

# Information Extraction from Business Documents

Case Study

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# Problem definition

- **Problem:** Read and understand business documents
- **Goal:** Automatization of payments from scanned invoices
- **Possible solutions:**
  - OCR -> Text only NER
  - OCR -> Token classification (based on text and position)
  - OCR -> MultiModal NER (based om position, image and text)

# Deep Learning OCR pipeline

- Pre-processing (Minimal)
- Text Detection
- Text Recognition
- Post-processing

# Deep Learning OCR

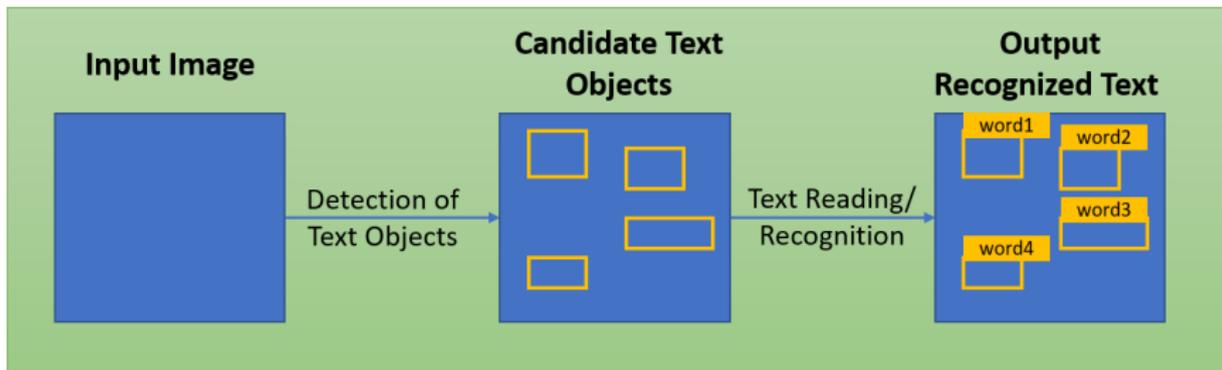


Figure: Deep Learning OCR pipeline

# OCR text recognition comparison

- Tesseract Version 5.0
  - CRNN ( CNN + LSTM )
- EasyOCR
  - CRNN
- Doctr
  - CRNN, MASTER and ViTSTR

# Born Digital Dataset

- we selected digitally-born documents, PDF files
- we extracted bounding boxes and letter via available python tools
- we filtered bad extraction, hidden symbols and got around 600k bounding box and text pairs (30k unique words)

# OCR Results

**Table:** Performance comparison of text recognition models on born-digital dataset

	<b>Exact</b>	<b>Partial</b>	<b>FPS</b>
<b>Tesseract v5</b>	0.90	0.90	3.35
<b>EasyOCR CRNN</b>	0.83	0.84	34.14
<b>Doctr CRNN</b>	0.89	0.89	27.36
<b>Doctr MASTER</b>	0.98	0.99	0.46
<b>Doctr ViTSTR</b>	0.75	0.83	18.84

# Multi-modal Information Extraction

- family of models, which use additional modalities compare to text only models
- modalities used:
  - text – WordPiece tokens
  - position of text – 2D position in the Document
  - image – vectorized representations of the image

# LayoutLM family

- family of multi-modal models from Microsoft:
- English models
  - LayoutLMv1 [8]
  - LayoutLMv2 [7]
  - LayoutLMv3 [2]
- Multilingual models
  - LayoutXLM [9]

# Layout(X)LM training

- Dataset
  - English
    - IIT-CDIP Test Collection 1.0 – 11 M scanned documents (6 M unique) [5]
  - Multilingual
    - born-digital documents crawled from web
    - including 53 languages
- Pretraining tasks
  - Masked Visual-Language Model
  - Multi-label Document Classification
  - Text-Image Alignment
  - Text-Image Matching

# Layout (X)LM architecture

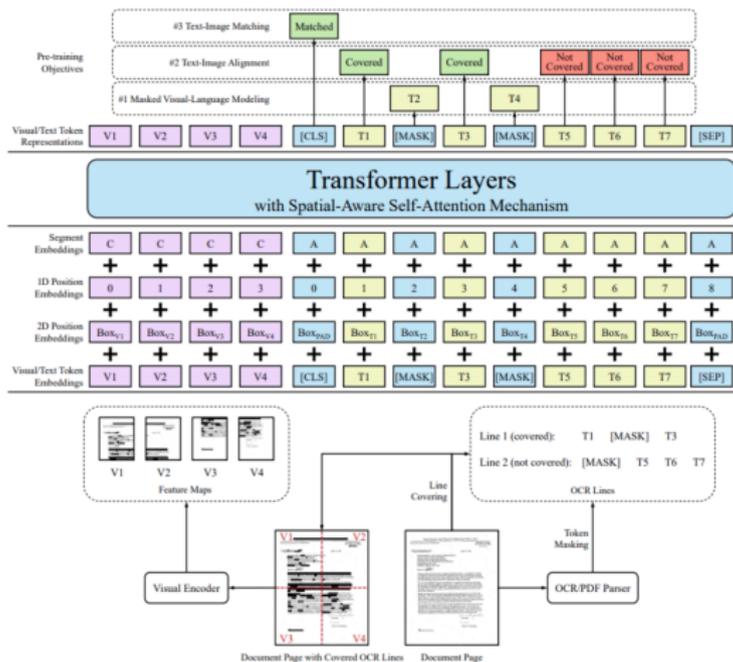


Figure: Example of one input data sample

## Other Related Work

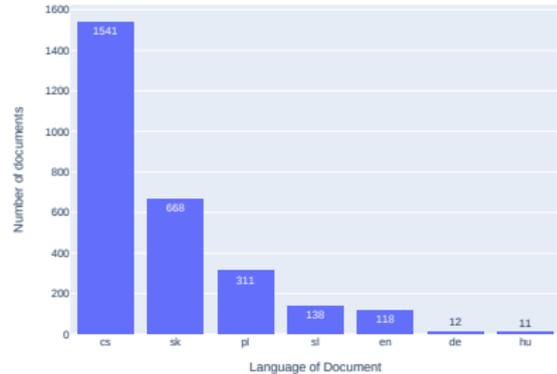
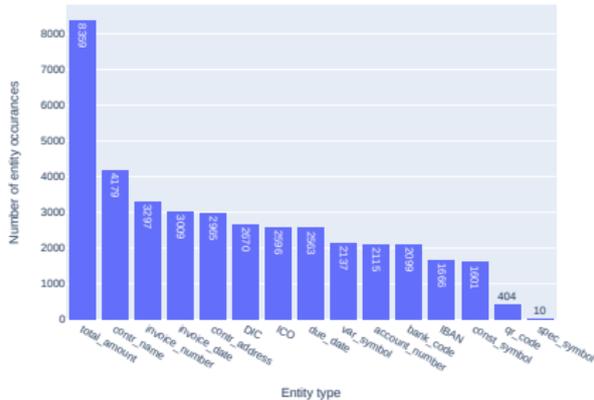
- MultiLingual
  - **LiLT** [6] - LayoutLM like model with independent text model
- English
  - **FormNet** [3] - models relationship between tokens by graph convolution
  - **DocFormer** [1] - similar model to LayoutLM family with different implementation of multimodal attention
  - **SelfDoc** [4] - uses larger semantic components instead of WordPiece tokens

# Dataset description

- we collected of set of documents, as no Czech documents dataset of a sufficient volume or quality is available
- dataset obtained by querying server uloz . to with keywords “faktura”, “smlouva” or “doklad”
- result collection after manually cleaning contains 6,849 invoice images
- dataset annotation
  - selecting a bounding box
  - assigning a category



# Dataset languages and entity types



**Figure:** Histograms of entity types (left) and languages of scrapped documents (right).

## Results

	F1-score	Precision	Recall
<b>BERT Base Multilingual Cased</b>	66.74	66.75	66.73
<b>XLM RoBERTa Base</b>	72.80	72.61	73.00
<b>RoBERTa Large</b>	78.25	77.52	79.00
<b>XLM RoBERTa Large</b>	79.36	80.30	78.44
<b>LayoutLM v2 Base</b>	77.83	75.99	79.76
<b>LayoutLM v2 Large</b>	<b>83.06</b>	<b>82.38</b>	<b>83.75</b>
<b>LayoutXLM Base</b>	79.40	78.75	80.06

**Table:** Performance comparison of Text-based and LayoutLM models on separated evaluation datasets.

# Conclusion & Future work

- Future work OCR
  - train EasyOCR model
  - data augmentation to imitate bad scans while training with born-digital documents
  - use language model as post-processing
  - End2End text detection and text recognition evaluation - number of found annotated entities
- Future work NER
  - implement post-processing merging for output bounding boxes
  - train LiLT model and compare to LayoutLm results
  - compare models trained with different OCR engines
- Common Future work
  - end2end evaluation – such as number of successful automatic payment transactions

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- [2] Yupan Huang et al. “LayoutLMv3: Pre-Training for Document AI with Unified Text and Image Masking”. In: *Proceedings of the 30th ACM International Conference on Multimedia*. MM '22. Lisboa, Portugal: Association for Computing Machinery, 2022, pp. 4083–4091. ISBN: 9781450392037. DOI: 10.1145/3503161.3548112.

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- [5] Ian Soboroff. *Complex Document Information Processing (CDIP) dataset*. 2022. DOI: 10.18434/mds2-2531. (Visited on 11/10/2022).

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- [7] Yang Xu et al. “LayoutLMv2: Multi-modal Pre-training for Visually-rich Document Understanding”. In: *Proceedings of the 59th Annual Meeting of the ACL and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. Online: ACL, Aug. 2021, pp. 2579–2591. DOI: 10.18653/v1/2021.acl-long.201. URL: <https://aclanthology.org/2021.acl-long.201>.

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- [9] Yiheng Xu et al. “LayoutXLM: Multimodal Pre-training for Multilingual Visually-rich Document Understanding”. In: *CoRR* abs/2104.08836 (2021). arXiv: 2104.08836. URL: <https://arxiv.org/abs/2104.08836>.

Thank you for your attention!

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