaging Apps Have Surpassed Social Networks

Global monthly active users for the top 4 messaging apps and social networks,
In millions



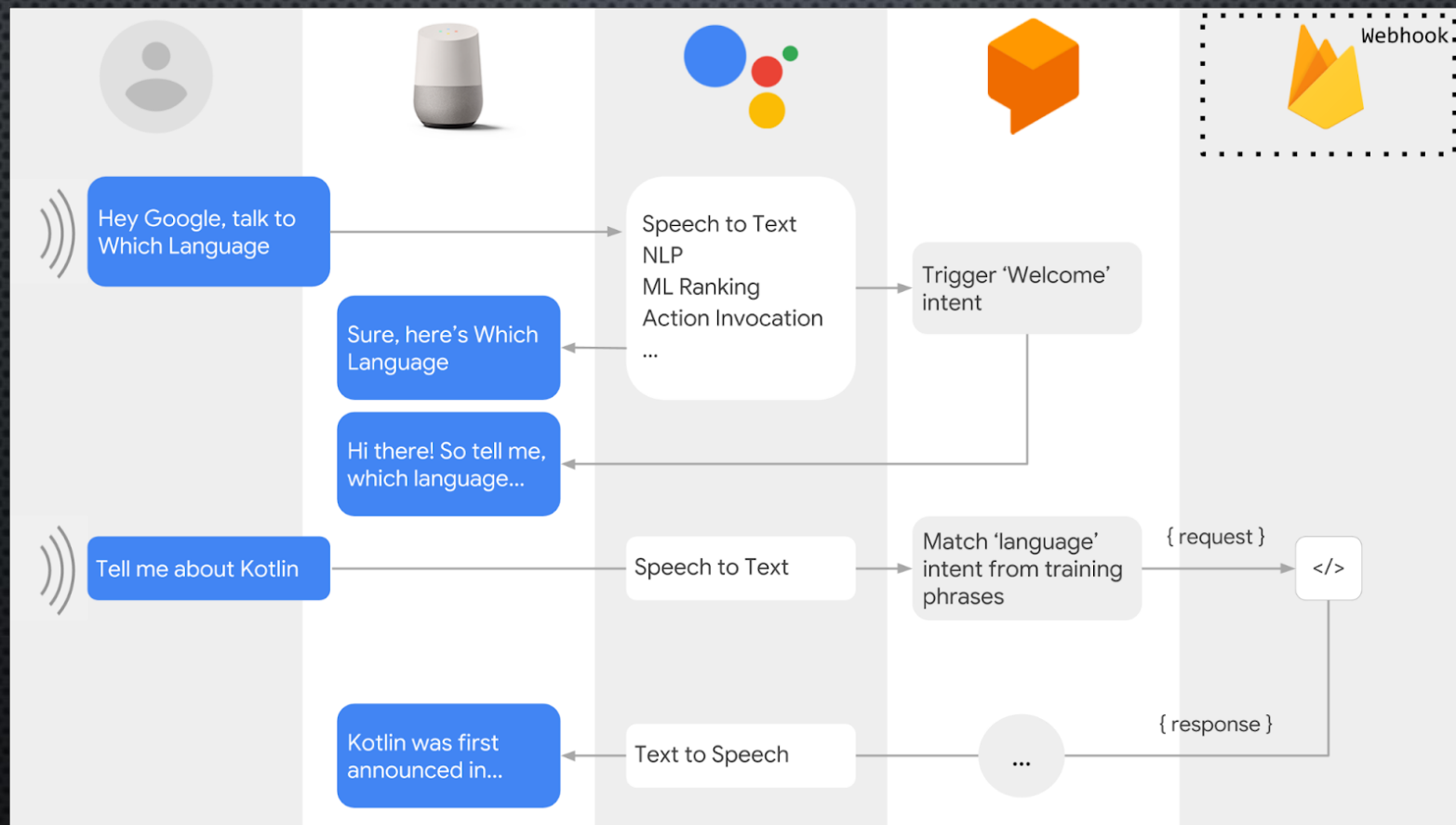
Note: Big 4 messaging apps are WhatsApp, Messenger, WeChat, Viber.
Big 4 social networks are Facebook, Instagram, Twitter, LinkedIn
Source: Companies, Apptopia, TechCrunch, BI Intelligence estimates, 2017

BI INTELLIGENCE



<https://lenoxhill.com.au/blog/chatbots-fad-future/>

HOW IT WORKS



YANN LECUN - THE NEXT STEP TOWARDS ARTIFICIAL INTELLIGENCE

What we can and cannot have with current Supervised & Reinforcement learning methods

► What we can have

- Safer cars, autonomous cars
- Better medical image analysis
- Personalized medicine
- Adequate language translation
- Useful but stupid chatbots
- Information search, retrieval, filtering
- Numerous applications in energy, finance, manufacturing, environmental protection, commerce, law, artistic creation, games,.....

► What we cannot have (yet)

- Machines with common sense
- Intelligent personal assistants
- "Smart" chatbots"
- Household robots
- Agile and dexterous robots
- Artificial General Intelligence (AGI)



Yann LeCun

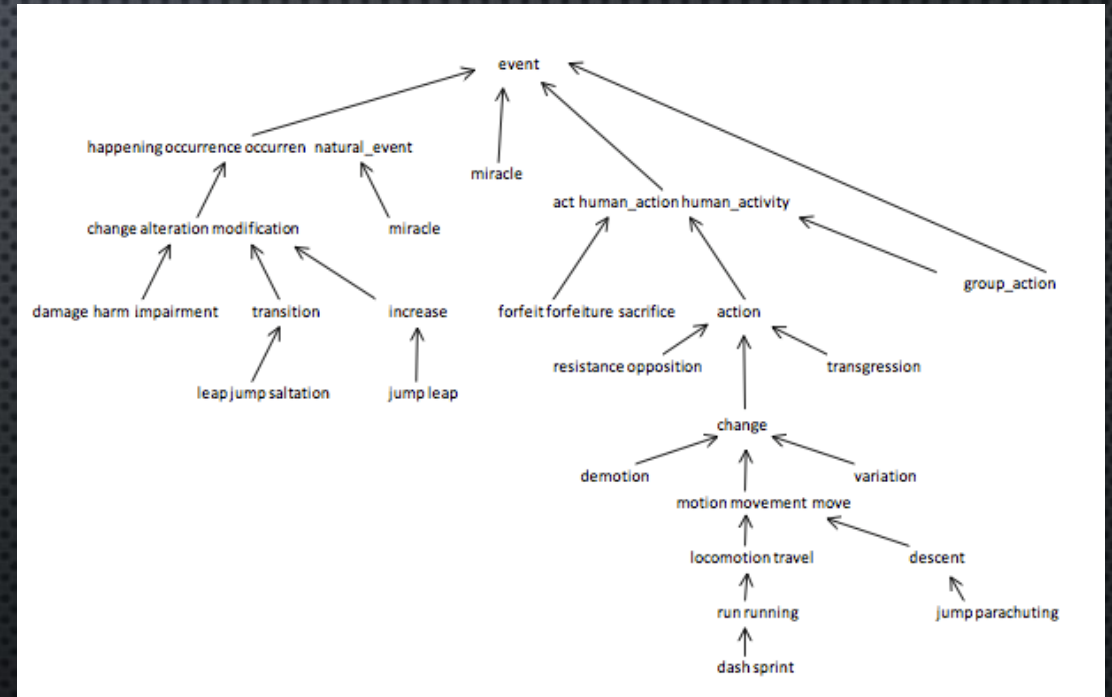
French computer scientist

Yann LeCun is a French computer scientist working primarily in the fields of machine learning, computer vision, mobile robotics, and computational neuroscience. He is the Silver Professor of the Courant Institute of Mathematical Sciences at New York University, and Vice President, Chief AI Scientist at Facebook. [Wikipedia](#)

<https://www.youtube.com/watch?v=U2mhZ9E8Fk8>

INFORMATION & KNOWLEDGE EXTRACTION

- STRUCTURED DATA
 - REQUIRES STRUCTURED KNOWLEDGE
 - WORDNET
- NOT ENOUGH STRUCTURED DATA FOR PRODUCTION USE



INFORMATION & KNOWLEDGE EXTRACTION

- UNSTRUCTURED DATA:
 - CAN WORK WITH (MOSTLY) NO STRUCTURED KNOWLEDGE
- NATURAL LANGUAGE PROCESSING (NLP)
- ENOUGH DATA FOR PRODUCTION USE, REQUIRES PREPROCESSING
- EMBEDDINGS

1. Initial state

Stack	Remaining Text
	the dog saw a man in the park

3. After reduce shift reduce

Stack	Remaining Text
NP N the dog	saw a man in the park

5. After building a complex NP

Stack	Remaining Text
NP V NP PP the dog saw a man in the park	

2. After one shift

Stack	Remaining Text
the	dog saw a man in the park

4. After recognizing the second NP

Stack	Remaining Text
NP V NP in the dog saw a man	the park

6. Built a complete parse tree

Stack	Remaining Text
S NP VP the dog saw NP PP the dog saw a man in the park	

<https://www.nltk.org/book/ch08.html>

WORD EMBEDDINGS

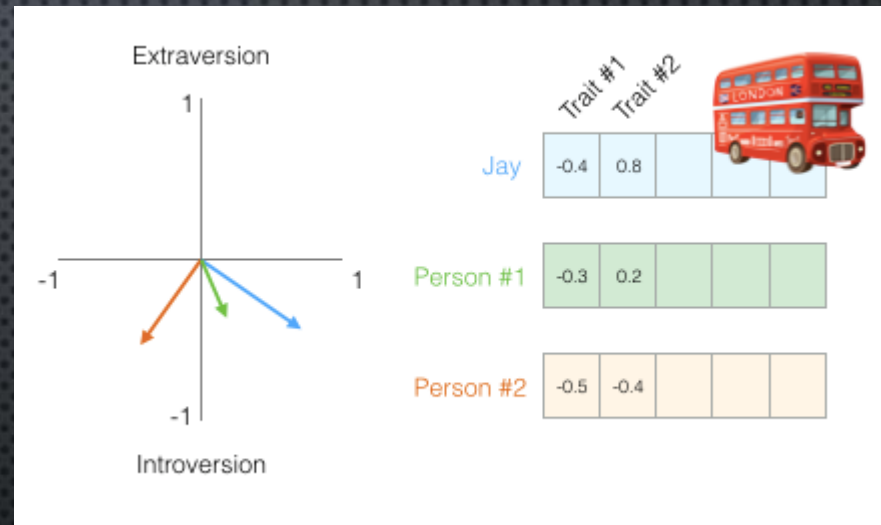
“You shall know a word by the company it keeps”
John Rupert Firth, 1957

WORD EMBEDDINGS

- **EFFICIENT ESTIMATION OF WORD REPRESENTATIONS IN VECTOR SPACE (TOMAS MIKOLOV, KAI CHEN, GREG CORRADO, JEFFREY DEAN, 2013)** [HTTPS://ARXIV.ORG/ABS/1301.3781](https://arxiv.org/abs/1301.3781)
- JEFFREY PENNINGTON, RICHARD SOCHER, AND CHRISTOPHER D. MANNING. 2014. [GLOVE: GLOBAL VECTORS FOR WORD REPRESENTATION](#)

WORD EMBEDDINGS

Openness to experience 79 out of 100
Agreeableness 75 out of 100
Conscientiousness 42 out of 100
Negative emotionality 50 out of 100
Extraversion 58 out of 100



$\text{cosine_similarity}(\text{Jay}, \text{Person \#1}) = 0.87$ ✓

$\text{cosine_similarity}(\text{Jay}, \text{Person \#2}) = -0.20$

WORD EMBEDDINGS

- I like deep learning.
- I like NLP.
- I enjoy flying.

counts	I	like	enjoy	deep	learning	NLP	flying	.
I	0	2	1	0	0	0	0	0
like	2	0	0	1	0	1	0	0
enjoy	1	0	0	0	0	0	1	0
deep	0	1	0	0	1	0	0	0
learning	0	0	0	1	0	0	0	1
NLP	0	1	0	0	0	0	0	1
flying	0	0	1	0	0	0	0	1
.	0	0	0	0	1	1	1	0

Co-correlation matrix:

- Not preserving word order!
- Gets HUGE fast (n^2)

WORD EMBEDDINGS

Thou shalt not make a machine in the likeness of a human mind

Sliding window across running text

thou	shalt	not	make	a	machine	in	the	...
thou	shalt	not	make	a	machine	in	the	
thou	shalt	not	make	a	machine	in	the	
thou	shalt	not	make	a	machine	in	the	
thou	shalt	not	make	a	machine	in	the	

Dataset

input 1	input 2	output
thou	shalt	not
shalt	not	make
not	make	a
make	a	machine
a	machine	in

<https://jalammar.github.io/illustrated-word2vec/>

WORD EMBEDDINGS

Continuous Bag of Words (CBOW)

Thou shalt not make a machine in the likeness of a human mind

Sliding window across running text

thou	shalt	not	make	a	machine	in	the	...
thou	shalt	not	make	a	machine	in	the	
thou	shalt	not	make	a	machine	in	the	
thou	shalt	not	make	a	machine	in	the	
thou	shalt	not	make	a	machine	in	the	

Dataset

input 1	input 2	output
thou	shalt	not
shalt	not	make
not	make	a
make	a	machine
a	machine	in

Skipgram

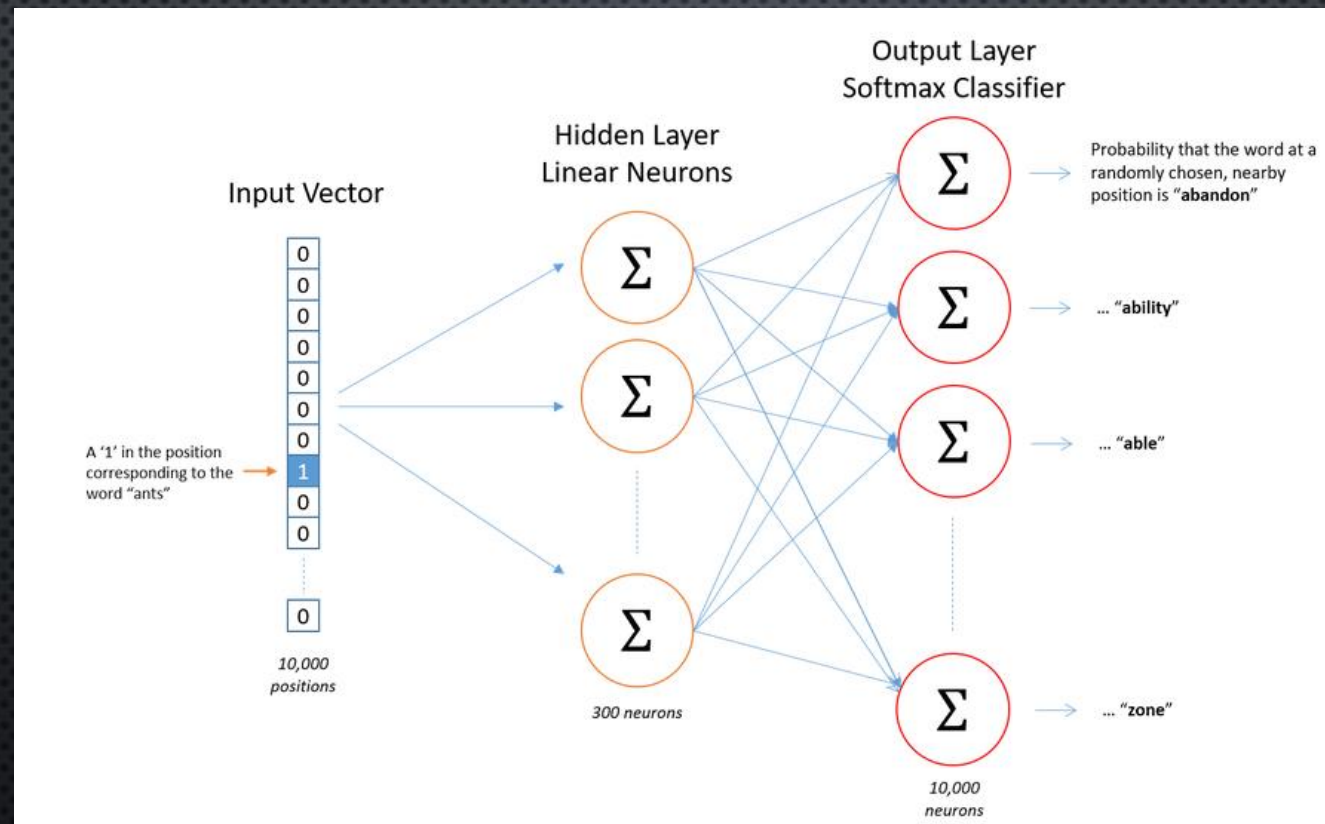
Thou shalt not make a machine in the likeness of a human mind

thou	shalt	not	make	a	machine	in	the	...
thou	shalt	not	make	a	machine	in	the	...
thou	shalt	not	make	a	machine	in	the	...
thou	shalt	not	make	a	machine	in	the	...
thou	shalt	not	make	a	machine	in	the	...

input word	target word
not	thou
not	shalt
not	make
not	a
make	shalt
make	not
make	a
make	machine
a	not
a	make
a	machine
a	in
machine	make
machine	a
machine	in
machine	the
in	a
in	machine
in	the
in	likeness

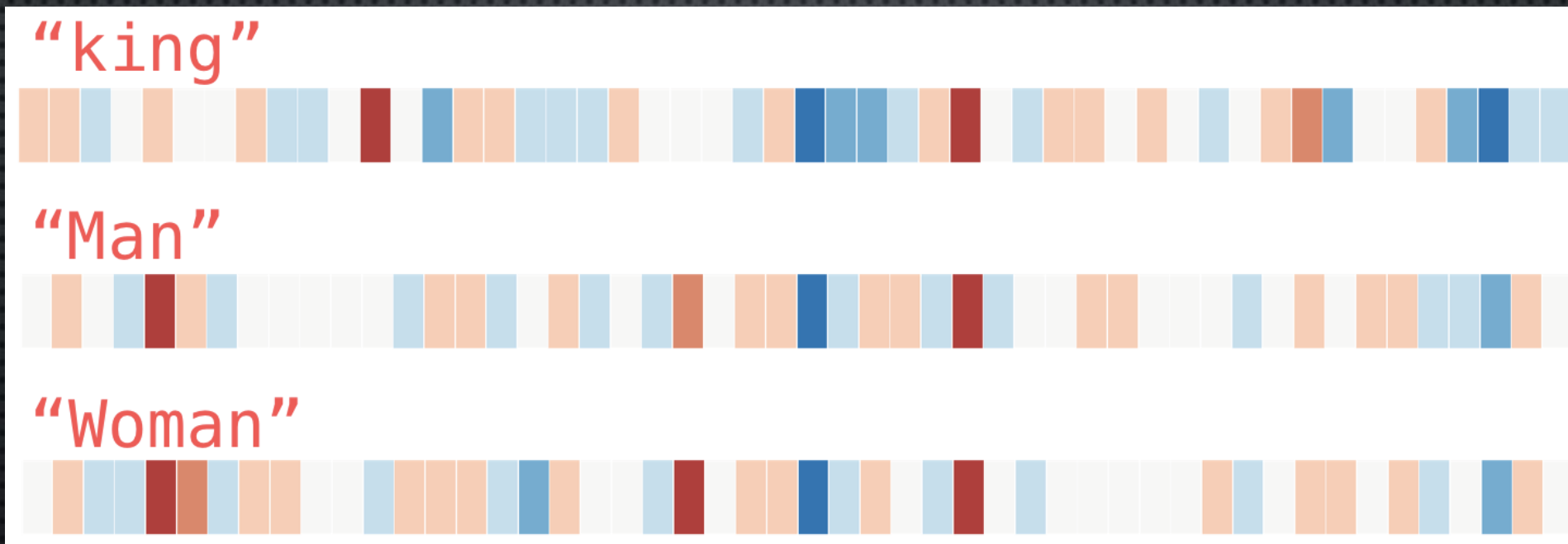
<https://jalammar.github.io/illustrated-word2vec/>

WORD EMBEDDINGS



<http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/>

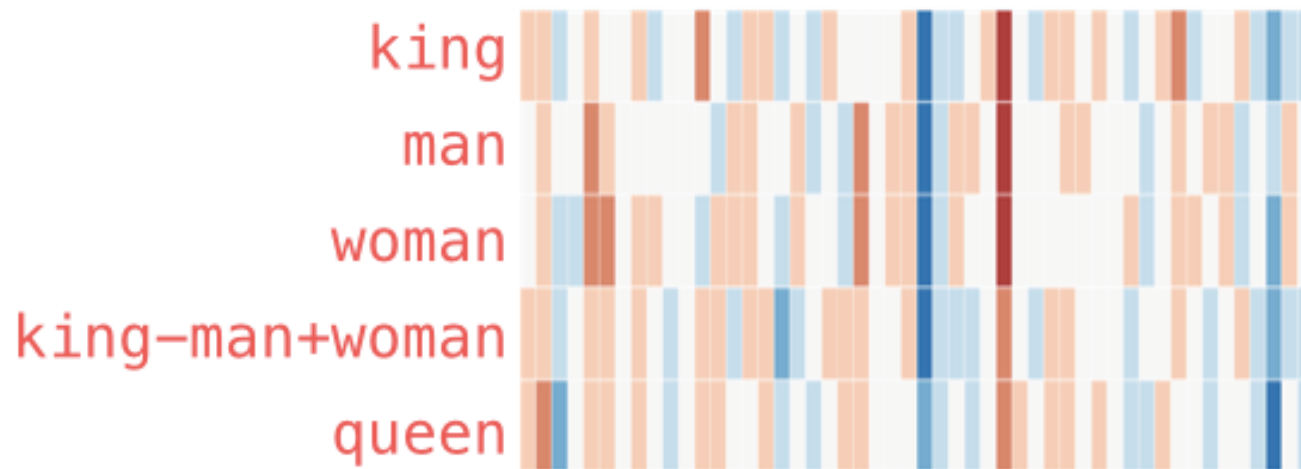
WORD EMBEDDINGS



<https://jalammar.github.io/illustrated-word2vec/>

WORD EMBEDDINGS

king - man + woman \approx queen

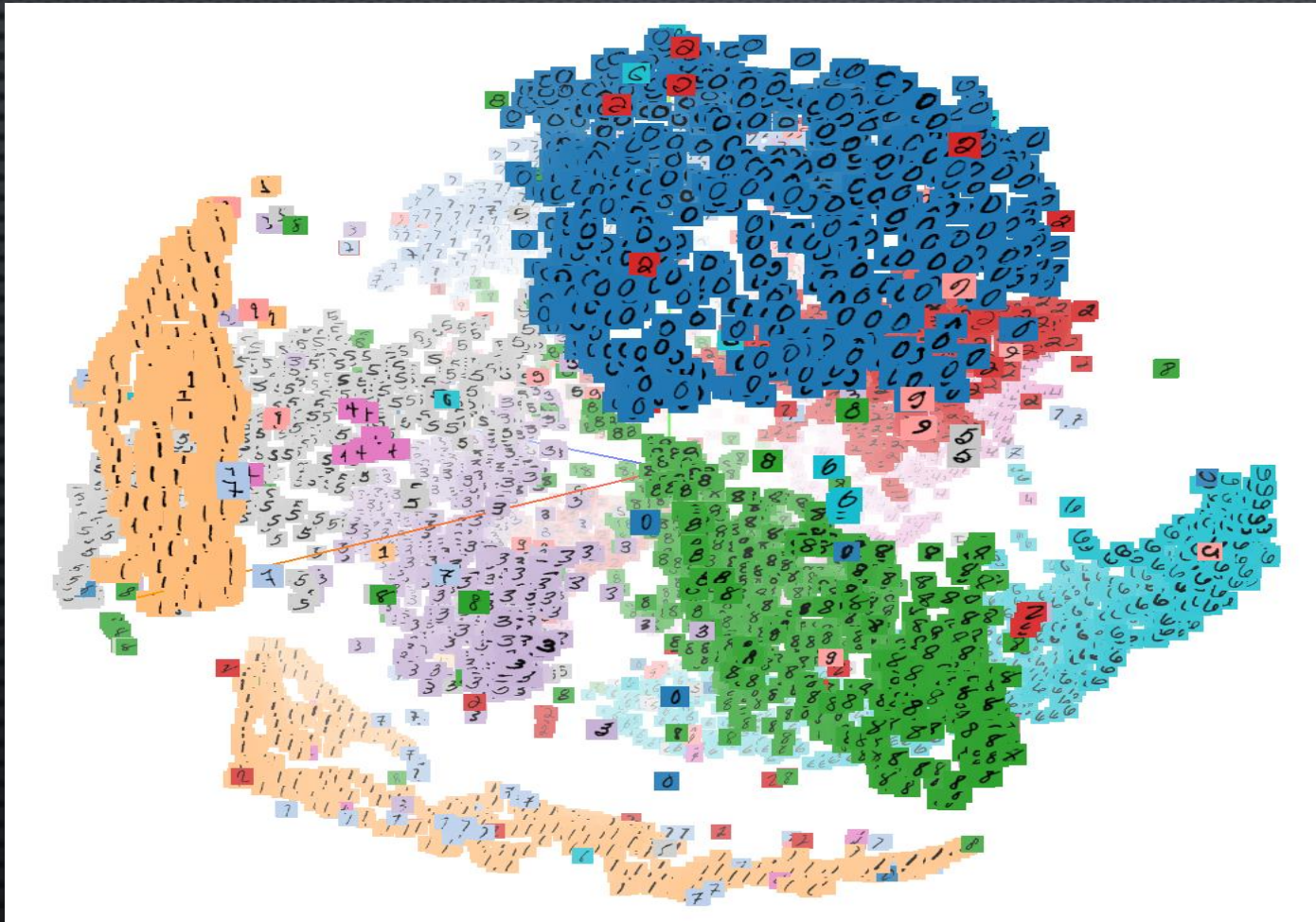


Select the odd one out:

- ☐ grandchildren
- ☐ sons
- ☐ visual
- ☐ grandson
- ☐ granddaughter

<https://jalammar.github.io/illustrated-word2vec/>

OTHER EMBEDDINGS



<http://projector.tensorflow.org/>

OTHER EMBEDDINGS

- IMAGES
- TEXT
- ENTITIES
- SPEECH2VEC
- **DOC2VEC**
- GRAPH2VEC
- TWEET2VEC

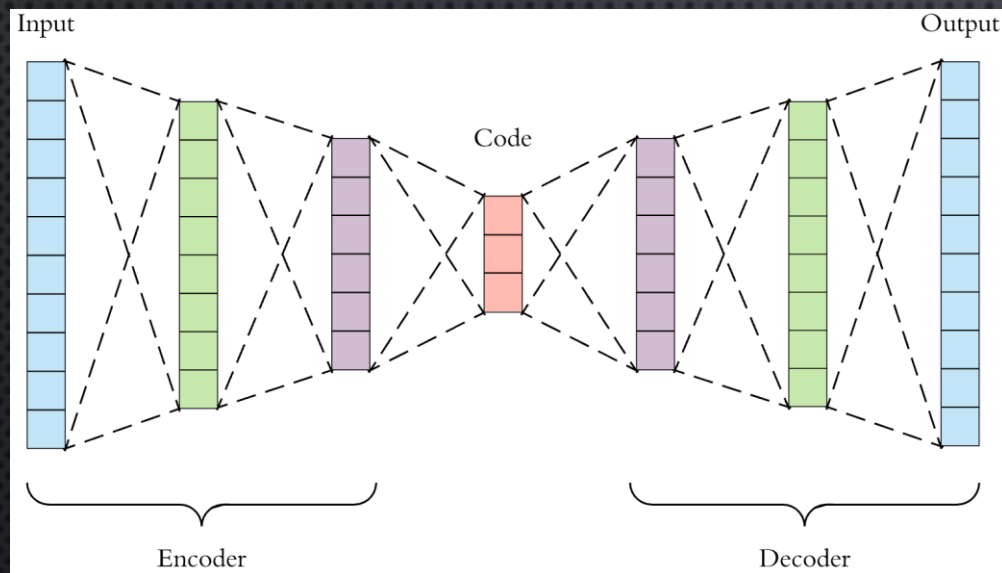
... MANY OTHERS

VECTOR SPACE -> FEATURE SPACE

- EMBEDDINGS ARE MYSTERIOUS AND NOT EXPLAINABLE
- SPINE: SPARSE INTERPRETABLE NEURAL EMBEDDINGS,
23 Nov 2017
([HTTPS://ARXIV.ORG/ABS/1711.08792](https://arxiv.org/abs/1711.08792))
- VECTOR SPACE -> SPARSE BINARY SPACE

VECTOR SPACE -> FEATURE SPACE

SPINE: SParse Interpretable Neural Embeddings



<table><tr><td>-0.4</td><td>-0.4</td><td>0.9</td></tr><tr><td>0.9</td><td>0.4</td><td>0.8</td></tr><tr><td>0.4</td><td>-0.4</td><td>-0.4</td></tr></table> W	-0.4	-0.4	0.9	0.9	0.4	0.8	0.4	-0.4	-0.4	≈ 0.2	<table><tr><td>-1</td><td>-1</td><td>1</td></tr><tr><td>1</td><td>1</td><td>1</td></tr><tr><td>1</td><td>-1</td><td>-1</td></tr></table> αW^B	-1	-1	1	1	1	1	1	-1	-1	$W^B = \text{sign}(W)$ $\alpha = \frac{1}{n} W _{l_1}$
-0.4	-0.4	0.9																			
0.9	0.4	0.8																			
0.4	-0.4	-0.4																			
-1	-1	1																			
1	1	1																			
1	-1	-1																			

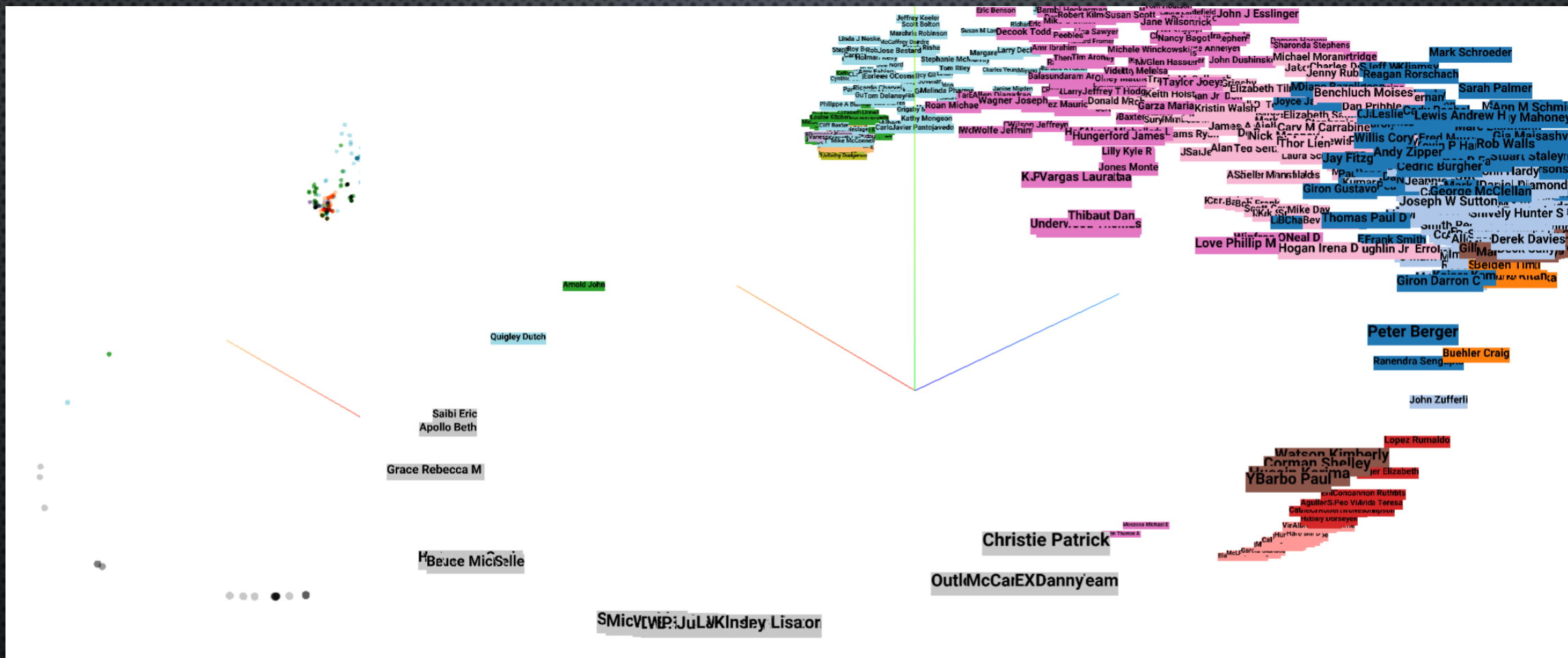
<https://software.intel.com/sites/default/files/managed/c0/e0/webops10048-fig1-binarization-procedure.png>

<https://towardsdatascience.com/applied-deep-learning-part-3-autoencoders-1c083af4d798>

KNOWLEDGE VECTORSPACE

- CREATE KNOWLEDGE VECTOR SPACE
 - DOC2VEC / CUSTOM AND MIXED EMBEDDING
 - TOPIC MODEL FOR PEOPLE, DOCUMENTS, REPORTS, FILES..
- FROM CONTEXT / TOPIC READ POINT IN SPACE
 - RECOMMEND DATA OBJECTS
 - VERIFY CURRENT CHOICE
 - FIND MISSING “CRUCIAL” OBJECTS

KNOWLEDGE VECTORSPACE



THANKS!

- QUESTIONS & COMMENTS?
- MUNTIS.RUDZITIS@GMAIL.COM

