



# Transfer Learning for Name Entity Linking with Deep Learning

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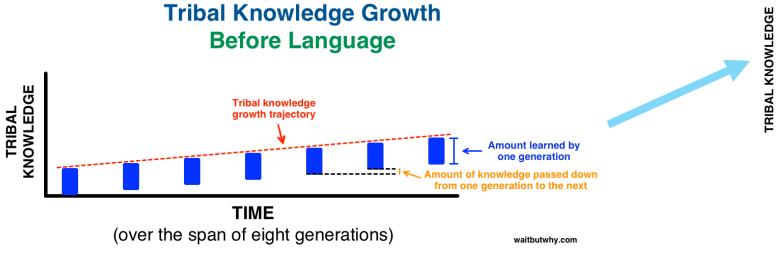
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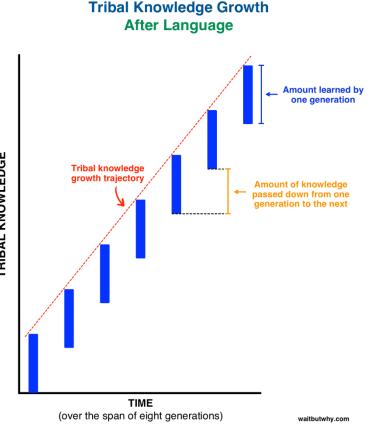
## Introduction Transfer Learning



Instead of designing a neural network from scratch:

- Use pretrained network and apply it's weights and biases to a different domain
- Adapt the network for the specific target
- → Advantage (here compared to the invention of human language): Transfer learned weights and biases from one system to another to improve in terms of progress and efficiency





Robin Otto - Master Thesis



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#### Motivation

#### Named Entity Linking and Transfer Learning in the Legal Domain



1.

#### Why Legal Domain?

Engineers, lawyers etc. rely on its content

#### Why Transfer Learning?

- 2.
- Scarcity of data for specific use cases
  - → Nearly impossible to implement a deep network from scratch
- Use of successful, available networks

#### Why Named Entity Linking?

- Wording of legal documents often unclear and confusing for people from other domains
- 3.
- Many stakeholders need to understand keywords from legal documents
  - → Link keywords to their definitions for an improved reading experience



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## Important Concepts

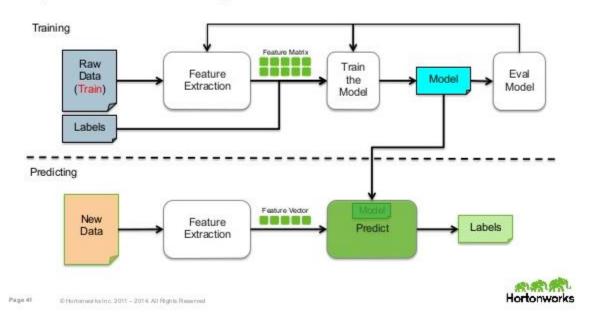
#### Supervised Learning



Labeled and preprocessed training set

Known inputs and outputs

#### Supervised Learning Workflow



Network determines function to map input to output

## Important Concepts

#### Named Entity Linking



- Named Entity Recognition (NER)
  - Subtask of information extraction
  - Extract and cluster named entities from text into categories

- Named Entity Disambiguation (NED)
  - Connect a named-entity occurrence to a data-/knowledge-base
  - Mostly Wikipedia-derived (DBpedia)

#### Named entity recognition (I)

 Detect names of persons, places, organisations





Nokia

This project is partially funded under the ICT Policy Support Programme (ICT PSP) as part of the Competitiveness and innovation Framework Programme by the European Community http://ec.europa.eu/sct\_psy.





Finland Nokia\_E72 E75 US\_(disambiguation)
Medical\_ultrasonography
United\_States
United\_States\_dollar

Nokia E72 and E75 smartphones have many features in common, but being sold by U.S. carriers is to one of them. That doesn't mean they won't work in the U.S., though. In fact, because they can be unlocked, both will operate on U.S. carriers if you install the selected carrier's SIM card and purchase an unlock code from the manufacturer. While the E72 was produced specifically for T-Mobile, the E75 is not

Nokia\_E72 E72 T-Mobile\_(Poland)
T-Mobile\_USA
T-Mobile\_UK
T-Mobile

Subscriber\_identity module



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#### Research Questions

#### Transfer Learning & Neural Net Comparison



1.

Is the use of Transfer Learning beneficial in the EU Regulation domain?

- Would a network with randomly initialized weights be better?
- Could other approaches lead to better results?

If so, which technique of Transfer Learning suits best?

- 2.
- Use the pretrained network's weights, append new trainable layers

Use the pretrained network's weights, replace last layer

 Use network weights as initial weights, train whole network, replace last layer

What algorithm should be used for Transfer Learning?

3.

Comparison needed with predefined criteria



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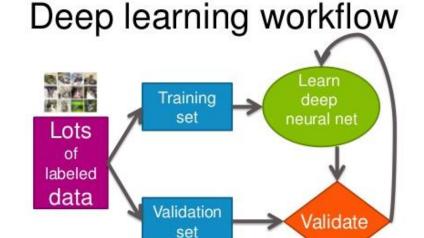
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## Approach

#### **Transfer Learning**

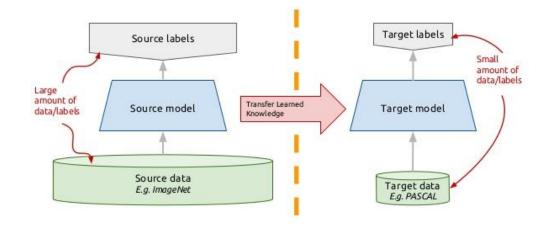
sebis

- Compare different pre-trained networks according to different criteria
  - E.g. based on speed, accuracy, etc.
  - Rank networks respectively
- Choose dedicated algorithm for the integration
- Big datasets used for transfer learning
  - Wikilinks
  - AIDA-CoNLL
- Apply Transfer Learning:
   Adapt pretrained algorithm to specific needs for private (smaller, unlabeled) datasets
- Here: Datasets from the legal domain that are going to be annotated by a bot. Topic: EU Regulation
- Test network and interpret results



Adjust parameters, network architecture...

#### Transfer learning: idea



#### **Dataset annotation**



#### REGULATION (EU) 2017/1938 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL

of 25 October 2017

concerning measures to safeguard the security of gas supply and repealing Regulation (EU) No 994/2010

(Text with EEA relevance)

#### THE EUROPEAN PARLIAMENT AND THE COUNCIL OF THE EUROPEAN UNION.

Having regard to the Treaty on the Functioning of the European Union, and in particular Article 194(7) thereof,

Having regard to the proposal from the European Commission,

After transmission of the draft legislative act to the national parliaments,

Having regard to the opinion of the European Economic and Social Committee (1),

After consulting the Committee of the Regions,

Acting in accordance with the ordinary legislative procedure (2),

#### Whereas:

- (1) Natural gas (gas) remains an essential component of the energy supply of the Union. A large proportion of such gas is imported into the Union from third countries.
- (2) A major disruption of gas supply can affect all Member States, the Union and Contracting Parties to the Treaty establishing the Energy Community, signed in Athens on 25 October 2005. It can also severely damage the Union economy and can have a major social impact, in particular on vulnerable groups of customers.
- This Regulation aims to ensure that all the necessary measures are taken to safeguard an uninterrupted supply of gas throughout the Union, in particular to protected customers in the event of difficult climatic conditions or disruptions of the gas supply. Those objectives should be achieved prough the most cost-effective measures and in such a way that gas markets are not distorted.
- Union law, in particular Directive 2009/72/EC of the European Parliament and of the Council (2), Directive 2009/73/EC of the European Parliament and of the Council (2), Regulation (EC) No 713/2009 of the European Parliament and of the Council (3), Regulation (EC) No 715/2009 of the European Parliament and of the Council (3), Regulation (EU)No 994/2010 of the European Parliament and of the Council (3), has already had a significant positive impact on the security of gas supply in the Union, both in terms of preparation and mitigation. Member States are better prepared to face a supply crisis now that they are required to establish preventive action plans and emergency plans and they are better protected now that they have to meet a number of obligations regarding infrastructure capacity and gas supply. However, the Commission's report on the implementation of Regulation (EU) No 994/2010 of October 2014 highlighted areas in which improvements to that Regulation could further bolster the security of gas supply in the Union.

Article 2

#### Demnitions

For the purposes

- 'security' means security as defined in point 32 of Article 2 of Directive 2009/73/EC;
- (2) 'customer' means customer as defined in point 24 of Article 2 of Directive 2009/73/EC;
- (3) 'household customer' means household customer as defined in point 25 of Article 2 of Directive 2009/73/EC;
- (4) 'essential social service' means a service related to healthcare, essential social care, emergency, security, education or public administration,



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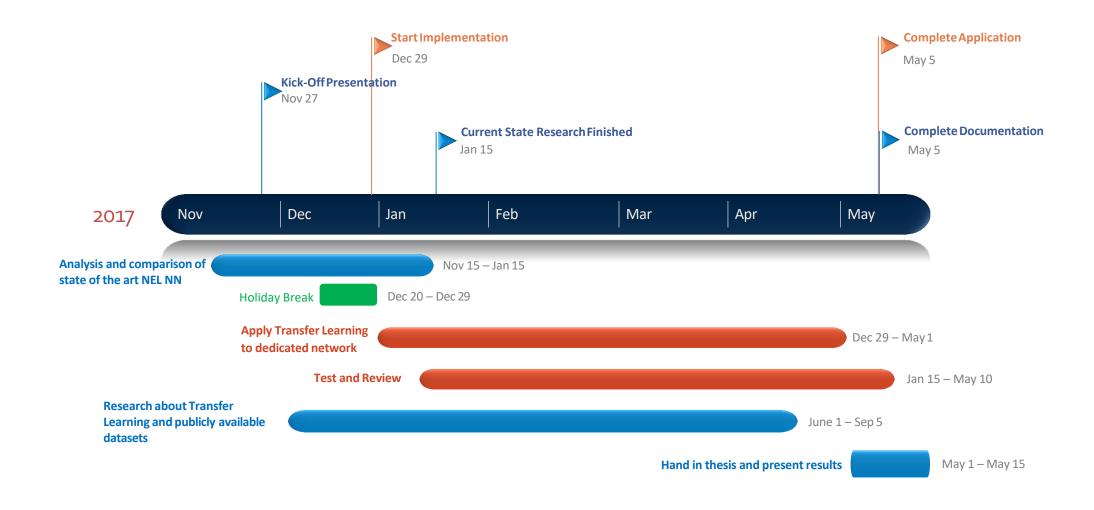
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#### Literature



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