Enhancing Handwritten Text Recognition with N-Gram Sequence Decomposition and Multitask Learning

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Motivation

Problem : Line Level Handwritten Text Recognition

Sequence of Visual Features → Sequence of Characters drawn from an alphabet

So far HTR has been handled as : Single Task

In this paper we handle the HTR as : Multitask

We formulate the Multitask Scheme as a way to **integrate language domain knowledge**. In HTR, the domain knowledge was integraded so far in the postprocessing step, the decoding via Statistical Language Models, either character level or word level. In our case, we integrate implicitly into the training procedure the n-gram character level information, since we "force" the model to learn except from unigrams, n-grams. As a result we obtain the visual n-gram probability.

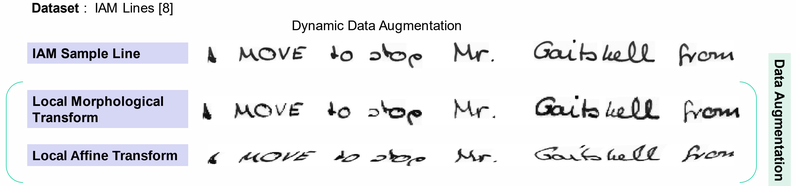
Goals :

- Enable language domain knowledge integration via Multitask Scheme
- Explore fine-to-coarse n-gram granulatities
- Explore Multitask Architectures
- Perform unigram level decoding in the inference. No computational burden in the decoding process

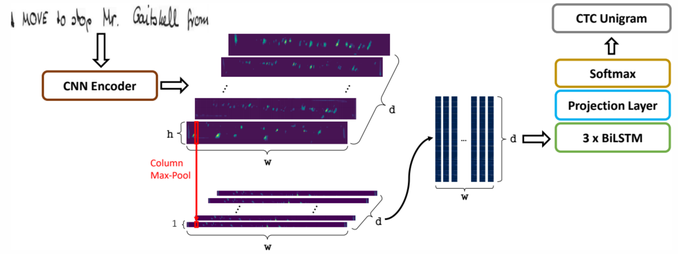
Baseline and Data Augmentation

Dataset : IAM Lines [8]

Dynamic Data Augmentation



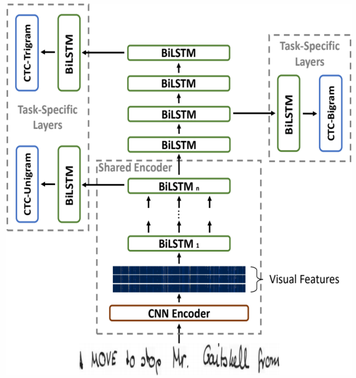
Baseline Architecture



Model Architectures

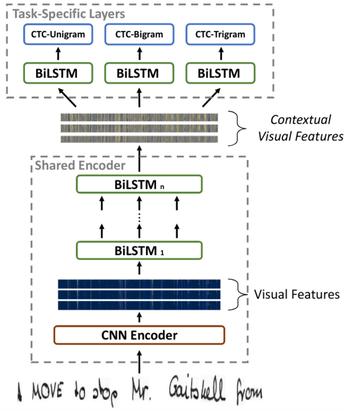
Hiearchical Multitask Architecture

Each n-gram builds its task specific layer upon previous n-gram layers



Block Multitask Architecture

All n-gram task-specific layers share the same encoder



Target Units Selection

Target Units	Word Decomposition
Unigram	b-e-t-t-e-r
All Bigrams	be-et-tt-te-er
Partial Bigrams	be-tt-er
All Trigrams	bet-ett-tte-ter
Partial Trigrams	bet-tte-ter

Example of a single alignmemt for word "better". In the case where a subset of all possible trigrams is selected as target units, the missing trigram in every word is substitued with the blank character "-" . The same applies to bigrams.

Training

CTC Objective :
Y : groundtruth text
A: set of all possible alignments of Y
P(Y|X) = Σ P(a| X)

Intuition : Sum up the probability to have the all possible alignments.
Consider them all when Maximimizing

Multitask CTC Loss : Composed of unigram, bigram and Trigram CTC losses.

$$L(\{y_u, y_b, y_t\}, "better") = L_{CTC}^{unigrams}(y_u, b\text{-}e\text{-}t\text{-}t\text{-}e\text{-}r) + L_{CTC}^{bigrams}(y_b, be\text{-}et\text{-}te\text{-}er) + L_{CTC}^{trigrams}(y_t, bet\text{-}ett\text{-}tte\text{-}ter)$$

Inference

B : Mapping that removes the repeating concecutive characters and Then the "blank" characters. Converts an alignment to sentence.

Greedy

$$y_{dec} = B(\arg\max_x \prod_{t=1}^{T} P(x_t|\boldsymbol{X}))$$

CTC Decoding + Character LM

$$_{dec} = B(\arg\max_x \sum(\prod_{t=1}^{T} P(x_t|\boldsymbol{X}) \cdot P_{LM}(x_t|y_{dec}(t-1))))$$

Evaluation and Conclusion

Evaluation Metrics : Word Error Rate, Character Error Rate

N-Grams	WER %	CER %
Single-Task		
Pham *et al.* [1]	35.10	10.80
Puigcerver *et al.* [2]	20.20	6.20
Castro *et al.* [3]	24.00	6.64
Michael *et al.* [4]	-	5.24
1-gram (ours)	19.10	5.60
Hierarchical MT		
1-grams + 2-grams	17.72	5.21
1-grams + 2-grams + 3-grams	17.70	5.37
1-grams + 2-grams + 3-grams + 4-grams	**17.68**	5.29
Block MT		
1-grams + 2-grams	17.96	5.28
1-grams + 2-grams + 3-grams	17.90	5.30
1-grams + 2-grams + 3-grams + 4-grams	**17.68**	**5.18**

Architecture	WER %	CER %
CTC Greedy Decoding		
Single-Task	19.10	5.60
BMT	17.68	5.18
CTC BeamSearch 4-Gram CharLM		
Single-Task	18.14	5.64
BMT	16.72	5.28
CTC BeamSearch 4-Gram WordLM		
Single-Task	14.81	4.60
BMT	**13.62**	**4.60**

- In all the above experiments we utilize only the unigram posteriors in the inference so as to keep the computational cost of decoding as low as possible
- There is no substantial difference in recognition performance between the Hierarchical and Block Architecture. Thus we focus on the BLock Mutitask architecture with Unigram and Bigram CTC levels
- Comparing our Single-task architecture with the Block Multiatsk we observe the improvement in both WER and CER in the greedy decoding where no explicit language knowledge was utilized. This result indicates that the using unigrams and bigrams (character level) in a multitask-scheme improves the internal learned representations and leads to better performance metrics

Aknowledgement

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