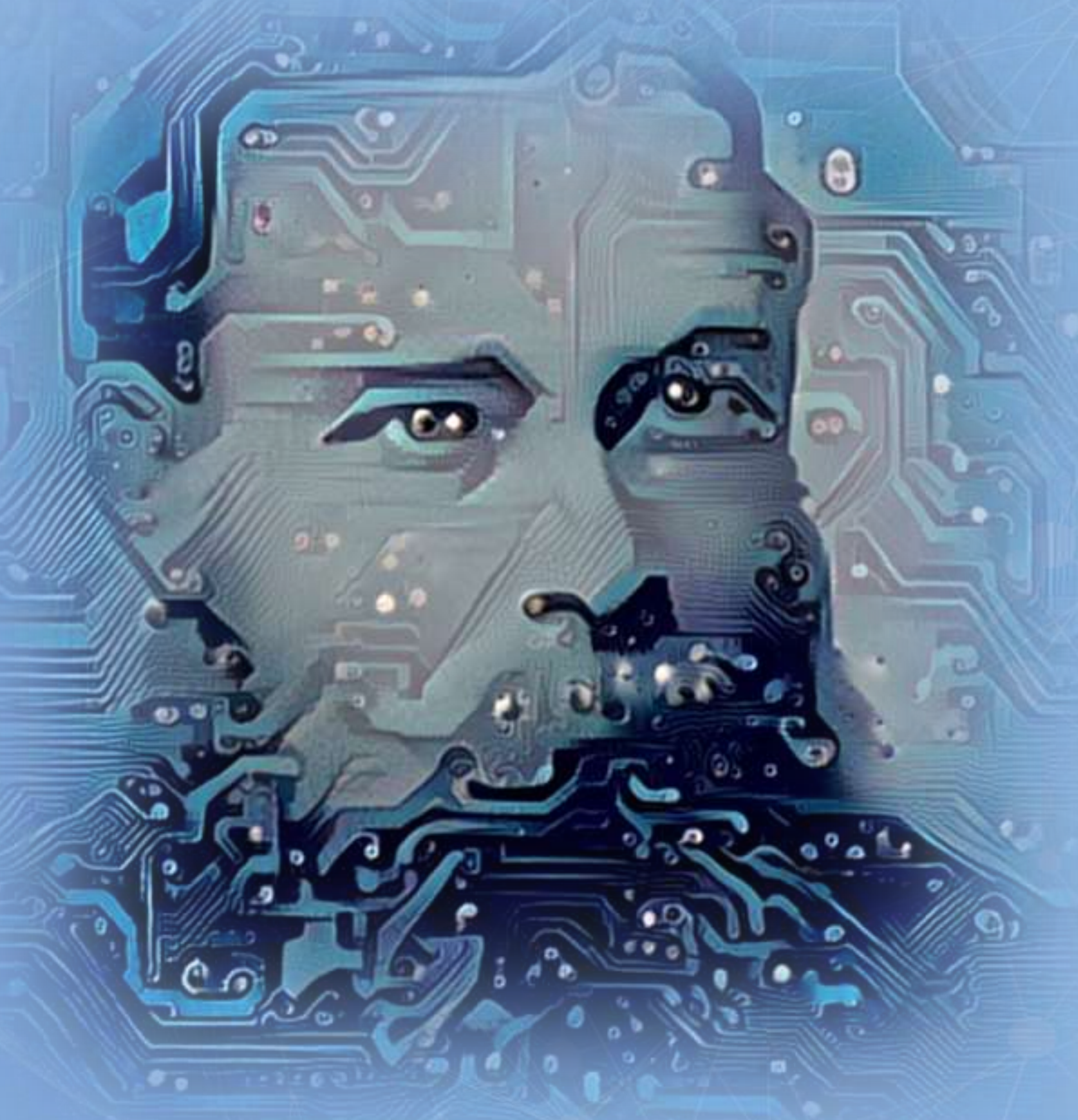

VECTORISING *Begriffsschrift*

On the relevance of recent forays into the deep learning of word meanings to some traditional philosophical problems and vice versa

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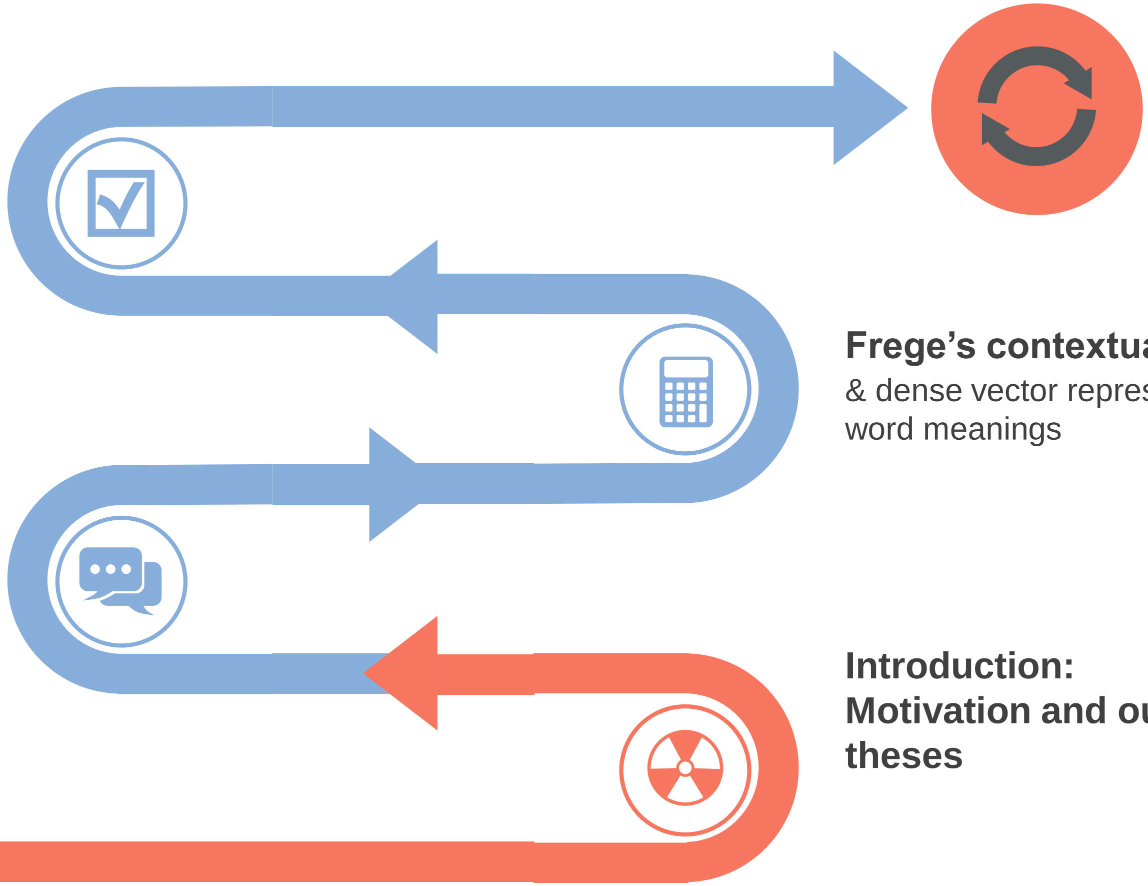
HaPoC 2019

Agenda of the presentation



Introduction: Motivation and our theses

NLP & Deep learning
Short review of the recent forays

Frege’s contextuality principle
& dense vector representation of word meanings

Indeterminacy of translation
And deep neural model for machine translation

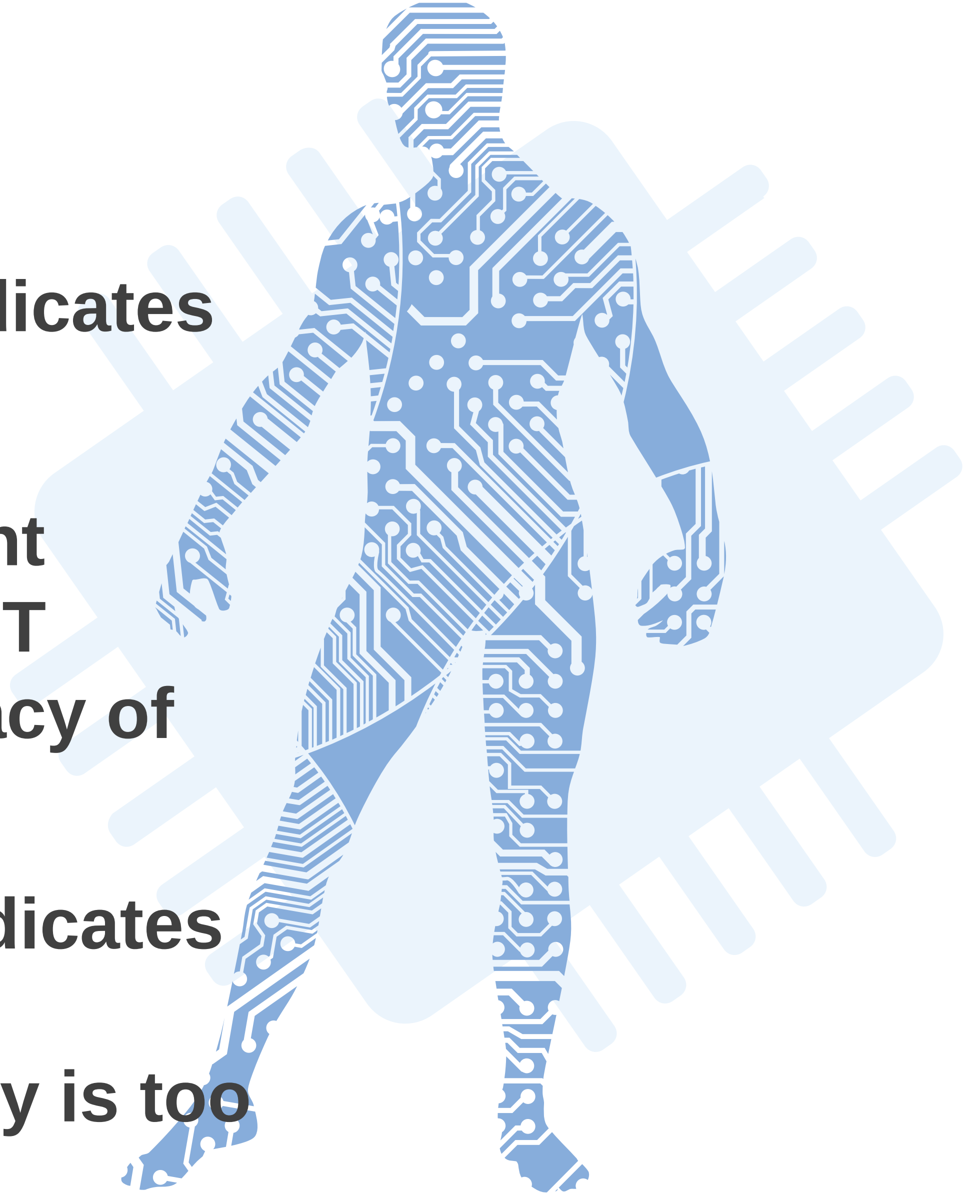
Discussion

OUR THESES

01 Developments in NLP vindicates Frege's context principle

02 Radical translation thought experiments restated in MT indicates that indeterminacy of reference is improbable

03 Transfer learning in MT indicates that Quine's conjecture on holophrastic indeterminacy is too strong



AI and NATURAL LANGUAGE UNDERSTANING

Deep Learning

and natural language understanding

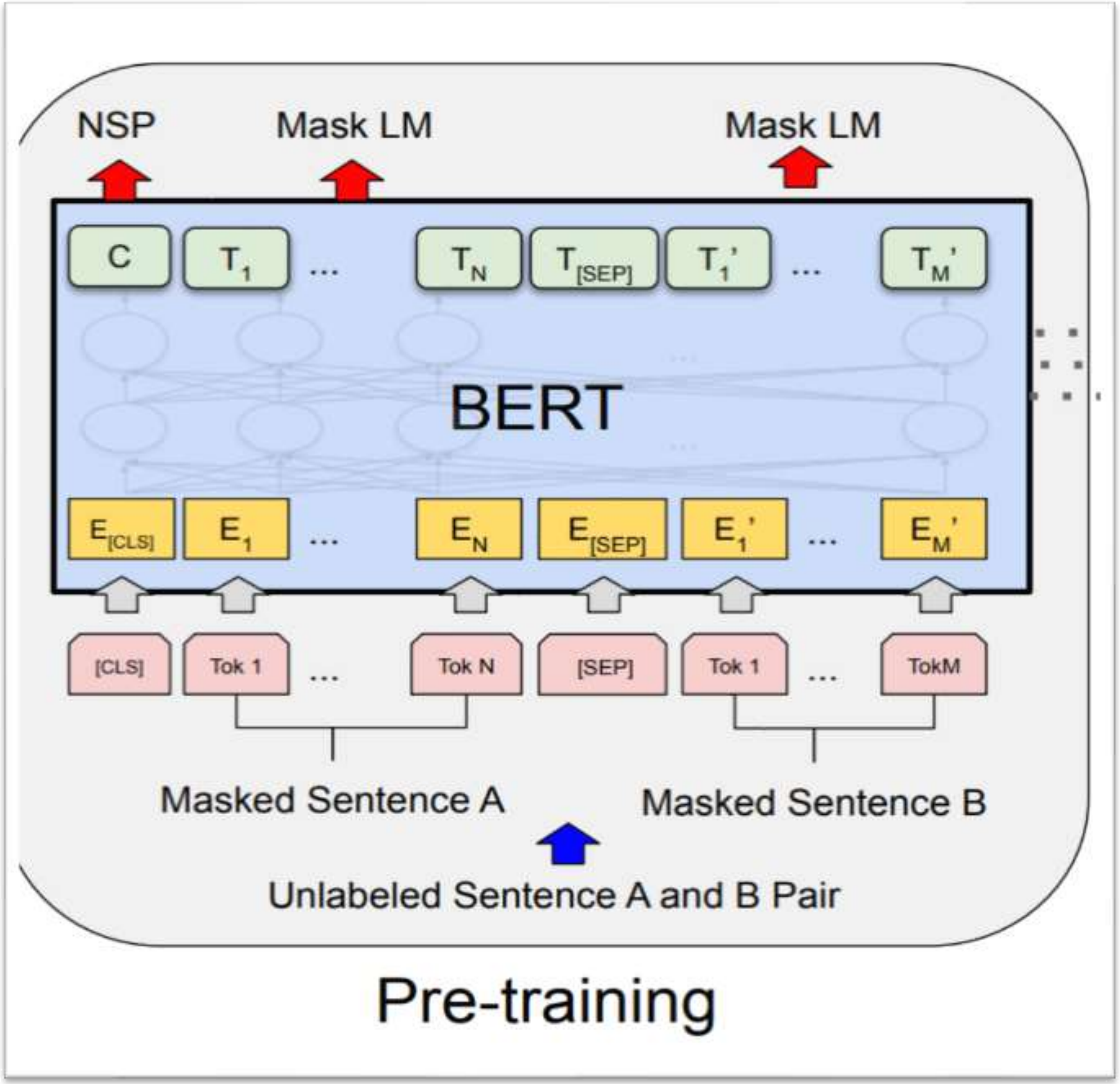
Neural language models
2001

Word embeddings, (bi-)LSTMs
2013

Seq2seq models
2014

Pretrained language models, transfer learning
2018

GOOGLE BERT
ARCHITECTURE



The recent foray in NLU using Transformers

Google BERT, Facebook’s XLM, OpenAI GPT, RoBERTa, ….

System	MNLI-(m/mm) 392k	QQP 363k	QNLI 108k	SST-2 67k	CoLA 8.5k	STS-B 5.7k	MRPC 3.5k	RTE 2.5k	**Average** -
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

FROM: Devlin at al (2018, May 2019 V2) BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

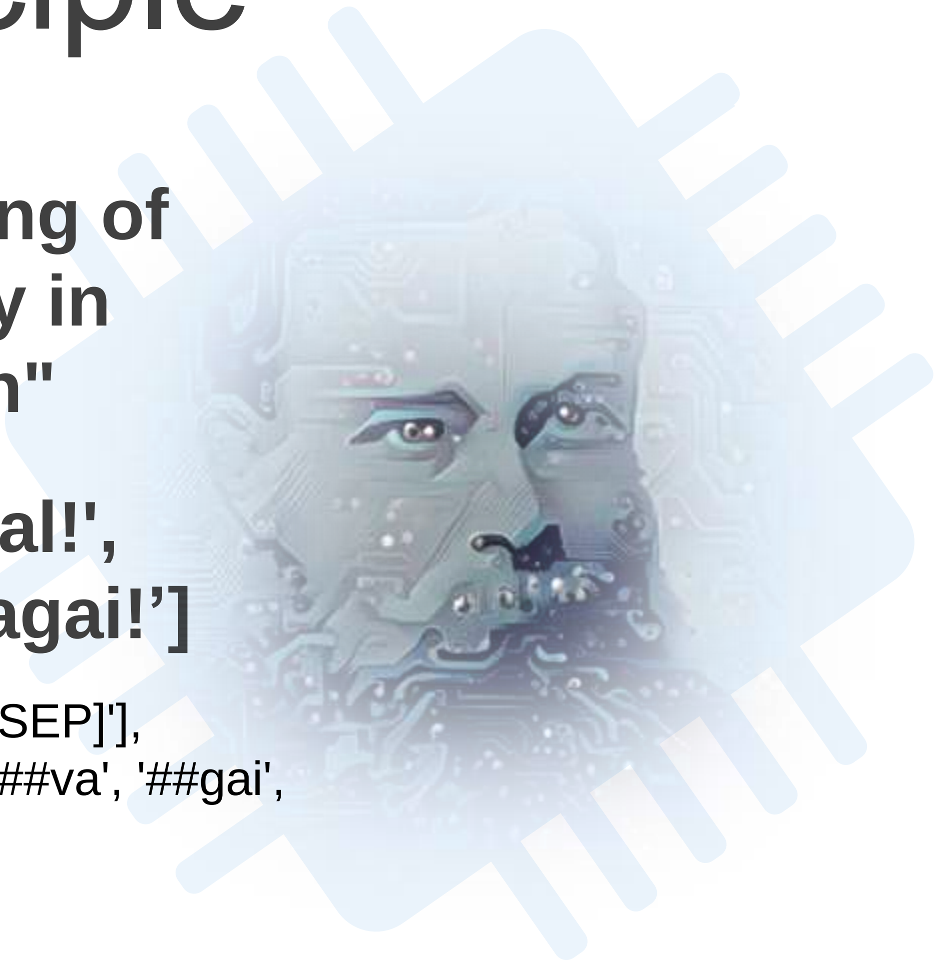
Frege’s Context Principle

01 **"never ... ask for the meaning of a word in isolation, but only in the context of a proposition"**

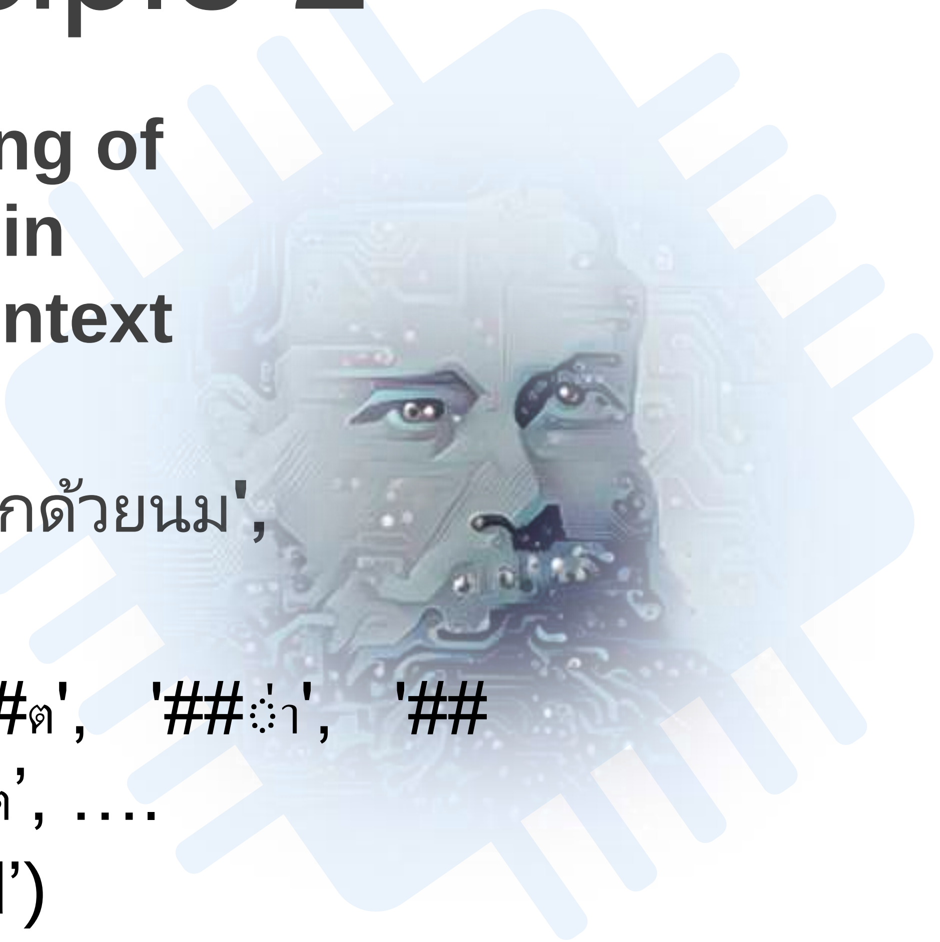
02 **sents = ['Rabbit is a mammal!', 'Rabbit is the same as Gavagai!’]**

03 [['[CLS]', 'Rabbit', 'is', 'a', 'mam', '##mal', '!', '[SEP]'],
['[CLS]', 'Rabbit', 'is’, ‘the’, 'same', 'as', 'Ga', '##va', '##gai',
'!', '[SEP]’]]
(‘bert-base-multilingual-cased’)

04 Vec(‘rabbit’) in the 1. & 2. sentence
cosine similarity 0.8167434



Frege’s Context Principle 2



01 **"never ... ask for the meaning of a (sub)word (a word piece) in isolation, but only in the context of a proposition"**

02 **sents = ['กระต่าย**เป็นสัตว์เลี้ยงลูกด้วยนม**',**
'กระต่ายไม่เหมือนกับ Gavagai’**]**

03 [['[CLS]', ['ก', '##ร', '##ะ', '##ต', '##่า', '##ย', '##เป็น', '##ส', '##ั', '##ต’, ….
('bert-base-multilingual-cased’)

04 Rabbit tokens (1-6) in the sentences
1-2 similarity 0.754323

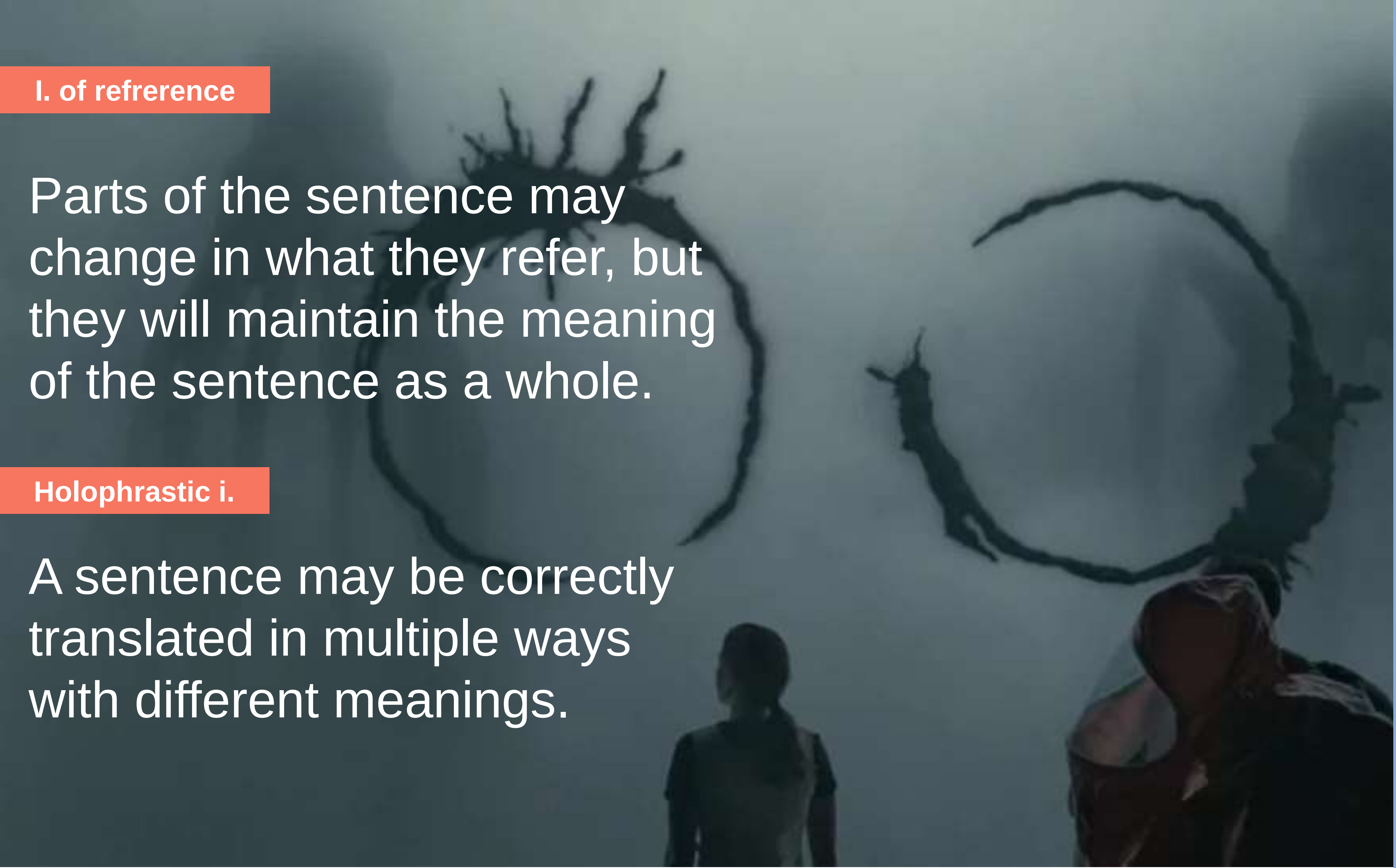
THE FIRST THESIS

The improvements of NLU metrics when word meanings are represented by sentence-relative dense vectors indicate that Frege’s context principle is correct.

INDERTERMINACY OF TRANSLATION

- indeterminacy of theories
- indeterminacy of reference
- holophrastic indeterminacy

indeterminacy of translation



I. of refrerence

Parts of the sentence may change in what they refer, but they will maintain the meaning of the sentence as a whole.

Holophrastic i.

A sentence may be correctly translated in multiple ways with different meanings.

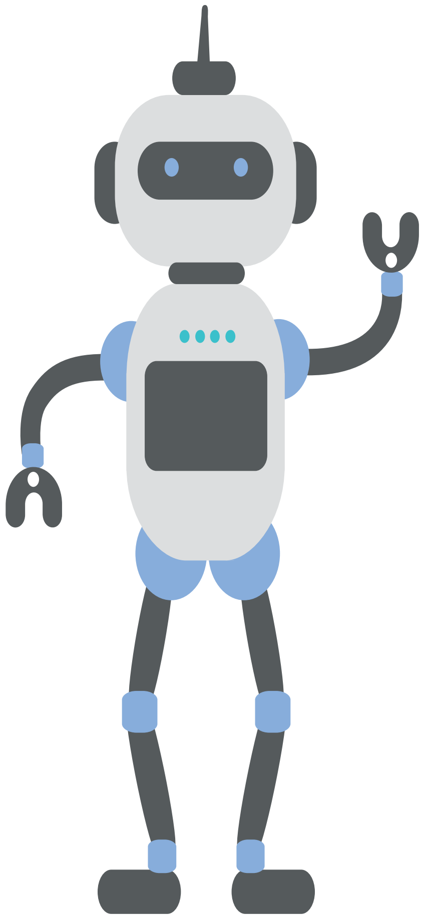
Ind. of reference and MT

Radical Translation	Machine Translation
A target language is neither historically nor culturally linked to any known language	A target language is not closely linked to the language pair (i.e. another language family)
Translation of theoretical sentences is indeterminate	All sentences are theoretical; translation is based on MT methods
Input: behaviour, non-linguistic elements	Input: a large parallel text corpus

Deep learned *Gavagai*

01 **Experiment measuring performance of the MT models trained on new (unseen) words**

02 **Experiment design:**
Dataset 1: IWSLT-14 English-German MT corpus, 160.239 sentence pairs, 33 „rabbit" sentences
Dataset 2: Ted Talk Thai-English sentences, 304.245, 40 „กระต่าย" sentences
Library: Facebook FairSeq
DS1: Transformer wmt16.en-de Model (Ott et al., 2018)
DS2: vanilla wmt16



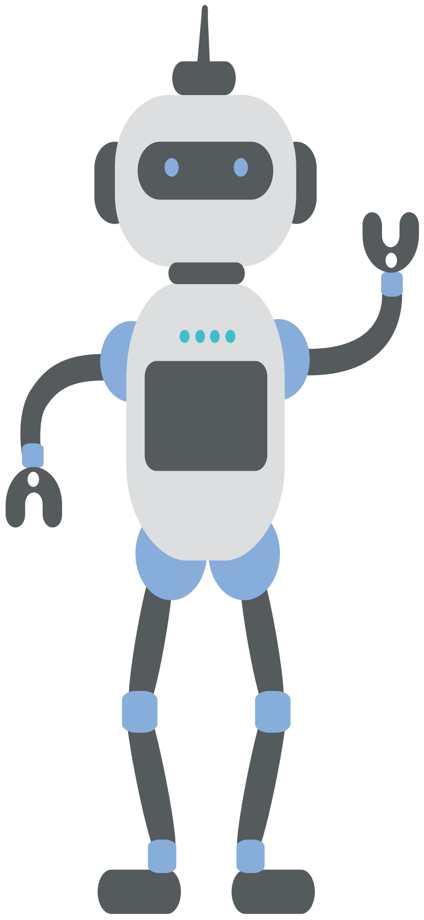
Deep learned *Gavagai 2*

03 **MT Model learned on IWSLT-14 dataset with ,,rabbit / bunny” and ,,Hase / Kaninchen” sentences removed**

- **100 epochs, loss 1.29**
- **%0 of test ,,rabbit” sentences translate correctly**

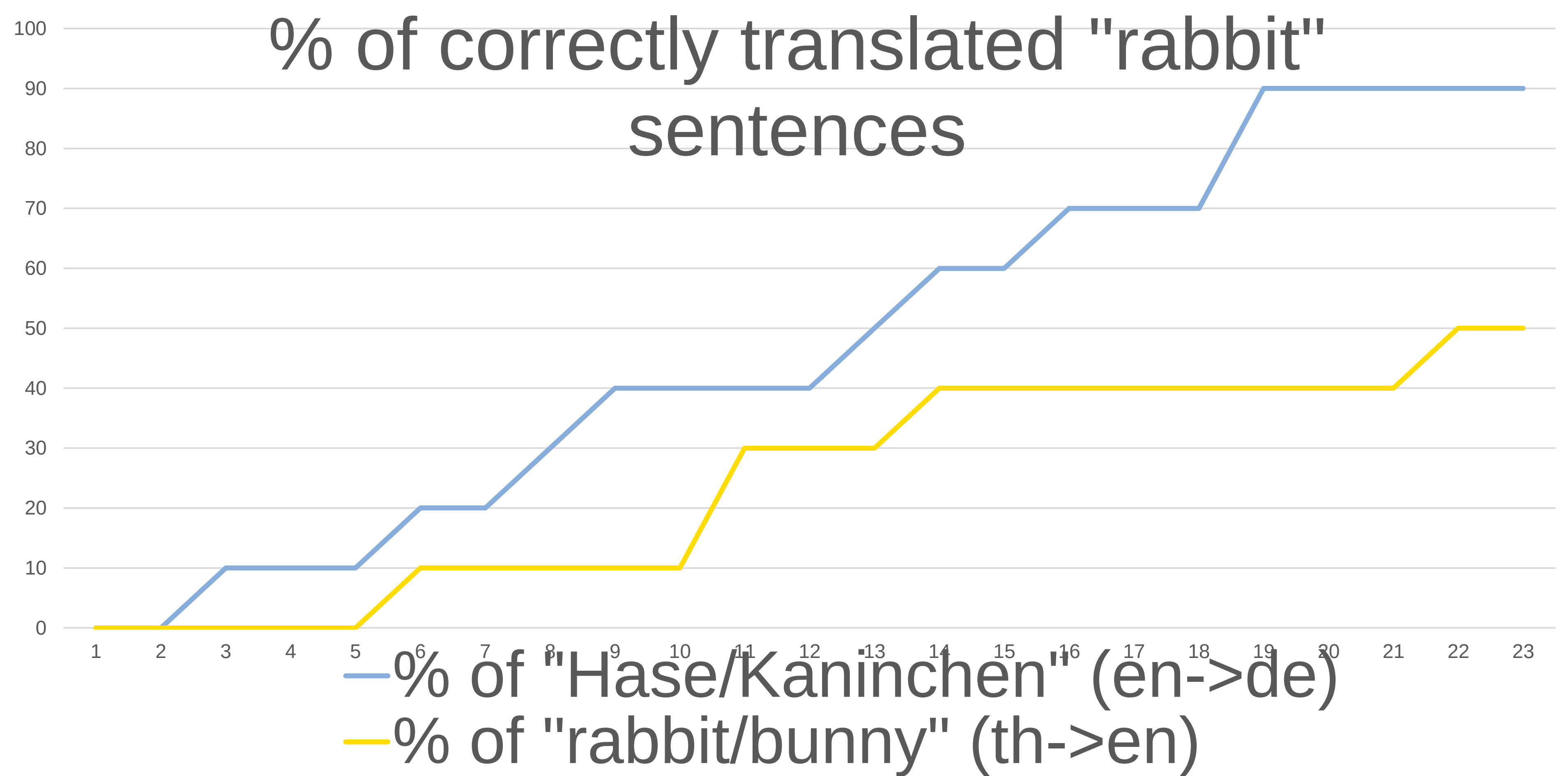
04 **MT Model learned on TED-talks DS without ,,กระต่าย” and ,,rabbit/bunny” sentences**

- **100 epochs, loss 1.61**
- **%0 of test “กระต่าย” sentences translate correctly**



Deep learned *Gavagai 3*

06 **Model is incrementally trained on „rabbit" sentences - 23 sentences, 50 epochs each**



THE SECOND THESIS

Radical translation thought experiments simulated with MT indicates that indeterminacy of reference is improbable.

Holophrasic ind. and MT

Translation manual	Deep NN model
Different possibilities of translating the same sentence (different meaning); impossible to determine the right one	Different possibilities of translating the same sentence (different meaning); but with a high probability of correctness of one translation
Rules of translation	Rules, probability, transfer knowledge, vector representation
Context non-sensitive	Context-sensitive

Holophrastic indeterminacy & transfer learning

Language Pair	Parent	Train Size	BLEU ↑	PPL ↓
Uzbek–English	None	1.8m	10.7	22.4
	French–English	1.8m	**15.0 (+4.3)**	**13.9**
French′–English	None	1.8m	13.3	28.2
	French–English	1.8m	**20.0 (+6.7)**	**10.9**

FROM: Zoph at al (2016) Transfer Learning for Low-Resource Neural Machine Translation

THE THIRD THESIS

Transfer learning in MT indicates that Quine’s conjecture on holophrastic indeterminacy is too strong.

Thank You

Discussion time