

# Recent advances in Natural Language Processing

Ekaterina Kochmar



**What is NLP?**

**NLP tasks and  
recent  
advances**

**Is “genuine”  
understanding  
possible?**

What is Natural Language  
Processing?

# Why Natural Language Processing

— — —

- ❑ Because language is inherently very interesting

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- ❑ Because it's the primary means of communication



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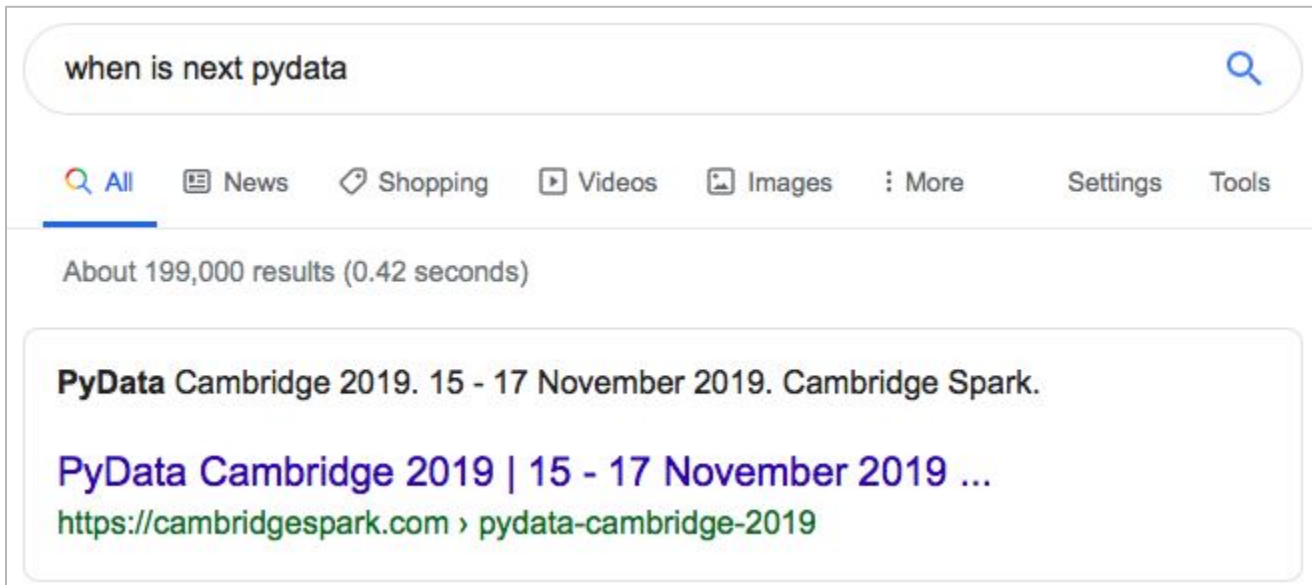


- ❑ Because it can help you achieve your goals in other domains (“downstream tasks”)

# Information Search

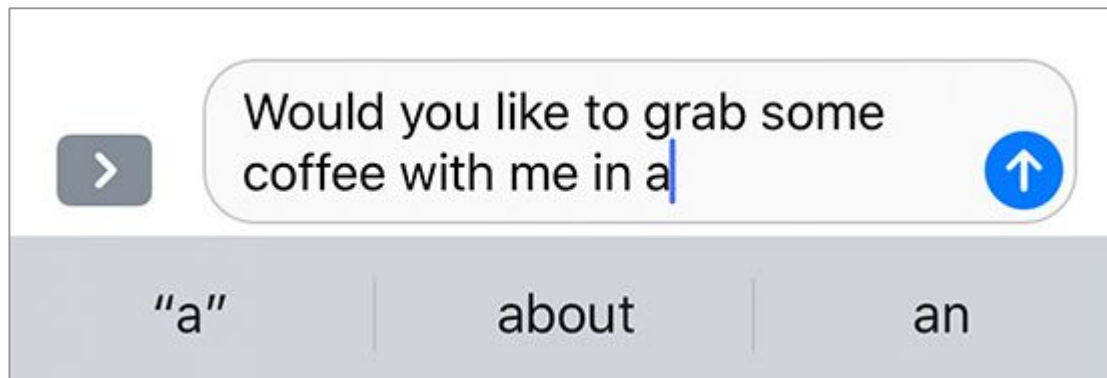
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- ❏ When you search for information on the web



# From predicting words ...

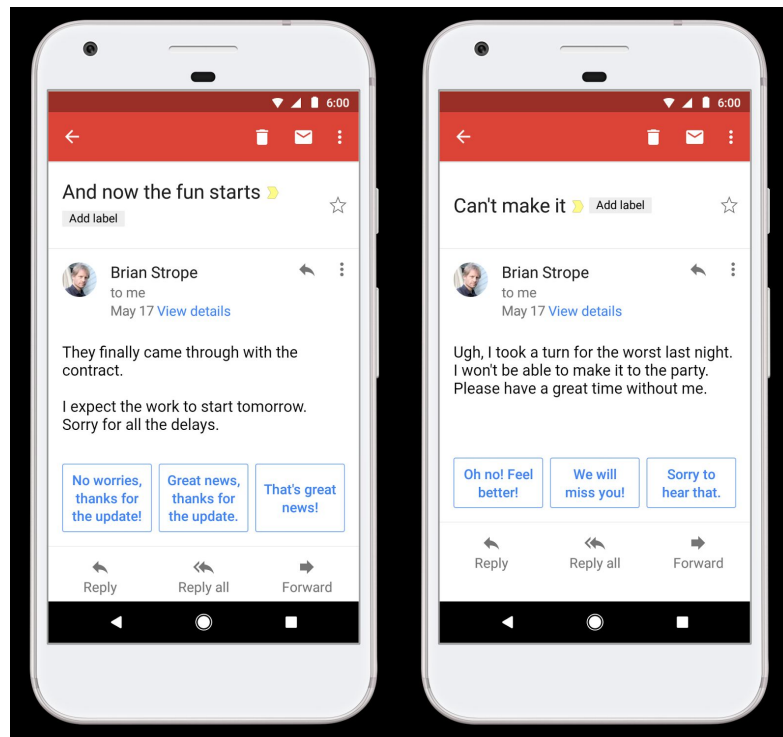
- ❑ Predictive keyboards have become a widely used feature on most phones
- ❑ It helps with speeding up typing text and autocorrecting



# ... to predicting whole conversations

Google's Smart Reply can now put together email responses for you

- ❑ Saves time and effort
- ❑ Helps avoid misspellings
- ❑ Often very accurate!



<https://blog.google/products/gmail/save-time-with-smart-reply-in-gmail/>

# Conversing with machines

— — —



<https://www.howtogeek.com/229308/26-actually-useful-things-you-can-do-with-siri/>

# Why NLP matters

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- ❑ Big tech companies use it
- ❑ A lot of support in Python community



How is this achieved?

# How does NLP help with these tasks?

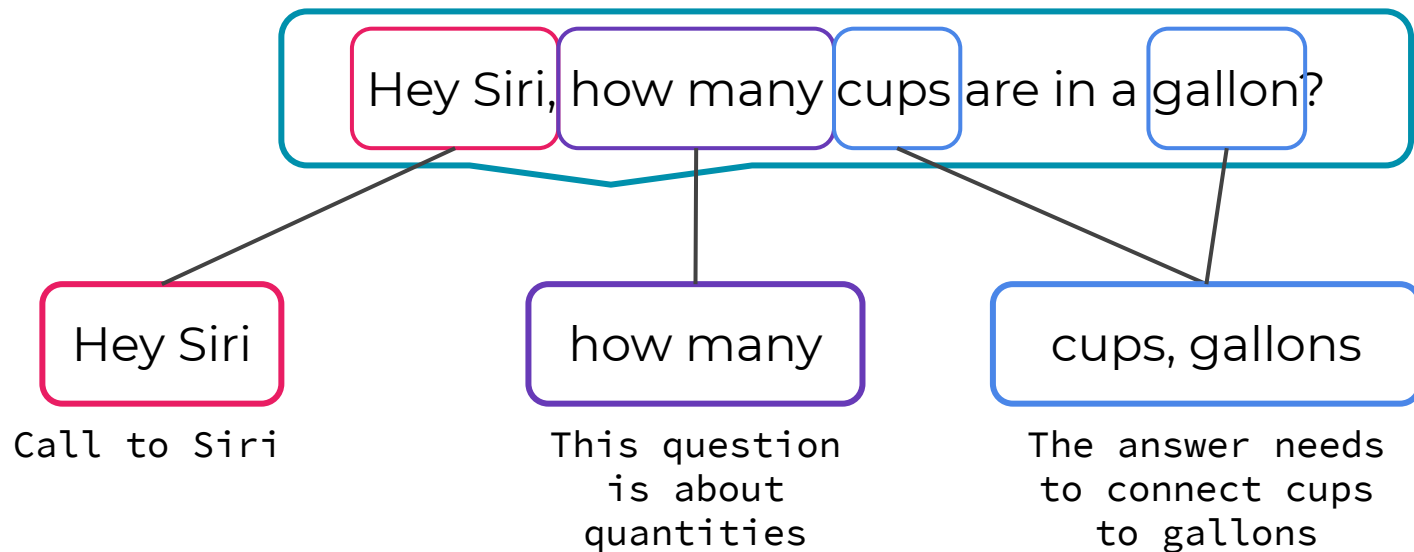
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- ❑ A combination of linguistic analysis tools and Machine Learning techniques

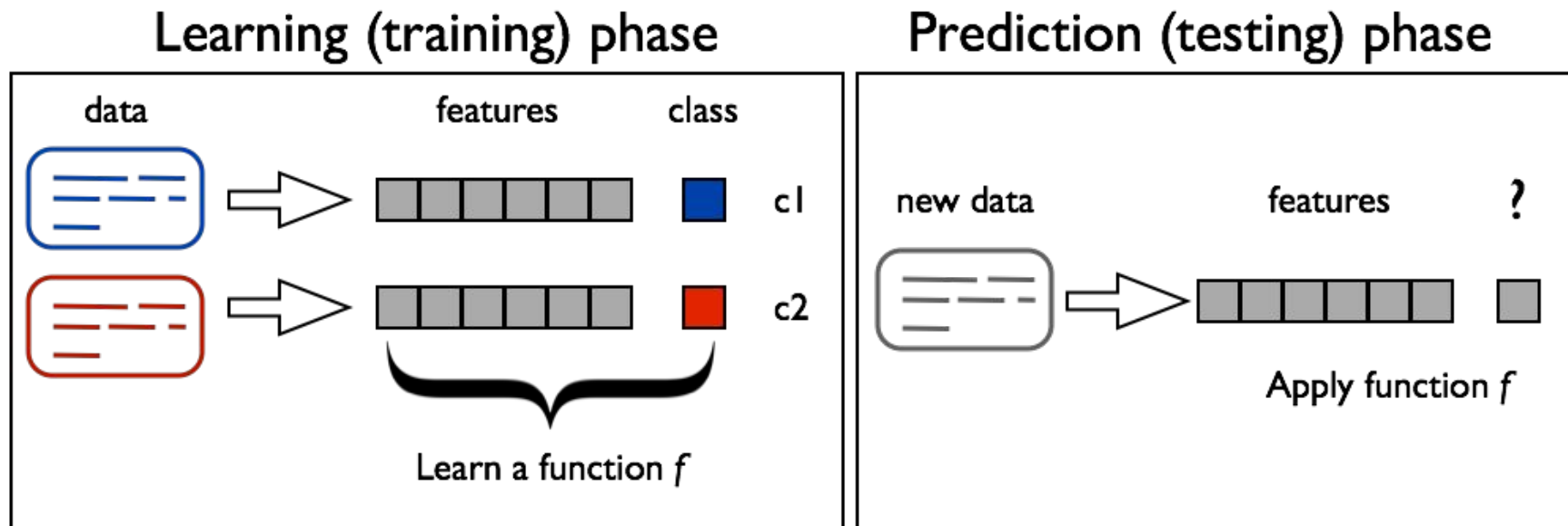


# Linguistic analysis

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# Machine Learning in a nutshell



# Machine Learning in NLP

- ❑ A lot can be achieved by learning patterns from data
- ❑ Language is creative but certain things are quite predictable: e.g. how many options are there to continue this phrase?

Would you like to grab some cof\_

- ❑ We can learn what's following based on the data for characters, words, and even whole dialogues!

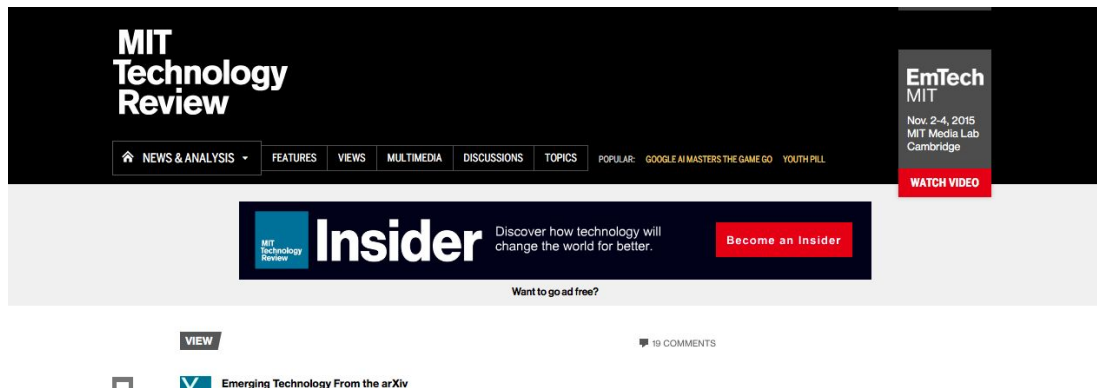
# Beyond learning patterns

— — —

- ❑ A number of things can't be learned on a pattern basis
- ❑ What does it mean for a machine to understand language?
  - ❑ Can a machine **understand** and reason about content: e.g., make conclusions, answer questions, show verbal reasoning abilities?
  - ❑ Can a machine **generate** free-form text?

# Can machines show such abilities?

GOOGLE MADE A CHATBOT  
THAT DEBATES THE MEANING  
OF LIFE



The image shows the top section of the MIT Technology Review website. The header is dark with the MIT Technology Review logo on the left. A navigation bar contains links for NEWS & ANALYSIS, FEATURES, VIEWS, MULTIMEDIA, DISCUSSIONS, and TOPICS. Below this is a banner for 'Insider' with the text 'Discover how technology will change the world for better.' and a 'Become an Insider' button. To the right, there is a section for 'EmTech MIT' with dates 'Nov. 2-4, 2015' and location 'MIT Media Lab Cambridge', along with a 'WATCH VIDEO' button.



Emerging Technology From the arXiv  
June 12, 2015

## Deep Learning Machine Beats Humans in IQ Test

Computers have never been good at answering the type of verbal reasoning questions found in IQ tests. Now a deep learning machine unveiled in China is changing that.

### CNN article:

**Document** The BBC producer allegedly struck by Jeremy Clarkson will not press charges against the “Top Gear” host, his lawyer said Friday. Clarkson, who hosted one of the most-watched television shows in the world, was dropped by the BBC Wednesday after an internal investigation by the British broadcaster found he had subjected producer Oisin Tymon “to an unprovoked physical and verbal attack.” ...

**Query** Producer **X** will not press charges against Jeremy Clarkson, his lawyer says.

**Answer** Oisin Tymon

# Has a human or a machine written this?

— — —

**1** “A shallow magnitude 4.7 earthquake was reported Monday morning five miles from Westwood, California, according to the U.S. Geological Survey. The temblor occurred at 6:25 a.m. Pacific time at a depth of 5.0 miles.”

**2** “Apple’s holiday earnings for 2014 were record shattering. The company earned an \$18 billion profit on \$74.6 billion in revenue. That profit was more than any company had ever earned in history.”

- 1 “A shallow magnitude 4.7 earthquake was reported Monday morning five miles from Westwood, California, according to the U.S. Geological Survey. The temblor occurred at 6:25 a.m. Pacific time at a depth of 5.0 miles.”

Human

✓ Computer

This excerpt of an initial report about a March 2014 earthquake was written by an algorithm.

- 2 “Apple’s holiday earnings for 2014 were record shattering. The company earned an \$18 billion profit on \$74.6 billion in revenue. That profit was more than any company had ever earned in history.”

✓ Human

This was an excerpt from an article on [Business Insider](#).

Computer

# How do machines “understand” language?

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Mikolov et al. (2013) showed that a machine can reason like a human, e.g. it can solve **analogy tasks**

Man is to woman as  
king is to \_\_\_\_\_ ?

We may be thinking along the following lines:

$\text{meaning}(\textit{king}) - \text{meaning}(\textit{man}) + \text{meaning}(\textit{woman}) = \text{what we are looking for}$

# How do machines “understand” language?

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- ❑ To machines, text is a sequence of symbols
- ❑ What machines are good with is numbers
- ❑ Let's build a numerical representation of a word that captures its meaning
- ❑ Imagine we can represent word meaning using a vector
- ❑ Then we can apply all sorts of operations:
  - ❑ Interpret similarity as distance in vector space
  - ❑ Find the word we are looking for using simple operations on vectors

# Analogy task solved with vectors

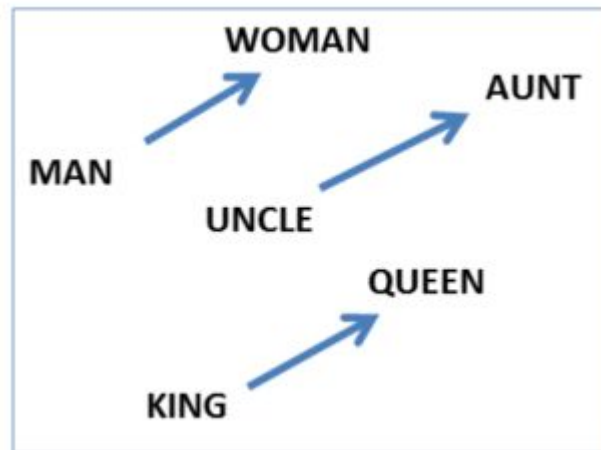
— — —

Here, we equate

```
meaning(king)  
- meaning(man)  
+ meaning(woman)  
= meaning(queen)
```

to operations on vectors

```
vector(king)  
- vector(man)  
+ vector(woman)  
= vector(queen)
```



# How do we learn such a vector representation?

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Earlier approaches relied on **distributional semantics**

*You shall know a word by the company it keeps*

(Firth, J. R. 1957)

queen

{  
royal  
gives speeches  
crown  
**female**  
}

king

{  
royal  
gives speeches  
crown  
**male**  
}

# Learn the properties from context

— — —

Her Majesty the **Queen**

The **Queen**'s speech during the State Visit to...

Buckingham Palace is the **Queen**'s official London residence...

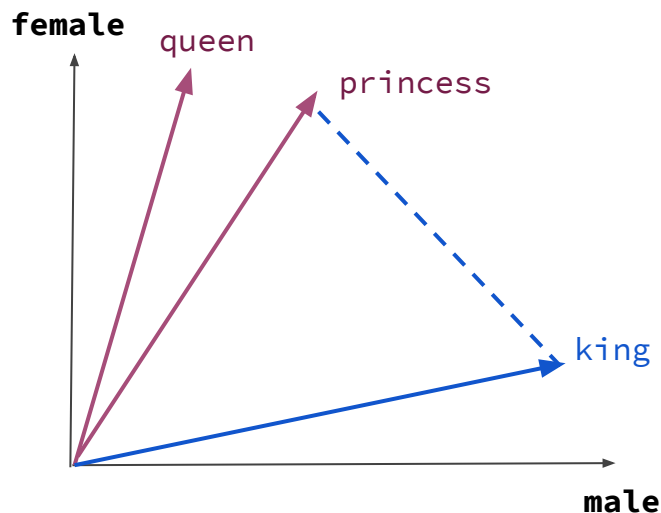
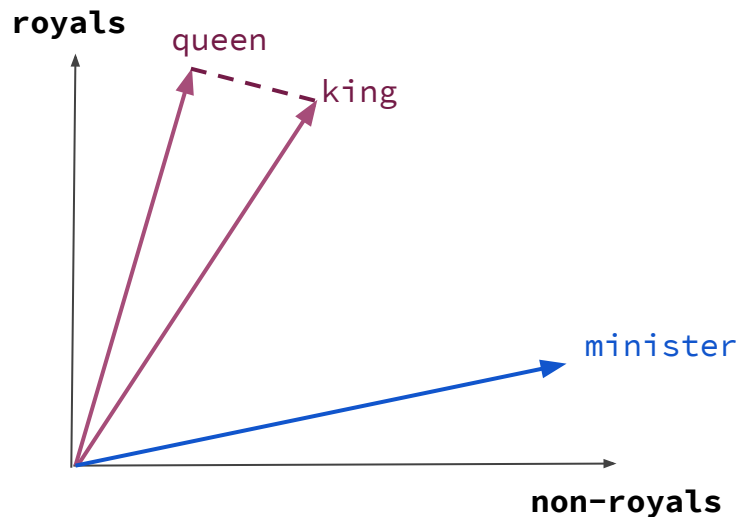
The Crown of **Queen** Elizabeth

The **Queen** Mother

	she	he	crown	palace
queen	55	2	32	29

# Build vectors based on these context properties

— — —



Note that this is extended to a multi-dimensional space, for as many dimensions as there are properties that define word meaning

# High quality pre-trained word vectors

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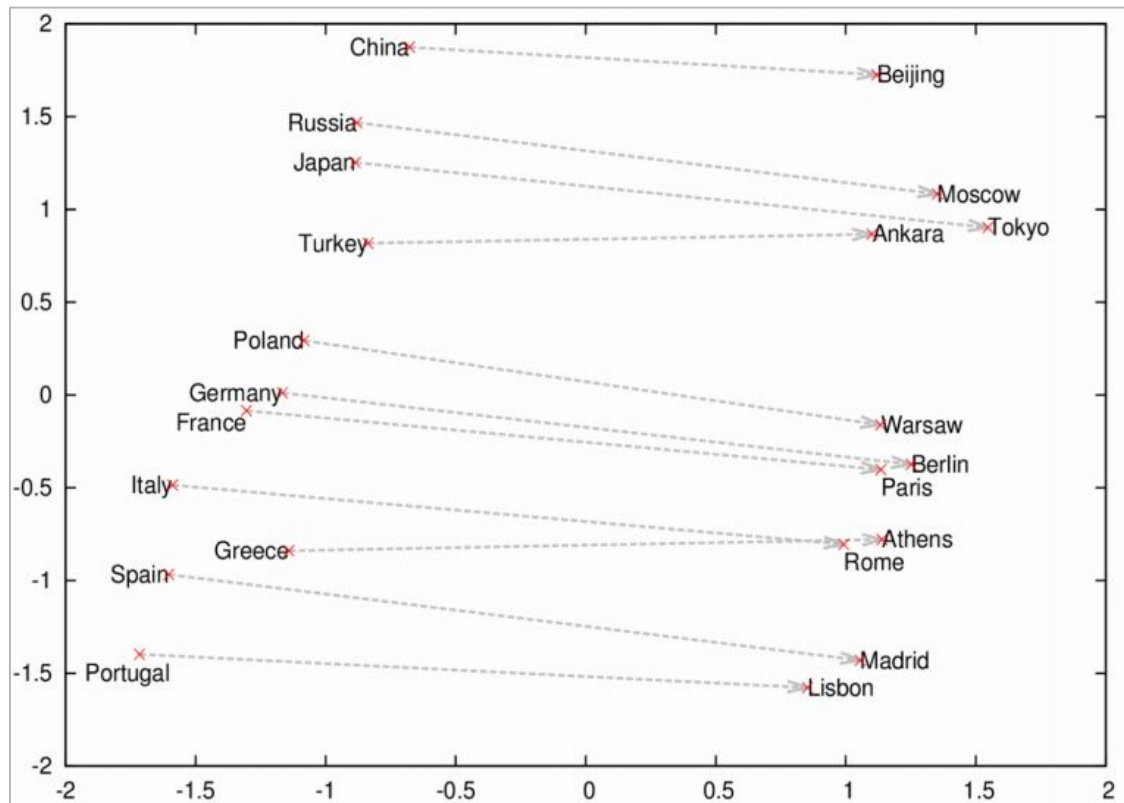
- ❑ **Word embeddings** – word vectors trained on large amounts of data such that:
  - ❑ Distance between vectors representing *similar* meaning is *minimised*
  - ❑ Distance between vectors representing *dissimilar* meaning *maximised*
- ❑ Word2vec (Mikolov et al., 2013)
  - ❑ <https://code.google.com/archive/p/word2vec/>
- ❑ GloVe (Pennington et al., 2014)
  - ❑ <https://nlp.stanford.edu/projects/glove/>

# Further analogy tasks

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The analogy tasks have been extended to a number of other scenarios:

- ❑ Famous personalities - field (Einstein - scientist)
- ❑ Country - food (Japan - sushi)
- ❑ Country - capital (Russia - Moscow)



# Easy to implement with python and spaCy

```
text = u'Amsterdam Ankara Athens Australia Barcelona Beijing Berlin Brazil Chicago China '  
text += u'France Germany Greece Italy Japan Lisbon London Madrid Moscow Paris '  
text += u'Poland Portugal Rome Russia Spain Switzerland Tokyo Turkey Venice Warsaw '  
words = nlp(text)
```

```
for word in words:  
    print(word)  
    print (word.vector[:5])
```

```
Amsterdam  
[ 0.41373 -0.095219  0.15888 -0.51876  0.41066 ]  
Ankara  
[ 0.10742 -0.39872  0.41782  0.80667 -0.022942]  
Athens  
[ 0.21507  0.080389  0.25134 -0.3766  0.49439 ]  
Australia  
[-0.19401  0.44029  0.18968 -0.52768  0.70956]
```

**nlp** - spaCy's NLP pipeline that gives you access to word vectors

# Easy to implement with python and spaCy

```
def analogy_task(country):
    question = u"Russia is to Moscow as " + country
    text = nlp(question)
    source1 = text[0]
    source2 = text[3]
    target1 = text[5]

    max_sim = 0.0
    target2 = "N/A"

    target2_vector = source2.vector - source1.vector + target1.vector

    for word in words:
        if not (str(word) == str(target1) or str(word) == str(source1) or str(word) == str(source2)):
            current_sim = cosine(target2_vector, word.vector)
            if current_sim >= max_sim:
                max_sim = current_sim
                target2 = word

    print(question)
    print("\t is to " + str(target2))

countries = ["China", "France", "Germany", "Greece", "Italy",
             "Japan", "Poland", "Portugal", "Spain", "Turkey"]

for country in countries:
    analogy_task(country)
```

```
Russia is to Moscow as China
                        is to Beijing
Russia is to Moscow as France
                        is to Paris
Russia is to Moscow as Germany
                        is to Berlin
Russia is to Moscow as Greece
                        is to Athens
Russia is to Moscow as Italy
                        is to Rome
Russia is to Moscow as Japan
                        is to Tokyo
Russia is to Moscow as Poland
                        is to Warsaw
Russia is to Moscow as Portugal
                        is to Lisbon
Russia is to Moscow as Spain
                        is to Barcelona
Russia is to Moscow as Turkey
                        is to Ankara
```

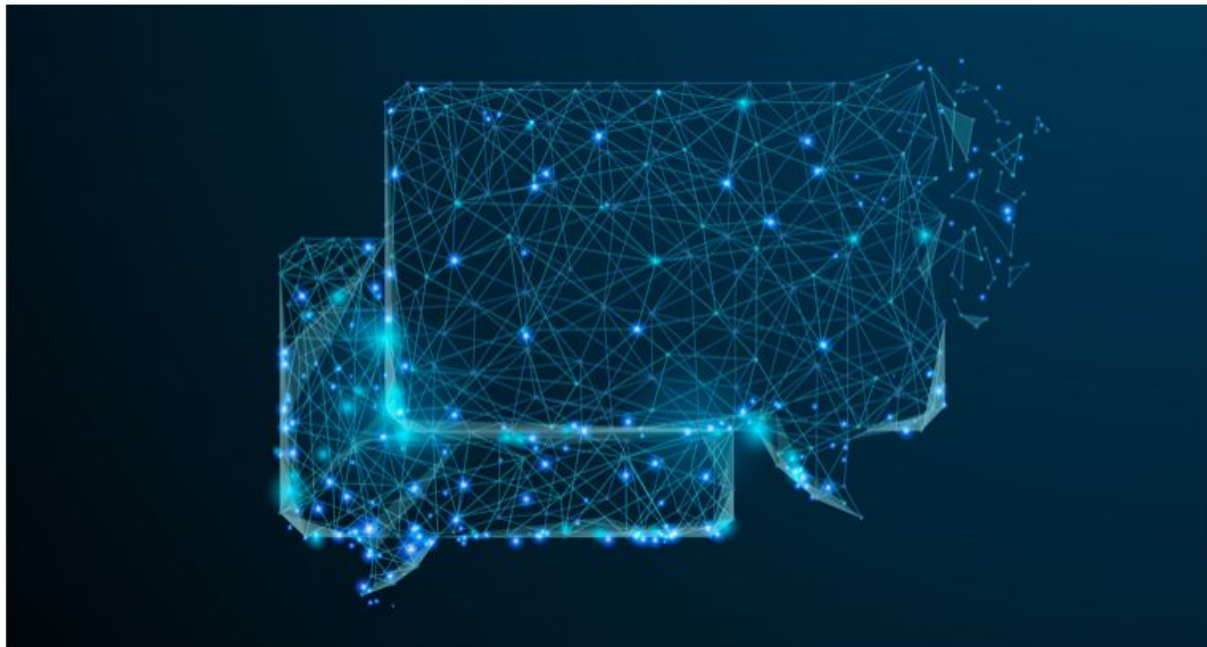
Further advances in language  
understanding

# Machines learn language better by using a deep understanding of words



Devin Coldewey @techcrunch / 6:53 pm BST • June 15, 2018

Comment



<https://techcrunch.com/2018/06/15/machines-learn-language-better-by-using-a-deep-understanding-of-words/>

# Challenges for word vector representations

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- ❑ Word embeddings incorporate previous knowledge at the first step (first layer of the network) only -> “shallow”
- ❑ Challenges:
  - ❑ Similar words with opposite meaning often used in similar contexts, so may result in very similar vectors (e.g., “hot” and “cold”)
  - ❑ One still needs to derive the meaning of sentences and texts from word vector building blocks
  - ❑ Ambiguous words get single representation



# Can one do better?

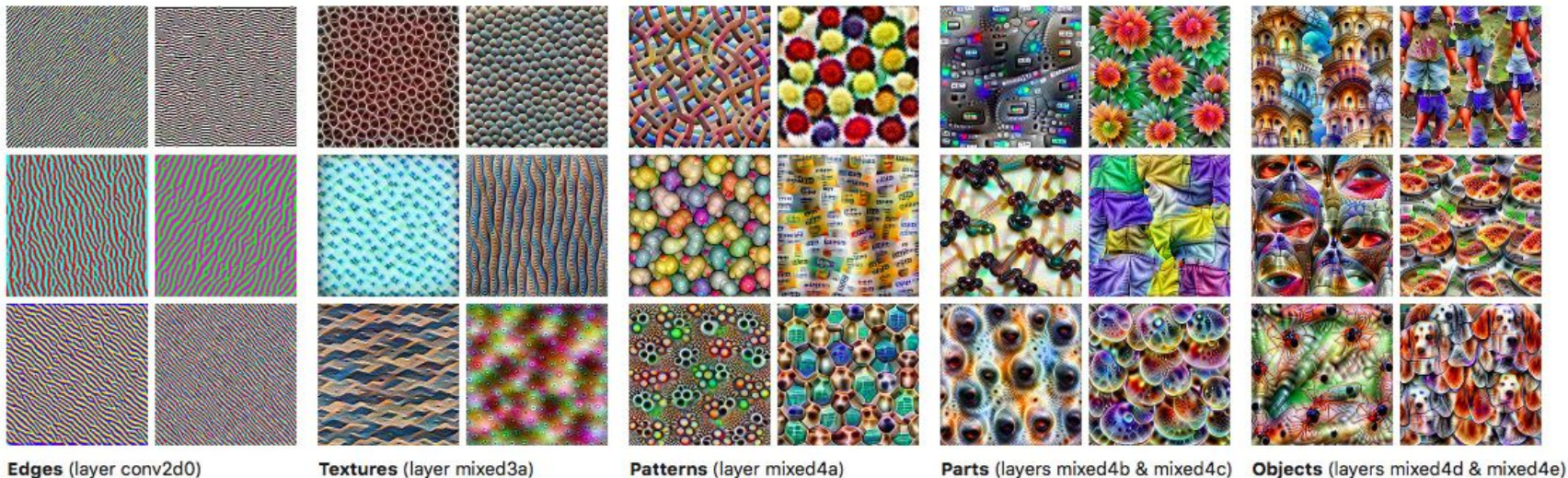
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- ❑ From “shallow” models to deep pre-trained language models
- ❑ Rather than initialising the first layer only, train the whole model hierarchically
- ❑ This move has been called the “ImageNet moment for NLP”
- ❑ That means having a very powerful pretrained model that captures peculiarities of meaning and can be easily fine-tuned to any new data (called *transfer learning*)

# Can one do better?

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Learning features that are likely to generalise beyond a particular dataset to new tasks in the problem domain



# How to train a better model?

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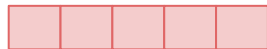
- ❑ Take a *sufficiently large dataset* (in order of millions of training examples)
- ❑ Define a task that is *representative of the problem space*
- ❑ **Language modelling** – predicting what comes next – ticks all the boxes

The service was poor, but the food was \_\_\_\_

# Training with a language model objective

— — —

Royal visit by the **Queen** and \_\_\_\_



**Queen**

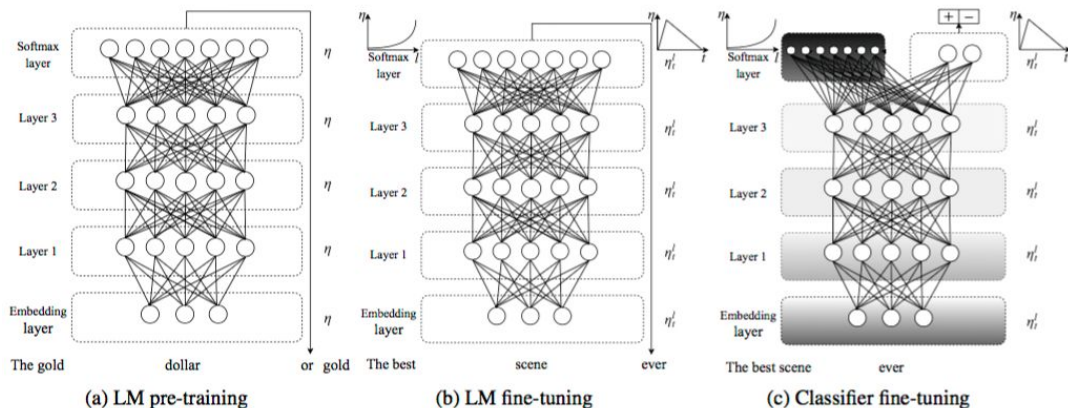
I moved my **queen** to \_\_\_\_



**queen**

# Example: ULMFiT

- Pre-train with a language model objective
- Fine-tune on any task of your choice



# Pre-trained models

— — —

- ❑ Universal Language Model Fine-Tuning (ULMFiT)
  - ❑ <http://nlp.fast.ai/category/classification.html>
- ❑ ELMo deep contextualised word representations
  - ❑ <https://allennlp.org/elmo>
- ❑ OpenAI Transformer model
  - ❑ <https://github.com/openai/finetune-transformer-lm>
- ❑ Deep Bidirectional Transformers (BERT)
  - ❑ <https://github.com/google-research/bert>

What does it mean for a  
machine to “understand”?

# The Great A.I. Awakening

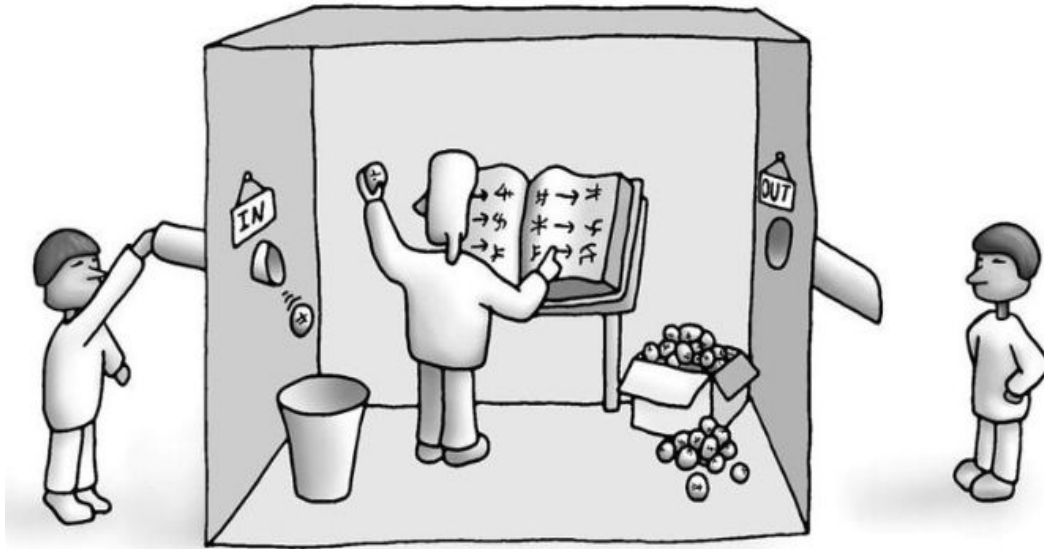
How Google used artificial intelligence to transform Google Translate, one of its more popular services — and how machine learning is poised to reinvent computing itself.

BY GIDEON LEWIS-KRAUS DEC. 14, 2016



# Chinese Room Thought Experiment

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source: wikicommons

- ❑ Proposed by John Searle (1980)
- ❑ It is perfectly possible to construct a machine that learns to take the correct sequence of actions to solve the task without “genuine” understanding

# What does it mean to genuinely understand for human?

— — —

- ❑ Most human beings understand what “water” means and will be able to describe most of its properties
- ❑ Unfortunately, many don’t understand that water is electrical conductor
- ❑ Does this constitute genuine understanding of the concept of “water”?


# What does it mean to genuinely understand for a machine?

Who did IBM's Deep Blue system defeat?

About 7,470,000 results (0.75 seconds)

## Kasparov

The victor **was** even more unusual: **IBM** supercomputer, **Deep Blue**. In **defeating** Kasparov on May 11 1997, **Deep Blue made** history as the first computer to **beat** a world champion in a six-game match under standard time controls. 11 May 2017



[Twenty years on from Deep Blue vs Kasparov: how a chess ...](#)  
[theconversation.com > twenty-years-on-from-deep-blue-vs-kasparov-how-a-...](#)

when?

About 16,730,000,000 results (0.80 seconds)

### Dictionary

Search for a word

**when**  
/wen/

**adverb**

at what time.  
"when did you last see him?"

**adverb**

at or on which (referring to a time or circumstance).  
"Saturday is the day when I get my hair done"

**conjunction**

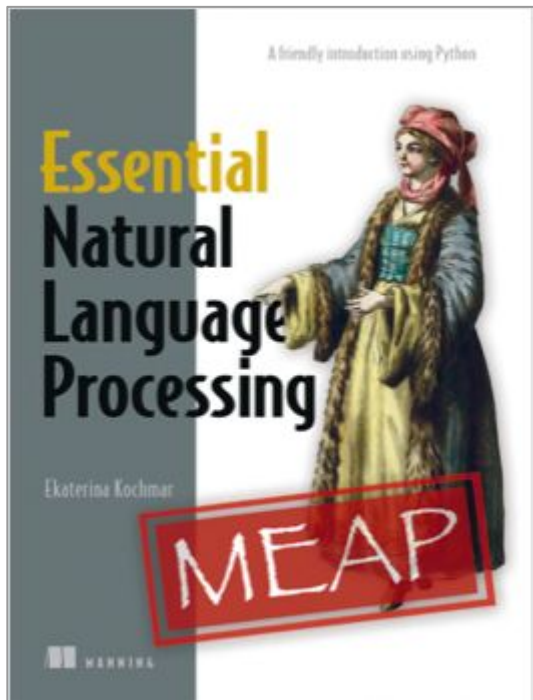
1. at or during the time that.  
"I loved maths when I was at school"
2. after which; and just then (implying suddenness).  
"he had just drifted off to sleep when the phone rang"

# Conclusion

— — —

- ❑ The notion of “genuine” understanding and intelligence is a fuzzy one
- ❑ Rather than asking for comprehensive “genuine” understanding define specific tasks the machine can excel at
- ❑ It is important to claim credit for successes in the field, as well as take ownership for shortcomings

# If you would like to learn more about NLP



- ❑ A friendly practical introduction to NLP
- ❑ Covers a range of topics from information search to sentiment analysis to summarisation
- ❑ Use **ctwpycbg19** to get a 40% discount
- ❑ Free e-book copies available (first 5 requests) – let me know

Thank you!

