

Deep Dive Sessions for Data Scientist

03 Feb 2022



Welcome!

- 9 00 9 05 Introduction
- 9 05 9 30 Information extraction
- 9 30 9 40 Breakout 1
- 9 40 9 50 Summary
- 9 50 10 00 Coffee break
- 10 00 10 40 Attention and Transformers
- 10 40 10 55 Breakout 2
- 10 55 11 00 Wrap up







Deep dive sessions

Support by targeting key roles

Provide a neutral arena where you can meet and discuss similar challenges

An outside-in perspective, inspiration & meet with other in the same situation



Data Scientist or similar function

Role description:

A Data Scientist needs to be able to:

- Autonomously and flexibly carry out advanced analytics in multiple domains and environments.
- Run advanced modeling on data in order to extract knowledge and/or predict future events.
- Autonomously create and develop concepts.
- Understand the complete analytics chain from storing, structuring, modeling, to visualizing and translating data into actionable insights.
- Review, advice and communicate in analytics use cases.





Attention, the heart of transformers, to improve Information extraction

Severine Verlinden Al Developer, Language Technology Al Sweden



Breakout session 1

Questions

- Which problems can be solved with Information Extraction in your area of work?
- Main points of the discussion





Breakout session 2

- Questions
- How do you think Attention or Transformers can be used in your area of work?
- How would you want to use language models?



Next step

- The General Survey
- Networking on Slack

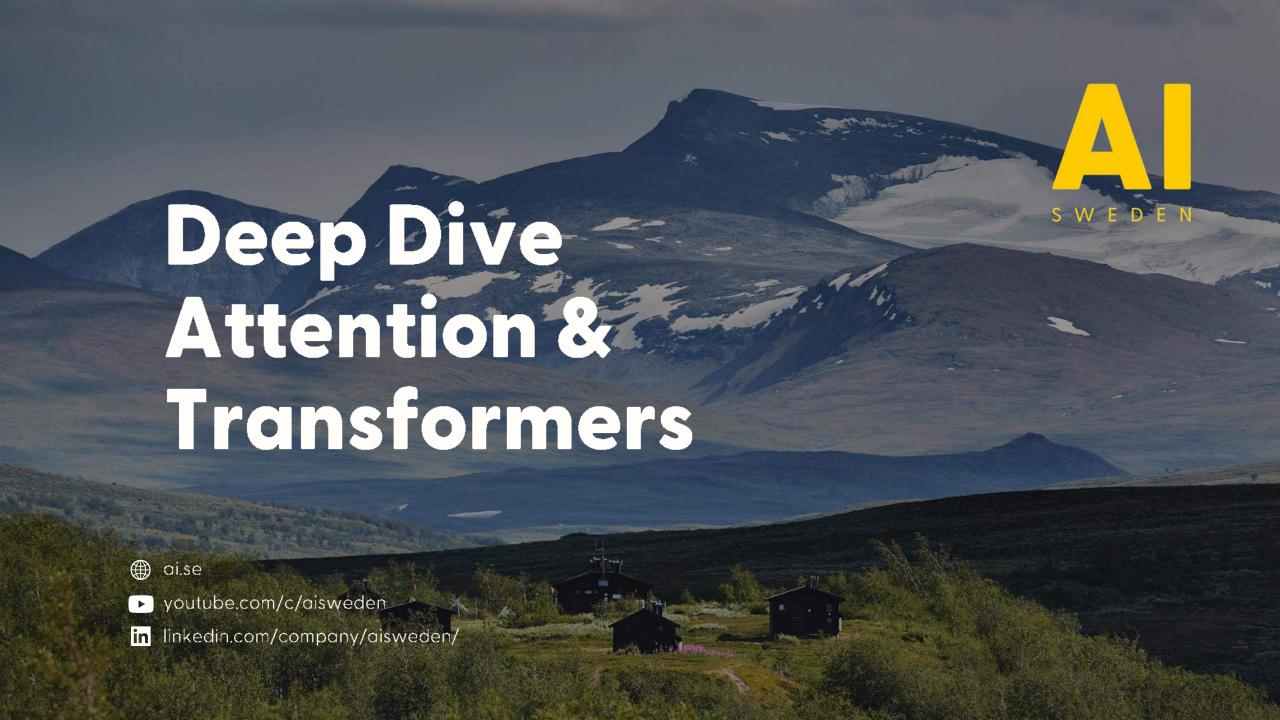


We need your feedback!

https://www.surveymonkey.com/r/MGBT6HR







What is Information Extraction?

Read more on this topic:

https://aclanthology.org/202
1.findings-acl.171.pdf











EUROPE

Hungary anti-LGBT+ law dispute overshadows EU summit

The European Commission and Hungary are at loggerheads over the discrimination of the LGBT+ community. The colors of the Pride rainbow were on conspicuous display in Brussels. Bernd Riegert reports.





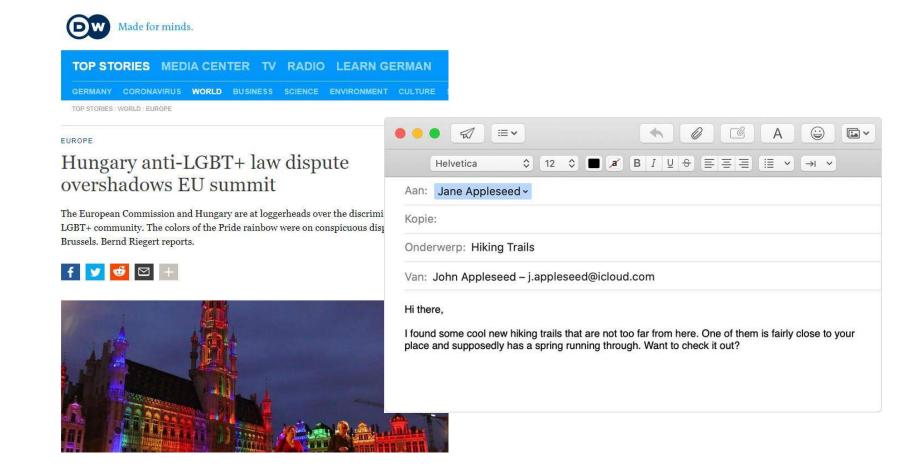




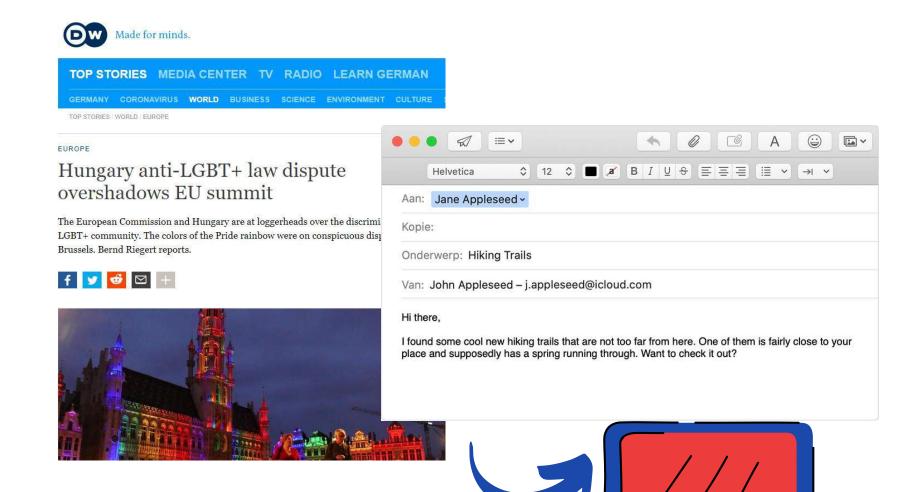




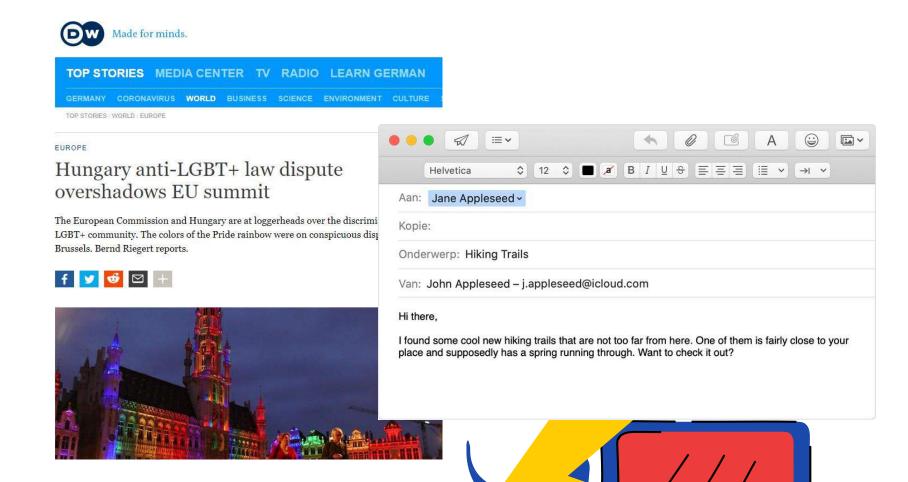














"We are very excited for Harry and Meghan. It has been wonderful getting to know Meghan and to see how happy she and Harry are together," Clarence House said in a tweet.

Named Entity recognition

Coreference Resolution

Relation Extraction

Mentions: Harry, Meghan, Clarence House...

Cluster: (Harry, Harry), (Meghan, Meghan), ...

Relation: Meghan-> in relation with ->Harry

"We are very excited for Harry and Meghan. It has been wonderful getting to know Meghan and to see how happy she and Harry are together," Clarence House said in a tweet.

Named Entity recognition

Coreference Resolution

Relation Extraction

Mentions: Harry, Meghan, Clarence House...

Cluster: (Harry, Harry), (Meghan, Meghan), ...

Relation: Meghan-> in relation with ->Harry

"We are very excited for Harry and Meghan. It has been wonderful getting to know Meghan and to see how happy she and Harry are together," Clarence House said in a tweet.

- Named Entity recognition
- Coreference Resolution
- Relation Extraction

Mentions: Harry, Meghan, Clarence House...

Cluster: (Harry, Harry), (Meghan, Meghan), ...

Relation: Meghan-> in relation with ->Harry

"We are very excited for Harry and Meghan. It has been wonderful getting to know Meghan and to see how happy she and Harry are together," Clarence House said in a tweet.

- Named Entity recognition
- Coreference Resolution
- Relation Extraction

Mentions: Harry, Meghan, Clarence House...

Cluster: (Harry, Harry), (Meghan, Meghan), ...

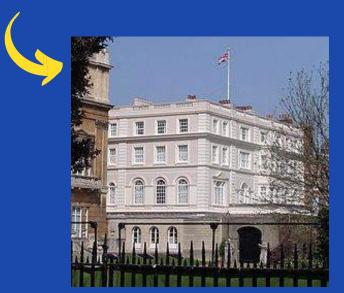
Relation: Meghan-> in relation with ? -> Harry

"We are very excited for Harry and Meghan. It has been wonderful getting to know Meghan and to see how happy she and Harry are together," Clarence House said in a tweet.



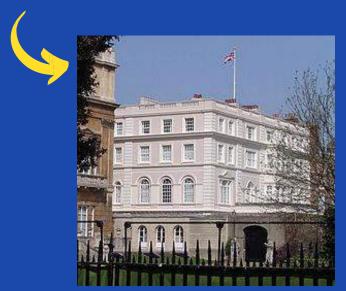
"We are very excited for Harry and Meghan. It has been wonderful getting to know Meghan and to see how happy she and Harry are together," Clarence House said in a tweet.





"We are very excited for Harry and Meghan. It has been wonderful getting to know Meghan and to see how happy she and Harry are together," Clarence House said in a tweet.





=> Wikipedia, Wikidata

Problem Statement



Improvement of the current IE algorithm



Including external knowledge of a knowledge base.

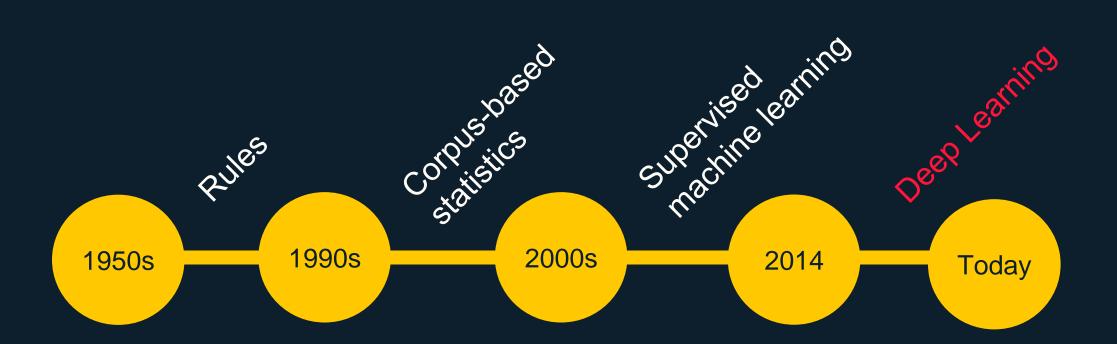
- Wikipedia
- Wikidata



Methods Part 02

Timeline



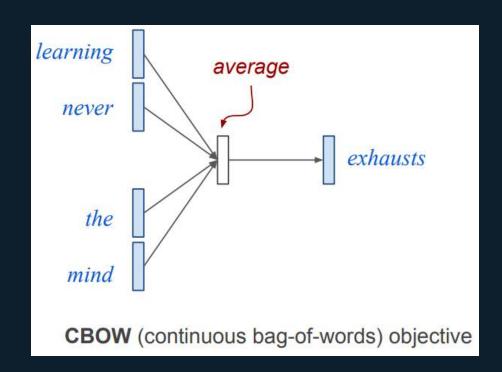


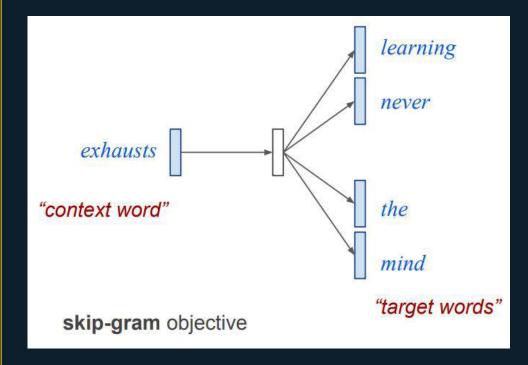


Woman I	U
Queen	0
Apple	0
Man	0
King	1
Orange	0
	0

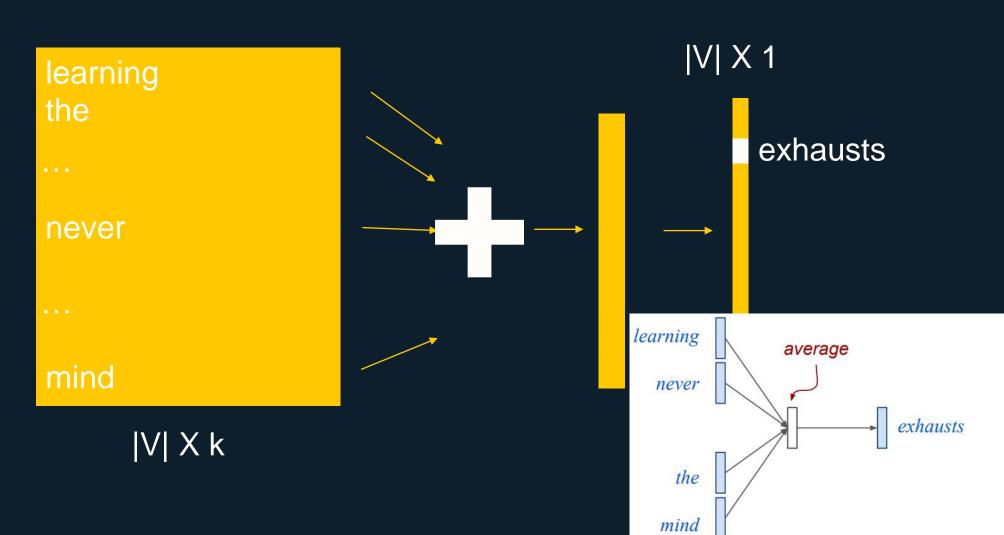
	. %		SWEDEN
	Cender	80/3	POS
Woman	1	0.02	0.02
Queen	0.98	0.95	0.69
Apple	-0.01	0.00	0.03
Man	-1	0.01	0.03
King	-0.95	0.93	0.70
Orange	0.00	0.01	-0.02











CBOW (continuous bag-of-words) objective

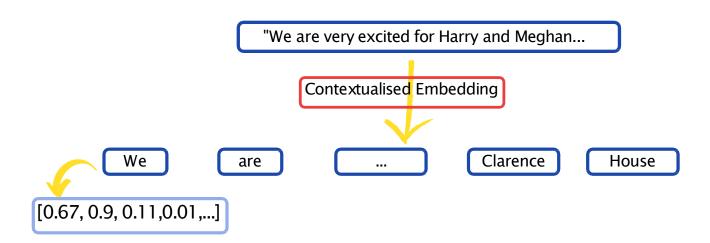
How? (*)

- NER
- RE
- CR
 - =>End-to-end
 - =>Jointly
 - =>Document-level

(*)Klim Zaporojets, Johannes Deleu, Chris Develder, and Thomas Demeester. 2021. DWIE: An entity-centric dataset for multi-task document-level information extraction. Information Processing & Management, 58(4):102563

How? (*)

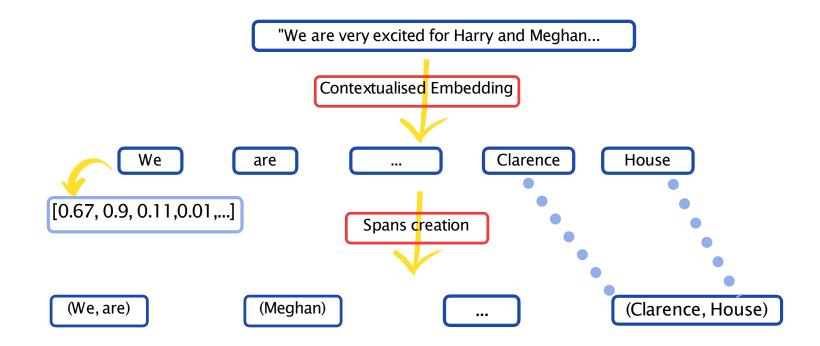
- NER
- RE
- CR
 - =>End-to-end
 - =>Jointly
 - =>Document-level



(*)Klim Zaporojets, Johannes Deleu, Chris Develder, and Thomas Demeester. 2021. DWIE: An entity-centric dataset for multi-task document-level information extraction. Information Processing & Management, 58(4):102563

How? (*)

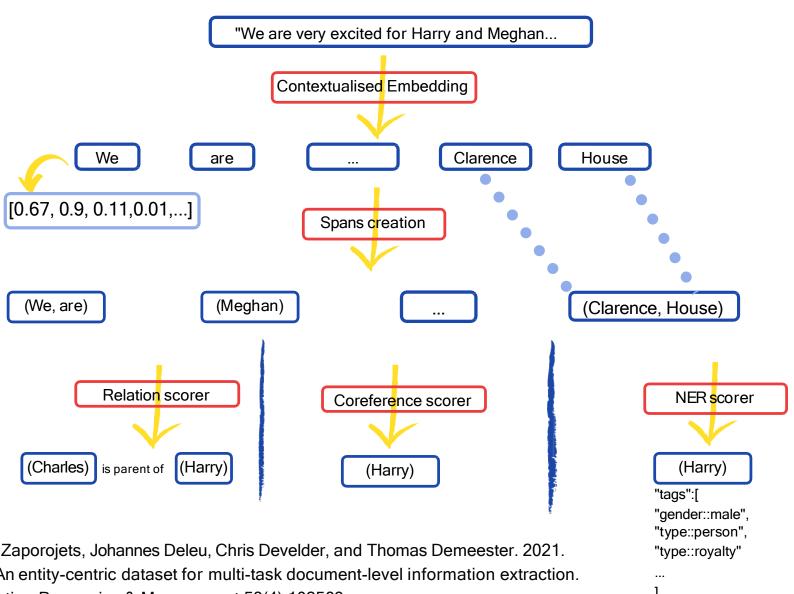
- NER
- RE
- CR
 - =>End-to-end
 - =>Jointly
 - =>Document-level



(*)Klim Zaporojets, Johannes Deleu, Chris Develder, and Thomas Demeester. 2021. DWIE: An entity-centric dataset for multi-task document-level information extraction. Information Processing & Management,58(4):102563

How? (*)

- NER
- CR
 - =>End-to-end
 - =>Jointly
 - =>Document-level



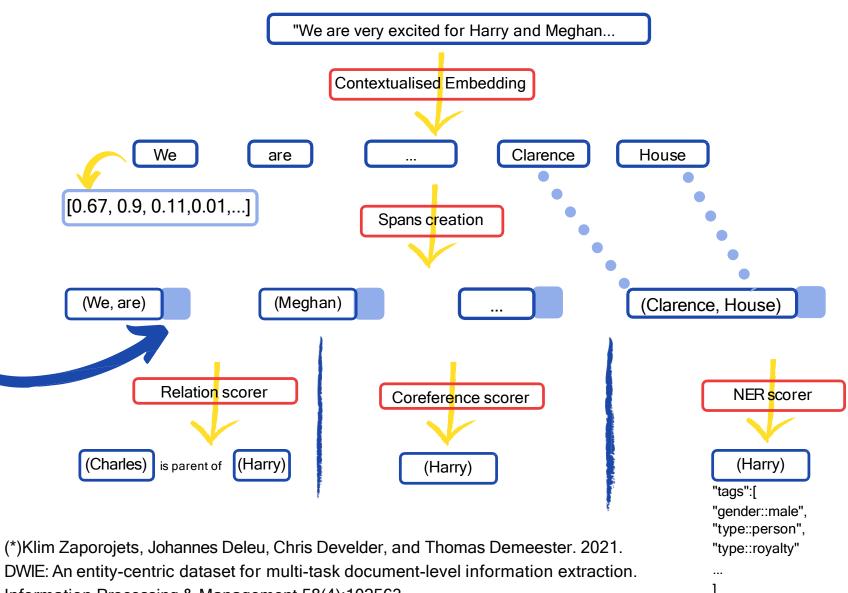
(*)Klim Zaporojets, Johannes Deleu, Chris Develder, and Thomas Demeester. 2021. DWIE: An entity-centric dataset for multi-task document-level information extraction. Information Processing & Management, 58(4):102563

How? (*)

- NER
- CR
 - =>End-to-end
 - =>Jointly
 - =>Document-level

External Knowledge

- Wikipedia
- Wikidata



DWIE: An entity-centric dataset for multi-task document-level information extraction. Information Processing & Management, 58(4):102563





(Meghan)

Candidates

- 1. "Meghan_Trainor"
- 2. "Meghan_McCain"
- 3. "Meghan, _Duchess_of_Sussex"
- 4. "Megan"
- 5. "Meghan Allen"

Prior

0.4

0.3

0.2

0.1

U. I

0.0



(Meghan)

Candidates

- 1. "Meghan Trainor"
- 2. "Meghan_McCain"
- 3. "Meghan, _Duchess_of_Sussex"
- 4. "Megan"
- 5. "Meghan Allen"

Prior

0.4

0.3

0.2

0.1

0.0

KB-text: [0.67, 0.9, 0.11,0.01,...]

Article Talk

Read

View source



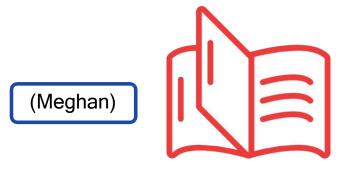
Meghan, Duchess of Sussex

From Wikipedia, the free encyclopedia

Meghan, Duchess of Sussex (/ mεgen/; born Rachel Meghan Markle, August 4, 1981), is an American member of the British royal family and a former actress.

Markle was born and raised in Los Angeles, California. Her acting career began while she was studying at Northwestern University. She attributed early career difficulties to her biracial heritage. Her most significant acting role is that of Rachel Zane in the American legal drama *Suits*, in which she starred for seven seasons (2011–2018). She simultaneously profited from a strong social media presence, including a lifestyle blog, *The Tig* (2014–2017). Through *The Tig* she gained recognition for her fashion sense, which led to creating and releasing two lines of clothing in 2015–2016. During her acting career, Markle became involved in charity work, focusing primarily on women's issues and social justice.

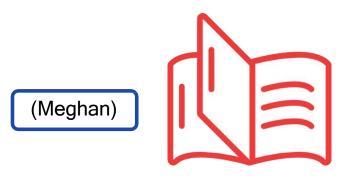
Different configurations



Candidates

- 1. "Meghan_Trainor"
- 2. "Meghan_McCain"
- 3. "Meghan,_Duchess_of_Sussex"
- 4. "Megan"
- 5. "Meghan_Allen"

Different configurations



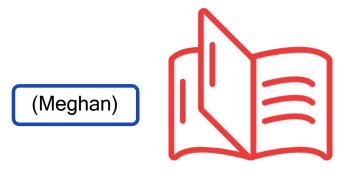
Candidates

- 1."Meghan_Trainor"
- 2. "Meghan_McCain"
- 3. "Meghan, _Duchess_of_Sussex"
- 4. "Megan"
- 5. "Meghan_Allen"

1weigthed entity embedding

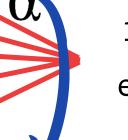
(Meghan)

Different configurations



Candidates

- 1. "Meghan_Trainor"
- 2. "Meghan_McCain"
- 3. "Meghan, Duchess of Sussex"-
- 4. "Megan"
- 5. "Meghan_Allen"



1weigthed entity embedding

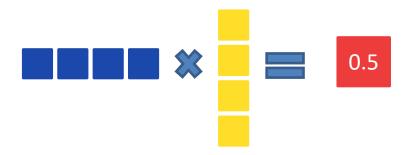
(Meghan)

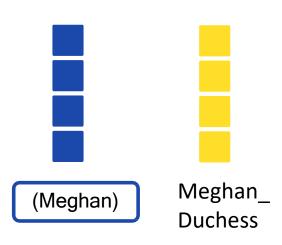
Oracle

Attention

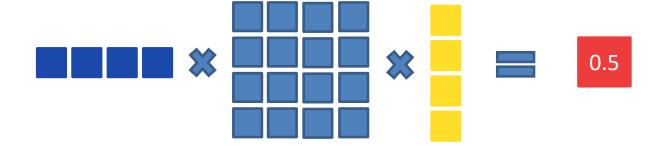
Attention

- Basic dot-product attention:





- Multiplicative attention:

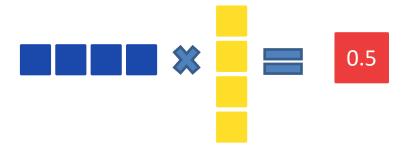


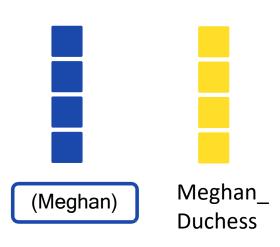
Additive attention:



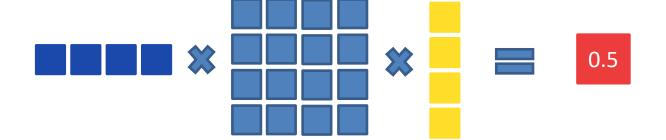
Attention

- Basic dot-product attention:





- Multiplicative attention:



- Additive attention:



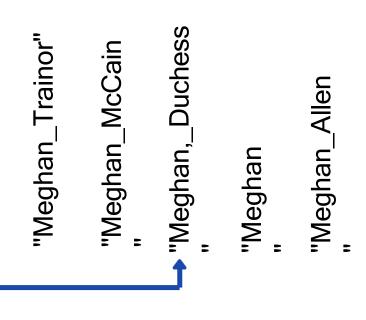
Different configurations α?

"Meghan_Trainor"
"Meghan_McCain
"
"Meghan,_Duchess
"
"Meghan
"
"
"Meghan_Allen
"

(Meghan)

Oracle

Different configurations α ?



(Meghan)

Oracle

Prior

•

Ш

0.3

0.1

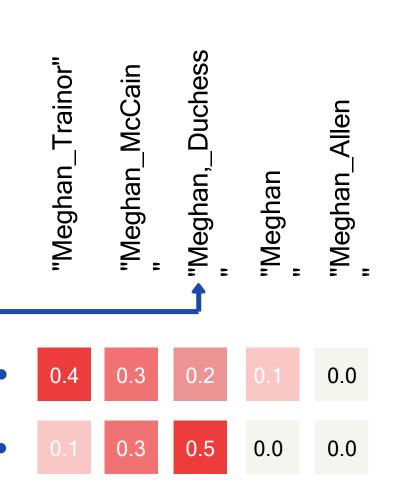
0

Different configurations α ?

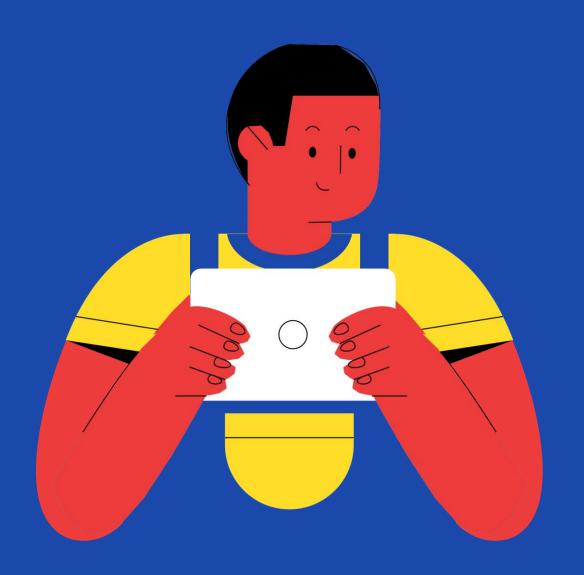
Oracle

Prior

Attention



(Meghan)



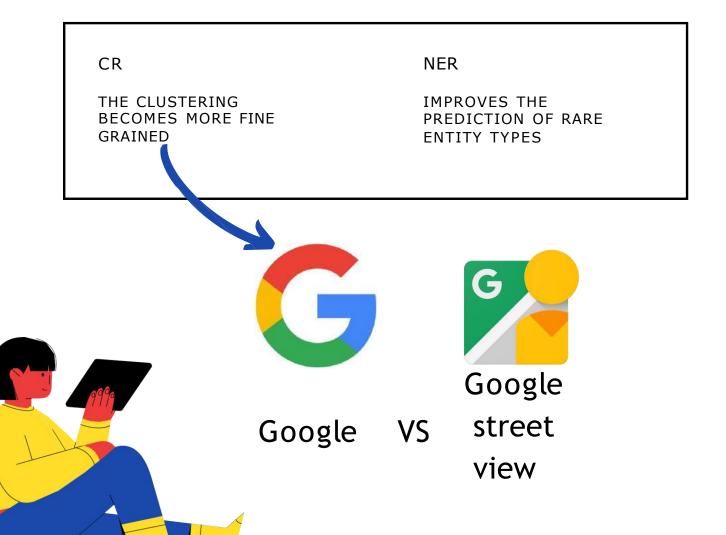
Results Part 03

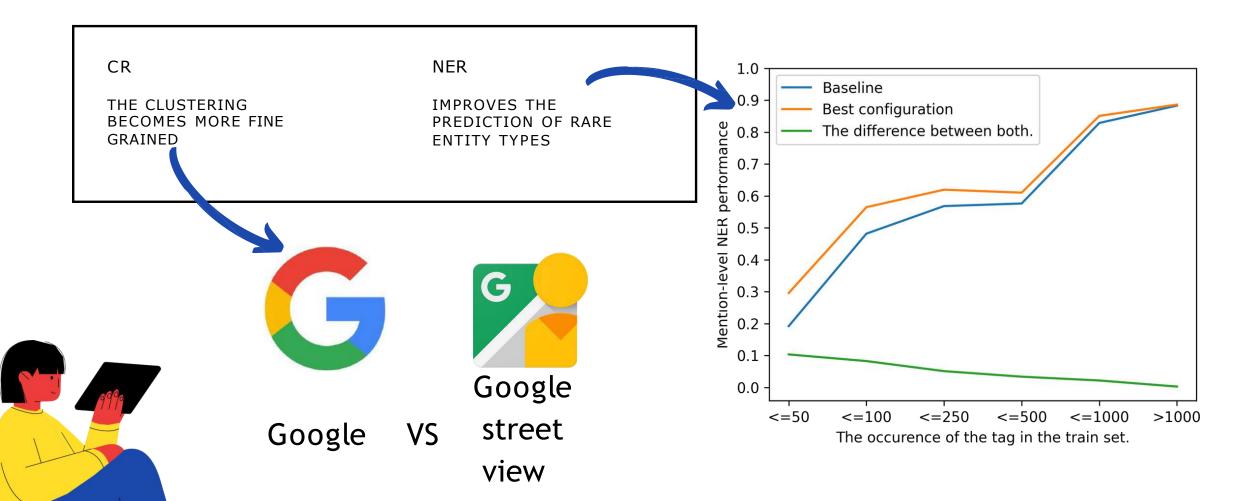
CR

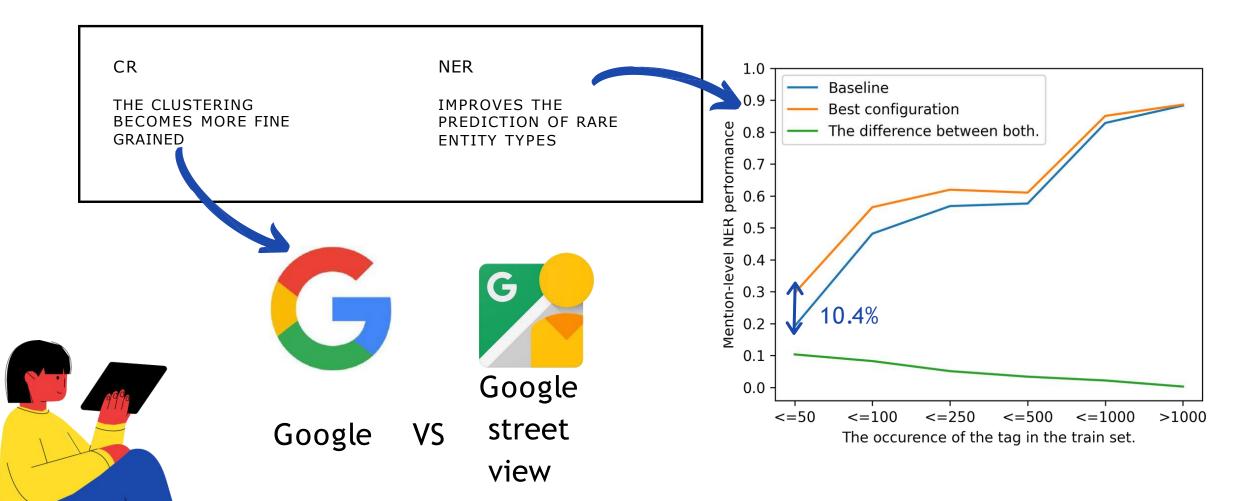
THE CLUSTERING BECOMES MORE FINE GRAINED





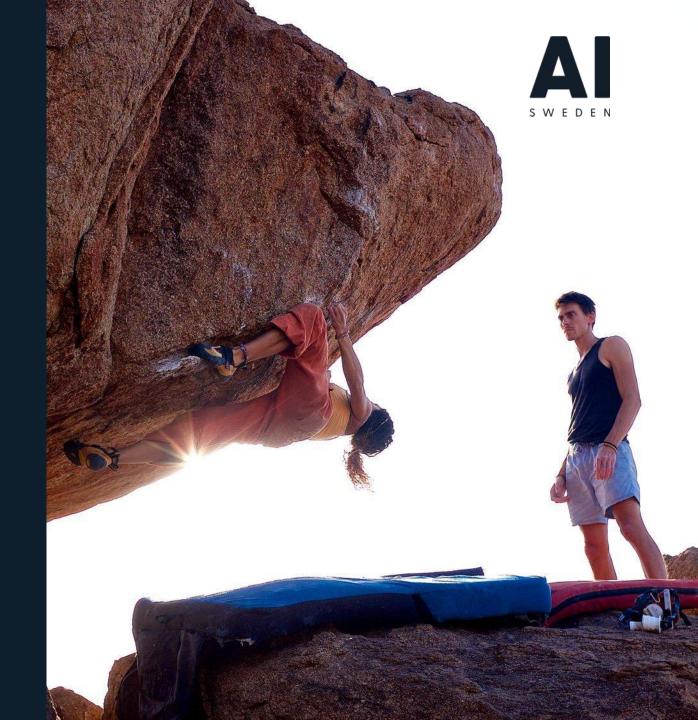






Questions

1.Which problems can be solved with Information Extraction in your current work field?







Transformers





Language Models Attention:

- -long range dependencies
- Omnidirectional





Transformers are

Language Models



Language Model

Language Modeling = Models the probability of text

Input = Where are we

Output = going

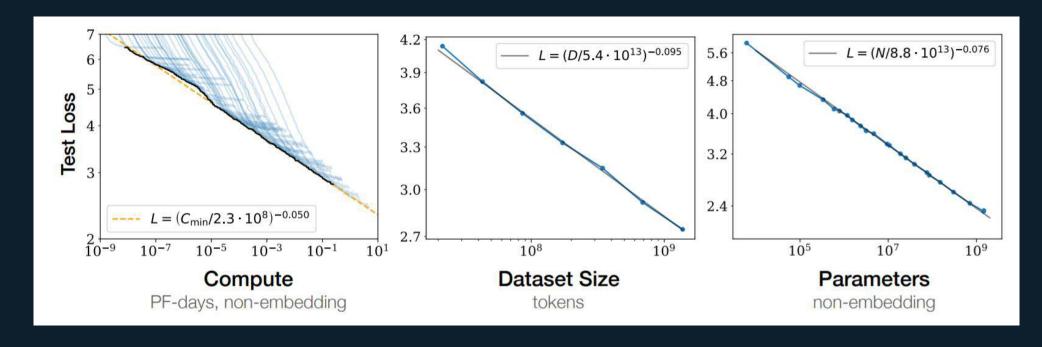
Use-cases: auto-complete, spelling correction



Language Model

Baseline = text characteristics + data in abundance





https://arxiv.org/pdf/2001.08361.pdf (Scaling Laws for Neural Language Models) "Performance depends strongly on scale, weakly on model shape"



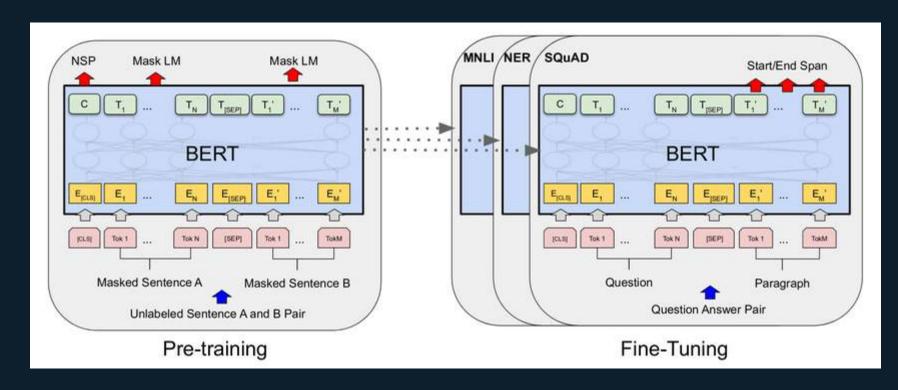
Scaling

GPT3:

175B parameters

cost of 4.6 M€ as lower bound per training run; between 11.5 and 27.6M€ total development cost





First: Pre-Training LM

Then: Fine-Tuning (Transfer Learning) and/or prompting

Prompting for Knowledge Acquisition



What does a GPT model know? <u>EleutherAl - text generation testing Ul</u>

One-shot: New Delhi is the capital of

Few-shot:

- 1. Stockholm is the capital of Sweden.
- 2. Brussels is the capital of Belgium.
- 3. Taipei is the capital of Taiwan.
- 4. Kampala is the capital of Uganda
- 5. New Delhi is the capital of

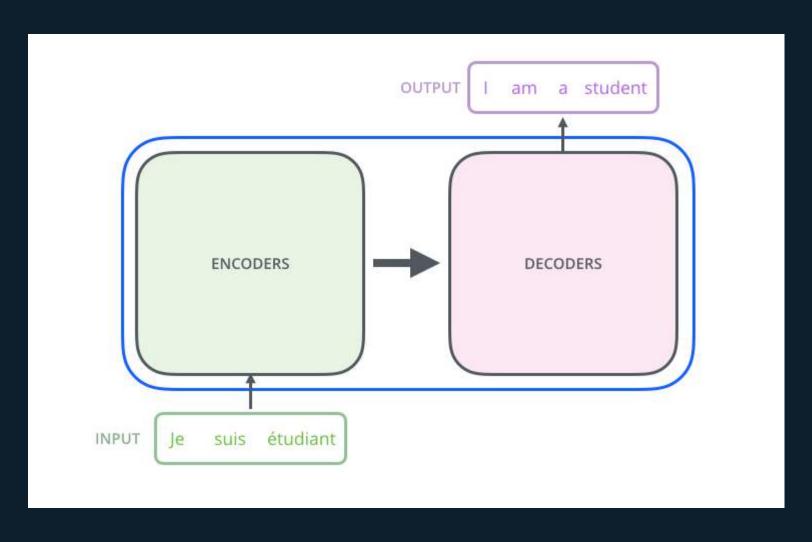




Architecture

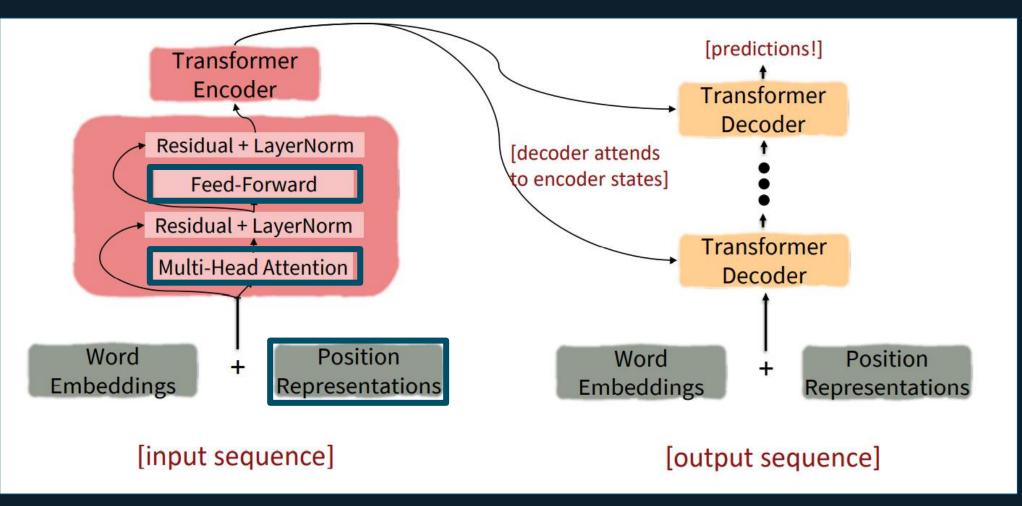
Attention



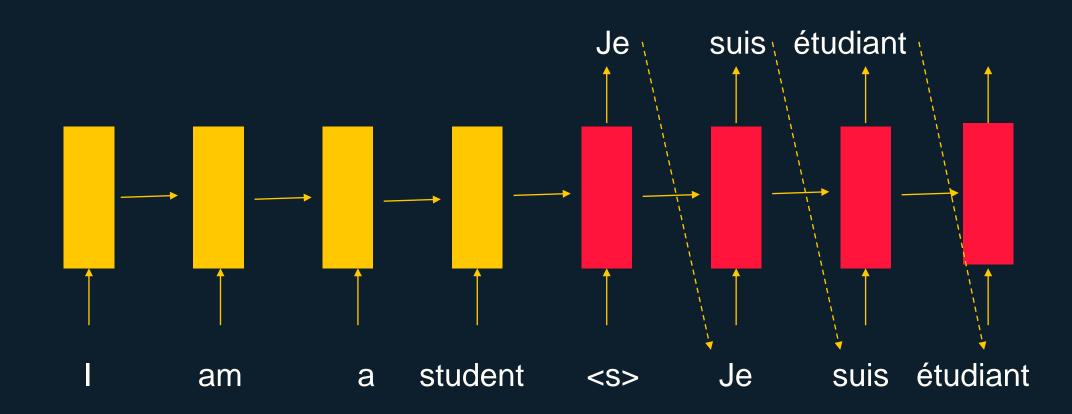


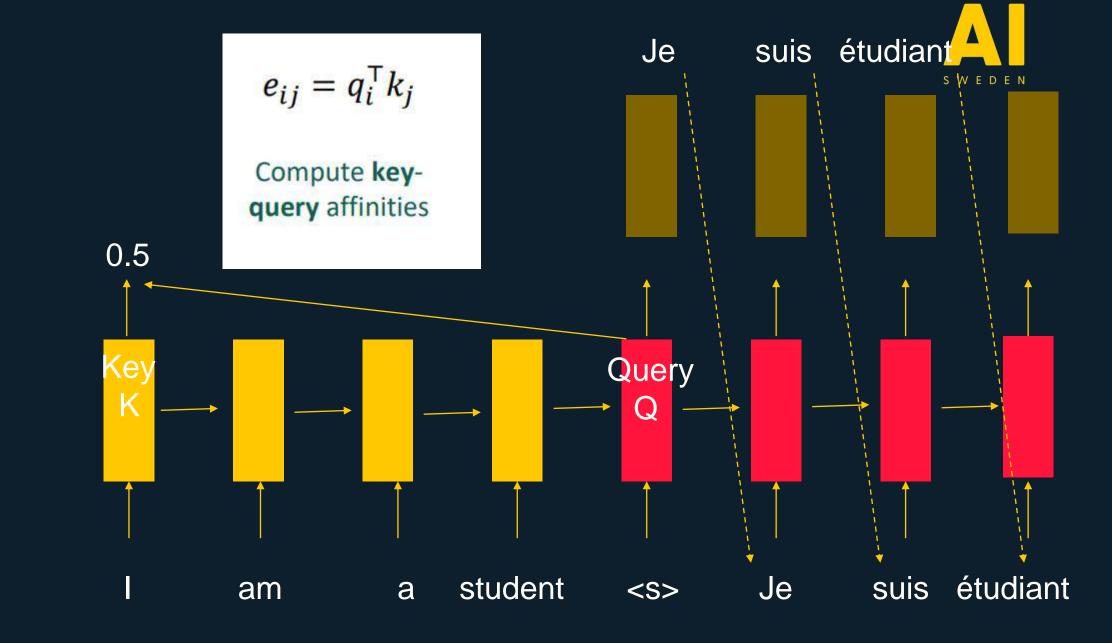
<u>The Illustrated Transformer – Jay Alammar – Visualizing machine learning</u> one concept at a time. (jalammar.github.io)

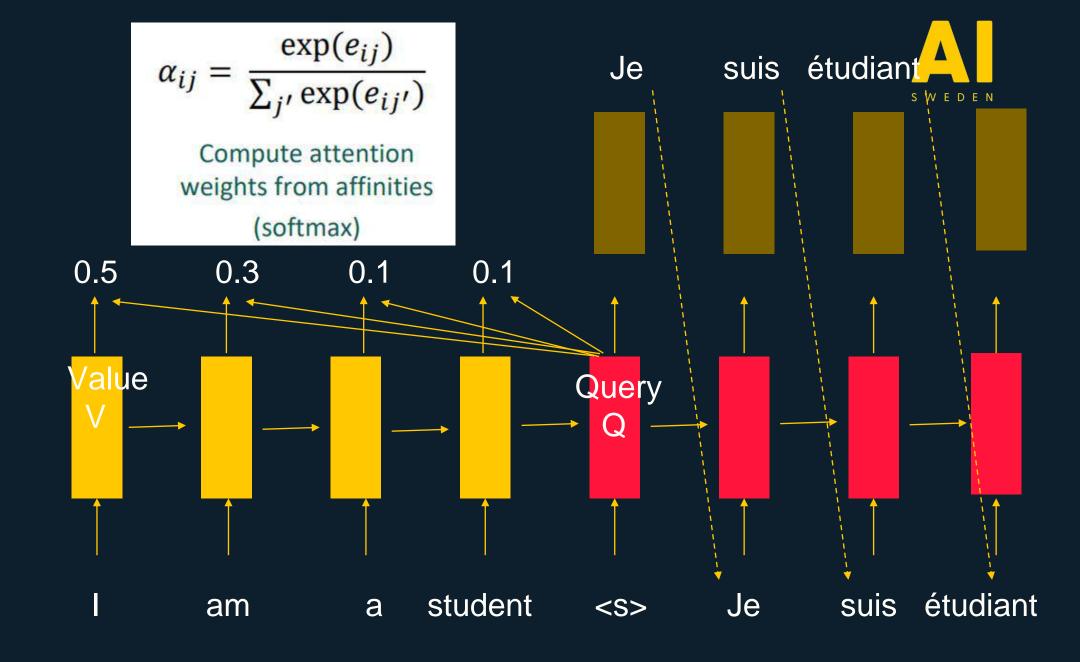






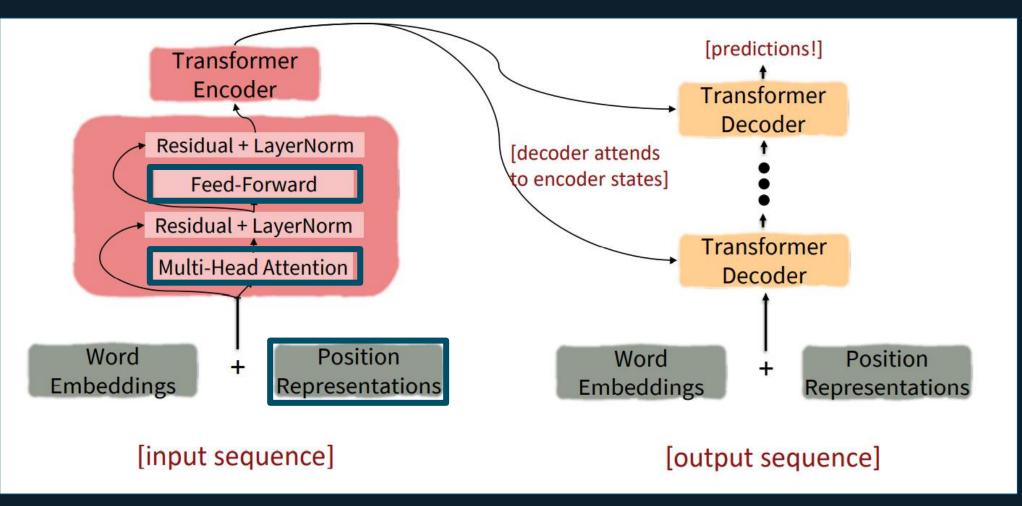




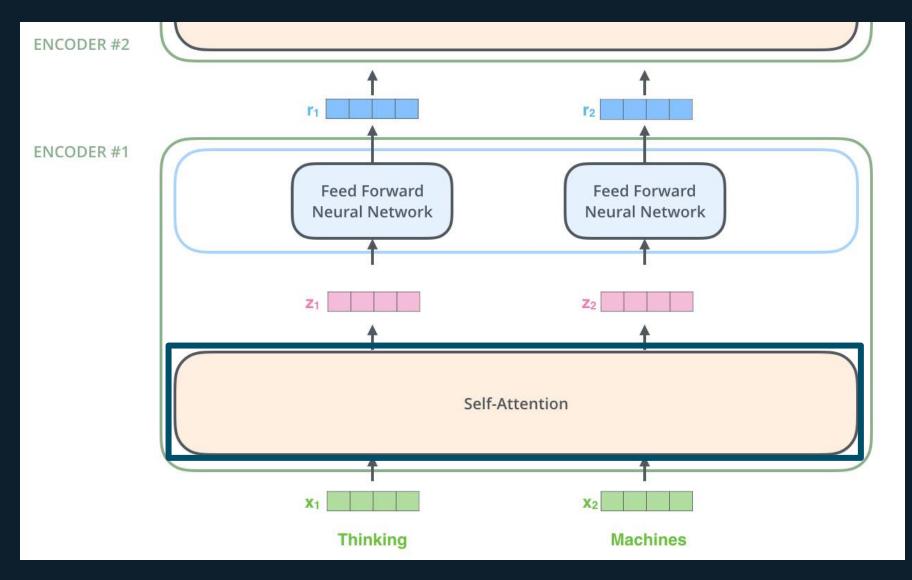


= Long-Range Dependencies









<u>The Illustrated Transformer – Jay Alammar – Visualizing machine learning one</u> <u>concept at a time. (jalammar.github.io)</u>



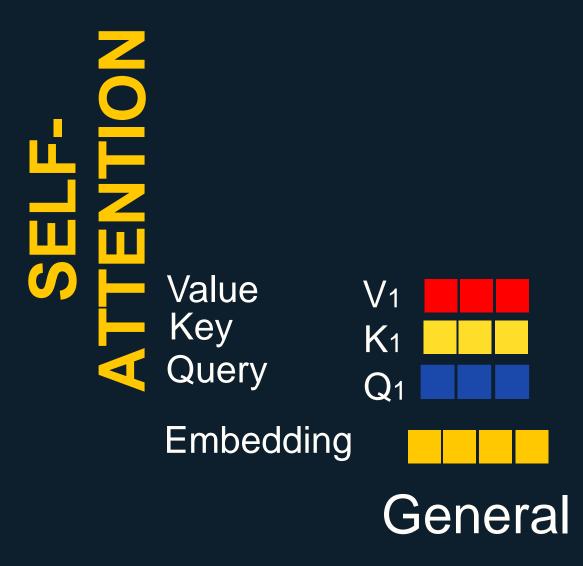
SELF-ATTENTION

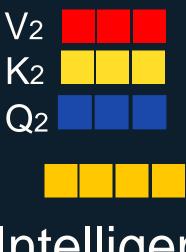
Embedding

General











Score

$$Q_1 * K_1 = 112$$

Value Key Query

Embedding



General

 $Q_1 * K_2 = 96$







Softmax

88.0

0.12

$$Q_1 * K_1 = 112$$

 $Q_1 * K_2 = 96$

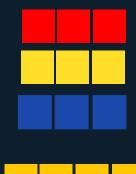
Value Key Query



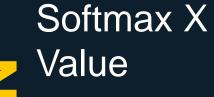
Embedding



General











Softmax

0.88

0.12

$$Q_1 * K_1 = 112$$

 $Q_1 * K_2 = 96$

Value Key Query

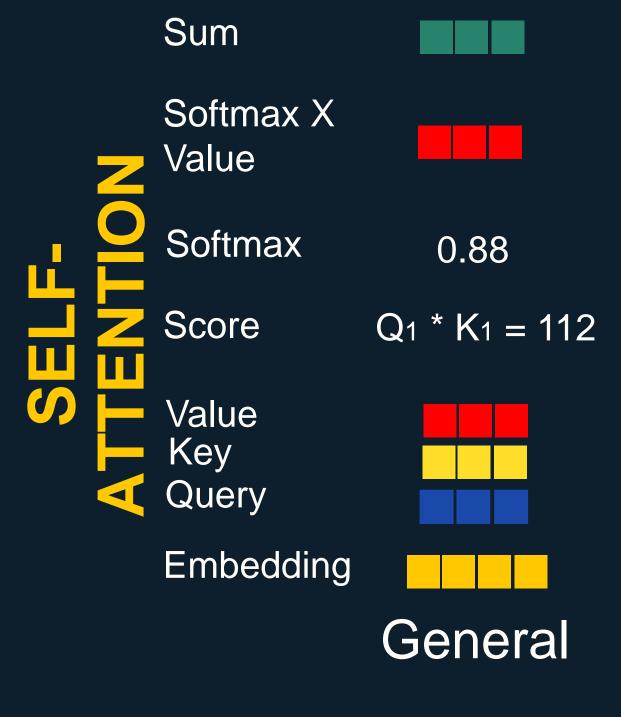


Embedding



General

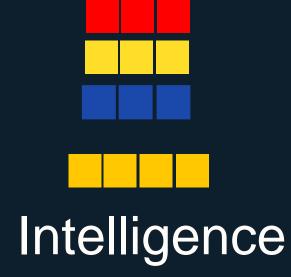








$$Q_1 * K_2 = 96$$



= Omni-Directional

Sum

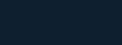






Softmax X Value

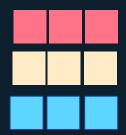




$$Q_1 * K_1 = 112$$

$$Q_1 * K_2 = 96$$

Value Key Query



Embedding

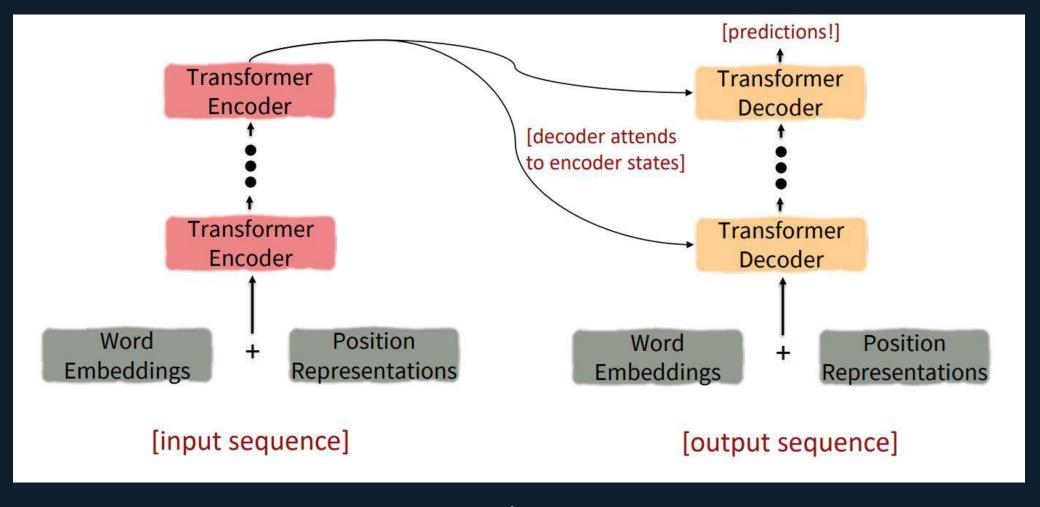


General





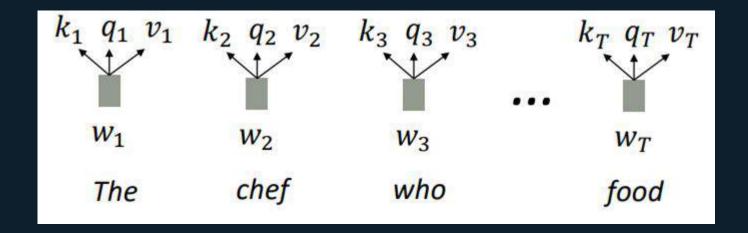




am a student





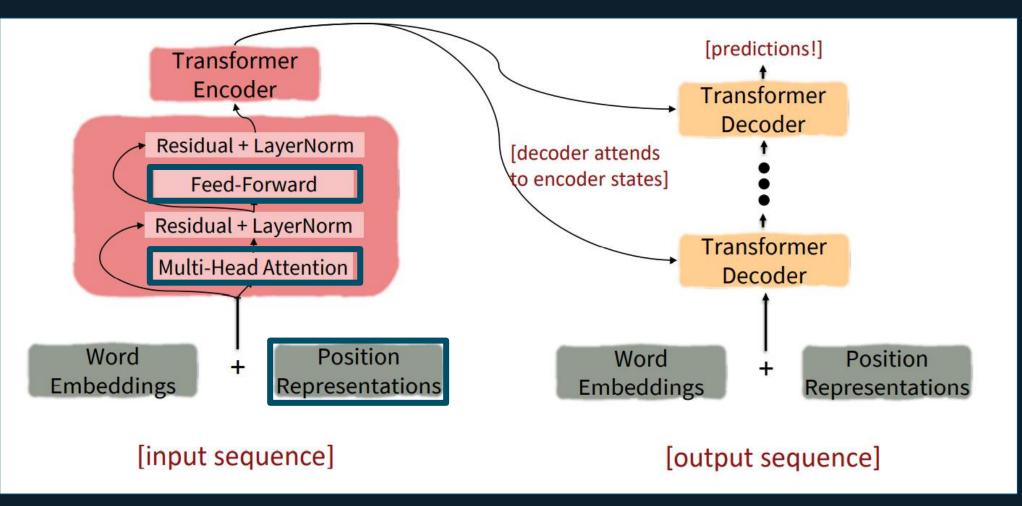




Postion Embeddings

- Learned embeddings
- Sinusoidal position representations







Types:

Sequenceto-sequence models

T5

Encoders

BERT, roBERTa, KG-BERT, BART, ...

Decoders

GPT-3, GPT-j, ...



Sed-To-Sed

ENCODER DECODER

INPUT OUTPUT

For example: input sequence target sequence machine translation: "translate English to German: That is good." "Das ist gut." natural language inference: "mnli premise: I hate pigeons. hypothesis: My "entailment" feelings towards pigeons are filled with animosity." A single generated word per class label. Winograd challenge: "The city councilmen refused the demonstrators a "The city councilmen" permit because *they* feared violence."



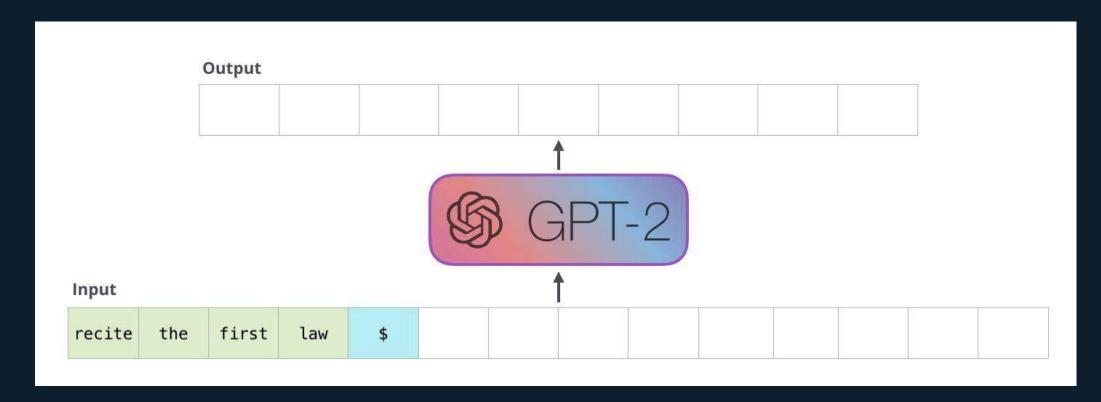


Goal: [CLS] my dog is cute [SEP] he likes play ##ing

1 (NSP) dog likes

Transformer

Input: [CLS] my [MASK] is cute [SEP] he [MASK] play ##ing



<u>The Illustrated Transformer – Jay Alammar – Visualizing machine learning one concept at a time. (jalammar.github.io)</u>





SWEDISH NLP



Overview: Swedish NLP

Datasets & Evaluation

Text Corpora

Labeled datasets

SuperLIM

Models

Encoders

Decoders

Seq2Seq

Use Cases



Swedish Datasets - Corpora

- Swedish Wikipedia (~2GB)
- Litteraturbanken, Swedish literature (< 1GB)
- Oscar, crawled corpus filtered for Swedish (~30GB)
- Swedish Forums (> 10GB)
- National Library (KB), OCR & Radio etc. (~ a lot)
- Data Collection, work in progress...



Swedish Datasets - Labeled Data

- SUC 3.0, Swedish NER Corpus, Swe-NERC, Swedish Medical NER (PoS & NER)
- Swedish Reviews (Sentiment Classification)
- Machine translated datasets (experimental)
- and more



Swedish Datasets - SuperLIM

- Swedish SuperGLUE evaluation suite
- Evaluates performance and bias

Swedish Datasets - SuperLIM

- Swedish SuperGLUE evaluation suite
- Evaluates performance and bias
- 13 test sets

Overview

Resource	Task
Aspect-Based Sentiment Analysis (Immigration)	Label the sentiment that the author of a text expressed towards immigration on the 15 scale
DaLAJ	Determine whether a sentence is correct Swedish or not
Swedish FAQ (mismatched)	Match the question with the answer within a category
SweSAT synonyms	Select the correct synonym or description of a word or expression
Swedish Analogy test set	Given two word pairs A:B and C:D, capture that the relation between A and B is the same as between C and D
Swedish Test Set for SemEval 2020 Task 1: Unsupervised Lexical Semantic Change Detection	Determine whether a given word has changed its meaning during a hundred year period
	Determine to what extent a given word has changed its meaning during a hundred year period
SweFraCas	Given the question and the premises, choose the suitable answer
SweWinograd	Resolve pronouns to their antecedents in items constructed to require reasoning (Winograd Schemata)
<u>SweWinogender</u>	Find the correct antecedent of a personal pronoun, avoiding the gender bias
SweDiagnostics	Determine the logical relation between the two sentences
SweParaphrase	Determine how similar two sentences are
SuperSim	Predict semantic word similarity and/or relatedness between words out of context.
SweWiC	Say if instances of a word in two contexts represent the same word sense.



Swedish Models - Decoders

• GPT-SW3

Swedish Models - Seq2Seq

Being explored



Swedish Models - Encoders

- AF-BERT (Swedish Public Employment Service)
- KB-BERT
- KB-ELECTRA
- KB-SBERT^[1]
- Bigger & better encoders desired



Swedish Models - Use Cases

Skatteverket: Anonymization

Severine likes good weather.

LINK:

https://www.ai.se/sites/default/files/content/swebert_best_practices_2021-02-03.pdf



Swedish Models - Use Cases

Skatteverket: Anonymization

Severine likes good weather.

LINK:

https://www.ai.se/sites/default/files/content/swebert_best_practices_2021-02-03.pdf





FUTURE CHALLENGES



Future:

AI & ETHICS

Data based, Reflects bias in society

EVALUATION IN NLP

Does the results of the benchmark improve because of task understanding?

GENERALIZ ATION

GPT-3, GPT-j, ...



Material based on

<u> https://jalammar.github.io/illustrated-transformer/</u>

<u> https://jalammar.github.io/illustrated-gpt2/</u>

https://jalammar.github.io/how-gpt3-works-visualizations-

animations/

Material based on NLP course of Stanford Stanford CS 224N | Natural Language Processing with Deep Learning

Questions

1. How do you think that Attention/Transformers can be used in your working field?

