Learning Efficient Representations for Sequence Retrieval

Colin Raffel

Boston Data Festival

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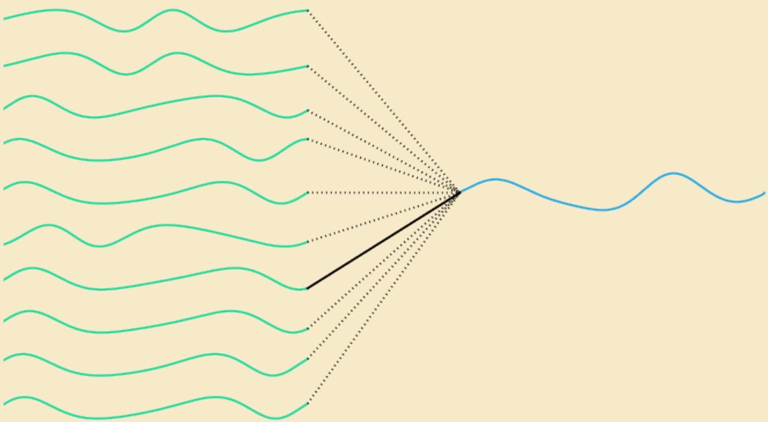
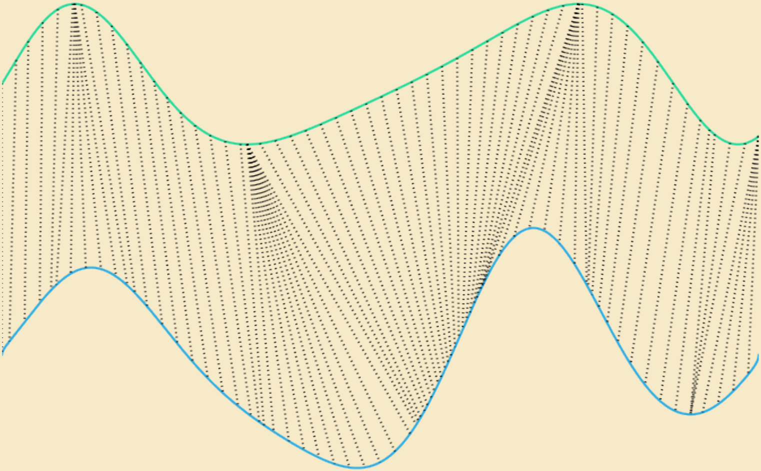
Sequence Retrieval



Dynamic Time Warping



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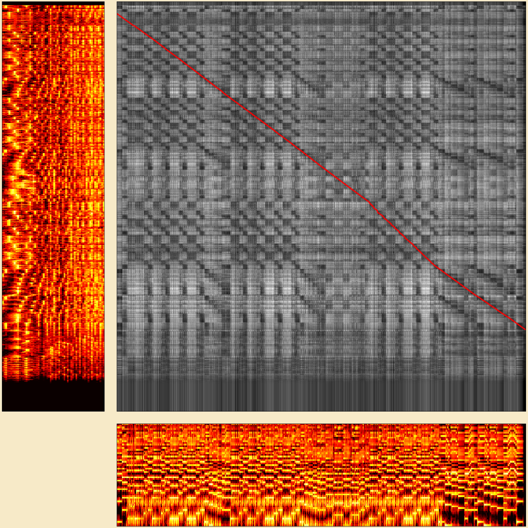

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2. Use DTW to find lowest-cost path through the distance matrix
3. Allow subsequence matching, with some tolerance
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5. Compute the total distance between aligned frames
6. Normalize by path length and mean of path submatrix

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- Data dimensionality can cause expensive “local distance” calculations
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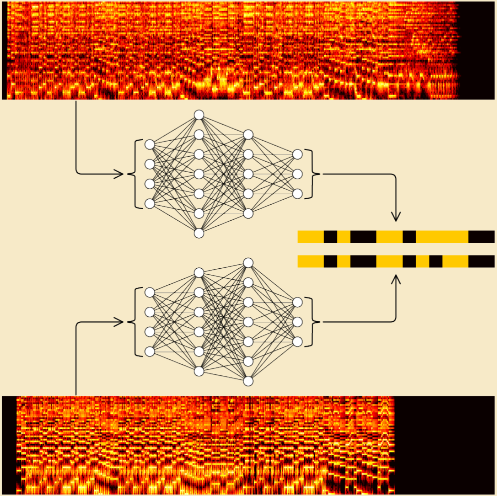
- Inappropriate when sequences come from different modalities
- Relies on a non-learned metric for comparing feature vectors

Similarity-Preserving Hashing



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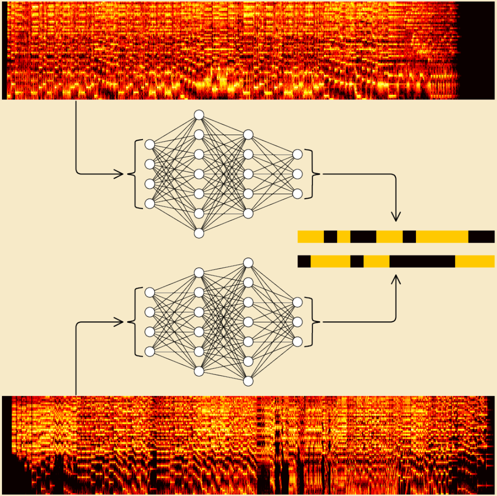
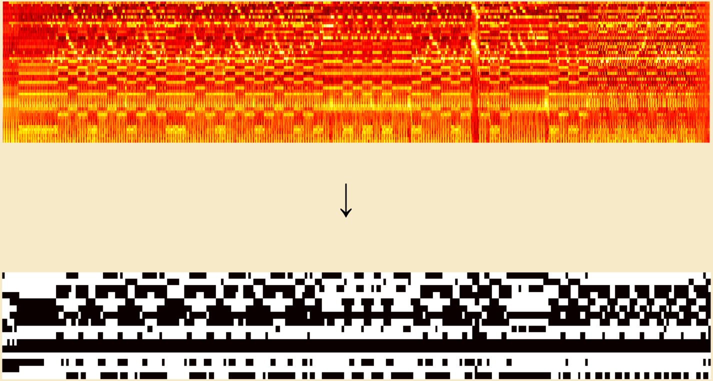
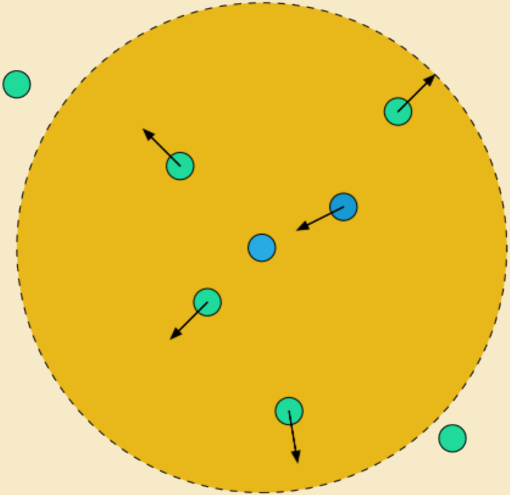


Hash Sequences



$$\mathtt{distance}[m, n] = \mathtt{bits\_set}[x[m] \oplus y[n]]$$

Loss function



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- Objective: Bhattacharyya distance of positive/negative examples distance distributions

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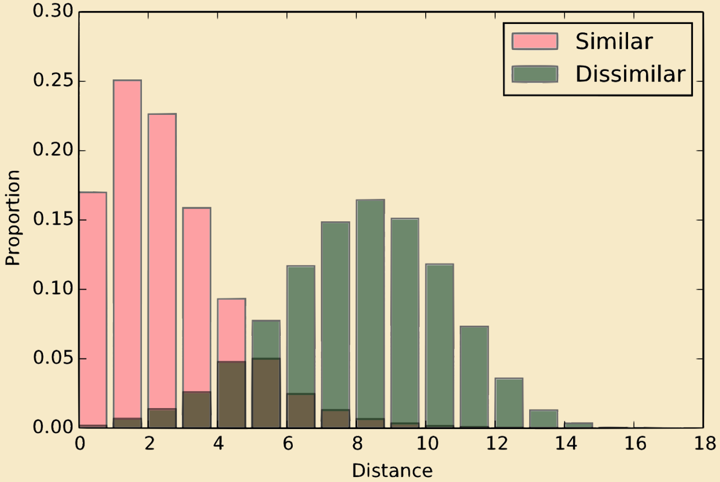
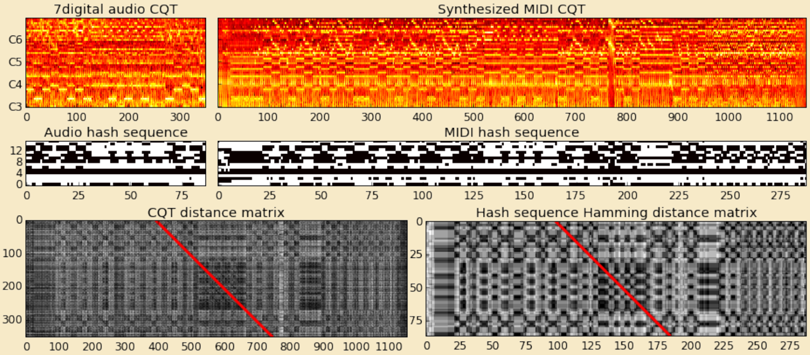
- Network made out of `lasagne`

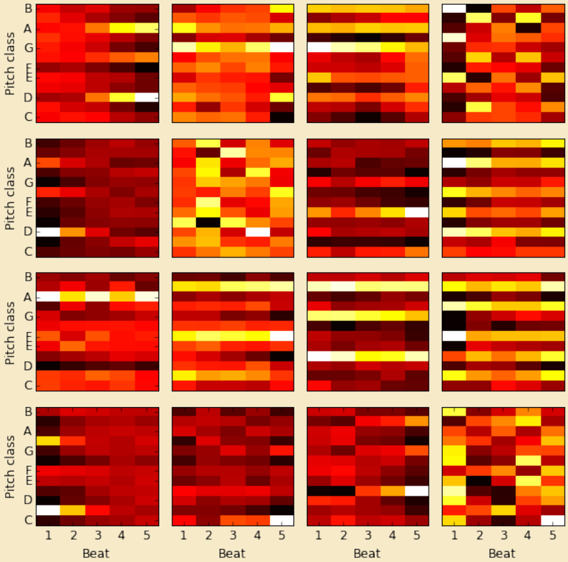
Validation Distance Distribution



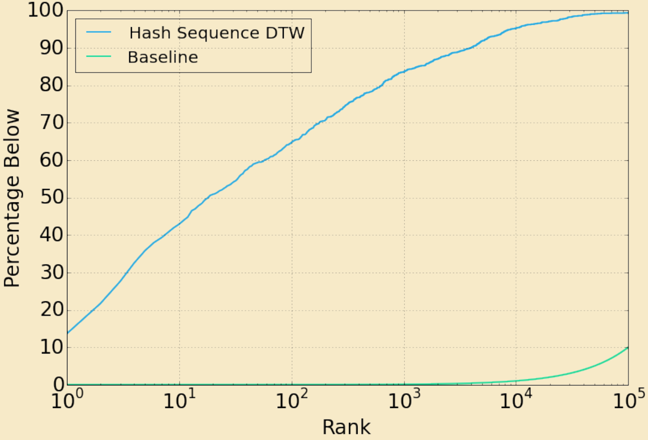
Example Sequence



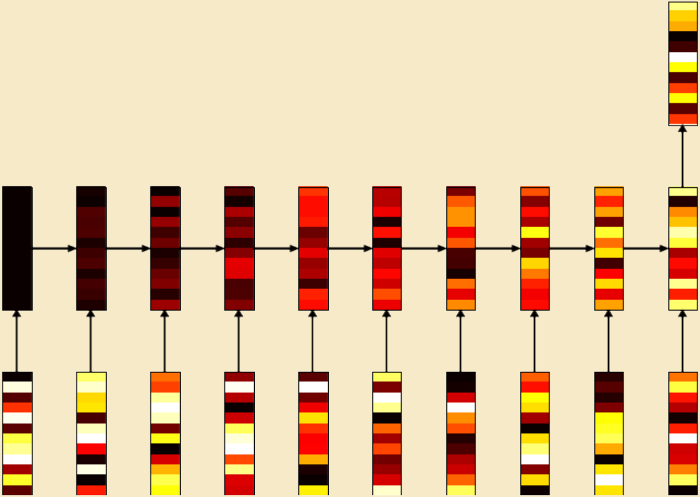
First Layer Filters



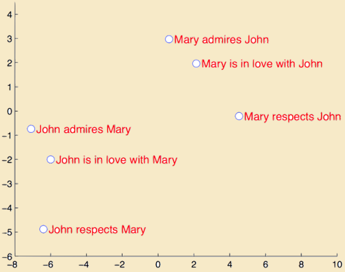
Correct Match Rank Results

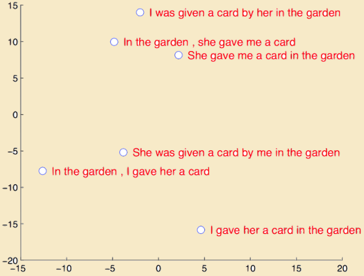


Sequence Embedding



Sentence Embeddings, with t-SNE





Sutskever et. al; *"Sequence to Sequence Learning with Neural Networks"*

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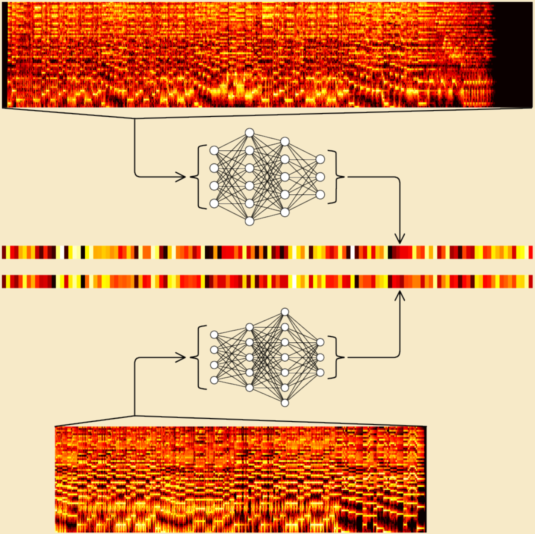

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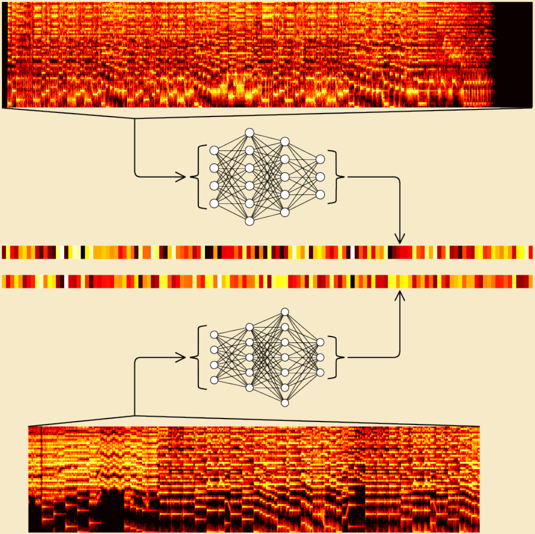
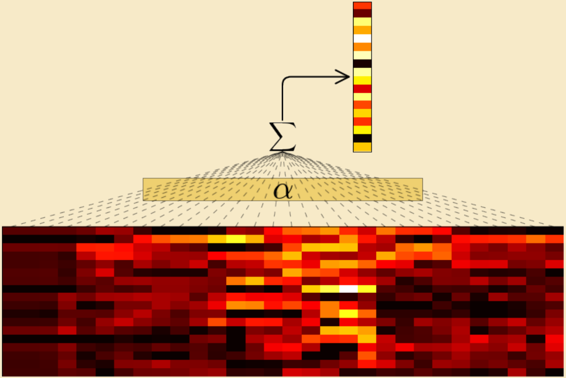


Attention



$$\alpha = \mathrm{softmax}(wx + b)$$

$$w \in \mathbb{R}^{\texttt{n\_features}},\ b \in \mathbb{R},\ \alpha \in \mathbb{R}^{\texttt{n\_steps}}$$

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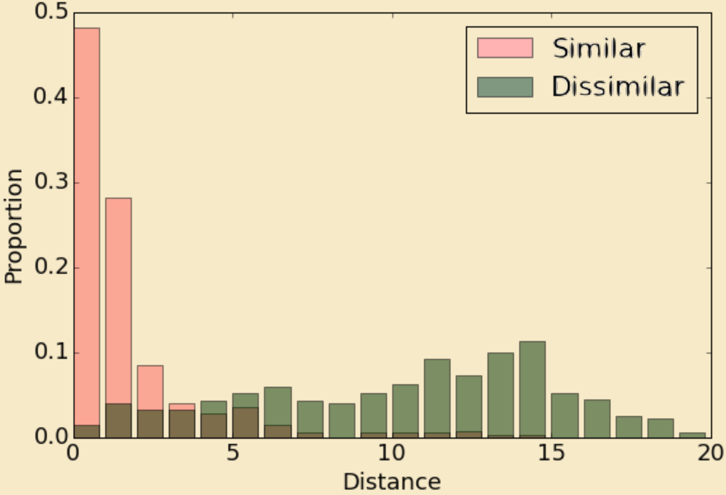
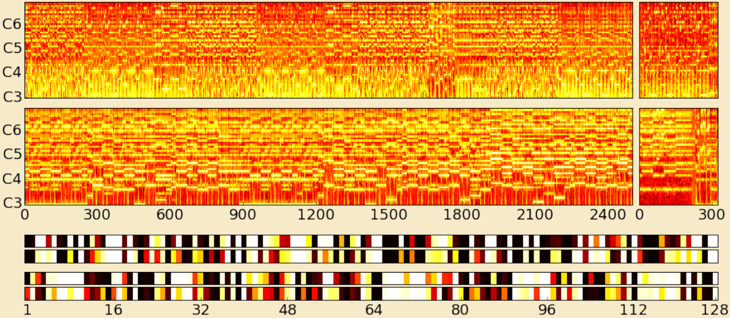
- Network structure is otherwise the same

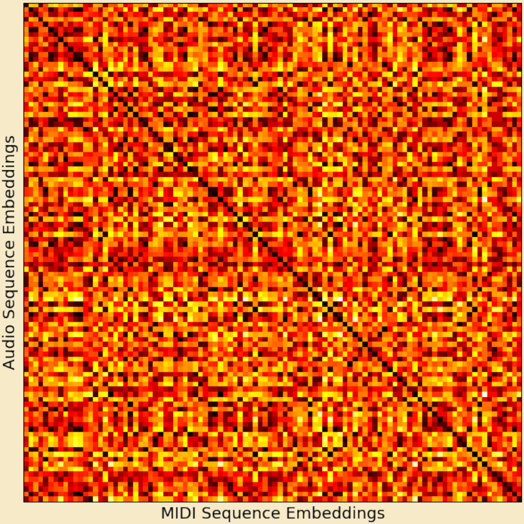
Validation Distance Distribution



Example Embeddings



Embedding Distance Matrix



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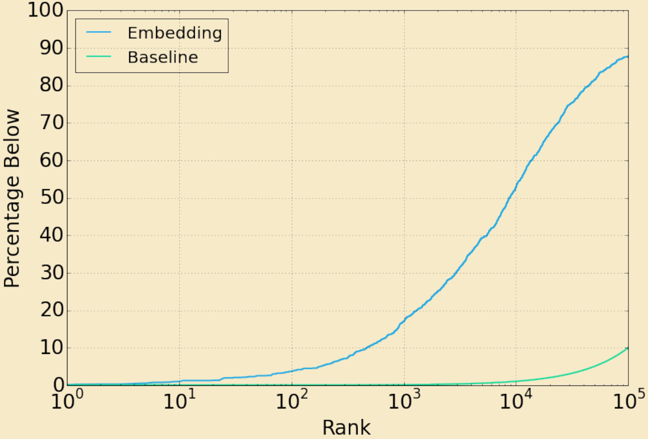

Thanks!

craffel@gmail.com

http://github.com/craffel/