Deep Learning Approaches for Natural Language Processing

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RESEARCH INSTITUTE



- **Areas of activity**: multilingual and multimodal interaction and multimedia information management, including human behavior modeling.
- **Staff**: 120+ (+50 across 16 start-ups)

EPFL
ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Agenda

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- Case Studies
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  - Case Study 2 - Fake News Detection
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  - Case Study 4 - Operant Motive Classification
  - Case Study 5 - Machine Translation
- Conclusion

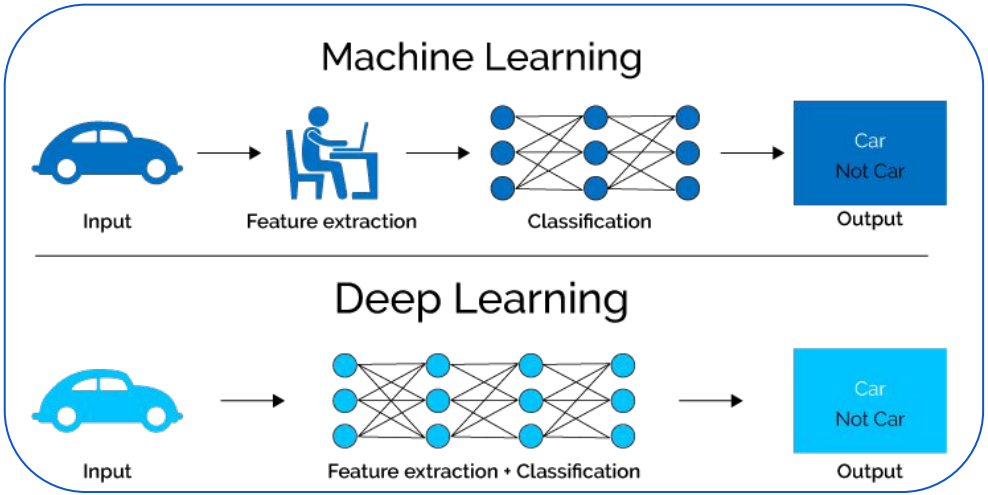
Overview

- Natural language processing (NLP) helps computers communicate with humans in their own language and scales other language-related tasks.
- NLP makes it possible for computers to read text, hear speech, interpret it, measure sentiment and determine which parts are important.



What is Deep Learning ?

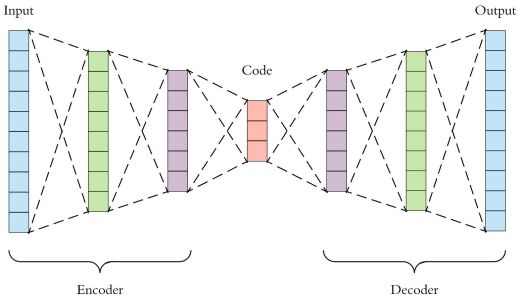
- A machine learning subfield of learning **representations** of data.
- Exceptionally effective at **learning patterns**.
- Deep learning algorithms attempt to learn (multiple levels of) representation by using a **hierarchy of multiple layers.**
- If you provide the system **tons of information**, it learns to respond in useful ways.



https://www.xenonstack.com/blog/static/public/uploads/media/machine-learning-vs-deep-learning.png

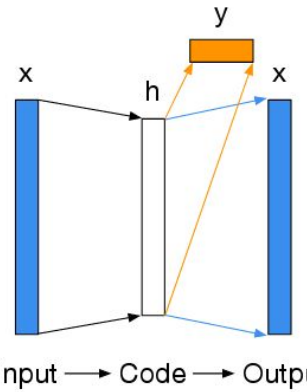
Deep Learning for NLP: Autoencoders

- Learning good representations lies at the core of Deep Learning (DL)
- Over the last few years, DL has made amazing advances in NLP
- Recently, autoencoders represent an alternative to contrastive unsupervised word learning
  - Are able to learn both linear and non-linear transformations
- Autoencoders can discover low-dimensional, less sparse, and robust features for classification



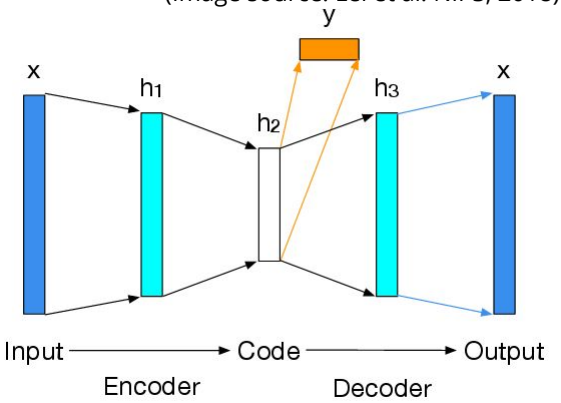
Supervised AutoEncoder

- A **supervised autoencoder** (**SAE**) is an autoencoder with the addition of a supervised loss on the representation layer
- The addition of supervised loss to the autoencoder acts as a regularizer and results better representation for the desired task
- Although **SAE** have been tested on many image classification tasks, they have **not** been extensively tested on **NLP** tasks



(Linear) supervised autoencoder

(Image source: Lei et al. NIPS, 2018)

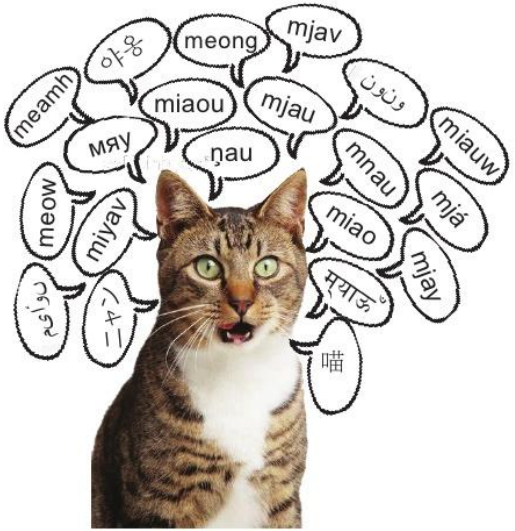


Deep supervised autoencoder

(Image source: Lei et al. NIPS, 2018)

Case1: Language Detection

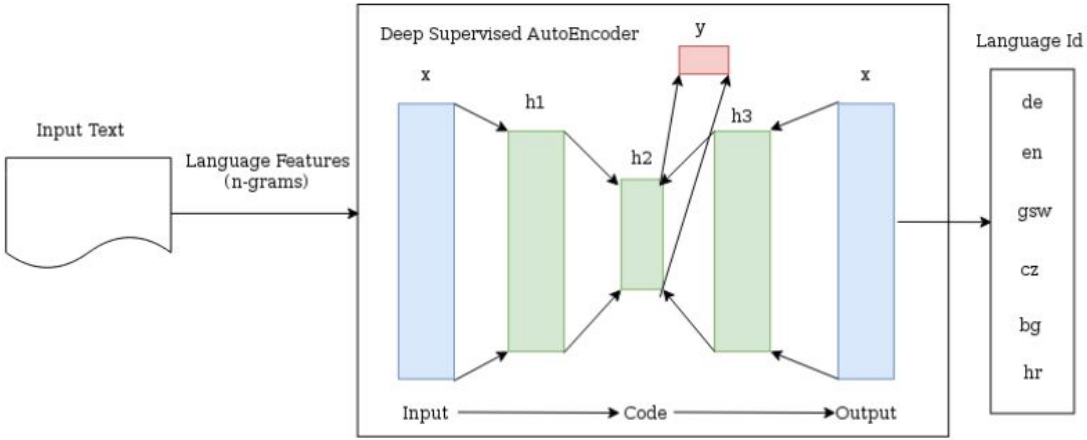
- Its challenging to detect languages that have similar origins or dialects (e.g. German dialect identification, Indo-Aryan language identification)
- It may not be possible to distinguish related dialects with very similar phoneme and grapheme inventories for some languages.





Method Description

- We used character n-gram for extracting features from the input text.
- Extracted features are input to the deep supervised autoencoder (SAE).
- Bayesian optimizer used for selecting the optimal hyperparameters.



Proposed model architecture

Dataset

DSL Dataset: Discriminating between Similar Language (DSL) contains 13 different languages based on 6 different language group. We used DSLCCv2.0 in our experiment.

Ling10 Dataset: It contains 190,000 sentences categorized into 10 languages (*English, French, Portuguese, Chinese Mandarin, Russian, Hebrew, Polish, Japanese, Italian, Dutch*).

Group Name	Language	Id
South Eastern Slavic	Bulgarian Macedonian	bg mk
South Western Slavic	Bosnian Croatian Serbian	bs hr sr
West-Slavic	Czech Slovak	cz sk
Ibero-Romance(Spanish)	Peninsular Spain Argentinian Spanish	es-ES es-AR
Ibero-Romance(Portuguese)	Brazilian Portuguese European Portuguese	pt-BR pt-PT
Astronesian	Indonesian Malay	id my

DSL Language Group. Similar languages with their language code.

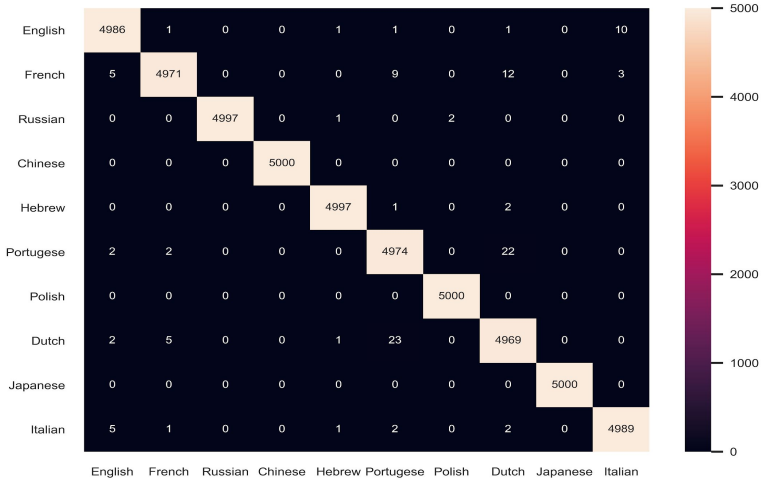
Result

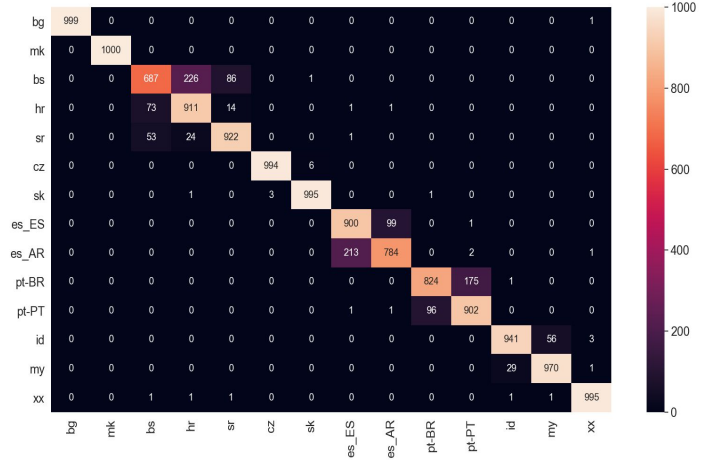
Dataset	Training	Development	Test
DSL	252,000	28,000	14,000
Ling10	140,000	-	50,000

Dataset Statistics

Model	Dataset	Accuracy (Test Set)
SAE (char-3gram)	Ling10	100%
SAE (char-3gram)	DSL	92%

Performance on test dataset.





Confusion matrix for the Ling10 and DSL test dataset.

Case 2: Fake News Detection @MEX-A3T

- The goal of IberLEF is to encourage the research community to organize competitive text processing, understanding and generation tasks in order to define new research challenges and setting new state-of-the-art results for the Natural Language Processing community, involving at least one of the following Iberian languages: Spanish, Portuguese, Catalan, Basque or Galician
- MEX-A3T 2020 had the following tracks:
  - Fake News detection
  - Aggressiveness detection
  - Both tracks contain documents in Mexican Spanish

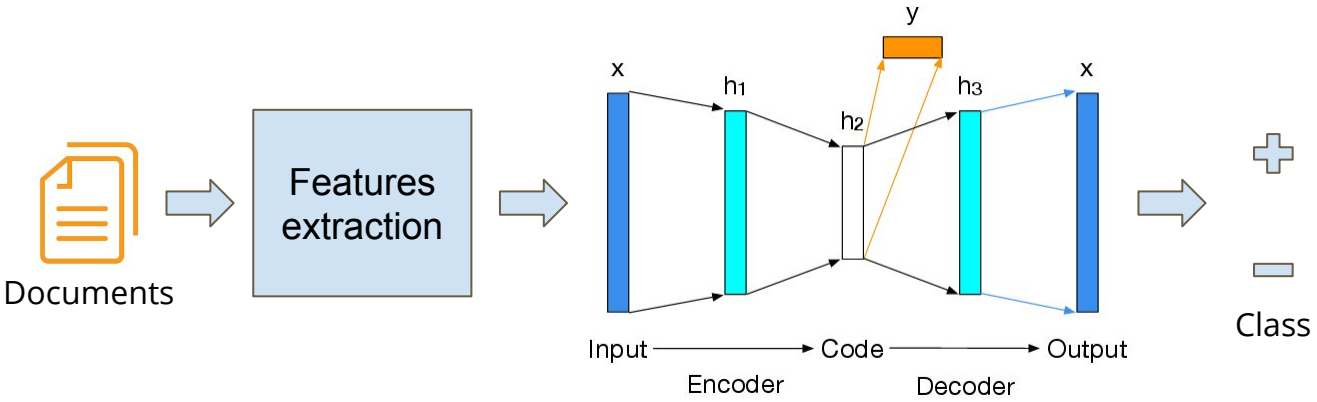
Fake News Detection



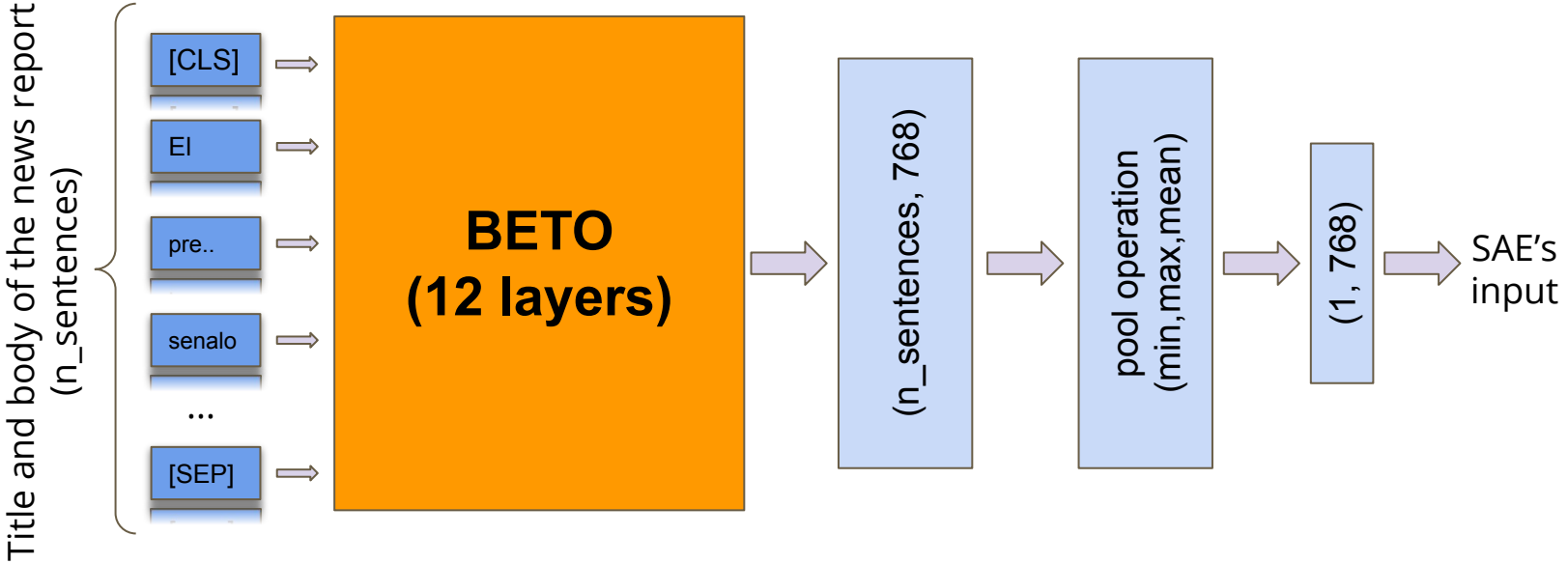
- **Fake news** provides information that aims to manipulate people for different purposes: terrorism, political elections, advertisement, satire, among others
- In social networks, misinformation extends in seconds among thousands of people
- A fake news detection system aims to help users detect and filter out potentially deceptive news
- The dataset consist of 971 documents, 676 for training and 295 for test
    - Documents are real news extracted from differents news media in Mexico

Methodology

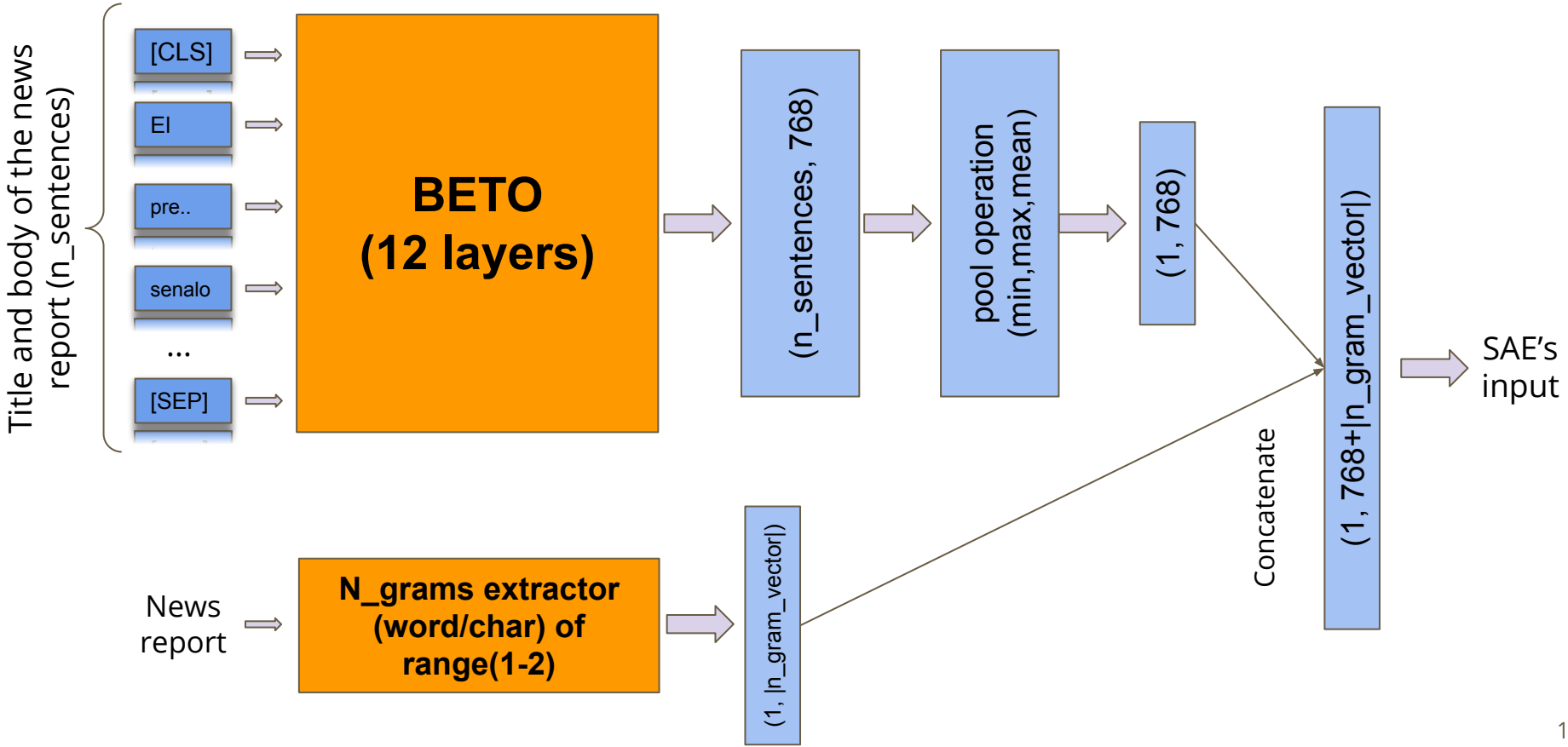
- Our goal was to evaluate the pertinence of deep SAE in these tasks
- As input features we used:
  - Spanish pre-trained **BERT** encodings (BETO)
  - Traditional text representation techniques such as **word** and **char n-grams** (ranges 1-2 and 1-3)
  - Combinations of BETO encodings plus traditional words/char n-grams vectors



Features extraction



Features extraction



Results (fake news task)

The best performance among 6 participating institutions



Table 3. Results in validation and test phases reported in F-score for [illegible] real-news (F-), and macro average of F-score (Fm).

		Validation phase			*Test phase*			
Input features	`min-df,max-df`	Fm	F+	F-	ID	Fm	F+	F-
W(1,2)	0.01, 0.5	0.775	0.793	0.758	-	-	-	-
W(1,3)	0.01, 0.5	0.778	0.798	0.758	-	-	-	-
C(1,2)	0.01, 0.5	0.697	0.719	0.674	-	-	-	-
C(1, 3)	0.01, 0.5	0.757	0.768	0.745	-	-	-	-
B(min-pooling)		**0.843**	0.842	0.845	2	**0.856**	**0.844**	**0.868**
B(max-pooling)		0.830	0.830	0.830	-	-	-	-
B(mean-pooling)		0.833	0.831	0.835	-	-	-	-
C(1, 3)+W(1,2)	0.01, 0.5	0.805	0.807	0.802	-	-	-	-
B+W(1,2)	0.01, 0.3	**0.845**	0.846	0.844	1	0.850	0.840	0.859
B+C(1,3)	0.01, 0.3	0.834	0.834	0.835	-	-	-	-
B+W(1,2)+C(1,3)	0.01, 0.3	0.833	0.831	0.835	-	-	-	-
B+W(1,2)+C(1,3)	0.01, 0.5	**0.848**	0.846	0.850	-	-	-	-
Third best system (in the track)						0.817	0.819	0.817
BOW-RF (baseline-given by track organizers)						0.786	0.785	0.787

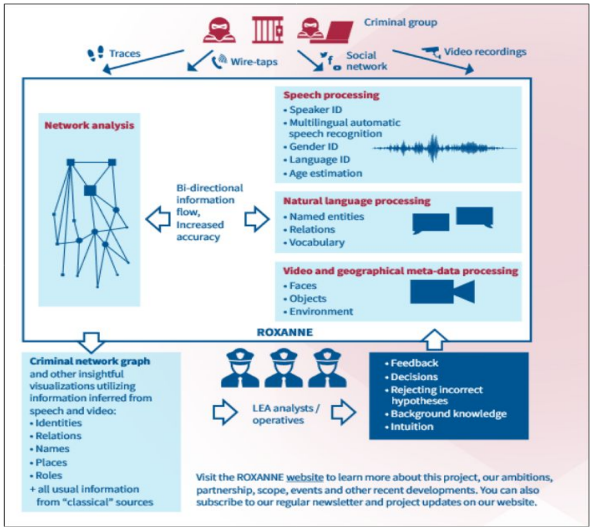
Case 3 - Crime Investigation

(Real time netwOrk, teXt, and speaker ANalytics for combating orgaNized crimE)

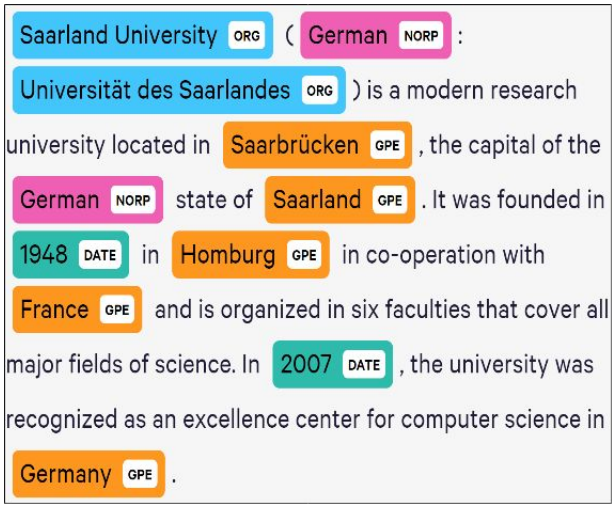
ROXANNE

- FCT H2020 project (http://roxanne-euproject.org).
- Various NLP technologies applied (potentially including summarization, entity detection, and topic detection).

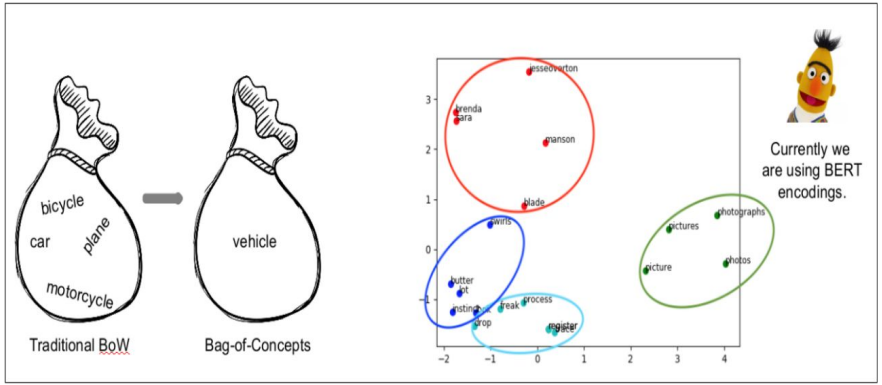
Project Overview



Entity Detection

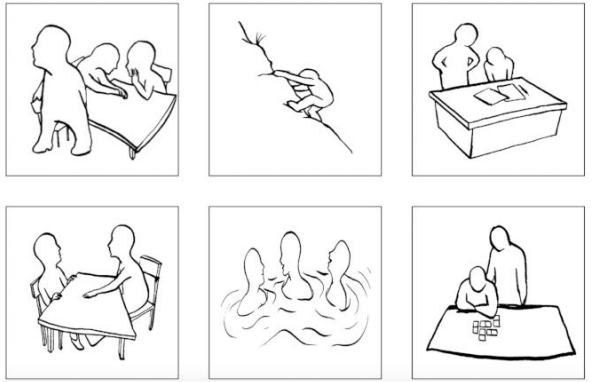


Topic Detection



Case 4: Operant Motive Detection

- According to Psycholinguistics theory, how we use language reveals information about our personality traits, educational level, age, etc.
- Operant methods are psychometrics, which are captured by having participants write free texts associated with faint images
  - Clinical research indicates that operant motives provide the possibility to assess behavioral long-term developments
- M - power, A - affiliation, L - achievement, F - freedom, 0 - zero, and corresponding levels (0 to 5).



Sample images that are shown to subjects during the OMT test

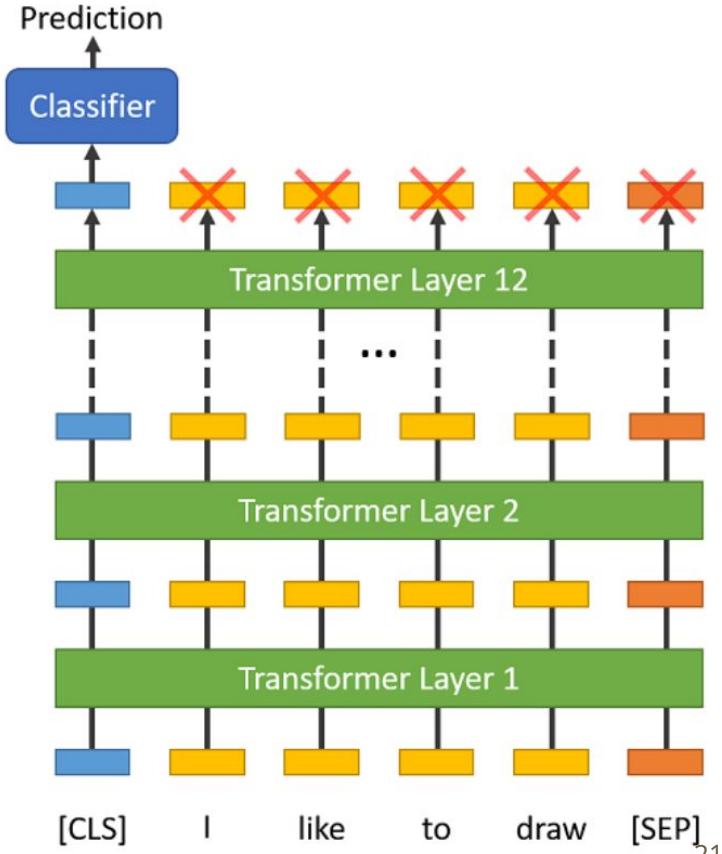
Task details

- The task is to predict motivational style solemnly based on tex
- The dataset:
  - Language: German
  - Training: 167,200*
  - Development: 20,900
  - Test: 20,900
  - Highly unbalanced

	Training	
	Average (σ)	*Total*
Tokens	20.27 ($\pm$12.08)	3,389,945
Vocabulary	18.07 ($\pm$9.82)	267,620
LR	0.92 ($\pm$ 0.08)	0.08
	Development	
	Average (σ)	*Total*
Tokens	20.38 ($\pm$12.17)	425,880
Vocabulary	18.17 ($\pm$9.94)	55,606
LR	0.92 ($\pm$ 0.08)	0.13
	Test	
	Average (σ)	*Total*
Tokens	20.24 ($\pm$12.01)	423,018
Vocabulary	18.05 ($\pm$9.76)	55,592
LR	0.92 ($\pm$0.08)	0.13

Methodology(1/3)

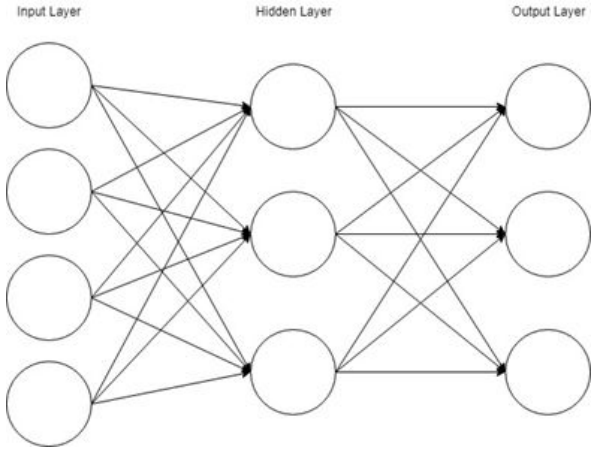
- **Simple transformers**: we add an untrained layer of neurons on the end, and re-train the model with the OMT classification task at the output
- **max_length** parameter is set to **90**, and models are re-trained up to **2 epochs**
- Three different configurations:
  - BERT
  - XLM
  - DistilBERT



Methodology(2/3)

- **Fully connected neural network (FC):** the FC is feed with the representation of the textual descriptions using:
  - **Pre-train** BERT
  - **Fine-tuned** BERT
- We reported results using two distinct ways for building the sentences representation
  - Last Hidden Layer
  - Concat Last Four Hidden

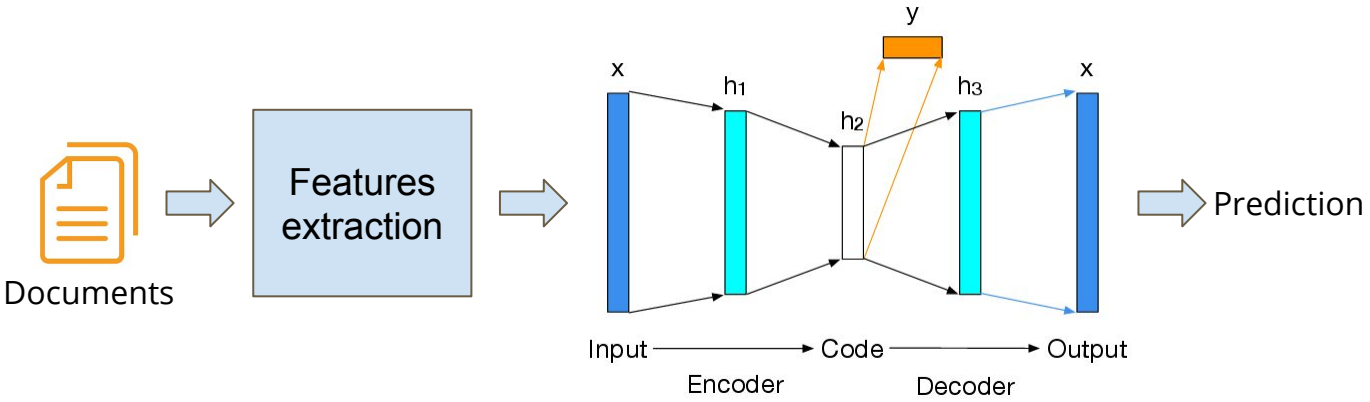




Hyper Parameter	Range
number of layers	3
number of hidden layers	1
nodes in hidden layer	16
activation function	ReLU

Methodology(3/3)

- We evaluate the performance of deep supervised autoencoders in the OMT task
- As input features we used:
  - German pre-trained and fine-tuned BERT encodings
  - Traditional text representation techniques such as word and char n-grams (ranges 1-2 and 1-3)
  - Combinations of BERT encodings plus traditional words/char n-grams vectors



Results (*test phase*)

The 2nd best performance among 3 (official) participating institutions



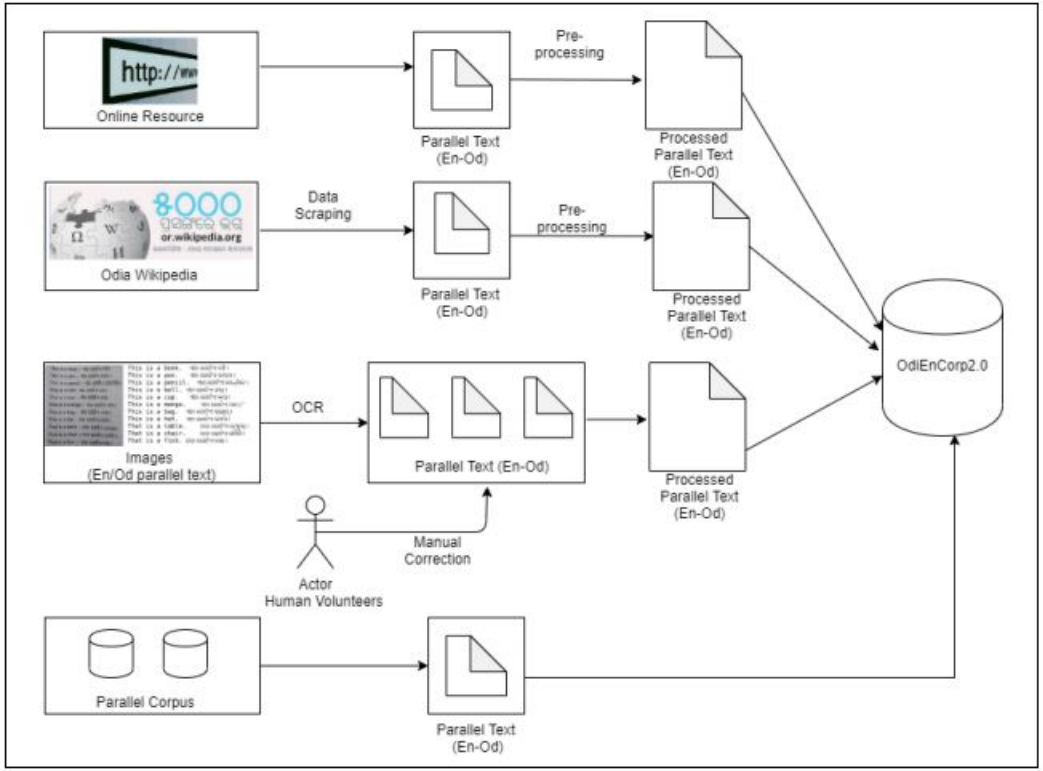
Method	*Configuration type*	*Configuration sub-type*	**F1-macro** *(dev)*	**F1-macro** *(test)*
ST	Bert	bert-base-german-cased	**0.694**	**0.698**
ST	XLM	xlm-mlm-ende-1024	0.688	0.686
ST	DistilBert	distilbert-base-german-cased	0.692	0.688
FC	Bert (pre-trained)	LHL	0.589	0.589
FC	Bert (pre-trained)	Concat4LHL	0.616	0.579
FC	Bert (fine-tuned)	LHL	0.673	0.671
FC	Bert (fine-tuned)	Concat4LHL	0.675	0.230
Baseline	SVM	*tf-idf*	0.639	0.644
1st place	–	–	–	0.704

Case 5 : Machine Translation

- Odia is an Indian language belonging to the Indo-Aryan branch of the Indo-European language family.
- Odia is one of 22 official languages of India and sixth Indian language to be designated as a Classical language.
- There is a demand for English↔Odia machine translation system.
- There is lack of Odia resources, particularly parallel corpora.
- Existing few English-Odia corpora are small in size, cover few domains not very suitable for machine translation, which motivates us for OdiEnCorp 2.0.

Data Sources

- Data extracted from other online resources.
- Data extracted from Odia Wikipedia.
- Data extracted using Optical Character. Recognition (OCR).
- Data reused from existing corpora.



Block diagram of the Corpus building process

Data Processing

- Extraction of plain text.
  - Python script to scrape plain text from HTML page.
- Manual processing.
  - Correction of noisy text extracted using OCR-based approach.
- Sentence segmentation.
  - Paragraph segmented into sentences based on English full stop (.) and Odia Danda (|) or Purnaviram.
- Sentence alignment.
  - Manual sentence alignment for Odia Wikipedia articles where text in two language are independent of each other.

Final Datasize and Domain Coverage

- The composition of OdiEnCorp 2.0 with statistics for individual sources.

Source	Sentences	Tokens		Book Name and Author (Parallel)	
		English	Odia		
Wikipedia Dump	5796	38249	37944	-	General Domain (Wiki data)
Globe Website	6222	40143	38248	-	Daily usage learning
Odisha District Website	761	15227	13132	-	General and Tourism Information
TamilCube Website	4434	7180	6776	-	Daily usage learning
OCR (Book 1)	356	4825	3909	A Tiger at Twilight by Manoj Dash	Literature
OCR (Book 2)	9499	117454	102279	Yajnaseni by Prativa Ray	
OCR (Book 3)	775	13936	12068	Wings of Fire by APJ Abdul Kalam with Arun Tiwari	
OCR (Book 4)	1211	1688	1652	Word Book by Shibashis Kar and Shreenath Chaterjee	
OCR (Book 5)	293	1492	1471	Spoken English by Partha Sarathi Panda and Prakhita Padhi	
Odia Virtual Academy (OVA)	1021	4297	3653	Sarala (Tribhasi) Bhasa Sikhana Petika	Daily usage learning
PMIndia	38588	690634	607611	-	Government Policies
OdiEnCorp 1.0	29346	756967	648025	-	Bible, Literature, Government Policies
Total	98302	1692092	1476768		

OdiEnCorp 2.0 parallel corpus details. Training, dev and test sets together

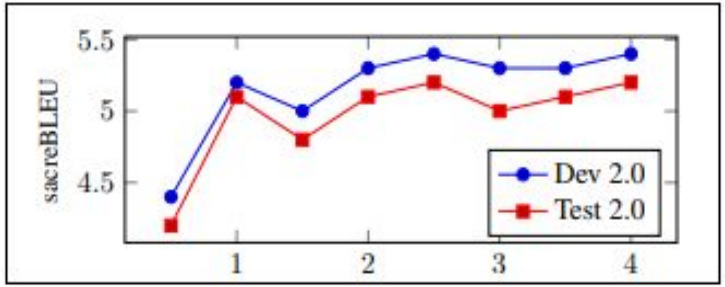
Baseline (Neural Machine Translation)

- Dataset
  - Removed duplicated sentence pairs and shuffled.

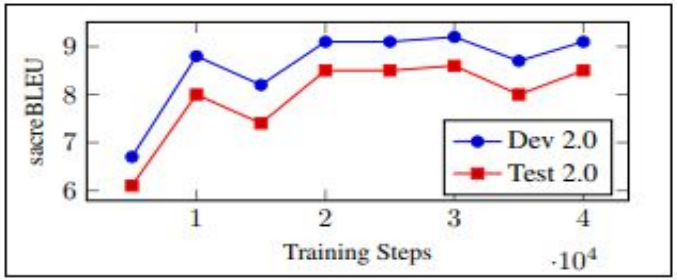
Dataset	#Sentences	#Tokens EN	#Tokens OD
Train 2.0	69260	1340371	1164636
Dev 2.0	13429	157951	140384
Test 2.0	14163	185957	164532

OdiEnCorp 2.0 processed for NMT experiments.

- NMT Setup
  - We used Transformer model as implemented in OpenNMT-py.
  - Generated vocabulary of 32K sub-word type jointly for source and target language.
  - Train using single GPU (learning rate: 0.2, 8000 warm-up steps).



Learning Curve (EN->OD)



Learning Curve (OD->EN)

Result

		sacreBLEU	
Training Corpus	Task	Dev 2.0	Test 2.0
OdiEnCorp 2.0	EN-OD	5.4	5.2
OdiEnCorp 2.0	OD-EN	9.2	8.6

Results for baseline NMT on Dev and Test sets for OdiEnCorp 2.0.

Availability

OdiEnCorp 2.0 is available for research and non-commercial use under a Creative Commons Attribution-NonCommercial-ShareAlike 4.0 License, CC-BY-NC-SA at :

http://hdl.handle.net/11234/1-3211

WAT 2020

Website: http://lotus.kuee.kyoto-u.ac.jp/WAT/WAT2020/index.html

WAT 2020
The 7th Workshop on Asian Translation

December, 2020
Suzhou, China
(Hosted by the AACL-IJCNLP 2020)

TRANSLATION TASK

Tasks:

- Scientific paper tasks: Asian Scientific Paper Excerpt Corpus (ASPEC)
  - English <--> Japanese
  - Chinese <--> Japanese
- Patent tasks: Japan Patent Office Patent Corpus 2.0 (JPC2)
  - Chinese <--> Japanese
  - Korean <--> Japanese
  - English <--> Japanese
  - Chinese -> Japanese expression pattern task
- Newswire tasks: JIJI Corpus
  - Japanese <--> English (description)
- News Commentary task:
  - Japanese <--> Russian
- IT and Wikinews tasks:
  - Hindi/Thai/Malay/Indonesian <--> English **(NEW!) (Multilingual Multi-domain evaluation task) (Collaboration with NICT-SAP)**
- Mixed-domain tasks:
  - UCSY and ALT corpora: Myanmar <--> English
  - ECCC and ALT corpora: Khmer <--> English
- Indic tasks:
  - UFAL (EnOdia) corpus: Odia <--> English **(NEW!)**
  - Bengali/Hindi/Malayalam/Tamil/Telugu/Marathi/Gujarati <--> English **(NEW!) (Modification of WAT 2018's Indic Multilingual evaluation task !)**
- Multimodal:
  - English --> Hindi
  - English <--> Japanese **(NEW!)**

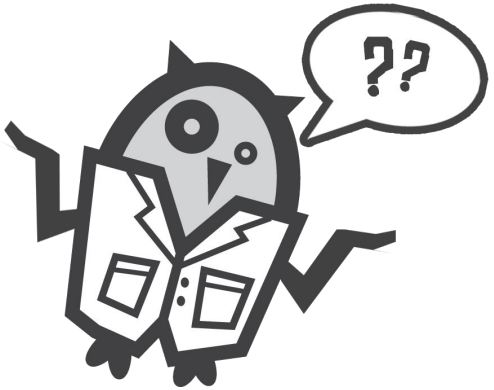
Conclusions and future work

- SAE with Bayesian Optimization for the language detection task found effectively for discriminating between very close languages or dialects
- SAE are able to generalize well, however, they seem to perform better on texts extracted from formal written
  - Fake news detection, best performance, documents extracted from real news media
  - During dev phase in the Language Detection task, SAE obtained very good results, however, during test phase, only tweets were provided
- SAE are less computationally expensive as compared to attention based DL models (e.g., transformers)
  - They do not require high volume of data

Conclusions and future work

- If there are plenty of data, fine-tuning of previous attention based DL models is an immediate and promising solution
  - This was the case for the OMT task
- We would like to evaluate the impact of hyper-parameter tuning
- Test **SAE** on other NLP tasks, e.g., topic detection and topic tracking
- Extending OdiEnCorp 2.0 with more parallel data, again by finding various new sources.

Q&A



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References

[1] Parida, S., Dash, S. R., Bojar, O., Motlıcek, P., Pattnaik, P., & Mallick, D. K. OdiEnCorp 2.0: Odia-English Parallel Corpus for Machine Translation. In *LREC 2020 Workshop Language Resources and Evaluation Conference 11–16 May 2020* (p. 14).

[2] Parida, S., ú Villatoro-Tello, E., Kumar, S., Motlicek, P., & Zhan, Q. (2020). Idiap Submission to Swiss-German Language Detection Shared Task. In Proceedings of the 5th Swiss Text Analytics Conference (SwissText) & 16th Conference on Natural Language Processing (KONVENS).

[3] Villatoro-Tello, E., Parida, S., Kumar, S., Motlicek, P., & Zhan, Q. (2020). Idiap & UAM participation at GermEval 2020: Classification and Regression of Cognitive and Motivational Style from Text. In Proceedings of the GermEval 2020 Task 1 Workshop in conjunction with the 5th SwissText & 16th KONVENS Joint Conference (pp. 11-16).

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Thank You