Predicting Multiple ICD-10 Codes from Brazilian-Portuguese Clinical Notes

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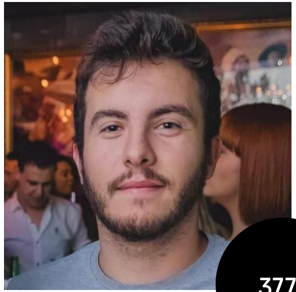

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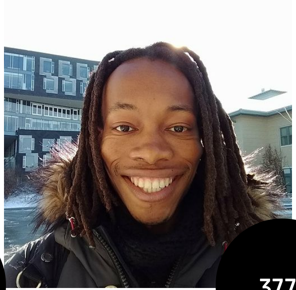

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SOCIEDADE BENEFICENTE DE SENHORAS

The ICD Coding Task

- International Classification of Diseases - WHO
- Standard classification of symptoms, clinical evolution, diagnoses and medical history
- Billing, Health plan communication, Database organization for research
- Expensive and time-consuming task

The ICD Coding Task

EHR - Compilation of Clinical Notes

Paciente masculino, 60 anos, admitido no pronto socorro com quadro de apendicite aguda (confirmada por US abdominal total + exames laboratoriais). Submetido a laparotomia...

Professional Coders

List of ICD Codes

K35.9 Apendicite aguda SOE
I10 Hipertensão essencial
Z871 Hist. pessoal de doenc. aparelho digestivo
E149 Diabetes mellitus NE
R11 Náusea e vômitos

The ICD Coding Task

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Free Text

AI

Thousands of ICD codes

Previous Work

- Hierarchical and rule-based models
  - Hierarchical (Baumel et al, 2017), ICD co-occurrence (Subotin et al, 2016)
- Machine Learning and Deep learning
  - kNN (Ruch et al, 2008), SVM (Perotte et al, 2014), Naive Bayes (Medori et al, 2010)
  - CNN (Li et al, 2017; Mullenbach et al, 2018)
  - RNN (Huang et al, 2019; Ayyar et al, 2017; Baumel et al, 2017)
  - Attention mechanisms (Li et al, 2019; Mullenbach et al, 2018)
  - **CAML** (Mullenbach et al, 2018) - current state-of-the-art
- Brazilian-portuguese
  - No public dataset, most works focus on small set of ICD codes
  - SVM (Oleynik et al, 2017) and RNN (Duarte et al, 2018)

Datasets - MIMIC-III

- Publicly accessible
- Patient information from Beth Israel Deaconess Medical Center collected between 2001 and 2012
- English Language
- Baseline for comparison
- Only Discharge Summaries selected
- 6918 ICD-9-CM codes
- 52722 hospital admissions from 41127 patients

Datasets - HSL

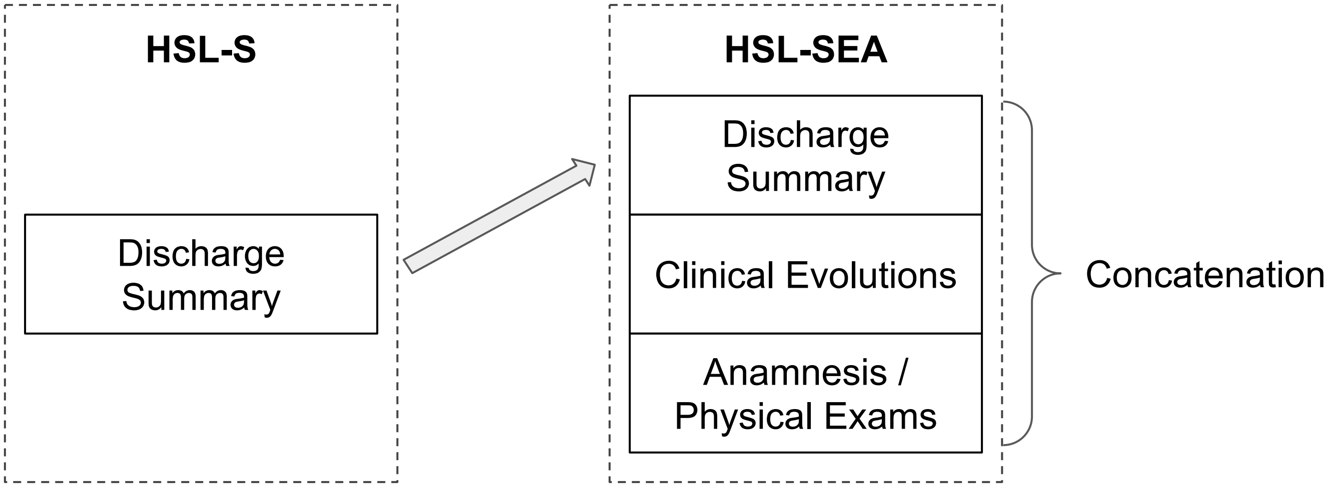
HOSPITAL SÍRIO-LIBANÊS

- Patient information from Syrian-Lebanese Hospital collected between 2016 and 2018
- Brazilian-Portuguese Language
- 5360 ICD-10 codes
- 77005 hospital admissions from 51298 patients

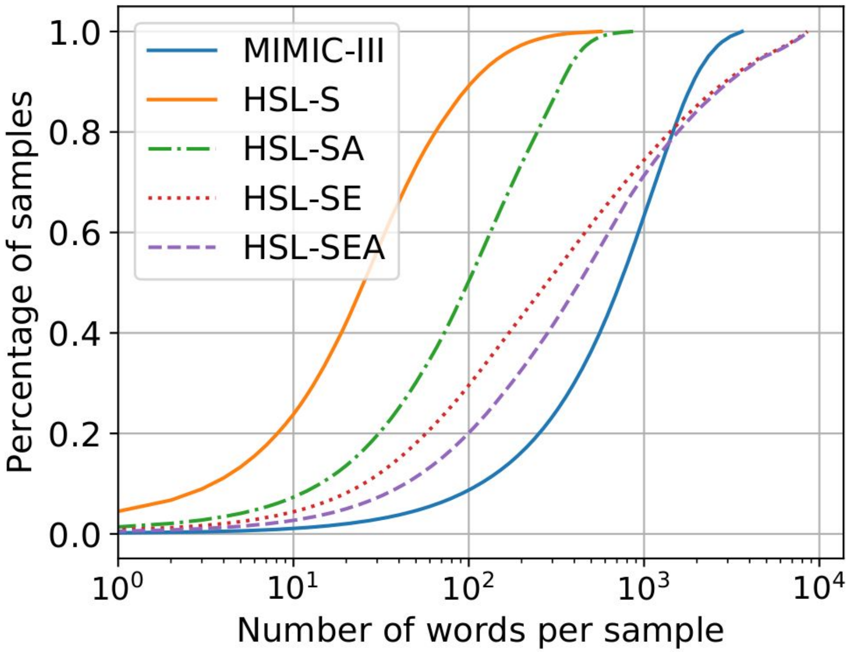
Datasets - HSL

HOSPITAL SÍRIO-LIBANÊS

- Initially, only Discharge Summaries selected
- Additional document types available:
  - Clinical Evolutions (E)
  - Anamnesis/Physical Exams (A)

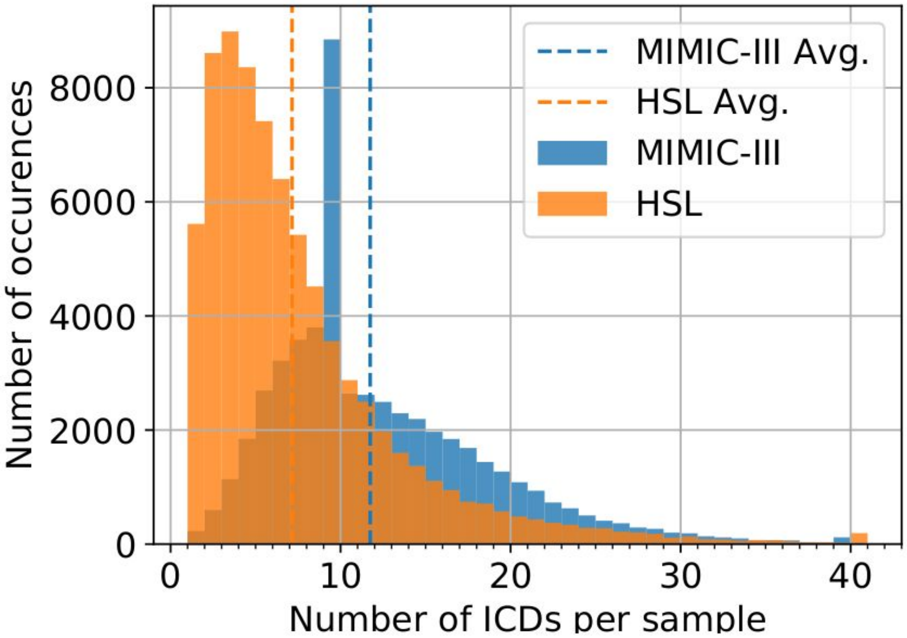


Datasets - Comparison



Dataset	Avg. words per sample
MIMIC-III	1327.5
HSL-S	94.6
HSL-SEA	1730.4

Datasets - Comparison



Percentages of samples that contain the most frequent ICD codes

Dataset	MIMIC-III	HSL
1st	38.02%	34.37%
10th	11.67%	10.71%
100th	2.23%	1.26%
1000th	0.15%	0.06%

Feature Extraction

- TF-IDF - only for Logistic Regression
  - Popular approach for baselines
  - Removed Stopwords
  - Limited vocabulary to 20000 most occurring words
- Word2Vec Word Embeddings - for Neural Networks
  - Self-trained due to language specificity
  - Skip-gram training algorithm
  - Context window of size 5 words
  - Experimented removing stopwords
  - 300 dimensional word vectors

Training Methods

- Preprocessing:
  - Light text preprocessing
  - Transform using trained feature extraction methods
  - For neural networks, pad/truncate input texts to a fixed length
  - Split data 90% / 3% / 7% as in Mullenbach et al. (2018)
- Training:
  - Train for 10 epochs
  - Restore weights from epoch with highest validation metrics

Metrics - Micro-averaged F1

- Chosen metrics:
  - Precision: Ability not to rate as positive a sample that is negative.
  - Recall: Ability to find all the positive samples.
  - **F-score**: Ponderation between precision and recall, through harmonic mean.
- Multi-label average methods
  - Macro: Metric is computed for each class, and then the average between classes is computed
    - Gives too much importance to rare ICDs - large and imbalanced set of classes
  - **Micro**: Metric is computed globally
- Threshold optimization over network predictions

Models - Baselines

- Top-k Baseline (Constant)
  - Predicts, for all samples, the *k* most occurring ICDs in the training set.
- Logistic Regression
  - Baseline in previous works
  - Multi-label problem into a set of binary classification problems
  - TF-IDF features as inputs
  - GridSearch (optimizers, learning rate, regularization)

Models - Convolutional Neural Network (CNN)

- Local context and parameter sharing
- Based on Mullenbach et al. (2018)
  - No Dropout
  - Added Batch Normalization
  - Global Average Pooling instead of Max Pooling
  - Increased kernel size from 4 to 10

Input
Embedding (size 300)
Conv1D (500 filters, kernel 10, tanh)
Batch Normalization
Global Average Pooling 1D
Output (sigmoid)

Models - Gated Recurrent Neural Network (GRU)

- Memory over long context
- GRU Units for training efficiency
- Experimented with different parameters:
    - Extra layers and Bi-directional layers
    - Optimizers and learning rates
    - Fine-tuning of embedding layer
    - Pooling methods

Input
Embedding (size 300)
GRU layer (500 filters, kernel 10, tanh)
Batch Normalization
Global Average Pooling 1D
Output (sigmoid)

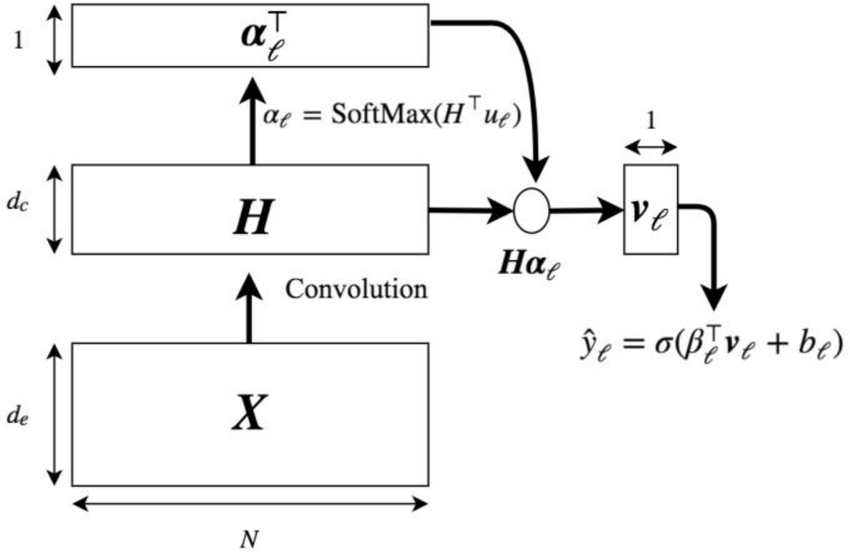
Models - CNN with Attention (CNN-Att)

- Based on Mullenbach et al. (2018)
- Our tests showed improvements when:
    - Removing Dropout and adding Batch Norm.
    - Increasing number of filters
    - Scheduling learning rate for faster training

Input
Embedding (size 300)
Conv1D (500 filters, kernel 10, tanh)
Batch Normalization
Attention
Output (sigmoid)

Models - CNN with Attention (CNN-Att)

- Attention layer allows per-label custom weightening of the Conv1D output feature map



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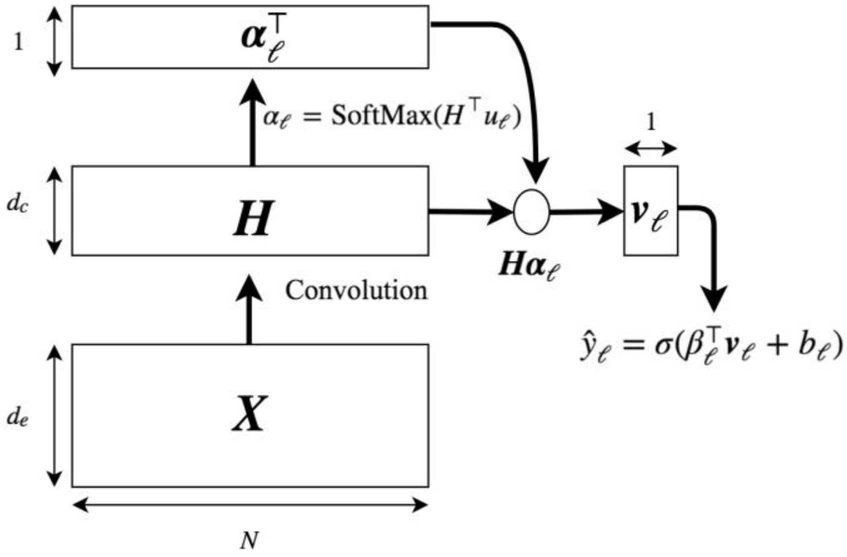
Embedded sequence input



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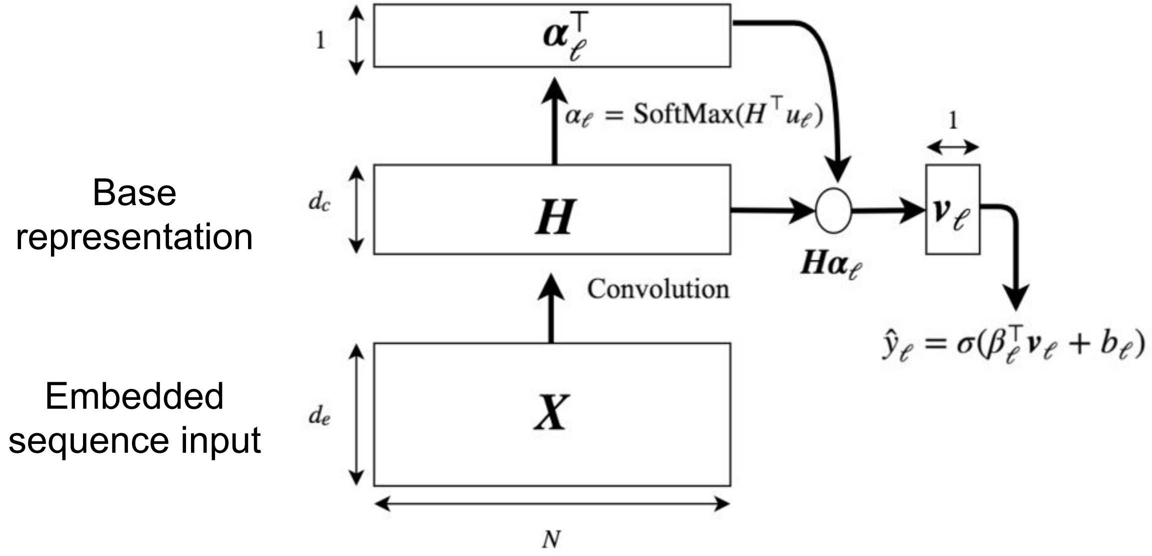

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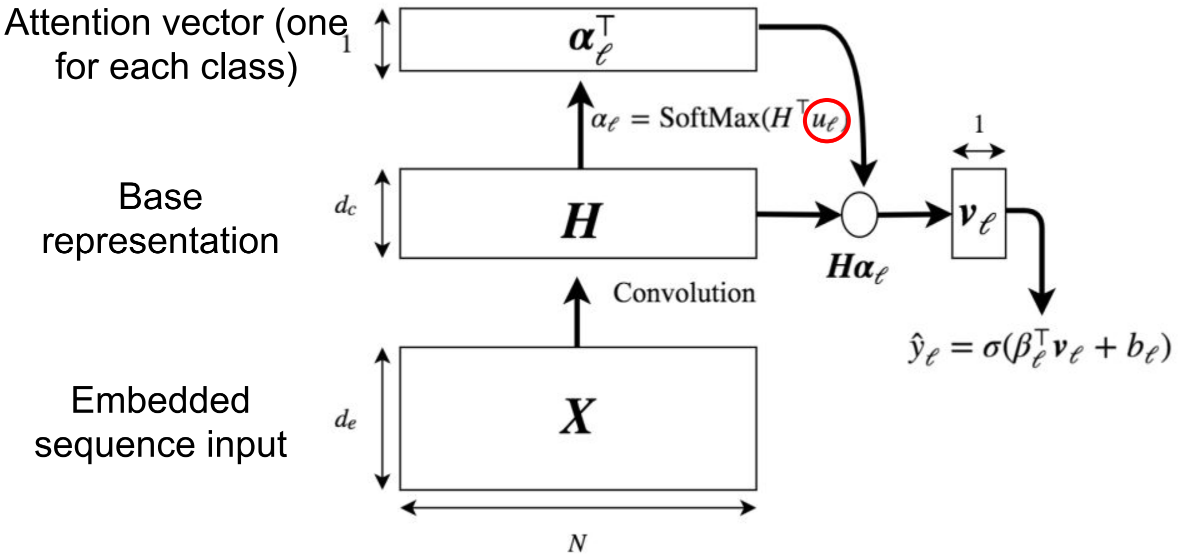

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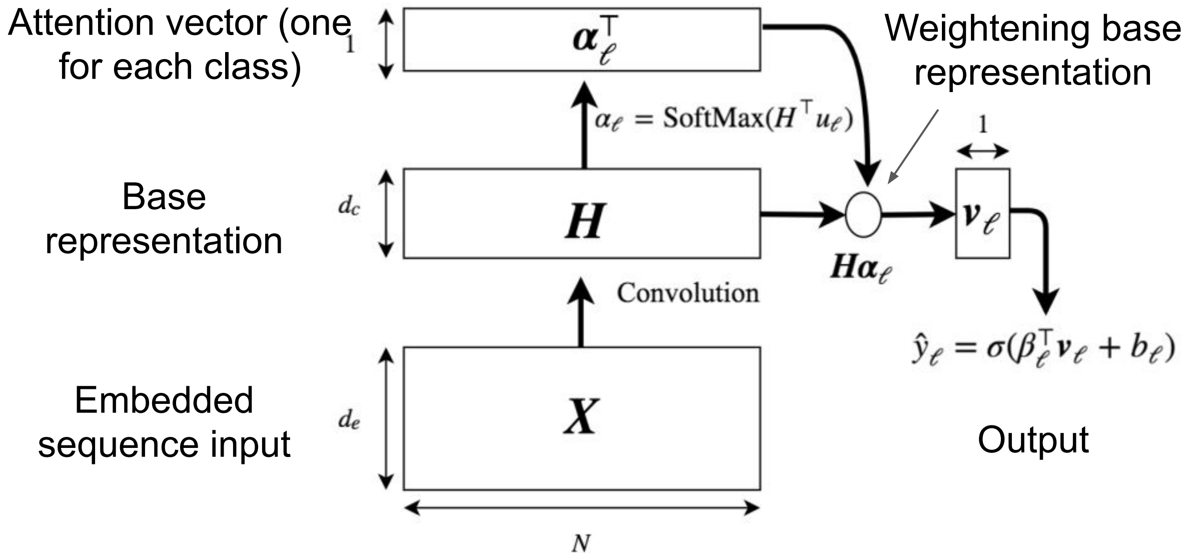

Results - MIMIC-III

Model	Threshold	F1	Precision	Recall
Constant	-	0.192	0.188	0.196
LR (Mullenbach et al, 2018)	-	0.242	-	-
flat-SVM (Li et al, 2019)	-	0.253	0.635	0.158
LR	0.19	0.406	0.425	0.388
CNN (Mullenbach et al, 2018)	-	0.402	-	-
CNN (Li et al, 2019)	-	0.399	0.440	0.366
CNN	0.30	0.423	0.467	0.387
Bi-GRU (Mullenbach et al, 2018)	-	0.393	-	-
GRU	0.32	0.468	0.543	0.412
CAML (Mullenbach et al, 2018)	-	0.524	-	-
CNN-Att	0.28	**0.537**	0.590	0.492

- Major improvements in LR family of models
- CNN-Att shows slight improvement over SOTA

Results - HSL

- LR model validation metrics with concatenation of different document types

Documents	Threshold	F1	Precision	Recall
S	0.26	0.316	0.320	0.312
S and A	0.25	0.347	0.359	0.336
S and E	0.27	0.357	0.382	0.336
S, E and A	0.25	**0.367**	0.390	0.346

S - Discharge Summaries
E - Clinical Evolutions
A - Anamnesis

- HSL-SEA results

Model	Threshold	F1	Precision	Recall
Constant	-	0.203	0.183	0.228
LR	0.25	0.368	0.400	0.340
CNN	0.26	0.374	0.386	0.363
GRU	0.29	0.441	0.508	0.390
CNN-Att	0.29	**0.485**	0.543	0.438

Discussion

- Metrics from the LR model show that HSL-S could not match MIMIC-III results
    - Much smaller average of words per sample
    - Empirically, MIMIC-III is much more detailed
    - The ICD coding process at the Syrian-Lebanese Hospital takes into account all available documents from a single patient, so using HSL-SEA for ICD prediction makes sense
- With HSL-SEA, results are still lower but much more comparable across all models
- The CNN-Att proved to be the better approach.

Conclusion

- Modifications over the current SOTA resulted in metric improvements and faster training
- Using only discharge summaries from our Brazilian-Portuguese dataset is insufficient to achieve satisfactory results
- Our CNN-Att achieves a performance only 10% lower in HSL-SEA compared to MIMIC-III, we conclude that this model is suited to be used to aid the current tagging process, allowing for speed improvements and a considerable decrease in errors.

Thank you!