

#### Berlin Buzzwords

#### Querying Elasticsearch with Deep Learning to Answer Natural Language Questions

Sebastian Blank, Hans-Peter Zorn

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## Sebastian Blank

Data Scientist @ inovex









Hans-Peter Zorn

Dr. Florian Wilhelm ØFlorianWilhelm Prof. Dr. Achim Rettinger Universität Trier





- 1. Use Case
- 2. Approach
- 3. Results
- 4. Learnings

Use Case



## Voice Control will shape our lifes



#### "You will be able to do pretty much anything via voice command."

Elon Musk about Teslas Model 3



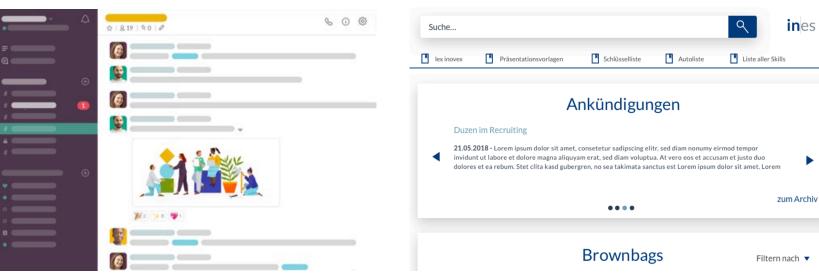
"Speech is going to be the interface at home." Kenn Harper, Nuance Communications





#### How it started







## Conversations require background information

# Who is the president of the United States?

# Which customers received a coupon and used it in our shop?

#### Who starred in Avatar?



# What appointments do I have tomorrow?



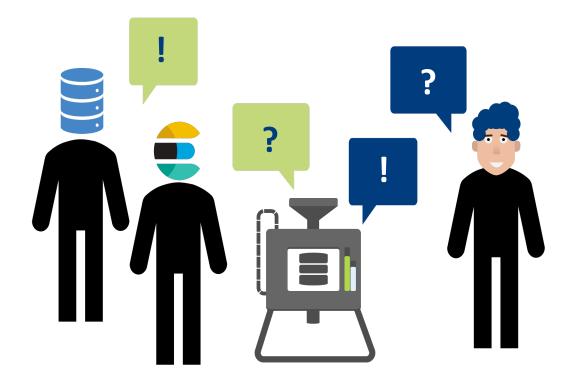
## Query languages impede access to information



## Leveraging DL to overcome this barrier

› Hard lookup

Soft lookup



### Hard lookup



P

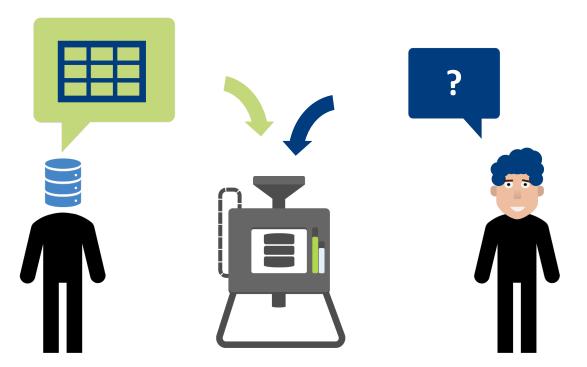
### How to access a database with natural language?

- Hard lookup
  - interpretable (+)
  - existing API (+)
  - > non-differentiable (-)
  - not end-to-end trainable (-)
  - labelling is costly (-)



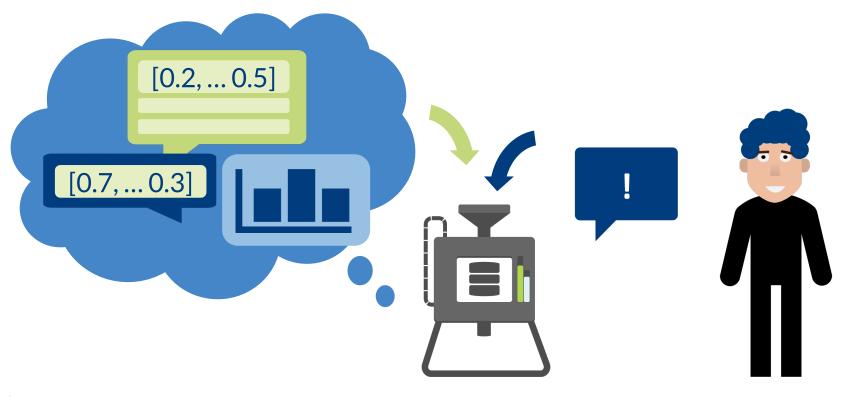














### How to access a database with natural language?

- Hard lookup
  - interpretable (+)
  - existing API (+)
  - > non-differentiable (-)
  - > not end-to-end trainable (-)
  - labelling is costly (-)

- Soft lookup
  - > end-to-end trainable (+)

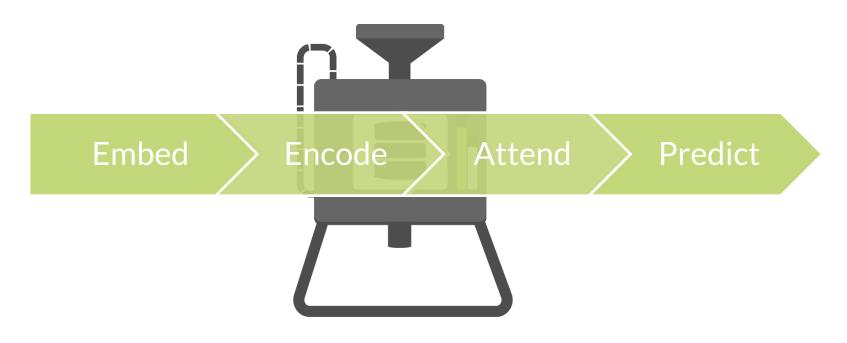
- > hard to interpret (-)
- impeded by security & privacy issues (-)
- capacity (-)



# Approach



### Let's build this machine

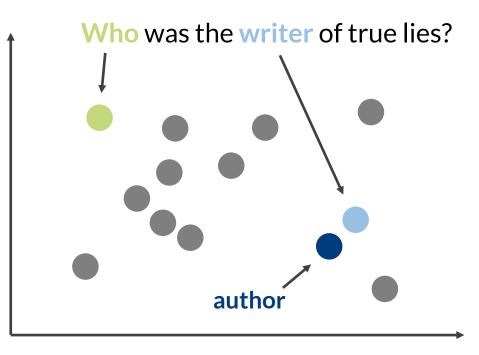








#### Representing words as continuous vectors

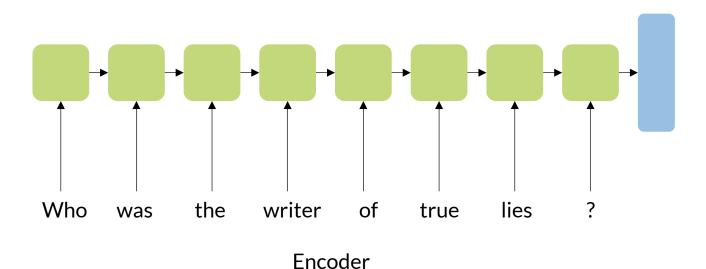








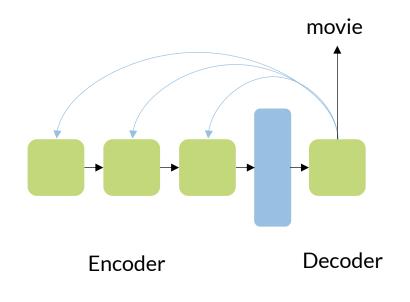
#### Creating a context representation of a sequence





## Decoding with Attention

#### Focussing on important subsets of the input



#### **Pointer Network**

[...] where v,  $W_s$  and  $W_t$  are trainable parameters and a decoder hidden state  $h_t$  is scored against an encoder hidden state  $\bar{h}_s$ . Pointer attention significantly decreases the output space and therefore reduces [...]

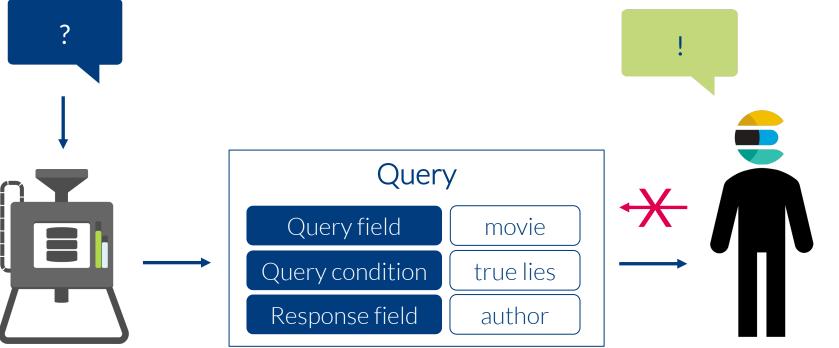
#### **Training Procedure**

For our benchmark, we implement PointerNet with a bidirectional twolayer LSTM as encoder and a unidirectional two-layer LSTM as decoder, where all recurrent layers consist of 100 units. [...]

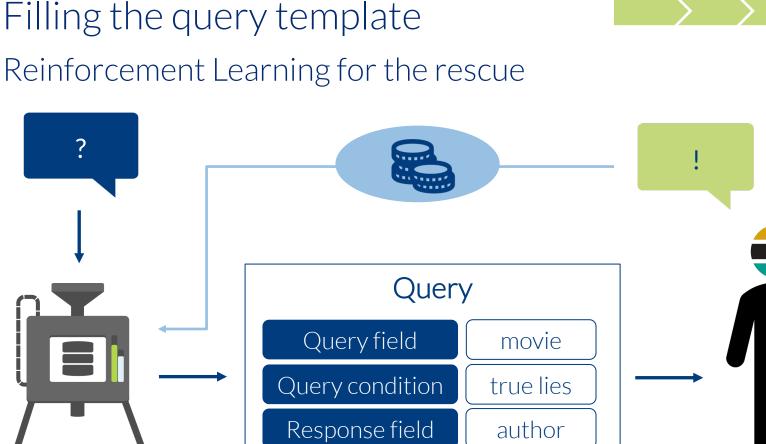




# Filling the query template Non-differentiability impedes end-to-end training

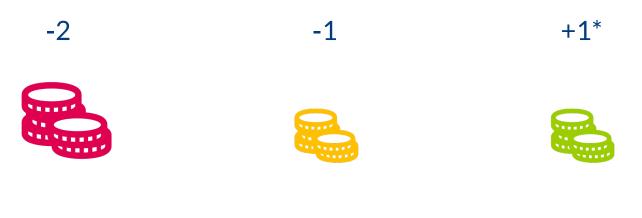








#### Rewards



#### invalid queries

valid queries incorrect results

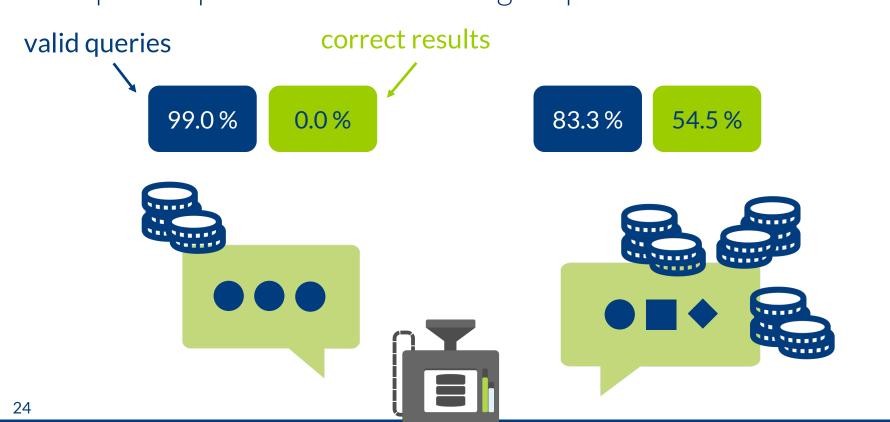
valid queries correct results



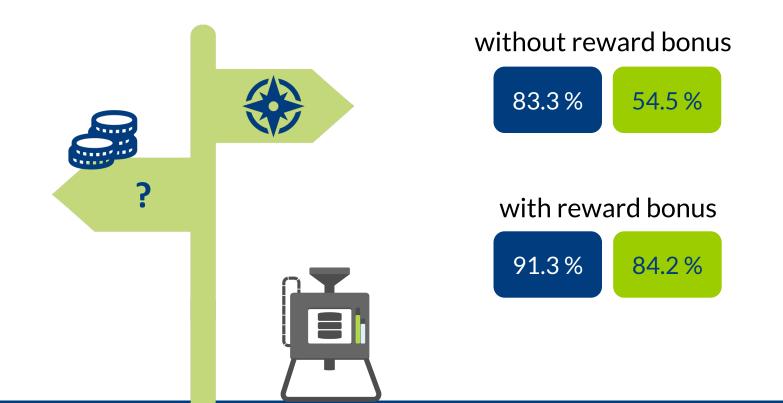
# Results



Design of the reward function matters Improved performance due to higher positive rewards



Design of the reward function matters Exploration boni improve performance



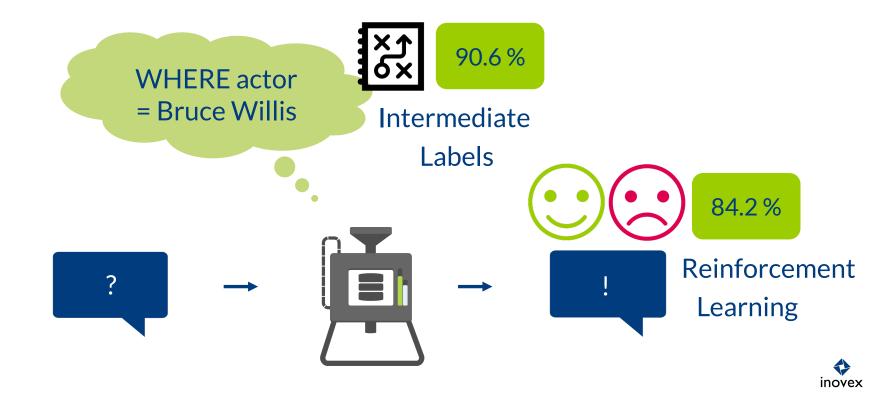


# Natural language is ambiguous Correct queries yield wrong results (~4%)





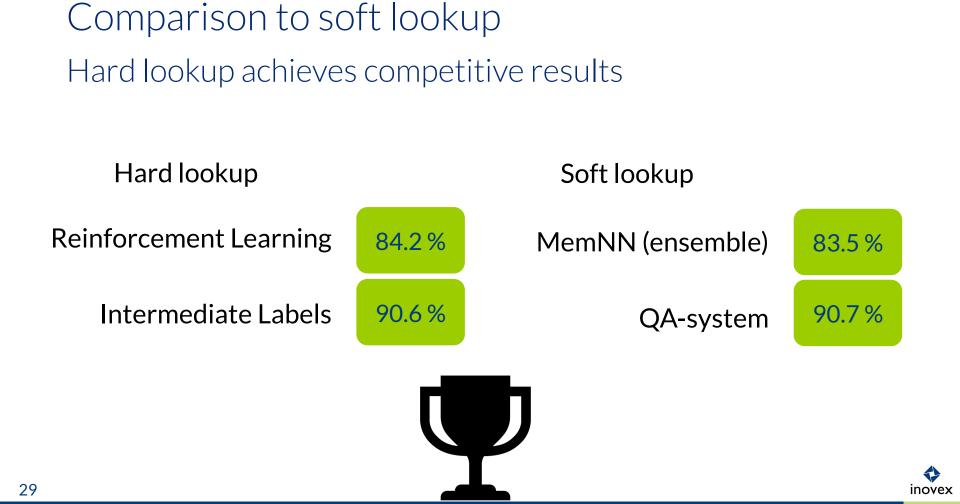
Comparison to supervised baseline Intermediate labels provide a better feedback signal



Comparison to supervised baseline Reinforcement learning requires a **LOT** of resources













- We applied a Seq2Seq approach with pointer attention to create database queries from natural language questions.
- Our model achieves end-to-end trainability due to the usage of policy-based Reinforcement Learning and thereby avoids costly intermediate labels.
- Furthermore, we overcome local optima through exploration induced by count-based reward boni.





> More complex questions & different corpora

Improve sample-efficiency of RL

Reduce latencies of database interaction





https://www.inovex.de/blog/

https://www.inovex.de/blog/seqpolicynet-nlp-elasticsearch/

http://www.aifb.kit.edu/images/d/d3/IAAI-19\_paper\_88.pdf



Thank you !

Sebastian Blank Data Scientist

inovex GmbH Ludwig-Erhard-Allee 6 76131 Karlsruhe

sebastian.blank@inovex.de

