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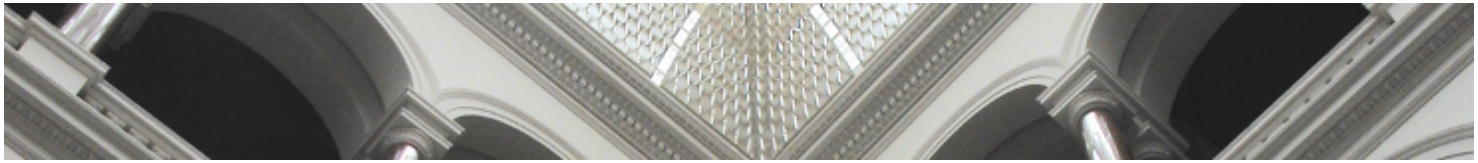
Designing Recurrent Neural Networks for Explainability

Pattarawat Chormai | Technische Universität Berlin | 14/11/2018



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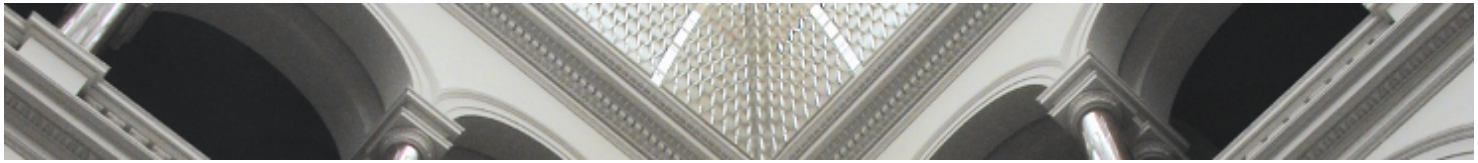
Motivation

- Impact of the architecture of RNNs on explainability
- Are deeper RNNs more explainable?
- Are there ways to make RNNs more explainable?



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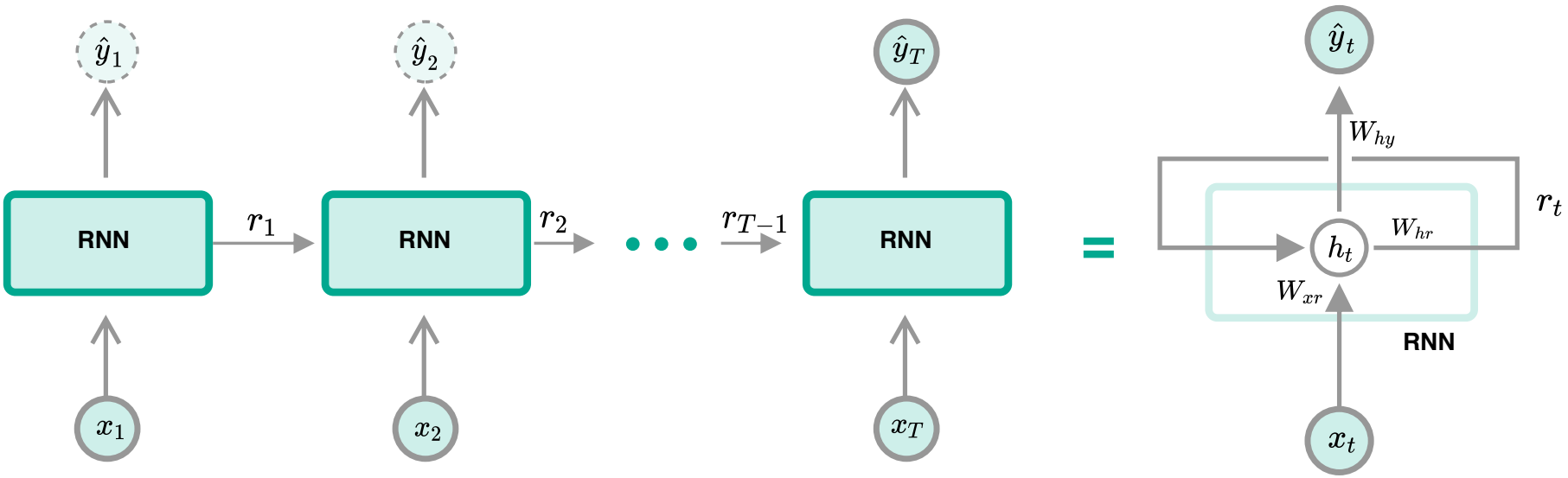
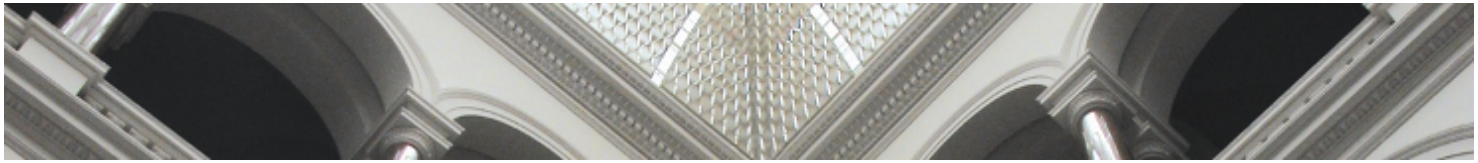
Recurrent Neural Networks (RNNs)





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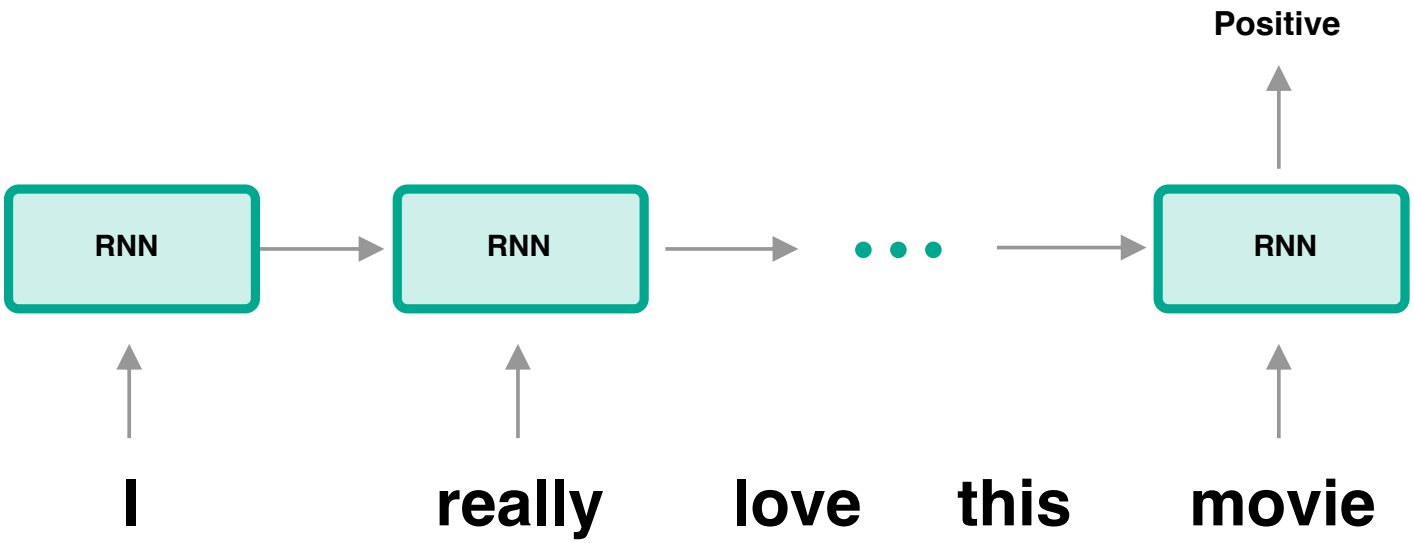
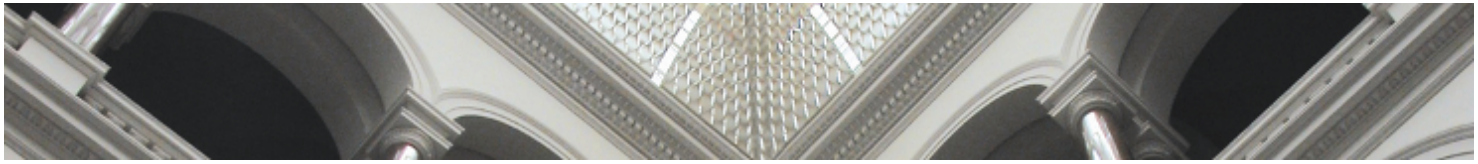
Recurrent Neural Networks (RNNs)

– Applications: sentiment analysis, NLP, machine translation, and image captioning





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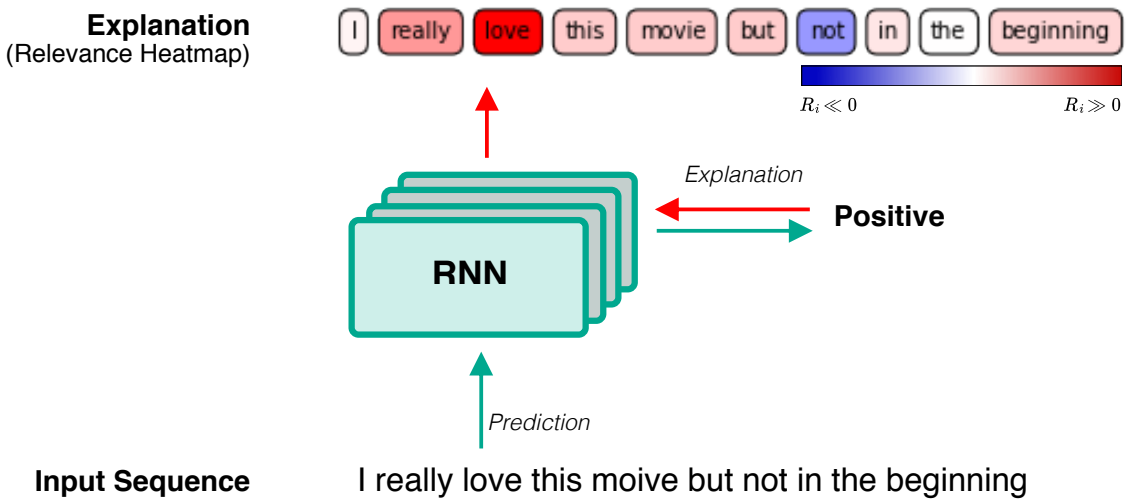
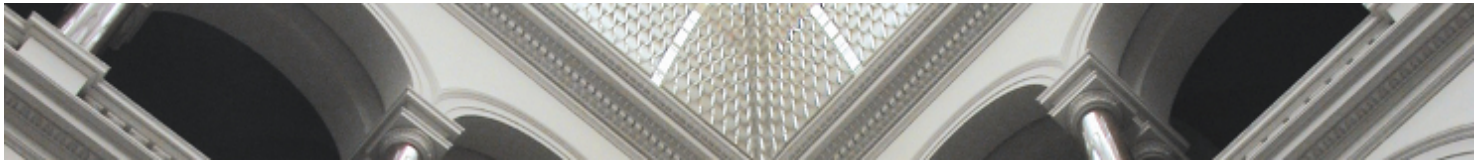
Explainability I

- Ability to provide sensible explanation towards how input associates to a particular output.
- For example, why does the RNN classify this text as a positive review?





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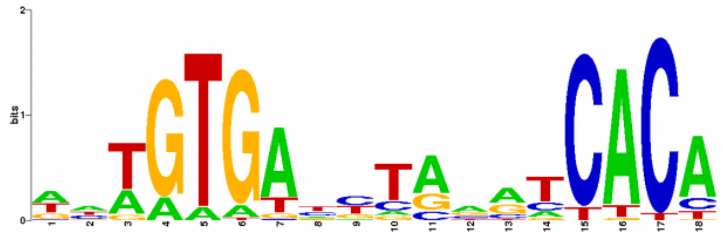
Explainability II

– Why do we need explainable models?

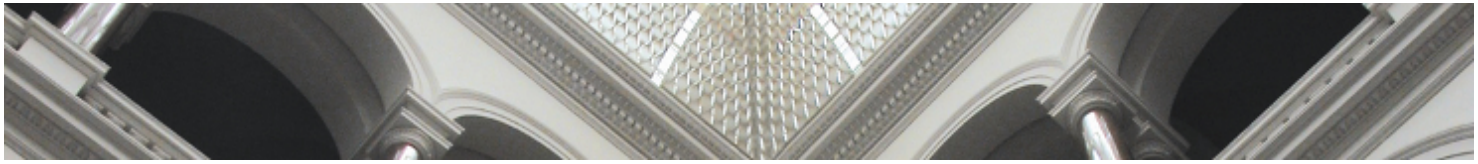
- Aid decision and establish trust in the system, especially in critical applications such as healthcare.

DNA Motif Discovery



taken from http://genomeinformatics.uni-due.de

- Developers can assure that trained models would work as expected.



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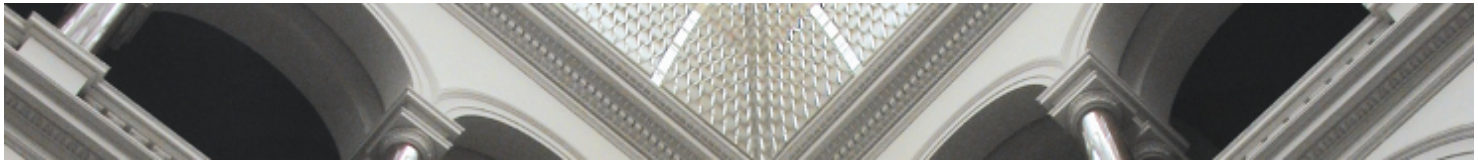
Explanation Methods I

1. Sensitivity Analysis [SVZ13]

$$R_i(\boldsymbol{x}) = \left(\frac{\partial f(\boldsymbol{x})}{\partial x_i} \right)^2$$

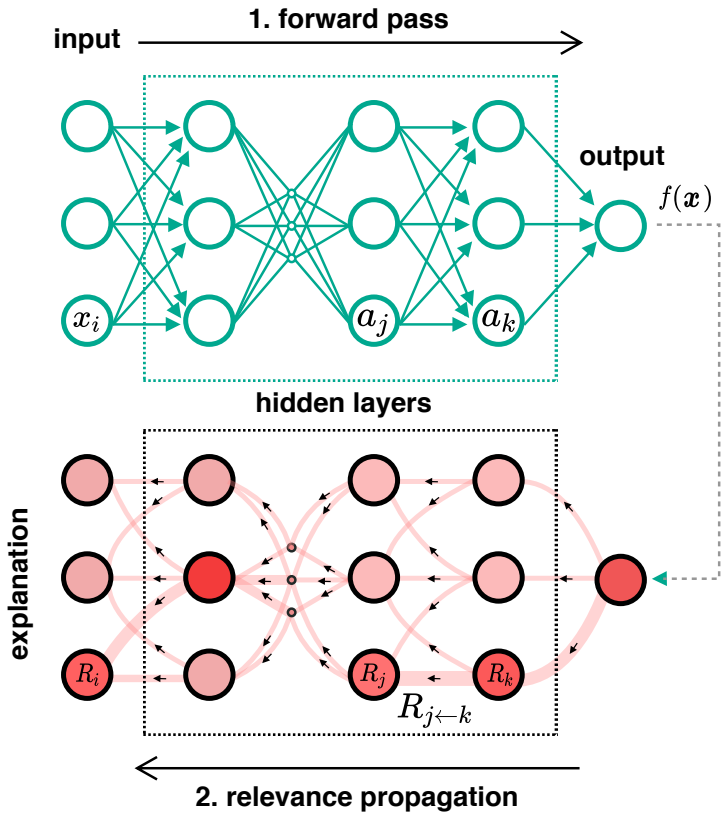
2. Guided Backprop [SDBR15]

$$\frac{\partial_* f(\boldsymbol{x})}{\partial h_j} = \mathbb{1}\left[h_j > 0 \right] \max\left(0, \frac{\partial_* f(\boldsymbol{x})}{\partial a_j} \right); \qquad R_i(\boldsymbol{x}) = \left(\frac{\partial_* f(\boldsymbol{x})}{\partial x_i} \right)^2$$

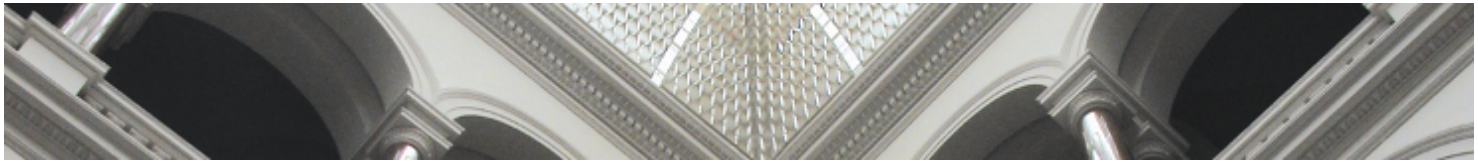


Explanation Methods II

3. Layer-wise Relevance Propagation (LRP) [BML+16]



$$R_j(\boldsymbol{x}) = \sum_k \left(\alpha \frac{a_j w_{jk}^+}{\sum_{j'} a_{j'} w_{j'k}^+} - \beta \frac{a_j w_{jk}^-}{\sum_{j'} a_{j'} w_{j'k}^-} \right) R_k(\boldsymbol{x})$$



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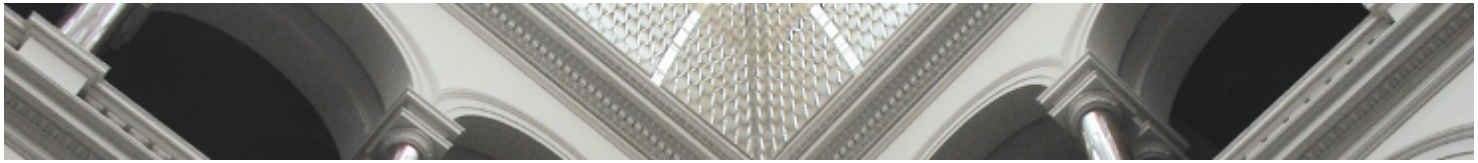
Explanation Methods III

4. Deep Taylor Decomposition [MLB$^+$17]
   - Based on LRP and derived specifically for explaining ReLU-based architectures
   - Two important propagation rules:
     – z^+ for $a_j \in \mathbb{R}^+$

$$R_j = \sum_k \frac{a_j w_{jk}^+}{\sum_j a_j w_{jk}^+} R_k$$

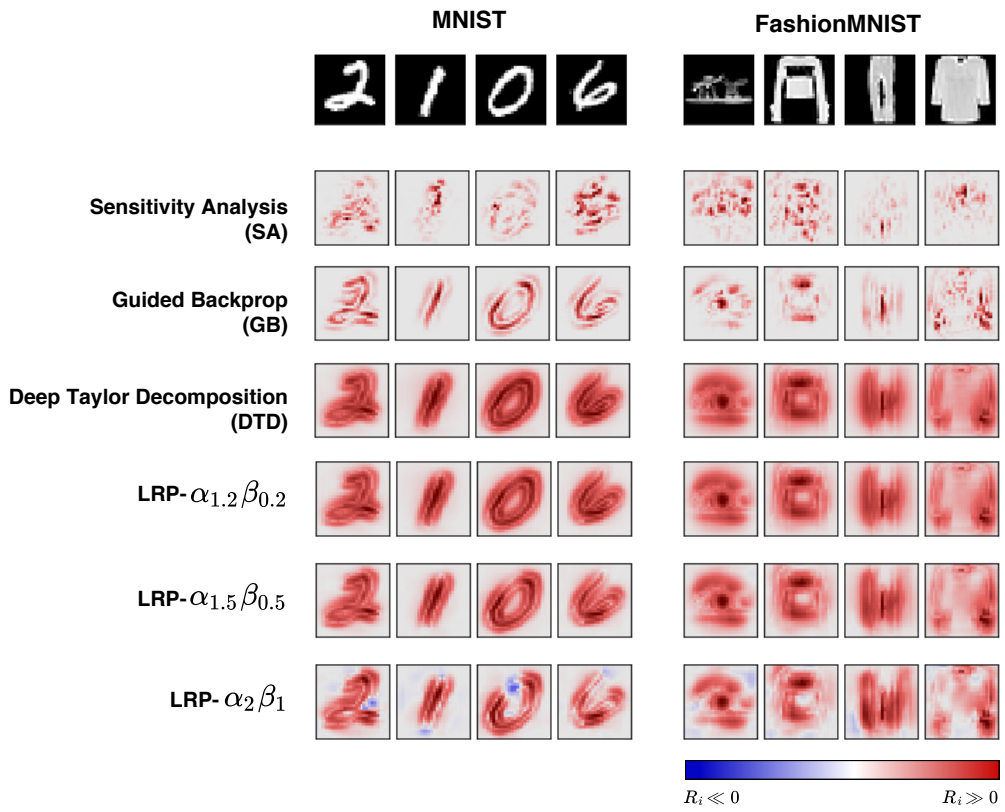
     – $z^{\mathcal{B}}$ for $a_j \in [l_j, h_j]$ where $l_j \leq 0 < h_j$

$$R_j = \sum_k \frac{a_j w_{jk} - l_j w_{jk}^+ - h_j w_{jk}^-}{\sum_{j'} a_{j'} w_{j'k} - l_{j'} w_{j'k}^+ - h_{j'} w_{j'k}^-}$$

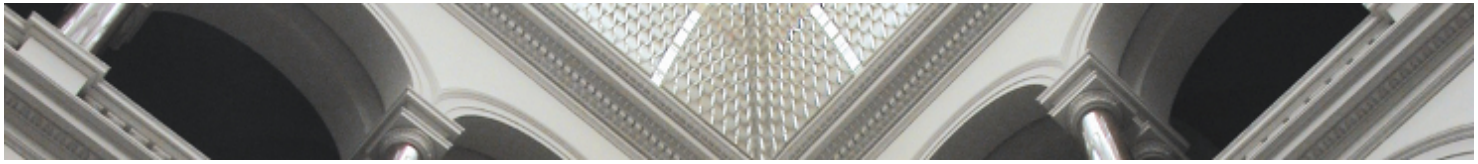


Example of relevance heatmaps

– Explaining the classification decisions of a LeNet-5 type network.



Architecture: CONV(5 × 5, 10) · AVGPOOL(2 × 2, 2, 2) · CONV(5 × 5, 25) · AVGPOOL(2 × 2, 2, 2) · CONV(4 × 4, 100)· AVGPOOL(2 × 2, 2, 2) · DENSE(100) · DENSE(10)



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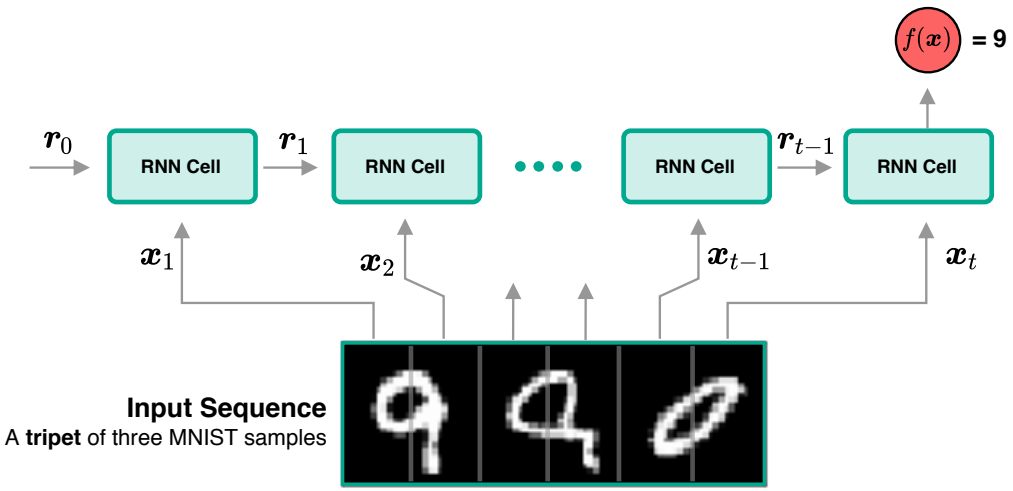
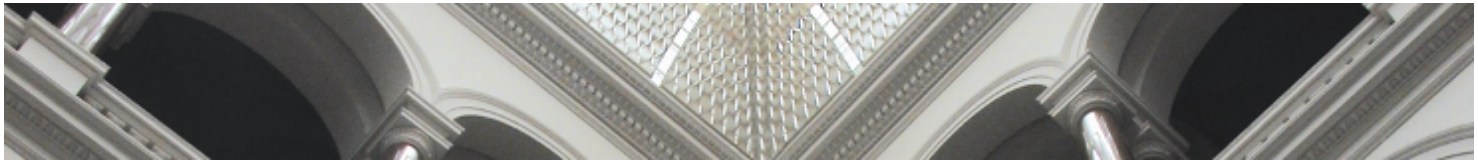
Experimental Setup

- **Problem:** Majority-Sample Sequence Classification
  - ▷ Minimum accuracy 98% for MNIST and 89% for FashionMNIST
  - ▷ Sequence length: 12 ($\{\boldsymbol{x}\}_{t=1}^{12}$)





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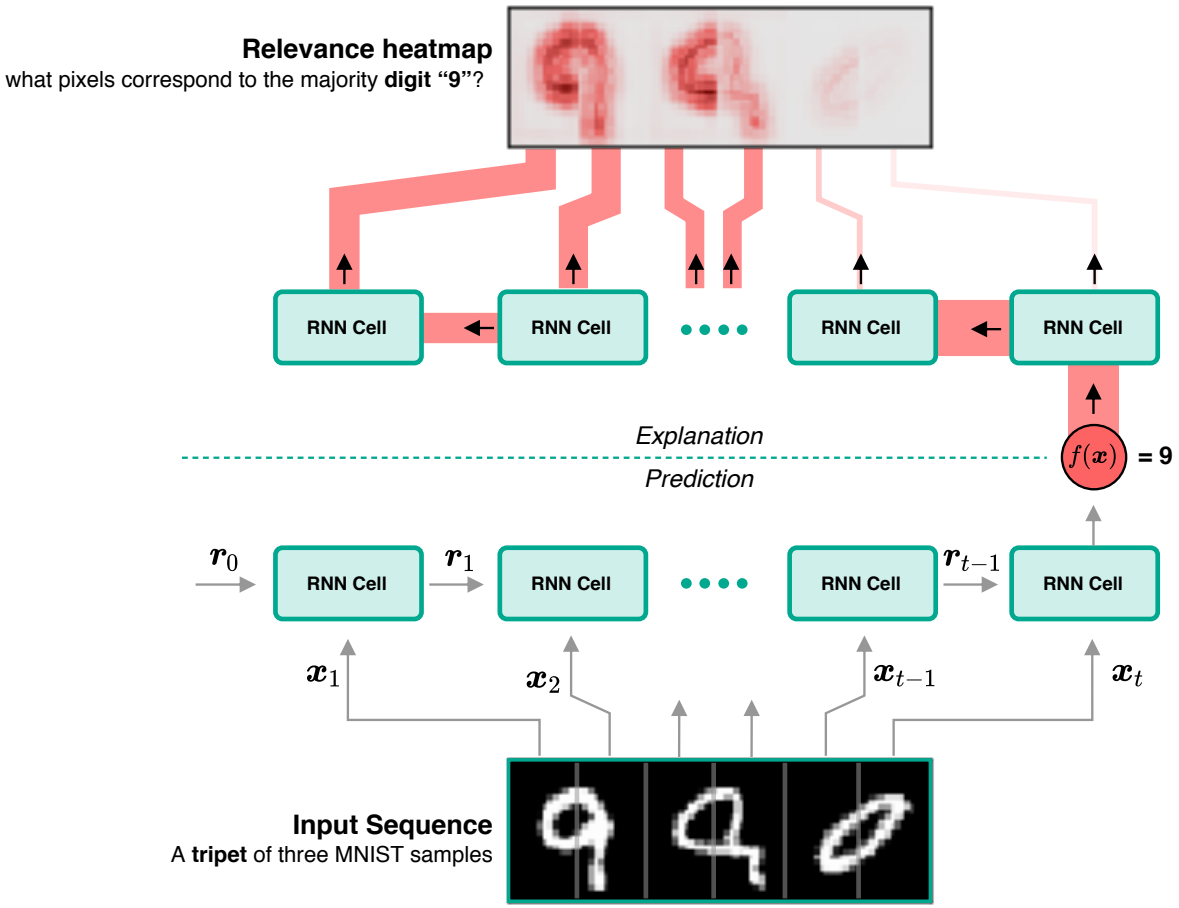
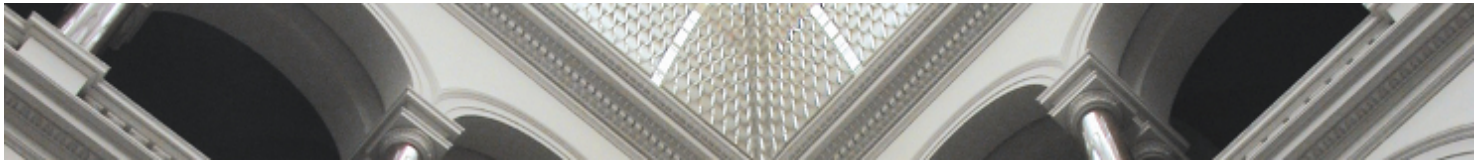
Experimental Setup

– **Problem:** Majority-Sample Sequence Classification





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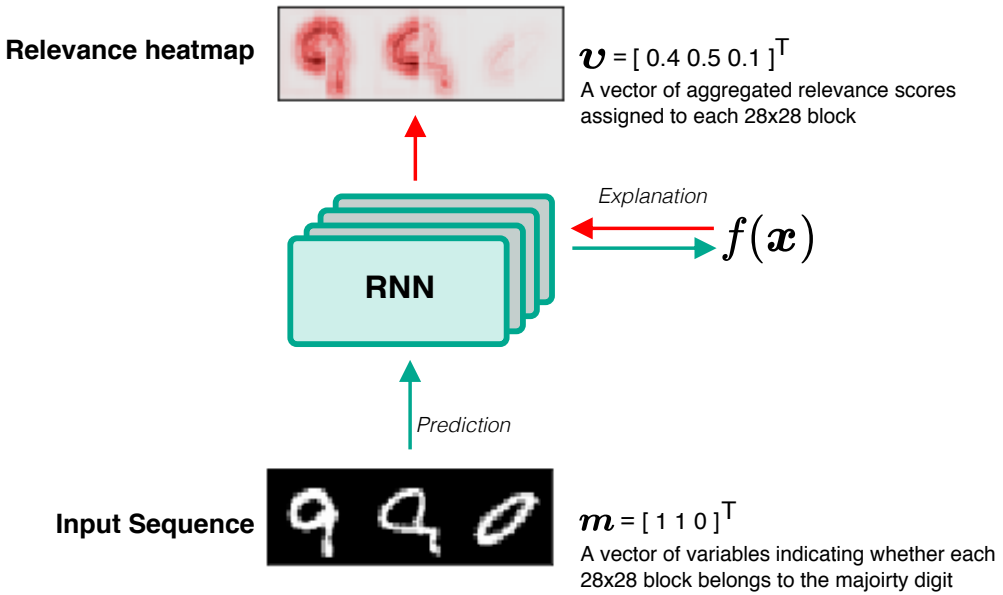
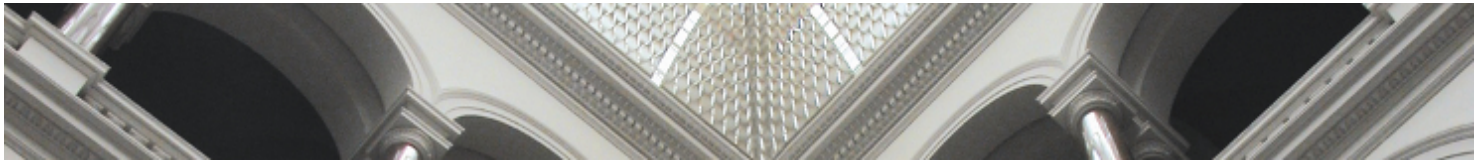
Experimental Setup

- **Problem:** Majority-Sample Sequence Classification
- **Evaluation:** Cosine similarity (averaged over test samples)



Heatmap Quality

$$\cos(\boldsymbol{m}, \boldsymbol{v}) = \frac{\boldsymbol{m}^T \boldsymbol{v}}{\|\boldsymbol{m}\| \|\boldsymbol{v}\|}$$



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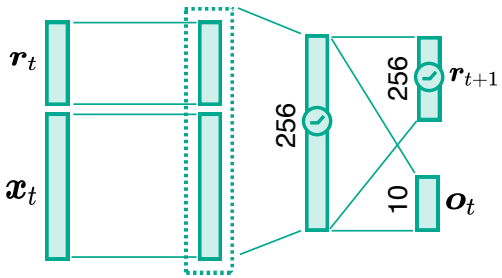
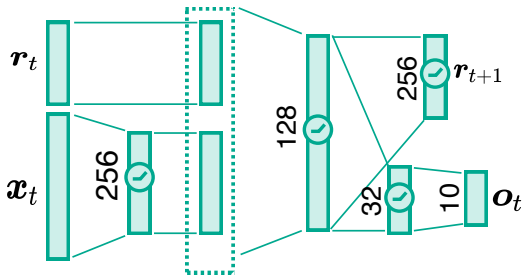
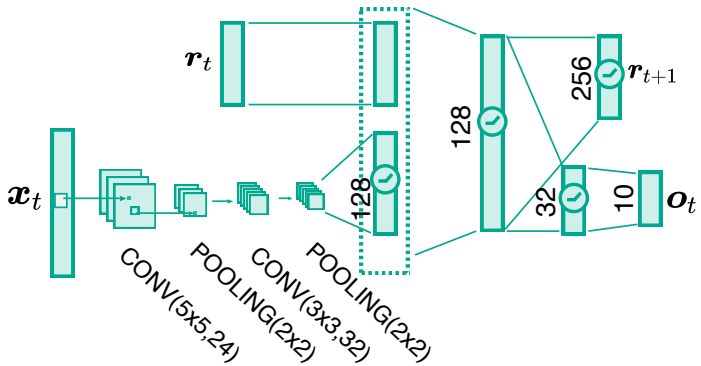
Experiment 1: Standard RNN Architectures



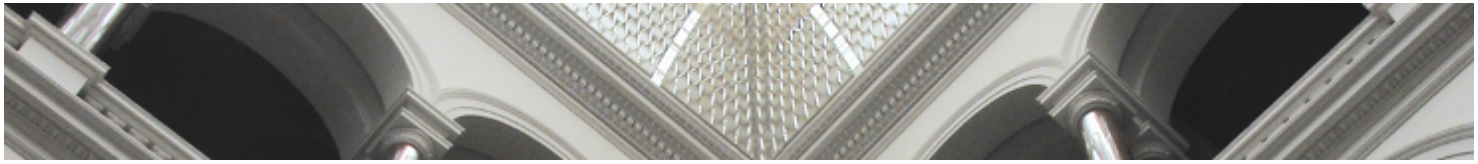
Shallow



Deep

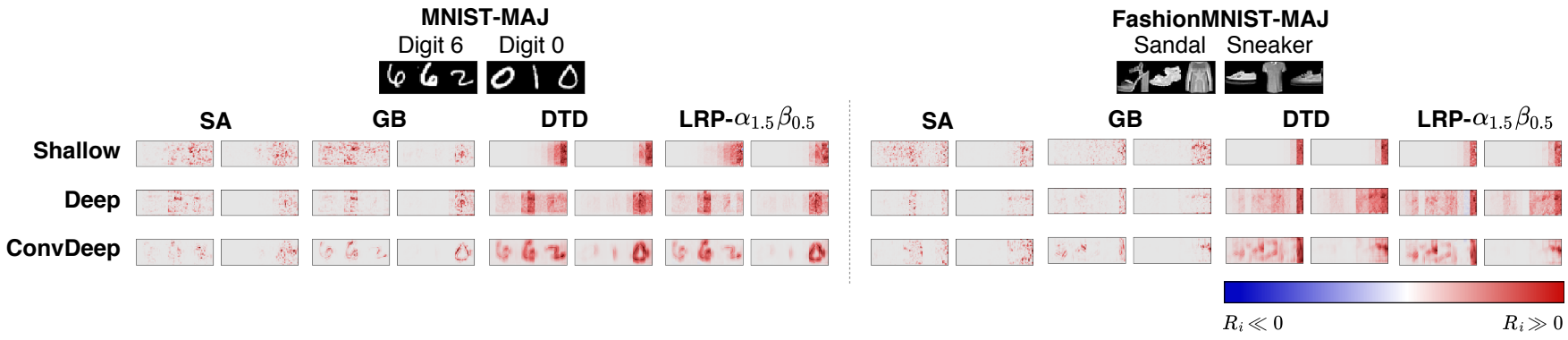


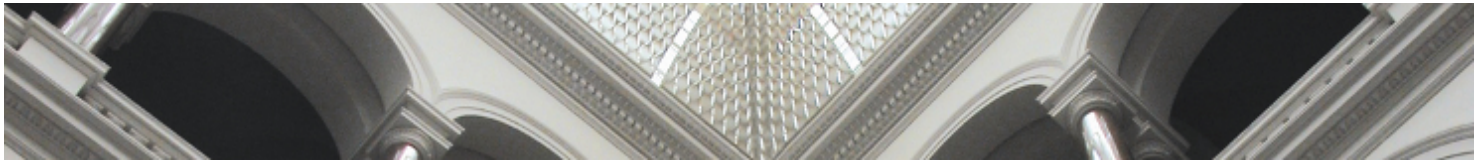
ConvDeep



Experiment 1: Standard RNN Architectures

Sample Relevance Heatmaps





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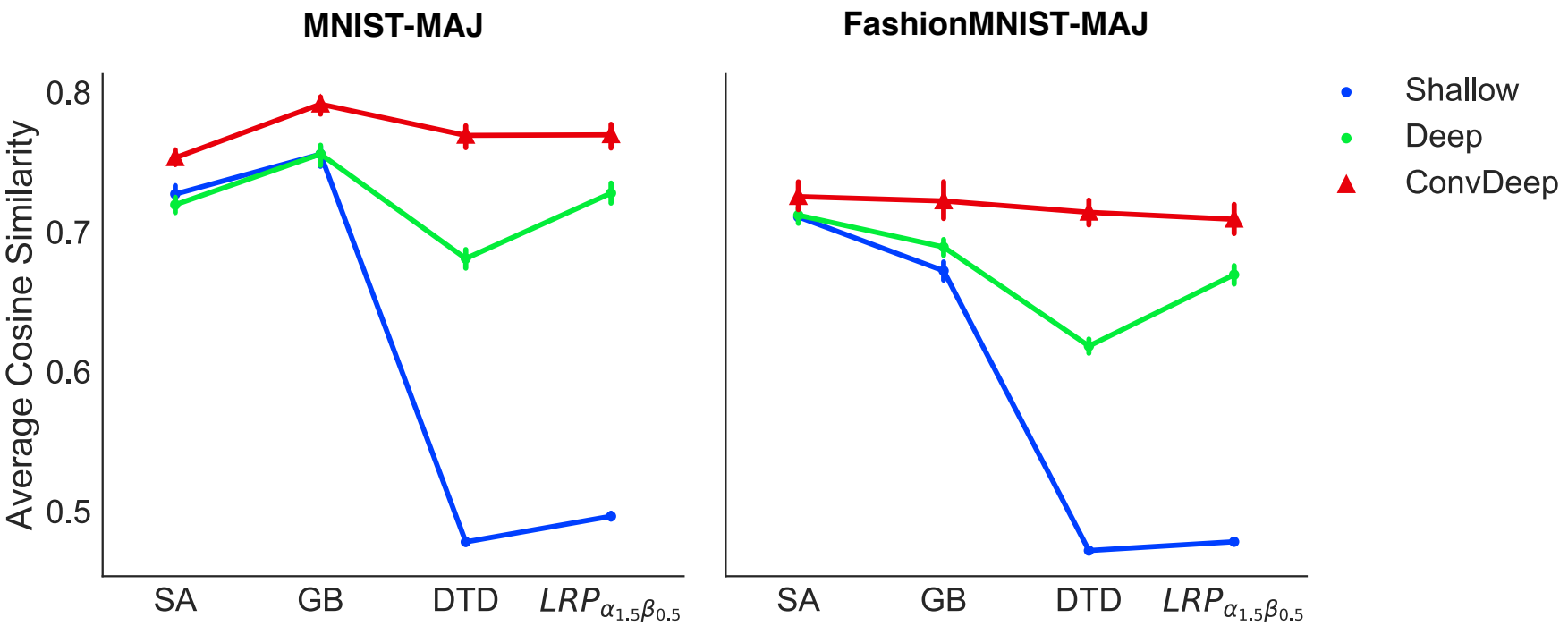
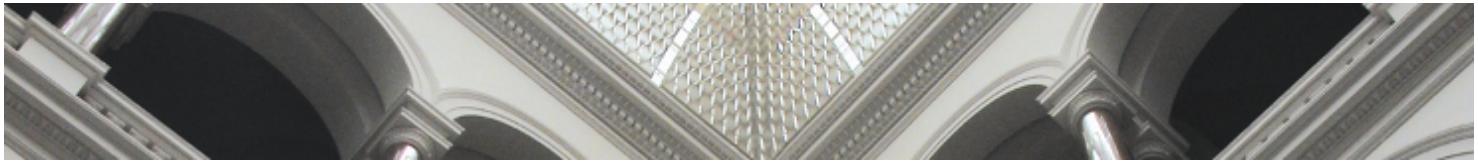
Experiment 1: Standard RNN Architectures

Cosine Similarity Evaluation





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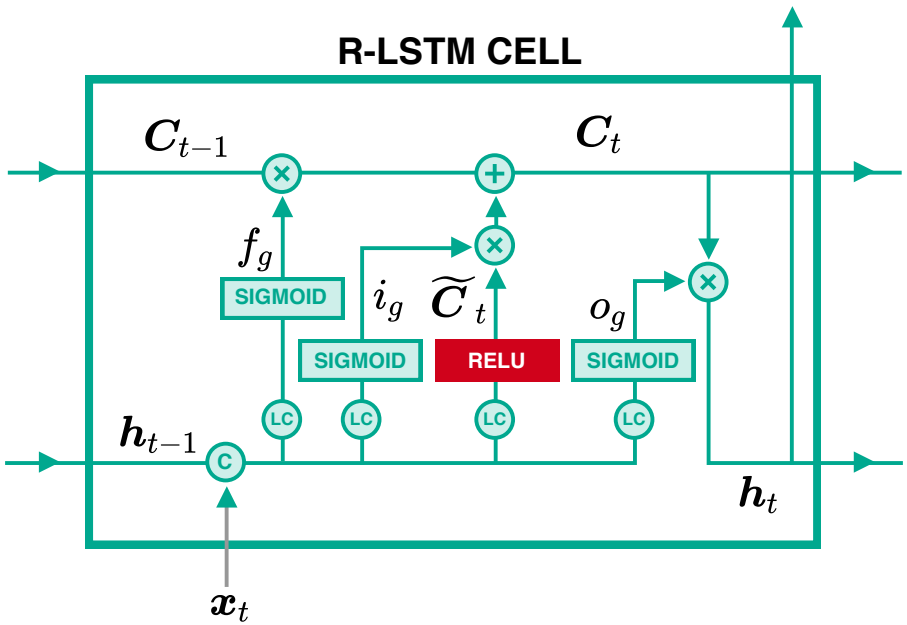
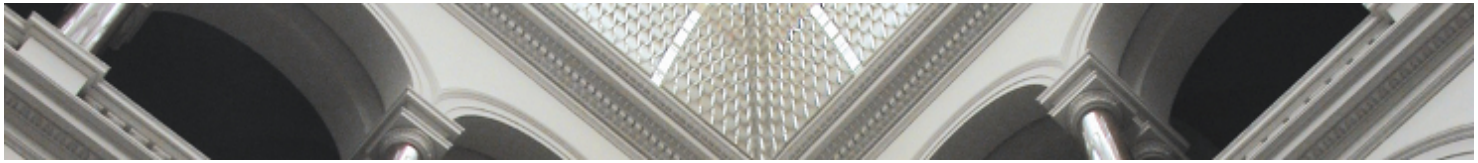
Experiment 2: More Explainable Models

1. LSTM [HS97] with tanh being replaced by ReLU (R-LSTM)
   — Gating units are ignored during explaining [AMMS17].



C Vector concatenation LC Linear combination ⊗ Element-wise multiplication ⊕ Element-wise addition



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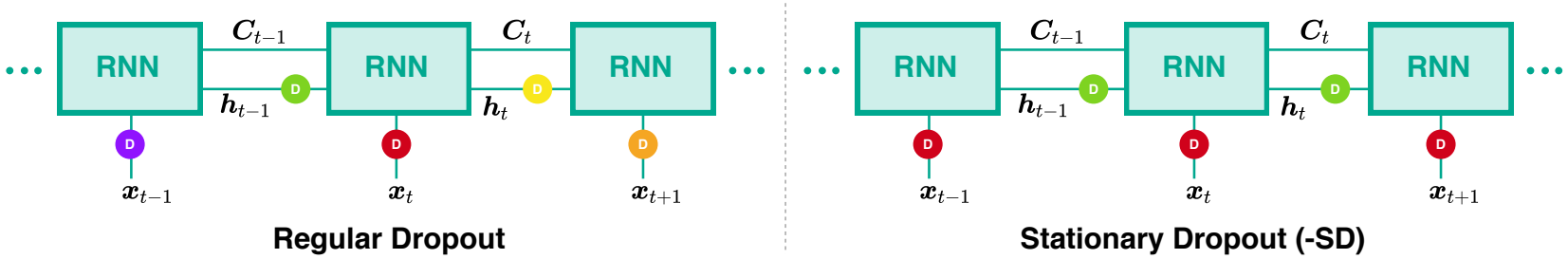
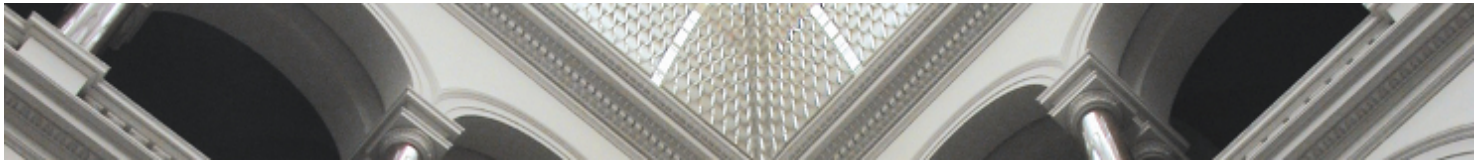
Experiment 2: More Explainable Models

1. LSTM [HS97] with tanh being replaced by ReLU (R-LSTM)
2. Stationary Dropout [GG16] (-SD)





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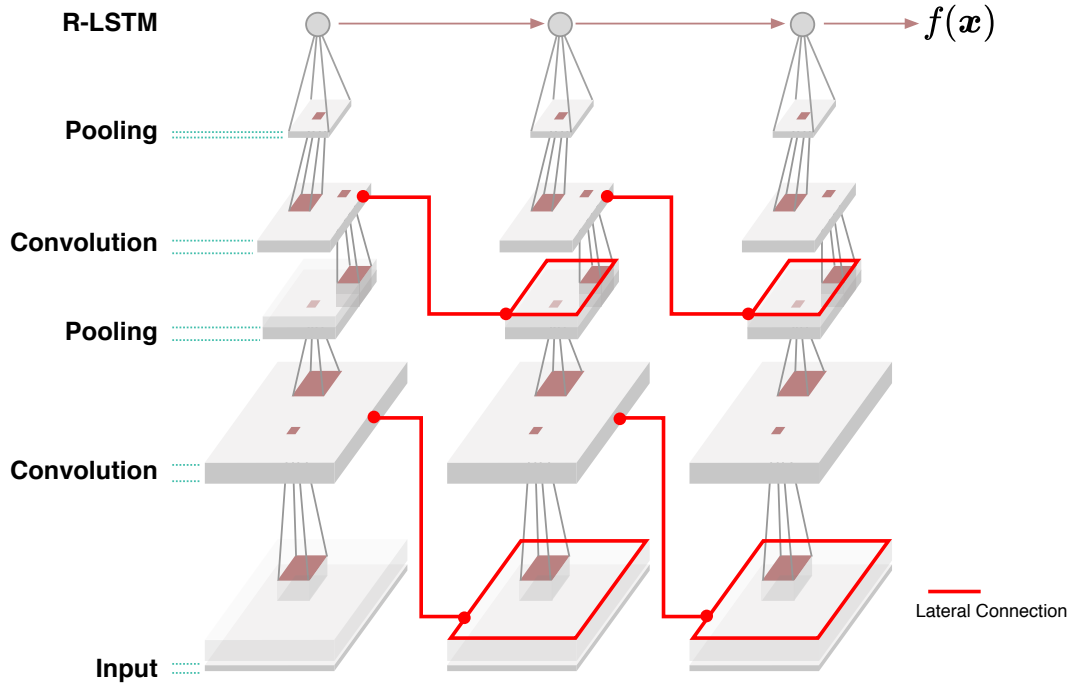
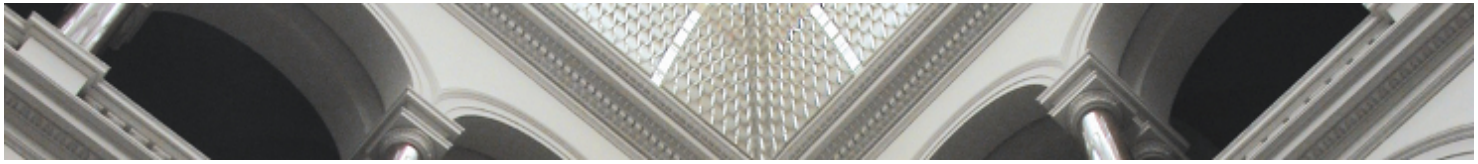
Experiment 2: More Explainable Models

1. LSTM [HS97] with tanh being replaced by ReLU (R-LSTM)
2. Stationary Dropout [GG16] (-SD)
3. Lateral Connections for convolutional layers (Conv^{+})





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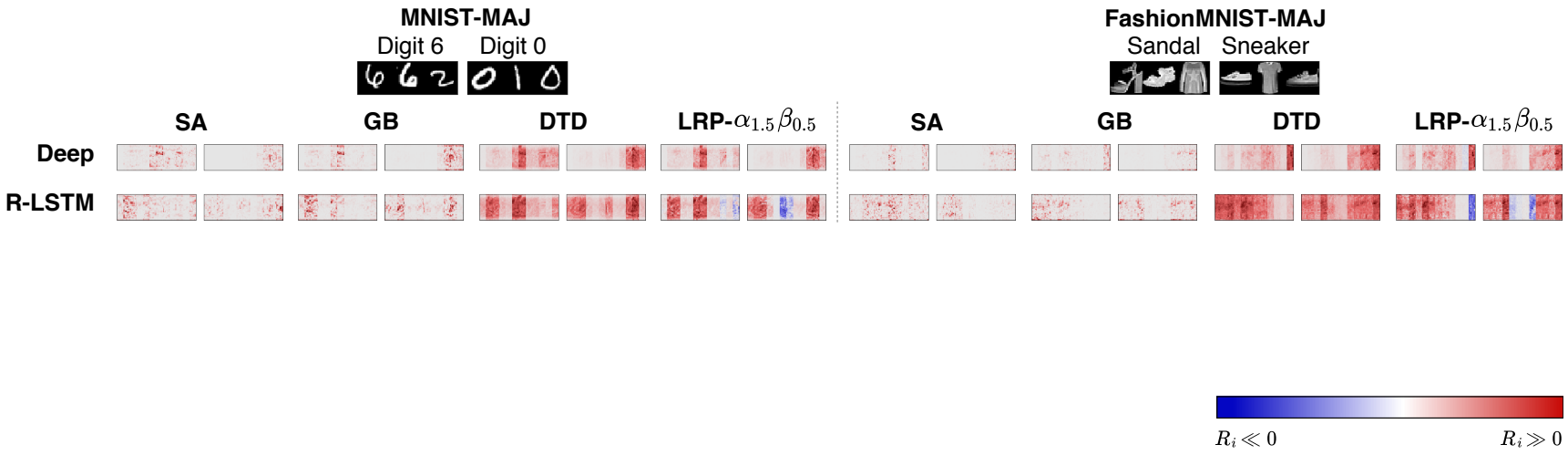
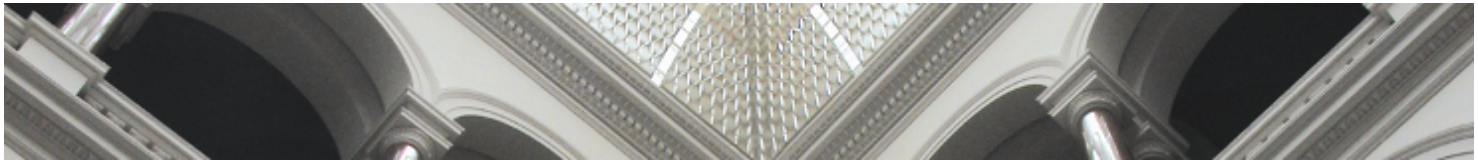
Experiment 2: More Explainable Models

Sample Relevance Heatmaps





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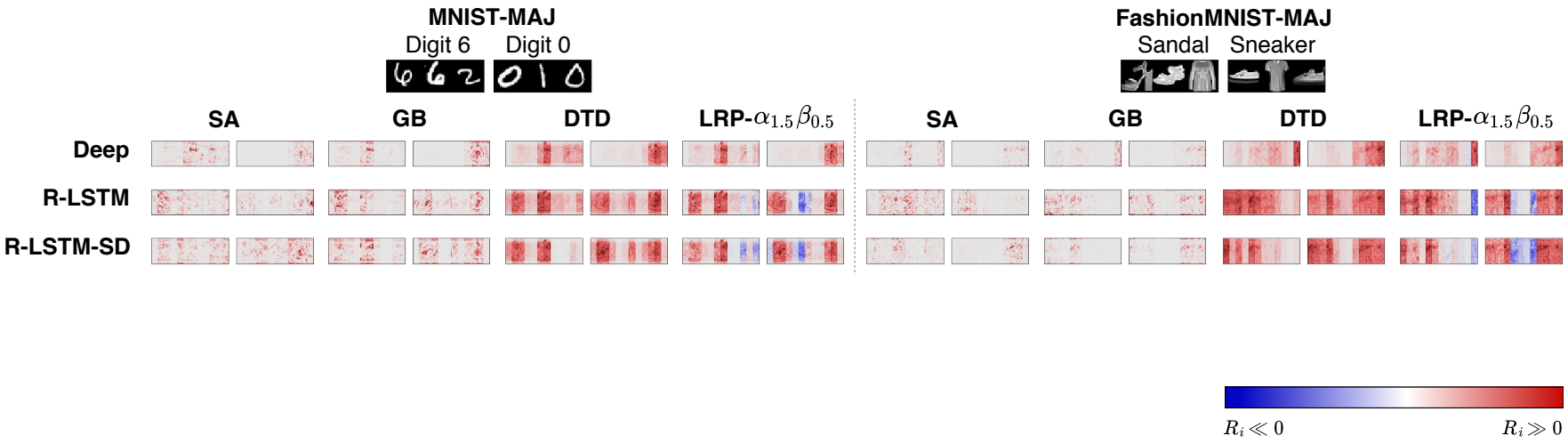

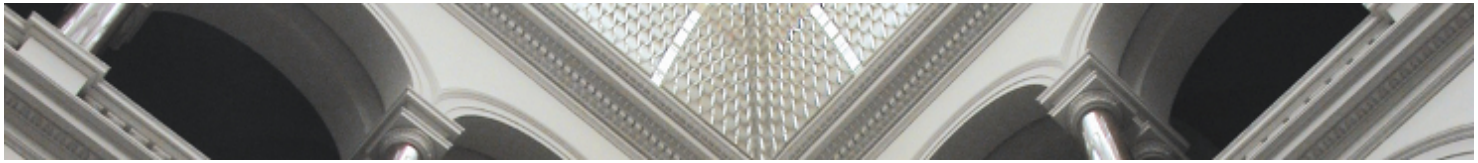

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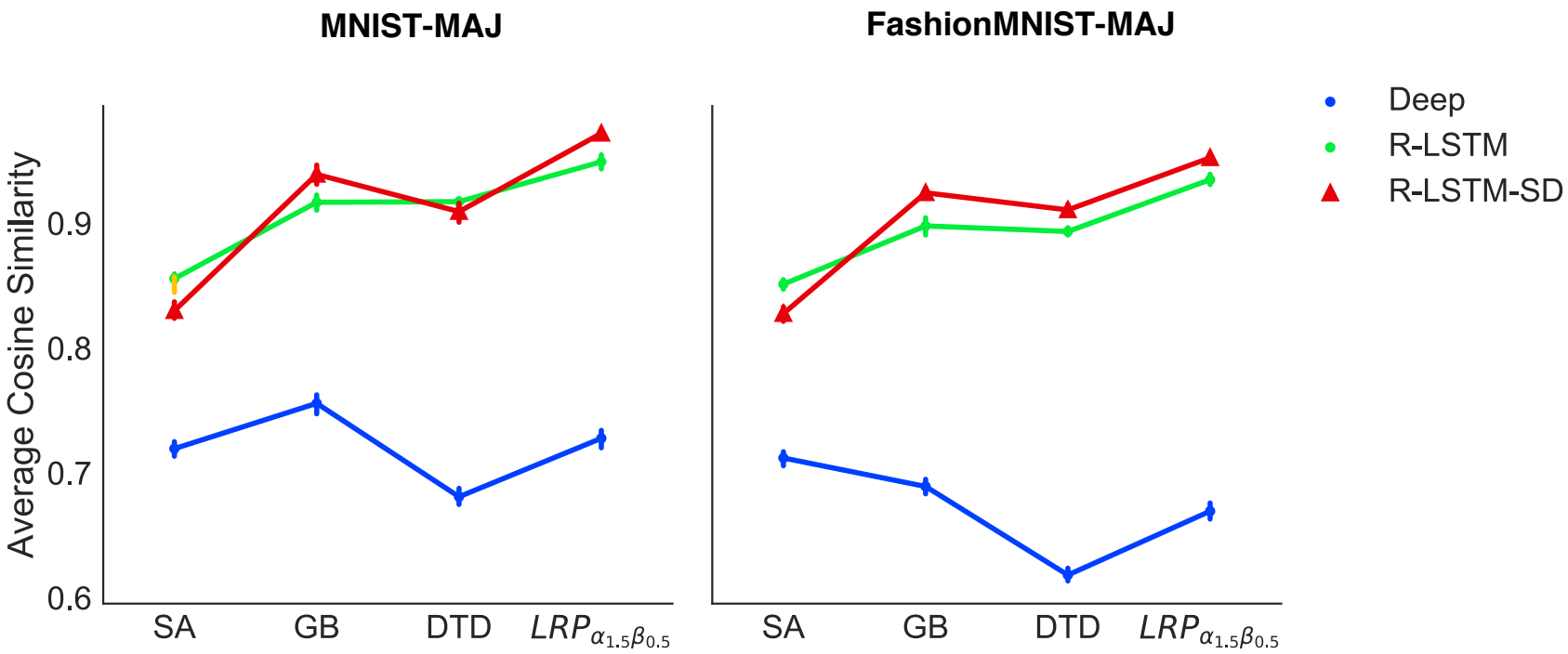
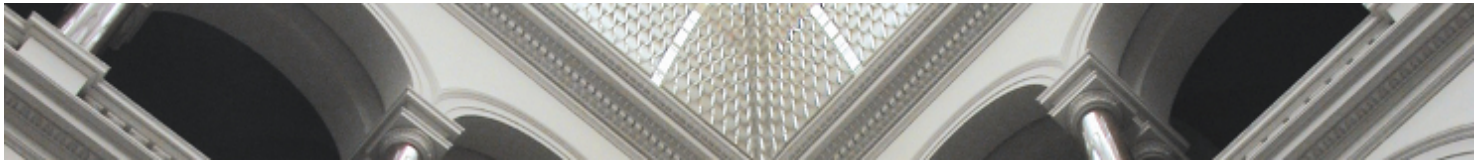
Experiment 2: More Explainable Models

Cosine Similarity Evaluation





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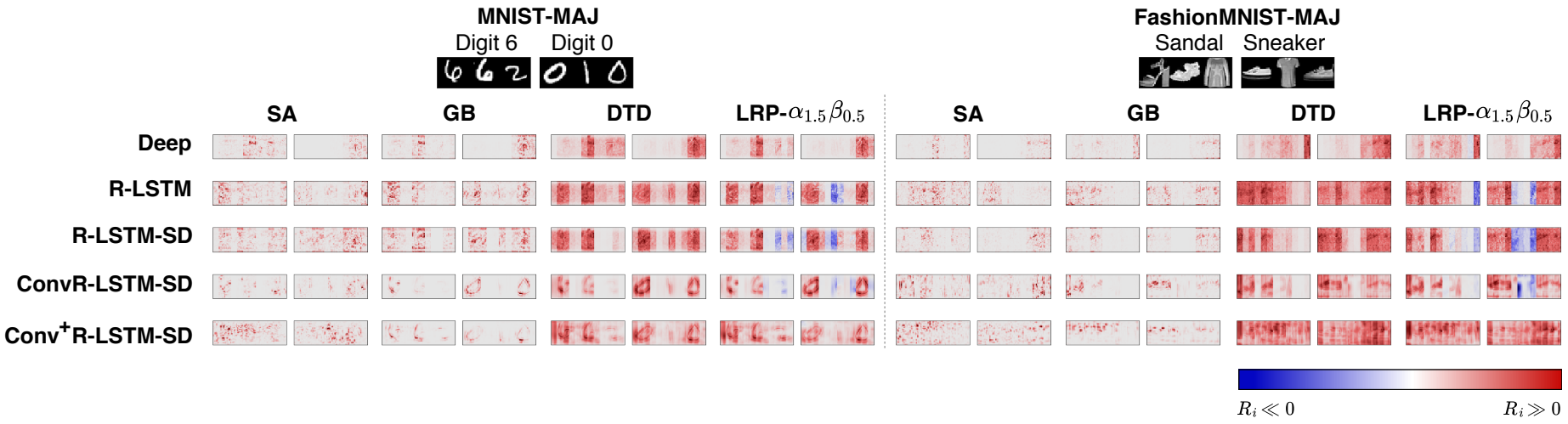
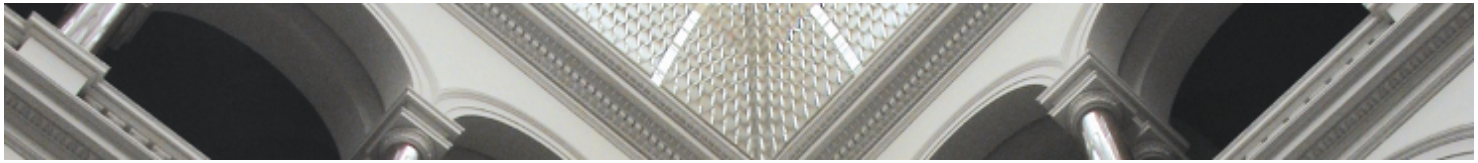
Experiment 2: More Explainable Models

Sample Relevance Heatmaps





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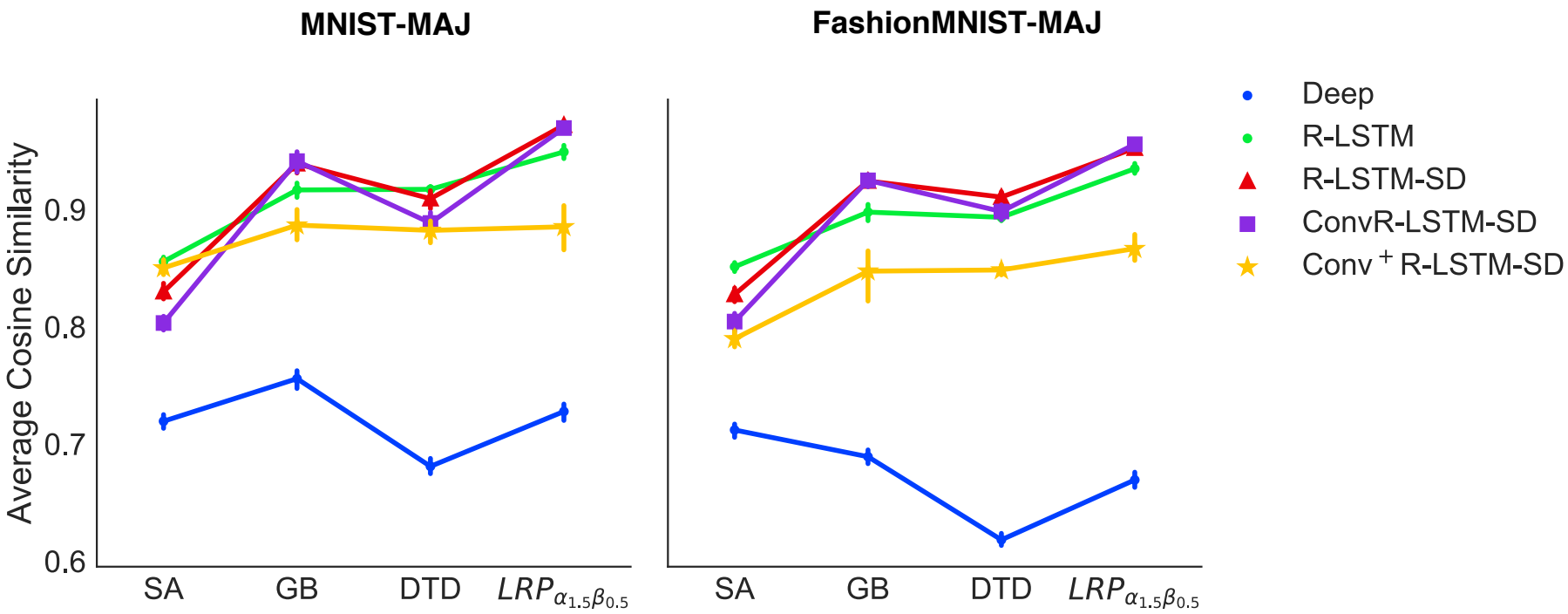
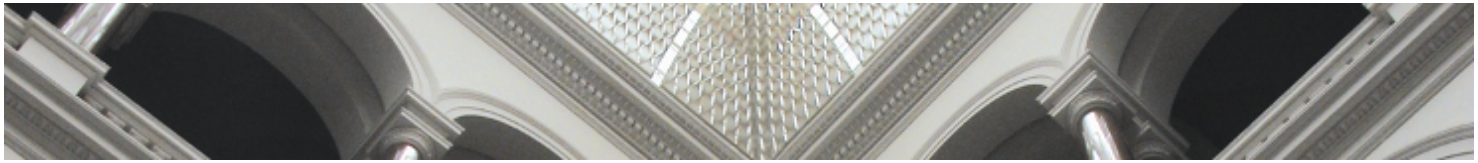
Experiment 2: More Explainable Models

Cosine Similarity Evaluation





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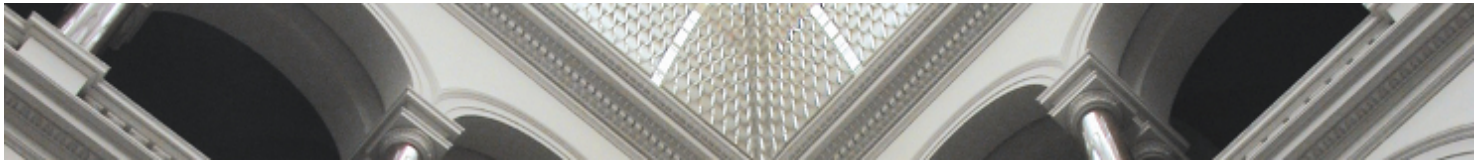
Conclusion

- **Deeper and LSTM-type RNNs** are more explainable.
- **Stationary dropout** could improve model's explainability.
- Explainability of RNNs should be considered in two aspects:
  - **Coarse-gained**: relevance adequately propagated to the relevant input steps
    — related to recurrent mechanism (solution: LSTMs)
  - **Fine-gained**: soundness of each input's explanation.
    — related to the choice of input layers (i.e. convolutional layer for image data)



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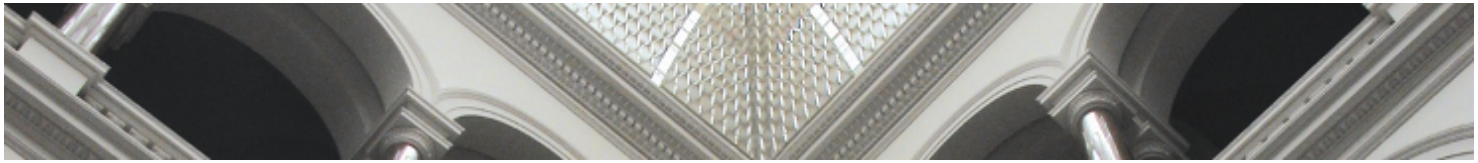

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