

Natural Language Processing in Industry

Successes and Challenges

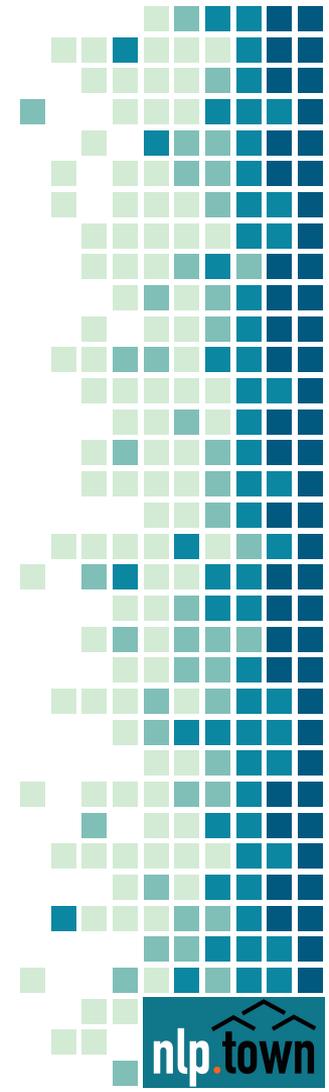
Yves Peirsman, NLP Town

NLP Town

We provide guidance to the NLP domain to companies that would like to develop their AI software in-house.

We develop software and train NLP models for challenging or domain-specific applications.

We bridge the gap between state-of-the-art NLP research and innovative industry applications.



Building an NLP Community

Meetups

4 times every year we organize the Belgium NLP Meetup



Hackathon

Earlier this year we co-organized the #NLP4Gov hackathon together with the Flemish Government.



Named Entity Recognition

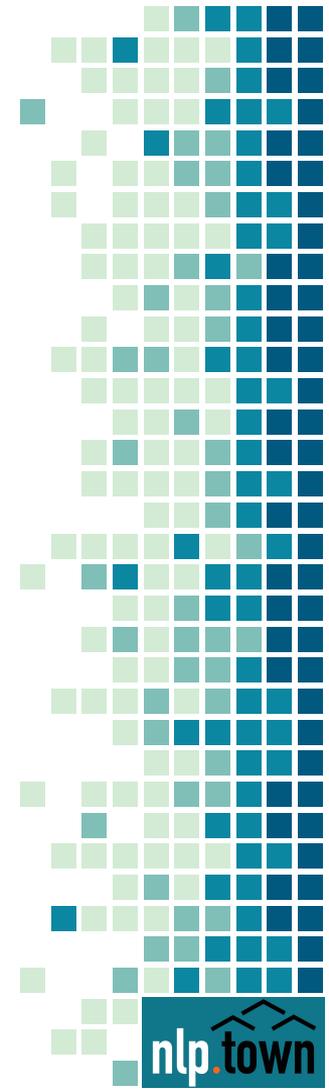
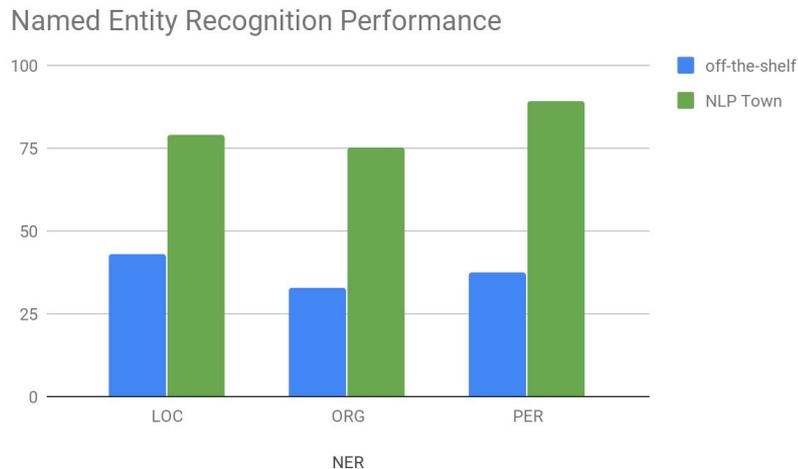
- Collaboration with a Dutch media company
- NER: identification of people, locations, organizations
- Specific domain: Dutch financial news

Tesla **ORG** founder Elon Musk **PERSON** must resign from his position as chairman of the board of directors within 45 days **DATE** .

Tesla **PER** -oprichter Elon Musk **PER** moet binnen de 45 dagen zijn functie als voorzitter van de raad van bestuur opgeven.

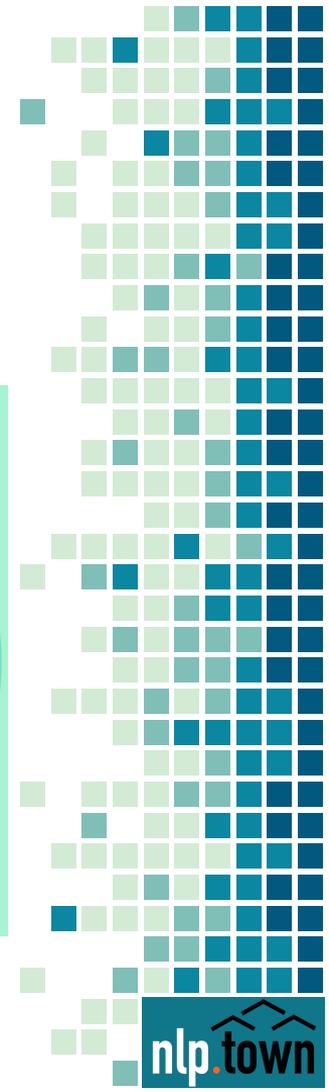
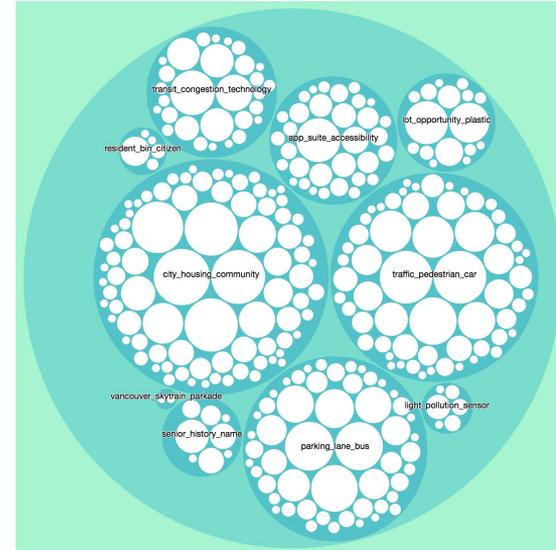
Named Entity Recognition

- Start from a pre-trained solution,
- Collect a large set of news articles automatically,
- Label a small set of financial articles manually.



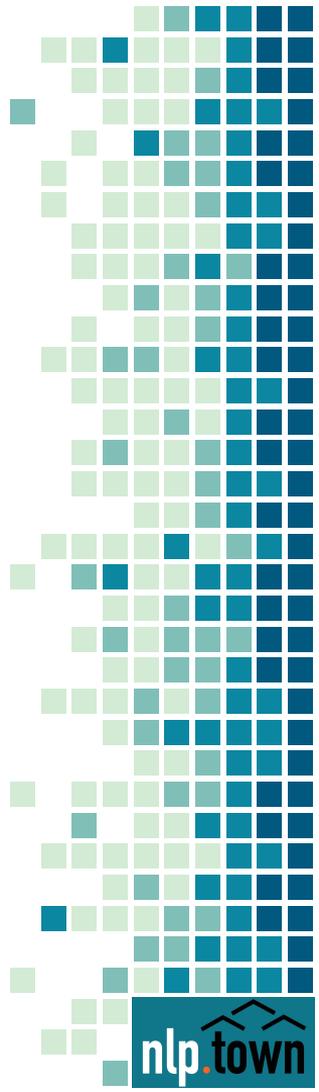
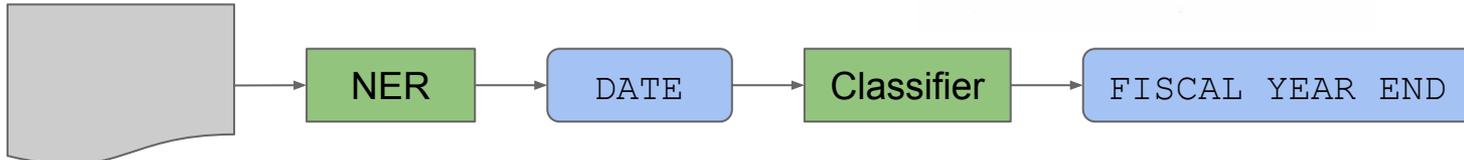
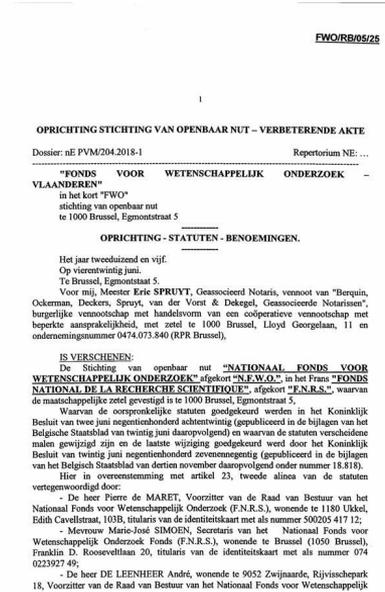
Text exploration

- Explore messages people send to their city council
- No labelled data
- Identification and clustering of similar messages
- Clustering does not need labelled data



Document parsing

- Collaboration with FEDNOT
- Parsing of founding deeds
- Combination of named entity recognition + classification



Challenges

Great expectations

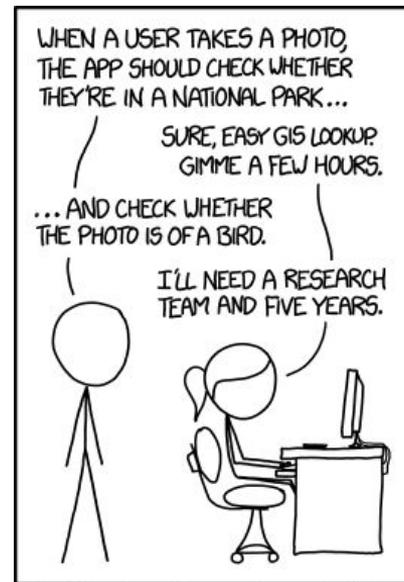
- AI hype has overblown expectations.
- Things that sound easy may be difficult and vice versa.

No one size fits all

- NLP models are language and domain-specific.
- Most resources/research are for English only.

Lack of data

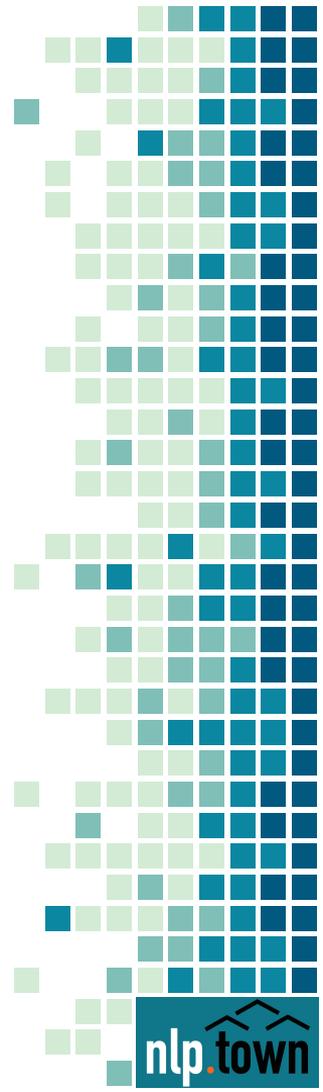
- For most tasks there is a lack of labelled data.



IN CS, IT CAN BE HARD TO EXPLAIN THE DIFFERENCE BETWEEN THE EASY AND THE VIRTUALLY IMPOSSIBLE.



BIG DATA BIG DATA BIG DATA BIG DATA BIG DATA



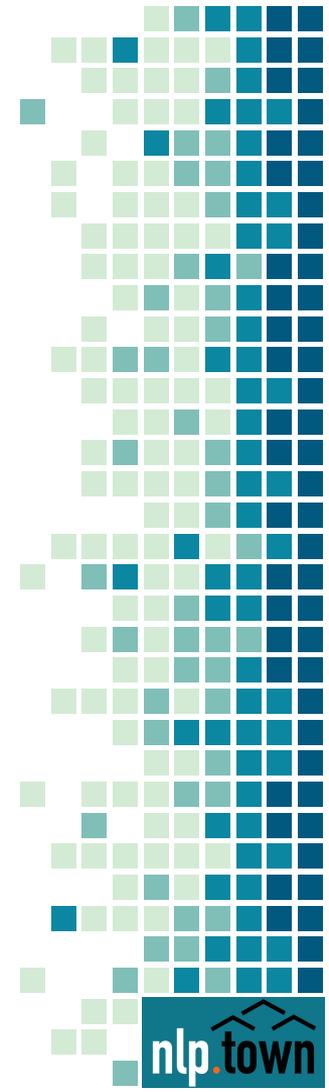
Data labelling

The problem with labelling

- Labelling training data is time-consuming and expensive.
- It is hard to label consistently.
- You may need several iterations you get your labels right.

We would like to reduce the labelling effort

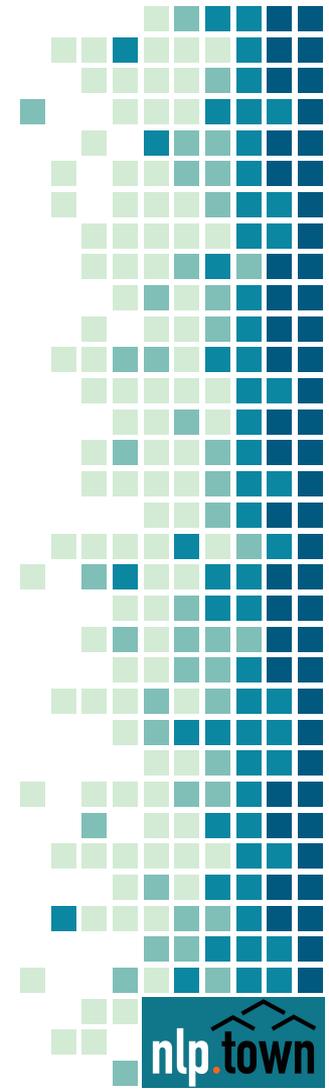
- Distant supervision
- Active learning
- Transfer learning



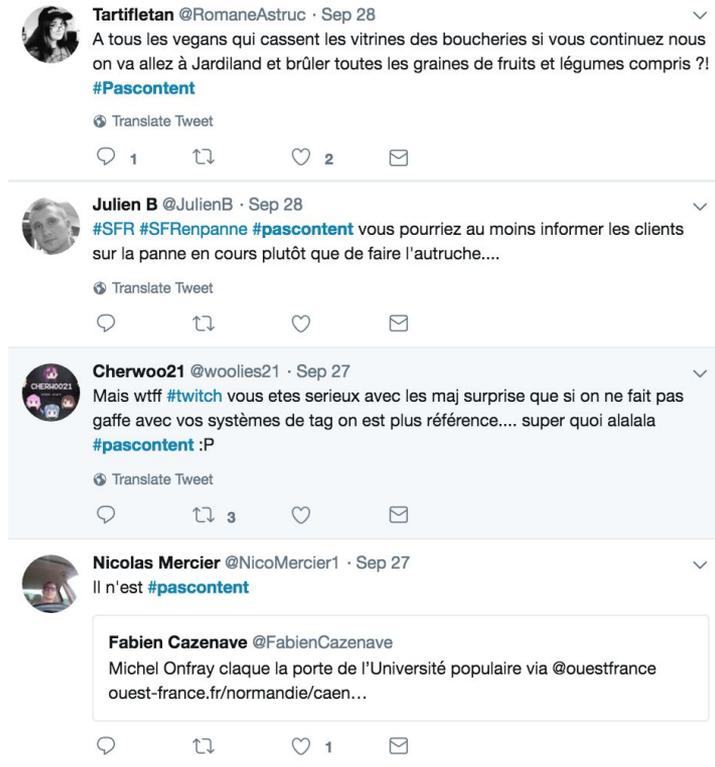
Distant supervision

Distant supervision automatically creates labelled data by relying on external knowledge.

- Entities in documents can be labelled on the basis of their metadata
- Semantic relations can be collected from databases such as Freebase
- Tweets can be labelled with sentiment on the basis of their hashtags and smileys.



Distant supervision



Tartifletan @RomaneAstruc · Sep 28
A tous les vegans qui cassent les vitrines des boucheries si vous continuez nous on va aller à Jardiland et brûler toutes les graines de fruits et légumes compris ?!
[#Pascontent](#)

Translate Tweet

1 2

Julien B @JulienB · Sep 28
[#SFR](#) [#SFRenpanne](#) [#pascontent](#) vous pourriez au moins informer les clients sur la panne en cours plutôt que de faire l'autruche....

Translate Tweet

1 1

Cherwoo21 @woolies21 · Sep 27
Mais wtf [#twitch](#) vous etes serieux avec les maj surprise que si on ne fait pas gaffe avec vos systèmes de tag on est plus référence.... super quoi alalala
[#pascontent](#) :P

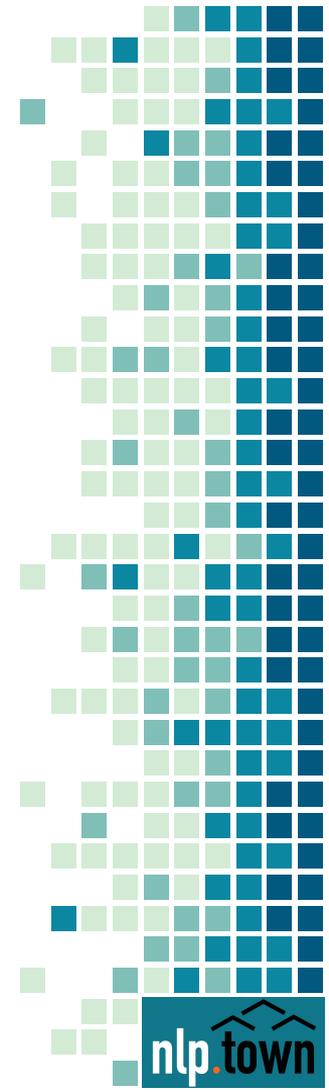
Translate Tweet

3 1

Nicolas Mercier @NicoMercier1 · Sep 27
Il n'est [#pascontent](#)

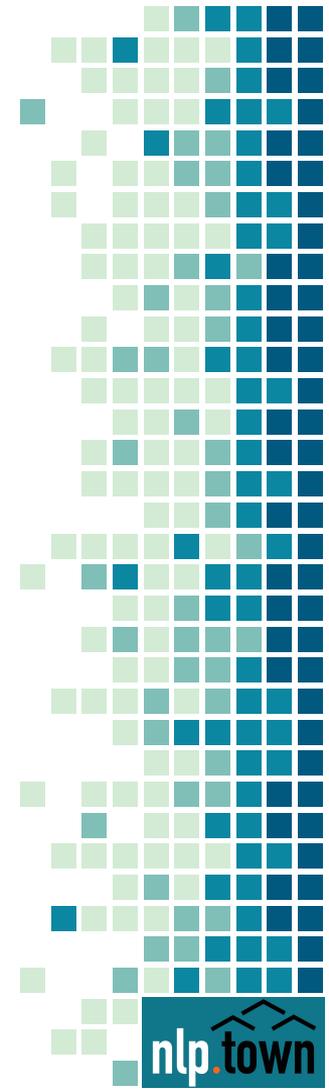
Fabien Cazenave @FabienCazenave
Michel Onfray claque la porte de l'Université populaire via @ouestfrance ouest-france.fr/normandie/caen...

1



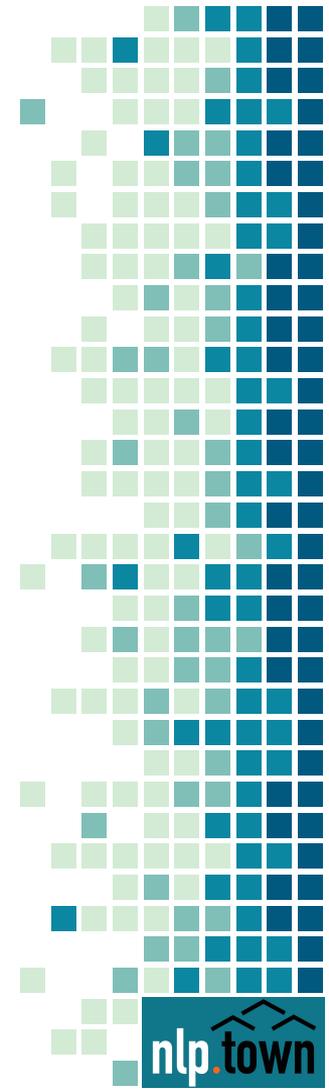
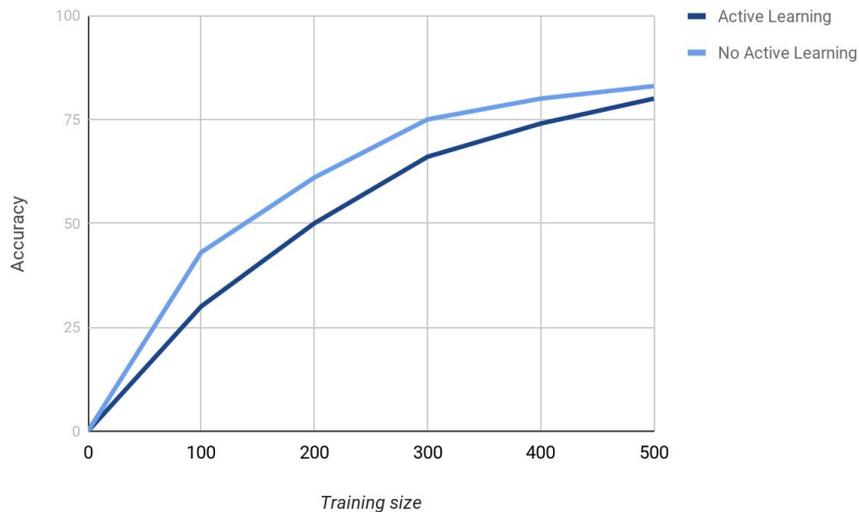
Active learning

- Distantly supervised data sets are large, but potentially noisy.
- Active learning focuses on *few, high-quality* examples.
- Reduce the labelling effort by selecting *informative* examples.
 - Uncertainty sampling: label uncertain examples first.



Active learning

- Models learn much more quickly with examples selected through active learning.



Active learning: Prodigy

The image shows a screenshot of the Prodigy web interface. The interface is divided into a left sidebar and a main content area. The sidebar contains sections for project details, progress, and recent annotations. The main content area displays a text snippet with a highlighted word and a control bar at the bottom with icons for accepting, rejecting, ignoring, and undoing annotations.

annotation project details

current progress

recent annotations

focus on one task at a time

accept, reject or ignore annotation

undo

prodigy

PROJECT INFO

PROJECT_ID	debug
VIEW_ID	ner

PROGRESS

THIS SESSION	2
TOTAL	2

0%

HISTORY

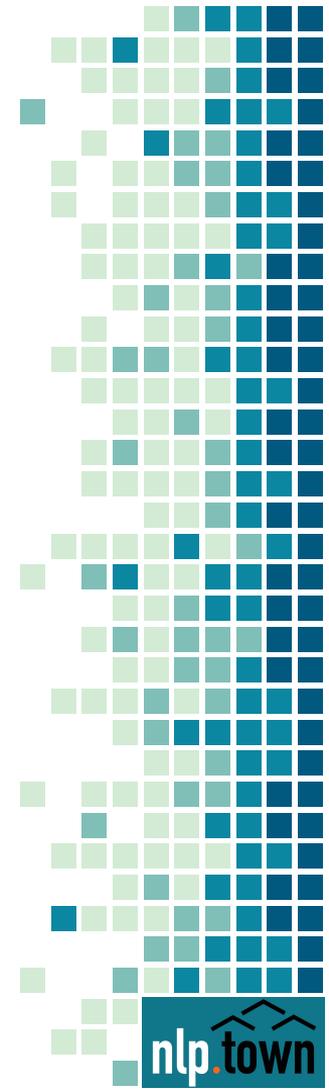
- Snapchat's take on TV is very d... X
- Apple updates its analytics ser... ✓

This guy built a travel dock for his Nintendo Switch PRODUCT and I want one

accept, reject or ignore annotation

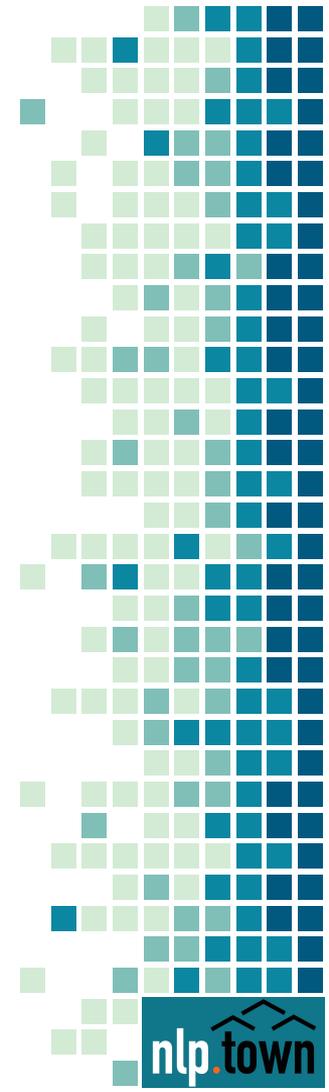
undo

© 2017 Explosion AI Prodigy v0.0.0

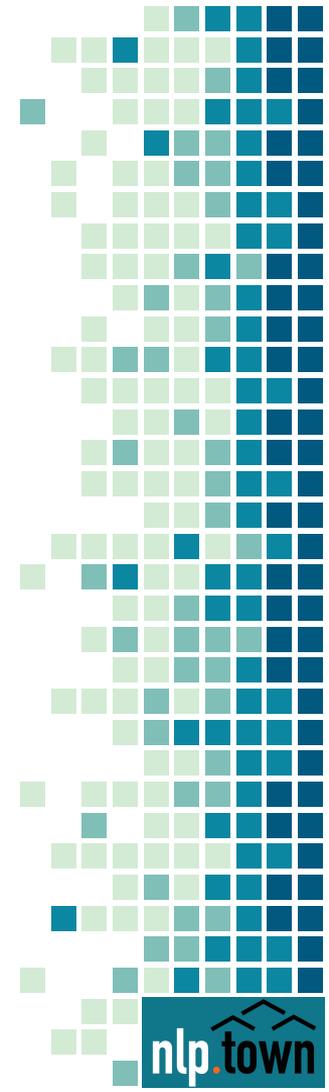
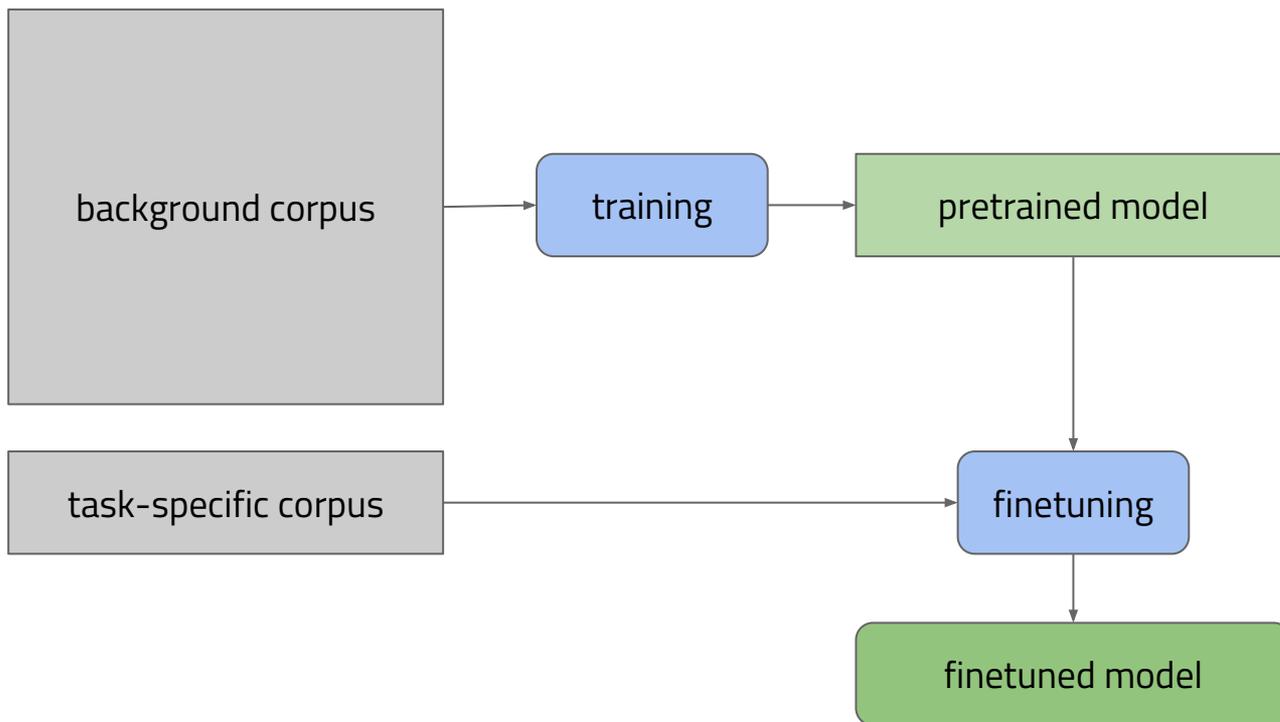


Transfer learning

- Transfer learning is one of the most exciting trends in NLP today.
- The central idea is to learn knowledge from one data source and task, and apply it to another task.
- The background data source can be labelled (see: NER before) or unlabelled (see: word embeddings).
- This can drastically reduce the number of training examples we need to build a high-quality model for the final task.



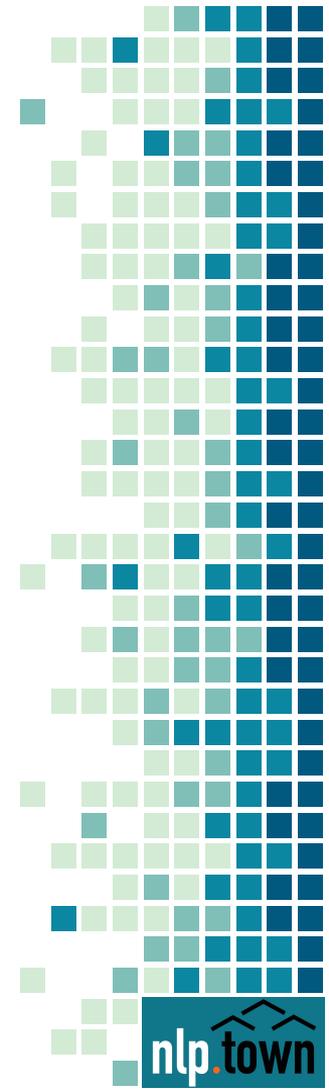
Transfer learning



Transfer learning

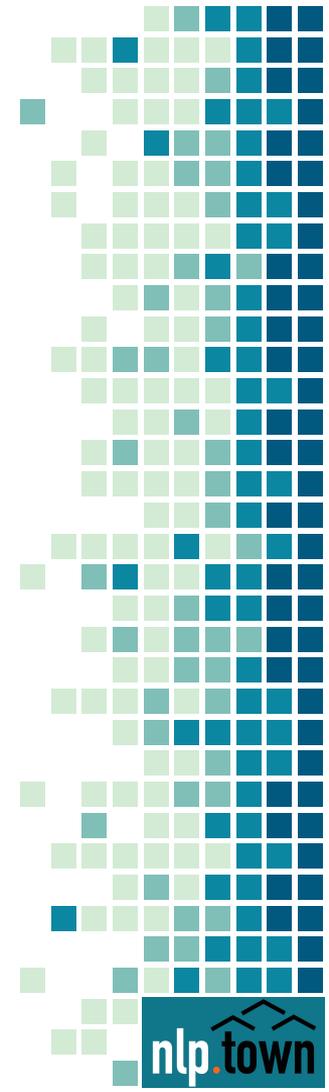
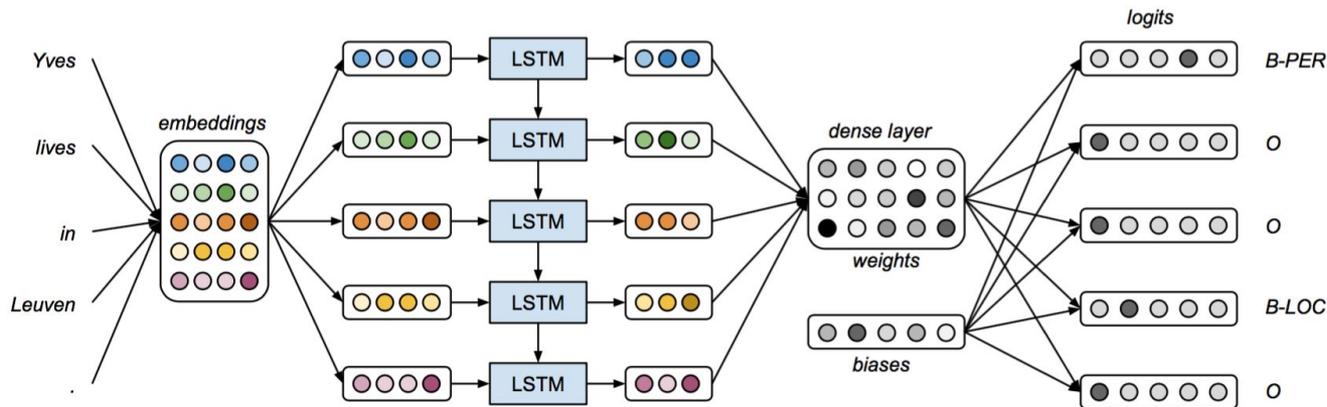
Many flavours of transfer learning have been applied:

- Word embeddings
- Multilingual word embeddings
- Language models



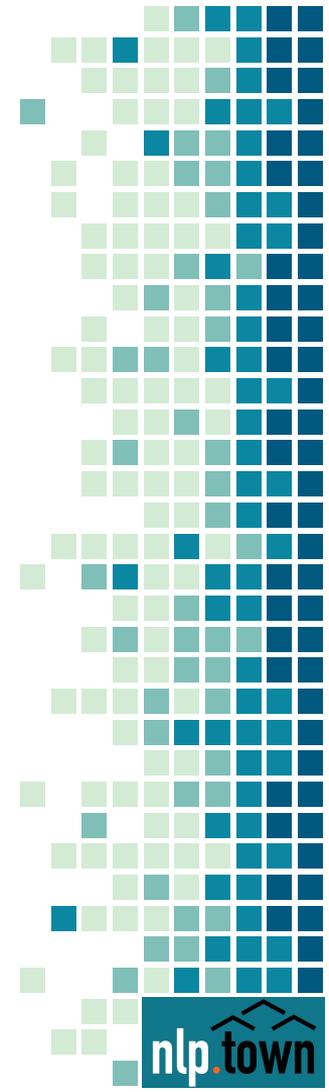
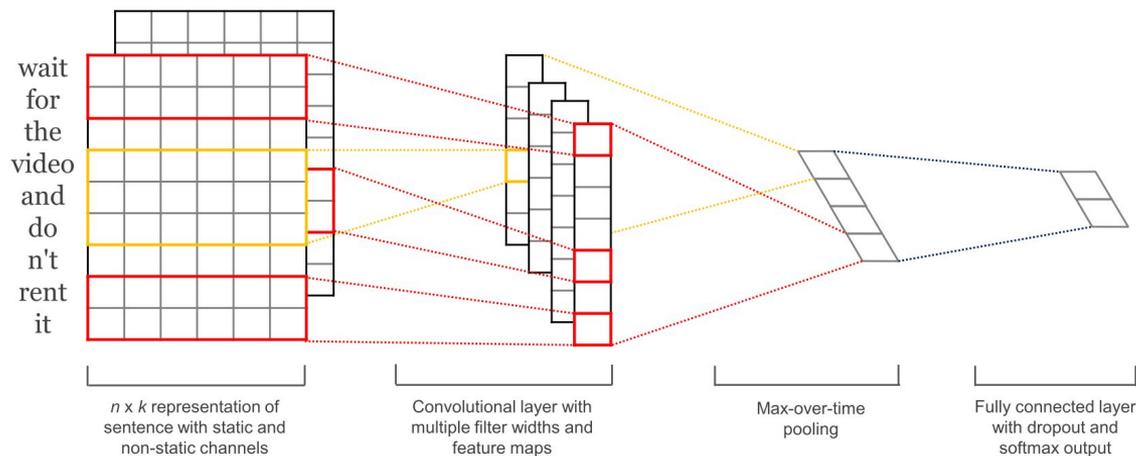
Transfer learning: word embeddings

- Most Deep Learning models start with an embedding layer.
- Pre-trained embeddings usually improve performance.



Transfer learning: cross-lingual

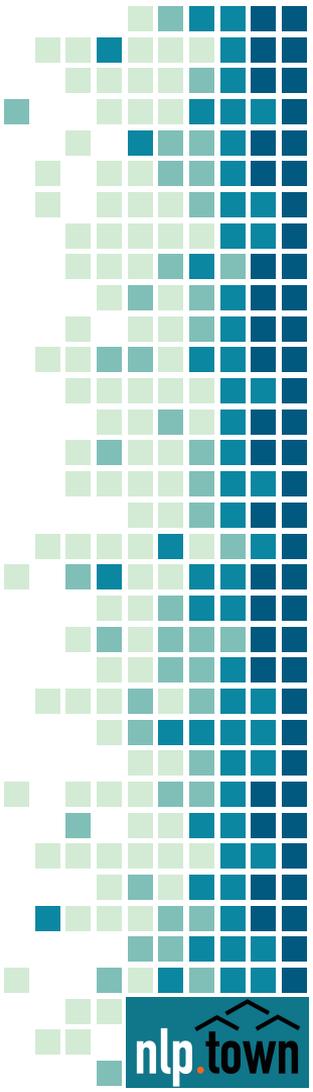
- Multilingual embeddings help us generalize across languages.
- We can swap the embedding layer and leave the rest intact.



Transfer learning: language models



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Who Criticized Trump PERSON in Texts, Is FiredImagePeter Strzok, a top F.B.I. GPE counterintelligence agent who was taken off the special counsel
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Transfer learning: language models



Unsupervised
language model

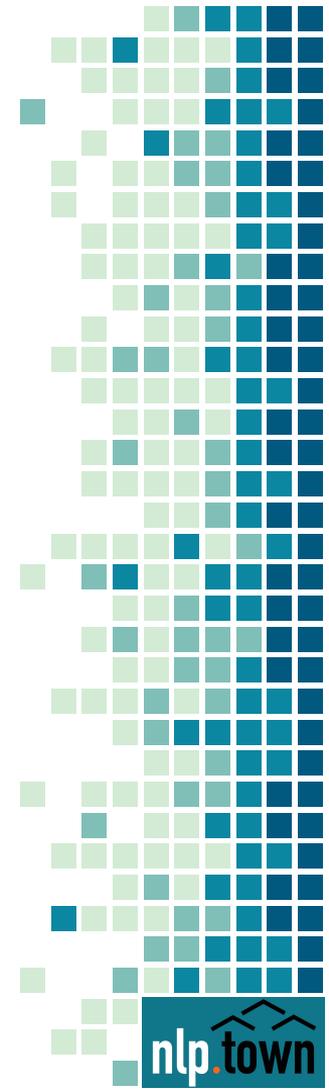
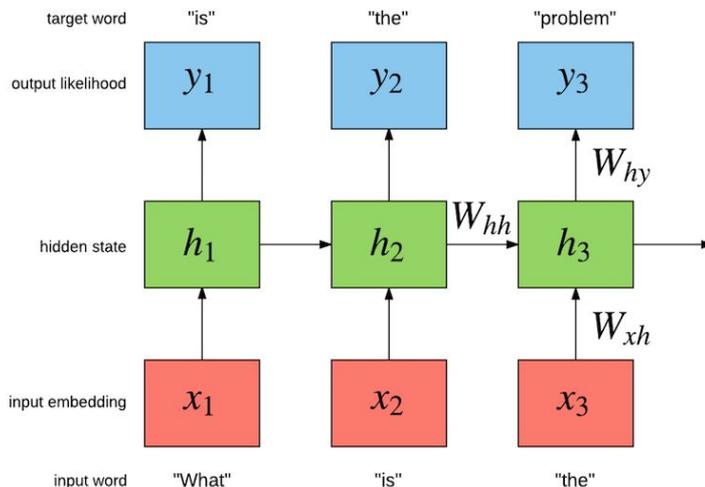


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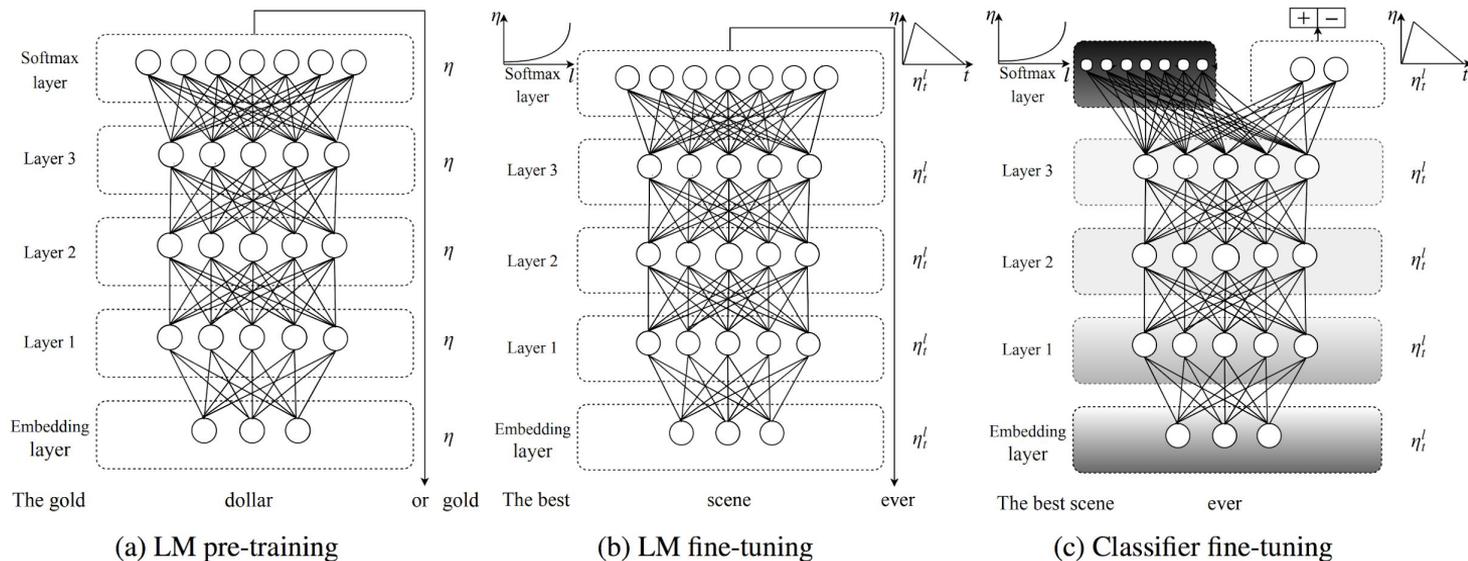
Supervised
finetuning

Transfer learning: language models

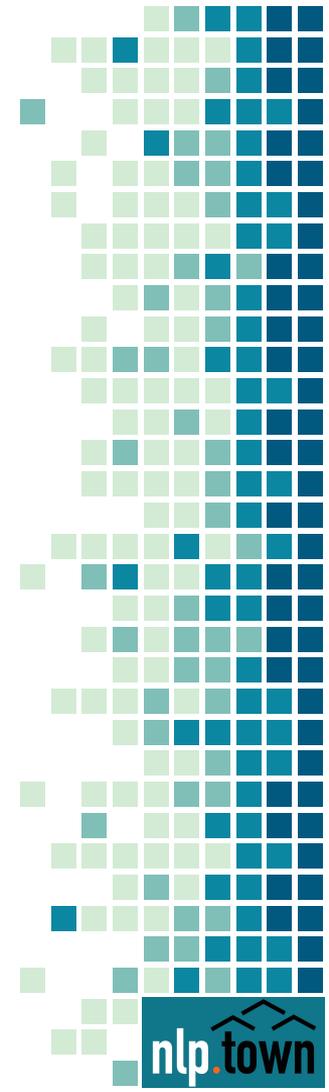
- Language models learn a lot about text by trying to predict the next word.
- This could be NLP's ImageNet moment.
- Many flavours of models:
 - ELMo Embeddings
 - ULMFit
 - BERT



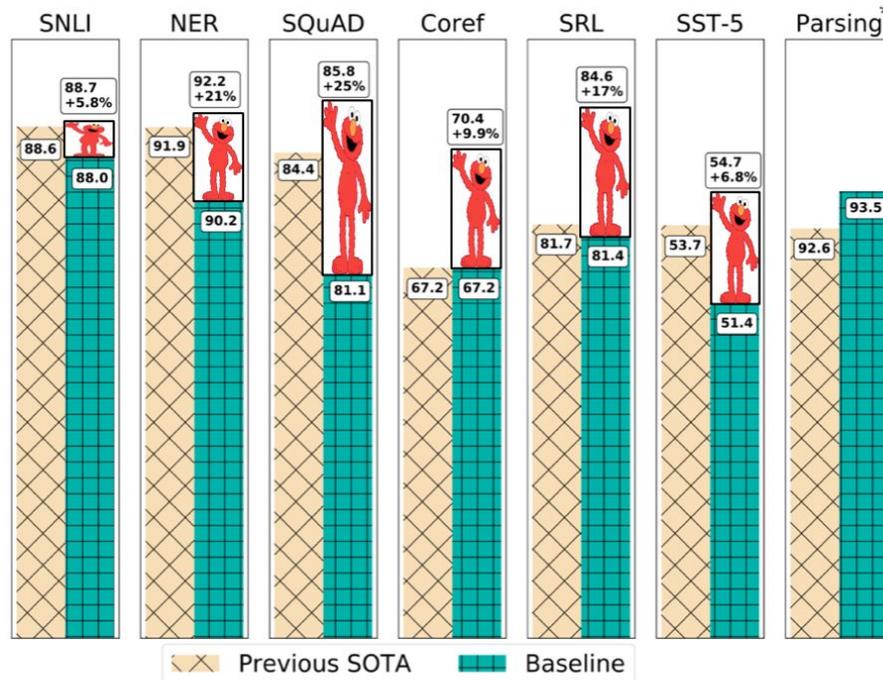
Transfer learning: language models



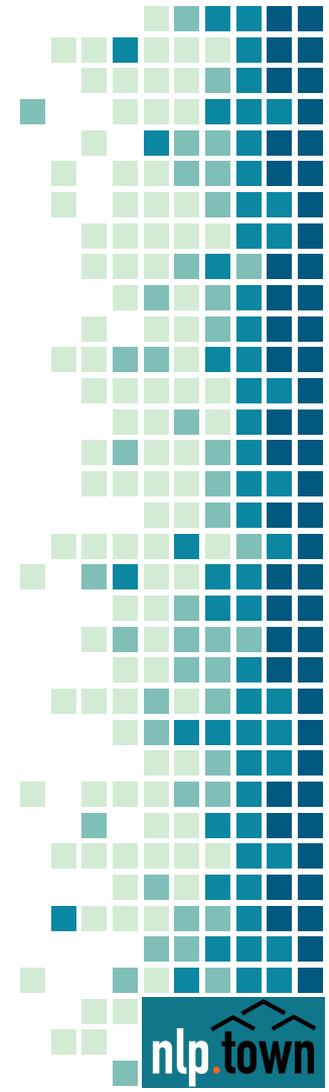
ULMFit, Howard and Ruder 2018.



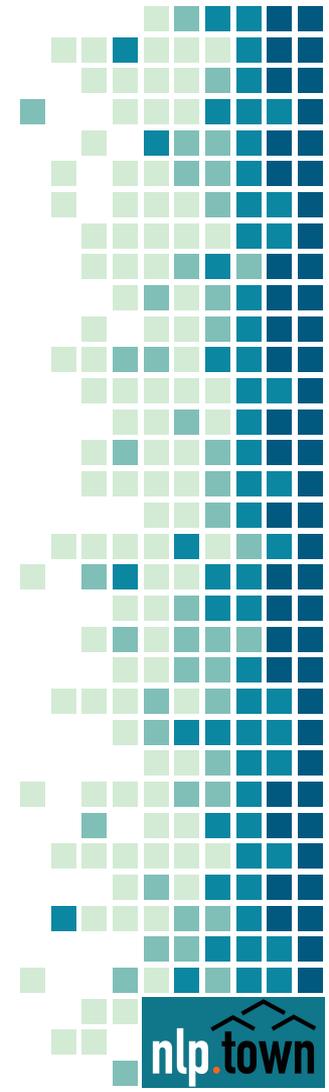
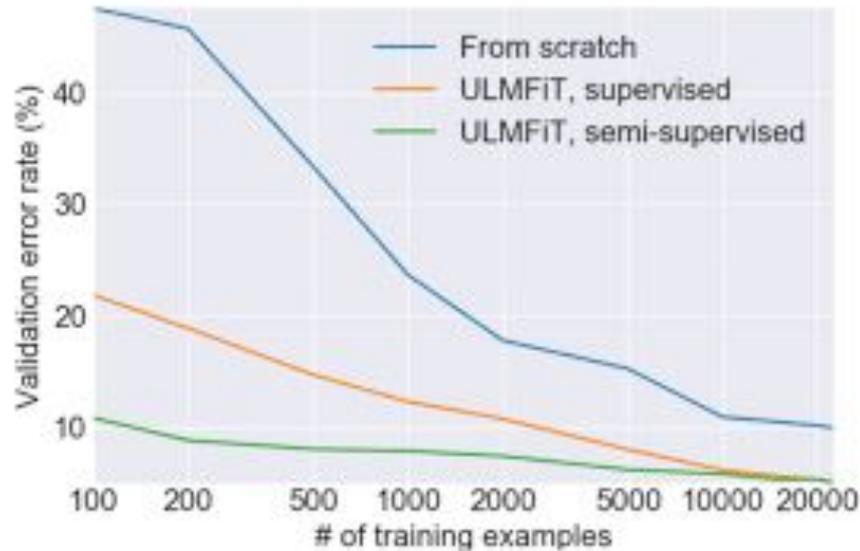
Transfer learning: language models



*Kitaev and Klein, ACL 2018 (see also Joshi et al., ACL 2018)

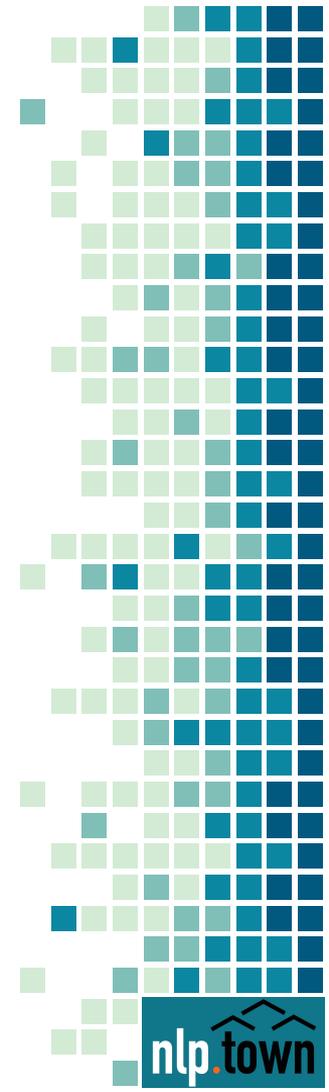
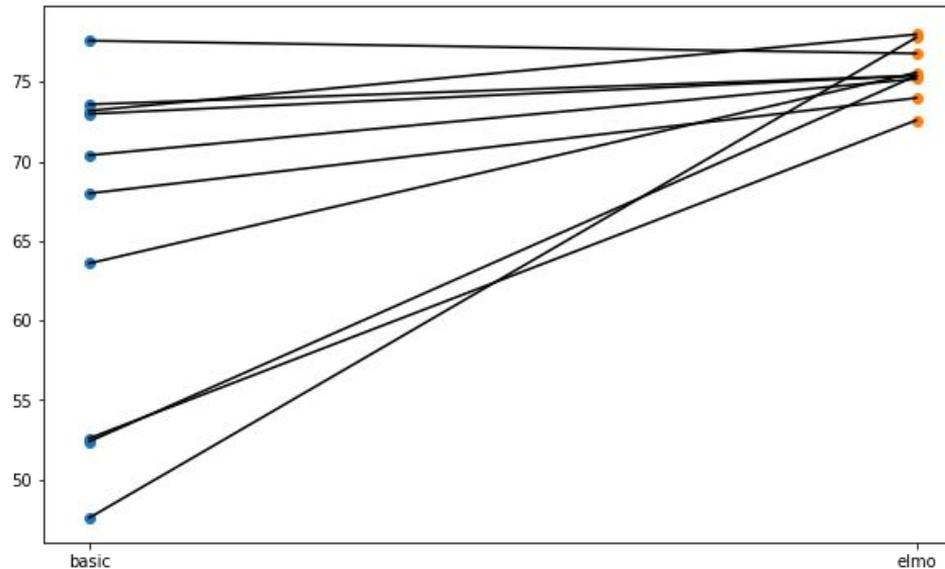


Transfer learning: language models



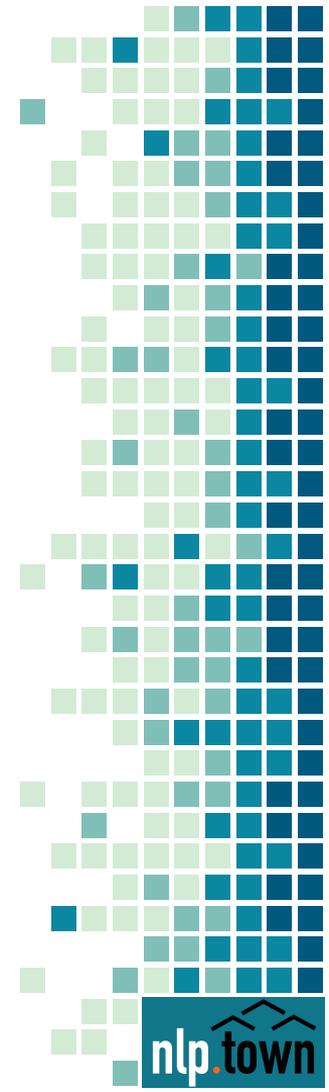
Transfer learning: language models

Training sentiment analysis on just 200 examples:



Conclusions

- For most practical NLP applications, there is a clear lack of data.
- Organizations need to wake up to the importance of *labelled* data from the *correct domain*.
- Invest more time in your data than in your algorithms.
- Established and emerging techniques help us deal with data scarcity.





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